Importing Libraries

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

Importing Dataset

In [2]: df=pd.read_csv("50_Startups.csv")
df

Out[2]:

	R&D Spend	Administration	Marketing Spend	State	Profit
0	165349.20	136897.80	471784.10	New York	192261.83
1	162597.70	151377.59	443898.53	California	191792.06
2	153441.51	101145.55	407934.54	Florida	191050.39
3	144372.41	118671.85	383199.62	New York	182901.99
4	142107.34	91391.77	366168.42	Florida	166187.94
5	131876.90	99814.71	362861.36	New York	156991.12
6	134615.46	147198.87	127716.82	California	156122.51
7	130298.13	145530.06	323876.68	Florida	155752.60
8	120542.52	148718.95	311613.29	New York	152211.77
9	123334.88	108679.17	304981.62	California	149759.96
10	101913.08	110594.11	229160.95	Florida	146121.95
11	100671.96	91790.61	249744.55	California	144259.40
12	93863.75	127320.38	249839.44	Florida	141585.52
13	91992.39	135495.07	252664.93	California	134307.35
14	119943.24	156547.42	256512.92	Florida	132602.65
15	114523.61	122616.84	261776.23	New York	129917.04
16	78013.11	121597.55	264346.06	California	126992.93
17	94657.16	145077.58	282574.31	New York	125370.37
18	91749.16	114175.79	294919.57	Florida	124266.90
19	86419.70	153514.11	0.00	New York	122776.86
20	76253.86	113867.30	298664.47	California	118474.03
21	78389.47	153773.43	299737.29	New York	111313.02
22	73994.56	122782.75	303319.26	Florida	110352.25
23	67532.53	105751.03	304768.73	Florida	108733.99
24	77044.01	99281.34	140574.81	New York	108552.04
25	64664.71	139553.16	137962.62	California	107404.34
26	75328.87	144135.98	134050.07	Florida	105733.54
27	72107.60	127864.55	353183.81	New York	105008.31
28	66051.52	182645.56	118148.20	Florida	103282.38
29	65605.48	153032.06	107138.38	New York	101004.64
30	61994.48	115641.28	91131.24	Florida	99937.59
31	61136.38	152701.92	88218.23	New York	97483.56
32	63408.86	129219.61	46085.25	California	97427.84
33	55493.95	103057.49	214634.81	Florida	96778.92

	R&D Spend	Administration	Marketing Spend	State	Profit
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0.00	116983.80	45173.06	California	14681.40

In [3]: df.columns=['RD_Spend',"Administration",'Marketing_Spend','State','Profit']
df

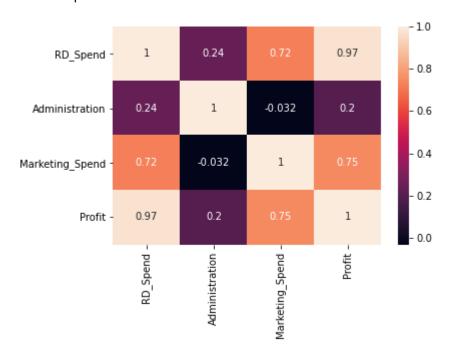
Out[3]

:		RD_Spend	Administration	Marketing_Spend	State	Profit
•	0	165349.20	136897.80	471784.10	New York	192261.83
	1	162597.70	151377.59	443898.53	California	191792.06
	2	153441.51	101145.55	407934.54	Florida	191050.39
	3	144372.41	118671.85	383199.62	New York	182901.99
	4	142107.34	91391.77	366168.42	Florida	166187.94
	5	131876.90	99814.71	362861.36	New York	156991.12
	6	134615.46	147198.87	127716.82	California	156122.51
	7	130298.13	145530.06	323876.68	Florida	155752.60
	8	120542.52	148718.95	311613.29	New York	152211.77
	9	123334.88	108679.17	304981.62	California	149759.96
	10	101913.08	110594.11	229160.95	Florida	146121.95
	11	100671.96	91790.61	249744.55	California	144259.40
	12	93863.75	127320.38	249839.44	Florida	141585.52
	13	91992.39	135495.07	252664.93	California	134307.35
	14	119943.24	156547.42	256512.92	Florida	132602.65
	15	114523.61	122616.84	261776.23	New York	129917.04
	16	78013.11	121597.55	264346.06	California	126992.93
	17	94657.16	145077.58	282574.31	New York	125370.37
	18	91749.16	114175.79	294919.57	Florida	124266.90
	19	86419.70	153514.11	0.00	New York	122776.86
	20	76253.86	113867.30	298664.47	California	118474.03
	21	78389.47	153773.43	299737.29	New York	111313.02
	22	73994.56	122782.75	303319.26	Florida	110352.25
	23	67532.53	105751.03	304768.73	Florida	108733.99
	24	77044.01	99281.34	140574.81	New York	108552.04
	25	64664.71	139553.16	137962.62	California	107404.34
	26	75328.87	144135.98	134050.07	Florida	105733.54
	27	72107.60	127864.55	353183.81	New York	105008.31
	28	66051.52	182645.56	118148.20	Florida	103282.38
	29	65605.48	153032.06	107138.38	New York	101004.64
	30	61994.48	115641.28	91131.24	Florida	99937.59
	31	61136.38	152701.92	88218.23	New York	97483.56
	32	63408.86	129219.61	46085.25	California	97427.84
	33	55493.95	103057.49	214634.81	Florida	96778.92

