```
In [2]: import numpy as np
         import random as rnd
        import pandas as pd
         # 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 score
        from sklearn.metrics import classification report,confusion matrix
        C:\ProgramData\Anaconda3\lib\site-packages\scipy\ init .py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required
        for this version of SciPy (detected version 1.24.3
          warnings.warn(f"A NumPy version >={np minversion} and <{np maxversion}"</pre>
In [3]: df = pd.read csv("C:/Users/Hp/House Price Prediction (MP)/house data.csv")
In [4]: print(df.columns.values)
        ['id' 'date' 'price' 'bedrooms' 'bathrooms' 'sqft living' 'sqft lot'
         'floors' 'waterfront' 'view' 'condition' 'grade' 'sqft above'
          'sqft_basement' 'yr_built' 'yr_renovated' 'zipcode' 'lat' 'long'
          'saft living15' 'saft lot15']
In [5]: df.head()
```

]:		id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	•••	grade	sqft_above	sqft_basement
	0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0		7	1180	0
	1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0		7	2170	400
	2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0		6	770	0
	3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0		7	1050	910
	4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0		8	1680	0

5 rows × 21 columns

In [6]: df.tail()

Out[5]

Out[6]:	id da		date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	•••	grade	sqft_above	sqft_basem
	21608	263000018	20140521T000000	360000.0	3	2.50	1530	1131	3.0	0	0		8	1530	
	21609	6600060120	20150223T000000	400000.0	4	2.50	2310	5813	2.0	0	0		8	2310	
	21610	1523300141	20140623T000000	402101.0	2	0.75	1020	1350	2.0	0	0		7	1020	
	21611	291310100	20150116T000000	400000.0	3	2.50	1600	2388	2.0	0	0		8	1600	
	21612	1523300157	20141015T000000	325000.0	2	0.75	1020	1076	2.0	0	0		7	1020	

5 rows × 21 columns

→

In [7]: df.isnull().sum()

```
id
                          0
Out[7]:
                          0
        date
        price
                          0
        bedrooms
                          0
        bathrooms
                          0
        sqft_living
                          0
        sqft_lot
                          0
        floors
                          0
        waterfront
                          0
        view
                          0
        condition
                          0
        grade
                          0
        sqft_above
                          0
        sqft_basement
                          0
        yr_built
                          0
        yr_renovated
                          0
        zipcode
                          0
        lat
                          0
        long
                          0
        sqft_living15
                          0
        sqft_lot15
                          0
        dtype: int64
```

In [8]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):

Data	COTUMNIS (COCAT	ZI COIUIIIIS).	
#	Column	Non-Null Count	Dtype
0	id	21613 non-null	int64
1	date	21613 non-null	object
2	price	21613 non-null	float64
3	bedrooms	21613 non-null	int64
4	bathrooms	21613 non-null	float64
5	sqft_living	21613 non-null	int64
6	sqft_lot	21613 non-null	int64
7	floors	21613 non-null	float64
8	waterfront	21613 non-null	int64
9	view	21613 non-null	int64
10	condition	21613 non-null	int64
11	grade	21613 non-null	int64
12	sqft_above	21613 non-null	int64
13	sqft_basement	21613 non-null	int64
14	yr_built	21613 non-null	int64
15	yr_renovated	21613 non-null	int64
16	zipcode	21613 non-null	int64
17	lat	21613 non-null	float64
18	long	21613 non-null	float64
19	sqft_living15	21613 non-null	int64
20	sqft_lot15	21613 non-null	int64
dtype	es: float64(5),	int64(15), object	ct(1)
memor	ry usage: 3.5+ N	ИΒ	

In [9]: df.describe().transpose()

Out	[9]	:	

	count	mean	std	min	25%	50%	75%	max
id	21613.0	4.580302e+09	2.876566e+09	1.000102e+06	2.123049e+09	3.904930e+09	7.308900e+09	9.900000e+09
price	21613.0	5.400881e+05	3.671272e+05	7.500000e+04	3.219500e+05	4.500000e+05	6.450000e+05	7.700000e+06
bedrooms	21613.0	3.370842e+00	9.300618e-01	0.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	3.300000e+01
bathrooms	21613.0	2.114757e+00	7.701632e-01	0.000000e+00	1.750000e+00	2.250000e+00	2.500000e+00	8.000000e+00
sqft_living	21613.0	2.079900e+03	9.184409e+02	2.900000e+02	1.427000e+03	1.910000e+03	2.550000e+03	1.354000e+04
sqft_lot	21613.0	1.510697e+04	4.142051e+04	5.200000e+02	5.040000e+03	7.618000e+03	1.068800e+04	1.651359e+06
floors	21613.0	1.494309e+00	5.399889e-01	1.000000e+00	1.000000e+00	1.500000e+00	2.000000e+00	3.500000e+00
waterfront	21613.0	7.541757e-03	8.651720e-02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
view	21613.0	2.343034e-01	7.663176e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	4.000000e+00
condition	21613.0	3.409430e+00	6.507430e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	5.000000e+00
grade	21613.0	7.656873e+00	1.175459e+00	1.000000e+00	7.000000e+00	7.000000e+00	8.000000e+00	1.300000e+01
sqft_above	21613.0	1.788391e+03	8.280910e+02	2.900000e+02	1.190000e+03	1.560000e+03	2.210000e+03	9.410000e+03
sqft_basement	21613.0	2.915090e+02	4.425750e+02	0.000000e+00	0.000000e+00	0.000000e+00	5.600000e+02	4.820000e+03
yr_built	21613.0	1.971005e+03	2.937341e+01	1.900000e+03	1.951000e+03	1.975000e+03	1.997000e+03	2.015000e+03
yr_renovated	21613.0	8.440226e+01	4.016792e+02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	2.015000e+03
zipcode	21613.0	9.807794e+04	5.350503e+01	9.800100e+04	9.803300e+04	9.806500e+04	9.811800e+04	9.819900e+04
lat	21613.0	4.756005e+01	1.385637e-01	4.715590e+01	4.747100e+01	4.757180e+01	4.767800e+01	4.777760e+01
long	21613.0	-1.222139e+02	1.408283e-01	-1.225190e+02	-1.223280e+02	-1.222300e+02	-1.221250e+02	-1.213150e+02
sqft_living15	21613.0	1.986552e+03	6.853913e+02	3.990000e+02	1.490000e+03	1.840000e+03	2.360000e+03	6.210000e+03
sqft_lot15	21613.0	1.276846e+04	2.730418e+04	6.510000e+02	5.100000e+03	7.620000e+03	1.008300e+04	8.712000e+05

