In [1]:
```
%config IPCompleter.greedy=True
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.utils import resample
from imblearn.over_sampling import SMOTENC,RandomOverSampler,KMeansSMOTE
from sklearn.impute import KNNImputer
from sklearn.preprocessing import LabelEncoder
import io
import requests
import numpy as np;
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import Ridge,Lasso,RidgeCV, LassoCV, ElasticNet, ElasticNetCV, LinearRegression
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
np.random.seed(0)
sns.set()
#pd.set_option("display.max_rows", None, "display.max_columns", None)


# 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
```

Step1: Acquire data

In [3]:
```
#url="https://raw.githubusercontent.com/BigDataGal/Python-for-Data-Science/master/titanic-train.csv"
#s=requests.get(url).content
#train_df=pd.read_csv(io.StringIO(s.decode('utf-8')))
train_df = pd.read_csv('./input/train.csv')
```

In [4]:
```
#train_df = pd.read_csv('./input/train.csv')
test_df = pd.read_csv('./input/test.csv')
combine = [train_df, test_df]
```

Step2: Analyze the dataset

In [5]:
```
train_df.shape,test_df.shape
```

Out[5]:
```
((891, 12), (418, 11))
```

In [6]:
```
train_df.columns.values, test_df.columns.values
```

Out[6]:
```
(array(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
        'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object),
 array(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
        'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object))
```

Observation:

Categorical: Survived, Sex, and Embarked. Ordinal: Pclass.

Continous: Age, Fare. Discrete: SibSp, Parch.

Note:

sibsp: Number of Siblings/Spouses Aboard

parch: Number of Parents/Children Aboard

In [7]:
```
train_df.head()
```

Out[7]:

	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

In [8]:
```
train_df.tail()
```

Out[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

In [9]:
```
test_df.head()
```

Out[9]:

	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 [10]:
```
test_df.tail()
```

Out[10]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
413	1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

Observation:

Ticket is a mix of numeric and alphanumeric data types. Cabin is alphanumeric.

Distribution of numerical feature

In [11]:
```
TotalPassenger= 2208
TrainingSample= train_df.shape[0]
SamplePopulationPercent= (TrainingSample/TotalPassenger)*100
SamplePopulationPercent
```

Out[11]:
```
40.35326086956522
```

In [12]:
```
train_df_temp = pd.DataFrame({'SibSp':train_df.SibSp })
sibsp_cnt=train_df_temp[train_df_temp.SibSp > 0].count()

PercentageSibSp= (sibsp_cnt/TrainingSample)*100
PercentageSibSp
```

Out[12]:
```
SibSp    31.762065
dtype: float64
```

In [13]:
```
train_df_temp = pd.DataFrame({'Parch':train_df.Parch })
parch_cnt=train_df_temp[train_df_temp.Parch > 0].count()

PercentageParch= (parch_cnt/TrainingSample)*100
PercentageParch
```

Out[13]:
```
Parch    23.905724
dtype: float64
```

In [14]:
```
train_df.describe()
```

Out[14]:

	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

In [15]:
```
train_df.groupby(["Sex", "Age"])["Sex"].count()
```

Out[15]:
```
Sex     Age  
female  0.75     2
        1.00     2
        2.00     6
        3.00     2
        4.00     5
                ..
male    70.00    2
        70.50    1
        71.00    2
        74.00    1
        80.00    1
Name: Sex, Length: 145, dtype: int64
```

Distribution of numerical feature observation:

Total samples are 891 or 40% of the actual number of passengers on board the Titanic (2,224).

Survived is a categorical feature with 0 or 1 values.

Nearly 30% of the passengers had siblings and/or spouse aboard.

Fares varied significantly with few passengers (<1%) paying as high as $512.

Few elderly passengers (<1%) within age range 65-80 and no female passenger with age greater than 63

Distribution of categorical feature

In [16]:
```
train_df['Name'].nunique()
```

Out[16]:
```
891
```

In [17]:
```
train_df.groupby(["Sex"])["Sex"].count()
```

Out[17]:
```
Sex
female    314
male      577
Name: Sex, dtype: int64
```

In [18]:
```
TrainingSample= train_df.shape[0]
FemalePopulationPercent= (train_df.groupby(["Sex"])["Sex"].count()['female']/TrainingSample)*100
MalePopulationPercent= (train_df.groupby(["Sex"])["Sex"].count()['male']/TrainingSample)*100
FemalePopulationPercent,MalePopulationPercent
```

Out[18]:
```
(35.24130190796858, 64.75869809203144)
```

In [19]:
```
train_df['Cabin'].unique()
```

Out[19]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

In [20]:
```
train_df.groupby(["Cabin","PassengerId"])["PassengerId"].count()
```

Out[20]:
```
Cabin  PassengerId
A10    584            1
A14    476            1
A16    557            1
A19    285            1
A20    600            1
                     ..
G6     11             1
       206            1
       252            1
       395            1
T      340            1
Name: PassengerId, Length: 204, dtype: int64
```

In [21]:
```
train_df.groupby(["Embarked"])["Embarked"].count().sort_values(ascending=False)
```

Out[21]:
```
Embarked
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [22]:
```
train_df.groupby(["Ticket"])["Ticket"].count().sort_values(ascending=False)
```

Out[22]:
```
Ticket
CA. 2343    7
1601        7
347082      7
347088      6
CA 2144     6
           ..
PC 17601    1
349239      1
349240      1
349241      1
347464      1
Name: Ticket, Length: 681, dtype: int64
```

Distribution of categorical feature observation:

Names are unique across the dataset (count=unique=891)

Sex variable as two possible values with 65% male (top=male, freq=577/count=891).

Cabin values have several dupicates across samples. Alternatively several passengers shared a cabin.

Embarked takes three possible values. S port used by most passengers (top=S)

Ticket feature has high ratio (22%) of duplicate values (unique=681).

Analyze by pivoting features.

Analyzing feature correlations by pivoting features against each other.

At this stage can be done for features which do not have any empty values. It also makes sense doing so only for features which are categorical (Sex), ordinal (Pclass) or discrete (SibSp, Parch) type.

In [23]:
```
train_df[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean().sort_values(by='Survived', ascending=
False)
```

Out[23]:

	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [24]:
```
train_df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

Out[24]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

In [25]:
```
train_df[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

Out[25]:

	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 [26]:
```
train_df[["Parch", "Survived"]].groupby(['Parch'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

Out[26]:

	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

Pivoting features observation:

Pclass significant correlation (>0.5) among Pclass=1 and Survived.

Sex Sex=female had very high survival rate at 74%.

Sibsp Sibsp=1, one sibling has high rate of survival at 54%

Parch Parch=1,2,3 one, two or three parch has high rate of survival at 54%

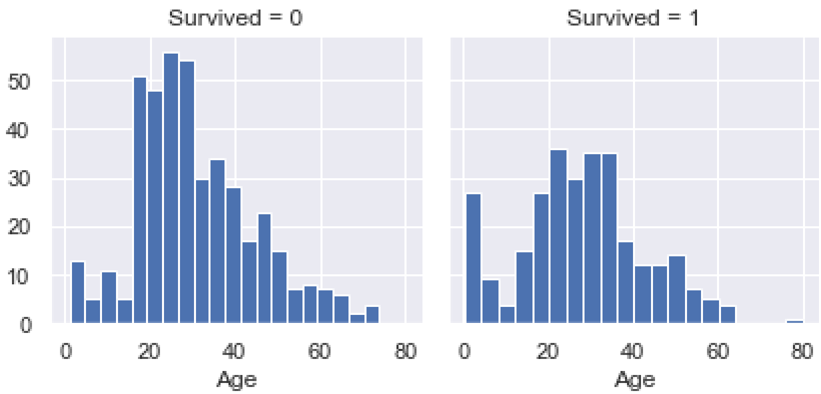
Multivariate Analysis

Analyze by visualizing data by Correlating numerical features

In [27]:
```
fig = plt.gcf()
g = sns.FacetGrid(train_df, col='Survived')
g.map(plt.hist, 'Age', bins=20)
```

Out[27]:
```
<seaborn.axisgrid.FacetGrid at 0x17161271d90>
```

```
<Figure size 432x288 with 0 Axes>
```



Analyze by visualizing data by Correlating numerical features

Observations

Infants (Age <=4) had high survival rate.

Oldest passengers (Age = 80) survived.

Large number of 16-28 year olds did not survive.

Most passengers are in 16-40 age range.

Decisions

We should consider Age in our model training.

Complete the Age feature for null values .

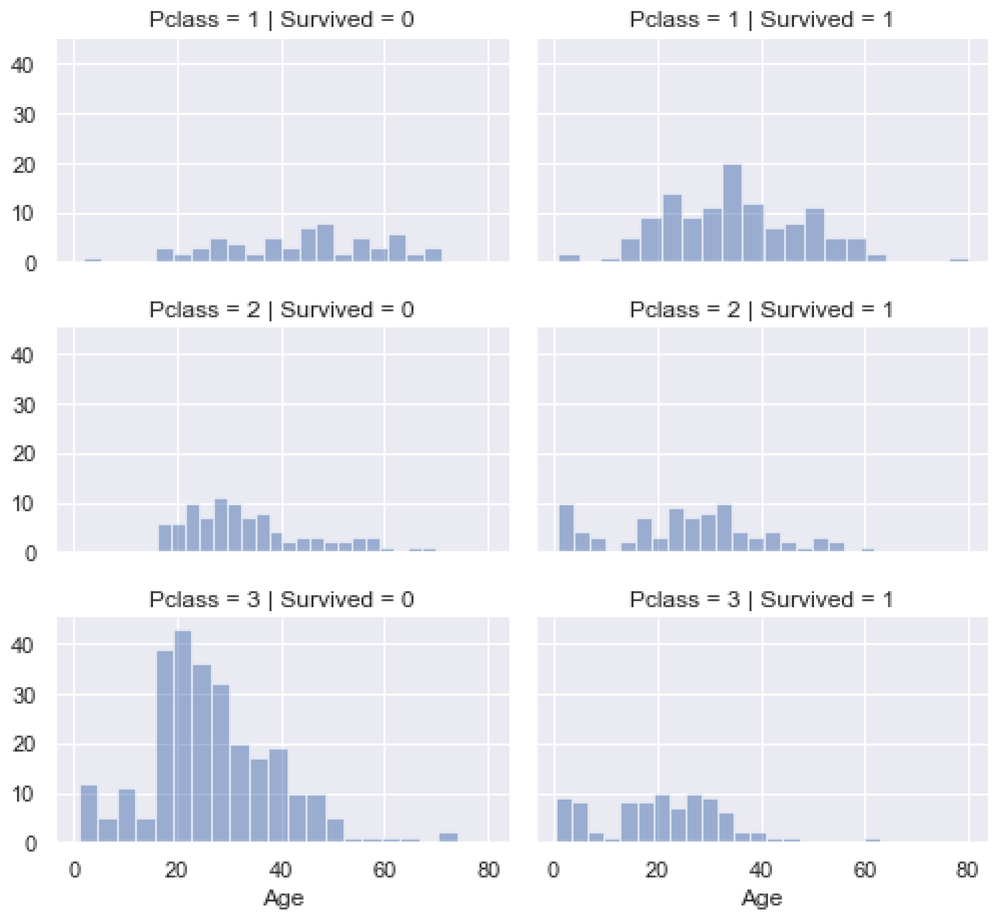
We should band age groups.

Multivariate Analysis

Correlating numerical and ordinal features

In [28]:
```
# grid = sns.FacetGrid(train_df, col='Pclass', hue='Survived')
grid = sns.FacetGrid(train_df, col='Survived', row='Pclass', size=2.2, aspect=1.6)
grid.map(plt.hist, 'Age', alpha=.5, bins=20)
grid.add_legend();
```

```
C:\Users\shivd\.conda\envs\MLProj\lib\site-packages\seaborn\axisgrid.py:243: UserWarning: The `size` parameter ha
s been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



Correlating numerical and ordinal features

Observations

Pclass=3 had most passengers, however most did not survive

Infant passengers in Pclass=2 and Pclass=3 mostly survived.

Most passengers in Pclass=1 survived.

Pclass varies in terms of Age distribution of passengers.

Decisions

Consider Pclass for model training.

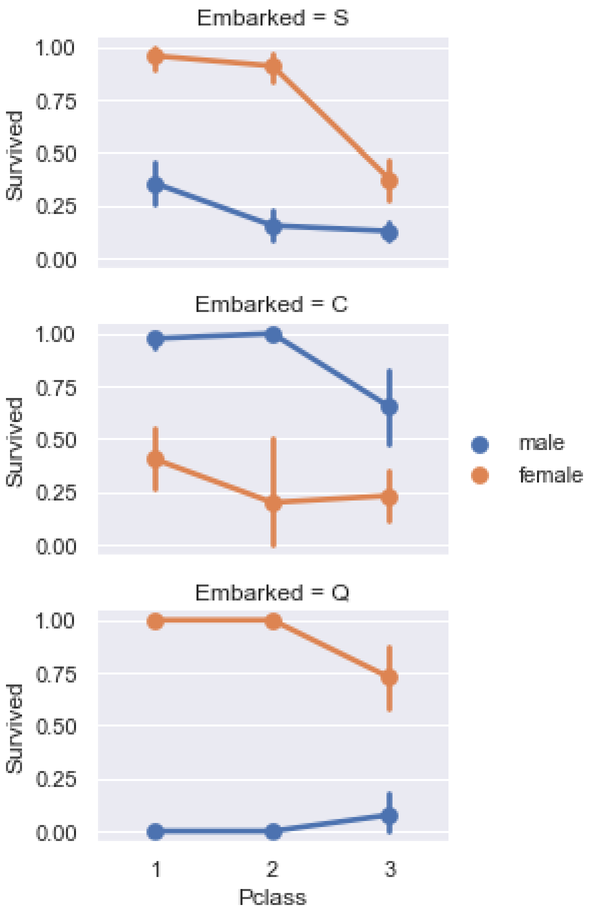
Multivariate Analysis

Correlating categorical features

In [29]:
```
grid = sns.FacetGrid(train_df, row='Embarked', size=2.2, aspect=1.6)
grid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette='deep')
grid.add_legend()
```

```
C:\Users\shivd\.conda\envs\MLProj\lib\site-packages\seaborn\axisgrid.py:723: UserWarning: Using the pointplot fun
ction without specifying `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\shivd\.conda\envs\MLProj\lib\site-packages\seaborn\axisgrid.py:728: UserWarning: Using the pointplot fun
ction without specifying `hue_order` is likely to produce an incorrect plot.
  warnings.warn(warning)
```

Out[29]: <seaborn.axisgrid.FacetGrid at 0x1716194c520>



Correlating categorical features

Observations

Female passengers had much better survival rate than males.

Exception in Embarked=C where males had higher survival rate.

This could be a correlation between Pclass and Embarked and in turn Pclass and Survived, not necessarily direct correlation between Embarked and Survived.

Males had better survival rate in Pclass=3 when compared with Pclass=2 for C and Q ports. Ports of embarkation have varying survival rates for Pclass=3 and among male passengers.

Decisions

Add Sex feature to model training.

Complete and add Embarked feature to model training.

Multivariate Analysis

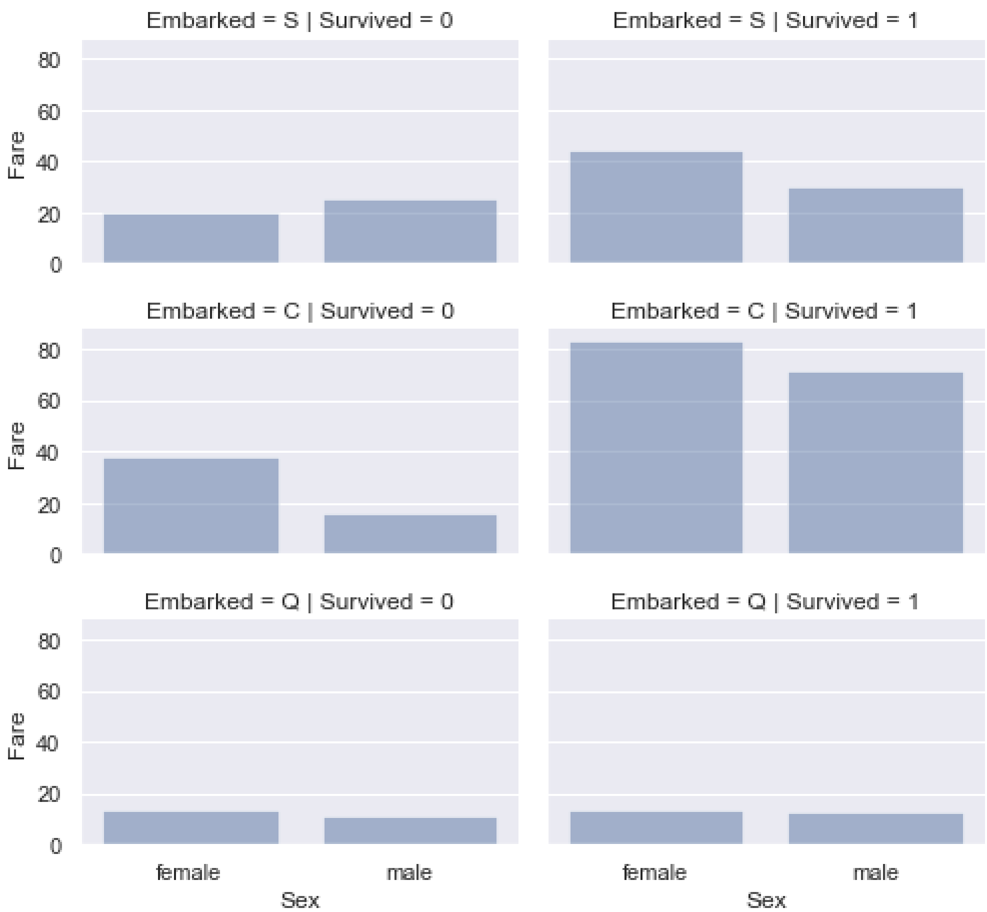
Correlating categorical and numerical features

Combining multiple features for identifying correlations using a single plot. This can be done with numerical and categorical features which have numeric values.

In [30]:
```
# grid = sns.FacetGrid(train_df, col='Embarked', hue='Survived', palette={0: 'k', 1: 'w'})
grid = sns.FacetGrid(train_df, row='Embarked', col='Survived', size=2.2, aspect=1.6)
grid.map(sns.barplot, 'Sex', 'Fare', alpha=.5, ci=None)
grid.add_legend()
```

```
C:\Users\shivd\.conda\envs\MLProj\lib\site-packages\seaborn\axisgrid.py:243: UserWarning: The `size` parameter ha
s been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
C:\Users\shivd\.conda\envs\MLProj\lib\site-packages\seaborn\axisgrid.py:723: UserWarning: Using the barplot funct
ion without specifying `order` is likely to produce an incorrect plot.
  warnings.warn(warning)
```

Out[30]: <seaborn.axisgrid.FacetGrid at 0x17162a506a0>



Correlating categorical and numerical features

Observations

Pclass=3 had most passengers, however most did not survive

Infant passengers in Pclass=2 and Pclass=3 mostly survived.

Most passengers in Pclass=1 survived.

Pclass varies in terms of Age distribution of passengers.

Decisions

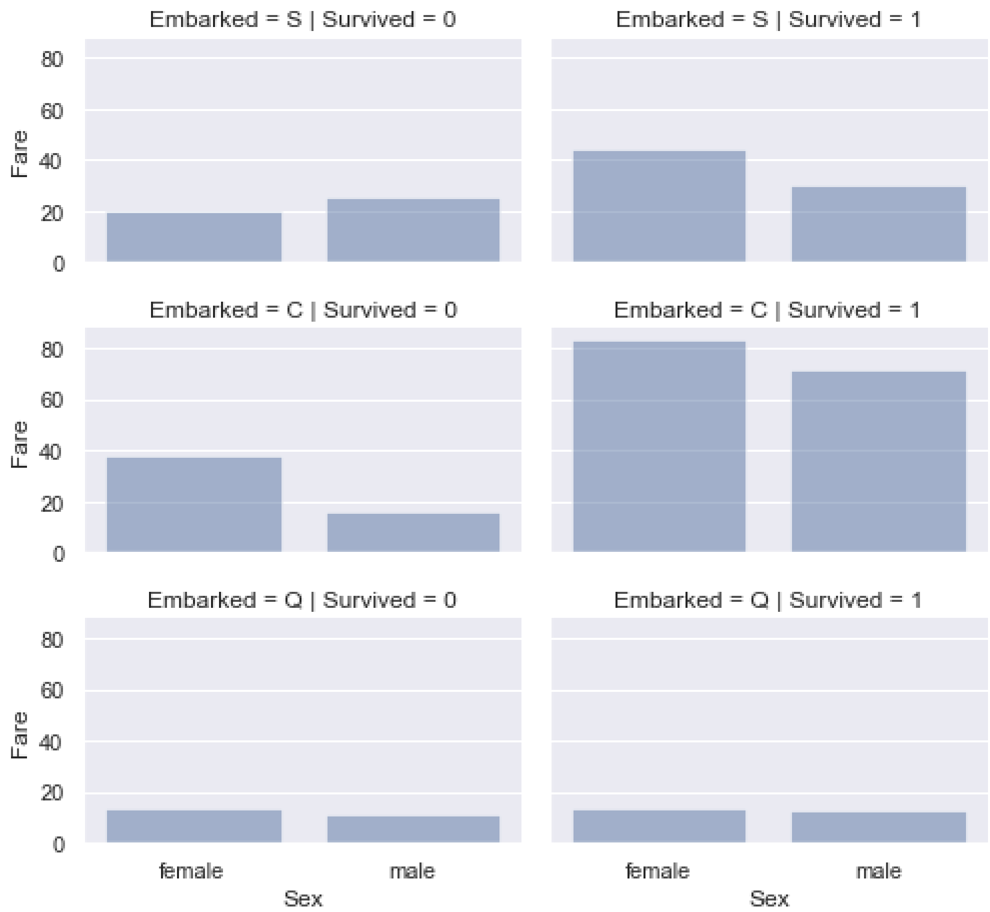
Consider Pclass for model training.

Multivariate Analysis

Correlating categorical and numerical features

In [31]:
```
# grid = sns.FacetGrid(train_df, col='Embarked', hue='Survived', palette={0: 'k', 1: 'w'})
grid = sns.FacetGrid(train_df, row='Embarked', col='Survived', size=2.2, aspect=1.6)
grid.map(sns.barplot, 'Sex', 'Fare', alpha=.5, ci=None)
grid.add_legend()
```

Out[31]:
```
<seaborn.axisgrid.FacetGrid at 0x17162c07550>
```



Correlating categorical and numerical features

Observations

Higher fare paying passengers had better survival. Port of embarkation correlates with survival rates.

Decisions

Consider banding Fare feature.

Data Preprocessing

Feature dropping

In [32]:
```
print("Before", train_df.shape, test_df.shape, combine[0].shape, combine[1].shape)

train_df = train_df.drop(['Ticket', 'Cabin'], axis=1)
test_df = test_df.drop(['Ticket', 'Cabin'], axis=1)
combine = [train_df, test_df]

"After", train_df.shape, test_df.shape, combine[0].shape, combine[1].shape
```

```
Before (891, 12) (418, 11) (891, 12) (418, 11)
```

Out[32]:
```
('After', (891, 10), (418, 9), (891, 10), (418, 9))
```

Creating new feature extracting from existing

In the following code we extract Title feature using regular expressions. The RegEx pattern (\w+.) matches the first word which ends with a dot character within Name feature. The expand=False flag returns a DataFrame.

In [33]:
```
for dataset in combine:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)

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

Out[33]:

Sex Title	female	male
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

Decisions

We can replace many titles with a more common name or classify them as Rare.

In [34]:
```
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')

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

Out[34]:

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

Decisions

We can convert the categorical titles to ordinal.

In [35]:
```
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)

    dataset['Title'] = dataset['Title'].replace('Rare', '5')
    dataset['Title'] = dataset['Title'].replace('Master', '4')
    dataset['Title'] = dataset['Title'].replace('Mrs', '3')
    dataset['Title'] = dataset['Title'].replace('Miss', '2')
    dataset['Title'] = dataset['Title'].replace('Mr', '1')


train_df.head()
```

Out[35]:

	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 [36]:
```
test_df.head()
```

Out[36]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	892	3	Kelly, Mr. James	male	34.5	0	0	7.8292	Q	1
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	7.0000	S	3
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	9.6875	Q	1
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	8.6625	S	1
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	12.2875	S	3

Decisions

Now droping the Name feature from training and testing datasets and PassengerId feature in the training dataset.

In [37]:
```
train_df = train_df.drop(['Name', 'PassengerId'], axis=1)
test_df = test_df.drop(['Name'], axis=1)
combine = [train_df, test_df]
train_df.shape, test_df.shape
```

Out[37]: ((891, 9), (418, 9))

In [38]:
```
train_df
```

Out[38]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	male	22.0	1	0	7.2500	S	1
1	1	1	female	38.0	1	0	71.2833	C	3
2	1	3	female	26.0	0	0	7.9250	S	2
3	1	1	female	35.0	1	0	53.1000	S	3
4	0	3	male	35.0	0	0	8.0500	S	1
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	5
887	1	1	female	19.0	0	0	30.0000	S	2
888	0	3	female	NaN	1	2	23.4500	S	2
889	1	1	male	26.0	0	0	30.0000	C	1
890	0	3	male	32.0	0	0	7.7500	Q	1

891 rows × 9 columns

Converting a categorical feature

Decisions

Starting by converting Sex feature to a new feature called Gender where female=1 and male=0.

Embarked feature takes S, Q, C values based on port of embarkation.The Training dataset has two missing values. Simply filling these with the most common occurance.

In [39]:
```
for dataset in combine:
    dataset['Sex'] = dataset['Sex'].map( {'female': 1, 'male': 0} ).astype(int)

train_df.head()
```

Out[39]:

	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 [40]:
```
freq_port = train_df.Embarked.dropna().mode()[0]
freq_port
```

Out[40]: 'S'

In [41]:
```
for dataset in combine:
    dataset['Embarked'] = dataset['Embarked'].fillna(freq_port)

train_df[['Embarked', 'Survived']].groupby(['Embarked'], as_index=False).mean().sort_values(by='Survived', ascend
ing=False)
```

Out[41]:

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.339009

In [42]:
```
#for dataset in combine:
#    dataset['Embarked'] = dataset['Embarked'].map( {'C': 0, 'Q': 1, 'S':2} ).astype(int)

# we will use get_dummies with that.
train_df_new=pd.get_dummies(train_df, columns=['Embarked'],drop_first=True)
train_df_new
```

Out[42]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Title	Embarked_Q	Embarked_S
0	0	3	0	22.0	1	0	7.2500	1	0	1
1	1	1	1	38.0	1	0	71.2833	3	0	0
2	1	3	1	26.0	0	0	7.9250	2	0	1
3	1	1	1	35.0	1	0	53.1000	3	0	1
4	0	3	0	35.0	0	0	8.0500	1	0	1
...	...	...	...	...	...	...	...	...	...	...
886	0	2	0	27.0	0	0	13.0000	5	0	1
887	1	1	1	19.0	0	0	30.0000	2	0	1
888	0	3	1	NaN	1	2	23.4500	2	0	1
889	1	1	0	26.0	0	0	30.0000	1	0	0
890	0	3	0	32.0	0	0	7.7500	1	1	0

891 rows × 10 columns

In [43]:
```
test_df_new=pd.get_dummies(test_df, columns=['Embarked'],drop_first=True)
test_df_new
```

Out[43]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Title	Embarked_Q	Embarked_S
0	892	3	0	34.5	0	0	7.8292	1	1	0
1	893	3	1	47.0	1	0	7.0000	3	0	1
2	894	2	0	62.0	0	0	9.6875	1	1	0
3	895	3	0	27.0	0	0	8.6625	1	0	1
4	896	3	1	22.0	1	1	12.2875	3	0	1
...	...	...	...	...	...	...	...	...	...	...
413	1305	3	0	NaN	0	0	8.0500	1	0	1
414	1306	1	1	39.0	0	0	108.9000	5	0	0
415	1307	3	0	38.5	0	0	7.2500	1	0	1
416	1308	3	0	NaN	0	0	8.0500	1	0	1
417	1309	3	0	NaN	1	1	22.3583	4	0	0

418 rows × 10 columns

In [44]:
```
train_df
```

Out[44]:

	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
...	...	...	...	...	...	...	...	...	...
886	0	2	0	27.0	0	0	13.0000	S	5
887	1	1	1	19.0	0	0	30.0000	S	2
888	0	3	1	NaN	1	2	23.4500	S	2
889	1	1	0	26.0	0	0	30.0000	C	1
890	0	3	0	32.0	0	0	7.7500	Q	1

891 rows × 9 columns

Imputing the null values

In [45]:
```
train_df_new.isna().sum()
```

Out[45]:
```
Survived        0
Pclass          0
Sex             0
Age           177
SibSp           0
Parch           0
Fare            0
Title           0
Embarked_Q      0
Embarked_S      0
dtype: int64
```

In [46]:
```
test_df_new.isna().sum()
```

Out[46]:
```
PassengerId     0
Pclass          0
Sex             0
Age            86
SibSp           0
Parch           0
Fare            1
Title           0
Embarked_Q      0
Embarked_S      0
dtype: int64
```

In [47]:
```
imputer=KNNImputer(n_neighbors=3, weights='uniform',missing_values=np.nan)
new_array=imputer.fit_transform(train_df_new) # impute the missing values
#convert the nd-array returned in the step above to a Dataframe
train_new_data=pd.DataFrame(data=np.round(new_array), columns=train_df_new.columns)
train_new_data
```

Out[47]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Title	Embarked_Q	Embarked_S
0	0.0	3.0	0.0	22.0	1.0	0.0	7.0	1.0	0.0	1.0
1	1.0	1.0	1.0	38.0	1.0	0.0	71.0	3.0	0.0	0.0
2	1.0	3.0	1.0	26.0	0.0	0.0	8.0	2.0	0.0	1.0
3	1.0	1.0	1.0	35.0	1.0	0.0	53.0	3.0	0.0	1.0
4	0.0	3.0	0.0	35.0	0.0	0.0	8.0	1.0	0.0	1.0
...	...	...	...	...	...	...	...	...	...	...
886	0.0	2.0	0.0	27.0	0.0	0.0	13.0	5.0	0.0	1.0
887	1.0	1.0	1.0	19.0	0.0	0.0	30.0	2.0	0.0	1.0
888	0.0	3.0	1.0	15.0	1.0	2.0	23.0	2.0	0.0	1.0
889	1.0	1.0	0.0	26.0	0.0	0.0	30.0	1.0	0.0	0.0
890	0.0	3.0	0.0	32.0	0.0	0.0	8.0	1.0	1.0	0.0

891 rows × 10 columns

In [48]:
```
train_new_data.isna().sum()
```

Out[48]:
```
Survived      0
Pclass        0
Sex           0
Age           0
SibSp         0
Parch         0
Fare          0
Title         0
Embarked_Q    0
Embarked_S    0
dtype: int64
```

In [49]:
```
imputer=KNNImputer(n_neighbors=3, weights='uniform',missing_values=np.nan)
new_array=imputer.fit_transform(test_df_new) # impute the missing values
#convert the nd-array returned in the step above to a Dataframe
test_new_data=pd.DataFrame(data=np.round(new_array), columns=test_df_new.columns)
test_new_data
```

Out[49]:

	PassengerId	Pclass	Sex	Age	SibSp	Parch	Fare	Title	Embarked_Q	Embarked_S
0	892.0	3.0	0.0	34.0	0.0	0.0	8.0	1.0	1.0	0.0
1	893.0	3.0	1.0	47.0	1.0	0.0	7.0	3.0	0.0	1.0
2	894.0	2.0	0.0	62.0	0.0	0.0	10.0	1.0	1.0	0.0
3	895.0	3.0	0.0	27.0	0.0	0.0	9.0	1.0	0.0	1.0
4	896.0	3.0	1.0	22.0	1.0	1.0	12.0	3.0	0.0	1.0
...	...	...	...	...	...	...	...	...	...	...
413	1305.0	3.0	0.0	23.0	0.0	0.0	8.0	1.0	0.0	1.0
414	1306.0	1.0	1.0	39.0	0.0	0.0	109.0	5.0	0.0	0.0
415	1307.0	3.0	0.0	38.0	0.0	0.0	7.0	1.0	0.0	1.0
416	1308.0	3.0	0.0	23.0	0.0	0.0	8.0	1.0	0.0	1.0
417	1309.0	3.0	0.0	22.0	1.0	1.0	22.0	4.0	0.0	0.0

418 rows × 10 columns

In [50]:
```
test_new_data.isna().sum()
```

Out[50]:
```
PassengerId    0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Fare           0
Title          0
Embarked_Q     0
Embarked_S     0
dtype: int64
```

All Imputation done.

In [51]:
```
combine_new = [train_new_data,test_new_data]
```

Create new feature combining existing features

Decision

Creating new feature for FamilySize = Parch + SibSp. to drop Parch and SibSp from our datasets.

In [52]:
```
for dataset in combine_new:
    dataset['FamilySize'] = dataset['SibSp'] + dataset['Parch'] + 1

train_new_data[['FamilySize', 'Survived']].groupby(['FamilySize'], as_index=False).mean().sort_values(by='Survive
d', ascending=False)
```

Out[52]:

	FamilySize	Survived
3	4.0	0.724138
2	3.0	0.578431
1	2.0	0.552795
6	7.0	0.333333
0	1.0	0.303538
4	5.0	0.200000
5	6.0	0.136364
7	8.0	0.000000
8	11.0	0.000000

Decision

Creating another feature called IsAlone.

In [53]:
```
for dataset in combine_new:
    dataset['IsAlone'] = 0
    dataset.loc[dataset['FamilySize'] == 1, 'IsAlone'] = 1

train_new_data[['IsAlone', 'Survived']].groupby(['IsAlone'], as_index=False).mean()
```

Out[53]:

	IsAlone	Survived
0	0	0.505650
1	1	0.303538

Decision

Droping Parch, SibSp, and FamilySize features in favor of IsAlone.

In [54]:
```
train1_df = train_new_data.drop(['Parch', 'SibSp', 'FamilySize'], axis=1)
test1_df = test_new_data.drop(['Parch', 'SibSp', 'FamilySize'], axis=1)
combine1 = [train1_df, test1_df]

train1_df
```

Out[54]:

	Survived	Pclass	Sex	Age	Fare	Title	Embarked_Q	Embarked_S	IsAlone
0	0.0	3.0	0.0	22.0	7.0	1.0	0.0	1.0	0
1	1.0	1.0	1.0	38.0	71.0	3.0	0.0	0.0	0
2	1.0	3.0	1.0	26.0	8.0	2.0	0.0	1.0	1
3	1.0	1.0	1.0	35.0	53.0	3.0	0.0	1.0	0
4	0.0	3.0	0.0	35.0	8.0	1.0	0.0	1.0	1
...	...	...	...	...	...	...	...	...	...
886	0.0	2.0	0.0	27.0	13.0	5.0	0.0	1.0	1
887	1.0	1.0	1.0	19.0	30.0	2.0	0.0	1.0	1
888	0.0	3.0	1.0	15.0	23.0	2.0	0.0	1.0	0
889	1.0	1.0	0.0	26.0	30.0	1.0	0.0	0.0	1
890	0.0	3.0	0.0	32.0	8.0	1.0	1.0	0.0	1

891 rows × 9 columns

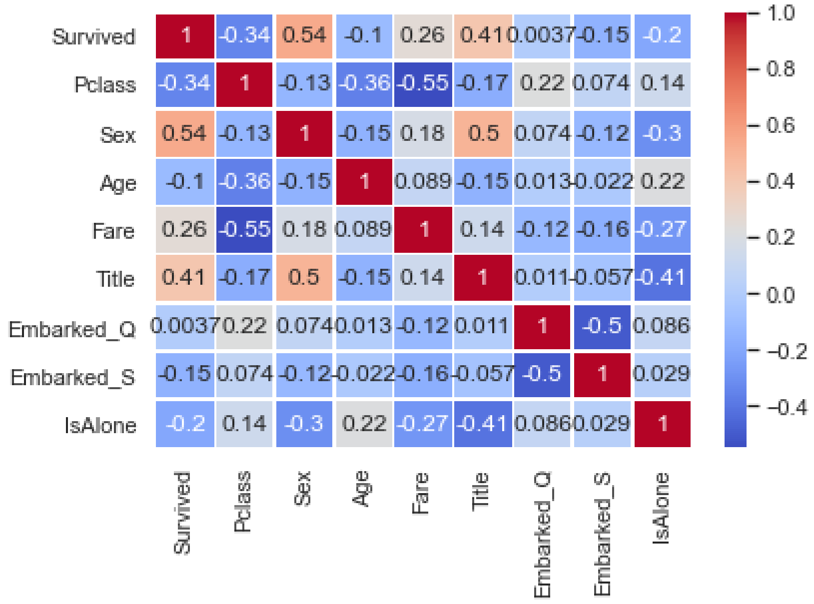
In [55]:
```
test1_df
```

Out[55]:

	PassengerId	Pclass	Sex	Age	Fare	Title	Embarked_Q	Embarked_S	IsAlone
0	892.0	3.0	0.0	34.0	8.0	1.0	1.0	0.0	1
1	893.0	3.0	1.0	47.0	7.0	3.0	0.0	1.0	0
2	894.0	2.0	0.0	62.0	10.0	1.0	1.0	0.0	1
3	895.0	3.0	0.0	27.0	9.0	1.0	0.0	1.0	1
4	896.0	3.0	1.0	22.0	12.0	3.0	0.0	1.0	0
...	...	...	...	...	...	...	...	...	...
413	1305.0	3.0	0.0	23.0	8.0	1.0	0.0	1.0	1
414	1306.0	1.0	1.0	39.0	109.0	5.0	0.0	0.0	1
415	1307.0	3.0	0.0	38.0	7.0	1.0	0.0	1.0	1
416	1308.0	3.0	0.0	23.0	8.0	1.0	0.0	1.0	1
417	1309.0	3.0	0.0	22.0	22.0	4.0	0.0	0.0	0

418 rows × 9 columns

In [56]:
```
ax = sns.heatmap(train1_df.corr(),annot=True,linewidth=0.5, cmap='coolwarm')
```



Decision

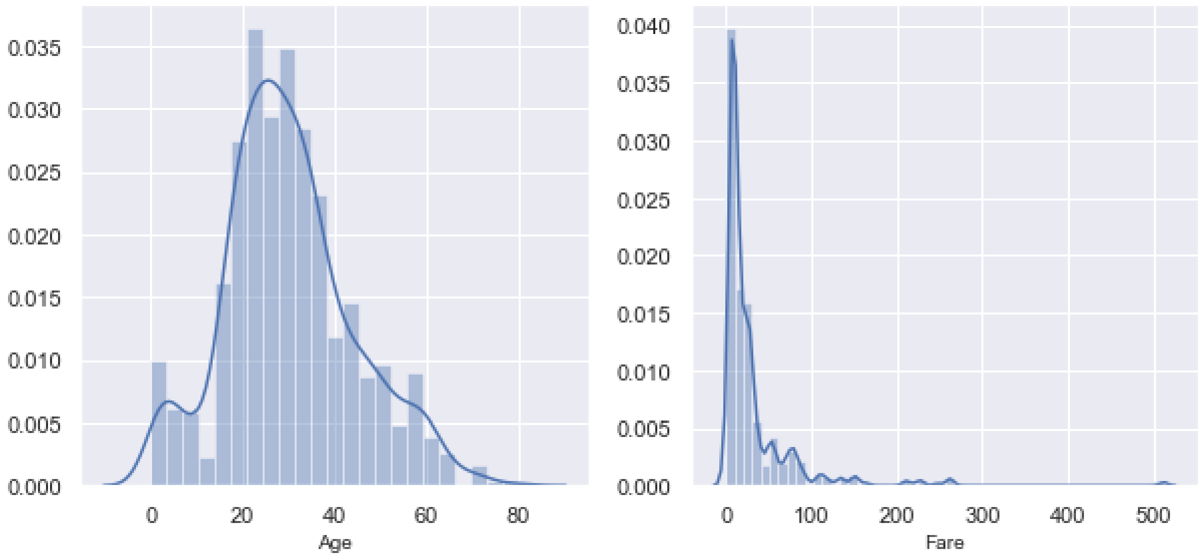
There is positive correlation between Gender and Survived. There is positive correlation between Title and Survived.

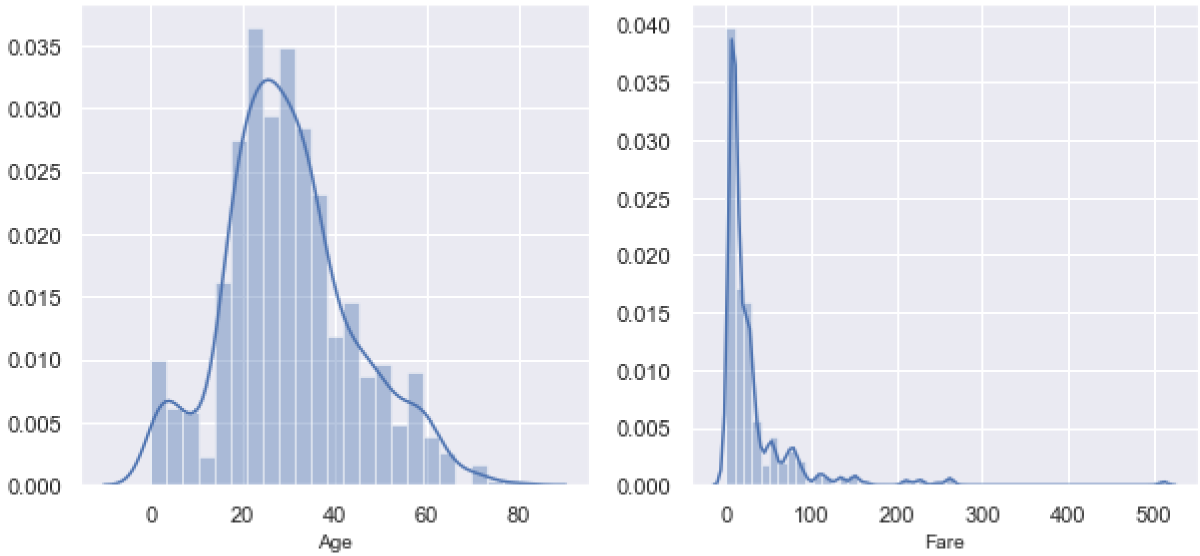
There is negative correlation between PClass and Fare.

We will further investigate using VIF.

Distribution for our continous data in the dataset:

In [57]:
```
columns = ['Age','Fare']
plt.figure(figsize=(10,15),facecolor='white')
plotnumber = 1

for column in columns:
    ax = plt.subplot(3,2,plotnumber)
    sns.distplot(train1_df[column])
    plt.xlabel(column,fontsize=10)
    plotnumber+=1
plt.show()
plt.figure(figsize=(10,15),facecolor='white')
plotnumber = 1

for column in columns:
    ax = plt.subplot(3,2,plotnumber)
    sns.distplot(train1_df[column])
    plt.xlabel(column,fontsize=10)
    plotnumber+=1
plt.show()
```



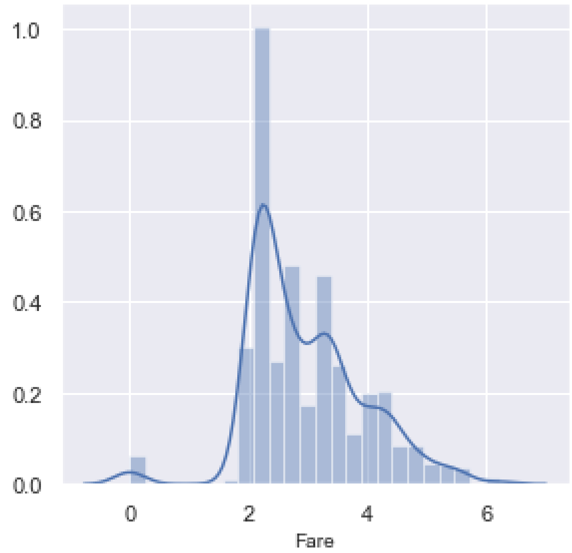


Before doing log transformation , let's add 1 to each valuue in the column to handle exception when we try to find log of '0'.

Age seems to follow Gaussian whereas Fare is heavily left skewed

In [58]:
```
columns = ['Fare']

plt.figure(figsize=(10,15),facecolor='white')
plotnumber = 1

plt.figure(figsize=(10,15),facecolor='white')
plotnumber = 1

for column in columns:
    train1_df[column]+=1
    ax = plt.subplot(3,2,plotnumber)
    sns.distplot(np.log(train1_df[column]))
    plt.xlabel(column,fontsize=10)
    plotnumber+=1
plt.show()
```

```
<Figure size 720x1080 with 0 Axes>
```



In [59]:
```
imputer=KNNImputer(n_neighbors=3, weights='uniform',missing_values=np.nan)
new_array=imputer.fit_transform(train1_df) # impute the missing values
#convert the nd-array returned in the step above to a Dataframe
train1_df=pd.DataFrame(data=np.round(new_array), columns=train1_df.columns)
train1_df

train1_df.isna().sum(),test1_df.isna().sum()
```

Out[59]:
```
(Survived      0
 Pclass        0
 Sex           0
 Age           0
 Fare          0
 Title         0
 Embarked_Q    0
 Embarked_S    0
 IsAlone       0
 dtype: int64,
 PassengerId    0
 Pclass         0
 Sex            0
 Age            0
 Fare           0
 Title          0
 Embarked_Q     0
 Embarked_S     0
 IsAlone        0
 dtype: int64)
```

In [60]:
```
train1_df.head()
```

Out[60]:

	Survived	Pclass	Sex	Age	Fare	Title	Embarked_Q	Embarked_S	IsAlone
0	0.0	3.0	0.0	22.0	8.0	1.0	0.0	1.0	0.0
1	1.0	1.0	1.0	38.0	72.0	3.0	0.0	0.0	0.0
2	1.0	3.0	1.0	26.0	9.0	2.0	0.0	1.0	1.0
3	1.0	1.0	1.0	35.0	54.0	3.0	0.0	1.0	0.0
4	0.0	3.0	0.0	35.0	9.0	1.0	0.0	1.0	1.0

In [61]:
```
scaler =StandardScaler()
X_scaled = scaler.fit_transform(train1_df.drop("Survived", axis=1))
```

In [62]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
variables = X_scaled

# we create a new data frame which will include all the VIFs
# note that each variable has its own variance inflation factor as this measure is variable specific (not model s
pecific)
# we do not include categorical values for mulitcollinearity as they do not provide much information as numerical
ones do
vif = pd.DataFrame()

# here we make use of the variance_inflation_factor, which will basically output the respective VIFs
vif["VIF"] = [variance_inflation_factor(variables, i) for i in range(variables.shape[1])]
# Finally, I like to include names so it is easier to explore the result
vif["Features"] = train1_df.drop("Survived", axis=1).columns
vif
```

Out[62]:

	VIF	Features
0	1.848594	Pclass
1	1.406100	Sex
2	1.311556	Age
3	1.583601	Fare
4	1.517758	Title
5	1.513002	Embarked_Q
6	1.444956	Embarked_S
7	1.343274	IsAlone

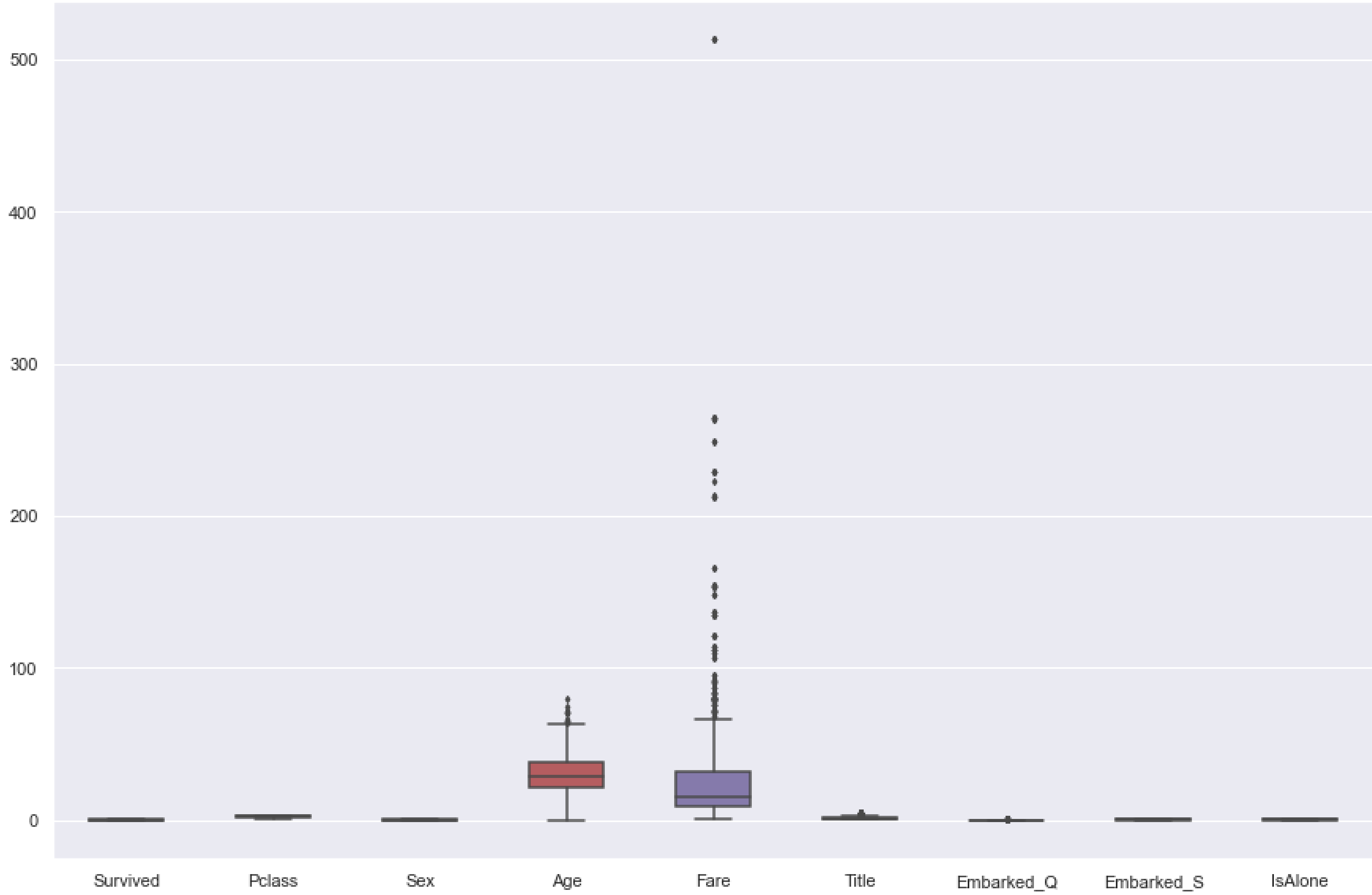
Decision

As we see the vif of all columns are less than 5, therefore there is no multicollinearity

Check for outliers

In [63]:
```
fig, ax = plt.subplots(figsize=(15,10))
sns.boxplot(data=train1_df, width= 0.5,ax=ax,  fliersize=3)
```

Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x171618fe7c0>

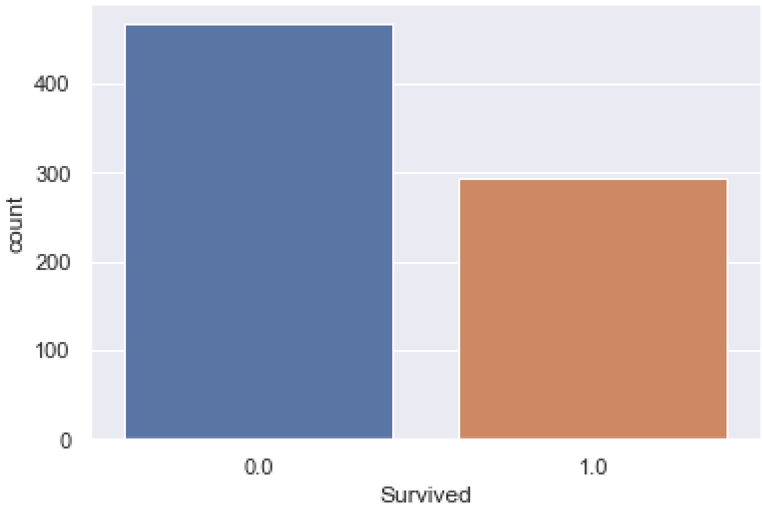


In [64]:
```
q = train1_df['Age'].quantile(0.95)
# we are removing the top 5% data from the Age column
train1_df  = train1_df[train1_df['Age']<q]


q = train1_df['Title'].quantile(0.99)
# we are removing the top 1% data from the Title column
train1_df  = train1_df[train1_df['Title']<q]

q = train1_df['Embarked_Q'].quantile(0.99)
# we are removing the top 1% data from the Embarked_Q column
train1_df  = train1_df[train1_df['Embarked_Q']<q]
```

Check for Imbalance Dataset

In [66]:
```
sns.countplot(train1_df['Survived'])
```

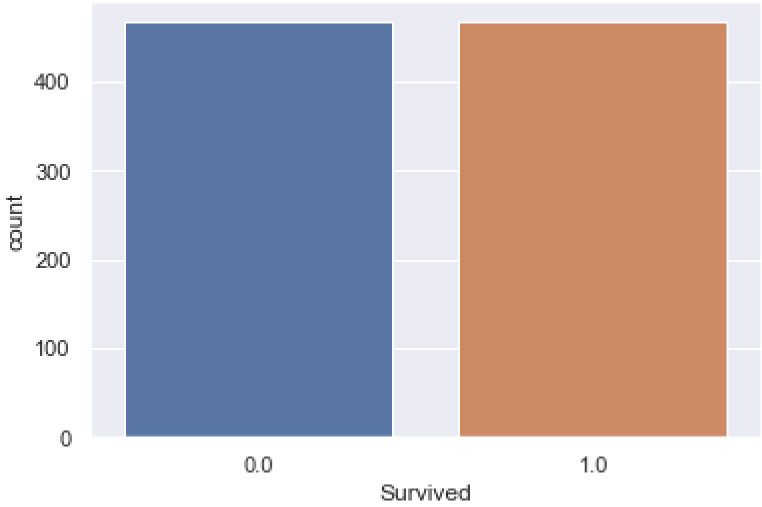
Out[66]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1716429b040>
```



In [67]:
```
X_train = train1_df.drop("Survived", axis=1)
Y_train = train1_df["Survived"]
X_test  = test1_df.drop("PassengerId", axis=1).copy()
X_train.shape, Y_train.shape, X_test.shape,X_train.shape
rdsmple = RandomOverSampler()
x_sampled,y_sampled  = rdsmple.fit_sample(X_train,Y_train)
```

In [68]:
```
y_sampled_temp = pd.DataFrame(y_sampled, columns = ['Survived'])
sns.countplot(y_sampled_temp['Survived'])
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x17164052130>



Decision

The dataset got balanced using RandomOverSampler.

ML Training and Prediction

KNN or k-Nearest Neighbors

Support Vector Machines

Naive Bayes classifier

Decision Tree

Random Forrest

In [69]:
```
#X_train = train1_df.drop("Survived", axis=1)
#Y_train = train1_df["Survived"]
X_test  = test1_df.drop("PassengerId", axis=1).copy()
x_sampled.shape, y_sampled.shape, X_test.shape
```

Out[69]: ((934, 8), (934,), (418, 8))

Decision Tree

In [70]:
```
decision_tree = DecisionTreeClassifier()
#decision_tree.fit(X_train, Y_train)
decision_tree.fit(x_sampled,y_sampled)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(x_sampled,y_sampled) * 100, 2)
acc_decision_tree
```

Out[70]: 97.11

In [71]:
```
submission = pd.DataFrame({
        "PassengerId": test_new_data["PassengerId"],
        "Survived": Y_pred
    })
submission.to_csv('./output/submission.csv', index=False)
```

Support Vector Machines

In [72]:
```
# Support Vector Machines

svc = SVC()
svc.fit(x_sampled,y_sampled)
Y_pred = svc.predict(X_test)
acc_svc = round(svc.score(x_sampled,y_sampled) * 100, 2)
acc_svc
```

Out[72]: 69.06

k-Nearest Neighbors algorithm

In [73]:
```
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(x_sampled,y_sampled)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(x_sampled,y_sampled) * 100, 2)
acc_knn
```

Out[73]: 86.83

Naive Bayes classifiers

In [74]:
```
gaussian = GaussianNB()
gaussian.fit(x_sampled,y_sampled)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(x_sampled,y_sampled) * 100, 2)
acc_gaussian
```

Out[74]: 77.62

Random Forests

In [75]:
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(x_sampled,y_sampled)
Y_pred = random_forest.predict(X_test)
random_forest.score(x_sampled,y_sampled)
acc_random_forest = round(random_forest.score(x_sampled,y_sampled) * 100, 2)
acc_random_forest
```

Out[75]: 97.11

Model evaluation

In [76]:
```
models = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN',
              'Random Forest', 'Naive Bayes',
              'Decision Tree'],
    'Score': [acc_svc, acc_knn,
              acc_random_forest, acc_gaussian, acc_decision_tree]})
models.sort_values(by='Score', ascending=False)
```

Out[76]:

	Model	Score
2	Random Forest	97.11
4	Decision Tree	97.11
1	KNN	86.83
3	Naive Bayes	77.62
0	Support Vector Machines	69.06

In [ ]:

In [ ]:

```

```