1. Linear Regression with the Iris Dataset

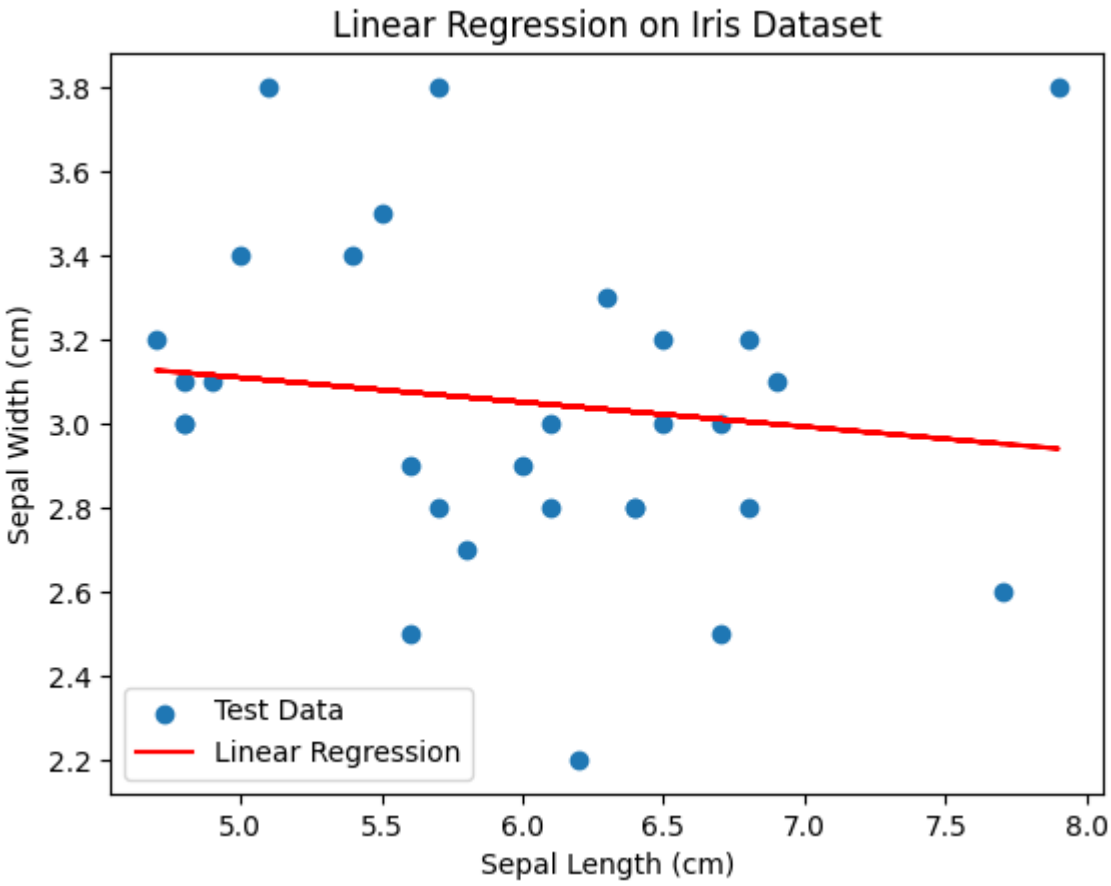
Linear regression is a statistical method used for modeling the relationship between a dependent variable and one or more independent variables. In this example, we'll perform linear regression using the well-known Iris dataset to predict the sepal width based on the sepal length.

Introduction

Linear regression aims to find the best-fitting line that minimizes the sum of squared differences between the predicted and actual values. The coefficients of the line represent the slope and intercept in the case of simple linear regression.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# For simplicity, use only one feature (sepal length) as the independent variabl
X = data['sepal length (cm)'].values.reshape(-1, 1)

# The dependent variable is sepal width
y = data['sepal width (cm)'].values

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a linear regression model
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = model.predict(X_test)

# Plot the original data and the linear regression line
plt.scatter(X_test, y_test, label='Test Data')
plt.plot(X_test, y_pred, 'r-', label='Linear Regression')
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Linear Regression on Iris Dataset')
plt.legend()
plt.show()
```



2. Logistic Regression with the Iris Dataset

Logistic regression is a classification algorithm that models the probability of a binary outcome. In this example, we'll use logistic regression to perform binary classification on the Iris dataset, predicting whether a flower belongs to a specific class or not.

Introduction

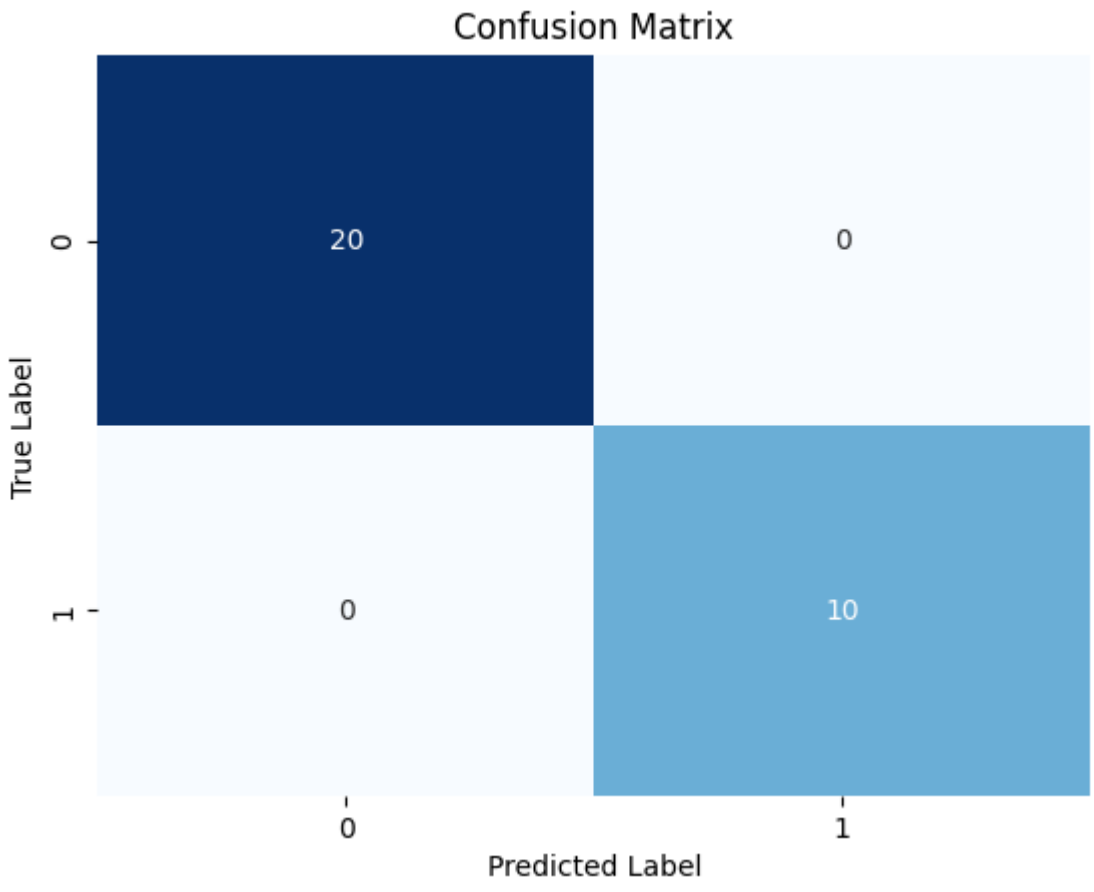
Logistic regression is suitable for binary classification problems, where the dependent variable has two classes. It models the probability that an instance belongs to a particular class.

Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# For simplicity, use only two classes (setosa and non-setosa)
```

```
data['target'] = (data['target'] == 0).astype(int)

# Define features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a logistic regression model
model = LogisticRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Visualize the confusion matrix
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()

# Display accuracy
print(f'Accuracy: {accuracy * 100:.2f}%')
```




```
Accuracy: 100.00%
```

3. Polynomial Regression

Polynomial regression is a type of regression algorithm that models the relationship between the independent variable and the dependent variable as an nth-degree polynomial. It allows us to capture more complex relationships in the data compared to linear regression.

Introduction

In polynomial regression, the relationship between the variables is modeled as a polynomial equation of degree n. The equation takes the form: [y = \beta_0 + \beta_1 x + \beta_2 x^2 + \ldots + \beta_n x^n]

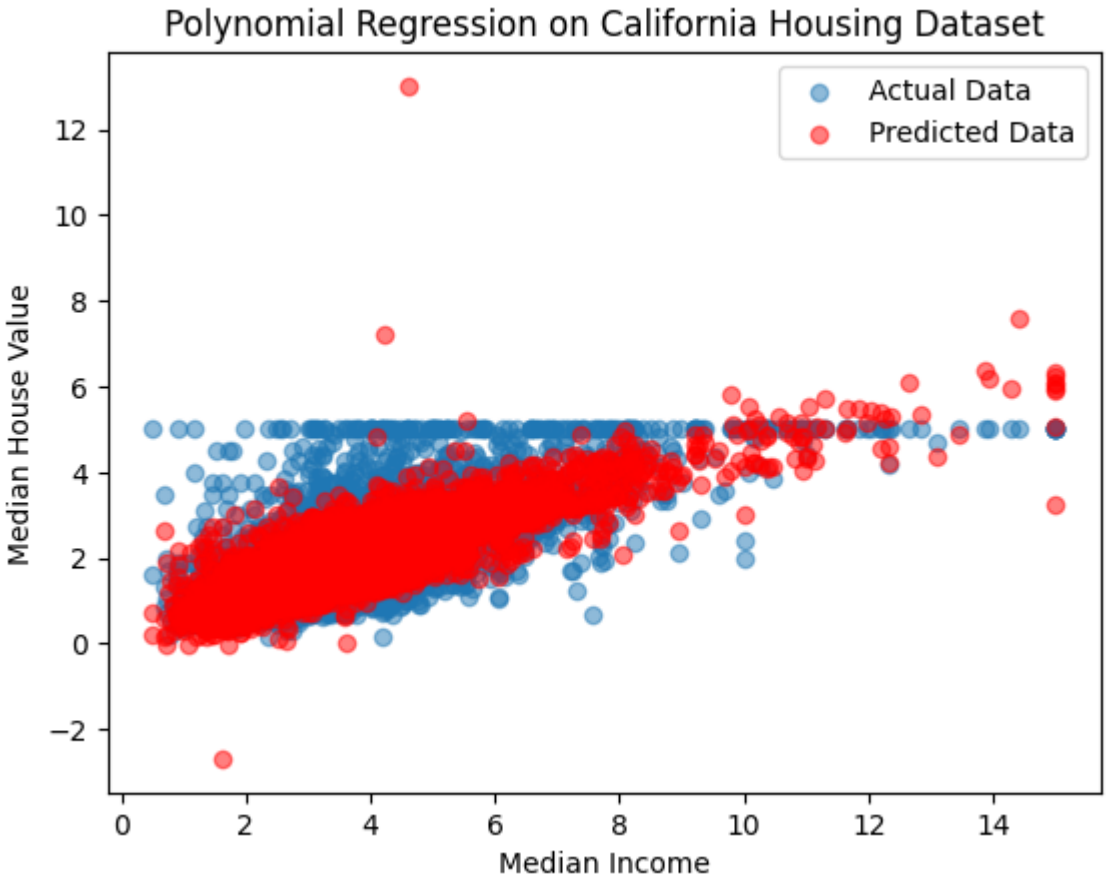
Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the California housing dataset
california_housing = fetch_california_housing()
data = pd.DataFrame(data=np.c_[california_housing.data, california_housing.targe
                    columns=california_housing.feature_names + ['target'])

# Select features (independent variables) and target (dependent variable)
X = data[['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Add polynomial features of degree 2
poly_features = PolynomialFeatures(degree=2, include_bias=False)
X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.transform(X_test)

# Create a linear regression model
poly_reg = LinearRegression()
poly_reg.fit(X_train_poly, y_train)

# Make predictions on the test data
y_pred = poly_reg.predict(X_test_poly)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse:.2f}')

# Visualize the results
plt.scatter(X_test['MedInc'], y_test, label='Actual Data', alpha=0.5)
plt.scatter(X_test['MedInc'], y_pred, color='red', label='Predicted Data', alpha
```

```
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.title('Polynomial Regression on California Housing Dataset')
plt.legend()
plt.show()
```

```
Mean Squared Error: 0.46
```



4. Ridge Regression with the California Housing Dataset

Ridge regression is a regularized linear regression algorithm that includes a regularization term to prevent overfitting. It is particularly useful when dealing with multicollinearity in the dataset.

Introduction

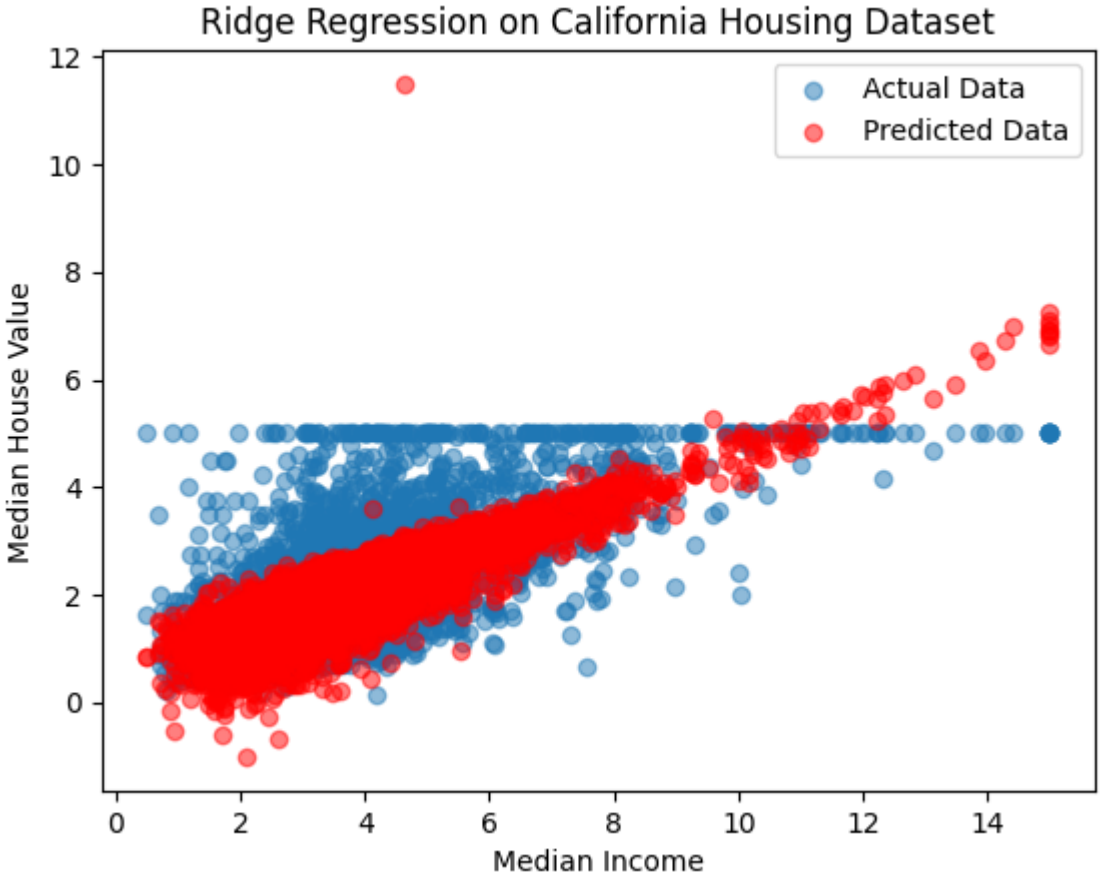
In Ridge regression, a penalty term is added to the linear regression cost function, which is proportional to the square of the magnitude of the coefficients. This regularization term helps to prevent the model from becoming too complex and overfitting the training data.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
```

```
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the California housing dataset
california_housing = fetch_california_housing()
data = pd.DataFrame(data=np.c_[california_housing.data, california_housing.targe
                    columns=california_housing.feature_names + ['target'])

# Select features (independent variables) and target (dependent variable)
X = data[['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create a Ridge regression model
ridge_reg = Ridge(alpha=1.0)  # alpha is the regularization strength
ridge_reg.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = ridge_reg.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse:.2f}')

# Visualize the results
plt.scatter(X_test['MedInc'], y_test, label='Actual Data', alpha=0.5)
plt.scatter(X_test['MedInc'], y_pred, color='red', label='Predicted Data', alpha
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.title('Ridge Regression on California Housing Dataset')
plt.legend()
plt.show()
```

```
Mean Squared Error: 0.56
```



5. Lasso Regression with the California Housing Dataset

Lasso regression is a regularized linear regression algorithm that includes a penalty term to prevent overfitting. It differs from Ridge regression by adding the absolute values of the coefficients as a penalty term, encouraging sparse models.

Introduction

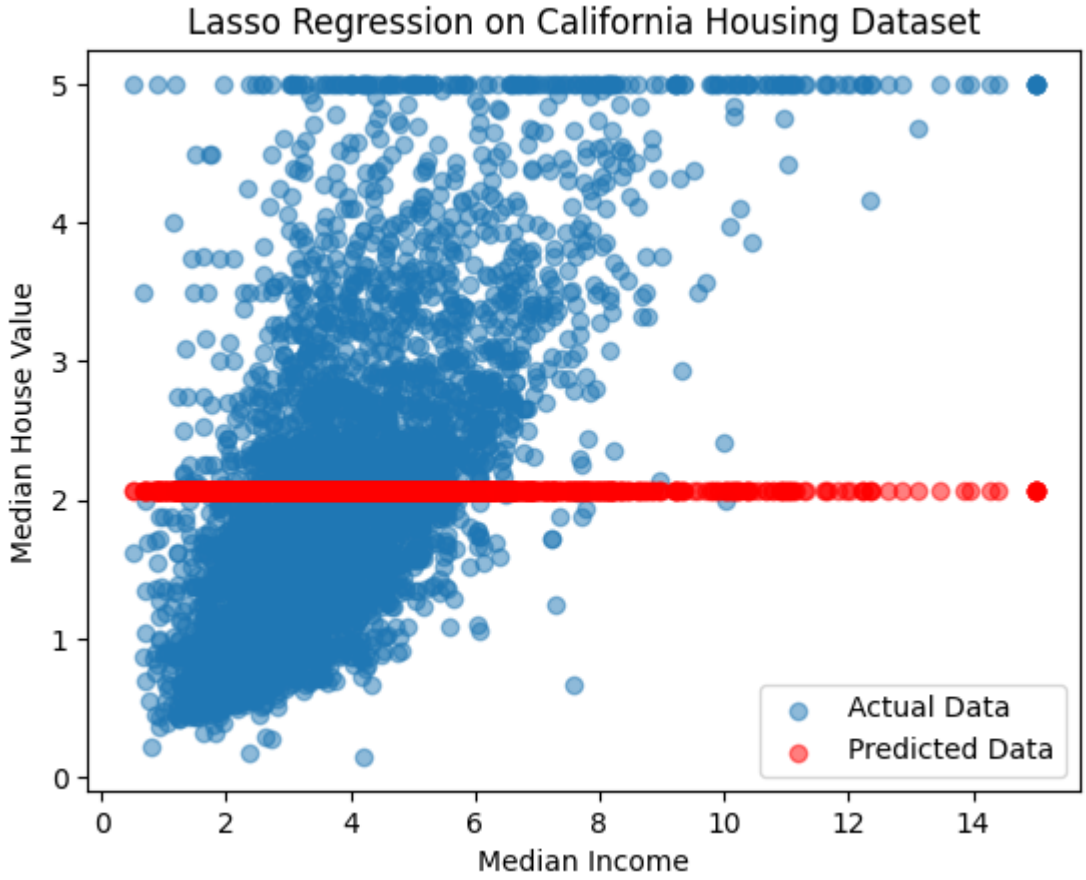
In Lasso regression, the penalty term added to the linear regression cost function is proportional to the absolute values of the coefficients. This regularization term helps to prevent the model from becoming too complex and encourages some coefficients to be exactly zero, effectively performing feature selection.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the California housing dataset
california_housing = fetch_california_housing()
data = pd.DataFrame(data=np.c_[california_housing.data, california_housing.targe
                    columns=california_housing.feature_names + ['target'])
```

```
# Select features (independent variables) and target (dependent variable)
X = data[['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create a Lasso regression model
lasso_reg = Lasso(alpha=1.0)  # alpha is the regularization strength
lasso_reg.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = lasso_reg.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse:.2f}')

# Visualize the results
plt.scatter(X_test['MedInc'], y_test, label='Actual Data', alpha=0.5)
plt.scatter(X_test['MedInc'], y_pred, color='red', label='Predicted Data', alpha
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.title('Lasso Regression on California Housing Dataset')
plt.legend()
plt.show()
```

```
Mean Squared Error: 1.31
```



6. Elastic Net Regression with the California Housing Dataset

Elastic Net regression is a linear regression algorithm that combines both L1 (Lasso) and L2 (Ridge) regularization terms. It is effective in handling datasets with a large number of features and addressing multicollinearity.

Introduction

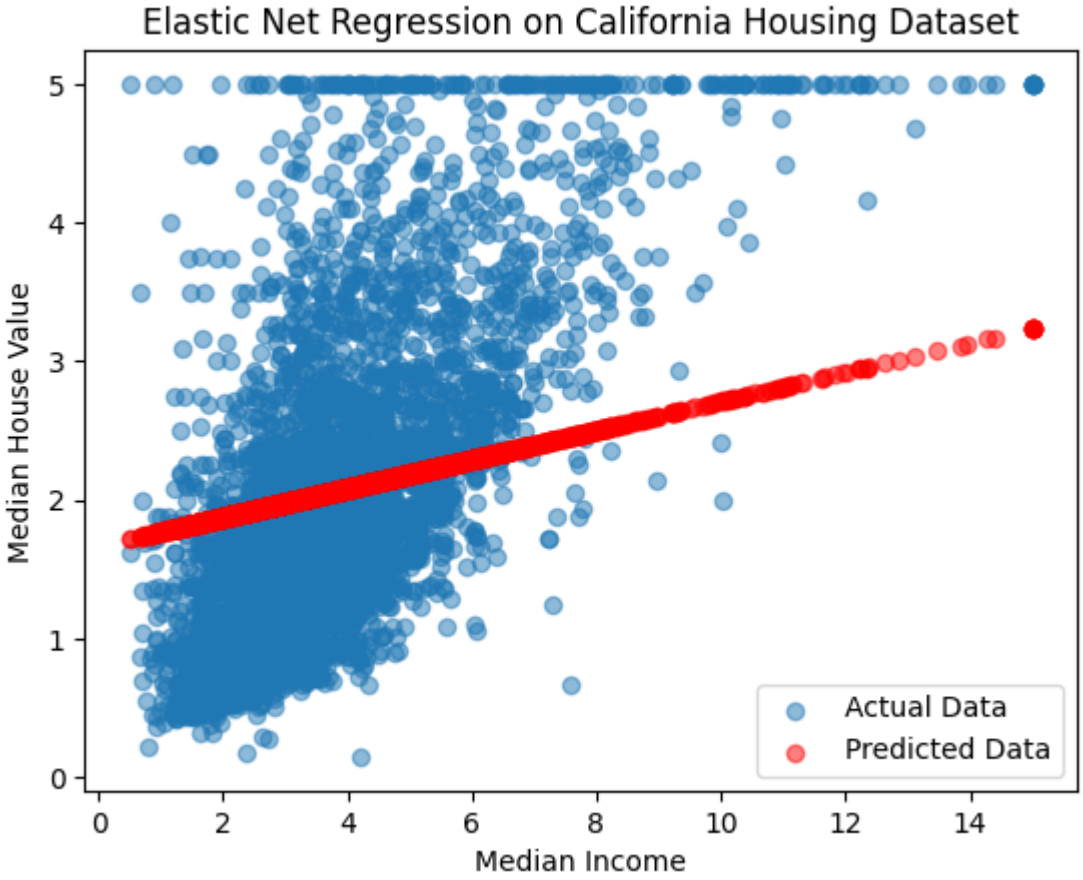
In Elastic Net regression, the cost function includes both L1 and L2 regularization terms. This combination allows Elastic Net to overcome some limitations of Lasso regression, such as selecting at most n variables if n features are correlated.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# Load the California housing dataset
california_housing = fetch_california_housing()
data = pd.DataFrame(data=np.c_[california_housing.data, california_housing.targe
                    columns=california_housing.feature_names + ['target'])
```

```
# Select features (independent variables) and target (dependent variable)
X = data[['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create an Elastic Net regression model
elastic_net_reg = ElasticNet(alpha=1.0, l1_ratio=0.5)  # alpha is the overall re
elastic_net_reg.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = elastic_net_reg.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse:.2f}')

# Visualize the results
plt.scatter(X_test['MedInc'], y_test, label='Actual Data', alpha=0.5)
plt.scatter(X_test['MedInc'], y_pred, color='red', label='Predicted Data', alpha
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.title('Elastic Net Regression on California Housing Dataset')
plt.legend()
plt.show()
```

```
Mean Squared Error: 1.04
```



7. Decision Trees with the Iris Dataset

Decision Trees are versatile machine learning algorithms used for both classification and regression tasks. They make decisions based on features and create a tree-like structure to predict the target variable.

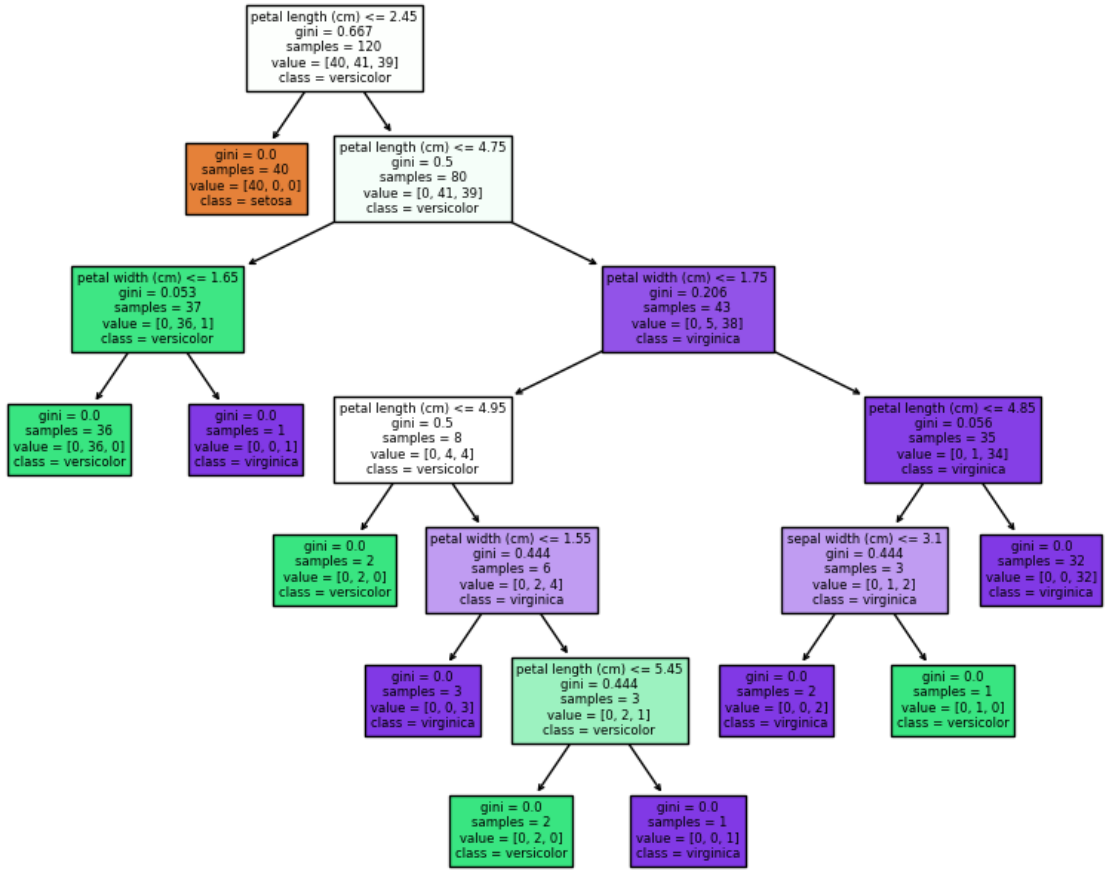
Introduction

In Decision Trees, the dataset is recursively split into subsets based on feature conditions. At each split, the algorithm selects the feature that provides the best separation according to a chosen criterion (e.g., Gini impurity, entropy). This process continues until a stopping condition is met.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat
```

```python
# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a Decision Tree classifier
tree_classifier = DecisionTreeClassifier(random_state=42)

# Fit the model to the training data
tree_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = tree_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Visualize the decision tree
plt.figure(figsize=(10, 8))
plot_tree(tree_classifier, feature_names=iris['feature_names'], class_names=iris
plt.show()

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```



```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

8. Random Forests with the Iris Dataset

Random Forests is an ensemble learning method that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

Introduction

In Random Forests, multiple decision trees are trained on different subsets of the data and the features. The final prediction is often a majority vote (classification) or an average (regression) of the predictions made by individual trees.

Example Code

In [ ]:

```python
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Fit the model to the training data
rf_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = rf_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

9. Gradient Boosting Machines with the Iris Dataset

Gradient Boosting Machines (GBM) is an ensemble learning method that builds a series of weak learners and combines their predictions to create a strong predictive model.

Introduction

In GBM, weak learners are added sequentially to the model, with each new learner focusing on the mistakes made by the existing ensemble. This iterative process continues until a predefined number of learners or a stopping criterion is reached.

Example Code

In [ ]:

```python
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a Gradient Boosting classifier
gbm_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,

# Fit the model to the training data
gbm_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = gbm_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

10. Gradient Boosting Machines with the Iris Dataset

Gradient Boosting Machines (GBM) is an ensemble learning method that builds a series of weak learners and combines their predictions to create a strong predictive model.

Introduction

In GBM, weak learners are added sequentially to the model, with each new learner focusing on the mistakes made by the existing ensemble. This iterative process continues until a predefined number of learners or a stopping criterion is reached.

Example Code

In [ ]:

```python
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a Gradient Boosting classifier
gbm_classifier = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,

# Fit the model to the training data
gbm_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = gbm_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

11. Light Gradient Boosting Machine (LightGBM) with the Iris Dataset

LightGBM is an efficient implementation of the gradient boosting algorithm, designed for distributed and efficient training.

Introduction

LightGBM builds a series of weak learners (typically decision trees) and combines their predictions to create a strong predictive model. It is optimized for speed, supports distributed training, and is memory-efficient.

Example Code

In [ ]:
```python
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import lightgbm as lgb
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a LightGBM classifier
lgb_classifier = lgb.LGBMClassifier(n_estimators=100, learning_rate=0.1, random_

# Fit the model to the training data
lgb_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = lgb_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing
was 0.000102 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 91
[LightGBM] [Info] Number of data points in the train set: 120, number of used fea
tures: 4
[LightGBM] [Info] Start training from score -1.098612
[LightGBM] [Info] Start training from score -1.073920
[LightGBM] [Info] Start training from score -1.123930
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Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

12. CatBoost with the Iris Dataset

CatBoost is a high-performance gradient boosting library designed for categorical feature support and efficient training.

Introduction

CatBoost builds a series of weak learners (typically decision trees) and combines their predictions to create a strong predictive model. It automatically handles categorical features, reducing the need for manual preprocessing.

Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from catboost import CatBoostClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a CatBoost classifier
catboost_classifier = CatBoostClassifier(iterations=100, learning_rate=0.1, rand

# Fit the model to the training data
catboost_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = catboost_classifier.predict(X_test)
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

13. K-Nearest Neighbors (KNN) with the Iris Dataset

K-Nearest Neighbors is a simple and effective classification algorithm that classifies a data point based on the majority class of its k nearest neighbors.

Introduction

In KNN, the class of a new data point is determined by the majority class among its k nearest neighbors. The distance metric used (e.g., Euclidean distance) defines the "closeness" of neighbors.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a KNN classifier with k=3
knn_classifier = KNeighborsClassifier(n_neighbors=3)

# Fit the model to the training data
knn_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = knn_classifier.predict(X_test)
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

14. Support Vector Machines (SVM) with the Iris Dataset

Support Vector Machines is a powerful machine learning algorithm for classification and regression tasks. It works by finding the hyperplane that best separates the data into different classes while maximizing the margin between them.

Introduction

In SVM, the goal is to find the hyperplane that maximizes the margin between different classes. It can handle linear and non-linear separation using different kernel functions.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create an SVM classifier with a linear kernel
svm_classifier = SVC(kernel='linear', C=1.0, random_state=42)

# Fit the model to the training data
svm_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = svm_classifier.predict(X_test)

# Evaluate the model
```

```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

15. Naive Bayes with the Iris Dataset

Naive Bayes is a probabilistic algorithm based on Bayes' theorem, commonly used for classification tasks.

Introduction

Naive Bayes assumes that features are conditionally independent given the class. It is particularly effective for text classification but can be applied to various types of data.

Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Create a Naive Bayes classifier using Gaussian Naive Bayes
nb_classifier = GaussianNB()

# Fit the model to the training data
nb_classifier.fit(X_train, y_train)

# Make predictions on the test data
y_pred = nb_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 100.00%
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

16. Artificial Neural Network (ANN) with the Iris Dataset

Artificial Neural Networks (ANN) are a class of machine learning models inspired by the structure and function of the human brain.

Introduction

ANN consists of layers of interconnected nodes (neurons) that process and transform input data to produce an output. It is widely used for various tasks, including classification and regression.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
y = data['target']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create an Artificial Neural Network (ANN) classifier
ann_classifier = MLPClassifier(hidden_layer_sizes=(8,), activation='relu', max_i

# Fit the model to the training data
ann_classifier.fit(X_train_scaled, y_train)

# Make predictions on the test data
```

```
y_pred = ann_classifier.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

# Display accuracy and confusion matrix
print(f'Accuracy: {accuracy * 100:.2f}%')
print('Confusion Matrix:')
print(conf_matrix)
```

```
Accuracy: 96.67%
Confusion Matrix:
[[10  0  0]
 [ 0  8  1]
 [ 0  0 11]]
```

```
d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\sklearn
\neural_network\_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Opt
imizer: Maximum iterations (1000) reached and the optimization hasn't converged y
et.
  warnings.warn(
```

17. Convolutional Neural Network (CNN) with the CIFAR-10 Dataset

Convolutional Neural Networks (CNNs) are deep neural networks designed for tasks such as image recognition.

Introduction

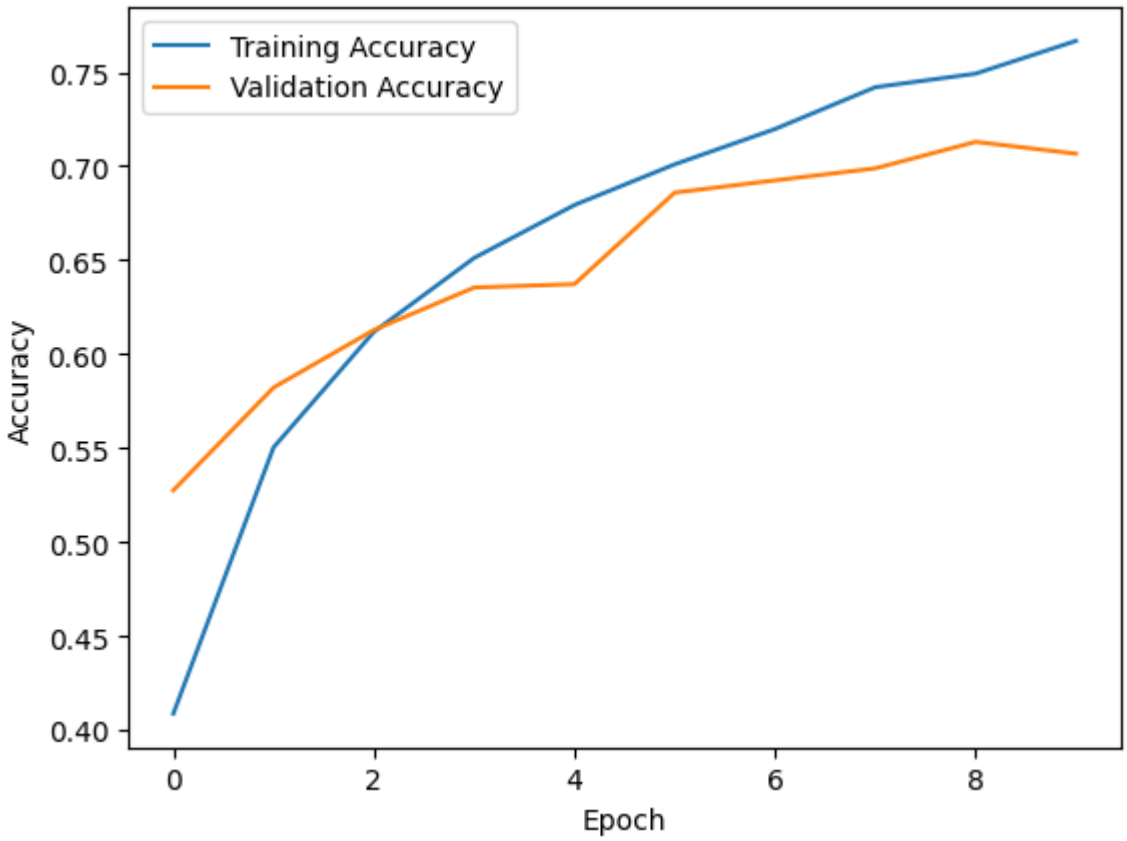
CNNs use convolutional layers to automatically and adaptively learn spatial hierarchies of features from input data. They are particularly effective for image-related tasks.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

# Load the CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Normalize pixel values to be between 0 and 1
x_train, x_test = x_train / 255.0, x_test / 255.0

# One-hot encode the labels
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Split the data into training and validation sets
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.

# Create a Convolutional Neural Network (CNN)
```

```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accur

# Train the model
history = model.fit(x_train, y_train, epochs=10, validation_data=(x_val, y_val))

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f'Test Accuracy: {test_acc * 100:.2f}%')

# Plot the training and validation accuracy over epochs
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 384s 2us/step
WARNING:tensorflow:From d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\keras\src\layers\pooling\max_pooling2d.py:161: The name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

Epoch 1/10
WARNING:tensorflow:From d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From d:\MusaddiqueHussainLabs\ml_exercise_playground\.conda\Lib\site-packages\keras\src\engine\base_layer_utils.py:384: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

1250/1250 [==============================] - 12s 9ms/step - loss: 1.6091 - accuracy: 0.4087 - val_loss: 1.3243 - val_accuracy: 0.5275
Epoch 2/10
1250/1250 [==============================] - 11s 9ms/step - loss: 1.2577 - accuracy: 0.5504 - val_loss: 1.1884 - val_accuracy: 0.5822
Epoch 3/10
1250/1250 [==============================] - 11s 9ms/step - loss: 1.0950 - accuracy: 0.6118 - val_loss: 1.0856 - val_accuracy: 0.6128
Epoch 4/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.9915 - accuracy: 0.6511 - val_loss: 1.0219 - val_accuracy: 0.6354
Epoch 5/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.9076 - accuracy: 0.6793 - val_loss: 1.0431 - val_accuracy: 0.6372
Epoch 6/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.8501 - accuracy: 0.7010 - val_loss: 0.9168 - val_accuracy: 0.6859
Epoch 7/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.7947 - accuracy: 0.7197 - val_loss: 0.8892 - val_accuracy: 0.6924
Epoch 8/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.7433 - accuracy: 0.7420 - val_loss: 0.8775 - val_accuracy: 0.6988
Epoch 9/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.7118 - accuracy: 0.7492 - val_loss: 0.8460 - val_accuracy: 0.7129
Epoch 10/10
1250/1250 [==============================] - 11s 9ms/step - loss: 0.6689 - accuracy: 0.7666 - val_loss: 0.8731 - val_accuracy: 0.7066
313/313 [==============================] - 2s 5ms/step - loss: 0.8975 - accuracy: 0.7001
Test Accuracy: 70.01%
```



18. Recurrent Neural Network (RNN) with the IMDB Dataset

Recurrent Neural Networks (RNNs) are designed for sequential data, where the order of elements matters.

Introduction

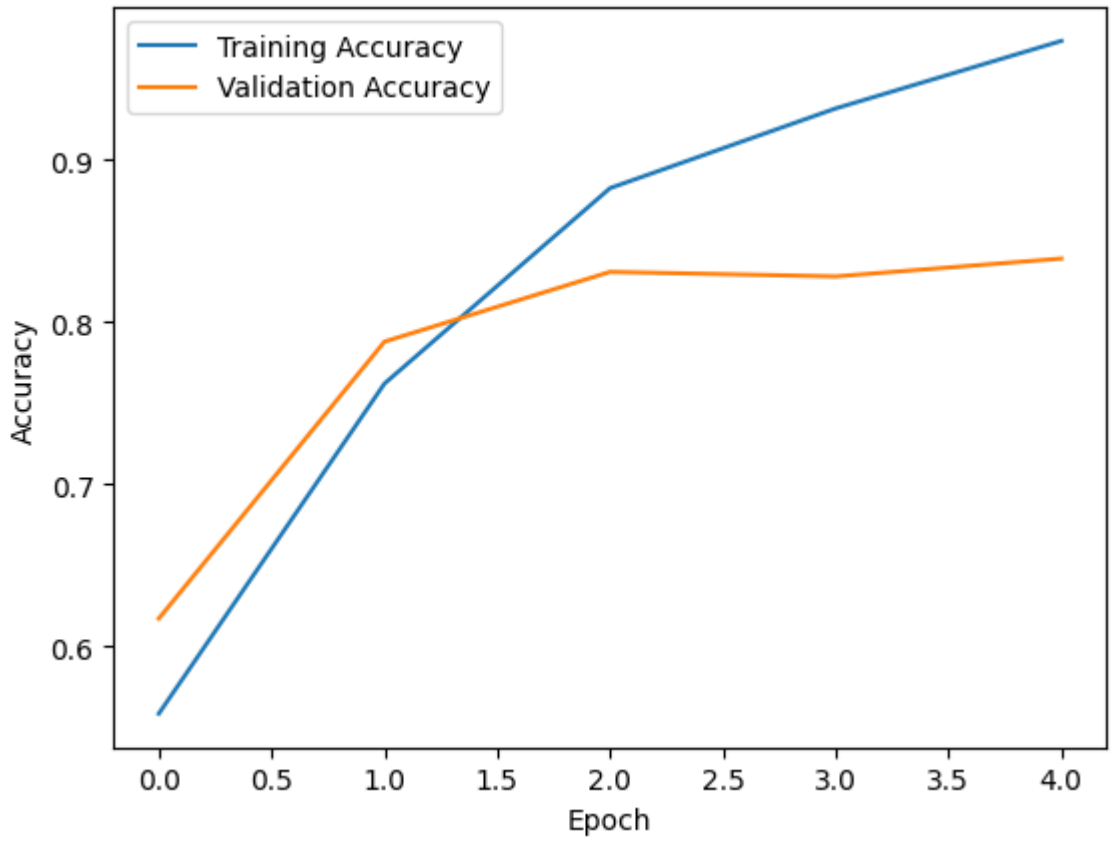
RNNs have connections that form directed cycles, allowing them to maintain a hidden state that captures information about previous inputs. They are suitable for tasks such as sequence classification.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing import sequence
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

# Load the IMDB dataset
max_features = 10000  # Consider the top 10,000 most frequent words
maxlen = 500  # Limit each review to 500 words
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

# Pad sequences to have consistent length
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
```

```
# Split the data into training and validation sets
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.

# Create a Recurrent Neural Network (RNN)
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']

# Train the model
history = model.fit(x_train, y_train, epochs=5, batch_size=128, validation_data=

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f'Test Accuracy: {test_acc * 100:.2f}%')

# Plot the training and validation accuracy over epochs
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-dataset
s/imdb.npz
17464789/17464789 [==============================] - 3s 0us/step
Epoch 1/5
157/157 [==============================] - 13s 73ms/step - loss: 0.6819 - accurac
y: 0.5586 - val_loss: 0.6572 - val_accuracy: 0.6172
Epoch 2/5
157/157 [==============================] - 12s 73ms/step - loss: 0.4966 - accurac
y: 0.7620 - val_loss: 0.4607 - val_accuracy: 0.7878
Epoch 3/5
157/157 [==============================] - 12s 75ms/step - loss: 0.2966 - accurac
y: 0.8824 - val_loss: 0.4013 - val_accuracy: 0.8308
Epoch 4/5
157/157 [==============================] - 12s 74ms/step - loss: 0.1917 - accurac
y: 0.9315 - val_loss: 0.4205 - val_accuracy: 0.8280
Epoch 5/5
157/157 [==============================] - 12s 74ms/step - loss: 0.0913 - accurac
y: 0.9731 - val_loss: 0.4652 - val_accuracy: 0.8390
782/782 [==============================] - 11s 15ms/step - loss: 0.4600 - accurac
y: 0.8336
Test Accuracy: 83.36%
```



19. Long Short-Term Memory (LSTM) with the IMDB Dataset

Long Short-Term Memory (LSTM) networks are designed to handle long-term dependencies in sequential data.

Introduction

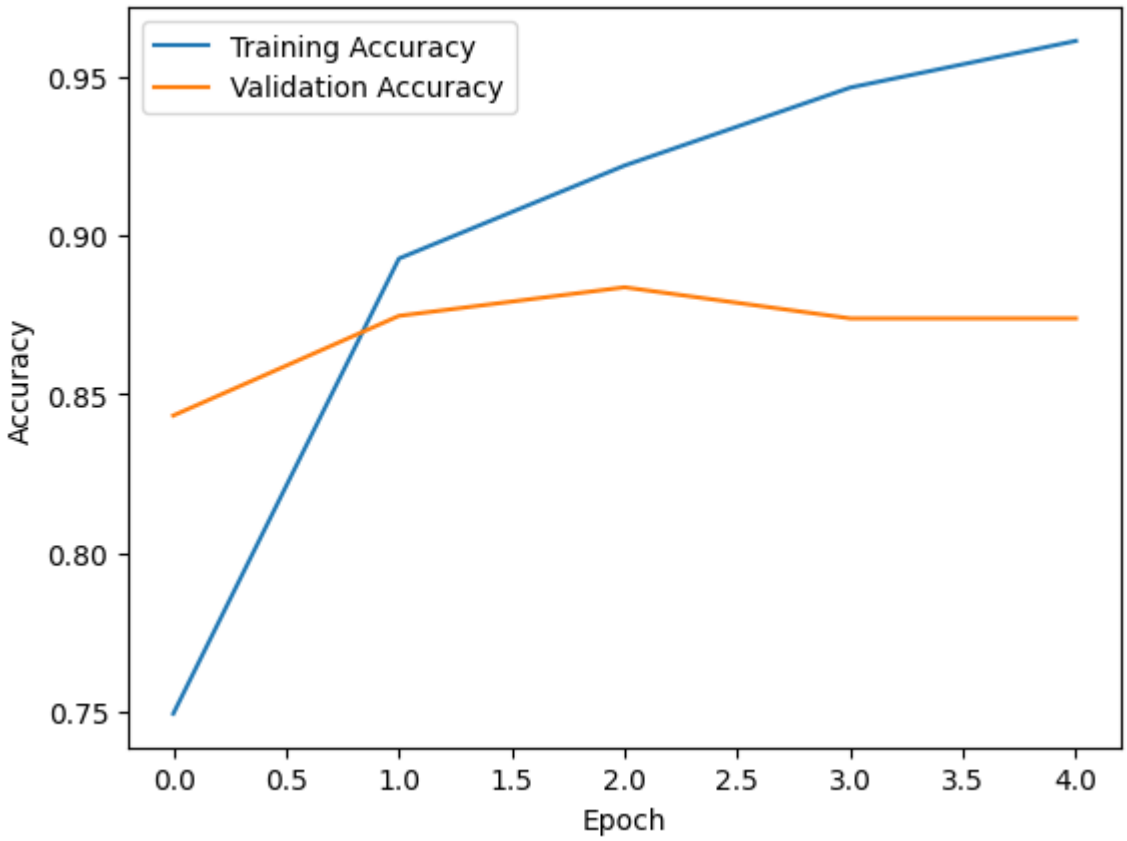
LSTMs are a type of recurrent neural network (RNN) that overcomes the vanishing gradient problem associated with traditional RNNs. They are particularly effective for tasks involving sequential data.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing import sequence
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

# Load the IMDB dataset
max_features = 10000  # Consider the top 10,000 most frequent words
maxlen = 500  # Limit each review to 500 words
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)

# Pad sequences to have consistent length
x_train = sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = sequence.pad_sequences(x_test, maxlen=maxlen)
```

```python
# Split the data into training and validation sets
x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.

# Create an LSTM network
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']

# Train the model
history = model.fit(x_train, y_train, epochs=5, batch_size=128, validation_data=

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f'Test Accuracy: {test_acc * 100:.2f}%')

# Plot the training and validation accuracy over epochs
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
Epoch 1/5
157/157 [==============================] - 32s 193ms/step - loss: 0.5131 - accura
cy: 0.7493 - val_loss: 0.3668 - val_accuracy: 0.8432
Epoch 2/5
157/157 [==============================] - 28s 180ms/step - loss: 0.2815 - accura
cy: 0.8927 - val_loss: 0.3232 - val_accuracy: 0.8746
Epoch 3/5
157/157 [==============================] - 29s 182ms/step - loss: 0.2128 - accura
cy: 0.9219 - val_loss: 0.3228 - val_accuracy: 0.8836
Epoch 4/5
157/157 [==============================] - 28s 180ms/step - loss: 0.1552 - accura
cy: 0.9465 - val_loss: 0.3028 - val_accuracy: 0.8738
Epoch 5/5
157/157 [==============================] - 29s 182ms/step - loss: 0.1197 - accura
cy: 0.9612 - val_loss: 0.3244 - val_accuracy: 0.8738
782/782 [==============================] - 20s 26ms/step - loss: 0.3493 - accurac
y: 0.8672
Test Accuracy: 86.72%
```



20. Autoencoder with the MNIST Dataset

Autoencoders are neural networks designed for unsupervised learning, particularly for feature learning and data compression.

Introduction

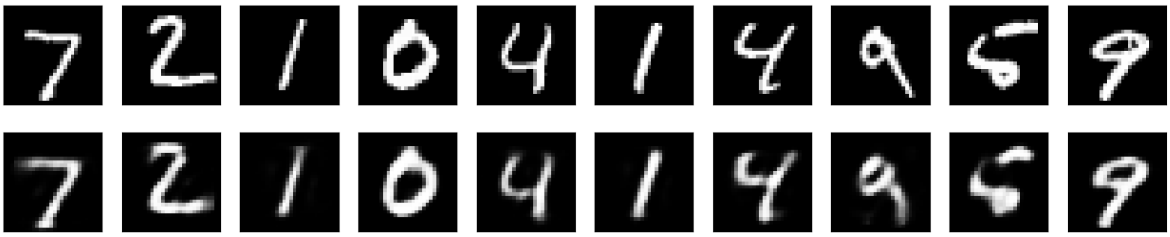
Autoencoders consist of an encoder and a decoder, where the encoder compresses the input data into a lower-dimensional representation, and the decoder reconstructs the original data from this representation.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, _), (x_test, _) = mnist.load_data()

# Normalize pixel values to be between 0 and 1
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# Flatten the images for the autoencoder
x_train_flat = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test_flat = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
```

```
# Define the autoencoder architecture
encoding_dim = 32
input_img = Input(shape=(784,))
encoded = Dense(encoding_dim, activation='relu')(input_img)
decoded = Dense(784, activation='sigmoid')(encoded)

# Create the autoencoder model
autoencoder = Model(input_img, decoded)

# Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

# Train the autoencoder on the MNIST data
autoencoder.fit(x_train_flat, x_train_flat, epochs=10, batch_size=256, shuffle=T

# Encode and decode the test set to see the reconstructed images
decoded_imgs = autoencoder.predict(x_test_flat)

# Plot some original and reconstructed images
n = 10  # Number of digits to display
plt.figure(figsize=(20, 4))
for i in range(n):
    # Original images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Reconstructed images
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

plt.show()
```

```
Epoch 1/10
235/235 [==============================] - 2s 5ms/step - loss: 0.2780 - val_loss:
0.1906
Epoch 2/10
235/235 [==============================] - 1s 5ms/step - loss: 0.1702 - val_loss:
0.1527
Epoch 3/10
235/235 [==============================] - 1s 6ms/step - loss: 0.1435 - val_loss:
0.1329
Epoch 4/10
235/235 [==============================] - 1s 6ms/step - loss: 0.1280 - val_loss:
0.1211
Epoch 5/10
235/235 [==============================] - 1s 5ms/step - loss: 0.1183 - val_loss:
0.1130
Epoch 6/10
235/235 [==============================] - 1s 5ms/step - loss: 0.1114 - val_loss:
0.1072
Epoch 7/10
235/235 [==============================] - 1s 6ms/step - loss: 0.1063 - val_loss:
0.1030
Epoch 8/10
235/235 [==============================] - 1s 5ms/step - loss: 0.1027 - val_loss:
0.0998
Epoch 9/10
235/235 [==============================] - 1s 5ms/step - loss: 0.0999 - val_loss:
0.0974
Epoch 10/10
235/235 [==============================] - 1s 5ms/step - loss: 0.0978 - val_loss:
0.0957
313/313 [==============================] - 1s 1ms/step
```



21. Generative Adversarial Network (GAN) with the MNIST Dataset

Generative Adversarial Networks (GANs) consist of a generator and a discriminator trained simultaneously through adversarial training.

Introduction

The generator generates fake data, and the discriminator tries to distinguish between real and fake data. Over time, the generator improves its ability to generate realistic data, while the discriminator becomes more adept at distinguishing real from fake data.

