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PROJECT INFORMATION

Project Overview:

This project aims to develop an advanced predictive analytics system for analyzing and predicting crime trends and patterns in the city of Los Angeles. Crime has detrimental effects on a community and can create significant social and economic repercussions. Monitoring crime rates and using the data can potentially help improve policing in communities, leading to reduced crime.

The goal of the project will be to identify trends in the data. Do we see seasonality in crime rates, and can we predict when crime increases? Are there certain demographic conditions that result in increases in crime? Determining the answer to these questions can help identify when and where to staff police officers and can give insights into the types of social programs that can be implemented to reduce crime. By leveraging historical crime data and other relevant variables, the system will provide law enforcement, policymakers and communities with valuable insights to help them implement more effective prevention and response strategies. Data from other cities may be considered depending on the availability of data for additional cities for this project.

Project Objectives:

- Crime prediction: Use data-driven methods to predict the probability of crime occurrence in specific areas and time periods, thereby achieving crime prevention and optimal allocation of resources.
- Trend Analysis: Identify trends in crime rates and correlations with underlying social and economic factors to help develop more targeted policies and interventions.
- Hot area identification: Identify high-risk areas and time periods to provide police departments with targeted patrol and intervention recommendations to enhance community safety.
- Risk assessment: Evaluate the impact of different factors (such as weather, economic conditions, social activities, etc.) on crime rates to provide a basis for social services and preventive measures.

Project Questions:

- Using time series analysis such as ARIMA (autoregressive integrated moving average) can trends such as seasonality or large increases in crime be predicted? Can the crime rate be predicted for the entire city as well as smaller locations?
- Using clustering techniques such as K-means, can we predict the demographics that are likely to result in increased crime rates? Which components of demographics such as income and education have the largest influence on crime rates?
- Can a regression model be used to predict accurate crime rates? For example, does an increase in income directly result in a reduction in crime and can this decrease be modeled to predict how crime rates may change because of changes in income?

Overview of the Proposed Solution:

- Data Collection and Preparation
    - Download data from city of Los Angeles
        - Los Angeles Dataset: https://data.lacity.org/Public-Safety/Crime-Data-from-2020-to-Present/2nrs-mtv8/about_data
    - Download data from other potential cities if available
        - Philadelphia Dataset: https://opendataphilly.org/datasets/crime-incidents/
    - Download other data regarding city demographics that can be used to help identify causes of trends, such as socioeconomic and educational attainment data.
    - Perform an exploratory data analysis and generate descriptive statistics
    - Determine possible ways to combine the crime data with the demographic data
    - Determine possible methods and models that can be used to analyze the data
- Data Cleaning and Transformation
    - Combine the crime and demographic datasets.
    - Determine how to proceed with missing and incomplete data
    - Clean and transform the data as needed.
- Model Creation
    - Analyze trends using several time series analysis models.
    - Analyze crime and demographic info using cluster models.

- Finalize Report
    - Create the final report, detailing the methods and models used for the analysis.
    - Report on the trends and insights found after completing the project.

Expected results:

- Improve early warning capabilities: By predicting and identifying potential high-risk crime areas and time periods, measures can be taken in advance to reduce the incidence of crime.
- Resource Optimization: Provide data support to police departments to help them allocate resources and plan patrol routes more efficiently.
- Policy Support: Provide scientific evidence to policymakers to improve community safety policies and intervention strategies.
- Community Engagement: Increase community awareness and involvement in crime prevention and promote community-law enforcement cooperation.

DATASET

Project Data:

Data for the project will come from two sources, the Los Angeles city website and the Census website. Additional information can also come from the Philadelphia open data site if the project is expanded to include multiple cities. We will use socioeconomic data such as income and education level from the census to analyze the relationship between crime and socioeconomic factors and predict possible crime hotspots.

Links:

Los Angeles City Data
2010-2020:
https://data.lacity.org/Public-Safety/Crime-Data-from-2010-to-2019/63jg-8b9z/about_data
2020-Present: https://data.lacity.org/Public-Safety/Crime-Data-from-2020-to-Present/2nrs-mtv8/about_data
Data description: Each crime record includes date, location, type of crime, victim information, whether a weapon was used, etc. The data format is CSV for easy analysis. Two existing datasets need to be merged, involving more than 3 million criminal records.

Philadelphia Data:
https://opendataphilly.org/datasets/crime-incidents/
Data description: This website uses the Carto platform, supports SQL queries, and returns data in JSON format. Processing this data requires certain format conversions.

Census Data: https://data.census.gov/
Data description: Use ZIP code zoning (ZCTAs) for query and download. The data for each ZIP area includes socioeconomic factors, such as income, education level, etc. This data requires further processing in order to be integrated into predictive models.

Detailed Descriptions:
The Los Angeles data that will be used will come from the Los Angeles police department. Currently the Los Angeles police department releases crime statistics every two weeks. The current dataset includes crime from 2010 to present, split into two datasets that will be combined. There are the same 28 columns in both datasets, including things such as date, location, type of crime, victim information, and if any weapons were used.

The data for Los Angeles can be downloaded in CSV format, making the data easy to use. Each line represents a separate incident that occurred. There are over 3 million incidents recorded in the combined datasets. Below is an example and description of some of the data.

DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	Crm Cd Desc
190326475	03/01/2020 12:00:00 AM	03/01/2020 12:00:00 AM	2130	7	Wilshire	784	1	510	VEHICLE - STOLEN
200106753	02/09/2020 12:00:00 AM	02/08/2020 12:00:00 AM	1800	1	Central	182	1	330	BURGLARY FROM VEHICLE
200320258	11/11/2020 12:00:00 AM	11/04/2020 12:00:00 AM	1700	3	Southwest	356	1	480	BIKE - STOLEN
200907217	05/10/2023 12:00:00 AM	03/10/2020 12:00:00 AM	2037	9	Van Nuys	964	1	343	SHOPLIFTING-GRAND THEFT ($950.01 & OVER)
220614831	08/18/2022 12:00:00 AM	08/17/2020 12:00:00 AM	1200	6	Hollywood	666	2	354	THEFT OF IDENTITY
231808869	04/04/2023 12:00:00 AM	12/01/2020 12:00:00 AM	2300	18	Southeast	1826	2	354	THEFT OF IDENTITY
230110144	04/04/2023 12:00:00 AM	07/03/2020 12:00:00 AM	900	1	Central	182	2	354	THEFT OF IDENTITY
220314085	07/22/2022 12:00:00 AM	05/12/2020 12:00:00 AM	1110	3	Southwest	303	2	354	THEFT OF IDENTITY
231309864	04/28/2023 12:00:00 AM	12/09/2020 12:00:00 AM	1400	13	Newton	1375	2	354	THEFT OF IDENTITY
211904005	12/31/2020 12:00:00 AM	12/31/2020 12:00:00 AM	1220	19	Mission	1974	2	624	BATTERY - SIMPLE ASSAULT
221804943	01/21/2022 12:00:00 AM	07/01/2020 12:00:00 AM	1335	18	Southeast	1822	2	354	THEFT OF IDENTITY

LA Crime Data Dictionary

Attribute Name	Description	Data Format	Example
DR_NO	Division of Records Number: Official file number made up of a 2 digit year, area ID, and 5 digits	Integer	1307355
Date Rptd	Date Reported	MM/DD/YYYY	02/20/2010
DATE OCC	Date Occurred	MM/DD/YYYY	02/20/2010
TIME OCC	Time of incident in 24-hour format	Integer	1350
AREA	The LAPD has 21 Community Police Stations referred to as Geographic Areas within the department. These Geographic Areas are sequentially numbered from 1-21.	Integer	13
AREA NAME	The 21 Geographic Areas or Patrol Divisions are also given a name designation that references a landmark or the surrounding community that it is responsible for.	Text	Newton
Rpt Dist No	A four-digit code that represents a sub-area within a Geographic Area. All crime records reference the "RD" that it occurred in for statistical comparisons.	Integer	1385

Part 1-2	Not described, seems to indicate dataset number data originally came from.	Integer	2
Crm Cd	Indicates the crime committed. (Same as Crime Code 1)	Text	900
Crm Cd Desc	Defines the Crime Code provided.	Text	VIOLATION OF COURT ORDER
Mocodes	Modus Operandi: Activities associated with the suspect in commission of the crime.	Number (May contain spaces)	0913 1814 2000
Vict Age	Victim Age	Integer	48
Vict Sex	Victim Sex F - Female M - Male X - Unknown	Character	M
Vict Descent	Victim Descent Descent Code: A - Other Asian B - Black C - Chinese D - Cambodian F - Filipino G - Guamanian H - Hispanic/Latin/Mexican I - American Indian/Alaskan Native J - Japanese K - Korean L - Laotian O - Other P - Pacific Islander S - Samoan U - Hawaiian V - Vietnamese W - White X - Unknown Z - Asian Indian	Character	H
Premis Cd	The type of structure, vehicle, or location where the crime took place.	Integer	501
Premis Desc	Defines the Premise Code provided.	Text	SINGLE FAMILY DWELLING
Weapon Used Cd	The type of weapon used in the crime.	Integer	102
Weapon Desc	Defines the Weapon Used Code provided.	Text	HAND GUN
Status	Status of the case. (IC is the default)	Two Characters	AA
Status Desc	Defines the Status Code provided.	Text	Adult Arrest
Crm Cd 1	Indicates the crime committed. Crime Code 1 is the primary and most serious one. Crime Code 2, 3, and 4 are respectively less serious offenses. Lower crime class numbers are more serious.	Integer	900
Crm Cd 2	May contain a code for an additional crime, less serious than Crime Code 1.	Integer	815
Crm Cd 3	May contain a code for an additional crime, less serious than Crime Code 1.	Integer	930
Crm Cd 4	May contain a code for an additional crime, less serious than Crime Code 1.	Integer	998
LOCATION	Street address of crime incident rounded to the nearest hundred block to maintain anonymity.	Text	300 E GAGE AV
Cross Street	Cross Street of rounded Address	Text	MANCHESTER AV
LAT	Latitude	Floating Number	33.9825
LON	Longitude	Floating Number	-118.2695

Census data will be used for demographic information. Data can be queried by zip code and downloaded. The census website uses ZIP Code Tabulation Areas (ZCTAs). These areas mostly correspond to the zip codes used by the Postal Service, with only a small number of zip codes missing in the Census data that could result in a situation where the census data is deanonymized. Since this project uses zip codes in Los Angeles, this is not a concern for this project and all data for nearly every zip code used in Los Angeles is available.

The data for the census website is stored in tables where the data can be downloaded for each zip code. Data for ZCTAs can be downloaded in either Excel, CSV, or Zip format. This format requires some manipulation in order to use in a predictive model. An example of some of the data for 90210 (Beverly Hills) is shown below.

Data dictionaries for the census will be located in the Appendix as the amount of variables is far too large to include it the written section of the report.

The data for Philadelphia will come from the city of Philadelphia. This website uses Carto and allows SQL queries to retrieve the data. The returned data is in plain text in a single row and will require significant manipulation to use. It appears that the data may be in JSON format, which will allow the data to be easier to manipulate. An example of the data is shown below.

{"rows":
[{"cartodb_id":1,"the_geom":"0101000020E610000017429450F6D052C00C1997C3D1FC4340","the_geom_webmercator":"0101000020110F0000A3F89A4F18F65FC17B0D2F015F8C5241","objectid":113,"dc_dist":"19","psa":"1","dispatch_date_time":"2011-09-27T10:41:00Z","dispatch_date":"2011-09-27","dispatch_time":"06:41:00","hour":6,"dc_key":201119085906,"location_block":"7500 BLOCK WOODCREST AV","ucr_general":"600","text_general_code":"Theft from Vehicle","point_x":-75.26503386,"point_y":39.97515149},
{"cartodb_id":2,"the_geom":"0101000020E6100000A51C8299A5C752C006342AD3DCFF4340","the_geom_webmercator":"0101000020110F0000F80DE2A145E65FC1E5EC7592BE8F5241","objectid":114,"dc_dist":"25","psa":"3","dispatch_date_time":"2023-03-11T17:12:00Z","dispatch_date":"2023-03-11","dispatch_time":"12:12:00","hour":12,"dc_key":202325014482,"location_block":"3300 BLOCK HARTVILLE ST","ucr_general":"300","text_general_code":"Robbery No Firearm","point_x":-75.1194824,"point_y":39.99892654},

DATA PREPARATION

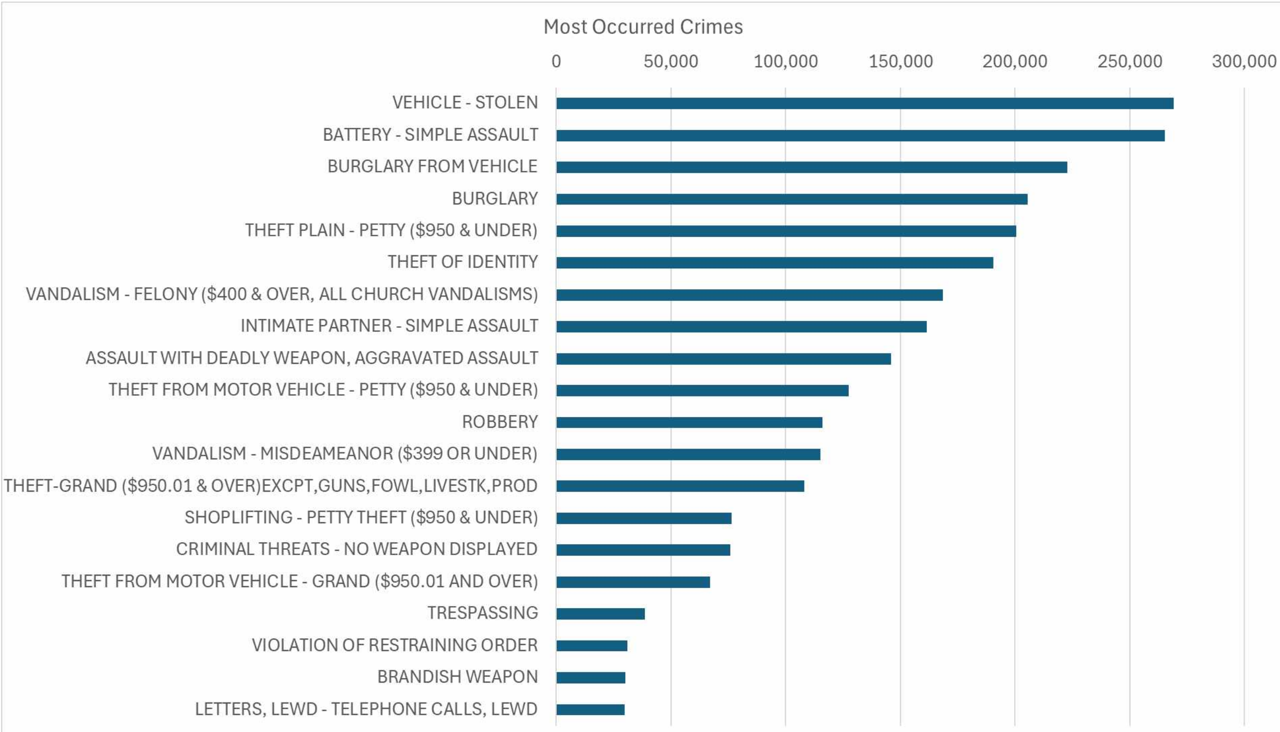
Data Cleaning:
Using the data downloaded from the Los Angeles police and Census websites, an analysis of the available data can be explored. The crime data will be explored first to check for any missing values and trends in the data.

The first step will be to look at any missing data in the crime dataset. The crime dataset contains 3,097,475 entries from 2010 until Sept 14, 2024. Each entry has one index number and 27 columns for attributes. The table below shows the number of values that are either missing or NA for each column that has missing data.

Attribute Name	Missing Entries	Attribute Name	Missing Entries
Crm.Cd.1	21	Vict.Descent	332,878
Crm.Cd.2	2,887,358	Premis.Cd	67
Crm.Cd.3	3,091,603	Premis.Desc	771
Crm.Cd.4	3,097,306	Weapon.Used.Cd	2,057,975
Mocodes	371,223	Status	4
Vict.Sex	332,822	Cross.Street	2,590,715

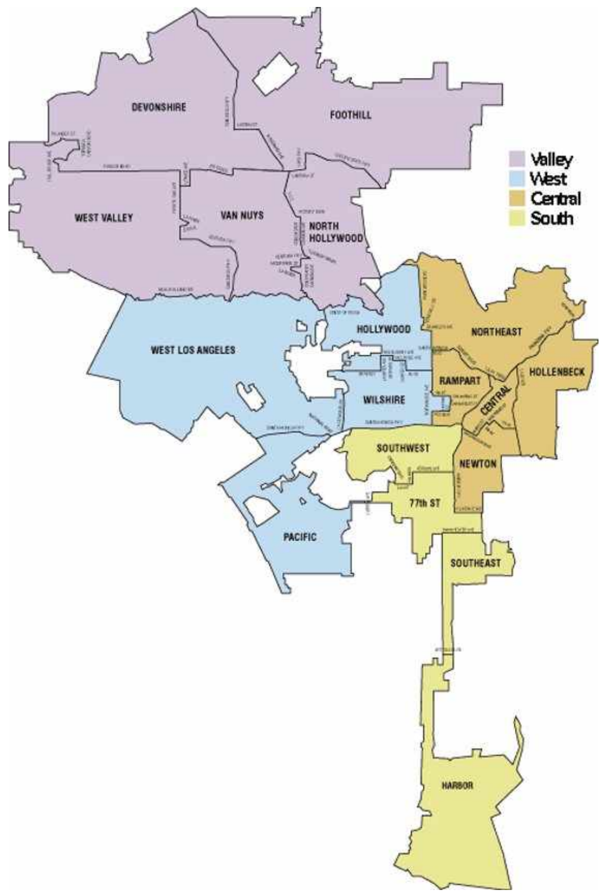
There are some important considerations regarding the missing data. Entries with a missing crime code will likely be discarded, as only 21 out of greater than three million incidents have a missing crime code. Most incidents only use 1 crime code, so there are many missing entries for crime codes 2-4. The most sever crime code appears in the crime code 1 column, so it is likely that only the crime code 1 column will be needed. Not all incidents have a weapon, some are non-violent crimes such as identity theft. In some cases, victim data does not exist. In these cases, victim age is set to 0 in the dataset. Victim data may not be needed for the analysis if the focus is only on the occurrence of crimes.

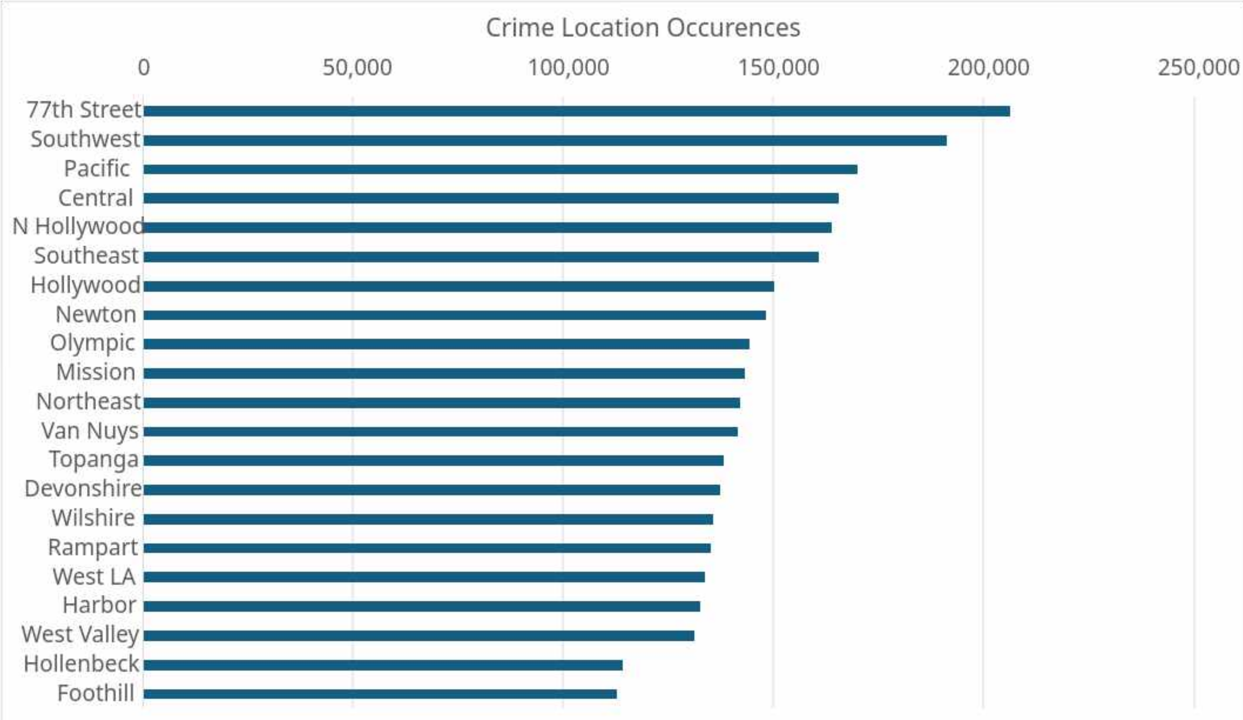
Some preliminary trends can be seen in the data and are shown in the charts below.



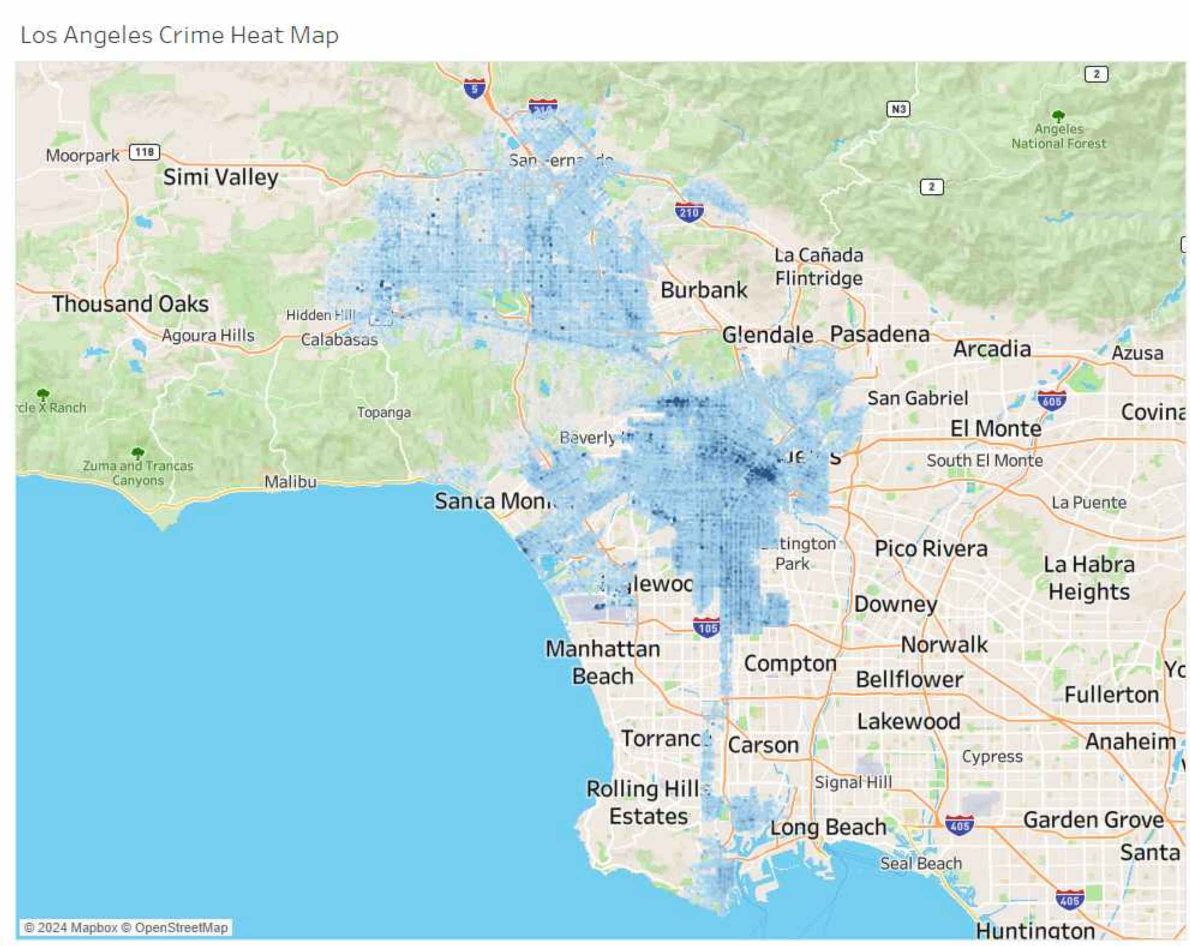
The most common crime occurring in the data set is stolen vehicle. Many of the other top crimes are some forms of theft or robbery. When cleaning the data, these different entries for theft and other crimes may need to be combined. The crimes can then be sorted into different categories such as violent and non-violent for the analysis.

A map of Los Angeles Police geographical locations from the Los Angeles police website is shown below. The area that the crime occurs is recorded for each entry in the crime dataset.



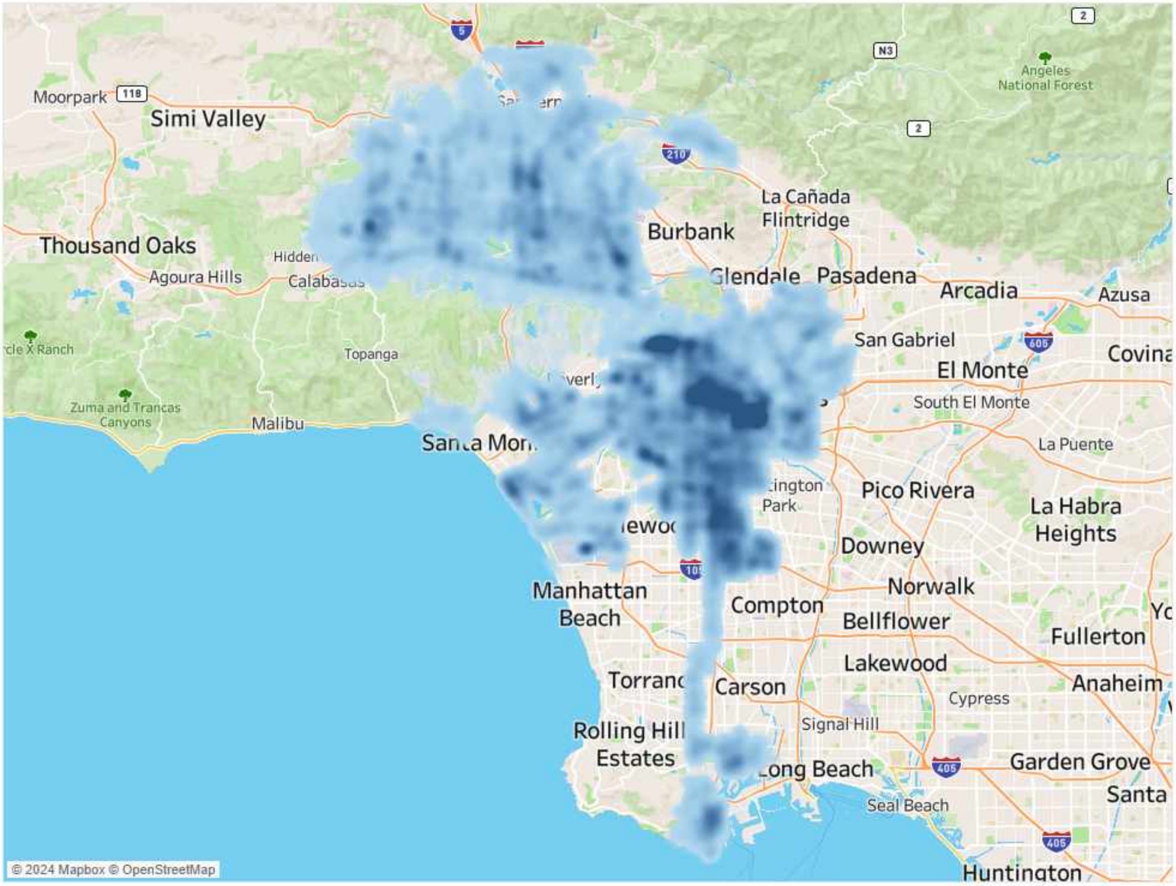


The summation of crime entries in each area shows that 77th Street has the most occurrences of crime. Crime occurrences are highest in the center of the city, such as in Southwest, Central, and Southeast. It may be possible that the reason the crimes are highest in these areas is simply that the population is also highest in these areas. When the datasets are combined, the rate per capita can be calculated to see if population alone is responsible for the higher occurrences in the center of the city.

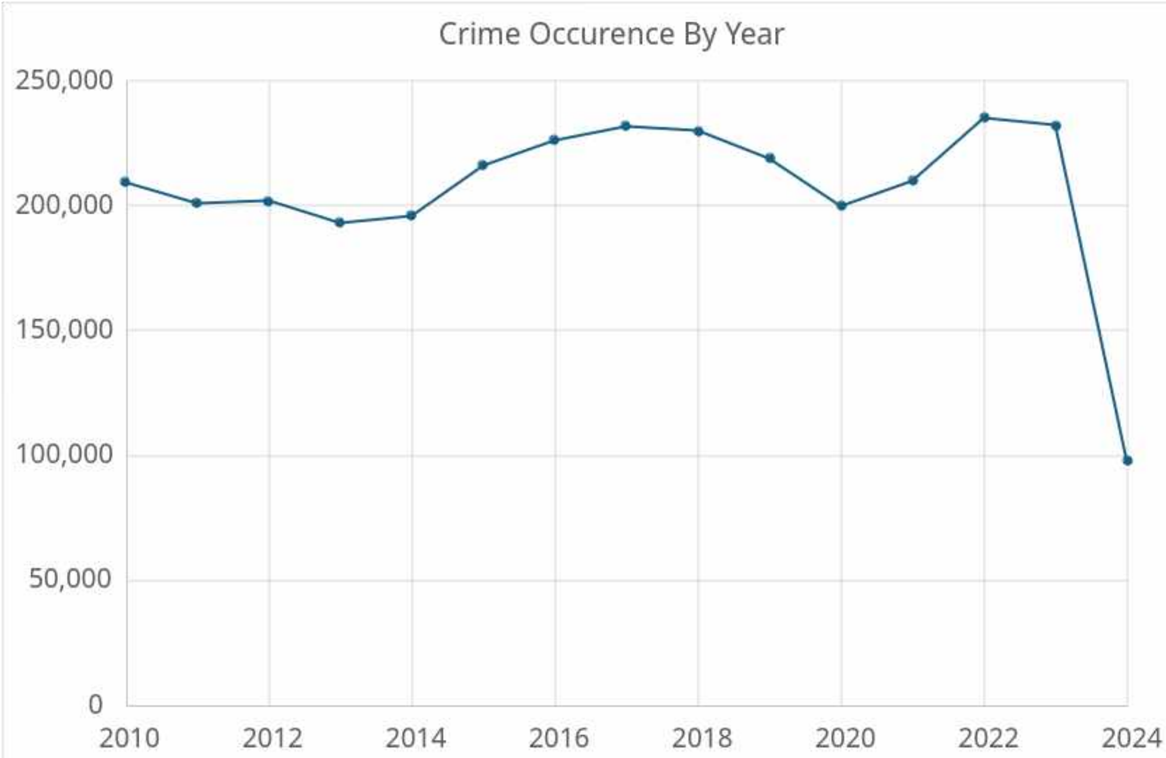


Looking at a heatmap for the occurrences of crime, the highest concentration represented by the dark blue appears in the central region of the city, as well as a high concentration of crime in a small section of the Hollywood area. This heat map has crimes grouped in small areas, so individual crimes tend to show as dots on this chart instead of being grouped together. The chart below shows the heatmap with larger areas where crimes are grouped together.

Los Angeles Crime Heat Map



In the second heatmap, grouping the crimes over larger areas still showed the highest concentrations in the central region and Hollywood. There are also darker areas in the 77th street and Southeast areas immediately north of Compton that were not initially observable when the crimes were grouped over smaller areas in the first chart. Overall, both charts show the crime has the highest occurrence in the center of the city.



Looking at crime occurrences over the years shows the number of occurrences is typically between 200,000 and 240,000 crimes reported each year. There was a rise in crime in 2015, peaking in 2017 before dropping. Crime started to rise again after 2020. Note that since this data was collected in 2024, the drop in 2024 is simply due only a partial year of data being available.

The project will use data from the DP (Demographic Profile) 02-05 tables. There are 679 demographic attributes available in these tables. Each attribute is available as an estimate of the number of occurrences such as people or households, or as a percentage of people or households. This data is available as 142 different zip code tabulation areas for the Los Angeles area.

An example of some of the available data is shown below. The code represents the table number and the entry number in the table. The E or PE represents estimated number or percent respectively. For example, the first entry in the table comes from DP02, entry 1. The entry is an estimate, which means the data is the total number of households in the zip code. By contrast, the second example in the table below is a percent, which gives the percent of the population that has a Bachelor’s degree above age 25.

Code	Description
DP02_0001E	Estimate-HOUSEHOLDS BY TYPE-Total households
DP02_0065PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree
DP03_0009PE	Percent-EMPLOYMENT STATUS-Civilian labor force-Unemployment Rate

Not all attributes will be used. The entry below gives an estimate of the number of grandparents living with their grandchildren under 18 years of age and have been responsible for them for 3 or 4 years. This information is very specific and will unlikely be useful as more general attributes will likely perform better for crime rate prediction.

DP02_0048E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-3 or 4 years

Due to the large number of attributes (679 available), we will not be able to use every attribute from the Census data. We will instead start with the attributes that are shown on the overview page of a zip code on the Census website. It is likely that these attributes that the Census Bureau considers important will also be a good starting point for our analysis. Our analysis will start with the main attributes used to describe an area profile on the census website. This would include attributes such as population, median income, percent with bachelor's degree, employment rate, and percent without health insurance. An example of the profile data on the Census website is shown below.

The data will need to be combined between the Los Angeles crime dataset and the Census profile tables. 142 zip code tabulation areas used in Los Angeles by the Census. The Los Angeles police department uses 21 geographical areas. There are two possible methods to combine the data:

- Option 1: Assign each zip code to one of the 21 geographical areas and combine the census data for each zip code into the 21 geographical areas.
- Option 2: Use the latitude and longitude data to determine zip code for each crime. There are some python packages or Tableau using zip code shape data could do this.

DATA TRANSFORMATION

Combining Data

The Los Angeles crime dataset and Census data were combined together to form one table that can be used for generating models. Variable selection will be performed using this combined table. A smaller table that uses crime rate per capita instead of all crimes was also created that can be used for generating models. Code for this section is located in the Appendix.

The Los Angeles crime dataset exist as two large CSV tables, from 2010-2019 and 2020-present. These two tables were downloaded from the Los Angeles City website. Since both datasets feature the exact same columns, the rows from the 2020-present table were simply added to the 2010-2019 table to combine the data.

The next step needed for the crime dataset is to add Zip Codes for each crime occurrence. The crime dataset lists location as coordinates, while the Census dataset uses Zip Codes. To create a Zip Code for each crime, Tableau was used with a shape data file from the link below. An intersect between the coordinate data and the shape data geometry was created that allowed each coordinate to be placed in a Zip Code. The Zip Code was added to the crime dataset and exported from Tableau.

Link for shape file:
https://datablends.us/2017/07/31/a-useful-usa-zip-code-shapefile-for-tableau-and-alteryx/

With Zip Codes added to the crime dataset, the next step was to prepare the Census data to be linked. Demographic Profile (DP) tables 02 to 05 were downloaded using code from Kevin Durkin, available in the Appendix. Each DP had multiple tables for each year data was available. For example, DP02-2011, DP02-2012, etc.

The data was originally downloaded in Excel format. In order to load the data easily in R, the data needed to be converted to CSV format and the years for each DP combined. All DPs would then be combined into one large table.

Excel files were converted to CSV using Libreoffice. The CSV files were then loaded into R and the different years for each DP were combined to form one large table for each DP. Newer Census data had more columns than older data so columns needed to be added to older years and filled with NA. As an example, DP02_0154E (Estimate of total households with a broadband Internet subscription) is in the 2020-2022 data but not in earlier data. This column was added to the earlier years and filled with NA.

Each row in the DP tables has year, Zip Code, and the demographic data columns. This allows the DP tables to be merged together using year and Zip Code. All tables were merged together to form one DP table that contains all demographic columns.

After completing these steps, both the crime dataset and the Census dataset now have both year and Zip Code data:

Crime Data:

Year	Zip Code	Crime Data Columns

Census Data:

Year	Zip Code	Census Demographic Data Columns

Data between the two data sets can now be merged. The demographic data columns were added to each crime occurrence corresponding to the year and Zip Code.

Variable Selection

Now that the data has been combined, the variables can be selected for the model. The Census contains a large number of attributes (679 available). This number will need to be reduced for our analysis.

We have multiple approaches that will be tried for variable selection:

1. Our analysis will start with the main attributes used to describe an area profile on the census website. This would include variables such as population, median income, percent with bachelor's degree, employment rate, percent without health insurance, etc.

2. PCA (Principle Component Analysis) can also be used to reduce the number of variables. The large number of variables will require splitting the variables into subgroups and applying PCA to each subgroup. This will however result in a loss in of some information as the individual variables will not be used in the model. Some

information can still be obtained by using the weights of each PCA variable to determine how much each demographic attribute contributes to the PCA variable.

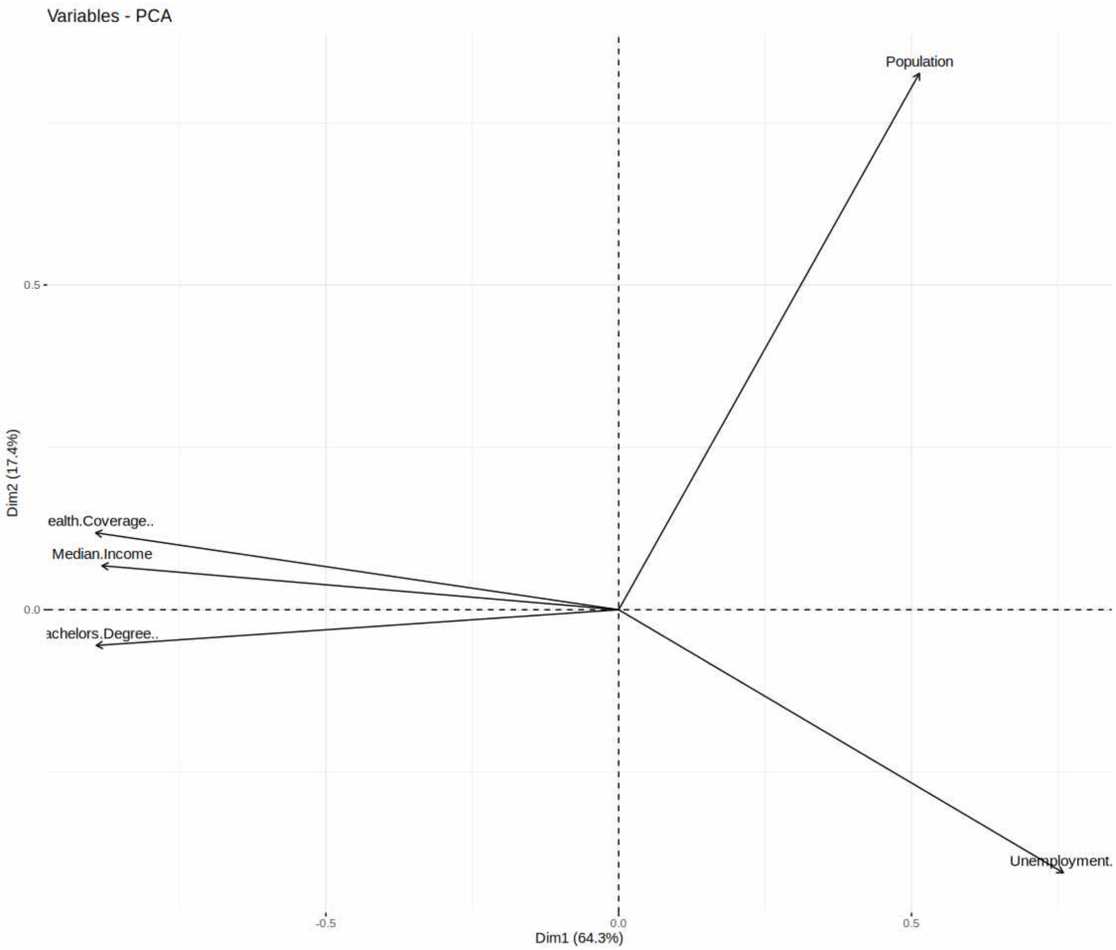
3. Boruta can also be used to help with variable selection. Variables that are not relevant can be removed, keeping variables that have a greater effect on the model.

