Cadent Data Science

August 28, 2017

Machine Learning from Disaster Predict survival on the Titanic

This notebook was done as a part of Cadent Data Science python coding benchmark. The data was obtained from Kaggle

The objective for this project is to predict survival using the Titanic Dataset

From a western perspective, the Titanic sinking is famous disaster and the machine learning problem behind it.

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, the Titanic sank on her maiden voyage after colliding with an iceberg, killing 1,502 out of 2,224 passengers and crew. This tragedy shocked the international community and led to improved safety regulations.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

I did a background search on this disaster to to familiarize myself with this data set. From what I found, the Titanic could carry a total of 3547 people, but at the time of the disaster, it only had 2224 people onboard. Which means that it was not even at its full capacity. However, the Titanic's lifeboat system was designed to ferry passengers to nearby rescue vessels, not to hold everyone onboard at once. There were a total of 18 lifeboats on Titatnic's upperdecks, but records show due to poor management some lifeboats left without filling to full capacity.

After the initial collision with the iceberg, it took two hours and forty minutes until it completely sank. The crew of the Titanic sent wireless messages asking for help but all nearby vessels were hours away. The Titanic was on its maiden voyage and some records show that the crew who was working on the Titanic didn't have the proper disaster management training. Also Titanic did receive the warning about ice fields before hand but at the time of the collision it was cruising at its full speed.

In summary, the lack of lifeboats, poor disaster management, and poor decision making cost 1,502 lives and completely change the maritime regulations.

The Impact point of the collision was the front right side of the ship, which is also known as the starboard. The impact, buckled the starboard which resulted in opening 5 of 6 compartments to the sea. Titanic had been designed to stay afloat with four of her forward compartments flooded but no more.

All 18 life boats of the ship were in the upper deck and 1st class passenger compartments were the closest to the upper deck. As a result, the 1st class passengers were in closer proximity to the life boats compared to 2nd and 3rd class passengers. This could have contributed to greater odds at surviving.

The figure above shows the floor plan on each deck and there were 7 in total.

0.1 Table of Content

0.1.5 1.1 Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

# set env
%matplotlib inline
sns.set_style( 'white' )

# ignore the warnings
import warnings
warnings.filterwarnings('ignore')
```

0.1.6 1.2 Load Data

In [2]:
```
train = pd.read_csv("./Data/train.csv")
test = pd.read_csv("./Data/test.csv")
train.head()
```

Out[2]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

In [3]:
```
# the test data set has 1 less column
# the missing column is survival which will be out prediction
train.shape, test.shape
```

Out[3]:
```
((891, 12), (418, 11))
```

In [4]:
```
# Get detail information about the data set
train.describe()
```

```
Out[4]:        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
```

0.1.7 1.3 Identify Missing Values

```
In [5]: # Get detail information about each column count
        train.info()
        print("---------------------------------------------------")
        test.info()
        # In Age, Cabin and Embarked has missing values
```

```
<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 [6]:
```
# Calculate the missing values in each column in both testing and training
missing_train = train.isnull().sum().sort_values(ascending=False)
missing_test = test.isnull().sum().sort_values(ascending=False)
missing_values = pd.concat([missing_train,missing_test], axis=1, keys=["Train","Test"])
missing_values
```

Out[6]:

	Train	Test
Age	177	86.0
Cabin	687	327.0
Embarked	2	0.0
Fare	0	1.0
Name	0	0.0
Parch	0	0.0
PassengerId	0	0.0
Pclass	0	0.0
Sex	0	0.0
SibSp	0	0.0
Survived	0	NaN
Ticket	0	0.0

In [7]:
```
# Age and Cabin has the highest missing values
missing_count = pd.concat([missing_values.loc["Age"],missing_values.loc["Cabin"]],axis=1
ax = missing_count.plot(kind='barh',title="Missing values in both test and train data se
ax.set_xlabel("Count")
ax.set_ylabel("Category")
```

Out[7]: <matplotlib.text.Text at 0x7fb3284d52b0>

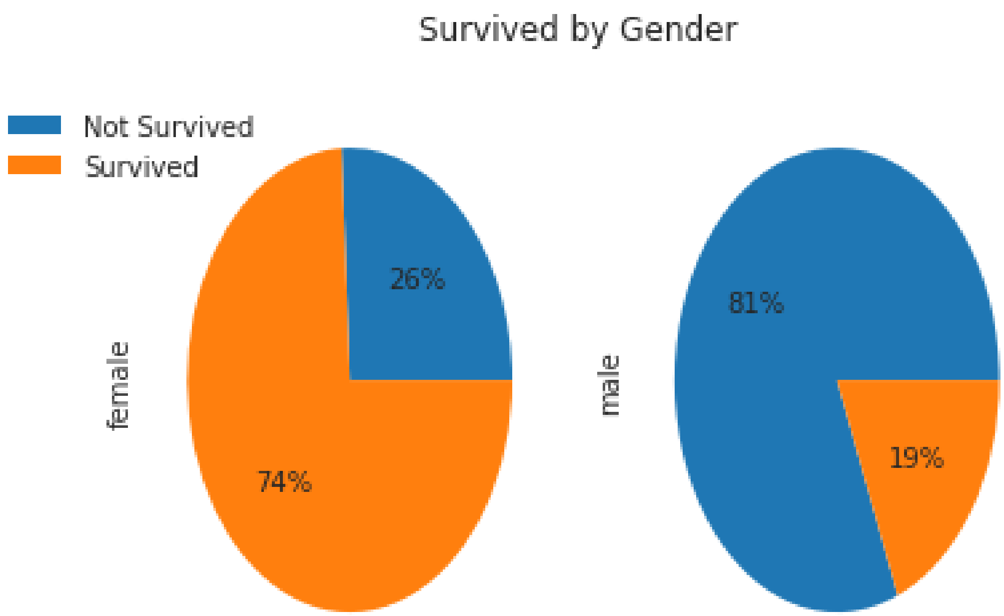
0.1.8 1.4 Run Statistical Summaries

```
In [8]: # From the training data we want to know the propotion of people survived compared to al

        survived = train.loc[train["Survived"] == 1]
        not_survived = train.loc[train["Survived"] == 0]
        survival_ratio_in_train = len(survived)/(len(not_survived)+len(survived))

        # this ratio could be useful if we have to split out train data in futher steps
        survival_ratio_in_train
```

```
Out[8]: 0.3838383838383838
```

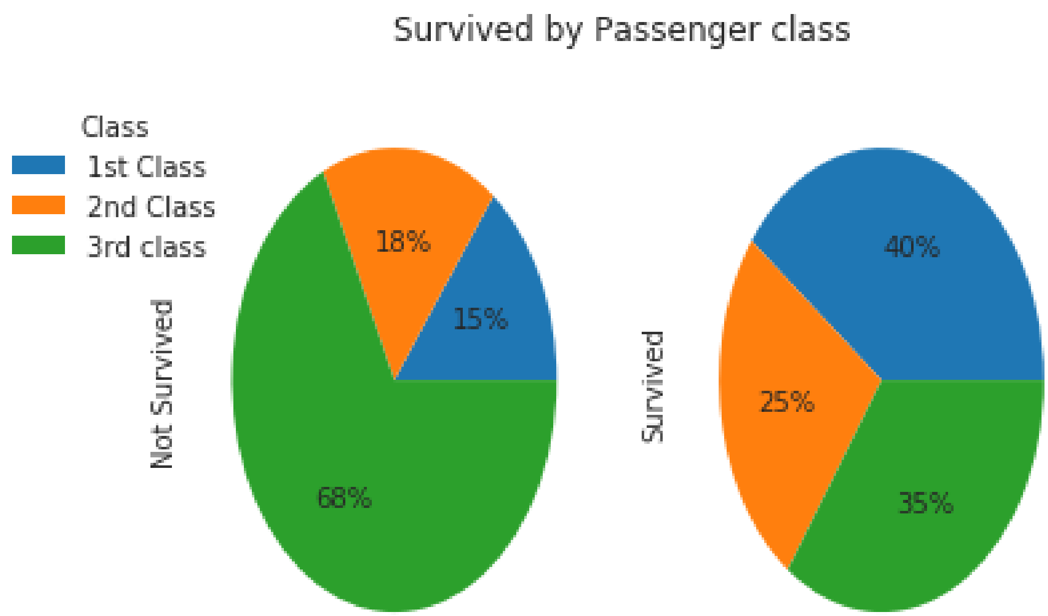
```
In [9]: # Survived by Gender

        survived_by_gender = pd.crosstab(train["Survived"],train["Sex"])
        ax1,ax2 = survived_by_gender.plot(kind='pie',title="Survived by Gender",legend=True,subp

        ax1.legend(['Not Survived', 'Survived'],loc='upper left',bbox_to_anchor=(-0.4, 1.))
```

```
Out[9]: <matplotlib.legend.Legend at 0x7fb35907d860>
```

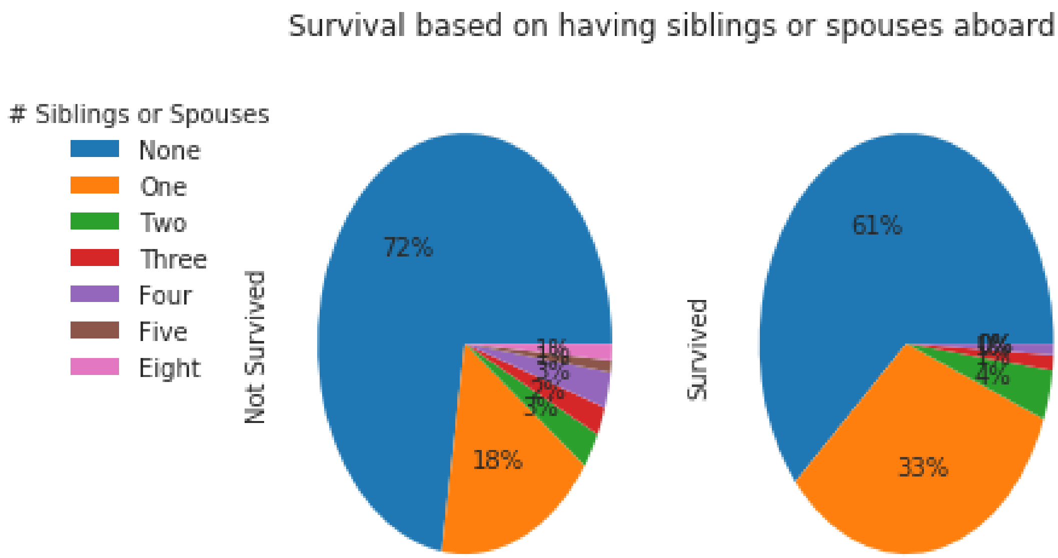


In [10]:
```
# Survived by Class

survived_by_class = pd.crosstab(train["Pclass"],train["Survived"])
survived_by_class.columns = ['Not Survived','Survived']
ax1,ax2 = survived_by_class.plot(kind='pie',title="Survived by Passenger class",subplot

ax1.legend(['1st Class', '2nd Class','3rd class'],title="Class",loc='upper left',bbox_t
```

Out[10]: <matplotlib.legend.Legend at 0x7fb3588026d8>

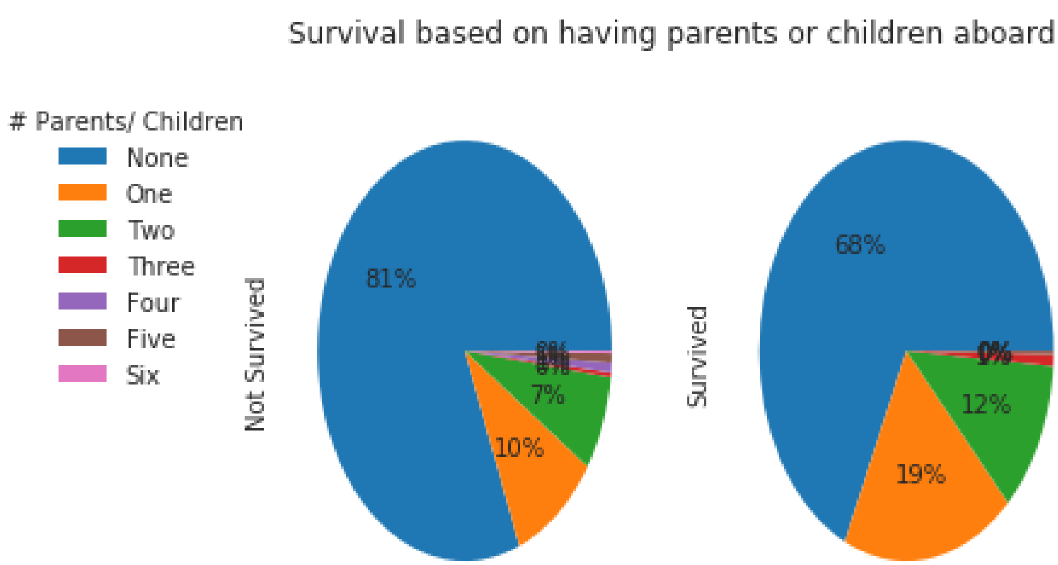



```
In [11]: # Survived by siblins or Spouse aborad

         survived_by_sibsp = pd.crosstab(train['SibSp'],train['Survived'])
         survived_by_sibsp.columns = ['Not Survived','Survived']

         ax1,ax2 = survived_by_sibsp.plot(kind='pie', title='Survival based on having siblings o

         ax1.legend(['None', 'One', 'Two', 'Three', 'Four', 'Five', 'Eight'], title = "# Sibling

Out[11]: <matplotlib.legend.Legend at 0x7fb3588029b0>
```

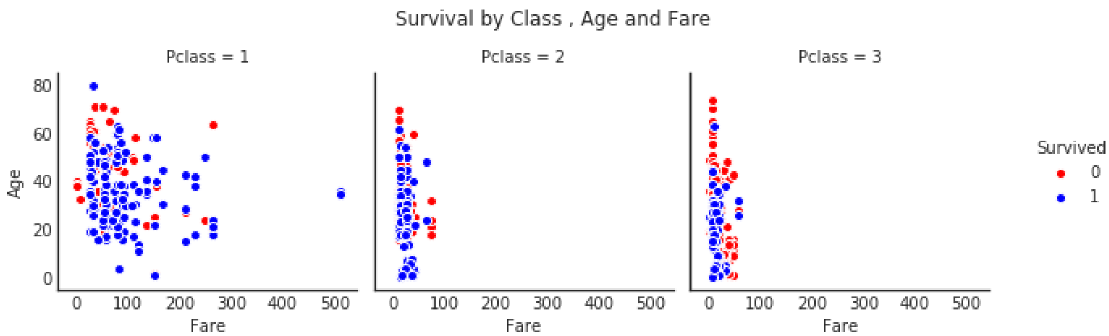



```
In [12]: # Survived by Parents or children aborad

         survived_by_parch = pd.crosstab(train['Parch'],train['Survived'])
         survived_by_parch.columns = ['Not Survived','Survived']

         ax1,ax2 = survived_by_parch.plot(kind='pie', title='Survival based on having parents or

         ax1.legend(['None', 'One', 'Two', 'Three', 'Four', 'Five', 'Six'],title="# Parents/ Chi
```

```
Out[12]: <matplotlib.legend.Legend at 0x7fb3255cf2b0>
```

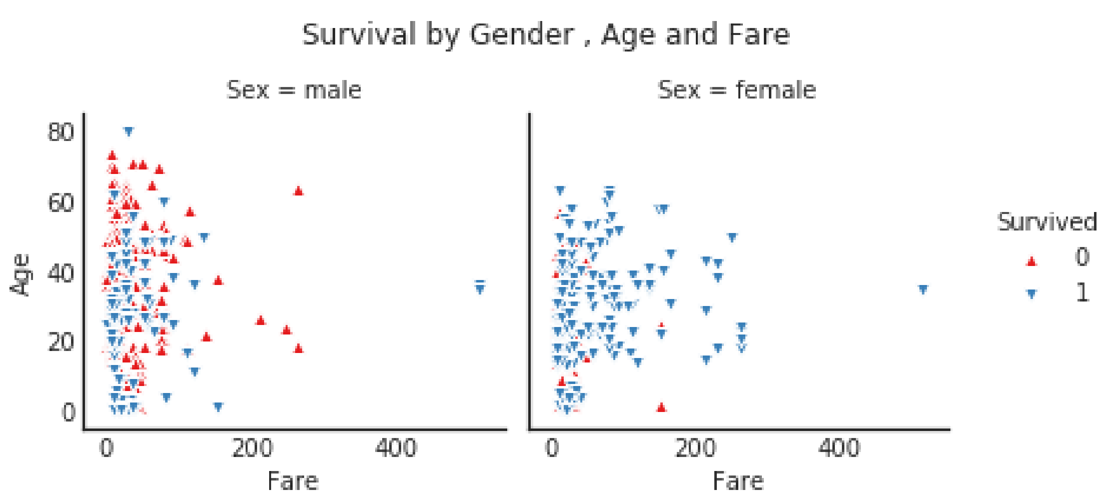


In [13]:
```
# Survived by Class, Far and Age

g = sns.FacetGrid(train, hue="Survived", col="Pclass", margin_titles=True,
                  palette={1:"blue", 0:"red"})
g = g.map(plt.scatter, "Fare", "Age",edgecolor="w").add_legend()
plt.subplots_adjust(top=0.8)
g.fig.suptitle('Survival by Class , Age and Fare');
```



In [14]:
```
# Survived by Age and Fare

g = sns.FacetGrid(train, hue="Survived", col="Sex", margin_titles=True,
                palette="Set1",hue_kws=dict(marker=["^", "v"]))
g.map(plt.scatter, "Fare", "Age",edgecolor="w").add_legend()
plt.subplots_adjust(top=0.8)
g.fig.suptitle('Survival by Gender , Age and Fare')
```

Out[14]:
```
<matplotlib.text.Text at 0x7fb32526a2e8>
```



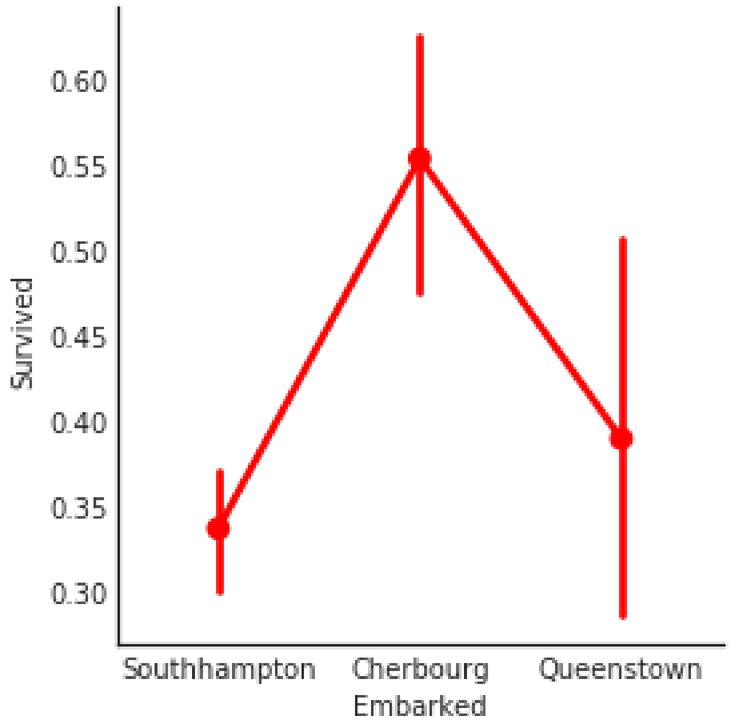
In [15]:
```python
# On its journey from Southhampton to NY, Titanic made 3 stops
# This embarked locations stands for those stops
# S = SounthHampton
# C = Cherbourg
# Q = Queenstown

train.loc[train["Embarked"] == "S", "Embarked"] = "Southhampton"
train.loc[train["Embarked"] == "C", "Embarked"] = "Cherbourg"
train.loc[train["Embarked"] == "Q", "Embarked"] = "Queenstown"

test.loc[test["Embarked"] == "S", "Embarked"] = "Southhampton"
test.loc[test["Embarked"] == "C", "Embarked"] = "Cherbourg"
test.loc[test["Embarked"] == "Q", "Embarked"] = "Queenstown"
```

In [16]:
```python
train.head()
```

Out[16]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin      Embarked
0      0         A/5 21171   7.2500   NaN  Southhampton
1      0          PC 17599  71.2833   C85     Cherbourg
2      0  STON/O2. 3101282   7.9250   NaN  Southhampton
3      0            113803  53.1000  C123  Southhampton
4      0            373450   8.0500   NaN  Southhampton
```

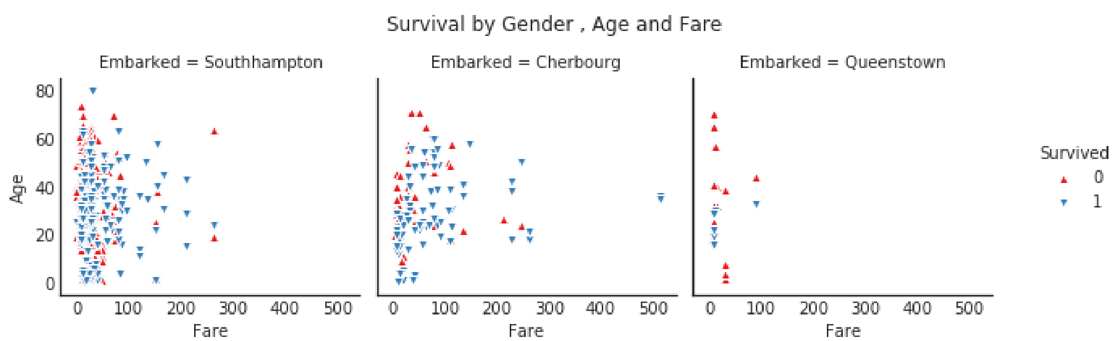
In [17]:
```python
# Let set the Embarked value to the original values
sns.factorplot(x ='Embarked', y="Survived", data=train, color="r")
```

Out[17]:
```
<seaborn.axisgrid.FacetGrid at 0x7fb325b58cf8>
```




```
In [18]: # survived by Fare and Age based on Embarked

         g = sns.FacetGrid(train, hue="Survived", col="Embarked", margin_titles=True,
                           palette="Set1",hue_kws=dict(marker=["^", "v"]))
         g.map(plt.scatter, "Fare", "Age",edgecolor="w").add_legend()
         plt.subplots_adjust(top=0.8)
         g.fig.suptitle('Survival by Gender , Age and Fare')
```

```
Out[18]: <matplotlib.text.Text at 0x7fb325190c50>
```



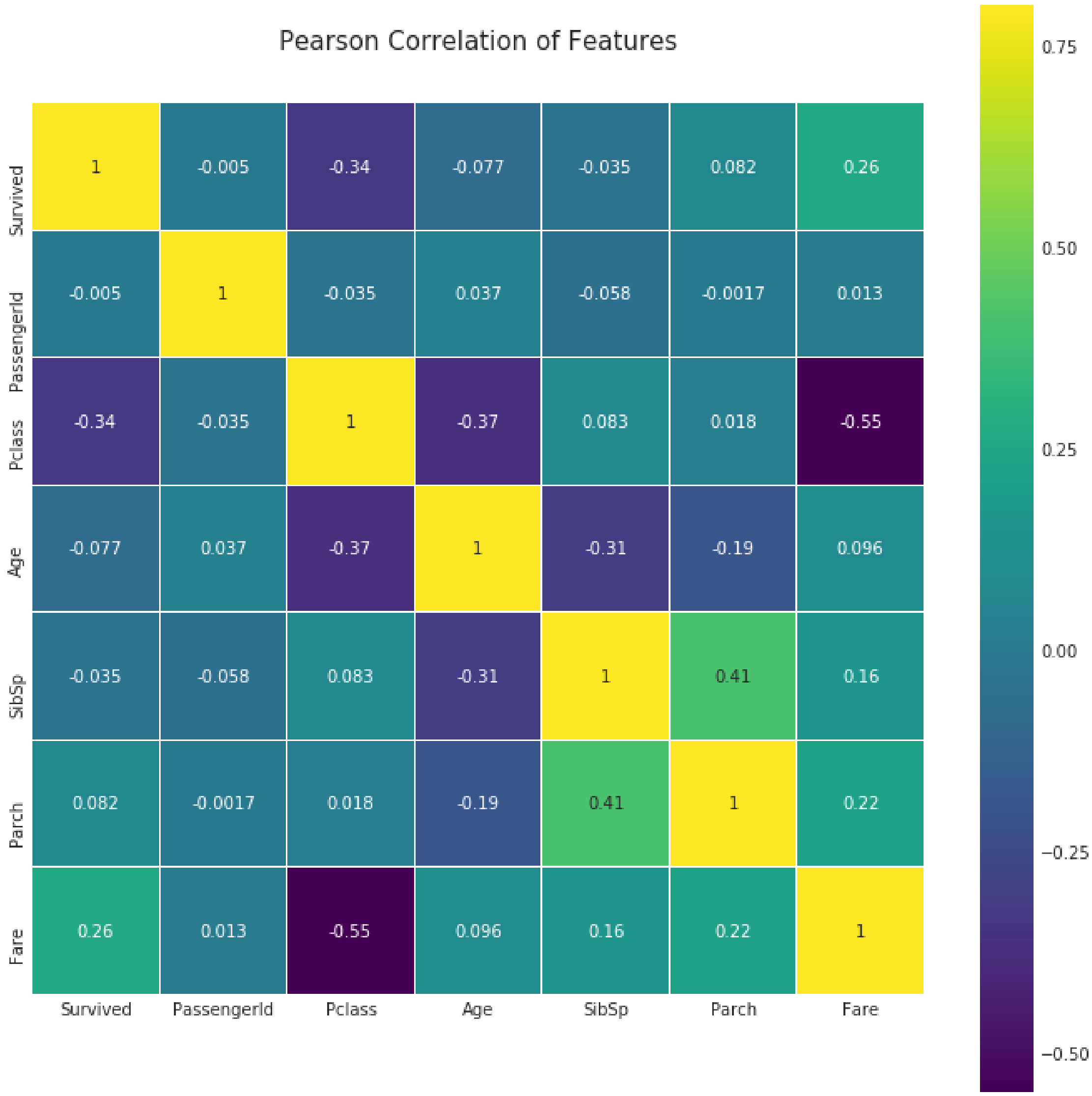
```
In [19]: # To calculate the Pesrson Coeff, let's make Survival as the 1st column

         cols = train.columns.tolist()
         cols[0],cols[1] = cols[1], cols[0]
         recol_train = train[cols]
         recol_train.head()
```

```
Out[19]:    Survived  PassengerId  Pclass  \
         0         0            1       3
         1         1            2       1
         2         1            3       3
         3         1            4       1
         4         0            5       3

                                                         Name     Sex   Age  SibSp  \
         0                            Braund, Mr. Owen Harris    male  22.0      1
         1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
         2                             Heikkinen, Miss. Laina  female  26.0      0
         3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
         4                           Allen, Mr. William Henry    male  35.0      0

            Parch            Ticket     Fare Cabin     Embarked
         0      0         A/5 21171   7.2500   NaN  Southhampton
         1      0          PC 17599  71.2833   C85     Cherbourg
         2      0  STON/O2. 3101282   7.9250   NaN  Southhampton
         3      0            113803  53.1000  C123  Southhampton
         4      0            373450   8.0500   NaN  Southhampton
```

0.1.9 1.5 Pearson Correlation with Target Variable

```
In [20]: colormap = plt.cm.viridis
         corr = recol_train.corr()
         plt.figure(figsize=(12, 12))
         sns.heatmap(corr, vmax=.8, linewidths=0.01,
                     square=True,annot=True,cmap=colormap,linecolor="white")
         plt.title('Pearson Correlation of Features', y=1.05, size=15)
```

```
Out[20]: <matplotlib.text.Text at 0x7fb3259510f0>
```



0.2 2.0 Missing Value Imputation

0.2.1 2.1 Train Data Missing Values in Column Embarked

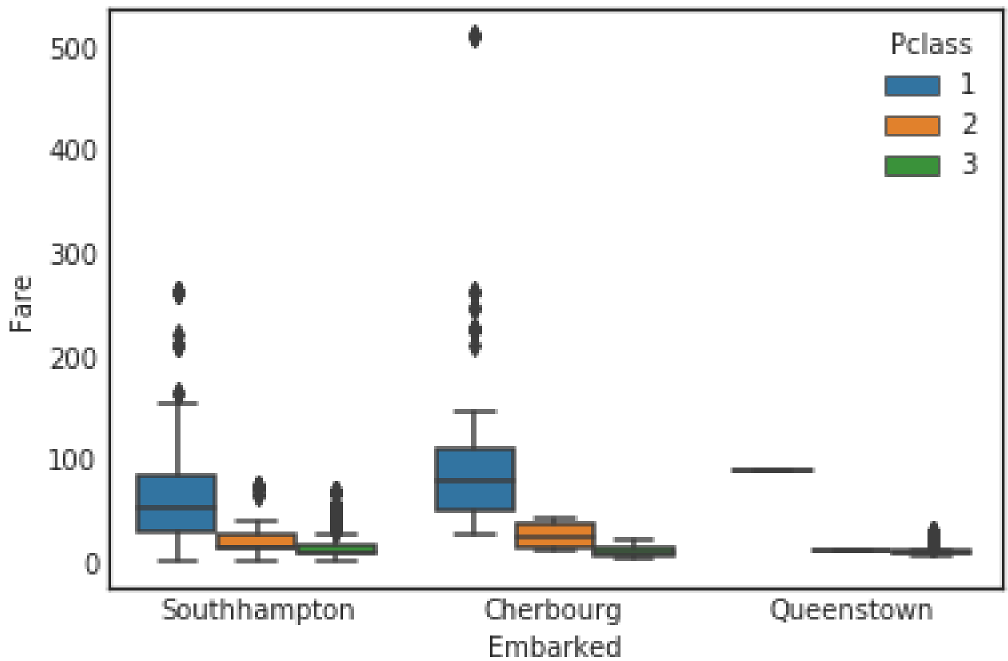
```
In [21]: train[train["Embarked"].isnull()]
         # both passengers 61 and 829 don't have embark value
         # however both of them are survived and in class 1
```

```
Out[21]:      PassengerId  Survived  Pclass                                       Name  \
         61            62         1       1                        Icard, Miss. Amelie
         829          830         1       1  Stone, Mrs. George Nelson (Martha Evelyn)

                 Sex   Age  SibSp  Parch  Ticket  Fare Cabin Embarked
```

```
61   female  38.0      0      0  113572  80.0   B28       NaN
829  female  62.0      0      0  113572  80.0   B28       NaN
```

In [22]:
```
# plot the fare vs embark values for all the classes
sns.boxplot(x="Embarked", y="Fare", hue="Pclass", data=train)
# embarked 'C' has median value of close to $80 and for 1st class
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb32546d5c0>
```



In [23]:
```
# Cherbourg has a Fare closer to 80

train["Embarked"] = train["Embarked"].fillna('Cherbourg')
```

0.2.2 2.2 Test Data Missing Values in Columns Fare

In [24]:
```
test[test['Fare'].isnull()]
```

Out[24]:
```
     PassengerId  Pclass                Name   Sex   Age  SibSp  Parch Ticket  \
152         1044       3  Storey, Mr. Thomas  male  60.5      0      0   3701

     Fare Cabin      Embarked
152   NaN   NaN  Southhampton
```

In [25]:
```
# This passenger is in class 3, Embarked from 'Southhampton'
# We'll take the median value for that category and repalce for the missing value
median_fair = test[(test["Pclass"] == 3) & (test["Embarked"] == "Southhampton")]['Fare'
test["Fare"] = test["Fare"].fillna(median_fair)
```

In [26]:
```
# Calculate the missing values in each column in both testing and training
missing_train = train.isnull().sum().sort_values(ascending=False)
missing_test = test.isnull().sum().sort_values(ascending=False)
missing_values = pd.concat([missing_train,missing_test], axis=1, keys=["Train","Test"])
missing_values
```

Out[26]:

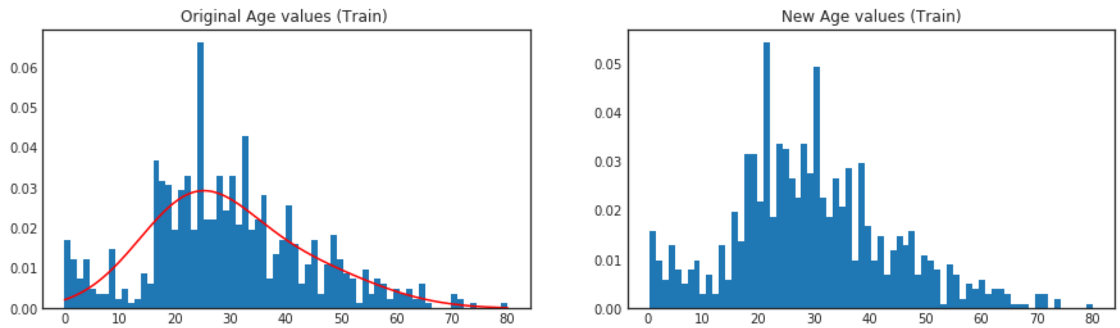
	Train	Test
Age	177	86.0
Cabin	687	327.0
Embarked	0	0.0
Fare	0	0.0
Name	0	0.0
Parch	0	0.0
PassengerId	0	0.0
Pclass	0	0.0
Sex	0	0.0
SibSp	0	0.0
Survived	0	NaN
Ticket	0	0.0

0.2.3 1.3 Expectation Maximization

In [27]:
```
from sklearn import mixture

# lets use Expectation maximization to fil the age imputation
# sklearn implements the EM algorithm with GMM

fig, (axis1,axis2) = plt.subplots(1,2,figsize=(15,4))
axis1.set_title('Original Age values (Train) ')
axis2.set_title('New Age values (Train)')

null_values = train['Age'].dropna().astype(int)
axis1.hist(null_values,70,normed=True)

X = train['Age'].dropna()
X = X.values.reshape(-1,1)

clf = mixture.GaussianMixture(n_components=2).fit(X) # fit 2 gaussians

Y1 = train['Age'].isnull().sum()
Y2 = test['Age'].isnull().sum()

xpdf1 = np.linspace(0,80,Y1)
xpdf1 = xpdf1.reshape(-1,1)
xpdf2 = np.linspace(0,80,Y2)
xpdf2 = xpdf2.reshape(-1,1)
```

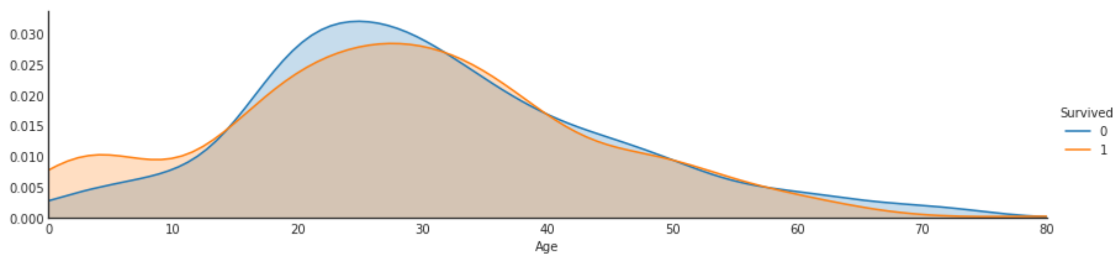
```python
density1 = np.exp(clf.score_samples(xpdf1))
axis1.plot(xpdf1,density1,'-r')

x1,y1 = clf.sample(Y1)
x2,y2 = clf.sample(Y2)

train['Age'][np.isnan(train['Age'])] = np.absolute(x1)
test['Age'][np.isnan(test['Age'])] = np.absolute(x2)

axis2.hist(train['Age'],70,normed=True)

# in the figure below we can see that the density fucntion is a good
# approximate for the data
# We use this gmm to miss the missing values
```

```
Out[27]: (array([ 0.01579561,  0.00987226,  0.00592335,  0.01283393,  0.0078978 ,
                  0.00493613,  0.0078978 ,  0.00987226,  0.00296168,  0.00691058,
                  0.00296168,  0.01283393,  0.00592335,  0.01974451,  0.01382116,
                  0.03159122,  0.03159122,  0.02171896,  0.05429741,  0.01875729,
                  0.03356567,  0.03257844,  0.02665509,  0.02270619,  0.03356567,
                  0.02764232,  0.04936128,  0.02270619,  0.01875729,  0.02665509,
                  0.02073174,  0.02862954,  0.00987226,  0.02961677,  0.01678283,
                  0.00987226,  0.01480838,  0.00691058,  0.01184671,  0.01480838,
                  0.01283393,  0.01579561,  0.00691058,  0.01085948,  0.00987226,
                  0.0078978 ,  0.00098723,  0.00888503,  0.00691058,  0.00197445,
                  0.00493613,  0.0039489 ,  0.00592335,  0.00296168,  0.0039489 ,
                  0.0039489 ,  0.00296168,  0.00098723,  0.00098723,  0.00098723,
                  0.        ,  0.00296168,  0.00296168,  0.        ,  0.00197445,
                  0.        ,  0.        ,  0.        ,  0.        ,  0.00098723]),
          array([  0.42      ,   1.55685714,   2.69371429,   3.83057143,
                   4.96742857,   6.10428571,   7.24114286,   8.378     ,
                   9.51485714,  10.65171429,  11.78857143,  12.92542857,
                  14.06228571,  15.19914286,  16.336     ,  17.47285714,
                  18.60971429,  19.74657143,  20.88342857,  22.02028571,
                  23.15714286,  24.294     ,  25.43085714,  26.56771429,
                  27.70457143,  28.84142857,  29.97828571,  31.11514286,
                  32.252     ,  33.38885714,  34.52571429,  35.66257143,
                  36.79942857,  37.93628571,  39.07314286,  40.21      ,
                  41.34685714,  42.48371429,  43.62057143,  44.75742857,
                  45.89428571,  47.03114286,  48.168     ,  49.30485714,
                  50.44171429,  51.57857143,  52.71542857,  53.85228571,
                  54.98914286,  56.126     ,  57.26285714,  58.39971429,
                  59.53657143,  60.67342857,  61.81028571,  62.94714286,
                  64.084     ,  65.22085714,  66.35771429,  67.49457143,
                  68.63142857,  69.76828571,  70.90514286,  72.042     ,
                  73.17885714,  74.31571429,  75.45257143,  76.58942857,
                  77.72628571,  78.86314286,  80.        ]),
          <a list of 70 Patch objects>)
```




```
In [28]: # Age Distribution

         facet = sns.FacetGrid(train, hue="Survived",aspect=4)
         facet.map(sns.kdeplot,'Age',shade= True)
         facet.set(xlim=(0, train['Age'].max()))
         facet.add_legend()
```

```
Out[28]: <seaborn.axisgrid.FacetGrid at 0x7fb324ee7e48>
```




```
In [29]: train.corr()["Age"]
         # train.corr()['Deck']
```

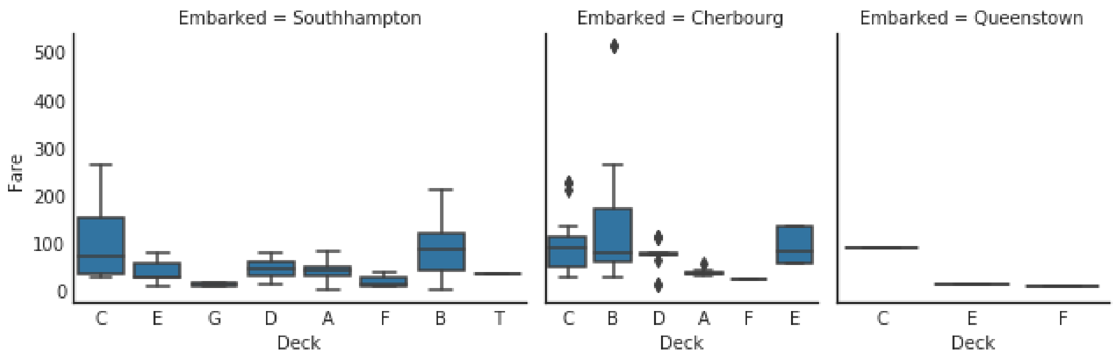
```
Out[29]: PassengerId    0.118091
         Survived      -0.074440
         Pclass        -0.307678
         Age            1.000000
         SibSp         -0.222814
         Parch         -0.157862
         Fare           0.076307
         Name: Age, dtype: float64
```

0.2.4 1.4 Distribution Correlation for Fare

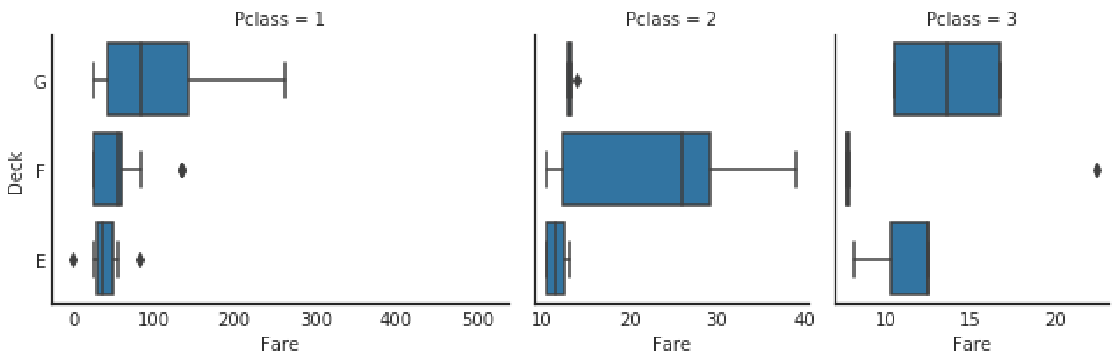
```
In [30]: train['Deck'] = train.Cabin.str[0]
         test['Deck'] = test.Cabin.str[0]
         train['Deck'].unique() # 0 is for null values
```

Out[30]: array([nan, 'C', 'E', 'G', 'D', 'A', 'B', 'F', 'T'], dtype=object)

In [31]:
```
# Deck distribution with Fare and Embarked

train = train.assign(Deck=train.Deck.astype(object))
g = sns.FacetGrid(train, col="Embarked", sharex=False,
                  gridspec_kws={"width_ratios": [5, 3, 3]})
g.map(sns.boxplot, "Deck", "Fare");
```



In [32]:
```
# Which class were in which Decks

train = train.assign(Deck=train.Deck.astype(object))
g = sns.FacetGrid(train, col="Pclass", sharex=False,
                  gridspec_kws={"width_ratios": [5, 3, 3]})
g.map(sns.boxplot, "Fare", "Deck");
```



In [33]:
```
# mean Fare for each class

first_class_price = train[(train["Pclass"] == 1)]['Fare'].mean()
print("First class price: $%s" % first_class_price) #lets say USD
```

```python
second_class_price = train[(train["Pclass"] == 2)]['Fare'].mean()
print("Second class price: $%s" % second_class_price) #lets say USD

thrid_class_price = train[(train["Pclass"] == 3)]['Fare'].mean()
print("Thrid class price: $%s" % thrid_class_price) #lets say USD
```

```
First class price: $84.15468749999992
Second class price: $20.66218315217391
Thrid class price: $13.675550101832997
```

In [34]:
```python
# 1st class decks
first_class_decks =  train.loc[(train["Pclass"] == 1), 'Deck'].unique()
first_class_decks
```

Out[34]:
```
array(['C', 'E', 'A', nan, 'B', 'D', 'T'], dtype=object)
```

In [35]:
```python
# 2nd class decks
second_class_decks =  train.loc[(train["Pclass"] == 2), 'Deck'].unique()
second_class_decks
```

Out[35]:
```
array([nan, 'D', 'F', 'E'], dtype=object)
```

In [36]:
```python
# 3rd class decks
third_class_decks =  train.loc[(train["Pclass"] == 3), 'Deck'].unique()
third_class_decks
```

Out[36]:
```
array([nan, 'G', 'F', 'E'], dtype=object)
```

In [37]:
```python
# Assigm decks based on the class

train.loc[(train['Deck'].isnull()) & (train['Pclass'] == 1), 'Deck'] = 'A'
train.loc[(train['Deck'].isnull()) & (train['Pclass'] == 2), 'Deck'] = 'D'
train.loc[(train['Deck'].isnull()) & (train['Pclass'] == 3), 'Deck'] = 'G'

test.loc[(test['Deck'].isnull()) & (test['Pclass'] == 1), 'Deck'] = 'A'
test.loc[(test['Deck'].isnull()) & (test['Pclass'] == 2), 'Deck'] = 'D'
test.loc[(test['Deck'].isnull()) & (test['Pclass'] == 3), 'Deck'] = 'G'

train.drop(['Cabin'],axis=1,inplace=True)
test.drop(['Cabin'],axis=1,inplace=True)
```

In [38]:
```python
# Calculate the missing values in each column in both testing and training

missing_train = train.isnull().sum().sort_values(ascending=False)
missing_test = test.isnull().sum().sort_values(ascending=False)
missing_values = pd.concat([missing_train,missing_test], axis=1, keys=["Train","Test"])
missing_values

# No missing values
```

Out[38]:
```
             Train  Test
Age              0   0.0
Deck             0   0.0
Embarked         0   0.0
Fare             0   0.0
Name             0   0.0
Parch            0   0.0
PassengerId      0   0.0
Pclass           0   0.0
Sex              0   0.0
SibSp            0   0.0
Survived         0   NaN
Ticket           0   0.0
```

1 3.0 Feature Engineering

1.0.1 3.1 Create the Family Feature

In [39]:
```
train.head()
```

Out[39]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare     Embarked Deck
0      0         A/5 21171   7.2500  Southhampton    G
1      0          PC 17599  71.2833     Cherbourg    C
2      0  STON/O2. 3101282   7.9250  Southhampton    G
3      0            113803  53.1000  Southhampton    C
4      0            373450   8.0500  Southhampton    G
```

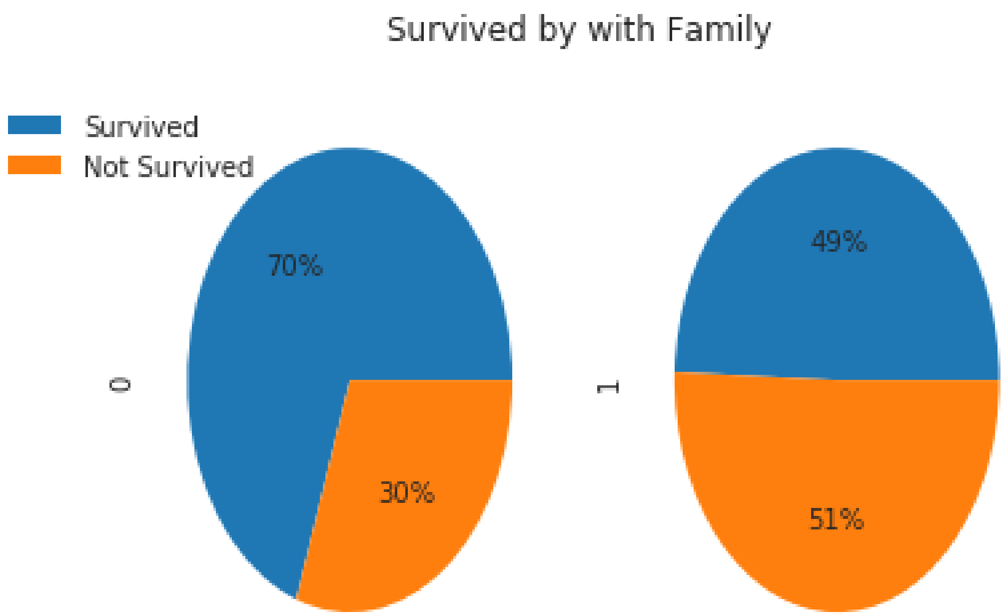
In [40]:
```
# Family If there is parents, siblings or spouse onboard
train['Family'] = train['Parch'] + train['SibSp']
train['Family'].loc[train['Family'] > 0] = 1
train['Family'].loc[train['Family'] == 0] = 0

test['Family'] = test['Parch'] + test['SibSp']
test['Family'].loc[test['Family'] > 0] = 1
test['Family'].loc[test['Family'] == 0] = 0
```

In [41]: train.head()

```
Out[41]:    PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare      Embarked Deck  Family
0      0         A/5 21171   7.2500  Southhampton    G       1
1      0          PC 17599  71.2833     Cherbourg    C       1
2      0  STON/O2. 3101282   7.9250  Southhampton    G       0
3      0            113803  53.1000  Southhampton    C       1
4      0            373450   8.0500  Southhampton    G       0
```

In [42]:
```
# Survival by Family

survived_by_family = pd.crosstab(train["Survived"],train["Family"])
ax1,ax2 = survived_by_family.plot(kind='pie',title="Survived by with Family",legend=Tru

ax1.legend(['Survived', 'Not Survived'],loc='upper left',bbox_to_anchor=(-0.4, 1.))
```

Out[42]: <matplotlib.legend.Legend at 0x7fb31f8b1438>




```
In [43]: # Having a family could wither be in SibSp or Parch
         # So we can drop those 2 columns
         train.drop(['SibSp','Parch'],axis=1,inplace=True)
         test.drop(['SibSp','Parch'],axis=1,inplace=True)

In [44]: train.head()

Out[44]:    PassengerId  Survived  Pclass  \
         0            1         0       3
         1            2         1       1
         2            3         1       3
         3            4         1       1
         4            5         0       3

                                                         Name     Sex   Age  \
         0                              Braund, Mr. Owen Harris    male  22.0
         1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
         2                               Heikkinen, Miss. Laina  female  26.0
         3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
         4                             Allen, Mr. William Henry    male  35.0

                     Ticket     Fare     Embarked Deck  Family
         0        A/5 21171   7.2500  Southhampton    G       1
         1         PC 17599  71.2833     Cherbourg    C       1
         2  STON/O2. 3101282   7.9250  Southhampton    G       0
```

```
3           113803  53.1000  Southhampton    C       1
4           373450   8.0500  Southhampton    G       0
```

1.0.2 3.2 Create a Title Feature

```
In [45]: import re

         train['Title'] = train['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)
         test['Title'] = test['Name'].str.extract(' ([A-Za-z]+)\.', expand=False)

         # Titles
         pd.crosstab(train['Title'], train['Sex'])
```

```
Out[45]: 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 [46]: def replaceRateTitle(df):
             rare_title = ['Dona', 'Lady', 'Countess','Capt', 'Col', 'Don',
                         'Dr', 'Major', 'Rev', 'Sir', 'Jonkheer']
             df.loc[df["Title"] == "Mlle", "Title"] = 'Miss'
             df.loc[df["Title"] == "Ms", "Title"] = 'Miss'
             df.loc[df["Title"] == "Mme", "Title"] = 'Mrs'
             df.loc[df["Title"] == "Dona", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Lady", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Countess", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Capt", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Col", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Don", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Major", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Rev", "Title"] = 'Rare Title'
             df.loc[df["Title"] == "Sir", "Title"] = 'Rare Title'
```

```
    df.loc[df["Title"] == "Jonkheer", "Title"] = 'Rare Title'
    df.loc[df["Title"] == "Dr", "Title"] = 'Rare Title'

    return df
```

In [47]:
```
train = replaceRateTitle(train)
train["Title"].value_counts()
```

Out[47]:
```
Mr            517
Miss          185
Mrs           126
Master         40
Rare Title     23
Name: Title, dtype: int64
```

In [48]:
```
test = replaceRateTitle(test)
test['Title'].value_counts()
```

Out[48]:
```
Mr            240
Miss           79
Mrs            72
Master         21
Rare Title      6
Name: Title, dtype: int64
```

In [49]:
```
train.head()
```

Out[49]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  \
0                            Braund, Mr. Owen Harris    male  22.0
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
2                             Heikkinen, Miss. Laina  female  26.0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
4                           Allen, Mr. William Henry    male  35.0

             Ticket     Fare      Embarked Deck  Family Title
0         A/5 21171   7.2500  Southhampton    G       1    Mr
1          PC 17599  71.2833     Cherbourg    C       1   Mrs
2  STON/O2. 3101282   7.9250  Southhampton    G       0  Miss
3            113803  53.1000  Southhampton    C       1   Mrs
4            373450   8.0500  Southhampton    G       0    Mr
```

1.0.3 3.3 Create Name Length

In [50]:
```
# Name Length
train['Name_Length'] = train['Name'].apply(len)
test['Name_Length'] = test['Name'].apply(len)

train.drop(['Name'],axis=1,inplace=True)
test.drop(['Name'],axis=1,inplace=True)
```

1.0.4 3.4 Create Ticket Numbers

In [51]:
```
# Create ticket numbers

train["TicketNumber"] = train["Ticket"].str.extract('(\d{2,})', expand=True)
train["TicketNumber"] = train["TicketNumber"].apply(pd.to_numeric)

test["TicketNumber"] = test["Ticket"].str.extract('(\d{2,})', expand=True)
test["TicketNumber"] = test["TicketNumber"].apply(pd.to_numeric)

train.TicketNumber.fillna(train["TicketNumber"].median(), inplace=True)
test.TicketNumber.fillna(test["TicketNumber"].median(), inplace=True)

train.drop(['Ticket','PassengerId'],axis=1,inplace=True)
test.drop(['Ticket','PassengerId'],axis=1,inplace=True)
```

In [52]:
```
train.head()
```

Out[52]:
```
   Survived  Pclass     Sex   Age     Fare     Embarked Deck  Family Title  \
0         0       3    male  22.0   7.2500  Southhampton    G       1    Mr
1         1       1  female  38.0  71.2833     Cherbourg    C       1   Mrs
2         1       3  female  26.0   7.9250  Southhampton    G       0  Miss
3         1       1  female  35.0  53.1000  Southhampton    C       1   Mrs
4         0       3    male  35.0   8.0500  Southhampton    G       0    Mr

   Name_Length  TicketNumber
0           23       21171.0
1           51       17599.0
2           22     3101282.0
3           44      113803.0
4           24      373450.0
```

In [53]:
```
train.corr()["TicketNumber"]
# the only correlation is with the class
```

Out[53]:
```
Survived       -0.096161
Pclass          0.284631
Age            -0.093632
Fare           -0.156104
Family         -0.037374
```

```
Name_Length    -0.050760
TicketNumber    1.000000
Name: TicketNumber, dtype: float64
```

In [54]:
```python
first_class_tickets =  train.loc[(train["Pclass"] == 1), 'TicketNumber'].unique()
print("Number of unique 1st class tickets", len(first_class_tickets))

second_class_tickets =  train.loc[(train["Pclass"] == 2), 'TicketNumber'].unique()
print("Number of unique 2nd class tickets", len(second_class_tickets))

thrid_class_tickets =  train.loc[(train["Pclass"] == 2), 'TicketNumber'].unique()
print("Number of unique 3rd class tickets" , len(thrid_class_tickets))
```

```
Number of unique 1st class tickets 146
Number of unique 2nd class tickets 140
Number of unique 3rd class tickets 140
```

In [55]:
```python
# Ticket number has a correlation with the class
# since there are many ticket numbers and it not a discrete value
# we'll drop this column

train.drop(['TicketNumber'],axis=1,inplace=True)
test.drop(['TicketNumber'],axis=1,inplace=True)
```

In [56]:
```python
train.head()
```

Out[56]:
```
   Survived  Pclass     Sex   Age     Fare     Embarked Deck  Family Title  \
0         0       3    male  22.0   7.2500  Southhampton    G       1    Mr
1         1       1  female  38.0  71.2833     Cherbourg    C       1   Mrs
2         1       3  female  26.0   7.9250  Southhampton    G       0  Miss
3         1       1  female  35.0  53.1000  Southhampton    C       1   Mrs
4         0       3    male  35.0   8.0500  Southhampton    G       0    Mr

   Name_Length
0           23
1           51
2           22
3           44
4           24
```

In [57]:
```python
train["Name_Length"].max(), train["Name_Length"].min()
```

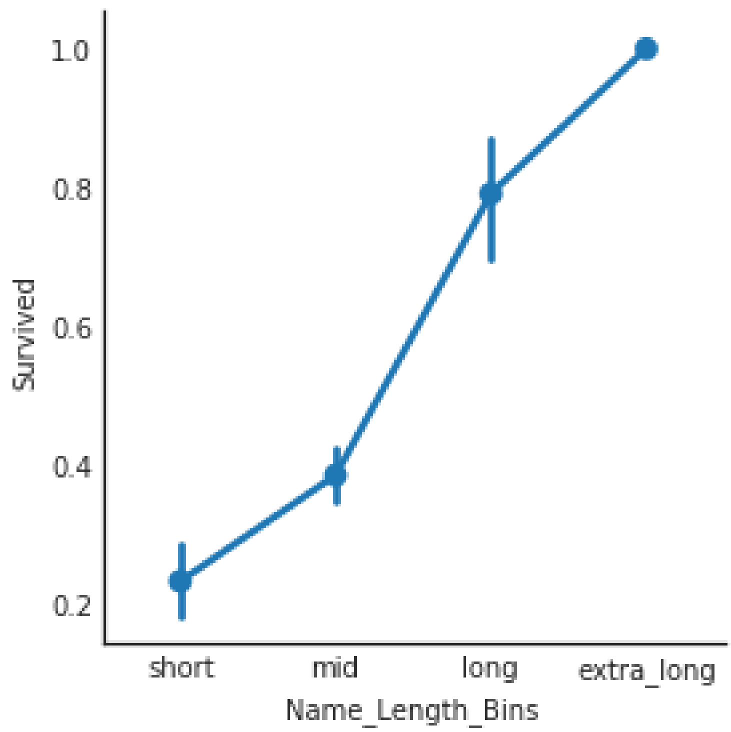
Out[57]:
```
(82, 12)
```

1.0.5 3.5 Create Bins using Name Length

In [58]:
```python
bins = [0, 20, 40, 57, 85]
group_names = ['short', 'mid', 'long', 'extra_long']
```

```
train['Name_Length_Bins'] = pd.cut(train['Name_Length'], bins, labels=group_names)
test['Name_Length_Bins'] = pd.cut(test['Name_Length'], bins, labels=group_names)

sns.factorplot(x="Name_Length_Bins", y="Survived", data=train)
print(train["Name_Length_Bins"].unique())
```

```
[mid, long, short, extra_long]
Categories (4, object): [short < mid < long < extra_long]
```




```
In [59]: train.drop(['Name_Length'],axis=1,inplace=True)
         test.drop(['Name_Length'],axis=1,inplace=True)
```

1.0.6 3.6 Data Scaling

```
In [60]: from sklearn.preprocessing import scale

         # Age and Fare in different scales
         cols = ['Age','Fare']

         for col in cols:
             train[cols] = scale(train[cols])
             test[cols] = scale(test[cols])
```

1.0.7 3.7 Convert Categorical Data into Numerical Values

In [61]:
```
from sklearn.preprocessing import LabelEncoder,OneHotEncoder

# convert the age bins into numerical value
labelEnc=LabelEncoder()

cat_vars=['Name_Length_Bins']
for col in cat_vars:
    train[col]=labelEnc.fit_transform(train[col])
    test[col]=labelEnc.fit_transform(test[col])
```

In [62]:
```
train.head()
```

Out[62]:
```
   Survived  Pclass     Sex       Age      Fare     Embarked Deck  Family  \
0         0       3    male -0.534310 -0.502445  Southhampton    G       1
1         1       1  female  0.576252  0.786845     Cherbourg    C       1
2         1       3  female -0.256669 -0.488854  Southhampton    G       0
3         1       1  female  0.368022  0.420730  Southhampton    C       1
4         0       3    male  0.368022 -0.486337  Southhampton    G       0

  Title  Name_Length_Bins
0    Mr                 2
1   Mrs                 1
2  Miss                 2
3   Mrs                 1
4    Mr                 2
```

In [63]:
```
test.head()
```

Out[63]:
```
   Pclass     Sex       Age      Fare     Embarked Deck  Family Title  \
0       3    male  0.302050 -0.497079    Queenstown    G       0    Mr
1       3  female  1.182718 -0.511942  Southhampton    G       1   Mrs
2       2    male  2.239521 -0.463770    Queenstown    D       0    Mr
3       3    male -0.226351 -0.482143  Southhampton    G       0    Mr
4       3  female -0.578619 -0.417167  Southhampton    G       1   Mrs

   Name_Length_Bins
0                 3
1                 2
2                 2
3                 3
4                 1
```

1.0.8 3.8 Create Dummy Variables

In [64]:
```
def preprocess_features(data):
    # convert categorical variables into numerical
```

```
        output = pd.DataFrame(index = data.index)

        for col, col_data in data.iteritems():
            if col_data.dtype == object:
                col_data = pd.get_dummies(col_data, prefix = col)
            output = output.join(col_data)

        return output
```

In [65]:
```
train = preprocess_features(train)
test = preprocess_features(test)
```

In [66]:
```
list(train)
```

Out[66]:
```
['Survived',
 'Pclass',
 'Sex_female',
 'Sex_male',
 'Age',
 'Fare',
 'Embarked_Cherbourg',
 'Embarked_Queenstown',
 'Embarked_Southhampton',
 'Deck_A',
 'Deck_B',
 'Deck_C',
 'Deck_D',
 'Deck_E',
 'Deck_F',
 'Deck_G',
 'Deck_T',
 'Family',
 'Title_Master',
 'Title_Miss',
 'Title_Mr',
 'Title_Mrs',
 'Title_Rare Title',
 'Name_Length_Bins']
```

In [67]:
```
list(test)
```

Out[67]:
```
['Pclass',
 'Sex_female',
 'Sex_male',
 'Age',
 'Fare',
 'Embarked_Cherbourg',
 'Embarked_Queenstown',
 'Embarked_Southhampton',
```

```
 'Deck_A',
 'Deck_B',
 'Deck_C',
 'Deck_D',
 'Deck_E',
 'Deck_F',
 'Deck_G',
 'Family',
 'Title_Master',
 'Title_Miss',
 'Title_Mr',
 'Title_Mrs',
 'Title_Rare Title',
 'Name_Length_Bins']
```

In [68]:
```
# There is no Deck_T in test data
# So we'll not use that feature in trianing
train.drop(['Deck_T'],axis=1,inplace=True)
```

In [69]:
```
train.head()
```

Out[69]:
```
   Survived  Pclass  Sex_female  Sex_male       Age      Fare  \
0         0       3           0         1 -0.534310 -0.502445
1         1       1           1         0  0.576252  0.786845
2         1       3           1         0 -0.256669 -0.488854
3         1       1           1         0  0.368022  0.420730
4         0       3           0         1  0.368022 -0.486337

   Embarked_Cherbourg  Embarked_Queenstown  Embarked_Southhampton  Deck_A  \
0                   0                    0                      1       0
1                   1                    0                      0       0
2                   0                    0                      1       0
3                   0                    0                      1       0
4                   0                    0                      1       0

         ...          Deck_E  Deck_F  Deck_G  Family  Title_Master  Title_Miss  \
0        ...               0       0       1       1             0           0
1        ...               0       0       0       1             0           0
2        ...               0       0       1       0             0           1
3        ...               0       0       0       1             0           0
4        ...               0       0       1       0             0           0

   Title_Mr  Title_Mrs  Title_Rare Title  Name_Length_Bins
0         1          0                 0                 2
1         0          1                 0                 1
2         0          0                 0                 2
3         0          1                 0                 1
4         1          0                 0                 2
```

```
[5 rows x 23 columns]
```

In [70]:
```
test.head()
```

Out[70]:
```
   Pclass  Sex_female  Sex_male       Age      Fare  Embarked_Cherbourg  \
0       3           0         1  0.302050 -0.497079                   0
1       3           1         0  1.182718 -0.511942                   0
2       2           0         1  2.239521 -0.463770                   0
3       3           0         1 -0.226351 -0.482143                   0
4       3           1         0 -0.578619 -0.417167                   0

   Embarked_Queenstown  Embarked_Southhampton  Deck_A  Deck_B  \
0                    1                      0       0       0
1                    0                      1       0       0
2                    1                      0       0       0
3                    0                      1       0       0
4                    0                      1       0       0

         ...         Deck_E  Deck_F  Deck_G  Family  Title_Master  Title_Miss  \
0        ...              0       0       1       0             0           0
1        ...              0       0       1       1             0           0
2        ...              0       0       0       0             0           0
3        ...              0       0       1       0             0           0
4        ...              0       0       1       1             0           0

   Title_Mr  Title_Mrs  Title_Rare Title  Name_Length_Bins
0         1          0                 0                 3
1         0          1                 0                 2
2         1          0                 0                 2
3         1          0                 0                 3
4         0          1                 0                 1

[5 rows x 22 columns]
```

1.0.9 4.0 Prediction

4.1 Load Modules for Prediction

In [71]:
```python
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn.decomposition import PCA
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold, train_test_sp
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoosti
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import precision_recall_curve
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, recall_score, precision_score, roc_curve, classif
```

1.0.10 4.2 Split Data into Training and Testing

In [72]:
```
X = train.drop(['Survived'],1)
y = train['Survived']


# use the survival_ratio_in_train for the split
x_train, x_test, y_train, y_test = train_test_split(X,
                                                     y,
                                                     test_size=survival_ratio_in_train,
                                                     stratify = y
                                                    )
```

1.0.11 4.3 Create the Estimators and the Pipeline

RandomForest, Logistic Regression, and Ada Boost classifiers are used for the pipeline. Trade off was made between selecting few classifiers and tuning greater amount of hyperparameters Vs selecting many classifiers and tuning a smaller amount of hyperparameters with avaliable computing resources.

In [73]:
```
nestedCV = KFold(n_splits=10, shuffle=True)

estimators = [('rForest',RandomForestClassifier()),
        ('logR', LogisticRegression()),
        ('ada', AdaBoostClassifier())]

pipe = Pipeline(estimators)

# These are the classfiers that will be used for the prediction

pipe.named_steps['rForest'], pipe.named_steps["logR"], pipe.named_steps["ada"]
```

Out[73]:
```
(RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
             max_depth=None, max_features='auto', max_leaf_nodes=None,
             min_impurity_split=1e-07, min_samples_leaf=1,
             min_samples_split=2, min_weight_fraction_leaf=0.0,
             n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
             verbose=0, warm_start=False),
 LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
           intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
           penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
           verbose=0, warm_start=False),
 AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None,
           learning_rate=1.0, n_estimators=50, random_state=None))
```

In [74]:
```
seed = 4 # for reproducibility
```

1.0.12 4.4 Set the Parameter Grid for Hyperparameter Tuning

Model parameters were tuned using GridSearch to find the best classifier and it's hyperparameters.

```
In [75]: # set parameters to do a parameters sweep for the classifiers

         param_grid = dict(rForest__n_estimators=[5,10,25,50], # of DTrees
                           rForest__max_features=[3,5,7,10],
                           rForest__class_weight=["balanced"],
                           rForest__random_state=[seed],
                           logR__penalty=["l2"], # norm selection
                           logR__class_weight=['balanced'],
                           logR__random_state=[seed],
                           ada__algorithm=["SAMME"],
                           ada__n_estimators=[25,50,100,250,350,500],
                           ada__learning_rate=[0.01,0.1,0.25],
                           ada__random_state=[seed])

         grid_search = GridSearchCV(pipe, param_grid=param_grid, cv=nestedCV)
```

1.0.13 4.5 Fit the Data to Models in the Pipeline

```
In [78]: grid_search = grid_search.fit(x_train,y_train)

         print(grid_search.best_params_)

{'ada__algorithm': 'SAMME', 'ada__learning_rate': 0.01, 'ada__n_estimators': 250, 'ada__random_s
```

1.0.14 4.6 Best Estimator and Hyperparameters

Grid Search best estimator was Random Forest witht following hyperparameters.

```
In [79]: clf = grid_search.best_estimator_
         print(clf)

Pipeline(steps=[('rForest', RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=None, max_features=3,
            max_leaf_nodes=None, min_impurity_split=1e-07,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n...ithm='SAMME', base_estimator=None, learning_rate=0
          n_estimators=250, random_state=4))])
```

1.0.15 4.7 Prediction for Validation

```
In [80]: y_pred = clf.predict(x_test)
```

In [81]:
```
predicted_f1 = f1_score(y_test, y_pred)
print("Final Evaluation score : ", predicted_f1)

acc = sum(y_test == y_pred) / float(len(y_pred))
print("Accuracy score: ", acc)

rec = recall_score(y_test,y_pred)
print("Recall score: ", rec)

pre = precision_score(y_test,y_pred)
print("Precision score: ", pre)

print("Grid search best score: ", grid_search.best_score_)
```

```
Final Evaluation score :  0.708171206226
Accuracy score:  0.780701754386
Recall score:  0.69465648855
Precision score:  0.722222222222
Grid search best score:  0.795992714026
```

In [85]:
```
print(classification_report(y_test, y_pred, target_names=["Not Survived", "Survived"]))
```

```
              precision    recall  f1-score   support

Not Survived       0.81      0.83      0.82       211
    Survived       0.72      0.69      0.71       131

 avg / total       0.78      0.78      0.78       342
```

1.0.16 4.8 Nested Score with Cross Validation

Classification metrics were evaluvated using nested corss validation. following scoring functions are used because it's a binary classification:

ROC_AUC = Area Under the Curve from prediction scores

F1 Score = weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0.

In [86]:
```
# computed the nested score with auc
nested_score_auc = cross_val_score(clf, X, y, cv=nestedCV, n_jobs=-1, scoring="roc_auc"
print("Cross Validation Accuracy in AUC: %0.2f (+/- %0.2f)" % (nested_score_auc.mean(),

# compute the nested score with f1_weight
nested_score_f1 = cross_val_score(clf, X, y, cv=nestedCV, n_jobs=-1, scoring="f1_weight
print("Corss Validation Accuracy in F1 score: %0.2f (+/- %0.2f)" % (nested_score_f1.mea
```

```
Cross Validation Accuracy in AUC: 0.80 (+/- 0.08)
Corss Validation Accuracy in F1 score: 0.78 (+/- 0.08)
```

Nested cross validation score is computed by spliting the data into testing and training k times (Kfold) and validating. To compute the above scores I used 10 folds. In K-fold cross validation the data is divided into k subsets and holdout method repeated k times. After that, the average error across all k trials are computed. By using this method every data point will get to be in the test set once and to be in the training k-1. The benefit of K-fold cross validation is that we can get a better understanding of how data behaves when it saw unseen data.

The final evaluation score is ignoring a portion of the dataset. We trained the model only using a subset of the test data and evaluate using the remaining set. We didn't properly utilize the test data set properly. This could result in underfit and would give lower accuracy scores.

As we can see the final evaluation score for the model is 0.7 but the cross validation score is 0.8. Therefore, by using cross validation we can build a general model.

1.0.17 4.9 Precision - Recall Curve

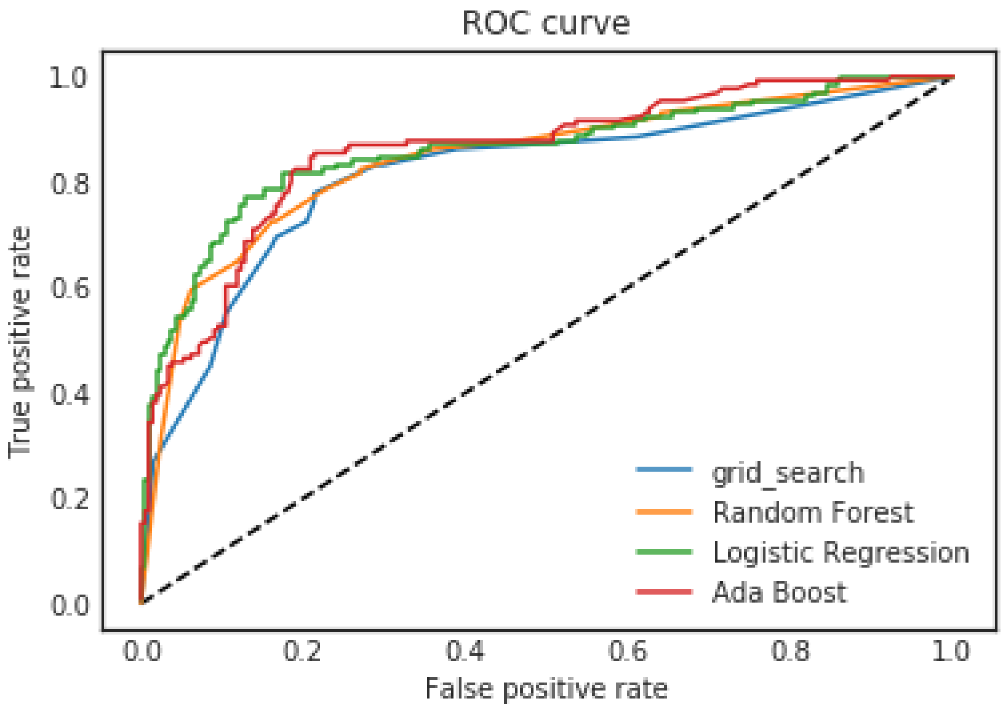
```
In [87]: y_pred_grid = clf.predict_proba(x_test)[:, 1]
         fpr_grid_lm, tpr_grid_lm, _ = roc_curve(y_test, y_pred_grid)

         rForest = RandomForestClassifier()
         rForest.fit(x_train, y_train)
         y_pred_rForest = rForest.predict_proba(x_test)[:,1]
         fpr_rForest_lm, tpr_rForest_lm, _ = roc_curve(y_test, y_pred_rForest)

         logR = LogisticRegression()
         logR.fit(x_train,y_train)
         y_pred_logR = logR.predict_proba(x_test)[:,1]
         fpr_logR_lm, tpr_logR_lm, _ = roc_curve(y_test, y_pred_logR)

         ada = AdaBoostClassifier()
         ada.fit(x_train,y_train)
         y_pred_ada = ada.predict_proba(x_test)[:,1]
         fpr_ada_lm, tpr_ada_lm, _ = roc_curve(y_test, y_pred_ada)
```

Final Evaluation including precision - recall curve

Precision and Recall curve generated using the tuned model and other classifiers used in the grid search but hyperparameters set to default values. By doing this we can compare the optimized model against default models.

```
In [88]: plt.figure(1)
         plt.plot([0, 1], [0, 1], 'k--')
         plt.plot(fpr_grid_lm, tpr_grid_lm, label='grid_search')
         plt.plot(fpr_rForest_lm, tpr_rForest_lm, label='Random Forest')
         plt.plot(fpr_logR_lm, tpr_logR_lm, label='Logistic Regression')
         plt.plot(fpr_ada_lm, tpr_ada_lm, label='Ada Boost')
         plt.xlabel('False positive rate')
         plt.ylabel('True positive rate')
```

```
plt.title('ROC curve')
plt.legend(loc='best')
plt.show()
```




```
In [97]: final_predictions = clf.predict(test)

         test1 = pd.read_csv("./Data/test.csv")

         final_predictions = final_predictions.astype(int)
         submission = pd.DataFrame({
                 "PassengerId": test1["PassengerId"],
                 "Survived": final_predictions
             })

         submission.to_csv("./Data/final_submission.csv", index=False)
```