In [26]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use("seaborn-darkgrid")

from collections import Counter

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the inpu

import warnings
warnings.filterwarnings("ignore")

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output whe
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current se
```

```
/kaggle/input/titanic/train.csv
/kaggle/input/titanic/test.csv
/kaggle/input/titanic/gender_submission.csv
```

INTRODUCTION TO TITANIC DATASET

Dataset containing information that died in the titanic accident

Features

0-PassengerId : Even the passenger's number

1-Survived : Survive status (1 - 0) after the accident

2-Pclass : Cabin status(theese status 1 - 2 - 3)

3-Name

4-Sex

5-Age

6-SibSp : Number of siblings

7-Parch : The passenger's childreen number

8-Ticket : The passenger's ticket number

9-Fare : The amount payable for the ticket

10-Cabin

11-Embarked: The passenger boarding port

Content

- The correlation of the features in the dataset,
- The frequencies of the numerical features,
- The outlier values and the survival rates depending on categorical features are examined.
- Feature that has missing value was filled with statstics proccessing ,
- Analyzed relation to survived with other features.

Library that used

- Seaborn matplot is used as visualization library
- Pandas
- Numpy

Load and check data

In [122]:

```
# read to dataset
data = pd.read_csv('/kaggle/input/titanic/train.csv')

# take a information from data(dtype , 'NaN' values etc..)
data.info()

# try to understand data with first 5 indexs
data.head()
```

```
<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    object 
 5   Age          714 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     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Out[122]:

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

Classification of features

Numerical features : *The type of feature that has numbers at certain intervals without a certain categorization.*

Categorical features : *The type of feature formed by assigning a certain set of features to indexes*

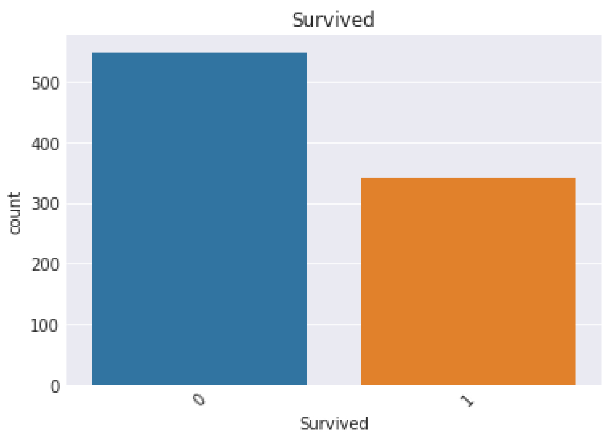
In [28]:

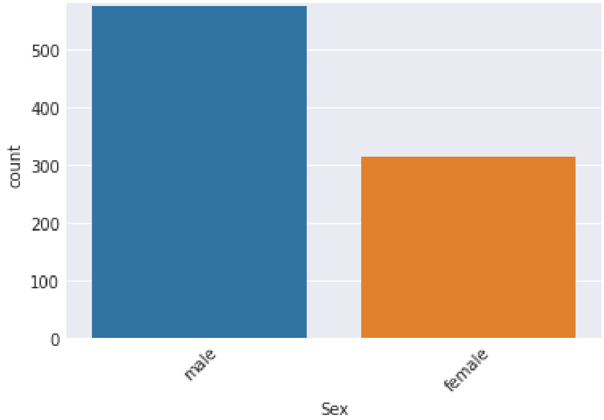
```
# numerical features
num_features = ['Age' , 'Fare']
# categorical features
cat_features = ['Survived' , 'Sex' , 'SibSp' , 'Parch' , 'Embarked']
```

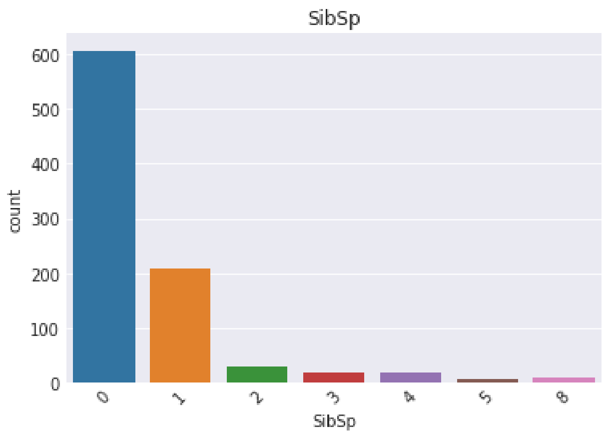
Numbers and visualization of categorical variables

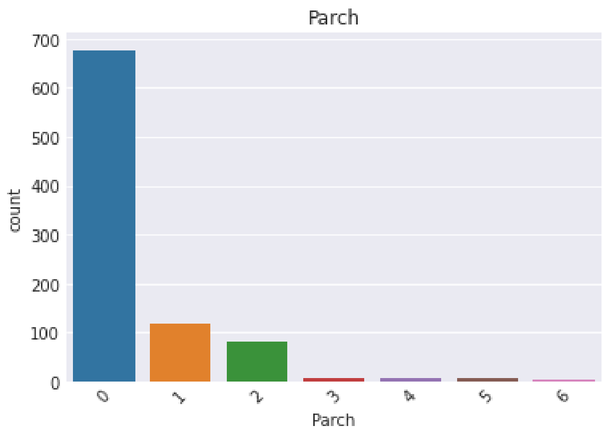
In [29]:

