Stochastic Process Model with Basketball Data

A Thesis
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Acknowledgements

I want to thank a few people.

Preface

This is an example of a thesis setup to use the reed thesis document class (for LaTeX) and the R bookdown package, in general.

Table of Contents

List of Tables

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Abstract

The preface pretty much says it all.

Second paragraph of abstract starts here.

Dedication

You can have a dedication here if you wish.

Chapter 1

thesisdowndss::thesis_word: default

Chapter 2

Boxscore

In basketball, a boxscore provides the statistical summary of the game via defensive, offensive, and overall success metrics. Popular metrics include rebounds per game (RBG), player efficiency rating (PER), free throw attempts (FTA), and 3 field goals made (3FGM). However, these metrics cannot capture the entirety of the game because they do not take into account the opposing team's defense/offense, nor previous plays that significantly influenced the flow of the game.

Chapter 3

Literature Review

Previous works have sought to capture the game more robustly. Below describes a summary of a few:

"Flow Motifs in Soccer: What can passing behavior tell us?" by Joris Bekkers and Shaunak Dabadghao was released in the 2017 MIT Sloan Sports Analytics Conference, and focused on the static passing networks of "the last 4 seasons of 6 big European leagues with 8219 matches, 3532 unique players and 155 unique teams." Passing sequences were denoted as a sequence of all players involved five seconds before an attempted score. This paper created radar graphs that illustrated the most popular passing sequences by player, and compared radar graphs to identify similar players. Passing sequences within teams were also compared between teams by clustering the different passing styles of the different teams. Key players were determined by the frequency that they were included in the passing sequences.

"Exploring Team Passing Networks and Player Movement Dynamics in Youth Association Football (Soccer)" by Bruno Goncalves, Diogo Coutinho, Sara Santos, Carlos Lago-Penas, Sergio Jimenez, and Jamie Sampaio compared the passing sequences of two games played by two groups that differ in age range, which showed that regardless of age, network centrality was distinctive in both groups, and affirmed the long-held belief that more passes lead to better game outcomes. Similar to the first paper, key players were the ones most frequently involved in the passing sequences. This paper created weighted graphs of the passing sequences, which better visualized the passing structure of the team, and made it easier to identify important players.

"Basketball Teams as Strategic Networks" by Jennifer H. Fewell, Dieter Armbruster, John Ingraham, Alexander Petersen, and James S. Waters provided measurements to assess team entropy. First recording the complete 30 seconds of a possession as a passing sequence, they discovered that recording the last three nodes (players) before a shot attempt was a better way to record passing sequences to avoid "noisy" passing data. Although they were able to recognize various aspects of team dynamics through weighted graphs like the second paper, they did not find a consistent predictor of positive game outcomes. This paper also identified that in general, teams typically range between two playing styles: always passing to the best player or having no distinct patterns in passing. These patterns can be noted by distinct betweenness scores and uniform betweenness scores, respectively. Weighted graphs clearly illustrated the two different playing styles. Also, the paper found that the positions most involved with successful shots were: 1. PG 2. SG 3. SF 4. PF 5. CN.

Joachim Gudmundsson and Michael Horton summarised a variety of methods that utilize object tracking data to analyze team and player performances in "Spatio-Temporal Analysis of Team Sports – A Survey." Their research survey spanned modeling passing networks via graph theory to calculating rebound probability with spatial coordinates. In particular, work conducted by Daniel Cervone, Alex D'Amour, Luke Bornn, and Kirk Goldsberry attempted to capture the game wholelistically via a new measure called Expected Possession Value (EPV) in the paper "A Multiresolution Stochastic Process Model for Predicting Basketball Possession Outcomes." This new metric uses three models–a Microtransition Model, Macrotransition Entrance Model, and a Macrotransition Exit Model–to capture the spatial biases of each player and the in-game effects of pressure, so that it can measure the likelihood of a successful play (made shot) given the previous sequence of events. To compare players against the league-average scores, they also calculated Expected Possession Value -Adjusted as an application for teams.

Chapter 4

Model Replication

4.1 Motivation

This paper is particularly interesting because EPV utilizes the spatio-temporal elements of the game, so it models the NBA game dynamically. Given Duke Basketball data, the motivation is to replicate "A Multiresolution Stochastic Process Model for Predicting Basketball Possession Outcomes," to better understand the Duke Men's team, as well as to compare professional basketball to collegiate basketball individual and team playing styles. Below is a brief overview of each model used in the paper to calculate EPV.

4.2 Microtransition Model

$x^l(t+\epsilon) = x^l(t) + \alpha_x^l[x^l(t) - x^l(t-\epsilon)] + \eta_x^l(t)$ where $\eta_x^l(t) \sim N(\mu_x^l(z^l(t)), (\sigma_x^l)^2)$

The microtransition model models the defensive conditions of the game based on the (x, y) coordinates of a player and their acceleration effects $(\alpha_x^l(t))$. It is also assumed that a player's spatial location is normally distributed. Since players play differently, each microtransition model is specifically fitted to the player.

4.3 Macrotransition Entrance Model

$P(M(t)|F_t^{(Z)}$ The macrotransition entrance model predicts whether the next move will be a pass (4 options), shot attempt, or turnover. The model is disjoint.

4.4 Macrotransition Exit Model

$P(C_{\delta_t}|M(t), F_t^{(Z)})$ Given the Macrotransition Entrance Model predicts a shot attempt, it indexes to a logistic regression model to calculate player l's successful shot probability. Given the Macrotransition Entrance Model predicts a pass,it indexes to a model that predicts where the pass will take place. Otherwise, a turnover is assumed.

Chapter 5

Macrotransition Exit Model

equation

Chapter 6

Implementation of this Model

6.1 in the works...

6.2 Next Steps (have yet to get this far)

Both metrics calculated via a semi-Markov process, EPV fails to capture the full nature of the possession because it only uses the last posession as a prior. The model would be more robust if it captured the entirety of the posession in its prior–however, the computational time of such an ordeal would prevent any real-time analyses. Thus, this paper proposes that a simpler model may perform more quickly and potentially just as robustly to allow for game-time analyses.

Here is a brief introduction into using *R Markdown*. *Markdown* is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. *R Markdown* provides the flexibility of *Markdown* with the implementation of **R** input and output. For more details on using *R Markdown* see `http://rmarkdown.rstudio.com`.

Be careful with your spacing in *Markdown* documents. While whitespace largely is ignored, it does at times give *Markdown* signals as to how to proceed. As a habit, try to keep everything left aligned whenever possible, especially as you type a new paragraph. In other words, there is no need to indent basic text in the Rmd document (in fact, it might cause your text to do funny things if you do).

6.3 Exploratory Data Analysis

-eda, write up literature

It's easy to create a list. It can be unordered like

- Item 1
- Item 2

or it can be ordered like

1. Item 1
2. Item 2

Notice that I intentionally mislabeled Item 2 as number 4. *Markdown* automatically figures this out! You can put any numbers in the list and it will create the list. Check it out below.

To create a sublist, just indent the values a bit (at least four spaces or a tab). (Here's one case where indentation is key!)

1. Item 1
2. Item 2
3. Item 3
    - Item 3a
    - Item 3b

6.4 Line breaks

Make sure to add white space between lines if you'd like to start a new paragraph. Look at what happens below in the outputted document if you don't:

Here is the first sentence. Here is another sentence. Here is the last sentence to end the paragraph. This should be a new paragraph.

Now for the correct way:

Here is the first sentence. Here is another sentence. Here is the last sentence to end the paragraph.

This should be a new paragraph.

6.5 R chunks

When you click the **Knit** button above a document will be generated that includes both content as well as the output of any embedded **R** code chunks within the document. You can embed an **R** code chunk like this (`cars` is a built-in **R** dataset):

```
summary(cars)
```

```
    speed           dist       
Min.   : 4.0   Min.   :  2.00  
1st Qu.:12.0   1st Qu.: 26.00  
Median :15.0   Median : 36.00  
Mean   :15.4   Mean   : 42.98  
3rd Qu.:19.0   3rd Qu.: 56.00  
Max.   :25.0   Max.   :120.00  
```

6.6 Inline code

If you'd like to put the results of your analysis directly into your discussion, add inline code like this:

> The `cos` of 2π is 1.

Another example would be the direct calculation of the standard deviation:

> The standard deviation of `speed` in `cars` is 5.2876444.

One last neat feature is the use of the `ifelse` conditional statement which can be used to output text depending on the result of an **R** calculation:

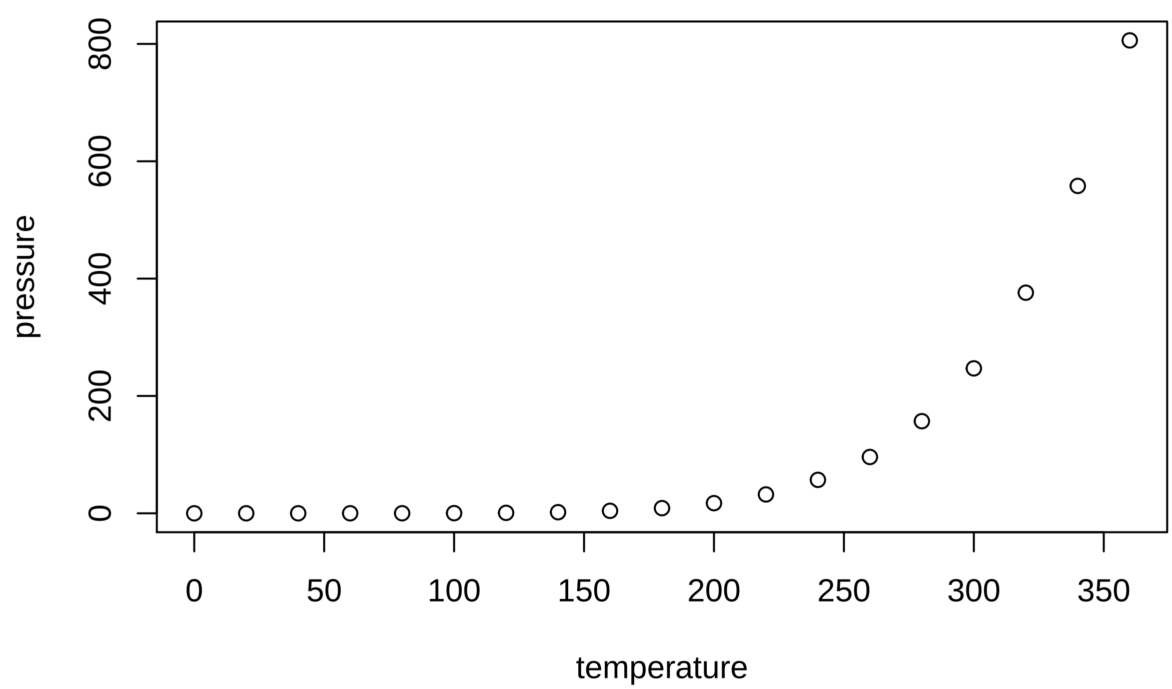
> The standard deviation is less than 6.

Note the use of `>` here, which signifies a quotation environment that will be indented.

As you see with `$2 \pi$` above, mathematics can be added by surrounding the mathematical text with dollar signs. More examples of this are in [Mathematics and Science] if you uncomment the code in Math.

6.7 Including plots

You can also embed plots. For example, here is a way to use the base **R** graphics package to produce a plot using the built-in `pressure` dataset:



Note that the `echo=FALSE` parameter was added to the code chunk to prevent printing of the **R** code that generated the plot. There are plenty of other ways to add chunk options. More information is available at `http://yihui.name/knitr/options/`.

