#### IMPORT LIBRARIES AND DATASETS

```
from google.colab import drive
drive.mount('/content/drive')
Mounted at /content/drive
!pip install jupyterthemes
Looking in indexes: <a href="https://pypi.org/simple">https://us-python.pkg.dev/colab-v</a>
Collecting jupyterthemes
     Downloading jupyterthemes-0.20.0-py2.py3-none-any.whl (7.0 MB)
                                                                                                               - 7.0/7.0 MB 64.8 MB/s eta 0:00:00
Requirement already satisfied: jupyter-core in /usr/local/lib/python3.8/dist-
Requirement already satisfied: ipython>=5.4.1 in /usr/local/lib/python3.8/dist
Requirement already satisfied: matplotlib>=1.4.3 in /usr/local/lib/python3.8/c
Requirement already satisfied: notebook>=5.6.0 in /usr/local/lib/python3.8/dis
Collecting lesscpy>=0.11.2
     Downloading lesscpy-0.15.1-py2.py3-none-any.whl (46 kB)
                                                                                                                — 46.7/46.7 KB 5.0 MB/s eta 0:00:0
Collecting jedi>=0.10
     Downloading jedi-0.18.2-py2.py3-none-anv.whl (1.6 MB)
                                                                                                                 — 1.6/1.6 MB 82.0 MB/s eta 0:00:00
Requirement already satisfied: backcall in /usr/local/lib/python3.8/dist-packa
Requirement already satisfied: decorator in /usr/local/lib/python3.8/dist-pack
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.8/dist
Requirement already satisfied: pygments in /usr/local/lib/python3.8/dist-packa
Requirement already satisfied: pexpect in /usr/local/lib/python3.8/dist-packac
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.8/di
Requirement already satisfied: prompt-toolkit<2.1.0,>=2.0.0 in /usr/local/lib,
Requirement already satisfied: pickleshare in /usr/local/lib/python3.8/dist-page 1.00 representation of the control of the con
Collecting ply
     Downloading ply-3.11-py2.py3-none-any.whl (49 kB)
                                                                                                                — 49.6/49.6 KB 5.7 MB/s eta 0:00:0
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.8/c
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.8/dist-page 1.11 in /usr/local/lib/python3
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /us
Requirement already satisfied: tornado<7,>=4.1 in /usr/local/lib/python3.8/dis
Requirement already satisfied: jupyter-client<7.0.0,>=5.2.0 in /usr/local/lib,
Requirement already satisfied: nbformat in /usr/local/lib/python3.8/dist-packa
Requirement already satisfied: pyzmg>=17 in /usr/local/lib/python3.8/dist-pack
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.8/di
Requirement already satisfied: terminado>=0.8.1 in /usr/local/lib/python3.8/d:
Requirement already satisfied: nbconvert<6.0 in /usr/local/lib/python3.8/dist-
```

```
Requirement already satisfied: jinja2<=3.0.0 in /usr/local/lib/python3.8/dist-
   Requirement already satisfied: prometheus-client in /usr/local/lib/python3.8/c
   Requirement already satisfied: ipykernel in /usr/local/lib/python3.8/dist-pack
   Requirement already satisfied: Send2Trash in /usr/local/lib/python3.8/dist-pac
   Requirement already satisfied: platformdirs>=2.5 in /usr/local/lib/python3.8/c
   Requirement already satisfied: parso<0.9.0,>=0.8.0 in /usr/local/lib/python3.{
   Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.8/d:
   Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.8/c
   Requirement already satisfied: bleach in /usr/local/lib/python3.8/dist-package
   Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/python3.
   Requirement already satisfied: defusedxml in /usr/local/lib/python3.8/dist-page
   Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/python3.8,
   Requirement already satisfied: testpath in /usr/local/lib/python3.8/dist-packa
   Requirement already satisfied: fastjsonschema in /usr/local/lib/python3.8/dist
   Requirement already satisfied: jsonschema>=2.6 in /usr/local/lib/python3.8/dis
   Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.8/dist-page
   Requirement already satisfied: wcwidth in /usr/local/lib/python3.8/dist-packag
   Requirement already satisfied: ptyprocess in /usr/local/lib/python3.8/dist-pac
   Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0
   Requirement already satisfied: importlib-resources>=1.4.0 in /usr/local/lib/py
   Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.8/dist-
   Requirement already satisfied: webencodings in /usr/local/lib/python3.8/dist-
   Danismant almosts catiofical sine_2 1 0 in /war/local/lib/mithan2 0/dist no
1 import pandas as pd
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from jupyterthemes import jtplot

jtplot.style(theme='monokai', context='notebook', ticks=True, grid=False)

# setting the style of the notebook to be monokai theme

# this line of code is important to ensure that we are able to see the x and y a

# If you don't run this code line, you will notice that the xlabel and ylabel or
```

1 house\_df = pd.read\_csv('/content/drive/MyDrive/real estate /realestate\_prices.cs

1 house\_df

	id	date	price	bedrooms	bathrooms	sqft_living	sq
0	7129300520	20141013T000000	221900.0	3	1.00	1180	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	
2	5631500400	20150225T000000	180000.0	2	1.00	770	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	
21608	263000018	20140521T000000	360000.0	3	2.50	1530	
21609	6600060120	20150223T000000	400000.0	4	2.50	2310	
21610	1523300141	20140623T000000	402101.0	2	0.75	1020	
21611	291310100	20150116T000000	400000.0	3	2.50	1600	
21612	1523300157	20141015T000000	325000.0	2	0.75	1020	

21613 rows × 21 columns

## 1 house\_df.head(5)

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_l
0	7129300520	20141013T000000	221900.0	3	1.00	1180	56
1	6414100192	20141209T000000	538000.0	3	2.25	2570	72
2	5631500400	20150225T000000	180000.0	2	1.00	770	100
3	2487200875	20141209T000000	604000.0	4	3.00	1960	50
4	1954400510	20150218T000000	510000.0	3	2.00	1680	80

5 rows × 21 columns

### 1 house\_df.tail(10)

	id	date	price	bedrooms	bathrooms	sqft_living s	(
21603	7852140040	20140825T000000	507250.0	3	2.50	2270	_
21604	9834201367	20150126T000000	429000.0	3	2.00	1490	
21605	3448900210	20141014T000000	610685.0	4	2.50	2520	
21606	7936000429	20150326T000000	1007500.0	4	3.50	3510	
21607	2997800021	20150219T000000	475000.0	3	2.50	1310	
21608	263000018	20140521T000000	360000.0	3	2.50	1530	
21609	6600060120	20150223T000000	400000.0	4	2.50	2310	
21610	1523300141	20140623T000000	402101.0	2	0.75	1020	
21611	291310100	20150116T000000	400000.0	3	2.50	1600	
21612	1523300157	20141015T000000	325000.0	2	0.75	1020	

10 rows × 21 columns

<class 'pandas.core.frame.DataFrame'>

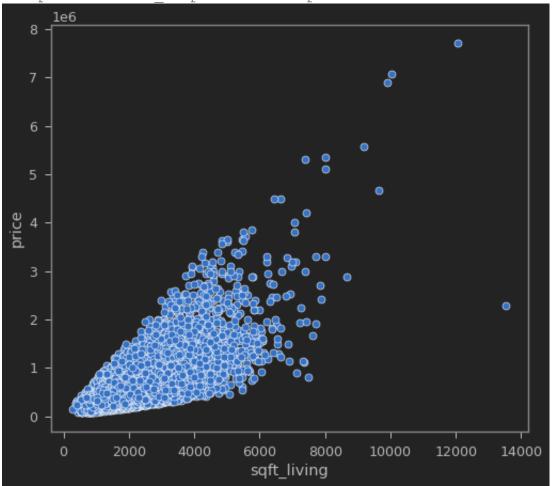
#### 1 house df.info()

RangeIndex: 21613 entries, 0 to 21612 Data columns (total 21 columns): # Column Non-Null Count Dtype 0 id 21613 non-null int64 1 date 21613 non-null object 21613 non-null float64 2 price 3 21613 non-null int64 bedrooms 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 21613 non-null int64 11 grade 12 sqft\_above 21613 non-null int64 13 sqft\_basement 21613 non-null int64 14 yr built 21613 non-null int64 15 21613 non-null int64 yr renovated 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 dtypes: float64(5), int64(15), object(1) memory usage: 3.5+ MB

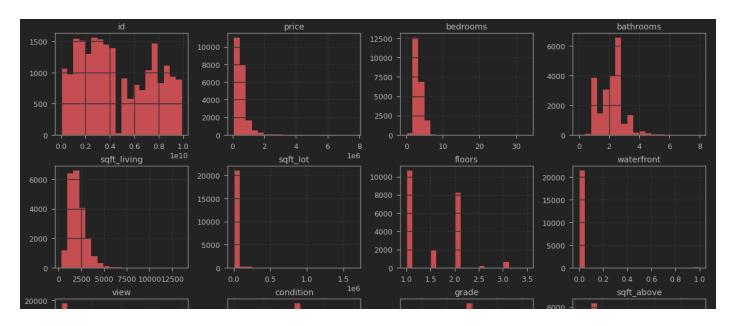
#### PERFORM DATA VISUALIZATION

1 sns.scatterplot(x = 'sqft\_living', y = 'price', data = house\_df)

<matplotlib.axes. subplots.AxesSubplot at 0x7f9a9a51c8b0>



1 house\_df.hist(bins = 20, figsize = (20,20), color = 'r');

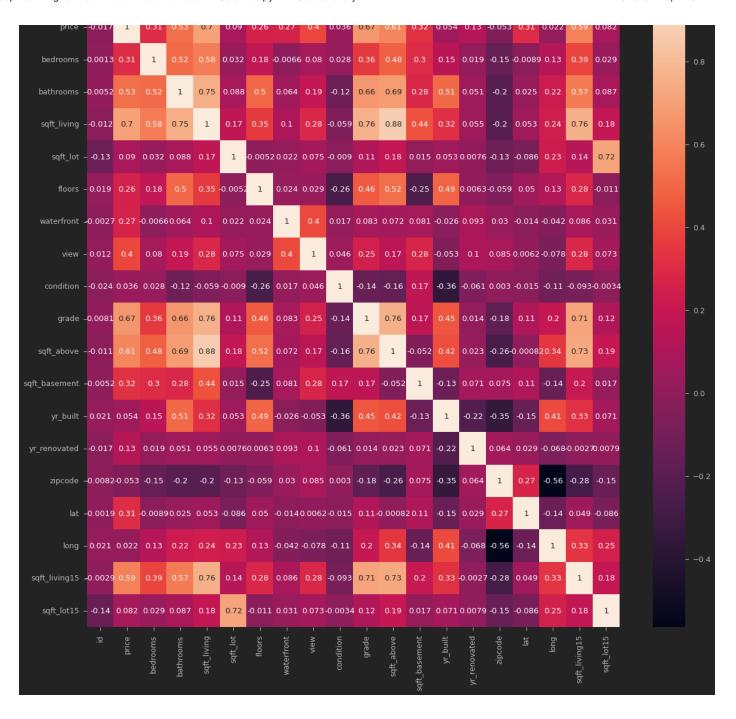




```
1 f, ax = plt.subplots(figsize = (20, 20))
2 sns.heatmap(house_df.corr(), annot = True)
```

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f9a995cbc40>





1 house\_df\_sample = house\_df[ ['price', 'bedrooms', 'bathrooms', 'sqft\_living', 's

1 house\_df\_sample

	price	bedrooms	bathrooms	sqft_living	sqft_lot	sqft_above	sqft_bas
0	221900.0	3	1.00	1180	5650	1180	
1	538000.0	3	2.25	2570	7242	2170	
2	180000.0	2	1.00	770	10000	770	
3	604000.0	4	3.00	1960	5000	1050	
4	510000.0	3	2.00	1680	8080	1680	
21608	360000.0	3	2.50	1530	1131	1530	
21609	400000.0	4	2.50	2310	5813	2310	
21610	402101.0	2	0.75	1020	1350	1020	
21611	400000.0	3	2.50	1600	2388	1600	
21612	325000.0	2	0.75	1020	1076	1020	

21613 rows × 8 columns

#### PERFORM DATA CLEANING AND FEATURE ENGINEERING

1 selected\_features = ['bedrooms', 'bathrooms', 'sqft\_living', 'sqft\_lot', 'floors']

1 X = house\_df[selected\_features]

1 X

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_base
0	3	1.00	1180	5650	1.0	1180	
1	3	2.25	2570	7242	2.0	2170	
2	2	1.00	770	10000	1.0	770	
3	4	3.00	1960	5000	1.0	1050	
4	3	2.00	1680	8080	1.0	1680	
21608	3	2.50	1530	1131	3.0	1530	
21609	4	2.50	2310	5813	2.0	2310	
21610	2	0.75	1020	1350	2.0	1020	
21611	3	2.50	1600	2388	2.0	1600	
21612	2	0.75	1020	1076	2.0	1020	

