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[1]: import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt

In [2]: df = pd.read_csv("B:\GetFreeCourses-Co-Udemy-Complete Tensorflow 2 and Keras Deep Learning Bootcamp\DATA\kc_house_data.csv")

In [4]: df.isnull().sum()

Out[4]:
id                0
date              0
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 [5]: df.describe().transpose()

Out[5]:

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	count	mean	std	min	25%	50%	75%	max
id	21597.0	4.580474e+09	2.876736e+09	1.000102e+06	2.123049e+09	3.904930e+09	7.308900e+09	9.900000e+09
price	21597.0	5.402966e+05	3.673681e+05	7.800000e+04	3.220000e+05	4.500000e+05	6.450000e+05	7.700000e+06
bedrooms	21597.0	3.373200e+00	3.678894e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	3.300000e+01
bathrooms	21597.0	2.115826e+00	1.688843e-01	5.000000e-01	1.750000e+00	2.250000e+00	2.500000e+00	8.000000e+00
sqft_living	21597.0	2.083222e+03	9.181061e+02	3.700000e+02	5.040000e+03	1.910000e+03	2.550000e+03	1.354000e+04
sqft_lot	21597.0	1.509941e+04	4.141264e+04	5.200000e+02	1.900000e+03	7.618000e+03	1.068500e+04	1.651359e+06
floors	21597.0	1.494090e+00	5.396828e-01	1.000000e+00	1.000000e+00	1.500000e+00	2.000000e+00	3.500000e+00
waterfront	21597.0	2.342918e-01	7.663886e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.000000e+00
view	21597.0	7.547345e-03	2.937523e-01	1.800000e-03	1.951000e+03	1.975000e+03	1.997000e+03	5.600000e+03
condition	21597.0	3.409825e+00	6.505456e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	5.000000e+00
grade	21597.0	7.657915e+00	1.173200e+00	3.000000e+00	7.000000e+00	7.000000e+00	8.000000e+00	1.300000e+01
sqft_above	21597.0	1.786597e+03	8.277598e+02	3.700000e+02	1.190000e+03	1.560000e+03	2.210000e+03	9.410000e+03
sqft_basement	21597.0	2.917250e+02	4.426678e+02	0.000000e+00	0.000000e+00	0.000000e+00	5.600000e+02	4.820000e+03
yr_built	21597.0	1.971000e+03	2.937523e-01	1.800000e-03	1.951000e+03	1.975000e+03	1.997000e+03	2.015000e+03
yr_renovated	21597.0	8.464790e-01	4.018214e+01	9.800100e-01	0.000000e+00	0.000000e+00	9.811800e+00	9.819900e+03
zipcode	21597.0	9.807795e+04	5.351307e-01	9.800100e+04	9.803300e+04	9.806500e+04	9.811800e+04	9.819900e+04
lat	21597.0	4.222140e+02	1.480725e-01	-1.225190e+01	4.747110e+01	4.757180e+01	4.767800e+01	4.777760e+01
long	21597.0	-1.221400e+02	1.305178e-01	-1.225190e+02	-1.223280e+02	-1.222310e+02	-1.221250e+02	-1.213150e+02
sqft_living15	21597.0	1.986620e+03	6.852305e+02	3.990000e+02	1.495000e+03	1.840000e+03	2.360000e+03	6.210000e+03
sqft_lot15	21597.0	1.275828e+04	2.727444e+04	6.510000e+02	5.100000e+03	7.620000e+03	1.008300e+04	8.712000e+05

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In [6]: sns.distplot(df['price'])

C:\Users\Aditya Singh\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 flexibility) or 'histplot' (an axes-level function for histograms).
warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='price', ylabel='Density'>

Out[6]:

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In [7]: sns.countplot(df['bedrooms'])

C:\Users\Aditya Singh\anaconda3\lib\site-packages\seaborn\_decorators.py:136: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be 'data', and passing other arguments without an explicit keyword will result in an error or misinterpretation.
warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='bedrooms', ylabel='count'>

Out[7]:

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In [11]: df.corr()['price'].sort_values()

Out[11]:
zipcode          -0.053402
id               -0.016732
long            -0.022036
condition       -0.036056
yr_built        -0.053953
sqft_lot15      -0.082845
sqft_lot        -0.089876
yr_renovated    -0.126424
floors          -0.236804
waterfront      -0.266398
lat             -0.306692
bedrooms        -0.308787
sqft_basement  -0.323789
view            -0.397370
bathrooms       -0.523906
sqft_living15   -0.585241
sqft_above      -0.605368
grade           -0.677951
sqft_living     -0.703117
price           1.000000
Name: price, dtype: float64

In [12]: sns.scatterplot(x='price',y='sqft_living',data=df)

Out[12]:
<AxesSubplot:xlabel='price', ylabel='sqft_living'>


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In [13]: sns.boxplot(x='bedrooms',y='price',data=df)

Out[13]:
<AxesSubplot:xlabel='bedrooms', ylabel='price'>


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In [15]: df.columns

Out[15]:
Index(['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', 'sqft_living15', 'sqft_lot15'],
      dtype='object')

In [16]: sns.scatterplot(x='price',y='long',data=df)

Out[16]:
<AxesSubplot:xlabel='price', ylabel='long'>


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In [17]: sns.scatterplot(x='price',y='lat',data=df)

Out[17]:
<AxesSubplot:xlabel='price', ylabel='lat'>


```

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In [19]: sns.scatterplot(x='long',y='lat',data=df,hue='price')

Out[19]:
<AxesSubplot:xlabel='long', ylabel='lat'>


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In [20]: df.sort_values('price',ascending=False).head(20)

Out[20]:

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	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_baseme
0	7245	6763700020	10/13/2014	7700000.0	6	8.00	12050	27600	2.5	0	3	...	13	8570
3910	9808700762	6/17/2014	7060000.0	5	4.50	10040	31725	2.0	1	2	...	11	7680	
9245	9208900037	9/19/2014	6890000.0	6	7.75	9890	31374	2.0	0	4	...	13	8860	
4407	2470100101	8/4/2014	5570000.0	5	5.75	9200	35069	2.0	0	0	...	13	6200	
1446	8907500070	4/13/2015	5350000.0	5	5.00	8000	23985	2.0	0	4	...	12	6720	
1313	7558700030	4/13/2015	5300000.0	6	6.00	7390	24829	2.0	1	4	...	12	5000	
1162	1247000105	10/20/2014	5110000.0	5	5.25	8010	45517	2.0	1	4	...	12	5990	
8085	1924059029	6/17/2014	4670000.0	5	6.75	9640	13068	1.0	1	4	...	12	4820	
2624	7738500731	8/15/2014	4500000.0	5	5.50	6640	40014	2.0	1	4	...	12	6350	
8629	3835600195	6/18/2014	4490000.0	4	3.00	6430	27517	2.0	0	0	...	12	6480	
12358	6065300370	5/6/2015	4210000.0	5	6.00	7440	21540	2.0	0	0	...	12	5550	
4145	6447300265	10/14/2014	4000000.0	4	5.50	7080	16573	2.0	0	0	...	12	5760	
2083	8106100105	11/14/2014	3850000.0	4	4.25	5770	21300	2.0	1	4	...	11	5770	
7028	8532000100	7/7/2014	3800000.0	5	5.50	7050	42840	1.0	0	2	...	13	4320	
19002	2303900100	9/11/2014	3800000.0	3	4.25	5510	35000	2.0	0	4	...	13	4910	
16288	7397300170	5/30/2014	3710000.0	4	3.50	5550	28078	2.0	0	2	...	12	3350	
18467	4389201095	5/11/2015	3650000.0	5	3.75	5020	8694	2.0	0	1	...	12	3970	
6502	4217402115	4/21/2015	3650000.0	6	4.75	5480	19401	1.5	1	4	...	11	3910	
15241	362549063	9/11/2014	3640000.0	4	3.25	4830	22257	2.0	1	4	...	11	4830	
19133	362549042	10/11/2014	3640000.0	5	6.00	5490	19897	2.0	0	0	...	12	5490	

```


20 rows × 21 columns

In [22]: len(df)*0.01

Out[22]:
215.97

In [23]: non_top_1_perc = df.sort_values('price',ascending=False).iloc[216:]

In [28]: sns.scatterplot(x='long',y='lat',data=non_top_1_perc,edgecolor=None,alpha=0.2,palette='b2g10m',hue='price')

Out[28]:
<AxesSubplot:xlabel='long', ylabel='lat'>


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In [29]: sns.boxplot(x='waterfront',y='price',data=df)

Out[29]:
<AxesSubplot:xlabel='waterfront', ylabel='price'>


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In [30]: df.head()

Out[30]:

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	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_baseme
0	7129300520	10/13/2014	4219900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180	
1	6414100192	12/9/2014	5380000.0	3	2.25	2570	7242	2.0	0	0	...	3	770	4
2	5631500400	2/25/2015	1800000.0	2	1.00	770	10000	1.0	0	0	...	6	1933	0
3	2487200875	12/9/2014	6040000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050	9
4	1954400510	2/18/2015	5100000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680	0

```


5 rows × 21 columns

In [31]: df = df.drop('id',axis=1)

In [33]: df['date'] = pd.to_datetime(df['date'])

In [34]: df['date']

Out[34]:
0      2014-10-13
1      2014-12-09
2      2015-02-23
3      2014-12-09
4      2015-02-18
...
21592  2014-05-21
21593  2015-02-23
21594  2014-06-23
21595  2015-01-16
21596  2014-10-15
Name: date, Length: 21597, dtype: datetime64[ns]

In [35]: df['year'] = df['date'].apply(lambda date: date.year)
df['month'] = df['date'].apply(lambda date: date.month)

In [36]: df.head()

Out[36]:

