In [1]:
```
#PREDICTING SURVIVAL ON THE TITANIC
import pandas as pd
import numpy as np
```

In [2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [8]:
```
titanic_train=pd.read_csv('titanic_train.csv')
```

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

Out[9]:

| | 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 [12]:
```
titanic_train.describe()  #Sissp: sibling & spouses , Parch=parents And children
```

Out[12]:

| | 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 [13]:
```
titanic_train.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
```

In [15]:
```
#Let's start with some exploratory data analysis
#Now we check for some missing data
titanic_train.isnull()
```

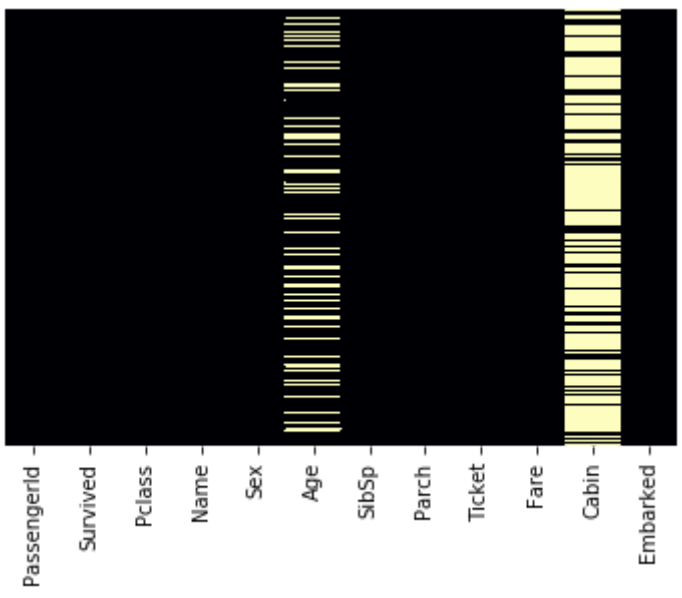
Out[15]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | False | False | False | False | False | False | False | False | False | False | True | False |
| **1** | False | False | False | False | False | False | False | False | False | False | False | False |
| **2** | False | False | False | False | False | False | False | False | False | False | True | False |
| **3** | False | False | False | False | False | False | False | False | False | False | False | False |
| **4** | False | False | False | False | False | False | False | False | False | False | True | False |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **886** | False | False | False | False | False | False | False | False | False | False | True | False |
| **887** | False | False | False | False | False | False | False | False | False | False | False | False |
| **888** | False | False | False | False | False | True | False | False | False | False | True | False |
| **889** | False | False | False | False | False | False | False | False | False | False | False | False |
| **890** | False | False | False | False | False | False | False | False | False | False | True | False |

891 rows × 12 columns

In [19]:
```
sns.heatmap(data=titanic_train.isnull(),yticklabels=False,cbar=False,cmap='magma') #cbar=False, because we are not doi
ng an actual colorbar
#Now this gives us an idea of what's missing, we can see that roughly 30% of age data is missing
#whereas
```

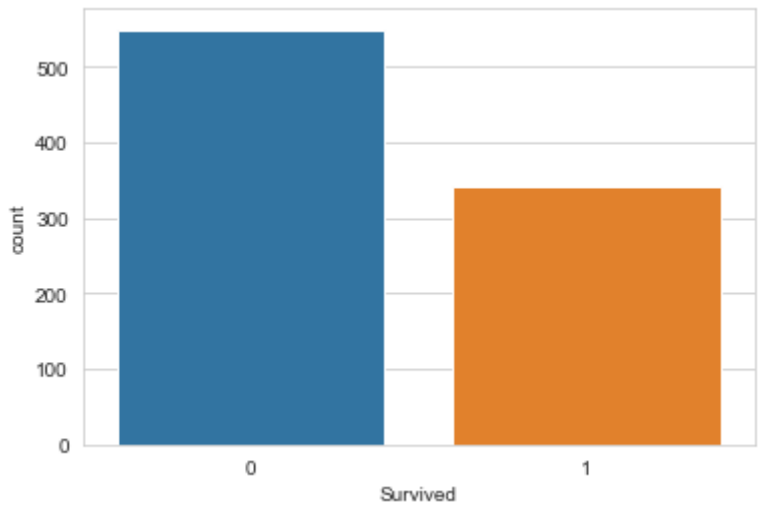
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x17611f76f88>




In [20]:
```
sns.set_style('whitegrid')
```

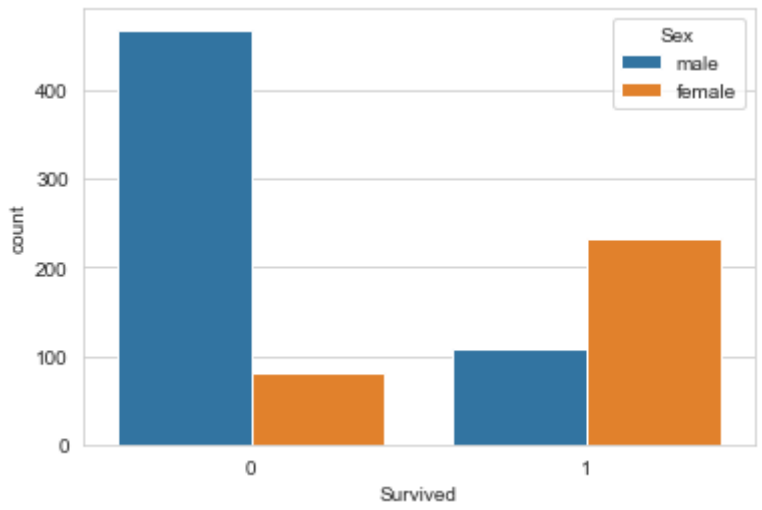
In [22]:
```
#Lets just visualize a count plot of who survived who did not, for classification problems it is a good idea to see th
e ratio of actual target labels.
sns.countplot(x='Survived',data=titanic_train)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x17612603ec8>



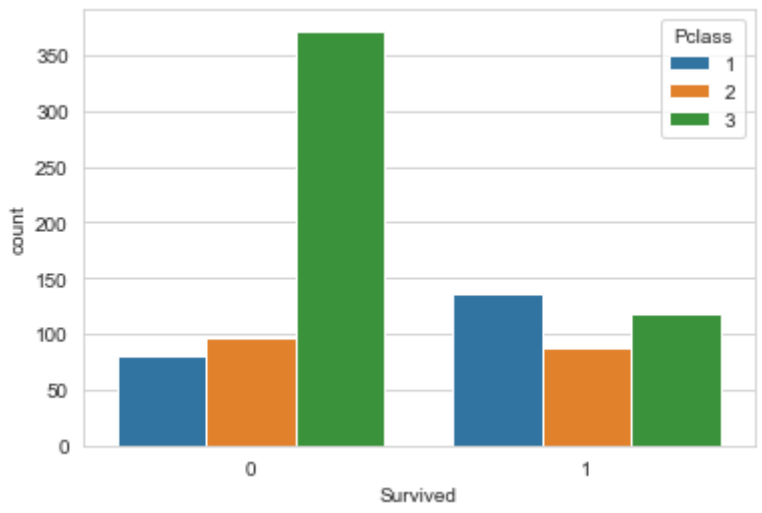
In [23]:
```
sns.countplot(x='Survived',hue='Sex',data=titanic_train) #survival based on gender
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x17611525ac8>




In [24]:
```
sns.countplot(x='Survived',hue='Pclass',data=titanic_train) #survival based on passenger class
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x176126bb788>



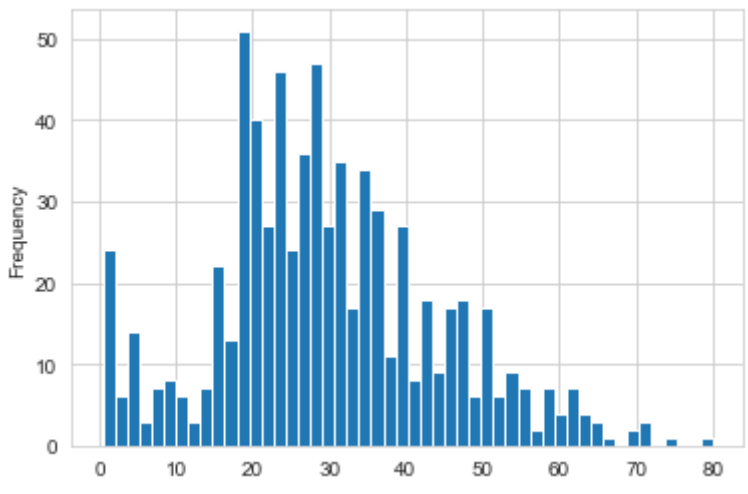

In [41]:
```
#Lets see what age group was predominantly travelling that day
sns.distplot(titanic_train['Age'].dropna(),kde=False,bins=50)
#HMMM seems like a bimodal plot, with more of the people in the 20-35 age bracket
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-41-763c2ef34cd7> in <module>
      1 #Lets see what age group was predominantly travelling that day
----> 2 sns.distplot(titanic_train['Age'].dropna(),kde=False,bins=50,hue='Sex')
      3 #HMMM seems like a bimodal plot, with more of the people in the 20-35 age bracket

TypeError: distplot() got an unexpected keyword argument 'hue'
```

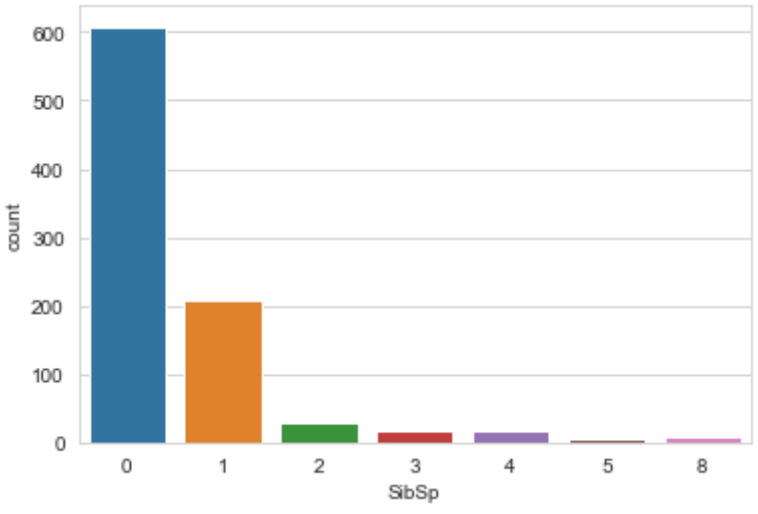
In [40]:
```
#Well i can use pandas directly for the above thing
titanic_train['Age'].plot.hist(bins=50)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x176167823c8>



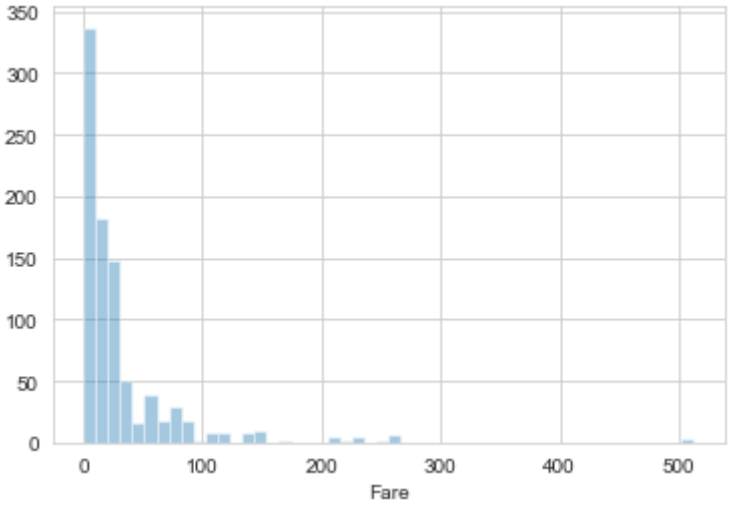
In [30]:
```
#Now let's get some info about siblings and spouses
sns.countplot(x='SibSp',data=titanic_train)
#Now this shows that most of the people are single on the Ship, no spouse or children.Whereas the rise of y on 1 proba
bly refers to a spouse rather than a a pair of siblings
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x1761398a608>




In [33]:
```
sns.distplot(titanic_train['Fare'],bins=50,kde=False)
#Makes sense that things are distributed towards cheaper fare tickets
```

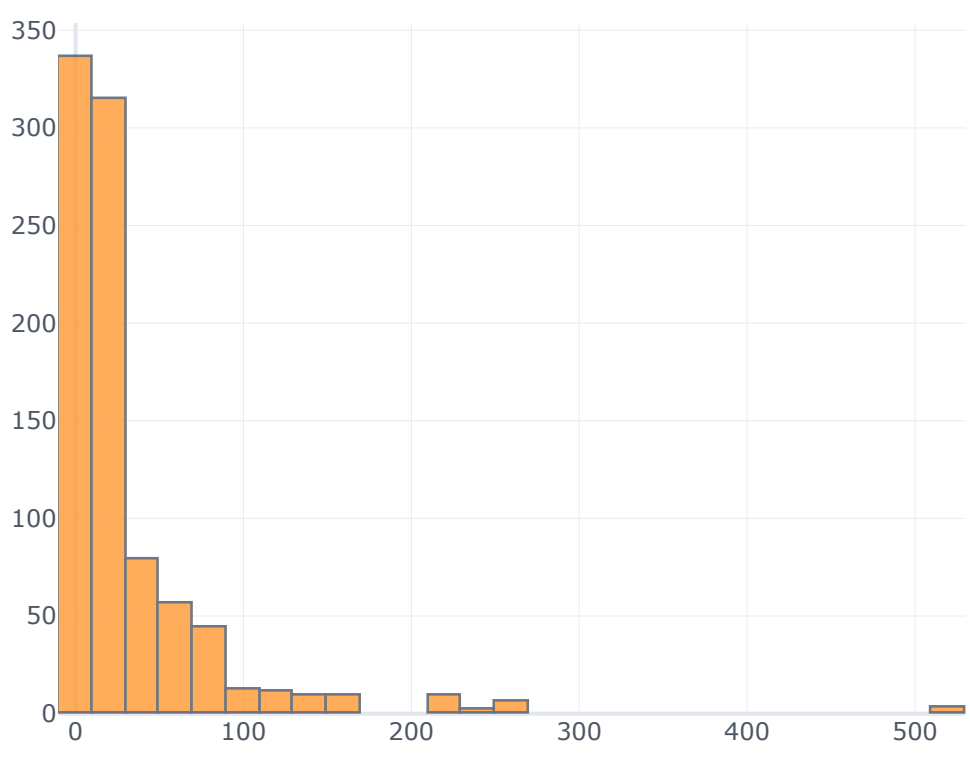
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x17614430c08>




In [34]:
```
#Lets say we want a more informative plot
import cufflinks as cf
```

In [35]:
```
cf.go_offline()
```

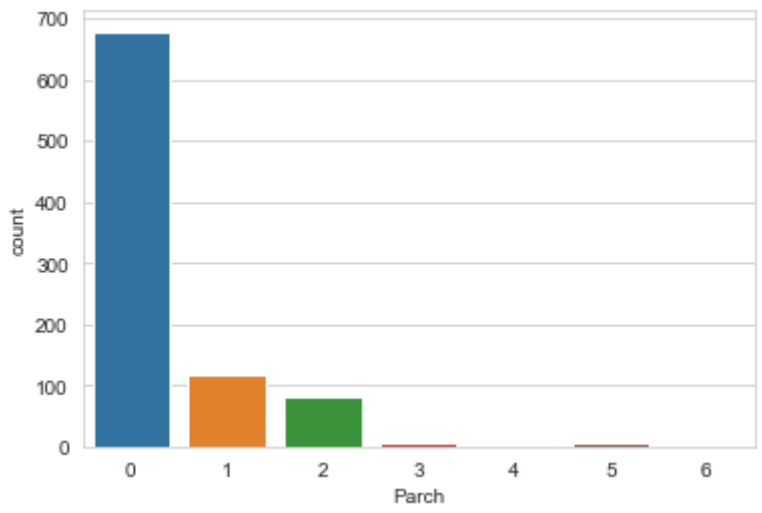
In [37]:
```
titanic_train['Fare'].iplot(kind='hist',bins=40)
```




Export to plot.ly »

In [38]:
```
sns.countplot(x='Parch',data=titanic_train) #Info about parents and children
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x17616618888>

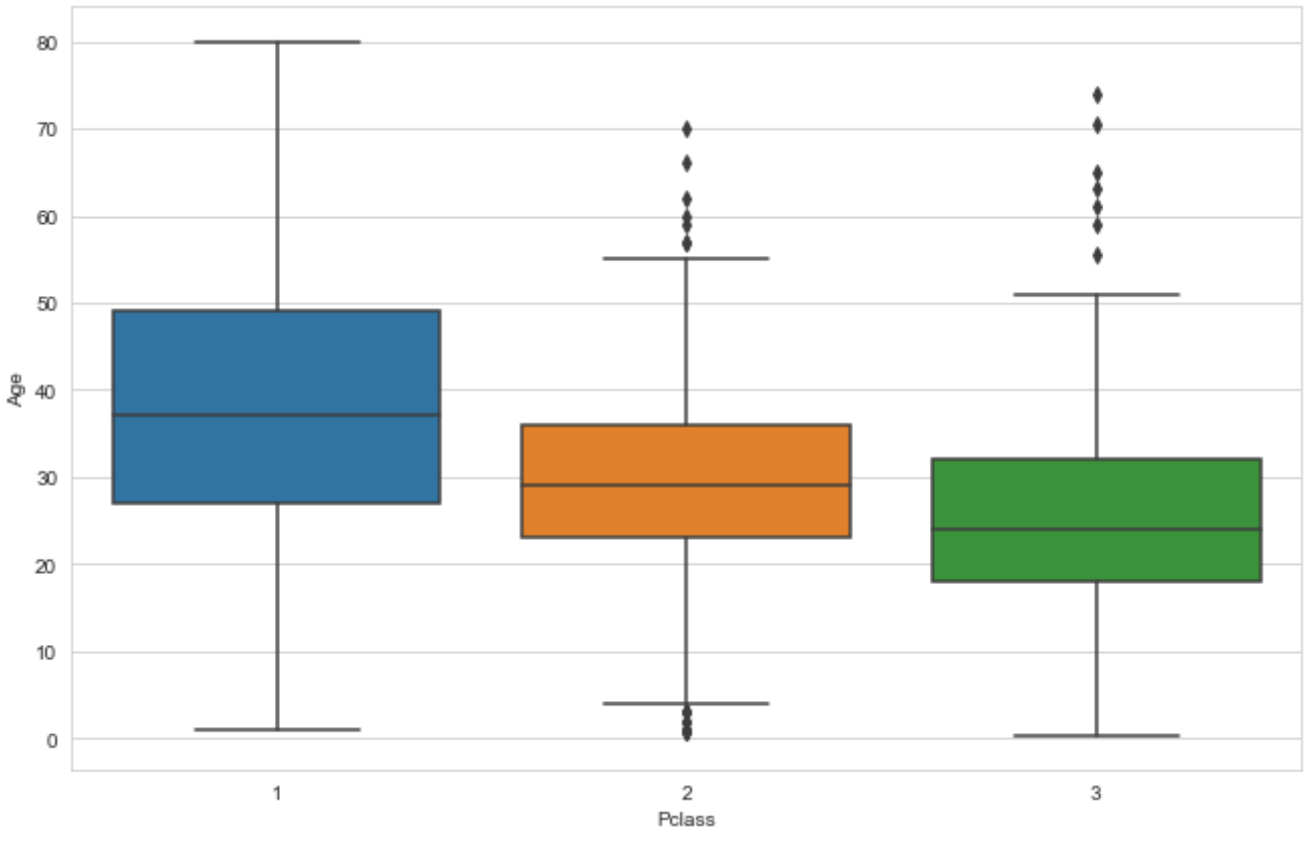



In [42]:
```
#Now we just went ahead and did some exploratory data anaalysis for some contextual inf0,
#Lets move on to some ML(Logistic Regression)

#Now we saw that some data was missing, basically we need to clean our data to convert it into an acceptable form for
 our machine learning algorithm.
#say instead of dropping all age rows with null values we can replace them with the mean age, this is called imputatio
n
#WE can do one better by classifying age by passenger class first and taking mean
#Lets see what i am taling about
```

In [46]:
```
plt.figure(figsize=(11,7))
sns.boxplot(x='Pclass',y='Age',data=titanic_train)
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x17616f0cf48>

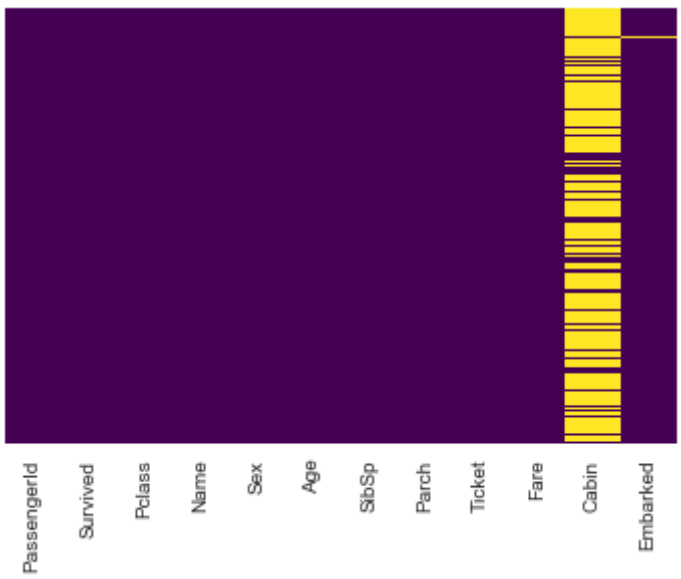



In [51]:
```
def impute(cols):
    Age=cols[0]
    Pclass=cols[1]
    if(pd.isnull(Age)):
        if(Pclass==1):
            return 36
        elif(Pclass==2):
            return 29
        else:
            return 25
    else:
        return Age
```

In [52]:
```
titanic_train['Age']=titanic_train[['Age','Pclass']].apply(impute,axis=1) #axis=1 as i want to apply this along the co
lumn
```

In [54]:
```
#NOw lets check the heatmap again
sns.heatmap(data=titanic_train.isnull(),cbar=False,yticklabels=False,cmap='viridis')
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x17616f6e788>




In [55]:
```
#Now we see that the age column has no more missing values
```

In [56]:
```
#Now about the cabin column , we hve just too many missing values so we'd better drop this
titanic_train.drop(columns='Cabin',inplace=True,axis=1)
```

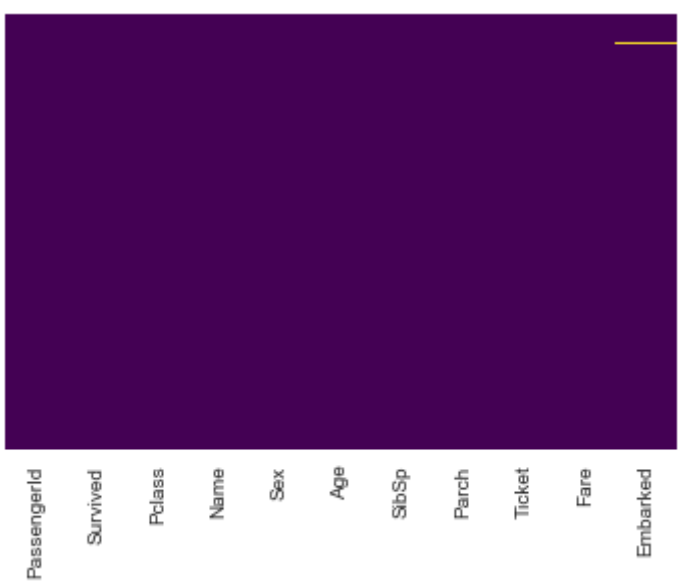
In [57]:
```
titanic_train.head()
```

Out[57]:

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

In [58]:
```
sns.heatmap(data=titanic_train.isnull(),cbar=False,yticklabels=False,cmap='viridis')
```

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x17616c48108>




In [60]:
```
titanic_train.dropna(inplace=True)
```

In [62]:
```
#Now we just got done with the first step that is dealing with missing data.
#Now we need to deal with the categorical values, by converting them into dummy variable
#i.e in a form understandable by ML algorithm
#Let's see how we can do that with help of pandas
```

In [63]:
```
pd.get_dummies(titanic_train['Sex'])#converts categorical variables into dummy or indicator variables
```

Out[63]:

| | female | male |
|---|---|---|
| **0** | 0 | 1 |
| **1** | 1 | 0 |
| **2** | 1 | 0 |
| **3** | 1 | 0 |
| **4** | 0 | 1 |
| **...** | ... | ... |
| **886** | 0 | 1 |
| **887** | 1 | 0 |
| **888** | 1 | 0 |
| **889** | 0 | 1 |
| **890** | 0 | 1 |

889 rows × 2 columns

In [64]:
```
#Now there is a slight problem here, one coloumn(say male) is a perfect predictor
#of the other coloumn, so we feed our algorithm both columns we'll have something called
#Multi-Co-linearity, which will mess up the algorithm because a bunch of columns will be perfect predictors of another
column
```

In [67]:
```
#Therefore to tackle the previous problem of multicolinearity
sex=pd.get_dummies(titanic_train['Sex'],drop_first=True)
#Similarly for embarked column
embarked=pd.get_dummies(titanic_train['Embarked'],drop_first=True)
```

In [68]:
```
sex.head()
```

Out[68]:

| | male |
|---|---|
| **0** | 1 |
| **1** | 0 |
| **2** | 0 |
| **3** | 0 |
| **4** | 1 |

In [69]:
```
embarked.head()
```

Out[69]:

| | Q | S |
|---|---|---|
| **0** | 0 | 1 |
| **1** | 0 | 0 |
| **2** | 0 | 1 |
| **3** | 0 | 1 |
| **4** | 0 | 1 |

In [70]:
```
titanic_train=pd.concat([titanic_train,sex,embarked],axis=1)
```

In [71]:
```
titanic_train.head()
```

Out[71]:

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

In [72]:
```
#We have the replacement coulumns, so we dont need the sex and embarked columns anymore
```

In [73]:
```
titanic_train.drop(['Sex','Embarked','Name','Ticket'],axis=1,inplace=True)
```

In [74]:
```
titanic_train.head()
```

Out[74]:

| | 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 |

In [77]:
```
#Loooks absolutely perfect for our Ml algorithm , all data is numerical,evrything concatenated
#one more thing, PassengerId seems a bit redundant doesn't it?? Its basically just index+1??
#and obviously not of much use, as we cannot get some info on survial based on passanegerid.
titanic_train.drop('PassengerId',axis=1,inplace=True)
```

In [78]:
```
#Let's look at our cleaned Data
titanic_train.head()
```

Out[78]:

| | 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 [79]:
```
#Another thing to note, if we look carefully, Pclass cloumn seems categorical doesn't it??
#We could have done getdummies on that too
pd.get_dummies(titanic_train['Pclass'])
```

Out[79]:

| | 1 | 2 | 3 |
|---|---|---|---|
| **0** | 0 | 0 | 1 |
| **1** | 1 | 0 | 0 |
| **2** | 0 | 0 | 1 |
| **3** | 1 | 0 | 0 |
| **4** | 0 | 0 | 1 |
| **...** | ... | ... | ... |
| **886** | 0 | 1 | 0 |
| **887** | 1 | 0 | 0 |
| **888** | 0 | 0 | 1 |
| **889** | 1 | 0 | 0 |
| **890** | 0 | 0 | 1 |

889 rows × 3 columns

In [80]:
```
#We'll check it out later once we are done with running the model once , so we
#get to know the difference of what would happen diffrently
```

In [81]:
```
#Now we are going to train and use a model and predict the classes of whether or not a passenger survived on the titan
ic
```

In [82]:
```
#Lets consider our titanic_train dataset as all our data
```

In [83]:
```
X=titanic_train.drop('Survived',axis=1)
y=titanic_train['Survived']
```

In [84]:
```
from sklearn.model_selection import train_test_split
```

In [85]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
```

In [86]:
```
from sklearn.linear_model import LogisticRegression
```

In [92]:
```
lrmodel=LogisticRegression()
```

In [94]:
```
lrmodel.fit(X_train,y_train)
```

```
C:\Users\anike\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:940: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

Out[94]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [95]:
```
predictions=lrmodel.predict(X_test)
```

In [96]:
```
from sklearn.metrics import classification_report
```

In [99]:
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.91      0.87       163
           1       0.84      0.70      0.76       104

    accuracy                           0.83       267
   macro avg       0.83      0.81      0.82       267
weighted avg       0.83      0.83      0.83       267
```

In [100]:
```
from sklearn.metrics import confusion_matrix
```

In [101]:
```
confusion_matrix(y_test,predictions) #TP TN ,FP, FN
```

Out[101]:
```
array([[149,  14],
       [ 31,  73]], dtype=int64)
```

In [102]:
```
#We can imporve the model through more feature Engineering, or using the complte test.csv file after cleaning and much
more
#That's all for now
```

In [ ]: