Exploring Survival on the Titanic

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Introduction

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. This sensational tragedy shocked the international community and led to better safety regulations for ships.

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

Question

In this study, the main question is what sorts of people were likely to survive. We will use the data to answer the stated question. We are going to analyze the observational differences and draw some tentative conclusions but we won't validate our observations with statistical measurements.

Data Exploration

Variables in the data file are as follows:

- survival = Survival (0 = No; 1 = Yes)
- pclass = Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
- name = Name
- sex = Sex (female; male)
- 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)

First, the data is imported and the heading are examined.

In [1022]:
```
# import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pylab as plt
%matplotlib inline
```

```
# load and check data heading
titanic_data = pd.read_csv('titanic-data.csv')
titanic_data.head()
```

Out[1022]:

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

let's check our data statistics and see which variables are more interesting to investigate.

In [1023]:
```
titanic_data.describe()
```

Out[1023]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00000
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	512.32920

Out of 891 passenger only %38 of them (342) survived and 549 not.

Let's split our data into two groups of *survived* and *not_survived* and explore their statistics more.

In [1024]:
```
# getting data statistics
titanic_data.groupby(['Survived']).describe()
```

Out[1024]:

		Age	Fare	Parch	PassengerId	Pclass	SibSp
Survived							
0	**count**	424.000000	549.000000	549.000000	549.000000	549.000000	549.000000
	mean	30.626179	22.117887	0.329690	447.016393	2.531876	0.553734
	std	14.172110	31.388207	0.823166	260.640469	0.735805	1.288399
	min	1.000000	0.000000	0.000000	1.000000	1.000000	0.000000
	25%	21.000000	7.854200	0.000000	211.000000	2.000000	0.000000
	50%	28.000000	10.500000	0.000000	455.000000	3.000000	0.000000
	75%	39.000000	26.000000	0.000000	675.000000	3.000000	1.000000
	max	74.000000	263.000000	6.000000	891.000000	3.000000	8.000000
1	**count**	290.000000	342.000000	342.000000	342.000000	342.000000	342.000000
	mean	28.343690	48.395408	0.464912	444.368421	1.950292	0.473684
	std	14.950952	66.596998	0.771712	252.358840	0.863321	0.708688
	min	0.420000	0.000000	0.000000	2.000000	1.000000	0.000000
	25%	19.000000	12.475000	0.000000	250.750000	1.000000	0.000000
	50%	28.000000	26.000000	0.000000	439.500000	2.000000	0.000000
	75%	36.000000	57.000000	1.000000	651.500000	3.000000	1.000000
	max	80.000000	512.329200	5.000000	890.000000	3.000000	4.000000

Pclass and **Parch** variables have a significant difference based on their mean, minimum, maximum and standard deviation values and we are planning to investigate them. In addition, we will check **Age** and **SibSp** for any exceptions. We cannot see any statistics regarding **Sex** variable here and it's because of its type (String). We will fix that issue and include it in our analysis as well. In short, we decided to investigate the following variables (as independent variables) and see how they are affecting the people's survival (as a dependent variable).

- age = Age
- sibsp = Number of Siblings/Spouses Aboard
- parch = Number of Parents/Children Aboard
- sex = Sex (female; male)
- pclass = Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)

Data Cleaning

The following issues are addressed in this section.

1. The **Sex** column variable type is *String* and we replace it with integer values (0 for female and 1 for male) so we are able to investigate and analyze it further.
2. The number of **Age** variable (714) are less than others (891). After a quick check we found out that some of the rows don't have entry for the **Age** column and we will remove them from our data set and continue the study with the rest.

In [1025]:
```
# chechinkg data types
titanic_data.dtypes
```

Out[1025]:
```
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
```

In [1036]:
```
# removing rows with no entery for Age
titanic_data_clean = titanic_data[titanic_data['Age'] >= 0]

# funtion for replacing Sex coloumn enteries with integer values
def Sex_to_index(string):
    if string == 'male':
        return int(1)
    elif string == 'female':
        return int(0)
    return string

# replacing Sex coloumn enteries with integer values
titanic_data_clean_mod = titanic_data_clean.applymap(Sex_to_index)
titanic_data_clean_mod.groupby(['Survived']).describe()
```

Out[1036]:

		Age	Fare	Parch	PassengerId	Pclass	Sex
Survived							
0	**count**	424.000000	424.000000	424.000000	424.000000	424.000000	424.000000
	mean	30.626179	22.965456	0.365566	442.299528	2.485849	0.849057
	std	14.172110	31.448825	0.878341	264.739548	0.743633	0.358417
	min	1.000000	0.000000	0.000000	1.000000	1.000000	0.000000
	25%	21.000000	7.895800	0.000000	200.750000	2.000000	1.000000

	50%	28.000000	11.887500	0.000000	436.000000	3.000000	1.000000
	75%	39.000000	26.550000	0.000000	683.250000	3.000000	1.000000
	max	74.000000	263.000000	6.000000	891.000000	3.000000	1.000000
1	**count**	290.000000	290.000000	290.000000	290.000000	290.000000	290.000000
	mean	28.343690	51.843205	0.527586	457.768966	1.872414	0.320690
	std	14.950952	70.458776	0.807147	250.845515	0.836617	0.467548
	min	0.420000	0.000000	0.000000	2.000000	1.000000	0.000000
	25%	19.000000	13.000000	0.000000	260.500000	1.000000	0.000000
	50%	28.000000	26.250000	0.000000	452.000000	2.000000	0.000000
	75%	36.000000	66.200000	1.000000	669.500000	3.000000	1.000000
	max	80.000000	512.329200	5.000000	890.000000	3.000000	1.000000

Now we can see a significant difference between **Sex** variable means.

As we mentioned before, the data set will be split into two groups of *survived* and *not_survived*.

In [1027]:
```
# split data into two groups of survived and not_survived
survived=titanic_data_clean_mod[titanic_data_clean_mod['Survived']==1]
not_survived = titanic_data_clean_mod[titanic_data_clean_mod['Survived']==0]
```

Analysis

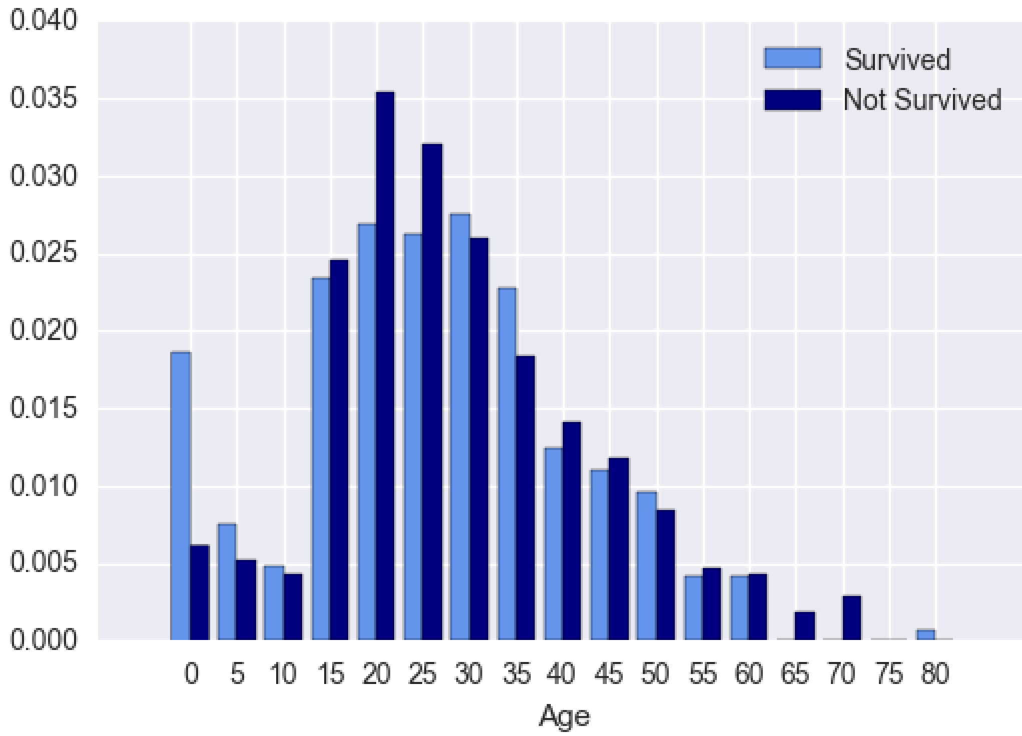
Age

The first variable to investigate is **Age**. Most of survived and not survived people belong to ages between 20 to 40. The shape of both histograms are similar except for these two groups.

- Children of 5 years old and younger were more likely to survive.
- Passengers older than 65 years had a lowest survival chance.

In [1028]:
```
# plotting hisogram for Age variables of both groups
plt.hist([survived_mod['Age'], not_survived_mod['Age']], bins=range(0, 85 + 1, 5), normed=True,
         color=['cornflowerblue', 'navy'], label=['Survived', 'Not Survived'], align='left')
plt.xlabel('Age')
plt.xticks(range(0, 85, 5))
plt.legend()
```

Out[1028]:
```
<matplotlib.legend.Legend at 0x11aff2f60>
```



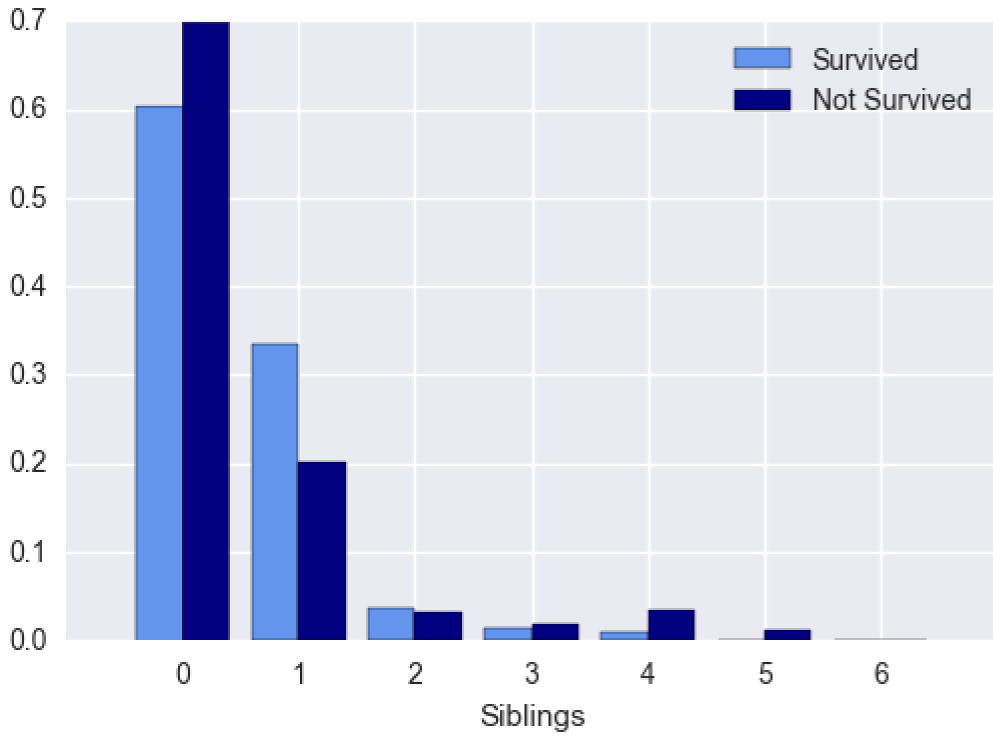
Siblings/Spouses Aboard

Next figure demonstrates that, passengers with no relatives had a slightly lower chance of survival and those with only one relative aboard had a better chance of survival.

However, these differences are not significant as it's shown in the table of statistics before.

In [1029]:
```
plt.hist([survived['SibSp'], not_survived['SibSp']], bins=range(0, 7 + 1, 1), normed=True,
         color=['cornflowerblue', 'navy'], label=['Survived', 'Not Survived'], align='left')
plt.xlabel('Siblings')
plt.xticks(range(0, 7))
plt.legend()
```

Out[1029]: `<matplotlib.legend.Legend at 0x11b3557f0>`



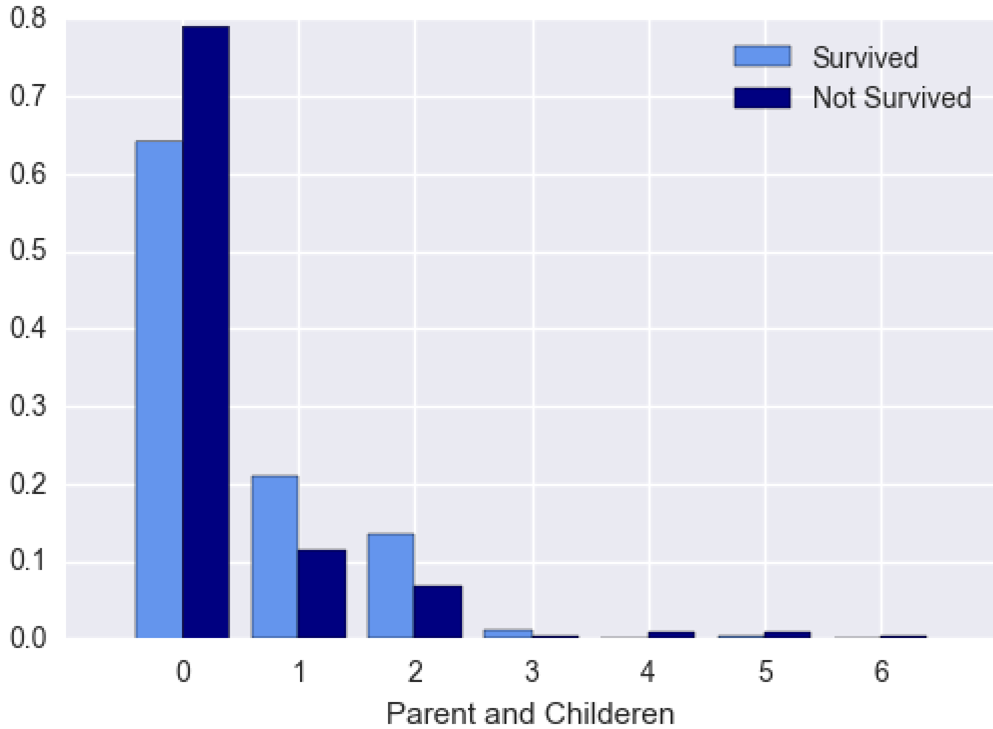
Parent and Children

Following plot shows that in general, single passengers had a lower chance of survival compering to family members. Having 1 or 2 family members seems to increase the chance of survival but not more than that.

We consider the effect of this variable (having Parent and Children) relatively significant.

In [1030]:
```
plt.hist([survived['Parch'], not_survived['Parch']], bins=range(0, 7 + 1, 1), normed=True,
         color=['cornflowerblue', 'navy'], label=['Survived', 'Not Survived'], align='left')
plt.xlabel('Parent and Childeren')
plt.xticks(range(0, 7))
plt.legend()
```

Out[1030]: <matplotlib.legend.Legend at 0x11afecc50>



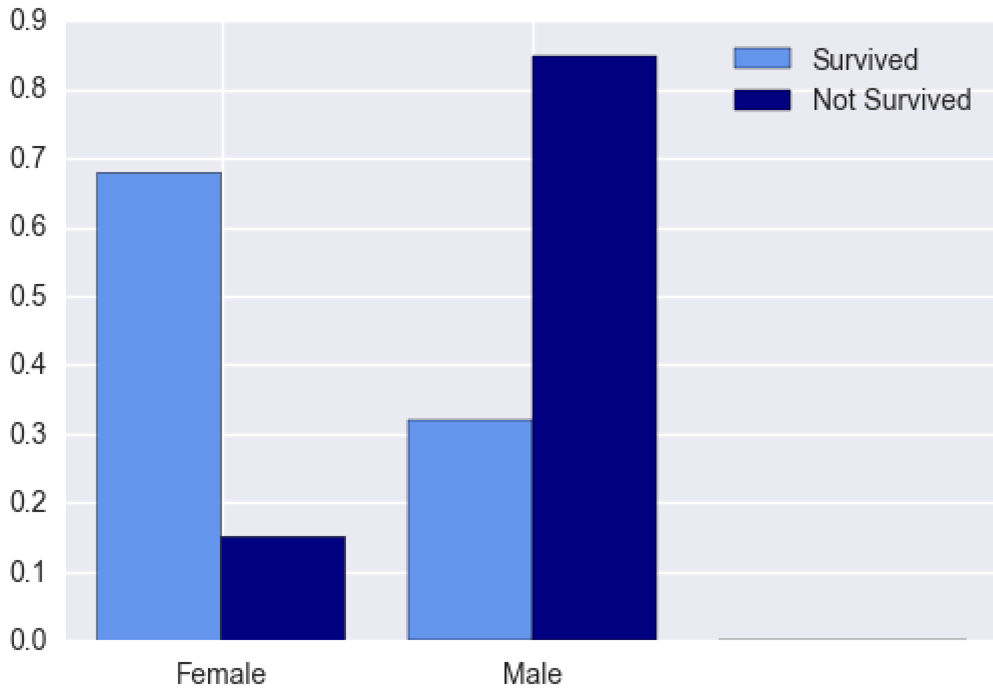
Female and Male

Comparing the bar proportions in the following histogram plot, we can see a huge difference between female and male chance of survival. Females passengers had survived the shipwreck almost four times more than male passengers.

We consider the effect of this variable (Sex) highly significant on survival.

In [1031]:
```
plt.hist([survived_mod['Sex'], not_survived_mod['Sex']], bins=range(0, 3 + 1, 1), normed=True,
         color=['cornflowerblue', 'navy'], label=['Survived', 'Not Survived'], align='left')
plt.xlabel('')
plt.xticks(range(0, 2),['Female','Male'])
plt.legend()
```

Out[1031]: <matplotlib.legend.Legend at 0x11b9dfc18>



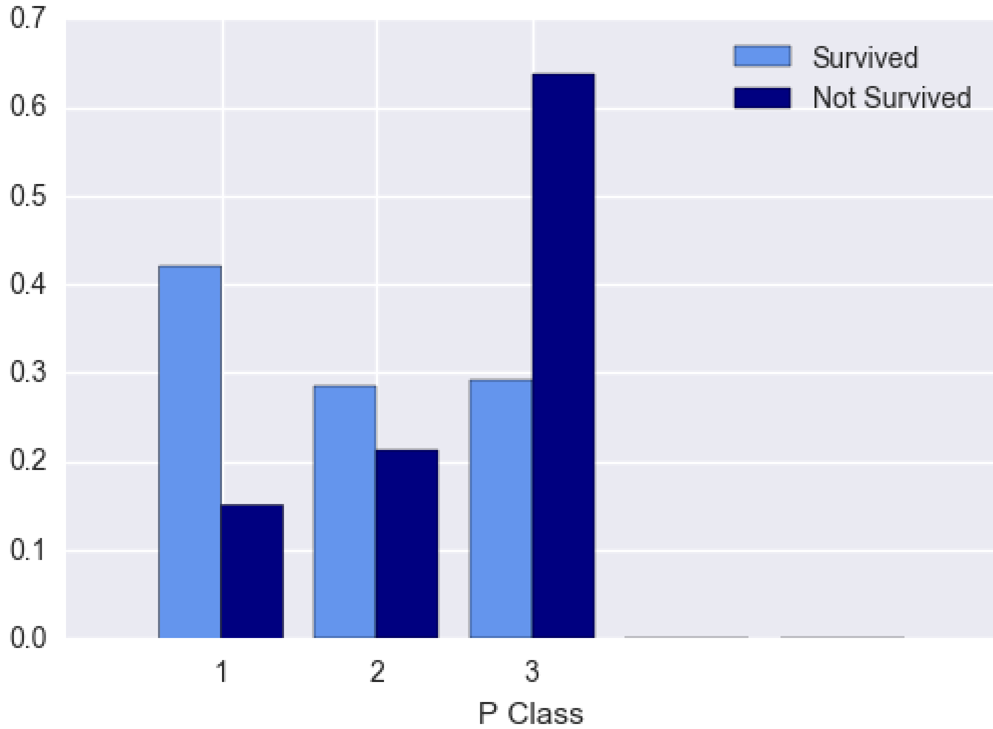
Passenger Class

Based on next figure, the passengers in *1st Class* had survived more than others and the passengers in *3rd Class* were the most unfortunate.

After Sex variable, we consider the effect of this variable (Passenger Class) highly significant on survival of passengers.

In [1032]:
```
plt.hist([survived['Pclass'], not_survived['Pclass']], bins=range(1, 6 +
1, 1), normed=True,
         color=['cornflowerblue', 'navy'], label=['Survived', 'Not Surviv
ed'], align='left')
plt.xlabel('P Class')
plt.xticks(range(1, 4))
plt.legend()
```

Out[1032]: <matplotlib.legend.Legend at 0x11bcdbe10>



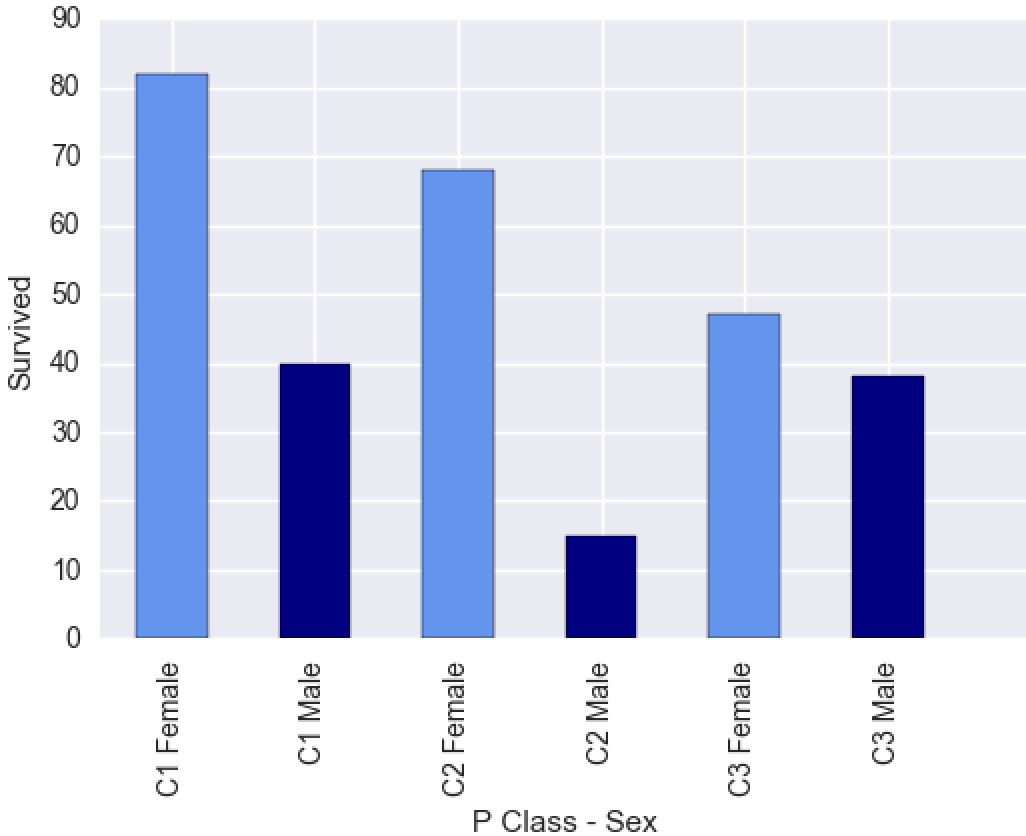
Female / Male + Passenger Class

The following two plots show the combined effects of **Sex** and **Pclass** variables on the chance of survival. It seems that *Females in 1st and 2nd Class* have the highest chance of the survival and *Males in 3rd Class* have the lowest chance.

The pie plot of passengers grouped by Survival, Class and Sex is shown in the last figure.

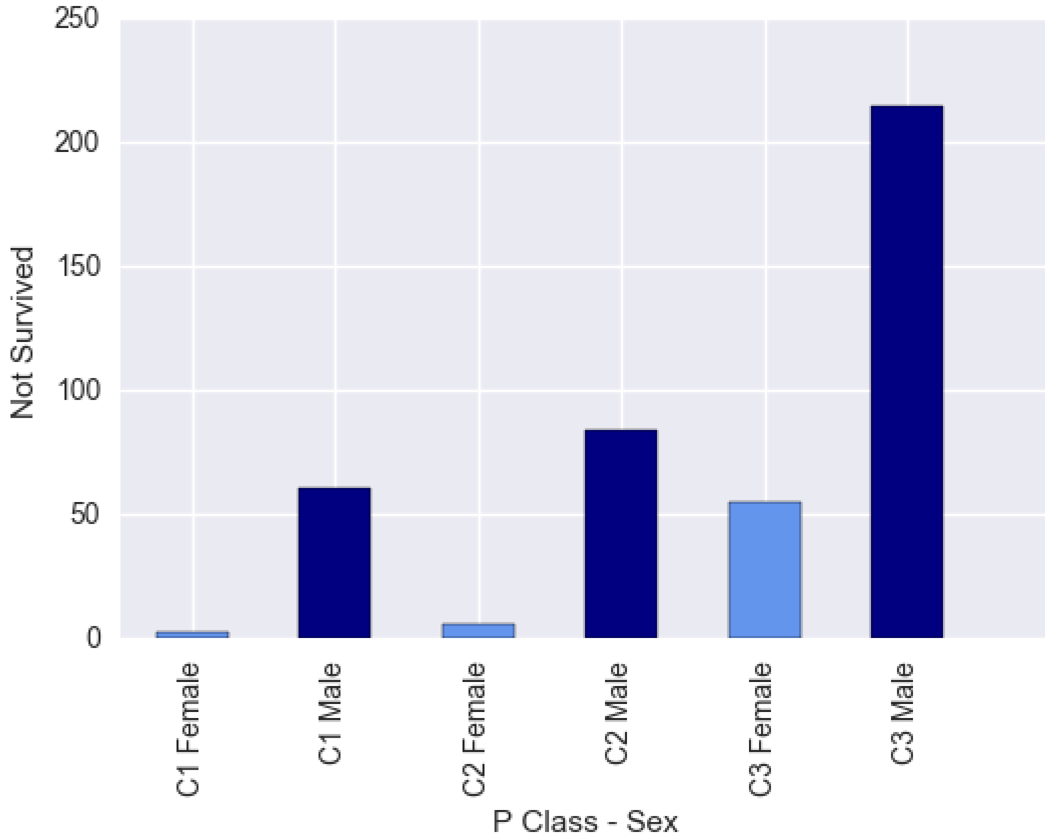
In [1033]:
```
t= survived.groupby(['Pclass','Sex']).count()['Survived']
t.plot(kind='bar', color=['cornflowerblue','navy'])
plt.xticks(range(0, 7),['C1 Female', 'C1 Male', 'C2 Female','C2 Male', 'C
3 Female','C3 Male'])
plt.xlabel('P Class - Sex')
plt.ylabel('Survived')
```

Out[1033]:
```
<matplotlib.text.Text at 0x11bf97da0>
```



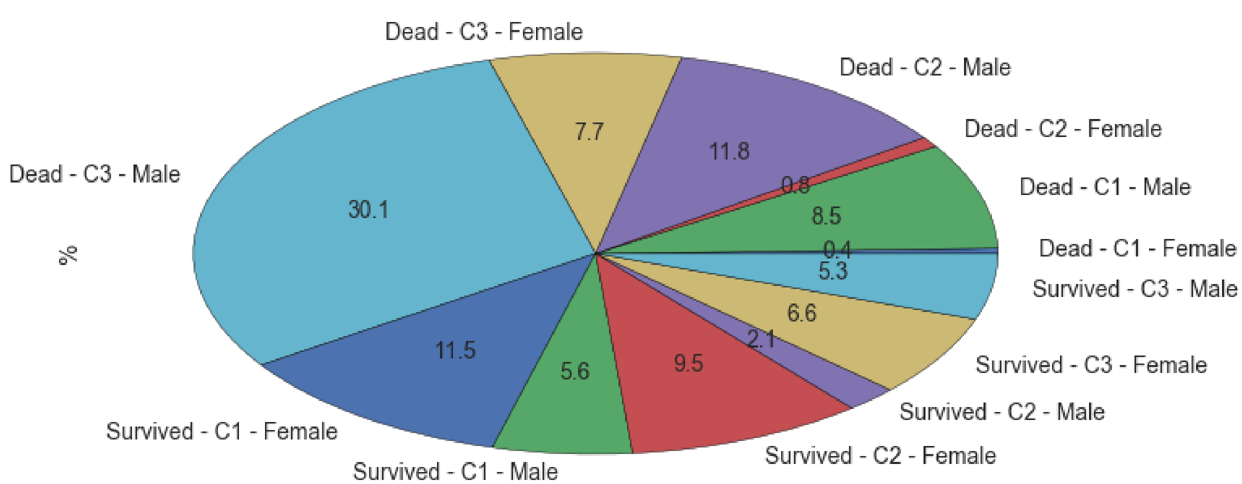
In [1034]:
```
t= not_survived.groupby(['Pclass','Sex']).count()['Survived']
t.plot(kind='bar', color=['cornflowerblue','navy'])
plt.xticks(range(0, 7),['C1 Female', 'C1 Male', 'C2 Female','C2 Male', 'C
3 Female','C3 Male'])
plt.xlabel('P Class - Sex')
plt.ylabel('Not Survived')
```

Out[1034]: <matplotlib.text.Text at 0x11c2eaeb8>



In [1035]:
```python
# pie plot of all the passengers grouped by Survival, P Class and Sex
grouped_by_Sur_Clas_Sex = titanic_data_clean_mod.groupby(['Survived','Pcl
ass','Sex']).count()['PassengerId']
lbls=['Dead - C1 - Female','Dead - C1 - Male','Dead - C2 - Female','Dead
- C2 - Male','Dead - C3 - Female',
        'Dead - C3 - Male','Survived - C1 - Female','Survived - C1 - Male
','Survived - C2 - Female',
        'Survived - C2 - Male','Survived - C3 - Female','Survived - C3 -
Male']
grouped_by_Sur_Clas_Sex.plot(kind='pie', autopct='%.1f', subplots=True, f
igsize=(8, 4), labels=lbls)
plt.ylabel('%')
```

Out[1035]: <matplotlib.text.Text at 0x11c58ec50>



Conclusions

Based on our explorations and observations we can say;

- **Female passengers and 1st Class passengers** are more likely to survive the shipwreck while being **Male and 3rd Class passenger** seems to be a tragedy.
- Moreover, it seems **Children under 5 years old** have a high chance of survival not because of their abilities but the special attention they get from others.
- Finally **Old people (older than 65 years)** are not likely to survive the shipwreck.

Limitations

As mentioned before in Introduction, all the observations in this analysis are tentative since no statistical significant analysis were performed. To rigorously check how likely it would be to see these results by random chance, we need to use statistics.

Moreover, our investigation shows some correlation between our independent variables (**Sex** and **Pclass**) and dependent variable (**Survival**) but it does not imply any causation. Some third factors could cause the correlation between our variables. Factors like;

- Passenger's ability to swim
- How far passengers were located from evacuation boats
- Which group had more life jackets and rescue boats
- Were there any priorities for passengers to get on rescue boats first

And since we do not know about these third factors, we cannot make any statement of causation. To find out whether one change causes another, we need to run some experiments (like A/B tests)

In addition, some variables, like **Siblings and Spouses Aboard** and **Parent and Children Aboard**, are general and to some extent vague. It does not distinguish between **Parents** and **Children**, or **Siblings** and **Spouses**. I think, in reality it's a one-directional factor meaning; Children, wives and old parents get more support and help from parents, husbands and sons (not the other way around) which can significantly change their survival chance. In this study we assumed that these factors are two-directional which could affect our conclusions.

One more aspect of the data set that could be explored more in detail is **Passengers Name**. One could investigate and see which passengers are famous, rich, celebrity, or athlete and how those characteristics affect their survival rate.