AI ASSIGNMENT 2

Getting the info of the dataframe

```
In [3]:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14620 entries, 0 to 14619
Data columns (total 21 columns):
 #   Column                                 Non-Null Count  Dtype  
---  ------                                 --------------  -----  
 0   number of bedrooms                     14620 non-null  int64  
 1   number of bathrooms                    14620 non-null  float64
 2   living area                            14620 non-null  int64  
 3   lot area                               14620 non-null  int64  
 4   number of floors                       14620 non-null  float64
 5   waterfront present                     14620 non-null  int64  
 6   number of views                        14620 non-null  int64  
 7   condition of the house                 14620 non-null  int64  
 8   grade of the house                     14620 non-null  int64  
 9   Area of the house(excluding basement)  14620 non-null  int64  
 10  Area of the basement                   14620 non-null  int64  
 11  Built Year                             14620 non-null  int64  
 12  Renovation Year                        14620 non-null  int64  
 13  Postal Code                            14620 non-null  int64  
 14  Lattitude                              14620 non-null  float64
 15  Longitude                              14620 non-null  float64
 16  living_area_renov                      14620 non-null  int64  
 17  lot_area_renov                         14620 non-null  int64  
 18  Number of schools nearby               14620 non-null  int64  
 19  Distance from the airport              14620 non-null  int64  
 20  Price                                  14620 non-null  int64  
dtypes: float64(4), int64(17)
memory usage: 2.3 MB
```

The inferrence from the above cell are discussed below,

- Only four columns "number of bathrooms", "number of floors", "Lattitude" and "Longitude" are float datatype.
- Rest of the columns have only int64 datatype.

Checking the NaN values from the dataframe

```
In [4]:
df.isna().sum()
```

```
Out[4]:
number of bedrooms                       0
number of bathrooms                      0
living area                              0
lot area                                 0
number of floors                         0
waterfront present                       0
number of views                          0
condition of the house                   0
grade of the house                       0
Area of the house(excluding basement)    0
Area of the basement                     0
Built Year                               0
Renovation Year                          0
Postal Code                              0
Lattitude                                0
Longitude                                0
living_area_renov                        0
lot_area_renov                           0
Number of schools nearby                 0
Distance from the airport                0
Price                                    0
dtype: int64
```

From the above cell it is founded that,

- There are no NaN values in the given dataset

Spliting independent and dependent variables as X and y

```
In [5]:
X = df.drop('Price', axis=1)
y = df['Price']
```

Spliting the train test separately

```
In [6]:
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state
=12)
```

Getting the shape of X, y train and test

```
In [7]:
print(f'\n shape of X_train - {X_train.shape}\n')
print(f' shape of X_test - {X_test.shape}\n')
print(f' shape of y_train - {y_train.shape}\n')
print(f' shape of y_test - {y_test.shape}\n')
```

```
 shape of X_train - (11696, 20)

 shape of X_test - (2924, 20)

 shape of y_train - (11696,)

 shape of y_test - (2924,)
```

Model building

In [8]:

```
number_of_features = len(X.columns)

model = Sequential()

model.add(layer=Input(shape=number_of_features))

model.add(layer=Dense(units=32, activation='relu'))

model.add(layer=Dense(units=64, activation='relu'))

model.add(layer=Dense(units=128, activation='relu'))

model.add(layer=Dense(units=256, activation='relu'))

model.add(layer=Dense(units=512, activation='relu'))

model.add(layer=Dense(units=1024, activation='relu'))

model.add(layer=Dense(units=2048, activation='relu'))

model.add(layer=Dense(units=256, activation='relu'))

model.add(layer=Dense(units=128, activation='relu'))

model.add(layer=Dense(units=64, activation='relu'))

model.add(layer=Dense(units=32, activation='relu'))

model.add(layer=Dense(units=16, activation='relu'))

model.add(layer=Dense(units=1, activation='linear'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 32)                672

 dense_1 (Dense)             (None, 64)                2112

 dense_2 (Dense)             (None, 128)               8320

 dense_3 (Dense)             (None, 256)               33024

 dense_4 (Dense)             (None, 512)               131584
 dense_5 (Dense)             (None, 1024)              525312

 dense_6 (Dense)             (None, 2048)              2099200

 dense_7 (Dense)             (None, 256)               524544

 dense_8 (Dense)             (None, 128)               32896

 dense_9 (Dense)             (None, 64)                8256

 dense_10 (Dense)            (None, 32)                2080

 dense_11 (Dense)            (None, 16)                528

 dense_12 (Dense)            (None, 1)                 17

=================================================================
Total params: 3,368,545
Trainable params: 3,368,545
Non-trainable params: 0
_________________________________________________________________
```

Compiling the model

```
In [9]:
model.compile(optimizer='adam', loss='mse', metrics=['mae', 'mape'])
```

Model Training

```
In [10]:
history = model.fit(X_train, y_train, epochs=100)
```

```
Epoch 1/100
366/366 [==============================] - 11s 6ms/step - loss: 115373219840.0000
 - mae: 223078.1875 - mape: 49.2277
Epoch 2/100
366/366 [==============================] - 2s 5ms/step - loss: 69455994880.0000 -
 mae: 175933.2812 - mape: 37.2717
Epoch 3/100
366/366 [==============================] - 2s 6ms/step - loss: 63709241344.0000 -
 mae: 169027.0156 - mape: 35.5546
Epoch 4/100
366/366 [==============================] - 2s 6ms/step - loss: 61131841536.0000 -
 mae: 165759.4219 - mape: 34.9124
Epoch 5/100
366/366 [==============================] - 2s 5ms/step - loss: 60745990144.0000 -
 mae: 167357.0938 - mape: 35.0202
Epoch 6/100
366/366 [==============================] - 2s 5ms/step - loss: 63253823488.0000 -
 mae: 168348.6562 - mape: 35.1488
Epoch 7/100
366/366 [==============================] - 2s 6ms/step - loss: 59147300864.0000 -
 mae: 164895.6562 - mape: 34.7841
Epoch 8/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 63616413696.0000 -
 mae: 169971.0000 - mape: 35.2147
Epoch 9/100
366/366 [==============================] - 2s 6ms/step - loss: 56888909824.0000 -
 mae: 161452.5312 - mape: 33.8793
Epoch 10/100
366/366 [==============================] - 2s 6ms/step - loss: 56831733760.0000 -
 mae: 160004.9688 - mape: 33.5284
Epoch 11/100
366/366 [==============================] - 2s 6ms/step - loss: 59214237696.0000 -
 mae: 162406.9219 - mape: 34.1977
Epoch 12/100
366/366 [==============================] - 2s 6ms/step - loss: 59529773056.0000 -
 mae: 163702.0625 - mape: 34.1877
Epoch 13/100
366/366 [==============================] - 2s 7ms/step - loss: 58980405248.0000 -
 mae: 161938.1562 - mape: 33.6812
Epoch 14/100
366/366 [==============================] - 2s 6ms/step - loss: 53838446592.0000 -
 mae: 155908.4219 - mape: 32.6511
Epoch 15/100
366/366 [==============================] - 2s 6ms/step - loss: 54630879232.0000 -
 mae: 156266.7656 - mape: 32.6601
Epoch 16/100
366/366 [==============================] - 2s 6ms/step - loss: 55835422720.0000 -
 mae: 158658.1875 - mape: 33.1131
Epoch 17/100
366/366 [==============================] - 2s 6ms/step - loss: 54464913408.0000 -
 mae: 157176.4844 - mape: 32.8886
Epoch 18/100
366/366 [==============================] - 2s 6ms/step - loss: 56984547328.0000 -
 mae: 161383.6719 - mape: 33.6896
Epoch 19/100
366/366 [==============================] - 2s 6ms/step - loss: 54241468416.0000 -
 mae: 155621.0000 - mape: 32.5170
Epoch 20/100
366/366 [==============================] - 2s 6ms/step - loss: 59135946752.0000 -
 mae: 163379.9688 - mape: 34.0004
Epoch 21/100
366/366 [==============================] - 2s 6ms/step - loss: 52663656448.0000 -
 mae: 154168.8594 - mape: 32.1560
Epoch 22/100
366/366 [==============================] - 2s 6ms/step - loss: 55579299840.0000 -
 mae: 157360.4844 - mape: 32.8772
Epoch 23/100
366/366 [==============================] - 2s 6ms/step - loss: 54586580992.0000 -
 mae: 156370.3594 - mape: 32.5105
Epoch 24/100
366/366 [==============================] - 2s 6ms/step - loss: 53262577664.0000 -
 mae: 155050.3906 - mape: 32.3967
Epoch 25/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 54075871232.0000 -
 mae: 157037.7812 - mape: 32.5757
Epoch 26/100
366/366 [==============================] - 2s 6ms/step - loss: 51292758016.0000 -
 mae: 151864.7812 - mape: 31.6146
Epoch 27/100
366/366 [==============================] - 2s 6ms/step - loss: 55897804800.0000 -
 mae: 157001.2969 - mape: 32.6494
Epoch 28/100
366/366 [==============================] - 2s 7ms/step - loss: 52807000064.0000 -
 mae: 154402.5312 - mape: 32.1374
Epoch 29/100
366/366 [==============================] - 2s 5ms/step - loss: 50559614976.0000 -
 mae: 150681.7656 - mape: 31.3239
Epoch 30/100
366/366 [==============================] - 2s 6ms/step - loss: 54030680064.0000 -
 mae: 155396.6719 - mape: 32.1251
Epoch 31/100
366/366 [==============================] - 2s 6ms/step - loss: 52283559936.0000 -
 mae: 153384.2031 - mape: 32.0258
Epoch 32/100
366/366 [==============================] - 2s 6ms/step - loss: 52832710656.0000 -
 mae: 154543.4375 - mape: 31.9707
Epoch 33/100
366/366 [==============================] - 2s 6ms/step - loss: 52489314304.0000 -
