CSE_351_project

May 8, 2022

Project : Titanic - Who will survive? - Youngjun Cho ,Hyeondeok Cho

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.impute import KNNImputer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import f1_score, recall_score, precision_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics


#Read train and test csv files and convert them to dataframe
titanic_train = pd.read_csv('train.csv')
titanic_test = pd.read_csv('test.csv')
```

[ ]:
```python
titanic_train
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …         …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3
```

```
                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 …     …   …    …
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[ ]:
```
#Check null values
titanic_train.isnull().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

It shows that there are 177 rows who have missing values in the column “Age” out of 891 rows, and we decided not to use mean value imputation because there are about 20 % missing values and it may result inaccurate analysis. We are going to use KNN(K-Nearest Neighbor) imputation instead.

[ ]:
```
#clean the dataset, remove the outliers, before any data analysis
#KNN imputation
imputer = KNNImputer(n_neighbors = 2, weights="uniform")
titanic_train['Age'] = imputer.fit_transform(titanic_train[['Age']])
titanic_test['Age'] = imputer.fit_transform(titanic_test[['Age']])
titanic_train
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …         …       …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex        Age  \
0                              Braund, Mr. Owen Harris    male  22.000000
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.000000
2                               Heikkinen, Miss. Laina  female  26.000000
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.000000
4                             Allen, Mr. William Henry    male  35.000000
..                                                 …     …        …
886                              Montvila, Rev. Juozas    male  27.000000
887                       Graham, Miss. Margaret Edith  female  19.000000
888           Johnston, Miss. Catherine Helen "Carrie"  female  29.699118
889                              Behr, Mr. Karl Howell    male  26.000000
890                                Dooley, Mr. Patrick    male  32.000000

     SibSp  Parch            Ticket     Fare Cabin Embarked
0        1      0         A/5 21171   7.2500   NaN        S
1        1      0          PC 17599  71.2833   C85        C
2        0      0  STON/O2. 3101282   7.9250   NaN        S
3        1      0            113803  53.1000  C123        S
4        0      0            373450   8.0500   NaN        S
..     …    …               …      …   …      …
886      0      0            211536  13.0000   NaN        S
887      0      0            112053  30.0000   B42        S
888      1      2        W./C. 6607  23.4500   NaN        S
889      0      0            111369  30.0000  C148        C
```

```
890       0      0             370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[ ]:
```python
#Convert values in the Age column to integer
titanic_train['Age']= round(titanic_train['Age'])
titanic_test['Age']= round(titanic_test['Age'])
titanic_train
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …         …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 …     …   …    …
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female  30.0      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q
```

```
[891 rows x 12 columns]
```

[ ]:
```
titanic_train.isnull().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

We don't think that handling missing values in the column "Cabin" is necessary since there are a large amount of missing values and we don't specifically know about its seating chart.

[ ]:
```
#remove the outlier using interquartile range
q1, q3 = np.percentile(titanic_train['Age'],[25,75])
```

[ ]:
```
iqr = q3 -q1
lower_bound = q1 - (1.5 * iqr)
upper_bound = q3 + (1.5 * iqr)
lower_bound
```

[ ]:
```
2.5
```

[ ]:
```
upper_bound
```

[ ]:
```
54.5
```

[ ]:
```
#we can safely remove the outlier which is greater than upper bound and less␣
 ↪than lower bound
clean_titanic_train = titanic_train[titanic_train['Age'] <= upper_bound]
clean_titanic_train = clean_titanic_train[titanic_train['Age'] >= lower_bound]
```

[ ]:
```
clean_titanic_train
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
```

```
3              4         1        1
4              5         0        3
..           ...       ...      ...
886          887         0        2
887          888         1        1
888          889         0        3
889          890         1        1
890          891         0        3

                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 ...     ...   ...    ...
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female  30.0      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     ...               ...      ...   ...      ...
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[825 rows x 12 columns]
```

[ ]:
```python
#Extract information from the non-numerical features
#Add the column "Gender" (male = 1, female = 0)
#Drop the column "Sex"

clean_titanic_train['Gender'] = clean_titanic_train["Sex"].apply(lambda x: 1 if␣
 ↪x=="male" else 0)
clean_titanic_train.drop("Sex", axis=1, inplace=True)

titanic_test['Gender'] = titanic_test["Sex"].apply(lambda x: 1 if x=="male"␣
 ↪else 0)
```

```
titanic_test.drop("Sex", axis=1, inplace=True)
```

[ ]:
```
clean_titanic_train.describe()
```

[ ]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   825.000000  825.000000  825.000000  825.000000  825.000000
mean    447.369697    0.380606    2.341818   28.938182    0.507879
std     257.088865    0.485830    0.824096   10.189458    1.090670
min       1.000000    0.000000    1.000000    3.000000    0.000000
25%     226.000000    0.000000    2.000000   22.000000    0.000000
50%     445.000000    0.000000    3.000000   30.000000    0.000000
75%     671.000000    1.000000    3.000000   34.000000    1.000000
max     891.000000    1.000000    3.000000   54.000000    8.000000

            Parch        Fare      Gender
count  825.000000  825.000000  825.000000
mean     0.357576   31.483615    0.643636
std      0.798599   49.956429    0.479215
min      0.000000    0.000000    0.000000
25%      0.000000    7.895800    0.000000
50%      0.000000   13.416700    1.000000
75%      0.000000   30.070800    1.000000
max      6.000000  512.329200    1.000000
```

[ ]:
```
#check duplicated Passenger ID becasue it must be unique.
clean_titanic_train[clean_titanic_train.duplicated(subset=['PassengerId'])]
```

[ ]:
```
Empty DataFrame
Columns: [PassengerId, Survived, Pclass, Name, Age, SibSp, Parch, Ticket, Fare,
Cabin, Embarked, Gender]
Index: []
```

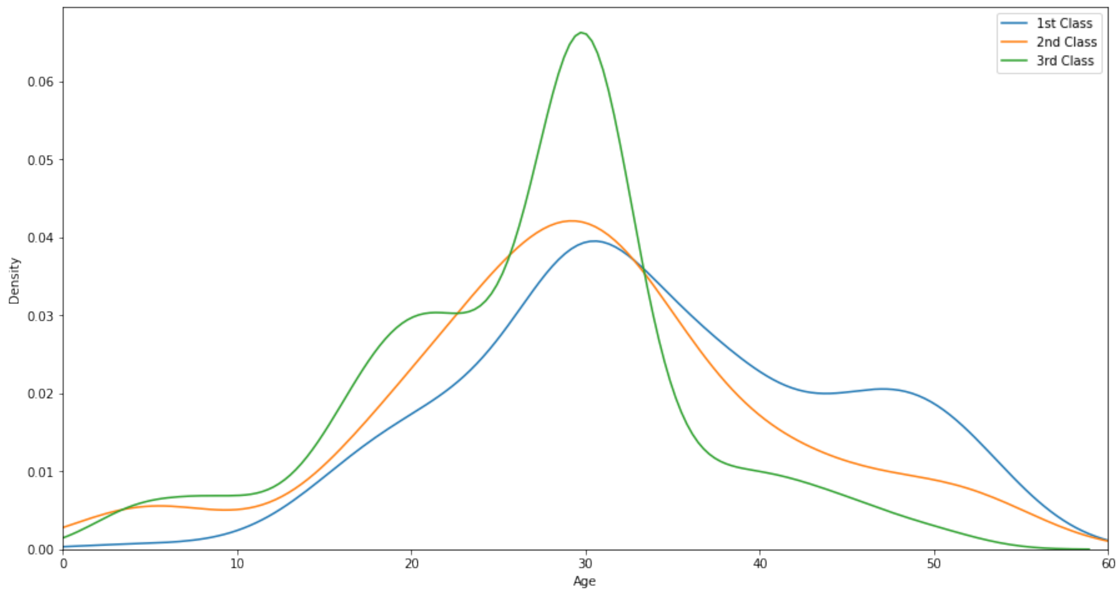
There is no duplicated passenger ID, and now we finshed cleaning the data and removing the outlier.

[ ]:
```
#Explore the socio-economic status of the passenger, is there any relationship␣
↪between socio-economic status with
# other features, such as age, gender, number of family members on board, etc.

#The one way we can distinguish a passenger's socio-ecnomic status can be␣
↪ticket class(Pclass) because they need to
#pay more to reserve good seats, which means that passengers who are in the␣
↪first class are likely to have higher
#social status than others.


#1.relationship between pclass(socio-economic status) and age
#Using KDE(Kernel Density Estimator) plot,
```

```
plt.figure(figsize=(15,8))
sns.kdeplot(clean_titanic_train.Age[clean_titanic_train.Pclass == 1],␣
↪shade=False)
sns.kdeplot(clean_titanic_train.Age[clean_titanic_train.Pclass == 2],␣
↪shade=False)
sns.kdeplot(clean_titanic_train.Age[clean_titanic_train.Pclass == 3],␣
↪shade=False)
plt.legend(('1st Class', '2nd Class','3rd Class'),loc='best')
plt.xlim([0, 60])
plt.show()
```



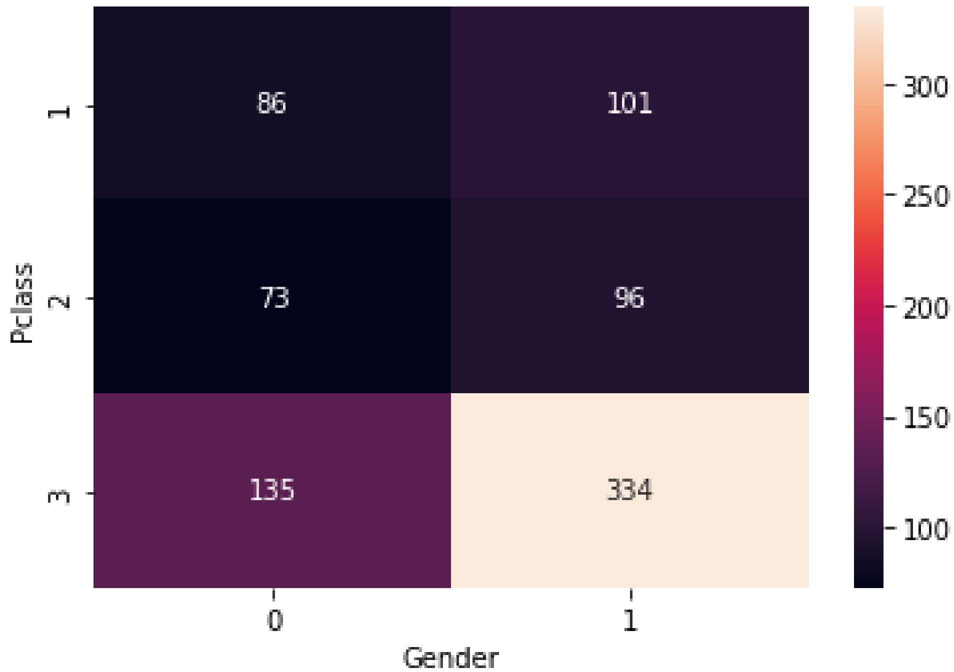
The plot shows that passengers in the age group of 30's had the lowest proportion of first class seats while passengers in the age group opf 40's and 50's had the highest proportion.

[ ]:
```
#2.relationship between pclass(socio-economic status) and gender
#Using heatmap,

heatmap_df = clean_titanic_train.groupby(['Pclass', 'Gender'])
pclass_gender = heatmap_df.size().unstack()

sns.heatmap(pclass_gender, annot = True, fmt ="d")
```

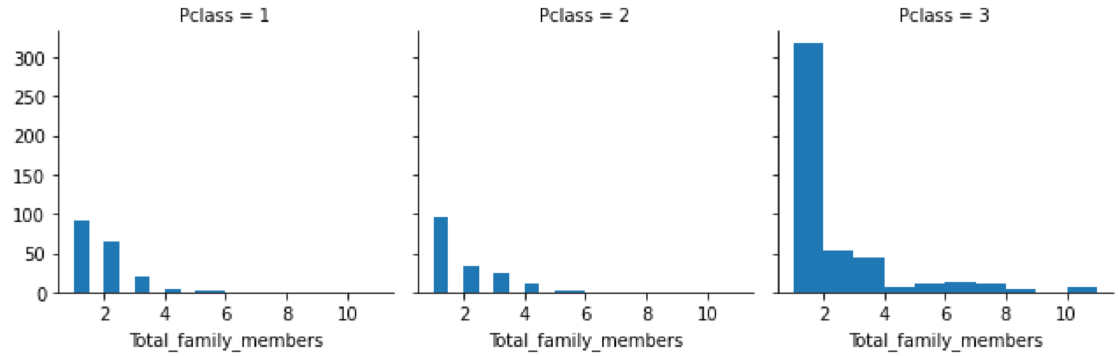
[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b7b7402d0>
```

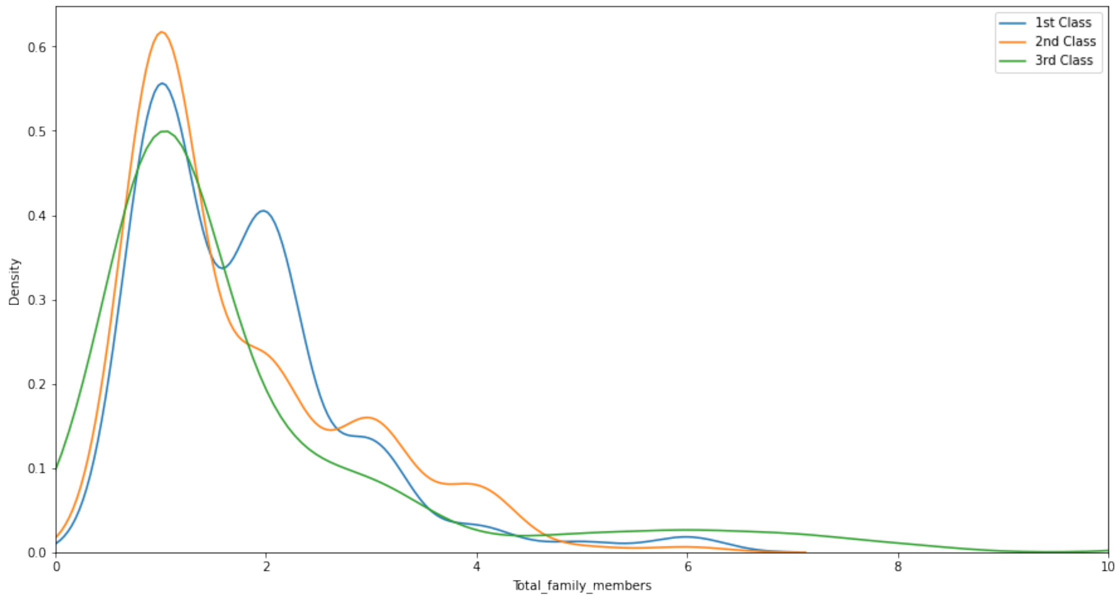



```
[ ]: #3.relationship between pclass(socio-economic status) and family member
#Add the column "Total family members"
#Total family members = Parch +SibSp + 1(including oneself)
for dt in clean_titanic_train:
    clean_titanic_train['Total_family_members'] = 1 + clean_titanic_train['Parch'] + clean_titanic_train['SibSp']

S = sns.FacetGrid(data = clean_titanic_train[clean_titanic_train['Total_family_members'].notna()], col = 'Pclass')
S.map(plt.hist, "Total_family_members")

plt.figure(figsize=(15,8))
sns.kdeplot(clean_titanic_train.Total_family_members[clean_titanic_train.Pclass == 1], shade=False)
sns.kdeplot(clean_titanic_train.Total_family_members[clean_titanic_train.Pclass == 2], shade=False)
sns.kdeplot(clean_titanic_train.Total_family_members[clean_titanic_train.Pclass == 3], shade=False)
plt.legend(('1st Class', '2nd Class','3rd Class'),loc='best')
plt.xlim([0, 10])
plt.show()
```





According to the figure above, a passenger whoose total family member is 2 has the highest proportion in the first class seats. We guess the reason is that couples came to celebrate for their anniversary and they want better seats for that.

[ ]:
```
# Now we are going to investigate how many couples are in the first class
couples = clean_titanic_train[clean_titanic_train['SibSp'] == 1]
couples = couples[couples['Parch'] == 0]
couples = couples[couples['Pclass'] == 1]
num_of_first_couples = len(couples)
num_of_first_couples
```

[ ]: 49

```
[ ]: num_of_first_passengers = clean_titanic_train[clean_titanic_train['Pclass']==1]
     num_of_first_passengers = len(num_of_first_passengers)
     num_of_first_passengers
```

```
[ ]: 187
```

About 30 percent of total number of passengers in the first class are couples, but it is hard to explain the relationship between socio-economic status and number of family members because the number of couples doesn't necessarily tell that they must have higher socio-economic status than others.

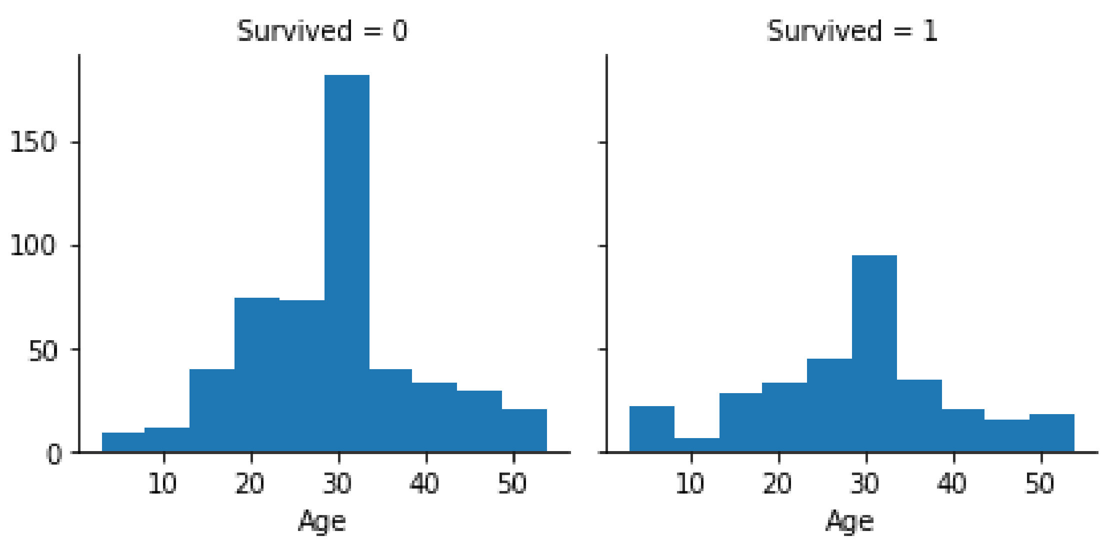
Below graphs represents that distribution of survival victims regard to age, gender, Pclass, SibSp, and Parch

```
[ ]: # Explore the distribution of survival victims in relation to age, gender,␣
      ↪socioeconomic
     # class, etc.

     # 1. relationship between Survived and Age

     A = sns.FacetGrid(data = clean_titanic_train[clean_titanic_train['Age'].
      ↪notna()], col = 'Survived')
     A.map(plt.hist, "Age")
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x7f1b76852250>
```

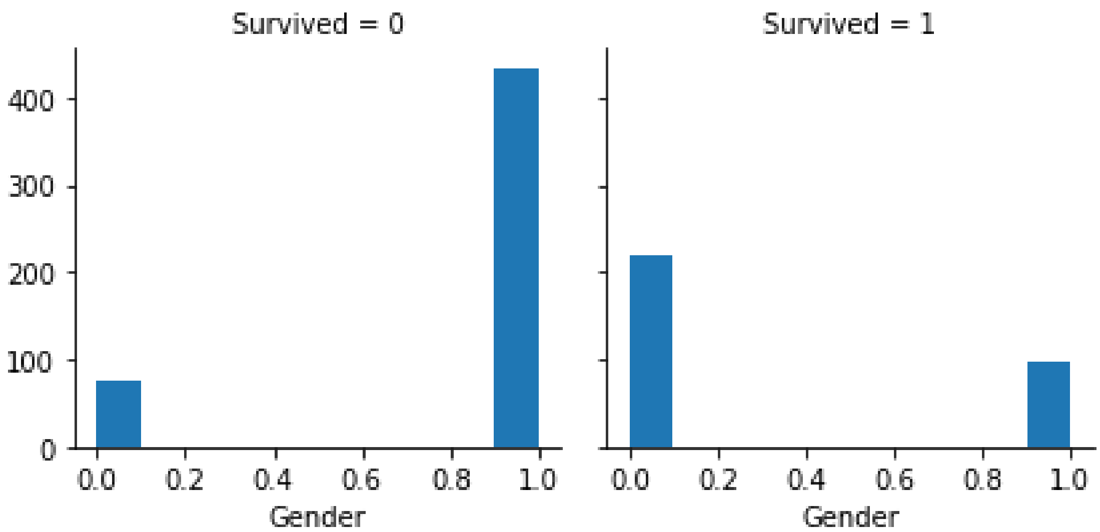


The number of passengers whose age group is in their 30s represents big portion of total passengers. So, there are a lot of passengers in their 30s who died or survived compared to other age groups.

[ ]:
```
# 2. relationship between Survived and Gender

G = sns.FacetGrid(data = clean_titanic_train[clean_titanic_train['Gender'].
 ↪notna()], col = 'Survived')
G.map(plt.hist, "Gender")
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f1b7663c350>

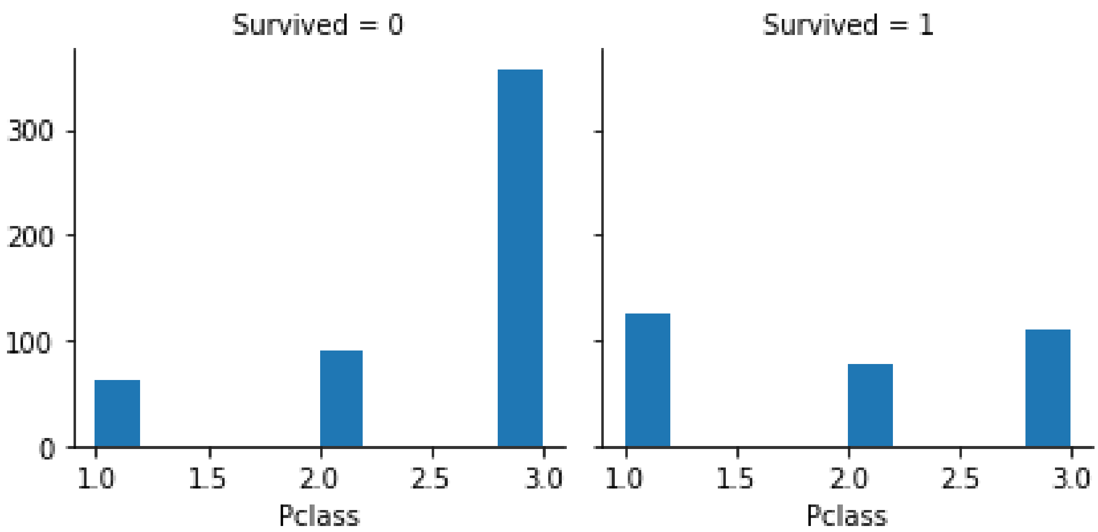


1 represents the male, and we can see that lots of male passengers died. Otherwise, survived rate of female passengers is higher than male passengers.

[ ]:
```
# 3. relationship between Survived and Pclass

C = sns.FacetGrid(data = clean_titanic_train[clean_titanic_train['Pclass'].
 ↪notna()], col = 'Survived')
C.map(plt.hist, "Pclass")
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f1b7646b7d0>

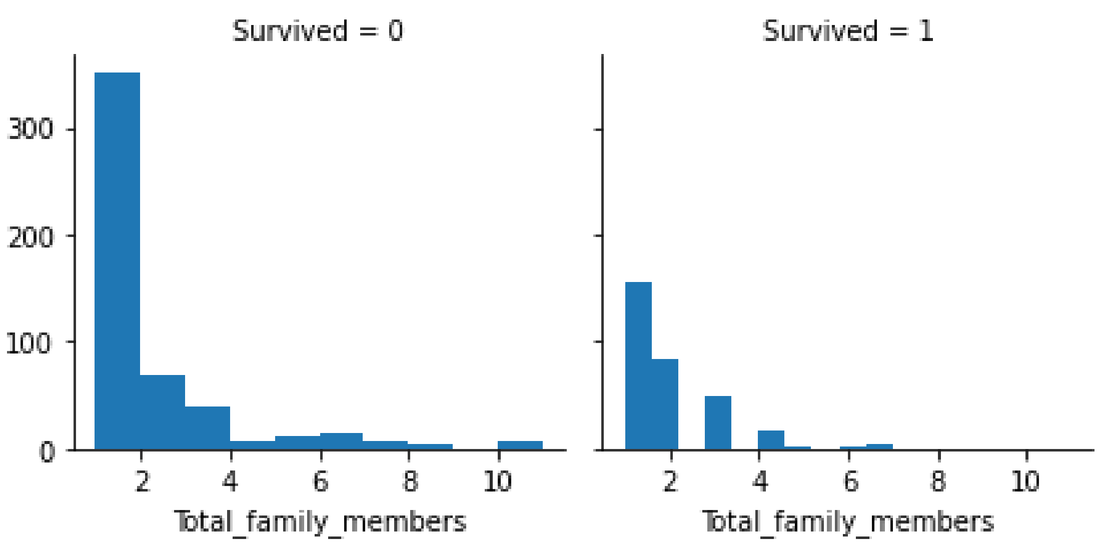


The passengers in first class died less than other classes and survived more compared to passengers in other classes.

[ ]:
```
# 4. relationship between Survived and Total family members

F = sns.FacetGrid(data =␣
↪clean_titanic_train[clean_titanic_train['Total_family_members'].notna()],␣
↪col = 'Survived')
F.map(plt.hist, "Total_family_members")
```

[ ]: `<seaborn.axisgrid.FacetGrid at 0x7f1b76550690>`

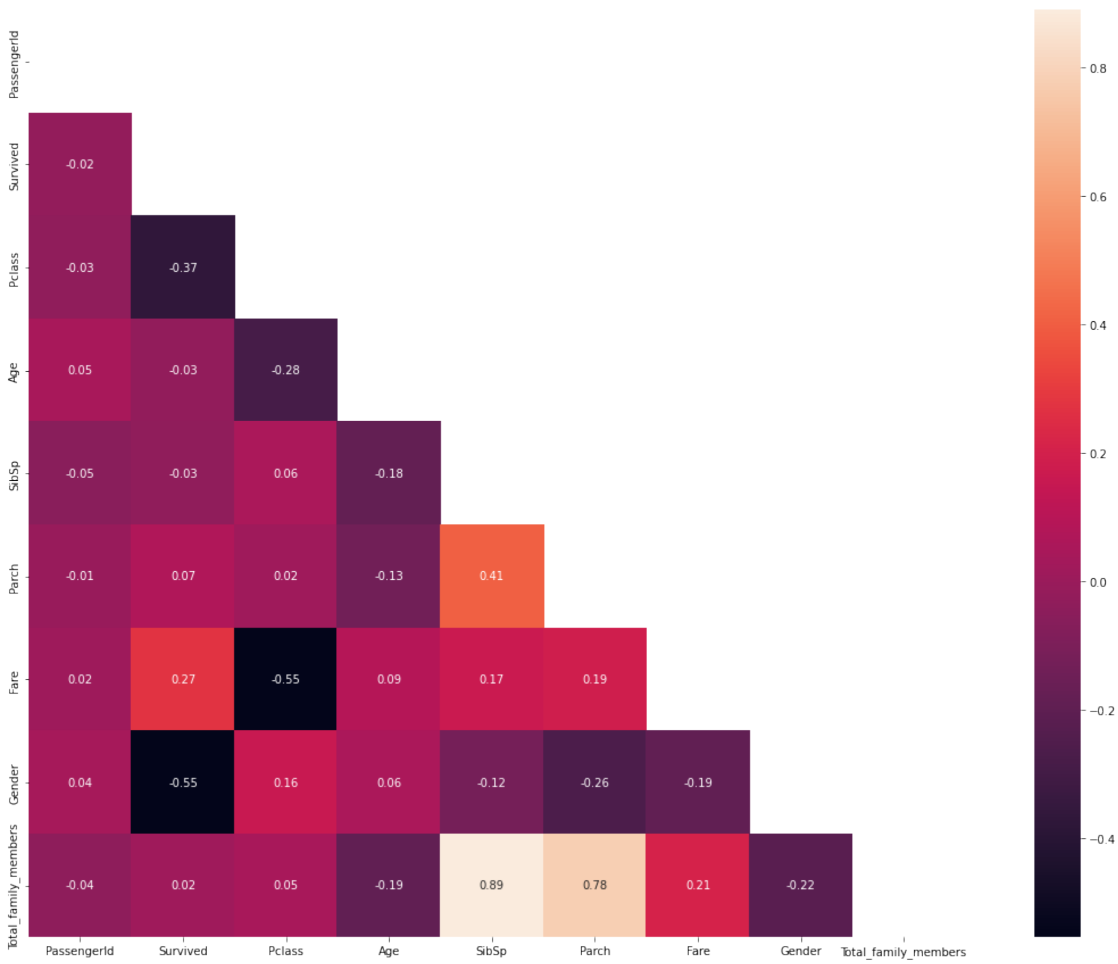


We can see that the number of passengers on board alone accounted for a large portion of total passengers. So, the passengers who boarded alone died or survived more compared to others.

[ ]:
```
# What features seem to be the most important ones? Perform a correlation analysis
# before your prediction task.

correlation = clean_titanic_train.corr(method = 'pearson')
mask = np.zeros_like(correlation)
mask[np.triu_indices_from(mask)] = True
plt.figure(figsize = (25,15))
sns.heatmap(correlation, annot = True, mask = mask, fmt=".2f", square = True,linecolor = "black")
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b7674ce90>
```



The heatmap shows that “Gender”, “Pclass” and “Fare” are highly correlated with survival. Specifically, “Gender” is the most related factor to survive, and the correlation -0.55 means that survival rate of female is higher than male's. So, we can use those factors as training and testing features.

[ ]:
```
#Build three models, train them on the training set, and predict the outcome on␣
↪the test set (after
#dropping the survival column in the test set). Explain how each model works␣
↪(briefly introduce
#the machine learning algorithms behind them).
#Evaluate the performance of each model based on the original outcome in the␣
↪test set. If your predictions are
#not so accurate, what do you think is the reason? Use other evaluation metrics␣
↪to evaluate your
#models (Precision, Recall, Fscore). Split the data further to include a cross␣
↪validation set.
#Did this improve your model's performance on the test set?

#1. Build a logistic regression model.
logistic_train_data = clean_titanic_train[70:]
logistic_training_features = logistic_train_data[['Gender', 'Pclass', 'Fare']]
logistic_training_label = logistic_train_data[['Survived']]

#70 testing set
logistic_test_data = clean_titanic_train[:70]
logistic_testing_features = logistic_test_data[['Gender', 'Pclass', 'Fare']]
logistic_testing_label = logistic_test_data[['Survived']]
```

[ ]:
```
#scaling the training and testing features
scaler = StandardScaler()
logistic_training_features = scaler.fit_transform(logistic_training_features)
logistic_testing_features = scaler.transform(logistic_testing_features)
```

[ ]:
```
#build logistic regression model
logisticReg = LogisticRegression()
logisticReg.fit(logistic_training_features, logistic_training_label.values.
↪ravel())
logistic_predicted = logisticReg.predict(logistic_testing_features)
```

[ ]:
```
#calculate the acurracy score of the logistic regression model
accuracy_score(logistic_testing_label, logistic_predicted)
```

[ ]: 0.7714285714285715

[ ]:
```
#calculate the F1 score of the logistic regression model
f1_score(logistic_testing_label, logistic_predicted)
```

[ ]: 0.7419354838709677

[ ]:
```
#calculate the recall score of the logistic regression model
recall_score(logistic_testing_label, logistic_predicted)
```

[ ]: 0.7666666666666667

[ ]:
```
#calculate the precision score of the logistic regression model
precision_score(logistic_testing_label, logistic_predicted)
```

[ ]: 0.71875

[ ]:
```
predicted_df = logistic_testing_label.copy()
predicted_df['Survived'] = logistic_predicted
predicted_df
```

[ ]:
```
    Survived
0          0
1          1
2          1
3          1
4          0
..       ...
71         1
72         0
73         0
74         0
75         0

[70 rows x 1 columns]
```

[ ]:
```
#2. Build a KNN model.
knn_train_data = clean_titanic_train[70:]
knn_training_features = knn_train_data[['Gender', 'Pclass', 'Fare']]
knn_training_label = knn_train_data[['Survived']]

#70 testing set
knn_test_data = clean_titanic_train[:70]
knn_testing_features = knn_test_data[['Gender', 'Pclass', 'Fare']]
knn_testing_label = logistic_test_data[['Survived']]
```

[ ]:
```
scaler = StandardScaler()
knn_training_features = scaler.fit_transform(knn_training_features)
knn_testing_features = scaler.transform(knn_testing_features)
```

[ ]:
```
KNN = KNeighborsClassifier(n_neighbors=5)
KNN.fit(knn_training_features, knn_training_label)
```

[ ]: KNeighborsClassifier()

[ ]:
```
knn_predicted = KNN.predict(knn_testing_features)
knn_predicted = knn_predicted.round()
```

[ ]:
```
#calculate the acurracy score of the Knn model
accuracy_score(knn_testing_label, knn_predicted)
```

[ ]: 0.7714285714285715

[ ]:
```
#calculate the F1 score of the Knn model
f1_score(knn_testing_label, knn_predicted)
```

[ ]: 0.7037037037037038

[ ]:
```
#calculate the recall score of the Knn model
recall_score(knn_testing_label, knn_predicted)
```

[ ]: 0.6333333333333333

[ ]:
```
#calculate the precision score of the Knn model
precision_score(knn_testing_label, knn_predicted)
```

[ ]: 0.7916666666666666

[ ]:
```
prediction_df = knn_testing_label.copy()
prediction_df['Survived'] = knn_predicted
prediction_df
```

[ ]:
```
    Survived
0          0
1          1
2          0
3          1
4          0
..       …
71         0
72         0
73         0
74         1
75         0

[70 rows x 1 columns]
```

[ ]:
```
#3. Build a Random Forest model.

rfc_train_data = clean_titanic_train[70:]
rfc_training_features =  rfc_train_data[['Gender', 'Pclass', 'Fare']]
rfc_training_label = rfc_train_data[['Survived']]
```

```
rfc_test_data = clean_titanic_train[:70]
rfc_testing_features = rfc_test_data[['Gender', 'Pclass', 'Fare']]
rfc_testing_label = rfc_test_data[['Survived']]

rfc = RandomForestClassifier(n_estimators=150)
rfc.fit(rfc_training_features, rfc_training_label)
rfc_predicted = rfc.predict(rfc_testing_features)

rfc_predicted_df = rfc_testing_label.copy()
rfc_predicted_df['Survived'] = rfc_predicted
rfc_predicted_df
```

[ ]:

```
    Survived
0          0
1          1
2          0
3          1
4          0
..       ...
71         0
72         0
73         0
74         1
75         0

[70 rows x 1 columns]
```

[ ]:

```
#calculate the acurracy score of the rfc model
accuracy_score(rfc_testing_label, rfc_predicted)
```

[ ]: 0.7428571428571429

[ ]:

```
#calculate the f1 score of the rfc model
f1_score(rfc_testing_label, rfc_predicted)
```

[ ]: 0.689655172413793

[ ]:

```
#calculate the recall score of the rfc model
recall_score(rfc_testing_label, rfc_predicted)
```

[ ]: 0.6666666666666666

[ ]:

```
#calculate the precision score of the rfc model
precision_score(rfc_testing_label, rfc_predicted)
```

[ ]: 0.7142857142857143

[ ]:
```
#cross validation (logistic regression model)
cv_scores_logistic = cross_val_score(logisticReg, logistic_training_features,␣
↪logistic_training_label)
cv_scores_logistic.mean()
```

[ ]: 0.7867549668874172

[ ]:
```
#cross validation (knn model)
cv_scores_knn = cross_val_score(KNN, knn_training_features, knn_training_label)
cv_scores_knn.mean()
```

[ ]: 0.8278145695364237

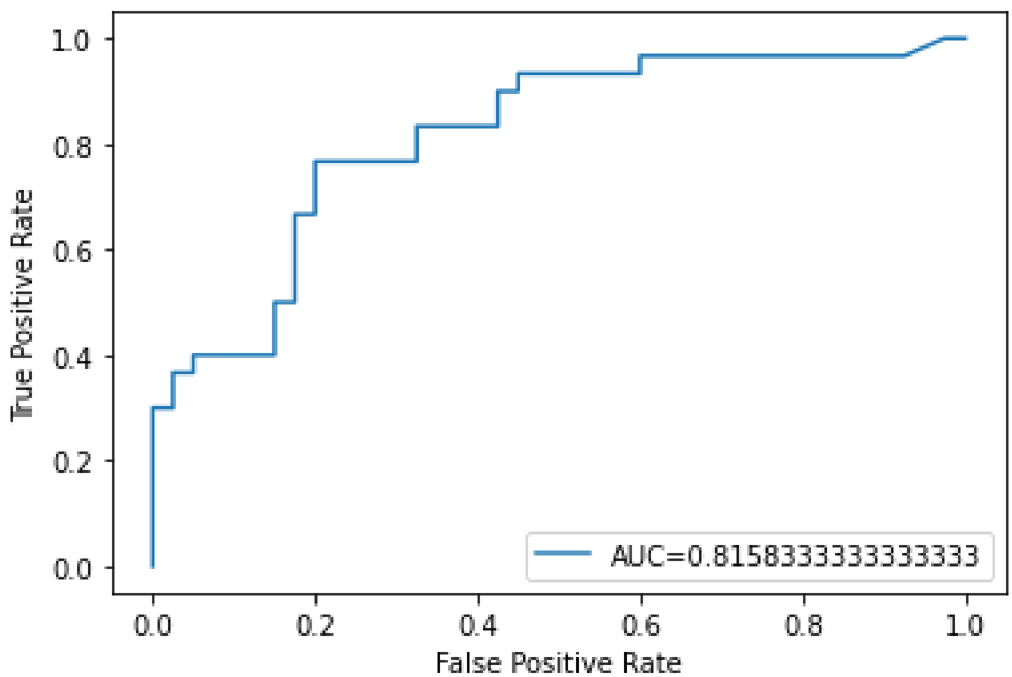
[ ]:
```
#cross validation (rfc model)
cv_scores_rfc = cross_val_score(rfc, rfc_training_features, rfc_training_label)
cv_scores_rfc.mean()
```

[ ]: 0.8172185430463577

[ ]:
```
#Compare models
```

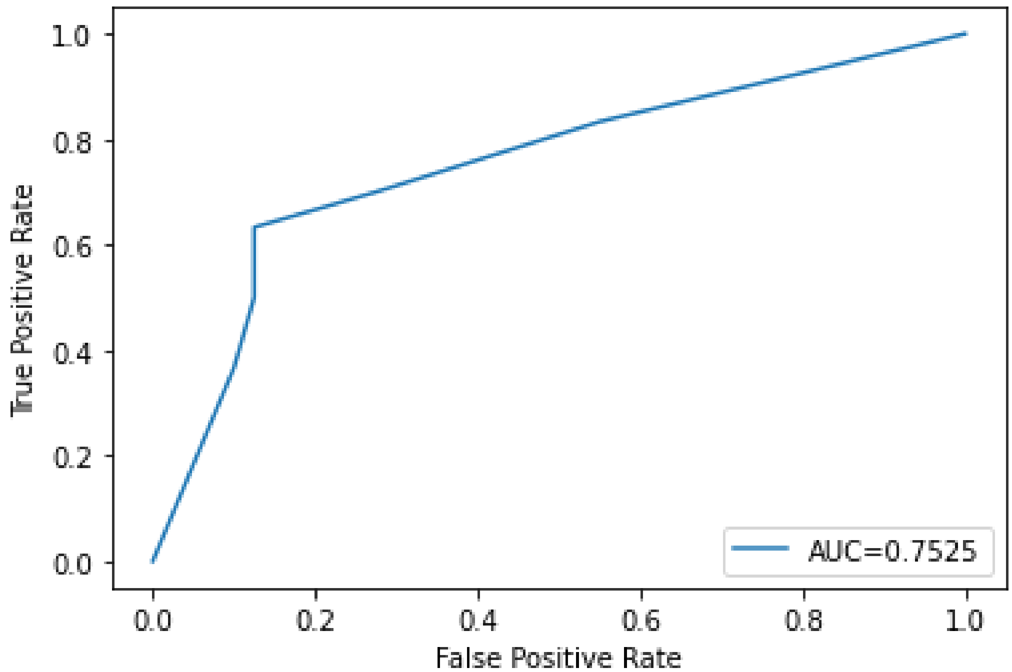
[ ]:
```
# ROC curve (logstic model)
label_logistic_predicted = logisticReg.
↪predict_proba(logistic_testing_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(logistic_testing_label,␣
↪label_logistic_predicted)
auc = metrics.roc_auc_score(logistic_testing_label, label_logistic_predicted)

plt.plot(fpr,tpr,label="AUC="+str(auc))
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend(loc=4)
plt.show()
```



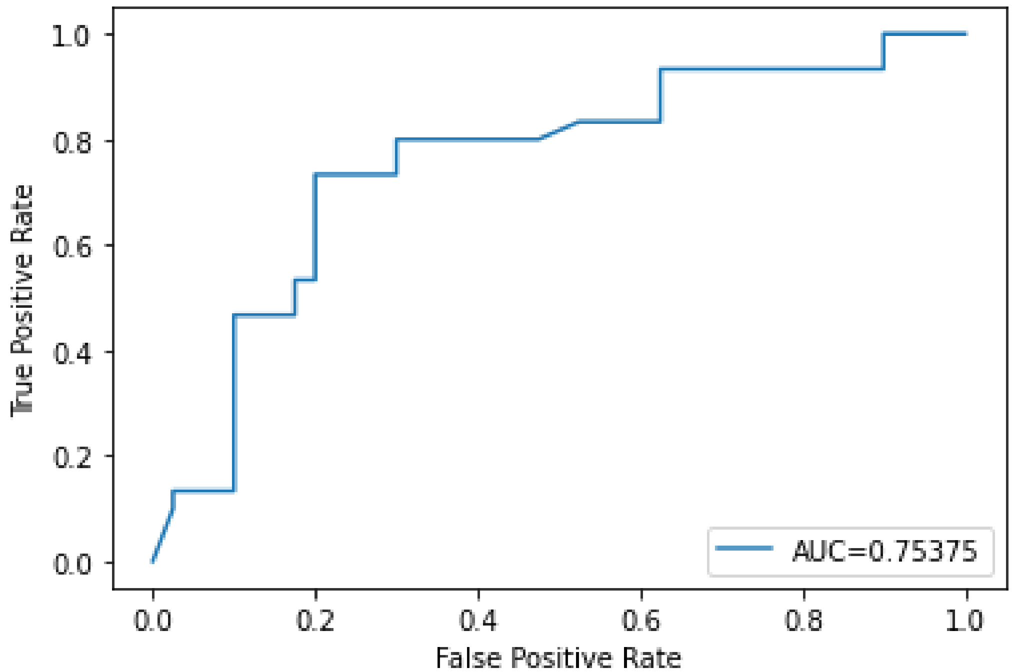
[ ]:
```
# ROC curve (KNN model)
label_knn_predicted = KNN.predict_proba(knn_testing_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(knn_testing_label, label_knn_predicted)
auc = metrics.roc_auc_score(knn_testing_label, label_knn_predicted)

plt.plot(fpr,tpr,label="AUC="+str(auc))
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend(loc=4)
plt.show()
```



[ ]:
```
# ROC curve (rfc model)
label_rfc_predicted = rfc.predict_proba(rfc_testing_features)[::,1]
fpr, tpr, _ = metrics.roc_curve(rfc_testing_label, label_rfc_predicted)
auc = metrics.roc_auc_score(rfc_testing_label, label_rfc_predicted)

plt.plot(fpr,tpr,label="AUC="+str(auc))
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend(loc=4)
plt.show()
```



We used ROC curve to compare performance of each model. Since logistic regression model has the biggest AUC(Area Under Curve) value, so we can say that logistic regression model is the best to use out of three models.