9. Unsupervised Techniques III: Topic Models

DS-GA 1015, Text as Data
Arthur Spirling

April 6, 2021

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Topic models are algorithms for discovering the main themes that pervade a large and otherwise unstructured collection of documents.

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

Recall: Clustering

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Document 1 → Cluster K

Document 2

Document 3

$\vdots$

Document N

Cluster 1

Cluster 2

$\vdots$

Cluster K

Recall: Clustering

Document 1	
Document 2	Cluster 1
Document 3	Cluster 2
$\vdots$	$\vdots$
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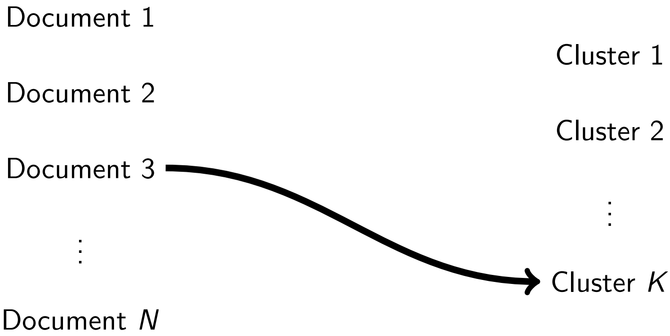
Recall: Clustering



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Topic Modeling

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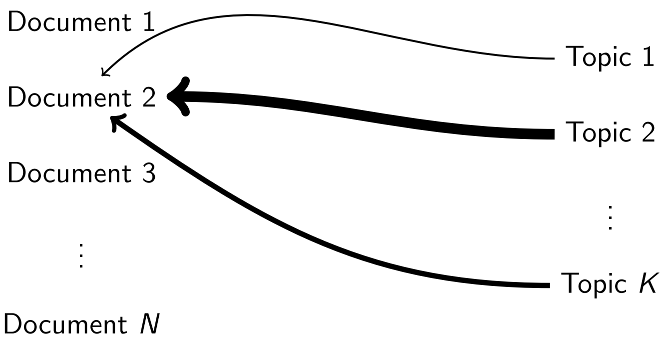
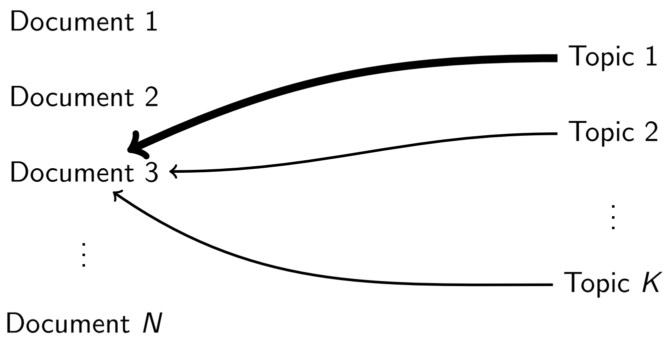


Topic Modeling



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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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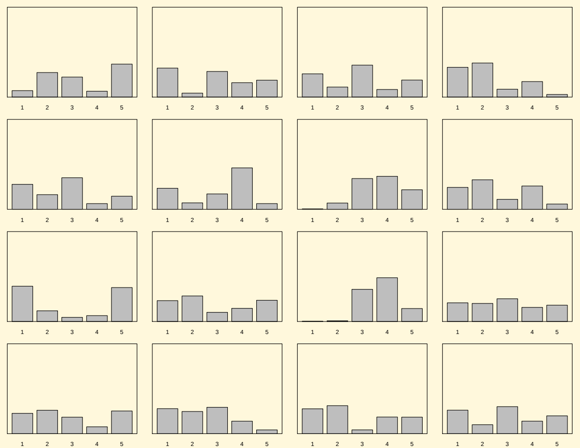

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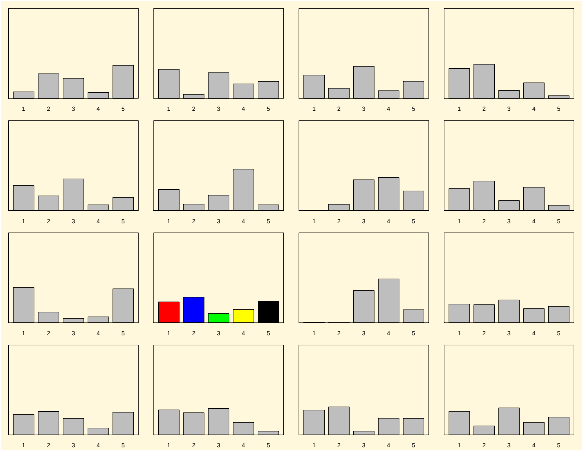

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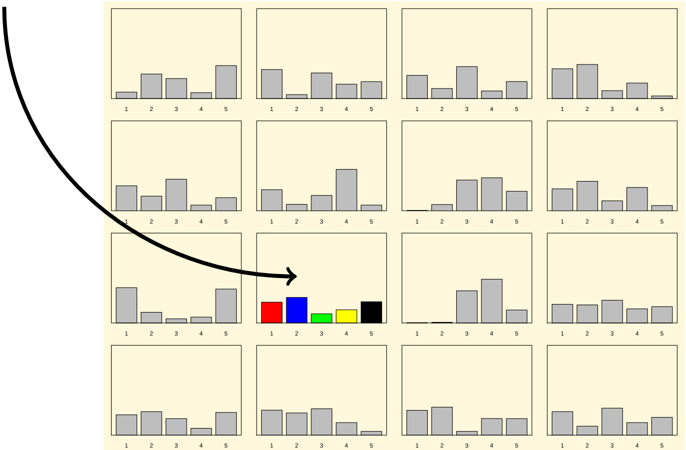

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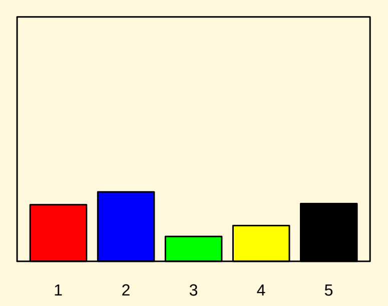

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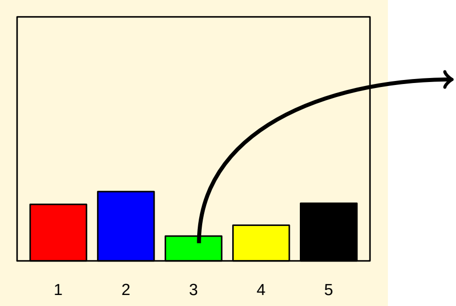

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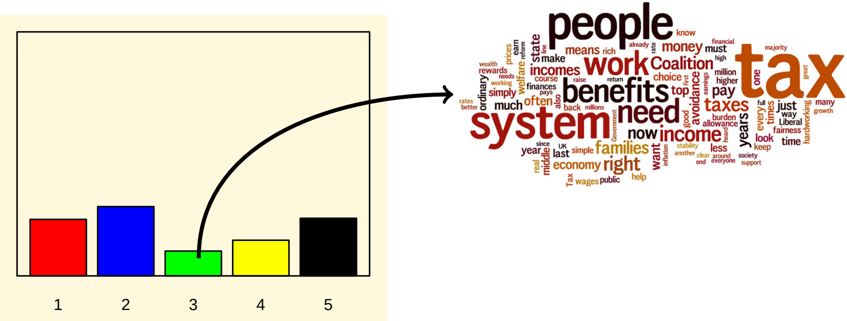

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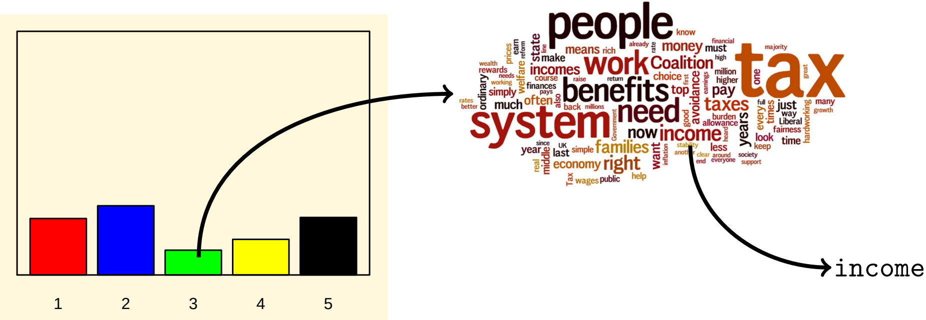

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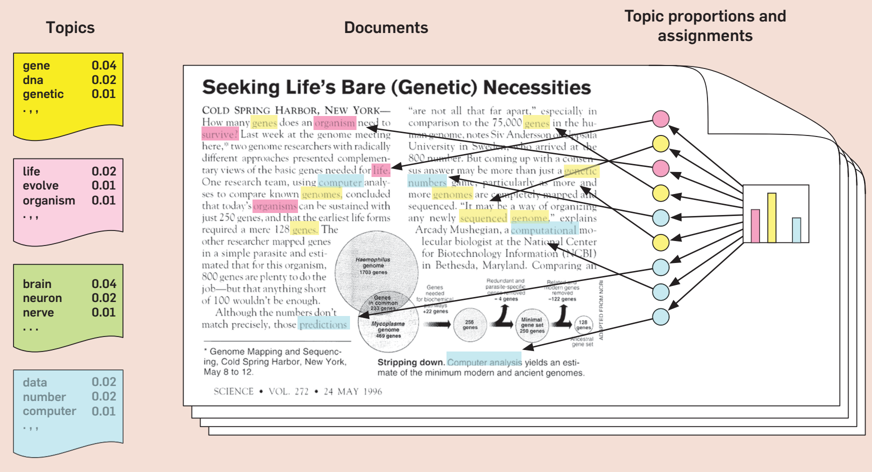

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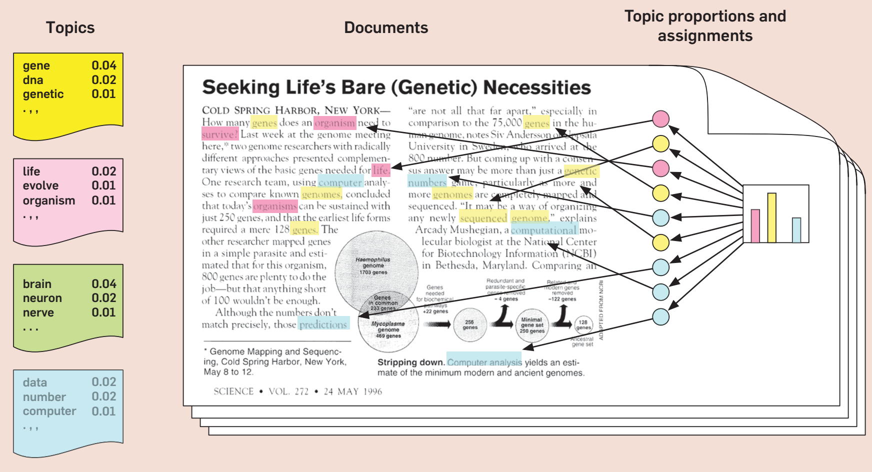

Note that all documents share same set of topics: but some (e.g. neuro) may be (basically) absent in a given document.

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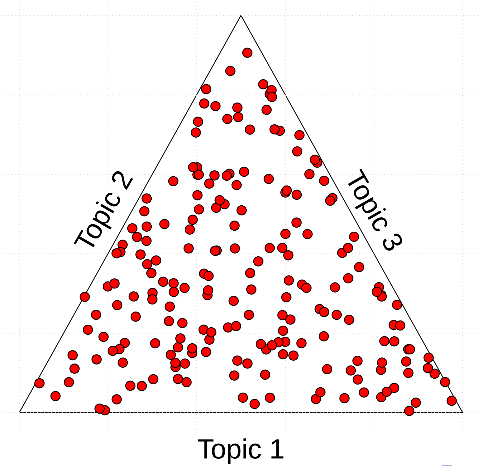
Larger values of α (assuming we are in symmetric case) mean we think (*a priori*) that documents are generally an even mix of the topics. If α is small (less than 1) we think a given document is generally from one or a few topics.

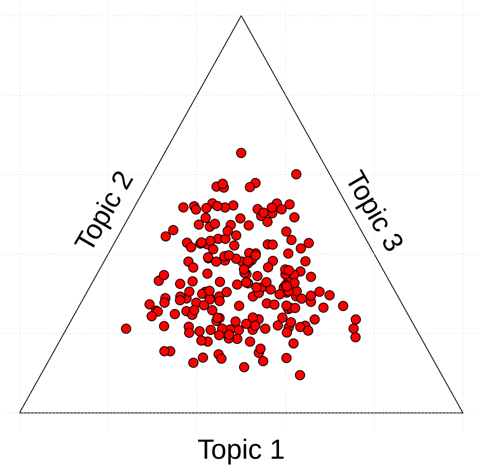
Example of Dirichlet

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



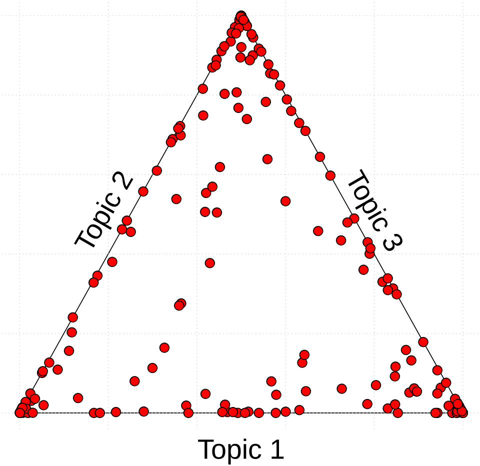
Example of Dirichlet

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

Plate Diagram for LDA

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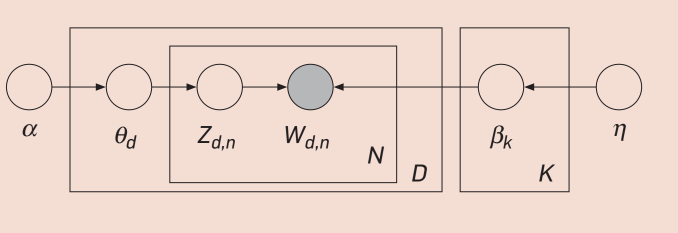

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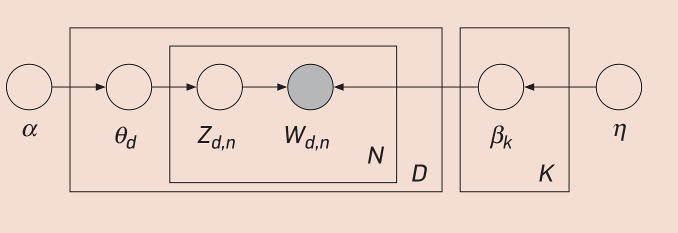

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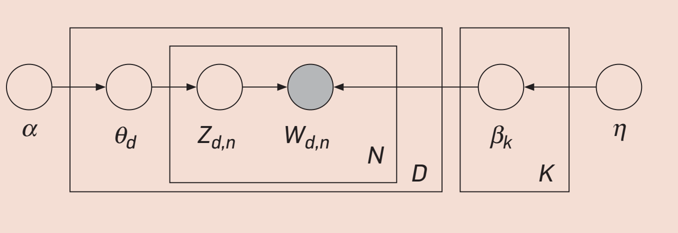

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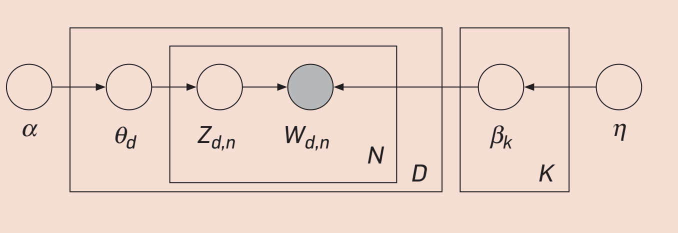

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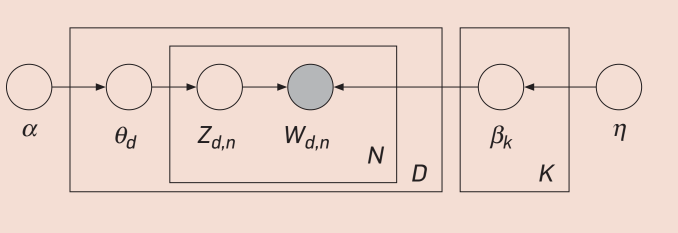

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Note that $w_{d,n}$ depends on $z_{d,n}$ (the mix of topics for that document) and $\beta_{1:K}$ (all the topics in terms of their distributions over the words).

Bayesian Inference: Crash Course/Reminder

Recall that. . .

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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 θ (weighted by how plausible each value is)

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Crash course complete: back to LDA

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Here (Blei, 2012), that is

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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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The word distribution for each topic.

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A Manifesto Example

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69 UK manifestos.

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69 UK manifestos. Some preprocessing.

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	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
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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
⋮	⋮	⋮	⋮	⋮	⋮

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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The topic distribution for each document. . .

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	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
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
⋮	⋮	⋮	⋮	⋮	⋮

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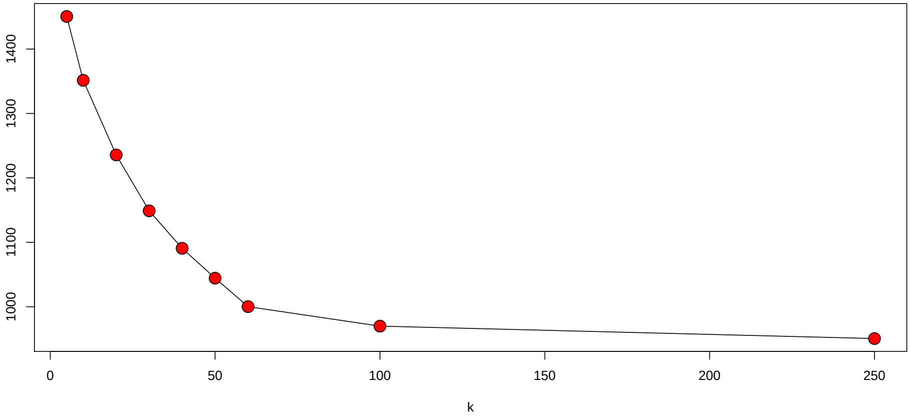
Perplexity Likes a Lot of Topics (manifestos)



Pork to Policy (Catalinac, 2016)

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Manifestos

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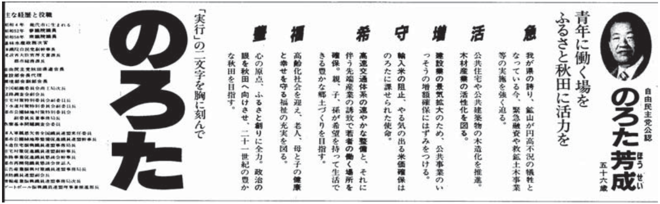

自由民主党公認
のろた芳成（ほうせい）
五十六歳

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
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「実行」の二文字を胸に刻んで

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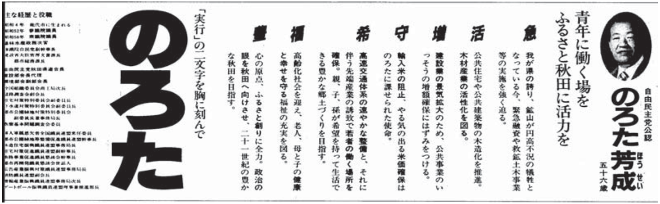
主な経歴と役職

Manifestos



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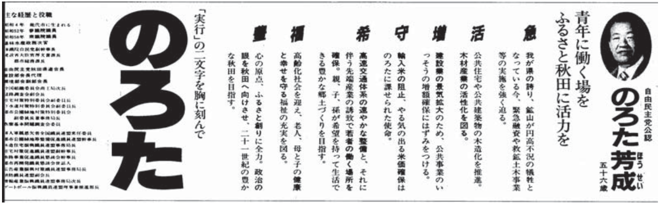

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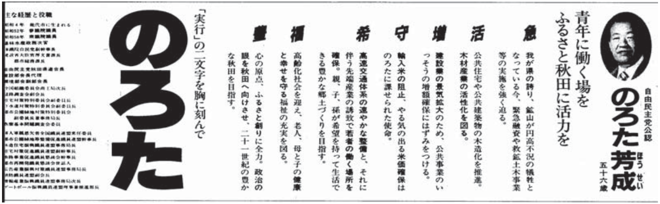
7,497. 1986–2009.

Manifestos



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

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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。

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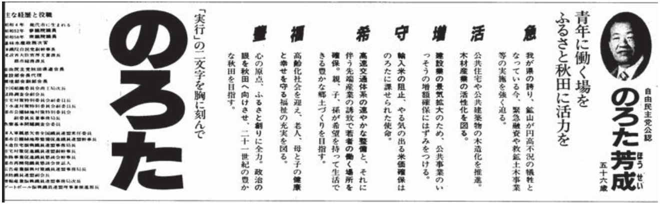

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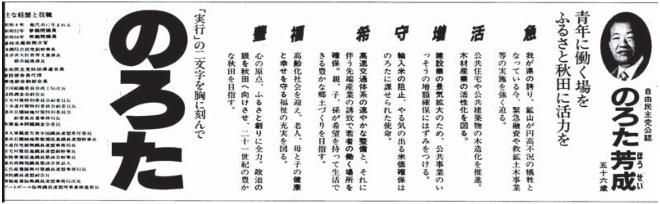

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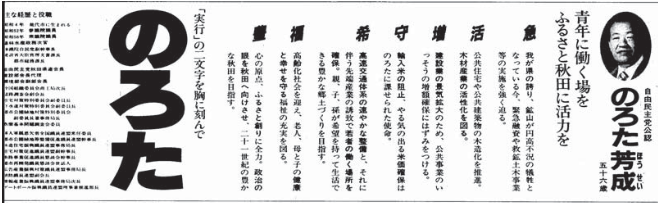

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主な経歴と役職
昭和4年 能代市に生まれる
昭和52年 参議院議員
昭和58年 衆議院議員

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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	改憲	基本

Change in proportion of ‘Pork’ Topic

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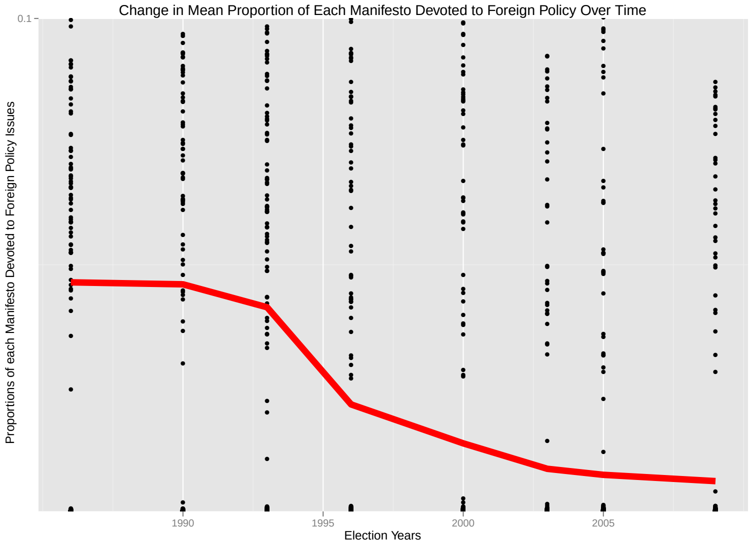

Change in proportion of 'Foreign Policy' Topic

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