Loading data using Pandas

In [3]:
```
import pandas as pd
titanic = pd.read_csv('https://raw.githubusercontent.com/dsrscientist/dataset1/master/titanic_train.csv')
titanic.head()
```

Out[3]:

	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

Checking the NULL values

In [4]:
```
titanic.isnull().sum()
```

Out[4]:
```
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
```

The columns having null values are: Age, Cabin, Embarked. They need to be filled up with appropriate values later on.

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

Categorical/Nominal: Variables that can be divided into multiple categories but having no order or priority. Eg. Embarked (C = Cherbourg; Q = Queenstown; S = Southampton)

Binary: A subtype of categorical features, where the variable has only two categories. Eg: Sex (Male/Female)

Ordinal: They are similar to categorical features but they have an order(i.e can be sorted). Eg. Pclass (1, 2, 3)

Continuous: They can take up any value between the minimum and maximum values in a column. Eg. Age, Fare

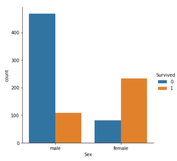
Count: They represent the count of a variable. Eg. SibSp, Parch

Useless: They don't contribute to the final outcome of an ML model. Here, PassengerId, Name, Cabin and Ticket might fall into this category.

Graphical Analysis

In [5]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.catplot(x ="Sex", hue ="Survived",
kind ="count", data = titanic)
```

Out[5]:
```
<seaborn.axisgrid.FacetGrid at 0x2c39e7aea80>
```

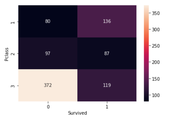


Just by observing the graph, it can be approximated that the survival rate of men is around 20% and that of women is around 75%. Therefore, whether a passenger is a male or a female plays an important role in determining if one is going to survive.

Pclass (Ordinal Feature) vs Survived

In [6]:
```
# Group the dataset by Pclass and Survived and then unstack them
group = titanic.groupby(['Pclass', 'Survived'])
pclass_survived = group.size().unstack()

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

Out[6]:
```
<AxesSubplot:xlabel='Survived', ylabel='Pclass'>
```

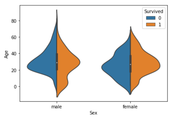


It helps in determining if higher-class passengers had more survival rate than the lower class ones or vice versa. Class 1 passengers have a higher survival chance compared to classes 2 and 3. It implies that Pclass contributes a lot to a passenger's survival rate.

Age (Continuous Feature) vs Survived

In [7]:
```
# Violinplot Displays distribution of data
# across all levels of a category.
sns.violinplot(x ="Sex", y ="Age", hue ="Survived",
data = titanic, split = True)
```

Out[7]:
```
<AxesSubplot:xlabel='Sex', ylabel='Age'>
```



This graph gives a summary of the age range of men, women and children who were saved. The survival rate is –

Good for children. High for women in the age range 20-50. Less for men as the age increases.

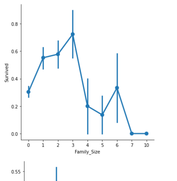
Since Age column is important, the missing values need to be filled, either by using the Name column(ascertaining age based on salutation – Mr, Mrs etc.) or by using a regressor. After this step, another column – Age_Range (based on age column) can be created and the data can be analyzed again.

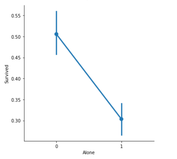
Factor plot for Family_Size (Count Feature) and Family Size.

In [8]:
```
# Adding a column Family_Size
titanic['Family_Size'] = 0
titanic['Family_Size'] = titanic['Parch']+titanic['SibSp']

# Adding a column Alone
titanic['Alone'] = 0
titanic.loc[titanic.Family_Size == 0, 'Alone'] = 1

# Factorplot for Family_Size
sns.factorplot(x ='Family_Size', y ='Survived', data = titanic)

# Factorplot for Alone
sns.factorplot(x ='Alone', y ='Survived', data = titanic)
```

```
D:\ANACONDA\lib\site-packages\seaborn\categorical.py:3717: UserWarning: The `factorplot` function has been renamed to `catplot`. The original name will be removed in a future release. Please update your code. Note that the default `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
D:\ANACONDA\lib\site-packages\seaborn\categorical.py:3717: UserWarning: The `factorplot` function has been renamed to `catplot`. The original name will be removed in a future release. Please update your code. Note that the default `kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
<seaborn.axisgrid.FacetGrid at 0x2c3a3b5c400>
```

Out[8]:





Family_Size denotes the number of people in a passenger's family. It is calculated by summing the SibSp and Parch columns of a respective passenger. Also, another column Alone is added to check the chances of survival of a lone passenger against the one with a family.

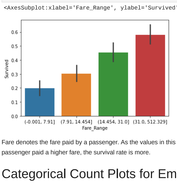
Important observations –

If a passenger is *alone*, the survival rate is less. If the family size is greater than 5, chances of survival decrease considerably.

Bar Plot for Fare (Continuous Feature)

In [9]:
```
# Divide Fare into 4 bins
titanic['Fare_Range'] = pd.qcut(titanic['Fare'], 4)

# Barplot - Shows approximate values based
# on the height of bars.
sns.barplot(x ='Fare_Range', y ='Survived',
data = titanic)
```

Out[9]:
```
<AxesSubplot:xlabel='Fare_Range', ylabel='Survived'>
```

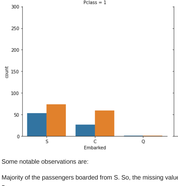


Fare denotes the fare paid by a passenger. As the values in this column are continuous, they need to be put in separate bins(as done for Age feature) to get a clear idea. It can be concluded that if a passenger paid a higher fare, the survival rate is more.

Categorical Count Plots for Embarked Feature

In [10]:
```
# Countplot
sns.catplot(x ='Embarked', hue ='Survived',
kind ="count", col ='Pclass', data = titanic)
```

Out[10]:
```
<seaborn.axisgrid.FacetGrid at 0x2c3a3834e20>
```



Some notable observations are:

Majority of the passengers boarded from *S*. So, the missing values can be filled with *S*. Majority of class 3 passengers boarded from Q. *S* looks lucky for class 1 and 2 passengers compared to class 3.

Conclusion :

The columns that can be dropped are:

PassengerId, Name, Ticket, Cabin: They are strings, cannot be categorized and don't contribute much to the outcome.

Age, Fare: Instead, the respective range columns are retained.

The titanic data can be analyzed using many more graph techniques and also more column correlations, than, as described in this article.

Once the EDA is completed, the resultant dataset can be used for predictions.

In [ ]:
```
THANK YOU..
```