

Logistics Regression

```
In [106... import pandas as pd
import numpy as np # Linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
```

```
In [107... data = pd.read_csv('xAPI-Edu-Data.csv')
```

```
In [108... data.head()
```

```
Out[108]:
```

	gender	Nationality	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Relation	raisedhands
0	M	KW	Kuwait	lowerlevel	G-04	A	IT	F	Father	
1	M	KW	Kuwait	lowerlevel	G-04	A	IT	F	Father	
2	M	KW	Kuwait	lowerlevel	G-04	A	IT	F	Father	
3	M	KW	Kuwait	lowerlevel	G-04	A	IT	F	Father	
4	M	KW	Kuwait	lowerlevel	G-04	A	IT	F	Father	

```
In [109... data.info()
```

```
<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
```

```
In [110... data.dtypes
```

```
Out[110]: gender          object
NationalITy          object
PlaceofBirth         object
StageID              object
GradeID              object
SectionID            object
Topic                object
Semester             object
Relation             object
raisedhands          int64
VisITedResources     int64
AnnouncementsView    int64
Discussion            int64
ParentAnsweringSurvey object
ParentschoolSatisfaction object
StudentAbsenceDays   object
Class                object
dtype: object
```

```
In [111]: data.isnull().sum()
```

```
Out[111]: gender          0
NationalITy          0
PlaceofBirth         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
```

```
In [112]: data.describe(include='object')
```

```
Out[112]:
```

	gender	NationalITy	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Re
count	480	480	480	480	480	480	480	480	
unique	2	14	14	3	10	3	12	2	
top	M	KW	KuwaIT	MiddleSchool	G-02	A	IT	F	
freq	305	179	180	248	147	283	95	245	

```
In [113]: unique_values = data.apply(lambda col: col.nunique())

# Display the unique values
print(unique_values)
```

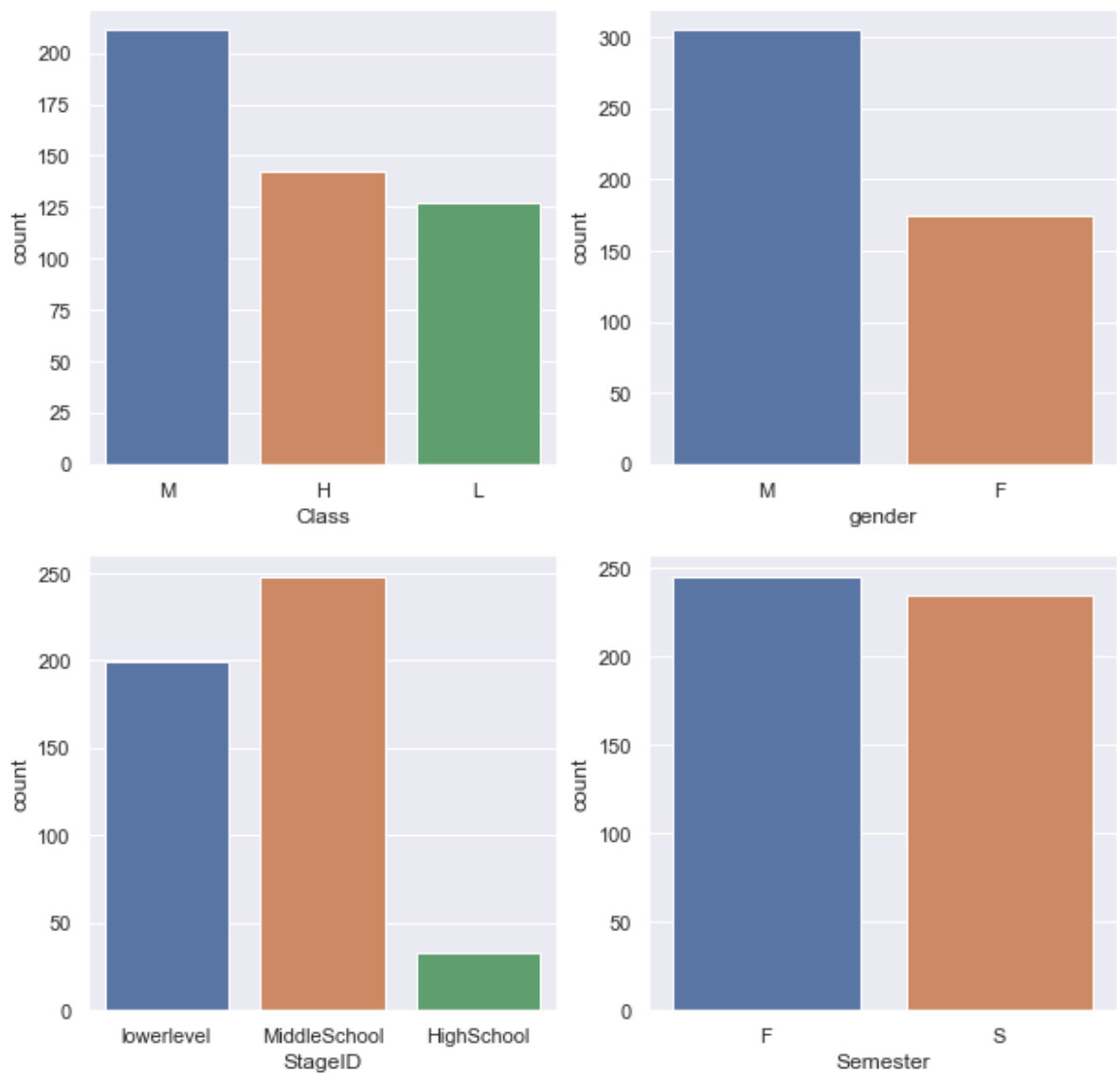
gender	2
NationalITY	14
PlaceofBirth	14
StageID	3
GradeID	10
SectionID	3
Topic	12
Semester	2
Relation	2
raisedhands	82
VisITedResources	89
AnnouncementsView	88
Discussion	90
ParentAnsweringSurvey	2
ParentschoolSatisfaction	2
StudentAbsenceDays	2
Class	3

dtype: int64

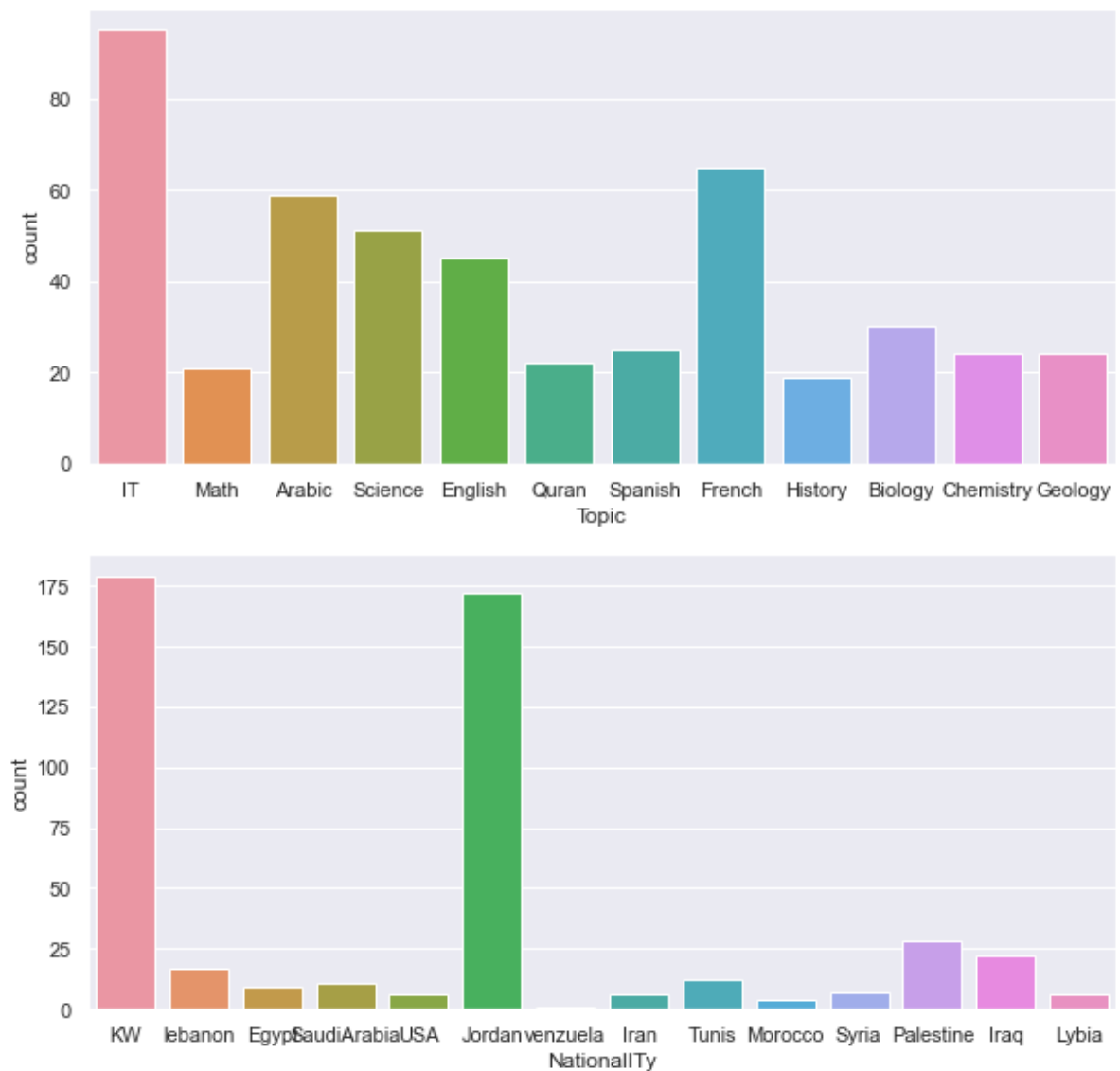
1. Visualize just the categorical features individually to see what options are included and how each option fares when it comes to count(how many times it appears) and see what can be deduce from that?

In [114...

```
plt.figure(figsize=(10,10))
plt.subplot(2,2,1)
sns.countplot(x='Class', data=data, order=['M','H','L'])
plt.subplot(2,2,2)
sns.countplot(x='gender', data=data, order=['M','F'])
plt.subplot(2,2,3)
sns.countplot(x='StageID', data=data)
plt.subplot(2,2,4)
sns.countplot(x='Semester', data=data)
plt.show()
```

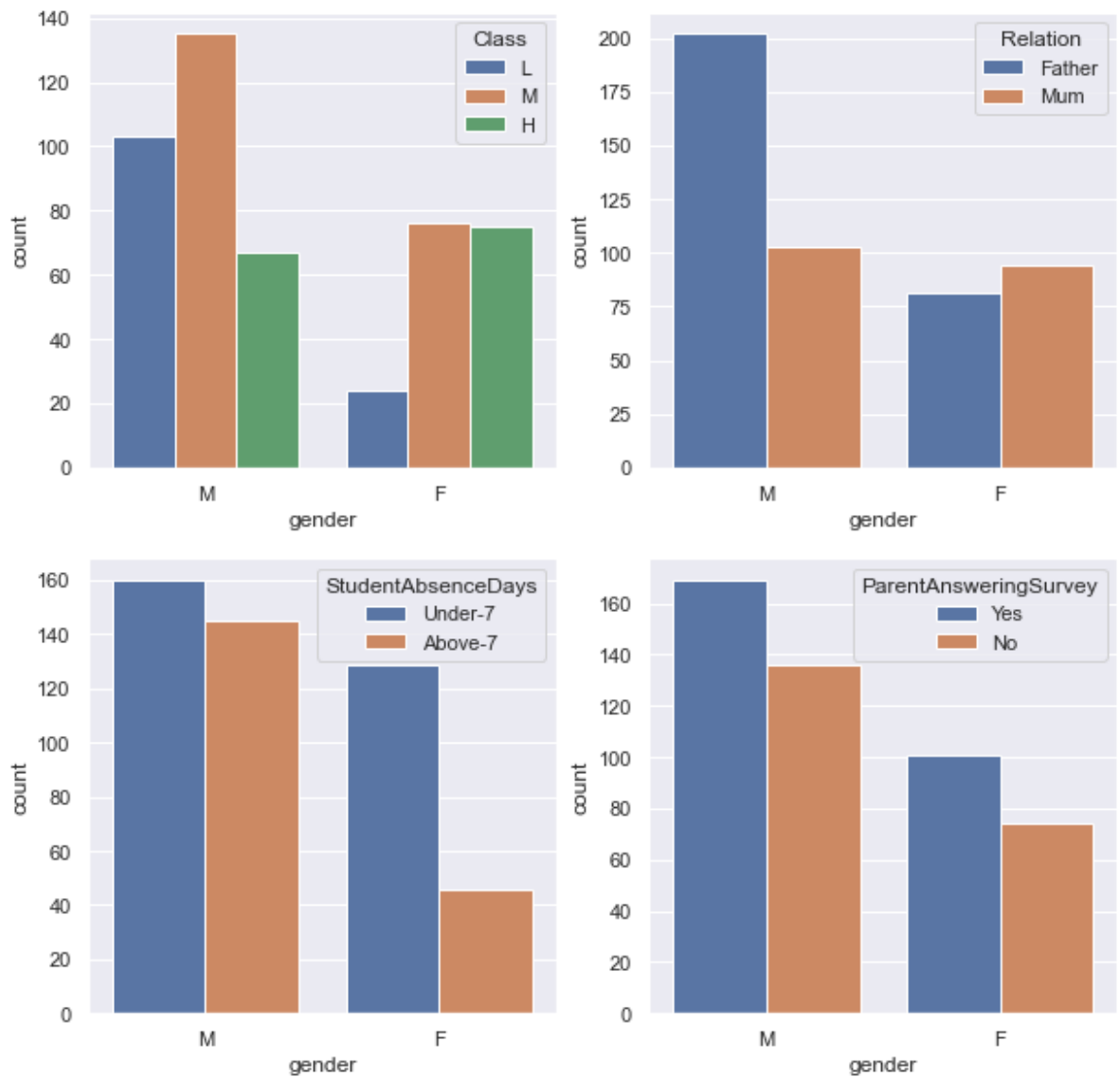


```
In [115... fig, (axis1, axis2) = plt.subplots(2, 1, figsize=(10,10))
sns.countplot(x='Topic', data=data, ax=axis1)
sns.countplot(x='NationalITY', data=data, ax=axis2)
plt.show()
```

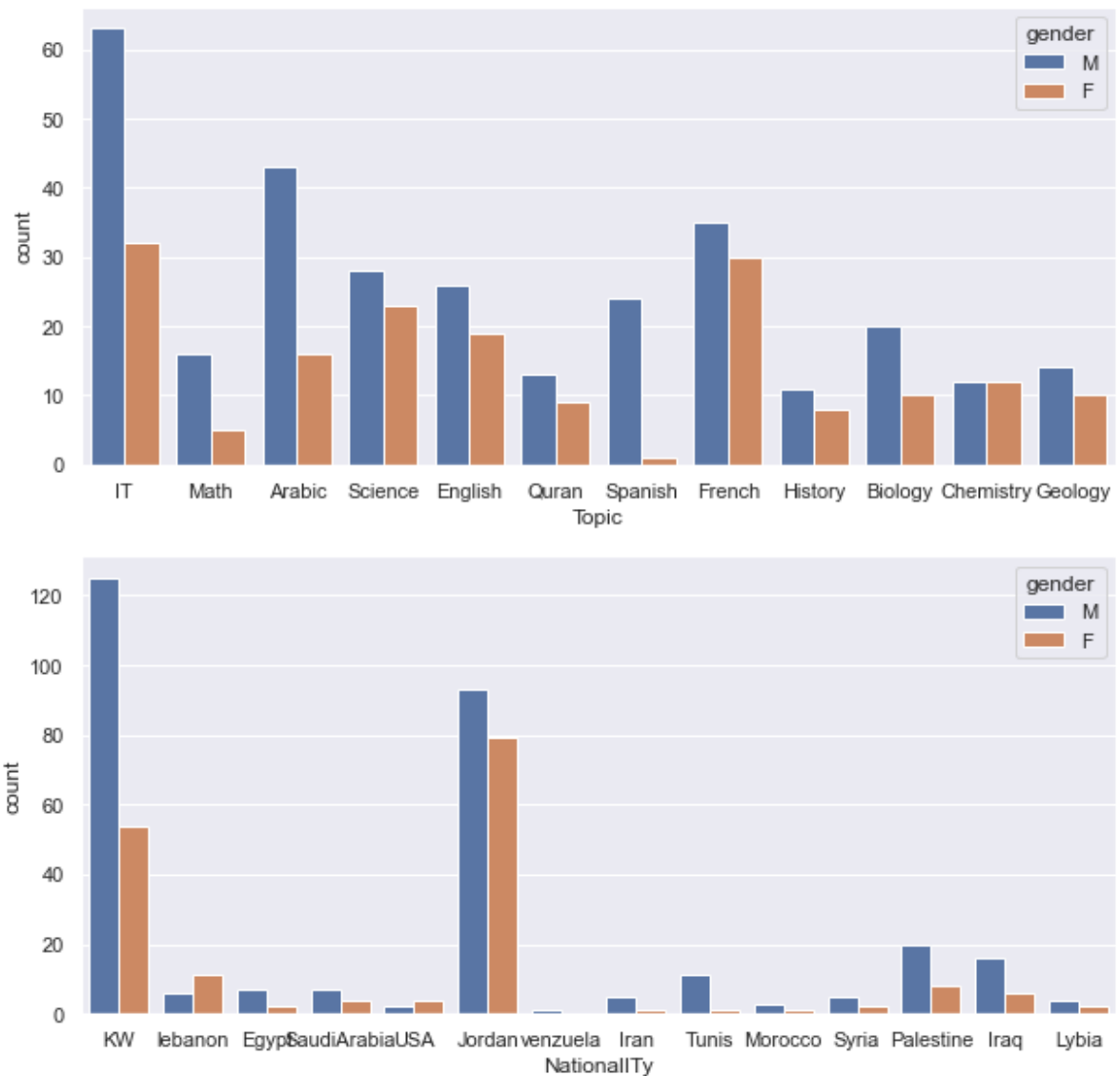


2. Look at some categorical features in relation to each other, to see what insights could be possibly read?

```
In [116... fig, axarr = plt.subplots(2,2,figsize=(10,10))
sns.countplot(x='gender', hue='Class', data=data, ax=axarr[0,0], order=['M','F'], palette='magma')
sns.countplot(x='gender', hue='Relation', data=data, ax=axarr[0,1], order=['M','F'], palette='magma')
sns.countplot(x='gender', hue='StudentAbsenceDays', data=data, ax=axarr[1,0], order=['M','F'], palette='magma')
sns.countplot(x='gender', hue='ParentAnsweringSurvey', data=data, ax=axarr[1,1], order=['M','F'], palette='magma')
plt.show()
```



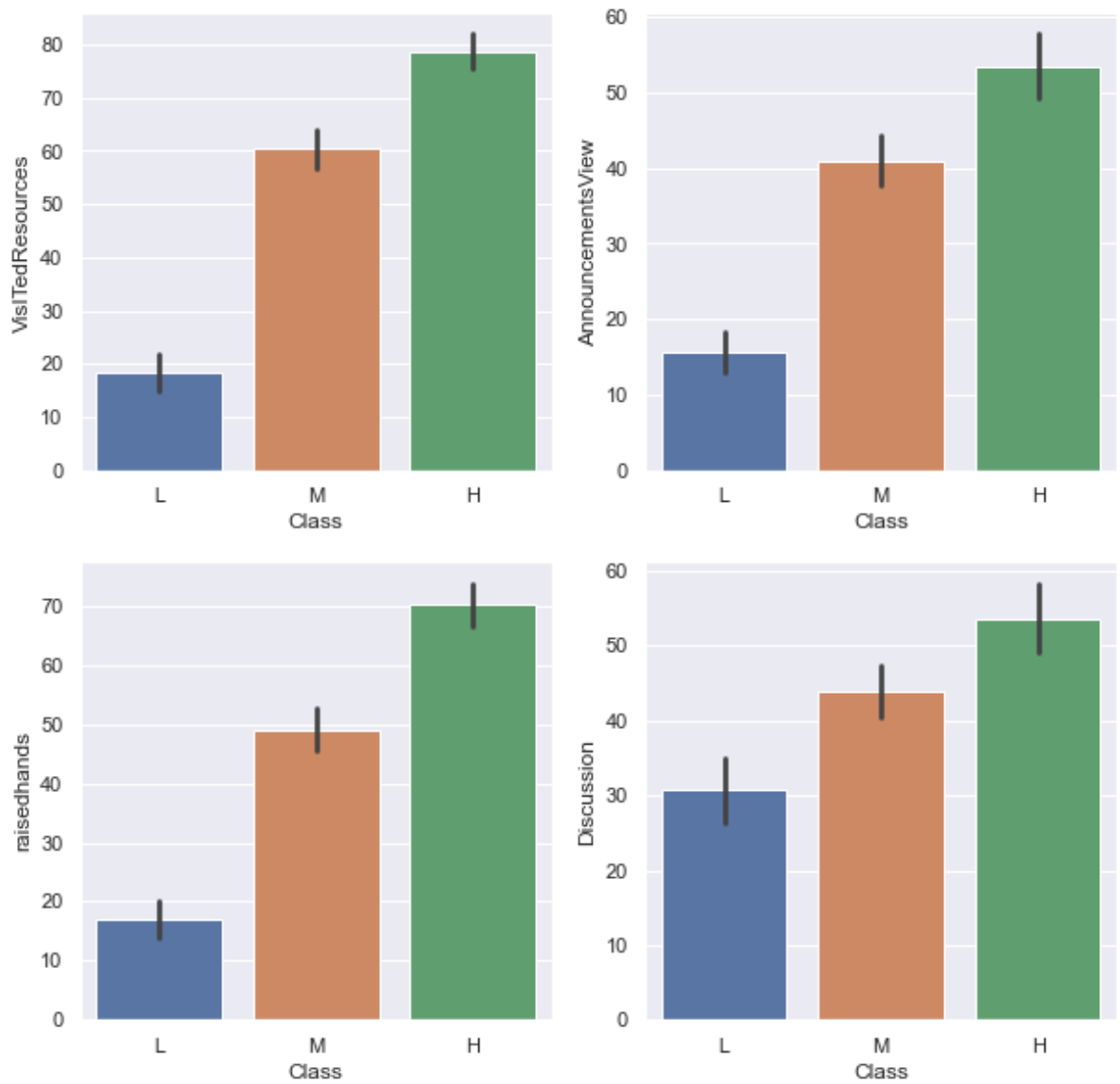
```
In [117... fig, (axis1, axis2) = plt.subplots(2, 1, figsize=(10,10))
sns.countplot(x='Topic', hue='gender', data=data, ax=axis1)
sns.countplot(x='NationalITY', hue='gender', data=data, ax=axis2)
plt.show()
```



- Girls seem to have performed better than boys
- In the case of girls, mothers seem to be more interested in their education than fathers
- Girls had much better attendance than boys
- No apparent gender bias when it comes to subject/topic choices, we cannot conclude that girls performed better because they perhaps took less technical subjects
- Gender disparity holds even at a country level. May just be as a result of the sampling

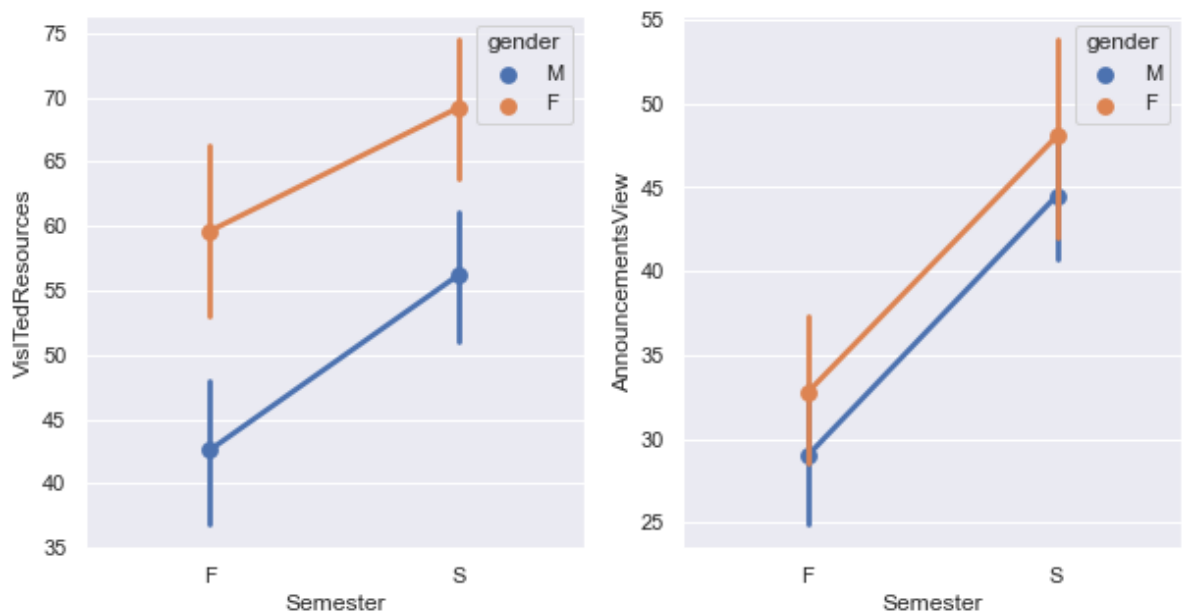
3. Visualize categorical variables with numerical variables and give conclusions?

```
In [118... plt.figure(figsize=(10,10))
plt.subplot(2,2,1)
sns.barplot(x='Class', y='VisITedResources', data=data, order=['L','M','H'])
plt.subplot(2,2,2)
sns.barplot(x='Class', y='AnnouncementsView', data=data, order=['L','M','H'])
plt.subplot(2,2,3)
sns.barplot(x='Class', y='raisedhands', data=data, order=['L','M','H'])
plt.subplot(2,2,4)
sns.barplot(x='Class', y='Discussion', data=data, order=['L','M','H'])
plt.show()
```



In [119...

```
plt.figure(figsize=(10,5))
plt.subplot(1, 2, 1)
sns.pointplot(x='Semester', y='VisITedResources', hue='gender', data=data)
plt.subplot(1, 2, 2)
sns.pointplot(x='Semester', y='AnnouncementsView', hue='gender', data=data)
plt.show()
```



Ans :

- As expected, those that participated more (higher counts in Discussion, raisedhands, AnnouncementViews, RaisedHands), performed better
- In the case of both visiting resources and viewing announcements, students were more vigilant in the second semester, perhaps that last minute need to boost your final grade

```
In [120...] ave_raisedhands = sum(data['raisedhands'])/len(data['raisedhands'])
ave_VisITedResources = sum(data['VisITedResources'])/len(data['VisITedResources'])
ave_AnnouncementsView = sum(data['AnnouncementsView'])/len(data['AnnouncementsView'])
unsuccess = data.loc[(data['raisedhands'] >= ave_raisedhands) & (data['VisITedResources'] >= ave_VisITedResources) & (data['AnnouncementsView'] >= ave_AnnouncementsView)]
```

```
In [121...] unsuccess
```

```
Out[121]:
```

	gender	NationalITy	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Result
444	M	Jordan	Jordan	MiddleSchool	G-08	A	Chemistry	F	
445	M	Jordan	Jordan	MiddleSchool	G-08	A	Chemistry	S	

4. From the above result, what are the factors that leads to get low grades of the students?

Note : Above two students have features ('raisedhands' , 'VisITedResources' , 'AnnouncementsView') greater than average

```
In [122...] data['numeric_class'] = [1 if data.loc[i, 'Class'] == 'L' else 2 if data.loc[i, 'Class'] == 'M' else 3 if data.loc[i, 'Class'] == 'H']
```

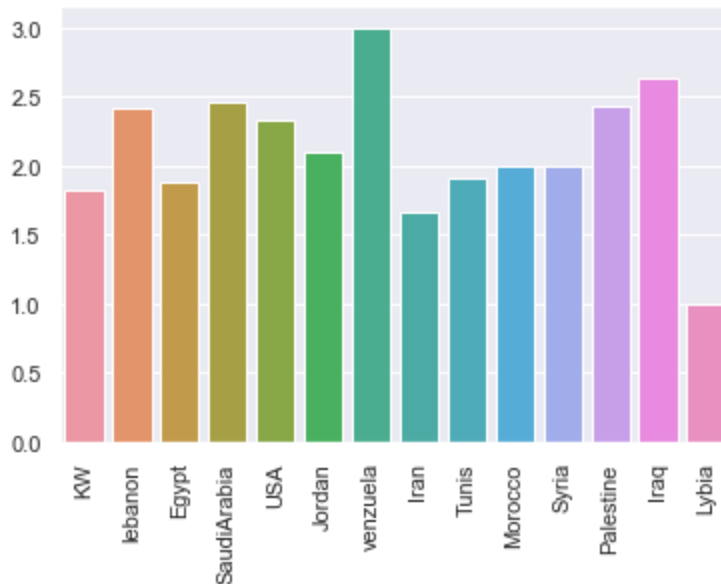
```
In [123...] grade_male_ave = sum(data[data.gender == 'M'].numeric_class)/float(len(data[data.gender == 'M']))
grade_female_ave = sum(data[data.gender == 'F'].numeric_class)/float(len(data[data.gender == 'F']))
```

- Gender comparison cannot completely explain low level grades

```
In [124...] # Now Lets look at nationality
nation = data.NationalITY.unique()
nation_grades_ave = [sum(data[data.NationalITY == i].numeric_class)/float(len(data[data.NationalITY == i])) for i in nation]
ax = sns.barplot(x=nation, y=nation_grades_ave)
jordan_ave = sum(data[data.NationalITY == 'Jordan'].numeric_class)/float(len(data[data.NationalITY == 'Jordan']))
print('Jordan average: '+str(jordan_ave))
plt.xticks(rotation=90)
```

Jordan average: 2.0930232558139537

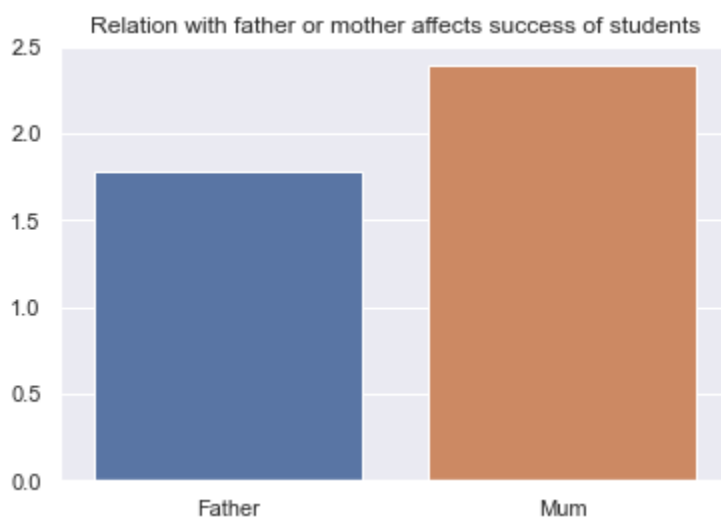
```
Out[124]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 [Text(0, 0, 'KW'),
  Text(1, 0, 'lebanon'),
  Text(2, 0, 'Egypt'),
  Text(3, 0, 'SaudiArabia'),
  Text(4, 0, 'USA'),
  Text(5, 0, 'Jordan'),
  Text(6, 0, 'venzuela'),
  Text(7, 0, 'Iran'),
  Text(8, 0, 'Tunis'),
  Text(9, 0, 'Morocco'),
  Text(10, 0, 'Syria'),
  Text(11, 0, 'Palestine'),
  Text(12, 0, 'Iraq'),
  Text(13, 0, 'Lybia')])
```



- Gender comparison cannot completely explain low level grades

```
In [125... # Lets look at relation with family members
relation = data.Relation.unique()
relation_grade_ave = [sum(data[data.Relation == i].numeric_class)/float(len(data[da
ax = sns.barplot(x=relation, y=relation_grade_ave)
plt.title('Relation with father or mother affects success of students')
```

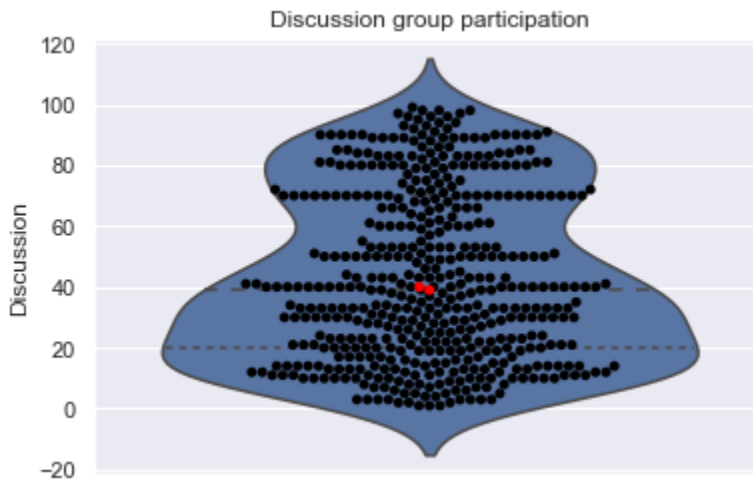
```
Out[125]: Text(0.5, 1.0, 'Relation with father or mother affects success of students')
```



- Having relation with mum has positive effect on these students

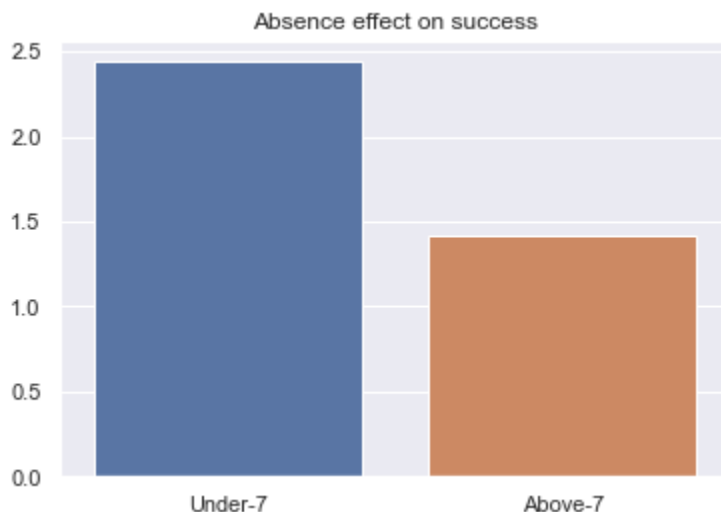
```
In [126... # Lets look at how many times the student participate on discussion groups
discussion = data.Discussion
discussion_ave = sum(discussion)/len(discussion)
ax = sns.violinplot(y=discussion,split=True,inner='quart')
ax = sns.swarmplot(y=discussion,color='black')
ax = sns.swarmplot(y = unsuccessful.Discussion, color='red')
plt.title('Discussion group participation')
```

Out[126]: Text(0.5, 1.0, 'Discussion group participation')



```
In [127... # Now Lastly Lets look at
absence_day = data.StudentAbsenceDays.unique()
absence_day_ave = [sum(data[data.StudentAbsenceDays == i].numeric_class)/float(len(
ax = sns.barplot(x=absence_day, y=absence_day_ave)
plt.title('Absence effect on success')
```

Out[127]: Text(0.5, 1.0, 'Absence effect on success')



Ans :

- These two students are under the average of discussion (43). Therefore, not participating in discussion groups can be important reason to get low grades
- Their absence days are above seven which resulted in low grades

5. Build classification model and present it's classification report ?

In [128... `data.head()`

Out[128]:

	gender	Nationality	PlaceofBirth	StageID	GradeID	SectionID	Topic	Semester	Relation	ra
0	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	
1	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	
2	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	
3	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	
4	M	KW	KuwaIT	lowerlevel	G-04	A	IT	F	Father	

In [129... `data1 = data.drop('Class',axis = 1)`
`data_with_dummies = pd.get_dummies(data1, drop_first=True)`

In [130... `data_with_dummies.head()`

Out[130]:

	raisedhands	VisiTedResources	AnnouncementsView	Discussion	numeric_class	gender_M	Nati
0	15	16	2	20	2	1	
1	20	20	3	25	2	1	
2	10	7	0	30	1	1	
3	30	25	5	35	1	1	
4	40	50	12	50	2	1	

5 rows × 61 columns

In [131... `Features = data_with_dummies.drop(['numeric_class'],axis = 1)`
`Target = data_with_dummies['numeric_class']`

In [132... `from sklearn.preprocessing import StandardScaler`
`scaler = StandardScaler()`
`scaler.fit(Features)`

Out[132]: `StandardScaler()`

In [133... `X = scaler.fit_transform(Features)`

In [134... `X_train, X_test, y_train, y_test = train_test_split(X, Target, test_size=0.3, random_state=42)`

In [135... `Logit_Model = LogisticRegression()`
`Logit_Model.fit(X_train,y_train)`

Out[135]: `LogisticRegression()`

```
In [136... Prediction = Logit_Model.predict(X_test)
Score = accuracy_score(y_test,Prediction)
Report = classification_report(y_test,Prediction)
```

```
In [137... Prediction
```

```
Out[137]: array([2, 2, 3, 1, 1, 1, 1, 3, 2, 2, 2, 3, 2, 2, 1, 1, 1, 2, 1, 1, 3, 3,
      2, 3, 2, 2, 3, 2, 2, 3, 3, 3, 3, 2, 2, 2, 3, 2, 2, 3, 1, 3, 2, 1,
      2, 2, 3, 2, 2, 2, 2, 1, 2, 2, 2, 2, 3, 2, 3, 1, 3, 1, 2, 2, 2, 2,
      1, 2, 1, 2, 2, 2, 1, 2, 2, 1, 2, 3, 2, 1, 2, 2, 3, 2, 3, 3, 3, 3,
      2, 3, 2, 1, 2, 1, 3, 3, 2, 3, 2, 3, 2, 1, 2, 1, 2, 2, 3, 2, 2, 1,
      3, 2, 2, 3, 2, 2, 2, 2, 1, 1, 3, 1, 3, 1, 3, 3, 1, 3, 3, 3, 1, 3,
      3, 3, 2, 1, 1, 1, 3, 2, 2, 1, 2, 2], dtype=int64)
```

```
In [138... Score
```

```
Out[138]: 0.7361111111111112
```

```
In [139... print(Report)
```

	precision	recall	f1-score	support
1	0.76	0.87	0.81	30
2	0.78	0.70	0.74	74
3	0.65	0.70	0.67	40
accuracy			0.74	144
macro avg	0.73	0.76	0.74	144
weighted avg	0.74	0.74	0.74	144

```
In [ ]:
```