DESCRIPTION

- Forecasting mortgages requires actionable insights into mortgage borrower profiles, geography business investment, and real estate market trends.
- The mortgage loan assist the to identify potential monthly mortgage expenses for each region based on monthly family income and other financial commitments.
- A statistical model needs to be created to predict the potential demand in dollar amount of loan for each of the regions in the USA.
- The model is also required to predict the expected income from the interest rate charged on the loan.
- The dashboard must demonstrate relationships and patterns for the top metro or micro areas in terms of loan, average loan income, monthly mortgage and owner costs, family income to mortgage cost comparison across different regions. The metrics described here are from the dashboard in the file.

1. Import required Libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.linear_regression import LinearRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score, SVR
```

2. Import Dataset

```
data = pd.read_csv('/home/aml1-user/Downloads/Mortgage.csv')
data.head(5)
```

```
data = pd.read_csv('/home/aml1-user/Downloads/Mortgage.csv')
data.head(5)
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.shape, data.info()
```

```
(32, 19)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 19):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   CBSA        32 non-null     int64
 1   MSACODE     32 non-null     int64
 2   SUMLEVEL    32 non-null     int64
 3   COUNTYFP    32 non-null     int64
 4   STATEFIP    32 non-null     int64
 5   CSAFP       0 non-null      float64
 6   CBSAPOP     32 non-null     int64
 7   DIV         32 non-null     int64
 8   REGION      32 non-null     int64
 9   STATEUSPS   32 non-null     object
 10  NAME LSAD   32 non-null     object
 11  LAND        32 non-null     float64
 12  WATER       32 non-null     float64
 13  TRACTS      32 non-null     float64
 14  LOANS       32 non-null     float64
 15  LOAN_AMT    32 non-null     float64
 16  MEDIAN_INC  32 non-null     float64
 17  MEDIAN_MORT 32 non-null     float64
 18  MEDIAN_OWNER 32 non-null    float64
dtypes: float64 10, int64 8, object 1
memory usage: 4.8 KB
(None)
```

- There are 32 observations in the dataset
- There are 19 variables in the dataset

```
data.sample(5)
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe()
```

```
data.describe()
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe(include=['object'])
```

```
data.describe(include=['object'])
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

- We can see there are missing values in many columns & no data in SUCCESS column.

```
data.isnull().sum
```

```
data.isnull().sum()
```

```
CBSA            0
MSACODE         0
SUMLEVEL        0
COUNTYFP        0
STATEFIP        0
CSAFP          32
CBSAPOP         0
DIV             0
REGION          0
STATEUSPS       0
NAME LSAD       0
LAND            0
WATER           0
TRACTS          0
LOANS           0
LOAN_AMT        0
MEDIAN_INC      0
MEDIAN_MORT     0
MEDIAN_OWNER    0
dtype: 0 NaN
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

- There are no duplicate records in the dataset. We have to remove these duplicate records before doing other analysis.

```
data.drop('CSAFP',axis=1,inplace=True)
data.drop('DIV',axis=1,inplace=True)
```

- There is one single value in 'REGION' column. So we will remove this column as we don't have any other data and values should be there.
- We have to remove 'CSAFP' column as it contains 100% missing values. Also we can drop variable 'DIV' as it contains single value.
- Variable 'STATEUSPS' is redundant as we have 'STATEFIP' variable.

```
data.drop('STATEUSPS',axis=1,inplace=True)
```

```
data.drop('STATEUSPS',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('REGION',axis=1,inplace=True)
```

```
data.drop('REGION',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('SUMLEVEL',axis=1,inplace=True)
```

```
data.drop('SUMLEVEL',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('STATEFIP',axis=1,inplace=True)
```

```
data.drop('STATEFIP',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('COUNTYFP',axis=1,inplace=True)
```

```
data.drop('COUNTYFP',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('MSACODE',axis=1,inplace=True)
```

```
data.drop('MSACODE',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('CBSA',axis=1,inplace=True)
```

```
data.drop('CBSA',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('CBSAPOP',axis=1,inplace=True)
```

```
data.drop('CBSAPOP',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('NAME LSAD',axis=1,inplace=True)
```

```
data.drop('NAME LSAD',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('LAND',axis=1,inplace=True)
```

```
data.drop('LAND',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('WATER',axis=1,inplace=True)
```

```
data.drop('WATER',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('TRACTS',axis=1,inplace=True)
```

```
data.drop('TRACTS',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('LOANS',axis=1,inplace=True)
```

```
data.drop('LOANS',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('LOAN_AMT',axis=1,inplace=True)
```

```
data.drop('LOAN_AMT',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('MEDIAN_INC',axis=1,inplace=True)
```

```
data.drop('MEDIAN_INC',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('MEDIAN_MORT',axis=1,inplace=True)
```

```
data.drop('MEDIAN_MORT',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('MEDIAN_OWNER',axis=1,inplace=True)
```

```
data.drop('MEDIAN_OWNER',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('MEDIAN_FAMILY',axis=1,inplace=True)
```

```
data.drop('MEDIAN_FAMILY',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('NAME',axis=1,inplace=True)
```

```
data.drop('NAME',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop('LSAD',axis=1,inplace=True)
```

```
data.drop('LSAD',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

- So we have duplicate records in the dataset. We have to remove these duplicate records before doing other analysis.

```
data.drop_duplicates(keep='first',inplace=True)
```

```
data.drop_duplicates(keep='first',inplace=True)
```

```
KeyboardInterrupt: 
```

- There is one single value in 'REGION' column. So we will remove this column as we don't have any other data and values should be there.
- We have to remove 'CSAFP' column as it contains 100% missing values. Also we can drop variable 'DIV' as it contains single value.
- Variable 'STATEUSPS' is redundant as we have 'STATEFIP' variable.

```
data.sample(5)
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe()
```

```
data.describe()
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe(include=['object'])
```

```
data.describe(include=['object'])
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.isnull().sum
```

```
data.isnull().sum()
```

```
CBSA            0
MSACODE         0
SUMLEVEL        0
COUNTYFP        0
STATEFIP        0
CSAFP          32
CBSAPOP         0
DIV             0
REGION          0
STATEUSPS       0
NAME LSAD       0
LAND            0
WATER           0
TRACTS          0
LOANS           0
LOAN_AMT        0
MEDIAN_INC      0
MEDIAN_MORT     0
MEDIAN_OWNER    0
dtype: 0 NaN
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.drop('CSAFP',axis=1,inplace=True)
data.drop('DIV',axis=1,inplace=True)
data.drop('STATEUSPS',axis=1,inplace=True)
data.drop('REGION',axis=1,inplace=True)
data.drop('SUMLEVEL',axis=1,inplace=True)
data.drop('STATEFIP',axis=1,inplace=True)
data.drop('COUNTYFP',axis=1,inplace=True)
data.drop('MSACODE',axis=1,inplace=True)
data.drop('CBSA',axis=1,inplace=True)
data.drop('CBSAPOP',axis=1,inplace=True)
data.drop('NAME LSAD',axis=1,inplace=True)
data.drop('LAND',axis=1,inplace=True)
data.drop('WATER',axis=1,inplace=True)
data.drop('TRACTS',axis=1,inplace=True)
data.drop('LOANS',axis=1,inplace=True)
data.drop('LOAN_AMT',axis=1,inplace=True)
data.drop('MEDIAN_INC',axis=1,inplace=True)
data.drop('MEDIAN_MORT',axis=1,inplace=True)
data.drop('MEDIAN_OWNER',axis=1,inplace=True)
data.drop('MEDIAN_FAMILY',axis=1,inplace=True)
data.drop('NAME',axis=1,inplace=True)
data.drop('LSAD',axis=1,inplace=True)
```

```
data.drop('CSAFP',axis=1,inplace=True)
data.drop('DIV',axis=1,inplace=True)
data.drop('STATEUSPS',axis=1,inplace=True)
data.drop('REGION',axis=1,inplace=True)
data.drop('SUMLEVEL',axis=1,inplace=True)
data.drop('STATEFIP',axis=1,inplace=True)
data.drop('COUNTYFP',axis=1,inplace=True)
data.drop('MSACODE',axis=1,inplace=True)
data.drop('CBSA',axis=1,inplace=True)
data.drop('CBSAPOP',axis=1,inplace=True)
data.drop('NAME LSAD',axis=1,inplace=True)
data.drop('LAND',axis=1,inplace=True)
data.drop('WATER',axis=1,inplace=True)
data.drop('TRACTS',axis=1,inplace=True)
data.drop('LOANS',axis=1,inplace=True)
data.drop('LOAN_AMT',axis=1,inplace=True)
data.drop('MEDIAN_INC',axis=1,inplace=True)
data.drop('MEDIAN_MORT',axis=1,inplace=True)
data.drop('MEDIAN_OWNER',axis=1,inplace=True)
data.drop('MEDIAN_FAMILY',axis=1,inplace=True)
data.drop('NAME',axis=1,inplace=True)
data.drop('LSAD',axis=1,inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.drop_duplicates(keep='first',inplace=True)
```

```
data.drop_duplicates(keep='first',inplace=True)
```

```
KeyboardInterrupt: 
```

```
data.sample(5)
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe()
```

```
data.describe()
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.describe(include=['object'])
```

```
data.describe(include=['object'])
```

	CBSA	MSACODE	SUMLEVEL	COUNTYFP	STATEFIP	CSAFP	CBSAPOP	DIV	REGION	STATEUSPS	NAME LSAD	LAND	WATER	TRACTS	LOANS	LOAN_AMT	MEDIAN_INC	MEDIAN_MORT	MEDIAN_OWNER	MEDIAN_FAMILY
0	10100	10100	040	000	01	NaN	14051	06	3	AL	Aliceville city	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
1	10300	10300	040	000	01	NaN	15036	06	3	AL	Anniston-Oxford-Jacksonville MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
2	10500	10500	040	000	01	NaN	53572	06	3	AL	Decatur MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
3	10700	10700	040	000	01	NaN	146431	06	3	AL	Dothan MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
4	10900	10900	040	000	01	NaN	82782	06	3	AL	Gadsden MSA	1.0000E+08	1.0000E+07	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00

```
data.isnull().sum
```

```
data.isnull().sum()
```

1000000	0x0000	0x0000
1000001	0x0000	0x0000
1000002	0x0000	0x0000
1000003	0x0000	0x0000
1000004	0x0000	0x0000

[illegible]

1.0	0.0
1.0	0.0
1.0	0.0

[illegible]

[illegible]

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1987-02	Dec-00
1987-03	Dec-00
1987-04	Dec-00
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[illegible]

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Calculate Bad Debt:

1. Bad Debt = 2nd mortgage + home equity loan
2. Bad Debt = second mortgage + home equity + home equity second mortgage

```
df['bad_debt'] = df['second_mortgage'] + df['home_equity'] + df['home_equity_second_mortgage']
df.head(10)[['first_name','last_name','city','state','county','zipcode','job','company','ssn','bad_debt']]
```

```
df.shape[0]-df.dropna().shape[0]
```

	FIRST_NAME	LAST_NAME	CITY	STATE	COUNTY	ZIPCODE	JOB	COMPANY	SSN	BAD_DEBT
0	Cecil	Folk	Flagstaff	AZ	Coconino County	86001	Forensic scientist	Test County	987-07-5733	78796.0
1	Carlene	Klein	Rancho Palos Verdes	CA	Los Angeles County	90275	Therapist, music	Pueblo Depot LLC	795-73-9038	10000.0
2	Max	Rios	San Francisco	CA	San Francisco County	94080	Merchandiser, visual	Stamps.com	615-62-7916	12869.0
3	Suzanne	Morales	Hoover	AL	Jefferson County	35226	Dentist	Smith, Smith and Smith	987-65-5431	65324.0
4	Garth	Knox	Beaverdale	IA	Dallas County	50049	Jewellery designer	Hartford Financial Services Group, Inc.	294-67-1823	19053.0
5	Linda	Real	Tarpon Springs	FL	Pinellas County	34689	Chemical engineer	Lifetime Brands, Inc	567-38-1248	51690.0
6	Clarence	Raber	Lincoln	NE	Lancaster County	68505	Farmer	Farmers National Company	132-97-7654	72929.0
7	Eddie	Farrow	Kansas City	MO	Jackson County	64111	Commercial horticulturist	Wal-Mart Stores, Inc.	987-12-1654	94853.0
8	Douglas	Bates	Chicago	IL	Cook County	60610	Insurance account manager	Blockbuster Inc.	453-07-5678	75004.0
9	Nancy	Waldron	Hockessin	DE	New Castle County	19707	Hotel manager	Encompass Services Corporation	351-62-0822	77034.0

```
df.shape[0]-df.dropna().shape[0]
```

```
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```

Pie charts to show overall debt and bad debt

```
labels = 'Bad Debt', 'Good Debt'
sizes = [df.bad_debt.sum(),
         df.home_equity.sum()+
         df.mortgage.sum()+
         df.second_mortgage.sum()]
explode = (0.1, 0)
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels,
        autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')
plt.show()
```

```
labels = 'Bad Debt', 'Good Debt'
sizes = [df.bad_debt.sum(),
         df.home_equity.sum()+
         df.mortgage.sum()+
         df.second_mortgage.sum()]
explode = (0.1, 0)
fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels,
        autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')
plt.show()
```

```
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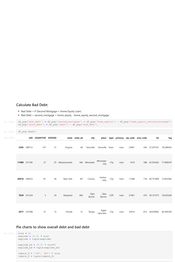


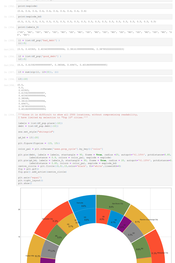
Box and whisker plot for the distribution of 2nd mortgage, home equity, good debt, and bad debt for different cities

```
df.groupby('city').sum()[['second_mortgage','home_equity','good_debt','bad_debt']].
sort_values('bad_debt',ascending=False).head(10)
```

```
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
df_cities = df.groupby('city').sum()[['second_mortgage','home_equity','good_debt','bad_debt']].
sort_values('bad_debt',ascending=False).head(10)
df_cities.columns = ['Second Mortgage','Home Equity','Good Debt','Bad Debt']
df_cities.T
```

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(111)
bp = df_cities.T.boxplot(vert=False)
df = df_cities.T
for i in range(0,len(df.columns.values.tolist())):
    print df.columns.values.tolist()[i],'median:',df[df.columns.values.tolist()[i]].median()
    print df.columns.values.tolist()[i],'mean:',df[df.columns.values.tolist()[i]].mean()
    print df.columns.values.tolist()[i],'1st qrtr:',df[df.columns.values.tolist()[i]].quantile(0.25)
    print df.columns.values.tolist()[i],'3rd qrtr:',df[df.columns.values.tolist()[i]].quantile(0.75)
    print df.columns.values.tolist()[i],'interquartile range:',df[df.columns.values.tolist()[i]].quantile(0.75)-df[df.columns.values.tolist()[i]].quantile(0.25)
plt.title('Second Mortgage Distribution by Cities')
plt.show()
```

```
Second Mortgage median: 1.0
Second Mortgage mean: 1.0
Second Mortgage 1st qrtr: 1.0
Second Mortgage 3rd qrtr: 1.0
Second Mortgage interquartile range: 0.0
Home Equity median: 1.0
Home Equity mean: 1.0
Home Equity 1st qrtr: 1.0
Home Equity 3rd qrtr: 1.0
Home Equity interquartile range: 0.0
Good Debt median: 1.0
Good Debt mean: 1.0
Good Debt 1st qrtr: 1.0
Good Debt 3rd qrtr: 1.0
Good Debt interquartile range: 0.0
Bad Debt median: 1.0
Bad Debt mean: 1.0
Bad Debt 1st qrtr: 1.0
Bad Debt 3rd qrtr: 1.0
Bad Debt interquartile range: 0.0
```




```
df.shape[0]-df.dropna().shape[0]
```

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```
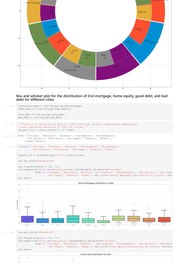

```
df.groupby('city').sum()[['second_mortgage']].sort_values('second_mortgage',ascending=False).head(10)
```

```
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
df_cities = df.groupby('city').sum()[['second_mortgage']].sort_values('second_mortgage',ascending=False).head(10)
df_cities.columns = ['Second Mortgage']
df_cities.T
```

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(111)
bp = df_cities.T.boxplot(vert=False)
df = df_cities.T
for i in range(0,len(df.columns.values.tolist())):
    print df.columns.values.tolist()[i],'median:',df[df.columns.values.tolist()[i]].median()
    print df.columns.values.tolist()[i],'mean:',df[df.columns.values.tolist()[i]].mean()
    print df.columns.values.tolist()[i],'1st qrtr:',df[df.columns.values.tolist()[i]].quantile(0.25)
    print df.columns.values.tolist()[i],'3rd qrtr:',df[df.columns.values.tolist()[i]].quantile(0.75)
    print df.columns.values.tolist()[i],'interquartile range:',df[df.columns.values.tolist()[i]].quantile(0.75)-df[df.columns.values.tolist()[i]].quantile(0.25)
plt.title('Second Mortgage Distribution by Cities')
plt.show()
```

```
Second Mortgage median: 1.0
Second Mortgage mean: 1.0
Second Mortgage 1st qrtr: 1.0
Second Mortgage 3rd qrtr: 1.0
Second Mortgage interquartile range: 0.0
```




```
df.groupby('city').sum()[['home_equity']].sort_values('home_equity',ascending=False).head(10)
```

```
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
df_cities = df.groupby('city').sum()[['home_equity']].sort_values('home_equity',ascending=False).head(10)
df_cities.columns = ['Home Equity']
df_cities.T
```

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(111)
bp = df_cities.T.boxplot(vert=False)
df = df_cities.T
for i in range(0,len(df.columns.values.tolist())):
    print df.columns.values.tolist()[i],'median:',df[df.columns.values.tolist()[i]].median()
    print df.columns.values.tolist()[i],'mean:',df[df.columns.values.tolist()[i]].mean()
    print df.columns.values.tolist()[i],'1st qrtr:',df[df.columns.values.tolist()[i]].quantile(0.25)
    print df.columns.values.tolist()[i],'3rd qrtr:',df[df.columns.values.tolist()[i]].quantile(0.75)
    print df.columns.values.tolist()[i],'interquartile range:',df[df.columns.values.tolist()[i]].quantile(0.75)-df[df.columns.values.tolist()[i]].quantile(0.25)
plt.title('Home Equity Distribution by Cities')
plt.show()
```

```
Home Equity median: 1.0
Home Equity mean: 1.0
Home Equity 1st qrtr: 1.0
Home Equity 3rd qrtr: 1.0
Home Equity interquartile range: 0.0
```

```
df.groupby('city').sum()[['good_debt']].sort_values('good_debt',ascending=False).head(10)
```

```
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
df_cities = df.groupby('city').sum()[['good_debt']].sort_values('good_debt',ascending=False).head(10)
df_cities.columns = ['Good Debt']
df_cities.T
```

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(111)
bp = df_cities.T.boxplot(vert=False)
df = df_cities.T
for i in range(0,len(df.columns.values.tolist())):
    print df.columns.values.tolist()[i],'median:',df[df.columns.values.tolist()[i]].median()
    print df.columns.values.tolist()[i],'mean:',df[df.columns.values.tolist()[i]].mean()
    print df.columns.values.tolist()[i],'1st qrtr:',df[df.columns.values.tolist()[i]].quantile(0.25)
    print df.columns.values.tolist()[i],'3rd qrtr:',df[df.columns.values.tolist()[i]].quantile(0.75)
    print df.columns.values.tolist()[i],'interquartile range:',df[df.columns.values.tolist()[i]].quantile(0.75)-df[df.columns.values.tolist()[i]].quantile(0.25)
plt.title('Good Debt Distribution by Cities')
plt.show()
```

```
Good Debt median: 1.0
Good Debt mean: 1.0
Good Debt 1st qrtr: 1.0
Good Debt 3rd qrtr: 1.0
Good Debt interquartile range: 0.0
```

```
df.groupby('city').sum()[['bad_debt']].sort_values('bad_debt',ascending=False).head(10)
```

```
# TRYING TO BUTTERFLY THE BOX AND WHISKER PLOTS BETWEEN DIFFERENT DEMOGRAPHICS
df_cities = df.groupby('city').sum()[['bad_debt']].sort_values('bad_debt',ascending=False).head(10)
df_cities.columns = ['Bad Debt']
df_cities.T
```

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(111)
bp = df_cities.T.boxplot(vert=False)
df = df_cities.T
for i in range(0,len(df.columns.values.tolist())):
    print df.columns.values.tolist()[i],'median:',df[df.columns.values.tolist()[i]].median()
    print df.columns.values.tolist()[i],'mean:',df[df.columns.values.tolist()[i]].mean()
    print df.columns.values.tolist()[i],'1st qrtr:',df[df.columns.values.tolist()[i]].quantile(0.25)
    print df.columns.values.tolist()[i],'3rd qrtr:',df[df.columns.values.tolist()[i]].quantile(0.75)
    print df.columns.values.tolist()[i],'interquartile range:',df[df.columns.values.tolist()[i]].quantile(0.75)-df[df.columns.values.tolist()[i]].quantile(0.25)
plt.title('Bad Debt Distribution by Cities')
plt.show()
```

```
Bad Debt median: 1.0
Bad Debt mean: 1.0
Bad Debt 1st qrtr: 1.0
Bad Debt 3rd qrtr: 1.0
Bad Debt interquartile range: 0.0
```

- Since Q1=Q3=median, we have a very narrow distribution.

Creating a colored income distribution chart for family income, house hold income and remaining income.

```
df[['family_income','house_hold_income','remaining_income']].
sort_values('family_income',ascending=False).head(10)
```

```
# Collated Income distribution
df[['family_income','house_hold_income','remaining_income']].
sort_values('family_income',ascending=False).head(10).T.plot(kind='bar')
plt.title('Collated Income Distribution')
```

Performing EDA & scoring out with insights into population density & age :

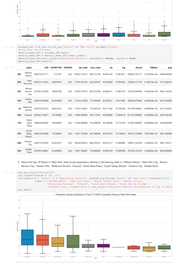
```
df.groupby('job').sum()[['good_debt']].
sort_values('good_debt',ascending=False).head(10)
```

	FIRST_NAME	LAST_NAME	CITY	STATE	COUNTY	ZIPCODE	JOB	COMPANY	SSN	GOOD_DEBT
CEO	Cecil	Folk	Flagstaff	AZ	Coconino County	86001	Forensic scientist	Test County	987-07-5733	81836.0
Therapist, music	Carlene	Klein	Rancho Palos Verdes	CA	Los Angeles County	90275	Therapist, music	Pueblo Depot LLC	795-73-9038	10000.0
Merchandiser, visual	Max	Rios	San Francisco	CA	San Francisco County	94080	Merchandiser, visual	Stamps.com	615-62-7916	12869.0
Dentist	Suzanne	Morales	Hoover	AL	Jefferson County	35226	Dentist	Smith, Smith and Smith	987-65-5431	65324.0
Jewellery designer	Garth	Knox	Beaverdale	IA	Dallas County	50049	Jewellery designer	Hartford Financial Services Group, Inc.	294-67-1823	19053.0
Chemical engineer	Linda	Real	Tarpon Springs	FL	Pinellas County	34689	Chemical engineer	Lifetime Brands, Inc	567-38-1248	51690.0
Farmer	Clarence	Raber	Lincoln	NE	Lancaster County	68505	Farmer	Farmers National Company	132-97-7654	72929.0
Commercial horticulturist	Eddie	Farrow	Kansas City	MO	Jackson County	64111	Commercial horticulturist	Wal-Mart Stores, Inc.	987-12-1654	94853.0
Insurance account manager	Douglas	Bates	Chicago	IL	Cook County	60610	Insurance account manager	Blockbuster Inc.	453-07-5678	75004.0
Hotel manager	Nancy	Waldron	Hockessin	DE	New Castle County	19707	Hotel manager	Encompass Services Corporation	351-62-0822	77034.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('job').sum()[['good_debt']].
sort_values('good_debt',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Jobs')
```




```
df.groupby('job').sum()[['bad_debt']].
sort_values('bad_debt',ascending=False).head(10)
```

JOB	BAD_DEBT
CEO	81836.0
Therapist, music	10000.0
Merchandiser, visual	12869.0
Dentist	65324.0
Jewellery designer	19053.0
Chemical engineer	51690.0
Farmer	72929.0
Commercial horticulturist	94853.0
Insurance account manager	75004.0
Hotel manager	77034.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('job').sum()[['bad_debt']].
sort_values('bad_debt',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Jobs')
```

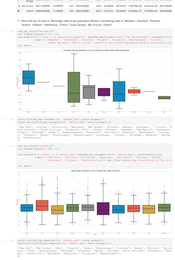
```
df.groupby('city').sum()[['bad_debt']].
sort_values('bad_debt',ascending=False).head(10)
```

CITY	BAD_DEBT
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['bad_debt']].
sort_values('bad_debt',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```




```
df.groupby('city').sum()[['good_debt']].
sort_values('good_debt',ascending=False).head(10)
```

CITY	GOOD_DEBT
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	81836.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['good_debt']].
sort_values('good_debt',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['family_income']].
sort_values('family_income',ascending=False).head(10)
```

CITY	FAMILY_INCOME
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['family_income']].
sort_values('family_income',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['house_hold_income']].
sort_values('house_hold_income',ascending=False).head(10)
```

CITY	HOUSE_HOLD_INCOME
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['house_hold_income']].
sort_values('house_hold_income',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['remaining_income']].
sort_values('remaining_income',ascending=False).head(10)
```

CITY	REMAINING_INCOME
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['remaining_income']].
sort_values('remaining_income',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['second_mortgage']].
sort_values('second_mortgage',ascending=False).head(10)
```

CITY	SECOND_MORTGAGE
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['second_mortgage']].
sort_values('second_mortgage',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['home_equity']].
sort_values('home_equity',ascending=False).head(10)
```

CITY	HOME_EQUITY
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['home_equity']].
sort_values('home_equity',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```



```
df.groupby('city').sum()[['mortgage']].
sort_values('mortgage',ascending=False).head(10)
```

CITY	MORTGAGE
Hoover	65324.0
Beaverdale	19053.0
Tarpon Springs	51690.0
Lincoln	72929.0
Kansas City	94853.0
Chicago	75004.0
Hockessin	77034.0
Flagstaff	78796.0
Rancho Palos Verdes	10000.0
San Francisco	12869.0

```
df.shape[0]-df.dropna().shape[0]
```

```
10
```

```
df.groupby('city').sum()[['mortgage']].
sort_values('mortgage',ascending=False).head(10).T.plot(kind='bar')
plt.title('Top 10 Cities')
```

```
[In]: plt.figure(figsize=(15,7))
      sns.boxplot(x='Q1 Age', y='Q2 Gender', data=df[df.Q2.isin(['Male', 'Female'])], palette='husl')
      plt.title('Gender Age Distribution of Top 10 Data Job Titles', fontsize=20)
      plt.xticks(rotation=90)
      plt.show()
```

```
[In]: df.Q3.value_counts[:10].index.tolist()
      plt.figure(figsize=(15,7))
      sns.boxplot(x='Q1 Age', y='Q3 Country', data=df[df.Q3.isin(['United States of America', 'India', 'Brazil', 'Russia', 'Other', 'Japan', 'Mexico', 'Spain', 'Ukraine', 'Poland'])], palette='husl')
      plt.title('Top 10 Data Science Hiring Countries Across Age Groups', fontsize=20)
      plt.xticks(rotation=90)
      plt.show()
```

- Across the top 10 Data Science Hiring Countries, the age range of participants is fairly balanced. Belgium, Belarus, Russia, Turkmenistan, Kyrgyzstan, Tajikistan, Kazakhstan, Tajikistan, Belarus, Uzbekistan, Pakistan, Iceland, Laos,Georgia.

```
[In]: df.Q3.value_counts[:10].index.tolist()
      plt.figure(figsize=(15,7))
      sns.boxplot(x='Q1 Age', y='Q3 Country', data=df[df.Q3.isin(['United States of America', 'India', 'Brazil', 'Russia', 'Other', 'Japan', 'Mexico', 'Spain', 'Ukraine', 'Poland'])], palette='husl')
      plt.title('Top 10 Data Science Hiring Countries Across Age Groups', fontsize=20)
      plt.xticks(rotation=90)
      plt.show()
```

- Across the top 10 Data Science Hiring Countries, the age range of participants is fairly balanced. Belgium, Belarus, Russia, Turkmenistan, Kyrgyzstan, Tajikistan, Kazakhstan, Tajikistan, Belarus, Uzbekistan, Pakistan, Iceland, Laos,Georgia.

Creating 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.

Analyzing & Visualizing *married, separated and divorced population*

```
[In]: df.Q15.value_counts[:10].index.tolist()
      df['Years_Coding'] = df.Q15.isin(['I have been writing code to analyze data for 10+ years', '5-10 years', '3-5 years', '1-3 years', 'Less than a year'])
      df['Years_Coding'].value_counts()
```

```
[Out]: False    10000
       Name: Years_Coding, dtype: int64
```

```
[In]: df.Q8.value_counts[:10].index.tolist()
      df['Salary_Range'] = df.Q8.isin(['$0-10,000', '$10,000-20,000', '$20,000-30,000', '$30,000-40,000', '$40,000-50,000', '$50,000-60,000', '$60,000-70,000', '$70,000-80,000', '$80,000-90,000', '$90,000-100,000'])
      df['Salary_Range'].value_counts()
```

```
[Out]: False    10000
       Name: Salary_Range, dtype: int64
```

```
[In]: df.Q4.value_counts[:10].index.tolist()
      df['Masters_Degree'] = df.Q4.isin(['Master's degree'])
      df['Masters_Degree'].value_counts()
```

```
[Out]: False    7000
       True     3000
       Name: Masters_Degree, dtype: int64
```

- Years Coding, Salary Range, Masters Degree are the new variables created.

```
[In]: df.Q15.value_counts[:10].index.tolist()
      df.Years_Coding.value_counts()
```

```
[Out]: False    10000
       Name: Years_Coding, dtype: int64
```

```
[In]: df.Q8.value_counts[:10].index.tolist()
      df.Salary_Range.value_counts()
```

```
[Out]: False    10000
       Name: Salary_Range, dtype: int64
```

```
[In]: df.Q4.value_counts[:10].index.tolist()
      df.Masters_Degree.value_counts()
```

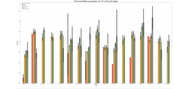
```
[Out]: False    7000
       True     3000
       Name: Masters_Degree, dtype: int64
```

- Age group Within the 18-21 Years Old, 22-24 Years Old, 25-29 Years Old, 30-34 Years Old, 35-39 Years Old, 40-44 Years Old, 45-49 Years Old, 50-54 Years Old, 55-59 Years Old, 60-69 Years Old, 70-79 Years Old

```
[In]: df.Q1.value_counts[:10].index.tolist()
      df['Married_Age_Group'] = df.Q1.isin(['18-21', '22-24', '25-29', '30-34', '35-39', '40-44', '45-49', '50-54', '55-59', '60-69', '70-79'])
      df['Married_Age_Group'].value_counts()
```

```
[Out]: False    10000
       Name: Married_Age_Group, dtype: int64
```

```
[In]: df.Q1.value_counts[:10].index.tolist()
      df.Married_Age_Group.
```

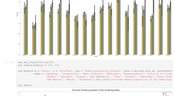



```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```

```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```

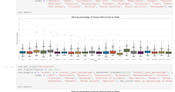
```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```

- Ohio, Georgia state can being Worst total male population?
- Florida has the highest number of Worst total male population.




```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```

```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```




```
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
[100 rows x 5 columns]
```

- New York is the only state having Worst female total.
- Maine state has the highest number of Worst female young adults.

Rent as a percentage of income at an overall level and for different states

```
In [24]: rent_income_overall = pd.read_csv('rent_income_overall.csv')
rent_income_overall.head()
```

	state	city	rent_median	ni_median	family_median
0	New York	Bronx	1000.0	34000.0	40000.0
1	Indiana	South Bend	500.0	37750.0	43333.0
2	Ohio	Cleveland	500.0	37500.0	43000.0
3	Pennsylvania	Philadelphia	600.0	37000.0	42500.0
4	Texas	Houston	667.0	37000.0	50312.0

```
In [25]: rent_income_state = pd.read_csv('rent_income_state.csv')
rent_income_state.head()
```

	state	city	rent_median	ni_median	family_median	overall_rent_percentage
0	New York	Bronx	1000.0	34000.0	40000.0	35.29
1	Georgia	South Bend	500.0	37750.0	43333.0	15.87
2	Ohio	Cleveland	500.0	37500.0	43000.0	15.96
3	Pennsylvania	Philadelphia	600.0	37000.0	42500.0	19.46
4	Texas	Houston	667.0	37000.0	50312.0	21.64

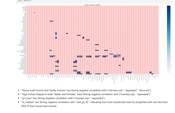
```
In [26]: rent_income_overall['overall_rent_percentage'] = rent_income_overall['rent_median']/rent_income_overall['ni_median']*100
rent_income_overall.head()
```

```
In [27]: Index(['state', 'city', 'rent_median', 'ni_median', 'family_median',
       'overall_rent_percentage'],
      dtype=object)
```

- Overall rent as a percentage of overall household income is around 17.9%.

```
In [28]: rent_income_state['overall_rent_percentage'] = rent_income_state['rent_median']/rent_income_state['ni_median']*100
rent_income_state.head()
```

```
In [29]: Index(['state', 'city', 'rent_median', 'ni_median', 'family_median',
       'overall_rent_percentage'],
      dtype=object)
```



Correlation analysis for all the relevant variables by creating heatmap

```
In [30]: rent_income_state.corr()
```

```
In [31]: rent_income_state.corr().T
```

```
In [32]: rent_income_state.corr().T.shape
```

```
In [33]: sns.heatmap(rent_income_state.corr())
```

- "Population parameters" have strong positive correlation with "Income Parameters".
- "Income gap" is negatively correlated with "Average gap".
- "Arts_deaths", "Arts_celebrate" has high positive correlation with "Ts_death", "Ts_celebrate". "Ts_celebrate" has high positive correlation with "Arts_celebrate", "Ts_death". "Ts_death" has high positive correlation with "Arts_celebrate", "Arts_death". "Arts_death" has high positive correlation with "Ts_death".
- "Ts_celebrate" has high positive correlation with "Arts_celebrate".
- "pct_pop" is positively correlated with "Women" and "women".

```
In [34]: rent_income_state.corr()
```

```
In [35]: rent_income_state.corr().T
```

```
In [36]: rent_income_state.corr().T.shape
```

```
In [37]: sns.heatmap(rent_income_state.corr(),annot=True)
```

- "Income Gap" is negatively correlated with "Income Parameters".
- "Population parameters" have strong positive correlation with "Income Parameters".
- "Income Gap" is negatively correlated with "Average gap".
- "Ts_celebrate" has strong positive correlation with "Arts_gp_25", indicating that most households look for properties with rent less than 25% of their household income.

5. Data Pre-processing

The accuracy of the regression depends on 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.

"Bartlett's test of sphericity" compares the observed correlation matrix to the identity matrix. If the test statistic is large and the significance is low, it is likely that the variables in the data set are sufficiently correlated for a factor analysis to be worthwhile. Bartlett's test of sphericity tests whether the correlation matrix is an identity matrix, which would indicate that the variables are unrelated and therefore unsuitable for factor analysis. In this dataset and given insight into the linear relationships in the data. Following are the list of latent variables.

- Population parameters data
- Median population age
- Median average earnings
- Median rent
- Median income

```
In [38]: from sklearn.decomposition import FactorAnalysis
fa = FactorAnalysis(n_components = 7, random_state=0)
fa.fit(rent_income_state[['rent_median', 'ni_median', 'family_median', 'overall_rent_percentage']])
```

```
array([[ 0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ],
       [
```

	Score 1	Score 2	Score 3	Score 4	Score 5	Score 6	Score 7	Score 8	Score 9	Score 10
Mean accuracy	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean precision	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean recall	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean f1_score	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean hamming_loss	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556
Mean exact_match	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean jaccard_score	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean log_loss	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703
Mean roc_auc_ovr	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean roc_auc_ovo	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean roc_auc_ovr_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean roc_auc_ovo_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean matthews_corrcoef	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667
Mean cohen_kappa	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667
Mean balanced_accuracy	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean specificity	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean sensitivity	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean f1_macro	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean f1_micro	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean f1_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean hinge_loss	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778
Mean cohen_kappa_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean matthews_corrcoef_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean cohen_kappa_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean matthews_corrcoef_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean cohen_kappa_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean matthews_corrcoef_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean kappa_scores	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Mean kappa_scores_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean kappa_scores_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Mean kappa_scores_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_kappa	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_kappa_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_kappa_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_kappa_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_accuracy	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_precision	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_recall	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_f1_score	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_hamming_loss	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556	0.0555556
Score_exact_match	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_jaccard_score	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_log_loss	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703	0.1918703
Score_roc_auc_ovr	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_roc_auc_ovo	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_roc_auc_ovr_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_roc_auc_ovo_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_matthews_corrcoef	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667
Score_cohen_kappa	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667	0.9166667
Score_balanced_accuracy	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_specificity	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_sensitivity	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_f1_macro	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_f1_micro	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_f1_weighted	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444	0.9444444
Score_hinge_loss	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778	0.2777778
Score_cohen_kappa_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_matthews_corrcoef_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_cohen_kappa_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_matthews_corrcoef_linear	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_cohen_kappa_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222
Score_matthews_corrcoef_linear_quadratic	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222	0.9722222

```
Mean kappa_scores: 0.9444444444444444
Mean kappa_scores_quadratic: 0.9722222222222222
Mean kappa_scores_linear: 0.9722222222222222
Mean kappa_scores_linear_quadratic: 0.9722222222222222
Score_kappa: 0.9444444444444444
Score_kappa_quadratic: 0.9722222222222222
Score_kappa_linear: 0.9722222222222222
Score_kappa_linear_quadratic: 0.9722222222222222
Score_accuracy: 0.9444444444444444
Score_precision: 0.9444444444444444
Score_recall: 0.9444444444444444
Score_f1_score: 0.9444444444444444
Score_hamming_loss: 0.0555555555555555
Score_exact_match: 0.9444444444444444
Score_jaccard_score: 0.9444444444444444
Score_log_loss: 0.1918703
Score_roc_auc_ovr: 0.9444444444444444
Score_roc_auc_ovo: 0.9444444444444444
Score_roc_auc_ovr_weighted: 0.9444444444444444
Score_roc_auc_ovo_weighted: 0.9444444444444444
Score_matthews_corrcoef: 0.9166666666666667
Score_cohen_kappa: 0.9166666666666667
Score_balanced_accuracy: 0.9444444444444444
Score_specificity: 0.9722222222222222
Score_sensitivity: 0.9444444444444444
Score_f1_macro: 0.9444444444444444
Score_f1_micro: 0.9444444444444444
Score_f1_weighted: 0.9444444444444444
Score_hinge_loss: 0.2777777777777778
Score_cohen_kappa_quadratic: 0.9722222222222222
Score_matthews_corrcoef_quadratic: 0.9722222222222222
Score_cohen_kappa_linear: 0.9722222222222222
Score_matthews_corrcoef_linear: 0.9722222222222222
Score_cohen_kappa_linear_quadratic: 0.9722222222222222
Score_matthews_corrcoef_linear_quadratic: 0.9722222222222222
```

```
# Cross-validation
cv = 10
for key, values in cv_dict.items():
    print(f"{key}: {values}")
```

```
Mean accuracy: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean precision: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean recall: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean f1_score: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean hamming_loss: [0.0555556 0.0555556 0.0555556 0.0555556 0.0555556 0.0555556
 0.0555556 0.0555556 0.0555556 0.0555556]
Mean exact_match: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean jaccard_score: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean log_loss: [0.1918703 0.1918703 0.1918703 0.1918703 0.1918703 0.1918703
 0.1918703 0.1918703 0.1918703 0.1918703]
Mean roc_auc_ovr: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean roc_auc_ovo: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean roc_auc_ovr_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444]
Mean roc_auc_ovo_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444]
Mean matthews_corrcoef: [0.9166667 0.9166667 0.9166667 0.9166667 0.9166667 0.9166667
 0.9166667 0.9166667 0.9166667 0.9166667]
Mean cohen_kappa: [0.9166667 0.9166667 0.9166667 0.9166667 0.9166667 0.9166667
 0.9166667 0.9166667 0.9166667 0.9166667]
Mean balanced_accuracy: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean specificity: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222]
Mean sensitivity: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean f1_macro: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean f1_micro: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean f1_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean hinge_loss: [0.2777778 0.2777778 0.2777778 0.2777778 0.2777778 0.2777778
 0.2777778 0.2777778 0.2777778 0.2777778]
Mean cohen_kappa_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean matthews_corrcoef_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean cohen_kappa_linear: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean matthews_corrcoef_linear: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean cohen_kappa_linear_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean matthews_corrcoef_linear_quadratic: [0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean kappa_scores: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Mean kappa_scores_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean kappa_scores_linear: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Mean kappa_scores_linear_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_kappa: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_kappa_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_kappa_linear: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_kappa_linear_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_accuracy: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_precision: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_recall: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_f1_score: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_hamming_loss: [0.0555556 0.0555556 0.0555556 0.0555556 0.0555556 0.0555556
 0.0555556 0.0555556 0.0555556 0.0555556]
Score_exact_match: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_jaccard_score: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_log_loss: [0.1918703 0.1918703 0.1918703 0.1918703 0.1918703 0.1918703
 0.1918703 0.1918703 0.1918703 0.1918703]
Score_roc_auc_ovr: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_roc_auc_ovo: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_roc_auc_ovr_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444]
Score_roc_auc_ovo_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444]
Score_matthews_corrcoef: [0.9166667 0.9166667 0.9166667 0.9166667 0.9166667 0.9166667
 0.9166667 0.9166667 0.9166667 0.9166667]
Score_cohen_kappa: [0.9166667 0.9166667 0.9166667 0.9166667 0.9166667 0.9166667
 0.9166667 0.9166667 0.9166667 0.9166667]
Score_balanced_accuracy: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_specificity: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222]
Score_sensitivity: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_f1_macro: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_f1_micro: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_f1_weighted: [0.9444444 0.9444444 0.9444444 0.9444444 0.9444444 0.9444444
 0.9444444 0.9444444 0.9444444 0.9444444]
Score_hinge_loss: [0.2777778 0.2777778 0.2777778 0.2777778 0.2777778 0.2777778
 0.2777778 0.2777778 0.2777778 0.2777778]
Score_cohen_kappa_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_matthews_corrcoef_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_cohen_kappa_linear: [0.9722222 0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_matthews_corrcoef_linear: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_cohen_kappa_linear_quadratic: [0.9722222 0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
Score_matthews_corrcoef_linear_quadratic: [0.9722222 0.9722222 0.9722222
 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222 0.9722222]
```

6. Data Modeling

Building a linear Regression model to predict the total monthly expenditure for home mortgage loan.

- As a model is a mere scan of the source code and it squeak out not satisfactory proceed to follow step
- Is the number created is Real and Positive (if it takes in 0.0)
- Is the model satisfactory? Check the Mean Squared Error and the model Coefficients
- Variables should have significant impact on predicting Monthly Mortgage and vice versa
- Unit test of prediction variable is over with Unit test hypothesis
- If squared of prediction and actual values are almost zero proceed
- Ensure Multi collinearity does not exist in dependent variables
- Tag if prediction model is normally distributed

```
home_data.shape
```

```
(1460, 81)
```

```
home_data.ndim
```

```
2
```

```
home_data.head(10).T # Transpose for easier view
```

	0	1	2	3	4	5	6	7	8	9
Id	1	2	3	4	5	6	7	8	9	10
MSSubClass	60	20	60	70	60	50	20	60	50	190
MSZoning	RL	RL	RL	RL	RL	RL	RL	RL	RL	RM
LotFrontage	65.0	80.0	68.0	60.0	84.0	85.0	75.0	NaN	51.0	50.0
LotArea	8450	9600	11250	9550	14260	14115	10084	10382	6120	7420
Street	Pave	Pave	Pave	Pave	Pave	Pave	Pave	Pave	Pave	Pave
Alley	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
LotShape	Reg	Reg	IR1	IR1	IR1	IR1	Reg	IR1	IR1	Reg
LandContour	Lvl	Lvl	Lvl	Lvl	Lvl	Lvl	Lvl	Lvl	Lvl	Lvl
Utilities	AllPub	AllPub	AllPub	AllPub	AllPub	AllPub	AllPub	AllPub	AllPub	AllPub
LotConfig	Inside	FR2	Inside	Corner	FR2	Inside	Inside	Corner	Inside	Inside
LandSlope	Gtl	Gtl	Gtl	Gtl	Gtl	Gtl	Gtl	Gtl	Gtl	Gtl
Neighborhood	CollgCr	Veenker	CollgCr	Crawfor	NoRidge	Mitchel	Somerst	NWAmes	OldTown	BrkSide
Condition1	Norm	Feedr	Norm	Norm	Norm	Norm	PosN	Norm	Artery	Artery
Condition2	Norm	Norm	Norm	Norm	Norm	Norm	Norm	Norm	Norm	Feedr
BldgType	1Fam	1Fam	1Fam	1Fam	1Fam	1Fam	1Fam	1Fam	1Fam	2fmCon
HouseStyle	2Story	1Story	2Story	2Story	2Story	1.5Fin	1Story	2Story	1.5Fin	1Story
OverallQual	7	6	7	7	8	5	8	7	5	4
OverallCond	5	8	5	5	5	5	5	6	8	5
YearBuilt	2003	1976	2001	1915	2000	1993	2004	1973	1931	1939
YearRemodAdd	2003	1976	2001	1970	2000	1995	2005	1973	1950	1950
RoofStyle	Gable	Gable	Gable	Gable	Gable	Gable	Gable	Gable	Gable	Gable
RoofMatl	CompShg	CompShg	CompShg	CompShg	CompShg	CompShg	CompShg	CompShg	CompShg	CompShg
Exterior1st	VinylSd	MetalSd	VinylSd	Wd Sdng	VinylSd	MetalSd	VinylSd	HdBoard	BrkFace	WdShing
Exterior2nd	VinylSd	MetalSd	VinylSd	Wd Shng	VinylSd	MetalSd	VinylSd	HdBoard	Wd Shng	WdShing
MasVnrType	BrkFace	None	BrkFace	None	BrkFace	BrkCmn	NaN	BrkFace	None	None
MasVnrArea	196.0	0.0	162.0	0.0	350.0	0.0	NaN	162.0	0.0	0.0
ExterQual	Gd	TA	Gd	TA	Gd	TA	Gd	TA	TA	TA
ExterCond	TA	TA	TA	TA	TA	TA	TA	TA	TA	TA
Foundation	PConc	CBlock	PConc	BrkTil	PConc	CBlock	PConc	CBlock	BrkTil	Stone
BsmtQual	Gd	Gd	Gd	TA	Gd	TA	Gd	TA	TA	TA
BsmtCond	TA	TA	TA	Gd	TA	TA	TA	TA	TA	TA
BsmtExposure	No	Gd	Mn	No	Av	No	No	No	No	No
BsmtFinType1	GLQ	ALQ	GLQ	ALQ	GLQ	ALQ	GLQ	ALQ	Unf	Unf
BsmtFinSF1	706	978	486	216	655	732	1369	859	0	851
BsmtFinType2	Unf	Unf	Unf	Unf	Unf	Unf	Unf	BLQ	Unf	Unf
BsmtFinSF2	0	0	0	0	0	0	0	32	0	0
BsmtUnfSF	150	284	434	540	490	64	317	216	952	140
TotalBsmtSF	856	1262	920	756	1145	796	1686	1107	952	991
Heating	GasA	GasA	GasA	GasA	GasA	GasA	GasA	GasA	GasA	GasA
HeatingQC	Ex	Ex	Ex	Gd	Ex	Ex	Ex	TA	TA	TA
CentralAir	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Electrical	SBrkr	SBrkr	SBrkr	SBrkr	SBrkr	SBrkr	SBrkr	SBrkr	SBrkr	FuseA
1stFlrSF	856	1262	920	961	1145	796	1694	1107	1022	1077
2ndFlrSF	854	0	866	756	1053	566	0	983	752	0
LowQualFinSF	0	0	0	0	0	0	0	0	0	0
GrLivArea	1710	1262	1786	1717	2198	1362	1694	2090	1774	1077
BsmtFullBath	1	0	1	1	1	1	1	1	0	1
BsmtHalfBath	0	1	0	0	0	0	0	0	1	0
FullBath	2	2	2	1	2	1	2	2	2	1
HalfBath	1	0	1	0	1	1	0	1	0	0
BedroomAbvGr	3	3	3	3	4	1	3	3	2	3
KitchenAbvGr	1	1	1	1	1	1	1	1	2	2
KitchenQual	Gd	TA	Gd	Gd	Gd	TA	Gd	TA	TA	TA
TotRmsAbvGrd	8	6	6	7	9	5	7	7	8	5
Functional	Typ	Typ	Typ	Typ	Typ	Typ	Typ	Typ	Typ	Typ
Fireplaces	0	1	1	1	1	0	1	2	2	2
FireplaceQu	NaN	TA	TA	Gd	TA	NaN	Gd	TA	TA	TA
GarageType	Attchd	Attchd	Attchd	Detchd	Attchd	Attchd	Attchd	Attchd	Detchd	Attchd
GarageYrBlt	2003.0	1976.0	2001.0	1998.0	2000.0	1993.0	2004.0	1973.0	1931.0	1939.0
GarageFinish	RFn	RFn	RFn	Unf	RFn	Unf	RFn	Unf	Unf	RFn
GarageCars	2	2	2	3	3	1	2	2	2	1
GarageArea	548	460	608	642	836	480	636	484	468	205
GarageQual	TA	TA	TA	TA	TA	TA	TA	TA	TA	TA
GarageCond	TA	TA	TA	TA	TA	TA	TA	TA	TA	TA
PavedDrive	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
WoodDeckSF	0	298	0	0	192	40	255	235	90	0
OpenPorchSF	61	0	42	35	84	30	57	204	0	4
EnclosedPorch	0	0	0	272	0	320	0	228	205	0
3SsnPorch	0	0	0	0	0	0	0	0	0	0
ScreenPorch	0	0	0	0	0	0	0	0	0	0
PoolArea	0	0	0	0	0	0	0	0	0	0
PoolQC	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Fence	NaN	NaN	NaN	NaN	NaN	MnPrv	NaN	NaN	NaN	NaN
MiscFeature	NaN	NaN	NaN	NaN	NaN	Shed	NaN	Shed	Shed	NaN
MiscVal	0	0	0	0	0	700	0	350	500	0
MoSold	2	5	9	2	12	10	8	11	4	1
YrSold	2008	2007	2008	2006	2008	2009	2007	2009	2008	2008
SaleType	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD
SaleCondition	Normal	Normal	Normal	Abnorml	Normal	Normal	Normal	Normal	Abnorml	Abnorml
SalePrice	208500	181500	223500	140000	250000	143000	307000	200000	129900	118000

```
home_data.describe(include='object').T # Transpose for easier view
```

	count	unique	top	freq
MSZo

```
[0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000 0.0000000
 
```