	RD_Spend	Administration	Marketing_Spend	State	Profit
34	46426.07	157693.92	210797.67	California	96712.80
35	46014.02	85047.44	205517.64	New York	96479.51
36	28663.76	127056.21	201126.82	Florida	90708.19
37	44069.95	51283.14	197029.42	California	89949.14
38	20229.59	65947.93	185265.10	New York	81229.06
39	38558.51	82982.09	174999.30	California	81005.76
40	28754.33	118546.05	172795.67	California	78239.91
41	27892.92	84710.77	164470.71	Florida	77798.83
42	23640.93	96189.63	148001.11	California	71498.49
43	15505.73	127382.30	35534.17	New York	69758.98
44	22177.74	154806.14	28334.72	California	65200.33
45	1000.23	124153.04	1903.93	New York	64926.08
46	1315.46	115816.21	297114.46	Florida	49490.75
47	0.00	135426.92	0.00	California	42559.73
48	542.05	51743.15	0.00	New York	35673.41
49	0.00	116983.80	45173.06	California	14681.40

In [4]: sns.heatmap(df.corr(),annot=True)

Out[4]: <AxesSubplot:>



Out[5]

:		RD_Spend	Administration	Marketing_Spend	State
	0	165349.20	136897.80	471784.10	New York
	1	162597.70	151377.59	443898.53	California
	2	153441.51	101145.55	407934.54	Florida
	3	144372.41	118671.85	383199.62	New York
	4	142107.34	91391.77	366168.42	Florida
	5	131876.90	99814.71	362861.36	New York
	6	134615.46	147198.87	127716.82	California
	7	130298.13	145530.06	323876.68	Florida
	8	120542.52	148718.95	311613.29	New York
	9	123334.88	108679.17	304981.62	California
	10	101913.08	110594.11	229160.95	Florida
	11	100671.96	91790.61	249744.55	California
	12	93863.75	127320.38	249839.44	Florida
	13	91992.39	135495.07	252664.93	California
	14	119943.24	156547.42	256512.92	Florida
	15	114523.61	122616.84	261776.23	New York
	16	78013.11	121597.55	264346.06	California
	17	94657.16	145077.58	282574.31	New York
	18	91749.16	114175.79	294919.57	Florida
	19	86419.70	153514.11	0.00	New York
	20	76253.86	113867.30	298664.47	California
	21	78389.47	153773.43	299737.29	New York
	22	73994.56	122782.75	303319.26	Florida
	23	67532.53	105751.03	304768.73	Florida
	24	77044.01	99281.34	140574.81	New York
	25	64664.71	139553.16	137962.62	California
	26	75328.87	144135.98	134050.07	Florida
	27	72107.60	127864.55	353183.81	New York
	28	66051.52	182645.56	118148.20	Florida
	29	65605.48	153032.06	107138.38	New York
	30	61994.48	115641.28	91131.24	Florida
	31	61136.38	152701.92	88218.23	New York
	32	63408.86	129219.61	46085.25	California
	33	55493.95	103057.49	214634.81	Florida

	RD_Spend	Administration	Marketing_Spend	State
34	46426.07	157693.92	210797.67	California
35	46014.02	85047.44	205517.64	New York
36	28663.76	127056.21	201126.82	Florida
37	44069.95	51283.14	197029.42	California
38	20229.59	65947.93	185265.10	New York
39	38558.51	82982.09	174999.30	California
40	28754.33	118546.05	172795.67	California
41	27892.92	84710.77	164470.71	Florida
42	23640.93	96189.63	148001.11	California
43	15505.73	127382.30	35534.17	New York
44	22177.74	154806.14	28334.72	California
45	1000.23	124153.04	1903.93	New York
46	1315.46	115816.21	297114.46	Florida
47	0.00	135426.92	0.00	California
48	542.05	51743.15	0.00	New York
49	0.00	116983.80	45173.06	California

In [6]: y=df.iloc[:,4:5]
y

Out[6]:

Profit

- 192261.83
- 191792.06
- 191050.39
- 182901.99
- 166187.94
- 156991.12
- 156122.51
- 155752.60
- 8 152211.77
- 9 149759.96
- 146121.95
- 144259.40
- 141585.52
- 134307.35
- 132602.65
- 129917.04
- 126992.93
- 125370.37
- 124266.90
- 122776.86
- 118474.03
- 111313.02
- 110352.25
- 108733.99
- 24 108552.04
- 107404.34
- 105733.54
- 105008.31
- 103282.38
- 101004.64
- 99937.59
- 97483.56
- 97427.84
- 96778.92

- 96712.80
- 96479.51
- 90708.19
- 89949.14
- 81229.06
- 81005.76
- 78239.91
- 77798.83
- 71498.49
- 69758.98
- 44 65200.33
- 64926.08
- 46 49490.75
- 42559.73
- 35673.41
- 14681.40

Performing Label Encoding

In []: from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()

```
In [8]: x['State']=le.fit transform(x['State'])
 Out[8]:
              RD_Spend Administration
                                      Marketing_Spend
              165349.20
                            136897.80
                                            471784.10
                                                         2
               162597.70
                            151377.59
                                            443898.53
                                                         0
            2
               153441.51
                            101145.55
                                            407934.54
                                                         1
            3
              144372.41
                            118671.85
                                            383199.62
                                                         2
                             91391.77
                                            366168.42
              142107.34
                                                         1
                                                         2
              131876.90
                             99814.71
                                            362861.36
               134615.46
                            147198.87
                                            127716.82
              130298.13
            7
                            145530.06
                                            323876.68
                                                         1
              120542.52
                                                         2
            8
                            148718.95
                                            311613.29
              123334.88
                            108679.17
                                            304981.62
                                                         0
           10
              101913.08
                             110594.11
                                            229160.95
                                                         1
               100671.96
                             91790.61
                                            249744.55
                                                         0
 In [9]: x.shape
 Out[9]: (50, 4)
         # Performing Sequential Operations
In [10]: from keras.layers.core import Dense
In [13]: from numpy import loadtxt
          from keras.models import Sequential
In [14]:
         model=Sequential()
          model.add(Dense(12,input_dim=4,kernel_initializer='normal',activation='relu'))
          model.add(Dense(8,kernel_initializer='normal',activation='relu'))
          model.add(Dense(1,kernel initializer='normal'))
In [15]: model.compile(loss='mean squared error',optimizer='adam')
In [16]: model
Out[16]: <tensorflow.python.keras.engine.sequential.Sequential at 0x1a48d649160>
         # Fitting the Model
```

In [19]: model.fit(x,y,epochs=500,batch_size=10)

```
Epoch 1/500
5/5 [============= ] - 0s 989us/step - loss: 179712944.0000
Epoch 2/500
Epoch 3/500
Epoch 4/500
Epoch 5/500
Epoch 6/500
Epoch 7/500
Epoch 8/500
Epoch 9/500
Epoch 10/500
5/5 [============ ] - 0s 1ms/step - loss: 177832496.0000
Epoch 11/500
5/5 [============= ] - 0s 979us/step - loss: 180587936.0000
Epoch 12/500
Epoch 13/500
5/5 [================ ] - 0s 1ms/step - loss: 179216080.0000
Epoch 14/500
5/5 [=============== ] - 0s 848us/step - loss: 177704304.0000
Epoch 15/500
5/5 [============ ] - 0s 1ms/step - loss: 177549840.0000
Epoch 16/500
Epoch 17/500
5/5 [=============== - - os 1ms/step - loss: 180217360.0000
Epoch 18/500
Epoch 19/500
5/5 [================ ] - 0s 1ms/step - loss: 179426384.0000
Epoch 20/500
Epoch 21/500
Epoch 22/500
5/5 [============ ] - 0s 1ms/step - loss: 178166944.0000
Epoch 23/500
Epoch 24/500
5/5 [================ ] - 0s 1ms/step - loss: 178853808.0000
Epoch 25/500
Epoch 26/500
5/5 [============ ] - 0s 1ms/step - loss: 178358544.0000
Epoch 27/500
5/5 [================ ] - 0s 1ms/step - loss: 177853008.0000
```

```
Epoch 28/500
Epoch 29/500
5/5 [============= ] - 0s 997us/step - loss: 177672688.0000
Epoch 30/500
5/5 [================ ] - 0s 1ms/step - loss: 181289248.0000
Epoch 31/500
Epoch 32/500
Epoch 33/500
5/5 [================= ] - 0s 1ms/step - loss: 178046000.0000
Epoch 34/500
Epoch 35/500
Epoch 36/500
Epoch 37/500
Epoch 38/500
Epoch 39/500
5/5 [=========== ] - 0s 1ms/step - loss: 177159696.0000
Epoch 40/500
Epoch 41/500
Epoch 42/500
Epoch 43/500
Epoch 44/500
5/5 [============== ] - ETA: 0s - loss: 222743808.000 - 0s 997u
s/step - loss: 178540912.0000
Epoch 45/500
5/5 [===========] - 0s 970us/step - loss: 178018912.0000
Epoch 46/500
5/5 [============= ] - 0s 858us/step - loss: 178674560.0000
Epoch 47/500
Epoch 48/500
Epoch 49/500
Epoch 50/500
5/5 [================ ] - 0s 2ms/step - loss: 177502624.0000
Epoch 51/500
5/5 [=========== ] - 0s 1ms/step - loss: 184402896.0000
Epoch 52/500
Epoch 53/500
5/5 [================ ] - 0s 1ms/step - loss: 184805088.0000
Epoch 54/500
Epoch 55/500
```

```
Epoch 56/500
Epoch 57/500
5/5 [============ ] - 0s 1ms/step - loss: 178428400.0000
Epoch 58/500
Epoch 59/500
5/5 [============ ] - 0s 1ms/step - loss: 178940480.0000
Epoch 60/500
Epoch 61/500
Epoch 62/500
Epoch 63/500
Epoch 64/500
Epoch 65/500
Epoch 66/500
Epoch 67/500
Epoch 68/500
Epoch 69/500
5/5 [================ ] - 0s 1ms/step - loss: 178176464.0000
Epoch 70/500
Epoch 71/500
Epoch 72/500
Epoch 73/500
Epoch 74/500
Epoch 75/500
5/5 [================ ] - 0s 1ms/step - loss: 178719808.0000
Epoch 76/500
Epoch 77/500
Epoch 78/500
Epoch 79/500
Epoch 80/500
Epoch 81/500
5/5 [============ ] - 0s 2ms/step - loss: 178705472.0000
Epoch 82/500
Epoch 83/500
5/5 [================ ] - 0s 1ms/step - loss: 178118432.0000
Epoch 84/500
```

```
Epoch 85/500
Epoch 86/500
Epoch 87/500
5/5 [============= ] - 0s 942us/step - loss: 182938240.0000
Epoch 88/500
Epoch 89/500
5/5 [================== ] - 0s 1ms/step - loss: 179928576.0000
Epoch 90/500
5/5 [============ ] - 0s 1ms/step - loss: 179325744.0000
Epoch 91/500
Epoch 92/500
Epoch 93/500
Epoch 94/500
Epoch 95/500
Epoch 96/500
5/5 [================ ] - 0s 1ms/step - loss: 179401296.0000
Epoch 97/500
5/5 [============== - - 0s 2ms/step - loss: 179163088.0000
Epoch 98/500
5/5 [=========== ] - 0s 1ms/step - loss: 178721600.0000
Epoch 99/500
5/5 [================ ] - 0s 1ms/step - loss: 178552960.0000
Epoch 100/500
5/5 [================ ] - 0s 809us/step - loss: 178345200.0000
Epoch 101/500
Epoch 102/500
5/5 [============ ] - 0s 895us/step - loss: 177912224.0000
Epoch 103/500
Epoch 104/500
5/5 [============ ] - 0s 758us/step - loss: 177795792.0000
Epoch 105/500
Epoch 106/500
5/5 [=============== ] - 0s 921us/step - loss: 178135248.0000
Epoch 107/500
5/5 [================= ] - 0s 1ms/step - loss: 177964112.0000
Epoch 108/500
Epoch 109/500
Epoch 110/500
5/5 [================ ] - 0s 882us/step - loss: 181360928.0000
Epoch 111/500
5/5 [============ ] - 0s 1ms/step - loss: 178303760.0000
Epoch 112/500
5/5 [============ ] - 0s 1ms/step - loss: 178452256.0000
```

```
Epoch 113/500
Epoch 114/500
Epoch 115/500
Epoch 116/500
Epoch 117/500
Epoch 118/500
Epoch 119/500
5/5 [=========== ] - 0s 1ms/step - loss: 178613904.0000
Epoch 120/500
Epoch 121/500
Epoch 122/500
Epoch 123/500
Epoch 124/500
5/5 [============ ] - 0s 1ms/step - loss: 178485520.0000
Epoch 125/500
Epoch 126/500
5/5 [================ ] - 0s 819us/step - loss: 177660144.0000
Epoch 127/500
Epoch 128/500
5/5 [=========== ] - 0s 1ms/step - loss: 177949696.0000
Epoch 129/500
Epoch 130/500
5/5 [============ ] - 0s 1ms/step - loss: 178645504.0000
Epoch 131/500
Epoch 132/500
5/5 [================ ] - 0s 1ms/step - loss: 178196160.0000
Epoch 133/500
Epoch 134/500
Epoch 135/500
Epoch 136/500
Epoch 137/500
5/5 [================ ] - 0s 2ms/step - loss: 178660224.0000
Epoch 138/500
5/5 [============== ] - 0s 1ms/step - loss: 177624304.0000
Epoch 139/500
Epoch 140/500
5/5 [================ ] - 0s 2ms/step - loss: 178439184.0000
Epoch 141/500
```

```
5/5 [============ ] - 0s 1ms/step - loss: 177270640.0000
Epoch 142/500
Epoch 143/500
5/5 [============== - - 0s 1ms/step - loss: 177981280.0000
Epoch 144/500
Epoch 145/500
Epoch 146/500
5/5 [================== ] - 0s 1ms/step - loss: 178324704.0000
Epoch 147/500
Epoch 148/500
5/5 [================ ] - 0s 1ms/step - loss: 179342320.0000
Epoch 149/500
Epoch 150/500
Epoch 151/500
Epoch 152/500
Epoch 153/500
Epoch 154/500
5/5 [============== ] - 0s 1ms/step - loss: 177970528.0000
Epoch 155/500
Epoch 156/500
Epoch 157/500
5/5 [============== ] - 0s 1ms/step - loss: 177933664.0000
Epoch 158/500
5/5 [============= ] - 0s 987us/step - loss: 178550464.0000
Epoch 159/500
5/5 [=========== ] - 0s 2ms/step - loss: 178295680.0000
Epoch 160/500
5/5 [============ ] - 0s 1ms/step - loss: 178164448.0000
Epoch 161/500
Epoch 162/500
Epoch 163/500
Epoch 164/500
5/5 [================ ] - 0s 2ms/step - loss: 177751280.0000
Epoch 165/500
5/5 [============ ] - 0s 1ms/step - loss: 178377360.0000
Epoch 166/500
Epoch 167/500
5/5 [================ ] - 0s 1ms/step - loss: 177752304.0000
Epoch 168/500
Epoch 169/500
```

```
Epoch 170/500
Epoch 171/500
Epoch 172/500
5/5 [================ ] - 0s 1ms/step - loss: 179125776.0000
Epoch 173/500
Epoch 174/500
Epoch 175/500
Epoch 176/500
5/5 [============= ] - 0s 862us/step - loss: 180728000.0000
Epoch 177/500
Epoch 178/500
Epoch 179/500
Epoch 180/500
Epoch 181/500
Epoch 182/500
Epoch 183/500
Epoch 184/500
Epoch 185/500
Epoch 186/500
Epoch 187/500
5/5 [============= ] - 0s 797us/step - loss: 179286080.0000
Epoch 188/500
5/5 [================ ] - 0s 1ms/step - loss: 178360080.0000
Epoch 189/500
Epoch 190/500
Epoch 191/500
5/5 [============= ] - 0s 996us/step - loss: 177673584.0000
Epoch 192/500
Epoch 193/500
Epoch 194/500
Epoch 195/500
Epoch 196/500
5/5 [================ ] - 0s 1ms/step - loss: 177920720.0000
Epoch 197/500
5/5 [================ ] - 0s 997us/step - loss: 178555520.0000
```

```
Epoch 198/500
Epoch 199/500
Epoch 200/500
5/5 [================ ] - 0s 1ms/step - loss: 177681936.0000
Epoch 201/500
Epoch 202/500
Epoch 203/500
Epoch 204/500
5/5 [=========== ] - 0s 1ms/step - loss: 178753344.0000
Epoch 205/500
Epoch 206/500
Epoch 207/500
5/5 [============= ] - 0s 771us/step - loss: 181476640.0000
Epoch 208/500
Epoch 209/500
Epoch 210/500
Epoch 211/500
Epoch 212/500
5/5 [============ ] - 0s 1ms/step - loss: 177308000.0000
Epoch 213/500
Epoch 214/500
Epoch 215/500
5/5 [============ ] - 0s 1ms/step - loss: 177888544.0000
Epoch 216/500
Epoch 217/500
5/5 [============ ] - 0s 1ms/step - loss: 178134944.0000
Epoch 218/500
Epoch 219/500
Epoch 220/500
Epoch 221/500
Epoch 222/500
5/5 [================ ] - 0s 1ms/step - loss: 177613232.0000
Epoch 223/500
5/5 [============== ] - 0s 1ms/step - loss: 178210576.0000
Epoch 224/500
5/5 [============ ] - 0s 1ms/step - loss: 177777856.0000
Epoch 225/500
5/5 [================ ] - 0s 1ms/step - loss: 177719296.0000
Epoch 226/500
```

```
Epoch 227/500
5/5 [=========== ] - 0s 1ms/step - loss: 177493968.0000
Epoch 228/500
5/5 [=============== ] - 0s 990us/step - loss: 178952432.0000
Epoch 229/500
Epoch 230/500
5/5 [================ ] - 0s 1ms/step - loss: 179196192.0000
Epoch 231/500
Epoch 232/500
Epoch 233/500
Epoch 234/500
Epoch 235/500
5/5 [============== ] - 0s 977us/step - loss: 178720720.0000
Epoch 236/500
5/5 [================ ] - 0s 1ms/step - loss: 178755136.0000
Epoch 237/500
Epoch 238/500
5/5 [================ ] - 0s 1ms/step - loss: 178234048.0000
Epoch 239/500
5/5 [============== - - 0s 1ms/step - loss: 178775280.0000
Epoch 240/500
5/5 [=========== ] - 0s 2ms/step - loss: 178190944.0000
Epoch 241/500
Epoch 242/500
5/5 [============== - - 0s 1ms/step - loss: 177741872.0000
Epoch 243/500
Epoch 244/500
Epoch 245/500
Epoch 246/500
5/5 [=========== ] - 0s 1ms/step - loss: 178318896.0000
Epoch 247/500
Epoch 248/500
5/5 [============== - - os 1ms/step - loss: 181917040.0000
Epoch 249/500
5/5 [================ ] - 0s 1ms/step - loss: 179480944.0000
Epoch 250/500
Epoch 251/500
5/5 [============ ] - 0s 1ms/step - loss: 179879888.0000
Epoch 252/500
Epoch 253/500
Epoch 254/500
5/5 [============= ] - 0s 952us/step - loss: 178574144.0000
```

```
Epoch 255/500
Epoch 256/500
Epoch 257/500
5/5 [================ ] - 0s 933us/step - loss: 179088320.0000
Epoch 258/500
Epoch 259/500
5/5 [=========== ] - 0s 1ms/step - loss: 177775536.0000
Epoch 260/500
5/5 [============= ] - 0s 970us/step - loss: 178031840.0000
Epoch 261/500
Epoch 262/500
Epoch 263/500
Epoch 264/500
Epoch 265/500
5/5 [============ ] - 0s 1ms/step - loss: 178227440.0000
Epoch 266/500
Epoch 267/500
Epoch 268/500
Epoch 269/500
Epoch 270/500
5/5 [============= ] - 0s 942us/step - loss: 180059888.0000
Epoch 271/500
5/5 [============= ] - 0s 694us/step - loss: 178167792.0000
Epoch 272/500
5/5 [============= ] - 0s 893us/step - loss: 180176240.0000
Epoch 273/500
Epoch 274/500
5/5 [============ ] - 0s 1ms/step - loss: 178047440.0000
Epoch 275/500
Epoch 276/500
5/5 [============ ] - 0s 1ms/step - loss: 178958576.0000
Epoch 277/500
Epoch 278/500
5/5 [=========== ] - 0s 1ms/step - loss: 178278560.0000
Epoch 279/500
Epoch 280/500
Epoch 281/500
Epoch 282/500
5/5 [================ ] - 0s 1ms/step - loss: 177889728.0000
Epoch 283/500
```

```
Epoch 284/500
Epoch 285/500
5/5 [=============== ] - 0s 958us/step - loss: 177951584.0000
Epoch 286/500
5/5 [============ ] - 0s 2ms/step - loss: 178587296.0000
Epoch 287/500
Epoch 288/500
5/5 [================== ] - 0s 1ms/step - loss: 178359360.0000
Epoch 289/500
Epoch 290/500
5/5 [================ ] - 0s 1ms/step - loss: 178033200.0000
Epoch 291/500
Epoch 292/500
Epoch 293/500
Epoch 294/500
Epoch 295/500
5/5 [================ ] - 0s 1ms/step - loss: 177720528.0000
Epoch 296/500
5/5 [================ ] - 0s 744us/step - loss: 178222816.0000
Epoch 297/500
Epoch 298/500
Epoch 299/500
5/5 [============== - - 0s 1ms/step - loss: 178433808.0000
Epoch 300/500
Epoch 301/500
Epoch 302/500
5/5 [=========== ] - 0s 1ms/step - loss: 179194560.0000
Epoch 303/500
Epoch 304/500
Epoch 305/500
5/5 [============== ] - 0s 1ms/step - loss: 178179488.0000
Epoch 306/500
5/5 [================ ] - 0s 1ms/step - loss: 178612544.0000
Epoch 307/500
5/5 [============ ] - 0s 1ms/step - loss: 179348704.0000
Epoch 308/500
Epoch 309/500
5/5 [================ ] - 0s 1ms/step - loss: 178864176.0000
Epoch 310/500
Epoch 311/500
```

```
Epoch 312/500
Epoch 313/500
Epoch 314/500
Epoch 315/500
Epoch 316/500
Epoch 317/500
5/5 [================ ] - 0s 1ms/step - loss: 178648896.0000
Epoch 318/500
Epoch 319/500
Epoch 320/500
Epoch 321/500
5/5 [============= ] - 0s 956us/step - loss: 180208352.0000
Epoch 322/500
5/5 [============ ] - 0s 1ms/step - loss: 178615424.0000
Epoch 323/500
Epoch 324/500
Epoch 325/500
Epoch 326/500
Epoch 327/500
Epoch 328/500
Epoch 329/500
Epoch 330/500
Epoch 331/500
5/5 [================ ] - 0s 1ms/step - loss: 177866336.0000
Epoch 332/500
5/5 [=========== ] - 0s 1ms/step - loss: 177744432.0000
Epoch 333/500
Epoch 334/500
5/5 [============= ] - 0s 926us/step - loss: 177942576.0000
Epoch 335/500
5/5 [============ ] - 0s 845us/step - loss: 177760032.0000
Epoch 336/500
Epoch 337/500
5/5 [============== ] - 0s 1ms/step - loss: 177977424.0000
Epoch 338/500
Epoch 339/500
Epoch 340/500
```

```
Epoch 341/500
5/5 [============ ] - 0s 1ms/step - loss: 178186144.0000
Epoch 342/500
5/5 [=============== ] - 0s 871us/step - loss: 178453232.0000
Epoch 343/500
5/5 [=========== ] - 0s 1ms/step - loss: 177767264.0000
Epoch 344/500
5/5 [================ ] - 0s 1ms/step - loss: 178863520.0000
Epoch 345/500
Epoch 346/500
5/5 [=========== ] - 0s 1ms/step - loss: 178146752.0000
Epoch 347/500
Epoch 348/500
5/5 [============= ] - 0s 966us/step - loss: 177672544.0000
Epoch 349/500
Epoch 350/500
5/5 [================ ] - 0s 1ms/step - loss: 178357776.0000
Epoch 351/500
Epoch 352/500
5/5 [=============== ] - 0s 1ms/step - loss: 178024864.0000
Epoch 353/500
5/5 [============== - - 0s 1ms/step - loss: 179337312.0000
Epoch 354/500
5/5 [=========== ] - 0s 1ms/step - loss: 179148640.0000
Epoch 355/500
Epoch 356/500
5/5 [=============== ] - 0s 880us/step - loss: 179300624.0000
Epoch 357/500
5/5 [============ ] - 0s 1ms/step - loss: 178523504.0000
Epoch 358/500
Epoch 359/500
5/5 [=========== ] - 0s 1ms/step - loss: 179192000.0000
Epoch 360/500
Epoch 361/500
Epoch 362/500
5/5 [============== - - os 1ms/step - loss: 180387904.0000
Epoch 363/500
Epoch 364/500
5/5 [============ ] - 0s 1ms/step - loss: 177639488.0000
Epoch 365/500
5/5 [============== ] - 0s 1ms/step - loss: 177549088.0000
Epoch 366/500
5/5 [================ ] - 0s 981us/step - loss: 177772464.0000
Epoch 367/500
5/5 [============= ] - 0s 917us/step - loss: 178712192.0000
Epoch 368/500
```

```
Epoch 369/500
Epoch 370/500
5/5 [============ ] - 0s 2ms/step - loss: 178741984.0000
Epoch 371/500
Epoch 372/500
Epoch 373/500
Epoch 374/500
Epoch 375/500
5/5 [============= ] - 0s 977us/step - loss: 179115136.0000
Epoch 376/500
Epoch 377/500
5/5 [============= ] - 0s 945us/step - loss: 177532720.0000
Epoch 378/500
Epoch 379/500
Epoch 380/500
5/5 [============== - - os 1ms/step - loss: 177366976.0000
Epoch 381/500
Epoch 382/500
5/5 [================ ] - 0s 1ms/step - loss: 178237872.0000
Epoch 383/500
5/5 [============== - - os 1ms/step - loss: 181091136.0000
Epoch 384/500
5/5 [============ ] - 0s 1ms/step - loss: 178362320.0000
Epoch 385/500
Epoch 386/500
5/5 [=========== ] - 0s 1ms/step - loss: 178246368.0000
Epoch 387/500
Epoch 388/500
Epoch 389/500
5/5 [============ ] - 0s 2ms/step - loss: 186462704.0000
Epoch 390/500
Epoch 391/500
5/5 [============== ] - 0s 1ms/step - loss: 178745184.0000
Epoch 392/500
Epoch 393/500
Epoch 394/500
Epoch 395/500
5/5 [============= ] - 0s 957us/step - loss: 178711712.0000
Epoch 396/500
```

```
Epoch 397/500
5/5 [=========== ] - 0s 1ms/step - loss: 178949488.0000
Epoch 398/500
5/5 [============== - - 0s 1ms/step - loss: 178247088.0000
Epoch 399/500
5/5 [============ ] - 0s 1ms/step - loss: 178944752.0000
Epoch 400/500
Epoch 401/500
5/5 [========================= ] - 0s 899us/step - loss: 182984256.0000
Epoch 402/500
5/5 [============= ] - 0s 959us/step - loss: 177873472.0000
Epoch 403/500
5/5 [================ ] - 0s 1ms/step - loss: 177863616.0000
Epoch 404/500
Epoch 405/500
Epoch 406/500
Epoch 407/500
Epoch 408/500
5/5 [================ ] - 0s 1ms/step - loss: 179061616.0000
Epoch 409/500
5/5 [=========== ] - 0s 1ms/step - loss: 179739968.0000
Epoch 410/500
5/5 [============= ] - 0s 859us/step - loss: 177862960.0000
Epoch 411/500
5/5 [================ ] - 0s 1ms/step - loss: 179338192.0000
Epoch 412/500
5/5 [============== ] - 0s 1ms/step - loss: 178726464.0000
Epoch 413/500
Epoch 414/500
Epoch 415/500
Epoch 416/500
5/5 [============ ] - 0s 1ms/step - loss: 179167296.0000
Epoch 417/500
Epoch 418/500
5/5 [============== - - os 1ms/step - loss: 179253120.0000
Epoch 419/500
5/5 [=============== ] - 0s 1ms/step - loss: 184539184.0000
Epoch 420/500
Epoch 421/500
Epoch 422/500
5/5 [================ ] - 0s 1ms/step - loss: 178605264.0000
Epoch 423/500
Epoch 424/500
```

```
Epoch 425/500
Epoch 426/500
Epoch 427/500
5/5 [================ ] - 0s 1ms/step - loss: 178976048.0000
Epoch 428/500
5/5 [=========== ] - 0s 2ms/step - loss: 178398496.0000
Epoch 429/500
Epoch 430/500
5/5 [================ ] - 0s 1ms/step - loss: 178710016.0000
Epoch 431/500
Epoch 432/500
Epoch 433/500
Epoch 434/500
Epoch 435/500
5/5 [============ ] - 0s 1ms/step - loss: 179168640.0000
Epoch 436/500
Epoch 437/500
Epoch 438/500
Epoch 439/500
Epoch 440/500
Epoch 441/500
Epoch 442/500
Epoch 443/500
Epoch 444/500
Epoch 445/500
Epoch 446/500
Epoch 447/500
Epoch 448/500
5/5 [============= ] - 0s 976us/step - loss: 180173536.0000
Epoch 449/500
5/5 [================ ] - 0s 1ms/step - loss: 179291712.0000
Epoch 450/500
Epoch 451/500
Epoch 452/500
5/5 [================ ] - 0s 1ms/step - loss: 177874048.0000
Epoch 453/500
```

```
Epoch 454/500
Epoch 455/500
5/5 [============== - - 0s 1ms/step - loss: 177722560.0000
Epoch 456/500
Epoch 457/500
Epoch 458/500
5/5 [================== ] - 0s 1ms/step - loss: 178920880.0000
Epoch 459/500
Epoch 460/500
Epoch 461/500
Epoch 462/500
5/5 [============ ] - 0s 1ms/step - loss: 177471040.0000
Epoch 463/500
Epoch 464/500
Epoch 465/500
Epoch 466/500
5/5 [============== - - 0s 2ms/step - loss: 178609152.0000
Epoch 467/500
5/5 [=========== ] - 0s 1ms/step - loss: 178437424.0000
Epoch 468/500
Epoch 469/500
5/5 [============== - - 0s 1ms/step - loss: 178770432.0000
Epoch 470/500
5/5 [=========== ] - 0s 1ms/step - loss: 179040544.0000
Epoch 471/500
Epoch 472/500
Epoch 473/500
Epoch 474/500
Epoch 475/500
5/5 [============== - - os 1ms/step - loss: 178810816.0000
Epoch 476/500
5/5 [================ ] - 0s 2ms/step - loss: 179423008.0000
Epoch 477/500
Epoch 478/500
Epoch 479/500
5/5 [================ ] - 0s 2ms/step - loss: 178909936.0000
Epoch 480/500
Epoch 481/500
5/5 [============ ] - 0s 1ms/step - loss: 179647856.0000
```

```
Epoch 482/500
Epoch 483/500
Epoch 484/500
Epoch 485/500
Epoch 486/500
Epoch 487/500
5/5 [================ ] - 0s 1ms/step - loss: 178027104.0000
Epoch 488/500
5/5 [============= ] - 0s 914us/step - loss: 182745296.0000
Epoch 489/500
Epoch 490/500
5/5 [============= ] - 0s 651us/step - loss: 177530352.0000
Epoch 491/500
Epoch 492/500
Epoch 493/500
Epoch 494/500
5/5 [============= ] - 0s 796us/step - loss: 177935792.0000
Epoch 495/500
5/5 [================ ] - 0s 1ms/step - loss: 179142160.0000
Epoch 496/500
Epoch 497/500
Epoch 498/500
Epoch 499/500
Epoch 500/500
```

Out[19]: <tensorflow.python.keras.callbacks.History at 0x1a48ec84400>

Predicting the output

```
In [26]: |y_pred=model.predict(x)
         y_pred
Out[26]: array([[201475.5
                            ],
                 [201956.5
                [176081.72],
                 [173299.45],
                 [161384.47],
                 [156542.64],
                [154832.58],
                 [167158.97],
                 [160220.03],
                [148604.34],
                 [127725.39],
                 [122370.61],
                [129103.75],
                 [130658.734],
                [157860.12],
                 [143335.84],
                 [117063.34],
                 [138134.33],
                 [126966.82],
                 [112000.086],
                [116072.58],
                 [130720.96],
                 [117746.81],
                 [107678.516],
                 [ 99021.94 ],
                 [103084.016],
                 [111900.56],
                 [122114.51],
                [116533.69],
                 [105655.805],
                 [ 89560.2 ],
                [100808.74],
                 91336.9
                 [ 90846.266],
                [101871.63],
                 [ 77441.28 ],
                 [ 78369.47 ],
                [ 64331.477],
                  51097.094],
                 [ 68939.49 ],
                 [73348.4],
                 [ 61013.516],
                [ 60372.59 ],
                [ 55585.297],
                 [ 68721.766],
                 [ 41408.848],
                 [ 62927.965],
                 [ 44211.203],
                 [ 17290.967],
                 [ 41866.48 ]], dtype=float32)
```

75000 100000 125000 150000 175000 200000

In []:

25000

25000

50000