University of Tokyo: Text-as-Data
Day 2, Part I

Arthur Spirling

June 4, 2017

Where Are We?

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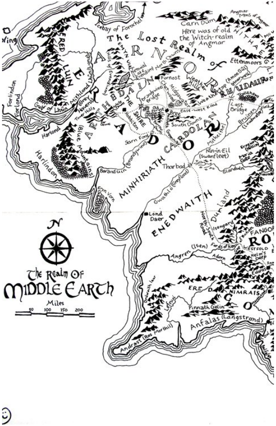
The Lost Realm of
ARNOR
Carn Dûm
Here was of old the Witch-realm of Angmar
Angmar
Ettenmoors
Forlindon
Forlond
Gulf of Lhûn
Grey Havens
Mithlond
Harlond
Harlindon
Blue Mountains
ERED LUIN
ERIADOR
ARTHEDAIN
THE SHIRE
Fornost
Weather Hills
Weathertop
RHUDAUR
Trollshaws
Last Bridge
East-West Road
Bree
South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

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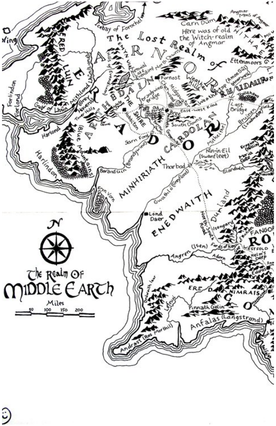

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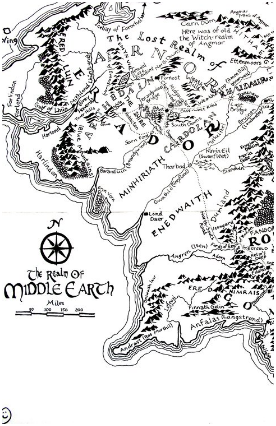

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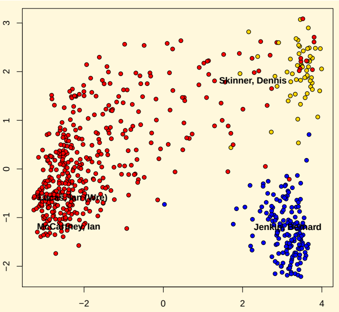

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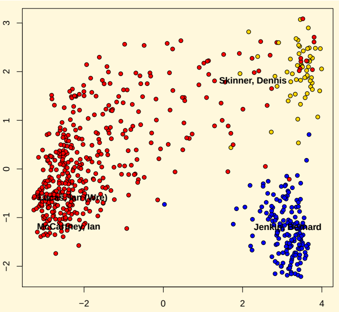

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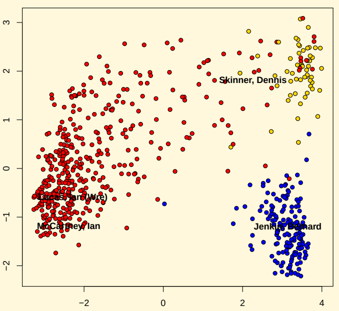

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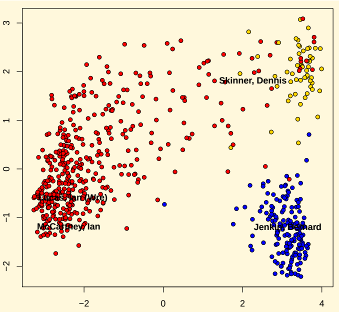

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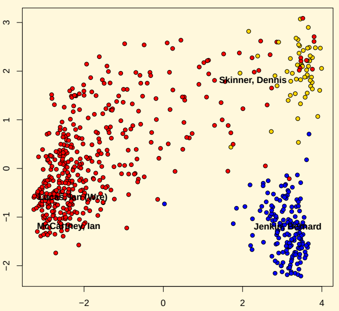

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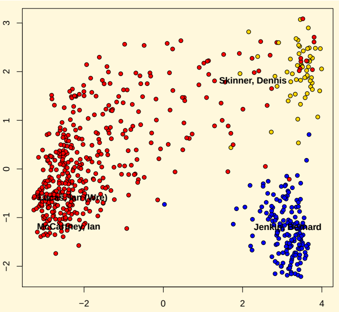

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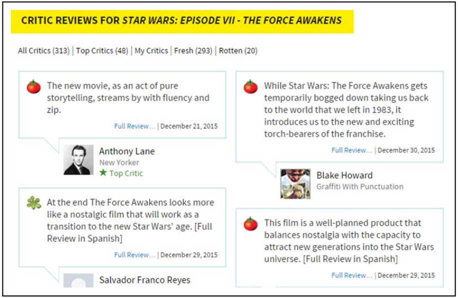

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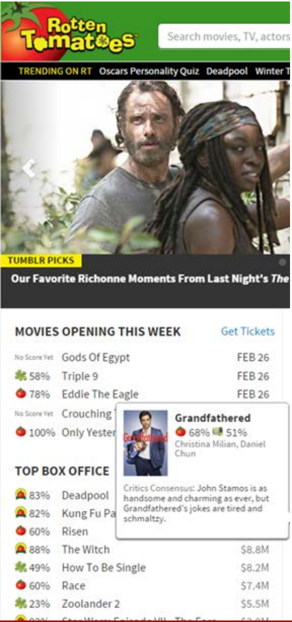

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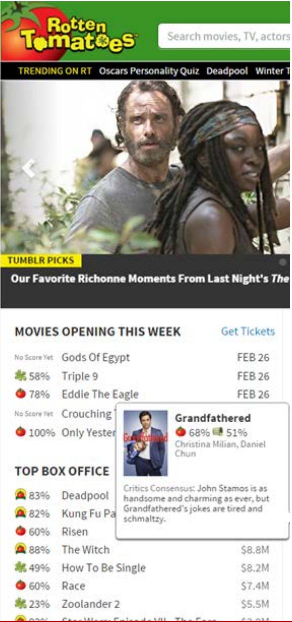

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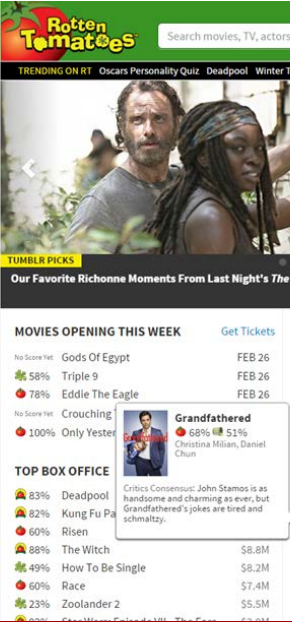

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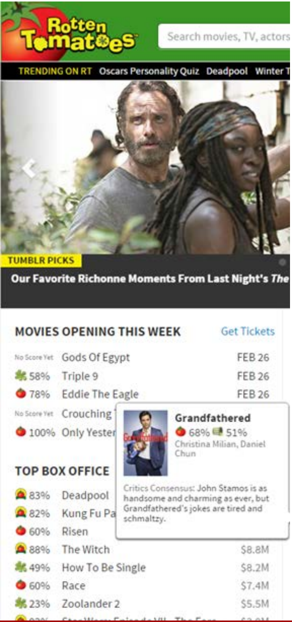

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3. Why might be generally nervous about BOW approaches?

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- Semin and Fielder categories: interpersonal/pyschological properties of words

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Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
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General Inquirer (selected)

Entry	Source	Positiv	Negativ	Pstv	Affil	Ngtv	Hostile	Strong	Power
ABILITY	H4Lvd	Positiv						Strong	
ABJECT	H4		Negativ						
ABLE	H4Lvd	Positiv		Pstv				Strong	
ABNORMAL	H4Lvd		Negativ			Ngtv			
ABOARD	H4Lvd								
ABOLISH	H4Lvd		Negativ			Ngtv	Hostile	Strong	Power
ABOLITION	Lvd								
ABOMINABLE	H4		Negativ					Strong	
ABRASIVE	H4		Negativ				Hostile	Strong	
ABROAD	H4Lvd								
ABRUPT	H4Lvd		Negativ			Ngtv			
ABSCOND	H4		Negativ				Hostile		
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e.g. ADULT has two meanings: one is a ‘virtue’, one is a ‘role’

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Vice	1.7%	1.1%
Overstated	5.6%	3.9%
Understated	0.6%	2.5%

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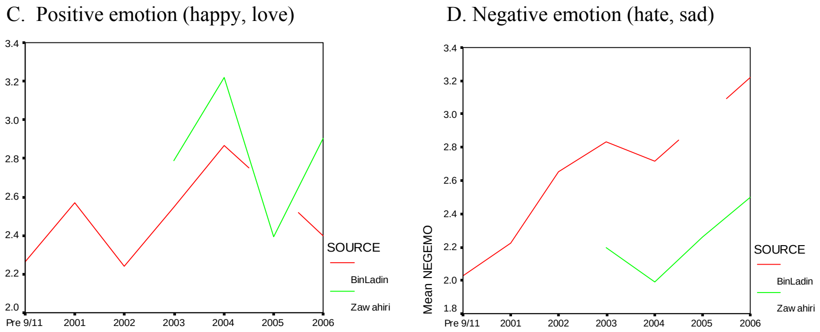

Application: Ramey, Klinger & Hollibaugh

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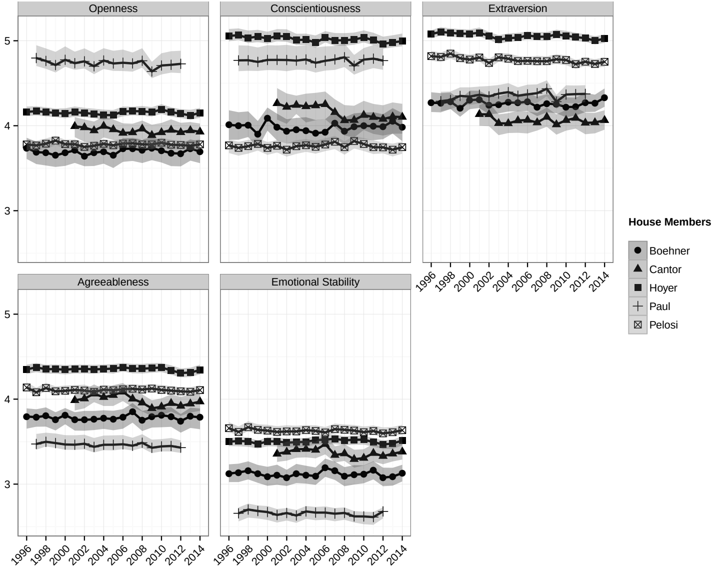

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1 1 1 ECONOMY/+State+/Budget
Budget

1 1 1 1 ECONOMY/+State+/Budget/Spending
Increase public spending

1 1 1 1 1 ECONOMY/+State+/Budget/Spending/Health

1 1 1 1 2 ECONOMY/+State+/Budget/Spending/Educ. and training

Dictionaries IV: Hu & Liu

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1,036 of 1,144 people found the following review helpful

★★★★★ **With Great Powers Comes Great Responsibility**

By Tommy H. on July 17, 2009

I admit it, I'm a ladies' man. And when you put this shirt on a ladies' man, it's like giving an AK-47 to a ninja. Sure it looks cool and probably would make for a good movie, but you know somebody is probably going to get hurt in the end (no pun intended). That's what almost happened to me, this is my story...

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btw humans *not* very good at producing discriminating terms for e.g. opinion mining (Pang et al, 2002)

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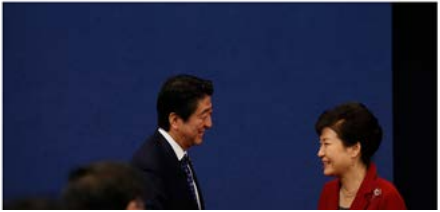
点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015



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120: Reject, not specified below

121: Reject material cooperation

- 1211: Reject economic cooperation
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CAMEO	**1222**
Name	**Reject request for military aid**
Description	Refuse to extend military assistance.
Example	The Turkish government has refused to commit to any direct assistance to the US-led war against Iraq, citing domestic opposition.

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UIG	Uighur (Chinese ethnic minority)
UIS	Unidentified state actors
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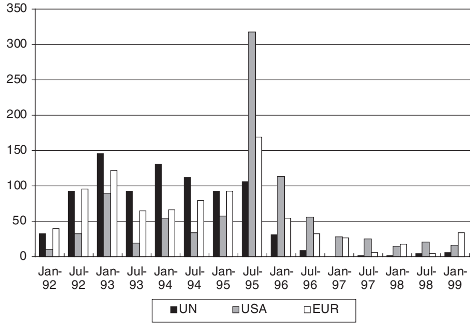

Figure 3: Six-Month Totals of Mediation Events in the Balkans by Mediator
NOTE: UN = United Nations; USA = United States; EUR = major European states, plus the European Union.

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→ previous approaches tend to overfit to obscure words or groups that don't have much validity in context.

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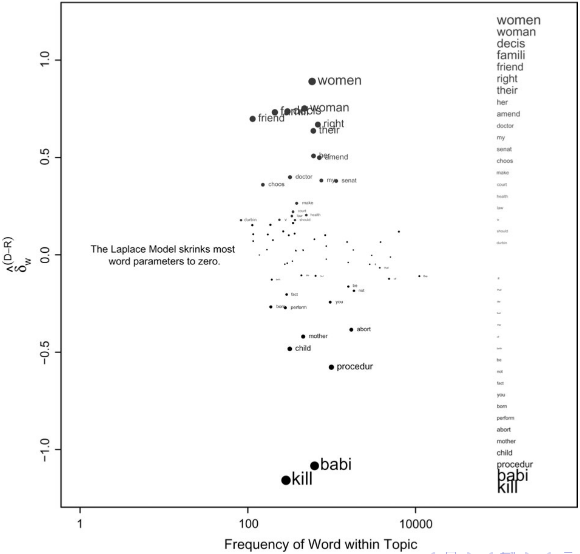

Supervised Learning

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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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Example

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training	1	money inherit prince	spam
	2	prince inherit amount	spam
	3	inherit plan money	ham
	4	cost amount amazon	ham
	5	prince william news	ham
test	6	prince prince money	?

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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?

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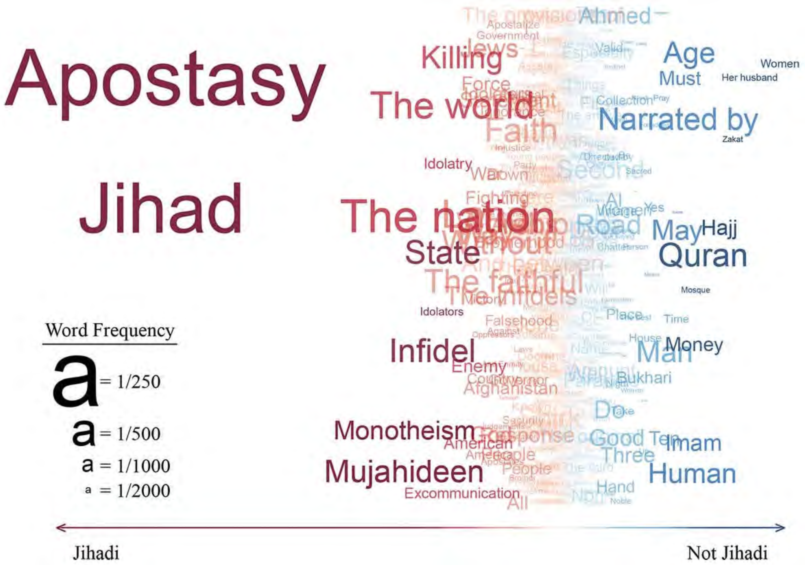
Then for each cleric, concatenate all works into one and give this 'document'/cleric a score.

Discriminating Words


Apostasy
Jihad
Killing
The world
Faith
Idolatry
The nation
State
The faithful
Idolators
Falsehood
Infidel
Enemy
Afghanistan
Monotheism
American
Mujahideen
Excommunication
Ahmed
Age
Must
Women
Her husband
Narrated by
Zakat
Road
May
Hajj
Quran
Mosque
Place
Time
Money
Man
Bukhari
Imam
Three
Human
Hand
Word Frequency
a = 1/250
a = 1/500
a = 1/1000
a = 1/2000
Jihadi
Not Jihadi

Validation: *Exoneration*

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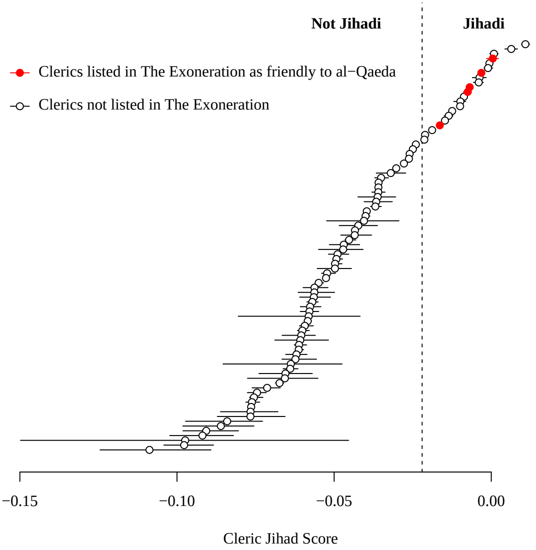

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*

Wordscores (Laver, Benoit & Garry, 2003)

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

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e.g. we find a 'left' document and give it score -1; and a 'right' document and give it score 1

2. Generate word scores from these reference texts

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

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$$P_{iR} = \frac{\frac{f_{iR}}{W_R}}{\frac{f_{iR}}{W_R} + \frac{f_{iL}}{W_L}}$$

Scoring the words

Suppose we have a given reference document R, which is scored as $A_R = 1$. E.g. Neo-Nazi manifesto.

In document R, count the number of times word i occurs, denote as f_{iR}. Also record the total number of words in document R, and denote as W_R .

Do the same for Communist party manifesto L, which we score as $A_L = -1$. Then calculate f_{iL} and W_L.

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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.

New Labour Moderates its Economic Policy

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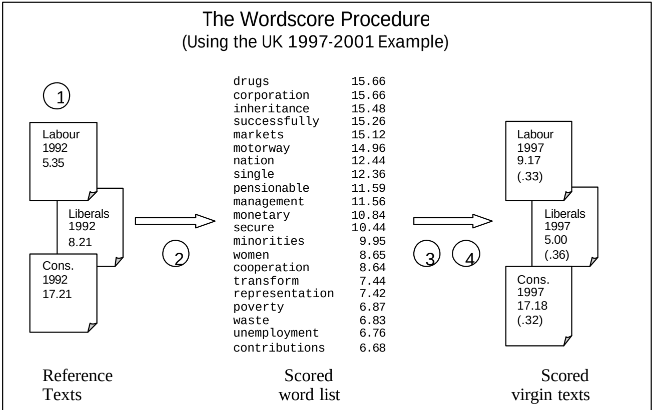

Step 1: Obtain reference texts with a priori known positions (`setref`)
Step 2: Generate word scores from reference texts (`wordscore`)
Step 3: Score each virgin text using word scores (`textscore`)
Step 4: (optional) Transform virgin text scores to original metric

Compared to Expert Surveys

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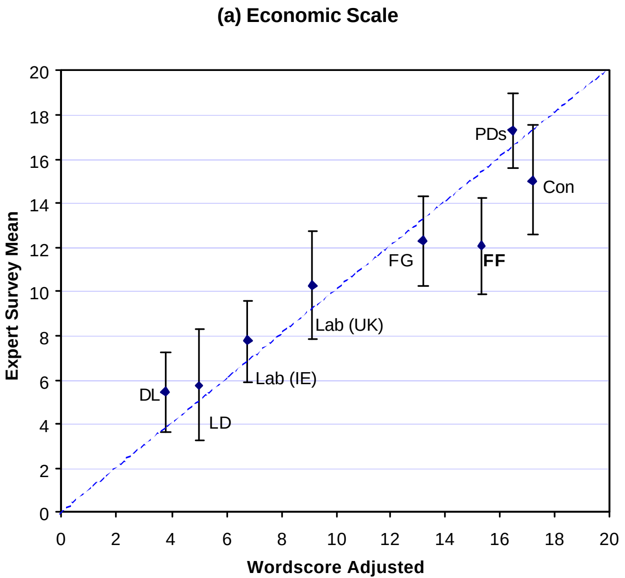

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while Beauchamp (2011) provides comparison and extension to more purely Bayesian approach.

Special Topic: Estimating Proportions

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$\rightarrow$ would like unbiased approach (and be nice if non-parametric), that avoids the intermediate step of document classification.

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NB "*among all documents in a given category, the prevalence of particular word profiles in the labeled set should be the same in expectation as in the population set*". This is key assumption. btw, what happened to the danger of drift?!

Performance: Congress, Editorials, Enron

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FIGURE 4 Additional Out-of-Sample Validation