Predictive Model for prediciting house prices

```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import sklearn

pwd=os.getcwd()
filepath=os.path.join(pwd,"housing.csv")
filepath

'c:\\Users\\pc\\Desktop\\Data project\\housing.csv'

housing_data=pd.read_csv(filepath)
housing_data

       longitude  latitude  housing_median_age  total_rooms  
total_bedrooms  \
0        -122.23     37.88                  41          880  
129.0
1        -122.22     37.86                  21         7099  
1106.0
2        -122.24     37.85                  52         1467  
190.0
3        -122.25     37.85                  52         1274  
235.0
4        -122.25     37.85                  52         1627  
280.0
...          ...       ...                 ...          ...  
...
20635    -121.09     39.48                  25         1665  
374.0
20636    -121.21     39.49                  18          697  
150.0
20637    -121.22     39.43                  17         2254  
485.0
20638    -121.32     39.43                  18         1860  
409.0
20639    -121.24     39.37                  16         2785  
616.0

       population  households  median_income  median_house_value  \
0             322         126         8.3252              452600  
1            2401        1138         8.3014              358500  
2             496         177         7.2574              352100  
3             558         219         5.6431              341300  
4             565         259         3.8462              342200  
```

```
...           ...         ...            ...                   ...
20635         845         330         1.5603                 78100
20636         356         114         2.5568                 77100
20637        1007         433         1.7000                 92300
20638         741         349         1.8672                 84700
20639        1387         530         2.3886                 89400

      ocean_proximity
0            NEAR BAY
1            NEAR BAY
2            NEAR BAY
3            NEAR BAY
4            NEAR BAY
...               ...
20635          INLAND
20636          INLAND
20637          INLAND
20638          INLAND
20639          INLAND

[20640 rows x 10 columns]
```

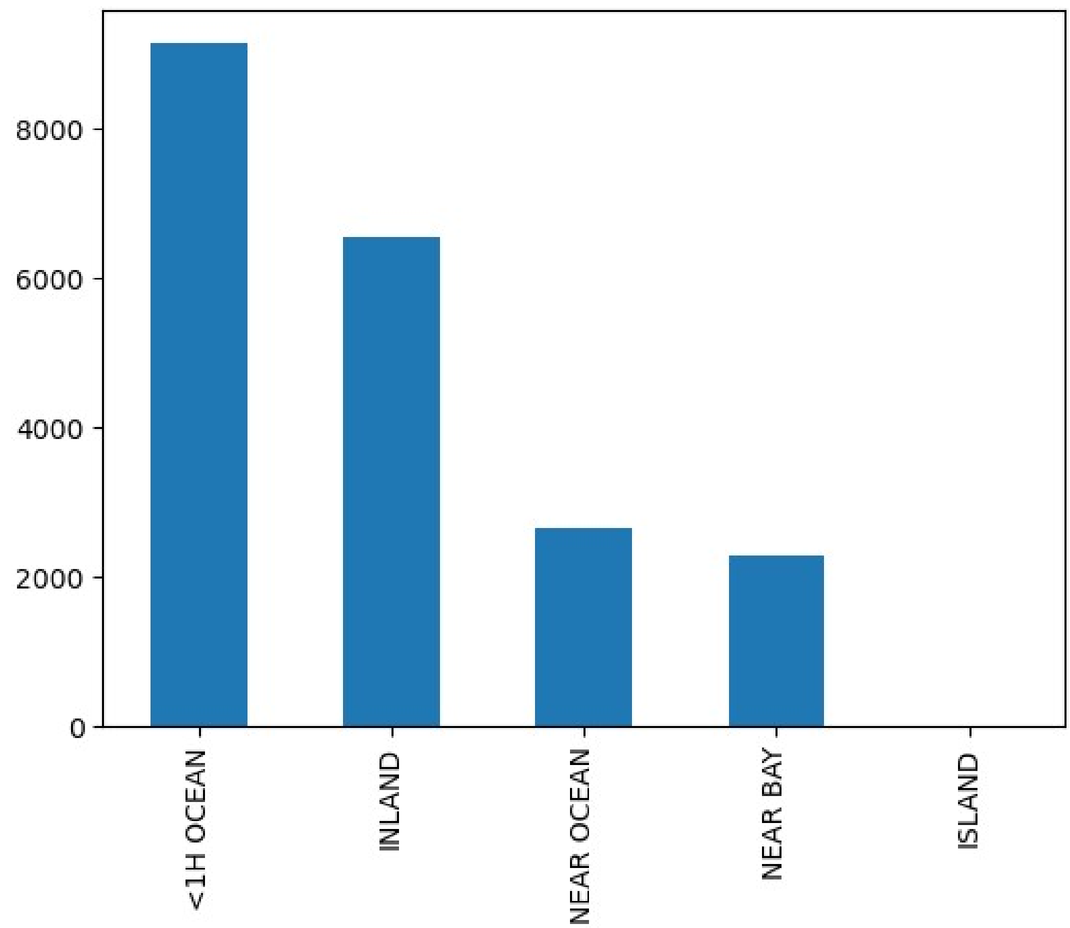
Data exploration and visualization

```
housing_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  int64
 3   total_rooms         20640 non-null  int64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  int64
 6   households          20640 non-null  int64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  int64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
```

```
housing_data['ocean_proximity'].value_counts().plot(kind="bar")
```

```
<Axes: >
```

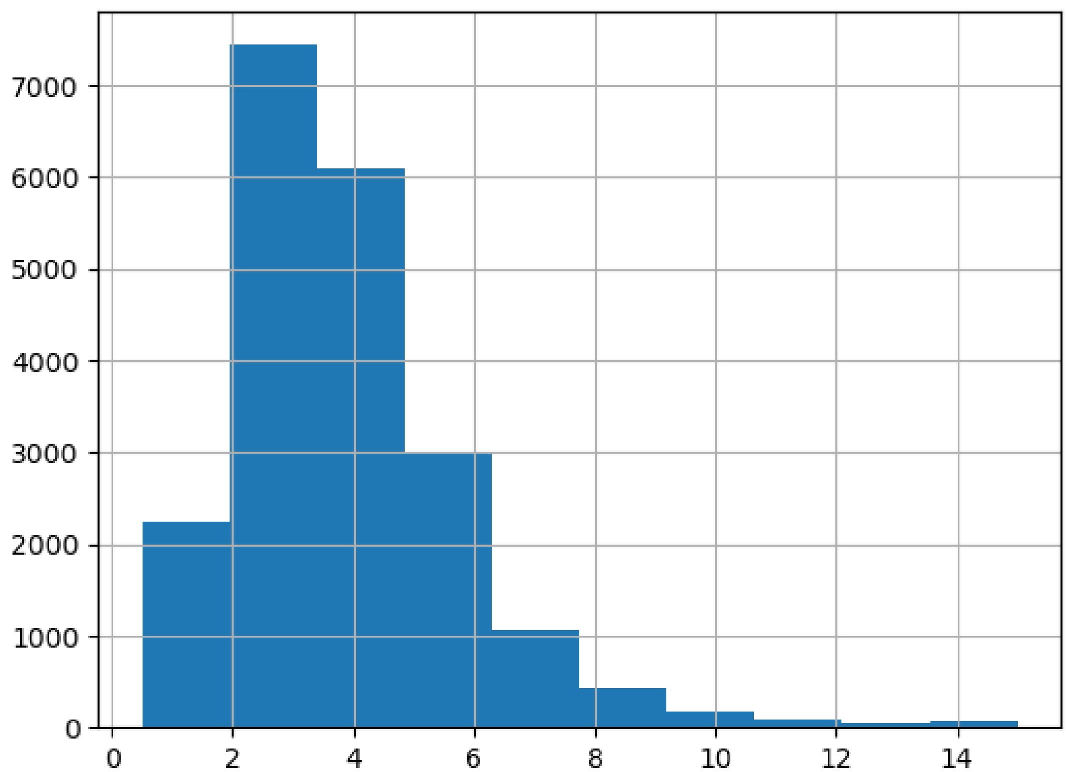



```
housing_data.describe()

         longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100
```

```
       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

```python
housing_data['median_income'].hist()
```

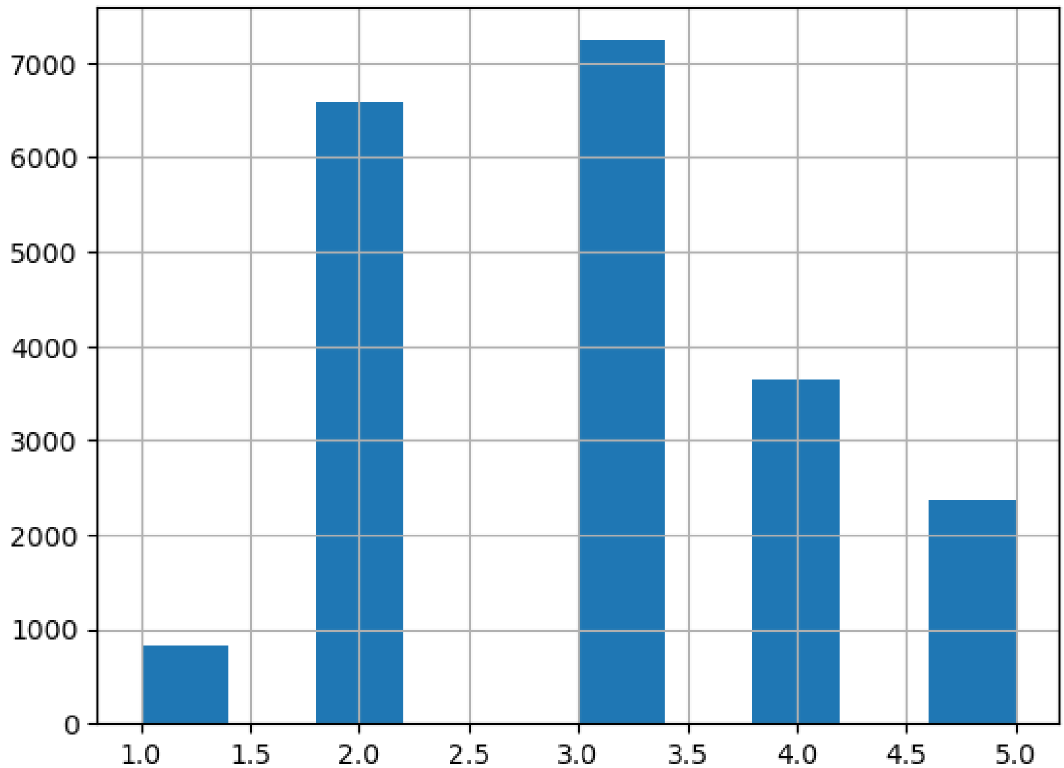
```
<Axes: >
```




```python
housing_data['income_cat']=pd.cut(housing_data['median_income'],
                                  bins=[0.,1.5,3.0,4.5,6.,np.inf],
                                  labels=[1,2,3,4,5])
housing_data['income_cat'].value_counts()
```

```
3    7236
2    6581
4    3639
5    2362
```

```
1      822
Name: income_cat, dtype: int64

housing_data['income_cat'].hist()

<Axes: >
```




```
y=housing_data["median_house_value"] # labels
X=housing_data.drop('median_house_value',axis=1)#to prop columns
=>axis=1 for rows => axis=0
X #Features

       longitude  latitude  housing_median_age  total_rooms
total_bedrooms  \
0        -122.23     37.88                  41          880
129.0
1        -122.22     37.86                  21         7099
1106.0
2        -122.24     37.85                  52         1467
190.0
3        -122.25     37.85                  52         1274
235.0
4        -122.25     37.85                  52         1627
280.0
...          ...       ...                 ...          ...
```

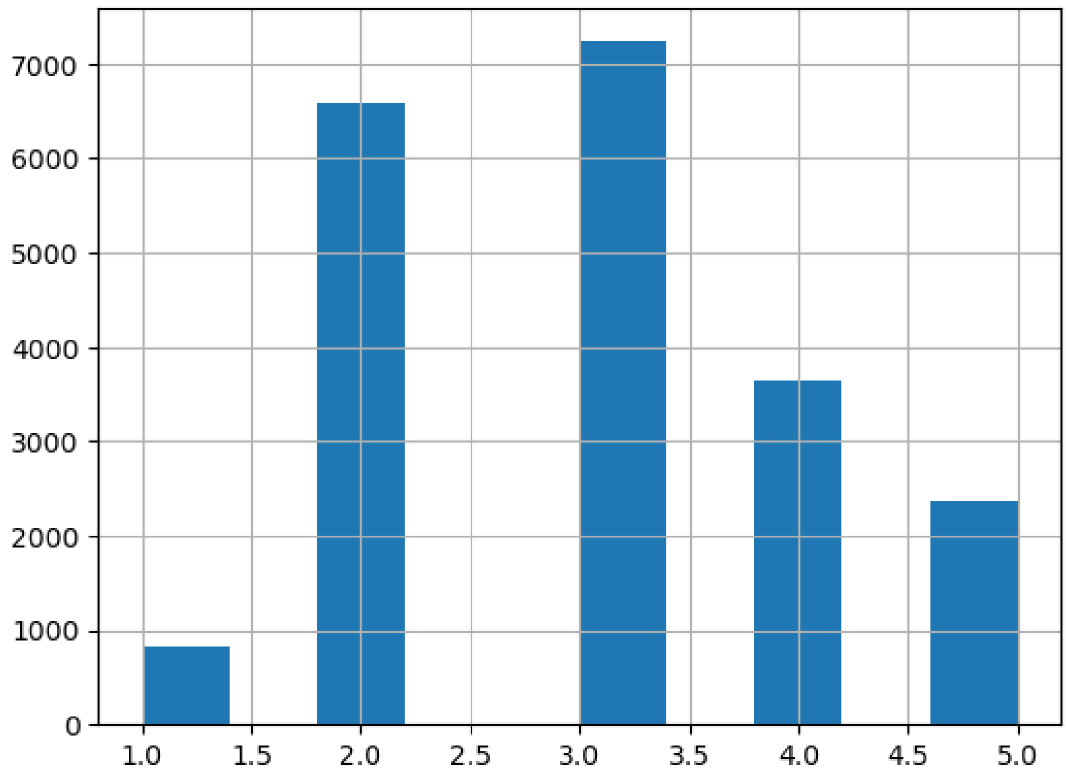
```
...
20635    -121.09     39.48                     25         1665
374.0
20636    -121.21     39.49                     18          697
150.0
20637    -121.22     39.43                     17         2254
485.0
20638    -121.32     39.43                     18         1860
409.0
20639    -121.24     39.37                     16         2785
616.0

       population  households  median_income ocean_proximity
income_cat
0             322         126         8.3252        NEAR BAY
5
1            2401        1138         8.3014        NEAR BAY
5
2             496         177         7.2574        NEAR BAY
5
3             558         219         5.6431        NEAR BAY
4
4             565         259         3.8462        NEAR BAY
3
...           ...         ...            ...             ...          ..
.
20635         845         330         1.5603          INLAND
2
20636         356         114         2.5568          INLAND
2
20637        1007         433         1.7000          INLAND
2
20638         741         349         1.8672          INLAND
2
20639        1387         530         2.3886          INLAND
2

[20640 rows x 10 columns]
```

Normal split

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.33) #
33 percent for test data

len(X_test)+len(X_train)

20640
```

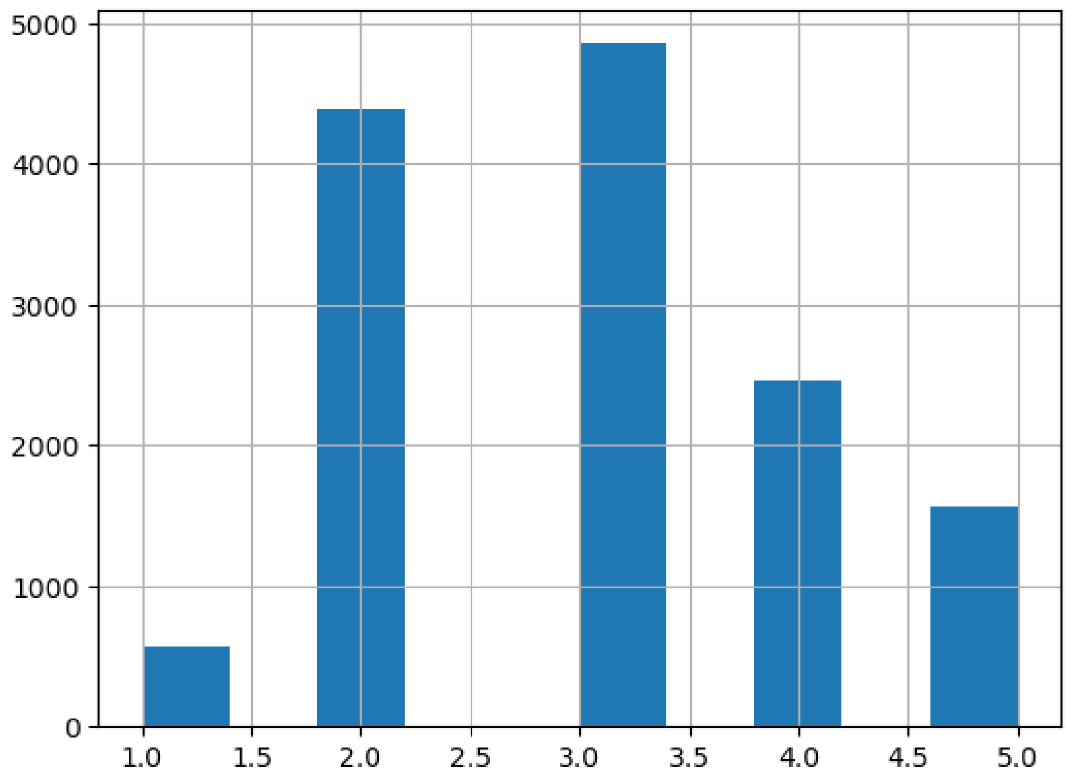
```
housing_data['income_cat'].hist()
```

```
<Axes: >
```




```
X_train['income_cat'].hist()
```

```
<Axes: >
```



Stratified Shuffle Split

```
from sklearn.model_selection import StratifiedShuffleSplit

split =
StratifiedShuffleSplit(n_splits=1,test_size=0.2,random_state=42)
for train_index, test_index in
split.split(housing_data,housing_data["income_cat"]):
    strat_train_set = housing_data.loc[train_index]
    strat_test_set = housing_data.loc[test_index]

strat_test_set['income_cat'].value_counts()/len(strat_test_set)

3    0.350533
2    0.318798
4    0.176357
5    0.114341
1    0.039971
Name: income_cat, dtype: float64

housing_data['income_cat'].value_counts()/len(housing_data)

3    0.350581
2    0.318847
4    0.176308
```

```
5    0.114438
1    0.039826
Name: income_cat, dtype: float64
```

```
strat_train_set.drop("income_cat",axis="columns",inplace=True)
strat_test_set.drop("income_cat",axis="columns",inplace=True)

strat_train_set
```

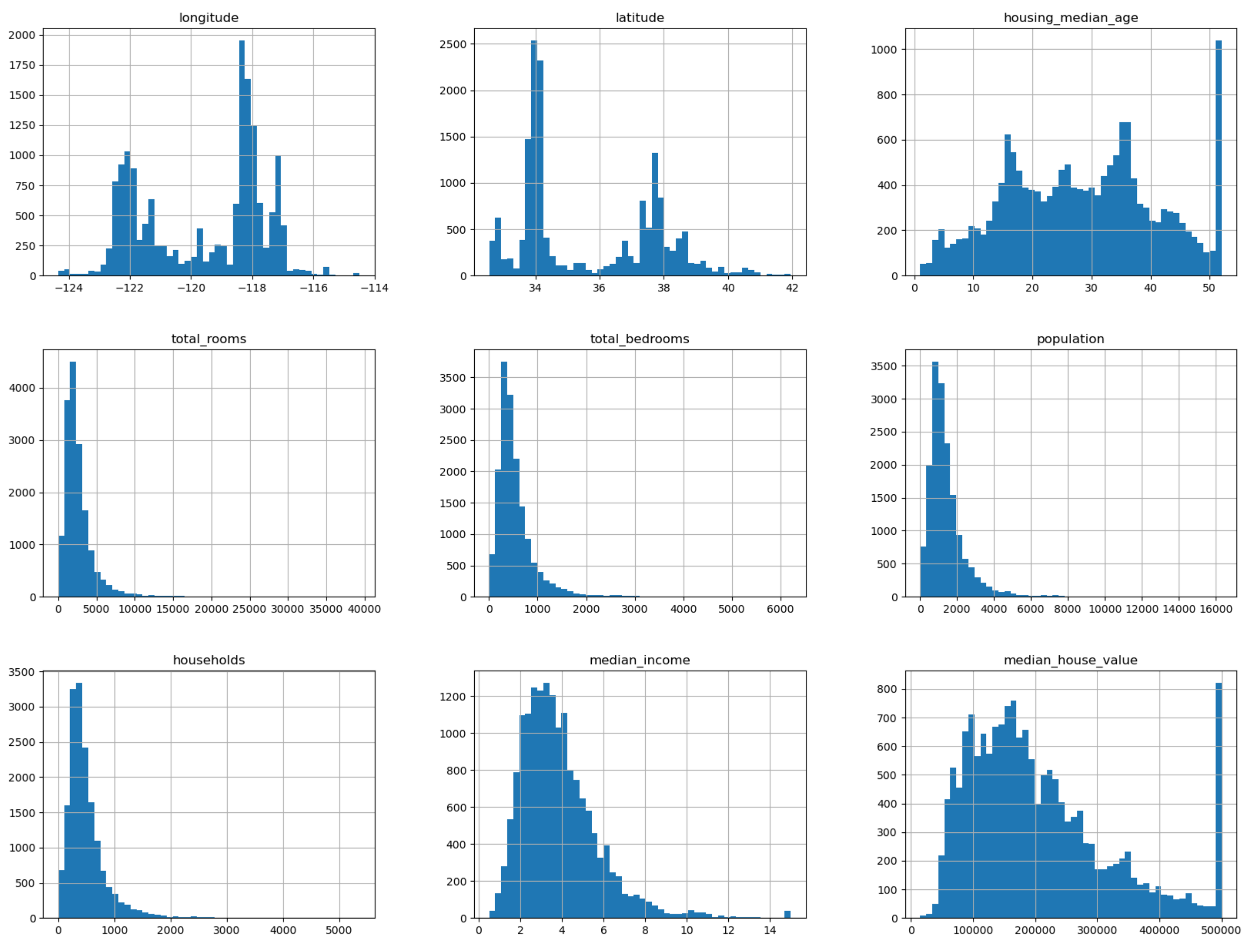
```
       longitude  latitude  housing_median_age  total_rooms
total_bedrooms  \
13096    -122.42     37.80                  52         3321
1115.0
14973    -118.38     34.14                  40         1965
354.0
3785     -121.98     38.36                  33         1083
217.0
14689    -117.11     33.75                  17         4174
851.0
20507    -118.15     33.77                  36         4366
1211.0
...          ...       ...                 ...          ...
...
14207    -118.40     33.86                  41         2237
597.0
13105    -119.31     36.32                  23         2945
592.0
19301    -117.06     32.59                  13         3920
775.0
19121    -118.40     34.06                  37         3781
873.0
19888    -122.41     37.66                  44          431
195.0

       population  households  median_income  median_house_value  \
13096        1576        1034         2.0987              458300
14973         666         357         6.0876              483800
3785          562         203         2.4330              101700
14689        1845         780         2.2618               96100
20507        1912        1172         3.5292              361800
...           ...         ...            ...                 ...
14207         938         523         4.7105              500001
13105        1419         532         2.5733               88800
19301        2814         760         4.0616              148800
19121        1725         838         4.1455              500001
19888         682         212         3.2833              233300

      ocean_proximity
13096        NEAR BAY
14973       <1H OCEAN
```

```
3785            INLAND
14689           INLAND
20507       NEAR OCEAN
...                ...
14207        <1H OCEAN
13105           INLAND
19301       NEAR OCEAN
19121        <1H OCEAN
19888       NEAR OCEAN

[16512 rows x 10 columns]
```

visualizing DATA

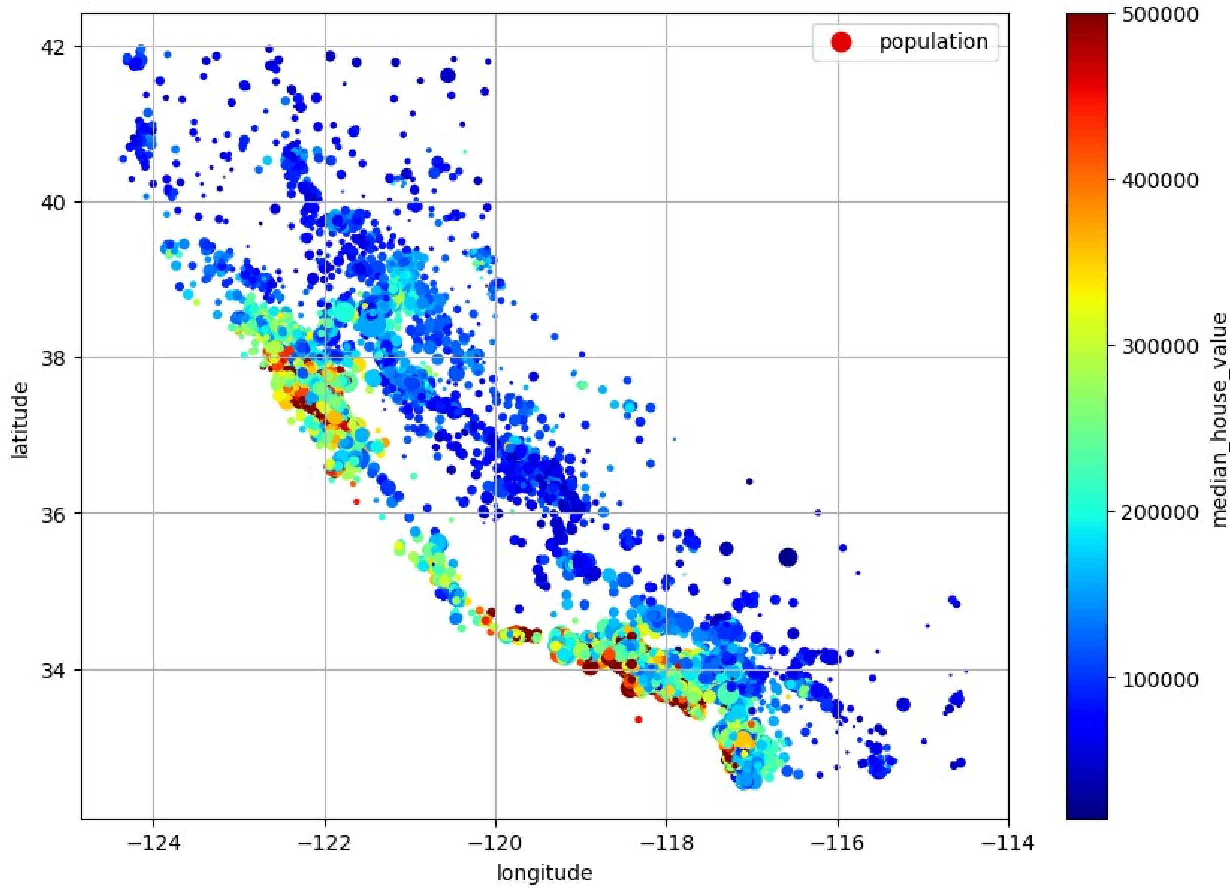
```
housing = strat_train_set.copy()

housing.hist(bins=50,figsize=(20,15))
```

```
array([[<Axes: title={'center': 'longitude'}>,
        <Axes: title={'center': 'latitude'}>,
        <Axes: title={'center': 'housing_median_age'}>],
       [<Axes: title={'center': 'total_rooms'}>,
        <Axes: title={'center': 'total_bedrooms'}>,
        <Axes: title={'center': 'population'}>],
       [<Axes: title={'center': 'households'}>,
        <Axes: title={'center': 'median_income'}>,
        <Axes: title={'center': 'median_house_value'}>]],
dtype=object)
```



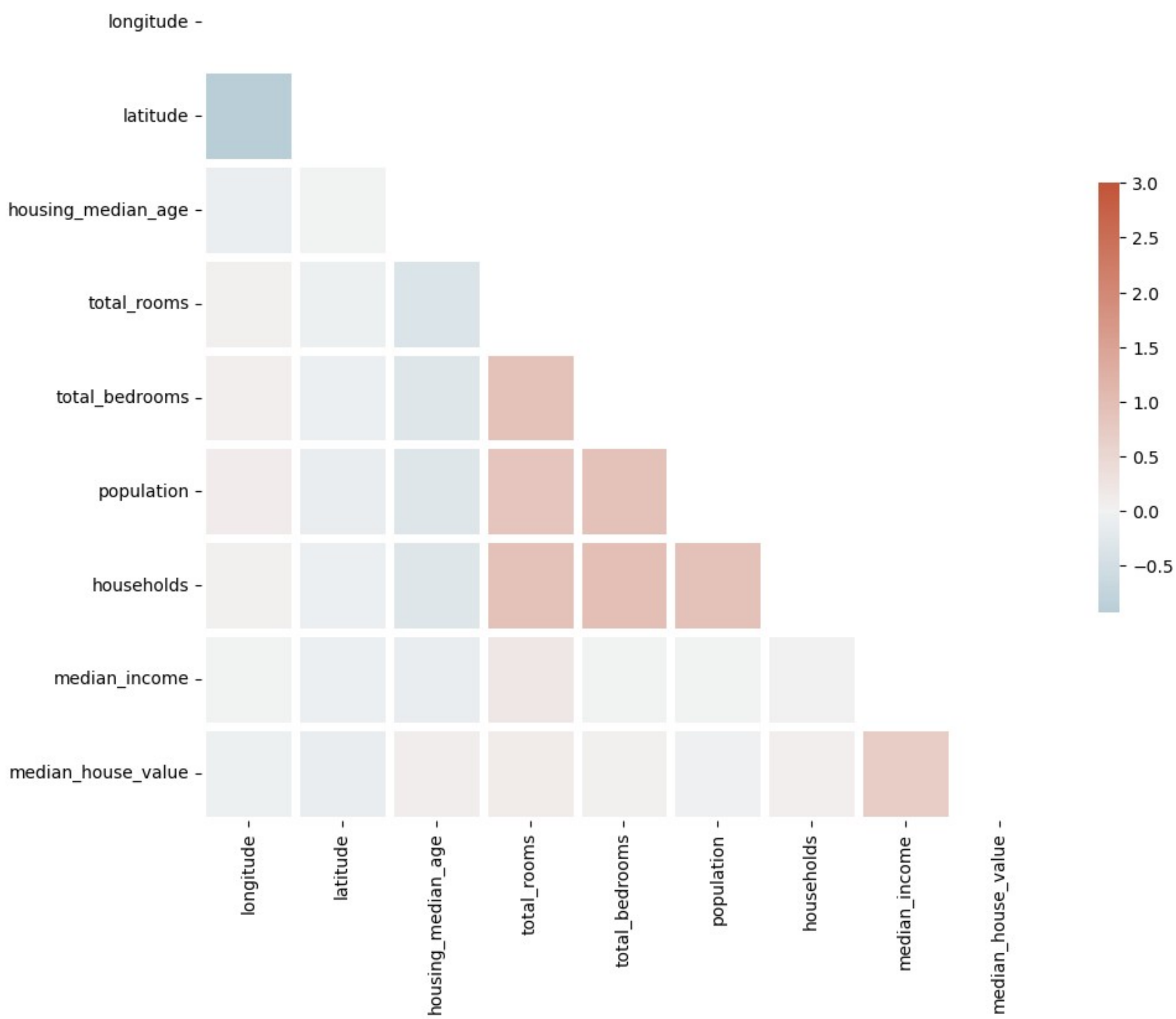
geographical visualising

```
housing.plot(kind="scatter", x="longitude", y="latitude", grid=True,
             s=housing["population"] / 100, label="population",
             c="median_house_value", cmap="jet", colorbar=True,
             legend=True, sharex=False, figsize=(10, 7))
plt.show()
```



corelation matrices

```
import seaborn as sns
corr=housing.corr()

mask =np.triu(np.ones_like(corr,dtype=bool))
f, ax=plt.subplots(figsize=(11,9))
cmap=sns.diverging_palette(230,20,as_cmap=True)
sns.heatmap(corr,mask=mask,cmap=cmap,vmax=3,center=0,square=True,linew
idths=5,cbar_kws={"shrink": .5})

C:\Users\pc\AppData\Local\Temp\ipykernel_11932\2087947216.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  corr=housing.corr()

<Axes: >
```



preparing Data

Data Pipline

```
housing = strat_train_set.drop('median_house_value',axis=1)

lables=strat_train_set['median_house_value'].copy()

def feature_engineering(data):
    data["rooms_per_household"] = data["total_rooms"] /
data["households"]
    data["bedrooms_ratio"] = data["total_bedrooms"] /
data["total_rooms"]
    data["people_per_household"] = data["population"] /
data["households"]
```

```
    return data

def data_transformation(data):
    ### Seperate lables if they exist
    if 'median_house_value' in data.columns:
        lables=data['median_house_value']
        data=data.drop('median_house_value',axis=1) # axis=1 ==>
columns
    else:
        lables=None
    ### Feature Engineering ###
    feature_engineered_data=feature_engineering(data)
    features=list(feature_engineered_data.columns)

    ###imputing Data###
    from sklearn.impute import SimpleImputer
    imputer=SimpleImputer(strategy='median')

housing_num=feature_engineered_data.select_dtypes(include=[np.number])
    imputed = imputer.fit_transform(housing_num)

    ### Encoding Categorical Data ###
    housing_cat =
feature_engineered_data.select_dtypes(exclude=[np.number])

    from sklearn.preprocessing import OneHotEncoder
    cat_encoder=OneHotEncoder(sparse=False) # gives dense matrix
    housing_cat_1hot=cat_encoder.fit_transform(housing_cat)
    features=features+cat_encoder.categories_[0].tolist()
    features.remove("ocean_proximity") # we dont want this feature
anymore as it is encoded

    ### Scaling Numerical Data ###
    from sklearn.preprocessing import StandardScaler
    scaler=StandardScaler()

    housing_scaled=scaler.fit_transform(imputed)

    ### Concatening all Data ###
    output = np.hstack([housing_scaled,housing_cat_1hot])
    return output ,lables ,features
```

Select and train model

```
train_data,train_lables,features=data_transformation(strat_train_set)
train_data

c:\Users\pc\miniconda3\envs\hands-on-machine-learning\Lib\site-
packages\sklearn\preprocessing\_encoders.py:868: FutureWarning:
`sparse` was renamed to `sparse_output` in version 1.2 and will be
```

```
removed in 1.4. `sparse_output` is ignored unless you leave `sparse`
to its default value.
  warnings.warn(

array([[-1.42303652,  1.0136059 ,  1.86111875, ...,  0.        ,
         1.        ,  0.        ],
       [ 0.59639445, -0.702103  ,  0.90762971, ...,  0.        ,
         0.        ,  0.        ],
       [-1.2030985 ,  1.27611874,  0.35142777, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [ 1.25620853, -1.42870103, -1.23772062, ...,  0.        ,
         0.        ,  1.        ],
       [ 0.58639727, -0.73960483,  0.66925745, ...,  0.        ,
         0.        ,  0.        ],
       [-1.41803793,  0.94797769,  1.22545939, ...,  0.        ,
         0.        ,  1.        ]])
```

```
test_data,test_lables,features=data_transformation(strat_test_set)
test_data
```

```
c:\Users\pc\miniconda3\envs\hands-on-machine-learning\Lib\site-
packages\sklearn\preprocessing\_encoders.py:868: FutureWarning:
`sparse` was renamed to `sparse_output` in version 1.2 and will be
removed in 1.4. `sparse_output` is ignored unless you leave `sparse`
to its default value.
  warnings.warn(

array([[-1.18804209,  0.69962912, -0.62700415, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.76723335, -0.8005624 ,  0.56519904, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.68286868, -0.8704471 ,  0.08831777, ...,  0.        ,
         0.        ,  1.        ],
       ...,
       [-1.71408066,  1.42642999,  0.32675841, ...,  0.        ,
         0.        ,  0.        ],
       [-1.22774311,  0.92791914, -0.38856351, ...,  0.        ,
         1.        ,  0.        ],
       [ 1.20890725, -1.33634509,  1.83688246, ...,  0.        ,
         0.        ,  1.        ]])
```

Linear Regression

```
from sklearn.linear_model import LinearRegression
lin_reg=LinearRegression()
lin_reg.fit(train_data,train_lables)

LinearRegression()
```

```
original_values= test_lables[:5]

predicted_values=lin_reg.predict(test_data[:5])

comparison_dataframe = 
pd.DataFrame(data={'original_values':original_values,"predicted_values
":predicted_values})
comparison_dataframe["Differences"]=comparison_dataframe['original_val
ues']-comparison_dataframe['predicted_values']

# comparison_dataframe
len(test_lables)

4128
```

(Mean square error)

```
from sklearn.metrics import mean_squared_error

line_mse=mean_squared_error(original_values,predicted_values)
line_rmse=np.sqrt(line_mse)
line_rmse

46698.461585863326
```

Desision Tree model

```
from sklearn.tree import DecisionTreeRegressor
tree_reg=DecisionTreeRegressor(random_state=42)
tree_reg.fit(train_data,train_lables)

DecisionTreeRegressor(random_state=42)
```

(Mean square error)

```
train_prediction=tree_reg.predict(test_data)
tree_mse=mean_squared_error(test_lables,train_prediction)
tree_rmse=np.sqrt(tree_mse)
tree_rmse

76214.25809366754
```

Random Forest model

```
from sklearn.ensemble import RandomForestRegressor

forest_reg=RandomForestRegressor(n_estimators=100,random_state=42)
forest_reg.fit(train_data,train_lables)

RandomForestRegressor(random_state=42)
```

(Mean square error)

```
train_predictions=forest_reg.predict(test_data)
forest_mse=mean_squared_error(test_lables,train_predictions)
forest_rmse=np.sqrt(forest_mse)
forest_rmse
```

```
59407.687727014716
```