Crime Rate

One of the goals of the project is to predict the crime rate. In order to compare multiple Zip Codes, the crime occurrences need to be converted to a rate. This was done by dividing the count of reported crimes by the population for a Zip Code to create a crime rate for each year and Zip Code. The demographic information will then be tied to the crime rate using the year and Zip Code. This creates a much smaller table, with only 1407 rows total compared to over 3 million rows when using each individual crime. This will be used as a starting point when generating models.

Preliminary PCA

An example of PCA using only a few variables are shown below. The variables were scaled prior to the PCA. In this example, the variables population, household income, unemployment rate, bachelor's degree attainment, and health coverage rate were used. The initial analysis shows that bachelor's degree attainment, health coverage, and income are correlated with each other. The unemployment rate and population appears to be not correlated with each other and only weakly negatively correlated with bachelor's degree attainment, health coverage, and income. This analysis will be expanded during the next assignment and used to select the variables for model creation.


Variables - PCA
Population
Unemployment.
ealth.Coverage..
Median.Income
achelors.Degree..
Dim2 (17.4%)
Dim1 (64.3%)
0.5
0.0
-0.5
0.0
0.5

VARIABLES

Variable Selection

Variable selection will be performed using three different methods. The first method will simply use eight variables that are used on the overview page of each Zip Code on the Census Bureau's website. The second method will use PCA to reduce the variables down to principle components. A third method will use boruta for feature selection.

The data for the project is currently in the following format below. Attributes that will not be used will be dropped from the dataset.

Zip Code	Year	Crime Rate	Demographic Attribute Columns

Method 1 – Census Website

This method will use the eight attributes that are listed on the Census website for an overview of the Zip Code. The number of employer establishments will be excluded since that data is not used in the American Community Survey data used for this project. It is assumed that since these attributes are listed first when viewing a zip code that the Census Bureau considers these some of the most important attributes to represent an area. These attributes will be tested to see if an effective model for predicting crimes rates can be created with only these attributes.

An example of the Census website is shown below. The eight variables that will be used for this method are:

DP02_0001E	Total Households
DP05_0001E	Total Population
DP03_0009PE	Unemployment Rate
DP03_0051E	Median Household Income
DP04_0001E	Total Housing Units
DP02_0065PE	Percent Population with Bachelor's Degree
DP03_0099PE	Percent without Health Insurance
DP05_0072PE	Percent Hispanic

Census Website Zip Code Overview

A simple linear regression model was created using only the eight attributes to evaluate if this method of variable selection appears to be usable for model creation. Note that these are quick tests to see if the data makes sense for predicting crime rates. Data was not split into test and train datasets, which will be performed in the following section of model evaluation.

```
Residuals:
    Min      1Q  Median      3Q     Max 
-0.2341 -0.0680 -0.0141  0.0318 11.3365 

Coefficients: (1 not defined because of singularities)
             Estimate   Std. Error   t value   Pr(>|t|)    
(Intercept)  0.064501     0.008351     7.724   2.05e-14 ***
DP02_0001E  -0.561831     0.127108    -4.420   1.06e-05 ***
DP03_0009PE -0.033946     0.009725    -3.491   0.000496 ***
DP03_0051E         NA           NA        NA         NA    
DP04_0001E   0.509627     0.126709     4.022   6.06e-05 ***
DP02_0065PE -0.084971     0.014220    -5.975   2.87e-09 ***
DP03_0099PE -0.032159     0.013344    -2.410   0.016076 *  
DP05_0072PE  0.005464     0.008566     0.638   0.523695    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3237 on 1496 degrees of freedom
Multiple R-squared:  0.04481,   Adjusted R-squared:  0.04098 
F-statistic:  11.7 on 6 and 1496 DF,  p-value: 7.663e-13
```

The basic model had an R-squared value of 0.04, indicating that these attributes are not enough to explain the variance and that additional data will be needed for predicting crime rates.

Method 2 – PCA

PCA will be used to reduce the variable list from the nearly 700 attributes to a much smaller number. Due to the considerable number of attributes, several smaller subsections of attributes will be used for multiple PCAs. The component variables of each PCA will then be added back together in a larger dataset that can be used for model creation.

Category information

The demographic attributes of the Census data is divided into four tables each with multiple subcategories. Each subcategory will be used for a separate PCA. The example below shows the first three categories of

Demographic Profile Table 2. Each variable is part of a subgroup such as Household or Relationship.

DP02_0001	HOUSEHOLDS BY TYPE-Total households
DP02_0002	HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02_0003	HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02_000	HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02_0005	HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02_0006	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02_0007	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02_0008	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02_0009	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0010	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02_0011	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years
DP02_0012	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone
DP02_0013	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0014	HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years
DP02_0015	HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over
DP02_0016	HOUSEHOLDS BY TYPE-Total households-Average household size
DP02_0017	HOUSEHOLDS BY TYPE-Total households-Average family size
DP02_0018	RELATIONSHIP-Population in households
DP02_0019	RELATIONSHIP-Population in households-Householder
DP02_0020	RELATIONSHIP-Population in households-Spouse
DP02_0021	RELATIONSHIP-Population in households-Unmarried partner
DP02_0022	RELATIONSHIP-Population in households-Child
DP02_0023	RELATIONSHIP-Population in households-Other relatives
DP02_0024	RELATIONSHIP-Population in households-Other nonrelatives
DP02_0025	MARITAL STATUS-Males 15 years and over
DP02_0026	MARITAL STATUS-Males 15 years and over-Never married
DP02_0027	MARITAL STATUS-Males 15 years and over-Now married, except separated

DP02_0028	MARITAL STATUS-Males 15 years and over-Separated
DP02_0029	MARITAL STATUS-Males 15 years and over-Widowed
DP02_0030	MARITAL STATUS-Males 15 years and over-Divorced
DP02_0031	MARITAL STATUS-Females 15 years and over
DP02_0032	MARITAL STATUS-Females 15 years and over-Never married
DP02_0033	MARITAL STATUS-Females 15 years and over-Now married, except separated
DP02_0034	MARITAL STATUS-Females 15 years and over-Separated
DP02_0035	MARITAL STATUS-Females 15 years and over-Widowed
DP02_0036	MARITAL STATUS-Females 15 years and over-Divorced

Data form and limitations

The percentage form of each attribute was used. Nearly all attributes have a percentage form except for the population types. An example of this is DP02_0001 HOUSEHOLDS BY TYPE-Total households, DP02_0016 HOUSEHOLDS BY TYPE-Total households-Average household size, and DP02_0017 HOUSEHOLDS BY TYPE-Total households-Average family size. These attributes were excluded since they are either summations or averages that do not have a percentage form.

It may be possible to add variables that use averages back into the analysis but total population attributes will remain excluded as the analysis is based on rate of crimes per capita. Total population attributes cannot be represented as a percentage or per capita basis, and zip code sizes vary, so they cannot be used to compare different zip codes in this analysis.

Another problem with the dataset is that percentage data is not available for many variables starting in 2019. The Census data spans from 2011-2022. An example of this is DP02_0025 MARITAL STATUS-Males 15 years and over. This attribute has percentage data from 2011-2018, representing the percent of the population that is male and 15 years or older. Starting in 2019, the data is only available as total population. Many attributes have this issue and so initially these variables have been excluded.

The effect of this exclusion will need to be examined during model creation. Removing a large number of attributes may result in a model that is missing data needed to account for the variance. If a low R^2 value exist in the regression model, then the variable selection will have to be reconsidered. There are two methods that can then be used. Either the data from 2019 and after can be removed, which would still give eight years of data from 2011-2018, or the missing percentages will need to be calculated for 2019-2022. Calculating the missing values is possible, but will require addition data transformation, as the population data for that attribute will need to be divided by the total population located in another column in order to create percentage data.

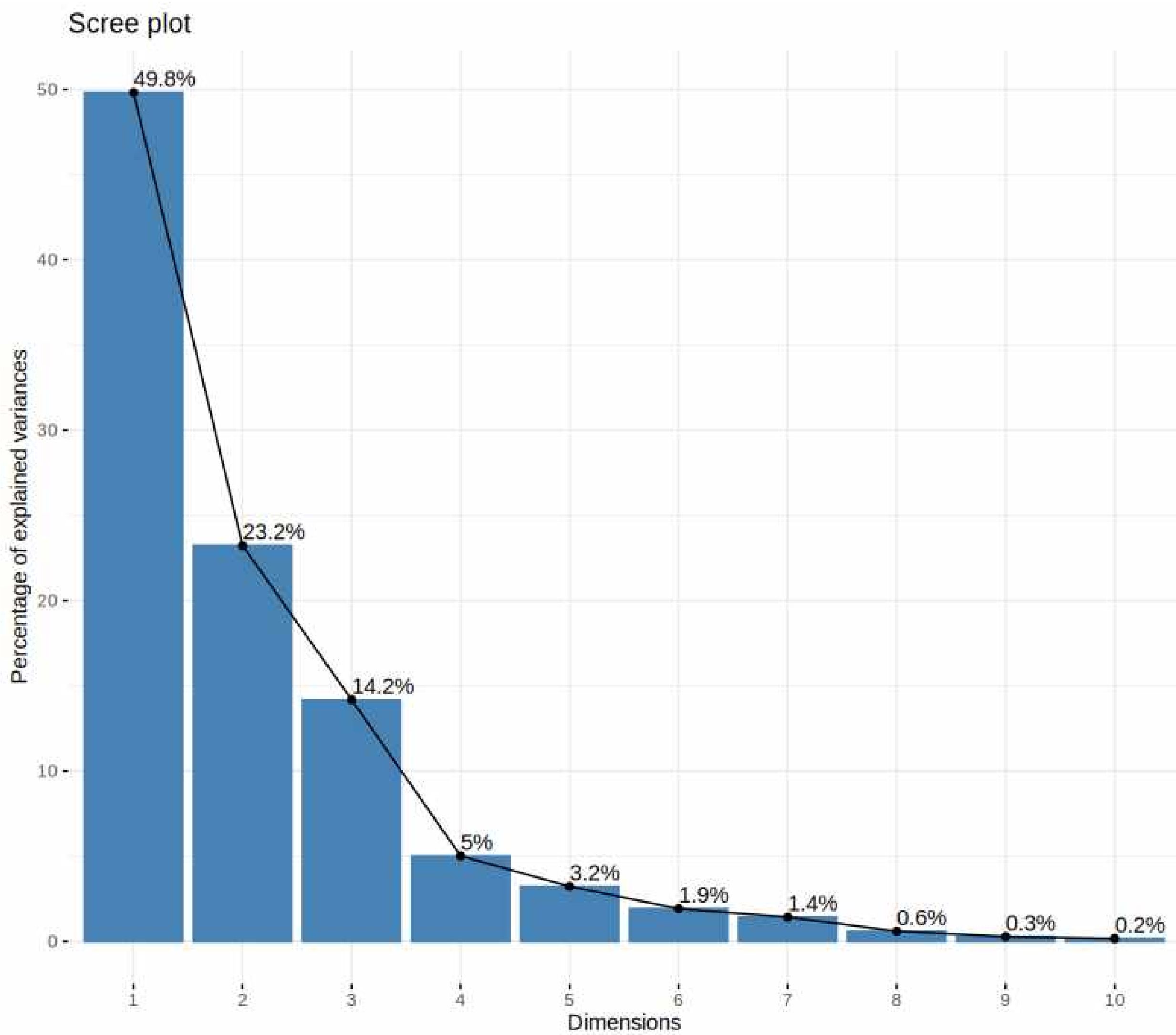
PCA Example – Household Data

An example of a PCA using the household data will be described to show the process of creating the variables for models. In this example, the variables that were used are shown below. DP02_0015 HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over was not used as the data appears unclear in the Census dataset. Percentages for 2011-2018 do appear to be available, but they are located in the wrong column. Percentages are available starting in 2019. Additional data cleaning would be needed to use the DP02_0015 attribute.

DP02_0002	HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02_0003	HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02_000	HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02_0005	HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02_0006	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02_0007	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02_0008	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02_0009	HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0010	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02_0011	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years
DP02_0012	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone
DP02_0013	HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0014	HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years

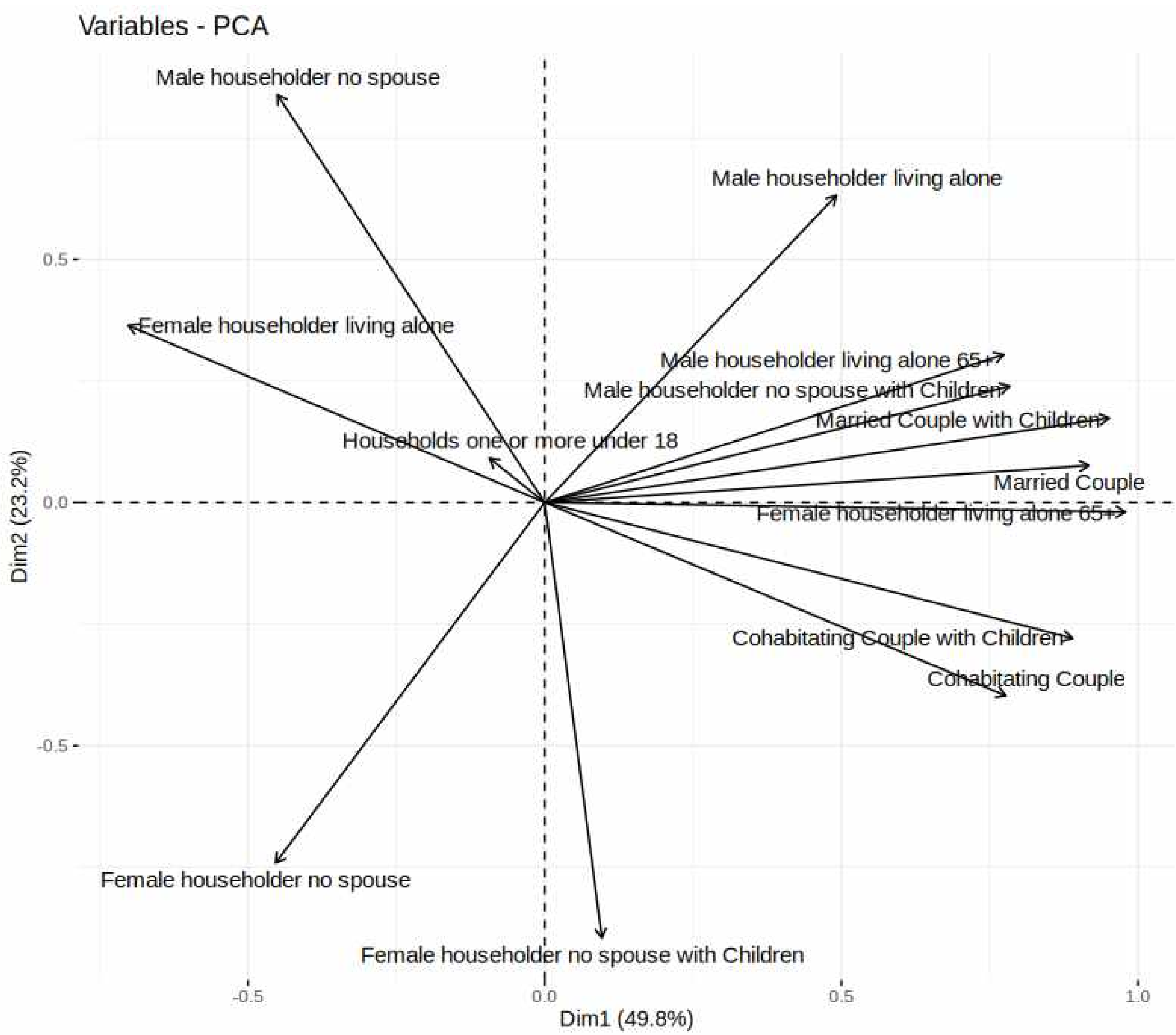
Performing PCA on these attributes gave the following results:

```
                          Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
Standard deviation     2.5439991 1.7374087 1.3573475 0.80687409 0.64680483
Proportion of Variance 0.4982094 0.2323710 0.1418274 0.05011752 0.03220509
Cumulative Proportion  0.4982094 0.7305804 0.8724078 0.92252527 0.95473036

                           Comp.6     Comp.7     Comp.8      Comp.9     Comp.10
Standard deviation     0.49936067 0.43001217 0.27709590 0.187610306 0.145827685
Proportion of Variance 0.01919582 0.01423441 0.00591069 0.002709514 0.001637035
Cumulative Proportion  0.97392618 0.98816059 0.99407128 0.996780797 0.998417831

                            Comp.11      Comp.12      Comp.13
Standard deviation     0.1073701252 0.0759047022 0.0571236373
Proportion of Variance 0.0008874521 0.0004435222 0.0002511943
Cumulative Proportion  0.9993052836 0.9997488057 1.0000000000
```



The PCA summary shows that the first two components account for 73% of the variance and three components account for 87% of the variance. This allows for the household data to be reduced from 13 variables to only two or three variables. The composition of each component is shown below as well as the correlation chart.

```
Loadings:
            Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7
DP02_0002PE  0.360         0.240                0.215  0.246
DP02_0003PE  0.374  0.100        -0.116         0.106  0.276
DP02_0004PE  0.305 -0.229  0.179  0.475        -0.203 -0.241
DP02_0005PE  0.350 -0.161  0.121  0.311  0.103 -0.217 -0.193
DP02_0006PE -0.177  0.483                0.193 -0.333 -0.347
DP02_0007PE  0.308  0.138 -0.220 -0.373        -0.723  0.264
DP02_0008PE  0.193  0.364 -0.362  0.161 -0.319  0.140 -0.470
DP02_0009PE  0.304  0.175 -0.323 -0.176 -0.337  0.343
DP02_0010PE -0.178 -0.427 -0.342        -0.169 -0.130
DP02_0011PE        -0.516 -0.264        -0.302        -0.122
DP02_0012PE -0.276  0.210         0.579 -0.467 -0.177  0.527
DP02_0013PE  0.385                0.144
DP02_0014PE                0.632 -0.312 -0.626 -0.164 -0.242

            Comp.8 Comp.9 Comp.10 Comp.11 Comp.12 Comp.13
DP02_0002PE  0.494  0.132  0.108   0.233   0.160   0.590
DP02_0003PE -0.471  0.467         -0.351   0.403  -0.104
DP02_0004PE  0.153 -0.396  0.207  -0.290   0.396  -0.182
DP02_0005PE -0.434        -0.126          -0.528   0.394
DP02_0006PE -0.196  0.103  0.401   0.319   0.301   0.228
DP02_0007PE  0.238 -0.102         -0.159  -0.111
DP02_0008PE  0.278  0.290 -0.315  -0.265
DP02_0009PE -0.291 -0.549  0.316                   0.123
DP02_0010PE -0.183        -0.386           0.478   0.445
DP02_0011PE  0.110  0.428  0.561   0.116  -0.122
DP02_0012PE
DP02_0013PE               -0.302   0.721   0.129  -0.420
DP02_0014PE
```



Variables - PCA
Male householder no spouse
Male householder living alone
Female householder living alone
Male householder living alone 65+
Male householder no spouse with Children
Married Couple with Children
Households one or more under 18
Married Couple
Female householder living alone 65+
Cohabitating Couple with Children
Cohabitating Couple
Female householder no spouse
Female householder no spouse with Children
0.5
0.0
-0.5
-0.5
0.0
0.5
1.0
Dim2 (23.2%)
Dim1 (49.8%)

PCA was repeated for each subcategory in the dataset. The predict function was then used to transform the initial Census dataset into the component variables for each subcategory. The top components for each subcategory where then selected to create a dataset that can be used for models. An example of the transformed variables using the showing the household, relationship, and marital attributes is shown below. Each subcategory typically has three or four component variables included in the dataset. Note that columns are continued across the row, but split below to be readable in this report.

Row	Household_Comp.1	Household_Comp.2	Household_Comp.3
1	5.992	2.334	-1.15
2	6.023	2.496	-1.207
3	5.813	2.625	-1.401

Row	Relationship_Comp.1	Relationship_Comp.2	Relationship_Comp.3
1	-2.445	-0.6771	0.7005
2	-2.499	-0.7605	0.7292
3	-2.471	-0.9421	0.763

Row	Marital_Comp.1	Marital_Comp.2	Marital_Comp.3	Marital_Comp.4
1	-0.3677	-0.0803	1.314	-0.7707
2	-0.191	-0.3822	1.226	-0.4217
3	-0.4264	-0.556	1.351	-0.5841

Regression Model

This method was also tested using a linear regression using only the DP02 table attributes. Only the first 10 variables are shown for the model below due to formatting.

```
Residuals:
    Min      1Q  Median      3Q     Max
-2.0291 -0.3492 -0.0234  0.2889  8.3590
Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)          -4.711e-17  1.944e-02   0.000 1.000000
Household_Comp.1     -1.411e-01  3.922e-02  -3.599 0.000332 ***
Household_Comp.2     -1.974e-01  6.162e-02  -3.204 0.001390 **
Household_Comp.3     -1.384e-01  3.291e-02  -4.205 2.78e-05 ***
Relationship_Comp.1   4.529e-01  9.587e-02   4.724 2.56e-06 ***
Relationship_Comp.2   7.405e-01  7.188e-02  10.302  < 2e-16 ***
Relationship_Comp.3   3.729e-01  1.556e-01   2.397 0.016665 *
Marital_Comp.1        5.316e-02  5.462e-02   0.973 0.330576
Marital_Comp.2       -1.500e-01  3.851e-02  -3.897 0.000102 ***
Marital_Comp.3        2.018e-01  3.644e-02   5.540 3.65e-08 ***
Marital_Comp.4       -3.185e-01  3.557e-02  -8.955  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.7147 on 1321 degrees of freedom
Multiple R-squared:  0.5005,     Adjusted R-squared:  0.4892
F-statistic: 44.13 on 30 and 1321 DF,  p-value: < 2.2e-16
```

The model shows an adjusted R-squared value of 0.49, a significant improvement from the model generated using only eight variables. The R-squared value is still low however, indicating the some of the variance is still unexplained. Additional attributes will be included the model creation section of the report to see if adding the remaining attributes improves the R-squared value.

Method 3 – Boruta

The last method of variable selection was performed using Boruta. This method takes the variables as they are and determines the most important variables for calculating crime rate. An example of the Boruta analysis for the DP02 data is shown below. Models created in the model creation section will use the full Census dataset.

```
Boruta performed 999 iterations in 5.920013 mins.
 66 attributes confirmed important: DP02_0002PE, DP02_0003PE, DP02_0004PE,
DP02_0005PE, DP02_0006PE and 61 more;
 No attributes deemed unimportant.
 1 tentative attributes left: DP02_0028PE;
```

The only tentative attribute was DP02_0028PE MARITAL STATUS-Males 15 years and over-Separated. No attributes were deemed unimportant so none could be eliminated. This method was tested as well using a linear regression using only the DP02 table attributes. The attributes were scaled but no further transformation of the data was completed. Only the first 10 variables are shown for the model below due to formatting.

```
Residuals:
    Min      1Q  Median      3Q     Max
-2.7173 -0.3252 -0.0172  0.2936  6.7725

Coefficients:
                Estimate   Std. Error   t value   Pr(>|t|)
(Intercept)   -7.007e-17    1.740e-02     0.000   1.000000
DP02_0002PE    1.241e+00    3.419e-01     3.630   0.000294 ***
DP02_0003PE    7.620e-01    1.645e-01     4.632   3.99e-06 ***
DP02_0004PE    4.422e-01    3.439e-01     1.286   0.198702
DP02_0005PE   -6.498e-01    2.123e-01    -3.061   0.002254 **
DP02_0006PE    2.848e-01    1.735e-01     1.641   0.100977
DP02_0007PE   -2.894e-01    5.507e-02    -5.254   1.74e-07 ***
DP02_0008PE    1.347e-01    1.273e-01     1.058   0.290430
DP02_0009PE   -4.721e-01    1.028e-01    -4.594   4.77e-06 ***
DP02_0010PE    1.338e-01    3.925e-01     0.341   0.733231
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6398 on 1285 degrees of freedom
Multiple R-squared:  0.6107,  Adjusted R-squared:  0.5907
F-statistic: 30.54 on 66 and 1285 DF,  p-value: < 2.2e-16
```

The R-squared value is 0.59, which is 0.10 greater than the regression model created by the PCA. The 0.59 indicates that some variance is still not explained by the model, so additional attributes are needed and will be tested in the next section. It is likely that a significant portion of the variables will be needed to order to improve the accuracy of predicting crime rates.

MODELS

Analytics Methods

This section will be divided into the different types of models that were used to predict crime rates. The first model that will be evaluated is a linear regression model. A random forest model will also be evaluated. Several iterations of each model will be described that attempt to improve the accuracy of the model.

The linear regression model will use three sets of variables. The first set using the eight attributes shown on the Census's website for a zip code. The next set of variables will be determined by PCA. The final set will be determined by the Boruta algorithm.

Linear Model

The first attempt at producing a working model will be using a linear regression model.

Method 1 – Census Website

The first tested model used the eight attributes on the census website. This analysis was already included in the previous section but will be repeated here. The total population is used to calculate the crime rate and not used as an independent variable in the model.

The eight variables are:

DP02_0001E	Total Households
DP05_0001E	Total Population
DP03_0009PE	Unemployment Rate
DP03_0051E	Median Household Income
DP04_0001E	Total Housing Units
DP02_0065PE	Percent Population with Bachelor's Degree
DP03_0099PE	Percent without Health Insurance
DP05_0072PE	Percent Hispanic

The results of the linear regression model are shown below:

```
Residuals:
    Min      1Q  Median      3Q     Max 
-0.2341 -0.0680 -0.0141  0.0318 11.3365 

Coefficients: (1 not defined because of singularities)
             Estimate   Std. Error   t value   Pr(>|t|)    
(Intercept)  0.064501     0.008351     7.724   2.05e-14 ***
DP02_0001E  -0.561831     0.127108    -4.420   1.06e-05 ***
DP03_0009PE -0.033946     0.009725    -3.491   0.000496 ***
DP03_0051E         NA           NA        NA         NA    
DP04_0001E   0.509627     0.126709     4.022   6.06e-05 ***
DP02_0065PE -0.084971     0.014220    -5.975   2.87e-09 ***
DP03_0099PE -0.032159     0.013344    -2.410   0.016076 *  
DP05_0072PE  0.005464     0.008566     0.638   0.523695    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3237 on 1496 degrees of freedom
Multiple R-squared:  0.04481, Adjusted R-squared:  0.04098 
F-statistic:  11.7 on 6 and 1496 DF,  p-value: 7.663e-13
```

The basic model had an R-squared value of 0.04, indicating that these attributes are not enough to explain the variance and that additional data will be needed for predicting crime rates.

Method 2 PCA:

The next selection of variables was chosen using Principle Component Analysis (PCA). This section will only focus on the results of the model. The process for creating the components for use in the models is explained in the previous section.

For this model, data was split into test and train datasets. Prior to performing PCA, cleaning was performed to remove missing or incomplete data as well as removing two rows that had crime rates far exceeding the normal range of crime rates that were typically seen. This resulted in 1,285 rows of crime rates and attribute data that were split into 1,029 rows for training and 256 rows used for testing, about an 80% training / 20% testing split.

PCA was performed using the training data. This produced the weighting of the components that could then be used to create the dimensionally reduced data for the training and testing sets. Both sets were reduced using the same component weighting, so that the models can be evaluated without concern that the weighting had an influence on the accuracy of the model.

An example of this is provided in the code below. The data is subset into the smaller categories specified in the Census data. In this example, the occupation variables are added to a data frame that is used for creating the PCA weights. Notice that the training data is used to create the weightings.

```
#PCA for Occupation data
PCAOccupation <- modeltrain[c("DP03_0027PE", "DP03_0028PE",
"DP03_0029PE", "DP03_0030PE", "DP03_0031PE")]
```

The weights are then created using the training data.

```
PCAOccupation.pca <- princomp(PCAOccupation)
```

Training data is then converted into the weighted components.

```
PredictOccupation <- data.frame(predict(PCAOccupation.pca, modeltrain))
colnames(PredictOccupation) <- paste("Occupation",
colnames(PredictOccupation), sep="_")
```

The test data is also converted into the weighted components.

```
TestPredictOccupation <- data.frame(predict(PCAOccupation.pca,
modeltest))
colnames(TestPredictOccupation) <- paste("Occupation",
colnames(TestPredictOccupation), sep="_")
```

These steps were performed for each subcategory of the census data and then components from each subcategory were merged into a combined data frame. The code below shows the method for combining the data using the cbind function. Note that not all columns are added to the data frame for each subcategory. This range of columns that was selected corresponds to the minimum number of components needed to account for at least 80% of the variance.

```
PCAModelData <- PredictHousehold[c(1:3)]
PCAModelData <- cbind(PCAModelData, PredictRelationship[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictMarital[c(1:4)])
...
```

This same method was also used for the test data.

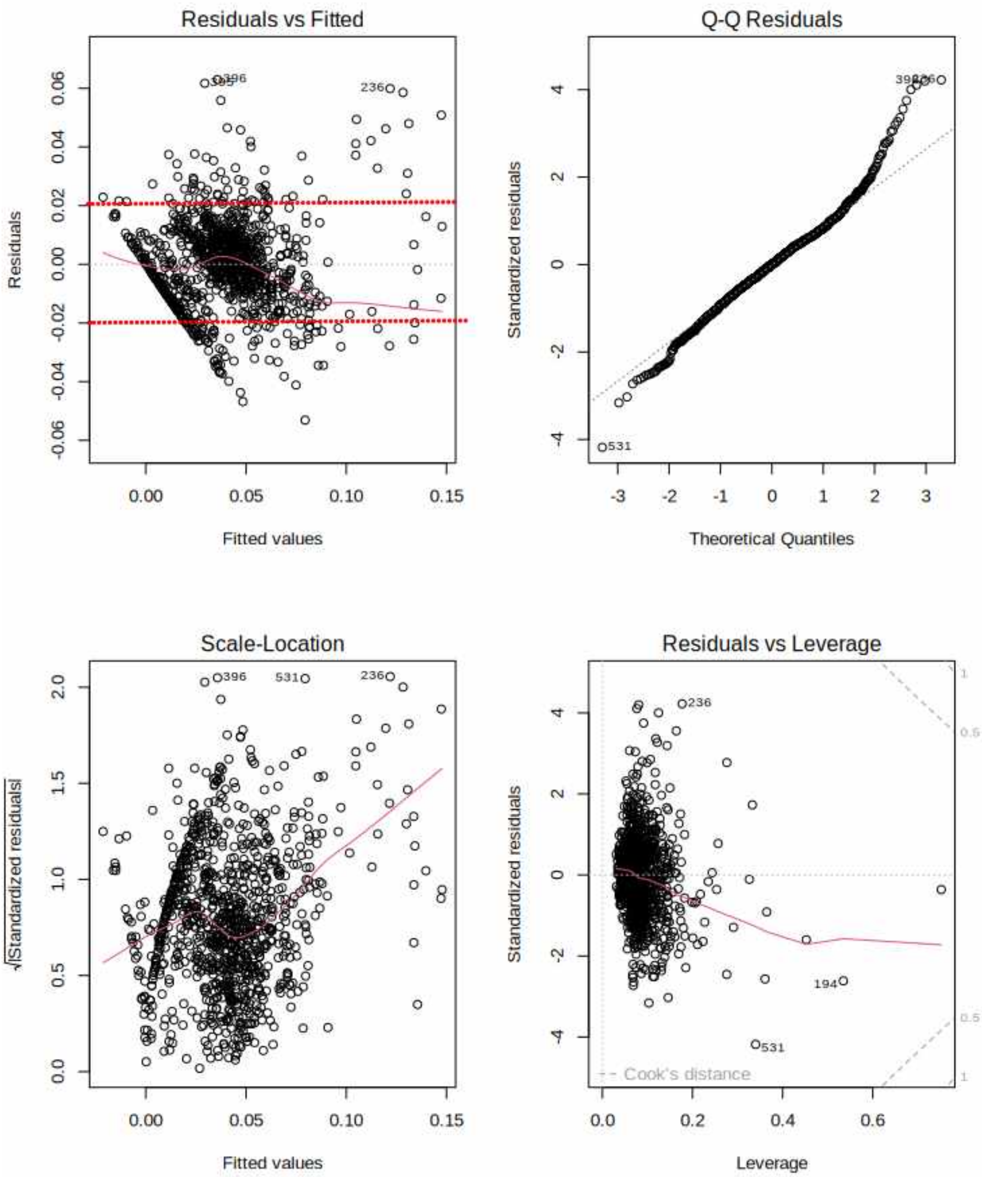
```
TestPCAModelData <- TestPredictHousehold[c(1:3)]
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictRelationship[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictMarital[c(1:4)])
...
```

The results of the linear regression model are shown below. Note that many of the coefficients are not shown to improve readability.

