Predicting Survivors of the Titanic

The purpose of this project is to create a model that predicts whether a passenger survived the sinking of the Titanic based on passenger information.

Importing libraries:

In [8]:
```
import pandas as pd
from pandas.api.types import CategoricalDtype
import numpy as np
from matplotlib import pyplot as plt
import sys
!{sys.executable} -m pip install "ethnicolr == 0.2.0"
from ethnicolr import *
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.linear_model import LogisticRegression
import sklearn.metrics
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.utils import shuffle
import statsmodels.api as sm
import sklearn.discriminant_analysis
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
```

...

Initial Data Exploration

Loading Data:

In [10]:
```
df = pd.read_csv('C:/Datasets/TitanicTrain.csv')
test = pd.read_csv('C:/Datasets/TitanicTest.csv')
test.insert(1,'Survived',np.NaN)
```

The training dataset is about twice as large as the test data set.

In [50]:
```
df.shape[0]
```

Out[50]:
```
891
```

In [51]:
```
test.shape[0]
```

Out[51]:
```
418
```

Below the list of features and the dataframe are displayed.

In [11]:
```
variables = list(df)
print(variables)
```

```
['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch', 'Tick
et', 'Fare', 'Cabin', 'Embarked']
```

In [16]:
```
df.head(20)
```

Out[16]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	Na
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E4
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	Na
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	Na
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	Na
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	C10
12	13	0	3	Saundercock, Mr. William Henry	male	20.0	0	0	A/5. 2151	8.0500	Na
13	14	0	3	Andersson, Mr. Anders Johan	male	39.0	1	5	347082	31.2750	Na
14	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0	0	350406	7.8542	Na

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
15	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55.0	0	0	248706	16.0000	Na
16	17	0	3	Rice, Master. Eugene	male	2.0	4	1	382652	29.1250	Na
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	Na
18	19	0	3	Vander Planke, Mrs. Julius (Emelia Maria Vande...	female	31.0	1	0	345763	18.0000	Na
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	Na

Feature Extraction

Functions for Feature Extraction from Passenger Name

The passenger names contain much information that can be extracted into new features. First the titles, which always end in a period, can be extracted with the following function.

In [13]:
```
def title(dataframe):
    dataframe['Title'] = dataframe['Name'].str.extract(r'((?<=, ).{1,12}?\.)', expan
    dataframe['Name'] = dataframe['Name'].str.replace(r'(, .{1,12}?\. )', ', ').str.
```

The maiden name, which is in parentheses, is extracted with this function.

In [14]:
```
def maidenname(dataframe):
    maiden = dataframe['Name'].str.extract(r'((?<=\().+(?=\)))',expand=False)
    dataframe['Maiden Name']=np.where(pd.isnull(maiden),dataframe['Name'],maiden)
    dataframe['Name'] = dataframe['Name'].str.replace(r'( \(.+\))', '').str.strip()
```

The nicknames, which are in quotes, are extracted as follows.

In [15]:
```
def nickname(dataframe):
    name = dataframe['Name']
    maiden = dataframe['Maiden Name']
    dataframe['Nickname'] = np.where(np.logical_or(name.str.contains('"'),maiden.str
    dataframe['Name'] = name.str.replace(r'( )?".+"','').str.strip()
    dataframe['Maiden Name'] = maiden.str.replace(r'( )?".+"','').str.strip()
    dataframe['Maiden Name'] = np.where(maiden=='',name,maiden)
```

The first, middle, and last name can then be split, for both the name and maiden name. This function is more complex because sometimes there is no middle name, and some names have a suffix.

```
In [17]: def splitnames(dataframe):
             def parsenames(string):
                 if ',' in string:
                     comma = string.index(',')
                     lastname = string[:comma]
                     firstname = None
                     middlename = None
                     if string[comma+2:]:
                         firstmiddle = string[comma+2:].split(' ')
                         firstname = firstmiddle[0]
                         if len(firstmiddle) > 2:
                             if firstmiddle[-1] not in ['Sr', 'Jr', 'II', 'III', 'IV']:
                                 middlename = ' '.join(firstmiddle[1:])
                             else:
                                 middlename = ' '.join(firstmiddle[1:-1])
                         elif len(firstmiddle) == 2:
                             if firstmiddle[1] not in ['Sr', 'Jr', 'II', 'III', 'IV']:
                                 middlename = firstmiddle[1]
                 else:
                     names = string.split(' ')
                     firstname = names[0]
                     lastname = None
                     middlename = None
                     if len(names)>1:
                         lastname = names[-1]
                     if len(names)>2:
                         middlename = ' '.join(names[1:-1])
                 return (firstname,middlename,lastname)
             def fillnames(name,maidenname):
                 names = parsenames(name)
                 maidennames = parsenames(maidenname)
                 first = ''
                 middle = ''
                 maidenmiddle = ''
                 maidenlast = ''
                 if names[0]:
                     first = names[0]
                 if names[1] and len(names[1]) > 1:
                     middle = names[1]
                 last = names[2]
                 maidenfirst = maidennames[0]
                 if maidennames[1] and len(maidennames[1]) > 1:
                     maidenmiddle = maidennames[1]
                 if maidennames[2]:
                     maidenlast = maidennames[2]
                 return pd.Series([first, middle, last, maidenfirst, maidenmiddle, maidenlast
             dataframe[['First Name','Middle Name','Last Name','Maiden First Name','Maiden Mi
                 dataframe.apply(lambda row:fillnames(row['Name'],row['Maiden Name']),axis=1)
```

The name can be used to predict the ethnicity, using the ethnicolr package. In addition, this crude function is used to further subdivide the British ethnicity into British and Irish, based on syllables common in Irish last names.

In [18]:
```
irishsyllables=[['Mac','Mc',"O'",'Fitz'],
                ['fitz','mac','don','ees','een','eer','oon','oy','gh','dh','enn','ay
                ['ne','uire','be','len','han','nan','lan','gan','non','hon','yan','i
                 'thy','ery','dy','ley','ney','lly','hy','fy','erty','oy','ay','mack
                 'wyer','yng','nna','ara','ea'],
                ['clark','thorn','well','hoyt','vell','stan','for','worth','green','
                 'ville','uck','ight','long','gask','shell','lane','bery','berry','t
                 'ham','sell','bon','gray','grey']]

def checkirish(string):
    count = 0
    for x in irishsyllables[0]:
        if string[:len(x)]==x:
            count+=1
    for x in irishsyllables[1]:
        if x in string:
            count +=1
    for x in irishsyllables[2]:
        if string[-1*len(x):]==x:
            count+=1
    for x in irishsyllables[3]:
        if x in string.lower():
            count -=1
    if count > 0:
        return True
    else:
        return False
```

The ethnicities are relabeled for simplicity.

In [19]:
```
def relabelethnicity(dataframe,racecolumn,namecolumn):
    def newlabel(race,lastname):
        if 'British' in race:
            if checkirish(lastname):
                return 'Irish'
            else:
                return 'British'
        elif 'Japanese' in race:
            return 'EastAsian'
        elif 'Africans' in race:
            return 'African'
        elif 'Indian' in race:
            return 'Indian'
        else:
            return race.split(',')[-1]
    dataframe[racecolumn]=dataframe.apply(lambda row: newlabel(row[racecolumn],row[n
```

Functions are defined to create features for family ethnicity (based on name) and birth ethnicity (based on maiden name if available).

```
In [20]: def familyethnicity(dataframe):
             pred_wiki_name(dataframe,'Last Name','First Name')
             dataframe.rename(columns={'race':'Family Race'},inplace=True)
             relabelethnicity(dataframe, 'Family Race','Last Name')

         def birthethnicity(dataframe):
             pred_wiki_name(dataframe, 'Maiden Last Name', 'Maiden First Name')
             dataframe.rename(columns={'race': 'Birth Race'}, inplace=True)
             relabelethnicity(dataframe, 'Birth Race','Maiden Last Name')
```

The title (prefix) for females indicates marital status sometimes. This can be extracted as follows.

```
In [21]: def femalemarital(dataframe):
             married = ['Mrs.','Mme.','Lady.','the Countess.']
             unmarried = ['Miss.','Mlle.']
             dataframe['Female Marital'] = np.where(dataframe['Title'].isin(married),0.5,
                                                    np.where(dataframe['Title'].isin(unmarrie
```

Titles can also indicate profession. The professions will be grouped into: Unknown, Nobility, Clergy, Doctor, and Military.

```
In [22]: def profession(dataframe):
             dataframe['Profession']='Unknown'
             dataframe.loc[dataframe['Title'].isin(['Sir.', 'Lady.', 'Lord.', 'Don.',
                                                    'Dona.', 'the Countess.', 'Jonkheer']),'P
             dataframe.loc[dataframe['Title'].isin(['Rev.', 'Minister.', 'Fr.', 'Pr.']),'Prof
             dataframe.loc[dataframe['Title'] == 'Dr.','Profession'] = 'Doctor'
             dataframe.loc[dataframe['Title'].isin(['Capt.', 'Major.', 'Col.']),'Profession']
```

The title "Master" is used for male children. This may be useful in age imputation.

```
In [23]: def master(dataframe):
             dataframe['Master']=np.where(dataframe['Title']=='Master.',1,0)
```

Functions for Feature Extraction from Ticket Number

First the ticket number is split into prefix and number.

```
In [24]: def splitticket(dataframe):
             dataframe['Ticket']=dataframe['Ticket'].str.strip()
             dataframe['Ticket Number']=dataframe['Ticket'].str.split().str[-1]
             dataframe['Ticket Prefix']=np.where(dataframe['Ticket'].str.contains(' '),
                 dataframe['Ticket'].str.split().str[:-1].str.join('').str.upper().str.replac
                                                           '').str.replace('/','').str.repl
             dataframe['Ticket Prefix']=np.where(dataframe['Ticket'].str.contains('LINE'),'LI
             dataframe['Ticket Number'] = np.where(dataframe['Ticket'].str.contains('LINE'),
             dataframe['Ticket Number'] = dataframe['Ticket Number'].astype('int')
```

A list of unique ticket prefixes is generated. A sorted version of the list is defined below for later use.

In [36]:
```
dfcopy = df[:]
splitticket(dfcopy)
dfcopy['Ticket Prefix'].unique()
```

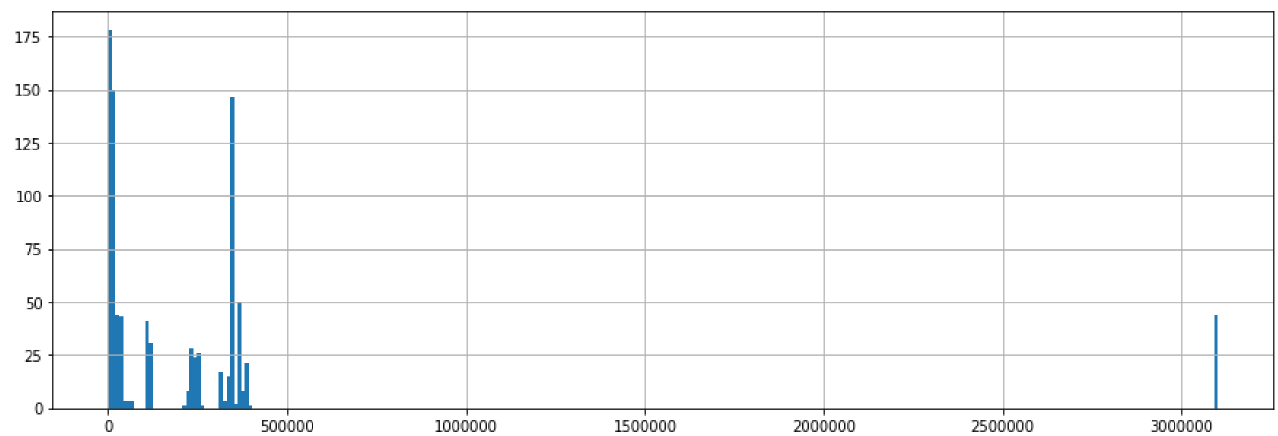
Out[36]:
```
array(['A5', 'PC', 'SOTONO2', 'No Prefix', 'PP', 'CA', 'SCPARIS', 'SCA4',
       'A4', 'SP', 'SOC', 'WC', 'SOTONOQ', 'WEP', 'C', 'SOP', 'FA',
       'LINE', 'FCC', 'SWPP', 'SCOW', 'PPP', 'SC', 'SCAH', 'AS',
       'SCAHBASLE', 'SOPP', 'FC', 'CASOTON'], dtype=object)
```

In [37]:
```
ticketprefixes = ['A2','A4','A5','AQ3','AQ4','AS','C','CA','CASOTON','FA','FC','FCC'
                  'SC','SCA3','SCA4','SCAH','SCAHBASLE','SCOW','SCPARIS','SOC','SOP'
                  'SP','SWPP','WC','WEP','No Prefix']
```

The ticket number is turned into a categorical feature by binning. Bins are defined based on the histogram below.

In [34]:
```
dfcopy['Ticket Number'].hist(bins=300, figsize=(15,5))
```

Out[34]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b971630e10>
```



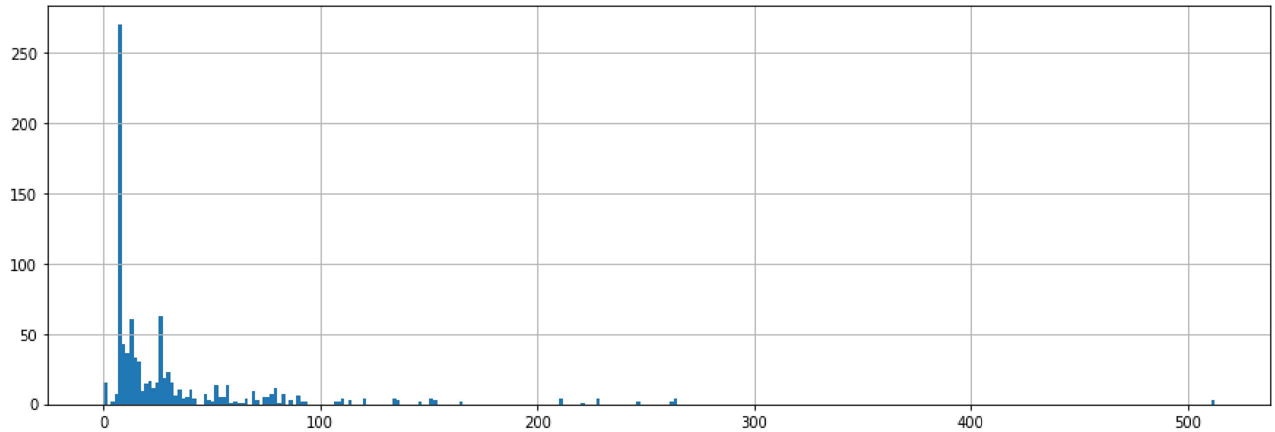
In [25]:
```
def bintickets(dataframe):
    bins = pd.IntervalIndex.from_tuples([(-1,100000),(100001,200000),(200001,260000)
    dataframe['Ticket Bin']=pd.cut(dataframe['Ticket Number'],bins)
```

Other Features

Fare is converted to a categorical feature by binning.

In [35]:
```
df['Fare'].hist(bins=300,figsize=(15,5))
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b971849f98>
```



In [38]:
```
def binfare(dataframe):
    bins =[-1,6,12,19,44,68,100,200,300,600]
    dataframe['Fare']=dataframe['Fare'].astype('float')
    dataframe['Fare Bin']=pd.cut(dataframe['Fare'],bins)
```

The deck can be extracted from the cabin number.

In [39]:
```
def deck(dataframe):
    dataframe['Deck']=np.where(pd.notnull(dataframe['Cabin']),dataframe['Cabin'].str
```

Defining Categorical Variables

In [40]:
```
def categorize(dataframe):
    dataframe['Sex'] = dataframe['Sex'].astype(CategoricalDtype(categories=['male',
    racetype = CategoricalDtype(categories=['African', 'British', 'EastAsian', 'East
                        'Hispanic', 'Indian', 'Irish', 'Italian', 'Jewish', 'Mus
    dataframe['Family Race'] = dataframe['Family Race'].astype(racetype)
    dataframe['Birth Race'] = dataframe['Birth Race'].astype(racetype)
    dataframe['Embarked'] = dataframe['Embarked'].astype(CategoricalDtype(categories
    dataframe['Profession'] = dataframe['Profession'].astype(CategoricalDtype(catego
                                                                        'Military','Nobi
    dataframe['Ticket Prefix'] = dataframe['Ticket Prefix'].astype(CategoricalDtype(

    dataframe['Deck'] = dataframe['Deck'].astype(CategoricalDtype(categories=['A', '
                                                                           'T', '
```

Dummy Coding

In [41]:
```
def dummies(dataframe):
    dataframe['Female'] = pd.get_dummies(dataframe['Sex'])['female']
    familyraces = pd.get_dummies(dataframe['Family Race'])
    familyraces = familyraces.rename(columns={x: x + ' Family' for x in list(familyr
    newdataframe = pd.concat([dataframe, familyraces, pd.get_dummies(dataframe['Birt
                              pd.get_dummies(dataframe['Profession']),pd.get_dummies
    newdataframe=newdataframe.rename(columns={'S':'Southhampton','Q':'Queenstown','C
    newdataframe = pd.concat([newdataframe, pd.get_dummies(dataframe['Deck']),
                              pd.get_dummies(dataframe['Pclass'])], axis=1)
    newdataframe = newdataframe.rename(columns={1: '1', 2: '2', 3: '3'})
    return newdataframe
```

Initial Pre-Processing

Now that all the feature extraction functions have been created, they can be applied to the test and training datasets. (Dummy coding is done after imputation).

In [42]:
```
def nameprocess(dataframe):
    title(dataframe)
    maidenname(dataframe)
    nickname(dataframe)
    splitnames(dataframe)
    familyethnicity(dataframe)
    birthethnicity(dataframe)
    femalemarital(dataframe)
    profession(dataframe)
    master(dataframe)
    deck(dataframe)
    splitticket(dataframe)
    bintickets(dataframe)
    categorize(dataframe)
```

In [43]:
```
nameprocess(df)
nameprocess(test)
```

...

In [44]:
```
df.head(10)
```
Out[44]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	...	Mai I Na
0	1	0	3	Braund, Owen Harris	male	22.0	1	0	A/5 21171	7.2500	...	Bra
1	2	1	1	Cumings, John Bradley	female	38.0	1	0	PC 17599	71.2833	...	Th
2	3	1	3	Heikkinen, Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	...	Heikk
3	4	1	1	Futrelle, Jacques Heath	female	35.0	1	0	113803	53.1000	...	I
4	5	0	3	Allen, William Henry	male	35.0	0	0	373450	8.0500	...	A
5	6	0	3	Moran, James	male	NaN	0	0	330877	8.4583	...	M
6	7	0	1	McCarthy, Timothy J	male	54.0	0	0	17463	51.8625	...	McCa
7	8	0	3	Palsson, Gosta Leonard	male	2.0	3	1	349909	21.0750	...	Pals
8	9	1	3	Johnson, Oscar W	female	27.0	0	2	347742	11.1333	...	E
9	10	1	2	Nasser, Nicholas	female	14.0	1	0	237736	30.0708	...	Ac

10 rows × 30 columns

Imputation

It is evident that some features require imputation.

In [53]:
```
np.sum(pd.isnull(df), axis=0)+np.sum(pd.isnull(test), axis=0)
```

Out[53]:
```
PassengerId             0
Survived              418
Pclass                  0
Name                    0
Sex                     0
Age                   263
SibSp                   0
Parch                   0
Ticket                  0
Fare                    1
Cabin                1014
Embarked                2
Title                   0
Maiden Name             0
Nickname                0
First Name              0
Middle Name             0
Last Name               0
Maiden First Name       0
Maiden Middle Name      0
Maiden Last Name        0
Family Race             0
Birth Race              0
Female Marital          0
Profession              0
Master                  0
Deck                 1014
Ticket Number           0
Ticket Prefix           0
Ticket Bin              0
dtype: int64
```

For imputation purposes, we will combine the test and training sets.

In [52]:
```
combined = pd.concat([df,test],ignore_index=True)
```

First, impute the 3rd class fare for the one passenger with the missing value. Imputation is performed by taking the mean of fares from the same passenger class. Then the binned fares are repopulated.

In [54]:
```
thirdclassfare = combined.groupby(['Pclass']).mean()['Fare'].iloc[-1]
def imputefare(dataframe):
    dataframe['Fare']=np.where(pd.isnull(dataframe['Fare']),thirdclassfare,dataframe
imputefare(combined)
binfare(combined)
```

Next is a function to calculate missing embarkation using the mode for passengers with the same fare bin and passenger class.

In [55]:
```
FareGroup = combined.groupby(['Pclass','Fare Bin'])['Embarked'].agg(lambda x:x.value
def imputeembark(dataframe):
    def fillembark(classcolumn,farecolumn,embarkcolumn):
        if not isinstance(embarkcolumn,str):
            return FareGroup[(classcolumn,farecolumn)]
        else:
            return embarkcolumn
    dataframe['Embarked']=dataframe.apply(lambda row:fillembark(row['Pclass'],
                                                               row['Fare Bin'],row[
```

The following function imputes the deck from passenger class, embarkation, ticket prefix, and ticket number. The mode for passengers with the same level for the above factors is used as the imputed value.

In [56]:
```
DeckFareGroup = combined.groupby(['Pclass','Embarked',
                              'Ticket Prefix','Ticket Bin','Fare Bin'])['Deck'].agg(
DeckGroup = combined.groupby(['Pclass','Embarked',
                              'Ticket Prefix','Ticket Bin'])['Deck'].agg(lambda x:x.
DeckLargeGroup =combined.groupby(['Pclass','Embarked'])['Deck'].agg(lambda x:x.value

def imputedeck(dataframe):
    def filldeck(classcol,embarkcol,prefixcol,bincol,deckcol,farecol):
        if not isinstance(deckcol,str):
            if DeckFareGroup[(classcol,embarkcol,prefixcol,bincol,farecol)]=='Unknow
                if DeckGroup[(classcol,embarkcol,prefixcol,bincol)]=='Unknown':
                    return DeckLargeGroup[(classcol,embarkcol)]
                else:
                    return DeckGroup[(classcol,embarkcol,prefixcol,bincol)]
            else:
                return DeckFareGroup[(classcol,embarkcol,prefixcol,bincol,farecol)]
        else:
            return deckcol
    dataframe['Deck']=dataframe.apply(lambda row:filldeck(row['Pclass'],row['Embarke
                                      row['Ticket Prefix'],row['Ticket Bin'],row['Deck
```

Next relations between passengers are inferred by ticket numbers. If the ticket numbers are the same for two passengers, they are considered to have some kind of relationship. If the ticket numbers are within 2 of each other, and the last names are also the same between passengers, they are assumed to be relatives.

In [58]:
```
ticketsorted = combined[['PassengerId','Ticket Number','Last Name','Maiden Last Name
ticketsorted['Relations','Relatives']=0
ticketsorted=ticketsorted.reset_index(drop=True)

def relations():
    global ticketsorted
    group = [0]
    familygroup = [0]
    for i in range(1,len(ticketsorted)):
        if ticketsorted.loc[i,'Ticket Number']-ticketsorted.loc[i-1,'Ticket Number']
            group.append(i)
        else:
            if ticketsorted.loc[i,'Ticket Number']-ticketsorted.loc[i-1,'Ticket Numb
                group.append(i)
            else:
                ticketsorted.loc[i, 'Relations'] = 0
            for j in group:
                ticketsorted.loc[j,'Relations']=len(group)-1
            group = [i]
        if ticketsorted.loc[i,'Ticket Number']-ticketsorted.loc[i-1,'Ticket Number']
            familygroup.append(i)
        else:
            if ticketsorted.loc[i,'Ticket Number']-ticketsorted.loc[i-1,'Ticket Numb
                familygroup.append(i)
            for j in familygroup:
                relatives = -1
                for k in familygroup:
                    if ticketsorted.loc[j, 'Last Name']==ticketsorted.loc[k, 'Last N
                        ticketsorted.loc[j, 'Maiden Last Name']==ticketsorted.loc[k,
                            ticketsorted.loc[j, 'Last Name'] == ticketsorted.loc[k,
                            ticketsorted.loc[j, 'Maiden Last Name'] == ticketsorted.
                        relatives+=1
                ticketsorted.loc[j, 'Relatives']=relatives
            familygroup = [i]
    ticketsorted = ticketsorted.sort_values(by=['PassengerId']).reset_index(drop=Tru
    df[['Relations','Relatives']]=ticketsorted.loc[:891,['Relations','Relatives']]
    combined[['Relations', 'Relatives']] = ticketsorted.loc[:, ['Relations', 'Relati
    test[['Relations', 'Relatives']] = ticketsorted.loc[891:, ['Relations', 'Relativ
```

The number of distant relatives are defined as the number of relatives (determined with the function above) minus the number of parents/children and spouse/siblings. The number of distant relations is defined by the number of relations (see above) minus the number of family members.

In [59]:
```
def distrelations(dataframe):
    distantrelatives = dataframe['Relatives']-dataframe['Parch']-dataframe['SibSp']
    dataframe['Distant Relatives']=np.where(distantrelatives<0,0,distantrelatives)
    distantrelations = dataframe['Relations'] - dataframe['Parch'] - dataframe['SibS
    dataframe['Distant Relations'] = np.where(distantrelations < 0, 0, distantrelati
    dataframe['Family Size']= dataframe['Distant Relatives']+dataframe['Parch']+data
```

To impute age, a new feature can be created that indicates if a passenger is traveling alone. In addition a feature will be created that indicates whether someone is known to have a job or not (based on the profession feature).

In [60]:
```
def alone(dataframe):
    dataframe['Alone']=np.where(dataframe['SibSp']*dataframe['Parch']*dataframe['Rel
```

In [61]:
```
def professional(dataframe):
    dataframe['Professional'] = np.where(dataframe['Profession'] !='Unknown', 1, 0)
```

Finally, age can be imputed based on marital status, 'Master' title, whether the individual is a professional, traveling alone, and the passenger class.

In [62]:
```
relations()
distrelations(df)
distrelations(test)
distrelations(combined)
alone(combined)
professional(combined)
AgeGroup = combined.groupby(['Female Marital','Master','Professional','Alone','Pclas
def imputeage(dataframe):
    def fillage(maritalcol,mastercol,profcol,alonecol,classcol,agecol):
        if np.isnan([agecol])[0]:
            return AgeGroup[(maritalcol,mastercol,profcol,alonecol,classcol)]
        else:
            return agecol
    dataframe['Age']=dataframe.apply(lambda row:fillage(row['Female Marital'],row['M
                                     row['Professional'],row['Alone'],row['Pclass'],r
```

...

Now imputation can be performed, along with dummy coding.

In [63]:
```
def imputation(dataframe):
    binfare(dataframe)
    imputeembark(dataframe)
    imputedeck(dataframe)
    alone(dataframe)
    professional(dataframe)
    imputeage(dataframe)

imputefare(test)
imputation(df)
imputation(test)
df=dummies(df)
test=dummies(test)
combined = dummies(combined)
```

...

Exploratory Data Analysis

Visualization

First, functions are defined to create the plots.

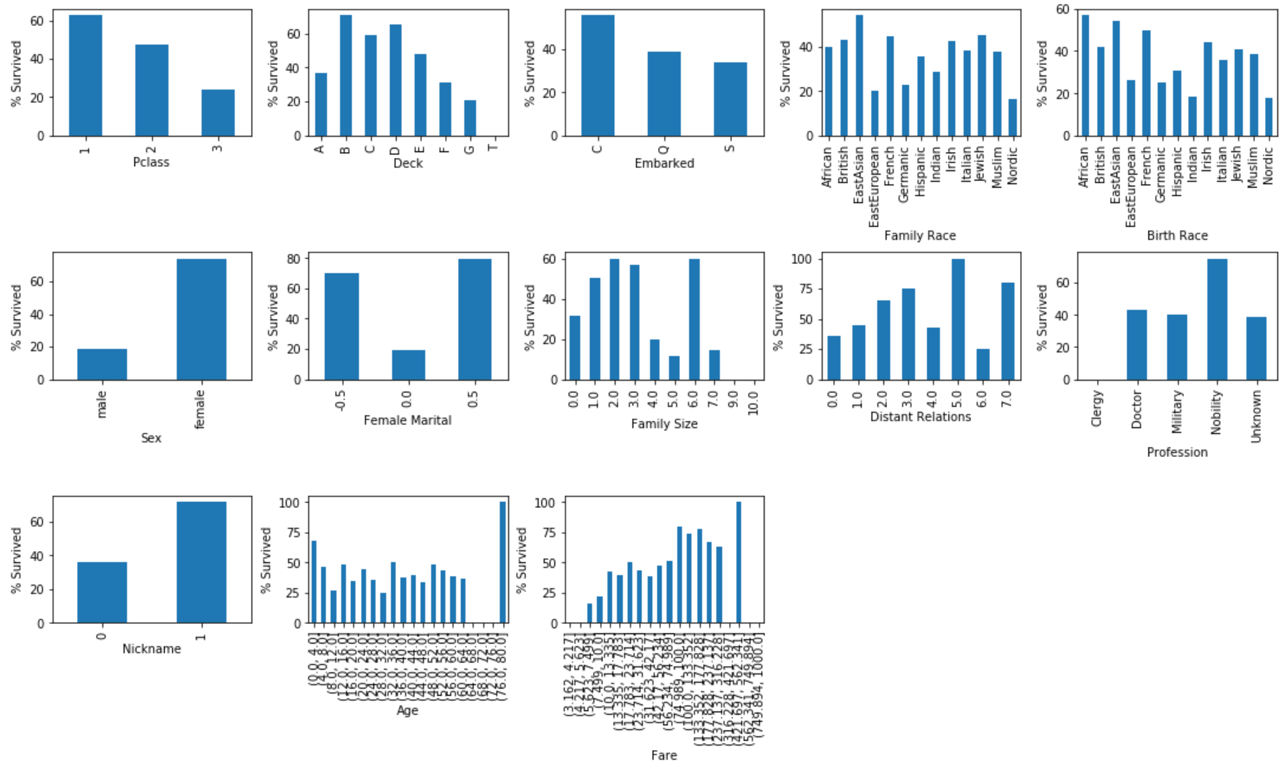
In [68]:
```
def survivalgroup(column,ax):
    percent=df.groupby(column)['Survived'].agg(lambda x:x.sum()/x.count()*100)
    if len(column)==1:
        percent.plot(kind='bar',ax=ax,legend=False)
    elif len(column)>1:
        percent.unstack().plot(kind='bar',ax=ax,legend=False)
    ax.set_ylabel('% Survived')

def survivalhist(column,secondcolumn=None,bins=None,ax=None):
    df['Histbins'] = pd.cut(column, bins)
    if not secondcolumn:
        percent=df.groupby(['Histbins'])['Survived'].agg(lambda x:x.sum()/x.count()*
        percent.plot(kind='bar',ax=ax,legend=False)
    else:
        percent = df.groupby(['Histbins']+secondcolumn)['Survived'].agg(lambda x: x.
        percent.unstack().plot(kind='bar',ax=ax,legend=False)
    ax.set_ylabel('% Survived')
```

Lists are created for the labels.

In [65]:
```
categoricalx = ['Pclass','Deck','Embarked','Family Race','Birth Race',
                'Sex','Female Marital','Family Size','Distant Relations','Profession
continuousx=['Age','Fare']
races = ['African', 'British', 'EastAsian', 'EastEuropean', 'French', 'Germanic','Hi
         'Italian', 'Jewish', 'Muslim', 'Nordic']
professions = ['Clergy', 'Doctor', 'Military','Nobility', 'Unknown']
decks = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'T']
```

The first set of plots are bar charts showing the frequency of survival by feature.

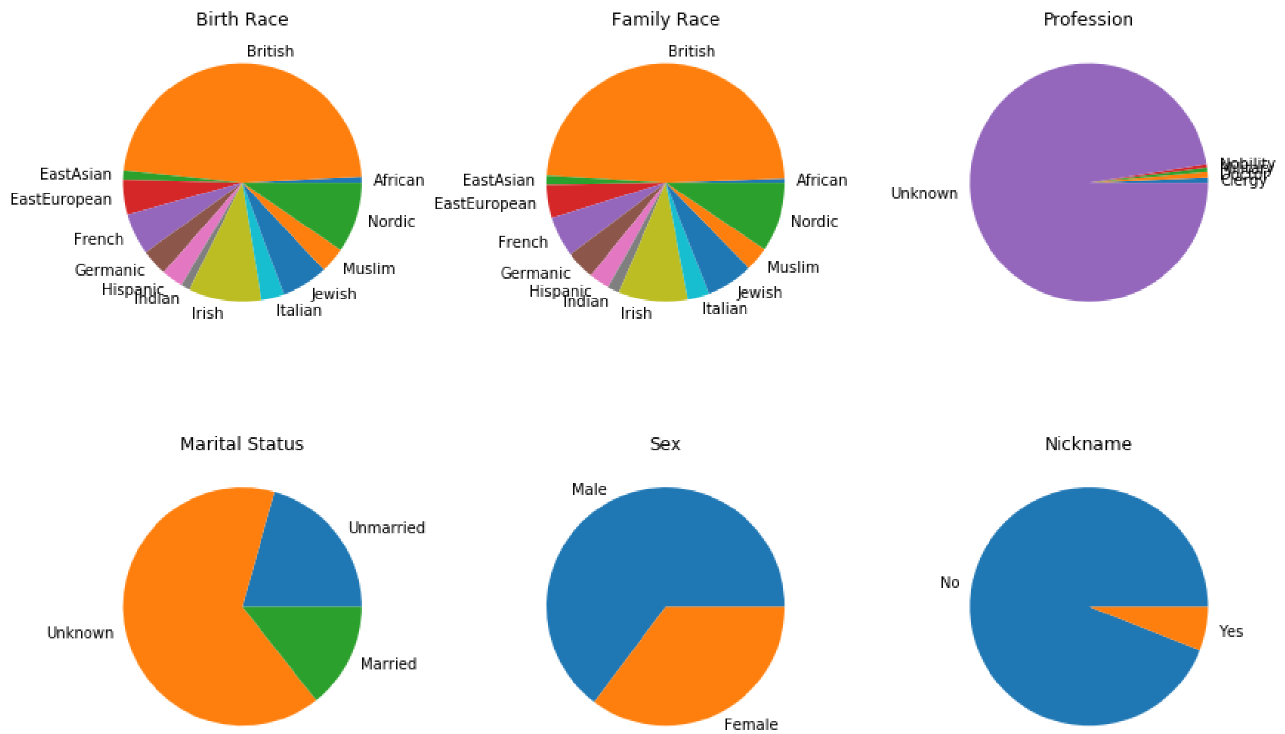
```
In [70]: fig0, ax0 = plt.subplots(3,5)
fig0.delaxes(ax0[2][3])
fig0.delaxes(ax0[2][4])
for i in range(len(categoricalx)):
    survivalgroup([categoricalx[i]],ax0[i//5,i%5])
survivalhist(df['Age'],bins=np.linspace(0,80,21),ax=ax0[2,1])
survivalhist(df['Fare'],bins=np.logspace(0.5,3,21),ax=ax0[2,2])
ax0[2,1].set_xlabel('Age')
ax0[2,2].set_xlabel('Fare')
fig0.set_size_inches(15,9)
fig0.tight_layout(pad=0.4,w_pad=0.5,h_pad=0.5)
```



Almost all features show some effect of the feature level on survival. Sex has the clearest effect (females are much more likely to survive). For embarkation, Cherbourg passengers seem to survive more. Passenger class, deck, and fare all show trends with survival. The surprising effect is that of having a nickname. This may be just coincidental, or perhaps having a nickname recorded indicates something about one's personality that makes the person more likely to survive.

Next, the distribution of levels of different features are shown in pie charts.

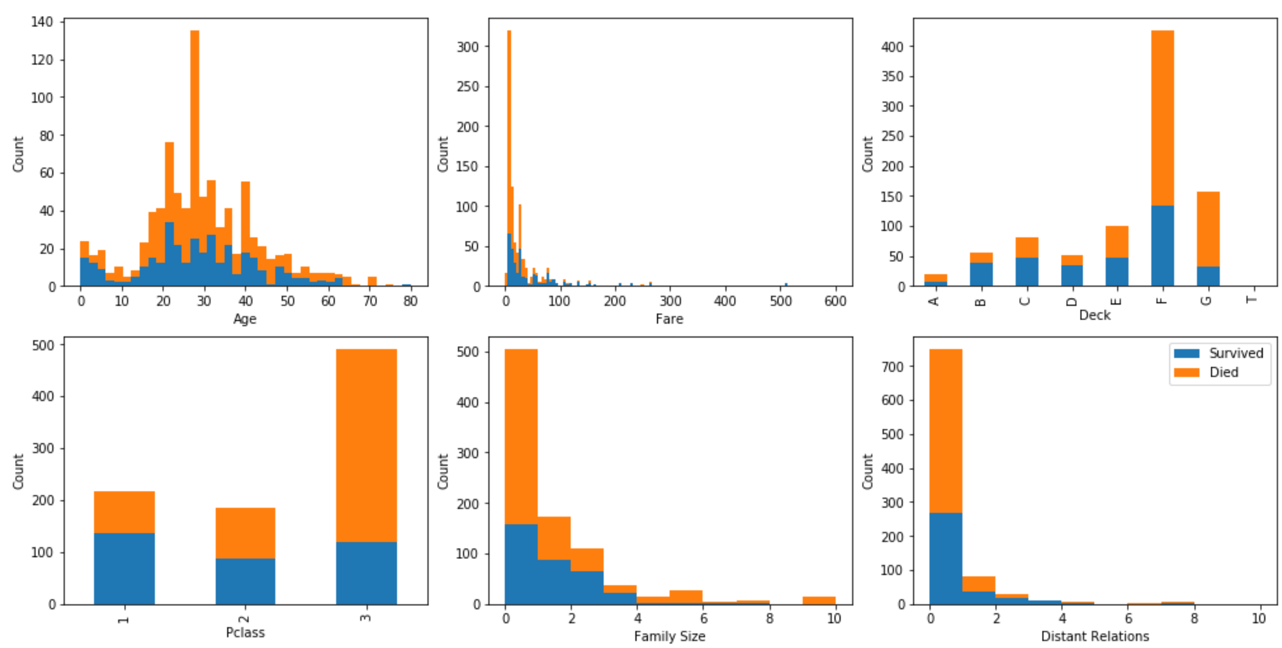
```
In [71]: fig1, ax1 = plt.subplots(2,3)
ax1[0,0].set_title('Birth Race')
ax1[0,1].set_title('Family Race')
ax1[0,2].set_title('Profession')
ax1[1,0].set_title('Marital Status')
ax1[1,1].set_title('Sex')
ax1[1,2].set_title('Nickname')
ax1[0,0].pie(df.groupby(['Birth Race'])['Survived'].count(),labels=races)
ax1[0,1].pie(df.groupby(['Family Race'])['Survived'].count(),labels=races)
ax1[0,2].pie(df.groupby(['Profession'])['Survived'].count(),labels=professions)
ax1[1,0].pie(df.groupby(['Female Marital'])['Survived'].count(),labels=['Unmarried',
ax1[1,1].pie(df.groupby(['Sex'])['Survived'].count(),labels=['Male','Female'])
ax1[1,2].pie(df.groupby(['Nickname'])['Survived'].count(),labels=['No','Yes'])
fig1.set_size_inches(12,8)
fig1.tight_layout(pad=0.4,w_pad=0.5,h_pad=0.5)
```



The feature levels are not uniformly distributed. However, there is some variation in most features except profession. Nickname also is quite imbalanced, which may have resulted in the apparent effect of nickname on survival.

The first set of % Survival plots may be skewed by groups with small numbers of passengers (the error will be higher for these groups). Therefore another set of plots showing the absolute number of passengers who survived and died is shown below to clarify some of the features with ambiguous effects.

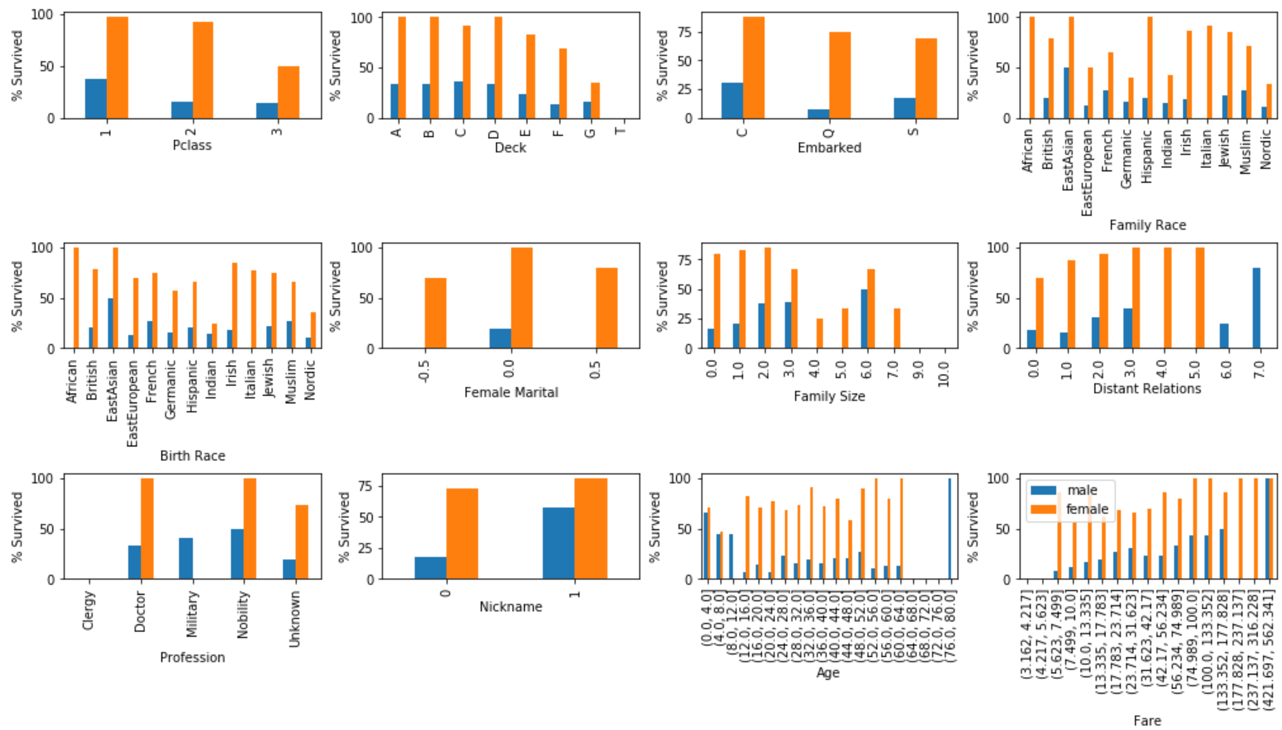
In [72]:
```
fig3, ax3 = plt.subplots(2,3)
ax3[0,0].hist([df.loc[df['Survived']==1,'Age'],df.loc[df['Survived']==0,'Age']],
              bins=np.linspace(0,80,40),stacked=True)
ax3[0,0].set_xlabel('Age')
ax3[0,1].hist([df.loc[df['Survived']==1,'Fare'],df.loc[df['Survived']==0,'Fare']],
              bins=np.linspace(0,600,120),stacked=True)
ax3[0,1].set_xlabel('Fare')
deckplot = pd.concat([df.groupby(['Deck'])['Survived'].apply(lambda x:(x==1).sum()),
                     df.groupby(['Deck'])['Survived'].apply(lambda x:(x==0).sum())],
deckplot.plot.bar(ax=ax3[0,2],stacked=True,legend=False)
classplot = pd.concat([df.groupby(['Pclass'])['Survived'].apply(lambda x:(x==1).sum(
                     df.groupby(['Pclass'])['Survived'].apply(lambda x:(x==0).sum())
classplot.plot.bar(ax=ax3[1,0],stacked=True, legend=False)
ax3[1,1].hist([df.loc[df['Survived']==1,'Family Size'],df.loc[df['Survived']==0,'Fam
              bins=np.linspace(0,10,11),stacked=True)
ax3[1,1].set_xlabel('Family Size')
ax3[1,2].hist([df.loc[df['Survived']==1,'Distant Relations'],df.loc[df['Survived']==
              bins=np.linspace(0,10,11),stacked=True)
ax3[1,2].set_xlabel('Distant Relations')
ax3[1,2].legend(['Survived','Died'])
for i in range(2):
    for j in range(3):
        ax3[i,j].set_ylabel('Count')
fig3.set_size_inches(14,7)
fig3.tight_layout(pad=0.4,w_pad=0.5,h_pad=0.5)
```



Here the effect of family size and distant relations becomes more evident. Many more survive if they have fewer family members or relations on board. Also, it is evident that a higher fraction of children under ~10-14 survive than older passengers.

Next, since gender had a large effect, interactions between gender and other features are explored with the following plots.

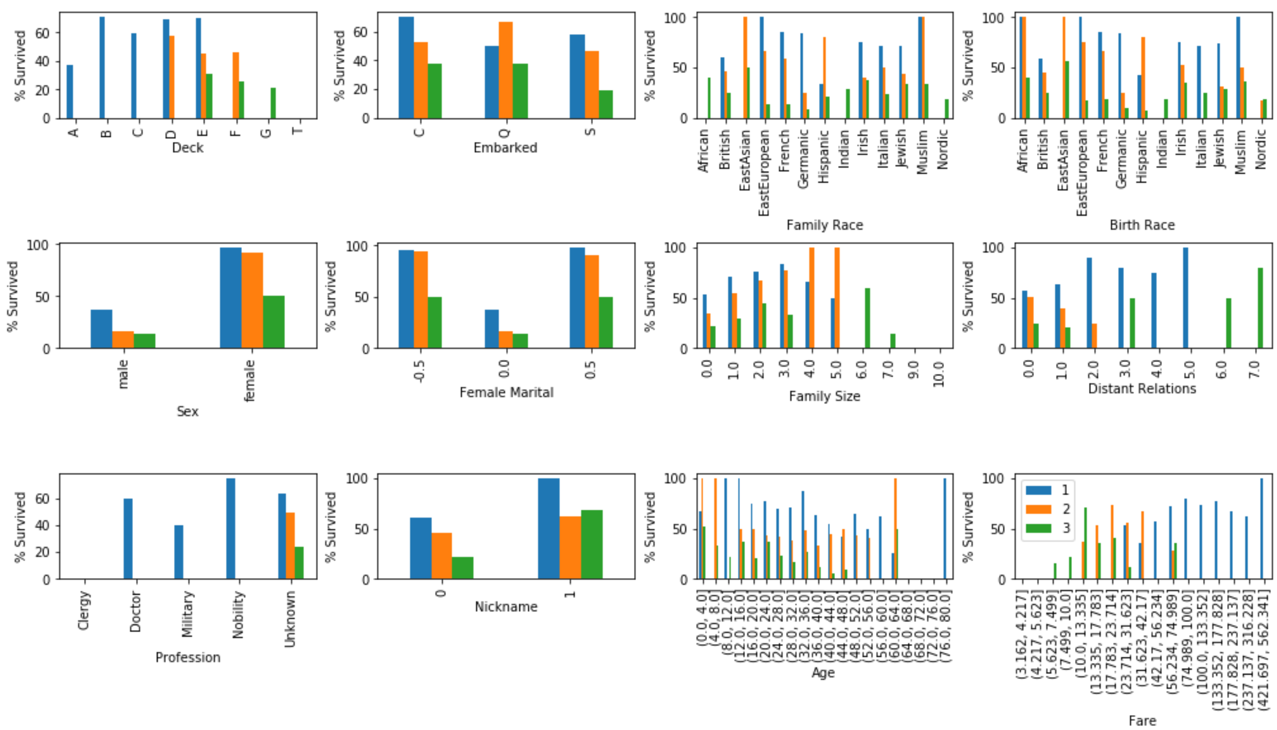
```
In [73]: fig4, ax4 = plt.subplots(3,4)
         categoricalx.remove('Sex')
         for i in range(len(categoricalx)):
             survivalgroup([categoricalx[i],'Sex'],ax4[i//4,i%4])
         survivalhist(df['Age'],['Sex'],bins=np.linspace(0,80,21),ax=ax4[2,2])
         survivalhist(df['Fare'],['Sex'],bins=np.logspace(0.5,3,21),ax=ax4[2,3])
         ax4[2,3].legend()
         ax4[2,2].set_xlabel('Age')
         ax4[2,3].set_xlabel('Fare')
         fig4.set_size_inches(14,8)
         fig4.tight_layout(pad=0.4,w_pad=0.5,h_pad=0.5)
         categoricalx.insert(5,'Sex')
```



The effect of class seems to be higher for males than females. The effect of age and fare is larger for males than females. Effects of family size, profession, and race vary without an obvious pattern. Interestingly the effect of nickname is higher for males than females.

Next, interactions between class and other features are explored.

In [74]:
```
fig5, ax5 = plt.subplots(3,4)
categoricalx.remove('Pclass')
for i in range(len(categoricalx)):
    survivalgroup([categoricalx[i],'Pclass'],ax5[i//4,i%4])
survivalhist(df['Age'],['Pclass'],bins=np.linspace(0,80,21),ax=ax5[2,2])
survivalhist(df['Fare'],['Pclass'],bins=np.logspace(0.5,3,21),ax=ax5[2,3])
ax5[2,3].legend()
ax5[2,2].set_xlabel('Age')
ax5[2,3].set_xlabel('Fare')
fig5.set_size_inches(14,8)
fig5.tight_layout(pad=0.4,w_pad=0.5,h_pad=0.5)
categoricalx.insert(0,'Pclass')
```



First class passengers are generally on higher decks and paid higher fares, so the two effects are likely to be related. The interactions are not as clear for other factors.

Randomness of Dataset

To check if the data needs to be shuffled, the correlation between the index and continuous variables is calculated.

In [75]:
```
correlationlist = []
index = df.index.tolist()
for i in ['Survived','Pclass','Female','Age','SibSp','Parch','Fare']:
    variable = df.loc[:,i]
    correlationlist.append([i,np.corrcoef(index,variable)[0,1]])
print(correlationlist)
```

```
[['Survived', -0.005006660767066487], ['Pclass', -0.03514399403037977], ['Female',
-0.04293888007878875], ['Age', 0.03855082908941326], ['SibSp', -0.0575268337844415
1], ['Parch', -0.001652012402718835], ['Fare', 0.012658219287491225]]
```

There are no strong correlations, indicating that the data is not sorted by any of these factors and does not need to be randomized further.

Transformation

The distribution of fares suggests a log transformation is appropriate, especially if a linear model is to be used. Also, since the effect of fare is mainly for males, the interaction between gender and fare will be created as a new feature. Also, since the distribution of age appears to be bimodal, age will be split into child age and adult age. A function for these transformations is defined below.

In [76]:
```
def transform(dataframe,agethreshold):
    # Log scale the fare
    dataframe['Log Fare'] = np.log(dataframe['Fare'] + 1)
    # Split Age
    dataframe['Child'] = np.where(dataframe['Age'] <= agethreshold, 1, 0)
    dataframe['Child Age'] = dataframe['Child'] * dataframe['Age']
    dataframe['Adult Age'] = -1 * (1 - dataframe['Child']) * dataframe['Age']
    # Log Fare x Female
    dataframe['Fare x Female']=dataframe['Female']*dataframe['Log Fare']
```

Also, the features will be scaled so that algorithms involving distance calculations may be applied.

In [77]:
```
def rescale(dataframe):
    for x in ['Log Fare','Fare','Fare x Female', 'Age', 'Child Age', 'Adult Age', 'F
        dataframe[x] = 0.5 * dataframe[x]/combined[x].mean()
```

The transformations are applied, along with adding a column for constant (column of 1s) which is required for statsmodels GLM. The age threshold for children is set to 12 based on the histograms.

In [78]:
```
df['Constant']=1
test['Constant']=1

transform(df,12)
transform(test,12)
transform(combined,12)
rescale(df)
rescale(test)
```

Feature and Model Selection

A list of all the model features is defined below. GLM in statsmodels will require the constant feature.

In [79]:
```
features = ['Log Fare','1','2','Cherbourg','Queenstown','A','B','C','D','E','F','G',
            'EastEuropean', 'French', 'Germanic', 'Hispanic', 'Indian', 'Irish', 'It
            'Nordic','Female','Child','Child Age','Adult Age','Family Size','Distant

featuresGLM = ['Constant']+features
```

Some functions for evaluation of all models are defined below. The evaluations use 3 fold cross validation, based on the size of training and test data sets.

In [80]:
```
def testmodel(xlist, model,ROC=True):
    X = df[xlist]
    y = df['Survived']
    matrix = pd.concat([X, y], axis=1)
    model.fit(X, y)
    if ROC:
        yscores = model.predict(X)
        fpr, tpr, thresholds = sklearn.metrics.roc_curve(y, yscores)
    ypredict = model.predict(X)
    print('Accuracy: ' + str(sklearn.metrics.accuracy_score(y, ypredict)))
    print('Precision: ' + str(sklearn.metrics.precision_score(y, ypredict)))
    print('Recall: ' + str(sklearn.metrics.recall_score(y, ypredict)))
    if ROC:
        print('ROC AUC: ' + str(sklearn.metrics.roc_auc_score(y, yscores)))
    cvscore = sum(cross_val_score(model, X, y, cv=3)) / 3
    for i in range(9):
        shuffled = shuffle(matrix)
        X = shuffled[xlist]
        y = shuffled['Survived']
        cvscore += sum(cross_val_score(model, X, y, cv=3)) / 3
    cvscore = cvscore / 10
    print('CV score: ' + str(cvscore))
    if ROC:
        return fpr,tpr

def optimize(alg,xlist,griddict):
    X = df[xlist]
    y = df['Survived']
    grid = [griddict]
    model = alg
    clf = GridSearchCV(model,grid,cv=3)
    clf.fit(X,y)
    print(clf.best_params_)
    ypredict = clf.predict(X)
    print(sklearn.metrics.accuracy_score(y, ypredict))
    print(sklearn.metrics.recall_score(y, ypredict, average=None))
    print(sklearn.metrics.precision_score(y, ypredict, average=None))
```

Generalized Linear Model (Logistic Regression)

In [89]:
```
def logistic(xlist, featurereduction = False):
    # First check for statistical significance of features using statsmodels (unregu
    if featurereduction:
        X = df[featuresGLM]
        y = df['Survived']
        logisticmodel = sm.GLM(y, X, family=sm.families.Binomial())
        results = logisticmodel.fit()
        print(results.summary())
    # Use sklearn regularized Logistic regression on reduced feature set
    else:
        model = LogisticRegression(solver='liblinear')
        fpr,tpr = testmodel(xlist,model)
        fig6, ax6 = plt.subplots(1,2)
        ax6[0].bar(xlist, model.coef_[0])
        ax6[0].set_xticklabels(xlist, rotation=90)
        ax6[0].set_title('Coefficients')
        ax6[1].plot(fpr, tpr)
        ax6[1].set_title('ROC Curve')
        fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

In [84]:
```
logistic(featuresGLM, featurereduction= True)
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               Survived   No. Observations:                  891
Model:                            GLM   Df Residuals:                      858
Model Family:                Binomial   Df Model:                           32
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -348.90
Date:                Fri, 09 Aug 2019   Deviance:                       697.80
Time:                        18:12:05   Pearson chi2:                     986.
No. Iterations:                    19   Covariance Type:             nonrobust
==================================================================================
==
                       coef    std err          z      P>|z|      [0.025      0.97
5]
----------------------------------------------------------------------------------
--
Constant           -22.4060   1.77e+04     -0.001      0.999   -3.48e+04    3.47e+
04
Log Fare             1.8078      1.162      1.556      0.120      -0.469       4.0
85
1                    2.5077      0.653      3.843      0.000       1.229       3.7
87
2                    0.9229      0.333      2.771      0.006       0.270       1.5
76
Cherbourg            0.6222      0.312      1.997      0.046       0.012       1.2
33
Queenstown           0.0784      0.454      0.173      0.863      -0.811       0.9
68
A                   19.1576   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
B                   20.0056   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
C                   19.7004   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
D                   20.4455   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
E                   20.4493   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
F                   20.3066   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
G                   20.2950   1.77e+04      0.001      0.999   -3.47e+04    3.48e+
04
Nickname             1.3927      0.412      3.379      0.001       0.585       2.2
01
African              0.0574      1.263      0.045      0.964      -2.417       2.5
32
EastAsian            1.9697      0.832      2.368      0.018       0.339       3.6
00
EastEuropean         0.2064      0.510      0.405      0.686      -0.793       1.2
06
French              -0.2104      0.451     -0.466      0.641      -1.095       0.6
74
Germanic            -0.2060      0.587     -0.351      0.726      -1.356       0.9
44
Hispanic            -0.3525      0.597     -0.591      0.555      -1.522       0.8
```

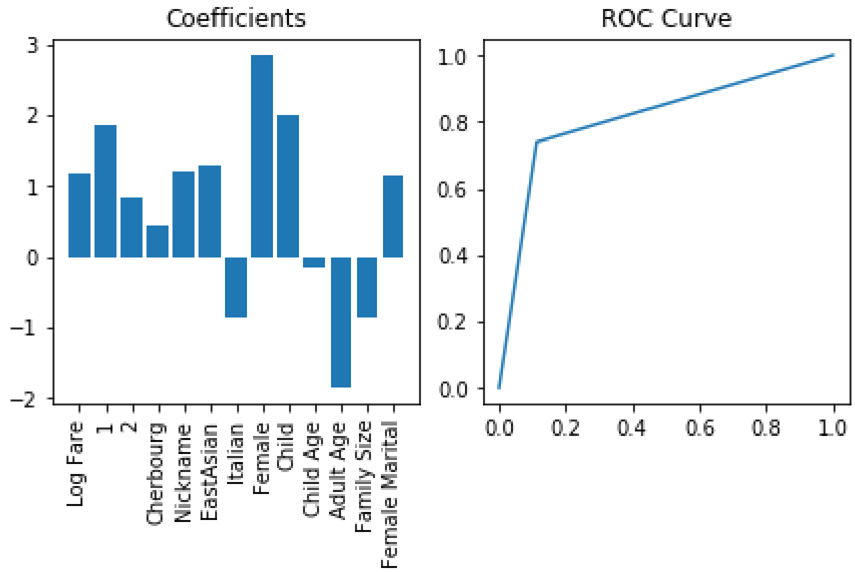
```
17
Indian                  -0.7232      0.947     -0.764      0.445      -2.580       1.1
33
Irish                    0.4974      0.385      1.292      0.196      -0.257       1.2
52
Italian                 -1.4658      0.644     -2.276      0.023      -2.728      -0.2
04
Jewish                   0.4404      0.401      1.098      0.272      -0.346       1.2
27
Muslim                   0.0762      0.589      0.129      0.897      -1.077       1.2
30
Nordic                   0.0060      0.400      0.015      0.988      -0.779       0.7
91
Female                   3.1962      0.245     13.030      0.000       2.715       3.6
77
Child                    3.0728      0.728      4.220      0.000       1.646       4.5
00
Child Age               -0.2573      0.089     -2.892      0.004      -0.432      -0.0
83
Adult Age               -2.3018      0.640     -3.598      0.000      -3.556      -1.0
48
Family Size             -1.1001      0.203     -5.418      0.000      -1.498      -0.7
02
Distant Relations        0.0232      0.080      0.289      0.772      -0.134       0.1
81
Female Marital           1.5866      0.386      4.116      0.000       0.831       2.3
42
==================================================================================
==
```

From the above results, the features can be reduced to the following list, based on accepting only features with $p < 0.05$.

In [85]:
```
reducedLR=['Log Fare','1','2','Cherbourg','Nickname','EastAsian','Italian',
            'Female','Child','Child Age','Adult Age','Family Size','Female Marital']
```

In [90]:
```
logistic(reducedLR, featurereduction= False)
```

```
Accuracy: 0.8305274971941639
Precision: 0.8031746031746032
Recall: 0.7397660818713451
ROC AUC: 0.8134167385677309
CV score: 0.8234567901234568
```



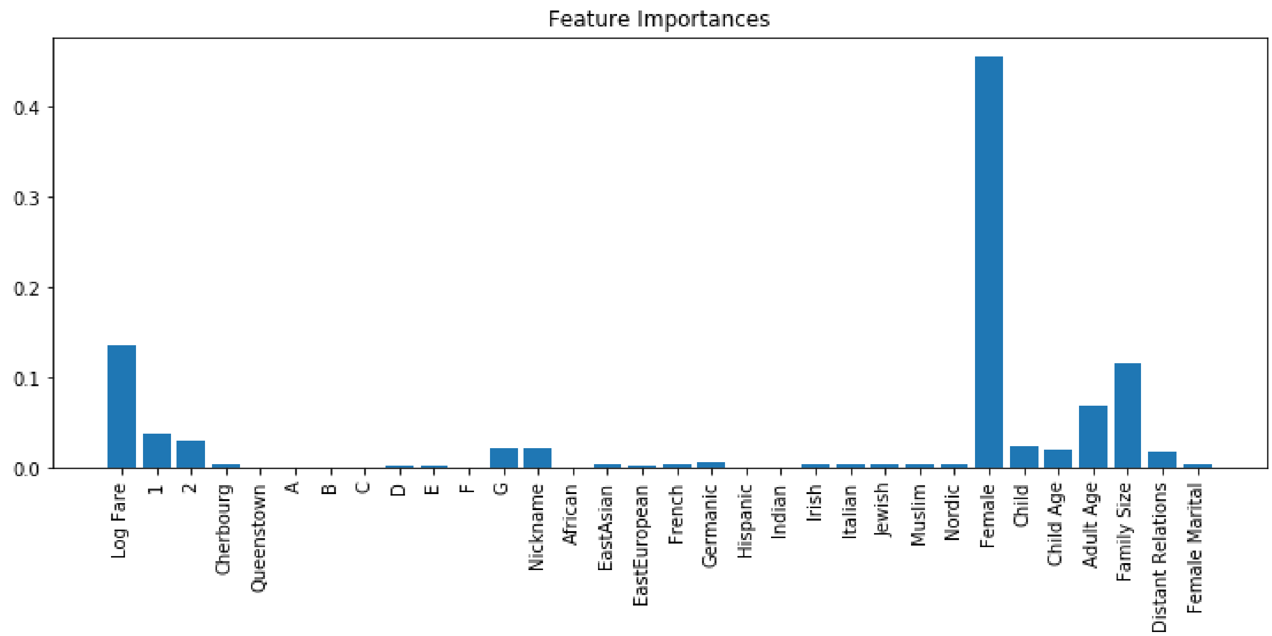
The CV score is similar to the overall accuracy, indicating that there is not much overfitting.

Gradient Boosted Tree

Features will be selected based on the feature importances from the full model using default hyperparameters.

In [108]:
```
model = GradientBoostingClassifier()
fpr,tpr = testmodel(features,model)
fig6, ax6 = plt.subplots(1)
ax6.bar(features, model.feature_importances_)
ax6.set_xticklabels(features, rotation=90)
ax6.set_title('Feature Importances')
fig6.set_size_inches((10,5))
fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

```
Accuracy: 0.898989898989899
Precision: 0.9064516129032258
Recall: 0.8216374269005848
ROC AUC: 0.8844070558910938
CV score: 0.8195286195286196
```



Based on the importances, the following features are selected.

In [109]:
```
reducedGB = ['Log Fare','1','2','G','Nickname','Female','Child','Child Age','Adult A
             'Family Size','Distant Relations']
```

This algorithm has a few hyperparameters that must be tuned.

In [118]:
```
model = GradientBoostingClassifier()
optimize(model, reducedGB, {'learning_rate':[0.01, 0.02, 0.05, 0.1, 0.2, 0.5],
                            'n_estimators':[10,20,50,100]})
```

```
{'learning_rate': 0.1, 'n_estimators': 20}
0.8507295173961841
[0.91256831 0.75146199]
[0.85494881 0.84262295]
```

In [124]:
```
model = GradientBoostingClassifier(learning_rate=0.1, n_estimators =20)
optimize(model, reducedGB, {'max_features':['log2','sqrt'],
                            'max_depth':[2, 3, 4, 5, 7, 10],
                            'min_samples_leaf':[2, 3, 4, 5, 7, 10]})
```

```
{'max_depth': 5, 'max_features': 'sqrt', 'min_samples_leaf': 3}
0.8731762065095399
[0.94717668 0.75438596]
[0.86092715 0.8989547 ]
```

In [125]:
```
model = GradientBoostingClassifier(learning_rate=0.1, n_estimators =20, max_features
                                  max_depth = 5, min_samples_leaf = 3)
optimize(model, reducedGB, {'subsample':[0.5, 0.6, 0.7, 0.8, 0.9, 1]})
```

```
{'subsample': 1}
0.8720538720538721
[0.93260474 0.7748538 ]
[0.86926995 0.87748344]
```

In [127]:
```
model = GradientBoostingClassifier(max_features='sqrt',max_depth = 5, min_samples_le
                                   subsample=1)
optimize(model, reducedGB, {'learning_rate':[0.01, 0.02, 0.05, 0.1, 0.2, 0.5],
                            'n_estimators':[10,20,50,100]})
```

```
{'learning_rate': 0.1, 'n_estimators': 100}
0.9180695847362514
[0.96357013 0.84502924]
[0.90893471 0.93527508]
```

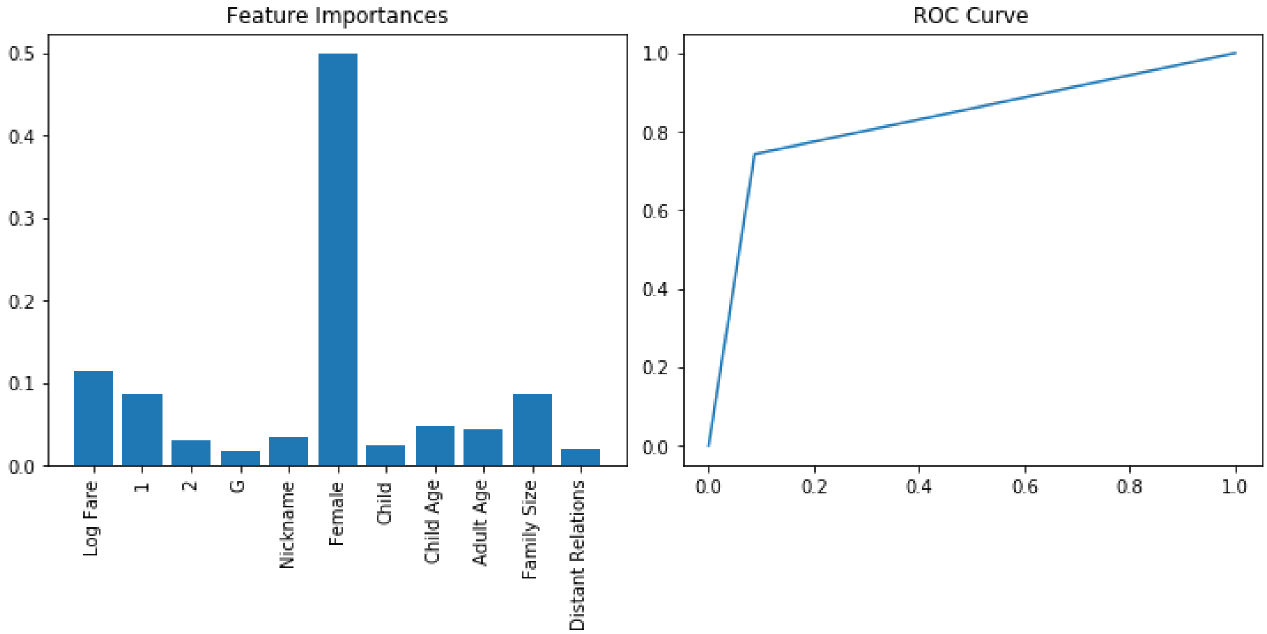
In [133]:
```
model = GradientBoostingClassifier(learning_rate=0.1, n_estimators =100,
                                   max_features='sqrt',subsample=1)
optimize(model, reducedGB, {'max_depth':[2, 3, 4, 5, 7, 10],
                            'min_samples_leaf':[2, 3, 4, 5, 7, 10]})
```

```
{'max_depth': 3, 'min_samples_leaf': 4}
0.8742985409652076
[0.92531876 0.79239766]
[0.87737478 0.86858974]
```

In [100]:
```
def treeboost(xlist):
    model = GradientBoostingClassifier(learning_rate=0.1,n_estimators=100, max_depth
                                       min_samples_leaf=4, max_features='sqrt', subs
    fpr,tpr = testmodel(xlist,model)
    fig6, ax6 = plt.subplots(1,2)
    ax6[0].bar(xlist, model.feature_importances_)
    ax6[0].set_xticklabels(xlist, rotation=90)
    ax6[0].set_title('Feature Importances')
    ax6[1].plot(fpr,tpr)
    ax6[1].set_title('ROC Curve')
    fig6.set_size_inches((10,5))
    fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

In [134]:
```
treeboost(reducedGB)
```

```
Accuracy: 0.8473625140291807
Precision: 0.8410596026490066
Recall: 0.7426900584795322
ROC AUC: 0.8276291822452306
CV score: 0.8307519640852975
```



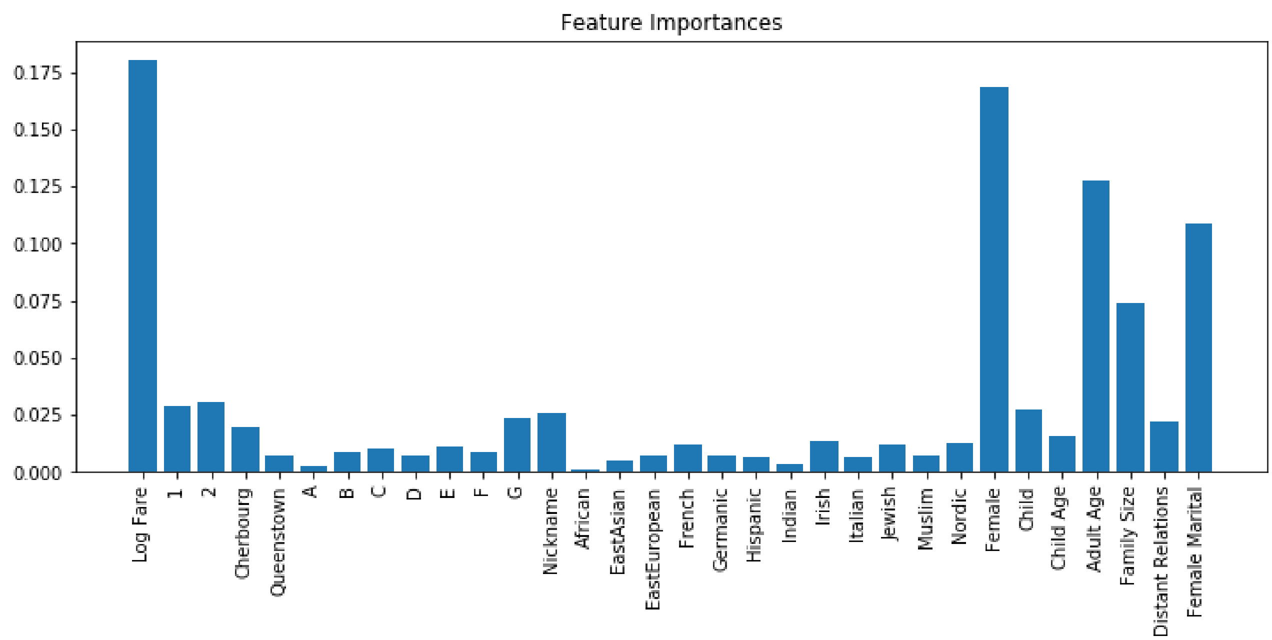
The CV result is similar to overall accuracy, so there is not much overfitting.

Random Forest

Feature selection:

In [139]:
```
model = RandomForestClassifier()
testmodel(features, model,ROC=False)
fig6, ax6 = plt.subplots(1)
ax6.bar(features, model.feature_importances_)
ax6.set_xticklabels(features, rotation=90)
ax6.set_title('Feature Importances')
fig6.set_size_inches((10,5))
fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

```
C:\Users\Nolan\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:246: FutureWa
rning: The default value of n_estimators will change from 10 in version 0.20 to 100
in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)

Accuracy: 0.9775533108866442
Precision: 0.9908536585365854
Recall: 0.9502923976608187
CV score: 0.8023569023569023
```



The reduced feature set is as follows.

In [140]:
```
reducedRF =['Log Fare','1','2','G','Cherbourg','Nickname','Female','Child','Child Ag
             'Adult Age','Family Size','Distant Relations','Female Marital']
```

Optimizing hyperparameters:

In [141]:
```
model = RandomForestClassifier()
optimize(model, reducedRF, {'max_depth':[2,3,5,10],'n_estimators':[20,50,70,100]})
```

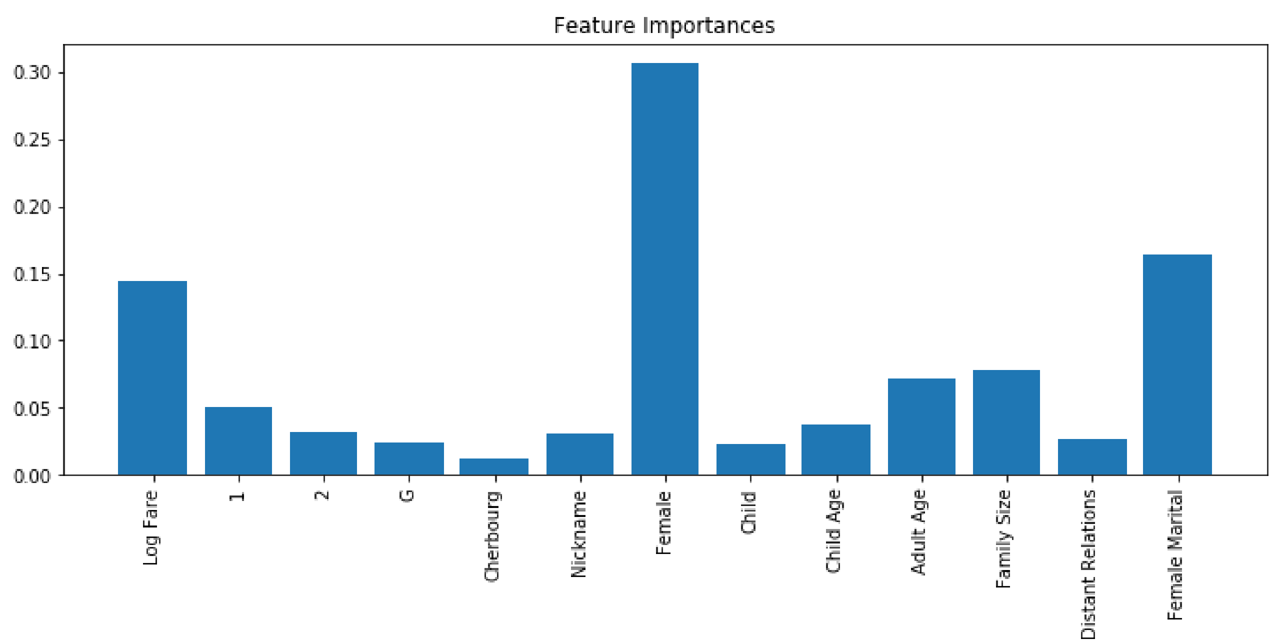
```
{'max_depth': 5, 'n_estimators': 50}
0.8507295173961841
[0.91256831 0.75146199]
[0.85494881 0.84262295]
```

In [148]:
```
model = RandomForestClassifier()
optimize(model, reducedRF, {'max_depth':[4,5,6,7],'n_estimators':[40, 40, 50, 60, 70
```

```
{'max_depth': 6, 'n_estimators': 60}
0.8641975308641975
[0.92531876 0.76608187]
[0.86394558 0.86468647]
```

In [151]:
```
model = RandomForestClassifier(n_estimators=60,max_depth=6)
testmodel(reducedRF, model,ROC=False)
fig6, ax6 = plt.subplots(1)
ax6.bar(reducedRF, model.feature_importances_)
ax6.set_xticklabels(reducedRF, rotation=90)
ax6.set_title('Feature Importances')
fig6.set_size_inches((10,5))
fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

```
Accuracy: 0.8653198653198653
Precision: 0.875
Recall: 0.7573099415204678
CV score: 0.831986531986532
```



The overall accuracy is a bit higher than the CV score, which indicates some overfitting. But the CV score is still the highest observed so far.

Support Vector Machine

For the rest of the models, the reduced feature lists from the logistic regression, boosted tree, and random forest will be combined.

In [154]:
```
reducedgeneral = list(set(reducedRF+reducedLR+reducedRF))
print(reducedgeneral)
```

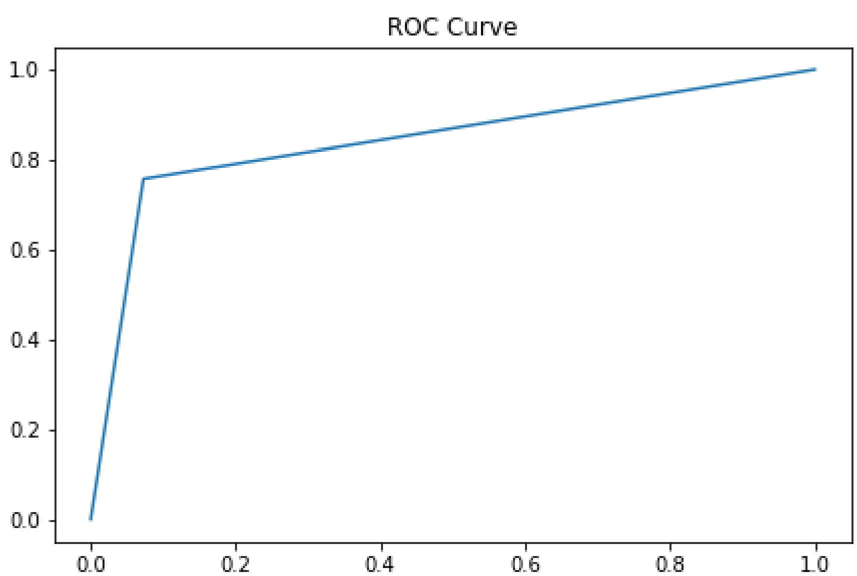
```
['1', 'Child Age', 'Nickname', 'EastAsian', 'Female Marital', 'Family Size', 'Femal
e', 'Log Fare', 'G', 'Distant Relations', 'Italian', 'Adult Age', 'Cherbourg', 'Chi
ld', '2']
```

In [159]:
```
model = sklearn.svm.SVC()
optimize(model, reducedgeneral, {'gamma':[0.001, 0.01, 0.1, 1],'C':[1, 10, 100],'ker
```

```
{'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
0.8619528619528619
[0.92714026 0.75730994]
[0.8597973  0.86622074]
```

In [162]:
```
model = svm.SVC(kernel='rbf',gamma=0.1,C=10)
fpr,tpr = testmodel(reducedgeneral,model)
fig6, ax6 = plt.subplots(1)
ax6.plot(fpr,tpr)
ax6.set_title('ROC Curve')
fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

```
Accuracy: 0.8619528619528619
Precision: 0.8662207357859532
Recall: 0.7573099415204678
ROC AUC: 0.8422250982647876
CV score: 0.8252525252525252
```



Once again, a little overfitting is observed.

k Nearest Neighbors

In [164]:
```
model = KNeighborsClassifier()
optimize(model, reducedgeneral, {'n_neighbors':[5,7,10,12,15]})
```

```
{'n_neighbors': 12}
0.8237934904601572
[0.9143898  0.67836257]
[0.82026144 0.83154122]
```

In [170]:
```
optimize(model, reducedgeneral, {'n_neighbors':[6,7,8,9,10,11,12,13,14,15]})
```

```
{'n_neighbors': 8}
0.8428731762065096
[0.93624772 0.69298246]
[0.83037157 0.87132353]
```

In [180]:
```
model = KNeighborsClassifier(n_neighbors=8)
testmodel(reducedgeneral,model,ROC=False)
```

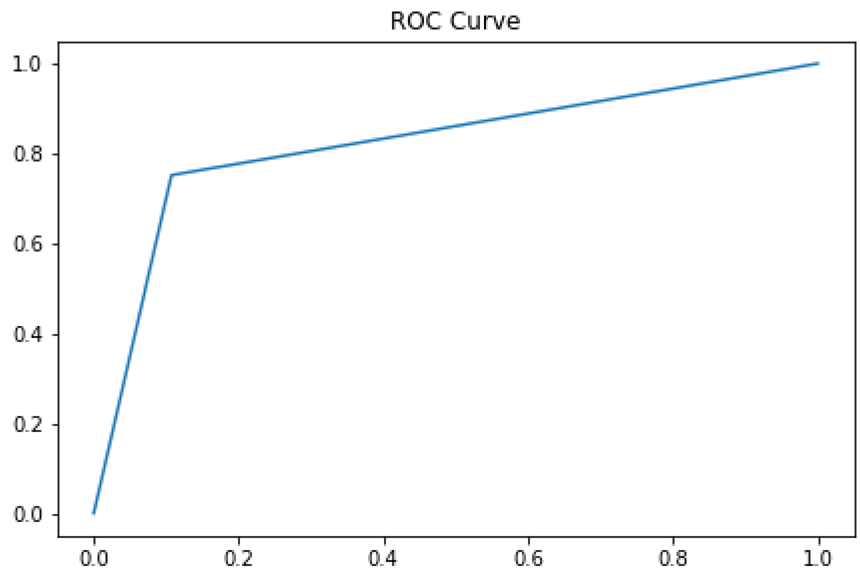
```
Accuracy: 0.8428731762065096
Precision: 0.8713235294117647
Recall: 0.6929824561403509
CV score: 0.8014590347923681
```

Overfitting is observed again, which is expected for this algorithm, since it relies on local data rather than the entire set.

Linear Discriminant Analysis

In [184]:
```
model = sklearn.discriminant_analysis.LinearDiscriminantAnalysis()
fpr, tpr = testmodel(reducedgeneral, model)
fig6, ax6 = plt.subplots(1)
ax6.plot(fpr, tpr)
ax6.set_title('ROC Curve')
fig6.tight_layout(pad=0.4, w_pad=0.5, h_pad=0.5)
```

```
Accuracy: 0.8383838383838383
Precision: 0.8132911392405063
Recall: 0.7514619883040936
ROC AUC: 0.8219969322212636
CV score: 0.8228956228956228
```



There is not much overfitting with LDA, but accuracy is poor in general. The model may be too simple.

Gaussian Naive Bayes

In [185]:
```
model = GaussianNB()
testmodel(reducedgeneral, model,ROC=False)
```

```
Accuracy: 0.8013468013468014
Precision: 0.7350427350427351
Recall: 0.7543859649122807
CV score: 0.7891133557800225
```

The overfitting is minimal for Naive Bayes as well, but the accuracy is the worst of all the algorithms, possibly because the assumption of independence of features does not hold.

Prediction

Most of the models performed similarly except for kNN and Naive Bayes, which were a few percentage points lower in terms of cross validation. The best performing model in terms of overall accuracy and cross validation accuracy was the random forest model. Therefore this model is used to make the final predictions.

In [187]:
```
model = RandomForestClassifier(n_estimators=60,max_depth=6)
testmodel(reducedRF,model)
test['Survived']=model.predict(test[reducedRF])
test.head(20)
```

```
Accuracy: 0.8641975308641975
Precision: 0.867109634551495
Recall: 0.7631578947368421
ROC AUC: 0.8451490748729747
CV score: 0.8301907968574636
```

Out[187]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	..
0	892	0	3	Kelly, James	male	0.577287	0	0	330911	0.117625	..
1	893	1	3	Wilkes, James	female	0.786449	1	0	363272	0.105168	..
2	894	0	2	Myles, Thomas Francis	male	1.037444	0	0	240276	0.145544	..
3	895	0	3	Wirz, Albert	male	0.451790	0	0	315154	0.130145	..
4	896	1	3	Hirvonen, Alexander	female	0.368125	1	1	3101298	0.184607	..
5	897	0	3	Svensson, Johan Cervin	male	0.234261	0	0	7538	0.138596	..
6	898	1	3	Connolly, Kate	female	0.501989	0	0	330972	0.114621	..
7	899	0	2	Caldwell, Albert Francis	male	0.435057	1	1	248738	0.435694	..
8	900	1	3	Abrahim, Joseph	female	0.301193	0	0	2657	0.108611	..
9	901	0	3	Davies, John Samuel	male	0.351392	2	0	A/4 48871	0.362828	..
10	902	0	3	Ilieff, Ylio	male	0.475040	0	0	349220	0.118626	..
11	903	0	1	Jones, Charles Cresson	male	0.769716	0	0	694	0.390623	..
12	904	1	1	Snyder, John Pillsbury	female	0.384858	1	0	21228	1.235970	..
13	905	0	2	Howard, Benjamin	male	1.054177	1	0	24065	0.390623	..
14	906	1	1	Chaffee, Herbert Fuller	female	0.786449	1	0	W.E.P. 5734	0.919090	..
15	907	1	2	del Carlo, Sebastiano	female	0.401591	1	0	SC/PARIS 2167	0.416476	..

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	...
16	908	0	2	Keane, Daniel	male	0.585654	0	0	233734	0.185546	...
17	909	0	3	Assaf, Gerios	male	0.351392	0	0	2692	0.108548	...
18	910	1	3	Ilmakangas, Ida Livija	female	0.451790	1	0	STON/O2. 3101270	0.119065	...
19	911	1	3	Assaf Khalil, Mariana	female	0.752983	0	0	2696	0.108548	...

20 rows × 89 columns