# 10. Unsupervised Techniques III: Topic Models

DS-GA 1015, Text as Data
Arthur Spirling

April 16, 2019

# Housekeeping

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1. Final homework is available! Deadline is May 3.

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2. Speaker series: Steinert-Threlkeld "The Effect of Violence, Cleavages, and Free-riding on Protest Size"

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Note that in social science we often use the outputs from topic models as a measurement strategy:

"who pays more attention to education policy, conservatives or liberals?"

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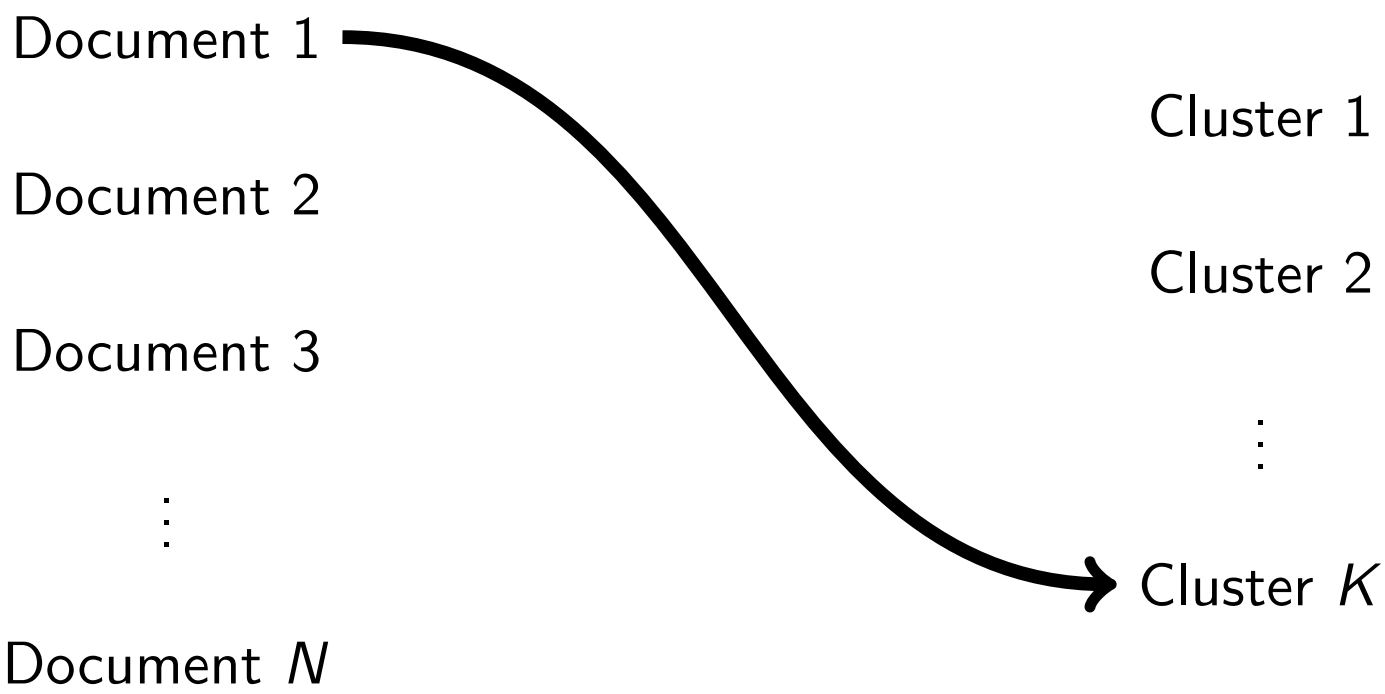

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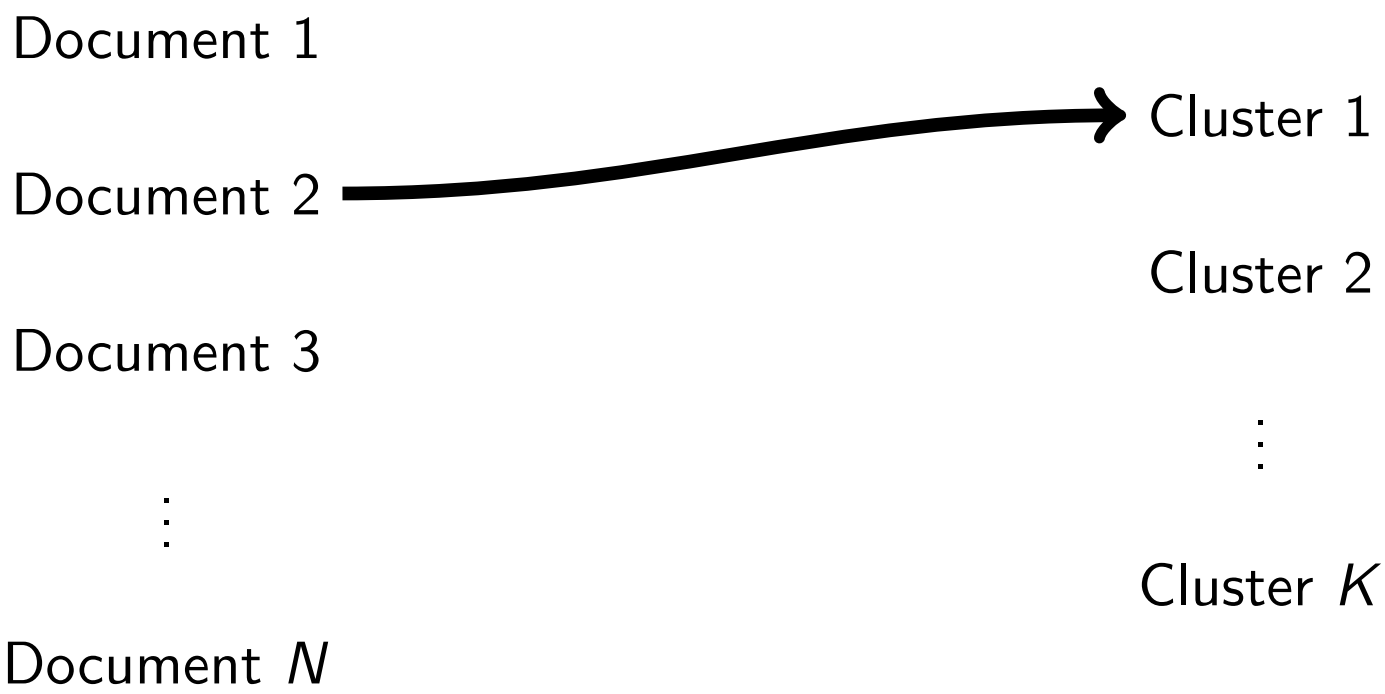

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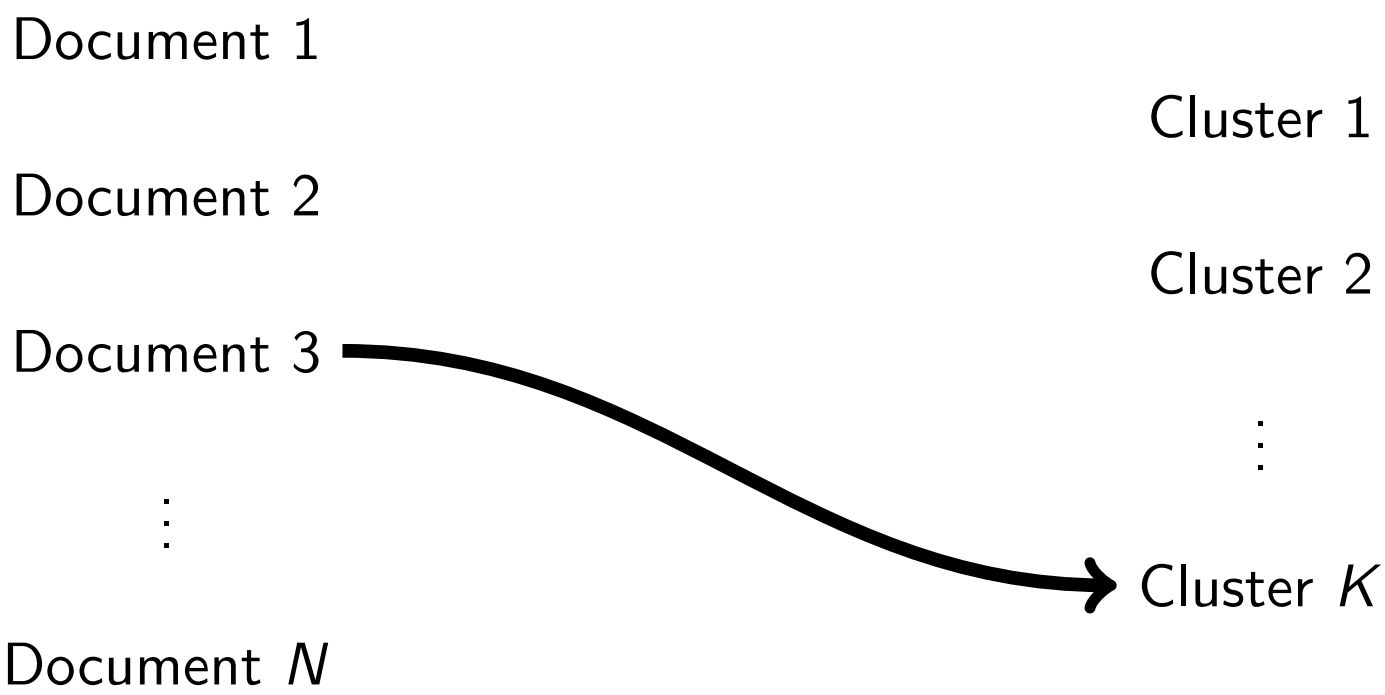

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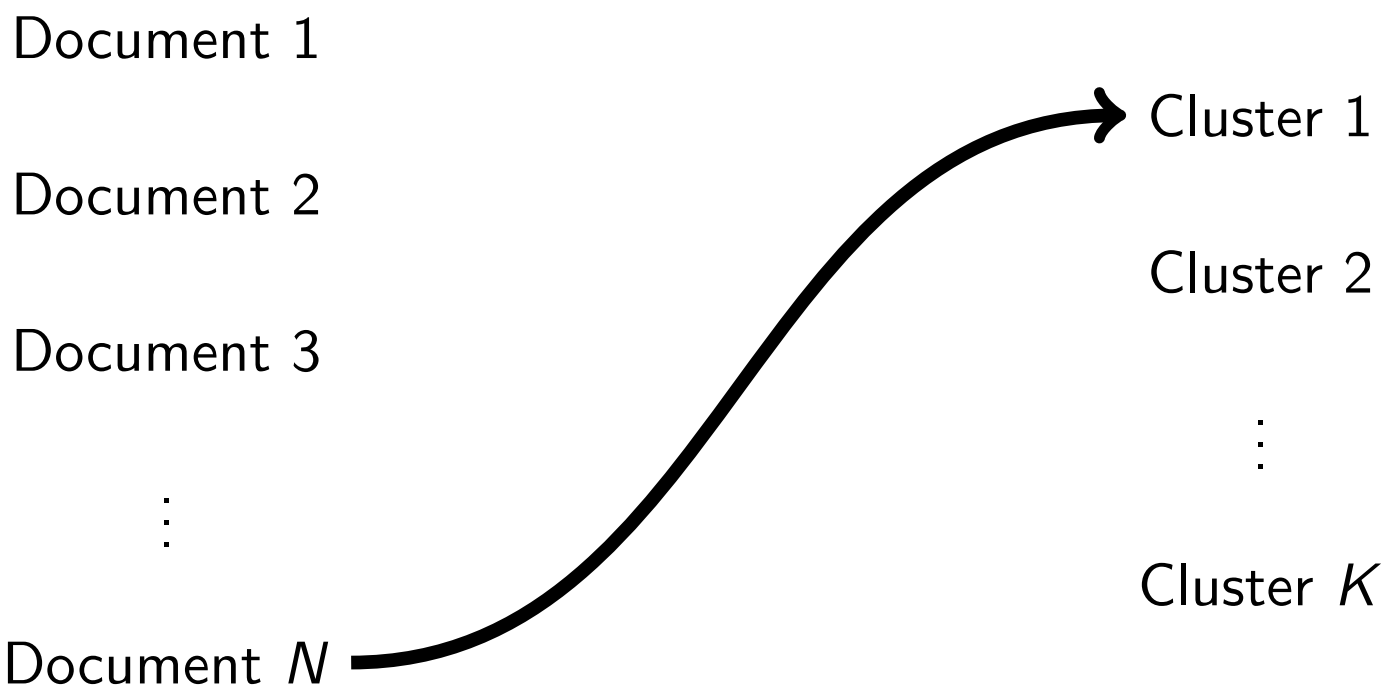

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Document 1

Document 2

Document 3

⋮

Document $N$

Cluster 1

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⋮

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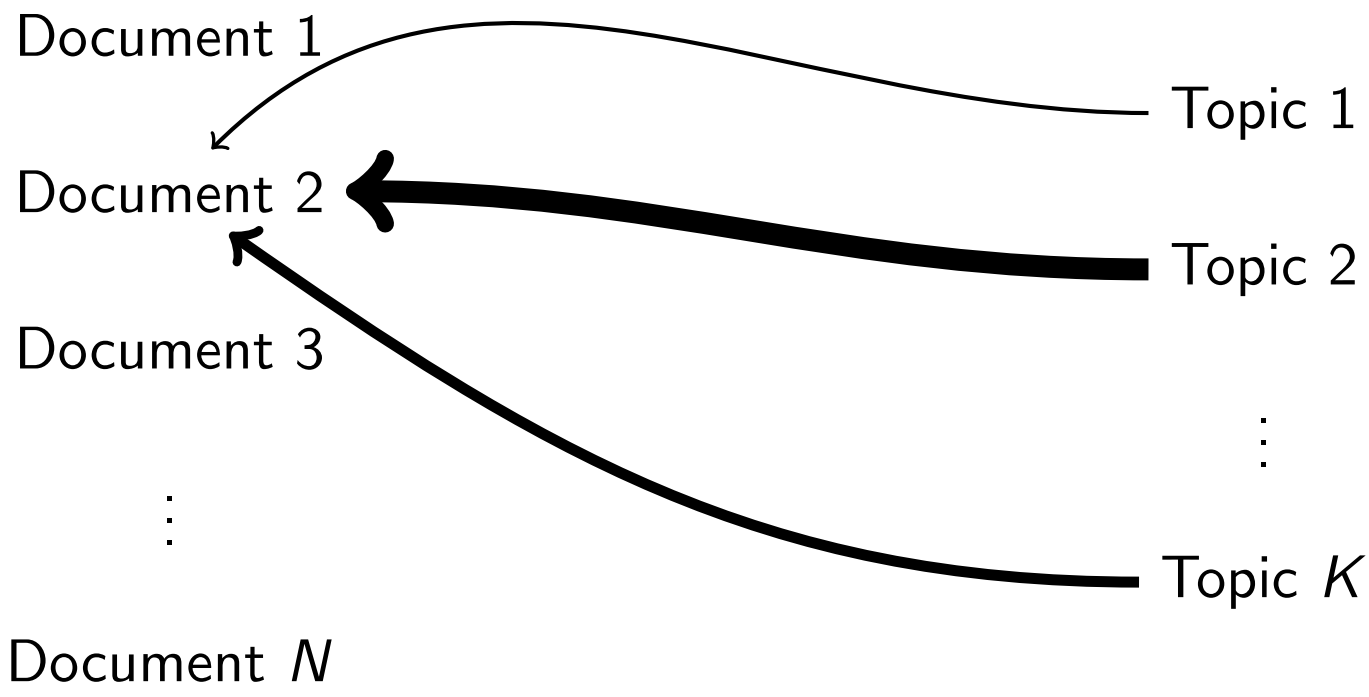

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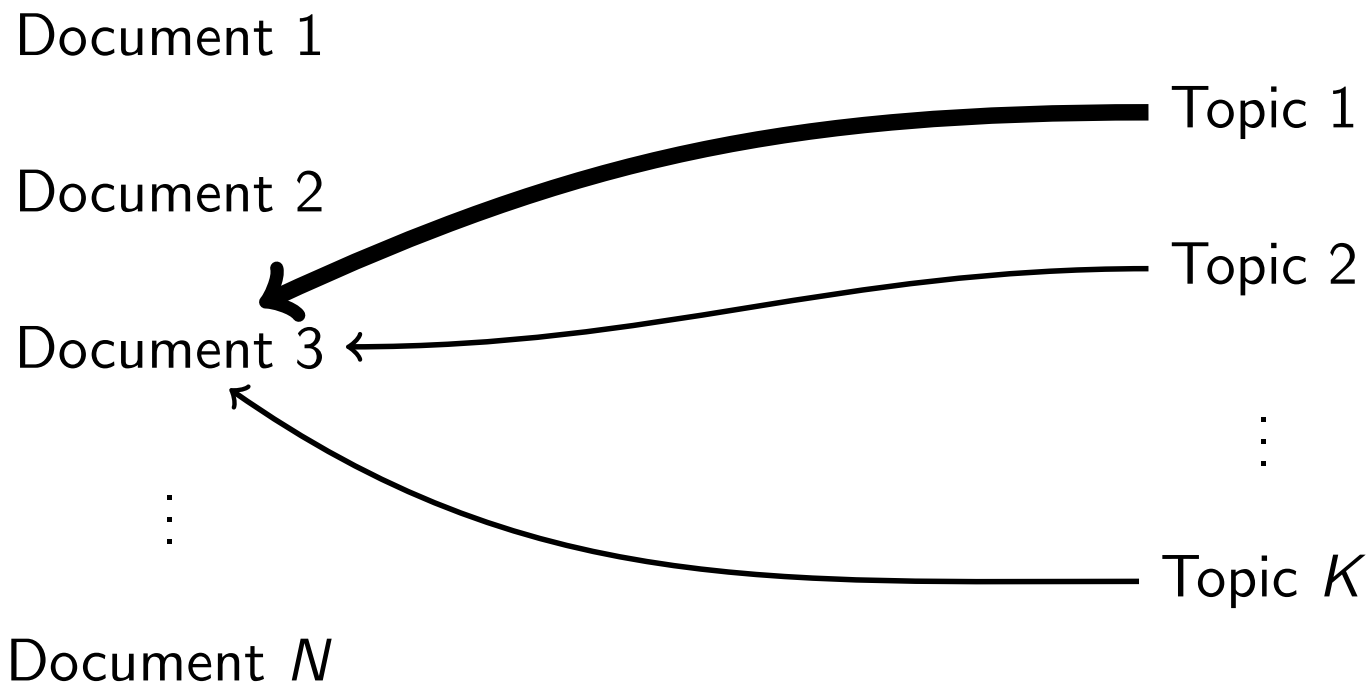

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Now, where do the words in the documents come from?

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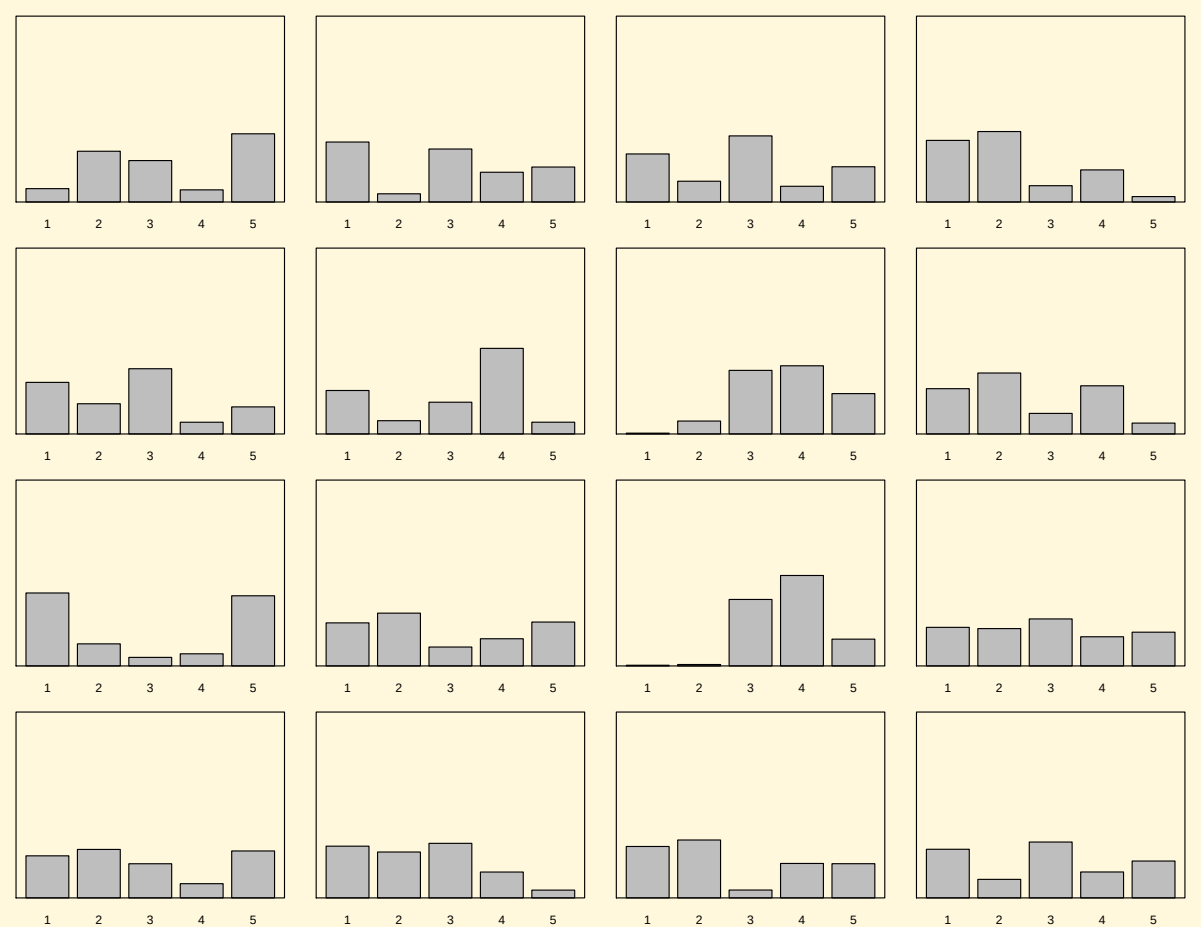

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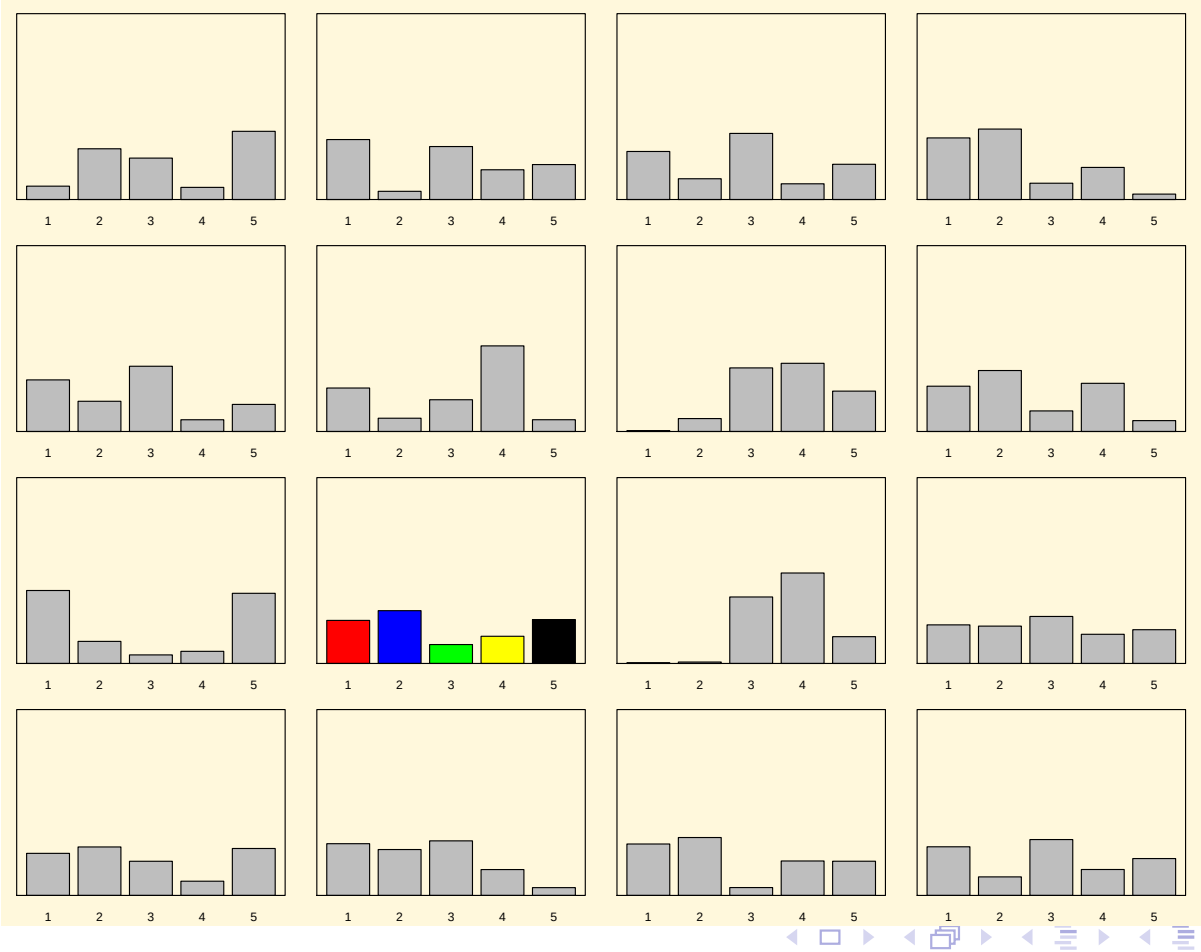

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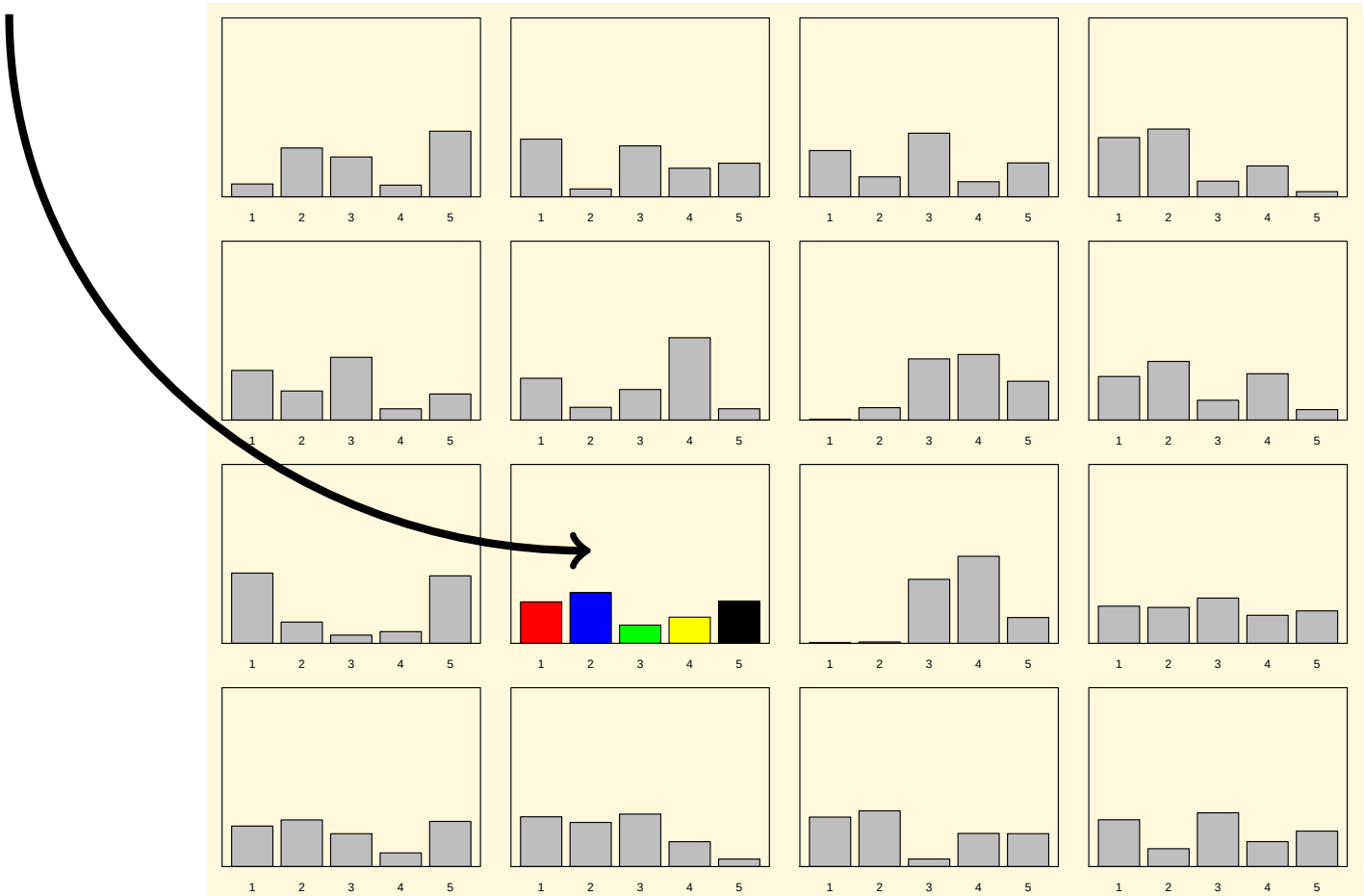

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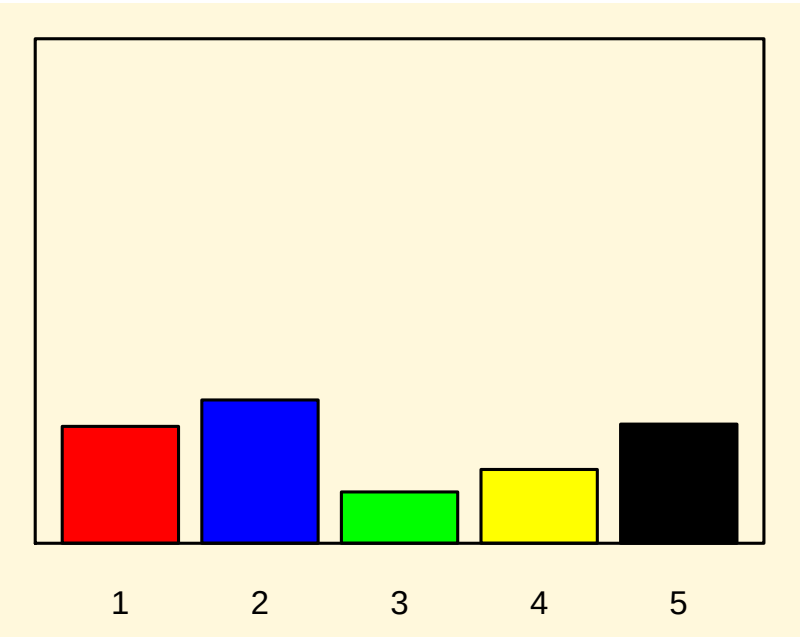

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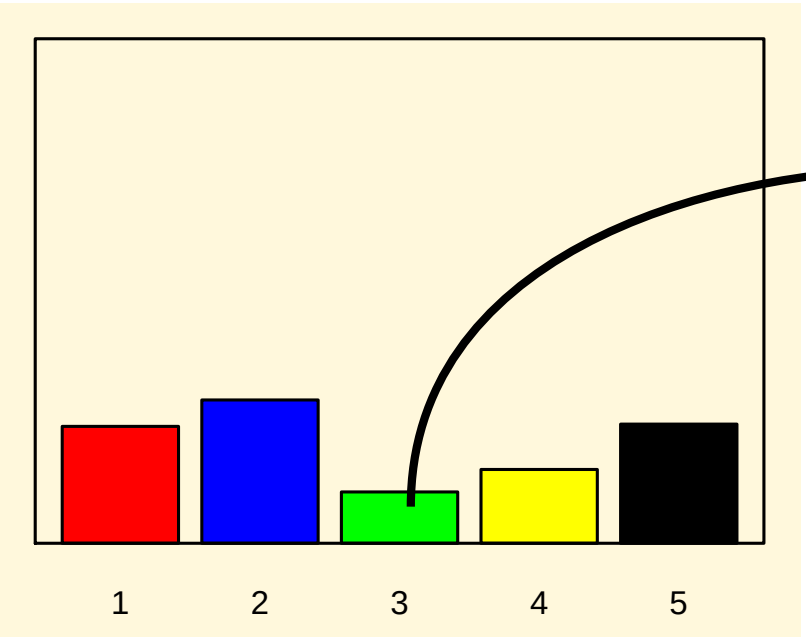

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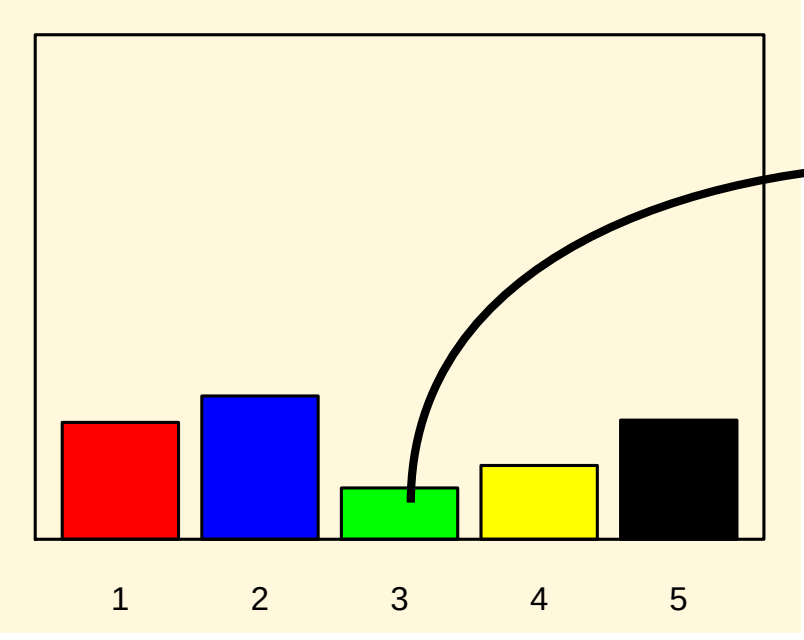


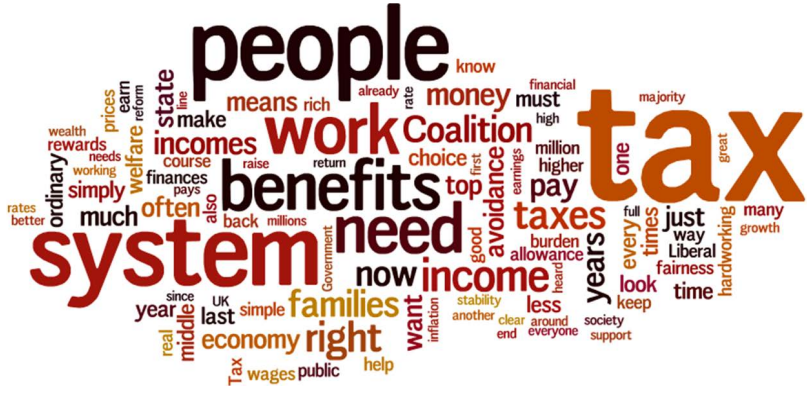

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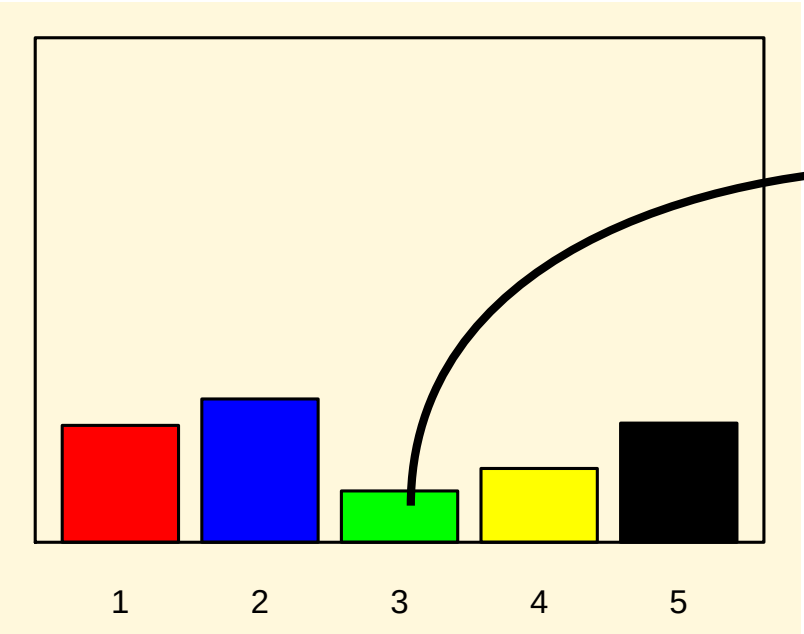


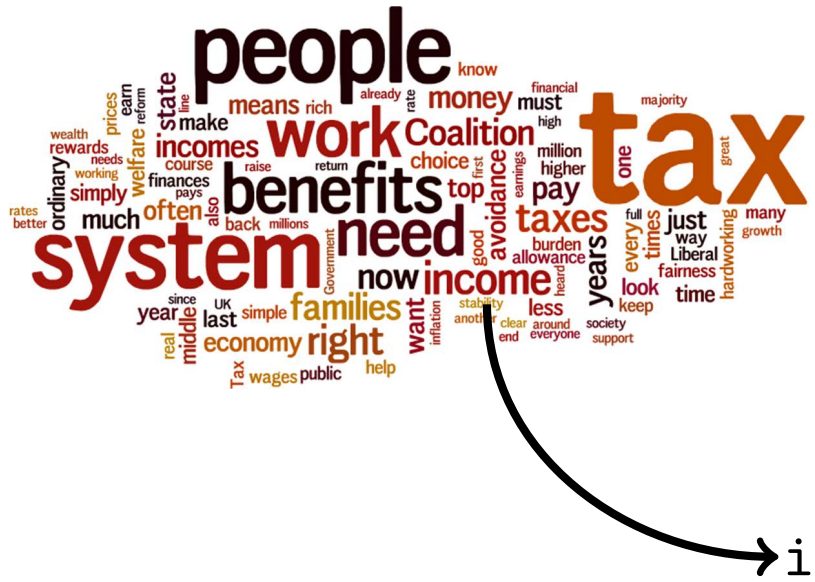


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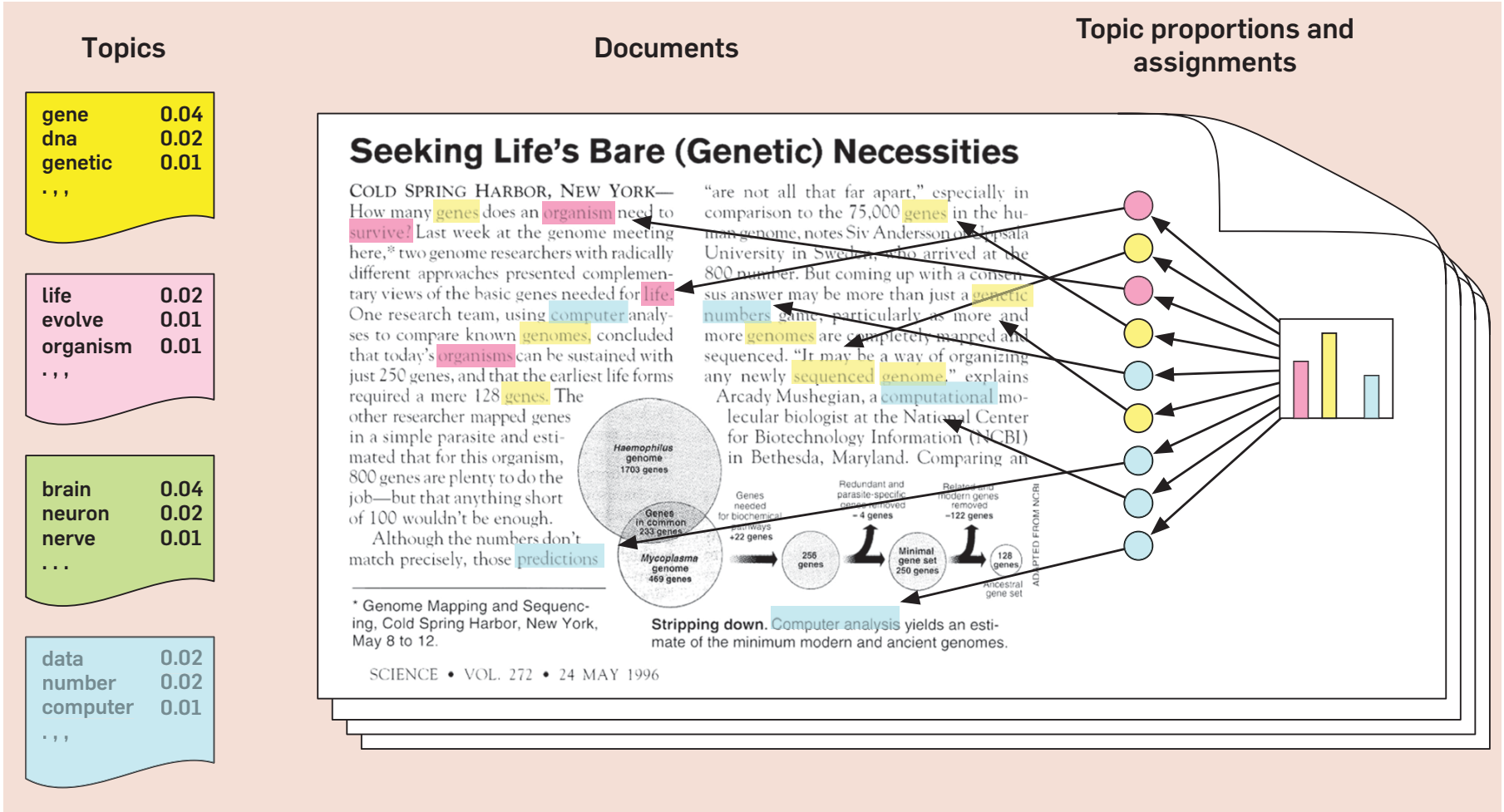


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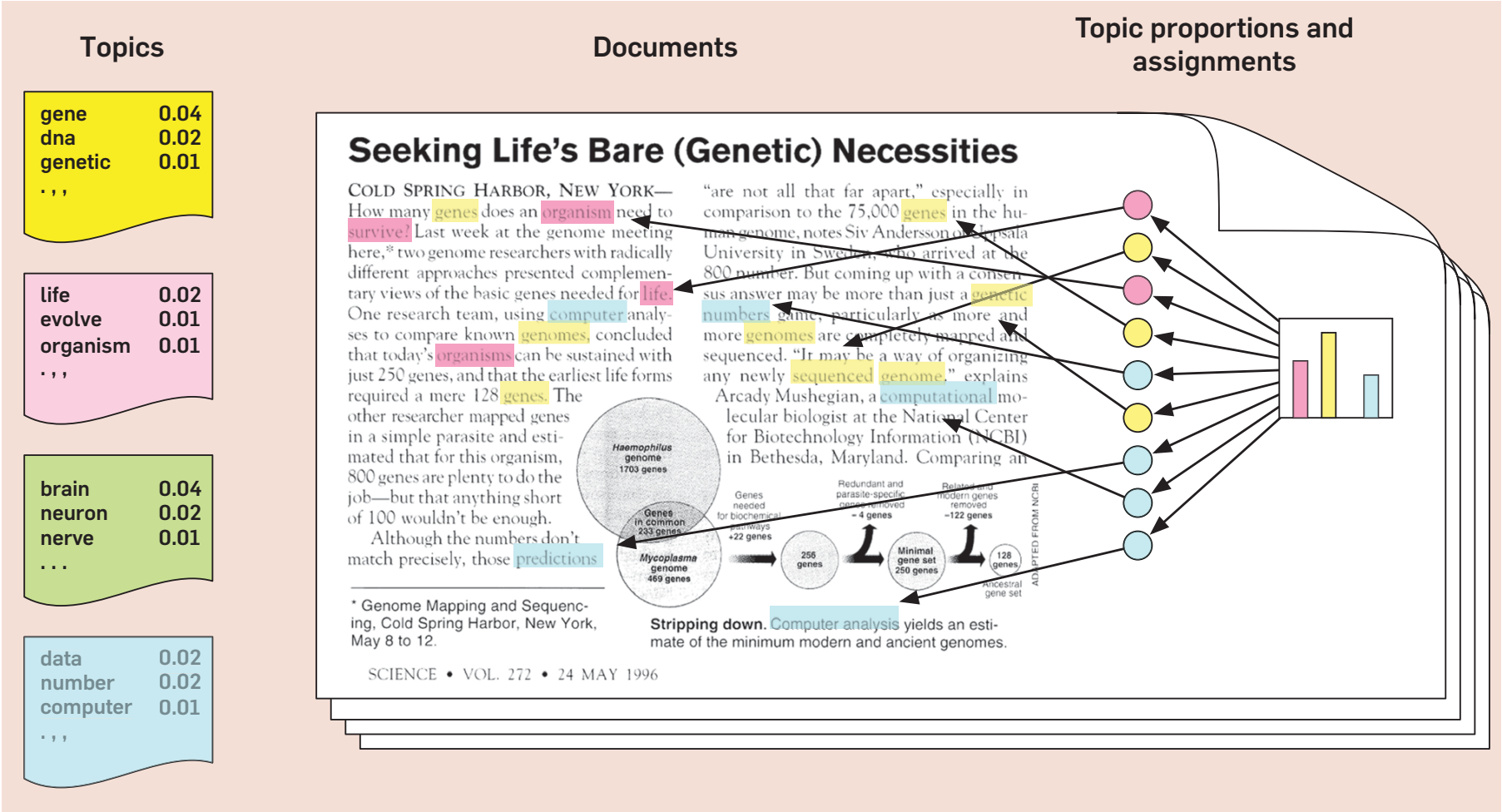


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The multinomial distribution for the $i$th topic is denoted $\beta_i$, and $|\beta_i| = V$, meaning that the 'size' of this multinomial is equal to the number of different words in the corpus.

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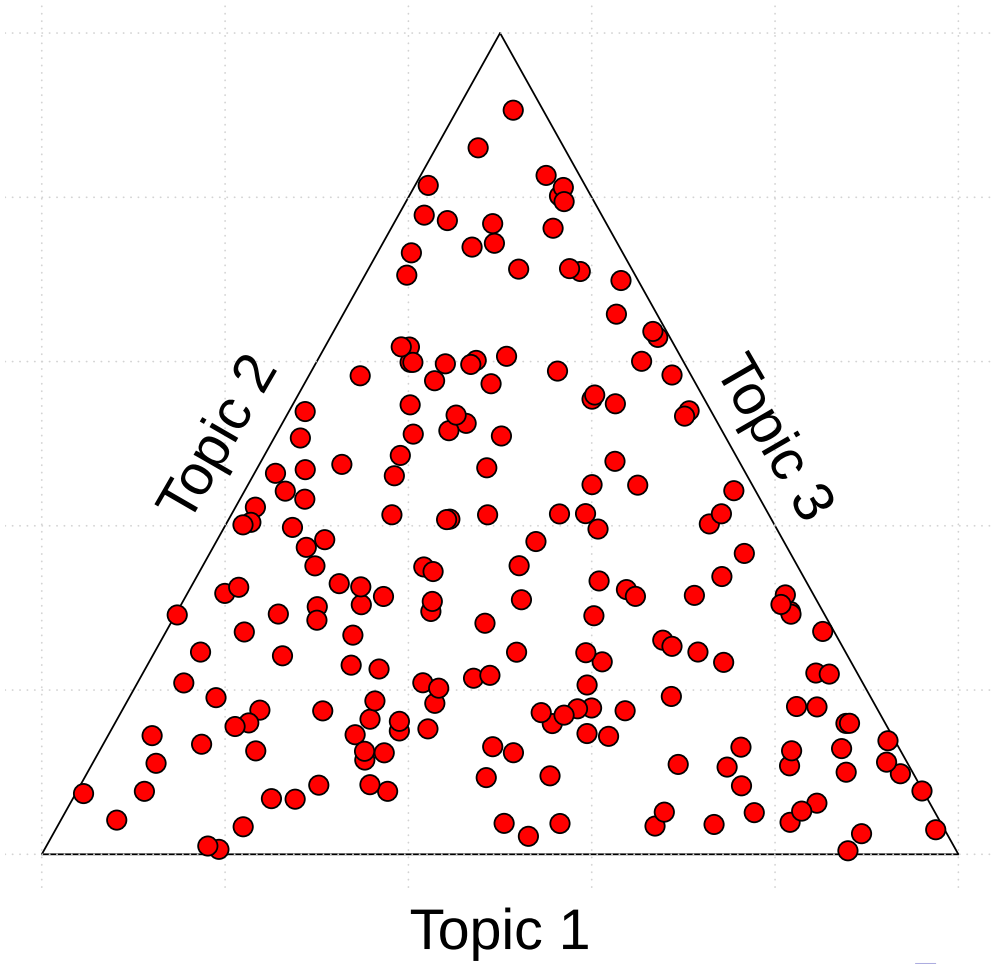
Larger values of $\alpha$ (assuming we are in symmetric case) mean we think (*a priori*) that documents are generally an even mix of the topics. If $\alpha$ is small (less than 1) we think a given document is generally from one or a few topics.

# Example of Dirichlet

200 documents, 3 topics, $\alpha = 1$
(uniform)



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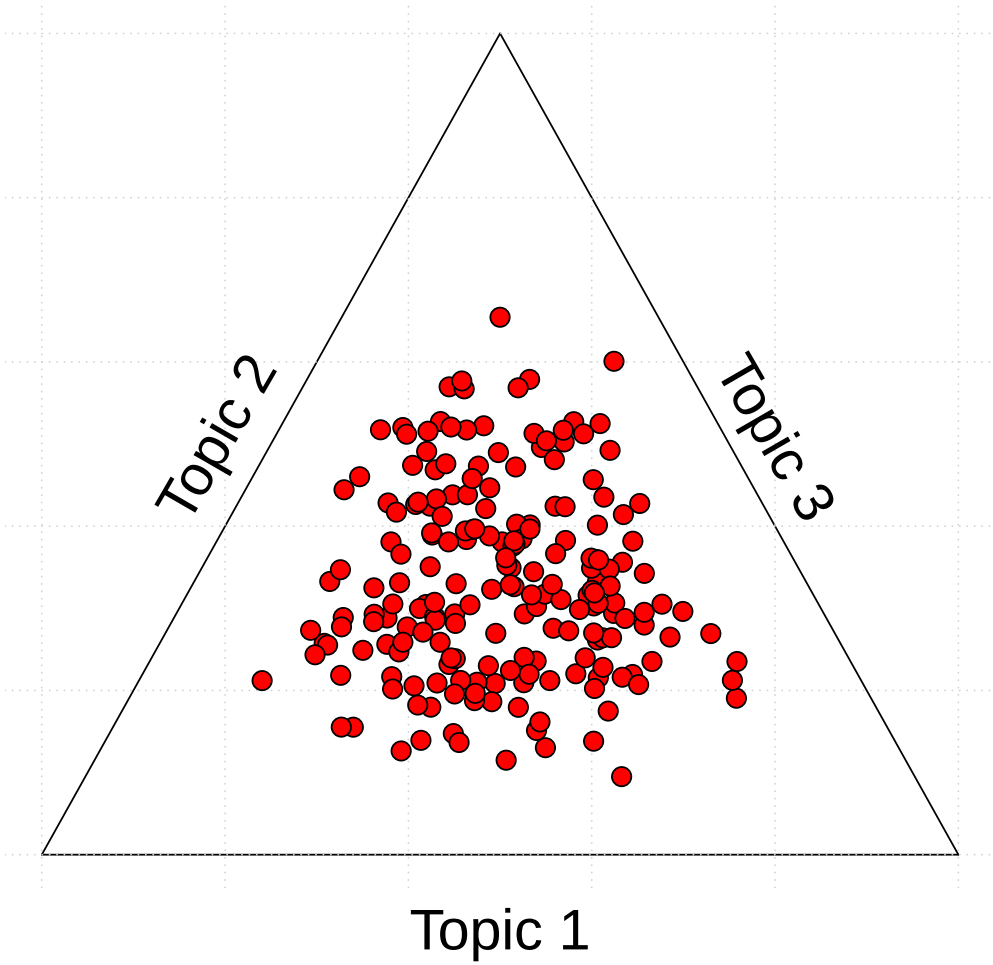
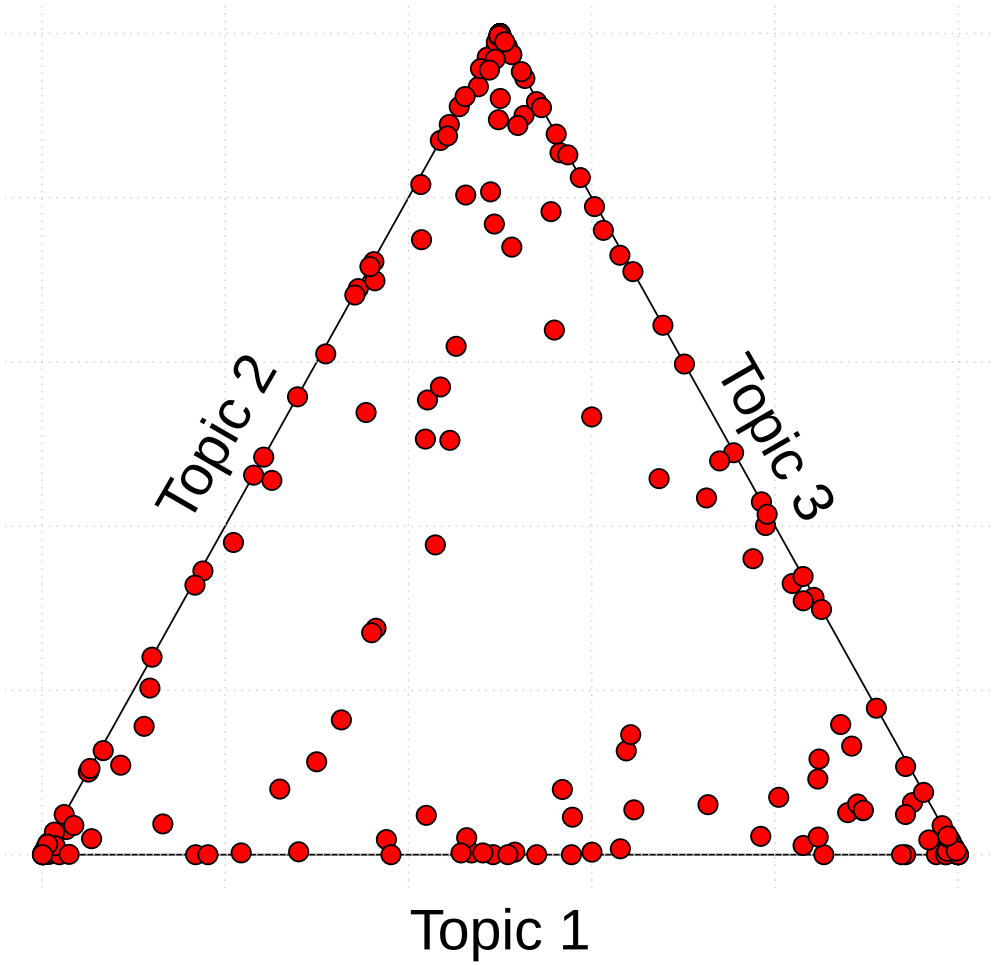
200 documents, 3 topics, $\alpha = 5$



# Example of Dirichlet

200 documents, 3 topics, $\alpha = 0.2$



# Partner Exercise

Would you pick a high, low or uniform (i.e. $= 1$) $\alpha$ prior for the following:

1. State of the Union addresses
2. Sports news bulletins (e.g. headlines summaries of results)
3. Tweets from `@NYUDataScience`
4. News stories from NYT

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**And** we know that the actual value that $w_{d,n}$ takes depends on the distribution over words that the relevant topic entails, the $\beta$ ("the word from topic 4 is "`income`" in this case")

While the $\beta$ depends on the prior for the relevant Dirichlet, $\eta$

# Plate Diagram for LDA

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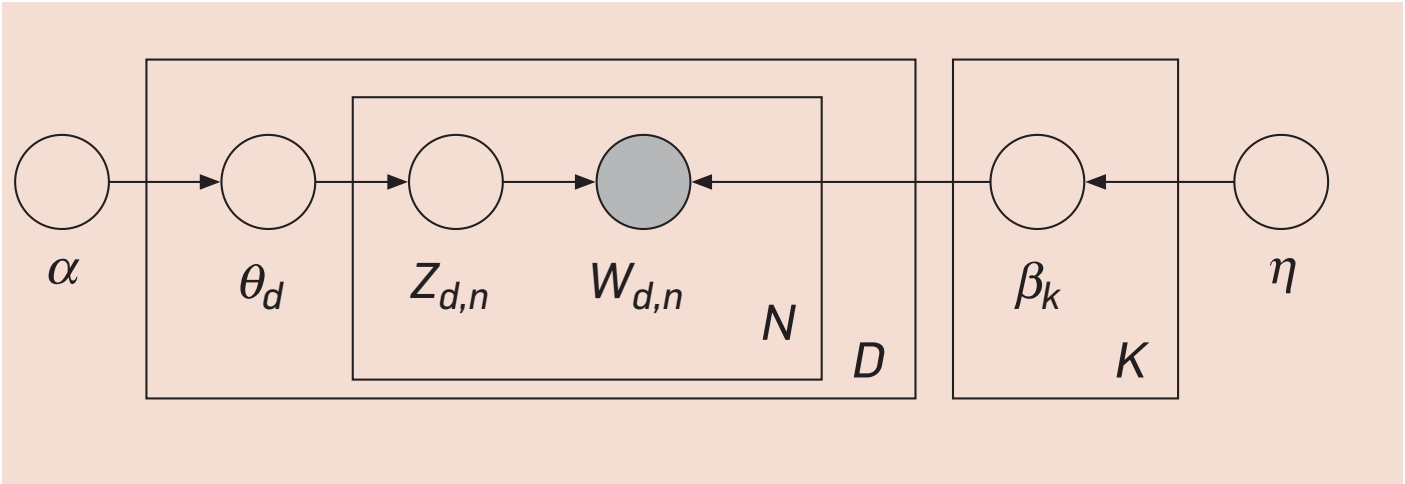

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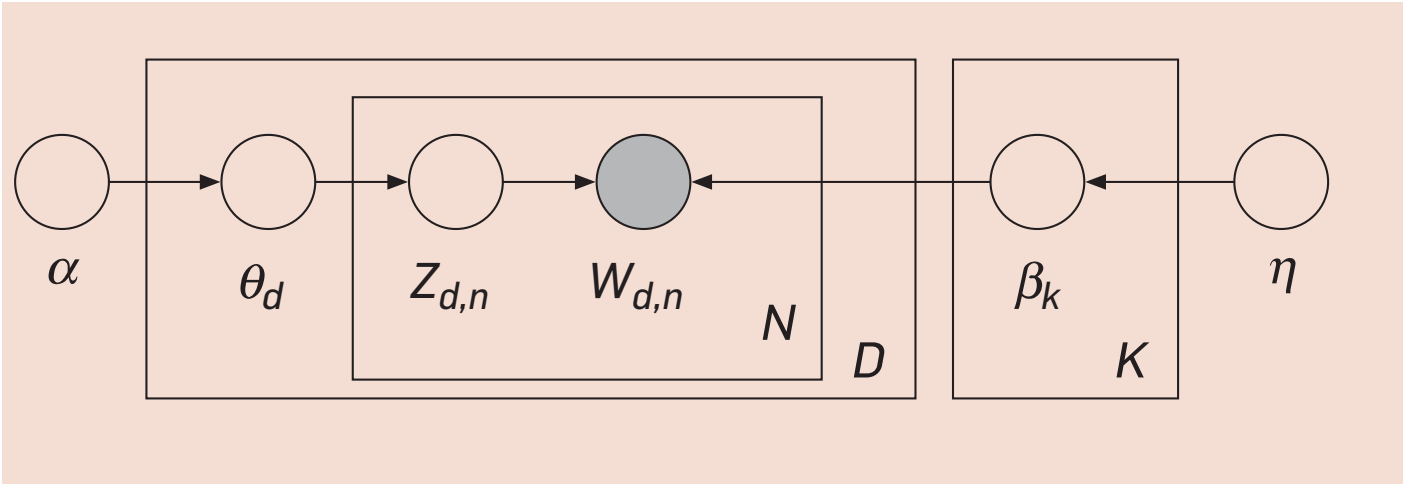


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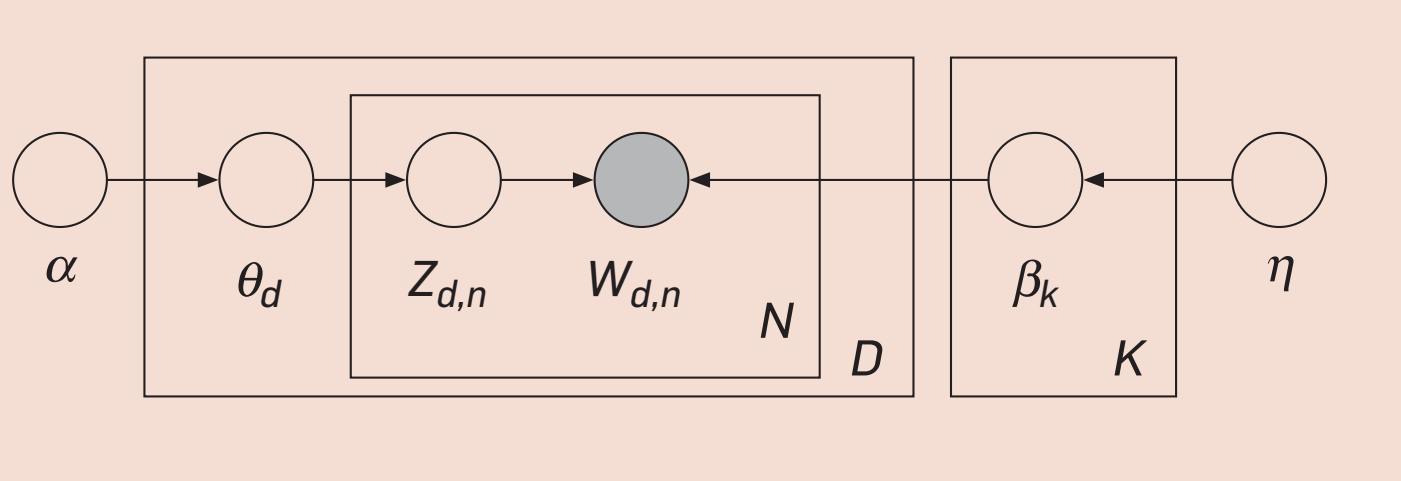


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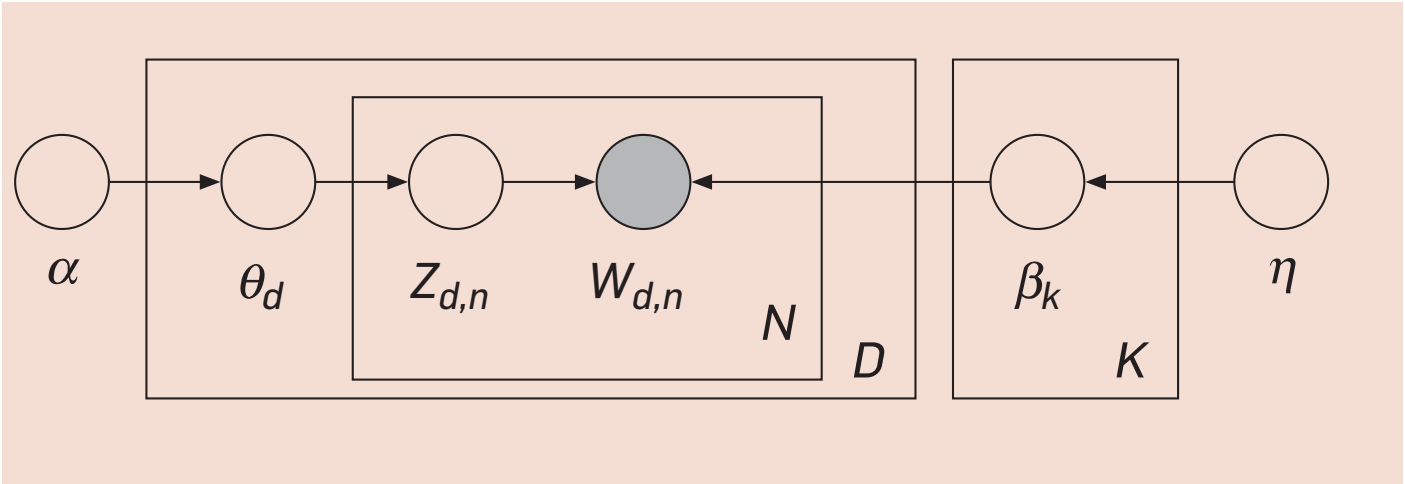


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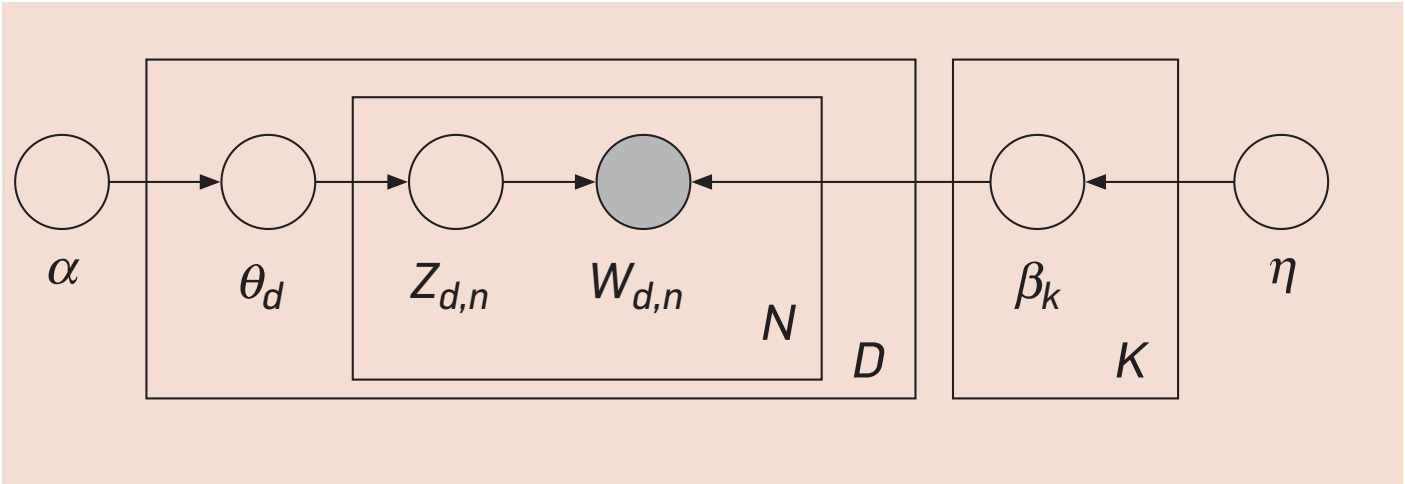


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Note that $w_{d,n}$ depends on $z_{d,n}$ (the mix of topics for that document) and $\beta_{1:K}$ (all the topics in terms of their distributions over the words).

# Bayesian Inference: Crash Course/Reminder

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So,

$$\Pr(A|B) = \frac{\Pr(A, B)}{\Pr(B)}$$

And, Bayes Theorem tell us that

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NB: sometimes called the evidence in the Bayesian context, and is integral of numerator over support of $\theta$ (weighted by how plausible each value is)

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2. Practicality: for many problems, MLE doesn't work well. Perhaps because there are lots of parameters, but not much data: priors can help here. Or perhaps because the model, like multinomial probit, involves evaluating something complicated, analytically: Bayesian methods can arbitrarily approximate the integral.

# Crash course complete: back to LDA

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$$\prod_{K}^{i=1} p(\beta_i) \prod_{D}^{d=1} p(\theta_d) \left( \prod_{N}^{n=1} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

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Generally we want

$$p(\boldsymbol{\theta}|\mathbf{X}, M) = \frac{p(\mathbf{X}, \boldsymbol{\theta}|M)}{\int p(\mathbf{X}, \boldsymbol{\theta}|M) d\boldsymbol{\theta}} = \boxed{\frac{p(\theta|M)p(\mathbf{X}|\boldsymbol{\theta}, M)}{p(\mathbf{X}|M)}}$$

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Here (Blei, 2012), that is

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}|w_{1:D}) = \frac{p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D})}{p(w_{1:D})}$$

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Can get 'evidence' (denominator) by summing joint distribution over every possible topic structure: every possible way of assigning each word to a topic. But this is impossible, so simulate/approximate.

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Some implementations allow you to estimate e.g. $\alpha$, in which case this is also returned. And perhaps some kind of fit statistic(s).

# A Manifesto Example

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69 UK manifestos.

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The (some selected) word distributions for each topic. Sum down the columns is one.

| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|---|---|---|---|---|---|
| conservative | 0.00188 | 0.00088 | 0.00185 | 0.00221 | 0.00168 |
| party | 0.00145 | 0.00067 | 0.00066 | 0.00577 | 0.00093 |
| general | 0.00073 | 0.00033 | 0.00018 | 0.00192 | 0.00040 |
| election | 0.00079 | 0.00053 | 0.00022 | 0.00235 | 0.00076 |
| manifesto | 0.00059 | 0.00078 | 0.00032 | 0.00099 | 0.00048 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

# Continued. . .

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'Top' 6 most frequent words in each topic:

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| 1 | people | new | [markup] | new | must |
| 2 | local | government | people | labour | government |
| 3 | government | people | new | government | labour |
| 4 | new | continue | work | people | shall |
| 5 | tax | can | [markup] | shall | can |
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Up to analyst to label the topics!

Meaningless 'junk' topics not unusual: debate as to whether one has to interpret every topic.

# Partner Exercise

This is the output for four topics (of a 100 topic model) produced for a sample of the Associated Press corpus (1988–1990).

Name/describe the topics.

| | | | |
|---|---|---|---|
| New | Million | Children | School |
| Film | Program | Women | Students |
| Show | Tax | People | Schools |
| Music | Budget | Child | Education |
| Movie | Billion | Years | Teachers |
| Play | Federal | Families | High |
| Musical | Year | Work | Public |
| Best | Spending | Parent | Teacher |
| Actor | New | Says | Bennett |
| First | State | Family | Manigat |
| York | Plan | Welfare | Namphy |
| Opera | Money | Men | State |
| Theater | Programs | Percent | President |
| Actress | Government | Care | Elementary |
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| doc 2 | 0.00011 | 0.00011 | 0.00011 | 0.00011 | 0.99954 |
| doc 3 | 0.00010 | 0.00010 | 0.00010 | 0.00010 | 0.99959 |
| doc 4 | 0.00006 | 0.00006 | 0.00006 | 0.00006 | 0.99978 |
| doc 5 | 0.00002 | 0.00002 | 0.00002 | 0.00002 | 0.99991 |
| doc 6 | 0.00019 | 0.00019 | 0.00019 | 0.00019 | 0.99924 |
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NB: social scientists typically fit far fewer topics than CS, even to same data.

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But: the topic models that hold-out calculations suggest are optimal and not much liked by humans!

# In practice...

Perplexity is popular option

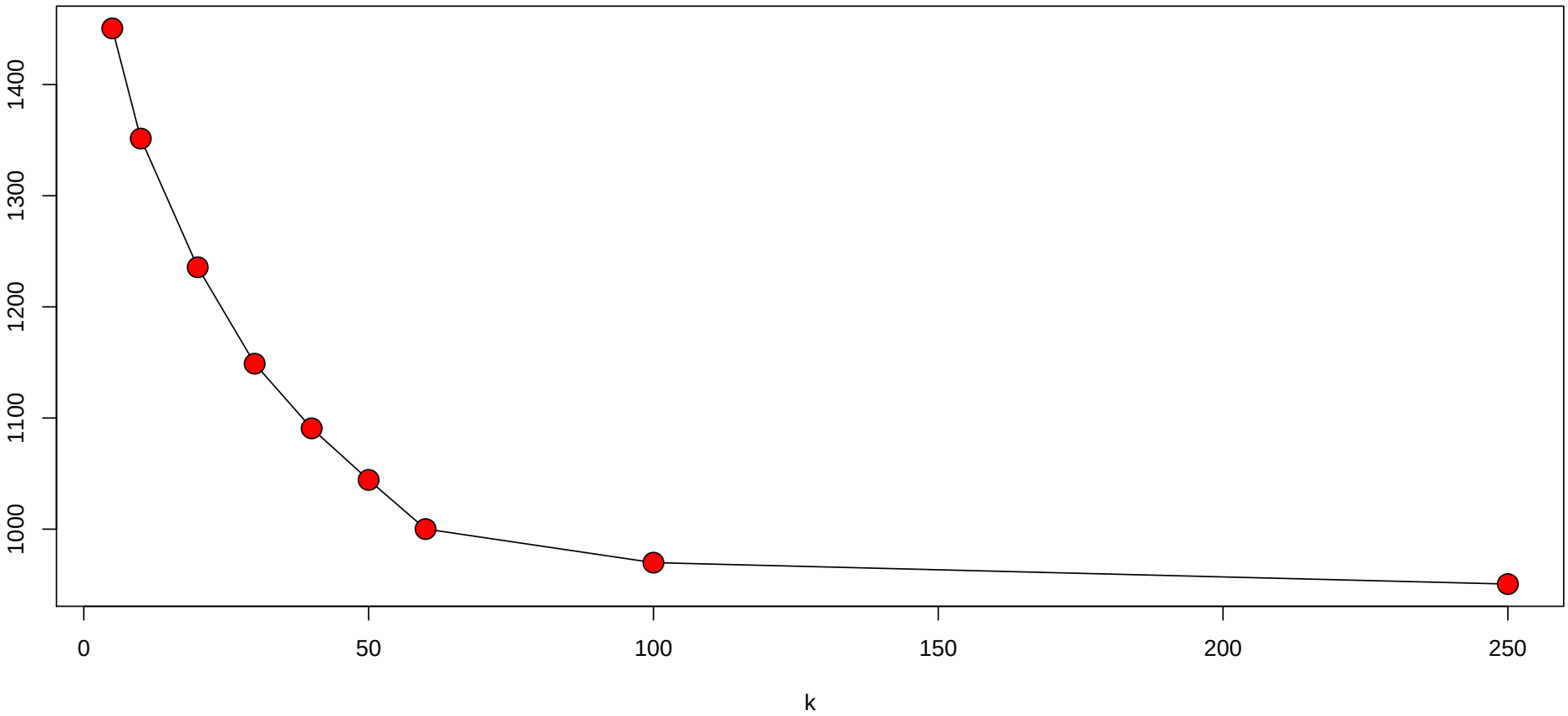
$$\text{perplexity} = \exp\left(-\frac{\mathcal{L}(\mathbf{w})}{\text{count of tokens}}\right),$$

where lower is better.

In general, $\mathcal{L}(\mathbf{w})$ is intractable, but there are ways to approximate it.

But: the topic models that hold-out calculations suggest are optimal and not much liked by humans! "Reading Tea Leaves: How Humans Interpret Topic Models" by Chang et al.

# Perplexity Likes a Lot of Topics (manifestos)



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To decide, we need data source that covers all lower house legislators where they set out their policy priorities over time. See if/when they shift priorities.

# Manifestos

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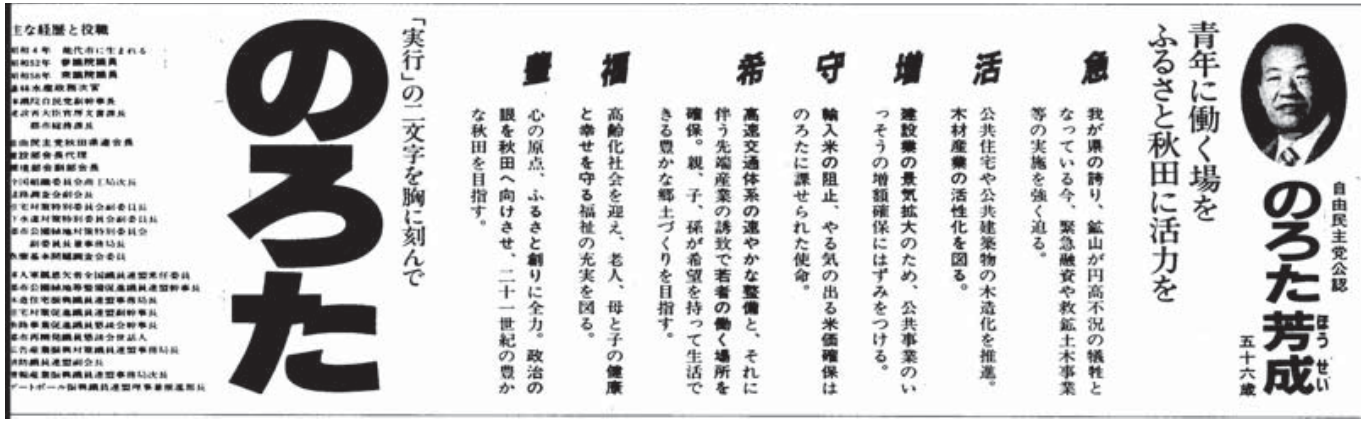


自由民主党公認

のろた芳成（ほうせい）

五十六歳

青年に働く場を
ふるさと秋田に活力を

**急**　我が県の誇り、鉱山が円高不況の犠牲となっている今、緊急融資や救鉱土木事業等の実施を強く迫る。

**活**　公共住宅や公共建築物の木造化を推進。木材産業の活性化を図る。

**増**　建設業の景気拡大のため、公共事業のいっそうの増額確保にはずみをつける。

**守**　輸入米の阻止、やる気の出る米価確保はのろたに課せられた使命。

**希**　高速交通体系の速やかな整備と、それに伴う先端産業の誘致で若者の働く場所を確保。親、子、孫が希望を持って生活できる豊かな郷土づくりを目指す。

**福**　高齢化社会を迎え、老人、母と子の健康と幸せを守る福祉の充実を図る。

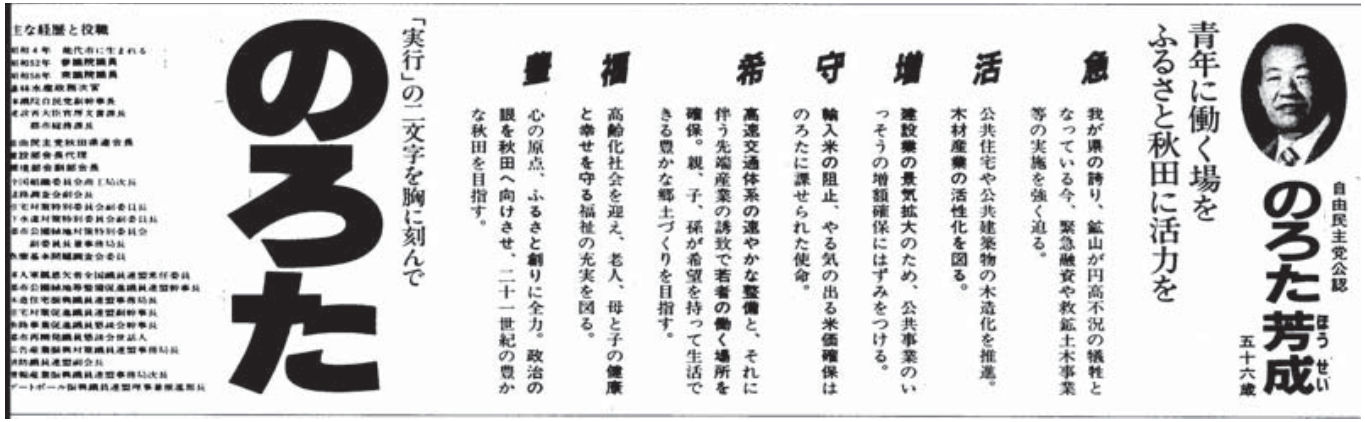
**豊**　心の原点、ふるさと創りに全力。政治の眼を秋田へ向けさせ、二十一世紀の豊かな秋田を目指す。

「実行」の二文字を胸に刻んで

のろた

主な経歴と役職

# Manifestos




7,497.

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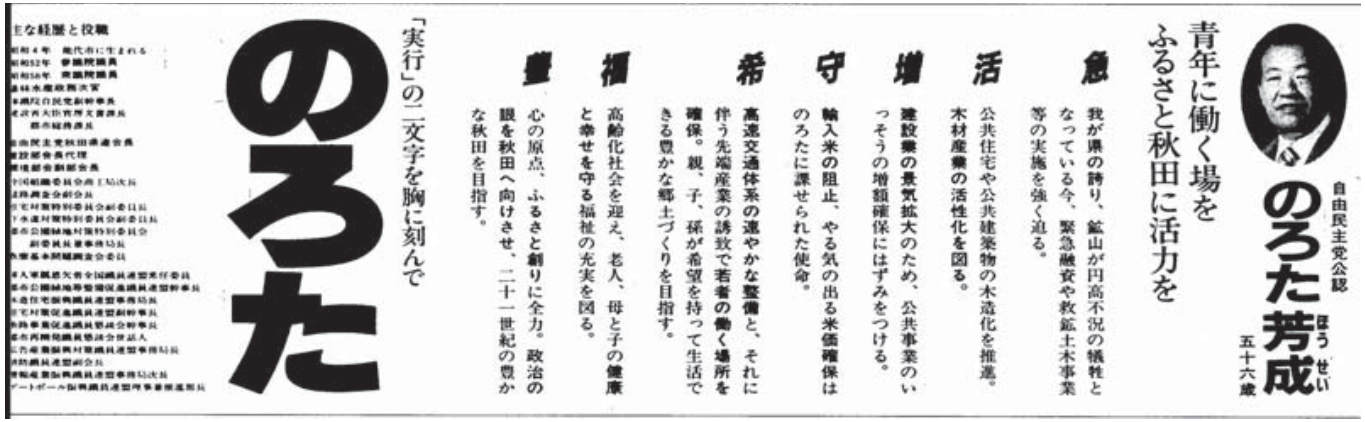


7,497. 1986–2009.

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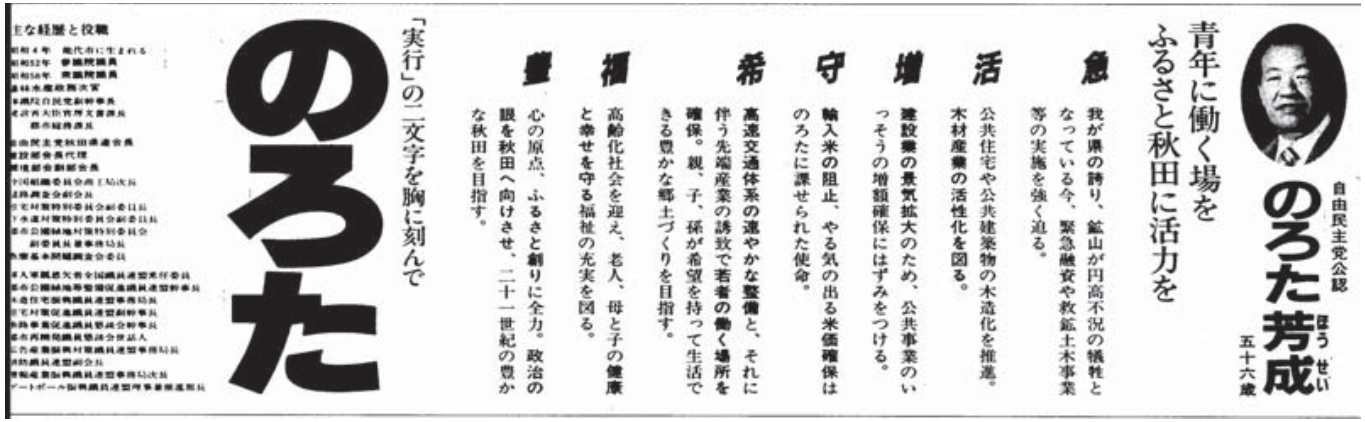


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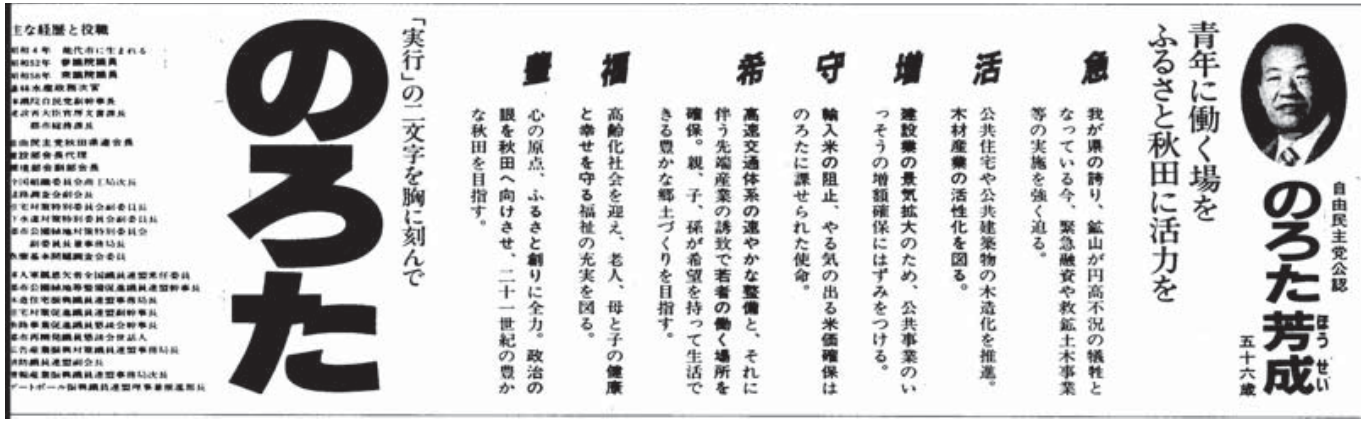


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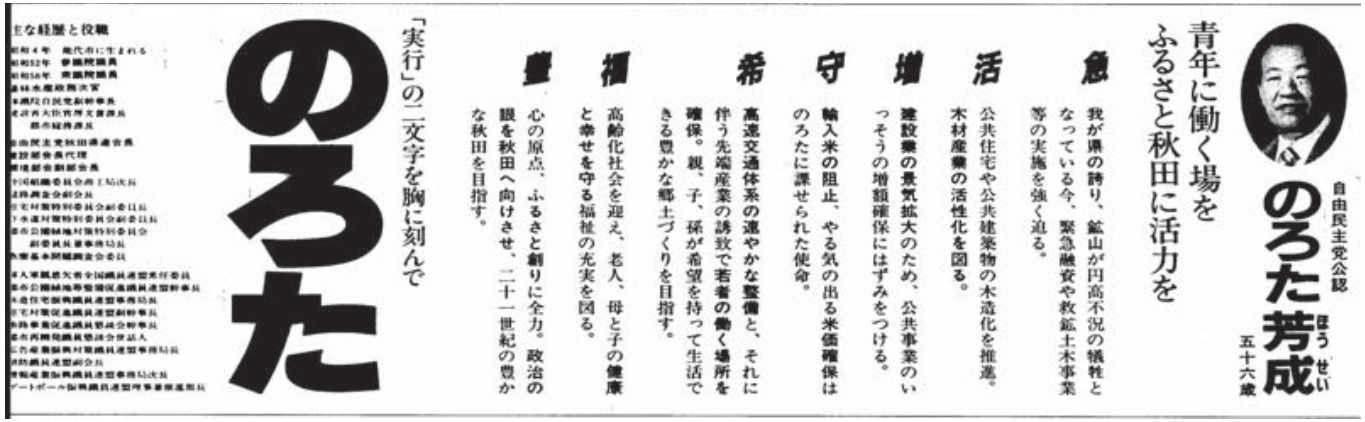


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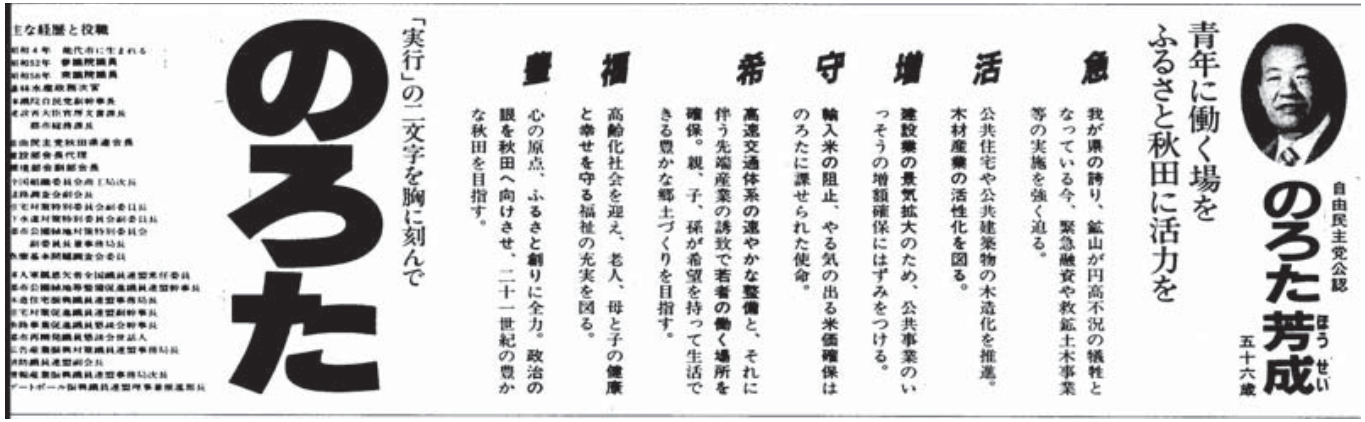


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# Topic Distribution over Words

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| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 |
|---|---|---|---|---|---|---|
| 1 | 改革 | 年金 | 推進 | 区 | 政治 | 日本 |
| 2 | 郵政 | 円 | 整備 | 政策 | 改革 | 国 |
| 3 | 民営 | 廃止 | 図る | 地域 | 国民 | 外交 |
| 4 | 小泉 | 改革 | つとめる | まち | 企業 | 国家 |
| 5 | 構造 | 兆 | 社会 | 鹿児島 | 自民党 | 社会 |
| 6 | 政府 | 実現 | 対策 | 全力 | 日本 | 国民 |
| 7 | 官 | 無駄 | 振興 | 選挙 | 共産党 | 保障 |
| 8 | 推進 | 日本 | 充実 | 国政 | 献金 | 安全 |
| 9 | 民 | 増税 | 促進 | 作り | 金権 | 地域 |
| 10 | 自民党 | 削減 | 安定 | 横浜 | 党 | 拉致 |
| 11 | 日本 | 一元化 | 確立 | 対策 | 選挙 | 経済 |
| 12 | 制度 | 政権 | 企業 | 中小 | 禁止 | 守る |
| 13 | 民間 | 子供 | 実現 | 発電 | 憲法 | 問題 |
| 14 | 年金 | 地域 | 中小 | 推進 | 腐敗 | 北朝鮮 |
| 15 | 実現 | ひと | 育成 | エネルギー | 団体 | 教育 |
| 16 | 進める | サラリーマン | 制度 | 企業 | 区 | 責任 |
| 17 | 断行 | 制度 | 政治 | 声 | ソ連 | 力 |
| 18 | 地方 | 議員 | 地域 | 実現 | 守る | 創る |
| 19 | 止める | 金 | 福祉 | 活性 | 平和 | 安心 |
| 20 | 保障 | 民主党 | 事業 | 自民党 | 円 | 目指す |
| 21 | 財政 | 年間 | 改革 | 地方 | 反対 | 誇り |
| 22 | 作る | 一掃 | 確保 | 尽くす | 真 | 憲法 |
| 23 | 賛成 | 郵政 | 強化 | 商店 | 是正 | 可能 |
| 24 | 社会 | 道路 | 教育 | いかす | 一掃 | 道 |
| 25 | 国民 | 交代 | 施設 | 全国 | 悪政 | 未来 |
| 26 | 公務員 | 社会保険庁 | 生活 | 政党 | 抜本 | ひと |
| 27 | 力 | 月額 | 支援 | ひと | 定数 | 再生 |
| 28 | 経済 | 手当 | 環境 | 支援 | 政党 | 将来 |
| 29 | 国 | 談合 | 発展 | 経済 | 金丸 | 解決 |
| 30 | 安心 | 支援 | 施策 | 福祉 | 改革 | 基本 |

# Change in proportion of ‘Pork’ Topic

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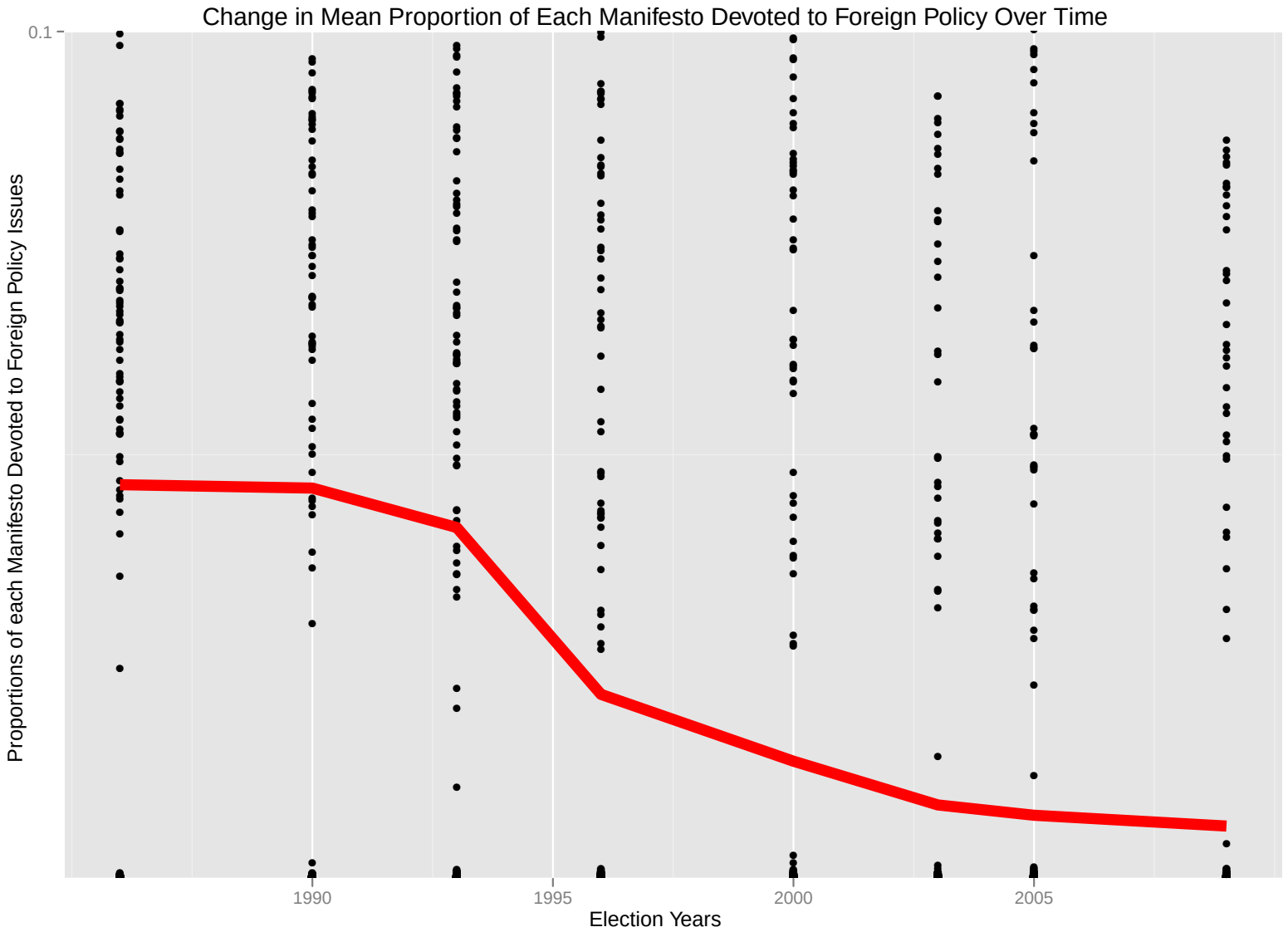

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