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.053115 -0.008980  0.000069  0.008765  0.062952

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           4.023e-02  4.878e-04  82.483  < 2e-16 ***
Household_Comp.1     -7.726e-03  1.575e-03  -4.905 1.10e-06 ***
Household_Comp.2      1.331e-03  1.939e-03   0.687 0.492543
Household_Comp.3     -7.066e-03  1.539e-03  -4.591 5.00e-06 ***
Relationship_Comp.1  -7.891e-03  3.091e-03  -2.553 0.010847 *
Relationship_Comp.2  -3.582e-03  2.873e-03  -1.247 0.212679
Relationship_Comp.3  -6.731e-03  4.934e-03  -1.364 0.172875
Marital_Comp.1       -2.610e-03  1.805e-03  -1.446 0.148611
Marital_Comp.2        3.555e-03  1.088e-03   3.268 0.001123 **
Marital_Comp.3        9.023e-05  9.051e-04   0.100 0.920612
Marital_Comp.4       -3.773e-03  1.402e-03  -2.692 0.007232 **
...
Rent_Comp.1          -4.582e-03  1.229e-03  -3.728 0.000205 ***
Rent_Comp.2          -4.409e-04  9.723e-04  -0.453 0.650322
Rent_Comp.3          -3.962e-05  9.931e-04  -0.040 0.968188
Gender                3.958e-03  8.628e-04   4.587 5.10e-06 ***
Age_Comp.1            7.768e-04  8.538e-04   0.910 0.363142
Race_Comp.1          -2.197e-04  5.485e-04  -0.401 0.688875
Hispanic_Comp.1      -1.015e-03  5.808e-04  -1.748 0.080803 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01564 on 940 degrees of freedom
Multiple R-squared:  0.7301,  Adjusted R-squared:  0.7048
F-statistic:  28.9 on 88 and 940 DF,  p-value: < 2.2e-16
```

The residual standard error for this model was 0.016. The crime rate ranges from 0 to 0.20, so at first glance this appears to be a relatively small error. The adjusted R-squared value is 0.7, indicating that 70% of the variance in the crime rate can be explained by the model.

The residuals were looked at more closely to see if this model appears a good fit over the entire range of crime rates.



As indicated in the top left graph, the residuals show that when the predicted crime rate is low, residuals average near zero, however when the crime rate is high, accuracy is lost and the residual error is not consistent throughout the model. This indicates that the model is not homeostatic, which is a necessary assumption for linear models. While this model could still be used with predicting lower crime rates, it must be used with caution when predicting high crime rates.

The residuals vs fitted chart also has two dotted lines on the chart that were added. These lines are marked at 0.02 and –0.02. Most of the errors are within these two bounds, although there are many predictions that were outside of this range. Since the crime rate range is from 0 to 0.20, large residual errors could have a great impact on the predicted crime rate. Some errors are as high as 0.04 and –0.04 with a few even at 0.06 and –0.06. High errors can result in a drastically different interpretation of the result. A value of 0.10 with a ±0.04 error could mean the actual value is between 0.06 to 0.14, a difference that changes the interpretation from an area with low crime at 0.06 to one of the highest crime areas at 0.14. This error in residuals is one of the main limitations of this model.

Another aspect of the residuals to note is the clustering of values in diagonal lines near zero. This is due to the crime rate having a natural cutoff at 0, as crime rates cannot be negative. Any fitted values below zero must have a positive residual and any fitted values above zero cannot have a negative residual greater than the fitted value, with results in the diagonal clustering seen in the graphs.

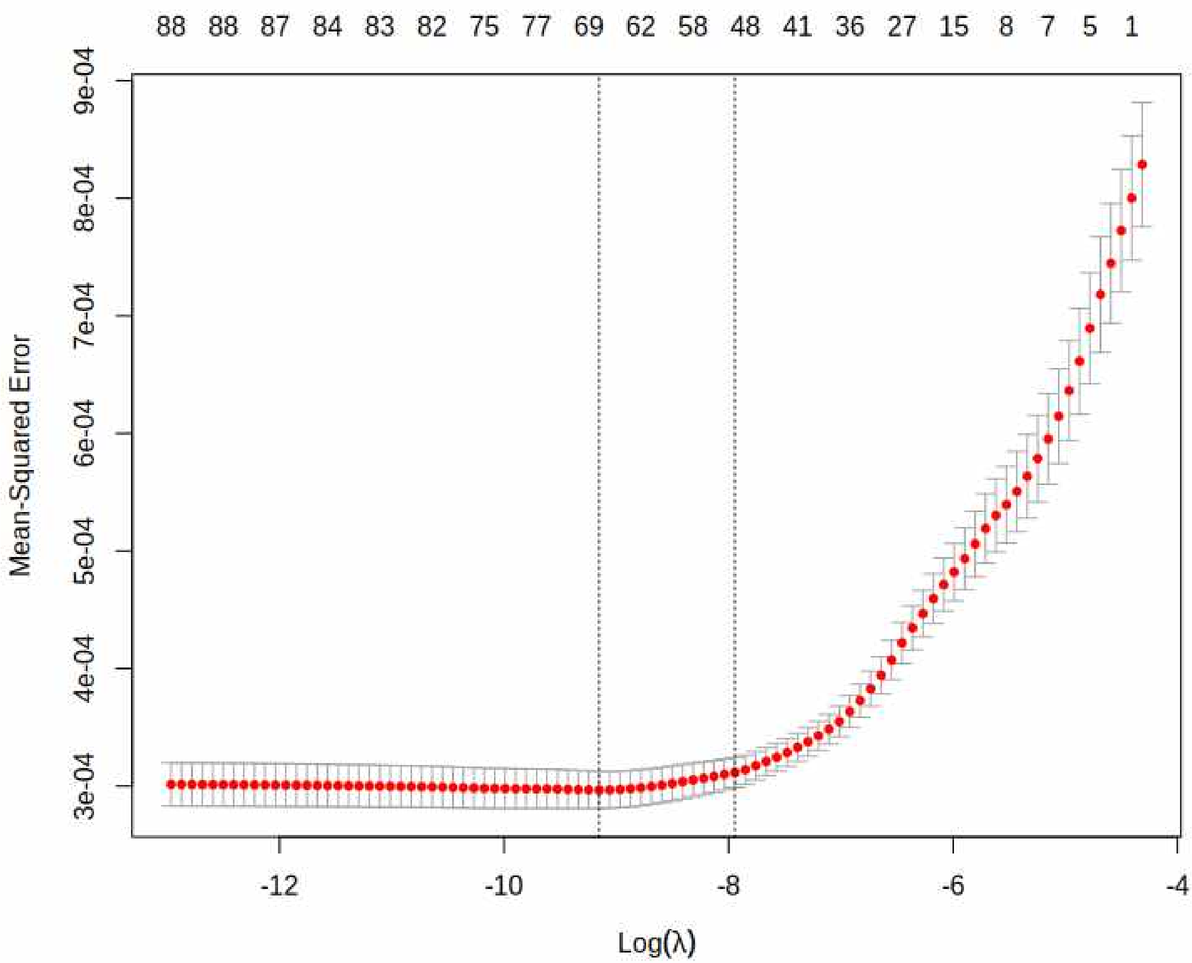
The Durbin-Watson test and variance inflation factor were also reviewed for this model. The Durbin-Watson was 1.9201, with a p-value of 0.098. While this would indicate some positive autocorrelation of the residuals, at 1.92 which is just under 2.0, it is likely small. The top scoring variables from the VIF test are shown below. Since these numbers are all far above 4, there appears to be significant multicollinearity in the PCA linear regression model.

VIF Test

Relationship_Comp.1	150.732
Occupation_Comp.1	91.125
PlaceBirth_Comp.1	85.295
Income_Comp.1	78.351
EduAttainment_Comp.2	77.699

Lasso Regression

Since the initial regression model showed high multicollinearity, Lasso regression will be used to create a model. The glmnet package in R is used to create the Lasso model by first finding the optimum lamda value that minimizes the mean squared error and then generating a model with that value.



The optimal lambda value was found to be 0.0001058777.

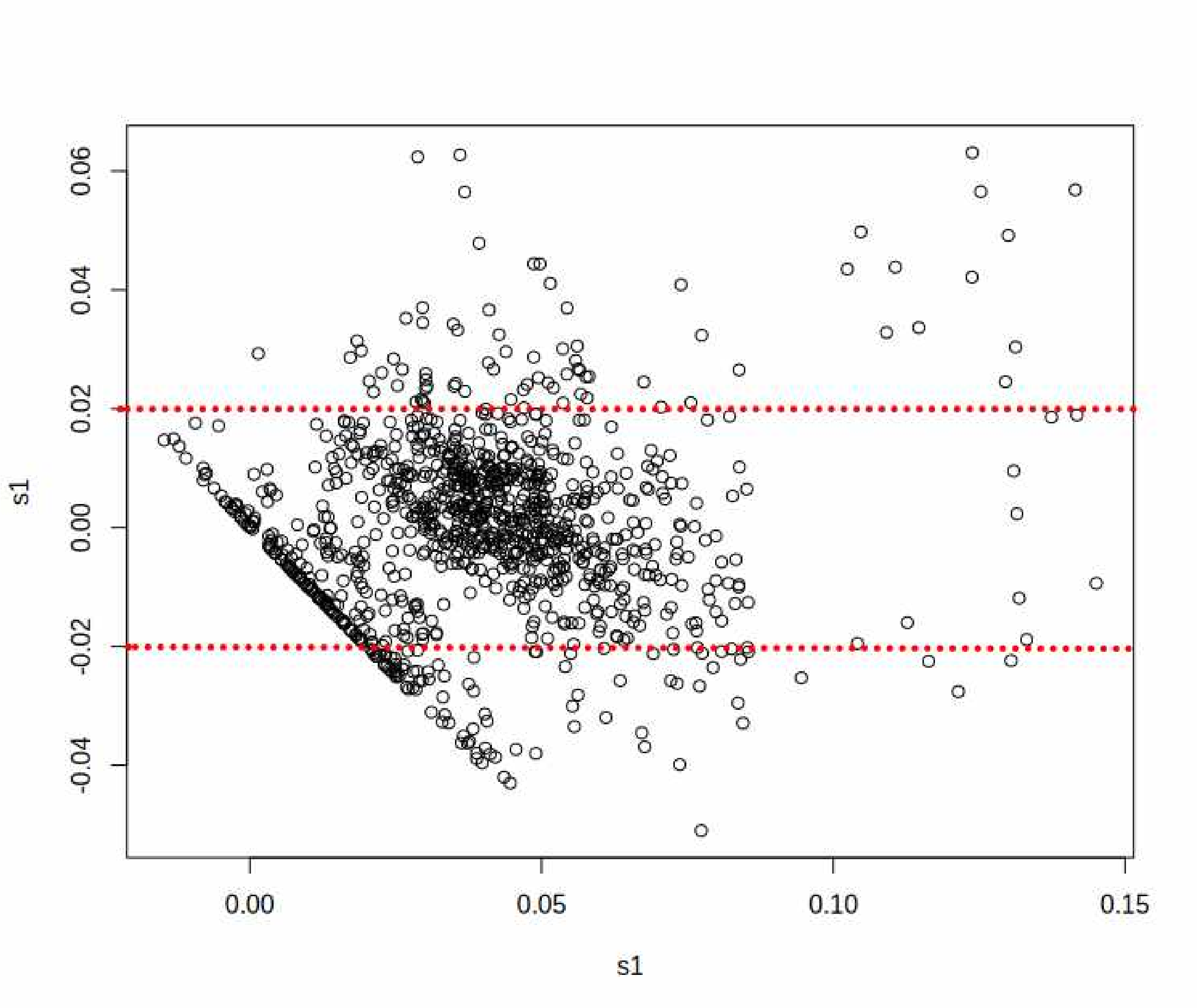
The generated models shows that some variables were removed from the model that were determined to be unneeded. As shown below, two of the relationship variables were removed. Note that only some of the variables are shown for readability.

```
(Intercept)           4.024164e-02
Household_Comp.1     -4.403027e-03
Household_Comp.2     -2.520885e-04
Household_Comp.3     -8.088998e-03
Relationship_Comp.1   .
Relationship_Comp.2   .
Relationship_Comp.3  -4.229678e-04
...
```

The SST and SSE can be calculated to determine the R-Squared Value.

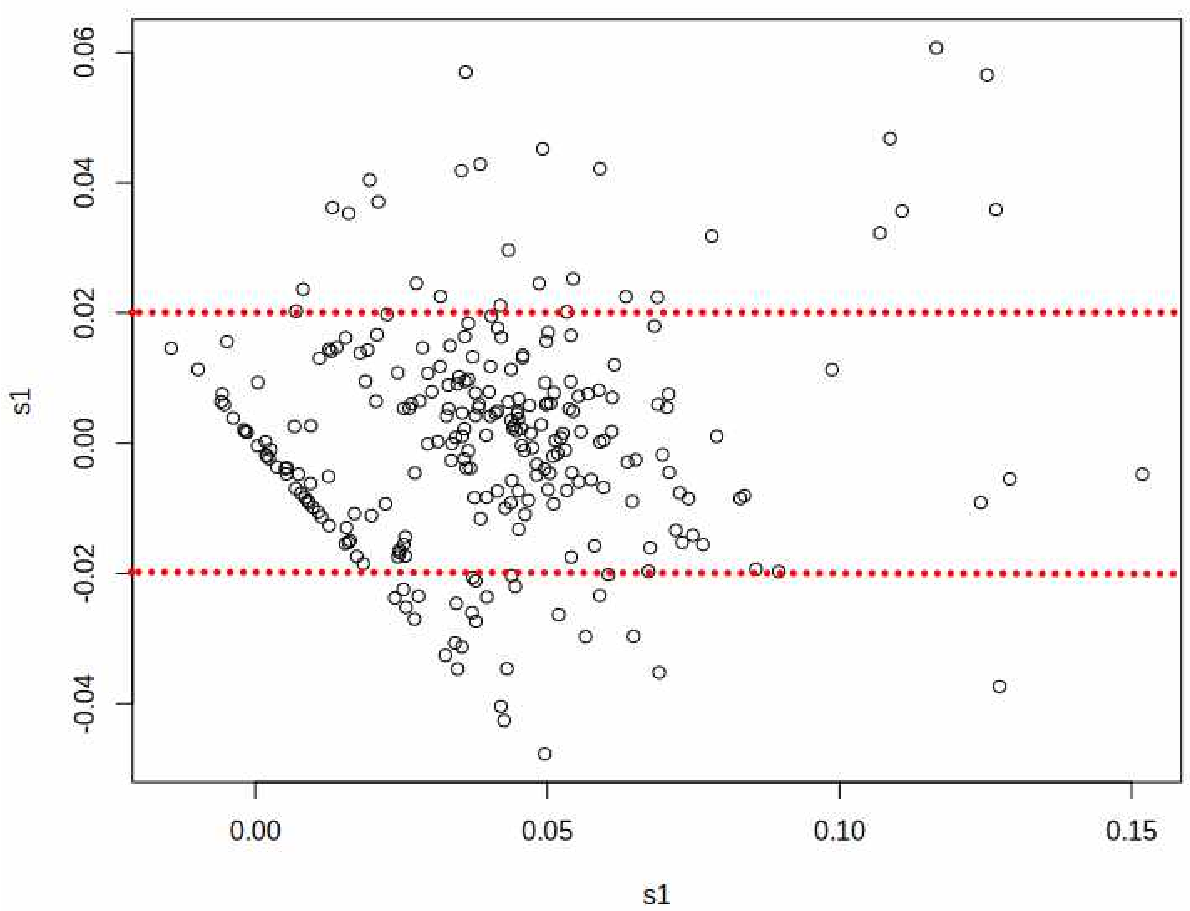
```
sstTrain <- sum((lrTrainY - mean(lrTrainY))^2)
sseTrain <- sum((ytrainfitted - lrTrainY)^2)
rsqTrain <- 1 - sseTrain/sstTrain
```

The R-squared value is 0.718, slightly higher than the initial linear regression model. While the glmnet package does not have a function to show residuals, it is still possible to calculate residuals manually and graph.



The residuals chart looks similar to the linear regression model, with most of the errors between –0.02 and 0.02.

The test data can also be used to evaluate how the model performed. Using the test data, the R-squared value was nearly the same at 0.715. The residual chart of the test data also looked similar to the training data residuals.



Boruta Model / Non-PCA Model

The Boruta algorithm was ran on the crime rate dataset to see if any unimportant variables could be identified. As shown in the results below, the Boruta algorithm was only able to identify a few variables that are unneeded. As a result, a model using variables identified as important by Boruta is not able to be created.

```
Boruta performed 999 iterations in 10.00273 mins.
 235 attributes confirmed important: DP02_0002PE, DP02_0003PE,
DP02_0004PE, DP02_0005PE, DP02_0006PE and 230 more;
 8 attributes confirmed unimportant: DP04_0015PE, DP04_0051PE,
DP04_0052PE, DP04_0066PE, DP04_0067PE and 3 more;
 3 tentative attributes left: DP04_0017PE, DP04_0053PE, DP05_0074PE;
```

Since nearly all variables were considered important, a linear regression model using all variables will be tested. This model will be again compared to a model with Lasso regression. These two models will then be compared to the models created using PCA to see if PCA is needed for this dataset.

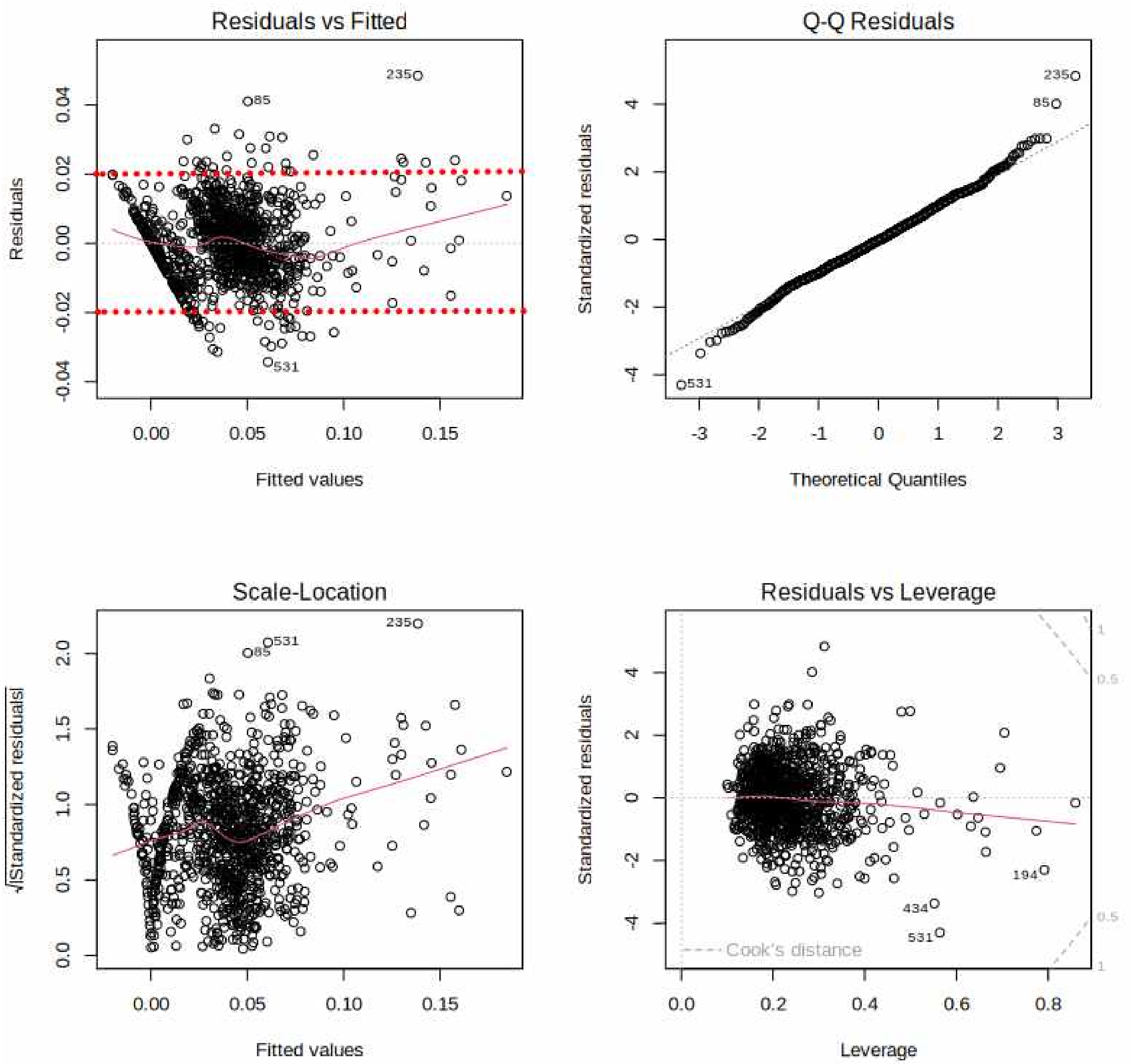
All Variables

Using all attributes from the Census data to create a linear regression model produced the following results:

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.034329 -0.006899 -0.000270  0.006694  0.048451

Coefficients: (3 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.048e-02  3.917e-04 103.349  < 2e-16 ***
DP02_0002PE -3.308e-03  1.038e-02  -0.319 0.749991
DP02_0003PE  1.733e-02  6.297e-03   2.752 0.006061 **
DP02_0004PE -7.844e-03  1.098e-02  -0.714 0.475196
DP02_0005PE -1.479e-02  6.154e-03  -2.404 0.016456 *
DP02_0006PE -8.135e-03  4.736e-03  -1.718 0.086236 .
DP02_0007PE -6.680e-03  1.663e-03  -4.018 6.44e-05 ***
DP02_0008PE -3.140e-03  3.771e-03  -0.833 0.405332
...
DP04_0068PE -7.218e-04  5.984e-04  -1.206 0.228086
DP04_0069PE -1.911e-03  6.631e-04  -2.882 0.004064 **
 [ reached getOption("max.print") -- omitted 45 rows ]
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01209 on 787 degrees of freedom
Multiple R-squared:  0.865,   Adjusted R-squared:  0.8237
F-statistic: 20.92 on 241 and 787 DF,  p-value: < 2.2e-16
```

The residual standard error appears to be low at 0.012 and the adjusted R-squared value is even higher than previous models at 0.824. While the p-values for many variables is above 0.05, indicating those variables are not reliable predictors, it appears at first glance that this model will perform better than previous models.

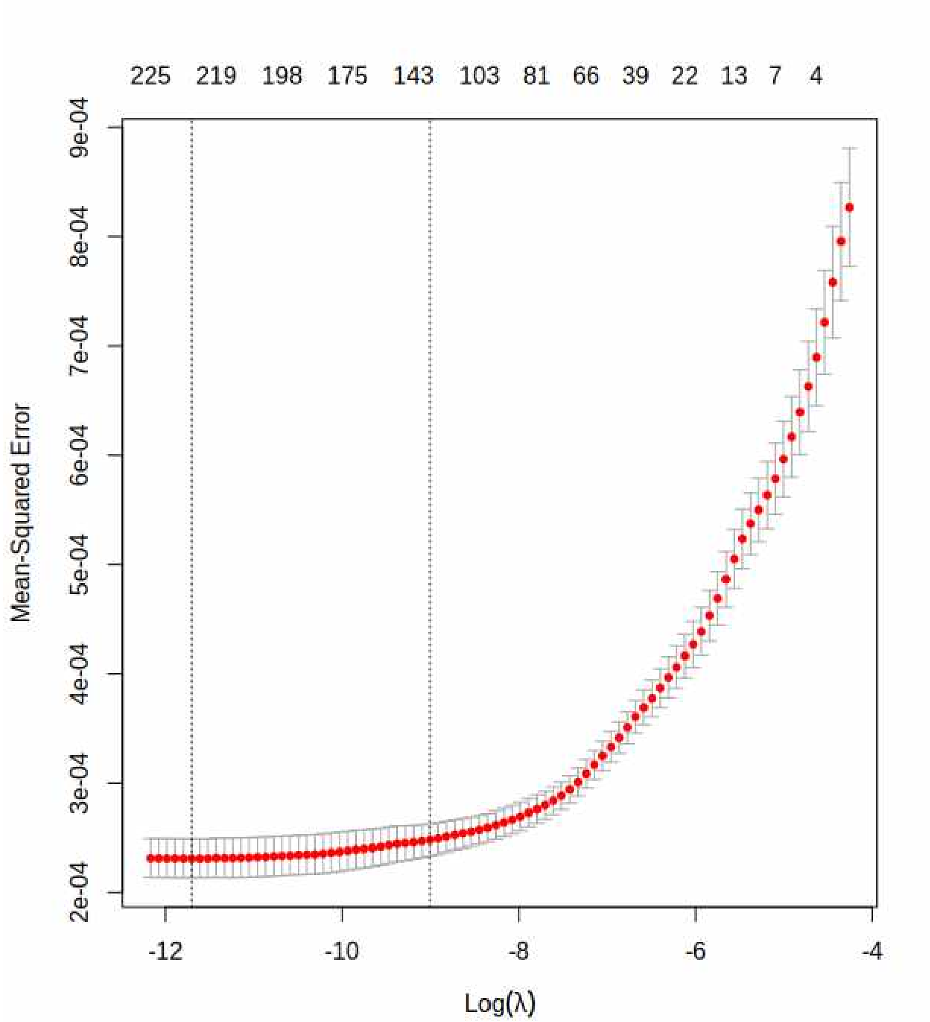
The residuals chart also appears similar to other models. Some of the higher fitted values appear to be more accurate with fewer residuals outside of the ± 0.02 range.



Performing the variance inflation factor analysis reveals aliased variables. This is a result of some census data being included twice, but in different forms. For example, DP03_0002PE Population 16 years and over-In labor force is perfectly negatively correlated with DP03_0007PE Population 16 years and over-Not in labor force. In this scenario, a person can only either be in the labor force or not in the labor force, so knowing just one of these variables will give the other. Since there is redundant variables, Lasso regression will be tested.

Lasso Model

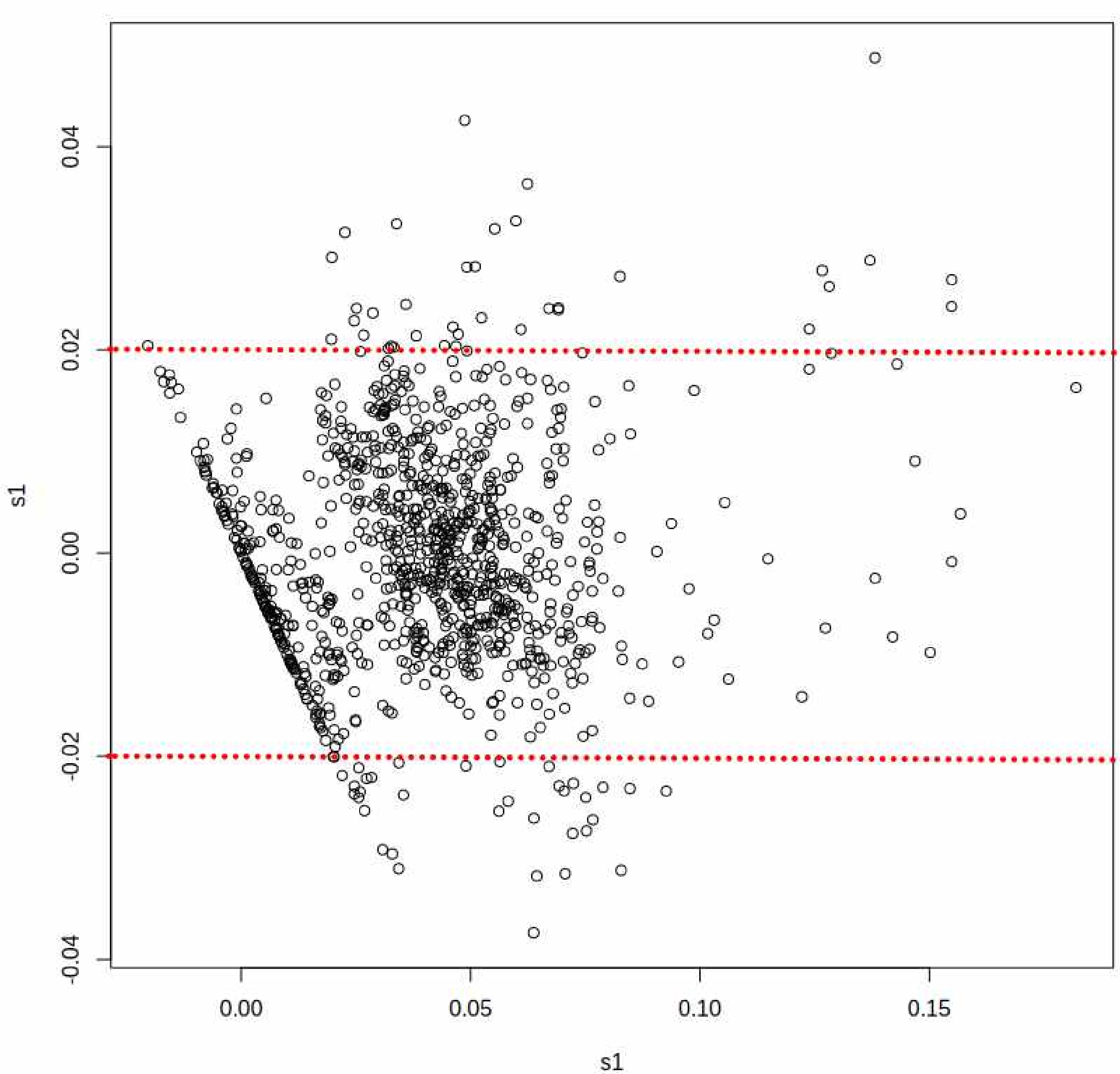
The optimal lambda number is calculated using the data as is and found to be 8.261055e-06.



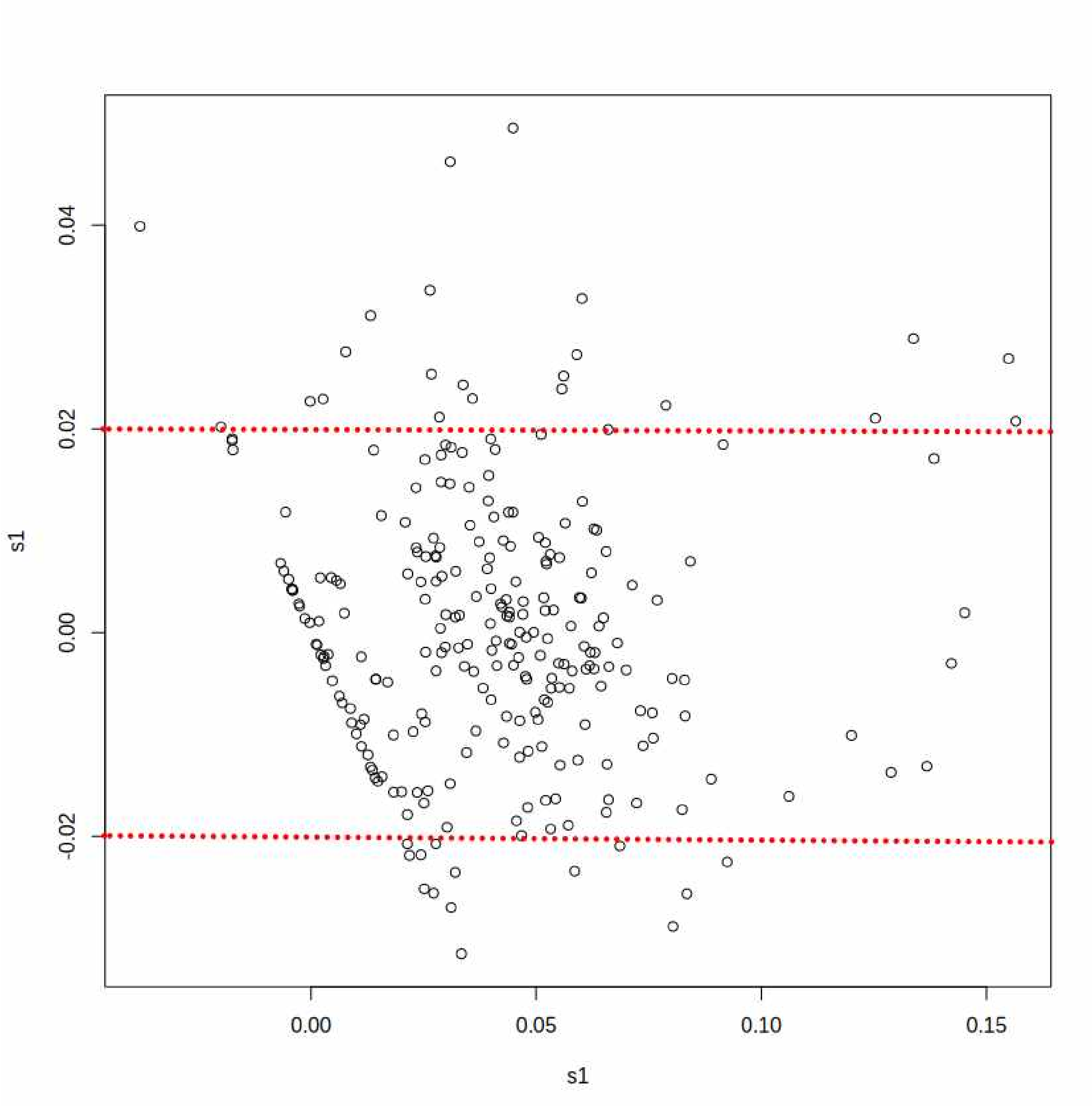
Several variables are also considered unneeded when using lasso regression, and were removed. An example of some of the coefficient values is shown below.

```
(Intercept)  4.049347e-02
DP02_0002PE  .
DP02_0003PE  1.475536e-02
DP02_0004PE  .
DP02_0005PE -1.473392e-02
DP02_0006PE -6.595744e-03
DP02_0007PE -6.037383e-03
DP02_0008PE -1.588445e-03
DP02_0009PE -6.593130e-03
DP02_0010PE  .
DP02_0011PE -1.459225e-02
```

The R-Squared value was calculated to be 0.856. Residuals are still similar to other models, but like the regression model using the variables as is, more of the residuals for higher fitted values are between ±0.02.



The test data for this Lasso regression was also evaluated. The R-squared value was 0.827 and the residuals are shown below.



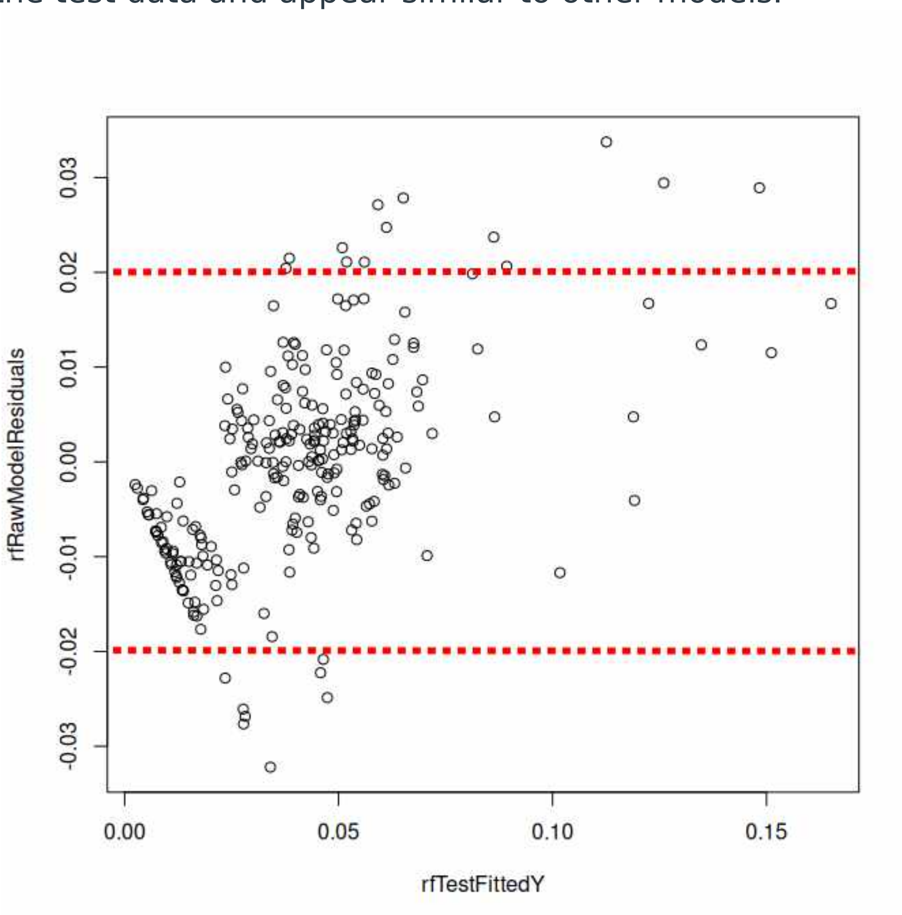
Random Forest

The random forest algorithm was also tried to see if it would be possible to improve model performance compared to using linear regression. Random forest models were created using both the data as is and the PCA reduced dataset. The random forest models also used the same training and test data as the linear regression models.

Random Forest was first tested without using PCA.

```
randomForest(formula = CrimeRate ~ ., data = rfRawTrainData)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 81

          Mean of squared residuals: 0.0001350839
                    % Var explained: 83.69
```

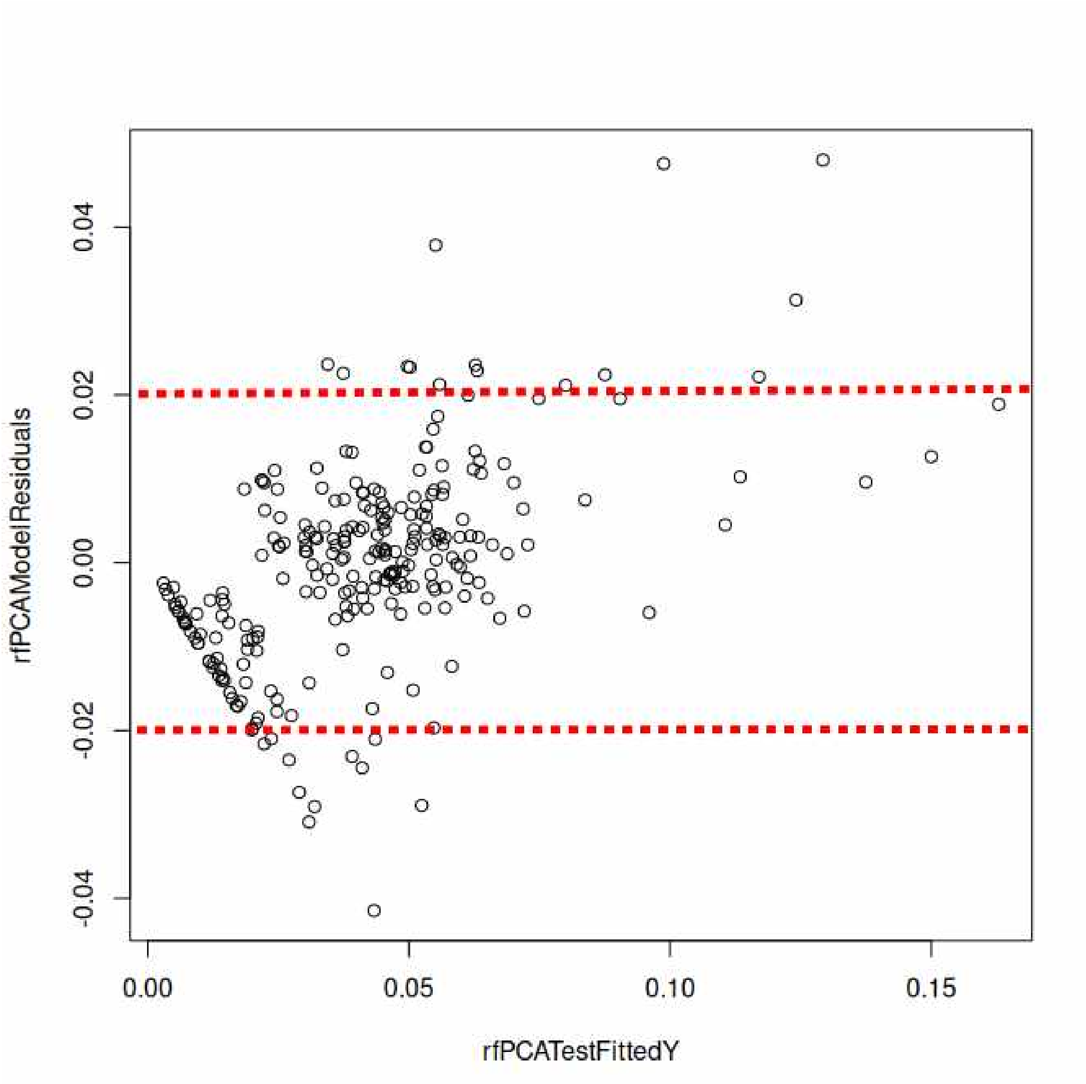
The percent variance explained is slightly lower than the Lasso regression model. Taking the square root of the mean of squared residuals gives the residual standard error used in the regression models, allowing the two types of models to be compared. The standard error for the random forest model 0.0116, slightly lower compared to the Lasso model. The residuals are shown below for the test data and appear similar to other models.



A second random forest model was also created using the PCA components.

```
randomForest(formula = CrimeRate ~ ., data = rfPCATrainData)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 29

          Mean of squared residuals: 0.0001558831
                    % Var explained: 81.18
```

This model had a lower percent of variance explained. The standard residual error was also higher at 0.0125. Residuals are shown in the chart below.



Model Comparison

The table below shows the residual standard error and R-Squared value for each model.

Model	Residual Standard Error Train	R-Squared Train	Residual Standard Error Test	R-Squared Test
Census Website Linear Regression	0.324	0.0448	Not Tested	Not Tested
Linear without PCA	0.0121	0.865	0.0142	0.814
Linear with PCA	0.0156	0.730	0.0175	0.718
Lasso without PCA	0.0219	0.855	0.0137	0.827
Lasso with PCA	0.0306	0.718	0.0176	0.715
Random Forest without PCA	0.0116	0.837	0.0106	0.896
Random Forest with PCA	0.0125	0.811	0.0120	0.867

The comparison shows that the random forest models had the highest R-squared and lowest residual standard error values with the test dataset. While the test data performed very well, the training data results are slightly worse. It's possible that the training data that was selected with seed 100 uniquely worked well with this model. The model needs to be cross validated with different training and test data to confirm that the random forest works consistently well.

PCA showed to be a negative when used as all models had worse performance with PCA. There also appeared to be more residuals outside of the ±0.02 range when models with PCA were tested. The reduced performance of models with PCA may be a result of how PCA was applied. Each subcategory had a separate PCA and the results were then combined. Performing PCA on the entire dataset may have worked better, as some critical attributes may have been excluded when the PCA was split by subcategory.

Lasso Regression also did not show much of a difference when compared to simply using all variables, as the linear regression and lasso regression that did not use PCA have very similar results.

In both the linear and lasso regression without PCA, there is a decrease in the R-squared value with the test data compared to the training data. This is a result of overfitting. Using more variables in a regression model also tends to artificially increase the R-squared value. To address this issue, other models will be evaluated with all variables as part of one PCA, instead of the variables being split into multiple subcategories with separate PCAs.

The R-squared value for the random forest models was greater for the testing data than the training data. This is due to only one split of the training and test data being evaluated, and the selected test set performing abnormally well. Each model will be cross validated to provide a better representation of the performance of each model.

Variable analysis
The objective of this project is to determine what demographic attributes have a large effect on crime rates. Since Lasso regression will weigh variables according to their importance, the coefficients can be used to determine which attributes have the greatest effect on crime rates. Large coefficients indicate that a smaller change in an attribute will have a larger change on the crime rate.

The table below shows the variables with the largest coefficients. The variables listed have the highest magnitude, so the sign of the coefficient can be either positive or negative.

Rank	Attribute	Coefficient
1	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over	-0.03867
2	Percent-MARITAL STATUS-Males 15 years and over-Now married, except separated	-0.03519
3	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over	-0.03114
4	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate or higher	+0.02915
5	Percent-VEHICLES AVAILABLE-Occupied housing units-No vehicles available	+0.01802
6	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over-18 to 64 years	+0.01703
7	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-With related children of the householder under 18 years	+0.01685
8	Percent-HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years	+0.01476
9	Percent-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years	-0.01473
10	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years	-0.01459

There are some expected results as well as some anomalies in this table. Poverty shows up in multiple attributes, which would be expected as a significant influencer of crime rate. Family structure also has multiple appearances. Other attributes such as educational attainment and transportation availability would also be expected.

One of the potential issues with this chart however is the direction that the crime rate moves for certain attributes. The sixth and seventh ranked attributes are both related to poverty. As the poverty percent increases, the coefficient indicates that the crime rate increases as well. This intuitively seems likely; however, the top ranked variable shows a decrease in crime as poverty increases. This creates a conflicting scenario where poverty changes appear to both increase and decrease crime rates regardless of the poverty direction of change.

The likely cause for this anomaly and others is that there is some hidden overlap in the attributes. The top ranked variable looks at the poverty percent for the population age 18 and over. The sixth ranked variable looks at the poverty percent for the population age 18 to 64. This means that both attributes have a significant overlap, as adults between 18 and 64 will show up in both attributes. This overlap may be causing some discrepancies in the model, which is why an increasing poverty rate appears to reduce crime for the top ranked variable.

This can be seen in some other variables as well. The second variable shows that crime rate decreases as the percentage of married men increases, however the eight ranked variable shows increase crime when couples are married with children. This variable also has nearly the exact opposite effect of the ninth ranked variable, cohabitating couples with children. There is also likely some overlap with married men included in both the second the eighth ranked variables that could be causing issues as well.

A review of the variables shows that the variable selection is still potentially an issue. Much of the work for this project has been focused on selecting the right attributes in order to create accurate models. Multiple methods such as PCA, Lasso, and Random Forest were tried to help correctly select the most important attributes. While the models show high R-squared values and relatively small errors, redundant variables and overlapping attributes have made improving the accuracy of the models difficult.

PCA Using All Variables

Since overfitting and multicollinearity appear present in multiple models and that there is some overlap in the population in variables of the same subcategories, PCA was performed using all variables in the dataset. There are 244 variables in the dataset, which will be reduced down to the number of components needed to account for 80% of the variance.

```
Importance of components:
                          Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
Standard deviation     7.7694528 5.6278329 4.9742149 3.47173476 3.23836125
Proportion of Variance 0.2513051 0.1318569 0.1030076 0.05017801 0.04365872
Cumulative Proportion  0.2513051 0.3831619 0.4861696 0.53634760 0.58000631
                           Comp.6     Comp.7     Comp.8     Comp.9
Standard deviation     2.82860404 2.52224820 2.19462286 2.14237003
Proportion of Variance 0.03330924 0.02648476 0.02005119 0.01910774
Cumulative Proportion  0.61331555 0.63980031 0.65985150 0.67895924
                          Comp.10    Comp.11    Comp.12    Comp.13
Standard deviation     2.06037365 1.95135393 1.62773542 1.61251066
Proportion of Variance 0.01767308 0.01585231 0.01103032 0.01082494
Cumulative Proportion  0.69663233 0.71248463 0.72351495 0.73433989
                          Comp.14     Comp.15    Comp.16     Comp.17
Standard deviation     1.60532806 1.533269397 1.47788871 1.432908957
Proportion of Variance 0.01072872 0.009787174 0.00909293 0.008547863
Cumulative Proportion  0.74506861 0.754855789 0.76394872 0.772496582
                          Comp.18     Comp.19     Comp.20     Comp.21
Standard deviation     1.38095857 1.335046763 1.281282317 1.262710488
Proportion of Variance 0.00793929 0.007420161 0.006834552 0.006637858
Cumulative Proportion  0.78043587 0.787856033 0.794690585 0.801328443
                          Comp.22     Comp.23     Comp.24     Comp.25
Standard deviation     1.21227337 1.169843969 1.156505455 1.140406096
Proportion of Variance 0.00611817 0.005697394 0.005568212 0.005414264
Cumulative Proportion  0.80744661 0.813144007 0.818712219 0.824126483
```

PCA results show that 80% of the variance can be accounted for using 21 components. A linear regression model was created using 21 components and the results are shown below.

```
Residuals:
     Min       1Q   Median       3Q      Max 
-0.07173 -0.01116  0.00102  0.01077  0.06658 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.0402410  0.0005967  67.444  < 2e-16 ***
Comp.1       0.0007351  0.0000768   9.573  < 2e-16 ***
Comp.2      -0.0002879  0.0001060  -2.716 0.006727 ** 
Comp.3      -0.0027780  0.0001200 -23.160  < 2e-16 ***
Comp.4      -0.0001808  0.0001719  -1.052 0.292970    
Comp.5       0.0015388  0.0001843   8.352  < 2e-16 ***
Comp.6      -0.0014053  0.0002109  -6.662 4.43e-11 ***
Comp.7       0.0001975  0.0002366   0.835 0.404034    
Comp.8      -0.0010679  0.0002719  -3.928 9.15e-05 ***
Comp.9       0.0007560  0.0002785   2.714 0.006755 ** 
Comp.10     -0.0006119  0.0002896  -2.113 0.034846 *  
Comp.11      0.0012011  0.0003058   3.928 9.14e-05 ***
Comp.12     -0.0025658  0.0003666  -7.000 4.68e-12 ***
Comp.13     -0.0012965  0.0003700  -3.504 0.000479 ***
Comp.14     -0.0041744  0.0003717 -11.231  < 2e-16 ***
Comp.15      0.0020709  0.0003891   5.322 1.27e-07 ***
Comp.16     -0.0063355  0.0004037 -15.693  < 2e-16 ***
Comp.17     -0.0004901  0.0004164  -1.177 0.239478    
Comp.18     -0.0003063  0.0004321  -0.709 0.478509    
Comp.19     -0.0001295  0.0004469  -0.290 0.772098    
Comp.20     -0.0031229  0.0004657  -6.706 3.32e-11 ***
Comp.21      0.0018981  0.0004725   4.017 6.33e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01914 on 1007 degrees of freedom
Multiple R-squared:  0.5671,	Adjusted R-squared:  0.5581 
F-statistic: 62.81 on 21 and 1007 DF,  p-value: < 2.2e-16
```

While the error of the model is not bad at 0.01914, the R-squared value is low at 0.5671. The test data had a standard error of 0.02051944 and an R-squared value of 0.02051944 and 0.6108224. While it would be expected that the R-squared value of the test data would be lower than the training value, only one set of test data was used which can result in a higher test value, and cross validation is needed to get a more representative value.

Increasing the number of components used will increase R-squared, but overfitting is still an issue as most cases have a higher training than test value. Note that cross validation was not used for these models.

Components Used	Residual Standard Error Train	R-Squared Train	Residual Standard Error Test	R-Squared Test
21	0.0191	0.567	0.0205	0.611
50	0.0173	0.656	0.0192	0.660
100	0.0154	0.742	0.0169	0.736
150	0.0141	0.795	0.0161	0.760
200	0.0130	0.837	0.0142	0.813
244	0.0121	0.865	0.0142	0.814

Cross Validation

All models were retested using cross validation. Since multiple models initially showed higher test R-squared values compared to training R-squared values, cross validation can be used to get a better representation of the model. The chart below shows average residual error and R-squared results as well as the number of models that were generated. Repeated random sub-sampling was used as the method for all cross validation.

The above models using an increasing number of PCA components were cross validated. All models showed a lower R-squared value for the testing data compared to the training data, indicating that the linear regression models are overfitting.

Linear Regression with PCA Using All Variables

Components Used	Models Generated	Residual Standard Error Train	R-Squared Train	Residual Standard Error Test	R-Squared Test
21	1000	0.0194	0.574	0.0197	0.543
50	1000	0.0174	0.668	0.0182	0.610
100	1000	0.0154	0.752	0.0167	0.671
150	1000	0.0142	0.804	0.0159	0.703
200	1000	0.0128	0.846	0.0150	0.733
244	1000	0.0122	0.871	0.0147	0.745

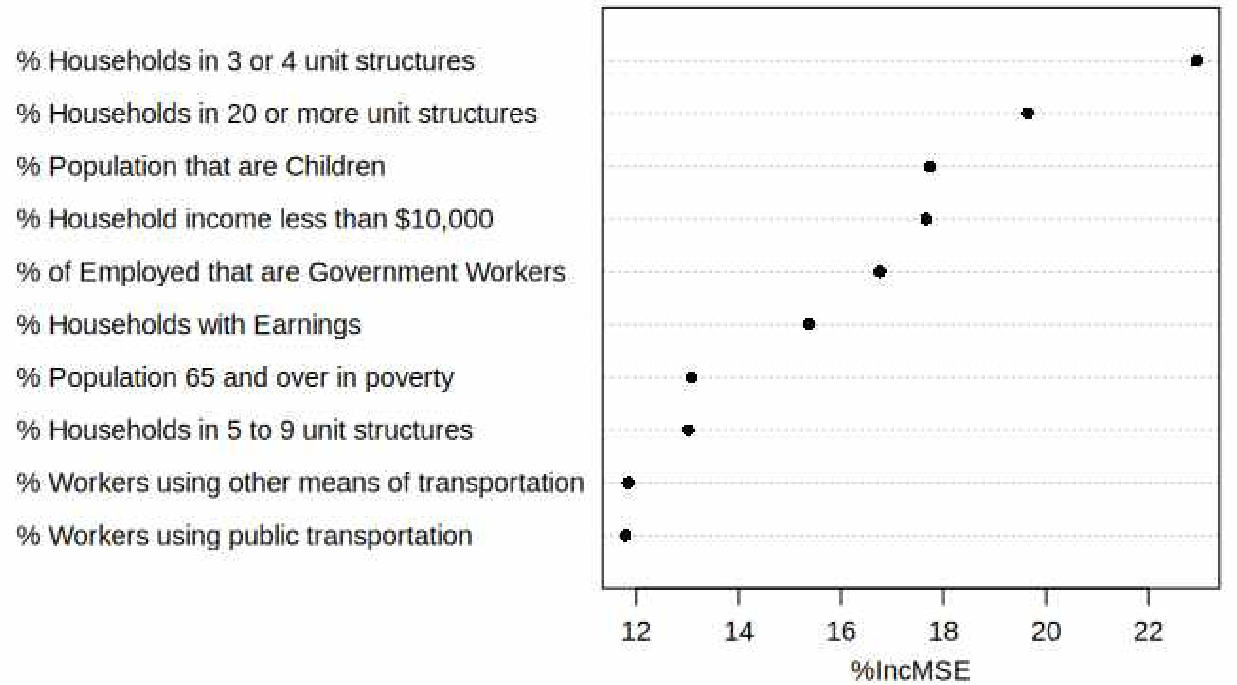
Original models cross validated – PCA using subcategories

Model	Models Generated	Residual Standard Error Train	R-Squared Train	Residual Standard Error Test	R-Squared Test	Train/Test R-Squared Difference
Linear without PCA	1000	0.0121	0.871	0.0147	0.746	0.125
Linear with PCA	1000	0.0157	0.738	0.0168	0.669	0.069
Lasso without PCA	1000	0.0111	0.858	0.0146	0.750	0.108
Lasso with PCA	1000	0.0152	0.732	0.0167	0.673	0.059
Random Forest without PCA	1000	0.0113	0.852	0.0112	0.853	-0.001
Random Forest with PCA	1000	0.0120	0.832	0.0119	0.833	-0.001

The original models discussed earlier were also cross validated. Note that the models with PCA used multiple PCAs with the variables split into subcategories, rather than using one PCA with all the variables. Both linear and lasso regression models had overfitting, as the test R-squared value is lower compared to the training R-squared value. The random forest models performed better, with the test r-squared values similar to the training R-squared values.

Variable Importance – Random Forest

Since the random forest model appears to have the highest accuracy without suffering from overfitting, the important variables in the random forest model were analyzed. This random forest model uses regression, so the method to determine the most important variable will be to look at the variables that affect the accuracy of the model the most by increasing the Mean Squared Error (MSE). The chart below shows the top variables that had the highest percent increase in MSE.



The most important variables are related to household structures, percent in poverty, percentage of population that are children, and transportation types. While none of the variables with highest importance are the same as the variables in the linear regression with the highest coefficients, there does appear to be a similarity in the categories the variables come from. The random forest model had multiple variables that focused on poverty or earnings, especially low earnings. There was also a focus on whether a person walked or took public transportation, similar to how the lasso regression marked households with no vehicles as an important variable. There is also a focus on family structure and the percentage of households that have children. While the random forest model simply looked at the percentage of the population that was children, the lasso regression model focused on households containing children under 18 years of age. These different attributes mostly capture the same population.

Conclusion

Comparing the important variables from multiple models can show some insight into what demographic attributes can affect crime rate. Poverty clearly plays an important role in crime rates, as many of the variables that were selected as important were either directly measuring poverty or are closely related to poverty such as household income. Methods of transportation were also important. It is likely that these variables share some overlap with poverty, as households that do not have cars and must either walk or use public transportation are also likely to have higher poverty rates. Finally, there is some indications that family structure also affects crime rate, as there was a decrease in crime rate observed for married men and cohabitating couples with children in the lasso regression. The percentage of the population that was children also was an important variable in the random forest model.

Multicollinearity must be addressed though with these models. Many of the variables capture the same population in slightly different ways. As explained above, the number of children in a zip code can be determined using either the percentage of population that are children or looking at percent of households containing individuals under 18 years old. These overlapping attributes are likely the cause of some of the unexpected behavior in the models, as observed in the lasso regression model, where some of the variables that are related appear to counteract each other. To properly build a more accurate model, it may be necessary to start with a small number of variables and slowly add variables that have minimal overlap to the model to improve accuracy.

Research Questions

At the beginning of the report, three questions were asked. Each of these consisted of whether a certain model could predict crime rates using ARIMA, K-Means, and regression. Since this project eventually ended only using regression, only the third question using regression will be considered. Since there were multiple parts of the question, each part will be addressed below.

Question 3:

Can a regression model be used to predict accurate crime rates? For example, does an increase in income directly result in a reduction in crime and can this decrease be modeled to predict how crime rates may change because of changes in income?

Can a regression model be used to predict accurate crime rates?

Regression models can be used to predict crime rates, although care needs to be paid to the type of regression model that is used for prediction. Both linear and lasso regression models showed signs of overfitting. R-squared values were lower for the test data, typically around 0.75 for models without PCA and 0.67 for models with PCA. The random forest models had better R-squared values, typically around 0.84.

The errors for each model are generally low. Linear and lasso regression models without PCA had a residual standard error of 0.015, while the models with PCA were slightly higher at 0.017. Random forest models typically had a residual standard error of 0.012. The error for the different models is similar, although the random forest had a slightly smaller error compared to linear and lasso models.

Does an increase in income directly result in a reduction in crime? Do specific attributes affect the crime rate?

As discussed in the variable importance sections, poverty and income were significant predictors of crime rates. Both the lasso regression and random forest models indicated that poverty and income variables were important. Poverty likely plays a significant role as even when the top variables were not poverty or income, the other top variables were likely influenced by poverty such as the lack of vehicles and relying on public transportation. Finally, family structure also seemed to influence crime rates.

Can this decrease be modeled to predict how crime rates may change because of changes in income? Can attribute changed be modeled to predict how crime rates may change?

While income is a significant predictor of the crime rate, trying to directly predict the crime rate change based on a change in income is far more difficult. As seen in the lasso regression, multiple poverty variables were considered important and affect the final predicted crime rate. While the random forest only included households under $10,000 per year as well as households that had any income at all in the top ten most important variables, it is likely that some of the more important variables outside of the top ten are also based on income and poverty. It is also very difficult to predict crime rate increases using the random forest model, as a single variable cannot be isolated unlike the linear and lasso regression models. In the linear and lasso regression models the coefficient is calculated for each variable, so the influence of a variable can be determined. If the influence of a single attribute is needed, the data must come from either the linear or lasso regression models, which had a lower overall accuracy.

Final notes

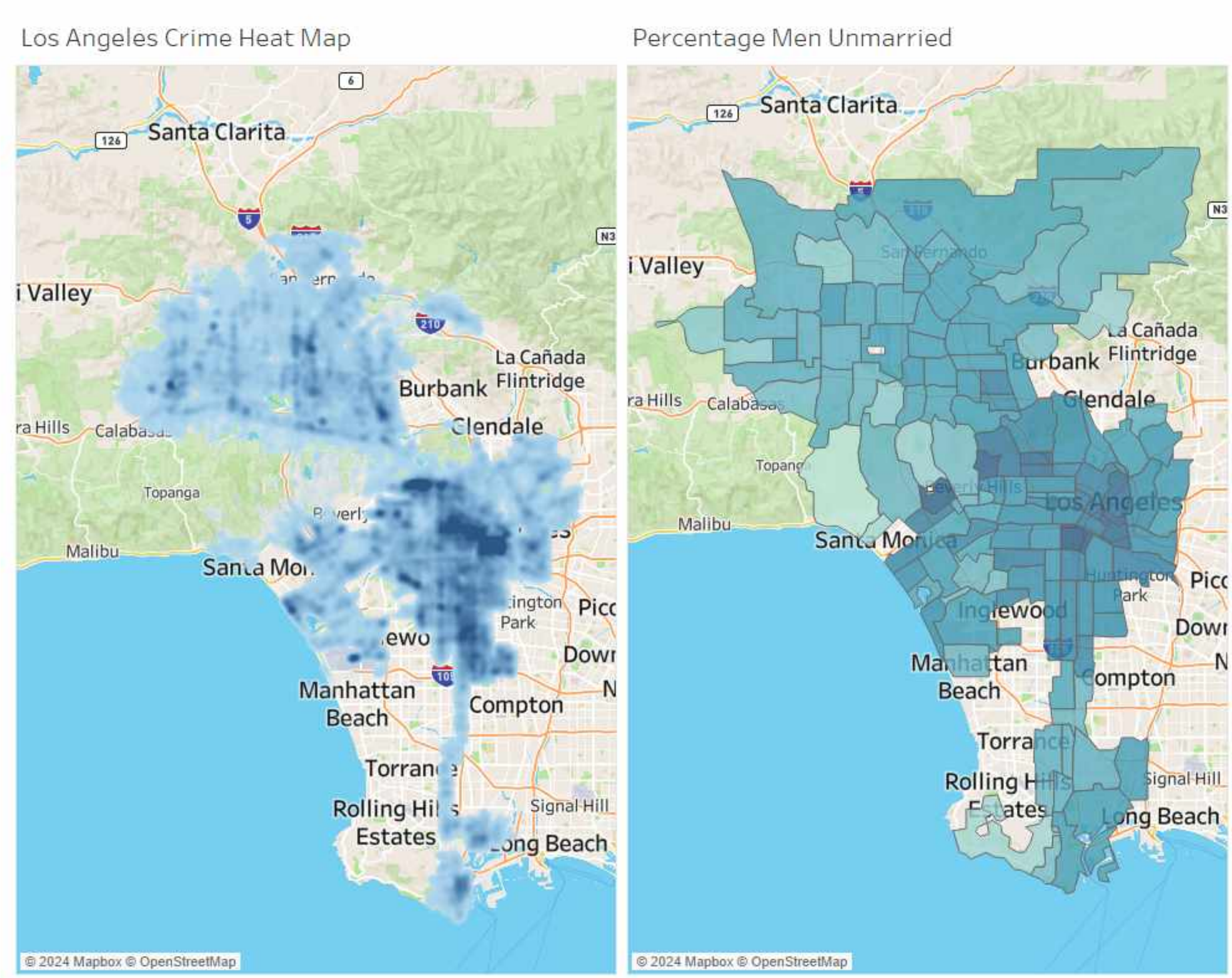
This project only offers a preliminary look into the prediction of crime and reasons for crime in Los Angeles. While the models, especially the random forest model, can predict the crime rate within ±0.02, where the crime rate range is from 0 to 0.20, identifying the reasons for crime is much more difficult. Poverty, income, family structure, and transportation availability seem to have a larger impact on crime rates than other variables based on the important variables in each model. The exact effect of each variable is harder to determine.

If policy were decided based on this report, only a general recommendation can be provided. Predicting an exact decrease in the crime rate would be more difficult. For example, if a policy reduces poverty by 10%, it is difficult to predict the exact decrease in crime that would be expected to follow. Thus this report can only recommend that policy focuses on poverty, income, family structure, and transportation availability, but cannot provide an expected decrease in crime rate if those variables are changed. This is a result of multicollinearity and overlap in the variables. Each variable is not truly independent of other variables, so that if one variable changes, others would be expected to change as well.

DATA VISUALIZATION

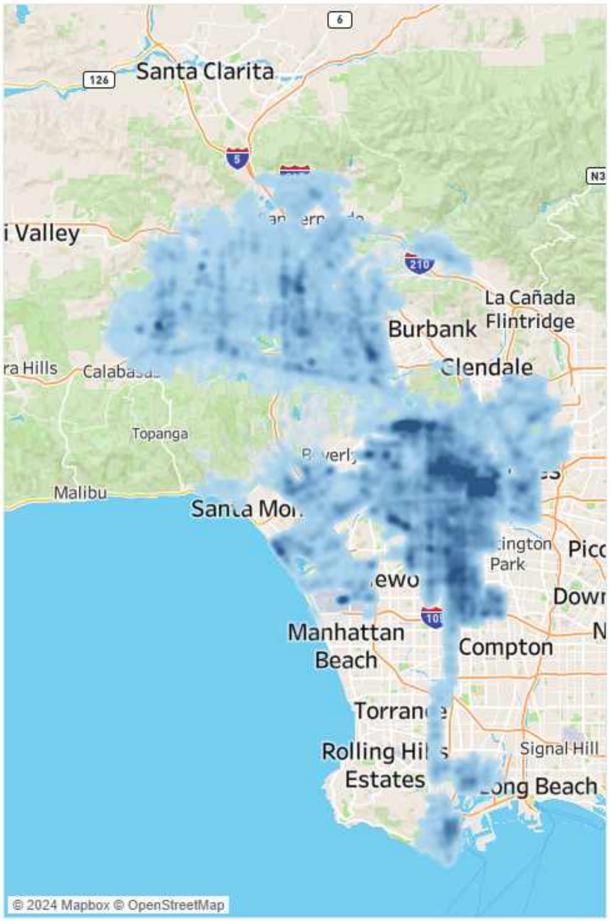
Visualizations

Several visualizations showing attributes of the Census data compared to the crime occurrences are shown below. These attributes were selected based on the important variables in each model. The crime occurrence maps are shown next to the zip code visualizations to directly compare crime occurrences and Census attributes.

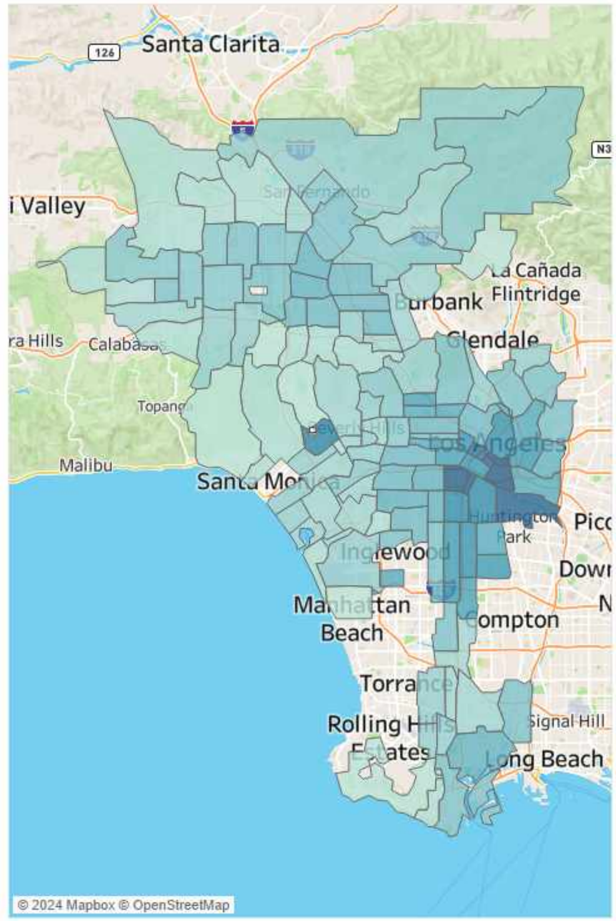


The first chart compares the percent of unmarried men in each zip code with the crime occurrences. The highest zip codes with unmarried men appear in the Downtown and Hollywood areas, which are the same areas that have the most crime occurrences.

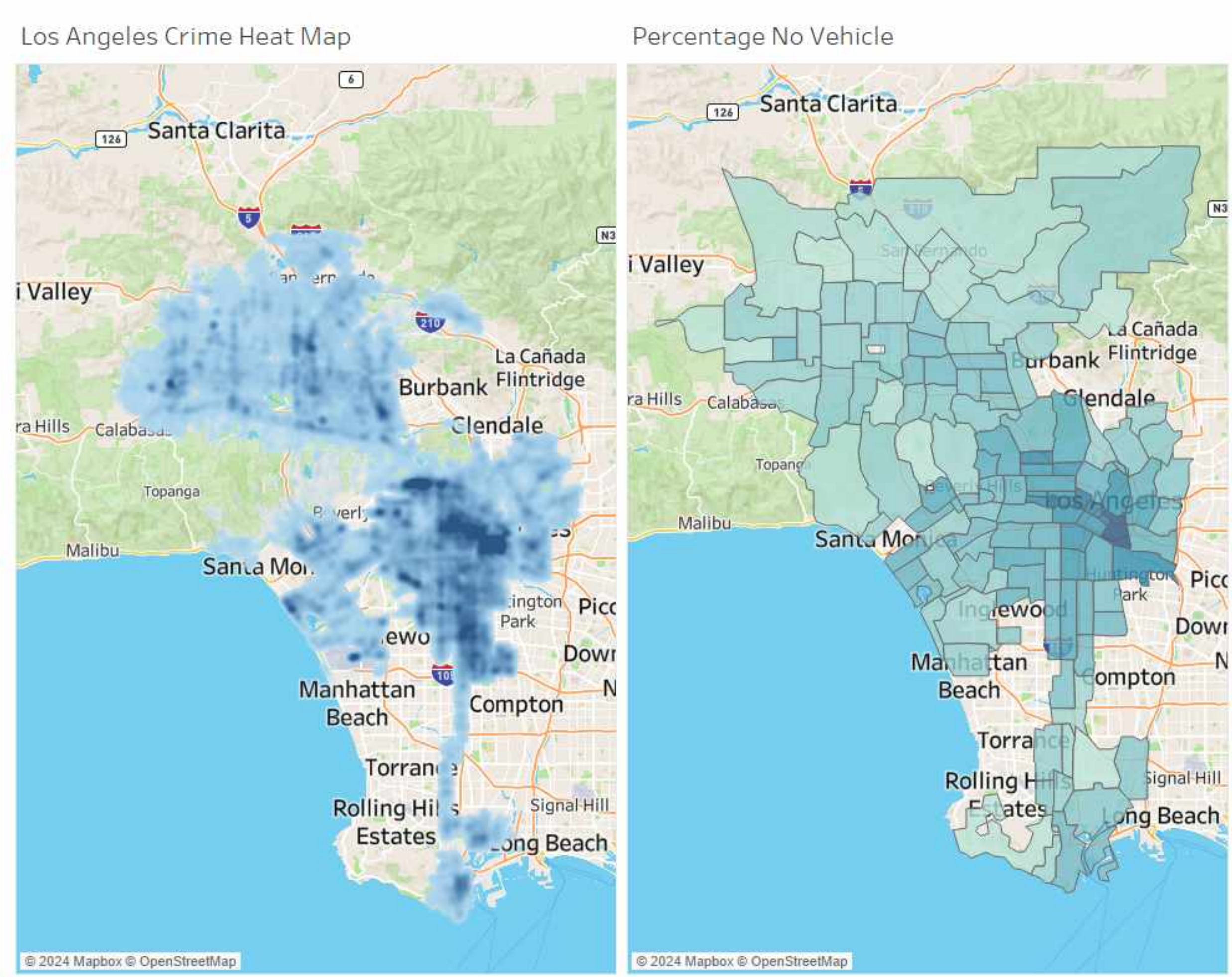
Los Angeles Crime Heat Map



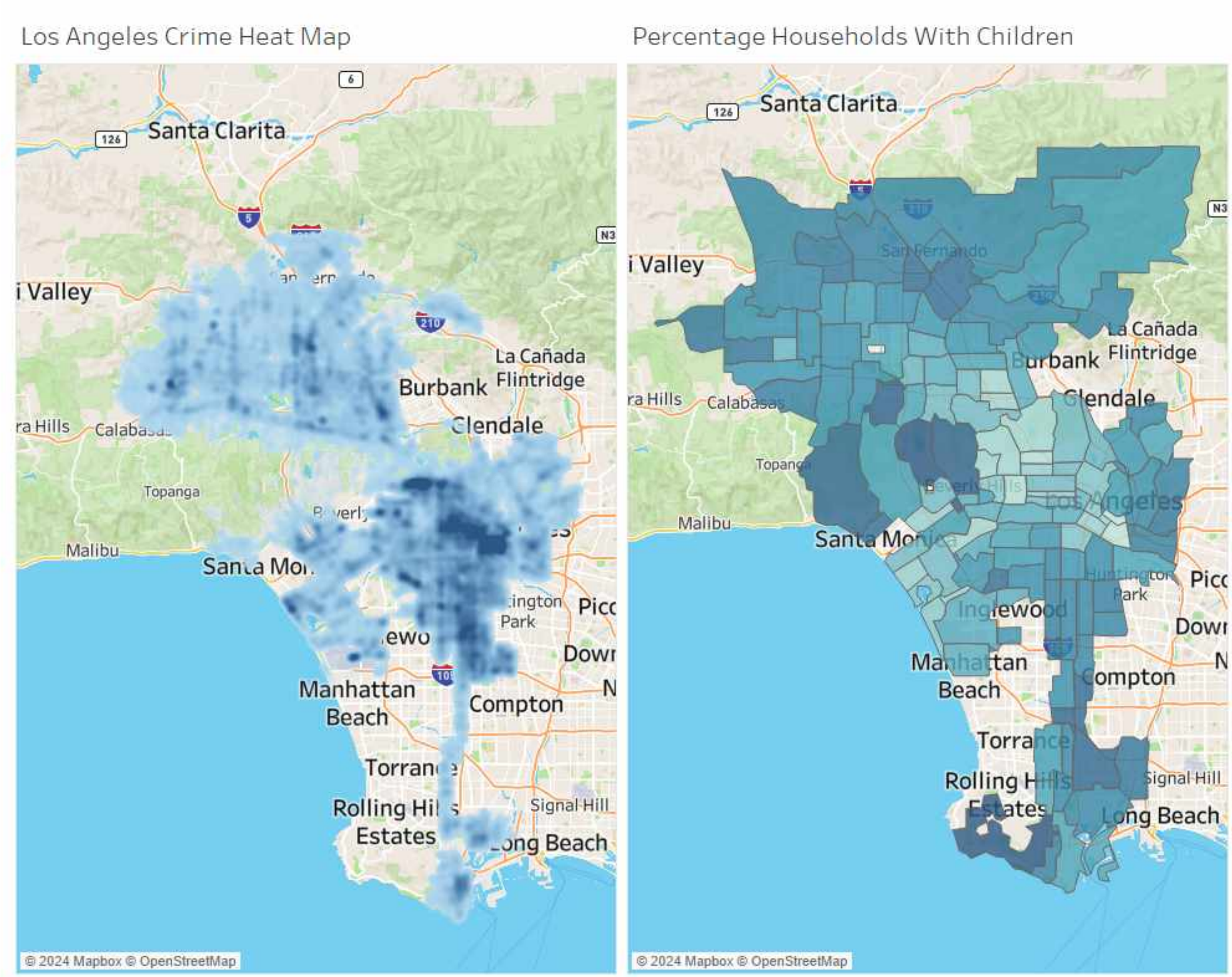
Percentage Poverty 18+



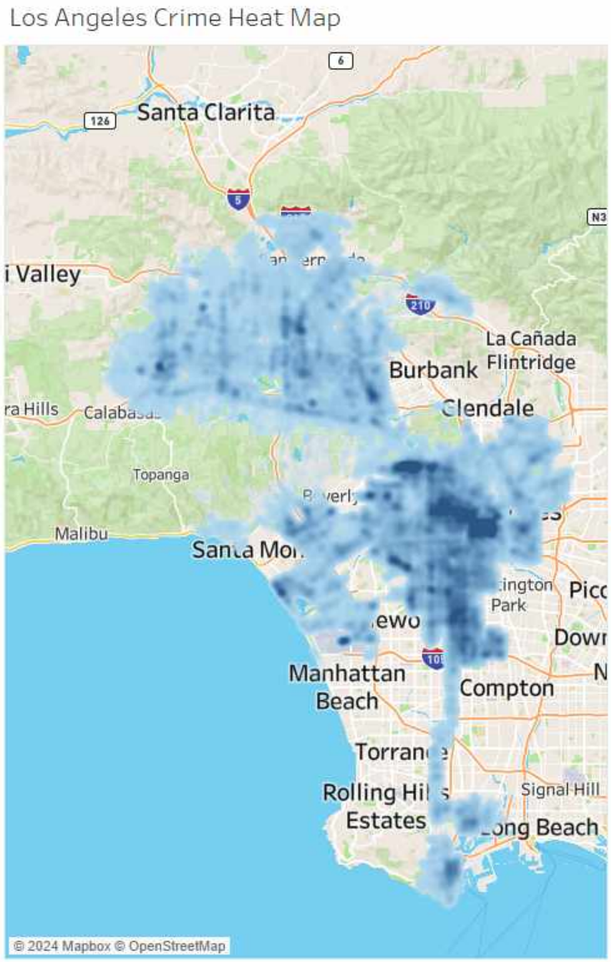
This chart looks at the percentage of poverty of 18 and older individuals in each zip code. The Downtown area has the highest poverty percentage and also the highest crime rates. The Hollywood area does not show as high a percentage of poverty, even though there are some areas with high crime. Zip Code 90024 in Beverly Hills also has a high amount of poverty, although since the LAPD does not cover parts of Beverly Hills, the crime occurrence map is incomplete in that area.

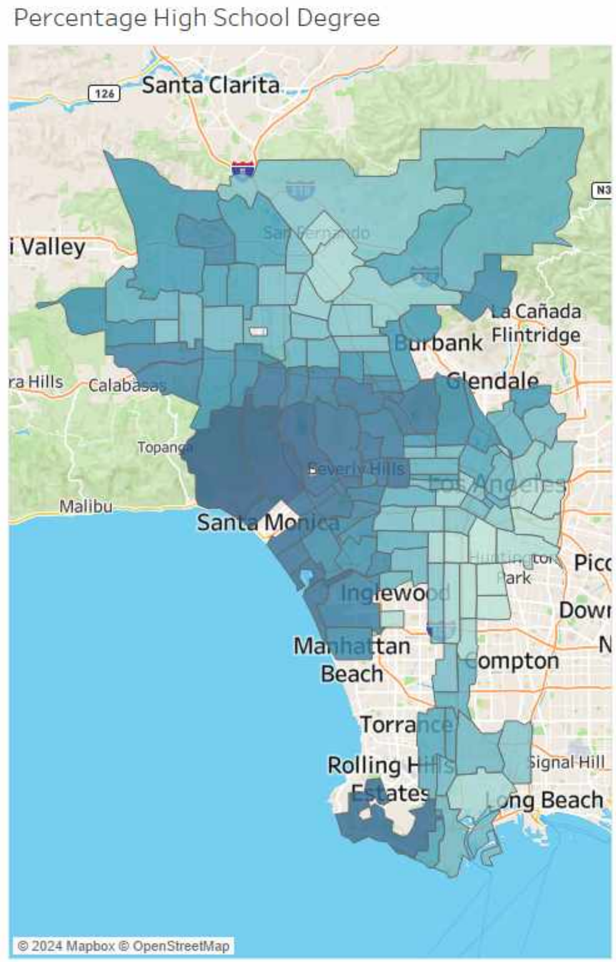


This chart looks at the percentage of households with no vehicles. The Downtown area shows the highest percentage of households without vehicles and the most crime occurrences.

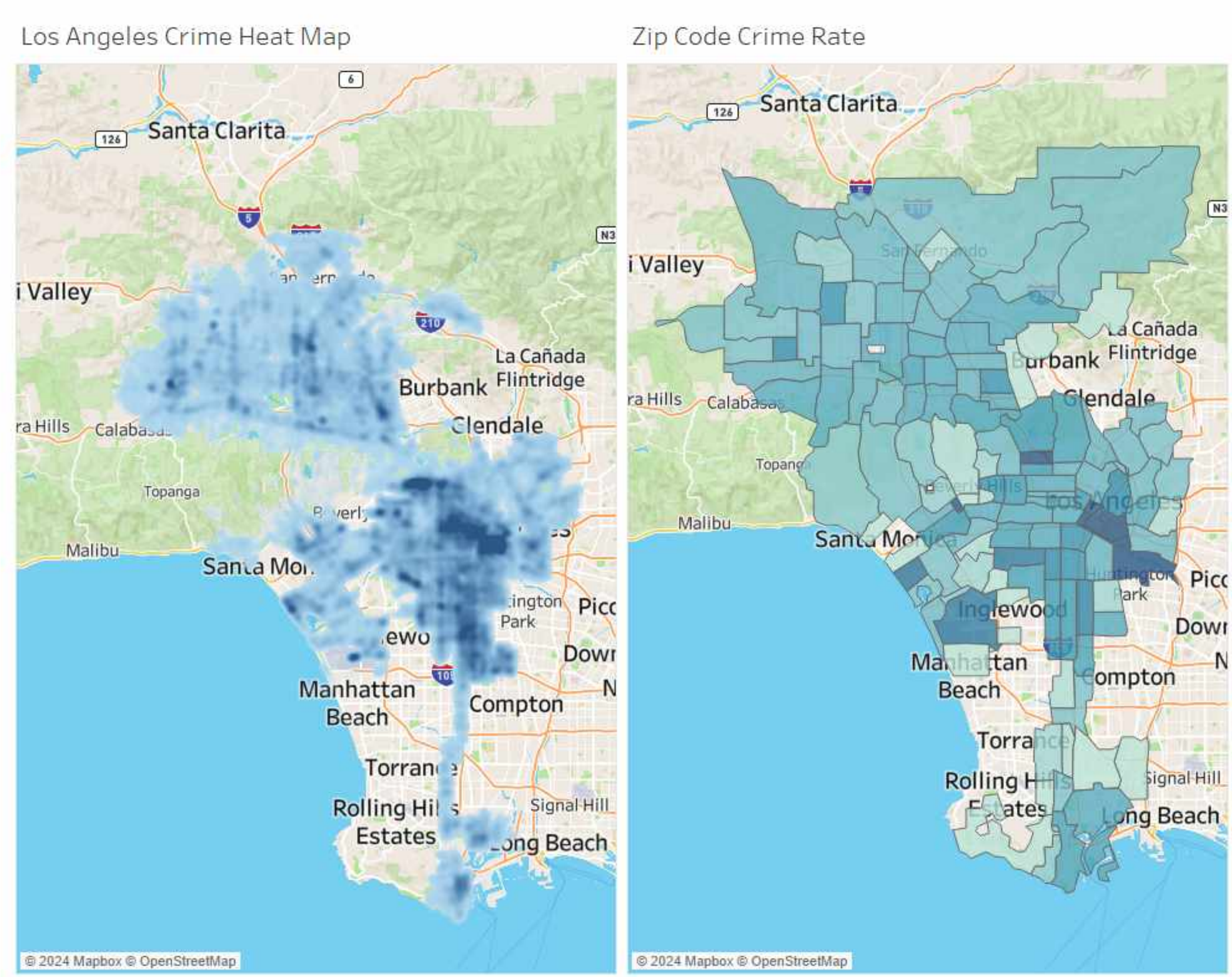


This chart looks at the percentage of households with children. There is a negative correlation where the zip codes with the highest percentage of children have less crime occurrences. The Downtown and Hollywood areas have the lowest percentage of households with children. An investigation would be needed to determine if having more households with children is a cause of lower crime rate, or if this division in households with children is an outcome of high crime rates, with families moving out of and avoiding high crime areas.





