# Lab2MD

April 9, 2025

[3]:
```
# Data manipulation and visualization
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Model development
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪GridSearchCV
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree

# Model evaluation
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    classification_report,
    confusion_matrix
)

# For displaying results nicely in the notebook
from IPython.display import display, HTML

# Set visualization style
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette('viridis')
```

```
# For reproducibility
import random
random.seed(42)
np.random.seed(42)
```

[4]:
```
# Read the student performance dataset
df = pd.read_csv('student_performance_data.csv')

# Remove StudentID column from the dataset, irrelevant for what I am finding
df = df.drop(columns=['StudentID'])

# Basic info about the dataset
print("Dataset shape:", df.shape)
print("\nFirst 5 rows of the dataset:")
display(df.head())

# Descriptive statistics
print("\nDescriptive statistics:")
display(df.describe())

# Check for missing values
print("\nMissing values per column:")
display(df.isnull().sum())

# Display information about data types and non-null counts
print("\nDataset information:")
display(df.info())
```

```
Dataset shape: (500, 8)

First 5 rows of the dataset:

   Gender  Age  StudyHoursPerWeek  AttendanceRate   GPA      Major  \
0    Male   24                 37           90.75  3.47       Arts
1  Female   22                 37           74.90  2.32  Education
2    Male   22                 10           53.36  2.38   Business
3    Male   24                 10           70.26  3.46    Science
4    Male   18                 19           74.87  2.31  Education

  PartTimeJob ExtraCurricularActivities
0         Yes                        No
1          No                        No
2          No                        No
3         Yes                        No
4         Yes                        No


Descriptive statistics:
```

```
              Age  StudyHoursPerWeek  AttendanceRate        GPA
count  500.000000         500.000000      500.000000  500.00000
mean    20.956000          19.876000       74.990380    2.98516
std      2.000517          11.471347       14.565917    0.56362
min     18.000000           1.000000       50.010000    2.00000
25%     19.000000          10.000000       62.607500    2.48750
50%     21.000000          20.500000       75.730000    3.00000
75%     23.000000          30.000000       87.220000    3.48000
max     24.000000          39.000000       99.970000    3.99000


Missing values per column:

Gender                        0
Age                           0
StudyHoursPerWeek             0
AttendanceRate                0
GPA                           0
Major                         0
PartTimeJob                   0
ExtraCurricularActivities     0
dtype: int64


Dataset information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Gender                     500 non-null    object
 1   Age                        500 non-null    int64
 2   StudyHoursPerWeek          500 non-null    int64
 3   AttendanceRate             500 non-null    float64
 4   GPA                        500 non-null    float64
 5   Major                      500 non-null    object
 6   PartTimeJob                500 non-null    object
 7   ExtraCurricularActivities  500 non-null    object
dtypes: float64(2), int64(2), object(4)
memory usage: 31.4+ KB

None
```

[5]:
```python
# Step 1: Create binary target based on GPA
gpa_column = 'GPA'
df['target'] = (df[gpa_column] >= 3.2).astype(int)

# Display the distribution of the target variable
print("Target distribution:")
print(df['target'].value_counts())
print(f"Percentage of students with GPA   3.2: {df['target'].mean()*100:.2f}%")

# Step 2: Prepare the data
# Exclude GPA and target from features
X = df.drop(columns=[gpa_column, 'target'])
y = df['target']

# Handle categorical features
categorical_features = X.select_dtypes(include=['object', 'category']).columns.
 ↪tolist()
numerical_features = X.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()

# Create preprocessing pipelines
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Step 3: 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_state=42, stratify=y)

# Step 4: Build the models
# Logistic Regression
log_reg_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(max_iter=1000, random_state=42))
])

# k-NN
knn_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', KNeighborsClassifier(n_neighbors=5))
])

# Decision Tree
dt_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', DecisionTreeClassifier(random_state=42))
])

# Dictionary of models
models = {
    'Logistic Regression': log_reg_pipeline,
    'k-Nearest Neighbors': knn_pipeline,
    'Decision Tree': dt_pipeline
}

# Step 5: Train and evaluate each model
results = {}

for name, model in models.items():
    print(f"\n{'-'*50}")
    print(f"Training and evaluating {name}...")

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

    # Make predictions
    y_pred = model.predict(X_test)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)

    # Store results
    results[name] = {
        'accuracy': accuracy,
        'predictions': y_pred
    }

    # Print classification report
    print(f"\nClassification Report for {name}:")
    print(classification_report(y_test, y_pred))

# Create and display confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['GPA < 3.2', 'GPA   3.2'],
                yticklabels=['GPA < 3.2', 'GPA   3.2'])
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix - {name}')
    plt.tight_layout()
    plt.show()

# Step 6: Compare model performance
model_comparison = pd.DataFrame({
    'Model': list(results.keys()),
    'Accuracy': [results[model]['accuracy'] for model in results]
})

# Sort by accuracy
model_comparison = model_comparison.sort_values('Accuracy', ascending=False).
 ↪reset_index(drop=True)

# Display comparison
print("\nModel Comparison:")
display(model_comparison)

# Visualize model comparison
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Accuracy', data=model_comparison)
plt.title('Model Accuracy Comparison')
plt.ylim(0, 1)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
Target distribution:
target
0    300
1    200
Name: count, dtype: int64
Percentage of students with GPA   3.2: 40.00%

--------------------------------------------------
Training and evaluating Logistic Regression…

Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.60      0.88      0.72        60
           1       0.42      0.12      0.19        40

    accuracy                           0.58       100
   macro avg       0.51      0.50      0.45       100
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weighted avg       0.53      0.58      0.51       100
```
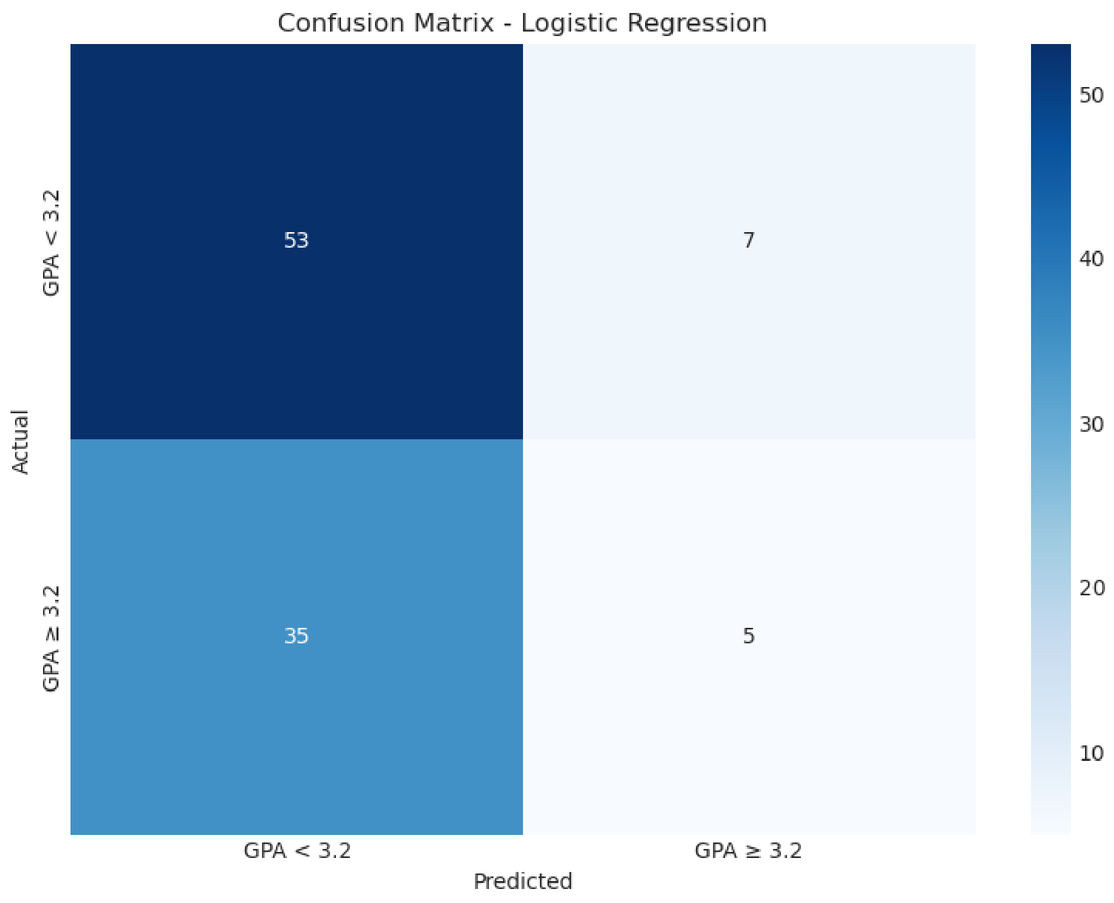
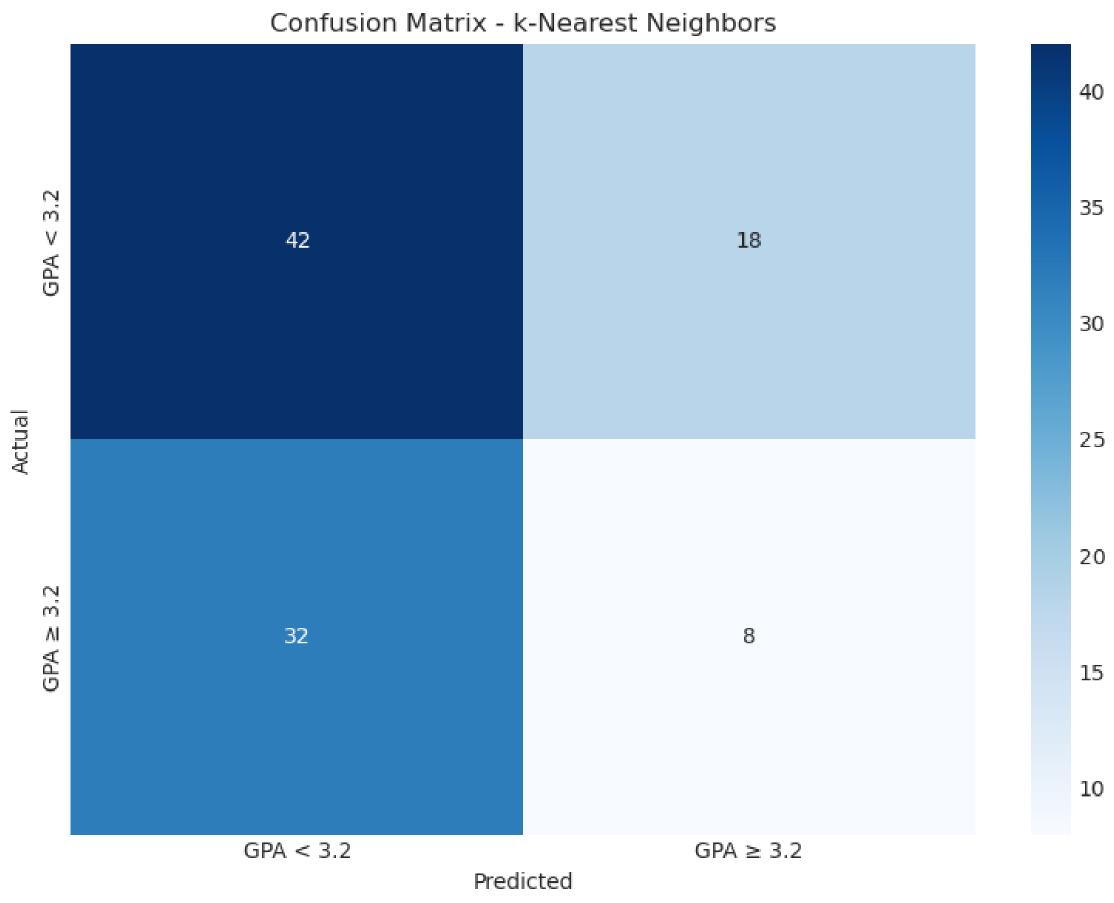
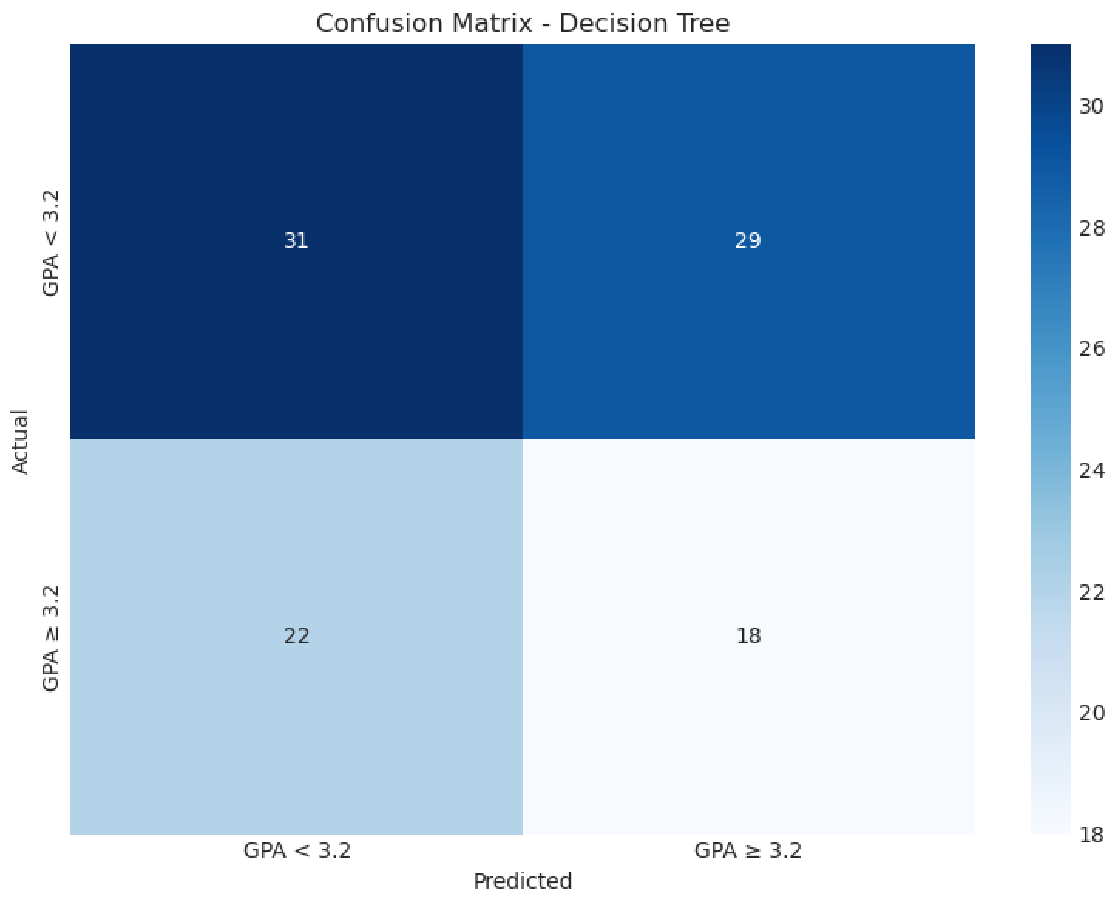



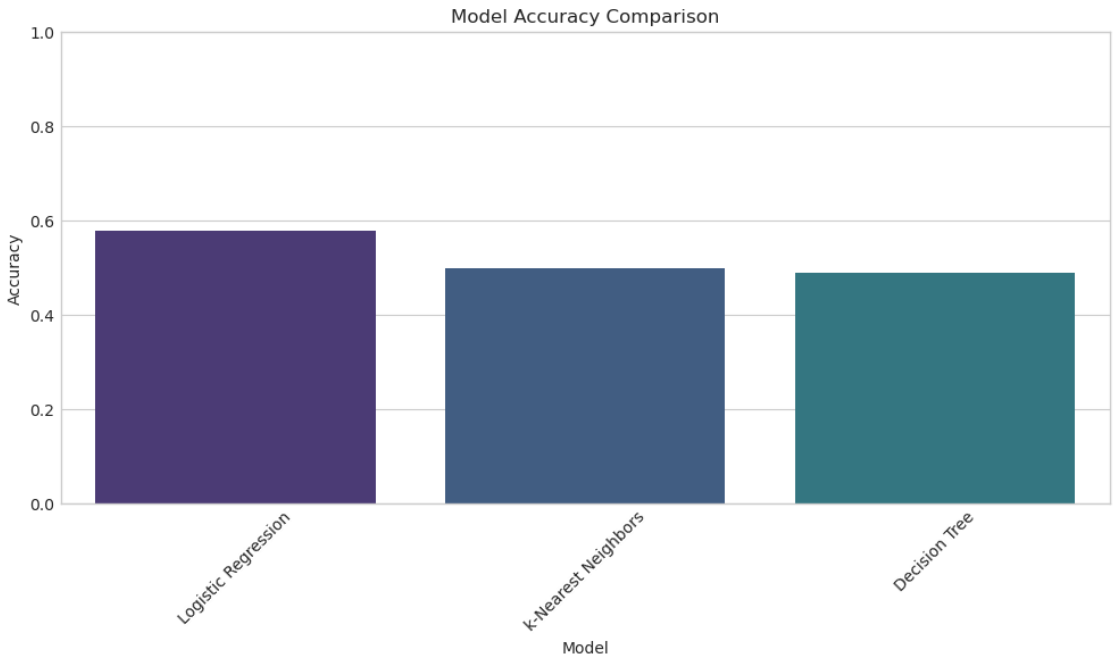
```
--------------------------------------------------
Training and evaluating k-Nearest Neighbors…

Classification Report for k-Nearest Neighbors:
              precision    recall  f1-score   support

           0       0.57      0.70      0.63        60
           1       0.31      0.20      0.24        40

    accuracy                           0.50       100
   macro avg       0.44      0.45      0.43       100
weighted avg       0.46      0.50      0.47       100
```



```
--------------------------------------------------
Training and evaluating Decision Tree…

Classification Report for Decision Tree:
              precision    recall  f1-score   support

           0       0.58      0.52      0.55        60
           1       0.38      0.45      0.41        40

    accuracy                           0.49       100
   macro avg       0.48      0.48      0.48       100
weighted avg       0.50      0.49      0.49       100
```



```
Model Comparison:

                 Model  Accuracy
0  Logistic Regression      0.58
1  k-Nearest Neighbors      0.50
2        Decision Tree      0.49
```


Model Accuracy Comparison
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
k-Nearest Neighbors
Decision Tree
Model