Programming Assignment 2 - Titanic Dataset

June 25, 2022

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1 Importing Data

[2]:
```
titanic_train = pd.read_csv('train.csv')
titanic_test = pd.read_csv('test.csv')
titanic_test.head()
```

[2]:
```
   PassengerId  Pclass                                          Name     Sex  \
0          892       3                              Kelly, Mr. James    male
1          893       3              Wilkes, Mrs. James (Ellen Needs)  female
2          894       2                     Myles, Mr. Thomas Francis    male
3          895       3                              Wirz, Mr. Albert    male
4          896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female

    Age  SibSp  Parch   Ticket     Fare Cabin Embarked
0  34.5      0      0   330911   7.8292   NaN        Q
1  47.0      1      0   363272   7.0000   NaN        S
2  62.0      0      0   240276   9.6875   NaN        Q
3  27.0      0      0   315154   8.6625   NaN        S
4  22.0      1      1  3101298  12.2875   NaN        S
```

[3]:
```
titanic_train.PassengerId.size
```

[3]: 891

[4]:
```
titanic_train.head()
```

[4]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
```

```
4            5          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

   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
```

[5]:
```python
titanic_train.dtypes
```

[5]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

Check quality of data

[6]:
```python
titanic_train.isnull().sum()
```

[6]:
```
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
```

[7]:
```
titanic_test.PassengerId.size,titanic_test.isnull().sum()
```

[7]:
```
(418,
 PassengerId      0
 Pclass           0
 Name             0
 Sex              0
 Age             86
 SibSp            0
 Parch            0
 Ticket           0
 Fare             1
 Cabin          327
 Embarked         0
 dtype: int64)
```

2 Data Cleaning

Both the training set and test set contain null values in the Age and Cabin columns. The training set contains missing values for the Embarked and for the test set the Fare. Cabin will be dropped from as the majority of the passengers do not have their cabin listed. For the Age and Fare the median will be used. For Embarked the mode will be used. Other columns to be dropped are passengerID and Ticket.

[8]:
```
data_raw = [titanic_train,titanic_test]

for df in data_raw:

    df['Age'].fillna(df['Age'].median(), inplace = True)

    df['Embarked'].fillna(df['Embarked'].mode()[0], inplace = True)

    df['Fare'].fillna(df['Fare'].median(), inplace = True)

drop_column = ['PassengerId','Cabin', 'Ticket']
titanic_train.drop(drop_column, axis=1, inplace = True)
```

Sex and Embarked are converted to inteters to be used in the classifier.

[9]:
```
sex_conv = {'male':0, 'female':1}
titanic_train['Sex'] = titanic_train['Sex'].map(sex_conv)
titanic_test['Sex'] = titanic_test['Sex'].map(sex_conv)

titanic_train.head()
```

[9]:
```
   Survived  Pclass                                               Name  Sex  \
0         0       3                            Braund, Mr. Owen Harris    0
1         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1
2         1       3                             Heikkinen, Miss. Laina    1
3         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1
4         0       3                           Allen, Mr. William Henry    0

    Age  SibSp  Parch     Fare Embarked
0  22.0      1      0   7.2500        S
1  38.0      1      0  71.2833        C
2  26.0      0      0   7.9250        S
3  35.0      1      0  53.1000        S
4  35.0      0      0   8.0500        S
```

[10]:
```
emb_conv = {'S':0, 'C':1, 'Q':2}
titanic_train['Embarked'] = titanic_train['Embarked'].map(emb_conv)
titanic_test['Embarked'] = titanic_test['Embarked'].map(emb_conv)

titanic_train.head()
```

[10]:
```
   Survived  Pclass                                               Name  Sex  \
0         0       3                            Braund, Mr. Owen Harris    0
1         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1
2         1       3                             Heikkinen, Miss. Laina    1
3         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)    1
4         0       3                           Allen, Mr. William Henry    0

    Age  SibSp  Parch     Fare  Embarked
0  22.0      1      0   7.2500         0
1  38.0      1      0  71.2833         1
2  26.0      0      0   7.9250         0
3  35.0      1      0  53.1000         0
4  35.0      0      0   8.0500         0
```

[11]:
```
titanic_train.dtypes
```

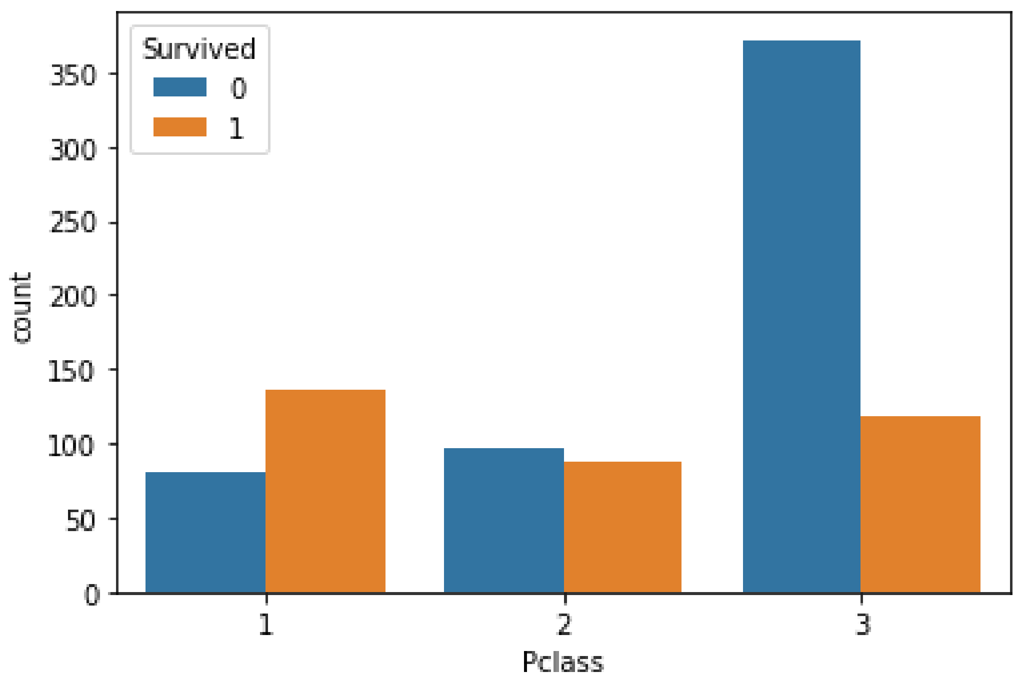
[11]:
```
Survived      int64
Pclass        int64
Name         object
Sex           int64
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked      int64
dtype: object
```

3 Data Exploration

My first thought was that those who are in a higher class cabin had a better chance of survival. Plotted the count of survivors (=1) and non-survivors(=0) by class.

[12]:
```
sns.countplot(x='Pclass',data = titanic_train, hue = 'Survived')
```

[12]: <matplotlib.axes._subplots.AxesSubplot at 0x192a731c400>



Looking at actual survival rates.

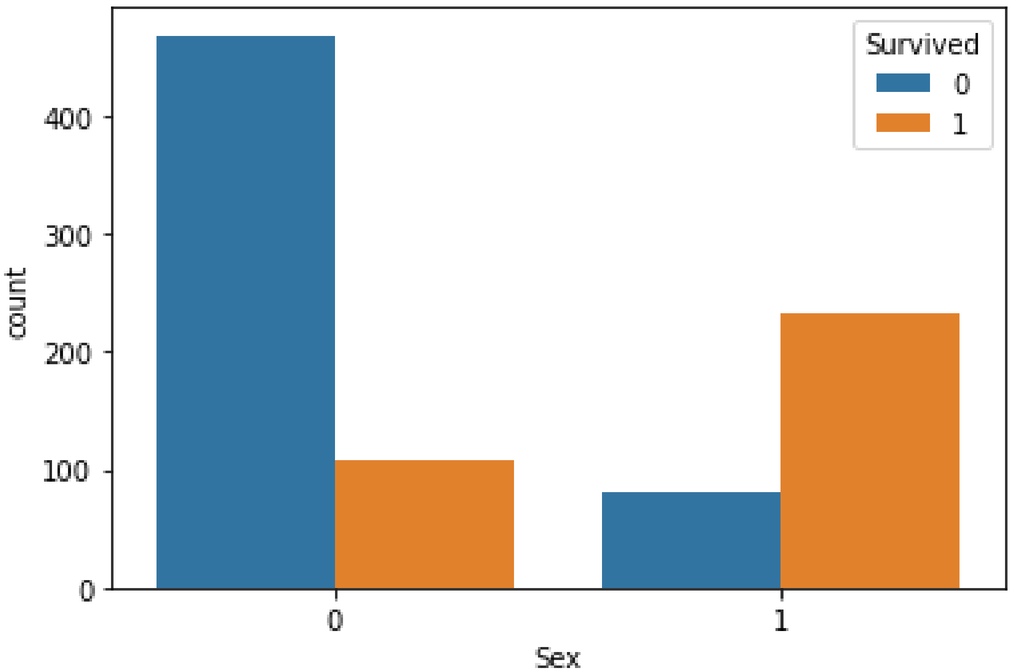
[13]:
```
titanic_train[['Pclass', 'Survived']].groupby(['Pclass']).mean().
 ↪sort_values(by='Survived')
```

[13]:
```
        Survived
Pclass
3       0.242363
2       0.472826
1       0.629630
```

Being in a higher class increaed your chances of survival. The same exercise is done for gender, where male = 0 and female = 1

[14]:
```
sns.countplot(x='Sex',data=titanic_train, hue='Survived')
```

[14]: <matplotlib.axes._subplots.AxesSubplot at 0x192a72da4f0>



[15]:
```
titanic_train[['Sex', 'Survived']].groupby(['Sex']).mean().
 ↪sort_values(by='Survived')
```

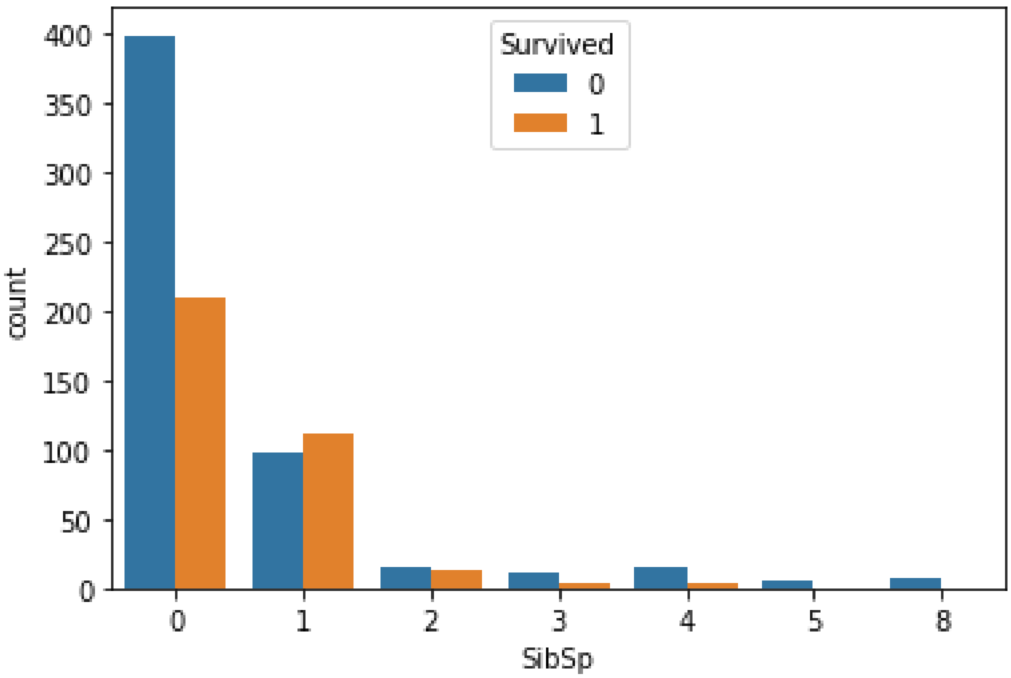
[15]:

	Survived
Sex	
0	0.188908
1	0.742038

Being female greatly increased the chances of survival. Number of siblings was looked at next

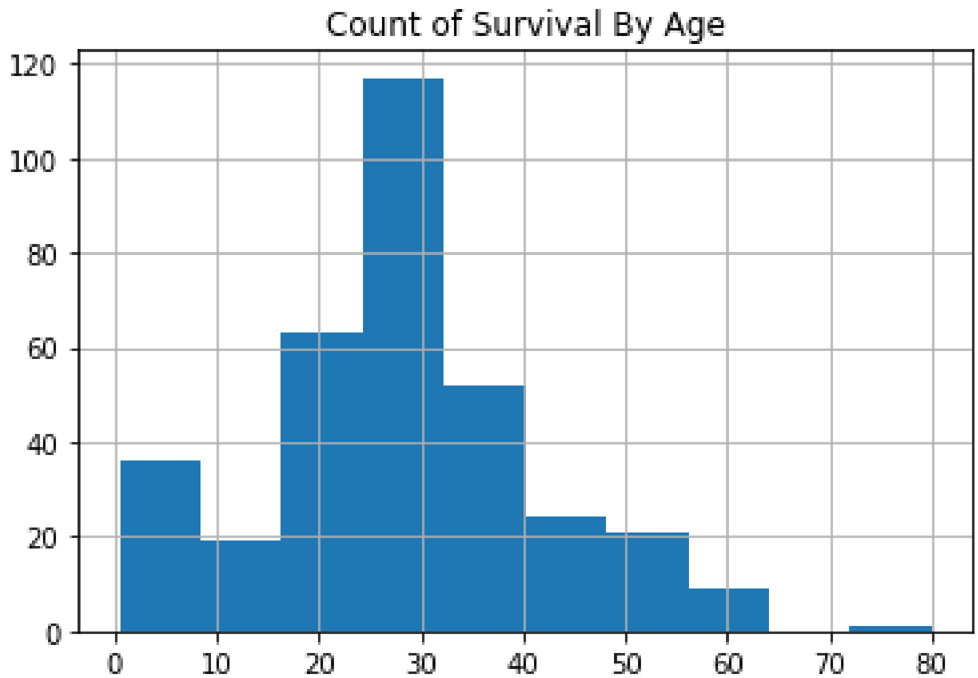
[16]:
```
sns.countplot(x='SibSp',data=titanic_train, hue='Survived')
```

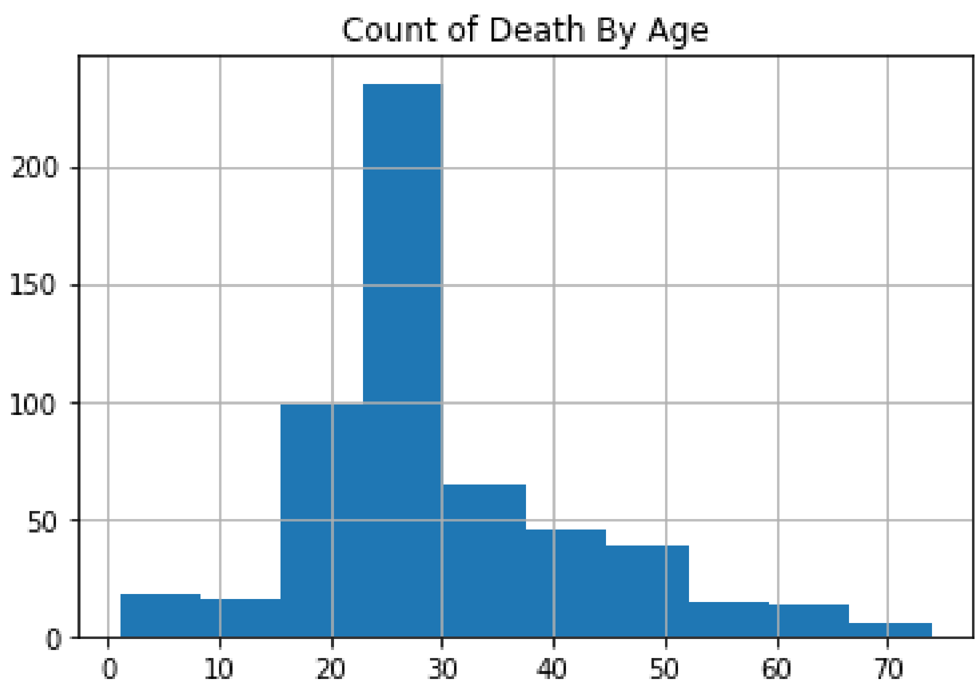
[16]: <matplotlib.axes._subplots.AxesSubplot at 0x192a7af2400>



No strong conclusions can be made with this data. Age was then looked at. First on two different histograms.

[17]:
```
titanic_train_survive = titanic_train[titanic_train['Survived'] == 1]
titanic_train_died = titanic_train[titanic_train['Survived'] == 0]

titanic_train_survive.Age.hist(bins = 10)
plt.title("Count of Survival By Age")
plt.show()
titanic_train_died.Age.hist(bins = 10)
plt.title("Count of Death By Age")
plt.show()
```

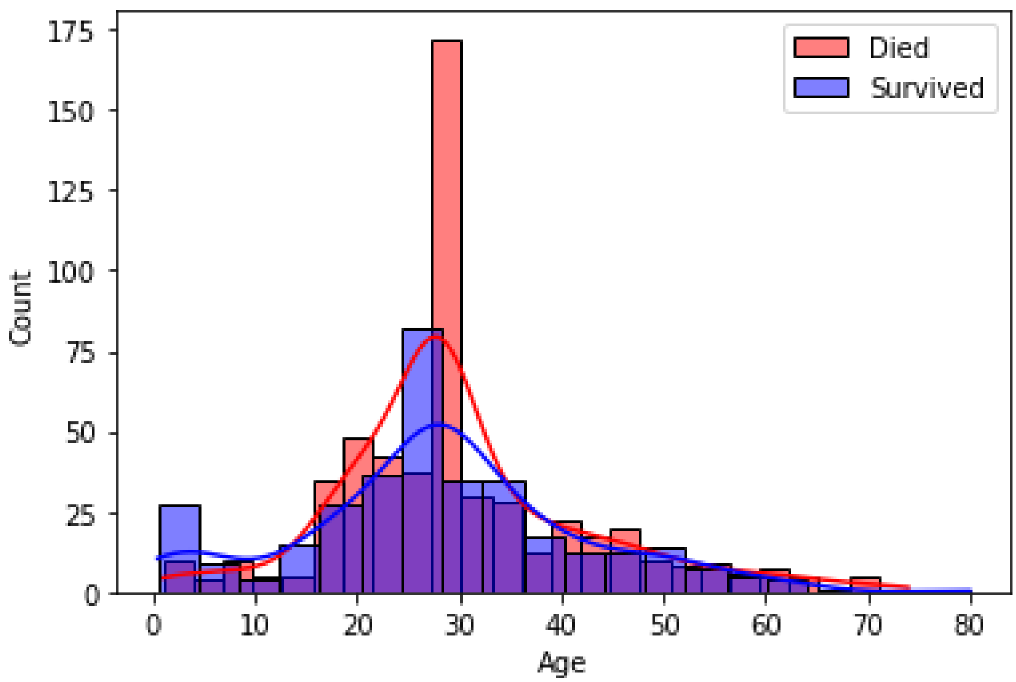




And then overlayed to compare distribution

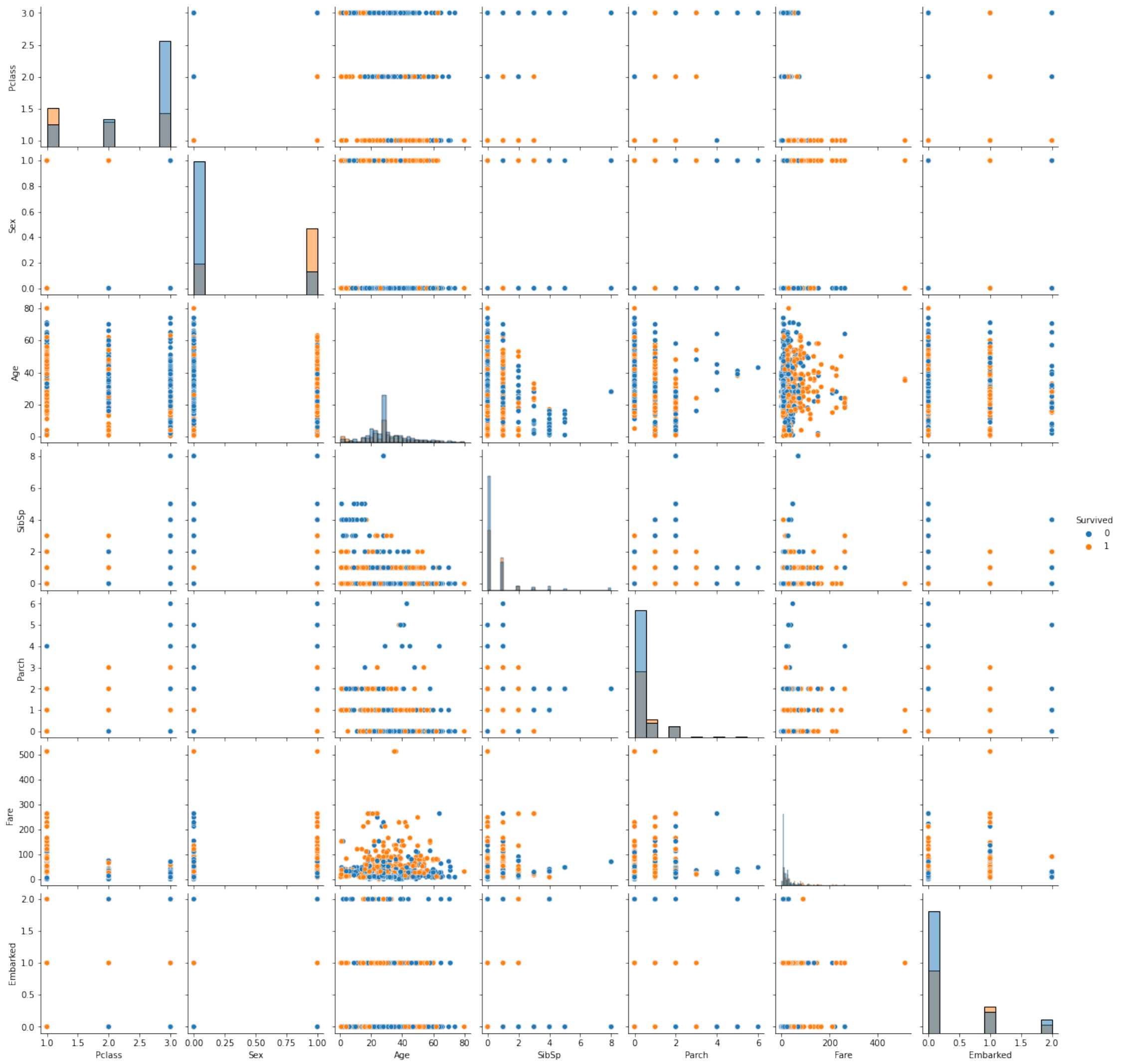
[18]:
```
fig,ax = plt.subplots()
sns.histplot(titanic_train[titanic_train['Survived']==0]['Age'],color =␣
↪'r',label = 'Died',ax=ax,kde = True)
sns.histplot(titanic_train[titanic_train['Survived']==1]['Age'],color =␣
↪'b',label = 'Survived',ax=ax,kde = True)
plt.legend()
```

[18]:
```
<matplotlib.legend.Legend at 0x192a7ca3370>
```



Being younger increased the change of survival. A pairplot was created to see if there are any other conclusions to be made.

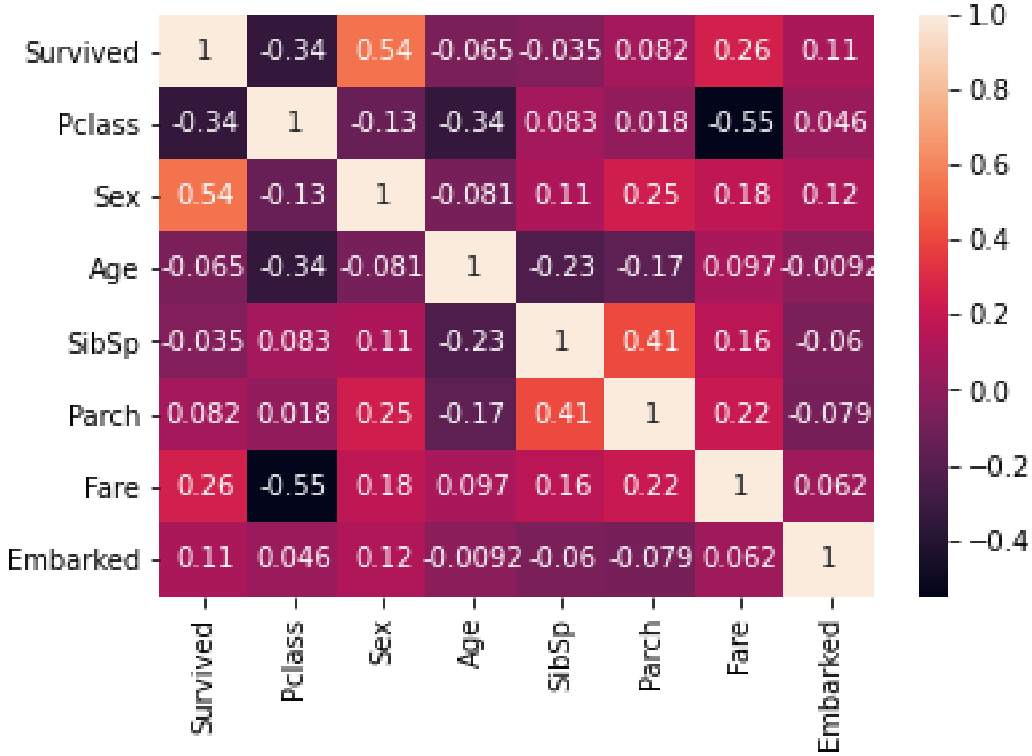
[19]:
```
g = sns.pairplot(titanic_train,diag_kind="hist",hue = 'Survived',dropna = True)
```



The pair plot shows that spending more on the fare also increase survival chances. A heatmap was created to see if there are any correlated variables that can be removed.

[20]:
```python
titanic_train_corr = titanic_train.corr()
sns.heatmap(titanic_train_corr,annot=True)
#print(titanic_train_corr)
#sns.heatmap(titanic_train_corr, fmt='g', cmap = 'Spectral').set(title =␣
 ↪'Correlation Matrix')
#plt.show()
```

[20]: <matplotlib.axes._subplots.AxesSubplot at 0x192aae17430>



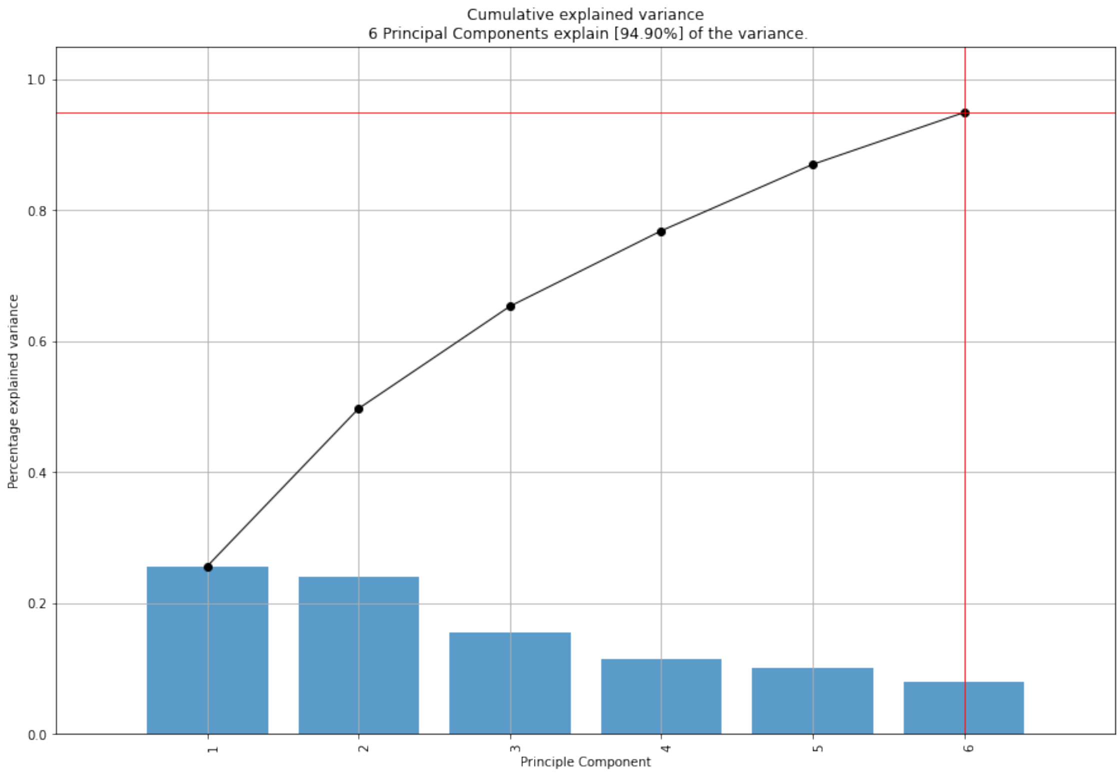
Heatmap confirms the high correlation bewteen Sex and Survived. Other correlations are not as stong. PCA was run to determine the variables that have more weight in determining survival.

[21]:
```
#pca analysis
from pca import pca

features = ['Pclass','Age','SibSp','Parch','Fare','Sex','Embarked']
X = titanic_train.loc[:,features].values
y = titanic_train.loc[:,'Survived'].values
```

[22]:
```
model = pca(n_components=6,normalize = True)
results = model.fit_transform(X,col_labels = features,row_labels = y)

# Plot explained variance
fig, ax = model.plot()
```

```
[pca] >Normalizing input data per feature (zero mean and unit variance)..
[pca] >The PCA reduction is performed on the [7] columns of the input dataframe.
[pca] >Fit using PCA.
[pca] >Compute loadings and PCs.
[pca] >Compute explained variance.
[pca] >Outlier detection using Hotelling T2 test with alpha=[0.05] and
n_components=[6]
```

```
[pca] >Outlier detection using SPE/DmodX with n_std=[2]
```




```
<Figure size 432x288 with 0 Axes>
```

[23]:
```
print(model.results['topfeat'])
```

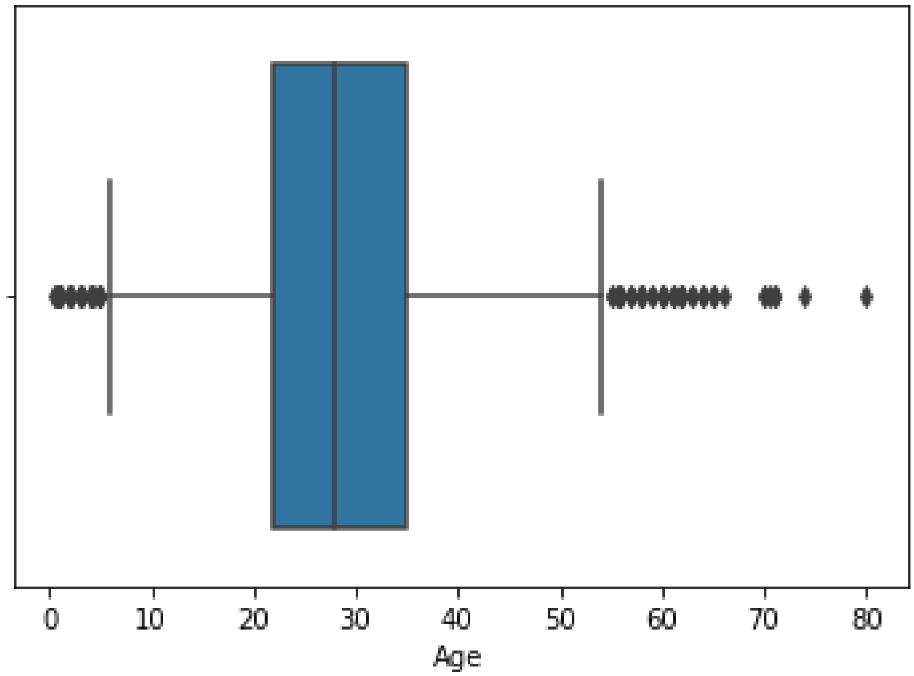
```
    PC   feature   loading  type
0  PC1      Fare  0.571703  best
1  PC2       Age  0.554338  best
2  PC3  Embarked  0.851590  best
3  PC4       Sex -0.749587  best
4  PC5       Age  0.787430  best
5  PC6     Parch  0.678252  best
6  PC2    Pclass -0.532689  weak
7  PC6     SibSp -0.658818  weak
```

In decending order: Fare, Age, Embarked, and Sex were the top four variables that explained the sample variance. Those four variables are the starting point for the algorithms.

Next is to remove any outliers in the data. Age and Fare are looked at for outliers as the other variables are categorical. An outier here is defined as a value outside of the 5-95 percentile.

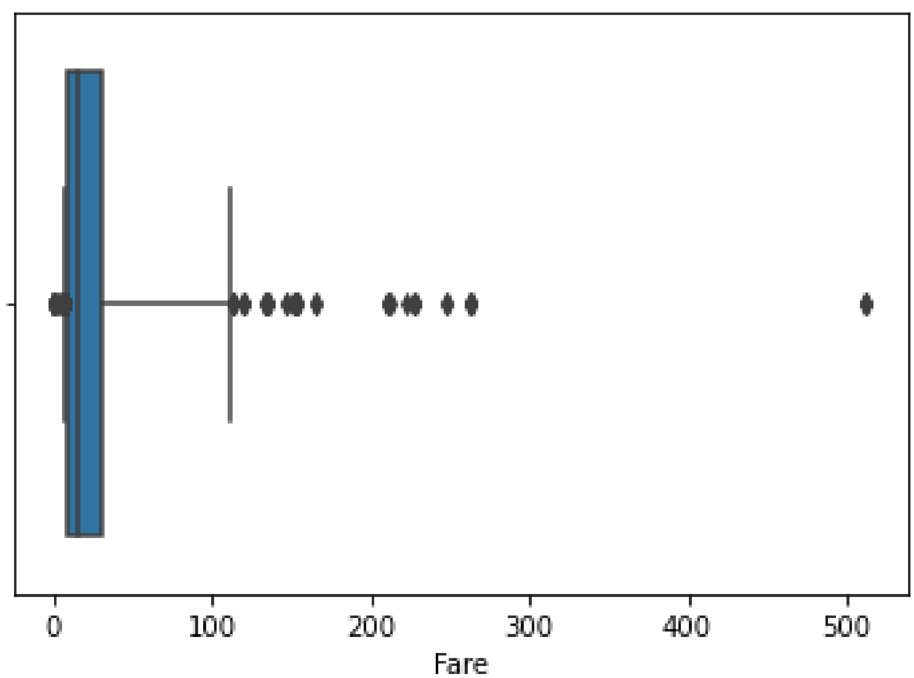
[24]:
```
sns.boxplot(x=titanic_train['Age'],whis=[5,95])
```

[24]: <matplotlib.axes._subplots.AxesSubplot at 0x192a72ebe50>



[25]:
```
sns.boxplot(x=titanic_train['Fare'],whis=[5,95])
```

[25]: <matplotlib.axes._subplots.AxesSubplot at 0x192ad2fd640>



[26]:
```python
titanic_train[["Age", "Fare"]].describe(percentiles = [.05,.25,.5,.75,.95])
```

[26]:
```
              Age        Fare
count  891.000000  891.000000
mean    29.361582   32.204208
std     13.019697   49.693429
min      0.420000    0.000000
5%       6.000000    7.225000
25%     22.000000    7.910400
50%     28.000000   14.454200
75%     35.000000   31.000000
95%     54.000000  112.079150
max     80.000000  512.329200
```

[27]:
```python
titanic_train.drop(titanic_train[titanic_train["Age"] >\
                                 (np.percentile(titanic_train["Age"], 95))].
 ↪index, inplace=True)
titanic_train.drop(titanic_train[titanic_train["Age"] <\
                                 (np.percentile(titanic_train["Age"], 5))].
 ↪index, inplace=True)

titanic_train.drop(titanic_train[titanic_train["Fare"] >\
                                 (np.percentile(titanic_train["Fare"], 95))].
 ↪index, inplace=True)
titanic_train.drop(titanic_train[titanic_train["Fare"] <\
                                 (np.percentile(titanic_train["Fare"], 5))].
 ↪index, inplace=True)
```

4 Classification Methods

Splitting the training set for training and validating. A 80/20 split was used.

[28]:
```python
from sklearn.model_selection import train_test_split

dataCM1 = titanic_train

X = dataCM1.drop('Survived',axis=1)
y = dataCM1['Survived']

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=.2,␣
 ↪random_state=15)
```

[29]:
```python
X_train.shape, X_val.shape
```

[29]: ((586, 8), (147, 8))

[30]:
```
X_val.head()
```

[30]:
```
     Pclass                           Name  Sex   Age  SibSp  Parch     Fare  \
369       1    Aubart, Mme. Leontine Pauline    1  24.0      0      0  69.3000
502       3  O'Sullivan, Miss. Bridget Mary    1  28.0      0      0   7.6292
140       3   Boulos, Mrs. Joseph (Sultana)    1  28.0      0      2  15.2458
384       3           Plotcharsky, Mr. Vasil    0  28.0      0      0   7.8958
686       3         Panula, Mr. Jaako Arnold    0  14.0      4      1  39.6875

     Embarked
369         1
502         2
140         1
384         0
686         0
```

Classification Method 1 - SVC

For the first attempt I am using Support Vector Classification. For the kernel I am using a 5th order polynomial. The important values kept at default are unlimited iterations (max_iter = -1) and the stopping criterion (tol = 1e-3).

[31]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
modelSVC = SVC(kernel = 'poly',degree = 5)

#Determined Important Features
features = ['Fare','Age','Embarked','Sex']

X_trainSVC = X_train.loc[:, features]

modelSVC.fit(X_trainSVC, y_train)

print('Training accuracy = ', accuracy_score(y_train, modelSVC.
 ↪predict(X_trainSVC)))
#print('Training accuracy = ', modelSVC.score(X_trainSVC, y_train)*100)

X_valSVC = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelSVC.
 ↪predict(X_valSVC)))
```

```
Training accuracy =  0.7116040955631399
Validation accuracy =  0.6666666666666666
```

As a second attempt I changed the kernal to Radial Basis Function which performed slightly better.

[32]:
```
modelSVC2 = SVC(kernel = 'rbf')

features = ['Fare','Age','Embarked','Sex']

X_trainSVC2 = X_train.loc[:, features]

modelSVC2.fit(X_trainSVC2, y_train)

print('Training accuracy = ', accuracy_score(y_train, modelSVC2.
 ↪predict(X_trainSVC2)))

X_valSVC2 = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelSVC2.
 ↪predict(X_valSVC2)))
```

```
Training accuracy =  0.6843003412969283
Validation accuracy =  0.6462585034013606
```

Classification Model 2 - Decision Tree

My second attempt used a decison tree classifier. The quality of a split was measured with entropy. The min samples to require a split was increased from the default of 2 to 20. After testing a few values, increasing the amount of samples to initiate a split improved the validation accuracy. It is possible for this dataset that with the default 2 there is excess overfitting to the training set. A greedy approach was used for splitting on the default value splitter="best".

[33]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

modelDTC = DecisionTreeClassifier(criterion = 'entropy',min_samples_split =␣
 ↪20,splitter = "best")

features = ['Fare','Age','Embarked','Sex']

X_trainDTC = X_train.loc[:, features]

modelDTC.fit(X_trainDTC,y_train)

print('Training accuracy = ', accuracy_score(y_train, modelDTC.
 ↪predict(X_trainDTC)))
#print('Training accuracy = ', modelDTC.score(X_trainDTC, y_train)*100)

X_valDTC = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelDTC.
 ↪predict(X_valDTC)))
```

```
Training accuracy =  0.8720136518771331
Validation accuracy =  0.7619047619047619
```

Classification Model 3 - Boosting

The third attempt used Gradient Boosting Classifier. The number of boosting stages was increased from 100 to 200. The min split and leaf values were kept as default due to GBCs resilience to over-fitting. The tolerance for stopping was kept at default tol=1e-4.

[34]:
```
from sklearn.ensemble import GradientBoostingClassifier

modelGBC = GradientBoostingClassifier(max_depth = 3, n_estimators = 200)

features = ['Fare','Age','Embarked','Sex']

X_trainGBC = X_train.loc[:, features]

modelGBC.fit(X_trainGBC,y_train)

print('Training accuracy = ', accuracy_score(y_train, modelGBC.
 ↪predict(X_trainGBC)))

X_valGBC = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelGBC.
 ↪predict(X_valGBC)))
```

```
Training accuracy =  0.9351535836177475
Validation accuracy =  0.7891156462585034
```

Test Prediction csv creation

[35]:
```
titanic_test.head()
```

[35]:
```
   PassengerId  Pclass                                          Name  Sex  \
0          892       3                              Kelly, Mr. James    0
1          893       3              Wilkes, Mrs. James (Ellen Needs)    1
2          894       2                     Myles, Mr. Thomas Francis    0
3          895       3                              Wirz, Mr. Albert    0
4          896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)    1

    Age  SibSp  Parch   Ticket     Fare Cabin  Embarked
0  34.5      0      0   330911   7.8292   NaN         2
1  47.0      1      0   363272   7.0000   NaN         0
2  62.0      0      0   240276   9.6875   NaN         2
3  27.0      0      0   315154   8.6625   NaN         0
4  22.0      1      1  3101298  12.2875   NaN         0
```

[36]:
```
titanic_test.isnull().sum()
```

[36]:
```
PassengerId      0
Pclass           0
Name             0
```

```
Sex             0
Age             0
SibSp           0
Parch           0
Ticket          0
Fare            0
Cabin         327
Embarked        0
dtype: int64
```

[37]:
```
#Prepare Test Data
features = ['Fare','Age','Embarked','Sex']
X_test = titanic_test.loc[:,features].copy()

#Classification Model 1 - SVC
submitSVC = pd.DataFrame(titanic_test['PassengerId'])
submitSVC['Survived'] = modelSVC2.predict(X_test)
submitSVC.to_csv('submitSVC.csv',index = False)

#Classification Model 1 - Decision Tree
submitDTC = pd.DataFrame(titanic_test['PassengerId'])
submitDTC['Survived'] = modelDTC.predict(X_test)
submitDTC.to_csv('submitDTC.csv',index = False)

#Classification Model 1 - Gradient Boosting
submitGBC = pd.DataFrame(titanic_test['PassengerId'])
submitGBC['Survived'] = modelGBC.predict(X_test)
submitGBC.to_csv('submitGBC.csv',index = False)
```

5 Results

[38]:
```
from IPython.display import Image
Image("Titanic_Predictions.png")
```

[38]:

8 submissions for MichaelB1234 | Sort by Select...

All Successful Selected

Submission and Description	Public Score
submitGBC.csv just now by MichaelB1234 Classification Model 3 - Gradient Boosting	0.77033
submitDTC.csv a few seconds ago by MichaelB1234 Classification Model 2 - Decision Tree	0.72727
submitSVC.csv a minute ago by MichaelB1234 Classification Model 1 - SVC	0.64593

[39]:
```python
from IPython.display import Image
Image("Titanic_Leaderboard.png")
```

[39]:

9124	zhangxize	0.77033	7	5h
9125	Vitalii8	0.77033	2	4h
9126	Kent Hui	0.77033	4	1h
9127	Masaru Umekawa	0.77033	1	25m
9128	**MichaelB1234**	0.77033	8	1s

Your Best Entry!
Your most recent submission scored 0.77033, which is the same as your previous score. Keep trying!

9129	Matthew Conger	0.76794	2	2mo
9130	Jason Lam #2	0.76794	4	2mo
9131	Grant Jensen	0.76794	1	2mo
9132	Yash Dubey	0.76794	3	2mo
9133	gokulraj3	0.76794	2	2mo

6 Conclusion

At the time of writing this, my 3rd classification model using Gradient Boosting had an accuracy of 77.03% and placed 9128th on the leader board. Some steps that can be taken to imporve accuracy is to change the split of training and validation, modify/optimize all hyperparameters, changing the input variables, and exploring other classification techniques. The way that the NaN for Age are filled can also be changes to use the mean or split the NaN over multiple values using a correlation to another value (classifying the age). The Sex category can be extended to have a 3rd option of ``Child'' as the chance of survival for a child was higher regardless of gender. Looking at the leaderboard there is some success using regressions which could be explored as well.

Other Models Tested

[40]:
```python
from sklearn.neighbors import KNeighborsClassifier

modelKNN = KNeighborsClassifier(n_neighbors = 3, weights = 'distance')

features = ['Fare','Age','Embarked','Sex']

X_trainKNN = X_train.loc[:, features]

modelKNN.fit(X_trainKNN,y_train)

print('Training accuracy = ', accuracy_score(y_train, modelKNN.
 ↪predict(X_trainKNN)))

X_valKNN = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelKNN.
 ↪predict(X_valKNN)))
```

```
Training accuracy =  0.9744027303754266
Validation accuracy =  0.7346938775510204
```

[41]:
```python
from sklearn.ensemble import RandomForestClassifier

modelRFC = RandomForestClassifier(n_estimators=100, max_depth = 6, criterion =␣
 ↪'gini',n_jobs = -1)

features = ['Fare','Age','Embarked','Sex','Parch']

X_trainRFC = X_train.loc[:, features]

modelRFC.fit(X_trainRFC,y_train)

print('Training accuracy = ', accuracy_score(y_train, modelRFC.
 ↪predict(X_trainRFC)))
```

```
X_valRFC = X_val.loc[:, features]
print('Validation accuracy = ', accuracy_score(y_val, modelRFC.
 ↪predict(X_valRFC)))
```

```
Training accuracy =  0.8737201365187713
Validation accuracy =  0.7278911564625851
```

[ ]:

```

```