An Introduction to Analyzing Political Texts
Part II

Arthur Spirling

New York University

November 15, 2019

Where Are We?

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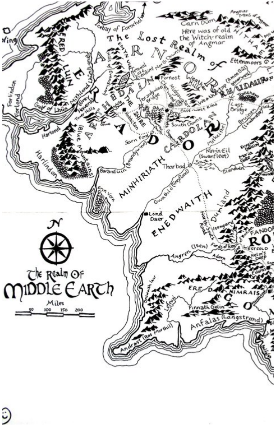
The Lost Realm of
ARNOR
Here was of old the Witch-realm of Angmar
Carn Dûm
Angmar
Ettenmoors
Weather Hills
Fornost
North Downs
RHUDAUR
Last Bridge
Bree
East-West Road
South Downs
THE SHIRE
Hobbiton
Brandywine Bridge
ARTHEDAIN
CARDOLAN
Sarn Ford
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
MINHIRIATH
Forlindon
Forlond
Gulf of Lhûn
Grey Havens
Mithlond
Harlond
Harlindon
Blue Mountains
Baranduin
Eryn Vorn
Lond Daer
ENEDWAITH
Dunland
Isengard
FANGORN
Fords of Isen
Isen
Angren
Adorn
WESTFOLD
Helm's Deep
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Lefnui
Druwaith Iaur
The Realm Of
MIDDLE EARTH
Miles
50 100 150 200

Where Are We?



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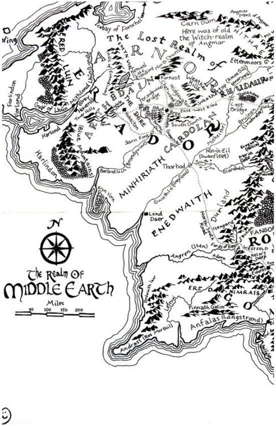

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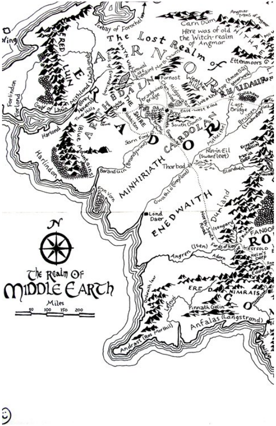

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$\rightarrow$ simple, fast dictionary based ways to classify/categorize

and move on to supervised and unsupervised learning problems.

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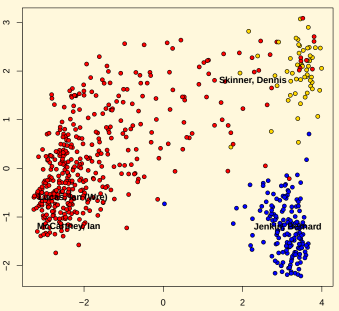

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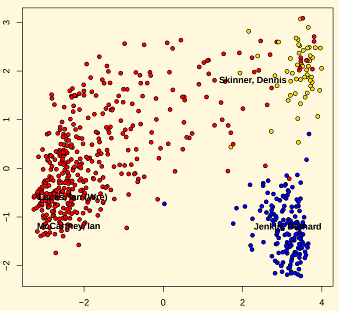

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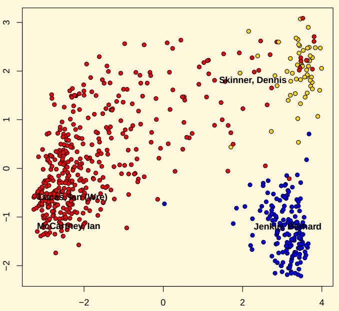

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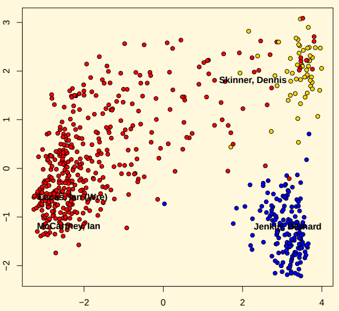

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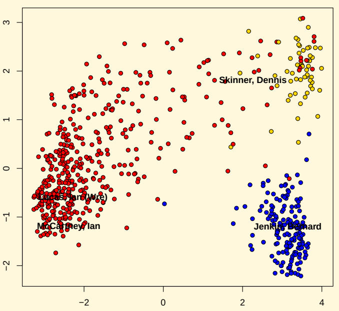

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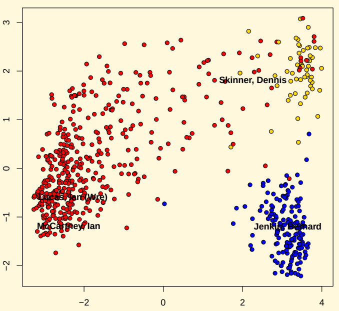

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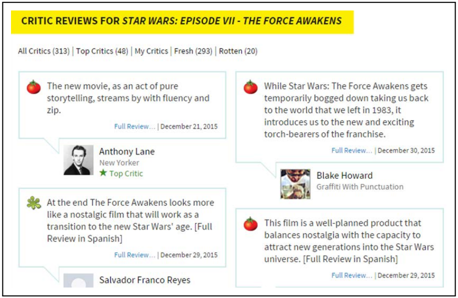

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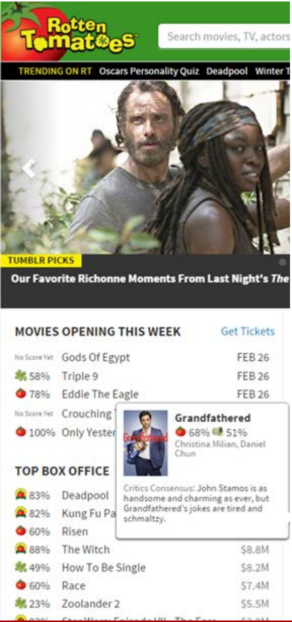

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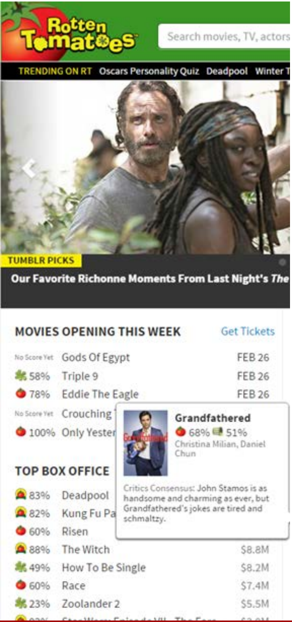

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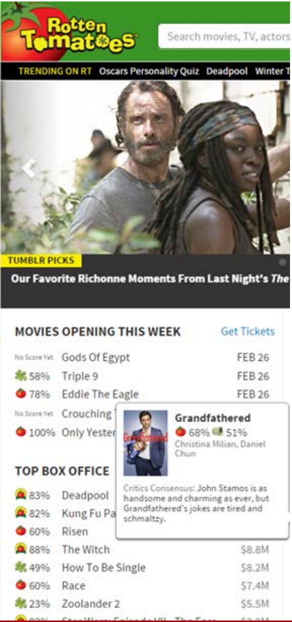

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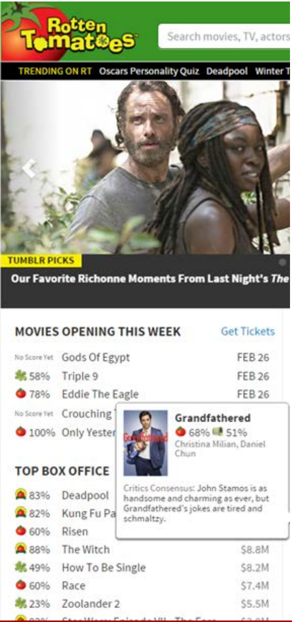

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3 Why might be generally nervous about BOW approaches?

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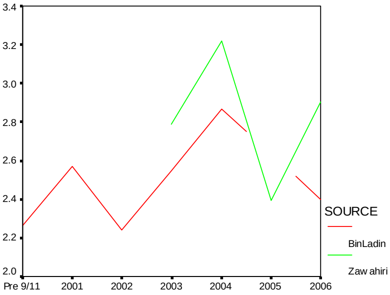
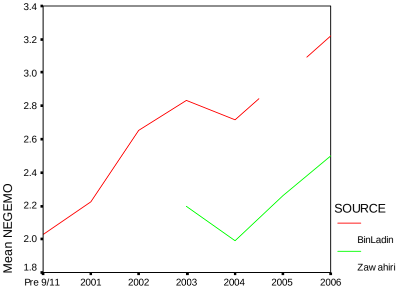


D. Negative emotion (hate, sad)



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Supervised Learning

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→ LBG suggest a way of scoring documents in a "naive Bayes" style, so that we can answer such questions.

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3 Score the virgin texts (test set) of texts using those word scores, possibly transform virgin scores to original metric.

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NB any new words in the virgin document that were *not* in the reference texts are ignored: the sum is only over the words we've seen in the reference texts.

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$\rightarrow$ can rescale these back to original $(-1, 1)$ dimension.

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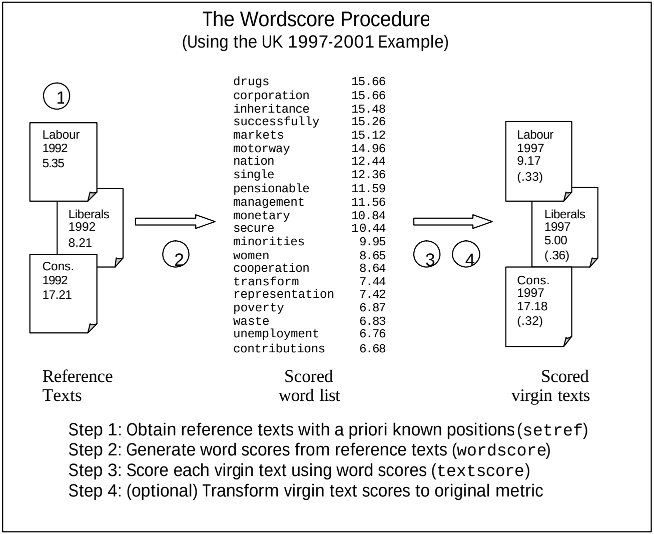