```

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_basement	yr_built	yr_renovated
0	2014-10-13	2219000	3	1.00	1180	5650	1.0	0	0	3	...	0	1955	0
1	2014-12-09	5380000	3	2.25	2570	7242	2.0	0	0	3	...	400	1951	1991
2	2015-02-25	1800000	2	1.00	770	10000	1.0	0	0	3	...	0	1933	0
3	2014-12-09	6040000	4	3.00	1960	5000	1.0	0	0	5	...	910	1965	0
4	2015-02-18	5100000	3	2.00	1680	8080	1.0	0	0	3	...	0	1987	0

```


5 rows × 22 columns

In [37]: sns.boxplot(x='month',y='price',data=df)

Out[37]:
<AxesSubplot:xlabel='month', ylabel='price'>


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In [48]: df.groupby('year').mean()['price'].plot()

Out[48]:
<AxesSubplot:xlabel='year'>


```

```


In [41]: df = df.drop('date',axis=1)

In [42]: df.head()

Out[42]:

```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	...	sqft_basement	yr_built	yr_renovated
0	2219000.0	3	1.00	1180	5650	1.0	0	0	3	7	...	0	1955	0
1	5380000.0	3	2.25	2570	7242	2.0	0	0	3	7	...	400	1951	1991
2	1800000.0	2	1.00	770	10000	1.0	0	0	3	6	...	0	1933	0
3	6040000.0	4	3.00	1960	5000	1.0	0	0	5	7	...	910	1965	0
4	5100000.0	3	2.00	1680	8080	1.0	0	0	3	8	...	0	1987	0

```


5 rows × 21 columns

In [43]: df['zipcode'].value_counts()

Out[43]:
98103    602
98038    589
98115    583
98052    574
98117    553
...
98102    104
98010    103
98024    80
98148    57
98039    50
Name: zipcode, Length: 70, dtype: int64

In [44]: df = df.drop('zipcode',axis=1)

In [45]: df['yr_renovated'].value_counts()

Out[45]:
0      20693
2014      91
2013      37
2003      36
2005      35
...
1951      1
1959      1
1948      1
1954      1
1944      1
Name: yr_renovated, Length: 70, dtype: int64

In [46]: df['sqft_basement'].value_counts()

Out[46]:
0      13110
600      221
700      218
500      214
800      206
...
574       1
784       1
906       1
248       1
Name: sqft_basement, Length: 306, dtype: int64

In [47]: x = df.drop('price',axis=1).values
y = df['price'].values

In [48]: from sklearn.model_selection import train_test_split

In [49]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)

In [50]: from sklearn.preprocessing import MinMaxScaler

In [51]: scaler = MinMaxScaler()

In [52]: X_train = scaler.fit_transform(X_train)

In [53]: X_test = scaler.transform(X_test)

In [55]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

In [56]: X_train.shape

Out[56]:
(15117, 19)

In [57]: model = Sequential()
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(19,activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam',loss='mse')

In [58]: model.fit(x=X_train,y=y_train,validation_data=(X_test,y_test),batch_size=128,epochs=400)
```



```
Epoch 1/400 - 1s 3ms/step - loss: 430227941760.0000 - val_loss: 41890528032.0000
Epoch 2/400 - 1s 2ms/step - loss: 429038174288.0000 - val_loss: 414673928192.0000
Epoch 3/400 - 1s 2ms/step - loss: 4167164168.0000 - val_loss: 415391372948.0000
Epoch 4/400 - 0s 2ms/step - loss: 32683960604.0000 - val_loss: 239524117504.0000
Epoch 5/400 - 0s 2ms/step - loss: 170861761920.0000 - val_loss: 108544974848.0000
Epoch 6/400 - 0s 2ms/step - loss: 10519598508.0000 - val_loss: 945984984.0000
Epoch 7/400 - 0s 2ms/step - loss: 3720302304.0000 - val_loss: 2348248944.0000
Epoch 8/400 - 0s 2ms/step - loss: 95592924080.0000 - val_loss: 1735996736.0000
Epoch 9/400 - 0s 2ms/step - loss: 93863045952.0000 - val_loss: 9003519088.0000
Epoch 10/400 - 0s 2ms/step - loss: 2043247236.0000 - val_loss: 8840945452.0000
Epoch 11/400 - 0s 3ms/step - loss: 9023029880.0000 - val_loss: 86515138560.0000
Epoch 12/400 - 0s 2ms/step - loss: 88346607616.0000 - val_loss: 846758464.0000
Epoch 13/400 - 0s 2ms/step - loss: 8632317656.0000 - val_loss: 8276952328.0000
Epoch 14/400 - 0s 2ms/step - loss: 8421890432.0000 - val_loss: 80712895424.0000
Epoch 15/400 - 0s 2ms/step - loss: 8213302960.0000 - val_loss: 78629314560.0000
Epoch 16/400 - 0s 2ms/step - loss: 7992517984.0000 - val_loss: 7650934224.0000
Epoch 17/400 - 0s 2ms/step - loss: 77506058956.0000 - val_loss: 7415654896.0000
Epoch 18/400 - 0s 2ms/step - loss: 75121336320.0000 - val_loss: 7172398498.0000
Epoch 19/400 - 0s 2ms/step - loss: 7261035440.0000 - val_loss: 6936186098.0000
Epoch 20/400 - 0s 2ms/step - loss: 7008139752.0000 - val_loss: 6689132416.0000
Epoch 21/400 - 0s 2ms/step - loss: 67406739072.0000 - val_loss: 6386346848.0000
Epoch 22/400 - 0s 3ms/step - loss: 64938819584.0000 - val_loss: 6194062752.0000
Epoch 23/400 - 0s 2ms/step - loss: 62356398816.0000 - val_loss: 5945887860.0000
Epoch 24/400 - 0s 2ms/step - loss: 60062322576.0000 - val_loss: 5745823072.0000
Epoch 25/400 - 0s 2ms/step - loss: 5790247932.0000 - val_loss: 5533307136.0000
Epoch 26/400 - 0s 3ms/step - loss: 56040759296.0000 - val_loss: 5319190594.0000
Epoch 27/400 - 0s 2ms/step - loss: 54466725232.0000 - val_loss: 5238510368.0000
Epoch 28/400 - 0s 2ms/step - loss: 531952384.0000 - val_loss: 5121841320.0000
Epoch 29/400 - 0s 2ms/step - loss: 52150819720.0000 - val_loss: 5029518904.0000
Epoch 30/400 - 0s 3ms/step - loss: 5125014192.0000 - val_loss: 4950078800.0000
Epoch 31/400 - 0s 3ms/step - loss: 5042420368.0000 - val_loss: 4891094336.0000
Epoch 32/400 - 0s 2ms/step - loss: 49756734560.0000 - val_loss: 4817654688.0000
Epoch 33/400 - 0s 2ms/step - loss: 49128747488.0000 - val_loss: 4759481876.0000
Epoch 34/400 - 0s 2ms/step - loss: 4851863264.0000 - val_loss: 47080161280.0000
Epoch 35/400 - 0s 2ms/step - loss: 47970938880.0000 - val_loss: 4659247190.0000
Epoch 36/400 - 0s 2ms/step - loss: 4746613552.0000 - val_loss: 4604656192.0000
Epoch 37/400 - 0s 2ms/step - loss: 4693828896.0000 - val_loss: 4558113408.0000
Epoch 38/400 - 0s 2ms/step - loss: 4651276976.0000 - val_loss: 4515946906.0000
Epoch 39/400 - 0s 2ms/step - loss: 4603419376.0000 - val_loss: 446939856.0000
Epoch 40/400 - 0s 2ms/step - loss: 4562994288.0000 - val_loss: 4433517120.0000
Epoch 41/400 - 0s 2ms/step - loss: 451143864.0000 - val_loss: 4381903096.0000
Epoch 42/400 - 0s 3ms/step - loss: 4411391712.0000 - val_loss: 4354845842.0000
Epoch 43/400 - 0s 2ms/step - loss: 4448227328.0000 - val_loss: 4299046928.0000
Epoch 44/400 - 0s 2ms/step - loss: 4386708716.0000 - val_loss: 4262276704.0000
Epoch 45/400 - 0s 2ms/step - loss: 4389631648.0000 - val_loss: 4230295360.0000
Epoch 46/400 - 0s 2ms/step - loss: 4317026304.0000 - val_loss: 4194362392.0000
Epoch 47/400 - 0s 2ms/step - loss: 42838970368.0000 - val_loss: 4155944108.0000
Epoch 48/400 - 0s 2ms/step - loss: 42476244992.0000 - val_loss: 4141927688.0000
Epoch 49/400 - 0s 2ms/step - loss: 4221442672.0000 - val_loss: 4087891980.0000
Epoch 50/400 - 0s 2ms/step - loss: 4184242920.0000 - val_loss: 4054718452.0000
Epoch 51/400 - 0s 2ms/step - loss: 4153541076.0000 - val_loss: 4026714932.0000
