Investigating a Dataset- The Titanic Dataset

This report is based on the sample of the Titanic dataset provided by Kaggle. The report will analyse the passenger and demographic information in python using its numpy and pandas libraries.

Before I can pose any questions, I need to take a look at the data set by initially loading it into a pandas dataframe.

In [3]:

```
import pandas as pd
import numpy as np

df = pd.read_csv('titanic_data.csv', header = 0)
```

In [4]:

```
print df.head(5)
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex  Age  Si
bSp  \
0                            Braund, Mr. Owen Harris    male   22
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female   38
1
2                             Heikkinen, Miss. Laina  female   26
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female   35
1
4                           Allen, Mr. William Henry    male   35
0

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

The data appears to have been read correctly into the 'df' dataframe.

In [5]:

```
print df.dtypes
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

The data types are as expected, however further investigation is required to ensure that there are no erroneous or missing values within these columns.

At this point I would also like to add the the Parch (number of parents and children) column and SibSp (number of siblings and spouses) column to give total family values for each passenger.

In [6]:

```
df['total_family']=df.SibSp + df.Parch
```

In [7]:

```
print df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 891 entries, 0 to 890
Data columns (total 13 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
total_family    891 non-null int64
dtypes: float64(2), int64(6), object(5)
memory usage: 97.5+ KB
None
```

Most columns contain complete data. The exceptions are Age, Cabin and Embarked.

In [8]:

```
print df.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare  total_family
count  891.000000  891.000000    891.000000
mean     0.381594   32.204208      0.904602
std      0.806057   49.693429      1.613459
min      0.000000    0.000000      0.000000
25%      0.000000    7.910400      0.000000
50%      0.000000   14.454200      0.000000
75%      0.000000   31.000000      1.000000
max      6.000000  512.329200     10.000000
```

From the summary data above, the mean survival rate is 0.38, implying that most people did not survive. The average age of the passengers was 29.7 (ignoring missing values) and there appears to have been some large families on board.

Going through the data in order to look for any erroneous values or outliers:

1. Survived - entries are either 0 or 1 (and I know this column is of type 'int')
2. Pclass - min 1, max 3 (and I know this column is of type 'int')
3. Age - the range seems reasonable
4. SibSp, Parch and total_family - again, the range seems reasonable
5. Fare - It looks as though someone paid $512 to be on board however this may be an error.

Aside from the fare column, the data looks to be in good shape.

Analysis

The key question for the titanic dataset would be 'what factors made people more likely to survive'? From this dataset the following factors will be examined:

1. Sex
2. Age
3. Class of travel
4. Since information on families is available, the survival rate for a person travelling with family will also be examined.

Data Wrangling

Since I require the Age column as part of my analysis, and since there are missing values in this column, I will need to clean the data up before I can begin my analysis.

Here, I can either replace the missing Age entries or delete them.

I will initially look at the spread of the data.

In [10]:

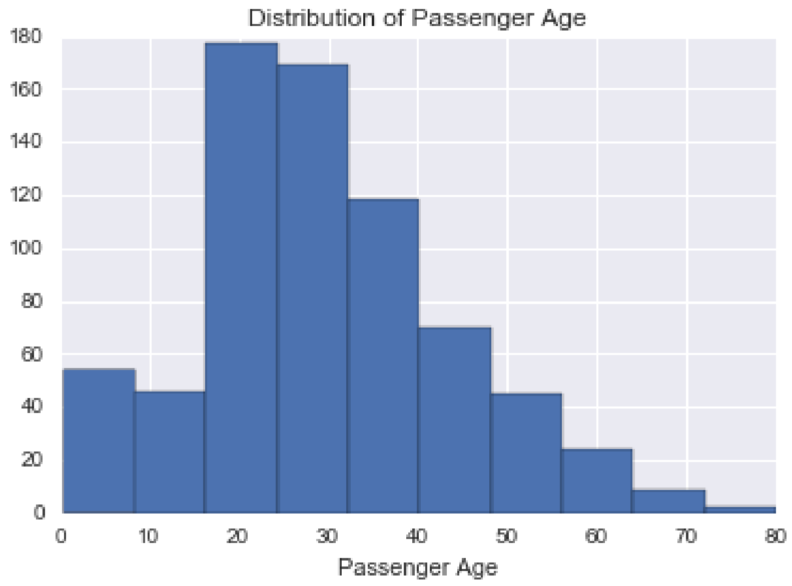
```
%pylab inline
import matplotlib.pyplot as plt
import seaborn as sns

df['Age'].hist()
plt.xlabel('Passenger Age')
plt.title('Distribution of Passenger Age')
plt.show
```

```
Populating the interactive namespace from numpy and matplotlib
```

Out[10]:

```
<function matplotlib.pyplot.show>
```



Looking at the above histogram (and taking the standard deviation of the age into account), the data is reasonably well spread out.

I could replace the missing entries with the mean however I do not want the assumption I have placed on the missing 'Age' data to affect my findings, it may not be a reasonable assumption to make due to the fact that the data is spread out. Removing the missing data will still leave me with most of the data left for my analysis.

I will therefore create a new dataframe excluding the missing 'Age' data. This dataframe should contain 714 entries.

In [11]:

```
new_df = df.dropna(subset=['Age'])
```

In [12]:

```
print new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 714 entries, 0 to 890
Data columns (total 13 columns):
PassengerId     714 non-null int64
Survived        714 non-null int64
Pclass          714 non-null int64
Name            714 non-null object
Sex             714 non-null object
Age             714 non-null float64
SibSp           714 non-null int64
Parch           714 non-null int64
Ticket          714 non-null object
Fare            714 non-null float64
Cabin           185 non-null object
Embarked        712 non-null object
total_family    714 non-null int64
dtypes: float64(2), int64(6), object(5)
memory usage: 78.1+ KB
None
```

In [13]:

```
print new_df.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   714.000000  714.000000  714.000000  714.000000  714.000000
mean    448.582633    0.406162    2.236695   29.699118    0.512605
std     259.119524    0.491460    0.838250   14.526497    0.929783
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     222.250000    0.000000    1.000000   20.125000    0.000000
50%     445.000000    0.000000    2.000000   28.000000    0.000000
75%     677.750000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    5.000000

            Parch        Fare  total_family
count  714.000000  714.000000    714.000000
mean     0.431373   34.694514      0.943978
std      0.853289   52.918930      1.483788
min      0.000000    0.000000      0.000000
25%      0.000000    8.050000      0.000000
50%      0.000000   15.741700      0.000000
75%      1.000000   33.375000      1.000000
max      6.000000  512.329200      7.000000
```

Examining the Data: Gender

Looking at which Gender was more likely to survive:

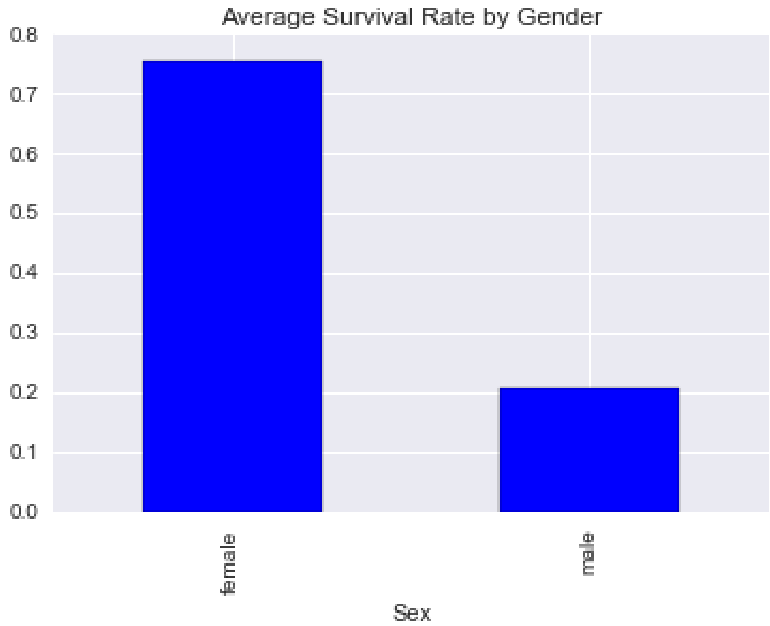
In [102]:

```
gender_survivors = new_df.groupby('Sex').mean()['Survived']
print gender_survivors
```

```
Sex
female    0.754789
male      0.205298
Name: Survived, dtype: float64
```

In [46]:

```
new_df.groupby('Sex').mean()['Survived'].plot(kind='bar')
plt.title('Average Survival Rate by Gender')
plt.show()
```



This shows that from our subset of data, 75% of females survived, and only 20% of males survived. this can also be run for our original dataframe:

In [103]:

```
gender_survivors_complete = df.groupby('Sex').mean()['Survived']
print gender_survivors_complete
```

```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
```

This shows similar ratios.

Examining the Data: Age

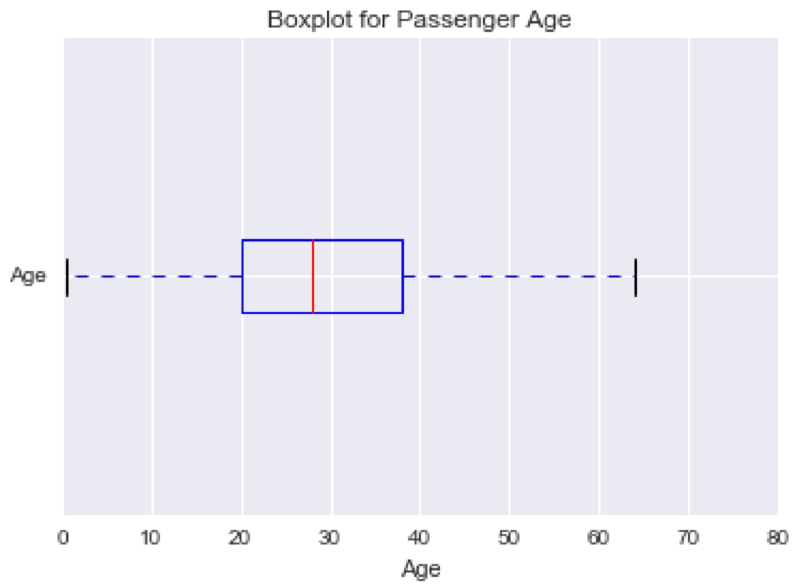
Now to look at the age of survivors vs the age of people who didnt survive. Firstly I'd like to look at a box plot to show the spread, mean, mediun and mode of the passengers in the dataframe.

In [18]:

```
#show(new_df.boxplot(column = 'Age',return_type='axes',vert=False))
new_df.boxplot(column = 'Age',return_type='axes',vert=False)
plt.title('Boxplot for Passenger Age')
plt.xlabel('Age')
plt.show
```

Out[18]:

<function matplotlib.pyplot.show>



Next I'd like to look at the mean age of survivors vs non-survivors and I will also show two histograms. The first showing the distribution of the age of the survivors, the second showing the distribution of the age of those that didnt survive.

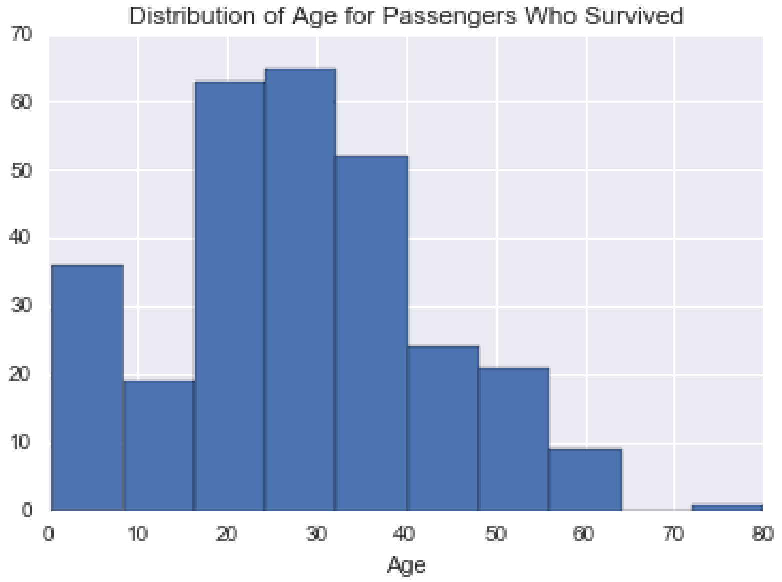
In [44]:

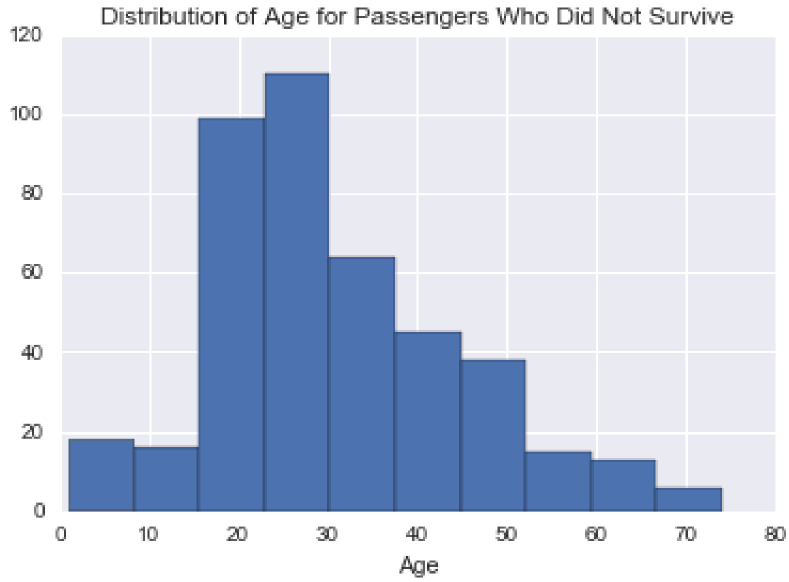
```
print 'The mean age of survivors was', np.round(new_df['Age'][(new_df['Survived']
== 1)].mean(),2)
print 'The mean age of those that did not survive was', np.round(new_df['Age'][(ne
w_df['Survived'] == 0)].mean(),2)
%pylab inline

age_survivors = new_df['Age'][(new_df['Survived'] == 1)].hist()
plt.title('Distribution of Age for Passengers Who Survived')
plt.xlabel('Age')
show(age_survivors)

age_nonsurvivors = new_df['Age'][(new_df['Survived'] == 0)].hist()
plt.title('Distribution of Age for Passengers Who Did Not Survive')
plt.xlabel('Age')
show(age_nonsurvivors)
```

```
The mean age of survivors was 28.34
The mean age of those that did not survive was 30.63
Populating the interactive namespace from numpy and matplotlib
```



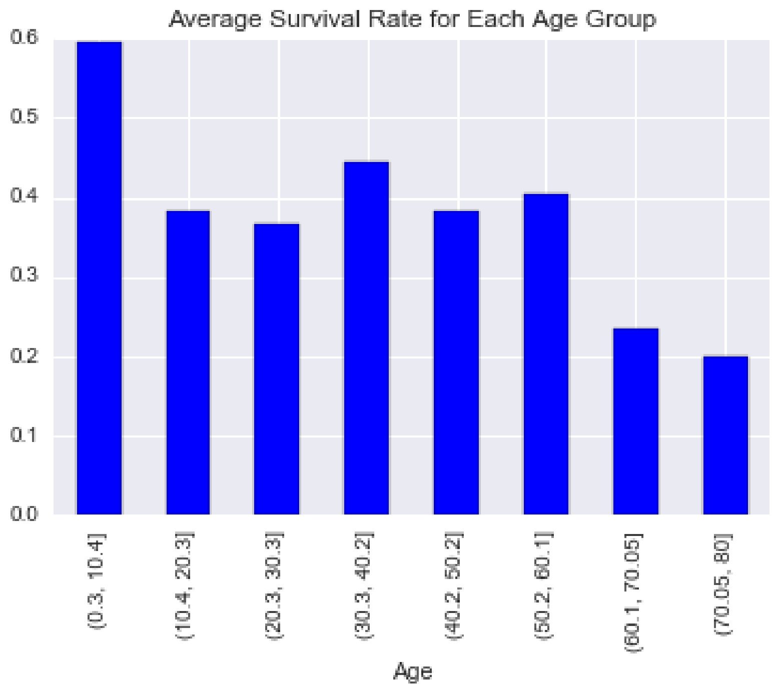


The histograms and the averages show that older people were less likely to survive.

Focussing on the survivors lets look at the average survival rate for each age group. This involves grouping the age data using '.cut'.

In [43]:

```
age_groups = new_df.groupby(pd.cut(new_df.Age,8,precision=1))
age_groups.mean()['Survived'].plot(kind='bar')
plt.title('Average Survival Rate for Each Age Group')
plt.show()
```



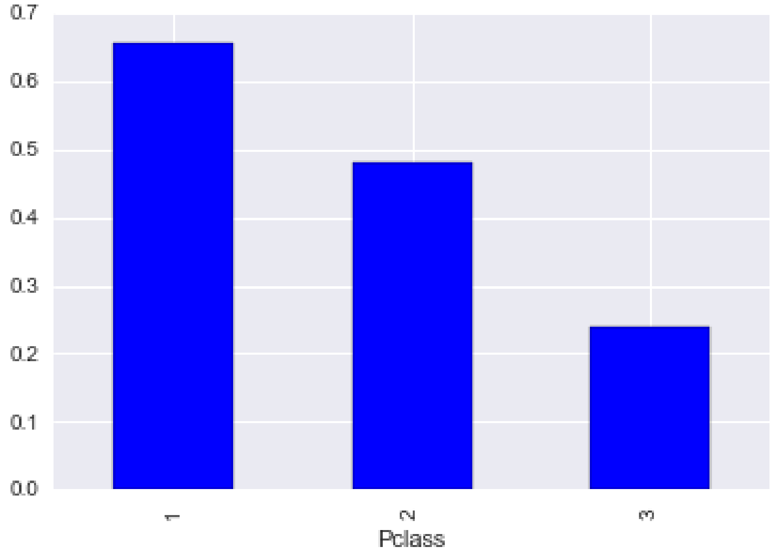
The above plot shows that most passengers under the age of 10 survived. The next highest age bracket was actually 30.3-40.2, however survival rates for all other age groups aside from the youngest was low.

Examining the Data: Passenger Class

The following bar chart shows the average survival rate by passenger class (Pclass).

In [107]:

```
show(new_df.groupby('Pclass').mean()['Survived'].plot(kind='bar'))
```



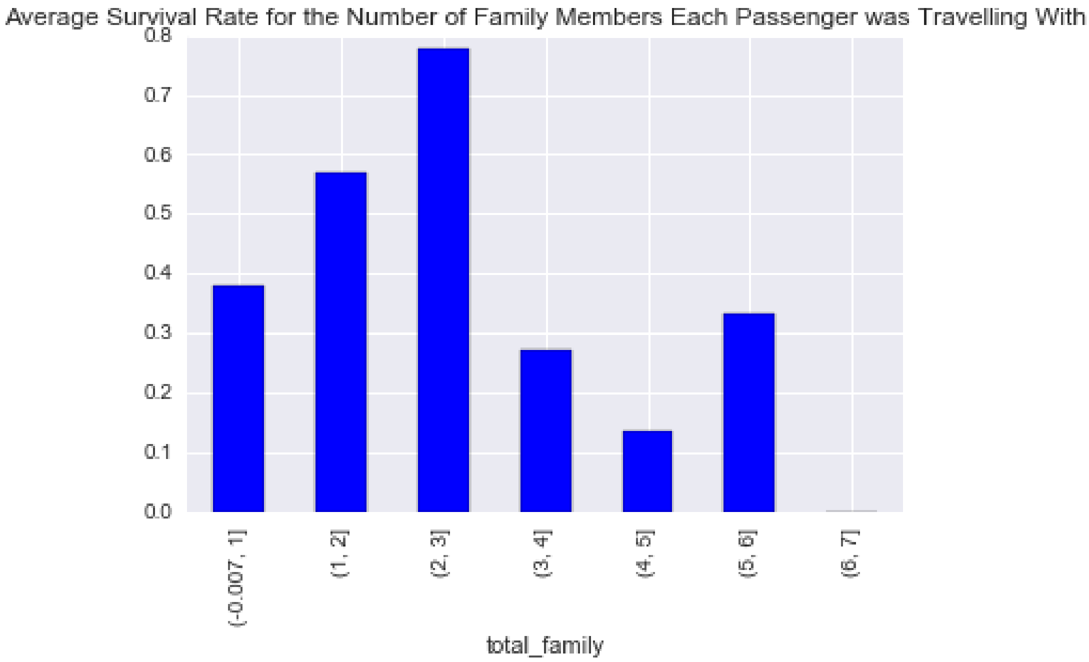
Examining the Data: Families

One final thing I will examine is the survival rate of passengers travelling with their families, and whether the size of the family an individual is travelling with effected their survival rate.

There are two columns that give family information, siblingsp which counts siblings and partners and parch with counts parents and children. I added these two columns earlier to give an approximate family size number for each person, however it should be noted, as stated in the variable descriptions this count will exclude fiances, mistresses, cousins, aunts and uncles.

In [48]:

```
family_groups = new_df.groupby(pd.cut(new_df.total_family,7,precision=1))
family_groups.mean()['Survived'].plot(kind='bar')
plt.title('Average Survival Rate for the Number of Family Members Each Passenger w
as Travelling With')
plt.show()
```



Couples seem to have the largest survival rate by far.

Conclusions

The analysis above shows that for this particular dataset, females, those under 10 years old, and those travelling in the first class were more likely to survive compared with their respective peers. Also those travelling as part of a couple were more likely to survive. However it should be noted that for this variable, assumptions have been made on the family size, since it excludes extended family.

Additionally the analysis itself does have limitations, since this is a sample of the entire data set, from which we have further reduced the dataset for passengers where their age data was missing.

Finally, a passenger being a female does not necessarily mean they will survive, and this is true for all other variables examined. The inferences made in this report remain hypothesis as to the factors which could have affected survival rates on the Titanic.

One aspect of the investigation that can be tested is my decision to remove passengers with missing age data from the analysis. Is the mean survival rate of the reduced dataset significantly different from the mean survival rate of the entire dataset? I will carry out a z-test to investigate this:

H0: $\mu c = \mu i$ (Where μc is the mean for the complete dataset and μi is the mean for the dataset with the missing age values removed) H1: $\mu c \neq \mu i$

As above, the null hypothesis is that there is no significant difference between the mean survival rate of the complete dataset and the mean survival rate of the sample with the missing age values removed. The alternative hypothesis states that there is a significant difference.

A z-test is being conducted since the sample size is large. I will conduct a two tailed test for alpha level 0.05.

$\mu c = 0.3838$ $\mu i = 0.4062$ std = 0.4866 n = 714

zcritical = +/- 1.96

z = (0.4062-0.3838)/(0.4866/sqrt(714)) = 1.23

since z<zcrit, we accept the null hypothesis, there is no significant difference between the mean survival rate of the complete dataset, and the mean survival rate of the data with the missing values removed. Therefore removing the passengers with missing age data would not have significantly affected the survival rate I was examining, at alpha level 0.05.

```
In [ ]:
```