4. Supervised Techniques I

DS-GA 1015, Text as Data
Arthur Spirling

March 2, 2020

Where Are We?

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Carn Dûm
Here was of old the Witch-realm of Angmar
The Lost Realm of Arnor
Ettenmoors
Fornost
Last Bridge
South Downs
Bree
Sarn Ford
Minhiriath
Cardolan
Enedwaith
Lond Daer
Dunland
Isengard
Helm's Deep
Harlindon
Harlond
Forlindon
Forlond
Gulf of Lhûn
Pinnath Gelin
Anfalas (Langstrand)
Angren
Adorn
The Realm of Middle Earth
Miles
50 100 150 200

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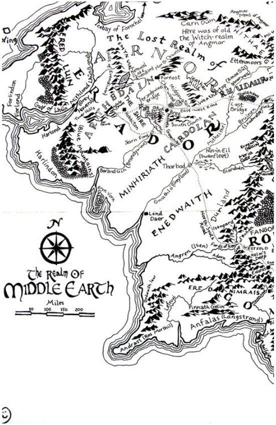

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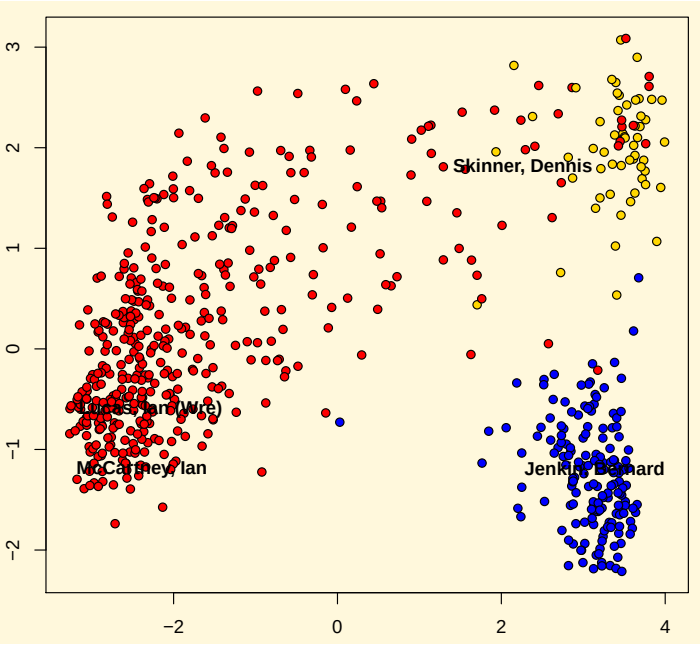

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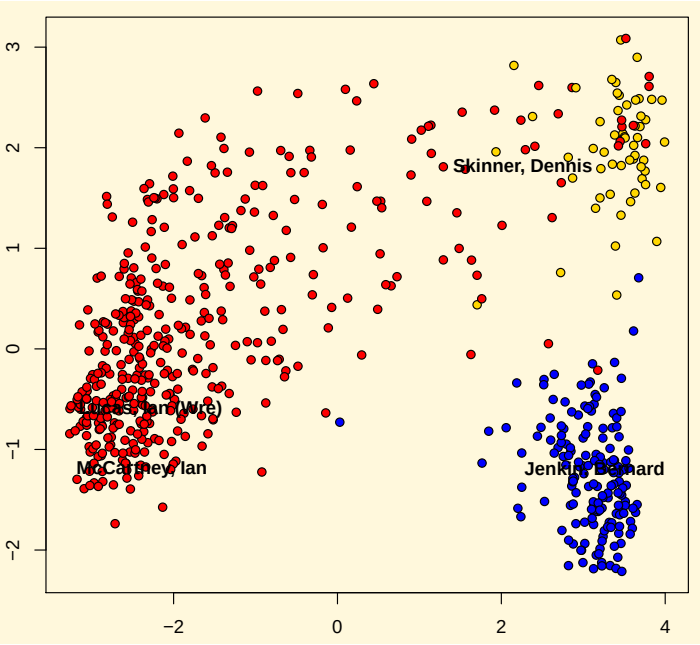

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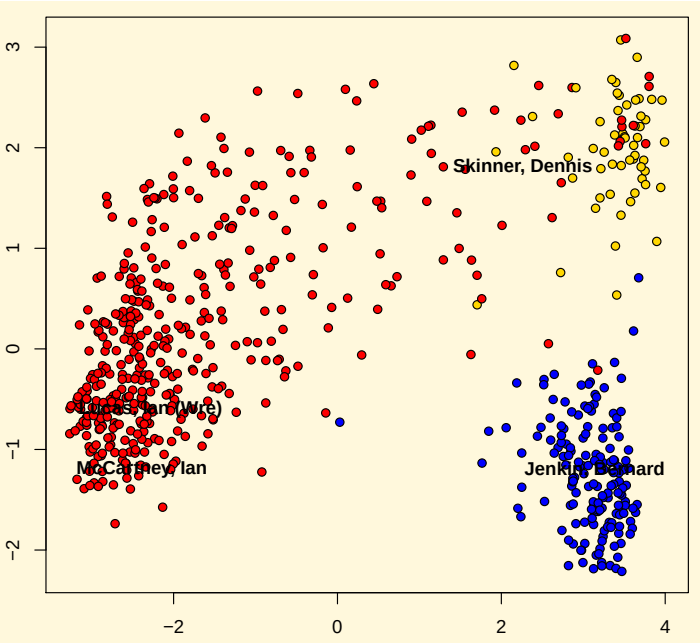

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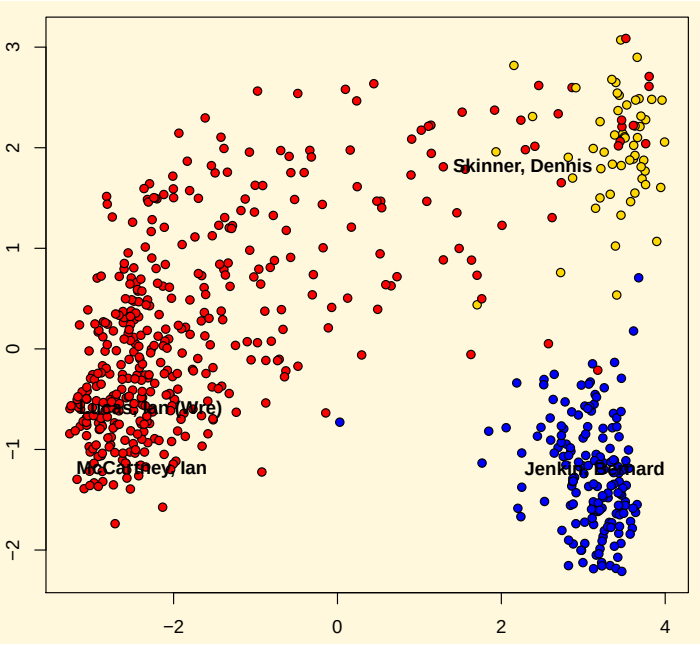

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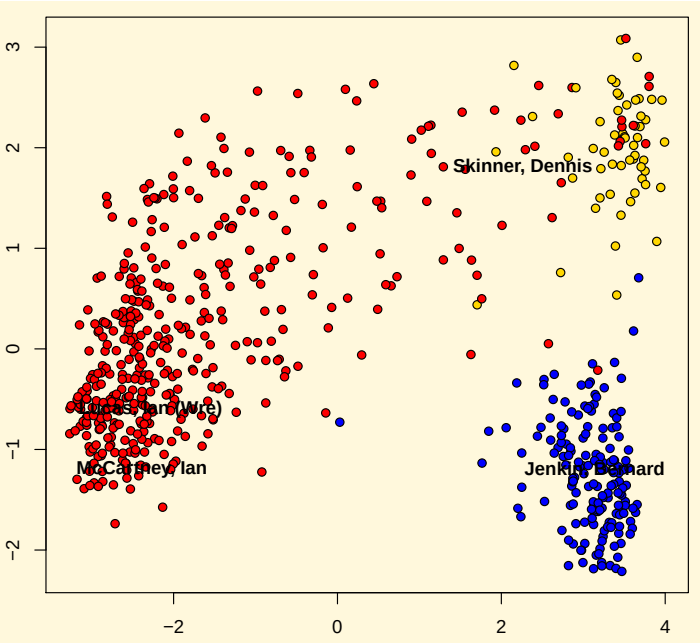

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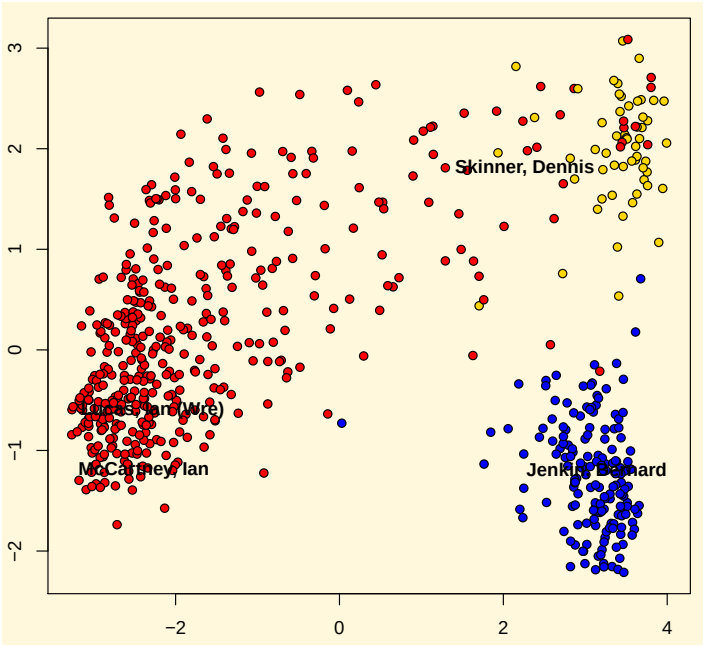

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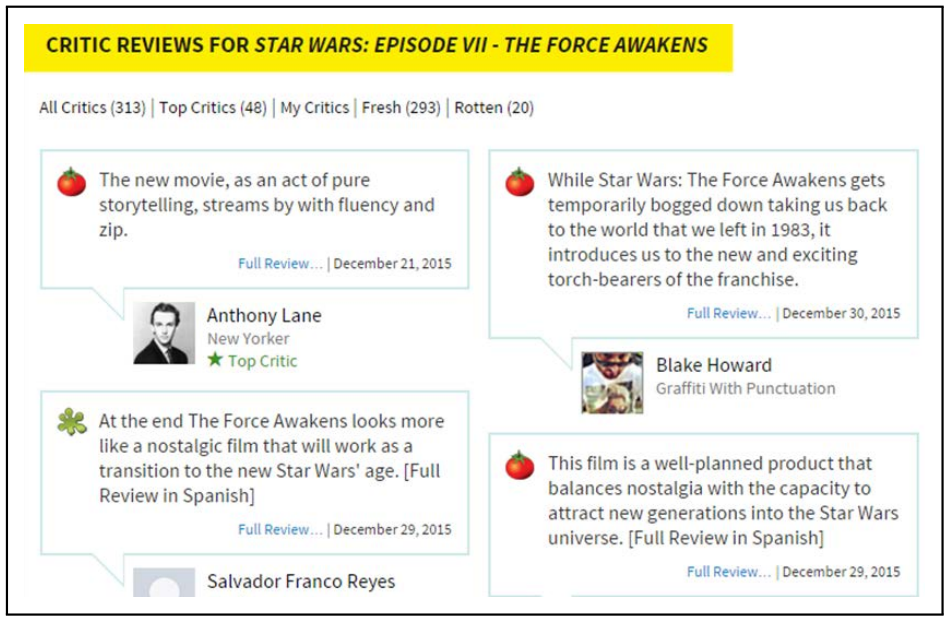

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$\rightarrow$ just add up the number of times the words appear and multiply by the score (normalizing by doc dictionary presence)

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

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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						
ABSENT#2	H4Lvd								
ABSENT-MINDED	H4		Negativ						
ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
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ABSENTEE	H4		Negativ				Hostile		
ABSOLUTE#1	H4Lvd							Strong	
ABSOLUTE#2	H4Lvd							Strong	

provides dictionaries and software, which performs some stemming and disambiguation in terms of context

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		
ABSENCE	H4Lvd		Negativ						
ABSENT#1	H4Lvd		Negativ						
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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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Virtue	3.9%	2.7%
Vice	1.7%	1.1%
Overstated	5.6%	3.9%
Understated	0.6%	2.5%

Dictionaries II: Linguistic Inquiry and Word Count (LIWC)

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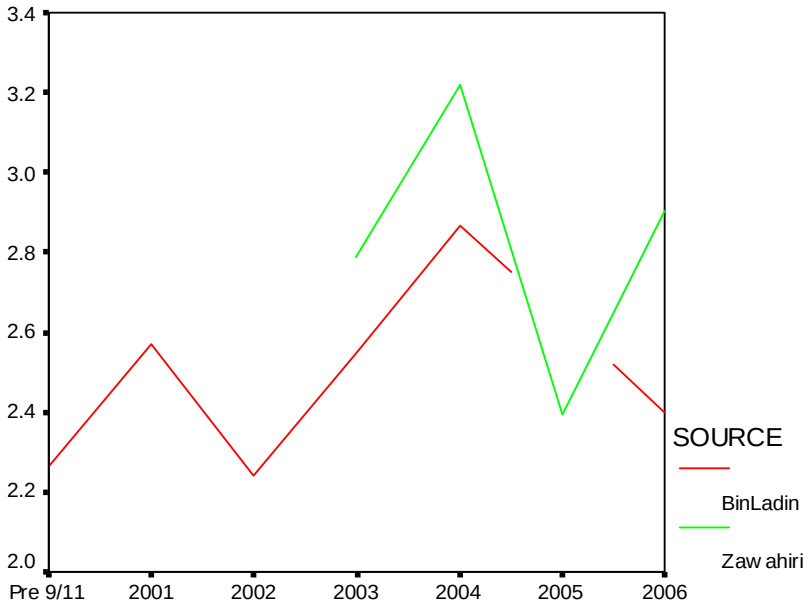
C. Positive emotion (happy, love)



