Assignment 3

Data preparation, exploration, visualization

Training data and test datasets are loaded. There are 12 columns in the training dataset.

Then I used isnull function to review how many values are missing in both datasets. There are a lot of null entries in age, and way too many in Cabin column (687/891 for training set). For that reason, the age data will need to be imputed later to fillna, and the Cabin column will be dropped for training.

I also grouped the data by gender and calculate mean survival, it is obvious that gender has large impact on whether one survived. Two histograms were made to display number of people in each Pclass and their age distribution as well as survival status (color coded). Three line-plots were also generated to display survival numbers for different passenger classes and embarked places. These plots show that there is a correlation between passenger class and survival, and embarked places and age are also related to survival.

A few unrelated or severely incomplete features were dropped: 'Ticket', 'Cabin', 'Name', 'PassengerId'. The Sex feature is transformed to numerical data by mapping Female:0 and Male:1. The null values in Age column are replaced by mean age and the empty Embarked entries are filled using the mode. The embarked feature is also mapped to integers, 'S': 0, 'C': 1, 'Q':2.

Finally, I used standard scaler to transform both training and testing datasets.

Review research design and modeling methods

The cleaned and transformed training dataset is used to train two different classification models:

Logistic regression and Naïve Bayes classification. Sklearn module is imported and predictions were made using the trained models for the test dataset.

Review results, evaluate models

The cross-validation is applied, with 5-fold, and the scoring method is “roc_auc” – area under the ROC curve. The mean score is calculated for both models.

The logistic regression model’s cross-validation mean AUC is 0.851 and the Bayes classification yield AUC 0.831, lower than the regression results.

I also evaluated the coefficients in the logistic regression model for each feature. The coefficients show Pclass, Gender and Age are most important factors affecting survival. Gender is the most important factor.

Implementation and programming as evidenced by Kaggle submission

The code is in the appendix. Two models were submitted to Kaggle and both yield score over 0.75, meaning that over 75% of the survivals were correctly predicted.

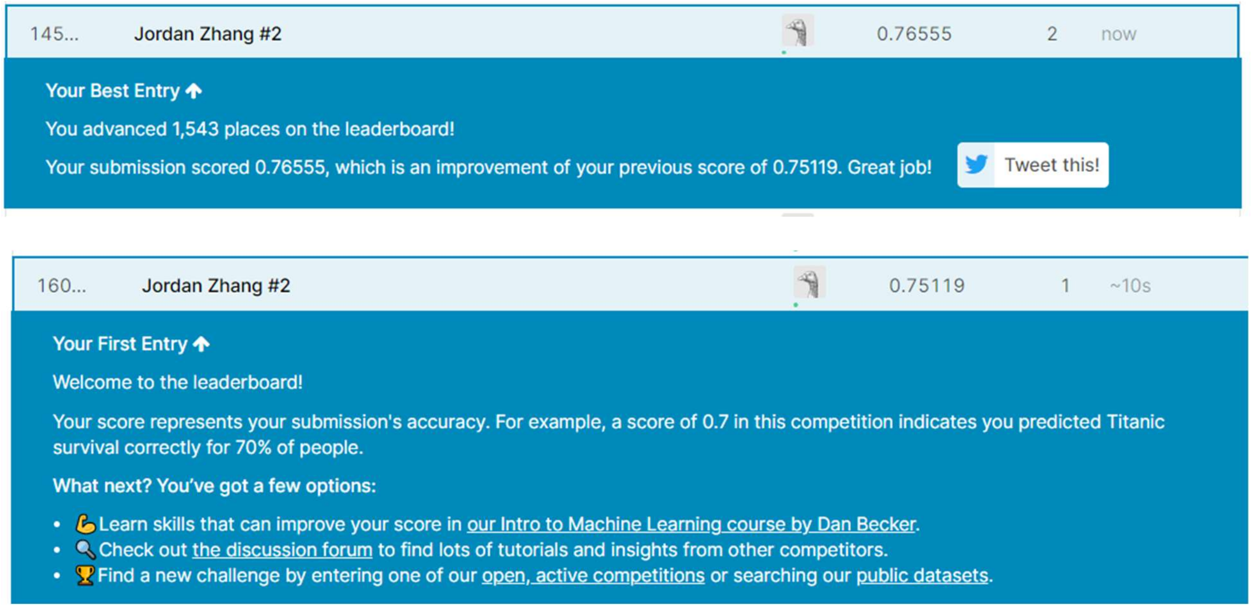
Exposition, problem description, and management recommendations

Regarding the management problem, imagine that you are providing evidence regarding characteristics associated with survival on this ill-fated voyage to a historian writing a book. Which of the two modeling methods would you recommend and why?

I will recommend the logistic regression model, as it is straightforward to understand, and yield better prediction accuracies than the Bayes model. The coefficients can be directly associated with each evaluated factor (scaled) - the characteristics with larger abs(coefficient) have larger impact on chance of survival.

Appendix

KAGGLE:



In [184]:

```
# This Python 3 environment comes with many helpful analytics libraries instal
led
# It is defined by the kaggle/python docker image: https://github.com/kaggle/d
ocker-python
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will lis
t all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.
```

```
/kaggle/input/titanic/train.csv
/kaggle/input/titanic/gender_submission.csv
/kaggle/input/titanic/test.csv
```

In [185]:

```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# machine learning
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score
#import data and combine in a list, so that both sets can be processed at the
 same time.
train_df = pd.read_csv('../input/titanic/train.csv')
test_df = pd.read_csv('../input/titanic/test.csv')
combine = [train_df, test_df]
```

In [186]:
```
train_df.head()
```

Out[186]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

In [187]:
```
train_df.isnull().sum()
#a lot of null entry in age. Too many in Cabin!
```

Out[187]:
```
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
```

In [188]:
```
test_df.isnull().sum()
```

Out[188]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

In [189]:
```
train_df.describe()
```

Out[189]:

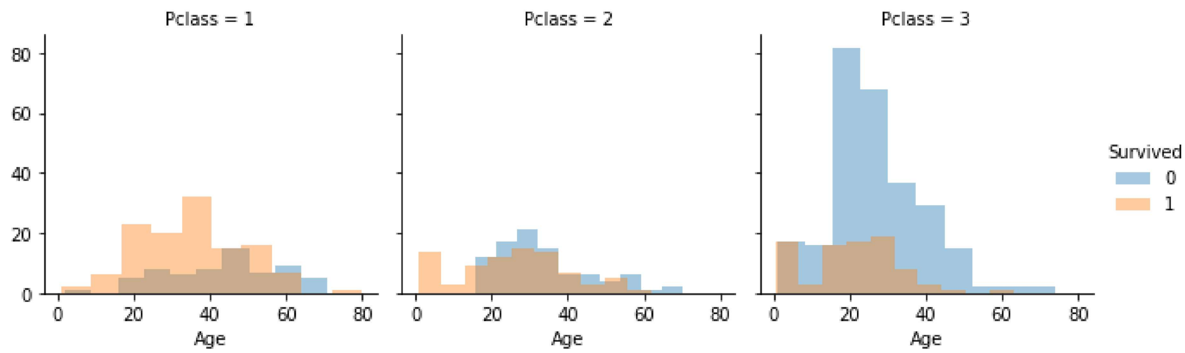
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [190]:
```
train_df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().sort_val
ues(by='Survived', ascending=False)
```

Out[190]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

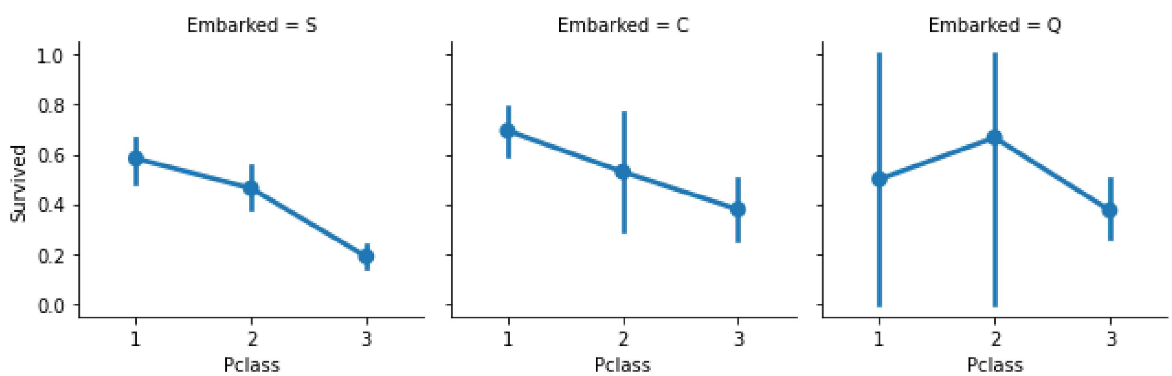
In [191]:
```
#visualization here
grid = sns.FacetGrid(train_df, col='Pclass', hue='Survived')
grid.map(plt.hist, 'Age', alpha=.4, bins=10)
grid.add_legend();
```



In [192]:
```
grid = sns.FacetGrid(train_df, col='Embarked')
#grid = sns.FacetGrid(train_df, row='Embarked', size=2.2, aspect=1.6)
grid.map(sns.pointplot, 'Pclass', 'Survived')
grid.add_legend()
```

```
/opt/conda/lib/python3.6/site-packages/seaborn/axisgrid.py:728: UserWarning:
Using the pointplot function without specifying `order` is likely to produce
an incorrect plot.
  warnings.warn(warning)
```

Out[192]: <seaborn.axisgrid.FacetGrid at 0x7fc4717427b8>



In [193]:

```
#drop a few unrelated or severely incomplete features
train_df1 = train_df.drop(['Ticket', 'Cabin','Name','PassengerId'],axis=1)
test_df1 = test_df.drop(['Ticket', 'Cabin','Name','PassengerId'],axis=1)
combine = [train_df1, test_df1]
train_df1.head()
```

Out[193]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	male	22.0	1	0	7.2500	S
1	1	1	female	38.0	1	0	71.2833	C
2	1	3	female	26.0	0	0	7.9250	S
3	1	1	female	35.0	1	0	53.1000	S
4	0	3	male	35.0	0	0	8.0500	S

In [194]:

```
#convert sex string to numbers and impute data
#impute age and fare using mean and embarked using mode.
for df in combine:
    df['Sex'] = df['Sex'].map( {'female': 1, 'male': 0} )
    df['Age'].fillna(df['Age'].mean(),inplace=True)
    df['Fare'].fillna(df['Fare'].mean(),inplace=True)
    df['Embarked'].fillna(df['Embarked'].mode()[0],inplace=True)
```

In [195]:

```
test_df1.head()
```

Out[195]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	0	34.5	0	0	7.8292	Q
1	3	1	47.0	1	0	7.0000	S
2	2	0	62.0	0	0	9.6875	Q
3	3	0	27.0	0	0	8.6625	S
4	3	1	22.0	1	1	12.2875	S

In [196]:

```
#convert Embark feature to number
for df in combine:
    df['Embarked'] = df['Embarked'].map( {'S': 0, 'C': 1, 'Q':2} ).astype(int)
    df['Age']=df['Age'].astype(int)

train_df1.head()
```

Out[196]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22	1	0	7.2500	0
1	1	1	1	38	1	0	71.2833	1
2	1	3	1	26	0	0	7.9250	0
3	1	1	1	35	1	0	53.1000	0
4	0	3	0	35	0	0	8.0500	0

In [197]:
```
# now ready to scale the data and then start modeling!
X_train=train_df1.drop(['Survived'],axis=1)
Y_train=train_df1['Survived']

from sklearn.preprocessing import StandardScaler
stds=StandardScaler()
X_train=pd.DataFrame(stds.fit_transform(X_train),index=X_train.index, columns=
X_train.columns)
test_df1=pd.DataFrame(stds.fit_transform(test_df1),index=test_df1.index, colum
ns=test_df1.columns)
```

In [198]:
```
# traing set now X_train. Test set to predict: test_df1
```

In [199]:
```
logreg = LogisticRegression()
logreg.fit(X_train, Y_train)
```

Out[199]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [200]:
```
Y_predreg = logreg.predict(test_df1)
```

In [201]:
```
regscores=cross_val_score(logreg, X_train, Y_train, cv=5, scoring='roc_auc')
```

In [202]:
```
regscores.mean()
#regression crossvalidation mean auc is 0.851
```

Out[202]:
```
0.8506566906778665
```

In [203]:
```
#Bayes classification
gaussian = GaussianNB()
gaussian.fit(X_train, Y_train)
Y_pred_Gaus = gaussian.predict(test_df1)
regscores=cross_val_score(gaussian, X_train, Y_train, cv=5, scoring='roc_auc')
regscores.mean()
#bayes classification yield auc 0.831, lower than the regression results.
```

Out[203]:
```
0.8309066716580386
```

In [211]:
```
X_train.columns
```

Out[211]:
```
Index(['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked'], dtype
='object')
```

In [207]:
```
logreg.coef_
```

Out[207]:
```
array([[-0.92146021,  1.28325114, -0.50709109, -0.35608979, -0.06970369,
         0.11430806,  0.15836238]])
```

In [ ]:
```
# the coefficients show Pclass, Gender and Age are most important factors affe
cting survival.
#Gender is the most important factor.
```