In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

In [116]:
```
#Reading/importation/loading of the train and test files into the notebook

train = pd.read_csv('titanic_train.csv')

test = pd.read_csv('titanic_test.csv')
```

LET US START WITH BASIC EDA AND PREPROCESSING FOR THE TRAIN DATASET

In [8]:
```
#Overview of the first 5 rows of the train dataset (Microsoft Excel can be use
d for this)

train.head()
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
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	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

In [64]:

```
#This gives a general information about each column(attributes) of the train d
ataset

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 [29]:

```
train.describe()
```

Out[29]:

	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 [65]:
```
#This gives information about the number of unique values each column(attribut
es) has

train.nunique()
```

Out[65]:
```
PassengerId    891
Survived         2
Pclass           3
Name           891
Sex              2
Age             88
SibSp            7
Parch            7
Ticket         681
Fare           248
Cabin          147
Embarked         3
dtype: int64
```

In [66]:
```
#This gives us information about the number of null (N/A), empty values in eac
h column(attributes)

train.isnull().sum()
```

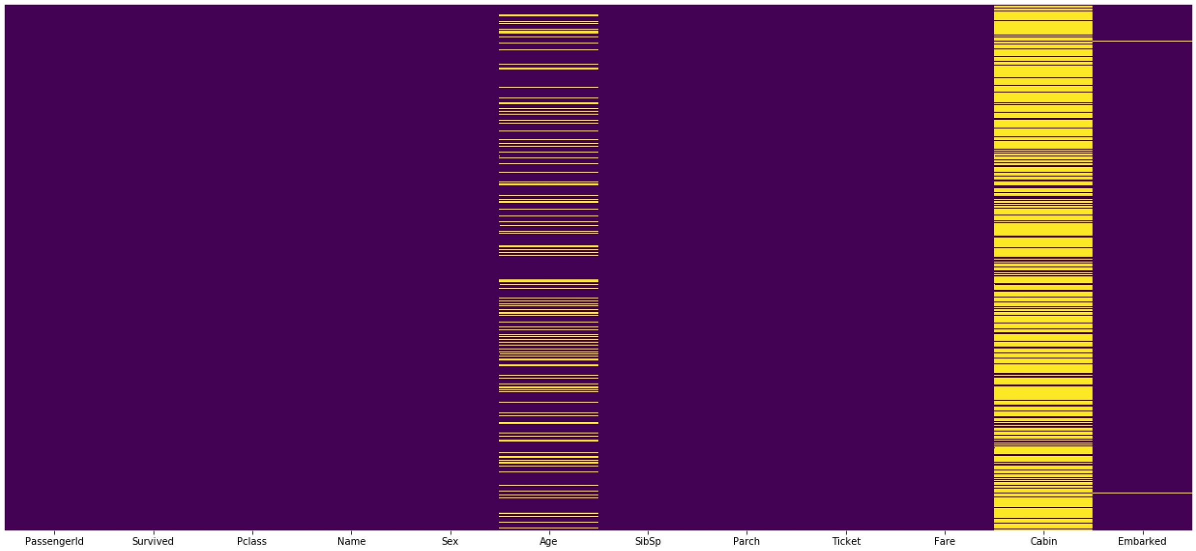
Out[66]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

From the above cell, we can see that three columns have null or missing values

In [14]:
```
#Visualization of columns with missing values

plt.figure(figsize=(22,10))
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef3424d080>

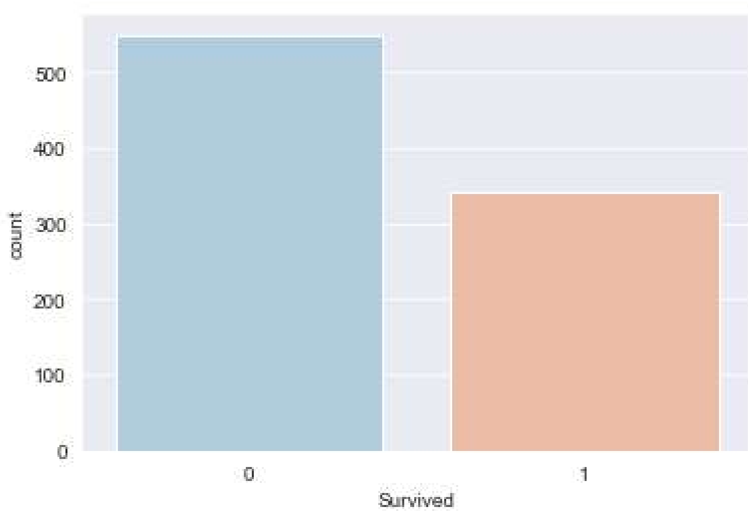


Roughly 20 percent of the Age data is missing. The proportion of Age missing is likely small enough for reasonable replacement with some form of imputation. Looking at the Cabin column, it looks like we are just missing too much of that data to do something useful with at a basic level. We'll probably drop this later, or change it to another feature like "Cabin Known: 1 or 0"

In [16]:
```
#Let visualize the target column which is 'Survived'

sns.set_style('darkgrid')
sns.countplot(x='Survived',data=train,palette='RdBu_r')
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef3427a470>

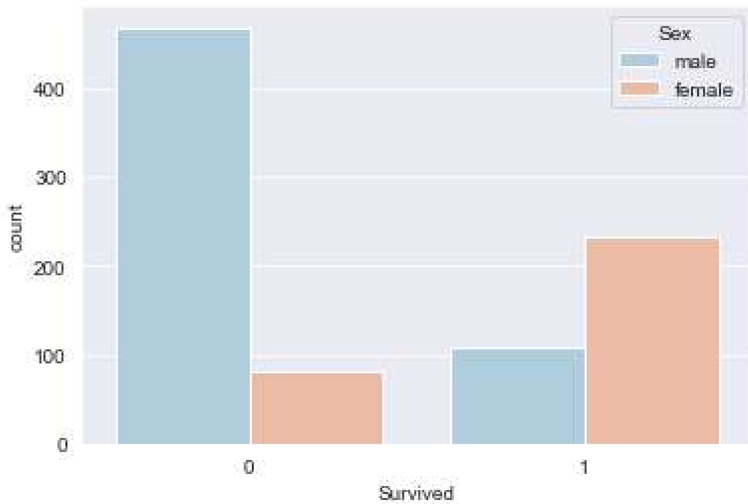


It can be see from the cell above that the people who did not survive were more than does that survived

In [19]:
```
#Let visualize the sex and Survived columns

sns.set_style('darkgrid')
sns.countplot(x='Survived',hue='Sex',data=train,palette='RdBu_r')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef34d71fd0>

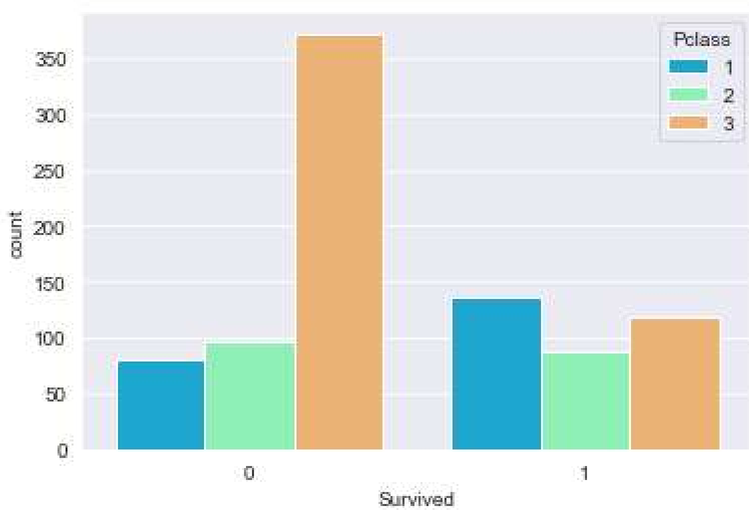


From above we can see that a high proportion of those that did not survive were of the male sex

In [21]:
```
#Let visualize the Pclass and Survived columns

sns.set_style('darkgrid')
sns.countplot(x='Survived',hue='Pclass',data=train,palette='rainbow')
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef34e378d0>

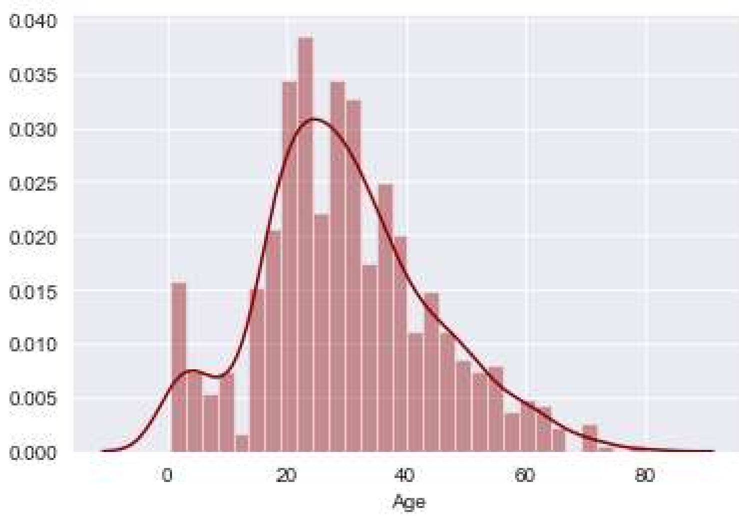


From above we can see that a high proprotion of those that did not survive came from the Pclass category 3 (third class)

In [22]:
```
#Lets plot the age distribution

sns.distplot(train['Age'].dropna(),kde=True,color='darkred',bins=30)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef34ea3b70>

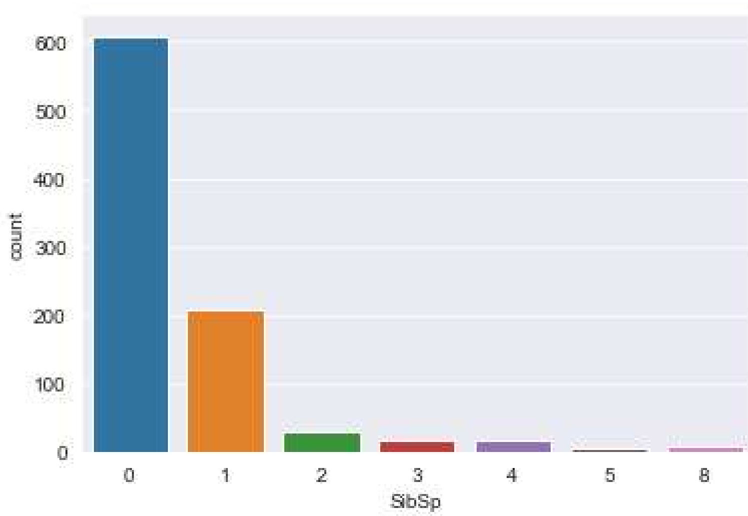


Seems a high proportion of people on the ship were between ages 20 and 40

In [23]:
```
#Let plot the siblings and spouses distribution

sns.countplot(x='SibSp',data=train)
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef350f0588>



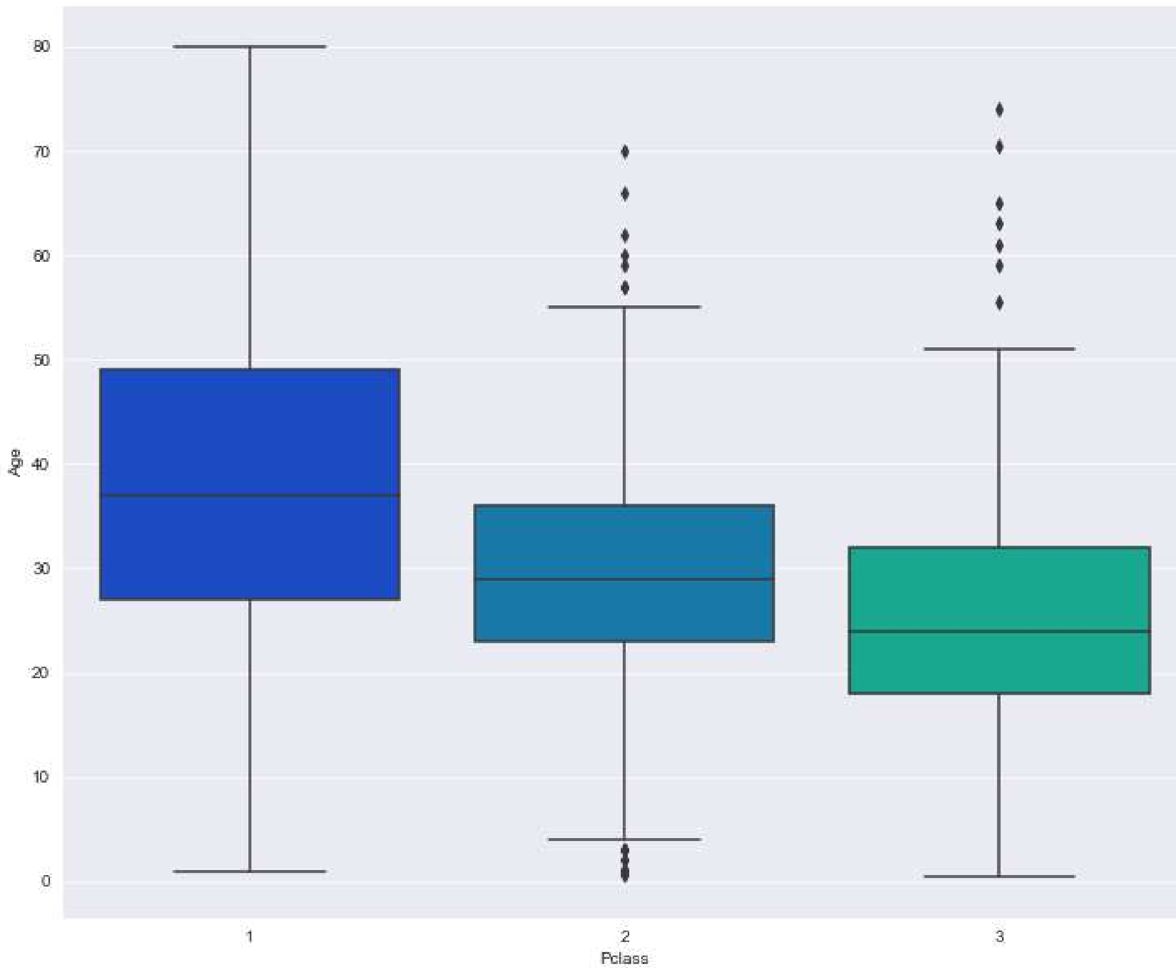
Seems most of passengers on the titanic were not siblings or spouses

Data Cleaning

We want to fill in missing age data instead of just dropping the missing age data rows. One way to do this is by filling in the mean age of all the passengers (imputation). However we can be smarter about this and check the average age by passenger class. For example:

In [30]:
```
plt.figure(figsize=(12, 10))
sns.boxplot(x='Pclass',y='Age',data=train,palette='winter')
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef350d4208>



We can see the wealthier passengers in the higher classes tend to be older, which makes sense. We'll use these average age values to impute based on Pclass for Age.

In [31]:
```
def impute_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
```

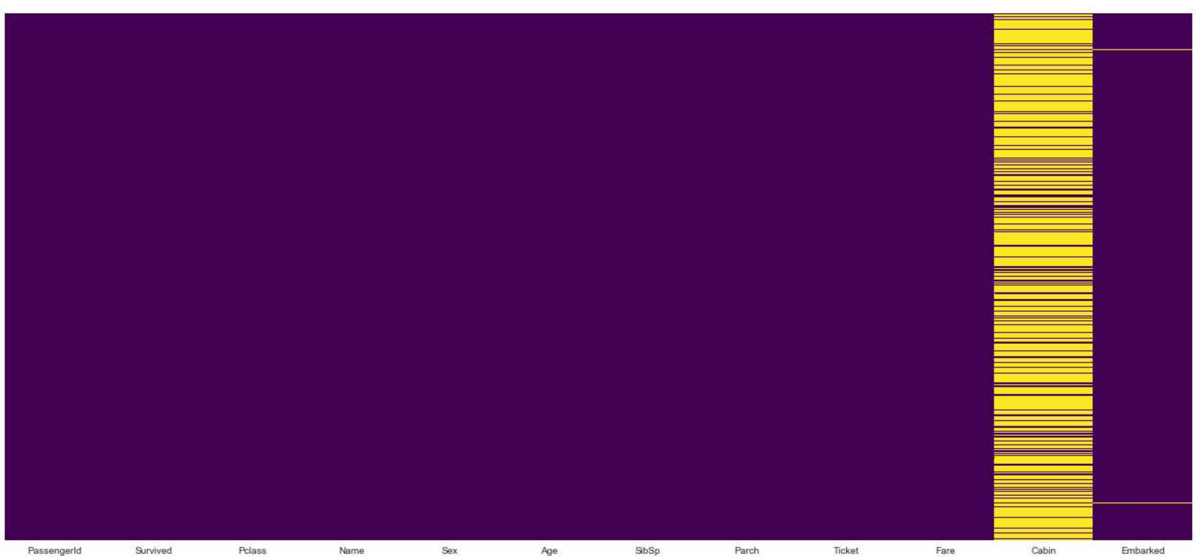
In [67]:
```
#LETS APPLY THE FUNCTION TO THE TRAIN DATASET

train['Age'] = train[['Age','Pclass']].apply(impute_age,axis=1)
```

In [68]:
```
#CHECKING AGAIN FOR THE MISSING VALUES

plt.figure(figsize=(22,10))
sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef30a27f28>



HURRAY OUR FUNCTION HAS HELPED TO IMPUTE THE MISSING VALUES IN AGE

In [69]:
```
#LETS GO AHEAD AND DROP THE CABIN COLUMN

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

In [70]:
```
train.head()
```

Out[70]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	E
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 [71]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 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            891 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

THE CABIN COLUMN IS GONE...

In [72]:
```
#Now lets drop the rows in Embarked that having null or missing values

train.dropna(inplace=True)
```

Converting Categorical Features

We'll need to convert categorical features to dummy variables using pandas! Otherwise our machine learning algorithm won't be able to directly take in those features as inputs.

In [73]:
```
train.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
```

TO IDENTIFY CATEGORICAL FEATURES THEY USUALLY THE ONES WITH THE 'object' DTYPE

FROM THE CELL ABOVE WE HAVE 4 OF SUCH FEATURES

In [74]:
```
#let us use convert sex and embarked to dummy variables

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

In [75]:
```
#Let us add this dummy variables to the train dataset

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

In [76]:
```
train_copy.head()
```

Out[76]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	E
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	

WE CAN SEE COLUMNS 'MALE', 'Q' AND 'S' these were the dummy variable gotten from sex and embarked

In [78]:
```
#Lets drop the original sex and embarked columns. We will also drop the Passen
gerId and ticket columns

train_copy.drop(['Sex','Embarked','Name','Ticket', 'PassengerId'],axis=1,inpla
ce=True)
```

WE DROPPED NAME, TICKET AND PASSENGERID BECAUSE ALL THE VALUES IN THOSE COLUMNS ARE UNIQUE

In [79]:
```
train_copy.head()
```

Out[79]:

	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
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

In [80]:
```
train_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 889 entries, 0 to 890
Data columns (total 9 columns):
Survived    889 non-null int64
Pclass      889 non-null int64
Age         889 non-null float64
SibSp       889 non-null int64
Parch       889 non-null int64
Fare        889 non-null float64
male        889 non-null uint8
Q           889 non-null uint8
S           889 non-null uint8
dtypes: float64(2), int64(4), uint8(3)
memory usage: 51.2 KB
```

FINISHED ...OUR DATA IS READY FOR MODELLING

BUT BEFORE WE MOVE ON TO THE TEST DATA LETS OUTPUT OUR CLEANED TRAIN DATASET INTO A CSV FILE

In [81]:
```
#outputting a file
train_output = train_copy

train_output.to_csv('CLEANED_TRAIN.csv', index=False)
```

LETS NOW DEAL WITH THE TEST DATASET

In [117]:
```
#Overview of the first 5 rows of the test dataset (Microsoft Excel can be used
for this)


test.head()
```

Out[117]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embar
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 [118]:
```
#This gives a general information about each column(attributes) of the test da
taset

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 [119]:
```
#This gives us information about the number of null (N/A), empty values in eac
h column(attributes)

test.isnull().sum()
```

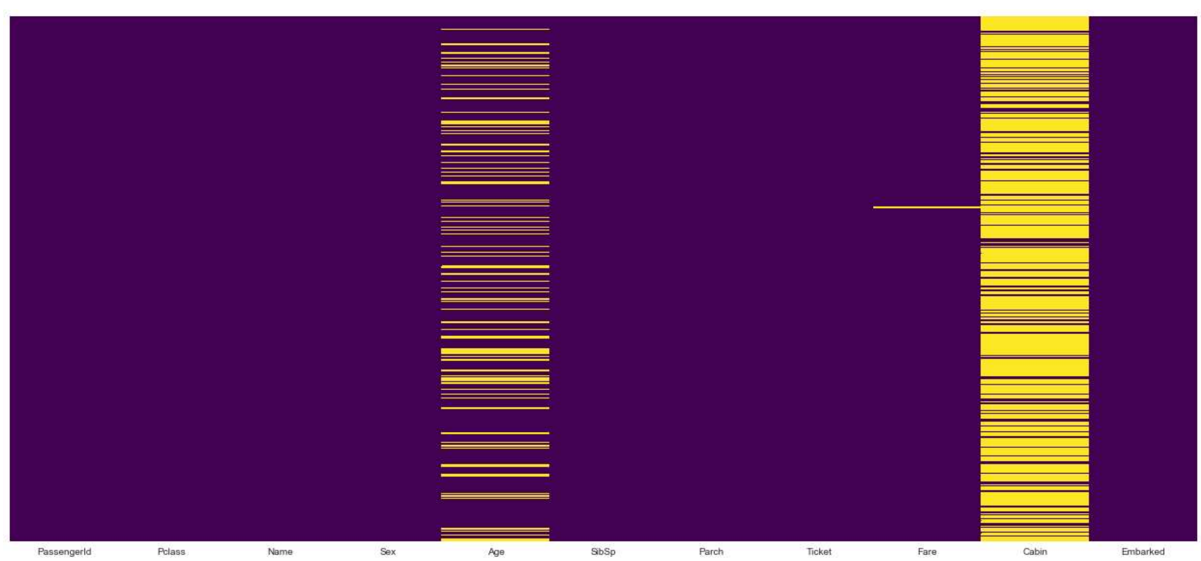
Out[119]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

THIS SHOWS THAT THE AGE, FARE AND CABIN COLUMNS OF THE TEST DATASET HVE MISSING VALUES

In [120]:
```
#Visualization of columns with missing values

plt.figure(figsize=(22,10))
sns.heatmap(test.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

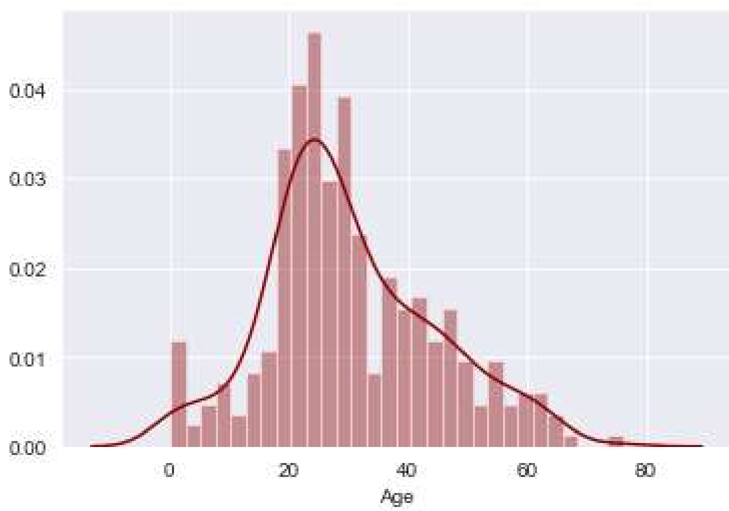
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef39da9f60>



In [121]:
```
#Lets check out the age distribution in the test dataset

sns.distplot(test['Age'].dropna(),kde=True,color='darkred',bins=30)
```

Out[121]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef3a013198>



SIMILAR TO THE AGE DISTRIBUTION ON THE TRAIN DATASET

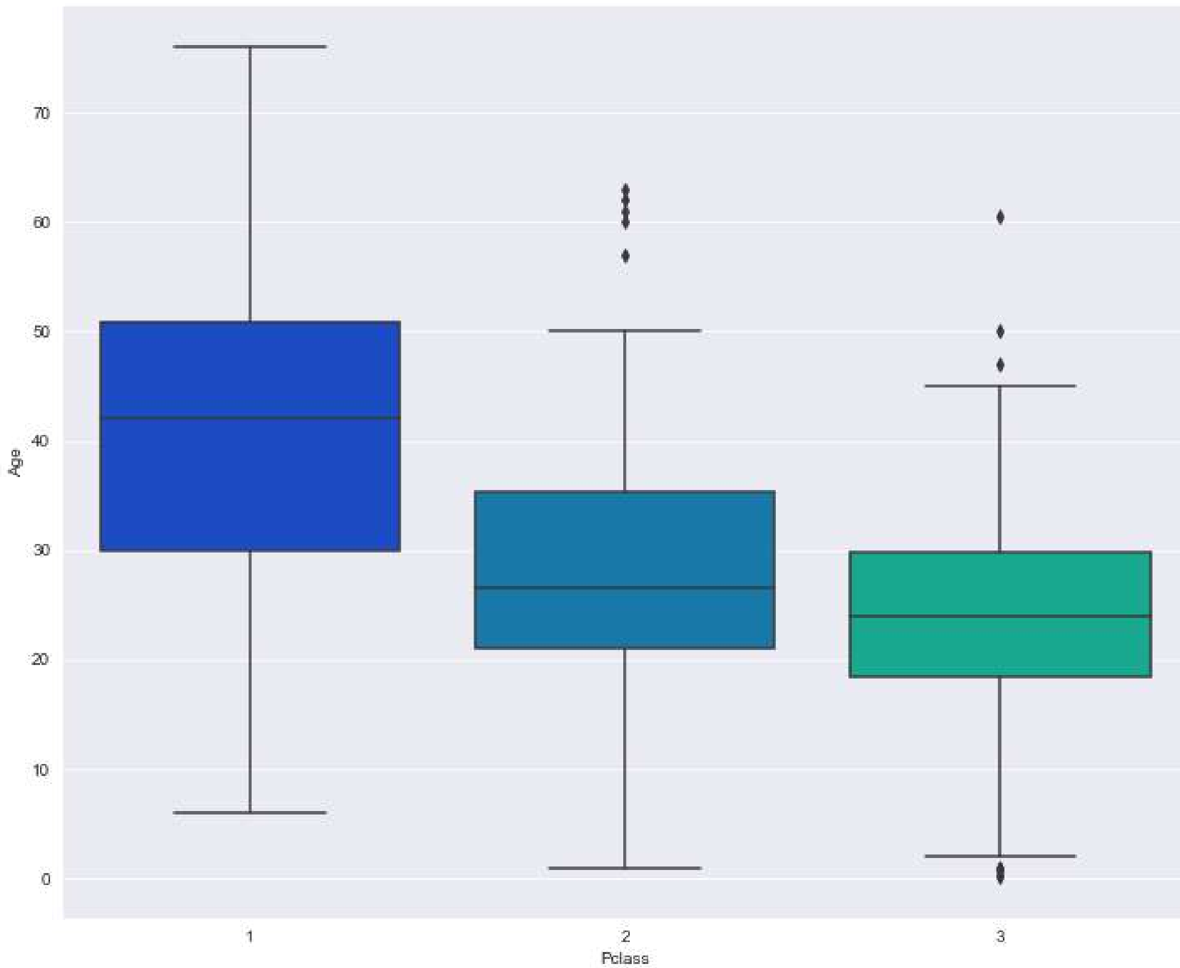
Data Cleaning

Data Cleaning We want to fill in missing age data instead of just dropping the missing age data rows.

In [122]:
```
#CHECKING OUT THE AGE DISTRIBUTION IN RELATION TO THE PCLASS

plt.figure(figsize=(12, 10))
sns.boxplot(x='Pclass',y='Age',data=test,palette='winter')
```

Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef3a0b4630>



We can see the wealthier passengers in the higher classes tend to be older which was also evidence in the train dataset

In [123]:
```
def impute_age_test(cols):
    Age = cols[0]
    Pclass = cols[1]

    if pd.isnull(Age):

        if Pclass == 1:
            return 42

        elif Pclass == 2:
            return 26

        else:
            return 24

    else:
        return Age
```

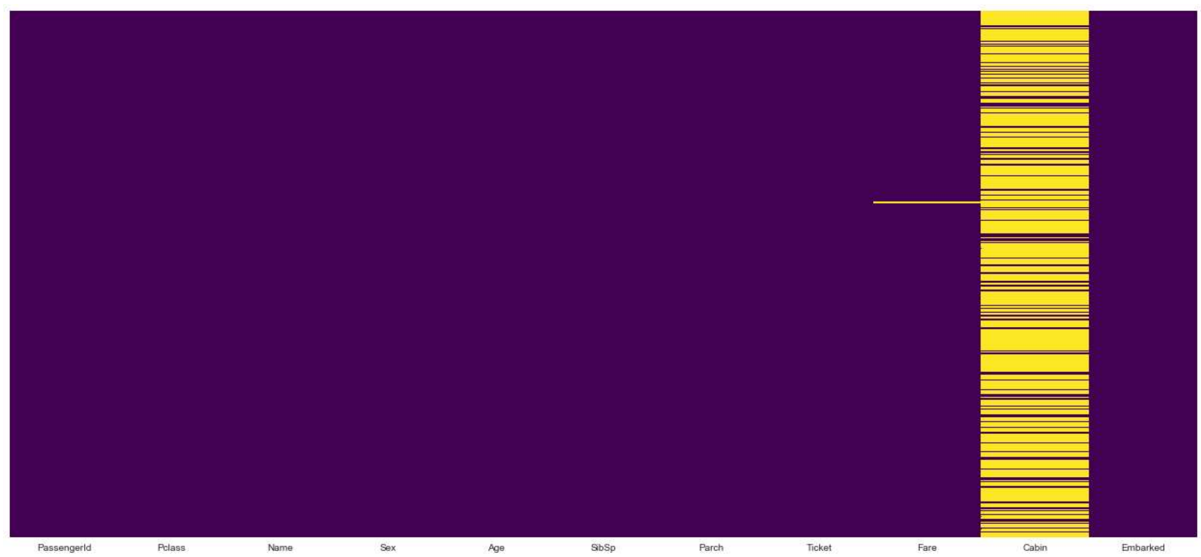
In [124]:
```
#LETS APPLY THE FUNCTION TO THE TEST DATASET

test['Age'] = test[['Age','Pclass']].apply(impute_age,axis=1)
```

In [125]:
```
#CHECKING AGAIN FOR THE MISSING VALUES

plt.figure(figsize=(22,10))
sns.heatmap(test.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x1ef3a075128>



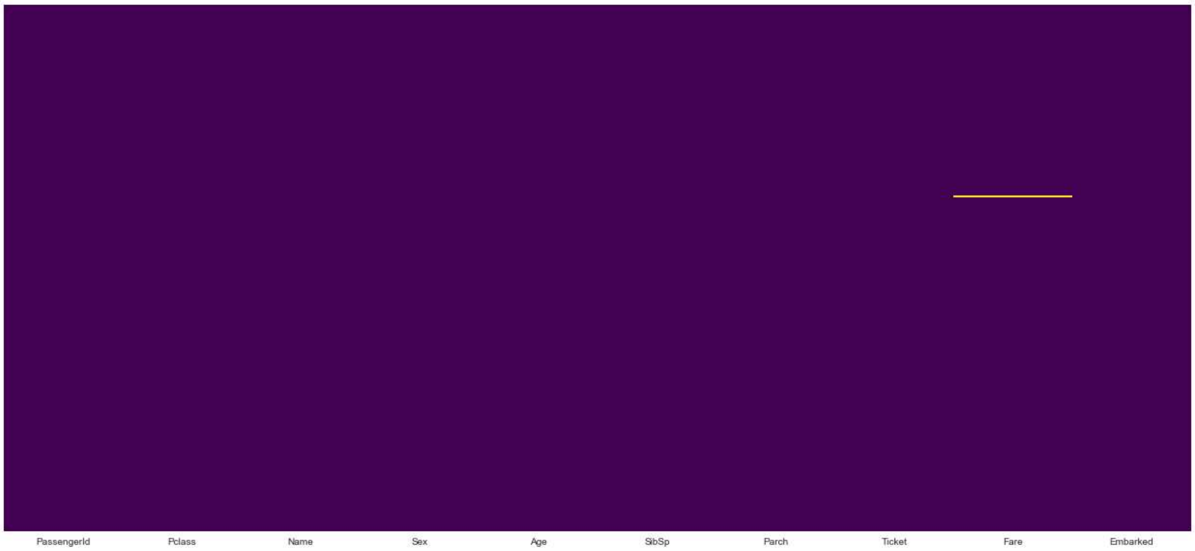
In [126]:
```
#LETS GO AHEAD AND DROP THE CABIN COLUMN

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

In [127]:
```
#CHECKING AGAIN FOR THE MISSING VALUES

plt.figure(figsize=(22,10))
sns.heatmap(test.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[127]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1ef3a428160>
```



In [128]:
```
#Now lets fill the row in column 'Fare'

test.fillna(np.mean(test['Fare']), inplace= True)
```

In [129]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 10 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            418 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           418 non-null float64
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(4)
memory usage: 32.8+ KB
```

ALL MISSING VALUE HAVE BEEN DEALT WITH

NOW LET US DEAL WITH THE CATEGORICAL VARIABLES

In [130]:
```
#Let us use convert sex and embarked to dummy variables

sex_test = pd.get_dummies(test['Sex'],drop_first=True)
embark_test = pd.get_dummies(test['Embarked'],drop_first=True)
```

In [131]:
```
#Let us add this dummy variables to the test dataset

test_copy = pd.concat([test,sex_test,embark_test],axis=1)
```

In [132]:
```
test_copy.head()
```

Out[132]:

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

In [133]:
```
#Lets drop the original sex and embarked columns. We will also drop ticket col
umns

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

In [134]:
```
test_copy.head()
```

Out[134]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare	male	Q	S
0	892	3	34.5	0	0	7.8292	1	1	0
1	893	3	47.0	1	0	7.0000	0	0	1
2	894	2	62.0	0	0	9.6875	1	1	0
3	895	3	27.0	0	0	8.6625	1	0	1
4	896	3	22.0	1	1	12.2875	0	0	1

FINISHED ...OUR DATA IS READY FOR MODELLING

LETS OUTPUT OUR CLEANED TEST DATASET INTO A CSV FILE

In [135]:
```
#outputting a file
test_output = test_copy

test_output.to_csv('CLEANED_TEST.csv', index=False)
```

NOW LETS US TRAIN OUR ALGORITHMS WITH THE CLEANED TRAIN DATA AND PREDICT ON THE CLEANED DATA...(Simple Basic Modelling.ipynb)