Task1 :TITANIC SURVIVAL PREDICTION

1. Use the Titanic dataset to build a model that predicts whether a passenger on the Titanic survived or not. This is a classic beginner project with readily available data.
2. The dataset typically used for this project contains information about individual passengers, such as their age, gender, ticket class, fare, cabin, and whether or not they survived.

Data Collection :

In [1]:
```
#import the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

In [2]:
```
# loading and reading the dataset
titanic_data= pd.read_csv("tested.csv")
titanic_data
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
413	1305	0	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	0	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	0	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	0	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

418 rows × 12 columns

```
#information of columns
Survival 0 = No, 1 = Yes

pclass: A proxy for socio-economic status (SES)
1st = Upper, 2nd = Middle, 3rd = Lower

age: Age is fractional if less than 1.
If the age is estimated, is it in the form of xx.5
```

```
sibsp: defines family relations in this way...
Sibling = brother, sister, stepbrother,
stepsister Spouse = husband, wife (mistresses and fiancés were ignored)

parch: defines family relations in this way...
1.Parent = mother, father
2.Child = daughter, son, stepdaughter, stepson
3.Some children travelled only with a nanny, therefore parch=0 for them.

embarked : Port of Embarkation
C = Cherbourg, Q = Queenstown, S = Southampton
```

In [3]:
```
#Printing top 5 rows
titanic_data.head()
```

Out[3]:

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

Types of features :

- Categorical =Sex , Embarked
- Continuous = Age,Fare
- Discrete = SibSp,Parch
- alphanumeric = Cabin

Data Preprocessing :

In [4]:
```
# number of rows and columns
titanic_data.shape
```

Out[4]:
```
(418, 12)
```

In [5]:
```
 # to get infomation about the data
 titanic_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  418 non-null    int64  
 1   Survived     418 non-null    int64  
 2   Pclass       418 non-null    int64  
 3   Name         418 non-null    object 
 4   Sex          418 non-null    object 
 5   Age          332 non-null    float64
 6   SibSp        418 non-null    int64  
 7   Parch        418 non-null    int64  
 8   Ticket       418 non-null    object 
 9   Fare         417 non-null    float64
 10  Cabin        91 non-null     object 
 11  Embarked     418 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 39.3+ KB
```

In [6]:
```
# check missing values
titanic_data.isnull().sum()
```

Out[6]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

In [7]:
```
# droping the cabin column from the dataframe because majority of values are missing i.e. 327
titanic_data=titanic_data.drop(columns='Cabin',axis=1)
```

In [8]:
```
# calculating mean of Age column
titanic_data['Age'].fillna(titanic_data['Age'].mean(), inplace=True)

# calculating mean of Fare column
titanic_data['Fare'].fillna(titanic_data['Fare'].mean(), inplace=True)
```

In [9]:
```
# again verifying the missing values
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
Embarked       0
dtype: int64
```

Exploratory Data Analysis :

In [10]:
```
#statistical summary of the numerical columns in the DataFrame
titanic_data.describe()
```

Out[10]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000
mean	1100.500000	0.363636	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.481622	0.841838	12.634534	0.896760	0.981429	55.840500
min	892.000000	0.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	0.000000	1.000000	23.000000	0.000000	0.000000	7.895800
50%	1100.500000	0.000000	3.000000	30.272590	0.000000	0.000000	14.454200
75%	1204.750000	1.000000	3.000000	35.750000	1.000000	0.000000	31.500000
max	1309.000000	1.000000	3.000000	76.000000	8.000000	9.000000	512.329200

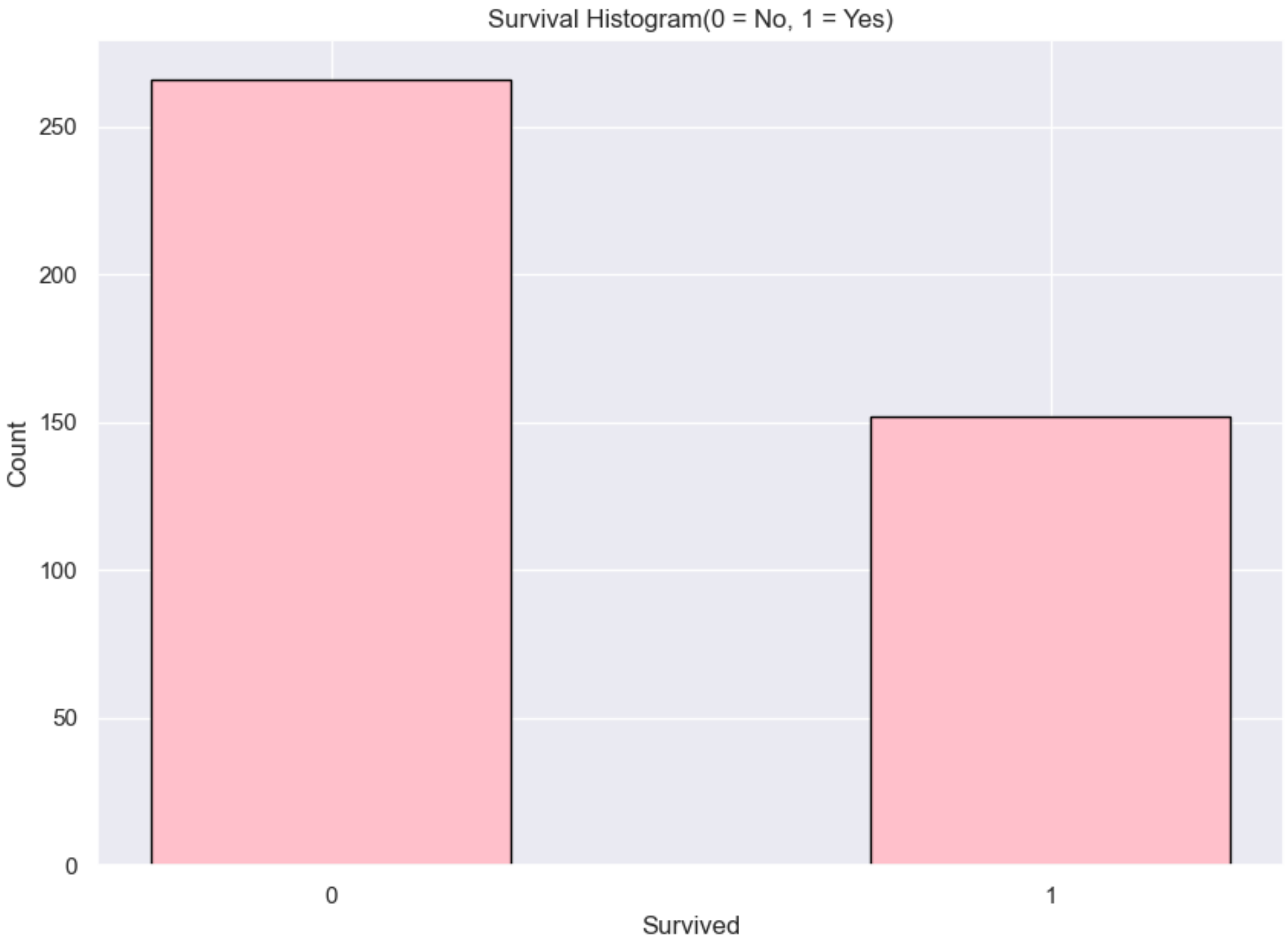
In [11]:
```
#counts of unique values in Survived column
titanic_data['Survived'].value_counts()
```

Out[11]:
```
0    266
1    152
Name: Survived, dtype: int64
```

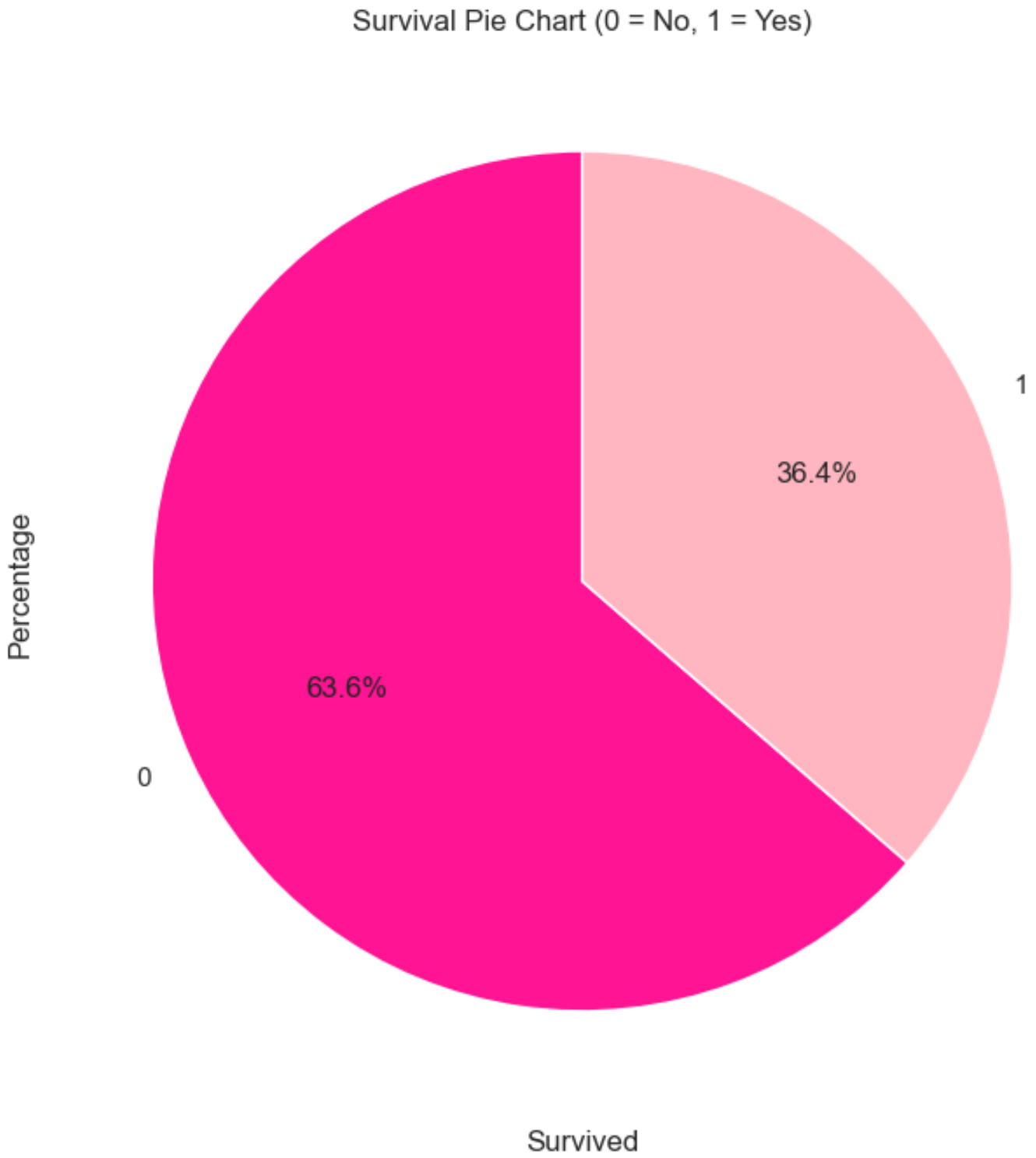
Data Visualization :

In [12]:
```
sns.set()
```

In [13]:
```
fig = plt.figure(figsize=(10, 7))
column = 'Survived'
plt.hist(
    titanic_data[column],
    bins=[-0.5, 0.5, 1.5],
    rwidth=0.5, align='mid',
    color='pink',
    edgecolor='black')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.title('Survival Histogram(0 = No, 1 = Yes)')
plt.xticks([0, 1])
plt.show()
```

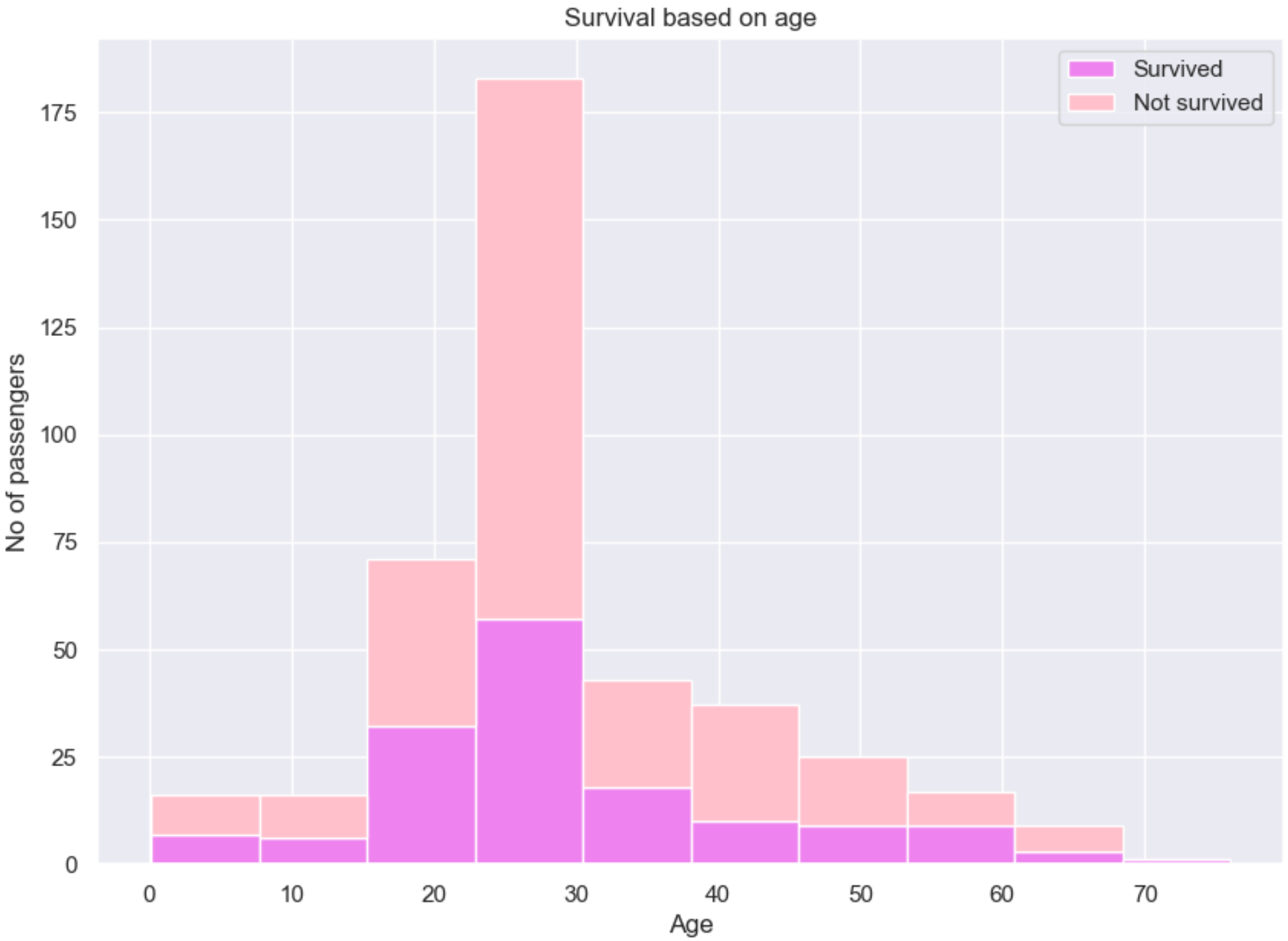

Survival Histogram(0 = No, 1 = Yes)
Count
250
200
150
100
50
0
0
1
Survived

In [14]:
```
#same visualization only in pie chart
survival_percentage = titanic_data['Survived'].value_counts(normalize=True) * 100
colors = ["#FF1493", "#FFB6C1"]
sns.set_palette(sns.color_palette(colors))
plt.figure(figsize=(8, 8))
plt.pie(survival_percentage, labels=survival_percentage.index, autopct='%1.1f%%', startangle=90)
plt.xlabel('Survived')
plt.ylabel('Percentage')
plt.title('Survival Pie Chart (0 = No, 1 = Yes)')
plt.show()
```


Survival Pie Chart (0 = No, 1 = Yes)
Percentage
Survived
0
1
63.6%
36.4%

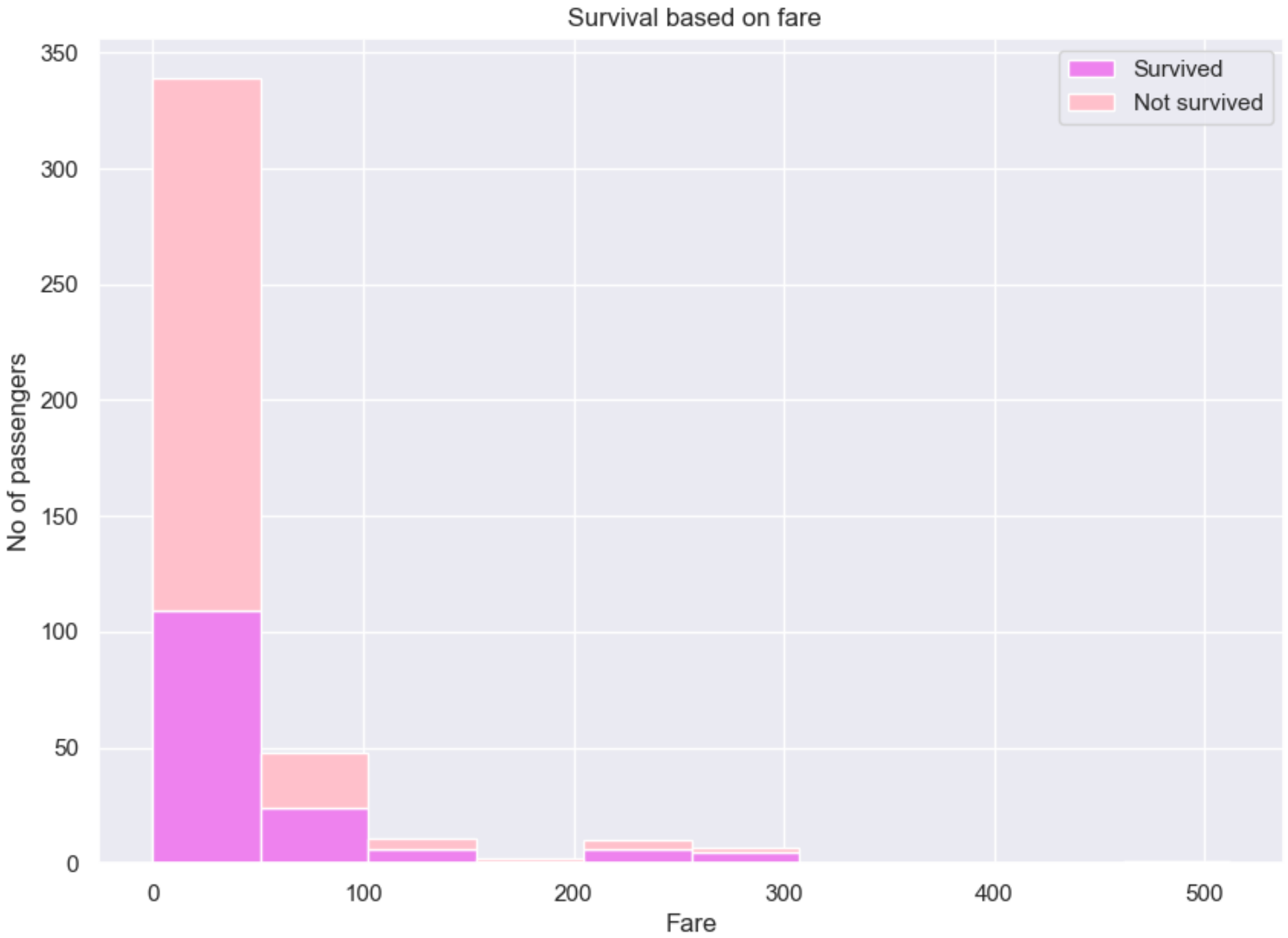
In [15]:
```
fig = plt.figure(figsize =(10, 7))
plt.hist(
    x = [titanic_data[titanic_data['Survived']==1]['Age'],
    titanic_data[titanic_data['Survived']==0]['Age']],
    stacked=True, color = ['violet','pink'],
    label = ['Survived','Not survived'])
plt.title('Survival based on age')
plt.xlabel('Age')
plt.ylabel('No of passengers')
plt.legend()
```

Out[15]:
```
<matplotlib.legend.Legend at 0x22078661610>
```


Survival based on age
Survived
Not survived
No of passengers
0
25
50
75
100
125
150
175
0
10
20
30
40
50
60
70
Age

In [16]:
```
fig = plt.figure(figsize =(10, 7))
plt.hist(
    x = [titanic_data[titanic_data['Survived']==1]['Fare'],
    titanic_data[titanic_data['Survived']==0]['Fare']],
    stacked=True,
    color = ['violet','pink'],
    label = ['Survived','Not survived'])
plt.title(' Survival based on fare')
plt.xlabel('Fare')
plt.ylabel('No of passengers')
plt.legend()
```

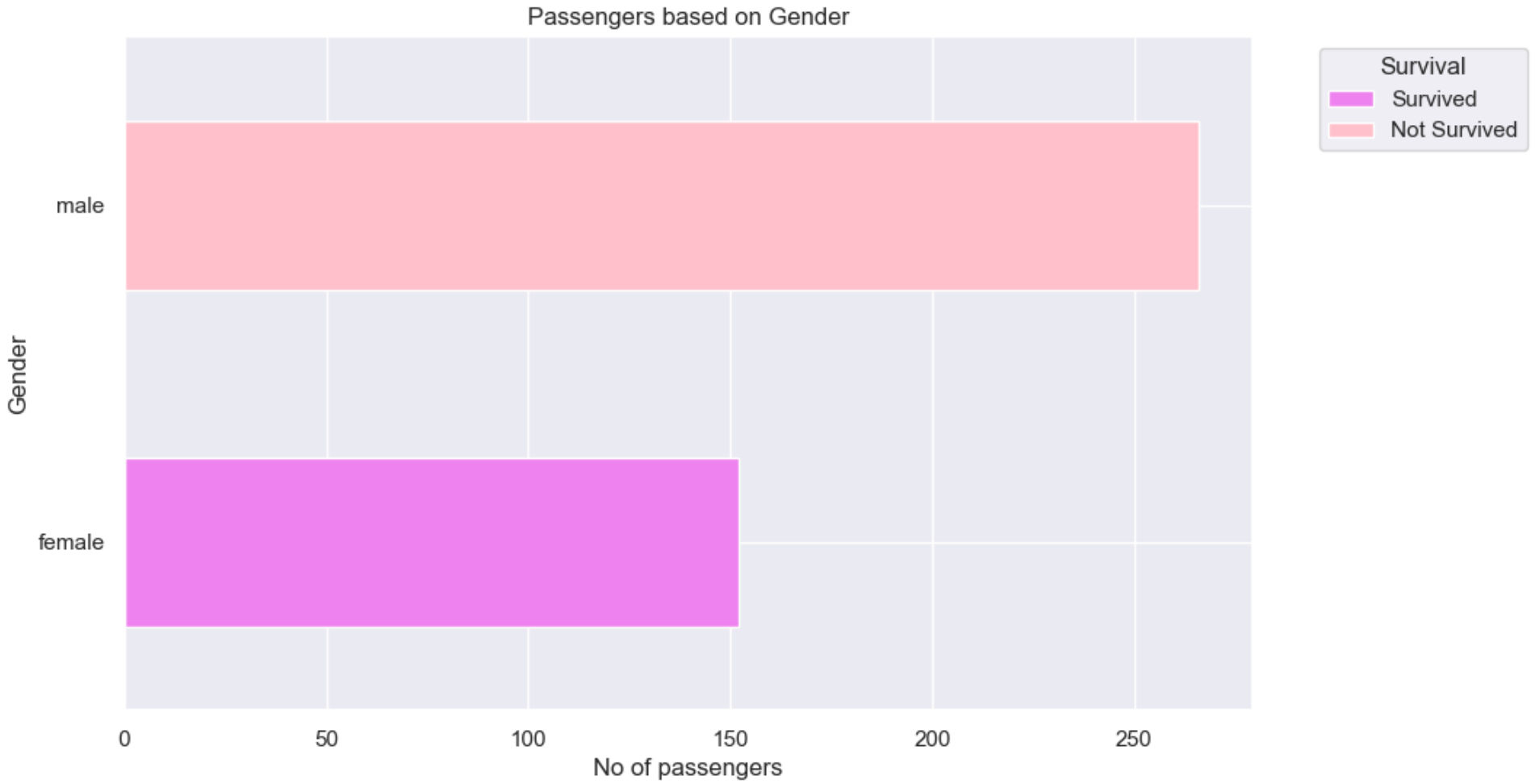
Out[16]:
```
<matplotlib.legend.Legend at 0x22079092b10>
```


Survival based on fare
Survived
Not survived
No of passengers
Fare
0
50
100
150
200
250
300
350
0
100
200
300
400
500

In [17]:
```
#counts of unique values in the 'Sex' column
titanic_data['Sex'].value_counts()
```

Out[17]:
```
male      266
female    152
Name: Sex, dtype: int64
```

In [18]:
```
survived_counts = titanic_data[titanic_data['Survived'] == 1]['Sex'].value_counts()
not_survived_counts = titanic_data[titanic_data['Survived'] == 0]['Sex'].value_counts()
gender_counts = pd.DataFrame({'Survived': survived_counts, 'Not Survived': not_survived_counts})
fig, ax = plt.subplots(figsize=(10, 6))
gender_counts.sort_values(by='Survived', ascending=True).plot(kind='barh', stacked=True, color=['violet', 'pink'
plt.title('Passengers based on Gender')
plt.xlabel('No of passengers')
plt.ylabel('Gender')
plt.legend(title='Survival', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



encoding

In [19]:
```
titanic_data['Embarked'].value_counts()
```

Out[19]:
```
S    270
C    102
Q     46
Name: Embarked, dtype: int64
```

In [20]:
```
# converting categorical into numerical column
titanic_data.replace({'Sex':{'male':0,'female':1}, 'Embarked':{'S':0,'C':1,'Q':2}}, inplace=True)
titanic_data.head()
```

Out[20]:

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

Split the Data :

In [21]:
```
#separating the features (X) and the target variable (Y) from dataset
X=titanic_data.drop(columns=['PassengerId','Name','Ticket','Survived'], axis=1)
Y=titanic_data['Survived']
```

In [22]:
```
print(X)
print(Y)
```

```
     Pclass  Sex       Age  SibSp  Parch      Fare  Embarked
0         3    0  34.50000      0      0    7.8292         2
1         3    1  47.00000      1      0    7.0000         0
2         2    0  62.00000      0      0    9.6875         2
3         3    0  27.00000      0      0    8.6625         0
4         3    1  22.00000      1      1   12.2875         0
..      ...  ...       ...    ...    ...       ...       ...
413       3    0  30.27259      0      0    8.0500         0
414       1    1  39.00000      0      0  108.9000         1
415       3    0  38.50000      0      0    7.2500         0
416       3    0  30.27259      0      0    8.0500         0
417       3    0  30.27259      1      1   22.3583         1

[418 rows x 7 columns]
0      0
1      1
2      0
3      0
4      1
      ..
413    0
414    1
415    0
416    0
417    0
Name: Survived, Length: 418, dtype: int64
```

In [23]:
```
#Spliting training and test data
X_train, X_test, Y_train, Y_test=train_test_split(X,Y,test_size=0.2,random_state=2)
print(X.shape,X_train.shape,X_test.shape)
```

```
(418, 7) (334, 7) (84, 7)
```

In [24]:
```
model=LogisticRegression()
model.fit(X_train, Y_train)
```

```
C:\Users\Admin\anaconda3.x\Lib\site-packages\sklearn\linear_model\_logistic.py:460: ConvergenceWarning: lbfgs f
ailed 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 (https://scikit-learn.org/stable/modules/preproc
essing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/sta
ble/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[24]:

▾ LogisticRegression

LogisticRegression()

Evaluate the Model:

In [25]:
```
# accuracy on training data
X_train_prediction=model.predict(X_train)
print(X_train_prediction)
```

```
[1 1 0 0 1 1 0 0 0 1 0 0 1 0 0 0 1 0 1 0 1 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0
 1 1 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 1 0 1 1 1 0 1
 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 0 0 0 0 0 0 0 1 0 1 1 1 0 1 0 1 0
 1 1 0 0 0 0 1 1 0 1 0 0 1 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 1 1 0 0
 0 0 1 1 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0 1 1 0 0 1 1 1 1 0 1 0 0 0 0 1 0 1 1
 1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 1 0 0 1 0 0 1 0 0
 1 0 1 0 0 0 0 0 1 0 0 0 1 1 0 0 0 1 1 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1
 0 1 1 1 1 0 0 0 1 1 0 0 1 0 1 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 1 0 1 1 0 0 0
 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 1 1 0 0 0 1 1 1
 1]
```

In [26]:
```
training_data_accuracy=accuracy_score(Y_train,X_train_prediction)
print('Accuracy score of training data :{:.2f}%'.format(training_data_accuracy*100 ))
```

```
Accuracy score of training data :100.00%
```

In [27]:
```
X_test_prediction=model.predict(X_test)
print(X_test_prediction)
```

```
[0 0 0 1 1 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0 0 0 0 1 1 0 1 0 0 1 1 0 1 0 0 1
 1 0 0 0 0 1 1 0 0 1 0 1 0 0 0 1 1 1 0 0 1 0 0 0 0 0 0 1 0 1 1 1 1 1 1 0 0
 0 1 1 0 1 0 0 0 0 0]
```

In [28]:
```
testing_data_accuracy=accuracy_score(Y_test,X_test_prediction)
print('Accuracy score of test data :{:.2f}%'.format(testing_data_accuracy*100 ))
```

```
Accuracy score of test data :100.00%
```

In [ ]:

In [ ]: