Lab2

April 17, 2025

[447]:
```
# Predicting Student Performance from Demographic Factors
```

[448]:
```
## Abstract: We’ll examine the question: Do students' demographic features␣
↪influence their grades? This lab report utilizes machine learning to␣
↪investigate the predictive value of demographic factors, such as gender,␣
↪age, and family income, in determining university students' final grades.␣
↪After processing a dataset of 5,000 students, we are left with 3,975 after␣
↪removing missing values. We compared three classification models: Decision␣
↪Tree, K-Nearest Neighbors (KNN), and Logistic Regression. The most important␣
↪factor was family income, which had a low prediction accuracy (21-22% across␣
↪models). These results are moderately weak and indicate the necessity for␣
↪perhaps more behavioral and academic features used in the model. Thus,␣
↪demographic features by themselves are not enough to reliably predict a␣
↪student's grade.
```

[449]:
```
## Introduction: A school department can apply a predictive model to evaluate␣
↪its current student population and tailor the curriculum or needs based on␣
↪the results from the model. If a model proves success, it can help boost␣
↪student learning and success through changes made by the school, which are␣
↪derived from the model
```

[450]:
```
## Related work: Current literature surrounding higher education institutions␣
↪shows much debate on student retention and graduation levels. Therefore,␣
↪institutions are more interested in student data than ever to help predict␣
↪student success. Understanding student data and their learning performance␣
↪could help institutions in assisting the student body towards academic␣
↪success (Marbouti, 2021). The data set below is taking from kaggle.com,␣
↪"Student Performance Analysis", a report written by Abdulqadir Mahmood.
```

[451]:
```
## Methodologies
# Import libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
```

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns
```

[452]:
```python
# Load data
df = pd.read_csv('Students_Grading_Dataset.csv')
df.head()
```

[452]:
```
  Student_ID First_Name Last_Name                    Email  Gender   Age  \
0        NaN        NaN       NaN                      NaN     NaN   NaN
1      S1000       Omar  Williams  student0@university.com  Female  22.0
2        NaN        NaN       NaN                      NaN     NaN   NaN
3      S1001      Maria     Brown  student1@university.com    Male  18.0
4        NaN        NaN       NaN                      NaN     NaN   NaN

    Department  Attendance (%)  Midterm_Score  Final_Score  …  \
0          NaN             NaN            NaN          NaN  …
1  Mathematics           97.36          40.61        59.61  …
2          NaN             NaN            NaN          NaN  …
3     Business           97.71          57.27        74.00  …
4          NaN             NaN            NaN          NaN  …

   Projects_Score  Total_Score  Grade  Study_Hours_per_Week  \
0             NaN          NaN    NaN                   NaN
1           62.84        83.49      C                  10.3
2             NaN          NaN    NaN                   NaN
3           98.23        92.29      F                  27.1
4             NaN          NaN    NaN                   NaN

   Extracurricular_Activities Internet_Access_at_Home  Parent_Education_Level  \
0                         NaN                     NaN                     NaN
1                         Yes                      No                Master's
2                         NaN                     NaN                     NaN
3                          No                      No             High School
4                         NaN                     NaN                     NaN

  Family_Income_Level Stress_Level (1-10) Sleep_Hours_per_Night
0                 NaN                 NaN                   NaN
1              Medium                 1.0                   5.9
2                 NaN                 NaN                   NaN
3                 Low                 4.0                   4.3
4                 NaN                 NaN                   NaN

[5 rows x 23 columns]
```

[453]:
```
## Clean the data
# Drop any rows with missing values including "NaNs"
df = df.dropna()
```

[454]:
```
df.head(2)
```

[454]:
```
  Student_ID First_Name Last_Name                    Email  Gender   Age  \
1      S1000       Omar  Williams  student0@university.com  Female  22.0
3      S1001      Maria     Brown  student1@university.com    Male  18.0

    Department  Attendance (%)  Midterm_Score  Final_Score  …  \
1  Mathematics           97.36          40.61        59.61  …
3     Business           97.71          57.27        74.00  …

   Projects_Score  Total_Score  Grade  Study_Hours_per_Week  \
1           62.84        83.49      C                  10.3
3           98.23        92.29      F                  27.1

   Extracurricular_Activities Internet_Access_at_Home  Parent_Education_Level  \
1                         Yes                      No                Master's
3                          No                      No             High School

  Family_Income_Level Stress_Level (1-10) Sleep_Hours_per_Night
1              Medium                 1.0                   5.9
3                 Low                 4.0                   4.3

[2 rows x 23 columns]
```

[455]:
```
# Get visual of columns
print(df.columns)
```

