Topic Modeling

Topic Modeling

Document 1

Document 2

Document 3

⋮

Document N

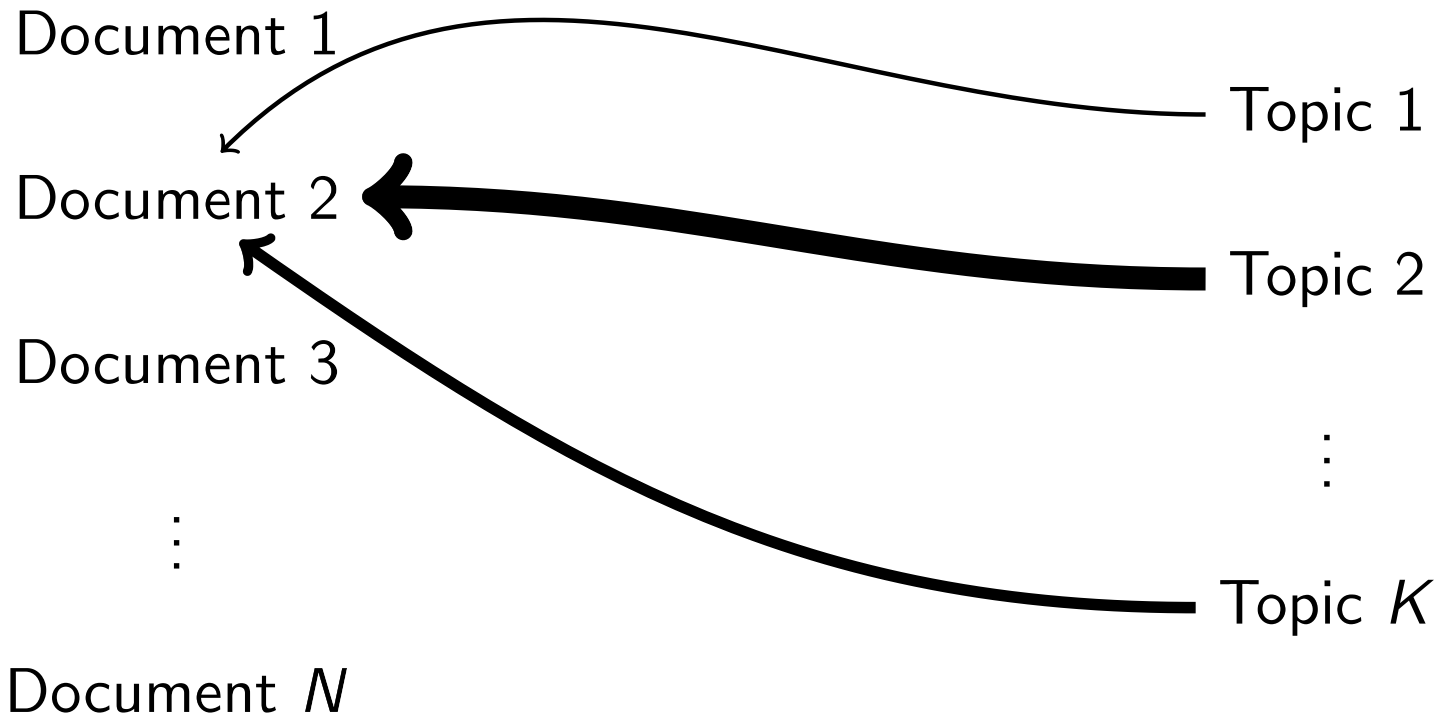
Topic 1

Topic 2

⋮

Topic K

Topic Modeling



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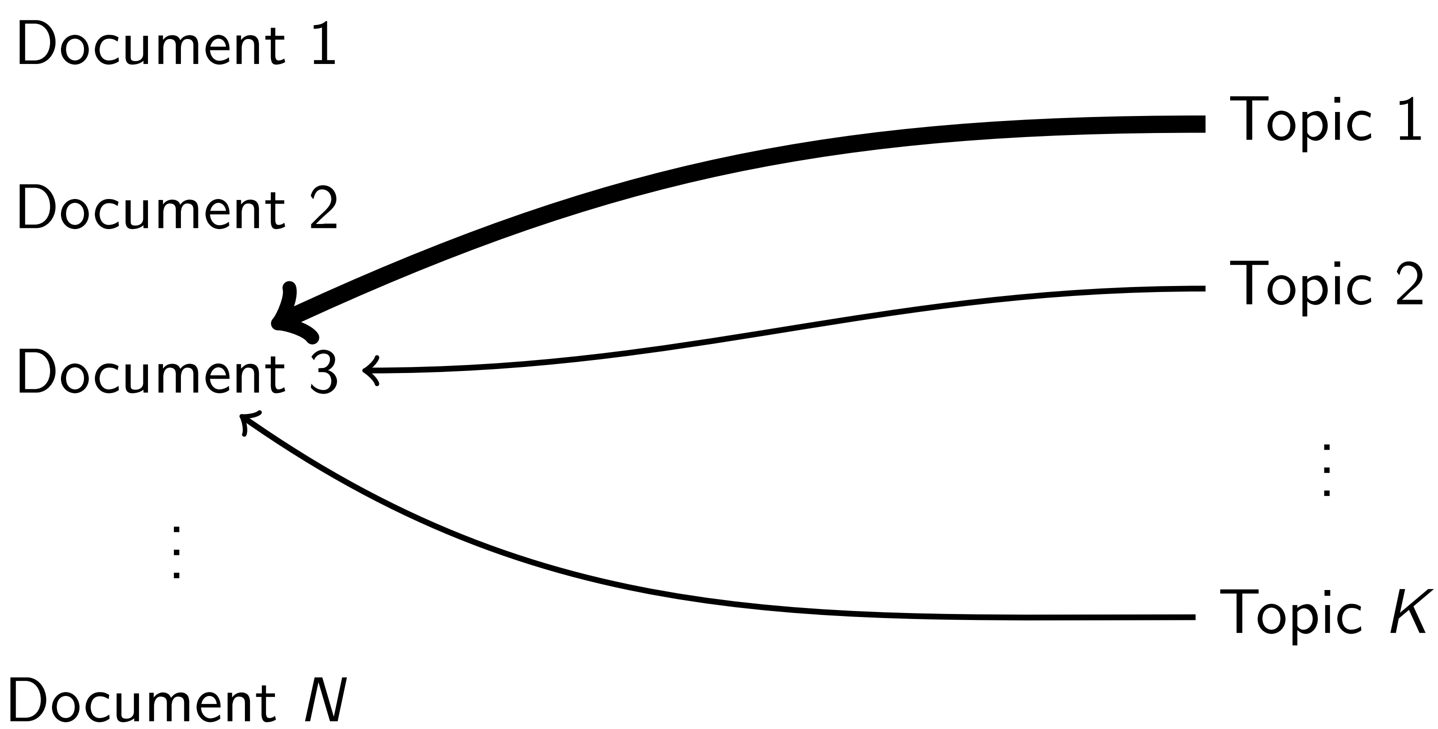

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Documents exhibit different topics,

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Documents exhibit different topics, and in different proportions.

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

Intuition: Generating Words

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For each document. . .

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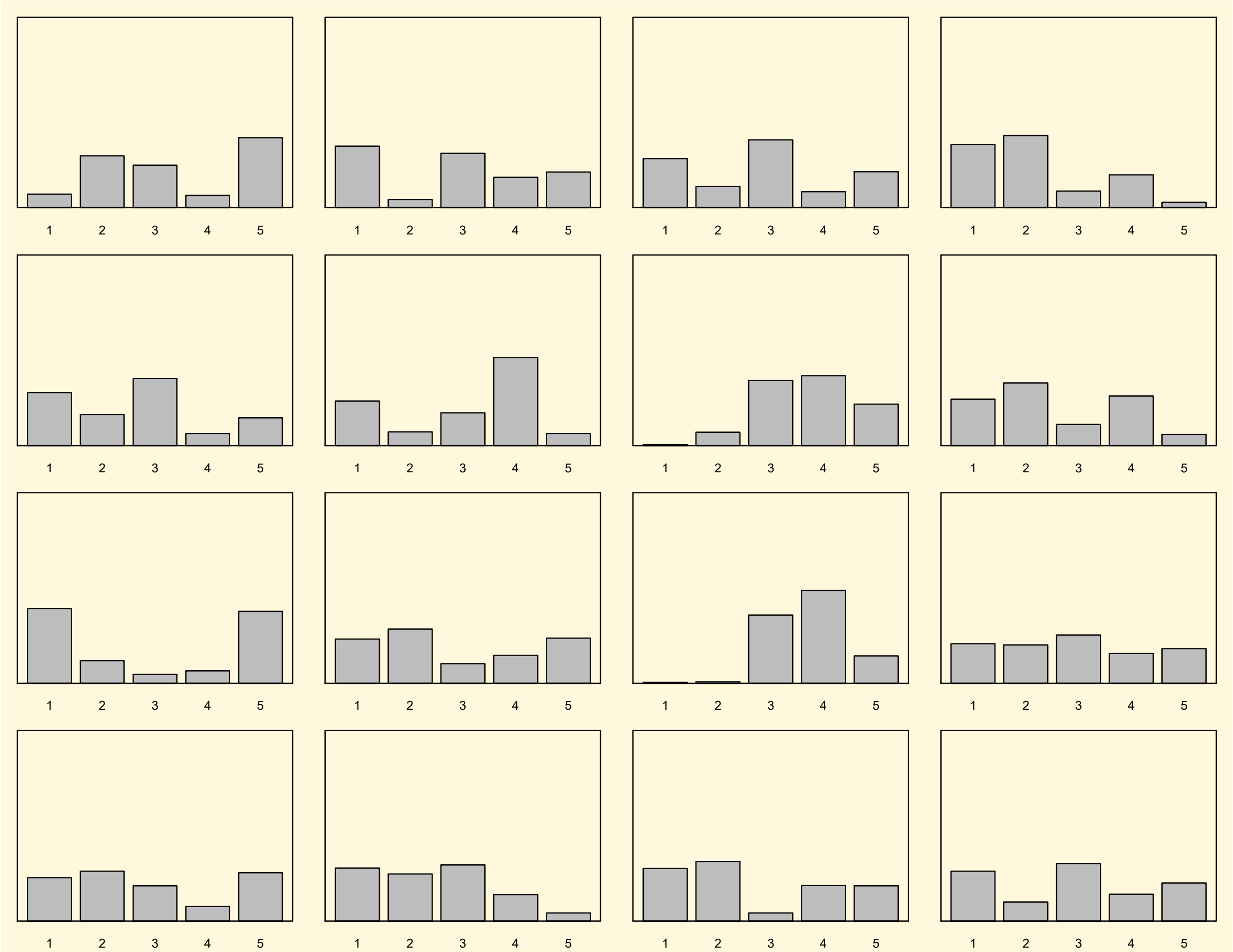

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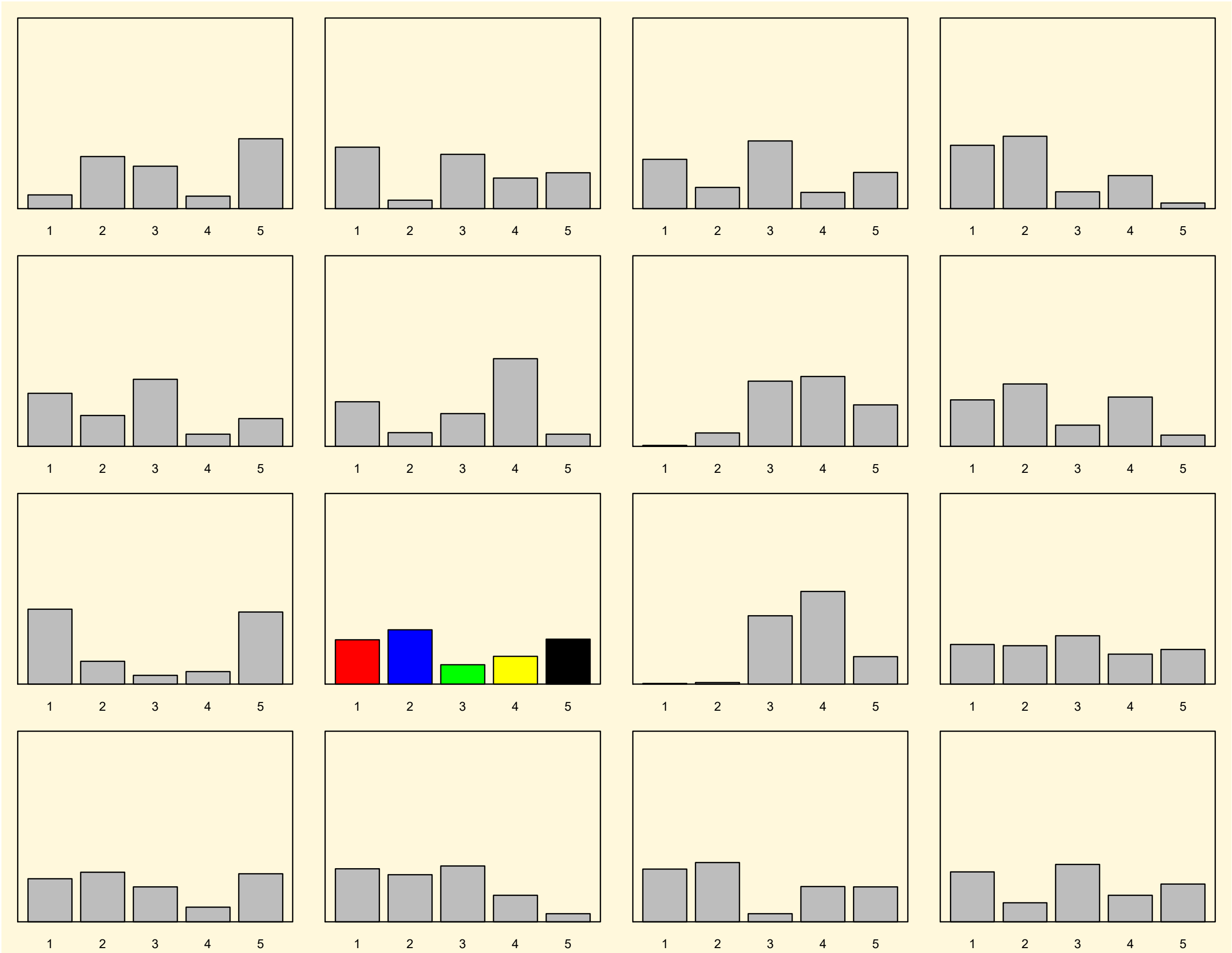

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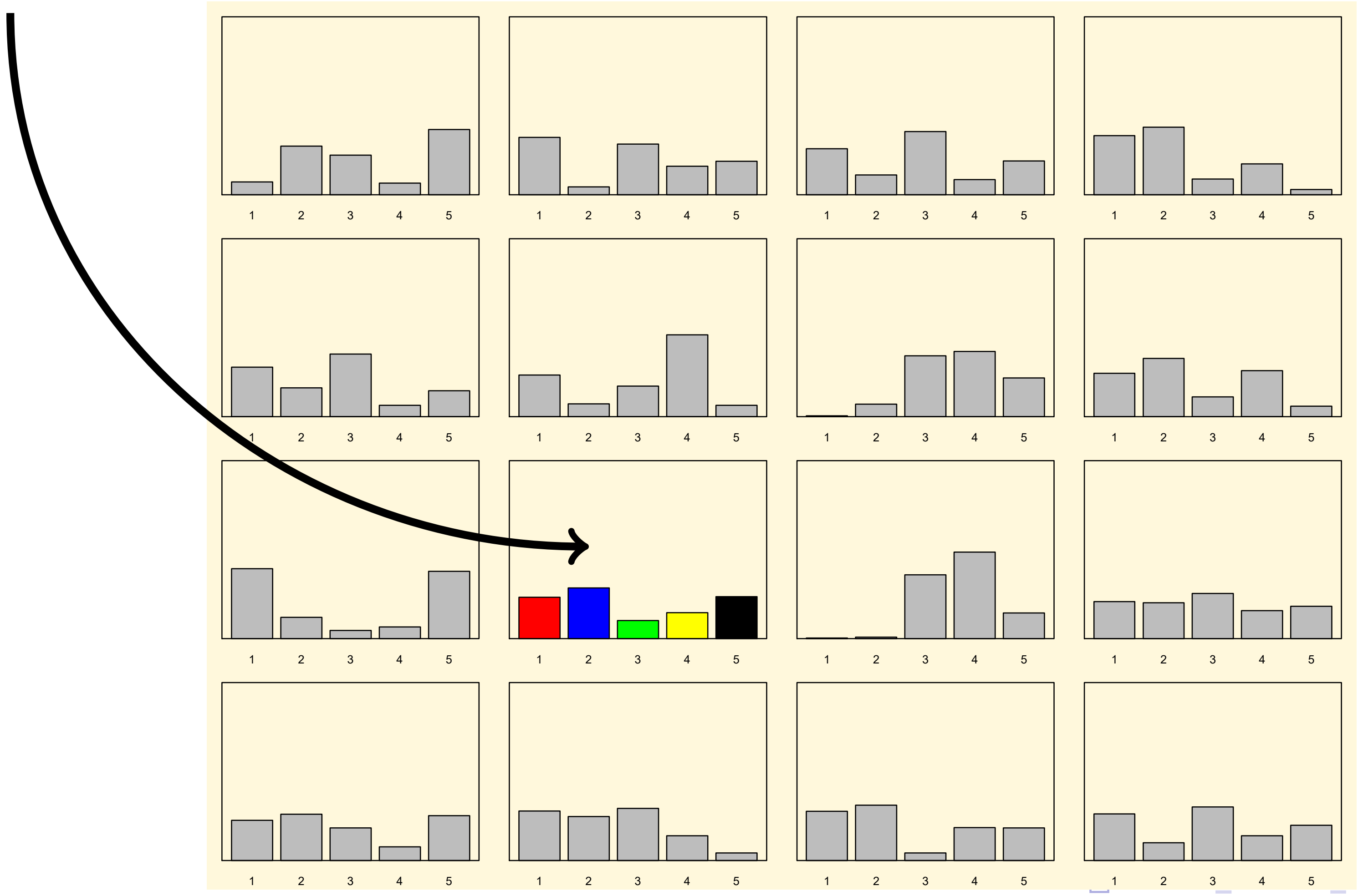

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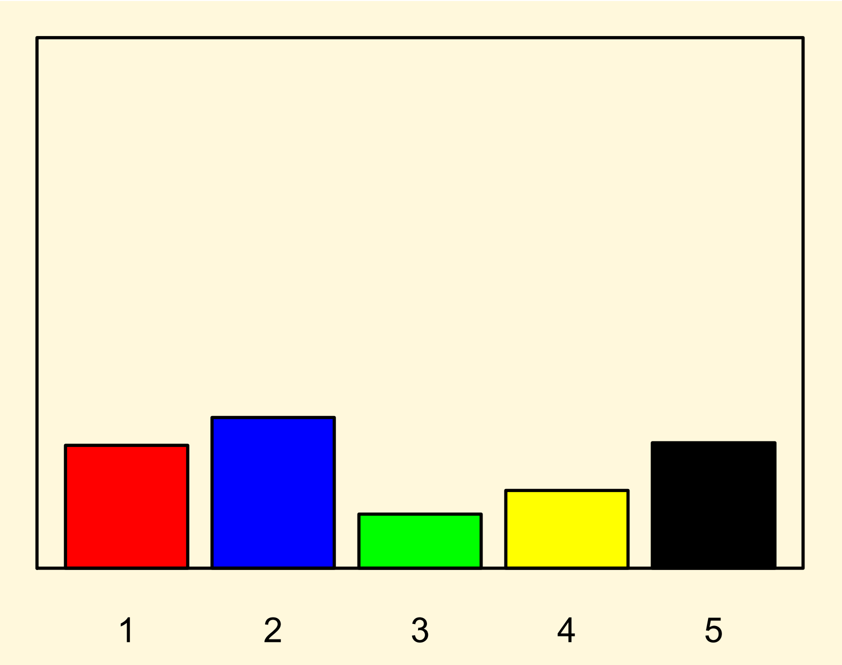

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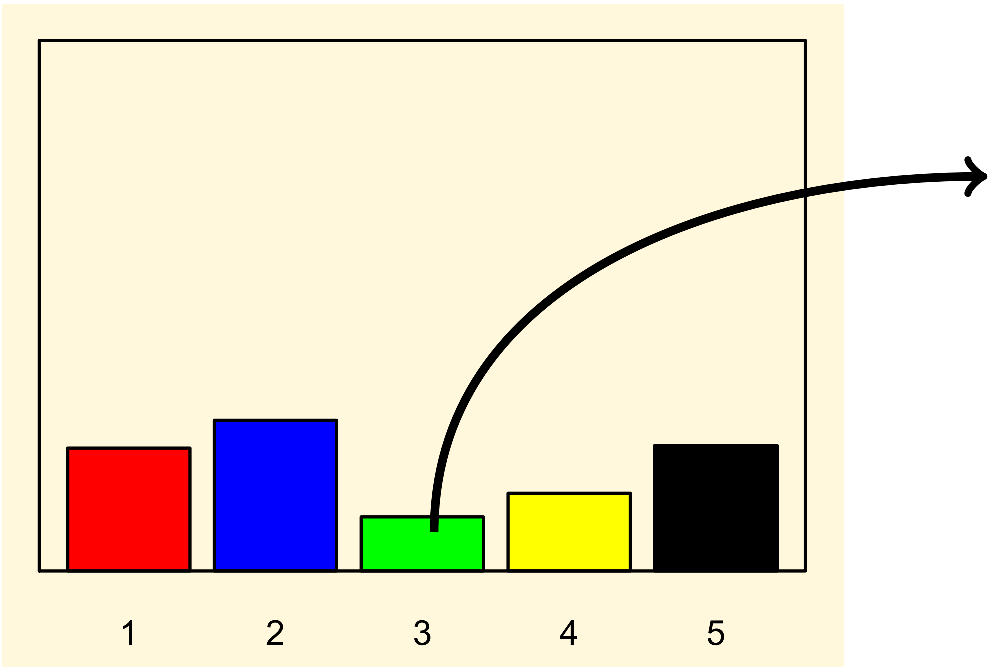

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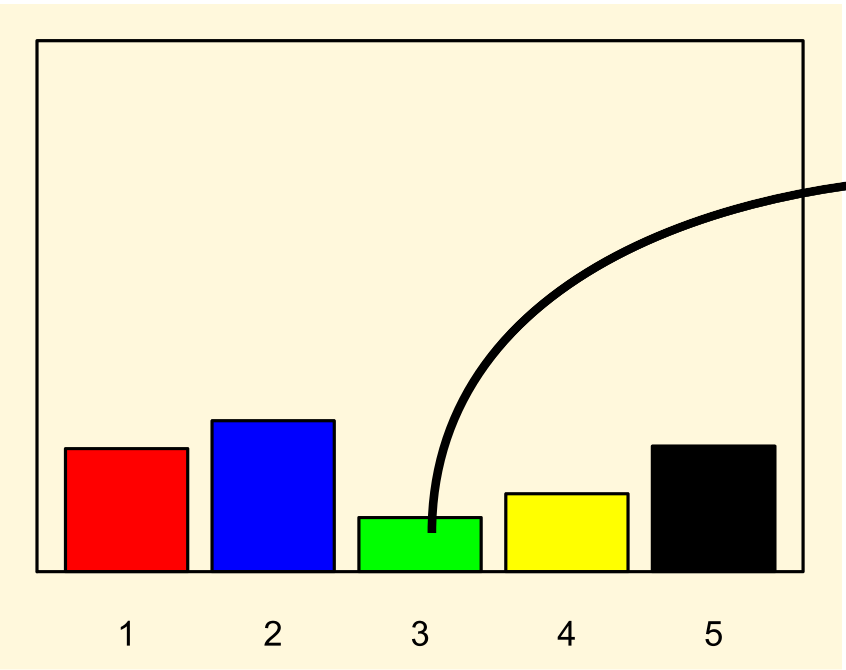

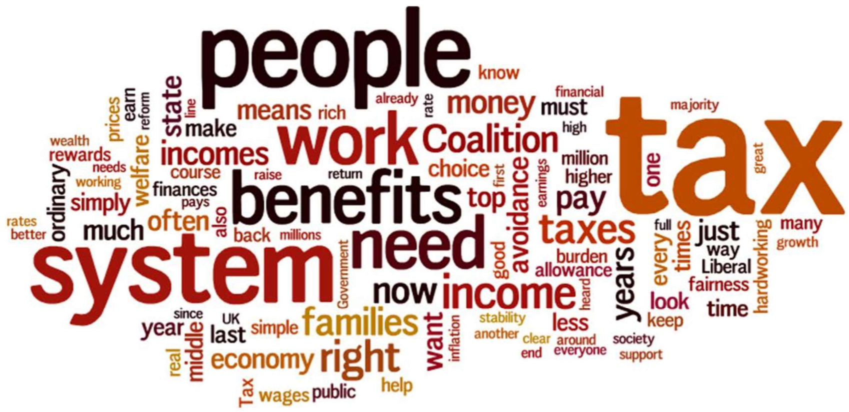

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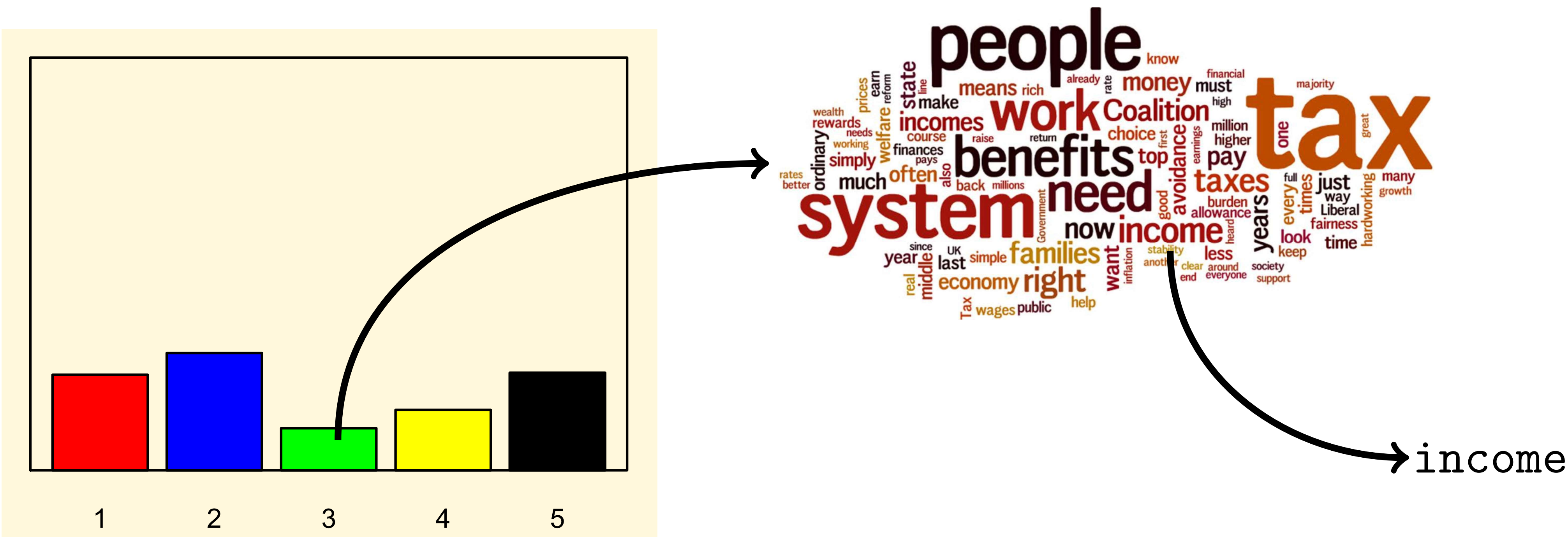

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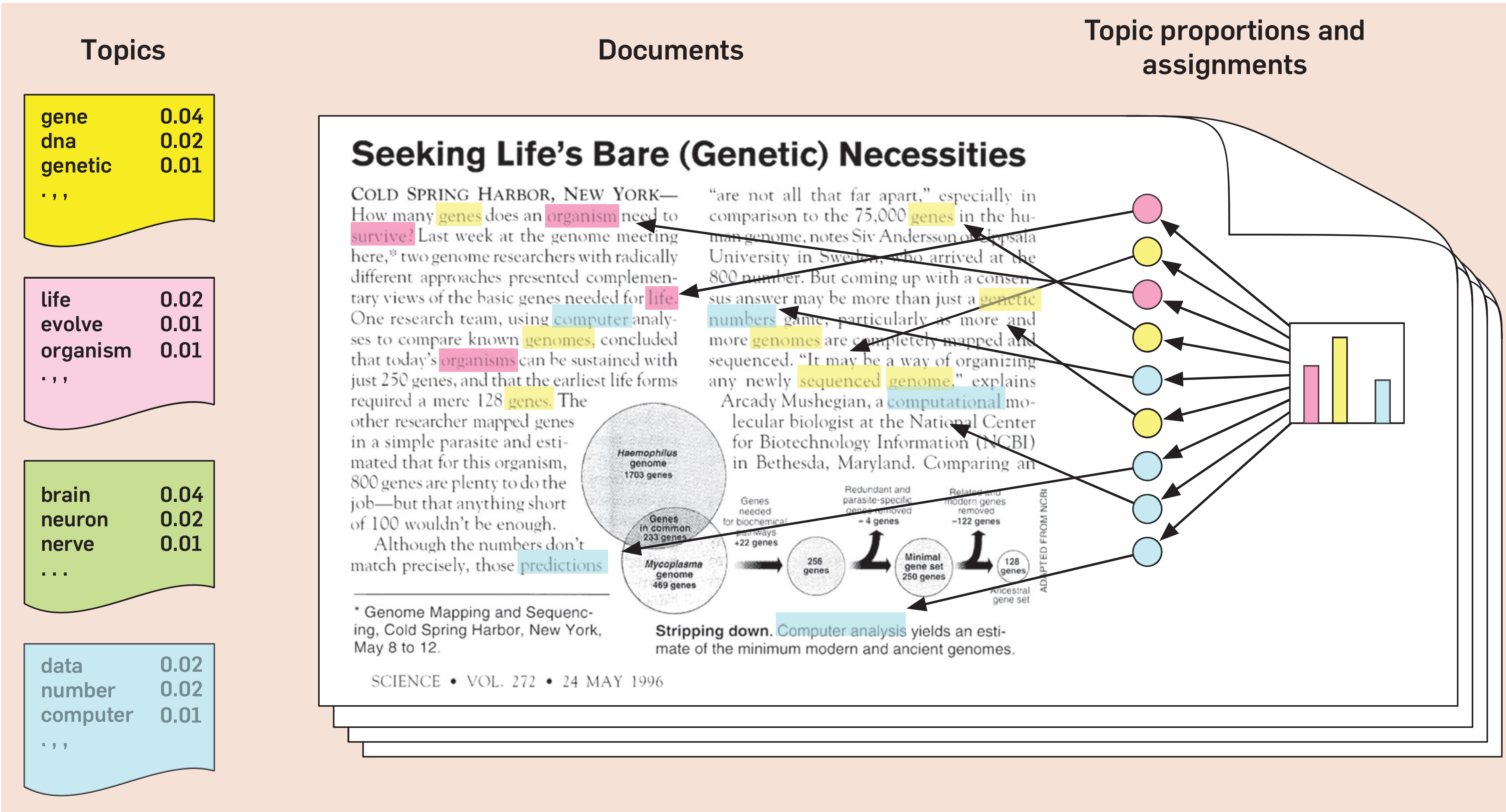

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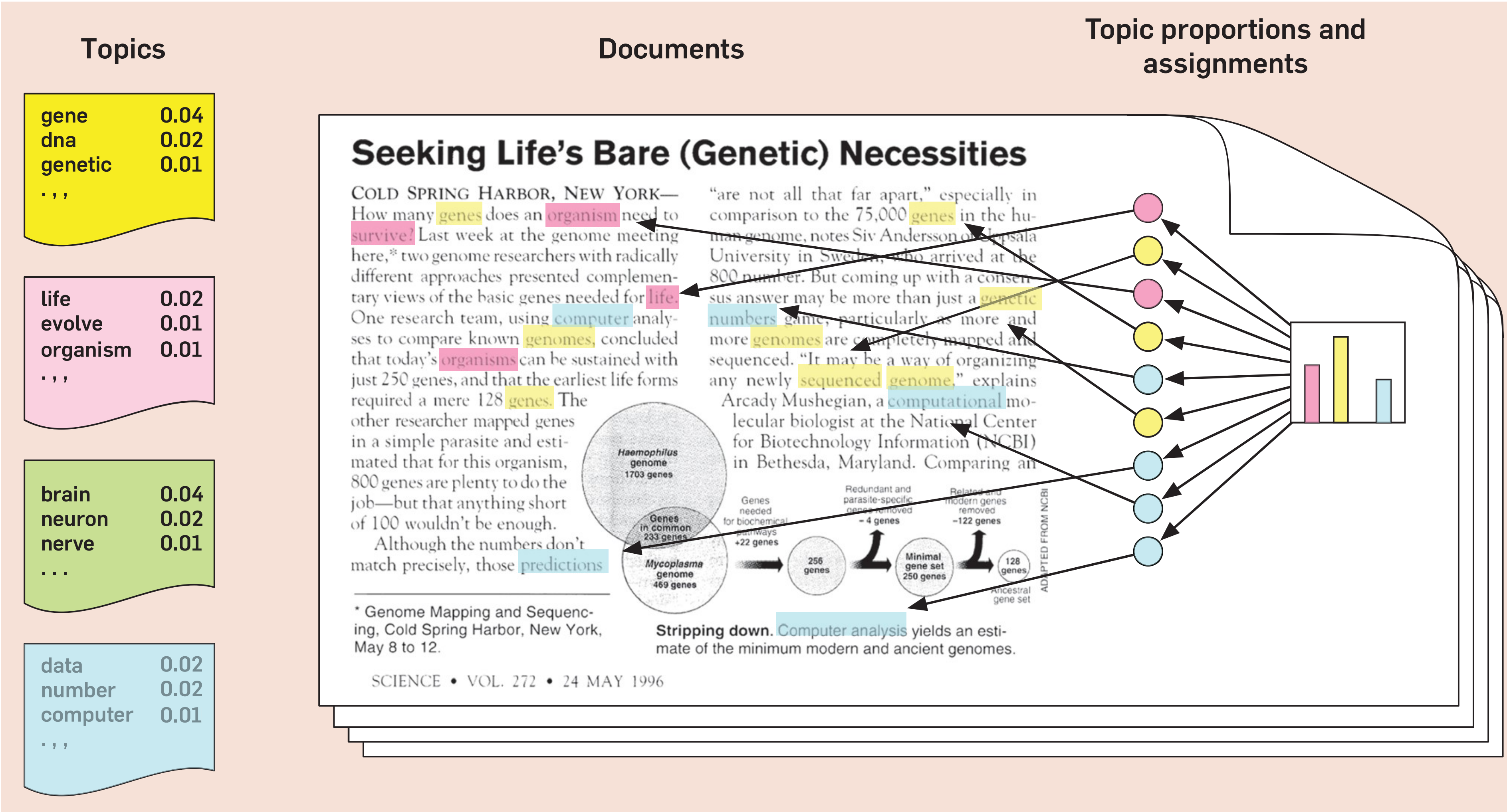

Note that all documents share same set of topics: but some (e.g. neuro) may be (basically) absent in a given document.

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For a user-selected k, a typical implementation of LDA will return...

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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.

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69 UK manifestos. Some preprocessing.

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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
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Continued. . .

Continued...

'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
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Continued...

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

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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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doc 4	0.00006	0.00006	0.00006	0.00006	0.99978
doc 5	0.00002	0.00002	0.00002	0.00002	0.99991
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Picking k, continued. . .

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CS: split into training and test sets.

Pork to Policy (Catalinac, 2016)

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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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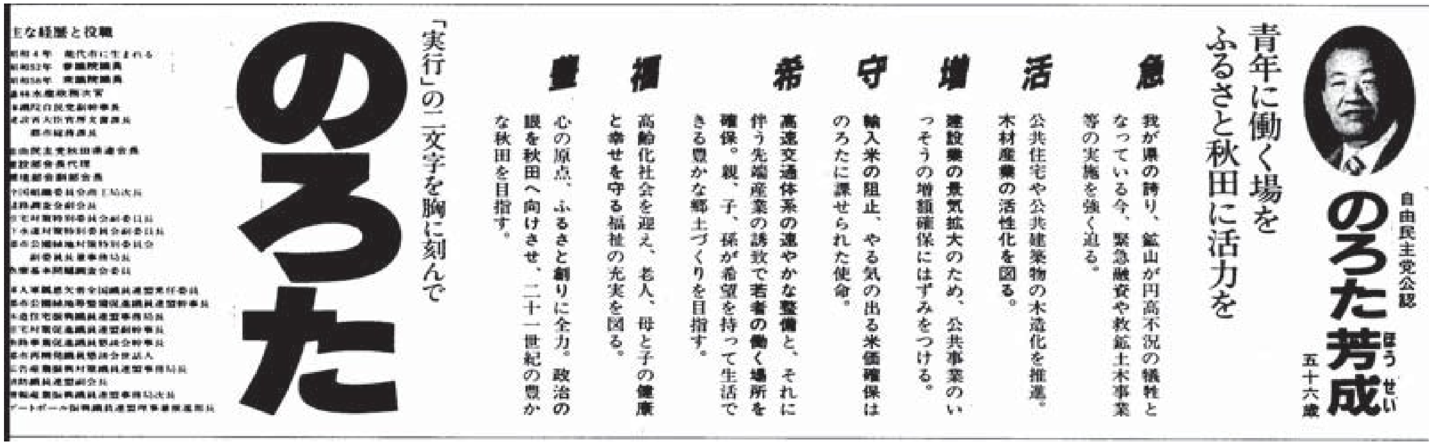
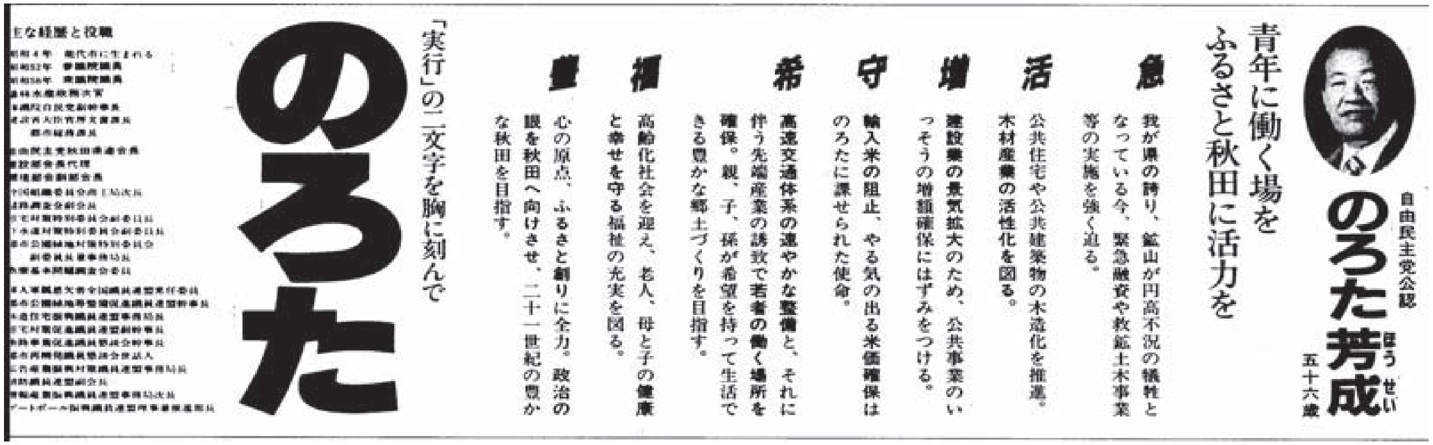
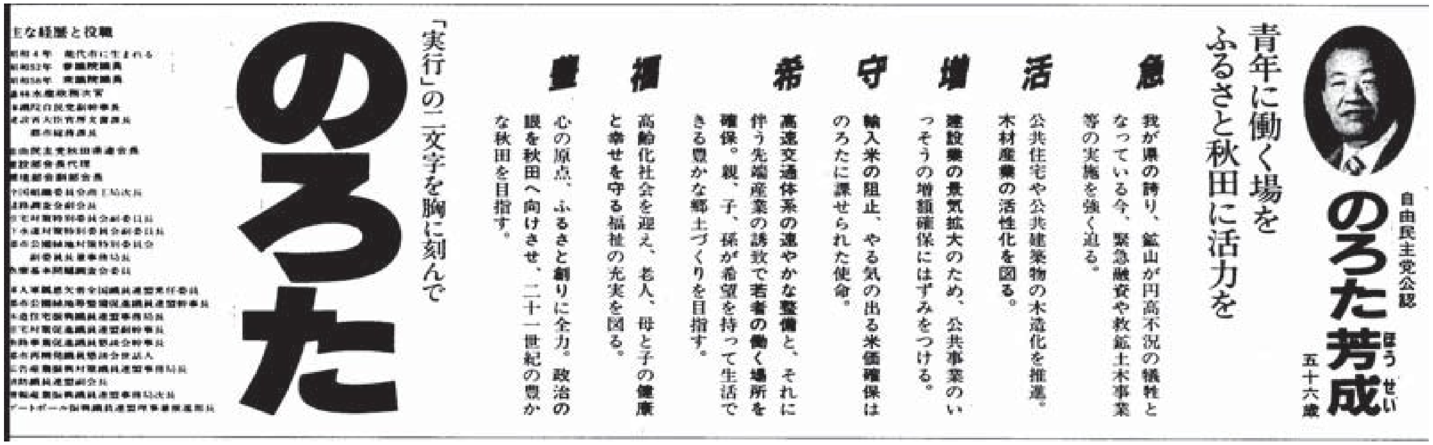


自由民主党公認
のろた芳成
ほうせい
五十六歳
青年に働く場を
ふるさと秋田に活力を
急
我が県の誇り、鉱山が円高不況の犠牲となっている今、緊急融資や救鉱土木事業等の実施を強く迫る。
活
公共住宅や公共建築物の木造化を推進。木材産業の活性化を図る。
増
建設業の景気拡大のため、公共事業のいっそうの増額確保にはずみをつける。
守
輸入米の阻止、やる気の出る米価確保はのろたに課せられた使命。
希
高速交通体系の速やかな整備と、それに伴う先端産業の誘致で若者の働く場所を確保。親、子、孫が希望を持って生活できる豊かな郷土づくりを目指す。
福
高齢化社会を迎え、老人、母と子の健康と幸せを守る福祉の充実を図る。
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

Manifestos



7,497.



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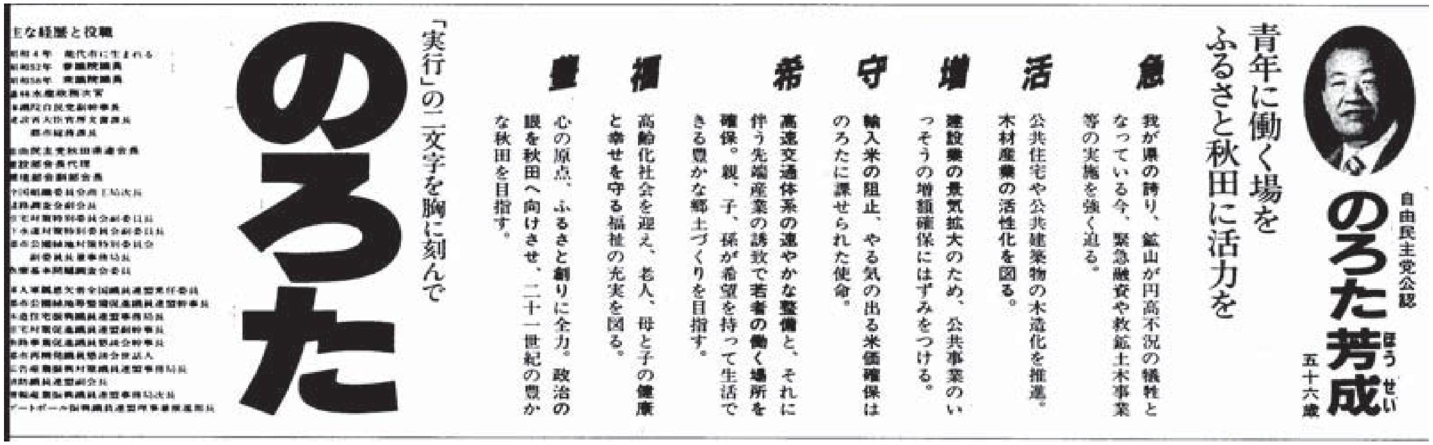

自由民主党公認

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

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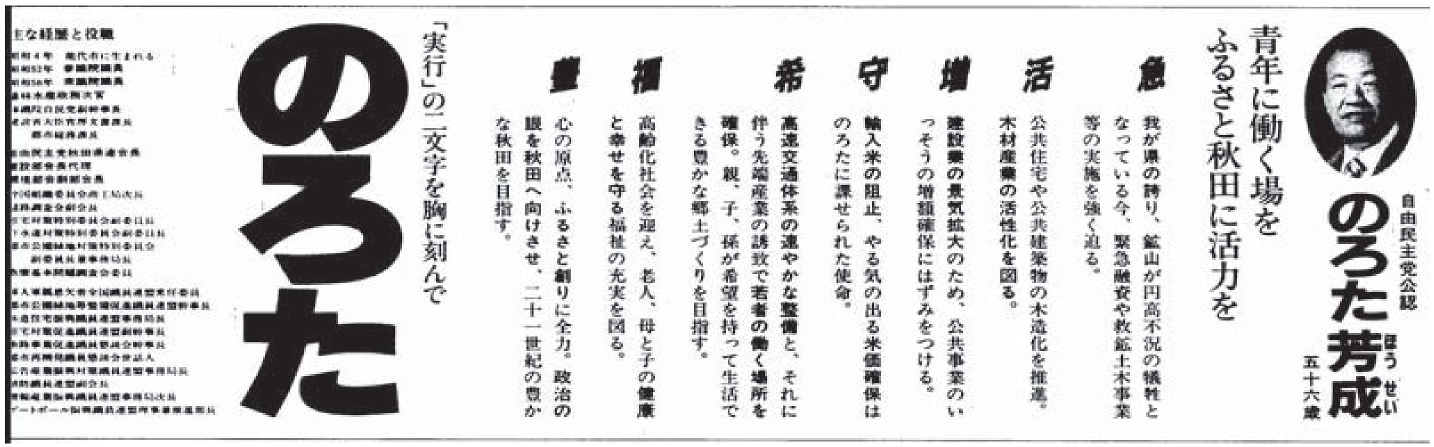
主な経歴と役職

7,497. 1986–2009. Standardized form.

Manifestos



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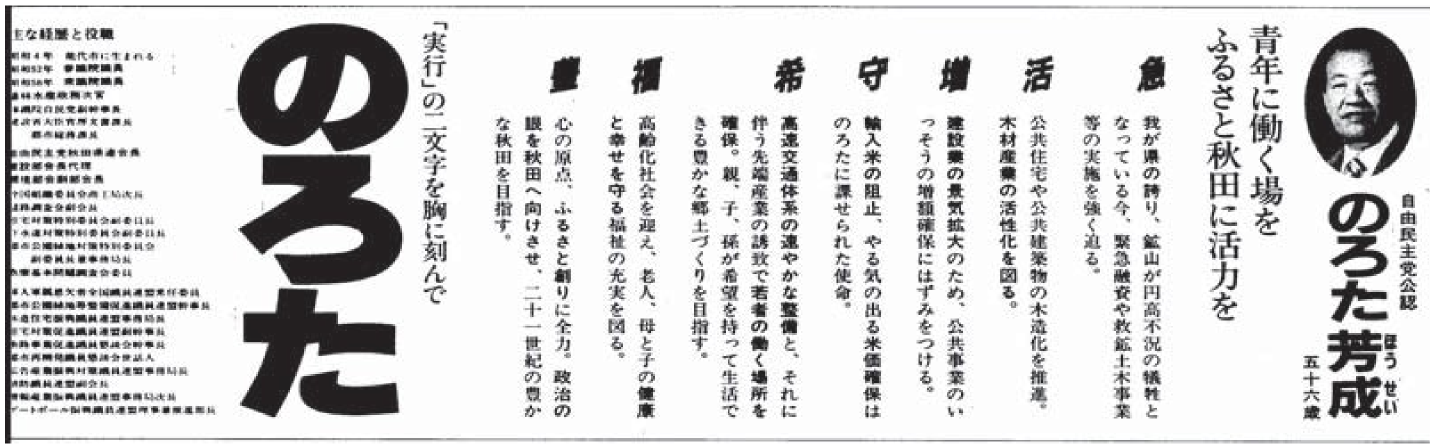

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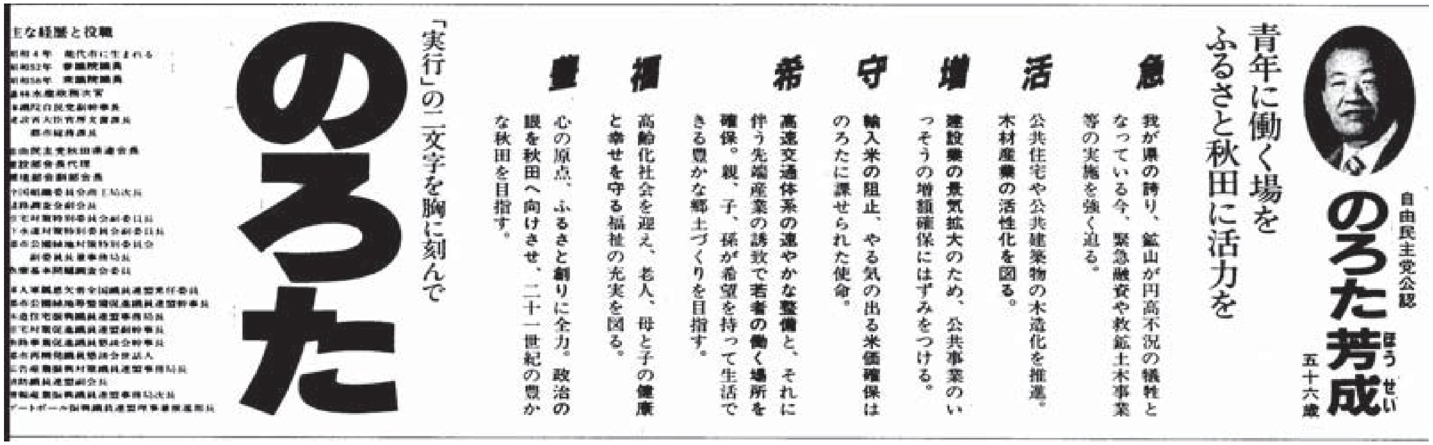
Manifestos



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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	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	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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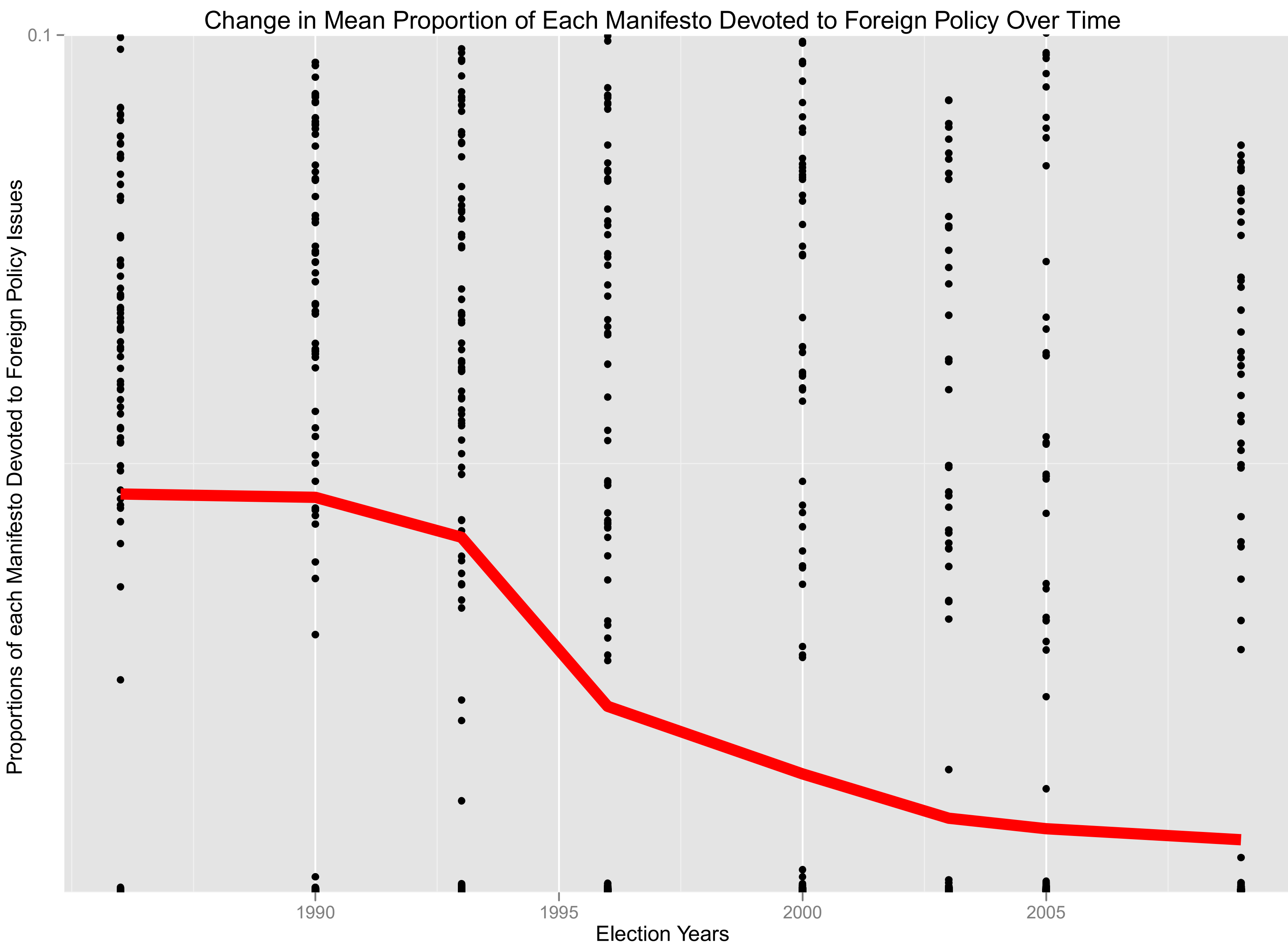

Change in proportion of 'Foreign Policy' Topic

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