Intro to Data Analysis Project: Investigate a Dataset

Titanic Data

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Background:

The data I will be analyzing is the Kaggle "Titanic: Machine Learning from Disaster" training set. This data describes the passengers travelling on the Titanic when it sunk. Let us load the data and take a quick look at it.

In [533]:
```
# Load the Data and get familiar with it
# Source: https://www.kaggle.com/c/titanic/data
# Refer to the Kaggle website for Variable Descriptions
# Note that for this Udacity project, the train.csv data is used and has been renamed 'titanic-data.csv'

import pandas as pd
import numpy as np
from pandas import DataFrame, Series
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

data = pd.read_csv('titanic-data.csv')
data.head()
```

Out[533]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

The Kaggle website (https://www.kaggle.com/c/titanic/data) for this data has excellent descriptions of variables in this data so I will not go into great detail about what each variable is. This data which lists a sample of the ship population could be used to estimate and describe the rest of the ship population. If I had additional data, I could describe this sample in terms of world or national populations at the time and compare Titanic passengers to the population that stayed on land during the ship's voyage. Instead I shall take inspiration from the Kaggle competition that tried to predict which passengers survived and which perished and examine which variables correlated with survival the most. Therefore, the dependent variable which will be studied in detail is 'Survived' which is an integer where a value of 0 means the passenger perished and a value of 1 means the passenger survived.

Questions:

Is the expression "Women and Children First" reflected in the rates of survival for these two groups in our data set? If the lifeboat boarding priority does follow this protocol, then women and children would survive at a higher rate than the other lifeboat boarding group: men. Is the data consistent with behavior of the men aboard the ship offering lifeboats seats to women and children first?

Does the captain go down with the ship?

Both questions could be nautical cliches steeped in some sort of romanticism about ship disasters and courageous ways to die at sea. Investigating whether survival correlated with these expressions should help gain insight to what kind of passengers survived the Titanic disaster.

Additionally, are there other variables that could have significantly affected survival rates in the lifeboat boarding groups?

Workflow stages

1. Acquire the data
2. Analyze, explore, and identify patterns in the data
3. Seperate passengers into boarding groups Women, Children, and Men and compare survival
4. Examine other variables and how they could possibly affect the "Women and Children First" protocol

1. Acquire the data

The data has been loaded and previewed above. We can see that each row corresponds to a passenger.

In [534]:
```
# Display summary statistics quickly
data.describe()
```

Out[534]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Applying the **describe** function tells us that there are 891 passengers in the sample set. About 38% of the passengers survived. The average age of the sample is 29.7 years old, and the median age is 28. There are also 177 passengers that have null values values for their ages which must be addressed in order to categorize them as children or not.

The describe function also hints that not all the variables are numerical. It only summarizes variables that are numerical so there are fewer columns listed than in a complete dataframe. The 'Name', 'Sex', 'Ticket', 'Cabin', and 'Embarked' variables seem to be strings. I can confirm this with the **info** function:

In [535]:
```
# Describe the DataFrame
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

Not all of the columns are numerical. Not all rows contain entries for certain columns, 'Age', 'Cabin', or 'Embarked'. This tells us which non-numerical data should be converted and null data substituted for.

In [536]:
```
# Categorical Data Summary
data.describe(include=['O'])
```

Out[536]:

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	Watson, Mr. Ennis Hastings	male	347082	G6	S
freq	1	577	7	4	644

The number of rows in the data frame is equal to the number of unique names in the 'Name' column. This makes the 'Name' column difficult to categorize.

The 'Sex' columm will be very easy to categorize.

There are fewer unique entries in the 'Ticket' column, I assumes this means a family or a group shared a ticket. The ticket with the most passengers was associated with 7 people.

Only 204 people stayed in cabins. The most people in a cabin was four.

2. Analyze, Explore, Identify Patterns in Data

The easiest way to find correlations in the data is to simply use the **corr** function. This requires converting some of the features into numerical features. Generally I will continue using the convention of the 'Survived' variable which is essentially a boolean variable represented as the integers 0 and 1. New variables 'Female', and 'Male' will be created from the 'Sex' column. Variables 'Pc1', 'Pc2', and 'Pc3' will represent the passenger class variable 'Pclass' and its three uniquee values: 1, 2, and 3. Variables 'Emb_C', 'Emb_Q', and 'Emb_S' will represent the 'Embarked' column and the embarkation ports of Cherbourg, Queenstown, and Southampton respectively.

In [537]:
```
# Convert variables into integers
# To improve code, used dictionaries

# Create new boolean variables for sex
data['Female'] = (data['Sex']=='female').astype(int)
data['Male'] = (data['Sex']=='male').astype(int)

# Create new boolean variables for passenger class
data['Pc1'] = (data['Pclass']==1).astype(int)
data['Pc2'] = (data['Pclass']==2).astype(int)
data['Pc3'] = (data['Pclass']==3).astype(int)

