4. Supervised Techniques I

DS-GA 1015, Text as Data
Arthur Spirling

February 26, 2019

Housekeeping

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2. Professor at Rutgers looking for RA on unsupervised learning (mostly topic models). Let me know if interested.

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"`The reporter who the senator attacked admitted the error`" is harder than "`The reporter who attacked the senator admitted the error`" because less obvious to whom 'who' refers.

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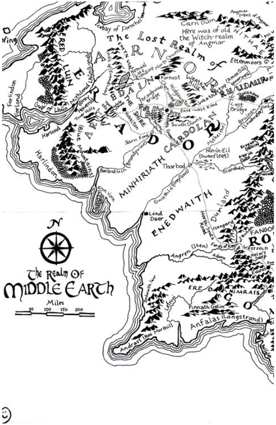

Carn Dûm
Here was of old the Witch-realm of Angmar
The Lost Realm of Arnor
Ettenmoors
Fornost
Weather Hills
Last Bridge
East-West Road
Bree
The Shire
Hobbiton
South Downs
Sarn Ford
Cardolan
Minhiriath
Tharbad
Enedwaith
Dunland
Lond Daer
Isengard
Fangorn
Helm's Deep
Edoras
Angren
Adorn
Forlindon
Forlond
Gulf of Lhûn
Harlond
Harlindon
Blue Mountains
Erin Vorn
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
N
The Realm of Middle Earth
Miles
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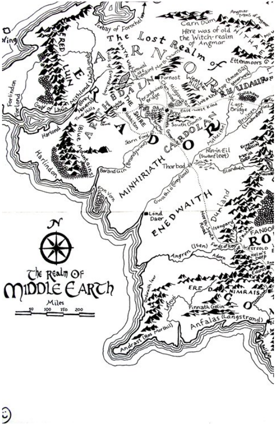

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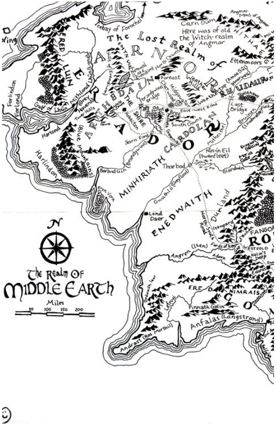

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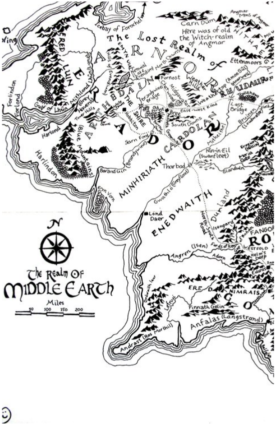

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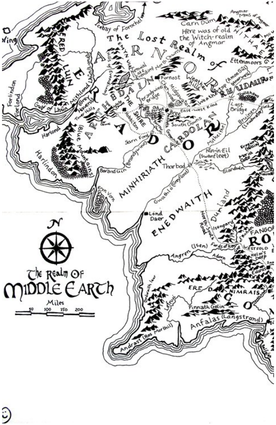

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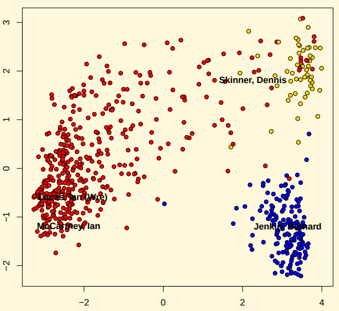

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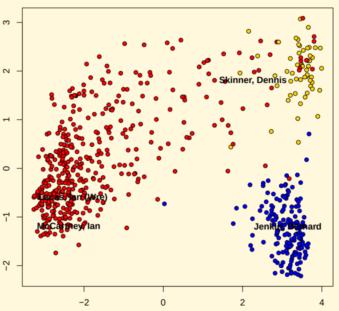

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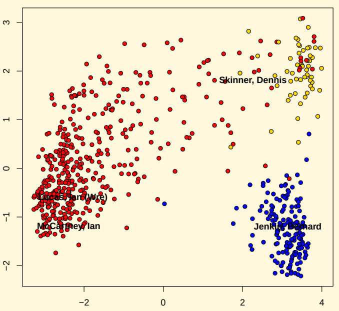

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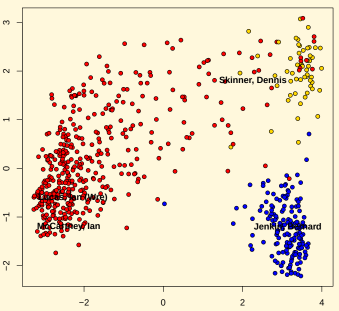

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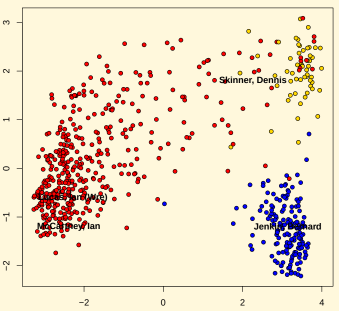

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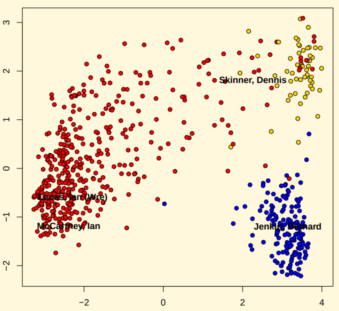

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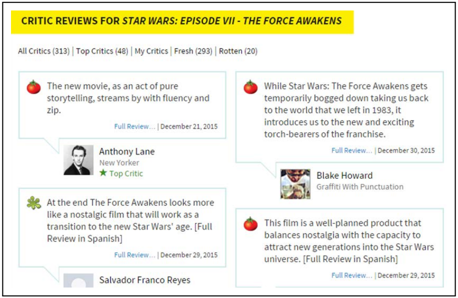

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$\rightarrow$ just add up the number of times the words appear and multiply by the score (normalizing by doc dictionary presence)

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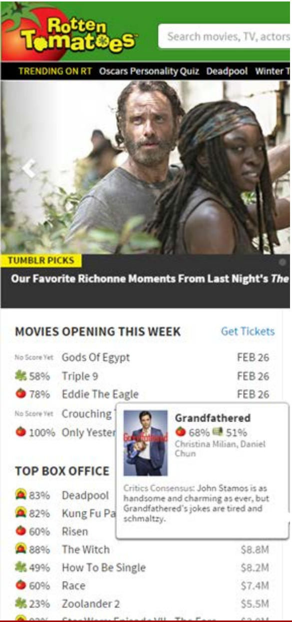

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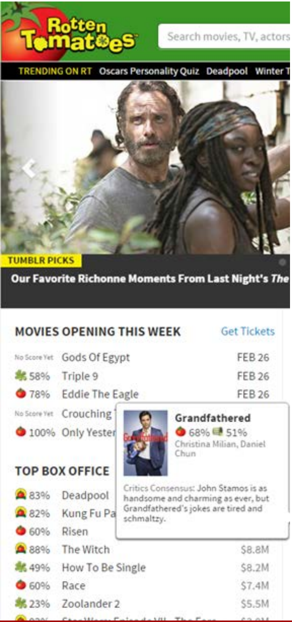

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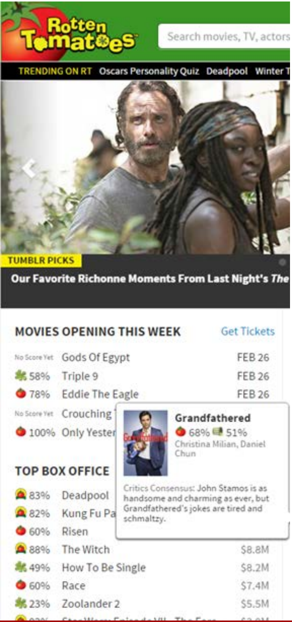

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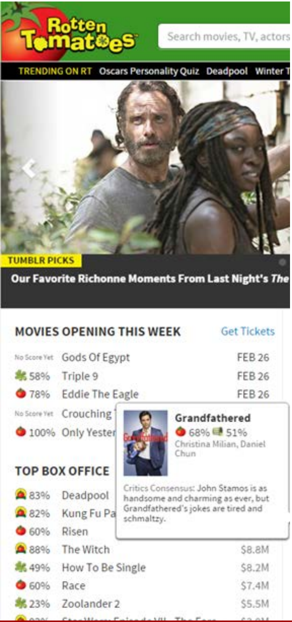

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3. Why might be generally nervous about BOW approaches?

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NB Bag-of-words assn may be especially dubious for some dictionary tasks

e.g. context matters: "was `not` good" gets $+1$!

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btw punctuation adds relatively little to accuracy.

Dictionaries I: General Inquirer

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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						
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e.g. ADULT has two meanings: one is a ‘virtue’, one is a ‘role’

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Based on somewhat involved human coding/judgement and proprietary.

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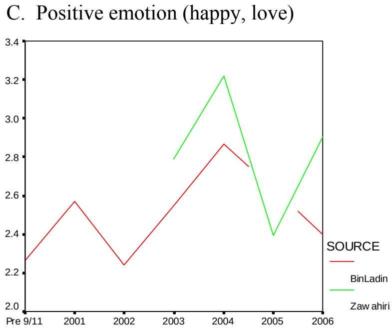

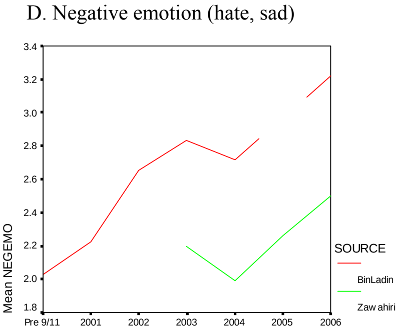

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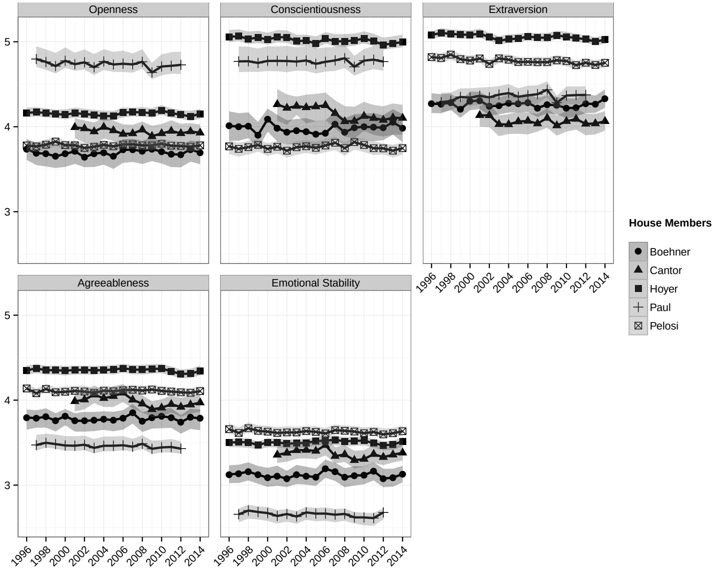

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

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Create dictionary specifically for political communication

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Predicting Liberal Poll Vote (2006) as function of media tone

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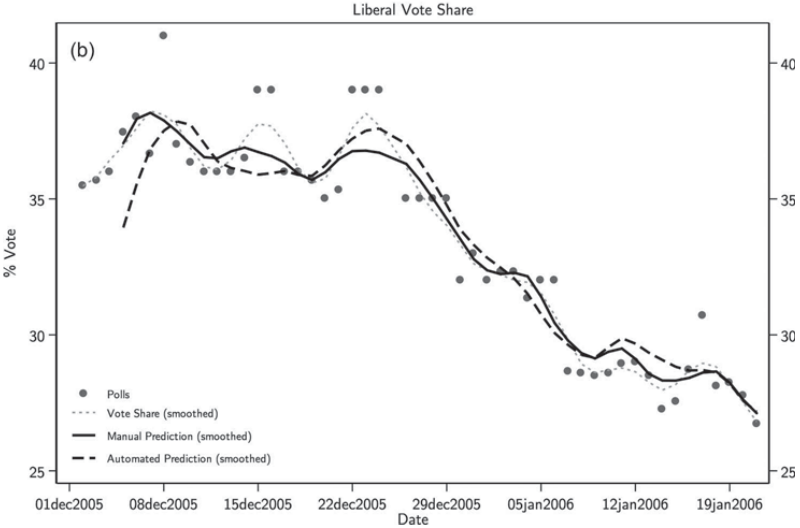

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1 1 1 ECONOMY/+State+/Budget
Budget

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 V: 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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The Weather

Today—Showers, thunderstorms, high in 80s. Tuesday—Fair, less humid. Chance of rain, 20% tonight. Winds variable, 10-15 m.p.h. Temperature range: Today, 72-88; Yesterday, 76-88. Details, Page D3.

The Washington Post

Times Herald

FINAL

92d Year No. 228

MONDAY, JULY 21, 1969

10¢

'The Eagle Has Landed'— Two Men Walk on the Moon

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The Washington Post

Times Herald

FINAL

Amusements
Calendar
City Life
Classified
Comics
Crossword
Editorials
Fed. Diary
Financial
Movie Guide
Obituaries
Sports
Style
TV-Radio

92d Year No. 228

MONDAY, JULY 21, 1969

Phone 223-6000

10c

'The Eagle Has Landed'—
Two Men Walk on the Moon

intransitive

BTW. . . intransitive verbs don't have a direct object

The Weather

The Washington Post

Times Herald

FINAL

92d Year No. 228 MONDAY, JULY 21, 1969 Phone 223-6000 10c

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intransitive (cf 'Walk the Moon')

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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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UGAREBLRA	Lord's Resistance Army
UIG	Uighur (Chinese ethnic minority)
UIS	Unidentified state actors
UKR	Ukraine
URY	Uruguay
USA	United States
USR	Union of Soviet Socialist Republics (USSR)
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Example: Dayton Peace Accords

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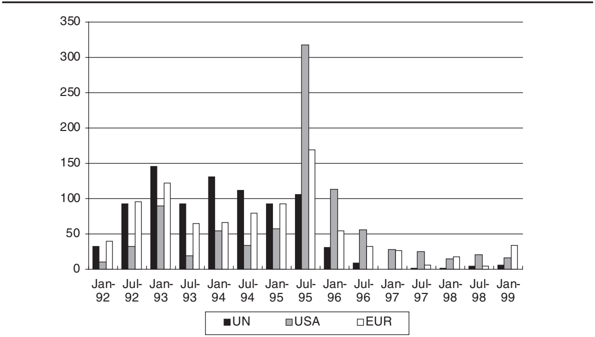

Figure 3: Six-Month Totals of Mediation Events in the Balkans by Mediator

NOTE: UN = United Nations; USA = United States; EUR = major European states, plus the European Union.

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

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

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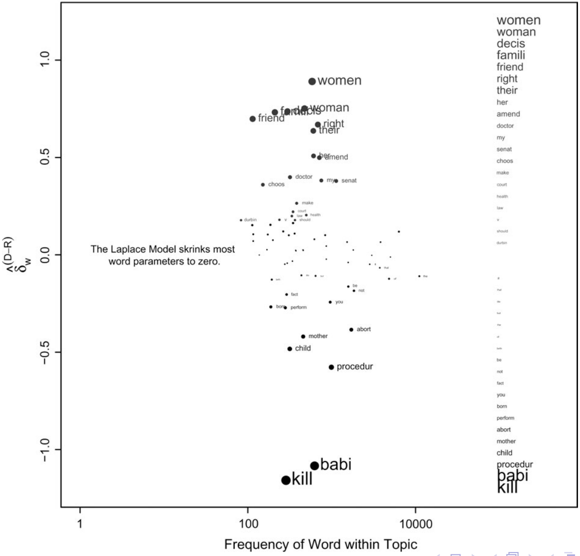

Goldman-Sachs Case Study

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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.

Partner Exercise

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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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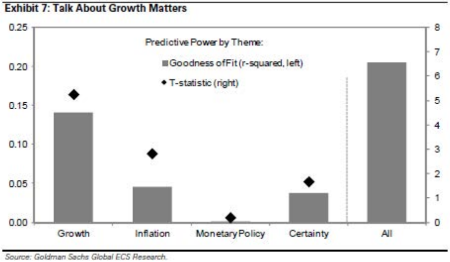

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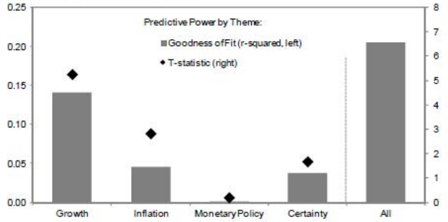
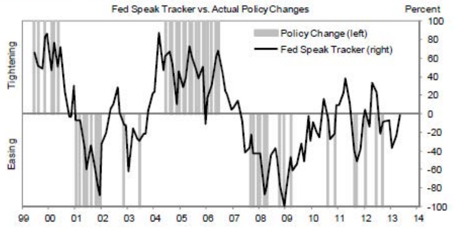
Exhibit 7: Talk About Growth Matters



Source: Goldman Sachs Global ECS Research.

Exhibit 8: The Fed Speak Tracker



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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					

Partner Exercise

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

Partner Exercise

- Q how would you expect deceiver's messages differ from truth tellers?
- → in terms of e.g. number of words, informality, uncertainty, complexity, pausality etc.

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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.