Importing basic libraries

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

from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

Data Collection & Processing

Reading the csv file

In [2]:
```
titanic_data=pd.read_csv("C:\\Users\\pinku\\Desktop\\mini project\\train.csv")
titanic_data
```

Out[2]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

Checking the no. of rows and columns in the dataset

In [3]:
```
titanic_data.shape
```

Out[3]:
```
(891, 12)
```

Fetching some informations about the data

In [4]:
```
titanic_data.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
```

Checking the no. of missing values in each column

In [5]:
```python
titanic_data.isnull().sum()
```

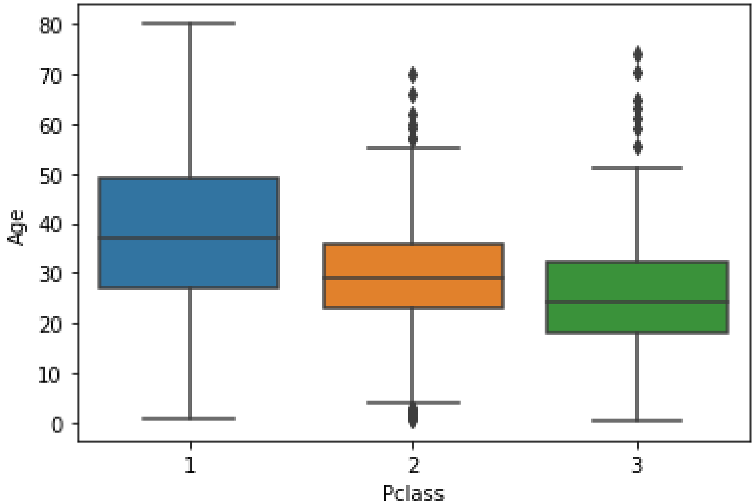
Out[5]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Handling the missing values

Handling to the Age Column

In [6]:
```python
sns.boxplot(x='Pclass',y='Age',data=titanic_data)
```

Out[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f3011c0>
```



The above plot shows that the average age of people in Class 1,2,3 were 37,29,24 respectively

In [7]:
```
def age_approx(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 [8]:
```
titanic_data['Age']=titanic_data[['Age','Pclass']].apply(age_approx,axis=1)
```

In [9]:
```
titanic_data.isnull().sum()
```

Out[9]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Heading to the Embarked Column

Finding the mode value of this column and replacing the missing values with it

In [10]:
```
print(titanic_data['Embarked'].mode())
```

```
0    S
dtype: object
```

```
In [11]: titanic_data['Embarked'].fillna(titanic_data['Embarked'].mode()[0],inplace=True)
```

```
In [12]: titanic_data.isnull().sum()
```

```
Out[12]: PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
dtype: int64
```

So all the missing values has been replaced

Dropping colums that are not required

```
In [13]: titanic_data.drop(columns={'PassengerId','Fare','Cabin','Name','Ticket'},axis=1,inplace=True)
```

Data Analysis

Statistical measures about the data

```
In [14]: titanic_data.describe()
```

Out[14]:

	Survived	Pclass	Age	SibSp	Parch
count	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.066409	0.523008	0.381594
std	0.486592	0.836071	13.244532	1.102743	0.806057
min	0.000000	1.000000	0.420000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000

	Survived	Pclass	Age	SibSp	Parch
50%	0.000000	3.000000	26.000000	0.000000	0.000000
75%	1.000000	3.000000	37.000000	1.000000	0.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000

Count for the no. of people survived and not survived

In [15]:

```
titanic_data['Survived'].value_counts()
```

Out[15]:

```
0    549
1    342
Name: Survived, dtype: int64
```

Data Visualization

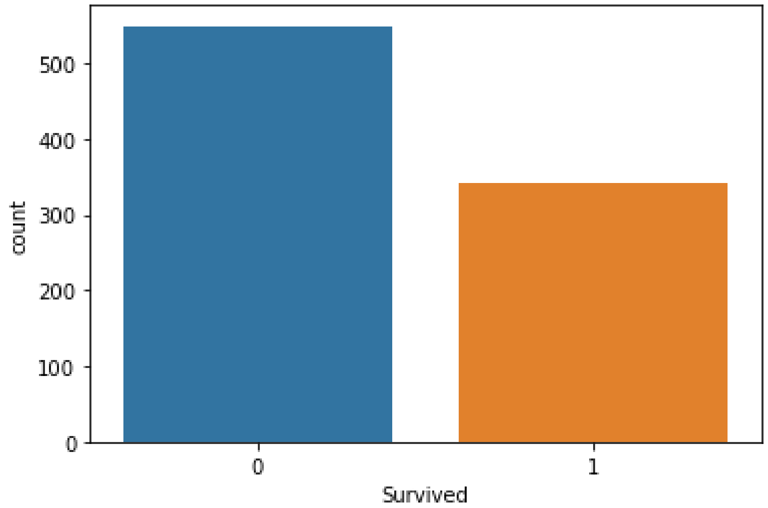
Count plot for "Survived" Column

In [16]:

```
print(sns.countplot("Survived",data=titanic_data))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

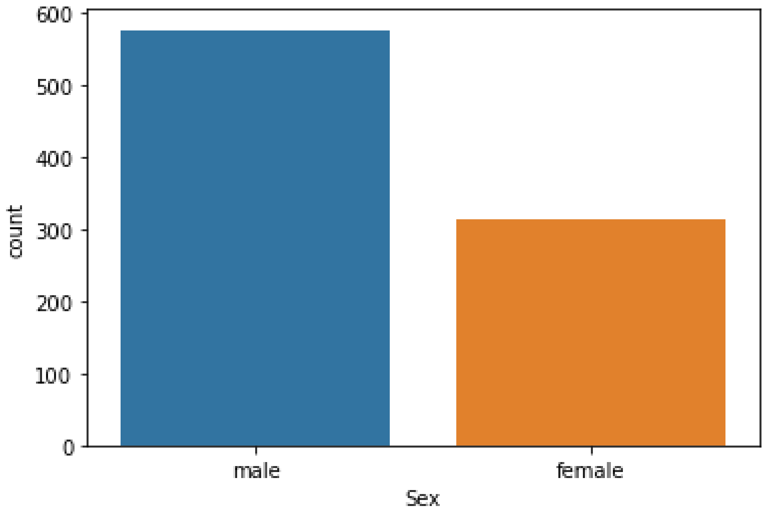


Count plot for "Sex" Column

In [17]:
```
print(sns.countplot("Sex",data=titanic_data))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

