Section VII: LDA and Text Scraping

450C

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Overview

1. Overview
2. Midterm Recap
3. Latent Dirichlet Allocation
4. Text Scraping using rvest

Midterm Recap

- Everyone did well!
- Mean of 86
- Median of 88.5

Midterm Recap

- The variance-bias tradeoff is inherent in **any** model that we fit.
- Whether we prioritise reducing MSE or Bias depends entirely on the task at hand
    - In causal inference, we still care a lot about the bias term.
    - Model choice will depend on whether we want to infer effect size ($\hat{\beta}$) or make good predictions ($\hat{y}$).
- Machine Learning is *not* a panacea to all of our problems
- Fitting the same model (e.g., LASSO) with slightly different options can give you very different results!

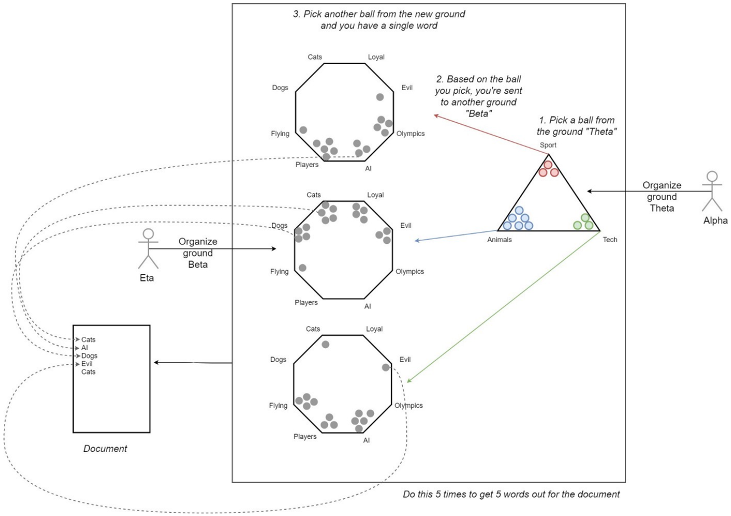
Latent Dirichlet Allocation

- The idea is to build a hierarchical model to predict probabilities of each document belonging to different clusters.
- LDA setup is very notation-heavy. (Notation slightly different from Justin's slides)
    - We have K topics, M documents, $1, \ldots, i, \ldots, N$ words in each document

$$
\begin{aligned}
\underset{1\times K}{\alpha} & \\
\underset{1\times K}{\theta_m} &\sim \mathrm{Dir}(\underset{1\times K}{\alpha}) \\
\underset{1\times K}{z_{im}} | \underset{1\times K}{\theta_m} &\sim \mathrm{Multinomial}(\underset{1\times K}{\theta_m}) \\
\underset{1\times N}{\beta_k} &\sim \mathrm{Dir}(\mathbf{1}) \\
\underset{1\times 1}{x_{im}} | \underset{1\times N}{\beta_k}, z_{imk} = 1 &\sim \mathrm{Multinomial}(\underset{1\times N}{\beta_k})
\end{aligned}
$$

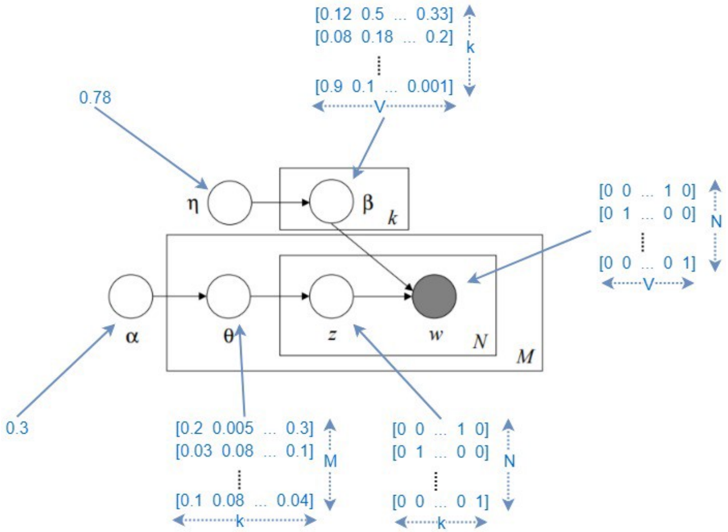
Latent Dirichlet Allocation (cont'd)

- We can depict the hierarchy using a more intuitive setting:



Latent Dirichlet Allocation (cont'd)

- Let's formalise the process a little bit, using plate notation.



Latent Dirichlet Allocation (cont'd)

- θ_m (what Justin calls π_i in his slides) is the vector that describes the probability of a document belonging to each topic.

- β_k (what Justin calls θ_k in his slides) is the vector that describes the probability of word i conditional on topic k.

- We have the theoretical model -- how do we compute these quantities?

  - Joint posterior can be approximated using Gibbs sampling.
  - $\rightarrow$ far deeper dive into material in 450D (Bayesian statistics)

- The neat feature of LDA is that topics and words are interdependent!

Application: Brexit-related speeches in British Parliament

- To the Code! $\longrightarrow$ `EXAMPLE (Brexit LDA)`

How to Get Text (Or Other Data)?

- Scrape from websites
  - use `beautifulSoup` in Python or `rvest` in R
  - easiest if provided data are accessible
  - with large datasets, hard to do (timeout and bandwidth problems)
  - scraping is significantly easier if you can discover regularities in the source data $\rightarrow$ `EXAMPLE (local elections)`

How to Get Text (Or Other Data)? (cont'd)

- Example use case for `rvest`:

```
library(rvest)
lego_movie <- read_html("http://www.imdb.com/title/tt1490017/")

rating <- lego_movie %>%
  html_nodes("strong span") %>%
  html_text() %>%
  as.numeric()
rating
#> [1] 7.8

cast <- lego_movie %>%
  html_nodes("#titleCast .primary_photo img") %>%
  html_attr("alt")
cast
#>  [1] "Will Arnett"     "Elizabeth Banks" "Craig Berry"
#>  [4] "Alison Brie"     "David Burrows"   "Anthony Daniels"
#>  [7] "Charlie Day"     "Amanda Farinos"  "Keith Ferguson"
#> [10] "Will Ferrell"    "Will Forte"      "Dave Franco"
#> [13] "Morgan Freeman"  "Todd Hansen"     "Jonah Hill"
```

How to Get Text (Or Other Data)? (cont'd)

- Scrape from pdfs
    - if text is machine-readable, use `pdftools` or `tabula`
    - if text is not recognised, use OCR software (e.g., `FineReader`)
- Bottom line: Original data easy to get once you're familiar with the tools!