Where are the best places to live in california?

Wouldn't it be nice to take publicly avialble Census data and analyze it to figure out which locations in California have the best combination of high median income, low median rental costs, and "good" neighborhoods? In this analysis I extract and clean California Census tract data, I create a metric to calculate the ratings of most of the Census tracts, I make models to try to understand which variables are highly correlated with "good" areas, and I create a heat map showing the rating of each tract.

Data analytics skills demonstrated here:

- Basic scraping
- API usage
- Cleaning data and imputing missing values
- Examining correlations between predictors
- Building ridge regression models
- Plotting geographic heat map of response variable using geopandas

Working with the Census API

In this project demographic data from US Census tables is extracted using the python Census library then processed using other python libraries (like pandas).

- An API key is required to request data from the census tables.
- These Census tables contain 10s of thousands of variables. For this analysis I examined variables from the 2019 American Community Survey 1-year data (acs1). This survey contains a broad range of demographic data. A description of all the variables for the 2019 acs1 can be found here.

You won't use all of the functions below

Many of these initial cells contain functions which were used to generate the 23.8 Mb data file that accompanies this notebook. Don't be alarmed if you see cells with functions that are never executed.

Ok, let's get started!

The first task is to use our API key to connect to the census tables so that we can request data.

In [163…

```
import pandas as pd
import numpy as np
from IPython.display import display

from census import Census # install python package to extrat data from census API tables
from us import states # us package simplifies FIPS codes for many geographies
import requests
from bs4 import BeautifulSoup
import re

from collections import defaultdict
```

```
from datetime import datetime

import warnings
warnings.filterwarnings('ignore')

# First locate the API key. Census API keys are available here:   https://www.census.gov

def connect_to_census(API_key_location):
    with open(API_key_location) as f:
        API_key_string = f.readlines()[0] # get the API key
    try:
        c = Census(API_key_string) # Make a connection to the census API
        print('Census API connections successful!')
    except:
        print('Error connecting to Census API')
        c = ''
    return c

# API_key_location = r'C:\Users\Edmund\census_API_key.txt' # Replace this with the path
# c = connect_to_census(API_key_location)
```

Now we have an API connection. But before we can make data requests we need to generate a list of variables of interest. I've used the BeautifulSoup package along with a simple regex command to extract estimates for population totals (not grouped by age, sex or race) from the 2019 acs1 variable description page.

In [131…

```
def get_variables(year):
    year = '2019'
    acs1_url = r"https://api.census.gov/data/" + year + r"/acs/acs1/variables.html" # UR
    # print(acs1_url)

    page = requests.get(acs1_url)
    soup = BeautifulSoup(page.content, 'html.parser') # parse html
    # Find all variable names from the acs1 tables by fitting the regex pattern below:
    # Only select from detailed tables (base tables B) estimates (E) for totals from all
    # Do not factor in race at this time to keep the number of variables at a more manag
    acs1_var_str = r'\"variables\/(B[0-9]{5}_001E)\.json\"'
    acs1_var_patt = re.compile(acs1_var_str)

    content = soup.prettify() # create a clean string out of all the html

    # now use re.findall
    acs1_vars = re.findall(acs1_var_patt, content) # find the variable names that fit th
    print("Number of acs1 variables: \n {}".format(len(acs1_vars)))

    return acs1_vars

# acs1_vars = get_variables('2019')
```

Scraping this page leaves us with 651 varialbes. This is a reasonable number to work with considering the 2019 acs tables contain over 26000 variables. Unfortunately, some of these selected variables are actually incompatible with the python Census package, and if we try to use it to request data for these variables we will get an error. Fortunately I found a table which groups all the 2019 acs variables by presence in acs1 or acs5 (5-year data), and I decided to only use variables that are present in both acs1 and acs5. This scheme allowed me to avoid errors while making data requests and reduced my variable count down to 620.

I created a file containing variable name prefixes for "allowed" variables. The following cell uses this file to reduce from 651 variables to 620 "allowed" variables:

In [132…

```
# now we need to see which variable prefixes can be use for requests and narrow our list
```

```
def get_allowed_vars(ap_location):
    allowed_prefixes = list(pd.read_csv(ap_location)['variable_prefix'])
    # print(len(allowed_prefixes))

    allowed_vars = []
    for var in acs1_vars:
        prefix, suffix = var.split('_')
        if prefix in allowed_prefixes:
            allowed_vars.append(var)

    print('total number of allowed variables: {}'.format(len(allowed_vars)))

    return allowed_vars

# # select location of file containing allowed prefixes
# ap_location = r'acs_allowed_prefixes.csv'

# allowed_vars = get_allowed_vars(ap_location)
```

Defining a "Good neighborhoods" metric

In addition to these 620 "allowed variables" I will manually add 2 variables related to:

- Poverty rate
- Labor force participation

These additional variables will be used to help create a "good neighborhoods" metric.

In [133…

```
# allowed_vars += ['B17020_002E', 'B23025_002E'] # Adding additional variables for "good
```

Now that we have 622 'allowed' variables that are compatible with the python census package. I will make API requests to get Census data for all Census tracts in all counties in California. The census API limits requests to 50 variables at a time, and sometimes requests fail. So I've made functions that make multiple requests (and retry if a request fails). After each request is complete the data is merged with a pandas DataFrame.

In [134…

```
def multi_request(allowed_vars, max_attempts = 3): # try doing a request and if it fails
    request_status = False
    attempt_num = 1
    while (attempt_num <= max_attempts) and (request_status == False):
        try:
            print('Attempting request {} of {}'.format(attempt_num, max_attempts))
            req = c.acs.state_county_tract(tuple(allowed_vars), states.CA.fips, '*', '*'
            print('Request successful!')
            request_status = True
            return req
        except:
            print('Warning: Request failed!')
        attempt_num += 1


def request_all_vars_all_vals(allowed_vars):
    sect = 23 # break list of all vars into sections of length sect and request one sect
    itterations = int(len(allowed_vars)/sect) # Number of requests excluding remainder.
    remainder = len(allowed_vars)%sect # final request, used if needed.
    print('Getting initial dataframe of first {} allowed variables...'.format(sect))
    request0 = multi_request(allowed_vars[0:sect]) # default of 3 request attempts
    print('Initial request successful. Creating dataframe and returning shape..')
    row_df = pd.DataFrame.from_dict(request0) # create DataFrame and populate with data
    row_df = row_df.convert_dtypes() # convert to more easily usable data types.
```

```
    row_df = row_df.fillna(value=np.nan) # replace None values with pd.NA

    for itt in range(1,iterations): # Now make more requests and merge data with existi
        vstart = itt*sect
        vend = (itt+1)*sect
        request = multi_request(allowed_vars[vstart:vend])
        print('creating requested_df ...')
        requested_df = pd.DataFrame.from_dict(request)
        requested_df = requested_df.convert_dtypes() # convert to more easily usable dat
        requested_df = requested_df.fillna(value=np.nan)# replace None values with pd.NA
        print('Shape of requested_df: {}'.format(requested_df.shape))
        print('merging with existing dataframe...')
        row_df = row_df.merge(requested_df, on = ["state","county","tract"], how = 'left
        print('merge successful, dataframe has the following shape: {}'.format(row_df.sh

    # now add on the last of the variables if there is a remainder.
    if remainder > 0:
        print('requesting remainder of variables:')
        print('resuming at variable index: {}'.format(vend))
        req_remainder = multi_request(allowed_vars[vend:])
        print('request for remainder of variables complete!')
        remainder_df = pd.DataFrame.from_dict(req_remainder)
        remainder_df = remainder_df.convert_dtypes() # convert to more easily usable dat
        remainder_df = remainder_df.fillna(value=np.nan)# replace None values with pd.NA
        row_df = row_df.merge(remainder_df, on = ["state","county","tract"], how = 'left
        print('shape of final dataframe: {}'.format(row_df.shape))

    return row_df

# acs1_full_df = request_all_vars_all_vals(allowed_vars)
```

Now that we've generated our DataFrame of interest we can export it to a csv file to use later.

In [135…

```
def full_df_to_csv(acs1_full_df):
    curr_date_time = datetime.now().strftime("%Y%m%d-%H%M%S")
    data_path = r'acs1_full_data_set' + curr_date_time + '.csv'
    acs1_full_df.to_csv(data_path, index=False) # see what this makes and see how big th

# full_df_to_csv(acs1_full_df)
```

In [136…

```
# #Checking shape of full data frame
# print(acs1_full_df.shape)
```

Data set for all CA Census tracts

This full DataFrame contains 9129 rows and 625 columns (625 variables for 9129 Census tracts). When I convert it into a csv file, the file is about 23.8 Mb.\ The full 23.8 Mb file is included in this Github repository and it will be used below for the rest of the analysis.

In [137…

```
# The function below generates a random sample from the full data set that is less than

# def sample_df_to_csv(acs1_full_df): # now sample 3650 rows at random so we can generat
#     acs1_sample_df = acs1_full_df.sample(3650, random_state = 3)
#     curr_date_time = datetime.now().strftime("%Y%m%d-%H%M%S")
#     data_path = r'acs1_sample' + curr_date_time + '.csv'
#     acs1_sample_df.to_csv(data_path, index=False) # see what this makes and see how bi

# sample_df_to_csv(acs1_full_df)
```

Now let's import the data from the CSV file and see what we are working with:

In [138…

```
# Although I've made a smaller subset of the data I'd actually like to try using the ful
csv_path = r'acs1_full_data_set20230424-082527.csv'
acs_sample_df = pd.read_csv(csv_path)
print('ACS 2019 data shape for all census tracts: {} '.format(acs_sample_df.shape))

# There appears to be an issue here: The number of tracts doesn't match the 2019 geodata
```

```
ACS 2019 data shape for all census tracts: (9129, 625)
```

Data cleaning

First I would like to detect DataFrame columns that are completely empty (filled with NaN values) and remove them from the data set

In [139…

```
print("Let's looks at a column with blank entries:")
display(acs_sample_df['B08133_001E'])
# It would be nice to remove any columns that are entirely NaN entries.
acs_df = acs_sample_df.copy()# First make a copy of acs_sample_df to play with.
for col in acs_sample_df.columns:
    if acs_sample_df[col].isna().all(): # If all entries for the column are NaN then rem
        del acs_df[col]
# After deleting empty columns what is the size of the data frame?
print('df shape after deleting empty columns: {}'.format(acs_df.shape))
```

```
Let's looks at a column with blank entries:
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN
         ..
9124    NaN
9125    NaN
9126    NaN
9127    NaN
9128    NaN
Name: B08133_001E, Length: 9129, dtype: float64
df shape after deleting empty columns: (9129, 523)
```

Wow, there were a lot of empty columns! removing these columns significantly decreases the variable count from 627 to 523!

Living with highly correlated variables

I suspect that many of the variables in this DataFrame correlate exactly with each other (correlation = 1). Variables that exactly correlate may be redundant (for example: "PEOPLE REPORTING ANCESTRY" and "ANCESTRY"), or they may be subsets of eachother (for example: "PEOPLE REPORTING ANCESTRY" and "HISPANIC OR LATINO ORIGIN").

The function below attempts to group all variables with correlation = 1 into sets. I can then pick out a single variable from each set and discard the others. Discarding redundant variables may make it easier to generate good models without sacrificing releavant information.

In [164…

```
# Now let's make a correlation matrix between all the variables. Variables that are perf

# can I make a correlation matrix despite NaN values?
acs_corr_mat1 = acs_df.corr()
# print(type(acs_corr_mat1))
print('Shape of correlation matrix: \n {}'.format(acs_corr_mat1.shape))
```

```
# print(acs_corr_mat1)

var_list_unchanged = False # Set this to true in the while loop if no new sets of variab
correlated_vars_lists = []
while not var_list_unchanged:
    var_list = [acs_corr_mat1.iloc[:,0].name] # first var in var_list is the zeroth colu
    for idx, col_name in enumerate(acs_corr_mat1.index):
        if (col_name != acs_corr_mat1.iloc[:,0].name) and (acs_corr_mat1.iloc[idx,0] ==
            var_list.append(col_name) # add name of pefectly correlated variable to the
    # print('length of var_list: {}'.format(len(var_list)))
    if var_list == [acs_corr_mat1.iloc[:,0].name]: # If no new high correlation variable
        var_list_unchanged = True
    else: # remove rows and columns from the correlation matrix then go back into the wh
        correlated_vars_lists.append(var_list) # append set to master list.
        del acs_corr_mat1[var_list[0]]# remove 0th column
        acs_corr_mat1.drop(var_list[1:], inplace = True)# remove rows with correlation s

print('Printing length of each list of perfectly correlated variables: {}'.format([len(x
print('Printing each list of perfectly correlated variables: {}'.format([x for x in corr
```

```
Shape of correlation matrix:
 (502, 502)
Printing length of each list of perfectly correlated variables: []
Printing each list of perfectly correlated variables: []
```

So are the sets of variables above essentially replicates of each other?\ Let's look at variables from each set and try to decide:

Set 0 (21 variables):

B01001_001E: "Estimate!!Total: SEX BY AGE"

B01003_001E: "Estimate!!Total: TOTAL POPULATION"

B02001_001E: "Estimate!!Total: RACE"

B03001_001E: "Estimate!!Total: HISPANIC OR LATINO ORIGIN BY SPECIFIC ORIGIN"

B03002_001E: "Estimate!!Total: HISPANIC OR LATINO ORIGIN BY RACE"

B03003_001E: "Estimate!!Total: HISPANIC OR LATINO ORIGIN"

B04006_001E: "Estimate!!Total: PEOPLE REPORTING ANCESTRY"

B04007_001E: "Estimate!!Total: ANCESTRY"

B05001_001E: "Estimate!!Total: NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES"

B05002_001E: "Estimate!!Total: PLACE OF BIRTH BY NATIVITY AND CITIZENSHIP STATUS"

B05003_001E: "Estimate!!Total: SEX BY AGE BY NATIVITY AND CITIZENSHIP STATUS"

B05012_001E: "Estimate!!Total: NATIVITY IN THE UNITED STATES"

B06001_001E: "Estimate!!Total: PLACE OF BIRTH BY AGE IN THE UNITED STATES"

B06003_001E: "Estimate!!Total: PLACE OF BIRTH BY SEX IN THE UNITED STATES"

B09019_001E: "Estimate!!Total: HOUSEHOLD TYPE (INCLUDING LIVING ALONE) BY RELATIONSHIP"

B99011_001E: "Estimate!!Total: ALLOCATION OF SEX"

B99012_001E: "Estimate!!Total: ALLOCATION OF AGE"

B99021_001E: "Estimate!!Total: ALLOCATION OF RACE"

B99031_001E: "Estimate!!Total: ALLOCATION OF HISPANIC OR LATINO ORIGIN"

B99051_001E: "Estimate!!Total: ALLOCATION OF CITIZENSHIP STATUS"

B99061_001E: "Estimate!!Total: ALLOCATION OF PLACE OF BIRTH"

Many of the perfectly correlated variables above refer to totals and seem to be redundant. Interestingly there are still variables here related to race despite my attempt to exclude them from the analysis. From set 0 I will only include B01003_001E (TOTAL POPULATION) and B03003_001E (HISPANIC OR LATINO ORIGIN) and remove the other variables from set 0.

Set 1 (3 variables):

B01002_001E: "Estimate!!Median age --!!Total: MEDIAN AGE BY SEX"

B05004_001E: "Estimate!!Total: MEDIAN AGE BY NATIVITY AND CITIZENSHIP STATUS BY SEX"

B06002_001E: "Estimate!!Median age --!!Total: MEDIAN AGE BY PLACE OF BIRTH IN THE UNITED STATES"

Using multiple variables related to median age would be redundant, So I will keep B01002_001E (MEDIAN AGE BY SEX) and discard the others.

Set 2

Set 2 contains both variables from set 0, so I will ignore set 2.

Now lets remove these "redundant" variables.

In [141…

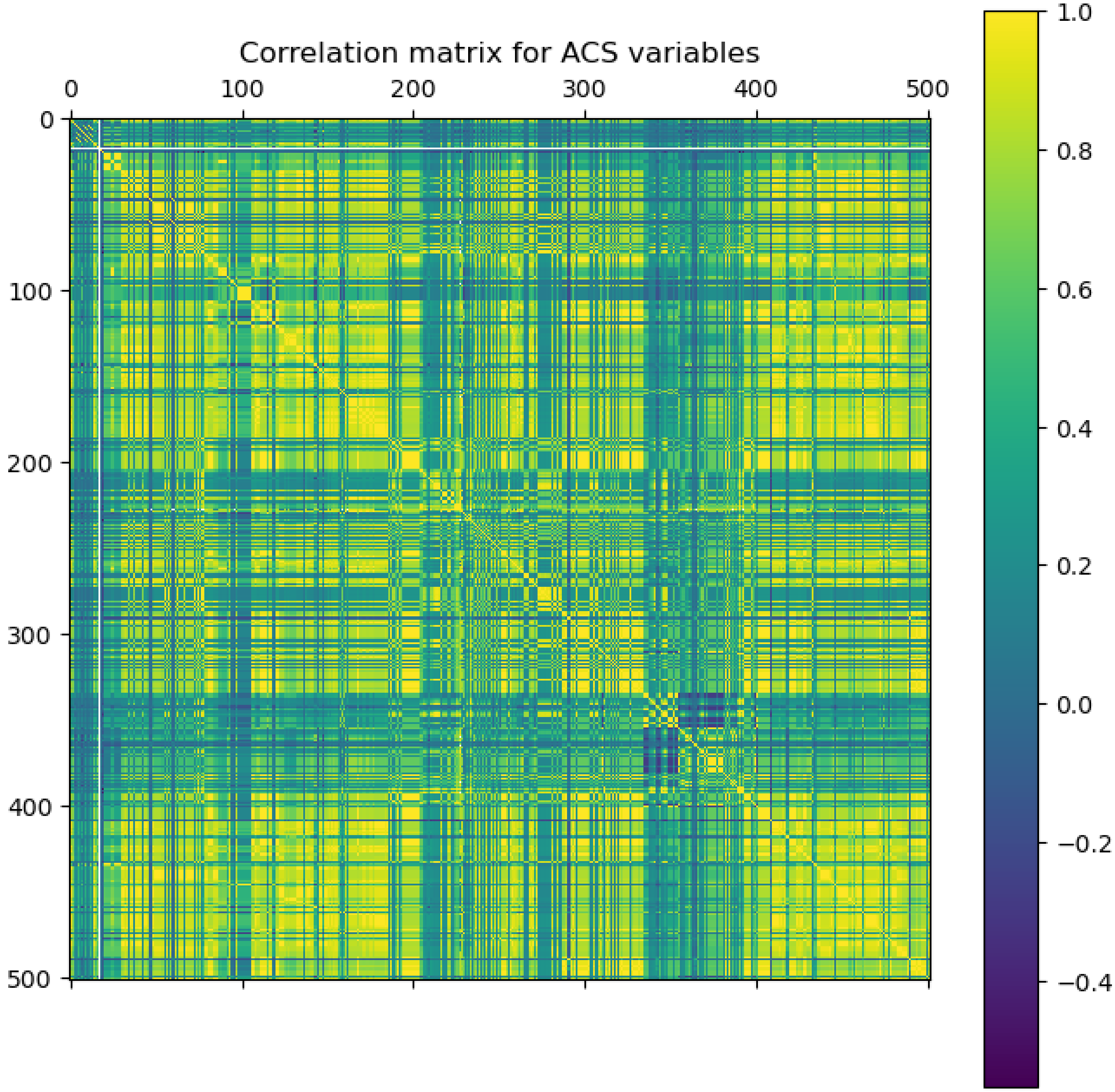
```
# removing some perfectly correlated variables that seem to be redundant
redundant_vars_set0 = set(correlated_vars_lists[0]) - set(['B01003_001E', 'B03003_001E']
print(redundant_vars_set0)
redundant_vars_set1 = set(correlated_vars_lists[1]) - set(['B01002_001E'])
print(redundant_vars_set1)
redundant_vars_set0.update(redundant_vars_set1) # update set0 to include set1

# remove redundant columns from acs_df:
acs_df.drop(list(redundant_vars_set0), axis=1, inplace = True)
# now check the size of the dataframe
print('acs_df shape after removing redundant variables: {}'.format(acs_df.shape))
```

```
{'B05001_001E', 'B01001_001E', 'B05012_001E', 'B06001_001E', 'B03001_001E', 'B99011_001
E', 'B04007_001E', 'B99012_001E', 'B06003_001E', 'B03002_001E', 'B09019_001E', 'B05002_0
01E', 'B02001_001E', 'B99021_001E', 'B99051_001E', 'B04006_001E', 'B99031_001E', 'B99061
_001E', 'B05003_001E'}
{'B05004_001E', 'B06002_001E'}
acs_df shape after removing redundant variables: (9129, 502)
```

So there are still about 502 variables left. I suspect that many of these 502 variables are highly correlated based on Census question type. We can get a sense of the number of correlated variables, and how they are grouped, by making a heat map of the correlation matrix for this dataframe:

In [142…

```
# now lets make a heat map of the correlation matrix and see how multicolinearity will e
import matplotlib.pyplot as plt
matfig = plt.figure(figsize=(8,8))
plt.matshow(acs_df.corr(), fignum=matfig.number)
plt.title('Correlation matrix for ACS variables')
plt.colorbar()
plt.show()
```



There appear to be many blocks of highly correlated variables. This should make building predictive models easy, but it may obscure some of the core variables that are true drivers of Census tract ratings.

Ridge regression

Since the variables in this set appear to have a high level of multicollinearity, I'll try ridge regression to create models for variables of interest with respect to the other ~500 variables. To test the concept I'll start by building a ridge model for variable "B19013_001E" (Median household income in the past 12 months):

In [143…

```
# First make sure this variable is still included in my dataframe:
print('Is B19013_001E in acs_df?:  {}'.format(('B19013_001E' in list(acs_df.columns))))
print('Any negative values in acs_df?: {}'.format(( (acs_df < 0).values.any())))
```

```
Is B19013_001E in acs_df?:  True
Any negative values in acs_df?: True
```

Imputing missing data

Before I can do ridge regression I need to impute data for all missing values in acs_df. I've decided to use sklearn's iterativeImpute function because it has the option to calculated imputed values based on the "n_nearest" most highly correlated features, and with this ACS data there are plenty of highly correlated features to go around:

In [160…
```
from sklearn.experimental import enable_iterative_imputer # packages needed for iterativ
from sklearn.impute import IterativeImputer

print("Let's look at some values in one of the columns before imputing values: {}".forma
print('Generating imputed values for NaN entries in acs_df. This may take around 30 seco
# convert pd.NA to np.nan so we can use sklearn's iterativeImpute function.
acs_df = acs_df.replace({pd.NA: np.nan})
acs_df[acs_df < 0] = np.nan # There are multiple occurances of the number -6.7e8 I think
# Create the fit function
# n_nearest_features looks for highly correlated features to help in imputation. Should
imp_func = IterativeImputer(n_nearest_features = 3, random_state = 3, min_value = 0.0, m
imp_func.fit(acs_df)
imp_mat = imp_func.transform(acs_df) # matrix with imputed values.
acs_imp_df = pd.DataFrame(imp_mat, columns = acs_df.columns) # make new df with imputed

print('Shape of DataFrame with imputed values: {}'.format(acs_imp_df.shape))
print('Any np.nan values left?:  {}'.format(acs_imp_df.isnull().values.any()))
print('Any negative values in acs_df?: {}'.format(( (acs_df < 0).values.any())))
print("Now let's look at one of the columns after imputing values: {}".format(acs_imp_df
```

```
Let's look at some values in one of the columns before imputing values: 0    NaN
1    NaN
2    NaN
3    NaN
4    NaN
Name: B08133_001E, dtype: float64
Generating imputed values for NaN entries in acs_df. This may take around 30 seconds...
Shape of DataFrame with imputed values: (9129, 502)
Any np.nan values left?:  False
Any negative values in acs_df?: False
Now let's look at one of the columns after imputing values: 0     57798.235940
1     37356.293604
2     63870.410027
3     91094.502371
4     36033.971561
Name: B08133_001E, dtype: float64
```

It looks like we've successfully imputed missing values for all of our columns. But before we start making models we need to split the data into training and test sets. We'll start by using 'B19013_001E' (Median household income) as our response variable, and all other variables (excluding 'state','county' and 'tract') as our predictors:

In [145…
```
from sklearn.model_selection import train_test_split
# Predictors include all variables except 'B19013_001E','state','county','tract'
X_column_names = list(set(acs_imp_df.columns) - set(['B19013_001E','state','county','tra
X = acs_imp_df[X_column_names]
y = acs_imp_df['B19013_001E'] # response variable
# Randomly sample 80% of data in acs_df for training/validation and save the other 20% f
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state 
```

In [161…
```
# ridge regression adapted from: https://www.statology.org/ridge-regression-in-python/

from sklearn.model_selection import RepeatedKFold
from sklearn.linear_model import RidgeCV


def acs_ridge_regression(X_train, y_train): # I need to reduce the number of variables t
```

```
    #define cross-validation method to evaluate model: sklearn.model_selection.RepeatedK
    cv = RepeatedKFold(n_splits=4, n_repeats=2, random_state=1)

    #define model:  sklearn.linear_model.RidgeCV
    model = RidgeCV(alphas=np.arange(0.1,1.1,0.1), cv=cv, normalize = True) # Do not alo

    #fit model
    model.fit(X_train, y_train)

    #display lambda that produced the lowest test MSE
    print('Ridge model lambda parameter for lowest MSE: {}'.format(model.alpha_))

    return model

ridge_model = acs_ridge_regression(X_train, y_train)
print('Number of coefficients calculated by ridge regression model: {}'.format(ridge_mod
```

```
Ridge model lambda parameter for lowest MSE: 0.1
Number of coefficients calculated by ridge regression model: 498
```

So we've done a basic ridge regression. Now let's sort the coefficients and see which ones are the largest:

In [147…

```
ridge_coeff_df = pd.DataFrame({'X column names':X_column_names, 'Ridge coefficients': ri
# sort the df from largest to smallest coefficients
ridge_coeff_df.sort_values(by=['Ridge coefficients'], inplace=True, ascending=False)
display(ridge_coeff_df.head()) # display twenty largest coefficients
print("Let's also look at some of the negative coefficients with the largest magnitude:"
display(ridge_coeff_df.tail()) # display twenty largest coefficients
```

	X column names	Ridge coefficients
149	B25021_001E	615.585218
79	B25018_001E	440.110893
406	B25010_001E	322.787586
355	B07002_001E	28.052751
188	B25105_001E	1.643174

```
Let's also look at some of the negative coefficients with the largest magnitude:
```

	X column names	Ridge coefficients
283	B23020_001E	-42.918954
55	B25071_001E	-58.089257
476	B25039_001E	-62.020223
151	B19082_001E	-651.189303
348	B19083_001E	-15054.712346

For this ridge regression our variable of interest is 'B19013_001E' (Median household income) The three variables with the largest positive coefficients are:

- 'B25021_001E' (MEDIAN NUMBER OF ROOMS BY TENURE)
- 'B25018_001E' (MEDIAN NUMBER OF ROOMS)
- 'B25010_001E' (AVERAGE HOUSEHOLD SIZE OF OCCUPIED HOUSING UNITS BY TENURE)

There are also variables with large negative coefficients which may be good predictors for median income; for example:

- 'B19083_001E' (GINI INDEX OF INCOME INEQUALITY)
- 'B19082_001E' (SHARES OF AGGREGATE HOUSEHOLD INCOME BY QUINTILE)
- 'B25039_001E' (MEDIAN YEAR HOUSEHOLDER MOVED INTO UNIT BY TENURE)

The strong relationships between most of the variables above to median household income are obvious, but this gives us evidence that this ridge model is realistic, and gives confidence that other ridge regression models for Census tract "goodness" are likely to give good results.

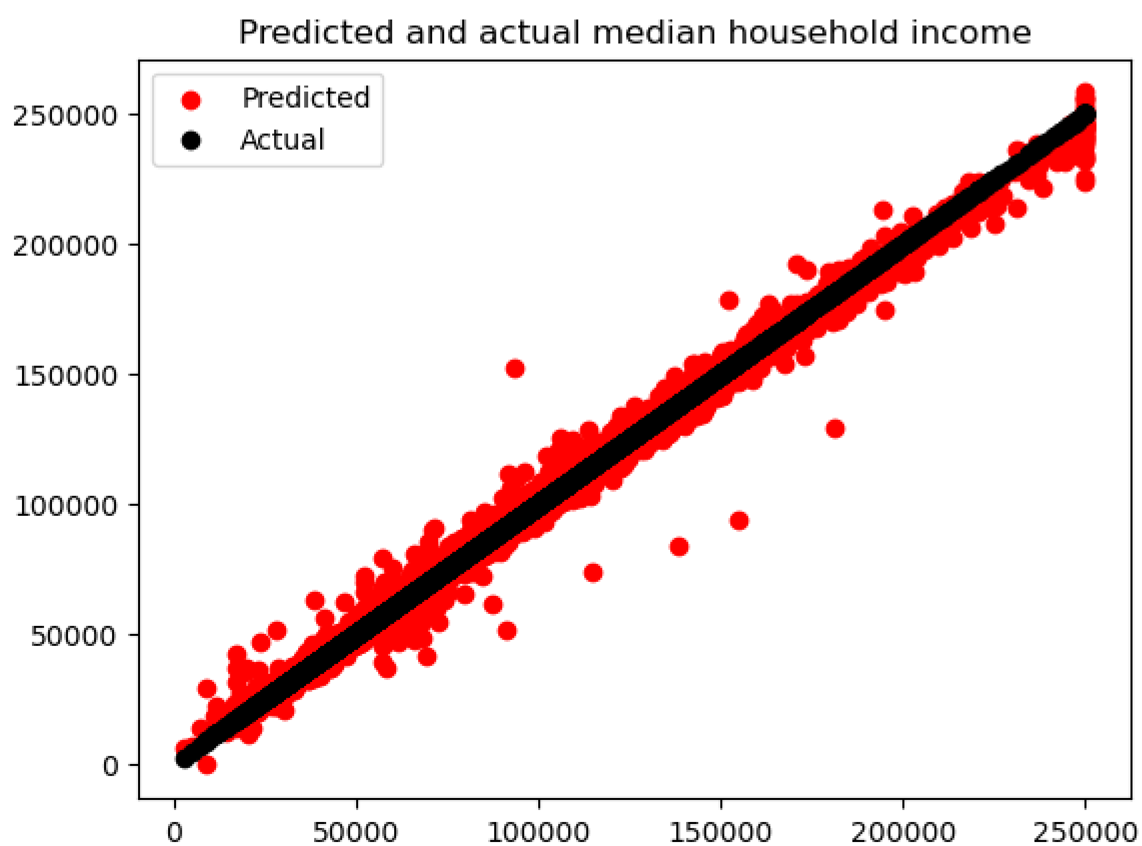
Personally, I was surprised that households that moved into rental units more recently have higher median household income.