# Create new numerical variables to describe embarkation ports
data['Emb_C'] = (data['Embarked']=='C').astype(int)
data['Emb_Q'] = (data['Embarked']=='Q').astype(int)
data['Emb_S'] = (data['Embarked']=='S').astype(int)
```

Now apply the **corr** function in terms of 'Survived':

In [538]:
```
(data.corr().Survived).sort_values(ascending= False)
```

Out[538]:
```
Survived       1.000000
Female         0.543351
Pc1            0.285904
Fare           0.257307
Emb_C          0.168240
Pc2            0.093349
Parch          0.081629
Emb_Q          0.003650
PassengerId   -0.005007
SibSp         -0.035322
Age           -0.077221
Emb_S         -0.155660
Pc3           -0.322308
Pclass        -0.338481
Male          -0.543351
Name: Survived, dtype: float64
```

The variable that correlated most positively to survival is 'Female'. The most negatively correlated was 'Male'. Clearly 'Sex' correlates well with 'Survival'. This makes it seem very likely that women were given preferential lifeboat boarding along with female children. The negative correlation of being male could mean that both men and male children were refused entry on lifeboats. I can't say for sure at this point whether both female and male children boarded lifeboats at different rate than the adults. This relationship will be studied in further detail.

The correlation between 'Age' and 'Survival' does not appear to be very strong but it is negatively correlated which means older people had lower rates of survival. This could indicate that children had a better chance of survival but more analysis is necessary.

The variable with the next highest magnitude after those related to gender is 'Pclass' which describes passengers as either 1, 2, or 3. What this means is that the 'Pclass' is negatively correlated with passenger class. The higher the number of your class, the less likely you will survive. This can be confusing because first class passengers are considered upper class and third class, lower class. Though there does seem to be a strong linear correlation between 'Pclass' and 'Survival', I think a linear correlation is inappropriate for describing what are just three datapoints on the 'Pclass' vs. 'Survival' curve. The 'Pclass' variable should still be treated as a categorical variable. Splitting up 'Pclass' into three boolean variables as I have done should make this clearer.

Among the variables describing each passenger class, 'Pc3' is most negatively correlated with 'Survival' and 'Pc1' is most positively correlated. 'Pc2' is also positively correlated with survival but to a lesser degree. The magnitudes of 'Pc3' and 'Pc1' correlations demand further analysis.

Next up, 'Fare' positively correlates with survival. This means that the more you paid for your ticket, the greater you likelihood for survival. I suspect however, that 'Fare' correlates strongly with 'Pclass'. I'll study this relationship further.

3. Differentiate groups of passengers and compare their survival rates

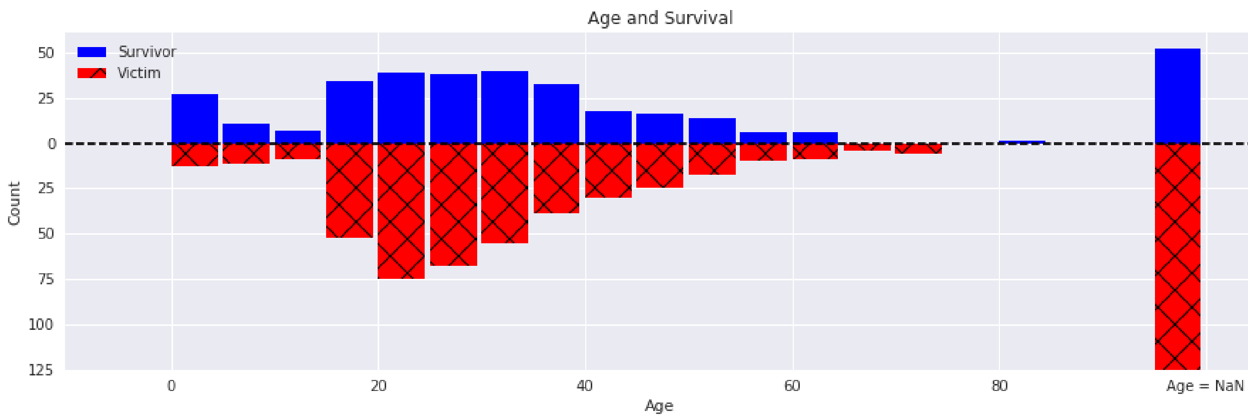
Age and Survival

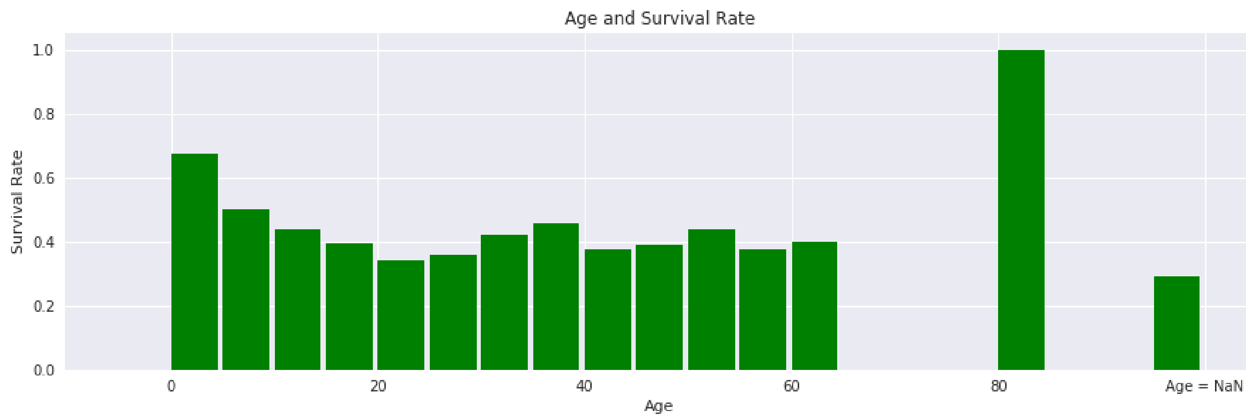
Let us quickly examine 'Age' and 'Survival' in a histogram. Please note that the passengers for whom 'Age' was NaN are grouped in the far right bin. The oldest passenger with a verified age was 80-years-old.

In [539]:

```
# Plot a frequency histogram with survivors and victims grouped by age
# Use the fillna function to differentiate those whose ages are NaN
# Set NaN to 100 which is much greater than max('Age') = 80

nan_sub = 100
survivors_age = data[data.Survived == True].Age.fillna(nan_sub)
victims_age = data[data.Survived == False].Age.fillna(nan_sub)


bin_width = 5
lower_bound = -5
upper_bound = 105
bar_width = 4.5
survivor_color = 'b'
victim_color = 'r'
rate_color = 'g'

bins = np.arange(lower_bound, upper_bound, bin_width)
index = bins[0:-1]

fig, (ax1, ax2) = plt.subplots(2,1, figsize = (15,10))
ax1.bar(index + 0.5*bar_width, np.histogram(survivors_age, bins)[0],
       color = survivor_color, width = bar_width)
ax1.bar(index + 0.5*bar_width, np.histogram(victims_age, bins)[0]*-1,
        color = victim_color, width = bar_width, hatch = 'x')

ax1.set_ylabel('Count')
ax1.set_xlabel('Age')
ax1.set_title('Age and Survival')
ax1.legend(['Survivor', 'Victim'])
ax1.axhline(0, color = 'k', linestyle = '--')
ax1.set_xticklabels(['',0, 20, 40, 60, 80, 'Age = NaN'])
ticks =  ax1.get_yticks()
ax1.set_yticklabels([int(abs(tick)) for tick in ticks])

# Plot Age vs. Survival rate

nan_sub = 100
survivors_age = data[data.Survived == True].Age.fillna(nan_sub)
all_age = data.Age.fillna(nan_sub)
age_rate = np.nan_to_num(np.histogram(survivors_age,bins)[0]/np.histogram(all_age,bins)[0])


ax2.bar(index+0.5*bar_width, age_rate,
        color = rate_color, width = bar_width)


ax2.set_ylabel('Survival Rate')
ax2.set_xlabel('Age')
ax2.set_title('Age and Survival Rate')
ax2.set_xticklabels(['',0, 20, 40, 60, 80, 'Age = NaN'])
plt.subplots_adjust(hspace = 0.3)
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/ipykernel/__main__.py:41: RuntimeWarning: invalid value
encountered in true_divide
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont:
Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```





This histogram suggest that chidren, especially those 5-years and younger, had better rates of survival than most of the sample. It also suggest that children travelled at a lower rate than adults since there is a discontinuity in the age distribution at around 15 years and younger. If the sample reflected the general human population, the age of passengers should be gradually decreasing as people age and die. This age discontinuity is also a threshold where passengers who were younger survived at higher rates than the rest of the sample. Though this initially suggests that children had a higher survival rate, the age cutoff for children will have to be explicitly definined in order to continue our analysis.

The histogram also shows that those for whom 'Age' is NaN are a significant portion of our sample and they also have the lowest likelihood of survival. Often missing values like this are filled in with a median or mean value from the rest of the sample but this would be reckless if our goal is to seperate adults and children. A mean or median substitution for 'Age' equal to NaN would group them all as adults. Alternatively, one could assign a random age to these passengers that reflects the age distribution of the rest of the sample but this could also be misleading.

I propose examining the sample closely to find some sort of other way of seperating the samples into children and adults. For now, I will assume that children are 18-years-old or younger.

In [540]:
```
# Explore passengers presume to be children
age_cutoff = 18
data[data.Age<age_cutoff].head()
```

Out[540]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Female	Male
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0	1
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1	0
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1	0
14	15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14.0	0	0	350406	7.8542	NaN	S	1	0
16	17	0	3	Rice, Master. Eugene	male	2.0	4	1	382652	29.1250	NaN	Q	0	1

In [541]:
```
# Explore passengers presumed to be adults
data[data.Age>=age_cutoff].head()
```

Out[541]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Female	Male
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1	0
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1	0
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1	0
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0	1

In [542]:
```
# Explore passengers whose 'Age' is NaN
data[data.Age.isnull()].head()
```

Out[542]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Female	Mal
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0	1
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	NaN	S	0	1
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	NaN	C	1	0
26	27	0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250	NaN	C	0	1
28	29	1	3	O'Dwyer, Miss. Ellen "Nellie"	female	NaN	0	0	330959	7.8792	NaN	Q	1	0

Children tend to have the titles of "Master", and "Miss". I would also pressume that any female with the title of "Mrs" to be married and considered an adult, though they seemed to get married a lot younger back then. The sample contains a few passengers with the 'Title' of "Mr" and "Mrs" who are less than 18 years old. Anyways, extracting titles from the 'Name' variable seems like a promising avenue to distinguish adults and children. A new variable 'Title' shall be created.

In [543]:
```
# Create a new variable 'Title'
# extract the string that preceeds a "."
# Quickly confirm that the operation was performed properly
import re
regex = re.compile('([A-Za-z]+)\.')
data['Title'] = data.Name.str.extract(regex, expand = True)
data['Title'].describe()
```

Out[543]:
```
count     891
unique     17
top        Mr
freq      517
Name: Title, dtype: object
```

Fortunately for us, every passenger in our sample has a title. Let us compare 'Title' to 'Sex' and get an idea of what was produced.

In [544]:
```
# Compare 'Title' and 'Sex'
data.pivot_table('Name', index = 'Title', columns = ['Sex'], aggfunc =('count')).fillna(0)
```

Out[544]:

Sex	female	male
Title		
Capt	0.0	1.0
Col	0.0	2.0
Countess	1.0	0.0
Don	0.0	1.0
Dr	1.0	6.0
Jonkheer	0.0	1.0
Lady	1.0	0.0
Major	0.0	2.0
Master	0.0	40.0
Miss	182.0	0.0
Mlle	2.0	0.0
Mme	1.0	0.0
Mr	0.0	517.0
Mrs	125.0	0.0
Ms	1.0	0.0
Rev	0.0	6.0
Sir	0.0	1.0

Survival of Captain

Now that each passenger has a title, we can determine if "The captain goes down with the ship".

In [545]:
```
data[data.Title == 'Capt']
```

Out[545]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	...	Embarked	Female	Male	Pc1	Pc2	P
745	746	0	1	Crosby, Capt. Edward Gifford	male	70.0	1	1	WE/P 5735	71.0	...	S	0	1	1	0	0

1 rows × 21 columns

It appears he did, but I advise caution when making conclusions about one sample.

Create Boarding Groups

I will create the new variables 'Child', 'Man', and 'Woman' which I will refer to as boarding groups. The 'Child' variable with be true if the passenger is less than 18-years-old. The 'Man' and 'Woman' variables with be true if the passenger is 18 years and older along and their 'Sex' corresponds to what is considered a man or woman.

In [546]:
```
# Define Child and Adult status by age
age_cutoff = 18
data['Child'] = (data.Age < age_cutoff).astype(int)
data['Woman'] = (data[data.Sex=='female'].Age>=age_cutoff).astype(int)
data['Man'] = (data[data.Sex=='male'].Age>=age_cutoff).astype(int)
data['Woman'] = (data['Woman']).fillna(0)
data['Man'] = (data['Man']).fillna(0)
```

In [547]:
```
# How much of the sample has been categorized?
data['Child'].sum()+data['Woman'].sum()+data['Man'].sum()
```
Out[547]: 714.0

In [548]:
```
data.Age.isnull().sum()
```
Out[548]: 177

177 passengers have 'Age' == to NaN. Now I will try to use the 'Title' variable to determine a boarding group for passengers whose 'Age' is NaN. All those with the 'Title' "Mrs" will be classified as 'Woman', those with "Mr", as 'Man', and those with "Master" as 'Child'. Already, there have been some passengers whose 'Title' was either "Mr" or "Mrs" who have been classified as children because of their age. They will not be reclassified, their 'Age' will take precedence in this categorization.

In [549]:
```
mask_m = (data.Age.isnull()) & (data.Title == 'Mr')
mask_w = (data.Age.isnull()) & (data.Title == 'Mrs')
mask_c = (data.Age.isnull()) & (data.Title =='Master')
data.loc[mask_m,'Man'] = 1
data.loc[mask_w, 'Woman'] =1
data.loc[mask_c, 'Child'] = 1

# How much of the sample has been categorized?
data['Child'].sum()+data['Woman'].sum()+data['Man'].sum()
```
Out[549]: 854.0

140 of the 'Age' == NaN have been categorized using the 'Title' variable. Is there any more categorization that can be performed on the 'Title' variable? What titles remain to be categorized?

In [550]:
```
# What unique titles remain in our group of uncategorized passengers?
data[data.Man ==0].loc[data.Woman ==0].loc[data.Child==0].Title.unique()
```
Out[550]: array(['Miss', 'Dr'], dtype=object)

As expected, 'Miss' is among the uncategorized since they could be children or unmarried women. Passengers whose 'Title' is 'Dr' are most likely an adults. More generally, let us categorize anyone who doesn't have the 'Title' of 'Miss' as adults.

In [551]:
```
# Categorize those without the 'Title' 'Miss' as adults, either 'Man' or 'Woman'

mask_m = ((data.Man == 0) & (data.Woman == 0) & (data.Child == 0) & (data.Title != 'Miss')
          & (data.Sex == 'male'))
mask_w = ((data.Man == 0) & (data.Woman == 0) & (data.Child == 0) & (data.Title != 'Miss')
          & (data.Sex == 'female'))
data.loc[mask_m, 'Man'] = 1
data.loc[mask_w, 'Woman'] =1

# How much of the sample has been categorized?
data['Child'].sum()+data['Woman'].sum()+data['Man'].sum()
```
Out[551]: 855.0

Now all that remain uncategorized are females with the 'Title' of "Miss". Assuming all are unwed, if 'SibSp' is greater than 0, that means they have siblings aboard. It is possible for adult siblings to be travelling together, but I am going to assume this is unlikely and assert that if 'SibSp' is not 0, then the passenger is a child. Also along that line of reasoning, if 'Parch' is not 0, then the passenger has a parent aboard or has a child. This could occur among adults and unwed mothers, but I am again going to assume this is unlikely and categorize these passengers as children.

In [552]:
```
# Categorize 'Miss' passengers who have SibSp or Parch greater than 0 as children
mask_c = (data.Child ==0) & (data.Woman ==0) & (data.Man ==0) & (data.SibSp > 0)
data.loc[mask_c, 'Child'] =1
mask_c = (data.Child ==0) & (data.Woman ==0) & (data.Man ==0) & (data.Parch > 0)
data.loc[mask_c, 'Child'] =1

# How much of the sample has been categorized?
data['Child'].sum()+data['Woman'].sum()+data['Man'].sum()
```
Out[552]: 869.0

Now we are left with 22 passengers out of the original 177 passengers whose 'Age' was NaN. They all have the 'Title' of "Miss". They can all be characterized as travelling solo. How do we decide whether they are 'Woman' or 'Child'? Travelling solo doesn't seem like something a child should do so can we make an assumption about where to place these solo females?

In [553]:
```
# Are women with the 'Title' "Miss" more likely to travel solo than children with 'Title' of "Miss"
miss_child = data[data.Child == 1].loc[data.Title == 'Miss'].PassengerId.count()
# 65 children with Title Miss
solo_miss_child = (data[data.Child == 1].loc[data.Title == 'Miss'].loc[data.SibSp == 0]
                   .loc[data.Parch ==0].PassengerId.count())
# 11 of them are travelling solo most are teenagers, one is 5 years old.

miss_woman = data[data.Woman == 1].loc[data.Title == 'Miss'].PassengerId.count()
# 95 Women with the Title Miss
solo_miss_woman = (data[data.Woman == 1].loc[data.Title == 'Miss'].loc[data.SibSp == 0]
                   .loc[data.Parch ==0].PassengerId.count())
# 67 are travelling solo
(solo_miss_woman/miss_woman)/(solo_miss_child/miss_child)
# Women with title of Miss are 4.2 times more likely to travel solo than girls
```

Out[553]: 4.1674641148325353

In [554]:
```
# Are women with the 'Title' "Miss" more likely to travel solo than those with 'Title' "Mrs"
woman = data[data.Woman == 1].PassengerId.count()
# 233 women
solo_woman = data[data.Woman ==1].loc[data.SibSp ==0].loc[data.Parch ==0].PassengerId.count()
# 93 are travelling solo
(solo_miss_woman/miss_woman)/(solo_woman/woman)
# Women with title of Miss are 1.7 times more likely to travel solo those with title of Mrs
```

Out[554]: 1.6911148839841539

In [555]:
```
# Do men travel solo more than boys?
boy = data[data.Child == 1].loc[data.Sex == 'male'].PassengerId.count()
# 62 male children
solo_boy = (data[data.Child == 1].loc[data.Sex == 'male'].loc[data.SibSp == 0]
            .loc[data.Parch ==0].PassengerId.count())
# 12 of them are travelling solo, all have the title Mr. ages 11-17
man = data[data.Man ==1].PassengerId.count()
# 515 Men
solo_man = data[data.Man == 1].loc[data.SibSp == 0].loc[data.Parch ==0].PassengerId.count()
# 399 are travelling solo
(solo_man/man)/(solo_boy/boy)
# Men are 4 times more likely to travel solo than boys
```

Out[555]: 4.0029126213592239

I feel comfortable categorizing all the passengers whose 'Age' is NaN, title 'Miss, and who are travelling solo as 'Woman'. Obviously I run a risk of miscategorizing some girls as women, but because more passengers with the 'Title' "Miss" are adults, and they are more likely to travel solo, I feel like this is a safe generalization. Another option would be to distribute these passengers randomly based on the probability that they are adults or children from the rest of the ship sample, but I don't think this will make the analysis more accurate.

In [556]:
```
# Create a mask for solo travelling Miss who are NaN old
data[data.Man ==0].loc[data.Woman ==0].loc[data.Child==0]
mask_miss_NaN = (data.Age.isnull()) & (data.Title == 'Miss') & (data.SibSp == 0) & (data.Parch ==0)

# Assign these passengers to the 'Woman' group
data.loc[mask_miss_NaN, 'Woman'] = 1

# How much of the sample has been categorized?
data['Child'].sum()+data['Woman'].sum()+data['Man'].sum()
```

Out[556]: 891.0

Summary of steps to identify Women, Children and Men

Less than 18 years old, a child. Otherwise a Man or Woman depending on 'Sex'
'Title' == 'Master' then child
'Title' == 'Mr' then man
'Title' == 'Mrs' then woman
If 'Title' != 'Miss', then probably an adult with a special title
If 'Title' == 'Miss' and SibSp' > 0 then Child
If 'Title' == 'Miss' and 'Parch' > 0 then Child
All remaining passengers are Women

All of the passengers fall under the boarding group categories 'Man', 'Woman', and 'Child' now. What this boarding group categorization did was to seperate adults and children without knowing a the ages of a signicant portion of the sample. What it did not do was assign an age to those whose 'Age' is NaN. I could simply assign the median age of their respective boarding groups to samples whose 'Age' is NaN. I could also distribute random ages to these samples based on the distribution of ages in their boarding groups. Both seem like reasonable ways to wrangle the data. However, 'Age' will not be studied at all in the rest of this analysis so I shall decline to perform this substitution.

Survival and Boarding Group

How did sex and childhood status affect survival? The table below sums things up. Being a woman correlated positively with survival. Women survived at a rate of 78% vs. 16% for men. Children survived at a higher rate than men. Being a child seemed to increase survival for males but decrease it for females. As for the "Women and Children First" expression, it seems accurate with women apparently boarding the lifeboats before the children.

In [557]:
```
# Survival Rates of Adults and Children by Sex
data.pivot_table('Survived', index = 'Sex', columns = 'Child', aggfunc = 'mean')
```

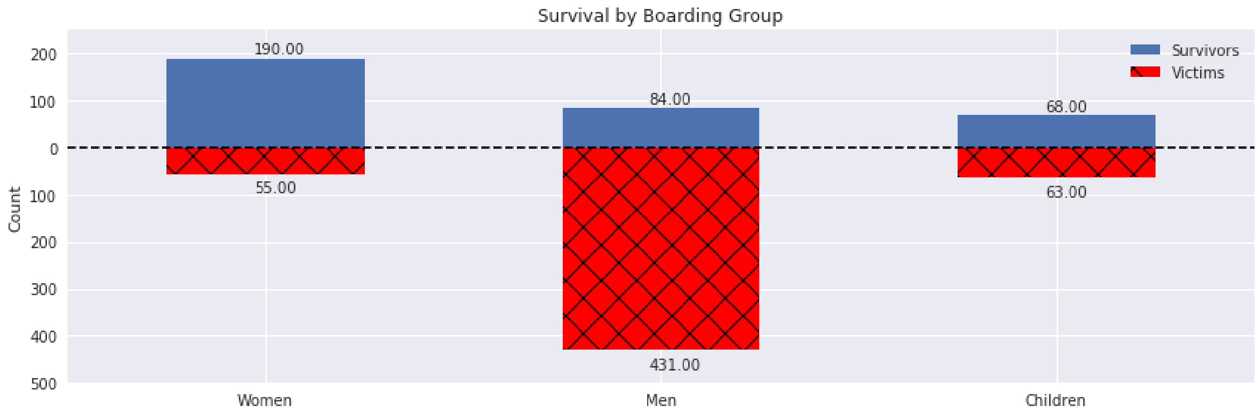
Out[557]:

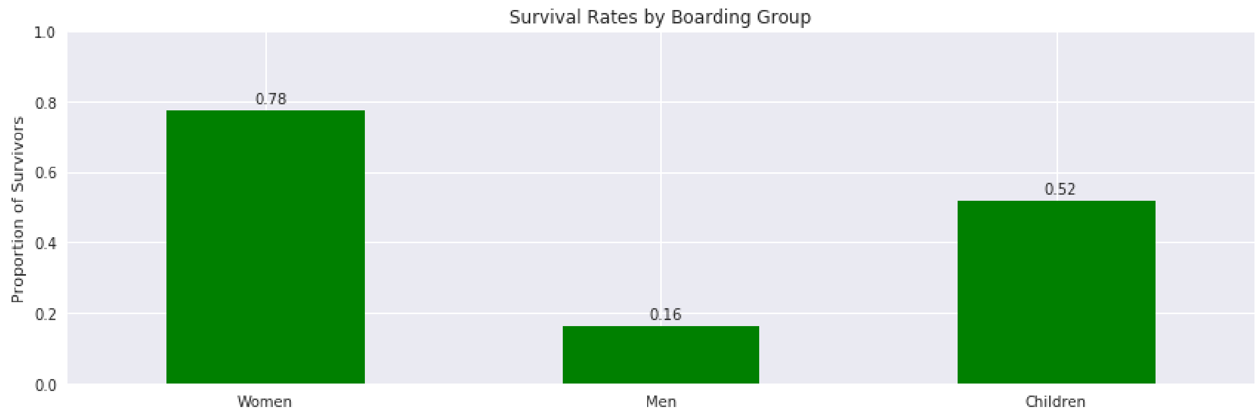
Child	**0**	**1**
Sex		
female	0.775510	0.623188
male	0.163107	0.403226

In [558]:

```
# Plot survival of boarding groups

fig, (ax1, ax2) = plt.subplots(nrows = 2, ncols = 1, figsize= (12,8))

survivors = data.loc[data.Child == 0].loc[data.Survived == 1].pivot_table('Survived', index = 'Sex',
                                                                          aggfunc = 'count')
victims = data.loc[data.Child == 0].loc[data.Survived == 0].pivot_table('Survived', index = 'Sex',
                                                                        aggfunc = 'count')
survivors['Children']=data.loc[data.Child == 1].loc[data.Survived == 1]['Survived'].count()
survivors = Series(survivors.values, index = ['Women', 'Men', 'Children'], name = 'Group')

victims['Children']= data.loc[data.Child ==1].loc[data.Survived ==0]['Survived'].count()
victims = Series(victims.values, index = ['Women', 'Men', 'Children'], name = 'Group')


fig = survivors.plot.bar(ax = ax1)
victims.apply(lambda x: -x).plot.bar(ax= ax1, hatch = 'x', color = 'r')

ax1.legend([ 'Survivors', 'Victims'])
ax1.axhline(0, color = 'k', linestyle = '--')
ax1.set_ylim([-500, 250])
ticks =  ax1.get_yticks()
ax1.set_yticklabels([int(abs(tick)) for tick in ticks])
ax1.set_xticklabels(ax1.xaxis.get_majorticklabels(), rotation =0)
ax1.set_ylabel('Count')
ax1.set_title('Survival by Boarding Group')

x_offset = -0.03
y_offset = 10
y_drop = -40

for p in [0,1,2]:
    b = ax1.patches[p].get_bbox()
    val = "{:.2f}".format(b.y1 + b.y0)
    ax1.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y1 + y_offset))

for p in [3,4,5]:
    b = ax1.patches[p].get_bbox()
    val = "{:.2f}".format(abs(b.y1 + b.y0))
    ax1.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y0 + y_drop))


# Plot survival rates of Women, Men, and Children

survival_rate = data[data.Child == 0].pivot_table('Survived', index = 'Sex', aggfunc = 'mean')
survival_rate['Children']=data[data.Child == 1]['Survived'].mean()
survival_rate = Series(survival_rate.values, index = ['Women', 'Men', 'Children'], name = 'Group')

survival_rate.plot.bar(ax = ax2, color = 'g')
ax2.set_ylim([0,1])
ax2.set_ylabel('Proportion of Survivors')
ax2.set_title('Survival Rates by Boarding Group')
ax2.set_xticklabels(ax2.xaxis.get_majorticklabels(), rotation =0)


x_offset = -0.03
y_offset = 0.02
for p in ax2.patches:
    b = p.get_bbox()
    val = "{:.2f}".format(b.y1 + b.y0)
    ax2.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y1 + y_offset))

plt.tight_layout()
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```





Supposing that the lifeboats were filled to capacity, it does appear that men took some seats that could have been occupied by women and children. As it was, 118 women and children died in our sample. If the men sacriced their seats, only 34 women or children would have perished. In fact the men could have made the sacrifice which allowed either all the women or all the children to survive in our sample. It seems as if the "Women and Children First" protocol was not followed by the 84 men who survived. Of course the sample does not really tell us why this happened.

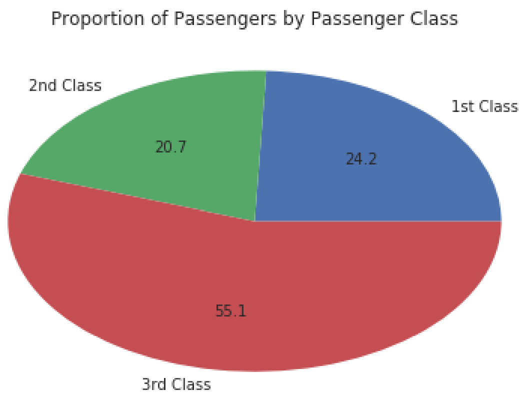
Still women and children survived at rates 4.9 and 3.3 times higher than the men so one would expect that this protocol was followed somewhat. The sample does show a correlation with being a woman or child with survival.

Passenger Class and Survival

The variable 'Plcass' had a strong correlation with 'Survival' especially for those in first class and third class.

In [559]:
```
# Plot proportion of 'Pclass' in pie chart

df = None
df = data.pivot_table('PassengerId', index = 'Pclass', aggfunc = 'count')

df.plot.pie(subplots = True, labels = ['1st Class', '2nd Class', '3rd Class'], legend = False,
           autopct = '%.1f')
plt.title('Proportion of Passengers by Passenger Class')
plt.ylabel('')
plt.tight_layout()
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont:
Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



In [560]:
```
data[['Survived', 'Pclass']].groupby('Pclass').mean()
```

Out[560]:

	Survived
Pclass	
1	0.629630
2	0.472826
3	0.242363

In [561]:
```
# Survival rate of 1st class vs. 3rd
data[data.Pclass ==1].Survived.mean()/data[data.Pclass==3].Survived.mean()
```

Out[561]: 2.597883597883598

In [562]:
```
# What percentage of victims were in third class
data[data.Survived ==0].Pc3.mean()
```

Out[562]: 0.6775956284153005

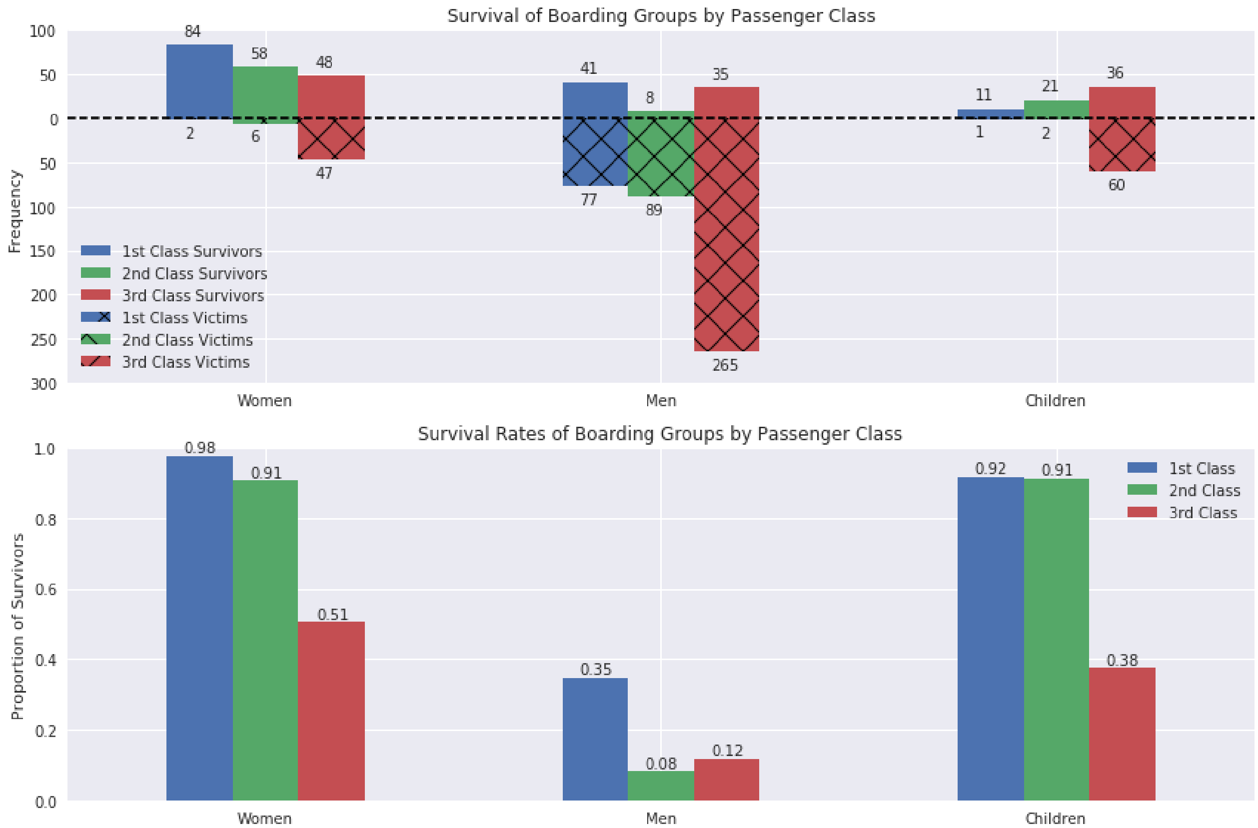
From above we see an almost linear relationship between 'Pclass', and the rate of survival. This translates into first class passengers chance of survival being 2.6 times greater than third class passengers. Combined with the fact that 55% of passengers were in third class, we find that 68% of the passengers who perished were in third class.

The plot below illustrates that first class males had a higher survival rate than the other males. We also see how being in third class meant much lower survival rates for both women and children.

In [563]:
```
# Plot survival for passenger class and boarding group
fig, (ax1, ax2) = plt.subplots(nrows = 2, ncols =1, figsize = (12,8))

survivors = DataFrame(columns = np.unique(data.Pclass.values))
survivors.loc['Woman'] = data[data.Woman ==1].pivot_table('Survived', columns = 'Pclass',
                                                          aggfunc = 'sum')
survivors.loc['Man'] = data[data.Man ==1].pivot_table('Survived', columns = 'Pclass',
                                                          aggfunc = 'sum')
survivors.loc['Child'] = data[data.Child ==1].pivot_table('Survived', columns = 'Pclass',
                                                          aggfunc = 'sum')
```

```
survivors.columns = ['1st Class', '2nd Class', '3rd Class']

victims = DataFrame(columns = np.unique(data.Pclass.values))
victims.loc['Women'] = data[data.Woman ==1].loc[data.Survived ==0].pivot_table('Survived', columns = 'Pcl
ass',
                                                                               aggfunc = 'count')
victims.loc['Men'] = data[data.Man ==1].loc[data.Survived ==0].pivot_table('Survived', columns = 'Pclass'
,
                                                                           aggfunc = 'count')
victims.loc['Children'] = data[data.Child ==1].loc[data.Survived ==0].pivot_table('Survived',
                                                                                  columns = 'Pclass',
                                                                                  aggfunc = 'count')


fig = survivors.plot.bar(ax = ax1)
victims.apply(lambda x: -x).plot.bar(ax = ax1, hatch = 'x')

ax1.legend(['1st Class Survivors', '2nd Class Survivors', '3rd Class Survivors',
            '1st Class Victims', '2nd Class Victims', '3rd Class Victims'])
ax1.axhline(0, color = 'k', linestyle = '--')
ax1.set_xticklabels(ax1.xaxis.get_majorticklabels(), rotation = 0)
ax1.set_ylabel('Frequency')
ax1.set_ylim([-300, 100])
ticks =  ax1.get_yticks()
ax1.set_yticklabels([int(abs(tick)) for tick in ticks])

ax1.set_title('Survival of Boarding Groups by Passenger Class')

x_offset = -0.04
y_offset = 10
y_drop = -20
for p in np.arange(0,9):
    b = ax1.patches[p].get_bbox()
    val = "{:.0f}".format(b.y1 + b.y0)
    ax1.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y1 + y_offset))

for p in np.arange(9,18):
    b = ax1.patches[p].get_bbox()
    val = "{:.0f}".format(abs(b.y1 + b.y0))
    ax1.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y0 + y_drop))

# Plot survival rates of Boarding Groups by Passenger Class

survival_rate = DataFrame(columns = np.unique(data.Pclass.values))
survival_rate.loc['Women'] = data[data.Woman == 1].pivot_table('Survived', columns = 'Pclass',
                                                               aggfunc = 'mean')
survival_rate.loc['Men'] = data[data.Man == 1].pivot_table('Survived', columns = 'Pclass',
                                                               aggfunc = 'mean')
survival_rate.loc['Children'] = data[data.Child == 1].pivot_table('Survived', columns = 'Pclass',
                                                                 aggfunc = 'mean')
survival_rate.columns = ['1st Class', '2nd Class', '3rd Class']


survival_rate.plot.bar(ax = ax2)
ax2.set_ylim([0,1])
ax2.set_ylabel('Proportion of Survivors')
ax2.legend()
ax2.set_title('Survival Rates of Boarding Groups by Passenger Class')
ax2.set_xticklabels(ax2.xaxis.get_majorticklabels(), rotation = 0)

x_offset = -0.04
y_offset = 0.01
for p in ax2.patches:
    b = p.get_bbox()
    val = "{:.2f}".format(b.y1 + b.y0)
    ax2.annotate(val, ((b.x0 + b.x1)/2 + x_offset, b.y1 + y_offset))

plt.tight_layout()
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Another aspect of these plots that is worth considering is how most of the male passengers travelled 3rd class. Being male has already shown a strong negative correlation with survival so it should be no surprise that 3rd class passengers overall had low survival rates. However, the fact that 1st class women men and children survived at rates 1.9 to 2.6 times higher than their 3rd class counterparts underscores how 'Pclass' correlates with 'Survived'.

Fare Paid and Survival

There is a positive correlation between 'Fare' and 'Survived'. I would assume that 'Fare' and 'Pclass' are also positively correlated to eachother which is why they are both positively correlated with 'Survived'. How strong is this correlation?

Also, does 'Fare' also correlate positively with 'Woman' which we already know has the strongest positive correlation with 'Survived'?

In [564]:
```
# How does 'Fare' correlate with other variables
data.corr().Fare.sort_values(ascending = False)
```

Out[564]:
```
Fare           1.000000
Pc1            0.591711
Emb_C          0.269335
Survived       0.257307
Parch          0.216225
Woman          0.194454
Female         0.182333
SibSp          0.159651
Age            0.096067
PassengerId    0.012658
Child         -0.008540
Emb_Q         -0.117216
Pc2           -0.118557
Emb_S         -0.166603
Man           -0.169676
Male          -0.182333
Pc3           -0.413333
Pclass        -0.549500
Name: Fare, dtype: float64
```

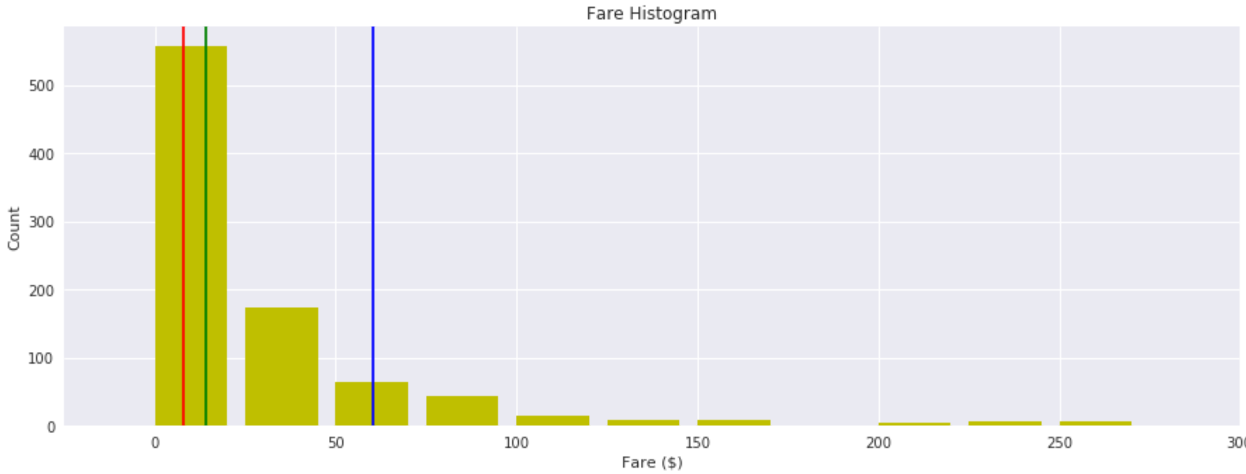
Indeed, 'Fare' does strongly correlate with 'Pclass'. 'Fare' and 'Woman' also have a positive correlation. This simply means that 1st class passengers and females tended to pay more and it has already been shown that these variables predict survival well. The fact that 'Fare' correlates with 'Survived' is consistent with what has already been analyzed in the 'Woman', 'Man', 'Child' and 'Pclass' variables.

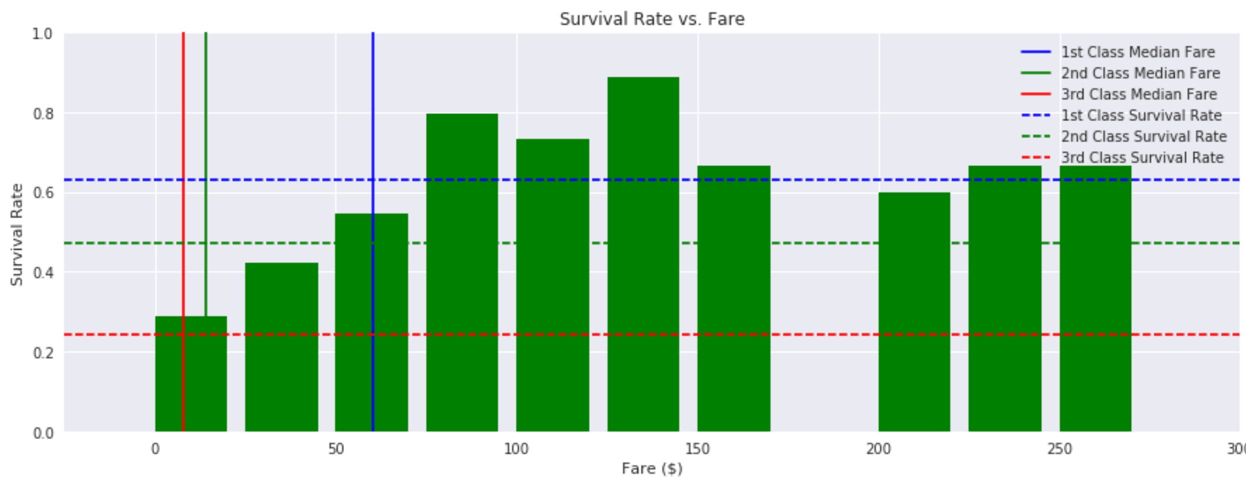
What can plotting the 'Fare' illustrate for us?

In [565]:

```
# Plot 'Fare' as a histogram, include median fares for each 'Pclass'

bin_width = 25
lower_bound = -25
upper_bound = 300
bar_width = 20
col_fare = 'y'
col_rate = 'g'
col_c1 = 'b'
col_c2 = 'g'
col_c3 = 'r'


bins = np.arange(lower_bound, upper_bound, bin_width)
index = bins[0:-1]


fig, (ax1, ax2) = plt.subplots(2,1, figsize = (15,12))

ax1.bar(index+0.5*bar_width, np.histogram(data.Fare, bins)[0],
         width = bar_width, color = col_fare)
ax1.set_xlim(lower_bound, upper_bound)

ax1.axvline(data[data.Pclass == 1].Fare.median(), color = col_c1)
ax1.axvline(data[data.Pclass == 2].Fare.median(), color = col_c2)
ax1.axvline(data[data.Pclass == 3].Fare.median(), color = col_c3)

ax1.set_ylabel('Count')
ax1.set_xlabel('Fare ($)')
ax1.set_title('Fare Histogram')


# Plot fares vs. survival rate, include average survival rate for each 'Pclass'

fare_rate = np.nan_to_num(np.histogram(data[data.Survived ==1].Fare,bins )[0]
                          /np.histogram(data.Fare, bins)[0])


ax2.bar(index+0.5*bar_width, fare_rate,
        color = col_rate, width = bar_width)
ax2.set_xlim(lower_bound, upper_bound)


ax2.axvline(data[data.Pclass == 1].Fare.median(), color = col_c1)
ax2.axvline(data[data.Pclass == 2].Fare.median(), color = col_c2)
ax2.axvline(data[data.Pclass == 3].Fare.median(), color = col_c3)
ax2.axhline(data[data.Pclass ==1].Survived.mean(), color = col_c1, linestyle = '--')
ax2.axhline(data[data.Pclass ==2].Survived.mean(), color = col_c2, linestyle = '--')
ax2.axhline(data[data.Pclass ==3].Survived.mean(), color = col_c3, linestyle = '--')
ax2.set_ylabel('Survival Rate')
ax2.set_xlabel('Fare ($)')
ax2.set_title('Survival Rate vs. Fare')
ax2.legend(['1st Class Median Fare',
            '2nd Class Median Fare',
            '3rd Class Median Fare',
            '1st Class Survival Rate',
            '2nd Class Survival Rate',
            '3rd Class Survival Rate'])
ax2.set_ylim(0,1)
plt.subplots_adjust(hspace = .3)
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/ipykernel/__main__.py:36: RuntimeWarning: invalid value
encountered in true_divide
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont:
Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



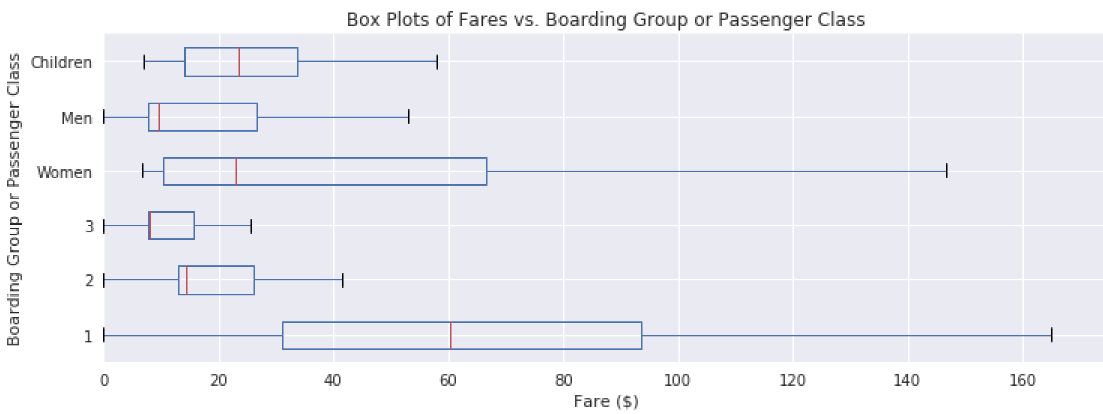


The histograms show how most passengers paid less than $50 dollars for their tickets and this group of passengers had the lowest survival rate. Passengers who paid more than the median fare for 1st class passengers had the best survival rates though their numbers are few.

Box plots of the fares paid will give a clearer understanding of what each passenger class paid. It will also give us a chance to examine how 'Fare' relates to boarding groups.

In [566]:
```
# Box plot 'Fare' for 'Man', 'Woman', 'Child' and 'Pclass'

df = DataFrame(columns = np.unique(data.Pclass.values))
df['Fare'] = data['Fare']
df[1] = data['Fare'].loc[data.Pclass ==1]
df[2] = data['Fare'].loc[data.Pclass ==2]
df[3] = data['Fare'].loc[data.Pclass ==3]
df['Women'] = data['Fare'].loc[data.Woman ==1]
df['Men'] = data['Fare'].loc[data.Man ==1]
df['Children'] = data['Fare'].loc[data.Child==1]
df.drop(['Fare'], axis =1, inplace = True)

fig, ax = plt.subplots(figsize=(12, 4))
fig = df.plot.box(vert = False, ax = ax)
ax.set_xlim([0,175])
ax.set_ylabel('Boarding Group or Passenger Class')
ax.set_xlabel('Fare ($)')
ax.set_title('Box Plots of Fares vs. Boarding Group or Passenger Class')
plt.show()
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/matplotlib/font_manager.py:1297: UserWarning: findfont:
Font family ['sans-serif'] not found. Falling back to DejaVu Sans
  (prop.get_family(), self.defaultFamily[fontext]))
```



Now it should be clear how 'Fare' positively correlates with 'Survived'. 'Fare' also has a strong positive correlation to 'Pclass' and 'Woman' which have even stronger correlations with 'Survived'.

Summary of factors influencing survival

The table below ranks the survival ranks of all the groups of passengers examined previously. It also lists what proportion of the overall passengers and victims the group comprised of. The a group is over or underrepresented in the victim totals is reflected in the 'Death Premium' column which is the proportion that the chance of perishing differs from the sample average. The 'Death Premium' is simply the proportion of victims divided by the proportion of the sample.

In [567]:

```
# Summarize survival rates
# Need to learn how to write a function for this

survival_rank = DataFrame(columns = ['Survival Rate', 'Count', 'Proportion Sample', 'Proportion Victims'
])
victims = data[data.Survived==0].PassengerId.count()

survival_rank.loc['Ship Total'] = [data.Survived.mean(),
                                      data.Survived.count(),
                                   1,
                                   1]

survival_rank.loc['Women'] = [data['Survived'][data.Woman ==1].mean(),
                              data['Survived'][data.Woman ==1].count(),
                             data.Woman.mean(),
                             data[data.Survived==0].Woman.mean()]

survival_rank.loc['Men'] = [data['Survived'][data.Man == 1].mean(),
                            data['Survived'][data.Man == 1].count(),
                           data.Man.mean(),
                           data[data.Survived==0].Man.mean()]

survival_rank.loc['Children'] = [data['Survived'][data.Child == 1].mean(),
                            data['Survived'][data.Child == 1].count(),
                           data.Child.mean(),
                           data[data.Survived==0].Child.mean()]

survival_rank.loc['First Class'] = [data['Survived'][data.Pc1 ==1].mean(),
                                    data['Survived'][data.Pc1 ==1].count(),
                                   data.Pc1.mean(),
                                   data[data.Survived==0].Pc1.mean()]

survival_rank.loc['Second Class'] = [data['Survived'][data.Pc2 ==1].mean(),
                                    data['Survived'][data.Pc2 ==1].count(),
                                    data.Pc2.mean(),
                                    data[data.Survived==0].Pc2.mean()]

survival_rank.loc['Third Class'] = [data['Survived'][data.Pc3 ==1].mean(),
                                    data['Survived'][data.Pc3 ==1].count(),
                                   data.Pc3.mean(),
                                   data[data.Survived==0].Pc3.mean()]


#survival_rank.sort_values(by = 'Survival Rate', ascending = False)

survival_rank['Death Premium'] = survival_rank['Proportion Victims']/survival_rank['Proportion Sample']-1
survival_rank.sort_values(by = 'Death Premium', ascending = True)
```

Out[567]:

	Survival Rate	Count	Proportion Sample	Proportion Victims	Death Premium
Women	0.775510	245.0	0.274972	0.100182	-0.635664
First Class	0.629630	216.0	0.242424	0.145719	-0.398907
Children	0.519084	131.0	0.147026	0.114754	-0.219497
Second Class	0.472826	184.0	0.206510	0.176685	-0.144423
Ship Total	0.383838	891.0	1.000000	1.000000	0.000000
Third Class	0.242363	491.0	0.551066	0.677596	0.229608
Men	0.163107	515.0	0.578002	0.785064	0.358237

The analysis of non-overlapping variables of the previous sections should have presented a general sense of what variables correlated wtih 'Survival' strongest. By showing them all together here, we can begin to see the relative strength of correlations with eachother, and how a sample having a certain combination of characteristics might survive or not.