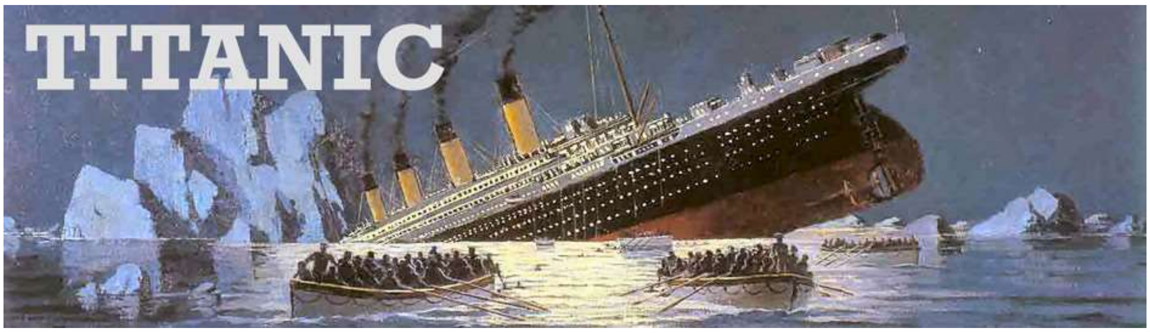
Predicting Survival on the Titanic



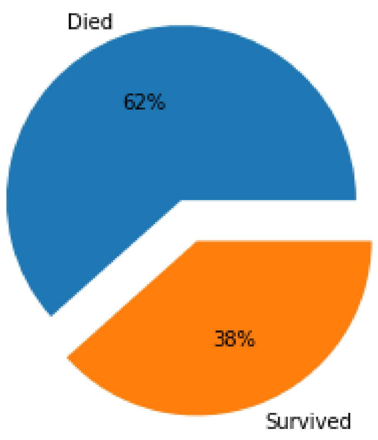
On April 14, 1912, the RMS Titanic hit an iceberg and sank. Of the 2223 aboard, only 706 were rescued. This notebook analyses the survival statistics to predict the likelihood of certain demographics surviving the disaster.

In [1]:
```
# (Optional) pip install pandas
# (Optional) !pip install seaborn
# (Optional) !pip install scikit-learn
import warnings
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import confusion_matrix, plot_confusion_matrix, ConfusionMatr
from sklearn.model_selection import GridSearchCV

warnings.simplefilter('ignore')
```

In [2]:
```
csv = pd.read_csv('dataset.csv')
dataset = pd.DataFrame(csv)
```

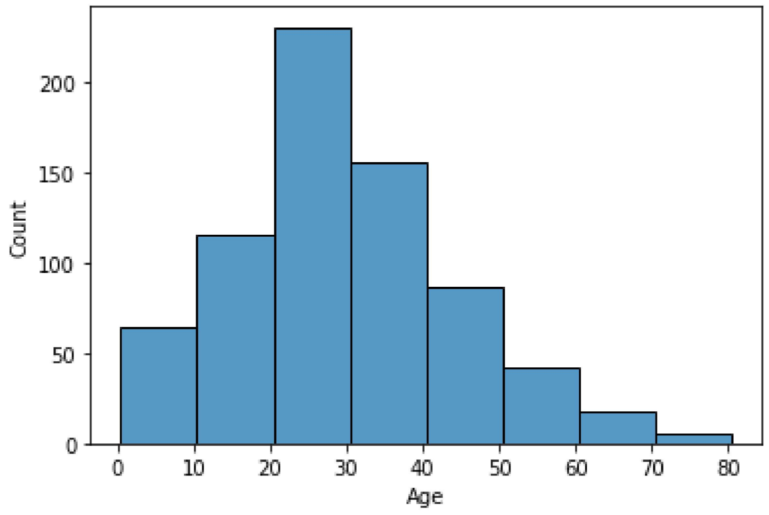
Before anything else, we perform basic visualisations to help intuit our data.

In [3]:
```
survival_data = dataset['Survived'].value_counts()
piechart_data = [survival_data[0], survival_data[1]]

label = ['Died', 'Survived']
explode = [0, 0.25]

plt.pie(piechart_data, labels = label, explode = explode, autopct='%.0f%%')
plt.show()
```



In [4]:
```
sns.histplot(data = dataset, x = 'Age', binwidth = 10)
```

Out[4]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```



We now have an idea of the age distribution of the passengers. We also know that the majority of them died. We can now move on to data cleaning. As our model cannot learn from irrelevant or absent data, we will begin inspecting fields for null values.

In [5]:
```
dataset.isnull().sum()
```

Out[5]:
```
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
```

Unfortunately, there are two fields with significant missing data: 'Age', and 'Cabin'. However, we can use mean and mode imputation to generate new age and cabin values, respectively.

In [6]:
```
dataset['Age'] = dataset['Age'].fillna(dataset['Age'].mean()) # Mean imp.
dataset['Cabin'] = dataset['Cabin'].fillna(dataset['Cabin'].value_counts().index[0
dataset[['Age', 'Cabin']].isnull().sum()
```

Out[6]:
```
Age      0
Cabin    0
dtype: int64
```

In [7]:
```
dataset[['Age', 'Cabin']].head()
```

Out[7]:

	Age	Cabin
0	22.0	B96 B98
1	38.0	C85
2	26.0	B96 B98
3	35.0	C123
4	35.0	B96 B98

After compensating for missing values, it seems that mode imputation is not a sensible approach for tackling the 'Cabin' field's null values. To avoid our model becoming affected by incomplete, irrelevant, or incorrect data, we will remove it (and other extraneous fields).

In [8]:
```
del dataset['PassengerId']
del dataset['Name']
del dataset['Ticket']
del dataset['Cabin']
del dataset['Embarked']
del dataset['Fare']
```

In [9]:
```
dataset.head()
```

Out[9]:

	Survived	Pclass	Sex	Age	SibSp	Parch
0	0	3	male	22.0	1	0
1	1	1	female	38.0	1	0
2	1	3	female	26.0	0	0
3	1	1	female	35.0	1	0
4	0	3	male	35.0	0	0

The next step involves converting our categorical variables into dummy variables for our model to understand. This includes: binning age values into child vs. adult binaries, and converting sex into male vs. female binaries.

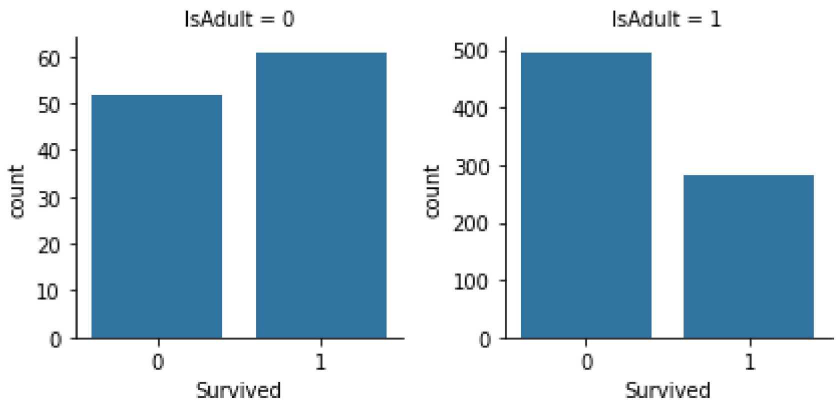
In [10]:
```
dataset['IsAdult'] = pd.cut(dataset['Age'], [0, 17, 999], labels=[0, 1])
del dataset['Age']
dataset.head()
```

Out[10]:

	Survived	Pclass	Sex	SibSp	Parch	IsAdult
0	0	3	male	1	0	1
1	1	1	female	1	0	1
2	1	3	female	0	0	1
3	1	1	female	1	0	1
4	0	3	male	0	0	1

In [11]:
```
adult_eda = sns.FacetGrid(data = dataset, col = 'IsAdult', col_wrap = 2, sharey = F
adult_eda.map(sns.countplot, 'Survived')
```

Out[11]:
```
<seaborn.axisgrid.FacetGrid at 0x141582665b0>
```



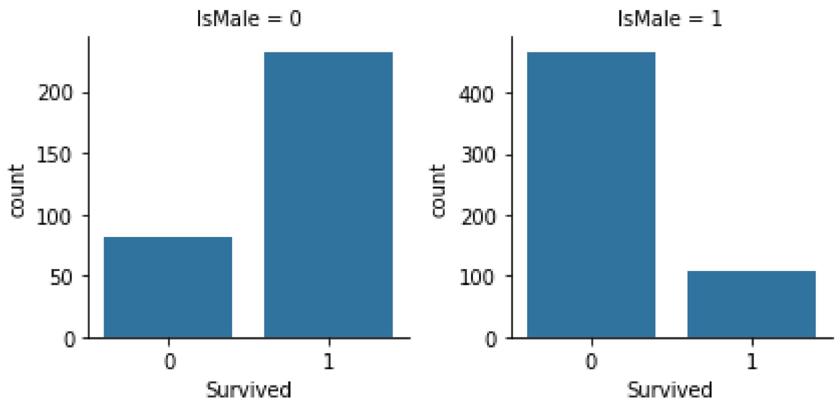
In [12]:
```
dataset = pd.get_dummies(dataset, columns=['Sex'], drop_first=True)
dataset.rename(columns = {'Sex_male':'IsMale'}, inplace = True)
dataset.head()
```

Out[12]:

	Survived	Pclass	SibSp	Parch	IsAdult	IsMale
0	0	3	1	0	1	1
1	1	1	1	0	1	0
2	1	3	0	0	1	0
3	1	1	1	0	1	0
4	0	3	0	0	1	1

In [13]:
```
adult_eda = sns.FacetGrid(data = dataset, col = 'IsMale', col_wrap = 2, sharey = Fa
adult_eda.map(sns.countplot, 'Survived')
```

Out[13]:
```
<seaborn.axisgrid.FacetGrid at 0x1415831aa60>
```



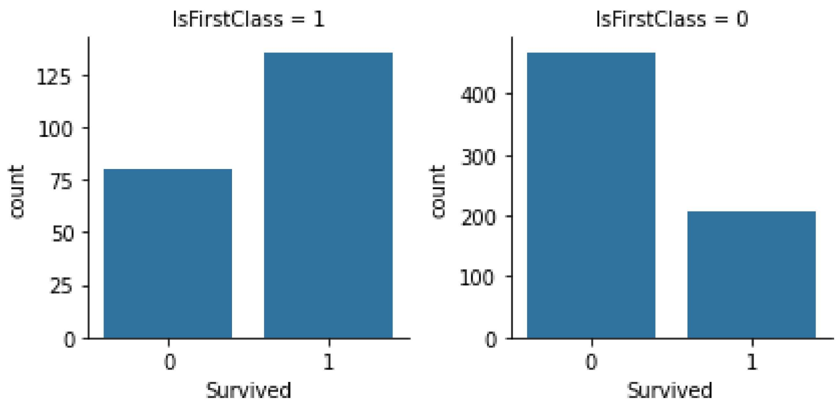
In [14]:
```
dataset['IsFirstClass'] = pd.cut(dataset['Pclass'], [0, 1, 3], labels=[1, 0])
del dataset['Pclass']
dataset.head()
```

Out[14]:

	Survived	SibSp	Parch	IsAdult	IsMale	IsFirstClass
0	0	1	0	1	1	0
1	1	1	0	1	0	1
2	1	0	0	1	0	0
3	1	1	0	1	0	1
4	0	0	0	1	1	0

In [15]:
```
class_eda = sns.FacetGrid(data = dataset, col = 'IsFirstClass', col_wrap = 2, share
class_eda.map(sns.countplot, 'Survived')
```

Out[15]:
```
<seaborn.axisgrid.FacetGrid at 0x14158341b20>
```



We have learned that the following demographics had the highest survival rates: children (marginal), females (significant), first-class (significant). Now, the final step before developing the model is splitting the data into testing and training sets.

In [16]:
```
dataset = dataset.values
sc = dataset[:, 0] # 'Survived' column
rc = dataset[:, 1:8] # Remaining columns
rc_train, rc_test, sc_train, sc_test = train_test_split(rc, sc, test_size = .90)
```

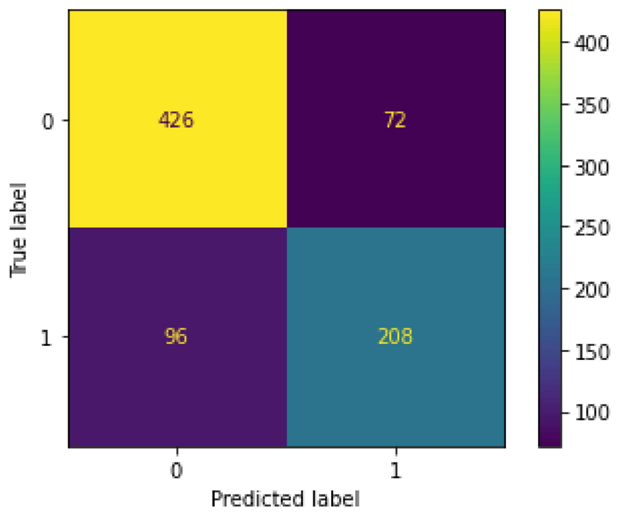
In [17]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_rc_train = scaler.fit_transform(rc_train)
scaled_rc_test = scaler.fit_transform(rc_test)
```

We now begin training a Logistic Regression model imported from the SciKit-Learn library.

In [18]:
```
model = LogisticRegression()
model.fit(scaled_rc_train, sc_train)
```

Out[18]:
```
▾ LogisticRegression
LogisticRegression()
```

In [19]:
```
sc_prediction = model.predict(scaled_rc_test)
accuracy_score = round(model.score(scaled_rc_test, sc_test)*100, 2)
print("Model accuracy: {0}%".format(accuracy_score))
```
```
Model accuracy: 79.05%
```

In [20]:
```
# (Optional) confusion_matrix(sc_test, sc_prediction)
cm = confusion_matrix(sc_test, sc_prediction)
cm_display = ConfusionMatrixDisplay(confusion_matrix=cm)
cm_display.plot()
```
Out[20]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x141584a1790>
```


Our model accuracy is reasonably high. Our confusion matrix shows the model's performance via the following metrics: true-positives (bottom-right), true-negatives (top-left), false-positives (top-right), and false-negatives (bottom-left). We can improve model parameters using grid-searching.

In [21]:
```
tolerances = [.1, .01, .001]
iterations = [100, 150, 200]
parameter_grid = dict(tol=tolerances, max_iter=iterations)
```

In [22]:
```
gs = GridSearchCV(estimator=model, param_grid=parameter_grid, cv=5)
scaled_rc = scaler.fit_transform(rc)
result = gs.fit(scaled_rc, sc)

best_score = round(result.best_score_*100, 2)
best_params = result.best_params_

print("Best accuracy: {0}%".format(best_score))
print("Best parameters:", best_params)
```
```
Best accuracy: 79.68%
Best parameters: {'max_iter': 100, 'tol': 0.1}
```

The model accuracy has increased after running a grid-search. We now have a functioning machine learning model capable of predicting passenger survival based on: class, number of siblings / spouses aboard, number of parents / children aboard, fare paid, age (i.e. adult vs. child status), and sex. It is tested below.

In [89]:
```
# REFERENCE: [SibSp, Parch, IsAdult, IsMale, IsFirstClass]
```

```
test01 = [0, 0, 0, 0, 1] # 1st-class child female (alone)
test02 = [0, 0, 1, 1 ,0] # Non-1st-class adult male (alone)
test03 = [0, 2, 0, 1, 1] # 1st-class child male (w. parents)

test_passengers = [test01, test02, test03]
```

In [94]:

```
index = 0

for passenger in test_passengers:
    print("Test #{0}: {1}".format(index+1, passenger))
    died_confidence = round(model.predict_proba(test_passengers)[index][0], 2) * 1
    survived_confidence = round(model.predict_proba(test_passengers)[index][1], 2)

    if (prediction[index] == 1):
        print('------ RESULT: Survived! ({0}% confidence)\n'.format(survived_confi
    else:
        print('------ RESULT: Died. ({0}% confidence)\n'.format(died_confidence))

    index = index + 1
```

```
Test #1: [0, 0, 0, 0, 1]
------ RESULT: Survived! (91.0% confidence)

Test #2: [0, 0, 1, 1, 0]
------ RESULT: Died. (80.0% confidence)

Test #3: [0, 2, 0, 1, 1]
------ RESULT: Died. (60.0% confidence)
```