Assignment 23

Problem Statement

Predicting Survival in the Titanic Data Set

We will be using a decision tree to make predictions about the Titanic data set from Kaggle. This data set provides information on the Titanic passengers and can be used to predict whether a passenger survived or not.

In [88]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.preprocessing import StandardScaler
```

In [89]:
```
# URL of where the dataset resides
url = 'https://raw.githubusercontent.com/BigDataGal/Python-for-Data-Science/master/titanic-train.csv'
```

In [90]:
```
# Read the dataset into a dataframe
titanic = pd.read_csv(url)
```

In [91]:
```
# Display the top 5 rows of the dataset
titanic.head()
```

Out[91]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [92]:
```
# See the column data types and non-missing values
titanic.info(0)
```

```
<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 [93]:
```
# Statistics for each column
titanic.describe()
```

Out[93]:

	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

In [94]:
```
# I am only going to use Pclass, Sex, Age, SibSp (Siblings Aboard), Parch (Parents and Children Aboard), and
 Fare to determine
# if the passenger survived or not. Therefore I am going to drop the PassengerId, Name, Ticket, Cabin, and Em
barked columns
# from my dataset.

titanic.drop(columns=['PassengerId', 'Name', 'Ticket', 'Cabin', 'Embarked'], inplace=True)
```

In [95]:
```
titanic.head()
```

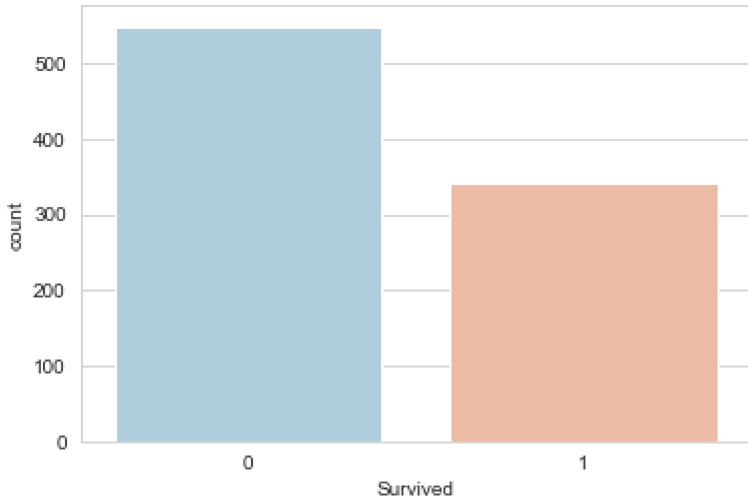
Out[95]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	male	22.0	1	0	7.2500
1	1	1	female	38.0	1	0	71.2833
2	1	3	female	26.0	0	0	7.9250
3	1	1	female	35.0	1	0	53.1000
4	0	3	male	35.0	0	0	8.0500

Exploratory Data Analysis

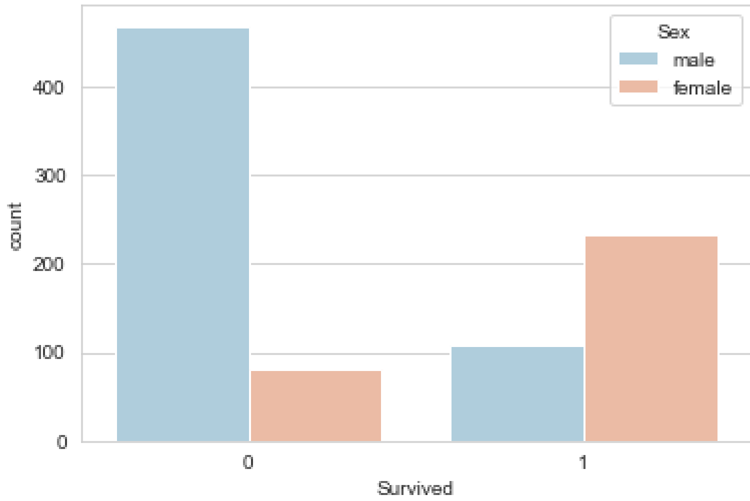
In [96]:
```
# Visualize how many survived and how many did not survived.
sns.set_style('whitegrid')
sns.countplot(x='Survived', data=titanic, palette='RdBu_r')
```

Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x262a5c1f208>



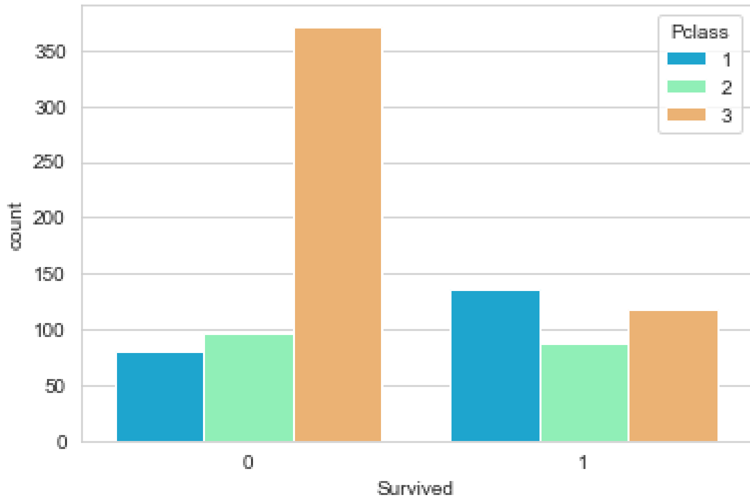
In [97]:
```
# Visualize how many Survived by Gender
sns.set_style('whitegrid')
sns.countplot(x='Survived', hue='Sex', data=titanic, palette='RdBu_r')
```

Out[97]: <matplotlib.axes._subplots.AxesSubplot at 0x262a5e29cc0>



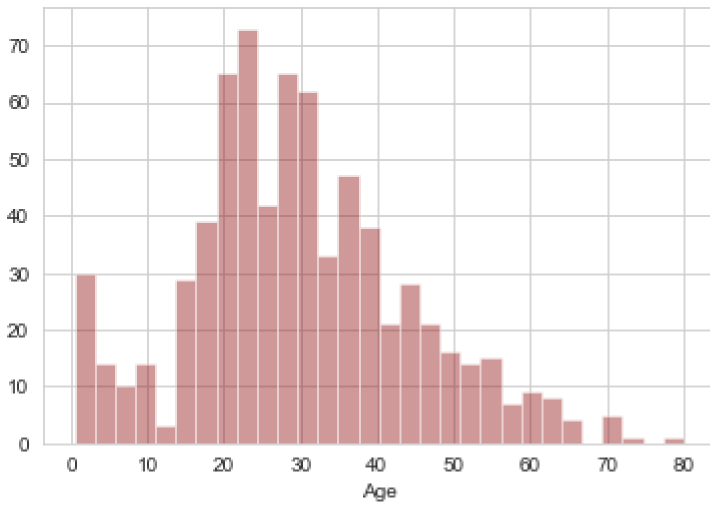
In [98]:
```
# Visualize how many Survived based on Passenger Class
sns.set_style('whitegrid')
sns.countplot(x='Survived', hue='Pclass', data=titanic, palette='rainbow')
```

Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0x262a5d58128>



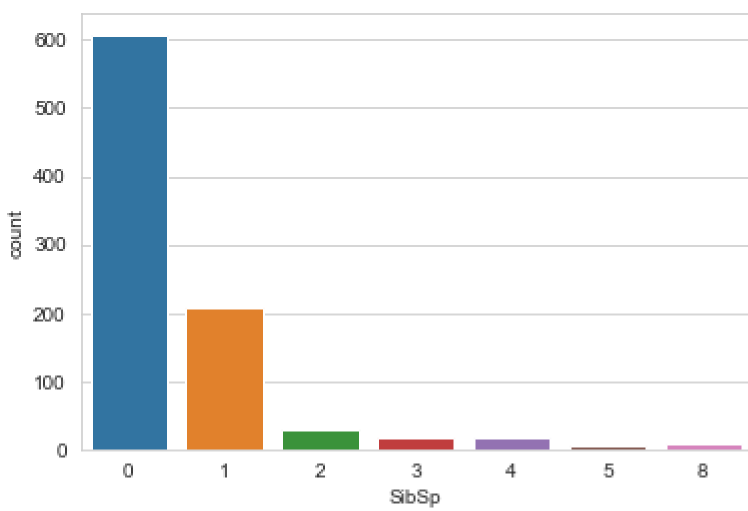
In [99]:
```
# Visualize the age distribution in our dataset after temporarily dropping the Null values in Age column.
sns.distplot(titanic['Age'].dropna(), kde=False, color='darkred', bins=30)
```

Out[99]: <matplotlib.axes._subplots.AxesSubplot at 0x262a5ce70f0>



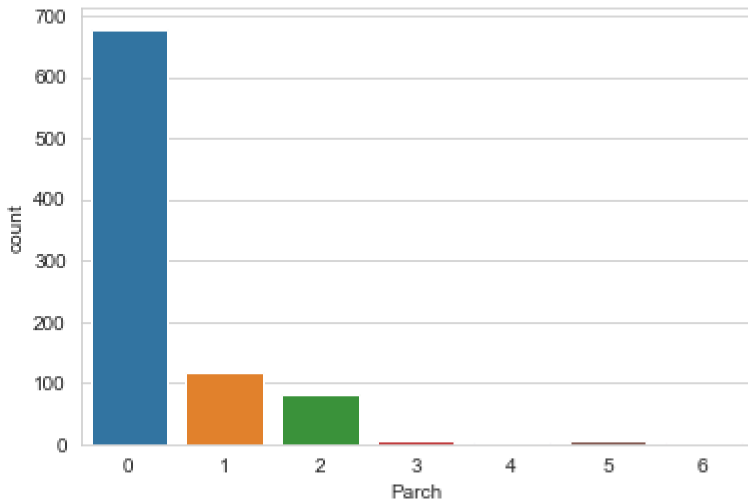
In [100]:
```
# Visualize the number of siblings and spouse are present in the dataset.
sns.countplot(x='SibSp', data=titanic)
```

Out[100]: <matplotlib.axes._subplots.AxesSubplot at 0x262a5dcbd68>



In [101]:
```
# Visualize the number of Parents and Childrens are present in the dataset.
sns.countplot(x='Parch', data=titanic)
```

Out[101]: <matplotlib.axes._subplots.AxesSubplot at 0x262a6015898>



Data Cleaning

In [102]:
```
# Count the number of null values in the columns
titanic.isnull().sum(axis=0)
```

Out[102]:
```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
dtype: int64
```

In [103]:
```
# Looks like the Age is only column with null values. We will find the average age of the passengers based on Passenger Class.

titanic.groupby('Pclass')['Age'].mean()
```

Out[103]:
```
Pclass
1    38.233441
2    29.877630
3    25.140620
Name: Age, dtype: float64
```

In [104]:
```
# Based on the average age by passenger class, I will create a function to replace the null values.

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

    if pd.isnull(Age):
        if Pclass == 1:
            return 38
        elif Pclass == 2:
            return 30
        else:
             return 25
    else:
        return Age
```

In [105]:
```
# Apply the function to replace the null values in the age column by the mean values
titanic['Age'] = titanic[['Age', 'Pclass']].apply(impute_age_titanic,axis=1)
```

In [106]:
```
titanic.isnull().sum(axis=0)
```

Out[106]:
```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
dtype: int64
```

Convert categorical features

In [107]:
```
# We will convert Sex into dummy variables and drop one value from Sex
sex = pd.get_dummies(titanic['Sex'], drop_first=True)
```

In [108]:
```
titanic.drop(columns=['Sex'], inplace=True)
```

In [109]:
```
titanic = pd.concat([titanic, sex], axis=1)
```

In [110]:
```
titanic.head()
```

Out[110]:

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

Building a Decision Tree Model

Split the data set into training set and test set

In [113]:
```
# Split the feature set and target set

features = titanic.drop(columns='Survived')
targets = titanic['Survived']
```

In [114]:
```
# Split the data into 70% training set and 30% test set

X_train, X_test, y_train, y_test = train_test_split(features, targets, test_size = 0.3, random_state = 42)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(623, 6)
(268, 6)
(623,)
(268,)
```

In [115]:
```
# Since the dataset is in different units ( Age = Years, Fare = Dollars), apply standard scaler to the X_trai
n and X_test.

sc = StandardScaler()

# Transform and fit both the training and testing data
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

```
C:\Users\KSamrari\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625: DataConversionWarning: Data
with input dtype uint8, int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\KSamrari\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversionWarning: Data with input dty
pe uint8, int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\KSamrari\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625: DataConversionWarning: Data
with input dtype uint8, int64, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\KSamrari\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversionWarning: Data with input dty
pe uint8, int64, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [116]:
```
# Classify the X train and Y train data and choose criterion as Entropy

classifier = DecisionTreeClassifier(criterion='entropy', random_state=42)
classifier.fit(X_train,y_train)
```

Out[116]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=42,
            splitter='best')
```

In [118]:
```
# Make predictions
y_pred = classifier.predict(X_test)
```

In [119]:
```
# Evaluate the model, look at the confusion matrix to see how our test data compares to the predicted data
conf_mat = confusion_matrix(y_test, y_pred)
```

In [120]:
```
conf_mat
```

Out[120]:
```
array([[145,  12],
       [ 48,  63]], dtype=int64)
```

In [122]:
```
# Calculate the accuracy of our model

accuracy = accuracy_score(y_test, y_pred)
```

In [124]:
```
print (' Decission Tree Model Performance on the test set: Accuracy = %0.4f' % accuracy)
```

```
 Decission Tree Model Performance on the test set: Accuracy = 0.7761
```

In [126]:
```
# Compare the Test values to the Predicted values

ActualvsPred = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
```

In [127]:
```
print(ActualvsPred.head(15))
```

```
     Actual  Predicted
709       1          0
439       0          0
840       0          0
720       1          1
39        1          1
290       1          0
300       1          0
333       0          0
208       1          0
136       1          1
137       0          0
696       0          0
485       0          0
244       0          0
344       0          0
```

In [ ]:
```
# Using the given titanic data set, our Decsion Tree Machine Learning model can predict
# if the Passenger Survived or not with 78% accuracy.
```