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Assignment 2, Data Mining

Put all deliverables into github repository in your profile. Share link to google form 24 hours before defense. Defend by explaining deliverables and answering questions.
Deliverables: .ipynb
Google form: https://docs.google.com/forms/d/e/1FAIpQLSe0GyNdOYlvM1tX_I_CtlPod5jBf-ACLGdHYZq1gVZbUeBzIg/viewform?usp=sf_link

Exercise 1: Feature Selection with `SelectKBest`

Objective: Use `SelectKBest` from scikit-learn to select the top k features from a dataset.

1. Load the Iris dataset from scikit-learn.
2. Split the dataset into features and target variable.
3. Use `SelectKBest` with the `chi2` score function to select the top 2 features.
4. Print the selected feature names.

In [1]:
```
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.feature_selection import SelectKBest, chi2

iris = load_iris()
X = iris.data
y = iris.target

df_X = pd.DataFrame(X, columns=iris.feature_names)

s = SelectKBest(score_func=chi2, k=2)
X_new = s.fit_transform(X, y)

mask = s.get_support()

selected_features = df_X.columns[mask]
print("Выбранные признаки:", selected_features)
```

```
Выбранные признаки: Index(['petal length (cm)', 'petal width (cm)'], dtype='object')
```

Exercise 2: Feature Importance with Random Forest

Objective: Use a Random Forest classifier to determine feature importance.

1. Load the Wine dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train a Random Forest classifier on the training data.
4. Extract and visualize feature importances.

In [1]:
```
import pandas as pd
from sklearn.datasets import load_wine
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import numpy as np

data = load_wine()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = data.target

print(X.head())
print()
print(X.info())
```

```
   alcohol  malic_acid   ash  alcalinity_of_ash  magnesium  total_phenols  \
0    14.23        1.71  2.43               15.6      127.0           2.80
1    13.20        1.78  2.14               11.2      100.0           2.65
2    13.16        2.36  2.67               18.6      101.0           2.80
3    14.37        1.95  2.50               16.8      113.0           3.85
4    13.24        2.59  2.87               21.0      118.0           2.80

   flavanoids  nonflavanoid_phenols  proanthocyanins  color_intensity   hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   od280/od315_of_diluted_wines  proline
0                          3.92   1065.0
1                          3.40   1050.0
2                          3.17   1185.0
3                          3.45   1480.0
4                          2.93    735.0

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   alcohol                       178 non-null    float64
 1   malic_acid                    178 non-null    float64
 2   ash                           178 non-null    float64
 3   alcalinity_of_ash             178 non-null    float64
 4   magnesium                     178 non-null    float64
 5   total_phenols                 178 non-null    float64
 6   flavanoids                    178 non-null    float64
 7   nonflavanoid_phenols          178 non-null    float64
 8   proanthocyanins               178 non-null    float64
 9   color_intensity               178 non-null    float64
 10  hue                           178 non-null    float64
 11  od280/od315_of_diluted_wines  178 non-null    float64
 12  proline                       178 non-null    float64
dtypes: float64(13)
memory usage: 18.2 KB
None
```

In [2]:
```
X1, X2, y1, y2 = train_test_split(X, y, test_size=0.3, random_state=42)

print(f"Train sets: {X1.shape}")
print(f"Test sets: {X2.shape}")
```

```
Train sets: (124, 13)
Test sets: (54, 13)
```

In [4]:
```
# RandomForest
rf = RandomForestClassifier(random_state=42)
rf.fit(X1, y1)
```

Out[4]:
```
RandomForestClassifier(random_state=42)
```

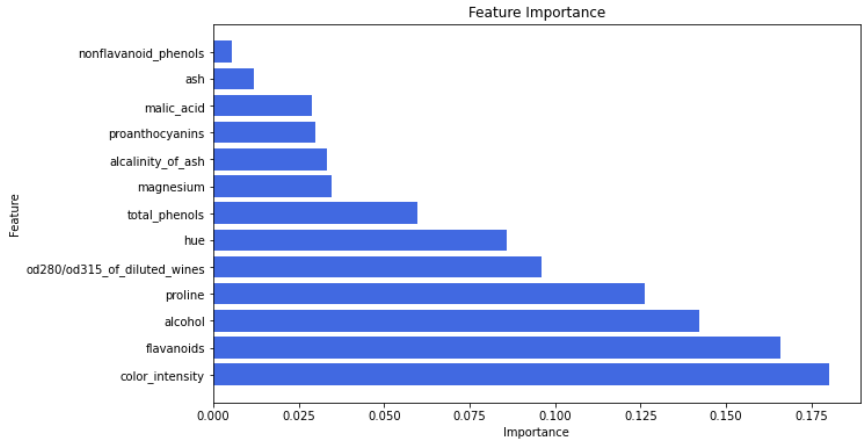
In [8]:
```
importances = rf.feature_importances_ # Извлечение важности признаков

fi_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importances
})

fi_df = fi_df.sort_values(by='Importance', ascending=False)
print(fi_df)
```

```
                        Feature  Importance
9                color_intensity    0.180198
6                     flavanoids    0.165947
0                        alcohol    0.142041
12                       proline    0.126080
11  od280/od315_of_diluted_wines    0.096032
10                           hue    0.085966
5                  total_phenols    0.059758
4                      magnesium    0.034673
3              alcalinity_of_ash    0.033211
8                proanthocyanins    0.029778
1                     malic_acid    0.028976
2                            ash    0.011859
7           nonflavanoid_phenols    0.005480
```

In [10]:
```
plt.figure(figsize=(10, 6))
plt.barh(fi_df['Feature'], fi_df['Importance'], color='royalblue')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance')
plt.show()
```



Exercise 3: Recursive Feature Elimination (RFE)

Objective: Use Recursive Feature Elimination (RFE) to select features and evaluate model performance.

1. Load the Breast Cancer dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Use RFE with a Support Vector Machine (SVM) classifier to select features.
4. Train an SVM model with the selected features and evaluate its performance.

In [1]:
```
import pandas as pd
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.feature_selection import RFE
from sklearn.metrics import accuracy_score

data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target)

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

svm_classifier = SVC(kernel="linear")
rfe = RFE(estimator=svm_classifier, n_features_to_select=10)
rfe.fit(X1, y1)

selected_features = X.columns[rfe.support_]
print("Выбранные признаки:")
print(selected_features)
print()

X1_rfe = rfe.transform(X1)
X2_rfe = rfe.transform(X2)

svm_classifier.fit(X1_rfe, y1)

y_pred = svm_classifier.predict(X2_rfe)
accuracy = accuracy_score(y2, y_pred)

print(f"Точность модели: {accuracy:.2f}")
```

```
Выбранные признаки:
Index(['mean radius', 'mean concavity', 'mean concave points', 'texture error',
       'worst radius', 'worst smoothness', 'worst compactness',
       'worst concavity', 'worst concave points', 'worst symmetry'],
      dtype='object')

Точность модели: 0.97
```

Exercise 4: L1 Regularization for Feature Selection

Objective: Use L1 regularization (Lasso) for feature selection.

1. Load the Diabetes dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Apply Lasso regression for feature selection.
4. Train a model using selected features and evaluate its performance.

In [2]:
```
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

data = load_diabetes()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

l = Lasso(alpha=0.1)
l.fit(X1, y1)
print(l.coef_)
```

```
[   0.         -152.66706552  552.6941724   303.37055083  -81.3648345
   -0.         -229.25829816    0.          447.91818931   29.64235375]
```

In [3]:
```
y_pred = l.predict(X2)

mse = mean_squared_error(y2, y_pred)
r2 = r2_score(y2, y_pred)

print(f"Средняя квадратичная ошибка: {mse:.2f}")
print(f"R^2: {r2:.2f}")
```

```
Средняя квадратичная ошибка: 2798.19
R^2: 0.47
```

Classification Exercises

Exercise 1: Logistic Regression

Objective: Build a logistic regression model to classify data.

1. Load the Iris dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train a logistic regression model on the training set.
4. Evaluate the model's performance on the test set using accuracy and a confusion matrix.

In [1]:
```
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

iris = load_iris()
X = iris.data
y = iris.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

l = LogisticRegression(max_iter=200)
l.fit(X1, y1)

y_pred = l.predict(X2)

result = accuracy_score(y2, y_pred)
print(f"Точность модели: {result:.2f}")

matrix = confusion_matrix(y2, y_pred)
print("Матрица ошибок:")
print(matrix)
```

```
Точность модели: 1.00
Матрица ошибок:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

Exercise 2: Support Vector Machine (SVM)

Objective: Use an SVM classifier to classify data.

1. Load the Breast Cancer dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train an SVM model on the training data.
4. Evaluate the model's performance on the test data using accuracy and a confusion matrix.

In [1]:
```
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix


data = load_breast_cancer()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

svm_model = SVC()
svm_model.fit(X1, y1)

y_pred = svm_model.predict(X2)


accuracy = accuracy_score(y2, y_pred)
print(f"Точность модели: {accuracy:.2f}")
print()


conf_matrix = confusion_matrix(y2, y_pred)
print("Матрица ошибок:")
print(conf_matrix)
```

```
Точность модели: 0.95

Матрица ошибок:
[[37  6]
 [ 0 71]]
```

Exercise 3: Decision Tree Classifier

Objective: Build a decision tree classifier and visualize it.

1. Load the Wine dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train a decision tree classifier on the training set.

4. Visualize the decision tree.

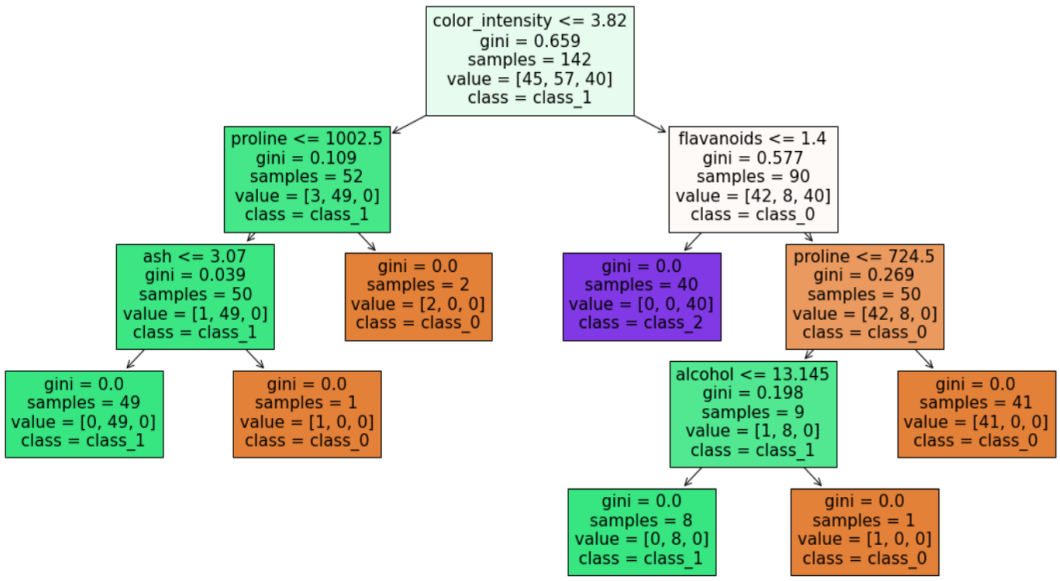
```
In [1]: from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import matplotlib.pyplot as plt

data = load_wine()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

dtc = DecisionTreeClassifier(random_state=42)
dtc.fit(X1, y1)

plt.figure(figsize=(20,10))
tree.plot_tree(dtc, feature_names=data.feature_names, class_names=data.target_names, filled=True)
plt.show()
```



Regression Exercises

Exercise 1: Linear Regression

Objective: Build a linear regression model to predict a continuous target variable.

1. Load the Boston Housing dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train a linear regression model on the training set.

4. Evaluate the model's performance using mean squared error (MSE) and R-squared score.

In [2]:
```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

data = fetch_california_housing()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

lr = LinearRegression()
lr.fit(X1, y1)

y_pred = lr.predict(X2)

mse = mean_squared_error(y2, y_pred)
print(f"(MSE): {mse:.2f}")

r2 = r2_score(y2, y_pred)
print(f"(R²): {r2:.2f}")
```

```
(MSE): 0.56
(R²): 0.58
```

Exercise 2: Ridge Regression

Objective: Use Ridge regression to perform regularized linear regression.

1. Load the Diabetes dataset from scikit-learn.
2. Split the dataset into training and testing sets.
3. Train a Ridge regression model on the training set.
4. Evaluate the model's performance using mean squared error (MSE) and R-squared score.

In [1]:
```
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error, r2_score

data = load_diabetes()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

ridge = Ridge(alpha=1.0)
ridge.fit(X1, y1)

y_pred = ridge.predict(X2)

mse = mean_squared_error(y2, y_pred)
r2 = r2_score(y2, y_pred)

print(f"(MSE): {mse:.2f}")
print(f"(R²): {r2:.2f}")
```

```
(MSE): 3077.41
(R²): 0.42
```

Exercise 3: Decision Tree Regression

Objective: Build a decision tree regression model and visualize it.

1. Load the Boston Housing dataset from scikit-learn.

2. Split the dataset into training and testing sets.
3. Train a decision tree regressor on the training set.
4. Evaluate the model's performance using mean squared error (MSE).
5. Visualize the decision tree.

In [1]:
```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

data = fetch_california_housing()
X = data.data
y = data.target

X1, X2, y1, y2 = train_test_split(X, y, test_size=0.2, random_state=42)

tree = DecisionTreeRegressor(random_state=42)
tree.fit(X1, y1)

y_pred = tree.predict(X2)
mse = mean_squared_error(y2, y_pred)
print(f"(MSE): {mse:.2f}")


plt.figure(figsize=(20, 10))
plot_tree(tree, filled=True, feature_names=data.feature_names, rounded=True, max_depth=3)
plt.show()
```

```
(MSE): 0.50
```