D. Negative emotion (hate, sad)

Application: Ramey, Klingler & Hollibaugh

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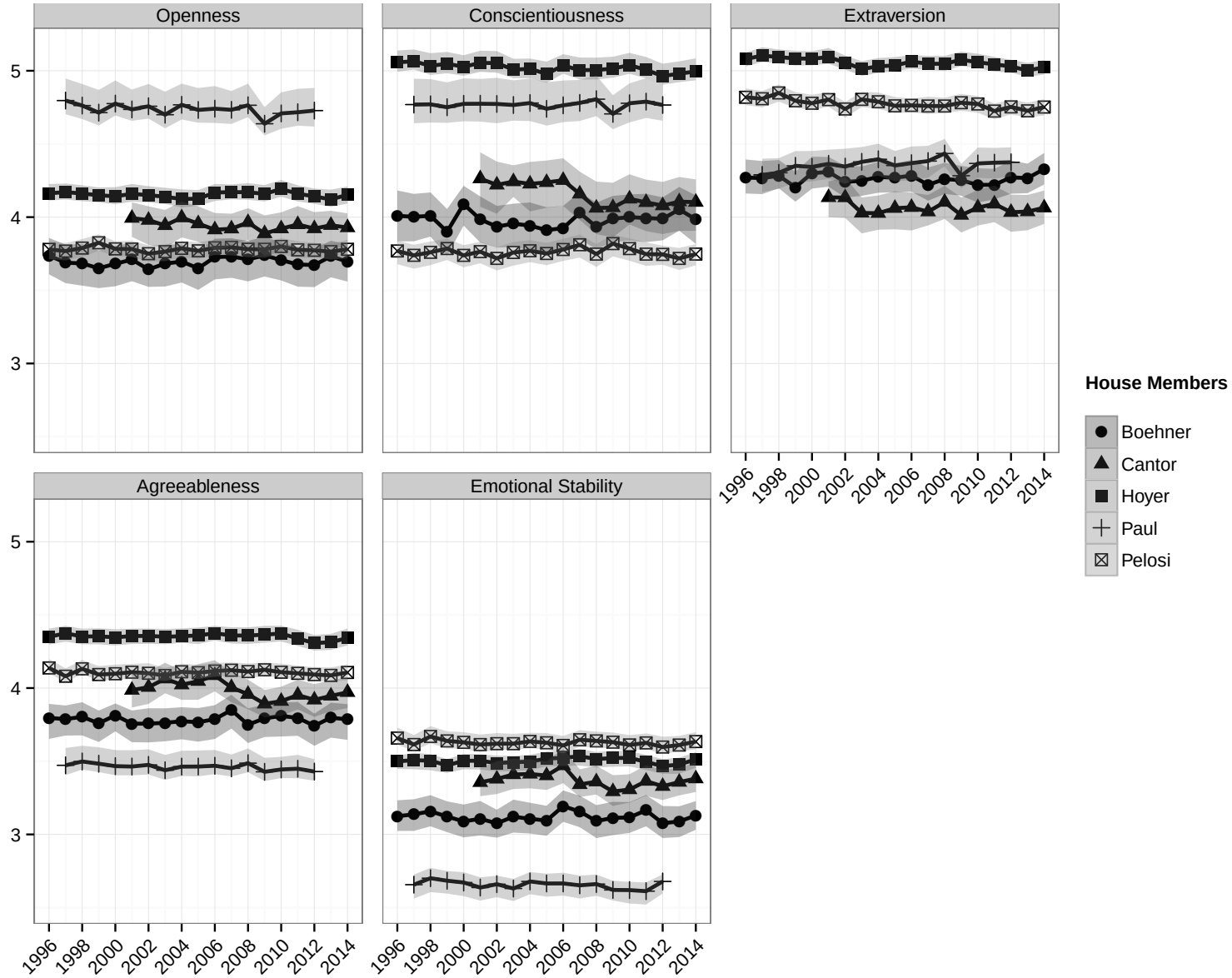

Dictionaries III: Young & Saroka's *Lexicoder Sentiment Dictionary*

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

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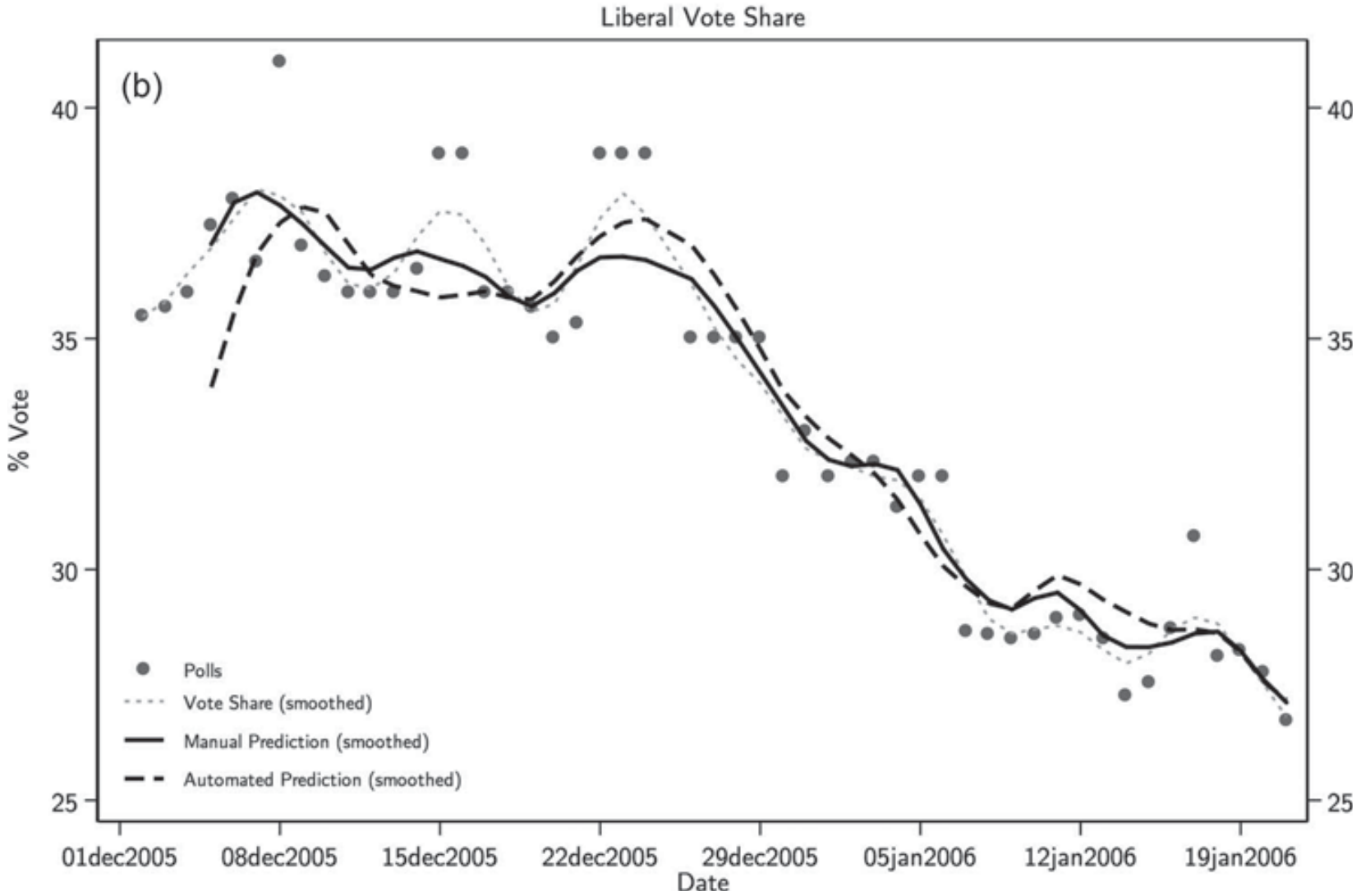

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```
1 1 1   ECONOMY/+State+/Budget
        Budget

        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
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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...

Being Careful. . .

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

Events

Events, dear boy...

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Scholars of International Relations need access to events

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The Washington Post

Times Herald

FINAL

96 Pages — 4 Sections

Amusements	B 6	Fed. Diary	C 5
Calendar	B 4	Financial	C 6
City Life	D 1	Movie Guide	B 7
Classified	D 4	Obituaries	D 2
Comics	C 4	Sports	C 1
Crossword	B 4	Style	B 1
Editorials	A10	TV-Radio	B 5

92d Year .... No. 228 © 1969 The Washington Post Co. MONDAY, JULY 21, 1969 Phone 223-6000 10c

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

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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
    1212: Reject military cooperation
122: Reject request or demand for material aid, not specified below
    1221: Reject request for economic aid
    1222: Reject request for military aid
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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
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URY	Uruguay
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UZB	Uzbekistan
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  Synonyms (and metonyms!) also require dictionaries (`WordNet`).

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  Care over verb/noun problems.

  e.g. '`attack`' as noun and verb

- Excellent performance relative to human coders (Lowe & King, 2003):

Delving More Deeply

- Begins with basic parsing: POS, stemming, stop words etc.

- Much effort to disambiguate:

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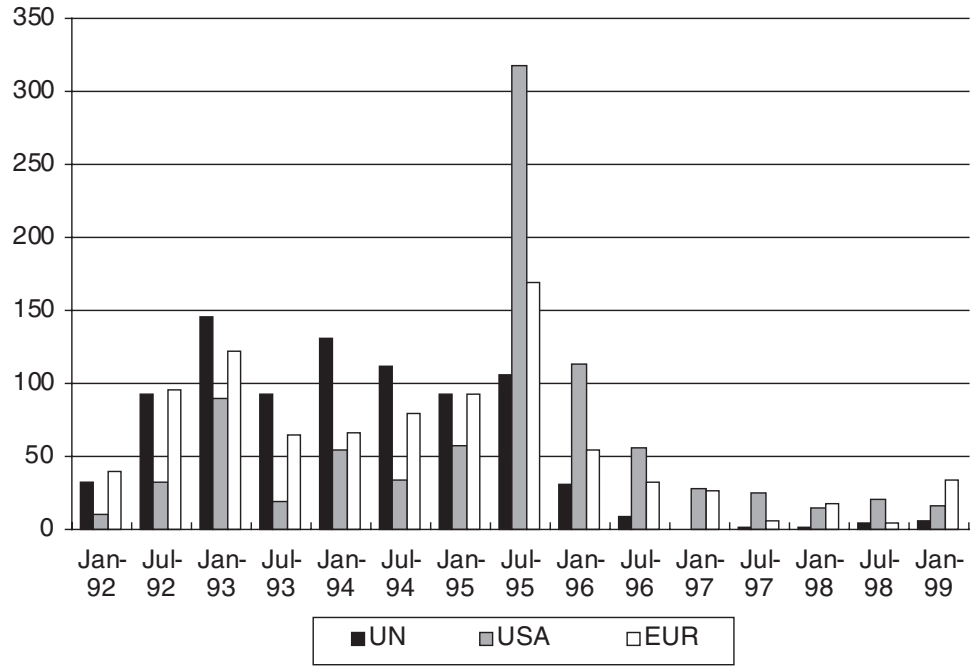

Figure 3: Six-Month Totals of Mediation Events in the Balkans by Mediator
NOTE: UN = United Nations; USA = United States; EUR = major European states, plus the European Union.

Back to Dictionaries

Making Dictionaries from Scratch

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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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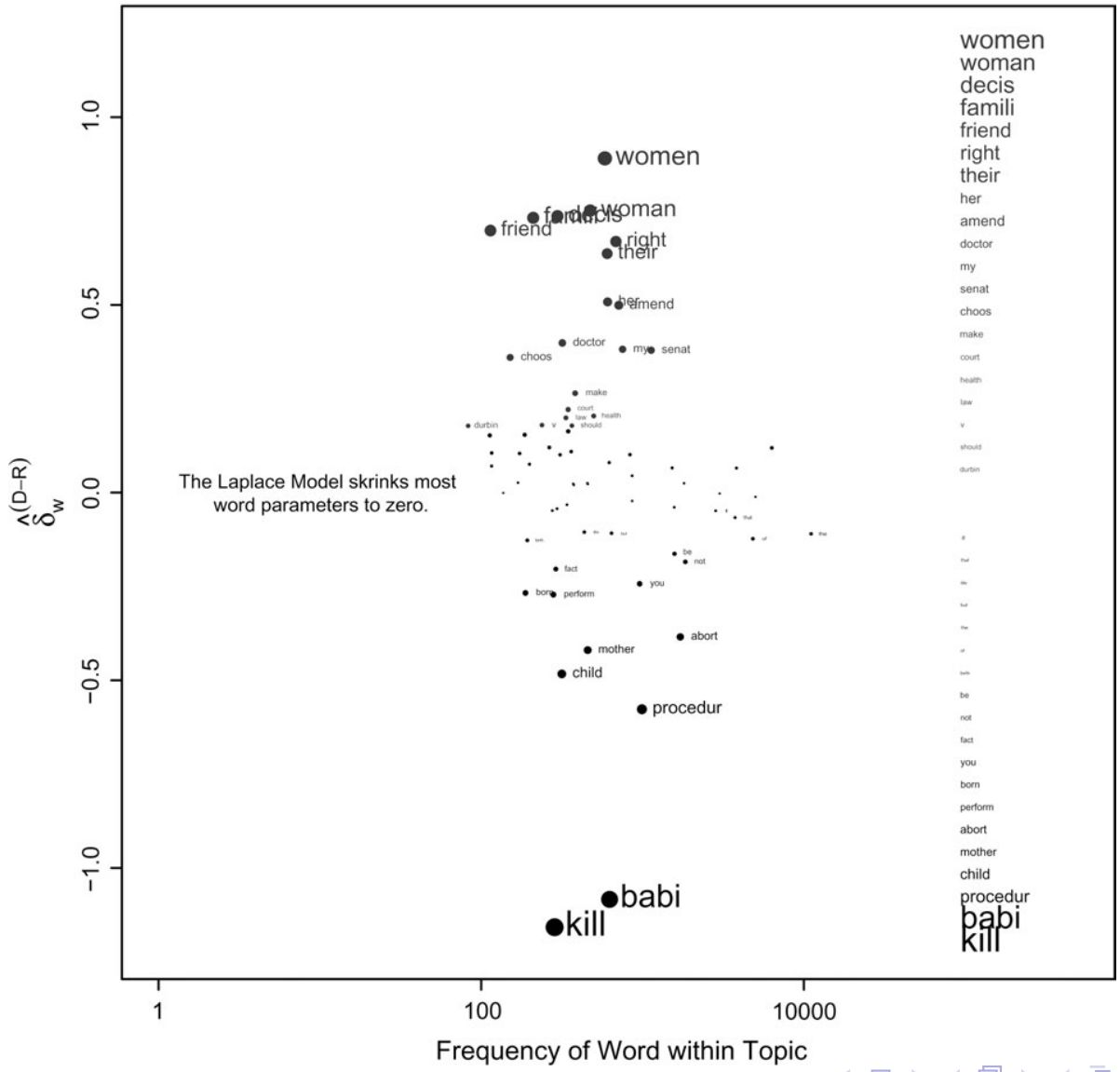

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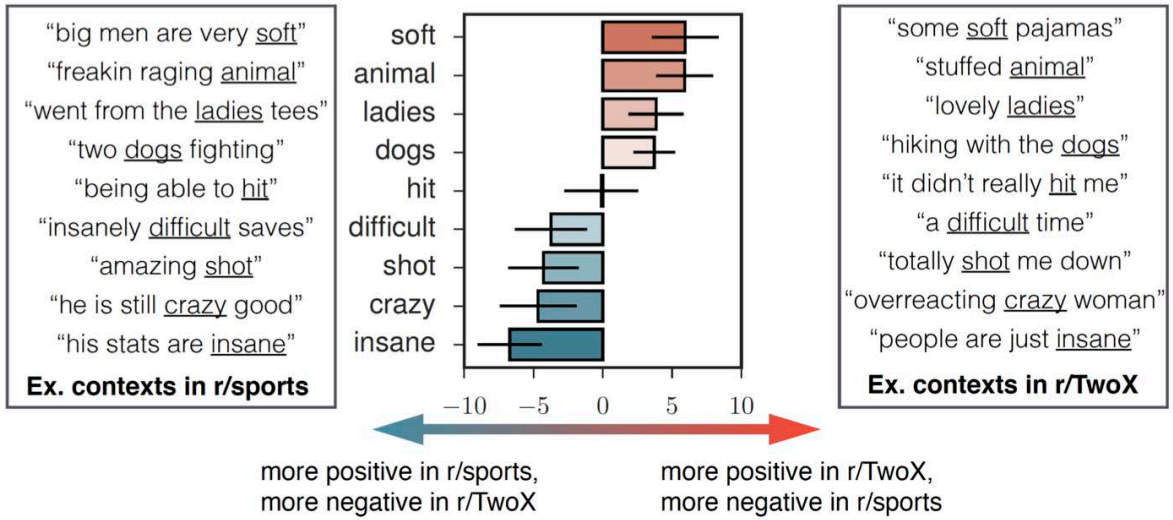

Industrial Applications

Goldman-Sachs Case Study

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GS world's largest investment bank,

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Problem and Approach

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

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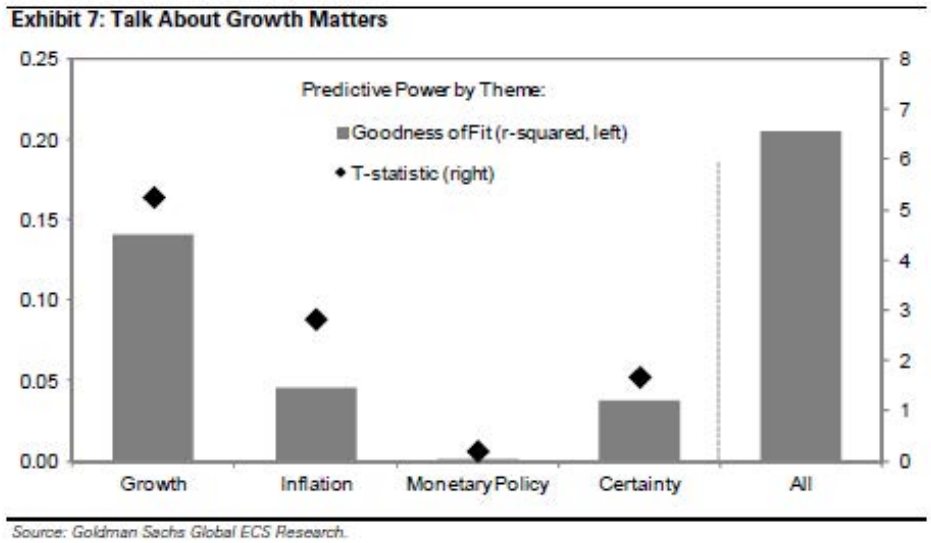

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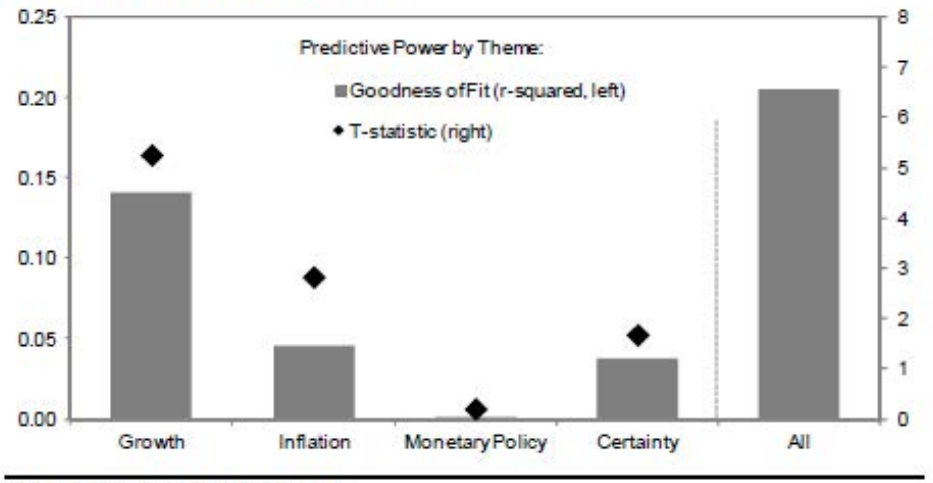
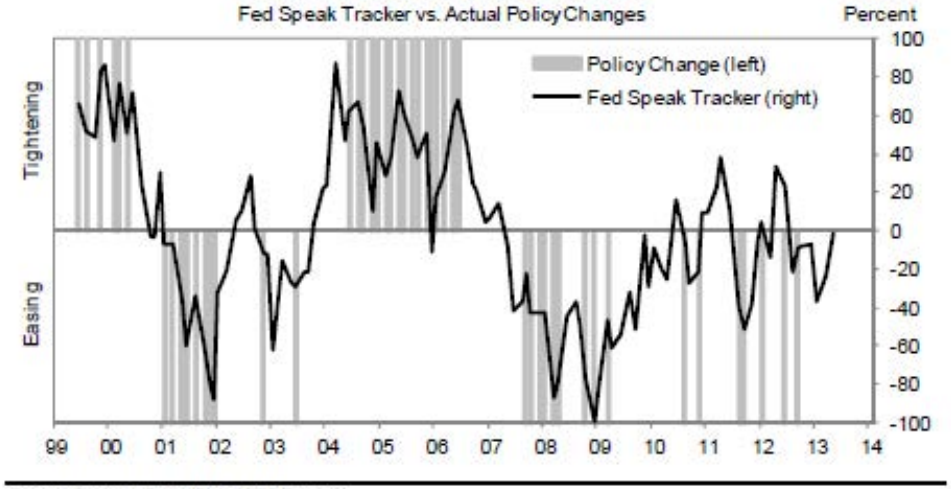
Exhibit 7: Talk About Growth Matters



Source: Goldman Sachs Global ECS Research.

Exhibit 8: The Fed Speak Tracker



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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					

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btw, passive voice means subject and object of sentence are switched:
"I am packing my bag" → "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.