In [10]: # Pearson correlation matrix

[#] We use the Pearson correlation coefficient to examine the strength and direction of the linear

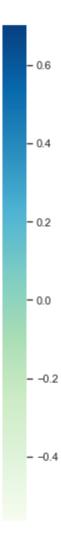
[#] relationship between two continuous variables.

[#] The correlation coefficient can range in value from -1 to +1.

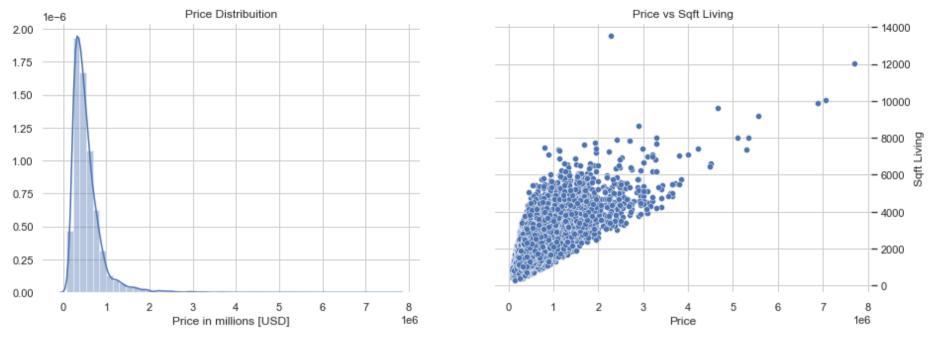
[#] The larger the absolute value of the coefficient, the stronger the relationship between the variables.

Pearson Correlation Matrix

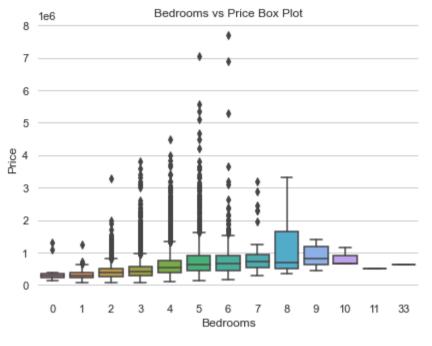
i caroon							OH	CIC	ilio		via	1117								
id	1	-0.017	0.0013	0.0052	-0.012	-0.13	0.019	-0.0027	0.012	40.024	0.0081	0.011	-0.0052	0.021	-0.017	-0.0082	-0.0019	0.021	-0.0029	-0.14
price	-0.017	1	0.31	0.53	0.7	0.09	026	027	04	0.036	0.67	0.61	0.32	0.054	0.13	-0.053	031	0.022	0.59	0.052
bedrooms	0.0013	0.31	1	0.52	0.55	0.032	0.15	-0.0066	0.05	0.025	0.36	0.45	0.3	0.15	0.019	-0.15	-0.0059	0.13	0.39	0.029
bathrooms	0.0052	0.53	0.52	1	0.75	0.055	0.5	0.064	0.19	-0.12	0.66	0.69	0.25	0.51	0.051	-0.2	0.025	0.22	0.57	0.087
sqft_living	-0.012	0.7	0.55	0.75	1	0.17	0.35	0.1	0.25	-0.059	0.76	0.55	0.44	0.32	0.055	-0.2	0.053	0.24	0.76	0.15
sqft_lot	-0.13	0.09	0.032	0.055	0.17	1	40.0052	0.022	0.075	-0.009	0.11	0.15	0.015	0.053	0.0076	-0.13	40.056	023	0.14	0.72
floors	0.019	0.26	0.15	0.5	0.35	-0.0052	1	0.024	0.029	-0.26	0.46	0.52	-0.25	0.49	0.0063	-0.059	0.05	0.13	0.25	-0.011
waterfront	40.0027	027	-0.0066	0.064	0.1	0.022	0.024	1	04	0.017	0.053	0.072	0.081	40.026	0.093	0.03	0.014	0.042	0.055	0.031
view	0.012	0.4	0.05	0.19	0.25	0.075	0.029	0.4	1	0.046	025	0.17	025	40.053	0.1	0.005	0.0062	-0.075	0.25	0.073
∞ndition	40.024	0.035	0.025	-0.12	40.059	40.009	-0.26	0.017	0.046	1	-0.14	-0.16	0.17	40.35	-0.051	0.003	-0.015	-0.11	-0.093	40.0034
grade	0.0051	0.67	0.36	0.66	0.76	0.11	0.46	0.053	025	-0.14	1	0.76	0.17	0.45	0.014	-0.15	0.11	02	071	0.12
sqft_above	-0.011	0.61	0.45	0.69	0.55	0.15	0.52	0.072	0.17	-0.16	0.76	1	-0.052	0.42	0.023	-0.26	-0.00082	0.34	0.73	0.19
sqft_basement	-0.0052	0.32	0.3	0.25	0.44	0.015	-0.25	0.051	0.25	0.17	0.17	40.052	1	-0.13	0.071	0.075	0.11	-0.14	0.2	0.017
yr_built	0.021	0.054	0.15	0.51	0.32	0.053	0.49	-0.026	-0.053	-0.36	0.45	0.42	-0.13	1	0.22	-0.35	-0.15	0.41	0.33	0.071
yr_renovated	-0.017	0.13	0.019	0.051	0.055	0.0076	0.0063	0.093	0.1	-0.061	0.014	0.023	0.071	-0.22	1	0.064	0.029	-0.065	-0.0027	0.0079
zipcode	40.0052	-0.053	-0.15	-0.2	-0.2	-0.13	-0.059	0.03	0.005	0.003	-0.15	-0.26	0.075	-0.35	0.064	1	027	-0.56	-0.25	-0.15
lat	-0.0019	0.31	40.0059	0.025	0.053	40.056	0.05	-0.014	0.0062	-0.015	0.11	-0.00052	0.11	-0.15	0.029	027	1	-0.14	0.049	-0.056
long	0.021	0.022	0.13	022	0.24	023	0.13	-0.042	-0.075	-0.11	02	034	-0.14	0.41	40.065	-0.55	-0.14	1	0.33	0.25
sqft_living15	40.0029	0.59	0.39	0.57	0.76	0.14	025	0.086	025	40.093	0.71	0.73	02	033	40.0027	-0.25	0.049	033	1	0.15
sqft_lot15	-0.14	0.052	0.029	0.087	0.15	0.72	-0.011	0.031	0.073	40.0034	0.12	0.19	0.017	0.071	0.0079	-0.15	40.056	025	0.15	1
	P	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15

