Project task 1:

Data import and preparation:

```
## importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
## importing data

train= pd.read_csv('train.csv')
test= pd.read_csv('test.csv')
```

```
df= pd.concat([test,train])
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39030 entries, 0 to 27320
Data columns (total 80 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   UID                       39030 non-null  int64
 1   BLOCKID                   0 non-null      float64
 2   SUMLEVEL                  39030 non-null  int64
 3   COUNTYID                  39030 non-null  int64
 4   STATEID                   39030 non-null  int64
 5   state                     39030 non-null  object
 6   state_ab                  39030 non-null  object
 7   city                      39030 non-null  object
 8   place                     39030 non-null  object
 9   type                      39030 non-null  object
 10  primary                   39030 non-null  object
 11  zip_code                  39030 non-null  int64
 12  area_code                 39030 non-null  int64
 13  lat                       39030 non-null  float64
 14  lng                       39030 non-null  float64
 15  ALand                     39030 non-null  float64
 16  AWater                    39030 non-null  int64
 17  pop                       39030 non-null  int64
 18  male_pop                  39030 non-null  int64
 19  female_pop                39030 non-null  int64
 20  rent_mean                 38568 non-null  float64
 21  rent_median               38568 non-null  float64
 22  rent_stdev                38568 non-null  float64
 23  rent_sample_weight        38568 non-null  float64
 24  rent_samples              38568 non-null  float64
 25  rent_gt_10                38567 non-null  float64
 26  rent_gt_15                38567 non-null  float64
 27  rent_gt_20                38567 non-null  float64
 28  rent_gt_25                38567 non-null  float64
 29  rent_gt_30                38567 non-null  float64
 30  rent_gt_35                38567 non-null  float64
 31  rent_gt_40                38567 non-null  float64
 32  rent_gt_50                38567 non-null  float64
 33  universe_samples          39030 non-null  int64
 34  used_samples              39030 non-null  int64
 35  hi_mean                   38640 non-null  float64
 36  hi_median                 38640 non-null  float64
 37  hi_stdev                  38640 non-null  float64
 38  hi_sample_weight          38640 non-null  float64
 39  hi_samples                38640 non-null  float64
 40  family_mean               38596 non-null  float64
 41  family_median             38596 non-null  float64
 42  family_stdev              38596 non-null  float64
 43  family_sample_weight      38596 non-null  float64
 44  family_samples            38596 non-null  float64
 45  hc_mortgage_mean          38189 non-null  float64
 46  hc_mortgage_median        38189 non-null  float64
 47  hc_mortgage_stdev         38189 non-null  float64
 48  hc_mortgage_sample_weight 38189 non-null  float64
 49  hc_mortgage_samples       38189 non-null  float64
 50  hc_mean                   38140 non-null  float64
 51  hc_median                 38140 non-null  float64
 52  hc_stdev                  38140 non-null  float64
```

```
df.head()
```

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type	...	female_age_mean	female_
0	255504	NaN	140	163	26	Michigan	MI	Detroit	Dearborn Heights City	CDP	...	34.78682	
1	252676	NaN	140	1	23	Maine	ME	Auburn	Auburn City	City	...	44.23451	
2	276314	NaN	140	15	42	Pennsylvania	PA	Pine City	Millerton	Borough	...	41.62426	
3	248614	NaN	140	231	21	Kentucky	KY	Monticello	Monticello City	City	...	44.81200	
4	286865	NaN	140	355	48	Texas	TX	Corpus Christi	Edroy	Town	...	40.66618	

5 rows × 80 columns

```
## checking for null values (in percentage %)

df.isnull().sum()*100/ len(df)
```

```
UID             0.000000
BLOCKID       100.000000
SUMLEVEL        0.000000
COUNTYID        0.000000
STATEID         0.000000
                  ...
pct_own         0.999231
married         0.704586
married_snp     0.704586
```

```
separated        0.704586
divorced         0.704586
Length: 80, dtype: float64
```

```
## number of null values in numbers

df.isnull().sum()
```

```
UID              0
BLOCKID      39030
SUMLEVEL         0
COUNTYID         0
STATEID          0
             ...
pct_own        390
married        275
married_snp    275
separated      275
divorced       275
Length: 80, dtype: int64
```

```
## removing null column

df.drop('BLOCKID', axis=1,inplace=True)
df.dropna(inplace=True)
```

```
## filling null values with mean of their respective column

for i in df.columns:
  if df[i].isnull().sum()!=0:
    df.fillna(df[i].mean(), inplace=True)
```

```
## checking for null values

df.isna().sum()
```

```
UID            0
SUMLEVEL       0
COUNTYID       0
STATEID        0
state          0
              ..
pct_own        0
married        0
married_snp    0
separated      0
divorced       0
Length: 79, dtype: int64
```

2,500 locations where the percentage of households with a second mortgage is the highest and percent ownership is above 10 percent.

```
top=df.nlargest(2500,'second_mortgage')
```

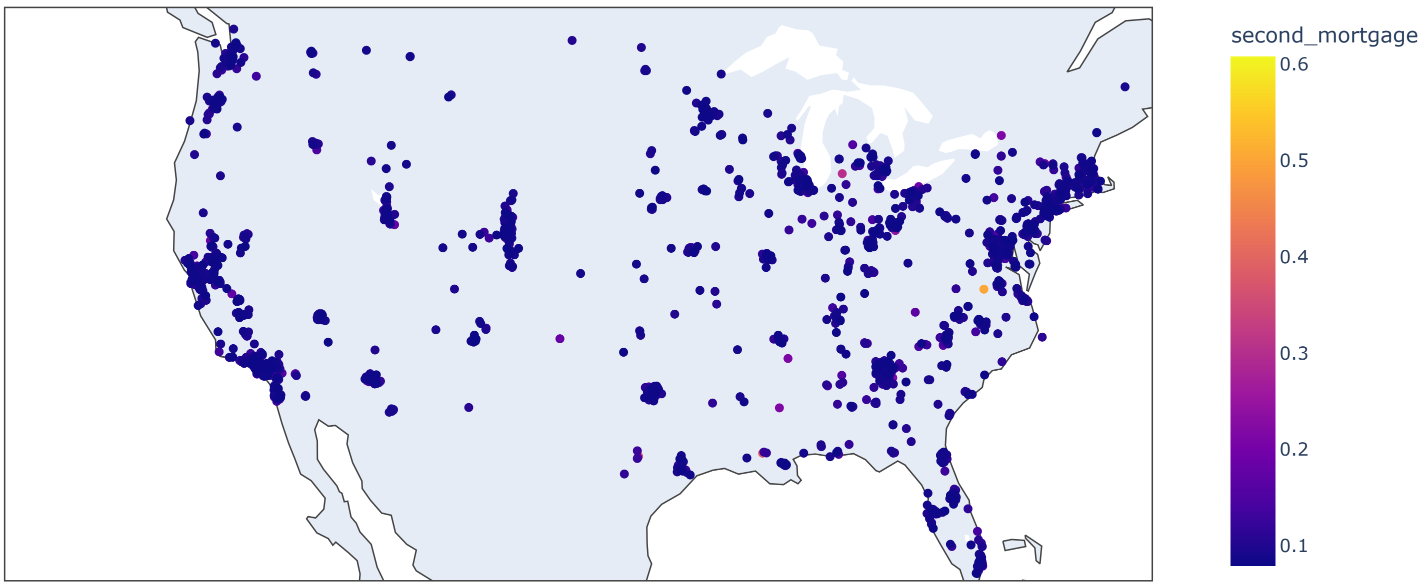
```
top= top.loc[:,['state','city','zip_code','area_code','lat','lng','second_mortgage']]
top.head()
```

	state	city	zip_code	area_code	lat	lng	second_mortgage
14014	New Jersey	Passaic	7055	973	40.867944	-74.114633	0.60870
6238	New York	Bronx	10452	718	40.842166	-73.926952	0.58824
3285	Virginia	Farmville	23901	434	37.297357	-78.396452	0.50000
21706	Arizona	Scottsdale	85257	480	33.458658	-111.955104	0.43750
11980	Massachusetts	Worcester	1610	508	42.254262	-71.800347	0.43363

```
import plotly.express as px
```

Scatter geo plot for top 2500 locations with highest second mortgage

```
px.scatter_geo(top, lat='lat',lon='lng',color= 'second_mortgage',hover_name= 'state',projection='mollweide' )
```



The geoplot shows scatterd dots for top 2500 locations in given dataset having highest second mortgage

Bad debt calculations

```
bad_debt= (df.second_mortgage  + df.home_equity) - df.home_equity_second_mortgage
```

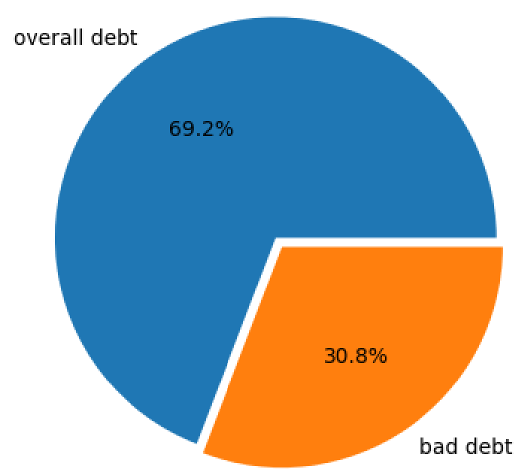
```
bad_debt
```

```
0        0.07651
1        0.14375
2        0.06744
3        0.01741
4        0.03440
          ...
27316    0.00000
27317    0.20908
27318    0.07857
27319    0.14305
27320    0.18362
Length: 37940, dtype: float64
```

```
overall_debt= df['second_mortgage'] + df['home_equity'] + bad_debt
```

```
d1= [overall_debt.sum(), bad_debt.sum()]
l1= ['overall debt', 'bad debt']
```

```
plt.pie(d1, labels= l1, explode= [0,0.05], autopct='%1.1f%%')
plt.show()
```




```
## adding bad debt column to our original dataset

df['bad_debt']= bad_debt
```

```
df.bad_debt.median()
```

```
0.09961
```

Box and whisker plot and for 2nd mortgage, home equity, good debt, and bad debt for cities with higest population

```
df.nlargest(4, 'pop')['city']
```

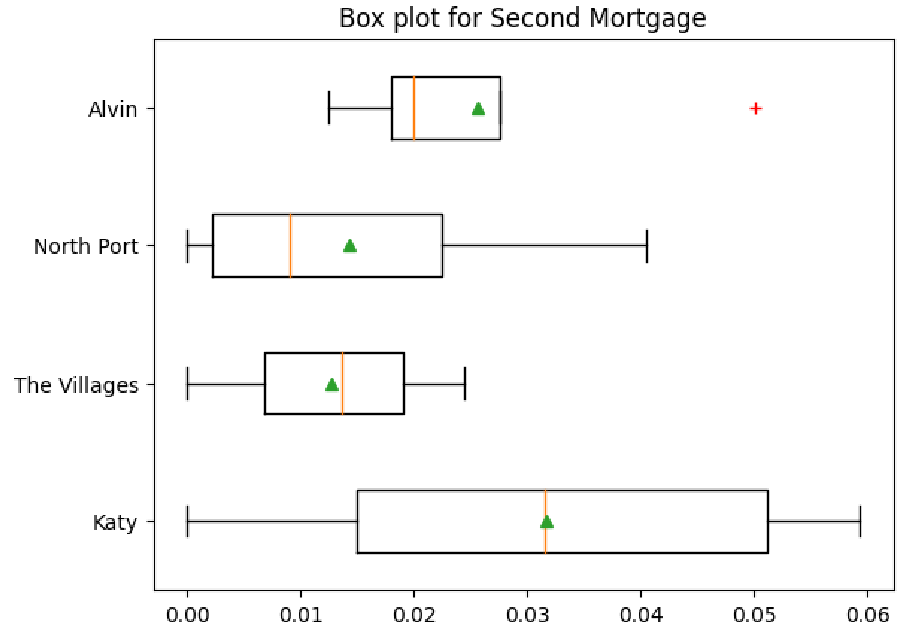
```
169              Katy
23985    The Villages
23565      North Port
15940           Alvin
Name: city, dtype: object
```

The yellow line in the interquartile range is the median

The green triangle in the interquartile range is the mean

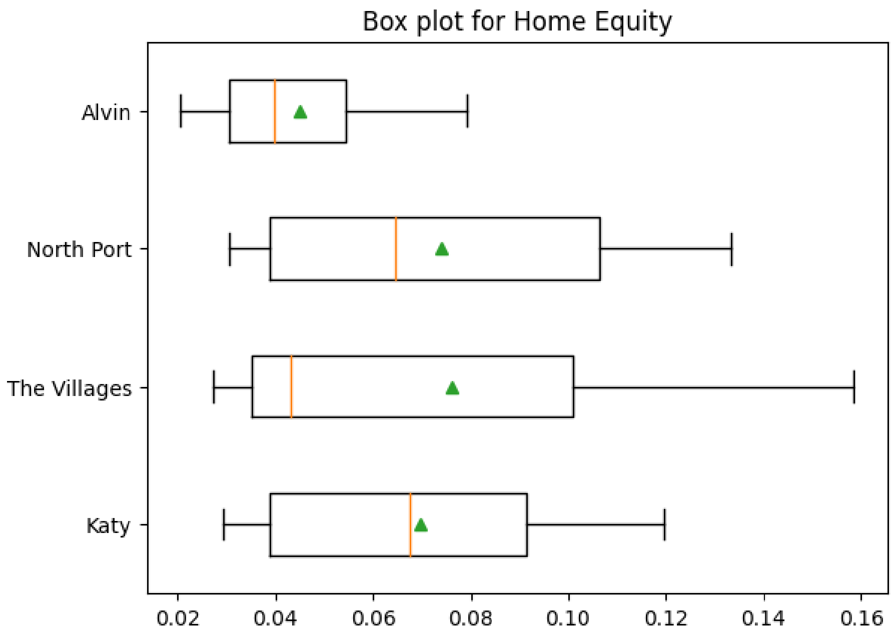
The '+' sign shows the presence of outliers in dataset

```
det= df.loc[df['city']== 'Katy','second_mortgage'].values
las= df.loc[df['city']== 'The Villages','second_mortgage'].values
pine= df.loc[df['city']== 'North Port','second_mortgage'].values
aub= df.loc[df['city']== 'Alvin','second_mortgage'].values
plt.boxplot([det,las,pine,aub],labels=['Katy','The Villages','North Port','Alvin'],showmeans=True, sym= 'r+',vert=False);
plt.title('Box plot for Second Mortgage')
plt.show()
```



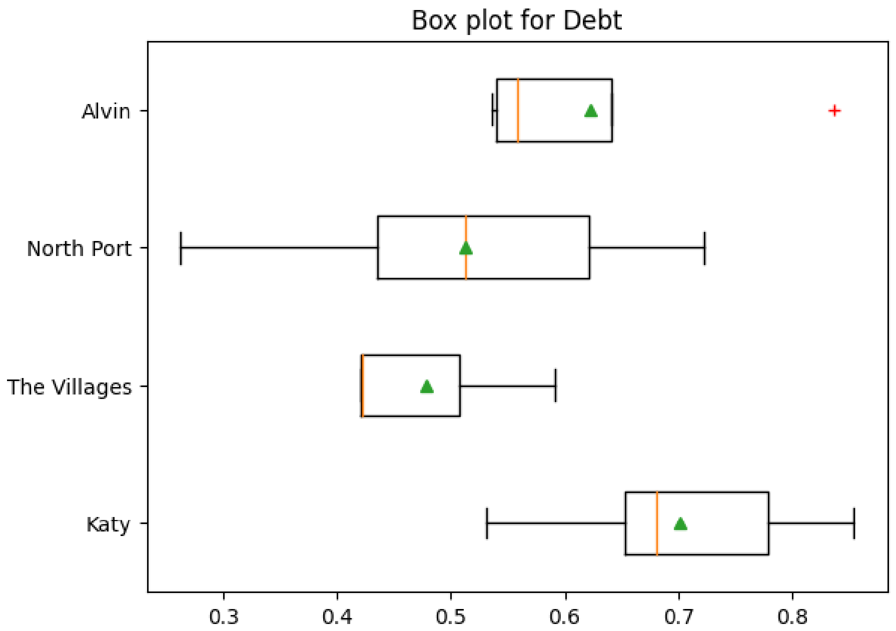
- From the above box plot we can observe the median value of the **second mortgage** data is much closer to the first quartile than the third quartile, which means the **distribution of Alvin, North Port and Katy is right-skewed**.
- From the above box plot we can observe the median value of the **second mortgage** data is much closer to the third quartile than the first quartile which means the **distribution of The Villages is left=skewed**.
- The data contains **outliers above upper quartile range** in the second mortgage data in **Alvin**, which means some people living in Alvin have much more second mortgage as compared to other population in Alvin.

```
was= df.loc[df['city']== 'Katy','home_equity'].values
gf= df.loc[df['city']== 'The Villages','home_equity'].values
bell= df.loc[df['city']== 'North Port','home_equity'].values
clark= df.loc[df['city']== 'Alvin','home_equity'].values
plt.boxplot([was,gf,bell,clark],labels=['Katy','The Villages','North Port','Alvin'],showmeans=True, sym= 'r+',vert=False);
plt.title('Box plot for Home Equity')
plt.show()
```



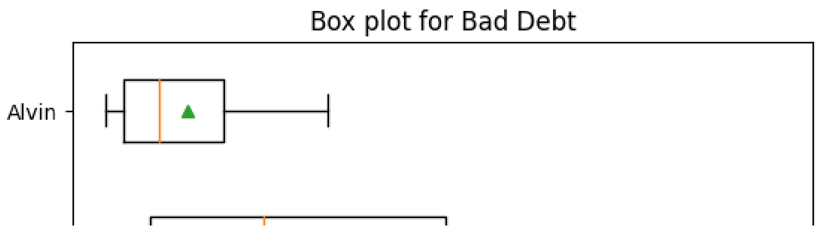
- From the above box plot we can see the median of the **home equity** data is much closer to the first quartile than the third quartile, which means the **distribution for Alvin, North Port, The Villages is right-skewed**.
- From the above box plot we can observe the median value of the **second mortgage** data is much closer to the third quartile than the first quartile which means the **distribution of Katy is left=skewed**.

```
seat= df.loc[df['city']== 'Katy','debt'].values
colu= df.loc[df['city']== 'The Villages','debt'].values
liver= df.loc[df['city']== 'North Port','debt'].values
frank = df.loc[df['city']== 'Alvin','debt'].values
plt.boxplot([seat,colu,liver,frank],labels=['Katy','The Villages','North Port','Alvin'],showmeans=True, sym= 'r+',vert=False);
plt.title('Box plot for Debt')
plt.show()
```



- From the above box plot we can see the median value of **debt** is much closer to the first quartile than the third quartile, which means the **distribution for Alvin, North Port, The Villages and Katy is right skewed**.
- The dataset contains **outliers in debt data above the upper quartile range** for Alvin, which means there are people with very high debt as compared to the median/mean debt of people living in Alvin.

```
ofx= df.loc[df['city']== 'Katy','bad_debt'].values
brook= df.loc[df['city']== 'The Villages','bad_debt'].values
chig= df.loc[df['city']== 'North Port','bad_debt'].values
ang= df.loc[df['city']== 'Alvin','bad_debt'].values
plt.boxplot([ofx,brook,chig,ang],labels=['Katy','The Villages','North Port','Alvin'],showmeans=True, sym= 'r+',vert=False);
plt.title('Box plot for Bad Debt')
plt.show()
```



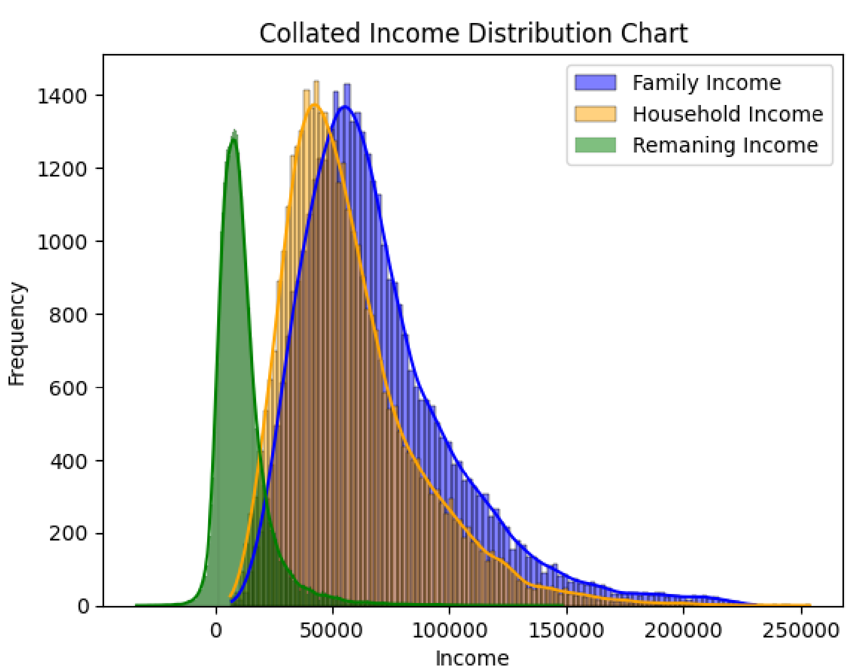
- From the above box plot we can see the median value of bad debt is much closer to the third quartile than the first quartile, which means the **distribution for Katy is left skewed**.
- From the above box plot we can see the median of the **home equity** data is much closer to the first quartile than the third quartile, which means the **distribution for Alvin, North Port and The Villages is right-skewed**

```
## calculating remaning income from family income and household income

remaning_inc= df['family_median'] - df['hi_median']
```

```
## comparing family income and househould income

df['family_median'].sum()  > df['hi_median'].sum()
```

```
True
```

```
sns.histplot(df['family_median'],kde=True, color='blue', label='Family Income',legend=True)
sns.histplot(df['hi_median'],kde=True, color='orange', label='Household Income',legend=True)
sns.histplot(remaning_inc,kde=True, color='green', label='Remaning Income',legend=True)
## kde parameter is kernel density estimate to smooth the distribution.

plt.title('Collated Income Distribution Chart')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



- We can observe from above collated distribution chart the overall family income and household income lies between 50,000 to 1,00,000 for the given population
- We can observe that the family income is slightly higer than household income for the given population
- The distribution is similar to normal distribution

```
# plt.hist(df['family_median'], bins=75, alpha=0.6, label='Family Income')
# plt.hist(df['hi_median'], bins=75, alpha=0.6, label='Household Income')
# plt.hist(remaning_inc, bins=75, alpha=0.6, label='Remaining Income')
# ## The alpha parameter is used for transparency to make overlapping histograms more visible.

# plt.title('Collated Income Distribution')
# plt.xlabel('Income')
# plt.ylabel('Frequency')
# plt.legend()
```

Project task 2:

Exploratory Data Analysis (EDA):

Double-click (or enter) to edit

```
## calculating density of area

density= df['pop']/df['ALand']
```

```
## adding density to original dataset

df['density']= density*100000
df['density']
```

```
0        126.029034
1         25.685467
2          1.523347
3          0.499905
4         45.157830
            ...
27316    264.981421
27317     81.834237
27318      0.213790
27319     61.879771
```

```
27320     47.791852
Name: density, Length: 37940, dtype: float64
```

```
density.nlargest(3)
```

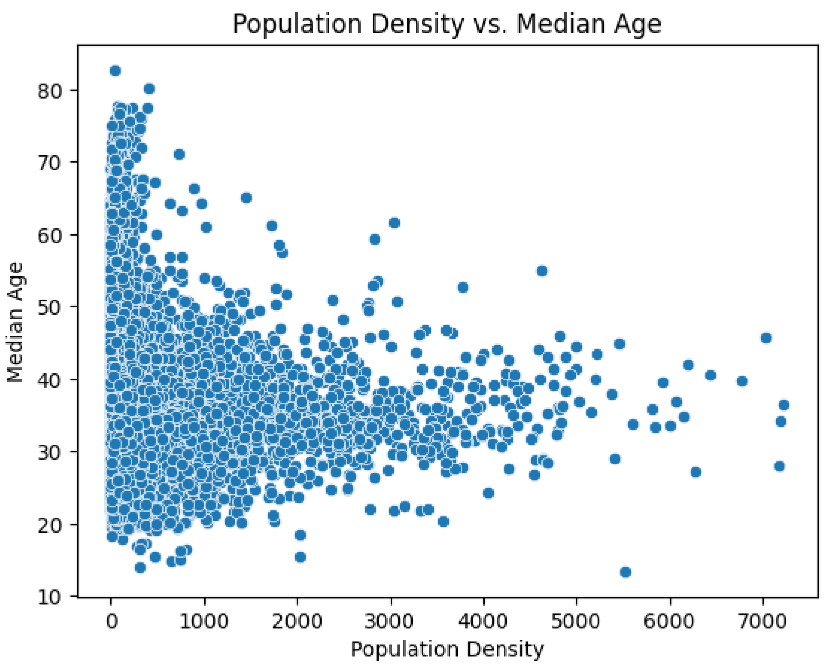
```
2677     0.175563
21050    0.072283
10251    0.071976
dtype: float64
```

```
df.drop(2677, inplace=True)
```

```
## calculating overall median age of male and female population

median_age_c= ((df['male_age_median']* df['male_pop']) + (df['female_age_median'] * df['female_pop'])) / (df['male_pop']+df['female_pop'])
```

```
df['median_age']= median_age_c
```

```
## Scatter plot of Population density vs. Age

sns.scatterplot(x='density', y='median_age', data=df)
plt.title('Population Density vs. Median Age')
plt.xlabel('Population Density')
plt.ylabel('Median Age')
plt.show()
```




```
## summary stats into population density and age

print("Summary Stats: \n")
df[['pop', 'ALand', 'density', 'median_age']].describe()
```

Summary Stats:

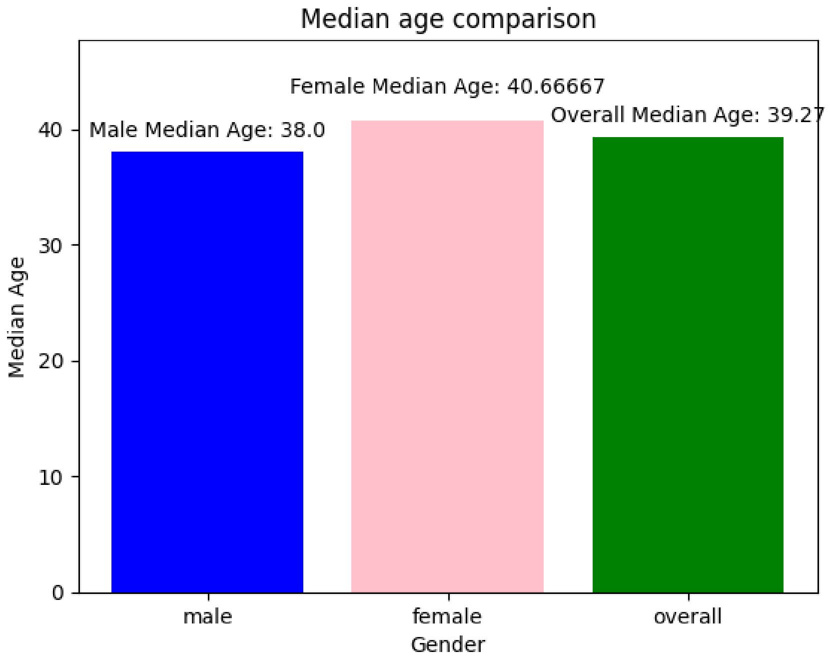
	pop	ALand	density	median_age
count	37940.000000	3.794000e+04	37940.000000	37940.000000
mean	4385.977570	1.251229e+08	200.150973	39.321703
std	2084.057931	1.158857e+09	433.836605	7.397916
min	38.000000	8.299000e+03	0.001172	13.378362
25%	2956.000000	1.824246e+06	12.790635	34.284358
50%	4106.000000	4.951182e+06	86.462514	39.272186
75%	5470.250000	3.453241e+07	206.700889	43.875669
max	53812.000000	1.039510e+11	17556.332088	82.664697

```
## creaing bins for age

pop_bins= pd.cut(df['pop'],5)
pop_bins
```

```
0        (-15.774, 10792.8]
1        (-15.774, 10792.8]
2        (-15.774, 10792.8]
3        (-15.774, 10792.8]
4        (-15.774, 10792.8]
                ...
27316    (-15.774, 10792.8]
27317    (-15.774, 10792.8]
27318    (-15.774, 10792.8]
27319    (10792.8, 21547.6]
27320    (-15.774, 10792.8]
Name: pop, Length: 37940, dtype: category
Categories (5, interval[float64, right]): [(-15.774, 10792.8] < (10792.8, 21547.6] <
                                           (21547.6, 32302.4] < (32302.4, 43057.2] <
                                           (43057.2, 53812.0]]
```

```
male= df['male_age_median'].median()
female= df['female_age_median'].median()
overall= median_age_c.median()
data1= [male,female ,overall]
label= ['male','female','overall']
```

```
## visulaizing overall, female and male median age for given population

plt.bar(label,data1, color=['blue','pink','green'])
plt.title('Median age comparison')
plt.xlabel('Gender')
plt.ylabel('Median Age')
plt.ylim(0, max(data1) + 7)
plt.text(0, male+1 , f'Male Median Age: {male}', ha='center', va='bottom', color='black')
plt.text(1, female+2, f'Female Median Age: {female}', ha='center', va='bottom', color='black')
plt.text(2, overall+1, f'Overall Median Age: {overall:.2f}', ha='center', va='bottom', color='black')
plt.show()
```



- The overall population median age is 39.27 years
- The male population median age is 38 years
- The fmale population median age is 38 years

```
df['state'].unique()
```

```
array(['Michigan', 'Maine', 'Pennsylvania', 'Kentucky', 'Texas',
       'Florida', 'Georgia', 'New York', 'California', 'Washington',
       'Illinois', 'Massachusetts', 'Maryland', 'Virginia', 'Nevada',
       'Tennessee', 'District of Columbia', 'Arkansas', 'Alabama',
       'Wisconsin', 'New Mexico', 'Mississippi', 'Ohio', 'Indiana',
       'Montana', 'Oregon', 'New Jersey', 'North Carolina', 'Louisiana',
       'South Carolina', 'Utah', 'Arizona', 'Rhode Island', 'Puerto Rico',
       'Oklahoma', 'Missouri', 'Minnesota', 'Nebraska', 'Colorado',
       'Iowa', 'Connecticut', 'Delaware', 'Kansas', 'West Virginia',
       'Vermont', 'Alaska', 'South Dakota', 'Idaho', 'New Hampshire',
       'Hawaii', 'Wyoming', 'North Dakota'], dtype=object)
```

```
overall_inc= df['family_median']
overall_rent= df['rent_median']
overall_rent_percent= (overall_rent / overall_inc *100 ).median()
```

```
michigan_inc = df.loc[df['state']=='Michigan','family_median']
michigan_rent = df.loc[df['state']=='Michigan','rent_median']
michigan_rent_percent= (michigan_rent/michigan_inc * 100).median()
```

```
texas_inc = df.loc[df['state']=='Texas','family_median']
texas_rent = df.loc[df['state']=='Texas','rent_median']
texas_rent_percent= (texas_rent/texas_inc * 100).median()
```

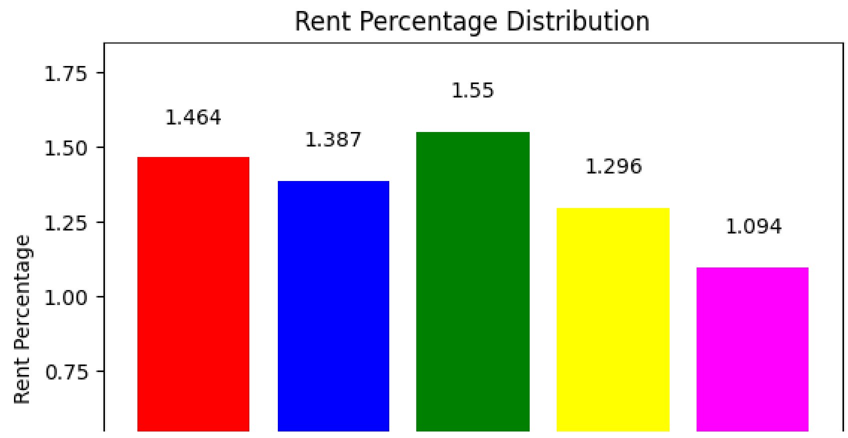
```
nyc_inc = df.loc[df['state']=='New York','family_median']
nyc_rent = df.loc[df['state']=='New York','rent_median']
nyc_rent_percent= (nyc_rent/nyc_inc * 100).median()
```

```
indiana_inc = df.loc[df['state']=='Indiana','family_median']
indiana_rent = df.loc[df['state']=='Indiana','rent_median']
indiana_rent_percent= (indiana_rent/indiana_inc * 100).median()
```

```
wyoming_inc = df.loc[df['state']=='Wyoming','family_median']
wyoming_rent = df.loc[df['state']=='Wyoming','rent_median']
wyoming_rent_percent= (wyoming_rent/wyoming_inc * 100).median()
```

```
data2= [overall_rent_percent, michigan_rent_percent, nyc_rent_percent,indiana_rent_percent,wyoming_rent_percent]
labels= ['Overall','Michigan','NewYork','Indiana','Wyoming']
```

```
plt.bar(labels, data2,color=['red','blue','green','yellow','magenta'])
plt.title('Rent Percentage Distribution')
plt.xlabel('States')
plt.ylabel('Rent Percentage')
plt.ylim(0, max(data2)+0.3)
plt.text(0, overall_rent_percent+0.1 , overall_rent_percent.round(3), ha='center', va='bottom', color='black')
plt.text(1, michigan_rent_percent+0.1, michigan_rent_percent.round(3), ha='center', va='bottom', color='black')
plt.text(2, nyc_rent_percent+0.1, nyc_rent_percent.round(3), ha='center', va='bottom', color='black')
plt.text(3, indiana_rent_percent+0.1, indiana_rent_percent.round(3), ha='center', va='bottom', color='black')
plt.text(4, wyoming_rent_percent+0.1, wyoming_rent_percent.round(3), ha='center', va='bottom', color='black')
plt.show();
```

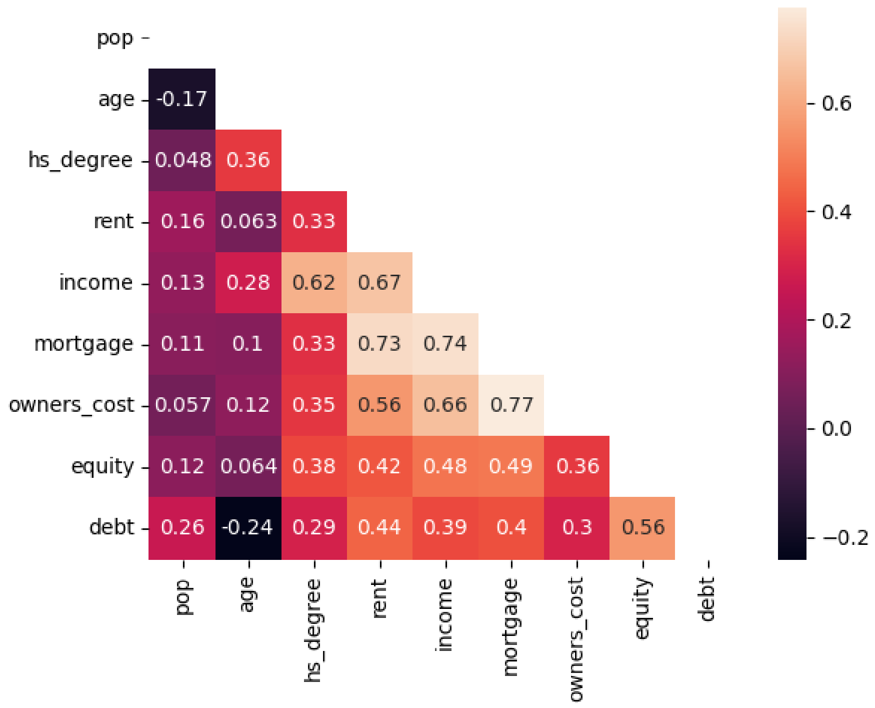


- The rent percentage are calulated diving the rent with family's income for the specific state.
- The overall USA rent percentage according to the family income of total population is 1.464%.
- The overall rent for Michigan state according the the family income of total population in Michigan is 1.387% which is lower than the overall country's rent percentage.
- The overall rent for New York according the the family income of total population in New York is 1.55% which is higher than the overall country's rent percentage.
- The overall rent for Indiana state according the the family income of total population in Indiana is 1.296% which is lower than the overall country's rent percentage.
- The overall rent for Wyoming state according the the family income of total population in Michigan is 1.094% which is lower than the overall country's rent percentage.

```
small_df= pd.DataFrame({
    'pop': df['pop'],
    'age': median_age_c,
    'hs_degree': df['hs_degree'],
    'rent': df['rent_median'],
    'income': df['family_median'],
    'mortgage': df['hc_mortgage_median'],
    # 'second_mortgage' : df['second_mortgage'],
    'owners_cost': df['hc_median'],
    'equity': df['home_equity'],
    'debt': df['debt']

})
```

```
corr= small_df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool)) ## genrate a mask for upper triangle
sns.heatmap(small_df.corr(),cbar=True,annot=True,mask= mask)
```

```
<Axes: >
```



From the above correlation heatmap we can observe that:

- There is a strong postive correlation between population and owners cost.
- There is negative correlation between individual's age and debt.
- There is strong postive correlation between highscool degree and individual's income.
- There is strong postive correlation between individual's income and rent.
- There is strong postive correlation between induvidual's rent and mortgage.
- There is strong postive correlation between individual's income and mortgage.
- There is strong postive correlation between mortgage and owners cost.
- There is postive correlation between equity and debt.

Project Task 3:

Data Pre-processing:

```
pip install factor_analyzer
```

```
from factor_analyzer import FactorAnalyzer
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import FactorAnalysis
```

```
own = 1- df['debt']
```

```
lat_var= pd.DataFrame({
    'hs_degree' :df['hs_degree'],
    'median_age': median_age_c,
    'second_mortgage': df['second_mortgage'],
     'percent_own': own,
     'bad_debt': bad_debt})
```

```
id_data= ['hs_degree','median_age','second_mortgage','percent_own','bad_debt']
```

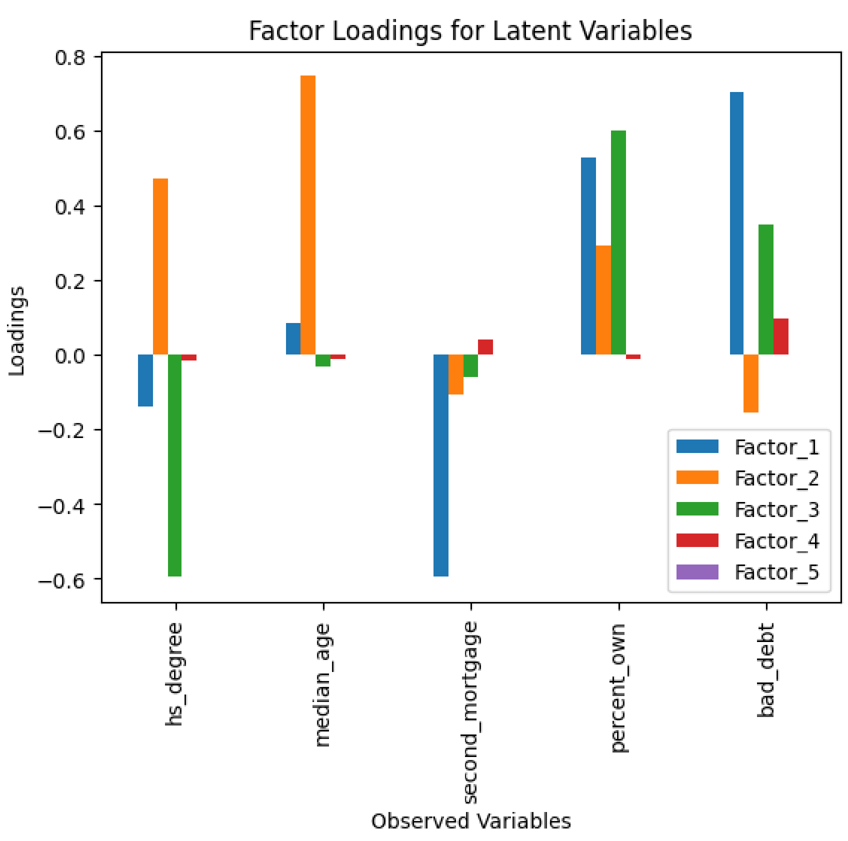
```
## standardizing the data

std= StandardScaler()
data_std= std.fit_transform(lat_var)
```

```
## Factor analysis
# Creating factor analysis object and perform factor analysis

n= len(id_data)
fa= FactorAnalyzer(n, rotation= 'varimax')
fa.fit(data_std)
```

```
FactorAnalyzer
FactorAnalyzer(n_factors=5, rotation='varimax', rotation_kwargs={})
```

```
loadings = pd.DataFrame(fa.loadings_, columns=[f'Factor_{i+1}' for i in range(n)], index=id_data)
```

```
## plotting the loadings of factor analysis

loadings.plot(kind='bar')
plt.title('Factor Loadings for Latent Variables')
plt.xlabel('Observed Variables')
plt.ylabel('Loadings')
plt.show()
```




