Predicting The Survival of Titanic Passengers

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1. Introduction

In this project, we are applying logistic regression model on famous Titanic dataset, in order to predict survival of passengers. The dataset is from Kaggle and includes the following:

- Pclass: Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)
- Sex: Sex
- Age: Age in years
- Sibsp: # of siblings / spouses aboard the Titanic
- Parch: # of parents / children aboard the Titanic
- Ticket: Ticket number
- Fare: Passenger fare
- Cabin: Cabin number
- Embarked: Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton
- Target variable: Survived: Survival (0 = No, 1 = Yes)

2. Data & Library

In [29]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [30]:
```
train = pd.read_csv('Train_Titanic.csv')
newdata = pd.read_csv('Test_Titanic.csv')  #newwdata has no target variable
```

In [31]:
```
# index reset
train.set_index('PassengerId')
newdata.set_index('PassengerId')
```

Out[31]:

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...
1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

418 rows × 10 columns

In [32]:
```
print(train.shape)
print(newdata.shape)
```

```
(891, 12)
(418, 11)
```

3. Methodology

a.Explanatory Analysis & Data Cleaning

Let's take a look at % of survived and that of not survived from train dataset. 38.38% of total passengers survived.

In [33]:
```
print("Total Passengers=", len(train))
print("Percentage Survived =", 1.*len(train[train['Survived']== 1])/len(train)*100.0, "%")
print("Percentage who did not survive =", 1.*len(train[train['Survived']== 0])/len(train)*100.0, "%")
```

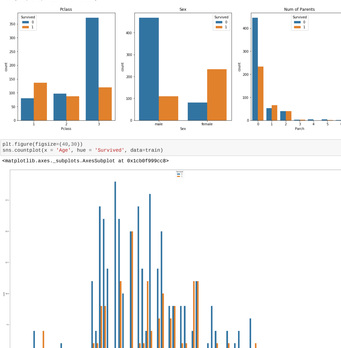
```
Total Passengers= 891
Percentage Survived = 38.38383838383838 %
Percentage who did not survive = 61.61616161616161 %
```

Using simple plots, we are going to visualize key variables such as *pclass*, sex and Parch (how many parents onboard)

From bar charts, it seems that passengers who are first class / female / with parents have a higher chance of survival. Also, from the age histogram we can see that passengers that are young show higher number of survival.

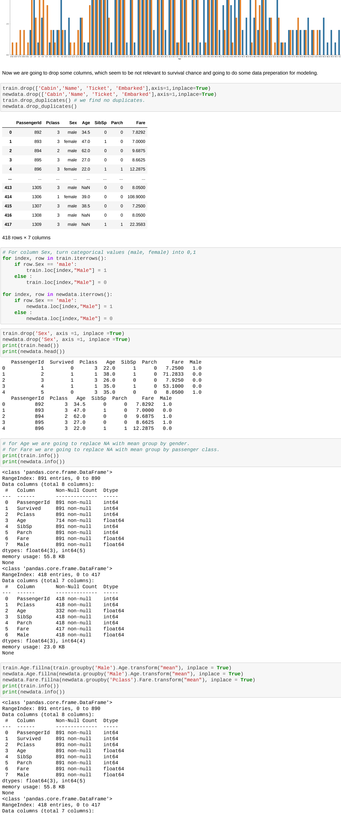
In [34]:
```
plt.figure(figsize=[10,6])
plt.subplot(231)
sns.countplot(x = 'Pclass', hue = 'Survived', data=train)
plt.title("Pclass")
plt.subplot(232)
sns.countplot(x = 'Sex', hue = 'Survived', data=train)
plt.title("Sex")
plt.subplot(233)
sns.countplot(x = 'Parch', hue = 'Survived', data=train)
plt.title("Num of Parents")
```

Out[34]:
```
Text(0.5, 1.0, 'Num of Parents')
```



In [35]:
```
plt.figure(figsize=(40,30))
sns.countplot(x = 'Age', hue = 'Survived', data=train)
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c0df99cc0>
```



Now we are going to drop some columns, which seem to be not relevant to survival chance and going to do some data preperation for modeling.

In [36]:
```
train.drop(['Cabin','Name', 'Ticket', 'Embarked'],axis=1,inplace=True)
newdata.drop(['Cabin','Name', 'Ticket', 'Embarked'],axis=1,inplace=True)
train.drop_duplicates() # we find no duplicates.
newdata.drop_duplicates()
```

Out[36]:

	Passengerid	Pclass	Sex	Age	SibSp	Parch	Fare
0	892	3	male	34.5	0	0	7.8292
1	893	3	female	47.0	1	0	7.0000
2	894	2	male	62.0	0	0	9.6875
3	895	3	male	27.0	0	0	8.6625
4	896	3	female	22.0	1	1	12.2875
...	...	...	...	...	...	...	...
413	1305	3	male	NaN	0	0	8.0500
414	1306	1	female	39.0	0	0	108.9000
415	1307	3	male	38.5	0	0	7.2500
416	1308	3	male	NaN	0	0	8.0500
417	1309	3	male	NaN	1	1	22.3583

418 rows × 7 columns

In [37]:
```
# For column Sex, turn categorical values (male, female) into 0,1
for index, row in train.iterrows():
    if row.Sex == 'male':
        train.loc[index,"Male"] = 1
    else:
        train.loc[index,"Male"] = 0

for index, row in newdata.iterrows():
    if row.Sex == 'male':
        newdata.loc[index,"Male"] = 1
    else:
        newdata.loc[index,"Male"] = 0
```

In [38]:
```
train.drop('Sex', axis =1, inplace =True)
newdata.drop('Sex', axis =1, inplace =True)
print(train.head())
print(newdata.head())
```

```
   PassengerId  Survived  Pclass   Age  SibSp  Parch     Fare  Male
0            1         0       3  22.0      1      0   7.2500   1.0
1            2         1       1  38.0      1      0  71.2833   0.0
2            3         1       3  26.0      0      0   7.9250   0.0
3            4         1       1  35.0      1      0  53.1000   0.0
4            5         0       3  35.0      0      0   8.0500   1.0
   Passengerid  Pclass   Age  SibSp  Parch     Fare  Male
0          892       3  34.5      0      0   7.8292   1.0
1          893       3  47.0      1      0   7.0000   0.0
2          894       2  62.0      0      0   9.6875   1.0
3          895       3  27.0      0      0   8.6625   1.0
4          896       3  22.0      1      1  12.2875   0.0
```

In [39]:
```
# for Age we are going to replace NA with mean group by gender.
# for Fare we are going to replace NA with mean group by passenger class.
print(train.info())
print(newdata.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Age          714 non-null    float64
 4   SibSp        891 non-null    int64
 5   Parch        891 non-null    int64
 6   Fare         891 non-null    float64
 7   Male         891 non-null    float64
dtypes: float64(3), int64(5)
memory usage: 55.8 KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Passengerid  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Age          332 non-null    float64
 3   SibSp        418 non-null    int64
 4   Parch        418 non-null    int64
 5   Fare         417 non-null    float64
 6   Male         418 non-null    float64
dtypes: float64(3), int64(4)
memory usage: 23.0 KB
None
```

In [40]:
```
train.Age.fillna(train.groupby('Male').Age.transform("mean"), inplace = True)
newdata.Age.fillna(newdata.groupby('Male').Age.transform("mean"), inplace = True)
newdata.Fare.fillna(newdata.groupby('Pclass').Fare.transform("mean"), inplace = True)
print(train.info())
print(newdata.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Age          891 non-null    float64
 4   SibSp        891 non-null    int64
 5   Parch        891 non-null    int64
 6   Fare         891 non-null    float64
 7   Male         891 non-null    float64
dtypes: float64(3), int64(5)
memory usage: 55.8 KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Age          418 non-null    float64
 3   SibSp        418 non-null    int64
 4   Parch        418 non-null    int64
 5   Fare         418 non-null    float64
 6   Male         418 non-null    float64
dtypes: float64(3), int64(4)
memory usage: 23.0 KB
None
```

b.Logistics Regression

In [41]:
```
X = train.drop('Survived',axis=1).values
y = train['Survived'].values
```

In [42]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=10)
```

In [43]:
```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

```
C:\Users\hanah\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:940: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[43]:
```
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=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

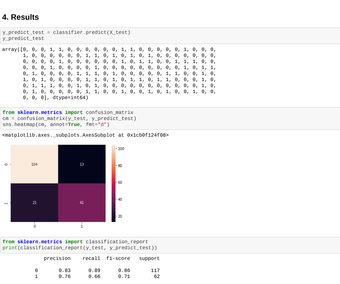
4. Results

In [44]:
```
y_predict_test = classifier.predict(X_test)
y_predict_test
```

Out[44]:
```
array([0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 1], dtype=int64)
```

In [45]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predict_test)
sns.heatmap(cm, annot=True, fmt='d')
```

Out[45]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c0df124f08>
```



In [46]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_predict_test))
```

```
              precision    recall  f1-score   support

           0       0.83      0.89      0.86       117
           1       0.76      0.66      0.71        62

    accuracy                           0.81       179
   macro avg       0.80      0.78      0.78       179
weighted avg       0.81      0.81      0.81       179
```

Now lets apply our trained model onto newdata.

In [47]:
```
y_predict = classifier.predict(newdata)
```

In [48]:
```
result = np.array(y_predict)
print ("Total Passengers (from New Data) =", len(newdata))
print ("Survived =", np.count_nonzero(result==1))
print ("Not Survived =", np.count_nonzero(result==0))
```

```
Total Passengers (from New Data) = 418
Survived = 254
Not Survived = 164
```

5. Discussion & Conclusion

From the confusion matrix above, we know that our model correctly predicted 145 cases out of total 179 observations. That is on avarnage, 81% accuracy. Lastly,when new data is given, the model predicted 254 passengers would survive out of total 418 .