Another useful chunk option is the setting of `cache=TRUE` as you see here. If document rendering becomes time consuming due to long computations or plots that are expensive to generate you can use knitr caching to improve performance. Later in this file, you'll see a way to reference plots created in **R** or external figures.

6.8 Loading and exploring data

Included in this template is a file called `flights.csv`. This file includes a subset of the larger dataset of information about all flights that departed from Seattle and Portland in 2014. More information about this dataset and its **R** package is available at `http://github.com/ismayc/pnwflights14`. This subset includes only Portland flights and only rows that were complete with no missing values. Merges were also done with the `airports` and `airlines` data sets in the `pnwflights14` package to get more descriptive airport and airline names.

We can load in this data set using the following command:

```
flights <- read.csv("data/flights.csv")
```

The data is now stored in the data frame called `flights` in **R**. To get a better feel for the variables included in this dataset we can use a variety of functions. Here we can see the dimensions (rows by columns) and also the names of the columns.

```
dim(flights)
```

```
[1] 52808    16
```

```
names(flights)
```

```
 [1] "month"        "day"          "dep_time"     "dep_delay"
 [5] "arr_time"     "arr_delay"    "carrier"      "tailnum"
 [9] "flight"       "dest"         "air_time"     "distance"
[13] "hour"         "minute"       "carrier_name" "dest_name"
```

Another good idea is to take a look at the dataset in table form. With this dataset having more than 50,000 rows, we won't explicitly show the results of the command here. I recommend you enter the command into the Console ***after*** you have run the **R** chunks above to load the data into **R**.

```
View(flights)
```

While not required, it is highly recommended you use the `dplyr` package to manipulate and summarize your data set as needed. It uses a syntax that is easy to understand using chaining operations. Below I've created a few examples of using `dplyr` to get information about the Portland flights in 2014. You will also see the use of the `ggplot2` package, which produces beautiful, high-quality academic visuals.

We begin by checking to ensure that needed packages are installed and then we load them into our current working environment:

```
# List of packages required for this analysis
pkg <- c("dplyr", "ggplot2", "knitr", "bookdown", "devtools")
# Check if packages are not installed and assign the
# names of the packages not installed to the variable new.pkg
new.pkg <- pkg[!(pkg %in% installed.packages())]
# If there are any packages in the list that aren't installed,
# install them
if (length(new.pkg))
  install.packages(new.pkg, repos = "http://cran.rstudio.com")
# Load packages (thesisdowndss will load all of the packages as well)
library(thesisdowndss)
```

The example we show here does the following:

- Selects only the `carrier_name` and `arr_delay` from the `flights` dataset and then assigns this subset to a new variable called `flights2`.
- Using `flights2`, we determine the largest arrival delay for each of the carriers.

```
flights2 <- flights %>%
  select(carrier_name, arr_delay)
max_delays <- flights2 %>%
  group_by(carrier_name) %>%
  summarize(max_arr_delay = max(arr_delay, na.rm = TRUE))
```

A useful function in the `knitr` package for making nice tables in *R Markdown* is called `kable`. It is much easier to use than manually entering values into a table by copying and pasting values into Excel or LaTeX. This again goes to show how nice reproducible documents can be! (Note the use of `results="asis"`, which will produce the table instead of the code to create the table.) The `caption.short` argument is used to include a shorter title to appear in the List of Tables.

```
kable(max_delays,
      col.names = c("Airline", "Max Arrival Delay"),
      caption = "Maximum Delays by Airline",
      caption.short = "Max Delays by Airline",
      longtable = TRUE,
      booktabs = TRUE)
```

Table 6.1: Maximum Delays by Airline

Airline	Max Arrival Delay
Alaska Airlines Inc.	338
American Airlines Inc.	1539
Delta Air Lines Inc.	651
Frontier Airlines Inc.	575
Hawaiian Airlines Inc.	407
JetBlue Airways	273
SkyWest Airlines Inc.	421
Southwest Airlines Co.	694
United Air Lines Inc.	472
US Airways Inc.	347
Virgin America	366

The last two options make the table a little easier-to-read.

We can further look into the properties of the largest value here for American

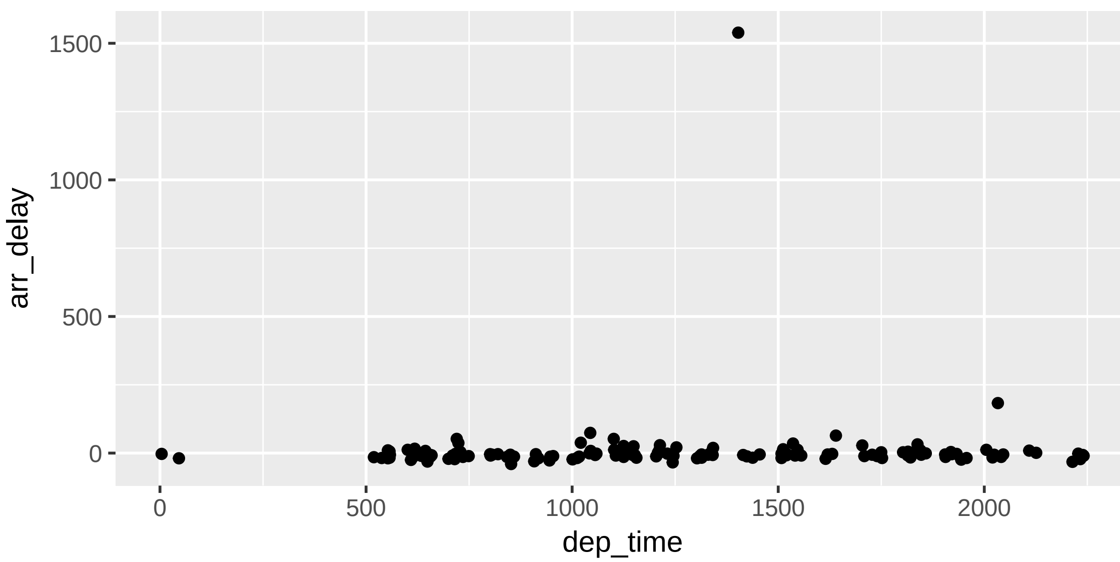
Airlines Inc. To do so, we can isolate the row corresponding to the arrival delay of 1539 minutes for American in our original `flights` dataset.

```
flights %>% filter(arr_delay == 1539,
                   carrier_name == "American Airlines Inc.") %>%
  select(-c(month, day, carrier, dest_name, hour,
            minute, carrier_name, arr_delay))
```

```
  dep_time dep_delay arr_time tailnum flight dest air_time distance
1     1403      1553     1934  N595AA   1568  DFW      182     1616
```

We see that the flight occurred on March 3rd and departed a little after 2 PM on its way to Dallas/Fort Worth. Lastly, we show how we can visualize the arrival delay of all departing flights from Portland on March 3rd against time of departure.

```
flights %>% filter(month == 3, day == 3) %>%
  ggplot(aes(x = dep_time, y = arr_delay)) + geom_point()
```



6.9 Additional resources

- *Markdown* Cheatsheet - `https://github.com/adam-p/markdown-here/wiki/Markdown-Cheatsheet`
- *R Markdown* Reference Guide - `https://www.rstudio.com/wp-content/uploads/2015/03/rmarkdown-reference.pdf`
- `dplyr` Documentation - `http://dplyr.tidyverse.org/`
- `ggplot2` Documentation - `http://ggplot2.tidyverse.org/`

Chapter 7

Math typesetting

7.1 Math

Chapter 8

This chunk ensures that the thesisdowndss package is

8.1 Tables

8.2 Figures

8.3 Footnotes and Endnotes

8.4 Bibliographies

8.5 Anything else?

Chapter 9

Organization

Conclusion

Chapter 10

The First Appendix

References