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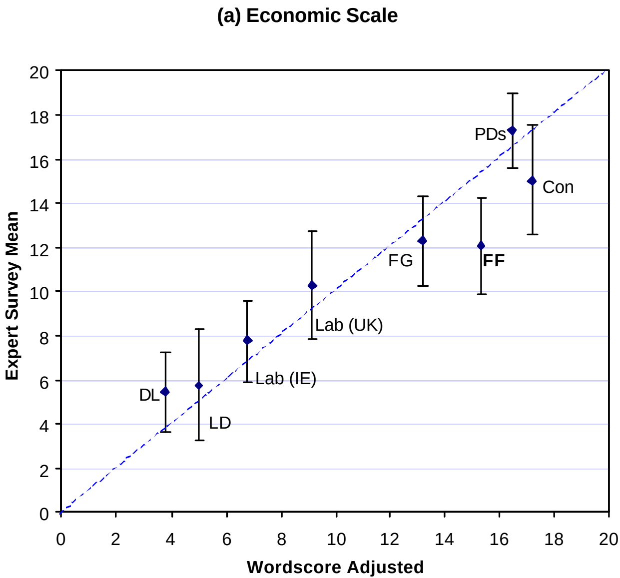

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Topic Models

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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?"

Topic Modeling

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Document 2

Document 3

$\vdots$

Document N

Topic 1

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$\vdots$

Topic K

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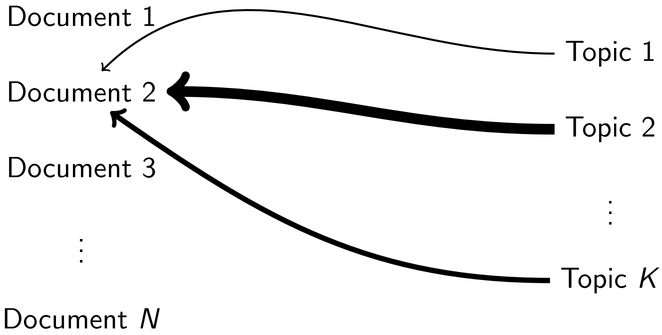

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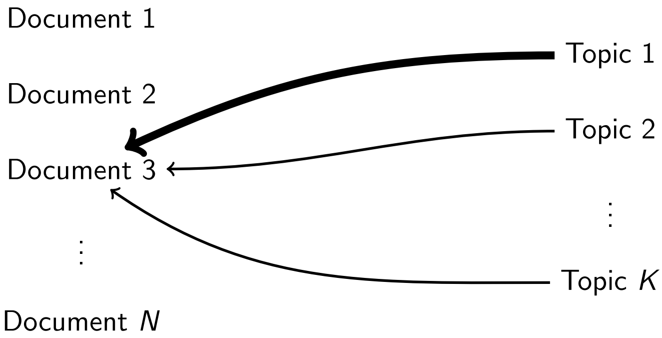

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Now, where do the words in the documents come from?

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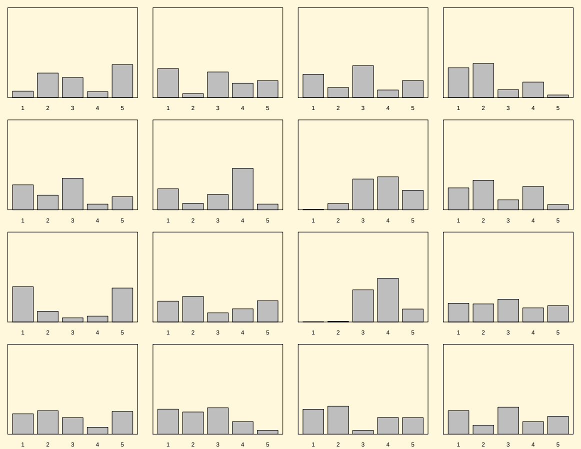

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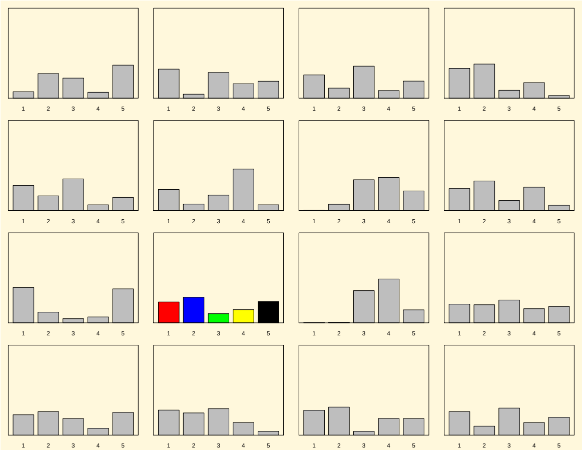

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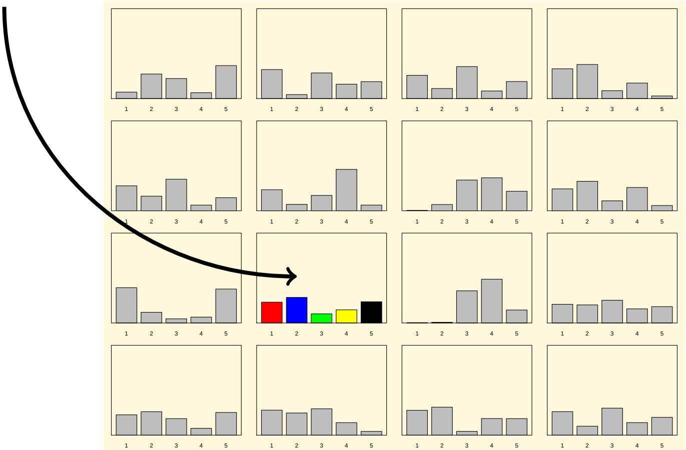

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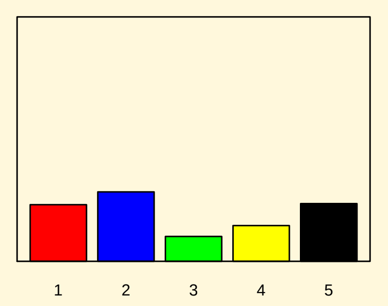

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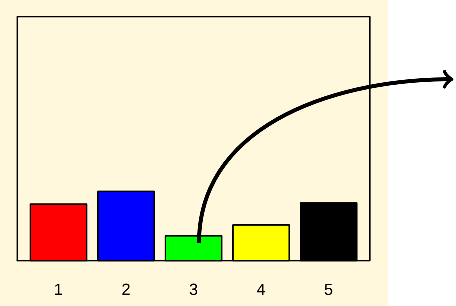

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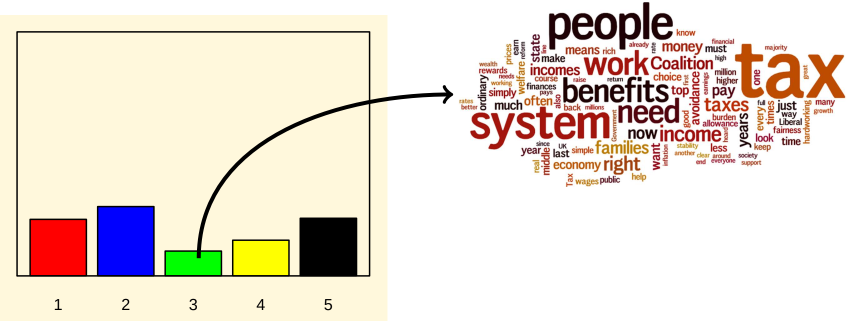

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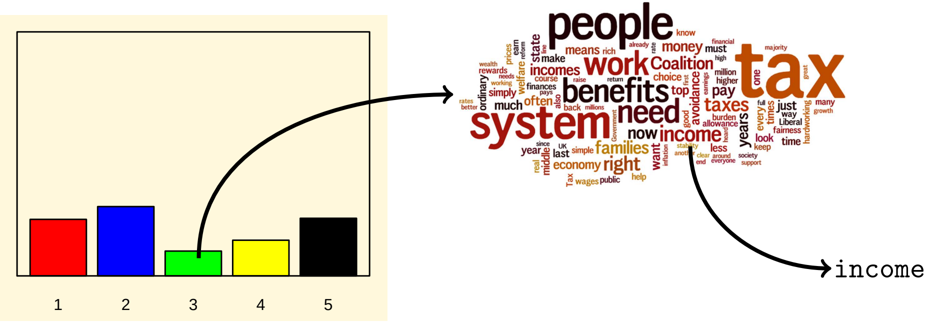

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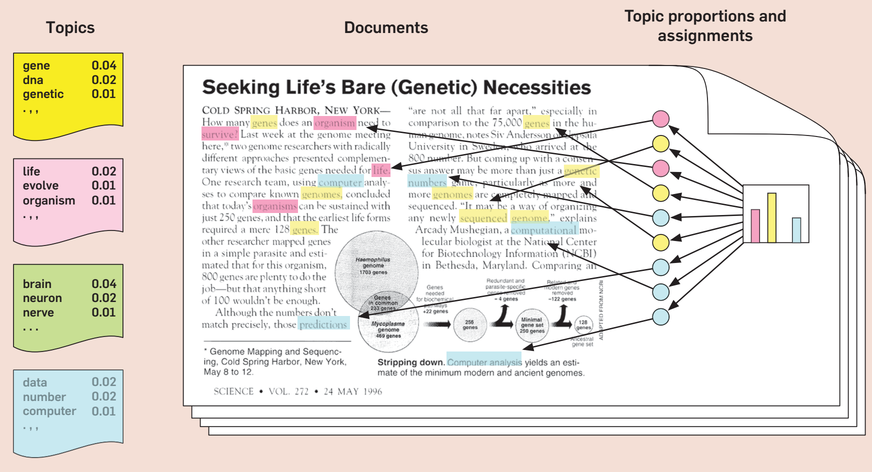

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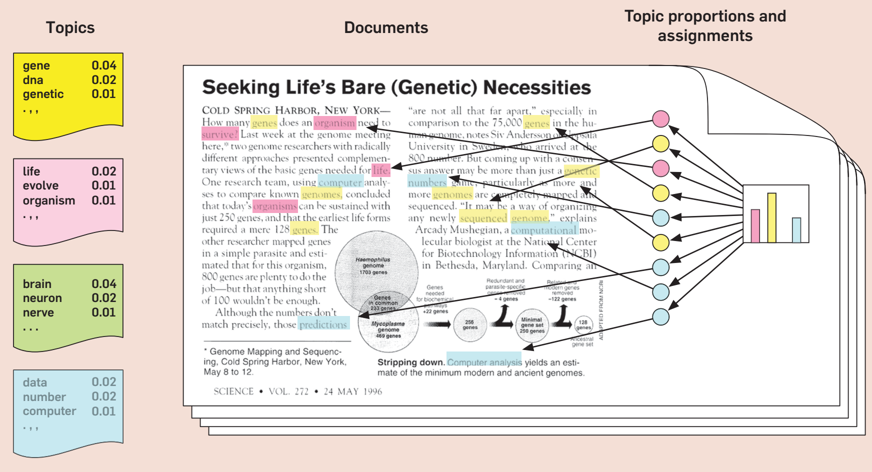

Note that all documents share same set of topics: but some (e.g. neuro) may be (basically) absent in a given document.

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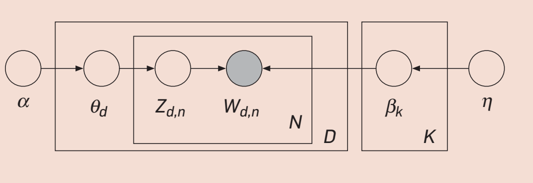

This is a complicated estimation problem, so we typically simulate/approximate the solution.

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A Manifesto Example

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69 UK manifestos.

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

Continued. . .

Continued…

'Top' 6 most frequent words in each topic:

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	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
1	people	new	[markup]	new	must
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3	government	people	new	government	labour
4	new	continue	work	people	shall
5	tax	can	[markup]	shall	can
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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
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Continued

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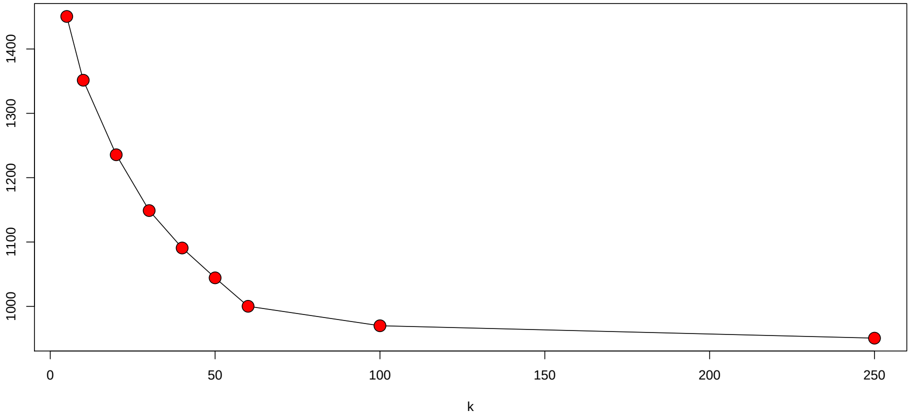
Perplexity Likes a Lot of Topics (manifestos)



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Manifestos

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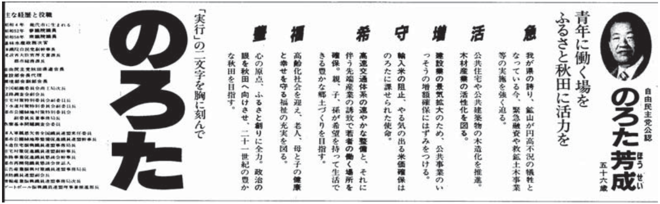


自由民主党公認
のろた芳成（ほうせい）
五十六歳

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。

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。

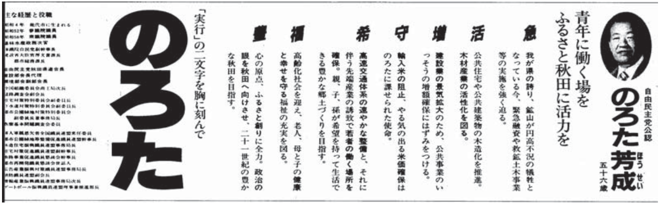
福
高齢化社会を迎え、老人、母と子の健康と幸せを守る福祉の充実を図る。

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
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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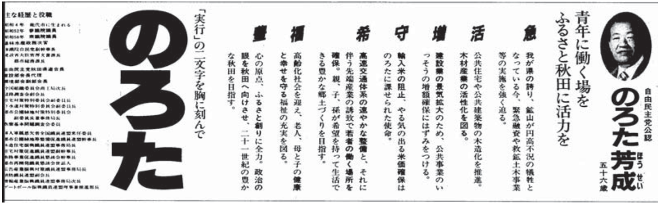

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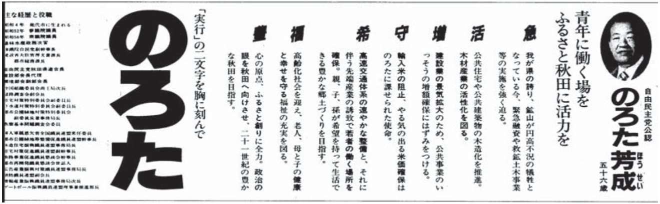
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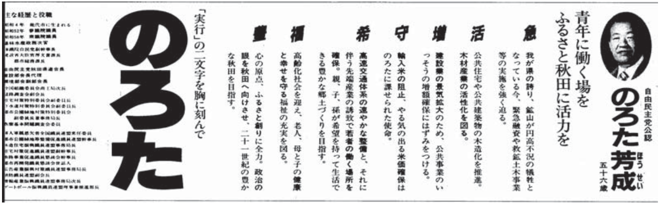
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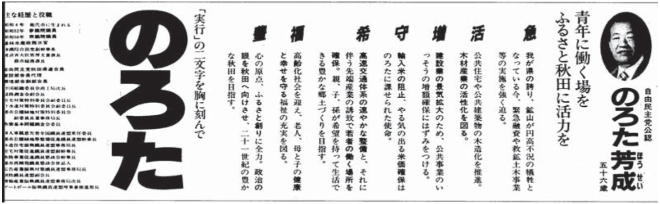

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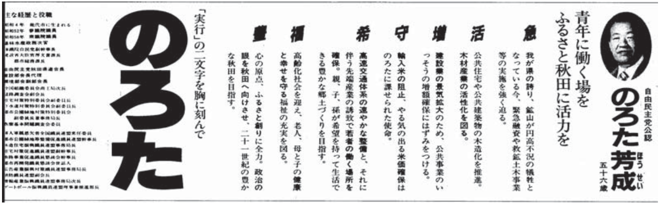
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Topic Distribution over Words

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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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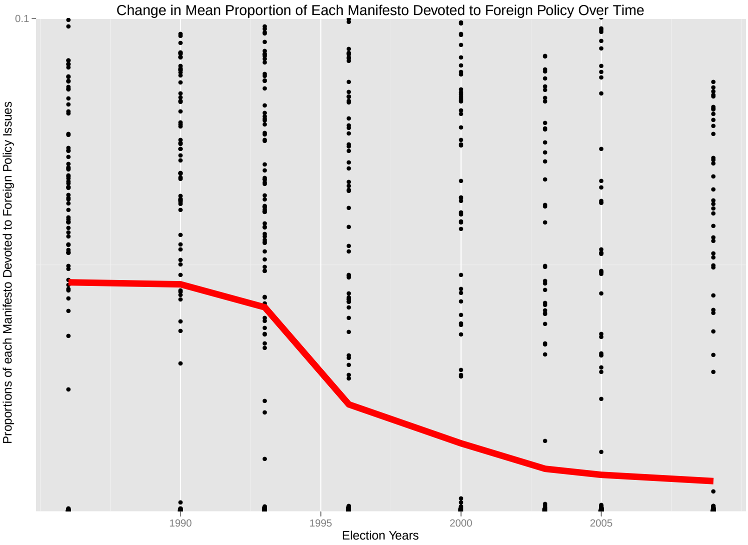

Change in proportion of 'Foreign Policy' Topic

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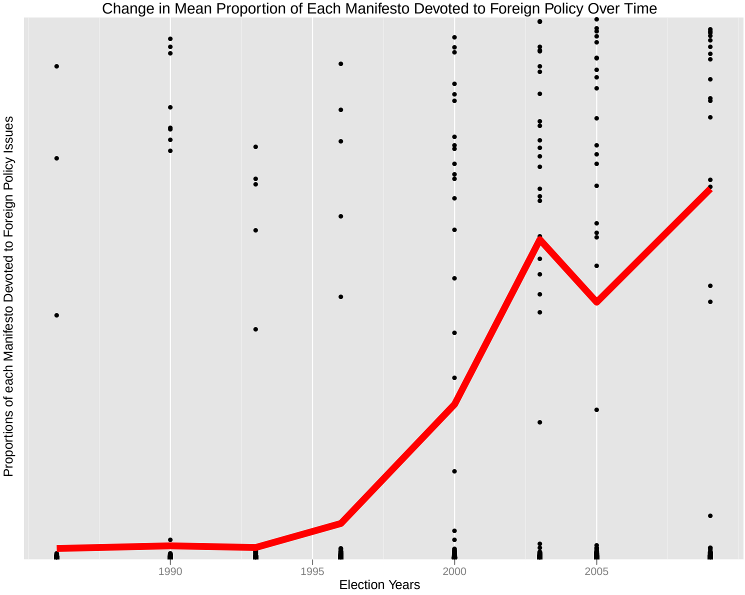

Special Topics: Structural Topic Model

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Also allows us to 'test' hypothesis in more sensible way (though be careful!)

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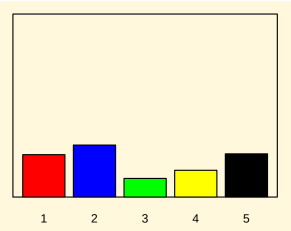

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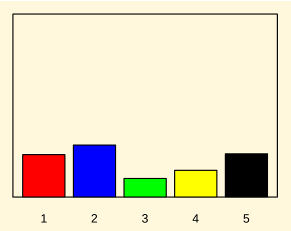

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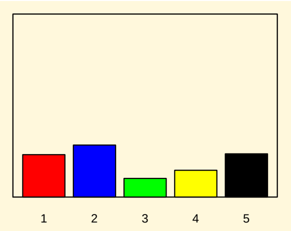

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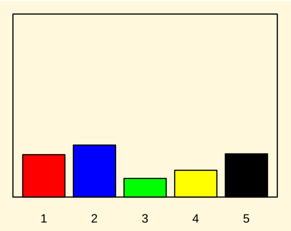

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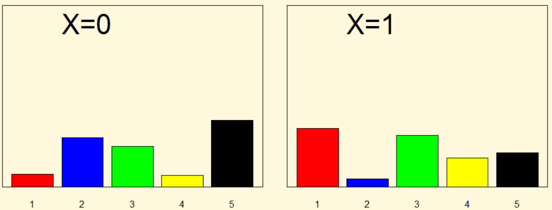

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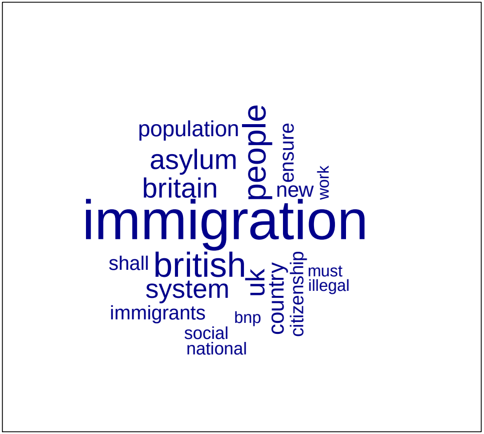

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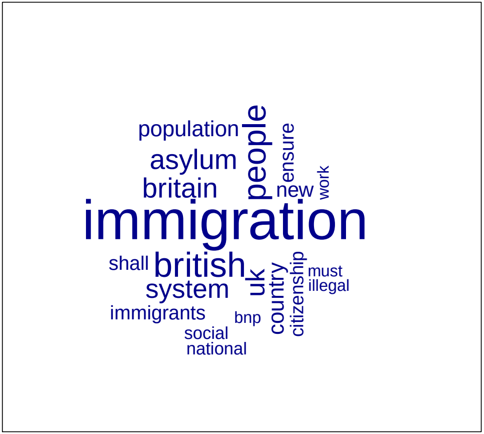

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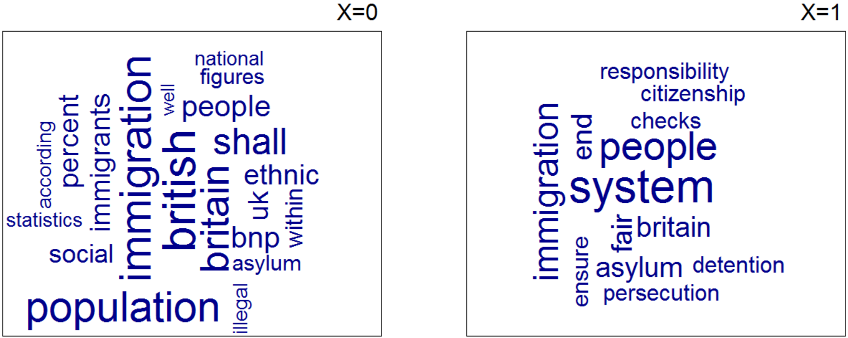

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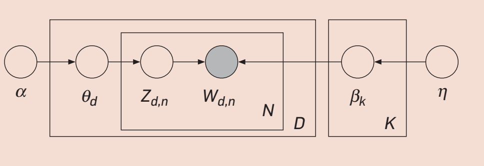

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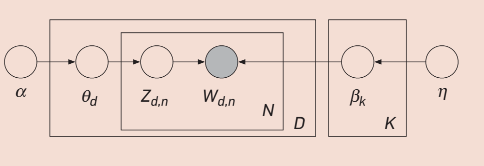

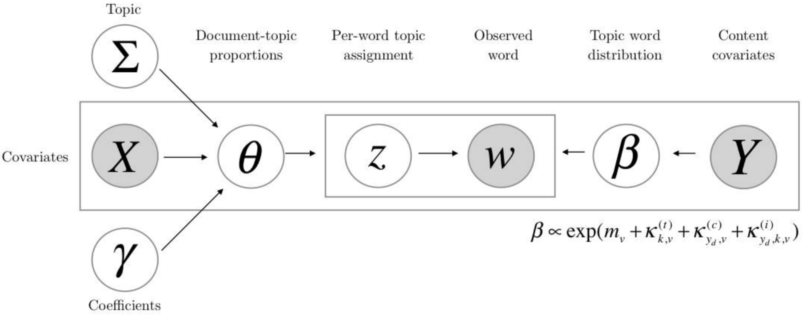

More Slides: Naive Bayes

Naive Bayes Classification

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$\rightarrow$ fast, simple, accurate, efficient and therefore popular.

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Set up

We're interested in the probability that an email is in a given category, given its features—i.e. frequency of terms.

The conditional probability of a term t_k occurring in a document, given that document is of class c, is $= \Pr(t_k|c)$

e.g. probability of seeing '`beneficiary`' in a spam email might be 0.9, because a lot of spam emails use that term.

NB we are assuming terms basically occur randomly throughout the document/no position effects

We can write the probability that a given email d contains all the terms, if it's from a class c, as

$$\Pr(d|c) = \prod_{k=1}^{K} \Pr(t_k|c)$$

but this is not what we want: we want $\Pr(c|d)$.

Reminder: Bayes' Theorem

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$$\Pr(A|B) \propto \Pr(A)\Pr(B|A)$$

Here, $\Pr(A)$ is our prior for A, while $\Pr(B|A)$ will be the likelihood for the data we saw.

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3 A subject claims to have psychic abilities—he can tell you how a (fair) coin will come down in nine tosses. He has less than a $\frac{1}{500}$ chance of being correct by chance, but he succeeds in the task! Do you 'update' that he has psychic abilities? Why or why not?

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where $\Pr(c)$ is the prior probability of a document occurring in class c; and $\Pr(t_k|c)$ is interpreted as "measure of the how much evidence t_k contributes that c is the correct class"

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$$\rightarrow \boxed{c_{map} = \text{spam}}$$

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1. Why does this happen?
2. What does this imply about the relationship between estimation ('modeling') and accuracy?

Example: Jihadi Clerics

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Indonesian cleric's support for ISIS increases the security threat

July 20, 2014 10.14pm EDT

Noor Huda Ismail
PhD Candidate in Politics and International Relations , Monash University

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Can assign a *Jihad Score* to each document: basically the logged likelihood ratio, $\sum_i \log \frac{\Pr(t_k|\text{Jihad})}{\Pr(t_k|\neg \text{ Jihad})}$ (note: doesn't know what 'real world' priors are, so drops them here)

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Then for each cleric, concatenate all works into one and give this 'document'/cleric a score.

Discriminating Words

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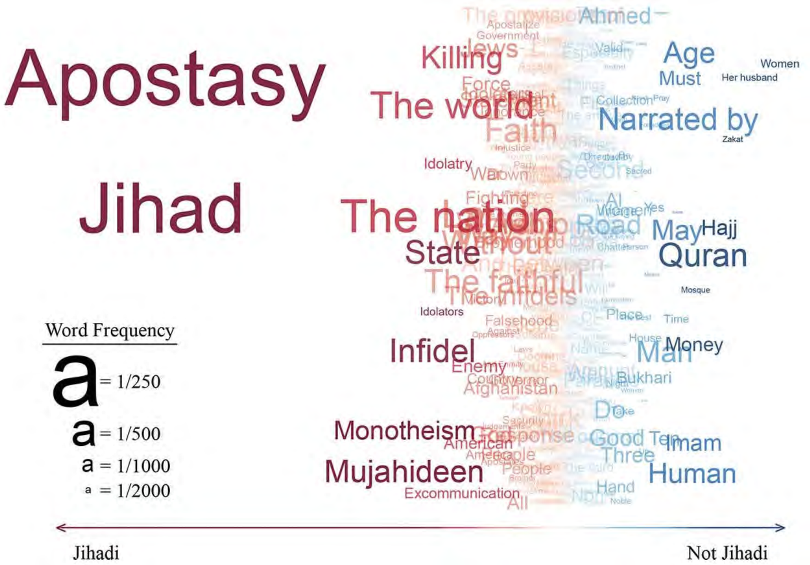

Validation: *Exoneration*

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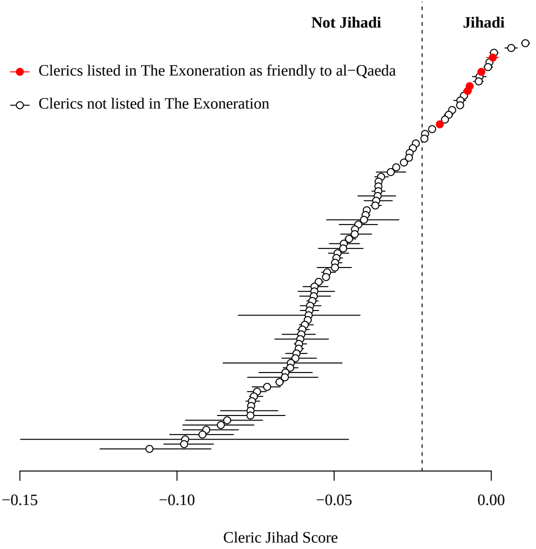

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*