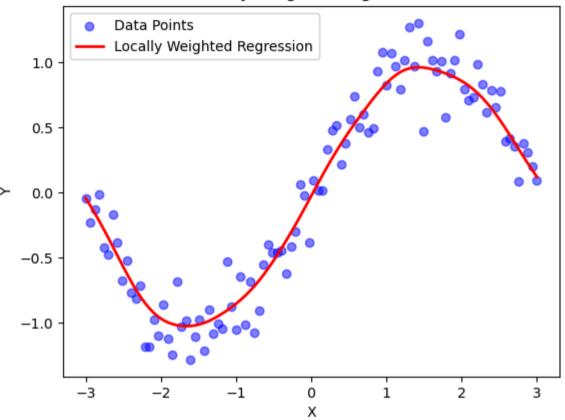
```
In [1]: #6
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.model selection import train test split
        np.random.seed(42)
        X = np.linspace(-3, 3, 100)
        Y = np.sin(X) + np.random.normal(0, 0.2, 100)
        X = X.reshape(-1, 1)
        Y = Y.reshape(-1, 1)
        def weight matrix(X, x query, tau):
             return np.diag(np.exp(-(X - x query)**2 / (2 * tau**2)).flatten())
        def locally weighted regression(X, Y, x query, tau=0.5):
            W = weight matrix(X, x query, tau)
            X bias = np.hstack((np.ones_like(X), X))
            theta = np.linalg.inv(X bias.T @ W @ X bias) @ X bias.T @ W @ Y
            return theta[0] + theta[1] * x query
        X \text{ test} = \text{np.linspace}(-3, 3, 100).\text{reshape}(-1, 1)
        Y pred = np.array([locally weighted regression(X, Y, x query, tau=0.3) for x query in X test])
        plt.scatter(X, Y, label="Data Points", color="blue", alpha=0.5)
        plt.plot(X test, Y pred, label="Locally Weighted Regression", color="red", linewidth=2)
        plt.xlabel("X")
        plt.ylabel("Y")
        plt.title("Locally Weighted Regression")
        plt.legend()
        plt.show()
```

## Locally Weighted Regression



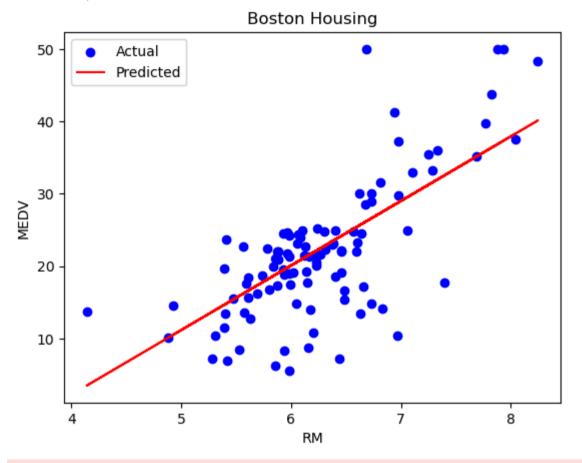
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score

def linear_regression_boston():
    df = pd.read_csv("BostonHousing.csv")
    X, y = df[['RM']], df['MEDV']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=43)
```

```
model = LinearRegression()
    model.fit(X train, y train)
    v pred = model.predict(X test)
    print("Linear Regression - Boston Housing")
    print(f"MSE: {mean squared error(y test, y pred):.2f}, R2: {r2 score(y test, y pred):.2f}")
    plt.scatter(X test, y test, color='blue', label='Actual')
    plt.plot(X test, v pred, color='red', label='Predicted')
    plt.xlabel('RM'), plt.ylabel('MEDV'), plt.title('Boston Housing')
    plt.legend(), plt.show()
def polynomial regression auto mpg():
    url = "https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data"
    cols = ['mpg', 'cyl', 'disp', 'hp', 'wt', 'acc', 'year', 'origin', 'name']
    df = pd.read csv(url, names=cols, delim whitespace=True, na values='?').dropna()
    df['hp'] = df['hp'].astype(float)
   X, y = df[['hp']], df['mpg']
   X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
    polv = PolynomialFeatures(degree=2)
    X train poly, X test poly = poly.fit transform(X train), poly.transform(X test)
    model = LinearRegression()
    model.fit(X train poly, y train)
    v pred = model.predict(X test poly)
    print("Polynomial Regression - Auto MPG")
    print(f"MSE: {mean squared error(y test, y pred):.2f}, R2: {r2 score(y test, y pred):.2f}")
    sorted idx = X test['hp'].argsort()
    plt.scatter(X test, y test, color='blue', label='Actual')
    plt.plot(X_test.iloc[sorted_idx], y_pred[sorted_idx], color='red', label='Polynomial Fit')
    plt.xlabel('Horsepower'), plt.ylabel('MPG'), plt.title('Auto MPG')
    plt.legend(), plt.show()
linear regression boston()
polynomial regression auto mpg()
```

Linear Regression - Boston Housing

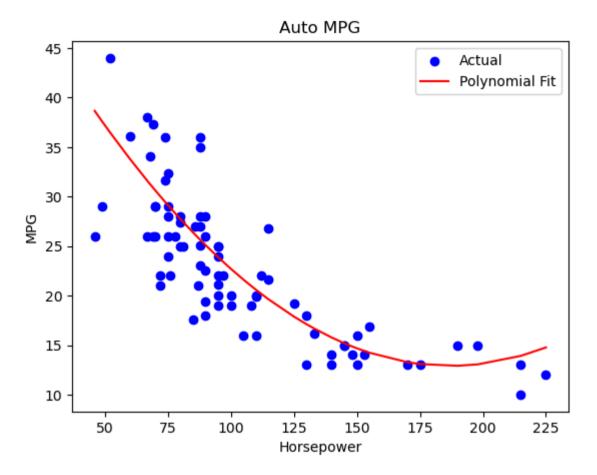
MSE: 44.84, R<sup>2</sup>: 0.51



C:\Users\Kusuma\AppData\Local\Temp\ipykernel\_27376\385270490.py:32: FutureWarning: The 'delim\_whitespace' keyword in pd.read\_cs
v is deprecated and will be removed in a future version. Use ``sep='\s+'`` instead
df = pd.read\_csv(url, names=cols, delim\_whitespace=True, na\_values='?').dropna()

Polynomial Regression - Auto MPG

MSE: 18.42, R<sup>2</sup>: 0.64



```
In [7]: #8
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt

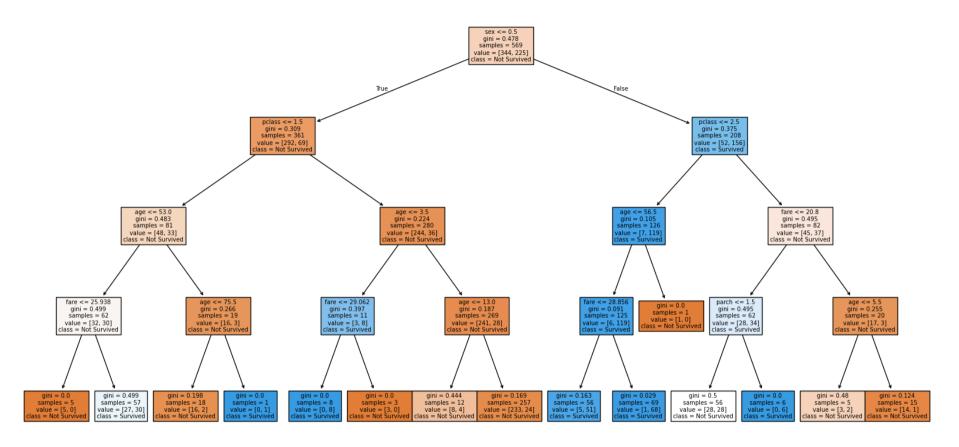
from sklearn.model_selection import train_test_split
    from sklearn.tree import DecisionTreeClassifier, plot_tree
    from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report

df = sns.load_dataset("titanic")

features = ['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare', 'embarked']
    df = df[features + ['survived']].dropna()
```

```
df['sex'] = df['sex'].map({'male': 0, 'female': 1})
df['embarked'] = df['embarked'].map({'S': 0, 'C': 1, '0': 2})
X = df[features]
y = df['survived']
X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
clf = DecisionTreeClassifier(max depth=4, random state=43)
clf.fit(X train, y train)
plt.figure(figsize=(20, 10))
plot tree(clf, feature names=features, class names=['Not Survived', 'Survived'], filled=True)
plt.title("Decision Tree - Titanic Survival Prediction")
plt.show()
y pred = clf.predict(X test)
accuracy = accuracy score(y test, y pred)
precision = precision score(y test, y pred)
recall = recall score(y test, y pred)
f1 = f1 score(y test, y pred)
print("Classification Report")
print(classification report(y test, y pred, target names=["Not Survived", "Survived"]))
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

## Decision Tree - Titanic Survival Prediction



Classification Report

```
recall f1-score
                     precision
                                                     support
       Not Survived
                          0.68
                                    0.82
                                              0.75
                                                          80
           Survived
                          0.70
                                    0.51
                                              0.59
                                                          63
           accuracy
                                              0.69
                                                         143
          macro avg
                          0.69
                                    0.67
                                              0.67
                                                         143
       weighted avg
                          0.69
                                    0.69
                                              0.68
                                                         143
       Accuracy: 0.69
       Precision: 0.70
       Recall: 0.51
       F1 Score: 0.59
In [9]: #9
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.datasets import load iris
        from sklearn.naive bayes import GaussianNB
        from sklearn.model selection import train test split
        from sklearn.metrics import accuracy score, classification report, confusion matrix
        iris = load iris()
        X = iris.data
        y = iris.target
        target names = iris.target names
        df = pd.DataFrame(X, columns=iris.feature names)
        df['species'] = y
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
        nb classifier = GaussianNB()
        nb_classifier.fit(X_train, y_train)
        y pred = nb classifier.predict(X test)
        accuracy = accuracy_score(y_test, y_pred)
```

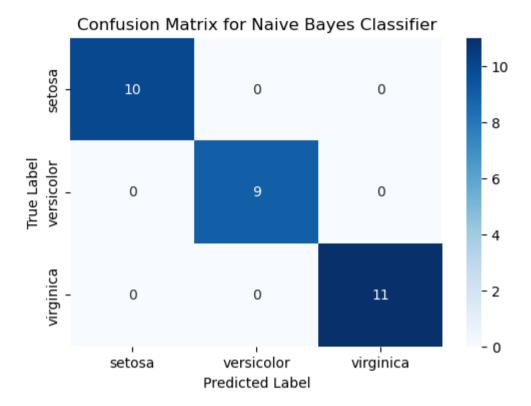
```
print("Classification Report")
print(classification_report(y_test, y_pred, target_names=target_names))
print(f"Accuracy of Naive Bayes Classifier: {accuracy:.2f}")

conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(conf_matrix, annot=True, cmap="Blues", xticklabels=target_names, yticklabels=target_names)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix for Naive Bayes Classifier")
plt.show()
```

## Classification Report

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	10
versicolor	1.00	1.00	1.00	9
virginica	1.00	1.00	1.00	11
accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

Accuracy of Naive Bayes Classifier: 1.00



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

from sklearn.datasets import load_breast_cancer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA

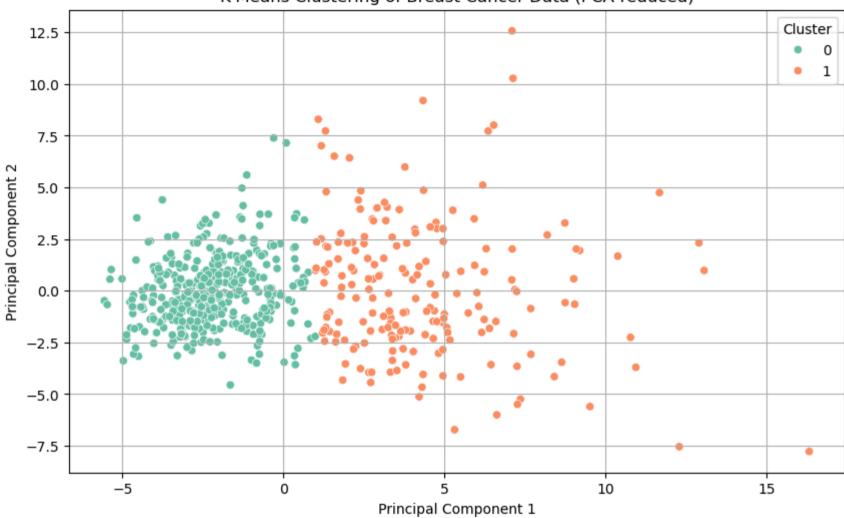
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)

scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)
```

```
kmeans = KMeans(n clusters=2, random state=42, n init=10)
kmeans.fit(scaled data)
clusters = kmeans.labels
df["Cluster"] = clusters
pca = PCA(n components=2)
pca components = pca.fit transform(scaled data)
df["PCA1"] = pca components[:, 0]
df["PCA2"] = pca components[:, 1]
plt.figure(figsize=(10, 6))
sns.scatterplot(x="PCA1", y="PCA2", hue="Cluster", palette="Set2", data=df)
plt.title("K-Means Clustering of Breast Cancer Data (PCA-reduced)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.show()
```

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak
on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OM
P\_NUM\_THREADS=3.
 warnings.warn(





In [ ]: