Assignment 2.

Name: Asad Haroon
SP17-BCS-012
Section: C

Titanic Problem

This is the legendary Titanic ML competition – the best, first challenge for you to dive into ML competitions and familiarize yourself with how the Kaggle platform works.

The competition is simple: use machine learning to create a model that predicts which passengers survived the Titanic shipwreck.

Goal: It is your job to predict if a passenger survived the sinking of the Titanic or not. For each in the test set, you must predict a 0 or 1 value for the variable.

Importing the Data

In [1]:
```
import pandas as pd
import numpy as np
titanic_train=pd.read_csv('datasets/train.csv')
titanic_test=pd.read_csv('datasets/test.csv')
print("Setup Complete")
```

```
Setup Complete
```

2. Data Understanding

Train Data

In [2]:
```
titanic_train.head(5)
```

Out[2]:

	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

Test Data

In [3]:
```
titanic_test.head(5)
```

Out[3]:

	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

Train Data Information

In [4]:
```
titanic_train.info()
print("titanic test data total rows are "+str(len(titanic_train)))
```

```
<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
titanic test data total rows are 891
```

In [5]:
```
# As total Rows in Data are 891. As you can see there are missing rows/data in test data
print("\n Missing Rows Count:")
print((titanic_train.isna().sum()))
```

```
 Missing Rows Count:
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
```

Test Data Information

In [6]:
```
titanic_test.info()
print("titanic test data total rows are "+str(len(titanic_test)))
```

```
<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
titanic test data total rows are 418
```

In [7]:
```
# As total Rows in Data are 418. As you can see there are missing rows/data in test data
print("\n Missing Rows Count:")
print((titanic_test.isna().sum()))
```

```
 Missing Rows Count:
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

Train Data Statistics

In [8]:
```
# Train Data Statistics
titanic_train.describe()
```

Out[8]:

	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

Test Data Statistics

In [9]:
```
titanic_test.describe()
```

Out[9]:

	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

Train Data Samples

In [10]:
```
titanic_train.head()
```

Out[10]:

	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

Test Data Samples

In [11]:
```
titanic_test.head()
```

Out[11]:

	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

In [12]:
```
#Total Train+Test Data Count/Observations are:
print("Total observations are: "+str(len(titanic_train)+len(titanic_test)))
```

```
Total observations are: 1309
```

VARIABLE DESCRIPTIONS:

We've got a sense of our variables, their class type, and the first few observations of each. We know we're working with 1309 observations of 12 variables. To make things a bit more explicit since a couple of the variable names aren't 100% illuminating, here's what we've got to deal with:

Variable Description

- Survived: Survived (1) or died (0)
- Pclass: Passenger's class
- Name: Passenger's name
- Sex: Passenger's sex
- Age: Passenger's age
- SibSp: Number of siblings/spouses aboard
- Parch: Number of parents/children aboard
- Ticket: Ticket number
- Fare: Fare
- Cabin: Cabin
- Embarked: Port of embarkation

In [13]:
```
def plot_numeric(df,var,target,**kwargs):
    row = kwargs.get( 'row' , None )
    col = kwargs.get( 'col' , None )
    facet = sns.FacetGrid( df , hue=target , aspect=4,row = row , col = col)
    facet.map( sns.kdeplot , var , shade= True )
    facet.set( xlim=( 0 , df[ var ].max() ) )
    facet.add_legend()
def plot_categorical( df , cat , target , **kwargs ):
    row = kwargs.get( 'row' , None )
    col = kwargs.get( 'col' , None )
    facet = sns.FacetGrid( df , row = row , col = col )
    facet.map( sns.barplot , cat , target )
    facet.add_legend()
```

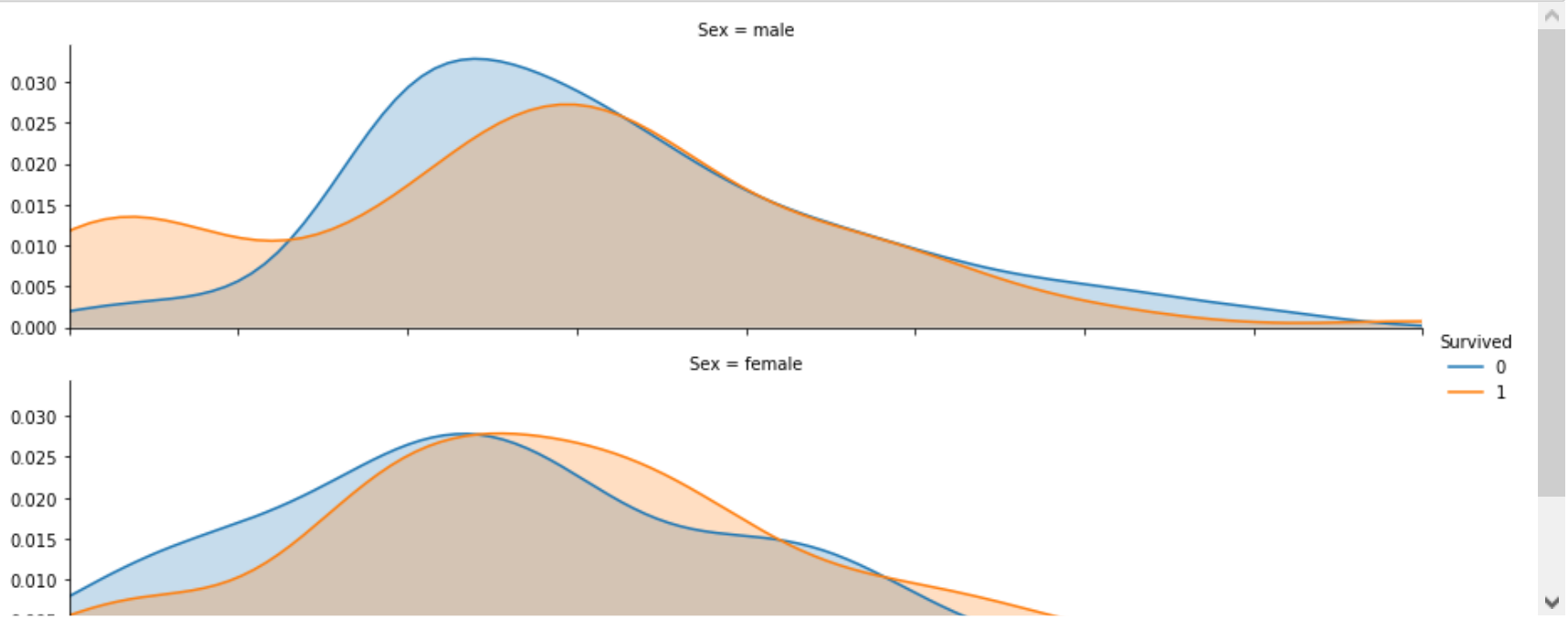
3.Understanding Relationships between features and Survival of Passengers

With Age

In [14]:
```
# With Age and Survival
import seaborn as sns
import matplotlib.pyplot as plt
g = sns.FacetGrid(titanic_train, col='Survived')
g.map(plt.hist, 'Age', bins=10)
```

Out[14]:
```
<seaborn.axisgrid.FacetGrid at 0x1d607c7d390>
```

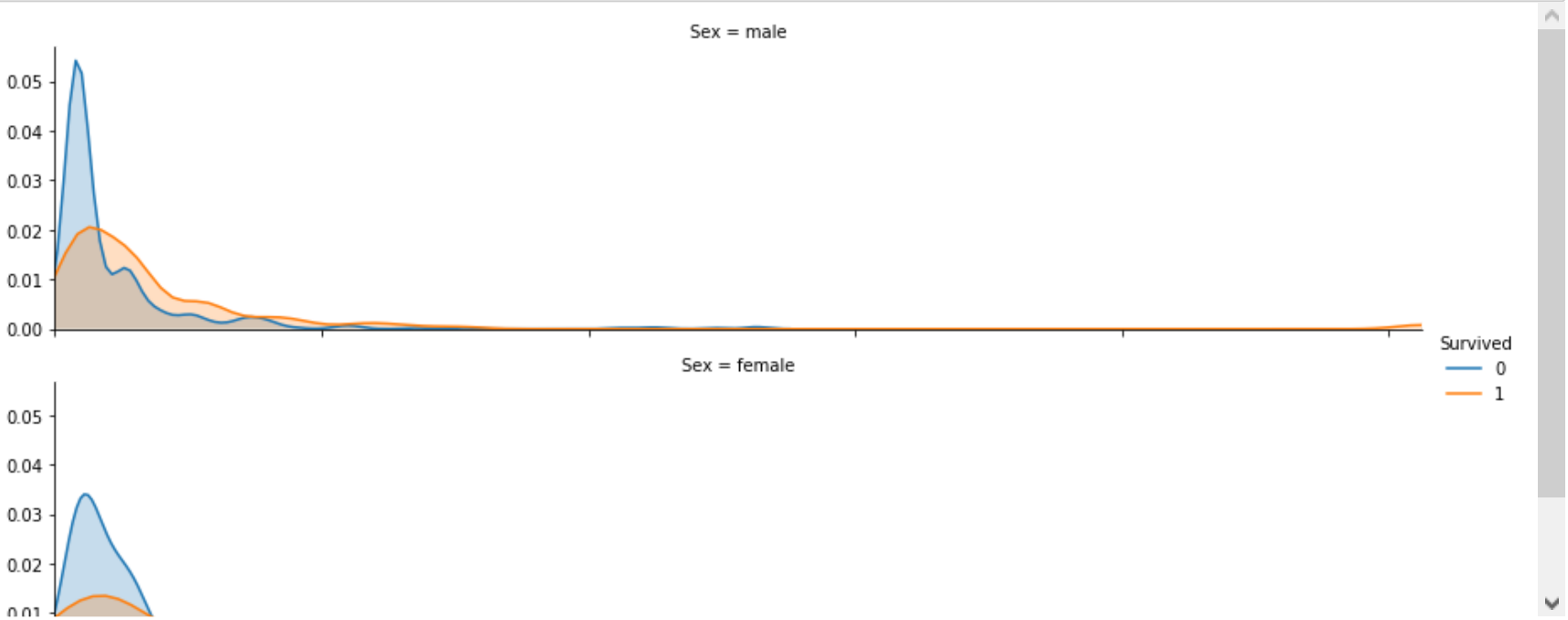
In [15]:
```
plot_numeric(titanic_train,'Age','Survived',row='Sex')
```



If two lines meet at same point then it would not be a good variable for predictive model

With Fare and Survival

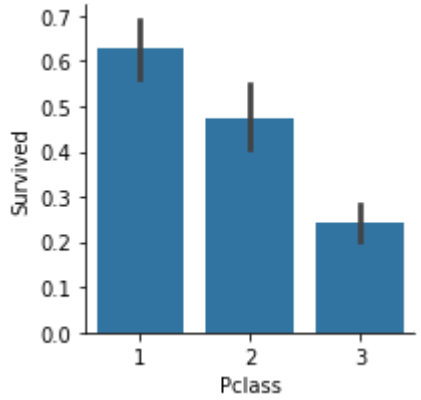
In [16]:
```
#With Fare and Survival
plot_numeric(df=titanic_train,var='Fare',target='Survived',row='Sex')
```



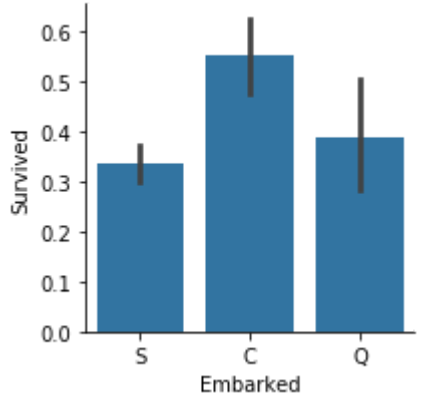
With Pclass and Survival

In [17]:
```
# With PClass and Survival
plot_categorical(df=titanic_train,cat='Pclass',target='Survived')
```

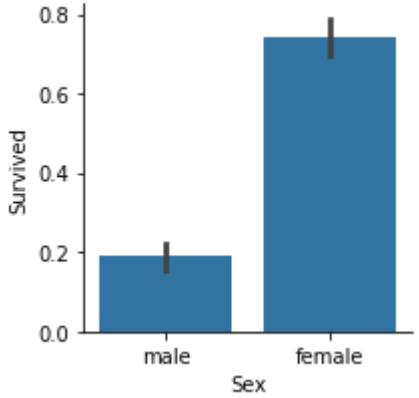
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\axisgrid.py:715: UserWarning: Using the barplot function wi
thout specifying `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
```



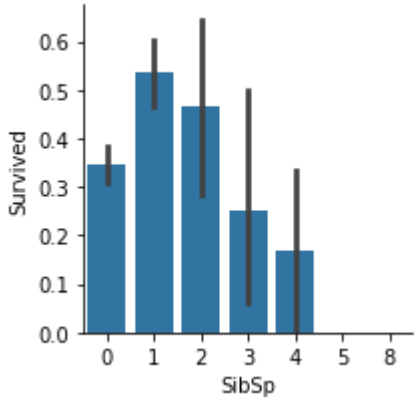
In [18]:
```
# With Embarked
# Plot survival rate by Embarked
plot_categorical( titanic_train , cat = 'Embarked' , target = 'Survived' )
```



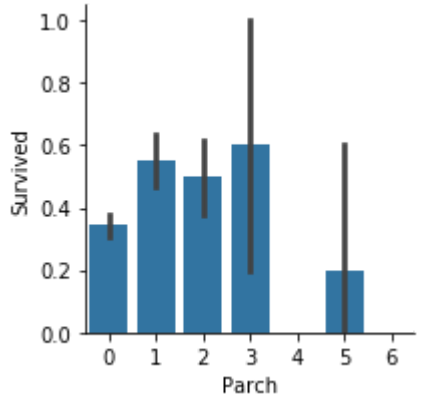
In [19]:
```
# Plot survival rate by Sex
plot_categorical( titanic_train , cat = 'Sex' , target = 'Survived' )
```



In [20]:
```
# Plot survival rate by SibSp
plot_categorical( titanic_train , cat = 'SibSp' , target = 'Survived' )
```



In [21]:
```
plot_categorical( titanic_train , cat = 'Parch' , target = 'Survived' )
```



4.Prepare Data for Consumption

The PassengerID and Ticket variables are assumed to be random unique identifiers, that have no impact on the outcome variable. Thus, they will be excluded from analysis.
The Name variable is a nominal datatype. It could be used in feature engineering to derive the gender from title, family size from surname, and SES from titles like doctor or master. Since these variables already exist, we'll make use of it to see if title, like master, makes a difference.
The SibSp represents number of related siblings/spouse aboard and Parch represents number of related parents/children aboard. Both are discrete quantitative datatypes. This can be used for feature engineering to create a family size and is alone variable
The Cabin variable is a nominal datatype that can be used in feature engineering for approximate position on ship when the incident occurred and SES from deck levels. However, since there are many null values, it does not add value and thus is excluded from analysis.

Clean Data and Filling Nan Values

In [22]:
```
combine=[titanic_train,titanic_test]
```

In [23]:
```
for dataset in combine:
    dataset['Title']=dataset['Name'].str.extract('([A-Za-z]+)\.')
```

In [24]:
```
titanic_train['Title'].isna().sum()
```

Out[24]: 0

In [25]:
```
titanic_test['Title'].isna().sum()
```

Out[25]: 0

In [26]:
```
drop_columns=['PassengerId','Name','Cabin','Ticket']
train_encoded=titanic_train.drop(drop_columns,axis=1)
test_encoded=titanic_test.drop(drop_columns,axis=1)
```

In [27]:
```
train_encoded.head()
```

Out[27]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	male	22.0	1	0	7.2500	S	Mr
1	1	1	female	38.0	1	0	71.2833	C	Mrs
2	1	3	female	26.0	0	0	7.9250	S	Miss
3	1	1	female	35.0	1	0	53.1000	S	Mrs
4	0	3	male	35.0	0	0	8.0500	S	Mr

In [28]:
```
combine=[train_encoded,test_encoded]
```

In [29]:
```
train_encoded['Embarked'].isna().sum()
```

Out[29]: 2

Filling Missing Data

In [30]:
```
title_mapping={"Mr":1,"Mrs":2,"Miss":2,"Master":3,"Don":4,"Rev":5,"Dr":6,"Mme":7,"Ms":8,"Major":9,"Lady":10,"Sir

for dataset in combine:
    dataset['Title']=dataset['Title'].map(title_mapping)
```

In [31]:
```
freq_port = train_encoded.Embarked.dropna().mode()[0]
freq_port
```

Out[31]: 'S'

In [32]:
```
freq_port_test = test_encoded.Embarked.dropna().mode()[0]
freq_port_test
```

Out[32]: 'S'

In [33]:
```
freq_Sex_train = train_encoded.Sex.dropna().mode()[0]
freq_Sex_train
```

Out[33]: 'male'

In [34]:
```
freq_Sex_test = test_encoded.Sex.dropna().mode()[0]
freq_Sex_test
```

Out[34]: 'male'

In [35]:
```
freq_Title_test = test_encoded.Title.dropna().mode()[0]
print(freq_Title_test)
test_encoded['Title']=test_encoded['Title'].fillna(freq_Title_test)
```

```
1.0
```

In [36]:
```
titles=train_encoded['Title'].unique()
```

In [37]:
```
train_encoded['Embarked']=train_encoded['Embarked'].fillna(freq_port)
test_encoded['Embarked']=test_encoded['Embarked'].fillna(freq_port_test)
train_encoded['Sex']=train_encoded['Sex'].fillna(freq_Sex_train)
test_encoded['Sex']=test_encoded['Sex'].fillna(freq_Sex_test)
```

In [38]:
```
sex_mapping={"male":0,"female":1}
embarked_mapping={"S":1,"Q":2,"C":3}
print(type(sex_mapping))
for dataset in combine:
    dataset['Sex']=dataset['Sex'].map(sex_mapping)
    dataset['Embarked']=dataset['Embarked'].map(embarked_mapping)
```

```
<class 'dict'>
```

In [39]:
```
test_encoded['Title'].isna().sum()
train_encoded['Title'].isna().sum()
```

Out[39]:
```
0
```

In [40]:
```
combine=[train_encoded,test_encoded]
```

In [ ]:
```

```

In [41]:
```
train_encoded.head()
```

Out[41]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	0	22.0	1	0	7.2500	1	1
1	1	1	1	38.0	1	0	71.2833	3	2
2	1	3	1	26.0	0	0	7.9250	1	2
3	1	1	1	35.0	1	0	53.1000	1	2
4	0	3	0	35.0	0	0	8.0500	1	1

In [42]:
```
train_encoded['Age'].isna().sum()
```

Out[42]:
```
177
```

In [43]:
```
test_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 8 columns):
Pclass      418 non-null int64
Sex         418 non-null int64
Age         332 non-null float64
SibSp       418 non-null int64
Parch       418 non-null int64
Fare        417 non-null float64
Embarked    418 non-null int64
Title       418 non-null float64
dtypes: float64(3), int64(5)
memory usage: 26.2 KB
```

In [44]:
```
import numpy as np
guess_ages = np.zeros((2,3))

for dataset in combine:
    for i in range(0, 2):
        for j in range(0, 3):
            guess_df = dataset[(dataset['Sex'] == i) & \
                               (dataset['Pclass'] == j+1)]['Age'].dropna()

            # age_mean = guess_df.mean()
            # age_std = guess_df.std()
            # age_guess = rnd.uniform(age_mean - age_std, age_mean + age_std)

            age_guess = guess_df.median()

            # Convert random age float to nearest .5 age
            guess_ages[i,j] = int( age_guess/0.5 + 0.5 ) * 0.5

    for i in range(0, 2):
        for j in range(0, 3):
            dataset.loc[ (dataset.Age.isnull()) & (dataset.Sex == i) & (dataset.Pclass == j+1),\
                    'Age'] = guess_ages[i,j]

    dataset['Age'] = dataset['Age'].astype(int)

train_encoded.head()
```

Out[44]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	0	22	1	0	7.2500	1	1
1	1	1	1	38	1	0	71.2833	3	2
2	1	3	1	26	0	0	7.9250	1	2
3	1	1	1	35	1	0	53.1000	1	2
4	0	3	0	35	0	0	8.0500	1	1

In [45]:
```
for train_data in combine:
    train_data.loc[ train_data['Age'] <= 16, 'Age'] = 0
    train_data.loc[(train_data['Age'] > 16) & (train_data['Age'] <= 32), 'Age'] = 1
    train_data.loc[(train_data['Age'] > 32) & (train_data['Age'] <= 48), 'Age'] = 2
    train_data.loc[(train_data['Age'] > 48) & (train_data['Age'] <= 64), 'Age'] = 3
    train_data.loc[ train_data['Age'] > 64, 'Age']=4
#train_data.head(35)
```

In [46]:
```
train_encoded.head()
```

Out[46]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	0	1	1	0	7.2500	1	1
1	1	1	1	2	1	0	71.2833	3	2
2	1	3	1	1	0	0	7.9250	1	2
3	1	1	1	2	1	0	53.1000	1	2
4	0	3	0	2	0	0	8.0500	1	1

In [47]:
```
for dataset in combine:
    dataset['FamilySize'] = dataset['SibSp'] + dataset['Parch'] + 1
```

In [48]:
```
for dataset in combine:
    dataset['IsAlone'] = 0
    dataset.loc[dataset['FamilySize'] == 1, 'IsAlone'] = 1
```

In [49]:
```
drop_columns1=['FamilySize','Parch','SibSp']

train_encoded=train_encoded.drop(drop_columns1,axis=1)
test_encoded=test_encoded.drop(drop_columns1,axis=1)
```

In [50]:
```
train_encoded.Fare.isna().sum()
```

Out[50]:
```
0
```

In [51]:
```
test_encoded.Fare.isna().sum()
```

Out[51]:
```
1
```

In [52]:
```
test_encoded['Fare'].fillna(test_encoded['Fare'].dropna().median(), inplace=True)
```

In [53]:
```
test_encoded
```

Out[53]:

	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone
0	3	0	2	7.8292	2	1.0	1
1	3	1	2	7.0000	1	2.0	0
2	2	0	3	9.6875	2	1.0	1
3	3	0	1	8.6625	1	1.0	1
4	3	1	1	12.2875	1	2.0	0
5	3	0	0	9.2250	1	1.0	1
6	3	1	1	7.6292	2	2.0	1
7	2	0	1	29.0000	1	1.0	0
8	3	1	1	7.2292	3	2.0	1
9	3	0	1	24.1500	1	1.0	0
10	3	0	1	7.8958	1	1.0	1
11	1	0	2	26.0000	1	1.0	1
12	1	1	1	82.2667	1	2.0	0
13	2	0	3	26.0000	1	1.0	0
14	1	1	2	61.1750	1	2.0	0
15	2	1	1	27.7208	3	2.0	0
16	2	0	2	12.3500	2	1.0	1
17	3	0	1	7.2250	3	1.0	1
18	3	1	1	7.9250	1	2.0	0
19	3	1	2	7.2250	3	2.0	1
20	1	0	3	59.4000	3	1.0	0
21	3	0	0	3.1708	1	3.0	0
22	1	1	2	31.6833	1	2.0	1
23	1	0	1	61.3792	3	1.0	0
24	1	1	2	262.3750	3	2.0	0

	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone
25	3	0	3	14.5000	1	1.0	0
26	1	1	1	61.9792	3	2.0	0
27	3	0	1	7.2250	3	1.0	1
28	1	0	2	30.5000	1	1.0	1
29	3	0	1	21.6792	3	1.0	0
...	...	...	...	...	...	...	...
388	3	0	1	7.7500	2	1.0	1
389	3	0	0	21.0750	1	3.0	0
390	1	0	1	93.5000	1	1.0	1
391	1	1	3	39.4000	1	2.0	0
392	3	0	0	20.2500	1	3.0	0
393	2	0	2	10.5000	1	1.0	1
394	3	0	1	22.0250	1	1.0	0
395	1	1	1	60.0000	1	2.0	0
396	3	0	1	7.2500	2	1.0	1
397	1	1	2	79.2000	3	2.0	0
398	3	0	1	7.7750	1	1.0	1
399	3	0	1	7.7333	2	1.0	1
400	1	1	1	164.8667	1	2.0	1
401	2	0	2	21.0000	1	1.0	0
402	1	1	1	59.4000	3	2.0	0
403	1	0	1	47.1000	1	1.0	1
404	1	0	2	27.7208	3	1.0	0
405	2	0	1	13.8625	3	1.0	1
406	2	0	1	10.5000	1	1.0	0
407	1	0	3	211.5000	3	1.0	0
408	3	1	1	7.7208	2	2.0	1

	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone
409	3	1	0	13.7750	1	2.0	0
410	3	1	1	7.7500	2	2.0	1
411	1	1	2	90.0000	2	2.0	0
412	3	1	1	7.7750	1	2.0	1
413	3	0	1	8.0500	1	1.0	1
414	1	1	2	108.9000	3	1.0	1
415	3	0	2	7.2500	1	1.0	1
416	3	0	1	8.0500	1	1.0	1
417	3	0	1	22.3583	3	3.0	0

418 rows × 7 columns

In [54]:
```
train_encoded['FareBand'] = pd.qcut(train_encoded['Fare'], 4)
train_encoded[['FareBand', 'Survived']].groupby(['FareBand'], as_index=False).mean().sort_values(by='FareBand',
```

Out[54]:

	FareBand	Survived
0	(-0.001, 7.91]	0.197309
1	(7.91, 14.454]	0.303571
2	(14.454, 31.0]	0.454955
3	(31.0, 512.329]	0.581081

In [55]:
```
train_encoded.Fare.isna().sum()
```

Out[55]: 0

In [56]:
```
test_encoded.Fare.isna().sum()
```

Out[56]: 0

In [57]:
```
test_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 7 columns):
Pclass      418 non-null int64
Sex         418 non-null int64
Age         418 non-null int32
Fare        418 non-null float64
Embarked    418 non-null int64
Title       418 non-null float64
IsAlone     418 non-null int64
dtypes: float64(2), int32(1), int64(4)
memory usage: 21.3 KB
```

In [58]:
```
combine=[train_encoded,test_encoded]
for dataset in combine:
    dataset.loc[ dataset['Fare'] <= 7.91, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7.91) & (dataset['Fare'] <= 14.454), 'Fare'] = 1
    dataset.loc[(dataset['Fare'] > 14.454) & (dataset['Fare'] <= 31), 'Fare']   = 2
    dataset.loc[ dataset['Fare'] > 31, 'Fare'] = 3
    dataset['Fare'] = dataset['Fare'].astype(int)

train_encoded = train_encoded.drop(['FareBand'], axis=1)
combine=[train_encoded,test_encoded]
```

In [59]:
```
train_encoded.columns
```

Out[59]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Title',
       'IsAlone'],
      dtype='object')
```

In [60]:
```
combine=[train_encoded,test_encoded]
for dataset in combine:
    dataset['Age*Class'] = dataset.Age * dataset.Pclass

train_encoded.loc[:, ['Age*Class', 'Age', 'Pclass']].head(10)
```

Out[60]:

	Age*Class	Age	Pclass
0	3	1	3
1	2	2	1
2	3	1	3
3	2	2	1
4	6	2	3
5	3	1	3
6	3	3	1
7	0	0	3
8	3	1	3
9	0	0	2

5.Train Test Split

In [61]:
```
from sklearn.model_selection import train_test_split
y=train_encoded['Survived']
X=train_encoded[['Pclass', 'Sex', 'Age', 'Fare', 'Embarked', 'Title','IsAlone','Age*Class']]
X_train,test_X,Y_train,test_Y=train_test_split(X,y,random_state=0)
```

Models

In [62]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
```

Decision Tree Classifier

In [63]:
```
from sklearn.tree import DecisionTreeClassifier
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
Y_pred = decision_tree.predict(test_X)
acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)
print("Accuracy is"+str(acc_decision_tree))
```

```
Accuracy is86.68
```

Linear SVC Model

In [64]:
```

linear_svc = LinearSVC()
linear_svc.fit(X_train, Y_train)
Y_pred = linear_svc.predict(test_X)
acc_linear_svc = round(linear_svc.score(X_train, Y_train) * 100, 2)
acc_linear_svc
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\svm\base.py:929: ConvergenceWarning: Liblinear failed to co
nverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

Out[64]:
```
79.34
```

In [65]:
```
from sklearn.metrics import mean_absolute_error
```

In [66]:
```
from sklearn.tree import DecisionTreeRegressor
```

Improving Error Using Decision Tree Regressor

In [67]:
```
#Improving Error
def get_mae(max_leaf_nodes, train_X, val_X, train_y, val_y):
    model = DecisionTreeRegressor(max_leaf_nodes=max_leaf_nodes, random_state=0)
    model.fit(train_X, train_y)
    preds_val = model.predict(val_X)
    mae = mean_absolute_error(val_y, preds_val)
    return(mae)
candidate_max_leaf_nodes = [5, 25, 50, 100, 250, 500]
li=[]
# Write loop to find the ideal tree size from candidate_max_leaf_nodes
for max_leaf_nodes in candidate_max_leaf_nodes:
    my_mae = get_mae(max_leaf_nodes, X_train, test_X, Y_train, test_Y)
    li.append(my_mae)
index=li.index(min(li))
index
```

Out[67]: 3

In [68]:
```
# Store the best value of max_leaf_nodes (it will be either 5, 25, 50, 100, 250 or 500)
best_tree_size = candidate_max_leaf_nodes[index]
final_model = DecisionTreeRegressor(max_leaf_nodes=best_tree_size)

# fit the final model and uncomment the next two lines
final_model.fit(X_train,Y_train)
ae=final_model.predict(test_X)
print(mean_absolute_error(test_Y,ae))
```

```
0.23412374588267104
```

Random Forest Classifier

In [69]:
```
X_test=test_X
X=X_train
y=Y_train

model = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=1)
model.fit(X, y)
predictions = model.predict(test_X)
acc=model.score(X_train,Y_train)*100
print("Accuracy is "+str(acc))
```

```
Accuracy is 84.58083832335329
```

In [79]:
```
full=titanic_train
full = titanic_train.append( titanic_test , ignore_index = True )
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:6692: FutureWarning: Sorting because non-conca
tenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
```

KNeighbors Classifiers

In [74]:
```
modelK = KNeighborsClassifier(n_neighbors = 3)
modelK.fit(X_train,Y_train)
ypred=modelK.predict(test_X)
sc=modelK.score(X_train,Y_train)
sc
```

Out[74]:
```
0.8398203592814372
```

Logistic Regression Model

In [77]:
```
modelLog = LogisticRegression()
modelLog.fit(X_train,Y_train)
ypred=modelLog.predict(test_X)
sc=modelLog.score(X_train,Y_train)
sc
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning: Default solver
will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[77]:
```
0.7964071856287425
```

6.Prediction on Test Data

In [78]:
```
test_Y = decision_tree.predict(test_encoded)
passenger_id = full[891:].PassengerId
test = pd.DataFrame( { 'PassengerId': passenger_id , 'Survived': test_Y } )
test.shape
test.head()
test.to_csv( 'titanic_pred.csv' , index = False )
```