```
Index(['Student_ID', 'First_Name', 'Last_Name', 'Email', 'Gender', 'Age',
       'Department', 'Attendance (%)', 'Midterm_Score', 'Final_Score',
       'Assignments_Avg', 'Quizzes_Avg', 'Participation_Score',
       'Projects_Score', 'Total_Score', 'Grade', 'Study_Hours_per_Week',
       'Extracurricular_Activities', 'Internet_Access_at_Home',
       'Parent_Education_Level', 'Family_Income_Level', 'Stress_Level (1-10)',
       'Sleep_Hours_per_Night'],
      dtype='object')
```

[456]:
```
# Only kept columns that refer to the student's demographics and grade
df = df.drop(['Student_ID', 'First_Name', 'Last_Name', 'Email',
       'Department', 'Study_Hours_per_Week',
       'Extracurricular_Activities', 'Internet_Access_at_Home',
       'Parent_Education_Level', 'Stress_Level (1-10)',
       'Sleep_Hours_per_Night', 'Attendance (%)', 'Midterm_Score',␣
 ↪'Final_Score',
```

```
       'Assignments_Avg', 'Quizzes_Avg', 'Participation_Score',
       'Projects_Score', 'Total_Score'], axis=1, errors='ignore')
```

[457]:
```
print(df.columns)
```

```
Index(['Gender', 'Age', 'Grade', 'Family_Income_Level'], dtype='object')
```

[458]:
```
df = df.rename(columns={'Family_Income_Level': 'Family_Income'})
```

[459]:
```
## Explore the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3975 entries, 1 to 9999
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Gender         3975 non-null   object
 1   Age            3975 non-null   float64
 2   Grade          3975 non-null   object
 3   Family_Income  3975 non-null   object
dtypes: float64(1), object(3)
memory usage: 155.3+ KB
```

[460]:
```
# Shape & Types
print(df.shape)
print(df.dtypes)
```

```
(3975, 4)
Gender            object
Age              float64
Grade             object
Family_Income     object
dtype: object
```

[461]:
```
# No missing values
df.isnull().sum()
```

[461]:
```
Gender           0
Age              0
Grade            0
Family_Income    0
dtype: int64
```

[462]:
```
# Visualize our target variable
print(df['Grade'].unique())
```

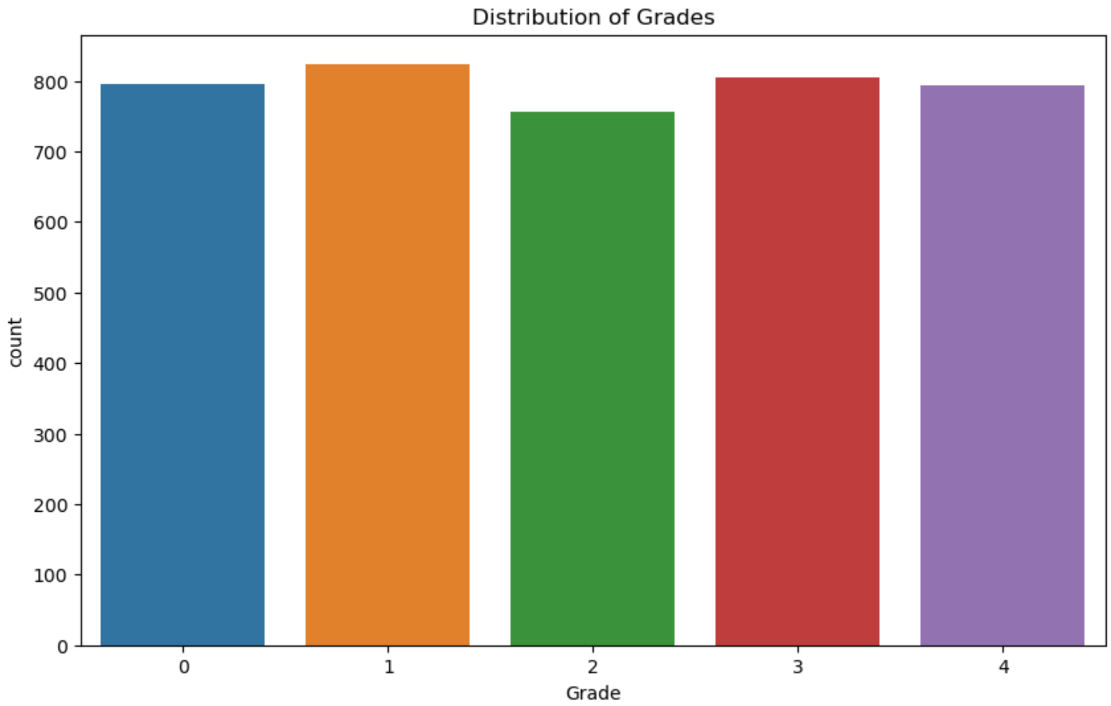
```
['C' 'F' 'A' 'D' 'B']
```

[463]:
```
# Convert categorical variables to numeric
df['Gender'] = df['Gender'].map({'Male': 0, 'Female': 1})
df['Family_Income'] = df['Family_Income'].map({'Low': 0, 'Medium': 1, 'High':␣
↪2})
df['Grade'] = df['Grade'].map({'A': 4, 'B': 3, 'C': 2, 'D': 1, 'F': 0})
#(Rustam, 2015)
```

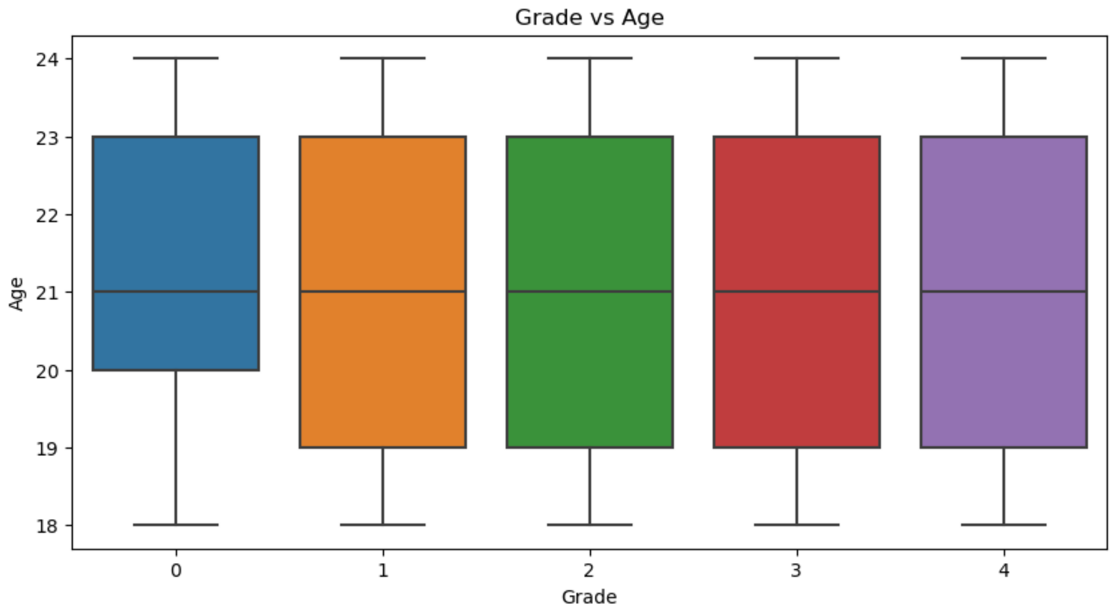
[464]:
```
# Summary statistics
print("\nSummary statistics:\n", df.describe())
```

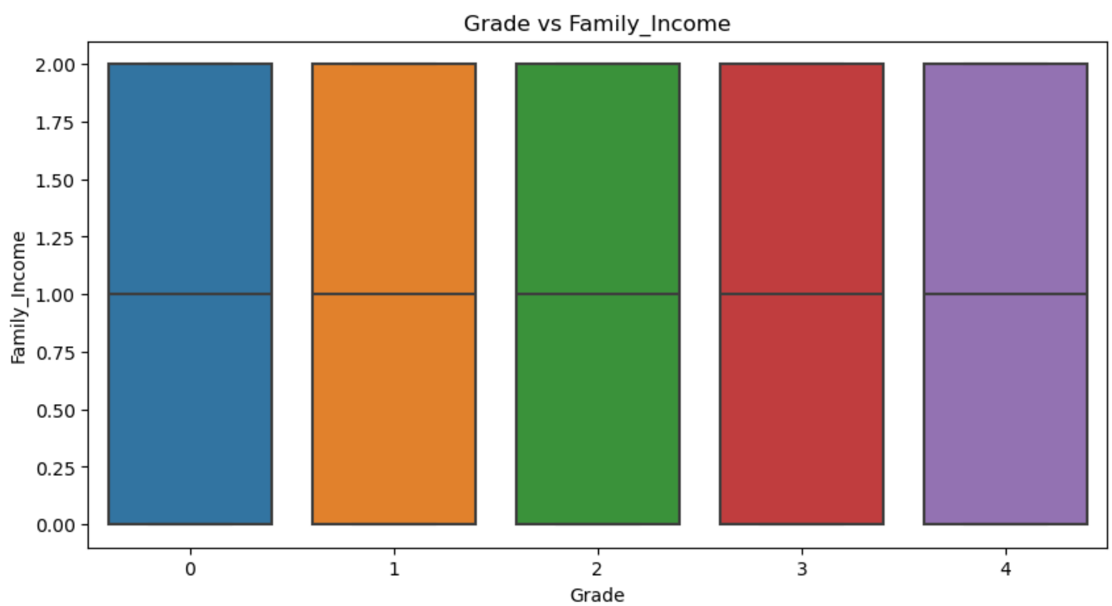
```
Summary statistics:
              Gender          Age        Grade  Family_Income
count  3975.000000  3975.000000  3975.000000    3975.000000
mean      0.490063    21.052327     1.994214       0.987421
std       0.499964     1.993770     1.417845       0.813105
min       0.000000    18.000000     0.000000       0.000000
25%       0.000000    19.000000     1.000000       0.000000
50%       0.000000    21.000000     2.000000       1.000000
75%       1.000000    23.000000     3.000000       2.000000
max       1.000000    24.000000     4.000000       2.000000
```

[465]:
```
# Figure 1, Grade Distribution
plt.figure(figsize=(10,6))
sns.countplot(data=df, x='Grade')
plt.title('Distribution of Grades')
plt.show()
#(Mahmood, 2025)
```



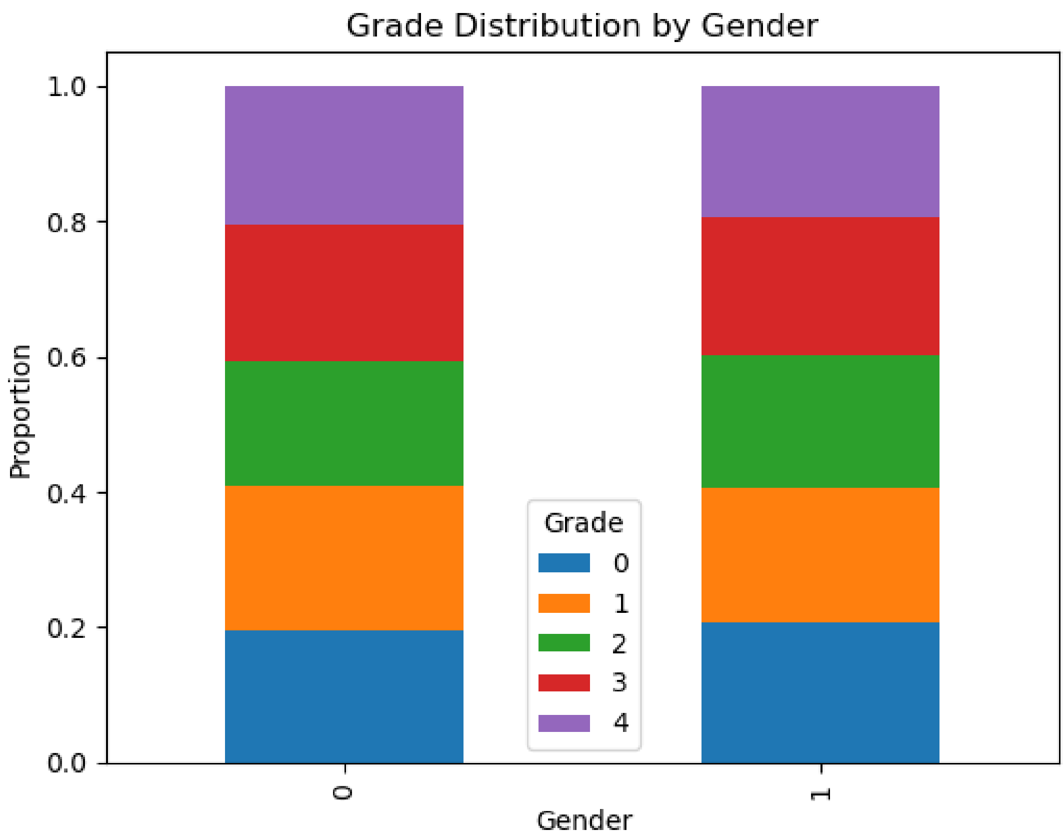
[466]:
```
# Figure 2 & 3, plot Grade with Age & Family_Income respectively
numeric_features = ['Age', 'Family_Income']
for feature in numeric_features:
    plt.figure(figsize=(10, 5))
    sns.boxplot(data=df, x='Grade', y=feature)
    plt.title(f'Grade vs {feature}')
    plt.show()
#(Pierson, 2024)
```





[467]:
```
# Figure 4, Grade distribution by Gender
pd.crosstab(df['Gender'], df['Grade'], normalize='index').plot(kind='bar',␣
↪stacked=True)
plt.title('Grade Distribution by Gender')
plt.ylabel('Proportion')
plt.show()
```

```
#(Pandas-dev, 2025)
```



[468]:
```
## Model development
# Split data into features and target into test sets
X = df.drop('Grade', axis=1)
y = df['Grade']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.7,␣
↪stratify=y, random_state=42)
# Scale
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
#(Galarnyk, 2020)
```

[469]:
```
X_train.shape, X_test.shape
```

[469]: ((1192, 3), (2783, 3))

[505]:
```
Classifier = DecisionTreeClassifier(random_state=1234)
model = Classifier.fit(X_train, y_train)
```

```
model.score(X_test, y_test)
#(Nwanganga, 2022)
```

[505]:

```
0.2030183255479698
```

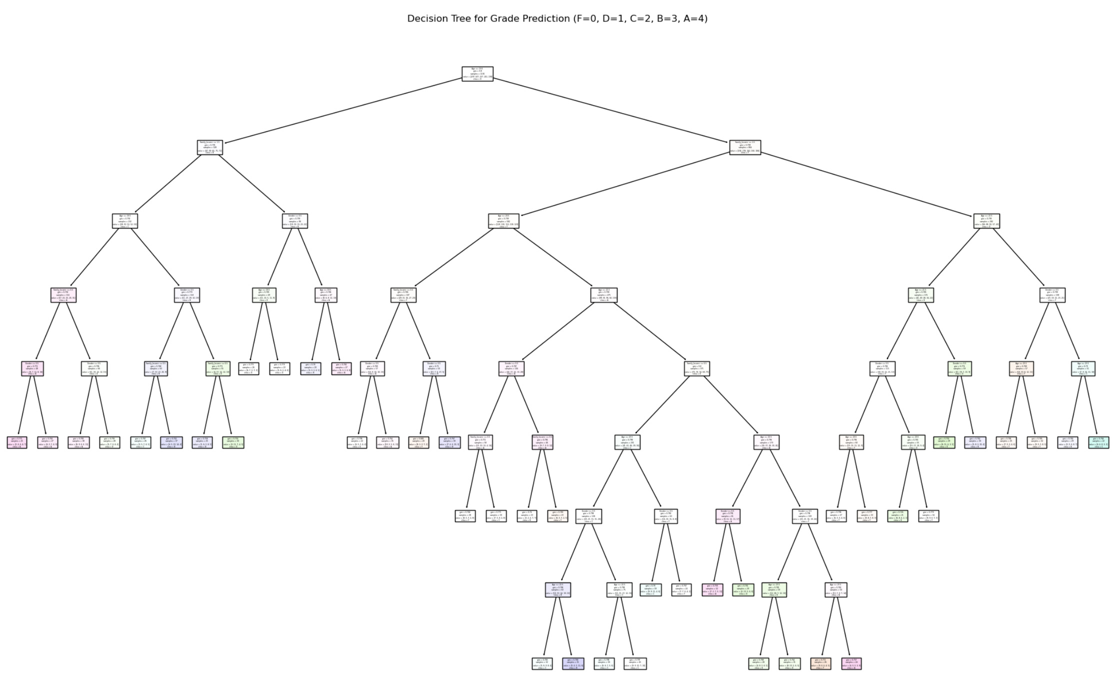
[471]:

```
print("Unique classes in model:", model.classes_)
```

```
Unique classes in model: [0 1 2 3 4]
```

[472]:

```
from sklearn import tree
plt.figure(figsize = (25, 15))
grade_mapping = {0: 'F', 1: 'D', 2: 'C', 3: 'B', 4: 'A'}
tree.plot_tree(model, feature_names = list(X.columns),␣
 ↪class_names=[grade_mapping[c] for c in model.classes_], filled = True);
plt.title("Decision Tree for Grade Prediction (F=0, D=1, C=2, B=3, A=4)",␣
 ↪pad=20)
plt.show()
#(Nwanganga, 2022)
```



[473]:

```
print(classification_report(y_test, model.predict(X_test),
                            target_names=['F', 'D', 'C', 'B', 'A']))
```

```
              precision    recall  f1-score   support

           F       0.20      0.24      0.22       557
```

```
           D       0.20      0.23      0.22       577
           C       0.21      0.20      0.20       529
           B       0.20      0.18      0.19       564
           A       0.20      0.16      0.18       556

    accuracy                           0.20      2783
   macro avg       0.20      0.20      0.20      2783
weighted avg       0.20      0.20      0.20      2783
```

[474]:
```python
# Prune Classification Tree
model.score(X_train, y_train)
```

[474]: 0.3028523489932886

[475]:
```python
model.score(X_test, y_test)
```

[475]: 0.2030183255479698

[476]:
```python
grid = {'max_depth':[2,3,4,5], 'min_samples_split':[2,3,4], 'min_samples_leaf':
 ↪[1,2,3,4,5,6]}
```

[477]:
```python
from sklearn.model_selection import GridSearchCV
Classifier = DecisionTreeClassifier(random_state=1234)
gcv = GridSearchCV(estimator =  Classifier , param_grid = grid )
gcv.fit(X_train, y_train)
#(Nwanganga, 2022)
```

[477]:
```
GridSearchCV(estimator=DecisionTreeClassifier(random_state=1234),
             param_grid={'max_depth': [2, 3, 4, 5],
                         'min_samples_leaf': [1, 2, 3, 4, 5, 6],
                         'min_samples_split': [2, 3, 4]})
```

[478]:
```python
model_ = gcv.best_estimator_
model_.fit(X_train, y_train)
```

[478]: DecisionTreeClassifier(max_depth=2, random_state=1234)

[479]:
```python
model_.score(X_train, y_train)
```

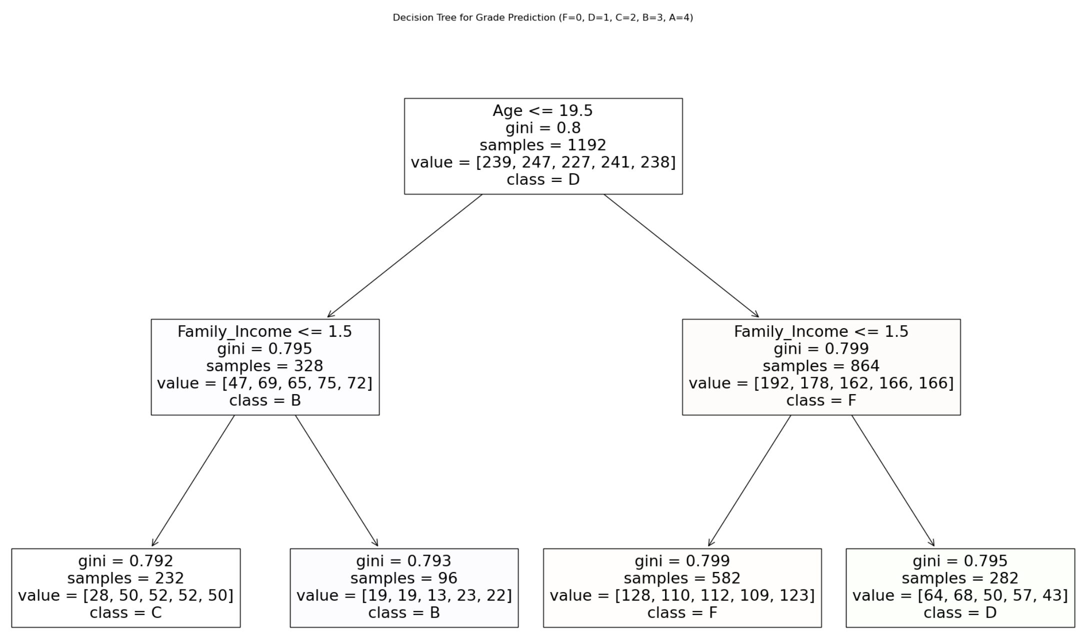
[479]: 0.2273489932885906

[480]:
```python
model_.score(X_test, y_test)
```

[480]: 0.20876751706791233

[481]:
```
# Our pruned classification tree model's accuracy increases by .003 for a poor
  ↪21% overall accuracy on the test data. While the training data decreases
  ↪from roughly 30% to 23%.
```

[482]:
```
plt.figure(figsize = (25, 15))
grade_mapping = {0: 'F', 1: 'D', 2: 'C', 3: 'B', 4: 'A'}
tree.plot_tree(model_, max_depth = 2, feature_names = list(X.columns),
  ↪class_names=[grade_mapping[c] for c in model.classes_], filled = True);
plt.title("Decision Tree for Grade Prediction (F=0, D=1, C=2, B=3, A=4)",
  ↪pad=20)
plt.show()
#(Nwanganga, 2022)
```



[483]:
```
print(f"Decision Tree Accuracy: {accuracy_dt:.2f}")
#(Itauma, 2019)
report = classification_report(y_test, y_pred_dt)
print(f"Classification Report:\n{report}")
```

```
Decision Tree Accuracy: 0.20
Classification Report:
              precision    recall  f1-score   support

           0       0.20      0.24      0.22       557
           1       0.20      0.23      0.22       577
           2       0.21      0.20      0.20       529
```

```
           3       0.20      0.18      0.19       564
           4       0.20      0.16      0.18       556

    accuracy                           0.20      2783
   macro avg       0.20      0.20      0.20      2783
weighted avg       0.20      0.20      0.20      2783
```

[484]:
```
#Logistic regression
X = df.drop('Grade', axis=1)
y = df['Grade']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.7,␣
 ↪stratify=y, random_state=42)
```

[485]:
```
import warnings
warnings.filterwarnings("ignore")
from sklearn.linear_model import LogisticRegression
Classifier = LogisticRegression()
model = Classifier.fit(X_train, y_train)
model.predict(X_test)
```

[485]:
```
array([3, 3, 0, …, 4, 4, 2])
```

[486]:
```
model.score(X_test, y_test)
```

[486]:
```
0.20337765001796623
```

[487]:
```
# The logistic regression model is only able to predict 20% of the labels in␣
 ↪the test data set.
```

[488]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, model.predict(X_test))
```

[488]:
```
array([[149, 150,  46,  96, 116],
       [176, 138,  44, 100, 119],
       [140, 142,  43,  94, 110],
       [140, 158,  41, 109, 116],
       [148, 145,  28, 108, 127]])
```

[489]:
```
cm = confusion_matrix(y_test, model.predict(X_test))
class_accuracy = np.diag(cm) / np.sum(cm, axis=1)
print(dict(zip(['F','D','C','B','A'], class_accuracy.round(2))))
#(Overflow, 2019)
```

```
{'F': 0.27, 'D': 0.24, 'C': 0.08, 'B': 0.19, 'A': 0.23}
```

[490]:
```
#The model is able to predict on avg 23% of all grade level with the exception␣
 ↪of C at 8% which is concerning.
```

[491]:
```python
#Interpret the model
model.intercept_
```

[491]:
```
array([-1.12160666, -0.29458731, -0.00364685,  0.72892921,  0.69091161])
```

[492]:
```python
coef_ = pd.DataFrame(model.coef_, columns=X.columns, index=['F', 'D', 'C', 'B',␣
 ↪'A'])
print(coef_)
```

```
     Gender       Age  Family_Income
F -0.088593  0.051245       0.087219
D -0.005347  0.010247       0.120929
C  0.067290  0.002085      -0.125409
B  0.003908 -0.035756       0.037952
A  0.022742 -0.027820      -0.120692
```

[493]:
```python
log_odds = np.round(model.coef_[4], 2)
log_odds
# We'll isolate Grade "A", row [4] as an example.
```

[493]:
```
array([ 0.02, -0.03, -0.12])
```

[494]:
```python
pd.DataFrame({'log odds': log_odds}, index=X.columns)
```

[494]:

	log odds
Gender	0.02
Age	-0.03
Family_Income	-0.12

[495]:
```python
#Log odds can be a bit confusing when trying to interpret the coefficients.␣
 ↪Let's convert them to odds.
```

[496]:
```python
odds = np.round(np.exp(log_odds), 2)
pd.DataFrame({'odds': odds}, index = X.columns)
```

[496]:

	odds
Gender	1.02
Age	0.97
Family_Income	0.89

[497]:
```python
# Gender doesn't significantly predict grade. An increase in Age of 1 year␣
 ↪indicates a 3% lower chance of getting an A. Higher income is a decrease of␣
 ↪11% of getting an A, which is surprising.
```

[498]:
```python
# Train the Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

```python
# Predict and evaluate
y_pred = logreg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Logistic Regression Accuracy: {accuracy:.2f}")
#(Itauma, 2019)

report = classification_report(y_test, y_pred)
print(f"Classification Report:\n{report}")
```

```
Logistic Regression Accuracy: 0.20
Classification Report:
              precision    recall  f1-score   support

           0       0.20      0.27      0.23       557
           1       0.19      0.24      0.21       577
           2       0.21      0.08      0.12       529
           3       0.21      0.19      0.20       564
           4       0.22      0.23      0.22       556

    accuracy                           0.20      2783
   macro avg       0.21      0.20      0.20      2783
weighted avg       0.21      0.20      0.20      2783
```

[ ]:

```python

```

[499]:

```python
## K-Nearest Neighbor Model
```

[500]:

```python
# Train the model
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)

# Predict and evaluate
y_pred_knn = knn.predict(X_test)
accuracy_knn = accuracy_score(y_test, y_pred_knn)

print(f"k-NN Accuracy: {accuracy_knn:.2f}")
#(Itauma, 2019)
```

```
k-NN Accuracy: 0.18
```

[501]:

```python
from sklearn.metrics import classification_report
# Classification Report
```

```
report = classification_report(y_test, y_pred_knn)
print(f"Classification Report:\n{report}")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.20      0.29      0.24       557
           1       0.17      0.19      0.18       577
           2       0.19      0.12      0.15       529
           3       0.18      0.25      0.21       564
           4       0.17      0.06      0.09       556

    accuracy                           0.18      2783
   macro avg       0.18      0.18      0.17      2783
weighted avg       0.18      0.18      0.17      2783
```

[502]:
```
# Comparison Table
evaluation = {'precision':[0.20,0.24, 0.20],
             'f1-score':[0.24, 0.22, 0.23],
             'recall':[0.29, 0.24, 0.27],
              'accuracy':[0.18, 0.20, 0.20]}
eval_df = pd.DataFrame(evaluation, columns=['precision', 'f1-score', 'recall',
 ↪'accuracy'], index=['KNN', 'Decision Tree', 'Logistic Regression'])
eval_df.columns.name = 'Model'
eval_df
#(Poola, 2020)
#Compared all results from Grade "F" or "0"
```

[502]:

Model	precision	f1-score	recall	accuracy
KNN	0.20	0.24	0.29	0.18
Decision Tree	0.24	0.22	0.24	0.20
Logistic Regression	0.20	0.23	0.27	0.20

[503]:
```
## Conclusion: All 3 models prediction accuracy is weak at roughly 20%. This is
 ↪a key indicator that demographics features are not enough to predict a
 ↪students success. I should have implemented more independent variables into
 ↪the models such as "Attendance%" and "Study Hours per Week". The K-Nearest
 ↪Neighbor model performed the best in the f1-score, as a higher score
 ↪indicates better performance. Is it also best at catching false negatives
 ↪with 29% (Goyal, 2019). Whereas, The decision tree suffers the most false
 ↪negatives with a recall of 24%. The logistic regression model is moderate
 ↪across the board yet performs poorly in the grand scheme of things. We could
 ↪most definitely improve all three models by potentially running confusion
 ↪matrix but more importantly adding other student features as independent
 ↪variables to help predict grades.
```

[504]:


```
## References
#Galarnyk, M. (2020, October 15). scikit-learn pipelines - Machine Learning␣
↪with Scikit-Learn. LinkedIn. https://www.linkedin.com/learning/
↪machine-learning-with-scikit-learn/scikit-learn-pipelines?
↪leis=LTI13&resume=false&u=279222306
#Goyal, S. (2021, July 20). Evaluation Metrics for Classification Models.␣
↪Analytics Vidhya. https://medium.com/analytics-vidhya/
↪evaluation-metrics-for-classification-models-e2f0d8009d69
#How to show precision in a confusion matrix. (2019, May 10). Stack Overflow.␣
↪https://stackoverflow.com/questions/56084882/
↪how-to-show-precision-in-a-confusion-matrix
#Itauma, I. (2019). Machine Learning using Python - 3  Chapter 3: Supervised␣
↪Learning - Classification. Quarto.pub. https://amightyo.quarto.pub/
↪machine-learning-using-python/Chapter_3.html
#Mahmood, A. (2025, March 26). Students Performance Analysis. Kaggle.com;␣
↪Kaggle. https://www.kaggle.com/code/abdulqadirmahmood/
↪students-performance-analysis/input
#Marbouti, F., Ulas, J., & Wang , C.-H. (2021, August). Academic and␣
↪Demographic Cluster Analysis of Engineering Student Success. Ieeexplore.ieee.
↪org. https://ieeexplore.ieee.org/abstract/document/9298459
#Nwanganga, F. (2022, May 20). How to build a classification tree in Python -␣
↪Machine Learning with Python: Decision Trees. LinkedIn. https://www.linkedin.
↪com/learning/machine-learning-with-python-decision-trees/
↪how-to-build-a-classification-tree-in-python?
↪leis=LTI13&resume=false&u=279222306
#Nwanganga, F. (2022, November 9). How to build a logistic regression model in␣
↪Python - Machine Learning with Python: Logistic Regression. LinkedIn. https:/
↪/www.linkedin.com/learning/machine-learning-with-python-logistic-regression/
↪how-to-build-a-logistic-regression-model-in-python?
↪leis=LTI13&resume=false&u=279222306
#pandas-dev. (2025). pandas/pandas/core/reshape/pivot.py at v2.2.3 · pandas-dev/
↪pandas. GitHub. https://github.com/pandas-dev/pandas/blob/v2.2.3/pandas/core/
↪reshape/pivot.py#L578-L748
#Pierson, L. (2024, March 12). Creating statistical data graphics in Seaborn -␣
↪Python for Data Science and Machine Learning Essential Training Part 1.␣
↪LinkedIn. https://www.linkedin.com/learning/
↪python-for-data-science-and-machine-learning-essential-training-part-1/
↪creating-statistical-data-graphics-in-seaborn?
↪leis=LTI13&resume=false&u=279222306
#Poola, H. (2020, July 5). KNN, Decision Tree, SVM, and Logistic Regression.
↪ipynb. Gist. https://gist.github.com/hrishipoola/
↪323d0459d9faeb466496d4e5ffbfb516
#Rustam, G. (2015, August 14). Convert categorical data in pandas dataframe.␣
↪Stack Overflow. https://stackoverflow.com/questions/32011359/
↪convert-categorical-data-in-pandas-dataframe
```