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Assignment - 8

Features: The titanic dataset has roughly the following types of features:

```
- Categorical/Nominal: Variables that can be divided into
multiple categories but having no order or priority.
Eg. Embarked (C = Cherbourg; Q = Queenstown; S = Southampton)
- Binary: A subtype of categorical features, where the
variable has only two categories.
Eg: Sex (Male/Female)
- Ordinal: They are similar to categorical features but they
have an order(i.e can be sorted).
Eg. Pclass (1, 2, 3)
- Continuous: They can take up any value between the minimum
and maximum values in a column.
Eg. Age, Fare
- Count: They represent the count of a variable.
Eg. SibSp, Parch
- Useless: They don’t contribute to the final outcome of an ML
model. Here, PassengerId, Name, Cabin and Ticket might fall
into this category.
```

In [ ]:

```
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:

```
data = pd.read_csv("titanic.csv")
```

In [ ]:

```
data.head()
```

Out[ ]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.283
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.100
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.050

In [ ]:

```
data.drop(columns=["Cabin","PassengerId","Name","Ticket"],inplace=True)
data.isnull().sum()
```

Out[ ]:

```
Survived      0
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Embarked      2
dtype: int64
```

In [ ]:

```
data["Age"].fillna(value=data["Age"].median(), inplace=True)
data["Embarked"] = data["Embarked"].fillna('S')
data.isnull().sum()
```

Out[ ]:

```
Survived    0
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Embarked    0
dtype: int64
```

In [ ]:

```
data.dtypes
```

Out[ ]:
```
Survived      int64
Pclass        int64
Sex          object
Age         float64
SibSp         int64
Parch         int64
Fare        float64
Embarked     object
dtype: object
```

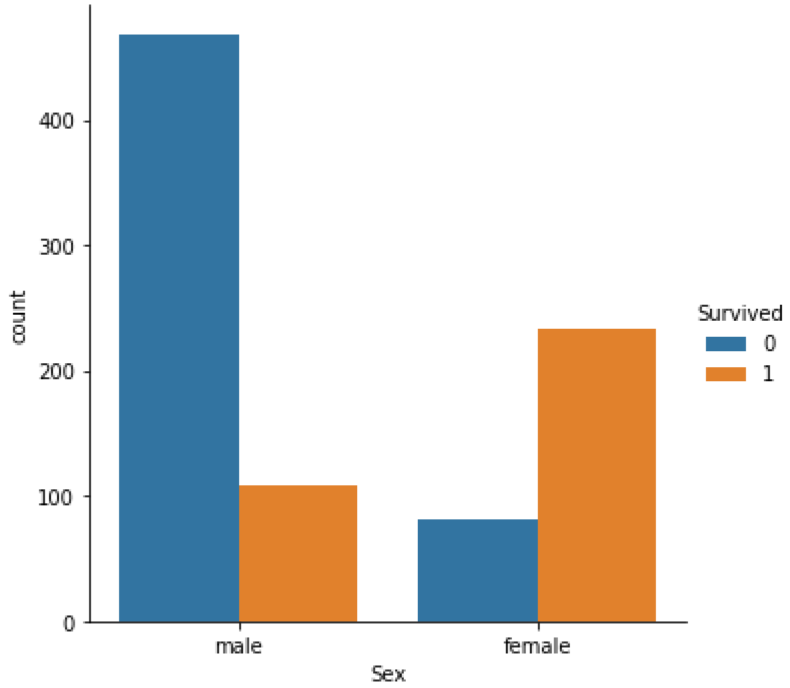
In [ ]:
```
data["Age"]= data["Age"].astype("int")
```

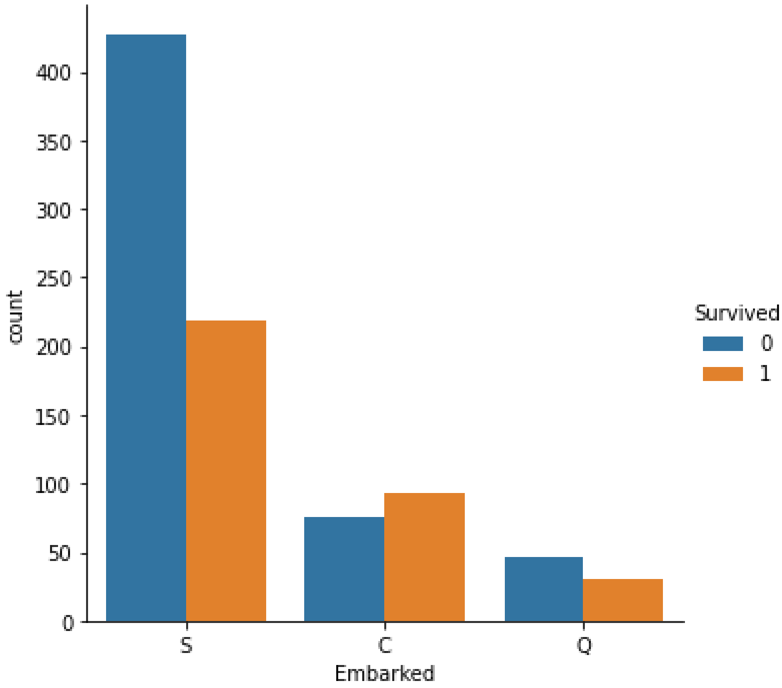
In [ ]:
```
# seperate the data into numeric and categorical
data_num = data[['Age','SibSp','Parch','Fare']]
data_cat = data[['Survived','Pclass','Sex']]
```

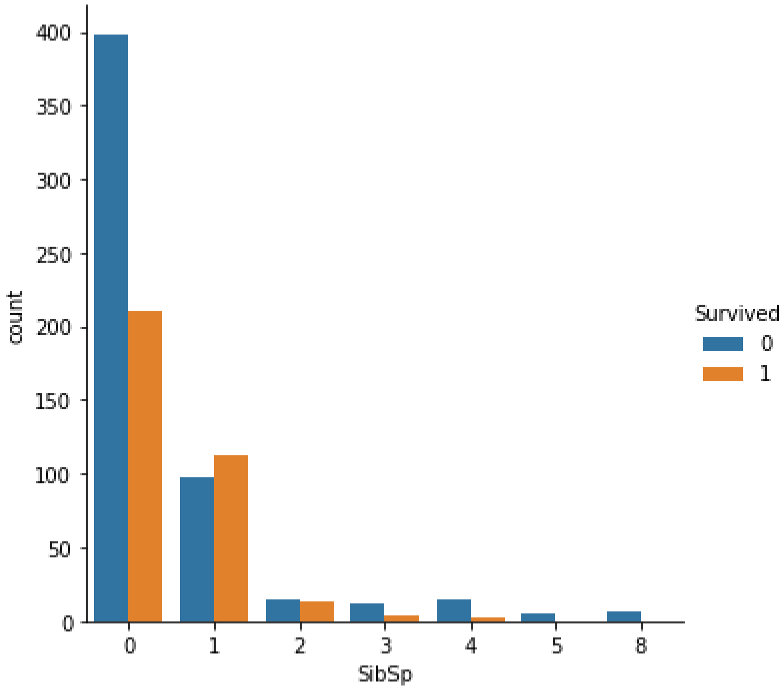
1. Finding patterns in the data

In [ ]:
```
sb.catplot(x="Sex", hue="Survived",kind="count",data=data)
sb.catplot(x="Embarked", hue="Survived",kind="count",data=data)
sb.catplot(x="SibSp", hue="Survived",kind="count",data=data)
```

Out[ ]: <seaborn.axisgrid.FacetGrid at 0x7f2569085700>







it can be approximated that the survival rate of men is around 20% and that of women is around 75%.

Pclass(Ordinal) vs Survived

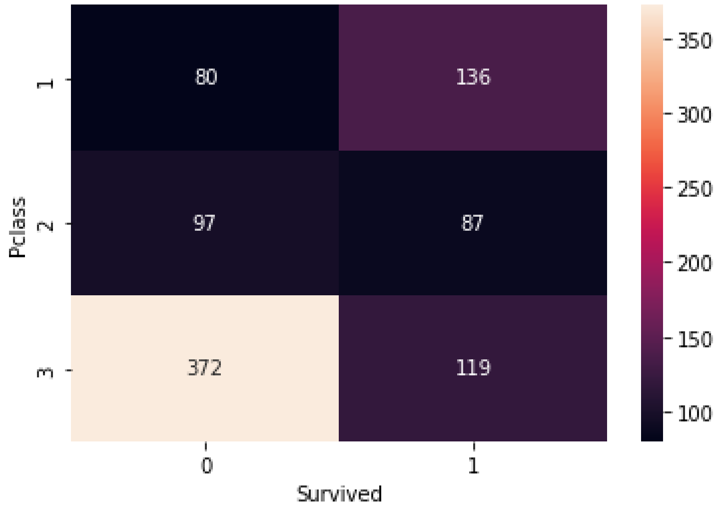
In [ ]:

```
group = data.groupby(['Pclass', 'Survived'])
pclass_survived = group.size().unstack() #creates a 2d matrix wrt Pclass

# Heatmap - Color encoded 2D representation of data.
sb.heatmap(pclass_survived, annot = True, fmt ="d")
```

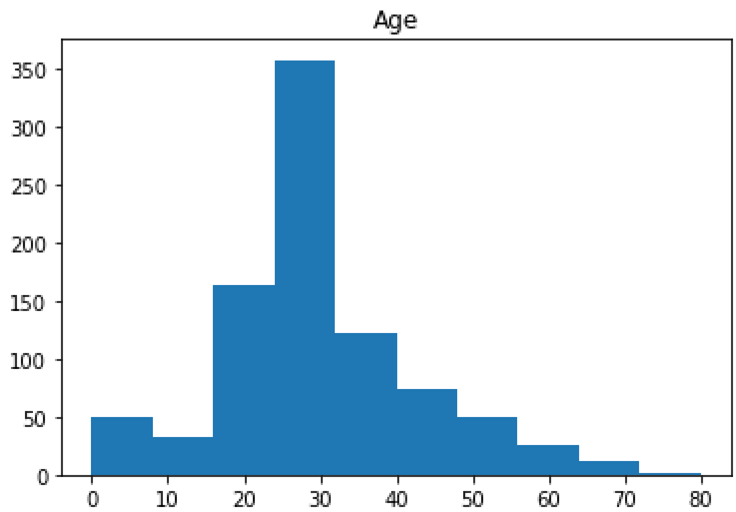
Out[ ]:

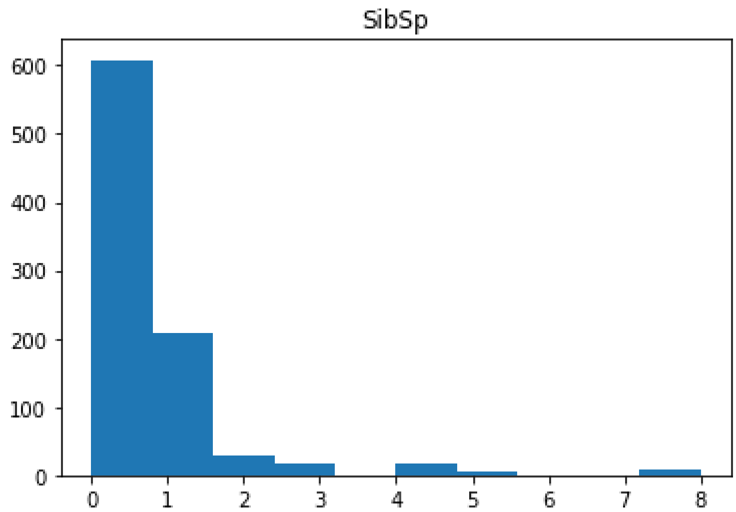
```
<AxesSubplot:xlabel='Survived', ylabel='Pclass'>
```

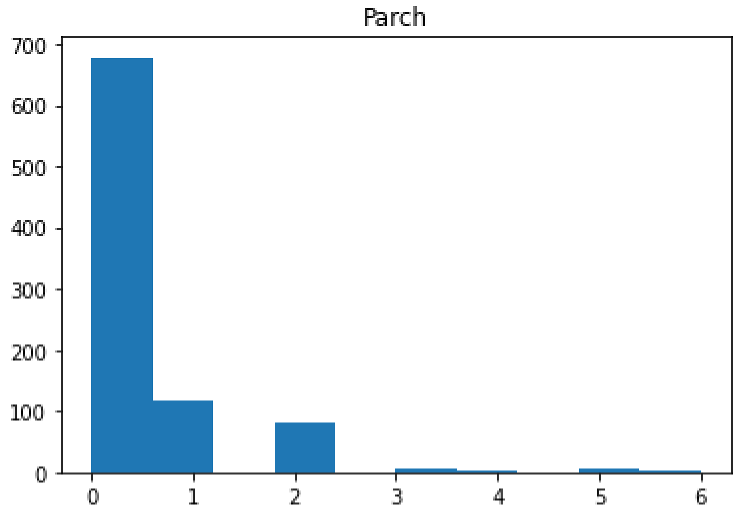


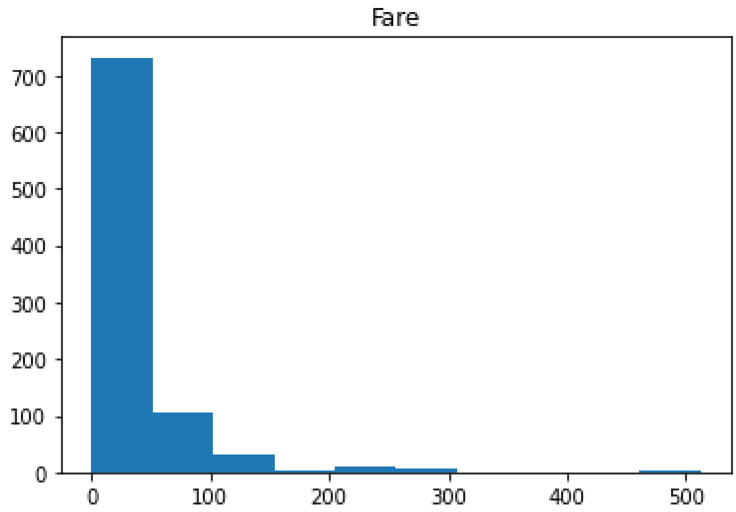
Plots for numeric data

In [ ]:
```
for i in data_num:
    plt.hist(data_num[i])
    plt.title(i)
    plt.show()
```





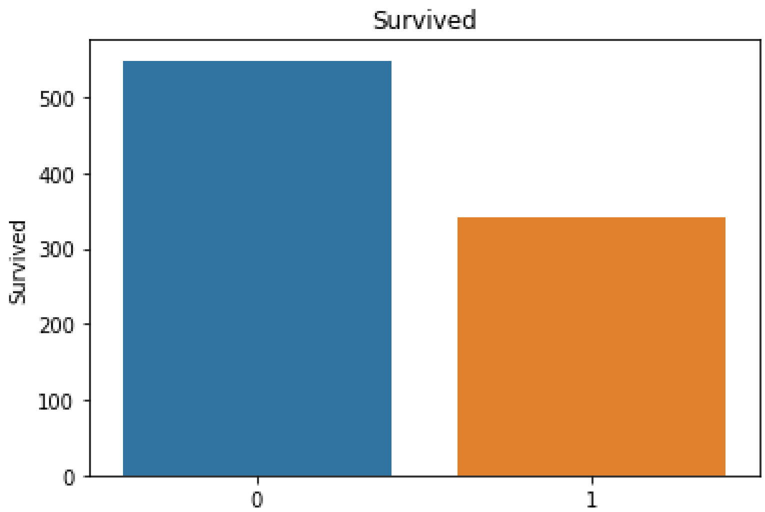


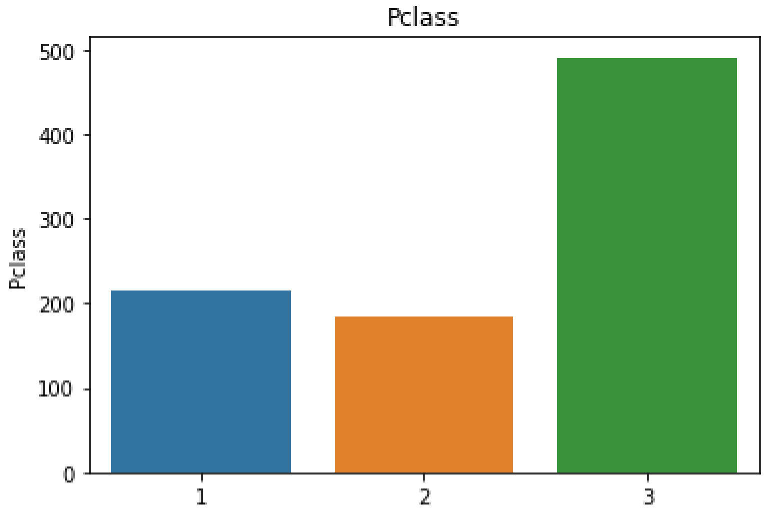


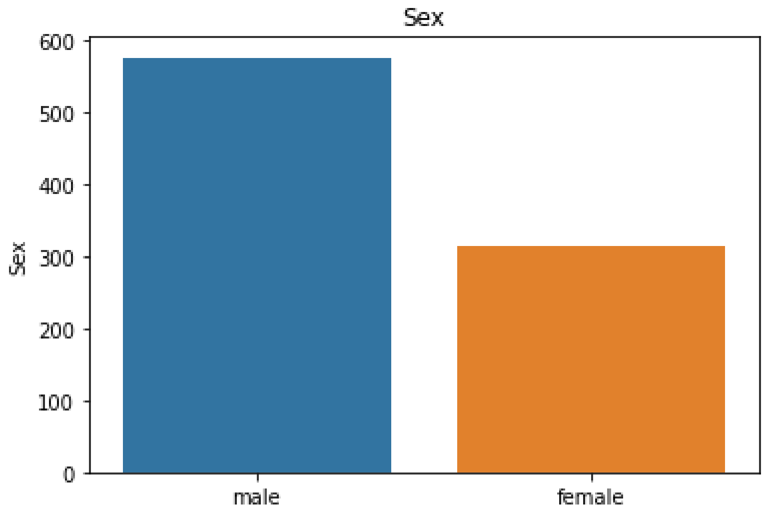
most of the distributions are scattered, except Age, it's pretty normalized.

Plots for categorical Data

In [ ]:
```
for i in data_cat.columns:
    sb.barplot(data_cat[i].value_counts().index,data_cat[i].value_counts())
    plt.show()
```





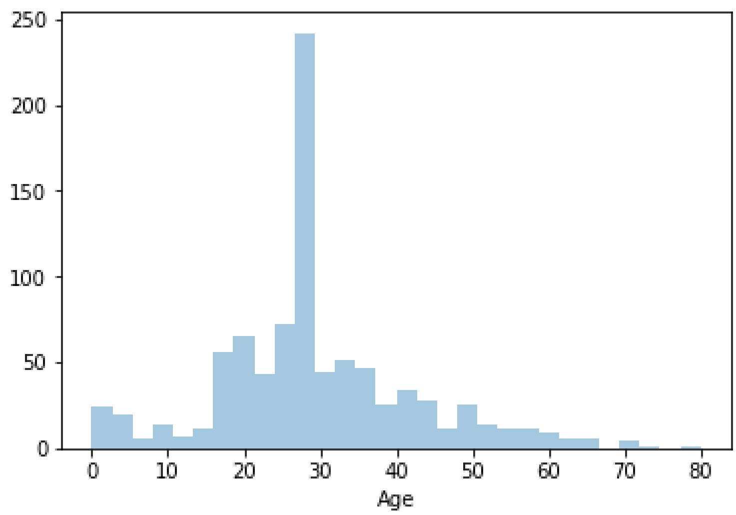


Histogram

In [ ]:

```
sb.distplot(data["Age"],kde=False,bins=30)
```

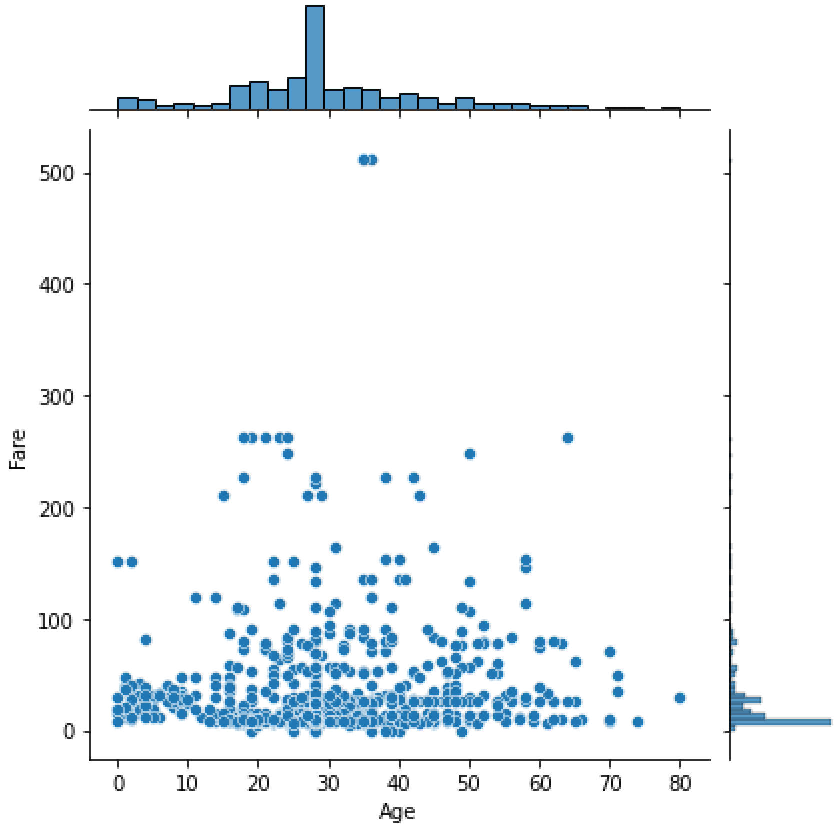
Out[ ]: <AxesSubplot:xlabel='Age'>



In [ ]:

```
sb.jointplot(x='Age', y='Fare', data=data)
```

Out[ ]: <seaborn.axisgrid.JointGrid at 0x7f255f869400>



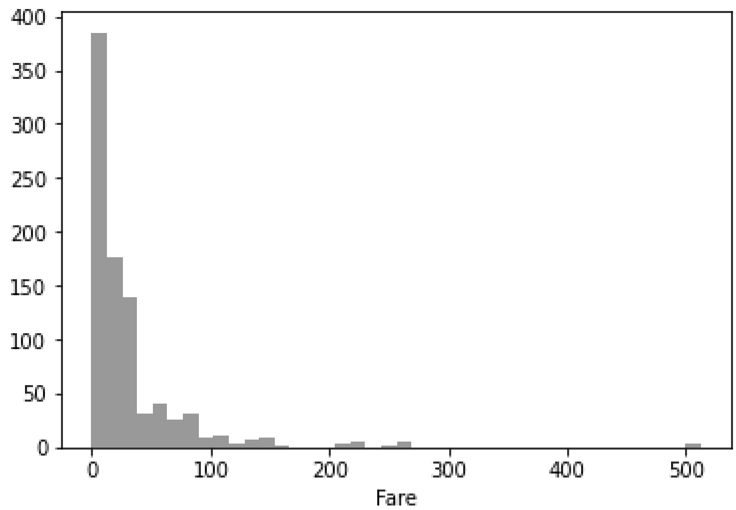
A distribution plot at the top for the column on the x-axis, a distribution plot on the right for the column on the y-axis and a scatter plot in between that shows the mutual distribution of data for both the columns. You can see that there is no correlation observed between prices and the fares.

2. Write a code to check how the price of the ticket (column name: 'fare') for each passenger is distributed by plotting a histogram.

In [ ]:

```
sb.distplot(data["Fare"],kde=False,bins=40, color='black')
# It is not normally distributed(right-only)
```

Out[ ]: <AxesSubplot:xlabel='Fare'>

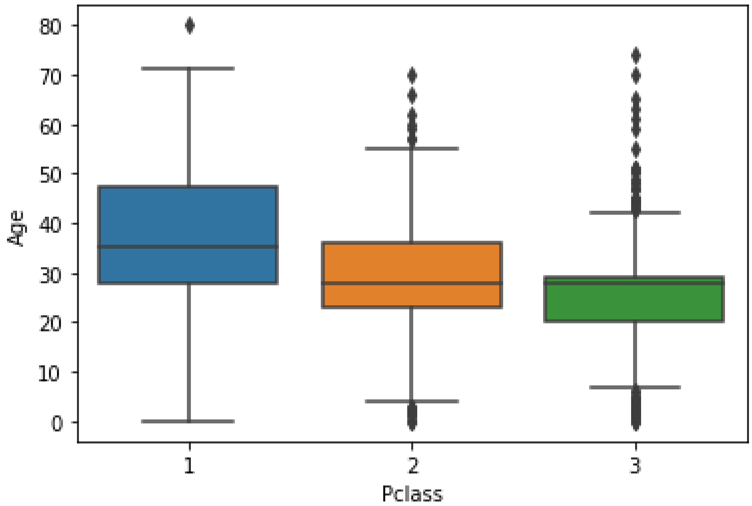


Looking for outliers

In [ ]:

```
sb.boxplot(x='Pclass', y='Age', data=data)
```

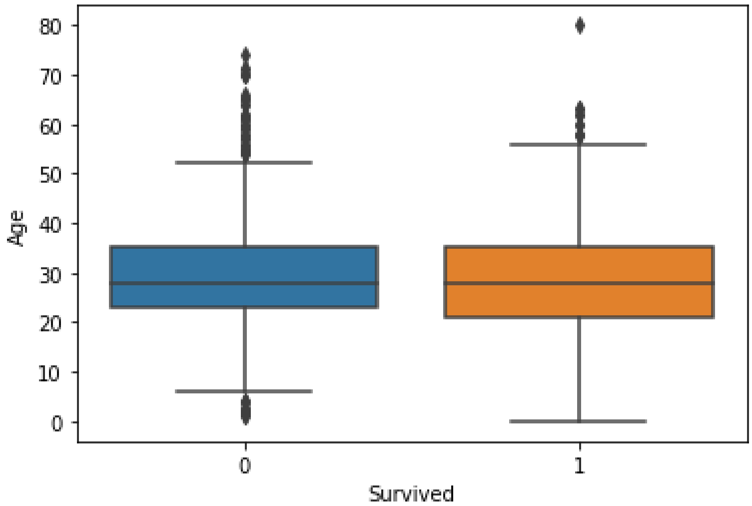
Out[ ]: <AxesSubplot:xlabel='Pclass', ylabel='Age'>



In [ ]:

```
sb.boxplot(x='Survived', y='Age', data=data)
```

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



To summarize, here're the characteristics of survivors compared to victims.

```
1. Survivors were more likely to have parents / children
aboard the Titanic and have relatively more expensive tickets.
2. Children were more likely to survive compared to victims
among all age groups.
Passengers with missing age were less likely to be survivors.
3. Passengers with higher pclass were more likely to survive.
4. Women were much more likely to survive than men.
5. Passengers embarked at Cherbourg had a higher chance to
survive than passengers embarked at Queenstown and
Southampton.
```