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

In [2]:
```
%config Completer.use_jedi = False
```

In [95]:
```
train=pd.read_csv('train_titanic.csv')
```

PassengerId

Survived -- 0 = No, 1 = Yes

Pclass -- Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd

Name -- Passenger name

Sex -- male / female

Age -- age in years

SibSp -- no. of siblings / spouses aboard the Titanic

Parch -- no. of parents / children aboard the Titanic

Ticket -- Ticket number

Fare -- Passenger fare

Cabin -- Cabin number

Embarked -- Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

In [7]:
```
train.head()
```

Out[7]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

In [8]:

```
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 [9]:

```
train.isnull()
```

Out[9]:

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

891 rows × 12 columns

In [10]:
```
train.isnull().sum()
```

Out[10]:
```
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
```

Calculate percentage of missing values

In [11]:
```
train.count()
```

Out[11]:
```
PassengerId    891
Survived       891
Pclass         891
Name           891
Sex            891
Age            714
SibSp          891
Parch          891
Ticket         891
Fare           891
Cabin          204
Embarked       889
dtype: int64
```

In [12]:
```
#to count total number of rows
train.isnull().count()
```

Out[12]:
```
PassengerId    891
Survived       891
Pclass         891
Name           891
Sex            891
Age            891
SibSp          891
Parch          891
Ticket         891
Fare           891
Cabin          891
Embarked       891
dtype: int64
```

In [4]:
```
#percentange of missing value
#round the value
percentage_missing_data=round(((train.isnull().sum())/(train.isnull().count()))*100,
percentage_missing_data
```

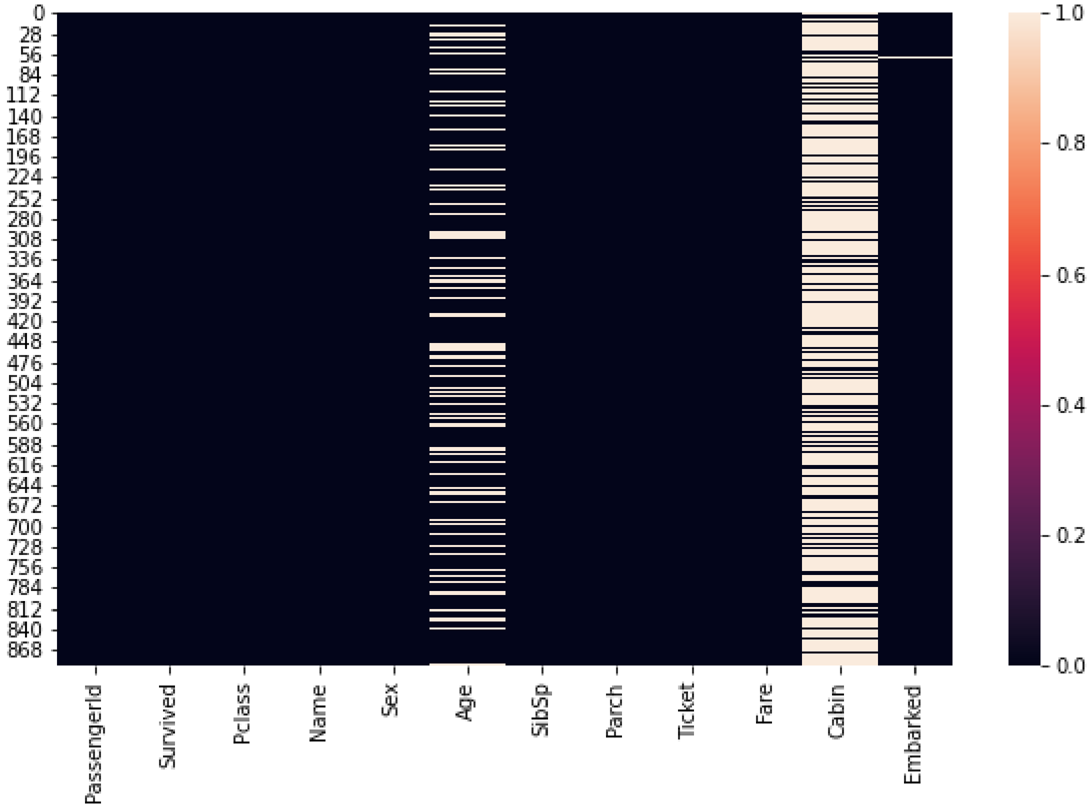
Out[4]:
```
PassengerId     0.0
Survived        0.0
Pclass          0.0
Name            0.0
Sex             0.0
Age            19.9
SibSp           0.0
```

