Introduction

This titanic dataset is related to the most notorious shipwrecks in history. This well-known sinking killed 1,502 of the 2,214 passengers and crew.
[DataSet Link (https://www.kaggle.com/competitions/titanic/data)](https://www.kaggle.com/competitions/titanic/data)

Content:

1. Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import scipy.stats

import matplotlib.pyplot as plt
plt.style.use("seaborn-whitegrid")

from collections import Counter
from itertools import combinations

import warnings
warnings.filterwarnings("ignore")
```

2. Load and Check Data

In [2]:

```
trainDf = pd.read_csv("train.csv")
testDf = pd.read_csv("test.csv")
genderSubDf = pd.read_csv("gender_submission.csv")
testPassengerIdDf = testDf["PassengerId"]
```

In [3]:

```
trainDf.columns
```

Out[3]:

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [4]:

```
trainDf.head()
```

Out[4]:

	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	

In [5]:

```
1 trainDf.describe()
```

Out[5]:

	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

4.Feature type change and droping

In [6]:

```
1 trainDf = trainDf.astype({"Parch":'object'})
```

In [7]:

```
1 trainDf.drop("Cabin", axis=1, inplace=True)
```

In [8]:

```
1 testDf.drop("Cabin", axis=1, inplace=True)
```

In [9]:

```
1 trainDf["Survived"].replace({0:"No",1:"Yes"}, inplace=True)
```

In [10]:

```
1 trainDf["Pclass"].replace({1:"1st",2:"2nd",3:"3rd"}, inplace=True)
```

In [11]:

```
1 trainDf["SibSp"].replace({0:"0 Sib",1:"1 Sib",2:"2 Sib",3:"3 Sib",4:"4 Sib",5:"5 Sib",8
```

4. Variable Desciption

In [12]:

```
with open("Titanic.txt","r") as f:
    for line in f:
        print(line, end="")
```

```
                                        TITANIC'S VARIABLES AND EXPLANATION

Variable        Definition      Key
survival        Survival        0 = No, 1 = Yes
pclass          Ticket class    1 = 1st, 2 = 2nd, 3 = 3rd
sex             Sex
Age             Age in years
sibsp           # of siblings / spouses aboard the Titanic
parch           # of parents / children aboard the Titanic
ticket          Ticket number
fare            Passenger fare
cabin           Cabin number
embarked        Port of Embarkation     C = Cherbourg, Q = Queenstown, S = S
outhampton


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

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

sibsp: The dataset defines family relations in this way...
Sibling = brother, sister, stepbrother, stepsister
Spouse = husband, wife (mistresses and fiancÃ©s were ignored)

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

In [13]:

```
trainDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    object 
 2   Pclass       891 non-null    object 
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    object 
 7   Parch        891 non-null    object 
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Embarked     889 non-null    object 
dtypes: float64(2), int64(1), object(8)
memory usage: 76.7+ KB
```

int64	object	float64
PassengerId	Name	Age
Survived	Sex	Fare
Pclass	Ticket	
SibSp	Cabin	
Parch	Embarked	

5. Univariate Variable Analysis

In [14]:

```
numerical_features = [i for i in trainDf.columns if trainDf[i].dtype !='O']
categorical_features = [i for i in trainDf.columns if trainDf[i].dtype =='O']
```

6. Categorical Variables

In [15]:

```
categorical_features
```

Out[15]:

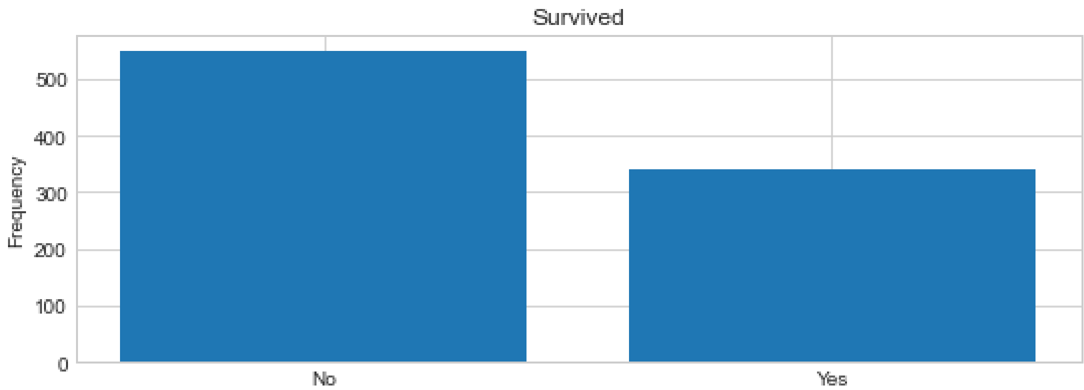
```
['Survived', 'Pclass', 'Name', 'Sex', 'SibSp', 'Parch', 'Ticket', 'Embarke
d']
```

In [16]:

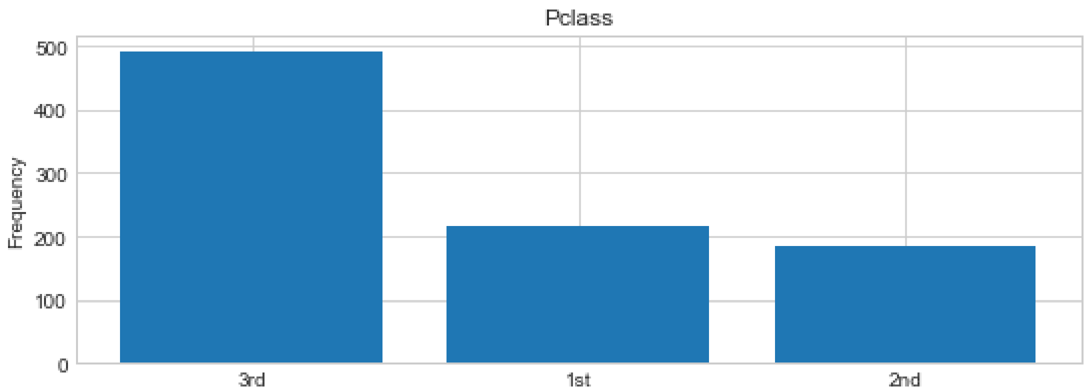
```
def bar_plot(variable):
    """
        input: variable eg: "sex"
        output: barplot & count value

    """
    # Taking feature
    var = trainDf[variable]
    # count number of categorical variable
    varValue = var.value_counts()

    # visualize
    plt.figure(figsize=(9,3))
    plt.bar(varValue.index, varValue)
    plt.xticks(varValue.index, varValue.index.values)
    plt.ylabel("Frequency")
    plt.title(variable)
    plt.show()
    print("{}: \n {} ".format(variable,varValue))

```

In [17]:

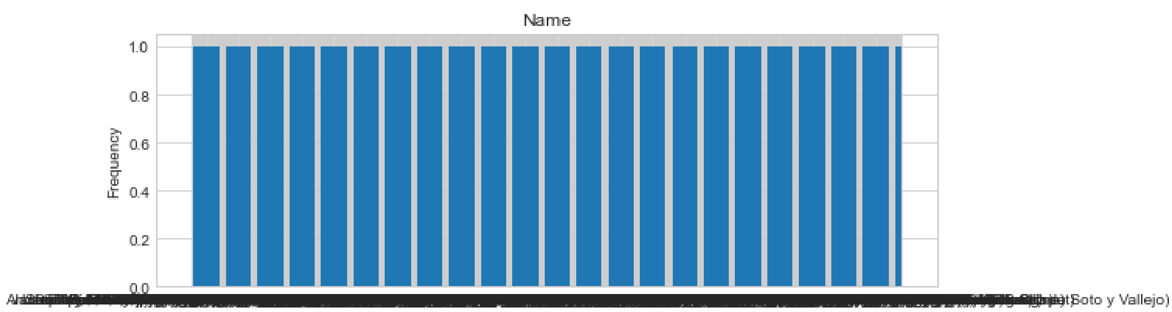
```
for i in categorical_features:
    bar_plot(i)
```




```
Survived:
 No     549
Yes    342
Name: Survived, dtype: int64
```

