

# Homework 7. Deep Learning

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### Step 1 - Description

This notebook performs regression to estimate the price of a car given various features.

### Step 2 - Load the data

- \* upload the data
- \* put the data in a pandas dataframe
- \* output the data shape (rows, cols)
- \* output the first few rows of the data

```
In [2]: from google.colab import files
from sklearn.preprocessing import MinMaxScaler, LabelBinarizer
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r
2_score
from keras import models
from keras import layers
from matplotlib import pyplot
from keras.models import Sequential

import seaborn as sb
import pandas as pd
import plotly.express as px
import numpy as np
import matplotlib.pyplot as plt
import math
```

```
In [3]: # reading and print the data dimensions rows and columns
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/audi.csv')

print('\n Data fram dimensions: Rows - Columns', df.shape)
```

Data fram dimensions: Rows - Columns (10668, 9)

```
In [4]: # printing data head
df.head
```

```
Out[4]: <bound method NDFrame.head of          model  year  price transmission
mileage fuelType  tax   mpg  engineSize
0          A1  2017  12500         Manual    15735   Petrol   150   55.4
1.4
1          A6  2016  16500      Automatic    36203   Diesel    20   64.2
2.0
2          A1  2016  11000         Manual    29946   Petrol    30   55.4
1.4
3          A4  2017  16800      Automatic    25952   Diesel   145   67.3
2.0
4          A3  2019  17300         Manual     1998   Petrol   145   49.6
1.0
...         ...    ...    ...         ...    ...    ...    ...    ...
...
10663       A3  2020  16999         Manual     4018   Petrol   145   49.6
1.0
10664       A3  2020  16999         Manual     1978   Petrol   150   49.6
1.0
10665       A3  2020  17199         Manual        609   Petrol   150   49.6
1.0
10666       Q3  2017  19499      Automatic     8646   Petrol   150   47.9
1.4
10667       Q3  2016  15999         Manual    11855   Petrol   150   47.9
1.4

[10668 rows x 9 columns]>
```

### Step 3 - Data Exploration

- \* print data type.
- \* change categorical column type from object to category.
- \* check for NAs.
- \* use describe() to examine the data.
- \* lineplot year and price.
- \* create another plot exploring the data.

```
In [5]: # data types
df.dtypes
```

```
Out[5]: model          object
        year          int64
        price         int64
        transmission   object
        mileage        int64
        fuelType       object
        tax            int64
        mpg            float64
        engineSize     float64
        dtype: object
```

```
In [6]: # changing categorical columns
df.model = df.model.astype('category')
df.transmission = df.transmission.astype('category')
df.fuelType = df.fuelType.astype('category')
```

```
In [7]: # check for NA's
df.isnull().sum()
```

```
Out[7]: model          0
        year          0
        price          0
        transmission   0
        mileage        0
        fuelType       0
        tax            0
        mpg            0
        engineSize     0
        dtype: int64
```

```
In [8]: # data describe
df.describe(include='all')
```

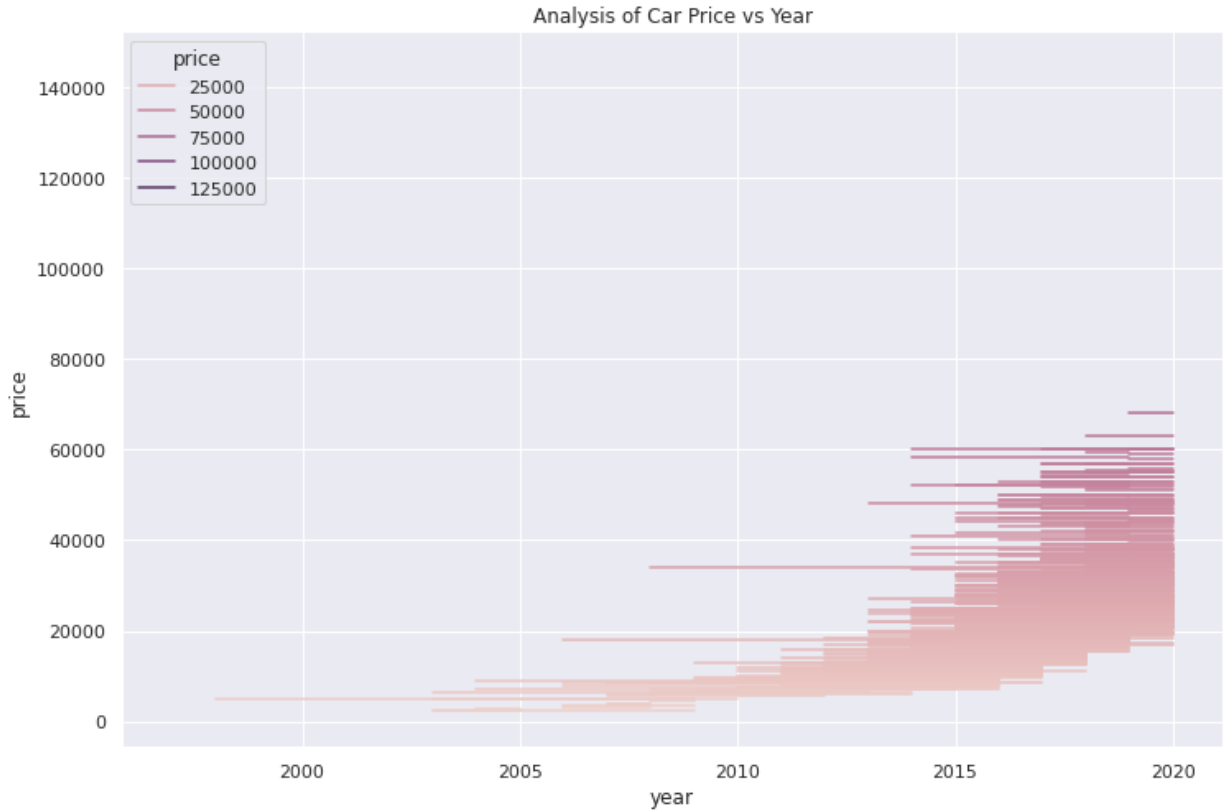
Out[8]:

	model	year	price	transmission	mileage	fuelType	
<b>count</b>	10668	10668.000000	10668.000000	10668	10668.000000	10668	10668.000
<b>unique</b>	26	NaN	NaN	3	NaN	3	↑
<b>top</b>	A3	NaN	NaN	Manual	NaN	Diesel	↑
<b>freq</b>	1929	NaN	NaN	4369	NaN	5577	↑
<b>mean</b>	NaN	2017.100675	22896.685039	NaN	24827.244001	NaN	126.011
<b>std</b>	NaN	2.167494	11714.841888	NaN	23505.257205	NaN	67.170
<b>min</b>	NaN	1997.000000	1490.000000	NaN	1.000000	NaN	0.000
<b>25%</b>	NaN	2016.000000	15130.750000	NaN	5968.750000	NaN	125.000
<b>50%</b>	NaN	2017.000000	20200.000000	NaN	19000.000000	NaN	145.000
<b>75%</b>	NaN	2019.000000	27990.000000	NaN	36464.500000	NaN	145.000
<b>max</b>	NaN	2020.000000	145000.000000	NaN	323000.000000	NaN	580.000

```
In [9]: # using seaborn, craete a lineplot() with year on the x axis and price
on the y axis
sb.set(rc = {'figure.figsize':(12,8)})

sb.lineplot(
    data=df,
    x= "year", y= "price", hue= "price",
    markers=True, dashes=False
).set(title= "Analysis of Car Price vs Year")
```

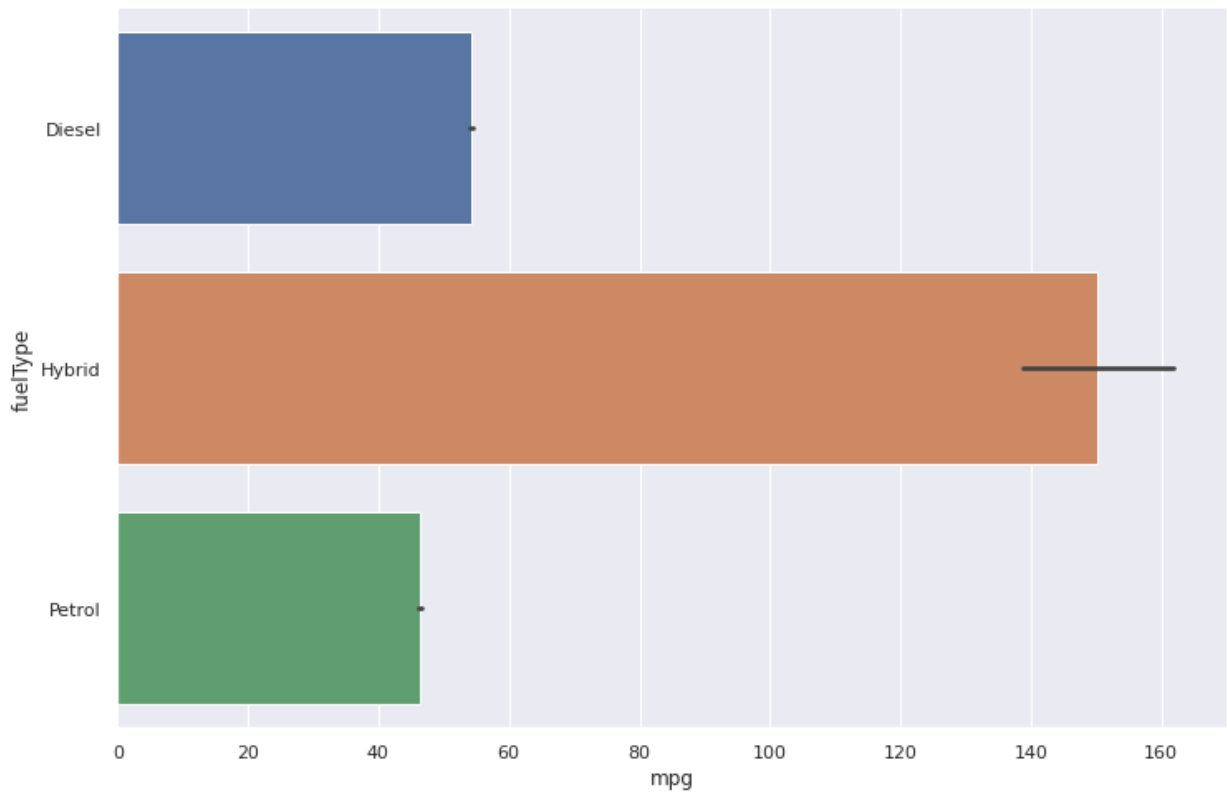
Out[9]: [Text(0.5, 1.0, 'Analysis of Car Price vs Year')]



```
In [ ]: # checking the engineSize vs mpg
fig = sb.lineplot(df, x="mpg", y="fuelType", color="fuelType", width=906, height=675,
                  title= 'Analisiss of Fuel Type vs MPG',
                  labels= dict(mpg= 'Miles per Gallon', fuelType= 'Fuel Type'))
fig.show()
```

```
In [29]: sb.barplot(data=df, x="mpg", y="fuelType")
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4590344390>
```



## Step 4 - Prepare Data

- \* set up x and y.
- \* scale the numeric data.
- \* one-hot encode the categorical data for model, transmission, and fuelType
- \* concatenate and print the train.

```
In [11]: # set up X and y
X = df.drop(columns=['price'],axis=1)
y = df['price']

X = X.apply(pd.to_numeric, errors='coerce')
Y = y.apply(pd.to_numeric, errors='coerce')

X.fillna(0, inplace=True)
Y.fillna(0, inplace=True)

X_train,X_test,y_train,y_test=train_test_split(X, y, test_size=0.2)
```

```
In [12]: # scale the numeric data
col_list = ['year', 'mileage', 'tax', 'mpg', 'engineSize']
scaler = MinMaxScaler()
train_numeric = scaler.fit_transform(X_train[col_list])
test_numeric = scaler.transform(X_test[col_list])
```

```
In [13]: # one-hot encode the categorical data for model, transmission, and fuelType

# model
zipBinarizer = LabelBinarizer().fit(df['model'])
train_model = zipBinarizer.transform(X_train['model'])
test_model = zipBinarizer.transform(X_test['model'])

# transmission
zipBinarizer = LabelBinarizer().fit(df['transmission'])
train_transmission = zipBinarizer.transform(X_train['transmission'])
test_transmission = zipBinarizer.transform(X_test['transmission'])

# fuelType
zipBinarizer = LabelBinarizer().fit(df['fuelType'])
train_fuelType = zipBinarizer.transform(X_train['fuelType'])
test_fuelType = zipBinarizer.transform(X_test['fuelType'])
```

```
/usr/local/lib/python3.7/dist-packages/numpy/lib/arraysetops.py:608:  
FutureWarning:
```

```
elementwise comparison failed; returning scalar instead, but in the  
future will perform elementwise comparison
```

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```

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```

```
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```

```
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future will perform elementwise comparison
```

```
/usr/local/lib/python3.7/dist-packages/numpy/lib/arraysetops.py:608:  
FutureWarning:
```

```
elementwise comparison failed; returning scalar instead, but in the  
future will perform elementwise comparison
```

```
/usr/local/lib/python3.7/dist-packages/numpy/lib/arraysetops.py:608:  
FutureWarning:
```

```
elementwise comparison failed; returning scalar instead, but in the  
future will perform elementwise comparison
```



```
In [14]: # concatenate and print x_train
X_train_input = np.hstack([train_numeric, train_model, train_transmission,
                             train_fuelType])
X_test_input = np.hstack([test_numeric, test_model, test_transmission,
                             test_fuelType])

print(X_train_input[:3])
```

```
[[0.95652174 0.01671832 0.25          0.11983471 0.31746032 0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          ]
 [0.82608696 0.05456364 0.34482759 0.12691854 0.31746032 0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          ]
 [0.91304348 0.03776792 0.25          0.08441558 0.47619048 0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          0.          0.          0.          0.          0.
  0.          ]]
```

## Step 5 - Linear regression

- \* run linear regression in sklearn.
- \* train the algorithm.
- \* make predictions.
- \* evaluation on test using mse, mae, and r2\_score.
- \* display the first 5 predictions.
- \* display the first 5 actual values.

```
In [15]: # model for linear regression and train
lr = LinearRegression()
lr.fit(X_train, y_train)
```

```
Out[15]: LinearRegression()
```

```
In [16]: # making predictions
lr_pred = lr.predict(X_test)
```

```
In [17]: # calculating mse, mean and r_squared
print("Lin. Regression MSE: ", mean_squared_error(y_test, lr_pred))
print("Lin. Regression MAE", mean_absolute_error(y_test, lr_pred))
print("Lin. Regression Correlation:", r2_score(y_test, lr_pred))
```

```
Lin. Regression MSE:  31702154.62103871
Lin. Regression MAE 3449.6599930869816
Lin. Regression Correlation: 0.7860856043642899
```

```
In [18]: # print 5 predictors
for x in range(5):
    print(lr_pred[x])
```

```
17529.93338991888
29530.59577485686
39687.05891479133
21916.146457525436
16242.303181847092
```

```
In [19]: # print 5 actual values
for x in range(5):
    print(y[x])
```

```
12500
16500
11000
16800
17300
```

## Step 6 - Regression in Keras

- \* build a sequential model.
- \* compile the model.
- \* train the model.
- \* output test mse and mae score.

```
In [20]: # make sequential model
bt_size = 128
epochs = 130

model = models.Sequential()

model.add(layers.Dense(512, activation= 'relu'))
model.add(layers.Dropout(0.2))

model.add(layers.Dense(128, activation= 'relu'))
model.add(layers.Dropout(0.2))
model.add(layers.Dense(1))
```

```
In [21]: # compiling the model
model.compile(loss= 'mse', optimizer= "rmsprop", metrics= ["mae"])
```

```
In [22]: # train and test
hist = model.fit(X_train, y_train, batch_size= bt_size, epochs= epochs
,
                verbose= 1, validation_data= (X_test, y_test))
```

```
Epoch 1/130
67/67 [=====] - 2s 9ms/step - loss: 2784327
36.0000 - mae: 12012.2080 - val_loss: 133910992.0000 - val_mae: 7565
.6362
Epoch 2/130
67/67 [=====] - 1s 8ms/step - loss: 1018126
56.0000 - mae: 6917.0586 - val_loss: 101839248.0000 - val_mae: 6285.
5229
Epoch 3/130
67/67 [=====] - 0s 7ms/step - loss: 9468921
6.0000 - mae: 6554.0781 - val_loss: 97617816.0000 - val_mae: 6113.65
38
Epoch 4/130
67/67 [=====] - 0s 7ms/step - loss: 9353242
4.0000 - mae: 6475.6284 - val_loss: 121567440.0000 - val_mae: 7066.2
056
Epoch 5/130
67/67 [=====] - 0s 7ms/step - loss: 9230732
8.0000 - mae: 6425.7842 - val_loss: 95758152.0000 - val_mae: 6102.82
13
Epoch 6/130
67/67 [=====] - 1s 8ms/step - loss: 8859027
2.0000 - mae: 6244.4585 - val_loss: 99295088.0000 - val_mae: 5861.37
26
Epoch 7/130
67/67 [=====] - 1s 8ms/step - loss: 8840092
0.0000 - mae: 6206.0664 - val_loss: 95151560.0000 - val_mae: 6023.46
```

```
88
Epoch 8/130
67/67 [=====] - 0s 7ms/step - loss: 8812884
0.0000 - mae: 6191.2271 - val_loss: 93214800.0000 - val_mae: 5883.96
92
Epoch 9/130
67/67 [=====] - 0s 7ms/step - loss: 8713189
6.0000 - mae: 6124.1260 - val_loss: 97610224.0000 - val_mae: 5991.66
06
Epoch 10/130
67/67 [=====] - 0s 7ms/step - loss: 8628608
8.0000 - mae: 6035.0352 - val_loss: 121836000.0000 - val_mae: 7216.6
230
Epoch 11/130
67/67 [=====] - 0s 7ms/step - loss: 8520432
8.0000 - mae: 6043.4033 - val_loss: 113217416.0000 - val_mae: 6820.2
549
Epoch 12/130
67/67 [=====] - 0s 7ms/step - loss: 8488788
0.0000 - mae: 5993.6274 - val_loss: 94364784.0000 - val_mae: 6487.26
76
Epoch 13/130
67/67 [=====] - 0s 7ms/step - loss: 8370919
2.0000 - mae: 5961.7744 - val_loss: 89907312.0000 - val_mae: 5627.16
02
Epoch 14/130
67/67 [=====] - 0s 7ms/step - loss: 8353215
2.0000 - mae: 5954.1636 - val_loss: 91481080.0000 - val_mae: 5450.73
19
Epoch 15/130
67/67 [=====] - 0s 7ms/step - loss: 8298216
8.0000 - mae: 5910.6255 - val_loss: 92442256.0000 - val_mae: 6301.03
27
Epoch 16/130
67/67 [=====] - 0s 7ms/step - loss: 8243690
4.0000 - mae: 5911.5796 - val_loss: 91912920.0000 - val_mae: 5476.79
20
Epoch 17/130
67/67 [=====] - 0s 7ms/step - loss: 8204755
2.0000 - mae: 5869.0093 - val_loss: 88345640.0000 - val_mae: 5529.97
56
Epoch 18/130
67/67 [=====] - 1s 8ms/step - loss: 8133399
2.0000 - mae: 5793.8540 - val_loss: 87989552.0000 - val_mae: 5738.98
49
Epoch 19/130
67/67 [=====] - 0s 7ms/step - loss: 8098149
6.0000 - mae: 5816.9385 - val_loss: 87677920.0000 - val_mae: 5459.98
88
Epoch 20/130
```

```
67/67 [=====] - 0s 7ms/step - loss: 8063101
6.0000 - mae: 5777.8818 - val_loss: 90833680.0000 - val_mae: 6425.32
81
Epoch 21/130
67/67 [=====] - 0s 7ms/step - loss: 7978304
0.0000 - mae: 5768.2935 - val_loss: 95530816.0000 - val_mae: 5745.96
68
Epoch 22/130
67/67 [=====] - 0s 7ms/step - loss: 7934343
2.0000 - mae: 5742.9897 - val_loss: 86596192.0000 - val_mae: 5455.72
90
Epoch 23/130
67/67 [=====] - 1s 14ms/step - loss: 784622
96.0000 - mae: 5708.7524 - val_loss: 89434624.0000 - val_mae: 6391.3
896
Epoch 24/130
67/67 [=====] - 1s 16ms/step - loss: 797984
16.0000 - mae: 5770.0288 - val_loss: 85091144.0000 - val_mae: 5360.7
656
Epoch 25/130
67/67 [=====] - 1s 17ms/step - loss: 784435
76.0000 - mae: 5697.6445 - val_loss: 84835568.0000 - val_mae: 5276.8
013
Epoch 26/130
67/67 [=====] - 1s 14ms/step - loss: 779074
56.0000 - mae: 5685.8696 - val_loss: 85716208.0000 - val_mae: 5411.4
121
Epoch 27/130
67/67 [=====] - 1s 16ms/step - loss: 778030
48.0000 - mae: 5658.5078 - val_loss: 83148952.0000 - val_mae: 5640.9
463
Epoch 28/130
67/67 [=====] - 1s 13ms/step - loss: 766541
36.0000 - mae: 5686.3081 - val_loss: 84053840.0000 - val_mae: 5322.2
788
Epoch 29/130
67/67 [=====] - 1s 13ms/step - loss: 764774
24.0000 - mae: 5623.7949 - val_loss: 89202128.0000 - val_mae: 5496.6
206
Epoch 30/130
67/67 [=====] - 1s 11ms/step - loss: 766268
64.0000 - mae: 5650.1792 - val_loss: 83930800.0000 - val_mae: 6014.4
980
Epoch 31/130
67/67 [=====] - 1s 12ms/step - loss: 752338
16.0000 - mae: 5594.2056 - val_loss: 80532464.0000 - val_mae: 5435.4
785
Epoch 32/130
67/67 [=====] - 1s 13ms/step - loss: 749248
72.0000 - mae: 5590.0391 - val_loss: 83417056.0000 - val_mae: 5185.8
```

```
286
Epoch 33/130
67/67 [=====] - 1s 12ms/step - loss: 741153
92.0000 - mae: 5524.4248 - val_loss: 78499936.0000 - val_mae: 5216.4
175
Epoch 34/130
67/67 [=====] - 1s 12ms/step - loss: 746509
04.0000 - mae: 5547.1382 - val_loss: 77365952.0000 - val_mae: 5153.7
817
Epoch 35/130
67/67 [=====] - 1s 11ms/step - loss: 730314
96.0000 - mae: 5521.2534 - val_loss: 76233680.0000 - val_mae: 5349.1
108
Epoch 36/130
67/67 [=====] - 1s 12ms/step - loss: 720354
56.0000 - mae: 5481.8154 - val_loss: 76346256.0000 - val_mae: 5074.4
609
Epoch 37/130
67/67 [=====] - 1s 12ms/step - loss: 724782
32.0000 - mae: 5455.7671 - val_loss: 75104160.0000 - val_mae: 5370.7
334
Epoch 38/130
67/67 [=====] - 1s 12ms/step - loss: 713948
08.0000 - mae: 5452.7085 - val_loss: 74502976.0000 - val_mae: 5008.3
008
Epoch 39/130
67/67 [=====] - 1s 12ms/step - loss: 715989
92.0000 - mae: 5477.4849 - val_loss: 79677464.0000 - val_mae: 5058.7
520
Epoch 40/130
67/67 [=====] - 1s 10ms/step - loss: 706405
92.0000 - mae: 5442.9160 - val_loss: 76038960.0000 - val_mae: 4970.3
618
Epoch 41/130
67/67 [=====] - 1s 12ms/step - loss: 685888
56.0000 - mae: 5347.4712 - val_loss: 82353712.0000 - val_mae: 5367.0
757
Epoch 42/130
67/67 [=====] - 1s 17ms/step - loss: 693123
92.0000 - mae: 5404.2642 - val_loss: 68843968.0000 - val_mae: 4987.1
992
Epoch 43/130
67/67 [=====] - 1s 15ms/step - loss: 682335
36.0000 - mae: 5354.1831 - val_loss: 88387016.0000 - val_mae: 5612.6
538
Epoch 44/130
67/67 [=====] - 1s 20ms/step - loss: 676496
16.0000 - mae: 5331.7266 - val_loss: 70378856.0000 - val_mae: 4872.7
510
Epoch 45/130
```

```
67/67 [=====] - 1s 22ms/step - loss: 674237
52.0000 - mae: 5314.7290 - val_loss: 68051968.0000 - val_mae: 4731.8
252
Epoch 46/130
67/67 [=====] - 1s 16ms/step - loss: 664668
60.0000 - mae: 5303.9004 - val_loss: 66056512.0000 - val_mae: 5041.2
280
Epoch 47/130
67/67 [=====] - 1s 12ms/step - loss: 645233
16.0000 - mae: 5253.7603 - val_loss: 75234336.0000 - val_mae: 6262.2
280
Epoch 48/130
67/67 [=====] - 1s 14ms/step - loss: 642217
60.0000 - mae: 5260.7949 - val_loss: 63451952.0000 - val_mae: 4992.3
340
Epoch 49/130
67/67 [=====] - 1s 13ms/step - loss: 638027
52.0000 - mae: 5257.7192 - val_loss: 67528304.0000 - val_mae: 4653.7
144
Epoch 50/130
67/67 [=====] - 1s 15ms/step - loss: 641993
20.0000 - mae: 5199.1797 - val_loss: 63008400.0000 - val_mae: 4908.9
204
Epoch 51/130
67/67 [=====] - 1s 14ms/step - loss: 638903
76.0000 - mae: 5276.2661 - val_loss: 74515752.0000 - val_mae: 6372.8
447
Epoch 52/130
67/67 [=====] - 1s 14ms/step - loss: 631348
64.0000 - mae: 5203.8481 - val_loss: 62482320.0000 - val_mae: 4836.0
659
Epoch 53/130
67/67 [=====] - 1s 12ms/step - loss: 620494
40.0000 - mae: 5191.9941 - val_loss: 61480944.0000 - val_mae: 5208.9
507
Epoch 54/130
67/67 [=====] - 1s 13ms/step - loss: 613672
36.0000 - mae: 5149.7388 - val_loss: 69103568.0000 - val_mae: 6005.1
274
Epoch 55/130
67/67 [=====] - 1s 11ms/step - loss: 609381
16.0000 - mae: 5122.0312 - val_loss: 65579564.0000 - val_mae: 4689.4
248
Epoch 56/130
67/67 [=====] - 1s 12ms/step - loss: 619877
84.0000 - mae: 5170.5972 - val_loss: 57789700.0000 - val_mae: 4735.3
745
Epoch 57/130
67/67 [=====] - 1s 13ms/step - loss: 611880
96.0000 - mae: 5182.8296 - val_loss: 58208944.0000 - val_mae: 5043.0
```

```
864
Epoch 58/130
67/67 [=====] - 1s 12ms/step - loss: 590154
16.0000 - mae: 5066.8228 - val_loss: 58043132.0000 - val_mae: 4536.1
567
Epoch 59/130
67/67 [=====] - 1s 11ms/step - loss: 601021
72.0000 - mae: 5129.2842 - val_loss: 71931992.0000 - val_mae: 4906.0
747
Epoch 60/130
67/67 [=====] - 1s 11ms/step - loss: 593036
84.0000 - mae: 5105.6934 - val_loss: 54458864.0000 - val_mae: 4610.2
925
Epoch 61/130
67/67 [=====] - 0s 7ms/step - loss: 5903369
2.0000 - mae: 5077.4111 - val_loss: 56919420.0000 - val_mae: 5213.49
41
Epoch 62/130
67/67 [=====] - 0s 7ms/step - loss: 5940912
0.0000 - mae: 5119.4082 - val_loss: 61696212.0000 - val_mae: 5774.57
57
Epoch 63/130
67/67 [=====] - 1s 8ms/step - loss: 5836700
8.0000 - mae: 5085.9492 - val_loss: 64322700.0000 - val_mae: 4665.32
91
Epoch 64/130
67/67 [=====] - 0s 7ms/step - loss: 5667316
0.0000 - mae: 5001.7661 - val_loss: 56147204.0000 - val_mae: 4559.47
12
Epoch 65/130
67/67 [=====] - 1s 8ms/step - loss: 5722581
6.0000 - mae: 5056.4829 - val_loss: 58838420.0000 - val_mae: 4559.07
08
Epoch 66/130
67/67 [=====] - 0s 7ms/step - loss: 5687380
4.0000 - mae: 5020.7666 - val_loss: 52731956.0000 - val_mae: 4515.25
20
Epoch 67/130
67/67 [=====] - 1s 8ms/step - loss: 5772012
4.0000 - mae: 5047.1978 - val_loss: 53850480.0000 - val_mae: 4533.22
56
Epoch 68/130
67/67 [=====] - 0s 7ms/step - loss: 5578135
6.0000 - mae: 5024.7739 - val_loss: 55884060.0000 - val_mae: 4494.46
48
Epoch 69/130
67/67 [=====] - 0s 7ms/step - loss: 5542510
0.0000 - mae: 4986.5767 - val_loss: 50601524.0000 - val_mae: 4455.64
45
Epoch 70/130
```



```
67/67 [=====] - 0s 7ms/step - loss: 5773767
2.0000 - mae: 5062.7388 - val_loss: 52216964.0000 - val_mae: 4431.15
62
Epoch 71/130
67/67 [=====] - 1s 8ms/step - loss: 5439835
6.0000 - mae: 4967.6875 - val_loss: 52384456.0000 - val_mae: 4522.02
10
Epoch 72/130
67/67 [=====] - 1s 8ms/step - loss: 5513067
6.0000 - mae: 4985.1729 - val_loss: 57753716.0000 - val_mae: 4557.22
90
Epoch 73/130
67/67 [=====] - 1s 8ms/step - loss: 5389211
6.0000 - mae: 4966.6348 - val_loss: 50899740.0000 - val_mae: 4625.36
72
Epoch 74/130
67/67 [=====] - 0s 7ms/step - loss: 5559876
0.0000 - mae: 5022.6938 - val_loss: 53806052.0000 - val_mae: 4468.83
15
Epoch 75/130
67/67 [=====] - 0s 7ms/step - loss: 5446341
2.0000 - mae: 4970.8384 - val_loss: 49544156.0000 - val_mae: 4592.90
82
Epoch 76/130
67/67 [=====] - 1s 8ms/step - loss: 5437811
2.0000 - mae: 5003.9277 - val_loss: 54467704.0000 - val_mae: 4837.25
54
Epoch 77/130
67/67 [=====] - 1s 8ms/step - loss: 5425845
2.0000 - mae: 5003.9966 - val_loss: 55363780.0000 - val_mae: 4622.36
08
Epoch 78/130
67/67 [=====] - 1s 8ms/step - loss: 5336451
6.0000 - mae: 4945.6782 - val_loss: 52081768.0000 - val_mae: 4612.03
47
Epoch 79/130
67/67 [=====] - 1s 8ms/step - loss: 5199083
2.0000 - mae: 4882.9795 - val_loss: 60461344.0000 - val_mae: 4737.30
71
Epoch 80/130
67/67 [=====] - 1s 8ms/step - loss: 5329193
2.0000 - mae: 4913.4199 - val_loss: 48755528.0000 - val_mae: 5044.81
35
Epoch 81/130
67/67 [=====] - 0s 7ms/step - loss: 5304703
2.0000 - mae: 4960.2021 - val_loss: 47920980.0000 - val_mae: 4306.35
30
Epoch 82/130
67/67 [=====] - 1s 8ms/step - loss: 5255142
4.0000 - mae: 4909.3989 - val_loss: 47503456.0000 - val_mae: 4649.42
```

```
92
Epoch 83/130
67/67 [=====] - 1s 8ms/step - loss: 5206137
6.0000 - mae: 4913.0410 - val_loss: 45854740.0000 - val_mae: 4450.80
27
Epoch 84/130
67/67 [=====] - 1s 8ms/step - loss: 5248062
0.0000 - mae: 4920.4268 - val_loss: 52034992.0000 - val_mae: 5260.50
59
Epoch 85/130
67/67 [=====] - 1s 8ms/step - loss: 5214202
4.0000 - mae: 4888.0127 - val_loss: 44996032.0000 - val_mae: 4362.05
91
Epoch 86/130
67/67 [=====] - 0s 7ms/step - loss: 5047339
6.0000 - mae: 4844.4502 - val_loss: 48533972.0000 - val_mae: 4417.19
82
Epoch 87/130
67/67 [=====] - 1s 7ms/step - loss: 5301475
6.0000 - mae: 4977.6553 - val_loss: 52025272.0000 - val_mae: 5515.38
62
Epoch 88/130
67/67 [=====] - 0s 7ms/step - loss: 5072026
8.0000 - mae: 4871.0815 - val_loss: 49527160.0000 - val_mae: 5060.67
09
Epoch 89/130
67/67 [=====] - 0s 7ms/step - loss: 5214727
2.0000 - mae: 4902.3984 - val_loss: 44623252.0000 - val_mae: 4232.35
25
Epoch 90/130
67/67 [=====] - 0s 7ms/step - loss: 5050853
6.0000 - mae: 4872.6187 - val_loss: 42327704.0000 - val_mae: 4562.67
68
Epoch 91/130
67/67 [=====] - 0s 7ms/step - loss: 5296538
0.0000 - mae: 4986.2812 - val_loss: 56127576.0000 - val_mae: 4577.72
71
Epoch 92/130
67/67 [=====] - 1s 7ms/step - loss: 5024728
8.0000 - mae: 4855.8691 - val_loss: 40976604.0000 - val_mae: 4351.43
70
Epoch 93/130
67/67 [=====] - 1s 8ms/step - loss: 4974514
4.0000 - mae: 4861.9385 - val_loss: 45284844.0000 - val_mae: 4406.85
89
Epoch 94/130
67/67 [=====] - 0s 7ms/step - loss: 5101797
2.0000 - mae: 4856.4243 - val_loss: 46966736.0000 - val_mae: 5145.64
31
Epoch 95/130
```

```
67/67 [=====] - 0s 7ms/step - loss: 5051407
6.0000 - mae: 4868.6235 - val_loss: 53312628.0000 - val_mae: 4468.40
62
Epoch 96/130
67/67 [=====] - 0s 7ms/step - loss: 5136664
4.0000 - mae: 4902.4375 - val_loss: 123203352.0000 - val_mae: 9116.5
684
Epoch 97/130
67/67 [=====] - 1s 8ms/step - loss: 5120042
0.0000 - mae: 4929.4058 - val_loss: 58168048.0000 - val_mae: 4612.55
22
Epoch 98/130
67/67 [=====] - 1s 7ms/step - loss: 4956714
4.0000 - mae: 4854.9692 - val_loss: 57284152.0000 - val_mae: 4743.46
29
Epoch 99/130
67/67 [=====] - 1s 8ms/step - loss: 4936932
4.0000 - mae: 4846.8555 - val_loss: 44125748.0000 - val_mae: 4959.46
39
Epoch 100/130
67/67 [=====] - 1s 8ms/step - loss: 4944854
0.0000 - mae: 4855.3857 - val_loss: 42288220.0000 - val_mae: 4254.22
12
Epoch 101/130
67/67 [=====] - 1s 8ms/step - loss: 5103696
8.0000 - mae: 4872.1724 - val_loss: 50787884.0000 - val_mae: 5420.57
37
Epoch 102/130
67/67 [=====] - 1s 8ms/step - loss: 4985498
4.0000 - mae: 4850.4131 - val_loss: 41092656.0000 - val_mae: 4488.84
67
Epoch 103/130
67/67 [=====] - 0s 7ms/step - loss: 4990025
2.0000 - mae: 4880.9653 - val_loss: 61210240.0000 - val_mae: 6090.28
12
Epoch 104/130
67/67 [=====] - 0s 7ms/step - loss: 4916230
4.0000 - mae: 4853.5332 - val_loss: 46517364.0000 - val_mae: 5257.07
86
Epoch 105/130
67/67 [=====] - 0s 7ms/step - loss: 4933920
4.0000 - mae: 4850.6509 - val_loss: 41953992.0000 - val_mae: 4504.61
18
Epoch 106/130
67/67 [=====] - 1s 8ms/step - loss: 4818564
4.0000 - mae: 4802.9814 - val_loss: 41853152.0000 - val_mae: 4289.78
27
Epoch 107/130
67/67 [=====] - 1s 7ms/step - loss: 4964771
2.0000 - mae: 4856.8862 - val_loss: 63929440.0000 - val_mae: 5250.88
```

```
57
Epoch 108/130
67/67 [=====] - 1s 8ms/step - loss: 4809805
6.0000 - mae: 4810.1987 - val_loss: 52539632.0000 - val_mae: 4467.09
33
Epoch 109/130
67/67 [=====] - 0s 7ms/step - loss: 4820527
6.0000 - mae: 4799.3569 - val_loss: 45509624.0000 - val_mae: 4399.07
32
Epoch 110/130
67/67 [=====] - 0s 7ms/step - loss: 4992756
0.0000 - mae: 4911.5117 - val_loss: 61523256.0000 - val_mae: 4707.89
79
Epoch 111/130
67/67 [=====] - 1s 8ms/step - loss: 4839866
0.0000 - mae: 4798.9683 - val_loss: 47761668.0000 - val_mae: 4320.85
35
Epoch 112/130
67/67 [=====] - 1s 8ms/step - loss: 4771672
4.0000 - mae: 4817.2163 - val_loss: 45169744.0000 - val_mae: 4263.59
33
Epoch 113/130
67/67 [=====] - 0s 7ms/step - loss: 4865908
8.0000 - mae: 4838.6221 - val_loss: 40763580.0000 - val_mae: 4818.37
65
Epoch 114/130
67/67 [=====] - 1s 8ms/step - loss: 4837287
6.0000 - mae: 4820.0864 - val_loss: 62501380.0000 - val_mae: 4976.63
57
Epoch 115/130
67/67 [=====] - 1s 8ms/step - loss: 4731226
8.0000 - mae: 4843.2417 - val_loss: 101890048.0000 - val_mae: 7105.3
960
Epoch 116/130
67/67 [=====] - 0s 7ms/step - loss: 4773476
0.0000 - mae: 4784.3569 - val_loss: 36168152.0000 - val_mae: 4244.67
29
Epoch 117/130
67/67 [=====] - 1s 8ms/step - loss: 4660655
6.0000 - mae: 4807.3628 - val_loss: 70670528.0000 - val_mae: 5540.45
41
Epoch 118/130
67/67 [=====] - 0s 7ms/step - loss: 4810625
6.0000 - mae: 4817.4922 - val_loss: 38836324.0000 - val_mae: 4234.48
97
Epoch 119/130
67/67 [=====] - 0s 7ms/step - loss: 4774614
4.0000 - mae: 4847.2837 - val_loss: 51554164.0000 - val_mae: 4753.43
16
Epoch 120/130
```

```
67/67 [=====] - 0s 7ms/step - loss: 4698984
4.0000 - mae: 4761.9067 - val_loss: 54932048.0000 - val_mae: 4707.28
76
Epoch 121/130
67/67 [=====] - 1s 8ms/step - loss: 4808948
0.0000 - mae: 4814.2549 - val_loss: 66038140.0000 - val_mae: 5069.51
12
Epoch 122/130
67/67 [=====] - 0s 7ms/step - loss: 4874363
2.0000 - mae: 4829.4570 - val_loss: 38871908.0000 - val_mae: 4516.73
49
Epoch 123/130
67/67 [=====] - 1s 7ms/step - loss: 4716704
8.0000 - mae: 4758.0322 - val_loss: 36078364.0000 - val_mae: 4345.04
59
Epoch 124/130
67/67 [=====] - 0s 7ms/step - loss: 4662518
4.0000 - mae: 4758.9346 - val_loss: 36456960.0000 - val_mae: 4368.86
23
Epoch 125/130
67/67 [=====] - 0s 7ms/step - loss: 4823791
2.0000 - mae: 4813.1021 - val_loss: 38151408.0000 - val_mae: 4081.16
55
Epoch 126/130
67/67 [=====] - 0s 7ms/step - loss: 4734928
0.0000 - mae: 4779.7485 - val_loss: 47047796.0000 - val_mae: 4403.92
09
Epoch 127/130
67/67 [=====] - 1s 8ms/step - loss: 4586451
6.0000 - mae: 4726.0889 - val_loss: 38626432.0000 - val_mae: 4660.80
27
Epoch 128/130
67/67 [=====] - 0s 7ms/step - loss: 4799407
2.0000 - mae: 4840.7734 - val_loss: 59207544.0000 - val_mae: 4688.31
35
Epoch 129/130
67/67 [=====] - 0s 7ms/step - loss: 4495511
2.0000 - mae: 4735.6836 - val_loss: 91817160.0000 - val_mae: 7894.28
32
Epoch 130/130
67/67 [=====] - 1s 8ms/step - loss: 4582368
8.0000 - mae: 4758.2070 - val_loss: 52763280.0000 - val_mae: 4625.10
06
```

```
In [23]: # printing test mse and mae
score = model.evaluate(X_test, y_test, verbose= 0)
print("Kera Reg. RMSE: ", math.sqrt(score[0]))
print("Kera Reg. MAE: ", score[1])
```

```
Kera Reg. RMSE: 7263.833423200177
Kera Reg. MAE: 4625.10009765625
```

```
In [24]: # checking other metics for Kera Regression
model.compile(loss='mse', optimizer='rmsprop', metrics=['accuracy', 'mape', 'mse'])
# train model
history = model.fit(X_train, y_train, epochs=epochs, batch_size= batch_size, verbose=1, validation_data=(X_test, y_test))
```

```
Epoch 1/130
67/67 [=====] - 1s 9ms/step - loss: 5591269
2.0000 - accuracy: 0.0000e+00 - mape: 23.1955 - mse: 55912692.0000 -
val_loss: 37855580.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.86
87 - val_mse: 37855580.0000
Epoch 2/130
67/67 [=====] - 1s 8ms/step - loss: 4645441
6.0000 - accuracy: 0.0000e+00 - mape: 22.4525 - mse: 46454416.0000 -
val_loss: 34861372.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.47
18 - val_mse: 34861372.0000
Epoch 3/130
67/67 [=====] - 1s 7ms/step - loss: 4796450
4.0000 - accuracy: 0.0000e+00 - mape: 22.8423 - mse: 47964504.0000 -
val_loss: 50038592.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.16
04 - val_mse: 50038592.0000
Epoch 4/130
67/67 [=====] - 1s 8ms/step - loss: 4513102
0.0000 - accuracy: 0.0000e+00 - mape: 22.4645 - mse: 45131020.0000 -
val_loss: 37049876.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.83
31 - val_mse: 37049876.0000
Epoch 5/130
67/67 [=====] - 0s 7ms/step - loss: 4732406
0.0000 - accuracy: 0.0000e+00 - mape: 23.1544 - mse: 47324060.0000 -
val_loss: 57303868.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.54
71 - val_mse: 57303868.0000
Epoch 6/130
67/67 [=====] - 0s 7ms/step - loss: 4582262
8.0000 - accuracy: 0.0000e+00 - mape: 22.6762 - mse: 45822628.0000 -
val_loss: 42723168.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.20
81 - val_mse: 42723168.0000
Epoch 7/130
67/67 [=====] - 0s 7ms/step - loss: 4676422
0.0000 - accuracy: 0.0000e+00 - mape: 22.6437 - mse: 46764220.0000 -
val_loss: 35582620.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.81
```

```
44 - val_mse: 35582620.0000
Epoch 8/130
67/67 [=====] - 1s 7ms/step - loss: 4622695
2.0000 - accuracy: 0.0000e+00 - mape: 22.8381 - mse: 46226952.0000 -
val_loss: 39920592.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.24
51 - val_mse: 39920592.0000
Epoch 9/130
67/67 [=====] - 0s 7ms/step - loss: 4389537
2.0000 - accuracy: 0.0000e+00 - mape: 22.2403 - mse: 43895372.0000 -
val_loss: 38795724.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.96
62 - val_mse: 38795728.0000
Epoch 10/130
67/67 [=====] - 1s 7ms/step - loss: 4462282
0.0000 - accuracy: 0.0000e+00 - mape: 22.8243 - mse: 44622820.0000 -
val_loss: 34028748.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.79
82 - val_mse: 34028748.0000
Epoch 11/130
67/67 [=====] - 0s 7ms/step - loss: 4444125
2.0000 - accuracy: 0.0000e+00 - mape: 22.3975 - mse: 44441252.0000 -
val_loss: 79594800.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.58
59 - val_mse: 79594800.0000
Epoch 12/130
67/67 [=====] - 1s 7ms/step - loss: 4775740
0.0000 - accuracy: 0.0000e+00 - mape: 22.9302 - mse: 47757400.0000 -
val_loss: 36181652.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.44
20 - val_mse: 36181652.0000
Epoch 13/130
67/67 [=====] - 0s 7ms/step - loss: 4463814
8.0000 - accuracy: 0.0000e+00 - mape: 22.6334 - mse: 44638148.0000 -
val_loss: 40675732.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.15
43 - val_mse: 40675732.0000
Epoch 14/130
67/67 [=====] - 1s 8ms/step - loss: 4599615
2.0000 - accuracy: 0.0000e+00 - mape: 22.9605 - mse: 45996152.0000 -
val_loss: 39198208.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.96
30 - val_mse: 39198208.0000
Epoch 15/130
67/67 [=====] - 1s 11ms/step - loss: 440051
12.0000 - accuracy: 0.0000e+00 - mape: 22.5076 - mse: 44005112.0000
- val_loss: 35493108.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.
8802 - val_mse: 35493108.0000
Epoch 16/130
67/67 [=====] - 1s 12ms/step - loss: 436505
24.0000 - accuracy: 0.0000e+00 - mape: 22.4919 - mse: 43650524.0000
- val_loss: 32968382.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.
8549 - val_mse: 32968382.0000
Epoch 17/130
67/67 [=====] - 1s 12ms/step - loss: 452891
04.0000 - accuracy: 0.0000e+00 - mape: 22.5929 - mse: 45289104.0000
- val_loss: 35097720.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.
```

```
7025 - val_mse: 35097720.0000
Epoch 18/130
67/67 [=====] - 1s 11ms/step - loss: 450948
52.0000 - accuracy: 0.0000e+00 - mape: 22.5010 - mse: 45094852.0000
- val_loss: 47303896.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.
0311 - val_mse: 47303896.0000
Epoch 19/130
67/67 [=====] - 1s 11ms/step - loss: 446771
68.0000 - accuracy: 0.0000e+00 - mape: 22.3405 - mse: 44677168.0000
- val_loss: 34294128.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.
9484 - val_mse: 34294128.0000
Epoch 20/130
67/67 [=====] - 1s 10ms/step - loss: 448074
08.0000 - accuracy: 0.0000e+00 - mape: 22.5356 - mse: 44807408.0000
- val_loss: 34758484.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.
8621 - val_mse: 34758484.0000
Epoch 21/130
67/67 [=====] - 1s 8ms/step - loss: 4436255
2.0000 - accuracy: 0.0000e+00 - mape: 22.4231 - mse: 44362552.0000 -
val_loss: 34702812.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.23
24 - val_mse: 34702812.0000
Epoch 22/130
67/67 [=====] - 0s 7ms/step - loss: 4550455
2.0000 - accuracy: 0.0000e+00 - mape: 22.5286 - mse: 45504552.0000 -
val_loss: 32609684.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.95
24 - val_mse: 32609684.0000
Epoch 23/130
67/67 [=====] - 1s 8ms/step - loss: 4447572
0.0000 - accuracy: 0.0000e+00 - mape: 22.3119 - mse: 44475720.0000 -
val_loss: 35919204.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.51
76 - val_mse: 35919204.0000
Epoch 24/130
67/67 [=====] - 0s 7ms/step - loss: 4453348
4.0000 - accuracy: 0.0000e+00 - mape: 22.4118 - mse: 44533484.0000 -
val_loss: 64164196.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.50
41 - val_mse: 64164196.0000
Epoch 25/130
67/67 [=====] - 1s 7ms/step - loss: 4424689
2.0000 - accuracy: 0.0000e+00 - mape: 22.4115 - mse: 44246892.0000 -
val_loss: 59033652.0000 - val_accuracy: 0.0000e+00 - val_mape: 32.21
11 - val_mse: 59033652.0000
Epoch 26/130
67/67 [=====] - 0s 7ms/step - loss: 4424968
8.0000 - accuracy: 0.0000e+00 - mape: 22.2744 - mse: 44249688.0000 -
val_loss: 32360734.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.34
24 - val_mse: 32360734.0000
Epoch 27/130
67/67 [=====] - 1s 8ms/step - loss: 4431635
2.0000 - accuracy: 0.0000e+00 - mape: 22.3440 - mse: 44316352.0000 -
val_loss: 33505192.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.64
```



```
91 - val_mse: 33505192.0000
Epoch 28/130
67/67 [=====] - 0s 7ms/step - loss: 4355860
8.0000 - accuracy: 0.0000e+00 - mape: 22.2741 - mse: 43558608.0000 -
val_loss: 45001064.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.87
82 - val_mse: 45001064.0000
Epoch 29/130
67/67 [=====] - 0s 7ms/step - loss: 4380708
8.0000 - accuracy: 0.0000e+00 - mape: 22.5918 - mse: 43807088.0000 -
val_loss: 35494628.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.26
50 - val_mse: 35494628.0000
Epoch 30/130
67/67 [=====] - 1s 8ms/step - loss: 4488182
0.0000 - accuracy: 0.0000e+00 - mape: 22.4736 - mse: 44881820.0000 -
val_loss: 32506812.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.70
53 - val_mse: 32506812.0000
Epoch 31/130
67/67 [=====] - 1s 7ms/step - loss: 4439885
6.0000 - accuracy: 0.0000e+00 - mape: 22.3101 - mse: 44398856.0000 -
val_loss: 38815660.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.83
74 - val_mse: 38815660.0000
Epoch 32/130
67/67 [=====] - 1s 7ms/step - loss: 4290688
8.0000 - accuracy: 0.0000e+00 - mape: 22.3255 - mse: 42906888.0000 -
val_loss: 32779252.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.22
21 - val_mse: 32779252.0000
Epoch 33/130
67/67 [=====] - 0s 7ms/step - loss: 4491098
0.0000 - accuracy: 0.0000e+00 - mape: 22.6856 - mse: 44910980.0000 -
val_loss: 36029848.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.01
93 - val_mse: 36029848.0000
Epoch 34/130
67/67 [=====] - 0s 7ms/step - loss: 4367894
4.0000 - accuracy: 0.0000e+00 - mape: 22.5019 - mse: 43678944.0000 -
val_loss: 47393232.0000 - val_accuracy: 0.0000e+00 - val_mape: 26.68
71 - val_mse: 47393232.0000
Epoch 35/130
67/67 [=====] - 0s 7ms/step - loss: 4429308
0.0000 - accuracy: 0.0000e+00 - mape: 22.1714 - mse: 44293080.0000 -
val_loss: 65832564.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.85
50 - val_mse: 65832564.0000
Epoch 36/130
67/67 [=====] - 1s 8ms/step - loss: 4353976
4.0000 - accuracy: 0.0000e+00 - mape: 22.1513 - mse: 43539764.0000 -
val_loss: 49724940.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.15
10 - val_mse: 49724940.0000
Epoch 37/130
67/67 [=====] - 0s 7ms/step - loss: 4393262
4.0000 - accuracy: 0.0000e+00 - mape: 22.0832 - mse: 43932624.0000 -
val_loss: 37941076.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.88
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26 - val_mse: 37941076.0000
Epoch 38/130
67/67 [=====] - 0s 7ms/step - loss: 4347446
4.0000 - accuracy: 0.0000e+00 - mape: 22.3898 - mse: 43474464.0000 -
val_loss: 34326564.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.84
47 - val_mse: 34326564.0000
Epoch 39/130
67/67 [=====] - 0s 7ms/step - loss: 4296374
4.0000 - accuracy: 0.0000e+00 - mape: 22.0373 - mse: 42963744.0000 -
val_loss: 33597688.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.99
98 - val_mse: 33597688.0000
Epoch 40/130
67/67 [=====] - 1s 7ms/step - loss: 4431101
6.0000 - accuracy: 0.0000e+00 - mape: 22.2751 - mse: 44311016.0000 -
val_loss: 84364408.0000 - val_accuracy: 0.0000e+00 - val_mape: 40.43
83 - val_mse: 84364408.0000
Epoch 41/130
67/67 [=====] - 1s 8ms/step - loss: 4316186
0.0000 - accuracy: 0.0000e+00 - mape: 22.1437 - mse: 43161860.0000 -
val_loss: 76578960.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.18
68 - val_mse: 76578960.0000
Epoch 42/130
67/67 [=====] - 0s 7ms/step - loss: 4428577
6.0000 - accuracy: 0.0000e+00 - mape: 22.2190 - mse: 44285776.0000 -
val_loss: 53779844.0000 - val_accuracy: 0.0000e+00 - val_mape: 29.19
41 - val_mse: 53779844.0000
Epoch 43/130
67/67 [=====] - 0s 7ms/step - loss: 4409455
6.0000 - accuracy: 0.0000e+00 - mape: 22.6569 - mse: 44094556.0000 -
val_loss: 55325236.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.40
94 - val_mse: 55325236.0000
Epoch 44/130
67/67 [=====] - 0s 7ms/step - loss: 4252110
0.0000 - accuracy: 0.0000e+00 - mape: 21.9000 - mse: 42521100.0000 -
val_loss: 35014836.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.62
04 - val_mse: 35014836.0000
Epoch 45/130
67/67 [=====] - 0s 7ms/step - loss: 4409724
0.0000 - accuracy: 0.0000e+00 - mape: 22.2212 - mse: 44097240.0000 -
val_loss: 46154412.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.94
01 - val_mse: 46154412.0000
Epoch 46/130
67/67 [=====] - 1s 8ms/step - loss: 4271499
6.0000 - accuracy: 0.0000e+00 - mape: 22.0472 - mse: 42714996.0000 -
val_loss: 130007008.0000 - val_accuracy: 0.0000e+00 - val_mape: 45.8
533 - val_mse: 130007008.0000
Epoch 47/130
67/67 [=====] - 0s 7ms/step - loss: 4329189
2.0000 - accuracy: 0.0000e+00 - mape: 22.3861 - mse: 43291892.0000 -
val_loss: 33626636.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.94
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25 - val_mse: 33626636.0000
Epoch 48/130
67/67 [=====] - 1s 7ms/step - loss: 4340411
6.0000 - accuracy: 0.0000e+00 - mape: 22.2644 - mse: 43404116.0000 -
val_loss: 34394640.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.75
05 - val_mse: 34394640.0000
Epoch 49/130
67/67 [=====] - 0s 7ms/step - loss: 4480841
2.0000 - accuracy: 0.0000e+00 - mape: 22.0859 - mse: 44808412.0000 -
val_loss: 37898352.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.55
81 - val_mse: 37898356.0000
Epoch 50/130
67/67 [=====] - 0s 7ms/step - loss: 4366285
2.0000 - accuracy: 0.0000e+00 - mape: 22.0639 - mse: 43662852.0000 -
val_loss: 33879212.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.24
17 - val_mse: 33879212.0000
Epoch 51/130
67/67 [=====] - 1s 8ms/step - loss: 4203471
2.0000 - accuracy: 0.0000e+00 - mape: 21.8149 - mse: 42034712.0000 -
val_loss: 33720920.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.87
22 - val_mse: 33720920.0000
Epoch 52/130
67/67 [=====] - 0s 7ms/step - loss: 4203780
4.0000 - accuracy: 0.0000e+00 - mape: 21.9708 - mse: 42037800.0000 -
val_loss: 62703632.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.51
35 - val_mse: 62703632.0000
Epoch 53/130
67/67 [=====] - 0s 7ms/step - loss: 4197932
0.0000 - accuracy: 0.0000e+00 - mape: 21.7719 - mse: 41979320.0000 -
val_loss: 65323516.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.70
38 - val_mse: 65323516.0000
Epoch 54/130
67/67 [=====] - 1s 8ms/step - loss: 4270251
6.0000 - accuracy: 0.0000e+00 - mape: 22.1885 - mse: 42702516.0000 -
val_loss: 43430152.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.10
90 - val_mse: 43430152.0000
Epoch 55/130
67/67 [=====] - 0s 7ms/step - loss: 4270302
0.0000 - accuracy: 0.0000e+00 - mape: 22.0780 - mse: 42703020.0000 -
val_loss: 31556990.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.89
69 - val_mse: 31556990.0000
Epoch 56/130
67/67 [=====] - 0s 7ms/step - loss: 4168753
2.0000 - accuracy: 0.0000e+00 - mape: 21.8378 - mse: 41687532.0000 -
val_loss: 34062084.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.30
49 - val_mse: 34062084.0000
Epoch 57/130
67/67 [=====] - 1s 8ms/step - loss: 4353518
4.0000 - accuracy: 0.0000e+00 - mape: 22.0577 - mse: 43535184.0000 -
val_loss: 32670674.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.76
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15 - val_mse: 32670674.0000
Epoch 58/130
67/67 [=====] - 0s 7ms/step - loss: 4287856
8.0000 - accuracy: 0.0000e+00 - mape: 21.8875 - mse: 42878568.0000 -
val_loss: 52144664.0000 - val_accuracy: 0.0000e+00 - val_mape: 31.52
58 - val_mse: 52144664.0000
Epoch 59/130
67/67 [=====] - 0s 7ms/step - loss: 4259518
8.0000 - accuracy: 0.0000e+00 - mape: 22.3684 - mse: 42595188.0000 -
val_loss: 33354376.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.01
79 - val_mse: 33354376.0000
Epoch 60/130
67/67 [=====] - 0s 7ms/step - loss: 4225129
6.0000 - accuracy: 0.0000e+00 - mape: 21.9349 - mse: 42251296.0000 -
val_loss: 66003344.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.66
66 - val_mse: 66003344.0000
Epoch 61/130
67/67 [=====] - 0s 7ms/step - loss: 4330384
8.0000 - accuracy: 0.0000e+00 - mape: 22.1489 - mse: 43303848.0000 -
val_loss: 38246220.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.16
80 - val_mse: 38246220.0000
Epoch 62/130
67/67 [=====] - 1s 8ms/step - loss: 4163045
2.0000 - accuracy: 0.0000e+00 - mape: 21.6498 - mse: 41630452.0000 -
val_loss: 37113196.0000 - val_accuracy: 0.0000e+00 - val_mape: 24.92
31 - val_mse: 37113196.0000
Epoch 63/130
67/67 [=====] - 1s 8ms/step - loss: 4310426
0.0000 - accuracy: 0.0000e+00 - mape: 22.1138 - mse: 43104260.0000 -
val_loss: 31559892.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.49
11 - val_mse: 31559892.0000
Epoch 64/130
67/67 [=====] - 1s 8ms/step - loss: 4207793
2.0000 - accuracy: 0.0000e+00 - mape: 22.0620 - mse: 42077932.0000 -
val_loss: 31082662.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.11
84 - val_mse: 31082662.0000
Epoch 65/130
67/67 [=====] - 1s 7ms/step - loss: 4190571
2.0000 - accuracy: 0.0000e+00 - mape: 21.8032 - mse: 41905712.0000 -
val_loss: 55309348.0000 - val_accuracy: 0.0000e+00 - val_mape: 25.46
51 - val_mse: 55309348.0000
Epoch 66/130
67/67 [=====] - 0s 7ms/step - loss: 4363883
2.0000 - accuracy: 0.0000e+00 - mape: 22.0092 - mse: 43638832.0000 -
val_loss: 35186224.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.84
86 - val_mse: 35186224.0000
Epoch 67/130
67/67 [=====] - 1s 8ms/step - loss: 4151676
8.0000 - accuracy: 0.0000e+00 - mape: 21.9185 - mse: 41516768.0000 -
val_loss: 33654840.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.11
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93 - val_mse: 33654840.0000
Epoch 68/130
67/67 [=====] - 0s 7ms/step - loss: 4076699
2.0000 - accuracy: 0.0000e+00 - mape: 21.7452 - mse: 40766992.0000 -
val_loss: 30424352.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.25
15 - val_mse: 30424352.0000
Epoch 69/130
67/67 [=====] - 0s 7ms/step - loss: 4137482
0.0000 - accuracy: 0.0000e+00 - mape: 22.0455 - mse: 41374820.0000 -
val_loss: 85269376.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.71
73 - val_mse: 85269376.0000
Epoch 70/130
67/67 [=====] - 0s 7ms/step - loss: 4373229
6.0000 - accuracy: 0.0000e+00 - mape: 22.0288 - mse: 43732296.0000 -
val_loss: 45988032.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.75
04 - val_mse: 45988032.0000
Epoch 71/130
67/67 [=====] - 1s 8ms/step - loss: 4097089
6.0000 - accuracy: 0.0000e+00 - mape: 21.6834 - mse: 40970896.0000 -
val_loss: 63178596.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.42
43 - val_mse: 63178596.0000
Epoch 72/130
67/67 [=====] - 1s 7ms/step - loss: 4131229
2.0000 - accuracy: 0.0000e+00 - mape: 21.7032 - mse: 41312292.0000 -
val_loss: 31223130.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.77
71 - val_mse: 31223130.0000
Epoch 73/130
67/67 [=====] - 1s 7ms/step - loss: 4383853
6.0000 - accuracy: 0.0000e+00 - mape: 22.1578 - mse: 43838536.0000 -
val_loss: 32972258.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.66
40 - val_mse: 32972258.0000
Epoch 74/130
67/67 [=====] - 0s 7ms/step - loss: 4141993
6.0000 - accuracy: 0.0000e+00 - mape: 21.8775 - mse: 41419936.0000 -
val_loss: 36945512.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.49
89 - val_mse: 36945512.0000
Epoch 75/130
67/67 [=====] - 0s 7ms/step - loss: 4159141
6.0000 - accuracy: 0.0000e+00 - mape: 21.7699 - mse: 41591416.0000 -
val_loss: 30811506.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.01
82 - val_mse: 30811506.0000
Epoch 76/130
67/67 [=====] - 0s 7ms/step - loss: 4217217
6.0000 - accuracy: 0.0000e+00 - mape: 21.8712 - mse: 42172176.0000 -
val_loss: 34740224.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.93
81 - val_mse: 34740224.0000
Epoch 77/130
67/67 [=====] - 1s 8ms/step - loss: 4184205
6.0000 - accuracy: 0.0000e+00 - mape: 21.9843 - mse: 41842056.0000 -
val_loss: 31560724.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.90
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87 - val_mse: 31560724.0000
Epoch 78/130
67/67 [=====] - 0s 7ms/step - loss: 4169103
6.0000 - accuracy: 0.0000e+00 - mape: 21.7108 - mse: 41691036.0000 -
val_loss: 42359404.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.37
73 - val_mse: 42359404.0000
Epoch 79/130
67/67 [=====] - 1s 7ms/step - loss: 4080767
2.0000 - accuracy: 0.0000e+00 - mape: 21.7770 - mse: 40807672.0000 -
val_loss: 42101220.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.92
25 - val_mse: 42101220.0000
Epoch 80/130
67/67 [=====] - 1s 7ms/step - loss: 4228558
8.0000 - accuracy: 0.0000e+00 - mape: 21.9450 - mse: 42285588.0000 -
val_loss: 33508520.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.76
09 - val_mse: 33508520.0000
Epoch 81/130
67/67 [=====] - 0s 7ms/step - loss: 4008297
2.0000 - accuracy: 0.0000e+00 - mape: 21.6987 - mse: 40082972.0000 -
val_loss: 74937160.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.74
96 - val_mse: 74937160.0000
Epoch 82/130
67/67 [=====] - 1s 8ms/step - loss: 4189218
0.0000 - accuracy: 0.0000e+00 - mape: 21.5866 - mse: 41892180.0000 -
val_loss: 30978504.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.18
39 - val_mse: 30978504.0000
Epoch 83/130
67/67 [=====] - 1s 8ms/step - loss: 4002269
6.0000 - accuracy: 0.0000e+00 - mape: 21.7372 - mse: 40022696.0000 -
val_loss: 50350628.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.02
63 - val_mse: 50350628.0000
Epoch 84/130
67/67 [=====] - 1s 8ms/step - loss: 4152780
4.0000 - accuracy: 0.0000e+00 - mape: 21.7807 - mse: 41527804.0000 -
val_loss: 30730480.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.68
60 - val_mse: 30730480.0000
Epoch 85/130
67/67 [=====] - 0s 7ms/step - loss: 4298965
2.0000 - accuracy: 0.0000e+00 - mape: 21.9917 - mse: 42989652.0000 -
val_loss: 39731024.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.98
57 - val_mse: 39731024.0000
Epoch 86/130
67/67 [=====] - 1s 8ms/step - loss: 4182899
2.0000 - accuracy: 0.0000e+00 - mape: 22.0256 - mse: 41828992.0000 -
val_loss: 41521260.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.24
71 - val_mse: 41521260.0000
Epoch 87/130
67/67 [=====] - 1s 7ms/step - loss: 3991854
0.0000 - accuracy: 0.0000e+00 - mape: 21.3326 - mse: 39918540.0000 -
val_loss: 47875144.0000 - val_accuracy: 0.0000e+00 - val_mape: 26.82
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58 - val_mse: 47875144.0000
Epoch 88/130
67/67 [=====] - 1s 8ms/step - loss: 4171537
6.0000 - accuracy: 0.0000e+00 - mape: 21.5885 - mse: 41715376.0000 -
val_loss: 37997500.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.15
58 - val_mse: 37997500.0000
Epoch 89/130
67/67 [=====] - 0s 7ms/step - loss: 4073157
2.0000 - accuracy: 0.0000e+00 - mape: 21.6425 - mse: 40731572.0000 -
val_loss: 37580576.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.29
52 - val_mse: 37580576.0000
Epoch 90/130
67/67 [=====] - 1s 8ms/step - loss: 4056574
0.0000 - accuracy: 0.0000e+00 - mape: 21.5620 - mse: 40565740.0000 -
val_loss: 86552096.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.97
38 - val_mse: 86552096.0000
Epoch 91/130
67/67 [=====] - 0s 7ms/step - loss: 4081336
4.0000 - accuracy: 0.0000e+00 - mape: 21.4608 - mse: 40813364.0000 -
val_loss: 41453188.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.59
24 - val_mse: 41453188.0000
Epoch 92/130
67/67 [=====] - 1s 11ms/step - loss: 404408
84.0000 - accuracy: 0.0000e+00 - mape: 21.5300 - mse: 40440884.0000
- val_loss: 33999612.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.
1466 - val_mse: 33999612.0000
Epoch 93/130
67/67 [=====] - 1s 11ms/step - loss: 414899
08.0000 - accuracy: 0.0000e+00 - mape: 21.9015 - mse: 41489908.0000
- val_loss: 49303964.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.
2651 - val_mse: 49303964.0000
Epoch 94/130
67/67 [=====] - 1s 15ms/step - loss: 398082
36.0000 - accuracy: 0.0000e+00 - mape: 21.4341 - mse: 39808236.0000
- val_loss: 70705704.0000 - val_accuracy: 0.0000e+00 - val_mape: 37.
6256 - val_mse: 70705704.0000
Epoch 95/130
67/67 [=====] - 0s 7ms/step - loss: 4217644
4.0000 - accuracy: 0.0000e+00 - mape: 21.5963 - mse: 42176444.0000 -
val_loss: 31995244.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.28
49 - val_mse: 31995244.0000
Epoch 96/130
67/67 [=====] - 1s 15ms/step - loss: 407424
96.0000 - accuracy: 0.0000e+00 - mape: 21.6524 - mse: 40742496.0000
- val_loss: 34176140.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.
9216 - val_mse: 34176140.0000
Epoch 97/130
67/67 [=====] - 1s 7ms/step - loss: 4054083
2.0000 - accuracy: 0.0000e+00 - mape: 21.7053 - mse: 40540832.0000 -
val_loss: 37578216.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.81
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23 - val_mse: 37578216.0000
Epoch 98/130
67/67 [=====] - 0s 7ms/step - loss: 4297267
2.0000 - accuracy: 0.0000e+00 - mape: 22.0064 - mse: 42972672.0000 -
val_loss: 33380734.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.68
80 - val_mse: 33380734.0000
Epoch 99/130
67/67 [=====] - 1s 7ms/step - loss: 4088601
2.0000 - accuracy: 0.0000e+00 - mape: 21.9072 - mse: 40886012.0000 -
val_loss: 59746236.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.92
32 - val_mse: 59746236.0000
Epoch 100/130
67/67 [=====] - 0s 7ms/step - loss: 4080546
0.0000 - accuracy: 0.0000e+00 - mape: 21.6739 - mse: 40805460.0000 -
val_loss: 44191888.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.66
51 - val_mse: 44191888.0000
Epoch 101/130
67/67 [=====] - 0s 7ms/step - loss: 3974523
6.0000 - accuracy: 0.0000e+00 - mape: 21.6558 - mse: 39745236.0000 -
val_loss: 48630056.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.93
18 - val_mse: 48630056.0000
Epoch 102/130
67/67 [=====] - 1s 8ms/step - loss: 4181136
0.0000 - accuracy: 0.0000e+00 - mape: 21.6895 - mse: 41811360.0000 -
val_loss: 31281862.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.26
07 - val_mse: 31281862.0000
Epoch 103/130
67/67 [=====] - 0s 7ms/step - loss: 4141059
2.0000 - accuracy: 0.0000e+00 - mape: 21.7315 - mse: 41410592.0000 -
val_loss: 39125040.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.73
42 - val_mse: 39125040.0000
Epoch 104/130
67/67 [=====] - 0s 7ms/step - loss: 4170037
6.0000 - accuracy: 0.0000e+00 - mape: 21.8453 - mse: 41700376.0000 -
val_loss: 31499182.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.12
40 - val_mse: 31499182.0000
Epoch 105/130
67/67 [=====] - 0s 7ms/step - loss: 4094360
8.0000 - accuracy: 0.0000e+00 - mape: 21.6565 - mse: 40943608.0000 -
val_loss: 40740588.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.51
08 - val_mse: 40740588.0000
Epoch 106/130
67/67 [=====] - 1s 8ms/step - loss: 4067349
6.0000 - accuracy: 0.0000e+00 - mape: 21.5391 - mse: 40673496.0000 -
val_loss: 40486300.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.33
75 - val_mse: 40486300.0000
Epoch 107/130
67/67 [=====] - 0s 7ms/step - loss: 4097907
6.0000 - accuracy: 0.0000e+00 - mape: 21.4397 - mse: 40979076.0000 -
val_loss: 31413618.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.39
```



```
32 - val_mse: 31413618.0000
Epoch 108/130
67/67 [=====] - 1s 8ms/step - loss: 3985640
4.0000 - accuracy: 0.0000e+00 - mape: 21.4338 - mse: 39856404.0000 -
val_loss: 36205892.0000 - val_accuracy: 0.0000e+00 - val_mape: 24.70
98 - val_mse: 36205892.0000
Epoch 109/130
67/67 [=====] - 1s 8ms/step - loss: 4117516
0.0000 - accuracy: 0.0000e+00 - mape: 21.7064 - mse: 41175160.0000 -
val_loss: 60198560.0000 - val_accuracy: 0.0000e+00 - val_mape: 31.66
88 - val_mse: 60198560.0000
Epoch 110/130
67/67 [=====] - 0s 7ms/step - loss: 4192314
8.0000 - accuracy: 0.0000e+00 - mape: 21.7507 - mse: 41923148.0000 -
val_loss: 39517532.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.58
07 - val_mse: 39517532.0000
Epoch 111/130
67/67 [=====] - 1s 8ms/step - loss: 4070632
4.0000 - accuracy: 0.0000e+00 - mape: 21.6955 - mse: 40706324.0000 -
val_loss: 79784776.0000 - val_accuracy: 0.0000e+00 - val_mape: 22.87
22 - val_mse: 79784776.0000
Epoch 112/130
67/67 [=====] - 1s 7ms/step - loss: 4162068
0.0000 - accuracy: 0.0000e+00 - mape: 21.6167 - mse: 41620680.0000 -
val_loss: 36317432.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.93
42 - val_mse: 36317432.0000
Epoch 113/130
67/67 [=====] - 0s 7ms/step - loss: 4121445
6.0000 - accuracy: 0.0000e+00 - mape: 21.9648 - mse: 41214456.0000 -
val_loss: 59771052.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.12
45 - val_mse: 59771052.0000
Epoch 114/130
67/67 [=====] - 1s 7ms/step - loss: 4121602
0.0000 - accuracy: 0.0000e+00 - mape: 21.5258 - mse: 41216020.0000 -
val_loss: 33305336.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.32
90 - val_mse: 33305336.0000
Epoch 115/130
67/67 [=====] - 1s 8ms/step - loss: 3842344
4.0000 - accuracy: 0.0000e+00 - mape: 21.0357 - mse: 38423444.0000 -
val_loss: 63622928.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.58
22 - val_mse: 63622928.0000
Epoch 116/130
67/67 [=====] - 1s 8ms/step - loss: 4127448
4.0000 - accuracy: 0.0000e+00 - mape: 21.2929 - mse: 41274484.0000 -
val_loss: 41354720.0000 - val_accuracy: 0.0000e+00 - val_mape: 27.86
77 - val_mse: 41354720.0000
Epoch 117/130
67/67 [=====] - 1s 8ms/step - loss: 4320446
4.0000 - accuracy: 0.0000e+00 - mape: 22.0543 - mse: 43204464.0000 -
val_loss: 35714064.0000 - val_accuracy: 0.0000e+00 - val_mape: 21.27
```

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56 - val_mse: 35714064.0000
Epoch 118/130
67/67 [=====] - 1s 8ms/step - loss: 3764456
0.0000 - accuracy: 0.0000e+00 - mape: 20.8456 - mse: 37644560.0000 -
val_loss: 29194280.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.03
08 - val_mse: 29194280.0000
Epoch 119/130
67/67 [=====] - 1s 8ms/step - loss: 4098382
0.0000 - accuracy: 0.0000e+00 - mape: 21.5726 - mse: 40983820.0000 -
val_loss: 42084240.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.58
91 - val_mse: 42084240.0000
Epoch 120/130
67/67 [=====] - 1s 7ms/step - loss: 3988605
2.0000 - accuracy: 0.0000e+00 - mape: 21.6268 - mse: 39886052.0000 -
val_loss: 35063348.0000 - val_accuracy: 0.0000e+00 - val_mape: 23.15
68 - val_mse: 35063348.0000
Epoch 121/130
67/67 [=====] - 0s 7ms/step - loss: 4075777
2.0000 - accuracy: 0.0000e+00 - mape: 21.7008 - mse: 40757772.0000 -
val_loss: 43881492.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.83
15 - val_mse: 43881492.0000
Epoch 122/130
67/67 [=====] - 1s 8ms/step - loss: 4122625
6.0000 - accuracy: 0.0000e+00 - mape: 21.5562 - mse: 41226256.0000 -
val_loss: 30947414.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.77
60 - val_mse: 30947414.0000
Epoch 123/130
67/67 [=====] - 0s 7ms/step - loss: 4096793
6.0000 - accuracy: 0.0000e+00 - mape: 21.4764 - mse: 40967936.0000 -
val_loss: 65951088.0000 - val_accuracy: 0.0000e+00 - val_mape: 20.47
90 - val_mse: 65951088.0000
Epoch 124/130
67/67 [=====] - 1s 7ms/step - loss: 4008844
8.0000 - accuracy: 0.0000e+00 - mape: 21.2964 - mse: 40088448.0000 -
val_loss: 30786196.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.39
09 - val_mse: 30786196.0000
Epoch 125/130
67/67 [=====] - 1s 7ms/step - loss: 3877685
2.0000 - accuracy: 0.0000e+00 - mape: 21.2576 - mse: 38776852.0000 -
val_loss: 52687428.0000 - val_accuracy: 0.0000e+00 - val_mape: 25.00
40 - val_mse: 52687428.0000
Epoch 126/130
67/67 [=====] - 1s 7ms/step - loss: 4076864
0.0000 - accuracy: 0.0000e+00 - mape: 21.6825 - mse: 40768640.0000 -
val_loss: 51263000.0000 - val_accuracy: 0.0000e+00 - val_mape: 19.27
62 - val_mse: 51263000.0000
Epoch 127/130
67/67 [=====] - 0s 7ms/step - loss: 4109839
2.0000 - accuracy: 0.0000e+00 - mape: 21.6708 - mse: 41098392.0000 -
val_loss: 31659818.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.96
```

```

98 - val_mse: 31659818.0000
Epoch 128/130
67/67 [=====] - 1s 8ms/step - loss: 3909379
2.0000 - accuracy: 0.0000e+00 - mape: 21.3819 - mse: 39093792.0000 -
val_loss: 47027536.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.50
82 - val_mse: 47027536.0000
Epoch 129/130
67/67 [=====] - 1s 8ms/step - loss: 4117478
0.0000 - accuracy: 0.0000e+00 - mape: 21.3854 - mse: 41174780.0000 -
val_loss: 29847868.0000 - val_accuracy: 0.0000e+00 - val_mape: 18.00
27 - val_mse: 29847868.0000
Epoch 130/130
67/67 [=====] - 1s 9ms/step - loss: 3919200
8.0000 - accuracy: 0.0000e+00 - mape: 21.5329 - mse: 39192008.0000 -
val_loss: 31566112.0000 - val_accuracy: 0.0000e+00 - val_mape: 17.73
58 - val_mse: 31566112.0000

```

## Linear Regression.

```

Lin. Regression MSE: 33198705.387708984
Lin. Regression MAE 3519.9429683879794
Lin. Regression Correlation: 0.7536695266563911

```

epoch = 100

```

Kera Reg. RMSE: 6369.461829699586
Kera Reg. MAE: 4255.84326171875

```

epoch = 130

```

Kera Reg. RMSE: 6530.3512922353575
Kera Reg. MAE: 4238.39453125

```

epoch = 500

```

Kera Reg. RMSE: 5537.493295707002
Kera Reg. MAE: 4054.353759765625

```

## Step 7 - Commentary

a: Compare metrics from sklearn and Keras.

- MAE on Keras is higher than Linear Regression for all values set on epochs, and RMSE is also higher.

Linear Regression not only have the best result but also run faster than Keras Regression.

b: Explore the data a bit more to speculate on why you achieved the results you got.

- Using Keras we need to (Define, Compile, Fit, Evaluate and Make the Network).

The using the tree simple Neural Network with input layer, hidden layer, and output layer.

This layers are matrices that input times and weights to a bias to activate the results repeat a few times

and gives the prediction.

- When we define a network, it is defined as a sequence of layers using sequential class.

The first layer will define the number of expect.

Then Keras will work like a filter the raw data are inputed at the top, calculated and predictions are output.

In Keras the raw data input is split into layers.

The activation signal transform to signal and extract the result learned and pass to the next layer (node).

The activation function defines the format of the predictions output, in this case I used 'relu'.

It transforms the layers into a high level matrix then the network is trained using back propagation algorithm,

and optimize according to optimization algorithm and loss function specified when compiled the model.

- Using this algorithm we can get the best result and fast since Keras is one of the faster way to make

predictions and the data is not very large.

c: Describe all the architectures/hyperparameters you tried and the results. What do you conclude?

- I tried the two different architecture shown on the book as example, the results were pretty the same the

difference was that one of these two had a better run time.

- I compared my results with a friend to see if the results would be the same since we worked with the same data,

but somehow all the results for Linear Regression and Keras Regression were also in this case a considerable value.

```
In [32]: # code to generate a html file
!jupyter nbconvert --to htm /content/drive/MyDrive/Colab Notebooks/DeepLearning.ipynb
```

```
[NbConvertApp] WARNING | pattern '/content/drive/MyDrive/Colab' matched no files
[NbConvertApp] WARNING | pattern 'Notebooks/DeepLearning.ipynb' matched no files
Traceback (most recent call last):
  File "/usr/local/bin/jupyter-nbconvert", line 8, in <module>
    sys.exit(main())
  File "/usr/local/lib/python3.7/dist-packages/jupyter_core/application.py", line 269, in launch_instance
    return super().launch_instance(argv=argv, **kwargs)
  File "/usr/local/lib/python3.7/dist-packages/traitlets/config/application.py", line 846, in launch_instance
    app.start()
  File "/usr/local/lib/python3.7/dist-packages/nbconvert/nbconvertapp.py", line 340, in start
    self.convert_notebooks()
  File "/usr/local/lib/python3.7/dist-packages/nbconvert/nbconvertapp.py", line 499, in convert_notebooks
    cls = get_exporter(self.export_format)
  File "/usr/local/lib/python3.7/dist-packages/nbconvert/exporters/base.py", line 113, in get_exporter
    % (name, ', '.join(get_export_names()))
ValueError: Unknown exporter "htm", did you mean one of: asciidoc, custom, html, latex, markdown, notebook, pdf, python, rst, script, slides?
```