Titanic - Machine Learning from Disaster

In [163]:
```
# importing important libraries
import os
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, cross_val_score, G
ridSearchCV
from dmba import plotDecisionTree, classificationSummary, regressionSumm
ary
from dmba import liftChart, gainsChart
from sklearn.metrics import r2_score, accuracy_score, recall_score, prec
ision_score, f1_score
from sklearn.metrics import confusion_matrix, auc, roc_curve, roc_auc_sc
ore
%matplotlib inline
```

In [164]:
```
import pandas as pd
df_train = pd.read_csv('train.csv')
print(df_train.shape)
df_train.head()
```

```
(891, 12)
```

Out[164]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	N
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	N

Data Preprocessing

In [165]:
```
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
```

In [166]:
```
# Defining the attribute Survived as categorical variable since we are d
oing Supervised learning: classification (output is categorical)
df_train['Survived'] = df_train['Survived'].astype('category')

# Dummy code the variable sex.
df_train['Sex'] = pd.get_dummies(df_train['Sex'], prefix_sep='_', drop_f
irst=True)
```

In [167]:
```
# Checking number of missing values for each attribute

for i in df_train.columns:
    print(i, df_train[i].isnull().sum())
```

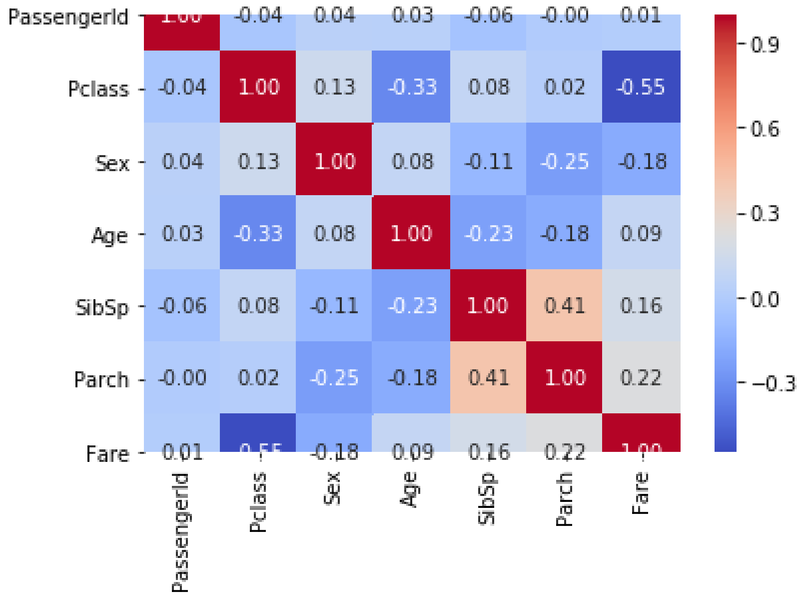
```
PassengerId 0
Survived 0
Pclass 0
Name 0
Sex 0
Age 177
SibSp 0
Parch 0
Ticket 0
Fare 0
Cabin 687
Embarked 2
```

In [168]:
```
# filling the missing ages with mean ages
df_train['Age'].fillna((df_train['Age'].mean()), inplace=True)
df_train.shape
```

Out[168]:
```
(891, 12)
```

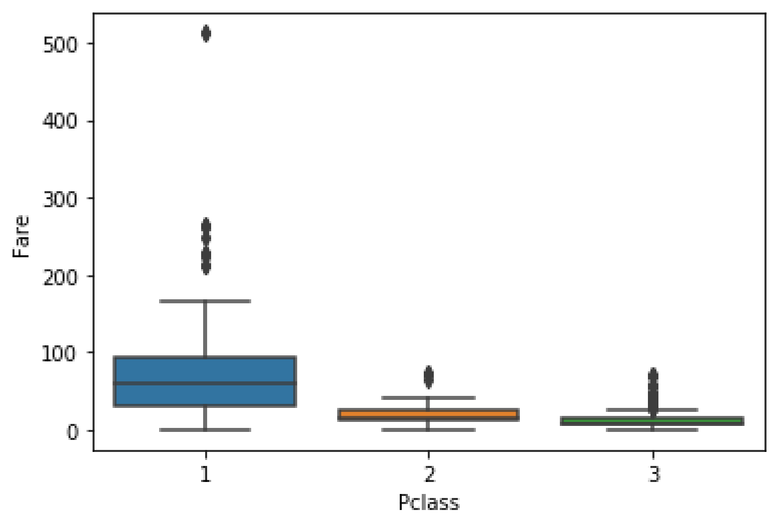
Exploratory Data Analysis

In [169]:
```
corr = df_train.corr()
plt.autoscale()
sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm")
plt.show()
```



In [170]:
```
sns.boxplot(data = df_train, x = 'Pclass', y = 'Fare')
```

Out[170]: <matplotlib.axes._subplots.AxesSubplot at 0x7f87b8d29d90>

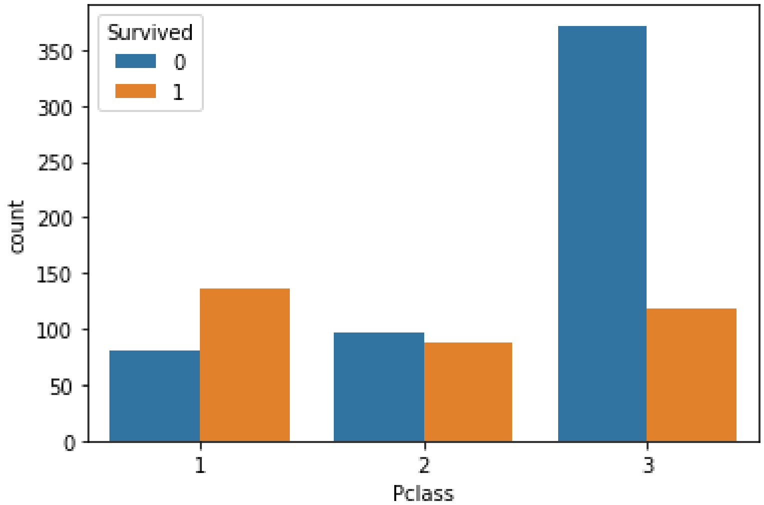


In [171]:
```
# Count of passengers per class

df_train["Pclass"].value_counts()
```

Out[171]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

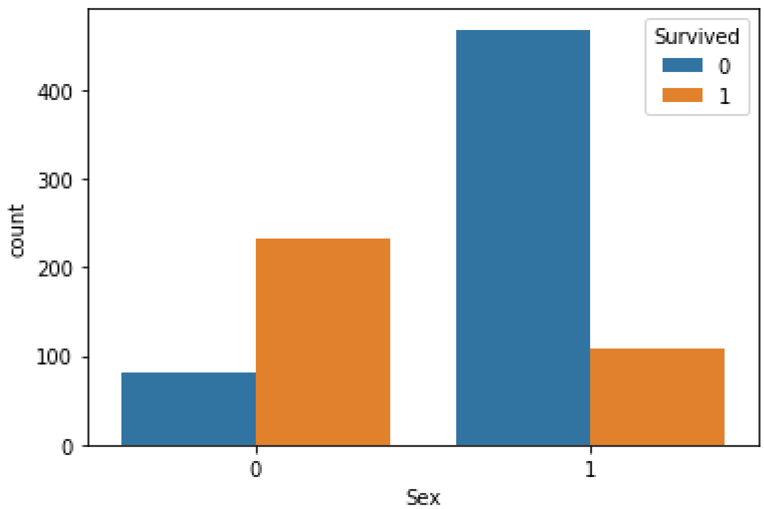
In [172]:
```
sns.countplot(df_train['Pclass'], hue = df_train['Survived'])
```

Out[172]: <matplotlib.axes._subplots.AxesSubplot at 0x7f87ba057510>



In [173]:
```
sns.countplot(df_train['Sex'], hue = df_train['Survived']) # Female=0, Male=1
```

Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0x7f87b8dc22d0>



In [174]:
```
df_train["Survived"].value_counts(normalize=True)*100
```

Out[174]:
```
0    61.616162
1    38.383838
Name: Survived, dtype: float64
```

In [175]:
```
# I dropped following variables- PassengerId, Name, Ticket, Cabin, Embar
ked
# because id, name, ticket number, cabin number and port from where pass
engers embarked
# cannot provide valuable information about survival

predictors = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']
outcome ='Survived'

X = df_train[predictors]
y = df_train[outcome]

# Split validation
from sklearn.model_selection import train_test_split
train_X, valid_X, train_y, valid_y= train_test_split(X,y, test_size=0.20
, random_state=1)
```

Modelling

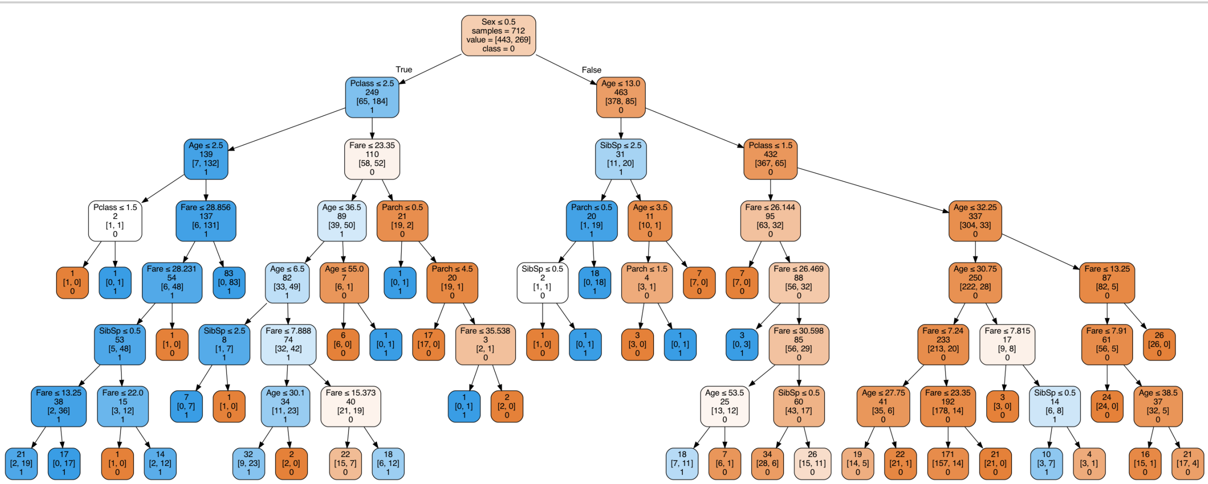
I test with 4 models to find the best model for prediction:

1. Decision Tree Classifier
2. Logistic Regression
3. Naive Bayes
4. Random Forest Classifier

Decision Tree Classifier

In [176]:
```
dt = DecisionTreeClassifier(max_depth = 7)
dt.fit(train_X, train_y)
plotDecisionTree(dt, feature_names=train_X.columns, class_names=dt.class
es_)
```

Out[176]:



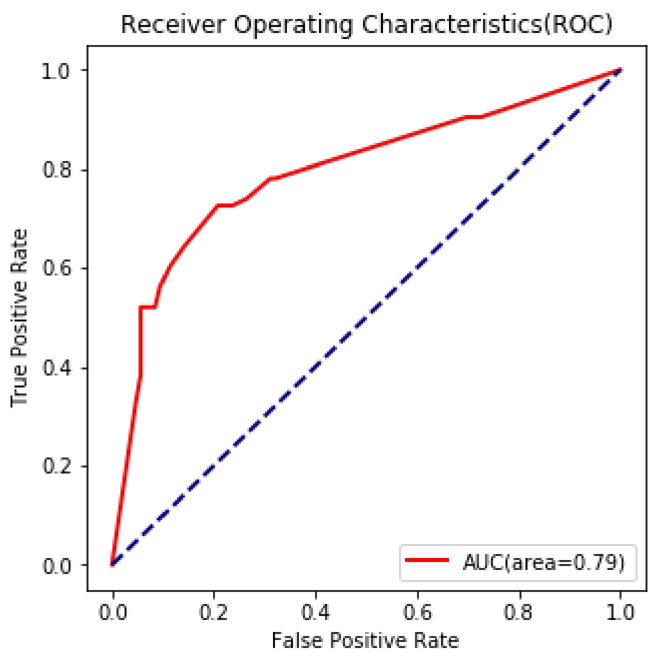
In [177]:
```
importances = dt.feature_importances_
df_imp = pd.DataFrame({'feature': train_X.columns, 'importance': importa
nces})
df_imp = df_imp.sort_values('importance', ascending = False)
print(df_imp)
```

```
  feature  importance
1     Sex    0.463870
0  Pclass    0.173659
2     Age    0.146453
5    Fare    0.116972
3   SibSp    0.077285
4   Parch    0.021761
```

In [178]:
```
# Model evaluation on training set
print("Accuracy with training set:",accuracy_score(train_y, dt.predict(t
rain_X)))
# Model evaluation on validation set
print("Accuracy with validation set:",accuracy_score(valid_y, dt.predict
(valid_X)))
print(" ")
print("precision score: ", precision_score(valid_y,dt.predict(valid_X)))
print("recall score: ", recall_score(valid_y,dt.predict(valid_X)))
print("f1-score: ", f1_score(valid_y,dt.predict(valid_X)))
```

```
Accuracy with training set: 0.8876404494382022
Accuracy with validation set: 0.770949720670391

precision score:  0.7857142857142857
recall score:  0.6027397260273972
f1-score:  0.6821705426356588
```

In [179]:
```
from sklearn.metrics import auc, roc_curve

# Creating a function for ROC graph plotting to be used by other models
def roc_graph(clf, valid_y, valid_X):
    fpr,tpr,_=roc_curve(valid_y,clf.predict_proba(valid_X)[:,1])
    area=auc(fpr,tpr)

    plt.figure(figsize=[5,5])
    plt.plot(fpr,tpr, color="red",lw=2, label="AUC(area=%.2f)" % area)
    plt.plot([0,1],[0,1],color="navy",linestyle="--",lw=2)
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("Receiver Operating Characteristics(ROC)")
    plt.legend(loc="lower right")
    plt.show()

# Calling the function with Decision tree classifier inputs
roc_graph(dt, valid_y, valid_X)
```



Logistic Regression

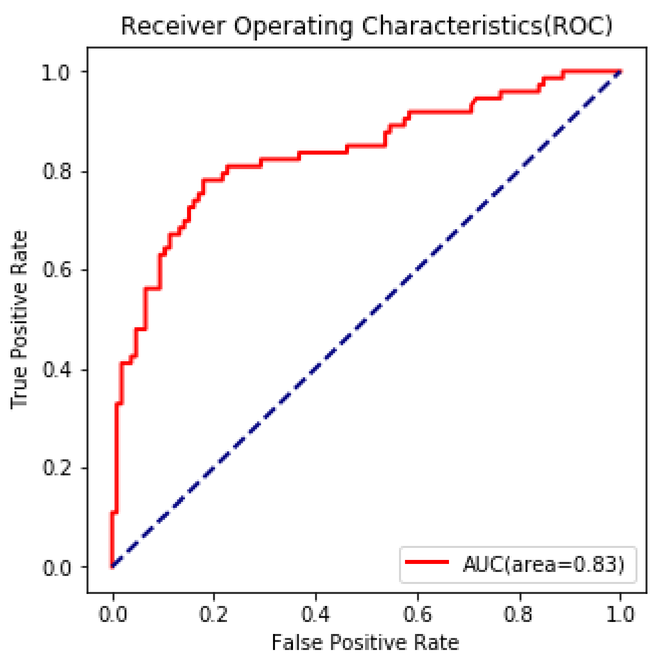
In [180]:
```
logit = LogisticRegression(penalty="l2", solver='liblinear')
logit.fit(train_X, train_y)
```

Out[180]:
```
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='liblinear', tol=0.0001, v
erbose=0,
                   warm_start=False)
```

In [181]:
```
# Model evaluation on training set
print("Accuracy with training set:",accuracy_score(train_y, logit.predic
t(train_X)))
# Model evaluation on validation set
print("Accuracy with validation set:",accuracy_score(valid_y, logit.pred
ict(valid_X)))
print(" ")
print("precision score: ", precision_score(valid_y,logit.predict(valid_X
)))
print("recall score: ", recall_score(valid_y,logit.predict(valid_X)))
print("f1-score: ", f1_score(valid_y,logit.predict(valid_X)))
```

```
Accuracy with training set: 0.7963483146067416
Accuracy with validation set: 0.7988826815642458

precision score:  0.8032786885245902
recall score:  0.6712328767123288
f1-score:  0.7313432835820896
```

In [182]:
```
# Calling the function with Decision tree classifier inputs
roc_graph(logit, valid_y, valid_X)
```



Naive Bayes

In [183]:
```
# run naive Bayes
nb = GaussianNB()
nb.fit(train_X,train_y)

# predict class membership
prediction_train_nb=nb.predict(valid_X)

# predict probabilities
pred_train_prob_nb = nb.predict_proba(valid_X)
```

In [184]:
```
# Model evaluation on training set
print("Accuracy with training set:",accuracy_score(train_y, nb.predict(t
rain_X)))
# Model evaluation on validation set
print("Accuracy with validation set:",accuracy_score(valid_y, nb.predict
(valid_X)))
print(" ")
print("precision score: ", precision_score(valid_y,nb.predict(valid_X)))
print("recall score: ", recall_score(valid_y,nb.predict(valid_X)))
print("f1-score: ", f1_score(valid_y,nb.predict(valid_X)))
```

```
Accuracy with training set: 0.7949438202247191
Accuracy with validation set: 0.7597765363128491

precision score:  0.734375
recall score:  0.6438356164383562
f1-score:  0.6861313868613139
```

Random Forest

In [185]:
```
rf=RandomForestClassifier(n_estimators=500, random_state=1)
rf.fit(train_X,train_y)
```

Out[185]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gi
ni',
                       max_depth=None, max_features='auto', max_leaf_no
des=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=1, ve
rbose=0,
                       warm_start=False)
```

In [186]:
```
# Model evaluation on training set
print("Accuracy with training set:",accuracy_score(train_y, rf.predict(train_X)))
# Model evaluation on validation set
print("Accuracy with validation set:",accuracy_score(valid_y, rf.predict(valid_X)))
print(" ")
print("precision score: ", precision_score(valid_y,rf.predict(valid_X)))
print("recall score: ", recall_score(valid_y,rf.predict(valid_X)))
print("f1-score: ", f1_score(valid_y,rf.predict(valid_X)))
```

```
Accuracy with training set: 0.9873595505617978
Accuracy with validation set: 0.7988826815642458

precision score:  0.8490566037735849
recall score:  0.6164383561643836
f1-score:  0.7142857142857144
```

Logistic Regression model shows best accuracy and highest Senstivity(Recall).That means there are less number of False negatives(people classified as dead but actually survived). The performance gap between the training and test sets is also minimal.

Predictions on Test set using Logistic Regression

In [187]:
```
df_test=pd.read_csv("test.csv")
df_test.head()
```

Out[187]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embark
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 [188]:
```
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
```

In [189]:
```
# Test Data Preprocessing
```

In [190]:
```
# Dummy code the variable sex.
df_test['Sex'] = pd.get_dummies(df_test['Sex'], prefix_sep='_', drop_fir
st=True)

# filling the missing ages with mean ages
df_test['Age'].fillna((df_test['Age'].mean()), inplace=True)
df_test['Fare'].fillna((df_test['Fare'].mean()), inplace=True)
df_test.shape
```

Out[190]:
```
(418, 11)
```

In [191]:
```
test_predictors = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']

X_test = df_test[predictors]
df_test["Survived"]= logit.predict(X_test)
df_test.head()
```

Out[191]:

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

In [192]:
```
df_test["Survived"].value_counts(normalize=True)*100
```

Out[192]:
```
0    64.114833
1    35.885167
Name: Survived, dtype: float64
```

In [193]:
```
import plotly.graph_objects as go
fig = go.Figure()
labels=["Died","Survived"]
fig.add_trace(go.Pie(labels=labels, values=df_test['Survived'].value_cou
nts()))
fig.update_layout(autosize=False, width=400, height=350)
fig.show()
```

In [194]:

```
df=df_test[["PassengerId","Survived"]]
df=df.set_index("PassengerId")
df.to_csv("Titanic_output_Ridhi.csv")
out=pd.read_csv("Titanic_output_Ridhi.csv")
out
```

Out[194]:

	PassengerId	Survived
0	892	0
1	893	0
2	894	0
3	895	0
4	896	1
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	0

418 rows × 2 columns