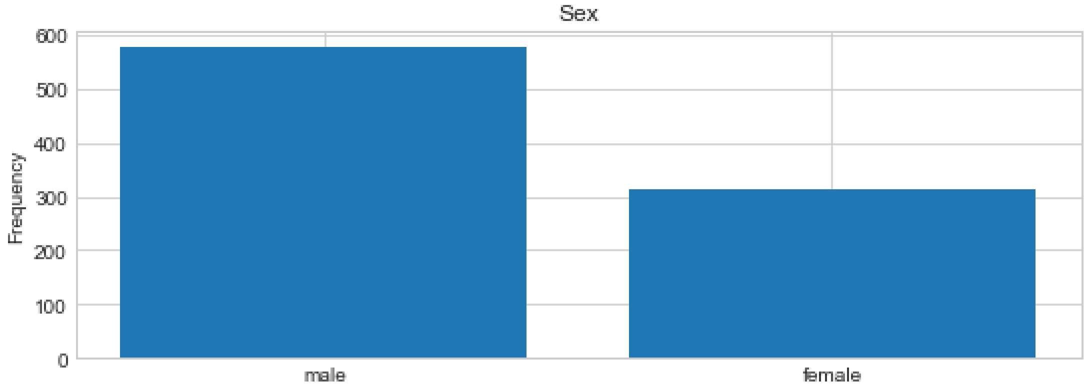



```
Pclass:
 3rd    491
1st    216
2nd    184
Name: Pclass, dtype: int64
```

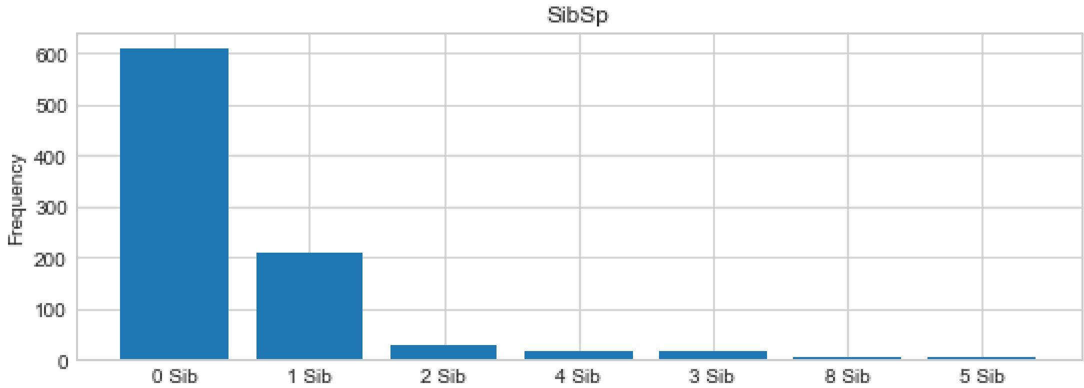



```
Name:
 Braund, Mr. Owen Harris                     1
Boulos, Mr. Hanna                           1
Frolicher-Stehli, Mr. Maxmillian            1
Gilinski, Mr. Eliezer                       1
Murdlin, Mr. Joseph                         1
                                           ..
Kelly, Miss. Anna Katherine "Annie Kate"    1
McCoy, Mr. Bernard                          1
Johnson, Mr. William Cahoone Jr             1
```

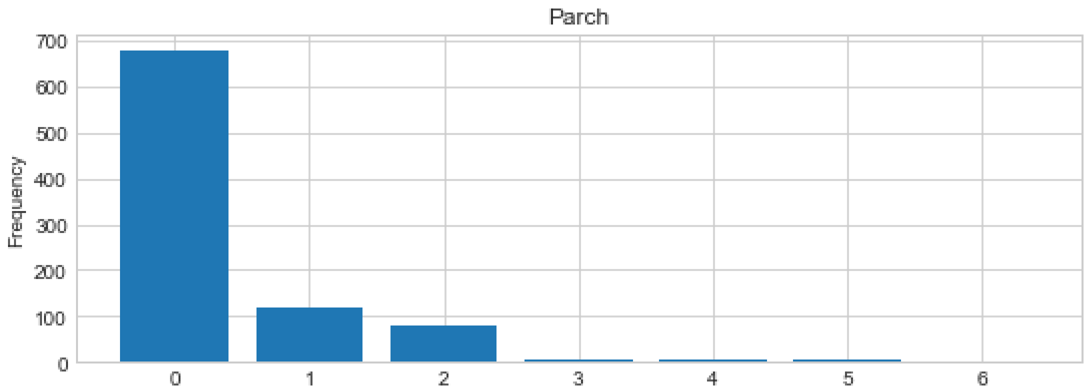
```
Keane, Miss. Nora A                          1
Dooley, Mr. Patrick                          1
Name: Name, Length: 891, dtype: int64
```




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

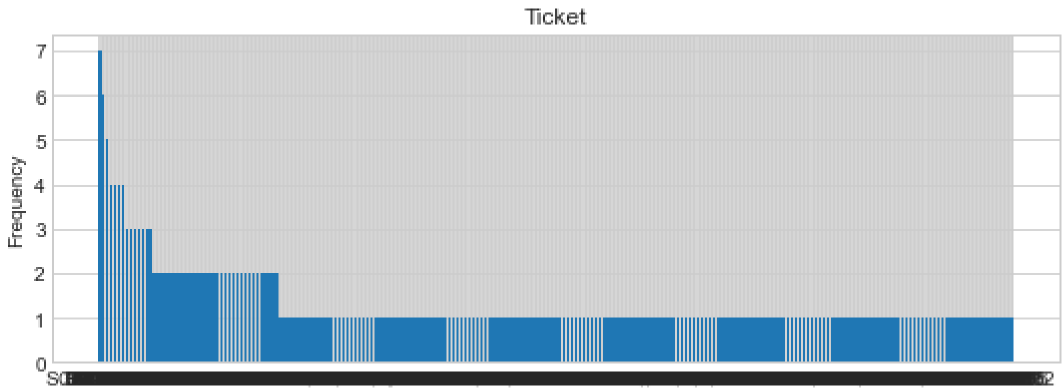



```
SibSp:
 0 Sib    608
1 Sib    209
2 Sib     28
4 Sib     18
3 Sib     16
8 Sib      7
5 Sib      5
Name: SibSp, dtype: int64
```

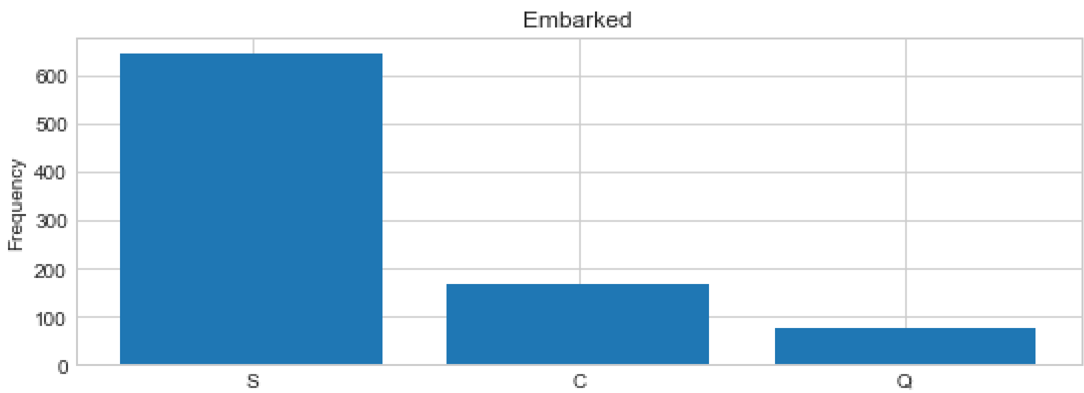



```
Parch:
 0    678
1    118
2     80
5      5
```

```
3       5
4       4
6       1
Name: Parch, dtype: int64
```




```
Ticket:
 347082      7
CA. 2343    7
1601        7
3101295     6
CA 2144     6
           ..
9234        1
19988       1
2693        1
PC 17612    1
370376      1
Name: Ticket, Length: 681, dtype: int64
```




```
Embarked:
 S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

7. Numerical Variables

In [18]:

```
numerical_features
```

Out[18]:

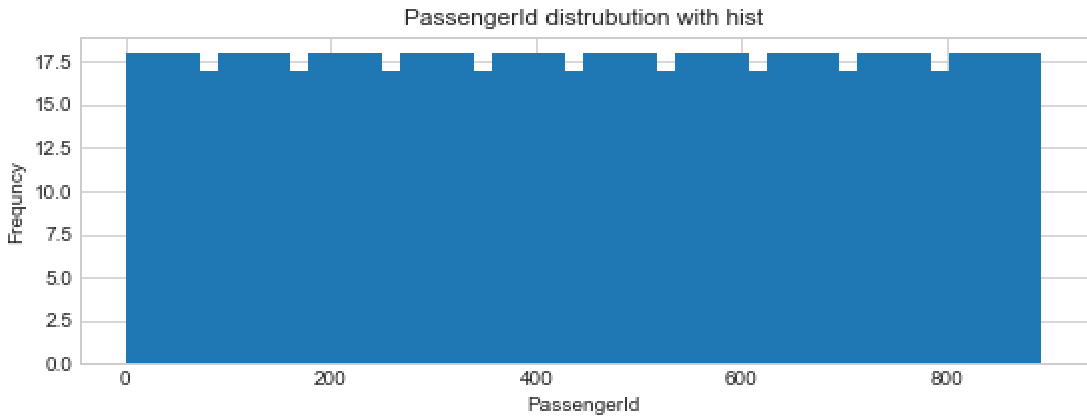
```
['PassengerId', 'Age', 'Fare']
```

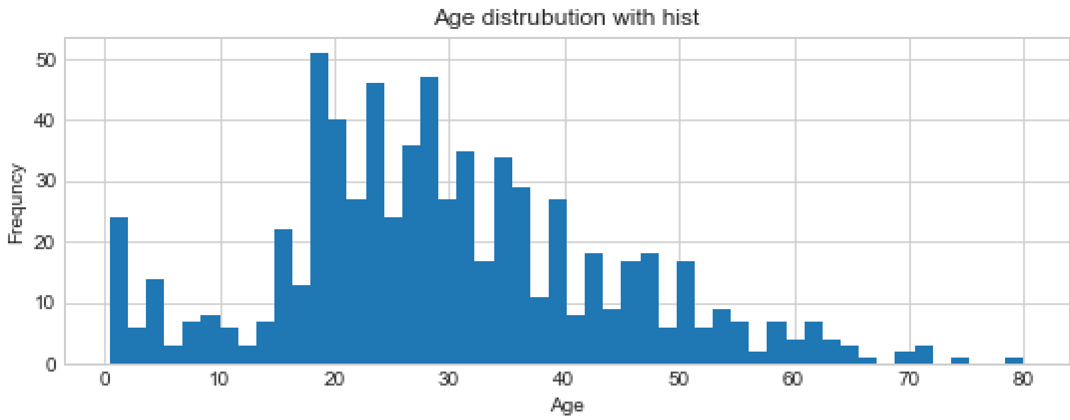
In [19]:

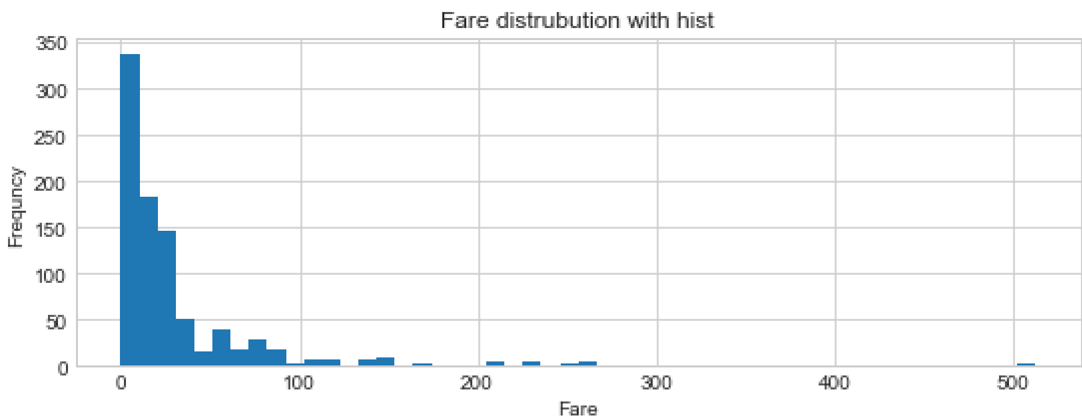
```
def plot_hist(variable):
    plt.figure(figsize=(9,3))
    plt.hist(trainDf[variable], bins=50)
    plt.xlabel(variable)
    plt.ylabel("Frequncy")
    plt.title("{} distrubution with hist".format(variable))
    plt.show()
```

In [20]:

```
for i in numerical_features:
    plot_hist(i)
```







Comment:

1. The price of 500 unit is shown in the chart. Maybe someone made a lump sum payment for their group.

2. The age range is mostly between 20 and 40 years old.

8. Outlier Detection

In [21]:

```
trainDf["SibSp"].replace({"0 Sib":0,"1 Sib":1,"2 Sib":2,"3 Sib":3,"4 Sib":4,"5 Sib":5,'
```

In [22]:

```
def detect_outlier(df,feature):
    outlierIndices = []

    for c in feature:
        # First Quartile
        Q1 = np.percentile(df[c],25)

        # Third Quartile
        Q3 = np.percentile(df[c],75)

        # IQR
        IQR = Q3 - Q1

        # Outlier step
        outlier_step = IQR * 1.5

        # Detect outlier and thier indices
        outlier_list_col = df[(df[c]< Q1 - outlier_step) | (df[c]> Q3 + outlier_step)].

        # Store indices
        outlierIndices.extend(outlier_list_col)
    outlierIndices = Counter(outlierIndices)
    multuple_outliers = list(i for i,v in outlierIndices.items() if v > 2)

    return multuple_outliers
```

In [23]:

```
trainDf.loc[detect_outlier(trainDf, ["SibSp", "Age","Fare","Parch"])]
```

Out[23]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	En
27	28	No	1st	Fortune, Mr. Charles Alexander	male	19.0	3	2	19950	263.00	
88	89	Yes	1st	Fortune, Miss. Mabel Helen	female	23.0	3	2	19950	263.00	
159	160	No	3rd	Sage, Master. Thomas Henry	male	NaN	8	2	CA. 2343	69.55	
180	181	No	3rd	Sage, Miss. Constance Gladys	female	NaN	8	2	CA. 2343	69.55	
201	202	No	3rd	Sage, Mr. Frederick	male	NaN	8	2	CA. 2343	69.55	
324	325	No	3rd	Sage, Mr. George John Jr	male	NaN	8	2	CA. 2343	69.55	
341	342	Yes	1st	Fortune, Miss. Alice Elizabeth	female	24.0	3	2	19950	263.00	
792	793	No	3rd	Sage, Miss. Stella Anna	female	NaN	8	2	CA. 2343	69.55	
846	847	No	3rd	Sage, Mr. Douglas Bullen	male	NaN	8	2	CA. 2343	69.55	
863	864	No	3rd	Sage, Miss. Dorothy Edith "Dolly"	female	NaN	8	2	CA. 2343	69.55	

In [24]:

```
#drop Outliers
trainDf = trainDf.drop(detect_outlier(trainDf, ["SibSp", "Age","Fare","Parch"]), axis =
```

9.Missing Value

In [25]:

```
trainDf_len = len(trainDf)
```

In [26]:

```
concatDf = pd.concat([trainDf,testDf], axis=0).reset_index(drop=True)
```

In [27]:

```
concatDf.head()
```

Out[27]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	I
0	1	No	3rd	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	Yes	1st	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	Yes	3rd	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	Yes	1st	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	
4	5	No	3rd	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

10.Find Missing Value

In [28]:

```
concatDf.columns[concatDf.isnull().any()]
```

Out[28]:

```
Index(['Survived', 'Age', 'Fare', 'Embarked'], dtype='object')
```

In [29]:

```
concatDf.isnull().sum()
```

Out[29]:

```
PassengerId      0
Survived       418
Pclass           0
Name             0
Sex              0
Age            256
SibSp            0
Parch            0
Ticket           0
Fare             1
Embarked         2
dtype: int64
```

11.Fill Missing Value

- Embarked has 2 missing values
- Fare has 1 missing value

In [30]:

```
concatDf[concatDf["Embarked"].isnull()]
```

Out[30]:

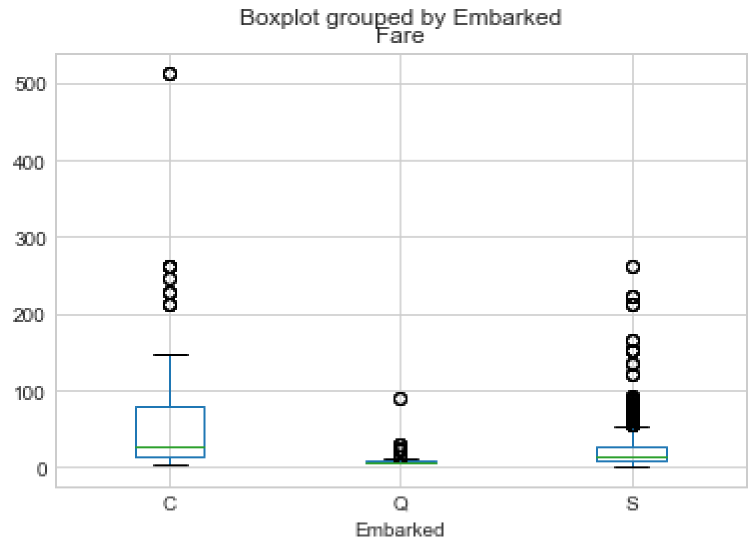
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embar
60	62	Yes	1st	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	N
821	830	Yes	1st	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	N

Comment:

1. We can fill nan of embarked value according to Fare.

In [31]:

```
concatDf.boxplot(column="Fare", by="Embarked")
plt.show()
```



Comment:

1. The graph shows us that 2 passengers could probably board the Titanic from C and We can fill with C

In [32]:

```
concatDf["Embarked"] = concatDf["Embarked"].fillna("C")
```

In [33]:

```
concatDf[concatDf["Fare"].isnull()]
```

Out[33]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embark
1033	1044	NaN	3	Storey, Mr. Thomas	male	60.5	0	0	3701	NaN	

Comment

1. We can fill in the Fare with the average of the money they paid according to their Embarked and the Pclass

In [34]:

```
concatDf["Fare"] = concatDf["Fare"].fillna(np.mean(concatDf[(concatDf["Pclass"] == 3) &
```

In [35]:

```
concatDf[concatDf["Fare"].isnull()]
```

Out[35]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked

Visulization

Correlation Between SipSb -- Parch -- Age -- Fare -- Survived

In [36]:

```
concatDf["Survived"].replace({"No":0,"Yes":1}, inplace=True)
```

In [37]:

```
list1 = ["SibSp", "Parch", "Age","Fare","Survived"]
sns.heatmap(concatDf[list1].corr(), annot = True, fmt= ".2f")
```

Out[37]:

<AxesSubplot:>

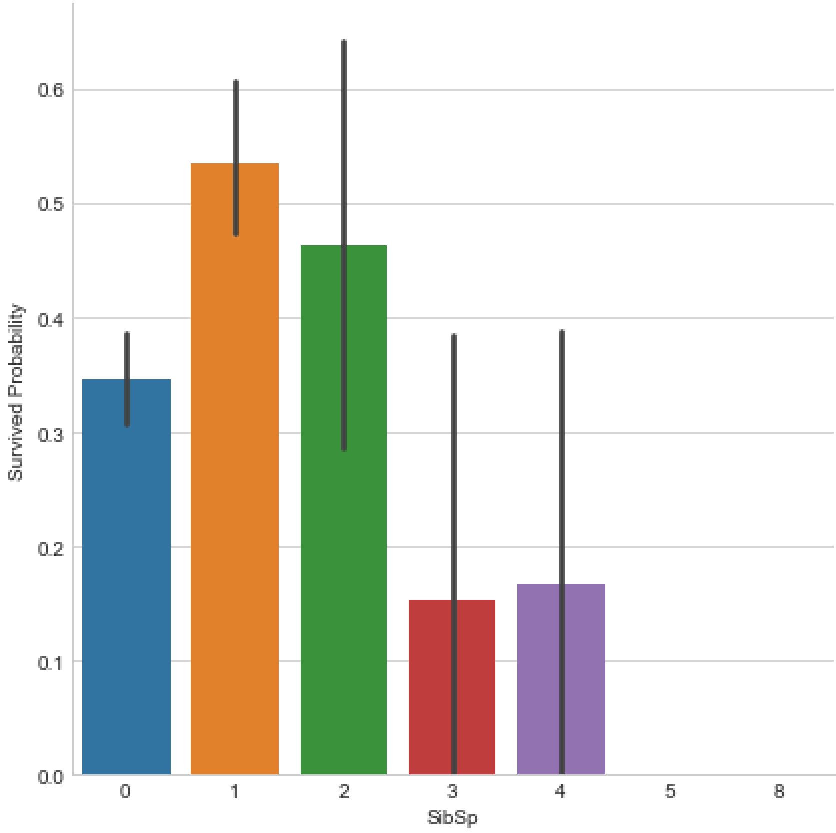
Comment:

1. Fare feature seems to have correlation with survived feature(.26)

SibSp -- Survived

In [38]:

```
g = sns.factorplot(x = "SibSp", y = "Survived", data = concatDf, kind = "bar", size = 6
g.set_ylabels("Survived Probability")
plt.show()
```



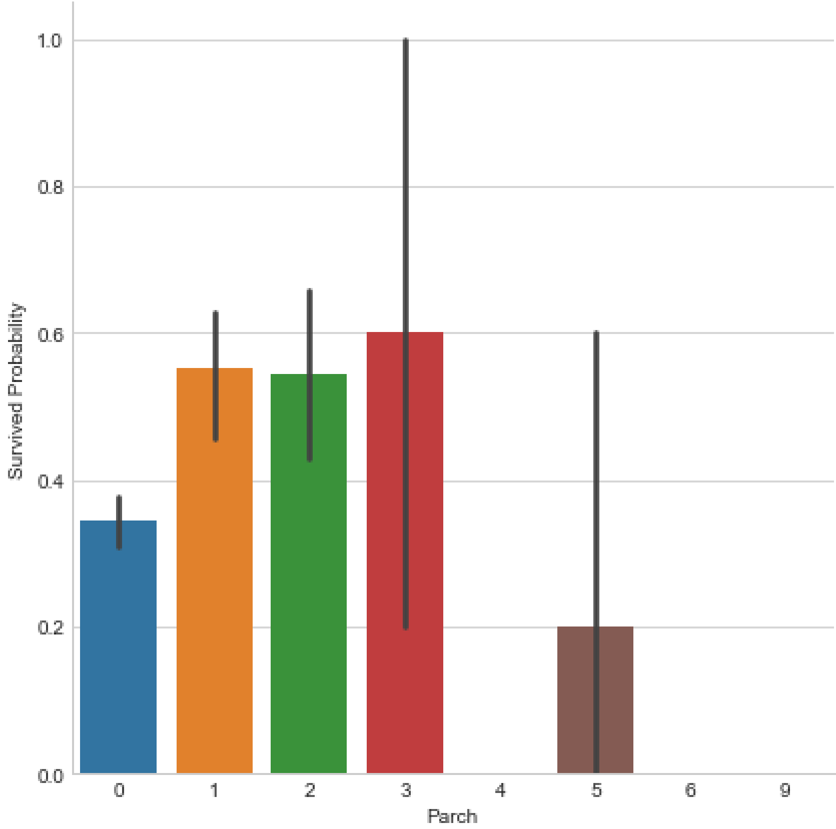
Comment:

1. If the family has got more than 2 members they have less chance to survive

Parch -- Survived

In [39]:

```
g = sns.factorplot(x = "Parch", y = "Survived",
                   data = concatDf, kind = "bar", size = 6)
g.set_ylabels("Survived Probability")
plt.show()
```



Comment:

1. 3 members of parch have got very large std. It means that although it shows us that survived probability equal to 0.6, it's going to be survived between 0.2 and 1.
2. 1 or 2 members of parch have got approximately 0.58 rate of survival.

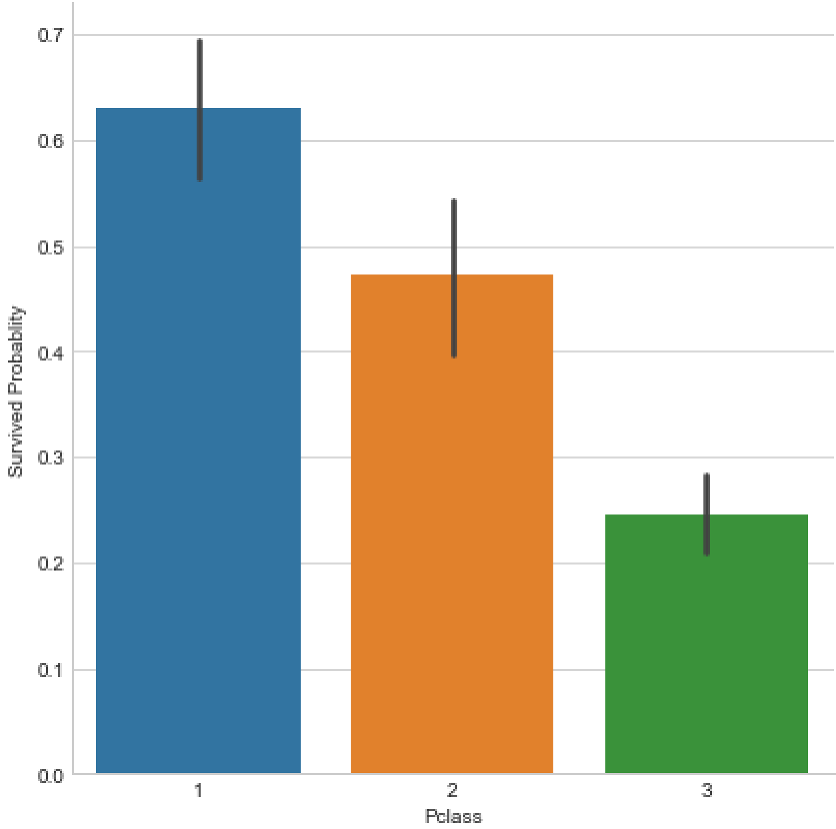
Pclass -- Survived

In [40]:

```
concatDf["Pclass"].replace({"1st":1,"2nd":2,"3rd":3}, inplace=True)
```

In [41]:

```
g = sns.factorplot(x = "Pclass", y = "Survived", data = concatDf,kind="bar",size = 6)
g.set_ylabels("Survived Probablity")
plt.show()
```



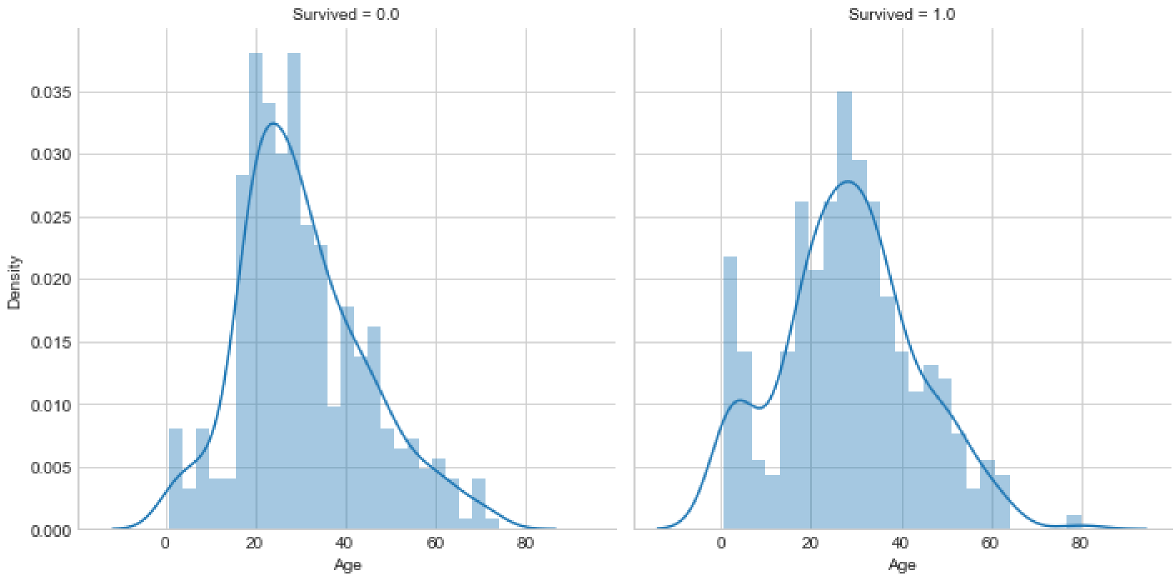
Comment:

1. If someone boards first class, She/He chance to survive more than others.

Age -- Survived

In [42]:

```
g = sns.FacetGrid(concatDf, col="Survived", size=5)
g.map(sns.distplot, "Age", bins= 25)
plt.show()
```



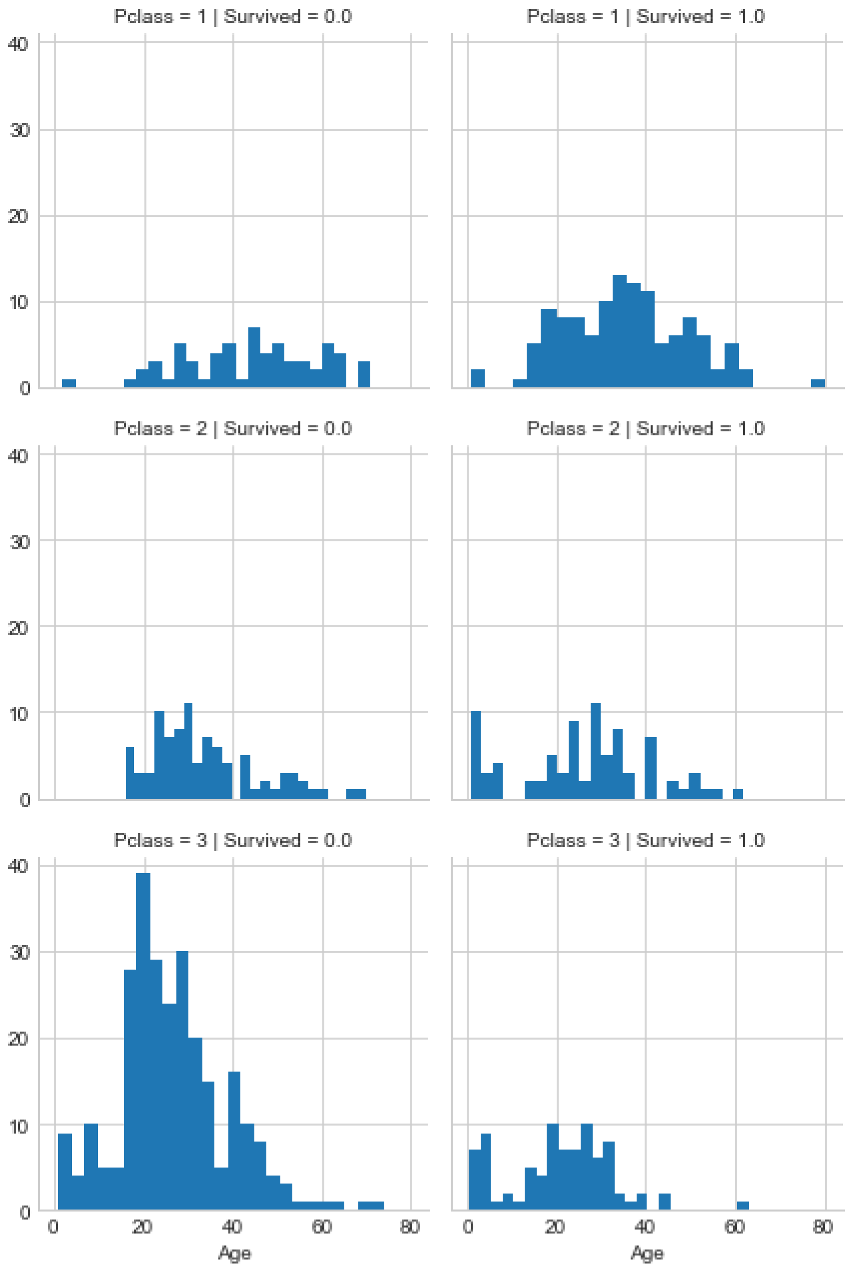
Comment:

1. Children who are between 0 and 10 years old have more chances of survival rate than others.
2. Oldest people survived.
3. Large number of 20 years old did not survived
4. Most passanger are in 15-35 age range

Pclass -- Age -- Survived

In [43]:

```
g = sns.FacetGrid(concatDf, col="Survived", row="Pclass",size=3)
g.map(plt.hist,"Age", bins= 25)
g.add_legend()
plt.show()
```



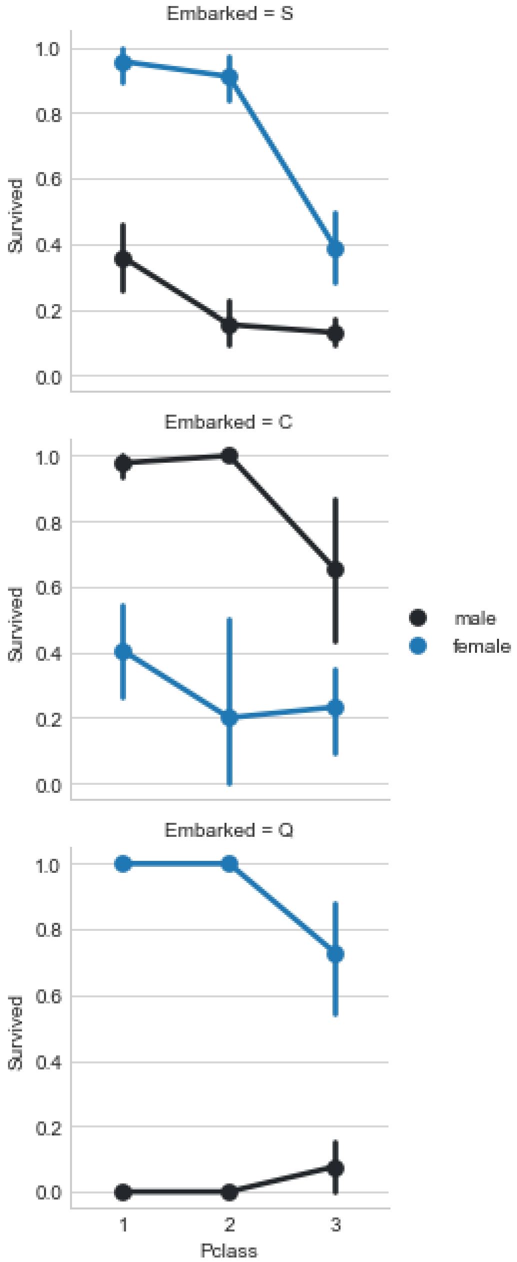
Comment:

1. Most of third class passangers did not survive

Embarked -- Sex -- Pclass -- Survived

In [44]:

```
g = sns.FacetGrid(concatDf, row= "Embarked", size = 3)
g.map(sns.pointplot, "Pclass", "Survived", "Sex")
g.add_legend()
plt.show()
```



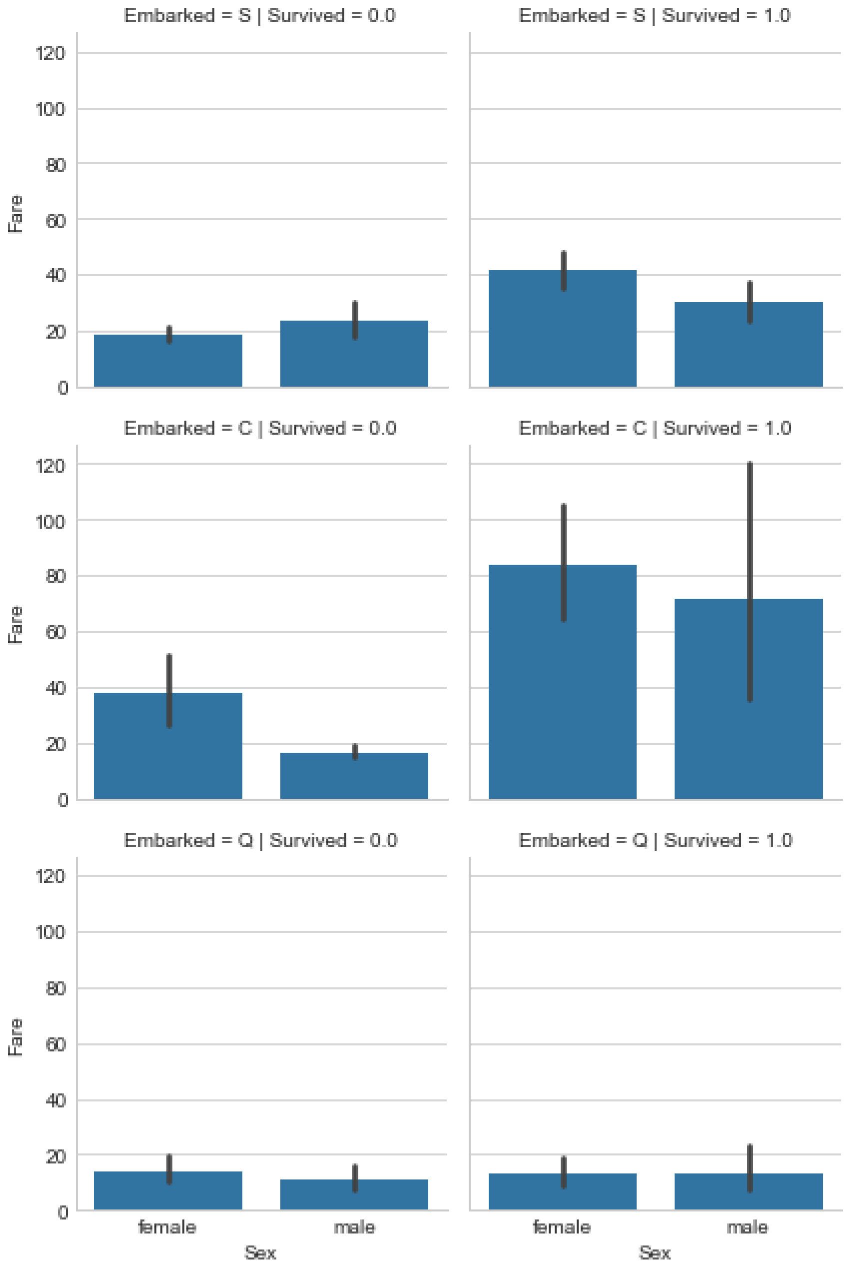
Comment:

1. Female passangers have much better survival rate than male passangers.
2. Pclass and Embarked have got relationship with each others
3. Male passangers have better survival rate in pclass in C
4. Q embarked; If you are female and your class is 1 or 2 you are most possibility survive.

Embarked -- Sex -- Fare -- Survived

In [45]:

```
g = sns.FacetGrid(concatDf, row= "Embarked", col= "Survived",
                  size = 3)
g.map(sns.barplot, "Sex","Fare")
g.add_legend()
plt.show()
```



Comment:

1. If you paid more money than others you might chance to survive more than others
2. If you board from Q you will most possibility to chance to survive.

Fill Missing Value: Age Feature

In [46]:

```
concatDf[concatDf["Age"].isnull()]
```

Out[46]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
5	6	0.0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583
17	18	1.0	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000
19	20	1.0	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250
26	27	0.0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250
27	29	1.0	3	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0	0	330959	7.8792
...	...	...	...	...	...	...	...	...	...	...
1289	1300	NaN	3	Riordan, Miss. Johanna Hannah""	female	NaN	0	0	334915	7.7208
1291	1302	NaN	3	Naughton, Miss. Hannah	female	NaN	0	0	365237	7.7500
1294	1305	NaN	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500
1297	1308	NaN	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500
1298	1309	NaN	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583

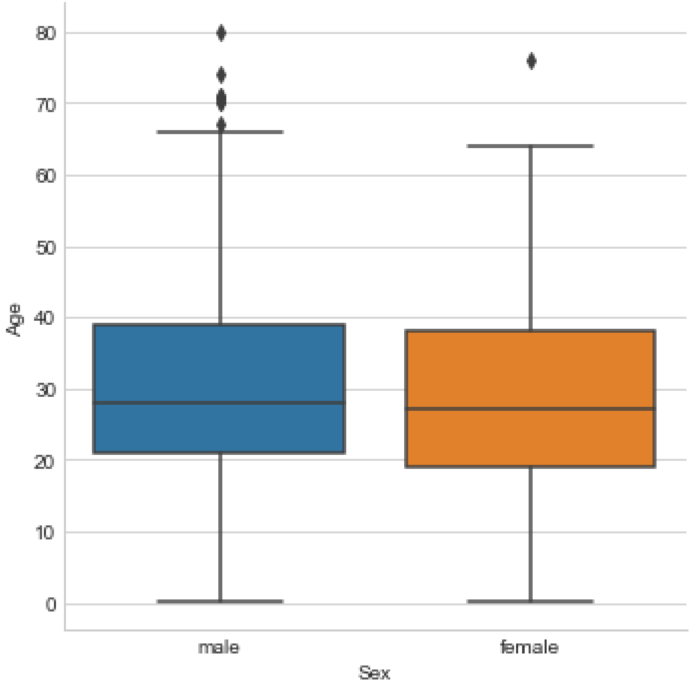
256 rows × 11 columns

Comment:

1. Age feature has got 256 nan values

In [47]:

```
# Firstly We can compare sex and age variable with each other.
sns.factorplot(x = "Sex", y= "Age", data = concatDf, kind= "box")
plt.show()
```

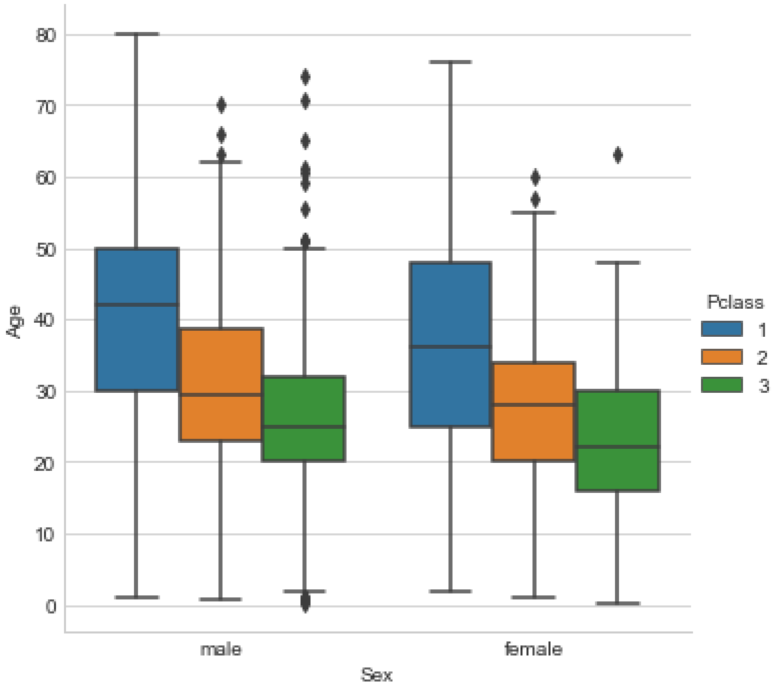


Comment:

1. We can see that the 2 features have got nearly the same median values. It means that We can not decide to compare to fill nan values.

In [48]:

```
sns.factorplot(x = "Sex", y= "Age", hue= "Pclass", data = concatDf, kind= "box")
plt.show()
```

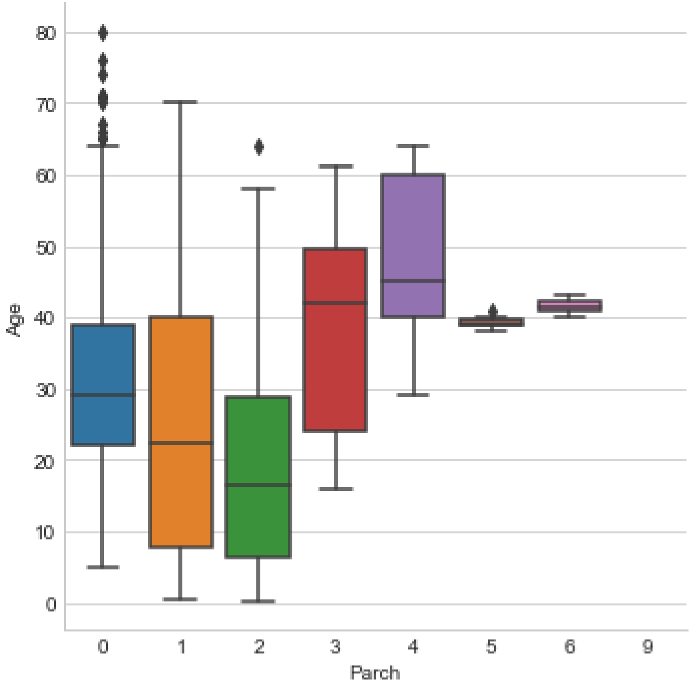


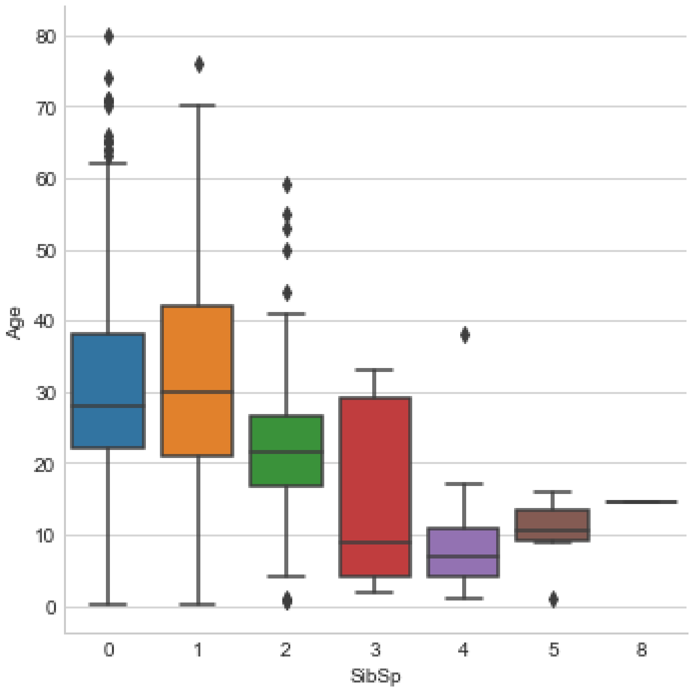
Comment:

1. If someone is in the third class median value is approximately 25.
2. If someone is in the second class median value is approximately 30.
3. If someone is in the first class median value is approximately 40.
4. To sum up: The younger passengers are in the third class.

In [49]:

```
sns.factorplot(x = "Parch", y= "Age", data = concatDf, kind= "box")
sns.factorplot(x = "SibSp", y= "Age", data = concatDf, kind= "box")
plt.show()
```





In [50]:

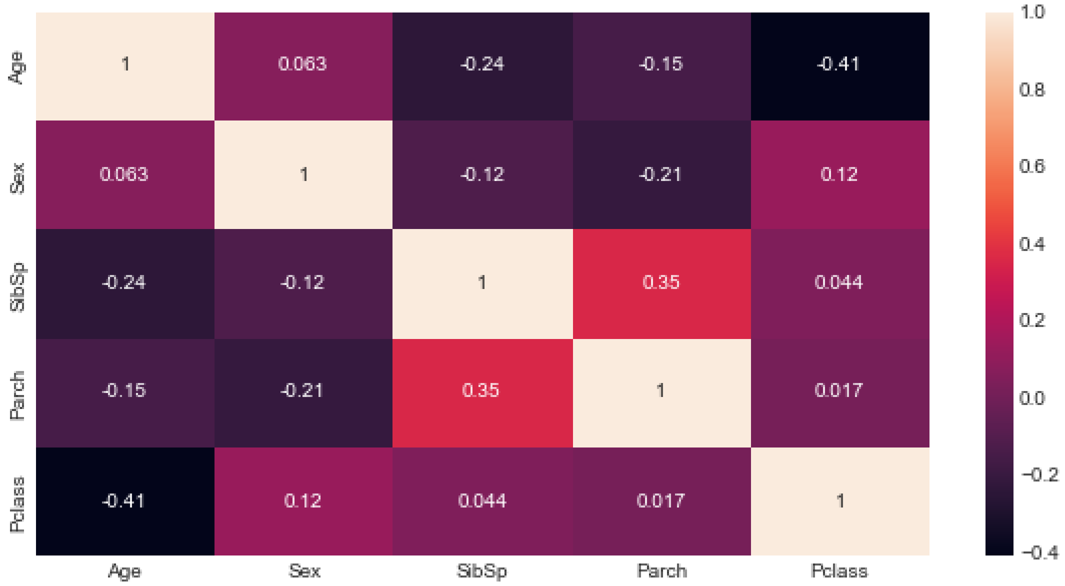
```
concatDf = concatDf.astype({"Parch":'int64'})
```

In [51]:

```
concatDf["Sex"] = [1 if i == "male" else 0 for i in concatDf["Sex"]]
```

In [52]:

```
plt.figure(figsize=(10,5))
sns.heatmap(concatDf[["Age","Sex","SibSp","Parch","Pclass"]].corr(), annot= True)
plt.show()
```



Comment:

1. Heatmap shows us that age and sex features do not correlate with each other.
2. On the other hand, age feature correlate with SibSp, Parch and Pclass

In [53]:

```
# We take indices of nan values of the age feature.
indices_nan_age = list(concatDf["Age"][concatDf["Age"].isnull()].index)
indices_nan_age
```

Out[53]:

```
[5,
 17,
 19,
 26,
 27,
 28,
 30,
 31,
 35,
 41,
 44,
 45,
 46,
 47,
 54,
 63,
 64,
 75,
```

In [54]:

```
for i in indices_nan_age:
    age_pred = concatDf["Age"][(concatDf["SibSp"]== concatDf.iloc[i]["SibSp"]) &
                               (concatDf["Parch"]== concatDf.iloc[i]["Parch"]) &
                               (concatDf["Pclass"]== concatDf.iloc[i]["Pclass"])].medi
    age_median = concatDf["Age"].median()
    if not np.isnan(age_pred):
        concatDf["Age"].iloc[i] = age_pred
    else:
        concatDf["Age"].iloc[i] = age_median
```

In [55]:

```
concatDf[concatDf["Age"].isnull()]
```

Out[55]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked

Comment:

1. We fill all age nan values

In [56]:

```
concatDf
```

Out[56]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fa
0	1	0.0	3	Braund, Mr. Owen Harris	1	22.0	1	0	A/5 21171	7.25
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	0	38.0	1	0	PC 17599	71.28
2	3	1.0	3	Heikkinen, Miss. Laina	0	26.0	0	0	STON/O2. 3101282	7.92
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	35.0	1	0	113803	53.10
4	5	0.0	3	Allen, Mr. William Henry	1	35.0	0	0	373450	8.05
...	...	...	...	...	...	...	...	...	...	
1294	1305	NaN	3	Spector, Mr. Woolf	1	25.0	0	0	A.5. 3236	8.05
1295	1306	NaN	1	Oliva y Ocana, Dona. Fermina	0	39.0	0	0	PC 17758	108.90
1296	1307	NaN	3	Saether, Mr. Simon Sivertsen	1	38.5	0	0	SOTON/O.Q. 3101262	7.25
1297	1308	NaN	3	Ware, Mr. Frederick	1	25.0	0	0	359309	8.05
1298	1309	NaN	3	Peter, Master. Michael J	1	16.0	1	1	2668	22.35

1299 rows × 11 columns

In [57]:

```
concatDf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1299 entries, 0 to 1298
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  1299 non-null   int64  
 1   Survived     881 non-null    float64
 2   Pclass       1299 non-null   int64  
 3   Name         1299 non-null   object 
 4   Sex          1299 non-null   int64  
 5   Age          1299 non-null   float64
 6   SibSp        1299 non-null   int64  
 7   Parch        1299 non-null   int64  
 8   Ticket       1299 non-null   object 
 9   Fare         1299 non-null   float64
 10  Embarked     1299 non-null   object 
dtypes: float64(3), int64(5), object(3)
memory usage: 111.8+ KB
```

In [58]:

```
concatDf.isnull().sum()
```

Out[58]:

```
PassengerId      0
Survived       418
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         0
dtype: int64
```

Conclusion:

1. First of all, We handled with dataset and made some changes
2. We separeted dataset between categorical and numerical
3. If the dataset includes outlier values We detected these.
4. We did some visualization studies to better understand the dataset..
5. Finding the missing value and filling this properly
    - We separated the age value because there were some problems with that.
6. We correlated values with each other and made decisions for filling or dropping.
7. We fill the nan value of age with the median values of SibSp, Parch, Pclass.
8. Survived feature has got nan value and it comes from test data set. We did not fill in these values because We will use in the machine-learning process

This study was done by Mehmet Ali YILMAZ.