Modeling Runners’ Times in the Cherry Blossom Race

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1 Introduction

The internet is a vast open resource for data, but internet data can be messy and difficult to wrangle. In this case study we collect data on participates of the Cherry Blossom Race from the Cherry Blossom Race website[1]. We find that there are a number of issues present in the data, including inconssitent web addressing formatting, inconsistent formatting, and missing data. We collect and clean this data to provide the Men’s and Women’s information in a format suitable for analysis.

2 Methods

2.1 Data

2.1.1 Data Collection

In this case study, we collected data on participants in the Cherry Blossom Race. We scraped the data for Men and Woman from 1999 to 2012. The data was stored under the base address in the following form, where the year is between 1999 and 2012 and page is a specific page name.

```
http://www.cherryblossom.org/results/<year>/<page>
```

The specific addresses where the data is stored are given in table 1. While the structure follows `results/<year>` consistently, the page naming for each year is not consistent. In some cases, the names for the men’s and women’s pages are `men` and `women`, repectively. In other cases, a code is used such as `cb99m` and `cb99f` in 1999 for `men` and `women` repectively.

[1] See http://www.cherryblossom.org/.

Table 1. Web Page Pages

Year	Men's Pages	Women's Pages
1999	`results/1999/cb99m.html`	`results/1999/cb99f.html`
2000	`results/2000/Cb003m.htm`	`results/2000/Cb003f.htm`
2001	`results/2001/oof_m.html`	`results/2001/oof_f.html`
2002	`results/2002/oofm.htm`	`results/2002/ooff.htm`
2003	`results/2003/CB03-M.HTM`	`results/2003/CB03-F.HTM`
2004	`results/2004/men.htm`	`results/2004/women.htm`
2005	`results/2005/CB05-M.htm`	`results/2005/CB05-F.htm`
2006	`results/2006/men.htm`	`results/2006/women.htm`
2007	`results/2007/men.htm`	`results/2007/women.ht`
2008	`results/2008/men.htm`	`results/2008/women.htm`
2009	`results/2009/09cucb-M.htm`	`results/2009/09cucb-F.htm`
2010	`results/2010/2010cucb10m-m.htm`	`results/2010/2010cucb10m-F.htm`
2011	`results/2011/2011cucb10m-m.htm`	`results/2011/2011cucb10m-F.htm`
2012	`results/2012/2012cucb10m-m.htm`	`results/2012/2012cucb10m-F.htm`

The data are successfully scraped from the urls that are given and we observe that the number of participants in the Cherry Blossom race has increased steadily from 1999 to 2012. We can use the `extractResTable` function to exptract all of the results, or to specify a single set of results.

We observe the formatting of the text data, such as the use of the `=` character can be used to transform the lines of text into a a matrix. We will used this pattern to identify the boundary between the headering and the body of the data. Once we defined the column names, we were free to use the text structure, such as the spacing of column names and data, to identify datapoints. We started with age, which denoted by the `"ag"` identifier. After we sucessfully used the structure of the text data to identify an index location for `"ag"` data points. We expanded the search to inlcude the spacing of text data to identify other data points. The spacing indices were used in a funtion that compiled a matrix of data points across the entire list of tables.

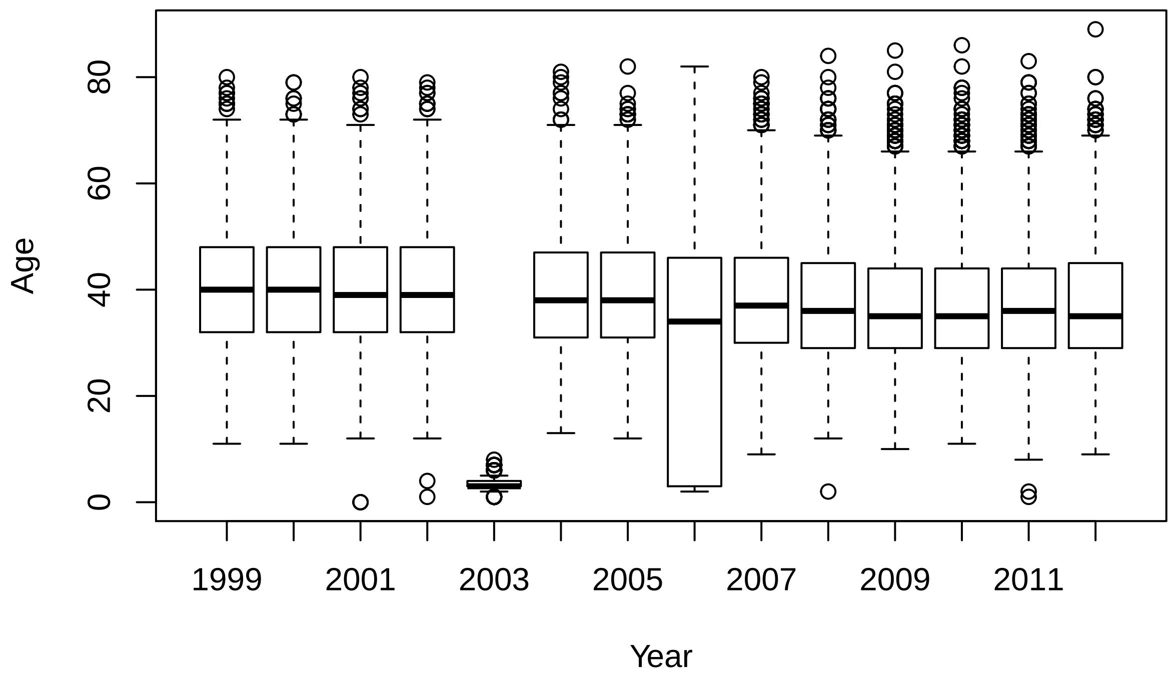
A function `findColLocs` was defined to use these space indices to locate the begin points for data throughout the extracted text data. `selectCols` is a tool that uses `findColLocs` to locate the data points for each column throughout the text for all of the race years. Our functions extracted almost all of the age data fomr the text, which aided in the identification errors within the dataset. To generalize this method, we defined a function, `extractVariables`, that combined the various processes we used to preprocess the data into a more machine readable format.

We now have a list of matrices. The original text data are in a much more machine readable format. Our number of rows for each matrix is equal to the number of original rows, minus the original text header. To perform statistical analyses on the numeric data, we must perform a datatype transformation.

There were anomalies in the data for the year 2003. After an examination of the original data table, we found that the spacing in the year 2003 data is not the same as the other years. We adjusted our `selectCols` function to better capture the data for 2003. We also observe anomalies in the formatting of the year 2001. We introduced fixes and re-scraped the data once more to form the list of matrices called `menResMat`.

" 1 1/1420 1 Ridouane Harroufi 27 Morocco 45:56 45:56# 4:36 "

" 27 " " " " " " 26 M" " 26 " " 23 Ken"



After these anomalies were corrected, we reformatted the datatypes. The `"ag"` data was changed to a numeric format for analysis, which revealed *more* anomalies. We observed suspiciously young ages between the years 2001 and 2003. These ages were revealed to be *erroneous* upon closer examination. These values were removed from the dataset.

To make the remaining analyses easier, we transformed the data structure from a list of matrices into a dataframe. Combining the data into a single dataframe facilitated the cleaning of the columns containing the time data for each runner. These values were stored as characters and were in an HR:MIN:SEC format. We can separate the values and convert them all into a standard time format, minutes. We defined a function that converts the time into a minute format.

The end result was a dataframe called menDF. With this process complete, we simply re-used the functions on the women's data.

Our dataset is complete, clean, and ready for further analysis.

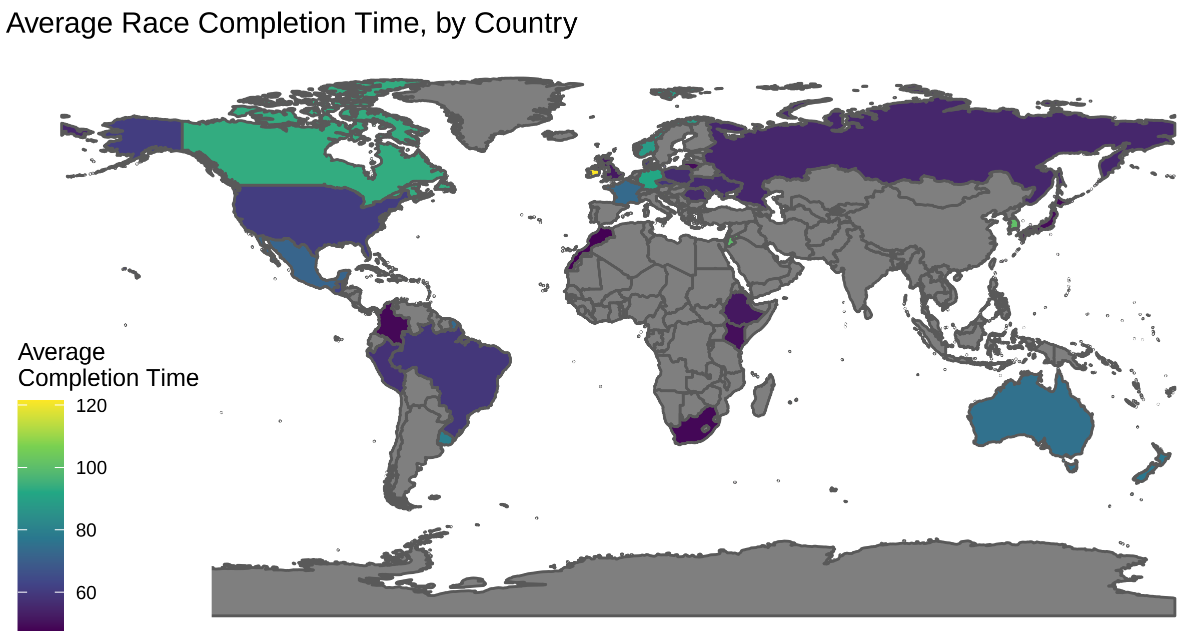
```
##   year sex                   name               home age  runTime
## 1 1999   M Worku Bikila          Ethiopia            28 46.98333
## 2 1999   M Lazarus Nyakeraka     Kenya               24 47.01667
## 3 1999   M James Kariuki         Kenya               27 47.05000
## 4 1999    M William Kiptum         Kenya                   28 47.11667
## 5 1999    M Joseph Kimani          Kenya                   26 47.51667
## 6 1999    M Josphat Machuka        Kenya                   25 47.55000
```

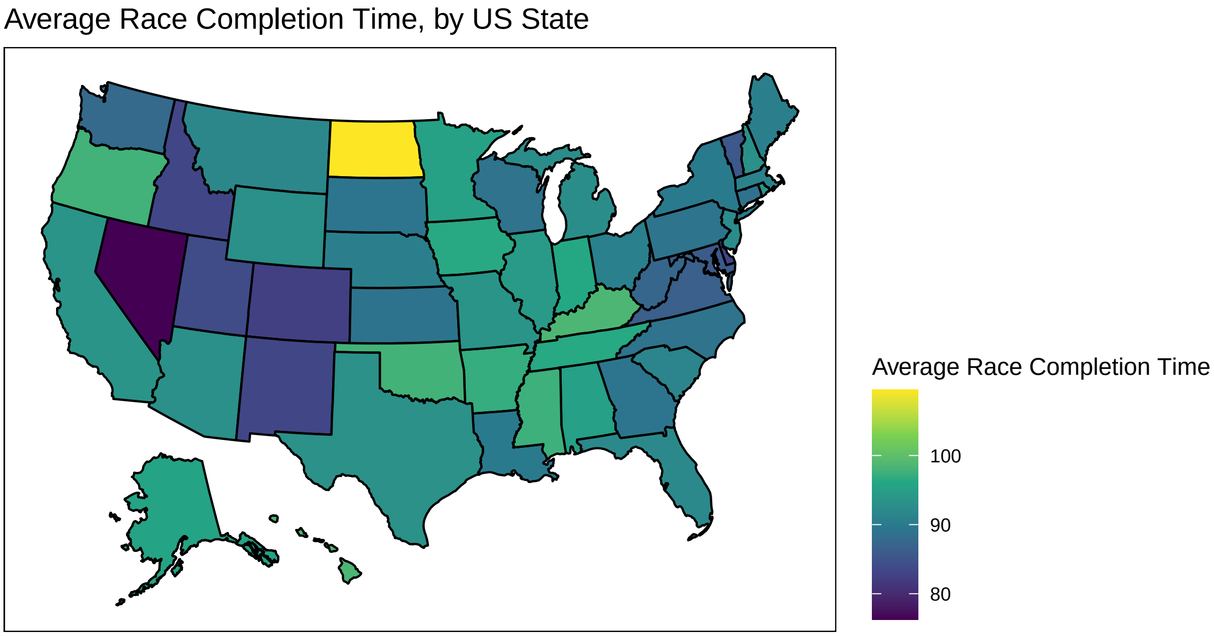
3 Conclusion

Additionally, we identified 12 runners without valid home addresses, which we imputed with valid addresses they had provided in previous races. For these runners, the states (including D.C. as Washington, D.C.) were the same. This was useful when determining race times.

Also, country names were standardized according to iso3166, which was useful for both naming consistency and production of the global map we used for visualizing race completion times.

These webscraping methods proved useful for identifying the times of race completion per runner from year 1999 through 2012. From this information we were able to identify average race completion times, by nation. Some of the fastest average runners in the world participating in the race come from Tanzania, Morocco, and Colombia while the nation represented by the slowest average runner is Ireland. With repsect to states, the state with the fastest average run time was Nevada across all years, while the slowest was North Dakota.




Average Race Completion Time, by US State
Average Race Completion Time
100
90
80

A Code

```
The code is cooool
```