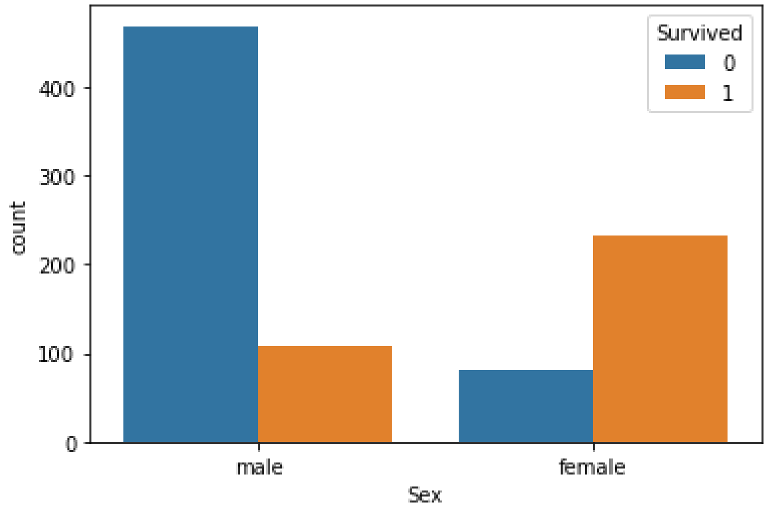


No. of surviovrs gender-wise

In [18]:
```
sns.countplot('Sex',hue='Survived',data=titanic_data)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f498490>
```



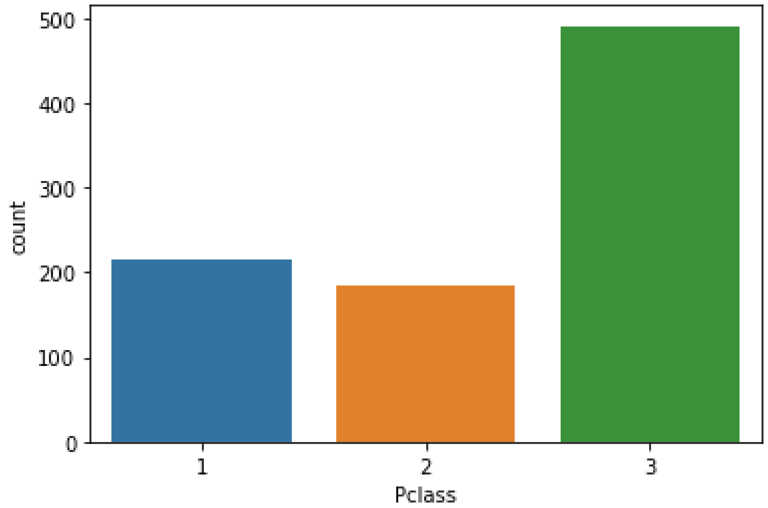
From the above graph more female survived as compared to male

count plot for "PClass" Column

In [19]:
```
print(sns.countplot("Pclass",data=titanic_data))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

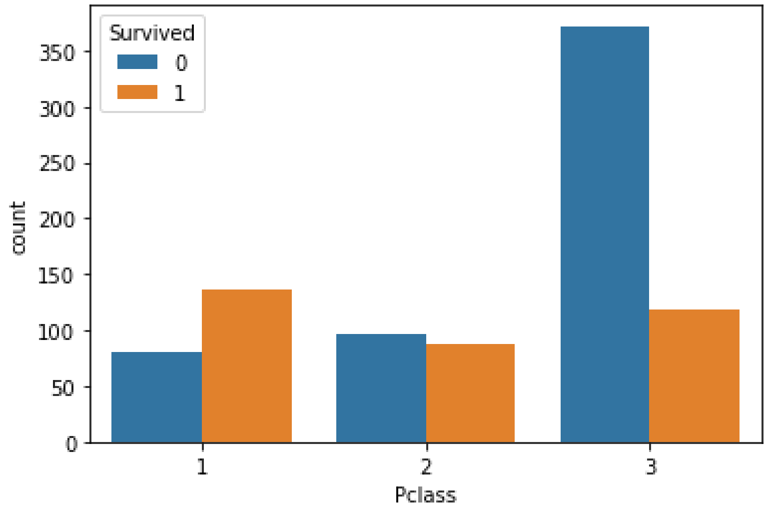


No. of surviovrs pclass-wise

In [20]:
```
sns.countplot('Pclass',hue='Survived',data=titanic_data)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f536220>
```

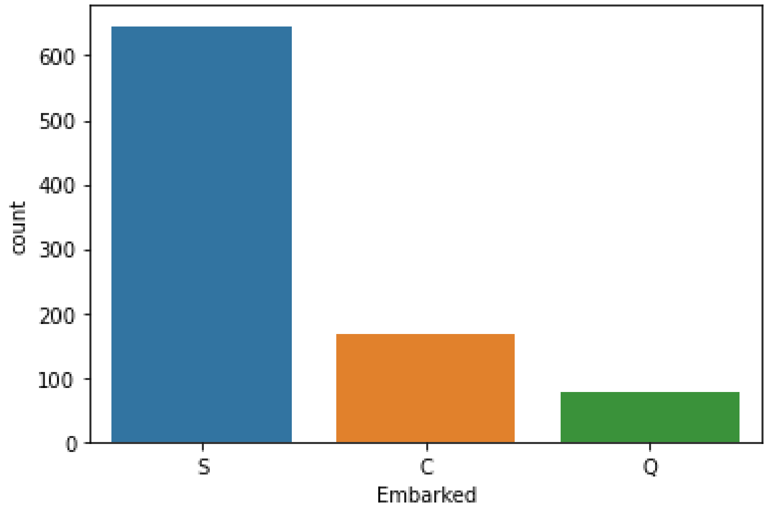


count plot for "Embarked" Column

In [21]:
```
print(sns.countplot("Embarked",data=titanic_data))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

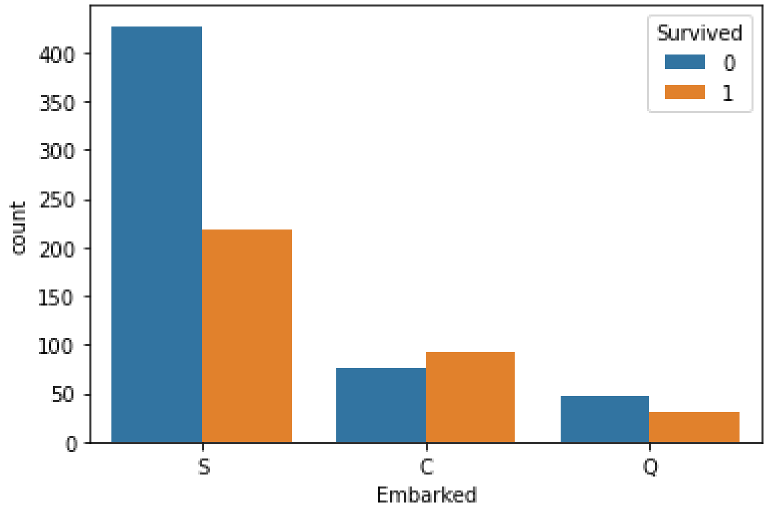


No. of surviovrs embarked-wise

In [22]:
```
sns.countplot('Embarked',hue='Survived',data=titanic_data)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a
keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit
hout an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f5da700>
```



Training part

Encoding the Categorical Columns

In [23]:
```
titanic_data['Sex'].value_counts()
```

Out[23]:
```
male      577
female    314
Name: Sex, dtype: int64
```

In [24]:
```
titanic_data['Embarked'].value_counts()
```

Out[24]:
```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

Converting categorical columns

In [25]:
```
embark=pd.get_dummies(titanic_data['Embarked'],drop_first=True)
embark
```

Out[25]:

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

891 rows × 2 columns

In [26]:

```
sex=pd.get_dummies(titanic_data['Sex'],drop_first=True)
sex
```

Out[26]:

	male
0	1
1	0
2	0
3	0
4	1
...	...
886	1
887	0

	male
888	0
889	1
890	1

891 rows × 1 columns

In [27]:
```
titanic_data.drop(['Sex','Embarked'],axis=1,inplace=True)

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

In [28]:
```
titanic_data.head()
```

Out[28]:

	Survived	Pclass	Age	SibSp	Parch	male	Q	S
0	0	3	22.0	1	0	1	0	1
1	1	1	38.0	1	0	0	0	0
2	1	3	26.0	0	0	0	0	1
3	1	1	35.0	1	0	0	0	1
4	0	3	35.0	0	0	1	0	1

In [29]:
```
titanic_data
```

Out[29]:

	Survived	Pclass	Age	SibSp	Parch	male	Q	S
0	0	3	22.0	1	0	1	0	1
1	1	1	38.0	1	0	0	0	0
2	1	3	26.0	0	0	0	0	1
3	1	1	35.0	1	0	0	0	1
4	0	3	35.0	0	0	1	0	1
...	...	...	...	...	...	...	...	...

	Survived	Pclass	Age	SibSp	Parch	male	Q	S
886	0	2	27.0	0	0	1	0	1
887	1	1	19.0	0	0	0	0	1
888	0	3	24.0	1	2	0	0	1
889	1	1	26.0	0	0	1	0	0
890	0	3	32.0	0	0	1	1	0

891 rows × 8 columns

Survival of the passengers of different age groups

In [30]:

```
df20=titanic_data.loc[titanic_data.Age<=20.0]

passengerCount20=df20.Age.count()
maleCount20=df20[df20['male']==1].male.count()
femaleCount20=df20[df20['male']==0].male.count()
maleSurvived20=(df20[(df20['male']==1) & (df20['Survived']==1)]).Survived.count()
femaleSurvived20=(df20[(df20['male']==0) & (df20['Survived']==1)]).Survived.count()
msp20=round((maleSurvived20/maleCount20)*100,2)
fsp20=round((femaleSurvived20/femaleCount20)*100,2)
totalsurvived20=df20[df20['Survived']==1].Survived.count()
tsp20=round((totalsurvived20/passengerCount20)*100,2)
```

In [31]:

```
df40=titanic_data[(titanic_data['Age']>=20) & (titanic_data['Age']<=40)]
passengerCount40=df40.Age.count()
maleCount40=df40[df40['male']==1].male.count()
femaleCount40=df40[df40['male']==0].male.count()
maleSurvived40=(df40[(df40['male']==1) & (df40['Survived']==1)]).Survived.count()
femaleSurvived40=(df40[(df40['male']==0) & (df40['Survived']==1)]).Survived.count()
msp40=round((maleSurvived40/maleCount40)*100,2)
fsp40=round((femaleSurvived40/femaleCount40)*100,2)
totalsurvived40=df40[df40['Survived']==1].Survived.count()
tsp40=round((totalsurvived40/passengerCount40)*100,2)
```

In [32]:

```
df60=titanic_data.loc[(titanic_data['Age']>=40) & (titanic_data['Age']<=60)]
```

```
passengerCount60=df60.Age.count()
maleCount60=df60[df60['male']==1].male.count()
femaleCount60=df60[df60['male']==0].male.count()
maleSurvived60=(df60[(df60['male']==1) & (df60['Survived']==1)]).Survived.count()
femaleSurvived60=(df60[(df60['male']==0) & (df60['Survived']==1)]).Survived.count()
msp60=round((maleSurvived60/maleCount60)*100,2)
fsp60=round((femaleSurvived60/femaleCount60)*100,2)
totalsurvived60=df60[df60['Survived']==1].Survived.count()
tsp60=round((totalsurvived60/passengerCount60)*100,2)
```

In [33]:

```
df100=titanic_data[titanic_data['Age']>60]
passengerCount100=df100.Age.count()
maleCount100=df100[df100['male']==1].male.count()
femaleCount100=df100[df100['male']==0].male.count()
maleSurvived100=(df100[(df100['male']==1) & (df100['Survived']==1)]).Survived.count()
femaleSurvived100=(df100[(df100['male']==0) & (df100['Survived']==1)]).Survived.count()
msp100=round((maleSurvived100/maleCount100)*100,2)
fsp100=round((femaleSurvived100/femaleCount100)*100,2)
totalsurvived100=df100[df100['Survived']==1].Survived.count()
tsp100=round((totalsurvived100/passengerCount100)*100,2)
```

In [34]:

```
data = pd.DataFrame({
     'Age Group':['0-20', '20-40','40-60','>60' ],

    'Total Count': [
                    passengerCount20,
                    passengerCount40,
                    passengerCount60,
                    passengerCount100
    ],
    'Total Survived':[
                   totalsurvived20,
                   totalsurvived40,
                   totalsurvived60,
                   totalsurvived100

    ],

    'Male Count': [
                   maleCount20,
                   maleCount40,
```

```
                    maleCount60,
                    maleCount100],

     'Female Count': [
                    femaleCount20,
                    femaleCount40,
                    femaleCount60,
                    femaleCount100],

     'Male Survived Count': [
                    maleSurvived20,
                    maleSurvived40,
                    maleSurvived60,
                    maleSurvived100],

     'Female Survived Count': [
                    femaleSurvived20,
                    femaleSurvived40,
                    femaleSurvived60,
                    femaleSurvived100],
     'Total Survived(%)':[
                    tsp20,
                    tsp40,
                    tsp60,
                    tsp100
     ],
     'Male Survived(%)': [
                    msp20,
                    msp40,
                    msp60,
                    msp100],
     'Female Survived(%)': [
                     fsp20,
                     fsp40,
                     fsp60,
                     fsp100]


     })
data
```

Out[34]:

	Age Group	Total Count	Total Survived	Male Count	Female Count	Male Survived Count	Female Survived Count	Total Survived(%)	Male Survived(%)	Female Survived(%)
0	0-20	179	82	102	77	29	53	45.81	28.43	68.83
1	20-40	577	208	386	191	65	143	36.05	16.84	74.87
2	40-60	141	56	90	51	17	39	39.72	18.89	76.47
3	>60	22	5	19	3	2	3	22.73	10.53	100.00

In [35]:

```
MS=maleSurvived20 + maleSurvived40 + maleSurvived60 + maleSurvived100
MT=maleCount20 + maleCount40 + maleCount60 + maleCount100
MSP=round((MS/MT)*100,2)
FS=femaleSurvived20 + femaleSurvived40 + femaleSurvived60 + femaleSurvived100
FT=femaleCount20 + femaleCount40 + femaleCount60 + femaleCount100
FSP=round((FS/FT)*100,2)
```

In [36]:

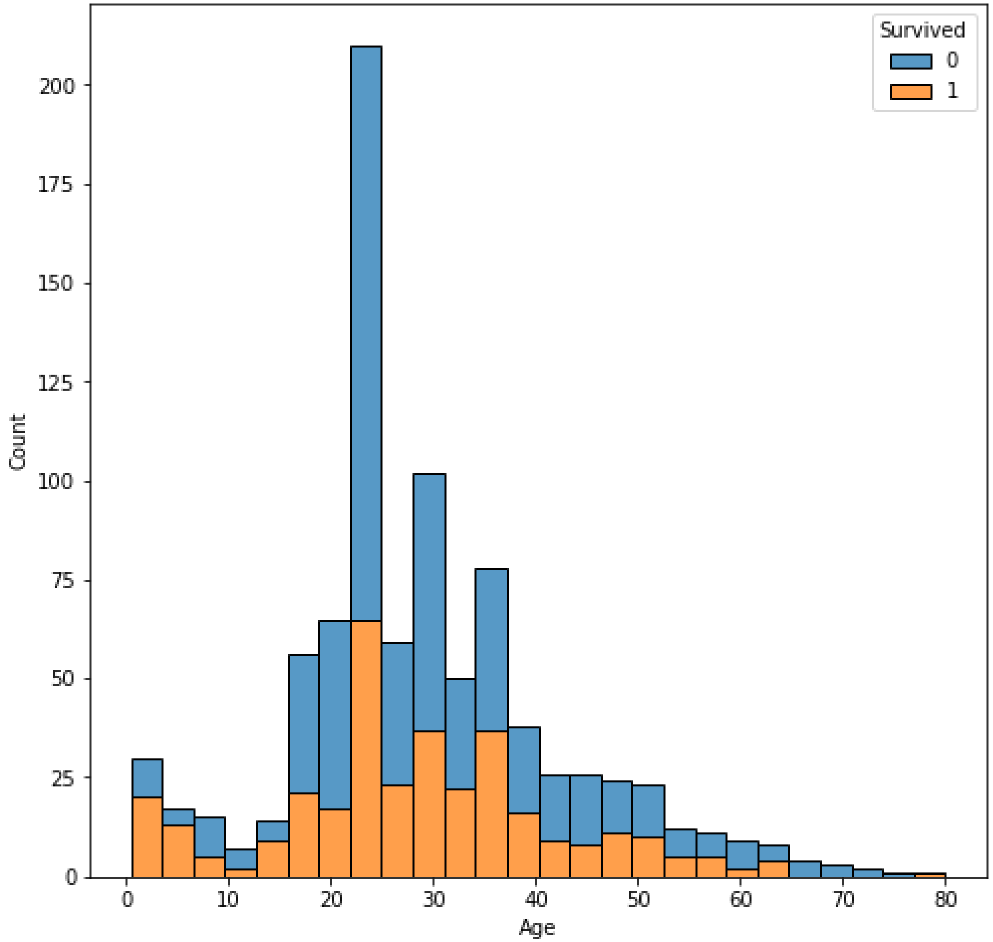
```
data = pd.DataFrame({
    'Label':['Male Total','Male Survived','Male Survived % ','Female Total','Female Survived','Female Survived %'],
    'Values':[MT,MS,MSP,FT,FS,FSP]
})
data
```

Out[36]:

	Label	Values
0	Male Total	597.00
1	Male Survived	113.00
2	Male Survived %	18.93
3	Female Total	322.00
4	Female Survived	238.00
5	Female Survived %	73.91

In [37]:

```
plt.figure(figsize=(8,8))
sns.histplot(x='Age',data=titanic_data,hue='Survived',multiple='stack')
plt.show()
```

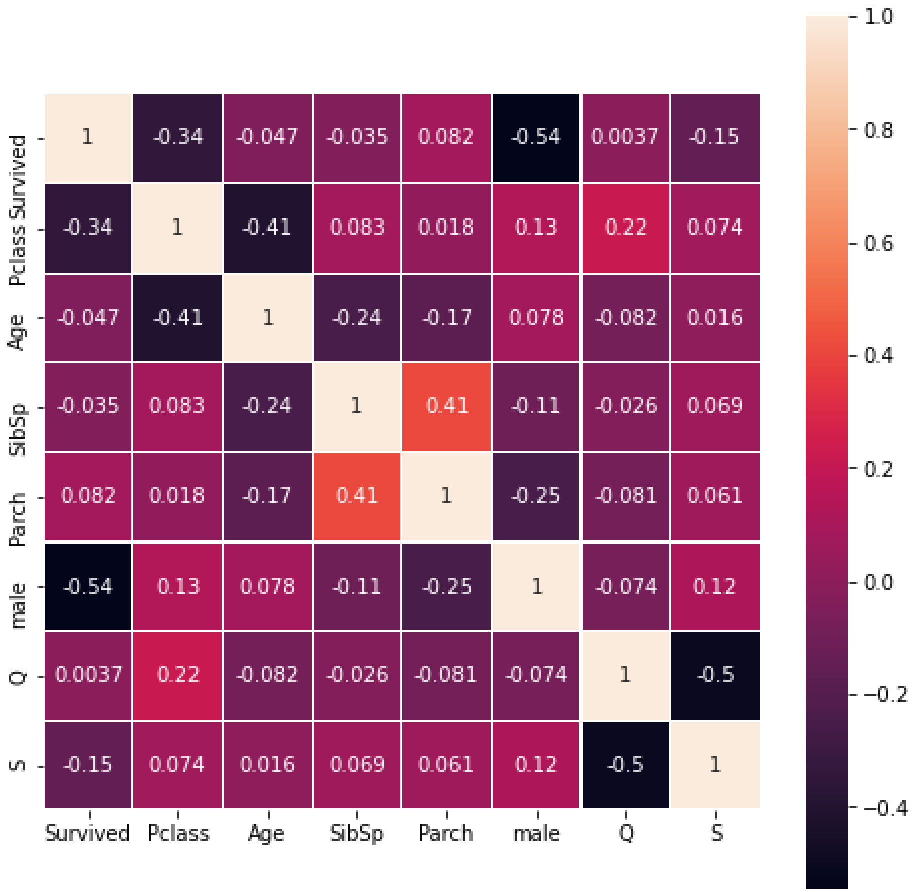


Conclusion- The above histogram shows how survival will be affected by age. We can see that as age increases, survival of people is going down. So we can say that Age and Survival are negatively correlated as shown by our correlation heatmap.

HeatMap

In [38]:

```
plt.figure(figsize=(8,8))
sns.heatmap(titanic_data.corr(),annot=True,linewidth=0.1,square=True,)
plt.show()
```



Explanation of the significance of the correlation coefficients between two features corresponding to each block given by the heatmap

Correlation is a term that is a measure of the strength of a linear relationship between two quantitative variables. Positive correlation is a relationship between two variables in which both variables move in the same direction. This is when one variable increases while the other increases and visa versa. For example, positive correlation may be that the more you exercise, the more calories you will burn. Whilst negative correlation is a relationship where one variable increases as the other decreases, and vice versa.

The correlation coefficient doesnot hold any other significance other than to show how strong or weak the relationship is between two features i.e. if one feature increases or decreases how fast or how slow the other feature increases or decreases compared to the first feature

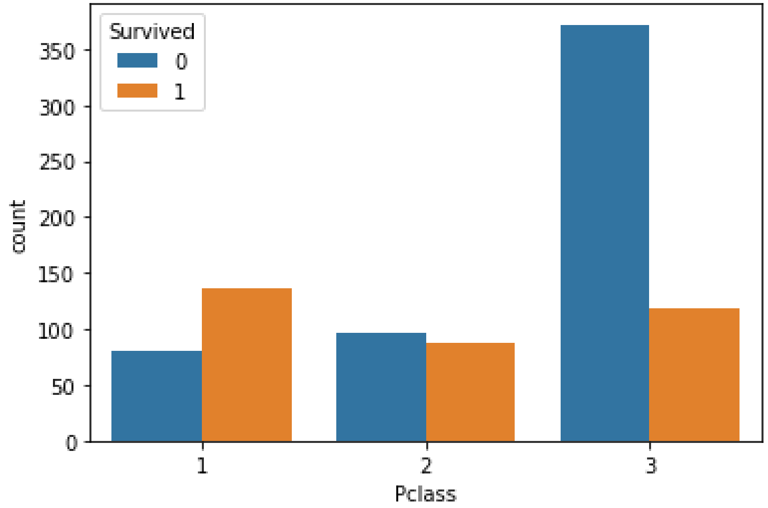
PLots

Pclass & Survived

In [39]:
```
sns.countplot('Pclass',hue='Survived',data=titanic_data)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[39]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f913d90>
```



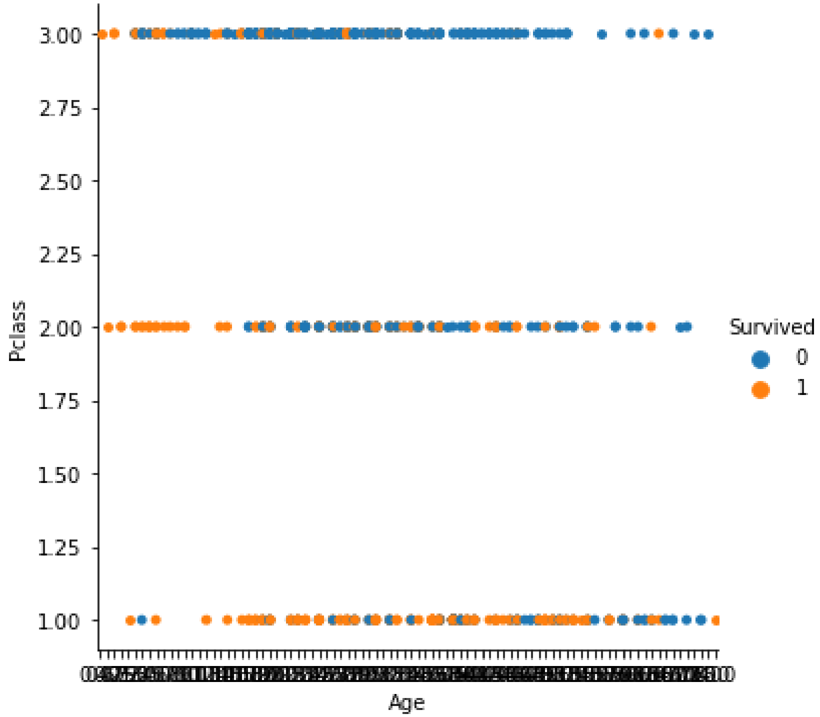
Conclusion-

1)As Pclass increases, survivality goes down which signifies the negative correlation between Pclass & Survival

Pclass & Age

In [40]:
```
plt.figure(figsize=(12,12))
sns.catplot(x='Age',y='Pclass',hue='Survived',data=titanic_data)
plt.show()
```

```
<Figure size 864x864 with 0 Axes>
```



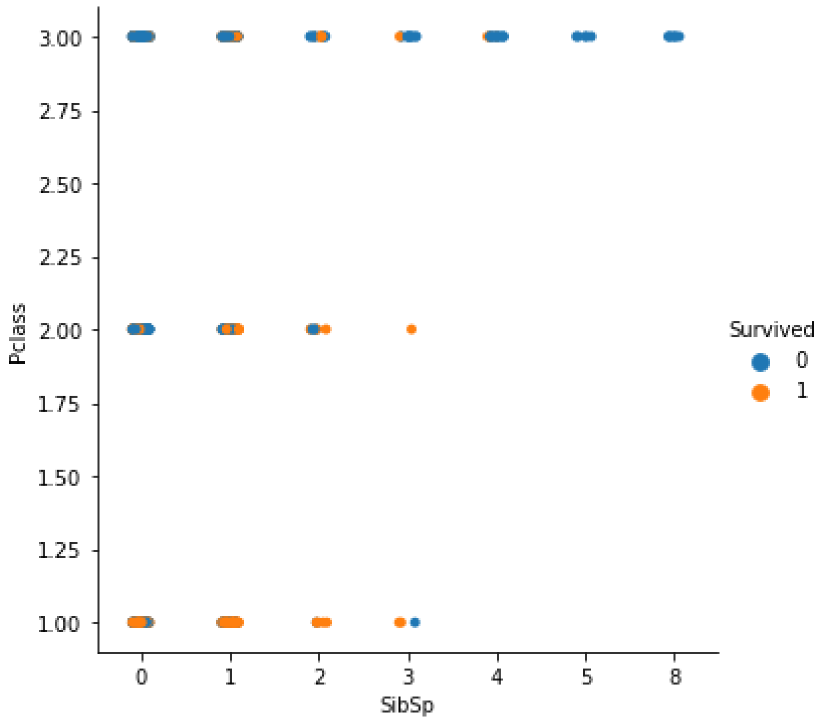
Conclusion-

As Pclass increases, the no. of people in the lower age group increases and the no. of people in the higher age group decreases which shows the negative correlation between the two.

Pclass v/s SibSp

In [41]:
```
sns.catplot(x='SibSp',y='Pclass',hue='Survived',data=titanic_data)
```

```
Out[41]: <seaborn.axisgrid.FacetGrid at 0x1f38f776ee0>
```



Conclusion-

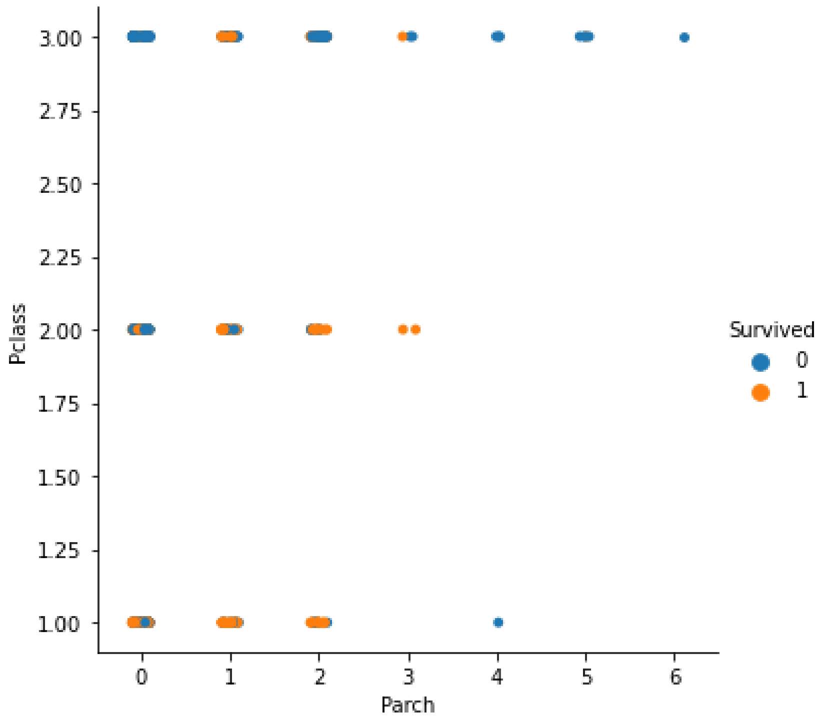
1) A passenger with more siblings/spouse chose a lower passenger class(for Pclass higher the no. lower is the class) i.e. as Pclass increases SibSp value increases which shows the positive correlation

2) If a person has more siblings/spouse their survival chances will decreases which shows the negative correlation

Pclass & Parch

```
In [42]: sns.catplot(x='Parch',y='Pclass',hue='Survived',data=titanic_data)
```

Out[42]: <seaborn.axisgrid.FacetGrid at 0x1f38f5278b0>

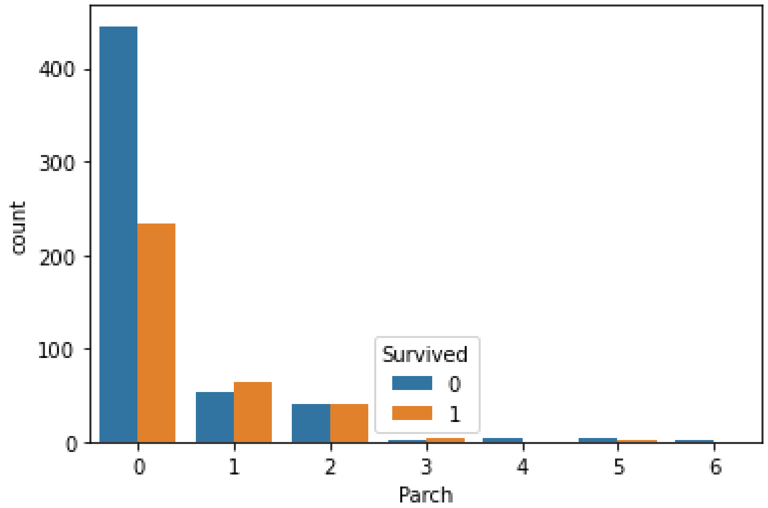


Conclusion-

1)A passenger with more parents/children chose a lower passenger class(for Pclass higher the no. lower is the class) i.e. as Pclass increases Parch value increases which shows the positive correlation

In [43]:
```
sns.countplot(x='Parch',hue='Survived',data=titanic_data)
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1f38fb5ea60>

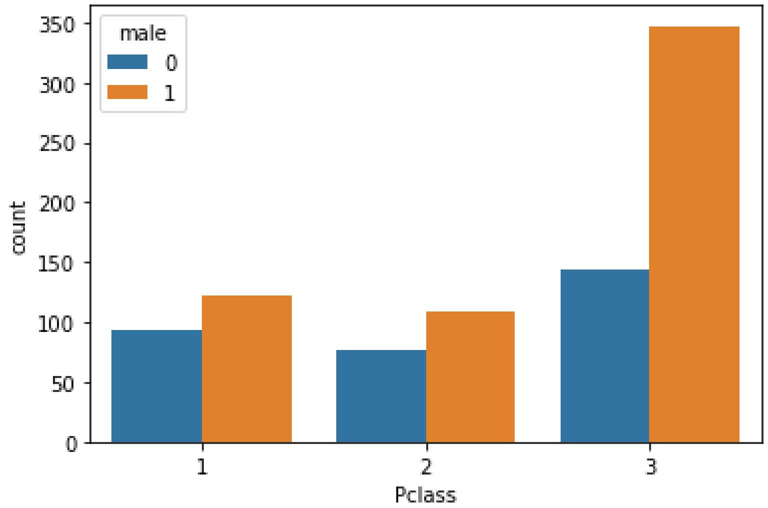


Pclass v/s male

In [46]:
```
sns.countplot('Pclass',hue='male',data=titanic_data)
```

```
C:\Users\Nitin\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f445ee0>
```

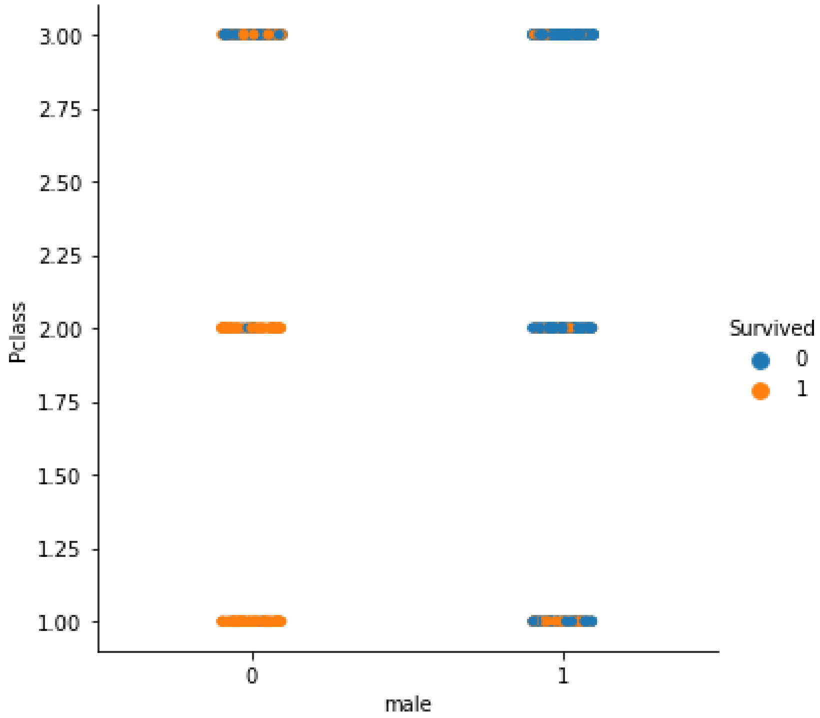


This plot shows the positive correlation between the pclass and male features

(From the plot both no. of females and no. of males increases as Pclass increases but we can see the no. of males increases much more than the no. of females. Thus it can be said that as Pclass increases the binary value (female=0 male=1) increases from 0 to 1 which shows the positive correlation)

In [47]:
```
sns.catplot(x='male',y='Pclass',hue='Survived',data=titanic_data)
```

Out[47]:
```
<seaborn.axisgrid.FacetGrid at 0x1f38f663970>
```



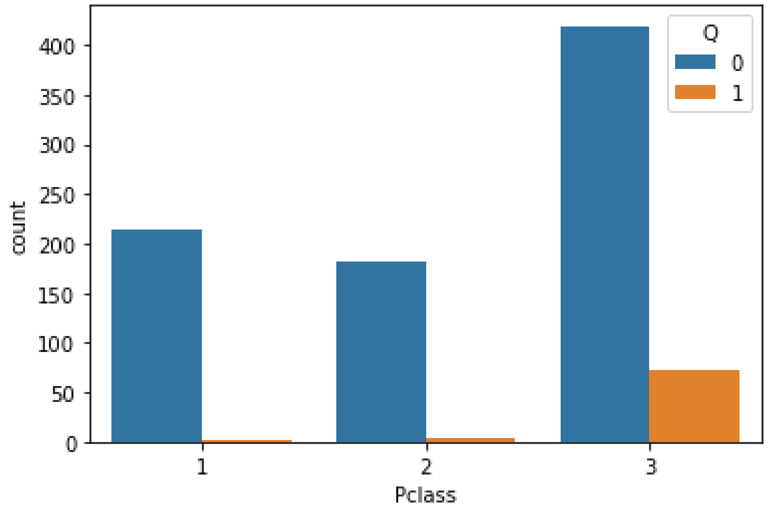
Conclusion-

1) Although the survival rate of female is high but a female belonging to the lowest passenger class will have higher chance of not surviving.

Pclass & Q

In [48]:
```
sns.countplot(x='Pclass',hue='Q',data=titanic_data)
```

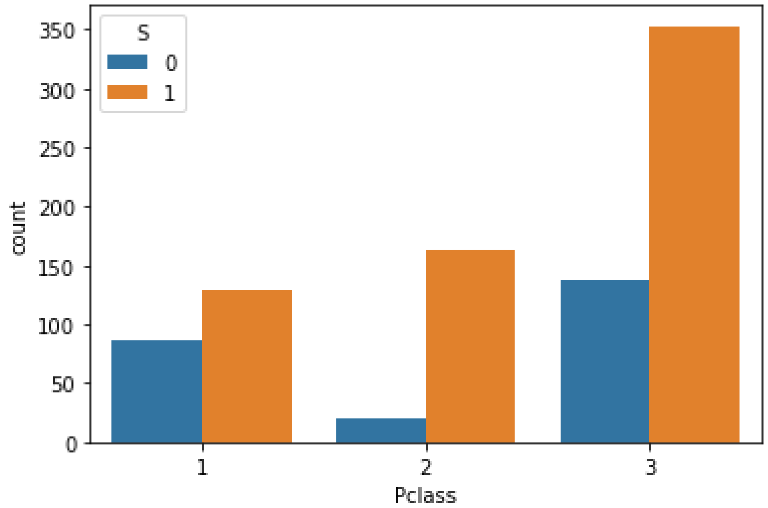
Out[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f38f78ccd0>
```



Pclass & S

In [49]:
```
sns.countplot(x='Pclass',hue='S',data=titanic_data)
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x1f38f5b73a0>



Separating the target("Survived") from features("other categories")

In [50]:
```
X=titanic_data.drop(columns='Survived',axis=1)
Y=titanic_data['Survived']
```

Splitting the data into Training data & Test data

Data will be splitted in random way

In [51]:
```
x_train,x_test,y_train,y_test=train_test_split(X,Y,test_size=0.2,random_state=2)
```

In [52]:
```
print(X.shape,x_train.shape,x_test.shape)
print(Y.shape,y_train.shape,y_test.shape)
```

```
(891, 7) (712, 7) (179, 7)
(891,) (712,) (179,)
```

Now we will train our data

Model Training

Logistic Regression Model

In [53]:
```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(x_train, y_train)
```

Out[53]:
```
LogisticRegression()
```

In [54]:
```
y_pred_log = logreg.predict(x_test)
```

In [55]:
```
acc_logreg =round(accuracy_score(y_pred_log, y_test) * 100, 2)
print(acc_logreg)
```

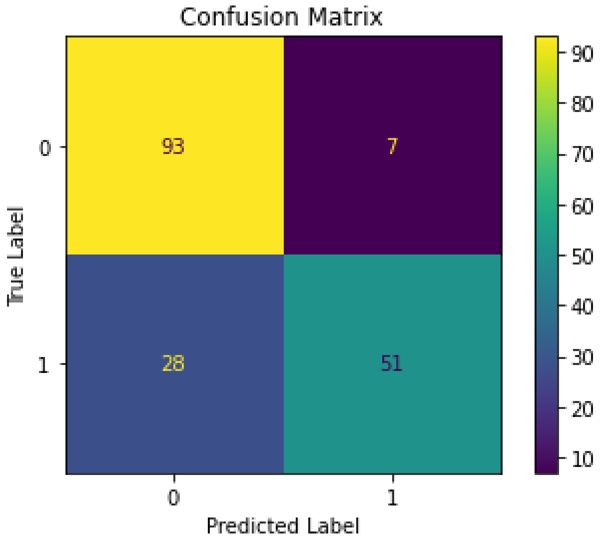
```
80.45
```

In [56]:
```
theta_0=logreg.intercept_
theta_s=logreg.coef_.T
```

Confusion matrix for Logistic Regression

In [57]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
```

In [58]:
```
matrix=plot_confusion_matrix(logreg,x_test,y_test)
matrix.ax_.set_title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



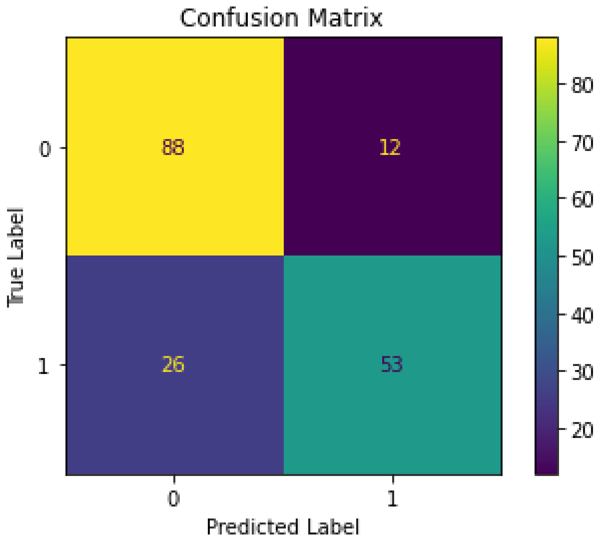
Gaussian Naive Bayes

In [59]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

gaussian = GaussianNB()
gaussian.fit(x_train, y_train)
y_pred_gaussian = gaussian.predict(x_test)
acc_gaussian = round(accuracy_score(y_pred_gaussian, y_test) * 100, 2)
print(acc_gaussian)
```

78.77

Confusion matrix for Gaussian Naive Bayes

In [60]:
```
matrix=plot_confusion_matrix(gaussian,x_test,y_test)
matrix.ax_.set_title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



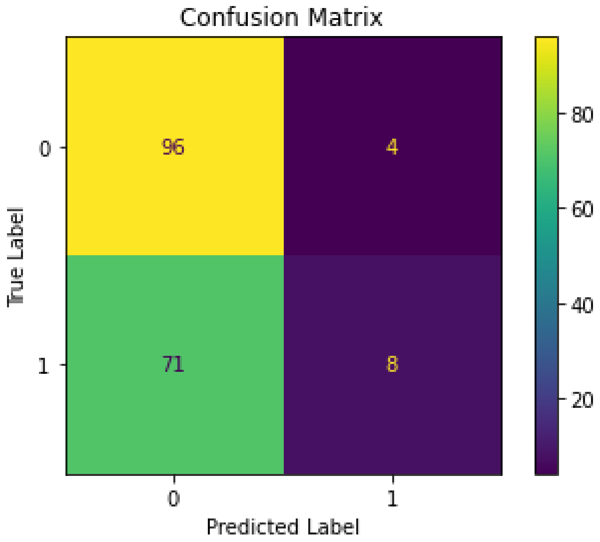
Support Vector Machines

In [61]:
```
from sklearn.svm import SVC

svc = SVC()
svc.fit(x_train, y_train)
y_pred_svc = svc.predict(x_test)
acc_svc = round(accuracy_score(y_pred_svc, y_test) * 100, 2)
print(acc_svc)
```

58.1

Confusion matrix for Support Vector Machine

In [62]:
```
matrix=plot_confusion_matrix(svc,x_test,y_test)
matrix.ax_.set_title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



Decision Tree

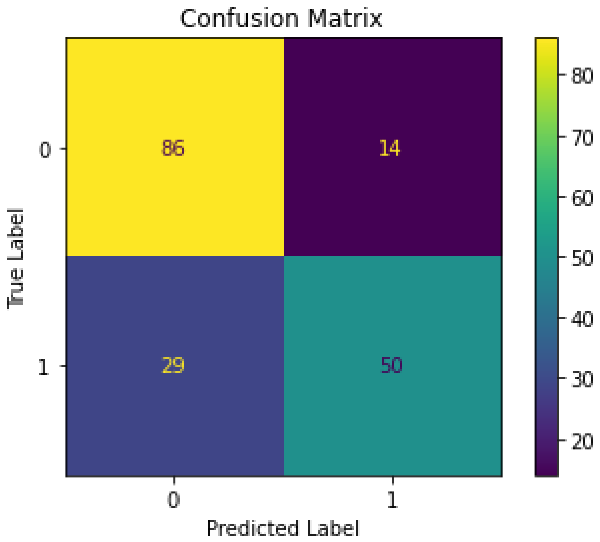
In [63]:
```
from sklearn.tree import DecisionTreeClassifier

decisiontree = DecisionTreeClassifier()
decisiontree.fit(x_train, y_train)
y_pred_dt = decisiontree.predict(x_test)
acc_decisiontree = round(accuracy_score(y_pred_dt, y_test) * 100, 2)
print(acc_decisiontree)
```

```
75.98
```

Confusion matrix for Decision Tree

In [64]:
```
matrix=plot_confusion_matrix(decisiontree,x_test,y_test)
matrix.ax_.set_title('Confusion Matrix')
```

```
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



Accuracies of each model

In [65]:

```
models = pd.DataFrame({
    'Model': [ 'Logistic Regression', 'Support Vector Machines',
                            'Decision Tree', 'Gaussian Naive Bayes'],
    'Score': [acc_logreg, acc_svc, acc_decisiontree,
                acc_gaussian,]})
models.sort_values(by='Score', ascending=False)
```

Out[65]:

	Model	Score
0	Logistic Regression	80.45
3	Gaussian Naive Bayes	78.77
2	Decision Tree	75.98
1	Support Vector Machines	58.10

```
demo = logreg.predict([[1,30.0,0,3,1,1,0]])
```

In [72]:
```
demo
```
Out[72]:
```
array([1], dtype=int64)
```

Analysis

In [67]:
```
pclass=int(input('Enter the PClass: '))
age=int(input('Enter the Age of the Passenger: '))
sibsp=int(input('Enter the no. of Sibling or Spouse: '))
parch=int(input('Enter the no. of Parch: '))
```
```
Enter the PClass: 1
Enter the Age of the Passenger: 30
Enter the no. of Sibling or Spouse: 0
Enter the no. of Parch: 3
```

In [68]:
```
gender=input('Enter male or female: ')
gender=gender.lower()
if gender=='male':
    sex=1
else:
    sex=0
```
```
Enter male or female: male
```

In [69]:
```
emb=input('Enter the port of embarkmaent ("C","Q","S"): ')
emb=emb.upper()
if emb=='C':
        Q=0
        S=0
elif emb=='Q':
        Q=1
        S=0
else:
        Q=0
        S=1
```
```
Enter the port of embarkmaent ("C","Q","S"): S
```

In [70]:
```
demo = logreg.predict([[pclass,age,sibsp,parch,sex,Q,S]])
n=int(demo)
y_pred1=logreg.predict_proba([[pclass,age,sibsp,parch,sex,Q,S]])
```

```
for idx,i in enumerate([[item] for sub in y_pred1 for item in sub]):
    if idx==0:
        a=round(i.pop()*100,2)
    else:
        b=round(i.pop()*100,2)
```

In [71]:

```
print(f'The chances of the survival of the passenger is : {b}%')
```

```
The chances of the survival of the passenger is : 49.32%
```

In [ ]:

In [ ]: