Investigate Titanic Dataset

1. Introduction

RMS Titanic was a British passenger liner that sank in the North Atlantic Ocean in the early morning of 15 April 1912, after colliding with an iceberg during her maiden voyage from Southampton to New York City. Of the 2,224 passengers and crew aboard, more than 1,500 died in the sinking, making it one of the deadliest commercial peacetime maritime disasters in modern history. Passengers and some crew members were evacuated in lifeboats and many of them were launched only partially loaded. There were not enought lifeboats for all the passangers and due to the ocean water temperature it was not possible to survive long time in the water.

As a side note on the night the Titanic sank, the recorded water temperature in the North Atlantic was registered at approx 30 degrees Fahrenheit. Water temperatures between 32 and 40 degrees Fahrenheit cause hypothermia, reducing body temperature below 95 degrees Fahrenheit. Hypothermia results in death within 30 to 90 minutes.

In [184]:

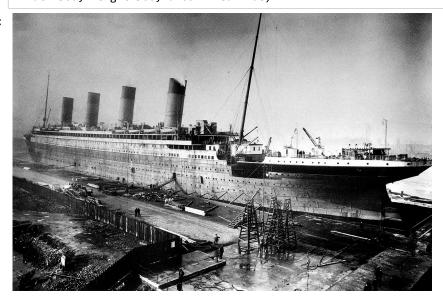
#Load image from url

from IPython.display import Image

from IPython.core.display import HTML

Image(url= "https://upload.wikimedia.org/wikipedia/commons/e/e1/Titanic_under_construction.jpg", width=500, height=500, unconfined=True)

Out[184]:



2. About the dataset

The dataset of study contains demographics and passenger information from 891 of the 2224 passengers and crew on board the Titanic. The variables included are:

Source of the data: https://www.kaggle.com/c/titanic VARIABLE DESCRIPTIONS: survival Survival (0 = No; 1 = Yes) pclass Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd) name Name sex Sex age Age sibsp Number of Siblings/Spouses Aboard parch Number of Parents/Children Aboard ticket Ticket Number fare Passenger Fare cabin Cabin embarked Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton) SPECIAL NOTES: Pclass is a proxy for socio-economic status (SES) * 1st: Upper * 2nd: Middle * 3rd: Lower Age is in Years; Fractional if Age less than One (1) If the Age is Estimated, it is in the form xx.5 With respect to the family relation variables (i.e. sibsp and parch) some relations were ignored. The following are the definitions used for sibsp and parch. Sibling: Brother, Sister, Stepbrother, or Stepsister of Passenger Aboard Titanic Spouse: Husband or Wife of Passenger Aboard Titanic (Mistresses and Fiances Ignored) Parent: Mother or Father of Passenger Aboard Titanic Child: Son, Daughter, Stepson, or Stepdaughter of Passenger Aboard Titanic Other family relatives excluded from this study include cousins, nephews/nieces, aunts/uncles, and in-laws. Some children travelled only with a nanny, therefore parch=0 for them. As well, some travelled with very close friends or neighbors in a village, however, the definitions do not support such relations.

In this project i will asses which factors had influence on chances of survival of the passangers. In my analysis i will take into the consideration data such as: age, cabin, location where the passanger embarked, sex. After assesing the data i will try to answer following questions?

- It's true in this case the phrase 'women and children first'? Did woman and children had higher chance of survival?
- Did the survival chance depended on the age of the passanger? Did young people have higher chance of survival?
- · Had first class passengers more chances of survival?
- Did the survival chance depended on location of embarkment of the passangers?
- Did the survival chance depended on which deck passangers were located?

3. Analysis and data cleaning of the provided data

I will start from importing all necesary modules.

3.1 Data loading

```
In [185]: #importing all required modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%pylab inline
```

Populating the interactive namespace from numpy and matplotlib

Provided titanic dataset is in cvs format so i will convert it pandas DataFrame.

In [186]: # Read Passenger In Survived of Pass

Out[186]:

	Passengerld	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	С
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [187]: #Renaming columns to follow CamelCase Python practice
 titanic_df = titanic_df.rename(columns={"Parch":"ParCh", "Pclass":"PClass"})

3.2 Assesing data

Out[188]:

	Passengerld	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	NaN	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	NaN	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	NaN	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

From the info function output we can already observe that certain data is missing. I will assess now how much data is missing in different columns and how it will affect the analysis.

I have also decided to change "Survived" column to bolean type. It will make plotting of the data easier in the later stage.

3.3 Calculating missing data in the dataset

Now i will calculate number of missing data:

```
In [189]: #Calculating total number of passangers(rows)
          total_pass = len(titanic_df)
          print "Total passanger count = ", total pass
          #Removing all the passangers(rows) with missing data
          cleaned_data =len(titanic_df.dropna())
          print "Available data after removing missing values = ", cleaned data
          #Calculating numer of passangers with all data available
          missing = total_pass - cleaned_data
          print "Missing data (if at least one type of data is missing in the row) = ", missing
          #Calculating percentage of missing data
          percent_misssing_data = (missing * 100) / total_pass
          print "Procent of missing data in titanic_df = ", percent_misssing_data, "%"
          Total passanger count = 891
          Available data after removing missing values = 183
          Missing data (if at least one type of data is missing in the row) = 708
          Procent of missing data in titanic_df = 79 %
```

We can observe that 79% of the data entries in the Titanic dataset are missing. This is quite big procentage of missing data and it will make the analysis of provided dataset more difficoult.

Now i will asses missing data in each column.

```
In [190]: #Calculating missing values in each column
          def missing_data(titanic_df,columnStr):
              missing_cabindata_rows = len(titanic_df[columnStr]) - titanic_df[columnStr].count()
              return '{} {} = {}'.format('Missing Rows in',columnStr, missing_cabindata_rows)
          print missing_data(titanic_df,'Age')
          print missing_data(titanic_df,'Cabin')
          print missing_data(titanic_df,'Embarked')
          print missing_data(titanic_df,'PClass')
          print missing_data(titanic_df,'Fare')
          print missing_data(titanic_df,'ParCh')
          print missing data(titanic df,'SibSp')
```

```
Missing Rows in Age = 177
Missing Rows in Cabin = 687
Missing Rows in Embarked = 2
Missing Rows in PClass = 0
Missing Rows in Fare = 0
Missing Rows in ParCh = 0
Missing Rows in SibSp = 0
```

We can observe that we are missing the most data points in Age and Cabin Column.

3.4 Creating new DataFrames for columns with missing data

Since quite a lot of data is missing in different columns i have decided to create new dataframe for them after removing all missing rows. I will also create number of different DataFrames. In my opinion this is the best way to make sure that we have maximum number of data points testing different hypothesis.

Age of the passangers

Below i will try to asses how many rows have no data in Age column.

```
In [191]: #Assesing missing rows in Age column
    missing_age = missing_data(titanic_df,'Age')
    print missing_age

Missing Rows in Age = 177

In [192]: #Calculating percentage of missing data
    percent_misssing_age_data = (177 * 100) / total_pass
    print "Procent of missing Age data in titanic_df = ", percent_misssing_age_data, "%"

Procent of missing Age data in titanic_df = 19 %
```

There are 177 missing data in row of Age column which represents 19% of total amount of the data.

Now i will create age Dataframe (after removing rows with missing data).

```
In [193]: # Create DataFrame with ages handled, remove any missing / use interpolation
known_age_passengers = titanic_df[titanic_df["Age"].notnull()]
print "Records after removing missing ages:", len(known_age_passengers)
```

Records after removing missing ages: 714

Cabin

Below i will try to asses how many rows have no data in Cabin column.

```
#Creating a series containing lists of cabins
In [197]:
          split_cabins = known_cabin_passengers["Cabin"].str.split(" ")
          #Splitting the lists in multiple rows
          split_cabins = split_cabins.apply(pd.Series, 1).stack()
          #Deleting the extra index column
          split_cabins.index = split_cabins.index.droplevel(-1)
          split_cabins.name = "Cabin"
          #Deleting original cabin column
          del known_cabin_passengers["Cabin"]
          #Insert new column
          known_cabin_passengers = known_cabin_passengers.join(split_cabins)
```

```
In [198]: decks = known_cabin_passengers["Cabin"].str[0]
          decks.name = "Deck"
          cabins = known_cabin_passengers["Cabin"].str[1:]
          cabins.name = "Cabin"
          del known cabin passengers["Cabin"]
          known_cabin_passengers = pd.concat([known_cabin_passengers, decks, cabins], join="inner",
          axis=1)
```

In [199]: #Displaying part of edited dataframe including splited Cabin data known_cabin_passengers.head()

Out[199]:

	Passengerld	Survived	PClass	Name	Sex	Age	SibSp	ParCh	Ticket	Fare	Embarked	Deck
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833	С	С
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S	С
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	S	E
10	11	1	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	S	G
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	S	С

Port of Embarkation

In [200]: #Assesing missing rows in Embarked column print missing_data(titanic_df, 'Embarked')

Missing Rows in Embarked = 2

```
In [201]:
          # Creating DataFrame with Point of Embarkation mising values removed
          available_embarked_passengers = titanic_df.dropna(subset = ['Embarked'])
          print "Records after removing missing ports of embarkation:", len(available_embarked_passengers)
```

Records after removing missing ports of embarkation: 889

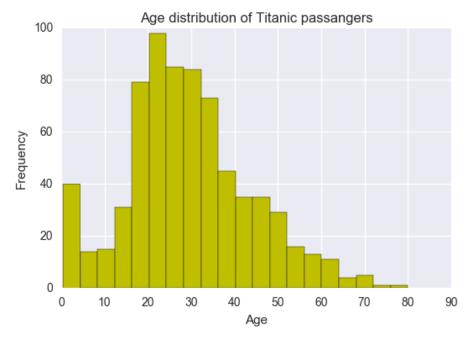
4. Exploring dataset

Here I adressed the questions I asked in the introduction, and I answered them based on the data, I also made some visualizations to help understanding the given numbers.

4.1 Exploring age data

No i will explore age data. I will start with displaying frequency distribution of age data using histogram.

```
In [202]:
          #Create histrogram of frequency distribution of age data
          known_age_passengers["Age"].hist(bins=20, color="y")
          plt.legend(prop={"size":15})
          plt.xlabel('Age')
          plt.ylabel('Frequency')
          plt.title('Age distribution of Titanic passangers')
          plt.show()
```



```
In [203]:
          #Show statistics of available age data
          known_age_passengers["Age"].describe()
Out[203]: count
                   714.000000
```

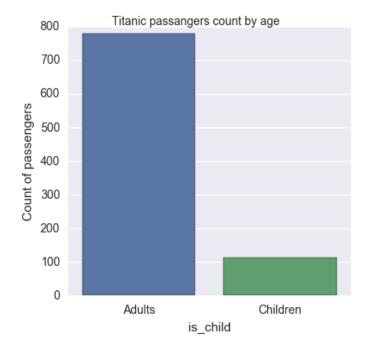
```
29.699118
mean
std
          14.526497
min
           0.420000
25%
          20.125000
50%
          28.000000
75%
          38,000000
          80.000000
max
Name: Age, dtype: float64
```

We can conclude following things from above presented table:

- * average age of the passangers was 29.6 years with standard deviations of 14.5
- * maximum passanger age was 80 years and minimum 3 moths

```
In [204]:
          #Assesing if a passanger is less than 18 years old (then consider to be a child)
          def is_child(passanger):
              if passanger < 18:</pre>
                  return 1
              else:
                   return 0
          #Adding additional column "is_child" in titanic_df Dataframe
          titanic_df["is_child"] = pd.Series(titanic_df["Age"].apply(is_child), index=titanic_df.index)
          #Changing is_child columns to bool type
          titanic_df.loc["is_child"] = titanic_df["is_child"].astype(bool)
          #Mapping value 1 to Child and 0 to an Adult
          titanic df["is child"]= titanic df.is child.map({1:'Children', 0:'Adults'})
          #Creating plot of number of children and adults onboard of titanic
          age_plot = sns.factorplot('is_child', data=titanic_df, kind='count')
          age plot.despine(left=True)
          age_plot.set_ylabels("Count of passengers")
          age_plot.fig.suptitle('Titanic passangers count by age')
```

Out[204]: <matplotlib.text.Text at 0x1af31a20>



```
In [205]:
          #Number of adults and childrens 1: 'Child', 0: 'Adult'
          titanic_df["is_child"].value_counts()
```

Out[205]: Adults 778 Children 113

Name: is_child, dtype: int64

There were 779 adults and 113 children onboard of titanic.

		Age	Fare	PClass	ParCh	Passengerld	SibSp	Survived
4.2 Exploring s	Se¥lata							

Now i will explore Sex data. I will start with displaying statistics of sex data:

In [206]: # Group series

passengers_by_sex = titanic_df.groupby("Sex") #Generate various summary statistics of 'Sex' data

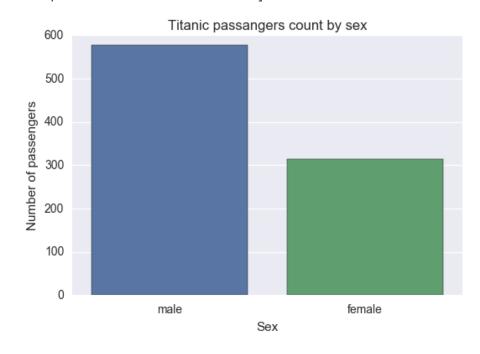
passengers_by_sex.describe()

Out[206]:

		Age	Fare	PClass	ParCh	Passengerld	SibSp	Survived
Sex								
	count	261.000000	314.000000	314.000000	314.000000	314.000000	314.000000	314.000000
	mean	27.915709	44.479818	2.159236	0.649682	431.028662	0.694268	0.742038
	std	14.110146	57.997698	0.857290	1.022846	256.846324	1.156520	0.438211
female	min	0.750000	6.750000	1.000000	0.000000	2.000000	0.000000	0.000000
Terriale	25%	NaN	12.071875	1.000000	0.000000	231.750000	0.000000	0.000000
	50%	NaN	23.000000	2.000000	0.000000	414.500000	0.000000	1.000000
	75%	NaN	55.000000	3.000000	1.000000	641.250000	1.000000	1.000000
	max	63.000000	512.329200	3.000000	6.000000	889.000000	8.000000	1.000000
	count	453.000000	577.000000	577.000000	577.000000	577.000000	577.000000	577.000000
	mean	30.726645	25.523893	2.389948	0.235702	454.147314	0.429809	0.188908
	std	14.678201	43.138263	0.813580	0.612294	257.486139	1.061811	0.391775
male	min	0.420000	0.000000	1.000000	0.000000	1.000000	0.000000	0.000000
illale	25%	NaN	7.895800	2.000000	0.000000	222.000000	0.000000	0.000000
	50%	NaN	10.500000	3.000000	0.000000	464.000000	0.000000	0.000000
	75%	NaN	26.550000	3.000000	0.000000	680.000000	0.000000	0.000000
	max	80.000000	512.329200	3.000000	5.000000	891.000000	8.000000	1.000000

```
In [207]:
          #Creating plot of number of male and female onboard of Titanic
          titanic_class = sns.countplot(x="Sex", data=titanic_df)
          titanic_class.set(xlabel='Sex', ylabel='Number of passengers', title = 'Titanic passangers count
           by sex')
```

```
Out[207]: [<matplotlib.text.Text at 0x1c6aaeb8>,
           <matplotlib.text.Text at 0x18664780>,
           <matplotlib.text.Text at 0x1d2ed748>]
```



```
In [208]: # group the passengers that survived by gender
          passengers_by_sex = titanic_df.groupby("Sex")
          # find total number of survived by gender
          total = passengers_by_sex["Survived"].count()
```

```
print "There were ",total["female"], "females and", total["male"], "males onboard of Titanic shi
In [209]:
          p."
```

There were 314 females and 577 males onboard of Titanic ship.

From the analysis of the sex data we can conclude that females had higher chance to survive Titanic catastrophe.

4.3 Exploring class data

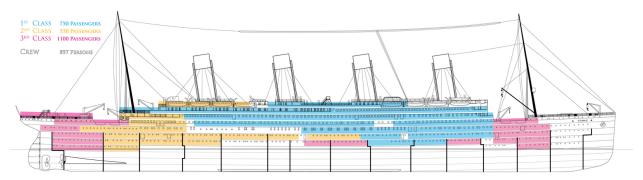
There were 3 classes of passangers on Titanic vessel. The Titanic's first class passenger list was a "who's who" of the rich and prominent of the upper class in 1912. Second classes passengers were leisure tourists, academics, members of the clergy and middle class English and American families. The third class passengers or steerage passengers left hoping to start new lives in the United States and Canada.

Image below shows location of each class on the vessel:

```
* 1st Class: blue
* 2nd Class: yellow
* 3rd class: red
```

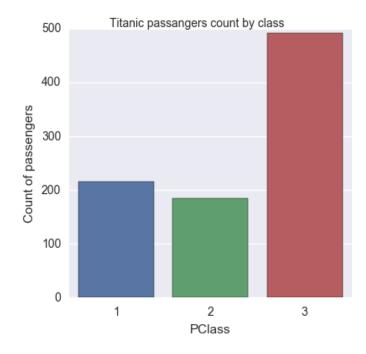
In [210]: #Load image from url Image(url= "http://img07.deviantart.net/af19/i/2014/307/c/f/r_m_s__titanic_class_system_by_monro egerman-d787jna.png", width=900, height=900, unconfined=True)

Out[210]:



In [211]: #Create histogram showing passanger count by class class_plot = sns.factorplot('PClass', order=[1,2,3], data=titanic_df, kind='count') class_plot.despine(left=True) class_plot.set_ylabels("Count of passengers") class_plot.fig.suptitle('Titanic passangers count by class')

Out[211]: <matplotlib.text.Text at 0x1d573518>



#Display passanger count by Class In [212]: titanic_df["PClass"].value_counts()

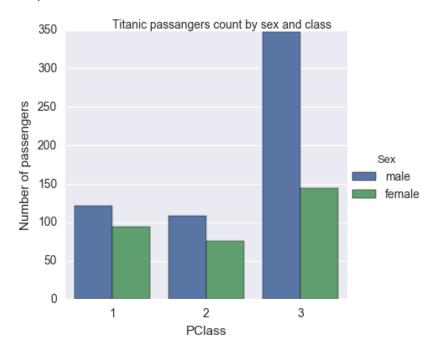
Out[212]: 3.0 491 1.0 216 2.0 184

Name: PClass, dtype: int64

We can observe that majority of passanger were 3rd class passangers.

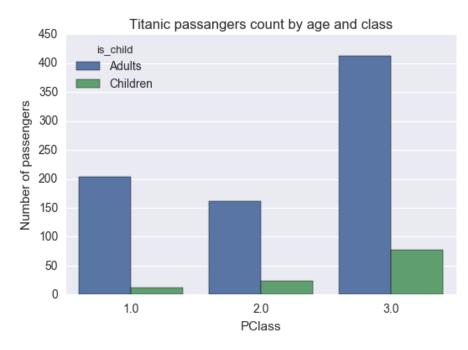
```
In [213]:
          #Create histogram showing passanger count by class
          class_plot = sns.factorplot('PClass', order=[1,2,3], hue = "Sex", data=titanic_df, kind='count')
          class_plot.despine(left=True)
          class_plot.set(xlabel='PClass', ylabel='Number of passengers')
          class_plot.fig.suptitle('Titanic passangers count by sex and class')
```

Out[213]: <matplotlib.text.Text at 0x1d5690b8>



#Create plot showing adults and children count per class In [214]: titanic_class = sns.countplot(x="PClass", hue="is_child", data=titanic_df) titanic class.set(xlabel='PClass', ylabel='Number of passengers', title = 'Titanic passangers co unt by age and class')

Out[214]: [<matplotlib.text.Text at 0x1d264400>, <matplotlib.text.Text at 0x1d73cdd8>, <matplotlib.text.Text at 0x1d9a5128>]



We can see that a lot more men were on the third class.

4.4 Exploring Embarked data

In [220]: #Display passanger count by Embarked location

available_embarked_passengers["Embarked"].value_counts()

Out[220]: S 644 C 168

Q

77

Name: Embarked, dtype: int64

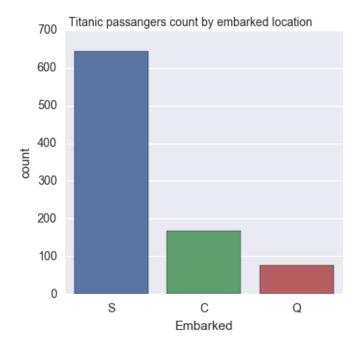
In [258]: ##Create histogam which shows number passangers by Embarked Location

embarked_plot = sns.factorplot('Embarked', data = available_embarked_passengers, kind='count')

embarked_plot.despine(left=True)

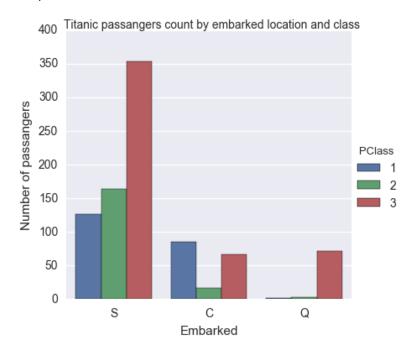
embarked_plot.fig.suptitle('Titanic passangers count by embarked location', fontsize=10)

Out[258]: <matplotlib.text.Text at 0x1f9e7a90>



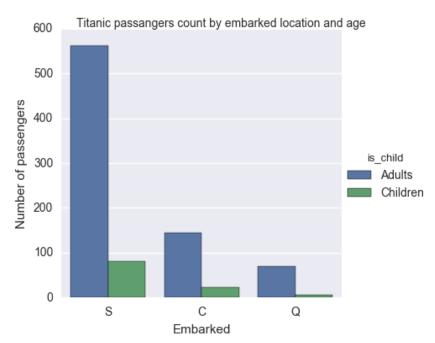
```
In [222]:
          embarked_plot_class = sns.factorplot('Embarked', hue = "PClass", data=available_embarked_passeng
          ers, kind='count')
          embarked_plot_class.despine(left=True)
          embarked_plot_class.set_ylabels("Number of passangers")
          embarked_plot_class.fig.suptitle('Titanic passangers count by embarked location and class')
```

Out[222]: <matplotlib.text.Text at 0x18645da0>



embarked_plot_is_child = sns.factorplot('Embarked', hue = "is_child", data=titanic_df, kind='cou In [225]: embarked_plot_is_child.despine(left=True) embarked_plot_is_child.set_ylabels("Number of passengers") embarked_plot_is_child.fig.suptitle('Titanic passangers count by embarked location and age')

Out[225]: <matplotlib.text.Text at 0x1bef95f8>

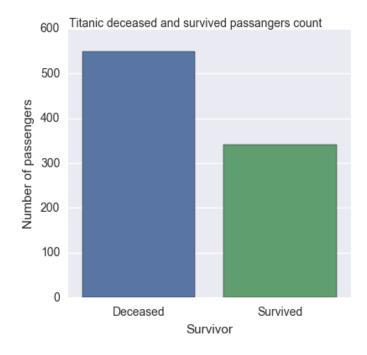


5. Survival estimation for passangers using Age, Gender, PClass, Embarked, Deck data

After performing analysis of the data and number of calculations, i will asses the groups and their survivalbility. Moreover, I will adressed the questions I asked in the introduction, and I answered them based on the data, I also made some visualizations to help understanding the given numbers.

```
In [224]:
          # Create plot showing deceased and survived passangers
          titanic df['Survivor']= titanic df.Survived.map({0:'Deceased', 1:'Survived'})
          survivor_plot = sns.factorplot('Survivor', data=titanic_df, kind='count', palette="deep")
          survivor plot.despine(left=True)
          survivor_plot.set_ylabels("Number of passengers")
          survivor_plot.fig.suptitle('Titanic deceased and survived passangers count', fontsize=10)
```

Out[224]: <matplotlib.text.Text at 0x1bcec4e0>



```
#Calculate number of survived and deceased passangers
titanic_df['Survivor'].value_counts()
```

Out[182]: Deceased 549 Survived 342

Name: Survivor, dtype: int64

Q1: Is there a difference on survival rate between passangers in regards to the age?

```
In [226]:
          #Create boxplot showing distribution of age vs survival
          survival_age_plot = sns.boxplot(data=titanic_df, x='Survived', y='Age')
          survival_age_plot.set(title='Age Distribution by Survival',
                      xlabel = 'Survival',
                      ylabel = 'Age distribution',
                      xticklabels = ['Deceased', 'Survived'])
```

```
Out[226]: [<matplotlib.text.Text at 0x1bee26a0>,
           [<matplotlib.text.Text at 0x1bcfe6a0>, <matplotlib.text.Text at 0x1c24e2b0>],
           <matplotlib.text.Text at 0x1bc1bac8>,
           <matplotlib.text.Text at 0x1c8a4748>]
```



```
#Display count of adults and children
titanic_df["is_child"].value_counts()
```

Out[52]: Adults 778 Children 113

Name: is_child, dtype: int64

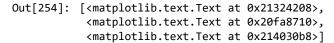
```
In [227]: # group the passengers that survived by is_child
          passengers_by_is_child = titanic_df.groupby("is_child")
          # find total count
          total = passengers_by_is_child["is_child"].count()
          # find total count of survived
          survived = passengers_by_is_child["Survived"].sum().astype(int)
          # find total count of deceased
          deceased = (total - survived).astype(int)
          print "Survived by", survived
          print " "
          print "Deceased by", deceased
```

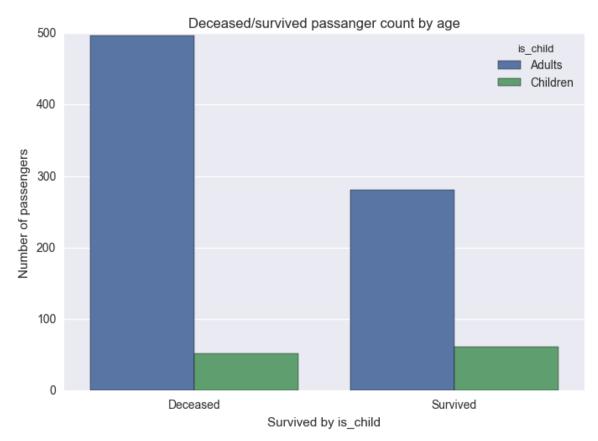
Survived by is_child Adults 281 Children 61

Name: Survived, dtype: int32

Deceased by is_child Adults 497 Children 52 dtype: int32

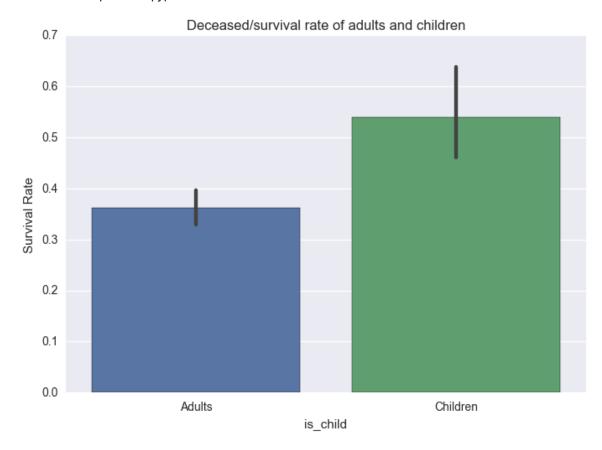
#Create histogram showing count of survived/deceased adults and children
survival_is_child_plot = sns.countplot(x="Survivor", hue="is_child", data=titanic_df) In [254]: survival_is_child_plot.set(xlabel='Survived by is_child', ylabel='Number of passengers', title = 'Deceased/survived passanger count by age')





```
In [229]:
          #Creating a bar plot of survived adults and children
          survived_adults_children = sns.set(style="darkgrid")
          survived_adults_children = sns.barplot(data=titanic_df, x="is_child", y="Survived", palette="dee
          p",)
          survived_adults_children.set(xlabel='is_child', ylabel='Survival Rate', title = 'Deceased/surviv
          al rate of adults and children')
          sns.plt.show
```

Out[229]: <function matplotlib.pyplot.show>



```
In [230]:
          \#Create correlation function between two parameters x and y
          def correlation(x, y):
              std_x = (x - x.mean()) / x.std(ddof=0)
              std_y = (y - y.mean()) / y.std(ddof=0)
              return (std_x * std_y).mean()
```

```
In [231]: age = titanic_df['Age']
          survival = titanic df['Survived']
          # Using correlation function show correlation between two variables - age and survival
          print "Pearsons R for age vs. survival: ", correlation(age, survival)
```

Pearsons R for age vs. survival: -0.0779826784139

The boxplot is showing us that the mean of survived and deceased passangers is very close to each other. Calculation of Pearsons R for age vs. survival doesn't show that there is very clear corelation.

Q2: Is there a difference on survival rate between passangers in regards to the sex?

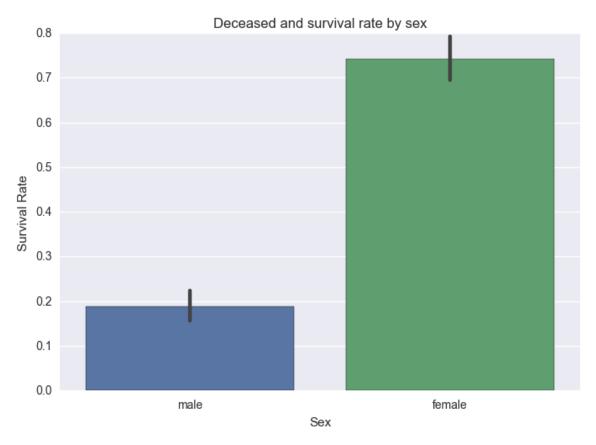
In [232]:

Out[232]:

		Age = tita	Fare c	.P.Class	ParCh	Passengerld	SibSp	Survived
passeng passeng Sex	ers_by ers_by	sex.descri	be()	poy(-sex)		- accongona	Спор	
		Age	Fare	PClass	ParCh	Passengerld	SibSp	Survived
Sex								
	count	261.000000	314.000000	314.000000	314.000000	314.000000	314.000000	314.000000
	mean	27.915709	44.479818	2.159236	0.649682	431.028662	0.694268	0.742038
	std	14.110146	57.997698	0.857290	1.022846	256.846324	1.156520	0.438211
female	min	0.750000	6.750000	1.000000	0.000000	2.000000	0.000000	0.000000
Temale	25%	NaN	12.071875	1.000000	0.000000	231.750000	0.000000	0.000000
	50%	NaN	23.000000	2.000000	0.000000	414.500000	0.000000	1.000000
	75%	NaN	55.000000	3.000000	1.000000	641.250000	1.000000	1.000000
	max	63.000000	512.329200	3.000000	6.000000	889.000000	8.000000	1.000000
	count	453.000000	577.000000	577.000000	577.000000	577.000000	577.000000	577.000000
	mean	30.726645	25.523893	2.389948	0.235702	454.147314	0.429809	0.188908
	std	14.678201	43.138263	0.813580	0.612294	257.486139	1.061811	0.391775
mala	min	0.420000	0.000000	1.000000	0.000000	1.000000	0.000000	0.000000
male	25%	NaN	7.895800	2.000000	0.000000	222.000000	0.000000	0.000000
	50%	NaN	10.500000	3.000000	0.000000	464.000000	0.000000	0.000000
	75%	NaN	26.550000	3.000000	0.000000	680.000000	0.000000	0.000000
	max	80.000000	512.329200	3.000000	5.000000	891.000000	8.000000	1.000000

In [253]: #Creating a bar plot of survived males and females survived_male_female = sns.set(style="darkgrid") survived_male_female = sns.barplot(data=titanic_df, x="Sex", y="Survived", palette="deep") survived_male_female.set(xlabel='Sex', ylabel='Survival Rate', title = 'Deceased and survival ra te by sex') plt.show

Out[253]: <function matplotlib.pyplot.show>



```
In [234]: # Find number of survived by gender
          survived = passengers_by_sex["Survived"].sum().astype(int)
          # Find number of deceased by gender
          deceased = (total - survived)
          print "Survived by", survived
          print " "
          print "Deceased by", deceased
```

Survived by Sex female 233 male 109

Name: Survived, dtype: int32

Deceased by Adults NaN Children NaN

female NaN male NaN dtype: float64

0

```
P2 Investigate+a+Titanic+dataset Paulina Grunwald
In [252]:
           #Creating a bar plot displaying number of survived/deceased males and females
           survived = passengers_by_sex["Survived"]
           survival.sex_plot = sns.countplot(x="Survivor", hue="Sex", data=titanic_df)
           survival.sex_plot.set(xlabel='Passangers status', ylabel='Number of passengers', title = 'Surviv
           al by sex')
Out[252]: [<matplotlib.text.Text at 0x20dcf668>,
            <matplotlib.text.Text at 0x20dd5358>,
            <matplotlib.text.Text at 0x210791d0>]
                                                       Survival by sex
               500
                                                                                                 Sex
                                                                                                male
                                                                                                female
               400
            Number of passengers
               300
               200
               100
```

```
In [236]: survived = passengers_by_sex["Survived"].sum().astype(int)
          # find total number of survived by gender
          total = passengers_by_sex["Survived"].count()
In [237]: | percent_survived_females = (survived["female"] * 100) / total["female"]
          print "Procent of survived females = ", percent survived females, "%"
          print ""
          #calculating % of survived males
          percent_survived_males = (survived["male"] * 100) / total["male"]
          print "Procent of survived males = ", percent survived males, "%"
          Procent of survived females = 74 %
          Procent of survived males = 18 %
```

Passangers status

Survived

From the analysis of the sex data we can conclude that females had much higher chance to survive Titanic catastrophe.

Deceased

Q3: Is there a difference on survival rate between passangers located in different classes?

Out[238]:

ers_by_	Agess = ti	t āāie _df.gr	ParCh "PC1a	PassengerId	SibSp	Survived
ers_by_	_class.desc	ribe()				
	Age	Fare	ParCh	Passengerld	SibSp	Survived
count	186.000000	216.000000	216.000000	216.000000	216.000000	216.000000
mean	38.233441	84.154687	0.356481	461.597222	0.416667	0.629630
std	14.802856	78.380373	0.693997	246.737616	0.611898	0.484026
min	0.920000	0.000000	0.000000	2.000000	0.000000	0.000000
25%	NaN	30.923950	0.000000	270.750000	0.000000	0.000000
50%	NaN	60.287500	0.000000	472.000000	0.000000	1.000000
75%	NaN	93.500000	0.000000	670.500000	1.000000	1.000000
max	80.000000	512.329200	4.000000	890.000000	3.000000	1.000000
count	173.000000	184.000000	184.000000	184.000000	184.000000	184.000000
mean	29.877630	20.662183	0.380435	445.956522	0.402174	0.472826
std	14.001077	13.417399	0.690963	250.852161	0.601633	0.500623
min	0.670000	0.000000	0.000000	10.000000	0.000000	0.000000
25%	NaN	13.000000	0.000000	234.500000	0.000000	0.000000
50%	NaN	14.250000	0.000000	435.500000	0.000000	0.000000
75%	NaN	26.000000	1.000000	668.000000	1.000000	1.000000
max	70.000000	73.500000	3.000000	887.000000	3.000000	1.000000
count	355.000000	491.000000	491.000000	491.000000	491.000000	491.000000
mean	25.140620	13.675550	0.393075	439.154786	0.615071	0.242363
std	12.495398	11.778142	0.888861	264.441453	1.374883	0.428949
min	0.420000	0.000000	0.000000	1.000000	0.000000	0.000000
25%	NaN	7.750000	0.000000	200.000000	0.000000	0.000000
50%	NaN	8.050000	0.000000	432.000000	0.000000	0.000000
75%	NaN	15.500000	0.000000	666.500000	1.000000	0.000000
max	74.000000	69.550000	6.000000	891.000000	8.000000	1.000000
	count mean std min 25% count mean std min 25% sow 75% max count mean std min 25% sow 75% max count mean std min 25% sow 75% sow 75% sow 75%	Age count 186.000000 mean 38.233441 std 14.802856 min 0.920000 25% NaN 50% NaN 75% NaN max 80.000000 count 173.000000 mean 29.877630 std 14.001077 min 0.670000 25% NaN 50% NaN row 70.000000 count 355.000000 mean 25.140620 std 12.495398 min 0.420000 25% NaN 50% NaN	Age Fare count 186.000000 216.000000 mean 38.233441 84.154687 std 14.802856 78.380373 min 0.920000 0.000000 25% NaN 30.923950 50% NaN 60.287500 75% NaN 93.500000 max 80.000000 512.329200 count 173.000000 184.000000 mean 29.877630 20.662183 std 14.001077 13.417399 min 0.670000 0.000000 25% NaN 13.000000 50% NaN 14.250000 75% NaN 26.000000 max 70.000000 73.500000 count 355.000000 491.000000 mean 25.140620 13.675550 std 12.495398 11.778142 min 0.420000 0.000000 25% NaN 7.750000 50% <th< td=""><td>Age Fare ParCh count 186.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 std 14.802856 78.380373 0.693997 min 0.920000 0.000000 0.000000 25% NaN 30.923950 0.000000 50% NaN 60.287500 0.000000 75% NaN 93.500000 0.000000 max 80.000000 512.329200 4.000000 max 80.000000 184.000000 184.00000 mean 29.877630 20.662183 0.380435 std 14.001077 13.417399 0.690963 min 0.670000 0.000000 0.000000 25% NaN 14.250000 0.000000 75% NaN 26.000000 1.000000 max 70.000000 73.500000 3.000000 count 355.000000 491.000000 491.000000 mean 25.140620<td>Age Fare ParCh PassengerId count 186.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 std 14.802856 78.380373 0.693997 246.737616 min 0.920000 0.000000 0.000000 2.000000 25% NaN 30.923950 0.000000 270.750000 50% NaN 93.500000 0.000000 472.000000 75% NaN 93.500000 0.000000 670.500000 max 80.000000 512.329200 4.000000 890.000000 count 173.000000 184.000000 184.000000 184.000000 mean 29.877630 20.662183 0.380435 445.956522 std 14.001077 13.417399 0.690963 250.852161 min 0.670000 0.000000 0.000000 10.000000 25% NaN 14.250000 0.000000 435.500000 7</td><td>Age Fare ParCh PassengerId SibSp count 186.000000 216.000000 216.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 0.416667 std 14.802856 78.380373 0.693997 246.737616 0.611898 min 0.920000 0.000000 0.000000 2.000000 0.000000 25% NaN 30.923950 0.000000 270.750000 0.000000 50% NaN 93.500000 0.000000 472.000000 0.000000 75% NaN 93.500000 0.000000 670.500000 1.000000 max 80.000000 512.329200 4.000000 890.000000 184.000000 max 80.000000 184.000000 184.000000 184.000000 184.000000 man 29.877630 20.662183 0.380435 445.956522 0.402174 std 14.001077 13.417399 0.690963 250.52161</td></td></th<>	Age Fare ParCh count 186.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 std 14.802856 78.380373 0.693997 min 0.920000 0.000000 0.000000 25% NaN 30.923950 0.000000 50% NaN 60.287500 0.000000 75% NaN 93.500000 0.000000 max 80.000000 512.329200 4.000000 max 80.000000 184.000000 184.00000 mean 29.877630 20.662183 0.380435 std 14.001077 13.417399 0.690963 min 0.670000 0.000000 0.000000 25% NaN 14.250000 0.000000 75% NaN 26.000000 1.000000 max 70.000000 73.500000 3.000000 count 355.000000 491.000000 491.000000 mean 25.140620 <td>Age Fare ParCh PassengerId count 186.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 std 14.802856 78.380373 0.693997 246.737616 min 0.920000 0.000000 0.000000 2.000000 25% NaN 30.923950 0.000000 270.750000 50% NaN 93.500000 0.000000 472.000000 75% NaN 93.500000 0.000000 670.500000 max 80.000000 512.329200 4.000000 890.000000 count 173.000000 184.000000 184.000000 184.000000 mean 29.877630 20.662183 0.380435 445.956522 std 14.001077 13.417399 0.690963 250.852161 min 0.670000 0.000000 0.000000 10.000000 25% NaN 14.250000 0.000000 435.500000 7</td> <td>Age Fare ParCh PassengerId SibSp count 186.000000 216.000000 216.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 0.416667 std 14.802856 78.380373 0.693997 246.737616 0.611898 min 0.920000 0.000000 0.000000 2.000000 0.000000 25% NaN 30.923950 0.000000 270.750000 0.000000 50% NaN 93.500000 0.000000 472.000000 0.000000 75% NaN 93.500000 0.000000 670.500000 1.000000 max 80.000000 512.329200 4.000000 890.000000 184.000000 max 80.000000 184.000000 184.000000 184.000000 184.000000 man 29.877630 20.662183 0.380435 445.956522 0.402174 std 14.001077 13.417399 0.690963 250.52161</td>	Age Fare ParCh PassengerId count 186.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 std 14.802856 78.380373 0.693997 246.737616 min 0.920000 0.000000 0.000000 2.000000 25% NaN 30.923950 0.000000 270.750000 50% NaN 93.500000 0.000000 472.000000 75% NaN 93.500000 0.000000 670.500000 max 80.000000 512.329200 4.000000 890.000000 count 173.000000 184.000000 184.000000 184.000000 mean 29.877630 20.662183 0.380435 445.956522 std 14.001077 13.417399 0.690963 250.852161 min 0.670000 0.000000 0.000000 10.000000 25% NaN 14.250000 0.000000 435.500000 7	Age Fare ParCh PassengerId SibSp count 186.000000 216.000000 216.000000 216.000000 216.000000 216.000000 mean 38.233441 84.154687 0.356481 461.597222 0.416667 std 14.802856 78.380373 0.693997 246.737616 0.611898 min 0.920000 0.000000 0.000000 2.000000 0.000000 25% NaN 30.923950 0.000000 270.750000 0.000000 50% NaN 93.500000 0.000000 472.000000 0.000000 75% NaN 93.500000 0.000000 670.500000 1.000000 max 80.000000 512.329200 4.000000 890.000000 184.000000 max 80.000000 184.000000 184.000000 184.000000 184.000000 man 29.877630 20.662183 0.380435 445.956522 0.402174 std 14.001077 13.417399 0.690963 250.52161

In [239]: # group the passengers that survived by class passengers_by_class = titanic_df.groupby("PClass") total = passengers_by_class["PClass"].count()

```
In [240]: #Total count of passangers in PClass
          print total
          print""
          #Count of survived passangers embarked in different classes
          survived = passengers_by_class["Survived"].sum().astype(int)
          print ""
          deceased = (total - survived).astype(int)
          print "Survived by", survived,
          print ""
          print "Deceased by", deceased,
          PClass
```

```
3.0
       491
Name: PClass, dtype: int64
Survived by PClass
1.0
       136
2.0
        87
3.0
       119
Name: Survived, dtype: int32
Deceased by PClass
1.0
       80
2.0
       97
3.0
       372
dtype: int32
```

1.0

2.0

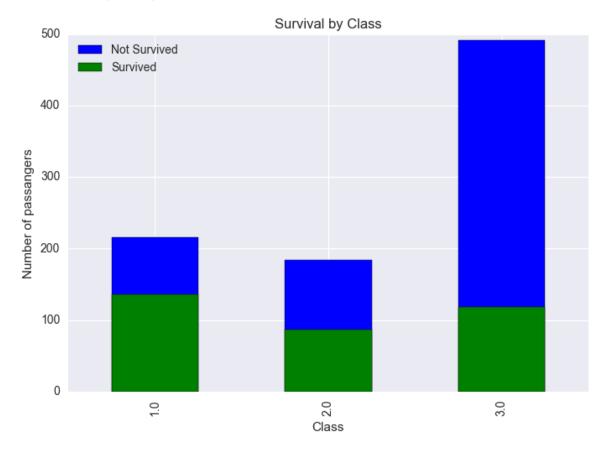
216

184

As we can see survived rate differs quite a lot between different classes. The first class passengers had the highest survival rate (63%), followed by the 2nd class (47%) and the 3rd class (24%).

```
In [241]:
          #Create plot which shows survived and deceased passanger count per class
          survival.class_plot_total = passengers_by_class["Survived"].count()
          survived = passengers_by_class["Survived"].sum()
          survival.class_plot_total.plot(kind="bar", color="b", label="Not Survived")
          survived.plot(kind="bar", color="g", label="Survived")
          plt.xlabel('Class')
          plt.ylabel('Number of passangers')
          plt.title('Survival by Class')
          plt.legend(loc=2)
```

Out[241]: <matplotlib.legend.Legend at 0xed87748>

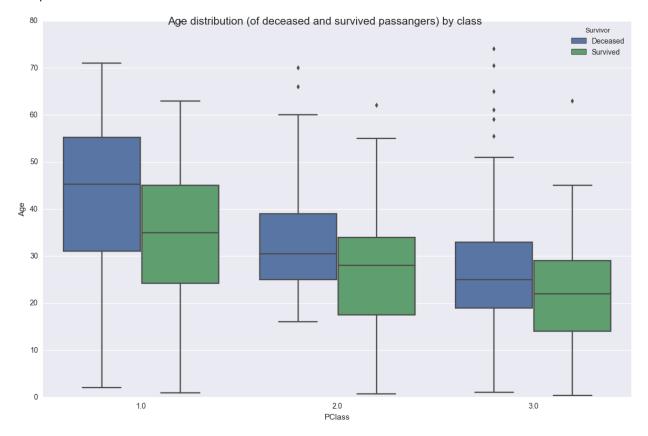


As we can remember from the exploration part there were more men than female in the third class, which in the end limited the chances of survival of the passangers in the third class.

Below boxplots represent Age distribution per class of survived Titanic passangers.

```
#create boxplot of age distribution in classes 1,2,3 vs, survived and deceased
boxplot = sns.factorplot(kind='box',
                                            # Boxplot
               y='Age',
                                  # Y-axis - values for boxplot
               x='PClass',
                                  # X-axis - first factor
               hue='Survivor',
                                  # Second factor denoted by color
               data=titanic_df,
                                     # Dataframe
                                  # Figure size (x100px)
               size=8,
                                  # Width = size * aspect
               aspect=1.5,
               legend_out=False)
boxplot.fig.suptitle('Age distribution (of deceased and survived passangers) by class', fontsize=
)
```

Out[246]: <matplotlib.text.Text at 0x209065f8>



Third-class and crew cabins were located in the hold, while promenade areas were on lower decks and in the quarter. They were separated from the promenade decks for wealthier passengers by special partitions - staircases leading to upper decks had metal gates, the keys to which were kept by stewards. Some sources claim that these partitions were required by American immigration laws at the time. The majority of passengers on the Titanic were emigrants. Only 25 percent of the Titanic's third-class passengers survived, with small percentage of male. On the other hand we can observe high survival rate in the passangers in the first class. It also has to be taken into the account that there were quite big precent of woman in the first class.

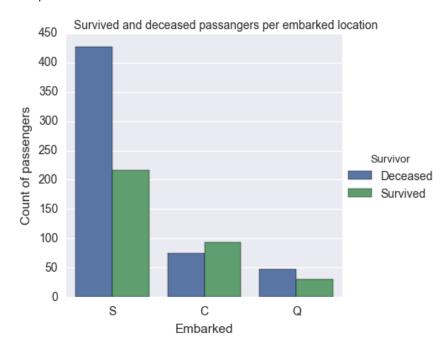
We can also observe from above displayed boxplots that younger people had slighty better chance to survive in classes 1,2,3.

Third class was the group hardest hit by the disaster and experiencing the greatest loss of life. According to many sources the reasons for could be: first and second class given more importance, many did not understand the true magnitude of the disaster right after the collision with the Titanic, at least some of the third class gates remained locked, and many of the passengers that were non-English speaking did not understand.

Q4: Is there a difference on survival rate between location of the embarkment of the passangers?

```
In [247]: #Create plot which shows deceased and survived passangers count per embarked location
          survival.embarked plot = sns.factorplot('Embarked', hue = "Survivor", data=titanic df, kind='cou
          survival.embarked_plot.despine(left=True)
          survival.embarked_plot.set_ylabels("Count of passengers")
          survival.embarked_plot.fig.suptitle('Survived and deceased passangers per embarked location', fo
          ntsize=10)
```

Out[247]: <matplotlib.text.Text at 0x20fc07b8>



Note: C = Cherbourg; Q = Queenstown; S = Southampton

```
In [248]: # group the passengers that survived by gender
          passengers_by_embarked = titanic_df.groupby("Embarked")
          # find the values and labels for the area circles
          total = passengers_by_embarked["Embarked"].count()
          #Total count of passangers embarked in Cherbourg, Queenstown, Southampton
          print total
          print""
          #Count of survived passangers embarked in Cherbourg, Queenstown, Southampton
          survived = passengers by embarked["Survived"].sum().astype(int)
          deceased = (total - survived).astype(int)
          print "Survived by", survived,
          print ""
          #Count of deceased passangers embarked in Cherbourg, Queenstown, Southampton
          print ""
          print "Deceased by", deceased,
          Embarked
          C
               168
          Q
                77
               644
          Name: Embarked, dtype: int64
          Survived by Embarked
          C
                93
          0
                30
               217
          Name: Survived, dtype: int32
          Deceased by Embarked
          C
                75
                47
               427
          dtype: int32
In [249]: #calculating % of survived by embarked location
          percent_survived_embarked = (survived["C"] * 100) / total["C"]
          print "Procent of survived passangers embarked in Cherbourg = ", percent_survived_embarked, "%"
          print ""
          percent_survived_embarked = (survived["Q"] * 100) / total["Q"]
          print "Procent of survived passangers embarked in Queenstown = ", percent_survived_embarked,
          "%"
          print ""
          percent_survived_embarked = (survived["S"] * 100) / total["S"]
          print "Procent of survived passangers embarked in Southampton = ", percent survived embarked,
          Procent of survived passangers embarked in Cherbourg = 55 %
          Procent of survived passangers embarked in Queenstown = 38 %
```

Q5: Is there a difference on survival rate between passangers located on different decks?

Procent of survived passangers embarked in Southampton = 33 %

```
P2 Investigate+a+Titanic+dataset Paulina Grunwald
In [250]: #known_cabin_passengers["Deck"].descibe()
           # group the passengers that survived by gender
           passengers_by_deck = known_cabin_passengers.groupby("Deck")
           # find the values and labels for the area circles
           total = passengers_by_deck["Deck"].count()
           #Total count of passangers embarked in Cherbourg, Queenstown, Southampton
           print total
          print""
           #Count of survived passangers embarked in Cherbourg, Queenstown, Southampton
           survived = passengers_by_deck["Survived"].sum().astype(int)
           deceased = (total - survived).astype(int)
           print "Survived by", survived,
           print ""
           #Count of deceased passangers embarked in Cherbourg, Queenstown, Southampton
           print ""
          print "Deceased by", deceased,
          Deck
          Α
               15
          В
               64
          C
               71
          D
               34
          Ε
               33
          F
               13
                7
          G
          Т
                1
          Name: Deck, dtype: int64
```

```
Survived by Deck
     48
В
C
     41
D
     26
Ε
     25
F
      8
G
      2
Т
Name: Survived, dtype: int32
Deceased by Deck
В
     16
C
      8
Ε
      8
F
      5
G
      5
      1
dtype: int32
```

```
In [251]: #calculating % of survived by embarked location
          percent_survived_deckA = (survived["A"] * 100) / total["A"]
          print "Procent of survived passangers on deck A = ", percent_survived_deckA, "%"
          print ""
          percent_survived_deckB = (survived["B"] * 100) / total["B"]
          print "Procent of survived passangers on deck B = ", percent_survived_deckB, "%"
          percent_survived_deckC = (survived["C"] * 100) / total["C"]
          print "Procent of survived passangers on deck C = ", percent survived deckC, "%"
          percent_survived_deckD = (survived["D"] * 100) / total["D"]
          print "Procent of survived passangers on deck C = ", percent_survived_deckD, "%"
          percent_survived_deckD = (survived["D"] * 100) / total["D"]
          print "Procent of survived passangers on deck D = ", percent_survived_deckD, "%"
          percent survived deckE = (survived["E"] * 100) / total["E"]
          print "Procent of survived passangers on deck E = ", percent_survived_deckE, "%"
          percent_survived_deckF = (survived["F"] * 100) / total["F"]
          print "Procent of survived passangers on deck F = ", percent_survived_deckF, "%"
          #No caluclation for Deck T as only 1 passanger present on that deck
```

```
Procent of survived passangers on deck A = 46 %
Procent of survived passangers on deck B = 75 %
Procent of survived passangers on deck C = 57 %
Procent of survived passangers on deck C = 76 %
Procent of survived passangers on deck D = 76 %
Procent of survived passangers on deck E = 75 %
Procent of survived passangers on deck F = 61 %
```

From above done analysis we can see that the least chance of survival had passngers located on deck A.

Conclusions

While using the Titanic dataset I found several limitations that made making deeper analysis more difficult and in some cases unreliable. The limitation i had to face are following:

- 1. Big number of data was missing. We had available data of only 891 passangers from 2224 that were present on titanic. This represents only 40% of the total passangers.
- 2. From 891 passangers so much as 708 passangers had at least one type of data missing (e.g age). This mean 79% of data is missing in the provided dataset. This is quite a big number and represents
- 3. Assesing age and cabin data turned out to be challenging as 177 and 687 data points were missing respectively in those columns.
- 4. There might be other factors that have impacted the chances of survival. It was reported in multiple articles that gates separating 3rd class were mostly closed and thus they could not escape so easily to the lifeboats.
- 5. Deck data might be not correct due to the fact that it's impossible to say where the passangers were at the time of the catastrophe. The same would apply to cabin data which i did not analyzed.

Main conclusions:

- 1. The number of surviving females (74%) exceeded the number of surviving males (18%) aboard RMS Titanic.
- 2. The number of children survived in the disaster significantly exceeded the number of survived adults.
- 3. Passsengers with age between 20 and 35 tended to survive the most. This is caused by the fact that the number of passanger in this age group was higher so i can not say that there is an actual correlation between age and survival rate.
- 4. Passangers in the first class had higher chance of survival than from class two and three. Survival precent of passangers in classes were following: 1st: 63%, 2nd Class 47%, 3rd Class 24%.
- 5. Passangers embarked in Cherbourg had higher chances of survival than passangers embarked in Queenstown or Southampton.
- 6. Passangers located on Deck A had the lowest chances of survival.

I think there is still a room for further analysis which due to the time constraint i did not manage to perform. Those would be following:

- 1. Asses if the people traveling with family(wife, husband, children) had higher chance to survive.
- 2. Asses if the size of family had a influence on chance of survival.
- 3. Asses distribution of the lifeboats on the titanic in comparision of survival on different decks/cabins.
- 4. Performing statistical testing to validating results in order to strengten validation of the correlational observations.

References

Additional informations:

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Plots:

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Pandas:

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Images:

- https://upload.wikimedia.org/wikipedia/commons/e/e1/Titanic_under_construction.jpg (https://upload.wikimedia.org/wikipedia/commons/e/e1/Titanic under construction.jpg)
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