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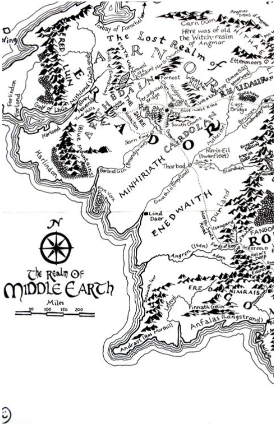

Carn Dûm
Here was of old the Witch-realm of Angmar
The Lost Realm of
ARNOR
Ettenmoors
Fornost
Weather Hills
Bree
East-West Road
Last Bridge
South Downs
Sarn Ford
Tharbad
MINHIRIATH
CARDOLAN
ENEDWAITH
Dunland
Isengard
Lond Daer
Forlindon
Forlond
Gulf of Lhûn
Harlond
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Blue Mountains
Pinnath Gelin
Anfalas (Langstrand)
The Realm of
MIDDLE EARTH
Miles

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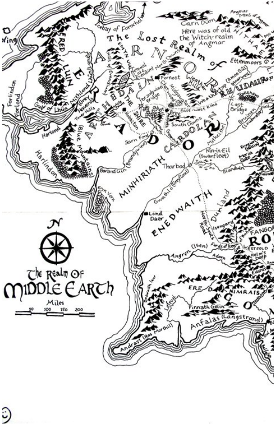

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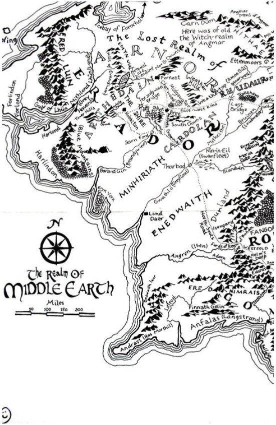

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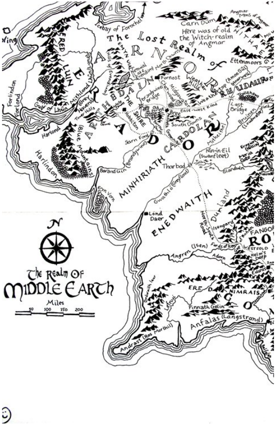

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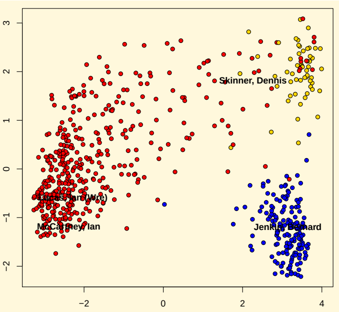

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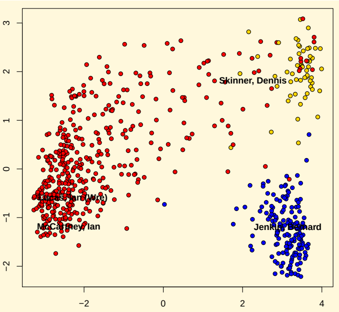

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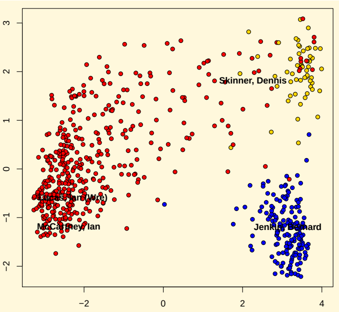

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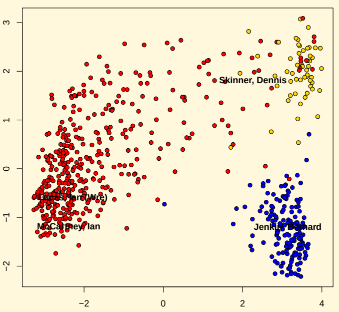

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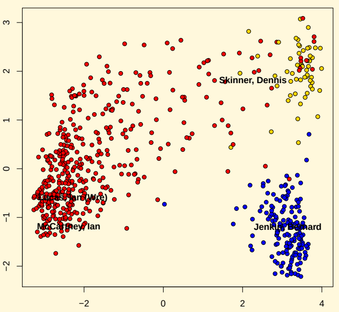

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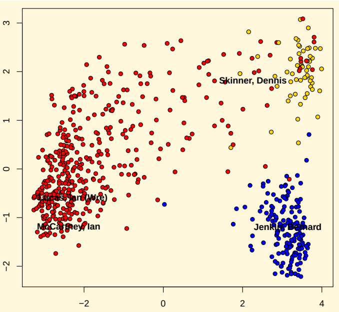

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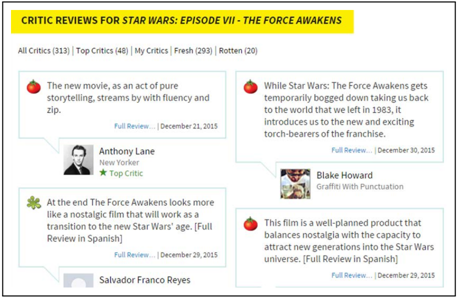

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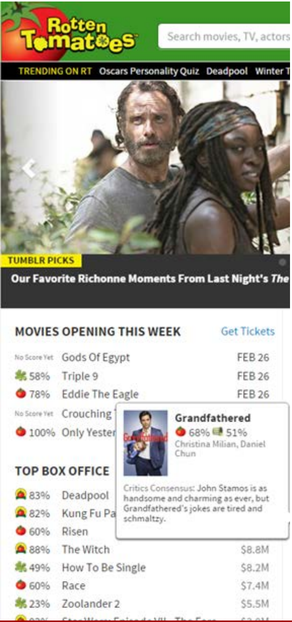

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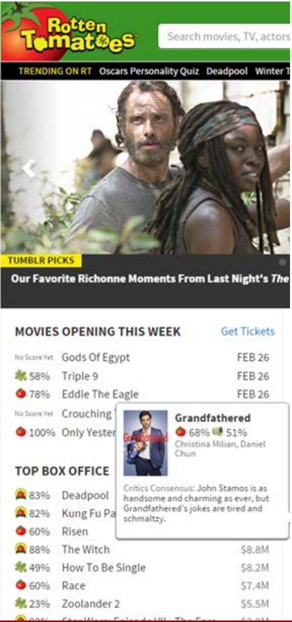

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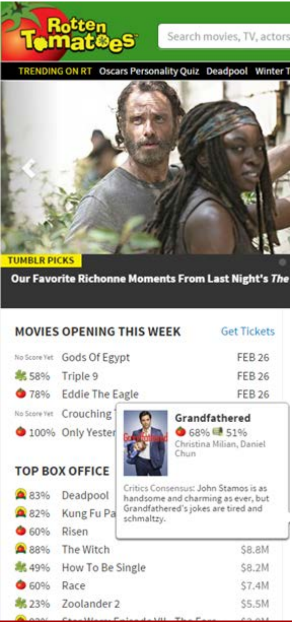

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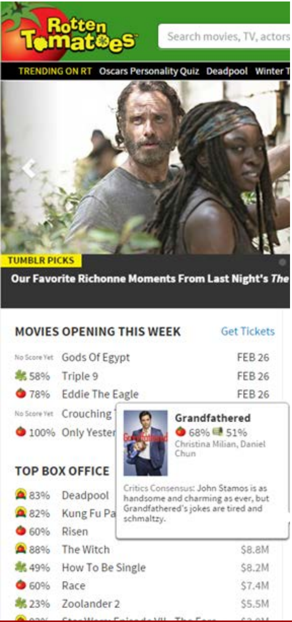

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3. Why might be generally nervous about BOW approaches?

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e.g. "Great for insomniacs!" (book review)

Early approaches simply used presence of tags e.g. `[laughter]` in proceedings to make inferences about what was sarcastic. Or prosody in spoken word (e.g. lower pitch).

Davidov et al ('Semi-Supervised Recognition of Sarcastic Sentences in Twitter and Amazon') get good results by looking for particular pattern: [high frequency word] [content word] [high frequency word] in reviews

btw punctuation adds relatively little to accuracy.

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

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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						
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ABSENT-MINDED	H4		Negativ						
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e.g. ADULT has two meanings: one is a ‘virtue’, one is a ‘role’

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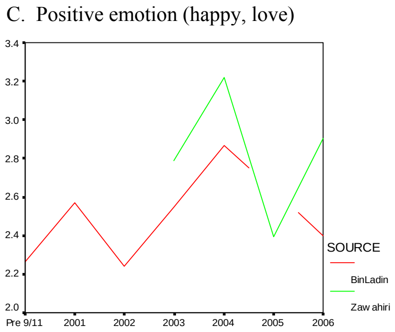

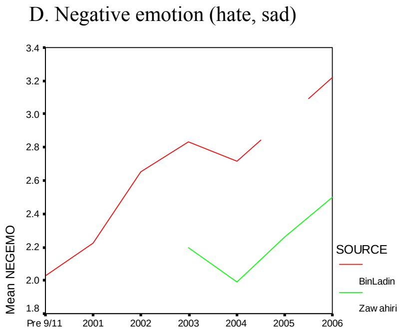

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1,036 of 1,144 people found the following review helpful

★★★★★ **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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ASIA PACIFIC

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NB Typically start with distinct types of documents (classified by hand), and learn which words are important for discriminating between them.

Word embeddings may offer automatic way forward here (Hamilton et al, "Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora")

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Most Democratic and Republican Words on Abortion (106th, Laplace prior)

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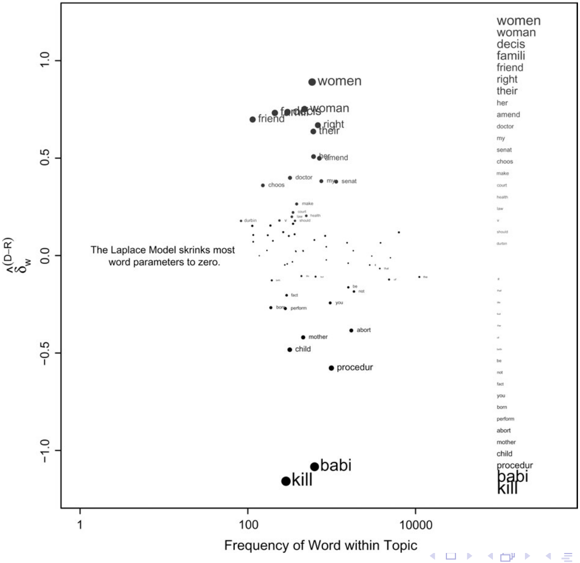

Goldman-Sachs Case Study

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The Committee continues to see the risks to the outlook for economic activity and the labor market as nearly balanced but is monitoring developments abroad. Inflation is anticipated to remain near its recent low level in the near term but the Committee expects inflation to rise gradually toward 2 percent over the medium term as the labor market improves further and the transitory effects of declines in energy and import prices dissipate.

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Can we predict interest rate decisions $\{-1, 0, +1\}$ at next meeting from prior FOMC statements, minutes, books since last meeting?

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→ rising to ~ 0.25 when all sources included (NB: speeches generally uninformative)

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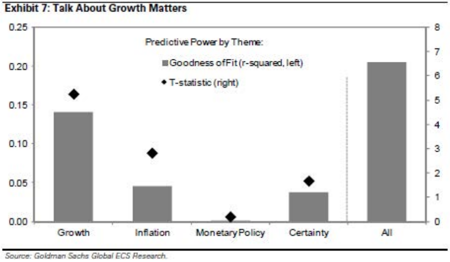

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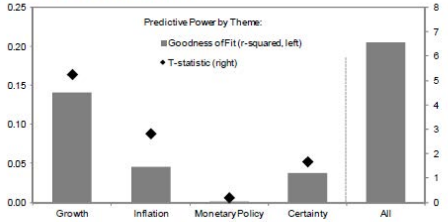
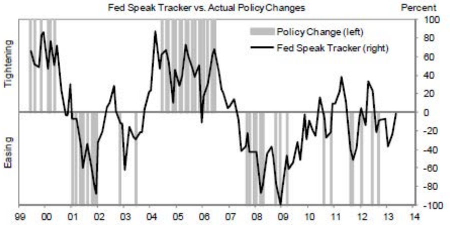
Exhibit 7: Talk About Growth Matters



Source: Goldman Sachs Global ECS Research.

Exhibit 8: The Fed Speak Tracker



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So Recruit undergrad students, and have them play roles in Desert Survival Problem where they need to agree on 12 items to take from crashed jeep.

+ one person in dyad told to deceive other and not represent true preferences about rank order.

Item	Your Rank	Actual Rank	Team Rank	Team Difference	Your Difference
A ball of steel wool					
A small ax					
A loaded .45-caliber pistol					
Can of Crisco shortening					
Newspapers (one per person)					
Cigarette lighter (without fluid)					
Extra shirt and pants for each survivor					
20 x 20 ft. piece of heavy-duty canvas					
A sectional air map made of plastic					
One quart of 100-proof whiskey					
A compass					
Family-size chocolate bars (one per person)					
Score					

Exercise

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Q how would you expect deceiver's messages differ from truth tellers?

Exercise

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→ in terms of e.g. number of words, informality, uncertainty, complexity, pausality etc.

Results

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Q how do deceiver's messages differ from truth tellers?

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A used more words, verbs, noun phrases, sentences

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Results

- Q how do deceiver's messages differ from truth tellers?
- A used more words, verbs, noun phrases, sentences

  more informality: more typos.

  more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

  less complex and less diverse (∼TTR)

Results

Q how do deceiver's messages differ from truth tellers?

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more informality: more typos.

more uncertain (weak modifiers e.g. 'about') and non-immediate (passive voice, externalizing)

less complex and less diverse (∼TTR)

less pausality (more punctuation), more group references ('we')

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more informality: more typos.

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btw, passive voice means subject and object of sentence are switched:

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less pausality (more punctuation), more group references ('we')

btw, passive voice means subject and object of sentence are switched: "I am packing my bag" $\rightarrow$ "My bag is being packed by me."

I will **definitely** see you next time, when I intend to forego persiflage and conduct a profound lucubration, skirring over new topics in a way that could never be described as prolix.