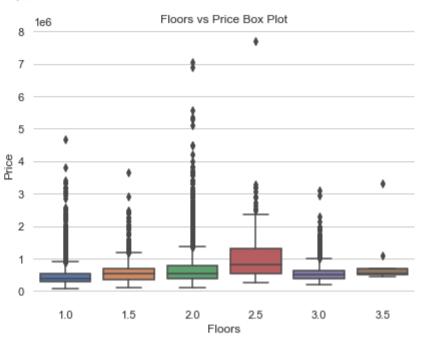


```
In [12]: price corr = df.corr()['price'].sort values(ascending=False)
          print(price corr)
         price
                          1.000000
         saft living
                           0.702035
         grade
                           0.667434
         saft above
                           0.605567
         saft living15
                           0.585379
         bathrooms
                           0.525138
         view
                           0.397293
         saft basement
                           0.323816
         bedrooms
                           0.308350
         lat
                           0.307003
         waterfront
                           0.266369
         floors
                           0.256794
         yr renovated
                           0.126434
         saft lot
                           0.089661
         sqft lot15
                           0.082447
         yr built
                           0.054012
         condition
                           0.036362
         long
                           0.021626
         id
                          -0.016762
         zipcode
                          -0.053203
         Name: price, dtype: float64
In [13]: f, axes = plt.subplots(1, 2, figsize=(15,5))
          sns.distplot(df['price'], ax=axes[0])
          sns.scatterplot(x='price',y='sqft living', data=df, ax=axes[1])
          sns.despine(bottom=True, left=True)
          axes[0].set(xlabel='Price in millions [USD]', ylabel='', title='Price Distribuition')
          axes[1].set(xlabel='Price', ylabel='Sqft Living', title='Price vs Sqft Living')
          axes[1].yaxis.set label position("right")
          axes[1].yaxis.tick right()
         C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and
         will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexib
         ility) or `histplot` (an axes-level function for histograms).
           warnings.warn(msg, FutureWarning)
```







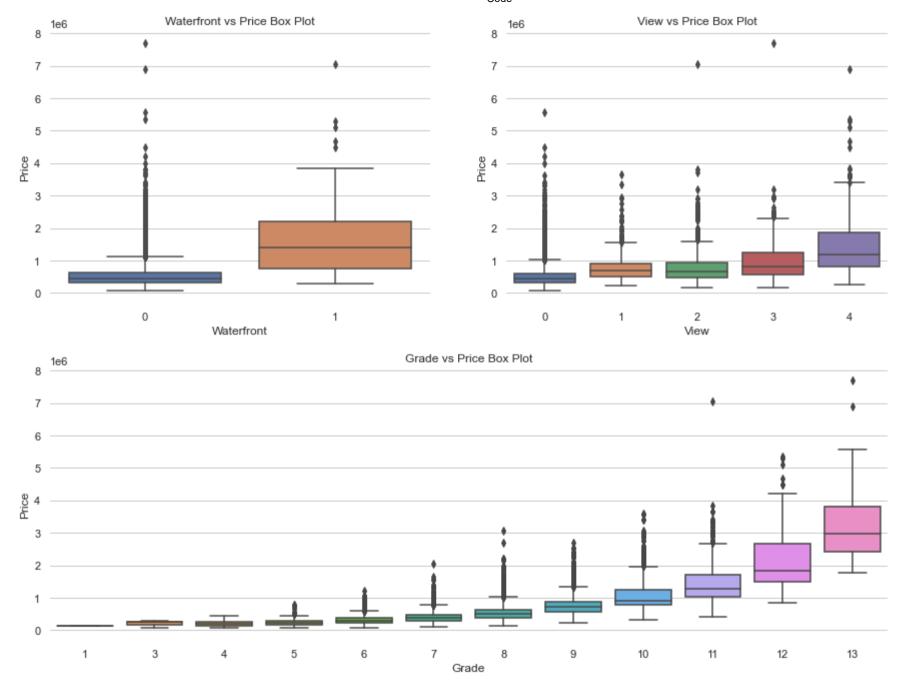


```
In [15]:
    f, axes = plt.subplots(1, 2,figsize=(15,5))
    sns.boxplot(x=df['waterfront'],y=df['price'], ax=axes[0])
    sns.boxplot(x=df['view'],y=df['price'], ax=axes[1])
    sns.despine(left=True, bottom=True)
    axes[0].set(xlabel='Waterfront', ylabel='Price', title='Waterfront vs Price Box Plot')
    axes[1].set(xlabel='View', ylabel='Price', title='View vs Price Box Plot')

    f, axe = plt.subplots(1, 1,figsize=(15,5))
    sns.boxplot(x=df['grade'],y=df['price'], ax=axe)
    sns.despine(left=True, bottom=True)
    axe.set(xlabel='Grade', ylabel='Price', title='Grade vs Price Box Plot')

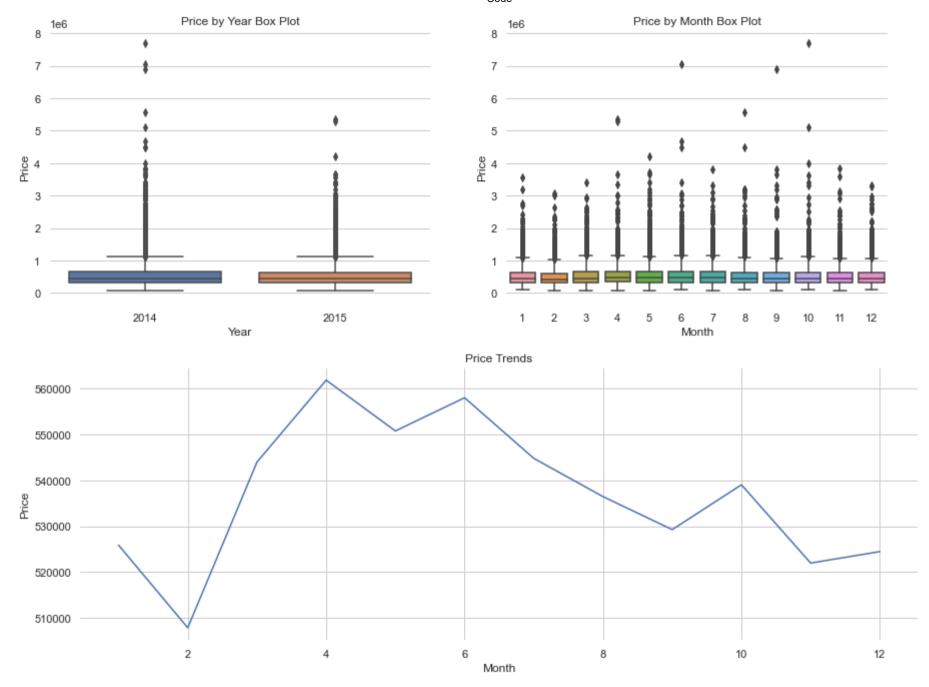
Out[15]: [Text(0.5, 0, 'Grade'),
    Text(0, 0.5, 'Price'),
    Text(0.5, 1.0, 'Grade vs Price Box Plot')]
```





```
In [16]: df = df.drop('id', axis=1)
         df = df.drop('zipcode',axis=1)
In [17]: 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)
         ['price' 'bedrooms' 'bathrooms' 'sqft living' 'sqft lot' 'floors'
          'waterfront' 'view' 'condition' 'grade' 'sqft above' 'sqft basement'
           'yr_built' 'yr_renovated' 'lat' 'long' 'sqft living15' 'sqft lot15'
           'month' 'year']
In [18]: f, axes = plt.subplots(1, 2,figsize=(15,5))
          sns.boxplot(x='year',y='price',data=df, ax=axes[0])
         sns.boxplot(x='month',y='price',data=df, ax=axes[1])
          sns.despine(left=True, bottom=True)
          axes[0].set(xlabel='Year', ylabel='Price', title='Price by Year Box Plot')
          axes[1].set(xlabel='Month', ylabel='Price', title='Price by Month Box Plot')
         f, axe = plt.subplots(1, 1,figsize=(15,5))
          df.groupby('month').mean()['price'].plot()
          sns.despine(left=True, bottom=True)
          axe.set(xlabel='Month', ylabel='Price', title='Price Trends')
         [Text(0.5, 0, 'Month'), Text(0, 0.5, 'Price'), Text(0.5, 1.0, 'Price Trends')]
Out[18]:
```





```
In [19]: 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=101)
         print(X train.shape)
         print(X test.shape)
         print(y train.shape)
         print(y test.shape)
         (15129, 19)
         (6484, 19)
         (15129,)
         (6484,)
In [20]: 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())
         Min: 0.0
In [21]: 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')
```

Epoch 1/400
119/119 [===================================
Epoch 2/400
119/119 [===================================
Epoch 3/400
119/119 [===================================
Epoch 4/400
119/119 [===================================
Epoch 5/400
119/119 [===================================
Epoch 6/400
119/119 [===================================
Epoch 7/400
119/119 [===================================
Epoch 8/400
119/119 [===================================
Epoch 9/400
119/119 [===================================
Epoch 10/400
119/119 [===================================
Epoch 11/400
119/119 [===================================
Epoch 12/400
119/119 [===================================
Epoch 13/400
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Epoch 14/400
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Epoch 15/400
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Epoch 16/400
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Epoch 17/400
119/119 [===================================
Epoch 18/400
119/119 [===================================
Epoch 19/400
119/119 [===================================
Epoch 20/400
119/119 [===================================
Epoch 21/400
119/119 [===================================
Epoch 22/400
119/119 [===================================
115,115 [

Epoch 23/400	0										
]	_	0s	4ms/step	_	loss:	65177268224.0000	_	val loss:	66019274752.0	0000
Epoch 24/400				•					_		
]	-	0s	4ms/step	-	loss:	62740652032.0000	_	val loss:	63446376448.6	0000
Epoch 25/400	-			•					_		
119/119 [==:	========]	-	1s	4ms/step	-	loss:	60519256064.0000	-	val_loss:	61048696832.6	0000
Epoch 26/400	0										
119/119 [==:	=======]	-	1s	4ms/step	-	loss:	58495442944.0000	-	<pre>val_loss:</pre>	58881351680.6	0006
Epoch 27/400	0										
119/119 [==:	=======]	-	1s	4ms/step	-	loss:	56749973504.0000	-	val_loss:	57055948800.0	9000
Epoch 28/400	0										
119/119 [==:	=======]	-	1s	5ms/step	-	loss:	55264292864.0000	-	val_loss:	55667138560.0	9000
Epoch 29/400											
_]	-	1s	5ms/step	-	loss:	54129172480.0000	-	val_loss:	54410203136.0	9000
Epoch 30/400											
_]	-	1s	5ms/step	-	loss:	53149380608.0000	-	val_loss:	53373616128.6	9000
Epoch 31/400						_					
_	=======]	-	1s	5ms/step	-	loss:	52341776384.0000	-	val_loss:	52457332736.6	9000
Epoch 32/400						_					
_]	-	1s	5ms/step	-	loss:	51571175424.0000	-	val_loss:	51725099008.0	9000
Epoch 33/400				- / 1		,	50034760344 0000			E40EE702420	2000
_		-	1s	5ms/step	-	loss:	50931/69344.0000	-	val_loss:	51055/92128.6	3000
Epoch 34/400			1 -	4		1	F02F424F664 0000			F04270667F2 6	2000
-	======================================	-	IS	4ms/step	-	1055:	50351345664.0000	-	vai_ioss:	5043/066/52.6	0000
Epoch 35/400	6 ===========]		0.0	Ams/stop		1000	4079E0010E6 0000		val locci	40060045504 6	2000
Epoch 36/400	-	-	05	4111S/Step	-	1055.	49765901056.0000	-	va1_1055.	49909045504.6	0000
	e ====================================	_	1 c	1mc/stan	_	1000	10302372352 0000	_	val loss:	10/1586022/ 0	aaaa
Epoch 37/406	-	_	13	41113/3CEP	-	1033.	49302372332.0000	_	vai_1033.	49413606224.6	0000
		_	05	4ms/sten	_	loss:	48832040960.0000	_	val loss:	48986226688.6	2000
Epoch 38/400	-		05	ты, эсер		1033.	1003201030010000		·u1_1033.	1030022000010	3000
		_	0s	4ms/step	_	loss:	48375721984.0000	_	val loss:	48514666496.0	9000
Epoch 39/400	-									.052.000.500	
]	_	0s	4ms/step	_	loss:	47965421568.0000	_	val loss:	48055619584.6	0000
Epoch 40/400	-								_		
119/119 [==:]	-	0s	4ms/step	-	loss:	47524749312.0000	-	val_loss:	47620239360.6	0000
Epoch 41/400	0			·					_		
119/119 [==:	=======]	-	1s	5ms/step	-	loss:	47128625152.0000	-	<pre>val_loss:</pre>	47162028032.0	0000
Epoch 42/400	0										
_	=======]	-	0s	4ms/step	-	loss:	46652321792.0000	-	<pre>val_loss:</pre>	46712086528.0	9000
Epoch 43/406											
119/119 [===]	-	0s	4ms/step	-	loss:	46198779904.0000	-	<pre>val_loss:</pre>	46191136768.6	9000
Epoch 44/400											
119/119 [===	========]	-	0s	4ms/step	-	loss:	45697814528.0000	-	val_loss:	45727473664.6	9000

Epoch 4	5/400									
	· [=========]	_	1s	4ms/step	_	loss:	45227720704.0000	_	val loss:	45155995648.0000
Epoch 4	-								_	
	[=======]	_	1s	5ms/step	-	loss:	44730437632.0000	_	val loss:	44661923840.0000
Epoch 4	-								_	
119/119	[========]	-	0s	4ms/step	-	loss:	44319883264.0000	-	val_loss:	44277370880.0000
Epoch 4	8/400									
119/119	[========]	-	0s	4ms/step	-	loss:	43958489088.0000	-	val_loss:	43893891072.0000
Epoch 4	9/400									
119/119	[=======]	-	0s	4ms/step	-	loss:	43584913408.0000	-	val_loss:	43642683392.0000
Epoch 5	0/400									
119/119	[=======]	-	0s	4ms/step	-	loss:	43248914432.0000	-	val_loss:	43219251200.0000
Epoch 5										
	[======]	-	0s	4ms/step	-	loss:	42982662144.0000	-	val_loss:	42911113216.0000
Epoch 5										
	[======]	-	0s	4ms/step	-	loss:	42655256576.0000	-	val_loss:	42560364544.0000
Epoch 5						_				
	[======]	-	0s	4ms/step	-	loss:	42410192896.0000	-	val_loss:	42317037568.0000
Epoch 5			_			_				
	[========]	-	0s	4ms/step	-	loss:	42197352448.0000	-	val_loss:	42215518208.0000
Epoch 5				4 / 1		,	44045043000 0000			44024076006 0000
	[========]	-	1s	4ms/step	-	loss:	41915813888.0000	-	val_loss:	418249/6896.0000
Epoch 5			1 -	A / - +		1	41633603606 0000			44.655007404.0000
	7/400	-	IS	4ms/step	-	TOSS:	41633693696.0000	-	vai_ioss:	4165508/104.0000
Epoch 5	///400 [==========]		0.0	Ams/ston		1000	41402047222 0000		val locci	11246600060 0000
Epoch 5	-	-	05	4IIIS/Scep	-	1055.	41402047232.0000	-	va1_1055.	41340000900.0000
•	.o/400 [=========]	_	۵c	1mc/cton	_	1000	11152311206 0000	_	val loss:	11019125110 0000
Epoch 5	-	_	03	41113/3CEP	_	1033.	41172311230.0000	_	vai_1033.	41048123440.0000
•	[=========]	_	95	4ms/sten	_	loss:	40870039552.0000	_	val loss:	40669057024.0000
Epoch 6	-		0.5	тэ, эсер		1033.	1007003333210000		1033.	1000303702110000
•	· [==========]	_	0s	4ms/step	_	loss:	40576733184.0000	_	val loss:	40370257920.0000
Epoch 6	-			5, 5 сер			.0370703020110000			.03/023/3200000
	[========]	_	1s	5ms/step	_	loss:	40291045376.0000	_	val loss:	40032321536.0000
Epoch 6	-								_	
119/119	[=======]	-	1s	4ms/step	-	loss:	40049356800.0000	-	val_loss:	39744962560.0000
Epoch 6	3/400								_	
119/119	[=======]	-	0s	4ms/step	-	loss:	39697076224.0000	-	val_loss:	39488634880.0000
Epoch 6	4/400									
	[======]	-	1s	4ms/step	-	loss:	39467507712.0000	-	<pre>val_loss:</pre>	39187169280.0000
Epoch 6										
119/119	[======]	-	1s	4ms/step	-	loss:	39200616448.0000	-	val_loss:	38953766912.0000
Epoch 6										
119/119	[======]	-	0s	4ms/step	-	loss:	38985289728.0000	-	val_loss:	38680535040.0000