Now let's see how accurate this model's predictions are:

In [148…

```
#Generate predictions for each census tract in the test data set:
y_pred_ridge = ridge_model.predict(X_test)
# Let's look at the coefficient of determination (R^2) for this ridge model:
ridge_score = ridge_model.score(X_test, y_test)
print("R^2 : {}".format(ridge_score))

# Let's also create a plot to examine predicted and actual median household income value
y_pred_all = ridge_model.predict(X) # predict median income for all X values using the r

plt.scatter(y, y_pred_all, color = 'red', label = 'Predicted')
plt.scatter(y , y, color = 'black', label = 'Actual')
plt.title('Predicted and actual median household income')
plt.legend()
plt.legend()

plt.show()
```

```
R^2 : 0.992739829399796
```



So the ridge model accounts for 99.3 % of the variance in the test data. That's a very good result. But we should expect good predictions given the huge number of highly correlated variables. Now that we know we can make decent models with ridge regression let's tackle a question that's a little more interesting:

"Good Neighborhoods"

In this analysis I've purposely included variables about:

- Poverty rate: Fraction of population below the poverty rate
- Labor force participation: Share of people at least 16 years old that are in the labor force

In addition I'll include a variable for median contract rent. The goal here is to look for "good" census tracts with reasonable rents. Let's create a new variable called tract_rating and define it as follows:

$$Tract\ Rating = \frac{(Median\ household\ income) * (Labor\ force\ participation) * (1 - Poverty\ rate)}{(Median\ contract\ rent)}$$

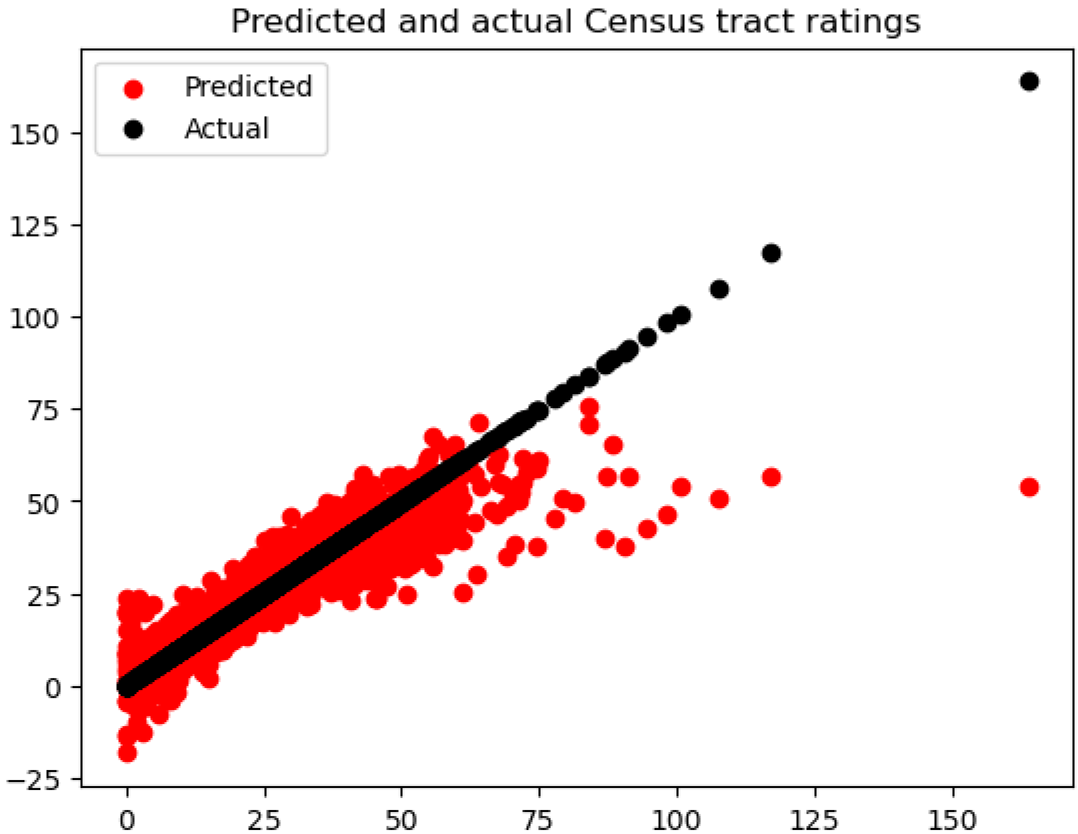
If it seems like the variables that make up tract_rating are arbitrary, it's because they are. I may use these variables to rank the best and worst places to live in California, but someone else might use a completely different critera.

Now I'll define the tract rating variable then create a ridge regression model based on it:

In [162…

```
# Before dividing by population 'B01003_001E'. We need to remove all Census tracts with
acs_imp_df = acs_imp_df[acs_imp_df['B01003_001E'] != 0] # Rows of the dataframe where th
# print('shape of acs_imp_df: {}'.format(acs_imp_df.shape))

# First let's define Labor force participation, and poverty rate:
labor_force_prtc = acs_imp_df['B23025_002E'] / acs_imp_df['B01003_001E']
# print('max labor force participation: {}'.format(max(labor_force_prtc)))
poverty_rate = acs_imp_df['B17020_002E'] / acs_imp_df['B01003_001E']
# print('max poverty rate: {}'.format(max(poverty_rate)))
median_income = acs_imp_df['B19013_001E'] # median household income
median_rent = acs_imp_df['B25058_001E'] # median contract rent
# print('min rent: {}'.format(min(median_rent)))

# tract goodness = y_tg
y_tg = median_income * labor_force_prtc * (1 - poverty_rate) / median_rent


# Exclude all variables that make up tract goodness from the set of predictors
X_tg_column_names = list(set(acs_imp_df.columns) - set(['B23025_002E', 'B01003_001E', 'B
X_tg = acs_imp_df[X_tg_column_names]
# Randomly sample 80% of data in acs_df for training/validation and save the other 20% f
X_tg_train, X_tg_test, y_tg_train, y_tg_test = train_test_split(X_tg, y_tg, test_size =
print('Creating new ridge regression model for tract ratings...')
ridge_model_tg = acs_ridge_regression(X_tg_train, y_tg_train)
#Generate predictions for each census tract in the test data set:
y_pred_tg = ridge_model_tg.predict(X_tg_test)
# Let's look at the coefficient of determination (R^2) for this ridge model:
ridge_score_tg = ridge_model_tg.score(X_tg_test, y_tg_test)
print("R^2 for tract rating model : {}".format(ridge_score_tg))

# let's also create a plot to show predicted versus actual tract goodness:
y_tg_pred_all = ridge_model_tg.predict(X_tg) # predict median income for all X values us

plt.scatter(y_tg, y_tg_pred_all, color = 'red', label = 'Predicted')
plt.scatter(y_tg , y_tg, color = 'black', label = 'Actual')
plt.title('Predicted and actual Census tract ratings')
plt.legend()
plt.show()
```

```
Creating new ridge regression model for tract ratings...
Ridge model lambda parameter for lowest MSE: 0.1
R^2 for tract rating model : 0.8278143590879867
```



Visualizing Census tract ratings

This ridge model makes good predictions when tract ratings are less than 100, but poor predictions for very high tract ratings. There could be a simple explanation, such as the model suffering from the effects of outliers, or there might be a non-linear relationship between the tract ratings and some of its most significant predictors. I may examine these ideas later, but first I would like to use the geopandas library to create heat maps showing the predicted and actual tract rating values for the full set of census tracts.

To construct the heatmap of California Census tracts I used a shape file (.shp) which contains geometric/geographic data to construct each Census tract and position it on the map. The U.S. Census bureau kindly supplies these files, and the year 2020 file that I'm using can be found here. (It turns out the 2019 ACS data corresponds to the 2020 shape file).

In [151…

```
# Adapted from geopandas example here: https://medium.com/@jl_ruiz/plot-maps-from-the-us

import contextily as ctx
import geopandas as gpd
import os
from mpl_toolkits.axes_grid1 import make_axes_locatable

# shape_path references a shape file containing geographic data for CA Census tracts. Th
# https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2020&layergroup=Census+Tr

# test to see what the shape of the 2020 shapefile is, because I expect more census trac
shape_path = r"C:\Users\Edmund\Personal Analytics Projects\public_projects\best_CA_neigh
geo_df = gpd.read_file(shape_path)
geo_df = geo_df.to_crs(epsg='4326')
geo_df[['COUNTYFP','TRACTCE']] = geo_df[['COUNTYFP','TRACTCE']].astype(int) # change cou
```

```
print('geo_df.shape: {}'.format(geo_df.shape))

# test_geo = geo_df.iloc[0,:] # let's try printing some info
# Test plot of CA Census tracts:
# geo_df.boundary.plot()
# plt.show()

# What variables do I have to work with here?
# display(test_geo)
# print(type(test_geo))
# display(geo_df.head())
```

```
geo_df.shape: (9129, 13)
```

I now have a geopandas dataframe containing my geometric/geographic data for each census tract. The last step before I make a heatmap will be to merge the tract rating values into the dataframe:

In [152…

```
# Make a function to do merge any pandas series (response variable) with geo_df to prep
def merge_response_var(X, y, y_name):
    y_named = y.rename(y_name) # rename response data series
    y_county_tract=pd.concat([X['county'].astype(int),y_named],axis=1) # add in 'county'
    y_county_tract=pd.concat([X['tract'].astype(int),y_county_tract],axis=1) # add in 't

    geo_y_df = geo_df.merge(y_county_tract, how='right', left_on = ['COUNTYFP','TRACTCE'
    # display(geo_df_ytg.head())
    # print('shape of geo_df_ytg: {}'.format(geo_df_ytg.shape))
    return geo_y_df

geo_df_ytg = merge_response_var(acs_imp_df, y_tg, 'y_tg')
```

In [153…

```
# Now we can make the heat map
# Example plotting with geopandas from: https://www.relataly.com/visualize-covid-19-data

# Here df is my geopandas dataframe including my resposne variable of interest and col i
def make_heat_map(df, y_col, title, about):
    # title = 'Goodness of selected Census tracts'
    # about = 'Heat map of Census tract goodness'
    col = df[y_col]
    vmin = col.min()
    vmax = col.max()
    cmap = 'viridis'
    # Create figure and axes for Matplotlib
    fig, ax = plt.subplots(1, figsize=(30, 30))
    # Remove the axis
    ax.axis('off')
    df.plot(column=col, ax=ax, edgecolor="face", linewidth=0.2, cmap=cmap)
    # Add a title
    ax.set_title(title, fontdict={'fontsize': '25', 'fontweight': '3'})
    # Create an annotation for the data source
    ax.annotate(about, xy=(0.1, .08), xycoords='figure fraction', horizontalalignment='l
                verticalalignment='bottom', fontsize=10)

    # Create colorbar as a legend
    sm = plt.cm.ScalarMappable(norm=plt.Normalize(vmin=vmin, vmax=vmax), cmap=cmap)
    # Empty array for the data range
    sm._A = []
    # Add the colorbar to the figure
    cbaxes = fig.add_axes([0.15, 0.25, 0.01, 0.4])
    cbar = fig.colorbar(sm, cax=cbaxes)
```

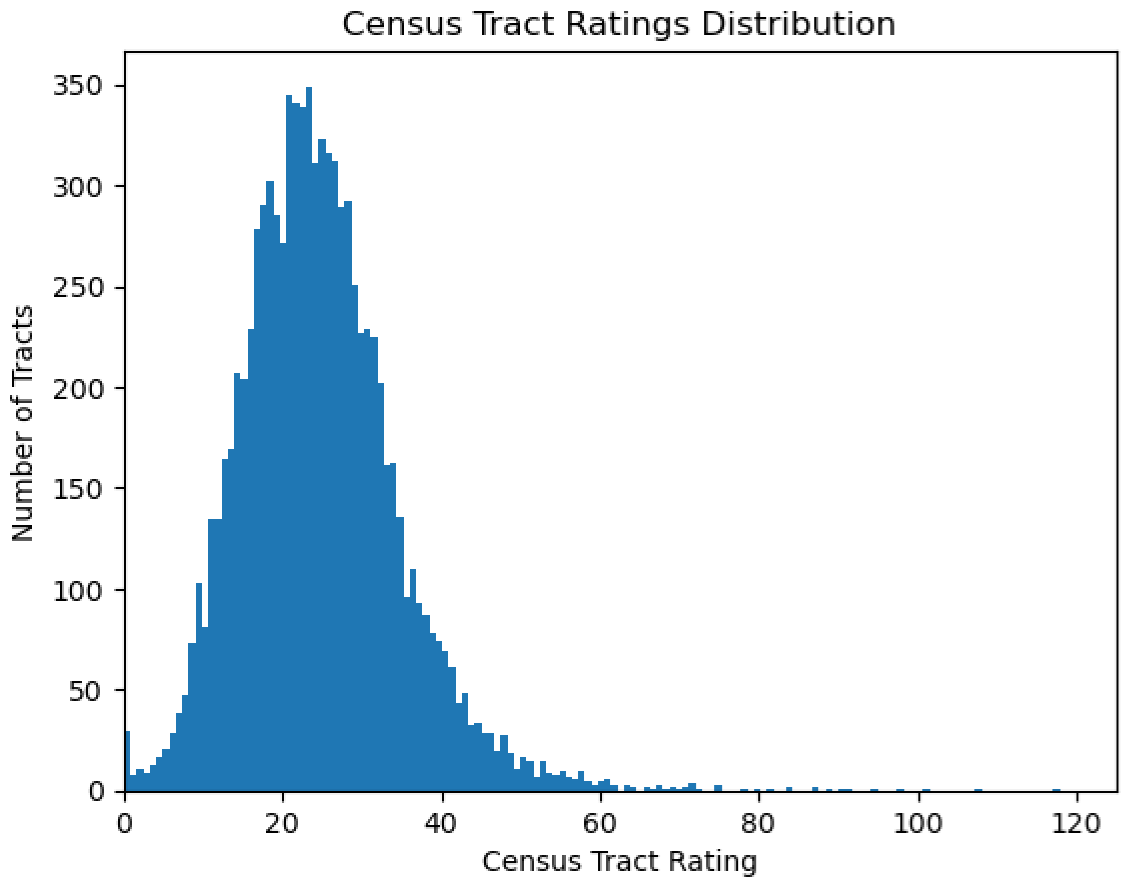
In [154…

```
# first make the histgram to see the distribution then decide what to plot:
ax = geo_df_ytg['y_tg'].plot.hist(bins=200, title = "Census Tract Ratings Distribution")
ax.set_xlabel("Census Tract Rating")
```

```
ax.set_ylabel("Number of Tracts")
ax.set_xlim(0,125)
```

Out[154]:

```
(0.0, 125.0)
```

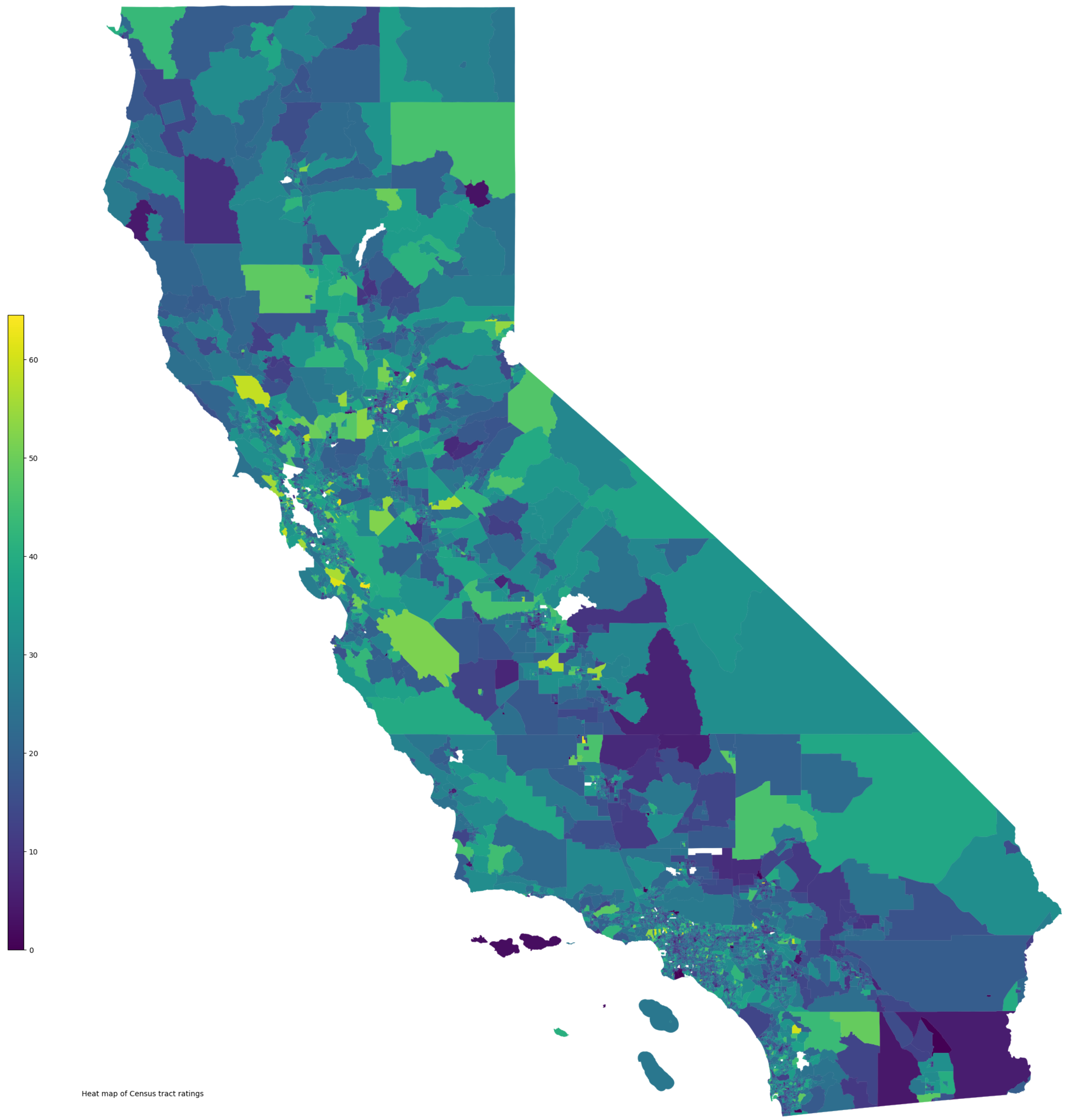


Using the ratings distribution plotted above we can exclude the outliers to make an easily readable heatmap of ratings:

In [155…

```
# To make it easier to spot trends, I'll create this map again only this time removing p
geo_df_ytg_under_65 = geo_df_ytg[geo_df_ytg['y_tg'] < 65]
title = 'Census tract ratings for almost all of California'
about = 'Heat map of Census tract ratings'
make_heat_map(geo_df_ytg_under_65, 'y_tg', title, about)
```

Census tract ratings for almost all of California



What does the map show?

I was a little surprised by this heat map of tract ratings. I was expecting some kind of trend related to proximity to the coast or the Sierra Nevada mountain range, but that doesn't seem to be the case. One pattern I see is that tracts with higher goodness scores tend to be larger census tracts (lower population density) that border smaller tracts (higher population denisty). Maybe that means that the best communities to live in are close enough to densly populated areas to enjoy their benefits, like access to higher income jobs, while far enough away to avoid the downsides of highly populated areas (like higher rent). Let's explore this idea below:

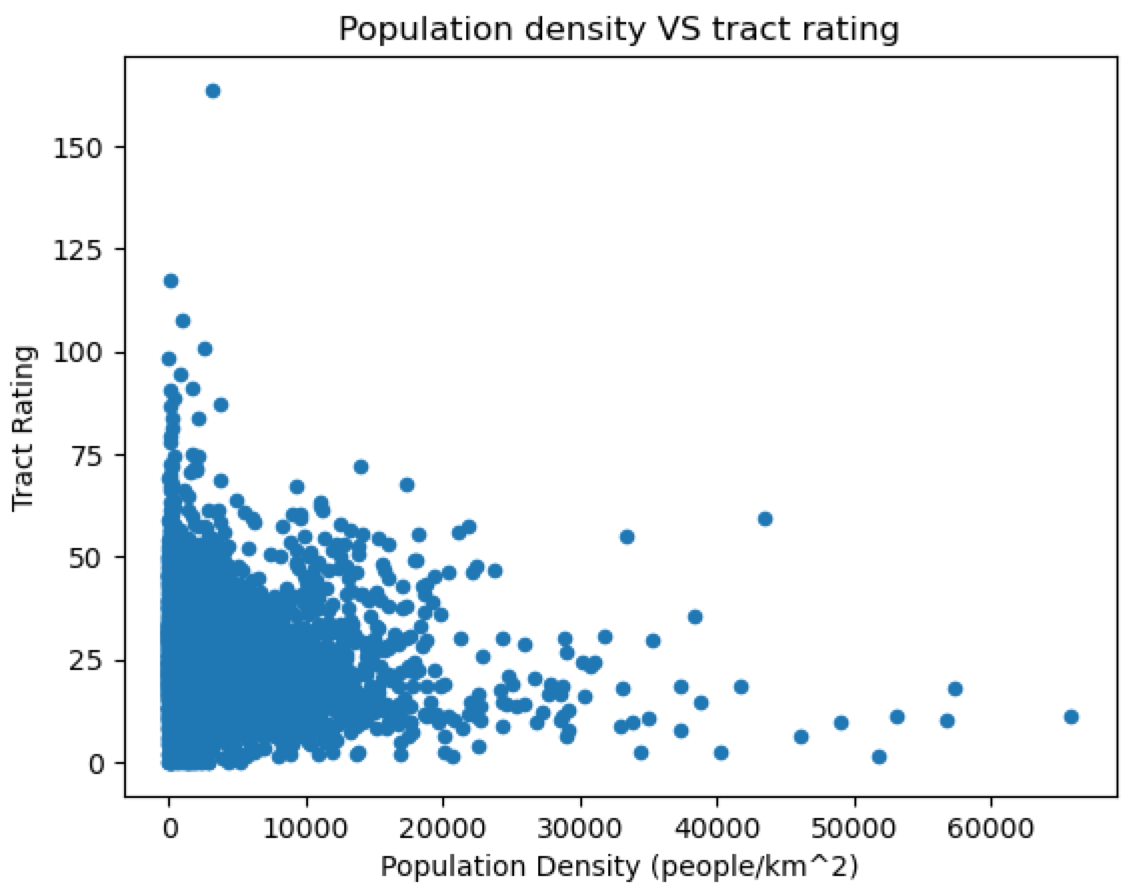
In [156…

```
geo_df_msquared = geo_df_ytg.copy() # Used to calculate census tract areas in m^2
geo_df_msquared['geometry'] = geo_df_msquared['geometry'].to_crs({'proj':'cea'})  # conv
geo_df_msquared['tract area (km^2)'] = (geo_df_msquared['geometry'].area / 1.0e6) # conv
```

```
# display(geo_df_msquared.head())

pop_density_df = acs_imp_df[['B01003_001E','county','tract']].merge(geo_df_msquared[['y_
# display(pop_density_df.head())
pop_density_df['pop density'] = pop_density_df['B01003_001E'] / pop_density_df['tract ar
ax = pop_density_df.plot.scatter(x = 'pop density', y = 'y_tg', title = "Population dens
ax.set_xlabel("Population Density (people/km^2)")
ax.set_ylabel("Tract Rating")
```

Out[156]:

```
Text(0, 0.5, 'Tract Rating')
```

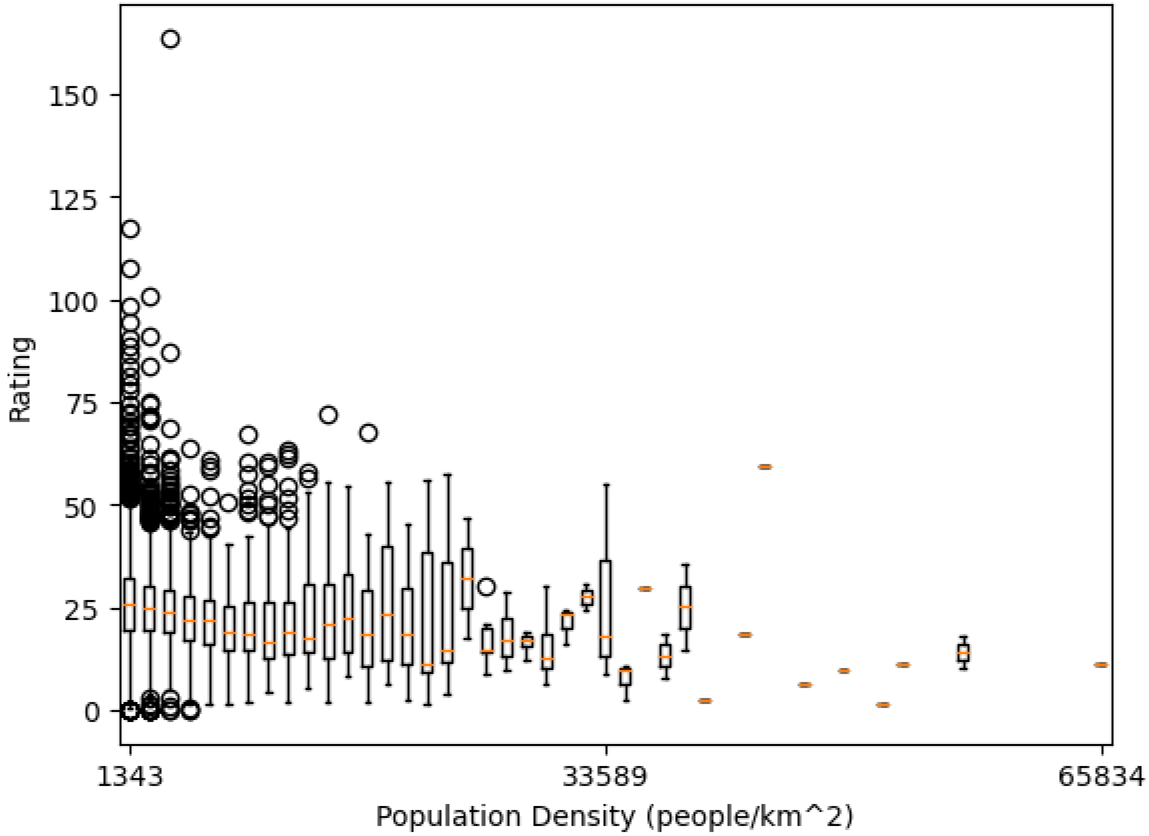


It's hard to establish a trend from this scatter plot. But if we bin the data then use a box plot the trend may be revealed:

In [157...

```
num_bins = 50 # number of poluation density bins
bins = np.linspace(min(pop_density_df['pop density']),max(pop_density_df['pop density'])
# print(bins)
bin_dict = {key:[] for key in list(range(1, num_bins +1))} # make dictionary of empty bi
digitized = np.digitize(pop_density_df['pop density'],bins)
# print(min(digitized))
# print(max(digitized))
for idx, goodness_val in enumerate(pop_density_df['y_tg']):
    # add goodness_val to its bin:
    bin_dict[digitized[idx]] += [goodness_val]


# make a new dictionary sorted by key:
bin_dict_sorted = {key:bin_dict[key] for key in sorted(bin_dict.keys())}

labels, data = [*zip(*bin_dict_sorted.items())]
#print(labels)
plt.boxplot(data)
xtick_vals = [1, len(bins)/2, len(bins)]
# print(xtick_vals)
xtick_labels = [str(int(bins[1])), str(int(bins[int(len(bins)/2)])), str(int(bins[-1]))]
plt.xticks(xtick_vals, xtick_labels)
```

```
plt.xlabel("Population Density (people/km^2)")
plt.ylabel("Rating")
plt.show()
```



The boxplot shows a small median rating increase as population density decreases. But there are also very high ratings that appears in tracts with low population density. These very high ratings are visible as outliers in the boxplots for tracts with low population density, and these outliers suggest that low population density tracts can be grouped into moderate rated and highly rated tracts. This could be an interesting trend to explore in a future analysis.

Which variables correlate with tract rating?

Before I end this analysis I would like to take a look at the most significant tract rating coefficients and see if we can learn anything interesting about the ratings from our ridge model:

In [158…

```
ridge_tg_coeff_df = pd.DataFrame({'X column names':X_tg_column_names, 'Ridge coefficient
# sort the df from largest to smallest coefficients
ridge_tg_coeff_df.sort_values(by=['Ridge coefficients'], inplace=True, ascending=False)
display(ridge_tg_coeff_df.head()) # display twenty largest coefficients
print("Let's also look at some of the negative coefficients with the largest magnitude:"
display(ridge_tg_coeff_df.tail()) # display twenty largest coefficients
```

	X column names	Ridge coefficients
284	B23020_001E	0.196498
80	B25018_001E	0.124227
150	B25021_001E	0.115152
392	B08103_001E	0.004413
92	B02016_001E	0.001754

```
Let's also look at some of the negative coefficients with the largest magnitude:
```

	X column names	Ridge coefficients
78	B25092_001E	-0.052123
475	B25039_001E	-0.054164
55	B25071_001E	-0.057862
406	B25010_001E	-0.344638
349	B19083_001E	-7.323700

From our ridge regression model, the three predictors with the largest positive correlation to tract ratings are:

B23020_001E : "MEAN USUAL HOURS WORKED IN THE PAST 12 MONTHS FOR WORKERS 16 TO 64 YEARS"
B25018_001E : "MEDIAN NUMBER OF ROOMS"
B25021_001E : "MEDIAN NUMBER OF ROOMS BY TENURE"

And the three predictors with the largest negative correlation to tract ratings are:

B19083_001E : "GINI INDEX OF INCOME INEQUALITY"
B25010_001E : "AVERAGE HOUSEHOLD SIZE OF OCCUPIED HOUSING UNITS BY TENURE"
B25071_001E : "MEDIAN GROSS RENT AS A PERCENTAGE OF HOUSEHOLD INCOME IN THE PAST 12 MONTHS (DOLLARS)"

Conclusions

- It's clear that many of these predictors are highly correlated with median household income, and that's why they were selected by the ridge model.
- One interesting observation is that median number of rooms is is positivly correlated with tract rating, while average household size is negatively correlated with tract rating.
- It's important to remember that my metric for Census tract ratings is very simple and different people will make different metrics depending on their priorities.

Thank's for your interest in my analysis! Send me a message at edale1283@gmail.com or find me on linkedin If you want to get in touch.