Titanic Data Analysis

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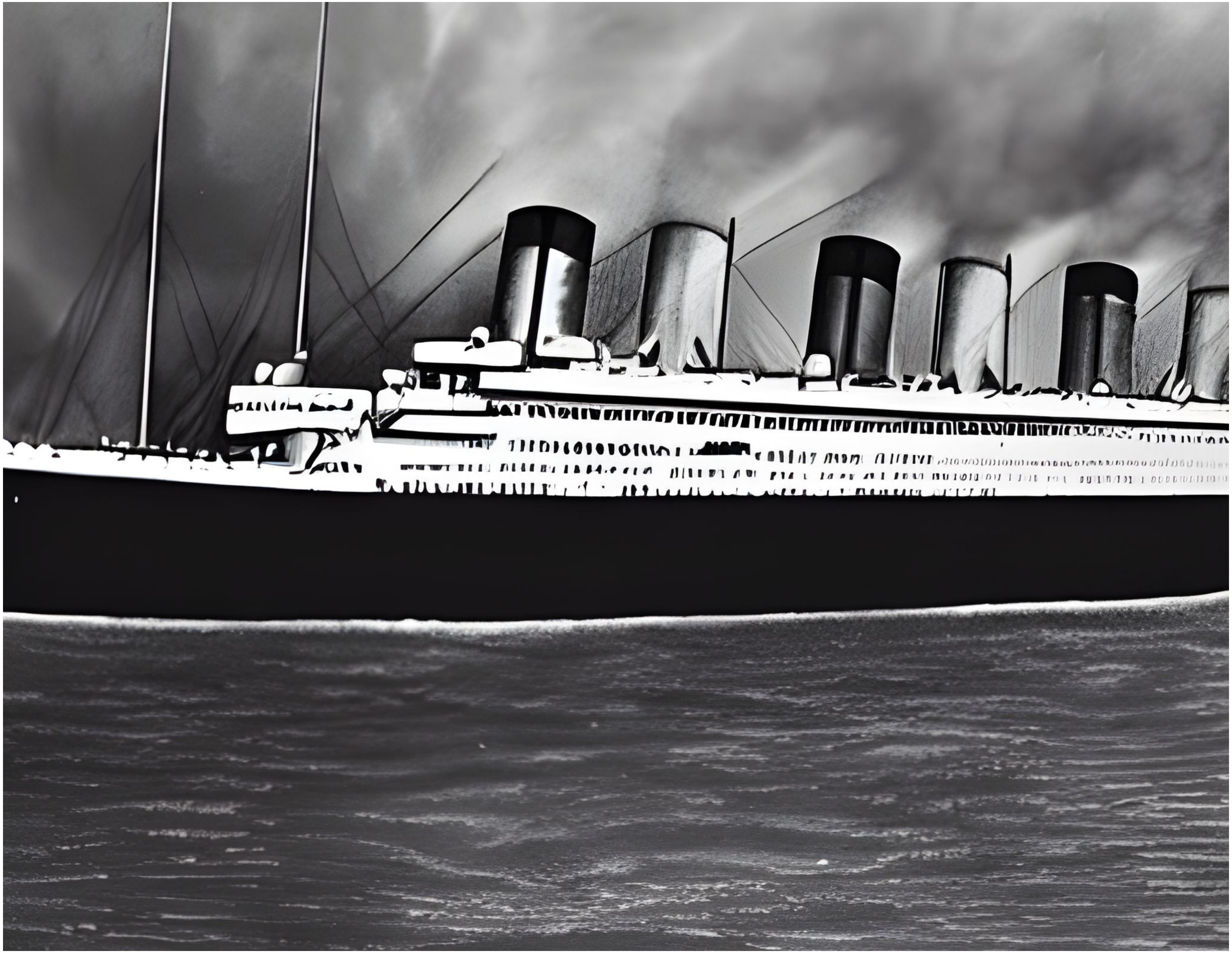


On April 10, 1912, the Titanic set sail from Southampton, England on its maiden voyage across the Atlantic Ocean. The ship was carrying 2,224 passengers and crew members and was touted as being “unsinkable” due to its 16 watertight compartments. However, on April 14, the Titanic struck an iceberg and began to sink. Over 1,500 people lost their lives in the disaster, making it one of the deadliest maritime accidents in history.In this analysis, we will explore the dataset of the Titanic – from its passengers to its survivors.

Obtaining the Data

In [47]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as matplt
import plotly.express as px
import seaborn as sns
from plotly.offline import plot, iplot, init_notebook_mode
import plotly.graph_objs as go
init_notebook_mode(connected=True)
%matplotlib inline
```

In [48]:
```
titanic = pd.read_csv("Titanic.csv")
```

Discription

- survival - Survival (0 = No; 1 = Yes)
- class - Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
- name - Name
- sex - Sex
- age - Age
- sibsp - Number of Siblings/Spouses Aboard
- parch - Number of Parents/Children Aboard
- ticket - Ticket Number
- fare - Passenger Fare
- cabin - Cabin
- embarked - Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

Scrubbing the Data

In [5]:
```
titanic.isnull().any()
```

Out[5]:
```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

The result above shows that there are missing values in Age, Cabin and in Embarked. we'll have to note this so we can make the appropriate correction before building our model.

In [6]:
```
pd.reset_option('display.max_row')
pd.reset_option('display.max_columns')
titanic.head(20).style.background_gradient(cmap='Purples_r')
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.000000	1	0	A/5 21171	7.250000	nan	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38.000000	1	0	PC 17599	71.283300	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.000000	0	0	STON/O2. 3101282	7.925000	nan	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.000000	1	0	113803	53.100000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.000000	0	0	373450	8.050000	nan	S
5	6	0	3	Moran, Mr. James	male	nan	0	0	330877	8.458300	nan	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.000000	0	0	17463	51.862500	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.000000	3	1	349909	21.075000	nan	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.000000	0	2	347742	11.133300	nan	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.000000	1	0	237736	30.070800	nan	C
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.000000	1	1	PP 9549	16.700000	G6	S
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.000000	0	0	113783	26.550000	C103	S
12	13	0	3	Saundercock, Mr. William Henry	male	20.000000	0	0	A/5. 2151	8.050000	nan	S
13	14	0	3	Andersson, Mr. Anders Johan	male	39.000000	1	5	347082	31.275000	nan	S
14	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14.000000	0	0	350406	7.854200	nan	S
15	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55.000000	0	0	248706	16.000000	nan	S
16	17	0	3	Rice, Master. Eugene	male	2.000000	4	1	382652	29.125000	nan	Q
17	18	1	2	Williams, Mr. Charles Eugene	male	nan	0	0	244373	13.000000	nan	S
18	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)	female	31.000000	1	0	345763	18.000000	nan	S

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
19	20	1	3	Masselmani, Mrs. Fatima	female	nan	0	0	2649	7.225000	nan	C

In [7]:
```
titanic = titanic.rename(columns={'PassengerId' : 'Passenger_ID',
                         'Survived' : 'Survived',
                         'Pclass' : 'Pclass',
                         'Name' : 'Names',
                         'Sex' : 'Gender',
                         'Age' : 'Age',
                         'SibSp' : 'SibSp',
                         'Parch' : 'Parch',
                         'Ticket' : 'Ticket',
                         'Fare' : 'Fare',
                         'Cabin' : 'Cabin',
                         'Embarked' : 'Embarked'
                         })
```

In [8]:
```
titanic.head(10).style.background_gradient(cmap='Purples_r')
```

Out[8]:

	Passenger_ID	Survived	Pclass	Names	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.000000	1	0	A/5 21171	7.250000	nan	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38.000000	1	0	PC 17599	71.283300	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.000000	0	0	STON/O2. 3101282	7.925000	nan	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.000000	1	0	113803	53.100000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.000000	0	0	373450	8.050000	nan	S
5	6	0	3	Moran, Mr. James	male	nan	0	0	330877	8.458300	nan	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.000000	0	0	17463	51.862500	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.000000	3	1	349909	21.075000	nan	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.000000	0	2	347742	11.133300	nan	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.000000	1	0	237736	30.070800	nan	C

In [9]:
```
front = titanic['Names']
titanic.drop(labels=['Names'], axis=1,inplace = True)
titanic.insert(0, 'Names', front)
titanic.head().style.background_gradient(cmap='Purples_r')
```

Out[9]:

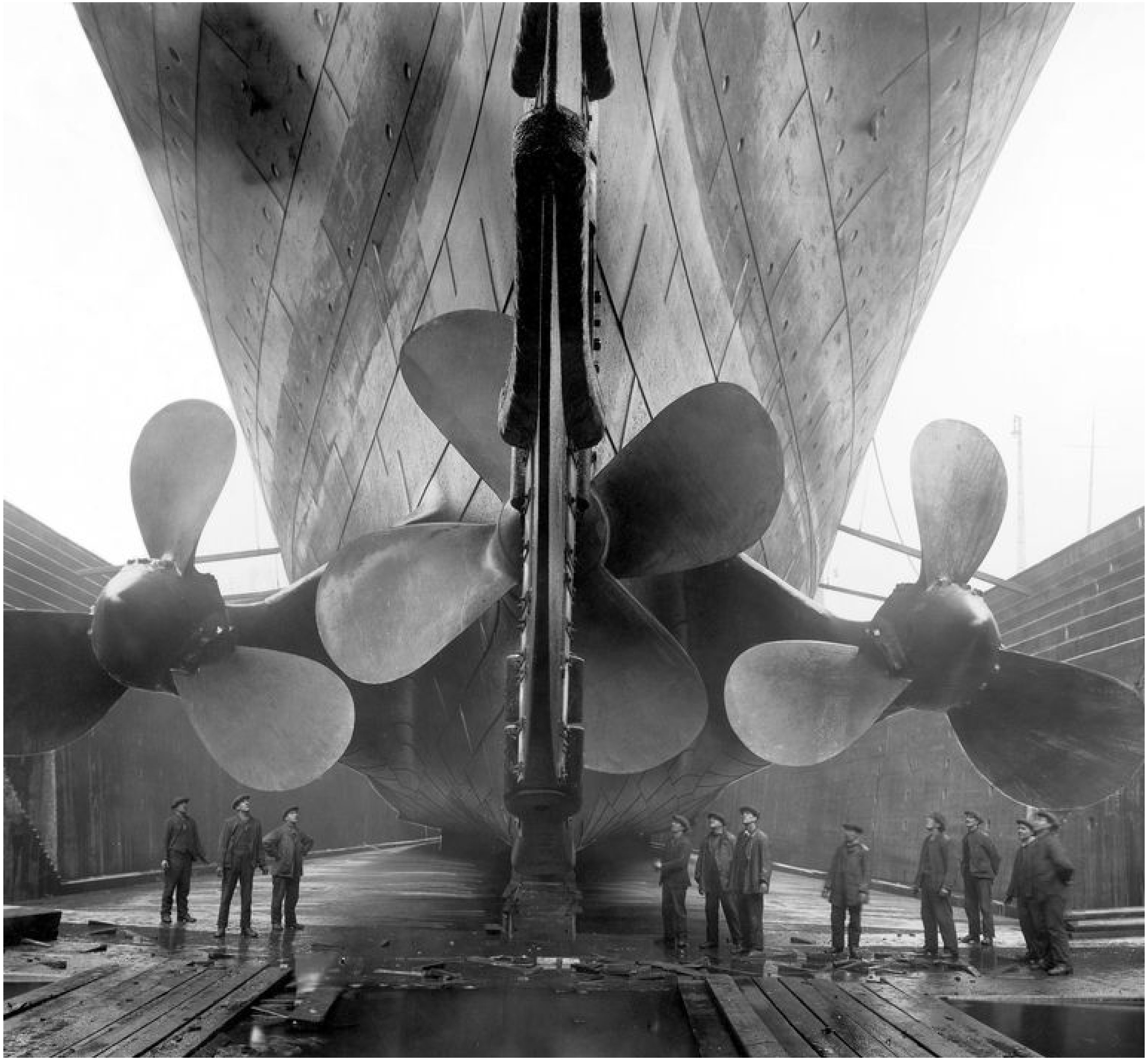
	Names	Passenger_ID	Survived	Pclass	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	Braund, Mr. Owen Harris	1	0	3	male	22.000000	1	0	A/5 21171	7.250000	nan	S
1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	2	1	1	female	38.000000	1	0	PC 17599	71.283300	C85	C
2	Heikkinen, Miss. Laina	3	1	3	female	26.000000	0	0	STON/O2. 3101282	7.925000	nan	S
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	4	1	1	female	35.000000	1	0	113803	53.100000	C123	S
4	Allen, Mr. William Henry	5	0	3	male	35.000000	0	0	373450	8.050000	nan	S

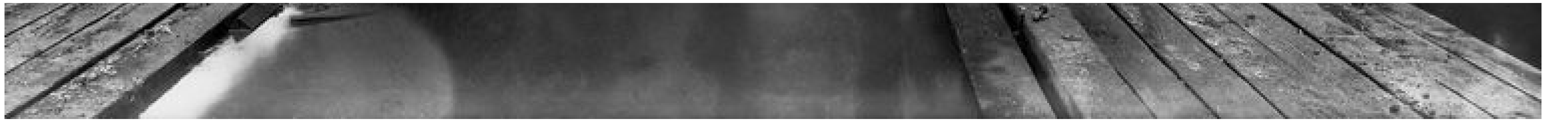
In [10]:
```
front = titanic['Passenger_ID']
titanic.drop(labels=['Passenger_ID'], axis=1,inplace = True)
titanic.insert(0, 'Passenger_ID', front)
titanic.head().style.background_gradient(cmap='Purples_r')
```

Out[10]:

	Passenger_ID	Names	Survived	Pclass	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	Braund, Mr. Owen Harris	0	3	male	22.000000	1	0	A/5 21171	7.250000	nan	S
1	2	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	1	1	female	38.000000	1	0	PC 17599	71.283300	C85	C
2	3	Heikkinen, Miss. Laina	1	3	female	26.000000	0	0	STON/O2. 3101282	7.925000	nan	S
3	4	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	1	female	35.000000	1	0	113803	53.100000	C123	S
4	5	Allen, Mr. William Henry	0	3	male	35.000000	0	0	373450	8.050000	nan	S

Exploring the Data





Statistical Overview

In [11]:
```python
# the dataset contain 12 columns and 891 observation
titanic.shape
```

Out[11]:
```
(891, 12)
```

In [12]:
```python
titanic.dtypes
```

Out[12]:
```
Passenger_ID      int64
Names            object
Survived          int64
Pclass            int64
Gender           object
Age             float64
SibSp             int64
Parch             int64
Ticket           object
Fare            float64
Cabin            object
Embarked         object
dtype: object
```

In [13]:
```python
Survived_rate = titanic.Survived.value_counts() / len(titanic)
Survived_rate
```

Out[13]:
```
0    0.616162
1    0.383838
Name: Survived, dtype: float64
```

The survivor's are about 38% of the passenger's from the data set

In [14]:
```
titanic.describe().style.background_gradient(cmap = "Purples")
```

Out[14]:

	Passenger_ID	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

The above is the Statistical overview of the Dataset(Titanic), the total count of each column **Note** That the column Age as some missing values we'll get back to that. the mean, the standard deviation, the minimum, the maximum and the quartiles

In [15]:
```
## Overview of summary (Survivor V.S. Non-Survivor)
Survived_summary = titanic.groupby('Survived')
Survived_summary.mean()
```

Out[15]:

	Passenger_ID	Pclass	Age	SibSp	Parch	Fare
Survived						
0	447.016393	2.531876	30.626179	0.553734	0.329690	22.117887
1	444.368421	1.950292	28.343690	0.473684	0.464912	48.395408

.

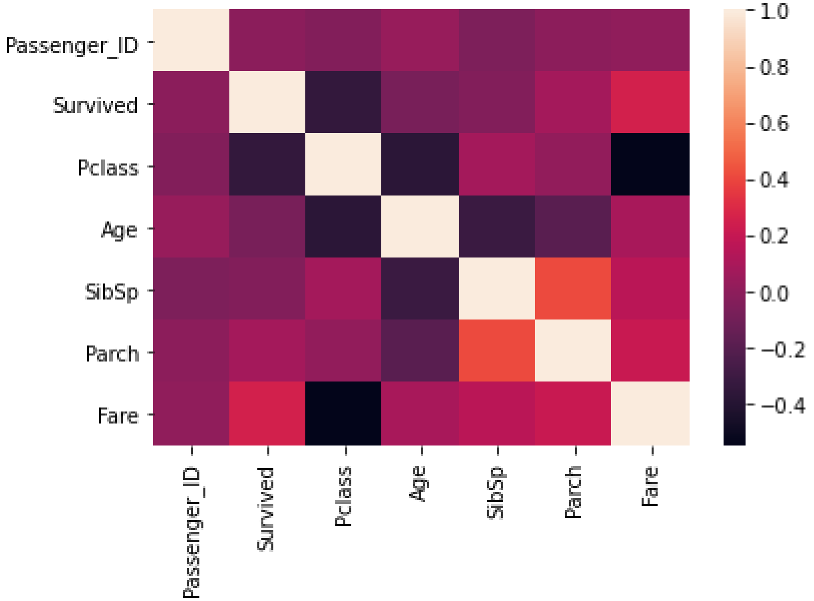
Correlation Matrix & Heatmap

In [16]:
```
corr = titanic.corr()
corr = (corr)
sns.heatmap(corr,
            xticklabels = corr.columns.values,
            yticklabels = corr.columns.values)

corr
```

Out[16]:

	Passenger_ID	Survived	Pclass	Age	SibSp	Parch	Fare
Passenger_ID	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000



Moderate Negatively Correlated Feature:

- Survived vs pclass: -0.338481
- Age vs Pclass: -0.369226
- SibSp vs Age: -0.308247
- Pclass vs Fare: -0.549500

Moderate Positively Correlated Features:

- Parch vs SibSp: 0.414838
- Survive vs Fare: 0.257307

From the heatmap, there is a positive(+) correlation between Parch and SlibSp For the negative(-) relationships, Pclass and Fare are highly correlated

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Statistical Test for Correlation

One-Sample T-Test

A one-sample t-test checks whether a sample mean differs from the population mean. Since Passenger Class has the highest correlation with our dependent variable Survived, let's test to see whether the average Passenger class level of People that had Survived differs from the those that had not Survived.

Hypothesis Testing: Is there significant difference in the means of Passanger class who had Survived and Passanger Class who had not Survived?

- **Null Hypothesis:** (H0: PCS = PCS) The null hypothesis would be that there is no difference in Passanger Class of people who did Survived and those who did not..
- **Alternate Hypothesis:** (HA: PCS!= PCS) The alternative hypothesis would be that there is a difference in Passanger Class of people who did Survived and those who did not..

In [17]:
```
Ps_population = titanic['Pclass'][titanic['Survived'] == 0].mean()
Ps_Survived_Pclass = titanic[titanic['Survived']==1]['Pclass'].mean()

print( 'The mean Passanger class for the population that did not Survived: ' + str(Ps_population))
print( 'The mean Passanger class for the population that did Survived: ' + str(Ps_Survived_Pclass))
```

```
The mean Passanger class for the population that did not Survived: 2.5318761384335153
The mean Passanger class for the population that did Survived: 1.9502923976608186
```

Conducting the T-Test

Let's conduct a t-test at **95% confidence level** and see if it correctly rejects the null hypothesis that the sample comes from the same distribution as the passanger population. To conduct a one sample t-test, we can use the stats.ttest_1samp() function:

In [18]:
```
import scipy.stats as stats
stats.ttest_1samp(a= titanic[titanic['Survived']==1]['Pclass'],
                  popmean = Ps_population)
```

Out[18]:
```
Ttest_1sampResult(statistic=-12.458139656460963, pvalue=1.2860105644736727e-29)
```

.

T-Test Quantile

In [19]:
```
degree_freedom = len(titanic[titanic['Survived']==1])

LQ = stats.t.ppf(0.025,degree_freedom)
RQ = stats.t.ppf(0.975,degree_freedom)

print('The t-distribution left quartile range is: ' + str(LQ))
print('The t-distribution right quartile range is: ' + str(RQ))
```

```
The t-distribution left quartile range is: -1.9669246454802793
The t-distribution right quartile range is: 1.966924645480279
```

In [20]:
```
degree_freedom = len(titanic[titanic['Pclass']==1])

LQ = stats.t.ppf(0.025,degree_freedom)
RQ = stats.t.ppf(0.975,degree_freedom)

print('The t-distribution left quartile range is: ' + str(LQ))
print('The t-distribution right quartile range is: ' + str(RQ))
```

```
The t-distribution left quartile range is: -1.9710074720029072
The t-distribution right quartile range is: 1.9710074720029067
```

One-Sample T-Test Summary

T-test=-12.4581| P-Value=1.28601_|Reject Null Hypothesis

Reject the null hypothesis because:

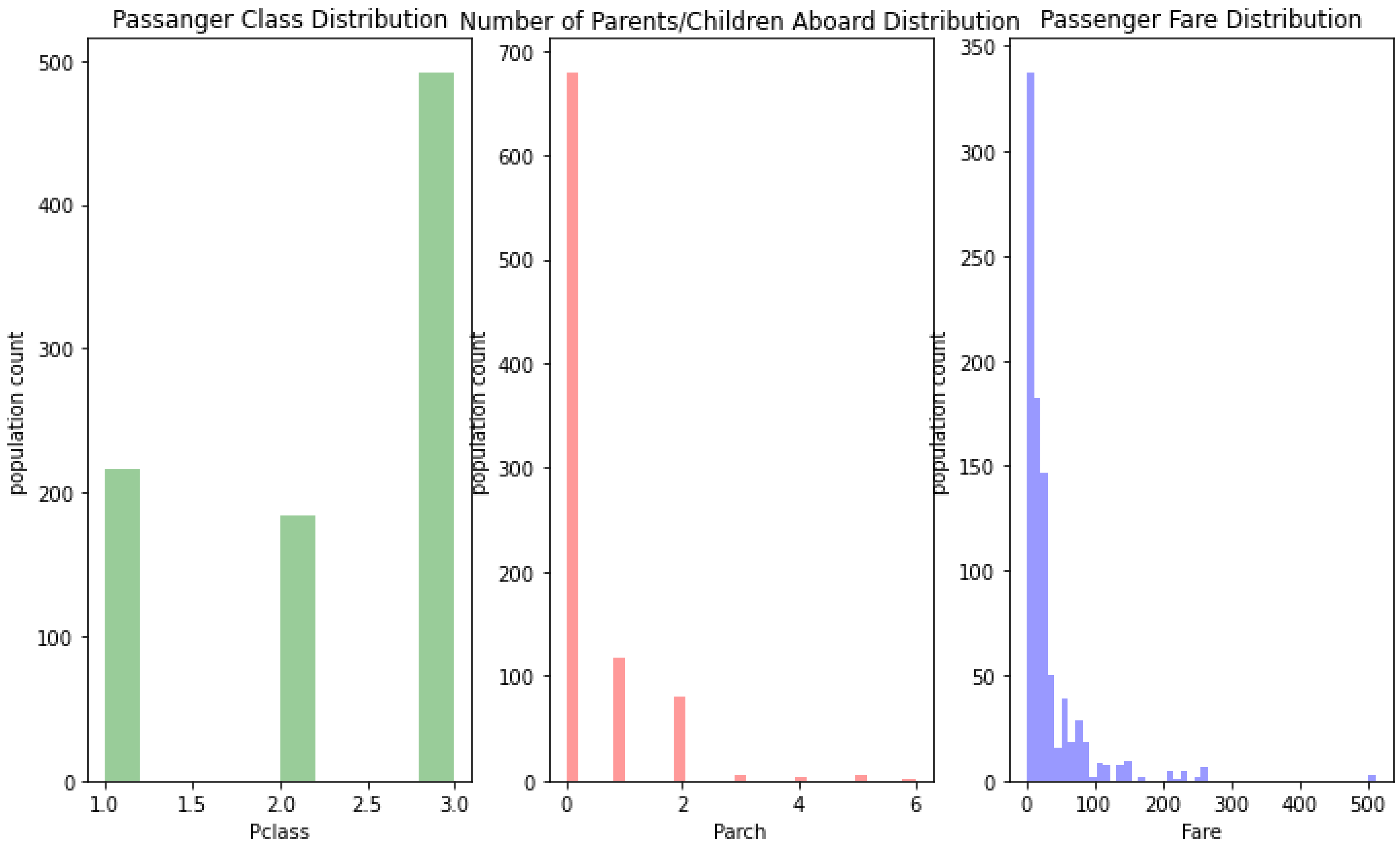
- T-Test score is outside the quantiles

.

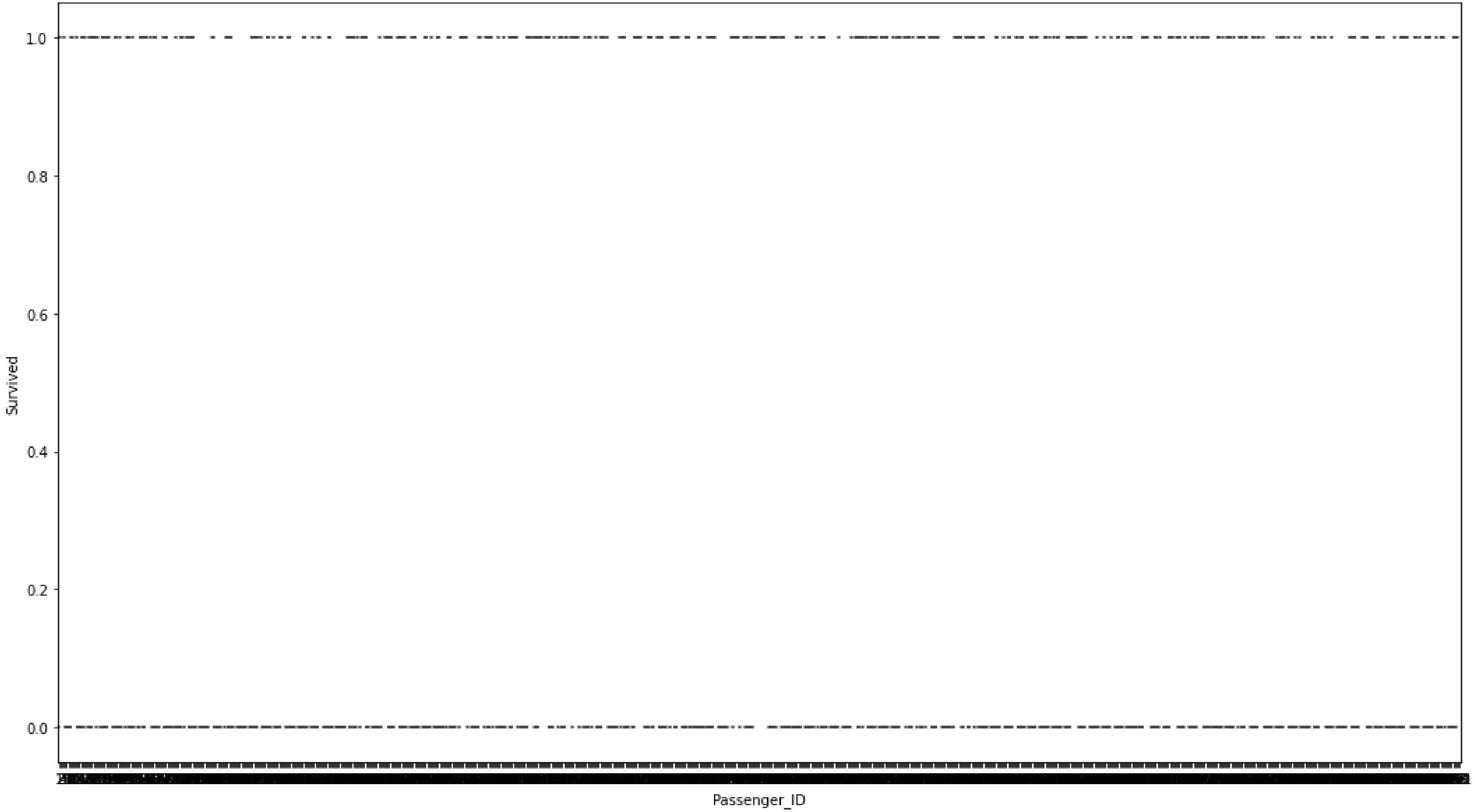
Distribution Plots

In [22]:
```
f, axes = plt.subplots(ncols=3, figsize=(12, 7))

sns.distplot(titanic.Pclass, kde=False, color="g",
             ax=axes[0]).set_title('Passanger Class Distribution')
axes[0].set_ylabel('population count')

sns.distplot(titanic.Parch, kde=False, color="r",
             ax=axes[1]).set_title('Number of Parents/Children Aboard Distribution')
axes[1].set_ylabel('population count')

sns.distplot(titanic.Fare, kde=False, color="b",
             ax=axes[2]).set_title('Passenger Fare Distribution')
axes[2].set_ylabel('population count')
```

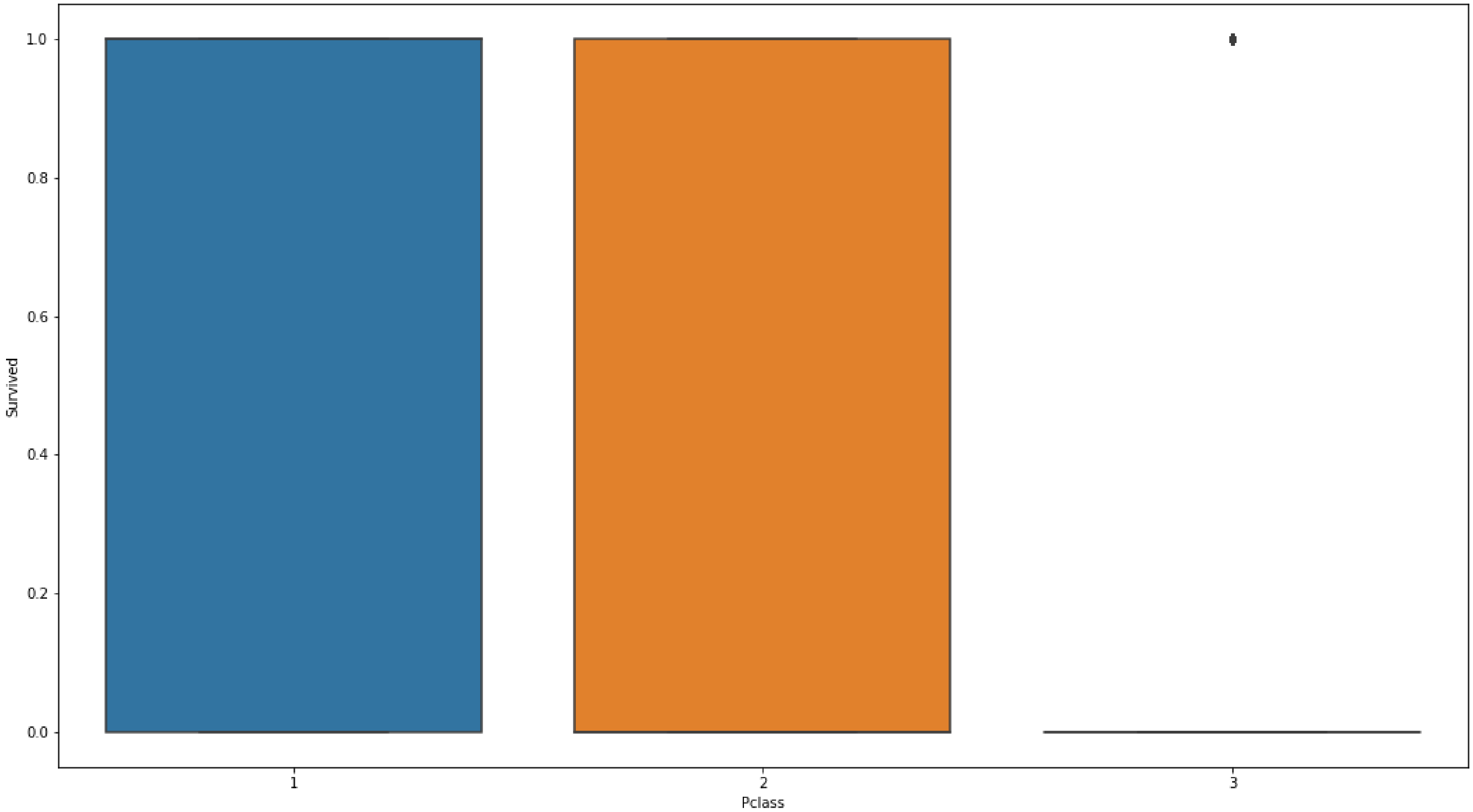
Out[22]:
```
Text(0, 0.5, 'population count')
```

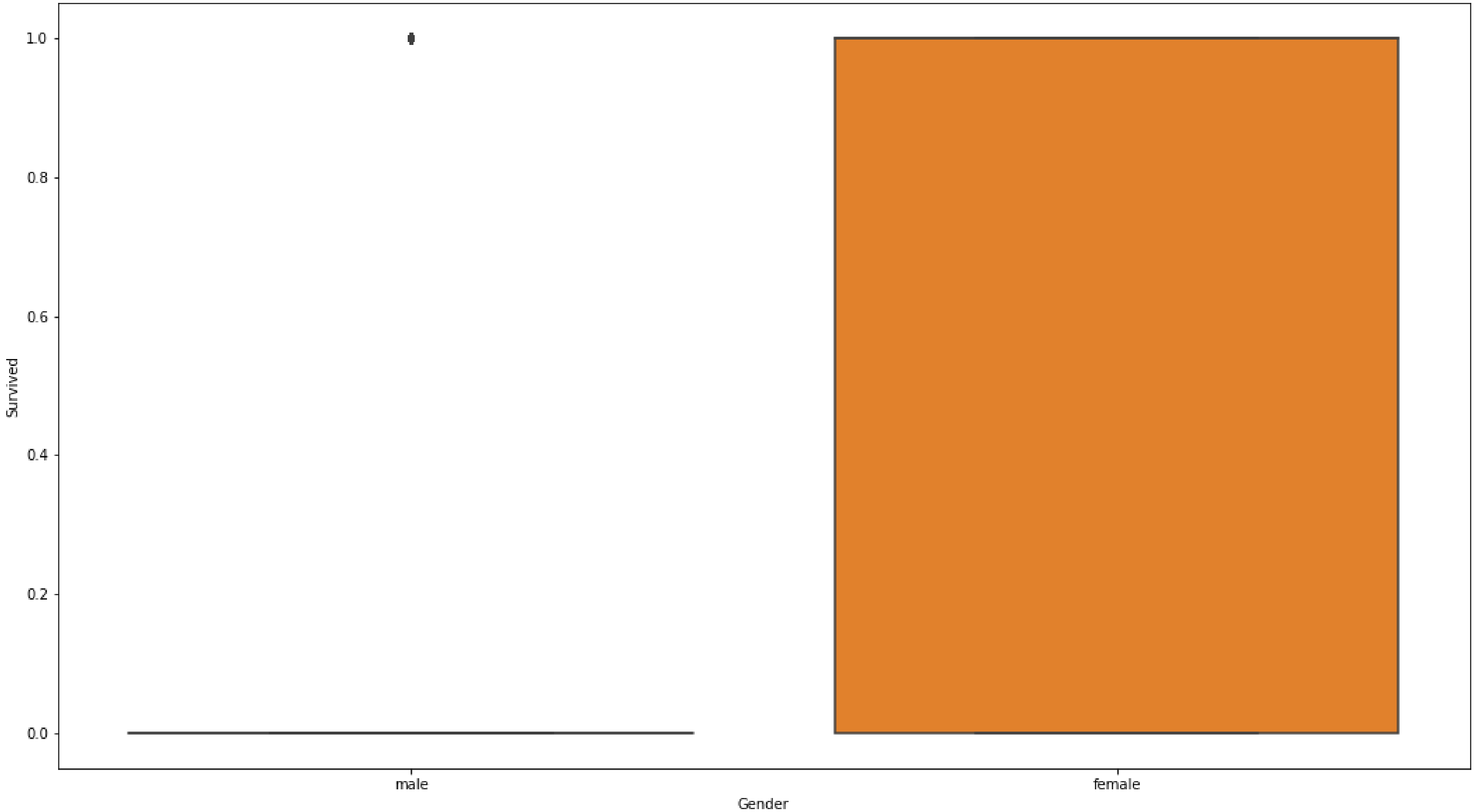

Passanger Class Distribution
Number of Parents/Children Aboard Distribution
Passenger Fare Distribution
population count
Pclass
Parch
Fare

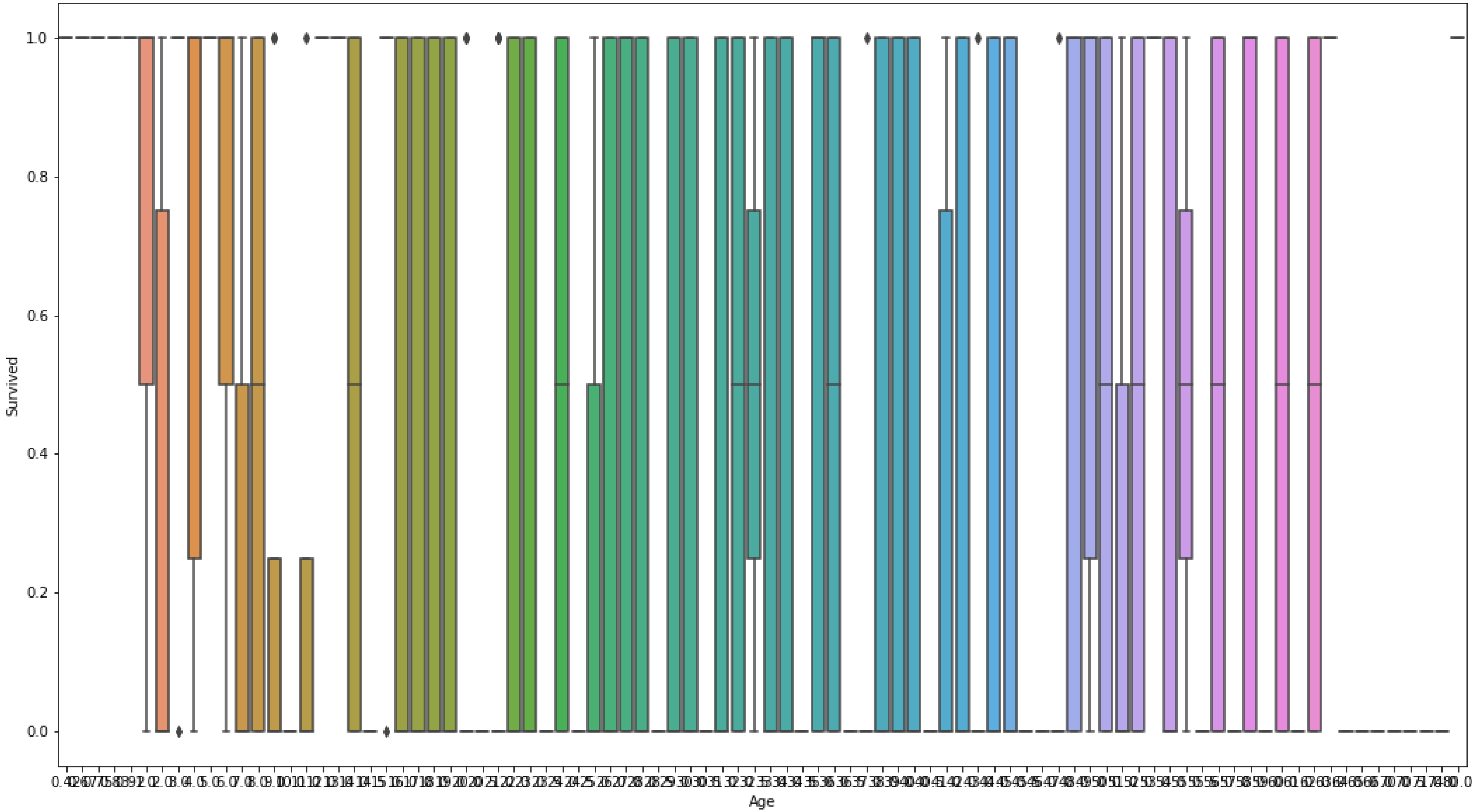
In [23]:
```
titanic_data = titanic.drop(['Survived'], axis = 1)
for var in titanic_data:
    plt.rcParams.update({'figure.max_open_warning': 0})
    f, ax = plt.subplots(figsize = (18, 10))
    fig = sns.boxplot(x = titanic_data[var], y = titanic['Survived'])
```

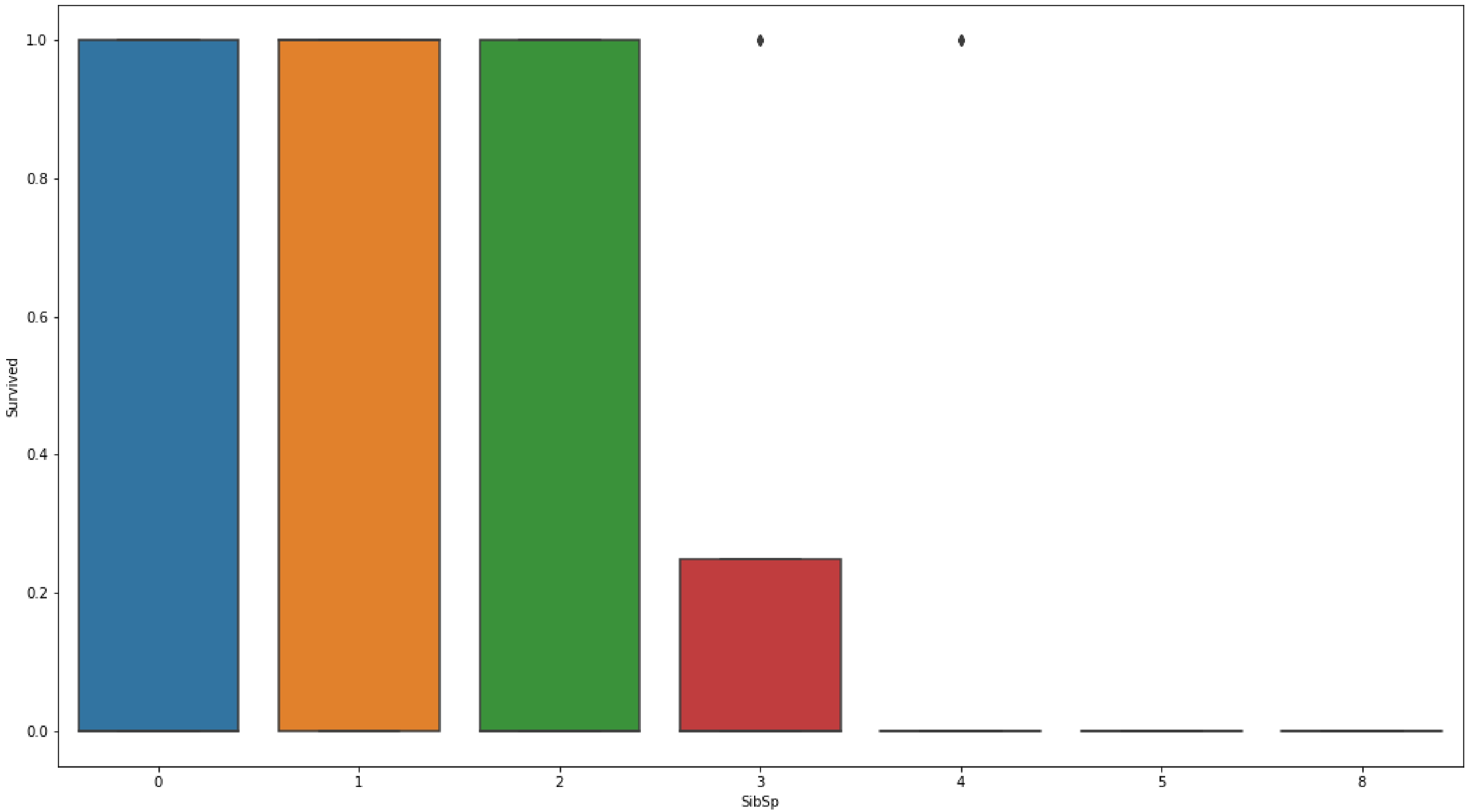


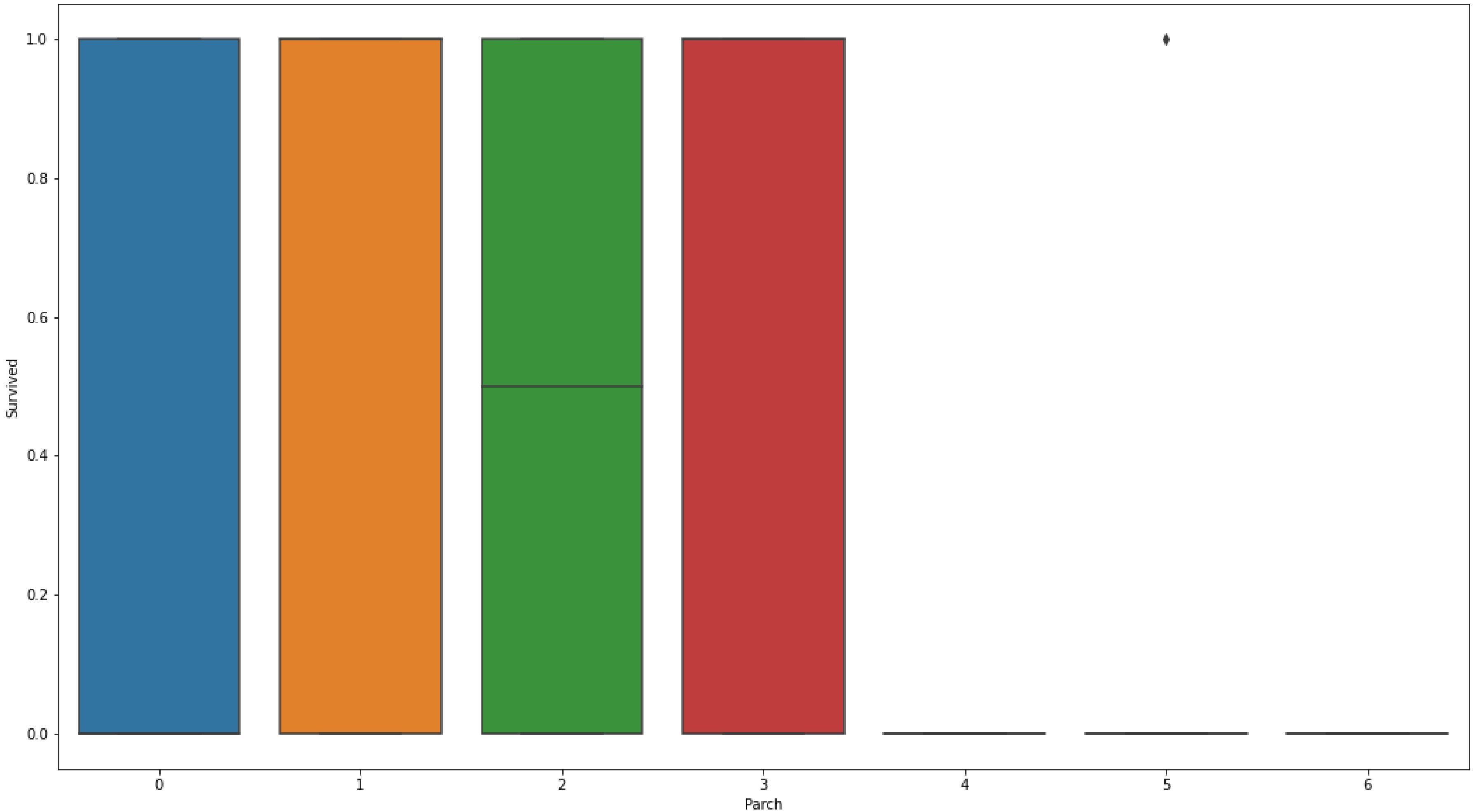

1.0
0.8
0.6
0.4
0.2
0.0
Survived
Names

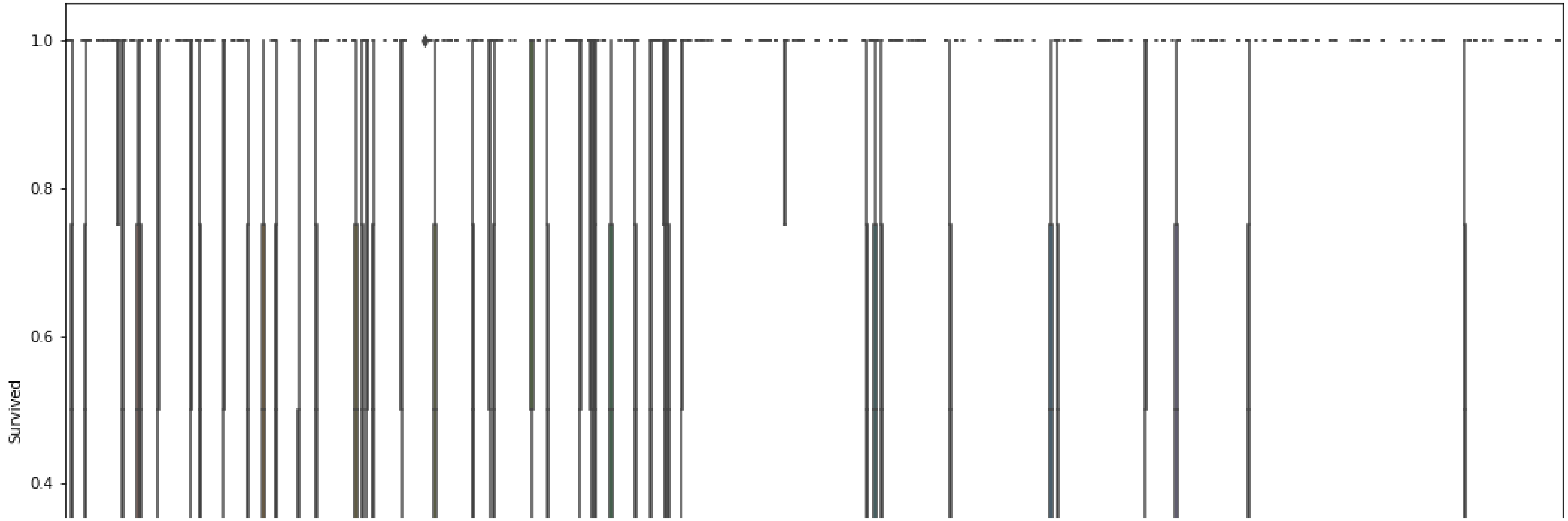

1.0
0.8
0.6
0.4
0.2
0.0
Survived
1
2
3
Pclass

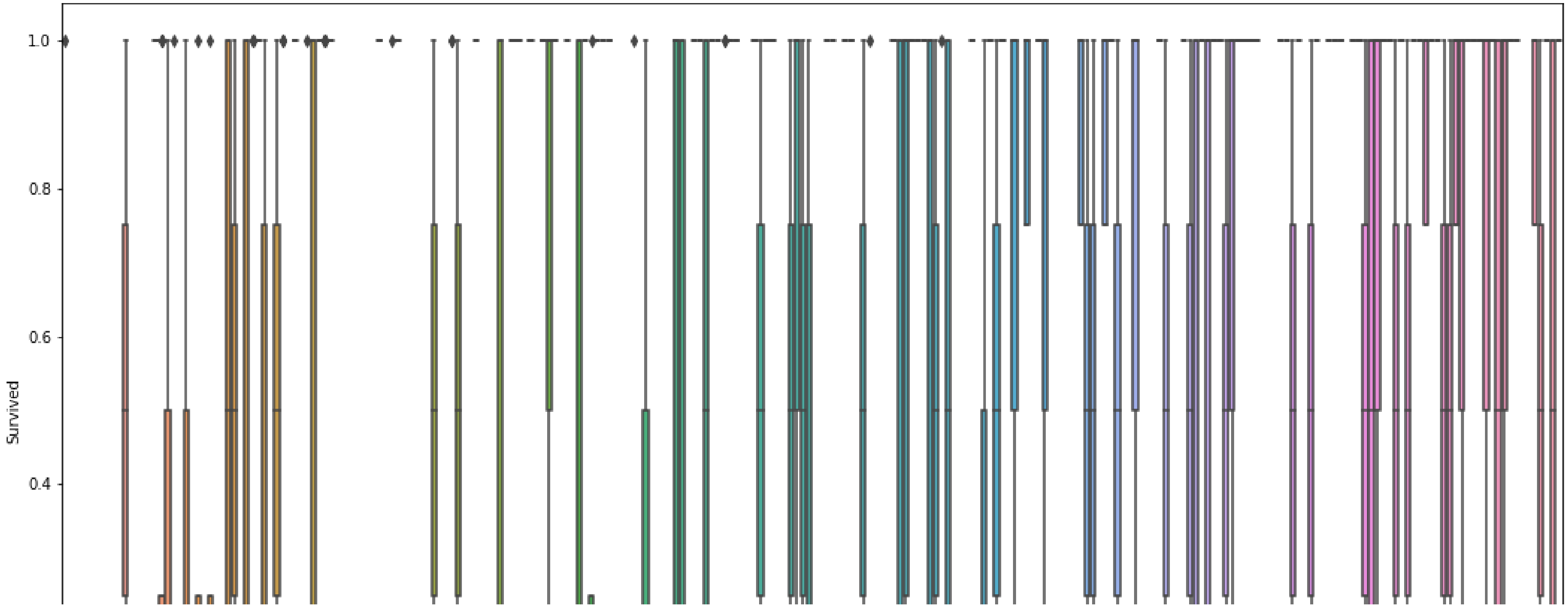

1.0
0.8
0.6
0.4
0.2
0.0
Survived
male
female
Gender

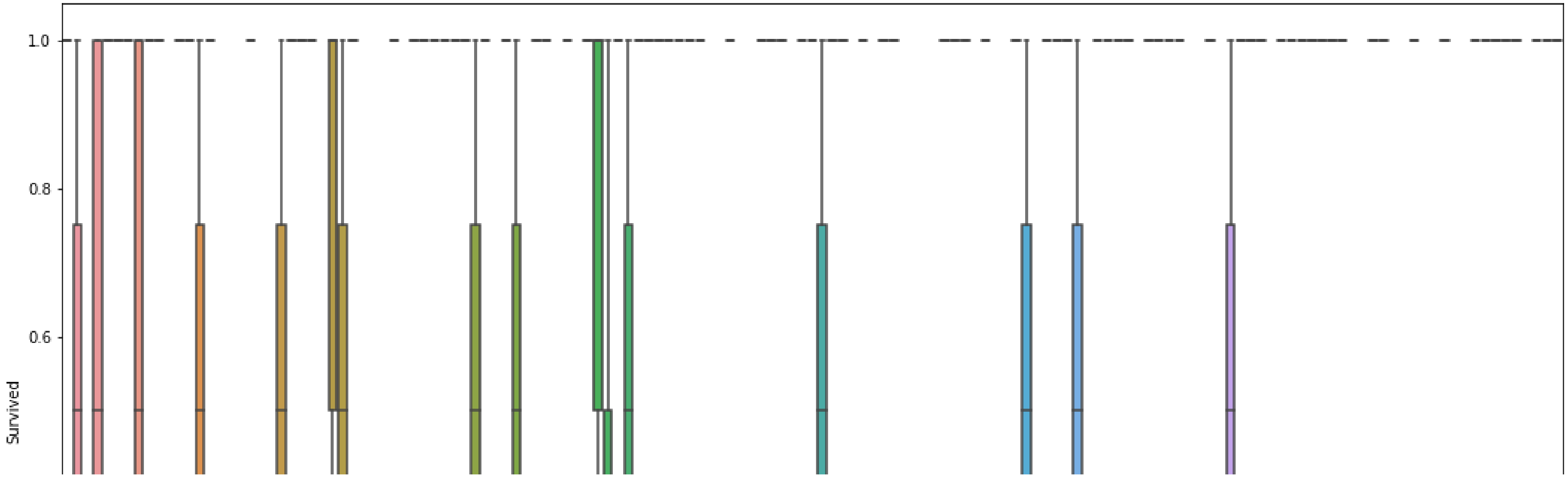

Survived
Age
1.0
0.8
0.6
0.4
0.2
0.0


1.0
0.8
0.6
0.4
0.2
0.0
Survived
0
1
2
3
4
5
8
SibSp


1.0
0.8
0.6
0.4
0.2
0.0
Survived
0
1
2
3
4
5
6
Parch


1.0
0.8
0.6
0.4
Survived


1.0
0.8
0.6
0.4
Survived


1.0
0.8
0.6
Survived

.

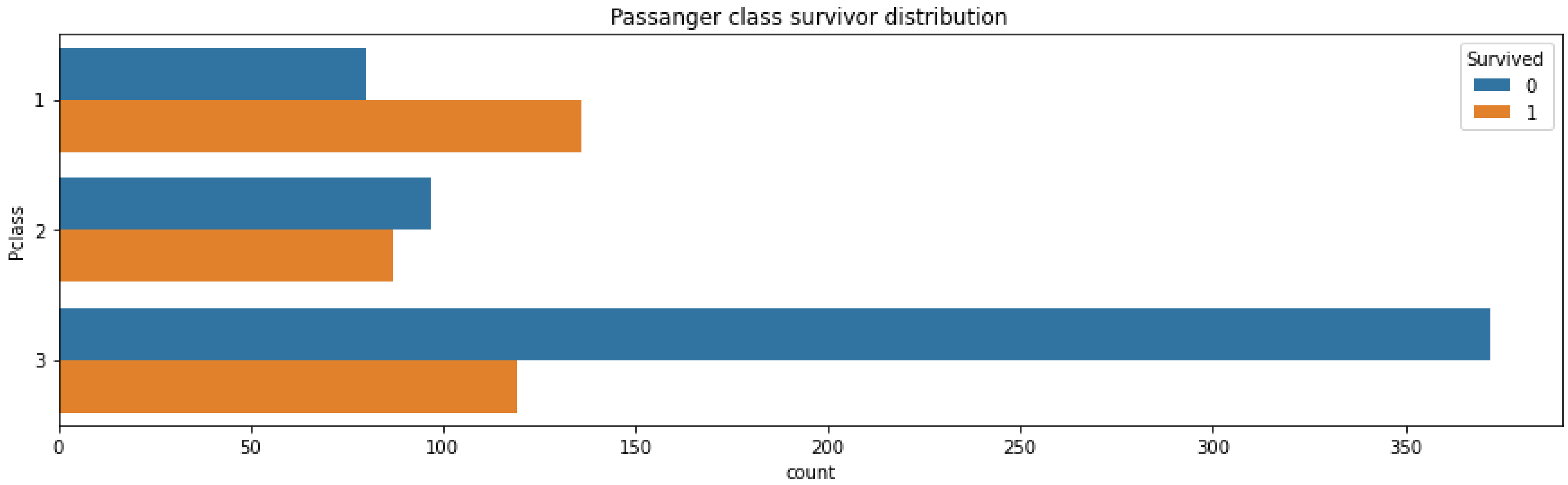
Passanger Class vs Survived

In [195]:
```
titanic[['Pclass','Survived']].groupby(['Pclass'], as_index=True).mean().sort_values(by='Survived', ascending = False)
```

Out[195]:

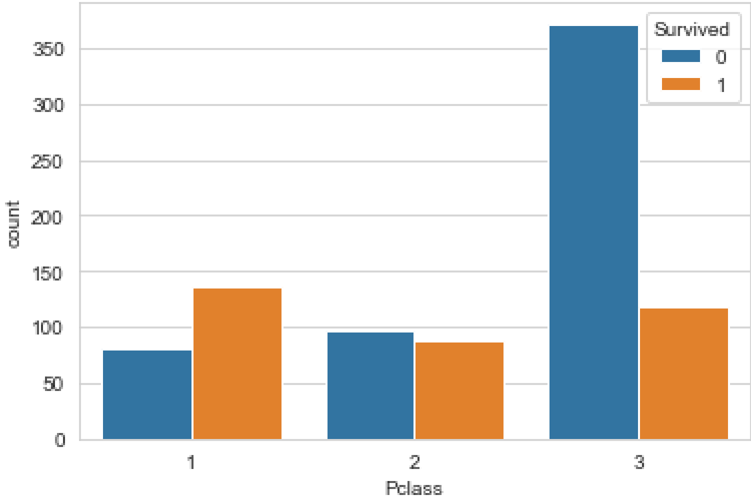
Pclass	Survived
1	0.629630
2	0.472826
3	0.242363

In [24]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Pclass", hue='Survived', data=titanic).set_title('Passanger class survivor distribution');
```



In [77]:
```
sns.set_style('whitegrid')
sns.countplot(x='Pclass',hue='Survived',data=titanic)

print(titanic['Pclass'].value_counts())
```

```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```



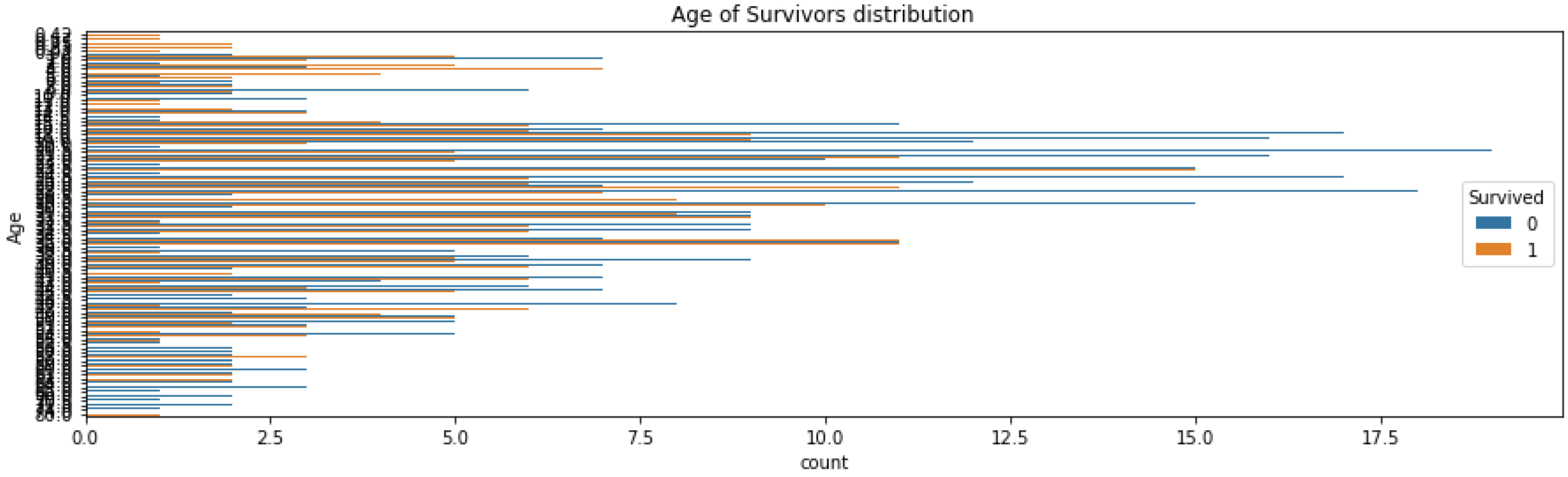
Passanger Class vs Survived this is not unusual majority of the population that survived are from the 1st class followed by the 3rd class i guess that the 2nd class where very unlucky

.

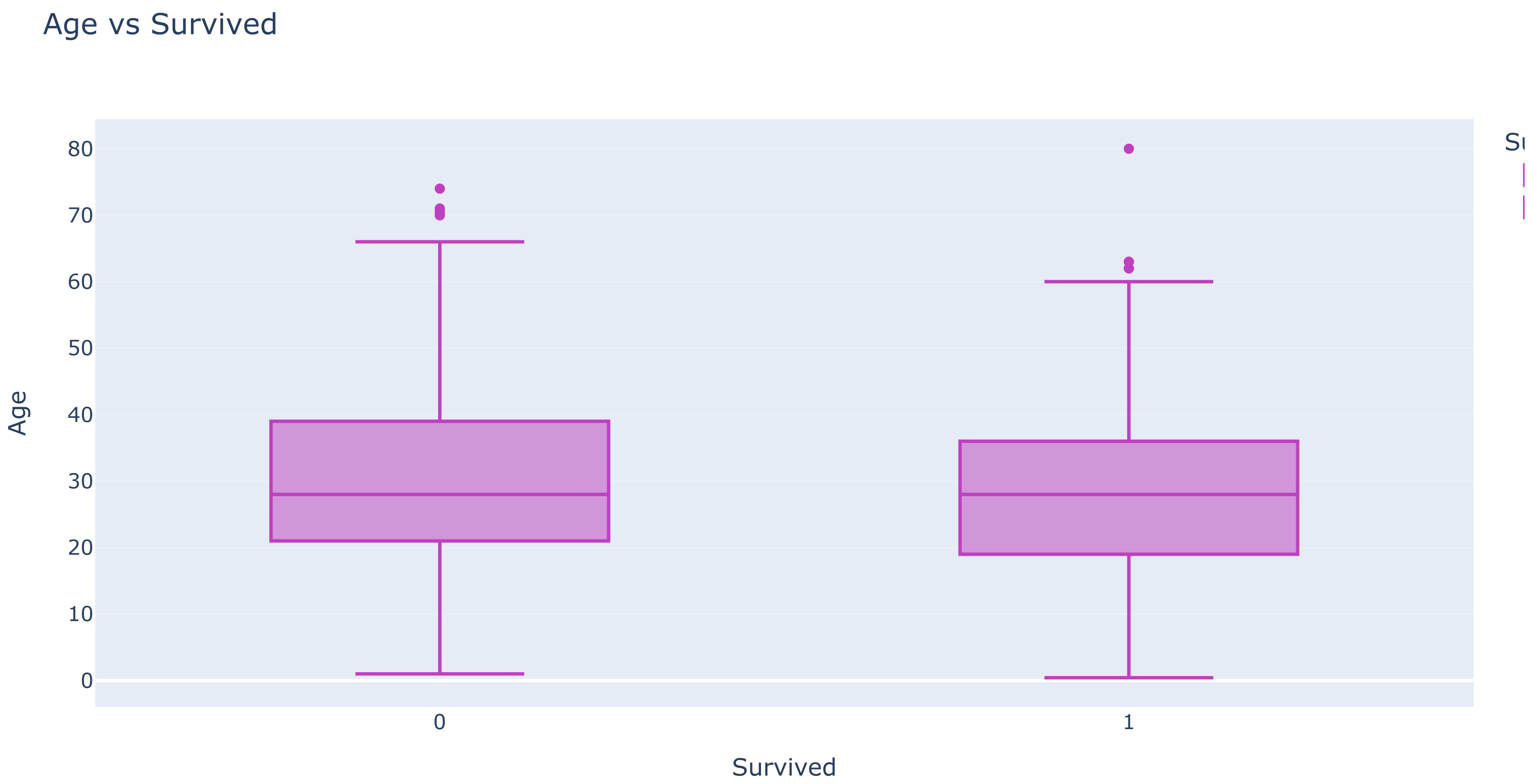
Age vs Survived

In [ ]:

In [25]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y='Age',hue='Survived', data=titanic).set_title('Age of Survivors distribution');
```

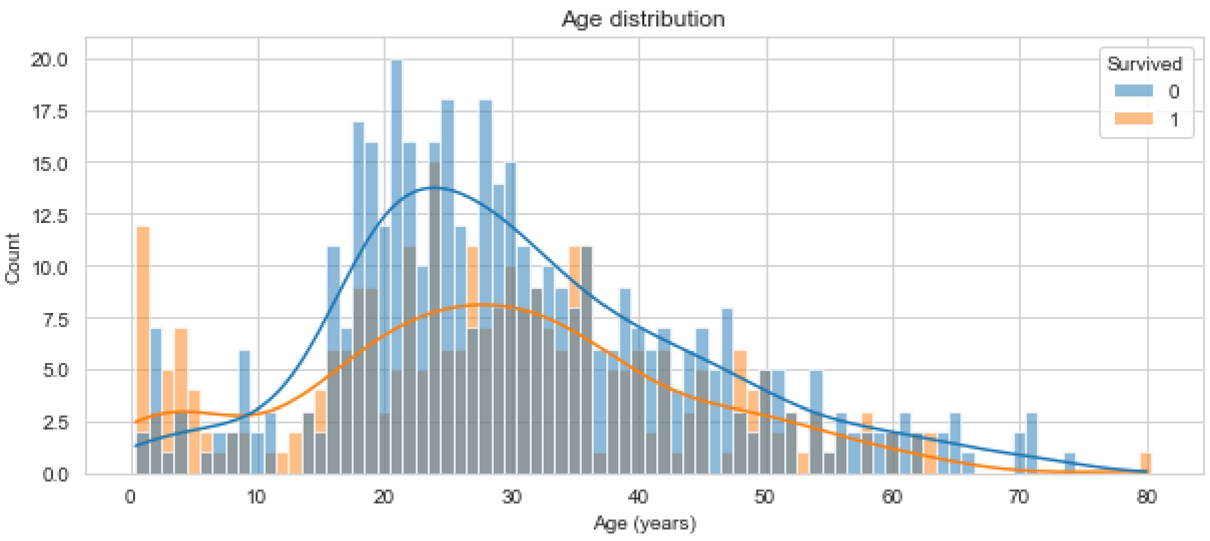


In [26]:
```
fig = px.box(titanic, x = "Survived", y = "Age", color = "Survived",
                  color_discrete_sequence = ["#BF40BF"],
                  title = "Age vs Survived")
fig.show()
```



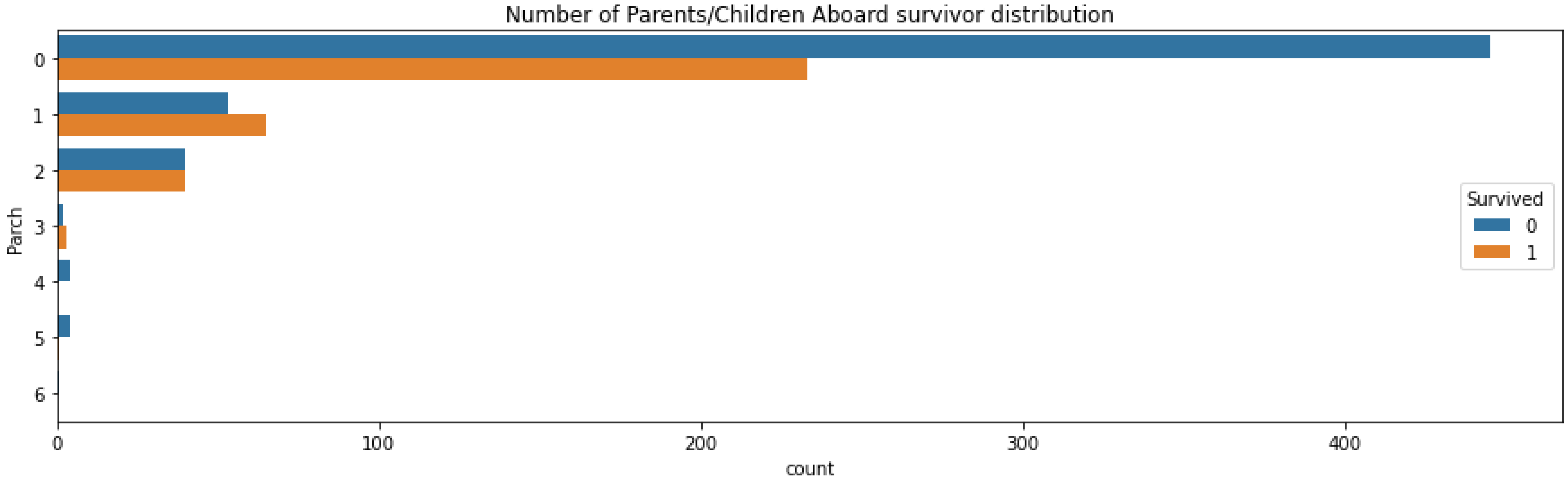
In [79]:
```
# Figure size
plt.figure(figsize=(10,4))
# Histogram
sns.histplot(data=titanic, x='Age', hue='Survived', binwidth=1, kde=True)
plt.title('Age distribution')
plt.xlabel('Age (years)')
```

Out[79]:
```
Text(0.5, 0, 'Age (years)')
```

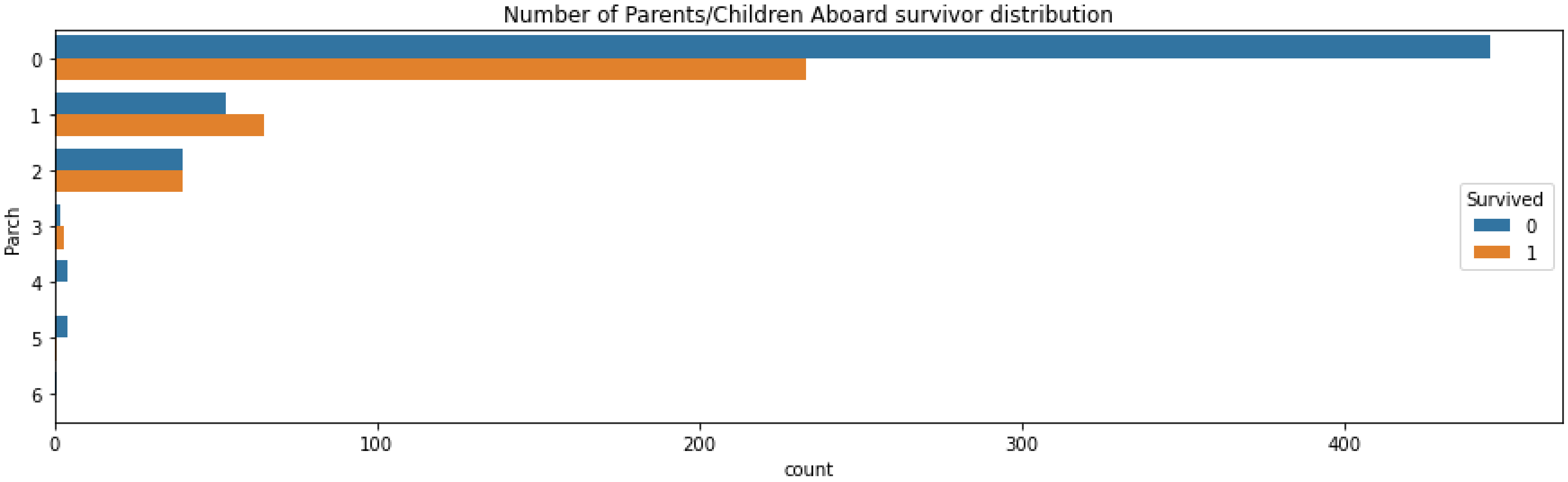


Number of Parents/Children Aboard vs Survived

In [57]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Parch", hue='Survived', data=titanic).set_title('Number of Parents/Children Aboard survivor distributio
```

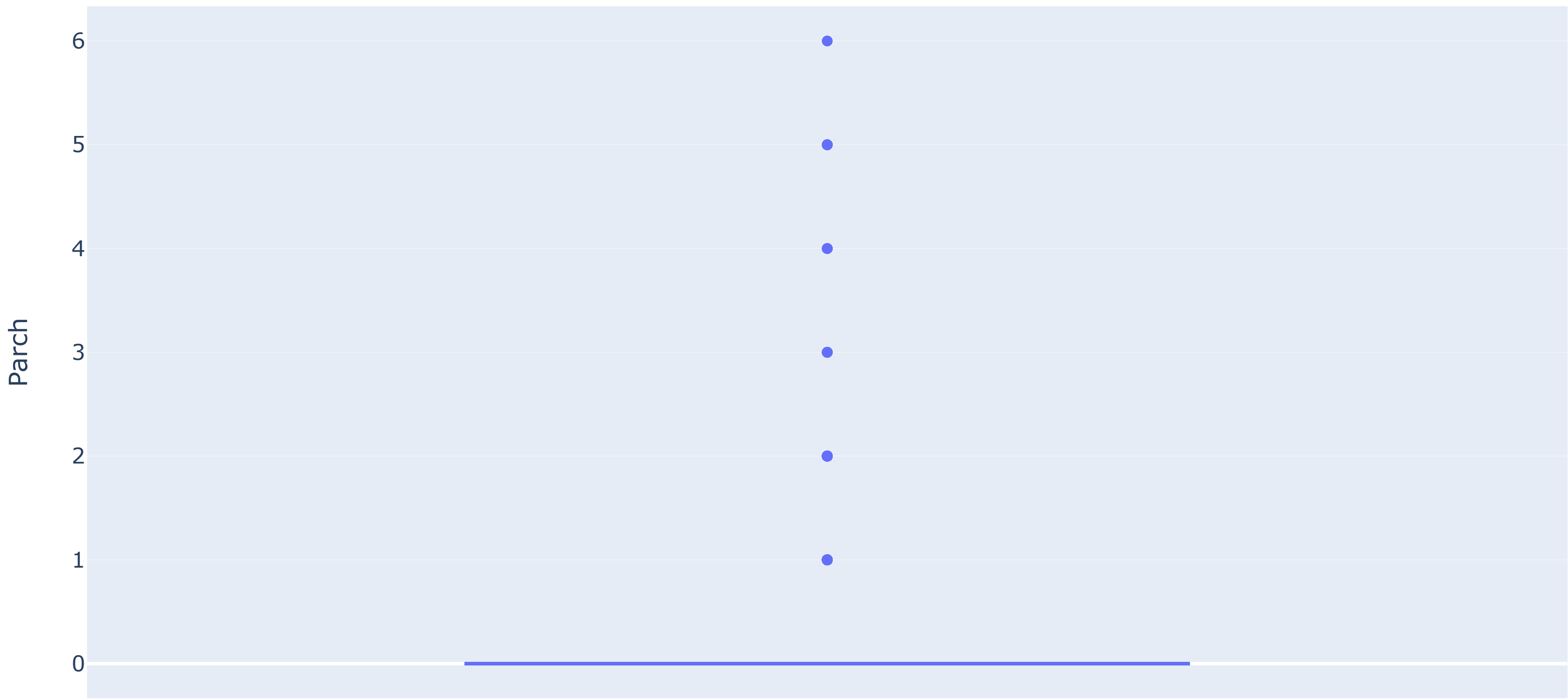


In [59]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Parch", hue='Survived', data=titanic).set_title('Number of Parents/Children Aboard survivor distributio
```



In [61]:
```
fig = px.box(titanic, x = "Survived", y = "Parch",
                  color_discrete_sequence = ["#CC8899"],
                  title = "Number of Parents/Children Aboard survivor distribution")
fig.show()
```

In [62]:
```
fig=px.box(titanic, y='Parch')
fig.show()
```



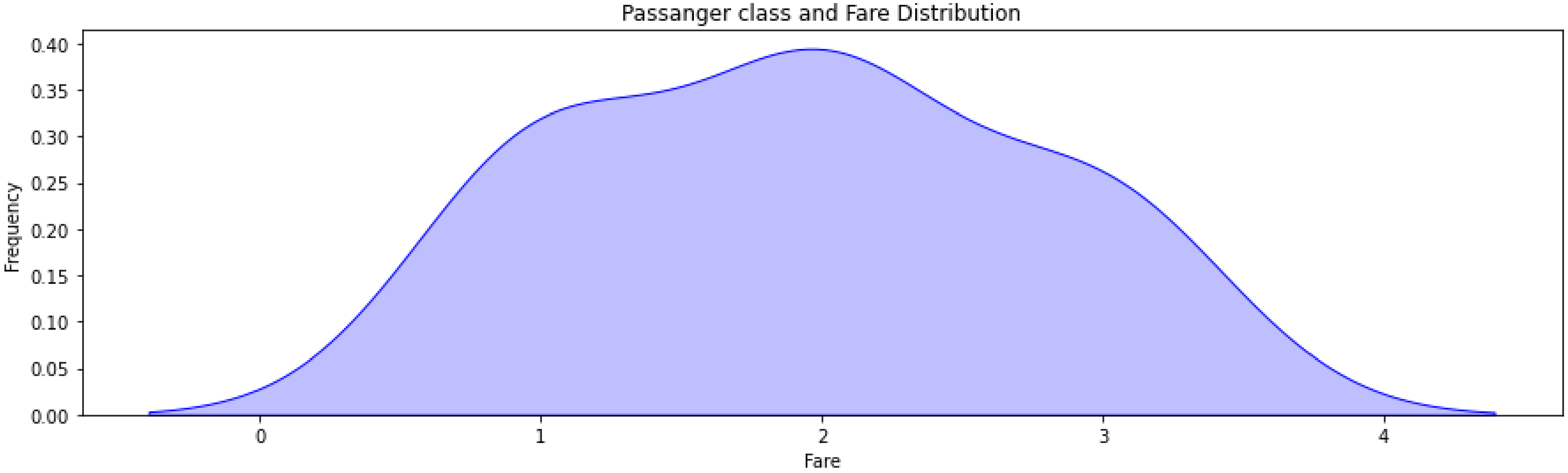
Number of Parents/Children Aboard vs Survived Close to half of passangerd without parent of children survived but based on the data there where not many passanger with parent.

.

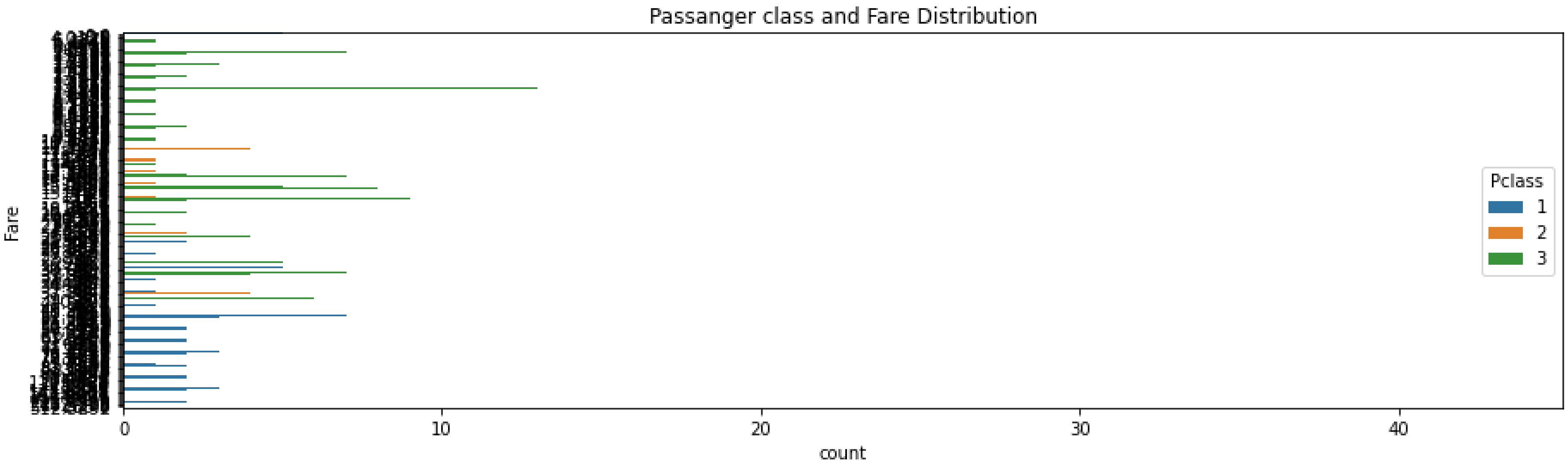
Passanger Class vs Passanger Fare

In [29]:
```
fig = plt.figure(figsize=(15,4),)
ax=sns.kdeplot(titanic.loc[(titanic['Fare'] == 0),'Pclass'] , color='b',shade=True,)
ax=sns.kdeplot(titanic.loc[(titanic['Fare'] == 1),'Pclass'] , color='r',shade=True, )
ax.set(xlabel='Fare', ylabel='Frequency')
plt.title('Passanger class and Fare Distribution')
```

Out[29]:
```
Text(0.5, 1.0, 'Passanger class and Fare Distribution')
```



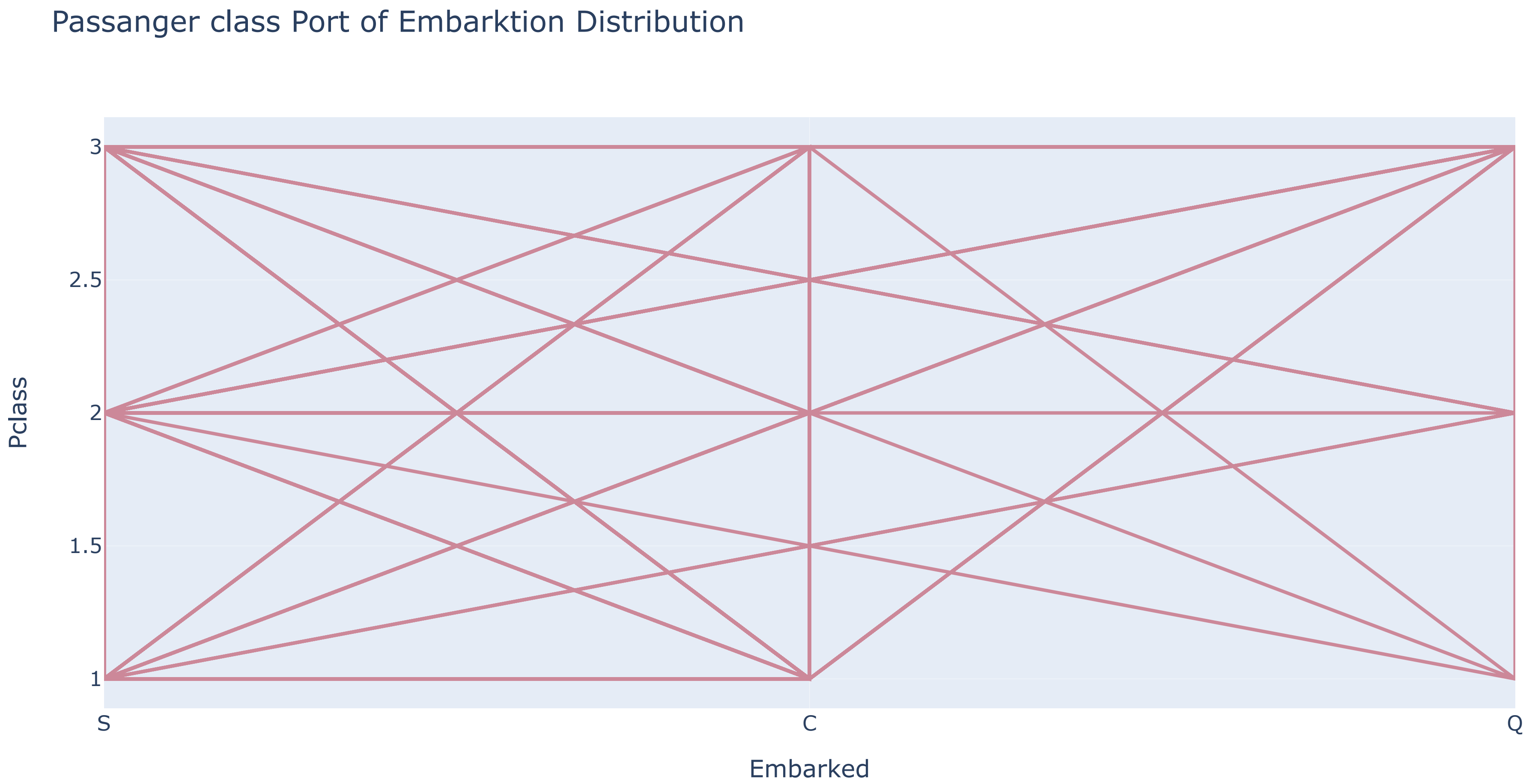
In [30]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Fare", hue='Pclass', data=titanic).set_title('Passanger class and Fare Distribution');
```



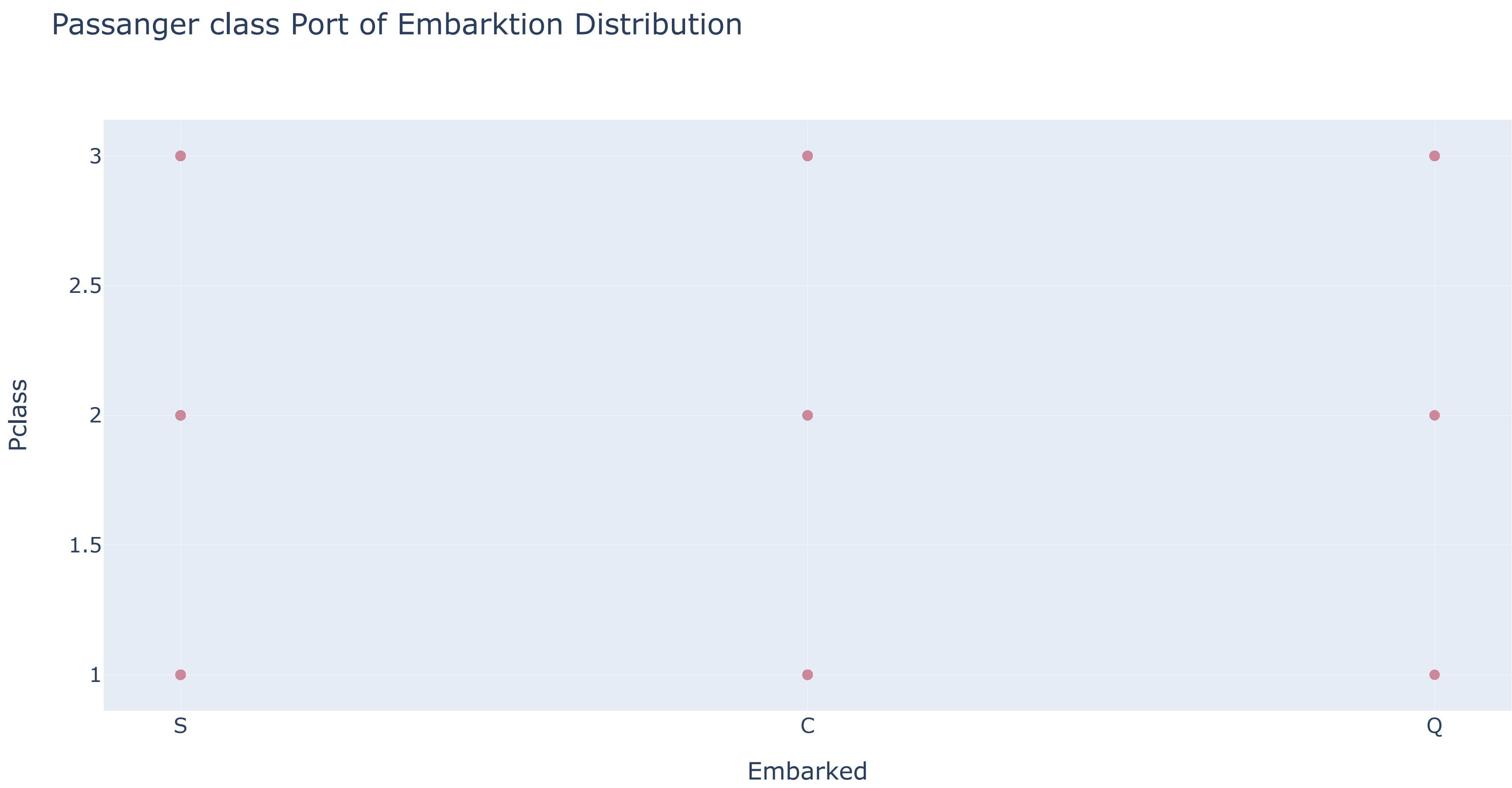
In [31]:
```
fig = px.box(titanic, x = "Pclass", y = "Fare",
                  color_discrete_sequence = ["#CC8899"],
                  title = "Passanger class and Fare Distribution")
fig.show()
```

Passanger Class vs Port of Embarkation

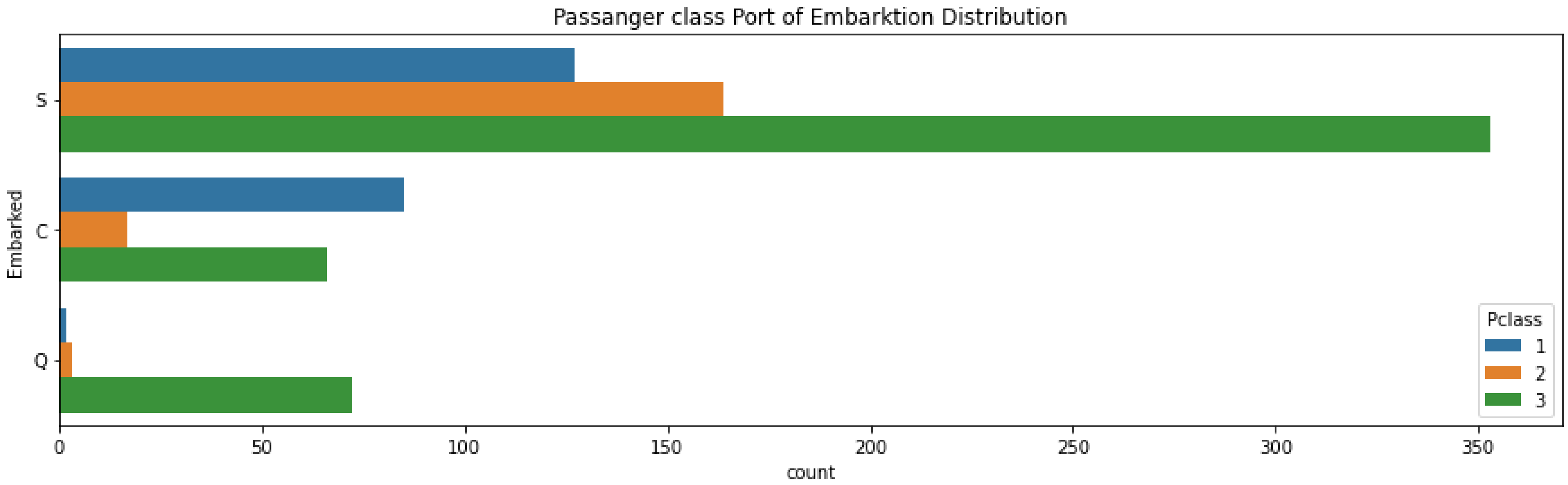
In [32]:
```
fig = px.line(titanic, x = "Embarked", y = "Pclass",
                  color_discrete_sequence = ["#CC8899"],
                  title = "Passanger class Port of Embarktion Distribution")
fig.show()
```



In [33]:
```
fig = px.scatter(titanic, x = "Embarked", y = "Pclass",
                  color_discrete_sequence = ["#CC8899"],
                  title = "Passanger class Port of Embarktion Distribution")
fig.show()
```

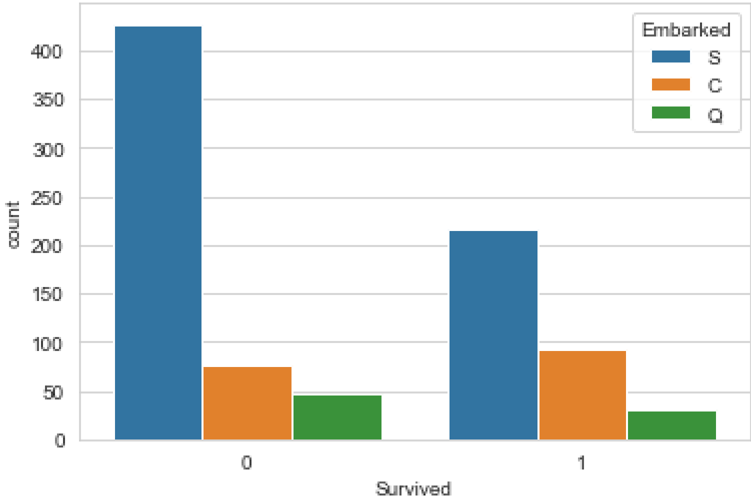


In [34]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Embarked", hue='Pclass', data=titanic).set_title('Passanger class Port of Embarktion Distribution');
```



In [82]:
```
titanic['Embarked'].value_counts()

sns.countplot(x='Survived',hue='Embarked',data=titanic)
```

Out[82]: <AxesSubplot:xlabel='Survived', ylabel='count'>



.

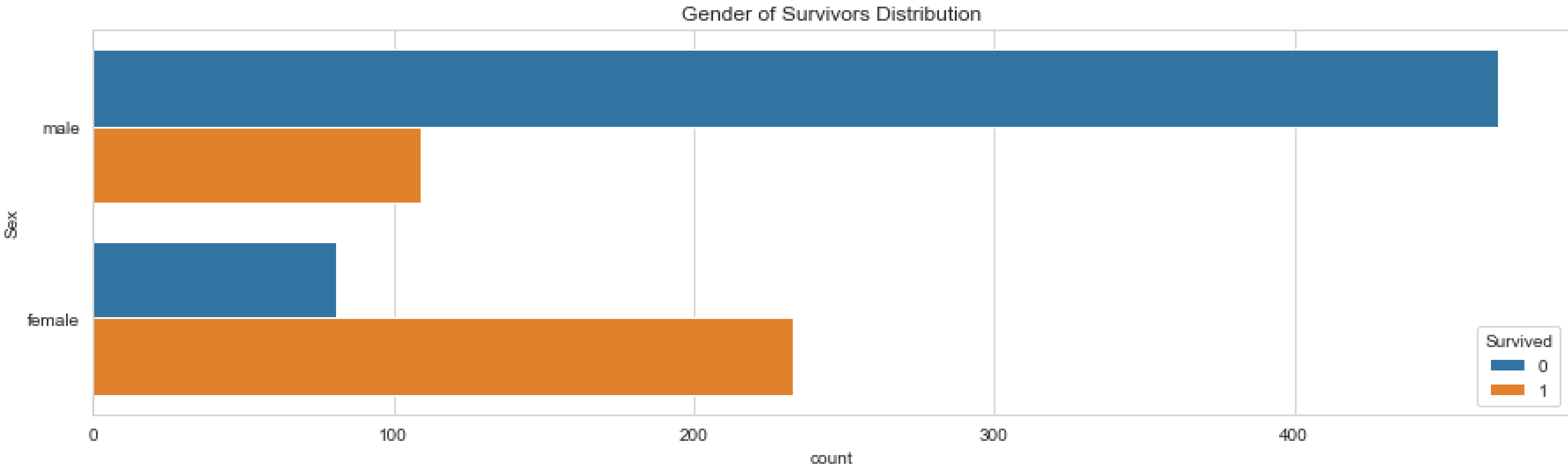
Gender vs Survived

In [194]:
```
titanic[['Sex','Survived']].groupby(['Sex'], as_index=True).mean().sort_values(by='Survived', ascending = False)
```

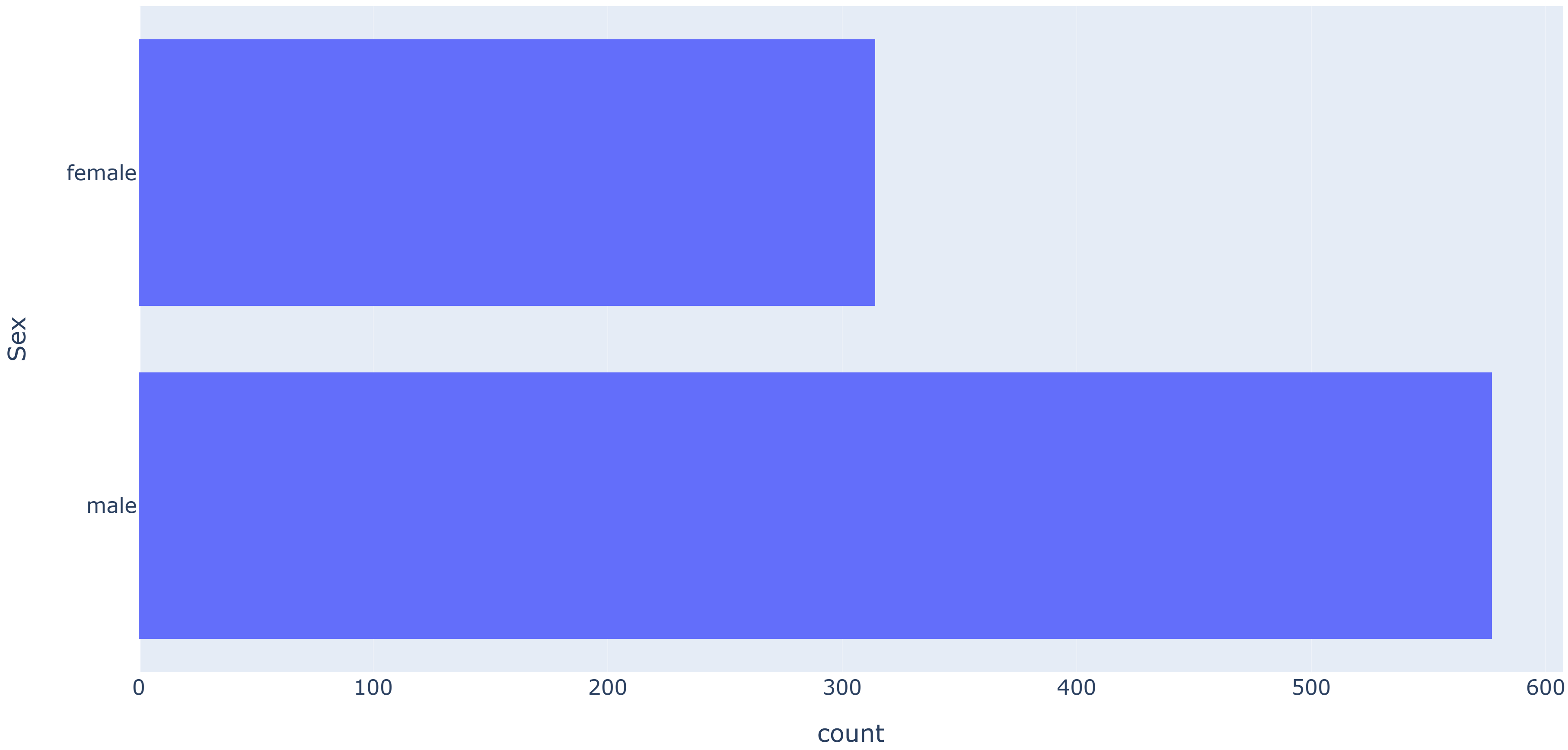
Out[194]:

	Survived
Sex	
0	0.742038
1	0.188908

In [85]:
```
fx, ax = plt.subplots(figsize=(15, 4))
sns.countplot(y="Sex", hue='Survived', data=titanic).set_title('Gender of Survivors Distribution');
```

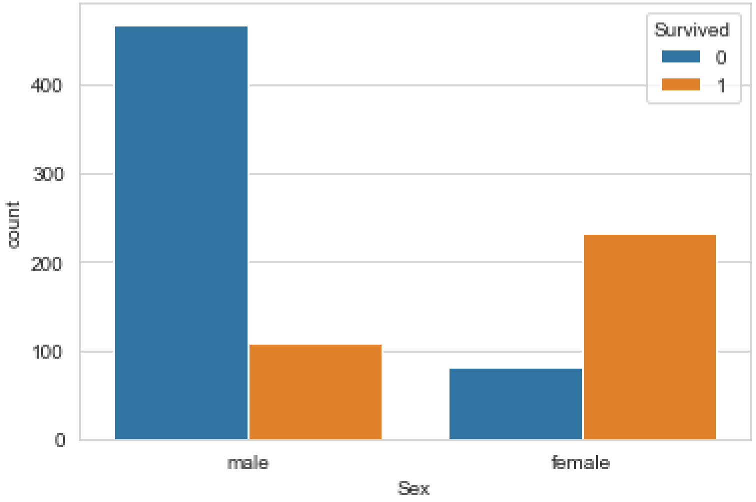


In [70]:
```
fig=px.histogram (titanic, y ='Sex')
fig.show()
```



In [75]:
```
sns.set_style('whitegrid')
sns.countplot(x='Sex',hue='Survived',data=titanic)

print(titanic['Sex'].value_counts())
```

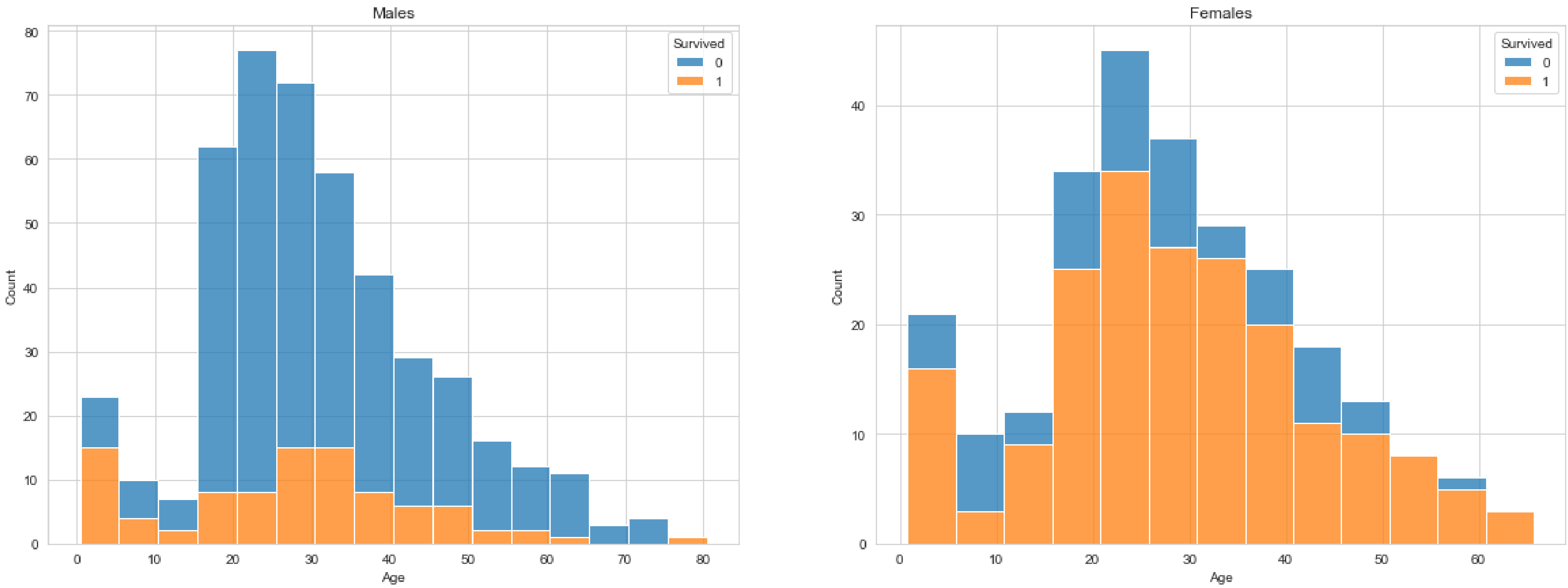
```
male      577
female    314
Name: Sex, dtype: int64
```



From the dataset there were more women who survived compred to men majority of the women survived.

In [80]:
```
sns.plot , ax = plt.subplots(1 , 2 , figsize=(20,7))
sns.histplot(data = titanic.loc[titanic["Sex"]=="male"] , x = "Age" , hue = "Survived",binwidth=5,ax = ax[0],multiple = 

sns.histplot(data = titanic.loc[titanic["Sex"]=="female"] , x = "Age" , hue = "Survived",binwidth=5,ax = ax[1],multiple 
```

Out[80]: Text(0.5, 1.0, 'Females')



Siblings and spouse on board distribution

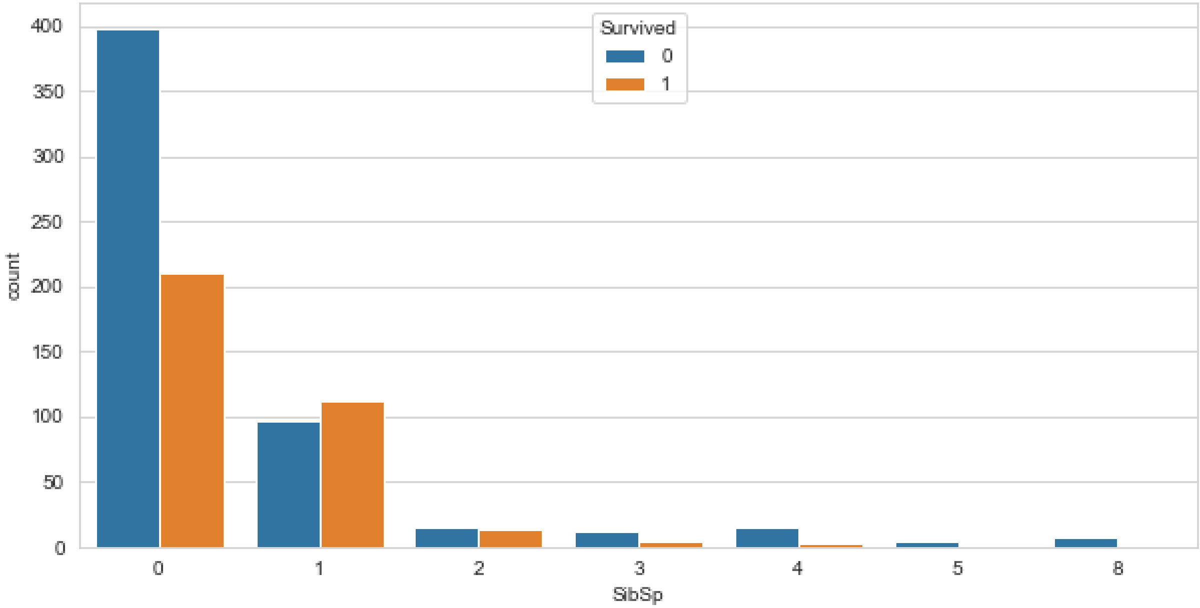
In [193]:
```
titanic[["SibSp", "Survived"]].groupby(['SibSp'], as_index=True).mean().sort_values(by='Survived', ascending=False)
```

Out[193]:

	Survived
SibSp	
1	0.535885
2	0.464286
0	0.345395
3	0.250000
4	0.166667
5	0.000000
8	0.000000

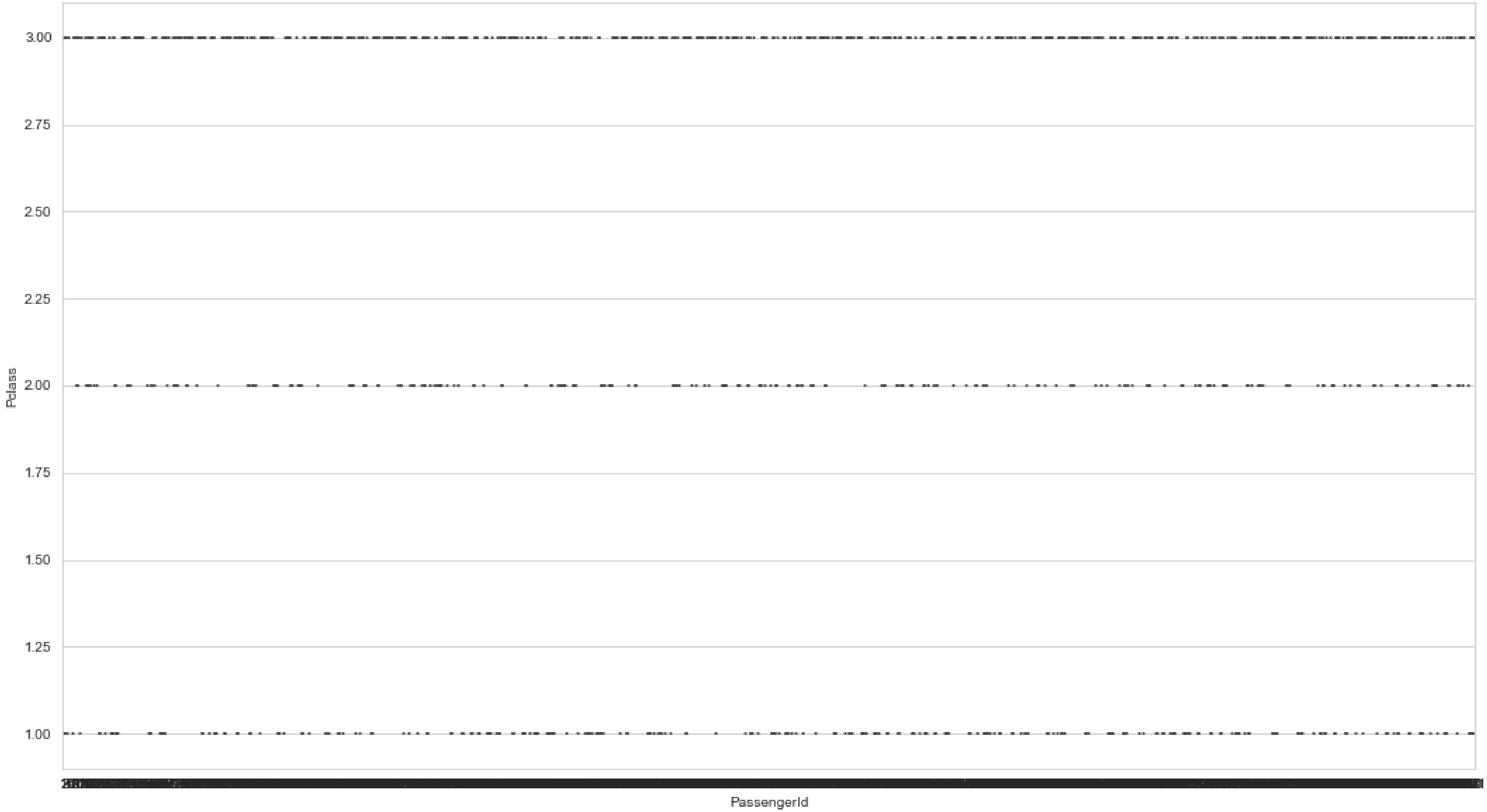
In [78]:
```
plt.figure(figsize=(10, 5))

sns.set_style('whitegrid')
sns.countplot(x='SibSp',hue='Survived',data=titanic)
```

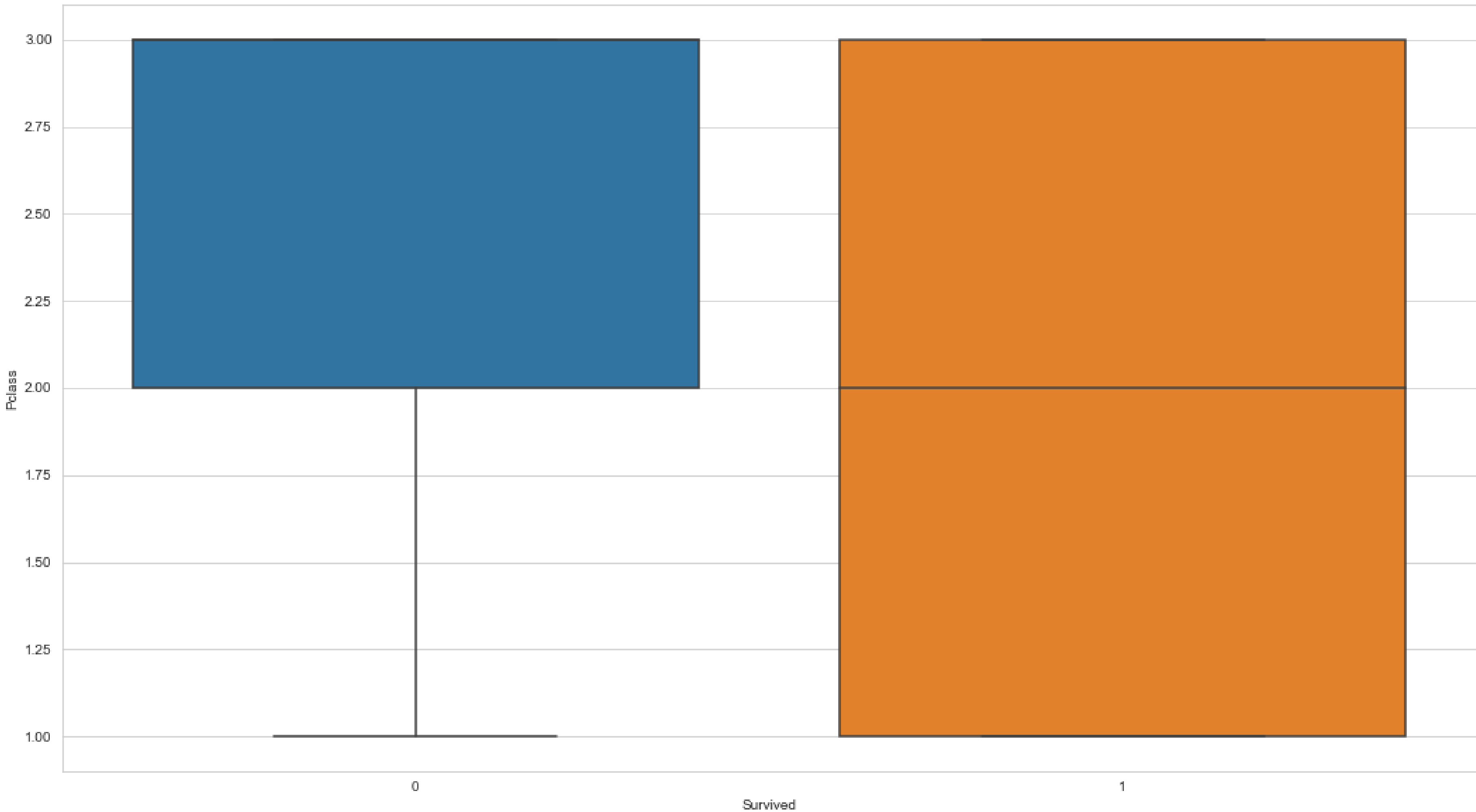
Out[78]: <AxesSubplot:xlabel='SibSp', ylabel='count'>

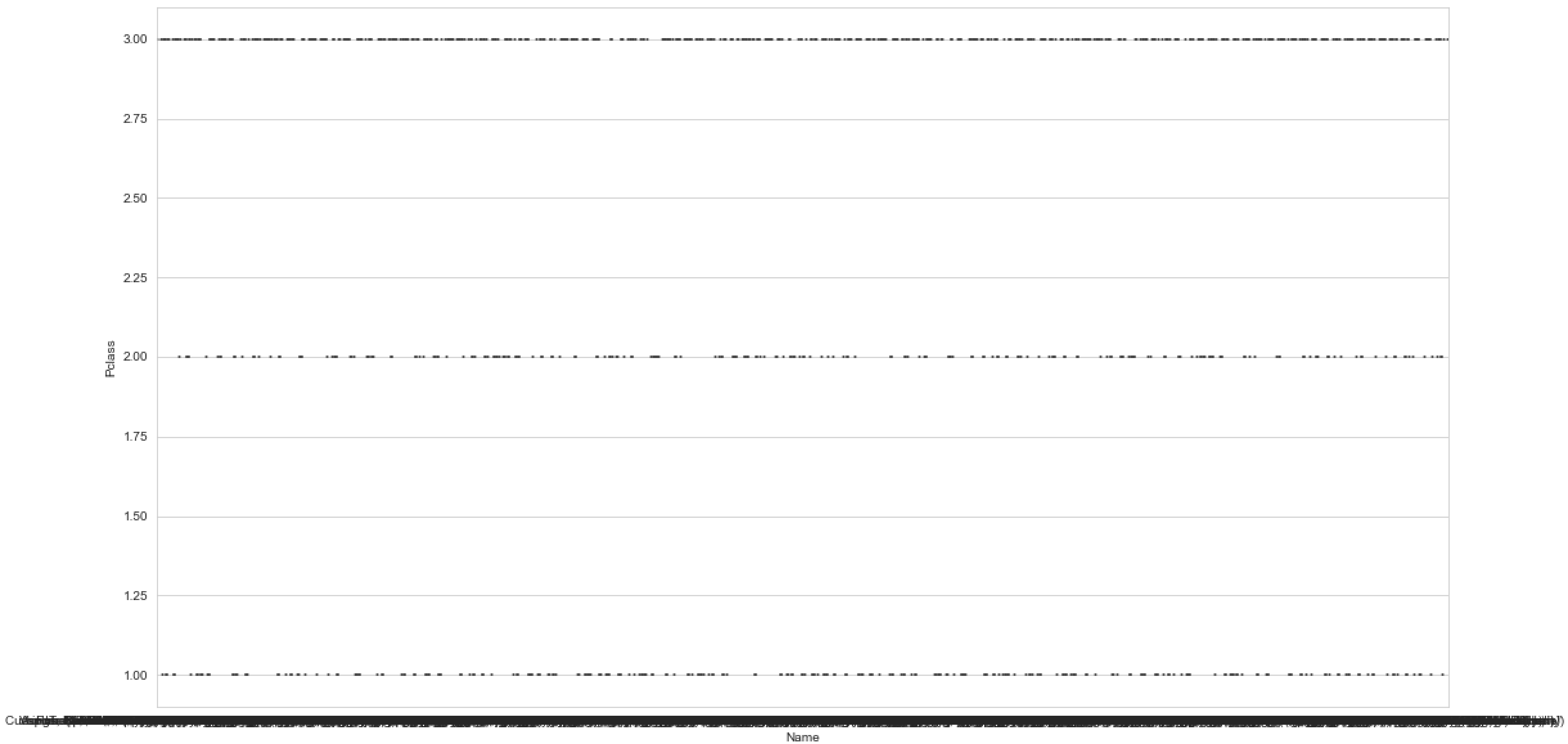


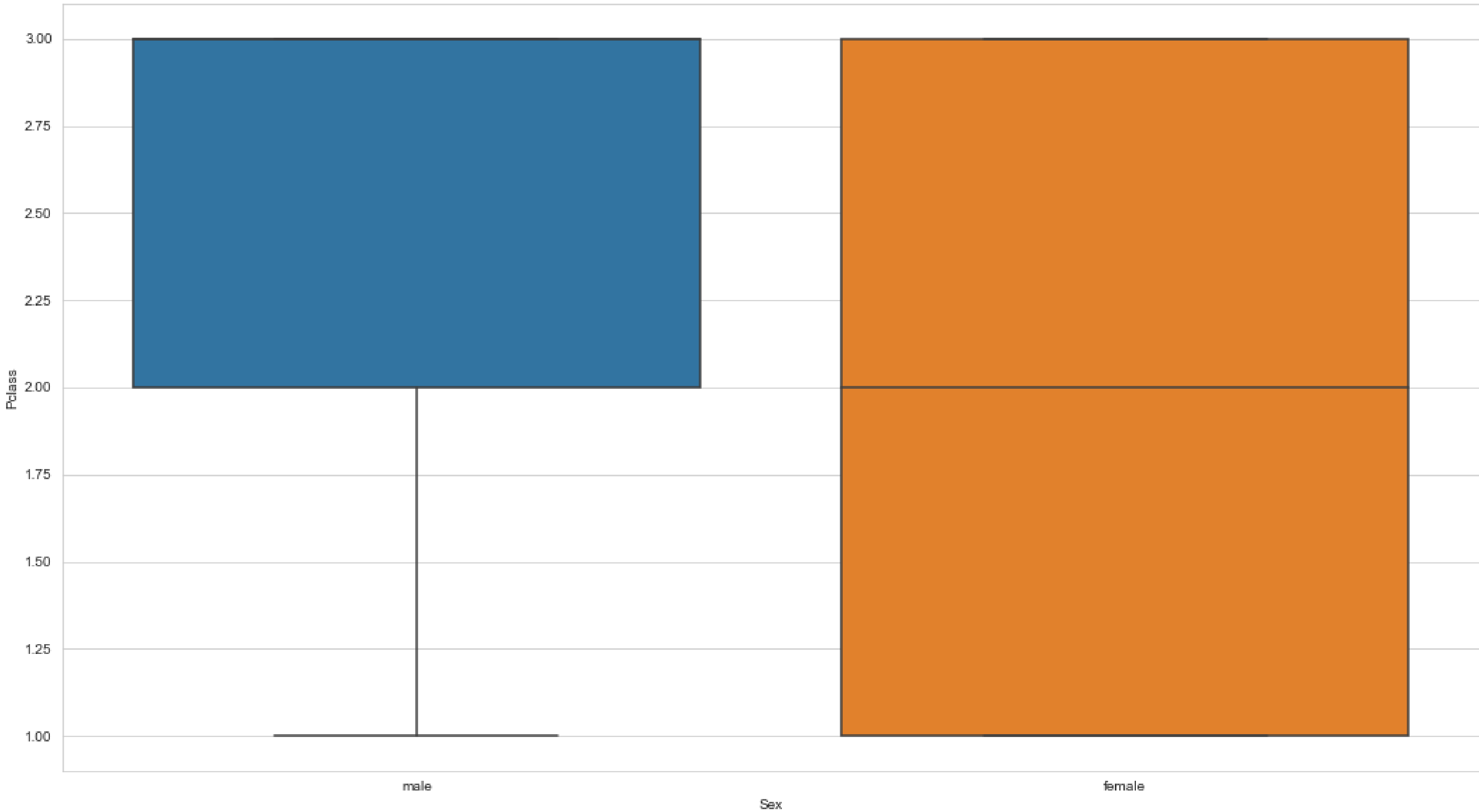
.

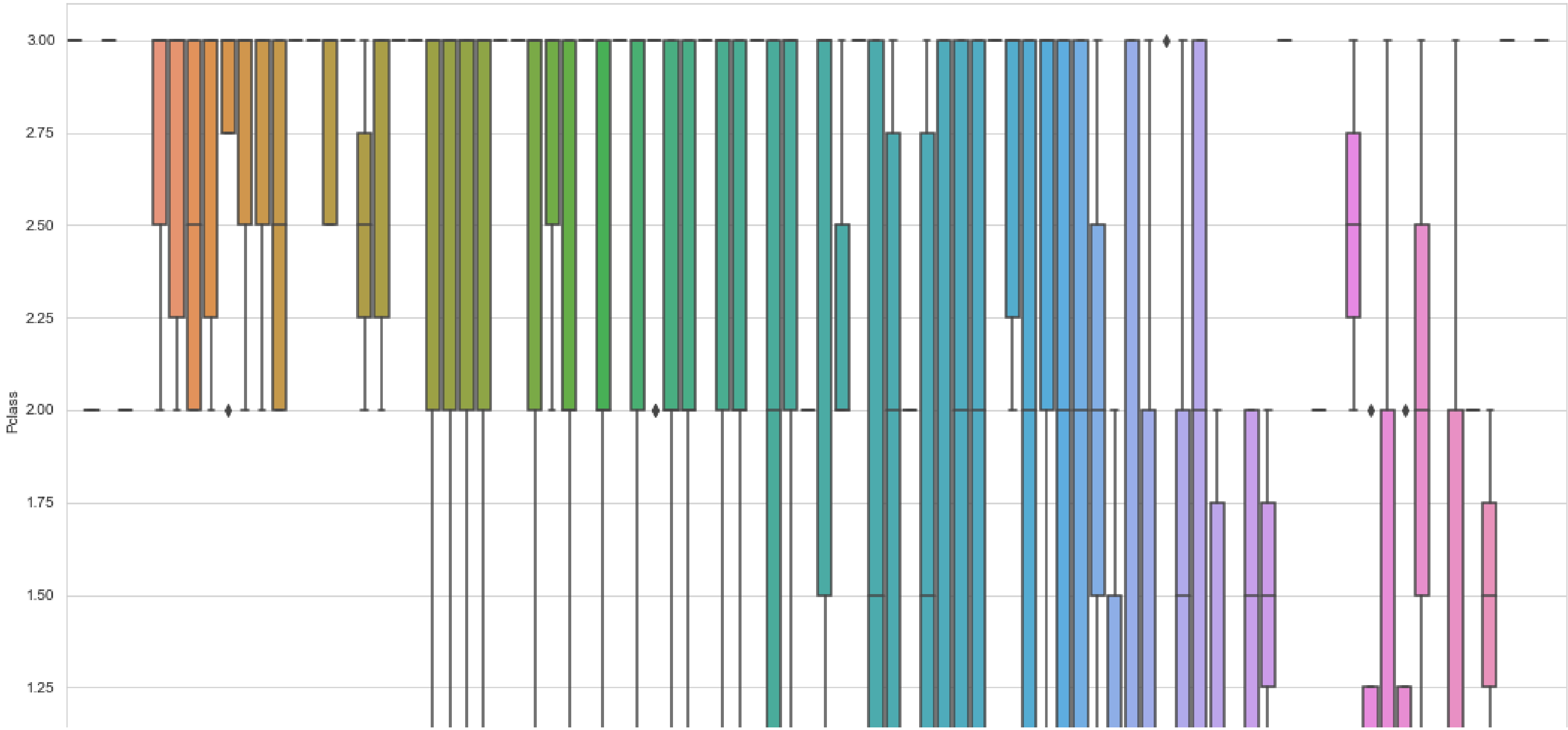
In [86]:
```
# Passanger class  Distribution
titanic_data = titanic.drop(['Pclass'], axis = 1)
for var in titanic_data:
    plt.rcParams.update({'figure.max_open_warning': 0})
    f, ax = plt.subplots(figsize = (18, 10))
    fig = sns.boxplot(x = titanic_data[var], y = titanic['Pclass'])
```



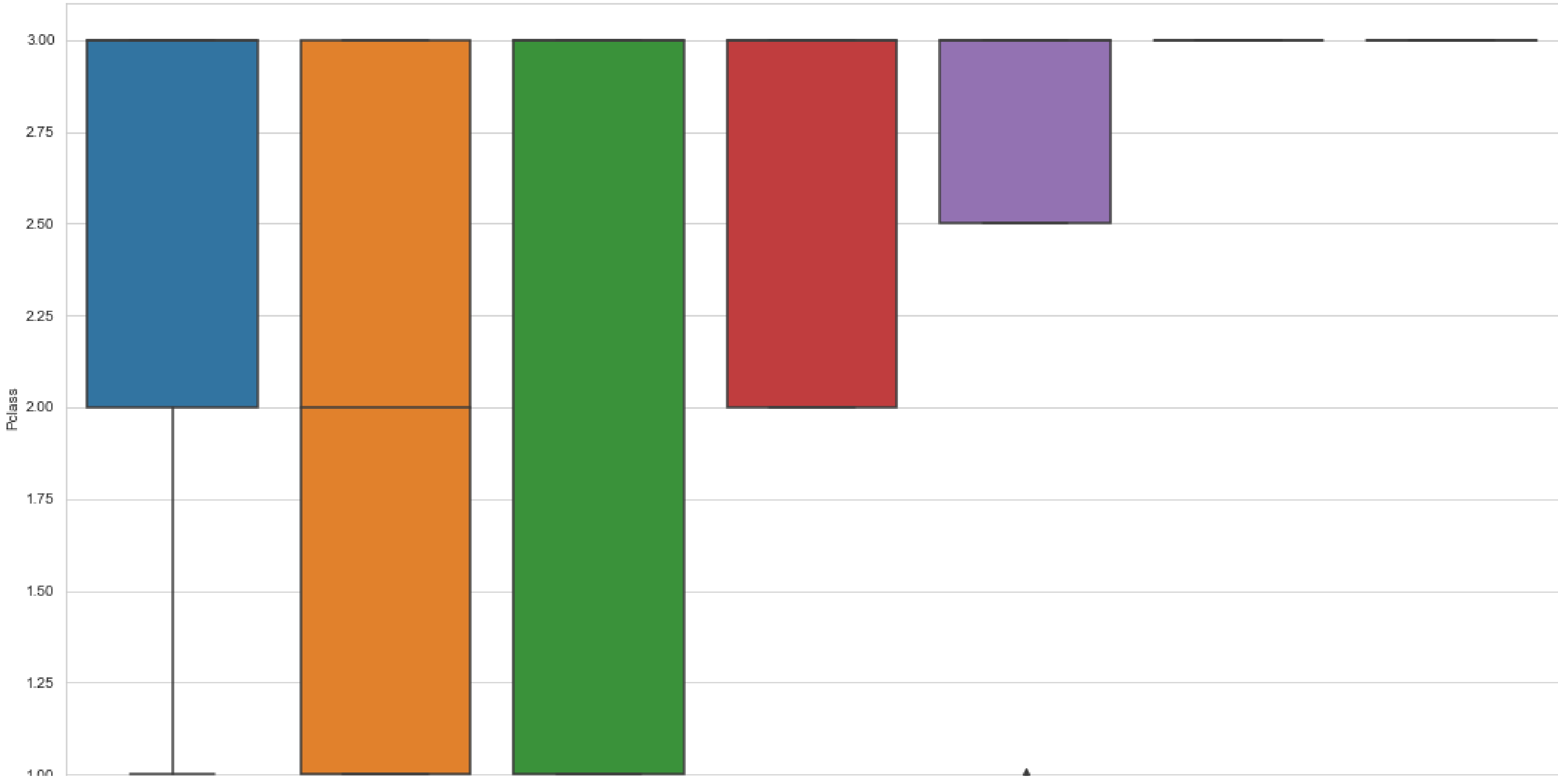

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass
0
1
Survived

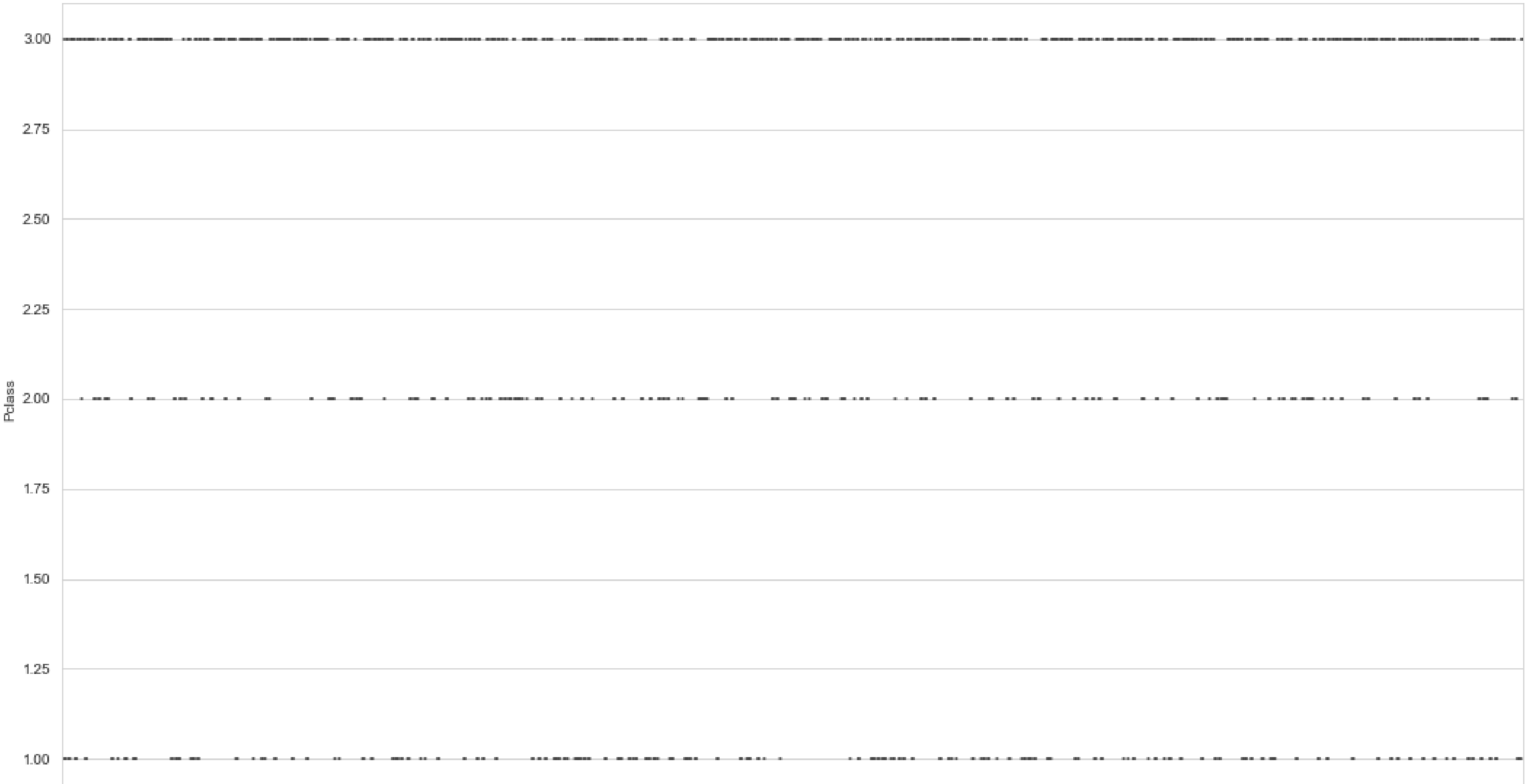

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass
Name

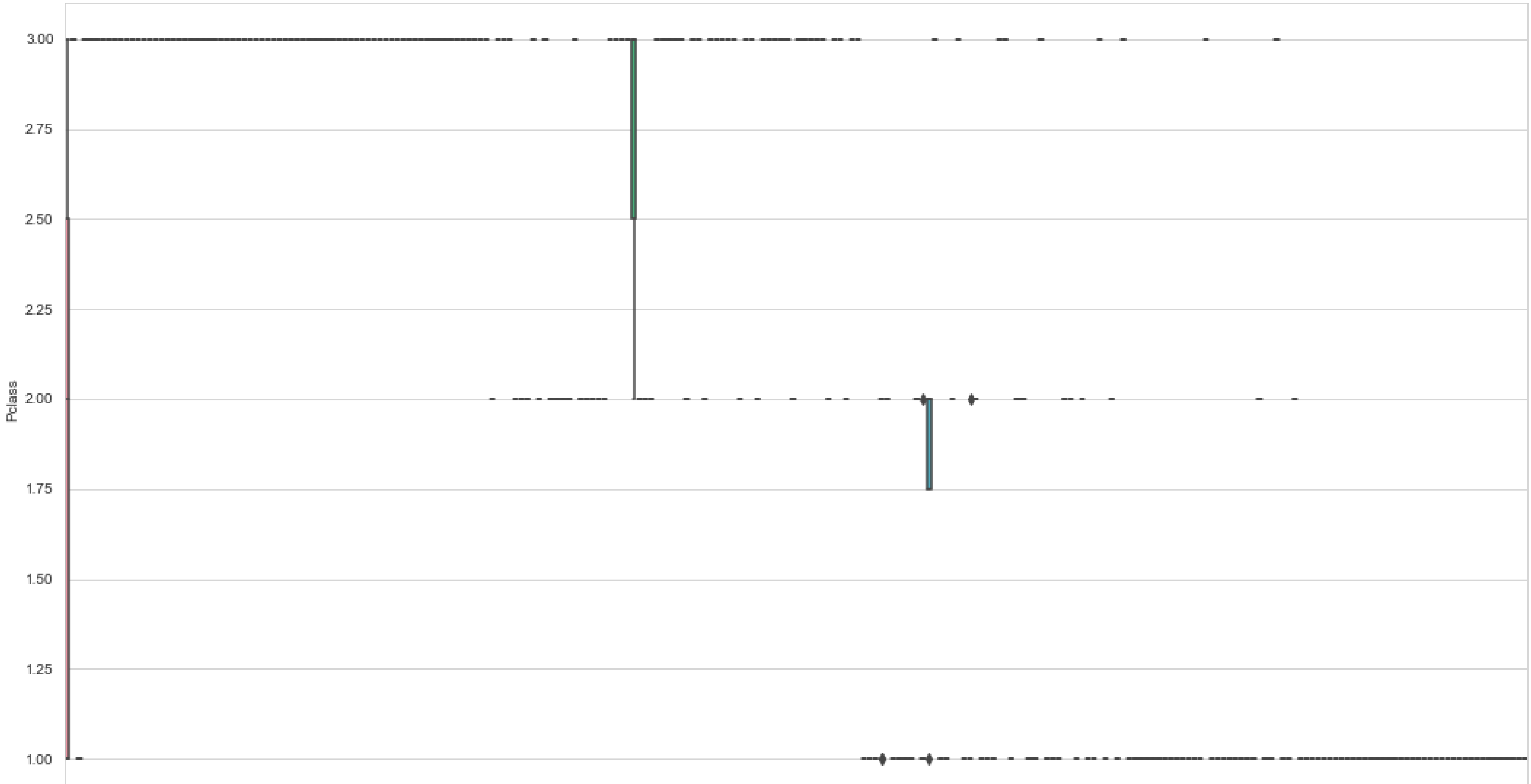

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass
male
female
Sex

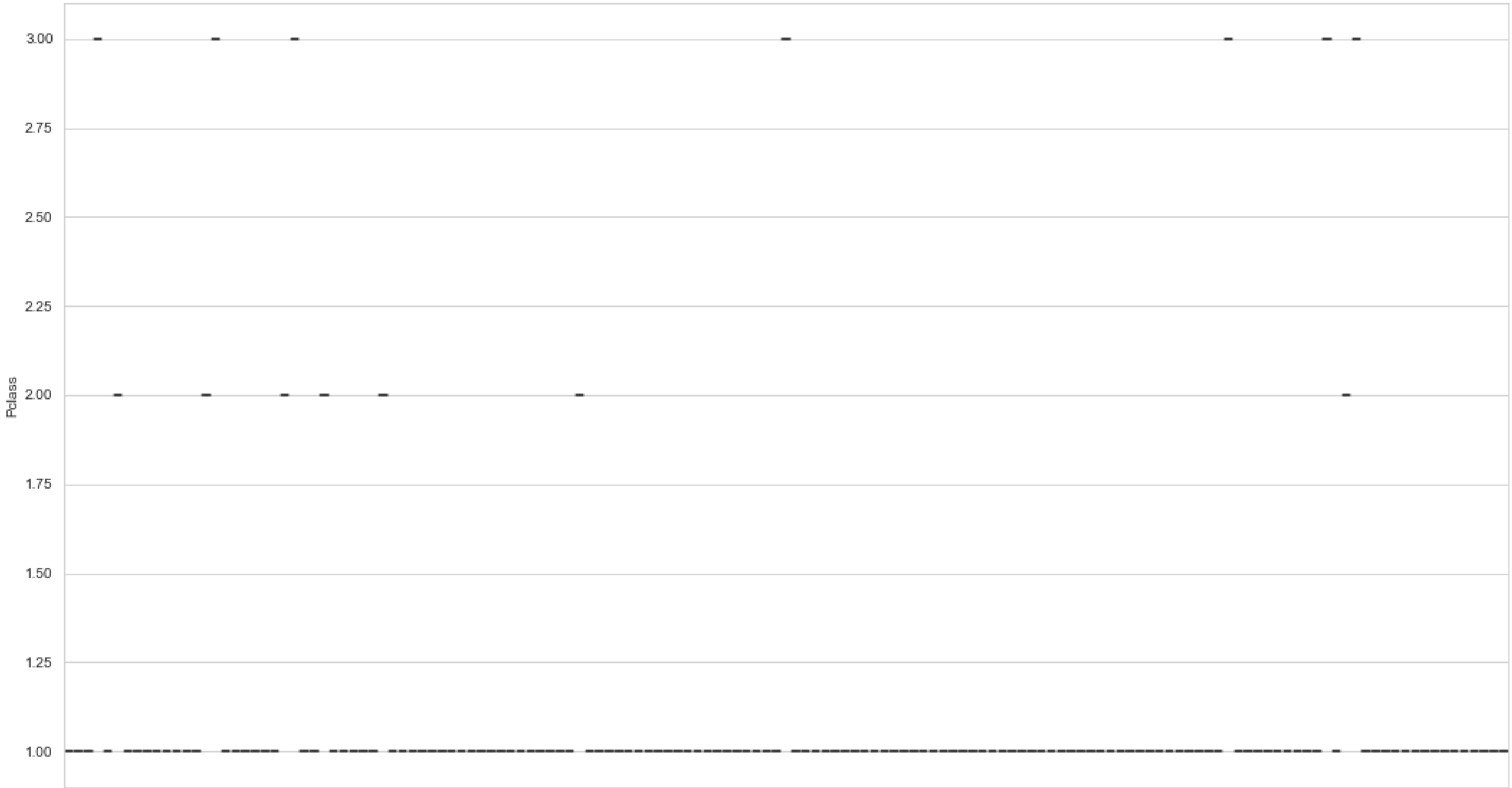

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
Pclass

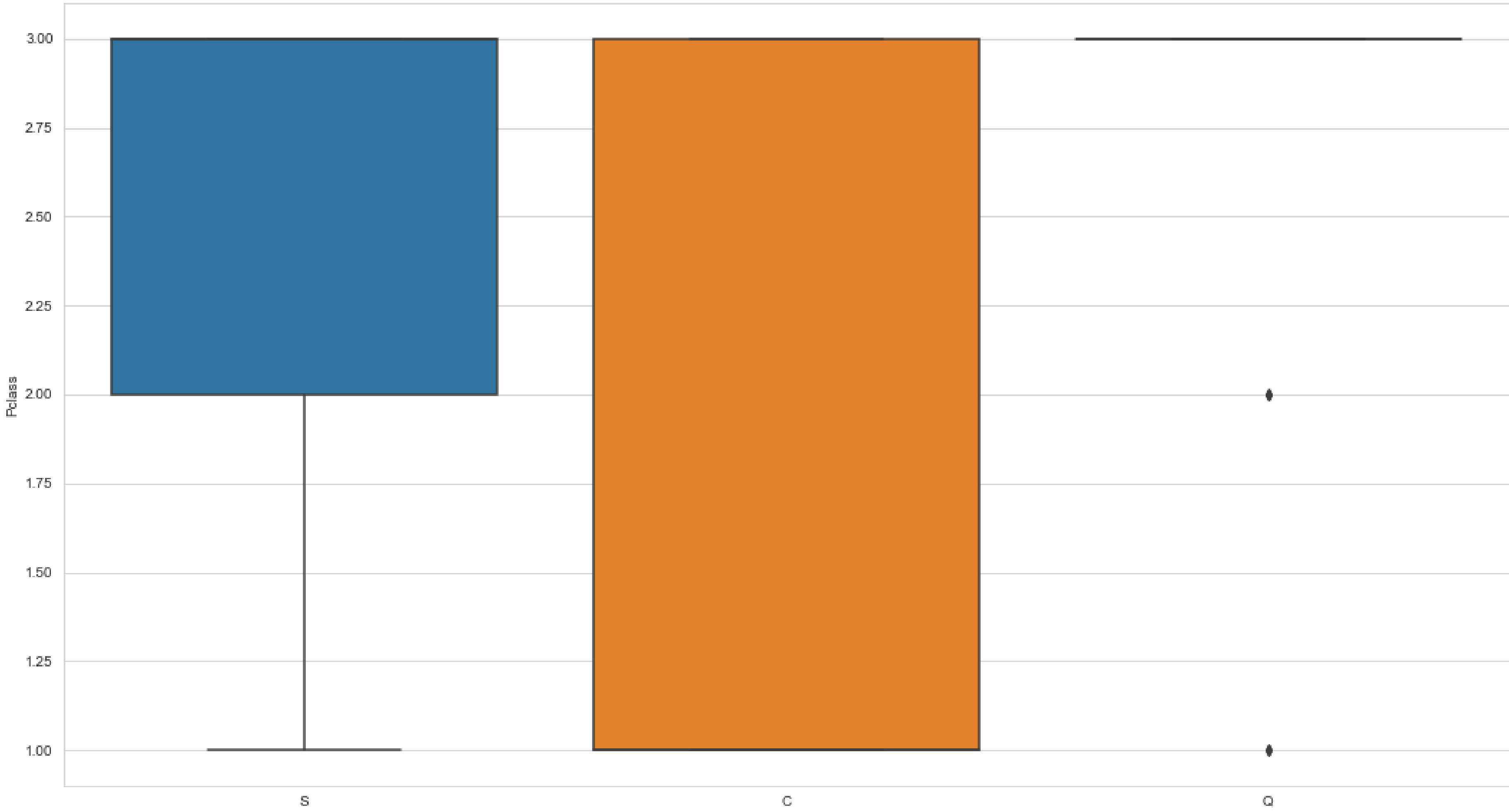

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
Pclass


3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass


3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass


3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass


3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass



3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass
S
C
Q

.

Missing values

Now we will be dealing with the missing value first to avoid any error or a biased model

In [212]:
```
from scipy import stats
from scipy.stats import skew, norm
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [150]:
```
! pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\osho emmanuel\anaconda3\lib\site-packages (1.7.0)
Requirement already satisfied: scipy in c:\users\osho emmanuel\anaconda3\lib\site-packages (from xgboost) (1.6.2)
Requirement already satisfied: numpy in c:\users\osho emmanuel\anaconda3\lib\site-packages (from xgboost) (1.20.1)
```

In [151]:
```
import xgboost
```

In [152]:
```
from xgboost import XGBRegressor
```

In [ ]:

In [228]:
```
print(titanic.shape)
```

```
(891, 12)
```

In [229]:
```
missing_val_count_by_column = (titanic.isnull().sum())
```

In [230]:
```
print(missing_val_count_by_column[missing_val_count_by_column > 0])
```

```
Cabin    687
dtype: int64
```

From the above we have abobe

- 177 missing data from Age
- 687 missing data from cabin and
- 2 missing data from Embarked

now this will lead to avery wrong predictions and error if we try to build a model using thid data so we have to find it missing value now we could drop the column but Age And Embarked are to important to drop anf if droped it will lead to a very biased model so we will use another option called **Imputation**.

Imputation fills in the missing values with some number **NoteThe imputed value won't be exactly right in most cases, but it usually leads to more accurate models than you would get from dropping the column entirely.**

.

let get our X and y

In [231]:
```
y = titanic.Survived
```

Befor we get Our X let convert our object data (Sex,and Embarked) numeric(intger) insted of writing another code for Categorical Variable

In [232]:
```
titanic.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    int64  
 5   Age          891 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     891 non-null    float64
dtypes: float64(3), int64(6), object(3)
memory usage: 83.7+ KB
```

In [233]:
```
titanic['Embarked']= titanic['Embarked'].replace(['C','S','Q'],[1,2,3])
```

In [234]:
```
titanic['Sex']=titanic['Sex'].replace(['female','male'],[0,1])
```

In [160]:
```
titanic.head()
```

Out[160]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	1	22.0	1	0	A/5 21171	7.2500	NaN	2.0
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	0	38.0	1	0	PC 17599	71.2833	C85	1.0
2	3	1	3	Heikkinen, Miss. Laina	0	26.0	0	0	STON/O2. 3101282	7.9250	NaN	2.0
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	35.0	1	0	113803	53.1000	C123	2.0
4	5	0	3	Allen, Mr. William Henry	1	35.0	0	0	373450	8.0500	NaN	2.0

In [ ]:

Note the Changes

In [161]:
```
feature_names = ['Pclass','Sex','Age','SibSp','Parch','Embarked']

X = titanic[feature_names]

X.head().style.background_gradient(cmap='Purples_r')
```

Out[161]:

	Pclass	Sex	Age	SibSp	Parch	Embarked
0	3	1	22.000000	1	0	2.000000
1	1	0	38.000000	1	0	1.000000
2	3	0	26.000000	0	0	2.000000
3	1	0	35.000000	1	0	2.000000
4	3	1	35.000000	0	0	2.000000

In [162]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X, y, train_size=0.8, test_size=0.2,
                                                       random_state=0)
```

In [ ]:

The MAE (The Mean absolute Error)

In [214]:
```
val_mae = mean_absolute_error(val_y, val_predictions)
print(mean_absolute_error(val_y, val_predictions))
```

```
0.2512322505596048
```

In [ ]:

In [163]:
```
def titanic_dataset(X_train, X_valid, y_train, y_valid):
    model = RandomForestRegressor(n_estimators=100, random_state=0)
    model.fit(X_train, y_train)
    preds = model.predict(X_valid)
    return mean_absolute_error(y_valid, preds)
```

IMPUTATION

In [164]:
```
my_imputer = SimpleImputer()
imputed_X_train = pd.DataFrame(my_imputer.fit_transform(X_train))
imputed_X_valid = pd.DataFrame(my_imputer.transform(X_valid))

imputed_X_train.columns = X_train.columns
imputed_X_valid.columns = X_valid.columns

print("MAE from Imputation:")
print(titanic_dataset(imputed_X_train, imputed_X_valid, y_train, y_valid))
```

```
MAE from Imputation:
0.2228912333490086
```

Filling Missing Value

In [165]:
```
titanic.Embarked.fillna(titanic.Embarked.dropna().max(), inplace=True)
```

In [166]:
```
#Age
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 [167]:
```
titanic['Age']=titanic[['Age','Pclass']].apply(impute_age,axis=1)
```

In [168]:
```
print(titanic.isnull().sum())
print(titanic.shape)
```

```
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
(891, 12)
```

In [169]:
```
X.head(30)
```

Out[169]:

	Pclass	Sex	Age	SibSp	Parch	Embarked
0	3	1	22.0	1	0	2.0
1	1	0	38.0	1	0	1.0
2	3	0	26.0	0	0	2.0
3	1	0	35.0	1	0	2.0
4	3	1	35.0	0	0	2.0
5	3	1	24.0	0	0	3.0
6	1	1	54.0	0	0	2.0
7	3	1	2.0	3	1	2.0
8	3	0	27.0	0	2	2.0
9	2	0	14.0	1	0	1.0
10	3	0	4.0	1	1	2.0
11	1	0	58.0	0	0	2.0
12	3	1	20.0	0	0	2.0
13	3	1	39.0	1	5	2.0
14	3	0	14.0	0	0	2.0
15	2	0	55.0	0	0	2.0
16	3	1	2.0	4	1	3.0
17	2	1	29.0	0	0	2.0
18	3	0	31.0	1	0	2.0
19	3	0	24.0	0	0	1.0
20	2	1	35.0	0	0	2.0
21	2	1	34.0	0	0	2.0
22	3	0	15.0	0	0	3.0
23	1	1	28.0	0	0	2.0

	Pclass	Sex	Age	SibSp	Parch	Embarked
24	3	0	8.0	3	1	2.0
25	3	0	38.0	1	5	2.0
26	3	1	24.0	0	0	1.0
27	1	1	19.0	3	2	2.0
28	3	0	24.0	0	0	3.0
29	3	1	24.0	0	0	2.0

In [ ]:

```
```

Model And Model Prediction

In [170]:

```
titanic_model = DecisionTreeRegressor(random_state=1)

titanic_model.fit(X, y)
```

Out[170]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=1)
```

In [171]:
```
predictions = titanic_model.predict(X)

print(predictions)
```

```
[0.         1.         1.         1.         0.         0.05
 0.         0.         1.         1.         1.         1.
 0.         0.         0.         1.         0.         0.125
 0.         1.         0.         0.33333333 1.         0.66666667
 0.         1.         0.06666667 0.         0.82352941 0.10204082
 0.5        1.         0.82352941 0.         0.         0.5
 0.06666667 0.08333333 0.         1.         0.         0.
 0.06666667 1.         1.         0.10204082 0.         0.82352941
 0.         0.         0.         0.08333333 1.         1.
 0.         0.26666667 1.         0.         1.         0.
 0.5        1.         0.         0.         0.16666667 1.
 1.         0.09090909 1.         0.         0.         0.
 0.         0.         0.55555556 0.16666667 0.10204082 0.10204082
 1.         0.5        0.         0.2        0.82352941 0.66666667
 1.         1.         0.         0.10204082 1.         0.10204082
 0.2        0.         0.         0.         0.         0.10204082
 0.         1.         1.         0.         0.         0.10204082
 0.         0.         0.         0.         1.         0.10204082
 0.         1.         0.         0.         0.         0.
 0.         0.08333333 0.         0.         0.         0.
 0.         0.10204082 0.         1.         0.         1.
 0.05       0.10204082 1.         0.5        0.         0.
 0.         1.         0.         0.         1.         0.
 0.2        0.         0.5        0.6        1.         0.
 0.         0.         0.75       0.         0.         0.5
 0.         1.         0.         0.         0.10204082 0.
 1.         0.2        0.10204082 0.         0.         1.
 0.16666667 0.         0.         1.         1.         0.
 0.26666667 0.         0.         0.         1.         0.08333333
 0.5        0.         0.         0.         0.         0.
 0.         0.5        0.         1.         1.         0.26666667
 1.         0.33333333 0.         0.         1.         0.33333333
 1.         1.         1.         1.         0.05       0.
 0.82352941 0.5        0.         0.         0.         0.
 0.2        0.5        0.         1.         1.         0.5
 0.10204082 1.         0.         0.         0.         1.
 1.         0.         1.         0.         0.2        0.
```

```
 0.         0.10204082 1.         0.         0.33333333 0.
 0.         0.         1.         0.2        0.         1.
 0.         0.         0.         1.         0.33333333 0.
 0.         1.         0.125      0.         0.         0.
 0.         1.         1.         0.         0.10204082 0.
 0.         0.         0.         1.         1.         1.
 1.         1.         0.05       1.         0.         0.
 0.82352941 0.         0.         0.33333333 1.         1.
 0.26666667 0.16666667 1.         0.         0.82352941 1.
 0.         0.125      0.         1.         0.         0.
 0.2        0.09090909 0.26666667 0.         0.2        0.
 0.5        1.         1.         1.         0.         0.
 0.10204082 0.16666667 0.         0.         0.26666667 1.
 0.82352941 1.         0.09090909 1.         0.10204082 1.
 1.         1.         0.         1.         1.         1.
 0.         0.         0.         1.         1.         0.
 1.         1.         0.         0.75       1.         1.
 0.         1.         0.         1.         1.         1.
 1.         0.         0.         0.         1.         0.10204082
 0.         1.         0.5        0.33333333 1.         1.
 0.         0.         0.         0.5        1.         1.
 1.         0.         0.         0.26666667 0.         0.33333333
 0.06666667 0.         1.         0.         0.82352941 0.82352941
 0.         0.         0.         0.         0.         0.2
 1.         1.         0.82352941 1.         1.         0.
 0.09090909 0.         0.         1.         0.6        0.
 0.5        0.09090909 1.         1.         0.55555556 1.
 0.10204082 0.         0.         1.         0.05       1.
 1.         0.08333333 0.         1.         1.         0.
 0.5        0.         0.         1.         0.33333333 0.16666667
 0.         0.         0.         0.         0.         1.
 0.08333333 0.         0.10204082 0.05       1.         0.125
 0.33333333 0.         1.         1.         0.         0.
 0.06666667 0.         0.2        0.         0.         0.10204082
 1.         1.         0.05       0.55555556 0.66666667 1.
 1.         0.         0.         1.         0.         1.
 0.         0.5        1.         0.         0.33333333 1.
 0.10204082 1.         1.         1.         1.         1.
 0.         0.         0.         1.         0.10204082 1.
 0.         1.         1.         0.05       1.         0.
 0.         0.         0.10204082 0.         0.125      0.
 0.05       1.         0.10204082 0.         1.         1.
```

```
 0.6        0.26666667 0.         0.         0.         0.5
 0.         0.125      0.         1.         1.         0.
 1.         0.         0.2        1.         0.         0.08333333
 0.         0.         0.08333333 0.06666667 1.         0.10204082
 0.         0.10204082 0.         0.         0.82352941 0.
 1.         0.         1.         0.26666667 0.         0.16666667
 1.         0.10204082 1.         1.         0.10204082 0.
 1.         0.05       1.         0.55555556 1.         0.
 0.06666667 1.         0.06666667 0.         1.         0.26666667
 0.33333333 0.         1.         0.06666667 0.         0.5
 0.5        1.         0.33333333 1.         0.10204082 1.
 1.         0.         0.         1.         0.         0.
 1.         0.5        0.         1.         1.         0.
 0.05       0.5        0.6        0.         1.         0.16666667
 1.         1.         0.05       0.         0.         0.10204082
 0.         0.         0.09090909 0.         0.06666667 0.55555556
 1.         1.         1.         0.82352941 0.2        0.09090909
 1.         1.         0.         0.55555556 1.         1.
 0.         0.         0.06666667 1.         0.         1.
 0.         0.10204082 0.         1.         0.         0.
 0.         0.         1.         0.         0.06666667 1.
 1.         0.10204082 0.26666667 0.33333333 1.         0.
 0.2        1.         1.         1.         0.         0.10204082
 1.         0.05       0.         1.         0.         0.
 1.         0.         0.         0.5        1.         0.08333333
 0.08333333 0.         0.         1.         0.16666667 0.05
 1.         0.         1.         0.26666667 0.         1.
 0.55555556 0.         0.         0.         0.         1.
 0.         0.10204082 1.         1.         0.09090909 0.5
 0.10204082 0.5        0.10204082 1.         0.08333333 0.82352941
 0.         0.         0.10204082 0.         0.         0.
 1.         0.         0.         0.         1.         0.
 0.         0.10204082 0.         1.         1.         0.5
 0.         0.5        0.125      0.2        0.         0.66666667
 0.         1.         0.82352941 1.         0.         0.
 0.         0.         0.         0.09090909 0.2        1.
 0.5        1.         0.10204082 0.         0.         0.
 0.33333333 0.82352941 0.         0.         1.         1.
 0.         0.         0.         0.         1.         1.
 1.         1.         1.         0.26666667 1.         0.2
 0.         0.09090909 1.         1.         0.05       0.
 1.         0.         0.33333333 0.         1.         0.
```

```
 1.         0.82352941 0.         0.         1.         0.
 0.125      0.         0.         0.         0.         1.
 0.10204082 0.10204082 0.26666667 0.         1.         0.
 0.5        0.         0.         1.         0.         0.
 1.         1.         0.         0.         1.         1.
 0.         0.         0.         1.         0.10204082 0.
 0.5        1.         0.2        1.         0.16666667 0.
 0.         0.55555556 0.10204082 0.         0.         0.06666667
 1.         0.2        0.05       1.         0.05       1.
 1.         1.         0.         0.         0.16666667 0.16666667
 0.66666667 0.         1.         0.         0.05       0.
 0.         0.16666667 0.16666667 0.         1.         0.5
 0.         0.         0.33333333 1.         1.         1.
 0.75       0.5        0.         0.66666667 0.         1.
 0.16666667 0.33333333 0.         0.         0.         0.26666667
 0.5        0.         0.         0.         1.         0.75
 0.         1.         0.         0.05       0.10204082 1.
 0.05       1.         1.         1.         0.06666667 0.
 0.2        1.         0.08333333 0.10204082 0.55555556 0.16666667
 0.         0.         1.         0.         0.         0.
 0.         0.         0.         1.         0.         0.
 0.         1.         0.         1.         1.         1.
 1.         0.06666667 0.         0.         1.         0.
 0.         1.         1.         0.         0.10204082 1.
 0.16666667 1.         0.         0.         1.         1.
 0.         0.09090909 0.10204082 1.         1.         0.
 0.6        0.         0.16666667 0.         0.         1.
 0.         1.         0.        ]
```

In [191]:

```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)
y_pred = decision_tree.predict(X_train)
acc_decision_tree = round(decision_tree.score(X_train, y_train) * 100, 2)
acc_decision_tree
```

Out[191]: 94.1

In [198]:
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, y_train)
y_pred = random_forest.predict(X_train)
random_forest.score(X_train, y_train)
acc_random_forest = round(random_forest.score(X_train, y_train) * 100, 2)
acc_random_forest
```

Out[198]:
```
94.1
```

In [ ]:

In [183]:
```
titanic_transformer = SimpleImputer(strategy='constant')
```

In [199]:
```
model = Pipeline(titanic_model)
```

Model Validation

In [172]:
```
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state=1)
```

In [173]:
```
titanic_model = DecisionTreeRegressor(random_state=1)

titanic_model.fit(train_X, train_y)
```

Out[173]:
```
DecisionTreeRegressor
DecisionTreeRegressor(random_state=1)
```

In [174]:
```python
val_predictions = titanic_model.predict(val_X)
print((val_y, val_predictions))
```

```
(862    1
223    0
84     1
680    0
535    1
      ..
506    1
467    0
740    1
354    0
449    1
Name: Survived, Length: 223, dtype: int64, array([1.        , 0.05714286, 1.        , 0.84615385, 1.        ,
       0.09090909, 0.        , 1.        , 1.        , 1.        ,
       0.2       , 1.        , 0.        , 0.        , 0.84615385,
       0.        , 0.        , 0.        , 0.        , 1.        ,
       0.71428571, 0.        , 1.        , 0.        , 1.        ,
       0.66666667, 1.        , 1.        , 0.        , 1.        ,
       0.66666667, 0.1       , 1.        , 1.        , 0.        ,
       0.        , 1.        , 0.05714286, 1.        , 0.        ,
       1.        , 1.        , 1.        , 0.        , 1.        ,
       0.        , 0.        , 0.        , 1.        , 0.        ,
       1.        , 1.        , 0.5       , 0.        , 0.        ,
       1.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.1       , 0.        , 0.        , 1.        ,
       0.        , 0.        , 0.        , 1.        , 0.        ,
       0.        , 0.        , 0.        , 0.05714286, 1.        ,
       0.        , 1.        , 0.        , 0.5       , 1.        ,
       0.        , 0.        , 0.05714286, 0.        , 1.        ,
       0.        , 0.05714286, 0.1       , 0.        , 1.        ,
       0.        , 0.1       , 0.2       , 0.84615385, 0.05714286,
       1.        , 0.        , 1.        , 0.1       , 0.05714286,
       0.2       , 0.        , 1.        , 1.        , 1.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       1.        , 1.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 1.        , 1.        , 0.        ,
       1.        , 0.        , 0.05714286, 0.        , 1.        ,
       1.        , 1.        , 0.66666667, 0.        , 0.        ,
       0.05714286, 0.        , 1.        , 1.        , 0.        ,
```

```
       1.        , 1.        , 0.        , 0.        , 0.        ,
       1.        , 0.5       , 1.        , 0.        , 0.05714286,
       1.        , 1.        , 0.05714286, 0.        , 0.        ,
       1.        , 0.        , 0.        , 0.        , 0.05714286,
       0.71428571, 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       1.        , 1.        , 0.05714286, 0.25      , 0.        ,
       1.        , 0.        , 1.        , 0.        , 1.        ,
       0.1       , 0.        , 0.        , 1.        , 0.        ,
       1.        , 1.        , 0.        , 0.        , 1.        ,
       0.        , 0.05714286, 1.        , 0.        , 1.        ,
       0.1       , 0.        , 0.84615385, 0.        , 1.        ,
       1.        , 0.        , 1.        , 0.05714286, 0.        ,
       0.        , 1.        , 0.1       , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.1       , 0.        ,
       1.        , 0.        , 0.        , 1.        , 0.        ,
       0.        , 0.        , 1.        , 1.        , 0.5       ,
       0.1       , 0.1       , 1.        ]))
```

Cross validation

In [202]:
```
my_pipeline = Pipeline(steps=[
    ('preprocessor', SimpleImputer()),
    ('model', RandomForestRegressor(n_estimators=50, random_state=0))
])
```

In [205]:
```
scores = -1 * cross_val_score(my_pipeline, X, y,
                              cv=5,
                              scoring='neg_mean_absolute_error')

print("Average MAE score:", scores.mean())
```

```
Average MAE score: 0.24191878696318048
```

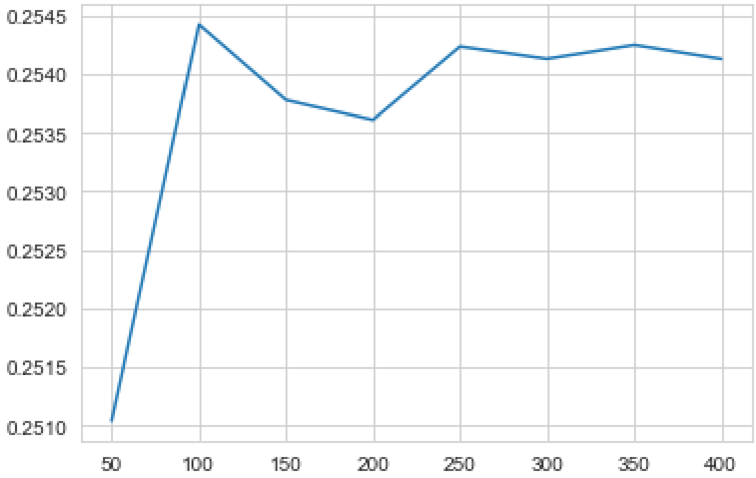
In [209]:
```
scores = -1 * cross_val_score(my_pipeline, X, y,
                              cv=5,
                              scoring='neg_mean_absolute_error')

print("MAE scores:\n", scores)
```

```
MAE scores:
 [0.29108357 0.21746023 0.24200446 0.23803627 0.22100939]
```

In [206]:
```
def get_score(n_estimators):
    """Return the average MAE over 3 CV folds of random forest model.

    Keyword argument:
    n_estimators -- the number of trees in the forest
    """
    my_pipeline = Pipeline(steps=[
    ('preprocessor', SimpleImputer()),
    ('model', RandomForestRegressor(n_estimators, random_state=0))
])

    scores = -1 * cross_val_score(my_pipeline, X, y,
                                  cv=3,
                                  scoring='neg_mean_absolute_error')
    return scores.mean()
```

In [208]:
```
results = {}
for i in range(1,9):
    results[50*i] = get_score(50*i)
```

In [210]:
```
import matplotlib.pyplot as plt
%matplotlib inline

plt.plot(list(results.keys()), list(results.values()))
plt.show()
```



.

Random Forests

In [220]:
```
titanicR_model =RandomForestRegressor(random_state=1)
titanicR_model.fit(train_X, train_y)
titanic_preds =titanicR_model.predict(val_X)
rf_val_me = mean_absolute_error(titanic_preds,val_y)
```

In [222]:
```
print("Validation MAE for Random Forest Model: {}".format(rf_val_me))
```

```
Validation MAE for Random Forest Model: 0.2667188466961562
```

```
.
```

XGBoost

In [235]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X, y)
```

In [237]:
```
y = titanic.Survived
feature_names = ['Pclass','Sex','Age','SibSp','Parch','Embarked']

X = titanic[feature_names]
```

In [238]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X, y)
```

In [239]:
```
from xgboost import XGBRegressor

my_model = XGBRegressor()
my_model.fit(X_train, y_train)
```

Out[239]:

XGBRegressor

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.300000012, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [240]:
```
predictions = my_model.predict(X_valid)
print("Mean Absolute Error: " + str(mean_absolute_error(predictions, y_valid)))
```

```
Mean Absolute Error: 0.2289092766286517
```

In [245]:
```
mae_1 = mean_absolute_error(predictions, y_valid)
print("Mean Absolute Error:" , mae_1)
```

```
Mean Absolute Error: 0.2289092766286517
```

In [254]:
```
my_model_1 = XGBRegressor(n_estimators=500)
my_model_1.fit(X_train, y_train,
             early_stopping_rounds=5,
             eval_set=[(X_valid, y_valid)],
             verbose=False)
```

Out[254]:

XGBRegressor

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.300000012, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=500, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [251]:
```
my_model_2 = XGBRegressor(n_estimators=1)

my_model_2.fit(X_train,y_train)

predictions_2 = my_model_2.predict(X_valid)

mae_2 = mean_absolute_error(predictions_2,y_valid)

print("Mean Absolute Error:" , mae_2)
```

```
Mean Absolute Error: 0.41749491191765653
```

In [255]:
```
my_model_3 = XGBRegressor(n_estimators=1000, learning_rate=0.05)
my_model_3.fit(X_train, y_train,
             early_stopping_rounds=5,
             eval_set=[(X_valid, y_valid)],
             verbose=False)
```

Out[255]:

XGBRegressor

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.05, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=1000, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [256]:
```
my_model_4 = XGBRegressor(n_estimators=1000, learning_rate=0.05, n_jobs=4)
my_model_4.fit(X_train, y_train,
             early_stopping_rounds=5,
             eval_set=[(X_valid, y_valid)],
             verbose=False)
```

Out[256]:

XGBRegressor

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.05, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=1000, n_jobs=4,
             num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [260]:
```
my_model_3 = XGBRegressor(n_estimators=1000, learning_rate=0.05)
my_model_3.fit(X_train, y_train,
             early_stopping_rounds=5,
             eval_set=[(X_valid, y_valid)],
             verbose=False)
predictions_3 = my_model_3.predict(X_valid)
mae_3 = mean_absolute_error(predictions_3,y_valid)
```

In [263]:
```
print("Mean Absolute Error:", mae_3)
```

```
Mean Absolute Error: 0.22388406896404087
```

In [ ]: