In [1]:

```
import numpy as np
import pandas as pd
```

In [2]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:

```
titanic = pd.read_csv(r'C:\Users\DELL\Downloads\3PythonCourse\Refactored_Py_DS_ML_Bootcamp-master\13-
titanic.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
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
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [4]:

```
titanic.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: 83.6+ KB
```

In [5]:

```
titanic.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
```

EDA

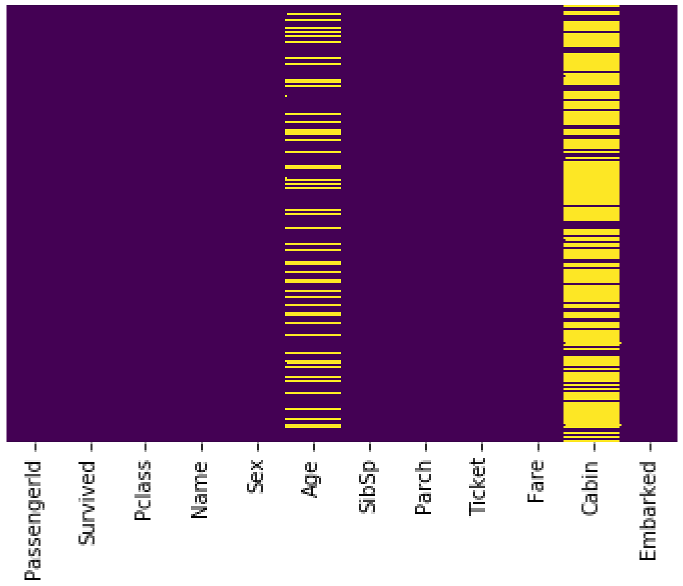
Lets begin our exploratory data analysis by analysing the missing values

In [6]:

```
sns.heatmap(titanic.isnull(), yticklabels = False, cbar = False, cmap = 'viridis')
```

Out[6]:

<matplotlib.axes._subplots.AxesSubplot at 0x149574fb898>



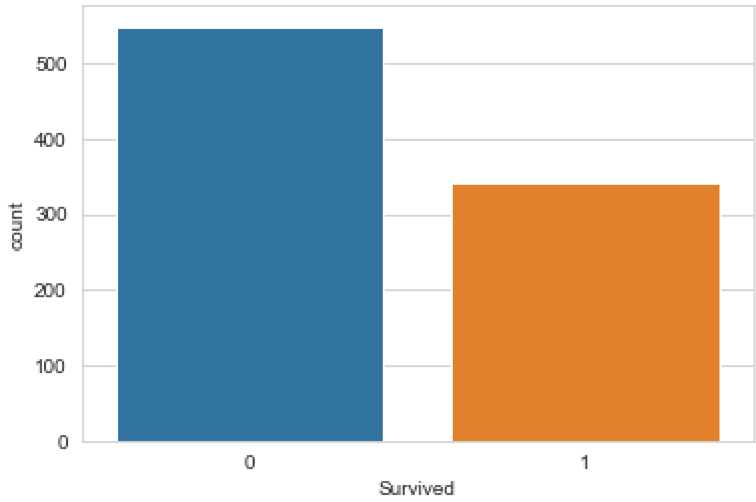
We can see that the columns Age and Cabin have null values However the column cabin have the highest number of null values

In [7]:

```
sns.set_style(style = 'whitegrid')
sns.countplot(x = 'Survived', data = titanic)
```

Out[7]:

<matplotlib.axes._subplots.AxesSubplot at 0x14957823358>

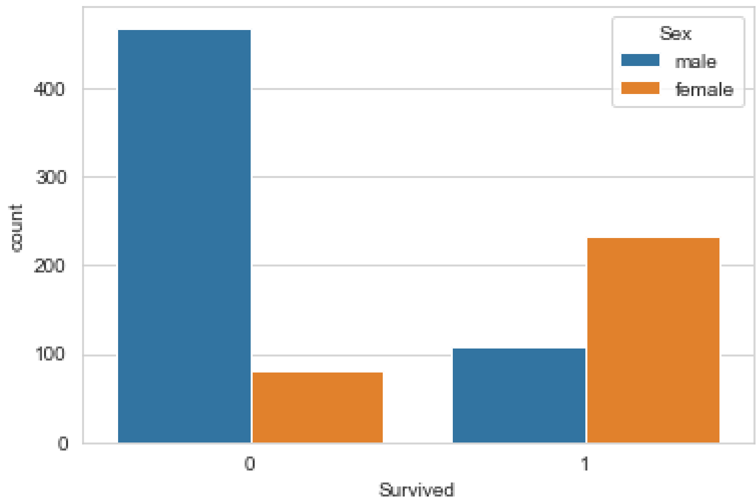


In [8]:

```
sns.set_style(style = 'whitegrid')
sns.countplot(x = 'Survived', data = titanic, hue = 'Sex')
```

Out[8]:

<matplotlib.axes._subplots.AxesSubplot at 0x1495786c9e8>

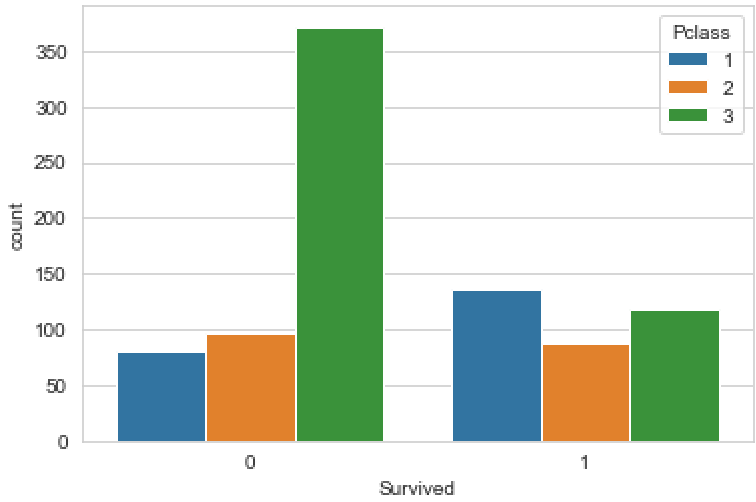


In [9]:

```
sns.set_style(style = 'whitegrid')
sns.countplot(x = 'Survived', data = titanic, hue = 'Pclass')
```

Out[9]:

<matplotlib.axes._subplots.AxesSubplot at 0x149578c5240>

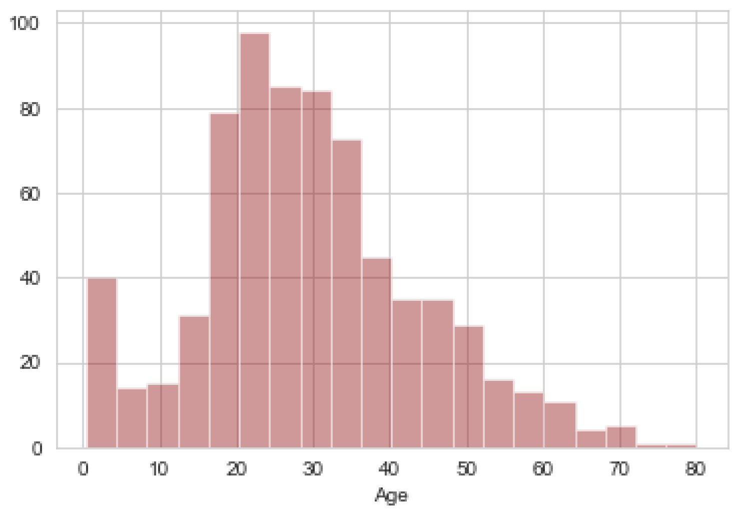


In [10]:

```
sns.distplot(titanic['Age'].dropna(), kde = False, color='darkred', bins = 20)
```

Out[10]:

<matplotlib.axes._subplots.AxesSubplot at 0x1495792ce80>

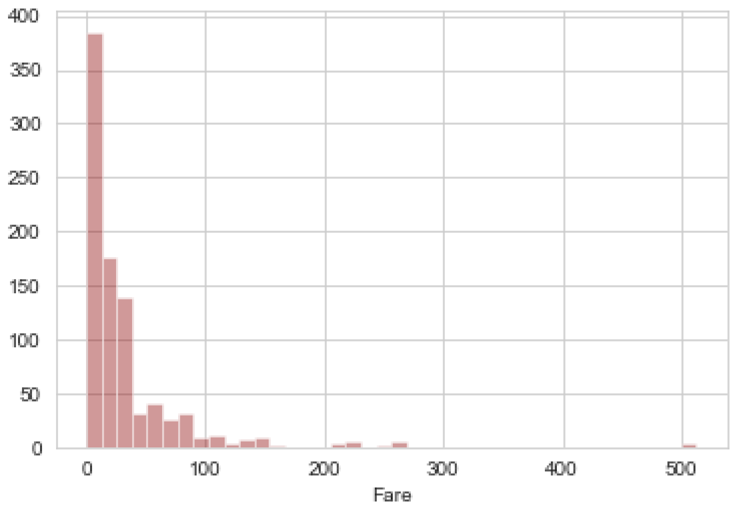


In [11]:

```
sns.distplot(titanic['Fare'], kde = False, color='darkred', bins = 40)
```

Out[11]:

<matplotlib.axes._subplots.AxesSubplot at 0x149579bd3c8>



Data Cleaning

As we have seen above that the column Age has null values. Therefore we need to fill in these null values. One way to do this is by dropping the null values rows but that would incur in the loss of so much information, other way to do this is by filling the mean value of all the passengers.

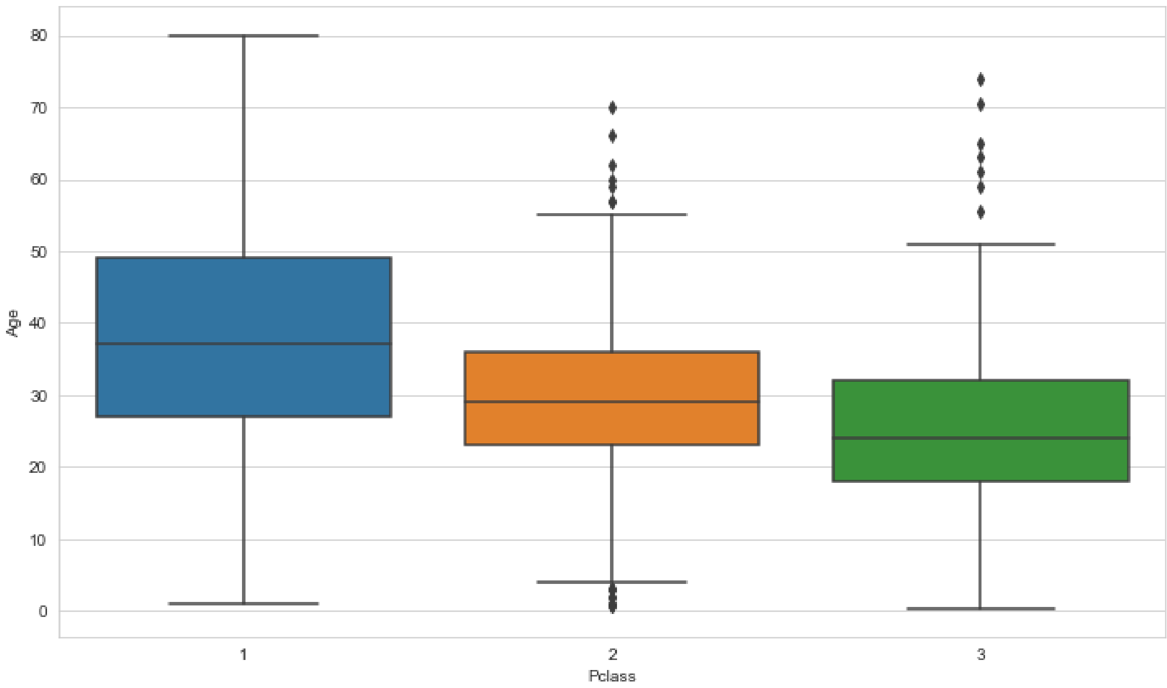
However we do have other option also where we will check the average age of the passengers wrt to their passenger_class.Let us see how.

In [12]:

```
plt.figure(figsize = (12, 7))
sns.boxplot(x = 'Pclass', y = 'Age', data = titanic )
```

Out[12]:

<matplotlib.axes._subplots.AxesSubplot at 0x149579bde10>



We can see that the passenger in 1st class seems to older as compared to others as they can be wealthier, which makes sense. We will take out average age of the passengers with respect to passenger class: For Pclass 1= 37, pclass 2= 29 and pclass 3 = 24

Now we will create a function using these average age values based on Pclass for age

In [13]:

```
def age(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):

        if Pclass == 1:
            return 37

        elif Pclass == 2:
            return 29

        else:
            return 24


    else:
        return Age
```

In [14]:

```
titanic['Age'] = titanic[['Age', 'Pclass']].apply(age, axis = 1)
```

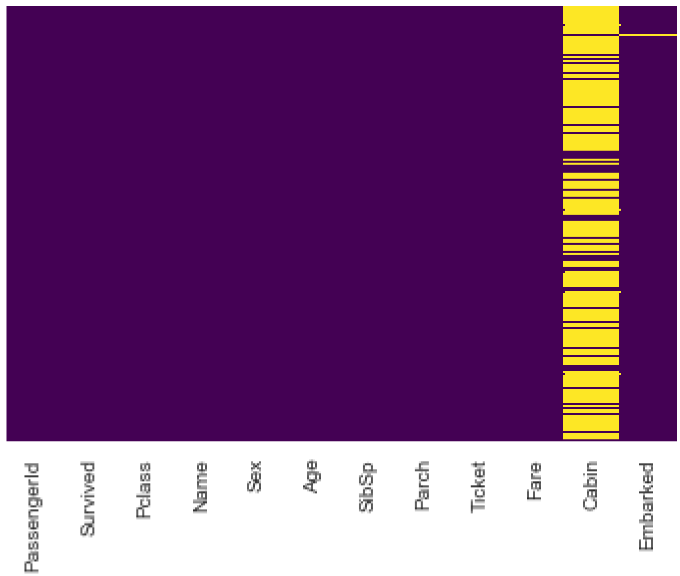
Let us check the heatmap again

In [15]:

```
sns.heatmap(titanic.isnull(), yticklabels = False, cbar = False, cmap = 'viridis')
```

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x14957cb6c50>



Now since the column 'Cabin' have a lot of missing data. Hence we will drop this particular table

In [16]:

```
titanic.drop('Cabin', axis = 1,  inplace = True)
```

In [17]:

```
titanic.head()
```

Out[17]:

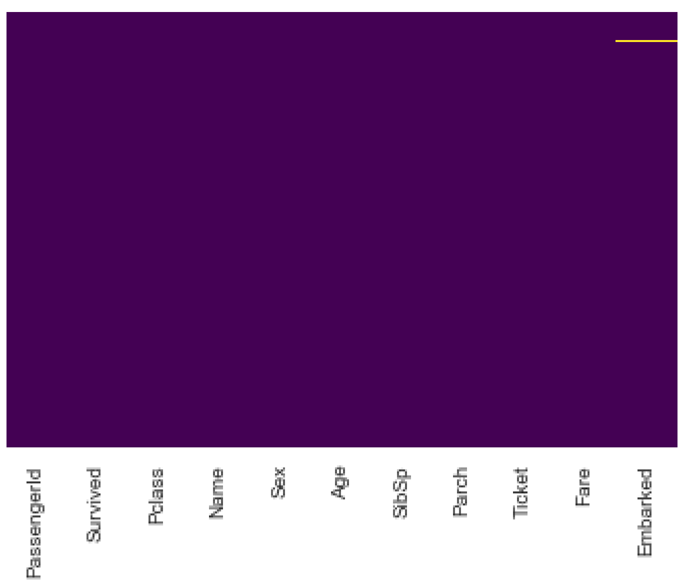
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	I
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

In [18]:

```
sns.heatmap(titanic.isnull(), yticklabels = False, cbar = False, cmap = 'viridis')
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x14957b124e0>



The dataset contains a single null value in the Embarked column hence we will drop that particular row

In [19]:

```
titanic.dropna(inplace = True)
```

Conversion of Categical variables

We will now convert the categorical variables into dummy variables as ML models algorithms don't take those features as inputs.

In [20]:

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 11 columns):
PassengerId    889 non-null int64
Survived       889 non-null int64
Pclass         889 non-null int64
Name           889 non-null object
Sex            889 non-null object
Age            889 non-null float64
SibSp          889 non-null int64
Parch          889 non-null int64
Ticket         889 non-null object
Fare           889 non-null float64
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(4)
memory usage: 83.3+ KB
```

The columns Sex and Embarked have categorical variables. Hence we will convert these into dummy variables.

In [21]:

```
sex = pd.get_dummies(titanic['Sex'], drop_first = True)
embark = pd.get_dummies(titanic['Embarked'], drop_first = True)
```

dropping all the unnecessary columns including Name and Ticket

In [22]:

```
titanic.drop(['Sex', 'Embarked', 'Name', 'Ticket'], axis = 1, inplace = True)
```

In [25]:

```
titanic = pd.concat([titanic, sex, embark], axis = 1)
```

In [26]:

```
titanic.head()
```

Out[26]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
0	1	0	3	22.0	1	0	7.2500	1	0	1
1	2	1	1	38.0	1	0	71.2833	0	0	0
2	3	1	3	26.0	0	0	7.9250	0	0	1
3	4	1	1	35.0	1	0	53.1000	0	0	1
4	5	0	3	35.0	0	0	8.0500	1	0	1

Building Logistic Regression Model

Since our data is ready we will now build the model. We will split the data into training and test data.

In [29]:

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

In [30]:

```
from sklearn.model_selection import train_test_split
```

In [31]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 101 )
```

Training the Model and Prediction

In [32]:

```
from sklearn.linear_model import LogisticRegression
```

In [33]:

```
logreg = LogisticRegression()
```

In [38]:

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

```
C:\Users\DELL\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:433: FutureWarni
ng: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[38]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [39]:

```
prediction = logreg.predict(X_test)
```

Evaluation

In [40]:

```
from sklearn.metrics import classification_report
```

In [41]:

```
print(classification_report(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.81      0.93      0.86       163
           1       0.85      0.65      0.74       104

   micro avg       0.82      0.82      0.82       267
   macro avg       0.83      0.79      0.80       267
weighted avg       0.82      0.82      0.81       267
```

In [ ]:

```

```