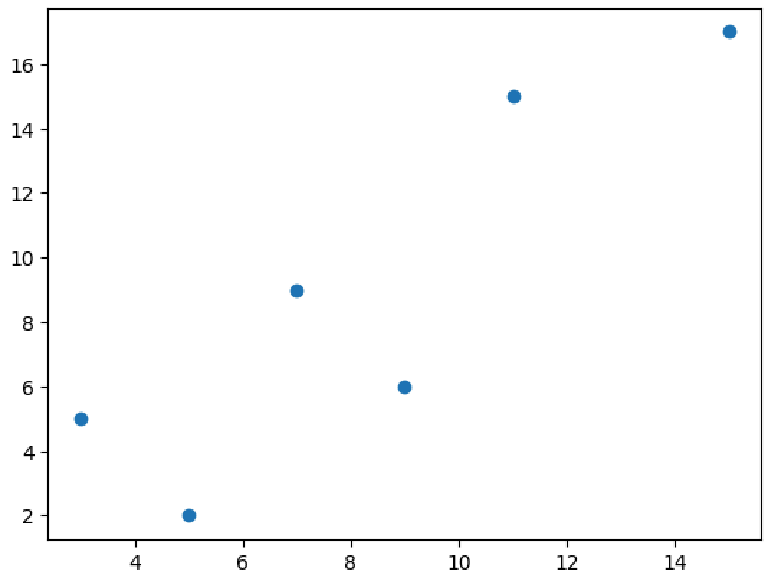
```
# Single Layer Perceptron:-


import keras
import tensorflow


from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam


import numpy as np
import matplotlib.pyplot as plt


x = np.array([3,7,5,9,11,15])
y = np.array([5,9,2,6,15,17])


plt.scatter(x,y)
plt.show()
```




```
# Single Layer Perceptron:-
model = Sequential()
# input & hidden layer:
model.add(Dense(1,input_dim = 1,activation='linear'))
# output layer:
model.add(Dense(1,activation='linear'))
model.compile(Adam(learning_rate=0.01),loss='mse')
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_d
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 1)	2
dense_3 (Dense)	(None, 1)	2

Total params: 4 (16.00 B)
Trainable params: 4 (16.00 B)

```
model.fit(x,y,epochs=20,verbose=1)
```

```
Epoch 1/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 7.4651
Epoch 2/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step - loss: 7.4608
Epoch 3/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 7.4570
Epoch 4/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step - loss: 7.4536
Epoch 5/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step - loss: 7.4505
Epoch 6/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step - loss: 7.4477
Epoch 7/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 51ms/step - loss: 7.4452
Epoch 8/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 62ms/step - loss: 7.4428
Epoch 9/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step - loss: 7.4405
Epoch 10/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step - loss: 7.4383
Epoch 11/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step - loss: 7.4362
Epoch 12/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step - loss: 7.4341
Epoch 13/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 7.4320
Epoch 14/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 7.4298
Epoch 15/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step - loss: 7.4276
Epoch 16/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 63ms/step - loss: 7.4253
Epoch 17/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step - loss: 7.4230
Epoch 18/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 7.4207
Epoch 19/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 61ms/step - loss: 7.4183
Epoch 20/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 7.4158
<keras.src.callbacks.history.History at 0x7e719fd52910>
```

```
model.predict(x)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
array([[ 4.0493546],
       [ 7.9864063],
       [ 6.017881 ],
       [ 9.954933 ],
       [11.92346  ],
       [15.860512 ]], dtype=float32)
```

```
# Multi-Layer Perceptron :-
```

```
# importing all packages:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Read the dataset:-
adv = pd.read_csv(r'/content/advertising.csv')
adv
```

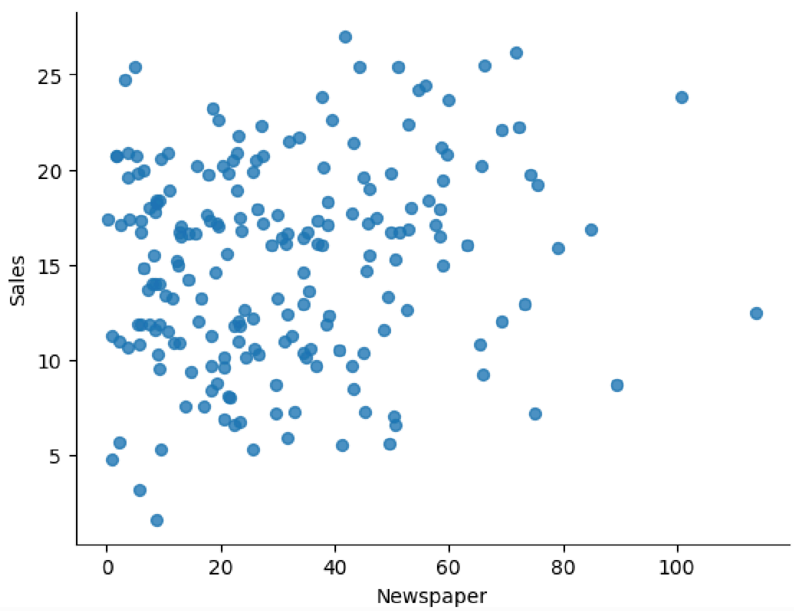
	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9
...	...	...	...	...
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

Next steps: Generate code with adv View recommended plots New interactive sheet

Newspaper vs Sales

```
# @title Newspaper vs Sales

from matplotlib import pyplot as plt
adv.plot(kind='scatter', x='Newspaper', y='Sales', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```




```
# Data Cleaning:-
adv.isnull().sum()
```

	0
TV	0
Radio	0
Newspaper	0
Sales	0

dtype: int64

```
adv.dtypes
```

	0
TV	float64
Radio	float64
Newspaper	float64
Sales	float64

dtype: object

```
for i in adv.columns:
  print(f"{i}:\n {adv[i].unique()}")
```

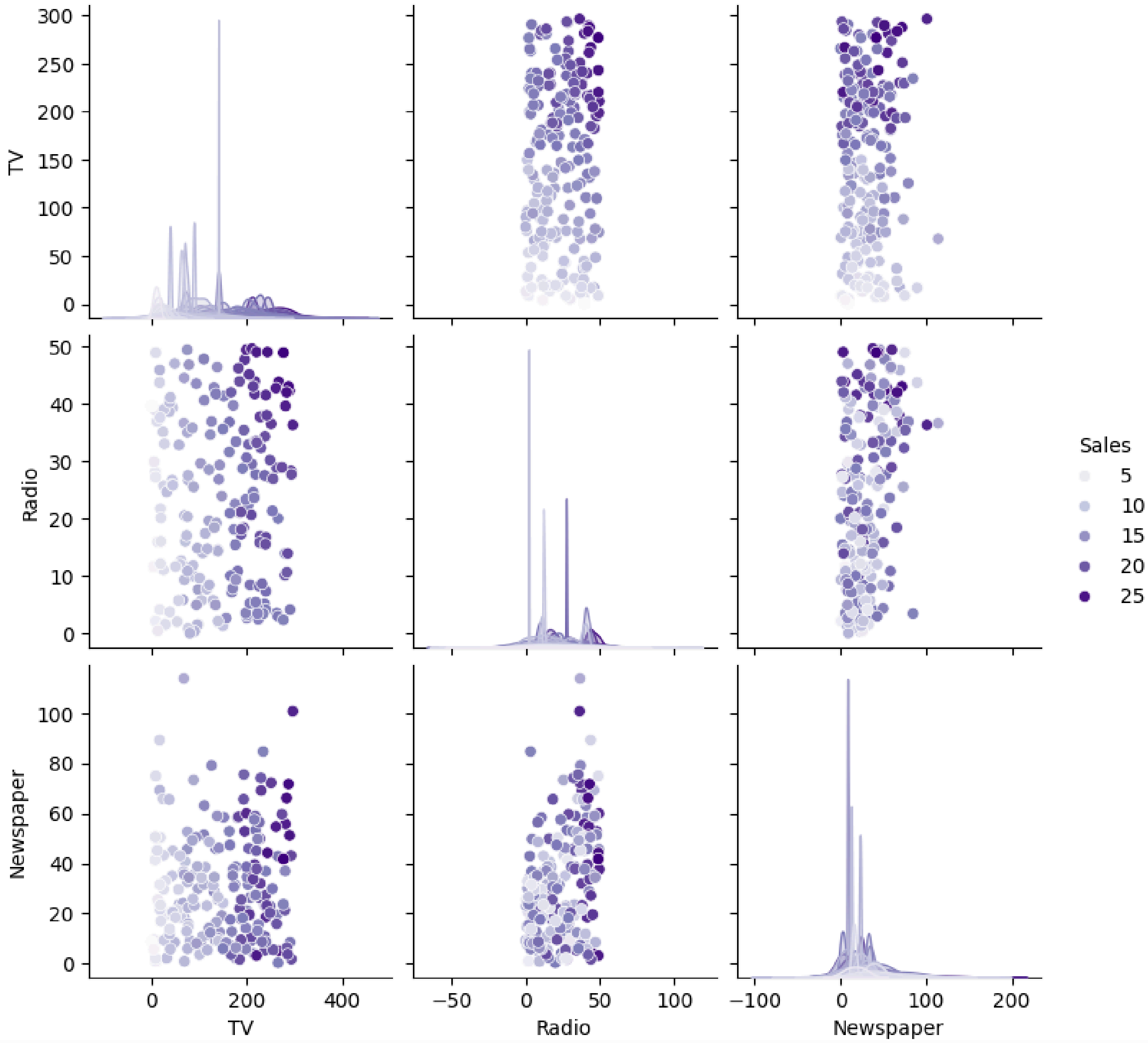
```
TV:
 [230.1  44.5  17.2 151.5 180.8   8.7  57.5 120.2   8.6 199.8  66.1 214.7
  23.8  97.5 204.1 195.4  67.8 281.4  69.2 147.3 218.4 237.4  13.2 228.3
  62.3 262.9 142.9 240.1 248.8  70.6 292.9 112.9  97.2 265.6  95.7 290.7
 266.9  74.7  43.1 228.  202.5 177.  293.6 206.9  25.1 175.1  89.7 239.9
 227.2  66.9 100.4 216.4 182.6 262.7 198.9   7.3 136.2 210.8 210.7  53.5
 261.3 239.3 102.7 131.1  69.   31.5 139.3 216.8 199.1 109.8  26.8 129.4
 213.4  16.9  27.5 120.5   5.4 116.   76.4 239.8  75.3  68.4 213.5 193.2
  76.3 110.7  88.3 134.3  28.6 217.7 250.9 107.4 163.3 197.6 184.9 289.7
 135.2 222.4 296.4 280.2 187.9 238.2 137.9  25.   90.4  13.1 255.4 225.8
 241.7 175.7 209.6  78.2  75.1 139.2 125.7  19.4 141.3  18.8 224.  123.1
 229.5  87.2   7.8  80.2 220.3  59.6   0.7 265.2   8.4 219.8  36.9  48.3
  25.6 273.7  43.   73.4 193.7 220.5 104.6  96.2 140.3 243.2  38.   44.7
 280.7 121.  171.3 187.8   4.1  93.9 149.8  11.7 131.7 172.5  85.7 188.4
 163.5 117.2 234.5  17.9 206.8 215.4 284.3  50.  164.5  19.6 168.4 276.9
 248.4 170.2 276.7 165.6 156.6 218.5  56.2 287.6 253.8 205.  139.5 191.1
 286.   18.7  39.5  75.5 166.8 149.7  38.2  94.2 283.6 232.1]
Radio:
 [37.8 39.3 45.9 41.3 10.8 48.9 32.8 19.6  2.1  2.6  5.8 24.  35.1  7.6
  32.9 47.7 36.6 39.6 20.5 23.9 27.7  5.1 15.9 16.9 12.6  3.5 29.3 16.7
  27.1 16.  28.3 17.4  1.5 20.   1.4  4.1 43.8 49.4 26.7 37.7 22.3 33.4
   8.4 25.7 22.5  9.9 41.5 15.8 11.7  3.1  9.6 41.7 46.2 28.8 28.1 19.2
  49.6 29.5  2.  42.7 15.5 29.6 42.8  9.3 24.6 14.5 27.5 43.9 30.6 14.3
  33.   5.7 43.7  1.6 28.5 29.9  7.7 20.3 44.5 43.  18.4 40.6 25.5 47.8
   4.9 33.5 36.5 14.  31.6 21.  42.3  4.3 36.3 10.1 17.2 34.3 46.4 11.
   0.3  0.4 26.9  8.2 38.  15.4 20.6 46.8 35.   0.8 36.9 26.8 21.7  2.4
  34.6 32.3 11.8 38.9  0.  49.  12.   2.9 27.2 38.6 47.  39.  28.9 25.9
  17.  35.4 33.2 14.8  1.9  7.3 40.3 25.8 13.9 23.3 39.7 21.1 11.6 43.5
   1.3 18.1 35.8 36.8 14.7  3.4 37.6  5.2 23.6 10.6 20.9 20.1  7.1 30.2
   7.8  2.3 10.   5.4 21.3 45.1 28.7 12.1 41.1 42.  35.6  3.7  8.6]
Newspaper:
 [ 69.2  45.1  69.3  58.5  58.4  75.   23.5  11.6   1.   21.2  24.2   4.
  65.9   7.2  46.   52.9 114.   55.8  18.3  19.1  53.4  49.6  26.2  19.5
  12.6  22.9  40.8  43.2  38.6  30.    0.3   7.4   8.5   5.   45.7  35.1
  32.   31.6  38.7   1.8  26.4  43.3  31.5  35.7  18.5  49.9  36.8  34.6
   3.6  39.6  58.7  15.9  60.   41.4  16.6  37.7   9.3  21.4  54.7  27.3
   8.4  28.9   0.9   2.2  10.2  11.   27.2  31.7  19.3  31.3  13.1  89.4
  20.7  14.2   9.4  23.1  22.3  36.9  32.5  35.6  33.8  65.7  16.   63.2
  73.4  51.4  33.   59.   72.3  10.9   5.9  22.   51.2  45.9  49.8 100.9
  17.9   5.3  29.7  23.2  25.6   5.5  56.5   2.4  10.7  34.5  52.7  14.8
  79.2  46.2  50.4  15.6  12.4  74.2  25.9  50.6   9.2   3.2  43.1   8.7
  43.    2.1  65.6  59.7  20.5   1.7  12.9  75.6  37.9  34.4  38.9   9.
  44.3  11.9  20.6  37.   48.7   9.5   5.7  50.5  24.3  45.2  30.7  49.3
   5.4  84.8  21.6  19.4  57.6   6.4  18.4  47.4  17.   12.8  41.8  20.3
  35.2  23.7  17.6   8.3  27.4  71.8  19.6  26.6  18.2   3.7  23.4   5.8
   6.   13.8   8.1  66.2]
Sales:
```

```
[22.1 10.4 12.  16.5 17.9  7.2 11.8 13.2  4.8 15.6 12.6 17.4  9.2 13.7
19.  22.4 12.5 24.4 11.3 14.6 18.  17.5  5.6 20.5  9.7 17.  15.  20.9
18.9 10.5 21.4 11.9 17.8 25.4 14.7 10.1 21.5 16.6 17.1 20.7  8.5 16.1
10.6 23.2 19.8 16.4 10.7 22.6 21.2 20.2 23.7  5.5 23.8 18.4  8.1 24.2
14.  16.  11.  13.4 22.3 18.3 12.4  8.8  8.7  6.9 14.2  5.3 17.3 13.6
21.7 12.9 16.7  7.3 19.4 22.2 11.5 16.9 17.2 19.7 21.8 12.2  9.4 15.9
 6.6 15.5  7.  15.2 24.7  1.6 17.7  5.7 19.6 10.8 11.6  9.5 20.8  9.6
10.9 19.2 20.1 12.3 10.3 18.2 20.6  3.2 15.3 13.3 19.9  8.  20.   8.4
 7.6 27.  16.8 17.6 26.2  6.7  5.9 14.8 25.5]
```

```
adv.describe()
```

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

```
# Data Visualization or EDA:-
sns.pairplot(adv,hue='Sales',palette='Purples')
plt.show()
```




```
# Encoding:-
```

```
# ip/op Creation:-
ip = adv.drop('Sales',axis=1)
op = adv.Sales
```

```
ip.head()
```

	TV	Radio	Newspaper
0	230.1	37.8	69.2
1	44.5	39.3	45.1
2	17.2	45.9	69.3
3	151.5	41.3	58.5
4	180.8	10.8	58.4

Next steps: Generate code with ip View recommended plots New interactive sheet

```
op.head()
```

	Sales
0	22.1
1	10.4
2	12.0
3	16.5
4	17.9

dtype: float64

```
# Train Test Split:-
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(ip,op,test_size=0.2)
```

```
# Standardization:-
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.fit_transform(xtest)
```

```
# Applying Multi-layer Perceptron Model:-
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam
```

```
# Creating the model:-
model = Sequential()
# input layer:-
model.add(Dense(30,input_dim = 3, activation='linear'))
# hidden layer:-
model.add(Dense(15,activation='linear'))
model.add(Dense(25,activation='linear'))
# Output layer:-
model.add(Dense(1,activation='linear'))
model.compile(Adam(learning_rate=0.01),loss='mse')
```

```
model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 30)	120
dense_5 (Dense)	(None, 15)	465
dense_6 (Dense)	(None, 25)	400
dense_7 (Dense)	(None, 1)	26

Total params: 1,011 (3.95 KB)
Trainable params: 1,011 (3.95 KB)

```
model.fit(xtrain,ytrain,validation_data=(xtest,ytest),epochs=25)
```

```
Epoch 1/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 93ms/step - loss: 250.6253 - val_loss: 207.4682
Epoch 2/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 190.2220 - val_loss: 137.0941
Epoch 3/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 111.4902 - val_loss: 68.7449
Epoch 4/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 38.0596 - val_loss: 5.7743
Epoch 5/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 6.2039 - val_loss: 11.0673
Epoch 6/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 17.3546 - val_loss: 7.6252
```

```
Epoch 7/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - loss: 9.2837 - val_loss: 2.8210
Epoch 8/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - loss: 2.9991 - val_loss: 4.2995
Epoch 9/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 3.6403 - val_loss: 5.1044
Epoch 10/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 4.9570 - val_loss: 3.9934
Epoch 11/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 3.1853 - val_loss: 3.1446
Epoch 12/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - loss: 3.1277 - val_loss: 2.6845
Epoch 13/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.8810 - val_loss: 2.5306
Epoch 14/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 2.6912 - val_loss: 2.4921
Epoch 15/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.6269 - val_loss: 2.6614
Epoch 16/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.6369 - val_loss: 3.0686
Epoch 17/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.8433 - val_loss: 2.9571
Epoch 18/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 3.6627 - val_loss: 2.8516
Epoch 19/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step - loss: 3.4676 - val_loss: 3.0501
Epoch 20/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.4530 - val_loss: 2.6259
Epoch 21/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 2.6160 - val_loss: 2.7820
Epoch 22/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 2.7570 - val_loss: 2.8411
Epoch 23/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 3.5431 - val_loss: 2.7908
Epoch 24/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 2.7827 - val_loss: 2.8829
Epoch 25/25
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 3.2370 - val_loss: 2.7975
<keras.src.callbacks.history.History at 0x7e7196e65a10>
```

```
pred = model.predict(xtest)
```

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 59ms/step
```

```
pred
```

```
array([[12.066243 ],
       [ 9.118465 ],
       [19.750584 ],
       [21.46641  ],
       [ 8.578441 ],
       [12.1315775],
       [22.024199 ],
       [13.87241651,
```