```python
# programmer - Sophia Quinton
# date - 11-3-21
# class - DSC -540
# assignment - Assignment 1

#libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns
from sklearn import datasets, linear_model
from sklearn.model_selection import train_test_split
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import metrics
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

#Part1 - Tools Readiness
##file from (Larose & Larose, 2019)
##pandas
frame = pd.read_csv("E:/GCU/Graduate Classes/DSC - 540 Machine Learning/Week 1/cereals.csv")
frame.head()
```

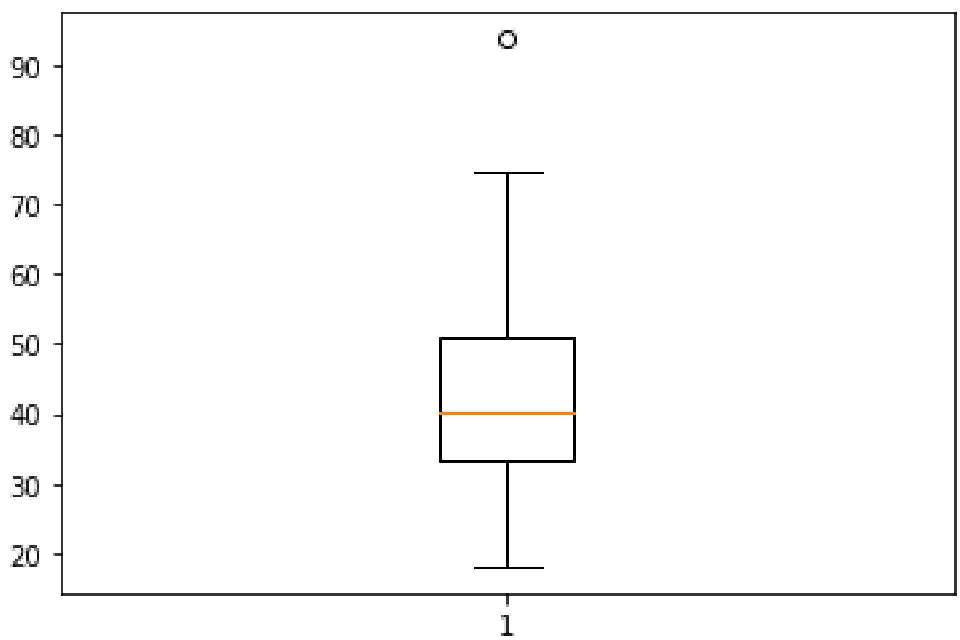
```
                        Name Manuf Type  Calories  Protein  Fat  Sodium  \
0                  100%_Bran     N    C        70        4    1     130
1          100%_Natural_Bran     Q    C       120        3    5      15
2                   All-Bran     K    C        70        4    1     260
3  All-Bran_with_Extra_Fiber     K    C        50        4    0     140
4             Almond_Delight     R    C       110        2    2     200

   Fiber  Carbo  Sugars  ...  Weight  Cups     Rating  Cold  Nabisco  Quaker
\
0   10.0    5.0     6.0  ...     1.0  0.33  68.402973     1        1       0
1    2.0    8.0     8.0  ...     1.0  1.00  33.983679     1        0       1
2    9.0    7.0     5.0  ...     1.0  0.33  59.425505     1        0       0
3   14.0    8.0     0.0  ...     1.0  0.50  93.704912     1        0       0
4    1.0   14.0     8.0  ...     1.0  0.75  34.384843     1        0       0

   Kelloggs  GeneralMills  Ralston  AHFP
0         0             0        0     0
1         0             0        0     0
2         1             0        0     0
3         1             0        0     0
4         0             0        1     0

[5 rows x 23 columns]
```

```
##numpy
rounded_rating = np.round(frame['Rating'][0], 3)
rounded_rating
```

```
68.403
```

```
##matplotlib
plt.boxplot(frame['Rating'])
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x20c3812e5e0>,
  <matplotlib.lines.Line2D at 0x20c3812e8b0>],
 'caps': [<matplotlib.lines.Line2D at 0x20c3812ec40>,
  <matplotlib.lines.Line2D at 0x20c3812efd0>],
 'boxes': [<matplotlib.lines.Line2D at 0x20c3812e190>],
 'medians': [<matplotlib.lines.Line2D at 0x20c3813e3a0>],
 'fliers': [<matplotlib.lines.Line2D at 0x20c3813e730>],
 'means': []}
```




```
##scikit-learn
frame_train, frame_test = train_test_split(frame, test_size=0.2,
random_state=25)
frame_train.head()
print(len(frame_train))
print(len(frame_test))
```

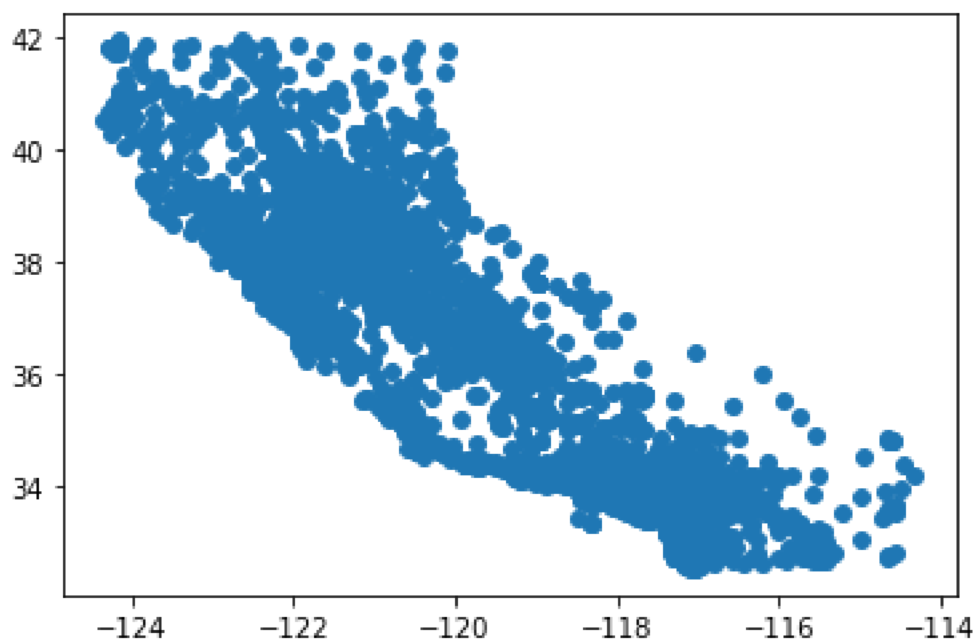
```
61
16
```

```
#Part2 - Review Predictive Models and Python Proficiency
##read in data
estate = pd.read_csv("E:/GCU/Graduate Classes/DSC - 540 Machine Learning/Week
```

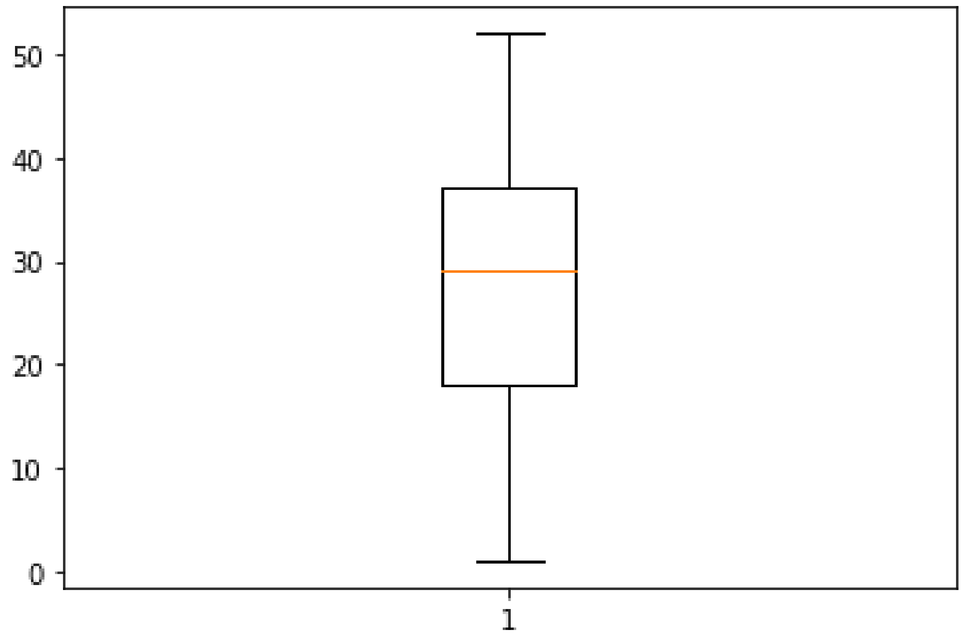
```
1/housing.csv")
estate.tail()
```

```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
20635    -121.09     39.48                25.0       1665.0           374.0
20636    -121.21     39.49                18.0        697.0           150.0
20637    -121.22     39.43                17.0       2254.0           485.0
20638    -121.32     39.43                18.0       1860.0           409.0
20639    -121.24     39.37                16.0       2785.0           616.0

       population  households  median_income  median_house_value  \
20635       845.0       330.0         1.5603             78100.0
20636       356.0       114.0         2.5568             77100.0
20637      1007.0       433.0         1.7000             92300.0
20638       741.0       349.0         1.8672             84700.0
20639      1387.0       530.0         2.3886             89400.0

      ocean_proximity
20635          INLAND
20636          INLAND
20637          INLAND
20638          INLAND
20639          INLAND
```

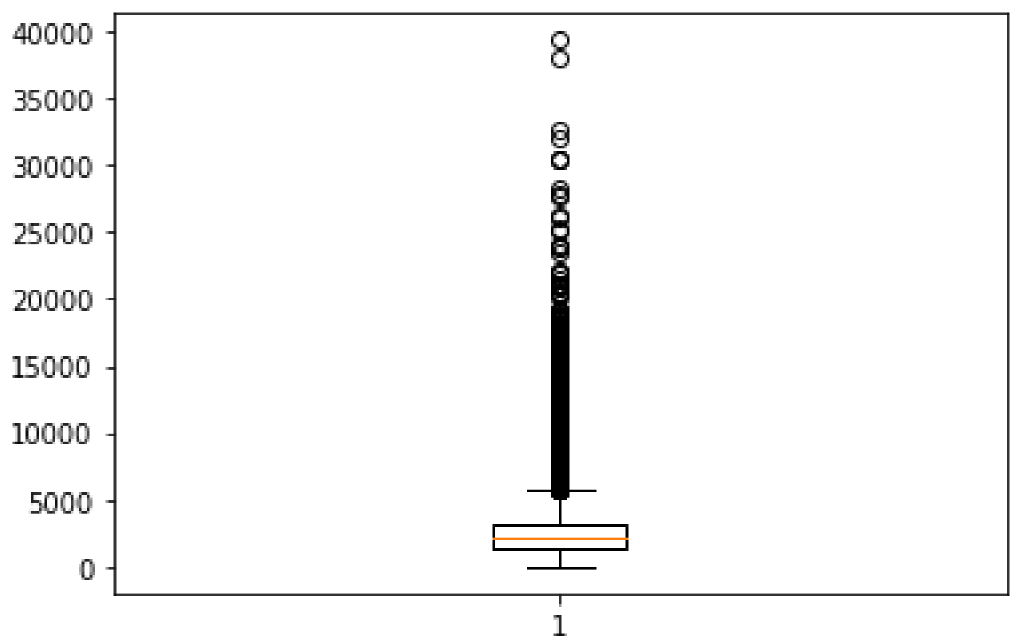
```
## view data
plt.scatter(estate['longitude'], estate['latitude'])
plt.show()
```



