Titanic Kaggle

June 12, 2021

1 1. Preparation for data

- Adopted from : https://www.kaggle.com/c/titanic

1.0.1 import module and data

[1]:
```
#normal import
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt

# visualization import
import seaborn as sb

# Disregard warning
import warnings
warnings.filterwarnings('ignore')
```

import data from csv (both test and train dataset)

[2]:
```
test = pd.read_csv("test.csv")
train = pd.read_csv("train.csv")
```

2 2. Data detail

2.1 1. Data Dictionary

1. Survival : survival or not (0 : No, 1 : Yes)
2. pclass : Ticket class
3. sex : sex
4. Age : age in years
5. sibsp : # of sibilings / spouses aborad the titanic

6. parch : # of parents / children aborad the titanic
7. ticket : Ticket number
8. fare : Passenger fare
9. cabin : Cabin number
10. embarked : Port of Embarkation (C : Cherborug, Q : Queenstown, S : Southampton)

2.2 2. Train data

[3]:
```
print(train.shape)
```

```
(891, 12)
```

[4]:
```
print(train.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: 83.7+ KB
None
```

[5]:
```
train.head()
```

[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1

```
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[6]:
```
train.describe()
```

[6]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[7]:
```
train.isnull().sum()
```

[7]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
```

```
Embarked         2
dtype: int64
```

In the train dataset, there are 891 data with 12 entries entered. With 891 data, there are 177 null data in Age entry, 687 null data in Cabin entry and 2 null data in Embarked entry.

2.3 3. Test data

[8]:
```
print(test.shape)
```

```
(418, 11)
```

[9]:
```
print(test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            332 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           417 non-null float64
Cabin          91 non-null object
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
None
```

[10]:
```
test.head()
```

[10]:

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

[11]:
```
test.describe()
```

[11]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

[12]:
```
test.isnull().sum()
```

[12]:
```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

For test dataset, there are 418 data with 11 entries entered (Differ from train set, 'Survived' entry has been omitted). With 418 data entered, there are 86 data are null in Age entry and 1 data is null in Fare and 327 data are null in Cabin entry.

2.4 4. More detail info for classification

[13]:
```
# For convinence, copy the data from original
train_survived = train[train['Survived'] == 1]
train_not_survived = train[train['Survived'] == 0]
```

[14]:
```
train['Survived'].value_counts()
```

[14]:
```
0    549
1    342
Name: Survived, dtype: int64
```

0 : Did not survived / 1 : survived
Among 891 data entered in train set, 342 people had been survived and 549 people were not.

[15]:
```
train['Sex'].value_counts()
```

[15]:
```
male      577
female    314
Name: Sex, dtype: int64
```

Among 891 data entered, 577 people were male and 314 people were female

[16]:
```
train['Pclass'].value_counts()
```

[16]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

Among 891 data entered, for 'Age' entry, 177 data are missing (NaN) and 687 data are missing for 'Cabin' entry and 2 data are missing in 'Embarked'

3 3. Data Analyzation

3.1 Detail data analyze according to 'Survived'

[17]:
```
train_survived.describe()
```

[17]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	342.000000	342.0	342.000000	290.000000	342.000000	342.000000	342.000000
mean	444.368421	1.0	1.950292	28.343690	0.473684	0.464912	48.395408
std	252.358840	0.0	0.863321	14.950952	0.708688	0.771712	66.596998
min	2.000000	1.0	1.000000	0.420000	0.000000	0.000000	0.000000
25%	250.750000	1.0	1.000000	19.000000	0.000000	0.000000	12.475000
50%	439.500000	1.0	2.000000	28.000000	0.000000	0.000000	26.000000
75%	651.500000	1.0	3.000000	36.000000	1.000000	1.000000	57.000000
max	890.000000	1.0	3.000000	80.000000	4.000000	5.000000	512.329200

[18]:
```
train_not_survived.describe()
```

[18]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	\
count	549.000000	549.0	549.000000	424.000000	549.000000	549.000000	
mean	447.016393	0.0	2.531876	30.626179	0.553734	0.329690	

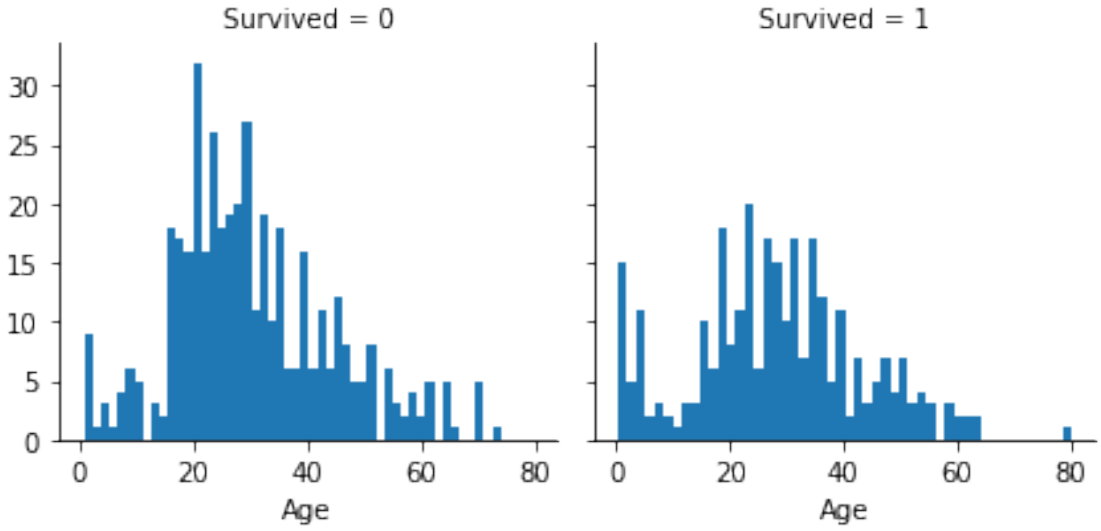
```
std     260.640469      0.0     0.735805   14.172110    1.288399    0.823166
min       1.000000      0.0     1.000000    1.000000    0.000000    0.000000
25%     211.000000      0.0     2.000000   21.000000    0.000000    0.000000
50%     455.000000      0.0     3.000000   28.000000    0.000000    0.000000
75%     675.000000      0.0     3.000000   39.000000    1.000000    0.000000
max     891.000000      0.0     3.000000   74.000000    8.000000    6.000000
```