 mae: 153925.0781 - mape: 31.7906
Epoch 34/100
366/366 [==============================] - 2s 6ms/step - loss: 59632648192.0000 -
 mae: 161197.2188 - mape: 33.5867
Epoch 35/100
366/366 [==============================] - 2s 5ms/step - loss: 52995551232.0000 -
 mae: 152778.0312 - mape: 31.5439
Epoch 36/100
366/366 [==============================] - 2s 6ms/step - loss: 51760218112.0000 -
 mae: 152372.9219 - mape: 31.5417
Epoch 37/100
366/366 [==============================] - 2s 6ms/step - loss: 51361501184.0000 -
 mae: 152362.2969 - mape: 31.6092
Epoch 38/100
366/366 [==============================] - 2s 6ms/step - loss: 53745012736.0000 -
 mae: 153568.5156 - mape: 31.8070
Epoch 39/100
366/366 [==============================] - 2s 6ms/step - loss: 52044754944.0000 -
 mae: 152404.7344 - mape: 31.6283
Epoch 40/100
366/366 [==============================] - 2s 6ms/step - loss: 52324454400.0000 -
 mae: 151717.5000 - mape: 31.5201
Epoch 41/100
366/366 [==============================] - 2s 6ms/step - loss: 51012214784.0000 -
 mae: 150878.4219 - mape: 31.4002
Epoch 42/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 51013070848.0000 -
 mae: 151318.3750 - mape: 31.3557
Epoch 43/100
366/366 [==============================] - 3s 7ms/step - loss: 52125188096.0000 -
 mae: 151897.7812 - mape: 31.5532
Epoch 44/100
366/366 [==============================] - 2s 6ms/step - loss: 49911029760.0000 -
 mae: 149106.8281 - mape: 30.9280
Epoch 45/100
366/366 [==============================] - 2s 6ms/step - loss: 51189428224.0000 -
 mae: 152566.5625 - mape: 31.6698
Epoch 46/100
366/366 [==============================] - 2s 6ms/step - loss: 50706468864.0000 -
 mae: 149443.4844 - mape: 30.8647
Epoch 47/100
366/366 [==============================] - 2s 6ms/step - loss: 51435798528.0000 -
 mae: 151232.4531 - mape: 31.4542
Epoch 48/100
366/366 [==============================] - 2s 6ms/step - loss: 48945655808.0000 -
 mae: 148143.1250 - mape: 30.8189
Epoch 49/100
366/366 [==============================] - 2s 6ms/step - loss: 53101506560.0000 -
 mae: 153325.5469 - mape: 31.6500
Epoch 50/100
366/366 [==============================] - 2s 6ms/step - loss: 52147609600.0000 -
 mae: 151818.1719 - mape: 31.4515
Epoch 51/100
366/366 [==============================] - 2s 6ms/step - loss: 50240663552.0000 -
 mae: 150436.9844 - mape: 31.1419
Epoch 52/100
366/366 [==============================] - 2s 6ms/step - loss: 49564909568.0000 -
 mae: 148995.1562 - mape: 31.0548
Epoch 53/100
366/366 [==============================] - 2s 6ms/step - loss: 51030122496.0000 -
 mae: 151829.7031 - mape: 31.3057
Epoch 54/100
366/366 [==============================] - 2s 6ms/step - loss: 50005434368.0000 -
 mae: 149201.5156 - mape: 31.0676
Epoch 55/100
366/366 [==============================] - 2s 6ms/step - loss: 48938049536.0000 -
 mae: 146918.7188 - mape: 30.4790
Epoch 56/100
366/366 [==============================] - 2s 6ms/step - loss: 49289723904.0000 -
 mae: 148141.9688 - mape: 30.6173
Epoch 57/100
366/366 [==============================] - 2s 6ms/step - loss: 49386569728.0000 -
 mae: 148052.7969 - mape: 30.6916
Epoch 58/100
366/366 [==============================] - 2s 7ms/step - loss: 49865011200.0000 -
 mae: 148512.9375 - mape: 30.8196
Epoch 59/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 48806412288.0000 -
 mae: 147634.5938 - mape: 30.6775
Epoch 60/100
366/366 [==============================] - 2s 6ms/step - loss: 48990040064.0000 -
 mae: 147891.5469 - mape: 30.9335
Epoch 61/100
366/366 [==============================] - 2s 6ms/step - loss: 49532538880.0000 -
 mae: 148435.2031 - mape: 30.7960
Epoch 62/100
366/366 [==============================] - 2s 6ms/step - loss: 49416626176.0000 -
 mae: 147605.6875 - mape: 30.6762
Epoch 63/100
366/366 [==============================] - 2s 6ms/step - loss: 48503390208.0000 -
 mae: 147891.4375 - mape: 30.7656
Epoch 64/100
366/366 [==============================] - 2s 6ms/step - loss: 48167800832.0000 -
 mae: 145974.1562 - mape: 30.3071
Epoch 65/100
366/366 [==============================] - 2s 6ms/step - loss: 48472039424.0000 -
 mae: 146392.1562 - mape: 30.4809
Epoch 66/100
366/366 [==============================] - 2s 6ms/step - loss: 47465766912.0000 -
 mae: 145686.1250 - mape: 30.3407
Epoch 67/100
366/366 [==============================] - 2s 6ms/step - loss: 48080560128.0000 -
 mae: 145239.3281 - mape: 30.2406
Epoch 68/100
366/366 [==============================] - 2s 6ms/step - loss: 47816654848.0000 -
 mae: 145906.5781 - mape: 30.3515
Epoch 69/100
366/366 [==============================] - 2s 6ms/step - loss: 48326881280.0000 -
 mae: 147244.9219 - mape: 30.5693
Epoch 70/100
366/366 [==============================] - 2s 6ms/step - loss: 48167899136.0000 -
 mae: 145695.2812 - mape: 30.3434
Epoch 71/100
366/366 [==============================] - 2s 6ms/step - loss: 46709411840.0000 -
 mae: 144538.7656 - mape: 30.0584
Epoch 72/100
366/366 [==============================] - 2s 5ms/step - loss: 47881138176.0000 -
 mae: 145494.6250 - mape: 30.2558
Epoch 73/100
366/366 [==============================] - 2s 6ms/step - loss: 47831670784.0000 -
 mae: 146193.8750 - mape: 30.4547
Epoch 74/100
366/366 [==============================] - 2s 6ms/step - loss: 48283926528.0000 -
 mae: 146402.7344 - mape: 30.5587
Epoch 75/100
366/366 [==============================] - 2s 6ms/step - loss: 49335169024.0000 -
 mae: 147990.4531 - mape: 30.8068
Epoch 76/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 46650712064.0000 -
 mae: 144099.5156 - mape: 30.0486
Epoch 77/100
366/366 [==============================] - 2s 6ms/step - loss: 48079314944.0000 -
 mae: 145554.9688 - mape: 30.2738
Epoch 78/100
366/366 [==============================] - 2s 5ms/step - loss: 46424326144.0000 -
 mae: 144024.5938 - mape: 30.0820
Epoch 79/100
366/366 [==============================] - 2s 6ms/step - loss: 45502382080.0000 -
 mae: 142833.1094 - mape: 29.9501
Epoch 80/100
366/366 [==============================] - 2s 6ms/step - loss: 46820442112.0000 -
 mae: 144880.7188 - mape: 30.0728
Epoch 81/100
366/366 [==============================] - 2s 6ms/step - loss: 49424752640.0000 -
 mae: 148025.7500 - mape: 30.7913
Epoch 82/100
366/366 [==============================] - 2s 6ms/step - loss: 48581087232.0000 -
 mae: 147064.2969 - mape: 30.5191
Epoch 83/100
366/366 [==============================] - 2s 6ms/step - loss: 45965008896.0000 -
 mae: 143562.7031 - mape: 30.1378
Epoch 84/100
366/366 [==============================] - 2s 6ms/step - loss: 47132475392.0000 -
 mae: 144201.1406 - mape: 30.0132
Epoch 85/100
366/366 [==============================] - 2s 6ms/step - loss: 46012600320.0000 -
 mae: 143252.1094 - mape: 29.8453
Epoch 86/100
366/366 [==============================] - 2s 6ms/step - loss: 47465938944.0000 -
 mae: 145318.7031 - mape: 30.3195
Epoch 87/100
366/366 [==============================] - 2s 6ms/step - loss: 46110588928.0000 -
 mae: 143106.4375 - mape: 29.8871
Epoch 88/100
366/366 [==============================] - 2s 7ms/step - loss: 46045933568.0000 -
 mae: 143356.4062 - mape: 29.9401
Epoch 89/100
366/366 [==============================] - 2s 6ms/step - loss: 47192424448.0000 -
 mae: 144077.8906 - mape: 30.0460
Epoch 90/100
366/366 [==============================] - 2s 6ms/step - loss: 46030782464.0000 -
 mae: 143928.2812 - mape: 30.1497
Epoch 91/100
366/366 [==============================] - 2s 6ms/step - loss: 47286464512.0000 -
 mae: 144318.2188 - mape: 30.0864
Epoch 92/100
366/366 [==============================] - 2s 6ms/step - loss: 46418128896.0000 -
 mae: 144305.5469 - mape: 30.2092
Epoch 93/100
```

```
366/366 [==============================] - 2s 6ms/step - loss: 45890568192.0000 -
 mae: 143217.1562 - mape: 29.9014
Epoch 94/100
366/366 [==============================] - 2s 6ms/step - loss: 44947415040.0000 -
 mae: 141036.0000 - mape: 29.5444
Epoch 95/100
366/366 [==============================] - 2s 6ms/step - loss: 44814655488.0000 -
 mae: 142566.5625 - mape: 29.8249
Epoch 96/100
366/366 [==============================] - 2s 5ms/step - loss: 45107769344.0000 -
 mae: 141834.5000 - mape: 29.7779
Epoch 97/100
366/366 [==============================] - 2s 6ms/step - loss: 44985761792.0000 -
 mae: 142067.0000 - mape: 29.6291
Epoch 98/100
366/366 [==============================] - 2s 6ms/step - loss: 44453998592.0000 -
 mae: 141057.8750 - mape: 29.5080
Epoch 99/100
366/366 [==============================] - 2s 6ms/step - loss: 45318406144.0000 -
 mae: 142222.6250 - mape: 29.7655
Epoch 100/100
366/366 [==============================] - 2s 6ms/step - loss: 45620596736.0000 -
 mae: 143098.0312 - mape: 29.9300
```

Prediting the unseen dataset

In [11]:
```
y_pred = model.predict(X_test)
```

```
92/92 [==============================] - 0s 2ms/step
```

In [12]:
```
y_pred
```

Out[12]:
```
array([[360362.7 ],
       [394695.16],
       [402347.7 ],
       ...,
       [415337.1 ],
       [324866.47],
       [523623.03]], dtype=float32)
```

In [13]:
```
y_test
```

Out[13]:
```
12149    640000
13581    650000
11595    325000
2769     373000
7393     355000
          ...
7362     497000
11132    400000
142      366750
```

```
1405     276000
6184     569000
Name: Price, Length: 2924, dtype: int64
```

Visual representation of the acutual value vs the predicted value

In [14]:
```
plt.scatter(y_test, y_pred, c=y_pred)
plt.show()
```

In [15]:
```
pd.DataFrame({'Actual Value':y_test.values.flatten(), 'Predicted Value':y_pred.flatte
n()})
```

Out[15]:

	Actual Value	Predicted Value
0	640000	360362.68750
1	650000	394695.15625
2	325000	402347.68750
3	373000	499798.25000
4	355000	514653.06250
...	...	...
2919	497000	497558.09375
2920	400000	374115.21875
2921	366750	415337.09375

	Actual Value	Predicted Value
2922	276000	324866.46875
2923	569000	523623.03125

2924 rows × 2 columns

The above cell maps the actual value and the predicted values

In [16]:
```
r2_score(y_pred=y_pred, y_true=y_test) * 100
```

Out[16]:
```
66.53464784299932
```

linkcode

Thus the model is trained with ANN and got an accuracy of 66.5%¶