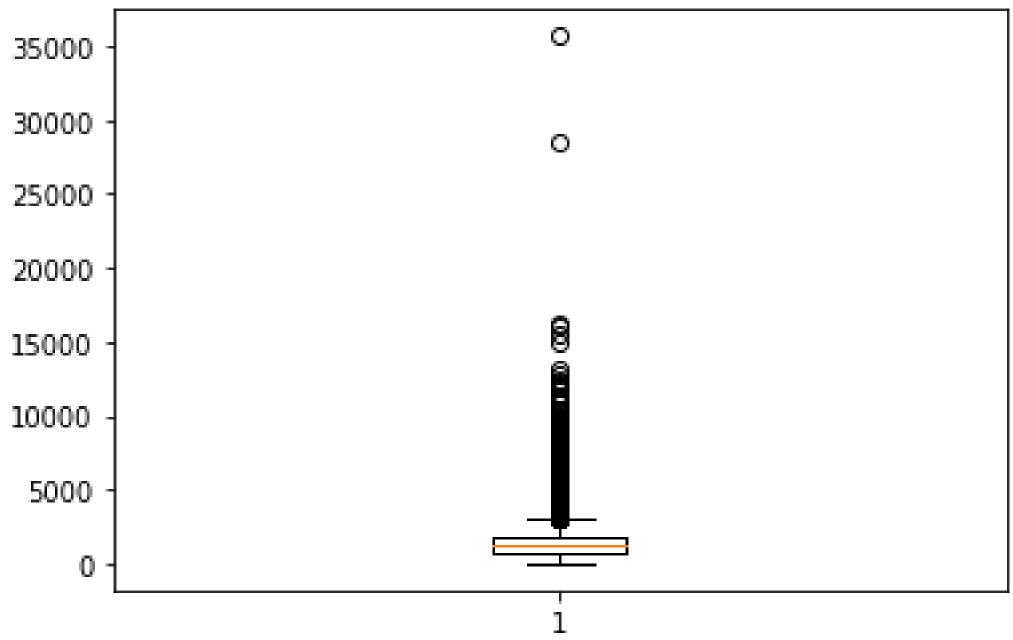
```
plt.boxplot(estate['housing_median_age'])
plt.show()
```



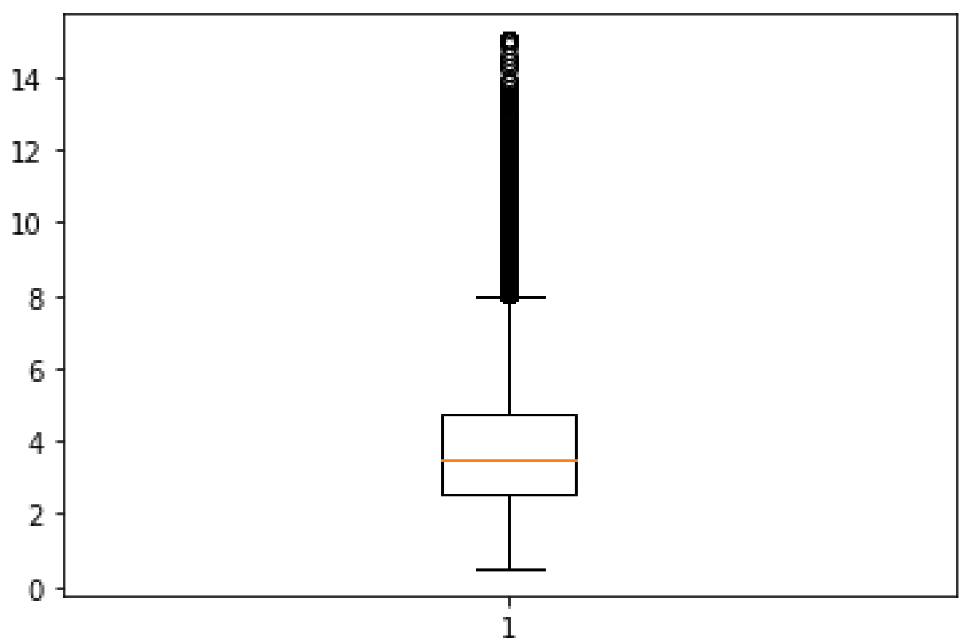

```
plt.boxplot(estate['total_rooms'])
plt.show()
```



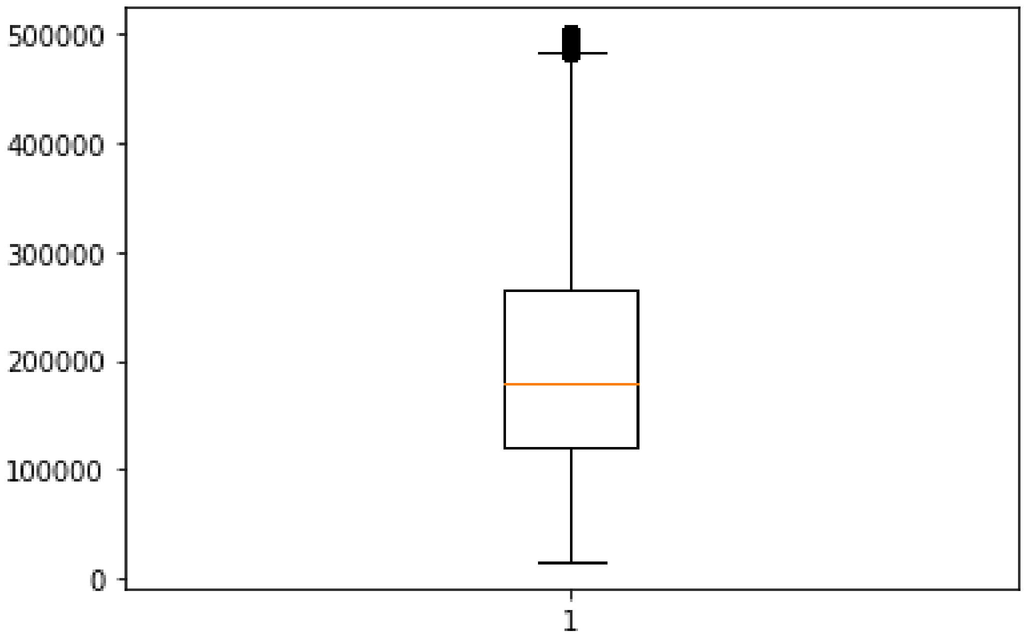

```
plt.boxplot(estate['population'])
plt.show()
```




```
plt.boxplot(estate['median_income'])
plt.show()
```




```
plt.boxplot(estate['median_house_value'])
plt.show()
```




```
##split data
estate_train, estate_test = train_test_split(estate, test_size=0.2,
random_state=25)

##prepare data (GeeksforGeeks, 2020)
test_columns = estate[['longitude', 'latitude', 'housing_median_age',
'total_rooms', 'population', 'median_income']]
vif = pd.DataFrame()
vif["variable"] = test_columns.columns
vif["VIF"] = [variance_inflation_factor(test_columns.values,i) for i in
range(test_columns.shape[1])]
vif

             variable         VIF
0           longitude  592.503040
1            latitude  538.400848
2  housing_median_age    7.238474
3         total_rooms   11.505213
4          population   11.408182
5       median_income    6.264782

##do PCA Analysis
x_estate_train = estate_train[['longitude', 'latitude', 'housing_median_age',
'total_rooms', 'population', 'median_income']]
x_estate_test = estate_test[['longitude', 'latitude', 'housing_median_age',
'total_rooms', 'population', 'median_income']]
y_estate_train = estate_train['median_house_value']
y_estate_test = estate_test['median_house_value']

scaler = StandardScaler()
```

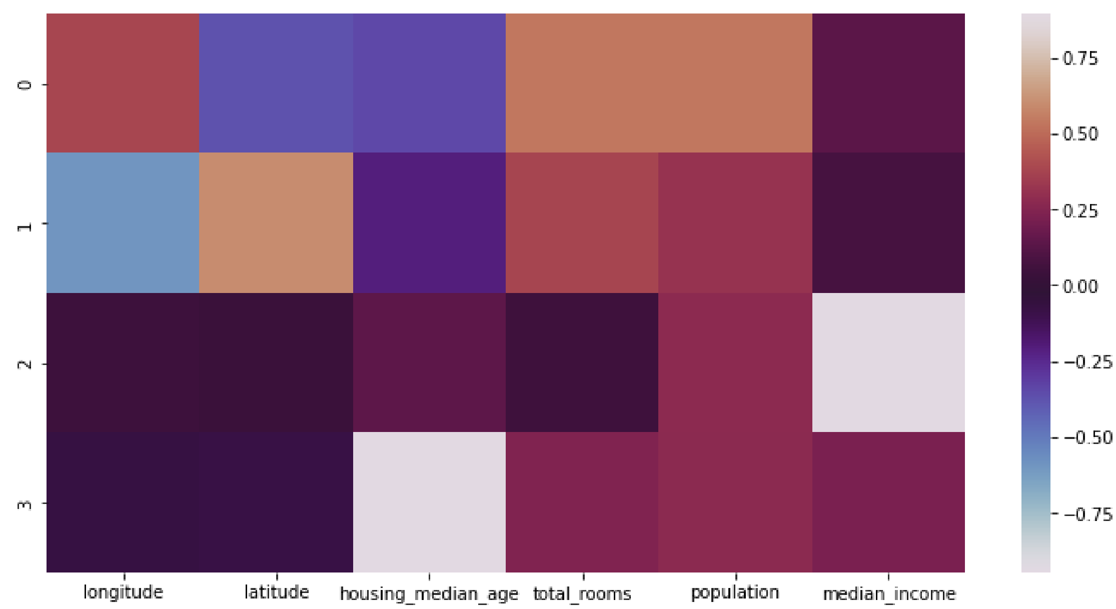
```
scaler.fit(x_estate_train)
x_estate_train = scaler.transform(x_estate_train)
x_estate_test = scaler.transform(x_estate_test)

pca = PCA(0.95)
pca.fit(x_estate_train)
x_estate_train = pca.transform(x_estate_train)
x_estate_test = pca.transform(x_estate_test)

##run model (Larose & Larose, 2019)
constantX = sm.add_constant(x_estate_train, prepend=True)
estate_model = sm.OLS(y_estate_train, constantX).fit()
estate_model.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
=
Dep. Variable:     median_house_value   R-squared:
0.528
Model:                            OLS   Adj. R-squared:
0.528
Method:                 Least Squares   F-statistic:
4619.
Date:                Mon, 01 Nov 2021   Prob (F-statistic):
0.00
Time:                        20:11:37   Log-Likelihood:              -
2.0975e+05
No. Observations:               16512   AIC:
4.195e+05
Df Residuals:                   16507   BIC:
4.196e+05
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-
const       2.066e+05    619.105    333.762      0.000    2.05e+05
2.08e+05
x1          7677.6593    418.833     18.331      0.000    6856.701
8498.617
x2           934.7505    458.486      2.039      0.041      36.068
1833.433
x3         -7.378e+04    615.501   -119.877      0.000    -7.5e+04    -
7.26e+04
x4          4.268e+04    695.343     61.375      0.000    4.13e+04
```

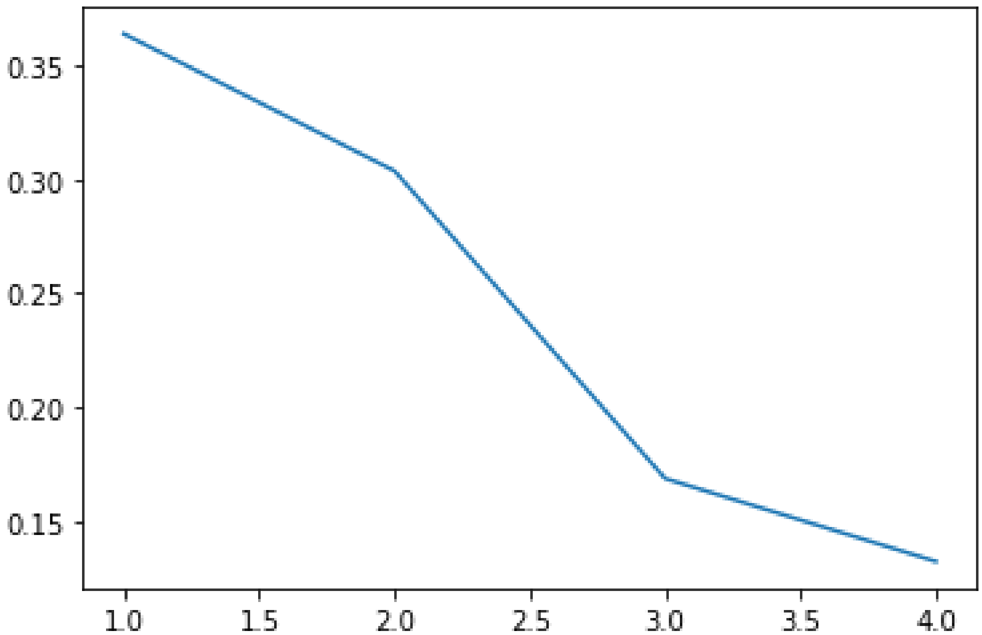
```
4.4e+04
==============================================================================
=
Omnibus:                     3482.398   Durbin-Watson:
1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
8769.875
Skew:                           1.158   Prob(JB):
0.00
Kurtosis:                       5.718   Cond. No.
1.66
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

```
##(DataScience+, nd)
map= pd.DataFrame(pca.components_,columns=['longitude', 'latitude',
'housing_median_age', 'total_rooms', 'population', 'median_income'])
plt.figure(figsize=(12,6))
sns.heatmap(map,cmap='twilight')
```

```
<AxesSubplot:>
```




```
##scree plot (Zach, 2021)
PC_values = np.arange(pca.n_components_) + 1
plt.plot(PC_values, pca.explained_variance_ratio_)
plt.show()
```




```
##validate data (Larose & Larose, 2019)
constantX_test = sm.add_constant(x_estate_test, prepend=True)
estate_model_test= sm.OLS(y_estate_test, constantX_test).fit()
estate_model_test.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
=
Dep. Variable:     median_house_value   R-squared:
0.527
Model:                            OLS   Adj. R-squared:
0.527
Method:                 Least Squares   F-statistic:
1149.
Date:                Mon, 01 Nov 2021   Prob (F-statistic):
0.00
Time:                        17:06:16   Log-Likelihood:                 -
52369.
No. Observations:                4128   AIC:
1.047e+05
Df Residuals:                    4123   BIC:
1.048e+05
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
=
                 coef    std err          t      P>|t|      [0.025
0.975]
```

```
------------------------------------------------------------------------------
-
const        2.092e+05   1218.673    171.633      0.000    2.07e+05
2.12e+05
x1           7460.1512    790.853      9.433      0.000    5909.652
9010.650
x2           -205.8746    893.178     -0.230      0.818   -1956.985
1545.235
x3          -7.419e+04   1231.663    -60.240      0.000   -7.66e+04   -
7.18e+04
x4           4.184e+04   1351.925     30.947      0.000    3.92e+04
4.45e+04
==============================================================================
=
Omnibus:                      809.222   Durbin-Watson:
2.045
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1785.669
Skew:                           1.123   Prob(JB):
0.00
Kurtosis:                       5.310   Cond. No.
1.72
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

```
ypred = estate_model.predict(constantX_test)
##MAE (Larose & Larose, 2019)
print("Model MAE: ", metrics.mean_absolute_error(y_true = y_estate_test,
y_pred = ypred))
print("base MAE: ", np.sqrt(metrics.mean_squared_error(y_true =
y_estate_test, y_pred = ypred)))
```

```
Model MAE:  58203.1309674163
base MAE:  78282.93963949986
```

```
# calculate s or standard deviation (Larose & Larose, 2019)
print("test MSE", np.sqrt(estate_model_test.scale))
print("Model MSE", np.sqrt(estate_model.scale))
```

```
test MSE 78268.50127486532
Model MSE 79554.41649151935
```