```
# Check Eigenvalues

ev, v = fa.get_eigenvalues()
ev
```

```
array([2.07288437, 1.38923744, 0.72091405, 0.45958903, 0.35737511])
```

```
# Create scree plot using matplotlib

plt.scatter(range(1,lat_var.shape[1]+1),ev)
plt.plot(range(1,lat_var.shape[1]+1),ev)
plt.title('Scree Plot')
plt.xlabel('Factors')
plt.ylabel('Eigenvalue')
plt.grid()
plt.show()
```

Scree Plot

Project Task 4:

Data modelling:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score , mean_absolute_percentage_error, accuracy_score
```

```
## Selecting independent and dependent variable

y= df['hc_mortgage_mean']
x= df.drop(['hc_mortgage_mean', 'UID','COUNTYID','STATEID','state','state_ab','place','type','lat','lng','zip_code','area_code','city','place','primary'],axis=1)
```

```
## Split the data into training and testing sets

x_train, x_test, y_train, y_test= train_test_split(x,y)
```

Factors

```
## initialize Linear Regression Model

model= LinearRegression()

# Train the model on the training set
model.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
## making predictions on test set

y_pred= model.predict(x_test)
```

```
## Evaluate the model

r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)

print(f'R-squared: {r2:.2f}')
print(f'Mean Squared Error: {mse:.2f}')
```

```
R-squared: 0.99
Mean Squared Error: 4493.00
```

```
## Model Prediction at State level

def state_model(state):

## print("Model Prediction at State level \n\n")

  state_df = df[df['state']== state]
  x_state= state_df.drop(['hc_mortgage_mean', 'UID','COUNTYID','STATEID','state','state_ab','place','type','lat','lng','zip_code','area_code','city','place','primary'],axis=1)
  y_state= state_df['hc_mortgage_mean']

  X_train, X_test, Y_train ,Y_test= train_test_split(x_state, y_state)

  model= LinearRegression()
  model.fit(X_train, Y_train)
  Y_pred= model.predict(X_test)

  r2 = r2_score(Y_test, Y_pred)
  mse = mean_squared_error(Y_test, Y_pred)
  #acc= accuracy_score(Y_test, Y_pred)
  mpe= mean_absolute_percentage_error(Y_test, Y_pred)

  print(f'R-squared for {state}: {r2:.3f}')
  print(f'Mean Squared error for {state}: {mse:.3f}')
  #print(f'Accuracy score for {state}: {acc:.2f}')
  print(f'Mean Absolute percentage error for {state}: {mpe:.4f}')
  print('\n')
```

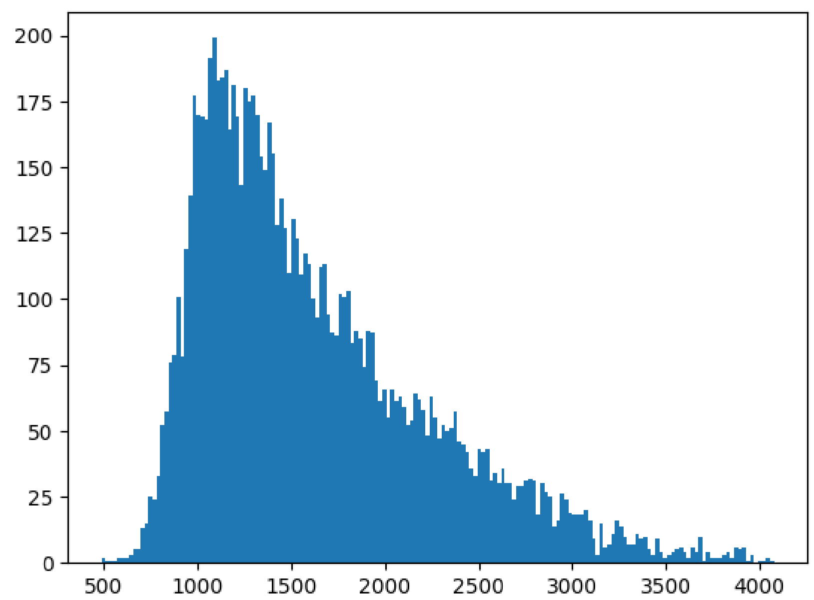
```
print("Model Prediction at State level \n\n")

for state in df['state'].unique() :
  state_model(state)
```

```
Model Prediction at State level


R-squared for Michigan: 0.985
Mean Squared error for Michigan: 1897.614
Mean Absolute percentage error for Michigan: 0.0248


R-squared for Maine: 0.890
Mean Squared error for Maine: 11185.662
Mean Absolute percentage error for Maine: 0.0617


R-squared for Pennsylvania: 0.990
Mean Squared error for Pennsylvania: 2175.769
Mean Absolute percentage error for Pennsylvania: 0.0241


R-squared for Kentucky: 0.987
Mean Squared error for Kentucky: 1557.072
Mean Absolute percentage error for Kentucky: 0.0266


R-squared for Texas: 0.987
Mean Squared error for Texas: 4036.328
Mean Absolute percentage error for Texas: 0.0290


R-squared for Florida: 0.984
Mean Squared error for Florida: 4664.281
```

```
Mean Absolute percentage error for Florida: 0.0296


R-squared for Georgia: 0.984
Mean Squared error for Georgia: 3299.331
Mean Absolute percentage error for Georgia: 0.0305


R-squared for New York: 0.973
Mean Squared error for New York: 15890.515
Mean Absolute percentage error for New York: 0.0403


R-squared for California: 0.982
Mean Squared error for California: 6920.065
Mean Absolute percentage error for California: 0.0282


R-squared for Washington: 0.987
Mean Squared error for Washington: 3041.014
Mean Absolute percentage error for Washington: 0.0228


R-squared for Illinois: 0.990
Mean Squared error for Illinois: 3154.931
Mean Absolute percentage error for Illinois: 0.0242
```

```
df.to_csv('df.csv')
```

```
plt.hist(y_pred,bins=170)
plt.show()
```




```
print('hello')
```

```
hello
```