```
Parch           0.0
Ticket          0.0
Fare            0.0
Cabin          77.1
Embarked        0.2
dtype: float64
```

Lets create Heatmap to visualize missing data

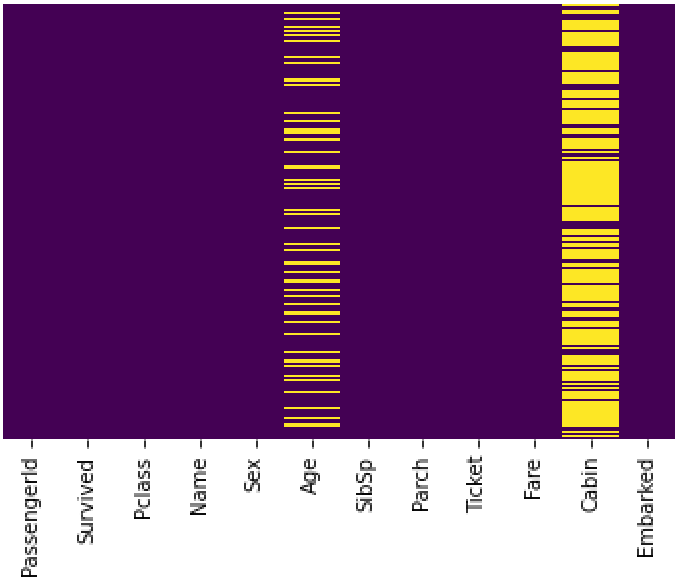
In [96]:
```
plt.subplots(figsize=(10,6))
sns.heatmap(train.isnull())
```

Out[96]: `<AxesSubplot:>`



In [8]:
```
#for better visualization
sns.heatmap(data=train.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

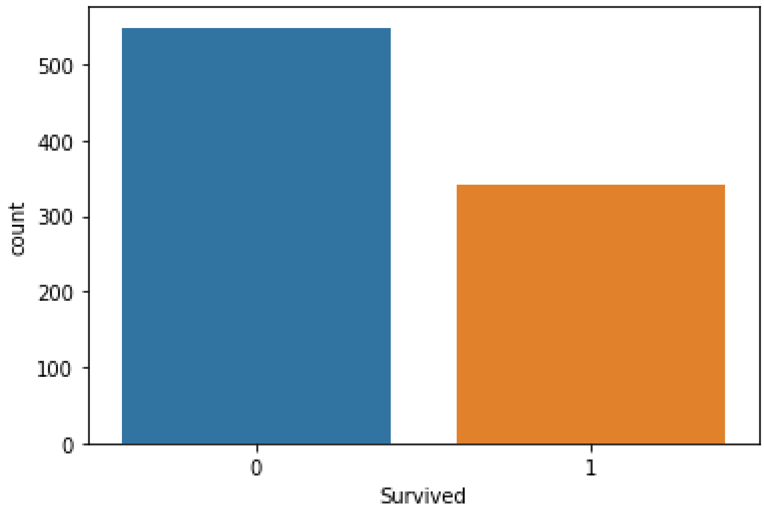
Out[8]: `<AxesSubplot:>`



In [9]:

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

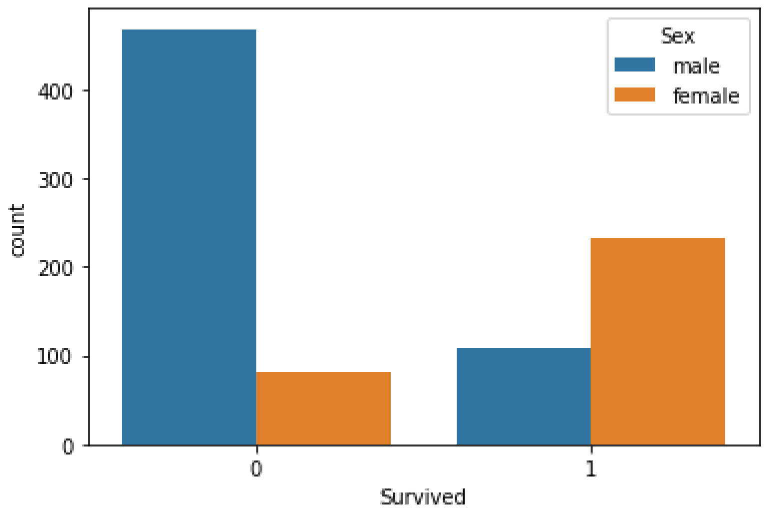
Out[9]: <AxesSubplot:xlabel='Survived', ylabel='count'>



In [12]:

```
#by adding Sex we can get to see which sex has more survival rate
sns.countplot(x='Survived',hue='Sex',data=train)
```

Out[12]: <AxesSubplot:xlabel='Survived', ylabel='count'>



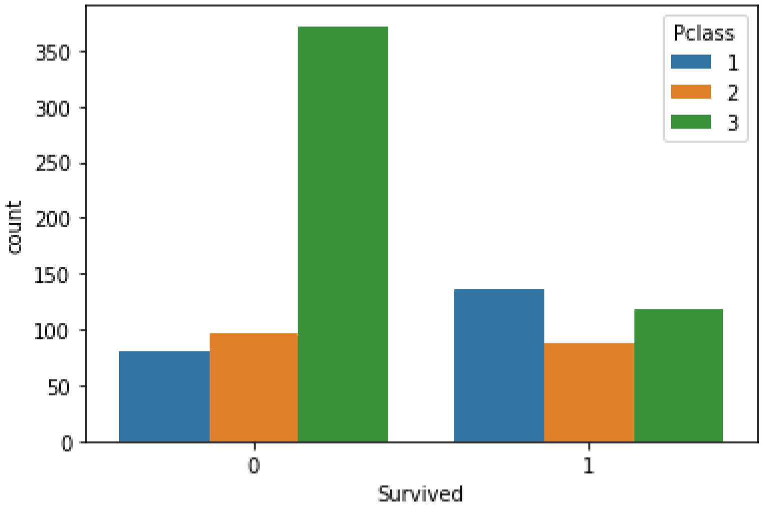
In [ ]:
```
sns.countplot(x='Survived',hue='Sex',data=train)
```

In [13]:
```
train['Pclass'].unique()
```

Out[13]:
```
array([3, 1, 2], dtype=int64)
```

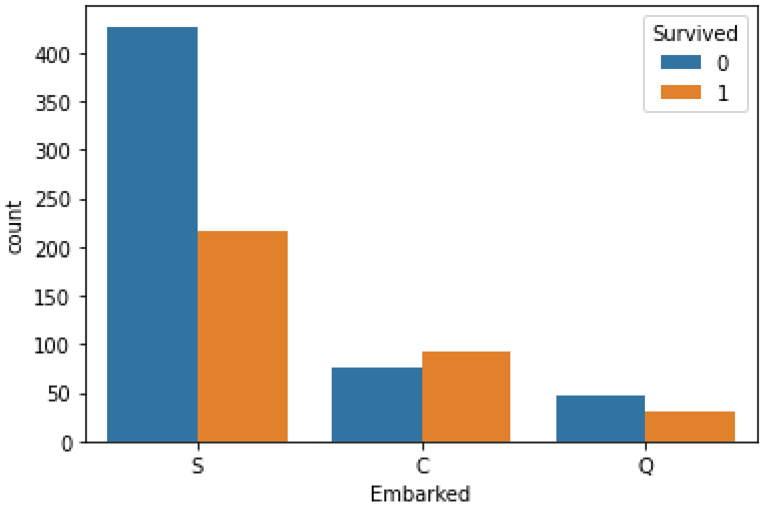
In [15]:
```
#which class survived the most
sns.countplot(x='Survived',hue='Pclass',data=train)
```

Out[15]:
```
<AxesSubplot:xlabel='Survived', ylabel='count'>
```



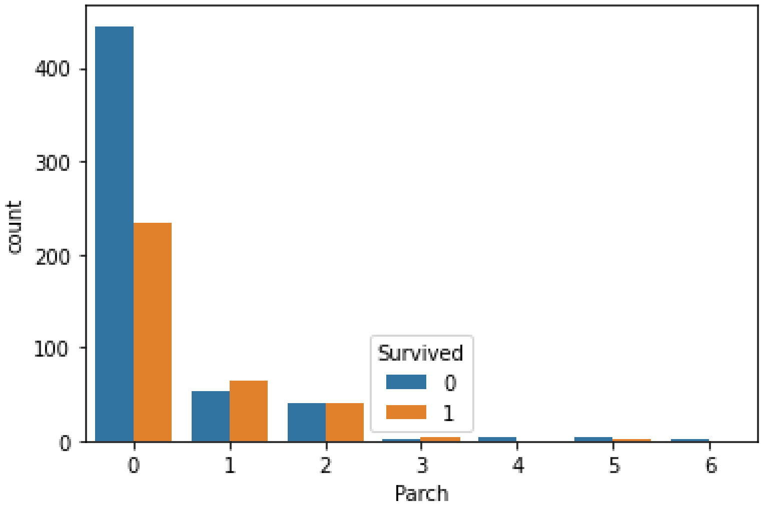
In [17]:
```
#which port has more survival count
sns.countplot(x='Embarked',hue='Survived',data=train)
```

Out[17]:
```
<AxesSubplot:xlabel='Embarked', ylabel='count'>
```



In [18]:
```
#which age group has more survival count
sns.countplot(x='Parch',hue='Survived',data=train)
```

Out[18]:
```
<AxesSubplot:xlabel='Parch', ylabel='count'>
```



In [16]:
```
train.columns
```

Out[16]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

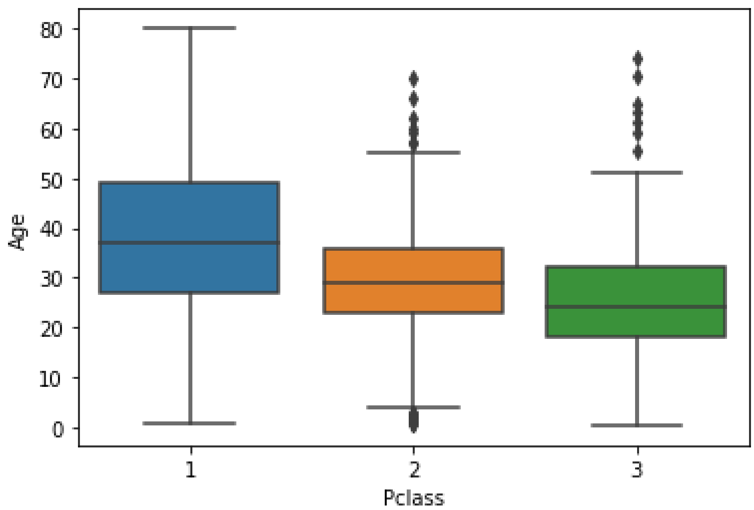
Part 2

In [19]:
```
percentage_missing_data
```

Out[19]:
```
PassengerId     0.0
Survived        0.0
Pclass          0.0
Name            0.0
Sex             0.0
Age            19.9
SibSp           0.0
Parch           0.0
Ticket          0.0
Fare            0.0
Cabin          77.1
Embarked        0.2
dtype: float64
```

In [20]:
```
#lets use box plot to explore any relationship between class and passenger age
sns.boxplot(x='Pclass',y='Age', data=train)
```

Out[20]:
```
<AxesSubplot:xlabel='Pclass', ylabel='Age'>
```



Average age of passenger in each class

In [23]:
```
train[['Pclass','Age']].groupby('Pclass').mean()
```

Out[23]:

Pclass	Age
1	38.233441
2	29.877630
3	25.140620

Custom function to fill in missing data

In [26]:
```
#this function returns the mean value computed on above cell
def impute_age(age_pclass):
    age=age_pclass[0]
    pclass=age_pclass[1]
    if(pd.isnull(age)):
        if pclass==1:
            return 38
        elif pclass==2:
            return 30
        else:
            return 25
    else:
        return age
```

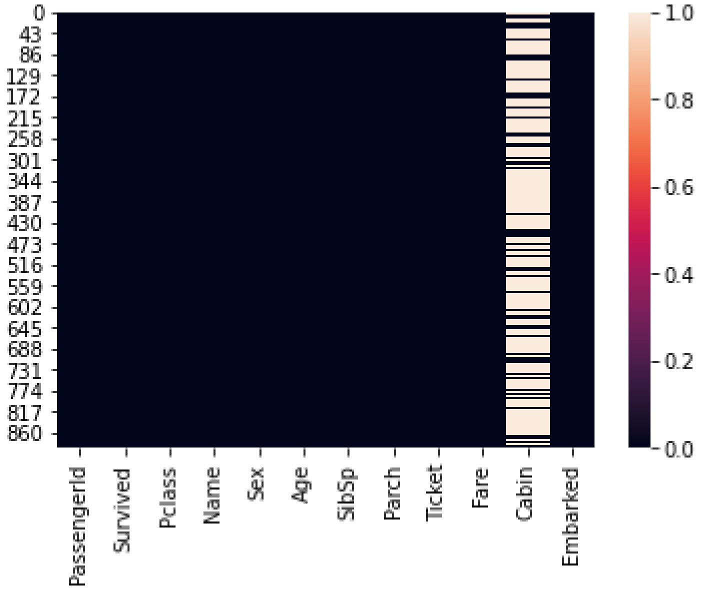
In [27]:
```
train[['Age','Pclass']].apply(impute_age,axis=1)
```

Out[27]:
```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888    25.0
889    26.0
890    32.0
Length: 891, dtype: float64
```

In [28]:
```
#Lets fill this in the age column
train['Age']=train[['Age','Pclass']].apply(impute_age,axis=1)
```

In [30]:
```
#Now create a heatmap to check the new value
sns.heatmap(data=train.isnull())
```

Out[30]:
```
<AxesSubplot:>
```



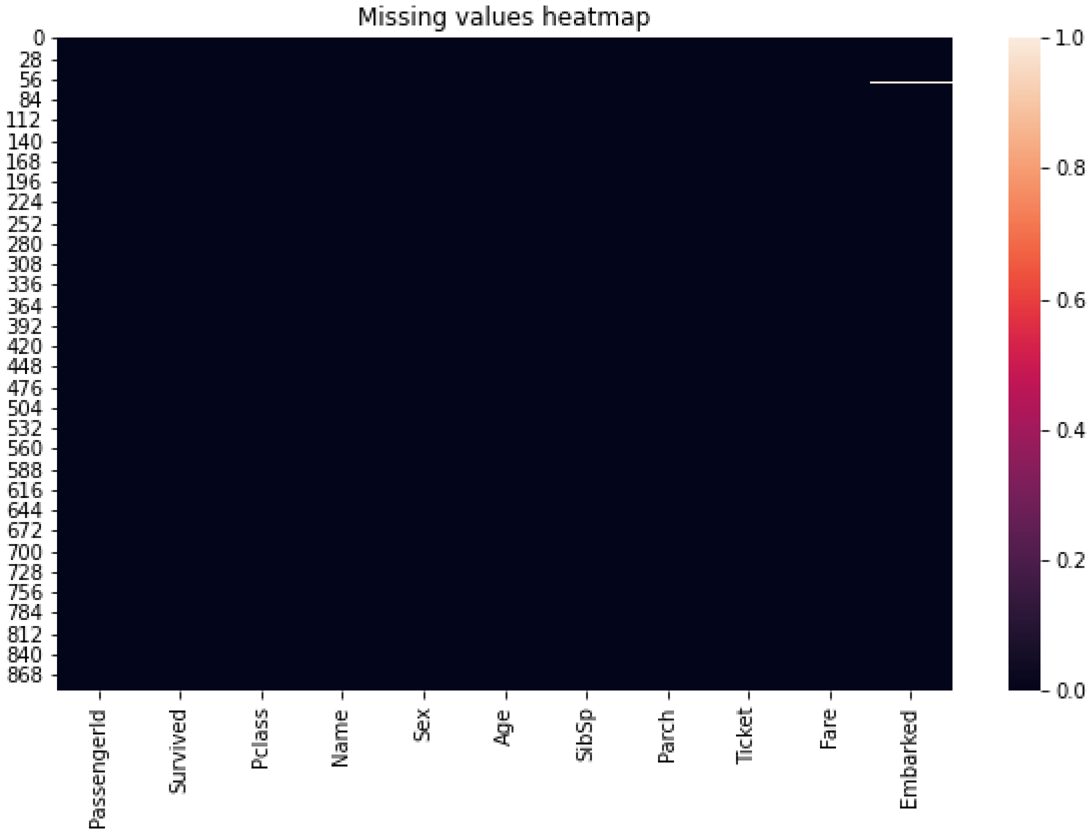
In [31]:

```
#as cabin column has more missing data lets drop as of now
train.drop('Cabin',axis=1,inplace=True)
```

In [58]:

```
plt.subplots(figsize=(10,6))
sns.heatmap(train.isnull()).set_title("Missing values heatmap")
```

Out[58]: Text(0.5, 1.0, 'Missing values heatmap')



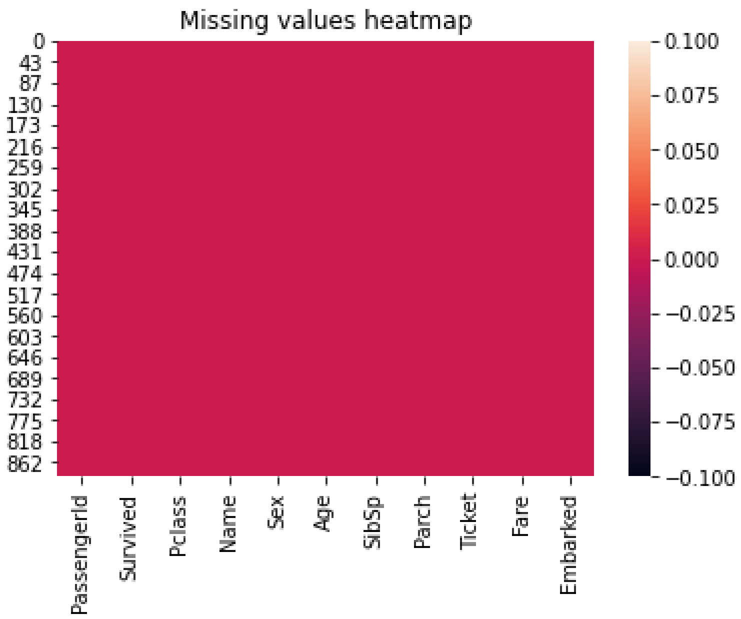
In [59]:

```
#we have 2 null values in  Embarked column, so lets drop it
train.dropna(inplace=True)
```

In [60]:

```
#Now lets see the HeatMap
sns.heatmap(train.isnull()).set_title("Missing values heatmap")
```

Out[60]: Text(0.5, 1.0, 'Missing values heatmap')



Lets work with categorical variables

In [61]:

```
#We have to remove variable with text value.
# that mean we have to remove them and add dummies
#pandas have some intersting thing to work with dummies
pd.get_dummies(train['Sex'])
```

Out[61]:

	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 [62]:

```
#Remove multicollinearity(*) by adding drop_first
sex=pd.get_dummies(train['Sex'],drop_first=True)
sex.head()
```

Out[62]:

	male
0	1

	male
1	0
2	0
3	0
4	1

In [63]:

```
#Lets do the same for Embarked
pd.get_dummies(train['Embarked'])
```

Out[63]:

	C	Q	S
0	0	0	1
1	1	0	0
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	...
886	0	0	1
887	0	0	1
888	0	0	1
889	1	0	0
890	0	1	0

889 rows × 3 columns

In [65]:

```
#Remove multicollinearity(*) by adding drop_first
embark=pd.get_dummies(train['Embarked'],drop_first=True)
embark.head()
```

Out[65]:

	Q	S
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1

In [67]:

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

Out[67]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embark

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embark
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 [70]:

```
#Lets drop some columns
#Sex, Embarked, Name, Ticket, PassengerId
train.drop(['Sex', 'Embarked', 'Name', 'Ticket','PassengerId'],axis=1,inplace=True)
```

In [73]:

```
train.head()
```

Out[73]:

	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 [ ]:

```

```

Part 3

Model Creation

In [74]:

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

In [75]:

```
X.head()
```

Out[75]:

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

In [76]:

```
y.head()
```

Out[76]:

```
0    0
1    1
2    1
3    1
4    0
Name: Survived, dtype: int64
```

In [82]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,
                                               y, test_size=0.33,
                                               random_state=42)
```

In [87]:

```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression(max_iter=2000)
```

In [88]:

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

Out[88]:

```
LogisticRegression(max_iter=2000)
```

In [89]:

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

Evaluation process

In [90]:

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

In [91]:

```
print(classification_report(y_test,predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.85      0.85       184
           1       0.75      0.76      0.76       110

    accuracy                           0.82       294
   macro avg       0.80      0.81      0.80       294
weighted avg       0.82      0.82      0.82       294
```

In [92]:

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,predict)
```

Out[92]:

```
array([[156,  28],
       [ 26,  84]], dtype=int64)
```

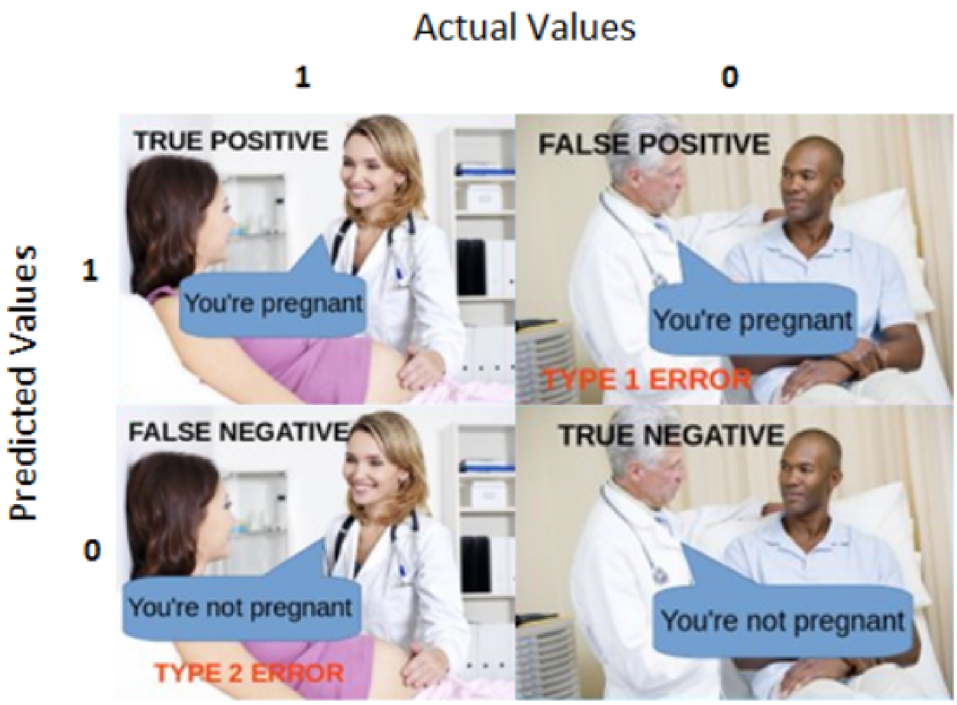
Understanding classification_report

There are four ways to check if the predictions are right or wrong: TN / True Negative: the case was negative and predicted negative TP / True Positive: the case was positive and predicted positive FN / False Negative: the case was positive but predicted negative FP / False Positive: the case was negative but predicted positive

Precision — What percent of your predictions were correct? Precision = TP/(TP + FP) Recall — What percent of the positive cases did you catch? Recall = TP/(TP+FN) F1 score — What percent of positive predictions were correct? F1 Score = 2*(Recall* Precision) / (Recall + Precision)

https://medium.com/@kohlishivam5522/understanding-a-classification-report-for-your-machine-learning-model-88815e2ce397

Understanding confusion_matrix



True Positive

```
Interpretation: You predicted positive and it’s true.
```

True Negative

```
Interpretation: You predicted negative and it’s true.
```

False Positive (Type 1 Error)

```
Interpretation: You predicted positive and it’s false.
```

False Negative (Type 2 Error)

```
Interpretation: You predicted negative and it’s false.
```

https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62