An Statistical Walk Aboard the Titanic

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Guiding Question

What characteristics separate those who survived from those who died?

Secondary Questions

1. Does Socioeconomic Status have an affect on Survival?
2. How do Gender and Age affect Survival Rates?
3. Does where a passenger was staying aboard the Titanic affect their probability of Surviviing?

1 Data Overview

Looking at the training data froma bird-eye view, there are 891 observations representing passengers and 12 variables. Since some of the variable name are a little cryptic, an description for each is provided below.

Variable Name	Description
PassengerId	Unique identifier for each passenger
Survived	Binary; 1 = Survied & 0 = Died
Pclass	Socio-economic status; 1 = Upper, 2 = Middle & 3 = Lower
Name	Passenger Name
Sex	Male or Female
Age	Passenger Age
SibSp	Number of siblings or spouse aboard ship
Parch	Number of parents or children aboard ship
Ticket	Ticket Number
Fare	Amount paid for ticket
Cabin	Cabin number
Embarked	The town from which the passenger boarded the ship; C = Cherbourg, Q = Queenstown & S = Southhampton

First and foremost, by running `str(training)` on the data, it is apparent that the first entries in the Cabin and Embarked columns are empty strings, indicating that the data is probably not perfectly clean (no surprises there). Checking to see where any Null's might be, it becomes clear that there are in fact no nulls, and that these spaces were intentionally left empty. In addition to null values, all the NA's are in the Age, accounting for roughly 20% of the values in that column. Both of these will need to be imputed intelligently when the time to create a predictive model comes around.

In addition to the missing values, it is important to note that some of the discrete attributes have been read in as continous variabes such as Pclass, Sibsp and Parch. Since these variables actually represent discrete characteristics of each passenger, changing them to be non-continuous will allow a more representative analysis.

Table 2: Attribute Null & NA Counts

	PassengerId	Survived	Pclass	Name	Sex	Age
Null Count	0	0	0	0	0	0
NA Count	0	0	0	0	0	177

Table 3: Attribute Null & NA Counts (continued)

	SibSp	Parch	Ticket	Fare	Cabin	Embarked
Null Count	0	0	0	0	0	0
NA Count	0	0	0	0	0	0

2 Does Socioeconomic Status have an affect on Survival?

2.1 Does Money Sink or Swim?

By creating a table with the Pclass (which refers to the socioeconomic status (SES) of the passenger) and Survived variables, I can get a good sense of the number of passengers that lived and died, based on their SES. Simple summation and division returns the probabilites of a passenger living given their respective SES

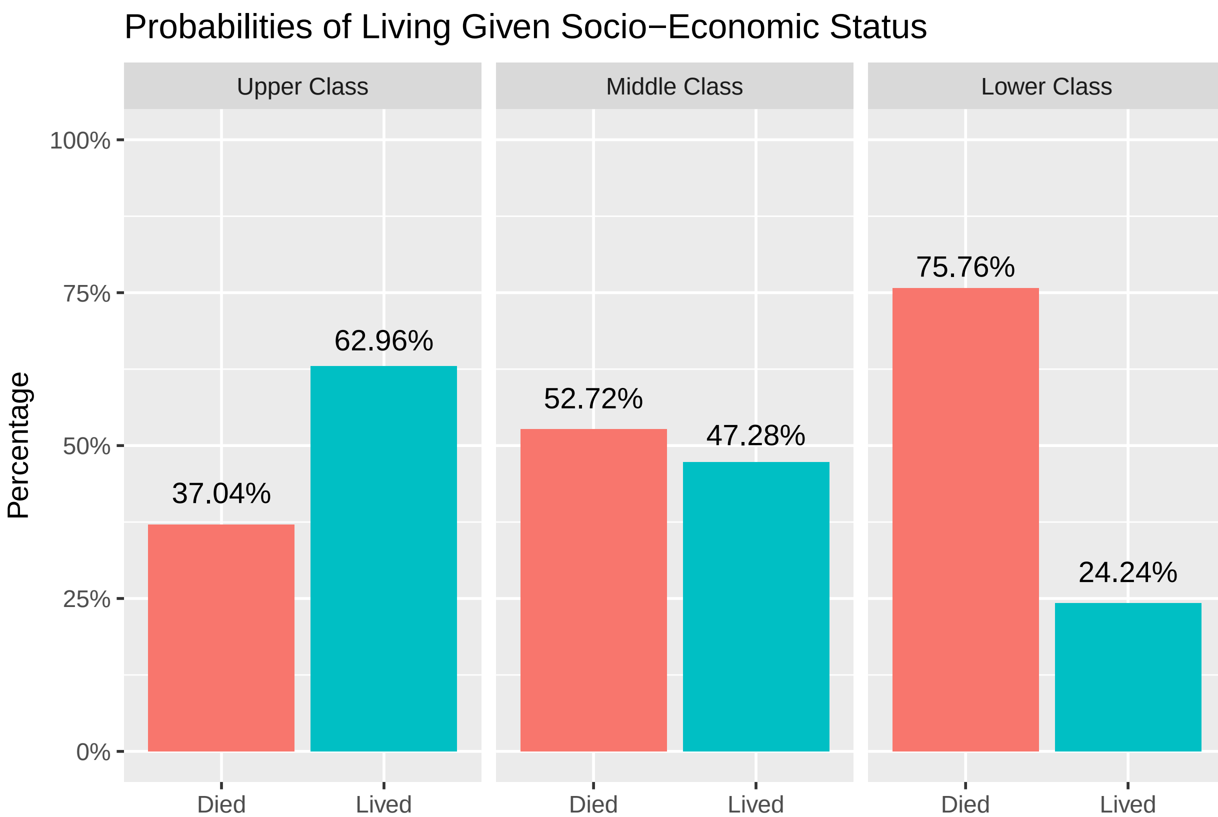
Table 4: Survival Counts by SES

	Upper	Middle	Lower
Died	80	97	372
Survived	136	87	119

Table 5: Survival Rates by SES

	Probability of Living
Upper Class	62.96%
Middle Class	47.28%
Lower Class	24.24%

This same information is displayed visually below.



2.1.1 Illustrating Bayes Theorem with Survival Rates and Socioeconomic Status

This type of classification problem creates a great opportunity to illustrate Bayes' Theorem. Recall that Bayes Theorem is defined as:

$$P(A|B) \;=\; \frac{P(B|A)P(A)}{P(B)}$$

where:

- $P(A|B)$ = Posterior
- $P(B|A)$ = Likelihood
- $P(A)$ = Prior
- $P(B)$ = Normalizing Constant.

The equation above can be rewritten to better match the problem context as:

$$P(\ ''X\ class\ citizen''\ |\ ''Lived''\ ) \;=\; \frac{P(\ ''Lived''\ |\ ''X\ class\ citizen''\ )\ P(\ ''X\ class\ citizen''\ )}{P(\ ''Lived''\ )}$$

where:

- $P(\ ''X\ class\ citizen''\ |\ ''Lived''\ )$ = Posterior
- $P(\ ''Lived''\ |\ ''X\ class\ citizen''\ )$ = Likelihood
- $P(\ ''X\ class\ citizen''\ )$ = Prior
- $P(\ ''Lived''\ )$ = Normalizing Constant.

$P(\text{ ''}Lived\text{'' })$, the Normalizing Constant, will be the probability of living, *regardless of SES.* This could be broken out into three terms,

$$P(\text{ ''}Lived\text{''} \mid \text{''}Upper\ class\ citizen\text{'' }) + P(\text{ ''}Lived\text{''} \mid \text{''}Middle\ class\ citizen\text{'' }) + P(\text{ ''}Lived\text{''} \mid \text{''}Lower\ class\ citizen\text{'' })$$

however it is far easier to calculate the proportion of those that lived over everyone that was aboard the ship. This comes out to be 38.38%.

The final term needed to complete the right hand side of the equation, the Prior, is simply the proportion of those on board that were Upper, Middle or Lower class. These come out to be 24.24%, 20.65% and 55.11%, respectively, shown in the table below.

Table 6: Socioeconomic Status Proportions Aboard the Titanic

	Probability of Being X Class
Upper Class	24.24%
Middle Class	20.65%
Lower Class	55.11%

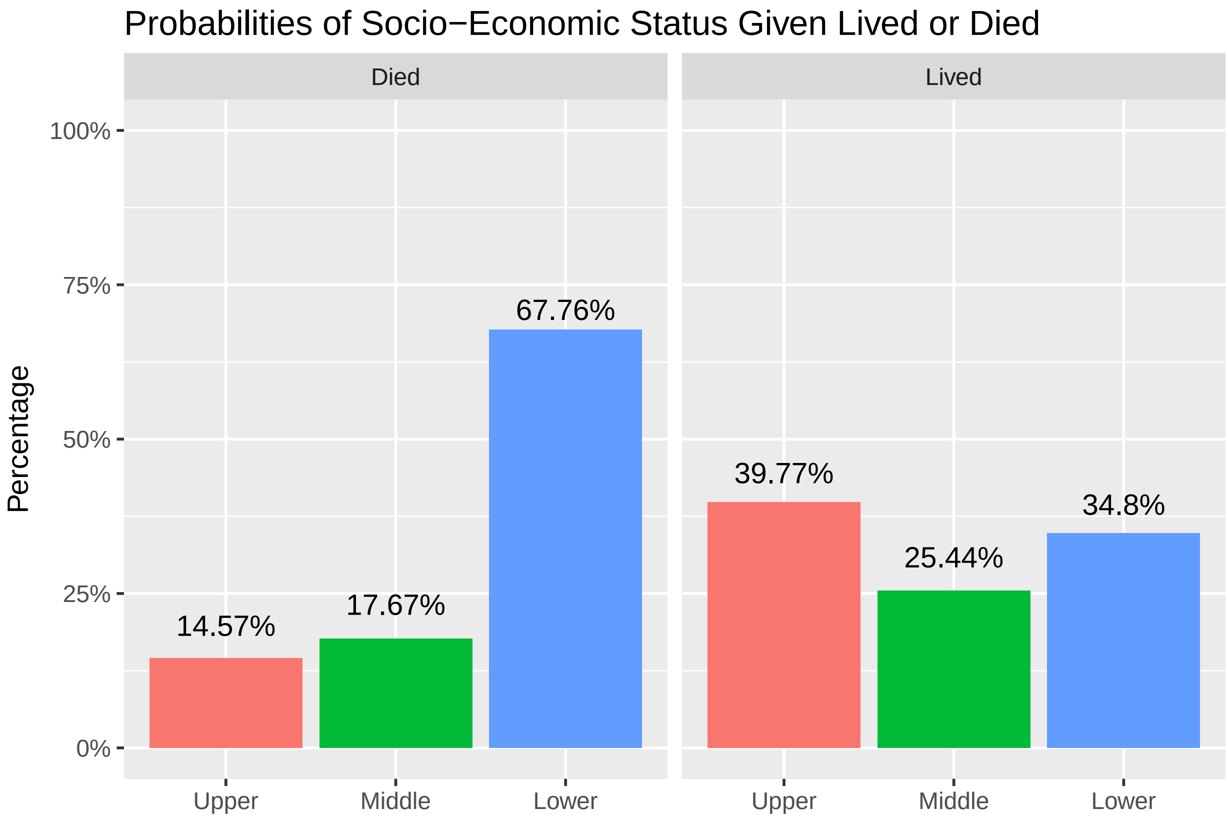
Now it is simply a matter of defining three different equations for each of the three possible socioeconomic status', and substituting in the corresponding numbers (Note that in the above percentages I rounded to two decimal places, however when calculating the final probability it is paramount that the entire number is used).

$$P(\text{ ''}Upper\ class\ citizen\text{''} \mid \text{''}Lived\text{'' }) = \frac{0.6296296 \cdot 0.2424242}{0.3838384} = 0.3976608 = 39.77\%$$

$$P(\text{ ''}Middle\ class\ citizen\text{''} \mid \text{''}Lived\text{'' }) = \frac{0.4728261 \cdot 0.2065095}{0.3838384} = 0.254386 = 25.44\%$$

$$P(\text{ ''}Lower\ class\ citizen\text{''} \mid \text{''}Lived\text{'' }) = \frac{0.2423625 \cdot 0.5510662}{0.3838384} = 0.3479532 = 34.8\%$$

This can be double checked visually by dividing the passengers into those that lived and died, and then, for each of those groups, plotting the percentage that were Upper, Middle and Lower class. Low and behold, Bayes was right.

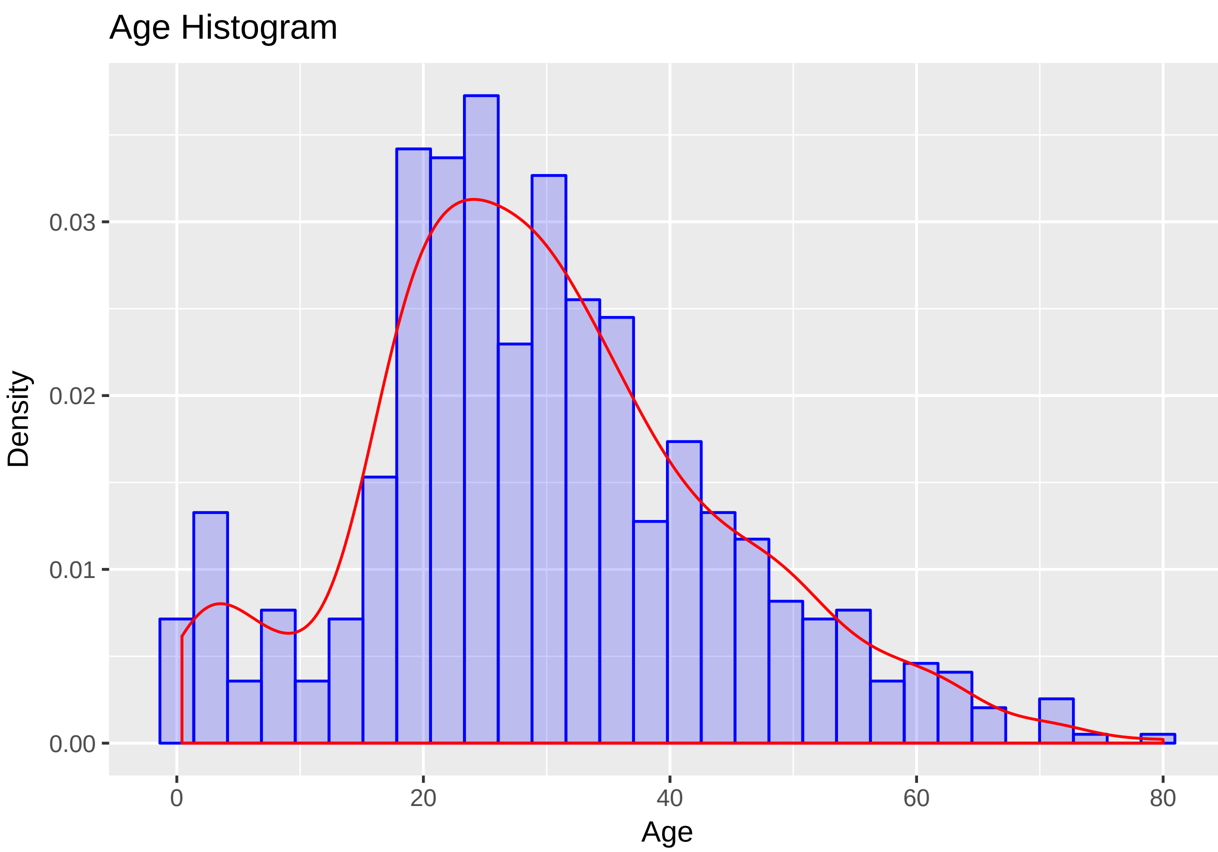


3 How do Gender and Age affect Survival Rates?

A quick overview of the Gender and Age variables are shown below, demonstrating that most people aboard were men and between 20 - 40 years old.

Table 7: Gender Proportions

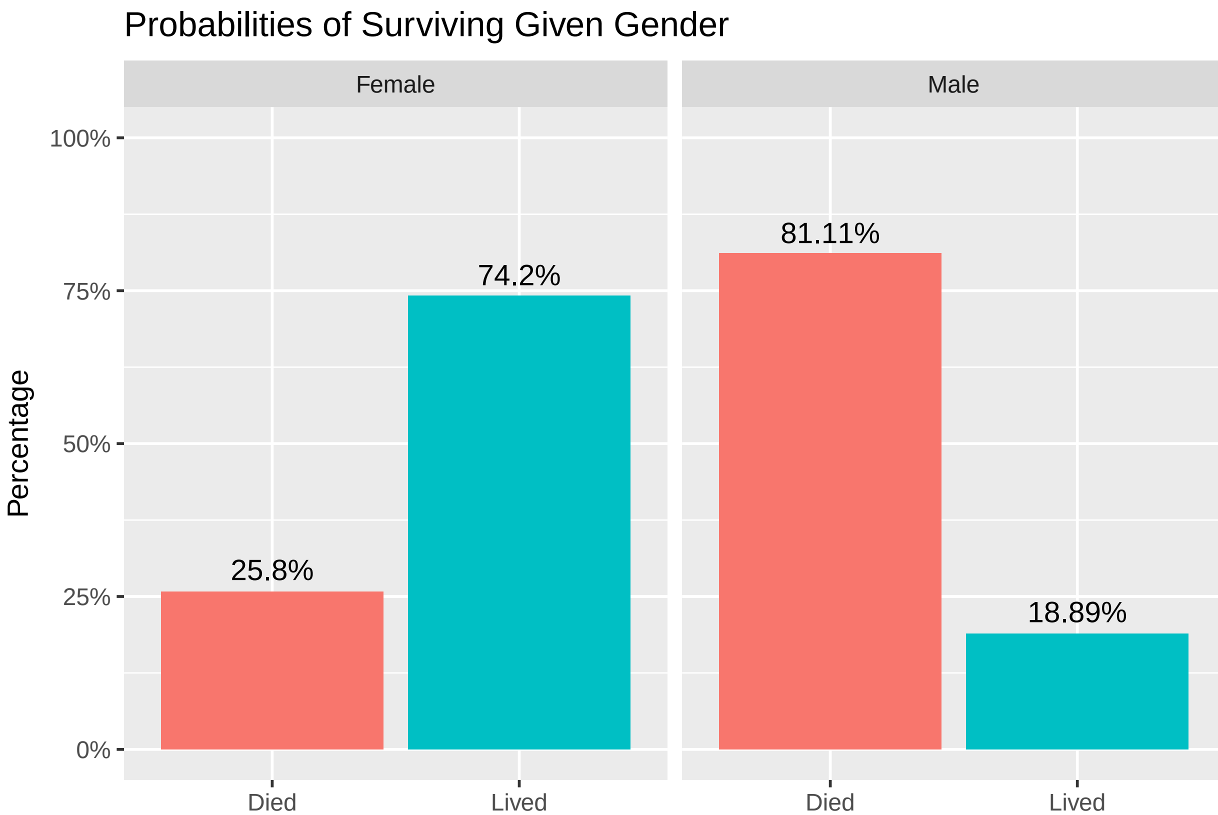
	Proportion
Female	35.24%
Male	64.76%

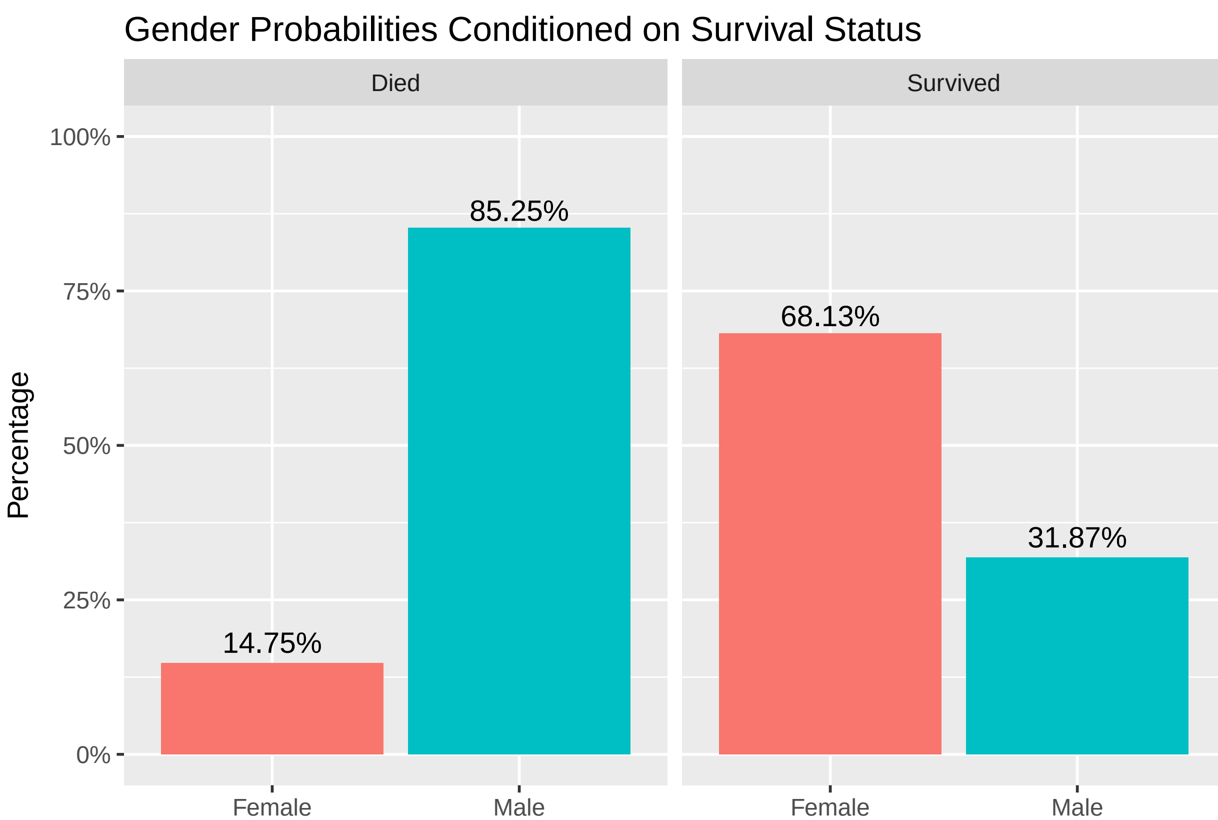


Gender

Looking at the two plots on the following page, it is apparent that given that a passenber was Female, her probability of Surviving was 74.2%. On the other hand, if a passenger was Male, he had over an 80% chance of dying.

The second plot shows the probabilities of a passenger being Male or Female, conditioned on whether they survived the sinking of the ship or not. Once again, there is a vast gender divide of the passengers that died, with 85% of all passenger that died being Male. Given that a passenger survived, there is more than double the chance that she was Female than Male.


Probabilities of Surviving Given Gender
Female
Male
Percentage
100%
75%
50%
25%
0%
25.8%
74.2%
81.11%
18.89%
Died
Lived
Died
Lived


Gender Probabilities Conditioned on Survival Status
Died
Survived
Percentage
100%
75%
50%
25%
0%
14.75%
85.25%
68.13%
31.87%
Female
Male
Female
Male

Interpretting Logistic Regression Using Passenger Age

If the goal of a model is a low error rate, using only one variable is rarely a good idea. However, if interpretability and inference are the goal, using linear or logistic regression can provide unique insight into our data. In order to see how a passenger's age affects their chance of surviving the sinking of the ship, I decided to create a new column that puts passengers into certain bins, based on their age. I created 7 different bins, outlined in the table below, which separates each age group into those who lived and those who died.

Table 8: Surival Counts by Age Group

	0-10	11-20	21-30	31-40	41-50	50-60	Over 60
Died	26	71	146	86	53	25	17
Survived	38	44	84	69	33	17	5

When a general linear model is fit using only this binned column, R one-hot-encodes the column, effectively creating a new column for each age group.The reason for the separation of the continuous age variable into bins becomes clear when the equation, with problem context accounted for, is expressed below.

$$Log\ Odds(Surviving) \ = \ \beta_1 \ (Age\ 0-10) \ + \ \beta_2 \ (Age\ 11-20) \ + \ \beta_3 \ (Age\ 21-30) \ ...\ etc.$$

Since each coefficient represents a change in the log odds of survival with a one unit change in its associated variable, **and only one variable will be non-zero (if a passenger is in the age group 0 to 10, they aren't going to be in any other age group)**, the log odds of a passenger in age group j will be equal to coefficient β_j.

$$Log\ Odds(Surviving) \ = \ \beta_1 \ (1) \ + \ \beta_2 \ (0) \ + \ \beta_3 \ (0) \ + \ \beta_4 \ (0) \ ...\ etc.$$

Removing all 0 terms from the equation, the formula simplifies to:

$$Log\ Odds(Surviving)_j \ = \ \beta_j$$

A little math will show us the probability that a passenger survives, given a specific age group. By exponentiating the log odds, the odds are returned, which can the be divided by one plus itself (equation below) to return the probability.

$$P \ = \ \frac{Odds}{1 \ + \ Odds}$$

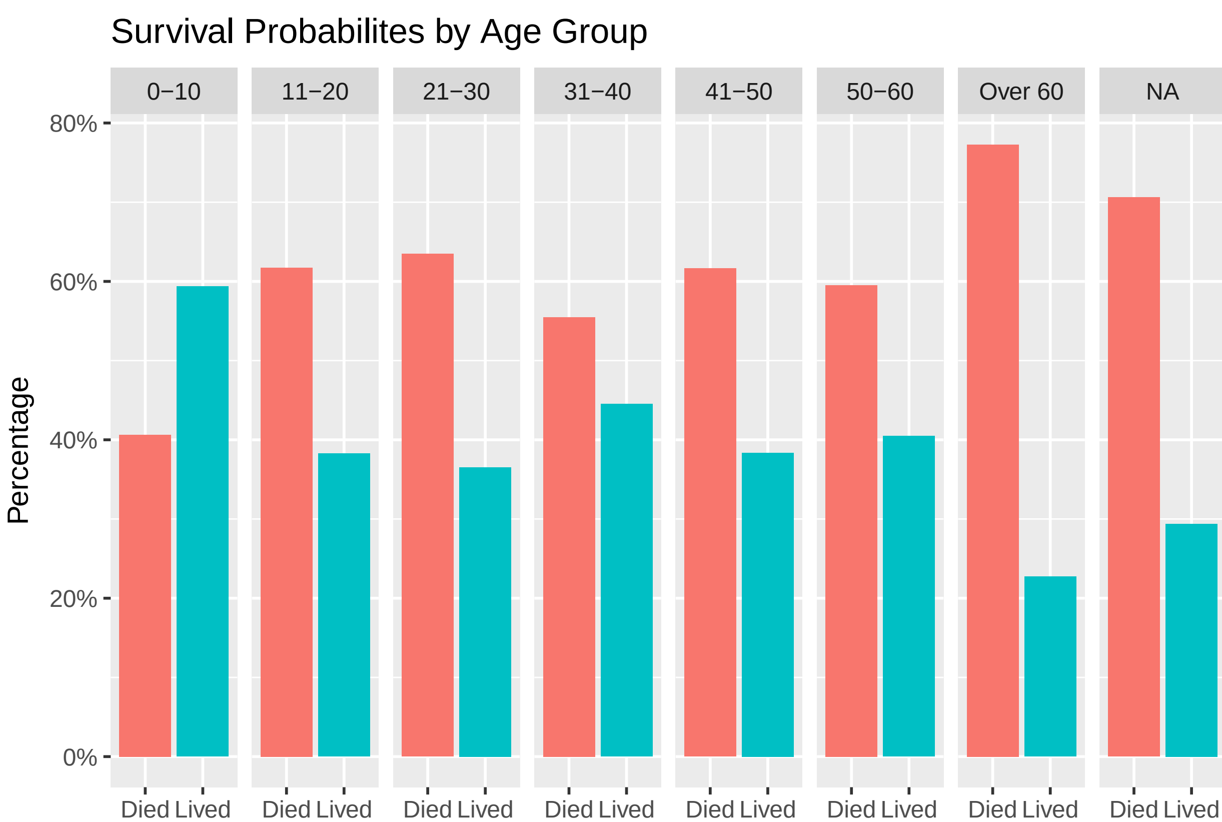
This is visually confirmed with a multi-faceted plot shown on the following page, in addition to taking the number of Survivors for each age group and dividing by the total number of passengers in that age group from the Survival Counts by Age Group Table.

Table 9: Logistic Regression Age Group Coefficients

	Coefficient
0 - 10	0.3794896
11 - 20	-0.4784902
21 - 30	-0.5527898
31 - 40	-0.2202408
41 - 50	-0.4737844
50 - 60	-0.3856625
Over 60	-1.2237754

Table 10: Probability of Surviving given Age Group

Age Group	Probability of Surviving
0 - 10	59.37%
11 - 20	38.26%
21 - 30	36.52%
31 - 40	44.52%
41 - 50	38.37%
50 - 60	40.48%
Over 60	22.73%



4 Cabin Classification

It seems logical that looking at *where* each passenger was when the Titanic started sinking could provide some insight as to why some lived and others did not. The "Sinking" section on the Titanic Wikipedia Page states that the iceberg was struck at 11:40 pm. Considering the time of night, combined with the likely cold air temperature, I think it is safe to say that most passengers were inside, if not in their rooms sleeping.

Finding out where each passenger was will be a two fold process:

1. Subsetting on the Deck they were on, noted by the letter in the Cabin column.
2. Subsetting where on that deck they were, noted by the number in the Cabin column.

An important note is that the vast majority of the passengers did not have an entry in the Cabin column. (There aren't any NA's, the entries are not even filled with spaces, they are simply "nothing"). In order to subset these observations, I used the ouput from a "nothing" observation in the logical statement.

After subsetting, summing the number of rows in each subset, *which should equal 891, the total number of observations,* returns 894. A little searching led to finding the duplicates, show below.

```
## [1] 894
```

```
##     PassengerId Survived Pclass                                     Name
## 76           76        0      3                   Moen, Mr. Sigurd Hansen
## 129         129        1      3                         Peter, Miss. Anna
## 700         700        0      3   Humblen, Mr. Adolf Mathias Nicolai Olsen
## 716         716        0      3 Soholt, Mr. Peter Andreas Lauritz Andersen
##        Sex Age SibSp Parch Ticket    Fare Cabin Embarked age_bin
## 76    male  25     0     0 348123  7.6500 F G73        S   21-30
## 129 female  NA     1     1   2668 22.3583 F E69        C    <NA>
## 700   male  42     0     0 348121  7.6500 F G63        S   41-50
## 716   male  19     0     0 348124  7.6500 F G73        S   11-20
```

```
##     PassengerId Survived Pclass
## 129         129        1      3
## 356         356        0      3
## 398         398        0      2
## 407         407        0      3
## 477         477        0      2
## 534         534        1      3
## 681         681        0      3
## 716         716        0      3
## 727         727        1      2
## 844         844        0      3
## 858         858        1      1
## 861         861        0      3
##                                         Name    Sex  Age SibSp Parch
## 129                        Peter, Miss. Anna female   NA     1     1
## 356                  Vanden Steen, Mr. Leo Peter   male 28.0     0     0
## 398                     McKane, Mr. Peter David   male 46.0     0     0
## 407             Widegren, Mr. Carl/Charles Peter   male 51.0     0     0
## 477                     Renouf, Mr. Peter Henry   male 34.0     1     0
## 534      Peter, Mrs. Catherine (Catherine Rizk) female   NA     0     2
## 681                       Peters, Miss. Katie female   NA     0     0
## 716  Soholt, Mr. Peter Andreas Lauritz Andersen   male 19.0     0     0
## 727 Renouf, Mrs. Peter Henry (Lillian Jefferys) female 30.0     3     0
## 844                  Lemberopolous, Mr. Peter L   male 34.5     0     0
## 858                     Daly, Mr. Peter Denis    male 51.0     0     0
```

```
## 861                     Hansen, Mr. Claus Peter   male 41.0     2     0
##     Ticket    Fare Cabin Embarked age_bin
## 129   2668 22.3583 F E69        C    <NA>
## 356 345783  9.5000              S   21-30
## 398  28403 26.0000              S   41-50
## 407 347064  7.7500              S   50-60
## 477  31027 21.0000              S   31-40
## 534   2668 22.3583              C    <NA>
## 681 330935  8.1375              Q    <NA>
## 716 348124  7.6500 F G73        S   11-20
## 727  31027 21.0000              S   21-30
## 844   2683  6.4375              C   31-40
## 858 113055 26.5500   E17        S   50-60
## 861 350026 14.1083              S   41-50
```

To decide which subset to assign these observations too, looking at the Embarked and Ticket columns for those observations in the g_class subset, I can see that everyone in this cabin class embarked from Southampton and had similar ticket

```
##         1
## 0.4666667
```

```
##         1
## 0.7446809
```

```
##         1
## 0.5932203
```

```
##         1
## 0.7575758
```

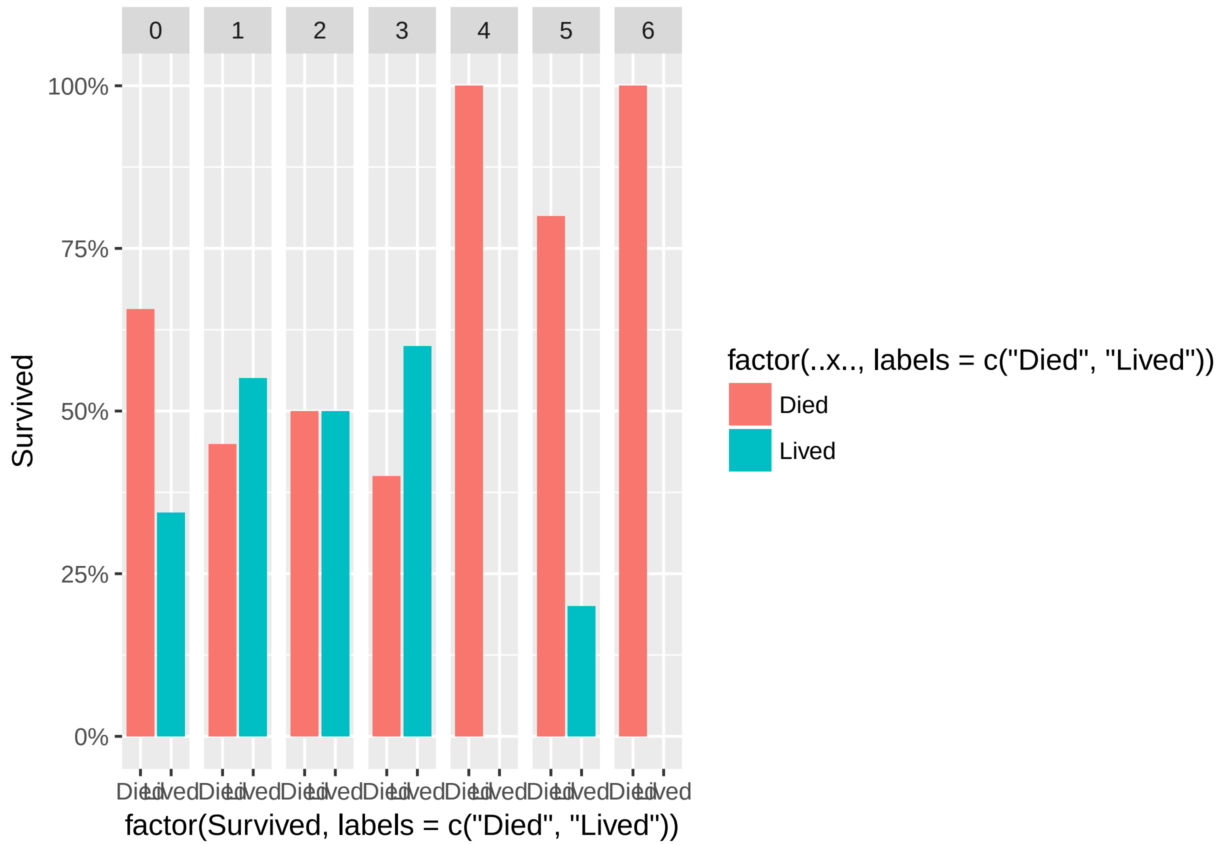
```
##         1
## 0.7575758
```

```
##         1
## 0.6153846
```

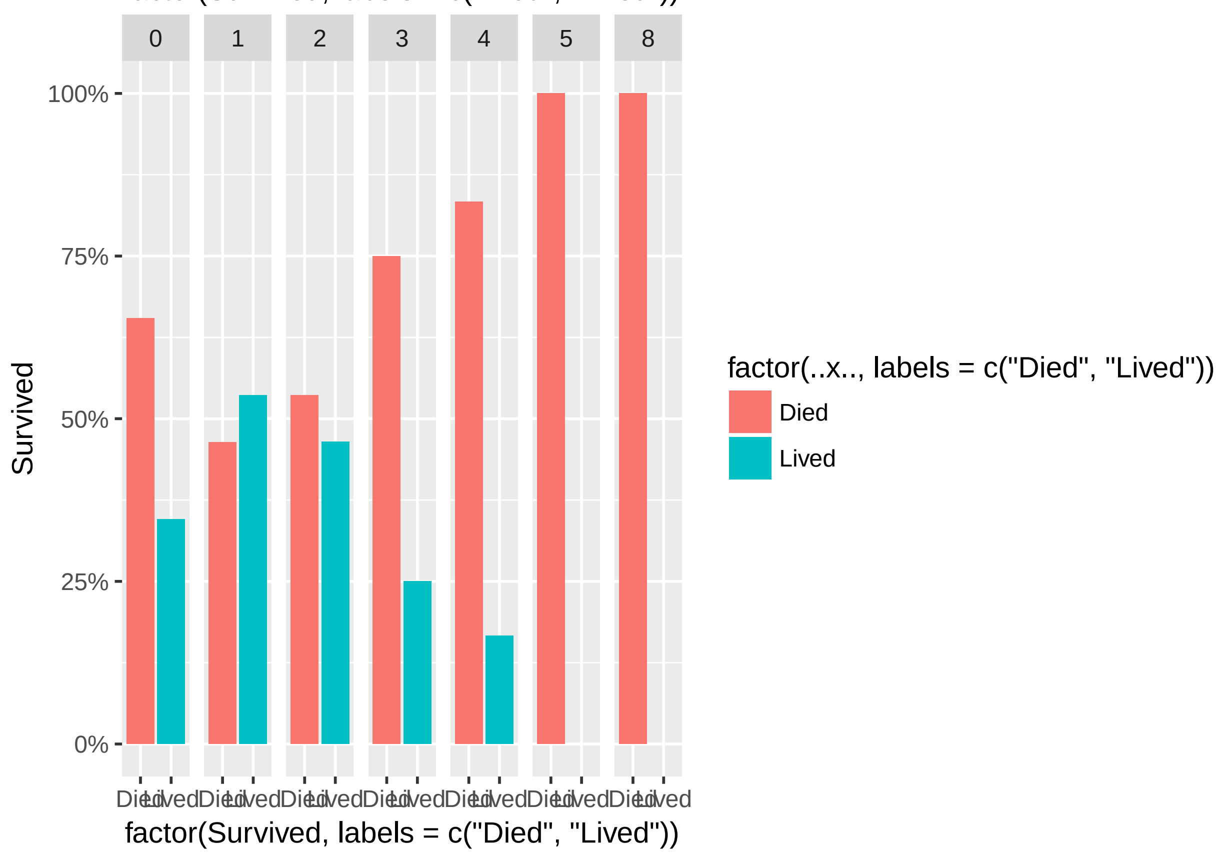
```
##         1
## 0.2857143
```

```
##         1
## 0.2998544
```

```
##
##       0   1
##   0 445 233
##   1  53  65
##   2  40  40
##   3   2   3
##   4   4   0
##   5   4   1
##   6   1   0
```



0
1
2
3
4
5
6
100%
75%
50%
25%
0%
Survived
Died Lived Died Lived Died Lived Died Lived Died Lived Died Lived Died Lived
factor(Survived, labels = c("Died", "Lived"))
factor(..x.., labels = c("Died", "Lived"))
Died
Lived



0
1
2
3
4
5
8
100%
75%
50%
25%
0%
Survived
Died Lived Died Lived Died Lived Died Lived Died Lived Died Lived Died Lived
factor(Survived, labels = c("Died", "Lived"))
factor(..x.., labels = c("Died", "Lived"))
Died
Lived