External Practical Exam - Practical-1

ID: 17CE023
Author: Bhishm Daslaniya

Aim: Apply Logistic on Students' Academic Performance Dataset

Instructions:

1. Load Dataset
2. Draw countplot (placeOfBirth vs Count, StudentAbsenceDays vs count, ParentSchoolSatisfaction vs count, Gender Comparison)
3. Draw pairplot (set hue="class")
4. Apply Label Encoding or on-hot encoding on Dataset (Whichever applicable)
5. Apply Logistic Regression and display precision, Recall, F1-score and support

In [14]:

```
import pandas as pd
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Loading and Exploring Dataset

In [6]:

```
#Load Dataset
data = pd.read_csv('17ce023 BHISHM DASLANIYA - Edu-Data.csv')
data.head()
```

Out[6]:

	gender	NationalITy	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Relation	raisedhands	VisITedResources	AnnouncementsView	Discussion	ParentAnsweringSurvey	Parentsc
0	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	15	16	2	20	Yes	
1	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	20	20	3	25	Yes	
2	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	10	7	0	30	No	
3	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	30	25	5	35	No	
4	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	40	50	12	50	No	

In [9]:

```
print(data.shape)
```

```
(480, 17)
```

In [10]:

```
data.columns
```

Out[10]:

```
Index(['gender', 'NationalITy', 'PlaceofBirth', 'StageID', 'GradeID',
       'SectionID', 'Topic', 'Semester', 'Relation', 'raisedhands',
       'VisITedResources', 'AnnouncementsView', 'Discussion',
       'ParentAnsweringSurvey', 'ParentschoolSatisfaction',
       'StudentAbsenceDays', 'Class'],
      dtype='object')
```

In [12]:

```
#check for missing values
data.isnull().sum()
```

Out[12]:

```
gender                      0
NationalITy                 0
PlaceofBirth                0
StageID                     0
GradeID                     0
SectionID                   0
Topic                       0
Semester                    0
Relation                    0
```

In [13]:

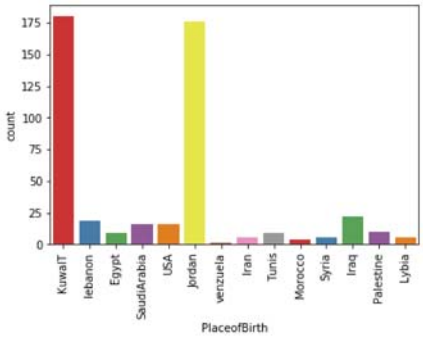
```
data['PlaceofBirth'].value_counts()
```

Out[13]:

```
KuwaIT         180
Jordan         176
Iraq            22
lebanon         19
SaudiArabia     16
USA             16
Palestine       10
Tunis            9
Egypt            9
Iran             6
Lybia            6
Syria            6
Morocco          4
venzuela         1
Name: PlaceofBirth, dtype: int64
```

In [24]:

```
#Plot place of birth vs count
POB = sns.countplot(x = 'PlaceofBirth', data=data, palette='Set1')
POB.set(xlabel='PlaceofBirth',ylabel='count', label= "Students Birth Place")
plt.setp(POB.get_xticklabels(), rotation=90)
plt.show()
```



In [25]:

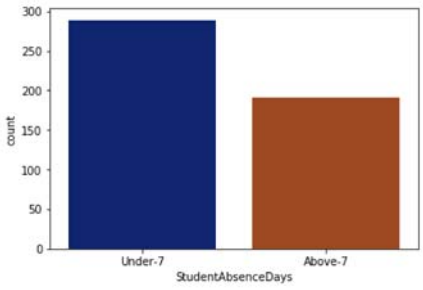
```
data['StudentAbsenceDays'].value_counts()
```

Out[25]:

```
Under-7    289
Above-7    191
Name: StudentAbsenceDays, dtype: int64
```

In [46]:

```
# Student absent day VS count
# Stu_AB = sns.countplot(x='StudentAbsenceDays',data = data,hue = 'Class',palette='dark')
Stu_AB = sns.countplot(x='StudentAbsenceDays',data = data,palette='dark')
```



In [32]:

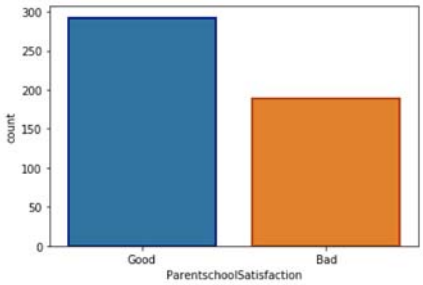
```
data['ParentschoolSatisfaction'].value_counts()
```

Out[32]:

```
Good    292
Bad     188
Name: ParentschoolSatisfaction, dtype: int64
```

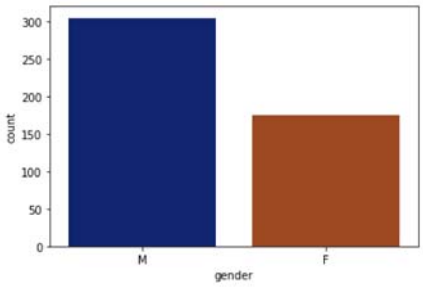
In [40]:

```
PS_Satisfaction = sns.countplot(x="ParentschoolSatisfaction",data=data,linewidth=2,edgecolor=sns.color_palette("dark"))
```



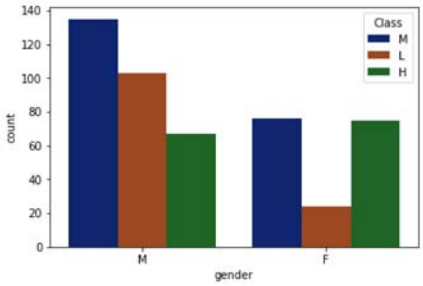
In [48]:

```
# Gender Comparision Simple
Gender_simple =  sns.countplot(x='gender',data = data,palette='dark')
```



In [49]:

```
#Gender Comparision Classwise
Gen_compare =  sns.countplot(x='gender',data = data,hue = 'Class',palette='dark')
```



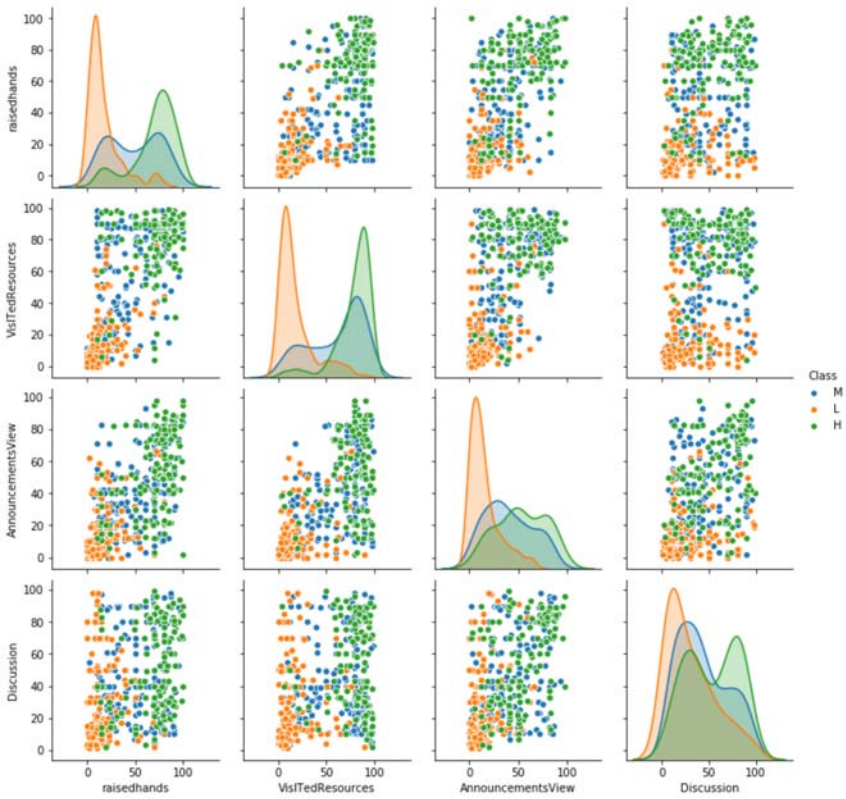
Pairplot

In [50]:

```
# Pairplot with hue = 'Class'
sns.pairplot(data,hue='Class')
```

Out[50]:

```
<seaborn.axisgrid.PairGrid at 0x1ebefa6c248>
```



In [52]:

```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
from sklearn.model_selection import cross_val_score
```

Label Encoding

In [53]:

```
label = LabelEncoder()
```

In [58]:

```
Features.head()
```

Out[58]:

	gender	NationalITy	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Relation	raisedhands	VisITedResources	AnnouncementsView	Discussion	ParentAnsweringSurvey	Parentsch
0	1	4	4	2	1	0	7	0	0	15	16	2	20	1	
1	1	4	4	2	1	0	7	0	0	20	20	3	25	1	
2	1	4	4	2	1	0	7	0	0	10	7	0	30	0	
3	1	4	4	2	1	0	7	0	0	30	25	5	35	0	
4	1	4	4	2	1	0	7	0	0	40	50	12	50	0	

Applying Logistic Regression

In [59]:

```
X_train, X_test, y_train, y_test = train_test_split(Features, Target, test_size=0.2, random_state=52)
```

In [70]:

```
model = LogisticRegression(solver='lbfgs',class_weight='balanced', max_iter=10000)
model.fit(X_train,y_train)
```

Out[70]:

```
LogisticRegression(C=1.0, class_weight='balanced', dual=False,
                   fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                   max_iter=10000, multi_class='auto', n_jobs=None,
                   penalty='l2', random_state=None, solver='lbfgs', tol=0.0001,
                   verbose=0, warm_start=False)
```

In [71]:

```
Prediction = model.predict(X_test)
Score = accuracy_score(y_test,Prediction)
Report = classification_report(y_test,Prediction)
```

In [72]:

```
print(Prediction)
```

```
['L' 'M' 'L' 'L' 'M' 'L' 'M' 'H' 'M' 'M' 'M' 'L' 'M' 'L' 'H' 'L' 'H' 'M'
 'H' 'M' 'H' 'H' 'L' 'L' 'H' 'L' 'H' 'H' 'H' 'L' 'M' 'H' 'L' 'M' 'M' 'M'
 'L' 'M' 'H' 'L' 'H' 'M' 'H' 'M' 'H' 'L' 'M' 'L' 'M' 'L' 'H' 'H' 'M' 'H'
 'H' 'L' 'H' 'L' 'L' 'H' 'L' 'H' 'M' 'M' 'H' 'H' 'L' 'L' 'H' 'H' 'H' 'H'
 'H' 'H' 'H' 'H' 'M' 'H' 'H' 'H' 'L' 'H' 'M' 'M' 'L' 'M' 'M' 'H' 'M' 'H'
 'L' 'M' 'M' 'H' 'H' 'H']
```

In [73]:

```
print(Score)
```

```
0.8229166666666666
```

In [74]:

```
print(Report)
```

```
              precision    recall  f1-score   support

           H       0.78      0.91      0.84        35
           L       0.81      0.95      0.88        22
           M       0.90      0.67      0.76        39

    accuracy                           0.82        96
   macro avg       0.83      0.85      0.83        96
weighted avg       0.83      0.82      0.82        96
```