Real Estate

Project Task: Week 1

df_train Import and Preparation:

1. Import df_train.
2. Figure out the primary key and look for the requirement of indexing.
3. Gauge the fill rate of the variables and devise plans for missing value treatment. Please explain explicitly the reason for the treatment chosen for each variable.

Exploratory df_train Analysis (EDA):

4. Perform debt analysis. You may take the following steps:

   a) Explore the top 2,500 locations where the percentage of households with a second mortgage is the highest and percent ownership is above 10 percent. Visualize using geo-map. You may keep the upper limit for the percent of households with a second mortgage to 50 percent

   b) Use the following bad debt equation: Bad Debt = P (Second Mortgage ∩ Home Equity Loan) Bad Debt = second_mortgage + home_equity - home_equity_second_mortgage

   c) Create pie charts to show overall debt and bad debt

   d) Create Box and whisker plot and analyze the distribution for 2nd mortgage, home equity, good debt, and bad debt for different cities

   e) Create a collated income distribution chart for family income, house hold income, and remaining income

Project Task: Week 2

Exploratory Data Analysis (EDA):

1. Perform EDA and come out with insights into population density and age. You may have to derive new fields (make sure to weight averages for accurate measurements):

   a) Use pop and ALand variables to create a new field called population density

   b) Use male_age_median, female_age_median, male_pop, and female_pop to create a new field called median age

   c) Visualize the findings using appropriate chart type

2. Create bins for population into a new variable by selecting appropriate class interval so that the number of categories don't exceed 5 for the ease of analysis.

   a) Analyze the married, separated, and divorced population for these population brackets

   b) Visualize using appropriate chart type

3. Please detail your observations for rent as a percentage of income at an overall level, and for different states.

4. Perform correlation analysis for all the relevant variables by creating a heatmap. Describe your findings.

Project Task: Week 3

Data Pre-processing:

1. The economic multivariate data has a significant number of measured variables. The goal is to find where the measured variables depend on a number of smaller unobserved common factors or latent variables.

2. Each variable is assumed to be dependent upon a linear combination of the common factors, and the coefficients are known as loadings. Each measured variable also includes a component due to independent random variability, known as "specific variance" because it is specific to one variable. Obtain the common factors and then plot the loadings. Use factor analysis to find latent variables in our dataset and gain insight into the linear relationships in the data. Following are the list of latent variables:

   • Highschool graduation rates

• Median population age

• Second mortgage statistics

• Percent own

• Bad debt expense

Project Task: Week 4

Data Modeling :

1. Build a linear Regression model to predict the total monthly expenditure for home mortgages loan. Please refer 'deplotment_RE.xlsx'. Column hc_mortgage_mean is predicted variable. This is the mean monthly mortgage and owner costs of specified geographical location. Note: Exclude loans from prediction model which have NaN (Not a Number) values for hc_mortgage_mean.

   a) Run a model at a Nation level. If the accuracy levels and R square are not satisfactory proceed to below step.

   b) Run another model at State level. There are 52 states in USA.

   c) Keep below considerations while building a linear regression model. Data Modeling :

   - `Variables should have significant impact on predicting Monthly mortgage and owner costs`
   - `Utilize all predictor variable to start with initial hypothesis`
   - `R square of 60 percent and above should be achieved`
   - `Ensure Multi-collinearity does not exist in dependent variables`
   - `Test if predicted variable is normally distributed`

Data Reporting:

2. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

   a) Box plot of distribution of average rent by type of place (village, urban, town, etc.).

   b) Pie charts to show overall debt and bad debt.

   c) Explore the top 2,500 locations where the percentage of households with a second mortgage is the highest and percent ownership is above 10 percent. Visualize using geo-map.

   d) Heat map for correlation matrix.

   e) Pie chart to show the population distribution across different types of places (village, urban, town etc.)

Week 1

df_train Import and Preparation:

1. Import df_train.

In [1]:
```
# Import df_train & libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#reading the df_train
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
print("Shape of train df_train:",df_train.shape)
print("Shape of test df_train:",df_test.shape)
```

```
Shape of train df_train: (27321, 80)
Shape of test df_train: (11709, 80)
```

2. Figure out the primary key and look for the requirement of indexing.

In [3]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27321 entries, 0 to 27320
Data columns (total 80 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   UID                          27321 non-null  int64  
 1   BLOCKID                      0 non-null      float64
 2   SUMLEVEL                     27321 non-null  int64  
 3   COUNTYID                     27321 non-null  int64  
 4   STATEID                      27321 non-null  int64  
 5   state                        27321 non-null  object 
 6   state_ab                     27321 non-null  object 
 7   city                         27321 non-null  object 
 8   place                        27321 non-null  object 
 9   type                         27321 non-null  object 
 10  primary                      27321 non-null  object 
 11  zip_code                     27321 non-null  int64  
 12  area_code                    27321 non-null  int64  
 13  lat                          27321 non-null  float64
 14  lng                          27321 non-null  float64
 15  ALand                        27321 non-null  float64
 16  AWater                       27321 non-null  int64  
 17  pop                          27321 non-null  int64  
 18  male_pop                     27321 non-null  int64  
 19  female_pop                   27321 non-null  int64  
 20  rent_mean                    27007 non-null  float64
 21  rent_median                  27007 non-null  float64
 22  rent_stdev                   27007 non-null  float64
 23  rent_sample_weight           27007 non-null  float64
 24  rent_samples                 27007 non-null  float64
 25  rent_gt_10                   27007 non-null  float64
 26  rent_gt_15                   27007 non-null  float64
 27  rent_gt_20                   27007 non-null  float64
 28  rent_gt_25                   27007 non-null  float64
 29  rent_gt_30                   27007 non-null  float64
 30  rent_gt_35                   27007 non-null  float64
 31  rent_gt_40                   27007 non-null  float64
 32  rent_gt_50                   27007 non-null  float64
 33  universe_samples             27321 non-null  int64  
 34  used_samples                 27321 non-null  int64  
 35  hi_mean                      27053 non-null  float64
 36  hi_median                    27053 non-null  float64
 37  hi_stdev                     27053 non-null  float64
 38  hi_sample_weight             27053 non-null  float64
 39  hi_samples                   27053 non-null  float64
 40  family_mean                  27023 non-null  float64
 41  family_median                27023 non-null  float64
 42  family_stdev                 27023 non-null  float64
 43  family_sample_weight         27023 non-null  float64
 44  family_samples               27023 non-null  float64
 45  hc_mortgage_mean             26748 non-null  float64
 46  hc_mortgage_median           26748 non-null  float64
 47  hc_mortgage_stdev            26748 non-null  float64
 48  hc_mortgage_sample_weight    26748 non-null  float64
 49  hc_mortgage_samples          26748 non-null  float64
 50  hc_mean                      26721 non-null  float64
 51  hc_median                    26721 non-null  float64
 52  hc_stdev                     26721 non-null  float64
 53  hc_samples                   26721 non-null  float64
 54  hc_sample_weight             26721 non-null  float64
 55  home_equity_second_mortgage  26864 non-null  float64
 56  second_mortgage              26864 non-null  float64
 57  home_equity                  26864 non-null  float64
 58  debt                         26864 non-null  float64
 59  second_mortgage_cdf          26864 non-null  float64
 60  home_equity_cdf              26864 non-null  float64
 61  debt_cdf                     26864 non-null  float64
 62  hs_degree                    27131 non-null  float64
 63  hs_degree_male               27121 non-null  float64
 64  hs_degree_female             27098 non-null  float64
 65  male_age_mean                27132 non-null  float64
 66  male_age_median              27132 non-null  float64
 67  male_age_stdev               27132 non-null  float64
 68  male_age_sample_weight       27132 non-null  float64
 69  male_age_samples             27132 non-null  float64
 70  female_age_mean              27115 non-null  float64
 71  female_age_median            27115 non-null  float64
 72  female_age_stdev             27115 non-null  float64
```

```
 73  female_age_sample_weight     27115 non-null  float64
 74  female_age_samples           27115 non-null  float64
 75  pct_own                      27053 non-null  float64
 76  married                      27130 non-null  float64
 77  married_snp                  27130 non-null  float64
 78  separated                    27130 non-null  float64
 79  divorced                     27130 non-null  float64
dtypes: float64(62), int64(12), object(6)
memory usage: 16.7+ MB
```

In [4]:

```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11709 entries, 0 to 11708
Data columns (total 80 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   UID                          11709 non-null  int64  
 1   BLOCKID                      0 non-null      float64
 2   SUMLEVEL                     11709 non-null  int64  
 3   COUNTYID                     11709 non-null  int64  
 4   STATEID                      11709 non-null  int64  
 5   state                        11709 non-null  object 
 6   state_ab                     11709 non-null  object 
 7   city                         11709 non-null  object 
 8   place                        11709 non-null  object 
 9   type                         11709 non-null  object 
 10  primary                      11709 non-null  object 
 11  zip_code                     11709 non-null  int64  
 12  area_code                    11709 non-null  int64  
 13  lat                          11709 non-null  float64
 14  lng                          11709 non-null  float64
 15  ALand                        11709 non-null  int64  
 16  AWater                       11709 non-null  int64  
 17  pop                          11709 non-null  int64  
 18  male_pop                     11709 non-null  int64  
 19  female_pop                   11709 non-null  int64  
 20  rent_mean                    11561 non-null  float64
 21  rent_median                  11561 non-null  float64
 22  rent_stdev                   11561 non-null  float64
 23  rent_sample_weight           11561 non-null  float64
 24  rent_samples                 11561 non-null  float64
 25  rent_gt_10                   11560 non-null  float64
 26  rent_gt_15                   11560 non-null  float64
 27  rent_gt_20                   11560 non-null  float64
 28  rent_gt_25                   11560 non-null  float64
 29  rent_gt_30                   11560 non-null  float64
 30  rent_gt_35                   11560 non-null  float64
 31  rent_gt_40                   11560 non-null  float64
 32  rent_gt_50                   11560 non-null  float64
 33  universe_samples             11709 non-null  int64  
 34  used_samples                 11709 non-null  int64  
 35  hi_mean                      11587 non-null  float64
 36  hi_median                    11587 non-null  float64
 37  hi_stdev                     11587 non-null  float64
 38  hi_sample_weight             11587 non-null  float64
 39  hi_samples                   11587 non-null  float64
 40  family_mean                  11573 non-null  float64
 41  family_median                11573 non-null  float64
 42  family_stdev                 11573 non-null  float64
 43  family_sample_weight         11573 non-null  float64
 44  family_samples               11573 non-null  float64
 45  hc_mortgage_mean             11441 non-null  float64
 46  hc_mortgage_median           11441 non-null  float64
 47  hc_mortgage_stdev            11441 non-null  float64
 48  hc_mortgage_sample_weight    11441 non-null  float64
 49  hc_mortgage_samples          11441 non-null  float64
 50  hc_mean                      11419 non-null  float64
 51  hc_median                    11419 non-null  float64
 52  hc_stdev                     11419 non-null  float64
 53  hc_samples                   11419 non-null  float64
 54  hc_sample_weight             11419 non-null  float64
 55  home_equity_second_mortgage  11489 non-null  float64
 56  second_mortgage              11489 non-null  float64
 57  home_equity                  11489 non-null  float64
 58  debt                         11489 non-null  float64
 59  second_mortgage_cdf          11489 non-null  float64
 60  home_equity_cdf              11489 non-null  float64
 61  debt_cdf                     11489 non-null  float64
 62  hs_degree                    11624 non-null  float64
 63  hs_degree_male               11620 non-null  float64
 64  hs_degree_female             11604 non-null  float64
 65  male_age_mean                11625 non-null  float64
 66  male_age_median              11625 non-null  float64
```

```
 67  male_age_stdev              11625 non-null  float64
 68  male_age_sample_weight      11625 non-null  float64
 69  male_age_samples            11625 non-null  float64
 70  female_age_mean             11613 non-null  float64
 71  female_age_median           11613 non-null  float64
 72  female_age_stdev            11613 non-null  float64
 73  female_age_sample_weight    11613 non-null  float64
 74  female_age_samples          11613 non-null  float64
 75  pct_own                     11587 non-null  float64
 76  married                     11625 non-null  float64
 77  married_snp                 11625 non-null  float64
 78  separated                   11625 non-null  float64
 79  divorced                    11625 non-null  float64
dtypes: float64(61), int64(13), object(6)
memory usage: 7.1+ MB
```

In [5]:
```python
print(df_train.shape)
df_train['UID'].nunique()
```

```
(27321, 80)
```

Out[5]: 27161

In [6]:
```python
print(df_test.shape)
df_test['UID'].nunique()
```

```
(11709, 80)
```

Out[6]: 11677

After checking the Feature 'UID' we can conclude that it is the primary key. But there are duplicate records with same UID so we need to remove those duplicate records

In [7]:
```python
df_train.UID.nunique()
```

Out[7]: 27161

In [8]:
```python
df_test.UID.nunique()
```

Out[8]: 11677

In [9]:
```python
grp_train = df_train.groupby('UID')
grp_train.size().sort_values(ascending=False).head(60)
# grp_train.get_group(282028)
grp_train.get_group(230058)
```

Out[9]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type	...	female_age_mean	female_ag
777	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
1623	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
17489	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
26046	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	

4 rows × 80 columns

In [10]:
```python
grp_test = df_train.groupby('UID')
grp_test.size().sort_values(ascending=False).head(60)
# grp_test.get_group(282028)
grp_test.get_group(230058)
```

Out[10]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type	...	female_age_mean	female_ag
777	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
1623	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
17489	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	
26046	230058	NaN	140	73	6	California	CA	Oceanside	Camp Pendleton North	City	...	19.99315	

4 rows × 80 columns

In [11]:
```
#Dropping the duplicate values
print("Before dropping the duplicates the total rows are:", df_train.shape[0], "Shape:", df_train.shape)
df_train.drop_duplicates(keep ='first', inplace = True)
print("After dropping the duplicates the total rows are:", df_train.shape[0], "Shape:", df_train.shape)
```

```
Before dropping the duplicates the total rows are: 27321 Shape: (27321, 80)
After dropping the duplicates the total rows are: 27161 Shape: (27161, 80)
```

In [12]:
```
#Dropping the duplicate values
print("Before dropping the duplicates the total rows are:", df_test.shape[0], "Shape:", df_test.shape)
df_test.drop_duplicates(keep ='first', inplace = True)
print("After dropping the duplicates the total rows are:", df_test.shape[0], "Shape:", df_test.shape)
```

```
Before dropping the duplicates the total rows are: 11709 Shape: (11709, 80)
After dropping the duplicates the total rows are: 11677 Shape: (11677, 80)
```

Now we can set the UID as the index

In [13]:
```
# backup
week1_bck_train = df_train.copy()
week1_bck_test = df_test.copy()
```

In [14]:
```
df_train.set_index('UID', inplace=True)
df_test.set_index('UID', inplace=True)
```

In [15]:
```
df_train
```

Out[15]:

	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type	primary	...	female_age_mean	f
UID													
267822	NaN	140	53	36	New York	NY	Hamilton	Hamilton	City	tract	...	44.48629	
246444	NaN	140	141	18	Indiana	IN	South Bend	Roseland	City	tract	...	36.48391	
245683	NaN	140	63	18	Indiana	IN	Danville	Danville	City	tract	...	42.15810	
279653	NaN	140	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	tract	...	47.77526	
247218	NaN	140	161	20	Kansas	KS	Manhattan	Manhattan City	City	tract	...	24.17693	
...	...	...	...	...	...	...	...	...	...	...	...	...	
279212	NaN	140	43	72	Puerto Rico	PR	Coamo	Coamo	Urban	tract	...	42.73154	
277856	NaN	140	91	42	Pennsylvania	PA	Blue Bell	Blue Bell	Borough	tract	...	38.21269	
233000	NaN	140	87	8	Colorado	CO	Weldona	Saddle Ridge	City	tract	...	43.40218	
287425	NaN	140	439	48	Texas	TX	Colleyville	Colleyville City	Town	tract	...	39.25921	
265371	NaN	140	3	32	Nevada	NV	Las Vegas	Paradise	City	tract	...	34.45345	

27161 rows × 79 columns

In [16]:
```
df_test
```

Out[16]:

UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type	primary	...	female_age_mean
255504	NaN	140	163	26	Michigan	MI	Detroit	Dearborn Heights City	CDP	tract	...	34.78682
252676	NaN	140	1	23	Maine	ME	Auburn	Auburn City	City	tract	...	44.23451
276314	NaN	140	15	42	Pennsylvania	PA	Pine City	Millerton	Borough	tract	...	41.62426
248614	NaN	140	231	21	Kentucky	KY	Monticello	Monticello City	City	tract	...	44.81200
286865	NaN	140	355	48	Texas	TX	Corpus Christi	Edroy	Town	tract	...	40.66618
...	...	...	...	...	...	...	...	...	...	...	...	...
238088	NaN	140	105	12	Florida	FL	Lakeland	Crystal Springs	City	tract	...	53.51255
242811	NaN	140	31	17	Illinois	IL	Chicago	Chicago City	Village	tract	...	33.14169
250127	NaN	140	9	25	Massachusetts	MA	Lawrence	Methuen Town City	City	tract	...	43.53905
241096	NaN	140	27	19	Iowa	IA	Carroll	Carroll City	City	tract	...	45.63179
287763	NaN	140	453	48	Texas	TX	Austin	Sunset Valley City	Town	tract	...	35.99955

11677 rows × 79 columns

3. Gauge the fill rate of the variables and devise plans for missing value treatment. Please explain explicitly the reason for the treatment chosen for each variable.

In [17]:

```
filter0 = (((df_train.isnull().sum()/df_train.shape[0])*100)>0)
df_delcols_train = df_train.loc[:,filter0.values]
print(df_delcols_train.isnull().sum()/df_delcols_train.shape[0]*100)
print("*"*41)
filter1 = (((df_test.isnull().sum()/df_test.shape[0])*100)>0)
df_delcols_test = df_test.loc[:,filter1.values]
print(df_delcols_test.isnull().sum()/df_delcols_test.shape[0]*100)
```

```
BLOCKID                        100.000000
rent_mean                        0.890983
rent_median                      0.890983
rent_stdev                       0.890983
rent_sample_weight               0.890983
rent_samples                     0.890983
rent_gt_10                       0.890983
rent_gt_15                       0.890983
rent_gt_20                       0.890983
rent_gt_25                       0.890983
rent_gt_30                       0.890983
rent_gt_35                       0.890983
rent_gt_40                       0.890983
rent_gt_50                       0.890983
hi_mean                          0.762122
hi_median                        0.762122
hi_stdev                         0.762122
hi_sample_weight                 0.762122
hi_samples                       0.762122
family_mean                      0.846802
family_median                    0.846802
family_stdev                     0.846802
family_sample_weight             0.846802
family_samples                   0.846802
hc_mortgage_mean                 1.627333
hc_mortgage_median               1.627333
hc_mortgage_stdev                1.627333
hc_mortgage_sample_weight        1.627333
hc_mortgage_samples              1.627333
hc_mean                          1.759876
hc_median                        1.759876
hc_stdev                         1.759876
hc_samples                       1.759876
hc_sample_weight                 1.759876
home_equity_second_mortgage      1.325430
second_mortgage                  1.325430
home_equity                      1.325430
debt                             1.325430
```

```
second_mortgage_cdf             1.325430
home_equity_cdf                 1.325430
debt_cdf                        1.325430
hs_degree                       0.533854
hs_degree_male                  0.566989
hs_degree_female                0.629579
male_age_mean                   0.544899
male_age_median                 0.544899
male_age_stdev                  0.544899
male_age_sample_weight          0.544899
male_age_samples                0.544899
female_age_mean                 0.592762
female_age_median               0.592762
female_age_stdev                0.592762
female_age_sample_weight        0.592762
female_age_samples              0.592762
pct_own                         0.762122
married                         0.552262
married_snp                     0.552262
separated                       0.552262
divorced                        0.552262
dtype: float64
*****************************************
BLOCKID                       100.000000
rent_mean                       1.147555
rent_median                     1.147555
rent_stdev                      1.147555
rent_sample_weight              1.147555
rent_samples                    1.147555
rent_gt_10                      1.156119
rent_gt_15                      1.156119
rent_gt_20                      1.156119
rent_gt_25                      1.156119
rent_gt_30                      1.156119
rent_gt_35                      1.156119
rent_gt_40                      1.156119
rent_gt_50                      1.156119
hi_mean                         0.959150
hi_median                       0.959150
hi_stdev                        0.959150
hi_sample_weight                0.959150
hi_samples                      0.959150
family_mean                     1.070480
family_median                   1.070480
family_stdev                    1.070480
family_sample_weight            1.070480
family_samples                  1.070480
hc_mortgage_mean                2.098142
hc_mortgage_median              2.098142
hc_mortgage_stdev               2.098142
hc_mortgage_sample_weight       2.098142
hc_mortgage_samples             2.098142
hc_mean                         2.286546
hc_median                       2.286546
hc_stdev                        2.286546
hc_samples                      2.286546
hc_sample_weight                2.286546
home_equity_second_mortgage     1.747024
second_mortgage                 1.747024
home_equity                     1.747024
debt                            1.747024
second_mortgage_cdf             1.747024
home_equity_cdf                 1.747024
debt_cdf                        1.747024
hs_degree                       0.667980
hs_degree_male                  0.702235
hs_degree_female                0.822129
male_age_mean                   0.659416
male_age_median                 0.659416
male_age_stdev                  0.659416
male_age_sample_weight          0.659416
male_age_samples                0.659416
female_age_mean                 0.745054
female_age_median               0.745054
female_age_stdev                0.745054
female_age_sample_weight        0.745054
female_age_samples              0.745054
pct_own                         0.959150
married                         0.659416
married_snp                     0.659416
separated                       0.659416
divorced                        0.659416
dtype: float64
```

Dropping Following features:

-'BLOCKID' as it is having all null values and 'SUMLEVEL' as well as 'primary' feature as it is having only 1 entry.

In [18]:
```
df_train.SUMLEVEL.nunique()
```

Out[18]:
```
1
```

In [19]:
```
print("Before dropping the feature from train data:",df_train.shape)
df_train.drop(columns = ['BLOCKID','primary', 'SUMLEVEL'], inplace = True)
print("After dropping the feature from train data:",df_train.shape)

print("Before dropping the feature from test data:",df_test.shape)
df_test.drop(columns = ['BLOCKID','primary', 'SUMLEVEL'], inplace = True)
print("After dropping the feature from test data:",df_test.shape)
```

```
Before dropping the feature from train data: (27161, 79)
After dropping the feature from train data: (27161, 76)
Before dropping the feature from test data: (11677, 79)
After dropping the feature from test data: (11677, 76)
```

In [20]:
```
filter0 = (((df_train.isnull().sum()/df_train.shape[0])*100)>0)
df_delcols_train = df_train.loc[:,filter0.values]
print(df_delcols_train.isnull().sum()/df_delcols_train.shape[0]*100)
print("*"*39)
filter1 = (((df_test.isnull().sum()/df_test.shape[0])*100)>0)
df_delcols_test = df_test.loc[:,filter1.values]
print(df_delcols_test.isnull().sum()/df_delcols_test.shape[0]*100)
```

```
rent_mean                      0.890983
rent_median                    0.890983
rent_stdev                     0.890983
rent_sample_weight             0.890983
rent_samples                   0.890983
rent_gt_10                     0.890983
rent_gt_15                     0.890983
rent_gt_20                     0.890983
rent_gt_25                     0.890983
rent_gt_30                     0.890983
rent_gt_35                     0.890983
rent_gt_40                     0.890983
rent_gt_50                     0.890983
hi_mean                        0.762122
hi_median                      0.762122
hi_stdev                       0.762122
hi_sample_weight               0.762122
hi_samples                     0.762122
family_mean                    0.846802
family_median                  0.846802
family_stdev                   0.846802
family_sample_weight           0.846802
family_samples                 0.846802
hc_mortgage_mean               1.627333
hc_mortgage_median             1.627333
hc_mortgage_stdev              1.627333
hc_mortgage_sample_weight      1.627333
hc_mortgage_samples            1.627333
hc_mean                        1.759876
hc_median                      1.759876
hc_stdev                       1.759876
hc_samples                     1.759876
hc_sample_weight               1.759876
home_equity_second_mortgage    1.325430
second_mortgage                1.325430
home_equity                    1.325430
debt                           1.325430
second_mortgage_cdf            1.325430
home_equity_cdf                1.325430
debt_cdf                       1.325430
hs_degree                      0.533854
hs_degree_male                 0.566989
hs_degree_female               0.629579
male_age_mean                  0.544899
male_age_median                0.544899
male_age_stdev                 0.544899
male_age_sample_weight         0.544899
male_age_samples               0.544899
female_age_mean                0.592762
female_age_median              0.592762
female_age_stdev               0.592762
female_age_sample_weight       0.592762
female_age_samples             0.592762
pct_own                        0.762122
```

```
married                        0.552262
married_snp                    0.552262
separated                      0.552262
divorced                       0.552262
dtype: float64
***************************************
rent_mean                      1.147555
rent_median                    1.147555
rent_stdev                     1.147555
rent_sample_weight             1.147555
rent_samples                   1.147555
rent_gt_10                     1.156119
rent_gt_15                     1.156119
rent_gt_20                     1.156119
rent_gt_25                     1.156119
rent_gt_30                     1.156119
rent_gt_35                     1.156119
rent_gt_40                     1.156119
rent_gt_50                     1.156119
hi_mean                        0.959150
hi_median                      0.959150
hi_stdev                       0.959150
hi_sample_weight               0.959150
hi_samples                     0.959150
family_mean                    1.070480
family_median                  1.070480
family_stdev                   1.070480
family_sample_weight           1.070480
family_samples                 1.070480
hc_mortgage_mean               2.098142
hc_mortgage_median             2.098142
hc_mortgage_stdev              2.098142
hc_mortgage_sample_weight      2.098142
hc_mortgage_samples            2.098142
hc_mean                        2.286546
hc_median                      2.286546
hc_stdev                       2.286546
hc_samples                     2.286546
hc_sample_weight               2.286546
home_equity_second_mortgage    1.747024
second_mortgage                1.747024
home_equity                    1.747024
debt                           1.747024
second_mortgage_cdf            1.747024
home_equity_cdf                1.747024
debt_cdf                       1.747024
hs_degree                      0.667980
hs_degree_male                 0.702235
hs_degree_female               0.822129
male_age_mean                  0.659416
male_age_median                0.659416
male_age_stdev                 0.659416
male_age_sample_weight         0.659416
male_age_samples               0.659416
female_age_mean                0.745054
female_age_median              0.745054
female_age_stdev               0.745054
female_age_sample_weight       0.745054
female_age_samples             0.745054
pct_own                        0.959150
married                        0.659416
married_snp                    0.659416
separated                      0.659416
divorced                       0.659416
dtype: float64
```

In [21]:

```
df_null_train = df_train[df_train.isna().any(axis=1)]
print("Shape of null df_train:", df_null_train.shape)
df_null_train.head()
df_null_test = df_test[df_test.isna().any(axis=1)]
print("Shape of null df_test:", df_null_test.shape)
df_null_test.head()
```

```
Shape of null df_train: (576, 76)
Shape of null df_test: (322, 76)
```

Out[21]:

UID	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_code	lat	...	female_age_mean	f
265339	3	32	Nevada	NV	Las Vegas	Winchester	City	89119	702	36.111448	...	33.57247	
287596	451	48	Texas	TX	San Angelo	San Angelo City	Town	76903	325	31.431831	...	21.40298	
250903	25	25	Massachusetts	MA	Cambridge	Cambridge City	City	2139	617	42.359478	...	22.53871	
287557	441	48	Texas	TX	Abilene	Tye City	Town	79607	325	32.423876	...	22.72458	
247510	209	20	Kansas	KS	Kansas City	Kansas City City	City	66104	913	39.171767	...	NaN	

5 rows × 76 columns

In [22]:
```python
percent_null_train = (df_null_train.shape[0]/df_train.shape[0])*100
print("% of null in train:",percent_null_train)
percent_null_test = (df_null_test.shape[0]/df_test.shape[0])*100
print("% of null in test:",percent_null_test)
```

```
% of null in train: 2.1206877508191893
% of null in test: 2.757557591847221
```

Now we know that the percentage of NULL data present in the dataset is very low that is 2.12%, which is very low compared to the dataset.

So we can conclude to dropping these null entries as we won't lose much information.

In [23]:
```python
df_train.dropna(inplace=True)
df_test.dropna(inplace=True)
```

In [24]:
```python
print(df_train.shape, df_test.shape)
```

```
(26585, 76) (11355, 76)
```

4. Perform debt analysis. You may take the following steps:

a) Explore the top 2,500 locations where the percentage of households with a second mortgage is the highest and percent ownership is above 10 percent. Visualize using geo-map. You may keep the upper limit for the percent of households with a second mortgage to 50 percent

Using SQL

In [25]:
```python
from pandasql import sqldf
```

In [26]:
```python
query1 = "SELECT place, pct_own, second_mortgage, lat, lng FROM df_train where pct_own > 0.10 AND second_mortga

query_func = lambda q : sqldf(q, globals())

top_2500 = query_func(query1)
```

In [27]:
```python
top_2500
```

Out[27]:

	place	pct_own	second_mortgage	lat	lng
0	Worcester City	0.20247	0.43363	42.254262	-71.800347
1	Harbor Hills	0.15618	0.31818	40.751809	-73.853582
2	Glen Burnie	0.22380	0.30212	39.127273	-76.635265
3	Egypt Lake-leto	0.11618	0.28972	28.029063	-82.495395
4	Lincolnwood	0.14228	0.28899	41.967289	-87.652434
...	...	...	...	...	...
2495	Cutler Bay	0.50519	0.06813	25.550391	-80.347791
2496	Jacksonburg	0.92888	0.06812	39.556756	-84.443252
2497	Keller City	0.97987	0.06812	32.913822	-97.204310
2498	Mays Landing	0.70642	0.06810	39.432879	-74.686137
2499	Oakland City	0.35225	0.06805	37.766197	-122.182303

2500 rows × 5 columns

In [28]:
```python
top_2500.pct_own.max()
```

Out[28]: 0.99249

In [29]:
```
top_2500.second_mortgage.max()
```

Out[29]: 0.43363

In the above steps, we first write include the sqldf function from the pandasql library and then we write the query where we specify that the percent ownership should be greater than 10% and the upper limit of second_mortgage to 50% & sorting the data in descending order of the 'second_mortgage' & limiting the records to 2500.

In [30]:
```
import plotly.express as px
import plotly.graph_objects as go
```

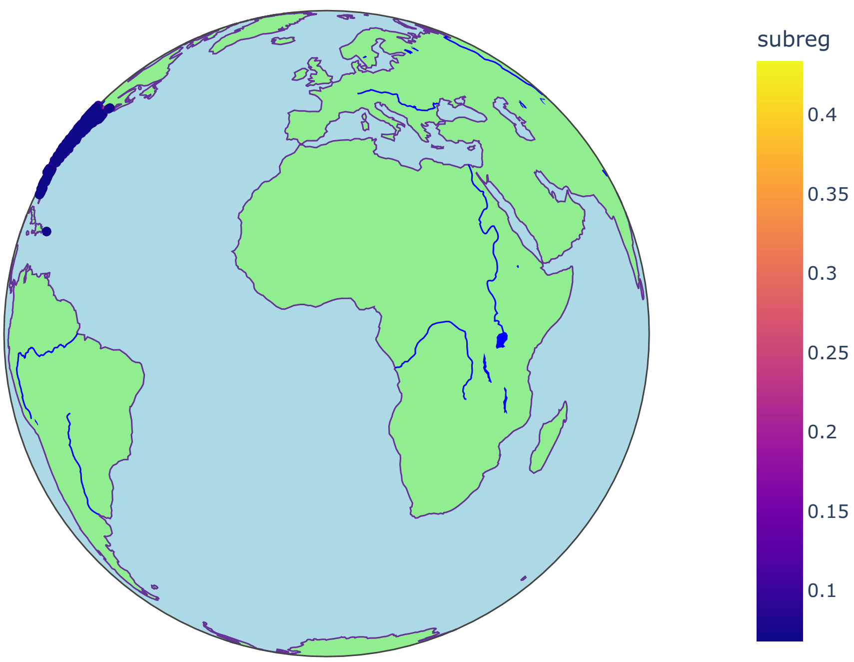
In [31]:
```
#Using graph objects
fig = go.Figure(data=go.Scattergeo(
    lat = top_2500['lat'],
    lon = top_2500['lng']),)
fig.update_traces(marker=dict(size=5))
fig.update_layout(geo=dict(
        scope = 'north america',
        showland = True,
        landcolor = "rgb(212, 212, 212)",
        subunitcolor = "rgb(255, 255, 255)",
        countrycolor = "rgb(255, 255, 255)",
        showlakes = True,
        lakecolor = "rgb(255, 255, 255)",
        showsubunits = True,
        showcountries = True,
        resolution = 50,
        projection = dict(
            type = 'conic conformal',
            rotation_lon = -100
        ),
        lonaxis = dict(
            showgrid = True,
            gridwidth = 0.5,
            range= [ -140.0, -55.0 ],
            dtick = 5
        ),
        lataxis = dict (
            showgrid = True,
            gridwidth = 0.5,
            range= [ 20.0, 60.0 ],
            dtick = 5
        )
    ), title='Top 2,500 locations with second mortgage is the highest and percent ownership is above 10 percent
fig.update_geos(
    projection_type="orthographic",
    resolution=50,
    showcoastlines=True, coastlinecolor="RebeccaPurple",
    showland=True, landcolor="LightGreen",
    showocean=True, oceancolor="LightBlue",
    showlakes=True, lakecolor="Blue",
    showrivers=True, rivercolor="Blue")
fig.show()
```

Top 2,500 locations with second mortgage is the highest and percent ownersh

In [32]:

```
#using Express
geo_df = pd.DataFrame(dict(lat=top_2500['lat'], lon=top_2500['lng'], subreg=top_2500['second_mortgage']))
fig = px.scatter_geo(geo_df, lat="lat", lon="lon", color="subreg", height= 600, projection = "orthographic",
                     title="Top 2,500 locations with second mortgage is the highest and percent ownership is ab
fig.update_geos(
    projection_type="orthographic",
    resolution=110,
    showcoastlines=True, coastlinecolor="RebeccaPurple",
    showland=True, landcolor="LightGreen",
    showocean=True, oceancolor="LightBlue",
    showlakes=True, lakecolor="Blue",
    showrivers=True, rivercolor="Blue"
)
fig.show()
```

Top 2,500 locations with second mortgage is the highest and percent ownersh



b) Use the following bad debt equation: Bad Debt = P (Second Mortgage ∩ Home Equity Loan) Bad Debt = second_mortgage + home_equity - home_equity_second_mortgage

In [33]:
```
df_train['BAD_DEBT'] = df_train['second_mortgage'] + df_train['home_equity'] - df_train['home_equity_second_mor
df_train
```

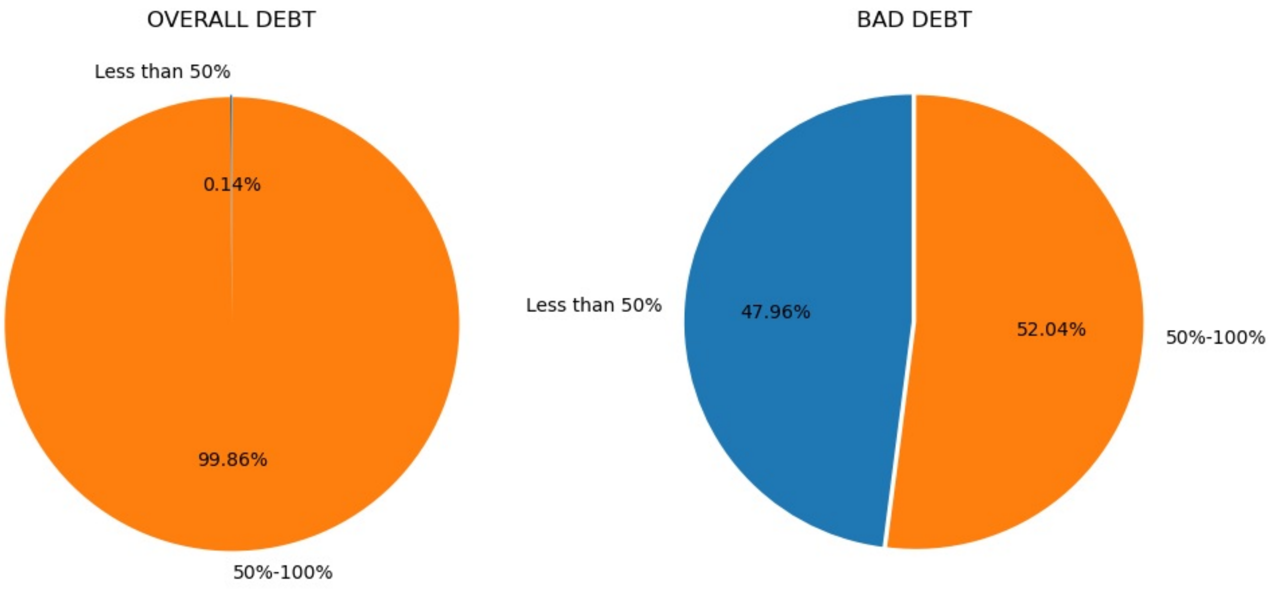
Out[33]:

UID	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_code	lat	...	female_age_median
267822	53	36	New York	NY	Hamilton	Hamilton	City	13346	315	42.840812	...	45.33333
246444	141	18	Indiana	IN	South Bend	Roseland	City	46616	574	41.701441	...	37.58333
245683	63	18	Indiana	IN	Danville	Danville	City	46122	317	39.792202	...	42.83333
279653	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	927	787	18.396103	...	50.58333
247218	161	20	Kansas	KS	Manhattan	Manhattan City	City	66502	785	39.195573	...	21.58333
...	...	...	...	...	...	...	...	...	...	...	...	...
279212	43	72	Puerto Rico	PR	Coamo	Coamo	Urban	769	787	18.076060	...	40.16667
277856	91	42	Pennsylvania	PA	Blue Bell	Blue Bell	Borough	19422	215	40.158138	...	39.50000
233000	87	8	Colorado	CO	Weldona	Saddle Ridge	City	80653	970	40.410316	...	46.33333
287425	439	48	Texas	TX	Colleyville	Colleyville City	Town	76034	817	32.904866	...	43.41667
265371	3	32	Nevada	NV	Las Vegas	Paradise	City	89123	702	36.064754	...	29.83333

26585 rows × 77 columns

c) Create pie charts to show overall debt and bad debt

In [34]:
```
df_train['BINS_OD'] = pd.cut(df_train['debt'], bins=[0,0.10,1], labels=['Less than 50%', '50%-100%'])
df_train['BINS_BD'] = pd.cut(df_train['BAD_DEBT'], bins=[0,0.10,1], labels=['Less than 50%', '50%-100%'])

pop1=(0,0.01)
pop2=(0.01,0.01)
plt.figure(figsize=(12,10))
plt.subplots_adjust(wspace=0.2)
plt.subplot(1,2,1)
plt.title('OVERALL DEBT')
df_train.groupby(['BINS_OD']).size().plot(kind = 'pie', subplots=True, startangle = 90, autopct = '%1.2f%%', ex
plt.ylabel("")
plt.subplot(1,2,2)
plt.title('BAD DEBT')
df_train.groupby(['BINS_BD']).size().plot(kind = 'pie', subplots=True, startangle = 90, autopct = '%1.2f%%', ex
plt.ylabel("")
plt.show()
```



d) Create Box and whisker plot and analyze the distribution for 2nd mortgage, home equity, good debt, and bad debt for different cities

In [35]:
```
city = df_train.city.value_counts()
```

```python
city_top_10 = city.head(10)
city_top_10.index
```

Out[35]:

```
Index(['Chicago', 'Brooklyn', 'Los Angeles', 'Houston', 'Philadelphia',
       'San Antonio', 'Baltimore', 'Las Vegas', 'Phoenix', 'Miami'],
      dtype='object')
```

In [36]:

```python
df_train['GOOD_DEBT'] = 1 - df_train.BAD_DEBT
df_train
```

Out[36]:

	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_code	lat	...	female_age_sample
UID												
267822	53	36	New York	NY	Hamilton	Hamilton	City	13346	315	42.840812	...	2618.
246444	141	18	Indiana	IN	South Bend	Roseland	City	46616	574	41.701441	...	1284.
245683	63	18	Indiana	IN	Danville	Danville	City	46122	317	39.792202	...	3238.
279653	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	927	787	18.396103	...	1559.
247218	161	20	Kansas	KS	Manhattan	Manhattan City	City	66502	785	39.195573	...	3051.
...	...	...	...	...	...	...	...	...	...	...	...	..
279212	43	72	Puerto Rico	PR	Coamo	Coamo	Urban	769	787	18.076060	...	938.
277856	91	42	Pennsylvania	PA	Blue Bell	Blue Bell	Borough	19422	215	40.158138	...	2039.
233000	87	8	Colorado	CO	Weldona	Saddle Ridge	City	80653	970	40.410316	...	1364.
287425	439	48	Texas	TX	Colleyville	Colleyville City	Town	76034	817	32.904866	...	5815.
265371	3	32	Nevada	NV	Las Vegas	Paradise	City	89123	702	36.064754	...	1911.

26585 rows × 80 columns

In [37]:

```python
new_df = df_train[['city','second_mortgage','home_equity','GOOD_DEBT','BAD_DEBT']]
new_df
```

Out[37]:

	city	second_mortgage	home_equity	GOOD_DEBT	BAD_DEBT
UID					
267822	Hamilton	0.02077	0.08919	0.90592	0.09408
246444	South Bend	0.02222	0.04274	0.95726	0.04274
245683	Danville	0.00000	0.09512	0.90488	0.09512
279653	San Juan	0.01086	0.01086	0.98914	0.01086
247218	Manhattan	0.05426	0.05426	0.94574	0.05426
...	...	...	...	...	...
279212	Coamo	0.00000	0.00000	1.00000	0.00000
277856	Blue Bell	0.02112	0.19641	0.79092	0.20908
233000	Weldona	0.02024	0.07857	0.92143	0.07857
287425	Colleyville	0.07550	0.12556	0.85695	0.14305
265371	Las Vegas	0.01412	0.18362	0.81638	0.18362

26585 rows × 5 columns

In [38]:

```python
new_df = new_df[new_df['city'].isin(city_top_10.index)]
new_df.city.value_counts()
```

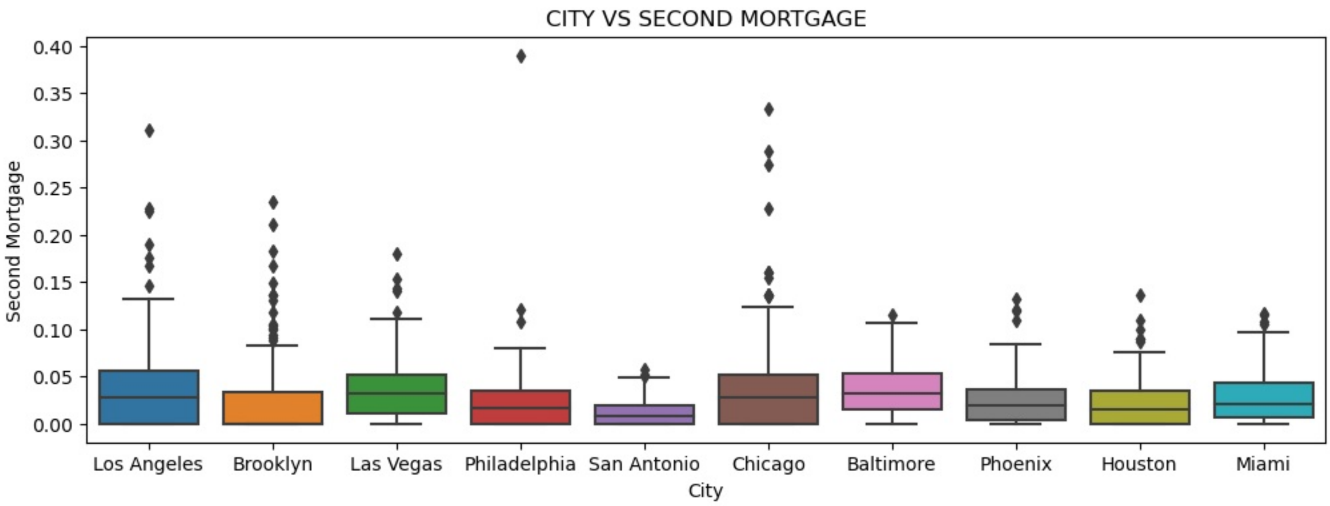
Out[38]:

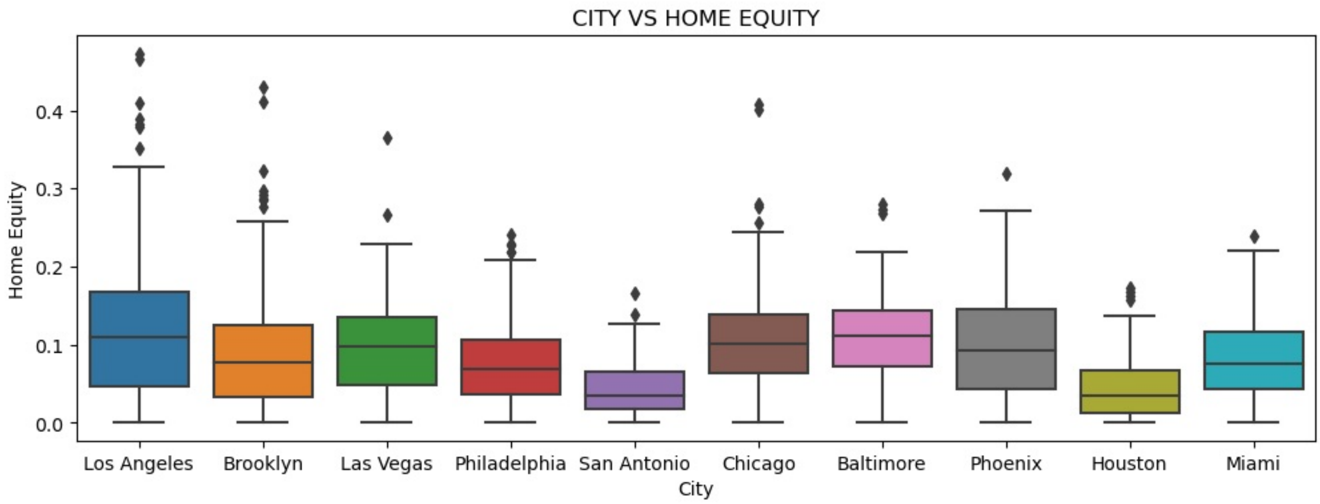
```
Chicago         286
Brooklyn        261
Los Angeles     219
Houston         213
Philadelphia    160
San Antonio     138
Baltimore       128
Las Vegas       123
Phoenix         114
Miami           105
Name: city, dtype: int64
```

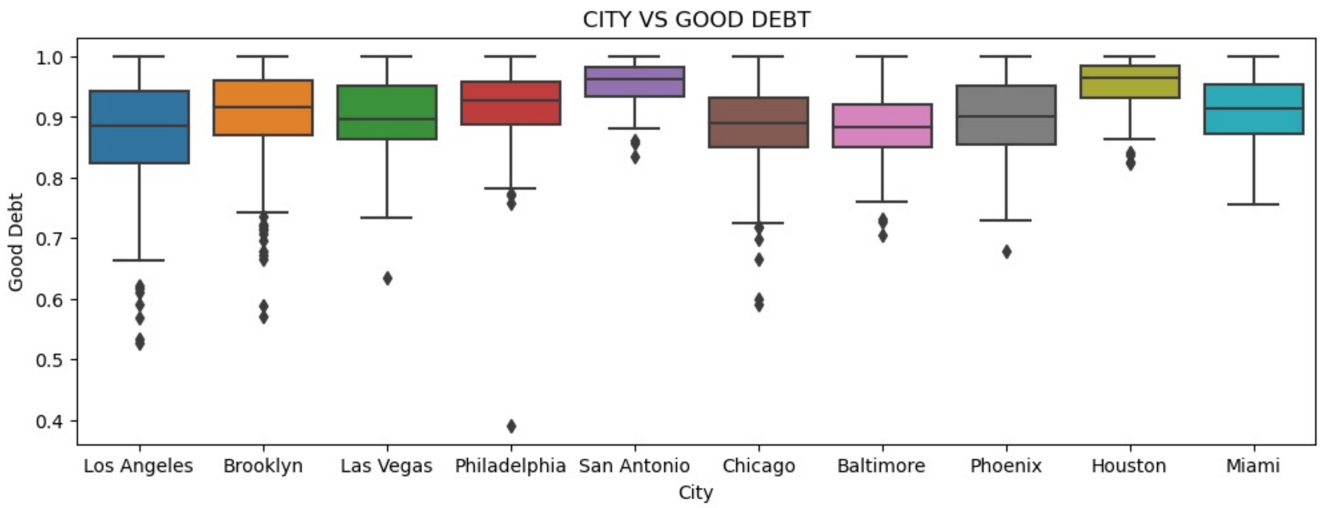
In [39]:

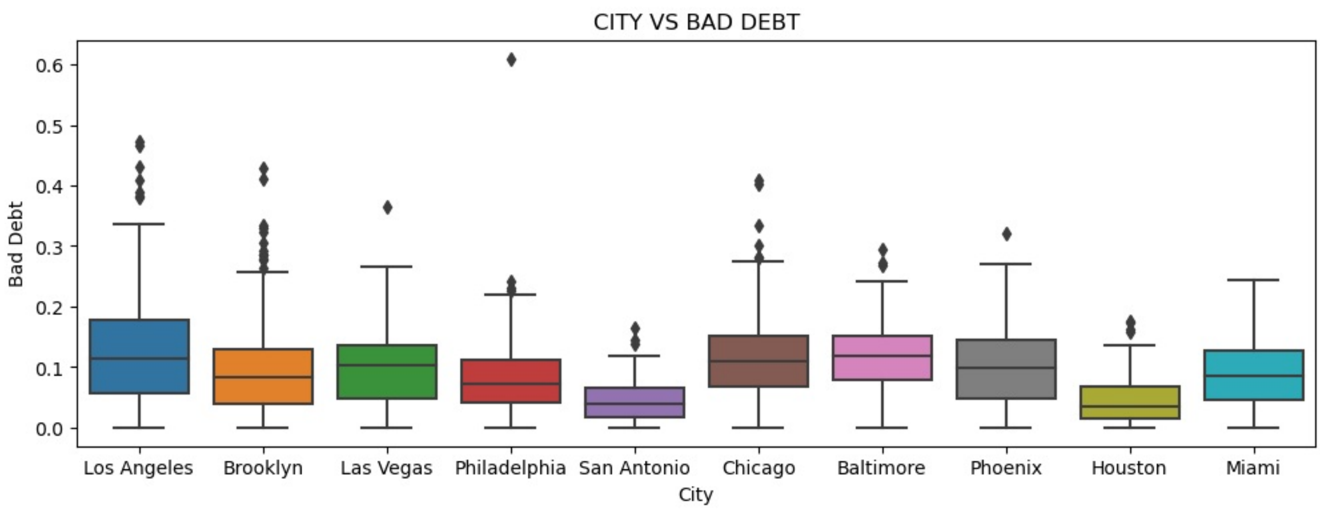
```python
plt.figure(figsize=(12,20))
```

```python
plt.subplots_adjust(hspace=0.35)

plt.subplot(4,1,1)
plt.title('CITY VS SECOND MORTGAGE')
sns.boxplot(x = 'city', y = 'second_mortgage', data = new_df)
plt.xlabel("City")
plt.ylabel("Second Mortgage")

plt.subplot(4,1,2)
plt.title('CITY VS HOME EQUITY')
sns.boxplot(x = 'city', y = 'home_equity', data = new_df)
plt.xlabel("City")
plt.ylabel("Home Equity")

plt.subplot(4,1,3)
plt.title('CITY VS GOOD DEBT')
sns.boxplot(x = 'city', y = 'GOOD_DEBT', data = new_df)
plt.xlabel("City")
plt.ylabel("Good Debt")

plt.subplot(4,1,4)
plt.title('CITY VS BAD DEBT')
sns.boxplot(x = 'city', y = 'BAD_DEBT', data = new_df)
plt.xlabel("City")
plt.ylabel("Bad Debt")

plt.show()
```


CITY VS SECOND MORTGAGE
Second Mortgage
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Los Angeles
Brooklyn
Las Vegas
Philadelphia
San Antonio
Chicago
Baltimore
Phoenix
Houston
Miami
City


CITY VS HOME EQUITY
Home Equity
0.4
0.3
0.2
0.1
0.0
Los Angeles
Brooklyn
Las Vegas
Philadelphia
San Antonio
Chicago
Baltimore
Phoenix
Houston
Miami
City


CITY VS GOOD DEBT
Good Debt
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Los Angeles
Brooklyn
Las Vegas
Philadelphia
San Antonio
Chicago
Baltimore
Phoenix
Houston
Miami
City


CITY VS BAD DEBT
Bad Debt
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Los Angeles
Brooklyn
Las Vegas
Philadelphia
San Antonio
Chicago
Baltimore
Phoenix
Houston
Miami
City

e) Create a collated income distribution chart for family income, house hold income, and remaining income

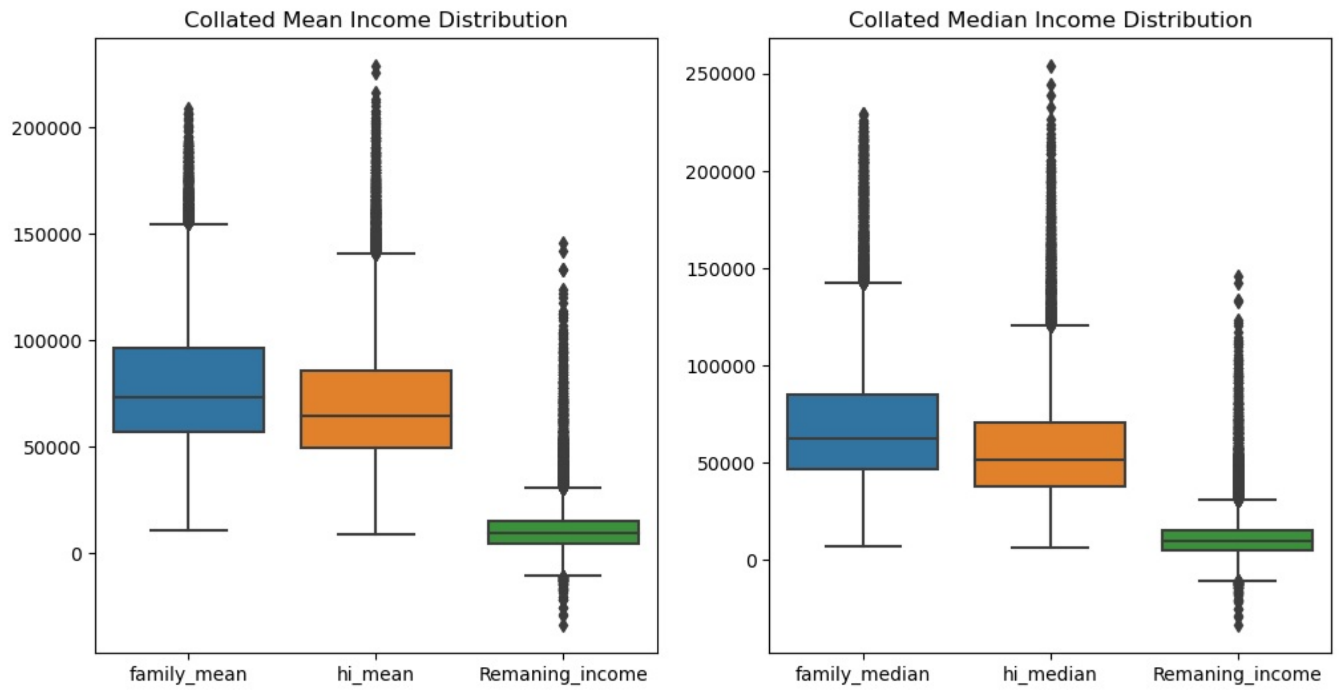
In [40]:
```
df_train['Remaning_income'] = df_train['family_median'] - df_train['hi_median']
df_train
```

Out[40]:

	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_code	lat	...	pct_own	married
UID													
267822	53	36	New York	NY	Hamilton	Hamilton	City	13346	315	42.840812	...	0.79046	0.57851
246444	141	18	Indiana	IN	South Bend	Roseland	City	46616	574	41.701441	...	0.52483	0.34886
245683	63	18	Indiana	IN	Danville	Danville	City	46122	317	39.792202	...	0.85331	0.64745
279653	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	927	787	18.396103	...	0.65037	0.47257
247218	161	20	Kansas	KS	Manhattan	Manhattan City	City	66502	785	39.195573	...	0.13046	0.12356
...	...	...	...	...	...	...	...	...	...	...	...	...	...
279212	43	72	Puerto Rico	PR	Coamo	Coamo	Urban	769	787	18.076060	...	0.60422	0.24603
277856	91	42	Pennsylvania	PA	Blue Bell	Blue Bell	Borough	19422	215	40.158138	...	0.68072	0.61127
233000	87	8	Colorado	CO	Weldona	Saddle Ridge	City	80653	970	40.410316	...	0.78508	0.70451
287425	439	48	Texas	TX	Colleyville	Colleyville City	Town	76034	817	32.904866	...	0.93970	0.75503
265371	3	32	Nevada	NV	Las Vegas	Paradise	City	89123	702	36.064754	...	0.27912	0.34426

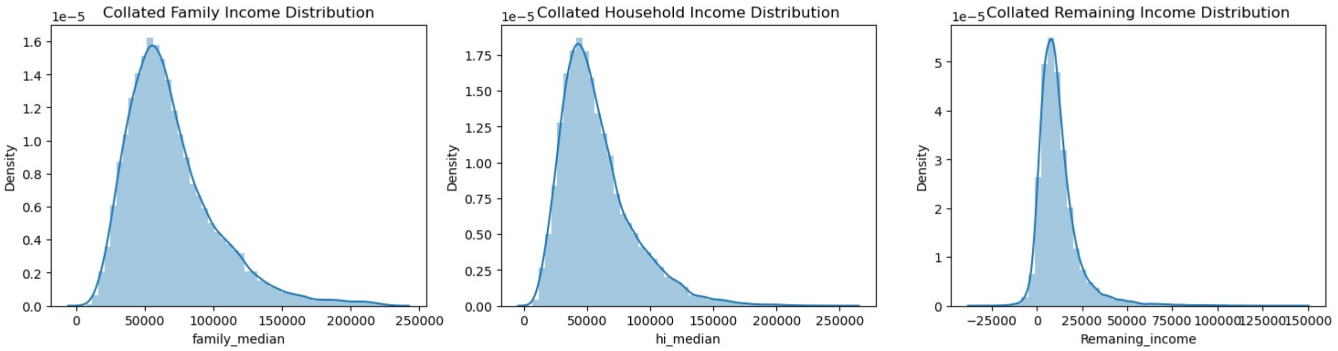
26585 rows × 81 columns

In [41]:
```
plt.figure(figsize=(12,6))
plt.subplots_adjust(wspace=0.20)
plt.subplot(1,2,1)
sns.boxplot(data = df_train[['family_mean', 'hi_mean', 'Remaning_income']])
plt.title("Collated Mean Income Distribution")
plt.subplot(1,2,2)
sns.boxplot(data = df_train[['family_median', 'hi_median', 'Remaning_income']])
plt.title("Collated Median Income Distribution")
plt.show()
```



In [42]:
```
plt.figure(figsize=(18,4))
plt.subplots_adjust(wspace=0.20)
plt.subplot(1,3,1)
sns.distplot(df_train['family_median'])
plt.title("Collated Family Income Distribution")
plt.subplot(1,3,2)
sns.distplot(df_train['hi_median'])
plt.title("Collated Household Income Distribution")
plt.subplot(1,3,3)
sns.distplot(df_train['Remaning_income'])
```

```
plt.title("Collated Remaining Income Distribution")
plt.show()
```

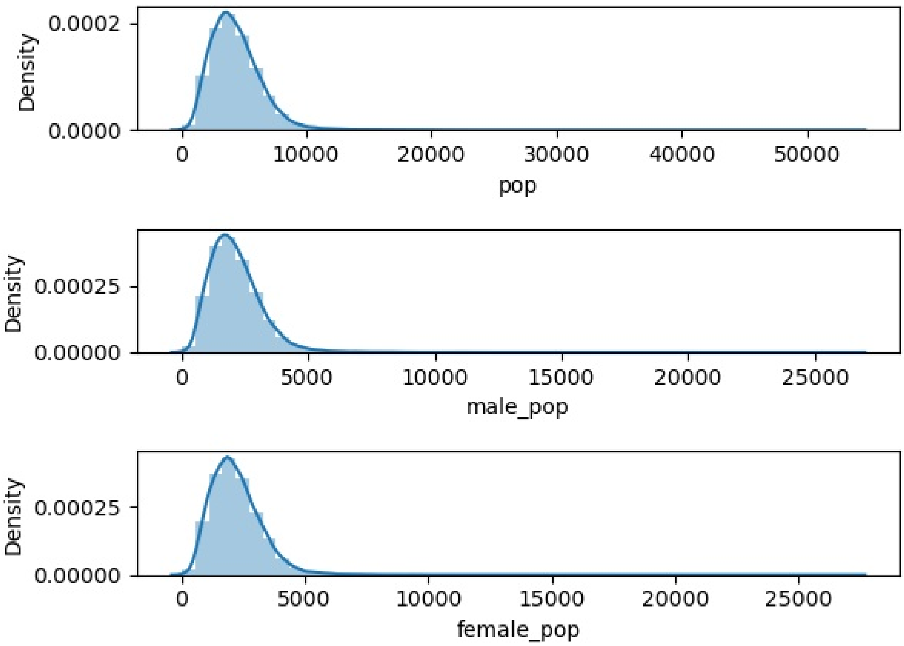


Week 2

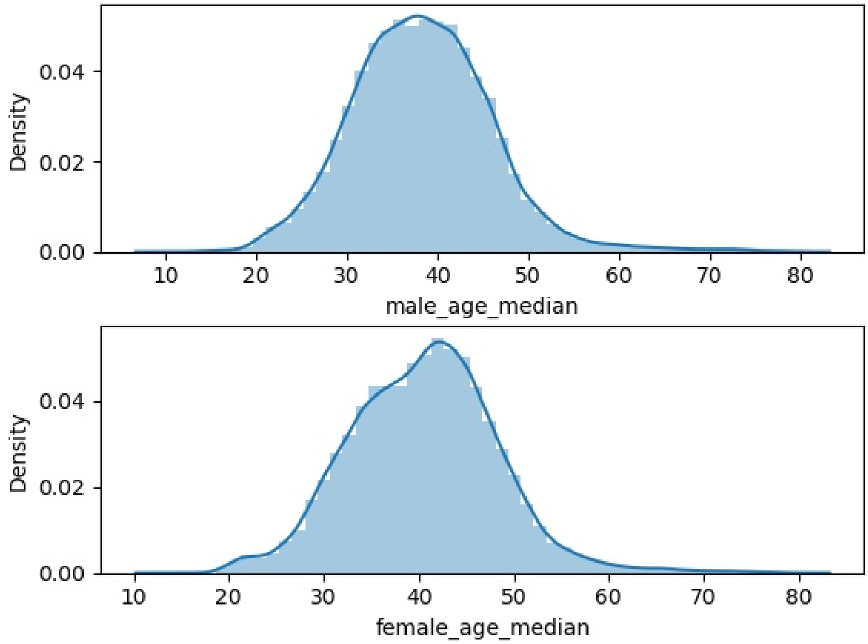
Exploratory Data Analysis (EDA):

1. Perform EDA and come out with insights into population density and age. You may have to derive new fields (make sure to weight averages for accurate measurements):

In [43]:
```
fig, (ax1, ax2, ax3) = plt.subplots(3,1)
sns.distplot(df_train['pop'], ax = ax1)
sns.distplot(df_train['male_pop'], ax = ax2)
sns.distplot(df_train['female_pop'], ax = ax3)
plt.subplots_adjust(hspace=0.8)
plt.show()
```



In [44]:
```
fig, (ax1, ax2) = plt.subplots(2,1)
sns.distplot(df_train['male_age_median'], ax = ax1)
sns.distplot(df_train['female_age_median'], ax = ax2)
plt.subplots_adjust(hspace=0.30)
plt.show()
```



a) Use pop and ALand variables to create a new field called population density

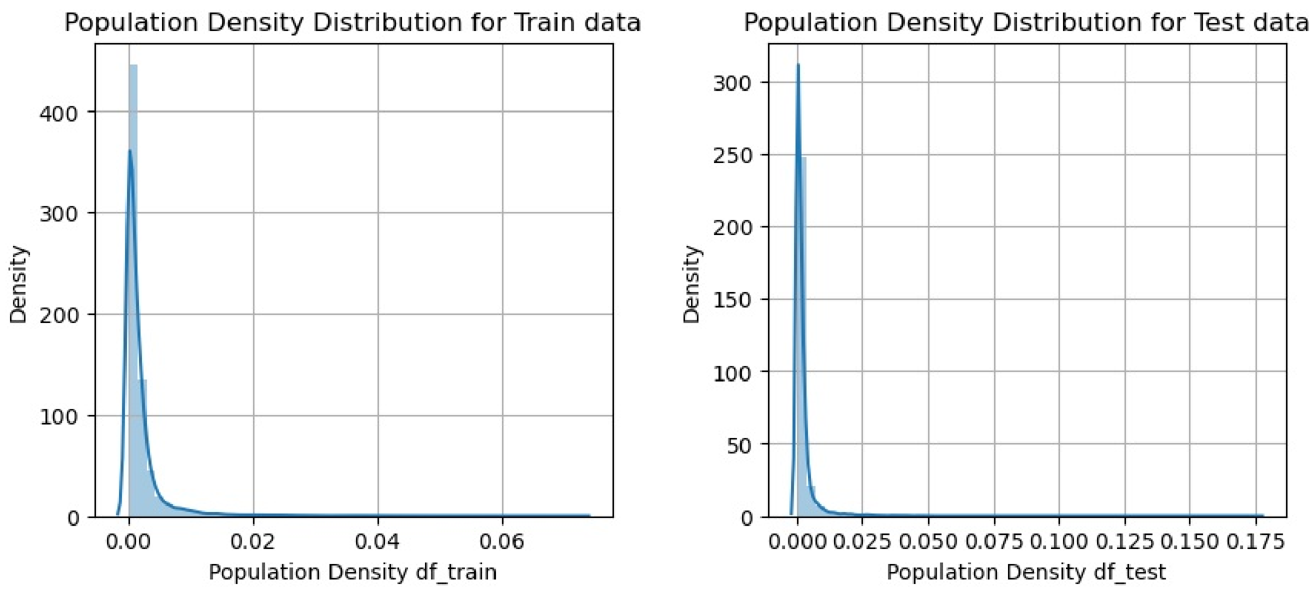
In [45]:
```
df_train['pop_density'] = df_train['pop']/df_train['ALand']
df_test['pop_density'] = df_test['pop']/df_test['ALand']
df_train.head()
```

Out[45]:

	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_code	lat	...	married	married_snp	sep
UID														
267822	53	36	New York	NY	Hamilton	Hamilton	City	13346	315	42.840812	...	0.57851	0.01882	0
246444	141	18	Indiana	IN	South Bend	Roseland	City	46616	574	41.701441	...	0.34886	0.01426	0
245683	63	18	Indiana	IN	Danville	Danville	City	46122	317	39.792202	...	0.64745	0.02830	0
279653	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	927	787	18.396103	...	0.47257	0.02021	0
247218	161	20	Kansas	KS	Manhattan	Manhattan City	City	66502	785	39.195573	...	0.12356	0.00000	0

5 rows × 82 columns

In [46]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.distplot(df_train['pop_density'])
plt.title("Population Density Distribution for Train data")
plt.xlabel("Population Density df_train")
plt.grid()
plt.subplot(1,2,2)
sns.distplot(df_test['pop_density'])
plt.title("Population Density Distribution for Test data")
plt.xlabel("Population Density df_test")
plt.grid()
plt.subplots_adjust(wspace= 0.30)
plt.show()
```



b) Use male_age_median, female_age_median, male_pop, and female_pop to create a new field called median age

In [47]:
```
df_train['Median_age'] = (df_train['male_age_median'] * df_train['male_pop'] +
                          df_train['female_age_median'] * df_train['female_pop'])/df_train['pop']
df_train[['pop', 'Median_age']].head()
```

Out[47]:

UID	pop	Median_age
267822	5230	44.667430
246444	2633	34.722748
245683	6881	41.774472
279653	2700	49.879012
247218	5637	21.965629

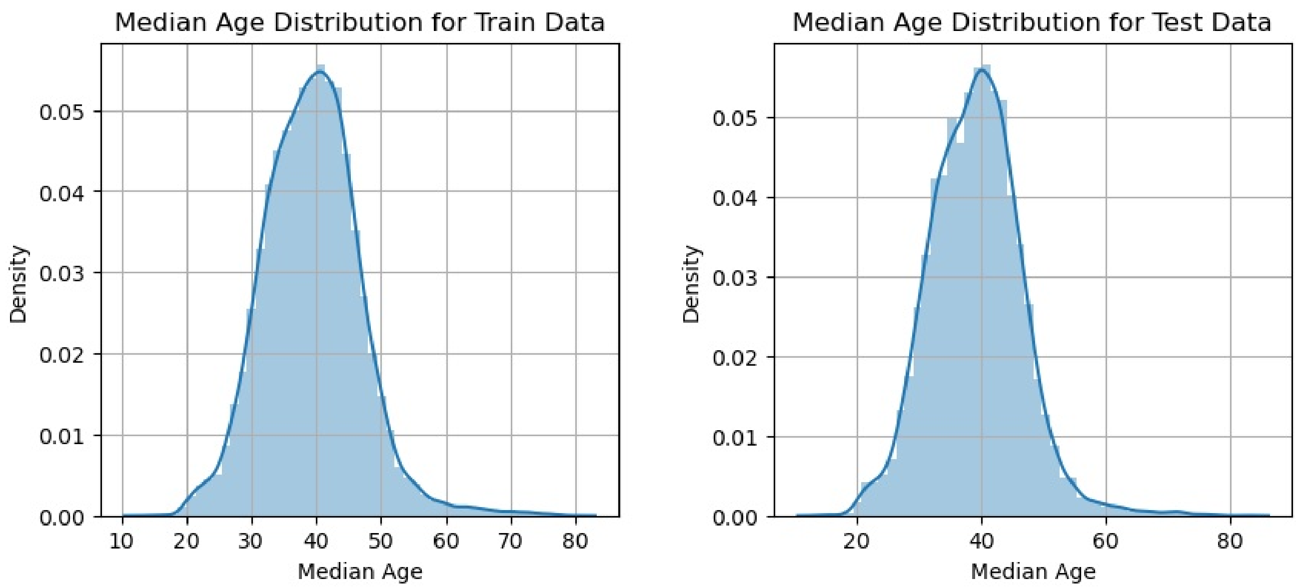
In [48]:
```
df_test['Median_age'] = (df_test['male_age_median'] * df_test['male_pop'] +
                        df_test['female_age_median'] * df_test['female_pop'])/df_test['pop']
df_test[['pop', 'Median_age']].head()
```

Out[48]:

UID	pop	Median_age
255504	3417	31.189053
252676	3796	46.382991
276314	3944	43.147420
248614	2508	45.155104
286865	6230	43.235983

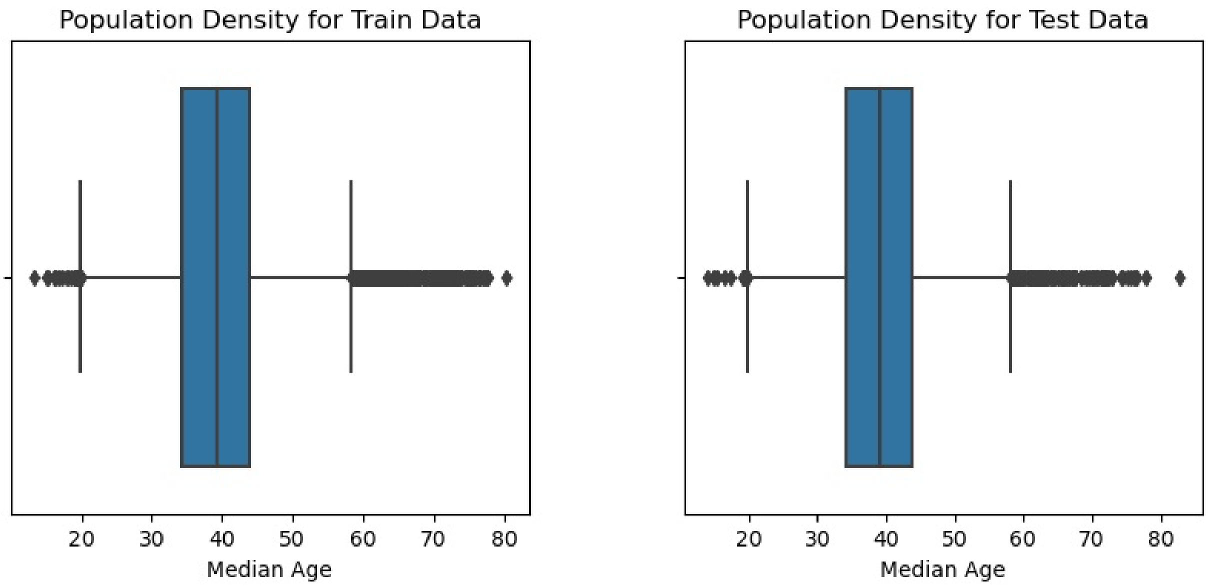
c) Visualize the findings using appropriate chart type

In [49]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.distplot(df_train['Median_age'])
plt.title("Median Age Distribution for Train Data")
plt.xlabel("Median Age")
plt.grid()
plt.subplot(1,2,2)
sns.distplot(df_test['Median_age'])
plt.title("Median Age Distribution for Test Data")
plt.xlabel("Median Age")
plt.grid()
plt.subplots_adjust(wspace= 0.30)
plt.show()
```



- Age ranges from 18 years to 75 years.
- The majority belongs to 40 years.
- Little right skewness is observed.

In [50]:
```
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
sns.boxplot(df_train['Median_age'])
plt.title("Population Density for Train Data")
plt.xlabel("Median Age")
plt.subplot(1,2,2)
sns.boxplot(df_test['Median_age'])
plt.title("Population Density for Test Data")
plt.xlabel("Median Age")
plt.subplots_adjust(wspace= 0.30)
plt.show()
```



2. Create bins for population into a new variable by selecting appropriate class interval so that the number of categories don’t exceed 5 for the ease of analysis.

In [51]:
```
df_train['pop'].describe()
```

Out[51]:
```
count    26585.000000
mean      4367.763438
std       2093.787018
min         63.000000
25%       2938.000000
50%       4078.000000
75%       5456.000000
max      53812.000000
Name: pop, dtype: float64
```

In [52]:
```
df_train['pop_bins'] = pd.cut(df_train['pop'], bins = 5, labels = ['Very Low', 'Low', 'Medium', 'High', 'Very Hi
```

In [53]:
```
df_test['pop_bins'] = pd.cut(df_test['pop'], bins = 5, labels = ['Very Low', 'Low', 'Medium', 'High', 'Very Higl
```

In [54]:
```
df_train[['pop', 'pop_bins']]
```

Out[54]:

UID	pop	pop_bins
267822	5230	Very Low
246444	2633	Very Low
245683	6881	Very Low
279653	2700	Very Low
247218	5637	Very Low
...	...	...
279212	1847	Very Low
277856	4155	Very Low
233000	2829	Very Low
287425	11542	Low
265371	3726	Very Low

26585 rows × 2 columns

In [55]:
```
df_test[['pop', 'pop_bins']]
```

Out[55]:

UID	pop	pop_bins
255504	3417	Very Low
252676	3796	Very Low
276314	3944	Very Low
248614	2508	Very Low
286865	6230	Low
...	...	...
238088	5611	Very Low
242811	2695	Very Low
250127	7392	Low
241096	5945	Low
287763	4117	Very Low

11355 rows × 2 columns

In [56]:
```
df_train.pop_bins.value_counts()
```

Out[56]:
```
Very Low     26334
Low            238
Medium           9
High             3
Very High        1
Name: pop_bins, dtype: int64
```

In [57]:
```
df_test.pop_bins.value_counts()
```

Out[57]:
```
Very Low     8977
Low          2306
Medium         58
High           11
Very High       3
Name: pop_bins, dtype: int64
```

a) Analyze the married, separated, and divorced population for these population brackets

In [58]:
```
df_train.groupby(by = 'pop_bins')[['married', 'separated', 'divorced']].count()
```

Out[58]:

pop_bins	married	separated	divorced
Very Low	26334	26334	26334
Low	238	238	238
Medium	9	9	9
High	3	3	3
Very High	1	1	1

In [59]:
```
df_train.groupby(by = 'pop_bins')[['married', 'separated', 'divorced']].agg(['mean', 'median'])
```

Out[59]:

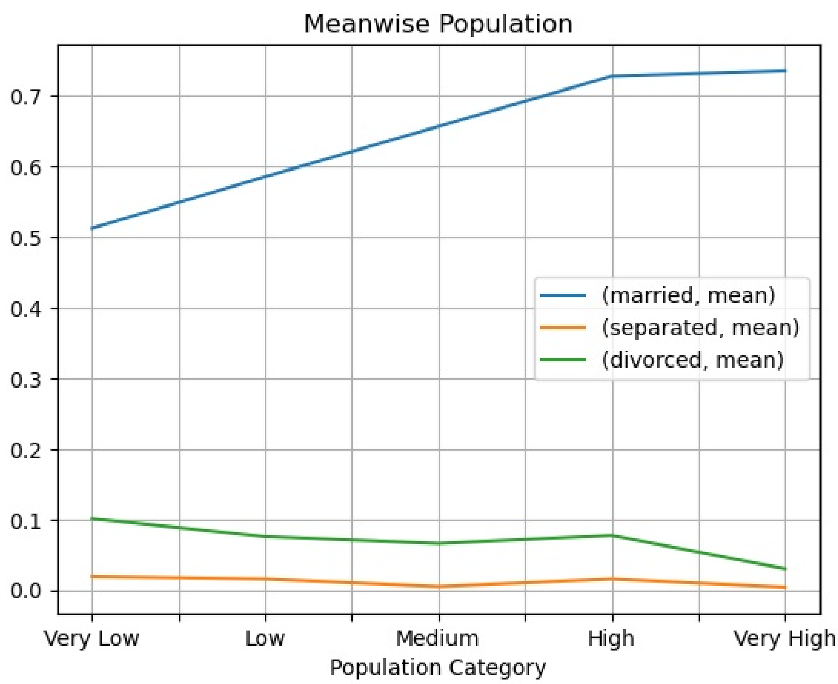
	married		separated		divorced	
	mean	median	mean	median	mean	median
pop_bins						
Very Low	0.511869	0.528105	0.019017	0.01351	0.101048	0.096090
Low	0.584691	0.592575	0.015655	0.01106	0.075749	0.070565
Medium	0.655737	0.618710	0.005003	0.00412	0.065927	0.064890
High	0.726957	0.736060	0.015663	0.00916	0.077310	0.063050
Very High	0.734740	0.734740	0.004050	0.00405	0.030360	0.030360

- In the Very Low population group, there are more divorced people as compared to the rest of the population category.
- Very High population group has highest number of married people, lowest number of separated as well as lowest number of divorced people as compared to the rest of the population category.

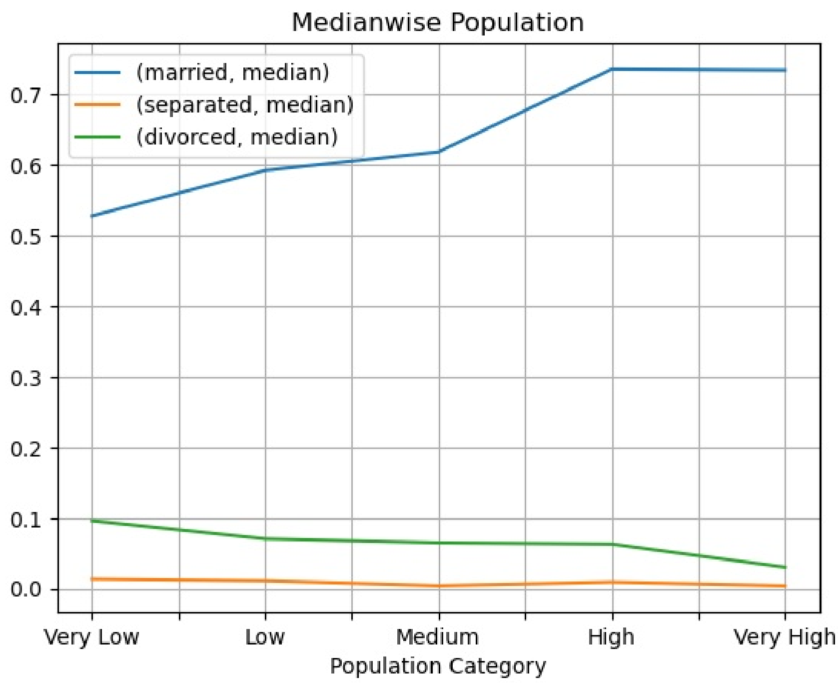
b) Visualize using appropriate chart type

In [60]:
```
pop_bin_mean = df_train.groupby(by = 'pop_bins')[['married', 'separated', 'divorced']].agg(['mean'])
pop_bin_median = df_train.groupby(by = 'pop_bins')[['married', 'separated', 'divorced']].agg(['median'])
```

In [61]:
```
pop_bin_mean.plot(title = "Meanwise Population")
plt.xlabel("Population Category")
plt.legend(loc = "best")
plt.grid()
plt.show()
```



In [62]:
```
pop_bin_median.plot(title = "Medianwise Population")
plt.xlabel("Population Category")
plt.legend(loc = "best")
plt.grid()
plt.show()
```



3. Please detail your observations for rent as a percentage of income at an overall level, and for different states.

In [63]:
```
df_train[['state','rent_mean', 'rent_median']]
```

Out[63]:

UID	state	rent_mean	rent_median
267822	New York	769.38638	784.0
246444	Indiana	804.87924	848.0
245683	Indiana	742.77365	703.0
279653	Puerto Rico	803.42018	782.0
247218	Kansas	938.56493	881.0
...	...	...	...
279212	Puerto Rico	439.42839	419.0
277856	Pennsylvania	1813.19253	1788.0
233000	Colorado	849.39107	834.0
287425	Texas	1972.45746	1843.0
265371	Nevada	949.84199	924.0

26585 rows × 3 columns

In [64]:
```
rent_state = df_train.groupby(by = 'state')['rent_mean'].mean()
rent_state.head()
```

Out[64]:
```
state
Alabama        768.810406
Alaska        1173.830410
Arizona       1101.133798
Arkansas       715.367386
California    1479.363998
Name: rent_mean, dtype: float64
```

In [65]:
```
income_state = df_train.groupby(by = 'state')['family_mean'].mean()
income_state.head()
```

Out[65]:
```
state
Alabama       66814.665178
Alaska        92504.826703
Arizona       73546.551858
Arkansas      64046.416919
California    88438.468548
Name: family_mean, dtype: float64
```

In [66]:
```
overall_percentage = rent_state/income_state
overall_percentage.head()
```

Out[66]:
```
state
Alabama       0.011507
Alaska        0.012689
Arizona       0.014972
Arkansas      0.011170
California    0.016728
dtype: float64
```

In [67]:
```
# Overall percentage
(df_train['rent_mean'].sum()/df_train['family_mean'].sum())*100
```

Out[67]:
```
1.329892795119824
```

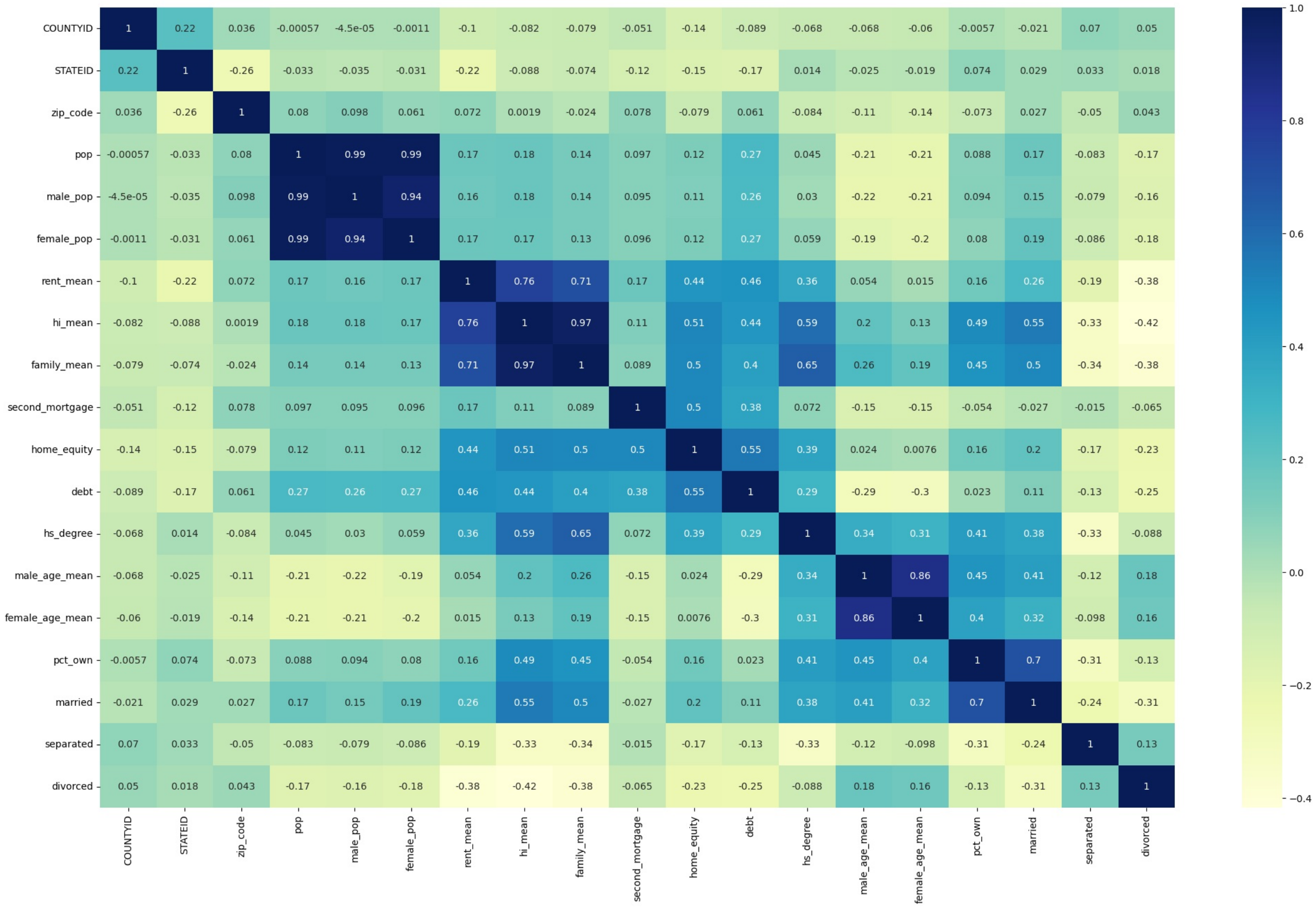
4. Perform correlation analysis for all the relevant variables by creating a heatmap. Describe your findings.

In [68]:
```
df_train.columns
```

Out[68]:
```
Index(['COUNTYID', 'STATEID', 'state', 'state_ab', 'city', 'place', 'type',
       'zip_code', 'area_code', 'lat', 'lng', 'ALand', 'AWater', 'pop',
       'male_pop', 'female_pop', 'rent_mean', 'rent_median', 'rent_stdev',
       'rent_sample_weight', 'rent_samples', 'rent_gt_10', 'rent_gt_15',
       'rent_gt_20', 'rent_gt_25', 'rent_gt_30', 'rent_gt_35', 'rent_gt_40',
       'rent_gt_50', 'universe_samples', 'used_samples', 'hi_mean',
       'hi_median', 'hi_stdev', 'hi_sample_weight', 'hi_samples',
       'family_mean', 'family_median', 'family_stdev', 'family_sample_weight',
       'family_samples', 'hc_mortgage_mean', 'hc_mortgage_median',
       'hc_mortgage_stdev', 'hc_mortgage_sample_weight', 'hc_mortgage_samples',
       'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_sample_weight',
       'home_equity_second_mortgage', 'second_mortgage', 'home_equity', 'debt',
       'second_mortgage_cdf', 'home_equity_cdf', 'debt_cdf', 'hs_degree',
       'hs_degree_male', 'hs_degree_female', 'male_age_mean',
       'male_age_median', 'male_age_stdev', 'male_age_sample_weight',
       'male_age_samples', 'female_age_mean', 'female_age_median',
       'female_age_stdev', 'female_age_sample_weight', 'female_age_samples',
       'pct_own', 'married', 'married_snp', 'separated', 'divorced',
       'BAD_DEBT', 'BINS_OD', 'BINS_BD', 'GOOD_DEBT', 'Remaning_income',
       'pop_density', 'Median_age', 'pop_bins'],
      dtype='object')
```

In [69]:
```
cols_heatmap = df_train[['COUNTYID', 'STATEID', 'state', 'city', 'type', 'zip_code', 'pop', 'male_pop', 'female_
                        'rent_mean', 'hi_mean', 'family_mean', 'second_mortgage', 'home_equity', 'debt','hs_deg
                        'male_age_mean', 'female_age_mean', 'pct_own', 'married', 'separated', 'divorced',]].co
```

In [70]:
```
plt.figure(figsize=(25,15))
sns.heatmap(cols_heatmap, annot=True, cmap='YlGnBu')
plt.show()
```



- Very High Positive Correlation is observed between
    - male_pop, female_pop & pop
    - family_mean & hi_mean
    - family_age_mean & male_age_mean
- High Positive Correlation is observed between
    - hi_mean & rent_mean
    - family_mean & rent_mean
    - hs_degree & family_mean
    - married & pct_own

Project Task: Week 3

Data Pre-processing:

1. The economic multivariate data has a significant number of measured variables. The goal is to find where the measured variables depend on a number of smaller unobserved common factors or latent variables.

2. Each variable is assumed to be dependent upon a linear combination of the common factors, and the coefficients are known as loadings. Each measured variable also includes a component due to independent random variability, known as "specific variance" because it is specific to one variable. Obtain the common factors and then plot the loadings. Use factor analysis to find latent variables in our dataset and gain insight into the linear relationships in the data. Following are the list of latent variables:

- `Highschool graduation rates`
- `Median population age`
- `Second mortgage statistics`
- `Percent own`
- `Bad debt expense`

In [71]:
```
from factor_analyzer import FactorAnalyzer
```

In [72]:
```
df_train.columns
```

Out[72]:
```
Index(['COUNTYID', 'STATEID', 'state', 'state_ab', 'city', 'place', 'type',
       'zip_code', 'area_code', 'lat', 'lng', 'ALand', 'AWater', 'pop',
       'male_pop', 'female_pop', 'rent_mean', 'rent_median', 'rent_stdev',
       'rent_sample_weight', 'rent_samples', 'rent_gt_10', 'rent_gt_15',
       'rent_gt_20', 'rent_gt_25', 'rent_gt_30', 'rent_gt_35', 'rent_gt_40',
       'rent_gt_50', 'universe_samples', 'used_samples', 'hi_mean',
       'hi_median', 'hi_stdev', 'hi_sample_weight', 'hi_samples',
       'family_mean', 'family_median', 'family_stdev', 'family_sample_weight',
       'family_samples', 'hc_mortgage_mean', 'hc_mortgage_median',
       'hc_mortgage_stdev', 'hc_mortgage_sample_weight', 'hc_mortgage_samples',
       'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_sample_weight',
       'home_equity_second_mortgage', 'second_mortgage', 'home_equity', 'debt',
       'second_mortgage_cdf', 'home_equity_cdf', 'debt_cdf', 'hs_degree',
       'hs_degree_male', 'hs_degree_female', 'male_age_mean',
       'male_age_median', 'male_age_stdev', 'male_age_sample_weight',
       'male_age_samples', 'female_age_mean', 'female_age_median',
       'female_age_stdev', 'female_age_sample_weight', 'female_age_samples',
       'pct_own', 'married', 'married_snp', 'separated', 'divorced',
       'BAD_DEBT', 'BINS_OD', 'BINS_BD', 'GOOD_DEBT', 'Remaning_income',
       'pop_density', 'Median_age', 'pop_bins'],
      dtype='object')
```

In [73]:
```
fa_df_train = df_train.select_dtypes(exclude=('category', 'object'))
```

In [74]:
```
fa_df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26585 entries, 267822 to 265371
Data columns (total 76 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   COUNTYID                     26585 non-null  int64  
 1   STATEID                      26585 non-null  int64  
 2   zip_code                     26585 non-null  int64  
 3   area_code                    26585 non-null  int64  
 4   lat                          26585 non-null  float64
 5   lng                          26585 non-null  float64
 6   ALand                        26585 non-null  float64
 7   AWater                       26585 non-null  int64  
 8   pop                          26585 non-null  int64  
 9   male_pop                     26585 non-null  int64  
 10  female_pop                   26585 non-null  int64  
 11  rent_mean                    26585 non-null  float64
 12  rent_median                  26585 non-null  float64
 13  rent_stdev                   26585 non-null  float64
 14  rent_sample_weight           26585 non-null  float64
 15  rent_samples                 26585 non-null  float64
 16  rent_gt_10                   26585 non-null  float64
 17  rent_gt_15                   26585 non-null  float64
 18  rent_gt_20                   26585 non-null  float64
 19  rent_gt_25                   26585 non-null  float64
 20  rent_gt_30                   26585 non-null  float64
 21  rent_gt_35                   26585 non-null  float64
 22  rent_gt_40                   26585 non-null  float64
 23  rent_gt_50                   26585 non-null  float64
 24  universe_samples             26585 non-null  int64  
 25  used_samples                 26585 non-null  int64  
 26  hi_mean                      26585 non-null  float64
 27  hi_median                    26585 non-null  float64
 28  hi_stdev                     26585 non-null  float64
 29  hi_sample_weight             26585 non-null  float64
 30  hi_samples                   26585 non-null  float64
 31  family_mean                  26585 non-null  float64
 32  family_median                26585 non-null  float64
 33  family_stdev                 26585 non-null  float64
 34  family_sample_weight         26585 non-null  float64
 35  family_samples               26585 non-null  float64
 36  hc_mortgage_mean             26585 non-null  float64
 37  hc_mortgage_median           26585 non-null  float64
 38  hc_mortgage_stdev            26585 non-null  float64
 39  hc_mortgage_sample_weight    26585 non-null  float64
 40  hc_mortgage_samples          26585 non-null  float64
 41  hc_mean                      26585 non-null  float64
 42  hc_median                    26585 non-null  float64
 43  hc_stdev                     26585 non-null  float64
 44  hc_samples                   26585 non-null  float64
 45  hc_sample_weight             26585 non-null  float64
 46  home_equity_second_mortgage  26585 non-null  float64
 47  second_mortgage              26585 non-null  float64
 48  home_equity                  26585 non-null  float64
 49  debt                         26585 non-null  float64
 50  second_mortgage_cdf          26585 non-null  float64
 51  home_equity_cdf              26585 non-null  float64
 52  debt_cdf                     26585 non-null  float64
 53  hs_degree                    26585 non-null  float64
 54  hs_degree_male               26585 non-null  float64
 55  hs_degree_female             26585 non-null  float64
 56  male_age_mean                26585 non-null  float64
 57  male_age_median              26585 non-null  float64
 58  male_age_stdev               26585 non-null  float64
 59  male_age_sample_weight       26585 non-null  float64
 60  male_age_samples             26585 non-null  float64
 61  female_age_mean              26585 non-null  float64
 62  female_age_median            26585 non-null  float64
 63  female_age_stdev             26585 non-null  float64
 64  female_age_sample_weight     26585 non-null  float64
 65  female_age_samples           26585 non-null  float64
 66  pct_own                      26585 non-null  float64
 67  married                      26585 non-null  float64
 68  married_snp                  26585 non-null  float64
 69  separated                    26585 non-null  float64
 70  divorced                     26585 non-null  float64
 71  BAD_DEBT                     26585 non-null  float64
 72  GOOD_DEBT                    26585 non-null  float64
 73  Remaning_income              26585 non-null  float64
 74  pop_density                  26585 non-null  float64
 75  Median_age                   26585 non-null  float64
dtypes: float64(66), int64(10)
memory usage: 15.6 MB
```

In [75]:
```python
#Creating FactorAnalyzer object and performing factor analysis
fa = FactorAnalyzer(n_factors=25, rotation=None)
fa.fit_transform(fa_df_train)
loadings = fa.loadings_

#Checking Eigenvalues
ev, v = fa.get_eigenvalues()
ev
```

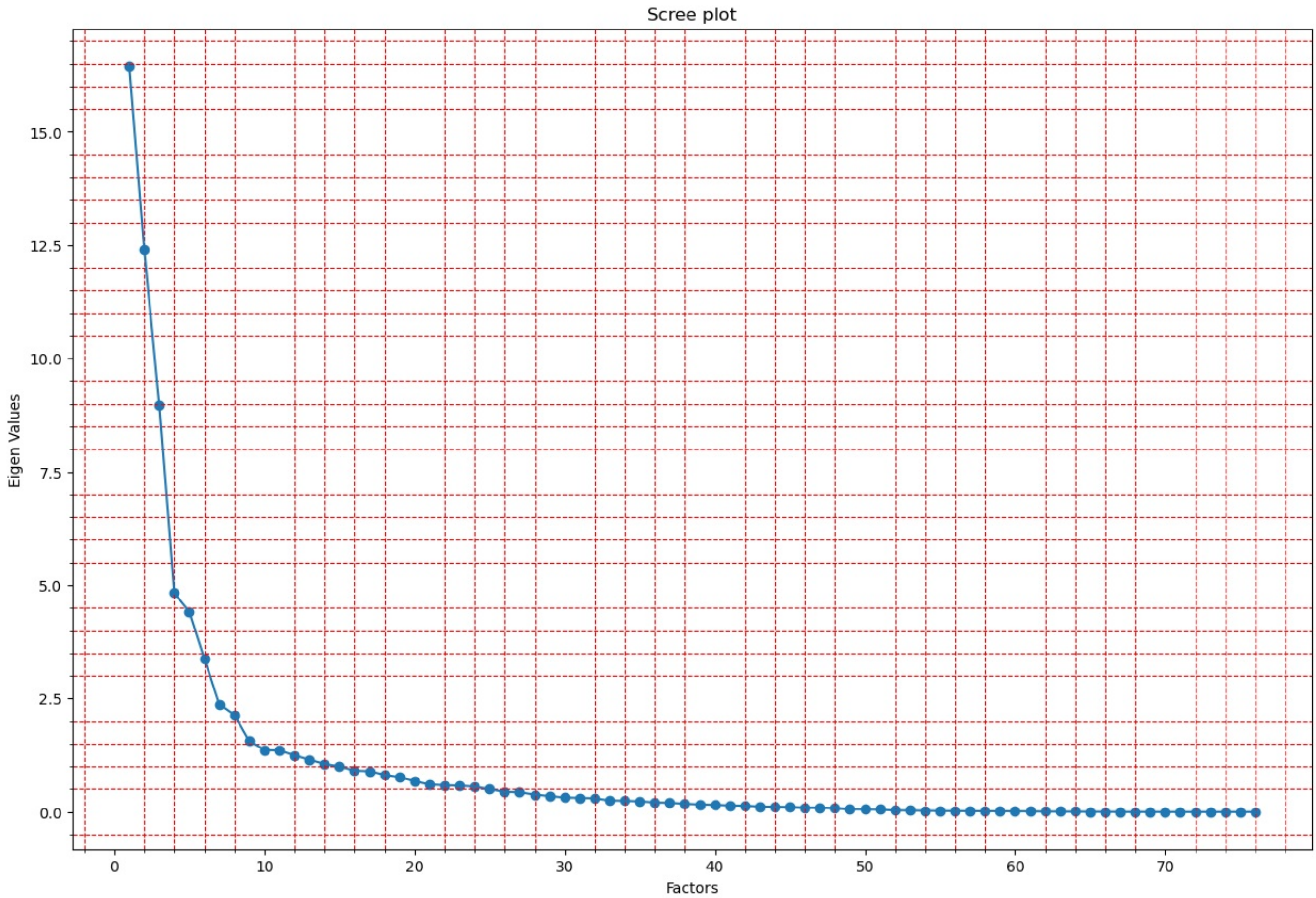
Out[75]:
```
array([ 1.64501148e+01,  1.24030533e+01,  8.97275988e+00,  4.82727495e+00,
        4.41962370e+00,  3.38627145e+00,  2.37428417e+00,  2.13727698e+00,
        1.55751411e+00,  1.36381406e+00,  1.35566796e+00,  1.24811683e+00,
        1.14947852e+00,  1.05550496e+00,  1.00038367e+00,  9.07628682e-01,
        8.94817155e-01,  8.14675358e-01,  7.65526716e-01,  6.77394083e-01,
        6.05864840e-01,  5.87074096e-01,  5.80551737e-01,  5.56982551e-01,
        5.02233653e-01,  4.41424562e-01,  4.32444174e-01,  3.80558847e-01,
        3.47430797e-01,  3.13759836e-01,  3.07917477e-01,  2.96755983e-01,
        2.48148044e-01,  2.41685681e-01,  2.31477964e-01,  2.04300234e-01,
        1.97722934e-01,  1.76401829e-01,  1.60281026e-01,  1.51455296e-01,
        1.39304980e-01,  1.32498515e-01,  1.14040925e-01,  1.07609203e-01,
        1.03411124e-01,  9.13602308e-02,  9.06169709e-02,  7.99567607e-02,
        6.03726669e-02,  5.82364639e-02,  5.27144553e-02,  3.38775446e-02,
        3.17521110e-02,  2.81266062e-02,  2.27876143e-02,  2.10862680e-02,
        1.91096745e-02,  1.61396717e-02,  1.52777975e-02,  1.42064289e-02,
        1.17953170e-02,  8.22671465e-03,  6.61210078e-03,  5.38723042e-03,
        3.98041349e-03,  3.57107401e-03,  9.52446172e-04,  7.43395646e-04,
        5.92393085e-04,  3.43997631e-16,  2.66265617e-16,  2.26121051e-16,
        1.08834830e-16,  5.73952315e-17, -1.35508288e-16, -1.55325980e-16])
```

In [76]:
```python
print("Sorted:",sorted(ev, reverse=True))
print("\nSize:",ev.size)
print("\nSize:",fa_df_train.shape[1])
```

```
Sorted: [16.450114838545417, 12.40305327737094, 8.97275987782638, 4.827274951210276, 4.419623696403794, 3.38627
14520271235, 2.374284165973279, 2.1372769776442353, 1.5575141141043185, 1.3638140600039537, 1.3556679565518985,
1.2481168257496817, 1.1494785225148565, 1.0555049624856776, 1.000383669709866, 0.9076286824534584, 0.8948171548
744023, 0.8146753582956832, 0.7655267160358757, 0.677394083326619, 0.6058648396198004, 0.5870740961474066, 0.58
05517365962005, 0.5569825511053841, 0.5022336533490541, 0.4414245620008767, 0.43244417359095744, 0.380558847211
3495, 0.34743079715819264, 0.31375983577529487, 0.3079174765280145, 0.2967559828340237, 0.2481480441346208, 0.2
4168568055860046, 0.23147796370530083, 0.20430023400679853, 0.19772293437052163, 0.1764018288102684, 0.16028102
638291536, 0.15145529649502545, 0.13930498047410328, 0.13249851450801228, 0.11404092486141937, 0.10760920253096
72, 0.10341112380139938, 0.09136023075056879, 0.09061697093655742, 0.0799567606555546, 0.060372666910959064, 0.
05823646386647841, 0.05271445525119728, 0.033877544638451634, 0.0317521110232445, 0.028126606150349686, 0.02278
761429873255, 0.02108626799074645, 0.019109674520868977, 0.01613967168761339, 0.015277797503950728, 0.014206428
922813057, 0.011795316972700639, 0.008226714650811862, 0.006612100779063703, 0.005387230420946085, 0.0039804134
8923252, 0.003571074012018963, 0.0009524461722090671, 0.0007433956461345817, 0.0005923930845492011, 3.439976305
463639e-16, 2.662656174824726e-16, 2.2612105112295604e-16, 1.0883483011441228e-16, 5.739523147963836e-17, -1.35
5082876556648e-16, -1.553259804951645e-16]

Size: 76

Size: 76
```

In [77]:
```python
xval = range(1, fa_df_train.shape[1]+1)
```

In [78]:
```python
plt.figure(figsize=(15,10))
plt.title("Scree plot")
plt.xlabel("Factors")
plt.ylabel("Eigen Values")
plt.scatter(xval, ev)
plt.plot(xval, ev)
plt.grid(b=True, which='minor', color='r', linestyle='--')
plt.minorticks_on()
plt.show()
```



In [79]:
```
df_Factors  = pd.DataFrame.from_records(loadings)

df_Factors = df_Factors.add_prefix('Factor ')

df_Factors.index = fa_df_train.columns
df_Factors
```

Out[79]:

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	...	Factor 15
COUNTYID	-0.121467	0.023864	0.064159	-0.049338	0.043508	-0.072132	-0.064150	-0.000500	0.019670	0.083287	...	-0.041960
STATEID	-0.116626	-0.025949	0.174363	-0.084042	0.098171	0.007296	-0.386308	-0.106417	0.052836	0.008942	...	0.140697
zip_code	-0.041975	0.108943	-0.068539	-0.144379	-0.033195	-0.202175	0.749217	0.441724	0.114256	-0.109741	...	0.181417
area_code	0.014956	0.020605	-0.011753	0.024296	-0.005710	-0.084730	0.015043	-0.055767	-0.037316	0.035503	...	-0.009654
lat	0.189045	-0.105997	-0.067375	-0.175523	-0.049946	0.186421	-0.188249	0.083182	0.126231	-0.245474	...	0.238567
...	...	...	...	...	...	...	...	...	...	...	...	...
BAD_DEBT	0.650683	0.029018	-0.323422	-0.111934	-0.461837	0.303323	-0.002725	-0.166413	0.066974	-0.127652	...	0.040025
GOOD_DEBT	-0.650683	-0.029018	0.323422	0.111934	0.461837	-0.303323	0.002725	0.166413	-0.066974	0.127652	...	-0.040025
Remaning_income	0.353804	-0.157782	0.001032	0.159686	0.306825	0.286105	-0.112850	0.184142	0.283166	0.064099	...	-0.210747
pop_density	-0.009890	0.084188	-0.413661	0.098072	0.328215	0.082651	0.008607	-0.192113	-0.067117	0.021249	...	-0.042315
Median_age	0.320412	-0.377575	0.616295	0.401649	-0.046410	0.313298	0.185335	-0.067104	-0.180255	0.069782	...	0.004953

76 rows × 25 columns

In [80]:
```
fa = FactorAnalyzer(n_factors=12 ,rotation="varimax")
fa.fit(fa_df_train)
new_load = fa.loadings_
```

In [81]:
```
New_Factors = pd.DataFrame.from_records(new_load)
New_Factors = New_Factors.add_prefix("Factor ")
New_Factors.index = fa_df_train.columns
New_Factors
```

Out[81]:

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Fact
COUNTYID	-0.094306	0.016231	-0.067259	-0.026929	-0.032105	-0.004703	-0.143706	-0.002368	0.048996	-0.008294	-0.049634	-0.00
STATEID	-0.115687	-0.002394	-0.065692	-0.032880	-0.094090	0.082233	-0.147470	-0.057465	0.335893	-0.047756	-0.088017	0.08
zip_code	-0.044881	0.049550	-0.105693	0.014041	-0.034214	0.003868	-0.069760	0.050855	-0.894686	-0.026567	0.012577	0.01
area_code	0.041746	0.030346	-0.017843	-0.054318	-0.004943	-0.075285	-0.030787	0.009855	0.004289	0.050287	-0.001366	-0.01
lat	0.079279	-0.110047	-0.077106	0.051019	-0.074011	0.251972	0.181171	0.046492	0.093402	-0.086824	0.079223	0.10
...	...	...	...	...	...	...	...	...	...	...	...	
BAD_DEBT	0.361262	0.045864	-0.017889	-0.041039	-0.026821	0.153037	0.846767	0.311941	0.026378	0.066470	0.070511	-0.02
GOOD_DEBT	-0.361262	-0.045864	0.017889	0.041039	0.026821	-0.153037	-0.846767	-0.311941	-0.026378	-0.066470	-0.070511	0.02
Remaning_income	0.371282	-0.101728	0.158945	0.193463	0.025081	0.355310	0.014490	-0.055318	0.059092	-0.085131	-0.216458	0.00
pop_density	0.255545	-0.060181	-0.114827	0.393536	0.084184	-0.271423	-0.038532	-0.021890	0.105213	0.027958	0.061886	-0.11
Median_age	0.133890	-0.072269	0.946916	-0.202673	-0.070110	0.111837	0.026530	-0.036789	0.032941	-0.038426	-0.024761	0.11

76 rows × 12 columns

In [82]:
```
New_Factors.columns
```

Out[82]:
```
Index(['Factor 0', 'Factor 1', 'Factor 2', 'Factor 3', 'Factor 4', 'Factor 5',
       'Factor 6', 'Factor 7', 'Factor 8', 'Factor 9', 'Factor 10',
       'Factor 11'],
      dtype='object')
```

In [83]:
```
New_Factors_df = round(New_Factors.loc[['hs_degree', 'hs_degree_male', 'hs_degree_female',"male_age_median", "fe
                                 "home_equity_second_mortgage", 'second_mortgage','second_mortgage_cdf','pct_own
```

In [84]:
```
def color_negative_red(value):
  """
  Colors elements in a dateframe
  green if positive and red if
  negative. Does not color NaN
  values.
  """

  if value < -0.6:
    color = 'red'
  elif value > 0.6:
    color = 'green'
  else:
    color = 'black'

  return 'color: %s' % color
```

In [85]:
```
New_Factors_df.style.applymap(color_negative_red)
```

Out[85]:

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Fa
hs_degree	0.000000	0.000000	0.000000	-0.000000	-0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.
hs_degree_male	0.000000	0.000000	0.000000	-0.000000	-0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.
hs_degree_female	0.000000	0.000000	0.000000	-0.000000	-0.000000	1.000000	0.000000	0.000000	0.000000	-0.000000	0.
male_age_median	0.000000	-0.000000	1.000000	-0.000000	-0.000000	0.000000	0.000000	-0.000000	0.000000	-0.000000	-0.
female_age_median	0.000000	-0.000000	1.000000	-0.000000	-0.000000	0.000000	0.000000	-0.000000	0.000000	-0.000000	-0.
home_equity_second_mortgage	0.000000	0.000000	-0.000000	0.000000	0.000000	-0.000000	0.000000	1.000000	-0.000000	0.000000	0.
second_mortgage	0.000000	0.000000	-0.000000	0.000000	0.000000	-0.000000	0.000000	1.000000	-0.000000	0.000000	0.
second_mortgage_cdf	-0.000000	-0.000000	0.000000	0.000000	0.000000	-0.000000	-0.000000	-1.000000	0.000000	-0.000000	-0.
pct_own	0.000000	0.000000	0.000000	-1.000000	-0.000000	0.000000	0.000000	0.000000	0.000000	-0.000000	-0.
BAD_DEBT	0.000000	0.000000	-0.000000	-0.000000	-0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.

We can see that 'Related parameters' are loading on Unique Factors

In [86]:
```
len(fa_df_train.columns)
```

Out[86]: 76

In [87]:
```
#Fetching the variance
fact_var = fa.get_factor_variance()
fact_var
```

Out[87]:
```
(array([12.32196237, 11.91316203,  5.58056077,  5.49365386,  4.74170788,
         3.78490369,  3.73084787,  2.75661873,  2.16353751,  1.90916053,
         1.76345868,  1.54623546]),
 array([0.16213108, 0.15675213, 0.07342843, 0.07228492, 0.06239089,
        0.04980136, 0.0490901 , 0.0362713 , 0.0284676 , 0.02512053,
        0.0232034 , 0.0203452 ]),
 array([0.16213108, 0.31888322, 0.39231165, 0.46459657, 0.52698746,
        0.57678882, 0.62587893, 0.66215023, 0.69061783, 0.71573836,
        0.73894176, 0.75928697]))
```

In [88]:
```
Factor_variance = pd.DataFrame.from_records(fact_var)
Factor_variance = Factor_variance.add_prefix("Factor ")
Factor_variance
```

Out[88]:

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Factor 11
0	12.321962	11.913162	5.580561	5.493654	4.741708	3.784904	3.730848	2.756619	2.163538	1.909161	1.763459	1.546235
1	0.162131	0.156752	0.073428	0.072285	0.062391	0.049801	0.049090	0.036271	0.028468	0.025121	0.023203	0.020345
2	0.162131	0.318883	0.392312	0.464597	0.526987	0.576789	0.625879	0.662150	0.690618	0.715738	0.738942	0.759287

In [89]:
```
Factor_variance.index = ['Loadings', 'Proportion Var', 'Cummulative Var']
round(Factor_variance,2)
```

Out[89]:

	Factor 0	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Factor 11
Loadings	12.32	11.91	5.58	5.49	4.74	3.78	3.73	2.76	2.16	1.91	1.76	1.55
Proportion Var	0.16	0.16	0.07	0.07	0.06	0.05	0.05	0.04	0.03	0.03	0.02	0.02
Cummulative Var	0.16	0.32	0.39	0.46	0.53	0.58	0.63	0.66	0.69	0.72	0.74	0.76

Project Task: Week 4

Data Modeling :

1. Build a linear Regression model to predict the total monthly expenditure for home mortgages loan. Please refer 'deplotment_RE.xlsx'. Column hc_mortgage_mean is predicted variable. This is the mean monthly mortgage and owner costs of specified geographical location. Note: Exclude loans from prediction model which have NaN (Not a Number) values for hc_mortgage_mean.

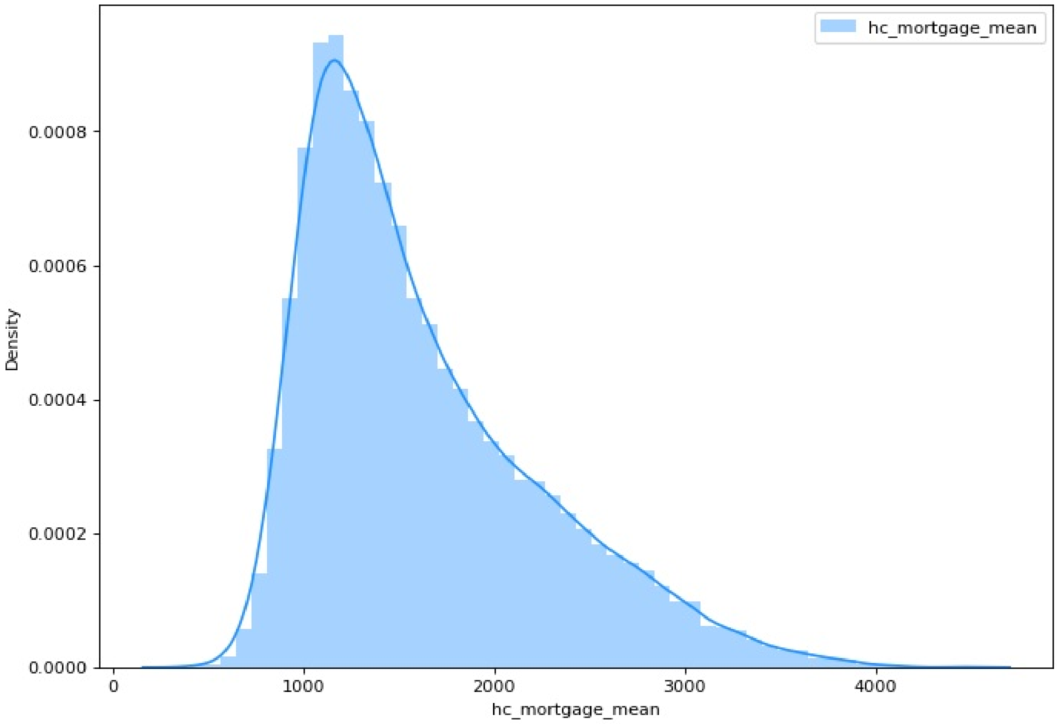
   a) Run a model at a Nation level. If the accuracy levels and R square are not satisfactory proceed to below step.

   b) Run another model at State level. There are 52 states in USA.

   c) Keep below considerations while building a linear regression model. Data Modeling :

   - `Variables should have significant impact on predicting Monthly mortgage and owner costs`
   - `Utilize all predictor variable to start with initial hypothesis`
   - `R square of 60 percent and above should be achieved`
   - `Ensure Multi-collinearity does not exist in dependent variables`
   - `Test if predicted variable is normally distributed`

In [90]:
```
plt.figure(figsize=(10,7), dpi= 80)
sns.distplot(df_train.hc_mortgage_mean, color="dodgerblue", label="hc_mortgage_mean")
plt.legend();
plt.show()
```



Target variable has a positive skewness

In [91]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error, accuracy_score
```

In [92]:
```
print(df_train.shape)
print(df_test.shape)
```

```
(26585, 84)
(11355, 79)
```

In [93]:
```
test_list = df_test.columns
lis = []
for col in df_train:
    if col not in test_list:
        lis.append(col)
lis
```

Out[93]:
```
['BAD_DEBT', 'BINS_OD', 'BINS_BD', 'GOOD_DEBT', 'Remaning_income']
```

In [94]:
```
print(df_train.shape)
df_train.drop(columns=['BAD_DEBT', 'BINS_OD', 'BINS_BD', 'GOOD_DEBT', 'Remaning_income'], inplace = True)
print(df_train.shape)
```

```
(26585, 84)
(26585, 79)
```

In [95]:
```
print(df_train.shape)
print(df_test.shape)
```

```
(26585, 79)
(11355, 79)
```

In [96]:
```
df_train[['hc_mortgage_mean']]
```

Out[96]:

UID	hc_mortgage_mean
267822	1414.80295
246444	864.41390
245683	1506.06758
279653	1175.28642
247218	1192.58759
...	...
279212	770.11560
277856	2210.84055
233000	1671.07908
287425	3074.83088
265371	1455.42340

26585 rows × 1 columns

In [97]:
```
df_train.dropna(axis = 0, inplace=True)
df_test.dropna(axis = 0, inplace=True)
```

In [98]:
```
print(df_train.shape)
print(df_test.shape)
```

```
(26585, 79)
(11355, 79)
```

In [99]:
```
feature_cols=['COUNTYID','STATEID','zip_code','pop', 'family_mean', 'second_mortgage', 'home_equity', 'debt','h
              'Median_age','pct_own', 'married','separated', 'divorced']
```

In [100…
```
week4_bck_train = df_train.copy()
week4_bck_test = df_test.copy()
```

In [101…
```
x_train = df_train[feature_cols]
y_train = df_train['hc_mortgage_mean']
x_test = df_test[feature_cols]
y_test = df_test['hc_mortgage_mean']
```

In [102…
```
from sklearn.preprocessing import StandardScaler
```

In [103…
```
x_train.describe()
```

Out[103]:

	COUNTYID	STATEID	zip_code	pop	family_mean	second_mortgage	home_equity	debt	hs_degree
count	26585.000000	26585.000000	26585.000000	26585.000000	26585.00000	26585.000000	26585.000000	26585.000000	26585.000000
mean	85.580440	28.256348	50134.895091	4367.763438	79282.24354	0.029876	0.100928	0.629911	0.859577
std	97.891735	16.370924	29492.900596	2093.787018	31125.02069	0.030664	0.065590	0.148977	0.110139
min	1.000000	1.000000	602.000000	63.000000	10706.26180	0.000000	0.000000	0.013590	0.186520
25%	29.000000	13.000000	27106.000000	2938.000000	57217.14016	0.008060	0.050450	0.539480	0.809700
50%	63.000000	27.000000	47905.000000	4078.000000	73119.26510	0.022730	0.094900	0.648080	0.889340
75%	109.000000	42.000000	77084.000000	5456.000000	96218.70699	0.042900	0.143680	0.736190	0.939040
max	840.000000	72.000000	99925.000000	53812.000000	208969.99390	0.608700	0.687500	0.978260	1.000000

In [104…
```
y_train.describe()
```

Out[104]:
```
count    26585.000000
mean      1627.898787
std        620.559056
min        402.681840
25%       1158.136460
50%       1459.286080
75%       1979.249110
max       4462.342290
Name: hc_mortgage_mean, dtype: float64
```

In [105…
```
sc = StandardScaler()
x_train_scaled = sc.fit_transform(x_train)
x_test_scaled =sc.fit_transform(x_test)
```

In [106…
```
x_train_scaled
```

Out[106]:
```
array([[-0.33282741,  0.47302145, -1.24740484, ...,  0.5043254 ,
        -0.32824767, -0.27477163],
       [ 0.56614179, -0.62650957, -0.11931554, ..., -1.25295184,
        -0.23547174, -0.22025652],
       [-0.23067182, -0.62650957, -0.13606565, ...,  1.03185291,
        -0.14518977,  0.12088226],
       ...,
       [ 0.0145016 , -1.23736014,  1.03478052, ...,  1.46847489,
        -0.68738034, -0.49660619],
       [ 3.6103784 ,  1.20604213,  0.87816361, ...,  1.85505293,
        -0.49035617, -1.01051593],
       [-0.84360537,  0.22868122,  1.32197368, ..., -1.28815095,
         0.55212616,  0.67924277]])
```

In [107…
```
x_test_scaled
```

Out[107]:
```
array([[ 0.77154843, -0.14787648, -0.06699701, ..., -1.71167277,
         0.94978465,  0.90847794],
       [-0.85528175, -0.32862972, -1.55088833, ...,  0.99225534,
        -0.95828531,  0.71431416],
       [-0.71469149,  0.81614082, -1.19158503, ...,  0.67232607,
        -0.27872617,  0.0086278 ],
       ...,
       [-0.77494446, -0.20812756, -1.63072977, ..., -0.05555059,
        -0.90424084, -0.56670348],
       [-0.59418555, -0.56963404,  0.03957057, ...,  1.17835505,
        -0.95828531, -1.11423691],
       [ 3.6837753 ,  1.17764731,  0.96113419, ...,  0.06859098,
         0.30275228,  0.12655808]])
```

Running a model at Nation Level.

In [108…
```
lr = LinearRegression()
```

In [109…
```
lr.fit(x_train_scaled, y_train)
```

Out[109]:
```
LinearRegression()
```

In [110…
```
y_pred = lr.predict(x_test_scaled)
```

In [111…
```
print("Overall R2 Score", r2_score(y_test, y_pred))
print("Overall RMSE", np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
Overall R2 Score 0.7513061476377627
Overall RMSE 314.79945199484854
```

R2 Score is 75% and RMSE is 314 which is good but we will still proceed with running the model at State Level

Running a model at state level

In [112…
```
uni_state = df_train.STATEID.unique()
uni_state[:10:2]
```

Out[112]:
```
array([36, 72,  1, 45,  5], dtype=int64)
```

In [113…
```
for i in [20, 1, 45]:
    print("*"*90)
    print("STATEID :", i)

    x_train_state = df_train[df_train.STATEID == i][feature_cols]
    y_train_state = df_train[df_train.STATEID == i]['hc_mortgage_mean']

    x_test_state = df_test[df_test.STATEID == i][feature_cols]
    y_test_state = df_test[df_test.STATEID == i]['hc_mortgage_mean']

    x_train_state_scaled = sc.fit_transform(x_train_state)
    x_test_state_scaled = sc.fit_transform(x_test_state)

    lr = LinearRegression()

    lr.fit(x_train_state_scaled, y_train_state)
    y_pred_state = lr.predict(x_test_state_scaled)

    print("Overall R2 Score for",i , ":", r2_score(y_test_state, y_pred_state))
    print("Overall RMSE for",i , ":", np.sqrt(mean_squared_error(y_test_state, y_pred_state)))
```

```
**************************************************************************************
STATEID : 20
Overall R2 Score for 20 : 0.8801114508360377
Overall RMSE for 20 : 143.41926392999306
**************************************************************************************
STATEID : 1
Overall R2 Score for 1 : 0.6729192403324948
Overall RMSE for 1 : 174.81015560089193
**************************************************************************************
STATEID : 45
Overall R2 Score for 45 : 0.7068418321829575
Overall RMSE for 45 : 181.52977719088605
```

Checking the Residuals

In [114…

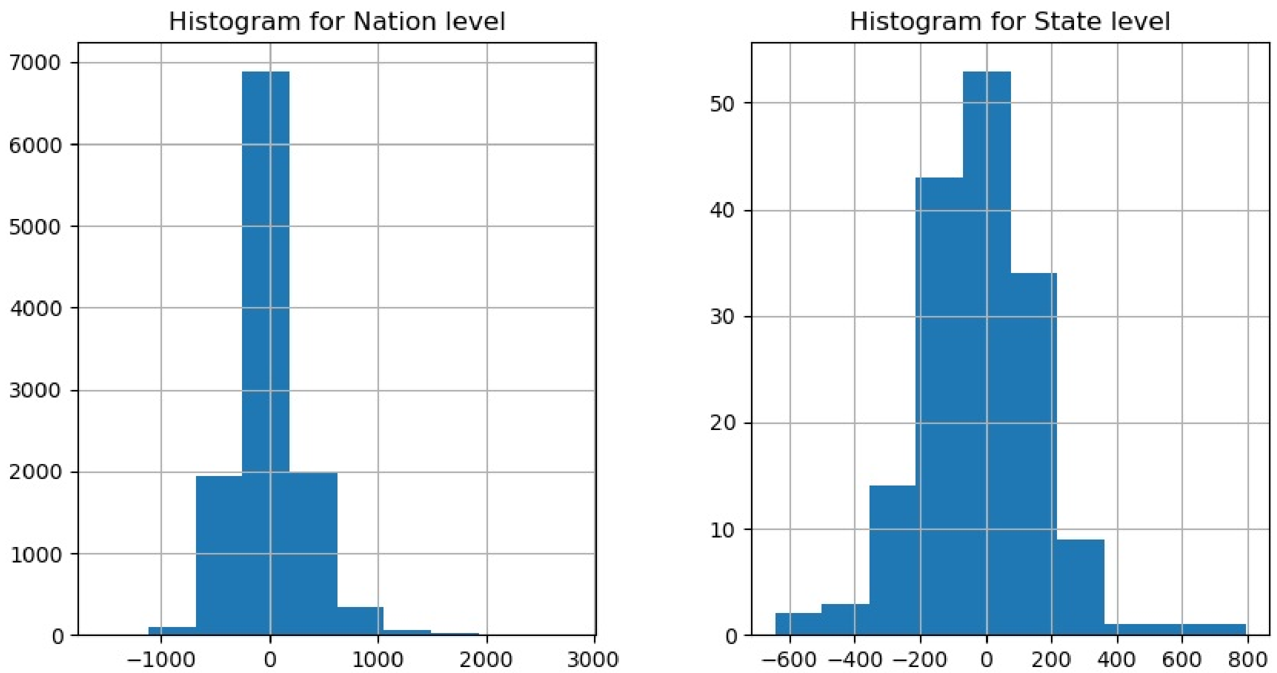
```
residuals = y_test - y_pred
residuals
```

Out[114]:

```
UID
255504    251.488994
252676     -7.849712
276314    107.468817
248614   -107.329935
286865    -54.941582
             ...
238088    -19.295706
242811   -163.964752
250127    -69.465187
241096   -274.083718
287763    222.932771
Name: hc_mortgage_mean, Length: 11355, dtype: float64
```

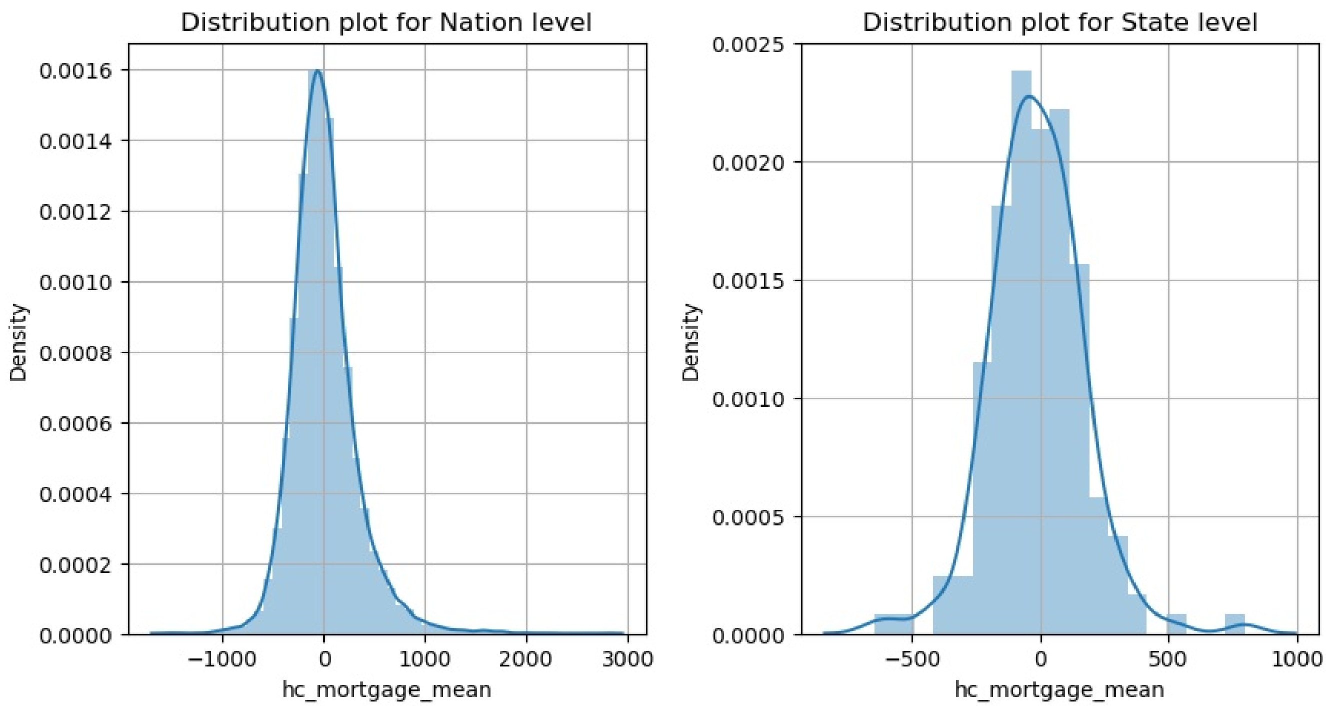
In [115…

```
plt.figure(figsize=(10,5))
plt.subplots_adjust(wspace=0.30)
plt.subplot(1,2,1)
plt.hist(residuals)
plt.grid()
plt.title("Histogram for Nation level")
plt.subplot(1,2,2)
plt.hist(y_test_state - y_pred_state)
plt.title("Histogram for State level")
plt.grid()
plt.show()
```

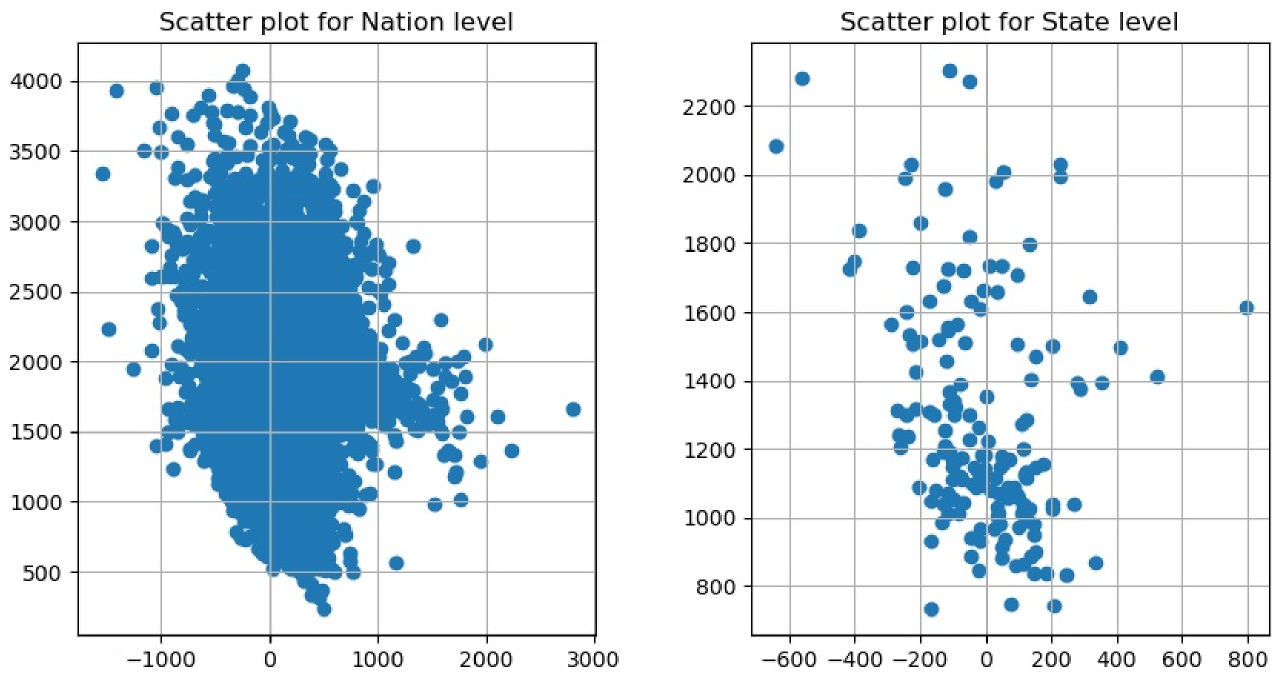


In [116…

```
plt.figure(figsize=(10,5))
plt.subplots_adjust(wspace=0.30)
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.grid()
plt.title("Distribution plot for Nation level")
plt.subplot(1,2,2)
sns.distplot(y_test_state - y_pred_state)
plt.title("Distribution plot for State level")
plt.grid()
plt.show()
```

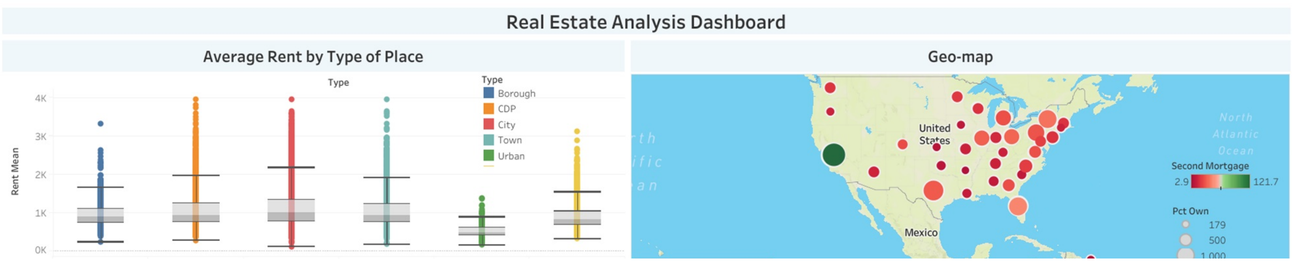


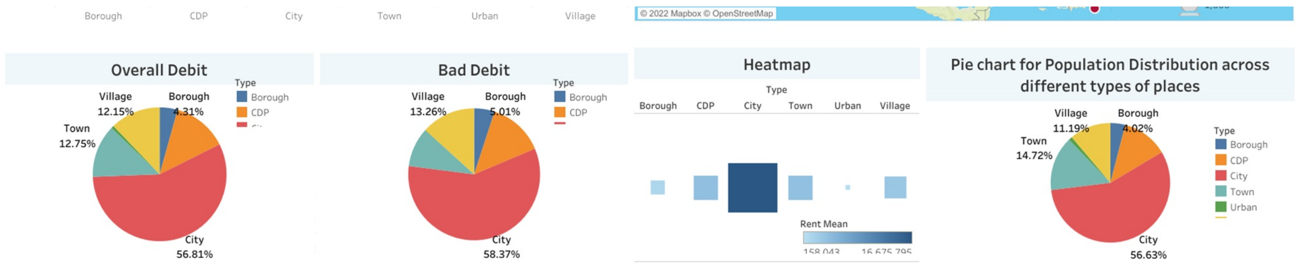

```
In [117…
plt.figure(figsize=(10,5))
plt.subplots_adjust(wspace=0.30)
plt.subplot(1,2,1)
plt.scatter(residuals, y_pred)
plt.grid()
plt.title("Scatter plot for Nation level")
plt.subplot(1,2,2)
plt.scatter((y_test_state - y_pred_state), y_pred_state)
plt.title("Scatter plot for State level")
plt.grid()
plt.show()
```



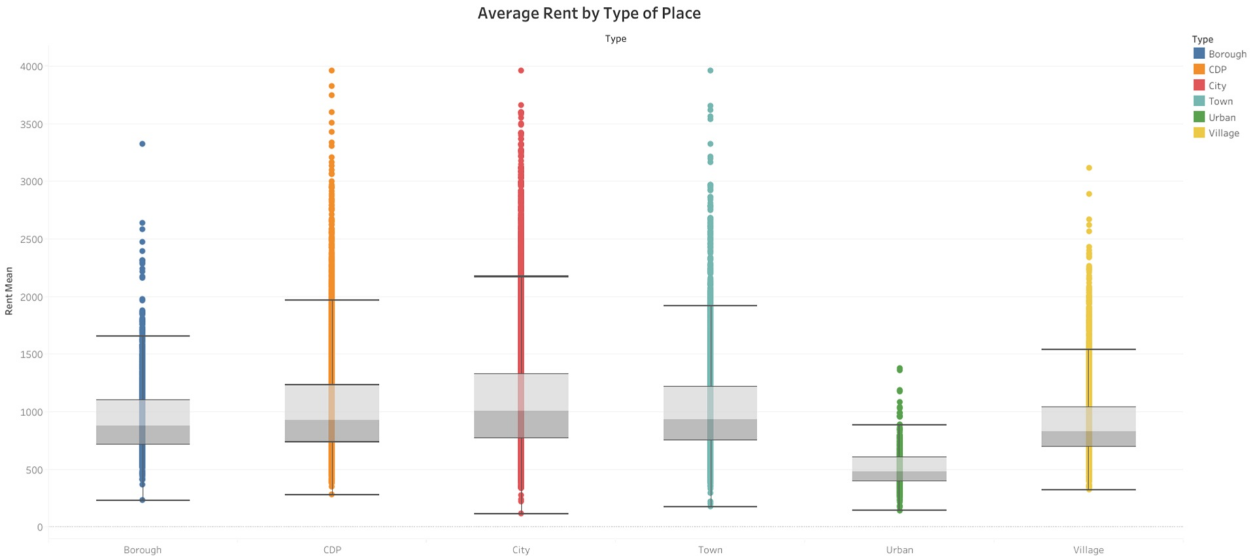
Data Reporting:

2. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

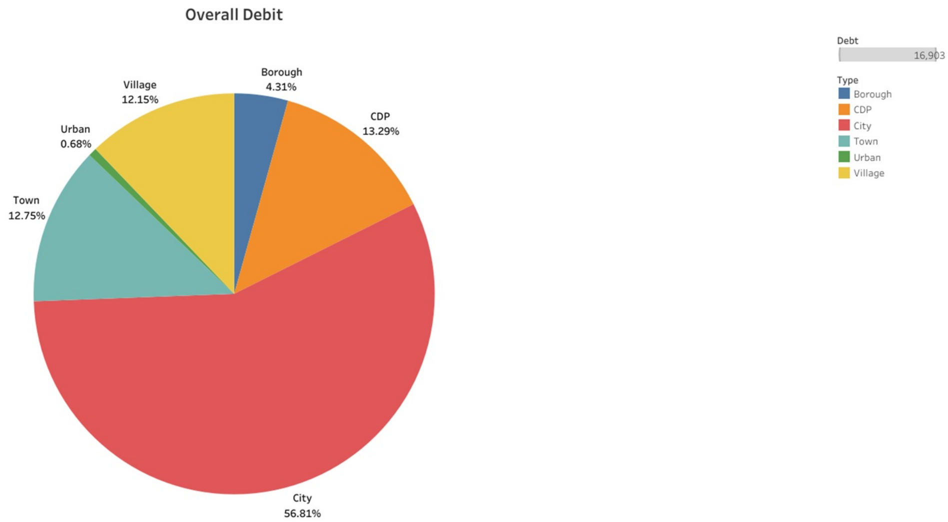


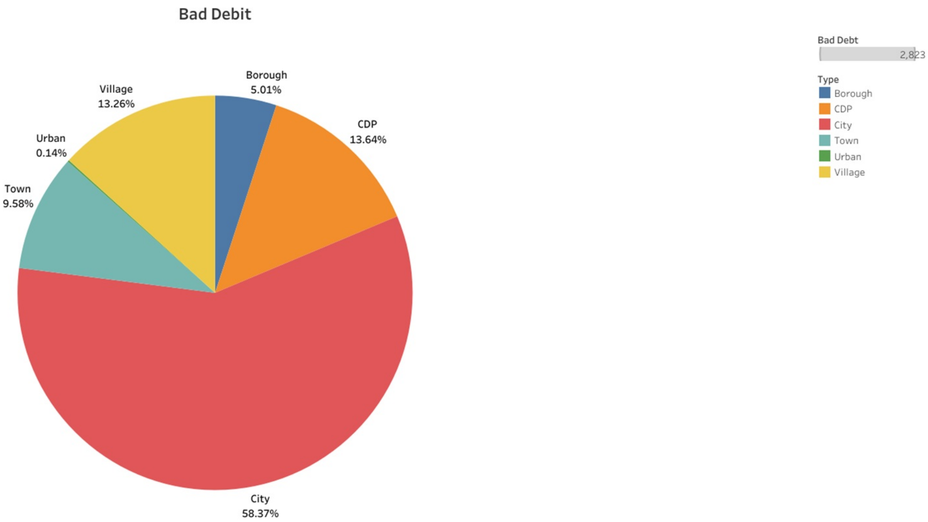


a) Box plot of distribution of average rent by type of place (village, urban, town, etc.).

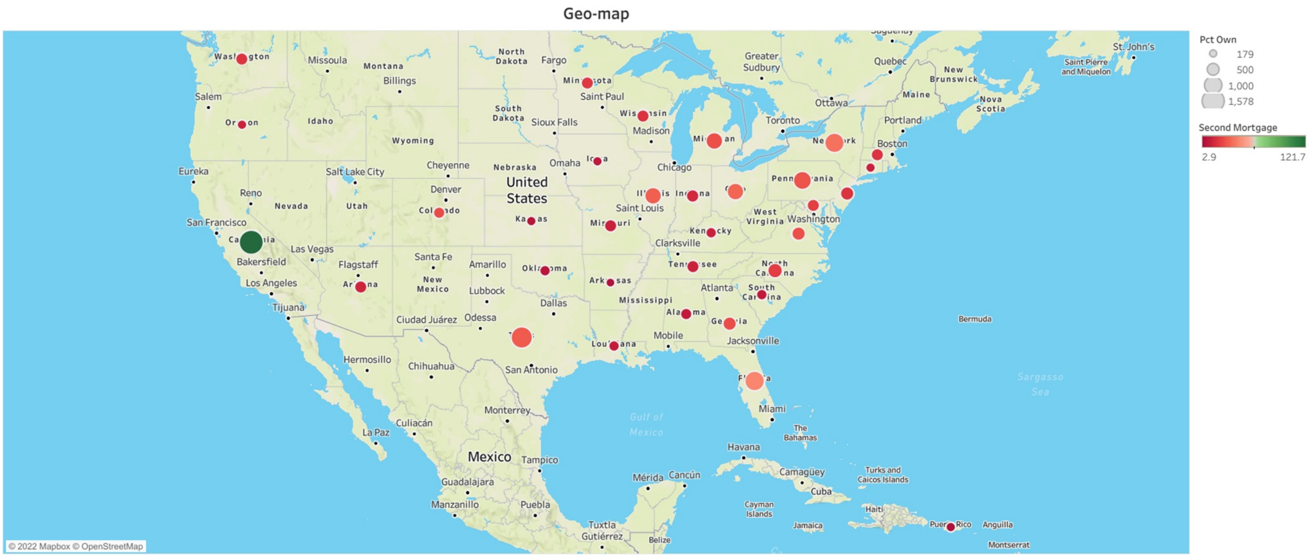


b) Pie charts to show overall debt and bad debt.

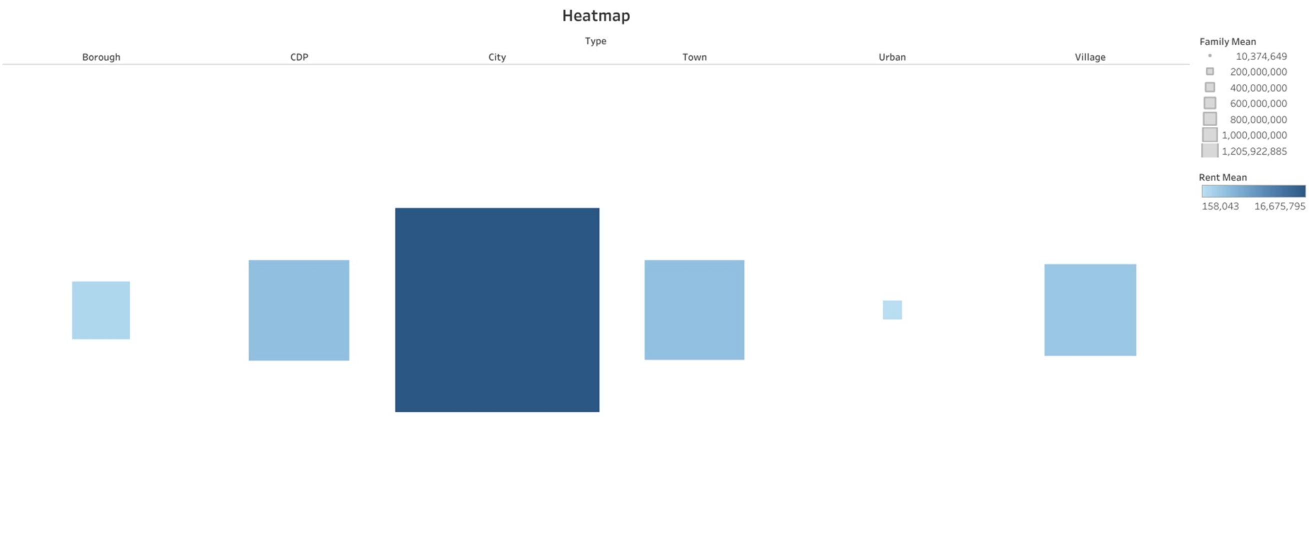




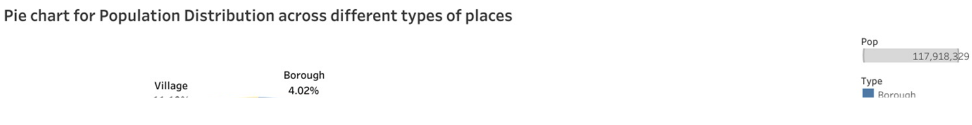
c) Explore the top 2,500 locations where the percentage of households with a second mortgage is the highest and percent ownership is above 10 percent. Visualize using geo-map.

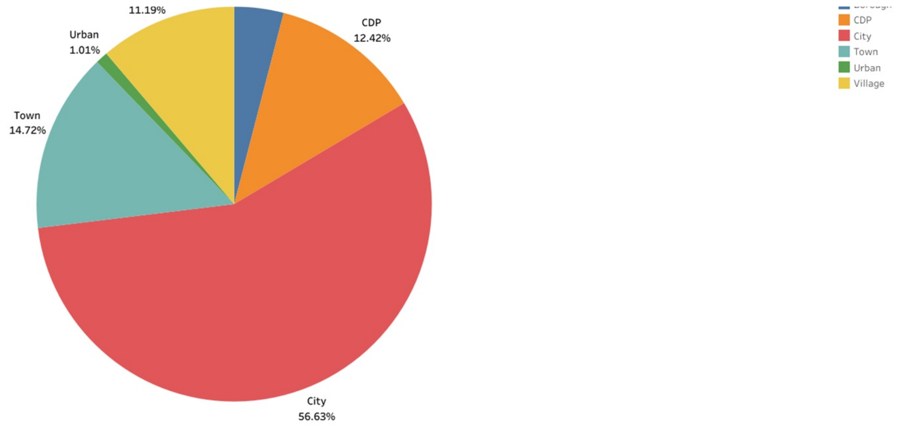


d) Heat map for correlation matrix.



e) Pie chart to show the population distribution across different types of places (village, urban, town etc.)





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