Problem Statement:

A banking institution requires actionable insights from the perspective of Mortgage-Backed Securities, Geographic Business Investment and Real Estate Analysis.

The objective is to identify white spaces/potential business in the mortgage loan. The mortgage bank would like to identify potential monthly mortgage expenses for each of region based on factors which are primarily monthly family income in a region and rented value of the real estate. Some of the regions are growing rapidly and Competitor banks are selling mortgage loans to subprime customers at a lower interest rate. The bank is strategizing for better market penetration and targeting new customers. A statistical model needs to be created to predict the potential demand in dollars amount of loan for each of the region in the USA. Also, there is a need to create a dashboard which would refresh periodically post data retrieval from the agencies. This would help to monitor the key metrics and trends.

The dashboard must demonstrate relationships and trends for the key metrics as follows: number of loans, average rental income, monthly mortgage and owner's cost, family income vs mortgage cost comparison across different regions. The metrics are described not to limit the dashboard to these few only.

Dataset Description

Following are the themes the fields fall under Home Owner Costs: Sum of utilities, property taxes.

☰ Second Mortgage: Households with a second mortgage statistics.

☰ Home Equity Loan: Households with a Home equity Loan statistics.

☰ Debt: Households with any type of debt statistics.

☰ Mortgage Costs: Statistics regarding mortgage payments, home equity loans, utilities and property taxes

☰ Home Owner Costs: Sum of utilities, property taxes statistics

☰ Gross Rent: Contract rent plus the estimated average monthly cost of utility features

☰ Gross Rent as Percent of Income Gross rent as the percent of income very interesting

☰ High school Graduation: High school graduation statistics.

☰ Population Demographics: Population demographic statistics.

☰ Age Demographics: Age demographic statistics.

☰ Household Income: Total income of people residing in the household.

☰ Family Income: Total income of people related to the householder

Project Task: Week 1

Import Required Libraries

In [1]:
```
import time
import random
from math import *
import operator
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
from pandas.plotting import scatter_matrix
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
```

Data Import and Preparation:

Import data.

In [2]:
```
df_train = pd.read_csv("train.csv")
```

In [3]:
```
df_test = pd.read_csv("test.csv")
```

In [4]:
```
df_train.head()
```

Out[4]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	p
0	267822	NaN	140	53	36	New York	NY	Hamilton	Ham
1	246444	NaN	140	141	18	Indiana	IN	South Bend	Rose
2	245683	NaN	140	63	18	Indiana	IN	Danville	Da
3	279653	NaN	140	127	72	Puerto Rico	PR	San Juan	Guay
4	247218	NaN	140	161	20	Kansas	KS	Manhattan	Manh

5 rows × 80 columns

In [5]:
```
df_train.shape
```

Out[5]:
```
(27321, 80)
```

In [6]:
```
df_test.head()
```

Out[6]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city
0	255504	NaN	140	163	26	Michigan	MI	Detroit
1	252676	NaN	140	1	23	Maine	ME	Auburn
2	276314	NaN	140	15	42	Pennsylvania	PA	Pine City
3	248614	NaN	140	231	21	Kentucky	KY	Monticello
4	286865	NaN	140	355	48	Texas	TX	Corpus Christi

5 rows × 80 columns

In [7]:
```
df_test.shape
```
Out[7]:
```
(11709, 80)
```

In [8]:
```
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 [9]:
```
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
```

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

In [10]:

```
#UID is the primary key

df_train.set_index(keys=['UID'], inplace=True)

df_test.set_index(keys=['UID'], inplace=True)
```

In [11]:

```
df_train.head(2)
```

Out[11]:

UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place
267822	NaN	140	53	36	New York	NY	Hamilton	Hamilton
246444	NaN	140	141	18	Indiana	IN	South Bend	Roseland

2 rows × 79 columns

In [12]:

```
df_test.head(2)
```

Out[12]:

UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place
255504	NaN	140	163	26	Michigan	MI	Detroit	Dearborn Heights City
252676	NaN	140	1	23	Maine	ME	Auburn	Auburn City

2 rows × 79 columns

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 [13]:

```
# percentage of missing values in train set
missing_list_train = df_train.isnull().sum()*100/len(df_train)

missing_values_df_train = pd.DataFrame(missing_list_train, columns=['Percen

missing_values_df_train.sort_values(by = ['Percentage_of_missing_values'],

missing_values_df_train[missing_values_df_train['Percentage_of_missing_valu
```

Out[13]:

	Percentage_of_missing_values
BLOCKID	100.000000
hc_samples	2.196113
hc_mean	2.196113
hc_median	2.196113
hc_stdev	2.196113
hc_sample_weight	2.196113
hc_mortgage_mean	2.097288

hc_mortgage_stdev	2.097288
hc_mortgage_sample_weight	2.097288
hc_mortgage_samples	2.097288
hc_mortgage_median	2.097288
home_equity_second_mortgage	1.672706
home_equity	1.672706
debt	1.672706
second_mortgage_cdf	1.672706
home_equity_cdf	1.672706
debt_cdf	1.672706
second_mortgage	1.672706
rent_gt_15	1.149299
rent_gt_50	1.149299
rent_gt_40	1.149299
rent_gt_35	1.149299
rent_gt_30	1.149299
rent_gt_25	1.149299
rent_gt_20	1.149299
rent_samples	1.149299
rent_gt_10	1.149299
rent_sample_weight	1.149299
rent_stdev	1.149299
rent_median	1.149299
rent_mean	1.149299
family_median	1.090736
family_samples	1.090736
family_sample_weight	1.090736
family_stdev	1.090736
family_mean	1.090736
hi_stdev	0.980930
hi_sample_weight	0.980930
hi_samples	0.980930
hi_median	0.980930
hi_mean	0.980930

pct_own	0.980930
hs_degree_female	0.816222
female_age_samples	0.753999
female_age_sample_weight	0.753999
female_age_stdev	0.753999
female_age_median	0.753999
female_age_mean	0.753999
hs_degree_male	0.732038
separated	0.699096
married_snp	0.699096
married	0.699096
divorced	0.699096
hs_degree	0.695436
male_age_stdev	0.691776
male_age_samples	0.691776
male_age_mean	0.691776
male_age_median	0.691776
male_age_sample_weight	0.691776

In [14]:
```
# percentage of missing values in test set
missing_list_test = df_test.isnull().sum()*100/len(df_train)

missing_values_df_test = pd.DataFrame(missing_list_test, columns=['Percenta

missing_values_df_test.sort_values(by = ['Percentage_of_missing_values'], 

missing_values_df_test[missing_values_df_test['Percentage_of_missing_value
```

Out[14]:

	Percentage_of_missing_values
BLOCKID	42.857143
hc_samples	1.061455
hc_mean	1.061455
hc_median	1.061455
hc_stdev	1.061455
hc_sample_weight	1.061455
hc_mortgage_mean	0.980930
hc_mortgage_stdev	0.980930

hc_mortgage_sample_weight	0.980930
hc_mortgage_samples	0.980930
hc_mortgage_median	0.980930
home_equity_second_mortgage	0.805241
home_equity	0.805241
debt	0.805241
second_mortgage_cdf	0.805241
home_equity_cdf	0.805241
debt_cdf	0.805241
second_mortgage	0.805241
rent_gt_20	0.545368
rent_gt_50	0.545368
rent_gt_40	0.545368
rent_gt_35	0.545368
rent_gt_30	0.545368
rent_gt_25	0.545368
rent_gt_10	0.545368
rent_gt_15	0.545368
rent_samples	0.541708
rent_sample_weight	0.541708
rent_stdev	0.541708
rent_median	0.541708
rent_mean	0.541708
family_median	0.497786
family_samples	0.497786
family_sample_weight	0.497786
family_stdev	0.497786
family_mean	0.497786
hi_stdev	0.446543
hi_median	0.446543
pct_own	0.446543
hi_mean	0.446543
hi_sample_weight	0.446543
hi_samples	0.446543

hs_degree_female	0.384320
female_age_mean	0.351378
female_age_sample_weight	0.351378
female_age_median	0.351378
female_age_stdev	0.351378
female_age_samples	0.351378
hs_degree_male	0.325757
hs_degree	0.311116
married_snp	0.307456
male_age_samples	0.307456
male_age_sample_weight	0.307456
male_age_stdev	0.307456
male_age_median	0.307456
male_age_mean	0.307456
married	0.307456
separated	0.307456
divorced	0.307456

BLOCKID has 100% missing values in train set, and 42% in test set we can drop it,dropping SUMLEVEL & primary too, as they are of no use for further exploration.

In [15]:
```
df_train.drop(columns=['BLOCKID','SUMLEVEL','primary'], inplace=True)
```

In [16]:
```
df_test.drop(columns=['BLOCKID','SUMLEVEL','primary'], inplace=True)
```

In [17]:
```
df_train.head(1)
```

Out[17]:

	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_co
UID									
267822	53	36	New York	NY	Hamilton	Hamilton	City	13346	3

1 rows × 76 columns

In [18]:
```
df_test.head(1)
```

Out[18]:

	COUNTYID	STATEID	state	state_ab	city	place	type	zip_code	area_
UID									
255504	163	26	Michigan	MI	Detroit	Dearborn Heights City	CDP	48239	

1 rows × 76 columns

In [19]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 27321 entries, 267822 to 265371
Data columns (total 76 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   COUNTYID                     27321 non-null  int64  
 1   STATEID                      27321 non-null  int64  
 2   state                        27321 non-null  object 
 3   state_ab                     27321 non-null  object 
 4   city                         27321 non-null  object 
 5   place                        27321 non-null  object 
 6   type                         27321 non-null  object 
 7   zip_code                     27321 non-null  int64  
 8   area_code                    27321 non-null  int64  
 9   lat                          27321 non-null  float64
 10  lng                          27321 non-null  float64
 11  ALand                        27321 non-null  float64
 12  AWater                       27321 non-null  int64  
 13  pop                          27321 non-null  int64  
 14  male_pop                     27321 non-null  int64  
 15  female_pop                   27321 non-null  int64  
 16  rent_mean                    27007 non-null  float64
 17  rent_median                  27007 non-null  float64
 18  rent_stdev                   27007 non-null  float64
 19  rent_sample_weight           27007 non-null  float64
 20  rent_samples                 27007 non-null  float64
 21  rent_gt_10                   27007 non-null  float64
 22  rent_gt_15                   27007 non-null  float64
 23  rent_gt_20                   27007 non-null  float64
 24  rent_gt_25                   27007 non-null  float64
 25  rent_gt_30                   27007 non-null  float64
 26  rent_gt_35                   27007 non-null  float64
 27  rent_gt_40                   27007 non-null  float64
 28  rent_gt_50                   27007 non-null  float64
 29  universe_samples             27321 non-null  int64  
 30  used_samples                 27321 non-null  int64  
 31  hi_mean                      27053 non-null  float64
 32  hi_median                    27053 non-null  float64
 33  hi_stdev                     27053 non-null  float64
 34  hi_sample_weight             27053 non-null  float64
 35  hi_samples                   27053 non-null  float64
 36  family_mean                  27023 non-null  float64
 37  family_median                27023 non-null  float64
 38  family_stdev                 27023 non-null  float64
 39  family_sample_weight         27023 non-null  float64
 40  family_samples               27023 non-null  float64
 41  hc_mortgage_mean             26748 non-null  float64
 42  hc_mortgage_median           26748 non-null  float64
 43  hc_mortgage_stdev            26748 non-null  float64
 44  hc_mortgage_sample_weight    26748 non-null  float64
 45  hc_mortgage_samples          26748 non-null  float64
 46  hc_mean                      26721 non-null  float64
 47  hc_median                    26721 non-null  float64
 48  hc_stdev                     26721 non-null  float64
 49  hc_samples                   26721 non-null  float64
 50  hc_sample_weight             26721 non-null  float64
 51  home_equity_second_mortgage  26864 non-null  float64
 52  second_mortgage              26864 non-null  float64
 53  home_equity                  26864 non-null  float64
 54  debt                         26864 non-null  float64
 55  second_mortgage_cdf          26864 non-null  float64
 56  home_equity_cdf              26864 non-null  float64
 57  debt_cdf                     26864 non-null  float64
 58  hs_degree                    27131 non-null  float64
 59  hs_degree_male               27121 non-null  float64
 60  hs_degree_female             27098 non-null  float64
 61  male_age_mean                27132 non-null  float64
 62  male_age_median              27132 non-null  float64
 63  male_age_stdev               27132 non-null  float64
 64  male_age_sample_weight       27132 non-null  float64
 65  male_age_samples             27132 non-null  float64
 66  female_age_mean              27115 non-null  float64
 67  female_age_median            27115 non-null  float64
 68  female_age_stdev             27115 non-null  float64
 69  female_age_sample_weight     27115 non-null  float64
 70  female_age_samples           27115 non-null  float64
 71  pct_own                      27053 non-null  float64
 72  married                      27130 non-null  float64
 73  married_snp                  27130 non-null  float64
 74  separated                    27130 non-null  float64
 75  divorced                     27130 non-null  float64
dtypes: float64(61), int64(10), object(5)
memory usage: 16.1+ MB
```

In [20]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11709 entries, 255504 to 287763
Data columns (total 76 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   COUNTYID                     11709 non-null  int64
 1   STATEID                      11709 non-null  int64
 2   state                        11709 non-null  object
 3   state_ab                     11709 non-null  object
 4   city                         11709 non-null  object
 5   place                        11709 non-null  object
 6   type                         11709 non-null  object
 7   zip_code                     11709 non-null  int64
 8   area_code                    11709 non-null  int64
 9   lat                          11709 non-null  float64
 10  lng                          11709 non-null  float64
 11  ALand                        11709 non-null  int64
 12  AWater                       11709 non-null  int64
 13  pop                          11709 non-null  int64
 14  male_pop                     11709 non-null  int64
 15  female_pop                   11709 non-null  int64
 16  rent_mean                    11561 non-null  float64
 17  rent_median                  11561 non-null  float64
 18  rent_stdev                   11561 non-null  float64
 19  rent_sample_weight           11561 non-null  float64
 20  rent_samples                 11561 non-null  float64
 21  rent_gt_10                   11560 non-null  float64
 22  rent_gt_15                   11560 non-null  float64
 23  rent_gt_20                   11560 non-null  float64
 24  rent_gt_25                   11560 non-null  float64
 25  rent_gt_30                   11560 non-null  float64
 26  rent_gt_35                   11560 non-null  float64
 27  rent_gt_40                   11560 non-null  float64
 28  rent_gt_50                   11560 non-null  float64
 29  universe_samples             11709 non-null  int64
 30  used_samples                 11709 non-null  int64
 31  hi_mean                      11587 non-null  float64
 32  hi_median                    11587 non-null  float64
 33  hi_stdev                     11587 non-null  float64
 34  hi_sample_weight             11587 non-null  float64
 35  hi_samples                   11587 non-null  float64
 36  family_mean                  11573 non-null  float64
 37  family_median                11573 non-null  float64
 38  family_stdev                 11573 non-null  float64
 39  family_sample_weight         11573 non-null  float64
 40  family_samples               11573 non-null  float64
 41  hc_mortgage_mean             11441 non-null  float64
 42  hc_mortgage_median           11441 non-null  float64
 43  hc_mortgage_stdev            11441 non-null  float64
 44  hc_mortgage_sample_weight    11441 non-null  float64
 45  hc_mortgage_samples          11441 non-null  float64
 46  hc_mean                      11419 non-null  float64
 47  hc_median                    11419 non-null  float64
 48  hc_stdev                     11419 non-null  float64
 49  hc_samples                   11419 non-null  float64
 50  hc_sample_weight             11419 non-null  float64
 51  home_equity_second_mortgage  11489 non-null  float64
 52  second_mortgage              11489 non-null  float64
 53  home_equity                  11489 non-null  float64
 54  debt                         11489 non-null  float64
 55  second_mortgage_cdf          11489 non-null  float64
 56  home_equity_cdf              11489 non-null  float64
 57  debt_cdf                     11489 non-null  float64
 58  hs_degree                    11624 non-null  float64
 59  hs_degree_male               11620 non-null  float64
 60  hs_degree_female             11604 non-null  float64
 61  male_age_mean                11625 non-null  float64
 62  male_age_median              11625 non-null  float64
 63  male_age_stdev               11625 non-null  float64
 64  male_age_sample_weight       11625 non-null  float64
 65  male_age_samples             11625 non-null  float64
 66  female_age_mean              11613 non-null  float64
 67  female_age_median            11613 non-null  float64
 68  female_age_stdev             11613 non-null  float64
 69  female_age_sample_weight     11613 non-null  float64
 70  female_age_samples           11613 non-null  float64
 71  pct_own                      11587 non-null  float64
 72  married                      11625 non-null  float64
 73  married_snp                  11625 non-null  float64
 74  separated                    11625 non-null  float64
 75  divorced                     11625 non-null  float64
dtypes: float64(60), int64(11), object(5)
memory usage: 6.9+ MB
```

In [21]:

```
missing_train_cols = []

for col in df_train.columns:
    if df_train[col].isnull().sum() != 0:
        missing_train_cols.append(col)

print(missing_train_cols)
```

```
['rent_mean', 'rent_median', 'rent_stdev', 'rent_sample_weight', 'rent_samp
les', 'rent_gt_10', 'rent_gt_15', 'rent_gt_20', 'rent_gt_25', 'rent_gt_30',
'rent_gt_35', 'rent_gt_40', 'rent_gt_50', 'hi_mean', 'hi_median', 'hi_stdev
', 'hi_sample_weight', 'hi_samples', 'family_mean', 'family_median', 'famil
y_stdev', 'family_sample_weight', 'family_samples', 'hc_mortgage_mean', 'hc
_mortgage_median', 'hc_mortgage_stdev', 'hc_mortgage_sample_weight', 'hc_mo
rtgage_samples', 'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_samp
le_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']
```

In [22]:

```
missing_test_cols = []

for col in df_test.columns:
    if df_test[col].isnull().sum() != 0:
        missing_test_cols.append(col)

print(missing_test_cols)
```

```
['rent_mean', 'rent_median', 'rent_stdev', 'rent_sample_weight', 'rent_samp
les', 'rent_gt_10', 'rent_gt_15', 'rent_gt_20', 'rent_gt_25', 'rent_gt_30',
'rent_gt_35', 'rent_gt_40', 'rent_gt_50', 'hi_mean', 'hi_median', 'hi_stdev
', 'hi_sample_weight', 'hi_samples', 'family_mean', 'family_median', 'famil
y_stdev', 'family_sample_weight', 'family_samples', 'hc_mortgage_mean', 'hc
_mortgage_median', 'hc_mortgage_stdev', 'hc_mortgage_sample_weight', 'hc_mo
rtgage_samples', 'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_samp
le_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']
```

Treating missing values by replacing it by mean as all the missing value col variables are numerical

In [23]:
```
for col in df_train.columns:
    if col in (missing_train_cols):
        df_train[col].replace(np.nan, df_train[col].mean(), inplace=True)
```

In [24]:
```
for col in df_test.columns:
    if col in (missing_test_cols):
        df_test[col].replace(np.nan, df_test[col].mean(), inplace=True)
```

In [25]:
```
df_train.isnull().sum().any()
```

Out[25]:
```
False
```

In [26]:
```
df_test.isnull().sum().any()
```

Out[26]:
```
False
```

Exploratory Data Analysis (EDA):

Perform debt analysis. You may take the following steps:

- 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

In [27]:
```
from pandasql import sqldf
q1 = "select place,pct_own,second_mortgage,lat,lng from df_train where pct_
pysqldf = lambda q: sqldf(q, globals())
df_train_location_mort_pct=pysqldf(q1)
```

In [28]:
```
df_train_location_mort_pct.head()
```

Out[28]:

	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

In [29]:
```
import plotly.express as px
import plotly.graph_objects as go
```

In [106…

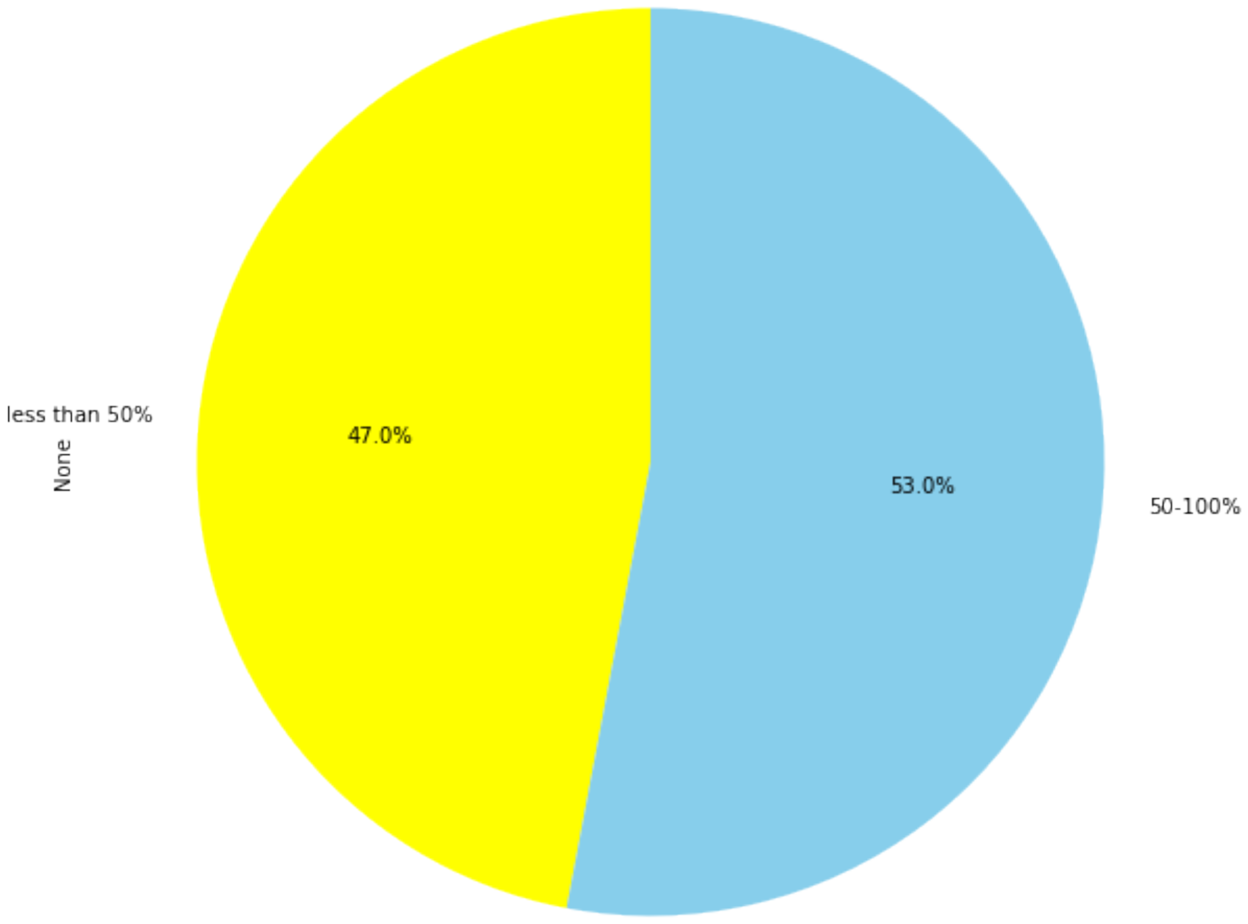
```
plt.figure(figsize=(15,30))
fig = go.Figure(data=go.Scattergeo(
    lat = df_train_location_mort_pct['lat'],
    lon = df_train_location_mort_pct['lng']),
    )
fig.update_layout(
    geo=dict(
        scope = 'north america',
        showland = True,
        landcolor = "rgb(212, 212, 212)",
        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 perc
fig.show()
```

```
<Figure size 1080x2160 with 0 Axes>
```

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

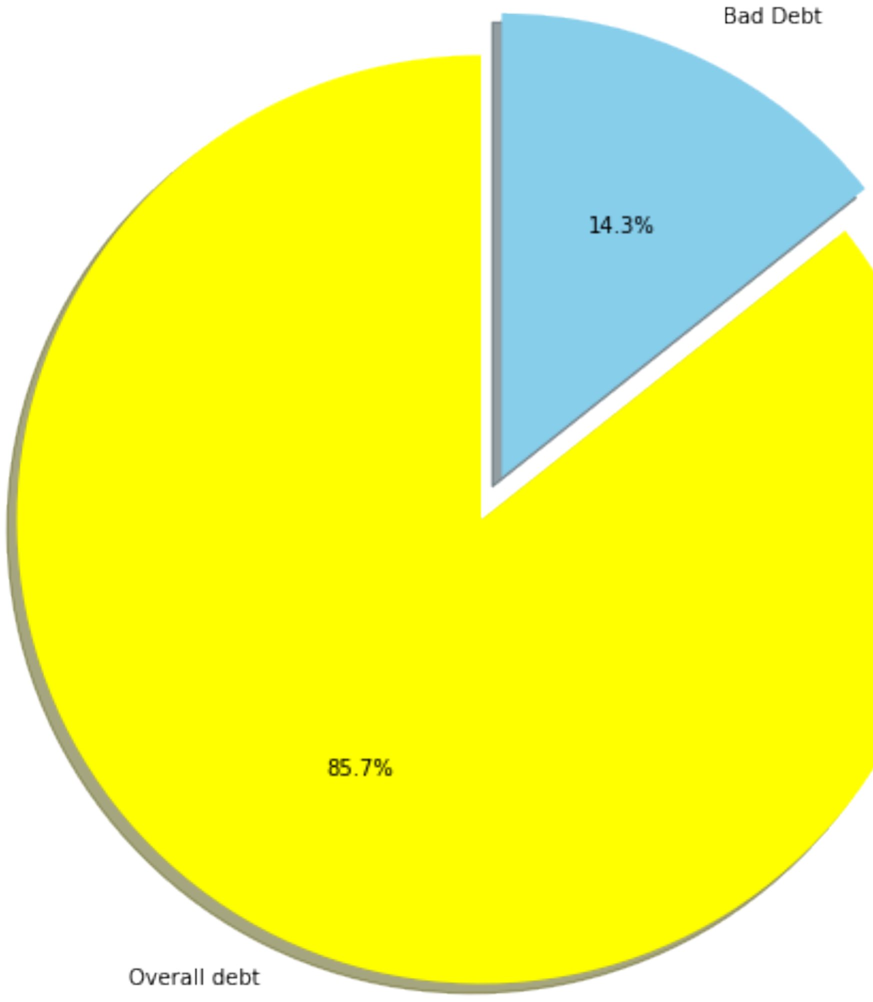
In [31]:
```
df_train["bad_debt"] = df_train['second_mortgage'] + df_train['home_equity
```

In [32]:
```
plt.figure(figsize=(15,10))
df_train['bins'] = pd.cut(df_train['bad_debt'],bins=[0,0.10,1], labels=["le
df_train.groupby(['bins']).size().plot(kind='pie', subplots=True,startangle
```



- Create pie charts to show overall debt and bad debt

In [33]:
```
plt.figure(figsize=(15,10))
label=["Overall debt","Bad Debt"]
values=[df_train["debt"].values.sum(),df_train["bad_debt"].values.sum()]
plt.pie(values,labels=label,autopct='%1.1f%%',explode=(0,.1),startangle=90
plt.show()
```



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

In [34]:
```
df_train['good_debt']=df_train['debt']-df_train['bad_debt']
```

In [35]:
```
df_train["city"].value_counts().sort_values(ascending=False)[:100]
```

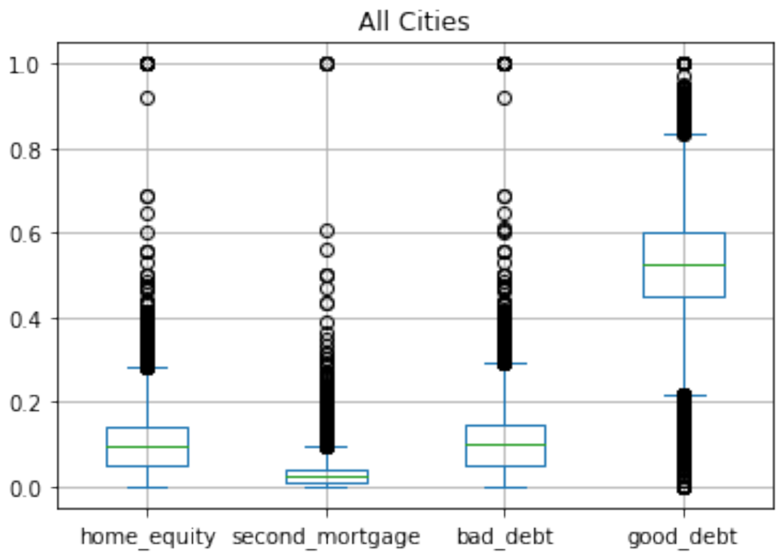
Out[35]:

```
Chicago          294
Brooklyn         282
Los Angeles      243
Houston          222
Philadelphia     165
                ...
Norfolk           32
Dayton            31
Staten Island     31
Manchester        31
Franklin          31
Name: city, Length: 100, dtype: int64
```

In [36]:

```
plt.figure(figsize=(15,10))
import matplotlib.pyplot as plt
all_cities=df_train[['home_equity','second_mortgage','bad_debt', 'good_debt
all_cities.plot.box(grid=True)
plt.title('All Cities')
plt.show()
```

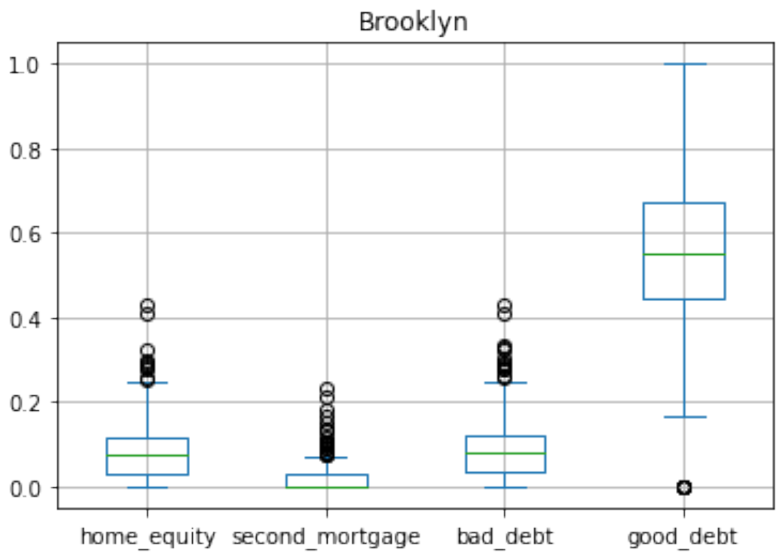
```
<Figure size 1080x720 with 0 Axes>
```



In [37]:

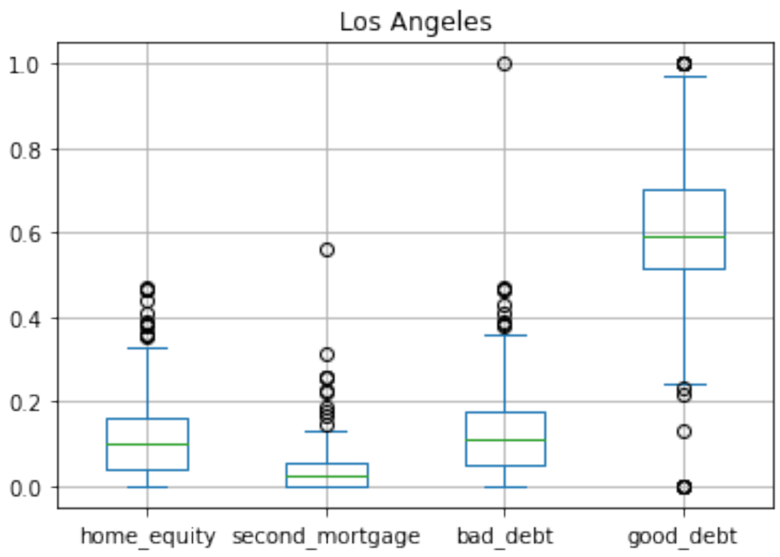
```
plt.figure(figsize=(15,10))
Brooklyn=df_train[df_train['city']=='Brooklyn']
Brooklyn=Brooklyn[['home_equity','second_mortgage','bad_debt', 'good_debt'
Brooklyn.plot.box(grid=True)
plt.title('Brooklyn')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



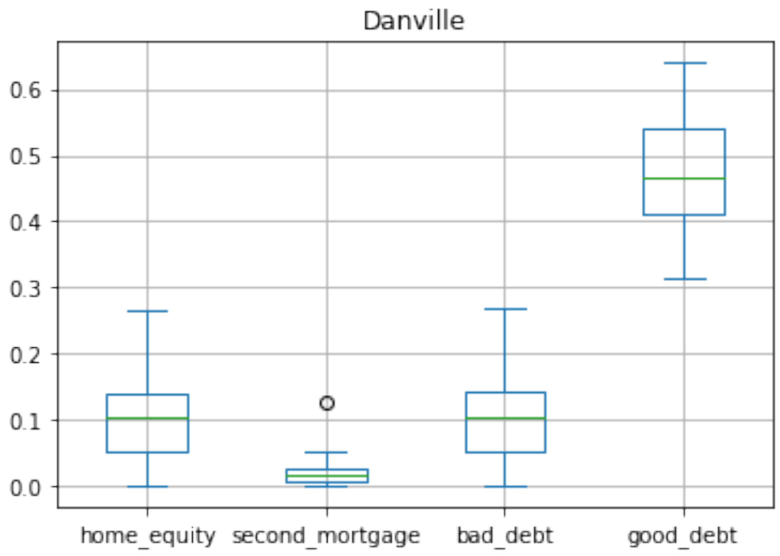
In [38]:
```
plt.figure(figsize=(15,10))
Los_Angeles  =df_train[df_train['city']=='Los Angeles']
Los_Angeles=Los_Angeles[['home_equity','second_mortgage','bad_debt', 'good_
Los_Angeles.plot.box(grid=True)
plt.title('Los Angeles')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



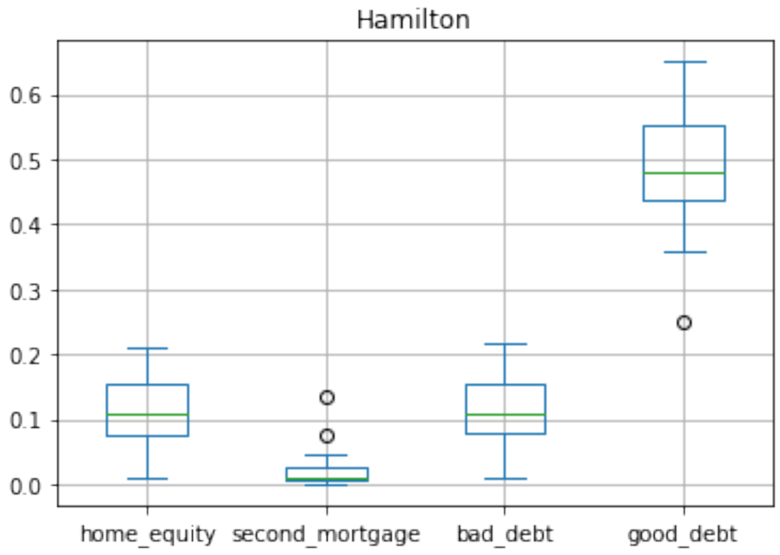
In [39]:
```
plt.figure(figsize=(15,10))
Danville=df_train[df_train['city']=='Danville']
Danville=Danville[['home_equity','second_mortgage','bad_debt', 'good_debt'
Danville.plot.box(grid=True)
plt.title('Danville')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



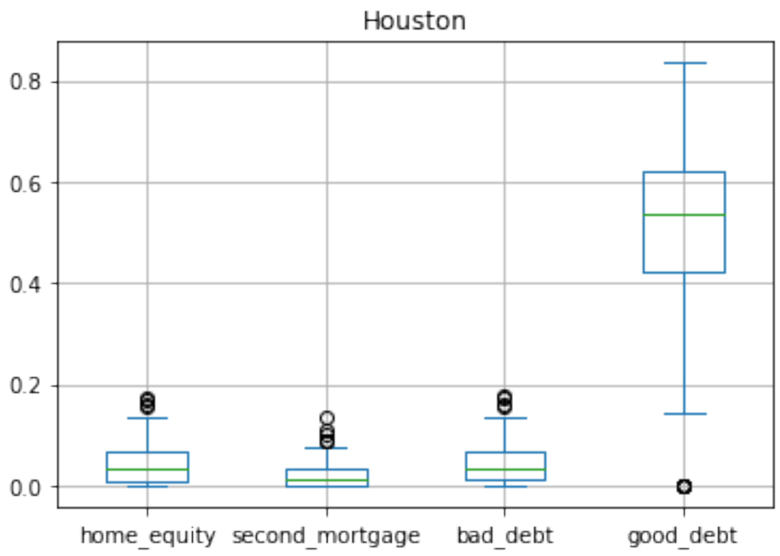
In [40]:
```
plt.figure(figsize=(15,10))
Hamilton=df_train[df_train['city']=='Hamilton']
Hamilton=Hamilton[['home_equity','second_mortgage','bad_debt', 'good_debt'
Hamilton.plot.box(grid=True)
plt.title('Hamilton')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



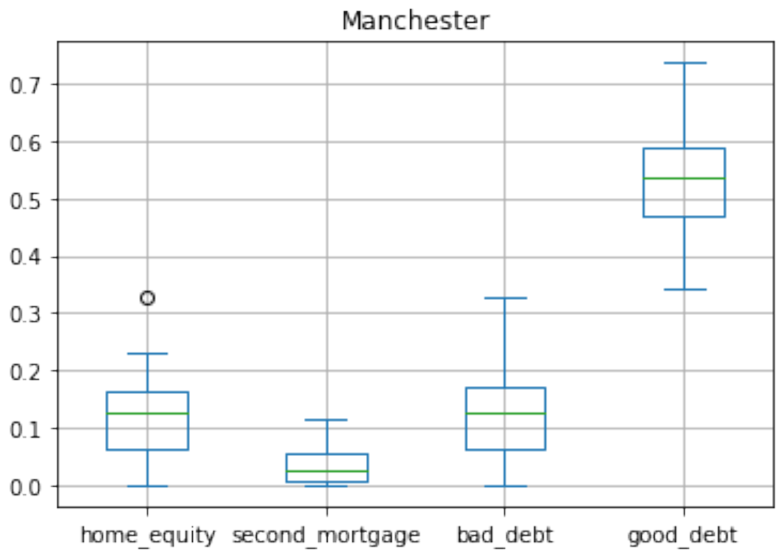
In [41]:
```
plt.figure(figsize=(15,10))
Houston  =df_train[df_train['city']=='Houston']
Houston=Houston[['home_equity','second_mortgage','bad_debt', 'good_debt']]
Houston.plot.box(grid=True)
plt.title('Houston')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



In [42]:
```
plt.figure(figsize=(15,10))
Manchester  =df_train[df_train['city']=='Manchester']
Manchester=Manchester[['home_equity','second_mortgage','bad_debt', 'good_de
Manchester.plot.box(grid=True)
plt.title('Manchester')
plt.show()
```

```
<Figure size 1080x720 with 0 Axes>
```



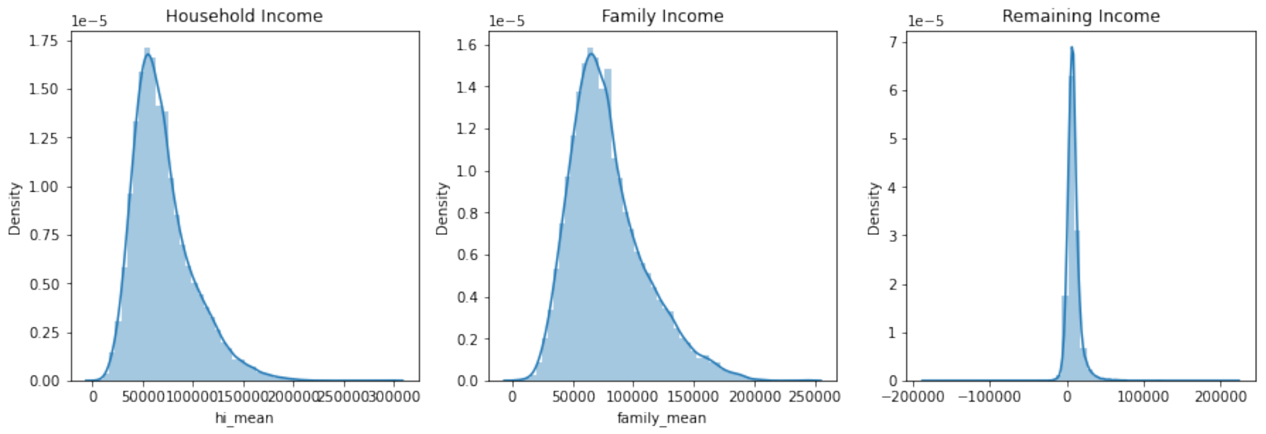
- Create a collated income distribution chart for family income, house hold income, and remaining income

In [43]:
```
plt.figure(figsize=(15,10))

plt.subplot(2,3,1)
sns.distplot(df_train['hi_mean'])
plt.title('Household Income')

plt.subplot(2,3,2)
sns.distplot(df_train['family_mean'])
plt.title('Family Income')

plt.subplot(2,3,3)
sns.distplot(df_train['family_mean']-df_train['hi_mean'])
plt.title('Remaining Income')
plt.show()
```



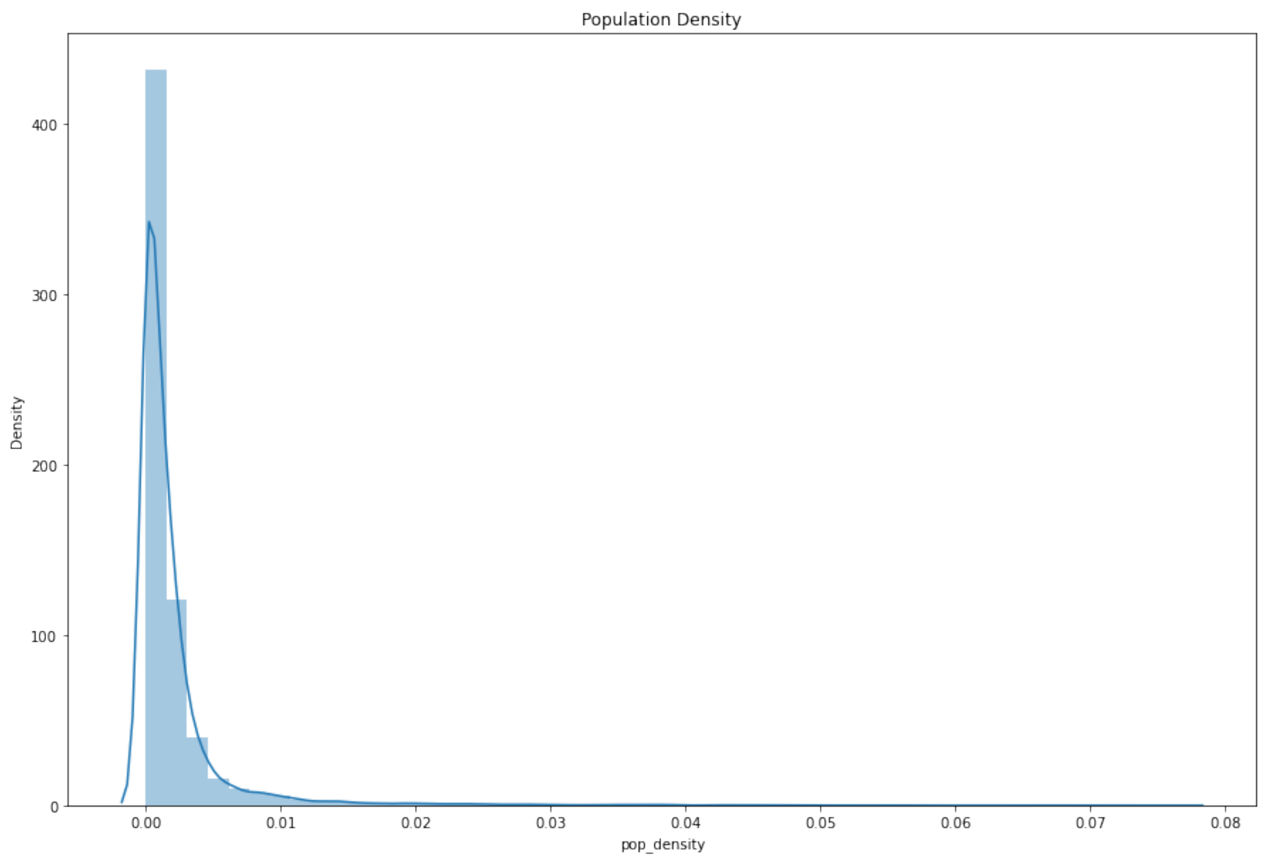
Perform EDA and come out with insights into population density and age. You may have to derive new fields (make sure to weight averages for accurate measurements):

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

In [44]:
```
df_train['pop_density']=df_train['pop']/df_train['ALand']
```

In [45]:
```
df_test['pop_density']=df_test['pop']/df_test['ALand']
```

In [46]:
```
plt.figure(figsize=(15,10))
sns.distplot(df_train['pop_density'])
plt.title('Population Density')
plt.show() # Very less density is noticed
```



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

In [47]:
```
df_train['age_median']=(df_train['male_age_median']+df_train['female_age_me
df_test['age_median']=(df_test['male_age_median']+df_test['female_age_media
```

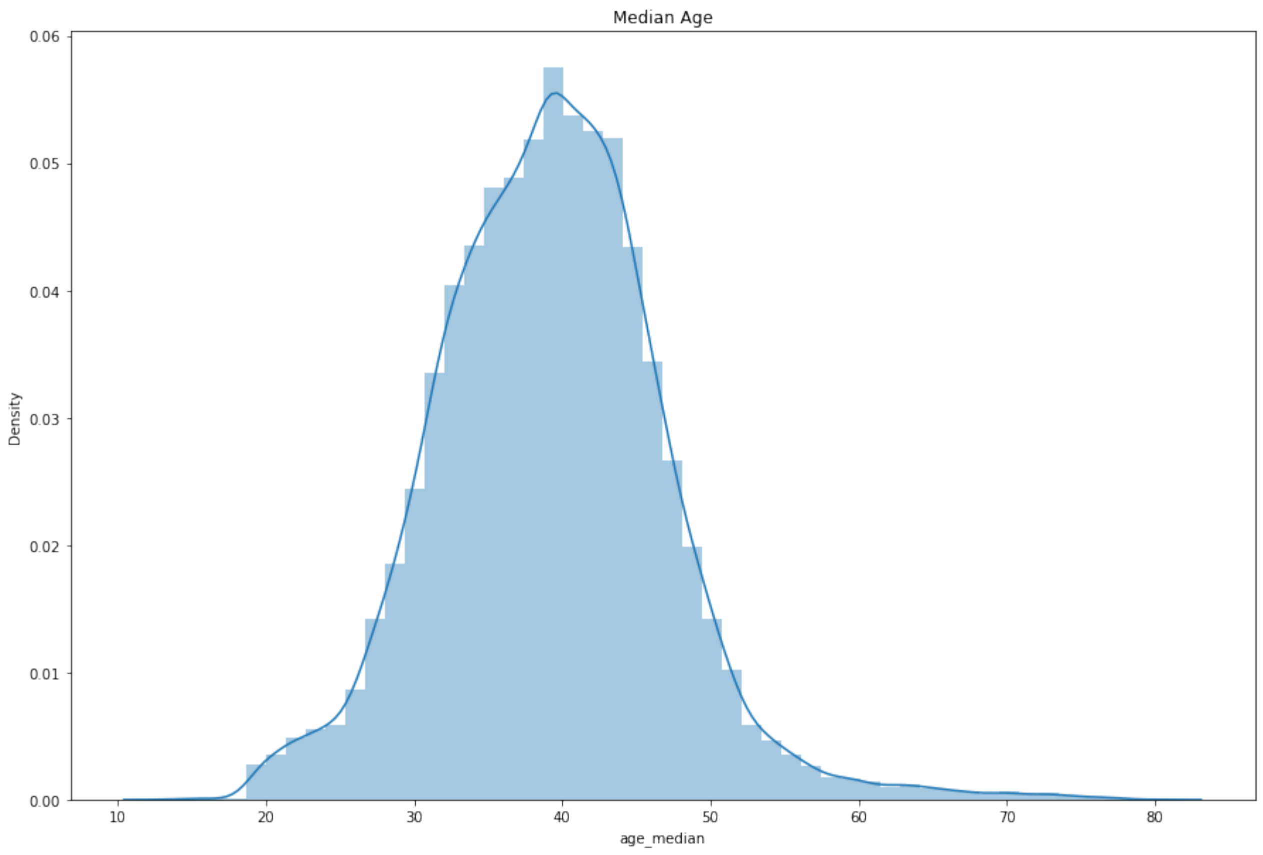
- Visualize the findings using appropriate chart type

In [48]:
```
df_train[['male_age_median','female_age_median','male_pop','female_pop','ag
```

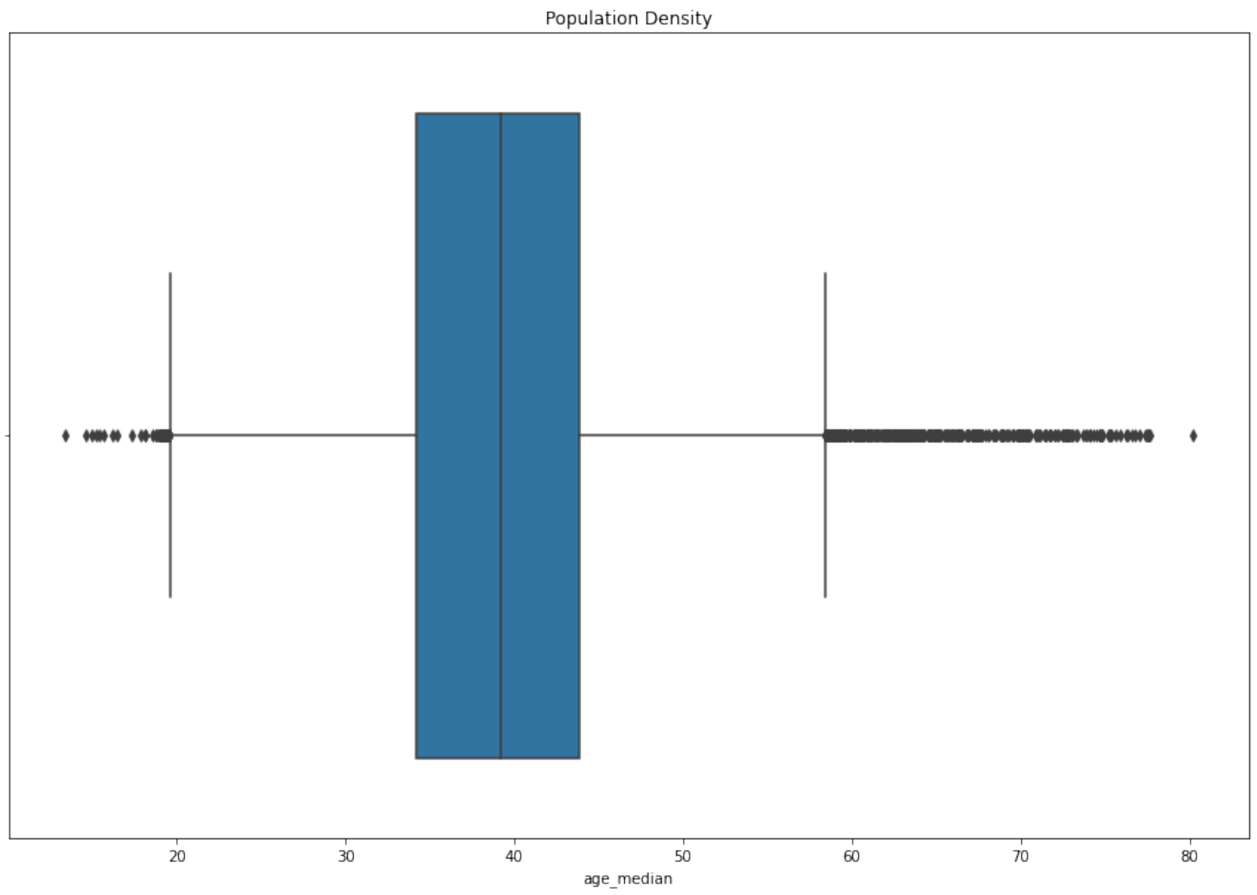
Out[48]:

	male_age_median	female_age_median	male_pop	female_pop	age_median
UID					
267822	44.00000	45.33333	2612	2618	44.666665
246444	32.00000	37.58333	1349	1284	34.791665
245683	40.83333	42.83333	3643	3238	41.833330
279653	48.91667	50.58333	1141	1559	49.750000
247218	22.41667	21.58333	2586	3051	22.000000

In [49]:
```
plt.figure(figsize=(15,10))
sns.distplot(df_train['age_median']);
plt.title("Median Age")
plt.show()
```



In [50]:
```
plt.figure(figsize=(15,10))
sns.boxplot(df_train['age_median']);
plt.title('Population Density')
plt.show()
```



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_bins'] = pd.cut(df_train['pop'],bins=5,labels=['very_low', 'l
```

In [52]:
```
df_train['pop_bins'].value_counts()
```

Out[52]:
```
very_low     27058
low            246
medium           9
high             7
very_high        1
Name: pop_bins, dtype: int64
```

- Analyze the married, separated, and divorced population for these population brackets

In [53]:
```
df_train.groupby(by='pop_bins')[['married', 'separated', 'divorced']].coun
```

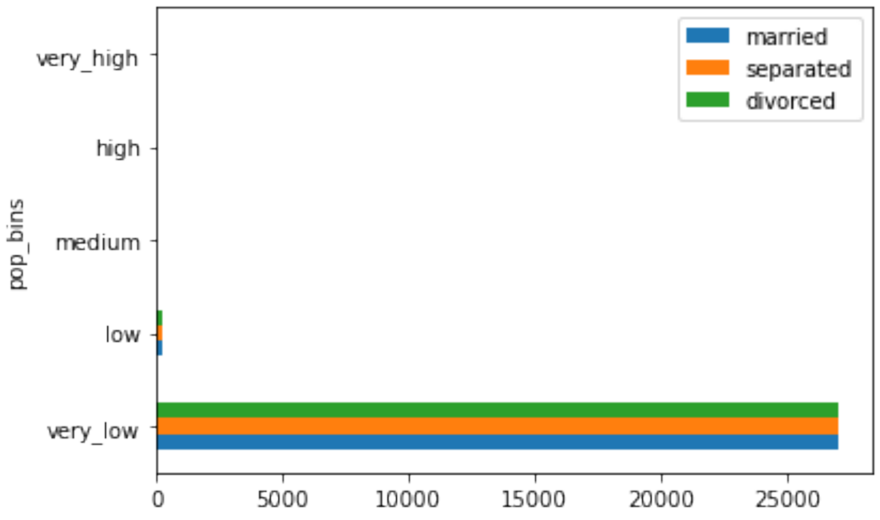
Out[53]:

pop_bins	married	separated	divorced
very_low	27058	27058	27058
low	246	246	246
medium	9	9	9
high	7	7	7
very_high	1	1	1

In [54]:

```
plt.figure(figsize=(15,10))
df_train.groupby(by='pop_bins')[['married', 'separated', 'divorced']].count
```

```
<Figure size 1080x720 with 0 Axes>
```



- Visualize using appropriate chart type

In [55]:

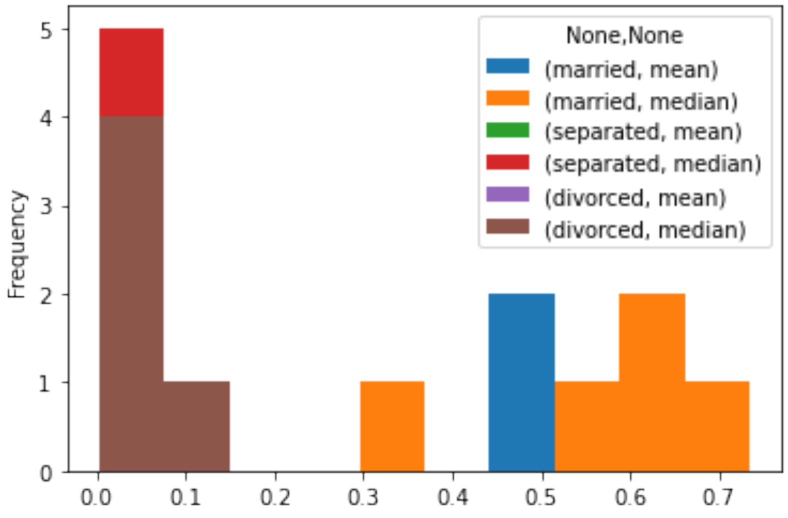
```
df_train.groupby(by='pop_bins')[['married', 'separated', 'divorced']].agg(
```

Out[55]:

	married		separated		divorced	
	mean	median	mean	median	mean	median
pop_bins						
very_low	0.507548	0.524680	0.019126	0.013650	0.100504	0.096020
low	0.584894	0.593135	0.015833	0.011195	0.075348	0.070045
medium	0.655737	0.618710	0.005003	0.004120	0.065927	0.064890
high	0.503359	0.335660	0.008141	0.002500	0.039030	0.010320
very_high	0.734740	0.734740	0.004050	0.004050	0.030360	0.030360

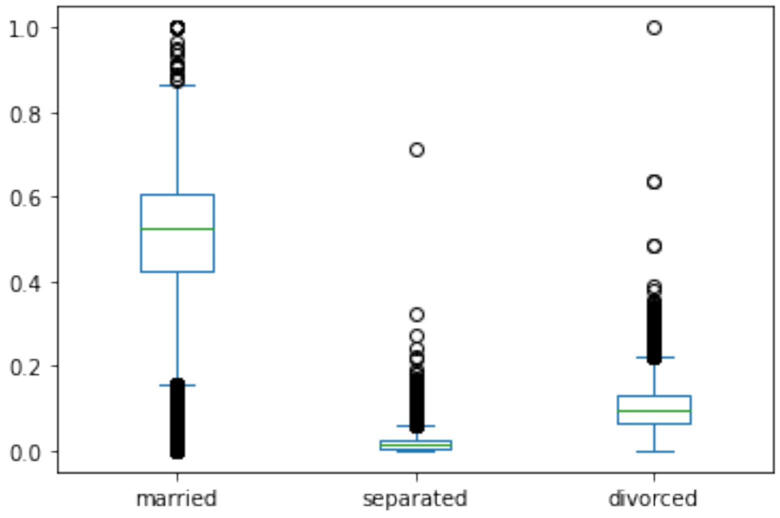
In [56]:
```
plt.figure(figsize=(15,10))
df_train.groupby(by='pop_bins')[['married', 'separated', 'divorced']].agg(
```

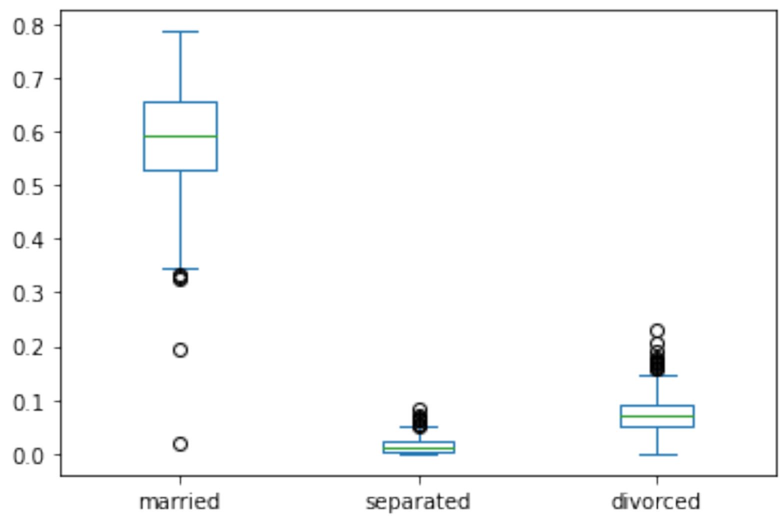
```
<Figure size 1080x720 with 0 Axes>
```

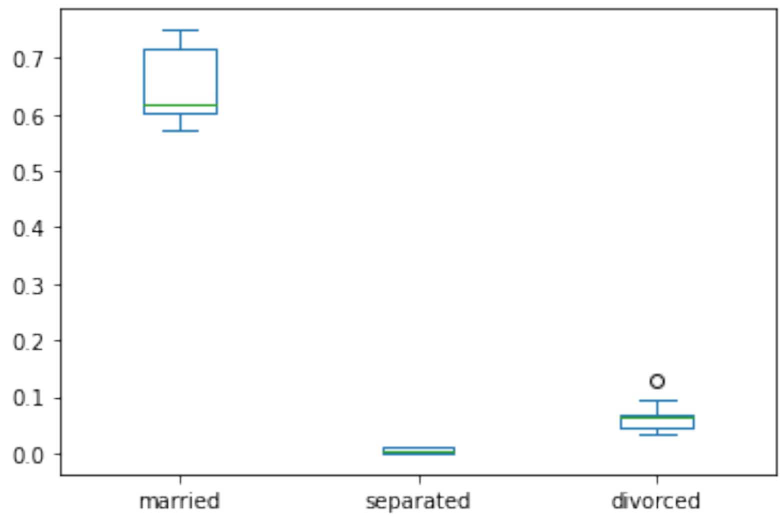


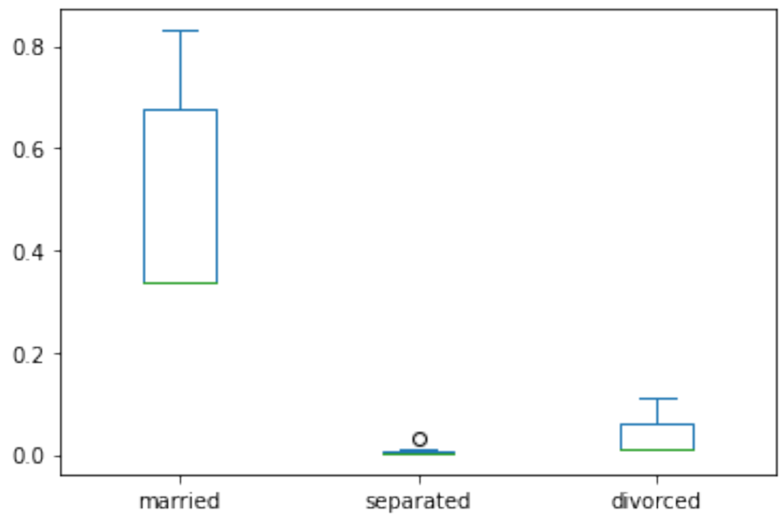
In [57]:
```
plt.figure(figsize=(15,10))
df_train.groupby(by='pop_bins')[['married', 'separated', 'divorced']].plot
```

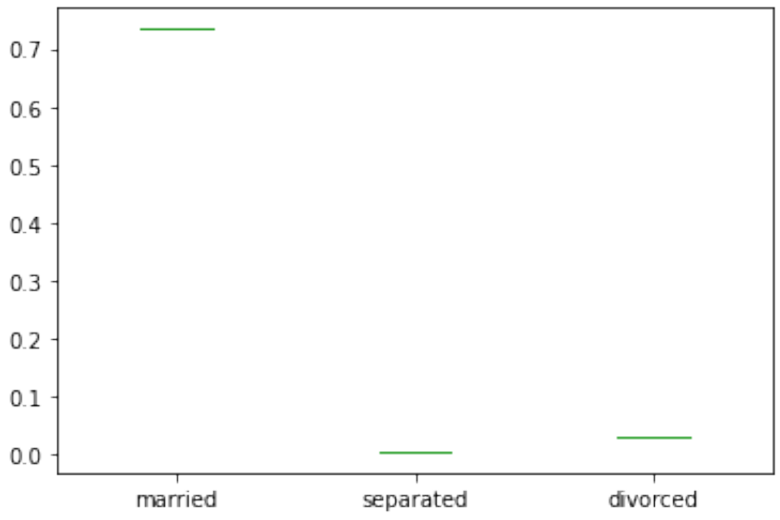
```
<Figure size 1080x720 with 0 Axes>
```




0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
married
separated
divorced


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
married
separated
divorced


0.8
0.6
0.4
0.2
0.0
married
separated
divorced

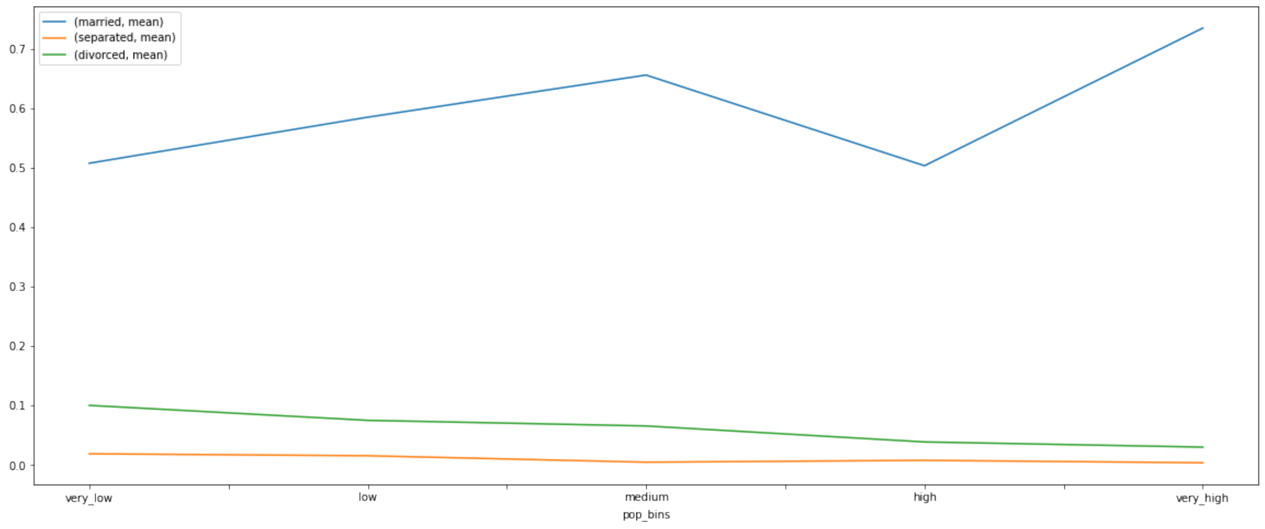


In [58]:

```
plt.figure(figsize=(10,5));
pop_bin_married = df_train.groupby(by='pop_bins')[['married', 'separated',

pop_bin_married.plot(figsize = (20,8));
plt.legend(loc='best');
plt.show();
```

```
<Figure size 720x360 with 0 Axes>
```



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

In [59]:

```
rent_state_mean = df_train.groupby(by='state')['rent_mean'].agg(["mean"])
rent_state_mean.head()
```

Out[59]:

state	mean
Alabama	774.004927
Alaska	1185.763570
Arizona	1097.753511
Arkansas	720.918575
California	1471.133857

In [60]:

```
income_state_mean = df_train.groupby(by='state')['family_mean'].agg(["mean'
income_state_mean.head()
```

Out[60]:

state	mean
Alabama	67030.064213
Alaska	92136.545109
Arizona	73328.238798
Arkansas	64765.377850
California	87655.470820

In [61]:

```
rent_per_of_income = rent_state_mean['mean']/income_state_mean['mean']
```

In [62]:

```
rent_per_of_income
```

Out[62]:
```
state
Alabama                 0.011547
Alaska                  0.012870
Arizona                 0.014970
Arkansas                0.011131
California              0.016783
Colorado                0.013529
Connecticut             0.012637
Delaware                0.012929
District of Columbia    0.013198
Florida                 0.015772
Georgia                 0.013161
Hawaii                  0.018224
Idaho                   0.011957
Illinois                0.012620
Indiana                 0.012022
Iowa                    0.009940
Kansas                  0.011066
Kentucky                0.011068
Louisiana               0.012160
Maine                   0.011674
Maryland                0.013947
Massachusetts           0.012312
Michigan                0.012766
Minnesota               0.011058
Mississippi             0.012428
Missouri                0.011670
Montana                 0.010789
Nebraska                0.010912
Nevada                  0.015242
New Hampshire           0.011949
New Jersey              0.013678
New Mexico              0.012330
New York                0.014410
North Carolina          0.012166
North Dakota            0.009303
Ohio                    0.011401
Oklahoma                0.011632
Oregon                  0.013253
Pennsylvania            0.011902
Puerto Rico             0.015133
Rhode Island            0.012292
South Carolina          0.012657
South Dakota            0.009192
Tennessee               0.012286
Texas                   0.012899
Utah                    0.013192
Vermont                 0.011743
Virginia                0.014050
Washington              0.013352
West Virginia           0.010341
Wisconsin               0.011189
Wyoming                 0.010785
Name: mean, dtype: float64
```

In [63]:
```
sum(df_train['rent_mean'])/sum(df_train['family_mean'])
```

Out[63]:
```
0.013358170721473864
```

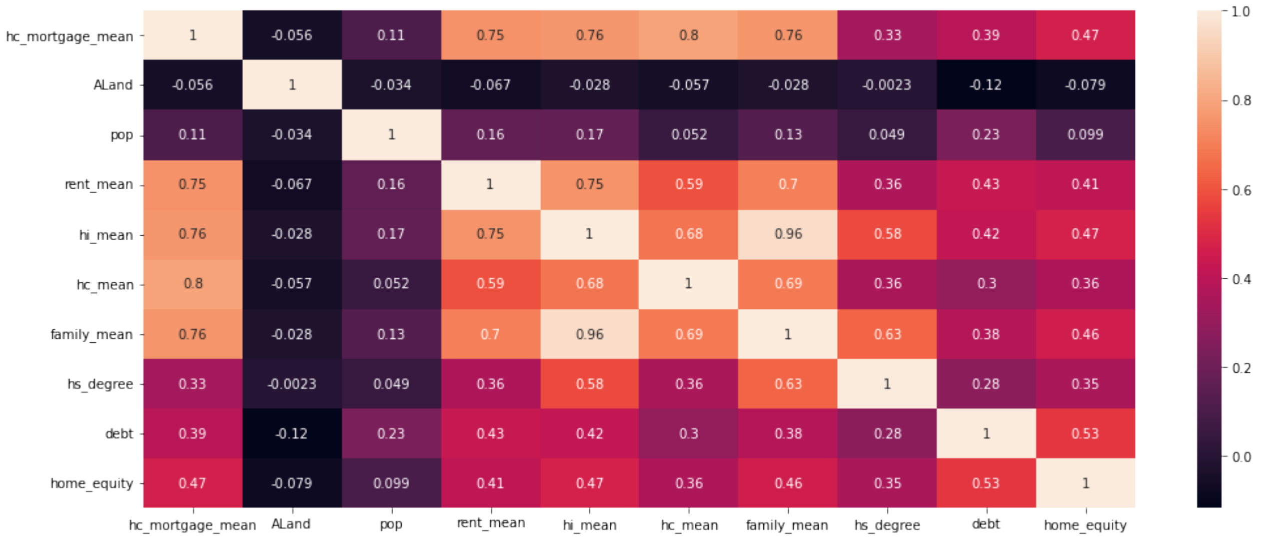
Perform correlation analysis for all the relevant variables by creating a heatmap. Describe your findings.

In [64]:
```
df_train[['hc_mortgage_mean','ALand','pop','rent_mean','hi_mean','hc_mean',
```

Out[64]:

	hc_mortgage_mean	ALand	pop	rent_mean	hi_mean	hc_
hc_mortgage_mean	1.000000	-0.056334	0.110659	0.750081	0.763128	0.7
ALand	-0.056334	1.000000	-0.033743	-0.067169	-0.028435	-0.0
pop	0.110659	-0.033743	1.000000	0.160590	0.166913	0.0
rent_mean	0.750081	-0.067169	0.160590	1.000000	0.753920	0.5
hi_mean	0.763128	-0.028435	0.166913	0.753920	1.000000	0.6
hc_mean	0.795012	-0.056723	0.051515	0.594499	0.675090	1.0
family_mean	0.759805	-0.027897	0.128173	0.701019	0.960624	0.6
hs_degree	0.333336	-0.002293	0.049238	0.362944	0.580284	0.3
debt	0.390902	-0.115591	0.231013	0.432481	0.418408	0.2
home_equity	0.466481	-0.079494	0.099352	0.408837	0.469863	0.3

In [65]:
```
plt.figure(figsize=(17,7))
sns.heatmap(df_train[['hc_mortgage_mean','ALand','pop','rent_mean','hi_mea
plt.show()
```



'rent_mean' , 'hi_mean', 'hc_mean', 'family_mean' has a good corr with our target variable - hc_mortgage_mean

Project Task: Week 2

Data Pre-processing:

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.

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 [66]:
```
from sklearn.decomposition import FactorAnalysis

from factor_analyzer import FactorAnalyzer
```

In [67]:
```
df_train.describe()
```

Out[67]:

	COUNTYID	STATEID	zip_code	area_code	lat	
count	27321.000000	27321.000000	27321.000000	27321.000000	27321.000000	27321.0000
mean	85.646426	28.271806	50081.999524	596.507668	37.508813	-91.2883
std	98.333097	16.392846	29558.115660	232.497482	5.588268	16.3438
min	1.000000	1.000000	602.000000	201.000000	17.929085	-165.4538
25%	29.000000	13.000000	26554.000000	405.000000	33.899064	-97.8160
50%	63.000000	28.000000	47715.000000	614.000000	38.755183	-86.5543
75%	109.000000	42.000000	77093.000000	801.000000	41.380606	-79.7825
max	840.000000	72.000000	99925.000000	989.000000	67.074017	-65.3793

8 rows × 75 columns

In [68]:
```
fa = FactorAnalyzer(n_factors=5)
```

In [69]:
```
fa.fit_transform(df_train.select_dtypes(exclude=('object','category')))
```

Out[69]:
```
array([[-0.39933034,  0.55583772,  1.07093896, -1.08698579,  0.65355193],
       [-0.99248908, -0.57075893, -0.12202251,  0.10554693,  0.28386921],
       [ 0.02533901,  1.21506669,  0.4946933 , -0.50562619, -0.28848015],
       ...,
       [ 0.02046437, -0.70649548,  0.81319778, -1.37996186,  0.00873314],
       [ 2.51731673,  3.10777987,  1.14759443, -0.0630024 , -1.63083959],
       [-0.33101021, -0.23542995, -1.63171941,  0.17824411, -0.12268557]])
```

In [70]:
```
fa.loadings_
```

Out[70]:
```
array([[-0.11482487,  0.01936373, -0.0245545 , -0.06169006,  0.03812136],
       [-0.11040899,  0.01429921,  0.02466482, -0.14796223,  0.11258263],
       [-0.0891633 ,  0.04864149, -0.12749732, -0.04931909, -0.11805326],
       [ 0.01614823,  0.0188282 ,  0.00574863,  0.02659233, -0.00973247],
       [ 0.09063446, -0.09926159, -0.05333377, -0.13305276, -0.14641972],
       [-0.00541231, -0.03861633,  0.13839861,  0.00876519,  0.1216676 ],
       [-0.04186143, -0.02024517,  0.03644117, -0.09300196,  0.06439296],
       [-0.00198676, -0.0150142 , -0.00250851, -0.04444931,  0.02563788],
       [ 0.07644546,  0.95538373, -0.08288847, -0.00717471, -0.05369428],
       [ 0.07116302,  0.91659973, -0.10342851, -0.02796311, -0.05283109],
       [ 0.07805518,  0.94595683, -0.05801542,  0.014232  , -0.05251385],
       [ 0.76054105,  0.00785577, -0.03725023,  0.11387679, -0.14404771],
       [ 0.70885225,  0.00394816, -0.04466907,  0.10817145, -0.15591822],
       [ 0.70643093,  0.02688275, -0.02517887,  0.10292387,  0.06883075],
       [-0.121171  ,  0.34301813, -0.51395397, -0.04394071,  0.31530346],
       [ 0.24323025,  0.44469406, -0.67418609, -0.02865328,  0.33289811],
       [-0.04675332,  0.03348746,  0.03198187,  0.44044074, -0.1698257 ],
       [-0.02516145,  0.01631269,  0.04136891,  0.66998302, -0.16155432],
       [-0.03634064, -0.01567031,  0.06956415,  0.82915629, -0.09407074],
       [-0.04712842, -0.03348549,  0.09423677,  0.91747318, -0.04414534],
       [-0.05620306, -0.04149989,  0.1177372 ,  0.94558341, -0.02041133],
       [-0.0412783 , -0.04959822,  0.12201166,  0.92570715,  0.00189047],
       [-0.03738612, -0.05602061,  0.11023791,  0.88082495,  0.01283847],
       [-0.02031965, -0.06992452,  0.07639516,  0.77345015,  0.03171296],
       [ 0.2251697 ,  0.47338185, -0.64943552, -0.02812309,  0.35439151],
       [ 0.24516516,  0.45397088, -0.66203053, -0.03064164,  0.32930185],
       [ 0.77424469,  0.0458412 ,  0.15426491, -0.20366713, -0.16645681],
       [ 0.69788075,  0.04545261,  0.14737086, -0.21735663, -0.22413606],
       [ 0.85744941,  0.04437585,  0.15809972, -0.11959275,  0.02692194],
       [-0.21235552,  0.85071284, -0.06515656,  0.06559846,  0.23273441],
       [ 0.14775965,  0.95466245,  0.01314345, -0.04816854,  0.09715259],
       [ 0.82240955,  0.03269749,  0.16390804, -0.20341937, -0.08254877],
       [ 0.78596814,  0.02645931,  0.15603318, -0.20627097, -0.09951158],
       [ 0.80935346,  0.04480529,  0.13331803, -0.1080682 ,  0.05512187],
       [-0.33493419,  0.86485945,  0.03359967,  0.08892098,  0.04245147],
       [ 0.04675907,  0.9327849 ,  0.15952872, -0.02606483, -0.10045735],
       [ 0.97737122, -0.03058639, -0.12023358,  0.04422083,  0.06391006],
       [ 0.95753903, -0.03670088, -0.13489606,  0.04450991,  0.05518235],
       [ 0.81891124,  0.0062711 ,  0.0606408 ,  0.01965969,  0.13413668],
       [-0.42447833,  0.71211816,  0.36471085, -0.07278991, -0.28356804],
       [ 0.06479058,  0.71798809,  0.30113511, -0.04925706, -0.36533169],
       [ 0.90925698, -0.05005301, -0.06873   , -0.00156445,  0.15344429],
       [ 0.8716504 , -0.0497007 , -0.07950161, -0.00230469,  0.141696  ],
       [ 0.75826576,  0.00185445,  0.02736492,  0.00374285,  0.25783346],
       [-0.11345437,  0.61298275,  0.62349709, -0.01999399,  0.284585  ],
       [-0.33349554,  0.5640579 ,  0.58243645, -0.02351225,  0.25401294],
       [-0.13962631, -0.02038193, -0.099815  ,  0.10703584, -0.61108334],
       [-0.1155693 , -0.02672498, -0.10052413,  0.12267069, -0.6194846 ],
       [ 0.26332311, -0.02989007,  0.02773139,  0.09313835, -0.58884017],
       [ 0.17605066,  0.06500774, -0.27623933,  0.01755758, -0.70238435],
       [ 0.09571295, -0.05641886, -0.0878796 , -0.09217904,  0.64282047],
       [-0.27816504, -0.00108849, -0.08724621, -0.09099697,  0.60287301],
       [-0.18822894, -0.05993517,  0.3221272 , -0.01484872,  0.70805651],
       [ 0.39096931,  0.05805001,  0.26868167, -0.2206138 , -0.17910889],
       [ 0.40449327,  0.06000692,  0.23582956, -0.21037746, -0.16855004],
       [ 0.35015101,  0.05083956,  0.28323451, -0.21703079, -0.17351309],
       [ 0.24845274, -0.04071472,  0.7828657 ,  0.09032636,  0.37052567],
       [ 0.25210151, -0.02708951,  0.80625444,  0.07208958,  0.28641364],
       [-0.05920176,  0.06895631,  0.57728575,  0.08529851,  0.12110191],
       [ 0.05379624,  0.81586993, -0.1714922 , -0.0147333 , -0.04544873],
       [ 0.06864777,  0.92118309, -0.10138082, -0.02787599, -0.05733179],
       [ 0.20884889, -0.03872551,  0.76992343,  0.13951893,  0.37840595],
       [ 0.20114043, -0.02576923,  0.83100793,  0.12749903,  0.29865452],
       [-0.09355638,  0.06379344,  0.46282287,  0.07177015,  0.13940071],
       [ 0.05905288,  0.87591732, -0.1452326 ,  0.02192923, -0.05554446],
       [ 0.07559661,  0.95252905, -0.0559462 ,  0.01535826, -0.05728285],
       [-0.04117527,  0.10599545,  0.80950398, -0.04276026, -0.26442385],
       [ 0.17123066,  0.18784317,  0.57209879, -0.12048879, -0.12264931],
       [-0.06001846, -0.06689816, -0.28697978,  0.12758949,  0.1806349 ],
       [-0.15149224, -0.06790769, -0.16008983,  0.12294432,  0.14495427],
       [-0.34836642, -0.05022182,  0.13810517,  0.02668981,  0.12886669],
       [ 0.26104601, -0.03305257,  0.02283549,  0.10263406, -0.60019879],
       [ 0.07779707,  0.09682759, -0.32690032, -0.03383985, -0.46819902],
       [ 0.35337036, -0.00539003, -0.42547832,  0.05776243,  0.27393594],
       [ 0.23903134, -0.02686691,  0.86480585,  0.10861162,  0.31067539]])
```

Data Modeling :

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:
```

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 [71]:
```
df_train.columns
```

Out[71]:
```
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_weigh
t',
       'family_samples', 'hc_mortgage_mean', 'hc_mortgage_median',
       'hc_mortgage_stdev', 'hc_mortgage_sample_weight', 'hc_mortgage_sampl
es',
       'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_sample_weight'
,
       'home_equity_second_mortgage', 'second_mortgage', 'home_equity', 'de
bt',
       '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', 'good_debt', 'pop_density', 'age_median',
       'pop_bins'],
      dtype='object')
```

In [72]:
```
df_train['type'].unique()
```

Out[72]:
```
array(['City', 'Urban', 'Town', 'CDP', 'Village', 'Borough'], dtype=object)
```

In [73]:
```
type_dict = {'type':{'City':1,'Urban':2,'Town':3,'CDP':4, 'Village':5,'Boro
```

In [74]:
```
df_train.replace(type_dict, inplace=True)
```

In [75]:
```
df_test.replace(type_dict, inplace=True)
```

In [76]:
```
df_train['type'].unique()
```

Out[76]:
```
array([1, 2, 3, 4, 5, 6])
```

In [77]:
```
feature_cols = ['COUNTYID','STATEID','zip_code','type','pop','family_mean',
               'hs_degree','age_median','pct_own','married','separated','di
```

In [78]:
```
X_train = df_train[feature_cols]

y_train = df_train['hc_mortgage_mean']
```

In [79]:
```
X_test = df_test[feature_cols]

y_test = df_test['hc_mortgage_mean']
```

In [80]:
```
X_train.shape, y_train.shape
```

Out[80]:
```
((27321, 15), (27321,))
```

In [81]:
```
X_test.shape, y_test.shape
```

Out[81]:
```
((11709, 15), (11709,))
```

In [82]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_er
```

In [83]:
```
X_test.head()
```

Out[83]:

	COUNTYID	STATEID	zip_code	type	pop	family_mean	second_mortgage	hon
UID								
255504	163	26	48239	4	3417	53802.87122	0.06443	
252676	1	23	4210	1	3796	85642.22095	0.01175	
276314	15	42	14871	6	3944	65694.06582	0.01316	
248614	231	21	42633	1	2508	44156.38709	0.00995	
286865	355	48	78410	3	6230	123527.02420	0.00000	

In [84]:
```
SC = StandardScaler()
```

In [85]:
```
X_train_Scaled = SC.fit_transform(X_train)
X_test_Scaled = SC.fit_transform(X_test)
```

In [86]:
```
Lr = LinearRegression()
```

```
In [87]: Lr.fit(X_train_Scaled,y_train)

Out[87]: LinearRegression()

In [88]: y_pred = Lr.predict(X_test_Scaled)

In [89]: r2_score(y_test,y_pred) #R2 square

Out[89]: 0.7348210754610929

In [90]: np.sqrt(mean_squared_error(y_test,y_pred)) #RMSE

Out[90]: 323.1018894984635
```

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

```
In [91]: state= df_train['STATEID'].nunique()

In [92]: state= df_train['STATEID'].unique()
         state

Out[92]: array([36, 18, 72, 20,  1, 48, 45,  6,  5, 24, 17, 19, 47, 32, 22,  8, 44,
                28, 34, 41,  4, 12, 55, 42, 37, 51, 26, 39, 40, 13, 16, 46, 27, 29,
                53, 56,  9, 54, 21, 25, 11, 15, 30,  2, 33, 49, 50, 31, 38, 35, 23,
                10])
```

In [93]:

```
for i in [11,33,35]:
    print("State_ID:",i)

    X_train_nation = df_train[df_train['COUNTYID']==i][feature_cols]

    y_train_nation = df_train[df_train['COUNTYID']==i]['hc_mortgage_mean']

    X_test_nation = df_test[df_test['COUNTYID']==i][feature_cols]

    y_test_nation = df_test[df_test['COUNTYID']==i]['hc_mortgage_mean']

    X_train_Scaled_nation = SC.fit_transform(X_train_nation)

    X_test_Scaled_nation = SC.fit_transform(X_test_nation)

    Lr.fit(X_train_Scaled_nation, y_train_nation)

    y_pred_nation = Lr.predict(X_test_Scaled_nation)

    print("Overall R2 score of linear regression model for state,",i,":-"
    print("Overall RMSE of linear regression model for state,",i,":-" ,np.
    print("\n")
```

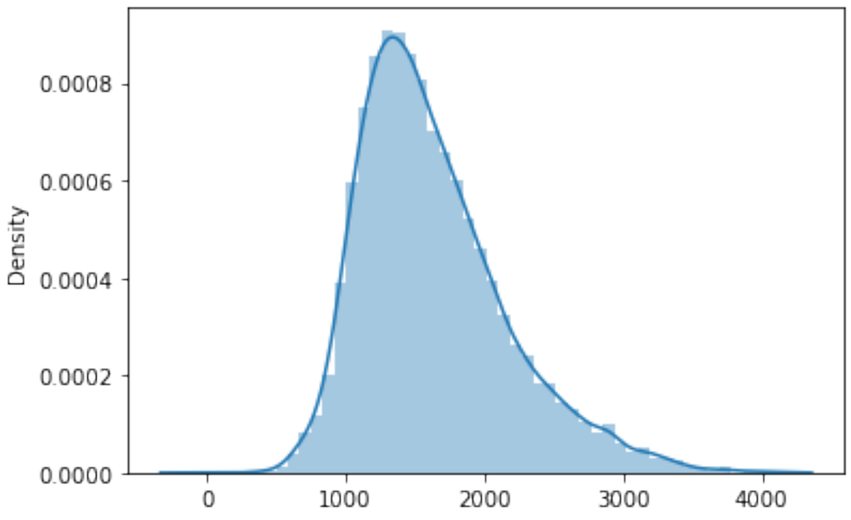
```
State_ID: 11
Overall R2 score of linear regression model for state, 11 :- 0.746485716944
4445
Overall RMSE of linear regression model for state, 11 :- 238.10563068257605


State_ID: 33
Overall R2 score of linear regression model for state, 33 :- 0.861561420773
1607
Overall RMSE of linear regression model for state, 33 :- 211.13273527746531


State_ID: 35
Overall R2 score of linear regression model for state, 35 :- 0.722243579050
943
Overall RMSE of linear regression model for state, 35 :- 255.6042328589991
```

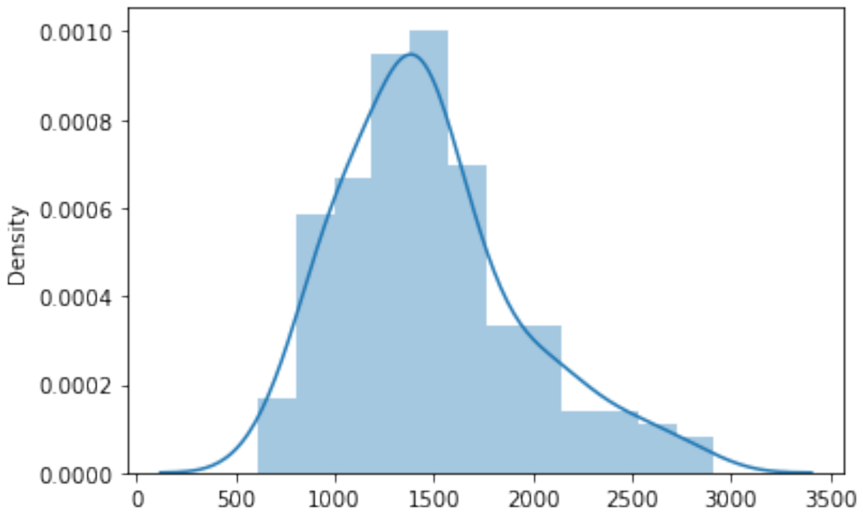
In [94]:

```
sns.distplot(y_pred)
plt.show()
```



In [95]:

```
sns.distplot(y_pred_nation)
plt.show()
```



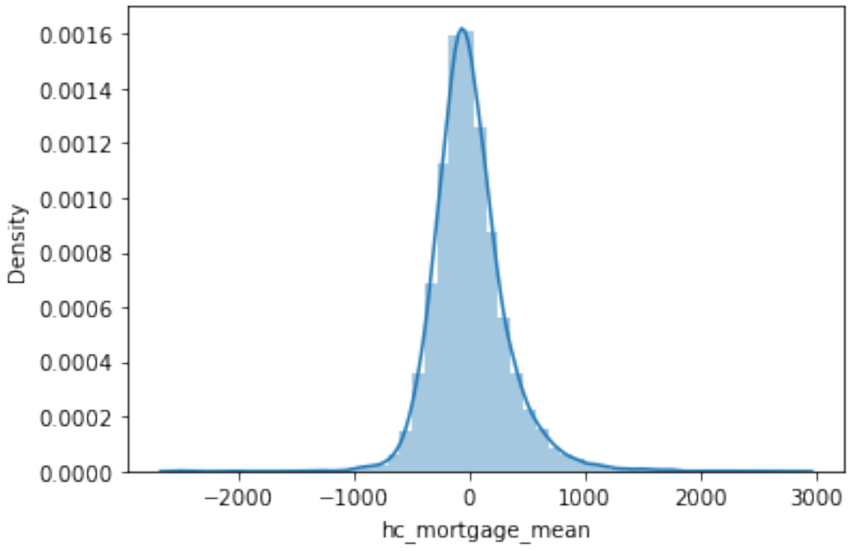
In [96]:

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

Out[96]:

```
UID
255504    281.969088
252676    -69.935775
276314    190.761969
248614   -157.290627
286865     -9.887017
             ...
238088    -67.541646
242811    -41.578757
250127   -127.427569
241096   -330.820475
287763    217.760642
Name: hc_mortgage_mean, Length: 11709, dtype: float64
```

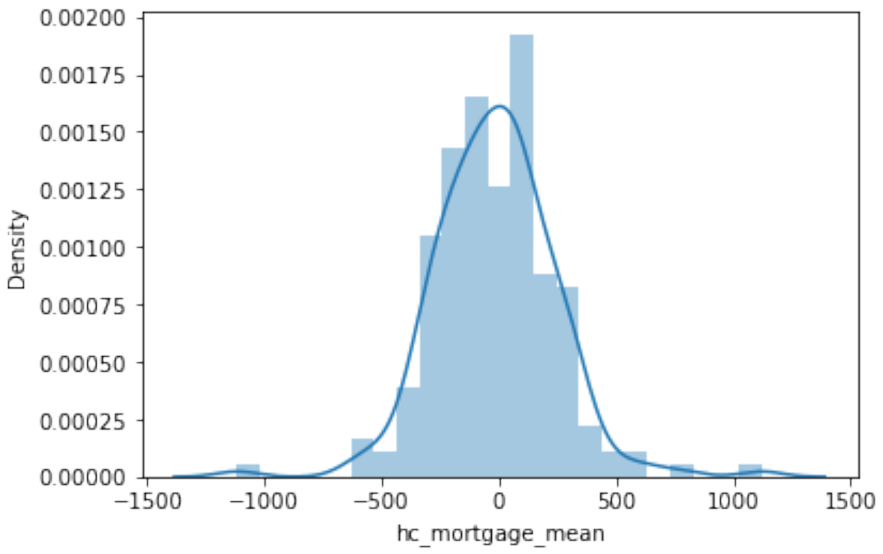
In [97]:
```
sns.distplot(residuals)
plt.show()
```



In [98]:
```
residuals_nation=y_test_nation-y_pred_nation
residuals_nation
```

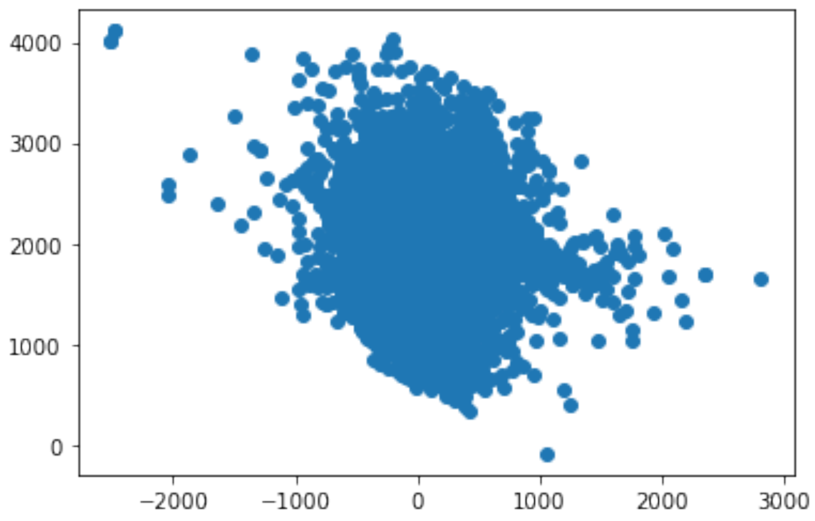
Out[98]:
```
UID
271383    -71.037462
271503    -92.539838
288357     84.266127
264513    -66.054827
288371    456.709228
             ...
288512     44.115107
280441    -48.716870
288475    -49.259951
253291     74.474223
288425    201.479714
Name: hc_mortgage_mean, Length: 187, dtype: float64
```

In [99]:
```
sns.distplot(residuals_nation)
plt.show()
```



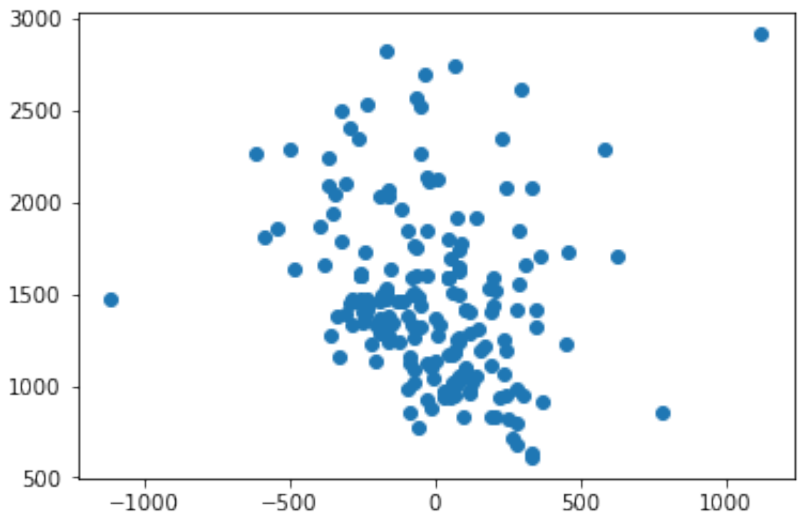
In [100…

```
plt.scatter(residuals,y_pred);
```



In [101…

```
plt.scatter(residuals_nation,y_pred_nation);
```



Data Reporting:

- Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:
- Box plot of distribution of average rent by type of place (village, urban, town, etc.).
- Pie charts to show overall debt and bad debt.
- 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.
- Heat map for correlation matrix.
- Pie chart to show the population distribution across different types of places (village, urban, town etc.).

In [102…

```
df_train_location_mort_pct.to_excel('df_train_location_mort_pct.xlsx')
```

In [103…

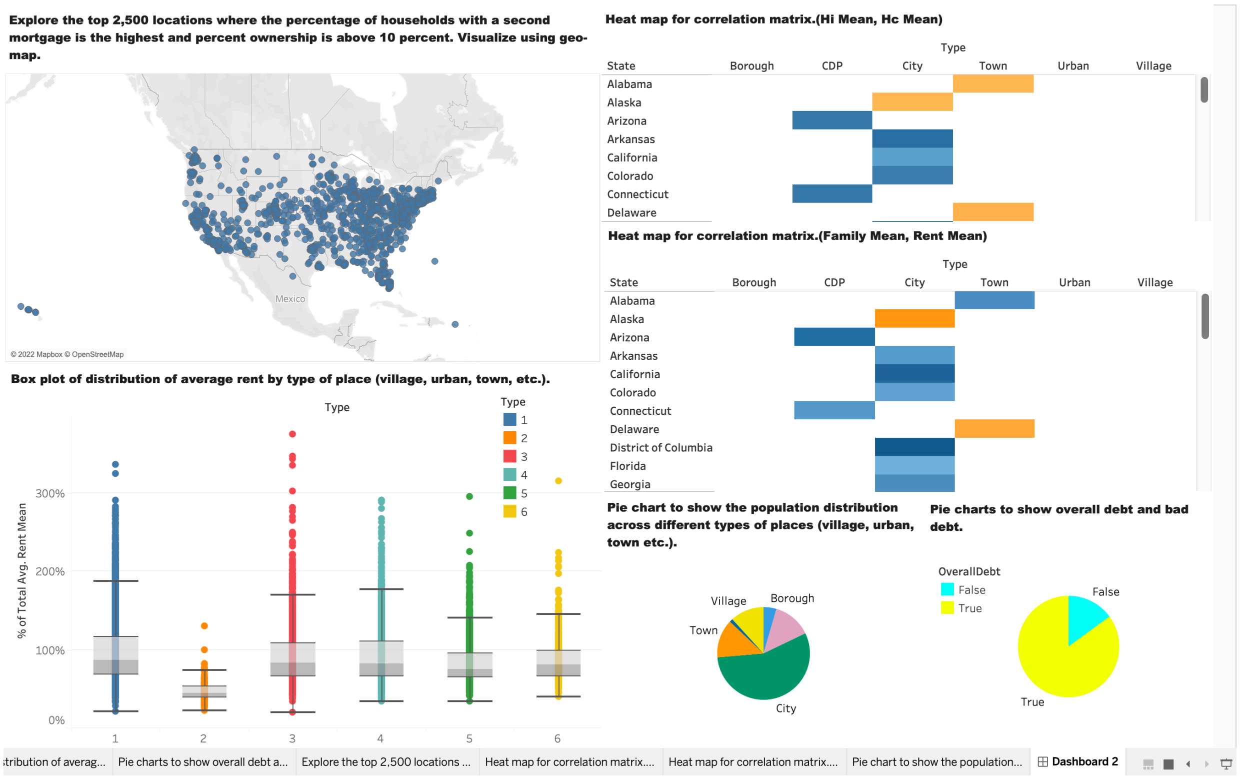
```
df_train.to_excel('df_train_.xlsx')
```

In [105…

```
df_test.to_excel('df_test_.xlsx')
```

In [107…

```
df_train.bad_debt.to_excel('bad_debt.xlsx')
```



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.

Heat map for correlation matrix.(Hi Mean, Hc Mean)

Heat map for correlation matrix.(Family Mean, Rent Mean)

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

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

Pie charts to show overall debt and bad debt.

https://public.tableau.com/app/profile/rushikesh.khankar/viz/RealEStatisticalAnalysisCapProject/Dashboard2

Thank You