Example Code

In [ ]:
```python
# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import mnist
```

```
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, LeakyReLU, BatchNormalization, Reshap
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, _), (_, _) = mnist.load_data()

# Normalize pixel values to be between -1 and 1
x_train = x_train / 127.5 - 1.0
x_train = np.expand_dims(x_train, axis=-1)

# Define the generator model
def build_generator(latent_dim):
    model = Sequential()
    model.add(Dense(256, input_dim=latent_dim))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))
    model.add(Dense(512))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))
    model.add(Dense(1024))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))
    model.add(Dense(28*28*1, activation='tanh'))
    model.add(Reshape((28, 28, 1)))
    return model

# Define the discriminator model
def build_discriminator(img_shape):
    model = Sequential()
    model.add(Flatten(input_shape=img_shape))
    model.add(Dense(1024))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dense(512))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dense(256))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dense(1, activation='sigmoid'))
    return model

# Build and compile the discriminator
img_shape = (28, 28, 1)
discriminator = build_discriminator(img_shape)
discriminator.compile(loss='binary_crossentropy', optimizer=Adam(0.0002, 0.5), m

# Build and compile the generator
latent_dim = 100
generator = build_generator(latent_dim)

# Build and compile the combined model (generator and discriminator)
discriminator.trainable = False
z = Input(shape=(latent_dim,))
img = generator(z)
validity = discriminator(img)
combined = Model(z, validity)
combined.compile(loss='binary_crossentropy', optimizer=Adam(0.0002, 0.5))

# Training the GAN
def train_gan(epochs=15, batch_size=128, save_interval=1):
```

```
    half_batch = batch_size // 2

    for epoch in range(epochs):
        # Train the discriminator
        idx = np.random.randint(0, x_train.shape[0], half_batch)
        imgs = x_train[idx]

        noise = np.random.normal(0, 1, (half_batch, latent_dim))
        gen_imgs = generator.predict(noise)

        d_loss_real = discriminator.train_on_batch(imgs, np.ones((half_batch, 1)
        d_loss_fake = discriminator.train_on_batch(gen_imgs, np.zeros((half_batc
        d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)

        # Train the generator
        noise = np.random.normal(0, 1, (batch_size, latent_dim))
        valid_labels = np.ones((batch_size, 1))

        g_loss = combined.train_on_batch(noise, valid_labels)

        # Print the progress
        print(f"{epoch}/{epochs} [D loss: {d_loss[0]} | D accuracy: {100 * d_los

        # Save generated images at specified intervals
        if epoch % save_interval == 0:
            save_generated_images(epoch)

# Save generated images
def save_generated_images(epoch, examples=10, dim=(1, 10), figsize=(10, 1)):
    noise = np.random.normal(0, 1, (examples, latent_dim))
    generated_images = generator.predict(noise)

    generated_images = 0.5 * generated_images + 0.5

    plt.figure(figsize=figsize)
    for i in range(generated_images.shape[0]):
        plt.subplot(dim[0], dim[1], i+1)
        plt.imshow(generated_images[i, :, :, 0], interpolation='nearest', cmap='
        plt.axis('off')
    plt.tight_layout()
    plt.savefig(f'gan_generated_image_epoch_{epoch}.png')

# Train the GAN
train_gan(epochs=100, batch_size=64, save_interval=5)
```

```
1/1 [==============================] - 0s 118ms/step
0/100 [D loss: 0.8905893564224243 | D accuracy: 10.9375] [G loss: 0.5522851347923
279]
1/1 [==============================] - 0s 90ms/step
1/1 [==============================] - 0s 24ms/step
1/100 [D loss: 0.3706478327512741 | D accuracy: 70.3125] [G loss: 0.5894843339920
044]
1/1 [==============================] - 0s 23ms/step
2/100 [D loss: 0.34606387466192245 | D accuracy: 79.6875] [G loss: 0.705910325050
354]
1/1 [==============================] - 0s 33ms/step
3/100 [D loss: 0.32683369889855385 | D accuracy: 89.0625] [G loss: 0.900247156620
0256]
1/1 [==============================] - 0s 16ms/step
4/100 [D loss: 0.30258067045360804 | D accuracy: 85.9375] [G loss: 1.148347616195
6787]
1/1 [==============================] - 0s 29ms/step
5/100 [D loss: 0.23959039151668549 | D accuracy: 100.0] [G loss: 1.55411028861999
51]
1/1 [==============================] - 0s 8ms/step
1/1 [==============================] - 0s 16ms/step
6/100 [D loss: 0.16004862124100327 | D accuracy: 100.0] [G loss: 1.89916813373565
67]
1/1 [==============================] - 0s 18ms/step
7/100 [D loss: 0.10689879860728979 | D accuracy: 100.0] [G loss: 2.25229382514953
6]
1/1 [==============================] - 0s 25ms/step
8/100 [D loss: 0.07711669988930225 | D accuracy: 100.0] [G loss: 2.62248992919921
88]
1/1 [==============================] - 0s 24ms/step
9/100 [D loss: 0.06282896874472499 | D accuracy: 100.0] [G loss: 2.91580605506896
97]
1/1 [==============================] - 0s 30ms/step
10/100 [D loss: 0.04649362666532397 | D accuracy: 100.0] [G loss: 3.2220442295074
463]
1/1 [==============================] - 0s 16ms/step
1/1 [==============================] - 0s 27ms/step
11/100 [D loss: 0.03689454309642315 | D accuracy: 100.0] [G loss: 3.5771479606628
42]
1/1 [==============================] - 0s 9ms/step
12/100 [D loss: 0.026390213053673506 | D accuracy: 100.0] [G loss: 3.692022323608
3984]
1/1 [==============================] - 0s 17ms/step
13/100 [D loss: 0.02409506868571043 | D accuracy: 100.0] [G loss: 3.8273198604583
74]
1/1 [==============================] - 0s 16ms/step
14/100 [D loss: 0.017465494107455015 | D accuracy: 100.0] [G loss: 4.076519012451
172]
1/1 [==============================] - 0s 13ms/step
15/100 [D loss: 0.016359396860934794 | D accuracy: 100.0] [G loss: 4.142683982849
121]
1/1 [==============================] - 0s 43ms/step
1/1 [==============================] - 0s 30ms/step
16/100 [D loss: 0.013489238219335675 | D accuracy: 100.0] [G loss: 4.363020420074
463]
1/1 [==============================] - 0s 16ms/step
17/100 [D loss: 0.012433754280209541 | D accuracy: 100.0] [G loss: 4.470632553100
586]
1/1 [==============================] - 0s 16ms/step
18/100 [D loss: 0.012497354997321963 | D accuracy: 100.0] [G loss: 4.509950637817
```

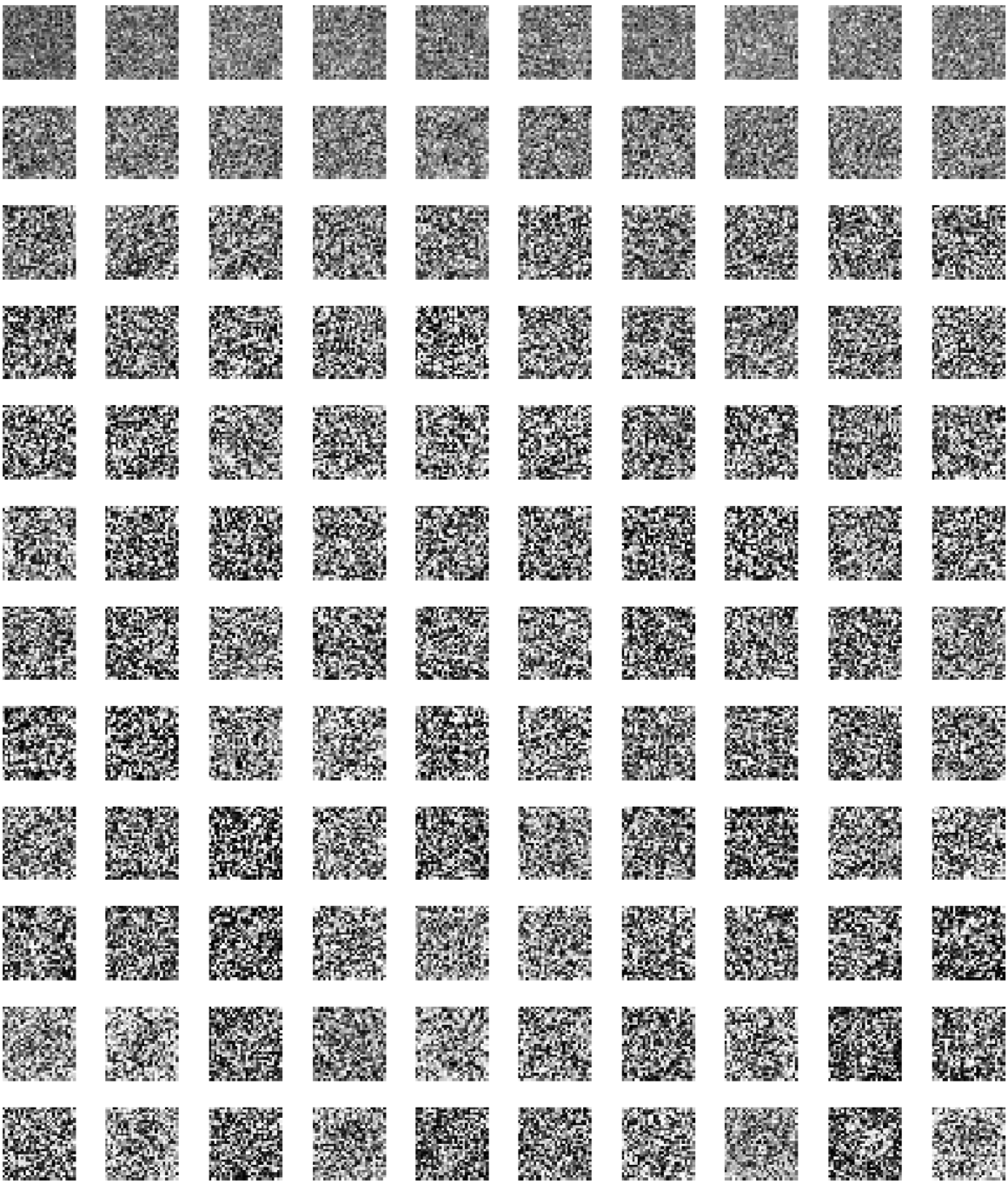
```
383]
1/1 [==============================] - 0s 10ms/step
19/100 [D loss: 0.013036285527050495 | D accuracy: 100.0] [G loss: 4.621259689331
055]
1/1 [==============================] - 0s 17ms/step
20/100 [D loss: 0.007699924171902239 | D accuracy: 100.0] [G loss: 4.798342227935
791]
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 17ms/step
21/100 [D loss: 0.008096366422250867 | D accuracy: 100.0] [G loss: 4.774236679077
148]
1/1 [==============================] - 0s 33ms/step
22/100 [D loss: 0.007560817874036729 | D accuracy: 100.0] [G loss: 4.808537483215
332]
1/1 [==============================] - 0s 16ms/step
23/100 [D loss: 0.0077645276905968785 | D accuracy: 100.0] [G loss: 4.90108585357
666]
1/1 [==============================] - 0s 40ms/step
24/100 [D loss: 0.008724022656679153 | D accuracy: 100.0] [G loss: 4.941816329956
055]
1/1 [==============================] - 0s 44ms/step
25/100 [D loss: 0.006234930362552404 | D accuracy: 100.0] [G loss: 5.005700111389
16]
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 101ms/step
26/100 [D loss: 0.006638941296841949 | D accuracy: 100.0] [G loss: 5.139234542846
68]
1/1 [==============================] - 0s 18ms/step
27/100 [D loss: 0.004927691130433232 | D accuracy: 100.0] [G loss: 5.038697242736
816]
1/1 [==============================] - 0s 31ms/step
28/100 [D loss: 0.0059834609273821115 | D accuracy: 100.0] [G loss: 5.17029285430
9082]
1/1 [==============================] - 0s 16ms/step
29/100 [D loss: 0.005180445848964155 | D accuracy: 100.0] [G loss: 5.266146659851
074]
1/1 [==============================] - 0s 31ms/step
30/100 [D loss: 0.0055849498603492975 | D accuracy: 100.0] [G loss: 5.33596324920
6543]
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 22ms/step
31/100 [D loss: 0.00604156986810267 | D accuracy: 100.0] [G loss: 5.4756617546081
54]
1/1 [==============================] - 0s 27ms/step
32/100 [D loss: 0.005488216469530016 | D accuracy: 100.0] [G loss: 5.535761833190
918]
1/1 [==============================] - 0s 31ms/step
33/100 [D loss: 0.01897994615137577 | D accuracy: 98.4375] [G loss: 5.26559734344
4824]
1/1 [==============================] - 0s 32ms/step
34/100 [D loss: 0.006391191564034671 | D accuracy: 100.0] [G loss: 5.328115463256
836]
1/1 [==============================] - 0s 25ms/step
35/100 [D loss: 0.0034172315208707005 | D accuracy: 100.0] [G loss: 5.52630519866
9434]
1/1 [==============================] - 0s 31ms/step
1/1 [==============================] - 0s 19ms/step
36/100 [D loss: 0.005052208420238458 | D accuracy: 100.0] [G loss: 5.452446937561
035]
1/1 [==============================] - 0s 19ms/step
```

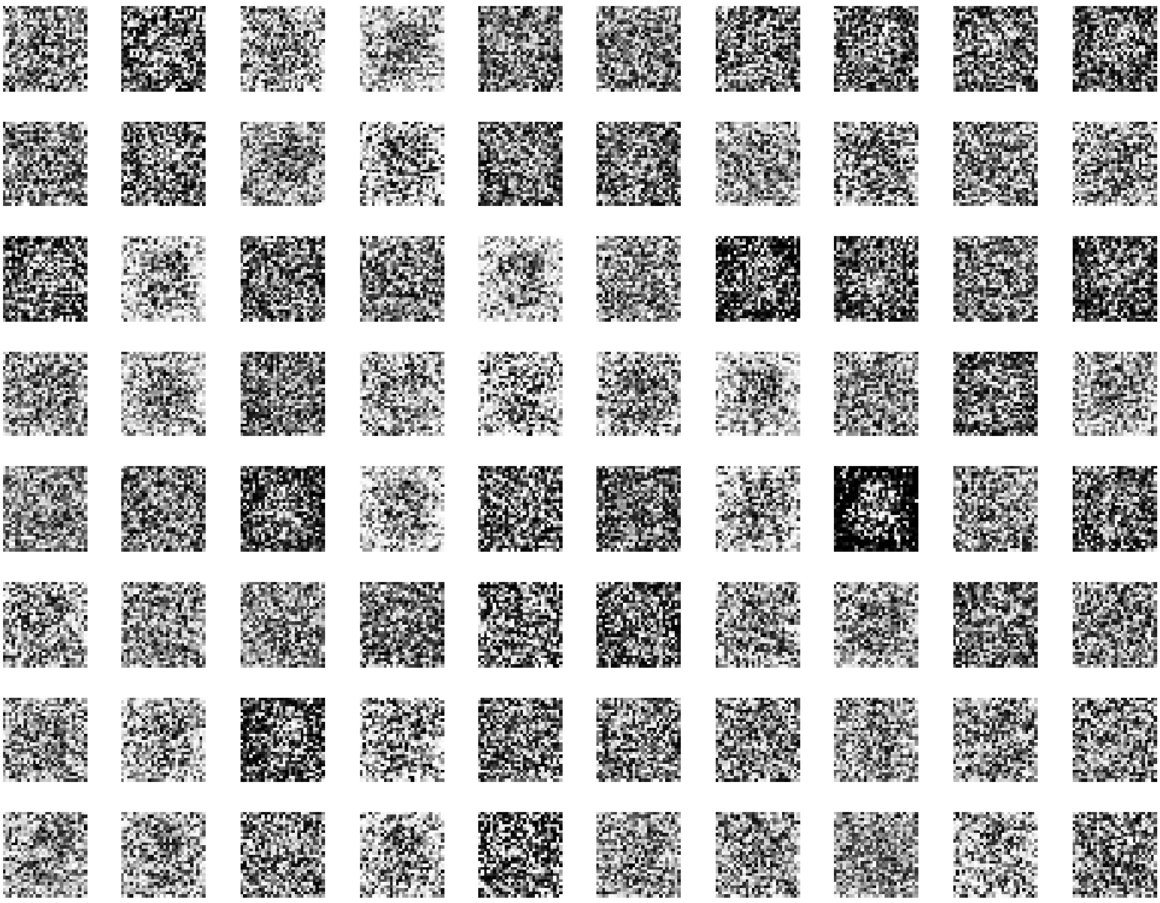
```
37/100 [D loss: 0.004731385095510632 | D accuracy: 100.0] [G loss: 5.646961212158
203]
1/1 [==============================] - 0s 32ms/step
38/100 [D loss: 0.006747660518158227 | D accuracy: 100.0] [G loss: 5.752487182617
1875]
1/1 [==============================] - 0s 30ms/step
39/100 [D loss: 0.004516128043178469 | D accuracy: 100.0] [G loss: 5.872076988220
215]
1/1 [==============================] - 0s 24ms/step
40/100 [D loss: 0.0023611330543644726 | D accuracy: 100.0] [G loss: 5.96249961853
0273]
1/1 [==============================] - 0s 32ms/step
1/1 [==============================] - 0s 32ms/step
41/100 [D loss: 0.0015251031436491758 | D accuracy: 100.0] [G loss: 5.89854431152
34375]
1/1 [==============================] - 0s 20ms/step
42/100 [D loss: 0.003472409793175757 | D accuracy: 100.0] [G loss: 5.935179710388
184]
1/1 [==============================] - 0s 16ms/step
43/100 [D loss: 0.007304891711100936 | D accuracy: 100.0] [G loss: 5.988724708557
129]
1/1 [==============================] - 0s 31ms/step
44/100 [D loss: 0.0021220827475190163 | D accuracy: 100.0] [G loss: 6.07479667663
5742]
1/1 [==============================] - 0s 18ms/step
45/100 [D loss: 0.004677186603657901 | D accuracy: 100.0] [G loss: 6.220773696899
414]
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 33ms/step
46/100 [D loss: 0.0033117805141955614 | D accuracy: 100.0] [G loss: 6.27185964584
3506]
1/1 [==============================] - 0s 24ms/step
47/100 [D loss: 0.008332281024195254 | D accuracy: 100.0] [G loss: 6.443689346313
477]
1/1 [==============================] - 0s 17ms/step
48/100 [D loss: 0.003135174047201872 | D accuracy: 100.0] [G loss: 6.445992469787
598]
1/1 [==============================] - 0s 21ms/step
49/100 [D loss: 0.0039053562213666737 | D accuracy: 100.0] [G loss: 6.64062452316
2842]
1/1 [==============================] - 0s 22ms/step
50/100 [D loss: 0.0036616662982851267 | D accuracy: 100.0] [G loss: 6.69247388839
7217]
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 21ms/step
51/100 [D loss: 0.0023979825200513005 | D accuracy: 100.0] [G loss: 6.43923139572
14355]
1/1 [==============================] - 0s 16ms/step
52/100 [D loss: 0.0049722634721547365 | D accuracy: 100.0] [G loss: 6.57799816131
5918]
1/1 [==============================] - 0s 25ms/step
53/100 [D loss: 0.004640236671548337 | D accuracy: 100.0] [G loss: 6.650444030761
719]
1/1 [==============================] - 0s 20ms/step
54/100 [D loss: 0.00447659648489207 | D accuracy: 100.0] [G loss: 6.8023324012756
35]
1/1 [==============================] - 0s 28ms/step
55/100 [D loss: 0.0013811865355819464 | D accuracy: 100.0] [G loss: 6.76983833312
9883]
1/1 [==============================] - 0s 16ms/step
```

```
1/1 [==============================] - 0s 23ms/step
56/100 [D loss: 0.0044112117029726505 | D accuracy: 100.0] [G loss: 6.712717056274414]
1/1 [==============================] - 0s 34ms/step
57/100 [D loss: 0.004383608349598944 | D accuracy: 100.0] [G loss: 6.916474342346191]
1/1 [==============================] - 0s 24ms/step
58/100 [D loss: 0.002038022503256798 | D accuracy: 100.0] [G loss: 6.850116729736328]
1/1 [==============================] - 0s 25ms/step
59/100 [D loss: 0.00483200082089752 | D accuracy: 100.0] [G loss: 6.799964904785156]
1/1 [==============================] - 0s 28ms/step
60/100 [D loss: 0.003355175198521465 | D accuracy: 100.0] [G loss: 6.821297645568848]
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 20ms/step
61/100 [D loss: 0.0057256725849583745 | D accuracy: 100.0] [G loss: 6.964934349060059]
1/1 [==============================] - 0s 16ms/step
62/100 [D loss: 0.004343814682215452 | D accuracy: 100.0] [G loss: 7.018633365631035]
1/1 [==============================] - 0s 26ms/step
63/100 [D loss: 0.010730910580605268 | D accuracy: 100.0] [G loss: 7.362045288085937]
1/1 [==============================] - 0s 26ms/step
64/100 [D loss: 0.0049395805690437555 | D accuracy: 100.0] [G loss: 7.380207538604736]
1/1 [==============================] - 0s 13ms/step
65/100 [D loss: 0.010126632172614336 | D accuracy: 100.0] [G loss: 6.938632011413574]
1/1 [==============================] - 0s 16ms/step
1/1 [==============================] - 0s 25ms/step
66/100 [D loss: 0.0015329001616919413 | D accuracy: 100.0] [G loss: 7.005700588226318]
1/1 [==============================] - 0s 24ms/step
67/100 [D loss: 0.016950414414168335 | D accuracy: 100.0] [G loss: 7.901505470275879]
1/1 [==============================] - 0s 16ms/step
68/100 [D loss: 0.011815753299742937 | D accuracy: 100.0] [G loss: 7.945936679840088]
1/1 [==============================] - 0s 24ms/step
69/100 [D loss: 0.014244820456951857 | D accuracy: 100.0] [G loss: 7.628850460052949]
1/1 [==============================] - 0s 16ms/step
70/100 [D loss: 0.003566236380720511 | D accuracy: 100.0] [G loss: 7.650438308715782]
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 22ms/step
71/100 [D loss: 0.0021490678191184998 | D accuracy: 100.0] [G loss: 7.726667404174805]
1/1 [==============================] - 0s 18ms/step
72/100 [D loss: 0.011866033310070634 | D accuracy: 100.0] [G loss: 8.145784378051758]
1/1 [==============================] - 0s 25ms/step
73/100 [D loss: 0.20700702257454395 | D accuracy: 92.1875] [G loss: 7.515073776245117]
1/1 [==============================] - 0s 20ms/step
74/100 [D loss: 0.007396723251986259 | D accuracy: 100.0] [G loss: 8.560319900512695]
```

```
1/1 [==============================] - 0s 14ms/step
75/100 [D loss: 0.0063017463544383645 | D accuracy: 100.0] [G loss: 8.48729705810
5469]
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 17ms/step
76/100 [D loss: 0.005435346509329975 | D accuracy: 100.0] [G loss: 8.457264900207
52]
1/1 [==============================] - 0s 17ms/step
77/100 [D loss: 0.01259373570792377 | D accuracy: 100.0] [G loss: 8.1753349304199
22]
1/1 [==============================] - 0s 17ms/step
78/100 [D loss: 0.007474656566046178 | D accuracy: 100.0] [G loss: 8.284544944763
184]
1/1 [==============================] - 0s 32ms/step
79/100 [D loss: 0.031566433142870665 | D accuracy: 98.4375] [G loss: 9.1670427322
3877]
1/1 [==============================] - 0s 17ms/step
80/100 [D loss: 1.8861193656921387 | D accuracy: 48.4375] [G loss: 7.872336864471
4355]
1/1 [==============================] - 0s 15ms/step
1/1 [==============================] - 0s 20ms/step
81/100 [D loss: 0.6291059256404392 | D accuracy: 81.25] [G loss: 6.94858360290527
3]
1/1 [==============================] - 0s 21ms/step
82/100 [D loss: 0.1520899564321212 | D accuracy: 90.625] [G loss: 4.8452444076538
09]
1/1 [==============================] - 0s 17ms/step
83/100 [D loss: 0.06531203892546955 | D accuracy: 98.4375] [G loss: 5.38763380050
6592]
1/1 [==============================] - 0s 22ms/step
84/100 [D loss: 0.0513535519130528 | D accuracy: 98.4375] [G loss: 5.983762264251
709]
1/1 [==============================] - 0s 17ms/step
85/100 [D loss: 0.033402787898239694 | D accuracy: 100.0] [G loss: 6.059297561645
508]
1/1 [==============================] - 0s 15ms/step
1/1 [==============================] - 0s 16ms/step
86/100 [D loss: 0.031029897413134222 | D accuracy: 98.4375] [G loss: 5.8145065307
61719]
1/1 [==============================] - 0s 17ms/step
87/100 [D loss: 0.02044698436577619 | D accuracy: 100.0] [G loss: 5.9547886848449
71]
1/1 [==============================] - 0s 16ms/step
88/100 [D loss: 0.015234864532999381 | D accuracy: 100.0] [G loss: 5.61865234375]
1/1 [==============================] - 0s 26ms/step
89/100 [D loss: 0.048881207733074916 | D accuracy: 96.875] [G loss: 6.08654117584
2285]
1/1 [==============================] - 0s 16ms/step
90/100 [D loss: 0.013979750306589267 | D accuracy: 100.0] [G loss: 5.822797775268
555]
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 19ms/step
91/100 [D loss: 0.021791864030092256 | D accuracy: 100.0] [G loss: 5.777299880981
445]
1/1 [==============================] - 0s 17ms/step
92/100 [D loss: 0.01722044704001746 | D accuracy: 100.0] [G loss: 5.8101434707641
6]
1/1 [==============================] - 0s 13ms/step
93/100 [D loss: 0.021392654038209002 | D accuracy: 100.0] [G loss: 5.710721015930
176]
```

```
1/1 [==============================] - 0s 25ms/step
94/100 [D loss: 0.01920245289511513 | D accuracy: 100.0] [G loss: 6.0459346771240
23]
1/1 [==============================] - 0s 17ms/step
95/100 [D loss: 0.01742328187538078 | D accuracy: 100.0] [G loss: 5.9754266738891
6]
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 16ms/step
96/100 [D loss: 0.02166393690276891 | D accuracy: 100.0] [G loss: 6.0853710174560
55]
1/1 [==============================] - 0s 24ms/step
97/100 [D loss: 0.017599972139578313 | D accuracy: 100.0] [G loss: 5.971339702606
201]
1/1 [==============================] - 0s 18ms/step
98/100 [D loss: 0.007370271603576839 | D accuracy: 100.0] [G loss: 6.054160118103
027]
1/1 [==============================] - 0s 22ms/step
99/100 [D loss: 0.011546501948032528 | D accuracy: 100.0] [G loss: 5.932551860809
326]
```





22. Principal Component Analysis (PCA) with the Iris Dataset

Principal Component Analysis (PCA) is a dimensionality reduction technique commonly used for feature extraction and data visualization.

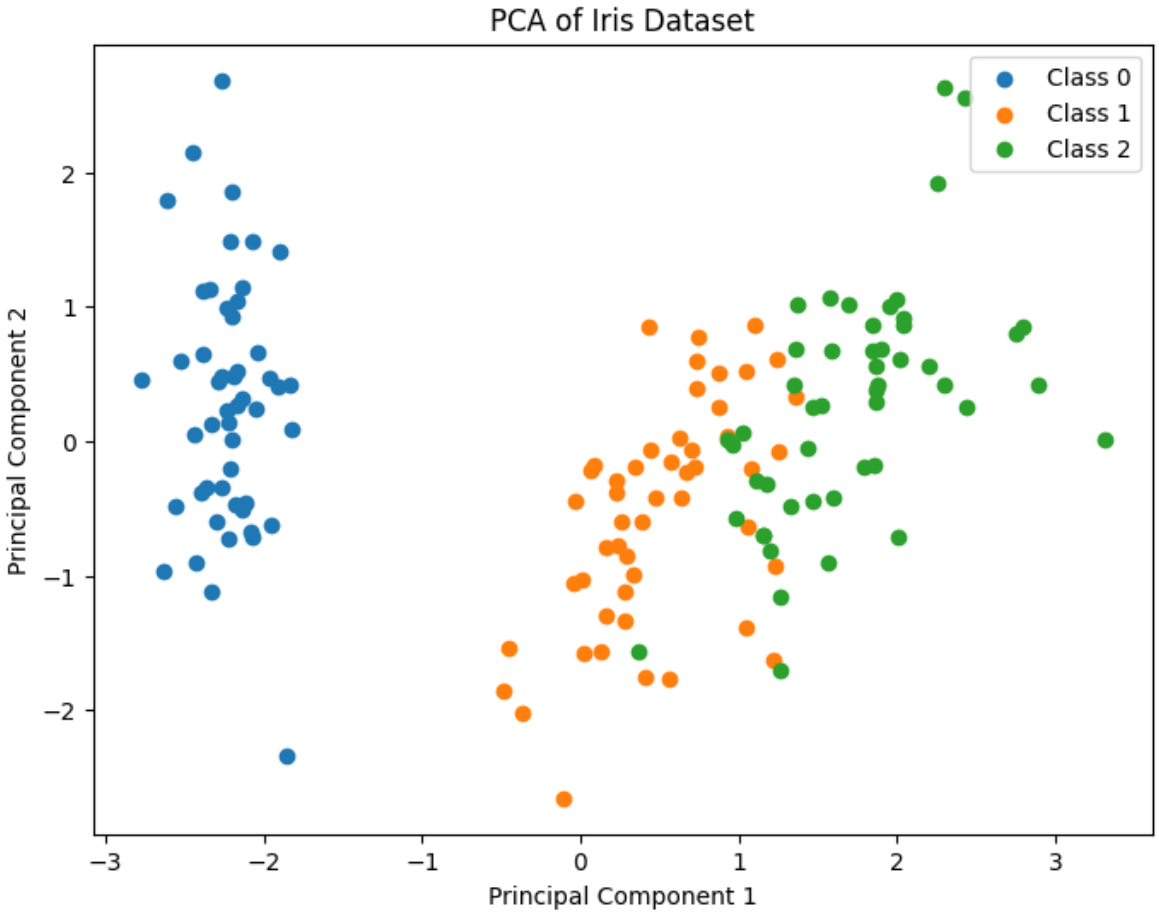
Introduction

PCA identifies the principal components in the data, which are the orthogonal axes along which the data varies the most. It projects the data onto these principal components, reducing the dimensionality while retaining as much of the original variance as possible.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data.iloc[:, :-1]
y = data.iloc[:, -1]
```

```
# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Plot the results
plt.figure(figsize=(8, 6))
for target in set(y):
    indices = (y == target)
    plt.scatter(X_pca[indices, 0], X_pca[indices, 1], label=f'Class {int(target)}')

plt.title('PCA of Iris Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()
```



23. t-Distributed Stochastic Neighbor Embedding (t-SNE) with the Iris Dataset

t-Distributed Stochastic Neighbor Embedding (t-SNE) is a non-linear dimensionality reduction technique commonly used for visualizing high-dimensional data in a lower-dimensional space.

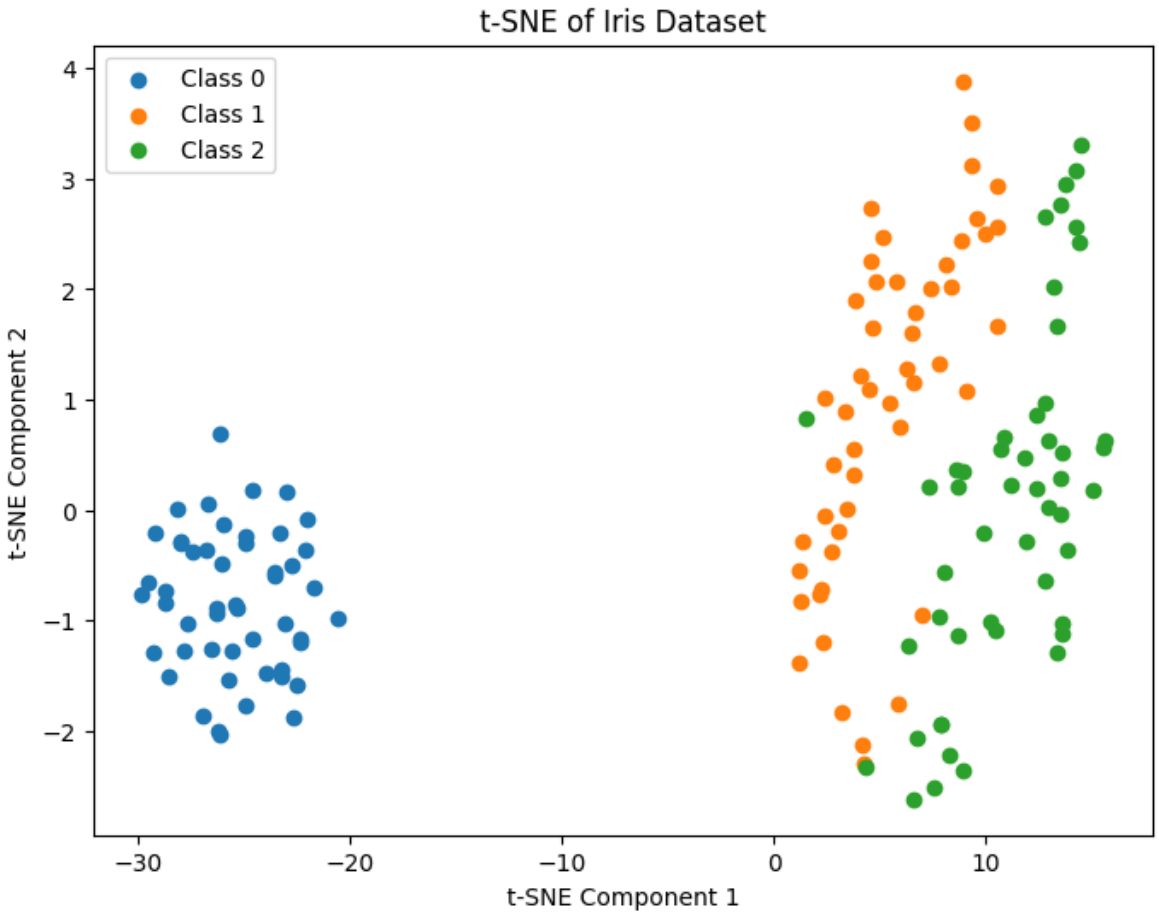
Introduction

t-SNE minimizes the divergence between two probability distributions: a distribution that measures pairwise similarities between the data points in the original space and a distribution that measures pairwise similarities in the reduced space.

Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data.iloc[:, :-1]
y = data.iloc[:, -1]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply t-SNE
tsne = TSNE(n_components=2, random_state=42)
X_tsne = tsne.fit_transform(X_scaled)

# Plot the results
plt.figure(figsize=(8, 6))
for target in set(y):
    indices = (y == target)
    plt.scatter(X_tsne[indices, 0], X_tsne[indices, 1], label=f'Class {int(targe

plt.title('t-SNE of Iris Dataset')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.legend()
plt.show()
```



24. K-Means Clustering with the Iris Dataset

K-Means Clustering is a partitioning method that divides a dataset into K distinct, non-overlapping subsets (clusters).

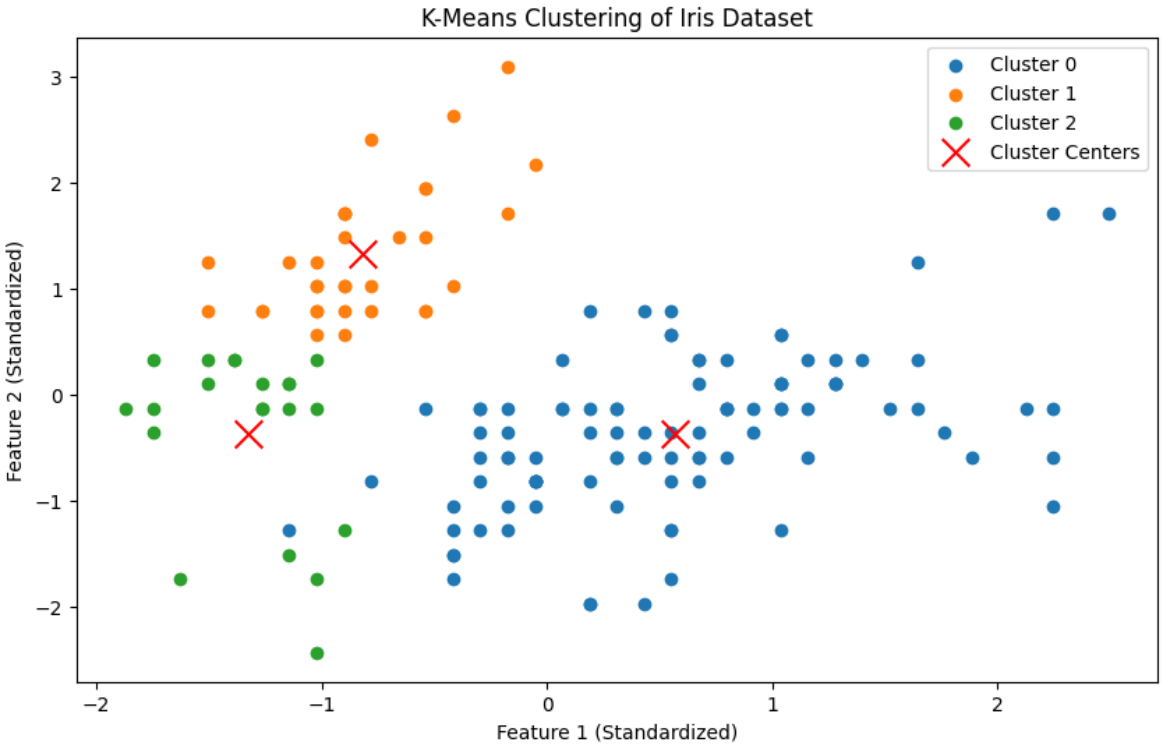
Introduction

Each data point belongs to the cluster with the nearest mean, and the center of the cluster is the mean of all the points in the cluster. It's an unsupervised learning algorithm commonly used for clustering.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables)
X = data.iloc[:, :-1]

# Standardize the features
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply K-Means clustering
kmeans = KMeans(n_clusters=3, random_state=42)
data['cluster'] = kmeans.fit_predict(X_scaled)

# Plot the results
plt.figure(figsize=(10, 6))

for cluster in set(data['cluster']):
    indices = (data['cluster'] == cluster)
    plt.scatter(X_scaled[indices, 0], X_scaled[indices, 1], label=f'Cluster {int

# Plot cluster centers
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], marker

plt.title('K-Means Clustering of Iris Dataset')
plt.xlabel('Feature 1 (Standardized)')
plt.ylabel('Feature 2 (Standardized)')
plt.legend()
plt.show()
```



25. Hierarchical Clustering with the Iris Dataset

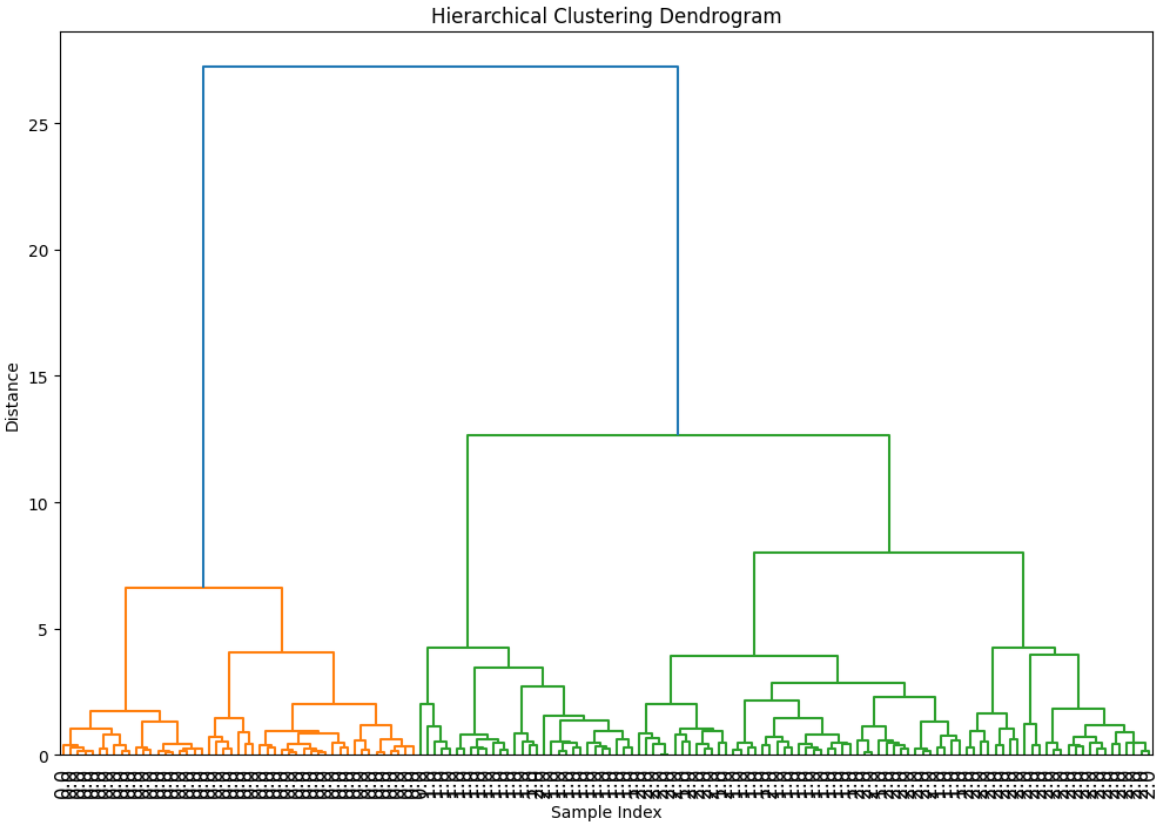
Hierarchical Clustering is a clustering algorithm that builds a hierarchy of clusters by recursively merging or splitting clusters based on their similarity.

Introduction

There are two main types of hierarchical clustering: agglomerative (bottom-up) and divisive (top-down).

Example Code

In [ ]:
```python
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import linkage, dendrogram
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables)
X = data.iloc[:, :-1]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply Agglomerative Hierarchical Clustering
linkage_matrix = linkage(X_scaled, method='ward')

# Plot the dendrogram
plt.figure(figsize=(12, 8))
dendrogram(linkage_matrix, labels=data['target'].values, leaf_rotation=90, leaf_
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
plt.show()
```



26. Gaussian Mixture Models (GMM) with the Iris Dataset

Gaussian Mixture Models (GMM) is a probabilistic model that represents a mixture of Gaussian distributions.

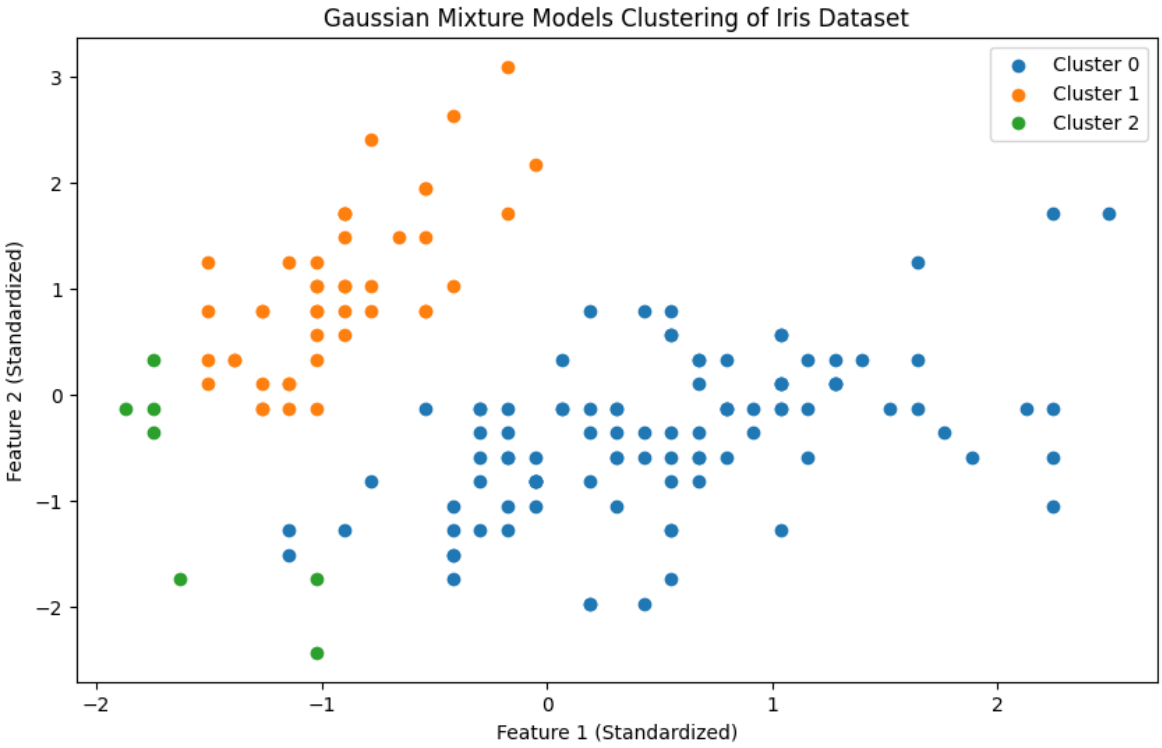
Introduction

GMM is commonly used for clustering and density estimation. It assumes that the data is generated from a mixture of several Gaussian distributions, each with its own set of parameters.

Example Code

In [ ]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.mixture import GaussianMixture
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables)
X = data.iloc[:, :-1]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply Gaussian Mixture Models
gmm = GaussianMixture(n_components=3, random_state=42)
data['cluster'] = gmm.fit_predict(X_scaled)

# Plot the results
plt.figure(figsize=(10, 6))

for cluster in set(data['cluster']):
    indices = (data['cluster'] == cluster)
    plt.scatter(X_scaled[indices, 0], X_scaled[indices, 1], label=f'Cluster {int

plt.title('Gaussian Mixture Models Clustering of Iris Dataset')
plt.xlabel('Feature 1 (Standardized)')
plt.ylabel('Feature 2 (Standardized)')
plt.legend()
plt.show()
```



27. Hidden Markov Models (HMM) with a Synthetic Dataset

Hidden Markov Models (HMM) represent a system with unobservable states, emitting observable symbols with certain probabilities.

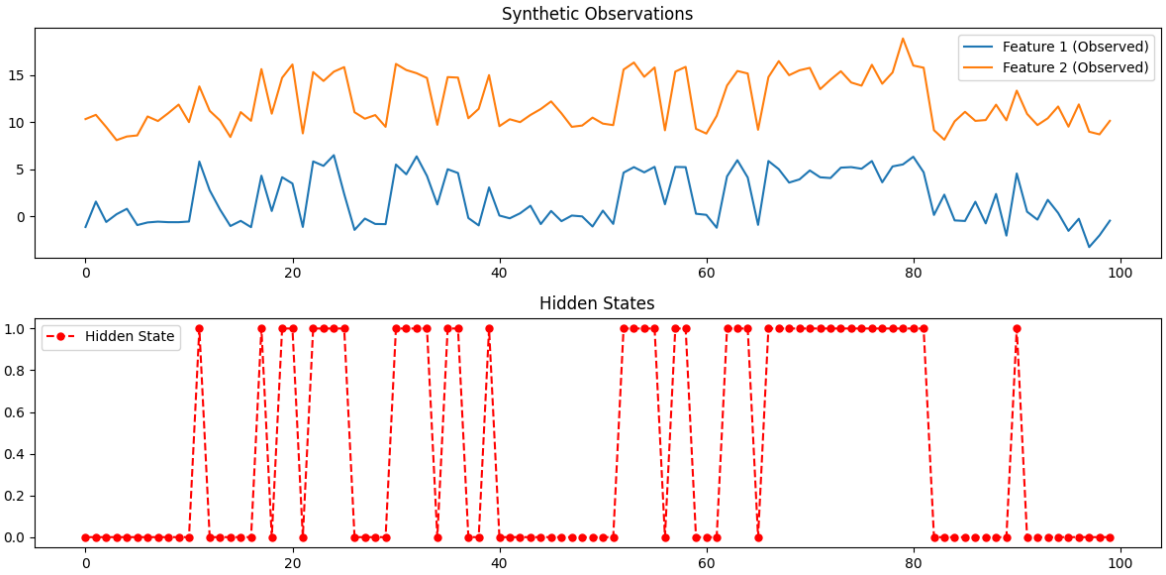
Introduction

HMMs are widely used for modeling time series data, particularly in fields such as speech recognition, bioinformatics, and finance.

Example Code

In [ ]:
```python
# Import necessary libraries
import numpy as np
import matplotlib.pyplot as plt
from hmmlearn import hmm

# Generate a synthetic dataset with two hidden states
np.random.seed(42)

# Transition matrix
trans_matrix = np.array([[0.7, 0.3], [0.4, 0.6]])

# Emission probabilities
emission_means = np.array([[0.0, 10.0], [5.0, 15.0]])
emission_covars = np.tile(np.identity(2), (2, 1, 1))

# Create and fit an HMM model
model = hmm.GaussianHMM(n_components=2, covariance_type="full", n_iter=100)
model.startprob_ = np.array([0.5, 0.5])
model.transmat_ = trans_matrix
model.means_ = emission_means
model.covars_ = emission_covars
```

```
# Generate synthetic samples
X, Z = model.sample(100)

# Plot the synthetic samples and the hidden states
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plt.plot(X[:, 0], label='Feature 1 (Observed)')
plt.plot(X[:, 1], label='Feature 2 (Observed)')
plt.title('Synthetic Observations')
plt.legend()

plt.subplot(2, 1, 2)
plt.plot(Z, label='Hidden State', color='red', linestyle='dashed', marker='o', m
plt.title('Hidden States')
plt.legend()

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



28. Linear Discriminant Analysis (LDA) with the Iris Dataset

Linear Discriminant Analysis (LDA) is a classification and dimensionality reduction technique that seeks to find linear combinations of features that best separate different classes.

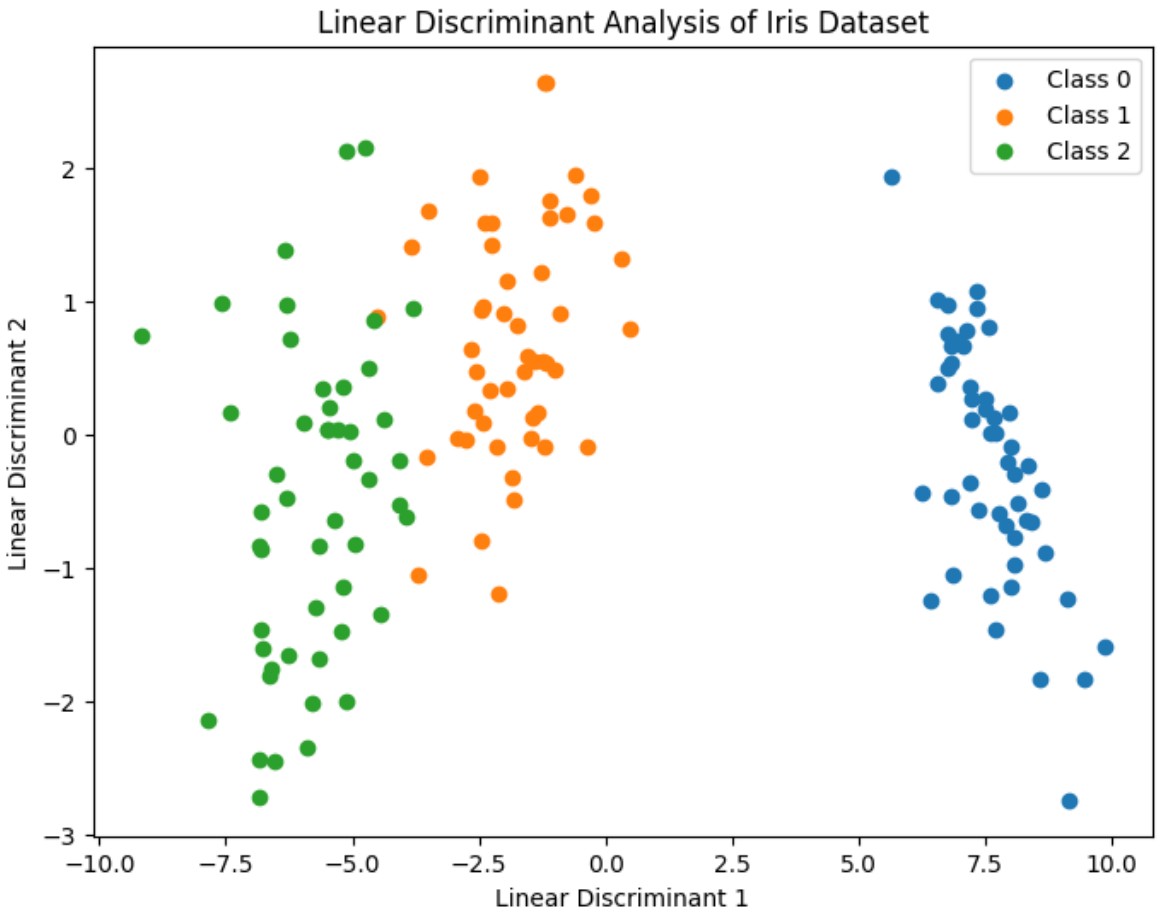
Introduction

LDA minimizes the within-class variance and maximizes the between-class variance.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import matplotlib.pyplot as plt

# Load the Iris dataset
```

```
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data.iloc[:, :-1]
y = data.iloc[:, -1]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply Linear Discriminant Analysis
lda = LinearDiscriminantAnalysis(n_components=2)
X_lda = lda.fit_transform(X_scaled, y)

# Plot the results
plt.figure(figsize=(8, 6))

for target in set(y):
    indices = (y == target)
    plt.scatter(X_lda[indices, 0], X_lda[indices, 1], label=f'Class {int(target)

plt.title('Linear Discriminant Analysis of Iris Dataset')
plt.xlabel('Linear Discriminant 1')
plt.ylabel('Linear Discriminant 2')
plt.legend()
plt.show()
```



29. Quadratic Discriminant Analysis (QDA) with the Iris Dataset

Quadratic Discriminant Analysis (QDA) is a classification and dimensionality reduction technique that allows each class to have its own covariance matrix.

Introduction

QDA is similar to Linear Discriminant Analysis (LDA), but it does not assume equal covariance matrices for all classes.

Example Code

In [ ]:
```
from sklearn.datasets import load_iris
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Load the Iris dataset
iris = load_iris()
X = iris.data
y = iris.target

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random

# Create QDA classifier
qda = QuadraticDiscriminantAnalysis()

# Train the model
qda.fit(X_train, y_train)

# Make predictions on the test set
y_pred = qda.predict(X_test)

# Evaluate model performance
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 1.0
```

30. Ensemble Learning with Random Forest on the Iris Dataset

Ensemble learning combines the predictions of multiple base models to improve overall performance and generalization.

Introduction

Random Forest is an ensemble learning method based on bagging.

Example Code

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
```

```python
from sklearn.metrics import accuracy_score, classification_report, confusion_mat

# Load the Iris dataset
iris = load_iris()
data = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feat

# Select features (independent variables) and target (dependent variable)
X = data.iloc[:, :-1]
y = data.iloc[:, -1]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Apply Random Forest
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)

# Make predictions on the test set
y_pred = rf_classifier.predict(X_test)

# Evaluate the performance
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(classification_rep)
```

```
Accuracy: 1.0
Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Classification Report:
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        10
         1.0       1.00      1.00      1.00         9
         2.0       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
```