import pandas as pd
import numpy as np
import random as rnd

visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

scaling and train test split
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

creating a model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.optimizers import Adam

evaluation on test data

from sklearn.metrics import mean_squared_error,mean_absolute_error,explained_variance
from sklearn.metrics import classification_report,confusion_matrix

df = pd.read_csv('/content/drive/MyDrive/House Price India.csv')

print(df.columns.values)

['id' 'Date' 'number of bedrooms' 'number of bathrooms' 'living area' 'lot area' 'number of floors' 'waterfront present' 'number of views' 'condition of the house' 'grade of the house' 'Area of the house(excluding basement)' 'Area of the basement' 'Built Year' 'Renovation Year' 'Postal Code' 'Lattitude' 'Longitude' 'living_area_renov' 'lot_area_renov' 'Number of schools nearby' 'Distance from the airport' 'Price']

preview the data
df.head()

	id	Date	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfront present	n
0	6762810145	42491	5	2.50	3650	9050	2.0	0	
1	6762810635	42491	4	2.50	2920	4000	1.5	0	
2	6762810998	42491	5	2.75	2910	9480	1.5	0	
3	6762812605	42491	4	2.50	3310	42998	2.0	0	
4	6762812919	42491	3	2.00	2710	4500	1.5	0	

5 rows × 23 columns

	id	Date	number of bedrooms	number of bathrooms	living area	lot area	number of floors	waterfron presen
14615	6762830250	42734	2	1.5	1556	20000	1.0	
14616	6762830339	42734	3	2.0	1680	7000	1.5	
14617	6762830618	42734	2	1.0	1070	6120	1.0	
14618	6762830709	42734	4	1.0	1030	6621	1.0	
14619	6762831463	42734	3	1.0	900	4770	1.0	

5 rows × 23 columns

df.isnull().sum()

id Date	0
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
<pre>grade of the house Area of the house(excluding basement)</pre>	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 Price	0
dtype: int64	U

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14620 entries, 0 to 14619
Data columns (total 23 columns):

#	Column	Non-Null Count	Dtype
0	id	14620 non-null	int64
1	Date	14620 non-null	int64
2	number of bedrooms	14620 non-null	int64
3	number of bathrooms	14620 non-null	float64
4	living area	14620 non-null	int64

5	lot area	14620 non-null	int64
6	number of floors	14620 non-null	float64
7	waterfront present	14620 non-null	int64
8	number of views	14620 non-null	int64
9	condition of the house	14620 non-null	int64
10	grade of the house	14620 non-null	int64
11	Area of the house(excluding basement)	14620 non-null	int64
12	Area of the basement	14620 non-null	int64
13	Built Year	14620 non-null	int64
14	Renovation Year	14620 non-null	int64
15	Postal Code	14620 non-null	int64
16	Lattitude	14620 non-null	float64
17	Longitude	14620 non-null	float64
18	living_area_renov	14620 non-null	int64
19	lot_area_renov	14620 non-null	int64
20	Number of schools nearby	14620 non-null	int64
21	Distance from the airport	14620 non-null	int64
22	Price	14620 non-null	int64

dtypes: float64(4), int64(19) memory usage: 2.6 MB

df.describe().transpose()

	count	mean	std	min	25%	
id	14620.0	6.762821e+09	6237.574799	6.762810e+09	6.762815e+09	6
Date	14620.0	4.260454e+04	67.347991	4.249100e+04	4.254600e+04	4
number of bedrooms	14620.0	3.379343e+00	0.938719	1.000000e+00	3.000000e+00	3
number of bathrooms	14620.0	2.129583e+00	0.769934	5.000000e-01	1.750000e+00	2
living area	14620.0	2.098263e+03	928.275721	3.700000e+02	1.440000e+03	1
lot area	14620.0	1.509328e+04	37919.621304	5.200000e+02	5.010750e+03	7
number of floors	14620.0	1.502360e+00	0.540239	1.000000e+00	1.000000e+00	1
waterfront	1462በ በ	7 660739e-03	N N87193	0 000000e+00	N NNNNNNe+NN	۲

