In [14]:

```python
#data analysis
import numpy as np
import pandas as pd
import random as rnd

#for  visualization
import seaborn as sb
import matplotlib.pyplot as plt
%matplotlib inline

# loading the data
titrain = pd.read_csv("D:/Kaggle/titanic/train.csv")
titest = pd.read_csv("D:/Kaggle/titanic/test.csv")
```

In [15]:

```python
#Combining a large training set
combine=[titrain, titest]

#look at the columns in the table
print(" Columns in the table")
print(titrain.columns.values)
```

```
 Columns in the table
['PassengerId' 'Survived' 'Pclass' 'Name' 'Sex' 'Age' 'SibSp' 'Parch'
 'Ticket' 'Fare' 'Cabin' 'Embarked']
```

In [16]:

```python
#to look at the data type of the column
titrain.head(1).info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 12 columns):
PassengerId    1 non-null int64
Survived       1 non-null int64
Pclass         1 non-null int64
Name           1 non-null object
Sex            1 non-null object
Age            1 non-null float64
SibSp          1 non-null int64
Parch          1 non-null int64
Ticket         1 non-null object
Fare           1 non-null float64
Cabin          0 non-null object
Embarked       1 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 176.0+ bytes
```

In [17]:
```
#to find the total number of null values in each column
titrain.info()
print('-'*40)
titest.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: 83.6+ KB
----------------------------------------
<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
```

In [18]:
```
#to look at the mean and std
print(titrain.describe())
```

```
       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  
```

In [22]:
```
titrain.describe(include = ['O'])
```

Out[22]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Fortune, Mr. Mark	male	1601	C23 C25 C27	S
freq	1	577	7	4	644

In [24]:
```
titrain[['Pclass','Survived']].groupby(['Pclass'], as_index= False).mean().sort_values(b
y='Survived', ascending= False)
```

Out[24]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [25]:
```
titrain[['Sex','Survived']].groupby(['Sex'], as_index= False).mean().sort_values(by='Sur
vived', ascending= False)
```

Out[25]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

In [26]:
```
titrain[['SibSp','Survived']].groupby(['SibSp'], as_index= False).mean().sort_values(by=
'Survived', ascending= False)
```

Out[26]:

	SibSp	Survived
1	1	0.535885
2	2	0.464286
0	0	0.345395
3	3	0.250000
4	4	0.166667
5	5	0.000000
6	8	0.000000

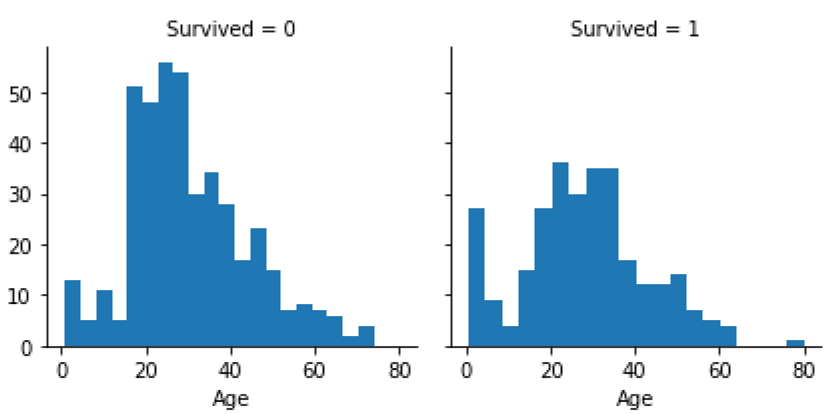
In [27]:
```
titrain[['Parch','Survived']].groupby(['Parch'], as_index= False).mean().sort_values(by=
'Survived', ascending= False)
```

Out[27]:

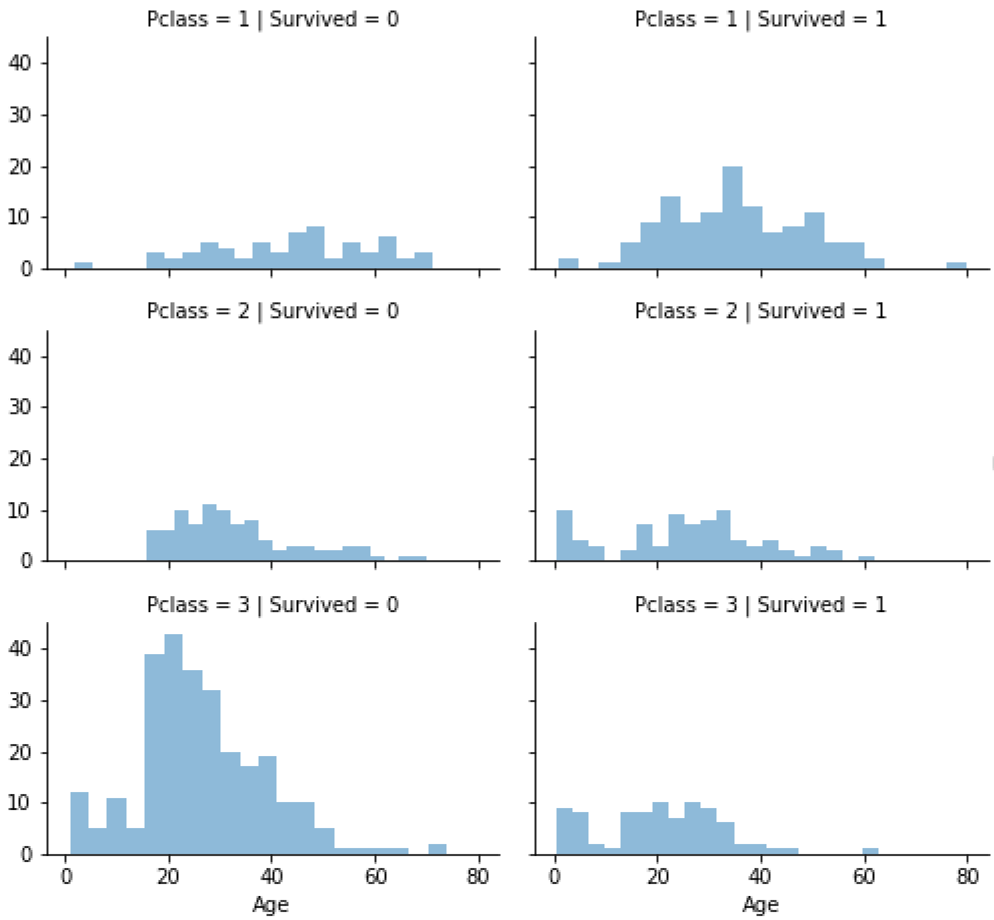
	Parch	Survived
3	3	0.600000
1	1	0.550847
2	2	0.500000
0	0	0.343658
5	5	0.200000
4	4	0.000000
6	6	0.000000

In [28]:
```
#figuring out the correlation of age and survival
g=sb.FacetGrid(titrain, col='Survived')
g.map(plt.hist,'Age',bins=20)
```

Out[28]: <seaborn.axisgrid.FacetGrid at 0x1e0c6a99908>

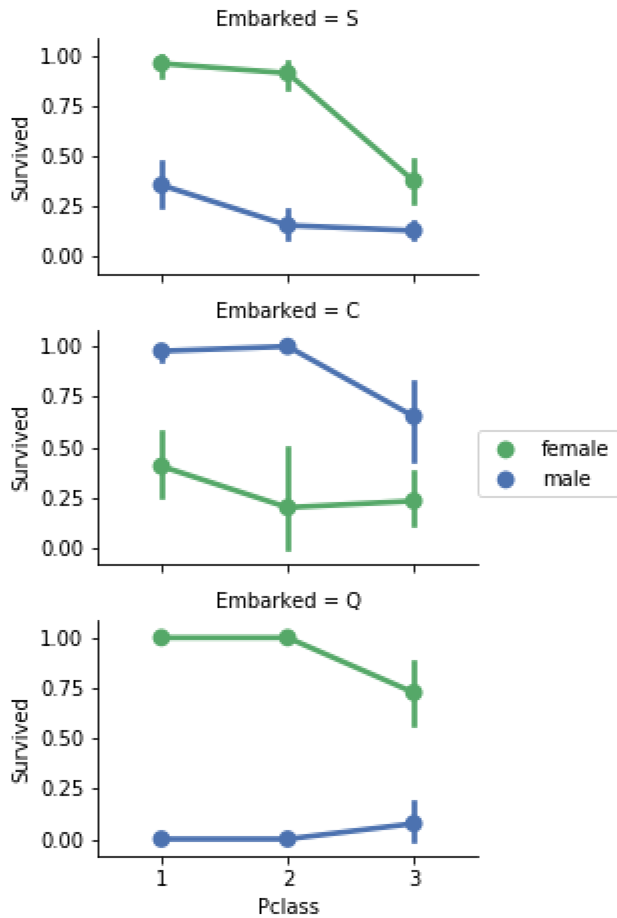


In [32]:
```
#figuring out the correlation of Pclass and survival
grid=sb.FacetGrid(titrain, col='Survived', row='Pclass', size=2.2, aspect=1.6)
grid.map(plt.hist,'Age',alpha=.5,bins=20)
grid.add_legend();
```



In [39]:
```
# correlating categorical value
grid=sb.FacetGrid(titrain,row='Embarked', size=2.2, aspect=1.6)
grid.map(sb.pointplot,'Pclass','Survived','Sex', palette='deep')
grid.add_legend();
```

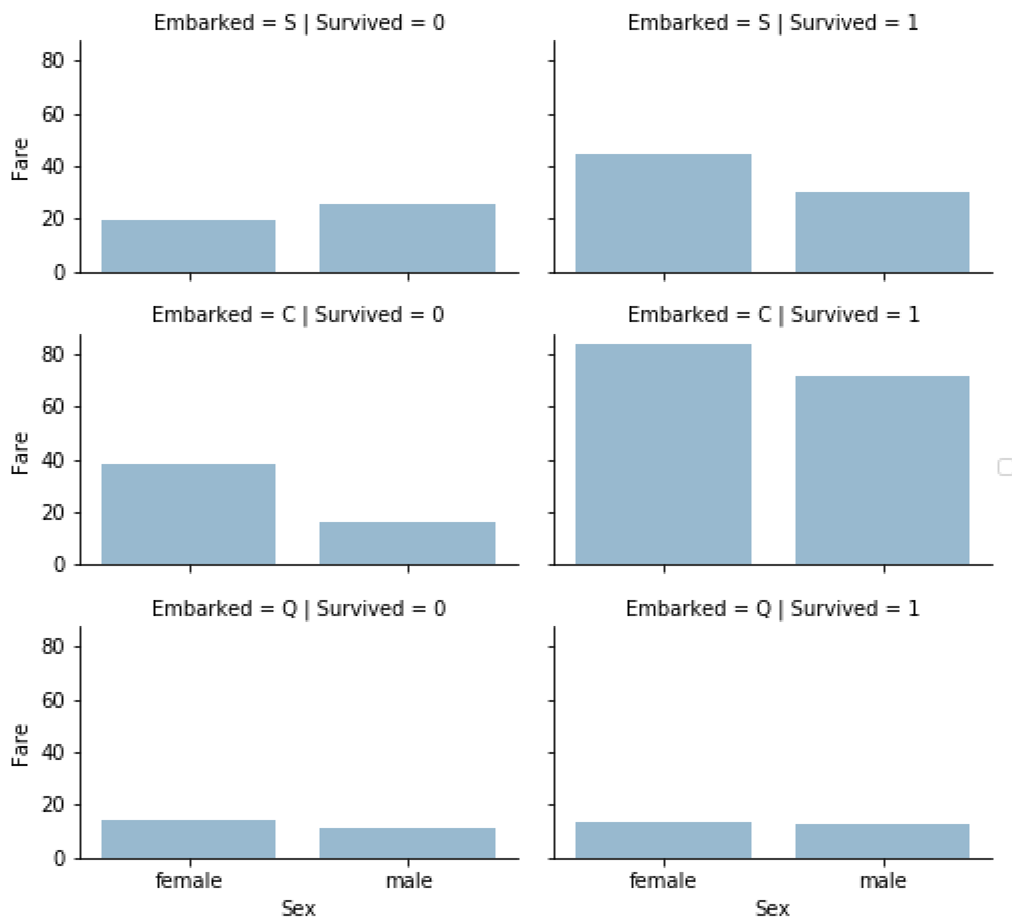
```
C:\Users\uthir\Anaconda3\lib\site-packages\seaborn\axisgrid.py:703: UserWarning: Using
the pointplot function without specifying `order` is likely to produce an incorrect plo
t.
  warnings.warn(warning)
C:\Users\uthir\Anaconda3\lib\site-packages\seaborn\axisgrid.py:708: UserWarning: Using
the pointplot function without specifying `hue_order` is likely to produce an incorrect
plot.
  warnings.warn(warning)
```



In [42]:
```
#correlating Embarked (Categorical non-numeric),
#Sex (Categorical non-numeric), Fare (Numeric continuous), with Survived (Categorical nu
meric).
grid = sb.FacetGrid(titrain, row='Embarked', col='Survived', size=2.2, aspect=1.6)
grid.map(sb.barplot, 'Sex', 'Fare', alpha=.5, ci=None)
grid.add_legend()
```

```
C:\Users\uthir\Anaconda3\lib\site-packages\seaborn\axisgrid.py:703: UserWarning: Using
the barplot function without specifying `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
```

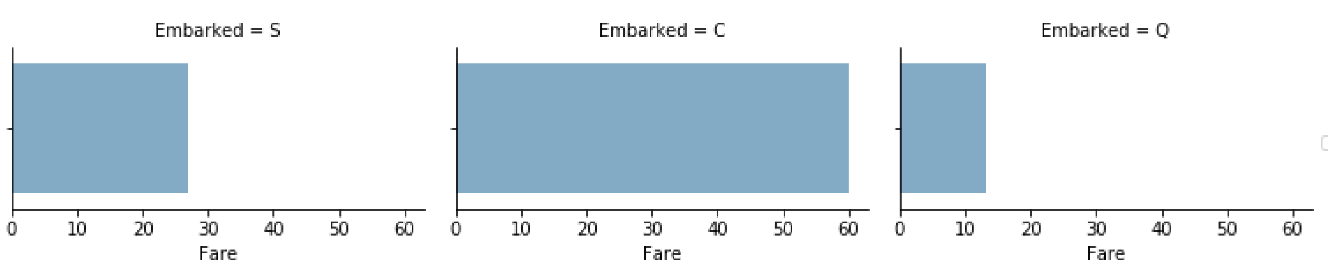
Out[42]: <seaborn.axisgrid.FacetGrid at 0x1e0c8f04c88>



In [48]:
```
#figuring out the correlation of age and survival
g=sb.FacetGrid(titrain, col='Embarked', size=2.2, aspect=1.6)
g.map(sb.barplot,'Fare',alpha=.6, ci=None)
g.add_legend()
```

```
C:\Users\uthir\Anaconda3\lib\site-packages\seaborn\axisgrid.py:703: UserWarning: Using
the barplot function without specifying `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
```

Out[48]: <seaborn.axisgrid.FacetGrid at 0x1e0c8963470>



In [49]:
```
print("Before", titrain.shape, titest.shape, combine[0].shape, combine[1].shape)

titrain = titrain.drop(['Ticket', 'Cabin'], axis=1)
titest = titest.drop(['Ticket', 'Cabin'], axis=1)
combine = [titrain, titest]

print("After", titrain.shape, titest.shape, combine[0].shape, combine[1].shape)
```

```
Before (891, 12) (418, 11) (891, 12) (418, 11)
After (891, 10) (418, 9) (891, 10) (418, 9)
```

In [51]:
```
for dataset in combine:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)

pd.crosstab(titrain['Title'], titrain['Sex'])
```

Out[51]:

Sex	female	male
Title		
Capt	0	1
Col	0	2
Countess	1	0
Don	0	1
Dr	1	6
Jonkheer	0	1
Lady	1	0
Major	0	2
Master	0	40
Miss	182	0
Mlle	2	0
Mme	1	0
Mr	0	517
Mrs	125	0
Ms	1	0
Rev	0	6
Sir	0	1

In [52]:
```
for dataset in combine:
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt', 'Col',\
        'Don', 'Dr', 'Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Rare')

    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')

titrain[['Title', 'Survived']].groupby(['Title'], as_index=False).mean()
```

Out[52]:

	Title	Survived
0	Master	0.575000
1	Miss	0.702703
2	Mr	0.156673
3	Mrs	0.793651
4	Rare	0.347826

In [53]:
```
title_mapping = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Rare": 5}
for dataset in combine:
    dataset['Title'] = dataset['Title'].map(title_mapping)
    dataset['Title'] = dataset['Title'].fillna(0)

titrain.head()
```

Out[53]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	7.2500	S	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	71.2833	C	3
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	7.9250	S	2
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	53.1000	S	3
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	8.0500	S	1

In [54]:
```
titrain = titrain.drop(['Name', 'PassengerId'], axis=1)
titest = titest.drop(['Name'], axis=1)
combine = [titrain, titest]
titrain.shape, titest.shape
```

Out[54]: ((891, 9), (418, 9))

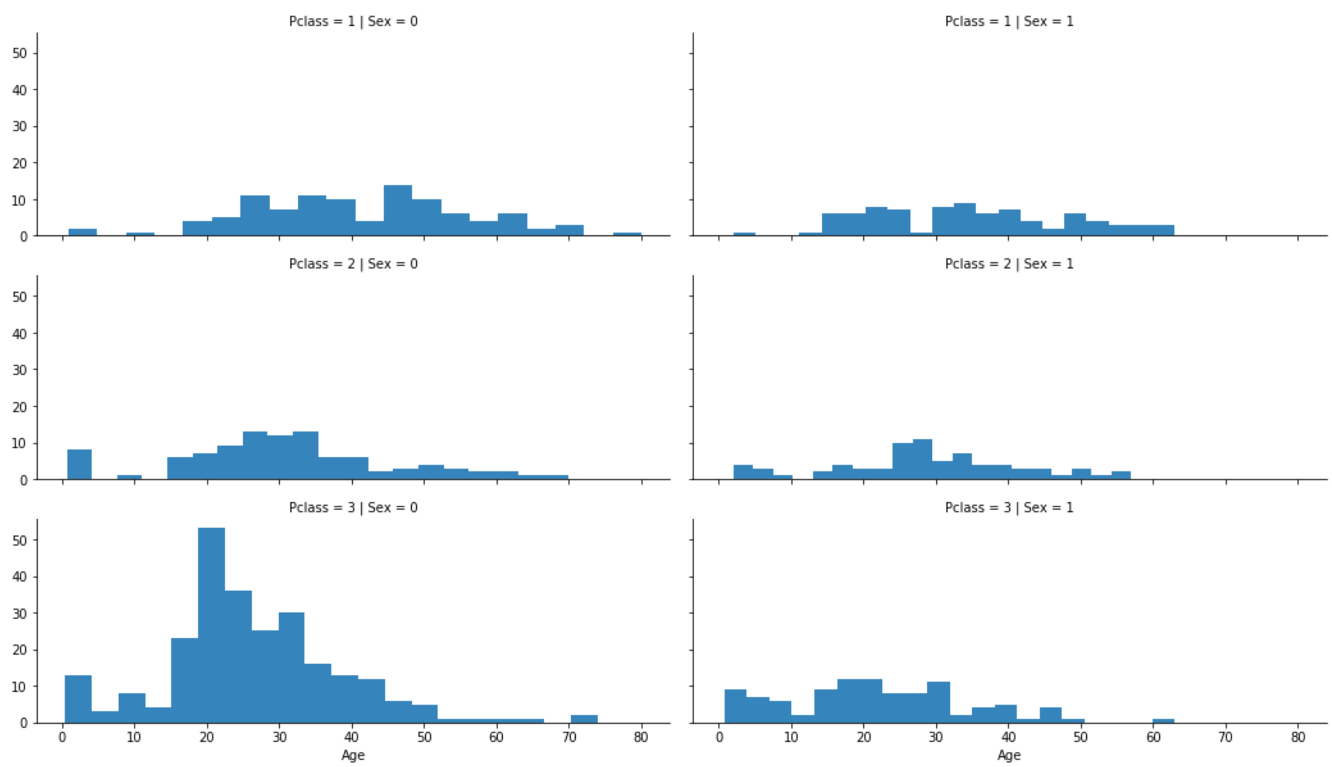
In [55]:
```
for dataset in combine:
    dataset['Sex']= dataset['Sex'].map({'female':1, 'male':0}).astype(int)
titrain.head()
```

Out[55]:

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

In [62]:
```
#looking for co realtion btw pclass and sex to determine age
grid=sb.FacetGrid(titrain, row='Pclass', col='Sex', size=2.8, aspect=2.6)
grid.map(plt.hist,'Age', alpha=0.9, bins=20)
grid.add_legend()
```

Out[62]: <seaborn.axisgrid.FacetGrid at 0x1e0c832b8d0>



In [63]:
```
guess_ages=np.zeros((2,3))
guess_ages
```

Out[63]:
```
array([[0., 0., 0.],
       [0., 0., 0.]])
```

In [64]:
```
for i in range(0,2):
    print(i)
```

```
0
1
```

In [66]:
```
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'].drop
na()
            age_guess=guess_df.median()
            guess_ages[i,j]=int(age_guess/0.5+0.5)*0.5
guess_ages
```

Out[66]:
```
array([[42., 28., 24.],
       [41., 24., 22.]])
```

In [68]:
```
for dataset in combine:
    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)
titrain.head()
```

Out[68]:

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

In [69]:
```
titrain['AgeBrand']=pd.cut(titrain['Age'],5)
```

In [71]:
```
titrain[['AgeBrand','Survived']].groupby(['AgeBrand'], as_index= False).mean().sort_valu
es(by='AgeBrand',ascending=True)
```

Out[71]:

	AgeBrand	Survived
0	(-0.08, 16.0]	0.550000
1	(16.0, 32.0]	0.337374
2	(32.0, 48.0]	0.412037
3	(48.0, 64.0]	0.434783
4	(64.0, 80.0]	0.090909

In [72]:
```
for dataset in combine:
    dataset.loc[ dataset['Age'] <= 16, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 16) & (dataset['Age'] <= 32), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 32) & (dataset['Age'] <= 48), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 48) & (dataset['Age'] <= 64), 'Age'] = 3
    dataset.loc[ dataset['Age'] > 64, 'Age']
titrain.head()
```

Out[72]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title	AgeBrand
0	0	3	0	1	1	0	7.2500	S	1	(16.0, 32.0]
1	1	1	1	2	1	0	71.2833	C	3	(32.0, 48.0]
2	1	3	1	1	0	0	7.9250	S	2	(16.0, 32.0]
3	1	1	1	2	1	0	53.1000	S	3	(32.0, 48.0]
4	0	3	0	2	0	0	8.0500	S	1	(32.0, 48.0]

In [73]:
```
titrain=titrain.drop(['AgeBrand'],axis=1)
combine=[titrain, titest]
titrain.head()
```

Out[73]:

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

In [75]:
```
for dataset in combine:
    dataset['FamilySize']=dataset['SibSp']+dataset['Parch']+1
titrain[['FamilySize','Survived']].groupby(['FamilySize'], as_index= False).mean().sort_
values(by='Survived', ascending=False)
```

Out[75]:

	FamilySize	Survived
3	4	0.724138
2	3	0.578431
1	2	0.552795
6	7	0.333333
0	1	0.303538
4	5	0.200000
5	6	0.136364
7	8	0.000000
8	11	0.000000

In [78]:
```
for dataset in combine:
    dataset['IsAlone']=0
    dataset.loc[dataset['FamilySize']==1, 'IsAlone']=1
titrain[['IsAlone','Survived']].groupby(['IsAlone'], as_index=False).mean()
```

Out[78]:

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

In [79]:
```
titrain=titrain.drop(['Parch','SibSp','FamilySize'],axis=1)
titest=titest.drop(['Parch','SibSp','FamilySize'], axis=1)
combine=[titrain, titest]
titrain.head()
```

Out[79]:

	Survived	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone
0	0	3	0	1	7.2500	S	1	0
1	1	1	1	2	71.2833	C	3	0
2	1	3	1	1	7.9250	S	2	1
3	1	1	1	2	53.1000	S	3	0
4	0	3	0	2	8.0500	S	1	1

In [81]:
```
for dataset in combine:
    dataset['Age*Class'] = dataset.Age * dataset.Pclass

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

Out[81]:

	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

In [82]:
```
frq_port=titrain.Embarked.dropna().mode()[0]
frq_port
```

Out[82]: 'S'

In [86]:
```
for dataset in combine:
    dataset['Embarked'] = dataset['Embarked'].fillna(frq_port)
```

In [154]:
```
titrain[['Embarked','Survived']].groupby(['Embarked'],as_index=False).mean()
```

Out[154]:

	Embarked	Survived
0	0	0.339009
1	1	0.553571
2	2	0.389610

In [156]:
```
for dataset in combine:
    dataset['Embarked'] = dataset['Embarked'].map( {'S': 0, 'C': 1, 'Q': 2} )
```

In [163]:
```
titrain.isnull().values.sum()
```

Out[163]: 0

In [165]:
```
titrain[['Embarked','Survived']].groupby(['Embarked'],as_index=False).mean()
```

Out[165]:

	Embarked	Survived
0	0	0.339009
1	1	0.553571
2	2	0.389610

In [119]:
```
train = pd.read_csv("D:/Kaggle/titanic/train.csv")
```

In [160]:
```
titrain['Embarked']=train['Embarked']
```

In [147]:
```
frq_port
```

Out[147]:
```
0    S
dtype: object
```

In [162]:
```
titrain['Embarked'] = titrain['Embarked'].fillna((titrain['Embarked']).mode()[0])
```

In [169]:
```
titest['Embarked'] = titest['Embarked'].fillna('S')
```

In [166]:
```
test = pd.read_csv("D:/Kaggle/titanic/test.csv")
```

In [171]:
```
titest['Embarked'] = titest['Embarked'].fillna((titest['Embarked']).mode()[0])
```

In [175]:
```
titest['Embarked'] = titest['Embarked'].map( {'S': 0, 'C': 1, 'Q': 2} )
```

In [176]:
```
titrain['Embarked']=titrain['Embarked'].astype(int)
```

In [177]:
```
titest['Embarked']=titest['Embarked'].astype(int)
```

In [178]:
```
titrain['Fare'].fillna(titrain['Fare'].dropna().median(), inplace=True)
titrain.head()
```

Out[178]:

	Survived	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone	Age*Class
0	0	3	0	1	7.2500	0	1	0	3
1	1	1	1	2	71.2833	1	3	0	2
2	1	3	1	1	7.9250	0	2	1	3
3	1	1	1	2	53.1000	0	3	0	2
4	0	3	0	2	8.0500	0	1	1	6

In [180]:
```
titrain['FareBand'] = pd.qcut(titrain['Fare'], 4)
titrain[['FareBand', 'Survived']].groupby(['FareBand'], as_index=False).mean().sort_valu
es(by='FareBand', ascending=True)
```

Out[180]:

	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 [183]:
```
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
```

In [182]:
```
titrain['Fare'].isnull().values.sum()
```

Out[182]: 0

In [184]:
```
titrain['Fare']=titrain['Fare'].astype(int)
```

In [189]:
```
titest['Fare']=titest['Fare'].astype(int)
```

In [188]:
```
titest['Fare'].isnull().values.sum()
```

Out[188]: 0

In [187]:
```
titest['Fare'].fillna(titest['Fare'].dropna().median(), inplace=True)
```

In [190]:
```
titrain = titrain.drop(['FareBand'], axis=1)
combine = [titrain, titest]

titrain.head(10)
```

Out[190]:

	Survived	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone	Age*Class
0	0	3	0	1	0	0	1	0	3
1	1	1	1	2	0	1	3	0	2
2	1	3	1	1	0	0	2	1	3
3	1	1	1	2	0	0	3	0	2
4	0	3	0	2	0	0	1	1	6
5	0	3	0	1	0	2	1	1	3
6	0	1	0	3	0	0	1	1	3
7	0	3	0	0	0	0	4	0	0
8	1	3	1	1	0	0	3	0	3
9	1	2	1	0	0	1	3	0	0

In [191]:
```
titest.head(10)
```

Out[191]:

	PassengerId	Pclass	Sex	Age	Fare	Embarked	Title	IsAlone	Age*Class
0	892	3	0	2	0	2	1	1	6
1	893	3	1	2	0	0	3	0	6
2	894	2	0	3	0	2	1	1	6
3	895	3	0	1	0	0	1	1	3
4	896	3	1	1	0	0	3	0	3
5	897	3	0	0	0	0	1	1	0
6	898	3	1	1	0	2	2	1	3
7	899	2	0	1	0	0	1	0	2
8	900	3	1	1	0	1	3	1	3
9	901	3	0	1	0	0	1	0	3

In [192]:
```
# machine learning
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
```

In [194]:
```
y_train=titrain["Survived"]
x_train=titrain.drop("Survived",axis=1)
x_test=titest.drop("PassengerId", axis=1).copy()
x_train.shape, y_train.shape, x_test.shape
```
Out[194]: ((891, 8), (891,), (418, 8))

In [195]:
```
#Logistic Regression
logreg=LogisticRegression()
logreg.fit(x_train,y_train)
y_pred=logreg.predict(x_test)
acc_log=round(logreg.score(x_train,y_train)*100,2)
acc_log
```
Out[195]: 80.36

In [197]:
```
coeff=pd.DataFrame(titrain.columns.delete(0))
coeff.columns=['Feature']
coeff['Correlation']=pd.Series(logreg.coef_[0])
coeff.sort_values(by='Correlation',ascending=False)
```
Out[197]:

	Feature	Correlation
1	Sex	2.199198
5	Title	0.389811
2	Age	0.275644
4	Embarked	0.271167
6	IsAlone	0.210186
3	Fare	0.000000
7	Age*Class	-0.300404
0	Pclass	-0.705445

In [198]:
```
#Support Vector Machine
svc=SVC()
svc.fit(x_train,y_train)
y_pred=svc.predict(x_test)
acc_svc=round(svc.score(x_train,y_train)*100,2)
acc_svc
```
Out[198]: 82.38

In [201]:
```
#K-Nearest Neighbor
knn=KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train,y_train)
y_pred=knn.predict(x_test)
acc_knn=round(knn.score(x_train, y_train)*100,2)
acc_knn
```
Out[201]: 81.93

In [202]:
```
# Gaussian Naive Bayes
gaussian=GaussianNB()
gaussian.fit(x_train,y_train)
y_pred=gaussian.predict(x_test)
acc_gaussian=round(gaussian.score(x_train,y_train)*100,2)
acc_gaussian
```

Out[202]: 72.17

In [203]:
```
#perceptron
perceptron=Perceptron()
perceptron.fit(x_train,y_train)
y_pred=perceptron.predict(x_test)
acc_perceptron=round(perceptron.score(x_train,y_train)*100,2)
acc_perceptron
```

```
C:\Users\uthir\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:
128: FutureWarning: max_iter and tol parameters have been added in <class 'sklearn.line
ar_model.perceptron.Perceptron'> in 0.19. If both are left unset, they default to max_i
ter=5 and tol=None. If tol is not None, max_iter defaults to max_iter=1000. From 0.21,
default max_iter will be 1000, and default tol will be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Out[203]: 75.65

In [204]:
```
#Linear SVC
linear_svc=LinearSVC()
linear_svc.fit(x_train,y_train)
y_pred=linear_svc.predict(x_test)
acc_linear_svc=round(linear_svc.score(x_train,y_train)*100,2)
acc_linear_svc
```

Out[204]: 78.79

In [206]:
```
#Stochastic Gradient Descent
sgd=SGDClassifier()
sgd.fit(x_train,y_train)
y_pred=sgd.predict(x_test)
acc_sgd=round(sgd.score(x_train,y_train)*100,2)
acc_sgd
```

```
C:\Users\uthir\Anaconda3\lib\site-packages\sklearn\linear_model\stochastic_gradient.py:
128: FutureWarning: max_iter and tol parameters have been added in <class 'sklearn.line
ar_model.stochastic_gradient.SGDClassifier'> in 0.19. If both are left unset, they defa
ult to max_iter=5 and tol=None. If tol is not None, max_iter defaults to max_iter=1000.
From 0.21, default max_iter will be 1000, and default tol will be 1e-3.
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

Out[206]: 78.11

In [207]:
```
#Decision Tree
decision_tree=DecisionTreeClassifier()
decision_tree.fit(x_train,y_train)
y_pred=decision_tree.predict(x_test)
acc_decision_tree=round(decision_tree.score(x_train,y_train)*100,2)
acc_decision_tree
```

Out[207]: 84.29

In [208]:

```
#Random Forest
random_forest=RandomForestClassifier(n_estimators=100)
random_forest.fit(x_train,y_train)
y_pred=random_forest.predict(x_test)
acc_random_forest=round(random_forest.score(x_train,y_train)*100,2)
acc_random_forest
```

Out[208]: 84.29

In [209]:

```
#model evaluation
models = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'Stochastic Gradient Decent', 'Linear SVC',
              'Decision Tree'],
    'Score': [acc_svc, acc_knn, acc_log,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, acc_linear_svc, acc_decision_tree]})
models.sort_values(by='Score', ascending=False)
```

Out[209]:

	Model	Score
3	Random Forest	84.29
8	Decision Tree	84.29
0	Support Vector Machines	82.38
1	KNN	81.93
2	Logistic Regression	80.36
7	Linear SVC	78.79
6	Stochastic Gradient Decent	78.11
5	Perceptron	75.65
4	Naive Bayes	72.17

In [214]:

```
submission=pd.DataFrame({
    'PassengerId':titest["PassengerId"],
    'Survived' : y_pred
})
submission.to_csv("D:/Kaggle/titanic/submission.csv", index=False)
```