Week 1 : Data Import & Preparation

In [1]:
```python
# Importing Libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# Importing module
import warnings
# Warnings filter.
warnings.filterwarnings('ignore')
# Import the necessary libraries
import plotly.offline as pyo
import plotly.graph_objs as go
# Set notebook mode to work in offline
pyo.init_notebook_mode()
```

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

Descriptive Analysis

In [3]:
```python
train.head()
```

Out[3]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place	type
0	267822	NaN	140	53	36	New York	NY	Hamilton	Hamilton	City
1	246444	NaN	140	141	18	Indiana	IN	South Bend	Roseland	City
2	245683	NaN	140	63	18	Indiana	IN	Danville	Danville	City
3	279653	NaN	140	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban
4	247218	NaN	140	161	20	Kansas	KS	Manhattan	Manhattan City	City

5 rows × 80 columns

In [4]:
```python
test.head()
```

Out[4]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	state	state_ab	city	place
0	255504	NaN	140	163	26	Michigan	MI	Detroit	Dearborn Heights City
1	252676	NaN	140	1	23	Maine	ME	Auburn	Auburn City
2	276314	NaN	140	15	42	Pennsylvania	PA	Pine City	Millerton
3	248614	NaN	140	231	21	Kentucky	KY	Monticello	Monticello City
								Corpus	

4	286865	NaN	140	355	48	Texas	TX	Corpus Christi	Edroy

5 rows × 80 columns

In [5]:
```
train.describe()
```

Out[5]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	zip_code	area_code
count	27321.000000	0.0	27321.0	27321.000000	27321.000000	27321.000000	27321.000000
mean	257331.996303	NaN	140.0	85.646426	28.271806	50081.999524	596.507668
std	21343.859725	NaN	0.0	98.333097	16.392846	29558.115660	232.497482
min	220342.000000	NaN	140.0	1.000000	1.000000	602.000000	201.000000
25%	238816.000000	NaN	140.0	29.000000	13.000000	26554.000000	405.000000
50%	257220.000000	NaN	140.0	63.000000	28.000000	47715.000000	614.000000
75%	275818.000000	NaN	140.0	109.000000	42.000000	77093.000000	801.000000
max	294334.000000	NaN	140.0	840.000000	72.000000	99925.000000	989.000000

8 rows × 74 columns

In [6]:
```
test.describe()
```

Out[6]:

	UID	BLOCKID	SUMLEVEL	COUNTYID	STATEID	zip_code	area_code
count	11709.000000	0.0	11709.0	11709.000000	11709.000000	11709.000000	11709.000000
mean	257525.004783	NaN	140.0	85.710650	28.489196	50123.418396	593.598514
std	21466.372658	NaN	0.0	99.304334	16.607262	29775.134038	232.074263
min	220336.000000	NaN	140.0	1.000000	1.000000	601.000000	201.000000
25%	238819.000000	NaN	140.0	29.000000	13.000000	25570.000000	404.000000
50%	257651.000000	NaN	140.0	61.000000	28.000000	47362.000000	612.000000
75%	276300.000000	NaN	140.0	109.000000	42.000000	77406.000000	787.000000
max	294333.000000	NaN	140.0	810.000000	72.000000	99929.000000	989.000000

8 rows × 74 columns

In [7]:
```
train.columns
```

Out[7]:
```
Index(['UID', 'BLOCKID', 'SUMLEVEL', 'COUNTYID', 'STATEID', 'state',
       'state_ab', 'city', 'place', 'type', 'primary', 'zip_code', 'area_cod
e',
       '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_2
5',
       'rent_gt_30', 'rent_gt_35', 'rent_gt_40', 'rent_gt_50',
       'universe_samples', 'used_samples', 'hi_mean', 'hi_median', 'hi_stde
v',
       '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', 'deb
t',
```

```
t',
       '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'],
      dtype='object')
```

In [8]:
```
test.columns
```

Out[8]:
```
Index(['UID', 'BLOCKID', 'SUMLEVEL', 'COUNTYID', 'STATEID', 'state',
       'state_ab', 'city', 'place', 'type', 'primary', 'zip_code', 'area_cod
e',
       '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_2
5',
       'rent_gt_30', 'rent_gt_35', 'rent_gt_40', 'rent_gt_50',
       'universe_samples', 'used_samples', 'hi_mean', 'hi_median', 'hi_stde
v',
       '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', 'deb
t',
       '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'],
      dtype='object')
```

In [9]:
```
# UID is unique userID value in the train and test dataset. So an index can
 be created from the UID feature
train.set_index(keys=['UID'],inplace=True)#Set the DataFrame index using exi
sting columns.
test.set_index(keys=['UID'],inplace=True)
```

In [10]:
```
# Handling Missing value
train.isnull().sum()/len(train)*100
```

Out[10]:
```
BLOCKID        100.000000
SUMLEVEL         0.000000
COUNTYID         0.000000
STATEID          0.000000
state            0.000000
                   ...
pct_own          0.980930
married          0.699096
married_snp      0.699096
separated        0.699096
divorced         0.699096
Length: 79, dtype: float64
```

In [11]:
```
train=train.drop(['BLOCKID','SUMLEVEL'],axis=1)
```

In [12]:
```
test.isnull().sum()/len(test)*100
```

Out[12]:
```
BLOCKID        100.000000
SUMLEVEL         0.000000
COUNTYID         0.000000
STATEID          0.000000
state            0.000000
                   ...
pct_own          1.041934
married          0.717397
married_snp      0.717397
separated        0.717397
divorced         0.717397
Length: 79, dtype: float64
```

In [13]:
```
test=test.drop(['BLOCKID','SUMLEVEL'],axis=1)
```

In [14]:
```
# Imputing  missing values with mean
missing_train_cols=[]
for col in train.columns:
    if train[col].isna().sum() !=0:
         missing_train_cols.append(col)
print(missing_train_cols)
```

```
['rent_mean', 'rent_median', 'rent_stdev', 'rent_sample_weight', 'rent_sampl
es', '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_stde
v', '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_mort
gage_samples', 'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_sample_
weight', 'home_equity_second_mortgage', 'second_mortgage', 'home_equity', 'd
ebt', '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_mea
n', 'female_age_median', 'female_age_stdev', 'female_age_sample_weight', 'fe
male_age_samples', 'pct_own', 'married', 'married_snp', 'separated', 'divorc
ed']
```

In [15]:
```
missing_test_cols=[]
for col in test.columns:
    if test[col].isna().sum() !=0:
         missing_test_cols.append(col)
print(missing_test_cols)
```

```
['rent_mean', 'rent_median', 'rent_stdev', 'rent_sample_weight', 'rent_sampl
es', '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_stde
v', '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_mort
gage_samples', 'hc_mean', 'hc_median', 'hc_stdev', 'hc_samples', 'hc_sample_
weight', 'home_equity_second_mortgage', 'second_mortgage', 'home_equity', 'd
ebt', '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_mea
n', 'female_age_median', 'female_age_stdev', 'female_age_sample_weight', 'fe
male_age_samples', 'pct_own', 'married', 'married_snp', 'separated', 'divorc
ed']
```

In [16]:
```python
# Missing cols are all numerical variables
for col in train.columns:
    if col in (missing_train_cols):
        train[col].replace(np.nan,train[col].mean(),inplace=True)
```

In [17]:
```python
for col in test.columns:
    if col in (missing_test_cols):
        test[col].replace(np.nan,test[col].mean(),inplace=True)
```

In [18]:
```python
train.isna().sum().sum()
```

Out[18]: 0

In [19]:
```python
test.isna().sum().sum()
```

Out[19]: 0

Week 1 Exploratory Data Analysis

In [20]:
```python
df = train[train['pct_own']>0.1]
df.shape
```

Out[20]: (26565, 77)

In [21]:
```python
df = df.sort_values(by='second_mortgage',ascending=False)
```

In [22]:
```python
pd.set_option('display.max_columns', None)
df.head()
```

Out[22]:

UID	COUNTYID	STATEID	state	state_ab	city	place	type	primary	zip_code
289712	147	51	Virginia	VA	Farmville	Farmville	Town	tract	23901
251185	27	25	Massachusetts	MA	Worcester	Worcester City	City	tract	1610
269323	81	36	New York	NY	Corona	Harbor Hills	City	tract	11368
251324	3	24	Maryland	MD	Glen Burnie	Glen Burnie	CDP	tract	21061
235788	57	12	Florida	FL	Tampa	Egypt Lake-leto	City	tract	33614

In [23]:
```python
top_2500_second_mortgage_pctown_10 = df.head(2500)
top_2500_second_mortgage_pctown_10
```

Out[23]:

UID	COUNTYID	STATEID	state	state_ab	city	place	type	primary	zip_code
289712	147	51	Virginia	VA	Farmville	Farmville	Town	tract	2390
251185	27	25	Massachusetts	MA	Worcester	Worcester City	City	tract	161
269323	81	36	New York	NY	Corona	Harbor Hills	City	tract	1136

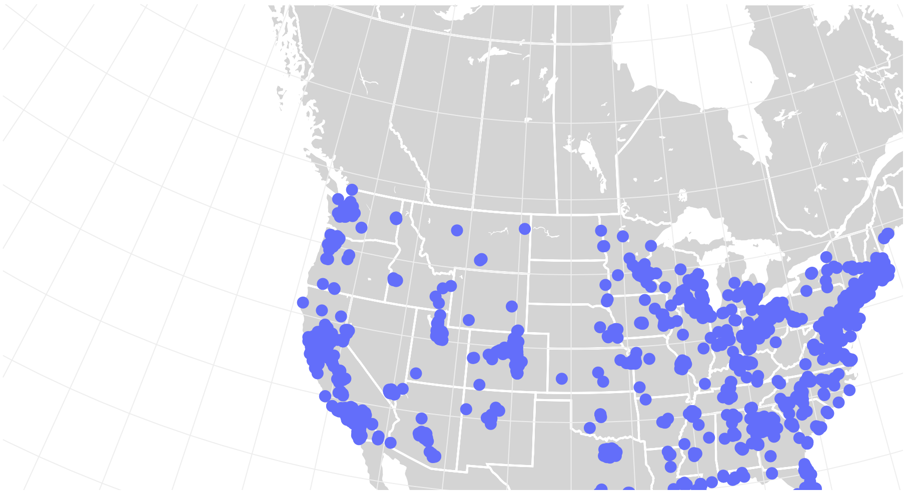
251324	3	24	Maryland	MD	Glen Burnie	Glen Burnie	CDP	tract	2106
235788	57	12	Florida	FL	Tampa	Egypt Lake-leto	City	tract	3361
...	...	...	...	...	...	...	...	...	..
229021	67	6	California	CA	Carmichael	Carmichael	City	tract	9560
261444	183	37	North Carolina	NC	Raleigh	Raleigh City	Village	tract	2760
225977	37	6	California	CA	Marina Del Rey	Marina Del Rey	City	tract	9029
251433	5	24	Maryland	MD	Baltimore	Lochearn	CDP	tract	2120
230480	77	6	California	CA	Manteca	Manteca City	City	tract	9533

2500 rows × 77 columns

In [24]:
```
import plotly.express as px
import plotly.graph_objects as go
```

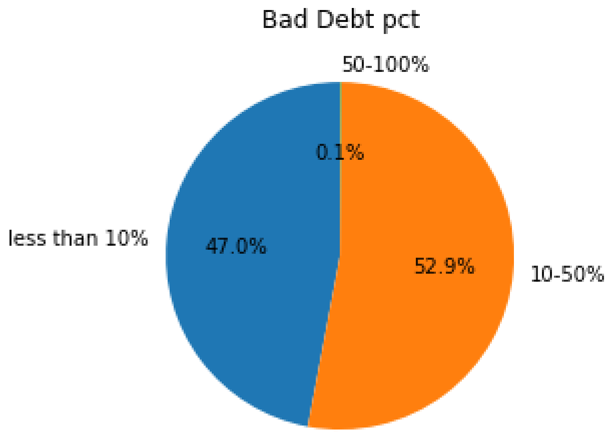
In [25]:
```
# Visualization 1 (Geo-Map):
fig = go.Figure(data=go.Scattergeo(
    lat = top_2500_second_mortgage_pctown_10['lat'],
    lon = top_2500_second_mortgage_pctown_10['lng']),
    )
fig.update_layout(
    geo=dict(
        scope = 'north america',
        showland = True,
        landcolor = "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 perce
nt ownership is above 10 percent')
fig.show()
```

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



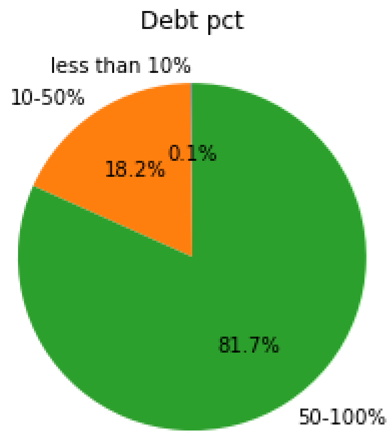
In [26]:
```
train['bad_debt']=train['second_mortgage']+train['home_equity']-train['home_
equity_second_mortgage']
```

In [27]:
```
# Visualization 2:
train['bins_bad_debt'] = pd.cut(train['bad_debt'],bins=[0,0.1,.5,1], labels=
["less than 10%","10-50%","50-100%"])
train.groupby(['bins_bad_debt']).size().plot(kind='pie',subplots=True,starta
ngle=90, autopct='%1.1f%%')
plt.title('Bad Debt pct')
plt.ylabel("")

plt.show()
```



In [28]:
```
# Visualization 3:
train['bins_debt'] = pd.cut(train['debt'],bins=[0,0.1,.5,1], labels=["less t
```

```
han 10%","10-50%","50-100%"])
train.groupby(['bins_debt']).size().plot(kind='pie',subplots=True,startangle
=90, autopct='%1.1f%%')
plt.title('Debt pct')
plt.ylabel("")

plt.show()
```

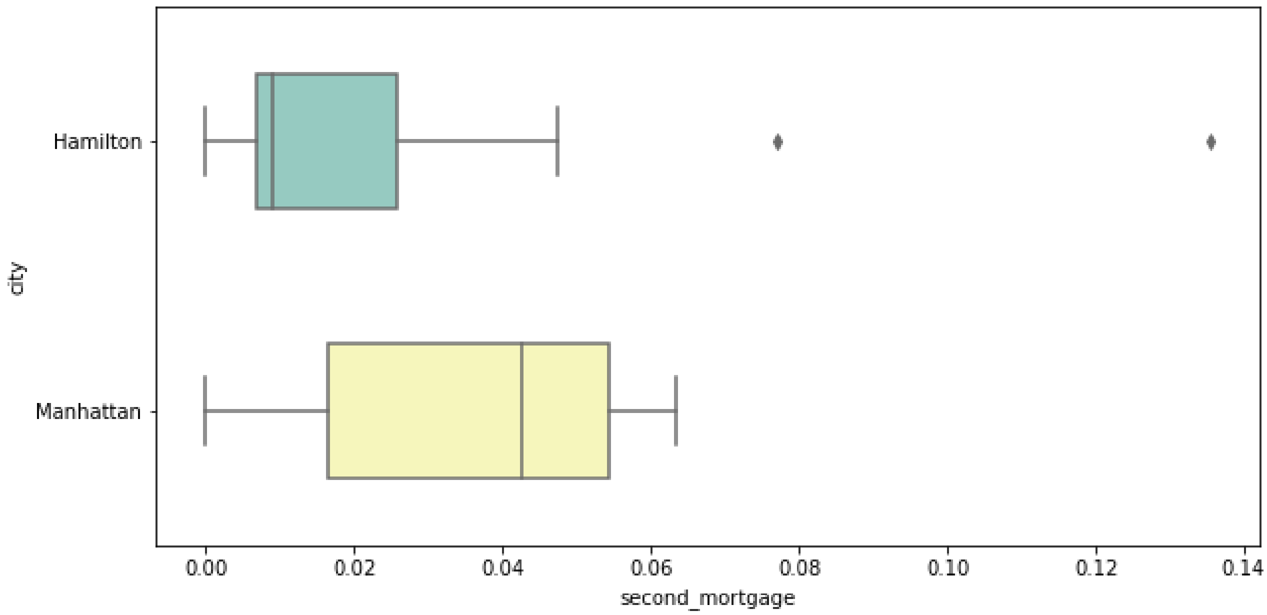


In [29]:
```
cols=['second_mortgage','home_equity','debt','bad_debt']
df_box_hamilton=train.loc[train['city'] == 'Hamilton']
df_box_manhattan=train.loc[train['city'] == 'Manhattan']
df_box_city=pd.concat([df_box_hamilton,df_box_manhattan])
df_box_city.head(4)
```

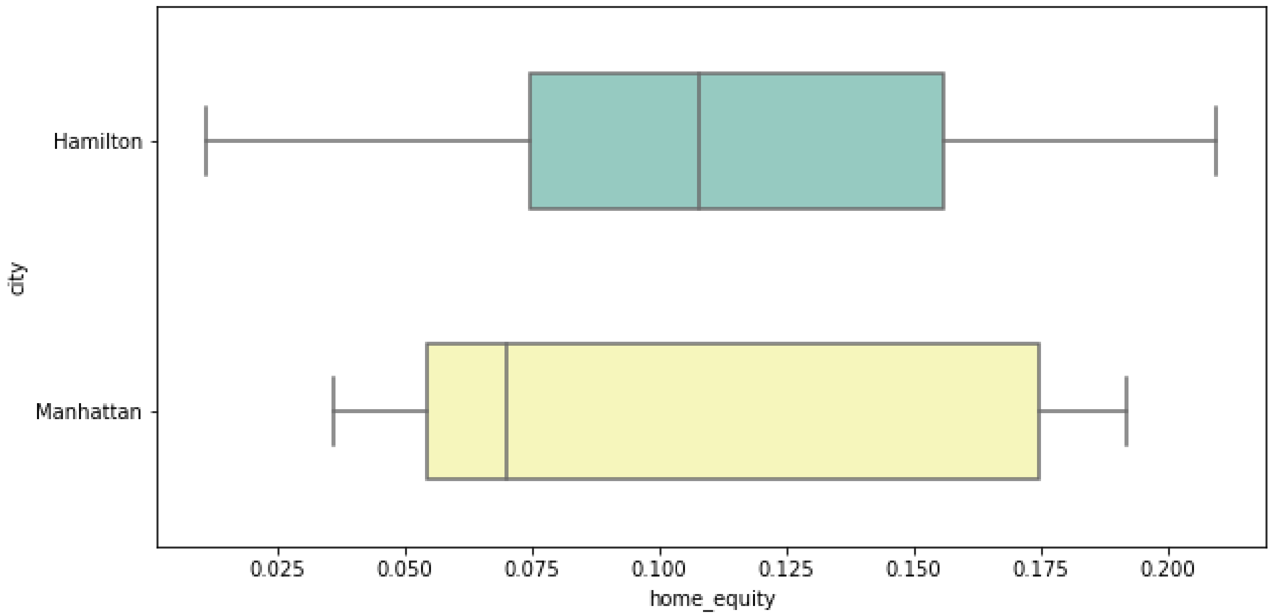
Out[29]:

	COUNTYID	STATEID	state	state_ab	city	place	type	primary	zip_code	area_
UID										
267822	53	36	New York	NY	Hamilton	Hamilton	City	tract	13346	
263797	21	34	New Jersey	NJ	Hamilton	Yardville	City	tract	8610	
270979	17	39	Ohio	OH	Hamilton	Hamilton City	Village	tract	45015	
259028	95	28	Mississippi	MS	Hamilton	Hamilton	CDP	tract	39746	

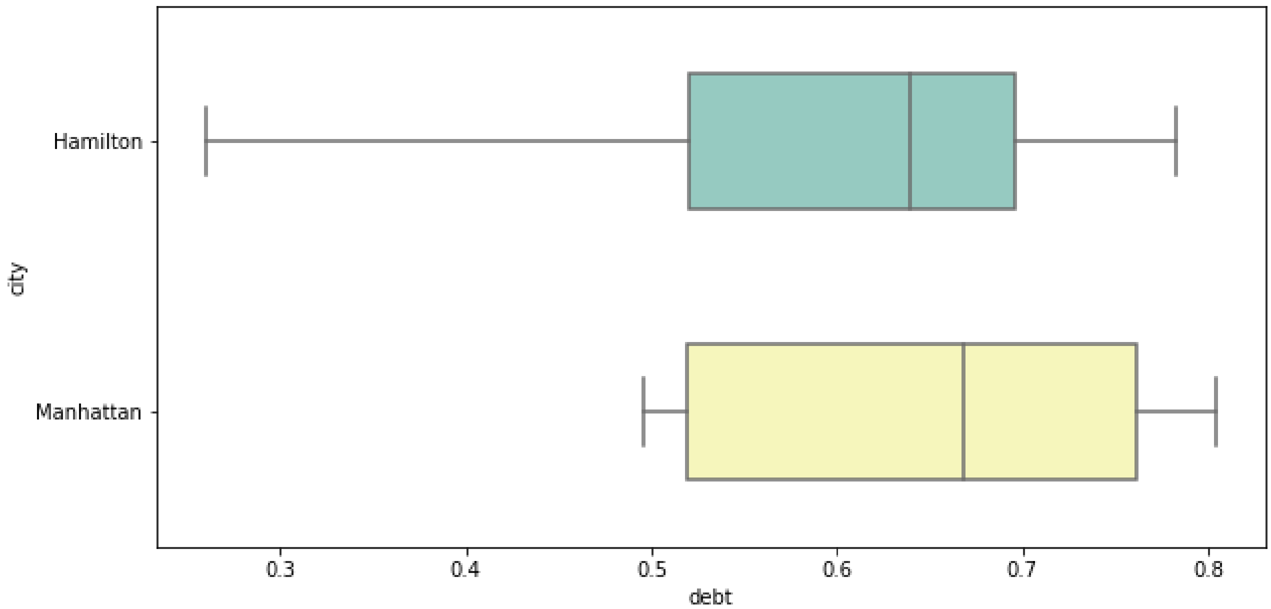
In [30]:
```
# Visualization 4:
plt.figure(figsize=(10,5))
sns.boxplot(data=df_box_city,x='second_mortgage', y='city',width=0.5,palette
="Set3")
plt.show()
```



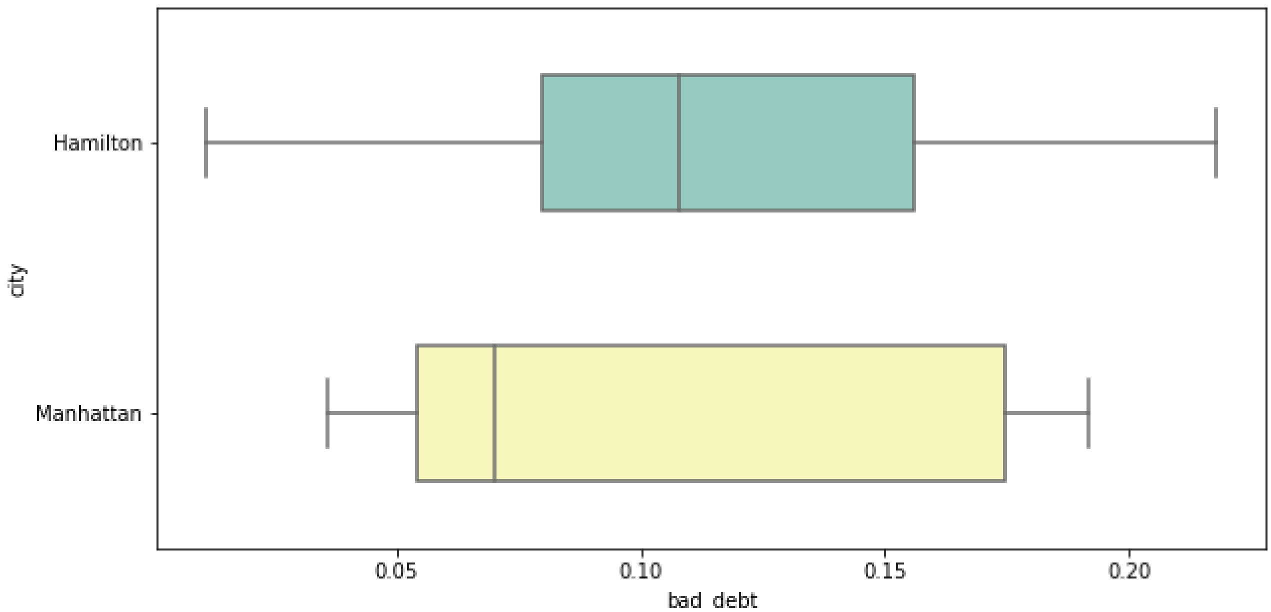
In [31]:
```
# Visualization 5:
plt.figure(figsize=(10,5))
sns.boxplot(data=df_box_city,x='home_equity', y='city',width=0.5,palette="Se
t3")
plt.show()
```



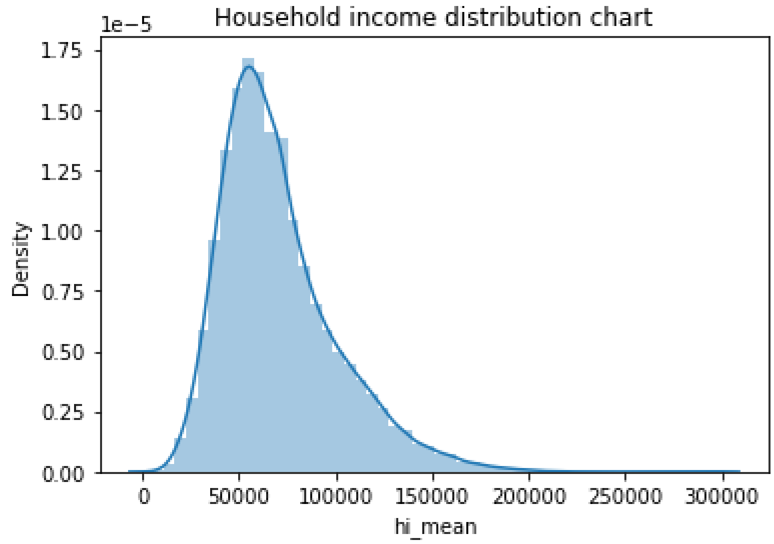
In [32]:
```
# Visualization 6:
plt.figure(figsize=(10,5))
sns.boxplot(data=df_box_city,x='debt', y='city',width=0.5,palette="Set3")
plt.show()
```



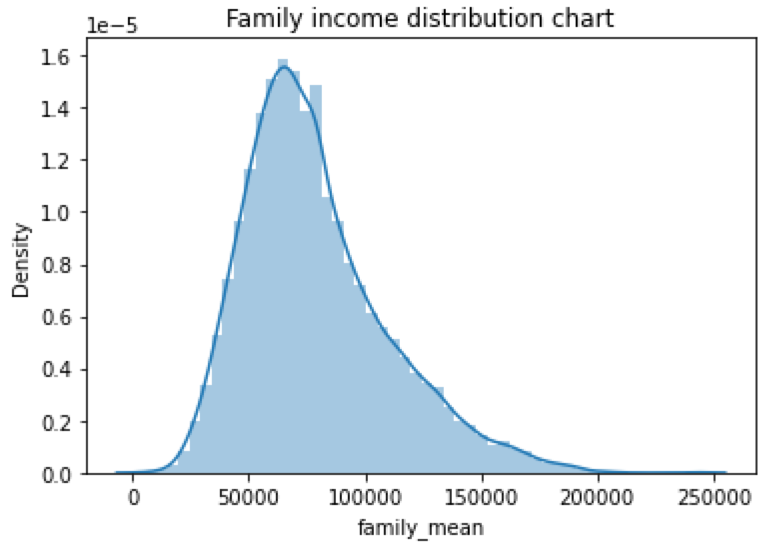
In [33]:
```
# Visualization 7:
plt.figure(figsize=(10,5))
sns.boxplot(data=df_box_city,x='bad_debt', y='city',width=0.5,palette="Set3"
)
plt.show()
```



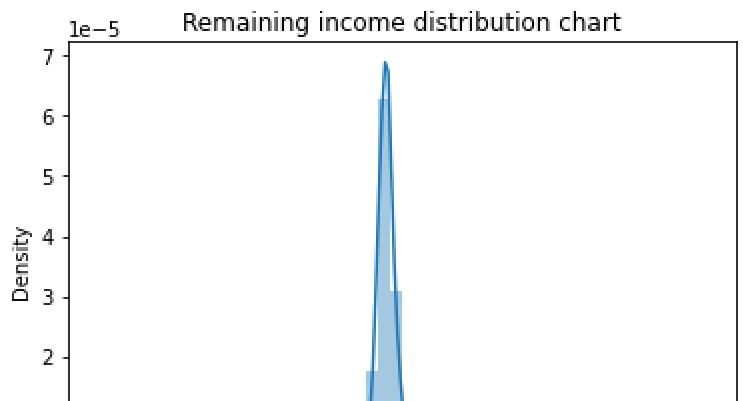
In [34]:
```
# Visualization 8:
sns.distplot(train['hi_mean'])
plt.title('Household income distribution chart')
plt.show()
```

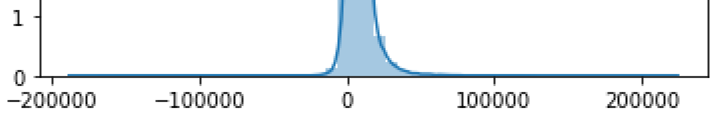


In [35]:
```
# Visualization 9:
sns.distplot(train['family_mean'])
plt.title('Family income distribution chart')
plt.show()
```



In [36]:
```
# Visualization 10:
sns.distplot(train['family_mean']-train['hi_mean'])
plt.title('Remaining income distribution chart')
plt.show()
```

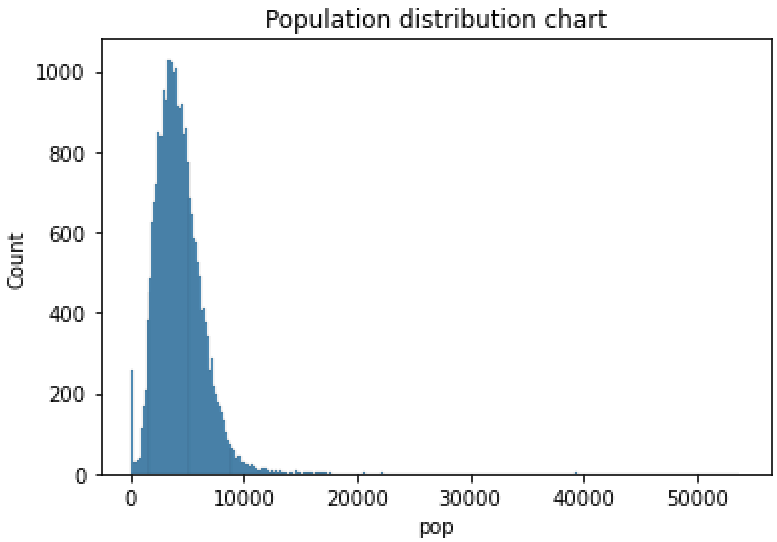




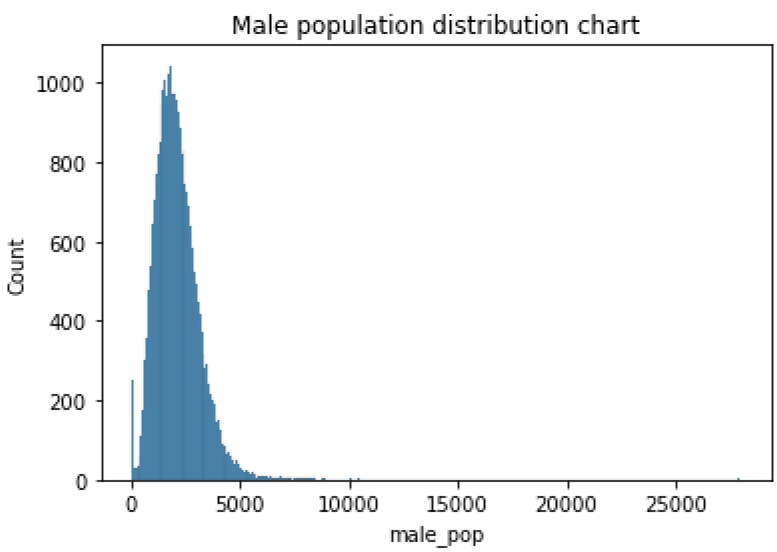
In [ ]:

Week 2 Exploratory Data Analysis:

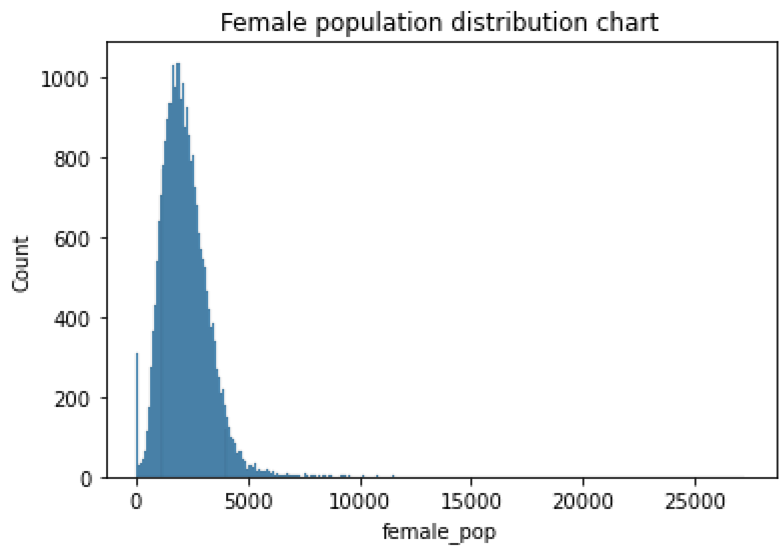
In [37]:
```
# Visualization 11:
sns.histplot(train['pop'])
plt.title('Population distribution chart')
plt.show()
```



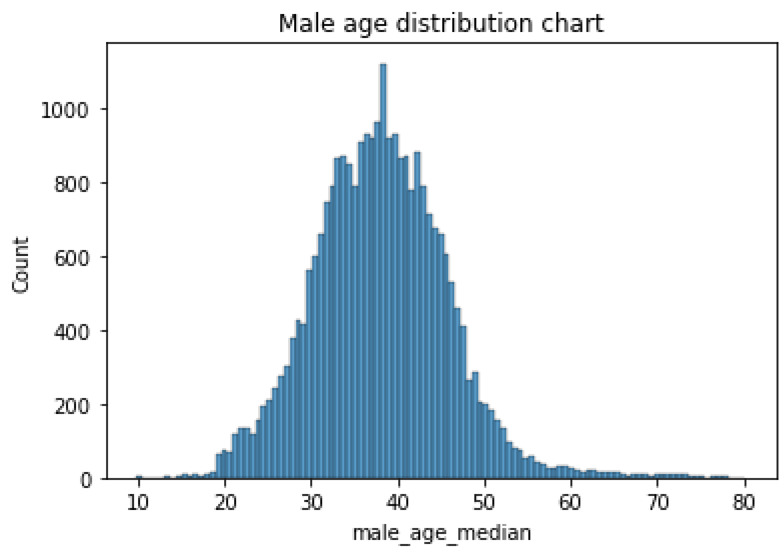
In [38]:
```
# Visualization 12:
sns.histplot(train['male_pop'])
plt.title('Male population distribution chart')
plt.show()
```



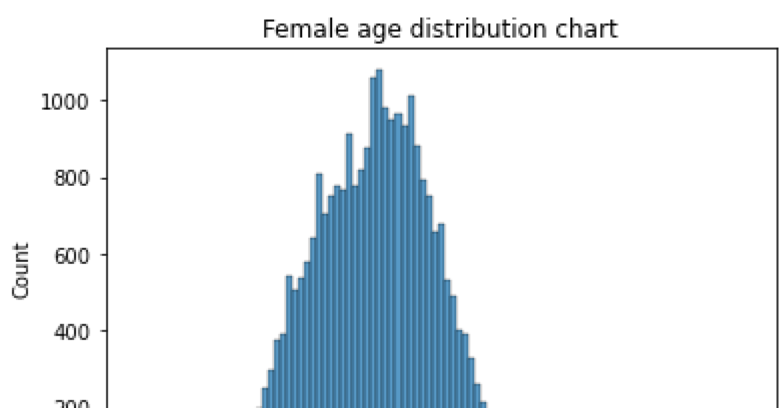
In [39]:
```
# Visualization 13:
sns.histplot(train['female_pop'])
plt.title('Female population distribution chart')
plt.show()
```

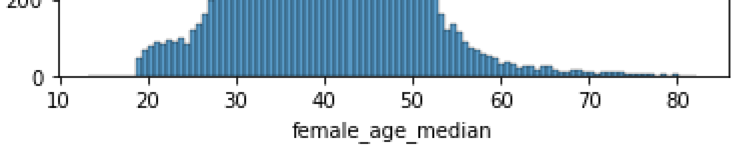


In [40]:
```
# Visualization 14:
sns.histplot(train['male_age_median'])
plt.title('Male age distribution chart')
plt.show()
```



In [41]:
```
# Visualization 15:
sns.histplot(train['female_age_median'])
plt.title('Female age distribution chart')
plt.show()
```

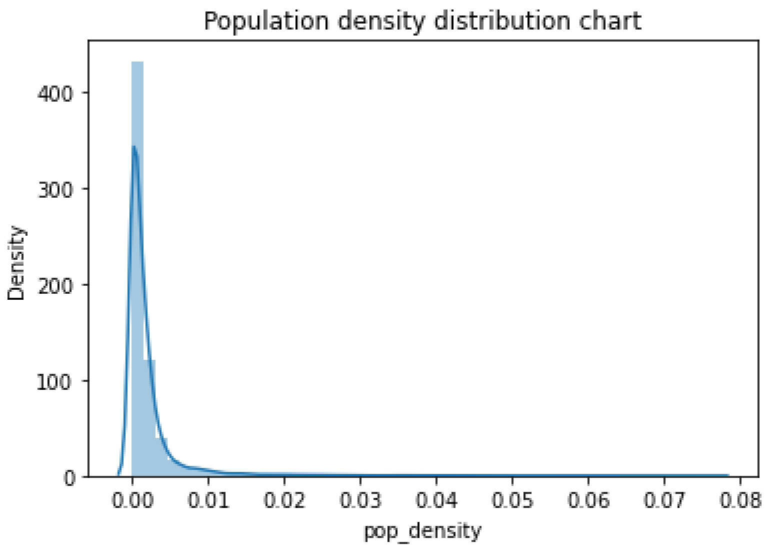




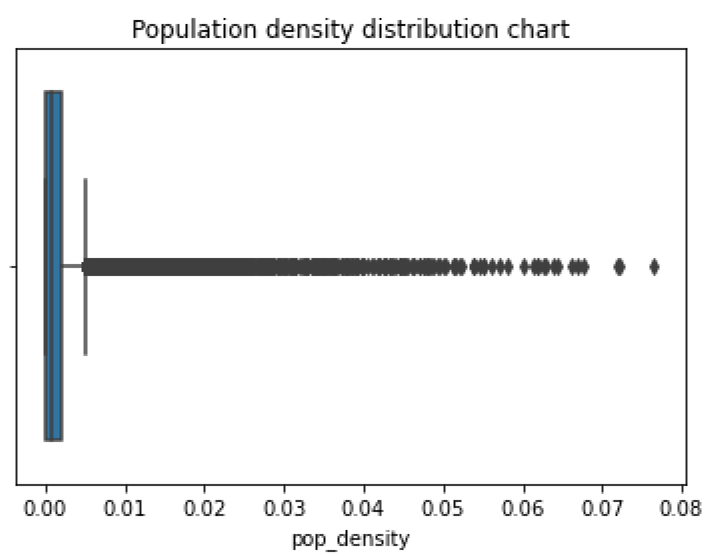
In [42]:
```
train["pop_density"]=train["pop"]/train["ALand"]
```

In [43]:
```
test["pop_density"]=test["pop"]/test["ALand"]
```

In [44]:
```
# Visualization 16:
sns.distplot(train['pop_density'])
plt.title('Population density distribution chart')
plt.show()
```



In [45]:
```
# Visualization 17:
sns.boxplot(train['pop_density'])
plt.title('Population density distribution chart')
plt.show()
```



In [46]:
```
train["median_age"]=(train["male_age_median"]+train["female_age_median"])/2
```

In [47]:
```
test["median_age"]=(test["male_age_median"]+test["female_age_median"])/2
```

In [48]:
```
train[['male_age_median','female_age_median','male_pop','female_pop','median
```

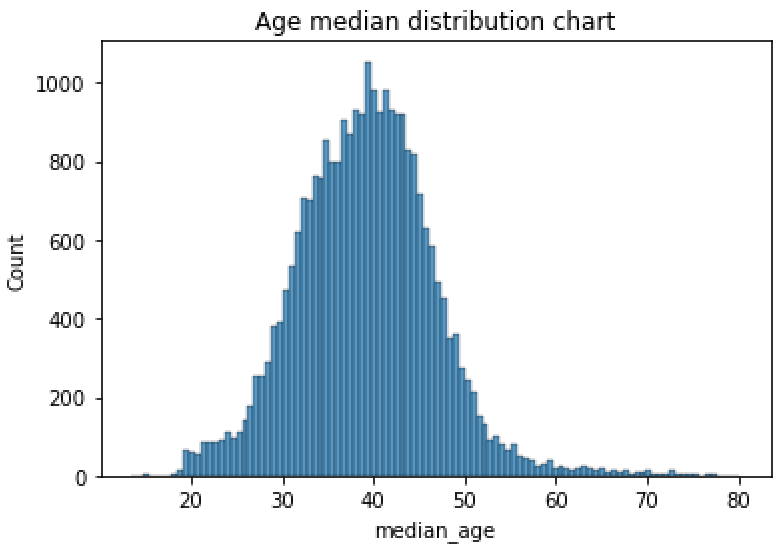
```
_age']].head()
```

Out[48]:

UID	male_age_median	female_age_median	male_pop	female_pop	median_age
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]:

```
# Visualization 18:
sns.histplot(train['median_age'])
plt.title('Age median distribution chart')
plt.show()
```



In [50]:

```
train["pop"].describe()
```

Out[50]:

```
count    27321.000000
mean      4316.032685
std       2169.226173
min          0.000000
25%       2885.000000
50%       4042.000000
75%       5430.000000
max      53812.000000
Name: pop, dtype: float64
```

In [51]:

```
train['pop_bins']=pd.cut(train['pop'],bins=5,labels=['very low','low','mediu
m','high','very high'])
```

In [52]:

```
train[['pop','pop_bins']]
```

Out[52]:

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

27321 rows × 2 columns

In [53]:
```
train['pop_bins'].value_counts()
```

Out[53]:
```
very low     27058
low            246
medium           9
high             7
very high        1
Name: pop_bins, dtype: int64
```

In [54]:
```
train.groupby(by='pop_bins')[['married','separated','divorced']].count()
```

Out[54]:

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

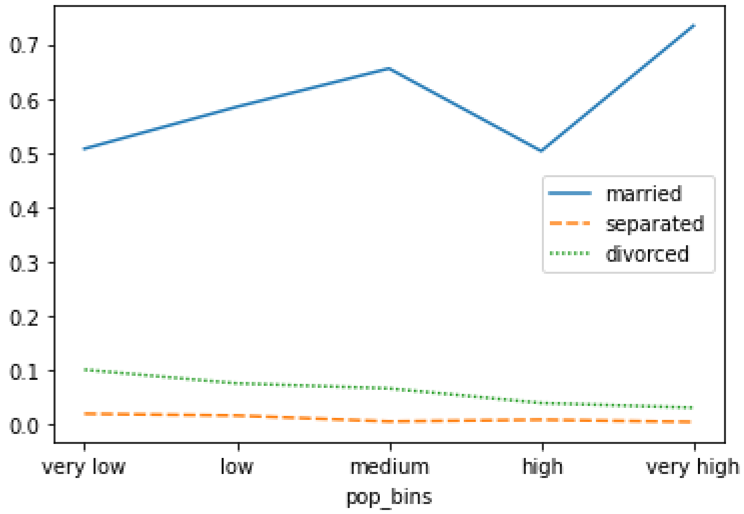
In [55]:
```
train.groupby(by='pop_bins')[['married','separated','divorced']].agg(["mean"
, "median"])
```

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]:
```
# Visualization 19:
pop_bin_married=train.groupby(by='pop_bins')[['married','separated','divorce
d']].agg(["mean"])
```

```
sns.lineplot(data=pop_bin_married)
plt.show()
```



In [57]:
```
rent_state_mean=train.groupby(by='state')['rent_mean'].agg(["mean"])
rent_state_mean.head()
```

Out[57]:

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

In [58]:
```
income_state_mean=train.groupby(by='state')['family_mean'].agg(["mean"])
income_state_mean.head()
```

Out[58]:

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

In [59]:
```
rent_perc_of_income=rent_state_mean['mean']/income_state_mean['mean']
rent_perc_of_income.head(10)
```

Out[59]:
```
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
Name: mean, dtype: float64
```

In [60]:
```
#overall level rent as a percentage of income
sum(train['rent_mean'])/sum(train['family_mean'])
```

Out[60]: 0.013358170721473864

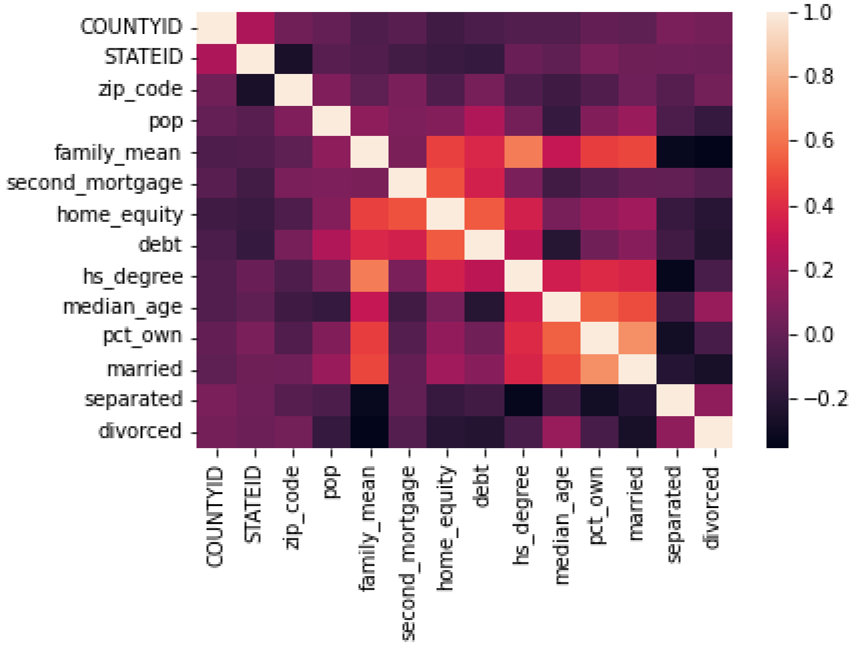
In [61]:
```
#Correlation analysis and heatmap
train[["COUNTYID","STATEID","zip_code", "type","pop","family_mean",'second_mortgage', 'home_equity', 'debt','hs_degree','median_age','pct_own', 'married','separated', 'divorced']].corr()
```

Out[61]:

	COUNTYID	STATEID	zip_code	pop	family_mean	second_mortgage	home_ec
COUNTYID	1.000000	0.224549	0.036527	-0.002662	-0.075688	-0.039283	-0.12
STATEID	0.224549	1.000000	-0.261465	-0.036599	-0.071612	-0.112512	-0.14
zip_code	0.036527	-0.261465	1.000000	0.083058	-0.024658	0.067693	-0.07
pop	-0.002662	-0.036599	0.083058	1.000000	0.128173	0.079675	0.09
family_mean	-0.075688	-0.071612	-0.024658	0.128173	1.000000	0.074703	0.45
second_mortgage	-0.039283	-0.112512	0.067693	0.079675	0.074703	1.000000	0.51
home_equity	-0.123939	-0.145301	-0.073191	0.099352	0.458973	0.510460	1.00
debt	-0.086231	-0.160532	0.057775	0.231013	0.378871	0.351298	0.53
hs_degree	-0.062703	0.014132	-0.077672	0.049238	0.634493	0.064412	0.35
median_age	-0.063521	-0.017172	-0.126150	-0.162499	0.300215	-0.116616	0.06
pct_own	-0.004632	0.069314	-0.069965	0.088457	0.450961	-0.054530	0.14
married	-0.021428	0.025763	0.030217	0.167656	0.480095	-0.006438	0.18
separated	0.069059	0.030409	-0.048023	-0.083182	-0.323433	-0.010731	-0.15
divorced	0.048850	0.018748	0.043310	-0.160931	-0.353274	-0.056991	-0.20

In [62]:
```
# Visualization 20:
sns.heatmap(train[["COUNTYID","STATEID","zip_code", "type","pop","family_mean",'second_mortgage', 'home_equity', 'debt','hs_degree','median_age','pct_own', 'married','separated', 'divorced']].corr())
```

Out[62]: <AxesSubplot:>



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 [63]:
```
from sklearn.decomposition import FactorAnalysis
```

In [64]:
```
fa = FactorAnalysis(n_components=5,random_state=11)
```

In [65]:
```
train_transformed = fa.fit_transform(train.select_dtypes(exclude=('object',
'category')))
```

In [66]:
```
train_transformed.shape
```

Out[66]: (27321, 5)

In [67]:
```
train_transformed
```

Out[67]:
```
array([[ 0.05640687, -0.05073008,  1.25002287, -0.32623122,  0.1814258 ],
       [-0.10015645,  0.01442735,  0.11011385, -0.95809505,  0.58805725],
       [-0.04710979, -0.0094559 ,  0.13106345,  0.45168299,  0.90055   ],
       ...,
       [ 0.93167634, -0.37995383, -0.96907522,  0.41947921,  0.30372189],
       [-0.08682288,  0.00848632, -0.88563901,  3.03163033,  1.15593996],
       [-0.09529886,  0.01164864, -1.3315217 , -0.69048311, -0.11200756]])
```

In [68]:
```
x_train = pd.read_csv('train.csv')
x_test = pd.read_csv('test.csv')
```

In [69]:
```
x_train.drop(['BLOCKID','SUMLEVEL'],axis=1,inplace=True)
```

In [70]:
```
x_train.dropna(axis=0,inplace=True)
x_train.head()
```

Out[70]:

	UID	COUNTYID	STATEID	state	state_ab	city	place	type	primary	zip_code	are
0	267822	53	36	New York	NY	Hamilton	Hamilton	City	tract	13346	
1	246444	141	18	Indiana	IN	South Bend	Roseland	City	tract	46616	
2	245683	63	18	Indiana	IN	Danville	Danville	City	tract	46122	
3	279653	127	72	Puerto Rico	PR	San Juan	Guaynabo	Urban	tract	927	
4	247218	161	20	Kansas	KS	Manhattan	Manhattan City	City	tract	66502	

In [71]:
```
x_train.drop_duplicates(inplace=True)
```

In [72]:
```
x_train.shape
```

Out[72]: (26585, 78)

In [73]:
```
x_test.head()
```

Out[73]:

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

In [74]:
```
x_test.shape
```

Out[74]: (11709, 80)

In [75]:
```python
x_test.drop(['BLOCKID','SUMLEVEL'],axis=1,inplace=True)
```

In [76]:
```python
x_test.isna().sum()
```

Out[76]:
```
UID            0
COUNTYID       0
STATEID        0
state          0
state_ab       0
            ...
pct_own      122
married       84
married_snp   84
separated     84
divorced      84
Length: 78, dtype: int64
```

In [77]:
```python
x_test.dropna(axis=0,inplace=True)
```

In [78]:
```python
x_test.drop_duplicates(inplace=True)
```

In [79]:
```python
x_test.shape
```

Out[79]: (11355, 78)

In [80]:
```python
imp_feature = x_train.select_dtypes(exclude=('object','category'))
```

In [81]:
```python
imp_feature.head()
```

Out[81]:

	UID	COUNTYID	STATEID	zip_code	area_code	lat	lng	ALand	AWater	p
0	267822	53	36	13346	315	42.840812	-75.501524	202183361.0	1699120	52
1	246444	141	18	46616	574	41.701441	-86.266614	1560828.0	100363	26
2	245683	63	18	46122	317	39.792202	-86.515246	69561595.0	284193	68
3	279653	127	72	927	787	18.396103	-66.104169	1105793.0	0	27
4	247218	161	20	66502	785	39.195573	-96.569366	2554403.0	0	56

In [82]:
```python
imp_feature.shape
```

Out[82]: (26585, 72)

In [83]:
```python
to_drop = ['UID','COUNTYID', 'STATEID', 'zip_code', 'area_code', 'lat', 'ln
g']
```

In [84]:
```python
for col in imp_feature.columns:
    if col in to_drop:
        imp_feature.drop(col,axis=1,inplace=True)
```

In [85]:
```python
imp_feature.head()
```

Out[85]:

	ALand	AWater	pop	male_pop	female_pop	rent_mean	rent_median	rent_stdev	rent_sampl
0	202183361.0	1699120	5230	2612	2618	769.38638	784.0	232.63967	2

0	202183361.0	1699126	5230	2612	2618	709.38638	784.0	232.63967	2
1	1560828.0	100363	2633	1349	1284	804.87924	848.0	253.46747	3
2	69561595.0	284193	6881	3643	3238	742.77365	703.0	323.39011	2
3	1105793.0	0	2700	1141	1559	803.42018	782.0	297.39258	2
4	2554403.0	0	5637	2586	3051	938.56493	881.0	392.44096	10

In [86]:
```
x_train_features = imp_feature[['pop','rent_median','hi_median','family_median','hc_mean','second_mortgage','home_equity','debt','hs_degree','pct_own','married','separated','divorced']]
```

In [87]:
```
x_train_features.head()
```

Out[87]:

	pop	rent_median	hi_median	family_median	hc_mean	second_mortgage	home_equity	debt	h
0	5230	784.0	48120.0	53245.0	570.01530	0.02077	0.08919	0.52963	
1	2633	848.0	35186.0	43023.0	351.98293	0.02222	0.04274	0.60855	
2	6881	703.0	74964.0	85395.0	556.45986	0.00000	0.09512	0.73484	
3	2700	782.0	37845.0	44399.0	288.04047	0.01086	0.01086	0.52714	
4	5637	881.0	22497.0	50272.0	443.68855	0.05426	0.05426	0.51938	

In [88]:
```
x_train_features.shape
```

Out[88]:
```
(26585, 13)
```

In [89]:
```
y_train = imp_feature['hc_mortgage_mean']
```

In [90]:
```
x_test_feature = x_test[['pop','rent_median','hi_median','family_median','hc_mean','second_mortgage','home_equity','debt','hs_degree','pct_own','married','separated','divorced']]
```

In [91]:
```
from sklearn.linear_model import LinearRegression
le = LinearRegression()
```

In [92]:
```
le.fit(x_train_features,y_train)
```

Out[92]:
```
LinearRegression()
```

In [93]:
```
y_pred = le.predict(x_test_feature)
```

In [94]:
```
y_test = x_test['hc_mortgage_mean']
```

In [95]:
```
from sklearn.metrics import r2_score,mean_squared_error
```

In [96]:
```
r2_score(y_test,y_pred)
```

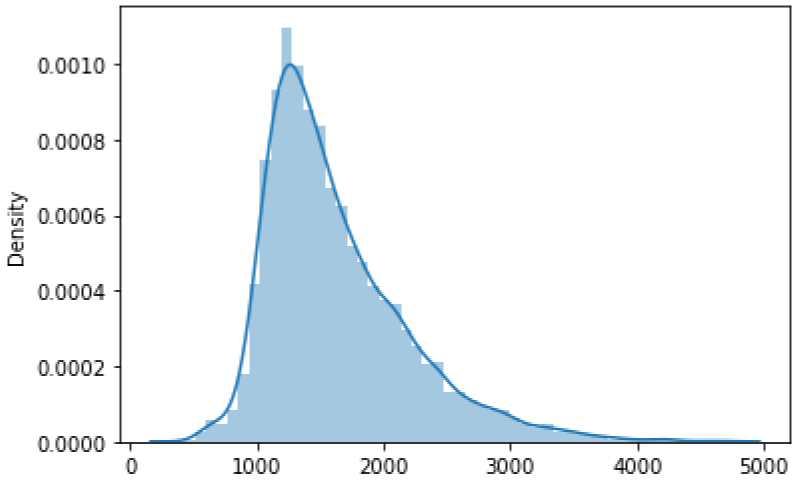
Out[96]:
```
0.8073813546881963
```

In [97]:
```
np.sqrt(mean_squared_error(y_test,y_pred))
```

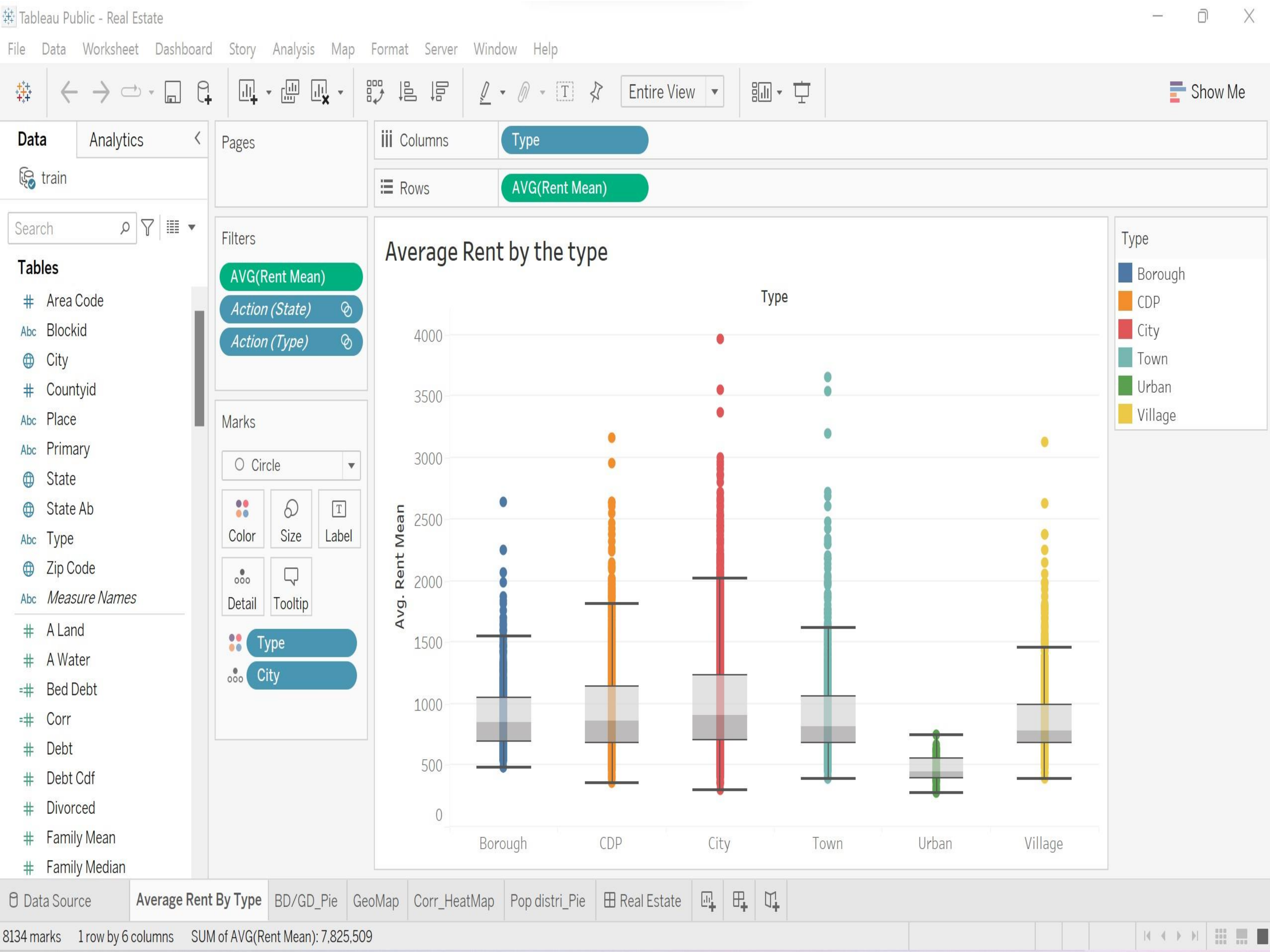
Out[97]:
```
277.04518388580743
```

In [98]:
```
# Visualization 21:
```

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



In [ ]: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Entire View
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Search
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Area Code
Blockid
City
Countyid
Place
Primary
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State Ab
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Zip Code
Measure Names
A Land
A Water
Bed Debt
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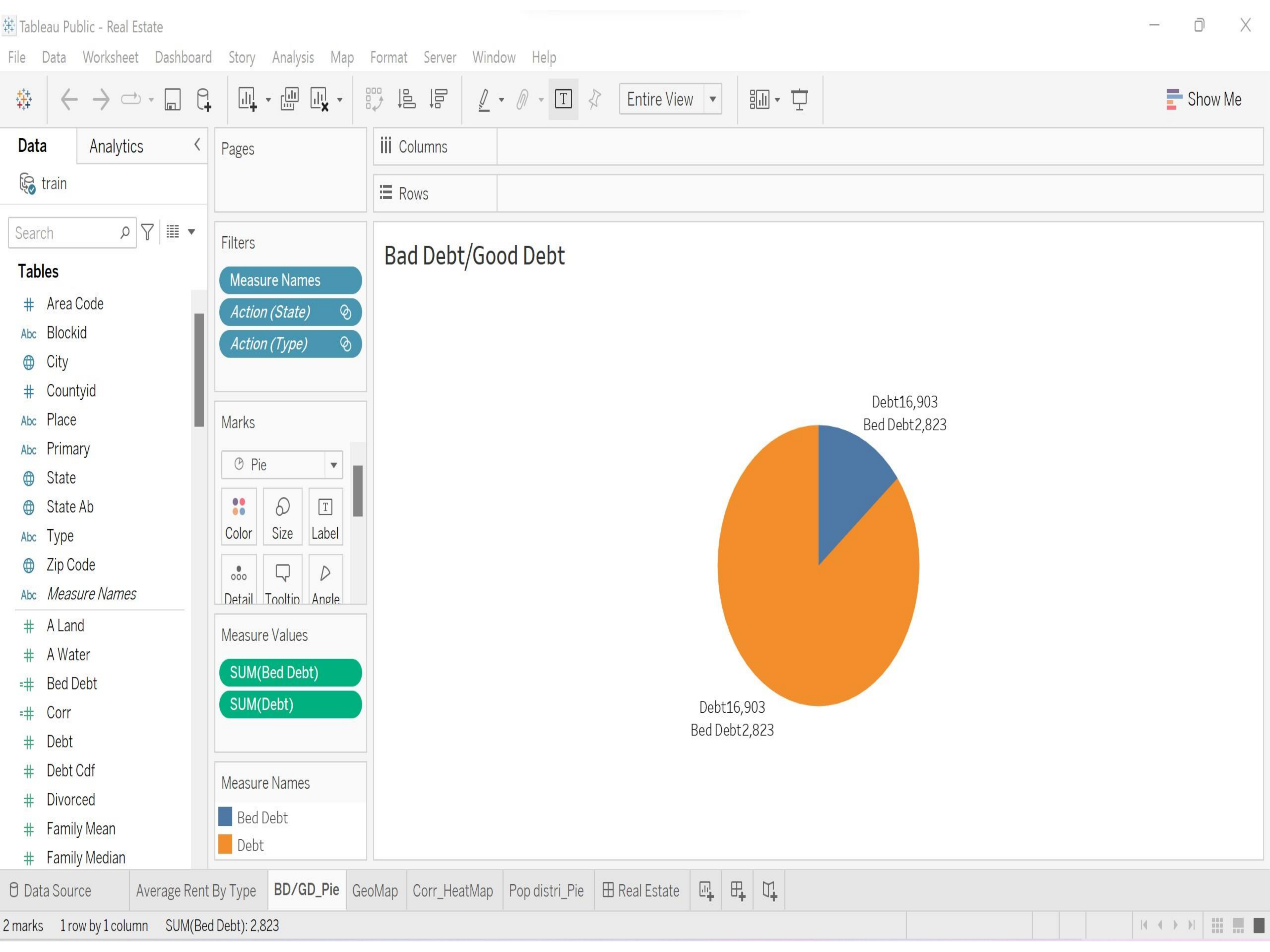
Debt
Debt Cdf
Divorced
Family Mean
Family Median
Pages
Filters
AVG(Rent Mean)
Action (State)
Action (Type)
Marks
Circle
Color
Size
Label
Detail
Tooltip
Type
City
Columns
Type
Rows
AVG(Rent Mean)
Average Rent by the type
Type
Avg. Rent Mean
4000
3500
3000
2500
2000
1500
1000
500
0
Borough
CDP
City
Town
Urban
Village
Type
Borough
CDP
City
Town
Urban
Village
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate
8134 marks
1 row by 6 columns
SUM of AVG(Rent Mean): 7,825,509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Area Code
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Type
Zip Code
Measure Names
A Land
A Water
Bed Debt
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Debt Cdf
Divorced
Family Mean
Family Median
Pages
Filters
Measure Names
Action (State)
Action (Type)
Marks
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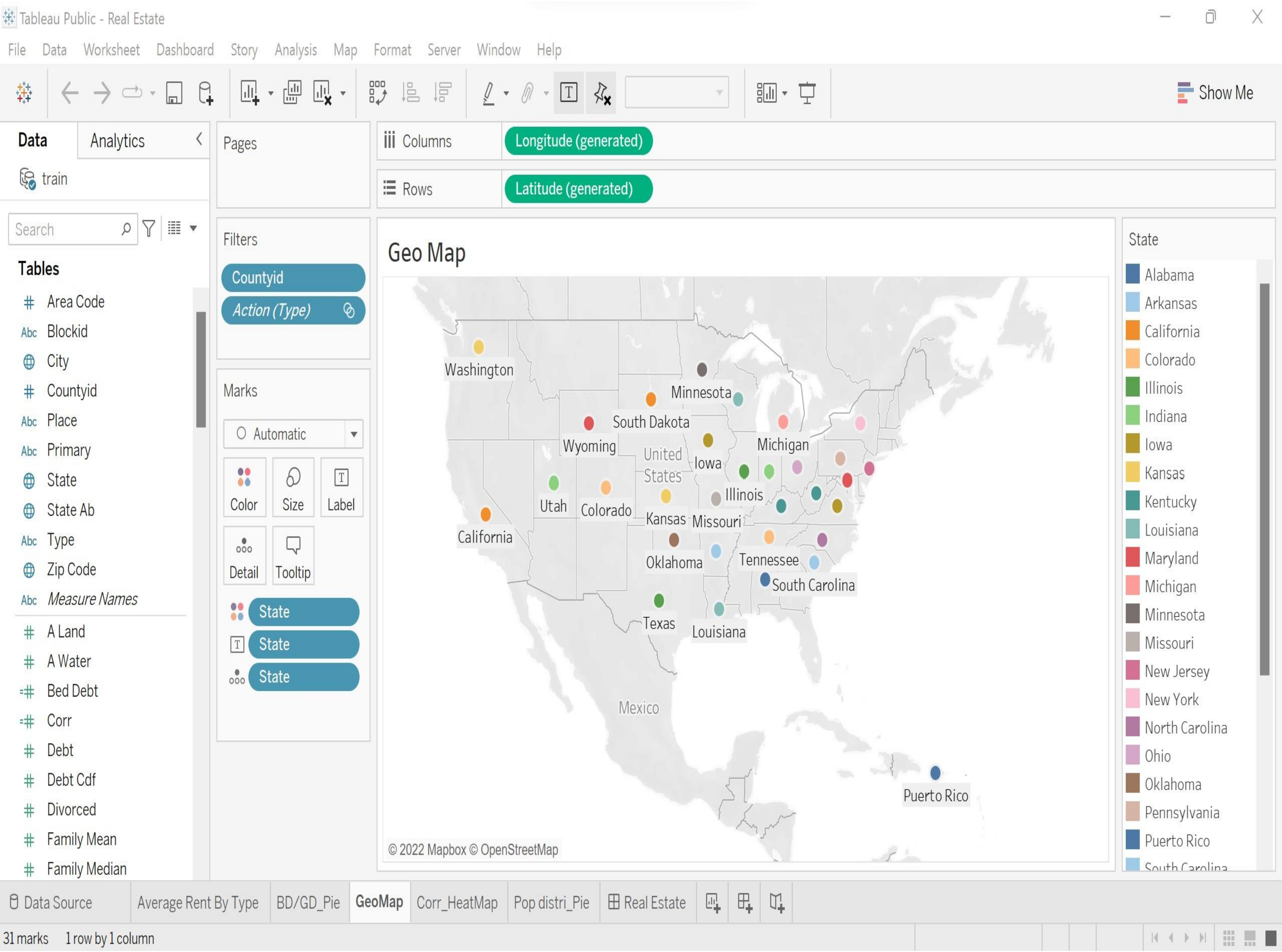
Size
Label
Detail
Tooltip
Angle
Measure Values
SUM(Bed Debt)
SUM(Debt)
Measure Names
Bed Debt
Debt
Columns
Rows
Bad Debt/Good Debt
Debt16,903
Bed Debt2,823
Debt16,903
Bed Debt2,823
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate
2 marks
1 row by 1 column
SUM(Bed Debt): 2,823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Analytics
train
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Tables
Area Code
Blockid
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A Land
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Bed Debt
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Divorced
Family Mean
Family Median
Pages
Filters
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Action (Type)
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Size
Label
Detail
Tooltip
State
State
State
Columns
Longitude (generated)
Rows
Latitude (generated)
Geo Map
Washington
Minnesota
South Dakota
Wyoming
United States
Iowa
Michigan
Illinois
Utah
Colorado
Kansas
Missouri
California
Oklahoma
Tennessee
South Carolina
Texas
Louisiana
Mexico
Puerto Rico
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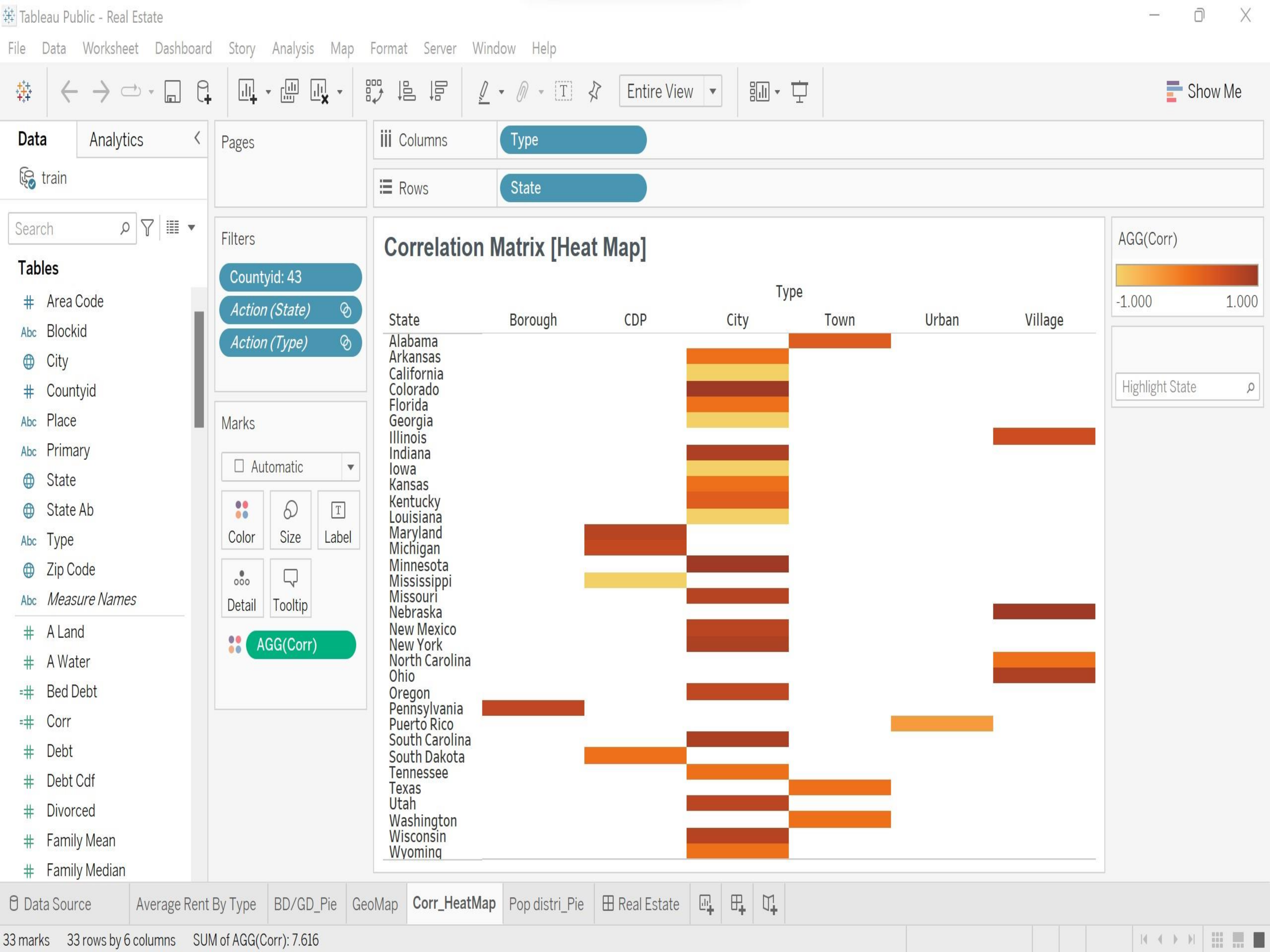
State
Alabama
Arkansas
California
Colorado
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maryland
Michigan
Minnesota
Missouri
New Jersey
New York
North Carolina
Ohio
Oklahoma
Pennsylvania
Puerto Rico
South Carolina
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate
31 marks
1 row by 1 column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Entire View
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Data Analytics
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Blockid
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Countyid
Place
Primary
State
State Ab
Type
Zip Code
Measure Names
A Land
A Water
Bed Debt
Corr
Debt
Debt Cdf
Divorced
Family Mean
Family Median
Pages
Filters
Countyid: 43
Action (State)
Action (Type)
Marks
Automatic
Color
Size
Label
Detail
Tooltip
AGG(Corr)
Columns
Type
Rows
State
Correlation Matrix [Heat Map]
Type
State
Borough
CDP
City
Town
Urban
Village
Alabama
Arkansas
California
Colorado
Florida
Georgia
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maryland
Michigan
Minnesota
Mississippi
Missouri
Nebraska
New Mexico
New York
North Carolina
Ohio
Oregon
Pennsylvania
Puerto Rico
South Carolina
South Dakota
Tennessee
Texas
Utah
Washington
Wisconsin
Wyoming
AGG(Corr)
-1.000
1.000
Highlight State
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate
33 marks
33 rows by 6 columns
SUM of AGG(Corr): 7.616

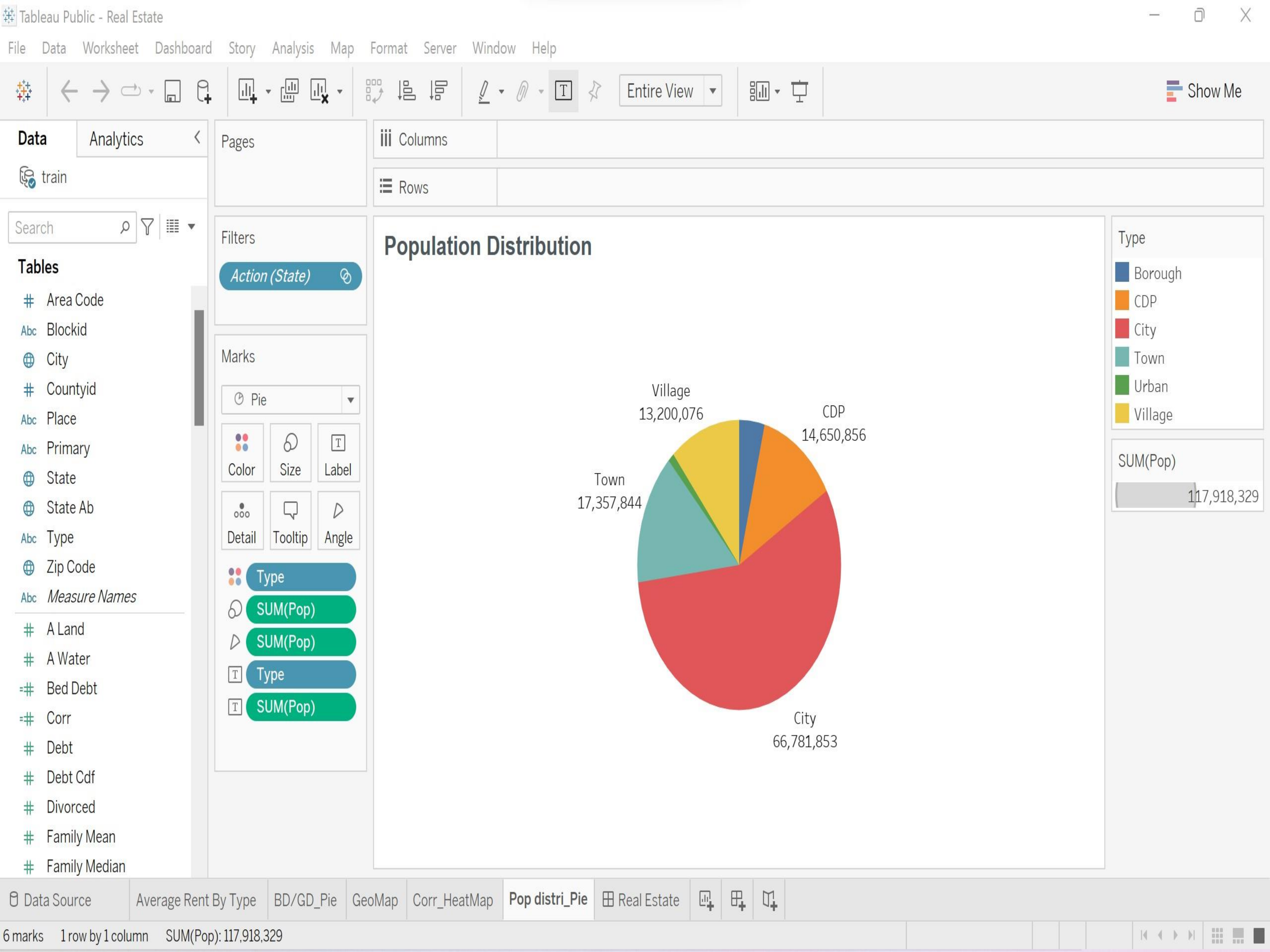
Tableau Public - Real Estate
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Entire View
Show Me
Data
Analytics
train
Search
Tables
Area Code
Blockid
City
Countyid
Place
Primary
State
State Ab
Type
Zip Code
Measure Names
A Land
A Water
Bed Debt
Corr
Debt
Debt Cdf
Divorced
Family Mean
Family Median
Pages
Filters
Action (State)
Marks
Pie
Color
Size
Label
Detail
Tooltip
Angle
Type
SUM(Pop)
SUM(Pop)
Type
SUM(Pop)
Columns
Rows
Population Distribution
Village
13,200,076
CDP
14,650,856
Town
17,357,844
City
66,781,853
Type
Borough
CDP
City
Town
Urban
Village
SUM(Pop)
117,918,329
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate
6 marks
1 row by 1 column
SUM(Pop): 117,918,329

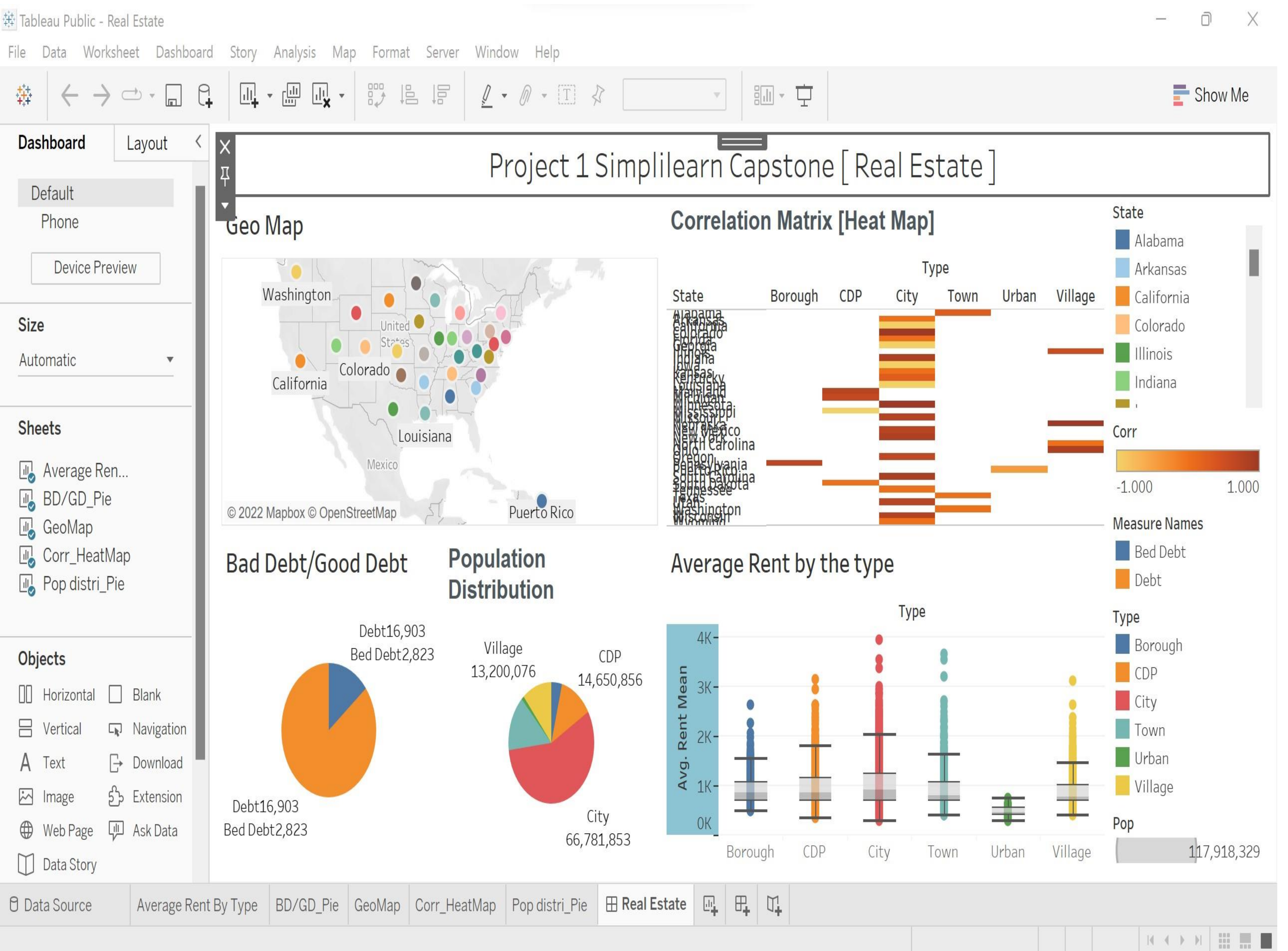
Tableau Public - Real Estate
File
Data
Worksheet
Dashboard
Story
Analysis
Map
Format
Server
Window
Help
Show Me
Dashboard
Layout
Default
Phone
Device Preview
Size
Automatic
Sheets
Average Ren...
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Objects
Horizontal
Blank
Vertical
Navigation
Text
Download
Image
Extension
Web Page
Ask Data
Data Story
Project 1 Simplilearn Capstone [Real Estate]
Geo Map
Washington
United States
Colorado
California
Louisiana
Mexico
Puerto Rico
© 2022 Mapbox © OpenStreetMap
Correlation Matrix [Heat Map]
Type
State
Borough
CDP
City
Town
Urban
Village
State
Alabama
Arkansas
California
Colorado
Illinois
Indiana
Corr
-1.000
1.000
Measure Names
Bed Debt
Debt
Bad Debt/Good Debt
Debt16,903
Bed Debt2,823
Debt16,903
Bed Debt2,823
Population Distribution
Village
13,200,076
CDP
14,650,856
City
66,781,853
Average Rent by the type
Type
Avg. Rent Mean
4K
3K
2K
1K
0K
Borough
CDP
City
Town
Urban
Village
Type
Borough
CDP
City
Town
Urban
Village
Pop
117,918,329
Data Source
Average Rent By Type
BD/GD_Pie
GeoMap
Corr_HeatMap
Pop distri_Pie
Real Estate