```
# logistic regression
# step 1 # import all the libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
# step 2 # creating data set
data = {
         'Age': [22, 25, 47, 52, 46, 56, 55, 60, 62, 61],
         'Salary': [25000, 27000, 42000, 50000, 41000, 60000, 58000, 61000, 65000, 62000],
         'Purchased': [0, 0, 1, 1, 1, 1, 1, 1, 1, 1] # 0 = No, 1 = Yes
df = pd.DataFrame(data)
# step 3  # x,y split (x values, and y values)
x = df[['Age', 'Salary']]
y = df['Purchased'] # Changed to a Series
# step 4 # train-test split
x_{train}, x_{test}, y_{train}, y_{test} = train_{test}, train_{train}, train
# step 5  # model train
model = LogisticRegression()
model.fit(x_train, y_train)
print(f"Training samples: {x_train.shape[0]}, Test samples: {x_test.shape[0]}")
print('Loan Default model is trained successfully')
# step 6 # prediction
y_pred = model.predict(x_test)
# step 7 # accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"accuracy: {accuracy:.2f}")
# step 8 # scottor plot visualize
plt.figure(figsize=(6,4))
sns.scatterplot(x = 'Age', y = 'Salary', hue = 'Purchased',
                               data = df, s = 100, palette = 'coolwarm')
plt.title('Age & Salary vs Purchased')
plt.xlabel('Age')
plt.ylabel('Salary')
plt.grid(True)
plt.show()
```

Training samples: 7, Test samples: 3
Loan Default model is trained successfully
accuracy: 1.00



```
# decision tree
# step 1
import pandas as pd
from sklearn.model_selection import train_test_split
from \ sklearn.tree \ import \ DecisionTreeClassifier, \ plot\_tree
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
# fruite size and sweetness
# step 2
           # create dataset
date = {
    'size': [3,4,5,7,9,6,2, 8],
    'sweetness':[4,5,6,8,9,9,7,3]
    'fruitetype':[0,0,0,1,1,1,1,0]
df = pd.DataFrame(date)
# step 3 # splitting x,y
x = df[['size', 'sweetness']]
y = df['fruitetype']
# step 4 # train-test split
x_train, x_test, y_train, y_test = train_test_split (x,y, test_size = 0.3, random_state = 42)
          # model train
# step 5
model = DecisionTreeClassifier(max depth = 3, random state = 42)
model.fit(x\_train, y\_train)
# step 6 # prediction
y_pred = model.predict(x_test)
# step 7 # accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
# step 8 # Visualize the decision tree
plt.figure(figsize=(12, 8))
plot_tree(model, feature_names=['size', 'sweetness'], class_names=['0', '1'], filled=True, rounded=True)
plt.show()
# step 9 # Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['0', '1'], yticklabels=['0', '1'])
```

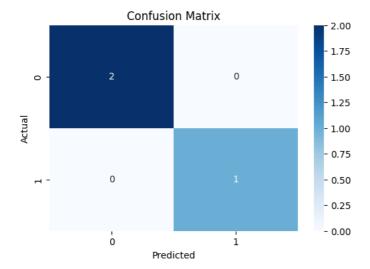
```
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

→ Accuracy: 1.00

```
sweetness <= 6.5
gini = 0.48
samples = 5
value = [2, 3]
class = 1

gini = 0.0
samples = 2
value = [2, 0]
class = 0

gini = 0.0
samples = 3
value = [0, 3]
class = 1
```



```
# random forest
```

```
from sklearn.datasets import load_digits
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Load the digits dataset
digits = load_digits()
X = digits.data
y = digits.target

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train the Random Forest model
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
```

- 30

- 10

- 0

```
# Predict
y_pred = clf.predict(X_test)
# Evaluate
print(accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
# Confusion matrix heatmap
plt.figure(figsize=(8, 6))
\verb|sns.heatmap| (\verb|confusion_matrix| (y_test, y_pred), annot=True, fmt='d', cmap='Blues')| \\
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Digits Classification Confusion Matrix')
plt.show()
→ 0.97222222222222
                  precision
                               recall f1-score
                                                  support
               0
                                 0.97
                                           0.98
                        1.00
                                                        33
                        0.97
                                 1.00
                                           0.98
                                                        28
                                           1.00
                        1.00
                                 1.00
                                                        33
               3
                        1.00
                                 0.94
                                           0.97
                                                        34
               4
                        0.98
                                 1.00
                                           0.99
                                                        46
               5
                        0.94
                                 0.96
                                           0.95
                                                        47
               6
                        0.97
                                 0.97
                                           0.97
                                                        35
                        0.97
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                                           0.97
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                        0.97
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                                           0.97
               8
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                                                        40
                        0.95
                                 0.95
                                           0.95
                                           0.97
                                                      360
        accuracy
                       0.97
                                 0.97
                                           0.97
                                                      360
       macro avg
     weighted avg
                       0.97
                                 0.97
                                           0.97
                                                      360
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                      0
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       0
          0 33 0 0 0 0 0 0 0]
             0 32
                   0
          0 0 0 46 0
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                   0 45
                                  1]
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          0 0 0 0 1 34 0 0 0]
       0
          0 0 0 0 0 0 33 0 1
       0
          1 0 0 0 0 0 0 29 01
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             0 0 0 1 0 1 0 38]]
          0
                        Digits Classification Confusion Matrix
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```

```
# svm (support vector machine)
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.datasets import load_iris
import seaborn as sns
import matplotlib.pyplot as plt
```

Predicted

Load dataset

```
data = load_iris()
X = data.data
y = data.target
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Create and train SVM model
model = SVC(kernel='linear')
model.fit(X_train, y_train)
# Predict
y_pred = model.predict(X_test)
# Evaluate
print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
print(classification_report(y_test, y_pred, target_names=data.target_names))
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, cmap='Blues', xticklabels=data.target_names, yticklabels=data.target_names)
plt.title("SVM - Iris Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
→ Accuracy: 1.00
                   precision
                                recall f1-score
                        1.00
                                  1.00
                                            1.00
                                                        19
          setosa
                                 1.00
       versicolor
                        1.00
                                            1.00
                                                        13
        virginica
                        1.00
                                 1.00
                                            1.00
                                                        13
```

45 accuracy 1.00 macro avg 1.00 1.00 1.00 45 weighted avg 1.00 1.00 1.00 45

SVM - Iris Confusion Matrix 17.5 setosa 19 0 0 15.0 - 12.5 /ersicolor 10.0 0 0 - 7.5 - 5.0 virginica 0 0 - 2.5 - 0.0 setosa versicolor virginica Predicted

```
# k-nearest neighbours knn
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
                                                               # 1=Fit, 0=Unfit
# sample data
data = {
    'Age': [25, 30, 45, 35, 50, 23, 40, 60, 55, 33],
    'ExerciseMins': [60, 45, 30, 50, 20, 70, 40, 15, 10, 55],
    'Fit': [1, 1, 0, 1, 0, 1, 0, 0, 0, 1]
df = pd.DataFrame(data)
# split x,y
```

```
x = df[['Age', 'ExerciseMins']]
y = df['Fit']
# train split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)
# model
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
# predict
y_pred = knn.predict(X_test)
# model evaluation
print("Test Data:\n", X_test)
print("\nPredictions:", y_pred)
print("\nActual:", y_test.values)
print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
→ Test Data:
        Age ExerciseMins
     8
     1 30
5 23
                        70
     Predictions: [0 1 1]
     Actual: [0 1 1]
     Accuracy: 1.0
     Confusion Matrix:
      [[1 0]
[0 2]]
```