

CapstoneProject

May 30, 2021

1 Predict Student Performance

1.0.1 Introduction

Implementing machine learning techniques is receiving considerable attention in the educational technology research field. Different systems and techniques were proposed to predict student performance and gain insights regarding their learning needs. Thus, in this project, I focused on exploring the use of classification algorithms to predict student performance (final grades) based on their interaction with learning resources. The dataset selected for this project is an opensource, gathered from learning management system (LMS) called Kalboard360. The dataset is available in [Kaggle](#). It included 480 records and 16 features collected through a learner activity tracker tool. According to [Abu Amrieh et al. \(2016\)](#) the data is collected using a learner activity tracker tool, which called experience API (xAPI). The xAPI is a component of the training and learning architecture (TLA) that enables to monitor learning progress and learner's actions like reading an article or watching a training video. The experience API helps the learning activity providers to determine the learner, activity and objects that describe a learning experience.

1.0.2 Dataset Description

The dataset consists of 480 student records and 16 features. The features are classified into three major categories: 1. Demographic features such as gender and nationality. 2. Academic background features such as educational stage, grade Level and section. 3. Behavioral features such as raised hand on class, opening resources, answering survey by parents, and school satisfaction.

Attributes

1. Gender - student's gender (nominal: 'Male' or 'Female')
2. Nationality- student's nationality (nominal: 'Kuwait', 'Lebanon', 'Egypt', 'SaudiArabia', 'USA', 'Jordan', 'Venezuela', 'Iran', 'Tunis', 'Morocco', 'Syria', 'Palestine', 'Iraq', 'Lybia')
3. Place of birth- student's Place of birth (nominal: 'Kuwait', 'Lebanon', 'Egypt', 'SaudiArabia', 'USA', 'Jordan', 'Venezuela', 'Iran', 'Tunis', 'Morocco', 'Syria', 'Palestine', 'Iraq', 'Lybia')
4. Educational Stages- educational level student belongs (nominal: 'lower-level', 'MiddleSchool', 'HighSchool')
5. Grade Levels- grade student belongs (nominal: 'G-01', 'G-02', 'G-03', 'G-04', 'G-05', 'G-06', 'G-07', 'G-08', 'G-09', 'G-10', 'G-11', 'G-12')
6. Section ID- classroom student belongs (nominal: 'A', 'B', 'C')

7. Topic- course topic (nominal: 'English', 'Spanish', 'French', 'Arabic', 'IT', 'Math', 'Chemistry', 'Biology', 'Science', 'History', 'Quran', 'Geology')
8. Semester- school year semester (nominal: 'First', 'Second')
9. Parent responsible for student (nominal: 'mom', 'father')
10. Raised hand- how many times the student raises his/her hand on classroom (numeric: 0-100)
11. Visited resources- how many times the student visits a course content (numeric: 0-100)
12. Viewing announcements- how many times the student checks the new announcements (numeric: 0-100)
13. Discussion groups- how many times the student participate on discussion groups (numeric: 0-100)
14. Parent Answering Survey- parent answered the surveys which are provided from school or not (nominal: 'Yes', 'No')
15. Parent School Satisfaction- the Degree of parent satisfaction from school (nominal: 'Yes', 'No')
16. Student Absence Days- the number of absence days for each student (nominal: above-7, under-7)

1.0.3 Phase 1. Read Dataset

```
[81]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
```

```
[66]: # Importing the dataset
data = pd.read_csv('education.csv')
data.isnull().any()
data = data.fillna(method='ffill')
data.head()
```

```
[66]:  gender NationalITY PlaceofBirth      StageID GradeID SectionID Topic \
0      M           KW      KuwaIT  lowerlevel    G-04         A      IT
1      M           KW      KuwaIT  lowerlevel    G-04         A      IT
2      M           KW      KuwaIT  lowerlevel    G-04         A      IT
3      M           KW      KuwaIT  lowerlevel    G-04         A      IT
4      M           KW      KuwaIT  lowerlevel    G-04         A      IT

      Semester Relation  raisedhands  VisITedResources  AnnouncementsView \
0      F      Father         15              16              2
1      F      Father         20              20              3
2      F      Father         10              7              0
3      F      Father         30              25              5
4      F      Father         40              50             12
```

	Discussion	ParentAnsweringSurvey	ParentschoolSatisfaction	\
0	20	Yes	Good	
1	25	Yes	Good	
2	30	No	Bad	
3	35	No	Bad	
4	50	No	Bad	

	StudentAbsenceDays	Class
0	Under-7	M
1	Under-7	M
2	Above-7	L
3	Above-7	L
4	Above-7	M

```
[67]: data.shape
```

```
[67]: (480, 17)
```

```
[68]: print(data.info(), "\n")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 480 entries, 0 to 479
Data columns (total 17 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   gender                                480 non-null    object
1   NationalITy                           480 non-null    object
2   PlaceofBirth                           480 non-null    object
3   StageID                               480 non-null    object
4   GradeID                               480 non-null    object
5   SectionID                             480 non-null    object
6   Topic                                 480 non-null    object
7   Semester                             480 non-null    object
8   Relation                              480 non-null    object
9   raisedhands                           480 non-null    int64
10  VisITedResources                       480 non-null    int64
11  AnnouncementsView                     480 non-null    int64
12  Discussion                             480 non-null    int64
13  ParentAnsweringSurvey                 480 non-null    object
14  ParentschoolSatisfaction               480 non-null    object
15  StudentAbsenceDays                   480 non-null    object
16  Class                                 480 non-null    object
dtypes: int64(4), object(13)
memory usage: 63.9+ KB
None
```

1.0.4 Phase 2. Cleaning Dataset

```
[69]: #Rename cols
data.rename(index=str, columns={'gender':'Gender', 'NationalITy':
    ↳'Nationality', 'raisedhands':'RaisedHands', 'VisITedResources':
    ↳'VisitedResources'}, inplace=True)
```

```
[70]: data.head()
```

```
[70]:   Gender Nationality PlaceofBirth   StageID GradeID SectionID Topic \
0      M           KW      KuwaIT  lowerlevel    G-04          A    IT
1      M           KW      KuwaIT  lowerlevel    G-04          A    IT
2      M           KW      KuwaIT  lowerlevel    G-04          A    IT
3      M           KW      KuwaIT  lowerlevel    G-04          A    IT
4      M           KW      KuwaIT  lowerlevel    G-04          A    IT

   Semester Relation  RaisedHands  VisitedResources  AnnouncementsView \
0          F  Father           15              16              2
1          F  Father           20              20              3
2          F  Father           10              7              0
3          F  Father           30              25              5
4          F  Father           40              50             12

   Discussion ParentAnsweringSurvey ParentschoolSatisfaction \
0          20                Yes                Good
1          25                Yes                Good
2          30                No                 Bad
3          35                No                 Bad
4          50                No                 Bad

   StudentAbsenceDays Class
0          Under-7      M
1          Under-7      M
2          Above-7      L
3          Above-7      L
4          Above-7      M
```

```
[71]: #Drop col PlaceofBirth because it denotes Nationality
data.drop(columns='PlaceofBirth', inplace=True)
```

```
[72]: data.describe()
```

```
[72]:   RaisedHands  VisitedResources  AnnouncementsView  Discussion
count    480.000000      480.000000      480.000000    480.000000
mean      46.775000      54.797917      37.918750     43.283333
std       30.779223      33.080007      26.611244     27.637735
min        0.000000        0.000000        0.000000        1.000000
25%       15.750000      20.000000      14.000000     20.000000
```

50%	50.000000	65.000000	33.000000	39.000000
75%	75.000000	84.000000	58.000000	70.000000
max	100.000000	99.000000	98.000000	99.000000

```
[10]: # check unique values
print("Unique Values:\n ",data.nunique(),"\n")
```

```
Unique Values:
  Gender                2
Nationality            14
StageID                3
GradeID               10
SectionID              3
Topic                 12
Semester               2
Relation               2
RaisedHands           82
VisitedResources       89
AnnouncementsView      88
Discussion             90
ParentAnsweringSurvey  2
ParentschoolSatisfaction 2
StudentAbsenceDays     2
Class                  3
dtype: int64
```

```
[12]: # explore values of col Topic
print("Topic: ", "\n\n", data["Topic"].value_counts(), "\n")
```

```
Topic:

  IT          95
French       65
Arabic       59
Science      51
English      45
Biology      30
Spanish      25
Geology      24
Chemistry    24
Quran        22
Math         21
History      19
Name: Topic, dtype: int64
```

The data includes 12 Topics

```
[15]: data.isna().sum()
```

```
[15]: Gender          0
      Nationality     0
      StageID        0
      GradeID        0
      SectionID      0
      Topic          0
      Semester       0
      Relation       0
      RaisedHands    0
      VisitedResources 0
      AnnouncementsView 0
      Discussion     0
      ParentAnsweringSurvey 0
      ParentschoolSatisfaction 0
      StudentAbsenceDays 0
      Class          0
      dtype: int64
```

1.0.5 Phase 3. Exploring Dataset

How is the student Performance according to their Nationality?

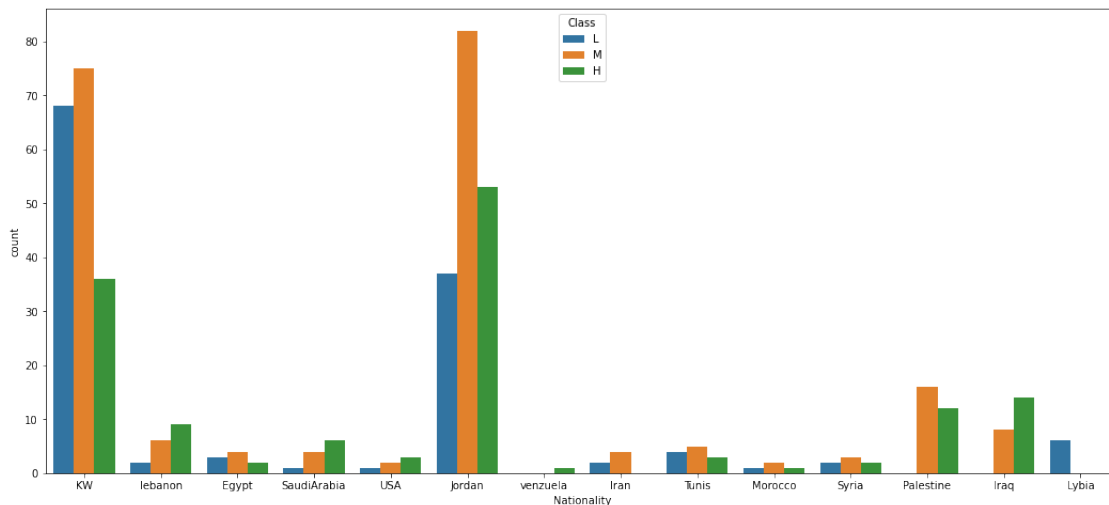
```
[14]: # Correlation between students' Nationality and topics
      display(pd.crosstab(data["Nationality"],data["Topic"]).reset_index())
```

Topic	Nationality	Arabic	Biology	Chemistry	English	French	Geology	\
0	Egypt	0	0	0	1	2	0	
1	Iran	0	0	0	0	2	0	
2	Iraq	6	4	2	2	2	2	
3	Jordan	21	16	22	17	33	20	
4	KW	20	0	0	15	5	0	
5	Lybia	0	2	0	0	4	0	
6	Morocco	3	0	0	0	1	0	
7	Palestine	4	6	0	6	4	2	
8	SaudiArabia	1	0	0	1	1	0	
9	Syria	0	2	0	0	3	0	
10	Tunis	0	0	0	0	3	0	
11	USA	0	0	0	1	1	0	
12	lebanon	4	0	0	2	4	0	
13	venzuela	0	0	0	0	0	0	

Topic	History	IT	Math	Quran	Science	Spanish
0	0	1	1	1	3	0
1	0	2	0	0	0	2
2	2	0	0	0	2	0
3	8	4	0	5	24	2
4	7	82	15	8	13	14

5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	2	0	0	0	4	0
8	0	2	1	1	3	1
9	0	0	0	1	0	1
10	0	0	0	4	2	3
11	0	2	2	0	0	0
12	0	1	2	2	0	2
13	0	1	0	0	0	0

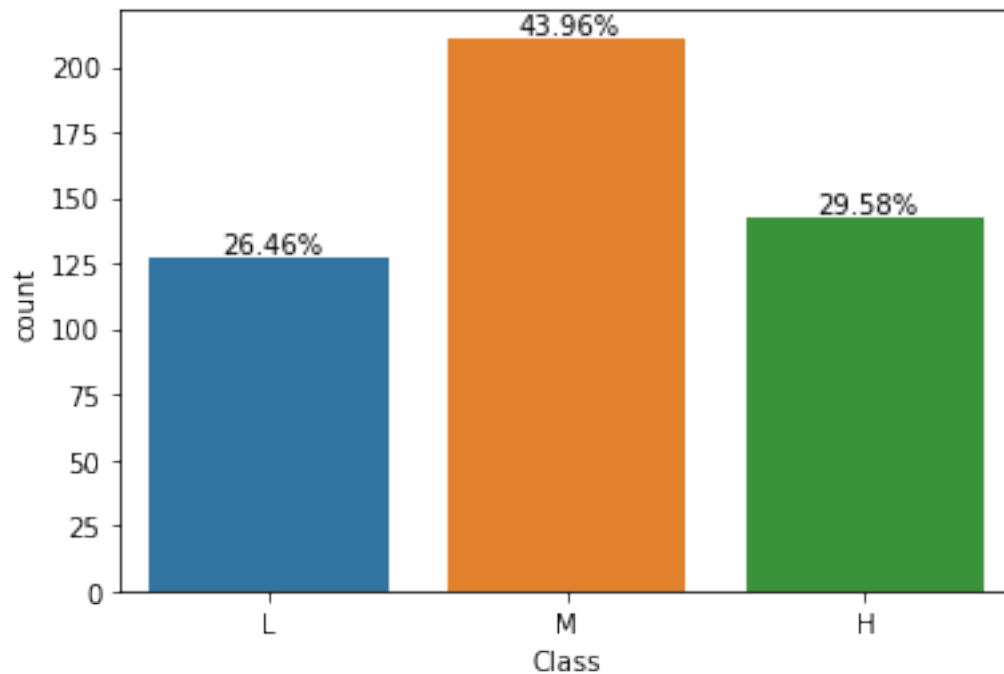
```
[33]: fig, ax = plt.subplots(figsize=(18, 8))
sns.countplot(x='Nationality', hue='Class', data=data, hue_order = ['L', 'M', 'H'], ax=ax)
plt.show()
```



The plot highlights that most of the enrolled students in the e-learning environment are from Jordan and Kuwait. Regarding student performance, the highest scores obtained among Jordanian students are middle, followed by Kuwaiti students.

How is the students general performance?

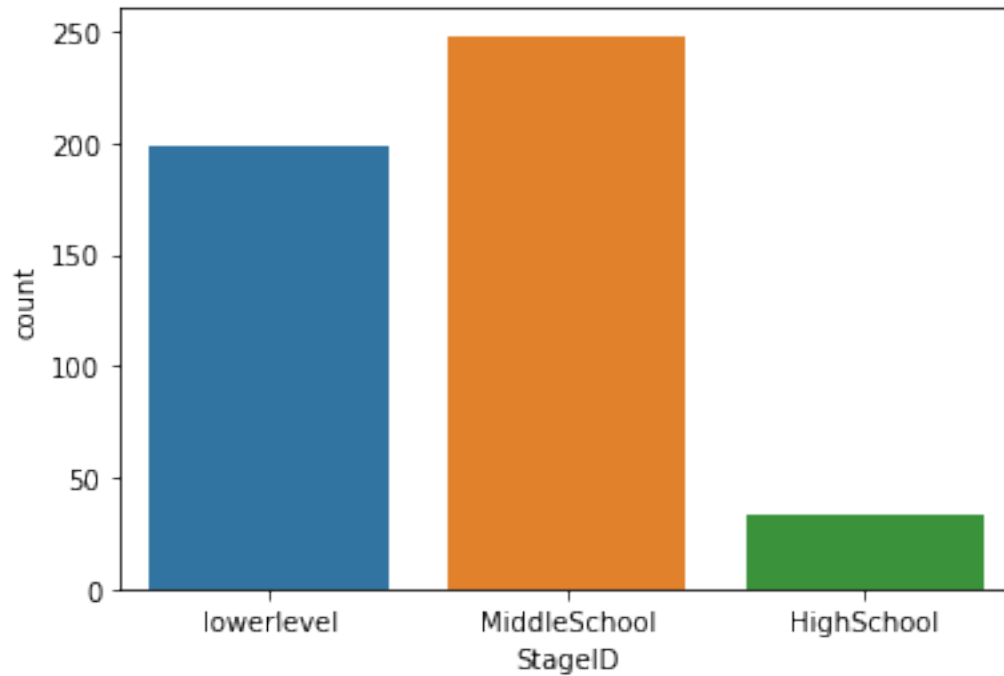
```
[17]: ax = sns.countplot(x='Class', data=data, order=['L', 'M', 'H'])
for p in ax.patches:
    ax.annotate('{:.2f}%'.format((p.get_height() * 100) / len(data)), (p.get_x() + 0.24, p.get_height() + 2))
plt.show()
```



Based on this plot, it can be revealed that for all students enrolled in the platform, the highest obtained scores are Middle with an average of 43.96%, followed by high with 29.58%, and low with 26.46%. The percentage of students obtaining low grades can be considered high.

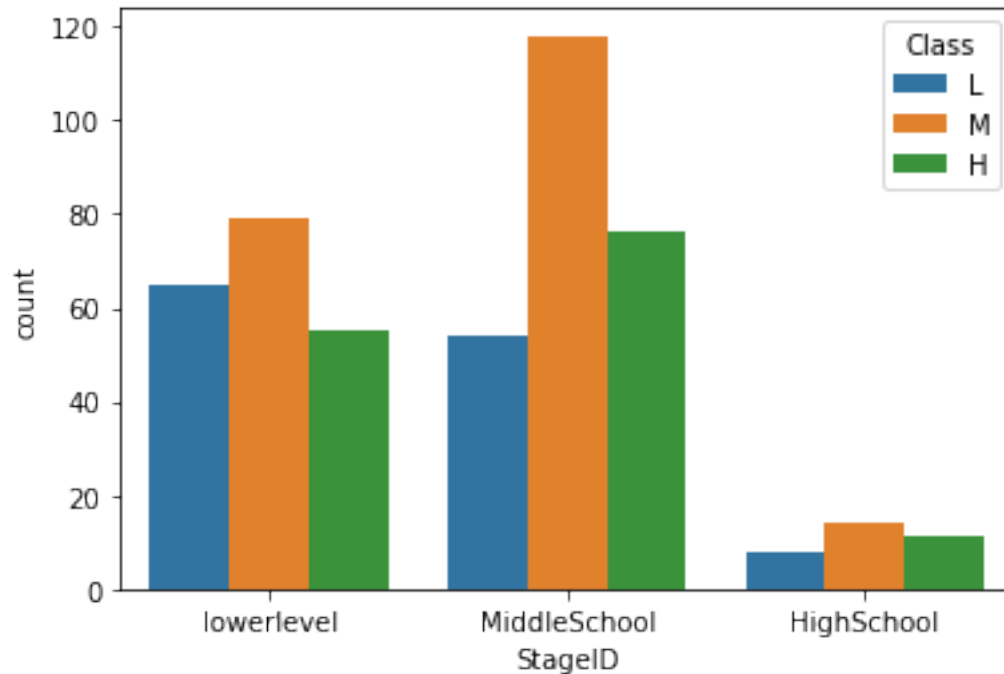
How is the student performance according to their educational level?

```
[34]: ax = sns.countplot(x='StageID', data=data)
      plt.show()
```

Most of the enrolled students are from middle schools with an average of 250 students, followed by lower educational levels with an average of 200 students. However, the number of high school students is only 50.

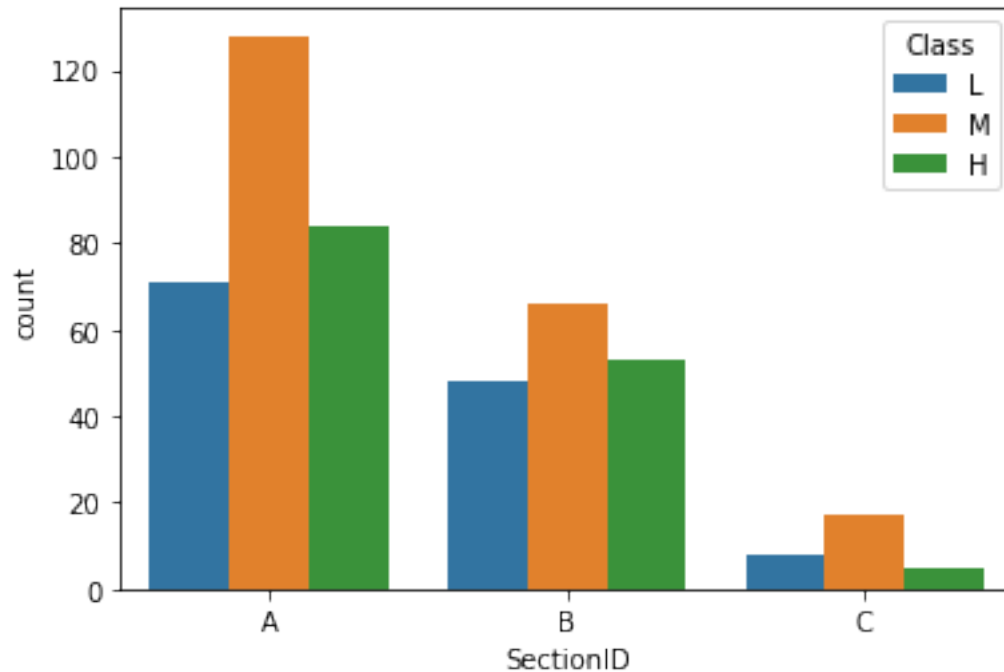
```
[35]: ax = sns.countplot(x='StageID', hue='Class', data=data, hue_order = ['L', 'M', 'H'])  
      plt.show()
```



Around 120 Students enrolled in Middle schools are obtaining middle grades. However, 60 are getting low grades. The plot also highlights that for the lower level, the average of students obtaining low grades is more important than those scoring high grades.

How is the student performance according to the sections?

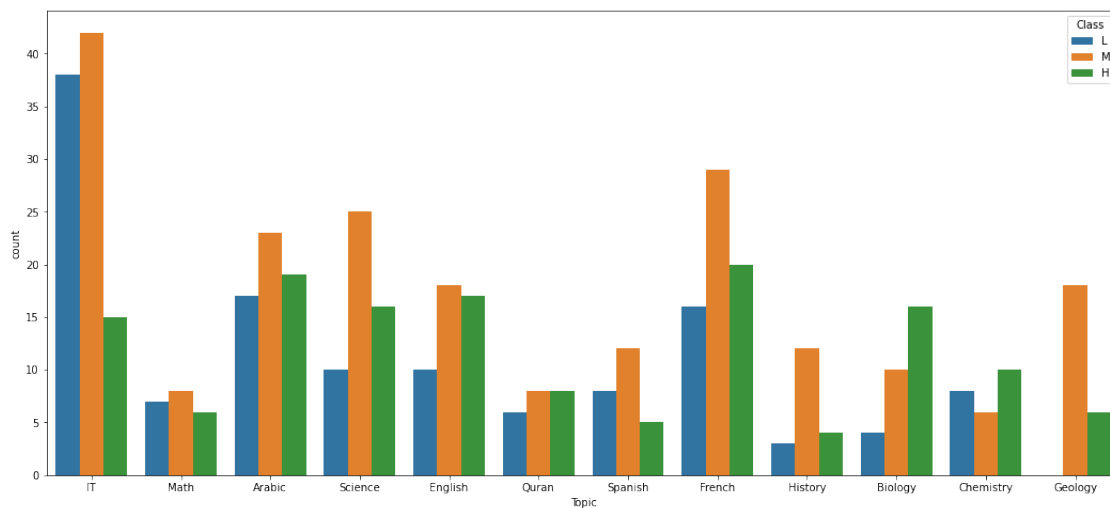
```
[37]: ax = sns.countplot(x='SectionID', hue='Class', data=data, order=['A', 'B', 'C'], hue_order = ['L', 'M', 'H'])  
plt.show()
```



From this plot it can be revealed that the highest performance is scored among students enrolled in section A. However, the lowest grades are obtained among students belonging to section C

How is the student performance according to the learning topics?

```
[39]: fig, ax = plt.subplots(figsize=(18, 8))
      ax = sns.countplot(x='Topic', hue='Class', data=data, hue_order = ['L', 'M', 'H'])
      plt.show()
```



The plot highlights that students performance is different according to the learning topic. It can be revealed that students are mostly obtaining middle and low grades in the IT topic. However, in the Maths the results are slightly similar.

```
[42]: data.groupby('Topic').median()
```

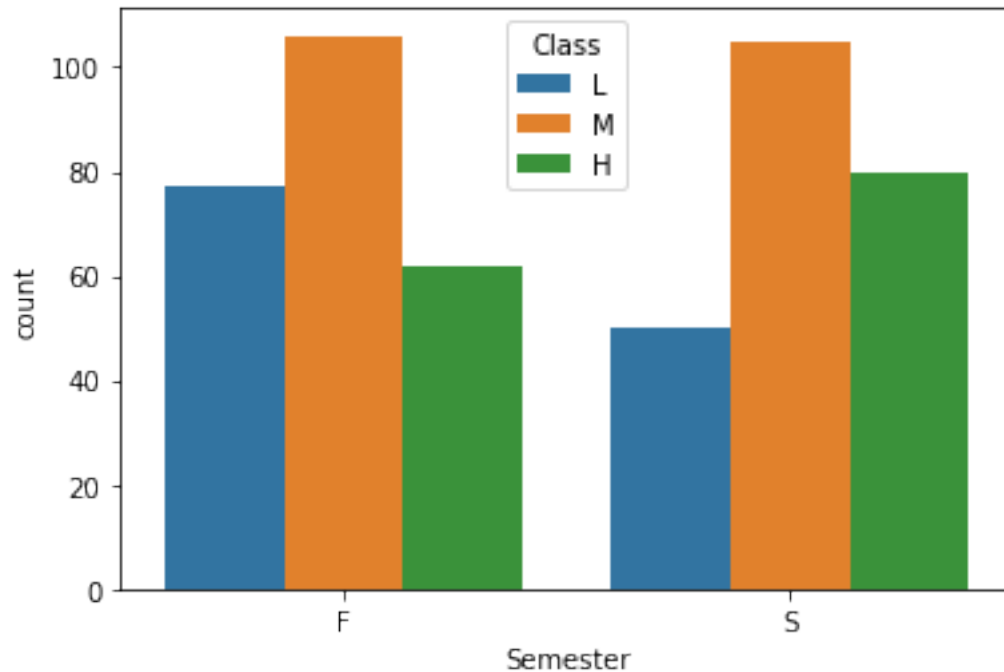
```
[42]:
```

	RaisedHands	VisitedResources	AnnouncementsView	Discussion
Topic				
Arabic	32.0	65.0	41.0	38.0
Biology	78.5	88.5	54.0	47.0
Chemistry	79.0	84.5	47.0	30.5
English	55.0	50.0	33.0	36.0
French	35.0	80.0	23.0	21.0
Geology	80.0	82.0	68.5	60.5
History	69.0	84.0	72.0	65.0
IT	20.0	25.0	10.0	40.0
Math	28.0	15.0	19.0	40.0
Quran	65.0	75.0	50.0	45.0
Science	62.0	64.0	58.0	66.0
Spanish	27.0	51.0	40.0	20.0

The correlation between students' interaction in the e-learning environment and the learning topics highlight that the highest interaction behavior is scored in the Biology topic. However, in Math, students are rarely visiting the resources or considering the announcements. This may denote an impact on students' interaction behavior and their learning performance.

How is the student performance according to the semester ?

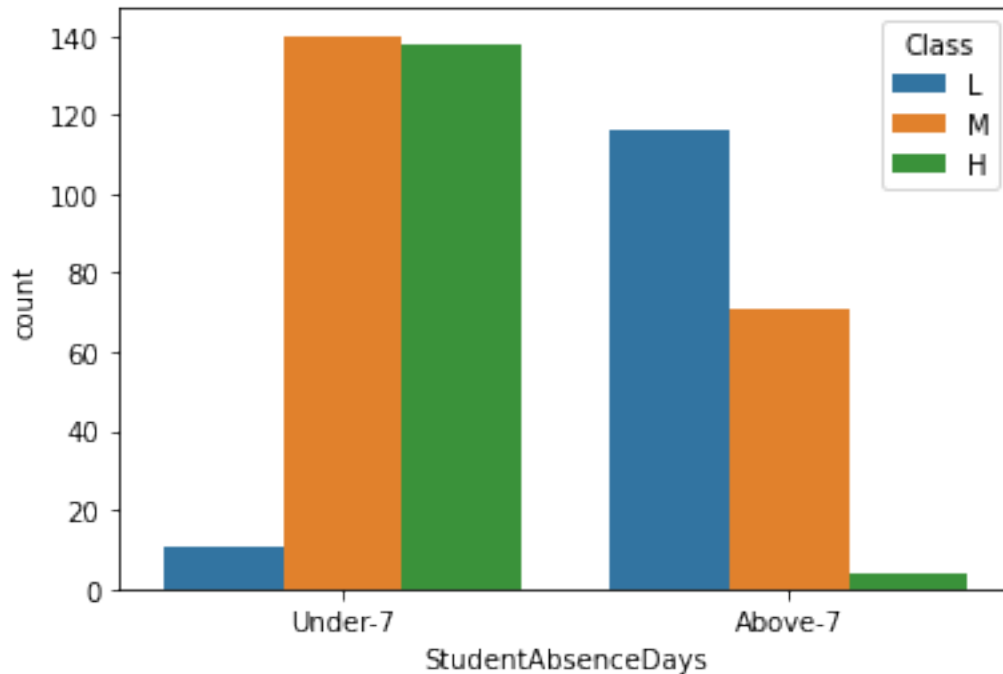
```
[40]: ax = sns.countplot(x='Semester', hue='Class', data=data, hue_order = ['L', 'M', 'H'])
plt.show()
```



From these results, it can be revealed that during the summer semester, the low grades increased compared to the fall semester. However, in terms of the middle grades, students performance remains similar.

How is the student performance according to their absence ?

```
[43]: ax = sns.countplot(x='StudentAbsenceDays', hue='Class', data=data,
    ↪order=['Under-7', 'Above-7'], hue_order = ['L', 'M', 'H'])
plt.show()
```



Based on this plot it can be pointed out that students being absent for more than 7 days are scoring low grades leading to their poor performance.

1.0.6 Phase 4. Data Modeling

The exploration of data highlights that student performance is impacted by different factors including their interaction behavior, learning engagement, and the enrolled topics. Thus, it is required to build a learning model to predict student performance and enhance it in the context of e-learning environment.

1. Features Encoding

```
[61]: data.groupby("Class").count()
grade_class = {"L":0, "M":1, "H":2}
data["Class"] = data["Class"].map(grade_class)
```

```
[77]: #Source https://www.kaggle.com/roshansharma/
      ↪ student-performance-analysis#Label-Encoding
from sklearn.preprocessing import LabelEncoder

# creating an encoder
le = LabelEncoder()

# label encoding for test preparation course
data['Class'] = le.fit_transform(data['Class'])
```

```

# label encoding for lunch
data['Gender'] = le.fit_transform(data['Gender'])

# label encoding for parental level of education
data['Nationality'] = le.fit_transform(data['Nationality'])

#label encoding for gender
data['StageID'] = le.fit_transform(data['StageID'])

# label encoding for pass_math
data['GradeID'] = le.fit_transform(data['GradeID'])

# label encoding for pass_reading
data['SectionID'] = le.fit_transform(data['SectionID'])

# label encoding for pass_writing
data['Topic'] = le.fit_transform(data['Topic'])

# label encoding for status
data['Semester'] = le.fit_transform(data['Semester'])

# label encoding for status
data['Relation'] = le.fit_transform(data['Relation'])

# label encoding for status
data['ParentAnsweringSurvey'] = le.fit_transform(data['ParentAnsweringSurvey'])

# label encoding for status
data['ParentschoolSatisfaction'] = le.
    ↳fit_transform(data['ParentschoolSatisfaction'])

# label encoding for status
data['StudentAbsenceDays'] = le.fit_transform(data['StudentAbsenceDays'])

```

```
[78]: data.head()
```

```

[78]:   Gender  Nationality  StageID  GradeID  SectionID  Topic  Semester  \
0      1             4         2         1           0      7         0
1      1             4         2         1           0      7         0
2      1             4         2         1           0      7         0
3      1             4         2         1           0      7         0
4      1             4         2         1           0      7         0

      Relation  RaisedHands  VisitedResources  AnnouncementsView  Discussion  \
0           0           15              16              2         20
1           0           20              20              3         25

```

2	0	10	7	0	30
3	0	30	25	5	35
4	0	40	50	12	50

	ParentAnsweringSurvey	ParentschoolSatisfaction	StudentAbsenceDays	Class
0	1	1	1	2
1	1	1	1	2
2	0	0	0	1
3	0	0	0	1
4	0	0	0	2

2. Splitting Data into training and testing sets

```
[80]: X = data.drop(columns='Class')
      y = data['Class']
```

```
[82]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
      ↪random_state=42)
```

```
[84]: X_train.shape
```

```
[84]: (336, 15)
```

```
[87]: #DecisionTree
      from sklearn.tree import DecisionTreeClassifier
      clf = DecisionTreeClassifier().fit(X_train, y_train)
      print('Accuracy of Decision Tree classifier on training set: {:.2f}'
            .format(clf.score(X_train, y_train)))
      print('Accuracy of Decision Tree classifier on test set: {:.2f}'
            .format(clf.score(X_test, y_test)))
```

Accuracy of Decision Tree classifier on training set: 1.00

Accuracy of Decision Tree classifier on test set: 0.61

```
[88]: #Linear Discriminant Analysis
      from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
      lda = LinearDiscriminantAnalysis()
      lda.fit(X_train, y_train)
      print('Accuracy of LDA classifier on training set: {:.2f}'
            .format(lda.score(X_train, y_train)))
      print('Accuracy of LDA classifier on test set: {:.2f}'
            .format(lda.score(X_test, y_test)))
```

Accuracy of LDA classifier on training set: 0.77

Accuracy of LDA classifier on test set: 0.76

```
[89]: #Gaussian Naive Bayes
      from sklearn.naive_bayes import GaussianNB
      gnb = GaussianNB()
```



```

gnb.fit(X_train, y_train)
print('Accuracy of GNB classifier on training set: {:.2f}'
      .format(gnb.score(X_train, y_train)))
print('Accuracy of GNB classifier on test set: {:.2f}'
      .format(gnb.score(X_test, y_test)))

```

Accuracy of GNB classifier on training set: 0.75
 Accuracy of GNB classifier on test set: 0.75

```

[90]: #Support Vector Machine
from sklearn.svm import SVC
svm = SVC()
svm.fit(X_train, y_train)
print('Accuracy of SVM classifier on training set: {:.2f}'
      .format(svm.score(X_train, y_train)))
print('Accuracy of SVM classifier on test set: {:.2f}'
      .format(svm.score(X_test, y_test)))

```

Accuracy of SVM classifier on training set: 0.65
 Accuracy of SVM classifier on test set: 0.63

```

[91]: #K-Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
print('Accuracy of K-NN classifier on training set: {:.2f}'
      .format(knn.score(X_train, y_train)))
print('Accuracy of K-NN classifier on test set: {:.2f}'
      .format(knn.score(X_test, y_test)))

```

Accuracy of K-NN classifier on training set: 0.75
 Accuracy of K-NN classifier on test set: 0.65

```

[92]: from sklearn.ensemble import RandomForestClassifier
#Create a Gaussian Classifier
rfc=RandomForestClassifier(n_estimators=100)
rfc.fit(X_train,y_train)
print('Accuracy of RandomForest classifier on training set: {:.2f}'
      .format(rfc.score(X_train, y_train)))
print('Accuracy of RandomForest classifier on test set: {:.2f}'
      .format(rfc.score(X_test, y_test)))

```

Accuracy of RandomForest classifier on training set: 1.00
 Accuracy of RandomForest classifier on test set: 0.81

```

[94]: from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
target_names = ['class 0(H)', 'class 1(L)', 'class 2(M)']
pred = rfc.predict(X_test)

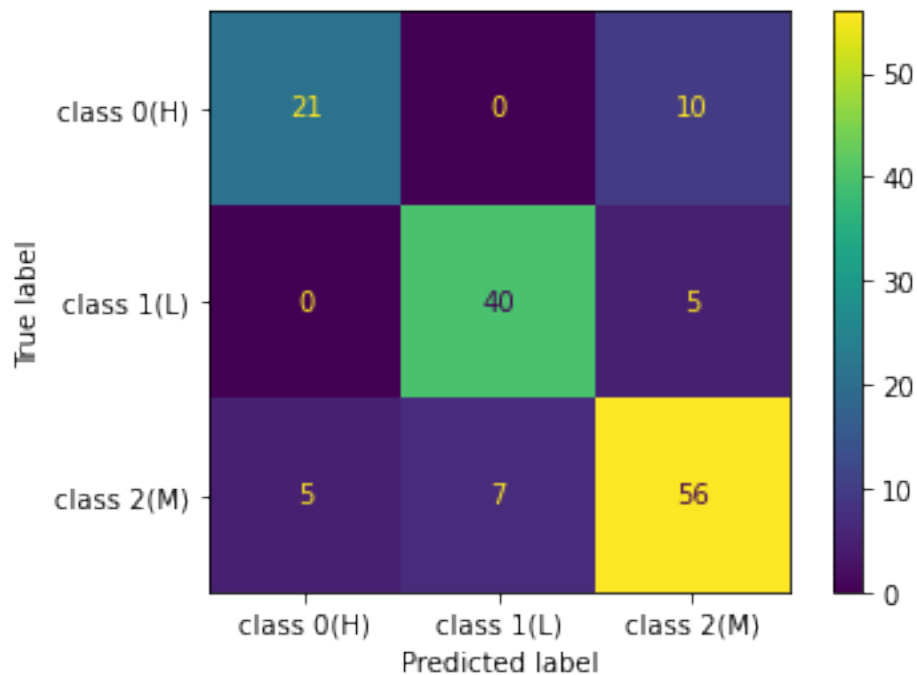
```

```
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred, target_names = target_names))
```

```
[[21  0 10]
 [ 0 40  5]
 [ 5  7 56]]
```

	precision	recall	f1-score	support
class 0(H)	0.81	0.68	0.74	31
class 1(L)	0.85	0.89	0.87	45
class 2(M)	0.79	0.82	0.81	68
accuracy			0.81	144
macro avg	0.82	0.80	0.80	144
weighted avg	0.81	0.81	0.81	144

```
[96]: from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(rfc, X_test, y_test, display_labels=target_names)
plt.show()
```



The confusion matrix highlights that among 144 students, Random Forest correctly classified 56 in the Middle Class, 40 were classified in the low class, however 20 were predicted in the high class

1.0.7 Results

The results pointed out that the use of features related to student profile, academic performance, and behavior with the virtual learning environment may lead to an accurate prediction of students performance while interacting with learning content. The classification results revealed that Random Forest outperformed other classifiers for both datasets with an accuracy of 81%. With the set of selected features, the results highlighted that Random Forest classifier would rank a randomly selected student and predict their performance based on their academic and behavioral interaction with the learning platform. Further improvements are required including: 1. The application of Gridsearch to find the optimal values for the classification model. 2. Including further classification techniques in the comparative phase 3. Explore features correlation to enhance the accuracy of the prediction model. Building student model will further support implementing recommendation strategies to (a) support the cognitive development of students, (b) detect their interaction behavior, (c) determine their preferences, and (d) empower their learning performance. Thus, in future work, I will consider examine the task of recommending activities to have a better understanding of the impact of interaction behavior on student performance in e-learning environment.

References

1. The dataset extracted from [Kaggle](#)
2. Thank you Udacity for supporting the knowledge building
3. Amrieh, E. A., Hamtini, T., & Aljarah, I. (2016). Mining Educational Data to Predict Student's academic Performance using Ensemble Methods. *International Journal of Database Theory and Application*, 9(8), 119-136.