21613 rows × 7 columns

```
1 y = house_df['price']
```

1 y

0	221900.0
1	538000.0
2	180000.0
3	604000.0
4	510000.0
21608	360000.0
21609	400000.0
21610	402101.0
21611	400000.0
21612	325000.0

Name: price, Length: 21613, dtype: float64

```
1 X. shape
   (21613, 7)
1 v.shape
   (21613,)
1 from sklearn.preprocessing import MinMaxScaler
2 scaler = MinMaxScaler()
3 X scaled = scaler.fit transform(X)
1 X_scaled
   array([[0.09090909, 0.125 , 0.06716981, ..., 0. , 0.09758772,
          0.
          [0.09090909, 0.28125
                                , 0.17207547, ..., 0.4 , 0.20614035,
          0.08298755],
          [0.06060606, 0.125
                                , 0.03622642, ..., 0.
                                                            , 0.05263158,
          0.
                    ],
          [0.06060606, 0.09375
                                , 0.05509434, ..., 0.4
                                                          , 0.08004386,
          [0.09090909, 0.3125
                                , 0.09886792, ..., 0.4 , 0.14364035,
                                , 0.05509434, ..., 0.4
                                                        , 0.08004386,
          [0.06060606, 0.09375
                   ]])
           0.
1 X_scaled.shape
   (21613, 7)
1 scaler.data_max_
   array([3.300000e+01, 8.000000e+00, 1.354000e+04, 1.651359e+06,
          3.500000e+00, 9.410000e+03, 4.820000e+03])
1 scaler.data min
   array([ 0., 0., 290., 520., 1., 290., 0.])
```

#### TRAIN A DEEP LEARNING MODEL WITH LIMITED NUMBER OF FEATURES

#### 1 model.summary()

Model: "sequential"

Output Shape	Param #
(None, 100)	800
(None, 100)	10100
(None, 100)	10100
(None, 1)	101
	(None, 100) (None, 100) (None, 100)

\_\_\_\_\_\_

Total params: 21,101 Trainable params: 21,101 Non-trainable params: 0

1 model.compile(optimizer = 'Adam', loss = 'mean\_squared\_error')

```
1 epochs hist = model.fit(X train, y train, epochs = 100, batch size = 50, validat
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
260/260 [=============] - 1s 2ms/step - loss: 0.0010 - val_l(
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
260/260 [----- | 1c 2mc/sten | loss 0 0010 | val 10
```

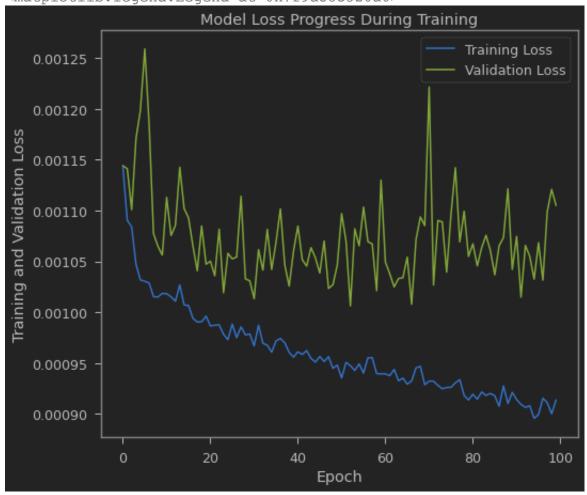
```
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
  _____1 10 2mg/c+cm locate 0 7060c 04
JEW /JEW [_____
```

#### EVALUATE TRAINED DEEP LEARNING MODEL PERFORMANCE

```
1 epochs_hist.history.keys()
    dict_keys(['loss', 'val_loss'])
```

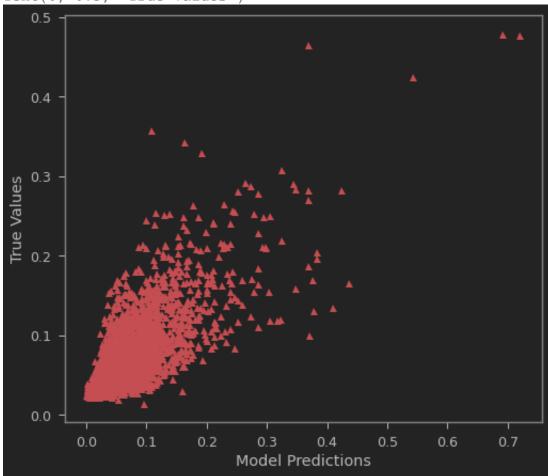
```
1 plt.plot(epochs_hist.history['loss'])
2 plt.plot(epochs_hist.history['val_loss'])
3 plt.title('Model Loss Progress During Training')
4 plt.xlabel('Epoch')
5 plt.ylabel('Training and Validation Loss')
6 plt.legend(['Training Loss', 'Validation Loss'])
```





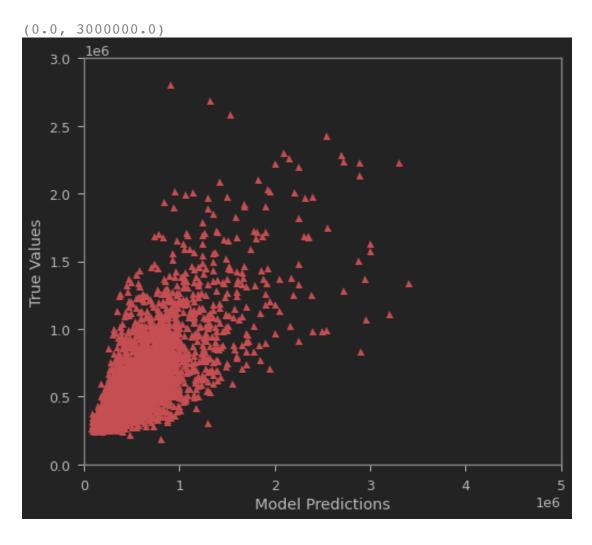
```
1 y_predict = model.predict(X_test)
2 plt.plot(y_test, y_predict, "^", color = 'r')
3 plt.xlabel('Model Predictions')
4 plt.ylabel('True Values')
```





```
1 y_predict_orig = scaler.inverse_transform(y_predict)
2 y_test_orig = scaler.inverse_transform(y_test)
```

```
1 plt.plot(y_test_orig, y_predict_orig, "^", color = 'r')
2 plt.xlabel('Model Predictions')
3 plt.ylabel('True Values')
4 plt.xlim(0, 5000000)
5 plt.ylim(0, 3000000)
```



```
1 k = X_test.shape[1]
2 n = len(X_test)
3 n
```

1 k

7

```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from math import sqrt

RMSE = float(format(np.sqrt(mean_squared_error(y_test_orig, y_predict_orig)),'.3

MSE = mean_squared_error(y_test_orig, y_predict_orig)

MAE = mean_absolute_error(y_test_orig, y_predict_orig)

r2 = r2_score(y_test_orig, y_predict_orig)

adj_r2 = 1-(1-r2)*(n-1)/(n-k-1)

print('RMSE =',RMSE, '\nMSE =',MSE, '\nMAE =',MAE, '\nR2 =', r2, '\nAdjusted R2

RMSE = 227049.828

MSE = 51551624455.33176

MAE = 152877.96062812267

R2 = 0.5760681183789966

Adjusted R2 = 0.5755181696815639
```

# TRAIN AND EVALUATE A DEEP LEARNING MODEL WITH INCREASED NUMBER OF FEATURES (INDEPENDANT VARIABLES)

```
selected_features = ['bedrooms','bathrooms','sqft_living','sqft_lot','floors', '
2 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15']

4 X = house_df[selected_features]

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

1 y = house_df['price']

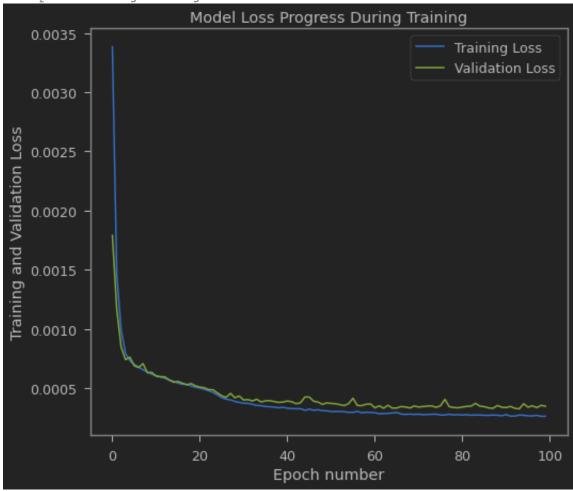
1 y = y.values.reshape(-1,1)
2 y_scaled = scaler.fit_transform(y)
3 from sklearn.model_selection import train_test_split
4 X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_scaled, test_siz
```

```
1 import tensorflow.keras
2 from tensorflow.keras.models import Sequential
3 from tensorflow.keras.layers import Dense
5 model = Sequential()
6 model.add(Dense(10, input_dim = 19, activation = 'relu'))
7 model.add(Dense(10, activation = 'relu'))
8 model.add(Dense(1, activation = 'linear'))
1 model.compile(optimizer = 'adam', loss = 'mean squared error')
1 epochs hist = model.fit(X_train, y_train, epochs = 100, batch_size = 50, verbose
 Epoch 1/100
 Epoch 2/100
 Epoch 3/100
 Epoch 4/100
 Epoch 5/100
 Epoch 6/100
 Epoch 7/100
 Epoch 8/100
 Epoch 9/100
 Epoch 10/100
 Epoch 11/100
 Epoch 12/100
 Epoch 13/100
 Epoch 14/100
 Epoch 15/100
 Epoch 16/100
 Epoch 17/100
```

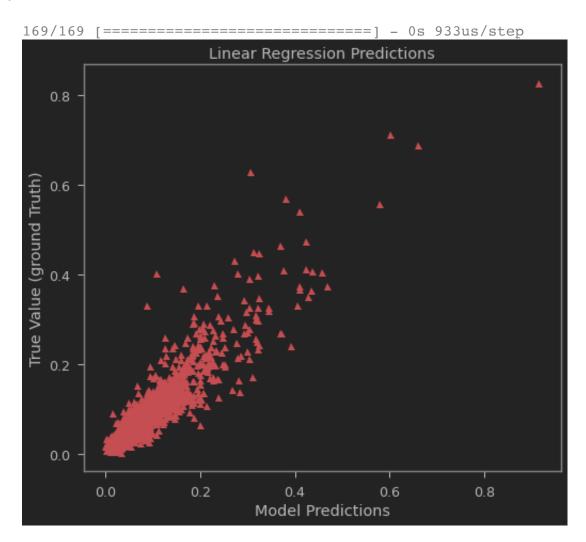
Epoch 18/100			•	
260/260 [========]	_	0s	2ms/step - loss	: 5.3390e-04 - va
Epoch 19/100				
260/260 [=======]	_	0s	2ms/step - loss	: 5.1736e-04 - va
Epoch 20/100				
260/260 [=======]	_	0s	2ms/step - loss	: 5.0727e-04 - va
Epoch 21/100				
260/260 [=======]	_	1s	2ms/step - loss	: 5.0021e-04 - va
Epoch 22/100				
260/260 [=======]	_	0s	2ms/step - loss	: 4.9025e-04 - va
Epoch 23/100				
260/260 [==========]	_	0s	2ms/step - loss	: 4.7798e-04 - va
Epoch 24/100		0	2 / 1	4 6077 04
260/260 [==========]	_	0s	2ms/step - loss	: 4.63//e-04 - Va
Epoch 25/100		0	2 / 1	4 4256 04
260/260 [====================================	_	ØS.	Zms/step - loss	: 4.4256e-04 - Va
Epoch 26/100		0.0	2ma/atan 1aaa	. 4 1010
260/260 [====================================	_	05	2111S/Step - toss	: 4.1919e-04 - Va
Epoch 27/100 260/260 [====================================		0.0	2mc/cton loss	. 4 06250 04 V
Epoch 28/100	_	05	ZIIIS/Step - 1055	: 4:0023E-04 - V
260/260 [==========]		0.0	2mc/sten = loss	. 1 00120-01 - v:
Epoch 29/100		05	ZIIIS/Step - tuss	. 4.0042C-04 - V
260/260 [==========]		Ως	1mc/cten - locc	• 3 97//0_0/ _ v:
Epoch 30/100	_	V S	TIII3/21Ch - 1022	. J.U/44C-V4 - V(
260/360 []		00	2mc/c+on 1occ	. 2 70600 0/1 V

```
1 plt.plot(epochs_hist.history['loss'])
2 plt.plot(epochs_hist.history['val_loss'])
3 plt.title('Model Loss Progress During Training')
4 plt.ylabel('Training and Validation Loss')
5 plt.xlabel('Epoch number')
6 plt.legend(['Training Loss', 'Validation Loss'])
```





```
1 y_predict = model.predict(X_test)
2 plt.plot(y_test, y_predict, "^", color = 'r')
3 plt.xlabel("Model Predictions")
4 plt.ylabel("True Value (ground Truth)")
5 plt.title('Linear Regression Predictions')
6 plt.show()
```



```
1 y_predict_orig = scaler.inverse_transform(y_predict)
2 y_test_orig = scaler.inverse_transform(y_test)
```

```
1 from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
2 from math import sqrt
3
4 RMSE = float(format(np.sqrt(mean_squared_error(y_test_orig, y_predict_orig)),'.3
5 MSE = mean_squared_error(y_test_orig, y_predict_orig)
6 MAE = mean_absolute_error(y_test_orig, y_predict_orig)
7 r2 = r2_score(y_test_orig, y_predict_orig)
8 adj_r2 = 1-(1-r2)*(n-1)/(n-k-1)
9
10 print('RMSE =',RMSE, '\nMSE =',MSE, '\nMAE =',MAE, '\nR2 =', r2, '\nAdjusted R2
11
RMSE = 148187.376
MSE = 21959498322.88438
MAE = 84156.12517059123
R2 = 0.849369982608905
Adjusted R2 = 0.8491745767301544
```

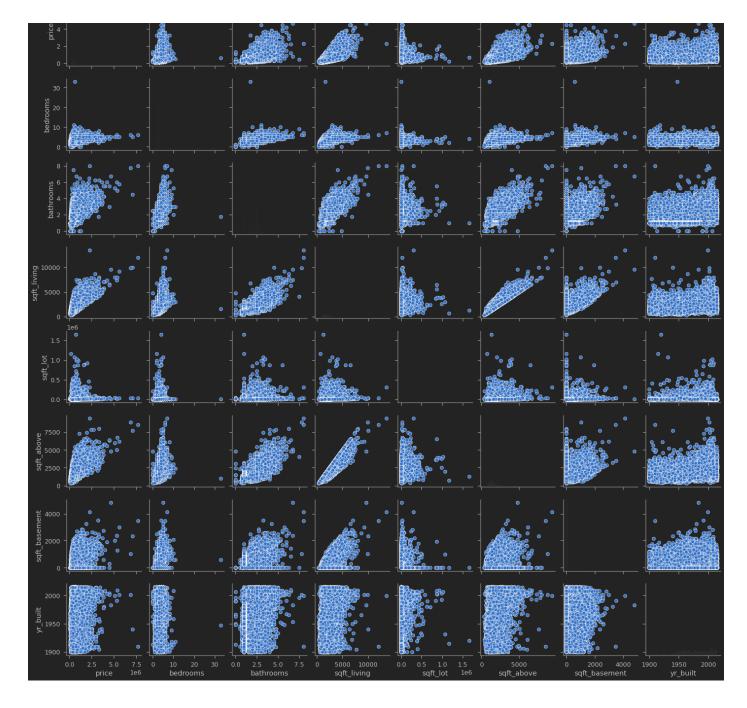
#### 1 house\_df.describe()

	id	price	bedrooms	bathrooms	sqft_living	sqft_l
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+

1 sns.pairplot(house\_df\_sample)

<seaborn.axisgrid.PairGrid at 0x7f9a3a3b96d0>





```
import tensorflow.keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

model = Sequential()
model.add(Dense(100, input_dim = 7, activation = 'relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(200, activation='relu'))
model.add(Dense(1, activation = 'linear'))

model.summary()

model.summary()
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
dense_7 (Dense)	(None, 100)	800
dense_8 (Dense)	(None, 100)	10100
dense_9 (Dense)	(None, 100)	10100
dense_10 (Dense)	(None, 200)	20200
dense_11 (Dense)	(None, 1)	201

------

Total params: 41,401 Trainable params: 41,401 Non-trainable params: 0

https://colab.research.google.com/drive/1a39blan\_dIUhTctXQQvzVYjsH1K0GBM7

```
import tensorflow.keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

model = Sequential()
model.add(Dense(10, input_dim = 19, activation = 'relu'))
model.add(Dense(10, activation = 'relu'))
model.add(Dense(200, activation = 'relu'))
model.add(Dense(200, activation = 'relu'))
model.add(Dense(1, activation = 'linear'))
model.add(Dense(1, activation = 'linear'))
```

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