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


from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, r2_score


import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers


data=pd.read_csv('boston_train.csv')


data
```

	ID	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	1	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	2	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	4	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
3	5	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2
4	7	0.08829	12.5	7.87	0	0.524	6.012	66.6	5.5605	5	311	15.2	395.60	12.43	22.9
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
328	500	0.17783	0.0	9.69	0	0.585	5.569	73.5	2.3999	6	391	19.2	395.77	15.10	17.5
329	502	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	22.4
330	503	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.6
331	504	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.9
332	506	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	11.9

333 rows × 15 columns

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

```
data.isnull().sum()
```

	0
ID	0
crim	0
zn	0
indus	0
chas	0
nox	0
rm	0
age	0
dis	0
rad	0
tax	0
ptratio	0
black	0
lstat	0
medv	0

dtype: int64

```
# Handle null values by filling them with the mean of the respective columns
data.fillna(data.mean(), inplace=True)
```

```
data.describe()
```

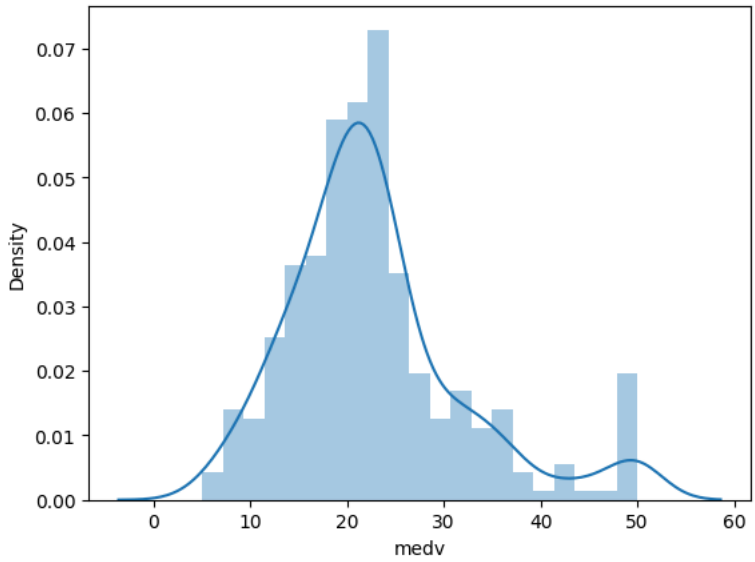
	ID	crim	zn	indus	chas	nox	rm	age	dis	rad	tax
count	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000	333.000000
mean	250.951952	3.360341	10.689189	11.293483	0.060060	0.557144	6.265619	68.226426	3.709934	9.633634	409.279279
std	147.859438	7.352272	22.674762	6.998123	0.237956	0.114955	0.703952	28.133344	1.981123	8.742174	170.841988
min	1.000000	0.006320	0.000000	0.740000	0.000000	0.385000	3.561000	6.000000	1.129600	1.000000	188.000000
25%	123.000000	0.078960	0.000000	5.130000	0.000000	0.453000	5.884000	45.400000	2.122400	4.000000	279.000000
50%	244.000000	0.261690	0.000000	9.900000	0.000000	0.538000	6.202000	76.700000	3.092300	5.000000	330.000000
75%	377.000000	3.678220	12.500000	18.100000	0.000000	0.631000	6.595000	93.800000	5.116700	24.000000	666.000000
max	506.000000	73.534100	100.000000	27.740000	1.000000	0.871000	8.725000	100.000000	10.710300	24.000000	711.000000

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 333 entries, 0 to 332
Data columns (total 15 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   ID       333 non-null    int64  
 1   crim     333 non-null    float64
 2   zn       333 non-null    float64
 3   indus    333 non-null    float64
 4   chas     333 non-null    int64  
 5   nox      333 non-null    float64
 6   rm       333 non-null    float64
 7   age      333 non-null    float64
 8   dis      333 non-null    float64
 9   rad      333 non-null    int64  
 10  tax      333 non-null    int64  
 11  ptratio  333 non-null    float64
 12  black    333 non-null    float64
 13  lstat    333 non-null    float64
 14  medv     333 non-null    float64
dtypes: float64(11), int64(4)
memory usage: 39.2 KB
```