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Epoch 111/400						
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Epoch 112/400		·			_	
119/119 [===================================	· 1s	5ms/step -	loss:	34231625728.0000	- val_loss:	33631059968.0000
Epoch 113/400						
119/119 [===================================	· 1s	5ms/step -	· loss:	34170359808.0000	- val_loss:	33666402304.0000
Epoch 114/400						
119/119 [========] -	· 0s	4ms/step -	· loss:	34187499520.0000	<pre>- val_loss:</pre>	33532704768.0000
Epoch 115/400						
119/119 [=======] -	· 0s	3ms/step -	· loss:	34045929472.0000	<pre>- val_loss:</pre>	33531418624.0000
Epoch 116/400						
119/119 [========] -	· 1s	4ms/step -	· loss:	34014740480.0000	<pre>- val_loss:</pre>	33444440064.0000
Epoch 117/400						
119/119 [======] -	· 1s	5ms/step -	· loss:	33998247936.0000	- val_loss:	33366534144.0000
Epoch 118/400						
119/119 [=======] -	· 1s	5ms/step -	· loss:	33938173952.0000	- val_loss:	33321508864.0000
Epoch 119/400	_					
119/119 [===================================	· 1s	4ms/step -	· loss:	33904394240.0000	- val_loss:	33409028096.0000
Epoch 120/400	_		-	2222222222		22445005400 0000
119/119 [===================================	· 1s	4ms/step -	· loss:	3382868/8/2.0000	- val_loss:	33415825408.0000
Epoch 121/400	0-	1 / a t a	1	22021771776 0000	1	22172275200 0000
119/119 [===================================	. 05	4ms/step -	. 1088:	33821//1//6.0000	- val_1088:	331/22/5200.0000
Epoch 122/400 119/119 [===================================	0.5	2mc/ston	1000	22757794064 0000	val locci	22115024260 0000
Epoch 123/400	. 62	sms/step -	. 1022:	33/3//84064.0000	- val_1055:	33113834388.0000
119/119 [===================================	۵۶	3ms/stan	1000	33685446656 0000	- val loss:	33070665738 0000
Epoch 124/400	03	эшэ/ эсер	1033.	33003440030.0000	- Vai_1033.	33070003720.0000
119/119 [===================================	. 05	3ms/sten -	. 1055	33651247104 0000	- val loss:	33024315392 0000
Epoch 125/400	03	эшэ, эсср	1033.	3303124710410000	va1_1055.	3302-313332.0000
119/119 [===================================	. 0s	3ms/step -	· loss:	33590308864.0000	- val loss:	33056505856.0000
Epoch 126/400		-,				
119/119 [=========] -	· 1s	4ms/step -	· loss:	33540769792.0000	- val loss:	32933941248.0000
Epoch 127/400					_	
119/119 [===================================	0s	4ms/step -	· loss:	33510795264.0000	<pre>- val_loss:</pre>	32879484928.0000
Epoch 128/400						
119/119 [===================================	0s	4ms/step -	· loss:	33494310912.0000	- val_loss:	32842688512.0000
Epoch 129/400						
119/119 [=======] -	· 0s	4ms/step -	· loss:	33441357824.0000	- val_loss:	32800417792.0000
Epoch 130/400						
119/119 [=======] -	0s	4ms/step -	loss:	33406195712.0000	<pre>- val_loss:</pre>	32758880256.0000
Epoch 131/400						
119/119 [=======] -	· 1s	5ms/step -	· loss:	33388220416.0000	- val_loss:	32701552640.0000
Epoch 132/400		_	_		_	
119/119 [========] -	· 1s	4ms/step -	· loss:	33302888448.0000	- val_loss:	32659169280.0000

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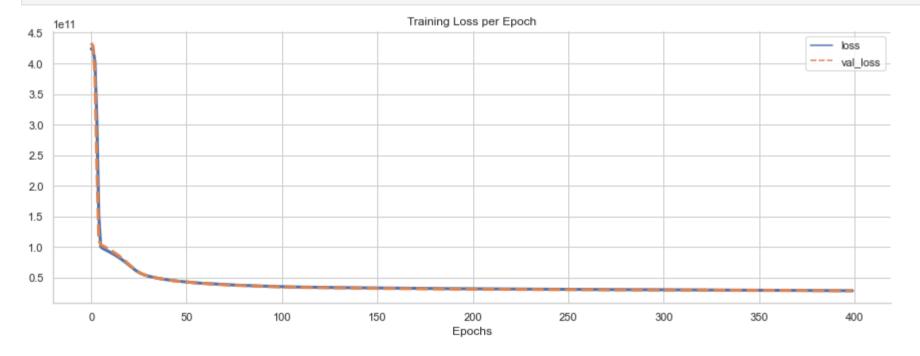
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119/119 [========]	-	0s	4ms/step	_	loss:	28565585920.0000	-	val loss:	28310460416.0000
Epoch 376/400			•					_	
119/119 [=========]	-	0s	4ms/step	_	loss:	28558852096.0000	-	val_loss:	28302307328.0000
Epoch 377/400									
119/119 [===================================	-	0s	4ms/step	-	loss:	28548110336.0000	-	<pre>val_loss:</pre>	28327620608.0000
Epoch 378/400									
119/119 [==========]	-	1s	4ms/step	-	loss:	28525918208.0000	-	<pre>val_loss:</pre>	28267317248.0000
Epoch 379/400									
119/119 [=========]	-	0s	4ms/step	-	loss:	28479782912.0000	-	<pre>val_loss:</pre>	28294139904.0000
Epoch 380/400									
119/119 [=========]	-	0s	4ms/step	-	loss:	28501995520.0000	-	<pre>val_loss:</pre>	28273096704.0000
Epoch 381/400									
119/119 [=========]	-	0s	4ms/step	-	loss:	28449822720.0000	-	val_loss:	28224956416.0000
Epoch 382/400									
119/119 [==========]	-	0s	4ms/step	-	loss:	28434583552.0000	-	val_loss:	28203780096.0000
Epoch 383/400					-				
119/119 [===================================	-	1s	4ms/step	-	loss:	28372133888.0000	-	val_loss:	28231297024.0000
Epoch 384/400		^			,	20204540672 0000			20247404242 0000
119/119 [===================================	-	0 S	4ms/step	-	loss:	283845406/2.0000	-	val_loss:	2824/181312.0000
Epoch 385/400		1.	Ems/stop		1000	20404770000 0000		val lace.	20102211206 0000
119/119 [===================================	-	15	sms/step	-	1088:	28404779008.0000	-	vai_ioss:	28192311296.0000
Epoch 386/400 119/119 [=======]		0.0	Ame /ston		1000	20262007104 0000		val locc.	20151040760 0000
Epoch 387/400	-	05	4IIIS/Scep	-	1055.	20303997104.0000	-	va1_1055.	20131040700.0000
119/119 [========]	_	۵c	1mc/stan	_	1000	283/1513510/ 0000	_	val loss.	28153198592 0000
Epoch 388/400		03	4 1113/3 сер		1033.	20343133104.0000		vai_1033.	20199190992.0000
119/119 [=========]	_	۵s	4ms/sten	_	loss.	28326596608 0000	_	val loss:	28132839424 0000
Epoch 389/400		03	-1113/ Эсер		1033.	20320330000.0000		va1_1033.	20132033424.0000
119/119 [=========]	_	1s	5ms/step	_	loss:	28324511744.0000	_	val loss:	28150126592.0000
Epoch 390/400			,						
119/119 [=========]	_	1s	4ms/step	_	loss:	28262467584.0000	_	val loss:	28107884544.0000
Epoch 391/400								_	
119/119 [===================================	-	0s	4ms/step	-	loss:	28338786304.0000	-	<pre>val_loss:</pre>	28110684160.0000
Epoch 392/400									
119/119 [===================================	-	0s	4ms/step	-	loss:	28275306496.0000	-	<pre>val_loss:</pre>	28139655168.0000
Epoch 393/400									
119/119 [========]	-	0s	4ms/step	-	loss:	28232558592.0000	-	<pre>val_loss:</pre>	28135030784.0000
Epoch 394/400									
119/119 [=========]	-	0s	3ms/step	-	loss:	28216418304.0000	-	<pre>val_loss:</pre>	28077905920.0000
Epoch 395/400									
119/119 [=========]	-	0s	3ms/step	-	loss:	28211036160.0000	-	val_loss:	28044828672.0000
Epoch 396/400					_				
119/119 [===================================	-	0s	3ms/step	-	loss:	28195665920.0000	-	val_loss:	28038311936.0000

Epoch 397/400

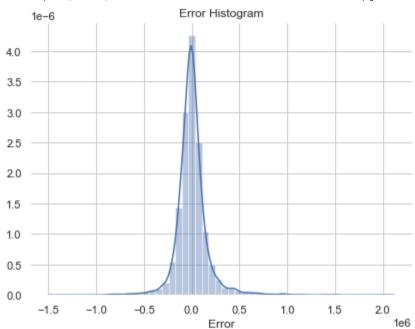
sns.despine()

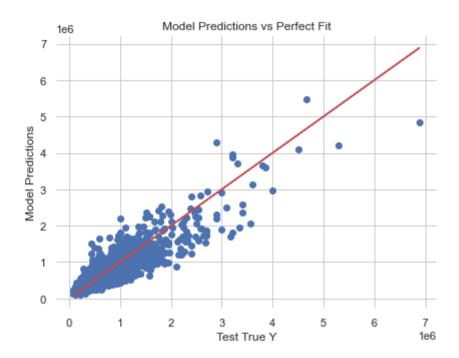


```
In [23]: # predictions on the test set
predictions = model.predict(X_test)
```

```
print('MAE: ',mean absolute error(y test,predictions))
          print('MSE: ',mean squared error(y test,predictions))
          print('RMSE: ',np.sqrt(mean squared error(y test,predictions)))
         print('Variance Regression Score: ',explained variance score(y test,predictions))
          print('\n\nDescriptive Statistics:\n',df['price'].describe())
         203/203 [========= ] - 1s 2ms/step
         MAE: 103301.46354006015
         MSE: 28003385904.85658
         RMSE: 167342.12232685642
         Variance Regression Score: 0.800453588663422
         Descriptive Statistics:
          count
                   2.161300e+04
         mean
                  5.400881e+05
                  3.671272e+05
         std
         min
                  7.500000e+04
         25%
                  3.219500e+05
         50%
                  4.500000e+05
         75%
                  6.450000e+05
                  7.700000e+06
         max
         Name: price, dtype: float64
In [24]: f, axes = plt.subplots(1, 2, figsize=(15,5))
          # Our model predictions
         plt.scatter(y test,predictions)
         # Perfect predictions
          plt.plot(v test,v test,'r')
          errors = y test.values.reshape(6484, 1) - predictions
          sns.distplot(errors, ax=axes[0])
          sns.despine(left=True, bottom=True)
         axes[0].set(xlabel='Error', ylabel='', title='Error Histogram')
         axes[1].set(xlabel='Test True Y', ylabel='Model Predictions', title='Model Predictions vs Perfect Fit')
         C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and
         will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexib
         ility) or `histplot` (an axes-level function for histograms).
           warnings.warn(msg, FutureWarning)
```

```
Out[24]: [Text(0.5, 0, 'Test True Y'),
Text(0, 0.5, 'Model Predictions'),
Text(0.5, 1.0, 'Model Predictions vs Perfect Fit')]
```





```
In [25]: # fueatures of new house
    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(single_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:
                   3,0000
bedrooms
bathrooms
                   1.0000
sqft living
                1180.0000
sqft lot
                5650.0000
floors
                   1.0000
waterfront
                   0.0000
view
                   0.0000
condition
                   3.0000
grade
                   7.0000
sqft above
                1180.0000
sqft basement
                   0.0000
yr built
                1955.0000
yr renovated
                   0.0000
lat
                  47.5112
long
                -122.2570
sqft living15
                1340.0000
saft lot15
                5650.0000
month
                  10.0000
vear
                2014.0000
Name: 0, dtype: float64
1/1 [======] - 0s 52ms/step
Prediction Price: 282012.62
Original Price: 221900.0
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but MinMaxScal
er was fitted with feature names
  warnings.warn(
```

In []: