Titanic - Machine Learning from Disaster

The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered “unsinkable” RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren’t enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

In this challenge, we ask you to 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).

Data Dictionary:

- survived - (0 - No, 1 - Yes)
- pclass - Ticket class
- Sex - Sex
- Age - Age in Years
- Sibsp - No: of siblings/spouses aboard the Titanic
- Parch - No: of parents/children aboard the Titanic
- Ticket - Ticket Number
- Fare - Passenger Fare
- Cabin - Cabin Number
- Embarked - Port of embarkation

Import necessary libraries

In [91]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Read 'titanic.csv' dataset and store it in a variable

In [92]:
```
df = pd.read_csv('titanic.csv')
```

View the top 5 rows

In [93]:
```
df.head()
```

Out[93]:

	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	I
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	I
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	I

View the bottom 5 rows

In [94]:
```
df.tail()
```

Out[94]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabir
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN

Find info about the dataset

In [95]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Find the statistical information about the dataset

In [96]:
```
df.describe()
```

Out[96]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Check for null values

In [97]:
```
df.isna().sum()
```

Out[97]:
```
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
```

Check the unique values in Embarked

In [98]:
```
df['Embarked'].unique()
```

Out[98]:
```
array(['S', 'C', 'Q', nan], dtype=object)
```

Clean the dataset

Remove unwanted features (PassengerId,Name, ticket, Cabin)

In [99]:
```
df.drop(columns = ['PassengerId', 'Name', 'Ticket', 'Cabin'], inplace = True)
df.head()
```

Out[99]:

	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

Fill null values in Age with mean

In [100]:
```
df['Age'].fillna(df['Age'].mean(), inplace = True)
```

In [101]:
```
df.isna().sum()
```

Out[101]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    2
dtype: int64
```

Fill null values in Embarked with 'Unknown'

In [102]:
```
df['Embarked'].fillna('Unknown', inplace = True)
```

In [103]:
```
df.isna().sum()
```

Out[103]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

Convert the categorical datas into numerical ('Sex', 'Embarked')

In [105]:
```
df = pd.get_dummies(df, drop_first= True)
df.head()
```

Out[105]:

	Survived	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Embark
0	0	3	22.0	1	0	7.2500	1	0	1	
1	1	1	38.0	1	0	71.2833	0	0	0	
2	1	3	26.0	0	0	7.9250	0	0	1	
3	1	1	35.0	1	0	53.1000	0	0	1	
4	0	3	35.0	0	0	8.0500	1	0	1	

Split the set into feature and target varibles(X,y)

In [106]:
```
X = df.drop(columns = ['Survived'])
y = df['Survived']
```

Check the shape of X and y

In [107]:
```
X.shape
```

Out[107]:
```
(891, 9)
```

In [108]:
```
y.shape
```

Out[108]:
```
(891,)
```

Standardise the data with standard scaler

In [109]:
```
from sklearn.preprocessing import StandardScaler
```

In [110]:
```
scaler = StandardScaler()
```

In [111]:
```
xcolumns = X.columns
```

In [112]:
```
X = scaler.fit_transform(X)
```

In [113]:
```
X = pd.DataFrame(X, columns = xcolumns)
```

In [114]:
```
X.head()
```

Out[114]:

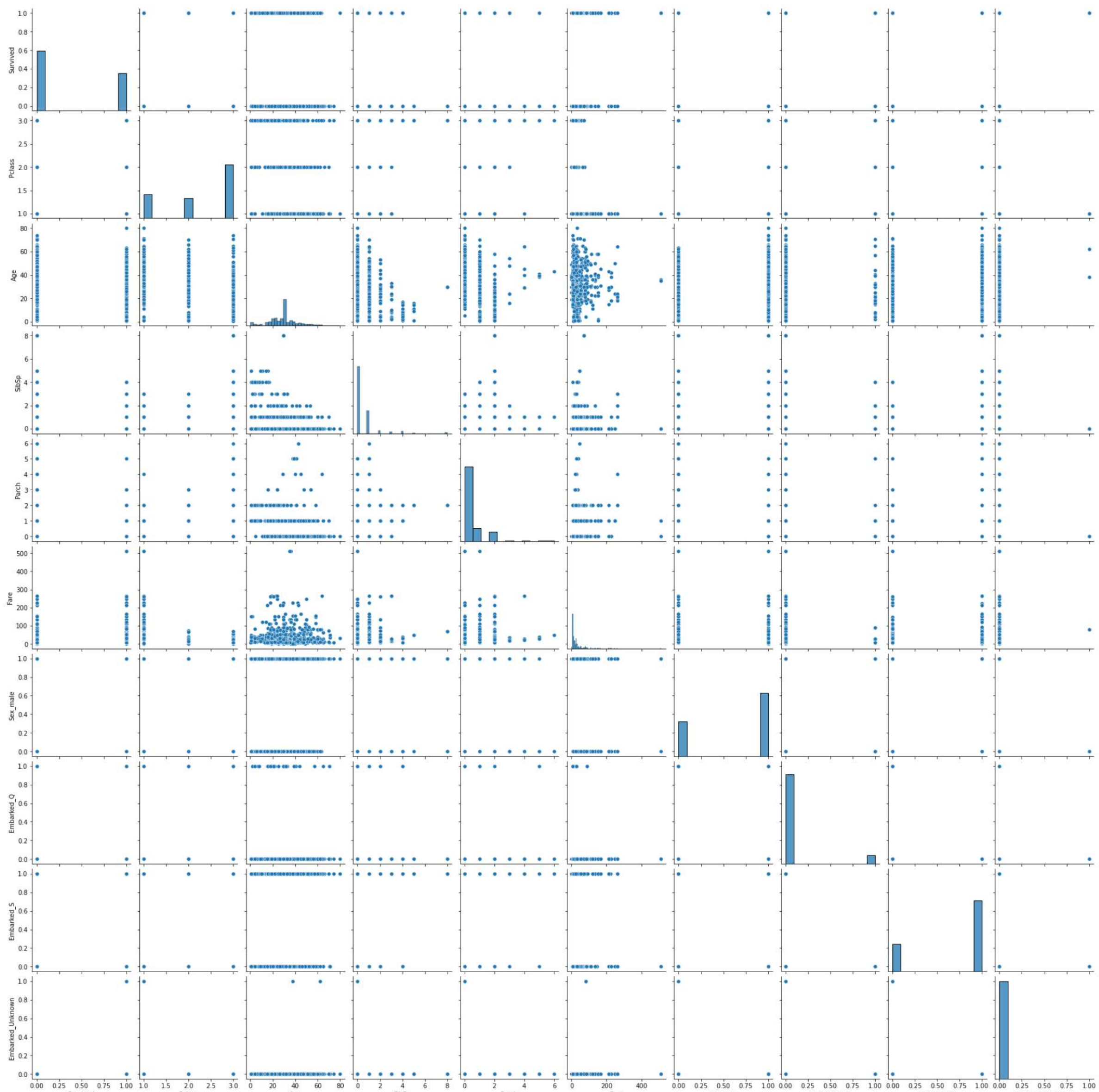
	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	E
0	0.827377	-0.592481	0.432793	-0.473674	-0.502445	0.737695	-0.307562	0.619306	
1	-1.566107	0.638789	0.432793	-0.473674	0.786845	-1.355574	-0.307562	-1.614710	
2	0.827377	-0.284663	-0.474545	-0.473674	-0.488854	-1.355574	-0.307562	0.619306	
3	-1.566107	0.407926	0.432793	-0.473674	0.420730	-1.355574	-0.307562	0.619306	
4	0.827377	0.407926	-0.474545	-0.473674	-0.486337	0.737695	-0.307562	0.619306	

Visualization

Plot a pair plot

In [115]:
```
sns.pairplot(df)
plt.plot()
```

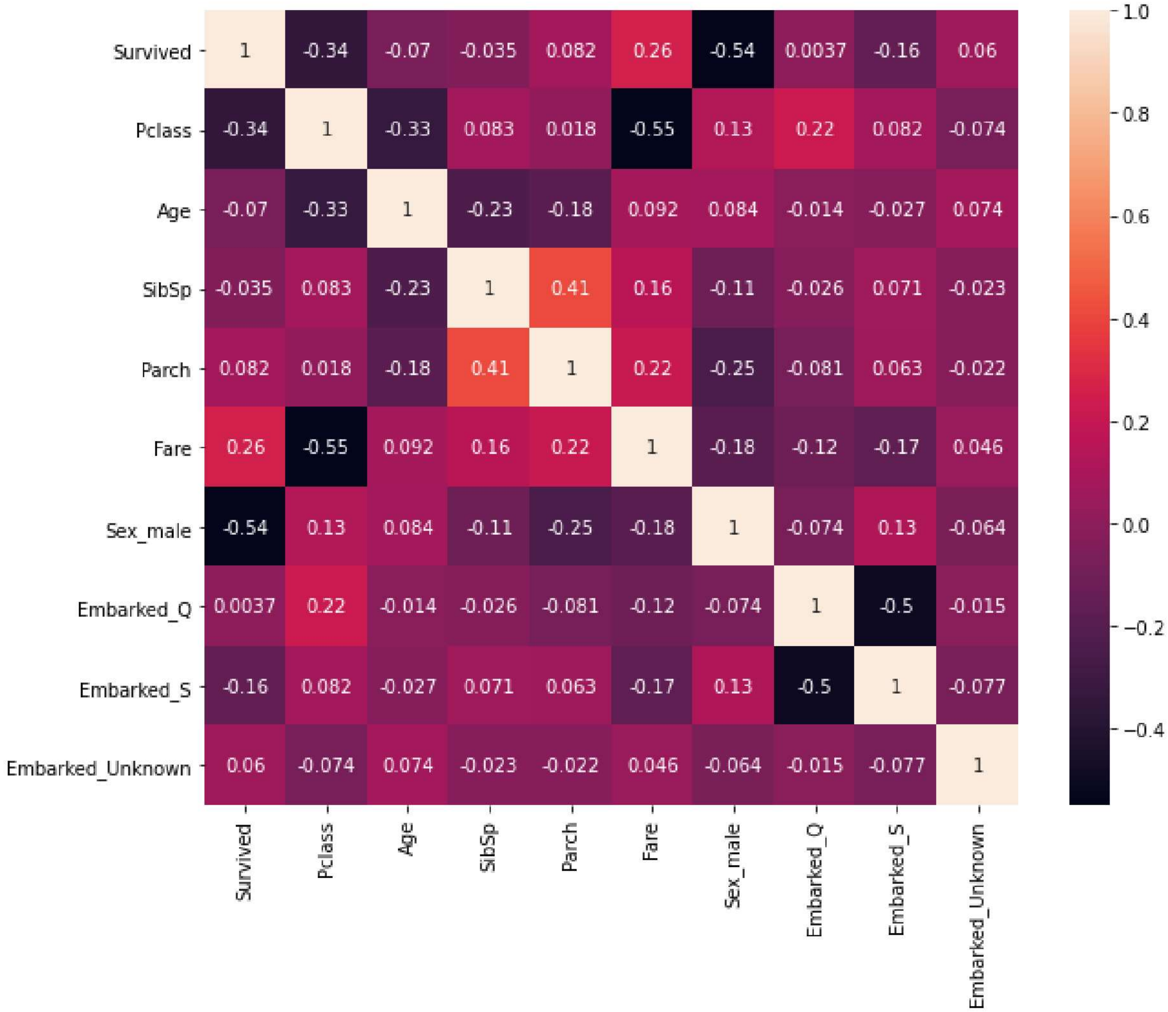
Out[115]: []



Plot a heat map to view the correlation between features

In [116]:
```
plt.figure(figsize = (10,8))
sns.heatmap(df.corr(), annot = True)
plt.plot()
```

Out[116]: []



Split the data into training and testing set

In [117]:
```
from sklearn.model_selection import train_test_split
```

In [118]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3, rand
```

Check the shape of X_train and X_test

In [119]:
```
X_train.shape
```

Out[119]:
```
(623, 9)
```

In [120]:
```
X_test.shape
```

Out[120]:
```
(268, 9)
```

Create a Logistic Regression model and Train it

In [121]:
```
from sklearn.linear_model import LogisticRegression
```

In [122]:
```
model = LogisticRegression()
```

In [123]:
```
# Train the model
model.fit(X_train, y_train)
```

Out[123]:
```
LogisticRegression()
```

Check the score of our model

In [124]:
```
model.score(X_train,y_train)
```

Out[124]:
```
0.8089887640449438
```

Make predictions using X_test

In [125]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[125]:
```
array([1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0,
       0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0,
       0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1,
       0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
       0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0,
       1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1,
       1, 0, 1, 0], dtype=int64)
```

Check the accuracy score

In [126]:
```
from sklearn import metrics
```

In [127]:
```
metrics.accuracy_score(y_test,y_pred)
```

Out[127]:
```
0.7910447761194029
```

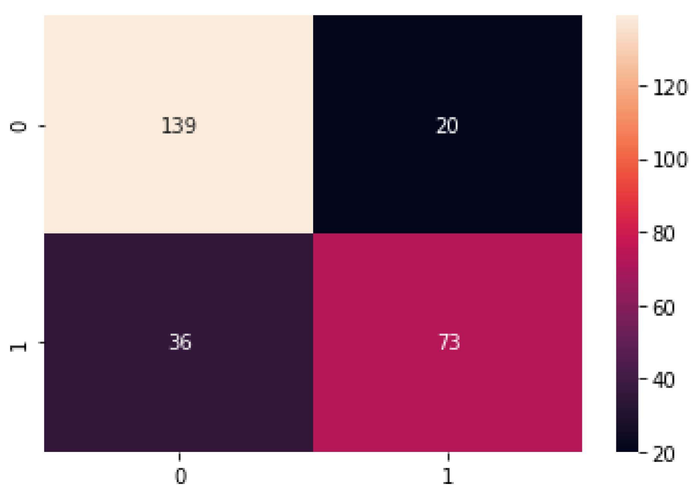
Check the confusion metrics

In [128]:
```
metrics.confusion_matrix(y_test,y_pred)
```

Out[128]:
```
array([[139,  20],
       [ 36,  73]], dtype=int64)
```

Plot confusion matrix

In [131]:
```
sns.heatmap(metrics.confusion_matrix(y_test,y_pred), annot = True, fmt = 'd')
plt.show()
```



Print the classification report

In [130]:
```
print(metrics.classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.79      0.87      0.83       159
           1       0.78      0.67      0.72       109

    accuracy                           0.79       268
   macro avg       0.79      0.77      0.78       268
weighted avg       0.79      0.79      0.79       268
```

EDURE LEARNING