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

Arthur Spirling

June 4, 2017

Where Are We?

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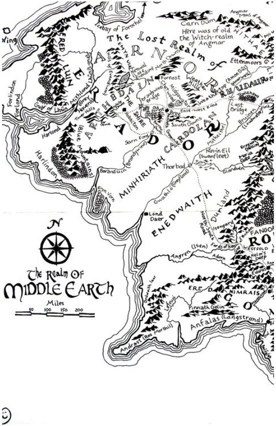
The Lost Realm of
Carn Dûm
Here was of old the Witch-realm of Angmar
Angmar
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Last Bridge
East-West Road
Bree
South Downs
Brandywine Bridge
Hobbiton
THE SHIRE
Sarn Ford
CARDOLAN
Forlindon
Forlond
Gulf of Lhûn
Grey Havens
Tower Hills
Mithlond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

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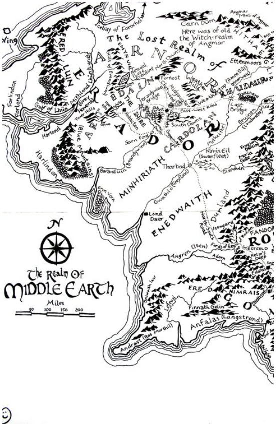

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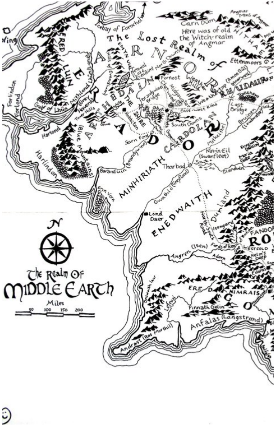

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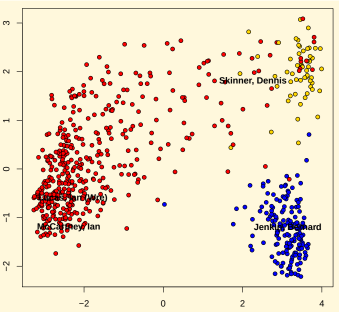

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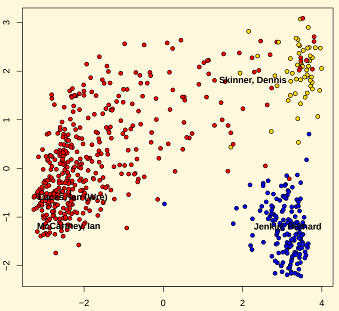

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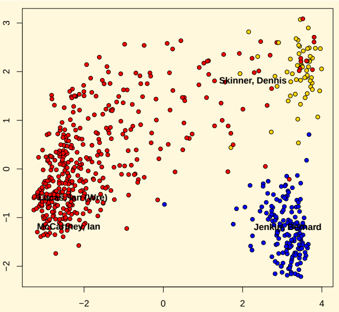

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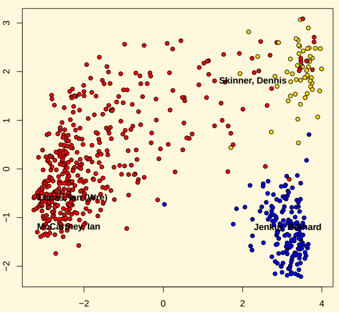

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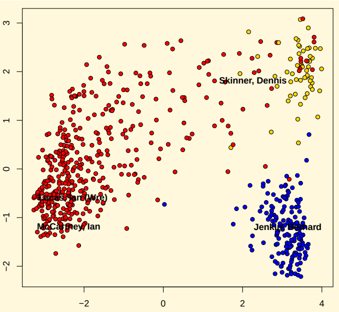

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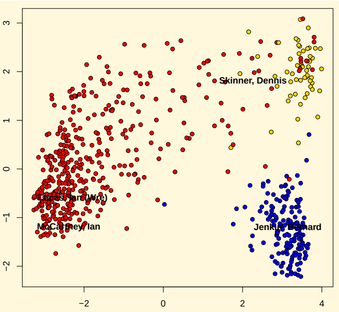

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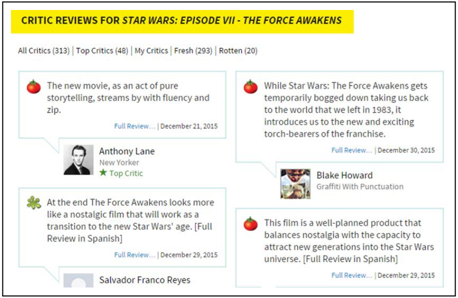

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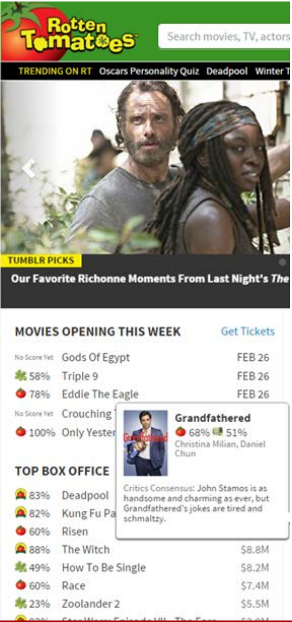

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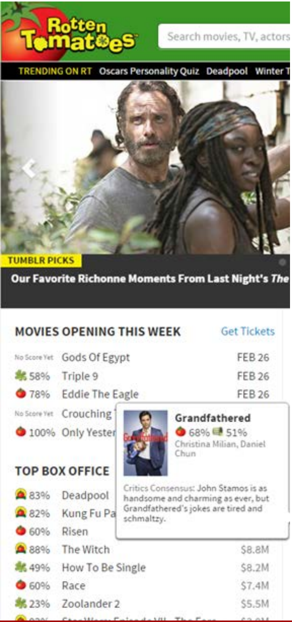

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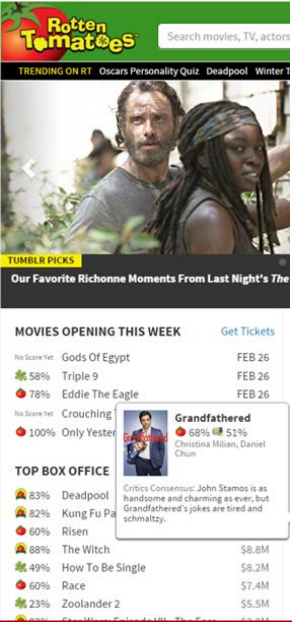

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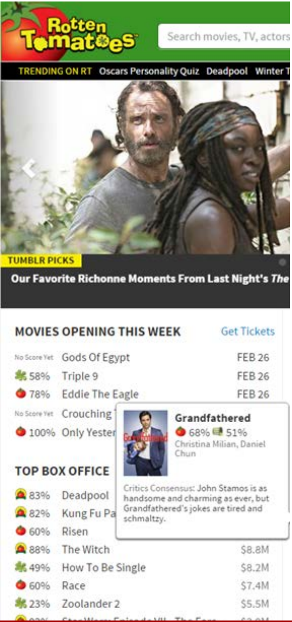

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3. Why might be generally nervous about BOW approaches?

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

General Inquirer (selected)

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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’

Bainbridge, “Personality Capture” (2014)

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Vice	1.7%	1.1%
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Based on somewhat involved human coding/judgement and proprietary.

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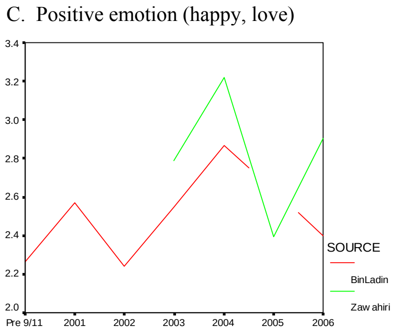

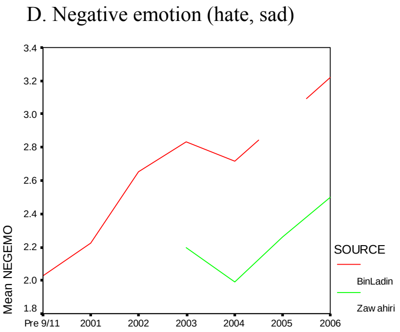

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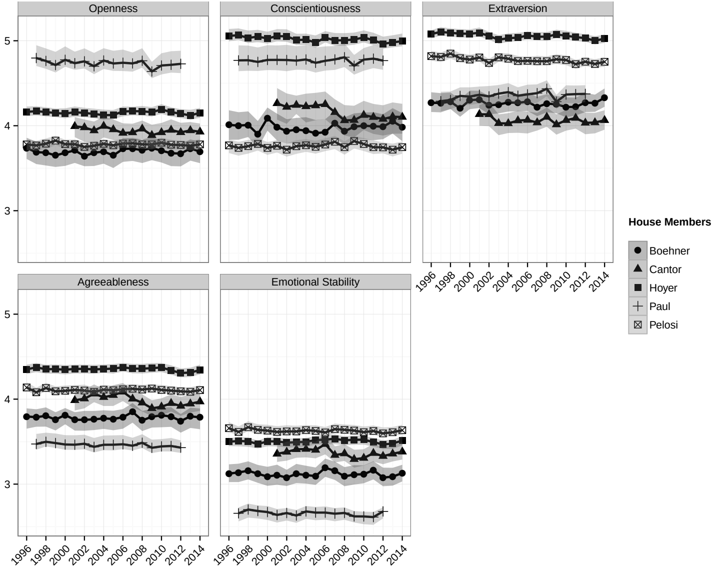

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1 1 1	ECONOMY/+State+/Budget Budget
1 1 1 1	ECONOMY/+State+/Budget/Spending Increase public spending
1 1 1 1 1	ECONOMY/+State+/Budget/Spending/Health
1 1 1 1 2	ECONOMY/+State+/Budget/Spending/Educ. and training

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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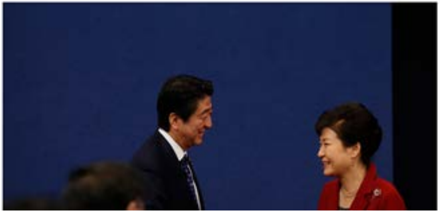
Leaders of South Korea and Japan Meet in Effort to Mend Ties

点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015



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Hierarchical Coding Scheme (CAMEO)/Dictionary

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12: REJECT

120: Reject, not specified below

121: Reject material cooperation

- 1211: Reject economic cooperation
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122: Reject request or demand for material aid, not specified below

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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.

Actors (CAMEO)/Dictionary

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UIG	Uighur (Chinese ethnic minority)
UIS	Unidentified state actors
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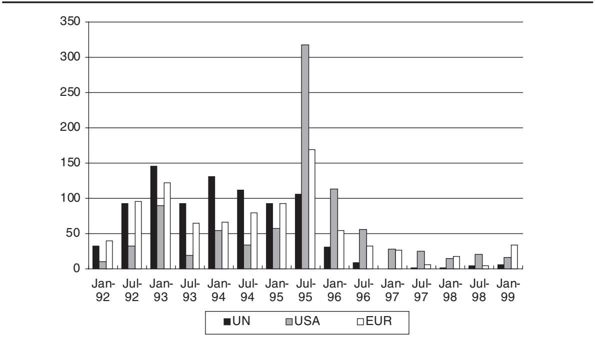

Figure 3: Six-Month Totals of Mediation Events in the Balkans by Mediator
NOTE: UN = United Nations; USA = United States; EUR = major European states, plus the European Union.

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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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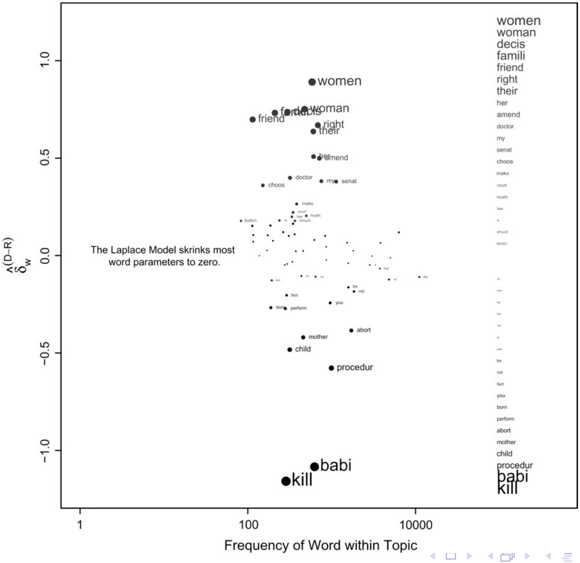

Supervised Learning

Naive Bayes Classification

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  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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training	1	money inherit prince	spam
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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	?

$$\Pr(\text{prince}|\text{ham}) = \tfrac{1}{9}$$
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$$\rightarrow \boxed{c_{map} = \text{spam}}$$

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

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July 20, 2014 10.14pm EDT

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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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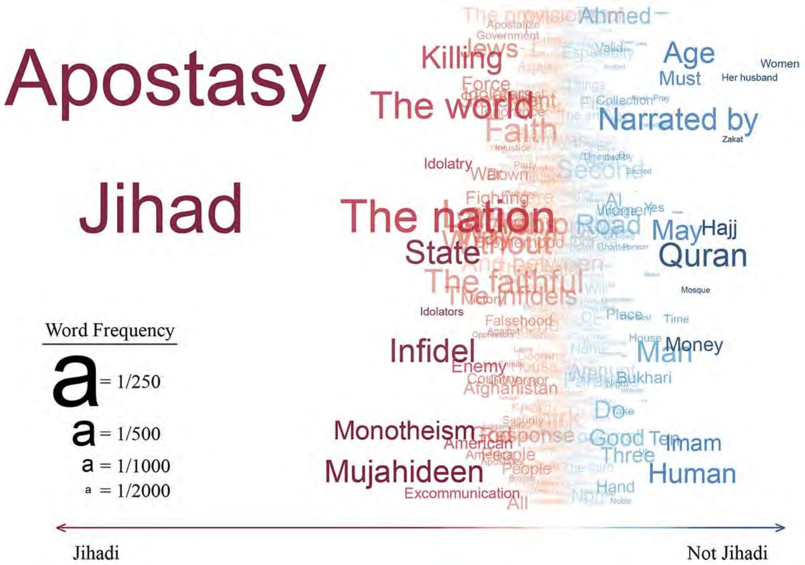

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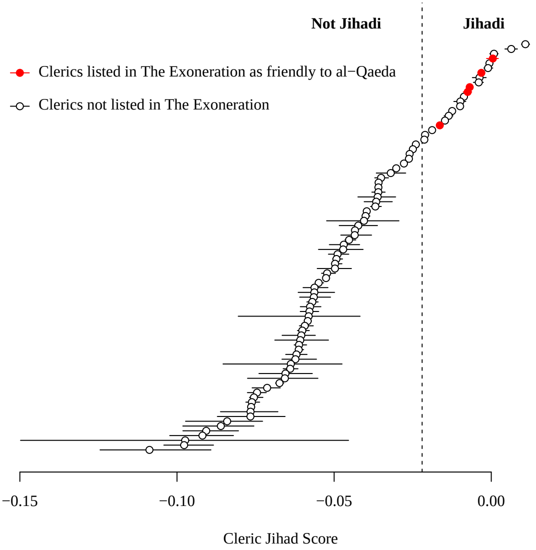

Figure 4.9: *Jihad Scores Predict Inclusion in The Exoneration*

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

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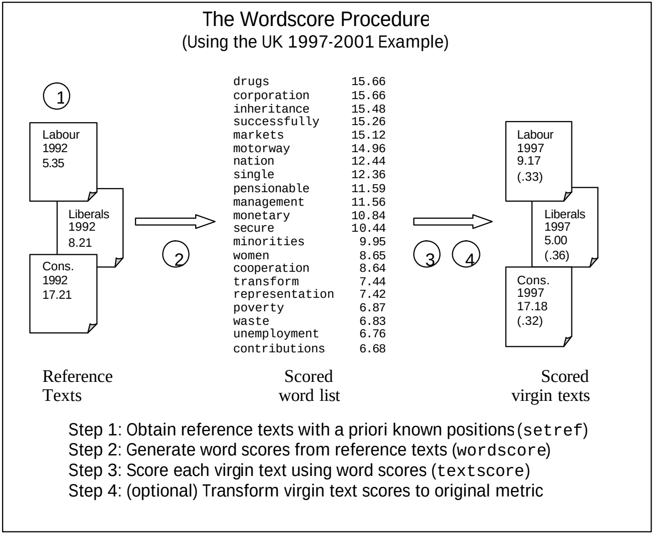

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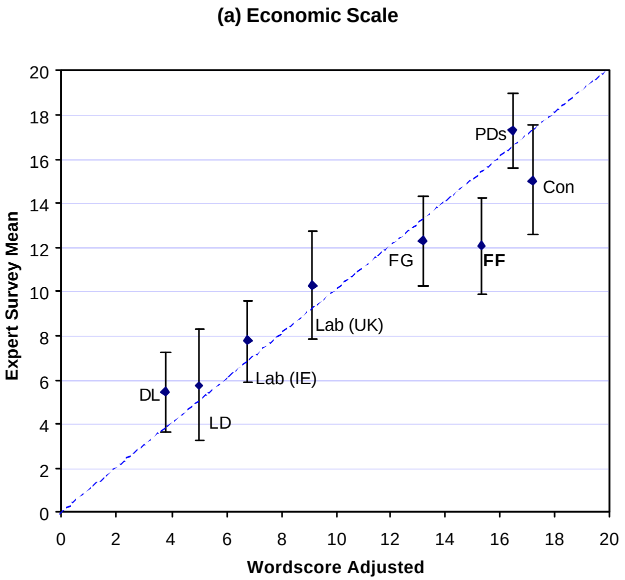

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while Beauchamp (2011) provides comparison and extension to more purely Bayesian approach.

Special Topic: Estimating Proportions

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→ 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

Figure 4 Additional Out-of-Sample Validation