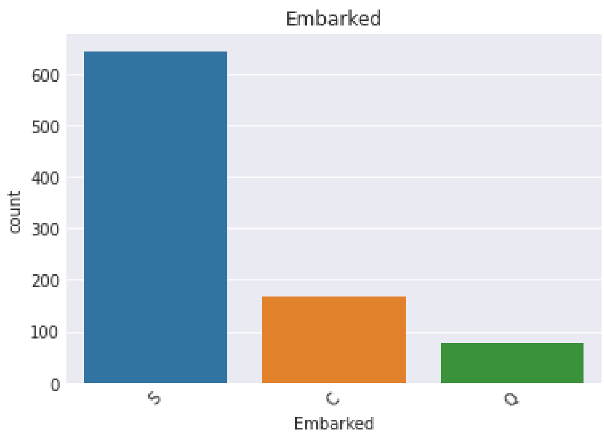
```
for i in cat_features:
    sns.countplot(data[i])
    plt.xticks(rotation = 45)
    plt.title('{}'.format(i))
    plt.show()
```







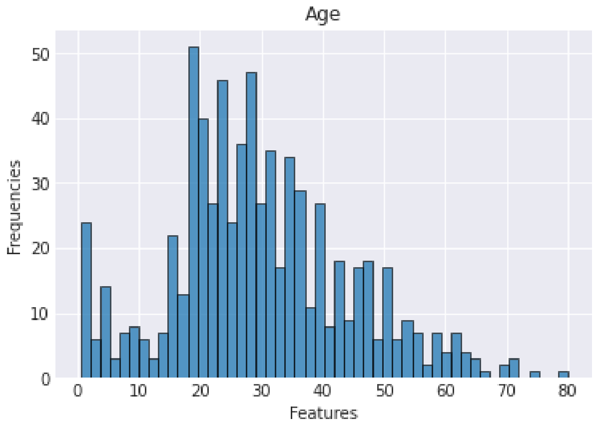


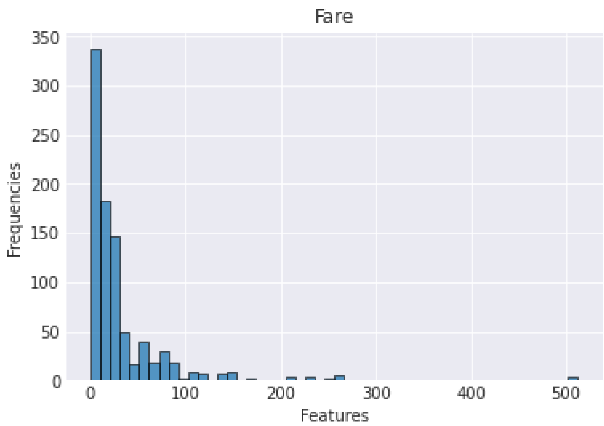


Frequencies of numerical properties

In [30]:

```
for i in num_features:
    sns.histplot(data[i] , bins = 50)
    plt.title('{}'.format(i))
    plt.xlabel('Features')
    plt.ylabel('Frequencies')
    plt.show()
```

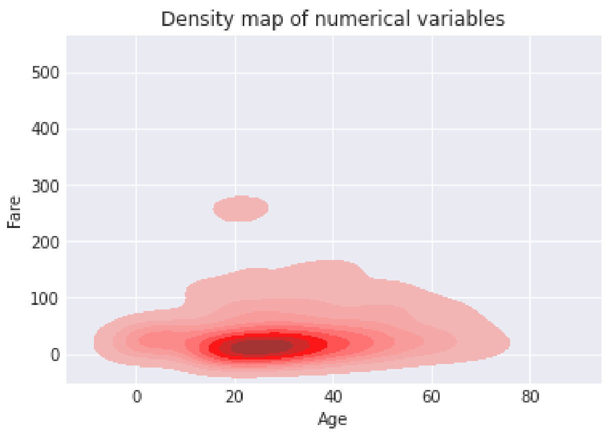




Density map of numerical variables

In [31]:

```
sns.kdeplot(x = 'Age' , y = 'Fare' , data = data , shade = True , color = 'red')
plt.title('Density map of numerical variables')
plt.show()
```



Comment : High density between the ages of 20 and 40 on the other hand, there was a distribution of 200 and 300 Euros

Detech the missing values

In [32]:

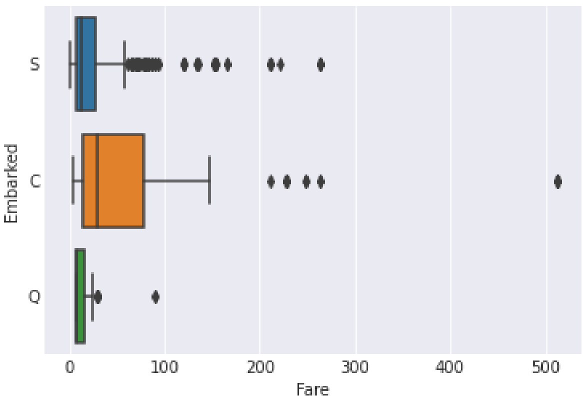
```
# null values counting
data.isnull().sum()

# detecth the missing values in embarked features
data[data['Embarked'].isnull()]
```

Out[32]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
61	62	1	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	B28	NaN
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	B28	NaN

In [33]:

```
# try to understand missing values in embarked features
sns.boxplot(x = 'Fare' , y = 'Embarked' , data = data)
plt.show()
```



Comment : With 80 units at the location of the Median, the most purchased type is C so we can fill the missing values with C

In [34]:

```
# filling missing value
data[data['Embarked'].isnull()].fillna('C')
```

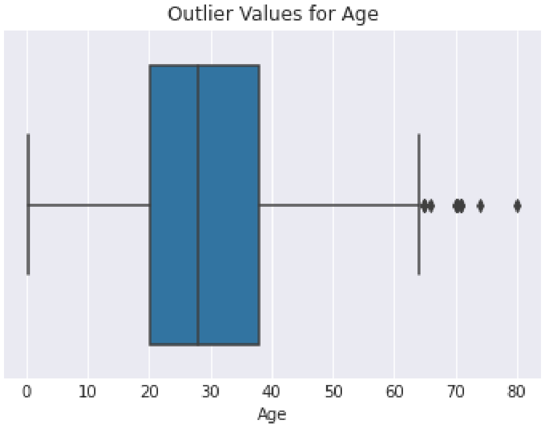
Out[34]:

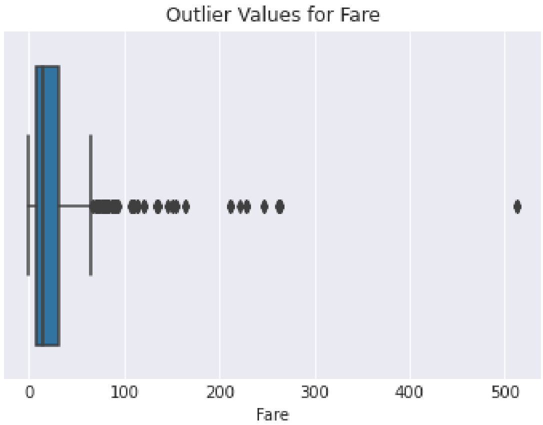
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
61	62	1	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	B28	C
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	B28	C

Detech the outlier values for numerical categorization

In [35]:

```
# outlier detection with visualization
for i in num_features:
    sns.boxplot(data[i])
    plt.xlabel('{}'.format(i))
    plt.title('Outlier Values for {}'.format(i))
    plt.show()
```





Filling the Age feature

In [49]:

```
# Calculate the NaN values
data['Age'].isnull().sum()
```

Out[49]:

```
177
```

In [50]:

```
# Detecth the null indexes
data[data['Age'].isnull()]
```

Out[50]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	NaN	S
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	NaN	C
26	27	0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250	NaN	C
28	29	1	3	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0	0	330959	7.8792	NaN	Q
...	...	...	...	...	...	...	...	...	...	...	...	...
859	860	0	3	Razi, Mr. Raihed	male	NaN	0	0	2629	7.2292	NaN	C
863	864	0	3	Sage, Miss. Dorothy Edith "Dolly"	female	NaN	8	2	CA. 2343	69.5500	NaN	S
868	869	0	3	van Melkebeke, Mr. Philemon	male	NaN	0	0	345777	9.5000	NaN	S
878	879	0	3	Laleff, Mr. Kristo	male	NaN	0	0	349217	7.8958	NaN	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S

177 rows × 12 columns

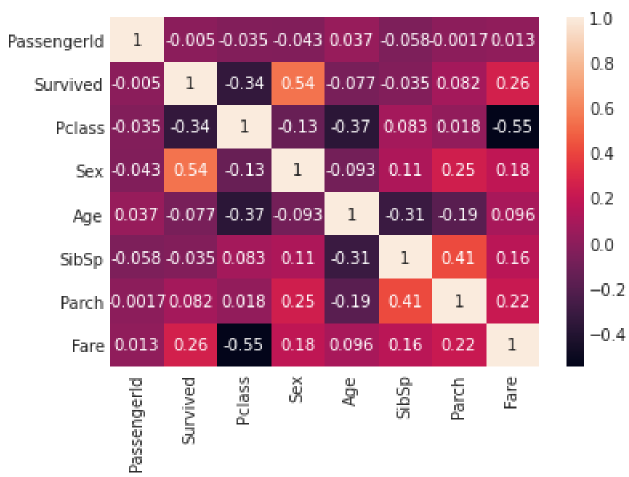
In [58]:

```
# Convert the Sex type for analyze the correlation with Age feature
# ! data['Sex'] = [1 if i == 'female' else 0 for i in data['Sex']]
data['Sex'].value_counts()
data.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          714 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     889 non-null    object 
dtypes: float64(2), int64(6), object(4)
memory usage: 83.7+ KB
```

In [59]:

```
# analyze the correlation with Age feature
sns.heatmap(data.corr() , annot = True)
plt.show()
```



Comment : Due to correlation map, we understood 'Pclass' , 'Parch' , 'SibSp' feature important in proccesing that filling the missing values for age feature

In [60]:

```
# Stored the index that has a NaN values in Age feature
indexes_null = list(data[data['Age'].isnull()].index)
indexes_null
```

Out[60]:

```
[5,
 17,
 19,
 26,
 28,
 29,
 31,
 32,
 36,
 42,
 45,
 46,
 47,
 48,
 55,
 64,
 65,
 76,
 77,
 82,
 87,
 95,
 101,
 107,
 109,
 121,
 126,
```

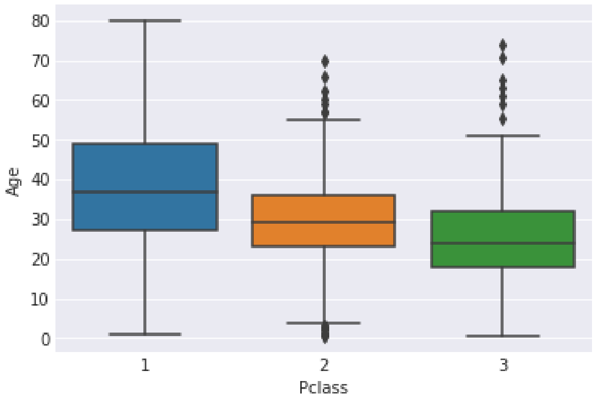
128,
140,
154,
158,
159,
166,
168,
176,
180,
181,
185,
186,
196,
198,
201,
214,
223,
229,
235,
240,
241,
250,
256,
260,
264,
270,
274,
277,
284,
295,
298,
300,
301,
303,
304,
306,
324,
330,
334,
335,
347,
351,
354,
358,
359,
364,
367,
368,
375,
384,
388,
409,
410,
411,
413,
415,
420,
425,
428,
431,
444,
451,
454,
457,
459,
464,
466,
468,
470,
475,
481,
485,
490,
495,
497,
502,
507,

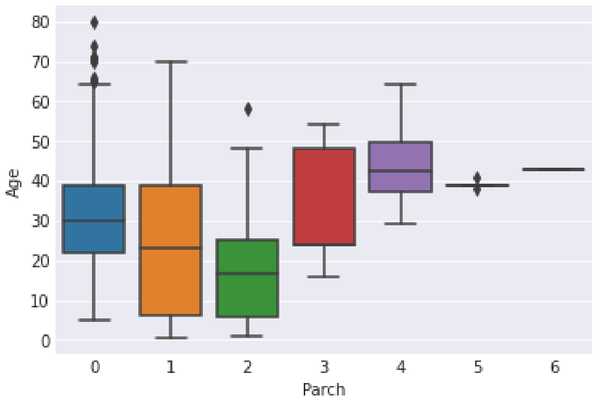
```
 511,
 517,
 522,
 524,
 527,
 531,
 533,
 538,
 547,
 552,
 557,
 560,
 563,
 564,
 568,
 573,
 578,
 584,
 589,
 593,
 596,
 598,
 601,
 602,
 611,
 612,
 613,
 629,
 633,
 639,
 643,
 648,
 650,
 653,
 656,
 667,
 669,
 674,
 680,
 692,
 697,
 709,
 711,
 718,
 727,
 732,
 738,
 739,
 740,
 760,
 766,
 768,
 773,
 776,
 778,
 783,
 790,
 792,
 793,
 815,
 825,
 826,
 828,
 832,
 837,
 839,
 846,
 849,
 859,
 863,
 868,
 878,
 888]
```

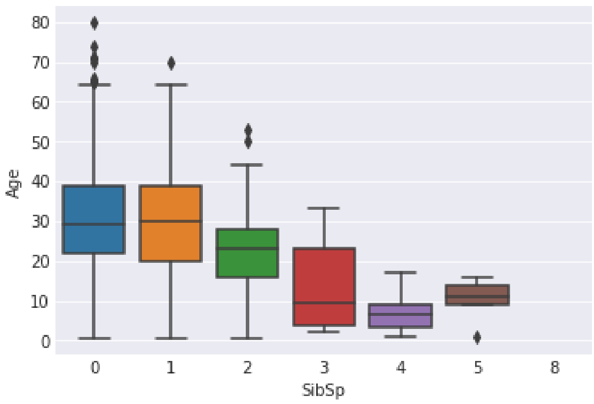
In [81]:

```
# Analyzed to pclass and age relation
sns.boxplot(x = 'Pclass' , y = 'Age', data = data)
```

```
plt.show()

# Analyzed to Parch and age relation
sns.boxplot(x = 'Parch' , y = 'Age' , data = data)
plt.show()

# Analyzed to SibSp and age relation
sns.boxplot(x = 'SibSp' , y = 'Age' , data = data)
plt.show()
```







Comment :

- *1st pclass passenger are older than 2nd class and 2nd class older than 3st class*
- *Parch feature can use for threshold that 0 , 1 , 2 features's median is almost '25' and the other feautures's median is almost '35'*
- *Same think possible for SibSp*

Proccesing that filling the missing value for Age feature

In [131]:

```
for i in indexes_null:
    age_pred = data["Age"][((data["SibSp"] == data.iloc[i]["SibSp"]) &(data["Parch"] == data.iloc[i]["Par
    age_med = data["Age"].median()

    if not np.isnan(age_pred):
        data["Age"].iloc[i] = age_pred

    else:
```

```
        data["Age"].iloc[i] = age_med
```

In [132]:

```
data['Age'].isnull().sum()
```

Out[132]:

```
0
```

Detecth the outlier values from numerical categorization

In [128]:

```
def detect_outliers(df,features):

    for c in features:
        # 1st quartile

        Q1 = np.percentile(data[c],25)

        # 3rd quartile

        Q3 = np.percentile(data[c],75)

        # IQR

        IQR = Q3 - Q1

        # Outlier step

        outlier_step = IQR * 1.5

        # detect outlier and their indeces

        outlier_list_col = data[(data[c] < Q1 - outlier_step) | (data[c] > Q3 + outlier_step)].index

        return outlier_list_col
```

In [129]:

```
data.loc[detect_outliers(data , ['Age' , 'Fare'])]
```

Out[129]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.00	0	0	113783	26.5500	C103	S
33	34	0	2	Wheadon, Mr. Edward H	male	66.00	0	0	C.A. 24579	10.5000	NaN	S
54	55	0	1	Ostby, Mr. Engelhart Cornelius	male	65.00	0	1	113509	61.9792	B30	C
78	79	1	2	Caldwell, Master. Alden Gates	male	0.83	0	2	248738	29.0000	NaN	S
94	95	0	3	Coxon, Mr. Daniel	male	59.00	0	0	364500	7.2500	NaN	S
96	97	0	1	Goldschmidt, Mr. George B	male	71.00	0	0	PC 17754	34.6542	A5	C
116	117	0	3	Connors, Mr. Patrick	male	70.50	0	0	370369	7.7500	NaN	Q
170	171	0	1	Van der hoef, Mr. Wyckoff	male	61.00	0	0	111240	33.5000	B19	S
195	196	1	1	Lurette, Miss. Elise	female	58.00	0	0	PC 17569	146.5208	B80	C
232	233	0	2	Sjostedt, Mr. Ernst Adolf	male	59.00	0	0	237442	13.5000	NaN	S
252	253	0	1	Stead, Mr. William Thomas	male	62.00	0	0	113514	26.5500	C87	S
268	269	1	1	Graham, Mrs. William Thompson (Edith Junkins)	female	58.00	0	1	PC 17582	153.4625	C125	S
275	276	1	1	Andrews, Miss. Kornelia Theodosia	female	63.00	1	0	13502	77.9583	D7	S
280	281	0	3	Duane, Mr. Frank	male	65.00	0	0	336439	7.7500	NaN	Q
305	306	1	1	Allison, Master. Hudson Trevor	male	0.92	1	2	113781	151.5500	C22 C26	S
326	327	0	3	Nysveen, Mr. Johan Hansen	male	61.00	0	0	345364	6.2375	NaN	S
366	367	1	1	Warren, Mrs. Frank Manley (Anna Sophia Atkinson)	female	60.00	1	0	110813	75.2500	D37	C
438	439	0	1	Fortune, Mr. Mark	male	64.00	1	4	19950	263.0000	C23 C25	S

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
438	439	0	1	Fortune, Mr. Mark	male	64.00	1	4	19950	263.0000	C25 C27	S
456	457	0	1	Millet, Mr. Francis Davis	male	65.00	0	0	13509	26.5500	E38	S
469	470	1	3	Baclini, Miss. Helene Barbara	female	0.75	2	1	2666	19.2583	NaN	C
483	484	1	3	Turkula, Mrs. (Hedwig)	female	63.00	0	0	4134	9.5875	NaN	S
487	488	0	1	Kent, Mr. Edward Austin	male	58.00	0	0	11771	29.7000	B37	C
493	494	0	1	Artagaveytia, Mr. Ramon	male	71.00	0	0	PC 17609	49.5042	NaN	C
545	546	0	1	Nicholson, Mr. Arthur Ernest	male	64.00	0	0	693	26.0000	NaN	S
555	556	0	1	Wright, Mr. George	male	62.00	0	0	113807	26.5500	NaN	S
570	571	1	2	Harris, Mr. George	male	62.00	0	0	S.W./PP 752	10.5000	NaN	S
587	588	1	1	Frolicher-Stehli, Mr. Maxmillian	male	60.00	1	1	13567	79.2000	B41	C
625	626	0	1	Sutton, Mr. Frederick	male	61.00	0	0	36963	32.3208	D50	S
630	631	1	1	Barkworth, Mr. Algernon Henry Wilson	male	80.00	0	0	27042	30.0000	A23	S
644	645	1	3	Baclini, Miss. Eugenie	female	0.75	2	1	2666	19.2583	NaN	C
659	660	0	1	Newell, Mr. Arthur Webster	male	58.00	0	2	35273	113.2750	D48	C
672	673	0	2	Mitchell, Mr. Henry Michael	male	70.00	0	0	C.A. 24580	10.5000	NaN	S
684	685	0	2	Brown, Mr. Thomas William Solomon	male	60.00	1	1	29750	39.0000	NaN	S
694	695	0	1	Weir, Col. John	male	60.00	0	0	113800	26.5500	NaN	S
745	746	0	1	Crosby, Capt. Edward Gifford	male	70.00	1	1	WE/P 5735	71.0000	B22	S
755	756	1	2	Hamalainen, Master. Viljo	male	0.67	1	1	250649	14.5000	NaN	S
803	804	1	3	Thomas, Master. Assad Alexander	male	0.42	0	1	2625	8.5167	NaN	C
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.00	0	0	113572	80.0000	B28	NaN
831	832	1	2	Richards, Master. George Sibley	male	0.83	1	1	29106	18.7500	NaN	S
851	852	0	3	Svensson, Mr. Johan	male	74.00	0	0	347060	7.7750	NaN	S

Relationship between categorical variables and survival rate

1 -) Sex - Survived

2 -) SibSp - Survived

3 -) Parch - Survived

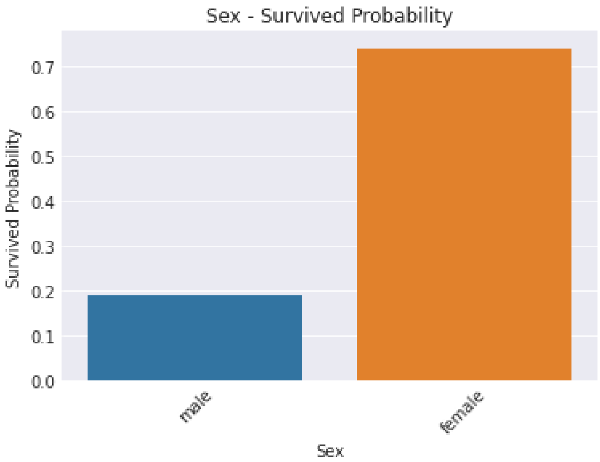
4 -) Embarked - Survived

Sex - Survived

In [38]:

```
# Sex and Survived
male_survived = data.Survived[data['Sex'] == 'male'].mean()
female_survived = data.Survived[data['Sex'] == 'female'].mean()

sex_list = list(data['Sex'].unique())
sex_survived_list = [male_survived , female_survived]

df_sex_survived = pd.DataFrame({'Sex' : sex_list , 'Survived Mean' : sex_survived_list})
df_sex_survived

# visualization

sns.barplot(x = 'Sex' , y = 'Survived Mean' , data = df_sex_survived , alpha = 1)
plt.xticks(rotation = 45)
plt.ylabel('Survived Probability')
```

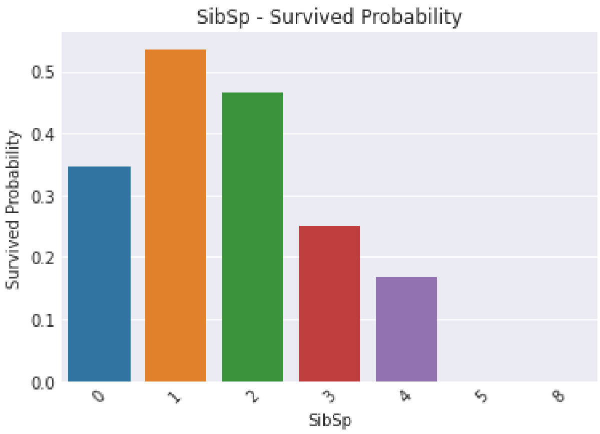
```
plt.xlabel('Sex')
plt.title('Sex - Survived Probability')
plt.show()
```



SibSp - Survived

In [39]:

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

# visualization
sns.barplot(x = 'SibSp' , y = 'Survived' , data = df_SibSp_Survived , alpha = 1)
plt.xticks(rotation = 45)
plt.ylabel('Survived Probability')
plt.xlabel('SibSp')
plt.title('SibSp - Survived Probability')
plt.show()
```

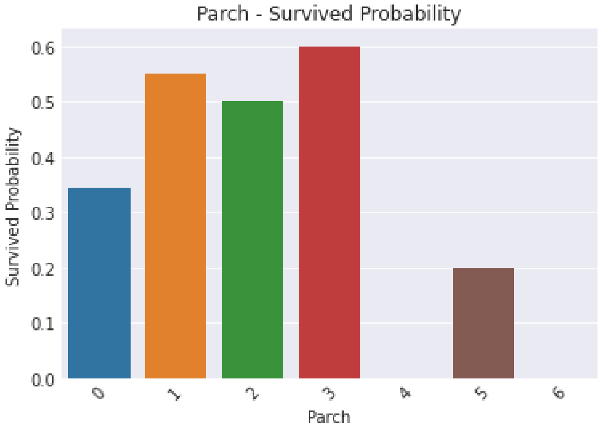


Comment : The data is not evenly distributed. However, by thresholding for classification, an intermediate level data on education

Parch - Survived

In [40]:

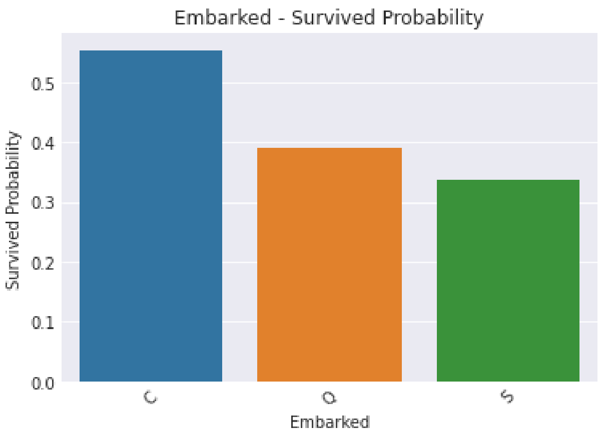
```
# parch - survived
df_parch_survived = data[['Parch' , 'Survived']].groupby('Parch' , as_index = False).mean()

# visualization
sns.barplot(x = 'Parch' , y = 'Survived' , data = df_parch_survived , alpha = 1)
plt.xticks(rotation = 45)
plt.ylabel('Survived Probability')
plt.xlabel('Parch')
plt.title('Parch - Survived Probability')
plt.show()
```



Embarked - Survived

In [41]:

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

# visualization
sns.barplot(x = 'Embarked' , y = 'Survived' , data = df_embarked_survived , alpha = 1)
plt.xticks(rotation = 45)
plt.ylabel('Survived Probability')
plt.xlabel('Embarked')
plt.title('Embarked - Survived Probability')
plt.show()
```

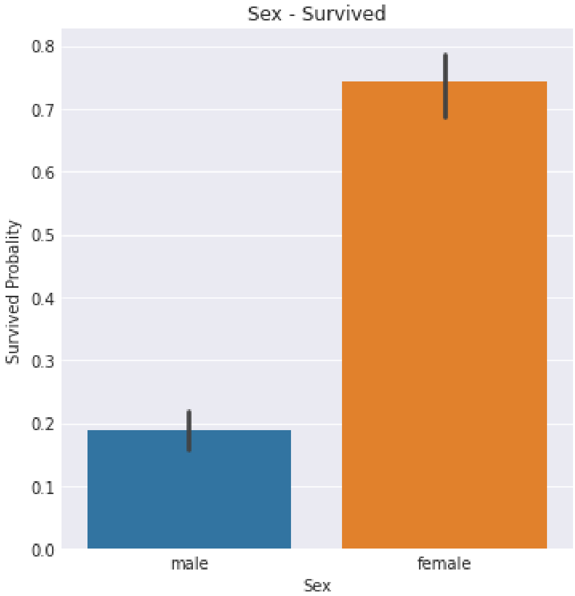


Relationship between categorical variables and survival rate with using factorplot

Sex - Survived

In [42]:

```
sns.factorplot(x = 'Sex' , y = 'Survived' , data = data , kind = 'bar')
plt.ylabel('Survived Probality')
plt.title('Sex - Survived')
plt.show()
```

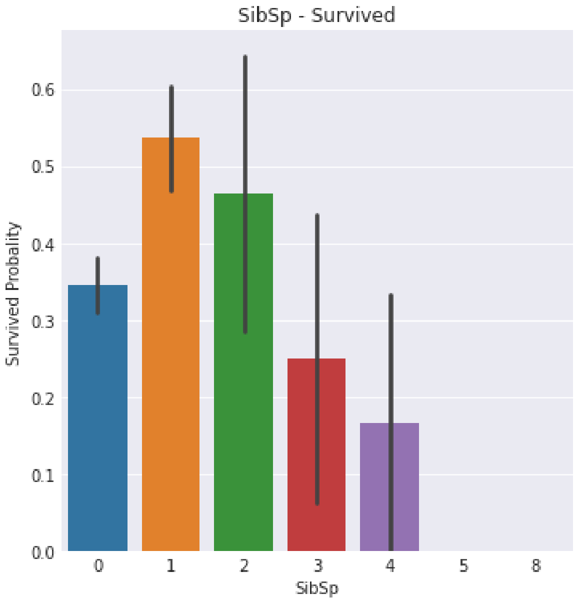


Comment: *Since the rate of having confidence in a learning algorithm is higher, we can directly define women as alive.*

SibSp - Survived

In [43]:

```
sns.factorplot(x = 'SibSp' , y = 'Survived' , data = data , kind = 'bar')
plt.ylabel('Survived Probality')
plt.title('SibSp - Survived')
plt.show()
```

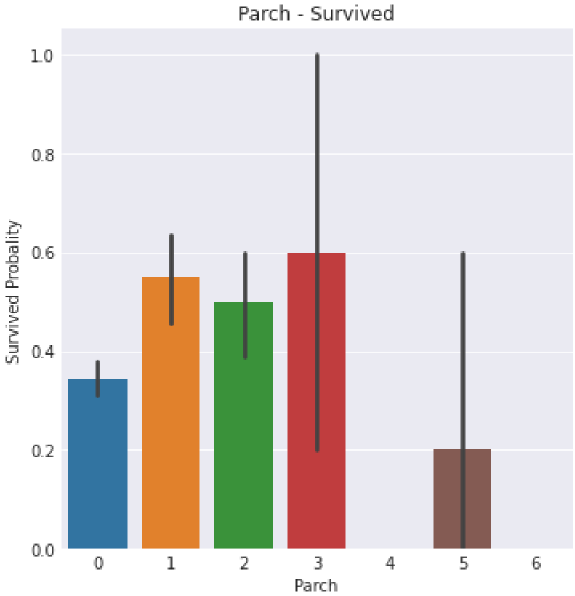


Comment : *if sibsp == 0 or 1 or 2, passenger has more chance to survive , we can consider a new feature describing these categories.*

Parch - Survived

In [44]:

```
sns.factorplot(x = 'Parch' , y = 'Survived' , data = data , kind = 'bar')
plt.ylabel('Survived Probality')
plt.title('Parch - Survived')
plt.show()
```

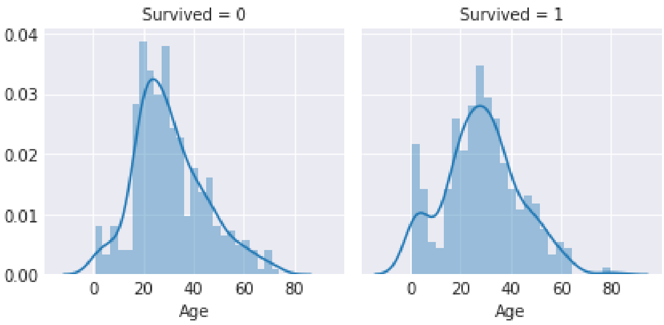


Comment : *In this data, the survival rate of small families is more standardized, resulting in the standard deviation of the survival rate of families with 3 or more family members.*

Age Survived

In [45]:

```
g = sns.FacetGrid(data , col = 'Survived')
g.map(sns.distplot , 'Age' , bins = 25)
plt.show()
```



Comment :

Age <= 10 has a high survival rate,

oldest passengers (80) survived,

large number of 20 years old did not survive,

most passengers are in 15-35 age range,

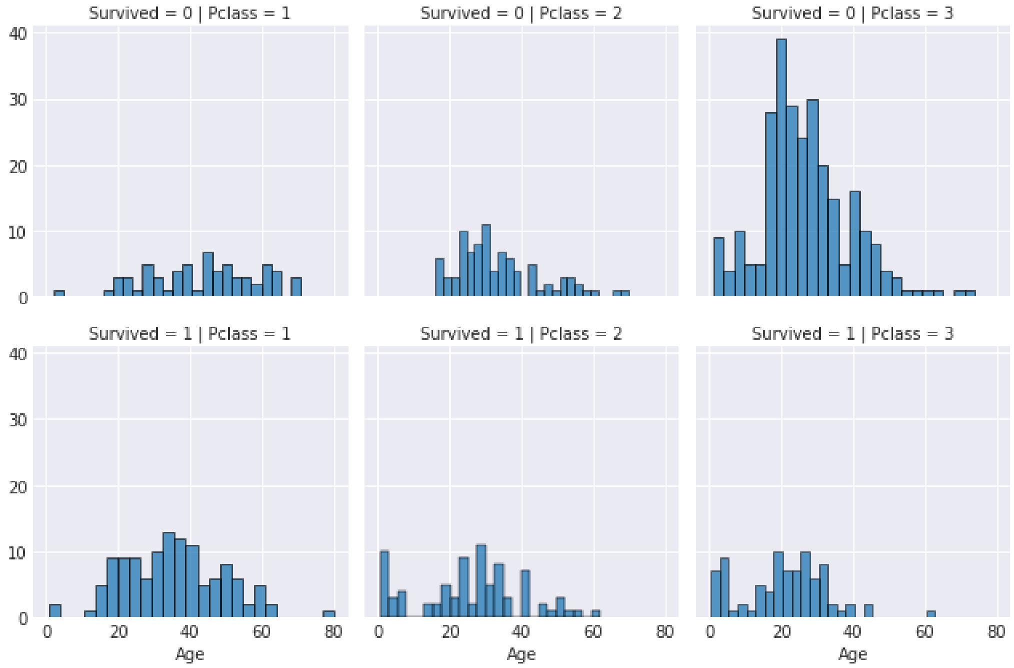
use age feature in training

use age distribution for missing value of age

Pclass Survived Age Relation with Survived

In [46]:

```
g = sns.FacetGrid(data , col = 'Pclass' , row = 'Survived')
g.map(sns.histplot , 'Age' , bins = 25)
plt.show()
```

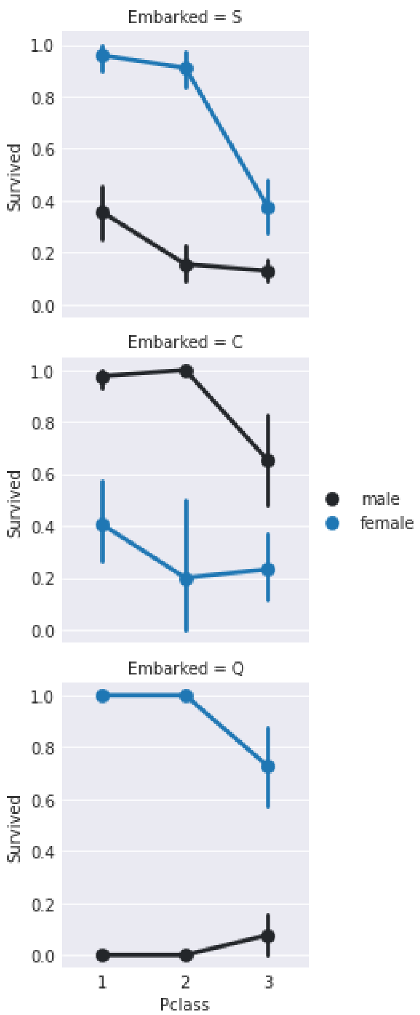


Comment : *If pclass is '3' the survival rate decreases, this can provide a good threshold for learning algorithms.*

Embarked - Pclass - Sex Relation with Survived

In [47]:

```
g = sns.FacetGrid(data , row = 'Embarked')
g.map(sns.pointplot , 'Pclass' , 'Survived' , 'Sex')
g.add_legend()
plt.show()
```



Comment : *Female passengers have much better survival rate than males. Males have better survşval rate in pclass 3 in C.*

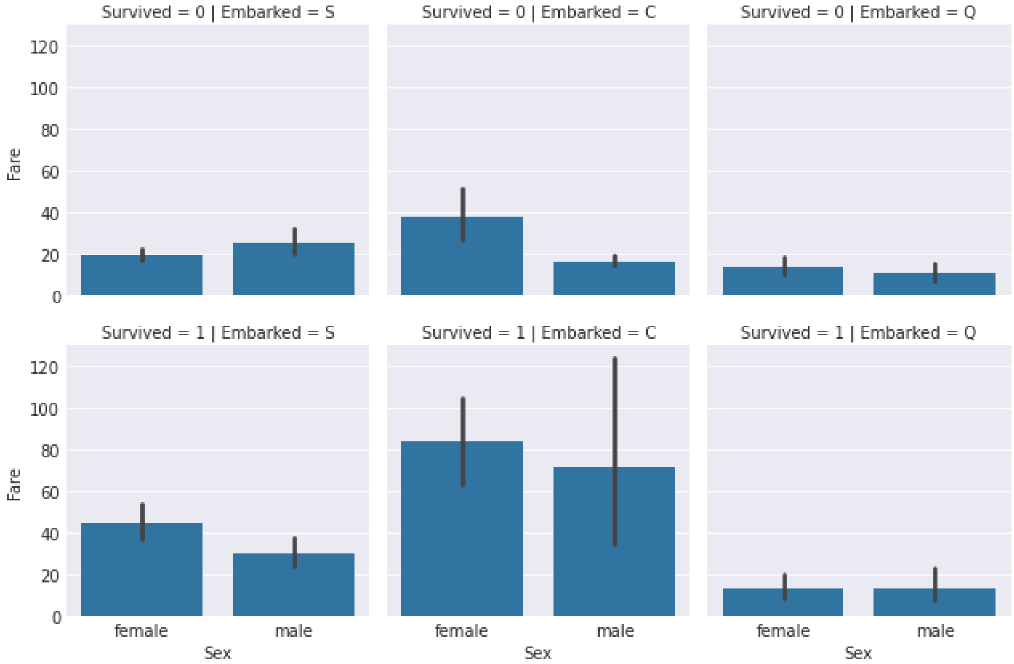
Embarked - Sex - Fare with relation with survived

In [48]:

```
g = sns.FacetGrid(data , row = 'Survived' , col = 'Embarked')
g.map(sns.barplot , 'Sex' , 'Fare')
```

Out[48]:

```
<seaborn.axisgrid.FacetGrid at 0x7f22395c1190>
```



Comment : *Passsengers who pay higher fare have better survival. Fare can be used as categorical for training.*