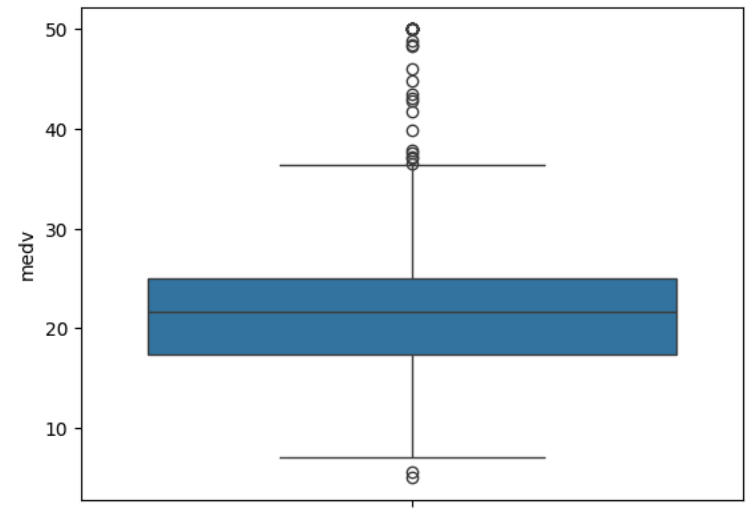
```
import seaborn as sns
sns.distplot(data.medv)
```

```
<ipython-input-12-0cca034db7bb>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data.medv)
<Axes: xlabel='medv', ylabel='Density'>
```



```
sns.boxplot(data.medv)
```

```
<Axes: ylabel='medv'>
```




```
correlation = data.corr()
correlation.loc['medv']
```

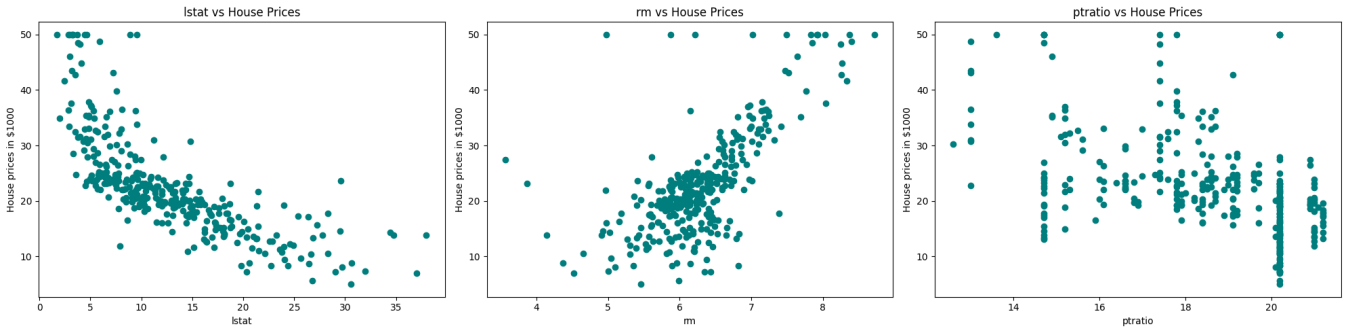
	medv
ID	-0.221694
crim	-0.407454
zn	0.344842
indus	-0.473932
chas	0.204390
nox	-0.413054
rm	0.689598
age	-0.358888
dis	0.249422
rad	-0.352251
tax	-0.448078
ptratio	-0.481376
black	0.336660
lstat	-0.738600
medv	1.000000

dtype: float64

```
# plotting the heatmap
import matplotlib.pyplot as plt
fig,axes = plt.subplots(figsize=(15,12))
sns.heatmap(correlation,square = True,annot = True)
```

<Axes: >


```
# Checking the scatter plot with the most correlated features
# rm (+0.69) — More rooms = higher price
# lstat (−0.74) — Higher % of low-income residents = lower price
# ptratio (−0.48) — Worse student-teacher ratio = lower price

plt.figure(figsize=(20, 5))
features = ['lstat', 'rm', 'ptratio']

for i, col in enumerate(features):
    plt.subplot(1, len(features), i + 1)
    x = data[col]
    y = data['medv']
    plt.scatter(x, y, marker='o', color='teal')
    plt.title(f'{col} vs House Prices')
    plt.xlabel(col)
    plt.ylabel('House prices in $1000')

plt.tight_layout()
plt.show()
```




```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt


# Splitting the dependent feature and independent feature
#X = data[['LSTAT','RM','PTRATIO']]
X = data.iloc[:,:-1]  #Select all columns except the last one
y = data.medv


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Step 5: Normalize (scale) the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)


# Step 6: Build the DNN model for Linear Regression
model = keras.Sequential([
    keras.layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(1)  # Output layer (1 neuron, no activation for regression)
])
```

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

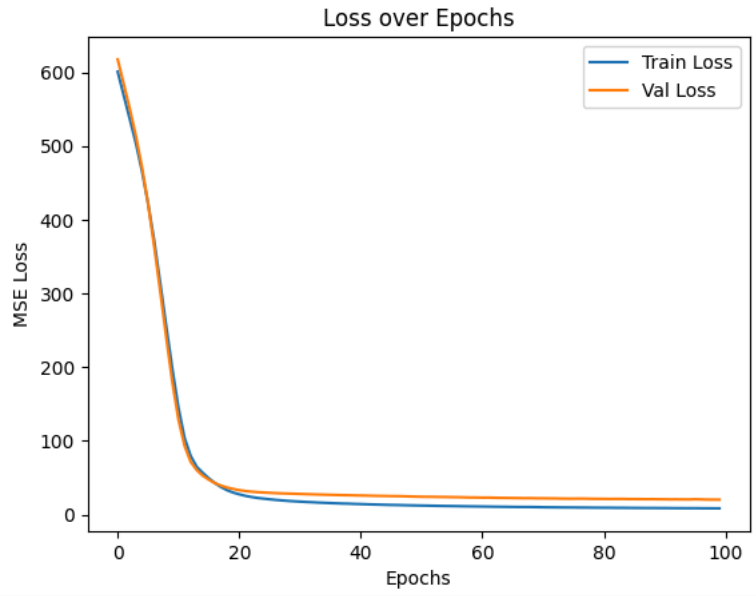
```
# Step 7: Compile the model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])


# Step 8: Train the model
history = model.fit(X_train_scaled, y_train, epochs=100, validation_split=0.2, verbose=1)
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 9.1791 - mae: 2.1572 - val_loss: 21.1273 - val_mae: 3.3333
Epoch 82/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 8.3525 - mae: 2.0711 - val_loss: 21.0283 - val_mae: 3.3415
Epoch 83/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 9.6371 - mae: 2.0675 - val_loss: 21.0972 - val_mae: 3.3633
Epoch 84/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 7.4043 - mae: 1.9621 - val_loss: 21.0802 - val_mae: 3.3492
Epoch 85/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 8.0247 - mae: 2.0647 - val_loss: 20.8981 - val_mae: 3.3308
Epoch 86/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 7.8134 - mae: 1.9918 - val_loss: 20.8646 - val_mae: 3.3339
Epoch 87/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 8.3109 - mae: 1.9807 - val_loss: 20.8548 - val_mae: 3.3282
Epoch 88/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 10.2546 - mae: 2.0771 - val_loss: 20.7348 - val_mae: 3.3135
Epoch 89/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 8.3922 - mae: 1.9453 - val_loss: 20.7893 - val_mae: 3.3197
Epoch 90/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 8.7145 - mae: 2.0079 - val_loss: 20.6962 - val_mae: 3.3022
Epoch 91/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 8.6174 - mae: 2.0015 - val_loss: 20.6425 - val_mae: 3.3149
Epoch 92/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 8.1573 - mae: 1.9641 - val_loss: 20.4997 - val_mae: 3.2854
Epoch 93/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 7.3306 - mae: 1.8930 - val_loss: 20.5276 - val_mae: 3.2830
Epoch 94/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 7.9608 - mae: 1.9863 - val_loss: 20.4450 - val_mae: 3.2884
Epoch 95/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 6.5874 - mae: 1.9438 - val_loss: 20.4215 - val_mae: 3.2799
Epoch 96/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 9.5818 - mae: 2.0660 - val_loss: 20.6796 - val_mae: 3.3181
Epoch 97/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 8.7032 - mae: 1.9665 - val_loss: 20.4686 - val_mae: 3.2925
Epoch 98/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 11.0686 - mae: 2.0983 - val_loss: 20.2096 - val_mae: 3.2756
Epoch 99/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 7.8955 - mae: 1.9425 - val_loss: 20.1619 - val_mae: 3.2561
Epoch 100/100
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 6.1606 - mae: 1.8103 - val_loss: 20.1199 - val_mae: 3.2567
```

```
# Step 9: Evaluate the model
loss, mae = model.evaluate(X_test_scaled, y_test, verbose=2)
print(f"\nMean Absolute Error on test data: ${mae * 1000:.2f}")
```

```
3/3 - 0s - 40ms/step - loss: 11.5588 - mae: 2.5694

Mean Absolute Error on test data: $2569.44
```

```
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss over Epochs')
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.legend()
plt.show()
```




```
test_data = pd.read_csv("boston_test.csv")
```

```
# Use the same scaler (already fitted on training data)
test_data_scaled = scaler.transform(test_data)

# Predict using the trained model
predictions = model.predict(test_data_scaled)

# Optional: Flatten to a clean array
predicted_prices = predictions.flatten()
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step
```

```
# Print or preview results
print("Predicted House Prices (in $1000s):")
print(predicted_prices)

# Or show with row index
df_results = pd.DataFrame({
    "Index": test_data.index,
    "Predicted Price ($1000s)": predicted_prices
})
print(df_results.head())
```

```
Predicted House Prices (in $1000s):
[31.127691  26.701221  17.635483  17.042656  16.78799   16.85224
 19.736197  16.104837  15.718434  16.104828  17.595278  18.555313
 13.832159  15.8231325 23.396004  22.002647  23.620955  31.801043
 19.004814  27.279922  19.245056  20.783731  20.737612  23.556492
 18.622671  22.12448   24.49215   27.01099   22.400188  28.95782
 41.790306  42.93439   35.589294  21.348215  19.538754  20.76233
 17.640188  16.869137  16.180628  21.759424  16.839733  18.821539
 18.845844  15.89807   14.64181   15.295183  17.111195  17.887455
 19.508873  20.330547  18.246716  32.59864   41.3465    22.376797
 21.854408  23.20356   29.87497   46.98911   39.43685   37.261833
 30.941444  42.275604  15.549473  20.019512  23.156237  24.08061
 21.8505    23.532492  22.043655  26.025602  32.352356  41.334984
 32.540623  31.851315  25.650002  24.28326   17.363392  14.978501
 16.753345  28.85303   23.070211  22.651478  40.105637  53.131844
 37.80468   34.826096  48.54008   25.252872  18.581371  32.08682
 32.083275  31.690844  27.134972  43.323772  22.76273   24.075089
 35.019577  21.935112  27.865211  26.408522  33.30165   29.350788
 31.01389   21.790514  20.734737  15.080288  23.39155   20.676588
 16.221346  23.368666  23.94623   17.823238  19.80094   21.218872
 18.493185  17.810204  16.323187  23.323616  23.062351  29.594095
 23.29449   24.926697  17.088423  28.243044  48.031906  46.974648
 24.103748  11.317445  13.353251  23.044418  14.5992155  8.7916975
 10.95758   17.46184   19.546856  18.337776  15.999541   9.010157
 15.1250105  6.1737857 10.861762  16.856457  15.789783  19.204807
 14.1648    13.211055   8.9592085 17.726604  17.619766  19.681602
 13.696758  17.200775  16.582067   8.398048  12.569894   6.699507
```