Titanic: Getting Started With R - Part 2: The Gender-Class Model

10.01.2014 16 Comments Share

Tutorial index

In the previous lesson, we covered the basics of navigating data in R, but only looked at the target variable as a predictor. Now it's time to try and use the other variables in the dataset to predict the target more accurately.

The disaster was famous for saving "women and children first", so let's take a look at the Sex and Age variables to see if any patterns are evident. We'll start with the gender of the passengers. After reloading the data into R, take a look at the summary of this variable:

```
> summary(train$Sex)
female   male
   314    577
```

So we see that the majority of passengers were male. Now let's expand the proportion table command we used last time to do a two-way comparison on the number of males and females that survived:

```
> prop.table(table(train$Sex, train$Survived))
                 0          1
  female 0.09090909 0.26150393
  male   0.52525253 0.12233446
```

Well that's not very clean, the proportion table command by default takes each entry in the table and divides by the total number of passengers. What we want to see is the row-wise proportion, ie, the proportion of each sex that survived, as separate groups. So we need to tell the command to give us proportions in the 1st dimension which stands for the rows (using '2' instead would give you column proportions):

```
> prop.table(table(train$Sex, train$Survived),1)
                0         1
  female 0.2579618 0.7420382
  male   0.8110919 0.1889081
```

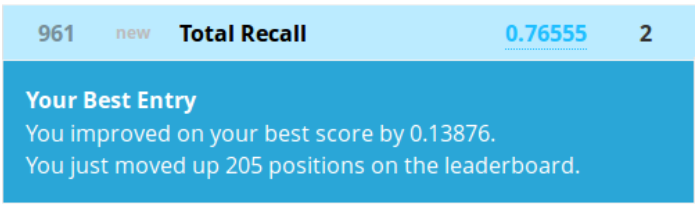
Okay, that's better. We now can see that the majority of females aboard survived, and a very low percentage of males did. In our last prediction we said they all met Davy Jones, so changing our prediction for this new insight should give us a big gain on the leaderboard! Let's update our old prediction and introduce some more R syntax:

```
test$Survived <- 0
test$Survived[test$Sex == 'female'] <- 1
```

Here we have begun with adding the 'everyone dies' prediction column as before, except that we'll ditch the rep command and just assign the zero to the whole column, it has the same effect. We then altered that same column with 1's for the subset of passengers where the variable 'Sex' is equal to 'female'.

We just used two new pieces of R syntax, the equality operator, ==, and the square bracket operator. The square brackets create a subset of the total dataframe, and apply our assignment of '1' to only those rows that meet the criteria specified. The double equals sign no longer works as an assignment here, now it is a boolean test to see if they are already equal.

Now let's write a new submission and send it to Kaggle to see how it's improved our position!



Nice! We're getting there, but let's start digging into the age variable now:

```
> summary(train$Age)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
   0.42   20.12   28.00   29.70   38.00   80.00     177
```

It is possible for values to be missing in data analytics, and this can cause a variety of problems out in the real world that can be quite difficult to deal with at times. For now we could assume that the 177 missing values are the average age of the rest of the passengers, ie. late twenties.

Our last few tables were on categorical variables, ie. they only had a few values. Now we have a continuous variable which makes drawing proportion tables almost useless, as there may only be one or two passengers for each age! So, let's create a new variable, Child, to indicate whether the passenger is below the age of 18:

```
train$Child <- 0
train$Child[train$Age < 18] <- 1
```

As with our prediction column, we have now created a new column in the training set dataframe indicating whether the passenger was a child or not. Beginning with the assumption that they were an adult, and then overwriting the value for passengers below the age of 18. To do this we used the less than operator, which is another boolean test, similar to the equality check used in our last predictions. If you click on the train object in the explorer, you will see that any passengers with an age of NA have been assigned a zero, this is because the NA will fail any boolean test. This is what we wanted though, since we had decided to use the average age, which was an adult.

Now we want to create a table with both gender and age to see the survival proportions for different subsets. Unfortunately our proportion table isn't equipped for this, so we're going to have to use a new R command, aggregate. First let's try to find the number of survivors for the different subsets:

```
> aggregate(Survived ~ Child + Sex, data=train, FUN=sum)
  Child    Sex Survived
1     0 female      195
2     1 female       38
3     0   male       86
4     1   male       23
```

The aggregate command takes a formula with the target variable on the left hand side of the tilde symbol and the variables to subset over on the right. We then tell it which dataframe to look at with the data argument, and finally what function to apply to these subsets. The command above subsets the whole dataframe over the different possible combinations of the age and gender variables and applies the sum function to the Survived vector for each of these subsets. As our target variable is coded as a 1 for survived, and 0 for not, the result of summing is the number of survivors. But we don't know the total number of people in each subset; let's find out:

```
> aggregate(Survived ~ Child + Sex, data=train, FUN=length)
  Child    Sex Survived
1     0 female      259
2     1 female       55
3     0   male      519
4     1   male       58
```

This simply looked at the length of the Survived vector for each subset and output the result, the fact that any of them were 0's or 1's was irrelevant for the length function. Now we have the totals for each group of passengers, but really, we would like to know the proportions again. To do this is a little more complicated. We need to create a function that takes the subset vector as input and applies both the sum and length commands to it, and then does the division to give us a proportion. Here is the syntax:

```
> aggregate(Survived ~ Child + Sex, data=train, FUN=function(x) {sum(x)/length(x)})
  Child    Sex  Survived
1     0 female 0.7528958
2     1 female 0.6909091
3     0   male 0.1657033
4     1   male 0.3965517
```

Well, it still appears that if a passenger is female most survive, and if they were male most don't, regardless of whether they were a child or not. So we haven't got anything to change our predictions on here. Let's take a look at a couple of other potentially interesting variables to see if we can find anything more: the class that they were riding in, and what they paid for their ticket.

While the class variable is limited to a manageable 3 values, the fare is again a continuous variable that needs to be reduced to something that can be easily tabulated. Let's bin the fares into less than $10, between $10 and $20, $20 to $30 and more than $30 and store it to a new variable:

```
train$Fare2 <- '30+'
train$Fare2[train$Fare < 30 & train$Fare >= 20] <- '20-30'
train$Fare2[train$Fare < 20 & train$Fare >= 10] <- '10-20'
train$Fare2[train$Fare < 10] <- '<10'
```

Now let's run a longer aggregate function to see if there's anything interesting to work with here:

```
> aggregate(Survived ~ Fare2 + Pclass + Sex, data=train, FUN=function(x) {sum(x)/length(x)})
   Fare2 Pclass    Sex  Survived
1  20-30      1 female 0.8333333
2    30+      1 female 0.9772727
3  10-20      2 female 0.9142857
4  20-30      2 female 0.9000000
5    30+      2 female 1.0000000
6    <10      3 female 0.5937500
7  10-20      3 female 0.5813953
8  20-30      3 female 0.3333333 **
9    30+      3 female 0.1250000 **
10   <10      1   male 0.0000000
11 20-30      1   male 0.4000000
12   30+      1   male 0.3837209
13   <10      2   male 0.0000000
14 10-20      2   male 0.1587302
15 20-30      2   male 0.1600000
16   30+      2   male 0.2142857
17   <10      3   male 0.1115385
18 10-20      3   male 0.2368421
19 20-30      3   male 0.1250000
20   30+      3   male 0.2400000
```

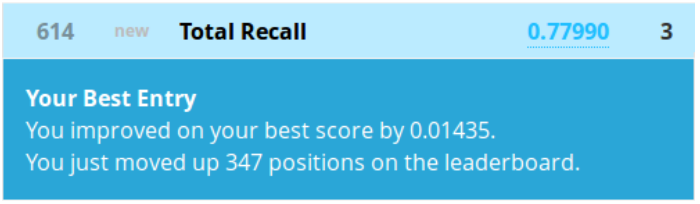
While the majority of males, regardless of class or fare still don't do so well, we notice that most of the class 3 women who paid more than $20 for their ticket actually also miss out on a lifeboat, I've indicated these with asterisks, but R won't know what you're looking for, so they won't show up in the console.

It's a little hard to imagine why someone in third class with an expensive ticket would be worse off in the accident, but perhaps those more expensive cabins were located close to the iceberg impact site, or further from exit stairs? Whatever the cause, let's make a new prediction based on the new insights.

```
test$Survived <- 0
test$Survived[test$Sex == 'female'] <- 1
test$Survived[test$Sex == 'female' & test$Pclass == 3 & test$Fare >= 20] <- 0
```

Most of the above code should be familiar to you by now. The only exception would be that there are multiple boolean checks all stringed together for the last adjustment. For more complicated boolean logic, you can combine the logical AND operator & with the logical OR operator |.

Okay, let's create the output file and see if we did any better!



Alright, now we're getting somewhere! We only improved our accuracy score by 1.5%, but jumped hundreds of spots on the leaderboard! But that was a lot of work, and creating more subsets that dive much deeper would take a lot of time.

Next lesson, we will automate this process by using decision trees. Go there now!

All code from this tutorial is available on my Github repository.

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<- '20-30'

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Trevor Stephens Mod ➚ Patrick Atwater • 6 months ago

It does initially label everyone as 30+, but then you refine the younger groups from there. You could easily initilize the column to NA's and then explicitly break out each group one-by-one, this way you just save yourself a line of code, that's all, the '30+' isn't a special group, you could even start with an intermediate group.

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Deepita Pai • 7 months ago

Hi Trevor,
I am a beginner in R and have thoroughly enjoyed solving the Titanic challenge all thanks to your easy to understand tutorials.There's just one tiny doubt that I have.
You've divided the train$Fare here into 3 intervals. I would like to know on what basis was that done? Given some other extremely huge dataset,if I had to do a similar thing,what R syntax should I use that'll tell me the distribution of continuous data so that I can divide the data into different intervals(say,<10,20-30,30+) as done above?

1 • Reply • Share ›

Trevor Stephens Mod ➚ Deepita Pai • 7 months ago

This section sought to replicate the 'Excel' tutorial found on Kaggle. So I replicated their splitting criteria. In a different dataset, you should probably look at the histogram, eg hist(train$fare), of the variable of interest, or break it up in some other logical fashion based on your prior knowledge of the problem at hand, and decide on what splits make sense. Every dataset is different! Of course our trees can make this determination for us, as we saw.

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Deepita Pai ➚ Trevor Stephens • 7 months ago

Thanks!

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Maca ➚ Deepita Pai • a month ago

Trevor, many thanks for the easy to follow R tutorials, they are very helpful.

In the Excel tutorial the decision to determine the bins used is also not discussed. In this case Summary(train$Fare) shows the quarters which I feel have been used as input for the bins.

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Martin Isaac • 3 days ago

Hi Trevor, very clear second part. One extra step I think is worthwhile here is when you run the aggregation to look at the proportion of survivors by gender, class and fare, is to also look at how many people are in each cell to judge whether we think the differences seen are likely to be significant. The proof of the pudding is in the eating anyway, but as an analyst it's always good to know the context behind figures. Eg would the 0.333 survival rate for the women in 3rd class seem meaningful if there were only 3 women in that cell? Or hypothetically we may have seen a 0 survival rate for say 2nd class women paying 10-20 but on investigation found only 1 woman in that cell. So I ran the simple aggregation using the length function to double check this (there are 21 & 16 women in the two cells so seems likely to be meaningful). I am just wondering if there is a way to run that aggregation so it shows you the proportion AND the number of observations in one step?

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Trevor Stephens Mod ➚ Martin Isaac • 2 days ago

Something like this should probably do what you want, just treat the two outputs as strings and use the function 'paste' to join them together...

aggregate(Survived ~ Fare2 + Pclass + Sex, data=train, FUN=function(x) {paste(length(x), sum(x)/length(x))})

• Reply • Share ›

Robert Birch • 4 months ago

How do I write the next submission? What does the code look like? I am a bit lost after this part here....
test$Survived <- 0
test$Survived[test$Sex == 'female'] <- 1

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Trevor Stephens Mod ↗ Robert Birch • 4 months ago

You can use the exact same code as when you wrote your first submission here: http://trevorstephens.com/post...

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Alfredo Cambera • 6 months ago

Hi Trevor,

I'm really new into Data Analysis and R. Your post has helped me lot to understand the basics. I have a doubt, probably very basic, why did you discard the other females?? There are proportions close and equal to one!!. What I'm missing?

• Reply • Share ›

Trevor Stephens Mod ↗ Alfredo Cambera • 6 months ago

Glad it's helping Alfredo!

Our base assumption from the earlier steps was that all females would survive. So, in aggregating down further to more granular groups, we are looking for those that won't. ie, only those groups with proportion of survivors is less than 50%.

Or on the male's side, we were looking for any groups where they were more likely to survive as our assumption was that they wouldn't, but there weren't any...

Feel free to split the passengers up in other ways and see if you can find any other groups that show a tendency one way or the other!

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AN • 8 months ago

Hi Trevor,

I'm a beginner in R, thank you so much for these tutorials.

I have a question on this set of R code as my results differ from yours:

```
> train$Child <- 0
> train$Child[train$Age < 18] <- 1
> aggregate(Survived ~ Child + Sex, data=train, FUN=sum)
```

My results are as below, where it differs is the number of surviving adults:
Child Sex Survived
0 female 195
1 female 38
0 male 86
1 male 23

After further tinkering with good ol' excel, I think the difference of the results is caused by the Child variable has the value "0" when Age value is missing - I can only get the same surviving adult result as yours when i assign the value "1" to Child when Age value is missing (but then the surviving child numbers are different).

However, my understanding is that when Age is missing we assume that the Child value for the observation is 0 (taking the average value of Age, which is an adult). Could you perhaps point out if I overlooked something here? Thanks.

• Reply • Share ›

Trevor Stephens Mod ↗ AN • 7 months ago

Hey An, thanks for bringing that to my attention. I had done some further subsetting when preparing the post that I forgot to undo. Your results are correct and I have updated the post to reflect that.

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