# Kinshuk Jagdev

# Logistic Regression

## Task

Build a predictive model that answers the question: “what sorts of people were more likely to survive?” using passenger data (ie name, age, gender, socio-economic class, etc).

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
```

# 1: Data Loading

First and Foremost Step is loading the data. We will use **Pandas** library to load the data into pandas **Dataframe**.

**Main Library Used:** Pandas

In [2]:

```
#importing pandas library
import pandas as pd

#importing numpy library
import numpy as np
```

In [3]:

```
#loading training dataset into dataframe

df_train = pd.read_csv('E:\\ml data\\train.csv')
```

In [4]:

```
#previewing the training data

df_train.head()
```

Out[4]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare |
|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 |

In [5]:

```
#obtaining data information

df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

## Analysis: Training dataset has 891 Entries

In [6]:

```
#loading the test data into dataframe

df_test = pd.read_csv('E:\\ml data\\test.csv')
```

In [7]:

```
#previewing the test data

df_test.head()
```

Out[7]:

| | PassengerId | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Emba |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 892 | 3 | Kelly, Mr. James | male | 34.5 | 0 | 0 | 330911 | 7.8292 | NaN | |
| 1 | 893 | 3 | Wilkes, Mrs. James (Ellen Needs) | female | 47.0 | 1 | 0 | 363272 | 7.0000 | NaN | |
| 2 | 894 | 2 | Myles, Mr. Thomas Francis | male | 62.0 | 0 | 0 | 240276 | 9.6875 | NaN | |
| 3 | 895 | 3 | Wirz, Mr. Albert | male | 27.0 | 0 | 0 | 315154 | 8.6625 | NaN | |
| 4 | 896 | 3 | Hirvonen, Mrs. Alexander (Helga E Lindqvist) | female | 22.0 | 1 | 1 | 3101298 | 12.2875 | NaN | |

In [8]:

```
#obtaining test data info

df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            332 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           417 non-null float64
Cabin          91 non-null object
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

### Analysis: Testing dataset has 418 Entries

# 2: Data Cleaning and Filling Null Values

We will be dropping **Name**, **Ticket** and **PassengerId** variables, as they are mostly unigue and have no significance in analysis

In [9]:

```
df_train = df_train.drop(['Name', 'Ticket', 'PassengerId'], 1)
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
Survived    891 non-null int64
Pclass      891 non-null int64
Sex         891 non-null object
Age         714 non-null float64
SibSp       891 non-null int64
Parch       891 non-null int64
Fare        891 non-null float64
Cabin       204 non-null object
Embarked    889 non-null object
dtypes: float64(2), int64(4), object(3)
memory usage: 62.8+ KB
```

In [10]:

```
passenger_data = df_test['PassengerId']
df_test = df_test.drop(['Name', 'Ticket', 'PassengerId'], 1)
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 8 columns):
Pclass      418 non-null int64
Sex         418 non-null object
Age         332 non-null float64
SibSp       418 non-null int64
Parch       418 non-null int64
Fare        417 non-null float64
Cabin       91 non-null object
Embarked    418 non-null object
dtypes: float64(2), int64(3), object(3)
memory usage: 26.2+ KB
```

## Getting the count of null values

In [11]:

```
df_train.isnull().sum()
```

Out[11]:

```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Cabin       687
Embarked      2
dtype: int64
```

## Analysis: Age and Cabin have 177 and 687 null values, while Embarked has only 2 null values

Since **Cabin** has roughly **77%** missing data we will **drop** this column

**Age** column has roughly **20%** missing data, we will simply fill null values with **mean** age values

In [12]:

```
df_train = df_train.drop(['Cabin'], 1)

#viewing new data
df_train.head()
```

Out[12]:

| | 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 |

## Filling null values in Embarked Column

This column has three stations from which people have boarded, so we will simply fill the null values with most common station, i.e. S

In [13]:

```
df_train["Embarked"].fillna(df_train['Embarked'].value_counts().idxmax(), inplace=True)
```

## Filling null values in Age Column

Filling mean values

In [14]:

```
df_train['Age'].fillna(df_train['Age'].mean(skipna=True), inplace = True)
```

# Analysing new data

In [15]:

```
df_train.isnull().sum()
```

Out[15]:

```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

**Conclusion:** : Data now has no null values, so we will repeat same process for testing data

In [16]:

```
df_test.isnull().sum()
```

Out[16]:

```
Pclass        0
Sex           0
Age          86
SibSp         0
Parch         0
Fare          1
Cabin       327
Embarked      0
dtype: int64
```

In [17]:

```
df_test = df_test.drop(['Cabin'], 1)

#viewing new data
df_test.head()
```

Out[17]:

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

In [18]:

```
df_test["Embarked"].fillna(df_test['Embarked'].value_counts().idxmax(), inplace=True)
```

In [19]:

```
df_test['Age'].fillna(df_test['Age'].mean(skipna=True), inplace = True)
```

## Fare Column

Fare Column has a missing value in test data, but not in train data, so we will simply replace it with mean value.

In [20]:

```
df_test['Fare'].fillna(df_test['Fare'].mean(skipna=True), inplace = True)
```

## Checking new data

In [21]:

```
df_test.isnull().sum()
```

Out[21]:

```
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

# 3: Dealing with Categorical Variables

We have SibSp and Parch variables, which tells us if an individual is travelling with family. So, we will simply create a variable, **travelling_alone** to optimize our data.

In [22]:

```
#creating travel_alone variable

df_train['travel_alone']=np.where((df_train["SibSp"]+df_train["Parch"])>0, 0, 1)
df_train.drop('SibSp', axis=1, inplace=True)
df_train.drop('Parch', axis=1, inplace=True)
```

### Getting Dummy Variables

The Dummy Variables enable us to use a single regression equation to represent multiple groups

In [23]:

```
#creating dummy variables bor "Sex" column

dum1 = pd.get_dummies(df_train, columns=['Sex'], prefix = 'Sex')
df_train = pd.concat([dum1], 1)
df_train.head()
```

Out[23]:

| | Survived | Pclass | Age | Fare | Embarked | travel_alone | Sex_female | Sex_male |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 3 | 22.0 | 7.2500 | S | 0 | 0 | 1 |
| 1 | 1 | 1 | 38.0 | 71.2833 | C | 0 | 1 | 0 |
| 2 | 1 | 3 | 26.0 | 7.9250 | S | 1 | 1 | 0 |
| 3 | 1 | 1 | 35.0 | 53.1000 | S | 0 | 1 | 0 |
| 4 | 0 | 3 | 35.0 | 8.0500 | S | 1 | 0 | 1 |

In [24]:

```
#dropping extra variable

df_train = df_train.drop(['Sex_female'], 1)
```

In [25]:

```
#checking the data

df_train.head()
```

Out[25]:

| | Survived | Pclass | Age | Fare | Embarked | travel_alone | Sex_male |
|---|---|---|---|---|---|---|---|
| 0 | 0 | 3 | 22.0 | 7.2500 | S | 0 | 1 |
| 1 | 1 | 1 | 38.0 | 71.2833 | C | 0 | 0 |
| 2 | 1 | 3 | 26.0 | 7.9250 | S | 1 | 0 |
| 3 | 1 | 1 | 35.0 | 53.1000 | S | 0 | 0 |
| 4 | 0 | 3 | 35.0 | 8.0500 | S | 1 | 1 |

In [26]:

```
#dummy variables for class and embarked variables

dm2=pd.get_dummies(df_train, columns=["Pclass","Embarked"])
dm2.head()
```

Out[26]:

| | Survived | Age | Fare | travel_alone | Sex_male | Pclass_1 | Pclass_2 | Pclass_3 | Embarked_C |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 22.0 | 7.2500 | 0 | 1 | 0 | 0 | 1 | 0 |
| 1 | 1 | 38.0 | 71.2833 | 0 | 0 | 1 | 0 | 0 | 1 |
| 2 | 1 | 26.0 | 7.9250 | 1 | 0 | 0 | 0 | 1 | 0 |
| 3 | 1 | 35.0 | 53.1000 | 0 | 0 | 1 | 0 | 0 | 0 |
| 4 | 0 | 35.0 | 8.0500 | 1 | 1 | 0 | 0 | 1 | 0 |

In [27]:

```
df_train = pd.concat([dm2], 1)
df_train.head()
```

Out[27]:

| | Survived | Age | Fare | travel_alone | Sex_male | Pclass_1 | Pclass_2 | Pclass_3 | Embarked_C |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 22.0 | 7.2500 | 0 | 1 | 0 | 0 | 1 | 0 |
| 1 | 1 | 38.0 | 71.2833 | 0 | 0 | 1 | 0 | 0 | 1 |
| 2 | 1 | 26.0 | 7.9250 | 1 | 0 | 0 | 0 | 1 | 0 |
| 3 | 1 | 35.0 | 53.1000 | 0 | 0 | 1 | 0 | 0 | 0 |
| 4 | 0 | 35.0 | 8.0500 | 1 | 1 | 0 | 0 | 1 | 0 |

## Repeating same steps for test data

In [28]:

```
df_test['travel_alone']=np.where((df_test["SibSp"]+df_test["Parch"])>0, 0, 1)
df_test.drop('SibSp', axis=1, inplace=True)
df_test.drop('Parch', axis=1, inplace=True)
```

**Dummy Variables** for **Test** data

In [29]:

```
dum1 = pd.get_dummies(df_test, columns=['Sex'], prefix = 'Sex')
df_test = pd.concat([dum1], 1)
df_test.head()
```

Out[29]:

| | Pclass | Age | Fare | Embarked | travel_alone | Sex_female | Sex_male |
|---|---|---|---|---|---|---|---|
| 0 | 3 | 34.5 | 7.8292 | Q | 1 | 0 | 1 |
| 1 | 3 | 47.0 | 7.0000 | S | 0 | 1 | 0 |
| 2 | 2 | 62.0 | 9.6875 | Q | 1 | 0 | 1 |
| 3 | 3 | 27.0 | 8.6625 | S | 1 | 0 | 1 |
| 4 | 3 | 22.0 | 12.2875 | S | 0 | 1 | 0 |

In [30]:

```
df_test = df_test.drop(['Sex_female'], 1)
```

In [31]:

```
df_test.head()
```

Out[31]:

| | Pclass | Age | Fare | Embarked | travel_alone | Sex_male |
|---|---|---|---|---|---|---|
| 0 | 3 | 34.5 | 7.8292 | Q | 1 | 1 |
| 1 | 3 | 47.0 | 7.0000 | S | 0 | 0 |
| 2 | 2 | 62.0 | 9.6875 | Q | 1 | 1 |
| 3 | 3 | 27.0 | 8.6625 | S | 1 | 1 |
| 4 | 3 | 22.0 | 12.2875 | S | 0 | 0 |

In [32]:

```
dm2=pd.get_dummies(df_test, columns=["Pclass","Embarked"])
dm2.head()
```

Out[32]:

| | Age | Fare | travel_alone | Sex_male | Pclass_1 | Pclass_2 | Pclass_3 | Embarked_C | Embarke |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 34.5 | 7.8292 | 1 | 1 | 0 | 0 | 1 | 0 | |
| 1 | 47.0 | 7.0000 | 0 | 0 | 0 | 0 | 1 | 0 | |
| 2 | 62.0 | 9.6875 | 1 | 1 | 0 | 1 | 0 | 0 | |
| 3 | 27.0 | 8.6625 | 1 | 1 | 0 | 0 | 1 | 0 | |
| 4 | 22.0 | 12.2875 | 0 | 0 | 0 | 0 | 1 | 0 | |

In [33]:

```
df_test = pd.concat([dm2], 1)
df_test.head()
```

Out[33]:

| | Age | Fare | travel_alone | Sex_male | Pclass_1 | Pclass_2 | Pclass_3 | Embarked_C | Embarke |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 34.5 | 7.8292 | 1 | 1 | 0 | 0 | 1 | 0 | |
| 1 | 47.0 | 7.0000 | 0 | 0 | 0 | 0 | 1 | 0 | |
| 2 | 62.0 | 9.6875 | 1 | 1 | 0 | 1 | 0 | 0 | |
| 3 | 27.0 | 8.6625 | 1 | 1 | 0 | 0 | 1 | 0 | |
| 4 | 22.0 | 12.2875 | 0 | 0 | 0 | 0 | 1 | 0 | |

Both test and training data now are in desired shape, now it is time to start with outlier treatment

# 4: Univariate Analysis

Since our data is in good condition now, it is time to start understanding data with Univariate Analysis. Univariate Analysis is the simplest analysis method.

**Main Library Used:** Seaborn

In [34]:

```
#importing necessary libraries for visualuzation of data

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

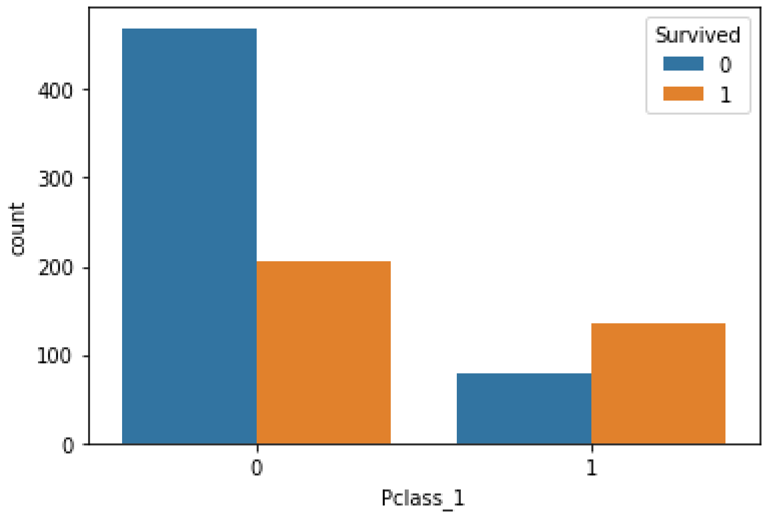
## Survival Based on Passenger Class

In [35]:

```
sns.countplot("Pclass_1", hue="Survived", data = df_train)
```

Out[35]:

<matplotlib.axes._subplots.AxesSubplot at 0x24021b93e48>

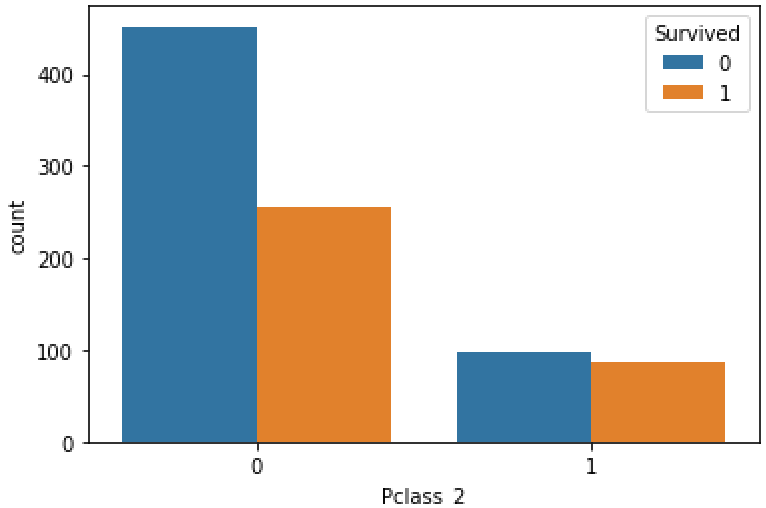



In [36]:

```
sns.countplot("Pclass_2", hue="Survived", data = df_train)
```

Out[36]:

<matplotlib.axes._subplots.AxesSubplot at 0x24021eb0248>

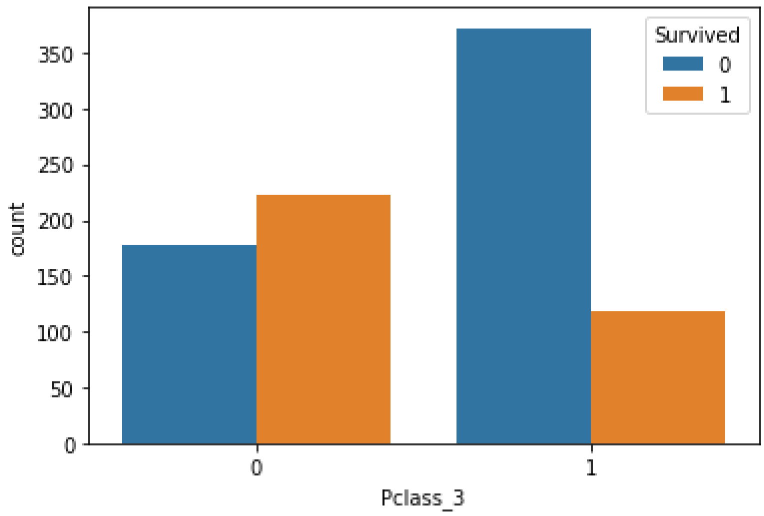


In [37]:

```
sns.countplot("Pclass_3", hue="Survived", data = df_train)
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24021f32208>
```




## Survival Percentages in Passenger Class

In [38]:

```
df_train[["Pclass_1", "Survived"]].groupby(['Pclass_1'], as_index=False).mean().sort_values
```

Out[38]:

| | Pclass_1 | Survived |
|---|---|---|
| 1 | 1 | 0.629630 |
| 0 | 0 | 0.305185 |

In [39]:

```
df_train[["Pclass_2", "Survived"]].groupby(['Pclass_2'], as_index=False).mean().sort_values
```

Out[39]:

| | Pclass_2 | Survived |
|---|---|---|
| 1 | 1 | 0.472826 |
| 0 | 0 | 0.360679 |

In [40]:

```
df_train[["Pclass_3", "Survived"]].groupby(['Pclass_3'], as_index=False).mean().sort_values
```

Out[40]:

| | Pclass_3 | Survived |
|---|---|---|
| 0 | 0 | 0.557500 |
| 1 | 1 | 0.242363 |

In [41]:

```
print('*'*50)
print("Class-1 Survival Rate: 62%")
print("Class-2 Survival Rate: 47%")
print("Class-3 Survival Rate: 24%")
print('*'*50)
```

```
**************************************************
Class-1 Survival Rate: 62%
Class-2 Survival Rate: 47%
Class-3 Survival Rate: 24%
**************************************************
```

**Analysis**: Class-1 Passengers have very high survival percentage while Class-3 Passengers have least survival rate

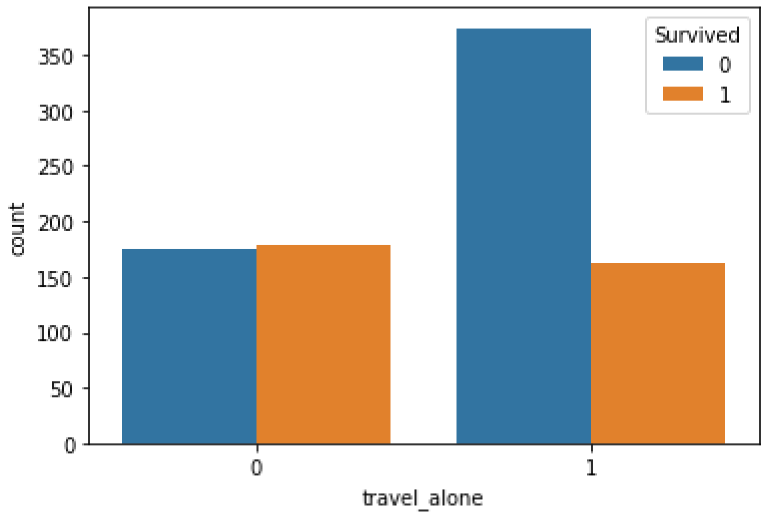
# Survival Based on If one is travelling alone

In [42]:

```
sns.countplot('travel_alone', hue='Survived', data=df_train)
```

Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24021fbf348>
```




### Survival Percentages in travel_alone

In [43]:

```
df_train[["travel_alone", "Survived"]].groupby(['travel_alone'], as_index=False).mean().sor
```

Out[43]:

| | travel_alone | Survived |
|---|---|---|
| 0 | 0 | 0.505650 |
| 1 | 1 | 0.303538 |

**Analysis:** Those travelling with families have had higher survival rate

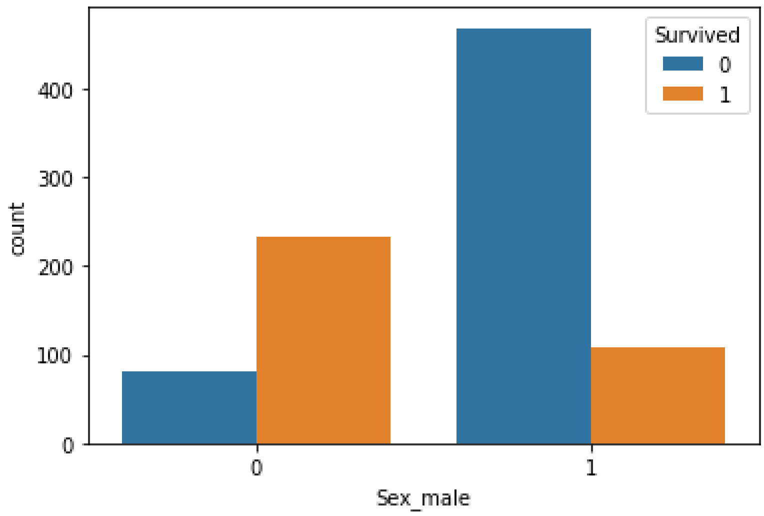
## Survival Based on Gender

In [44]:

```
sns.countplot('Sex_male', hue='Survived', data=df_train)
```

Out[44]:

<matplotlib.axes._subplots.AxesSubplot at 0x2402202d388>




### Survival Percentages in Gender

In [45]:

```
df_train[["Sex_male", "Survived"]].groupby(['Sex_male'], as_index=False).mean().sort_values
```

Out[45]:

| | Sex_male | Survived |
|---|---|---|
| 0 | 0 | 0.742038 |
| 1 | 1 | 0.188908 |

**Analysis:** Females have higher survival rate than Males

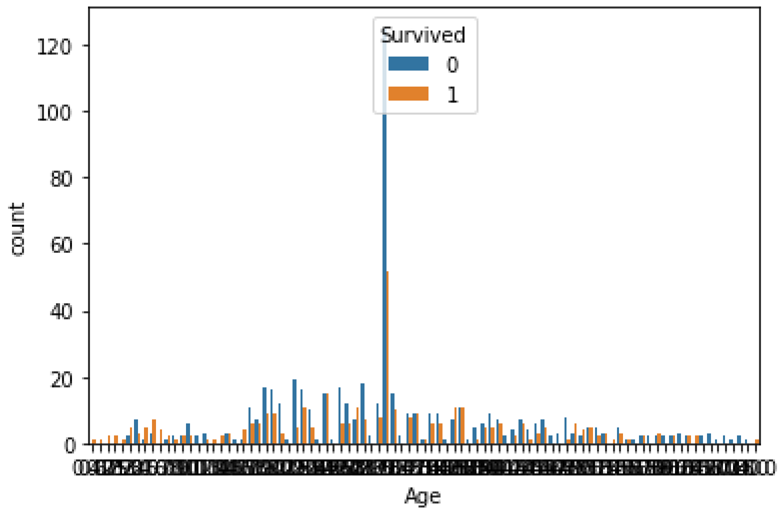
## Survival Based on Age

In [46]:

```
sns.countplot('Age', hue='Survived', data=df_train)
```

Out[46]:

<matplotlib.axes._subplots.AxesSubplot at 0x24022095888>



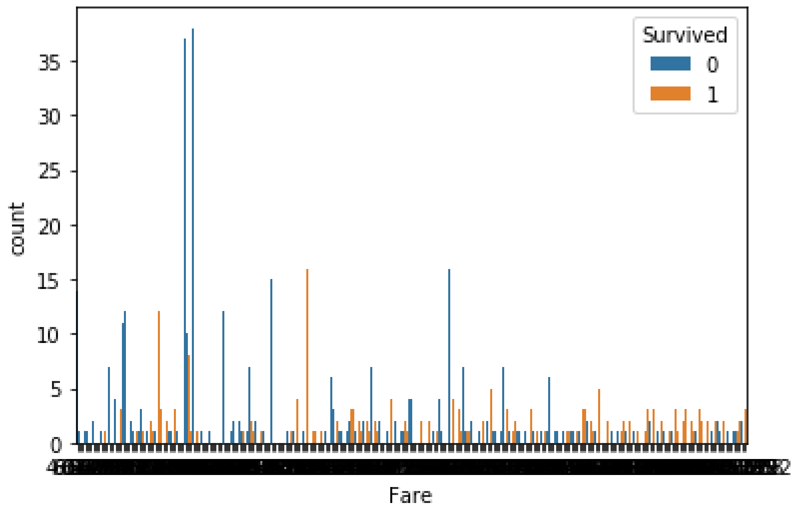

## Survival Based on Fare

In [47]:

```
sns.countplot('Fare', hue='Survived', data=df_train)
```

Out[47]:

<matplotlib.axes._subplots.AxesSubplot at 0x24022399288>



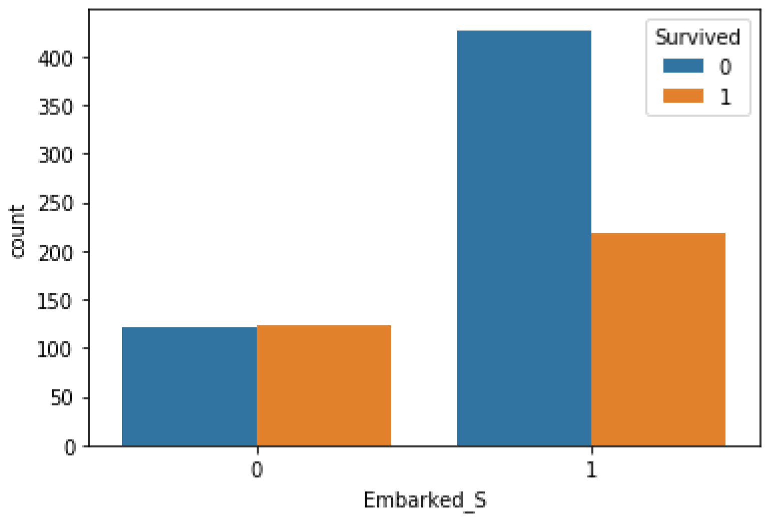

## Survival Based on Embarkment

In [48]:

```
sns.countplot("Embarked_S", hue="Survived", data = df_train)
```

Out[48]:

<matplotlib.axes._subplots.AxesSubplot at 0x24022c79ec8>

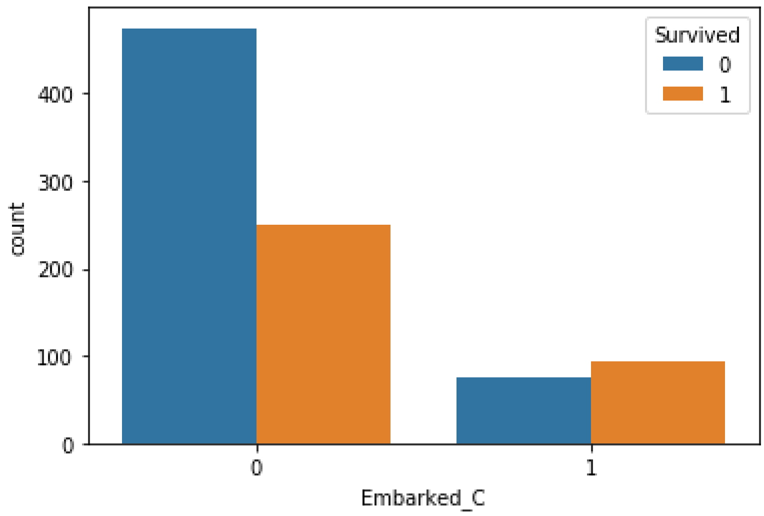


In [49]:

```
sns.countplot("Embarked_C", hue="Survived", data = df_train)
```

Out[49]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24022ba7d08>
```

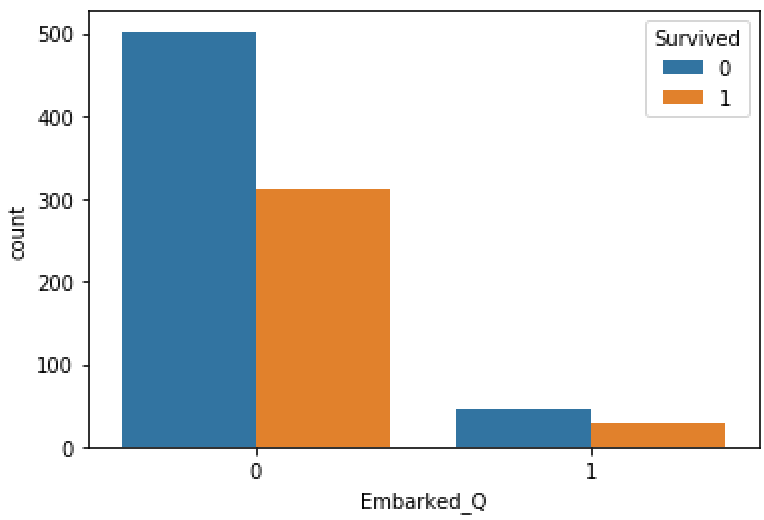



In [50]:

```
sns.countplot("Embarked_Q", hue="Survived", data = df_train)
```

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24022d1df88>
```




# Survival Percentages in Different Boarding Locations

In [51]:

```
df_train[["Embarked_C", "Survived"]].groupby(['Embarked_C'], as_index=False).mean().sort_va
```

Out[51]:

| | Embarked_C | Survived |
|---|---|---|
| 1 | 1 | 0.553571 |
| 0 | 0 | 0.344398 |

In [52]:

```
df_train[["Embarked_S", "Survived"]].groupby(['Embarked_S'], as_index=False).mean().sort_va
```

Out[52]:

| | Embarked_S | Survived |
|---|---|---|
| 0 | 0 | 0.502041 |
| 1 | 1 | 0.339009 |

In [53]:

```
df_train[["Embarked_Q", "Survived"]].groupby(['Embarked_Q'], as_index=False).mean().sort_va
```

Out[53]:

| | Embarked_Q | Survived |
|---|---|---|
| 1 | 1 | 0.389610 |
| 0 | 0 | 0.383292 |

In [54]:

```
print('*'*50)
print("Port-C Survival Rate: 55%")
print("Port-S Survival Rate: 34%")
print("Port-Q Survival Rate: 39%")
print('*'*50)
```

```
**************************************************
Port-C Survival Rate: 55%
Port-S Survival Rate: 34%
Port-Q Survival Rate: 39%
**************************************************
```

**Analysis:** Port-C has highest survival rate while Port-S has least survival rate

## Adding final categorical variable, for age, as it is important column for analysis

In [55]:

```
df_train['Minor']=np.where(df_train['Age']<=16, 1, 0)

df_test['Minor']=np.where(df_test['Age']<=16, 1, 0)
```

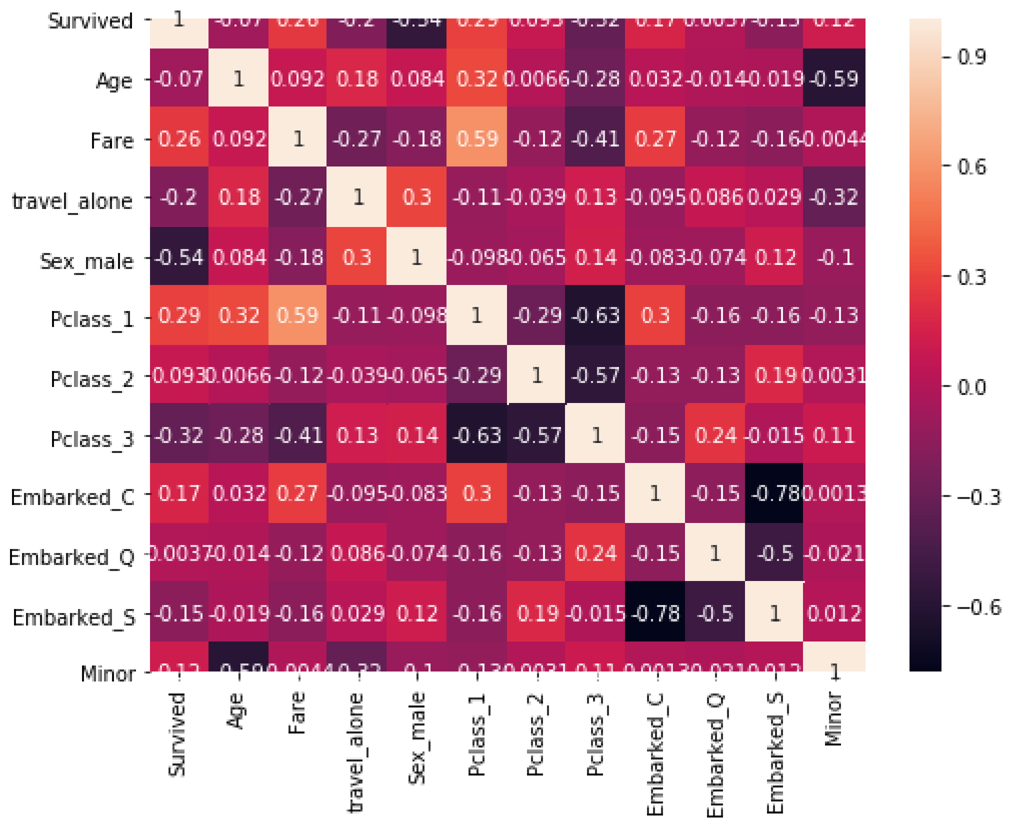
# 5: Logistic Regression Model Building

Since we are now familiar with our data, now we can finally perform Logistic Regression **Main Library Used:** Sklearn

## Initially Checking The Correlation:

In [56]:

```
plt.figure(figsize = (8,6))
sns.heatmap(df_train.corr(), annot = True)
plt.show()
```




## Building the model

Splitting X and Y training data

In [57]:

```
#using sklearn for Logistic Regression
from sklearn.linear_model import LogisticRegression

#getting RFE for feature selection
from sklearn.feature_selection import RFE
```

In [58]:

```
#getting initial variables
vars = ["Age","Fare","travel_alone","Pclass_1","Pclass_2","Embarked_C","Embarked_S","Sex_ma

#splitting into X and Y training datasets
X_train = df_train[vars]
y_train = df_train['Survived']
```

## Feature Selection Using RFE

In [59]:

```
#creating logistic regresssion model
md = LogisticRegression()

#using rfe for feature selection
rfe = RFE(md, 8)
rfe = rfe.fit(X_train, y_train)
list(X_train.columns[rfe.support_])
```

Out[59]:

```
['Age',
 'travel_alone',
 'Pclass_1',
 'Pclass_2',
 'Embarked_C',
 'Embarked_S',
 'Sex_male',
 'Minor']
```

Finally, we have our variables ready, so we can move forward with model building

In [60]:

```
#updating training and testing datasets

vars = ['Age', 'travel_alone','Pclass_1','Pclass_2','Embarked_C', 'Embarked_S', 'Sex_male',
X_train = df_train[vars]
X_test = df_test[vars]
X_train.columns
```

Out[60]:

```
Index(['Age', 'travel_alone', 'Pclass_1', 'Pclass_2', 'Embarked_C',
       'Embarked_S', 'Sex_male', 'Minor'],
      dtype='object')
```

In [61]:

```
#fitting final model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[61]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

# 6: Testing the Model

In [62]:

```
#Testing the data and saving predictions

y_pred = logreg.predict(X_test)
```

### Getting VIF values

In [63]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [64]:

```
vif = pd.DataFrame()
vif['vars'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[64]:

| | vars | VIF |
|---|---|---|
| 0 | Age | 6.84 |
| 5 | Embarked_S | 6.04 |
| 6 | Sex_male | 3.21 |
| 1 | travel_alone | 2.90 |
| 4 | Embarked_C | 2.38 |
| 2 | Pclass_1 | 1.88 |
| 3 | Pclass_2 | 1.48 |
| 7 | Minor | 1.43 |

**Analysis** : VIF values are normal, so we can continue with this model

### Creating Dataframe for Submission

In [65]:

```
#passenger ids from test data
l1 = passenger_data.tolist()

#creating dataframe
#logreg_submission = pd.DataFrame({"PassengerId": l1, "Survived": y_pred})

#dataframe to csv conversion
#logreg_submission.to_csv('2ndlogreg_submission.csv', index=False)
```

# 7: Post Submission Analysis:

**Model Score**: 0.7727

The Model Score recieved is actually good, and the best the we could achieve at the moment. Although, we acknowledge that there is scope for improvement.

### Thank you