```
             Fare
count  549.000000
mean    22.117887
std     31.388207
min      0.000000
25%      7.854200
50%     10.500000
75%     26.000000
max    263.000000
```

3.2 Survived or not by age

[19]:
```
age_survived = sb.FacetGrid(train, col = 'Survived')
age_survived.map(plt.hist, 'Age', bins = 50)
```

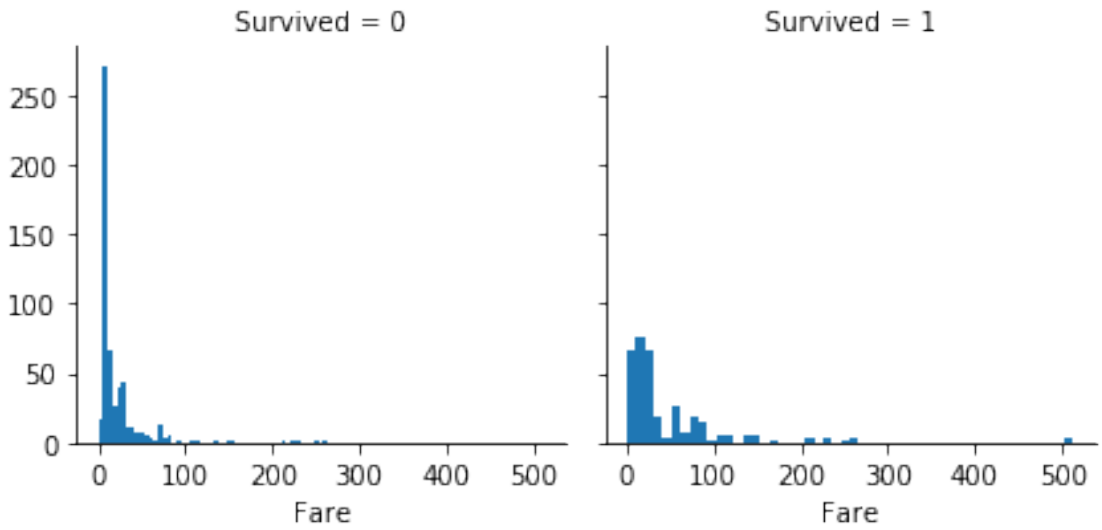
[19]:
```
<seaborn.axisgrid.FacetGrid at 0x7f81abced410>
```



3.3 Survived or not by Fare

[20]:
```
fare_survived = sb.FacetGrid(train, col = 'Survived')
fare_survived.map(plt.hist, 'Fare', bins = 50)
```

[20]:
```
<seaborn.axisgrid.FacetGrid at 0x7f81ac2a1750>
```



3.4 Survived or not by sex

[21]:
```
train_survived['Sex'].value_counts()
```

[21]:
```
female    233
male      109
Name: Sex, dtype: int64
```

[22]:
```
train_not_survived['Sex'].value_counts()
```

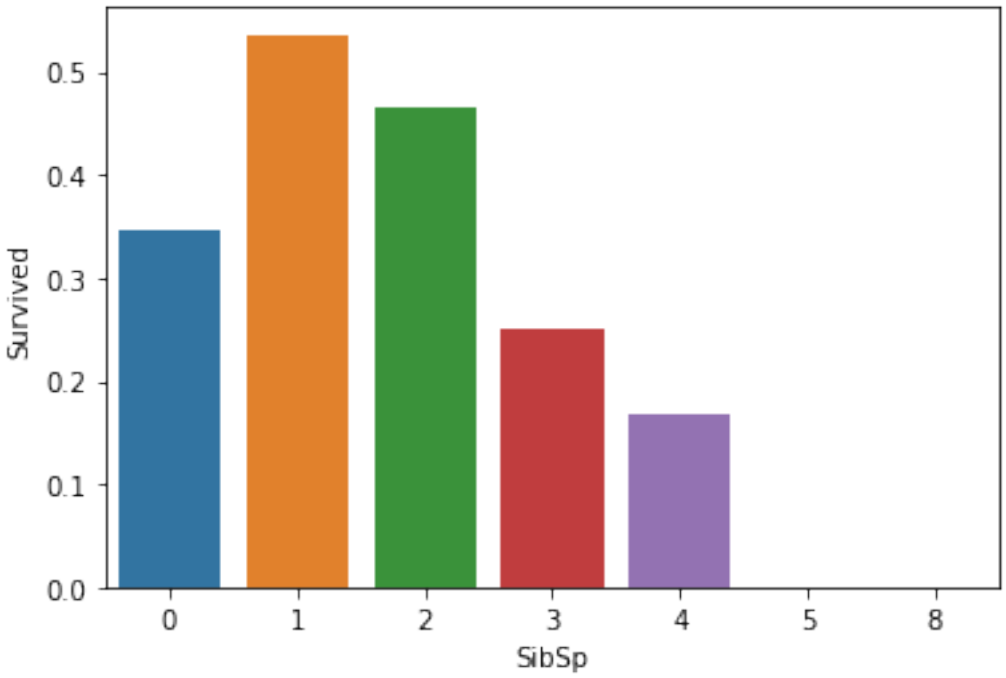
[22]:
```
male      468
female     81
Name: Sex, dtype: int64
```

Among the group who survived, 233 people were female and 109 people are male.
Among the group who were not survived 81 people were female and 468 people are male.
Therefore, 74% women among women population survived, 26% in total population.
18 % men among men population survived, 12% in total population

3.5 Survived or not by SibSp

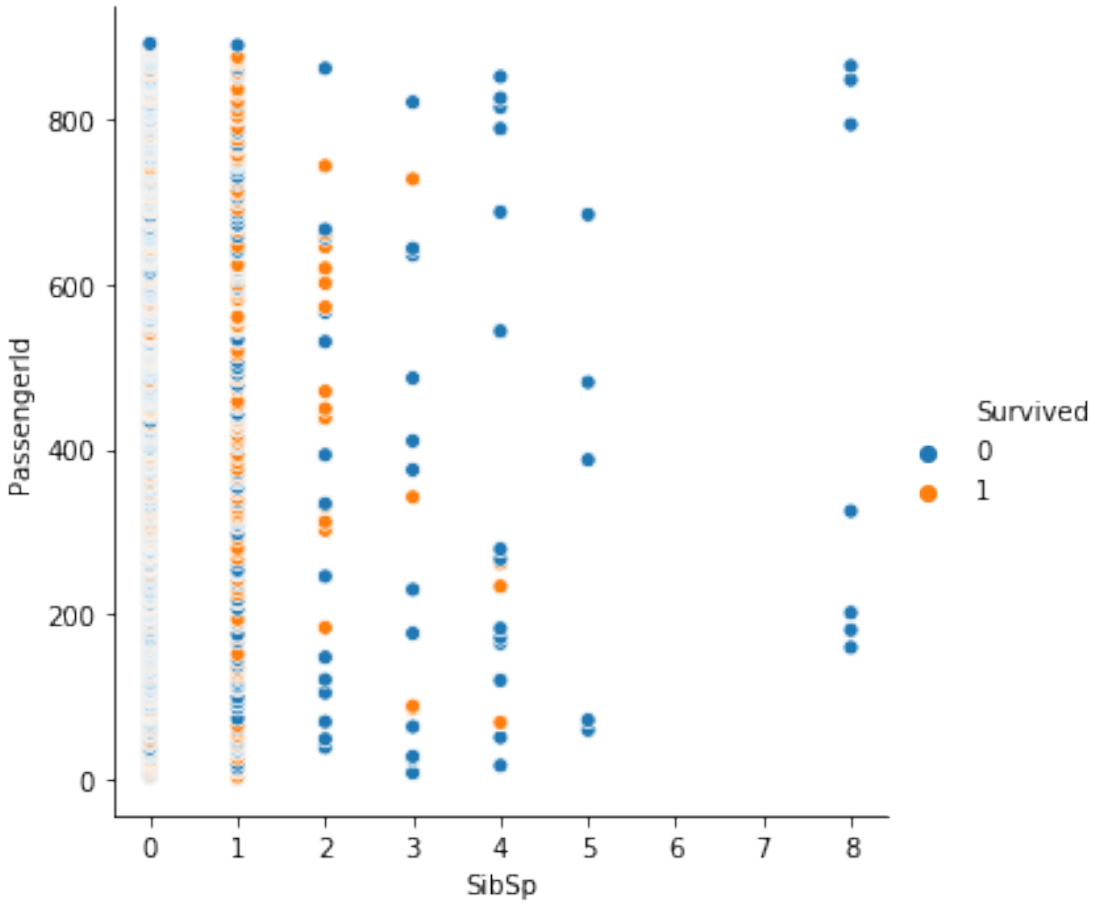
[23]:
```
sb.barplot(x = 'SibSp', y = 'Survived', ci = None, data = train)
```

[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f81abccea50>
```



[24]:
```
sb.relplot(x = 'SibSp', y = 'PassengerId', hue = 'Survived', data = train)
```

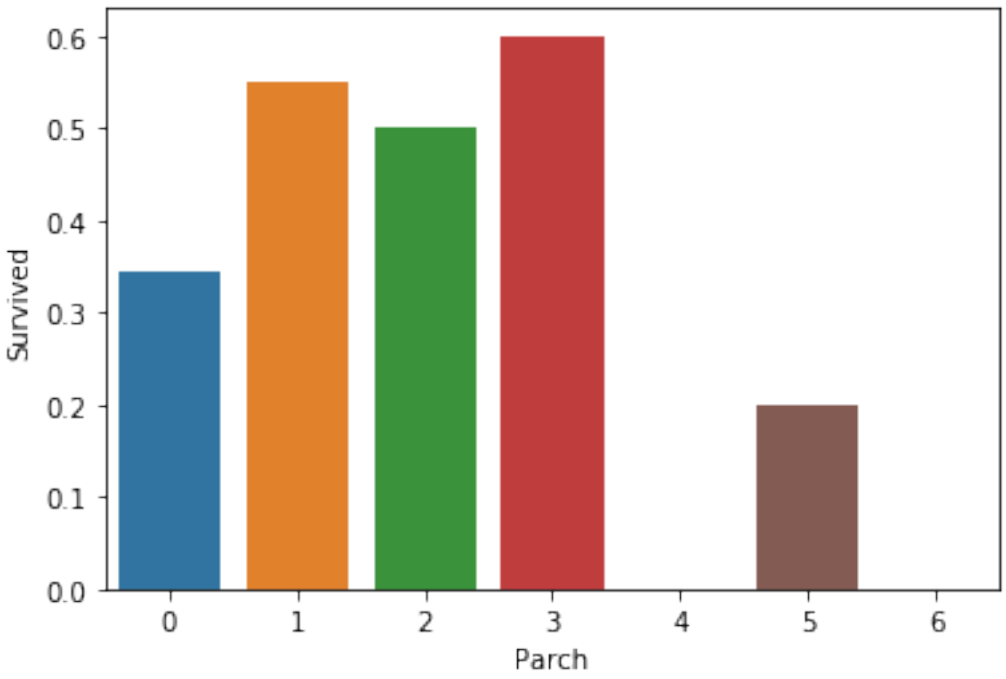
[24]:
```
<seaborn.axisgrid.FacetGrid at 0x7f81abd53c50>
```



3.6 Survived or not by Parch

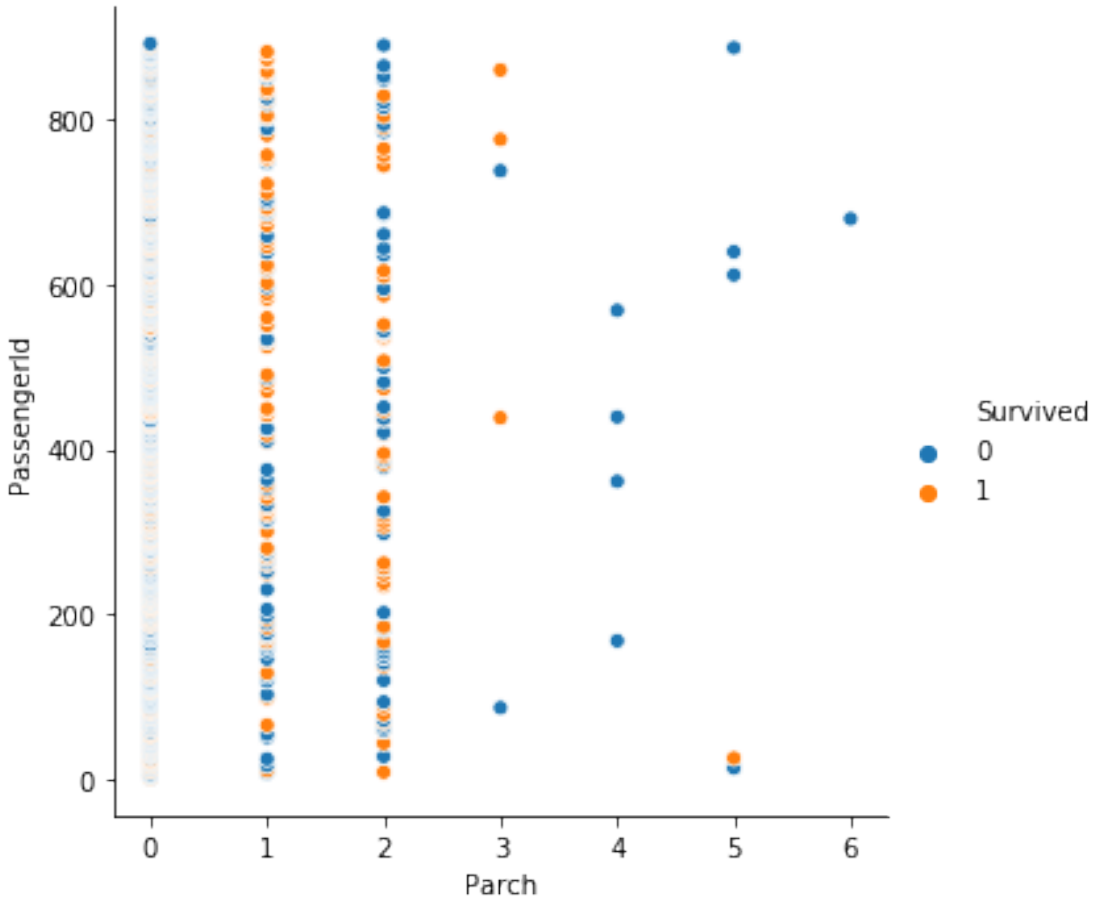
[25]:
```
sb.barplot(x = 'Parch', y = 'Survived', ci = None, data = train)
```

[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f81ac6fc3d0>
```



[26]:
```
sb.relplot(x = 'Parch', y = 'PassengerId', hue = 'Survived', data = train)
```

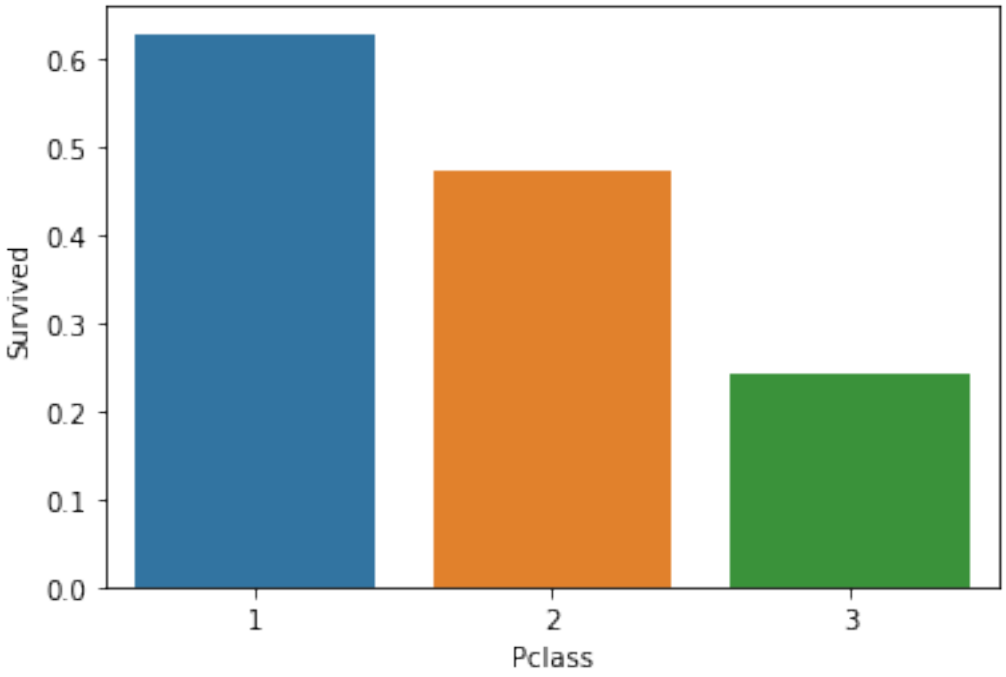
[26]: <seaborn.axisgrid.FacetGrid at 0x7f81ac784250>



3.7 Survived or not by Pclass

[27]:
```
sb.barplot(x = 'Pclass', y = 'Survived', ci = None, data = train)
```

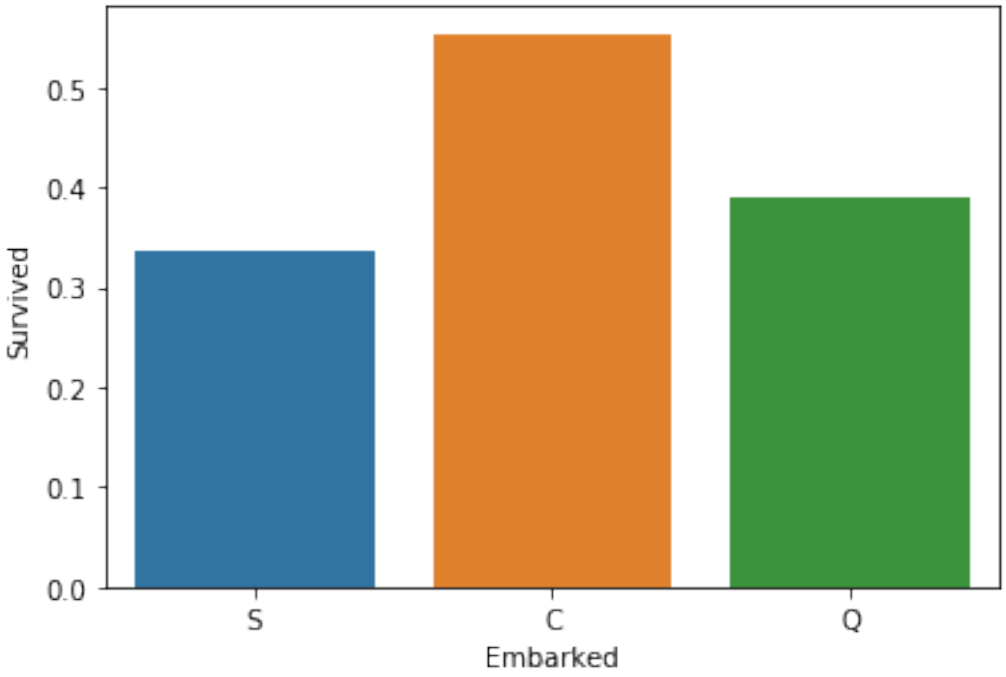
[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f81ac98f110>
```



Since Survived = 1 is people who survived and Survived = 0 is people who did not survive, higher mean of survived means people survived more. Therefore according to bar graph above, people who are in pclass = 1 do survive more and then pclass = 2 the next. Pclass = 3 do have least number of people who survived.

[28]:
```
sb.barplot(x = 'Embarked', y = 'Survived', ci = None, data = train)
```

[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f81acb2aa10>
```



With entry of Embarked, similar with Pclass, higher survived rate means higher number of people who survived. According to the bar graph, C class does have highest and Q and S do have similar rate of people who survived.

4 4. Classify with classifiers

4.1 Setup for classification

import module for classification

[29]:
```
# Classification module
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

delete unnecessary entries

[30]:
```
drop_features = ['Name', 'Ticket', 'Cabin', 'PassengerId']
train_fixed = train.drop(drop_features, axis = 1)
test_fixed = test.drop(drop_features, axis = 1)
```

Since mean of age does not have big difference between 'Survived' and 'not Survived', replace Null age entry with the mean of the age.

[31]:
```
train_fixed['Age'].fillna(train['Age'].mean(), inplace = True)
test_fixed['Age'].fillna(train['Age'].mean(), inplace = True)
```

Edit Age entry with numerical value (male = 0 / female = 1)

[32]:
```
train_fixed['Sex'] = train_fixed['Sex'].map({'male' : 0, 'female' : 1}).
↪astype(int)
test_fixed['Sex'] = test_fixed['Sex'].map({'male' : 0, 'female' : 1}).
↪astype(int)
```

[33]:
```
test_fixed['Fare'].fillna(train['Fare'].mean(), inplace = True)
```

Since most of the Embarked entry is focused on 'S', therefore for null value for Embarked in trainset, replace with 'S'

[34]:
```
train_fixed['Embarked'].fillna('S', inplace = True)
```

Edit Embarked entry with numerical value (S = 0 / C = 1 / Q = 2)

[35]:
```
train_fixed['Embarked'] = train_fixed['Embarked'].map({'S' : 0, 'C' : 1, 'Q':␣
↪2}).astype(int)
test_fixed['Embarked'] = test_fixed['Embarked'].map({'S' : 0, 'C' : 1, 'Q': 2}).
↪astype(int)
```

Edit SibSp entry as 0 ~ 3 : 0 and 4 ~ 8 : 1

[36]:
```
train_fixed['SibSp'] = train_fixed['SibSp'].map({0 : 0, 1 : 0, 2 : 0, 3 : 0, 4 :
↪ 1, 5 : 1, 6 : 1, 7 : 1, 8 : 1}).astype(int)
```

Edit Parch entry as 1,2,3 as 1 and others to 0

[37]:
```
train_fixed['Parch'] = train_fixed['Parch'].map({1 : 1, 2: 1, 3 : 1, 0 : 0, 4 :␣
↪0, 5 : 0, 6 : 0}).astype(int)
```

5 5. Classification

[38]:
```
X_train = train_fixed.drop('Survived', axis = 1)
Y_train = train_fixed['Survived']
X_test = test_fixed
X_test = X_test.dropna()
```

5.1 1. Try different classification methods

5.1.1 1. Logistic Regression

[39]:
```
logis_classify = LogisticRegression()
logis_classify.fit(X_train, Y_train)
Y_prediction = logis_classify.predict(X_test)
logis_score = logis_classify.score(X_train, Y_train)
print("The score of Logistic Regression is : " + str(logis_score))
```

```
The score of Logistic Regression is : 0.7968574635241302
```

5.1.2 2. Support Vector Machine (SVM)

[40]:
```
svm_classify = SVC()
svm_classify.fit(X_train, Y_train)
Y_prediction_svm = svm_classify.predict(X_test)
svm_score = svm_classify.score(X_train, Y_train)
print("The score of SVM is : " + str(svm_score))
```

```
The score of SVM is : 0.8765432098765432
```

5.1.3 3. k-Nearest Neighbor(KNN)

[41]:
```
knn_classify = KNeighborsClassifier(n_neighbors = 2)
knn_classify.fit(X_train, Y_train)
Y_prediction_knn = knn_classify.predict(X_test)
knn_score = knn_classify.score(X_train, Y_train)
print("The score of KNN is : " + str(knn_score))
```

```
The score of KNN is : 0.8372615039281706
```

5.1.4 4. Decision tree

[42]:
```
tree_classify = DecisionTreeClassifier()
tree_classify.fit(X_train, Y_train)
Y_prediction_tree = tree_classify.predict(X_test)
tree_score = tree_classify.score(X_train, Y_train)
print("The score of Decision tree is : " + str(tree_score))
```

```
The score of Decision tree is : 0.9809203142536476
```

5.1.5 5. Random Forest

[43]:
```
forest_classify = RandomForestClassifier()
forest_classify.fit(X_train, Y_train)
Y_prediction_forest = forest_classify.predict(X_test)
forest_score = forest_classify.score(X_train, Y_train)
print("The score of Random Forest is : " + str(forest_score))
```

```
The score of Random Forest is : 0.9607182940516273
```

6 5. Submission

[48]:
```
submission = pd.DataFrame({"PassengerId": test["PassengerId"], "Survived":␣
↪Y_prediction_tree})
submission.to_csv('submission.csv', index=False)
```