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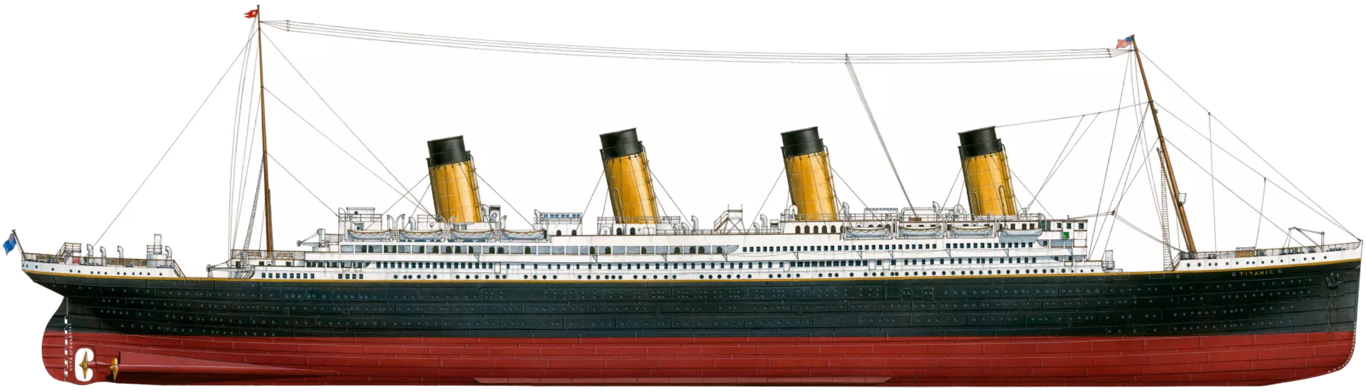
데이터분석 프로그래밍

Get Help From Youtube and Kaggle

Titanic 타이타니크 머신 러닝



Introduction

1.Data source Kaggle + Youtube

2.To predict whether a passenger on the titanic would have been survived or not.

Import libraries

import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import matplotlib.pyplot as plt

%matplotlib inline

Getting the data

In [2]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

```
data = pd.read_csv('train.csv')
data.head()
```

Out[3]:

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

From the table above, we can note a few things. First of all, that we need to convert a lot of features into numeric ones later on, so that the machine learning algorithms can process them. Furthermore, we can see that the features have widely different ranges, that we will need to convert into roughly the same scale. We can also spot some more features, that contain missing values (NaN = not a number), that wee need to deal with.

Data Exploration/Analysis

In [4]:

```
data.shape
```

Out[4]:

```
(891, 12)
```

In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

The training-set has 891 examples and 11 features + the target variable (survived). 2 of the features are floats, 5 are integers and 5 are objects.

Through this data we would like to find the effect of various factors such as age, sex, station of Embarkment,their class and no. of relatives present on survival chances of passangers.our cabin column has lots of null values.so we would not like to modify it much. there is only 2 entries in embarked column having null values,so we will replace it with mode value of point of embarktion

In [6]:

```
data.describe()
```

Out[6]:

	PassengerId	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

Above we can see that 38% out of the training-set survived the Titanic. We can also see that the passenger ages range from 0.4 to 80. On top of that we can already detect some features, that contain missing values, like the ‘Age’ feature.

total number of survived passanger

In [7]:

```
data.Survived.sum()
```

Out[7]:

342

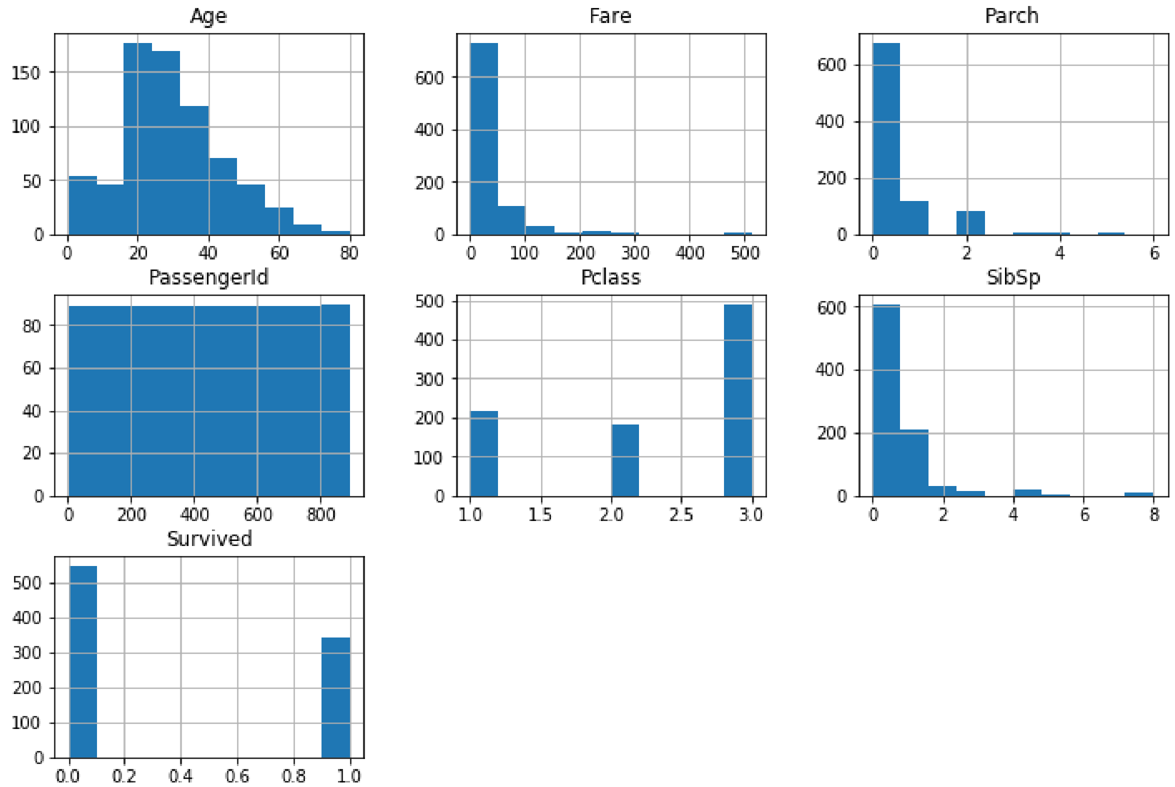
Visulaly analyzing

In [8]:

```
data.hist(figsize=(12,8))
plt.figure()
```

Out[8]:

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

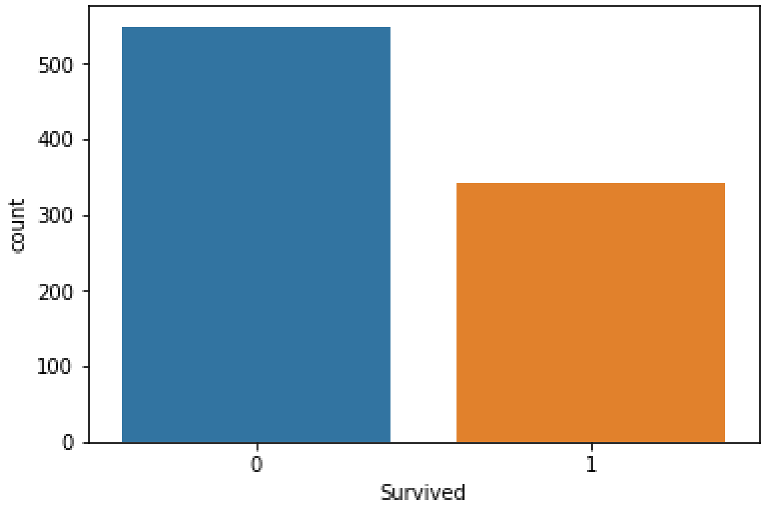
Survived

In [12]:

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

Out[12]:

<matplotlib.axes._subplots.AxesSubplot at 0xbea6d30>

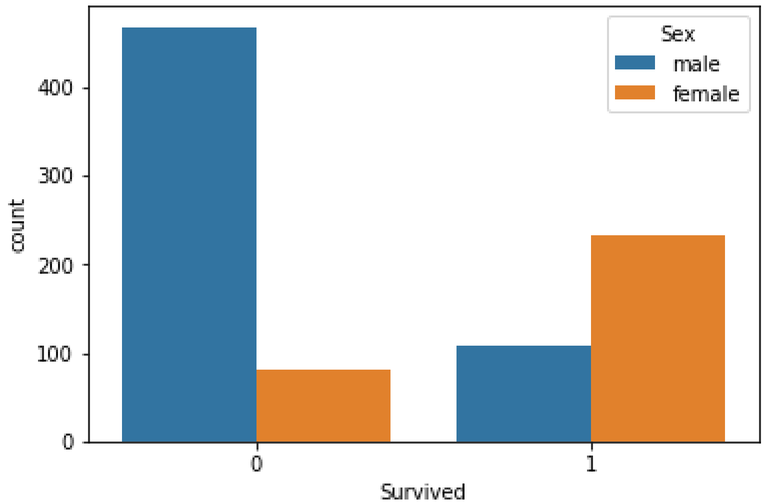


In [13]:

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

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x745ab00>

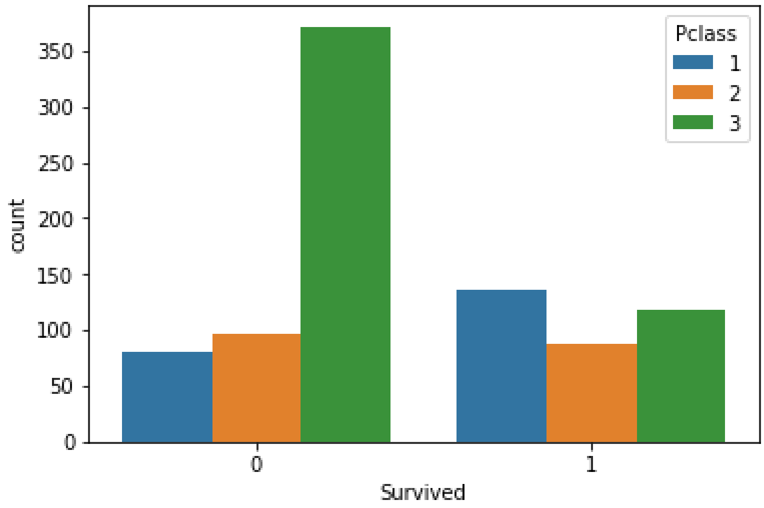


In [14]:

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

Out[14]:

<matplotlib.axes._subplots.AxesSubplot at 0x74b2b70>

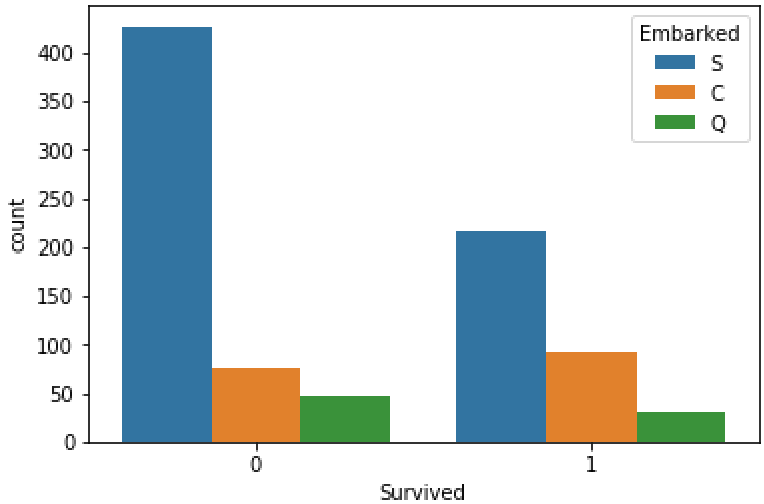


In [15]:

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

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x7515860>



In [ ]:

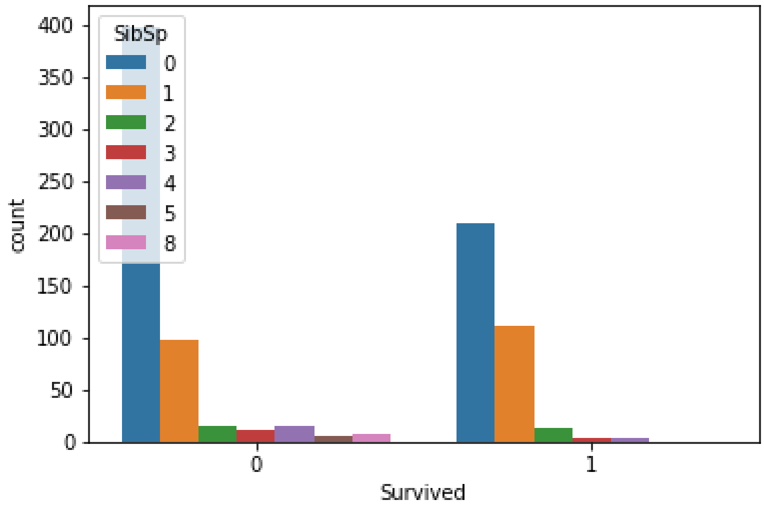
```

```

In [16]:

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

Out[16]:

<matplotlib.axes._subplots.AxesSubplot at 0x7595390>



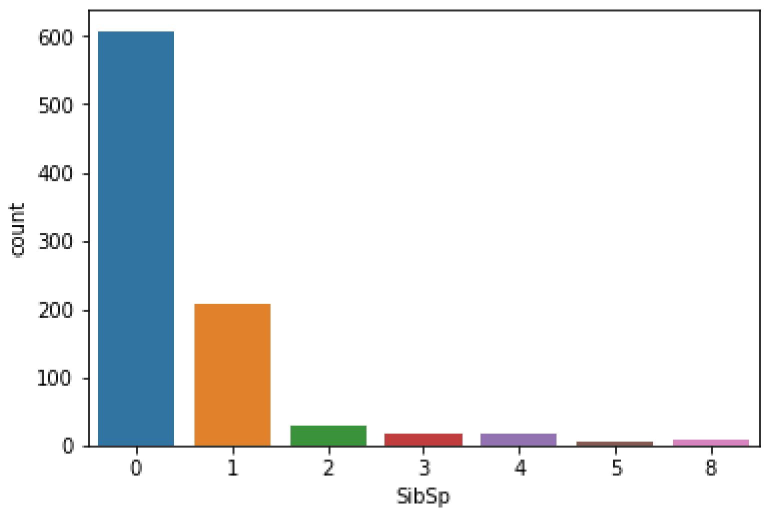
SibSp

In [17]:

```
sns.countplot(x='SibSp',data=data)
```

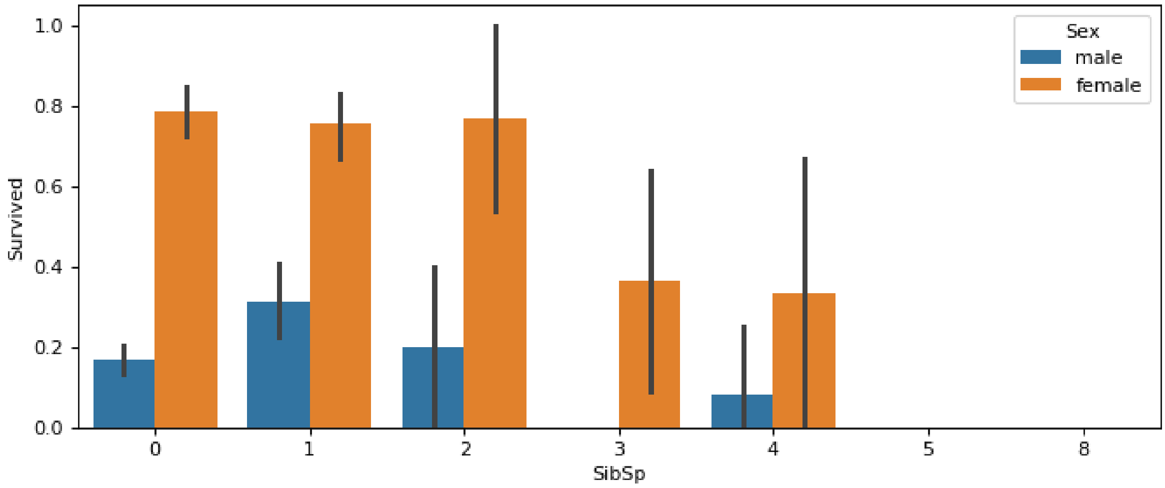
Out[17]:

<matplotlib.axes._subplots.AxesSubplot at 0x76c65c0>



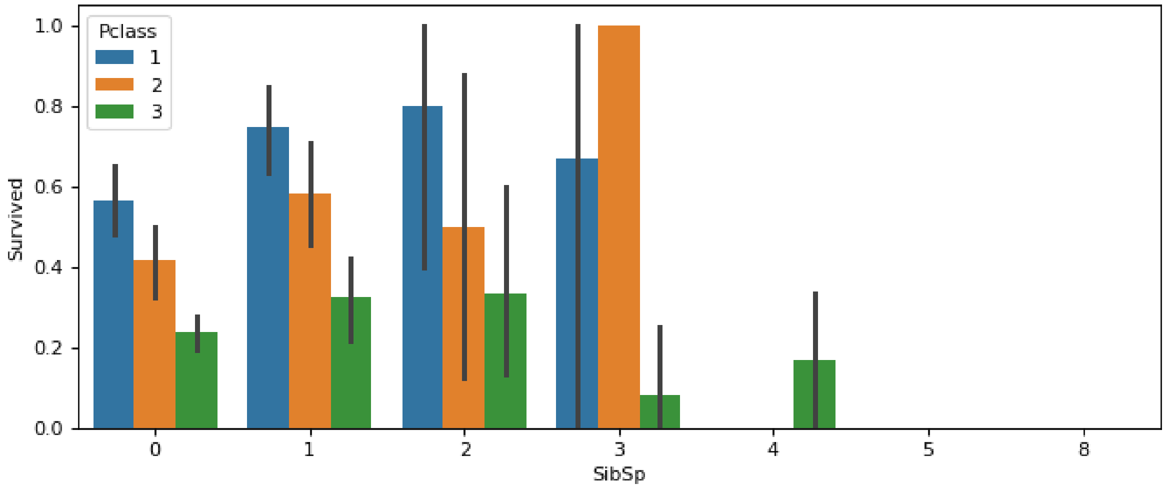
In [18]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='SibSp', y='Survived', hue="Sex", data=data)
plt.show()
```



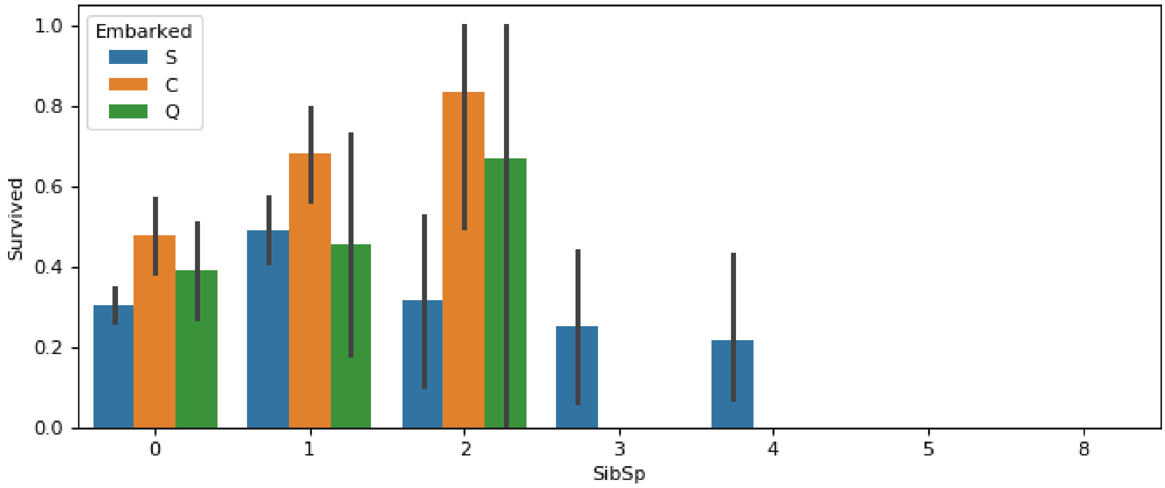
In [19]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='SibSp', y='Survived', hue="Pclass", data=data)
plt.show()
```



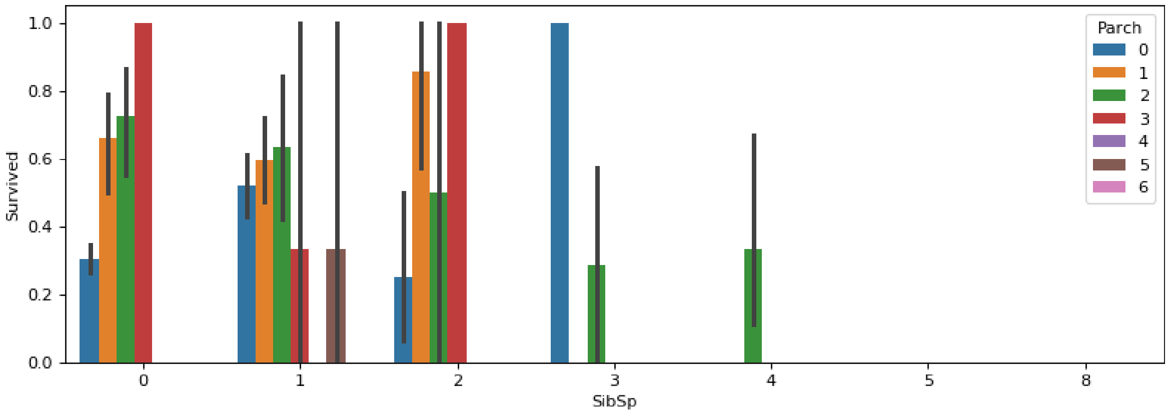
In [20]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='SibSp', y='Survived', hue="Embarked", data=data)
plt.show()
```



In [21]:

```
plt.figure(num=None, figsize=(12, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='SibSp', y='Survived', hue="Parch", data=data)
plt.show()
```



>> SibSp and Parch would make more sense as a combined feature, that shows the total number of relatives, a person has on the Titanic. I will create it below and also a feature that sows if someone is not alone.

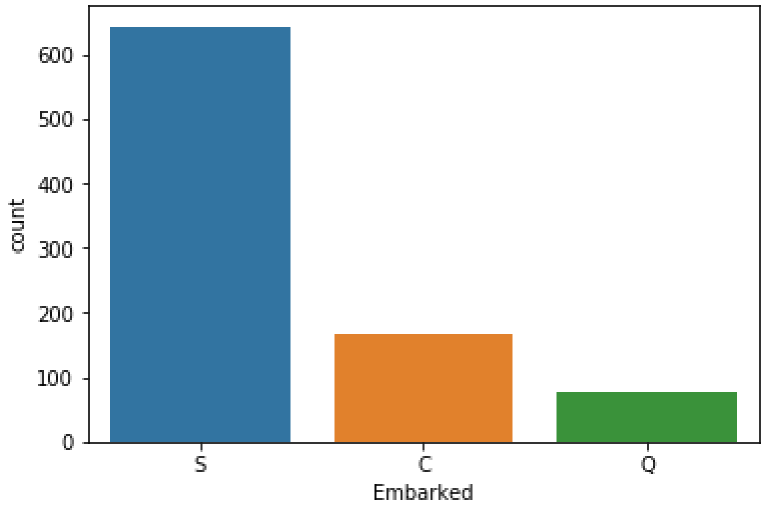
Embarked

In [22]:

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

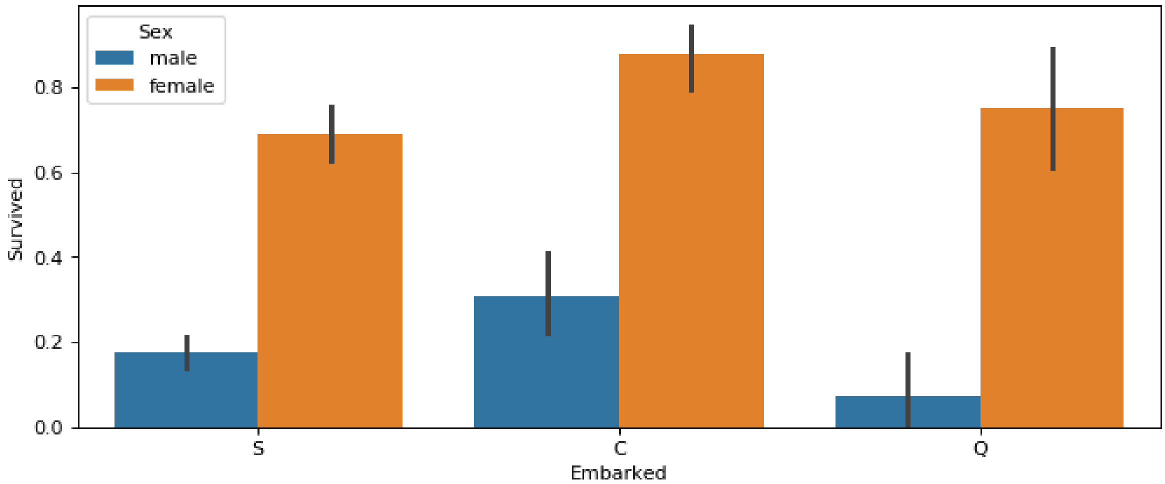
Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xbafbe10>
```



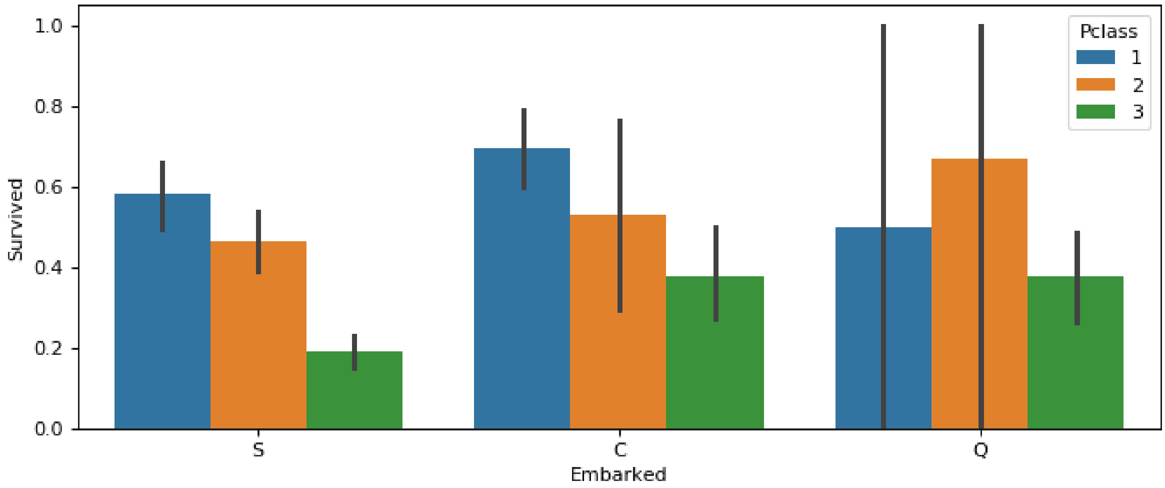
In [23]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Embarked', y='Survived', hue="Sex", data=data)
plt.show()
```



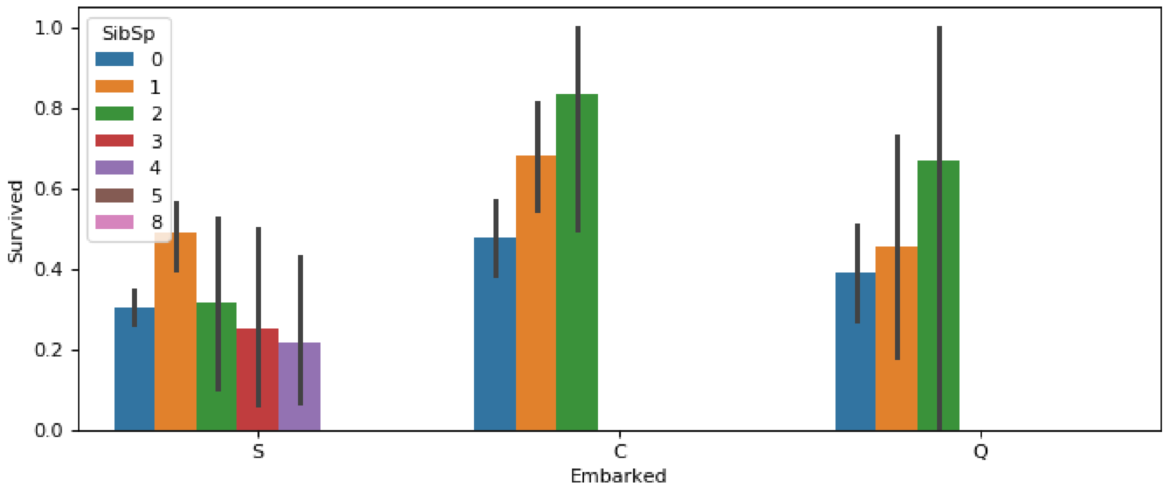
In [24]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Embarked', y='Survived', hue="Pclass", data=data)
plt.show()
```



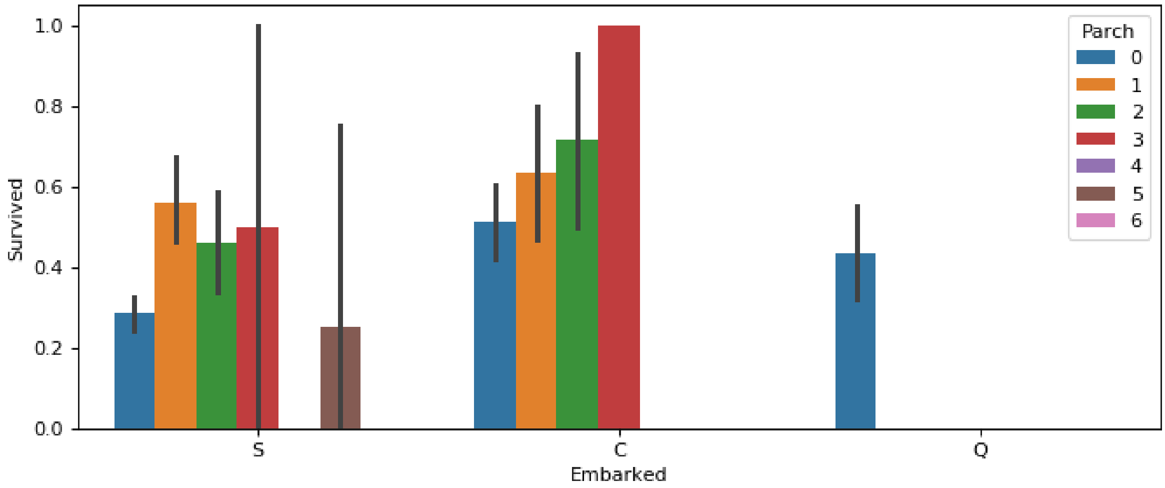
In [25]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Embarked', y='Survived', hue="SibSp", data=data)
plt.show()
```



In [26]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Embarked', y='Survived', hue="Parch", data=data)
plt.show()
```



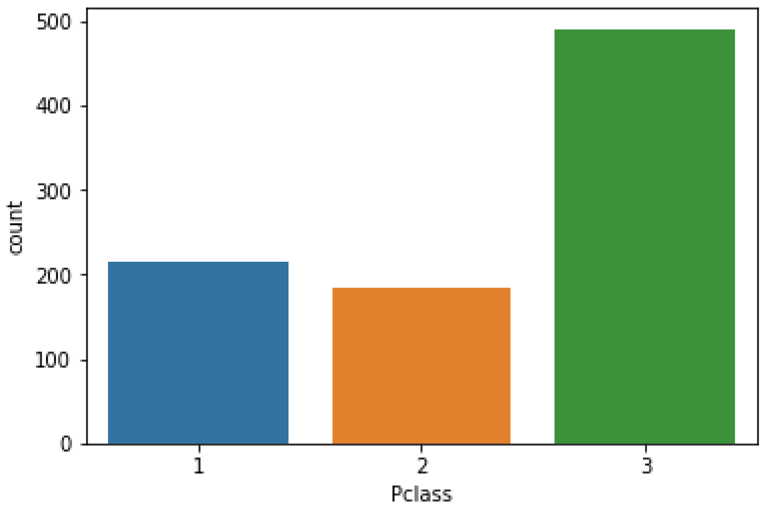
Pclass

In [27]:

```
sns.countplot(x='Pclass',data=data)
```

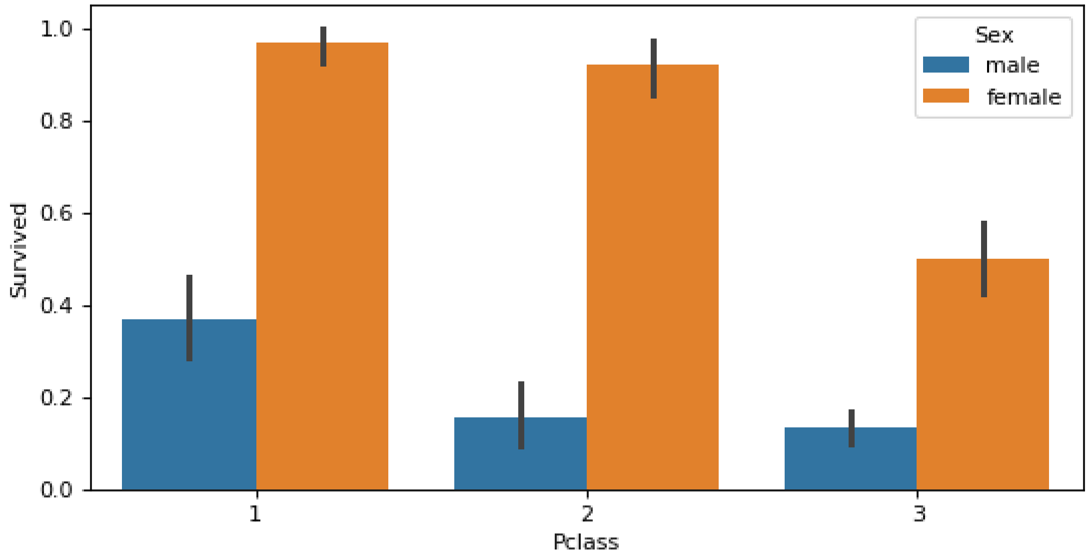
Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xcfb6320>
```



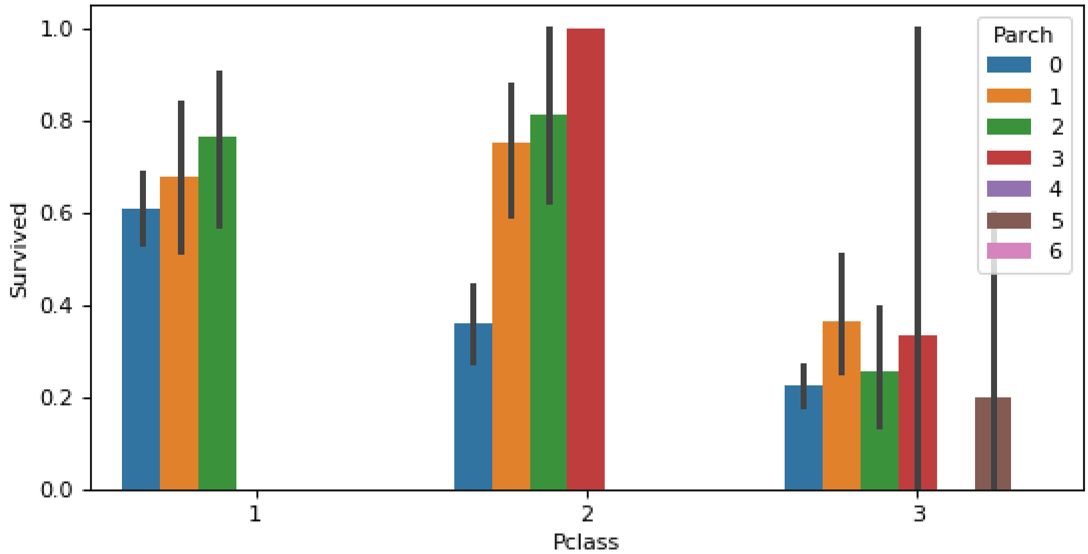
In [28]:

```
plt.figure(num=None, figsize=(8, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Pclass', y='Survived', hue="Sex", data=data)
plt.show()
```



In [29]:

```
plt.figure(num=None, figsize=(8, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(x='Pclass', y='Survived', hue="Parch", data=data)
plt.show()
```



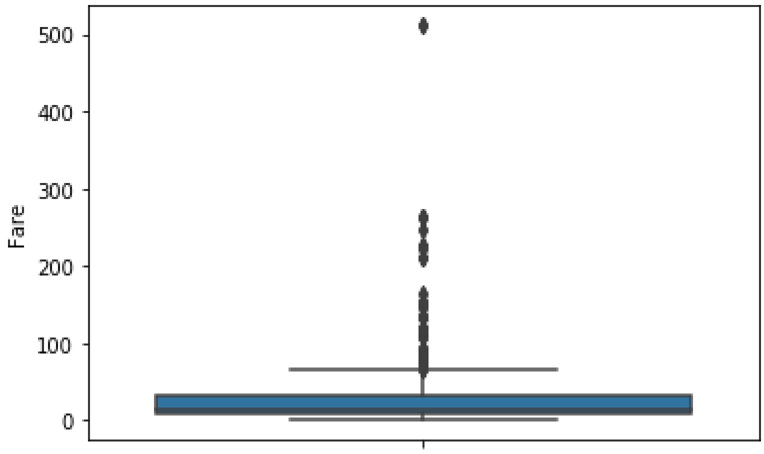
Fare

In [30]:

```
sns.boxplot(y='Fare',data=data)
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x7749208>

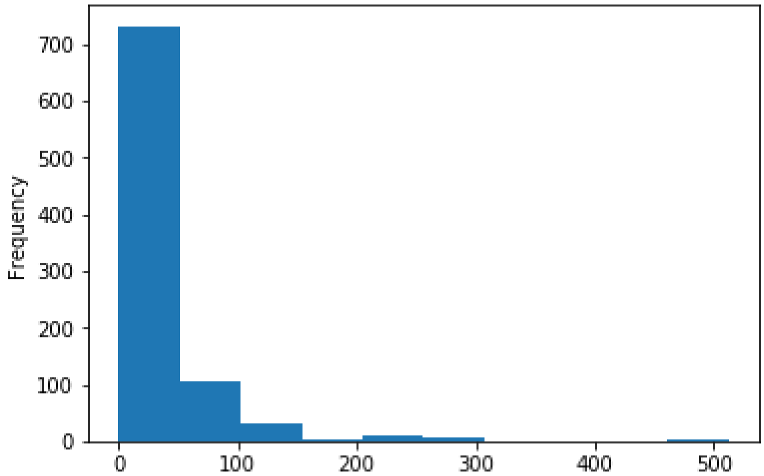


In [35]:

```
data['Fare'].plot.hist()
```

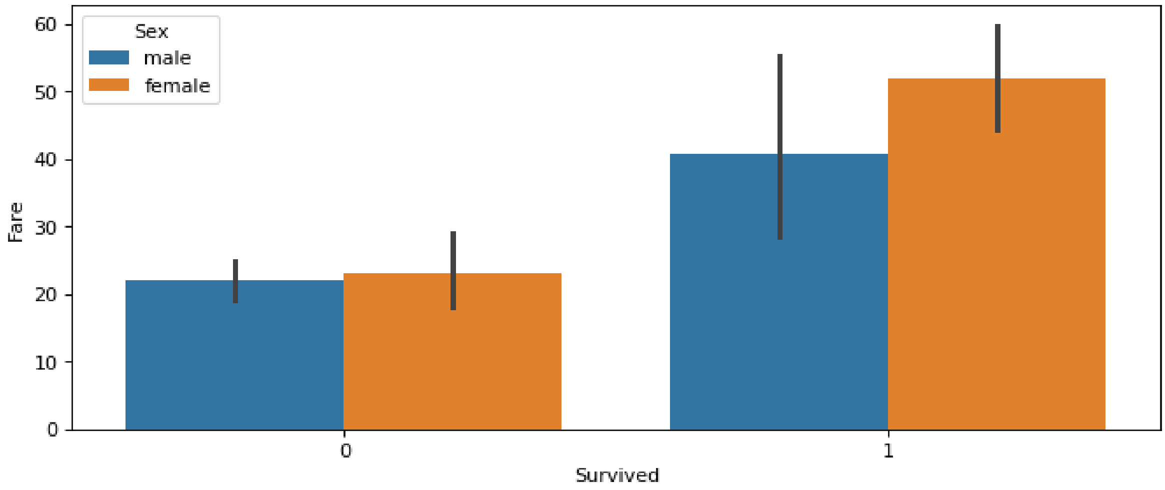
Out[35]:

<matplotlib.axes._subplots.AxesSubplot at 0xa1599e8>



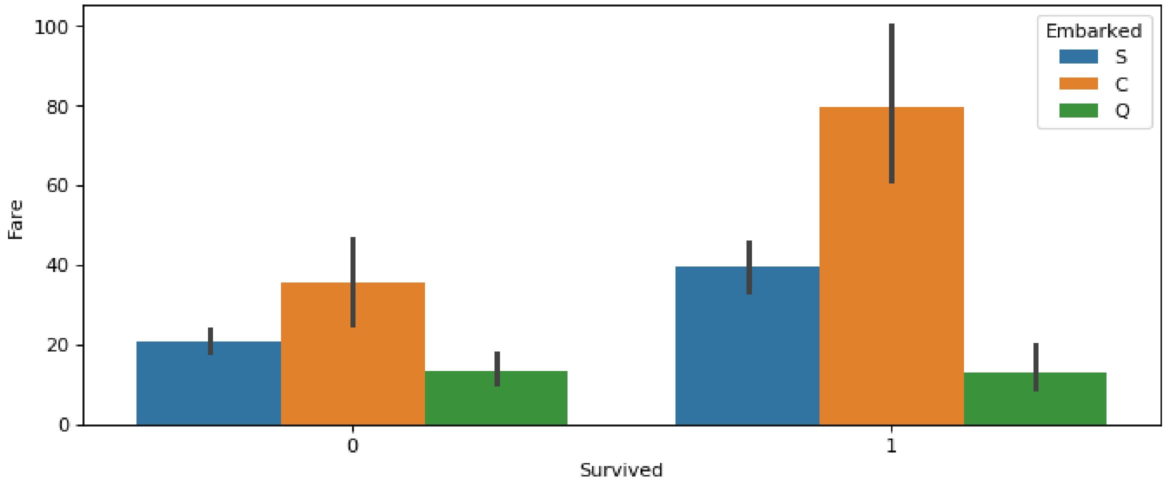
In [31]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(y='Fare', x='Survived', hue="Sex", data=data)
plt.show()
```



In [32]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(y='Fare', x='Survived', hue="Embarked", data=data)
plt.show()
```

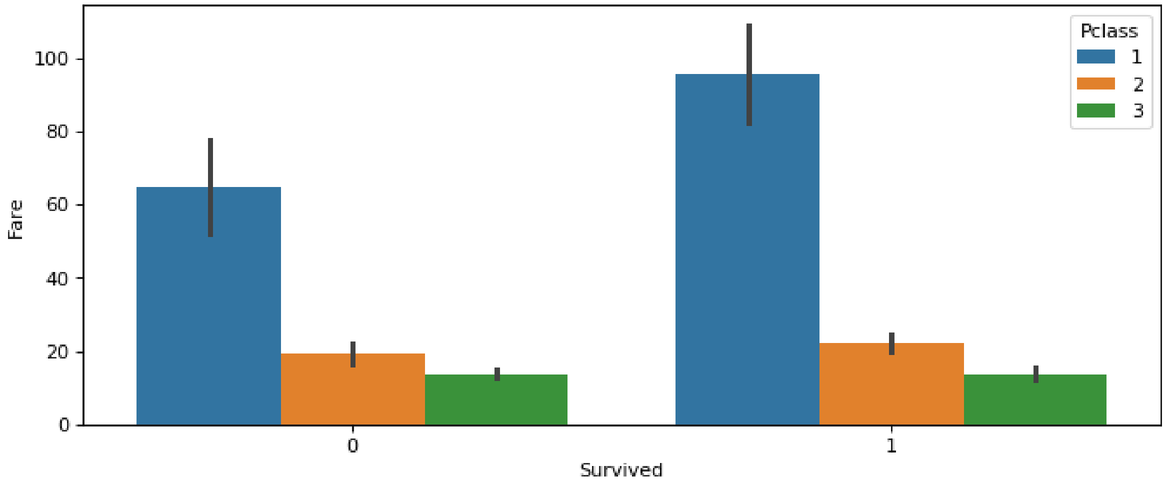


>> In this plot we see that Fare is directly proportional to Embarked and Embarked is proprtional to Survived. Embarked C survied more in comprission to S and Q.

>> Fare and Survived is in the order of C>S>Q

In [33]:

```
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w', edgecolor='k')
# specify hue="categorical_variable"
sns.barplot(y='Fare', x='Survived', hue="Pclass", data=data)
plt.show()
```



Age Feature

In [34]:

```
Ag=data.Age.sort_values().value_counts()
Ag.head(10)
```

Out[34]:

```
24.0    30
22.0    27
18.0    26
28.0    25
30.0    25
19.0    25
21.0    24
25.0    23
36.0    22
29.0    20
Name: Age, dtype: int64
```

In [35]:

```
print('Oldest Passenger was :',data['Age'].max(),'Years')
print('Youngest Passenger was :',data['Age'].min(),'Years')
print('Average Age on the ship was:',data['Age'].mean(),'Years')
```

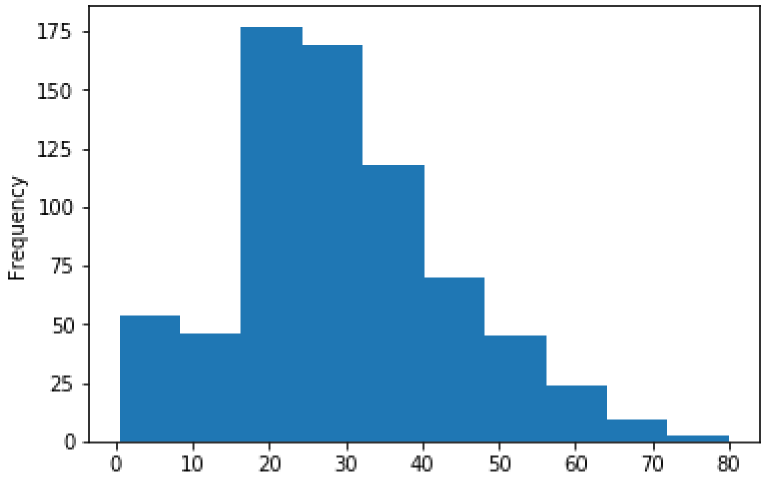
```
Oldest Passenger was : 80.0 Years
Youngest Passenger was : 0.42 Years
Average Age on the ship was: 29.69911764705882 Years
```

In [39]:

```
data['Age'].plot.hist()
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xbbaa5c0>
```



Age histogram based on Pclass,Survived

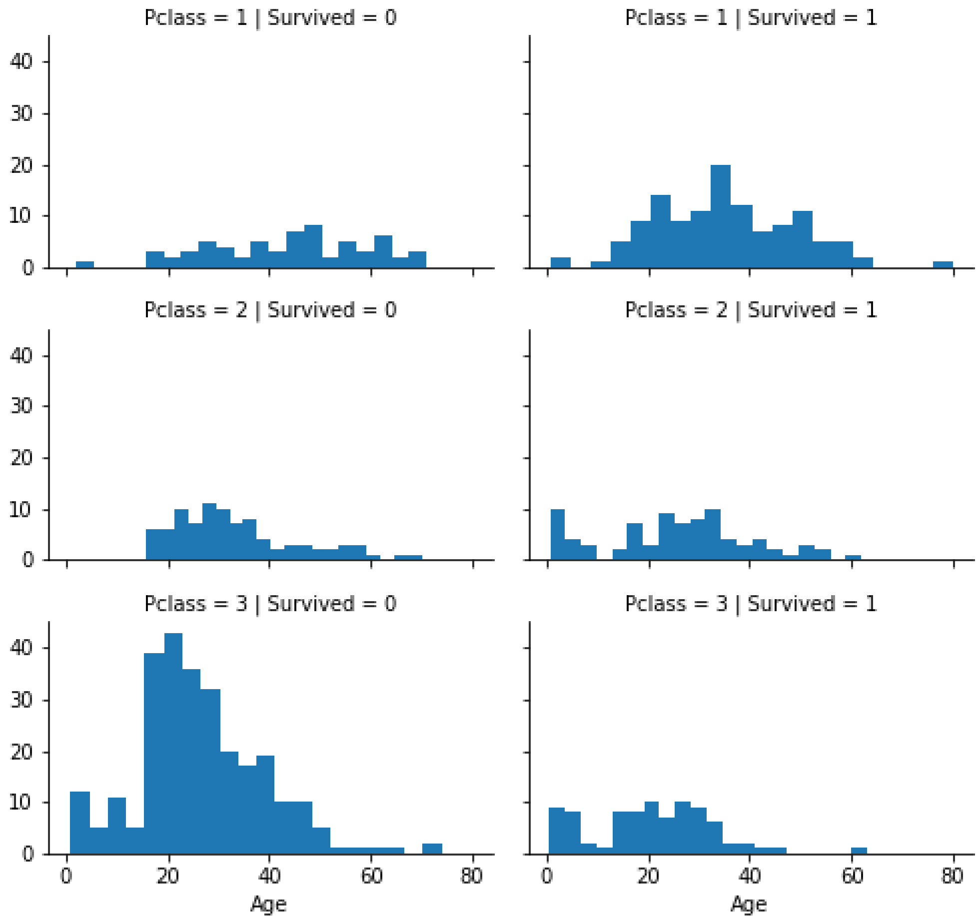
In [40]:

```
grid = sns.FacetGrid(data, col='Survived', row='Pclass', size=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', bins=20)
```

```
C:\Users\krish\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: The
`size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

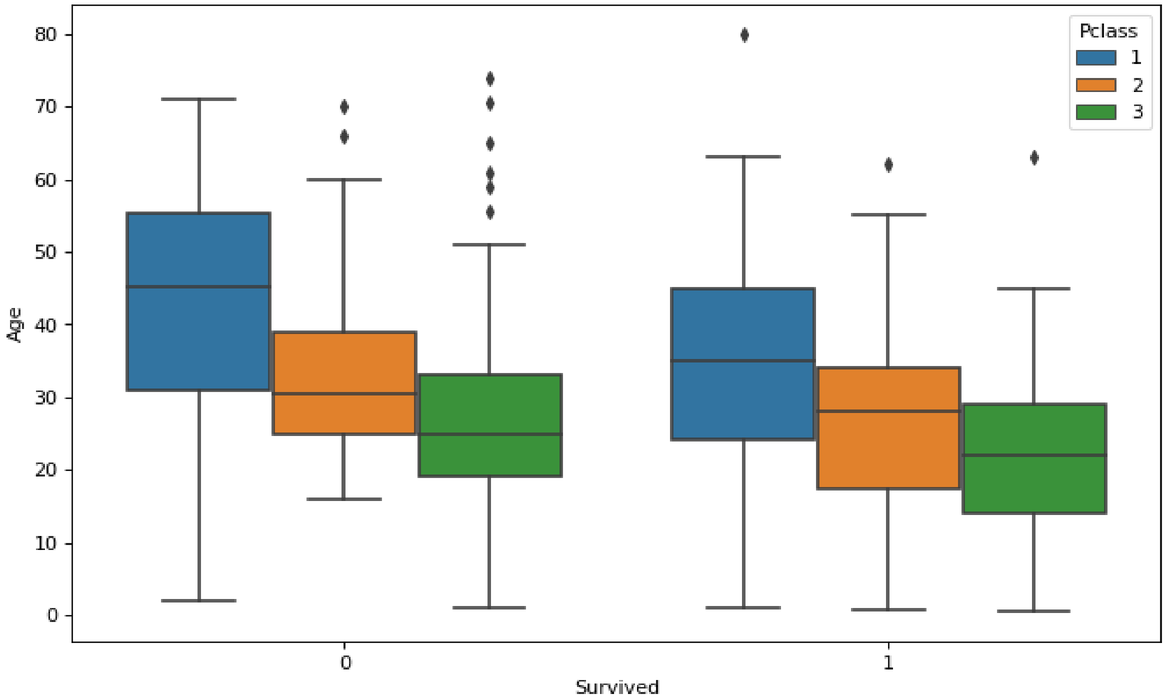
Out[40]:

```
<seaborn.axisgrid.FacetGrid at 0xba0af60>
```



In [41]:

```
plt.figure(num=None, figsize=(10, 6), dpi=80, facecolor='w', edgecolor='k')

# specify hue="categorical_variable"
sns.boxplot(y='Age', x='Survived', hue="Pclass", data=data)
plt.show()
```



>> we see that more no. of passangers survived in upper classes and also children were almost certain to survive if they belonged to higher classes.

Age Histogram based on Gender and Survived

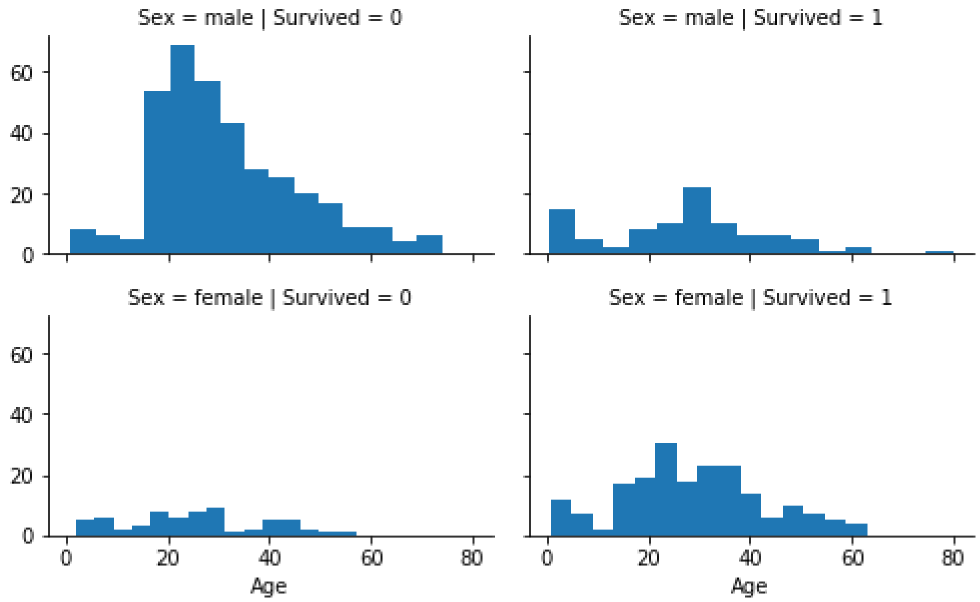
In [42]:

```
grid = sns.FacetGrid(data, col='Survived', row='Sex', size=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', bins=15)
```

```
C:\Users\krish\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: The
`size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

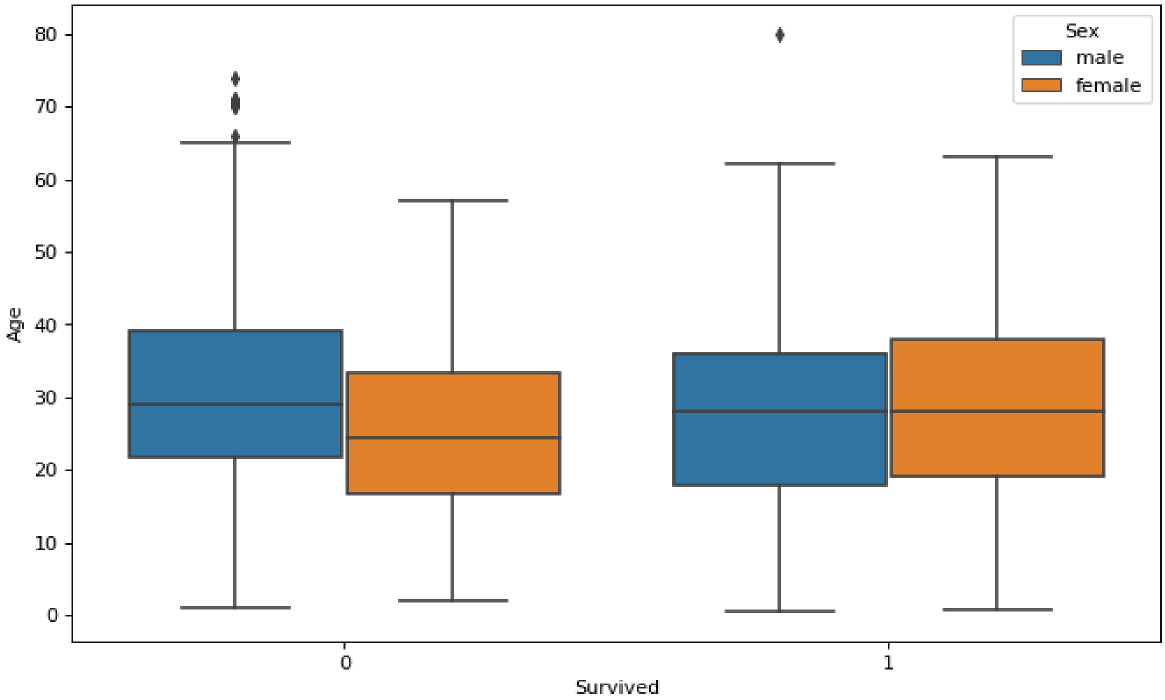
Out[42]:

<seaborn.axisgrid.FacetGrid at 0xbe13710>



In [43]:

```
plt.figure(num=None, figsize=(10, 6), dpi=80, facecolor='w', edgecolor='k')

# specify hue="categorical_variable"
sns.boxplot(y='Age', x='Survived', hue="Sex", data=data)
plt.show()
```



Age histogram based on Embarked,Survived

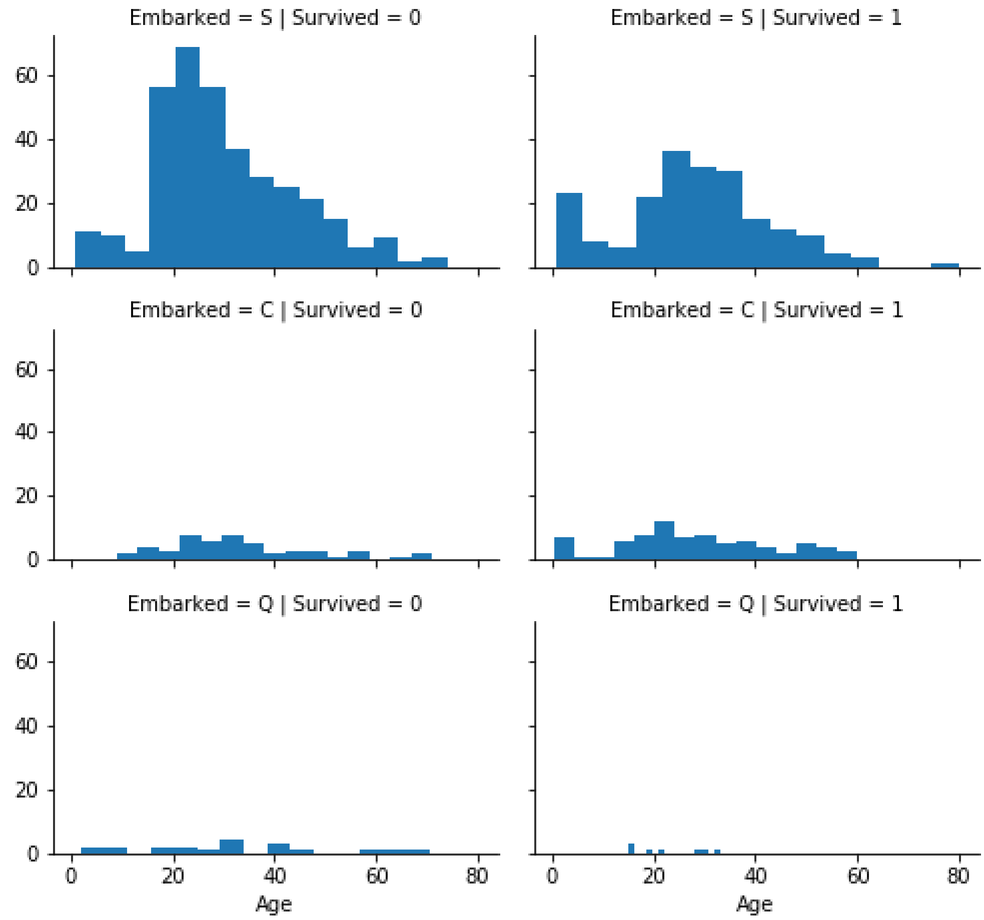
In [44]:

```
grid = sns.FacetGrid(data, col='Survived', row='Embarked', size=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', bins=15)
```

```
C:\Users\krish\Anaconda3\lib\site-packages\seaborn\axisgrid.py:230: UserWarning: The
`size` paramter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

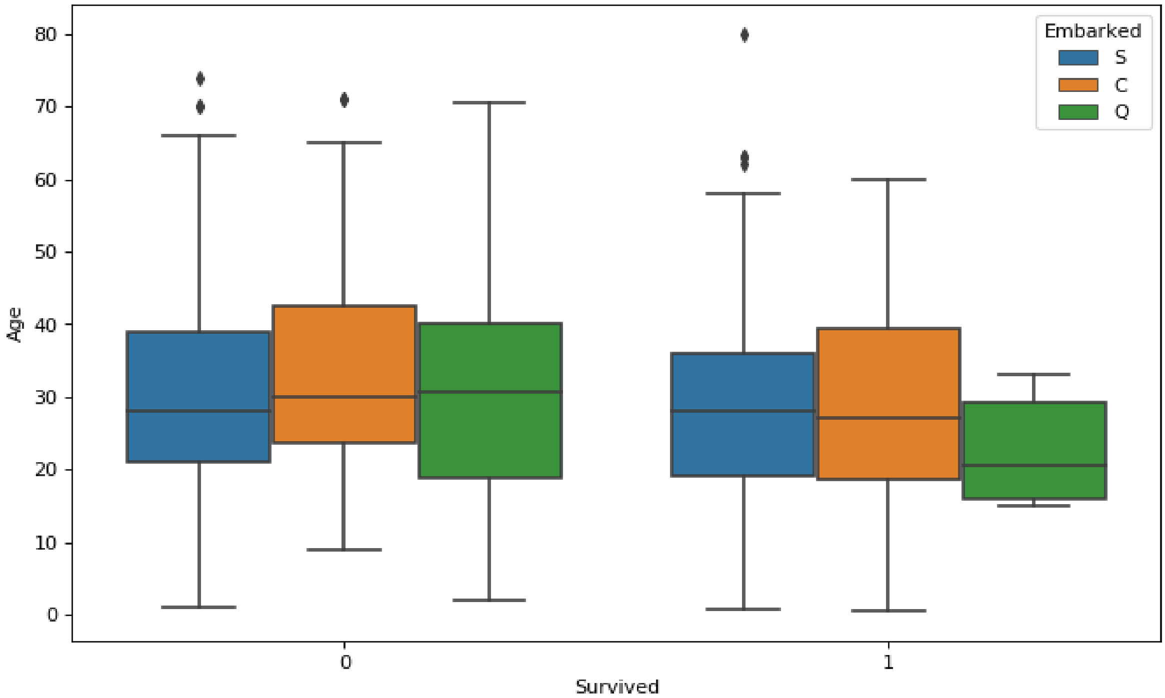
Out[44]:

```
<seaborn.axisgrid.FacetGrid at 0xd2ba860>
```



In [45]:

```
plt.figure(num=None, figsize=(10, 6), dpi=80, facecolor='w', edgecolor='k')

# specify hue="categorical_variable"
sns.boxplot(y='Age', x='Survived', hue="Embarked", data=data)
plt.show()
```

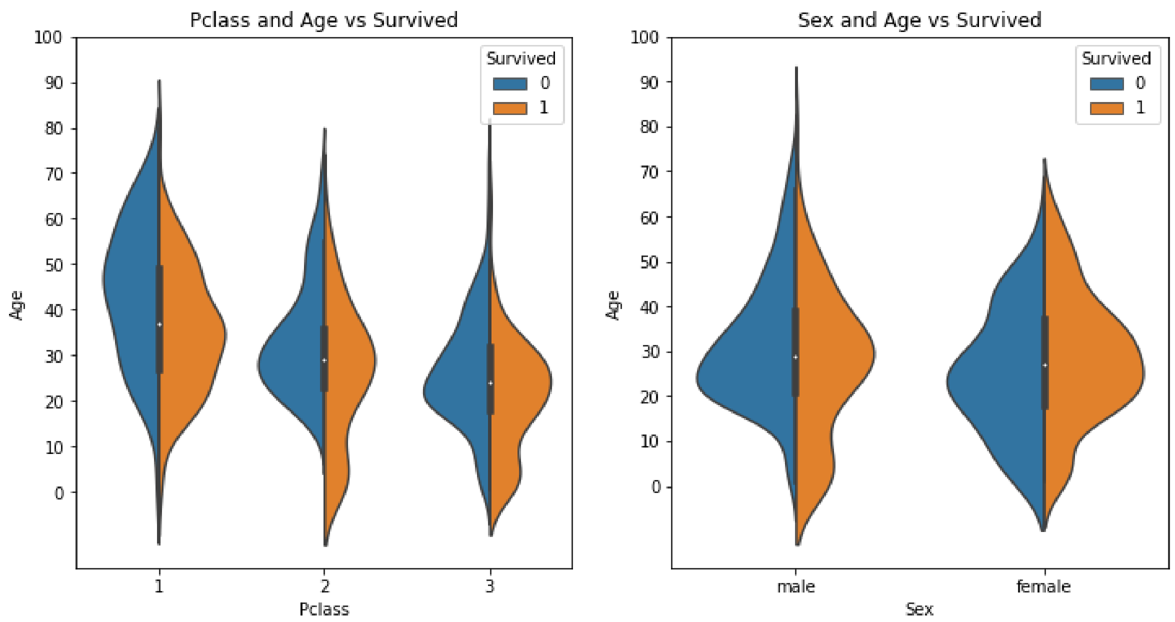


>> we can clearly see that women had very higher survival rate.

Age violinplot based on Pclass,Survived

In [46]:

```
f,ax=plt.subplots(1,2,figsize=(12,6))
sns.violinplot("Pclass","Age", hue="Survived", data=data,split=True,ax=ax[0])
ax[0].set_title('Pclass and Age vs Survived')
ax[0].set_yticks(range(0,110,10))
sns.violinplot("Sex","Age", hue="Survived", data=data,split=True,ax=ax[1])
ax[1].set_title('Sex and Age vs Survived')
ax[1].set_yticks(range(0,110,10))
plt.show()
```



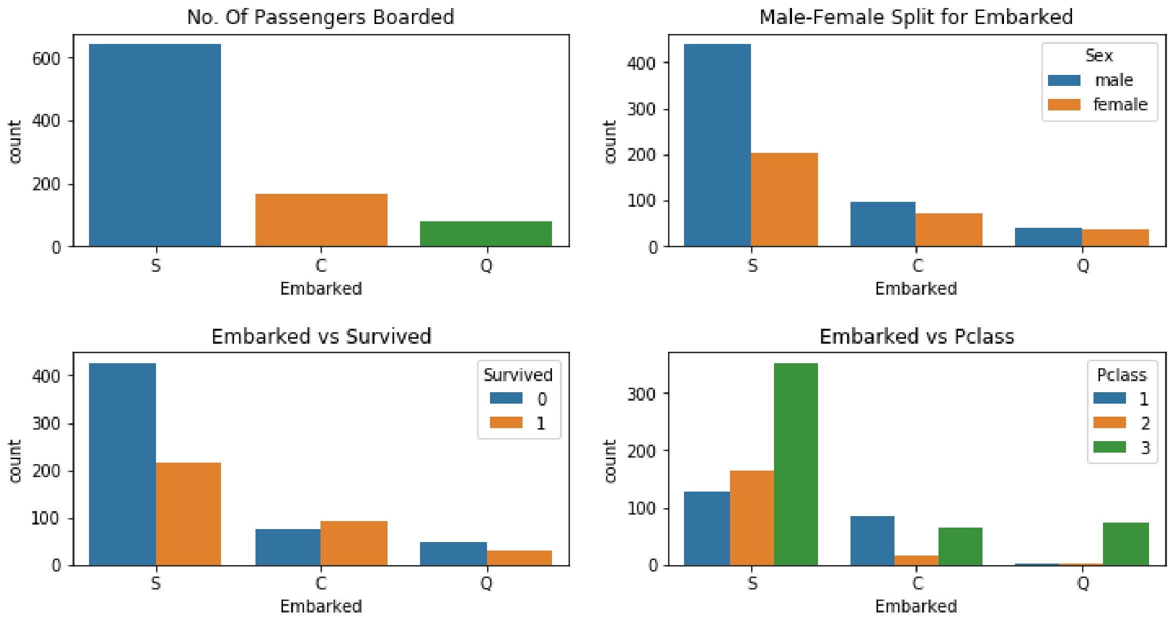
>> You can see that men have a high probability of survival when they are between 18 and 30 years old, which is also a little bit true for women but not fully. For women the survival chances are higher between 14 and 40.

>> For men the probability of survival is very low between the age of 5 and 18, but that isn't true for women. Another thing to note is that infants also have a little bit higher probability of survival.

>> For males, the survival chances decreases with an increase in age.Survival chances for Womens Passenegers aged 20-50 from Pclass1 is high,As we had seen earlier, the Age feature has 177 null values.

In [47]:

```
f,ax=plt.subplots(2,2,figsize=(12,6))
sns.countplot('Embarked',data=data,ax=ax[0,0])
ax[0,0].set_title('No. Of Passengers Boarded')
sns.countplot('Embarked',hue='Sex',data=data,ax=ax[0,1])
ax[0,1].set_title('Male-Female Split for Embarked')
sns.countplot('Embarked',hue='Survived',data=data,ax=ax[1,0])
ax[1,0].set_title('Embarked vs Survived')
sns.countplot('Embarked',hue='Pclass',data=data,ax=ax[1,1])
ax[1,1].set_title('Embarked vs Pclass')
plt.subplots_adjust(wspace=0.2,hspace=0.5)
plt.show()
```



Maximum passenegers boarded from S. Majority of them being from Pclass3.The Passengers from C look to be lucky as a good proportion of them survived.Port Q had almost 95% of the passengers were from Pclass3, passengers from Pclass3 around 81% didn't survive.

Correlation

It is used to describe the linear relationship between two continuous variables (e.g., height and weight). In general, correlation tends to be used when there is no identified response variable. It measures the strength (qualitatively) and direction of the linear relationship between two or more variables.

In [42]:

```
data.corr()
```

Out[42]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	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

Let's see feature corelation

In [43]:

```
data.groupby('Pclass',as_index=False)['Survived'].mean()
```

Out[43]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

there seems to have little corelation among survived and Pclass.Higher class passangers are more likely to survive.

In [44]:

```
data.groupby('Sex',as_index=False)['Survived'].mean()
```

Out[44]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

that's pretting amazing correlation. females are 4 times more likely to survive

In [49]:

```
data.groupby('Embarked',as_index=False)['Survived'].mean()
```

Out[49]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.336957

In [50]:

```
data.groupby('SibSp',as_index=False)['Survived'].mean().sort_values(by='Survived',ascending=False)
```

Out[50]:

	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000

Having more sibling can be corelated to less survival rate

In [51]:

```
data.groupby('Parch',as_index=False)['Survived'].mean().sort_values(by='Survived',ascending=False)
```

Out[51]:

	Parch	Survived
3	3	0.600000
1	1	0.550847
2	2	0.500000
0	0	0.343658
5	5	0.200000
4	4	0.000000
6	6	0.000000

Persons with more parents or children seem to have low chances.Let's divide our age data into bands and let's see if there is some corelation.

In [52]:

```
fig,ax = plt.subplots(figsize=(8,7))
ax = sns.heatmap(data.corr(), annot=True,linewidths=.5,fmt='.1f')
plt.show()
```

Creating Dummy Variables

from the dataset 'sex', 'Embarked', 'sibsp' are categorical variables we'll turn them into dummy variables.

Sex:

Convert ‘Sex’ feature into numeric.

In [53]:

```
gender=pd.get_dummies(data['Sex'],prefix='sx',drop_first=True)
gender.head()
```

Out[53]:

	sx_male
0	1
1	0
2	0
3	0
4	1

Embarked:

Convert ‘Embarked’ feature into numeric

In [54]:

```
embarked=pd.get_dummies(data['Embarked'],prefix='emb',drop_first=True)
embarked.head()
```

Out[54]:

	emb_Q	emb_S
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1

Pclass

Convert 'Pclass' feature into numeric

In [55]:

```
pcl=pd.get_dummies(data['Pclass'],prefix='pcl',drop_first=True)
pcl.head()
```

Out[55]:

	pcl_2	pcl_3
0	0	1
1	0	0
2	0	1
3	0	0
4	0	1

In [56]:

```
data=pd.concat([data,gender,embarked,pcl],axis=1)
```

Data cleaning

In [60]:

```
total=data.isnull().sum()
percent = (data.isnull().sum()/data.isnull().count()).sort_values(ascending=True)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'],sort=True)
missing_data.head(13)
```

Out[60]:

	Total	Percent
Age	177	0.198653
Cabin	687	0.771044
Embarked	2	0.002245
Fare	0	0.000000
Name	0	0.000000
Parch	0	0.000000
PassengerId	0	0.000000
Pclass	0	0.000000
Sex	0	0.000000
SibSp	0	0.000000
Survived	0	0.000000
Ticket	0	0.000000
emb_Q	0	0.000000

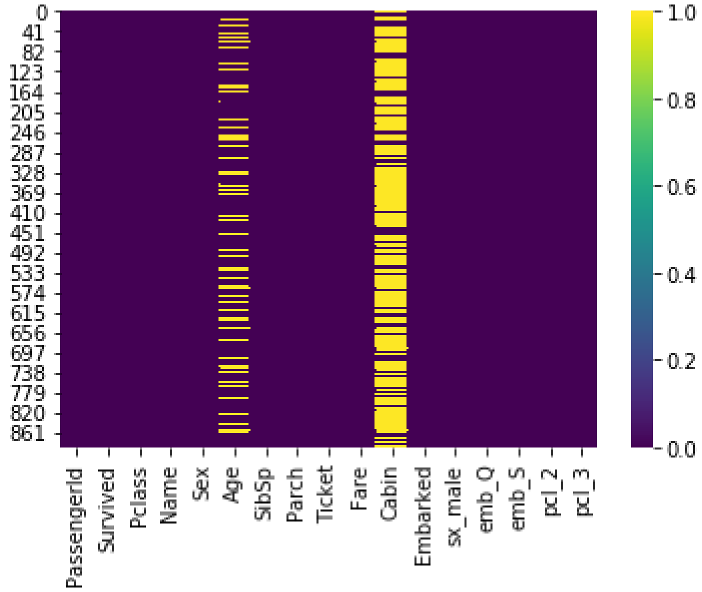
As a reminder, we have to deal with Cabin (687), Embarked (2) and Age (177). First I thought, we have to delete the ‘Cabin’ variable but then I found something interesting. A cabin number looks like ‘C123’ and the letter refers to the deck. Therefore we’re going to extract these and create a new feature, that contains a persons deck. Afterwords we will convert the feature into a numeric variable. The missing values will be converted to zero.

In [61]:

```
sns.heatmap(data.isnull(),cmap='viridis')
```

Out[61]:

<matplotlib.axes._subplots.AxesSubplot at 0xd1650f0>



In [62]:

```
data.drop('Cabin',axis=1,inplace=True)
data.head()
```

Out[62]:

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

In [63]:

```
data.dropna(inplace=True)
```

In [64]:

```
data.drop(['Pclass','Sex','PassengerId','Name','Ticket'],axis=1,inplace=True)
```

In [65]:

```
data.drop(['Age','Fare','Embarked'],axis=1,inplace=True)
```

In [66]:

```
data.head()
```

Out[66]:

	Survived	SibSp	Parch	sx_male	emb_Q	emb_S	pcl_2	pcl_3
0	0	1	0	1	0	1	0	1
1	1	1	0	0	0	0	0	0
2	1	0	0	0	0	1	0	1
3	1	1	0	0	0	1	0	0
4	0	0	0	1	0	1	0	1

Building Machine Learning Models & Train Data

Now we will train several Machine Learning models and compare their results. Note that because the dataset does not provide labels for their testing-set, we need to use the predictions on the training set to compare the algorithms with each other. Later on, we will use cross validation.

In [67]:

```
from sklearn.linear_model import LogisticRegression #logistic regression
from sklearn import svm #support vector Machine
from sklearn.ensemble import RandomForestClassifier #Random Forest
from sklearn.neighbors import KNeighborsClassifier #KNN
from sklearn.naive_bayes import GaussianNB #Naive bayes
from sklearn.tree import DecisionTreeClassifier #Decision Tree
from sklearn.model_selection import train_test_split #training and testing data split
from sklearn import metrics #accuracy measure
from sklearn.metrics import confusion_matrix #for confusion matrix
```

In [68]:

```
train,test=train_test_split(data,test_size=0.3,random_state=0,stratify=data['Survived'])
train_X=train[train.columns[1:]]
train_Y=train[train.columns[:1]]
test_X=test[test.columns[1:]]
test_Y=test[test.columns[:1]]
X=data[data.columns[1:]]
Y=data['Survived']
```

What is Support Vector Machine?

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space(N— the number of features) that distinctly classifies the data points. Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. For categorical variables a dummy variable is created with case values as either 0 or

In [73]:

```
model=svm.SVC(kernel='rbf',C=1,gamma=0.1)
model.fit(train_X,train_Y)
prediction1=model.predict(test_X)
print('Accuracy is ',metrics.accuracy_score(prediction1,test_Y))
```

```
Accuracy is  0.8271028037383178

C:\Users\krish\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: DataConv
ersionWarning: A column-vector y was passed when a 1d array was expected. Please cha
nge the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

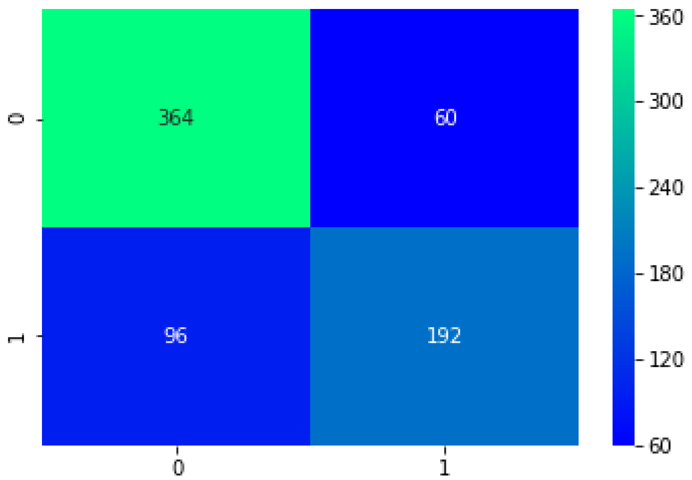
In [70]:

```
model=svm.SVC(kernel='linear',C=0.1,gamma=0.1)
model.fit(train_X,train_Y)
prediction2=model.predict(test_X)
print('Accuracy for linear SVM is',metrics.accuracy_score(prediction2,test_Y))
```

```
Accuracy for linear SVM is 0.8177570093457944

C:\Users\krish\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: DataConv
ersionWarning: A column-vector y was passed when a 1d array was expected. Please cha
nge the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [74]:

```
from sklearn.model_selection import KFold #for K-fold cross validation
from sklearn.model_selection import cross_val_score #score evaluation
from sklearn.model_selection import cross_val_predict #prediction
from sklearn.ensemble import AdaBoostClassifier
ada=AdaBoostClassifier(n_estimators=200,random_state=0,learning_rate=0.05)
result=cross_val_predict(ada,X,Y,cv=10)
sns.heatmap(confusion_matrix(Y,result),cmap='winter',annot=True,fmt='2.0f')
plt.show()
```



Confusion matrix

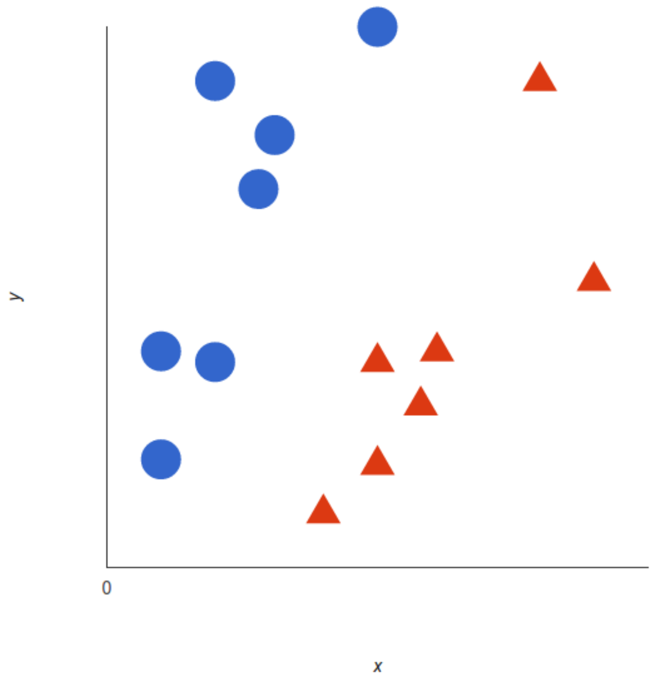
The first row is about the not-survived-predictions: 364 passengers were correctly classified as not survived (called true negatives) and 60 where wrongly classified as not survived (false positives).

The second row is about the survived-predictions: 96passengers where wrongly classified as survived (false negatives) and 192re correctly classified as survived (true positives).

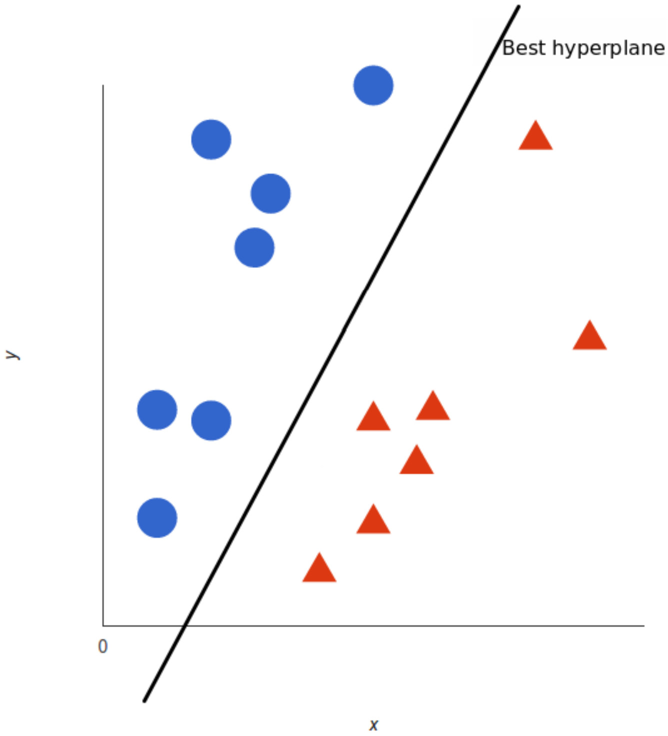
A confusion matrix gives you a lot of information about how well your model does, but theres a way to get even more, like computing the classifiers precision.

How does SVM work?

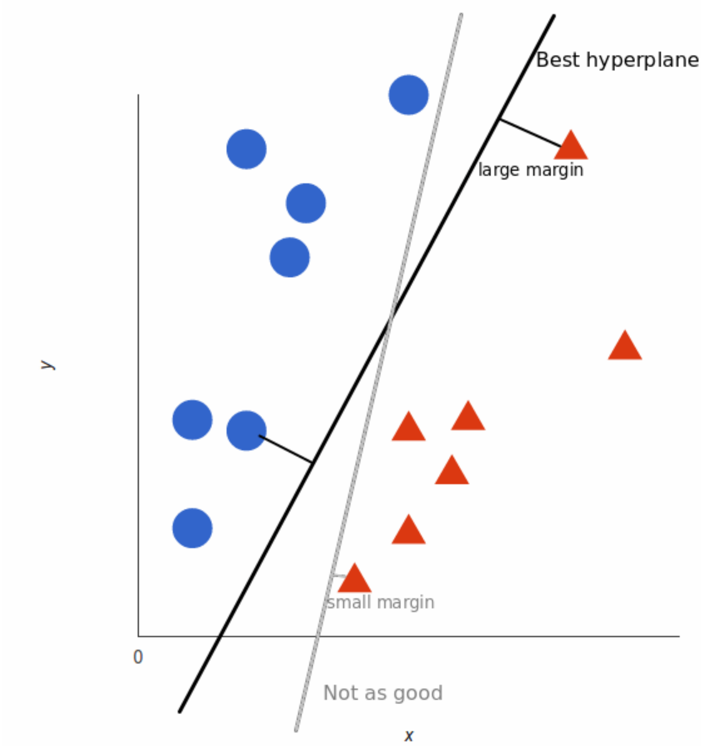
The basics of Support Vector Machines and how it works are best understood with a simple example. Let's imagine we have two tags: red and blue, and our data has two features: x and y. We want a classifier that, given a pair of (x,y) coordinates, outputs if it's either red or blue. We plot our already labeled training data on a plane:



A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the decision boundary: anything that falls to one side of it we will classify as blue, and anything that falls to the other as red.



But, what exactly is the best hyperplane? For SVM, it's the one that maximizes the margins from both tags. In other words: the hyperplane (remember it's a line in this case) whose distance to the nearest element of each tag is the largest.



Thank You Very Much