In [76]:
```
# Nmae : Himanshu Agarwal , Net id: HXA180027 ,
#q2.2 Titanic dataset
#mporting libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

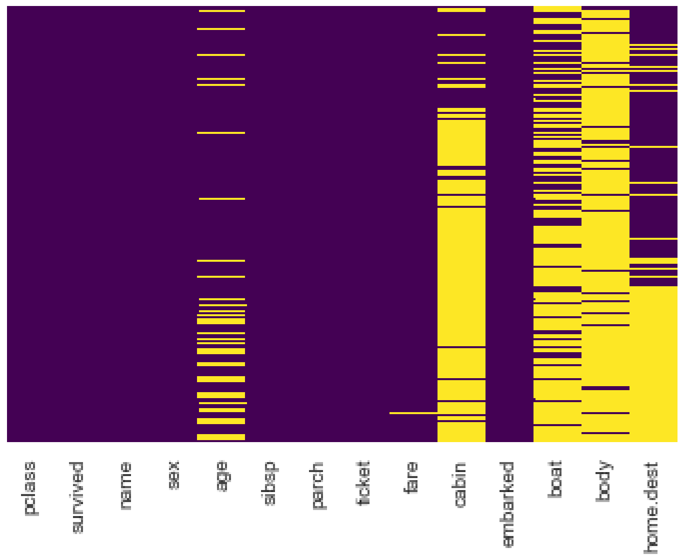
In [77]:
```
#import data using the pandas libraries.
titanic3_dataset = pd.read_csv('titanic3.csv')
titanic3_dataset.head()
```

Out[77]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	embarked
0	1	1	Allen, Miss. Elisabeth Walton	female	29.00	0	0	24160	211.3375	B5	S
1	1	1	Allison, Master. Hudson Trevor	male	0.92	1	2	113781	151.5500	C22 C26	S
2	1	0	Allison, Miss. Helen Loraine	female	2.00	1	2	113781	151.5500	C22 C26	S
3	1	0	Allison, Mr. Hudson Joshua Creighton	male	30.00	1	2	113781	151.5500	C22 C26	S
4	1	0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	female	25.00	1	2	113781	151.5500	C22 C26	S

In [78]:
```
#Heatmap to check the missig values
sns.heatmap(titanic3_dataset.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

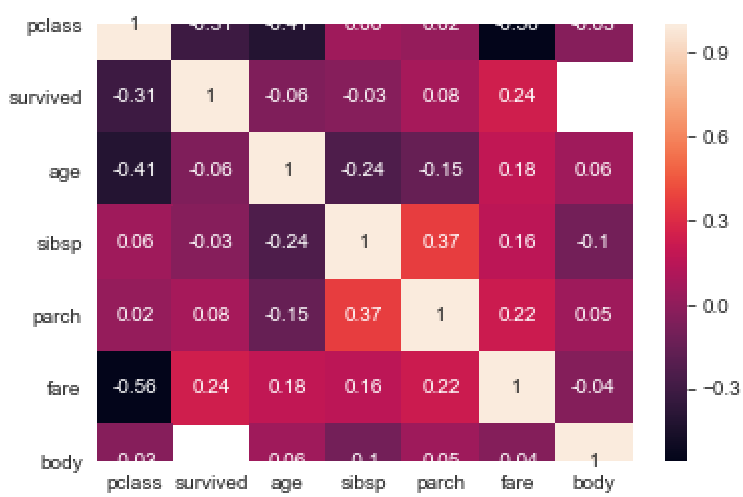
Out[78]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd5446b88>



In [ ]:

In [79]:
```
# create a correlation matrix that measures the linear relationships between the variables.
#The correlation matrix can be formed by using the corr function from the pandas dataframe library.
#We will use the heatmap function from the seaborn library to plot the correlation matrix
correlation_matrix = titanic3_dataset.corr().round(2)
sns.heatmap(data=correlation_matrix, annot=True)
```

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd54f6888>

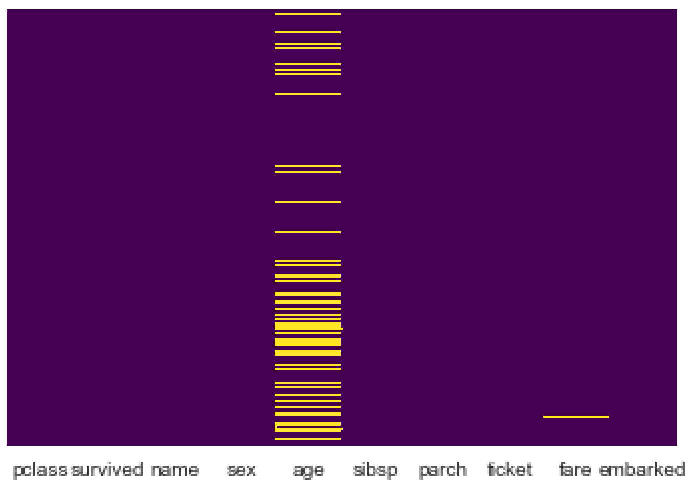


In [80]:
```
#Through Correlation matrix we can see that few columns are not present which shows they are independent and has no correlation.
#We can drop those features as they will not play any role in deciding the target feature.
#So dropping features 'Cabin','body','boat', and 'home.dest'.Same way name and ticket.
```

In [81]:
```
titanic3_dataset.drop('cabin',axis=1,inplace=True)
titanic3_dataset.drop('body',axis=1,inplace=True)
titanic3_dataset.drop('boat',axis=1,inplace=True)
titanic3_dataset.drop('home.dest',axis=1,inplace=True)
```

In [82]:
```
#Heatmap to check the missig values
sns.heatmap(titanic3_dataset.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

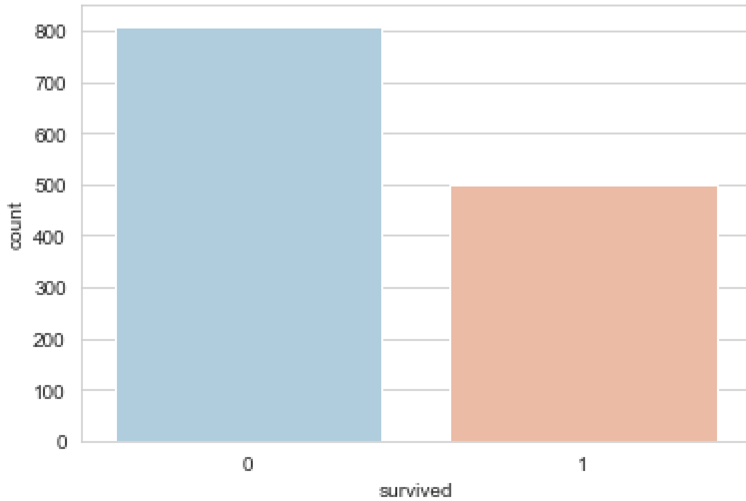
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd6784548>



In [83]:
```
#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.
```

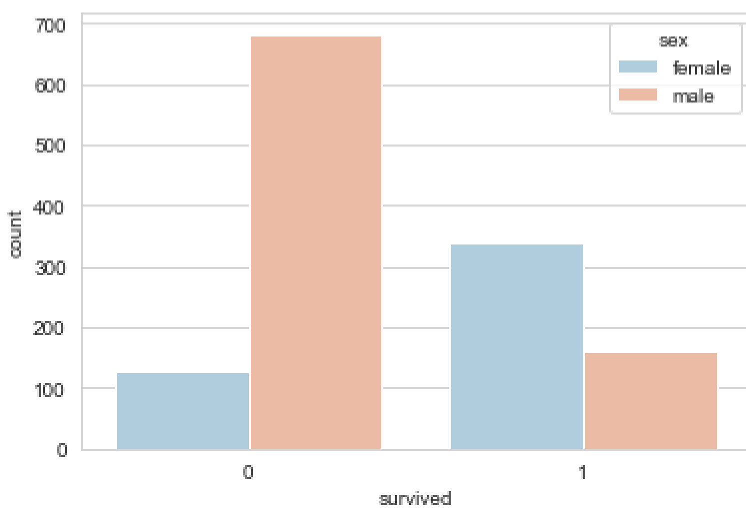
In [84]:
```
#Data Visualization
#using count plot checking how many passangers survived
sns.set_style('whitegrid')
sns.countplot(x='survived',data=titanic3_dataset,palette='RdBu_r')
```

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd67bf808>



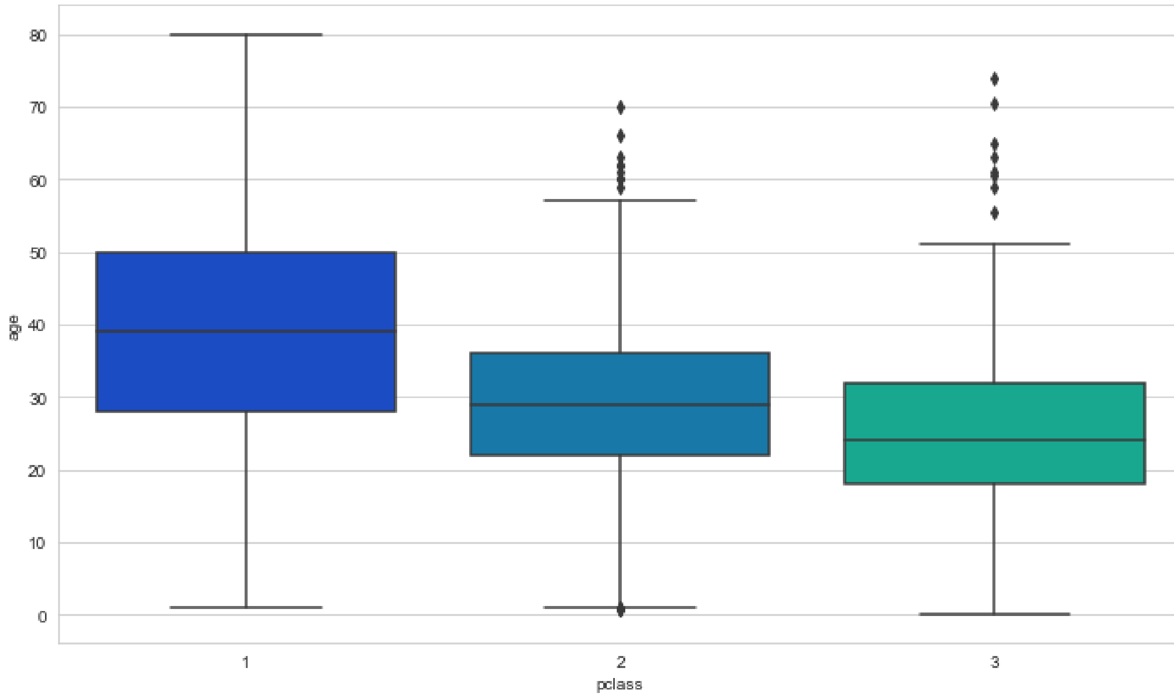
In [85]:
```
#using count plot checking how many passangers of different genders survived
sns.set_style('whitegrid')
sns.countplot(x='survived',hue='sex',data=titanic3_dataset,palette='RdBu_r')
```

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd680cfc8>



In [86]:
```
#Data cleaning
#using box plot checking class wise average age of passangers
plt.figure(figsize=(12, 7))
sns.boxplot(x='pclass',y='age',data=titanic3_dataset,palette='winter')
```

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x1fcd6872388>



In [87]:
```
#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 (imput
ation).
#However we can be smarter about this and check the average age by passenger c
lass.
```

In [88]:
```
#Method to get the average age for a class
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 [89]:
```
#imputing the missing age values for each class.
titanic3_dataset['age'] = titanic3_dataset[['age','pclass']].apply(impute_age,
axis=1)

#to see the count of the missing values left in eachh column
titanic3_dataset.isnull().sum()
```

Out[89]:
```
pclass      0
survived    0
name        0
sex         0
age         0
sibsp       0
parch       0
ticket      0
fare        1
embarked    2
dtype: int64
```

In [90]:
```
#As the number of rows with null data for fare and embarked are too low as com
pared to total size of the dataset, so we can drop them.
titanic3_dataset.dropna(inplace=True)
```

In [91]:
```
#We'll need to convert categorical features to dummy variables using pandas! L
ike 'sex' and 'embarked' features.
#Otherwise our machine learning algorithm won't be able to directly take in th
ose features as inputs.
#the 'Name' and 'Ticket' column have no relationship with whether the person s
urvived or not,observed using correlation matrix.
#So we drop these 2 columns and we convert the other two columns into numerica
l values
```

In [92]:
```
sex = pd.get_dummies(titanic3_dataset['sex'],drop_first=True)
embark = pd.get_dummies(titanic3_dataset['embarked'],drop_first=True)
titanic3_dataset.drop(['sex','embarked','name','ticket'],axis=1,inplace=True)
```

In [93]:
```
#Data is ready to apply Logistic regression
titanic3_dataset.head()
```

Out[93]:

	pclass	survived	age	sibsp	parch	fare
0	1	1	29.00	0	0	211.3375
1	1	1	0.92	1	2	151.5500
2	1	0	2.00	1	2	151.5500
3	1	0	30.00	1	2	151.5500
4	1	0	25.00	1	2	151.5500

In [94]:
```
#Preprocessing of Data for logistic regression
```

In [95]:
```
#train the model with 80% of the samples and test with the remaining 20%. #We
 do this to assess the model’s performance on unseen data.
n = int(len(titanic3_dataset)*0.80)
#spliting data in training and test set in the ration of 80% and 20% respectiv
ely
df_train, df_test = titanic3_dataset.iloc[:n, :], titanic3_dataset.iloc[n:, :]
titanic3_dataset.columns
```

Out[95]:
```
Index(['pclass', 'survived', 'age', 'sibsp', 'parch', 'fare'], dtype='objec
t')
```

In [96]:
```
# Initial Coefficients

B = np.array([0, 0, 0, 0, 0, 0]) #Weights array
alpha = 0.0001 # Learning rate
```

In [97]:
```
#Spliting the training and testing data in X,Y train and test sets.
dt = df_train
m = len(df_train.iloc[:,:-1])
x0 = np.ones(m)
Xtrain = np.array([x0, dt['pclass'],dt['age'],dt['sibsp'],dt['parch'],dt['far
e']]).T
ytrain = np.array(dt['survived'])

m = len(df_test.iloc[:,:-1])
x0 = np.ones(m)
dt= df_test
Xtest= np.array([x0, dt['pclass'],dt['age'],dt['sibsp'],dt['parch'],dt['fare'
]]).T
ytest= np.array(dt['survived'])
```

In [98]:
```
#Cost function
def cost_function(X, Y, B):
    m = len(Y)
    J = np.sum((X.dot(B) - Y) ** 2)/(2 * m)
    return J
```

In [99]:
```
#Sigmoid fuction to get the result in 0-1 range
def sigmoid(z):
        return 1 / (1 + np.exp(-z))
```

In [100]:
```
#we are implementing SGD, we will pick up random K points from the data to fin
d our optimal W and b. Thus for every iteration,
#we need to iterate the gradient(derivative) calculations and we will update o
ur W and for n_iteration times.
```

In [ ]:

In [101]:
```
#mplementation of Logistic regression for the given numbers of iterations.
def gradient_descent(titanic3_data, B, alpha, iterations):
    cost_history = [0] * iterations

    k=10 #mini batch size
    for iteration in range(iterations):

        # Sampling the dataset, getting k random records
        dt= titanic3_data.sample(k)
        m = k
        x0 = np.ones(m)
        #Getting X and Y, from the random sample of size k.
        X1 = np.array([x0, dt['pclass'],dt['age'],dt['sibsp'],dt['parch'],dt[
'fare']]).T
        Y1 = np.array(dt['survived'])
        z = X1.dot(B)
        h = sigmoid(z)   #Calcultating the sigmoid of the  hypothesis
        # Difference b/w Hypothesis and Actual Y
        loss = h - Y1
        # Gradient Calculation
        gradient = X1.T.dot(loss) /k
        # Changing Values of B using Gradient
        B = B - alpha * (gradient)
        # New Cost Value
        cost = cost_function(X1, Y1, B)
        cost_history[iteration] = cost

    return B, cost_history
```

In [102]:
```
alpha= 0.001 #Learning rate
iterations=10000 #Number of epocks\number odf iterartion
theta , cost = gradient_descent(df_train, B, alpha, iterations)  #Calling the
 imlemented function to get the weights(theta) for each feaure and also the to
tal cost incurred.
```

In [103]:
```
#Method to predict the value of output feature based on the weights received a
fter training.
def predict(X, theta):
        return sigmoid(np.dot(X, theta)).round()
```

In [104]:
```
#using scikit-learn's Libraries to get the reports.
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score


predictions_train = predict(Xtrain,theta) # Making prediction on training set
print("Classification Report on Training data")
print(classification_report(ytrain,predictions_train))
print("Accuracy on Training data:",accuracy_score(ytrain, predictions_train))
```

```
Classification Report on Training data
              precision    recall  f1-score   support

           0       0.64      0.92      0.75       601
           1       0.72      0.30      0.42       443

    accuracy                           0.65      1044
   macro avg       0.68      0.61      0.59      1044
weighted avg       0.67      0.65      0.61      1044

Accuracy on Training data: 0.6532567049808429
```

In [105]:
```
predictions_test = predict(Xtest,theta) # Making prediction on test set
print("Classification Report on test data")
print(classification_report(ytest,predictions_test))
print("Accuracy on test data:",accuracy_score(ytest, predictions_test))
```

```
Classification Report on test data
              precision    recall  f1-score   support

           0       0.79      0.97      0.87       207
           1       0.12      0.02      0.03        55

    accuracy                           0.77       262
   macro avg       0.46      0.49      0.45       262
weighted avg       0.65      0.77      0.69       262

Accuracy on test data: 0.767175572519084
```

In [ ]:

In [ ]:

In [ ]:

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In [ ]: