Topic Modeling

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Document 1	Topic 1
Document 2	Topic 2
Document 3	⋮
⋮	Topic K
Document N	

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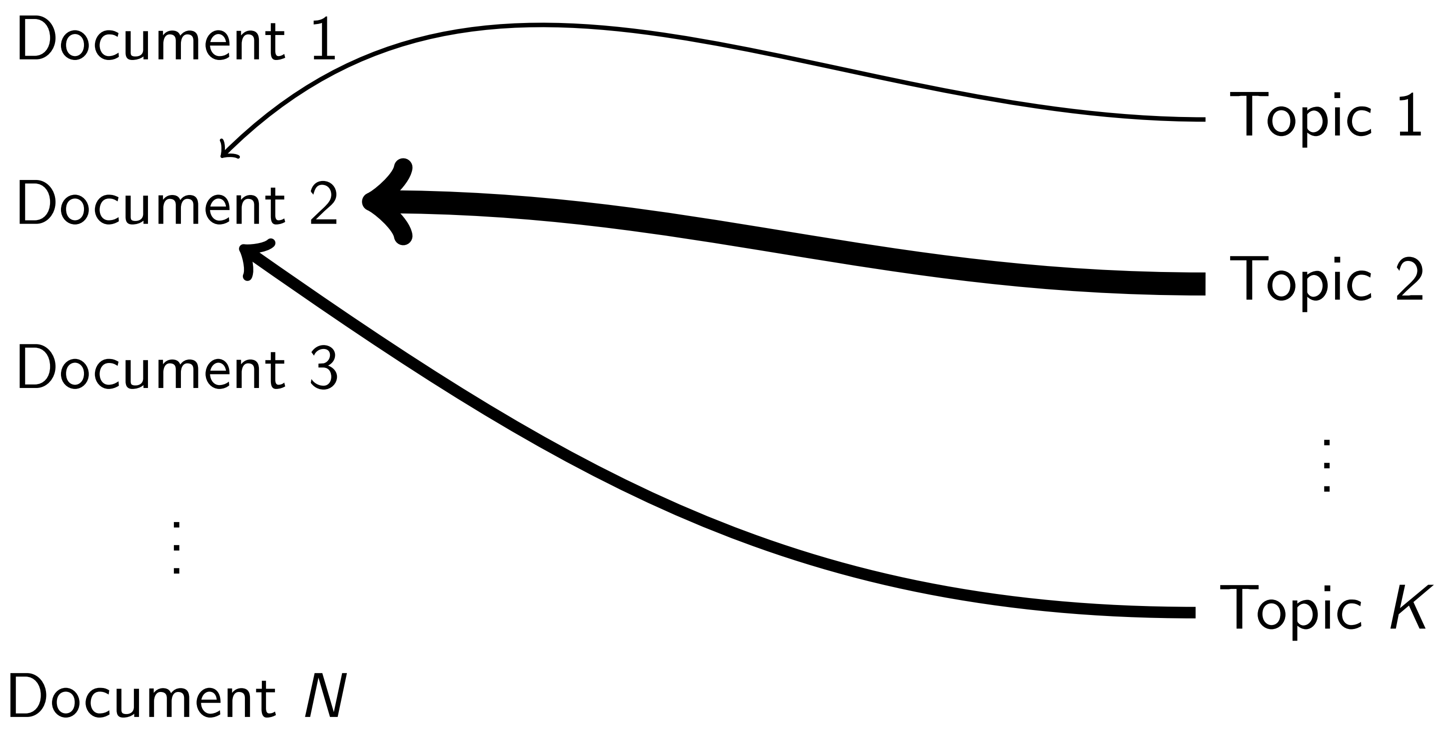

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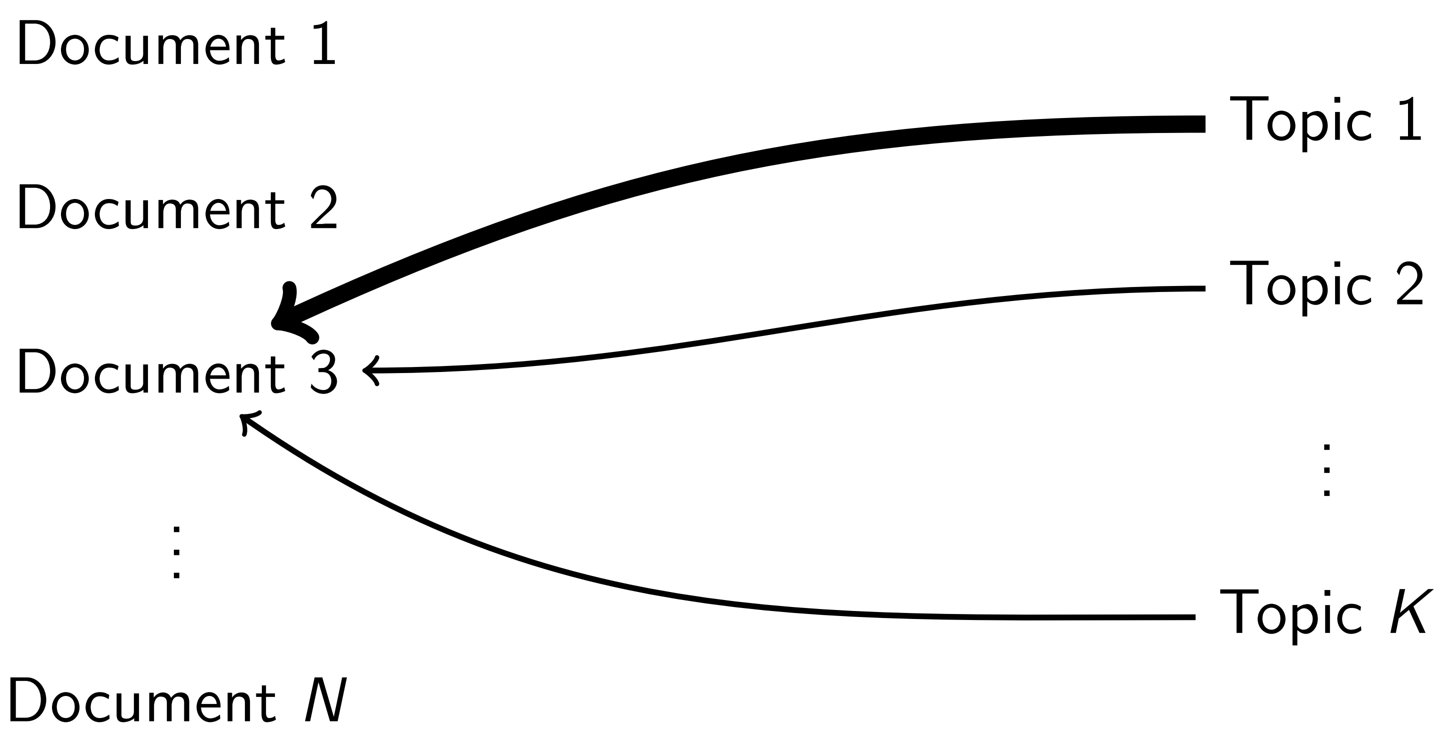

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Now, where do the words in the documents come from?

Intuition: Generating Words

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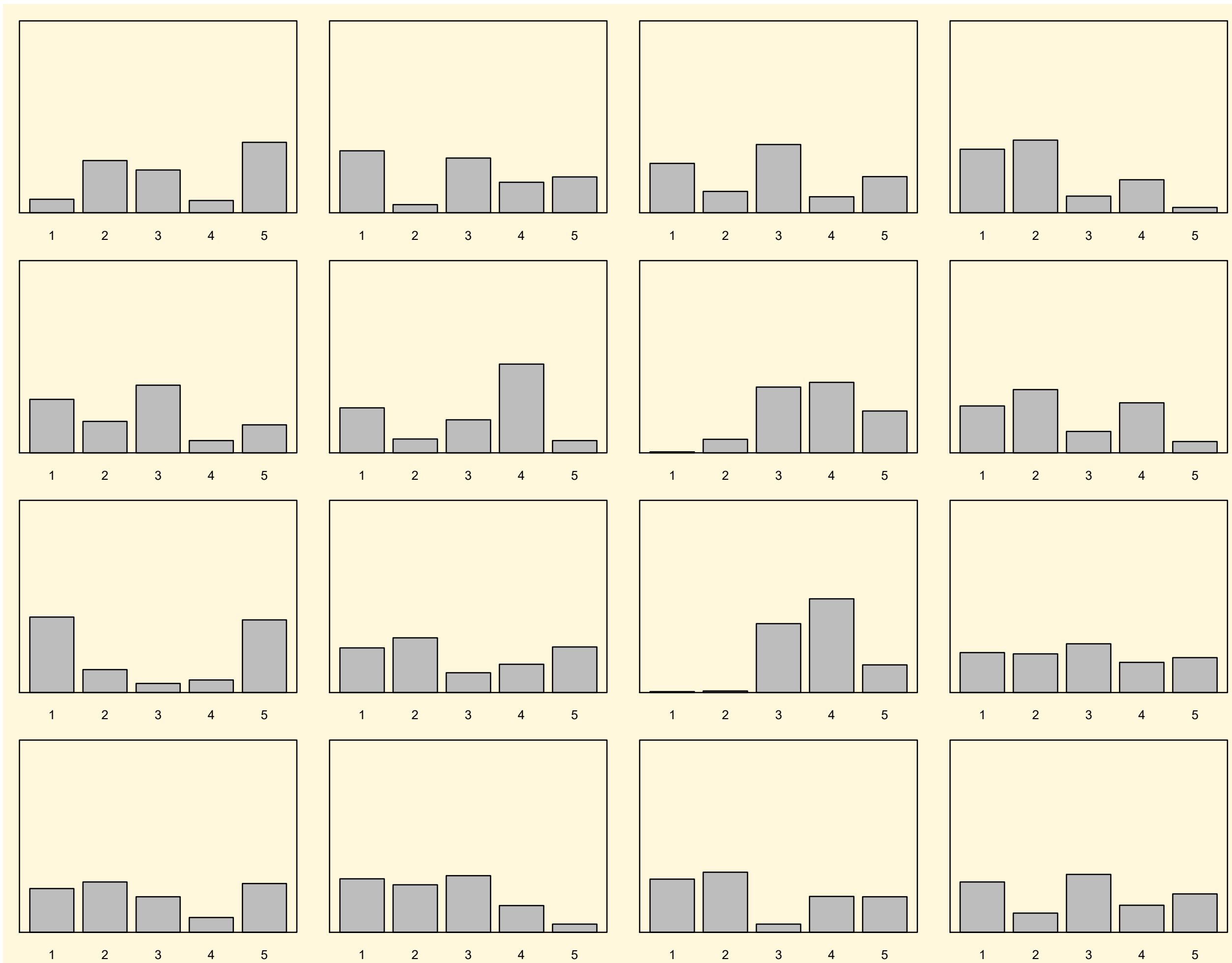

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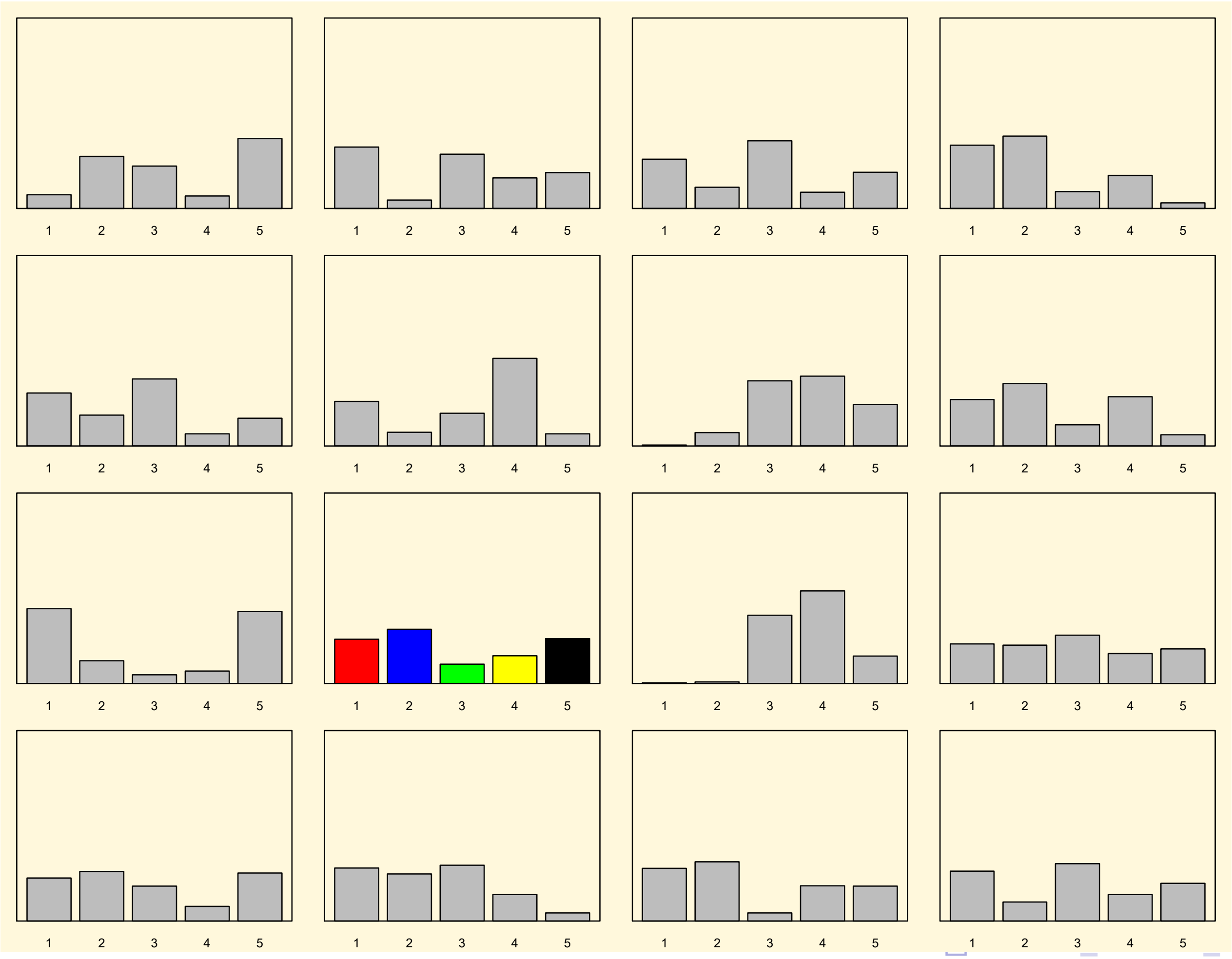

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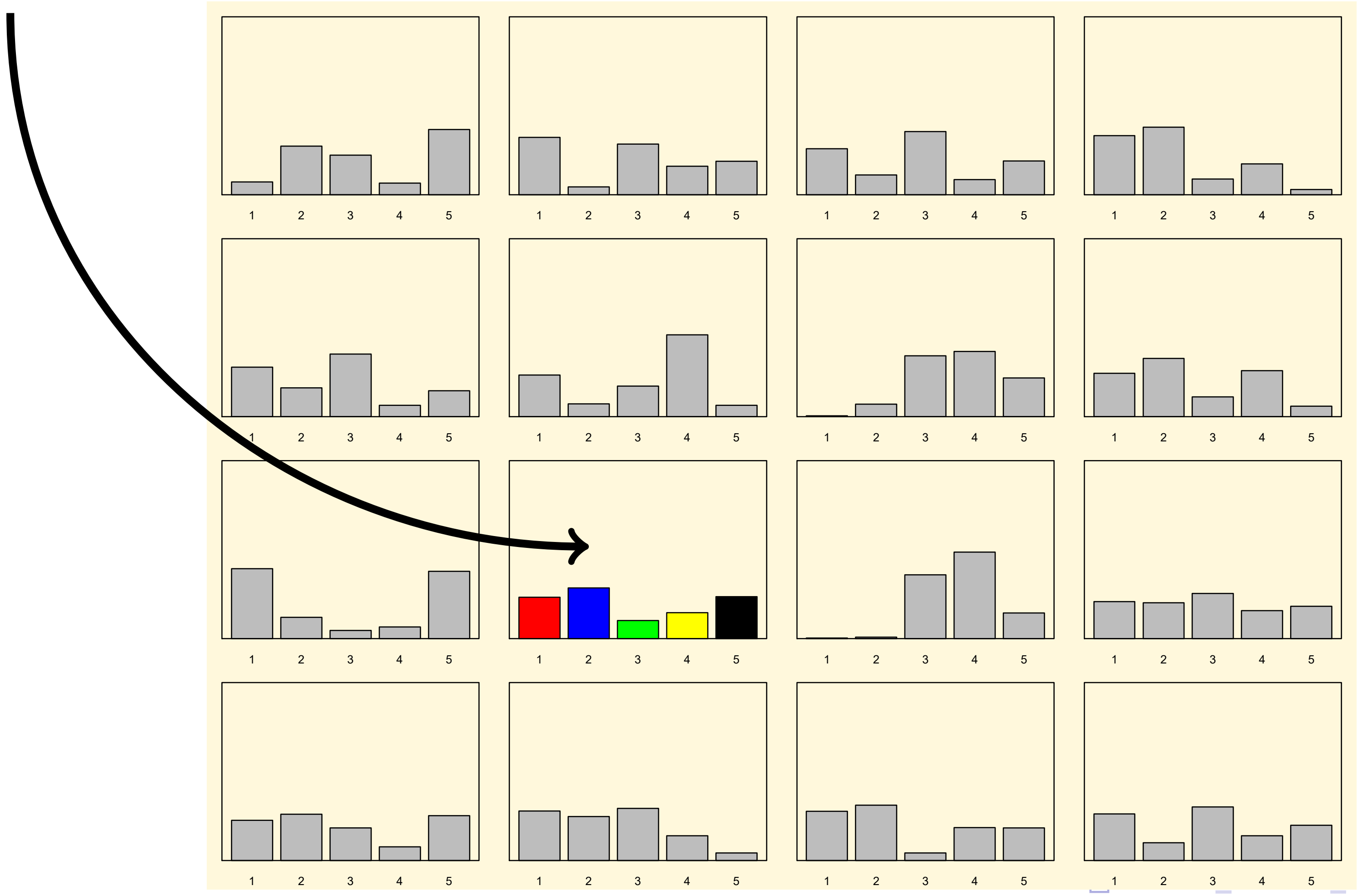

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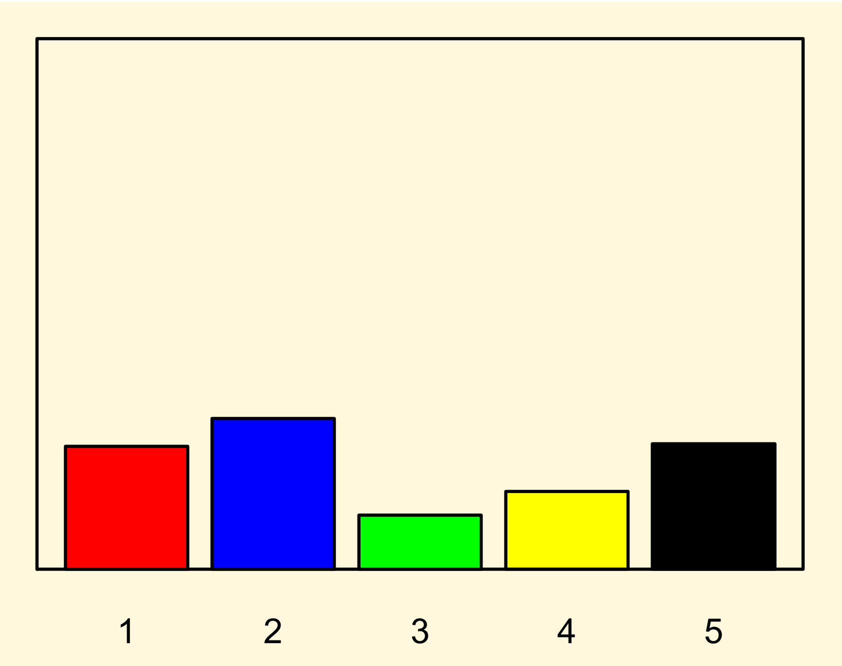

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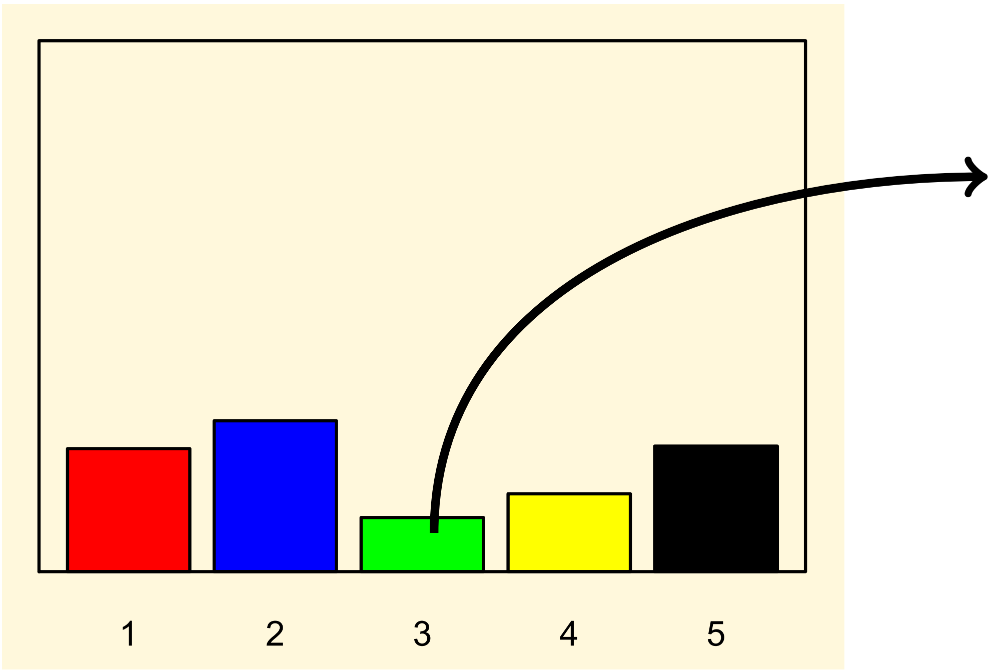

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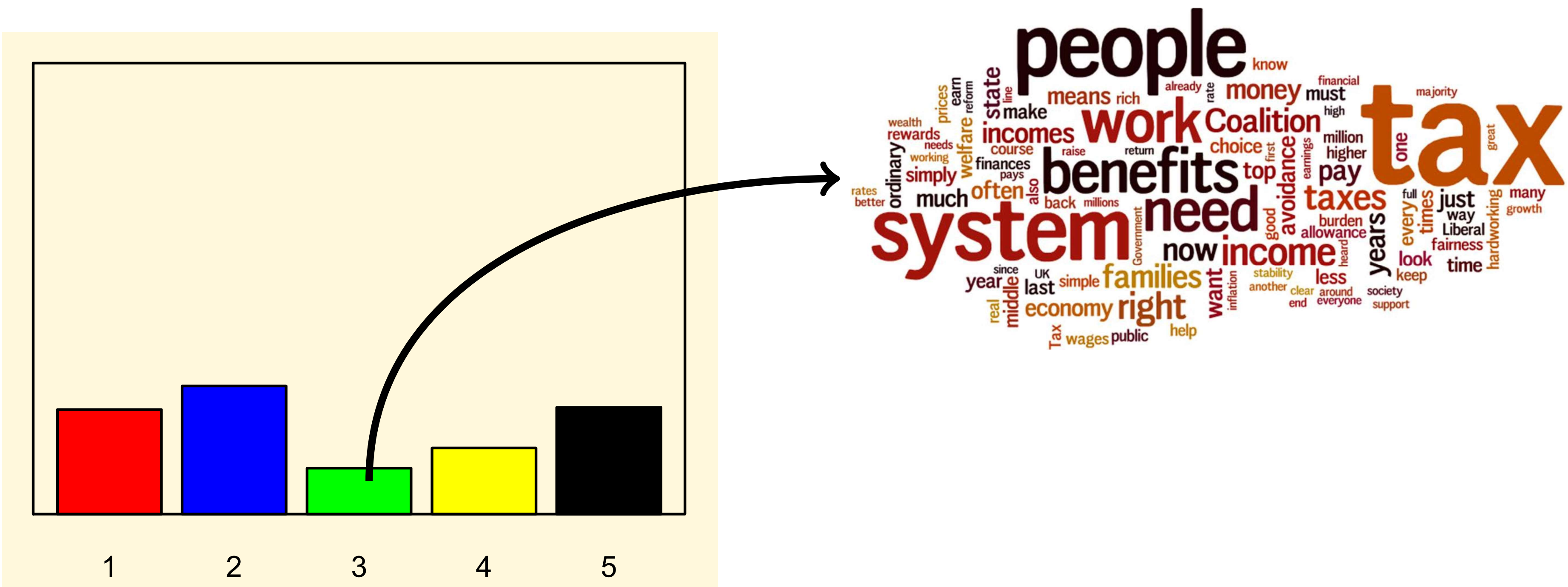

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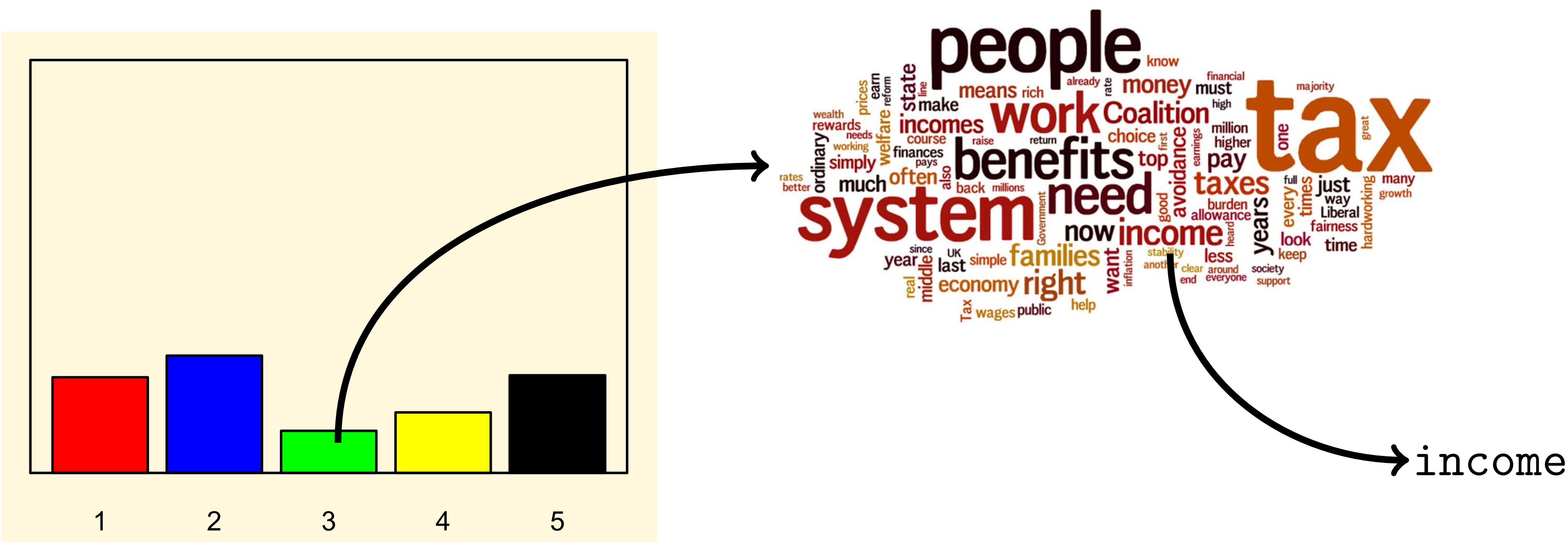

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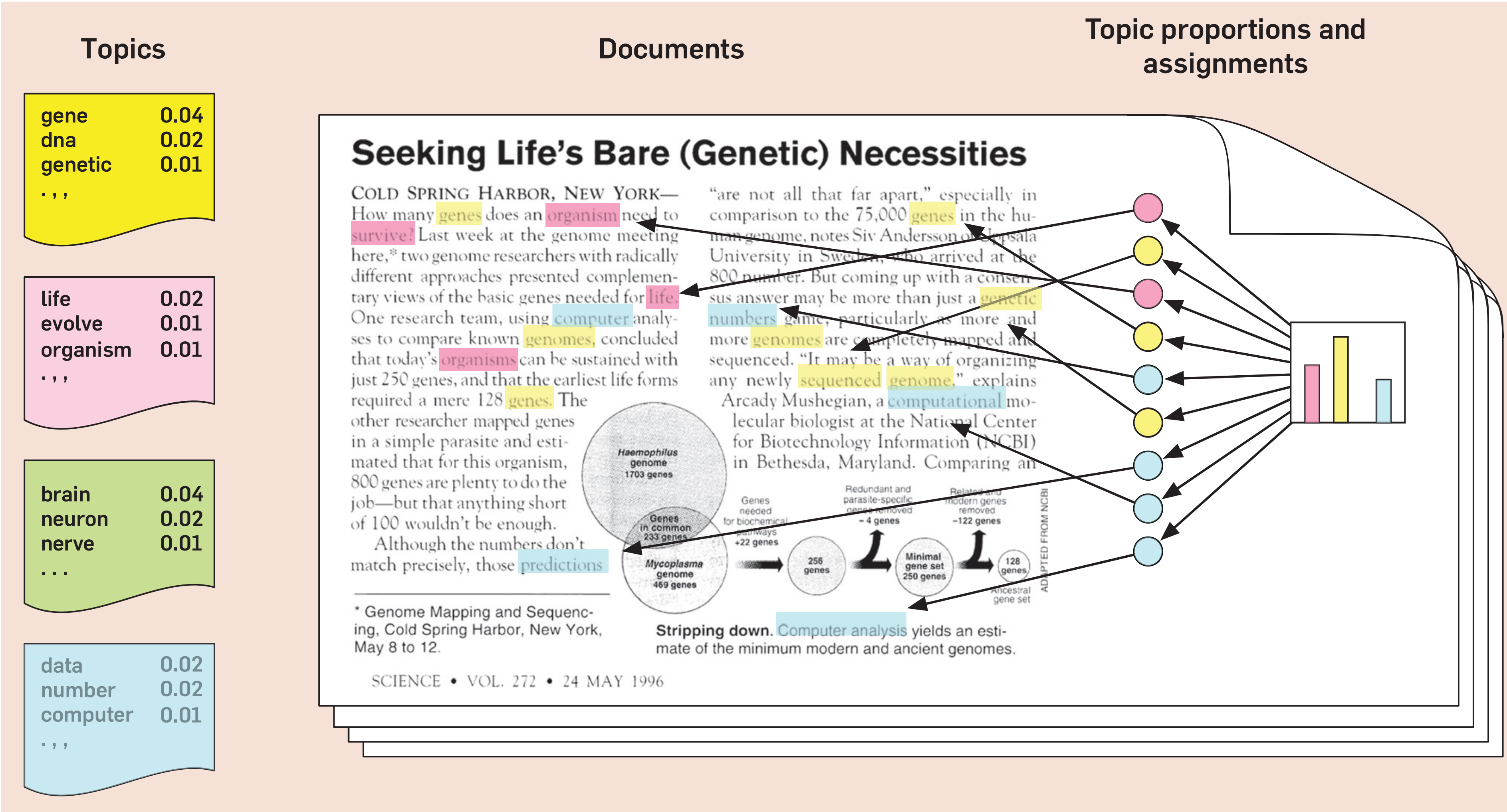

Note that all documents share same set of topics:

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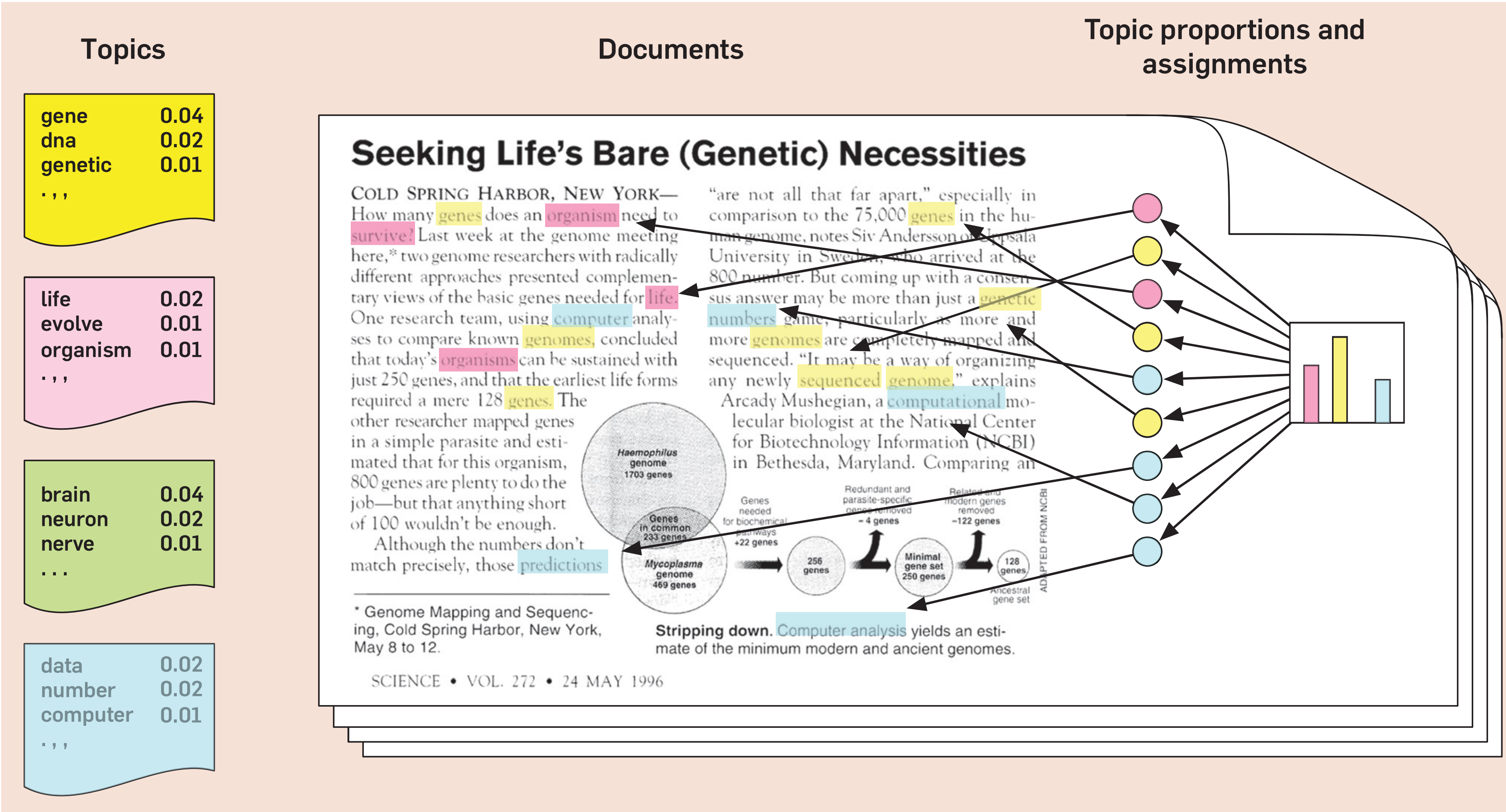

Note that all documents share same set of topics: but some (e.g. neuro) may be (basically) absent in a given document.

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We need a distribution from which to draw the per-document topic distribution. We use a Dirichlet distribution as a prior for that.

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$\rightarrow$ Latent Dirichlet Allocation. **LDA**.

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The multinomial distribution for the ith topic is denoted β_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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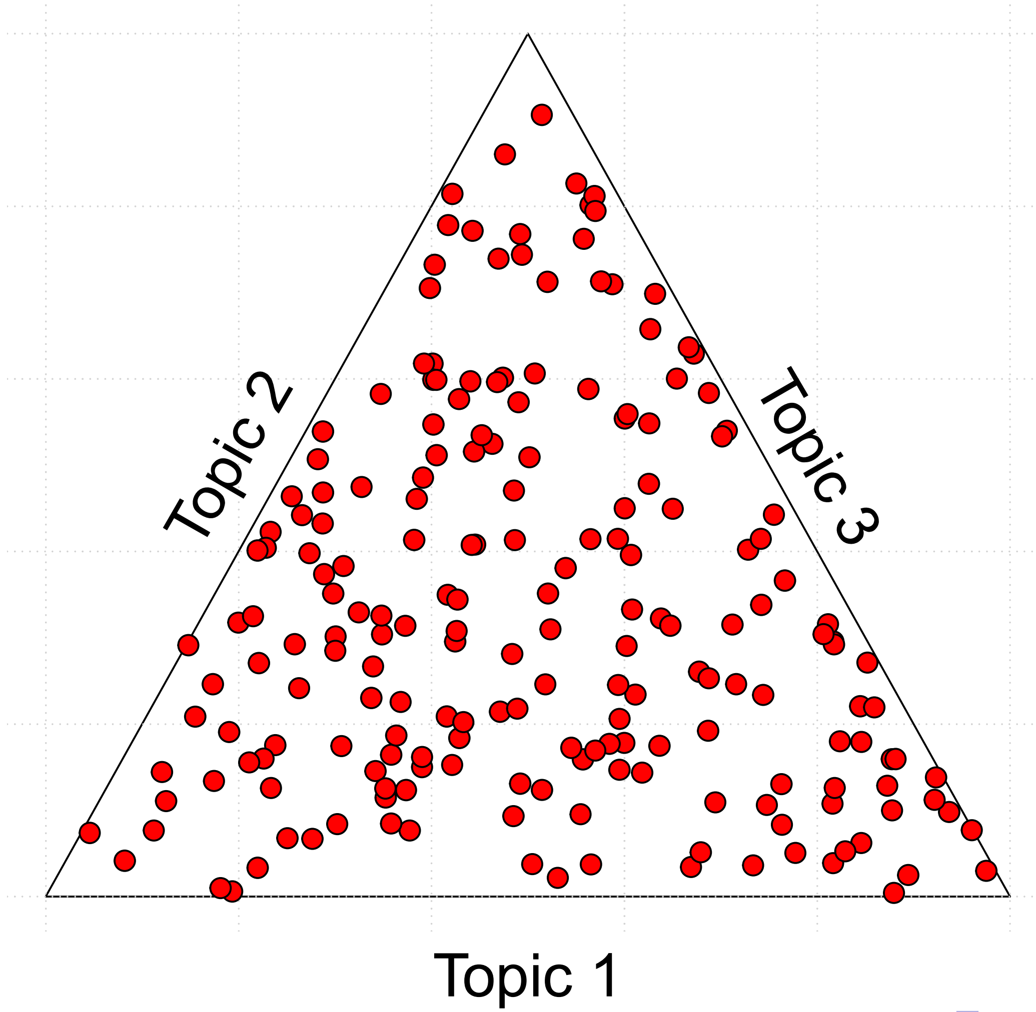
Larger values of α (assuming we are in symmetric case) mean we think (*a priori*) that documents are generally an even mix of the topics. If α is small (less than 1) we think a given document is generally from one or a few topics.

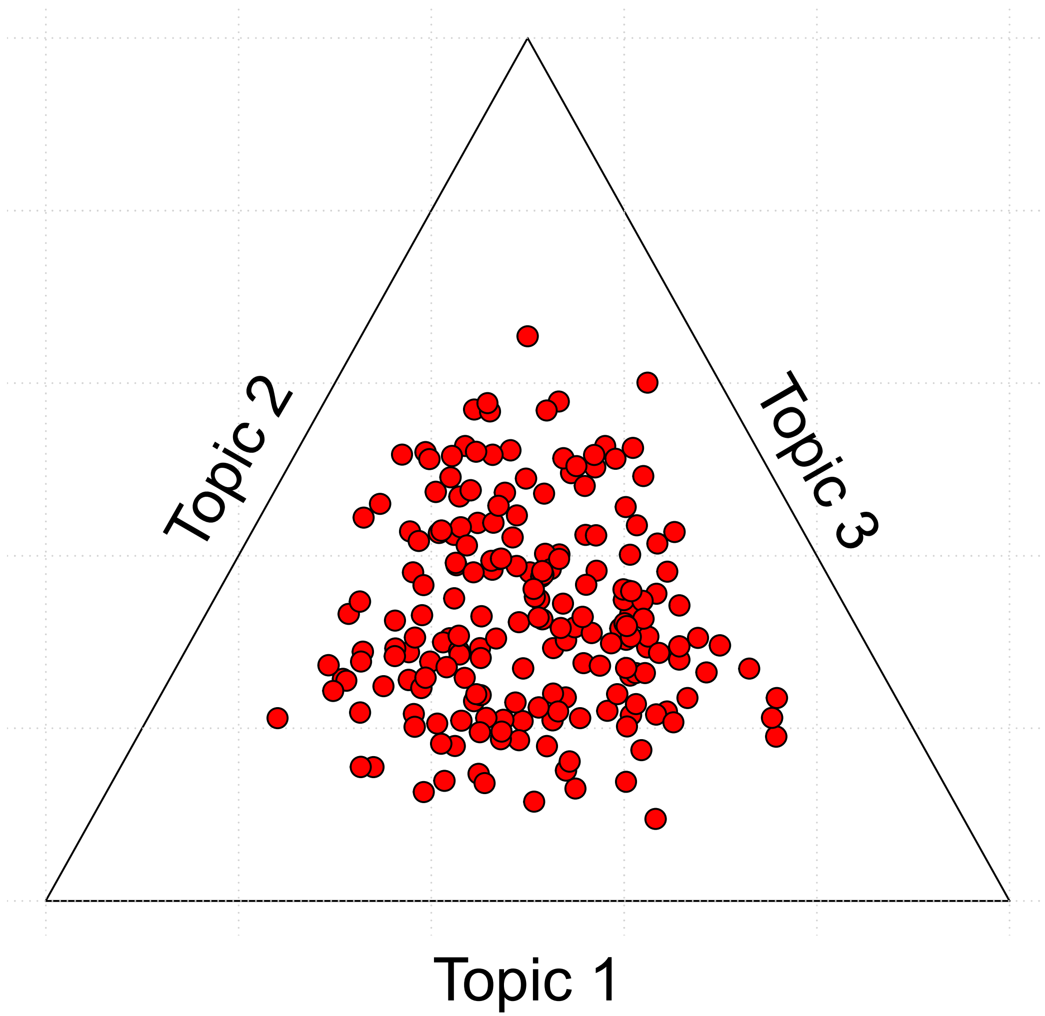
Example of Dirichlet

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



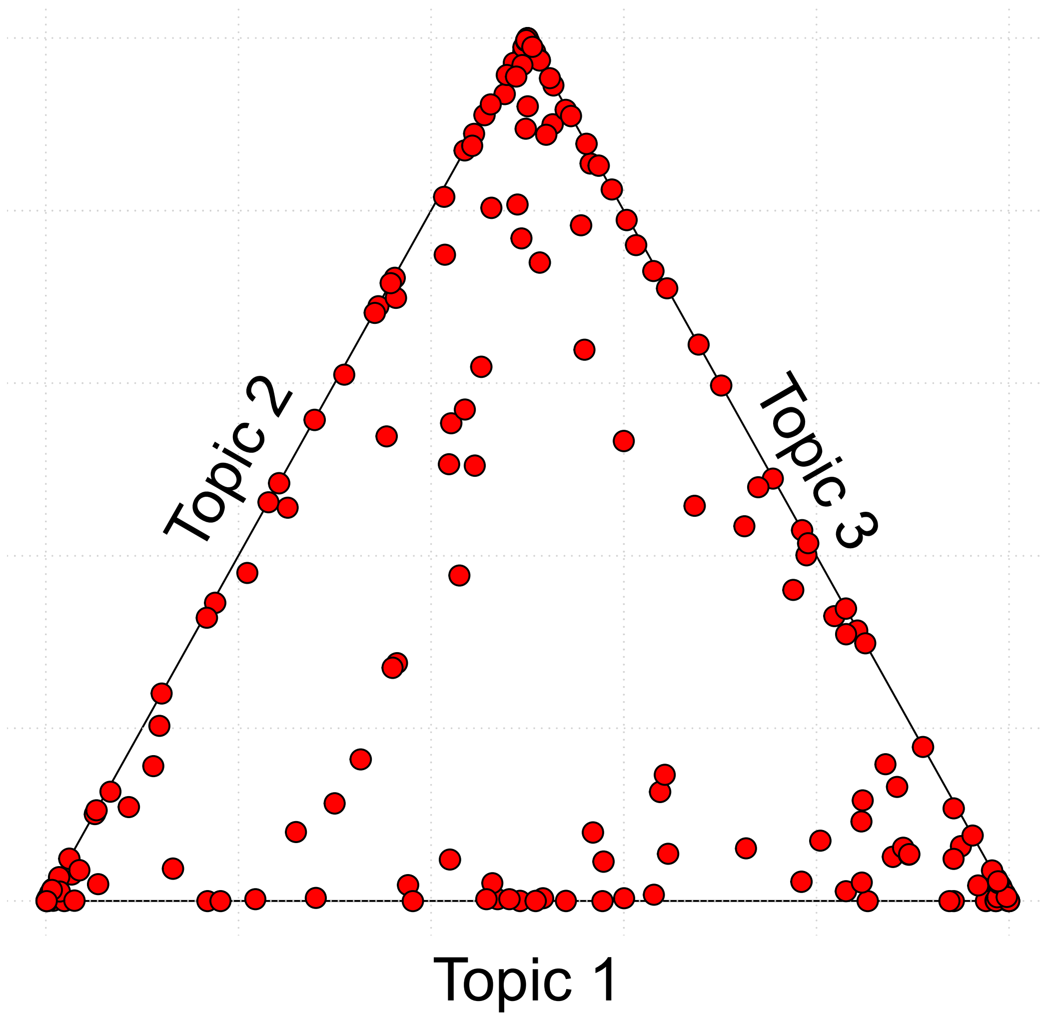
Example of Dirichlet

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



Example of Dirichlet

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



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The θ_d depends on our prior for the relevant Dirichlet, α.

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

While the β depends on the prior for the relevant Dirichlet, η

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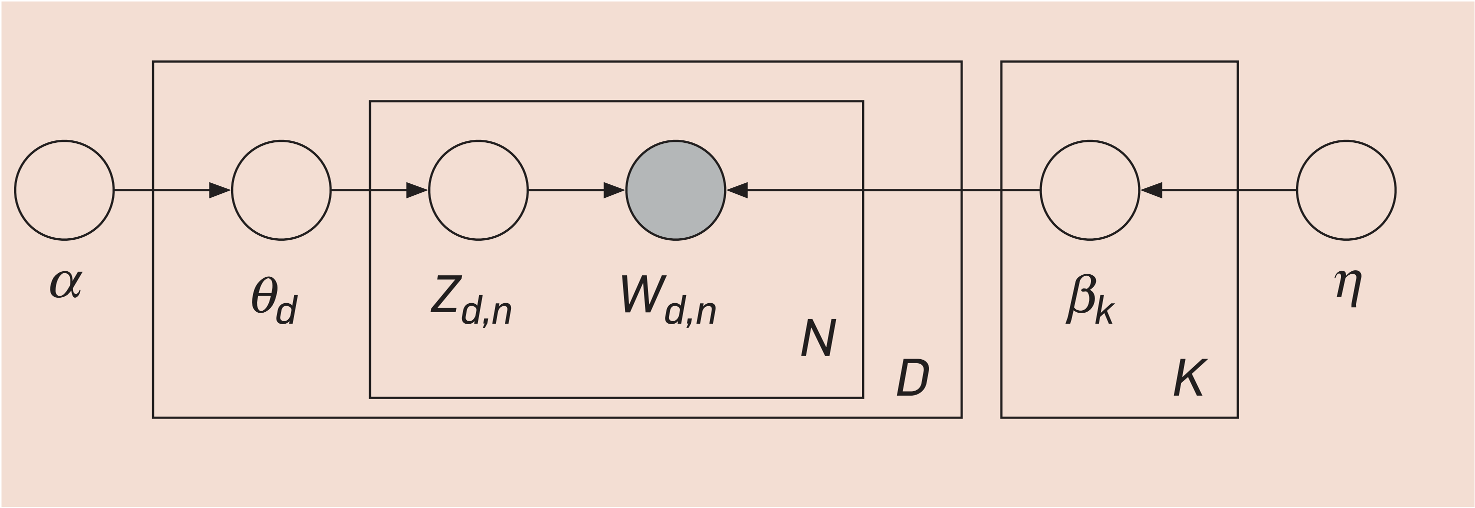

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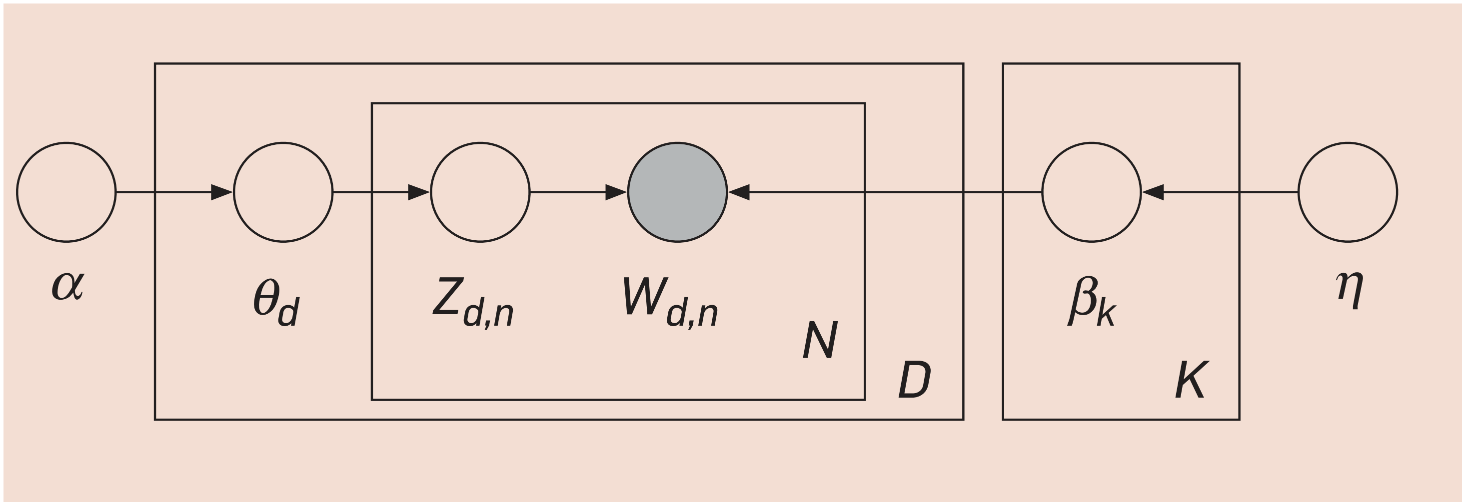

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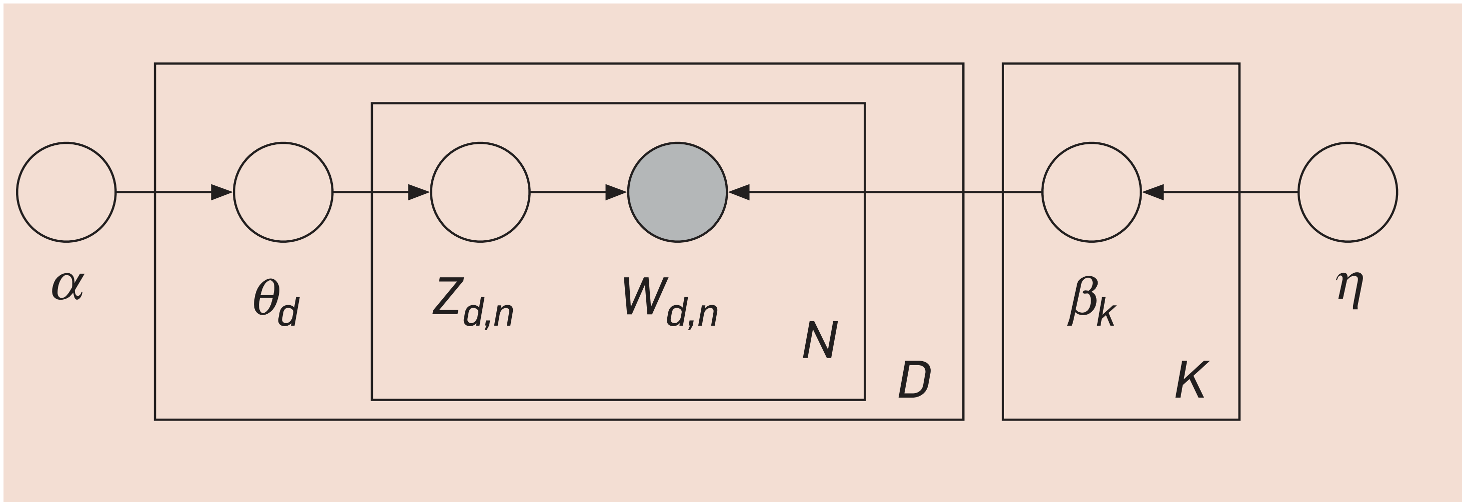

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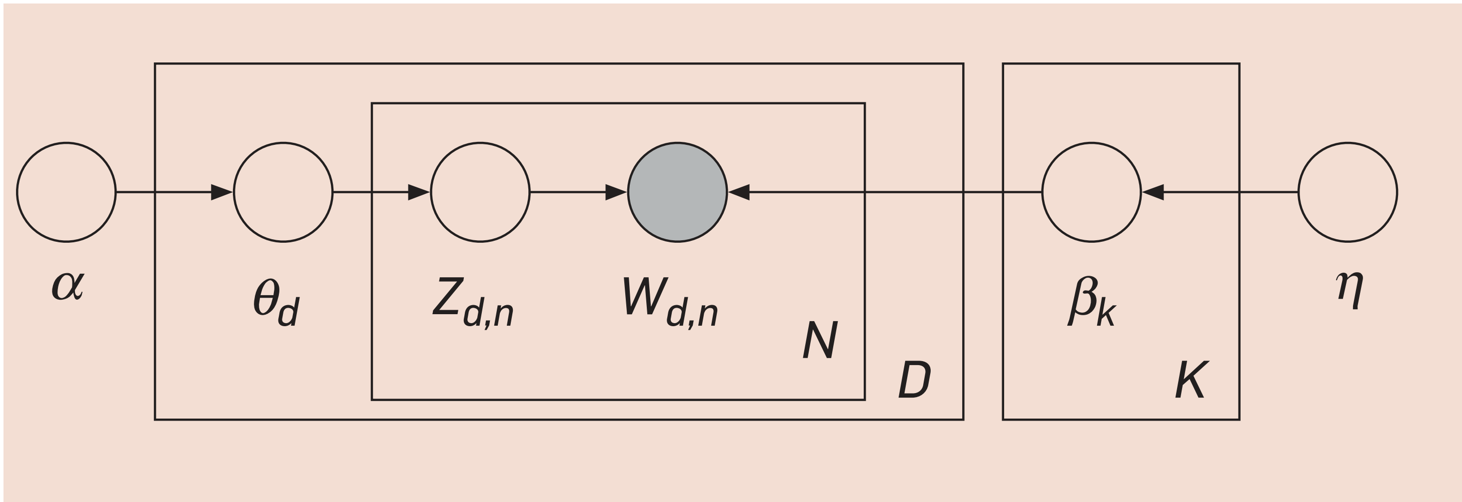

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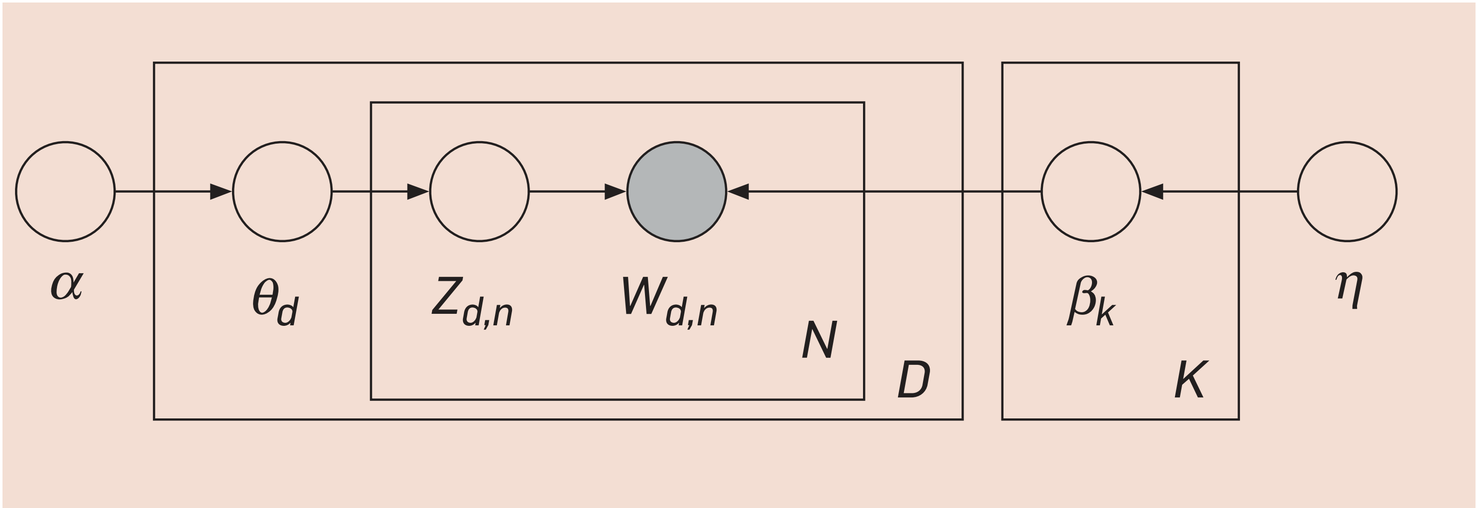
Plates imply replication.

Plate Diagram for LDA



Solid nodes are observed; empty nodes are latent.

Plates imply replication.

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

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The word distribution for each topic.

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Some implementations allow you to estimate e.g. α, 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.

A Manifesto Example

69 UK manifestos. Some preprocessing.

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	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:

Continued. . .

'Top' 6 most frequent words in each topic: might help interpretation (!)

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
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
6	liberal	conservative	support	britain	policy

Continued...

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

Continued

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doc 1	0.00009	0.00009	0.00009	0.00009	0.99965
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
⋮	⋮	⋮	⋮	⋮	⋮

Continued

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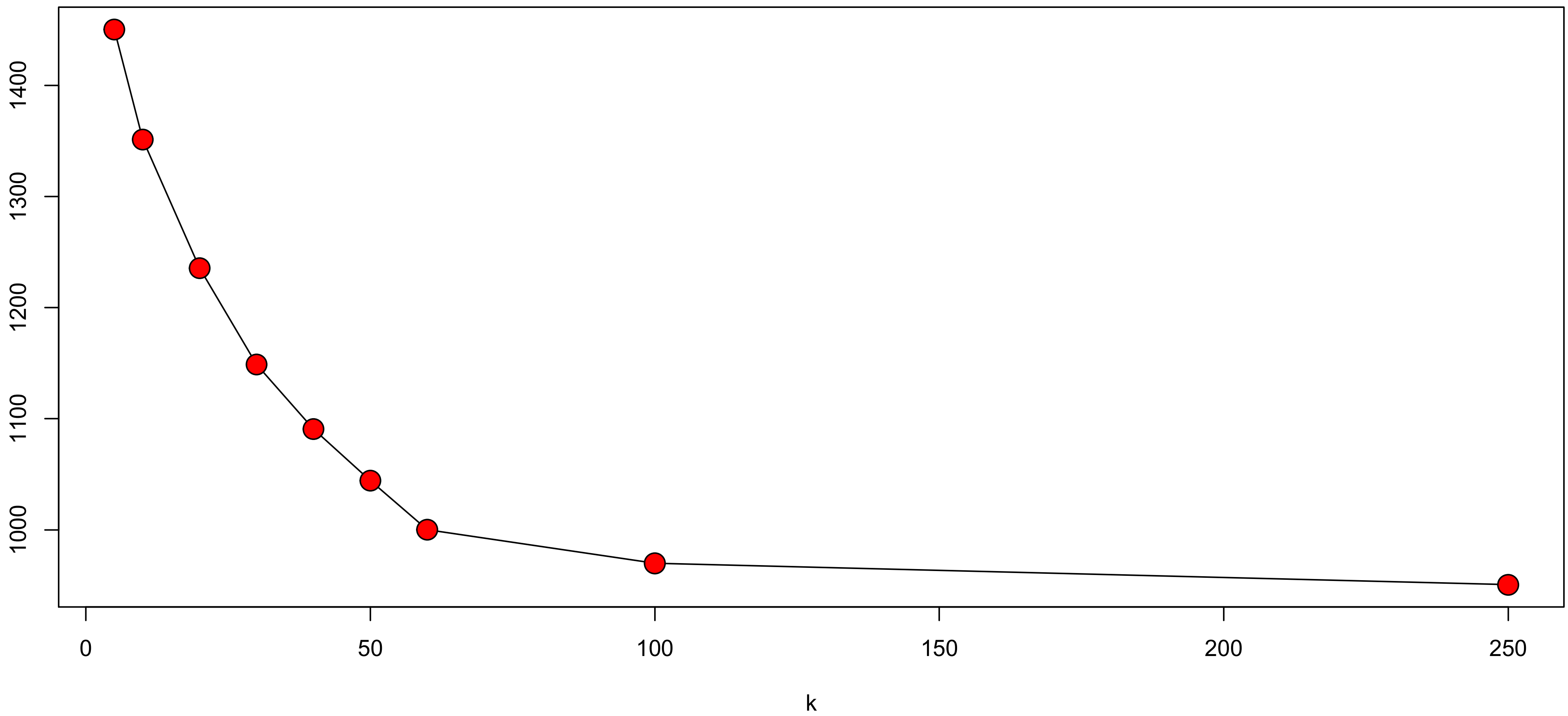
But: the topic models that hold-out calculations suggest are optimal and not much liked by humans! "Reading Tea Leaves: How Humans Interpret Topic Models" by Chang et al.

Perplexity Likes a Lot of Topics (manifestos)



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Manifestos

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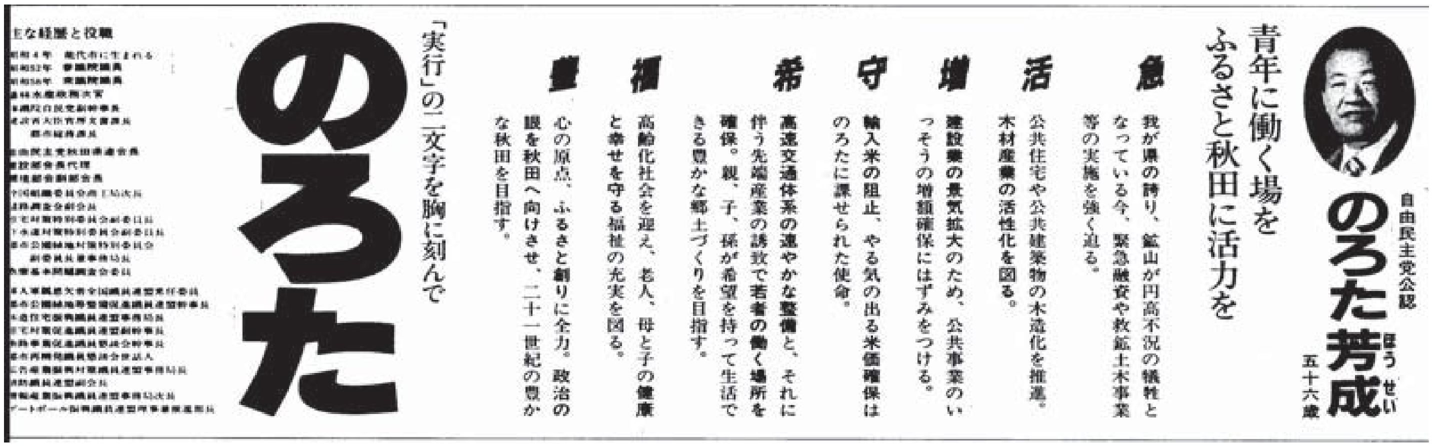

自由民主党公認

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。

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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。

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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。

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「実行」の二文字を胸に刻んで

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主な経歴と役職

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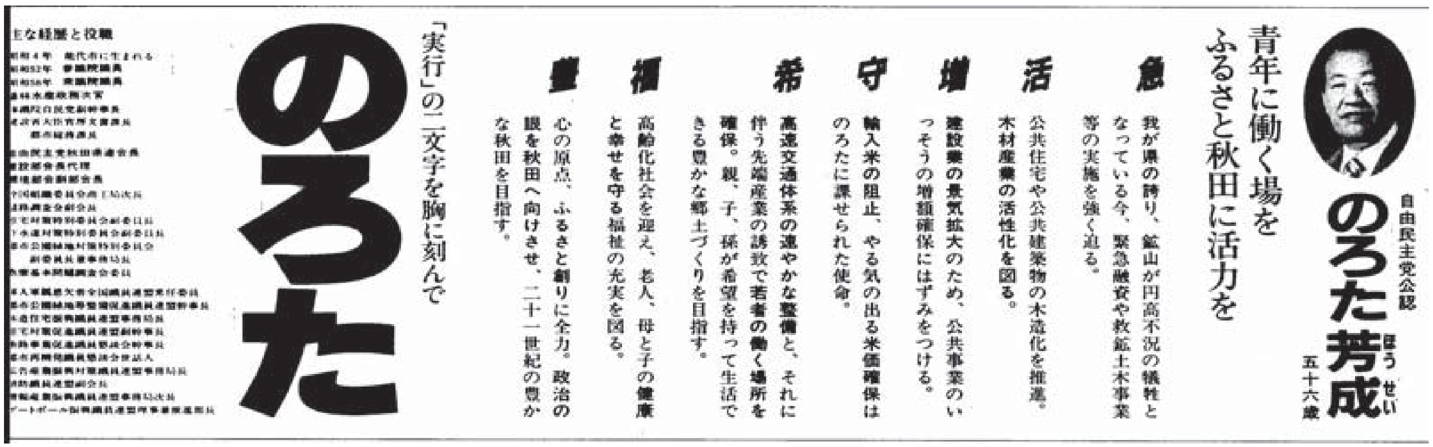

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[illegible]

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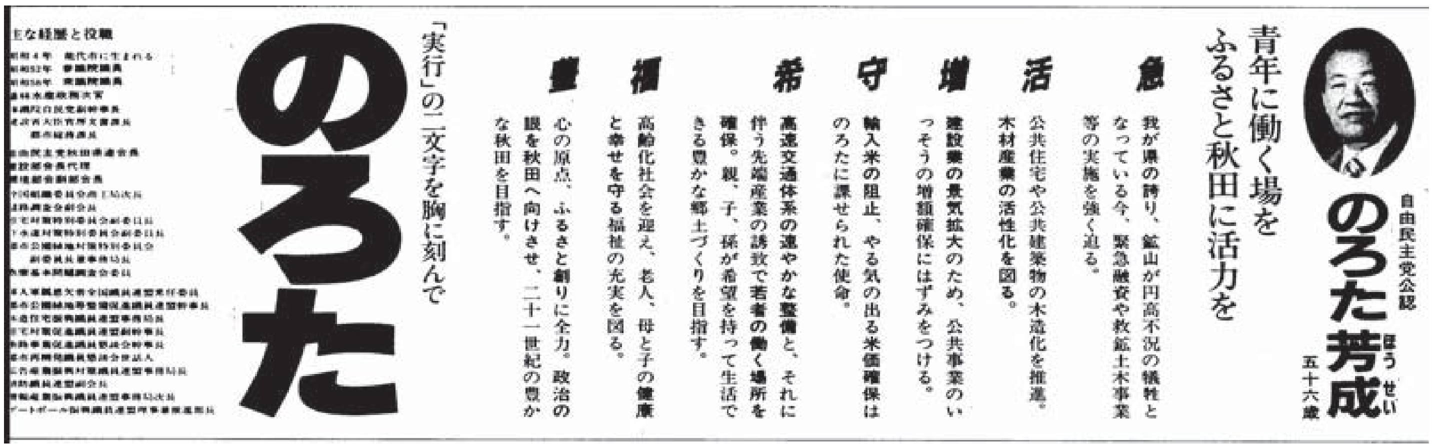

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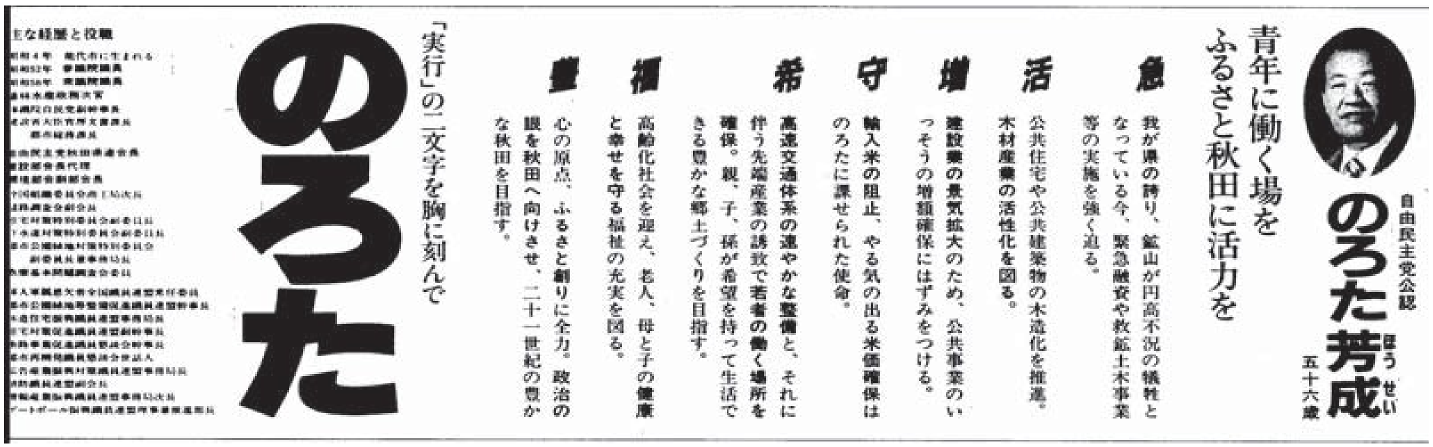

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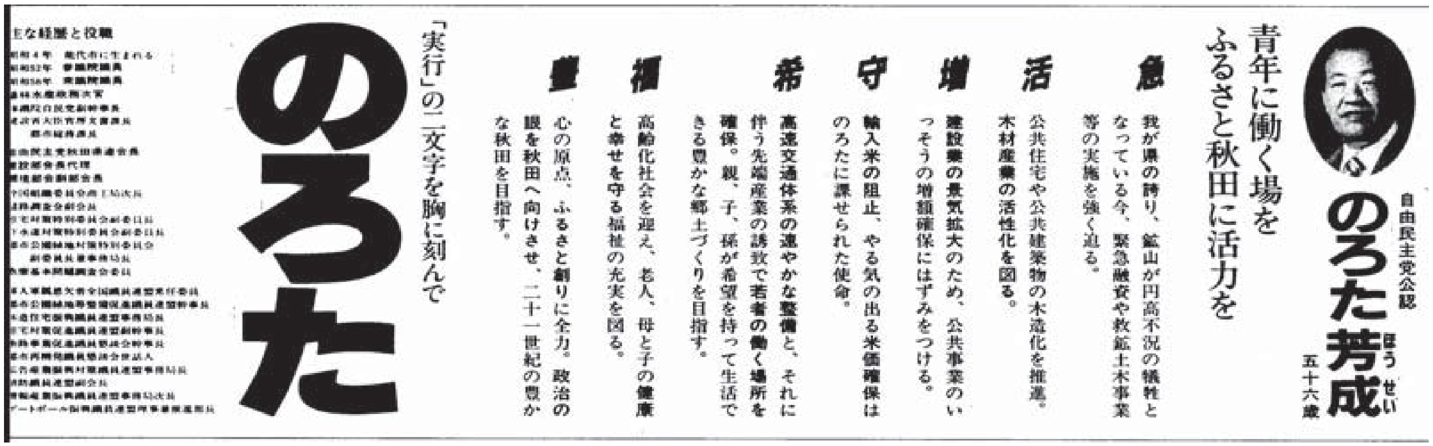

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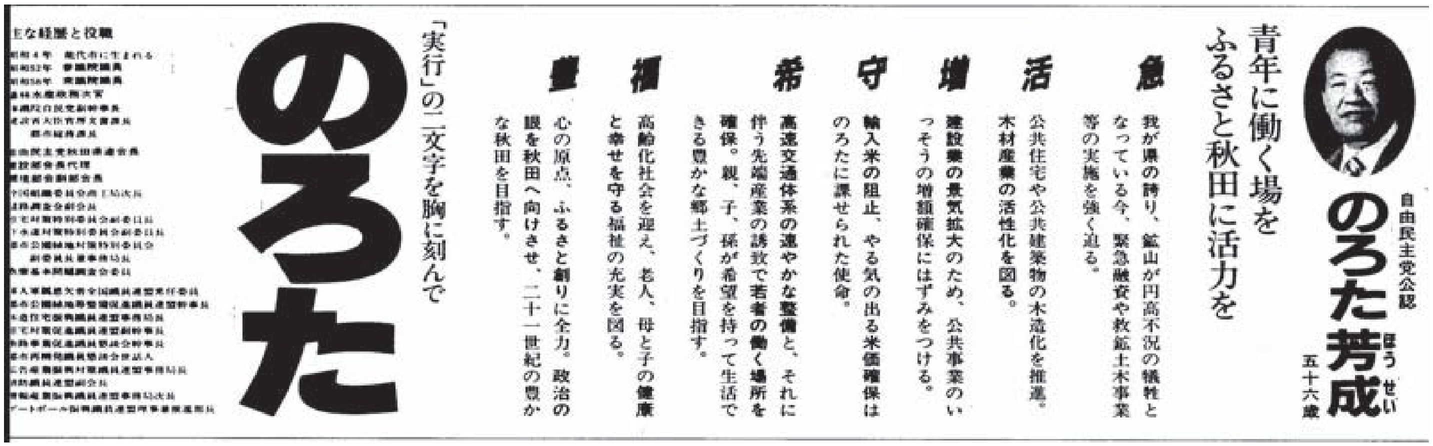

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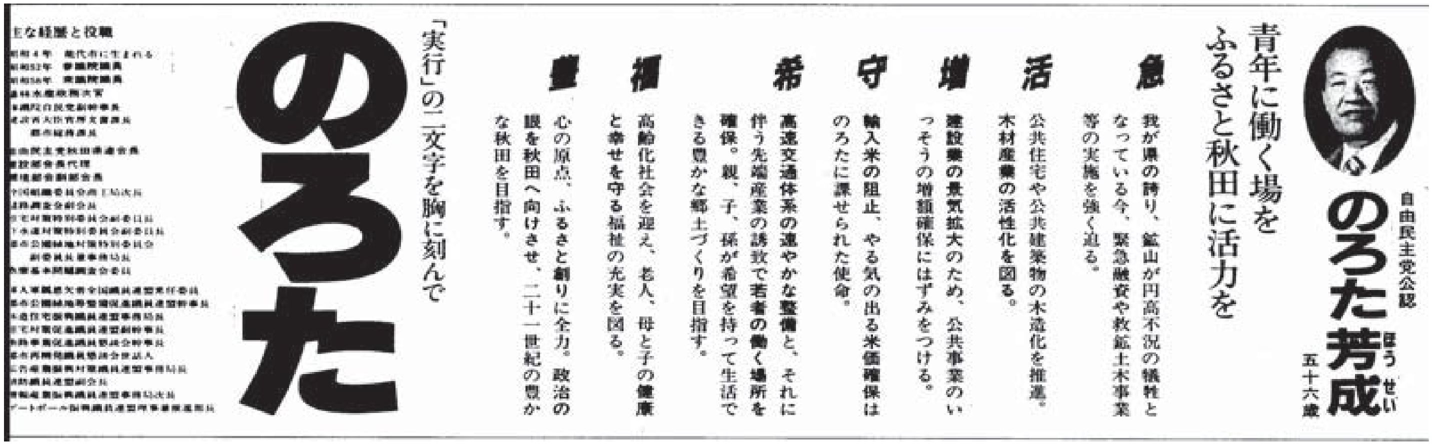

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青年に働く場を
ふるさと秋田に活力を

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

7,497. 1986–2009. Standardized form.

"...instructed to write whatever they want in the form and return it before 5 PM of the first day of the campaign. At least two days before the election, local electoral commissions are required to distribute the forms of all candidates running in the district to all registered voters"

Manifestos were hand transcribed from microfilm. Japanese install of Windows/R used to fit LDA.

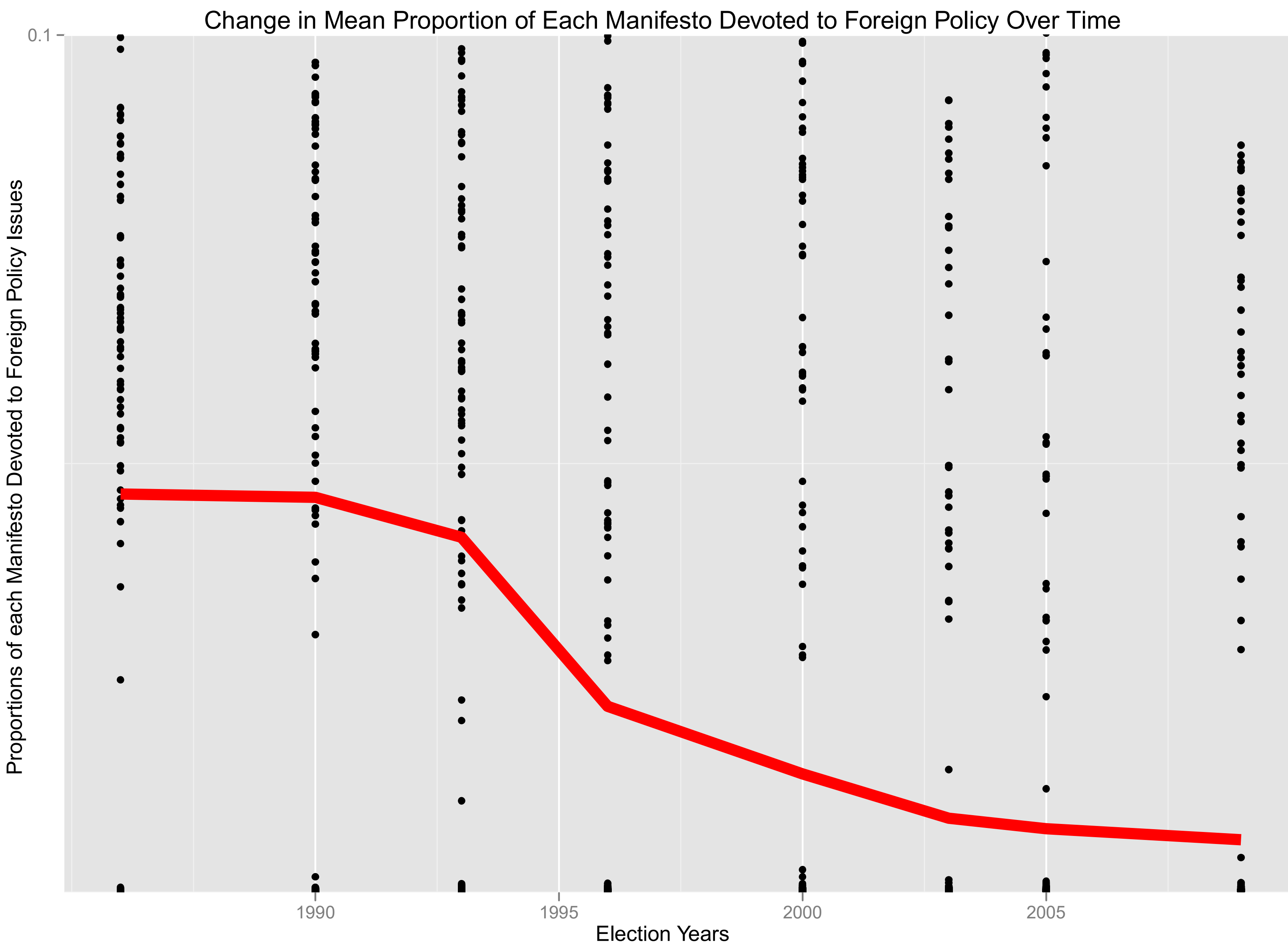
Topic Distribution over Words

Topic Distribution over Words

	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	誤り
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	総合	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

Change in proportion of 'Pork' Topic



Change in proportion of ‘Foreign Policy’ Topic

Change in proportion of 'Foreign Policy' Topic