Epoch 52/400 - 0s 2ms/step - loss: 4125831776.0000 - val_loss: 3995106984.0000
Epoch 53/400 - 0s 2ms/step - loss: 4098622976.0000 - val_loss: 3967192832.0000
Epoch 54/400 - 0s 2ms/step - loss: 4065240860.0000 - val_loss: 3937288000.0000
Epoch 55/400 - 0s 2ms/step - loss: 4034683264.0000 - val_loss: 3908371232.0000
Epoch 56/400 - 0s 2ms/step - loss: 4000462988.0000 - val_loss: 38789612288.0000
Epoch 57/400 - 0s 2ms/step - loss: 39808810496.0000 - val_loss: 3854361696.0000
Epoch 58/400 - 0s 2ms/step - loss: 3958297088.0000 - val_loss: 3828654080.0000
Epoch 59/400 - 0s 2ms/step - loss: 3930640156.0000 - val_loss: 3802897664.0000
Epoch 60/400 - 0s 2ms/step - loss: 3906800256.0000 - val_loss: 3779234016.0000
Epoch 61/400 - 0s 2ms/step - loss: 3884394860.0000 - val_loss: 3753159452.0000
Epoch 62/400 - 0s 2ms/step - loss: 3861840640.0000 - val_loss: 3730953568.0000
Epoch 63/400 - 0s 2ms/step - loss: 3839649488.0000 - val_loss: 37073984.0000
Epoch 64/400 - 0s 2ms/step - loss: 3819791552.0000 - val_loss: 3686091616.0000
Epoch 65/400 - 0s 2ms/step - loss: 3797968960.0000 - val_loss: 3663513984.0000
Epoch 66/400 - 0s 2ms/step - loss: 3779006120.0000 - val_loss: 3653282752.0000
Epoch 67/400 - 0s 2ms/step - loss: 3760915074.0000 - val_loss: 3629710312.0000
Epoch 68/400 - 0s 2ms/step - loss: 3749683984.0000 - val_loss: 36140210368.0000
Epoch 69/400 - 0s 2ms/step - loss: 3730860648.0000 - val_loss: 3593830784.0000
Epoch 70/400 - 0s 2ms/step - loss: 3714761932.0000 - val_loss: 3585985600.0000
Epoch 71/400 - 0s 2ms/step - loss: 3701031732.0000 - val_loss: 3568692032.0000
Epoch 72/400 - 0s 2ms/step - loss: 3688982496.0000 - val_loss: 3549898000.0000
Epoch 73/400 - 0s 2ms/step - loss: 3675960492.0000 - val_loss: 3541707512.0000
Epoch 74/400 - 0s 2ms/step - loss: 3664054156.0000 - val_loss: 3540274556.0000
Epoch 75/400 - 0s 2ms/step - loss: 364862136.0000 - val_loss: 3517826288.0000
Epoch 76/400 - 0s 2ms/step - loss: 3634067044.0000 - val_loss: 3503074092.0000
Epoch 77/400 - 0s 2ms/step - loss: 3621148864.0000 - val_loss: 3491725216.0000
Epoch 78/400 - 0s 2ms/step - loss: 3615528960.0000 - val_loss: 3480841012.0000
Epoch 79/400 - 0s 3ms/step - loss: 3599745832.0000 - val_loss: 3467034244.0000
Epoch 80/400 - 0s 3ms/step - loss: 3587760108.0000 - val_loss: 3453035616.0000
Epoch 81/400 - 0s 2ms/step - loss: 35822010368.0000 - val_loss: 3448508448.0000
Epoch 82/400 - 0s 2ms/step - loss: 3565808848.0000 - val_loss: 34407305216.0000
Epoch 83/400 - 0s 2ms/step - loss: 3555149568.0000 - val_loss: 3435308896.0000
Epoch 84/400 - 0s 2ms/step - loss: 3548923760.0000 - val_loss: 3416033980.0000
Epoch 85/400 - 0s 2ms/step - loss: 3538404172.0000 - val_loss: 3405147744.0000
Epoch 86/400 - 0s 3ms/step - loss: 352700784.0000 - val_loss: 3387713284.0000
Epoch 87/400 - 0s 2ms/step - loss: 3502972126.0000 - val_loss: 3380735744.0000
Epoch 88/400 - 0s 2ms/step - loss: 350512740.0000 - val_loss: 3367991368.0000
Epoch 89/400 - 0s 3ms/step - loss: 3494217760.0000 - val_loss: 3363516288.0000
Epoch 90/400 - 0s 3ms/step - loss: 3485920870.0000 - val_loss: 3355427840.0000
Epoch 91/400 - 0s 3ms/step - loss: 3478293894.0000 - val_loss: 3341857998.0000
Epoch 92/400 - 0s 2ms/step - loss: 3464841216.0000 - val_loss: 3324446372.0000
Epoch 93/400 - 0s 2ms/step - loss: 345625104.0000 - val_loss: 3309239396.0000
Epoch 94/400 - 0s 2ms/step - loss: 3463780716.0000 - val_loss: 3321618432.0000
Epoch 95/400 - 0s 2ms/step - loss: 3446768848.0000 - val_loss: 3315502800.0000
Epoch 96/400 - 0s 2ms/step - loss: 3442513088.0000 - val_loss: 3312666944.0000
Epoch 97/400 - 0s 2ms/step - loss: 3437203856.0000 - val_loss: 3302711076.0000
Epoch 98/400 - 0s 2ms/step - loss: 3432255480.0000 - val_loss: 3298102468.0000
Epoch 99/400 - 0s 2ms/step - loss: 3424118208.0000 - val_loss: 3289474936.0000
Epoch 100/400 - 0s 2ms/step - loss: 341360128.0000 - val_loss: 3285856040.0000
Epoch 101/400 - 0s 2ms/step - loss: 3417821388.0000 - val_loss: 328456328.0000
Epoch 102/400 - 0s 2ms/step - loss: 3412748280.0000 - val_loss: 3284583288.0000
Epoch 103/400 - 0s 2ms/step - loss: 3410836712.0000 - val_loss: 3279545776.0000
Epoch 104/400 - 0s 2ms/step - loss: 3401360128.0000 - val_loss: 3269975248.0000
Epoch 105/400 - 0s 2ms/step - loss: 33959397120.0000 - val_loss: 3261401902.0000
Epoch 106/400 - 0s 2ms/step - loss: 33897934752.0000 - val_loss: 3256562432.0000
Epoch 107/400 - 0s 2ms/step - loss: 3387953200.0000 - val_loss: 3250376704.0000
Epoch 108/400 - 0s 2ms/step - loss: 3384048452.0000 - val_loss: 3246708216.0000
Epoch 109/400 - 0s 2ms/step - loss: 3375626160.0000 - val_loss: 3254013496.0000
Epoch 110/400 - 0s 2ms/step - loss: 3371738464.0000 - val_loss: 3242276544.0000
Epoch 111/400 - 0s 2ms/step - loss: 3370256936.0000 - val_loss: 3231972568.0000
Epoch 112/400 - 0s 2ms/step - loss: 3367460608.0000 - val_loss: 3234973902.0000
Epoch 113/400 - 0s 2ms/step - loss: 3361454464.0000 - val_loss: 32224581632.0000
Epoch 114/400 - 0s 2ms/step - loss: 3355909392.0000 - val_loss: 3217696352.0000
Epoch 115/400 - 0s 2ms/step - loss: 335143176.0000 - val_loss: 3208414720.0000
Epoch 116/400 - 0s 2ms/step - loss: 3352613984.0000 - val_loss: 3206643720.0000
Epoch 117/400 - 0s 2ms/step - loss: 3344800384.0000 - val_loss: 3201947808.0000
Epoch 118/400 - 0s 2ms/step - loss: 3337601088.0000 - val_loss: 3208959304.0000
Epoch 119/400 - 0s 2ms/step - loss: 3337640148.0000 - val_loss: 31928559616.0000
Epoch 120/400 - 0s 2ms/step - loss: 3330409472.0000 - val_loss: 3193522856.0000
Epoch 121/400 - 0s 2ms/step - loss: 3331542208.0000 - val_loss: 3187658848.0000
Epoch 122/400 - 0s 2ms/step - loss: 3323167488.0000 - val_loss: 3187467884.0000
Epoch 123/400 - 0s 2ms/step - loss: 3322941744.0000 - val_loss: 3176192144.0000
Epoch 124/400 - 0s 2ms/step - loss: 3318803044.0000 - val_loss: 3167109888.0000
Epoch 125/400 - 0s 2ms/step - loss: 3313247844.0000 - val_loss: 3167170748.0000
Epoch 126/400 - 0s 2ms/step - loss: 3308905624.0000 - val_loss: 3161797408.0000
Epoch 127/400 - 0s 2ms/step - loss: 3306216384.0000 - val_loss: 3154922496.0000
Epoch 128/400 - 0s 2ms/step - loss: 3300941206.0000 - val_loss: 3154363920.0000
Epoch 129/400 - 0s 2ms/step - loss: 3298932512.0000 - val_loss: 3127218324.0000
Epoch 130/400 - 0s 2ms/step - loss: 3296801648.0000 - val_loss: 3141373856.0000
Epoch 131/400 - 0s 3ms/step - loss: 3299475044.0000 - val_loss: 3141780480.0000
Epoch 132/400 - 0s 2ms/step - loss: 3285990016.0000 - val_loss: 3136604800.0000
Epoch 133/400 - 0s 2ms/step - loss: 328647144.0000 - val_loss: 3128662496.0000
Epoch 134/400 - 0s 2ms/step - loss: 3278785792.0000 - val_loss: 3123624960.0000
Epoch 135/400 - 0s 2ms/step - loss: 3278785840.0000 - val_loss: 3133249344.0000
Epoch 136/400 - 0s 3ms/step - loss: 3283323494.0000 - val_loss: 3148119396.0000
Epoch 137/400 - 0s 2ms/step - loss: 3273717504.0000 - val_loss: 31423094952.0000
Epoch 138/400 - 0s 2ms/step - loss: 327570864.0000 - val_loss: 3134513920.0000
Epoch 139/400 - 0s 2ms/step - loss: 32711497728.0000 - val_loss: 3132730672.0000
Epoch 140/400 - 0s 2ms/step - loss: 3268600544.0000 - val_loss: 3137089824.0000
Epoch 141/400 - 0s 2ms/step - loss: 3261532368.0000 - val_loss: 3107072496.0000
Epoch 142/400 - 0s 2ms/step - loss: 32596617216.0000 - val_loss: 3103006106.0000
Epoch 143/400 - 0s 2ms/step - loss: 32565194752.0000 - val_loss: 3103303040.0000
Epoch 144/400 - 0s 2ms/step - loss: 3256194752.0000 - val_loss: 3103952448.0000
Epoch 145/400 - 0s 2ms/step - loss: 3251441152.0000 - val_loss: 3103952448.0000
Epoch 146/400 - 0s 2ms/step - loss: 32565194752.0000 - val_loss: 3103952448.0000
Epoch 147/400 - 0s 2ms/step - loss: 32486122624.0000 - val_loss: 3091419546.0000
Epoch 148/400 - 0s 2ms/step - loss: 3245594096.0000 - val_loss: 30880581632.0000
Epoch 149/400 - 0s 2ms/step - loss: 3244000384.0000 - val_loss: 3087882752.0000
Epoch 150/400 - 0s 2ms/step - loss: 3248629824.0000 - val_loss: 3086708216.0000
Epoch 151/400 - 0s 2ms/step - loss: 3239273920.0000 - val_loss: 3085930306.0000
Epoch 152/400 - 0s 2ms/step - loss: 3235066752.0000 - val_loss: 3079754368.0000
Epoch 153/400 - 0s 2ms/step - loss: 3231880398.0000 - val_loss: 3079550720.0000
Epoch 154/400 - 0s 2ms/step - loss: 3233473884.0000 - val_loss: 3075703080.0000
Epoch 155/400 - 0s 2ms/step - loss: 3231831040.0000 - val_loss: 3069147794.0000
Epoch 156/400 - 0s 2ms/step - loss: 3228201416.0000 - val_loss: 3062597272.0000
Epoch 157/400 - 0s 2ms/step - loss: 3228656512.0000 - val_loss: 3067308416.0000
Epoch 158/400 - 0s 2ms/step - loss: 3221478496.0000 - val_loss: 3068650368.0000
Epoch 159/400 - 0s 2ms/step - loss: 3221075456.0000 - val_loss: 3056619312.0000
Epoch 160/400 - 0s 2ms/step - loss: 3216351072.0000 - val_loss: 3055123856.0000
Epoch 161/400 - 0s 2ms/step - loss: 321352224.0000 - val_loss: 30483456768.0000
Epoch 162/400 - 0s 3ms/step - loss: 3213913984.0000 - val_loss: 3048138080.0000
Epoch 163/400 - 0s 2ms/step - loss: 3207345136.0000 - val_loss: 3054309580.0000
Epoch 164/400 - 0s 2ms/step - loss: 3200546176.0000 - val_loss: 3054954968.0000
Epoch 165/400 - 0s 2ms/step - loss: 3200643036.0000 - val_loss: 30462908416.0000
Epoch 166/400 - 0s 2ms/step - loss: 3204048000.0000 - val_loss: 3037652782.0000
Epoch 167/400 - 0s 2ms/step - loss: 3197830680.0000 - val_loss: 3034897648.0000
Epoch 168/400 - 0s 2ms/step - loss: 3197832192.0000 - val_loss: 3035097392.0000
Epoch 169/400 - 0s 3ms/step - loss: 3197291312.0000 - val_loss: 3034959736.0000
Epoch 170/400 - 0s 2ms/step - loss: 31950338048.0000 - val_loss: 3032818272.0000
Epoch 171/400 - 0s 2ms/step - loss: 31926713696.0000 - val_loss: 3032115808.0000
Epoch 172/400 - 0s 2ms/step - loss: 3194993664.0000 - val_loss: 3024286400.0000
Epoch 173/400 - 0s 3ms/step - loss: 31897610240.0000 - val_loss: 3022187072.0000
Epoch 174/400 - 0s 2ms/step - loss: 3188690400.0000 - val_loss: 3021100320.0000
Epoch 175/400 - 0s 2ms/step - loss: 3185347084.0000 - val_loss: 3018815282.0000
Epoch 176/400 - 0s 3ms/step - loss: 3183971624.0000 - val_loss: 3013674680.0000
Epoch 177/400 - 0s 2ms/step - loss: 31829829632.0000 - val_loss: 30136193024.0000
Epoch 178/400 - 0s 2ms/step - loss: 3179911860.0000 - val_loss: 3023154760.0000
Epoch 179/400 - 0s 2ms/step - loss: 3175972640.0000 - val_loss: 3009624976.0000
Epoch 180/400 - 0s 2ms/step - loss: 3172677820.0000 - val_loss: 30070536192.0000
Epoch 181/400 - 0s 2ms/step - loss: 3175942388.0000 - val_loss: 3002913408.0000
Epoch 182/400 - 0s 3ms/step - loss: 31698608128.0000 - val_loss: 3001972146.0000
Epoch 183/400 - 0s 2ms/step - loss: 31681329920.0000 - val_loss: 3001121776.0000
Epoch 184/400 - 0s 2ms/step - loss: 3169410352.0000 - val_loss: 2997127180.0000
Epoch 185/400 - 0s 2ms/step - loss: 3165532824.0000 - val_loss: 2998463996.0000
Epoch 186/400 - 0s 2ms/step - loss: 3167693264.0000 - val_loss: 2998121344.0000
Epoch 187/400 - 0s 2ms/step - loss: 3163960796.0000 - val_loss: 29964320768.0000
Epoch 188/400 - 0s 2ms/step - loss: 3158893280.0000 - val_loss: 29879728128.0000
Epoch 189/400 - 0s 2ms/step - loss: 3158099680.0000 - val_loss: 2985393266.0000
Epoch 190/400 - 0s 2ms/step - loss: 3154947864.0000 - val_loss: 2982214650.0000
Epoch 191/400 - 0s 2ms/step - loss: 3155876996.0000 - val_loss: 2988365824.0000
Epoch 192/400 - 0s 2ms/step - loss: 31505321984.0000 - val_loss: 2982366176.0000
Epoch 193/400 - 0s 2ms/step - loss: 31509882880.0000 - val_loss: 2975924288.0000
Epoch 194/400 - 0s 2ms/step - loss: 31506737152.0000 - val_loss: 2973252864.0000
Epoch 195/400 - 0s 3ms/step - loss: 31474051072.0000 - val_loss: 2976024576.0000
Epoch 196/400 - 0s 2ms/step - loss: 3145865216.0000 - val_loss: 2971132584.0000
Epoch 197/400 - 0s 2ms/step - loss: 3144697408.0000 - val_loss: 2968162240.0000
Epoch 198/400 - 0s 3ms/step - loss: 3144379648.0000 - val_loss: 2967720356.0000
Epoch 199/400 - 0s 2ms/step - loss: 3142342512.0000 - val_loss: 2964513176.0000
Epoch 200/400 - 0s 3ms/step - loss: 3138592384.0000 - val_loss: 2965597760.0000
Epoch 201/400 - 0s 2ms/step - loss: 3136960196.0000 - val_loss: 2965535616.0000
Epoch 202/400 - 0s 2ms/step - loss: 3140845362.0000 - val_loss: 2962230468.0000
Epoch 203/400 - 0s 2ms/step - loss: 3136909584.0000 - val_loss: 2962881868.0000
Epoch 204/400 - 0s 2ms/step - loss: 3136829594.0000 - val_loss: 2956356192.0000
Epoch 205/400 - 0s 2ms/step - loss: 3131807744.0000 - val_loss: 2954581368.0000
Epoch 206/400 - 0s 2ms/step - loss: 3129628472.0000 - val_loss: 2959512880.0000
Epoch 207/400 - 0s 2ms/step - loss: 312750764.0000 - val_loss: 2953734592.0000
Epoch 208/400 - 0s 2ms/step - loss: 31285813248.0000 - val_loss: 2948761304.0000
Epoch 209/400 - 0s 2ms/step - loss: 3124812800.0000 - val_loss: 2947981696.0000
Epoch 210/400 - 0s 2ms/step - loss: 3122768832.0000 - val_loss: 294512576.0000
Epoch 211/400 - 0s 2ms/step - loss: 3120890266.0000 - val_loss: 2943272496.0000
Epoch 212/400 - 0s 2ms/step - loss: 3120470256.0000 - val_loss: 29394720768.0000
Epoch 213/400 - 0s 2ms/step - loss: 3120554188.0000 - val_loss: 2936447808.0000
Epoch 214/400 - 0s 2ms/step - loss: 3114677676.0000 - val_loss: 2936079396.0000
Epoch 
```



```
In [75]: model.predict(single_house)

Out[75]: array([[1286098.25]], dtype=float32)

In [76]: df.head(1)

Out[76]:
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	yr_built	yr_renovated
0	221900.0	3	1.0	1180	5650	1.0	0	0	3	7	1180	0	1955	

```
In [ ]:
```