This chart shows the percentage of the population 25 and over that obtained at least a high school degree. The central area of the city has the lowest percentage of people with high school degrees while the western side of the city in the Beverly Hills and Santa Monica areas have the highest percentage of people with high school degrees.



This final map is a reference to compare the actual locations of crimes to the crime rate in each zip code. The zip codes with the highest crime correlate to the locations of crime occurrences, with the Downown areas and 90028 (Hollywood) having the highest crime rates. There are also high rates in 90045 (LAX airport) and 90291 (Playa Del Rey - Venice Beach area) which may be a result of those being typical travel and tourist areas.

CODE APPENDIX

Census data download code:
This python script was provided by Kevin Durkin (kcd5342@psu.edu) to assist in downloading large amounts of data from the Census website. The specific table that is downloaded can be changed by changing the API URLs in the create URL function.

```
import requests
import pandas as pd

# List of zip codes
zip_codes = ["90001", "90002", "90003", "90004", "90005", "90006", "90007", "90008", "90010",
"90011", "90012", "90013", "90014", "90015", "90016", "90017", "90018", "90019", "90020", "90021",
"90023", "90024", "90025", "90026", "90027", "90028", "90029", "90031", "90032", "90033", "90034",
"90035", "90036", "90037", "90038", "90039", "90041", "90042", "90043", "90044", "90045", "90046",
"90047", "90048", "90049", "90052", "90056", "90057", "90058", "90061", "90062", "90063", "90064",
"90065", "90066", "90067", "90068", "90069", "90071", "90077", "90079", "90089", "90090", "90094",
"90095", "90210", "90211", "90212", "90230", "90232", "90245", "90247", "90248", "90272", "90275",
"90280", "90290", "90291", "90292", "90293", "90302", "90304", "90402", "90403", "90405", "90501",
"90502", "90710", "90717", "90731", "90732", "90744", "90745", "90810", "90813", "91030", "91040",
"91042", "91201", "91206", "91214", "91302", "91303", "91304", "91306", "91307", "91311", "91316",
"91321", "91324", "91325", "91326", "91330", "91331", "91335", "91340", "91342", "91343", "91344",
"91345", "91352", "91356", "91364", "91367", "91371", "91401", "91402", "91403", "91405", "91406",
"91411", "91423", "91436", "91504", "91505", "91506", "91601", "91602", "91604", "91605", "91606",
"91607", "91608"]

def fetch_census_data(url):
  response = requests.get(url)
  if response.status_code == 200:
   try:
    return response.json()
   except ValueError as e:
    print(f"Error decoding JSON for URL {url}: {e}")
    return None
  else:
   print(f"Failed to fetch data for URL {url}: HTTP {response.status_code} - {response.text}")
   return None

# Function to create the URL for each year and zip code
def create_url(year, zip_code):
  if year > 2020:
   base_url = "https://api.census.gov/data/{year}/acs/acs5/profile?
get=group(DP03)&ucgid=860Z200US{zip_code}"
  #860Z200US90210
```

```
  else:
   base_url = "https://api.census.gov/data/{year}/acs/acs5/profile?
get=group(DP03)&ucgid=8600000US{zip_code}"
    #https://api.census.gov/data/2011/acs/acs5/profile?get=group(DP05)&ucgid=8600000US90210
  return base_url.format(year=year, zip_code=zip_code)

# Initialize a list to store all the data
all_data = []
header_set = False
columns = []

# Fetch data for each year and zip code

for year in range(2011, 2023):
  for zip_code in zip_codes:
    url = create_url(year, zip_code)
    data = fetch_census_data(url)
    if data:
     if not header_set:
      columns = ["Year", "Zip Code"] + data[0]
      header_set = True
     for row in data[1:]: # Skip the header row
      all_data.append([year, zip_code] + row)
      print("Appending " + str(year) + "-" + str(zip_code))
  if all_data:
      #print(all_data)
   df = pd.DataFrame(all_data, columns=columns)
      # Write the DataFrame to an Excel file
   df.to_excel("DP03-" + str(year)+ ".xlsx", index=False)
   print("Data has been written to file - " + str(year))
   all_data = []
   header_set = False
   columns = []
  else:
   print("No data fetched successfully.")
```

R code:
This section contains the R code for the project.

#Loops to combine datasets
#Not all DP tables have all columns in earlier years. The setdiff and names functions are used to add and sort missing columns

```
#DP02 Loop
dp02 <- read.csv("DP02-2022.csv")
fileLocationStart <- "/DP02-"
fileLocationEnd <- ".csv"
for (x in 1:11) {
  yearSelected <- 2022-x
  dp02n <- read.csv(paste(fileLocationStart, yearSelected, fileLocationEnd, sep=""))
  dp02n[setdiff(names(dp02), names(dp02n))] <- NA
  dp02n[names(dp02)]
  dp02 <- rbind(dp02, dp02n)
}

#DP03 Loop
dp03 <- read.csv("/DP03-2011.csv")
fileLocationStart <- "DP03-"
fileLocationEnd <- ".csv"
for (x in 1:11) {
  yearSelected <- 2011+x
  dp03n <- read.csv(paste(fileLocationStart, yearSelected, fileLocationEnd, sep=""))
  dp03 <- rbind(dp03, dp03n)
}

#DP04 Loop
dp04 <- read.csv("DP04-2022.csv")
fileLocationStart <- "DP04-"
fileLocationEnd <- ".csv"
for (x in 1:11) {
  yearSelected <- 2022-x
  dp04n <- read.csv(paste(fileLocationStart, yearSelected, fileLocationEnd, sep=""))
  dp04n[setdiff(names(dp04), names(dp04n))] <- NA
  dp04n[names(dp04)]
  dp04 <- rbind(dp04, dp04n)
}

#DP05 Loop
dp05 <- read.csv("DP05-2022.csv")
fileLocationStart <- "DP05-"
```

```
fileLocationEnd <- ".csv"
for (x in 1:11) {
  yearSelected <- 2022-x
  dp05n <- read.csv(paste(fileLocationStart, yearSelected, fileLocationEnd, sep=""))
  dp05n[setdiff(names(dp05), names(dp05n))] <- NA
  dp05n[names(dp05)]
  dp05 <- rbind(dp05, dp05n)
}

#Remove unneeded columns
dropColumns <- c("GEO_ID", "NAME", "ucgid")
dp02 <- dp02[,!(names(dp02) %in% dropColumns)]
dp03 <- dp03[,!(names(dp03) %in% dropColumns)]
dp04 <- dp04[,!(names(dp04) %in% dropColumns)]
dp05 <- dp05[,!(names(dp05) %in% dropColumns)]

dpcombined <- dp02
dpcombined <- merge(x=dpcombined,y=dp03, by=c("Year","Zip.Code"), all.x=TRUE)
dpcombined <- merge(x=dpcombined,y=dp04, by=c("Year","Zip.Code"), all.x=TRUE)
dpcombined <- merge(x=dpcombined,y=dp05, by=c("Year","Zip.Code"), all.x=TRUE)

#check for duplicate rows
dups <- dpcombined[c("Year", "Zip.Code")]
nrow(dups[duplicated(dups), ])

#Check if data merged correctly
subset(dpcombined, Year == 2016 & Zip.Code == 90210, select=DP05_0081E)
subset(dp05, Year == 2016 & Zip.Code == 90210, select=DP05_0081E)

#Write combined table
write.table(dpcombined, file = "CensusCombined.csv", sep = "|", quote = FALSE, row.names = FALSE )

#load data with zip codes from Tableau
ladatazp <- read.csv(Combined LA Crime Data with Zip Codes.csv")

#Remove duplicate DR numbers and copy only DR numbers and Zip Codes to new data frame
ladatazpnd <- ladatazp[!duplicated(ladatazp$Dr.No), ]
DrNo <- ladatazpnd[c("Dr.No", "Zip.Code")]

#Convert data format and extract year
ladatazpnd$Date.Conv <- strptime(ladatazpnd$Date.Occ, "%m/%d/%Y %H:%M:%S %p")
ladatazpnd$Year <- as.numeric(format(ladatazpnd$Date.Conv,'%Y'))

#Open original crime data and remove duplicate DR Numbers
```

```
ladata <- read.csv("Combined LA Crime Data.csv")
ladatand <- ladata[!duplicated(ladata$DR_NO), ]
names(DrNo)[names(DrNo) == 'Dr.No'] <- 'DR_NO'

#Merge Zip Codes with LA crime data
ladata <- merge(x=ladatand,y=DrNo, by=c("DR_NO"), all.x=TRUE)
```

```
#Convert Year
ladata$Date.Conv <- strptime(ladata$DATE.OCC, "%m/%d/%Y %H:%M:%S %p")
ladata$Year <- as.numeric(format(ladata$Date.Conv,'%Y'))

#Generate crime count
crimeCount <- data.frame(table(ladata[c("Zip.Code", "Year")]))

#Add population data an create per capita stat
crimeCount <- merge(x=crimeCount,y=censusdata[c("Zip.Code", "Year", "DP05_0001E")],
by=c("Zip.Code", "Year"), all.x=TRUE)
crimeCount <- na.omit(crimeCount)
crimeCount$CrimeRate <- crimeCount$Freq / crimeCount$DP05_0001E

#For the PCA:
#Add some demographic data
crimeCensus <- merge(x=crimeCount,y=censusdata[c("Zip.Code", "Year", "DP03_0062E",
"DP03_0009PE", "DP02_0065PE", "DP03_0096PE")], by=c("Zip.Code", "Year"), all.x=TRUE)

#Drop zero and negative values
crimeCensus <- crimeCensus[!(crimeCensus$DP05_0001E == 0),]
crimeCensus <- crimeCensus[!(crimeCensus$DP03_0062E < 0),]
crimeCensus <- crimeCensus[!(crimeCensus$DP03_0009PE < 0),]
crimeCensus <- crimeCensus[!(crimeCensus$DP02_0065PE < 0),]
crimeCensus <- crimeCensus[!(crimeCensus$DP03_0096PE < 0),]

#PCA
#Rename variables
names(crimeCensus)[names(crimeCensus) == 'DP05_0001E'] <- 'Population'
names(crimeCensus)[names(crimeCensus) == 'DP03_0062E'] <- 'Median Income'
names(crimeCensus)[names(crimeCensus) == 'DP03_0009PE'] <- 'Unemployment %'
names(crimeCensus)[names(crimeCensus) == 'DP02_0065PE'] <- 'Bachelors Degree %'
names(crimeCensus)[names(crimeCensus) == 'DP03_0096PE'] <- 'Health Coverage %'
names(crimeCensus)[names(crimeCensus) == 'DP05_0038PE'] <- 'Black'

#Perform PCA
crimeCensusNorm <- subset(crimeCensus, select = -c(Year, Zip.Code, Freq, CrimeRate))
crimeCensusNorm <- data.frame(scale(crimeCensusNorm))
crimeCensusNorm.pca <- princomp(crimeCensusNorm)
summary(crimeCensusNorm.pca)
crimeCensusNorm.pca$loadings
fviz_pca_var(crimeCensusNorm.pca, col.var = "black")
```

Basic Model Code

```
#Create dataset for models
BasicModelData <- censusdata[c("Year", "Zip.Code", "DP02_0001E",
"DP05_0001E", "DP03_0009PE", "DP03_0051E",
                          "DP04_0001E", "DP02_0065PE", "DP03_0099PE",
"DP05_0072PE")]

#Remove bad data
BasicModelData <- na.omit(BasicModelData)
BasicModelData <- BasicModelData[!(BasicModelData$DP05_0001E <= 0),]
lesszero <- apply(BasicModelData, 1, function(x){any(x < 0)})
BasicModelData <- BasicModelData[!lesszero,]

#Merge Rate Data
BasicModelData <- merge(x=BasicModelData,y=CrimeCount[c("Zip.Code", "Year",
"CrimeRate")], by=c("Zip.Code", "Year"), all.x=TRUE)

#Separate Data to scale
TempData <- BasicModelData[c("Zip.Code", "Year", "CrimeRate", "DP05_0001E")]
BasicModelData <- subset(BasicModelData, select = -c(Year, Zip.Code,
CrimeRate, DP05_0001E))

#Scale Data
BasicModelData <- data.frame(scale(BasicModelData))

#Add Missing Data Back
#BasicModelData$Zip.Code <- TempData$Zip.Code
#BasicModelData$Year <- TempData$Year
BasicModelData$CrimeRate <- TempData$CrimeRate

lmBasicCrimeRate = lm(CrimeRate~., data = BasicModelData)
summary(lmBasicCrimeRate)
```

PCA Model Code

```
#Create dataset for models
ModelData <- censusdata[c("Year", "Zip.Code", "DP05_0001E", "DP02_0002PE",
"DP02_0003PE", "DP02_0004PE",
                          "DP02_0005PE", "DP02_0006PE", "DP02_0007PE",
"DP02_0008PE", "DP02_0009PE",
                          "DP02_0010PE", "DP02_0011PE", "DP02_0012PE",
"DP02_0013PE", "DP02_0014PE",
                          "DP02_0019PE", "DP02_0020PE", "DP02_0021PE",
"DP02_0022PE", "DP02_0023PE",
                          "DP02_0026PE", "DP02_0027PE", "DP02_0028PE",
"DP02_0029PE",
                          "DP02_0032PE", "DP02_0033PE", "DP02_0034PE",
"DP02_0035PE",
                          "DP02_0045PE", "DP02_0046PE", "DP02_0047PE",
"DP02_0048PE", "DP02_0051PE",
                          "DP02_0053PE", "DP02_0054PE", "DP02_0055PE",
"DP02_0056PE", "DP02_0057PE",
                          "DP02_0059PE", "DP02_0060PE", "DP02_0061PE",
"DP02_0062PE", "DP02_0063PE",
                          "DP02_0064PE", "DP02_0065PE", "DP02_0066PE",
"DP02_0067PE",
                          "DP02_0080PE", "DP02_0081PE", "DP02_0082PE",
"DP02_0083PE", "DP02_0084PE",
                          "DP02_0085PE", "DP02_0087PE",
                          "DP02_0089PE", "DP02_0090PE", "DP02_0091PE",
"DP02_0092PE", "DP02_0094PE",
                          "DP02_0113PE", "DP02_0114PE", "DP02_0115PE",
"DP02_0116PE", "DP02_0117PE",
                          "DP02_0118PE", "DP02_0119PE", "DP02_0120PE",
"DP02_0121PE")]

#Remove bad data
ModelData <- na.omit(ModelData)
ModelData <- ModelData[!(ModelData$DP05_0001E <= 0),]
lesszero <- apply(ModelData, 1, function(x){any(x < 0)})
ModelData <- ModelData[!lesszero,]

#Merge Rate Data
ModelData <- merge(x=ModelData,y=CrimeCount[c("Zip.Code", "Year",
"CrimeRate")], by=c("Zip.Code", "Year"), all.x=TRUE)

#Separate Data to scale
TempData <- ModelData[c("Zip.Code", "Year", "CrimeRate", "DP05_0001E")]
ModelData <- subset(ModelData, select = -c(Year, Zip.Code, CrimeRate,
DP05_0001E))

#Scale Data
ModelData <- data.frame(scale(ModelData))
```

```
#Add Missing Data Back
ModelData$Zip.Code <- TempData$Zip.Code
ModelData$Year <- TempData$Year
ModelData$CrimeRate <- TempData$CrimeRate

#At This Step, Run the PCA Methods

#PCA for Household data
PCAHousehold <- ModelData[c("DP02_0002PE", "DP02_0003PE", "DP02_0004PE",
"DP02_0005PE", "DP02_0006PE", "DP02_0007PE", "DP02_0008PE", "DP02_0009PE",
                             "DP02_0010PE", "DP02_0011PE", "DP02_0012PE",
"DP02_0013PE", "DP02_0014PE")]
PCAHousehold.pca <- princomp(PCAHousehold)
PredictHousehold <- data.frame(predict(PCAHousehold.pca, ModelData))
colnames(PredictHousehold) <- paste("Household", colnames(PredictHousehold),
sep="_")
summary(PCAHousehold.pca)

#PCA for Relationship data
PCARelationship <- ModelData[c("DP02_0019PE", "DP02_0020PE", "DP02_0021PE",
"DP02_0022PE", "DP02_0023PE")]
PCARelationshipNorm.pca <- princomp(PCARelationship)
PredictRelationship <- data.frame(predict(PCARelationshipNorm.pca,
ModelData))
colnames(PredictRelationship) <- paste("Relationship",
colnames(PredictRelationship), sep="_")
summary(PCARelationshipNorm.pca)

#PCA for Marital Status data
PCAMarital <- ModelData[c("DP02_0026PE", "DP02_0027PE", "DP02_0028PE",
"DP02_0029PE",
                           "DP02_0032PE", "DP02_0033PE", "DP02_0034PE",
"DP02_0035PE")]
PCAMaritalNorm.pca <- princomp(PCAMarital)
PredictMarital <- data.frame(predict(PCAMaritalNorm.pca, ModelData))
colnames(PredictMarital) <- paste("Marital", colnames(PredictMarital),
sep="_")
summary(PCAMaritalNorm.pca)

#PCA for Grandparents data
PCAGrandparents <- ModelData[c("DP02_0045PE", "DP02_0046PE", "DP02_0047PE",
"DP02_0048PE", "DP02_0051PE")]
PCAGrandparentsNorm.pca <- princomp(PCAGrandparents)
PredictGrandparents <- data.frame(predict(PCAGrandparentsNorm.pca,
ModelData))
colnames(PredictGrandparents) <- paste("Grandparents",
colnames(PredictGrandparents), sep="_")
summary(PCAGrandparentsNorm.pca)
```

```
#PCA for School Enrollment data
PCASchoolEnroll <- ModelData[c("DP02_0053PE", "DP02_0054PE", "DP02_0055PE",
"DP02_0056PE", "DP02_0057PE")]
PCASchoolEnrollNorm.pca <- princomp(PCASchoolEnroll)
PredictSchoolEnroll <- data.frame(predict(PCASchoolEnrollNorm.pca,
ModelData))
colnames(PredictSchoolEnroll) <- paste("SchoolEnroll",
colnames(PredictSchoolEnroll), sep="_")
summary(PCASchoolEnrollNorm.pca)

#PCA for Education Attainment data
PCAEduAttainment <- ModelData[c("DP02_0059PE", "DP02_0060PE", "DP02_0061PE",
"DP02_0062PE", "DP02_0063PE",
                                 "DP02_0064PE", "DP02_0065PE", "DP02_0066PE",
"DP02_0067PE")]
PCAEduAttainmentNorm.pca <- princomp(PCAEduAttainment)
PredictEduAttainment <- data.frame(predict(PCAEduAttainmentNorm.pca,
ModelData))
colnames(PredictEduAttainment) <- paste("EduAttainment",
colnames(PredictEduAttainment), sep="_")
summary(PCAEduAttainmentNorm.pca)

#PCA for Residence 1 year ago data
PCARes1Year <- ModelData[c("DP02_0080PE", "DP02_0081PE", "DP02_0082PE",
"DP02_0083PE", "DP02_0084PE",
                            "DP02_0085PE", "DP02_0087PE")]
PCARes1YearNorm.pca <- princomp(PCARes1Year)
PredictRes1Year <- data.frame(predict(PCARes1YearNorm.pca, ModelData))
colnames(PredictRes1Year) <- paste("Res1Year", colnames(PredictRes1Year),
sep="_")
summary(PCARes1YearNorm.pca)

#PCA for Place of Birth data
PCAPlaceBirth <- ModelData[c("DP02_0089PE", "DP02_0090PE", "DP02_0091PE",
"DP02_0092PE", "DP02_0094PE")]
PCAPlaceBirthNorm.pca <- princomp(PCAPlaceBirth)
PredictPlaceBirth <- data.frame(predict(PCAPlaceBirthNorm.pca, ModelData))
colnames(PredictPlaceBirth) <- paste("PlaceBirth",
colnames(PredictPlaceBirth), sep="_")
summary(PCAPlaceBirthNorm.pca)

#PCA for Language at Home data
PCALanguageHome <- ModelData[c("DP02_0113PE", "DP02_0114PE", "DP02_0115PE",
"DP02_0116PE", "DP02_0117PE",
                                "DP02_0118PE", "DP02_0119PE", "DP02_0120PE",
"DP02_0121PE")]
PCALanguageHomeNorm.pca <- princomp(PCALanguageHome)
```

```
PredictLanguageHome <- data.frame(predict(PCALanguageHomeNorm.pca,
ModelData))
colnames(PredictLanguageHome) <- paste("LanguageHome",
colnames(PredictLanguageHome), sep="_")
summary(PCALanguageHomeNorm.pca)

#Add PCA variables to PCA Data Model
PCAModelData <- PredictHousehold[c(1:3)]
PCAModelData <- cbind(PCAModelData, PredictRelationship[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictMarital[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictGrandparents[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictSchoolEnroll[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictEduAttainment[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictRes1Year[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictPlaceBirth[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictLanguageHome[c(1:4)])
PCAModelData$CrimeRate <- scale(ModelData$CrimeRate)

lmCrimeRate = lm(CrimeRate~., data = PCAModelData)
summary(lmCrimeRate)
```

Boruta Code

```
#Create dataset for models
BorutaModelData <- censusdata[c("Year", "Zip.Code", "DP05_0001E",
"DP02_0002PE", "DP02_0003PE", "DP02_0004PE",
                          "DP02_0005PE", "DP02_0006PE", "DP02_0007PE",
"DP02_0008PE", "DP02_0009PE",
                          "DP02_0010PE", "DP02_0011PE", "DP02_0012PE",
"DP02_0013PE", "DP02_0014PE",
                          "DP02_0019PE", "DP02_0020PE", "DP02_0021PE",
"DP02_0022PE", "DP02_0023PE",
                          "DP02_0026PE", "DP02_0027PE", "DP02_0028PE",
"DP02_0029PE",
                          "DP02_0032PE", "DP02_0033PE", "DP02_0034PE",
"DP02_0035PE",
                          "DP02_0045PE", "DP02_0046PE", "DP02_0047PE",
"DP02_0048PE", "DP02_0051PE",
                          "DP02_0053PE", "DP02_0054PE", "DP02_0055PE",
"DP02_0056PE", "DP02_0057PE",
                          "DP02_0059PE", "DP02_0060PE", "DP02_0061PE",
"DP02_0062PE", "DP02_0063PE",
                          "DP02_0064PE", "DP02_0065PE", "DP02_0066PE",
"DP02_0067PE",
                          "DP02_0080PE", "DP02_0081PE", "DP02_0082PE",
"DP02_0083PE", "DP02_0084PE",
                          "DP02_0085PE", "DP02_0087PE",
                          "DP02_0089PE", "DP02_0090PE", "DP02_0091PE",
"DP02_0092PE", "DP02_0094PE",
                          "DP02_0113PE", "DP02_0114PE", "DP02_0115PE",
"DP02_0116PE", "DP02_0117PE",
                          "DP02_0118PE", "DP02_0119PE", "DP02_0120PE",
"DP02_0121PE")]

#Remove bad data
BorutaModelData <- na.omit(BorutaModelData)
BorutaModelData <- BorutaModelData[!(BorutaModelData$DP05_0001E <= 0),]
lesszero <- apply(BorutaModelData, 1, function(x){any(x < 0)})
BorutaModelData <- BorutaModelData[!lesszero,]

#Merge Rate Data
BorutaModelData <- merge(x=BorutaModelData,y=CrimeCount[c("Zip.Code", "Year",
"CrimeRate")], by=c("Zip.Code", "Year"), all.x=TRUE)

#Remove Year and Zip Code
BorutaModelData <- subset(BorutaModelData, select = -c(Year, Zip.Code))

#Scale Data
ScaledBorutaModelData <- data.frame(scale(BorutaModelData))

#Run Boruta Model
```

```
set.seed(100)
boruta.BorutaModelData <- Boruta(CrimeRate~., data = BorutaModelData, doTrace
= 2, maxRuns = 1000,)
print(boruta.BorutaModelData)

boruta.ScaledBorutaModelData <- Boruta(CrimeRate~., data =
ScaledBorutaModelData, doTrace = 2, maxRuns = 1000,)
print(boruta.ScaledBorutaModelData)

NonPCAModelData <- subset(ModelData, select = -c(Year, Zip.Code, CrimeRate))
NonPCAModelData$CrimeRate <- scale(ModelData$CrimeRate)

lmCrimeRate2 = lm(CrimeRate~., data = NonPCAModelData)
summary(lmCrimeRate2)
```

Model Code

```
# This file contains the one-click version of model generation. Simple
select all
# and run in order generate the various models for the project.

#load libraries
library(ggplot2)
library(lmtest)
library(car)
library(glmnet)
library(Boruta)
library(randomForest)

#load Census Data
censusdata <- read.csv("CensusCombined-1.csv", sep = "|")

#load crime rates
CrimeCount <- read.csv("Crime Count.csv", sep = "|")

#Create dataset for models
ModelData <- censusdata[c("Year", "Zip.Code", "DP05_0001E",
"DP02_0002PE", "DP02_0003PE", "DP02_0004PE",
                          "DP02_0005PE", "DP02_0006PE", "DP02_0007PE",
"DP02_0008PE", "DP02_0009PE",
                          "DP02_0010PE", "DP02_0011PE", "DP02_0012PE",
"DP02_0013PE", "DP02_0014PE",
                          "DP02_0019PE", "DP02_0020PE", "DP02_0021PE",
"DP02_0022PE", "DP02_0023PE",
                          "DP02_0026PE", "DP02_0027PE", "DP02_0028PE",
"DP02_0029PE",
                          "DP02_0032PE", "DP02_0033PE", "DP02_0034PE",
"DP02_0035PE",
                          "DP02_0045PE", "DP02_0046PE", "DP02_0047PE",
"DP02_0048PE", "DP02_0051PE",
                          "DP02_0053PE", "DP02_0054PE", "DP02_0055PE",
"DP02_0056PE", "DP02_0057PE",
                          "DP02_0059PE", "DP02_0060PE", "DP02_0061PE",
"DP02_0062PE", "DP02_0063PE",
                          "DP02_0064PE", "DP02_0065PE", "DP02_0066PE",
"DP02_0067PE",
                          "DP02_0080PE", "DP02_0081PE", "DP02_0082PE",
"DP02_0083PE", "DP02_0084PE",
                          "DP02_0085PE", "DP02_0087PE",
                          "DP02_0089PE", "DP02_0090PE", "DP02_0091PE",
"DP02_0092PE", "DP02_0094PE",
                          "DP02_0113PE", "DP02_0114PE", "DP02_0115PE",
"DP02_0116PE", "DP02_0117PE",
                          "DP02_0118PE", "DP02_0119PE", "DP02_0120PE",
"DP02_0121PE",
                          "DP03_0002PE", "DP03_0003PE", "DP03_0004PE",
"DP03_0005PE", "DP03_0006PE",
```

```
                           "DP03_0007PE", "DP03_0009PE", "DP03_0011PE",
"DP03_0012PE", "DP03_0013PE",
                           "DP03_0015PE", "DP03_0017PE",
                           "DP03_0019PE", "DP03_0020PE", "DP03_0021PE",
"DP03_0022PE", "DP03_0023PE",
                           "DP03_0024PE",
                           "DP03_0027PE", "DP03_0028PE", "DP03_0029PE",
"DP03_0030PE", "DP03_0031PE",
                           "DP03_0033PE", "DP03_0034PE", "DP03_0035PE",
"DP03_0036PE", "DP03_0037PE",
                           "DP03_0038PE", "DP03_0039PE", "DP03_0040PE",
"DP03_0041PE", "DP03_0042PE",
                           "DP03_0043PE", "DP03_0044PE", "DP03_0045PE",
                           "DP03_0047PE", "DP03_0048PE", "DP03_0049PE",
"DP03_0050PE",
                           "DP03_0052PE", "DP03_0053PE", "DP03_0054PE",
"DP03_0055PE", "DP03_0056PE",
                           "DP03_0057PE", "DP03_0058PE", "DP03_0059PE",
"DP03_0060PE", "DP03_0061PE",
                           "DP03_0064PE", "DP03_0066PE", "DP03_0068PE",
"DP03_0070PE", "DP03_0072PE",
                           "DP03_0076PE", "DP03_0077PE", "DP03_0078PE",
"DP03_0079PE", "DP03_0080PE",
                           "DP03_0081PE", "DP03_0082PE", "DP03_0083PE",
"DP03_0084PE", "DP03_0085PE",
                           "DP03_0119PE", "DP03_0120PE", "DP03_0121PE",
"DP03_0122PE", "DP03_0123PE",
                           "DP03_0124PE", "DP03_0125PE", "DP03_0126PE",
"DP03_0127PE", "DP03_0128PE",
                           "DP03_0129PE", "DP03_0130PE", "DP03_0131PE",
"DP03_0132PE", "DP03_0133PE",
                           "DP03_0134PE", "DP03_0135PE", "DP03_0136PE",
"DP03_0137PE",
                           "DP04_0002PE", "DP04_0003PE",
                           "DP04_0007PE", "DP04_0008PE", "DP04_0009PE",
"DP04_0010PE", "DP04_0011PE",
                           "DP04_0012PE", "DP04_0013PE", "DP04_0014PE",
"DP04_0015PE",
                           "DP04_0017PE", "DP04_0018PE", "DP04_0019PE",
"DP04_0020PE", "DP04_0021PE",
                           "DP04_0022PE", "DP04_0023PE", "DP04_0024PE",
"DP04_0025PE",
                           "DP04_0028PE", "DP04_0029PE", "DP04_0030PE",
"DP04_0031PE", "DP04_0032PE",
                           "DP04_0033PE", "DP04_0034PE", "DP04_0035PE",
                           "DP04_0039PE", "DP04_0040PE", "DP04_0041PE",
"DP04_0042PE", "DP04_0043PE",
                           "DP04_0046PE",
                           "DP04_0051PE", "DP04_0052PE", "DP04_0053PE",
"DP04_0054PE", "DP04_0055PE",
                           "DP04_0058PE", "DP04_0059PE", "DP04_0060PE",
```

```
                              "DP04_0063PE", "DP04_0064PE", "DP04_0065PE",
"DP04_0066PE", "DP04_0067PE",
                              "DP04_0068PE", "DP04_0069PE", "DP04_0070PE",
                              "DP04_0081PE", "DP04_0082PE", "DP04_0083PE",
"DP04_0084PE", "DP04_0085PE",
                              "DP04_0086PE", "DP04_0087PE",
                              "DP04_0091PE",
                              "DP04_0094PE", "DP04_0095PE", "DP04_0096PE",
"DP04_0097PE", "DP04_0098PE",
                              "DP04_0099PE",
                              "DP04_0127PE", "DP04_0128PE", "DP04_0129PE",
"DP04_0130PE", "DP04_0131PE",
                              "DP05_0002PE", "DP05_0003PE",
                              "DP05_0005PE", "DP05_0006PE", "DP05_0007PE",
"DP05_0008PE", "DP05_0009PE",
                              "DP05_0010PE", "DP05_0011PE", "DP05_0012PE",
"DP05_0013PE", "DP05_0014PE",
                              "DP05_0015PE", "DP05_0016PE",
                              "DP05_0066PE", "DP05_0067PE", "DP05_0068PE",
"DP05_0069PE", "DP05_0070PE",
                              "DP05_0071PE",
                              "DP05_0073PE", "DP05_0074PE", "DP05_0075PE",
"DP05_0076PE", "DP05_0077PE"
)]

#Remove bad data
ModelData <- na.omit(ModelData)
ModelData <- ModelData[!(ModelData$DP05_0001E <= 0),]
lesszero <- apply(ModelData, 1, function(x){any(x < 0)})
ModelData <- ModelData[!lesszero,]

#Merge Rate Data
ModelData <- merge(x=ModelData,y=CrimeCount[c("Zip.Code", "Year",
"CrimeRate")], by=c("Zip.Code", "Year"), all.x=TRUE)

#Separate Data to scale
TempData <- ModelData[c("Zip.Code", "Year", "CrimeRate",
"DP05_0001E")]
ModelData <- subset(ModelData, select = -c(Year, Zip.Code, CrimeRate,
DP05_0001E))

#Scale Data
ModelData <- data.frame(scale(ModelData))

#Add Missing Data Back
ModelData$Zip.Code <- TempData$Zip.Code
ModelData$Year <- TempData$Year
ModelData$CrimeRate <- TempData$CrimeRate


#Remove Outliers
ModelData <- ModelData[!(ModelData$CrimeRate >= 0.5),]
```

```
#Generate test and training groups
set.seed(100)
ModelRandom <- ModelData[sample(nrow(ModelData)), ]
modeltrain <- ModelRandom[1:1029, ]
modeltest <- ModelRandom[1029:1285, ]

#At This Step, Run the PCA Methods

#PCA for Household data
PCAHousehold <- modeltrain[c("DP02_0002PE", "DP02_0003PE",
"DP02_0004PE", "DP02_0005PE", "DP02_0006PE", "DP02_0007PE",
"DP02_0008PE", "DP02_0009PE",
                             "DP02_0010PE", "DP02_0011PE",
"DP02_0012PE", "DP02_0013PE", "DP02_0014PE")]
PCAHousehold.pca <- princomp(PCAHousehold)
PredictHousehold <- data.frame(predict(PCAHousehold.pca, modeltrain))
colnames(PredictHousehold) <- paste("Household",
colnames(PredictHousehold), sep="_")
TestPredictHousehold <- data.frame(predict(PCAHousehold.pca,
modeltest))
colnames(TestPredictHousehold) <- paste("Household",
colnames(TestPredictHousehold), sep="_")
summary(PCAHousehold.pca)

#PCA for Relationship data
PCARelationship <- modeltrain[c("DP02_0019PE", "DP02_0020PE",
"DP02_0021PE", "DP02_0022PE", "DP02_0023PE")]
PCARelationshipNorm.pca <- princomp(PCARelationship)
PredictRelationship <- data.frame(predict(PCARelationshipNorm.pca,
modeltrain))
colnames(PredictRelationship) <- paste("Relationship",
colnames(PredictRelationship), sep="_")
TestPredictRelationship <- data.frame(predict(PCARelationshipNorm.pca,
modeltest))
colnames(TestPredictRelationship) <- paste("Relationship",
colnames(TestPredictRelationship), sep="_")
summary(PCARelationshipNorm.pca)

#PCA for Marital Status data
PCAMarital <- modeltrain[c("DP02_0026PE", "DP02_0027PE",
"DP02_0028PE", "DP02_0029PE",
                           "DP02_0032PE", "DP02_0033PE",
"DP02_0034PE", "DP02_0035PE")]
PCAMaritalNorm.pca <- princomp(PCAMarital)
PredictMarital <- data.frame(predict(PCAMaritalNorm.pca, modeltrain))
colnames(PredictMarital) <- paste("Marital", colnames(PredictMarital),
sep="_")
TestPredictMarital <- data.frame(predict(PCAMaritalNorm.pca,
modeltest))
colnames(TestPredictMarital) <- paste("Marital",
colnames(TestPredictMarital), sep="_")
```

```
summary(PCAMaritalNorm.pca)

#PCA for Grandparents data
PCAGrandparents <- modeltrain[c("DP02_0045PE", "DP02_0046PE",
"DP02_0047PE", "DP02_0048PE", "DP02_0051PE")]
PCAGrandparentsNorm.pca <- princomp(PCAGrandparents)
PredictGrandparents <- data.frame(predict(PCAGrandparentsNorm.pca,
modeltrain))
colnames(PredictGrandparents) <- paste("Grandparents",
colnames(PredictGrandparents), sep="_")
TestPredictGrandparents <- data.frame(predict(PCAGrandparentsNorm.pca,
modeltest))
colnames(TestPredictGrandparents) <- paste("Grandparents",
colnames(TestPredictGrandparents), sep="_")
summary(PCAGrandparentsNorm.pca)

#PCA for School Enrollment data
PCASchoolEnroll <- modeltrain[c("DP02_0053PE", "DP02_0054PE",
"DP02_0055PE", "DP02_0056PE", "DP02_0057PE")]
PCASchoolEnrollNorm.pca <- princomp(PCASchoolEnroll)
PredictSchoolEnroll <- data.frame(predict(PCASchoolEnrollNorm.pca,
modeltrain))
colnames(PredictSchoolEnroll) <- paste("SchoolEnroll",
colnames(PredictSchoolEnroll), sep="_")
TestPredictSchoolEnroll <- data.frame(predict(PCASchoolEnrollNorm.pca,
modeltest))
colnames(TestPredictSchoolEnroll) <- paste("SchoolEnroll",
colnames(TestPredictSchoolEnroll), sep="_")
summary(PCASchoolEnrollNorm.pca)

#PCA for Education Attainment data
PCAEduAttainment <- modeltrain[c("DP02_0059PE", "DP02_0060PE",
"DP02_0061PE", "DP02_0062PE", "DP02_0063PE",
                                 "DP02_0064PE", "DP02_0065PE",
"DP02_0066PE", "DP02_0067PE")]
PCAEduAttainmentNorm.pca <- princomp(PCAEduAttainment)
PredictEduAttainment <- data.frame(predict(PCAEduAttainmentNorm.pca,
modeltrain))
colnames(PredictEduAttainment) <- paste("EduAttainment",
colnames(PredictEduAttainment), sep="_")
TestPredictEduAttainment <-
data.frame(predict(PCAEduAttainmentNorm.pca, modeltest))
colnames(TestPredictEduAttainment) <- paste("EduAttainment",
colnames(TestPredictEduAttainment), sep="_")
summary(PCAEduAttainmentNorm.pca)

#PCA for Residence 1 year ago data
PCARes1Year <- modeltrain[c("DP02_0080PE", "DP02_0081PE",
"DP02_0082PE", "DP02_0083PE", "DP02_0084PE",
                            "DP02_0085PE", "DP02_0087PE")]
PCARes1YearNorm.pca <- princomp(PCARes1Year)
```

```
PredictRes1Year <- data.frame(predict(PCARes1YearNorm.pca,
modeltrain))
colnames(PredictRes1Year) <- paste("Res1Year",
colnames(PredictRes1Year), sep="_")
TestPredictRes1Year <- data.frame(predict(PCARes1YearNorm.pca,
modeltest))
colnames(TestPredictRes1Year) <- paste("Res1Year",
colnames(TestPredictRes1Year), sep="_")
summary(PCARes1YearNorm.pca)

#PCA for Place of Birth data
PCAPlaceBirth <- modeltrain[c("DP02_0089PE", "DP02_0090PE",
"DP02_0091PE", "DP02_0092PE", "DP02_0094PE")]
PCAPlaceBirthNorm.pca <- princomp(PCAPlaceBirth)
PredictPlaceBirth <- data.frame(predict(PCAPlaceBirthNorm.pca,
modeltrain))
colnames(PredictPlaceBirth) <- paste("PlaceBirth",
colnames(PredictPlaceBirth), sep="_")
TestPredictPlaceBirth <- data.frame(predict(PCAPlaceBirthNorm.pca,
modeltest))
colnames(TestPredictPlaceBirth) <- paste("PlaceBirth",
colnames(TestPredictPlaceBirth), sep="_")
summary(PCAPlaceBirthNorm.pca)

#PCA for Language at Home data
PCALanguageHome <- modeltrain[c("DP02_0113PE", "DP02_0114PE",
"DP02_0115PE", "DP02_0116PE", "DP02_0117PE",
                                "DP02_0118PE", "DP02_0119PE",
"DP02_0120PE", "DP02_0121PE")]
PCALanguageHomeNorm.pca <- princomp(PCALanguageHome)
PredictLanguageHome <- data.frame(predict(PCALanguageHomeNorm.pca,
modeltrain))
colnames(PredictLanguageHome) <- paste("LanguageHome",
colnames(PredictLanguageHome), sep="_")
TestPredictLanguageHome <- data.frame(predict(PCALanguageHomeNorm.pca,
modeltest))
colnames(TestPredictLanguageHome) <- paste("LanguageHome",
colnames(TestPredictLanguageHome), sep="_")
summary(PCALanguageHomeNorm.pca)

#PCA for Employment status data
PCAEmployStatus <- modeltrain[c("DP03_0002PE", "DP03_0003PE",
"DP03_0004PE", "DP03_0005PE", "DP03_0006PE",
                                "DP03_0007PE", "DP03_0009PE",
"DP03_0011PE", "DP03_0012PE", "DP03_0013PE",
                                "DP03_0015PE", "DP03_0017PE")]
PCAEmployStatus.pca <- princomp(PCAEmployStatus)
PredictEmployStatus <- data.frame(predict(PCAEmployStatus.pca,
modeltrain))
colnames(PredictEmployStatus) <- paste("EmployStatus",
colnames(PredictEmployStatus), sep="_")
```

```
TestPredictEmployStatus <- data.frame(predict(PCAEmployStatus.pca,
modeltest))
colnames(TestPredictEmployStatus) <- paste("EmployStatus",
colnames(TestPredictEmployStatus), sep="_")
summary(PCAEmployStatus.pca)

#PCA for Commuting data
PCACommute <- modeltrain[c("DP03_0019PE", "DP03_0020PE",
"DP03_0021PE", "DP03_0022PE", "DP03_0023PE",
                           "DP03_0024PE")]
PCACommute.pca <- princomp(PCACommute)
PredictCommute <- data.frame(predict(PCACommute.pca, modeltrain))
colnames(PredictCommute) <- paste("Commute", colnames(PredictCommute),
sep="_")
TestPredictCommute <- data.frame(predict(PCACommute.pca, modeltest))
colnames(TestPredictCommute) <- paste("Commute",
colnames(TestPredictCommute), sep="_")
summary(PCACommute.pca)

#PCA for Occupation data
PCAOccupation <- modeltrain[c("DP03_0027PE", "DP03_0028PE",
"DP03_0029PE", "DP03_0030PE", "DP03_0031PE")]
PCAOccupation.pca <- princomp(PCAOccupation)
PredictOccupation <- data.frame(predict(PCAOccupation.pca,
modeltrain))
colnames(PredictOccupation) <- paste("Occupation",
colnames(PredictOccupation), sep="_")
TestPredictOccupation <- data.frame(predict(PCAOccupation.pca,
modeltest))
colnames(TestPredictOccupation) <- paste("Occupation",
colnames(TestPredictOccupation), sep="_")
summary(PCAOccupation.pca)

#PCA for Industry data
PCAIndustry <- modeltrain[c("DP03_0033PE", "DP03_0034PE",
"DP03_0035PE", "DP03_0036PE", "DP03_0037PE",
                            "DP03_0038PE", "DP03_0039PE",
"DP03_0040PE", "DP03_0041PE", "DP03_0042PE",
                            "DP03_0043PE", "DP03_0044PE",
"DP03_0045PE")]
PCAIndustry.pca <- princomp(PCAIndustry)
PredictIndustry <- data.frame(predict(PCAIndustry.pca, modeltrain))
colnames(PredictIndustry) <- paste("Industry",
colnames(PredictIndustry), sep="_")
TestPredictIndustry <- data.frame(predict(PCAIndustry.pca, modeltest))
colnames(TestPredictIndustry) <- paste("Industry",
colnames(TestPredictIndustry), sep="_")
summary(PCAIndustry.pca)

#PCA for Class of Worker data
PCAClassWorker <- modeltrain[c("DP03_0047PE", "DP03_0048PE",
"DP03_0049PE", "DP03_0050PE")]
```

```
PCAClassWorker.pca <- princomp(PCAClassWorker)
PredictClassWorker <- data.frame(predict(PCAClassWorker.pca,
modeltrain))
colnames(PredictClassWorker) <- paste("ClassWorker",
colnames(PredictClassWorker), sep="_")
TestPredictClassWorker <- data.frame(predict(PCAClassWorker.pca,
modeltest))
colnames(TestPredictClassWorker) <- paste("ClassWorker",
colnames(TestPredictClassWorker), sep="_")
summary(PCAClassWorker.pca)

#PCA for Income data
PCAIncome <- modeltrain[c("DP03_0052PE", "DP03_0053PE", "DP03_0054PE",
"DP03_0055PE", "DP03_0056PE",
                          "DP03_0057PE", "DP03_0058PE", "DP03_0059PE",
"DP03_0060PE", "DP03_0061PE",
                          "DP03_0064PE", "DP03_0066PE", "DP03_0068PE",
"DP03_0070PE", "DP03_0072PE",
                          "DP03_0076PE", "DP03_0077PE", "DP03_0078PE",
"DP03_0079PE", "DP03_0080PE",
                          "DP03_0081PE", "DP03_0082PE", "DP03_0083PE",
"DP03_0084PE", "DP03_0085PE")]
PCAIncome.pca <- princomp(PCAIncome)
PredictIncome <- data.frame(predict(PCAIncome.pca, modeltrain))
colnames(PredictIncome) <- paste("Income", colnames(PredictIncome),
sep="_")
TestPredictIncome <- data.frame(predict(PCAIncome.pca, modeltest))
colnames(TestPredictIncome) <- paste("Income",
colnames(TestPredictIncome), sep="_")
summary(PCAIncome.pca)

#PCA for poverty level data
PCAPoverty<- modeltrain[c("DP03_0119PE", "DP03_0120PE", "DP03_0121PE",
"DP03_0122PE", "DP03_0123PE",
                          "DP03_0124PE", "DP03_0125PE", "DP03_0126PE",
"DP03_0127PE", "DP03_0128PE",
                          "DP03_0129PE", "DP03_0130PE", "DP03_0131PE",
"DP03_0132PE", "DP03_0133PE",
                          "DP03_0134PE", "DP03_0135PE", "DP03_0136PE",
"DP03_0137PE")]
PCAPoverty.pca <- princomp(PCAPoverty)
PredictPoverty <- data.frame(predict(PCAPoverty.pca, modeltrain))
colnames(PredictPoverty) <- paste("Poverty", colnames(PredictPoverty),
sep="_")
TestPredictPoverty <- data.frame(predict(PCAPoverty.pca, modeltest))
colnames(TestPredictPoverty) <- paste("Poverty",
colnames(TestPredictPoverty), sep="_")
summary(PCAPoverty.pca)

#PCA for Occupancy data - PCA Not Needed, columns are negatively
correlated
PCAOccupancy <- modeltrain[c("DP04_0002PE")]
```

```
PredictOccupancy<- data.frame(modeltrain$DP04_0002PE)
names(PredictOccupancy)[names(PredictOccupancy) ==
'modeltrain.DP04_0002PE'] <- 'Occupancy'
TestPredictOccupancy<- data.frame(modeltest$DP04_0002PE)
names(TestPredictOccupancy)[names(TestPredictOccupancy) ==
'modeltest.DP04_0002PE'] <- 'Occupancy'

#PCA for Units in Structure data
PCAUnits <- modeltrain[c("DP04_0007PE", "DP04_0008PE", "DP04_0009PE",
"DP04_0010PE", "DP04_0011PE",
                         "DP04_0012PE", "DP04_0013PE", "DP04_0014PE",
"DP04_0015PE")]
PCAUnits.pca <- princomp(PCAUnits)
PredictUnits <- data.frame(predict(PCAUnits.pca, modeltrain))
colnames(PredictUnits) <- paste("Units", colnames(PredictUnits),
sep="_")
TestPredictUnits <- data.frame(predict(PCAUnits.pca, modeltest))
colnames(TestPredictUnits) <- paste("Units",
colnames(TestPredictUnits), sep="_")
summary(PCAUnits.pca)

#PCA for Year Structure Built data
PCAYearBuilt <- modeltrain[c("DP04_0017PE", "DP04_0018PE",
"DP04_0019PE", "DP04_0020PE", "DP04_0021PE",
                             "DP04_0022PE", "DP04_0023PE",
"DP04_0024PE", "DP04_0025PE")]
PCAYearBuilt.pca <- princomp(PCAYearBuilt)
PredictYearBuilt <- data.frame(predict(PCAYearBuilt.pca, modeltrain))
colnames(PredictYearBuilt) <- paste("YearBuilt",
colnames(PredictYearBuilt), sep="_")
TestPredictYearBuilt <- data.frame(predict(PCAYearBuilt.pca,
modeltest))
colnames(TestPredictYearBuilt) <- paste("YearBuilt",
colnames(TestPredictYearBuilt), sep="_")
summary(PCAYearBuilt.pca)

#PCA for Rooms data
PCARooms <- modeltrain[c("DP04_0028PE", "DP04_0029PE", "DP04_0030PE",
"DP04_0031PE", "DP04_0032PE",
                         "DP04_0033PE", "DP04_0034PE", "DP04_0035PE")]
PCARooms.pca <- princomp(PCARooms)
PredictRooms <- data.frame(predict(PCARooms.pca, modeltrain))
colnames(PredictRooms) <- paste("Rooms", colnames(PredictRooms),
sep="_")
TestPredictRooms <- data.frame(predict(PCARooms.pca, modeltest))
colnames(TestPredictRooms) <- paste("Rooms",
colnames(TestPredictRooms), sep="_")
summary(PCARooms.pca)

#PCA for Bedrooms data
PCABedrooms <- modeltrain[c("DP04_0039PE", "DP04_0040PE",
"DP04_0041PE", "DP04_0042PE", "DP04_0043PE")]
```

```
PCABedrooms.pca <- princomp(PCABedrooms)
PredictBedrooms <- data.frame(predict(PCABedrooms.pca, modeltrain))
colnames(PredictBedrooms) <- paste("Bedrooms",
colnames(PredictBedrooms), sep="_")
TestPredictBedrooms <- data.frame(predict(PCABedrooms.pca, modeltest))
colnames(TestPredictBedrooms) <- paste("Bedrooms",
colnames(TestPredictBedrooms), sep="_")
summary(PCABedrooms.pca)

#PCA for Tenure data
PCATenure <- modeltrain[c("DP04_0046PE")]
PredictTenure<- data.frame(modeltrain$DP04_0046PE)
names(PredictTenure)[names(PredictTenure) == 'modeltrain.DP04_0046PE']
<- 'Tenure'
TestPredictTenure<- data.frame(modeltest$DP04_0046PE)
names(TestPredictTenure)[names(TestPredictTenure) ==
'modeltest.DP04_0046PE'] <- 'Tenure'

#PCA for Move-in data
PCAMovein <- modeltrain[c("DP04_0051PE", "DP04_0052PE", "DP04_0053PE",
"DP04_0054PE", "DP04_0055PE")]
PCAMovein.pca <- princomp(PCAMovein)
PredictMovein <- data.frame(predict(PCAMovein.pca, modeltrain))
colnames(PredictMovein) <- paste("Movein", colnames(PredictMovein),
sep="_")
TestPredictMovein <- data.frame(predict(PCAMovein.pca, modeltest))
colnames(TestPredictMovein) <- paste("Movein",
colnames(TestPredictMovein), sep="_")
summary(PCAMovein.pca)

#PCA for Vehicles Available data
PCAVehicles <- modeltrain[c("DP04_0058PE", "DP04_0059PE",
"DP04_0060PE")]
PCAVehicles.pca <- princomp(PCAVehicles)
PredictVehicles <- data.frame(predict(PCAVehicles.pca, modeltrain))
colnames(PredictVehicles) <- paste("Vehicles",
colnames(PredictVehicles), sep="_")
TestPredictVehicles <- data.frame(predict(PCAVehicles.pca, modeltest))
colnames(TestPredictVehicles) <- paste("Vehicles",
colnames(TestPredictVehicles), sep="_")
summary(PCAVehicles.pca)

#PCA for House Heating Fuel data
PCAHeating <- modeltrain[c("DP04_0063PE", "DP04_0064PE",
"DP04_0065PE", "DP04_0066PE", "DP04_0067PE",
                           "DP04_0068PE", "DP04_0069PE",
"DP04_0070PE")]
PCAHeating.pca <- princomp(PCAHeating)
PredictHeating <- data.frame(predict(PCAHeating.pca, modeltrain))
colnames(PredictHeating) <- paste("Heating", colnames(PredictHeating),
sep="_")
TestPredictHeating <- data.frame(predict(PCAHeating.pca, modeltest))
```

```
colnames(TestPredictHeating) <- paste("Heating",
colnames(TestPredictHeating), sep="_")
summary(PCAHeating.pca)

#PCA for Value data
PCAValue<- modeltrain[c("DP04_0081PE", "DP04_0082PE", "DP04_0083PE",
"DP04_0084PE", "DP04_0085PE",
                        "DP04_0086PE", "DP04_0087PE")]
PCAValue.pca <- princomp(PCAValue)
PredictValue <- data.frame(predict(PCAValue.pca, modeltrain))
colnames(PredictValue) <- paste("Value", colnames(PredictValue),
sep="_")
TestPredictValue <- data.frame(predict(PCAValue.pca, modeltest))
colnames(TestPredictValue) <- paste("Value",
colnames(TestPredictValue), sep="_")
summary(PCAValue.pca)

#PCA for Mortgage data - only 1 variable
PCAMortgage <- modeltrain[c("DP04_0091PE")]
PredictMortgage <- data.frame(modeltrain$DP04_0091PE)
names(PredictMortgage)[names(PredictMortgage) ==
'modeltrain.DP04_0091PE'] <- 'Mortgage'
TestPredictMortgage <- data.frame(modeltest$DP04_0091PE)
names(TestPredictMortgage)[names(TestPredictMortgage) ==
'modeltest.DP04_0091PE'] <- 'Mortgage'

#PCA for Monthly Costs data
PCAMonthlyCosts<- modeltrain[c("DP04_0094PE", "DP04_0095PE",
"DP04_0096PE", "DP04_0097PE", "DP04_0098PE",
                               "DP04_0099PE")]
PCAMonthlyCosts.pca <- princomp(PCAMonthlyCosts)
PredictMonthlyCosts <- data.frame(predict(PCAMonthlyCosts.pca,
modeltrain))
colnames(PredictMonthlyCosts) <- paste("MonthlyCosts",
colnames(PredictMonthlyCosts), sep="_")
TestPredictMonthlyCosts <- data.frame(predict(PCAMonthlyCosts.pca,
modeltest))
colnames(TestPredictMonthlyCosts) <- paste("MonthlyCosts",
colnames(TestPredictMonthlyCosts), sep="_")
summary(PCAMonthlyCosts.pca)

#PCA for Monthly Rent data
PCARent<- modeltrain[c("DP04_0127PE", "DP04_0128PE", "DP04_0129PE",
"DP04_0130PE", "DP04_0131PE")]
PCARent.pca <- princomp(PCARent)
PredictRent <- data.frame(predict(PCARent.pca, modeltrain))
colnames(PredictRent) <- paste("Rent", colnames(PredictRent), sep="_")
TestPredictRent <- data.frame(predict(PCARent.pca, modeltest))
colnames(TestPredictRent) <- paste("Rent", colnames(TestPredictRent),
sep="_")
summary(PCARent.pca)
```

```
#PCA for Gender data - Perfect negative correlation, only 1 variable
needed
PCAGender<- modeltrain[c("DP05_0002PE")]
PredictGender <- data.frame(modeltrain$DP05_0002PE)
names(PredictGender)[names(PredictGender) == 'modeltrain.DP05_0002PE']
<- 'Gender'
TestPredictGender <- data.frame(modeltest$DP05_0002PE)
names(TestPredictGender)[names(TestPredictGender) ==
'modeltest.DP05_0002PE'] <- 'Gender'

#PCA for Age data
PCAAge<- modeltrain[c("DP05_0005PE", "DP05_0006PE", "DP05_0007PE",
"DP05_0008PE", "DP05_0009PE",
                      "DP05_0010PE", "DP05_0011PE", "DP05_0012PE",
"DP05_0013PE", "DP05_0014PE",
                      "DP05_0015PE", "DP05_0016PE")]
PCAAge.pca <- princomp(PCAAge)
PredictAge <- data.frame(predict(PCAAge.pca, modeltrain))
colnames(PredictAge) <- paste("Age", colnames(PredictAge), sep="_")
TestPredictAge <- data.frame(predict(PCAAge.pca, modeltest))
colnames(TestPredictAge) <- paste("Age", colnames(TestPredictAge),
sep="_")
summary(PCAAge.pca)

PCARace<- modeltrain[c("DP05_0066PE", "DP05_0067PE", "DP05_0068PE",
"DP05_0069PE", "DP05_0070PE",
                       "DP05_0071PE")]
PCARace.pca <- princomp(PCARace)
PredictRace <- data.frame(predict(PCARace.pca, modeltrain))
colnames(PredictRace) <- paste("Race", colnames(PredictRace), sep="_")
TestPredictRace <- data.frame(predict(PCARace.pca, modeltest))
colnames(TestPredictRace) <- paste("Race", colnames(TestPredictRace),
sep="_")
summary(PCARace.pca)

#PCA for Hispanic data
PCAHispanic<- modeltrain[c("DP05_0073PE", "DP05_0074PE",
"DP05_0075PE", "DP05_0076PE", "DP05_0077PE")]
PCAHispanic.pca <- princomp(PCAHispanic)
PredictHispanic <- data.frame(predict(PCAHispanic.pca, modeltrain))
colnames(PredictHispanic) <- paste("Hispanic",
colnames(PredictHispanic), sep="_")
TestPredictHispanic <- data.frame(predict(PCAHispanic.pca, modeltest))
colnames(TestPredictHispanic) <- paste("Hispanic",
colnames(TestPredictHispanic), sep="_")
summary(PCAHispanic.pca)

#Add PCA variables to PCA Data Model
PCAModelData <- PredictHousehold[c(1:3)]
PCAModelData <- cbind(PCAModelData, PredictRelationship[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictMarital[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictGrandparents[c(1:4)])
```

```
PCAModelData <- cbind(PCAModelData, PredictSchoolEnroll[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictEduAttainment[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictRes1Year[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictPlaceBirth[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictLanguageHome[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictEmployStatus[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictCommute[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictOccupation[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictIndustry[c(1:5)])
PCAModelData <- cbind(PCAModelData, PredictClassWorker[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictIncome[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictPoverty[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictOccupancy[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictUnits[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictYearBuilt[c(1:5)])
PCAModelData <- cbind(PCAModelData, PredictRooms[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictBedrooms[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictTenure[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictMovein[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictVehicles[c(1:2)])
PCAModelData <- cbind(PCAModelData, PredictHeating[c(1:4)])
PCAModelData <- cbind(PCAModelData, PredictValue[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictMortgage[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictMonthlyCosts[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictRent[c(1:3)])
PCAModelData <- cbind(PCAModelData, PredictGender[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictAge[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictRace[c(1:1)])
PCAModelData <- cbind(PCAModelData, PredictHispanic[c(1:1)])


#Add test data to model
TestPCAModelData <- TestPredictHousehold[c(1:3)]
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictRelationship[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictMarital[c(1:4)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictGrandparents[c(1:4)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictSchoolEnroll[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictEduAttainment[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictRes1Year[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictPlaceBirth[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictLanguageHome[c(1:4)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictEmployStatus[c(1:3)])
```

```
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictCommute[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictOccupation[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictIndustry[c(1:5)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictClassWorker[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictIncome[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictPoverty[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictOccupancy[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictUnits[c(1:4)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictYearBuilt[c(1:5)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictRooms[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictBedrooms[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictTenure[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictMovein[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictVehicles[c(1:2)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictHeating[c(1:4)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictValue[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictMortgage[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictMonthlyCosts[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictRent[c(1:3)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictGender[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictAge[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData, TestPredictRace[c(1:1)])
TestPCAModelData <- cbind(TestPCAModelData,
TestPredictHispanic[c(1:1)])


#Model Generation - Linear Regression
lmtraindata <- PCAModelData
lmtraindata$CrimeRate <- modeltrain$CrimeRate

lmCrimeRate = lm(CrimeRate~., data = lmtraindata)
summary(lmCrimeRate)

par(mfrow=c(2,2))
plot(lmCrimeRate)
lmtest::dwtest(lmCrimeRate)
vif(lmCrimeRate)

#Test Linear Model
lmtestdata <- TestPCAModelData
```

```
lmtestdata$CrimeRate <- modeltest$CrimeRate
lmPCATestfitted <- predict(lmCrimeRate, lmtestdata)

#find SST/SSE/R-Squared
sstlmPCATest <- sum((lmtestdata$CrimeRate -
mean(lmtestdata$CrimeRate))^2)
sselmPCATest <- sum((lmPCATestfitted - lmtestdata$CrimeRate)^2)
rsqlmPCATest <- 1 - sselmPCATest/sstlmPCATest
rsqlmPCATest
sqrt(mean(sselmPCATest/(1285-1028)))

#Lasso Model
#Create datasets
lrTrainData <- data.matrix(PCAModelData)
lrTrainY <- modeltrain$CrimeRate
lrTestData <- data.matrix(TestPCAModelData)
lrTestY <- modeltest$CrimeRate

#perform cross-validation to find optimal lambda
crossvalModel <- cv.glmnet(lrTrainData, lrTrainY, alpha = 1)

#find optimal lambda value that minimizes test MSE
optimalLambda <- crossvalModel$lambda.min
optimalLambda

#produce plot of test MSE by lambda value
par(mfrow=c(1,1))
plot(crossvalModel)

optimalModel <- glmnet(lrTrainData, lrTrainY, alpha = 1, lambda =
optimalLambda)
coef(optimalModel)

#Train Model
#use fitted best model to make predictions
ytrainfitted <- predict(optimalModel, s = optimalLambda, newx =
lrTrainData)

#find SST/SSE/R-Squared
sstTrain <- sum((lrTrainY - mean(lrTrainY))^2)
sseTrain <- sum((ytrainfitted - lrTrainY)^2)
rsqTrain <- 1 - sseTrain/sstTrain
rsqTrain
sqrt(mean(sseTrain/(1285-1028)))

#Train Residual chart
calcTrainResiduals <- lrTrainY - ytrainfitted
TrainResiduals <- data.frame(ytrainfitted)
TrainResiduals <- cbind(TrainResiduals, calcTrainResiduals)
plot(TrainResiduals)
mean(calcTrainResiduals)
```

```
#Test Model
#use fitted best model to make predictions
ytestfitted <- predict(optimalModel, s = optimalLambda, newx =
lrTestData)

#find SST/SSE/R-Squared
sstTest <- sum((lrTestY - mean(lrTestY))^2)
sseTest <- sum((ytestfitted - lrTestY)^2)
rsqTest <- 1 - sseTest/sstTest
rsqTest
sqrt(mean(sseTest/(1285-1028)))

#Test Residual chart
calcTestResiduals <- lrTestY - ytestfitted
TestResiduals <- data.frame(ytestfitted)
TestResiduals <- cbind(TestResiduals, calcTestResiduals)
plot(TestResiduals)
mean(calcTestResiduals)

#Boruta Model
#Run Boruta Model
set.seed(100)
BorutaModelData <- Boruta(CrimeRate~., data = ModelData, doTrace = 2,
maxRuns = 1000,)
print(BorutaModelData)

#Generate LM model without PCA
#Model Generation - Linear Regression
lmRawTrainData <- modeltrain
lmRawTrainData <- subset(lmRawTrainData, select = -c(Year, Zip.Code))
lmRawTestData <- modeltest
lmRawTestData <- subset(lmRawTestData, select = -c(Year, Zip.Code))

lmRawCrimeRate = lm(CrimeRate~., data = lmRawTrainData)
summary(lmRawCrimeRate)

par(mfrow=c(2,2))
plot(lmRawCrimeRate)
lmtest::dwtest(lmRawCrimeRate)
vif(lmRawCrimeRate)
cor(lmRawTrainData)

#Test Linear Model
lmRawTestfitted <- predict(lmRawCrimeRate, lmRawTestData)

#find SST/SSE/R-Squared
sstlmRawTest <- sum((lmRawTestData$CrimeRate -
mean(lmRawTestData$CrimeRate))^2)
sselmRawTest <- sum((lmRawTestfitted - lmRawTestData$CrimeRate)^2)
rsqlmRawTest <- 1 - sselmRawTest/sstlmRawTest
rsqlmRawTest
sqrt(mean(sselmRawTest/(1285-1028)))
```

```
#Model Generation - Lasso Regression
#Create datasets
lrRawTrainData <- data.matrix(subset(lmRawTrainData, select =
-c(CrimeRate)))
lrRawTrainY <- lmRawTrainData$CrimeRate
lrRawTestData <- data.matrix(subset(lmRawTestData, select =
-c(CrimeRate)))
lrRawTestY <- lmRawTestData$CrimeRate

#perform cross-validation to find optimal lambda
crossvalRawModel <- cv.glmnet(lrRawTrainData, lrRawTrainY, alpha = 1)

#find optimal lambda value that minimizes test MSE
optimalRawLambda <- crossvalRawModel$lambda.min
optimalRawLambda

#produce plot of test MSE by lambda value
par(mfrow=c(1,1))
plot(crossvalRawModel)

optimalRawModel <- glmnet(lrRawTrainData, lrRawTrainY, alpha = 1,
lambda = optimalRawLambda)
coef(optimalRawModel)
optimalRawModel

#Train Model
#use fitted best model to make predictions
ytrainfittedraw <- predict(optimalRawModel, s = optimalRawLambda, newx
= lrRawTrainData)

#find SST/SSE/R-Squared
sstTrainRaw <- sum((lrRawTrainY - mean(lrRawTrainY))^2)
sseTrainRaw <- sum((ytrainfittedraw - lrRawTrainY)^2)
rsqTrainRaw <- 1 - sseTrainRaw/sstTrainRaw
rsqTrainRaw
sqrt(mean(sseTrainRaw/(1285-1028)))

#Train Residual chart
calcTrainResidualsRaw <- lrRawTrainY - ytrainfittedraw
TrainResidualsRaw <- data.frame(ytrainfittedraw)
TrainResidualsRaw <- cbind(TrainResidualsRaw, calcTrainResidualsRaw)
plot(TrainResidualsRaw)
mean(calcTrainResidualsRaw)

#Test Model
#use fitted best model to make predictions
ytestfittedraw <- predict(optimalRawModel, s = optimalRawLambda, newx
= lrRawTestData)

#find SST/SSE/R-Squared
sstTestRaw <- sum((lrRawTestY - mean(lrRawTestY))^2)
```

```
sseTestRaw <- sum((ytestfittedraw - lrRawTestY)^2)
rsqTestRaw <- 1 - sseTestRaw/sstTestRaw
rsqTestRaw
sqrt(mean(sseTestRaw/(1285-1028)))

#Test Residual chart
calcTestResidualsRaw <- lrRawTestY - ytestfittedraw
TestResidualsRaw <- data.frame(ytestfittedraw)
TestResidualsRaw <- cbind(TestResidualsRaw, calcTestResidualsRaw)
plot(TestResidualsRaw)
mean(calcTestResidualsRaw)

#Random Forest Model
#No PCA Model
rfRawTrainData <- modeltrain
rfRawTrainData <- subset(rfRawTrainData, select = -c(Year, Zip.Code))
rfRawTestData <- modeltest
rfRawTestData <- subset(rfRawTestData, select = -c(Year, Zip.Code))

rfRawModel <- randomForest(formula = CrimeRate ~ ., data =
rfRawTrainData)
rfRawModel

rfTestFittedY <- predict(rfRawModel, newdata = rfRawTestData)
rfRawModelResiduals <-  rfRawTestData$CrimeRate - rfTestFittedY
rfResidualGraph <- data.frame(rfTestFittedY)
rfResidualGraph <- cbind(rfResidualGraph, rfRawModelResiduals)
plot(rfResidualGraph)

#Test Statistics
sstRfTestRaw <- sum((rfRawTestData$CrimeRate -
mean(rfRawTestData$CrimeRate))^2)
sseRfTestRaw <- sum((rfTestFittedY - rfRawTestData$CrimeRate)^2)
rsqRfTestRaw <- 1 - sseRfTestRaw/sstRfTestRaw
rsqRfTestRaw
sqrt(mean(sseRfTestRaw/(1285-1028)))

#Use PCA
rfPCATrainData <- PCAModelData
rfPCATrainData$CrimeRate <- modeltrain$CrimeRate
rfPCATestData <- TestPCAModelData
rfPCATestData$CrimeRate <- modeltest$CrimeRate

rfPCAModel <- randomForest(formula = CrimeRate ~ ., data =
rfPCATrainData)
rfPCAModel

rfPCATestFittedY <- predict(rfPCAModel, newdata = rfPCATestData)
rfPCAModelResiduals <-  rfPCATestData$CrimeRate - rfPCATestFittedY
rfPCAResidualGraph <- data.frame(rfPCATestFittedY)
rfPCAResidualGraph <- cbind(rfPCAResidualGraph, rfPCAModelResiduals)
plot(rfPCAResidualGraph)
```

```
#Test Statistics
sstRfTestPCA <- sum((rfPCATestData$CrimeRate -
mean(rfPCATestData$CrimeRate))^2)
sseRfTestPCA <- sum((rfPCATestFittedY - rfPCATestData$CrimeRate)^2)
rsqRfTestPCA <- 1 - sseRfTestPCA/sstRfTestPCA
rsqRfTestPCA
sqrt(mean(sseRfTestPCA/(1285-1028)))
```

CENSUS TABLES VARIABLE LIST

DP02 through DP05

Code	Description
DP02_0001E	Estimate-HOUSEHOLDS BY TYPE-Total households
DP02_0001PE	Percent-HOUSEHOLDS BY TYPE-Total households
DP02_0002E	Estimate-HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02_0002PE	Percent-HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02_0003E	Estimate-HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02_0003PE	Percent-HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02_0004E	Estimate-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02_0004PE	Percent-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02_0005E	Estimate-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02_0005PE	Percent-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02_0006E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02_0006PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02_0007E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02_0007PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02_0008E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02_0008PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02_0009E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0009PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0010E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02_0010PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02_0011E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years
DP02_0011PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years
DP02_0012E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone
DP02_0012PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no

	spouse/partner present-Householder living alone
DP02_0013E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0013PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02_0014E	Estimate-HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years
DP02_0014PE	Percent-HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years
DP02_0015E	Estimate-HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over
DP02_0015PE	Percent-HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over
DP02_0016E	Estimate-HOUSEHOLDS BY TYPE-Total households-Average household size
DP02_0016PE	Percent-HOUSEHOLDS BY TYPE-Total households-Average household size
DP02_0017E	Estimate-HOUSEHOLDS BY TYPE-Total households-Average family size
DP02_0017PE	Percent-HOUSEHOLDS BY TYPE-Total households-Average family size
DP02_0018E	Estimate-RELATIONSHIP-Population in households
DP02_0018PE	Percent-RELATIONSHIP-Population in households
DP02_0019E	Estimate-RELATIONSHIP-Population in households-Householder
DP02_0019PE	Percent-RELATIONSHIP-Population in households-Householder
DP02_0020E	Estimate-RELATIONSHIP-Population in households-Spouse
DP02_0020PE	Percent-RELATIONSHIP-Population in households-Spouse
DP02_0021E	Estimate-RELATIONSHIP-Population in households-Unmarried partner
DP02_0021PE	Percent-RELATIONSHIP-Population in households-Unmarried partner
DP02_0022E	Estimate-RELATIONSHIP-Population in households-Child
DP02_0022PE	Percent-RELATIONSHIP-Population in households-Child
DP02_0023E	Estimate-RELATIONSHIP-Population in households-Other relatives
DP02_0023PE	Percent-RELATIONSHIP-Population in households-Other relatives
DP02_0024E	Estimate-RELATIONSHIP-Population in households-Other nonrelatives
DP02_0024PE	Percent-RELATIONSHIP-Population in households-Other nonrelatives
DP02_0025E	Estimate-MARITAL STATUS-Males 15 years and over
DP02_0025PE	Percent-MARITAL STATUS-Males 15 years and over
DP02_0026E	Estimate-MARITAL STATUS-Males 15 years and over-Never married
DP02_0026PE	Percent-MARITAL STATUS-Males 15 years and over-Never married
DP02_0027E	Estimate-MARITAL STATUS-Males 15 years and over-Now married, except separated
DP02_0027PE	Percent-MARITAL STATUS-Males 15 years and over-Now married, except separated
DP02_0028E	Estimate-MARITAL STATUS-Males 15 years and over-Separated
DP02_0028PE	Percent-MARITAL STATUS-Males 15 years and over-Separated
DP02_0029E	Estimate-MARITAL STATUS-Males 15 years and over-Widowed
DP02_0029PE	Percent-MARITAL STATUS-Males 15 years and over-Widowed

DP02_0030E	Estimate-MARITAL STATUS-Males 15 years and over-Divorced
DP02_0030PE	Percent-MARITAL STATUS-Males 15 years and over-Divorced
DP02_0031E	Estimate-MARITAL STATUS-Females 15 years and over
DP02_0031PE	Percent-MARITAL STATUS-Females 15 years and over
DP02_0032E	Estimate-MARITAL STATUS-Females 15 years and over-Never married
DP02_0032PE	Percent-MARITAL STATUS-Females 15 years and over-Never married
DP02_0033E	Estimate-MARITAL STATUS-Females 15 years and over-Now married, except separated
DP02_0033PE	Percent-MARITAL STATUS-Females 15 years and over-Now married, except separated
DP02_0034E	Estimate-MARITAL STATUS-Females 15 years and over-Separated
DP02_0034PE	Percent-MARITAL STATUS-Females 15 years and over-Separated
DP02_0035E	Estimate-MARITAL STATUS-Females 15 years and over-Widowed
DP02_0035PE	Percent-MARITAL STATUS-Females 15 years and over-Widowed
DP02_0036E	Estimate-MARITAL STATUS-Females 15 years and over-Divorced
DP02_0036PE	Percent-MARITAL STATUS-Females 15 years and over-Divorced
DP02_0037E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months
DP02_0037PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months
DP02_0038E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)
DP02_0038PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)
DP02_0039E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)-Per 1,000 unmarried women
DP02_0039PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)-Per 1,000 unmarried women
DP02_0040E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 50 years old
DP02_0040PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 50 years old
DP02_0041E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 19 years old
DP02_0041PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 19 years old
DP02_0042E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 20 to 34 years old
DP02_0042PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 20 to 34 years old
DP02_0043E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 35 to 50 years old
DP02_0043PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 35 to 50 years old
DP02_0044E	Estimate-GRANDPARENTS-Number of grandparents living with own

	grandchildren under 18 years
DP02_0044PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years
DP02_0045E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Grandparents responsible for grandchildren
DP02_0045PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Grandparents responsible for grandchildren
DP02_0046E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-Less than 1 year
DP02_0046PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-Less than 1 year
DP02_0047E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-1 or 2 years
DP02_0047PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-1 or 2 years
DP02_0048E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-3 or 4 years
DP02_0048PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-3 or 4 years
DP02_0049E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-5 or more years
DP02_0049PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-5 or more years
DP02_0050E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years
DP02_0050PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years
DP02_0051E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are female
DP02_0051PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are female
DP02_0052E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are married
DP02_0052PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are married
DP02_0053E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school
DP02_0053PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school
DP02_0054E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Nursery school, preschool
DP02_0054PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Nursery school, preschool
DP02_0055E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Kindergarten
DP02_0055PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in

	school-Kindergarten
DP02_0056E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Elementary school (grades 1-8)
DP02_0056PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Elementary school (grades 1-8)
DP02_0057E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-High school (grades 9-12)
DP02_0057PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-High school (grades 9-12)
DP02_0058E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-College or graduate school
DP02_0058PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-College or graduate school
DP02_0059E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over
DP02_0059PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over
DP02_0060E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Less than 9th grade
DP02_0060PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Less than 9th grade
DP02_0061E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-9th to 12th grade, no diploma
DP02_0061PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-9th to 12th grade, no diploma
DP02_0062E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate (includes equivalency)
DP02_0062PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate (includes equivalency)
DP02_0063E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Some college, no degree
DP02_0063PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Some college, no degree
DP02_0064E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Associate's degree
DP02_0064PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Associate's degree
DP02_0065E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree
DP02_0065PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree
DP02_0066E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Graduate or professional degree
DP02_0066PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Graduate or professional degree
DP02_0067E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate or higher
DP02_0067PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate or higher
DP02_0068E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree or higher

DP02_0068PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree or higher
DP02_0069E	Estimate-VETERAN STATUS-Civilian population 18 years and over
DP02_0069PE	Percent-VETERAN STATUS-Civilian population 18 years and over
DP02_0070E	Estimate-VETERAN STATUS-Civilian population 18 years and over-Civilian veterans
DP02_0070PE	Percent-VETERAN STATUS-Civilian population 18 years and over-Civilian veterans
DP02_0071E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population
DP02_0071PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population
DP02_0072E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population-With a disability
DP02_0072PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population-With a disability
DP02_0073E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years
DP02_0073PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years
DP02_0074E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years-With a disability
DP02_0074PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years-With a disability
DP02_0075E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years
DP02_0075PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years
DP02_0076E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years-With a disability
DP02_0076PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years-With a disability
DP02_0077E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over
DP02_0077PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over
DP02_0078E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over-With a disability
DP02_0078PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over-With a disability
DP02_0079E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over
DP02_0079PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over
DP02_0080E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Same house

DP02_0080PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Same house
DP02_0081E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)
DP02_0081PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)
DP02_0082E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.
DP02_0082PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.
DP02_0083E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Same county
DP02_0083PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Same county
DP02_0084E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county
DP02_0084PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county
DP02_0085E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county-Same state
DP02_0085PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county-Same state
DP02_0086E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county-Different state
DP02_0086PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Different house in the U.S.-Different county-Different state
DP02_0087E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Abroad
DP02_0087PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in the U.S. or abroad)-Abroad
DP02_0088E	Estimate-PLACE OF BIRTH-Total population
DP02_0088PE	Percent-PLACE OF BIRTH-Total population
DP02_0089E	Estimate-PLACE OF BIRTH-Total population-Native
DP02_0089PE	Percent-PLACE OF BIRTH-Total population-Native
DP02_0090E	Estimate-PLACE OF BIRTH-Total population-Native-Born in United States
DP02_0090PE	Percent-PLACE OF BIRTH-Total population-Native-Born in United States
DP02_0091E	Estimate-PLACE OF BIRTH-Total population-Native-Born in United States-State of residence
DP02_0091PE	Percent-PLACE OF BIRTH-Total population-Native-Born in United States-State of residence
DP02_0092E	Estimate-PLACE OF BIRTH-Total population-Native-Born in United States-Different state
DP02_0092PE	Percent-PLACE OF BIRTH-Total population-Native-Born in United States-Different state
DP02_0093E	Estimate-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico, U.S. Island areas, or born abroad to American parent(s)

DP02_0093PE	Percent-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico, U.S. Island areas, or born abroad to American parent(s)
DP02_0094E	Estimate-PLACE OF BIRTH-Total population-Foreign born
DP02_0094PE	Percent-PLACE OF BIRTH-Total population-Foreign born
DP02_0095E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population
DP02_0095PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population
DP02_0096E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population-Naturalized U.S. citizen
DP02_0096PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population-Naturalized U.S. citizen
DP02_0097E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population-Not a U.S. citizen
DP02_0097PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population-Not a U.S. citizen
DP02_0098E	Estimate-YEAR OF ENTRY-Population born outside the United States
DP02_0098PE	Percent-YEAR OF ENTRY-Population born outside the United States
DP02_0099E	Estimate-YEAR OF ENTRY-Population born outside the United States-Native
DP02_0099PE	Percent-YEAR OF ENTRY-Population born outside the United States-Native
DP02_0100E	Estimate-YEAR OF ENTRY-Population born outside the United States-Native-Entered 2010 or later
DP02_0100PE	Percent-YEAR OF ENTRY-Population born outside the United States-Native-Entered 2010 or later
DP02_0101E	Estimate-YEAR OF ENTRY-Population born outside the United States-Native-Entered before 2010
DP02_0101PE	Percent-YEAR OF ENTRY-Population born outside the United States-Native-Entered before 2010
DP02_0102E	Estimate-YEAR OF ENTRY-Population born outside the United States-Foreign born
DP02_0102PE	Percent-YEAR OF ENTRY-Population born outside the United States-Foreign born
DP02_0103E	Estimate-YEAR OF ENTRY-Population born outside the United States-Foreign born-Entered 2010 or later
DP02_0103PE	Percent-YEAR OF ENTRY-Population born outside the United States-Foreign born-Entered 2010 or later
DP02_0104E	Estimate-YEAR OF ENTRY-Population born outside the United States-Foreign born-Entered before 2010
DP02_0104PE	Percent-YEAR OF ENTRY-Population born outside the United States-Foreign born-Entered before 2010
DP02_0105E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea
DP02_0105PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea
DP02_0106E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Europe
DP02_0106PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Europe
DP02_0107E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Asia

DP02_0107PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Asia
DP02_0108E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Africa
DP02_0108PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Africa
DP02_0109E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Oceania
DP02_0109PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Oceania
DP02_0110E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Latin America
DP02_0110PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Latin America
DP02_0111E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Northern America
DP02_0111PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Northern America
DP02_0112E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over
DP02_0112PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over
DP02_0113E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-English only
DP02_0113PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-English only
DP02_0114E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English
DP02_0114PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English
DP02_0115E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English-Speak English less than \"very well\", "concept
DP02_0115PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English-Speak English less than \"very well\", "concept
DP02_0116E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish
DP02_0116PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish
DP02_0117E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish-Speak English less than \"very well\", "concept
DP02_0117PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish-Speak English less than \"very well\", "concept
DP02_0118E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages
DP02_0118PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages
DP02_0119E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages-Speak English less than \"very well\",

	"concept
DP02_0119PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages-Speak English less than \"very well\", "concept
DP02_0120E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages
DP02_0120PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages
DP02_0121E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages-Speak English less than \"very well\", "concept
DP02_0121PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages-Speak English less than \"very well\", "concept
DP02_0122E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages
DP02_0122PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages
DP02_0123E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages-Speak English less than \"very well\", "concept
DP02_0123PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages-Speak English less than \"very well\", "concept
DP02_0124E	Estimate-ANCESTRY-Total population
DP02_0124PE	Percent-ANCESTRY-Total population
DP02_0125E	Estimate-ANCESTRY-Total population-American
DP02_0125PE	Percent-ANCESTRY-Total population-American
DP02_0126E	Estimate-ANCESTRY-Total population-Arab
DP02_0126PE	Percent-ANCESTRY-Total population-Arab
DP02_0127E	Estimate-ANCESTRY-Total population-Czech
DP02_0127PE	Percent-ANCESTRY-Total population-Czech
DP02_0128E	Estimate-ANCESTRY-Total population-Danish
DP02_0128PE	Percent-ANCESTRY-Total population-Danish
DP02_0129E	Estimate-ANCESTRY-Total population-Dutch
DP02_0129PE	Percent-ANCESTRY-Total population-Dutch
DP02_0130E	Estimate-ANCESTRY-Total population-English
DP02_0130PE	Percent-ANCESTRY-Total population-English
DP02_0131E	Estimate-ANCESTRY-Total population-French (except Basque)
DP02_0131PE	Percent-ANCESTRY-Total population-French (except Basque)
DP02_0132E	Estimate-ANCESTRY-Total population-French Canadian
DP02_0132PE	Percent-ANCESTRY-Total population-French Canadian
DP02_0133E	Estimate-ANCESTRY-Total population-German
DP02_0133PE	Percent-ANCESTRY-Total population-German

DP02_0134E	Estimate-ANCESTRY-Total population-Greek
DP02_0134PE	Percent-ANCESTRY-Total population-Greek
DP02_0135E	Estimate-ANCESTRY-Total population-Hungarian
DP02_0135PE	Percent-ANCESTRY-Total population-Hungarian
DP02_0136E	Estimate-ANCESTRY-Total population-Irish
DP02_0136PE	Percent-ANCESTRY-Total population-Irish
DP02_0137E	Estimate-ANCESTRY-Total population-Italian
DP02_0137PE	Percent-ANCESTRY-Total population-Italian
DP02_0138E	Estimate-ANCESTRY-Total population-Lithuanian
DP02_0138PE	Percent-ANCESTRY-Total population-Lithuanian
DP02_0139E	Estimate-ANCESTRY-Total population-Norwegian
DP02_0139PE	Percent-ANCESTRY-Total population-Norwegian
DP02_0140E	Estimate-ANCESTRY-Total population-Polish
DP02_0140PE	Percent-ANCESTRY-Total population-Polish
DP02_0141E	Estimate-ANCESTRY-Total population-Portuguese
DP02_0141PE	Percent-ANCESTRY-Total population-Portuguese
DP02_0142E	Estimate-ANCESTRY-Total population-Russian
DP02_0142PE	Percent-ANCESTRY-Total population-Russian
DP02_0143E	Estimate-ANCESTRY-Total population-Scotch-Irish
DP02_0143PE	Percent-ANCESTRY-Total population-Scotch-Irish
DP02_0144E	Estimate-ANCESTRY-Total population-Scottish
DP02_0144PE	Percent-ANCESTRY-Total population-Scottish
DP02_0145E	Estimate-ANCESTRY-Total population-Slovak
DP02_0145PE	Percent-ANCESTRY-Total population-Slovak
DP02_0146E	Estimate-ANCESTRY-Total population-Subsaharan African
DP02_0146PE	Percent-ANCESTRY-Total population-Subsaharan African
DP02_0147E	Estimate-ANCESTRY-Total population-Swedish
DP02_0147PE	Percent-ANCESTRY-Total population-Swedish
DP02_0148E	Estimate-ANCESTRY-Total population-Swiss
DP02_0148PE	Percent-ANCESTRY-Total population-Swiss
DP02_0149E	Estimate-ANCESTRY-Total population-Ukrainian
DP02_0149PE	Percent-ANCESTRY-Total population-Ukrainian
DP02_0150E	Estimate-ANCESTRY-Total population-Welsh
DP02_0150PE	Percent-ANCESTRY-Total population-Welsh
DP02_0151E	Estimate-ANCESTRY-Total population-West Indian (excluding Hispanic origin groups)
DP02_0151PE	Percent-ANCESTRY-Total population-West Indian (excluding Hispanic origin groups)
DP02_0152E	Estimate-COMPUTERS AND INTERNET USE-Total households
DP02_0152PE	Percent-COMPUTERS AND INTERNET USE-Total households

DP02_0153E	Estimate-COMPUTERS AND INTERNET USE-Total households-With a computer
DP02_0153PE	Percent-COMPUTERS AND INTERNET USE-Total households-With a computer
DP02_0154E	Estimate-COMPUTERS AND INTERNET USE-Total households-With a broadband Internet subscription
DP02_0154PE	Percent-COMPUTERS AND INTERNET USE-Total households-With a broadband Internet subscription
DP02PR_0001E	Estimate-HOUSEHOLDS BY TYPE-Total households
DP02PR_0001PE	Percent-HOUSEHOLDS BY TYPE-Total households
DP02PR_0002E	Estimate-HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02PR_0002PE	Percent-HOUSEHOLDS BY TYPE-Total households-Married-couple household
DP02PR_0003E	Estimate-HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02PR_0003PE	Percent-HOUSEHOLDS BY TYPE-Total households-Married-couple household-With children of the householder under 18 years
DP02PR_0004E	Estimate-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02PR_0004PE	Percent-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household
DP02PR_0005E	Estimate-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02PR_0005PE	Percent-HOUSEHOLDS BY TYPE-Total households-Cohabiting couple household-With children of the householder under 18 years
DP02PR_0006E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02PR_0006PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present
DP02PR_0007E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02PR_0007PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-With children of the householder under 18 years
DP02PR_0008E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02PR_0008PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone
DP02PR_0009E	Estimate-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02PR_0009PE	Percent-HOUSEHOLDS BY TYPE-Total households-Male householder, no spouse/partner present-Householder living alone-65 years and over
DP02PR_0010E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02PR_0010PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present
DP02PR_0011E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years
DP02PR_0011PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-With children of the householder under 18 years

DP02PR_0012E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone
DP02PR_0012PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone
DP02PR_0013E	Estimate-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02PR_0013PE	Percent-HOUSEHOLDS BY TYPE-Total households-Female householder, no spouse/partner present-Householder living alone-65 years and over
DP02PR_0014E	Estimate-HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years
DP02PR_0014PE	Percent-HOUSEHOLDS BY TYPE-Total households-Households with one or more people under 18 years
DP02PR_0015E	Estimate-HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over
DP02PR_0015PE	Percent-HOUSEHOLDS BY TYPE-Total households-Households with one or more people 65 years and over
DP02PR_0016E	Estimate-HOUSEHOLDS BY TYPE-Total households-Average household size
DP02PR_0016PE	Percent-HOUSEHOLDS BY TYPE-Total households-Average household size
DP02PR_0017E	Estimate-HOUSEHOLDS BY TYPE-Total households-Average family size
DP02PR_0017PE	Percent-HOUSEHOLDS BY TYPE-Total households-Average family size
DP02PR_0018E	Estimate-RELATIONSHIP-Population in households
DP02PR_0018PE	Percent-RELATIONSHIP-Population in households
DP02PR_0019E	Estimate-RELATIONSHIP-Population in households-Householder
DP02PR_0019PE	Percent-RELATIONSHIP-Population in households-Householder
DP02PR_0020E	Estimate-RELATIONSHIP-Population in households-Spouse
DP02PR_0020PE	Percent-RELATIONSHIP-Population in households-Spouse
DP02PR_0021E	Estimate-RELATIONSHIP-Population in households-Unmarried partner
DP02PR_0021PE	Percent-RELATIONSHIP-Population in households-Unmarried partner
DP02PR_0022E	Estimate-RELATIONSHIP-Population in households-Child
DP02PR_0022PE	Percent-RELATIONSHIP-Population in households-Child
DP02PR_0023E	Estimate-RELATIONSHIP-Population in households-Other relatives
DP02PR_0023PE	Percent-RELATIONSHIP-Population in households-Other relatives
DP02PR_0024E	Estimate-RELATIONSHIP-Population in households-Other nonrelatives
DP02PR_0024PE	Percent-RELATIONSHIP-Population in households-Other nonrelatives
DP02PR_0025E	Estimate-MARITAL STATUS-Males 15 years and over
DP02PR_0025PE	Percent-MARITAL STATUS-Males 15 years and over
DP02PR_0026E	Estimate-MARITAL STATUS-Males 15 years and over-Never married
DP02PR_0026PE	Percent-MARITAL STATUS-Males 15 years and over-Never married
DP02PR_0027E	Estimate-MARITAL STATUS-Males 15 years and over-Now married, except separated
DP02PR_0027PE	Percent-MARITAL STATUS-Males 15 years and over-Now married, except separated
DP02PR_0028E	Estimate-MARITAL STATUS-Males 15 years and over-Separated

DP02PR_0028PE	Percent-MARITAL STATUS-Males 15 years and over-Separated
DP02PR_0029E	Estimate-MARITAL STATUS-Males 15 years and over-Widowed
DP02PR_0029PE	Percent-MARITAL STATUS-Males 15 years and over-Widowed
DP02PR_0030E	Estimate-MARITAL STATUS-Males 15 years and over-Divorced
DP02PR_0030PE	Percent-MARITAL STATUS-Males 15 years and over-Divorced
DP02PR_0031E	Estimate-MARITAL STATUS-Females 15 years and over
DP02PR_0031PE	Percent-MARITAL STATUS-Females 15 years and over
DP02PR_0032E	Estimate-MARITAL STATUS-Females 15 years and over-Never married
DP02PR_0032PE	Percent-MARITAL STATUS-Females 15 years and over-Never married
DP02PR_0033E	Estimate-MARITAL STATUS-Females 15 years and over-Now married, except separated
DP02PR_0033PE	Percent-MARITAL STATUS-Females 15 years and over-Now married, except separated
DP02PR_0034E	Estimate-MARITAL STATUS-Females 15 years and over-Separated
DP02PR_0034PE	Percent-MARITAL STATUS-Females 15 years and over-Separated
DP02PR_0035E	Estimate-MARITAL STATUS-Females 15 years and over-Widowed
DP02PR_0035PE	Percent-MARITAL STATUS-Females 15 years and over-Widowed
DP02PR_0036E	Estimate-MARITAL STATUS-Females 15 years and over-Divorced
DP02PR_0036PE	Percent-MARITAL STATUS-Females 15 years and over-Divorced
DP02PR_0037E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months
DP02PR_0037PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months
DP02PR_0038E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)
DP02PR_0038PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)
DP02PR_0039E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)-Per 1,000 unmarried women
DP02PR_0039PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Unmarried women (widowed, divorced, and never married)-Per 1,000 unmarried women
DP02PR_0040E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 50 years old
DP02PR_0040PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 50 years old
DP02PR_0041E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 19 years old
DP02PR_0041PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 15 to 19 years old
DP02PR_0042E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 20 to 34 years old
DP02PR_0042PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 20 to 34 years old
DP02PR_0043E	Estimate-FERTILITY-Number of women 15 to 50 years old who had a birth in

	the past 12 months-Per 1,000 women 35 to 50 years old
DP02PR_0043PE	Percent-FERTILITY-Number of women 15 to 50 years old who had a birth in the past 12 months-Per 1,000 women 35 to 50 years old
DP02PR_0044E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years
DP02PR_0044PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years
DP02PR_0045E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Grandparents responsible for grandchildren
DP02PR_0045PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Grandparents responsible for grandchildren
DP02PR_0046E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-Less than 1 year
DP02PR_0046PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-Less than 1 year
DP02PR_0047E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-1 or 2 years
DP02PR_0047PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-1 or 2 years
DP02PR_0048E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-3 or 4 years
DP02PR_0048PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-3 or 4 years
DP02PR_0049E	Estimate-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-5 or more years
DP02PR_0049PE	Percent-GRANDPARENTS-Number of grandparents living with own grandchildren under 18 years-Years responsible for grandchildren-5 or more years
DP02PR_0050E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years
DP02PR_0050PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years
DP02PR_0051E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are female
DP02PR_0051PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are female
DP02PR_0052E	Estimate-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are married
DP02PR_0052PE	Percent-GRANDPARENTS-Number of grandparents responsible for own grandchildren under 18 years-Who are married
DP02PR_0053E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school
DP02PR_0053PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school
DP02PR_0054E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Nursery school, preschool
DP02PR_0054PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in

	school-Nursery school, preschool
DP02PR_0055E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Kindergarten
DP02PR_0055PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Kindergarten
DP02PR_0056E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Elementary school (grades 1-8)
DP02PR_0056PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-Elementary school (grades 1-8)
DP02PR_0057E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-High school (grades 9-12)
DP02PR_0057PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-High school (grades 9-12)
DP02PR_0058E	Estimate-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-College or graduate school
DP02PR_0058PE	Percent-SCHOOL ENROLLMENT-Population 3 years and over enrolled in school-College or graduate school
DP02PR_0059E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over
DP02PR_0059PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over
DP02PR_0060E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Less than 9th grade
DP02PR_0060PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Less than 9th grade
DP02PR_0061E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-9th to 12th grade, no diploma
DP02PR_0061PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-9th to 12th grade, no diploma
DP02PR_0062E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate (includes equivalency)
DP02PR_0062PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate (includes equivalency)
DP02PR_0063E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Some college, no degree
DP02PR_0063PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Some college, no degree
DP02PR_0064E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Associate's degree
DP02PR_0064PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Associate's degree
DP02PR_0065E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree
DP02PR_0065PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree
DP02PR_0066E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Graduate or professional degree
DP02PR_0066PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Graduate or professional degree
DP02PR_0067E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate or higher

DP02PR_0067PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-High school graduate or higher
DP02PR_0068E	Estimate-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree or higher
DP02PR_0068PE	Percent-EDUCATIONAL ATTAINMENT-Population 25 years and over-Bachelor's degree or higher
DP02PR_0069E	Estimate-VETERAN STATUS-Civilian population 18 years and over
DP02PR_0069PE	Percent-VETERAN STATUS-Civilian population 18 years and over
DP02PR_0070E	Estimate-VETERAN STATUS-Civilian population 18 years and over-Civilian veterans
DP02PR_0070PE	Percent-VETERAN STATUS-Civilian population 18 years and over-Civilian veterans
DP02PR_0071E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population
DP02PR_0071PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population
DP02PR_0072E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population-With a disability
DP02PR_0072PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Total Civilian Noninstitutionalized Population-With a disability
DP02PR_0073E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years
DP02PR_0073PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years
DP02PR_0074E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years-With a disability
DP02PR_0074PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-Under 18 years-With a disability
DP02PR_0075E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years
DP02PR_0075PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years
DP02PR_0076E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years-With a disability
DP02PR_0076PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-18 to 64 years-With a disability
DP02PR_0077E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over
DP02PR_0077PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over
DP02PR_0078E	Estimate-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over-With a disability
DP02PR_0078PE	Percent-DISABILITY STATUS OF THE CIVILIAN NONINSTITUTIONALIZED POPULATION-65 years and over-With a

	disability
DP02PR_0079E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over
DP02PR_0079PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over
DP02PR_0080E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Same house
DP02PR_0080PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Same house
DP02PR_0081E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)
DP02PR_0081PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)
DP02PR_0082E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.
DP02PR_0082PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.
DP02PR_0083E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico
DP02PR_0083PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico
DP02PR_0084E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico-Same municipio
DP02PR_0084PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico-Same municipio
DP02PR_0085E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico-Different municipio
DP02PR_0085PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In Puerto Rico-Different municipio
DP02PR_0086E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In the United States
DP02PR_0086PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Different house in Puerto Rico or the U.S.-In the United States
DP02PR_0087E	Estimate-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Elsewhere
DP02PR_0087PE	Percent-RESIDENCE 1 YEAR AGO-Population 1 year and over-Different house (in Puerto Rico, the U.S., or elsewhere)-Elsewhere
DP02PR_0088E	Estimate-PLACE OF BIRTH-Total population
DP02PR_0088PE	Percent-PLACE OF BIRTH-Total population
DP02PR_0089E	Estimate-PLACE OF BIRTH-Total population-Native
DP02PR_0089PE	Percent-PLACE OF BIRTH-Total population-Native
DP02PR_0090E	Estimate-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the

	United States
DP02PR_0090PE	Percent-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the United States
DP02PR_0091E	Estimate-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the United States-In Puerto Rico
DP02PR_0091PE	Percent-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the United States-In Puerto Rico
DP02PR_0092E	Estimate-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the United States-In the United States
DP02PR_0092PE	Percent-PLACE OF BIRTH-Total population-Native-Born in Puerto Rico or the United States-In the United States
DP02PR_0093E	Estimate-PLACE OF BIRTH-Total population-Native-Born in U.S. Island Areas, or born abroad of American parents
DP02PR_0093PE	Percent-PLACE OF BIRTH-Total population-Native-Born in U.S. Island Areas, or born abroad of American parents
DP02PR_0094E	Estimate-PLACE OF BIRTH-Total population-Foreign born
DP02PR_0094PE	Percent-PLACE OF BIRTH-Total population-Foreign born
DP02PR_0095E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population
DP02PR_0095PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population
DP02PR_0096E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population-Naturalized U.S. citizen
DP02PR_0096PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population-Naturalized U.S. citizen
DP02PR_0097E	Estimate-U.S. CITIZENSHIP STATUS-Foreign-born population-Not a U.S. citizen
DP02PR_0097PE	Percent-U.S. CITIZENSHIP STATUS-Foreign-born population-Not a U.S. citizen
DP02PR_0098E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico
DP02PR_0098PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico
DP02PR_0099E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Native
DP02PR_0099PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Native
DP02PR_0100E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Native-Entered 2010 or later
DP02PR_0100PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Native-Entered 2010 or later
DP02PR_0101E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Native-Entered before 2010
DP02PR_0101PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Native-Entered before 2010
DP02PR_0102E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born
DP02PR_0102PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born
DP02PR_0103E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born-Entered 2010 or later
DP02PR_0103PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born-Entered 2010 or later
DP02PR_0104E	Estimate-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born-Entered before 2010

DP02PR_0104PE	Percent-YEAR OF ENTRY-Population born outside Puerto Rico-Foreign born-Entered before 2010
DP02PR_0105E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea
DP02PR_0105PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea
DP02PR_0106E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Europe
DP02PR_0106PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Europe
DP02PR_0107E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Asia
DP02PR_0107PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Asia
DP02PR_0108E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Africa
DP02PR_0108PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Africa
DP02PR_0109E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Oceania
DP02PR_0109PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Oceania
DP02PR_0110E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Latin America
DP02PR_0110PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Latin America
DP02PR_0111E	Estimate-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Northern America
DP02PR_0111PE	Percent-WORLD REGION OF BIRTH OF FOREIGN BORN-Foreign-born population, excluding population born at sea-Northern America
DP02PR_0112E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over
DP02PR_0112PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over
DP02PR_0113E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-English only
DP02PR_0113PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-English only
DP02PR_0114E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English
DP02PR_0114PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English
DP02PR_0115E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English-Speak English less than \"very well\", "concept
DP02PR_0115PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Language other than English-Speak English less than \"very well\", "concept
DP02PR_0116E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish
DP02PR_0116PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish

DP02PR_0117E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish-Speak English less than \"very well\", "concept
DP02PR_0117PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Spanish-Speak English less than \"very well\", "concept
DP02PR_0118E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages
DP02PR_0118PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages
DP02PR_0119E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages-Speak English less than \"very well\", "concept
DP02PR_0119PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other Indo-European languages-Speak English less than \"very well\", "concept
DP02PR_0120E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages
DP02PR_0120PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages
DP02PR_0121E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages-Speak English less than \"very well\", "concept
DP02PR_0121PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Asian and Pacific Islander languages-Speak English less than \"very well\", "concept
DP02PR_0122E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages
DP02PR_0122PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages
DP02PR_0123E	Estimate-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages-Speak English less than \"very well\", "concept
DP02PR_0123PE	Percent-LANGUAGE SPOKEN AT HOME-Population 5 years and over-Other languages-Speak English less than \"very well\", "concept
DP02PR_0124E	Estimate-ANCESTRY-Total population
DP02PR_0124PE	Percent-ANCESTRY-Total population
DP02PR_0125E	Estimate-ANCESTRY-Total population-American
DP02PR_0125PE	Percent-ANCESTRY-Total population-American
DP02PR_0126E	Estimate-ANCESTRY-Total population-Arab
DP02PR_0126PE	Percent-ANCESTRY-Total population-Arab
DP02PR_0127E	Estimate-ANCESTRY-Total population-Czech
DP02PR_0127PE	Percent-ANCESTRY-Total population-Czech
DP02PR_0128E	Estimate-ANCESTRY-Total population-Danish
DP02PR_0128PE	Percent-ANCESTRY-Total population-Danish
DP02PR_0129E	Estimate-ANCESTRY-Total population-Dutch

DP02PR_0129PE	Percent-ANCESTRY-Total population-Dutch
DP02PR_0130E	Estimate-ANCESTRY-Total population-English
DP02PR_0130PE	Percent-ANCESTRY-Total population-English
DP02PR_0131E	Estimate-ANCESTRY-Total population-French (except Basque)
DP02PR_0131PE	Percent-ANCESTRY-Total population-French (except Basque)
DP02PR_0132E	Estimate-ANCESTRY-Total population-French Canadian
DP02PR_0132PE	Percent-ANCESTRY-Total population-French Canadian
DP02PR_0133E	Estimate-ANCESTRY-Total population-German
DP02PR_0133PE	Percent-ANCESTRY-Total population-German
DP02PR_0134E	Estimate-ANCESTRY-Total population-Greek
DP02PR_0134PE	Percent-ANCESTRY-Total population-Greek
DP02PR_0135E	Estimate-ANCESTRY-Total population-Hungarian
DP02PR_0135PE	Percent-ANCESTRY-Total population-Hungarian
DP02PR_0136E	Estimate-ANCESTRY-Total population-Irish
DP02PR_0136PE	Percent-ANCESTRY-Total population-Irish
DP02PR_0137E	Estimate-ANCESTRY-Total population-Italian
DP02PR_0137PE	Percent-ANCESTRY-Total population-Italian
DP02PR_0138E	Estimate-ANCESTRY-Total population-Lithuanian
DP02PR_0138PE	Percent-ANCESTRY-Total population-Lithuanian
DP02PR_0139E	Estimate-ANCESTRY-Total population-Norwegian
DP02PR_0139PE	Percent-ANCESTRY-Total population-Norwegian
DP02PR_0140E	Estimate-ANCESTRY-Total population-Polish
DP02PR_0140PE	Percent-ANCESTRY-Total population-Polish
DP02PR_0141E	Estimate-ANCESTRY-Total population-Portuguese
DP02PR_0141PE	Percent-ANCESTRY-Total population-Portuguese
DP02PR_0142E	Estimate-ANCESTRY-Total population-Russian
DP02PR_0142PE	Percent-ANCESTRY-Total population-Russian
DP02PR_0143E	Estimate-ANCESTRY-Total population-Scotch-Irish
DP02PR_0143PE	Percent-ANCESTRY-Total population-Scotch-Irish
DP02PR_0144E	Estimate-ANCESTRY-Total population-Scottish
DP02PR_0144PE	Percent-ANCESTRY-Total population-Scottish
DP02PR_0145E	Estimate-ANCESTRY-Total population-Slovak
DP02PR_0145PE	Percent-ANCESTRY-Total population-Slovak
DP02PR_0146E	Estimate-ANCESTRY-Total population-Subsaharan African
DP02PR_0146PE	Percent-ANCESTRY-Total population-Subsaharan African
DP02PR_0147E	Estimate-ANCESTRY-Total population-Swedish
DP02PR_0147PE	Percent-ANCESTRY-Total population-Swedish
DP02PR_0148E	Estimate-ANCESTRY-Total population-Swiss
DP02PR_0148PE	Percent-ANCESTRY-Total population-Swiss

DP02PR_0149E	Estimate-ANCESTRY-Total population-Ukrainian
DP02PR_0149PE	Percent-ANCESTRY-Total population-Ukrainian
DP02PR_0150E	Estimate-ANCESTRY-Total population-Welsh
DP02PR_0150PE	Percent-ANCESTRY-Total population-Welsh
DP02PR_0151E	Estimate-ANCESTRY-Total population-West Indian (excluding Hispanic origin groups)
DP02PR_0151PE	Percent-ANCESTRY-Total population-West Indian (excluding Hispanic origin groups)
DP02PR_0152E	Estimate-COMPUTERS AND INTERNET USE-Total households
DP02PR_0152PE	Percent-COMPUTERS AND INTERNET USE-Total households
DP02PR_0153E	Estimate-COMPUTERS AND INTERNET USE-Total households-With a computer
DP02PR_0153PE	Percent-COMPUTERS AND INTERNET USE-Total households-With a computer
DP02PR_0154E	Estimate-COMPUTERS AND INTERNET USE-Total households-With a broadband Internet subscription
DP02PR_0154PE	Percent-COMPUTERS AND INTERNET USE-Total households-With a broadband Internet subscription
DP03_0001E	Estimate-EMPLOYMENT STATUS-Population 16 years and over
DP03_0001PE	Percent-EMPLOYMENT STATUS-Population 16 years and over
DP03_0002E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-In labor force
DP03_0002PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-In labor force
DP03_0003E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force
DP03_0003PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force
DP03_0004E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force-Employed
DP03_0004PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force-Employed
DP03_0005E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force-Unemployed
DP03_0005PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Civilian labor force-Unemployed
DP03_0006E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Armed Forces
DP03_0006PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-In labor force-Armed Forces
DP03_0007E	Estimate-EMPLOYMENT STATUS-Population 16 years and over-Not in labor force
DP03_0007PE	Percent-EMPLOYMENT STATUS-Population 16 years and over-Not in labor force
DP03_0008E	Estimate-EMPLOYMENT STATUS-Civilian labor force
DP03_0008PE	Percent-EMPLOYMENT STATUS-Civilian labor force
DP03_0009E	Estimate-EMPLOYMENT STATUS-Civilian labor force-Unemployment Rate
DP03_0009PE	Percent-EMPLOYMENT STATUS-Civilian labor force-Unemployment Rate

DP03_0010E	Estimate-EMPLOYMENT STATUS-Females 16 years and over
DP03_0010PE	Percent-EMPLOYMENT STATUS-Females 16 years and over
DP03_0011E	Estimate-EMPLOYMENT STATUS-Females 16 years and over-In labor force
DP03_0011PE	Percent-EMPLOYMENT STATUS-Females 16 years and over-In labor force
DP03_0012E	Estimate-EMPLOYMENT STATUS-Females 16 years and over-In labor force-Civilian labor force
DP03_0012PE	Percent-EMPLOYMENT STATUS-Females 16 years and over-In labor force-Civilian labor force
DP03_0013E	Estimate-EMPLOYMENT STATUS-Females 16 years and over-In labor force-Civilian labor force-Employed
DP03_0013PE	Percent-EMPLOYMENT STATUS-Females 16 years and over-In labor force-Civilian labor force-Employed
DP03_0014E	Estimate-EMPLOYMENT STATUS-Own children of the householder under 6 years
DP03_0014PE	Percent-EMPLOYMENT STATUS-Own children of the householder under 6 years
DP03_0015E	Estimate-EMPLOYMENT STATUS-Own children of the householder under 6 years-All parents in family in labor force
DP03_0015PE	Percent-EMPLOYMENT STATUS-Own children of the householder under 6 years-All parents in family in labor force
DP03_0016E	Estimate-EMPLOYMENT STATUS-Own children of the householder 6 to 17 years
DP03_0016PE	Percent-EMPLOYMENT STATUS-Own children of the householder 6 to 17 years
DP03_0017E	Estimate-EMPLOYMENT STATUS-Own children of the householder 6 to 17 years-All parents in family in labor force
DP03_0017PE	Percent-EMPLOYMENT STATUS-Own children of the householder 6 to 17 years-All parents in family in labor force
DP03_0018E	Estimate-COMMUTING TO WORK-Workers 16 years and over
DP03_0018PE	Percent-COMMUTING TO WORK-Workers 16 years and over
DP03_0019E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Car, truck, or van -- drove alone
DP03_0019PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Car, truck, or van -- drove alone
DP03_0020E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Car, truck, or van -- carpooled
DP03_0020PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Car, truck, or van -- carpooled
DP03_0021E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Public transportation (excluding taxicab)
DP03_0021PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Public transportation (excluding taxicab)
DP03_0022E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Walked
DP03_0022PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Walked
DP03_0023E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Other means
DP03_0023PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Other means
DP03_0024E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Worked from

	home
DP03_0024PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Worked from home
DP03_0025E	Estimate-COMMUTING TO WORK-Workers 16 years and over-Mean travel time to work (minutes)
DP03_0025PE	Percent-COMMUTING TO WORK-Workers 16 years and over-Mean travel time to work (minutes)
DP03_0026E	Estimate-OCCUPATION-Civilian employed population 16 years and over
DP03_0026PE	Percent-OCCUPATION-Civilian employed population 16 years and over
DP03_0027E	Estimate-OCCUPATION-Civilian employed population 16 years and over-Management, business, science, and arts occupations
DP03_0027PE	Percent-OCCUPATION-Civilian employed population 16 years and over-Management, business, science, and arts occupations
DP03_0028E	Estimate-OCCUPATION-Civilian employed population 16 years and over-Service occupations
DP03_0028PE	Percent-OCCUPATION-Civilian employed population 16 years and over-Service occupations
DP03_0029E	Estimate-OCCUPATION-Civilian employed population 16 years and over-Sales and office occupations
DP03_0029PE	Percent-OCCUPATION-Civilian employed population 16 years and over-Sales and office occupations
DP03_0030E	Estimate-OCCUPATION-Civilian employed population 16 years and over-Natural resources, construction, and maintenance occupations
DP03_0030PE	Percent-OCCUPATION-Civilian employed population 16 years and over-Natural resources, construction, and maintenance occupations
DP03_0031E	Estimate-OCCUPATION-Civilian employed population 16 years and over-Production, transportation, and material moving occupations
DP03_0031PE	Percent-OCCUPATION-Civilian employed population 16 years and over-Production, transportation, and material moving occupations
DP03_0032E	Estimate-INDUSTRY-Civilian employed population 16 years and over
DP03_0032PE	Percent-INDUSTRY-Civilian employed population 16 years and over
DP03_0033E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Agriculture, forestry, fishing and hunting, and mining
DP03_0033PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Agriculture, forestry, fishing and hunting, and mining
DP03_0034E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Construction
DP03_0034PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Construction
DP03_0035E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Manufacturing
DP03_0035PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Manufacturing
DP03_0036E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Wholesale trade
DP03_0036PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Wholesale trade
DP03_0037E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Retail trade

DP03_0037PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Retail trade
DP03_0038E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Transportation and warehousing, and utilities
DP03_0038PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Transportation and warehousing, and utilities
DP03_0039E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Information
DP03_0039PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Information
DP03_0040E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Finance and insurance, and real estate and rental and leasing
DP03_0040PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Finance and insurance, and real estate and rental and leasing
DP03_0041E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Professional, scientific, and management, and administrative and waste management services
DP03_0041PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Professional, scientific, and management, and administrative and waste management services
DP03_0042E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Educational services, and health care and social assistance
DP03_0042PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Educational services, and health care and social assistance
DP03_0043E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Arts, entertainment, and recreation, and accommodation and food services
DP03_0043PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Arts, entertainment, and recreation, and accommodation and food services
DP03_0044E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Other services, except public administration
DP03_0044PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Other services, except public administration
DP03_0045E	Estimate-INDUSTRY-Civilian employed population 16 years and over-Public administration
DP03_0045PE	Percent-INDUSTRY-Civilian employed population 16 years and over-Public administration
DP03_0046E	Estimate-CLASS OF WORKER-Civilian employed population 16 years and over
DP03_0046PE	Percent-CLASS OF WORKER-Civilian employed population 16 years and over
DP03_0047E	Estimate-CLASS OF WORKER-Civilian employed population 16 years and over-Private wage and salary workers
DP03_0047PE	Percent-CLASS OF WORKER-Civilian employed population 16 years and over-Private wage and salary workers
DP03_0048E	Estimate-CLASS OF WORKER-Civilian employed population 16 years and over-Government workers
DP03_0048PE	Percent-CLASS OF WORKER-Civilian employed population 16 years and over-Government workers
DP03_0049E	Estimate-CLASS OF WORKER-Civilian employed population 16 years and over-Self-employed in own not incorporated business workers
DP03_0049PE	Percent-CLASS OF WORKER-Civilian employed population 16 years and over-

	Self-employed in own not incorporated business workers
DP03_0050E	Estimate-CLASS OF WORKER-Civilian employed population 16 years and over-Unpaid family workers
DP03_0050PE	Percent-CLASS OF WORKER-Civilian employed population 16 years and over-Unpaid family workers
DP03_0051E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households
DP03_0051PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households
DP03_0052E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-Less than $10,000
DP03_0052PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-Less than $10,000
DP03_0053E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$10,000 to $14,999
DP03_0053PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$10,000 to $14,999
DP03_0054E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$15,000 to $24,999
DP03_0054PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$15,000 to $24,999
DP03_0055E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$25,000 to $34,999
DP03_0055PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$25,000 to $34,999
DP03_0056E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$35,000 to $49,999
DP03_0056PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$35,000 to $49,999
DP03_0057E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$50,000 to $74,999
DP03_0057PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$50,000 to $74,999
DP03_0058E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$75,000 to $99,999
DP03_0058PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$75,000 to $99,999
DP03_0059E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$100,000 to $149,999
DP03_0059PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$100,000 to $149,999
DP03_0060E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$150,000 to $199,999
DP03_0060PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$150,000 to $199,999
DP03_0061E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$200,000 or more
DP03_0061PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-$200,000 or more
DP03_0062E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED

	DOLLARS)-Total households-Median household income (dollars)
DP03_0062PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-Median household income (dollars)
DP03_0063E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-Mean household income (dollars)
DP03_0063PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-Mean household income (dollars)
DP03_0064E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With earnings
DP03_0064PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With earnings
DP03_0065E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With earnings-Mean earnings (dollars)
DP03_0065PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With earnings-Mean earnings (dollars)
DP03_0066E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Social Security
DP03_0066PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Social Security
DP03_0067E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Social Security-Mean Social Security income (dollars)
DP03_0067PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Social Security-Mean Social Security income (dollars)
DP03_0068E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With retirement income
DP03_0068PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With retirement income
DP03_0069E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With retirement income-Mean retirement income (dollars)
DP03_0069PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With retirement income-Mean retirement income (dollars)
DP03_0070E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Supplemental Security Income
DP03_0070PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Supplemental Security Income
DP03_0071E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Supplemental Security Income-Mean Supplemental Security Income (dollars)
DP03_0071PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Supplemental Security Income-Mean Supplemental Security Income (dollars)
DP03_0072E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With cash public assistance income
DP03_0072PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With cash public assistance income
DP03_0073E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED

	DOLLARS)-Total households-With cash public assistance income-Mean cash public assistance income (dollars)
DP03_0073PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With cash public assistance income-Mean cash public assistance income (dollars)
DP03_0074E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Food Stamp/SNAP benefits in the past 12 months
DP03_0074PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Total households-With Food Stamp/SNAP benefits in the past 12 months
DP03_0075E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families
DP03_0075PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families
DP03_0076E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Less than $10,000
DP03_0076PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Less than $10,000
DP03_0077E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$10,000 to $14,999
DP03_0077PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$10,000 to $14,999
DP03_0078E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$15,000 to $24,999
DP03_0078PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$15,000 to $24,999
DP03_0079E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$25,000 to $34,999
DP03_0079PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$25,000 to $34,999
DP03_0080E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$35,000 to $49,999
DP03_0080PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$35,000 to $49,999
DP03_0081E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$50,000 to $74,999
DP03_0081PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$50,000 to $74,999
DP03_0082E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$75,000 to $99,999
DP03_0082PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$75,000 to $99,999
DP03_0083E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$100,000 to $149,999
DP03_0083PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$100,000 to $149,999
DP03_0084E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$150,000 to $199,999
DP03_0084PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED

	DOLLARS)-Families-$150,000 to $199,999
DP03_0085E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$200,000 or more
DP03_0085PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-$200,000 or more
DP03_0086E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Median family income (dollars)
DP03_0086PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Median family income (dollars)
DP03_0087E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Mean family income (dollars)
DP03_0087PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Families-Mean family income (dollars)
DP03_0088E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Per capita income (dollars)
DP03_0088PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Per capita income (dollars)
DP03_0089E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households
DP03_0089PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households
DP03_0090E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households-Median nonfamily income (dollars)
DP03_0090PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households-Median nonfamily income (dollars)
DP03_0091E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households-Mean nonfamily income (dollars)
DP03_0091PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Nonfamily households-Mean nonfamily income (dollars)
DP03_0092E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for workers (dollars)
DP03_0092PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for workers (dollars)
DP03_0093E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for male full-time, year-round workers (dollars)
DP03_0093PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for male full-time, year-round workers (dollars)
DP03_0094E	Estimate-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for female full-time, year-round workers (dollars)
DP03_0094PE	Percent-INCOME AND BENEFITS (IN 2022 INFLATION-ADJUSTED DOLLARS)-Median earnings for female full-time, year-round workers (dollars)
DP03_0095E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population
DP03_0095PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population
DP03_0096E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-With health insurance coverage
DP03_0096PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-With health insurance coverage
DP03_0097E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized

	population-With health insurance coverage-With private health insurance
DP03_0097PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-With health insurance coverage-With private health insurance
DP03_0098E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-With health insurance coverage-With public coverage
DP03_0098PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-With health insurance coverage-With public coverage
DP03_0099E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-No health insurance coverage
DP03_0099PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population-No health insurance coverage
DP03_0100E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population under 19 years
DP03_0100PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population under 19 years
DP03_0101E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population under 19 years-No health insurance coverage
DP03_0101PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population under 19 years-No health insurance coverage
DP03_0102E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years
DP03_0102PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years
DP03_0103E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:
DP03_0103PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:
DP03_0104E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:
DP03_0104PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:
DP03_0105E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage
DP03_0105PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage
DP03_0106E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage-With private health insurance
DP03_0106PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage-With private health insurance
DP03_0107E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage-With public coverage
DP03_0107PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-With health insurance coverage-With public coverage
DP03_0108E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized

	population 19 to 64 years-In labor force:-Employed:-No health insurance coverage
DP03_0108PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Employed:-No health insurance coverage
DP03_0109E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:
DP03_0109PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:
DP03_0110E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage
DP03_0110PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage
DP03_0111E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage-With private health insurance
DP03_0111PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage-With private health insurance
DP03_0112E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage-With public coverage
DP03_0112PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-With health insurance coverage-With public coverage
DP03_0113E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-No health insurance coverage
DP03_0113PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-In labor force:-Unemployed:-No health insurance coverage
DP03_0114E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:
DP03_0114PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:
DP03_0115E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage
DP03_0115PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage
DP03_0116E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage-With private health insurance
DP03_0116PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage-With private health insurance
DP03_0117E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage-With public coverage

DP03_0117PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-With health insurance coverage-With public coverage
DP03_0118E	Estimate-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-No health insurance coverage
DP03_0118PE	Percent-HEALTH INSURANCE COVERAGE-Civilian noninstitutionalized population 19 to 64 years-Not in labor force:-No health insurance coverage
DP03_0119E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families
DP03_0119PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families
DP03_0120E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-With related children of the householder under 18 years
DP03_0120PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-With related children of the householder under 18 years
DP03_0121E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0121PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0122E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families
DP03_0122PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families
DP03_0123E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families-With related children of the householder under 18 years
DP03_0123PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families-With related children of the householder under 18 years
DP03_0124E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0124PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Married couple families-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0125E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Families with female householder, no spouse present
DP03_0125PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-

	Families with female householder, no spouse present
DP03_0126E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Families with female householder, no spouse present-With related children of the householder under 18 years
DP03_0126PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Families with female householder, no spouse present-With related children of the householder under 18 years
DP03_0127E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Families with female householder, no spouse present-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0127PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All families-Families with female householder, no spouse present-With related children of the householder under 18 years-With related children of the householder under 5 years only
DP03_0128E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people
DP03_0128PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people
DP03_0129E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years
DP03_0129PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years
DP03_0130E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years
DP03_0130PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years
DP03_0131E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years-Related children of the householder under 5 years
DP03_0131PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years-Related children of the householder under 5 years
DP03_0132E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years-Related children of the householder 5 to 17 years
DP03_0132PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Under 18 years-Related children of the householder under 18 years-Related

	children of the householder 5 to 17 years
DP03_0133E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over
DP03_0133PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over
DP03_0134E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over-18 to 64 years
DP03_0134PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over-18 to 64 years
DP03_0135E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over-65 years and over
DP03_0135PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-18 years and over-65 years and over
DP03_0136E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-People in families
DP03_0136PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-People in families
DP03_0137E	Estimate-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Unrelated individuals 15 years and over
DP03_0137PE	Percent-PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL-All people-Unrelated individuals 15 years and over
DP04_0001E	Estimate-HOUSING OCCUPANCY-Total housing units
DP04_0001PE	Percent-HOUSING OCCUPANCY-Total housing units
DP04_0002E	Estimate-HOUSING OCCUPANCY-Total housing units-Occupied housing units
DP04_0002PE	Percent-HOUSING OCCUPANCY-Total housing units-Occupied housing units
DP04_0003E	Estimate-HOUSING OCCUPANCY-Total housing units-Vacant housing units
DP04_0003PE	Percent-HOUSING OCCUPANCY-Total housing units-Vacant housing units
DP04_0004E	Estimate-HOUSING OCCUPANCY-Total housing units-Homeowner vacancy rate
DP04_0004PE	Percent-HOUSING OCCUPANCY-Total housing units-Homeowner vacancy rate
DP04_0005E	Estimate-HOUSING OCCUPANCY-Total housing units-Rental vacancy rate
DP04_0005PE	Percent-HOUSING OCCUPANCY-Total housing units-Rental vacancy rate
DP04_0006E	Estimate-UNITS IN STRUCTURE-Total housing units
DP04_0006PE	Percent-UNITS IN STRUCTURE-Total housing units
DP04_0007E	Estimate-UNITS IN STRUCTURE-Total housing units-1-unit, detached
DP04_0007PE	Percent-UNITS IN STRUCTURE-Total housing units-1-unit, detached

DP04_0008E	Estimate-UNITS IN STRUCTURE-Total housing units-1-unit, attached
DP04_0008PE	Percent-UNITS IN STRUCTURE-Total housing units-1-unit, attached
DP04_0009E	Estimate-UNITS IN STRUCTURE-Total housing units-2 units
DP04_0009PE	Percent-UNITS IN STRUCTURE-Total housing units-2 units
DP04_0010E	Estimate-UNITS IN STRUCTURE-Total housing units-3 or 4 units
DP04_0010PE	Percent-UNITS IN STRUCTURE-Total housing units-3 or 4 units
DP04_0011E	Estimate-UNITS IN STRUCTURE-Total housing units-5 to 9 units
DP04_0011PE	Percent-UNITS IN STRUCTURE-Total housing units-5 to 9 units
DP04_0012E	Estimate-UNITS IN STRUCTURE-Total housing units-10 to 19 units
DP04_0012PE	Percent-UNITS IN STRUCTURE-Total housing units-10 to 19 units
DP04_0013E	Estimate-UNITS IN STRUCTURE-Total housing units-20 or more units
DP04_0013PE	Percent-UNITS IN STRUCTURE-Total housing units-20 or more units
DP04_0014E	Estimate-UNITS IN STRUCTURE-Total housing units-Mobile home
DP04_0014PE	Percent-UNITS IN STRUCTURE-Total housing units-Mobile home
DP04_0015E	Estimate-UNITS IN STRUCTURE-Total housing units-Boat, RV, van, etc.
DP04_0015PE	Percent-UNITS IN STRUCTURE-Total housing units-Boat, RV, van, etc.
DP04_0016E	Estimate-YEAR STRUCTURE BUILT-Total housing units
DP04_0016PE	Percent-YEAR STRUCTURE BUILT-Total housing units
DP04_0017E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 2020 or later
DP04_0017PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 2020 or later
DP04_0018E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 2010 to 2019
DP04_0018PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 2010 to 2019
DP04_0019E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 2000 to 2009
DP04_0019PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 2000 to 2009
DP04_0020E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1990 to 1999
DP04_0020PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1990 to 1999
DP04_0021E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1980 to 1989
DP04_0021PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1980 to 1989
DP04_0022E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1970 to 1979
DP04_0022PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1970 to 1979
DP04_0023E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1960 to 1969
DP04_0023PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1960 to 1969
DP04_0024E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1950 to 1959
DP04_0024PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1950 to 1959
DP04_0025E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1940 to 1949
DP04_0025PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1940 to 1949
DP04_0026E	Estimate-YEAR STRUCTURE BUILT-Total housing units-Built 1939 or earlier
DP04_0026PE	Percent-YEAR STRUCTURE BUILT-Total housing units-Built 1939 or earlier
DP04_0027E	Estimate-ROOMS-Total housing units

DP04_0027PE	Percent-ROOMS-Total housing units
DP04_0028E	Estimate-ROOMS-Total housing units-1 room
DP04_0028PE	Percent-ROOMS-Total housing units-1 room
DP04_0029E	Estimate-ROOMS-Total housing units-2 rooms
DP04_0029PE	Percent-ROOMS-Total housing units-2 rooms
DP04_0030E	Estimate-ROOMS-Total housing units-3 rooms
DP04_0030PE	Percent-ROOMS-Total housing units-3 rooms
DP04_0031E	Estimate-ROOMS-Total housing units-4 rooms
DP04_0031PE	Percent-ROOMS-Total housing units-4 rooms
DP04_0032E	Estimate-ROOMS-Total housing units-5 rooms
DP04_0032PE	Percent-ROOMS-Total housing units-5 rooms
DP04_0033E	Estimate-ROOMS-Total housing units-6 rooms
DP04_0033PE	Percent-ROOMS-Total housing units-6 rooms
DP04_0034E	Estimate-ROOMS-Total housing units-7 rooms
DP04_0034PE	Percent-ROOMS-Total housing units-7 rooms
DP04_0035E	Estimate-ROOMS-Total housing units-8 rooms
DP04_0035PE	Percent-ROOMS-Total housing units-8 rooms
DP04_0036E	Estimate-ROOMS-Total housing units-9 rooms or more
DP04_0036PE	Percent-ROOMS-Total housing units-9 rooms or more
DP04_0037E	Estimate-ROOMS-Total housing units-Median rooms
DP04_0037PE	Percent-ROOMS-Total housing units-Median rooms
DP04_0038E	Estimate-BEDROOMS-Total housing units
DP04_0038PE	Percent-BEDROOMS-Total housing units
DP04_0039E	Estimate-BEDROOMS-Total housing units-No bedroom
DP04_0039PE	Percent-BEDROOMS-Total housing units-No bedroom
DP04_0040E	Estimate-BEDROOMS-Total housing units-1 bedroom
DP04_0040PE	Percent-BEDROOMS-Total housing units-1 bedroom
DP04_0041E	Estimate-BEDROOMS-Total housing units-2 bedrooms
DP04_0041PE	Percent-BEDROOMS-Total housing units-2 bedrooms
DP04_0042E	Estimate-BEDROOMS-Total housing units-3 bedrooms
DP04_0042PE	Percent-BEDROOMS-Total housing units-3 bedrooms
DP04_0043E	Estimate-BEDROOMS-Total housing units-4 bedrooms
DP04_0043PE	Percent-BEDROOMS-Total housing units-4 bedrooms
DP04_0044E	Estimate-BEDROOMS-Total housing units-5 or more bedrooms
DP04_0044PE	Percent-BEDROOMS-Total housing units-5 or more bedrooms
DP04_0045E	Estimate-HOUSING TENURE-Occupied housing units
DP04_0045PE	Percent-HOUSING TENURE-Occupied housing units
DP04_0046E	Estimate-HOUSING TENURE-Occupied housing units-Owner-occupied
DP04_0046PE	Percent-HOUSING TENURE-Occupied housing units-Owner-occupied

DP04_0047E	Estimate-HOUSING TENURE-Occupied housing units-Renter-occupied
DP04_0047PE	Percent-HOUSING TENURE-Occupied housing units-Renter-occupied
DP04_0048E	Estimate-HOUSING TENURE-Occupied housing units-Average household size of owner-occupied unit
DP04_0048PE	Percent-HOUSING TENURE-Occupied housing units-Average household size of owner-occupied unit
DP04_0049E	Estimate-HOUSING TENURE-Occupied housing units-Average household size of renter-occupied unit
DP04_0049PE	Percent-HOUSING TENURE-Occupied housing units-Average household size of renter-occupied unit
DP04_0050E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units
DP04_0050PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units
DP04_0051E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2021 or later
DP04_0051PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2021 or later
DP04_0052E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2018 to 2020
DP04_0052PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2018 to 2020
DP04_0053E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2010 to 2017
DP04_0053PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2010 to 2017
DP04_0054E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2000 to 2009
DP04_0054PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 2000 to 2009
DP04_0055E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 1990 to 1999
DP04_0055PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 1990 to 1999
DP04_0056E	Estimate-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 1989 and earlier
DP04_0056PE	Percent-YEAR HOUSEHOLDER MOVED INTO UNIT-Occupied housing units-Moved in 1989 and earlier
DP04_0057E	Estimate-VEHICLES AVAILABLE-Occupied housing units
DP04_0057PE	Percent-VEHICLES AVAILABLE-Occupied housing units
DP04_0058E	Estimate-VEHICLES AVAILABLE-Occupied housing units-No vehicles available
DP04_0058PE	Percent-VEHICLES AVAILABLE-Occupied housing units-No vehicles available
DP04_0059E	Estimate-VEHICLES AVAILABLE-Occupied housing units-1 vehicle available
DP04_0059PE	Percent-VEHICLES AVAILABLE-Occupied housing units-1 vehicle available
DP04_0060E	Estimate-VEHICLES AVAILABLE-Occupied housing units-2 vehicles available
DP04_0060PE	Percent-VEHICLES AVAILABLE-Occupied housing units-2 vehicles available
DP04_0061E	Estimate-VEHICLES AVAILABLE-Occupied housing units-3 or more vehicles

	available
DP04_0061PE	Percent-VEHICLES AVAILABLE-Occupied housing units-3 or more vehicles available
DP04_0062E	Estimate-HOUSE HEATING FUEL-Occupied housing units
DP04_0062PE	Percent-HOUSE HEATING FUEL-Occupied housing units
DP04_0063E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Utility gas
DP04_0063PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Utility gas
DP04_0064E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Bottled, tank, or LP gas
DP04_0064PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Bottled, tank, or LP gas
DP04_0065E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Electricity
DP04_0065PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Electricity
DP04_0066E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Fuel oil, kerosene, etc.
DP04_0066PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Fuel oil, kerosene, etc.
DP04_0067E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Coal or coke
DP04_0067PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Coal or coke
DP04_0068E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Wood
DP04_0068PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Wood
DP04_0069E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Solar energy
DP04_0069PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Solar energy
DP04_0070E	Estimate-HOUSE HEATING FUEL-Occupied housing units-Other fuel
DP04_0070PE	Percent-HOUSE HEATING FUEL-Occupied housing units-Other fuel
DP04_0071E	Estimate-HOUSE HEATING FUEL-Occupied housing units-No fuel used
DP04_0071PE	Percent-HOUSE HEATING FUEL-Occupied housing units-No fuel used
DP04_0072E	Estimate-SELECTED CHARACTERISTICS-Occupied housing units
DP04_0072PE	Percent-SELECTED CHARACTERISTICS-Occupied housing units
DP04_0073E	Estimate-SELECTED CHARACTERISTICS-Occupied housing units-Lacking complete plumbing facilities
DP04_0073PE	Percent-SELECTED CHARACTERISTICS-Occupied housing units-Lacking complete plumbing facilities
DP04_0074E	Estimate-SELECTED CHARACTERISTICS-Occupied housing units-Lacking complete kitchen facilities
DP04_0074PE	Percent-SELECTED CHARACTERISTICS-Occupied housing units-Lacking complete kitchen facilities
DP04_0075E	Estimate-SELECTED CHARACTERISTICS-Occupied housing units-No telephone service available
DP04_0075PE	Percent-SELECTED CHARACTERISTICS-Occupied housing units-No telephone service available
DP04_0076E	Estimate-OCCUPANTS PER ROOM-Occupied housing units
DP04_0076PE	Percent-OCCUPANTS PER ROOM-Occupied housing units
DP04_0077E	Estimate-OCCUPANTS PER ROOM-Occupied housing units-1.00 or less

DP04_0077PE	Percent-OCCUPANTS PER ROOM-Occupied housing units-1.00 or less
DP04_0078E	Estimate-OCCUPANTS PER ROOM-Occupied housing units-1.01 to 1.50
DP04_0078PE	Percent-OCCUPANTS PER ROOM-Occupied housing units-1.01 to 1.50
DP04_0079E	Estimate-OCCUPANTS PER ROOM-Occupied housing units-1.51 or more
DP04_0079PE	Percent-OCCUPANTS PER ROOM-Occupied housing units-1.51 or more
DP04_0080E	Estimate-VALUE-Owner-occupied units
DP04_0080PE	Percent-VALUE-Owner-occupied units
DP04_0081E	Estimate-VALUE-Owner-occupied units-Less than $50,000
DP04_0081PE	Percent-VALUE-Owner-occupied units-Less than $50,000
DP04_0082E	Estimate-VALUE-Owner-occupied units-$50,000 to $99,999
DP04_0082PE	Percent-VALUE-Owner-occupied units-$50,000 to $99,999
DP04_0083E	Estimate-VALUE-Owner-occupied units-$100,000 to $149,999
DP04_0083PE	Percent-VALUE-Owner-occupied units-$100,000 to $149,999
DP04_0084E	Estimate-VALUE-Owner-occupied units-$150,000 to $199,999
DP04_0084PE	Percent-VALUE-Owner-occupied units-$150,000 to $199,999
DP04_0085E	Estimate-VALUE-Owner-occupied units-$200,000 to $299,999
DP04_0085PE	Percent-VALUE-Owner-occupied units-$200,000 to $299,999
DP04_0086E	Estimate-VALUE-Owner-occupied units-$300,000 to $499,999
DP04_0086PE	Percent-VALUE-Owner-occupied units-$300,000 to $499,999
DP04_0087E	Estimate-VALUE-Owner-occupied units-$500,000 to $999,999
DP04_0087PE	Percent-VALUE-Owner-occupied units-$500,000 to $999,999
DP04_0088E	Estimate-VALUE-Owner-occupied units-$1,000,000 or more
DP04_0088PE	Percent-VALUE-Owner-occupied units-$1,000,000 or more
DP04_0089E	Estimate-VALUE-Owner-occupied units-Median (dollars)
DP04_0089PE	Percent-VALUE-Owner-occupied units-Median (dollars)
DP04_0090E	Estimate-MORTGAGE STATUS-Owner-occupied units
DP04_0090PE	Percent-MORTGAGE STATUS-Owner-occupied units
DP04_0091E	Estimate-MORTGAGE STATUS-Owner-occupied units-Housing units with a mortgage
DP04_0091PE	Percent-MORTGAGE STATUS-Owner-occupied units-Housing units with a mortgage
DP04_0092E	Estimate-MORTGAGE STATUS-Owner-occupied units-Housing units without a mortgage
DP04_0092PE	Percent-MORTGAGE STATUS-Owner-occupied units-Housing units without a mortgage
DP04_0093E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage
DP04_0093PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage
DP04_0094E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-Less than $500
DP04_0094PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-Less than $500

DP04_0095E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$500 to $999
DP04_0095PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$500 to $999
DP04_0096E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$1,000 to $1,499
DP04_0096PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$1,000 to $1,499
DP04_0097E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$1,500 to $1,999
DP04_0097PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$1,500 to $1,999
DP04_0098E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$2,000 to $2,499
DP04_0098PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$2,000 to $2,499
DP04_0099E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$2,500 to $2,999
DP04_0099PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$2,500 to $2,999
DP04_0100E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$3,000 or more
DP04_0100PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-$3,000 or more
DP04_0101E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-Median (dollars)
DP04_0101PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units with a mortgage-Median (dollars)
DP04_0102E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage
DP04_0102PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage
DP04_0103E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-Less than $250
DP04_0103PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-Less than $250
DP04_0104E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$250 to $399
DP04_0104PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$250 to $399
DP04_0105E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$400 to $599
DP04_0105PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$400 to $599
DP04_0106E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$600 to $799
DP04_0106PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$600 to $799
DP04_0107E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$800 to $999

DP04_0107PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$800 to $999
DP04_0108E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$1,000 or more
DP04_0108PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-$1,000 or more
DP04_0109E	Estimate-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-Median (dollars)
DP04_0109PE	Percent-SELECTED MONTHLY OWNER COSTS (SMOC)-Housing units without a mortgage-Median (dollars)
DP04_0110E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)
DP04_0110PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)
DP04_0111E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-Less than 20.0 percent
DP04_0111PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-Less than 20.0 percent
DP04_0112E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-20.0 to 24.9 percent
DP04_0112PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-20.0 to 24.9 percent
DP04_0113E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-25.0 to 29.9 percent
DP04_0113PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-25.0 to 29.9 percent
DP04_0114E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-30.0 to 34.9 percent
DP04_0114PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-30.0 to 34.9 percent
DP04_0115E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-35.0 percent or more
DP04_0115PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-35.0 percent or more
DP04_0116E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-Not computed
DP04_0116PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF

	HOUSEHOLD INCOME (SMOCAPI)-Housing units with a mortgage (excluding units where SMOCAPI cannot be computed)-Not computed
DP04_0117E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)
DP04_0117PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)
DP04_0118E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-Less than 10.0 percent
DP04_0118PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-Less than 10.0 percent
DP04_0119E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-10.0 to 14.9 percent
DP04_0119PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-10.0 to 14.9 percent
DP04_0120E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-15.0 to 19.9 percent
DP04_0120PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-15.0 to 19.9 percent
DP04_0121E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-20.0 to 24.9 percent
DP04_0121PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-20.0 to 24.9 percent
DP04_0122E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-25.0 to 29.9 percent
DP04_0122PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-25.0 to 29.9 percent
DP04_0123E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-30.0 to 34.9 percent
DP04_0123PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-30.0 to 34.9 percent
DP04_0124E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-35.0 percent or more
DP04_0124PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-35.0 percent or more

DP04_0125E	Estimate-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-Not computed
DP04_0125PE	Percent-SELECTED MONTHLY OWNER COSTS AS A PERCENTAGE OF HOUSEHOLD INCOME (SMOCAPI)-Housing unit without a mortgage (excluding units where SMOCAPI cannot be computed)-Not computed
DP04_0126E	Estimate-GROSS RENT-Occupied units paying rent
DP04_0126PE	Percent-GROSS RENT-Occupied units paying rent
DP04_0127E	Estimate-GROSS RENT-Occupied units paying rent-Less than $500
DP04_0127PE	Percent-GROSS RENT-Occupied units paying rent-Less than $500
DP04_0128E	Estimate-GROSS RENT-Occupied units paying rent-$500 to $999
DP04_0128PE	Percent-GROSS RENT-Occupied units paying rent-$500 to $999
DP04_0129E	Estimate-GROSS RENT-Occupied units paying rent-$1,000 to $1,499
DP04_0129PE	Percent-GROSS RENT-Occupied units paying rent-$1,000 to $1,499
DP04_0130E	Estimate-GROSS RENT-Occupied units paying rent-$1,500 to $1,999
DP04_0130PE	Percent-GROSS RENT-Occupied units paying rent-$1,500 to $1,999
DP04_0131E	Estimate-GROSS RENT-Occupied units paying rent-$2,000 to $2,499
DP04_0131PE	Percent-GROSS RENT-Occupied units paying rent-$2,000 to $2,499
DP04_0132E	Estimate-GROSS RENT-Occupied units paying rent-$2,500 to $2,999
DP04_0132PE	Percent-GROSS RENT-Occupied units paying rent-$2,500 to $2,999
DP04_0133E	Estimate-GROSS RENT-Occupied units paying rent-$3,000 or more
DP04_0133PE	Percent-GROSS RENT-Occupied units paying rent-$3,000 or more
DP04_0134E	Estimate-GROSS RENT-Occupied units paying rent-Median (dollars)
DP04_0134PE	Percent-GROSS RENT-Occupied units paying rent-Median (dollars)
DP04_0135E	Estimate-GROSS RENT-Occupied units paying rent-No rent paid
DP04_0135PE	Percent-GROSS RENT-Occupied units paying rent-No rent paid
DP04_0136E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)
DP04_0136PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)
DP04_0137E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-Less than 15.0 percent
DP04_0137PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-Less than 15.0 percent
DP04_0138E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-15.0 to 19.9 percent
DP04_0138PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-15.0 to 19.9 percent
DP04_0139E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME

	(GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-20.0 to 24.9 percent
DP04_0139PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-20.0 to 24.9 percent
DP04_0140E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-25.0 to 29.9 percent
DP04_0140PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-25.0 to 29.9 percent
DP04_0141E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-30.0 to 34.9 percent
DP04_0141PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-30.0 to 34.9 percent
DP04_0142E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-35.0 percent or more
DP04_0142PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-35.0 percent or more
DP04_0143E	Estimate-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-Not computed
DP04_0143PE	Percent-GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME (GRAPI)-Occupied units paying rent (excluding units where GRAPI cannot be computed)-Not computed
DP05_0001E	Estimate-SEX AND AGE-Total population
DP05_0001PE	Percent-SEX AND AGE-Total population
DP05_0002E	Estimate-SEX AND AGE-Total population-Male
DP05_0002PE	Percent-SEX AND AGE-Total population-Male
DP05_0003E	Estimate-SEX AND AGE-Total population-Female
DP05_0003PE	Percent-SEX AND AGE-Total population-Female
DP05_0004E	Estimate-SEX AND AGE-Total population-Sex ratio (males per 100 females)
DP05_0004PE	Percent-SEX AND AGE-Total population-Sex ratio (males per 100 females)
DP05_0005E	Estimate-SEX AND AGE-Total population-Under 5 years
DP05_0005PE	Percent-SEX AND AGE-Total population-Under 5 years
DP05_0006E	Estimate-SEX AND AGE-Total population-5 to 9 years
DP05_0006PE	Percent-SEX AND AGE-Total population-5 to 9 years
DP05_0007E	Estimate-SEX AND AGE-Total population-10 to 14 years
DP05_0007PE	Percent-SEX AND AGE-Total population-10 to 14 years
DP05_0008E	Estimate-SEX AND AGE-Total population-15 to 19 years
DP05_0008PE	Percent-SEX AND AGE-Total population-15 to 19 years

DP05_0009E	Estimate-SEX AND AGE-Total population-20 to 24 years
DP05_0009PE	Percent-SEX AND AGE-Total population-20 to 24 years
DP05_0010E	Estimate-SEX AND AGE-Total population-25 to 34 years
DP05_0010PE	Percent-SEX AND AGE-Total population-25 to 34 years
DP05_0011E	Estimate-SEX AND AGE-Total population-35 to 44 years
DP05_0011PE	Percent-SEX AND AGE-Total population-35 to 44 years
DP05_0012E	Estimate-SEX AND AGE-Total population-45 to 54 years
DP05_0012PE	Percent-SEX AND AGE-Total population-45 to 54 years
DP05_0013E	Estimate-SEX AND AGE-Total population-55 to 59 years
DP05_0013PE	Percent-SEX AND AGE-Total population-55 to 59 years
DP05_0014E	Estimate-SEX AND AGE-Total population-60 to 64 years
DP05_0014PE	Percent-SEX AND AGE-Total population-60 to 64 years
DP05_0015E	Estimate-SEX AND AGE-Total population-65 to 74 years
DP05_0015PE	Percent-SEX AND AGE-Total population-65 to 74 years
DP05_0016E	Estimate-SEX AND AGE-Total population-75 to 84 years
DP05_0016PE	Percent-SEX AND AGE-Total population-75 to 84 years
DP05_0017E	Estimate-SEX AND AGE-Total population-85 years and over
DP05_0017PE	Percent-SEX AND AGE-Total population-85 years and over
DP05_0018E	Estimate-SEX AND AGE-Total population-Median age (years)
DP05_0018PE	Percent-SEX AND AGE-Total population-Median age (years)
DP05_0019E	Estimate-SEX AND AGE-Total population-Under 18 years
DP05_0019PE	Percent-SEX AND AGE-Total population-Under 18 years
DP05_0020E	Estimate-SEX AND AGE-Total population-16 years and over
DP05_0020PE	Percent-SEX AND AGE-Total population-16 years and over
DP05_0021E	Estimate-SEX AND AGE-Total population-18 years and over
DP05_0021PE	Percent-SEX AND AGE-Total population-18 years and over
DP05_0022E	Estimate-SEX AND AGE-Total population-21 years and over
DP05_0022PE	Percent-SEX AND AGE-Total population-21 years and over
DP05_0023E	Estimate-SEX AND AGE-Total population-62 years and over
DP05_0023PE	Percent-SEX AND AGE-Total population-62 years and over
DP05_0024E	Estimate-SEX AND AGE-Total population-65 years and over
DP05_0024PE	Percent-SEX AND AGE-Total population-65 years and over
DP05_0025E	Estimate-SEX AND AGE-Total population-18 years and over
DP05_0025PE	Percent-SEX AND AGE-Total population-18 years and over
DP05_0026E	Estimate-SEX AND AGE-Total population-18 years and over-Male
DP05_0026PE	Percent-SEX AND AGE-Total population-18 years and over-Male
DP05_0027E	Estimate-SEX AND AGE-Total population-18 years and over-Female
DP05_0027PE	Percent-SEX AND AGE-Total population-18 years and over-Female
DP05_0028E	Estimate-SEX AND AGE-Total population-18 years and over-Sex ratio (males per 100 females)

DP05_0028PE	Percent-SEX AND AGE-Total population-18 years and over-Sex ratio (males per 100 females)
DP05_0029E	Estimate-SEX AND AGE-Total population-65 years and over
DP05_0029PE	Percent-SEX AND AGE-Total population-65 years and over
DP05_0030E	Estimate-SEX AND AGE-Total population-65 years and over-Male
DP05_0030PE	Percent-SEX AND AGE-Total population-65 years and over-Male
DP05_0031E	Estimate-SEX AND AGE-Total population-65 years and over-Female
DP05_0031PE	Percent-SEX AND AGE-Total population-65 years and over-Female
DP05_0032E	Estimate-SEX AND AGE-Total population-65 years and over-Sex ratio (males per 100 females)
DP05_0032PE	Percent-SEX AND AGE-Total population-65 years and over-Sex ratio (males per 100 females)
DP05_0033E	Estimate-RACE-Total population
DP05_0033PE	Percent-RACE-Total population
DP05_0034E	Estimate-RACE-Total population-One race
DP05_0034PE	Percent-RACE-Total population-One race
DP05_0035E	Estimate-RACE-Total population-Two or More Races
DP05_0035PE	Percent-RACE-Total population-Two or More Races
DP05_0036E	Estimate-RACE-Total population-One race
DP05_0036PE	Percent-RACE-Total population-One race
DP05_0037E	Estimate-RACE-Total population-One race-White
DP05_0037PE	Percent-RACE-Total population-One race-White
DP05_0038E	Estimate-RACE-Total population-One race-Black or African American
DP05_0038PE	Percent-RACE-Total population-One race-Black or African American
DP05_0039E	Estimate-RACE-Total population-One race-American Indian and Alaska Native
DP05_0039PE	Percent-RACE-Total population-One race-American Indian and Alaska Native
DP05_0040E	Estimate-RACE-Total population-One race-American Indian and Alaska Native-Cherokee tribal grouping
DP05_0040PE	Percent-RACE-Total population-One race-American Indian and Alaska Native-Cherokee tribal grouping
DP05_0041E	Estimate-RACE-Total population-One race-American Indian and Alaska Native-Chippewa tribal grouping
DP05_0041PE	Percent-RACE-Total population-One race-American Indian and Alaska Native-Chippewa tribal grouping
DP05_0042E	Estimate-RACE-Total population-One race-American Indian and Alaska Native-Navajo tribal grouping
DP05_0042PE	Percent-RACE-Total population-One race-American Indian and Alaska Native-Navajo tribal grouping
DP05_0043E	Estimate-RACE-Total population-One race-American Indian and Alaska Native-Sioux tribal grouping
DP05_0043PE	Percent-RACE-Total population-One race-American Indian and Alaska Native-Sioux tribal grouping
DP05_0044E	Estimate-RACE-Total population-One race-Asian
DP05_0044PE	Percent-RACE-Total population-One race-Asian

DP05_0045E	Estimate-RACE-Total population-One race-Asian-Asian Indian
DP05_0045PE	Percent-RACE-Total population-One race-Asian-Asian Indian
DP05_0046E	Estimate-RACE-Total population-One race-Asian-Chinese
DP05_0046PE	Percent-RACE-Total population-One race-Asian-Chinese
DP05_0047E	Estimate-RACE-Total population-One race-Asian-Filipino
DP05_0047PE	Percent-RACE-Total population-One race-Asian-Filipino
DP05_0048E	Estimate-RACE-Total population-One race-Asian-Japanese
DP05_0048PE	Percent-RACE-Total population-One race-Asian-Japanese
DP05_0049E	Estimate-RACE-Total population-One race-Asian-Korean
DP05_0049PE	Percent-RACE-Total population-One race-Asian-Korean
DP05_0050E	Estimate-RACE-Total population-One race-Asian-Vietnamese
DP05_0050PE	Percent-RACE-Total population-One race-Asian-Vietnamese
DP05_0051E	Estimate-RACE-Total population-One race-Asian-Other Asian
DP05_0051PE	Percent-RACE-Total population-One race-Asian-Other Asian
DP05_0052E	Estimate-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander
DP05_0052PE	Percent-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander
DP05_0053E	Estimate-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Chamorro
DP05_0053PE	Percent-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Chamorro
DP05_0054E	Estimate-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Native Hawaiian
DP05_0054PE	Percent-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Native Hawaiian
DP05_0055E	Estimate-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Samoan
DP05_0055PE	Percent-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Samoan
DP05_0056E	Estimate-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Other Native Hawaiian and Other Pacific Islander
DP05_0056PE	Percent-RACE-Total population-One race-Native Hawaiian and Other Pacific Islander-Other Native Hawaiian and Other Pacific Islander
DP05_0057E	Estimate-RACE-Total population-One race-Some Other Race
DP05_0057PE	Percent-RACE-Total population-One race-Some Other Race
DP05_0058E	Estimate-RACE-Total population-Two or More Races
DP05_0058PE	Percent-RACE-Total population-Two or More Races
DP05_0059E	Estimate-RACE-Total population-Two or More Races-White and Black or African American
DP05_0059PE	Percent-RACE-Total population-Two or More Races-White and Black or African American
DP05_0060E	Estimate-RACE-Total population-Two or More Races-White and American Indian and Alaska Native
DP05_0060PE	Percent-RACE-Total population-Two or More Races-White and American Indian

	and Alaska Native
DP05_0061E	Estimate-RACE-Total population-Two or More Races-White and Asian
DP05_0061PE	Percent-RACE-Total population-Two or More Races-White and Asian
DP05_0062E	Estimate-RACE-Total population-Two or More Races-White and Some Other Race
DP05_0062PE	Percent-RACE-Total population-Two or More Races-White and Some Other Race
DP05_0063E	Estimate-RACE-Total population-Two or More Races-Black or African American and American Indian and Alaska Native
DP05_0063PE	Percent-RACE-Total population-Two or More Races-Black or African American and American Indian and Alaska Native
DP05_0064E	Estimate-RACE-Total population-Two or More Races-Black or African American and Some Other Race
DP05_0064PE	Percent-RACE-Total population-Two or More Races-Black or African American and Some Other Race
DP05_0065E	Estimate-Race alone or in combination with one or more other races-Total population
DP05_0065PE	Percent-Race alone or in combination with one or more other races-Total population
DP05_0066E	Estimate-Race alone or in combination with one or more other races-Total population-White
DP05_0066PE	Percent-Race alone or in combination with one or more other races-Total population-White
DP05_0067E	Estimate-Race alone or in combination with one or more other races-Total population-Black or African American
DP05_0067PE	Percent-Race alone or in combination with one or more other races-Total population-Black or African American
DP05_0068E	Estimate-Race alone or in combination with one or more other races-Total population-American Indian and Alaska Native
DP05_0068PE	Percent-Race alone or in combination with one or more other races-Total population-American Indian and Alaska Native
DP05_0069E	Estimate-Race alone or in combination with one or more other races-Total population-Asian
DP05_0069PE	Percent-Race alone or in combination with one or more other races-Total population-Asian
DP05_0070E	Estimate-Race alone or in combination with one or more other races-Total population-Native Hawaiian and Other Pacific Islander
DP05_0070PE	Percent-Race alone or in combination with one or more other races-Total population-Native Hawaiian and Other Pacific Islander
DP05_0071E	Estimate-Race alone or in combination with one or more other races-Total population-Some Other Race
DP05_0071PE	Percent-Race alone or in combination with one or more other races-Total population-Some Other Race
DP05_0072E	Estimate-HISPANIC OR LATINO AND RACE-Total population
DP05_0072PE	Percent-HISPANIC OR LATINO AND RACE-Total population
DP05_0073E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)
DP05_0073PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)

DP05_0074E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Mexican
DP05_0074PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Mexican
DP05_0075E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Puerto Rican
DP05_0075PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Puerto Rican
DP05_0076E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Cuban
DP05_0076PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Cuban
DP05_0077E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Other Hispanic or Latino
DP05_0077PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Hispanic or Latino (of any race)-Other Hispanic or Latino
DP05_0078E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino
DP05_0078PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino
DP05_0079E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-White alone
DP05_0079PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-White alone
DP05_0080E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Black or African American alone
DP05_0080PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Black or African American alone
DP05_0081E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-American Indian and Alaska Native alone
DP05_0081PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-American Indian and Alaska Native alone
DP05_0082E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Asian alone
DP05_0082PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Asian alone
DP05_0083E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Native Hawaiian and Other Pacific Islander alone
DP05_0083PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Native Hawaiian and Other Pacific Islander alone
DP05_0084E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Some Other Race alone
DP05_0084PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Some Other Race alone
DP05_0085E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races
DP05_0085PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races
DP05_0086E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races-Two races including Some Other Race

DP05_0086PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races-Two races including Some Other Race
DP05_0087E	Estimate-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races-Two races excluding Some Other Race, and three or more races
DP05_0087PE	Percent-HISPANIC OR LATINO AND RACE-Total population-Not Hispanic or Latino-Two or More Races-Two races excluding Some Other Race, and three or more races
DP05_0088E	Estimate-Total housing units
DP05_0088PE	Percent-Total housing units
DP05_0089E	Estimate-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population
DP05_0089PE	Percent-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population
DP05_0090E	Estimate-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population-Male
DP05_0090PE	Percent-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population-Male
DP05_0091E	Estimate-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population-Female
DP05_0091PE	Percent-CITIZEN, VOTING AGE POPULATION-Citizen, 18 and over population-Female