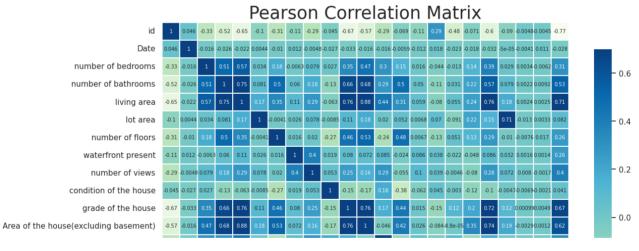
sns.set(style="whitegrid", font_scale=1)

plt.figure(figsize=(13,13))

plt.title('Pearson Correlation Matrix',fontsize=25)

sns.heatmap(df.corr(),linewidths=0.25,vmax=0.7,square=True,cmap="GnBu",linecolor='w', annot=True, annot_kws={"size":7}, cbar_kws={"shrink": .7})

<Axes: title={'center': 'Pearson Correlation Matrix'}>



price_corr = df.corr()
print(price_corr)

· (p. 200_00)			
	id	Date	number of bedrooms
id	1.000000	0.045966	-0.329034
Date	0.045966	1.000000	-0.015663
number of bedrooms	-0.329034	-0.015663	1.000000
number of bathrooms	-0.516909	-0.026485	0.509784
living area	-0.648127	-0.021958	0.570526
lot area	-0.100269	0.004392	0.034416
number of floors	-0.312305	-0.010335	0.177294
waterfront present	-0.112937	0.012006	-0.006257
number of views	-0.293004	-0.004782	0.078665
condition of the house	-0.045061	-0.027402	0.026597
grade of the house	-0.673448	-0.033097	0.352945
Area of the house(excluding basement)	-0.565116	-0.015994	0.473599
Area of the basement	-0.290806		0.300332
Built Year	-0.068645	-0.005869	0.152954
Renovation Year	-0.109155	-0.011636	0.016132
Postal Code	0.294709	0.018243	-0.044156
Lattitude	-0.479334	-0.023327	-0.013163
Longitude	-0.070841	-0.018231	0.135712
living_area_renov	-0.599900	-0.032495	0.389855
lot_area_renov	-0.089604	-0.000050	0.029400
Number of schools nearby	-0.004821	-0.004071	0.003397
Distance from the airport	-0.004542	0.011457	-0.006157
Price	-0.773114	-0.027919	0.308460
	number of	f bathrooms	living area \
id		-0.516909	O
Date		-0.026485	
number of bedrooms		0.509784	
number of bathrooms		1.000000	0.753517
living area		0.753517	
lot area		0.080806	0.174420
number of floors		0.502924	
waterfront present		0.060104	
number of views		0.183789	
condition of the house		-0.128232	
grade of the house		0.663054	0.761835
_			

```
Area of the house(excluding basement)
                                                       0.684391
                                                                    0.875793
     Area of the basement
                                                       0.287190
                                                                    0.441491
     Built Year
                                                       0.498127
                                                                    0.309602
     Renovation Year
                                                       0.049669
                                                                    0.059400
     Postal Code
                                                      -0.105546
                                                                   -0.080303
     Lattitude
                                                       0.031156
                                                                  0.054518
                                                       0.223904
     Longitude
                                                                    0.240208
     living_area_renov
                                                       0.570530
                                                                    0.757571
     lot area renov
                                                       0.078627
                                                                    0.180312
     Number of schools nearby
                                                       0.002180
                                                                    0.002370
     Distance from the airport
                                                       0.009206
                                                                    0.002511
     Price
                                                       0.531735
                                                                    0.712169
                                            lot area number of floors ∖
     id
                                                             -0.312305
                                           -0.100269
     Date
                                            0.004392
                                                             -0.010335
     number of bedrooms
                                            0.034416
                                                             0.177294
     number of bathrooms
                                            0.080806
                                                             0.502924
     living area
                                            0.174420
                                                             0.354743
     lot area
                                            1.000000
                                                            -0.004138
     number of floors
                                           -0.004138
                                                             1.000000
     waterfront present
                                            0.026282
                                                              0.016316
sns.set(style="whitegrid", font scale=1)
f, axes = plt.subplots(1, 2,figsize=(15,5))
sns.boxplot(x=df['living area'],y=df['Price'], ax=axes[0])
sns.boxplot(x=df['number of floors'],y=df['Price'], ax=axes[1])
sns.despine(bottom=True, left=True)
axes[0].set(xlabel='living area', ylabel='Price', title='living area vs Price Box Plo
axes[1].set(xlabel='number of floors', ylabel='Price', title=' vs Price Box Plot')
     [Text(0.5, 0, 'number of floors'),
      Text(0, 0.5, 'Price'),
      Text(0.5, 1.0, ' vs Price Box Plot')]
       8 living area vs Price Box Plot
                                                              vs Price Box Plot
                                                 8 le6
```

```
f, axes = plt.subplots(1, 2,figsize=(15,5))
sns.boxplot(x=df['waterfront present'],y=df['Price'], ax=axes[0])
sns.boxplot(x=df['number of floors'],y=df['Price'], ax=axes[1])
```

```
df = df.drop('Postal Code', axis=1)
df = df.drop('lot area',axis=1)

df['Date'] = pd.to_datetime(df['Date'])
```

```
df['month'] = df['Date'].apply(lambda date:date.month)
df['year'] = df['Date'].apply(lambda date:date.year)
df = df.drop('Date',axis=1)
# Check the new columns
print(df.columns.values)
      ['number of bedrooms' 'number of bathrooms' 'living area'
       'number of floors' 'waterfront present' 'number of views'
       'condition of the house' 'grade of the house'
       'Area of the house(excluding basement)' 'Area of the basement'
       'Built Year' 'Renovation Year' 'Lattitude' 'Longitude'
       'living_area_renov' 'lot_area_renov' 'Number of schools nearby'
       'Distance from the airport' 'Price' 'month' 'year']
# Features
X = df.drop('Price',axis=1)
# Label
y = df['Price']
# Split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=10
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
      (10234, 20)
      (4386, 20)
      (10234,)
      (4386,)
scaler = MinMaxScaler()
# fit and transfrom
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# everything has been scaled between 1 and 0
print('Max: ',X_train.max())
print('Min: ', X_train.min())
     Max: 1.00000000000000002
     Min: 0.0
model = Sequential()
# input layer
model.add(Dense(19,activation='relu'))
# hidden layers
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
# output layer
```

```
model.add(Dense(1))
model.compile(optimizer='adam',loss='mse')
model.fit(x=X_train,y=y_train.values,
          validation_data=(X_test,y_test.values),
          batch size=128,
          epochs=400,
          verbose=2)
     Epoch 1/400
     80/80 - 2s - loss: 425401450496.0000 - val loss: 425759834112.0000 - 2s/epoch
     Epoch 2/400
     80/80 - Os - loss: 425223225344.0000 - val loss: 425189736448.0000 - 333ms/epoch
     Epoch 3/400
     80/80 - Os - loss: 423075872768.0000 - val_loss: 420195893248.0000 - 322ms/epoch
     Epoch 4/400
     80/80 - 0s - loss: 411137409024.0000 - val loss: 398059700224.0000 - 316ms/epoch
     Epoch 5/400
     80/80 - Os - loss: 371945504768.0000 - val_loss: 337670799360.0000 - 206ms/epoch
     Epoch 6/400
     80/80 - Os - loss: 288151928832.0000 - val_loss: 231803879424.0000 - 207ms/epoch
     Epoch 7/400
     80/80 - Os - loss: 178511429632.0000 - val_loss: 133073543168.0000 - 226ms/epoch
     Epoch 8/400
     80/80 - Os - loss: 112337772544.0000 - val_loss: 102041051136.0000 - 209ms/epoch
     Epoch 9/400
     80/80 - Os - loss: 99842580480.0000 - val_loss: 99232309248.0000 - 221ms/epoch -
     Epoch 10/400
     80/80 - Os - loss: 98124103680.0000 - val_loss: 97883815936.0000 - 223ms/epoch -
     Epoch 11/400
     80/80 - Os - loss: 96622043136.0000 - val_loss: 96390930432.0000 - 225ms/epoch -
     Epoch 12/400
     80/80 - Os - loss: 95040888832.0000 - val_loss: 94858723328.0000 - 201ms/epoch -
     Epoch 13/400
     80/80 - Os - loss: 93416529920.0000 - val_loss: 93233651712.0000 - 224ms/epoch -
     Epoch 14/400
     80/80 - Os - loss: 91684757504.0000 - val_loss: 91578900480.0000 - 206ms/epoch -
     Epoch 15/400
     80/80 - Os - loss: 89940025344.0000 - val_loss: 89774481408.0000 - 218ms/epoch -
     Epoch 16/400
     80/80 - Os - loss: 88102903808.0000 - val_loss: 88037498880.0000 - 227ms/epoch -
     Epoch 17/400
     80/80 - Os - loss: 86223413248.0000 - val_loss: 86146310144.0000 - 208ms/epoch -
     Epoch 18/400
     80/80 - Os - loss: 84279771136.0000 - val_loss: 84245405696.0000 - 223ms/epoch -
     Epoch 19/400
     80/80 - Os - loss: 82268717056.0000 - val_loss: 82269331456.0000 - 226ms/epoch -
     Epoch 20/400
     80/80 - Os - loss: 80172343296.0000 - val loss: 80242098176.0000 - 207ms/epoch -
     Epoch 21/400
     80/80 - 0s - loss: 78057365504.0000 - val_loss: 78123130880.0000 - 217ms/epoch -
     Epoch 22/400
     80/80 - Os - loss: 75879964672.0000 - val_loss: 75995299840.0000 - 257ms/epoch -
     Epoch 23/400
     80/80 - Os - loss: 73651929088.0000 - val_loss: 73840271360.0000 - 246ms/epoch -
     Epoch 24/400
     80/80 - Os - loss: 71414980608.0000 - val_loss: 71657275392.0000 - 222ms/epoch -
     Epoch 25/400
     80/80 - Os - loss: 69177393152.0000 - val_loss: 69455020032.0000 - 217ms/epoch -
```

```
Epoch 26/400
80/80 - 0s - loss: 66930868224.0000 - val_loss: 67291369472.0000 - 233ms/epoch - Epoch 27/400
80/80 - 0s - loss: 64734511104.0000 - val_loss: 65313955840.0000 - 201ms/epoch - Epoch 28/400
80/80 - 0s - loss: 62659198976.0000 - val_loss: 63283535872.0000 - 196ms/epoch - Epoch 29/400
80/80 - 0s - loss: 60650418176.0000 - val_loss: 61439680512.0000 - 221ms/epoch - Epoch 30/400
```

losses = pd.DataFrame(model.history.history)

```
plt.figure(figsize=(15,5))
sns.lineplot(data=losses,lw=3)
plt.xlabel('Epochs')
plt.ylabel('')
plt.title('Training Loss per Epoch')
sns.despine()
```



Descriptive Statistics: count 1.462000e+04

```
5.389322e+05
     mean
              3.675324e+05
     std
              7.800000e+04
     min
              3.200000e+05
     25%
              4.500000e+05
     50%
     75%
              6.450000e+05
              7.700000e+06
     max
     Name: Price, dtype: float64
single_house = df.drop('Price',axis=1).iloc[0]
print(f'Features of new house:\n{single_house}')
# reshape the numpy array and scale the features
single_house = scaler.transform('grade of the house'.values.reshape(-1, 19))
# run the model and get the price prediction
print('\nPrediction Price:',model.predict(single_house)[0,0])
# original price
print('\nOriginal Price:',df.iloc[0]['Price'])
```

Features of new house:	
number of bedrooms	5.0000
number of bathrooms	2.5000
living area	3650.0000
number of floors	2.0000
waterfront present	0.0000
number of views	4.0000

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