Real-Estate-Project

May 2, 2024

It is a Regression project.

[1]:
```
# import the library

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
print('All Library imported')

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

```
All Library imported
```

[2]:
```
# 1. Import the dataset

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

[3]:
```
df_train.shape
```

[3]:
```
(27321, 80)
```

[4]:
```
df_test.shape
```

[4]:
```
(11709, 80)
```

[5]:
```
df_train.head()
```

[5]:
```
      UID  BLOCKID  SUMLEVEL  COUNTYID  STATEID        state state_ab  \
0  267822      NaN       140        53       36     New York       NY
1  246444      NaN       140       141       18      Indiana       IN
2  245683      NaN       140        63       18      Indiana       IN
3  279653      NaN       140       127       72  Puerto Rico       PR
4  247218      NaN       140       161       20       Kansas       KS

         city          place   type  … female_age_mean  female_age_median  \
```

```
0    Hamilton         Hamilton   City  …        44.48629           45.33333
1  South Bend         Roseland   City  …        36.48391           37.58333
2    Danville         Danville   City  …        42.15810           42.83333
3    San Juan         Guaynabo  Urban  …        47.77526           50.58333
4   Manhattan  Manhattan City   City  …        24.17693           21.58333

   female_age_stdev  female_age_sample_weight  female_age_samples  pct_own  \
0          22.51276                 685.33845              2618.0  0.79046
1          23.43353                 267.23367              1284.0  0.52483
2          23.94119                 707.01963              3238.0  0.85331
3          24.32015                 362.20193              1559.0  0.65037
4          11.10484                1854.48652              3051.0  0.13046

   married  married_snp  separated  divorced
0  0.57851      0.01882    0.01240   0.08770
1  0.34886      0.01426    0.01426   0.09030
2  0.64745      0.02830    0.01607   0.10657
3  0.47257      0.02021    0.02021   0.10106
4  0.12356      0.00000    0.00000   0.03109

[5 rows x 80 columns]
```

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

[6]:
```
      UID  BLOCKID  SUMLEVEL  COUNTYID  STATEID         state state_ab  \
0  255504      NaN       140       163       26      Michigan       MI
1  252676      NaN       140         1       23         Maine       ME
2  276314      NaN       140        15       42  Pennsylvania       PA
3  248614      NaN       140       231       21      Kentucky       KY
4  286865      NaN       140       355       48         Texas       TX

             city                  place     type  … female_age_mean  \
0         Detroit  Dearborn Heights City      CDP  …        34.78682
1          Auburn           Auburn City     City  …        44.23451
2       Pine City              Millerton  Borough  …        41.62426
3      Monticello        Monticello City     City  …        44.81200
4  Corpus Christi                  Edroy     Town  …        40.66618

   female_age_median  female_age_stdev  female_age_sample_weight  \
0           33.75000          21.58531                 416.48097
1           46.66667          22.37036                 532.03505
2           44.50000          22.86213                 453.11959
3           48.00000          21.03155                 263.94320
4           42.66667          21.30900                 709.90829

   female_age_samples  pct_own  married  married_snp  separated  divorced
0              1938.0  0.70252  0.28217      0.05910    0.03813   0.14299
```

```
1             1950.0  0.85128  0.64221     0.02338    0.00000   0.13377
2             1879.0  0.81897  0.59961     0.01746    0.01358   0.10026
3             1081.0  0.84609  0.56953     0.05492    0.04694   0.12489
4             2956.0  0.79077  0.57620     0.01726    0.00588   0.16379

[5 rows x 80 columns]
```

[7]:
```
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
```

0.0.1 2. Figure out the Primary key and look for requirement of Indexing

[8]:
```python
# UID is the primary key, so index must be created

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

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

[9]:
```python
df_train.head(2)
```

[9]:
```
        BLOCKID  SUMLEVEL  COUNTYID  STATEID     state state_ab        city  \
UID
267822      NaN       140        53       36  New York       NY    Hamilton
246444      NaN       140       141       18   Indiana       IN  South Bend

           place  type primary  …  female_age_mean  female_age_median  \
UID                             …
267822  Hamilton  City   tract  …         44.48629           45.33333
246444  Roseland  City   tract  …         36.48391           37.58333

        female_age_stdev  female_age_sample_weight  female_age_samples  \
UID
267822          22.51276                 685.33845              2618.0
246444          23.43353                 267.23367              1284.0

        pct_own  married  married_snp  separated  divorced
UID
267822  0.79046  0.57851      0.01882    0.01240    0.0877
246444  0.52483  0.34886      0.01426    0.01426    0.0903

[2 rows x 79 columns]
```

[10]:
```python
df_test.head(2)
```

[10]:
```
        BLOCKID  SUMLEVEL  COUNTYID  STATEID     state state_ab     city  \
UID
255504      NaN       140       163       26  Michigan       MI  Detroit
252676      NaN       140         1       23     Maine       ME   Auburn

                          place  type primary  …  female_age_mean  \
UID                                            …
255504  Dearborn Heights City   CDP   tract  …         34.78682
252676            Auburn City  City   tract  …         44.23451

        female_age_median  female_age_stdev  female_age_sample_weight  \
```

```
UID
255504             33.75000           21.58531                     416.48097
252676             46.66667           22.37036                     532.03505

        female_age_samples  pct_own  married  married_snp  separated  divorced
UID
255504              1938.0  0.70252  0.28217      0.05910    0.03813   0.14299
252676              1950.0  0.85128  0.64221      0.02338    0.00000   0.13377

[2 rows x 79 columns]
```

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

[11]:
```python
# percentage of missing values in train set

missing_values=df_train.isnull().sum()/len(df_train)*100

# adding the column to the Dataframe to sort the column later
missing_values_df=pd.DataFrame(missing_values,columns=['Percentage of Missing␣
↪values'])
```

[12]:
```python
missing_values_df.sort_values(by=['Percentage of Missing␣
↪values'],inplace=True,ascending=False)

missing_values_df
```

[12]:
```
            Percentage of Missing values
BLOCKID                       100.000000
hc_samples                      2.196113
hc_mean                         2.196113
hc_median                       2.196113
hc_stdev                        2.196113
…                                    …
state                           0.000000
zip_code                        0.000000
city                            0.000000
place                           0.000000
state_ab                        0.000000

[79 rows x 1 columns]
```

[13]:
```python
# To view only the top 10 values

missing_values_df[missing_values_df['Percentage of Missing values']>0][:10]
```

[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

[14]:

```
# percentage of missing values in test set

missing_values=df_test.isnull().sum()/len(df_test)*100

missing_values_df_test=pd.DataFrame(missing_values,columns=['Percentage of␣
↪Missing values'])

missing_values_df_test.sort_values(by=['Percentage of Missing␣
↪values'],inplace=True,ascending=False)

missing_values_df_test[missing_values_df_test['Percentage of Missing␣
↪values']>0][:10]
```

[14]:

	Percentage of Missing values
BLOCKID	100.000000
hc_samples	2.476727
hc_mean	2.476727
hc_median	2.476727
hc_stdev	2.476727
hc_sample_weight	2.476727
hc_mortgage_mean	2.288838
hc_mortgage_stdev	2.288838
hc_mortgage_sample_weight	2.288838
hc_mortgage_samples	2.288838

DROP

1. BLOCKID as it is completely empty
2. SUMLEVEL as it does not have any predictive power as it has same value for every user.

[15]:

```
# Drop the BlockID & Sum level from train dataset

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

[16]:
```
#  Drop the BlockID & Sum level from test dataset

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

[17]:
```
df_train.shape
```

[17]: (27321, 77)

[18]:
```
df_test.shape
```

[18]: (11709, 77)

[19]:
```
# Missing values can be filled with Mean as it is quite difficult to check for␣
↪each individual column if it has normal distribution or skewed.
# So better to follow a common approach.

missing_values_cols=[]

for col in df_train.columns:

    if df_train[col].isna().sum()!=0:     # searching for missing values

        missing_values_cols.append(col)

print(len(missing_values_cols), ' columns have missing values')
```

```
58  columns have missing values
```

[20]:
```
# impute the missing values with the mean

for col in df_train.columns:

    if col in (missing_values_cols):

        df_train[col].replace(np.nan,df_train[col].mean(),inplace=True)
```

[21]:
```
# check if any missing values still left in training data

df_train.isnull().sum().any()
```

[21]: False

[ ]:
```

```

[22]:
```
#Create col of missing values in test data

missing_values_cols=[]
```

```
for col in df_test.columns:
    if df_test[col].isna().sum()!=0:
        missing_values_cols.append(col)
print(len(missing_values_cols), ' columns have missing values')
```

```
58  columns have missing values
```

[23]:
```
# impute the missing values with the mean
for col in df_test.columns:
    if col in (missing_values_cols):
        df_test[col].replace(np.nan,df_test[col].mean(),inplace=True)
```

[24]:
```
# missing values
df_test.isnull().sum().any()
```

[24]:
```
False
```

0.0.3 Exploratory Data Analysis (EDA):

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

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

   b. Use the following bad debt equation:

      Bad Debt = P (Second Mortgage Home Equity Loan) Bad Debt = second_mortgage + home_equity - home_equity_second_mortgage Create pie charts to show overall debt and bad debt

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

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

0.1 4a

[25]:
```
!pip install pandasql
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pandasql in /voc/work/.local/lib/python3.10/site-
packages (0.7.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/site-packages
(from pandasql) (1.23.5)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/site-packages
(from pandasql) (1.5.3)
Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.10/site-
packages (from pandasql) (1.4.20)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/site-packages (from pandas->pandasql) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/site-
packages (from pandas->pandasql) (2022.1)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.10/site-packages (from sqlalchemy->pandasql) (1.1.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/site-
packages (from python-dateutil>=2.8.1->pandas->pandasql) (1.16.0)

[notice] A new release of pip is
available: 23.3 -> 24.0
[notice] To update, run:
pip install --upgrade pip
```

[26]:
```
from pandasql import sqldf

# its not compulsory to use SQL here , you can use pandas as well.

q1='select place,pct_own,second_mortgage,lat,lng from df_train where pct_own>0.
↪10 and second_mortgage<0.5 order by second_mortgage DESC LIMIT 2500;'

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

df_train_location_mort_pct=query_df(q1)
```

[27]:
```
df_train_location_mort_pct.head(2)
```

[27]:

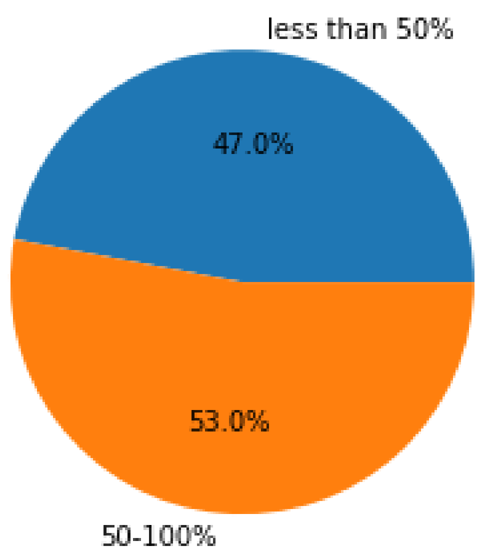
	place	pct_own	second_mortgage	lat	lng
0	Worcester City	0.20247	0.43363	42.254262	-71.800347
1	Harbor Hills	0.15618	0.31818	40.751809	-73.853582

0.2 4b

[28]:
```
df_train['bad_debt']=df_train['second_mortgage']+df_train['home_equity']-df_train['home_equity
df_train['bad_debt']
```

[28]:
```
UID
267822    0.09408
246444    0.04274
245683    0.09512
279653    0.01086
247218    0.05426
            …
279212    0.00000
277856    0.20908
233000    0.07857
287425    0.14305
265371    0.18362
Name: bad_debt, Length: 27321, dtype: float64
```

[29]:
```
# Create pie charts  to show overall debt and bad debt

df_train['bins'] = pd.cut(df_train['bad_debt'],bins=[0,0.10,1],labels=["less␣
↪than 50%",'50-100%'])

df_train.groupby(['bins']).size().plot(kind='pie',subplots=True,autopct='%1.
↪1f%%')

plt.show()
```



0.3 4c

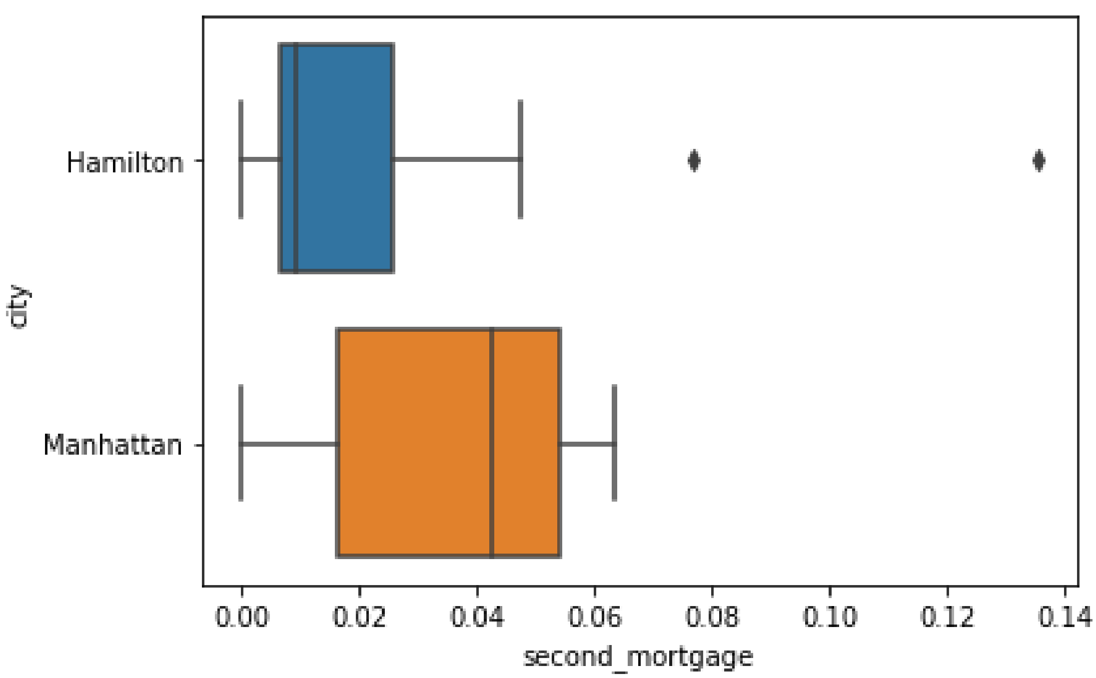
[30]:
```
# Create Box and whisker plot and analyze the distribution for 2nd mortgage,␣
↪home equity, good debt, and bad debt for different cities

# take 2 cities randomly

cols=['second_mortgage','home_equity','debt','bad_debt']

df_Hamilton = df_train.loc[df_train['city'] =='Hamilton']

df_Manhattan = df_train.loc[df_train['city'] =='Manhattan']

df_city = pd.concat([df_Hamilton,df_Manhattan])
```

[31]:
```
df_city.shape
```

[31]: (24, 79)

[32]:
```
sns.boxplot(data=df_city, x='second_mortgage', y='city')
```

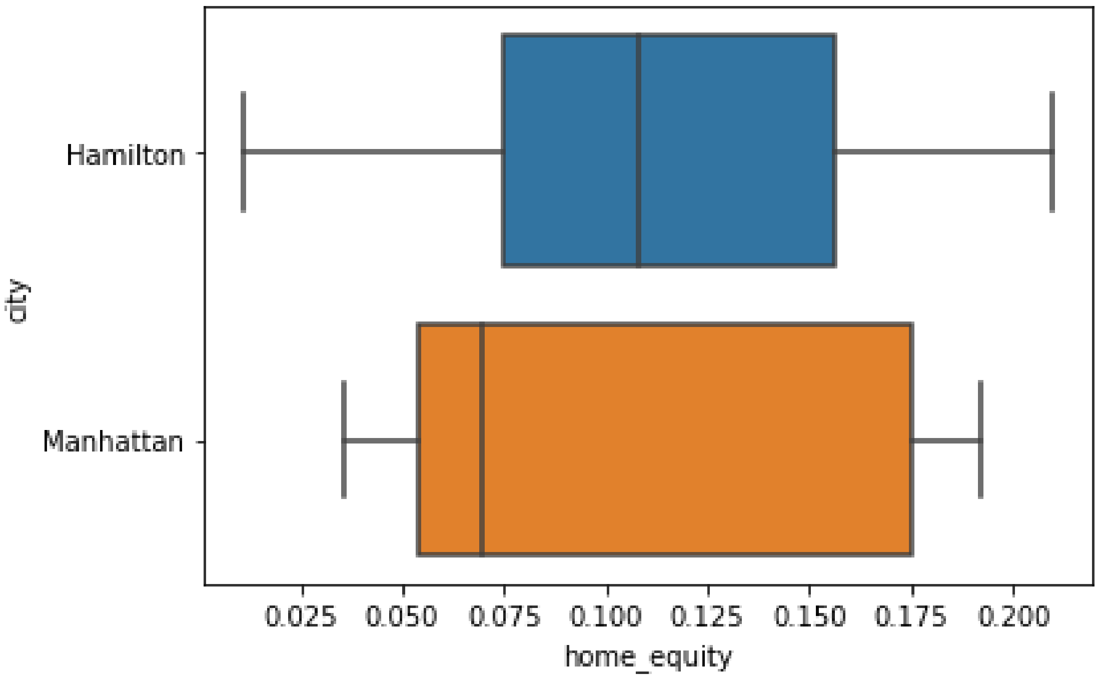
[32]: <AxesSubplot: xlabel='second_mortgage', ylabel='city'>



Manhattan has more 2nd mortgage

[33]:
```
sns.boxplot(data=df_city,x='home_equity',y='city')
```

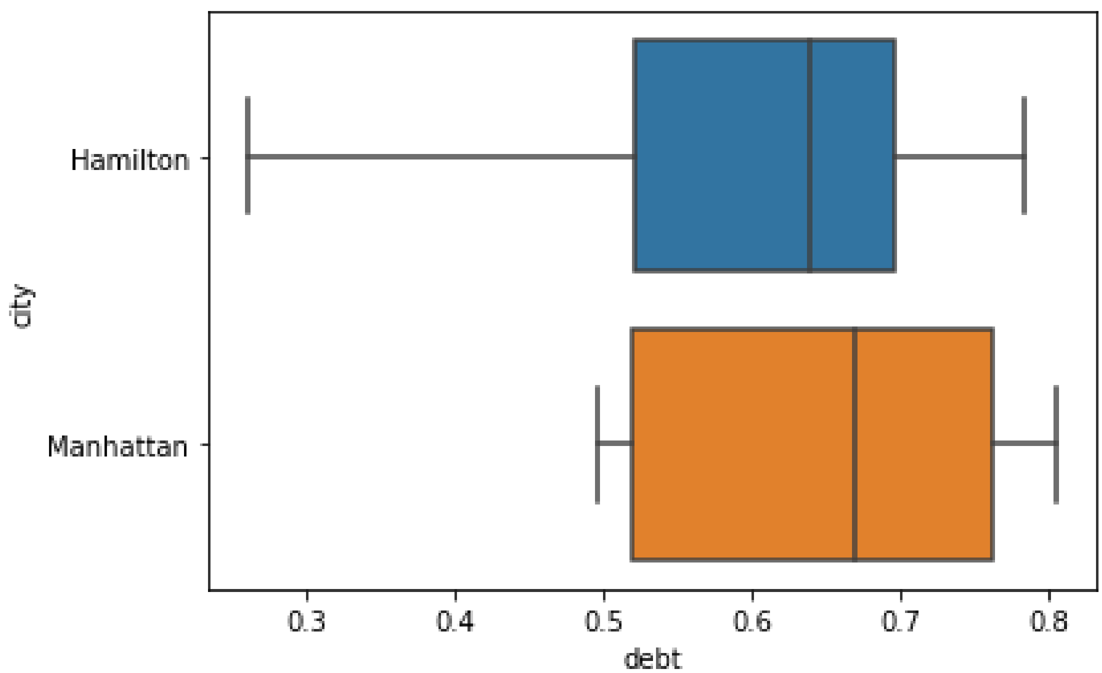
[33]: <AxesSubplot: xlabel='home_equity', ylabel='city'>



Manhattan has more home equity range for hamilton is high, IQR for manhattan is high ; median is very left side -> skewed distribution for Manhattan

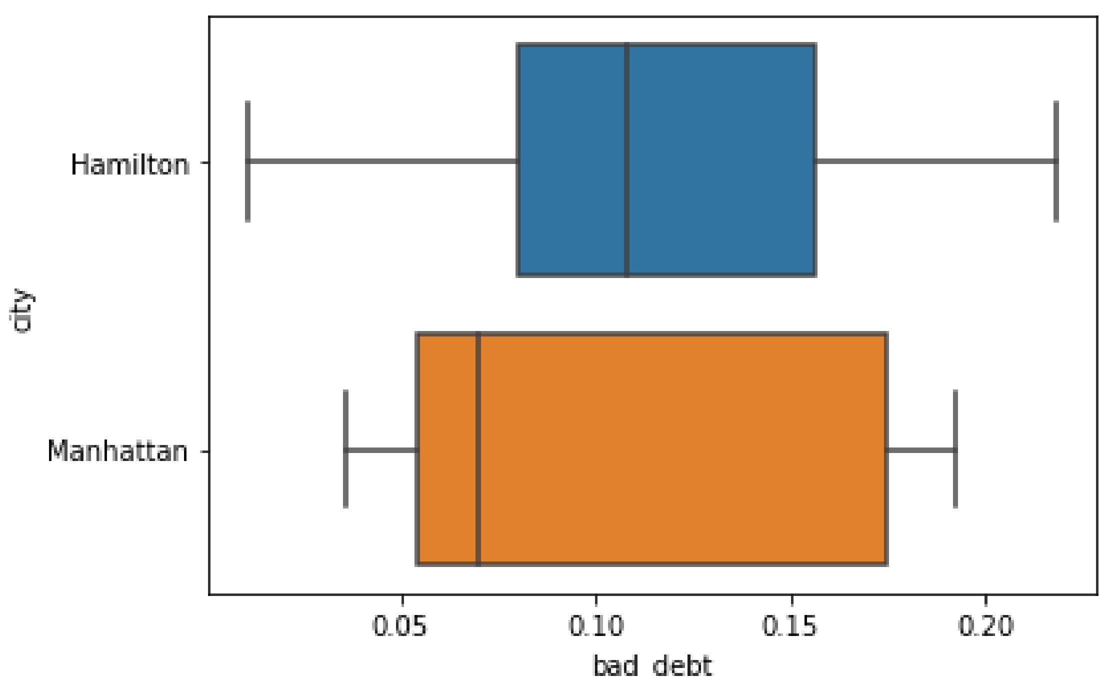
[34]:
```
sns.boxplot(data=df_city,x='debt',y='city')
```

[34]: <AxesSubplot: xlabel='debt', ylabel='city'>




```
[35]: sns.boxplot(data=df_city,x='bad_debt',y='city')
```

```
[35]: <AxesSubplot: xlabel='bad_debt', ylabel='city'>
```

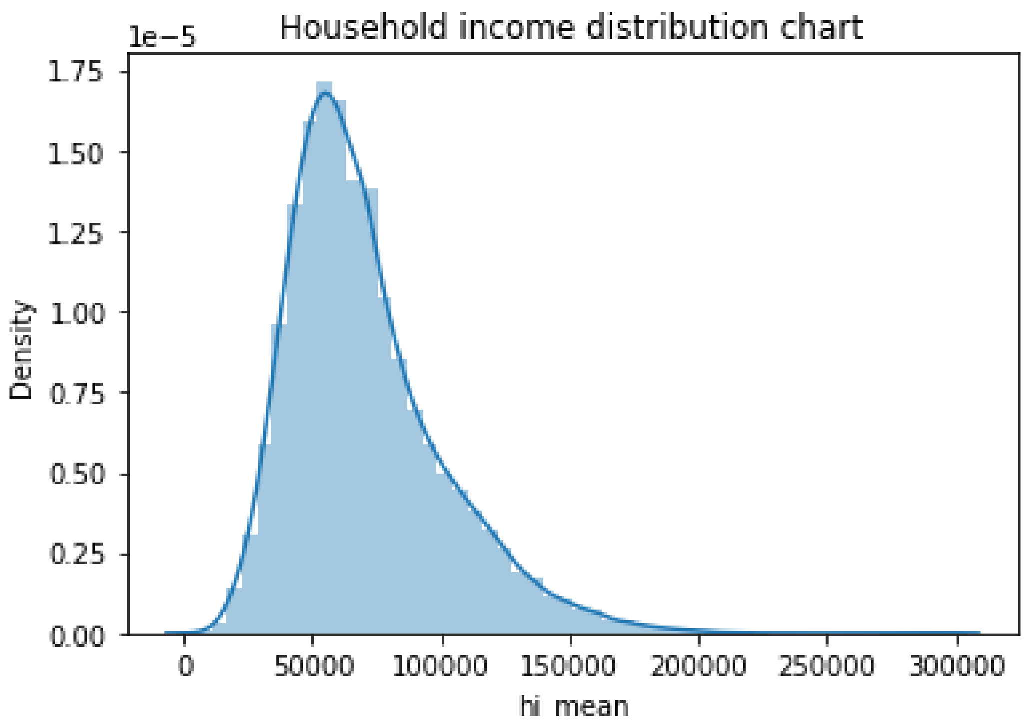


0.3.1 After comparing all these graphs we see that Manhattan has higher matrics compared to Hamilton

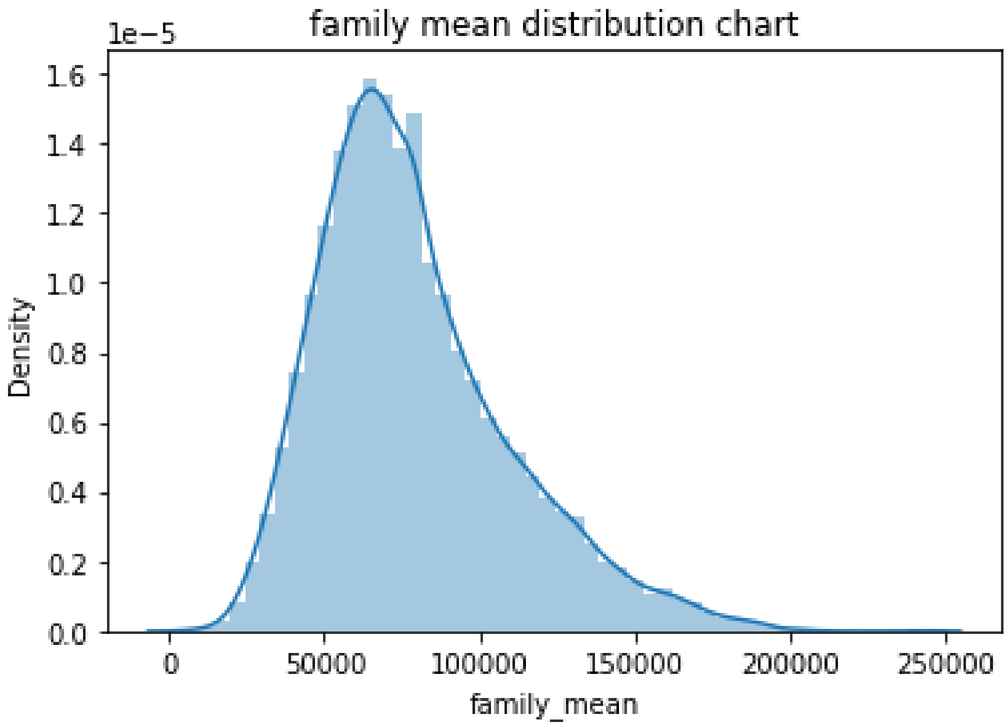
0.4 4 d

[36]:
```
#  Create a collated income distribution chart for family income, house hold␣
↪income, and remaining income
```

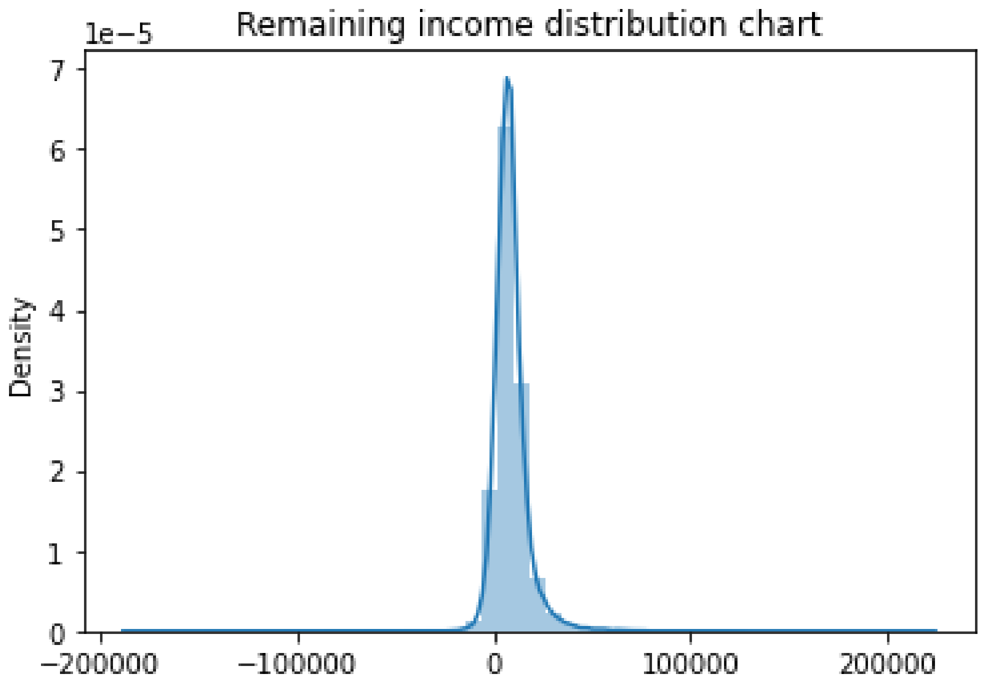
[37]:
```
sns.distplot(df_train['hi_mean'])

plt.title('Household income distribution chart')

plt.show()
```



[38]:
```
sns.distplot(df_train['family_mean'])

plt.title('family mean distribution chart')

plt.show()
```



[39]:
```
# Remaining income = family mean - household income mean

sns.distplot(df_train['family_mean']-df_train['hi_mean'])

plt.title('Remaining income distribution chart')

plt.show()
```

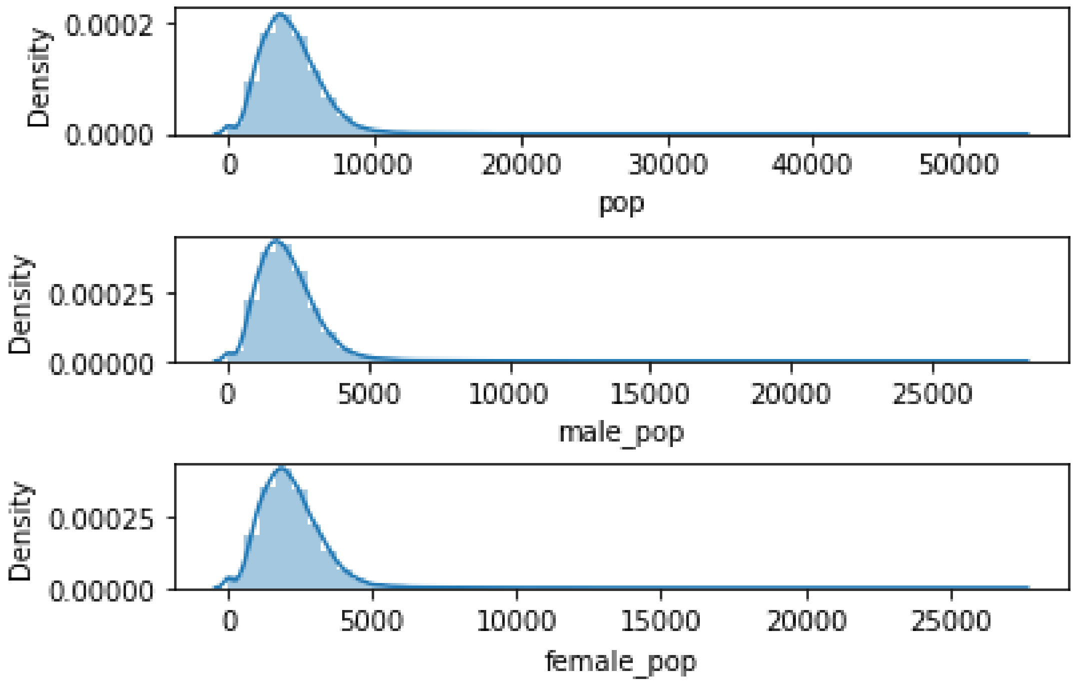


Normally distributed

0.5 5. 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):

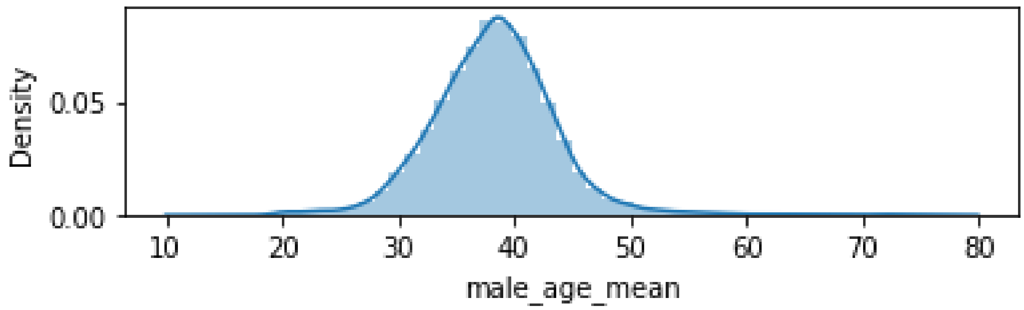
```
Use pop and ALand variables to create a new field called population density

Use male_age_median, female_age_median, male_pop, and female_pop to create a new field called r

Visualize the findings using appropriate chart type
```

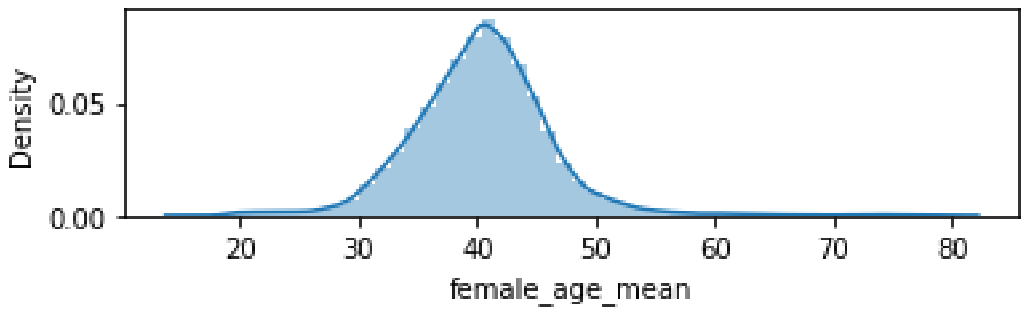
[40]:
```
# Population Charts

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



[41]:

```
# Doing the above chart for Age now

fig,(ax1,ax2)=plt.subplots(2,1)

sns.distplot(df_train['male_age_mean'],ax=ax1)

sns.distplot(df_train['female_age_mean'],ax=ax2)

plt.subplots_adjust(wspace=0.8,hspace=0.8)

plt.show()
```

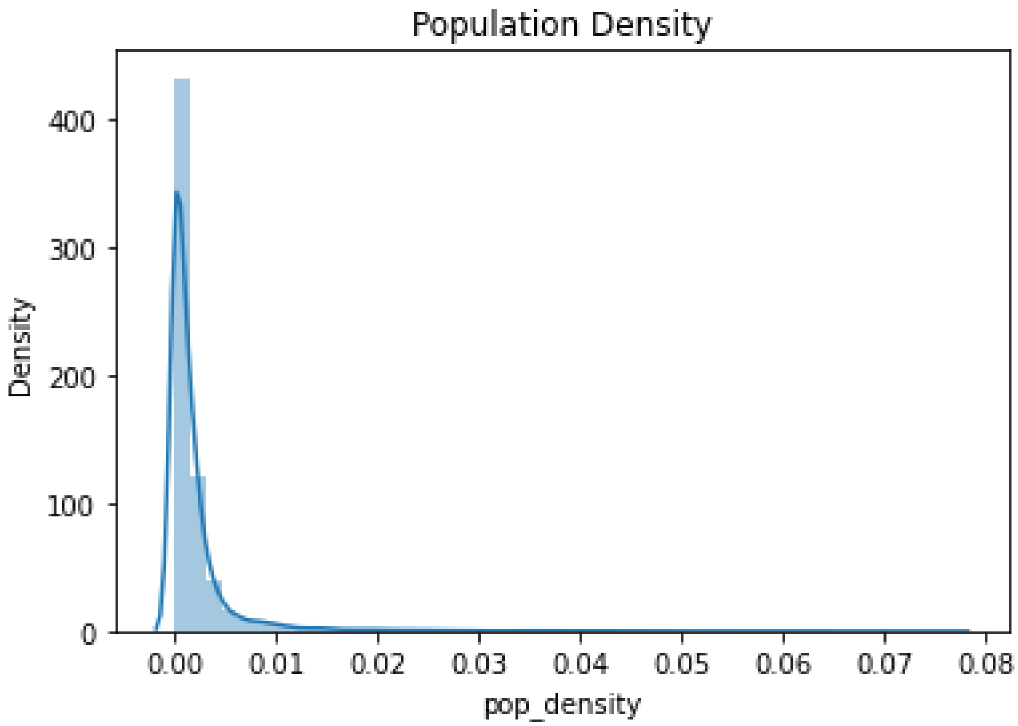




[42]:
```
# calculate population density
# ALand - The square area of land at the geographic or track location. what is␣
↪the area occupied at that geographic location.

df_train['pop_density'] = df_train['pop']/df_train['ALand']
```

[43]:
```
df_test['pop_density'] = df_test['pop']/df_test['ALand']
```

[44]:
```
# Analyse density is high or low?

sns.distplot(df_train['pop_density'])
plt.title('Population Density')
plt.show()
```



Population density is very less.

[45]:
```
# Use male_age_median, female_age_median, male_pop, and female_pop to create a␣
↪new field called median age

df_train['age_median'] = (df_train['male_age_median'] +␣
↪df_train['female_age_median'])/2

df_test['age_median'] = (df_test['male_age_median'] +␣
↪df_test['female_age_median'])/2
```

[46]:
```
df_train[['male_age_median','female_age_median','male_pop','female_pop','age_median']].
↪head()
```

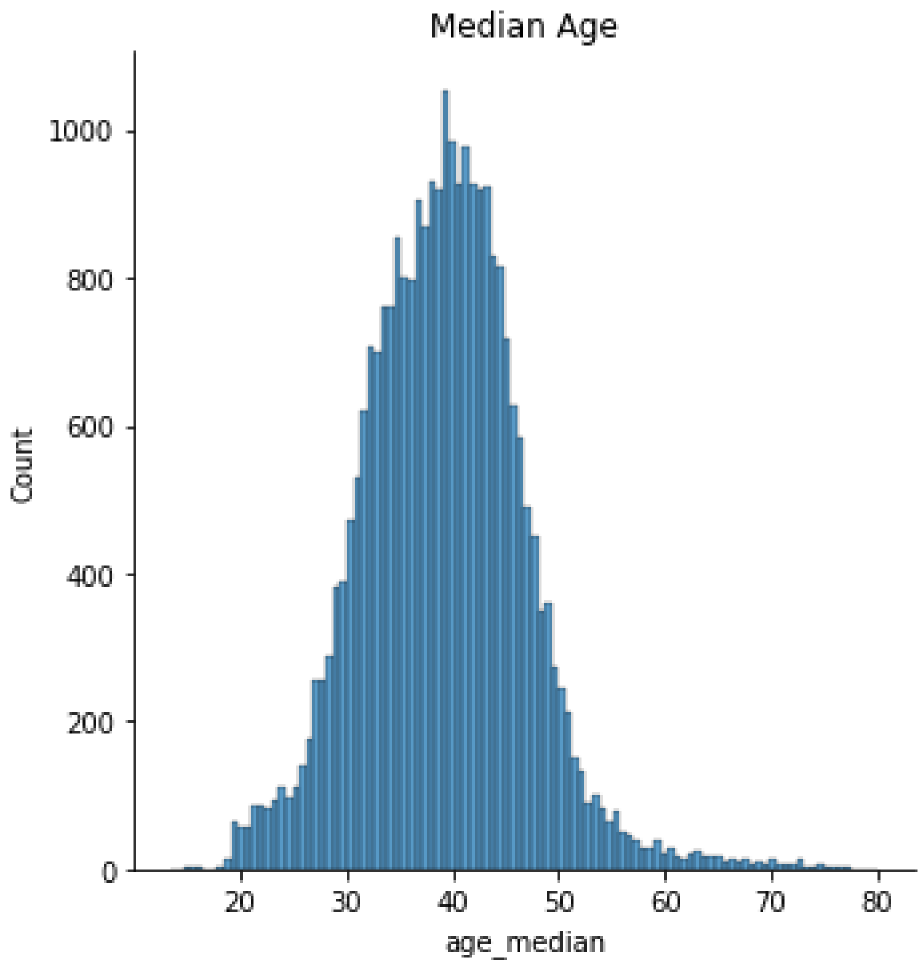
[46]:

UID	male_age_median	female_age_median	male_pop	female_pop	age_median
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

0.5.1 UID is like pincode here. It is the ID of the location.

location where age median is high expenses would be more.

[47]:
```
# Plotting chart for age median

sns.displot(df_train['age_median'])
plt.title('Median Age')
plt.show()

# Age of population is mostly between 20 and 60
# Majority are of age around 40
# Median age distribution has a gaussian distribution
# Some right skewness is noticed
```



0.6 6. 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.

[48]:
```
df_train['pop'].describe()
```

[48]:
```
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
```

[49]:
```
df_train['pop_bins']=pd.cut(df_train['pop'],bins=5,labels=['very␣
↪low','low','medium','high','very high'])
```

[50]:
```
df_train[['pop','pop_bins']]
```

[50]:
```
          pop  pop_bins
UID
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 x 2 columns]
```

[51]:
```
df_train['pop_bins'].value_counts()
```

[51]:
```
very low     27058
low            246
medium           9
high             7
very high        1
Name: pop_bins, dtype: int64
```

0.6.1 Analyze the married, separated, and divorced population for these population brackets.

[52]:
```
df_train.groupby(by='pop_bins')[['married','separated','divorced']].count()

# but it's showing same numbers for each column so we nned to work with some␣
↪aggregate function.
```

[52]:

	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

[53]:
```
df_train.groupby(by='pop_bins')[['married','separated','divorced']].
↪agg(["mean", "median"])
```

[53]:

	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

Very high population group has more married people and less percantage of separated and divorced couples.

In very low population groups, there are more married people

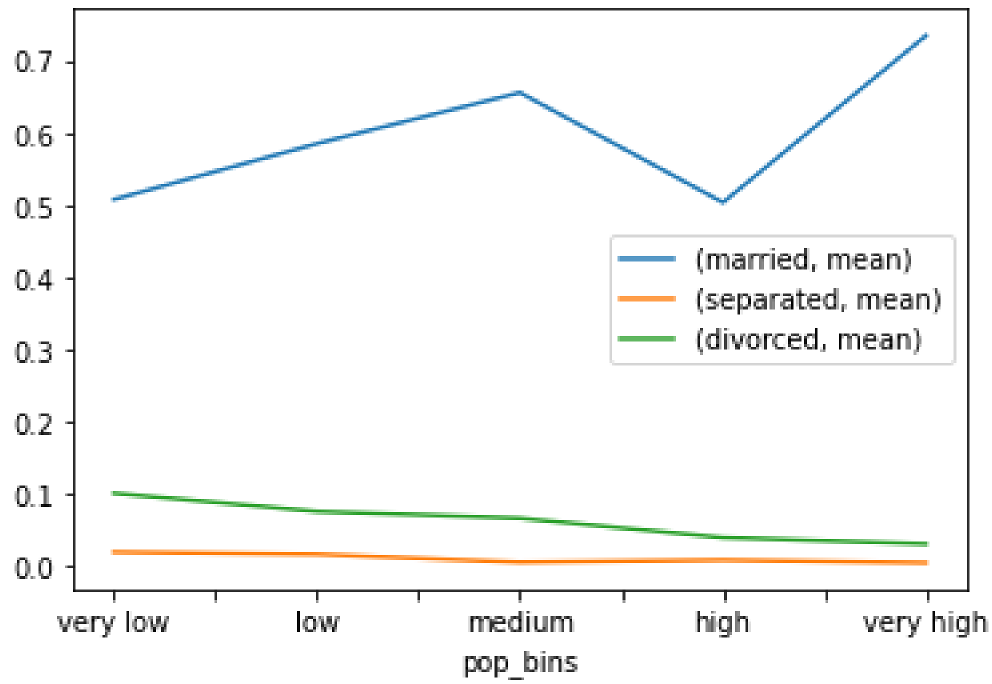
For all categories of divorced column, we can see that it is high for very low category. and it is very less in very high population bin.

0.6.2 Visualize using appropriate chart type

[54]:
```
# Creating a line chart

plt.figure(figsize=(10,5))

pop_bin=df_train.groupby(by='pop_bins')[['married','separated','divorced']].
↪agg(["mean"])

pop_bin.plot()

plt.legend(loc='best')
```

```
plt.show()
```

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



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

[55]:
```
# State-wise rent mean

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

[55]:

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

[56]:
```
# State-wise income mean

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

[56]:
```
                        mean
state
Alabama     67030.064213
Alaska      92136.545109
Arizona     73328.238798
Arkansas    64765.377850
California  87655.470820
```

[57]:
```
# rent as a percentage of income for different states

rent_perc_of_income=(rent_state_mean['mean']/income_state_mean['mean'])*100
rent_perc_of_income.head(5)
```

[57]:
```
state
Alabama       1.154713
Alaska        1.286963
Arizona       1.497041
Arkansas      1.113123
California    1.678314
Name: mean, dtype: float64
```

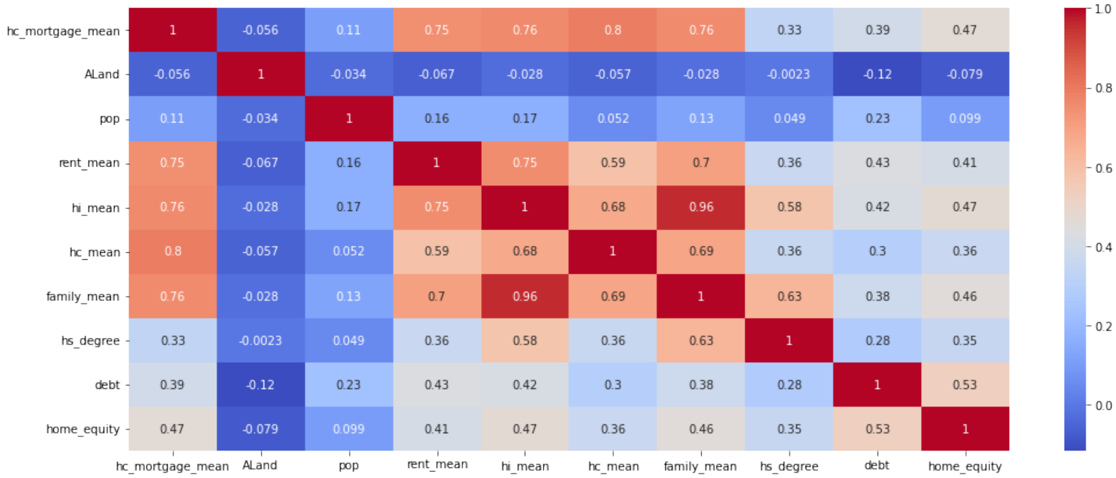
[58]:
```
# rent as a percentage of income at an overall level

(sum(df_train['rent_mean'])/sum(df_train['family_mean']))*100
```

[58]:
```
1.3358170721473863
```

0.7.1 Overall Rent as a percentage of Overall House Hold Income is around 1.33%

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

[59]:
```
plt.figure(figsize=(17,7))
sns.
 ↪heatmap(data=df_train[['hc_mortgage_mean','ALand','pop','rent_mean','hi_mean','hc_mean','fa
                            'hs_degree','debt','home_equity']].
 ↪corr(),annot=True, cmap='coolwarm')
plt.show()
```



Household Income mean and family income mean are highly positively correlated. “Family Income” and “hc_mortgage” are positively correlated.

[ ]:

[ ]: