Imported Packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
import sklearn as skl
import random
from scipy.stats import iqr
import scipy.stats as stats
import seaborn as sns
```

Importing the Dataset

```
data = pd.read_csv('/Users/raph/Desktop/titanic/train.csv').set_index('PassengerId')
print(data.head())
data.dtypes
```

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name     Sex   Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    male  22.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
3                                       Heikkinen, Miss. Laina  female  26.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
5                                     Allen, Mr. William Henry    male  35.0

             SibSp  Parch            Ticket     Fare Cabin Embarked
PassengerId
1                1      0         A/5 21171   7.2500   NaN        S
2                1      0          PC 17599  71.2833   C85        C
3                0      0  STON/O2. 3101282   7.9250   NaN        S
4                1      0            113803  53.1000  C123        S
5                0      0            373450   8.0500   NaN        S
Survived      int64
Pclass        int64
Name         object
Sex          object
Age         float64
SibSp         int64
Parch         int64
Ticket       object
Fare        float64
Cabin        object
Embarked     object
dtype: object
```

Cleaning the Data

```
data.Age = data.Age.replace(np.nan, 0)
```

Creating Filters

```
# Cutting down the dataset
mod_data = data[['Survived', 'Pclass', 'Age', 'Sex', 'SibSp', 'Parch', 'Fare' ]]


# Classifiers
male_df = mod_data[mod_data.Sex == 'male'].drop(['Sex'], axis = 1)
female_df = mod_data[mod_data.Sex == 'female'].drop(['Sex'], axis = 1)

# Explanatory Variables
in_df_m = male_df.iloc[:,1:7]
in_df_f = female_df.iloc[:,1:7]

#Exploratory Variable
dep_m = male_df.Survived
dep_f = female_df.Survived
```

```
male_df
```

PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
1	0	3	22.0	1	0	7.2500
5	0	3	35.0	0	0	8.0500
6	0	3	0.0	0	0	8.4583
7	0	1	54.0	0	0	51.8625
8	0	3	2.0	3	1	21.0750
...	...	...	...	...	...	...
884	0	2	28.0	0	0	10.5000
885	0	3	25.0	0	0	7.0500
887	0	2	27.0	0	0	13.0000
890	1	1	26.0	0	0	30.0000
891	0	3	32.0	0	0	7.7500

577 rows × 6 columns

Exploratory Data Analysis

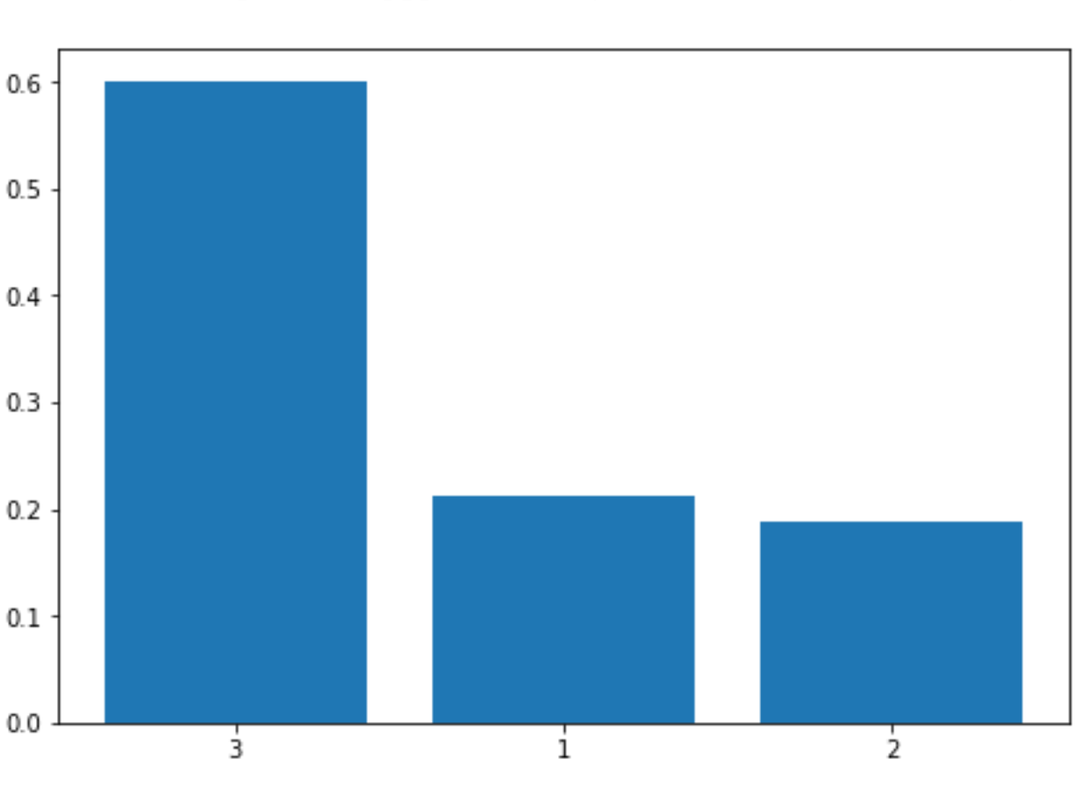
Male Population

PClass

As seen from the data, majority of the male passengers onboard the Titanic are shown to be in Passenger Class 3 having over 60%. Passenger Class 1 coming in second with just over 20% and Passenger Class 2 having the least with just shy of 20%.

```
print(male_df.Pclass.value_counts())
print('============================')
index_pclass = list(map(str,np.array(male_df.Pclass.value_counts().reset_index()).T[0]))
count_pclass =np.array(male_df.Pclass.value_counts().reset_index()).T[1]
norm_pclass = count_pclass/count_pclass.sum()
# Histogram of the PClasses
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(index_pclass, norm_pclass)
plt.show
```

```
3    347
1    122
2    108
Name: Pclass, dtype: int64
============================
[347 122 108]
<function matplotlib.pyplot.show(close=None, block=None)>
```



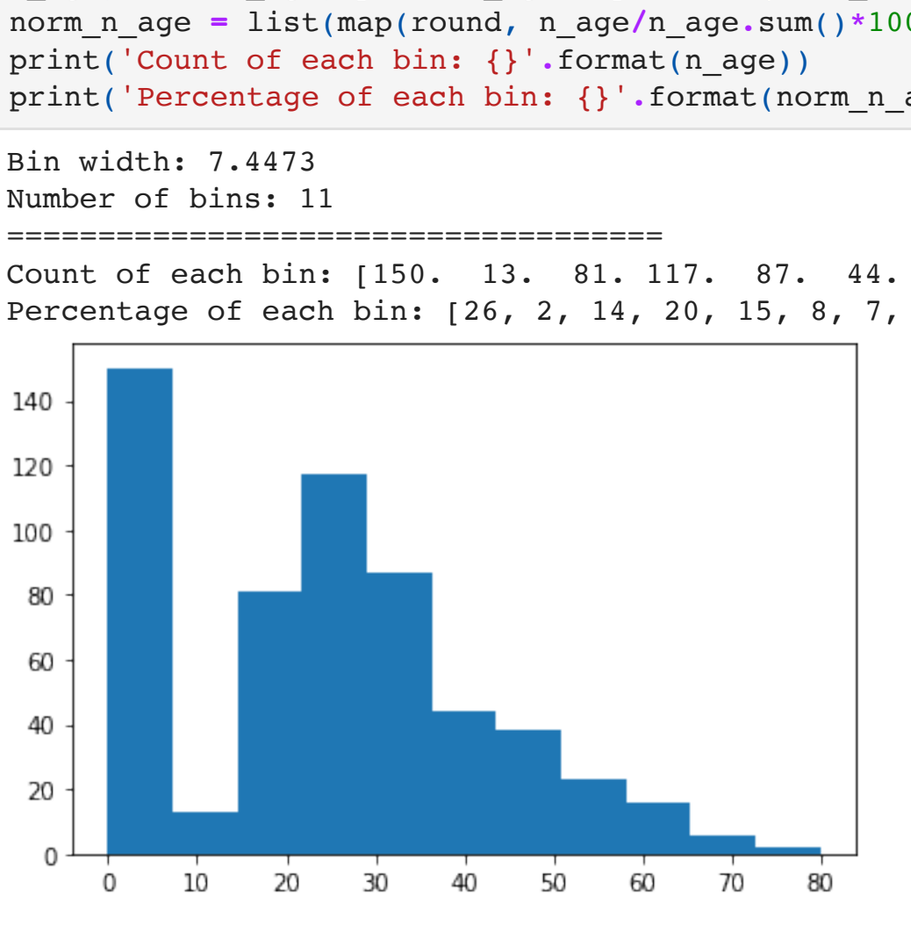
Applying the Freedman-Diacones Rule

```
def bin_range(df):
    vals = df.values
    bin_width = 2 * (iqr(vals) / (len(vals) ** (1./3)))
    num_bins = int((np.amax(vals) + bin_width) / bin_width)
    return bin_width, num_bins

def histo_viz(df):
    vals = df.values
    bin_width, num_bins = bin_range(df)
    hist = df.hist(bins=num_bins)
    return hist
```

Ages

```
# Bar graph of the ages

width_age, numbin_age = bin_range(male_df.Age)
print('Bin width: {}'.format(round(width_age,4)))
print('Number of bins: {}'.format(numbin_age))
print('===================================')
n_age, binval_age, patches_age = plt.hist(male_df.Age,bins=numbin_age)
norm_n_age = list(map(round, n_age/n_age.sum()*100))
print('Count of each bin: {}'.format(n_age))
print('Percentage of each bin: {}'.format(norm_n_age))
```

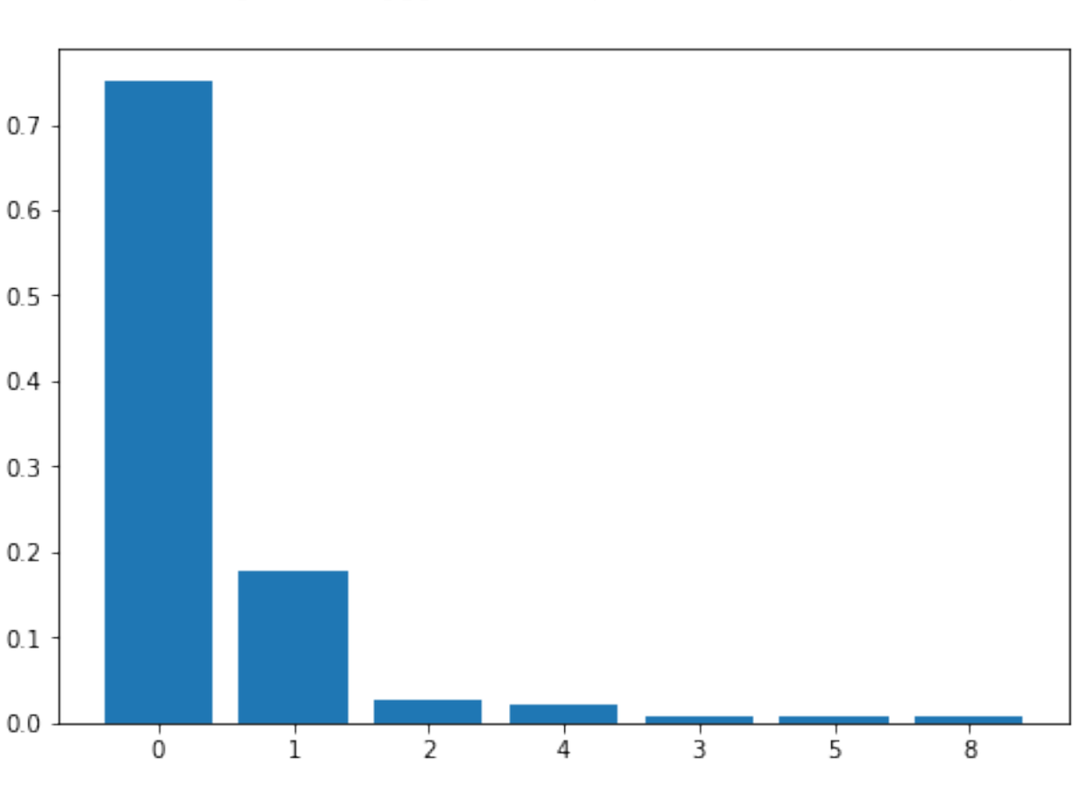
```
Bin width: 7.4473
Number of bins: 11
===================================
Count of each bin: [150.  13.  81. 117.  87.  44.  38.  23.  16.   6.   2.]
Percentage of each bin: [26, 2, 14, 20, 15, 8, 7, 4, 3, 1, 0]
```



SibSp

```
print(male_df.SibSp.value_counts())
print('============================')
index_sibsp = list(map(str,np.array(male_df.SibSp.value_counts().reset_index()).T[0]))
count_sibsp =np.array(male_df.SibSp.value_counts().reset_index()).T[1]

# Histogram of the SibSp
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(index_sibsp, count_sibsp/count_sibsp.sum())
plt.show
```

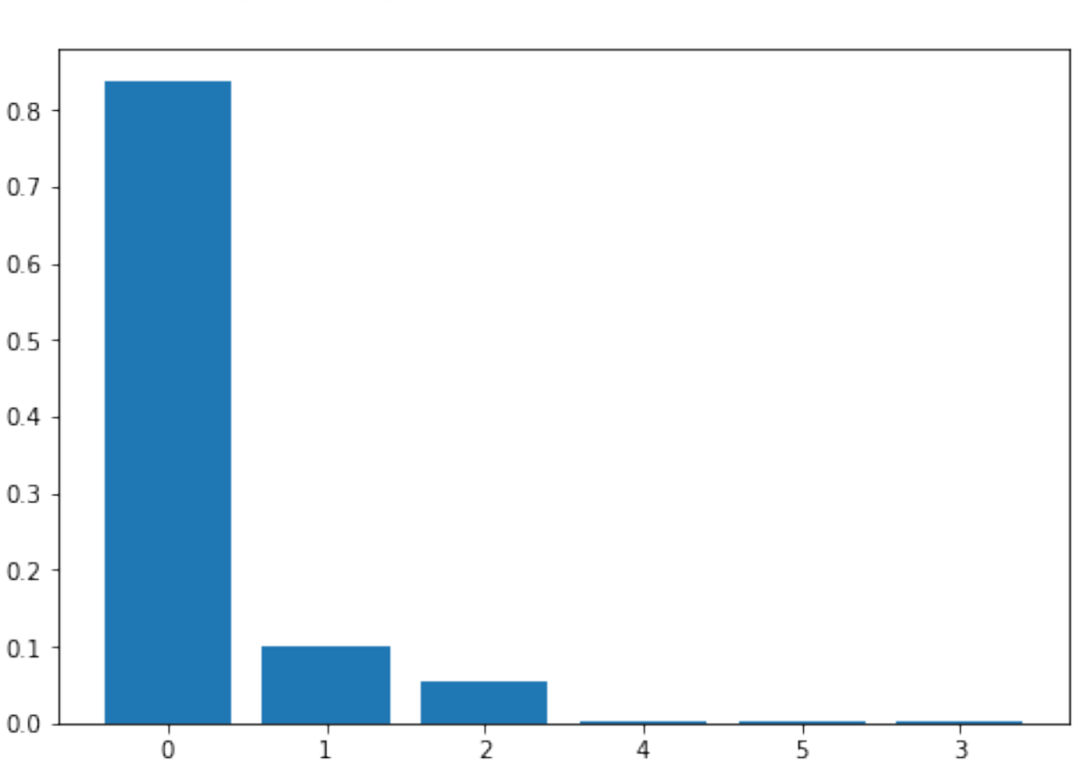
```
0    434
1    103
2     15
4     12
3      5
5      4
8      4
Name: SibSp, dtype: int64
============================
<function matplotlib.pyplot.show(close=None, block=None)>
```



Parch

```
print(male_df.Parch.value_counts())
print('============================')
index_parch = list(map(str,np.array(male_df.Parch.value_counts().reset_index()).T[0]))
count_parch =np.array(male_df.Parch.value_counts().reset_index()).T[1]

# Histogram of the SibSp
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(index_parch, count_parch/count_parch.sum())
plt.show
```

```
0    484
1     58
2     31
4      2
5      1
3      1
Name: Parch, dtype: int64
============================
<function matplotlib.pyplot.show(close=None, block=None)>
```



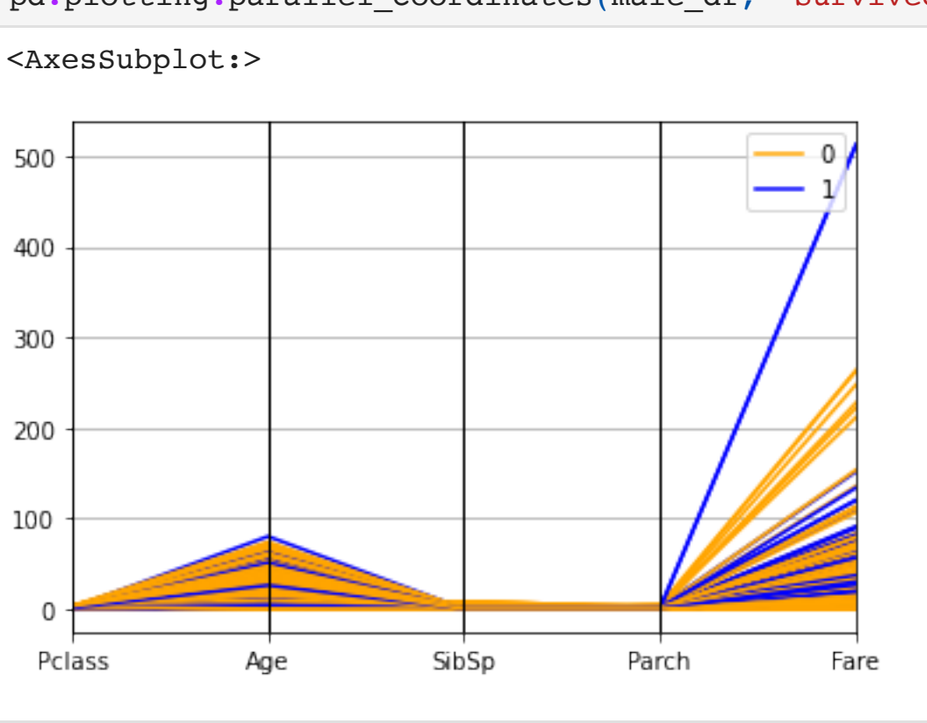
Visualization of the Data

Parallel Coordinates

Looking at the data may show that Parch and Fare show that they greatly affect the data while both the SibSp and Age may have little effect on the data. However, by normalizing the data, the results vary as follows:

```
# Initial Data
pd.plotting.parallel_coordinates(male_df, 'Survived', color=('#FFA500', '#0000FF'))
```

<AxesSubplot:>



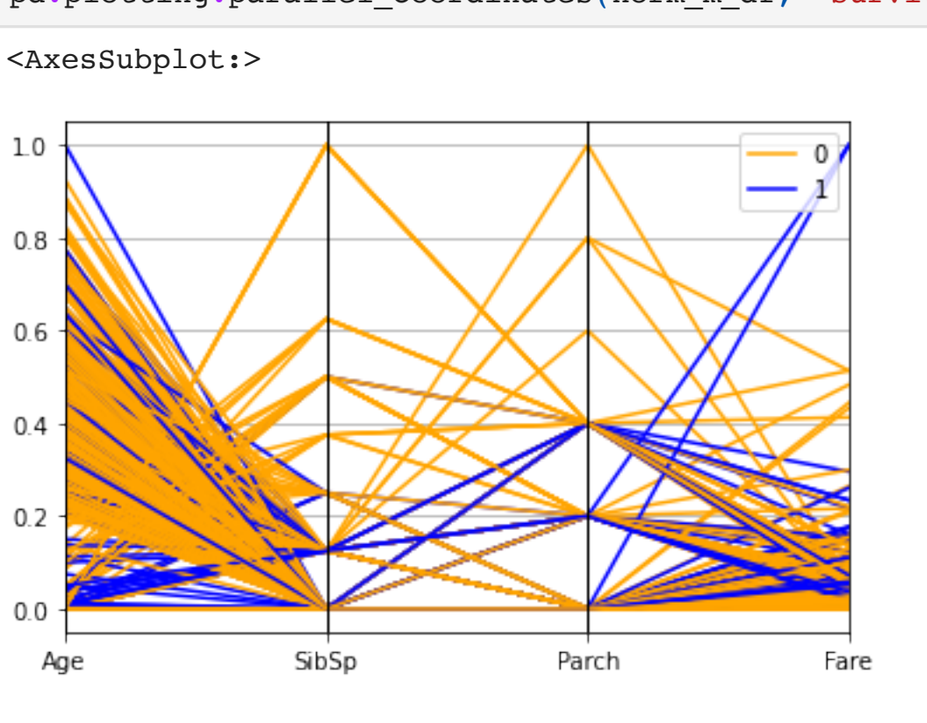
```
# norm_m_df = (male_df.iloc[:,2:6] -male_df.iloc[:,2:6].mean())/male_df.iloc[:,2:6].std()
# norm_m_df = pd.merge(norm_m_df, dep_m, right_index= True, left_index= True)
# norm_m_df.head()

norm_m_df = male_df.iloc[:,2:6]/male_df.iloc[:,2:6].max()
norm_m_df = pd.merge(norm_m_df, dep_m, right_index= True, left_index= True)
norm_m_df.head()
```

PassengerId	Age	SibSp	Parch	Fare	Survived
1	0.2750	0.125	0.0	0.014151	0
5	0.4375	0.000	0.0	0.015713	0
6	0.0000	0.000	0.0	0.016510	0
7	0.6750	0.000	0.0	0.101229	0
8	0.0250	0.375	0.2	0.041136	0

Normalizing the data now shows that most points can be distinguished from one another throughout the 4 variables used. Now we move on to checking the correlation of the data using a heatmap. Thus, we can conclude that all 4 varaibles can be applicable in distinguihing the data.

```
pd.plotting.parallel_coordinates(norm_m_df, 'Survived', color=('#FFA500', '#0000FF'))
```

<AxesSubplot:>

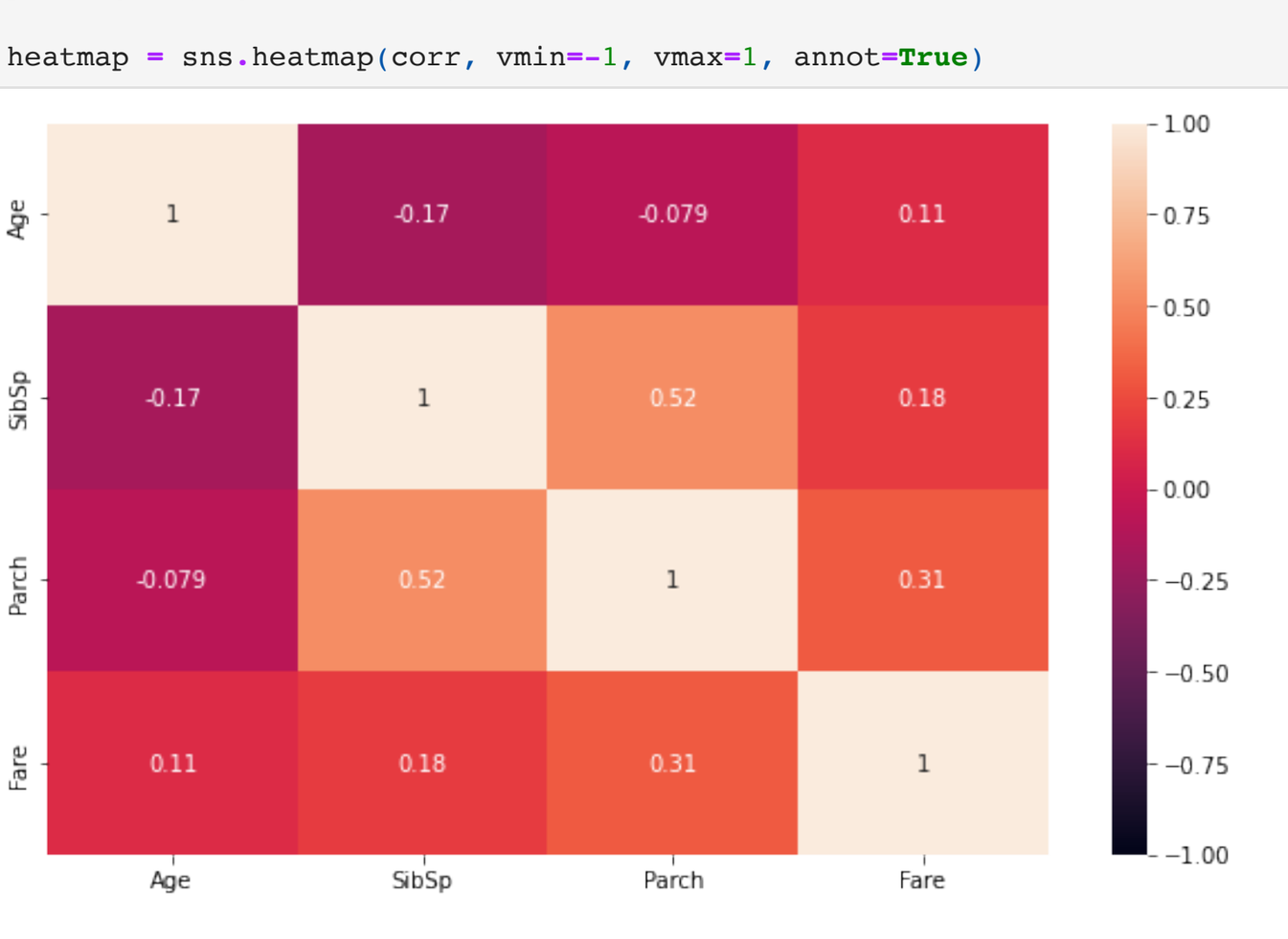


Heat Map (Correlation Coefficient)

```
temp = norm_m_df.drop(['Survived'], axis=1)
corr = temp.corr()
print(corr)
adj_norm_m_df = corr[((corr > 0.3) & (corr != 1)) | ((corr < -0.3) & (corr != 1))]
print('===============================')
print(adj_norm_m_df.count())
print('===============================')
print('Total number of correlations that fit into the desire correlation conditions: {}'. format(sum(adj_norm_m_df.count())))
```

```
            Age     SibSp     Parch      Fare
Age    1.000000 -0.173230 -0.079041  0.106134
SibSp -0.173230  1.000000  0.524849  0.181804
Parch -0.079041  0.524849  1.000000  0.312197
Fare   0.106134  0.181804  0.312197  1.000000
===============================
Age      0
SibSp    1
Parch    2
Fare     1
dtype: int64
===============================
Total number of correlations that fit into the desire correlation conditions: 4
```

```
plt.figure(figsize=(10, 6))

heatmap = sns.heatmap(corr, vmin=-1, vmax=1, annot=True)
```



Logistic Regression

```
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from statsmodels.stats.anova import anova_lm # One-way ANOVA
```

```
norm_m_df
```

PassengerId	Age	SibSp	Parch	Fare	Survived
1	0.2750	0.125	0.0	0.014151	0
5	0.4375	0.000	0.0	0.015713	0
6	0.0000	0.000	0.0	0.016510	0
7	0.6750	0.000	0.0	0.101229	0
8	0.0250	0.375	0.2	0.041136	0
...	...	...	...	...	...
884	0.3500	0.000	0.0	0.020495	0
885	0.3125	0.000	0.0	0.013761	0
887	0.3375	0.000	0.0	0.025374	0
890	0.3250	0.000	0.0	0.058556	1
891	0.4000	0.000	0.0	0.015127	0

577 rows × 5 columns

```
logit_model=sm.Logit(dep_m,norm_m_df.iloc[:,0:4])
result=logit_model.fit()
print(result.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.530050
         Iterations 6
                         Results: Logit
===============================================================
Model:              Logit            Pseudo R-squared: -0.094
Dependent Variable: Survived         AIC:              619.6782
Date:               2022-06-01 18:24 BIC:              637.1096
No. Observations:   577              Log-Likelihood:   -305.84
Df Model:           3                LL-Null:          -279.63
Df Residuals:       573              LLR p-value:      1.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     6.0000
-----------------------------------------------------------------
         Coef.    Std.Err.      z      P>|z|     [0.025    0.975]
-----------------------------------------------------------------
Age     -3.5075     0.3524   -9.9520   0.0000   -4.1983   -2.8167
SibSp   -4.0503     1.1152   -3.6318   0.0003   -6.2361   -1.8645
Parch    1.3693     0.9465    1.4467   0.1480   -0.4858    3.2244
Fare     2.0469     1.1371    1.8002   0.0718   -0.1817    4.2756
===============================================================
```

Since the p-values for the Age and the Parch are greater than 0.05, we remove them to create a more parsiomonios model

```
logit_model=sm.Logit(dep_m,norm_m_df.iloc[:,[0,1,3]])
result=logit_model.fit()
print(result.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.531769
         Iterations 6
                         Results: Logit
===============================================================
Model:              Logit            Pseudo R-squared: -0.097
Dependent Variable: Survived         AIC:              619.6619
Date:               2022-06-01 18:25 BIC:              632.7354
No. Observations:   577              Log-Likelihood:   -306.83
Df Model:           2                LL-Null:          -279.63
Df Residuals:       574              LLR p-value:      1.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     6.0000
-----------------------------------------------------------------
         Coef.    Std.Err.      z      P>|z|     [0.025    0.975]
-----------------------------------------------------------------
Age     -3.4864     0.3516   -9.9149   0.0000   -4.1756   -2.7972
SibSp   -3.3130     0.9596   -3.4526   0.0006   -5.1937   -1.4323
Fare     2.5051     1.1354    2.2063   0.0274    0.2797    4.7305
===============================================================
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

```
norm_m_df
```

PassengerId	Age	SibSp	Parch	Fare	Survived
1	0.2750	0.125	0.0	0.014151	0
5	0.4375	0.000	0.0	0.015713	0
6	0.0000	0.000	0.0	0.016510	0
7	0.6750	0.000	0.0	0.101229	0
8	0.0250	0.375	0.2	0.041136	0
...	...	...	...	...	...
884	0.3500	0.000	0.0	0.020495	0
885	0.3125	0.000	0.0	0.013761	0
887	0.3375	0.000	0.0	0.025374	0
890	0.3250	0.000	0.0	0.058556	1
891	0.4000	0.000	0.0	0.015127	0

577 rows × 5 columns

```
X_train = norm_m_df.iloc[:,[0,1,3]]
y_train = dep_m

X_test = pd.read_csv('/Users/raph/Desktop/titanic/test.csv').set_index('PassengerId')
X_test.drop(['Pclass','Name','Sex','Cabin','Embarked','Ticket','Parch'], axis = 1, inplace = True)

X_test.Age = X_test.Age.replace(np.nan, 0)
X_test.Fare = X_test.Fare.replace(np.nan, 0)
X_test.dropna(inplace = True)


y_test = pd.read_csv('/Users/raph/Desktop/titanic/gender_submission.csv').set_index('PassengerId')

logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

▾ LogisticRegression

LogisticRegression()

```
X_test = X_test/X_test.max()
X_test
```

PassengerId	Age	SibSp	Fare
892	0.453947	0.000	0.015282
893	0.618421	0.125	0.013663
894	0.815789	0.000	0.018909
895	0.355263	0.000	0.016908
896	0.289474	0.125	0.023984
...	...	...	...
1305	0.000000	0.000	0.015713
1306	0.513158	0.000	0.212559
1307	0.506579	0.000	0.014151
1308	0.000000	0.000	0.015713
1309	0.000000	0.125	0.043640

418 rows × 3 columns

```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg.score(X_test, y_test)))
```

```
Accuracy of logistic regression classifier on test set: 0.64
```

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[266   0]
 [151   1]]
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.64      1.00      0.78       266
           1       1.00      0.01      0.01       152

    accuracy                           0.64       418
   macro avg       0.82      0.50      0.40       418
weighted avg       0.77      0.64      0.50       418
```