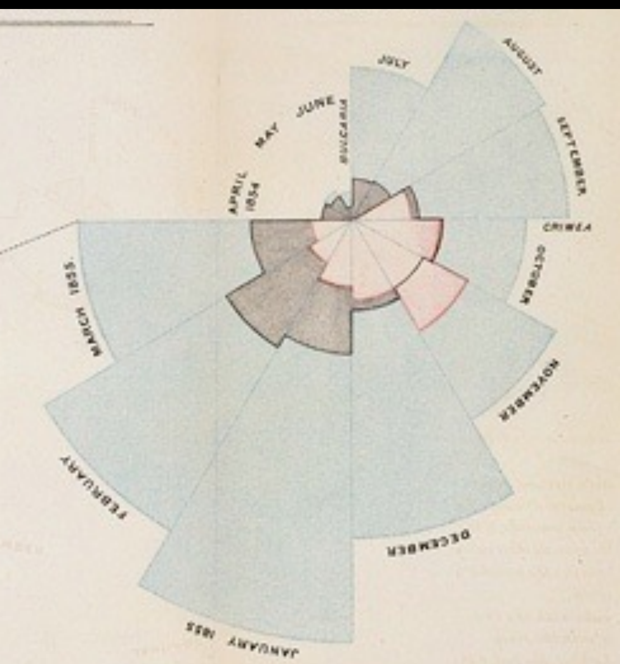
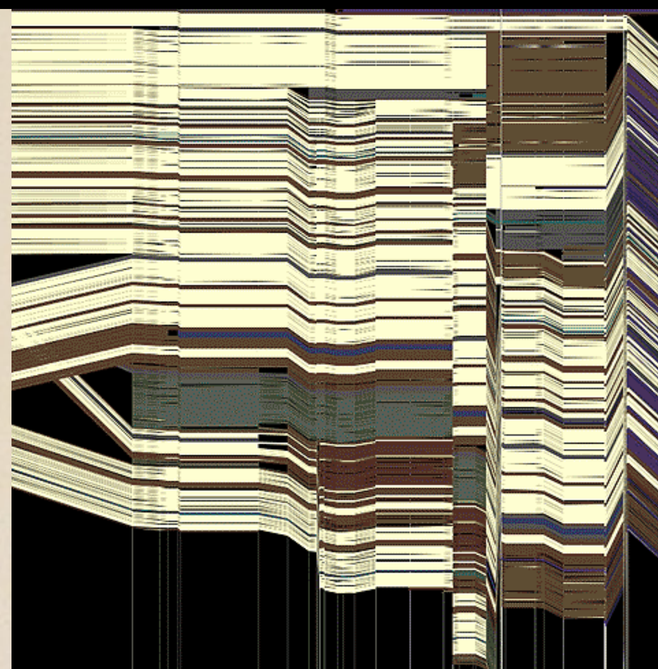
CSE 442 - Data Visualization

Text Visualization






Jeffrey Heer University of Washington

Why Visualize Text?

Why Visualize Text?

Understanding – get the “gist” of a document

Grouping – cluster for overview or classification

Comparison – compare document collections, or inspect evolution of collection over time

Correlation – compare patterns in text to those in other data, e.g., correlate with social network

Text as Data

Documents

Articles, books and novels

E-mails, web pages, blogs

Tags, comments

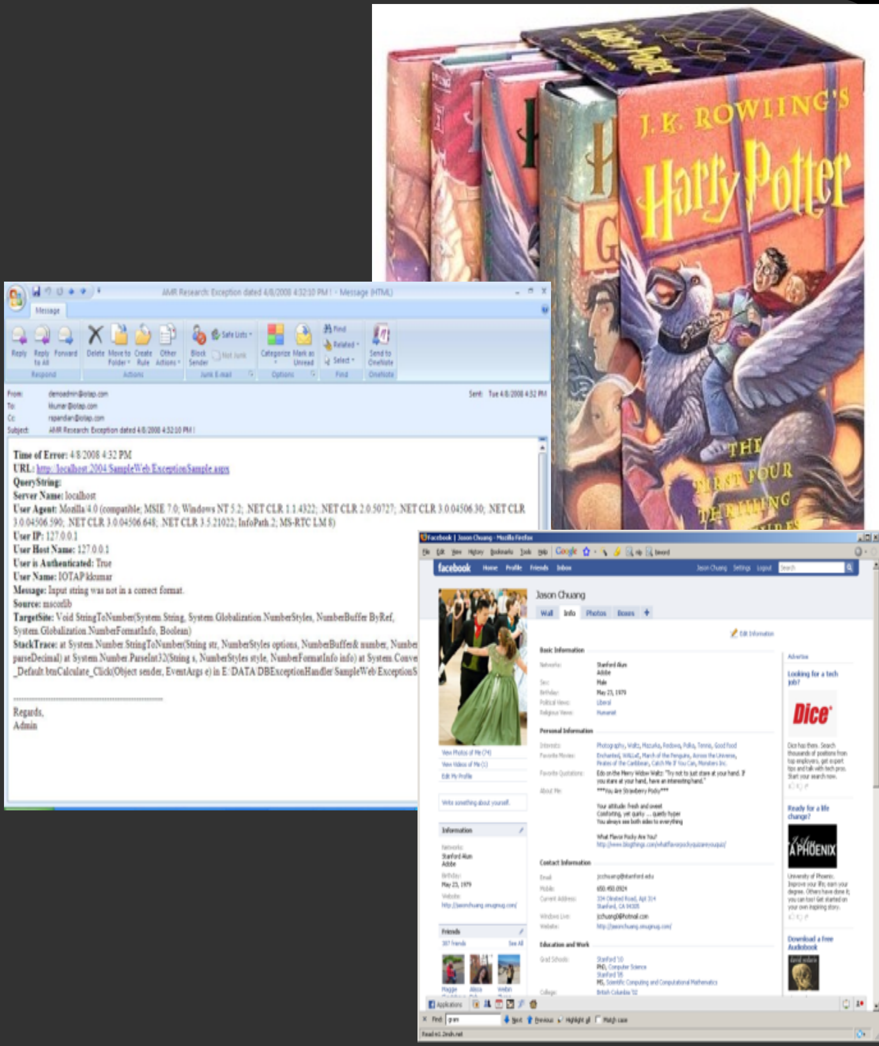
Computer programs, logs

Collections of Documents

Messages (e-mail, blogs, tags, comments)

Social networks (personal profiles)

Academic collaborations (publications)



Example:
Health Care Reform

Example: Health Care Reform

Recent History

Initiatives by President Clinton

Overhaul by President Obama

Text Data

News articles

Speech transcriptions

Legal documents

What questions might you want to answer?

What visualizations might help?

A Concrete Example

September 10, 2009

TEXT

Obama's Health Care Speech to Congress

Following is the prepared text of President Obama's speech to Congress on the need to overhaul health care in the United States, as released by the White House.

Madame Speaker, Vice President Biden, Members of Congress, and the American people:

When I spoke here last winter, this nation was facing the worst economic crisis since the Great Depression. We wer losing an average of 700,000 jobs per month. Credit was frozen. And our financial system was on the verge of collapse.

As any American who is still looking for work or a way to pay their bills will tell you, we are by no means out of the woods. A full and vibrant recovery is many months away. And I will not let up until those Americans who seek jobs can find them; until those businesses that seek capital and credit can thrive; until all responsible homeowners can stay in their homes. That is our ultimate goal. But thanks to the bold and decisive action we have taken since January, I can stand here with confidence and say that we have pulled this economy back from the brink.

I want to thank the members of this body for your efforts and your support in these last several months, and especially those who have taken the difficult votes that have put us on a path to recovery. I also want to thank the American people for their patience and resolve during this trying time for our nation.

But we did not come here just to clean up crises. We came to build a future. So tonight, I return to speak to all of yo

Tag Clouds: Word Count

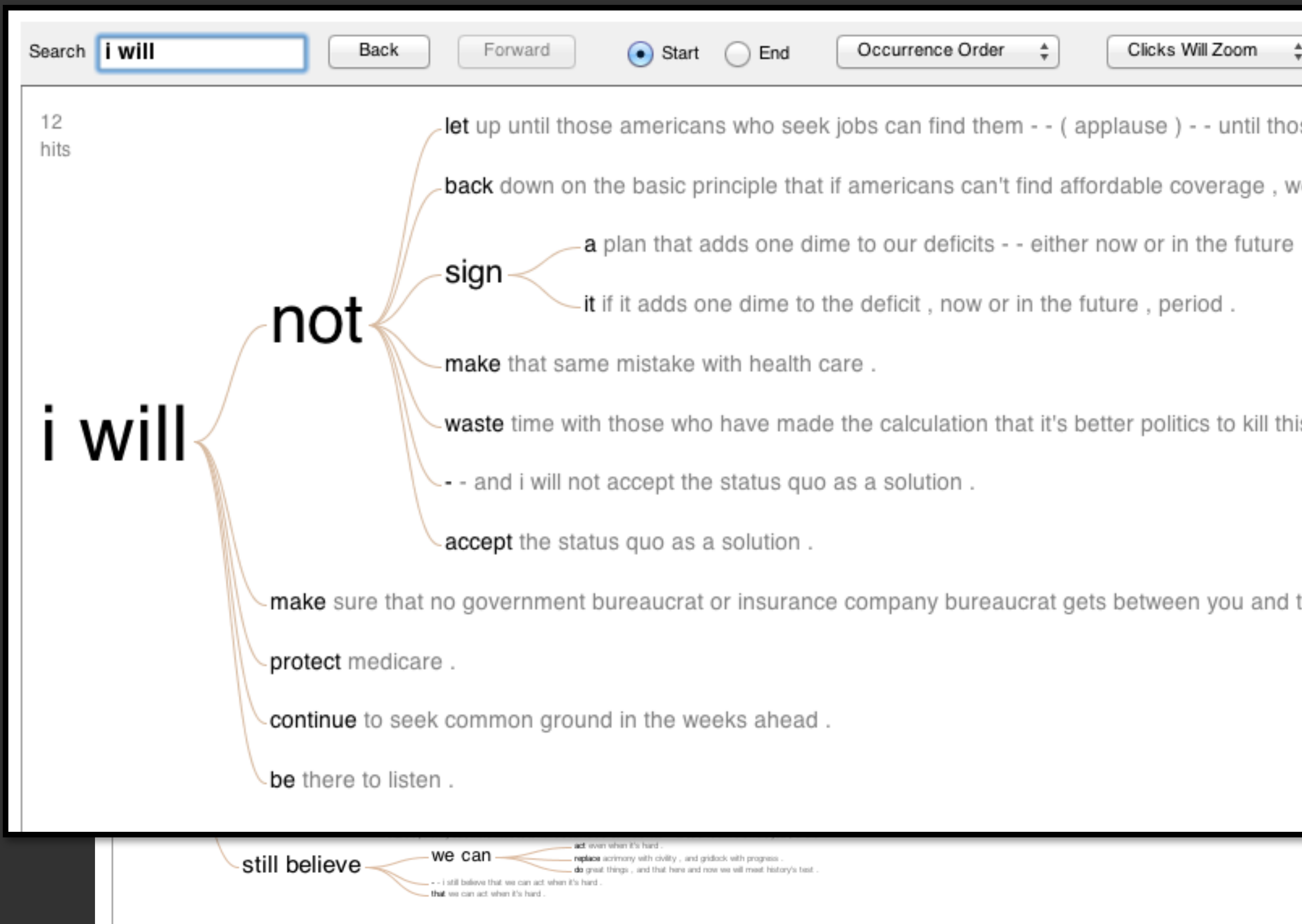
President Obama's Health Care Speech to Congress [NY Times]

Bill Clinton 1993

Barack Obama 2009

economix.blogs.nytimes.com/2009/09/09/obama-in-09-vs-clinton-in-93

Word Tree: Word Sequences


Search
i will
Back
Forward
Start
End
Occurrence Order
Clicks Will Zoom
12
hits
i will
not
let up until those americans who seek jobs can find them - - (applause) - - until tho
back down on the basic principle that if americans can't find affordable coverage , w
sign
a plan that adds one dime to our deficits - - either now or in the future
it if it adds one dime to the deficit , now or in the future , period .
make that same mistake with health care .
waste time with those who have made the calculation that it's better politics to kill thi
- - and i will not accept the status quo as a solution .
accept the status quo as a solution .
make sure that no government bureaucrat or insurance company bureaucrat gets between you and t
protect medicare .
continue to seek common ground in the weeks ahead .
be there to listen .
still believe
we can
act even when it's hard .
replace acrimony with civility , and gridlock with progress .
do great things , and that here and now we will meet history's test .
- - i still believe that we can act when it's hard .
that we can act when it's hard .

Gulfs of Evaluation

Many text visualizations do not represent the text directly. They represent the output of a **language model** (word counts, word sequences, etc.).

- Can you interpret the visualization? How well does it convey the properties of the model?
- Do you trust the model? How does the model enable us to reason about the text?

Text Visualization Challenges

High Dimensionality

Where possible use text to represent text…

… which terms are the most descriptive?

Context & Semantics

Provide relevant context to aid understanding.

Show (or provide access to) the source text.

Modeling Abstraction

Determine your analysis task.

Understand abstraction of your language models.

Match analysis task with appropriate tools and models.

Topics

Text as Data

Visualizing Document Content

Visualizing Conversation

Document Collections

Text as Data

Words as nominal data?

High dimensional (10,000+)

More than equality tests

Words have meanings and relations

- Correlations: *Hong Kong, Puget Sound, Bay Area*
- Order: *April, February, January, June, March, May*
- Membership: *Tennis, Running, Swimming, Hiking, Piano*
- Hierarchy, antonyms & synonyms, entities, …

Text Processing Pipeline

1. Tokenization

    Segment text into terms.

    Remove stop words? *a, an, the, of, to, be*

    Numbers and symbols? *#huskies, @UW, OMG!!!!!!!!*

    Entities? *Washington State, O'Connor, U.S.A.*

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2. Stemming

   Group together different forms of a word.

   Porter stemmer?   *visualization(s), visualize(s), visually* -> *visual*

   Lemmatization?   *goes, went, gone* -> *go*

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3. Ordered list of terms

Bag of Words Model

Ignore ordering relationships within the text

A document ≈ vector of term weights

- Each dimension corresponds to a term (10,000+)
- Each value represents the relevance
  - For example, simple term counts

Aggregate into a document-term matrix

- Document vector space model

Document-Term Matrix

Each document is a vector of term weights

Simplest weighting is to just count occurrences

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

WordCounts (Harris '04)

http://wordcount.org

Visualizations : Wordle of Sarah Palin RNC 9/3/2008 Speech

Creator: Anonymous
Tags:

Edit Language Font Layout Color

Data file: Sarah Palin speaks at the Republican National Convention, 9/3/2008 Data source: SFGate / AP This data set has not yet been rated

Tag Clouds

Strengths

Can help with gisting and initial query formation.

Weaknesses

Sub-optimal visual encoding (size vs. position)

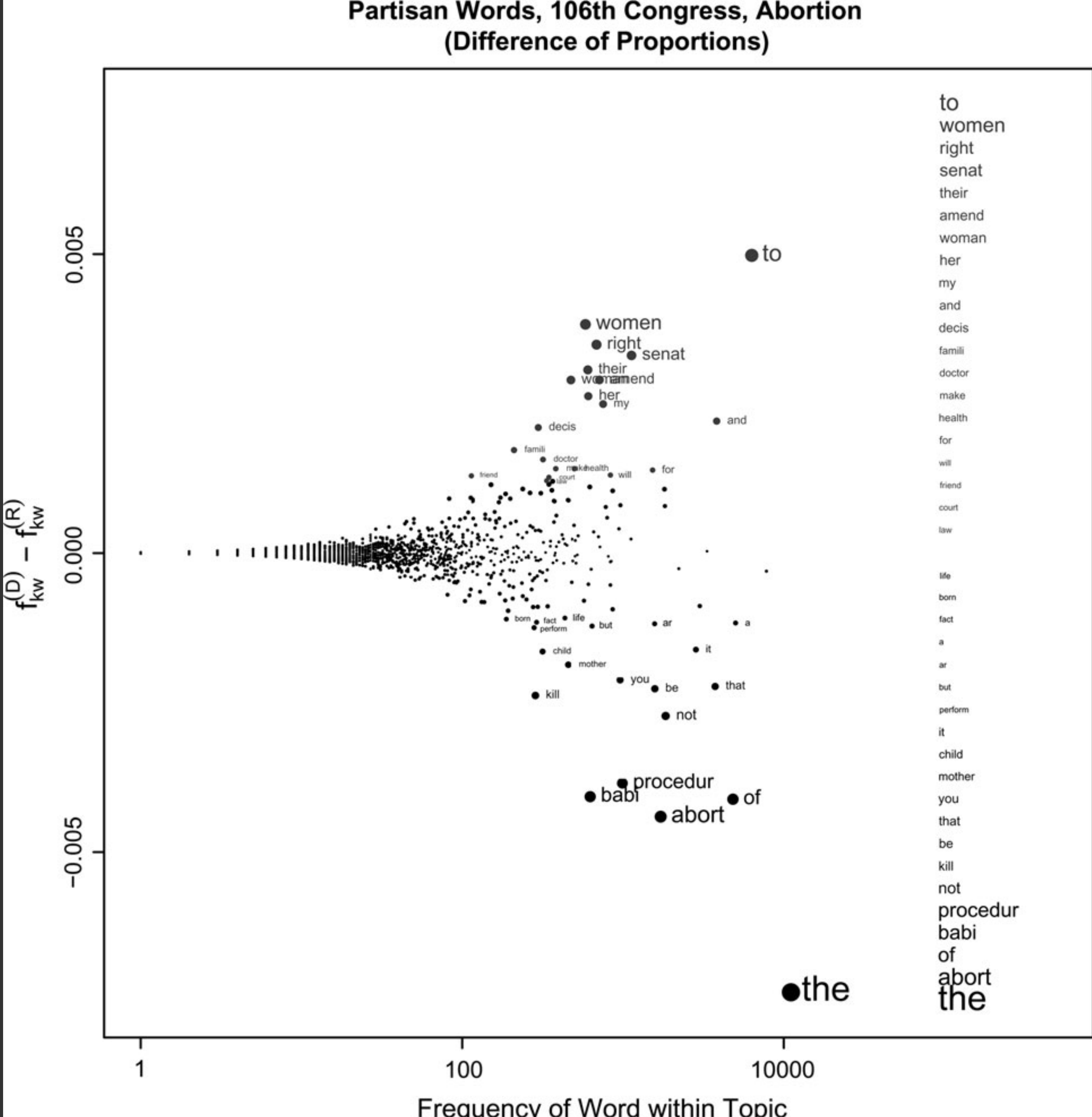
Inaccurate size encoding (long words are bigger)

May not facilitate comparison (unstable layout)

Term frequency may not be meaningful

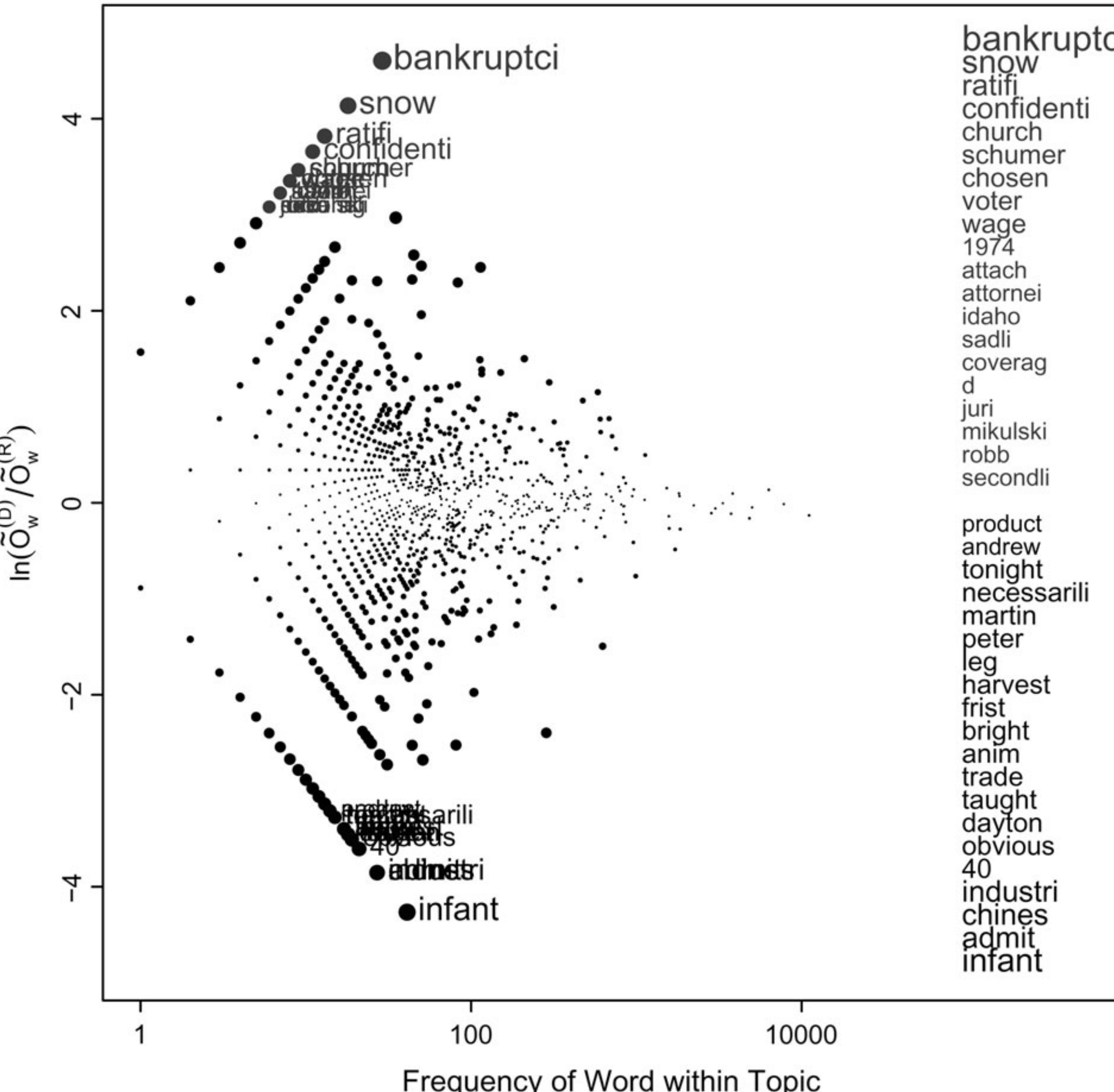
Does not show the structure of the text

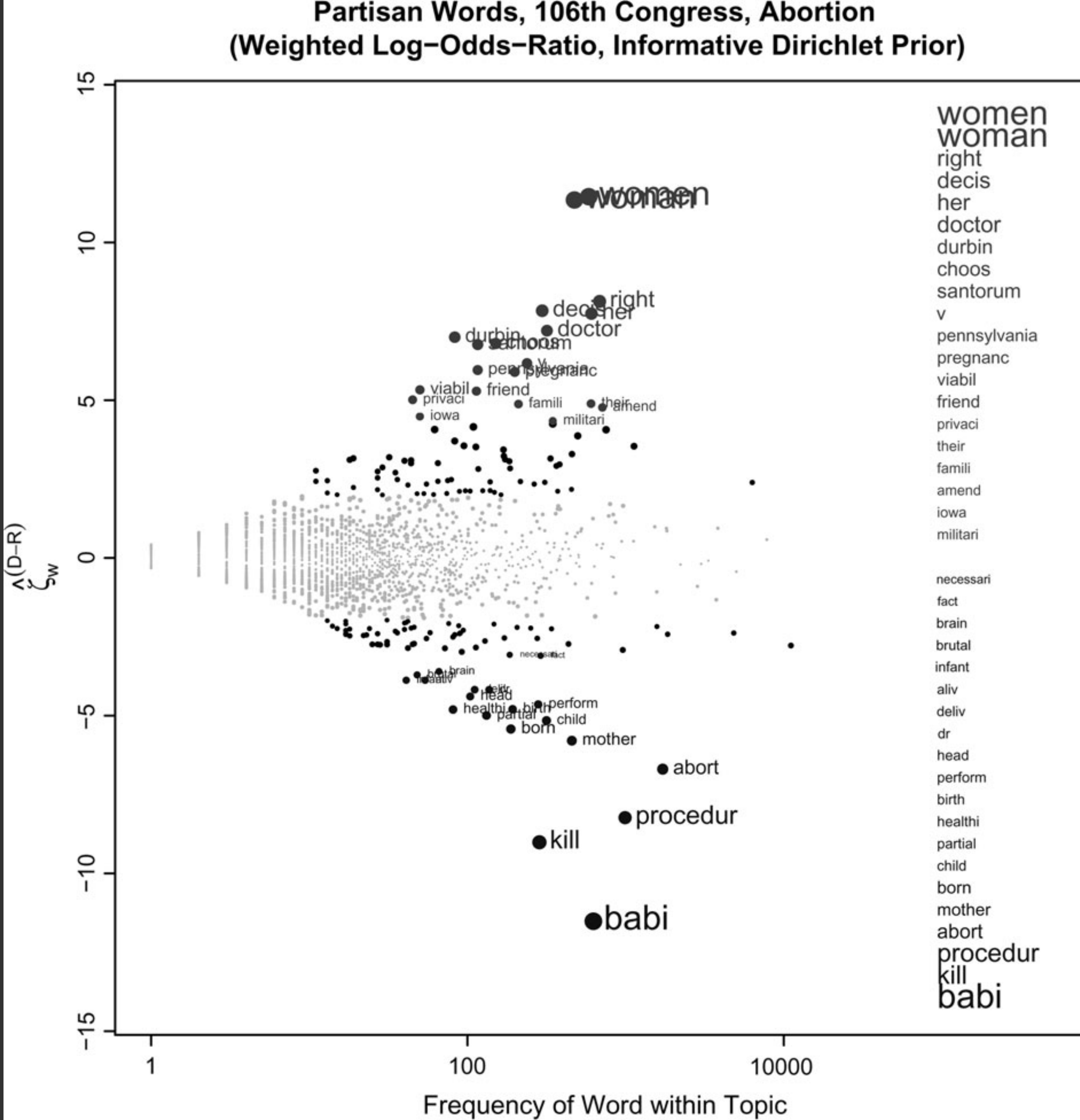
Given a text, what are the best descriptive words?



Partisan Words, 106th Congress, Abortion
(Difference of Proportions)
$f_{kw}^{(D)} - f_{kw}^{(R)}$
0.005
0.000
-0.005
1
100
10000
Frequency of Word within Topic
to
women
right
senat
their
amend
woman
her
my
and
decis
famili
doctor
make
health
for
will
friend
court
law
life
born
fact
a
ar
but
perform
it
child
mother
you
that
be
kill
not
procedur
babi
of
abort
the

Partisan Words, 106th Congress, Abortion
(Log−Odds−Ratio, Smoothed Log−Odds−Ratio)





Partisan Words, 106th Congress, Abortion
(Weighted Log−Odds−Ratio, Informative Dirichlet Prior)
$\hat{\zeta}_w^{(D-R)}$
Frequency of Word within Topic
1
100
10000
15
10
5
0
−5
−10
−15
women
woman
right
decis
her
doctor
durbin
choos
santorum
v
pennsylvania
pregnanc
viabil
friend
privaci
their
famili
amend
iowa
militari
necessari
fact
brain
brutal
infant
aliv
deliv
dr
head
perform
birth
healthi
partial
child
born
mother
abort
procedur
kill
babi

Keyword Weighting

Term Frequency

tf_{td} = count(t) in d

Can take log frequency: $\log(1 + tf_{td})$

Can normalize to show proportion: $tf_{td} / \Sigma_t \, tf_{td}$

Keyword Weighting

Term Frequency

tf_{td} = count(t) in d

TF.IDF: Term Freq by Inverse Document Freq

$tf.idf_{td} = \log(1 + tf_{td}) \times \log(N/df_t)$

df_t = # docs containing t; N = # of docs

Keyword Weighting

Require comparison across full corpus!

Term Frequency

tf_{td} = count(t) in d

TF.IDF: Term Freq by Inverse Document Freq

$tf.idf_{td} = \log(1 + tf_{td}) \times \log(N/df_t)$

df_t = # docs containing t; N = # of docs

G^2: Probability of different word frequency

$E_1 = |d| \times (tf_{td} + tf_{t(C\text{-}d)}) / |C|$

$E_2 = |C\text{-}d| \times (tf_{td} + tf_{t(C\text{-}d)}) / |C|$

$G^2 = 2 \times (tf_{td} \log(tf_{td}/E_1) + tf_{t(C\text{-}d)} \log(tf_{t(C\text{-}d)}/E_2))$

Limitations of Freq. Statistics

Typically focus on unigrams (single terms)

Often favors frequent (TF) or rare (IDF) terms

- Not clear that these provide best description

A “bag of words” ignores additional information

- Grammar / part-of-speech
- Position within document
- Recognizable entities

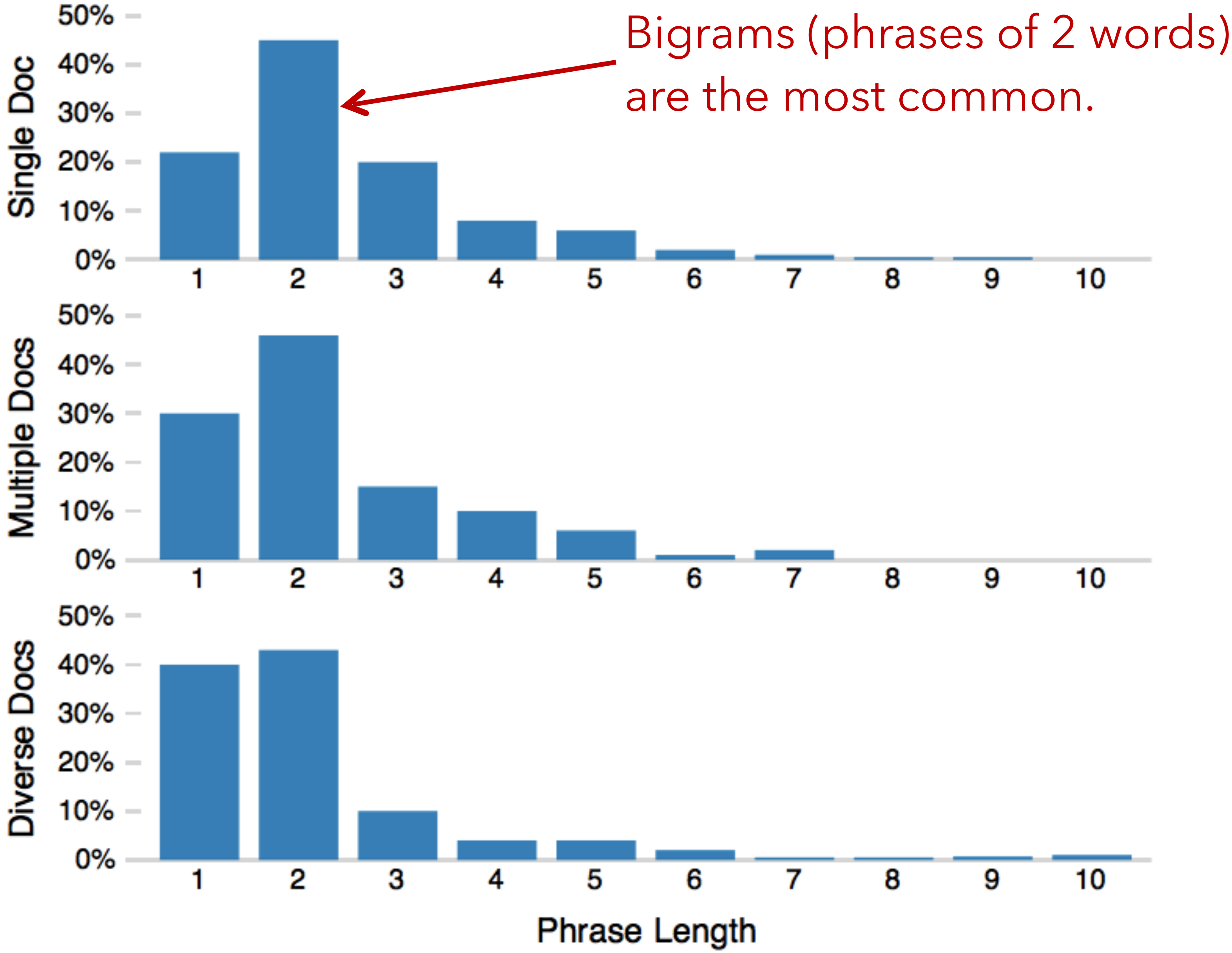
How do people describe text?

We asked 69 subjects (graduate students) to read and describe dissertation abstracts.

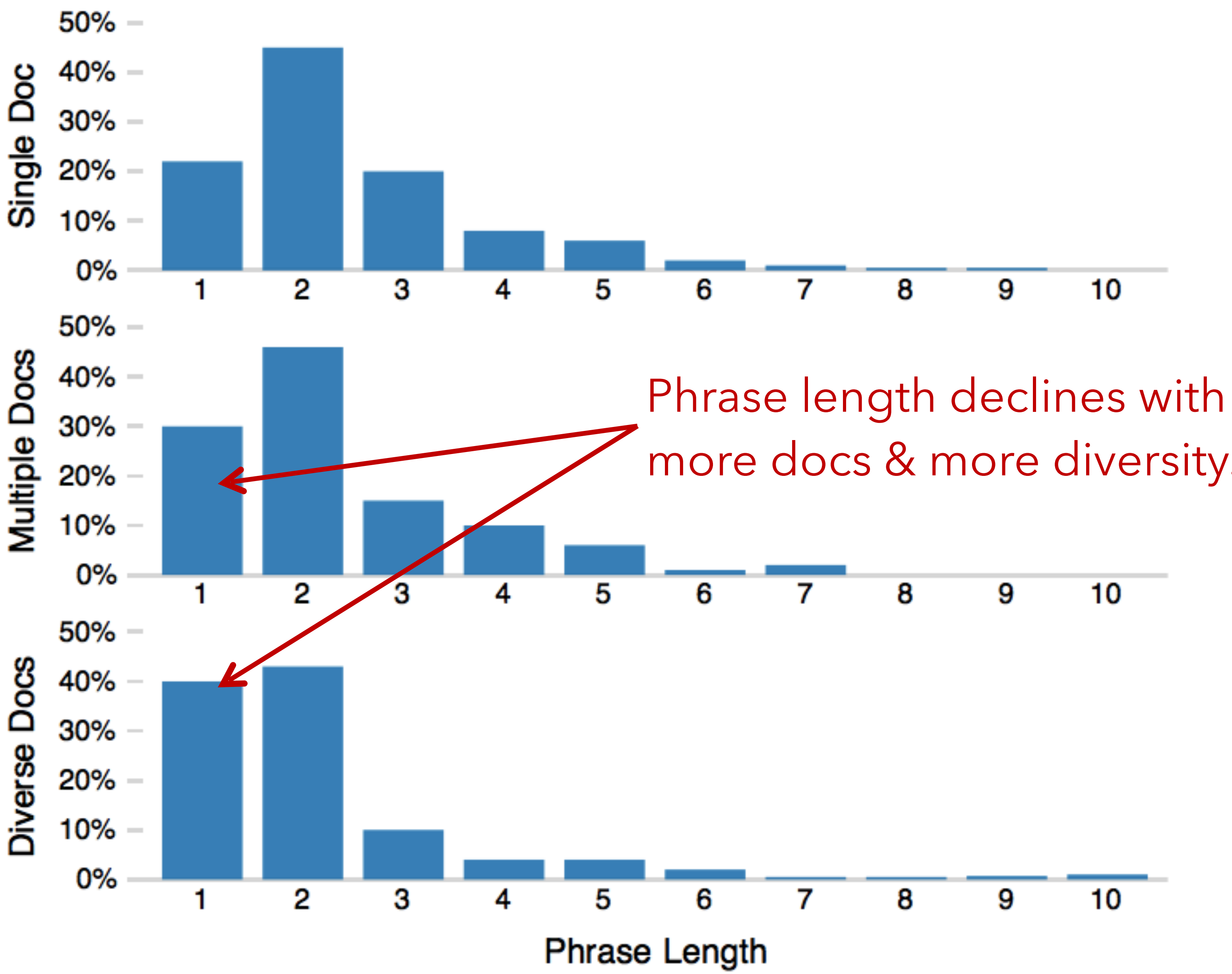
Students were given 3 documents in sequence; they then described the collection as a whole.

Students were matched to both *familiar* and *unfamiliar* topics; *topical diversity* within a collection was varied systematically.

[Chuang, Manning & Heer, 2012]



Bigrams (phrases of 2 words)
are the most common.
Single Doc
Multiple Docs
Diverse Docs
50%
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
Phrase Length



Single Doc
Multiple Docs
Diverse Docs
50%
40%
30%
20%
10%
0%
1
2
3
4
5
6
7
8
9
10
Phrase Length
Phrase length declines with
more docs & more diversity.

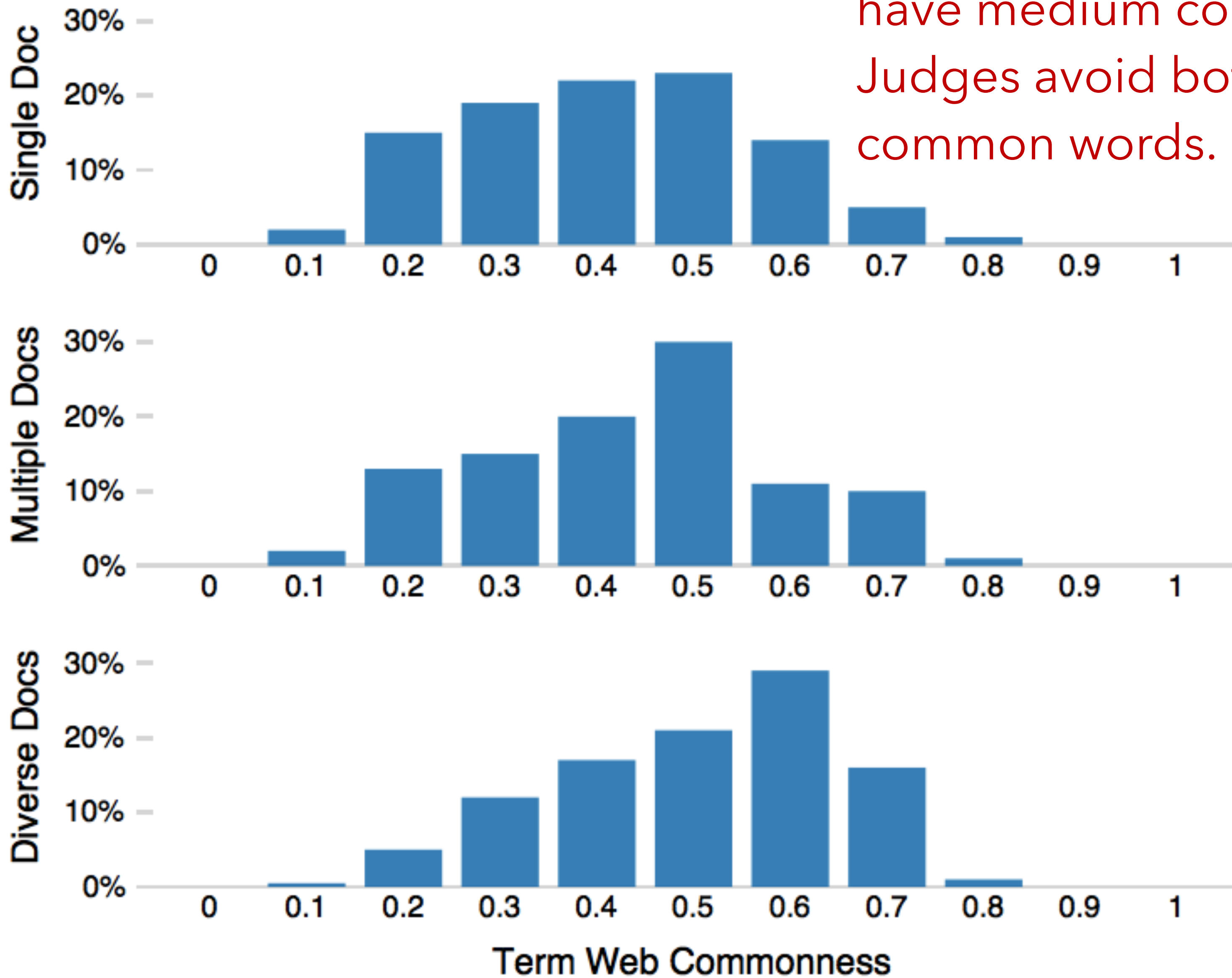
Term Commonness

$$\log(tf_w) \;/\; \log(tf_{the})$$

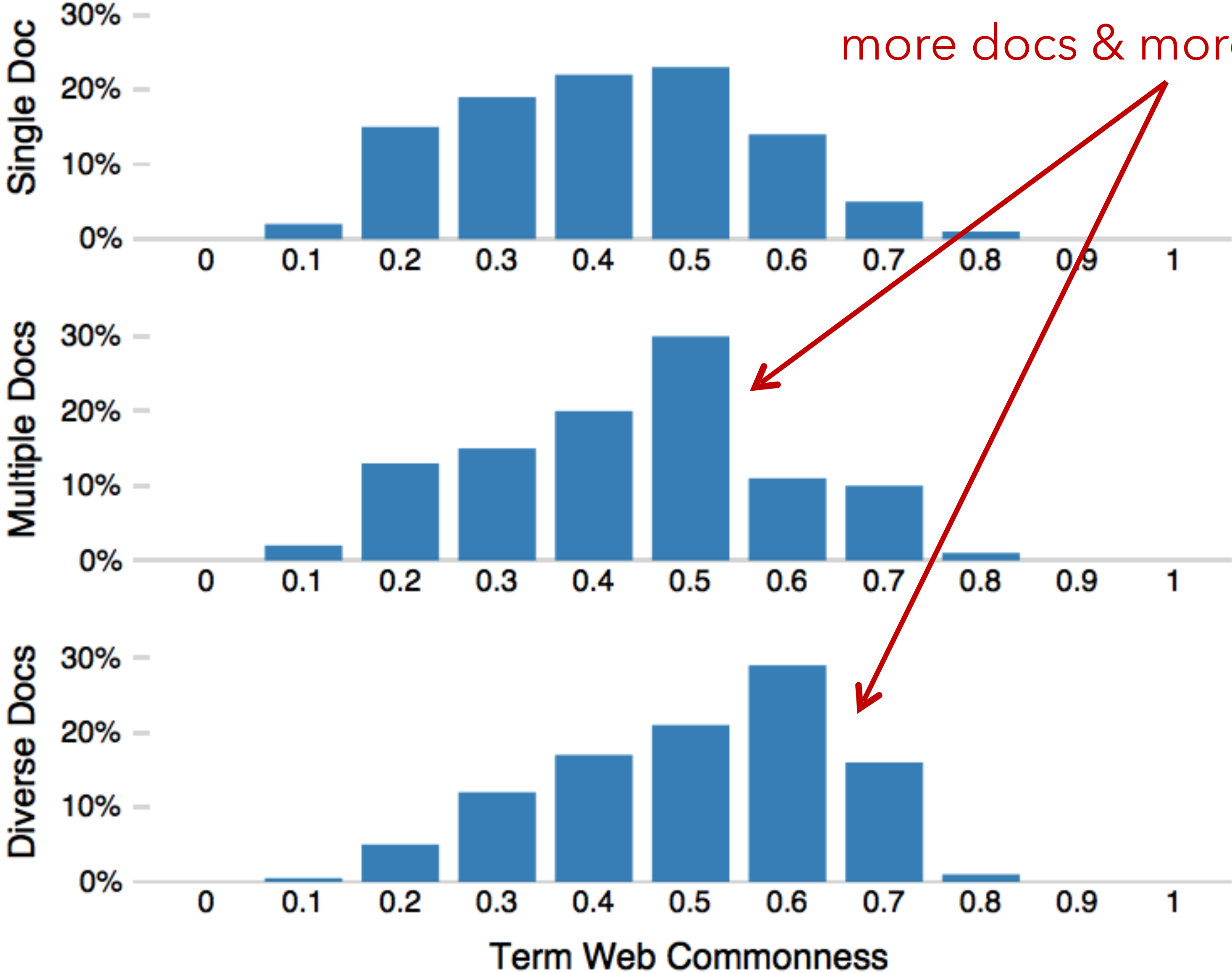
The normalized term frequency relative to the most frequent n-gram, e.g., the word "the".

Measured across a corpus or across the entire English language (using Google n-grams)

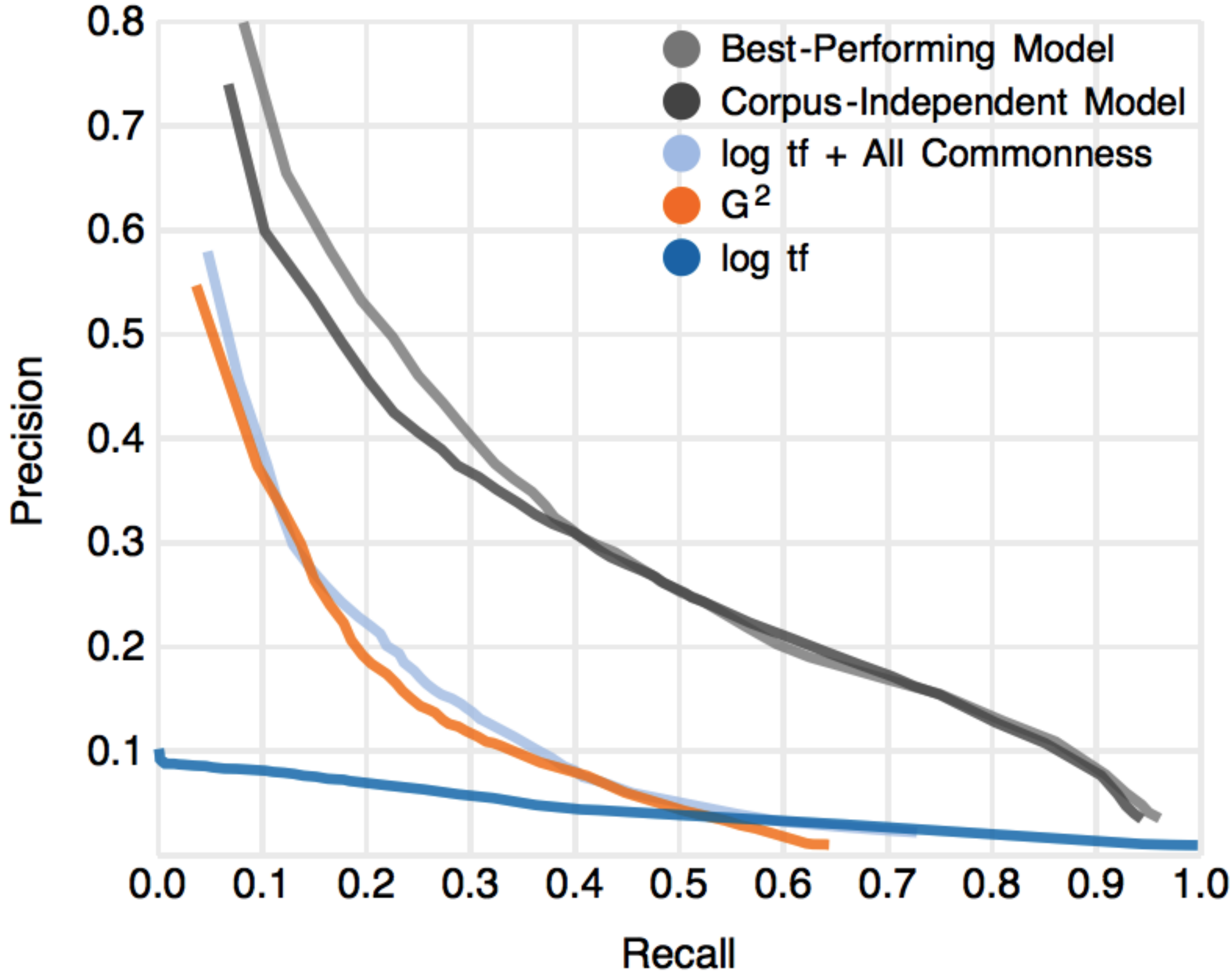
Selected descriptive terms have medium commonness. Judges avoid both rare and common words.



Commonness increases with more docs & more diversity.



Scoring Terms with Freq, Grammar & Position



A fighter jet rain check

Story and video by Chamila Jayaweera

Have you ever thought about what it takes to make sure that sea-based fighter jets stay dry?

When it comes to the F/A-18 Super Hornet, Boeing engineers in St. Louis use a special process called the Water Check Test to rule out areas where moisture could seep into the aircraft and its electronics suite.

CHAMILA JAYAWEERA/BOEING

The Water Check team rolls in a large metal frame, which they affectionately call their "spray tree," over a Super Hornet inside a St. Louis hangar.

Program experts douse the jet with simulated rain at a 15-inch-per-hour rate for about 20 minutes inside an enormous hangar in St. Louis.

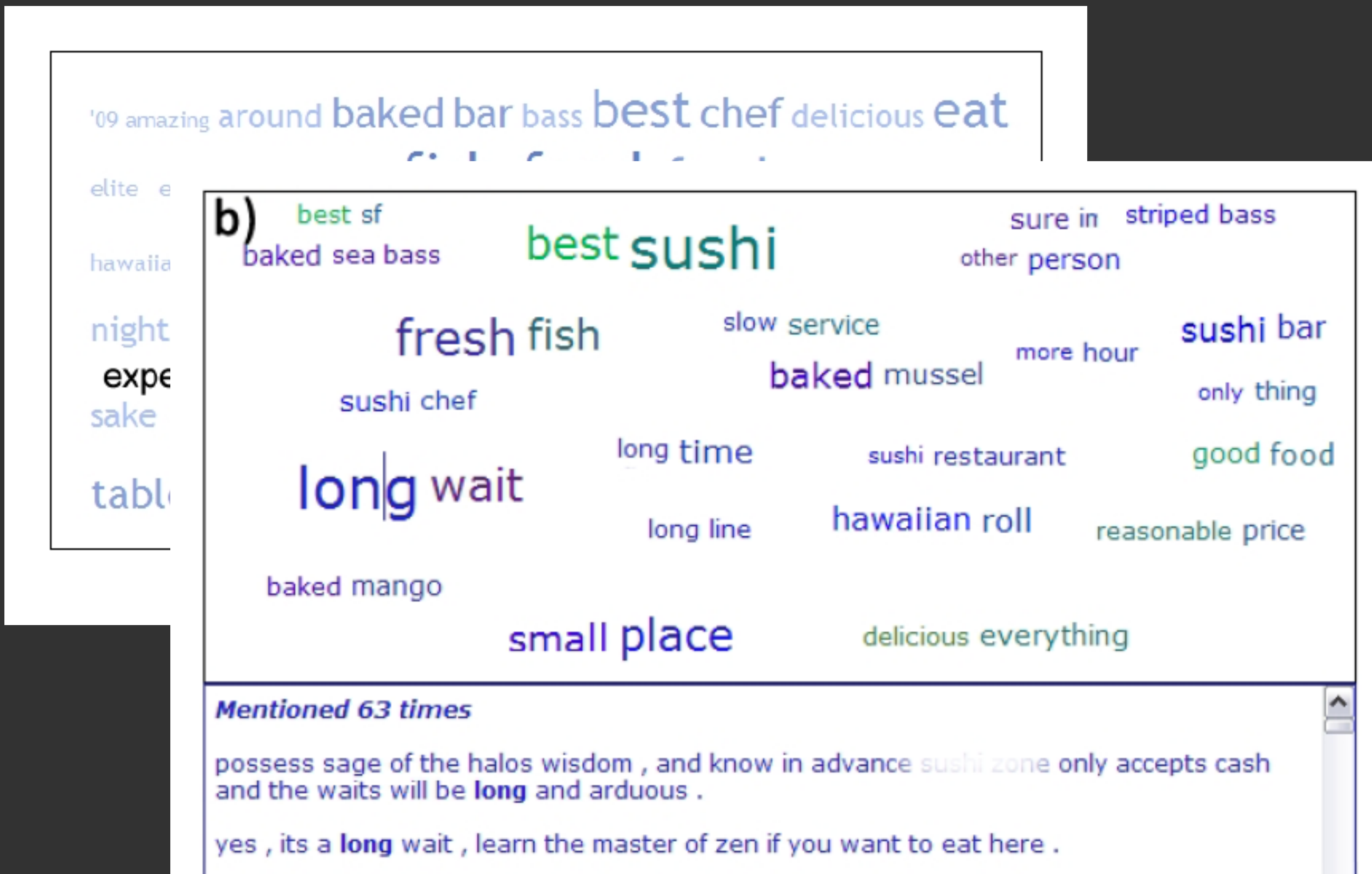
"Our ultimate customers are U.S. Navy fighter pilots, and we want to ensure their safety in flight and on the ground, and water-tight integrity of the aircraft also helps increase their effectiveness," said Boeing's Rich Baxter, F/A-18 Super Hornet final assembly manager.

To find out moreabout how the process works and watch the action unfold, click above to see the video story.

G^2	Regression Model
fighter	Super Hornet
F/A	F/A -18
Hornet	fighter jet
Super	Boeing engineers
Boeing	special process
-18	rain check
rain	electronics suite
St.	Program experts
jet	simulated rain
Louis	ultimate customers
15-inch-per-hour	enormous hangar
douse	water-tight integrity
hangar	Rich Baxter
water-tight	15-inch-per-hour rate
Check	video story
Baxter	aircraft
sea-based	U.S. Navy fighter pilots
aircraft	Super Hornet final assembly manager
Rich	U.S.
seep	Navy fighter
click	fighter pilots
Navy	sea-based fighter
sure	
Water	
moisture	
watch	
enormous	
stay	
want	

Yelp Review Spotlight (Yatani 2011)

Yelp Review Spotlight (Yatani 2011)



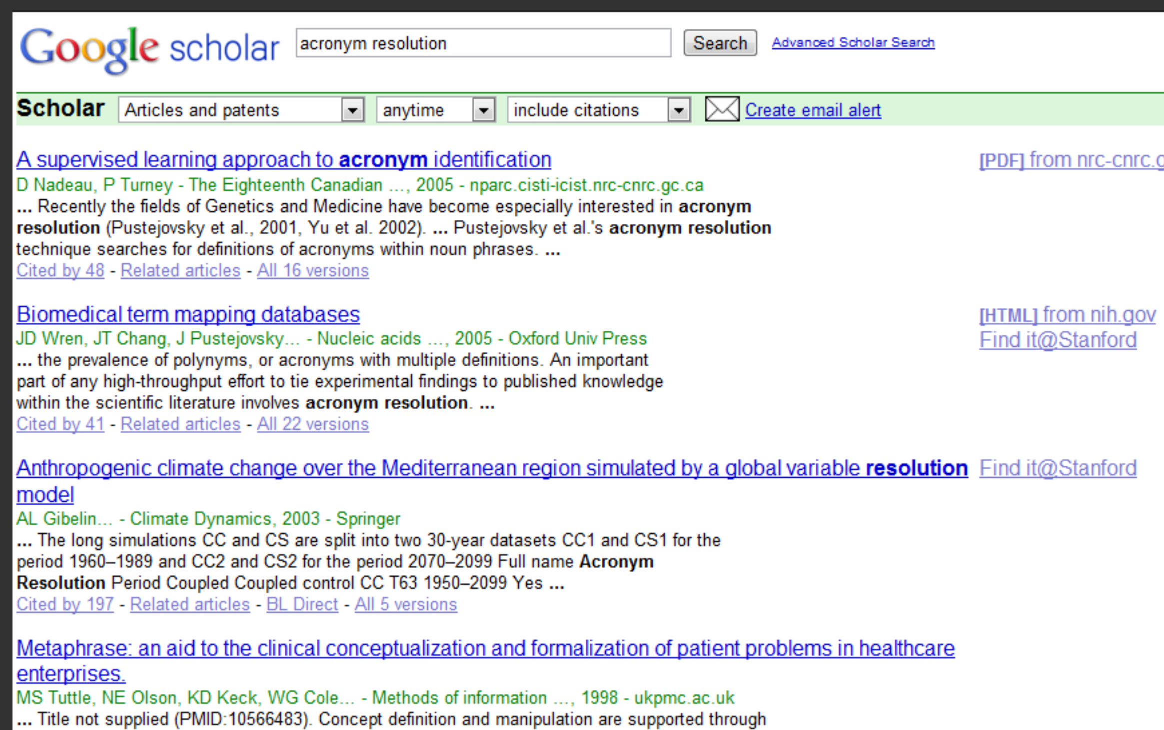
Tips: Descriptive Phrases

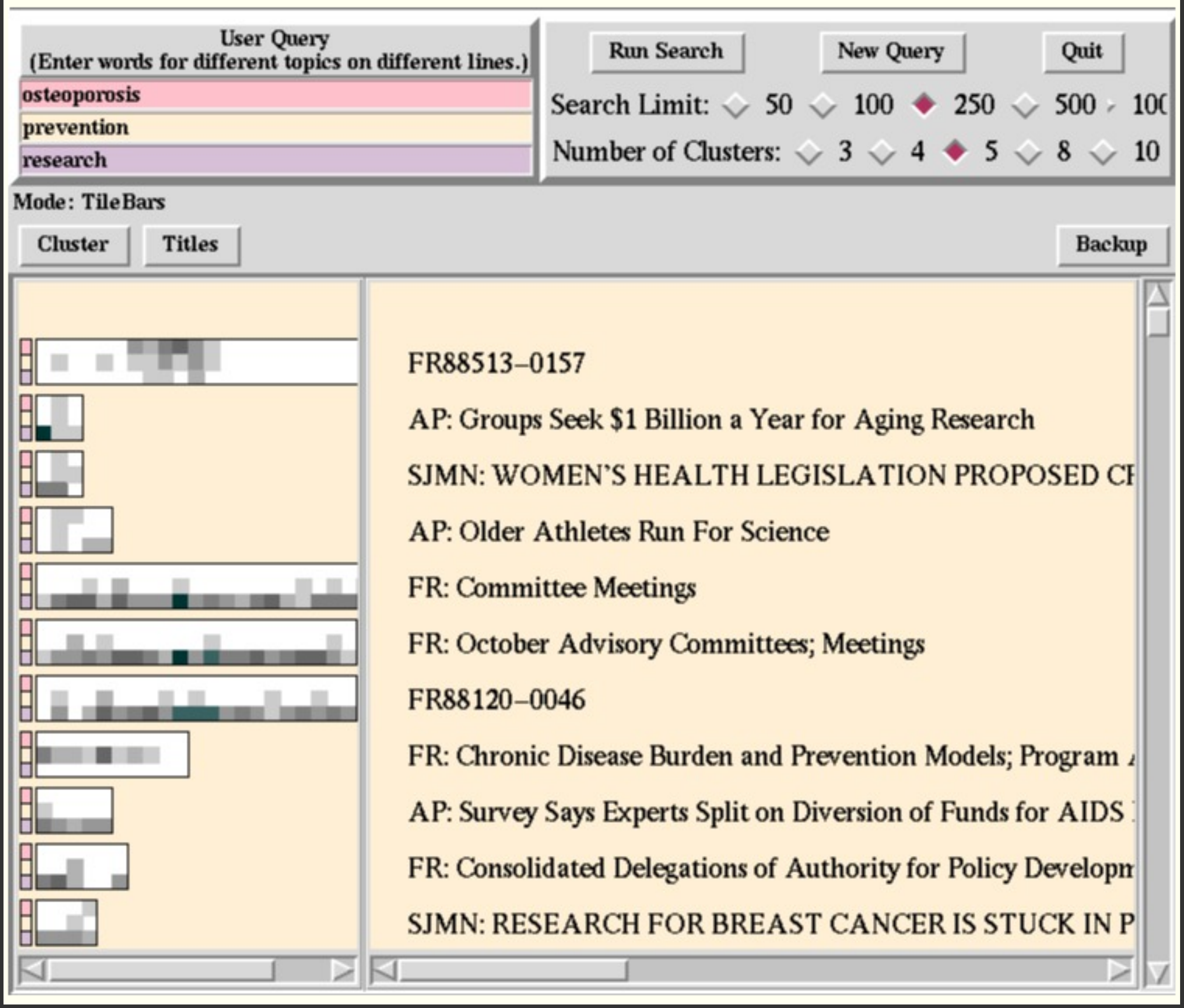
- Understand the limitations of your language model.
  - Bag of words:
    - Easy to compute
    - Single words
    - Loss of word ordering
- Select appropriate model and visualization
  - Generate longer, more meaningful phrases
  - Adjective-noun word pairs for reviews
  - Show keyphrases within source text

Document Content

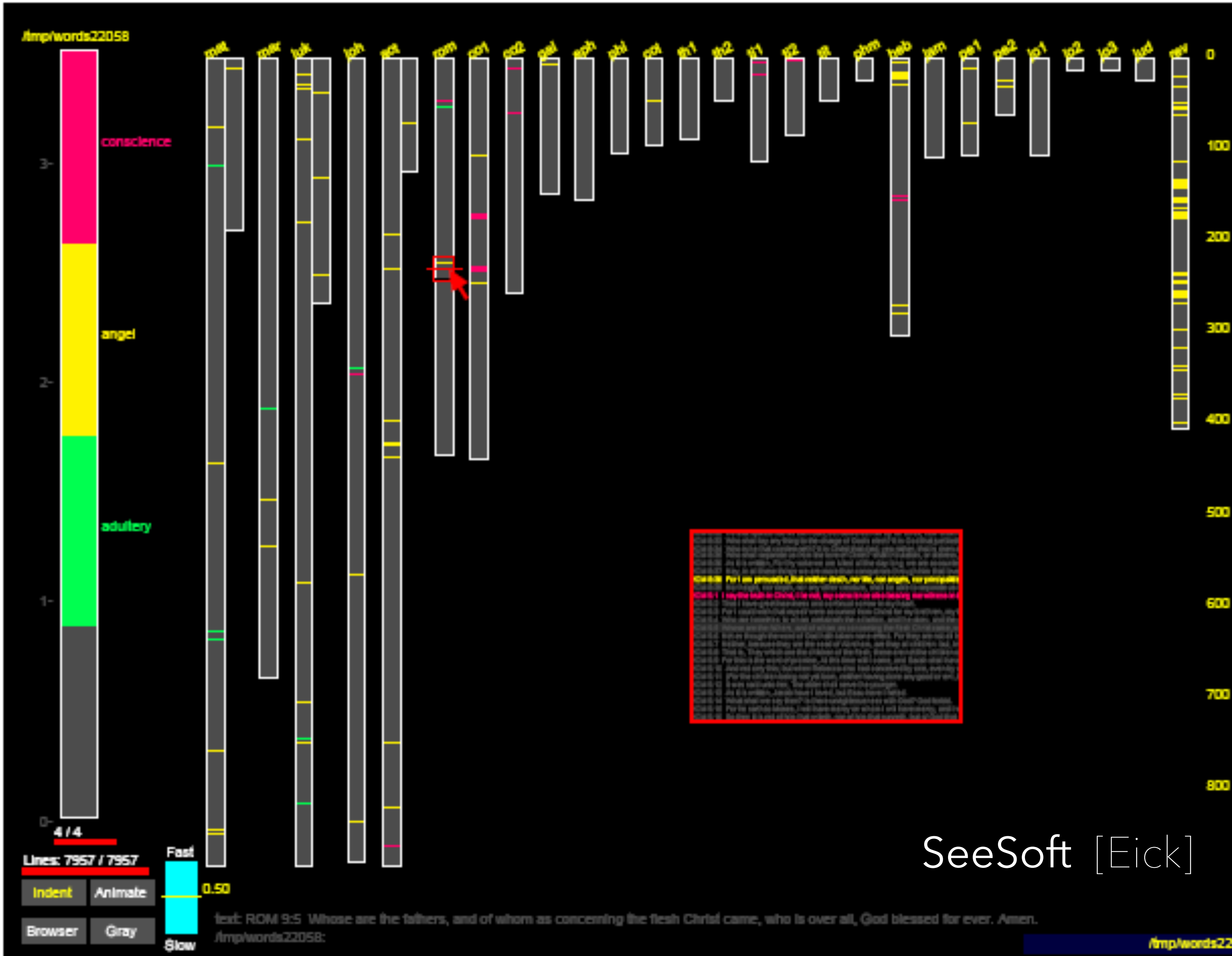
Information Retrieval

Search for documents
Match query string with documents
Visualization to **contextualize results**





TileBars [Hearst]



SeeSoft [Eick]

THE WORDS THAT WERE USED

READ 2007 SPEECH | FEEDBACK

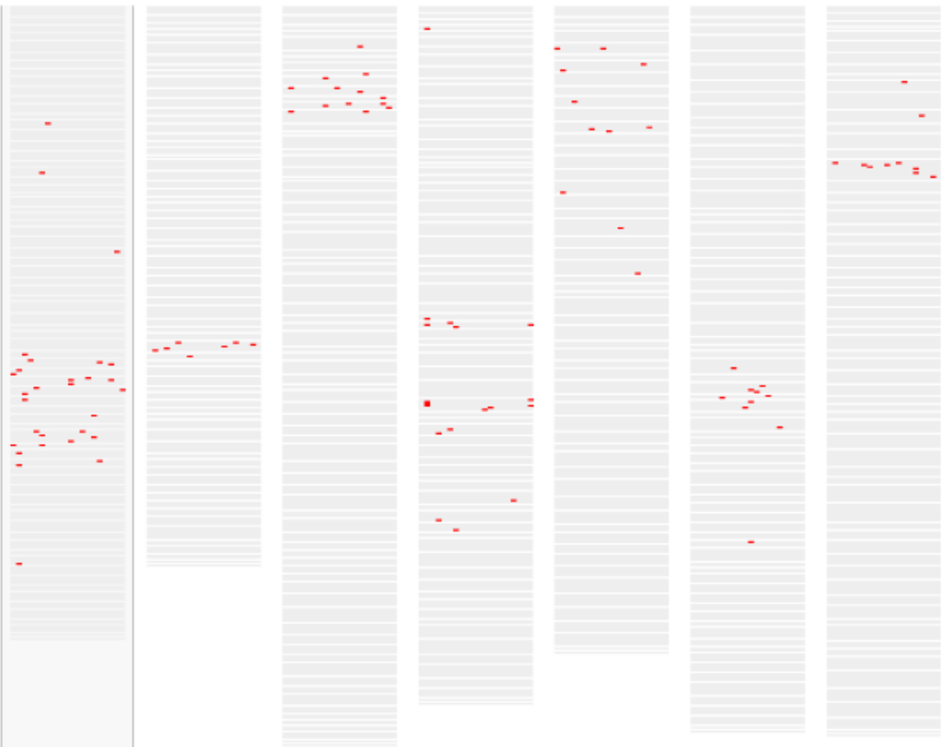
The 2007 State of the Union Address

Over the years, President Bush's State of the Union address has averaged almost 5,000 words each, meaning the the President has delivered over 34,000 words. Some words appear frequently while others appear only sporadically. Use the tools below to analyze what Mr. Bush has said.

Search | or choose a word here.

Use of the phrase "Tax" in past State of the Union Addresses

2001*	2002	2003	2004	2005	2006	2007
29	7	13	21	11	10	10



The word in context

Next Instance of 'Tax'

I believe in local control of schools. We should not, and we will not, run public schools from Washington, D.C. Yet when the federal government spends **TAX** dollars, we must insist on results. Children should be tested on basic reading and math skills every year between grades three and eight. Measuring is the only way to know whether all our children are learning. And I want to know, because I refuse to leave any child behind in America.

-- 2001 (Paragraph 14 of 73)

New York Times

Compared with other words

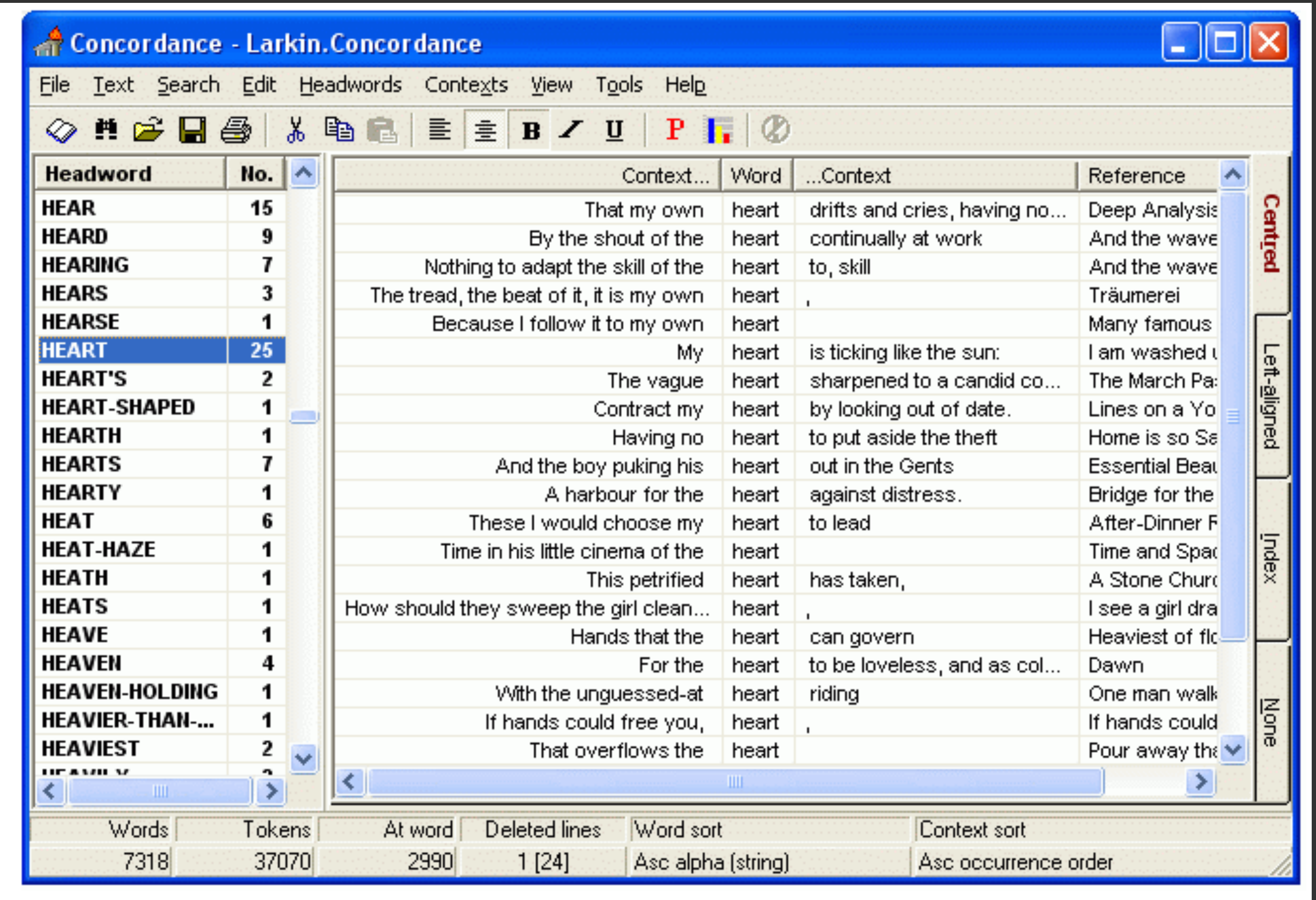
	2001*	2002	2003	2004	2005	2006	2007
Tax	29	7	13	21	11	10	10
Afghanistan	-	13	3	5	3	2	4
Economy(ic)	6	7	13	17	14	23	8
Insurance	2	-	1	6	1	3	14
Iraq/Iraqi(s)	-	2	21	24	27	16	34
Iran	-	2	3	1	3	6	5
Oil	-	1	-	-	-	3	9
Social Security	15	2	2	2	18	3	2

* As a newly elected president, Mr. Bush did not deliver a formal State of the Union address in 2001. His Feb. 27 speech to a joint session of Congress was analogous to the State of the Union, but without the title.

Ben Werschkul/The New York Times

Concordance

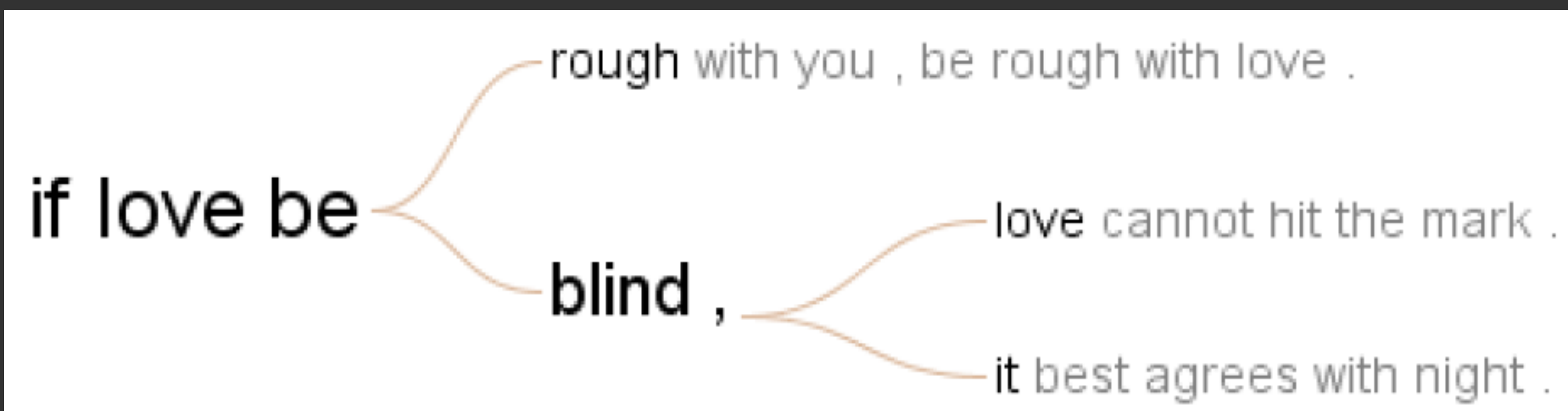
What is the common local context of a term?



if love be rough with you , be rough with love .

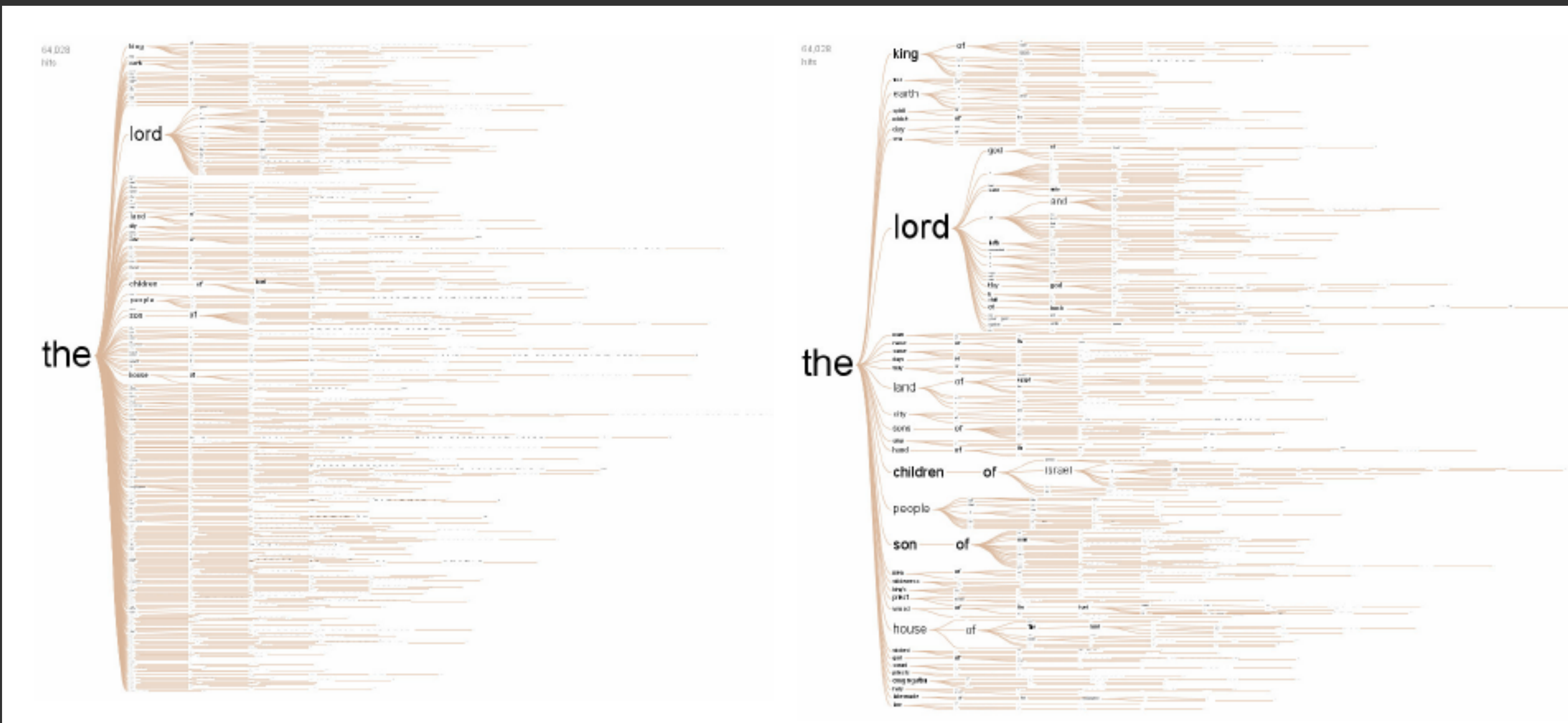
if love be blind , love cannot hit the mark .

if love be blind , it best agrees with night .

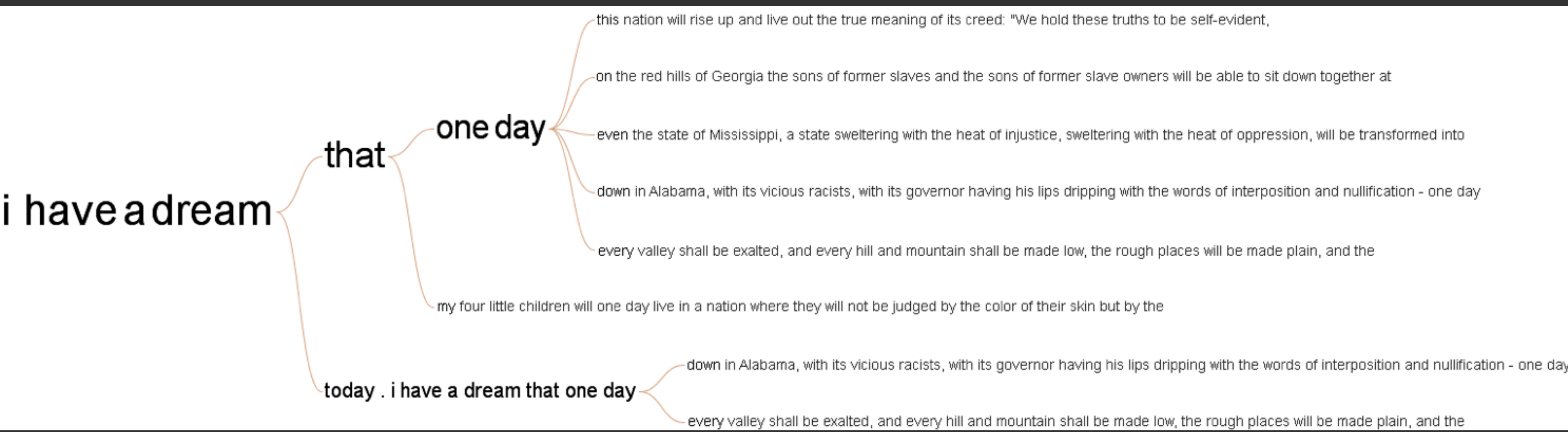


Word Tree [Wattenberg et al.]

Filter Infrequent Runs



Recurrent Themes in Speeches

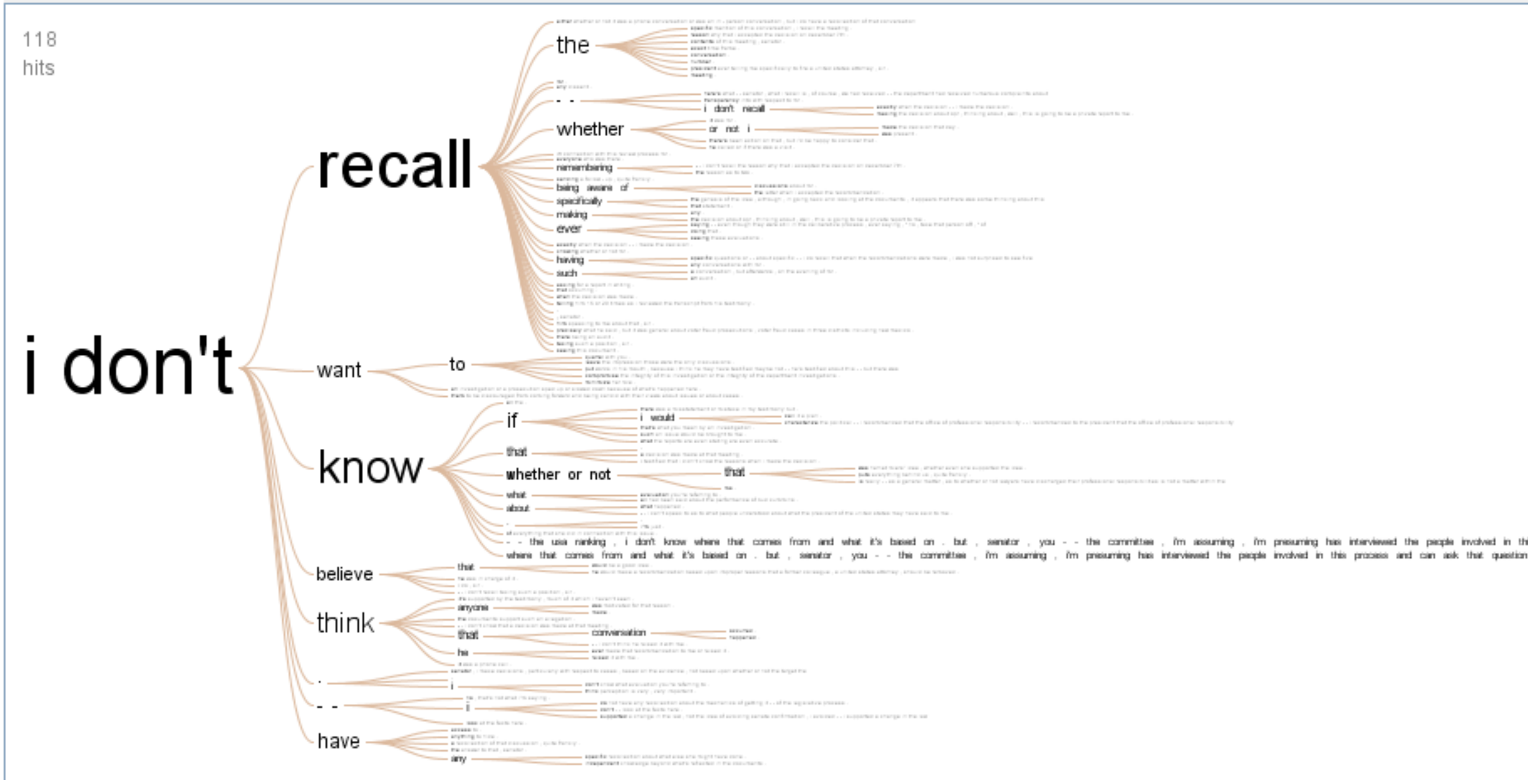


Visualizations : Word tree / Alberto Gonzales

Creator: Martin Wattenberg

Tags:

Search i don't Back Forward Start End Occurrence Order Clicks Will Zoom



Data file: Word in testimony from Gonzales, 4/19/2007 Data source: CQ Transcript Wire via the Washington Post

This data set has not yet been rated

full image share this watch this add to topic hub rate this

Comments (4)

currently showing

This visualization has 4 positive and 0 negative

explore
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- data sets
- comments
- topic hubs

participate
- create visualization
- upload data set
- create topic hub
- register

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- quick start
- visualization types
- data format & style
- about Many Eyes
- FAQ
- blog

contact Us
- contact
- report a bug

legal
- terms of use

Popular Dataset Tags

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Glimpses of Structure…

Concordances show local, repeated structure

But what about other types of patterns?

Lexical: <A> at <B>

Syntactic: <Noun> <Verb> <Object>

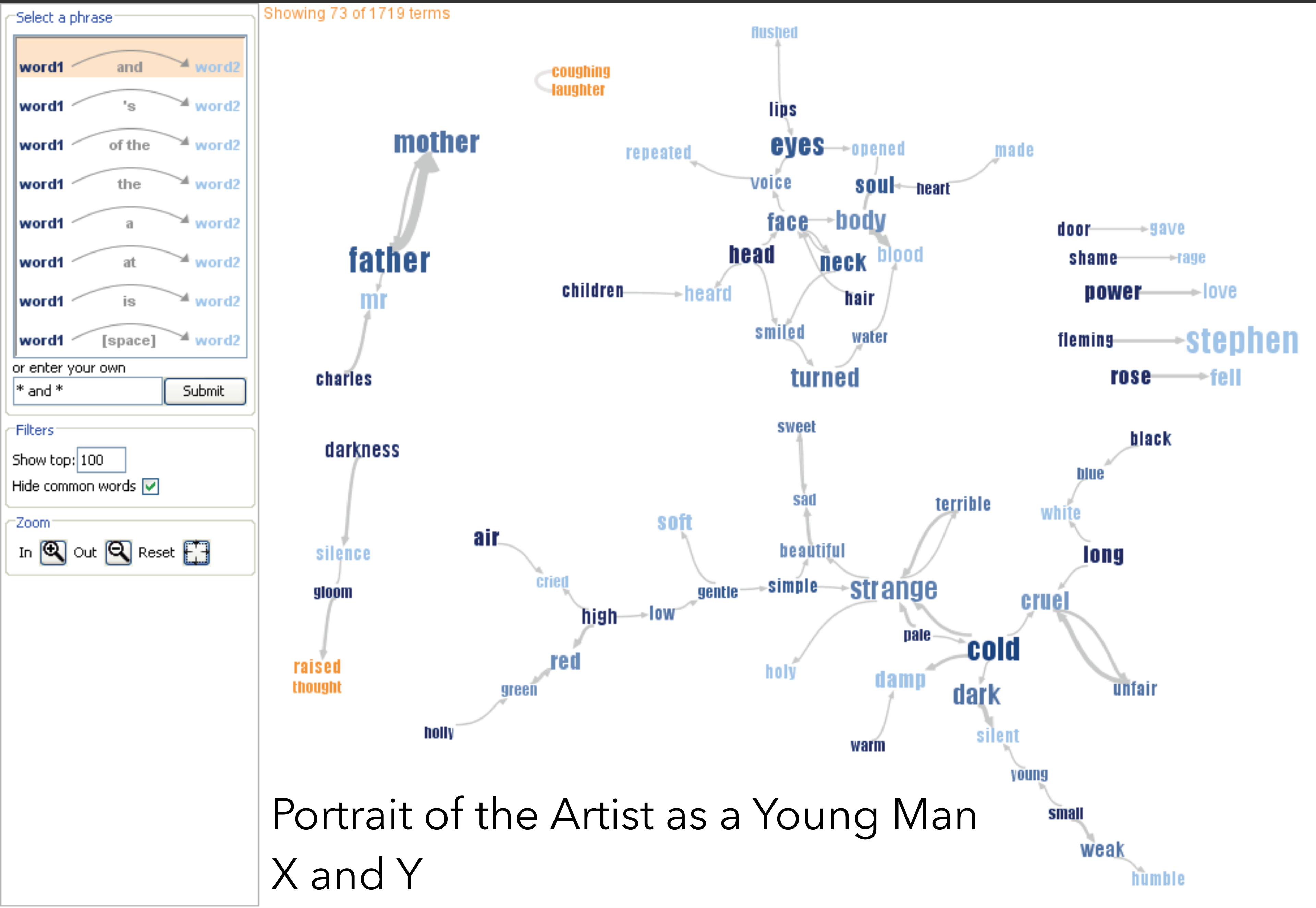
Phrase Nets [van Ham et al.]

Look for specific **linking patterns** in the text:

- 'A and B', 'A at B', 'A of B', etc
- Could be output of regexp or parser.

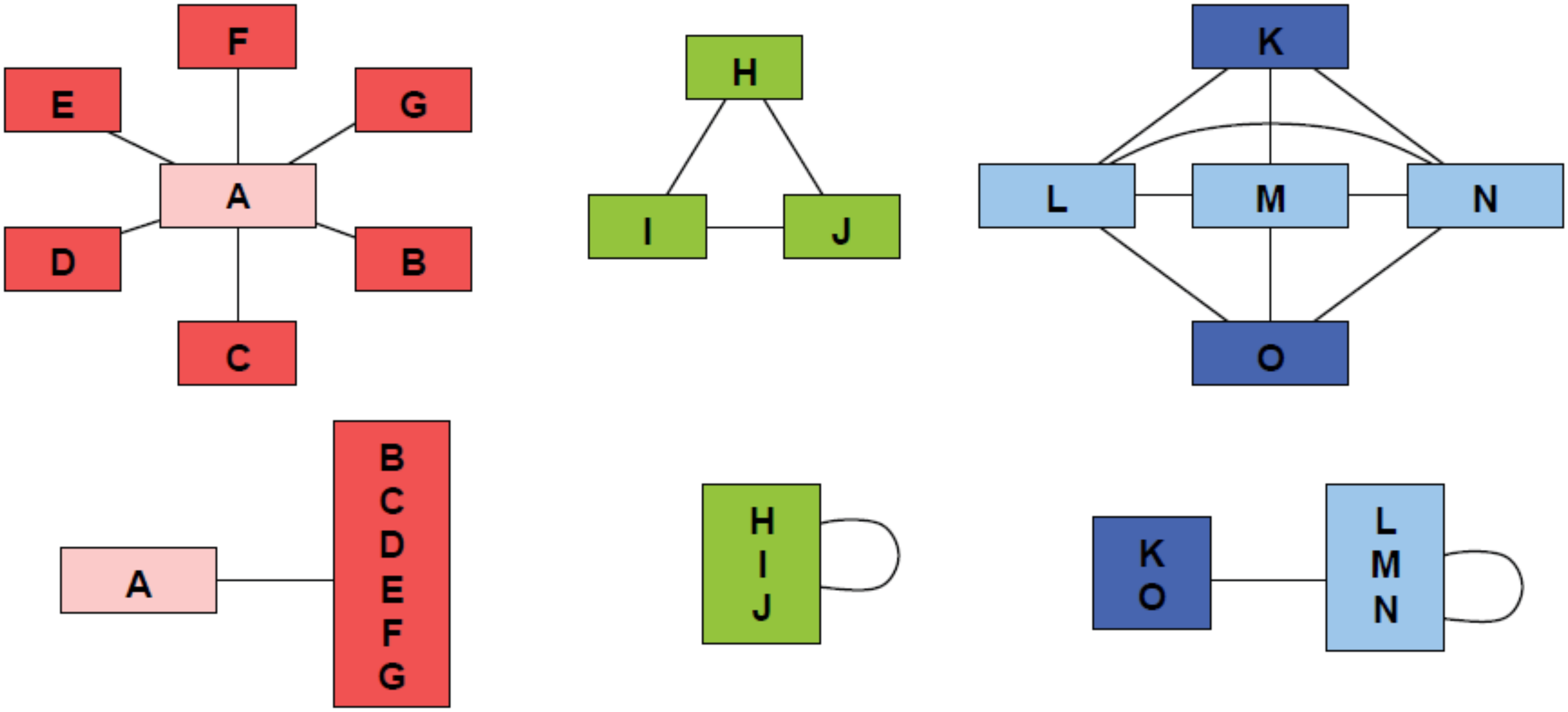
Visualize patterns in a node-link view

- Occurrences -> Node size
- Pattern position -> Edge direction



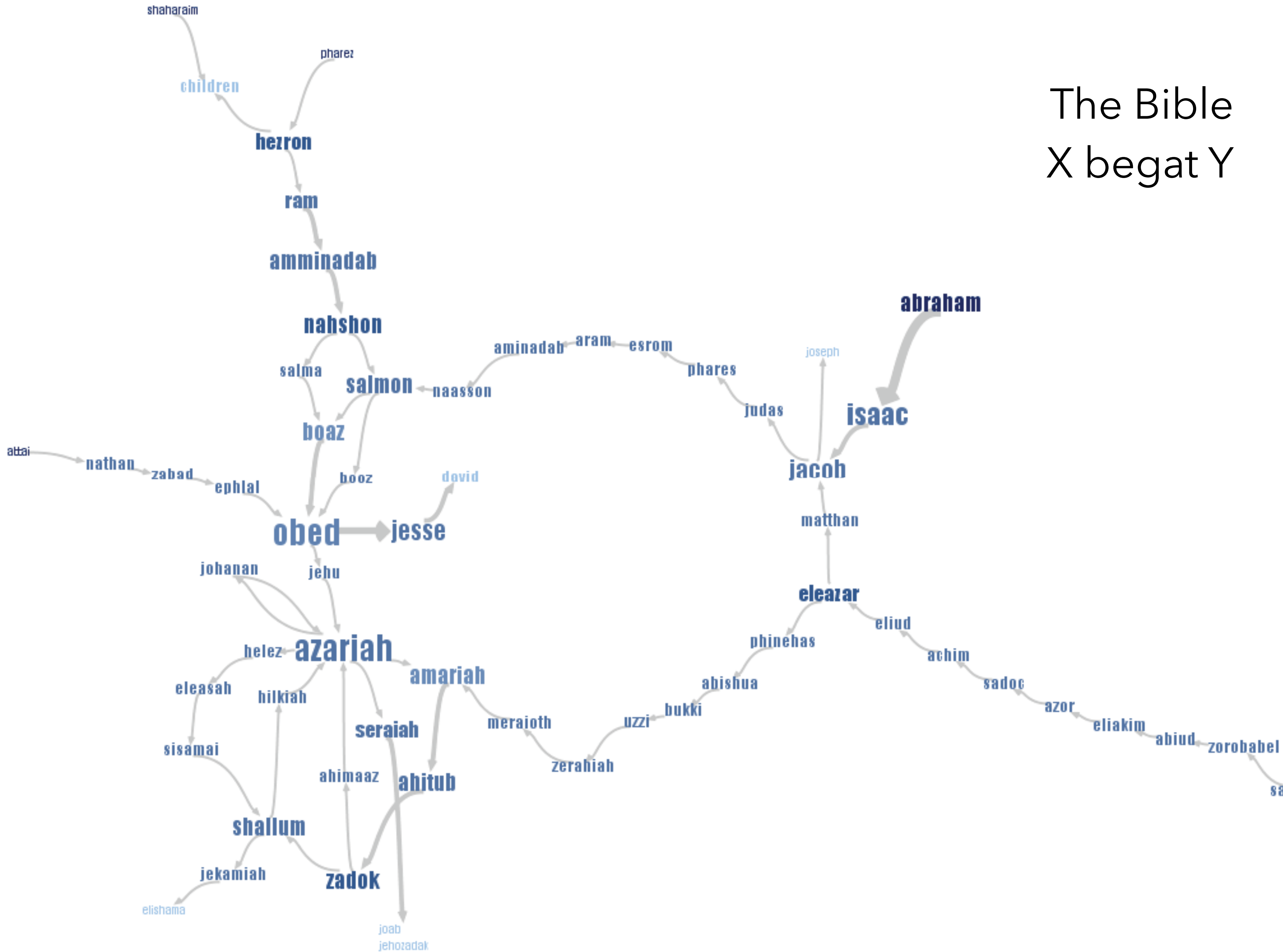
Portrait of the Artist as a Young Man
X and Y

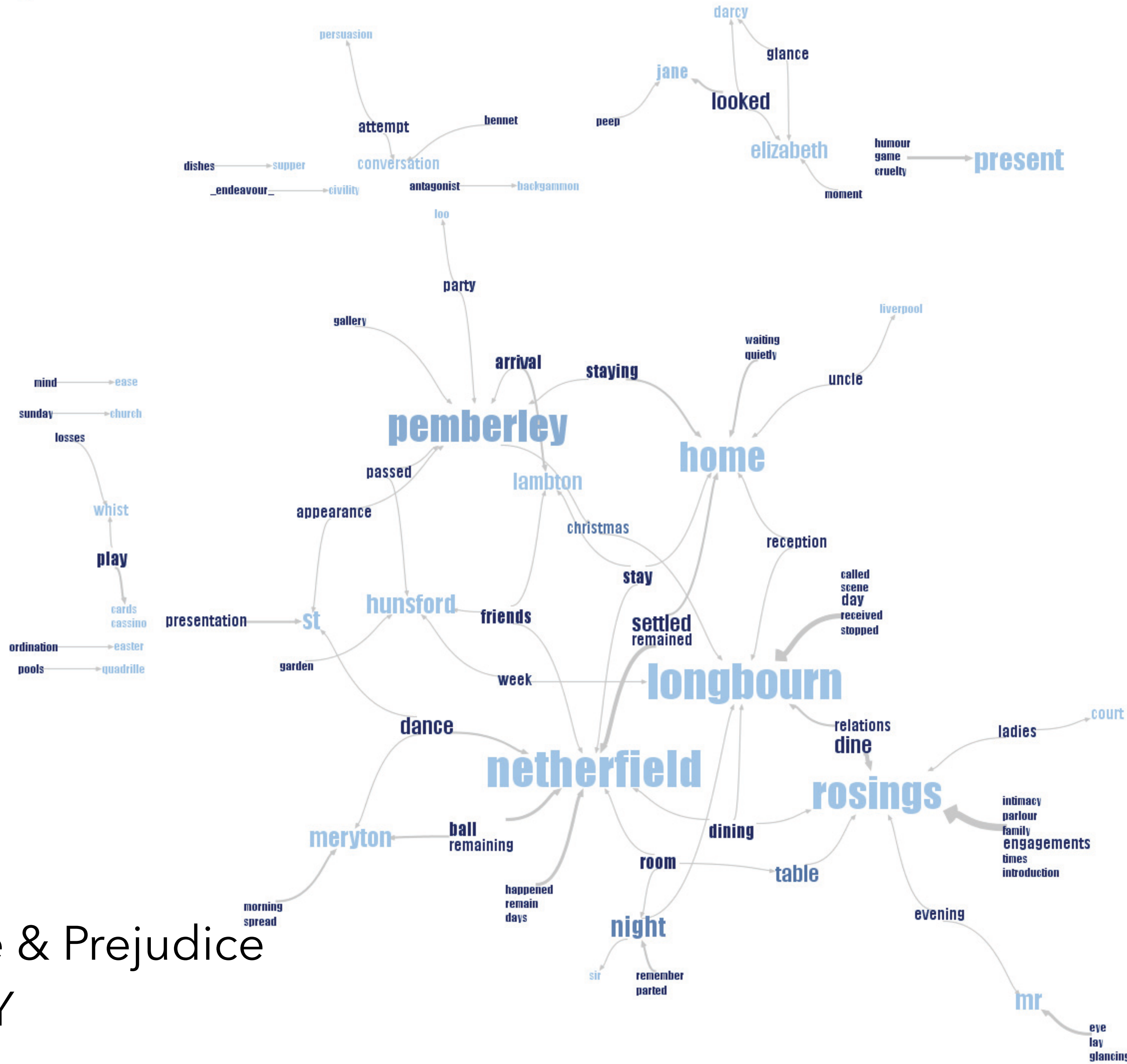
Node Grouping



(a) (b) (c)

The Bible
X begat Y

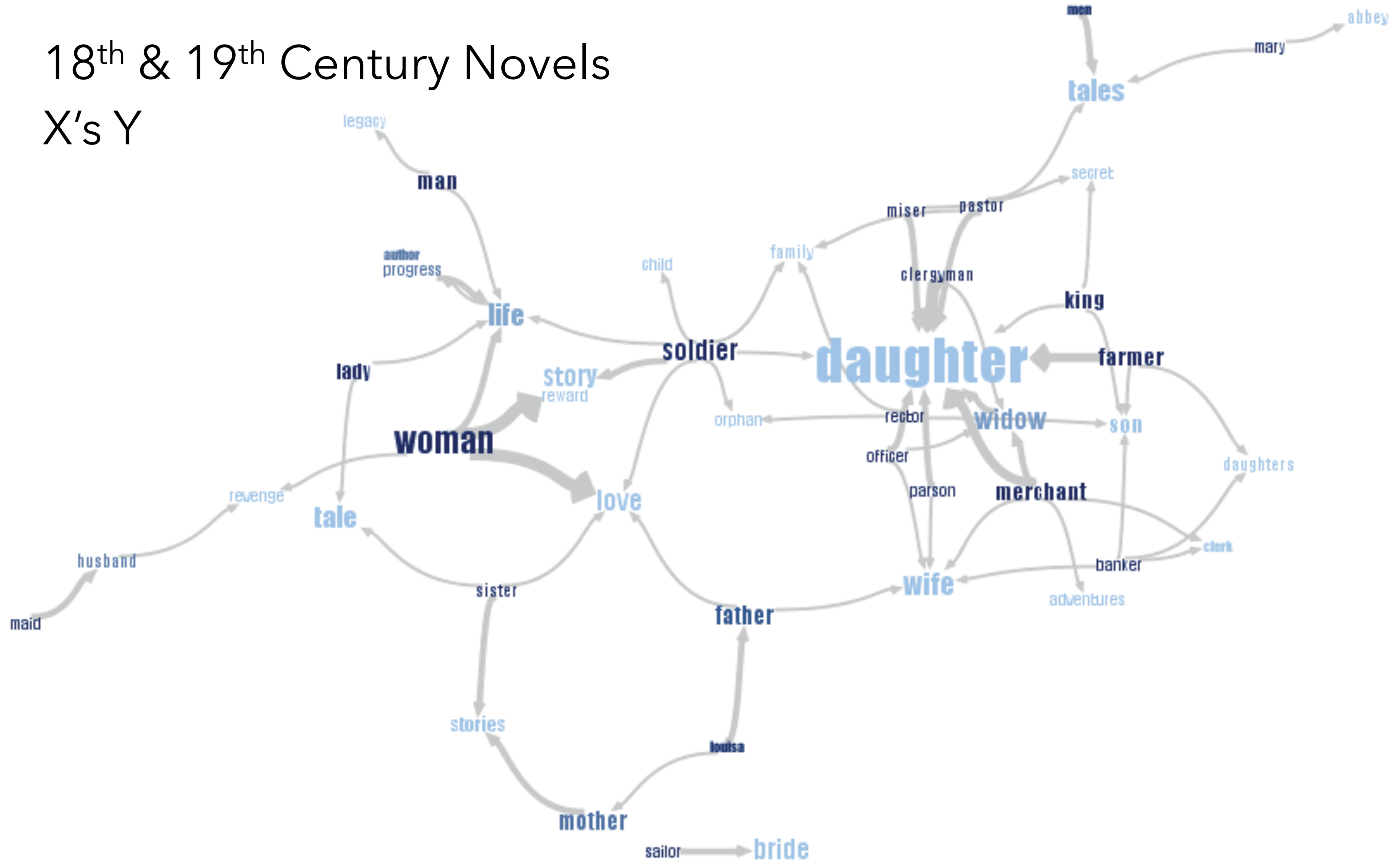




Pride & Prejudice

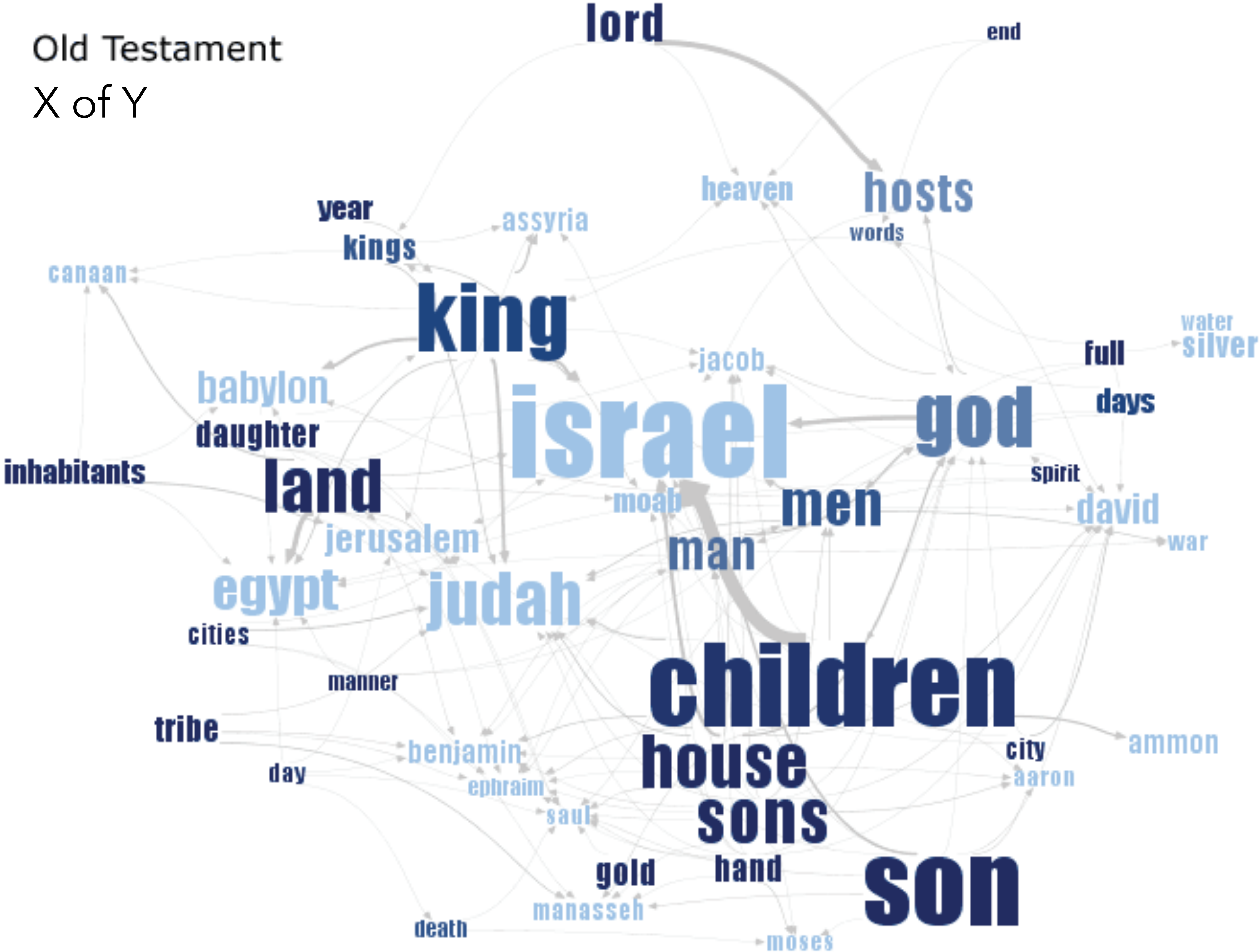
X at Y

18th & 19th Century Novels
X's Y



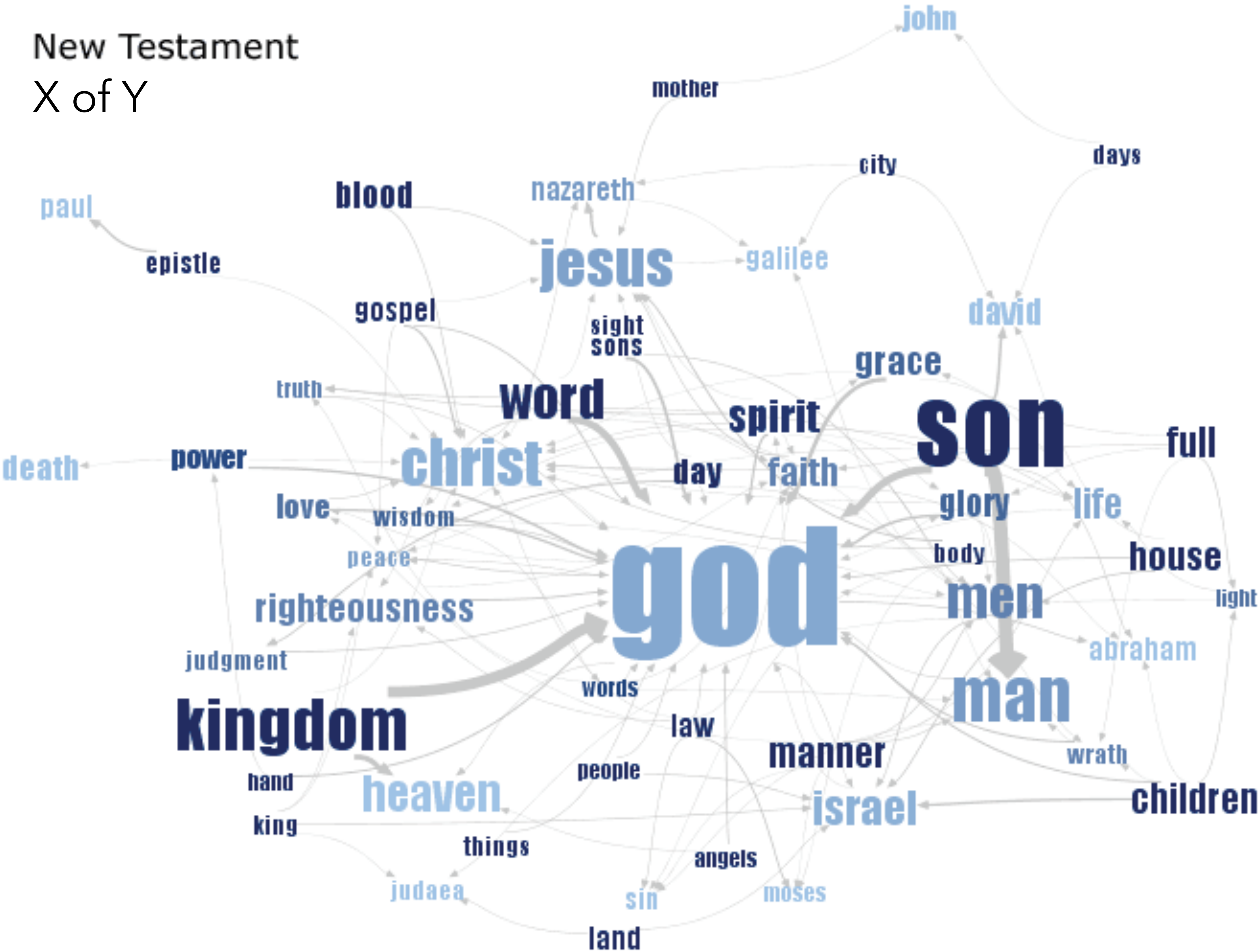
Old Testament

X of Y



New Testament

X of Y



Document Content

Understand Your Analysis Task

Visually: Word position, browsing, brush & link
Semantically: Word sequence, hierarchy, clustering
Both: Spatial layout reflects semantic relationships

The Role of Interaction

Language model supports visual analysis cycles
Allow modifications to the model: custom patterns for expressing contextual or domain knowledge

Conversations

Visualizing Conversation

Many dimensions to consider:

Who (senders, receivers)

What (the content of communication)

When (temporal patterns)

Interesting cross-products:

What x When -> Topic “Zeitgeist”

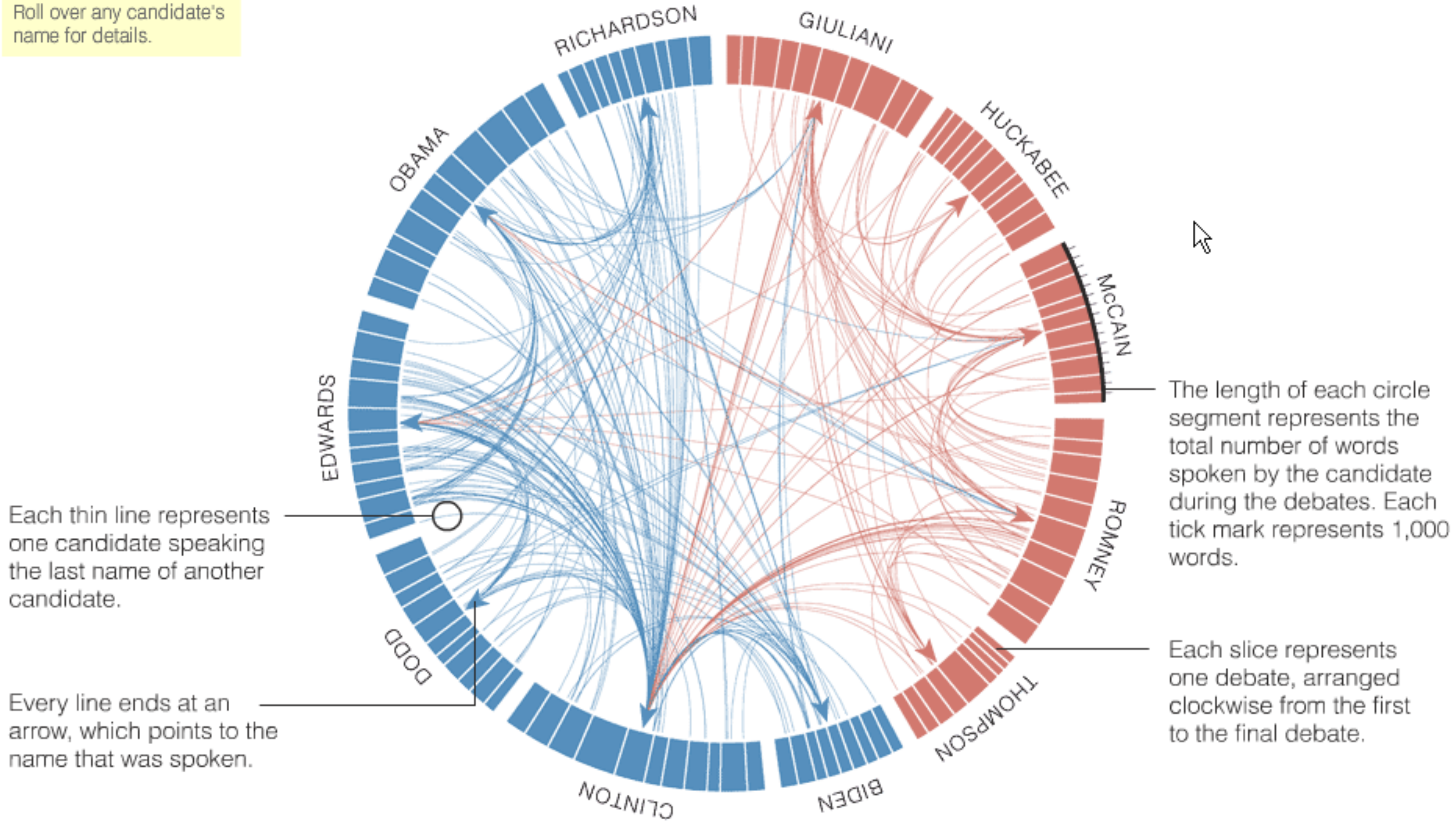
Who x Who -> Social network

Who x Who x What x When -> Information flow

Naming Names

Names used by major presidential candidates in the series of Democratic and Republican debates leading up to the Iowa caucuses.

Roll over any candidate's name for details.



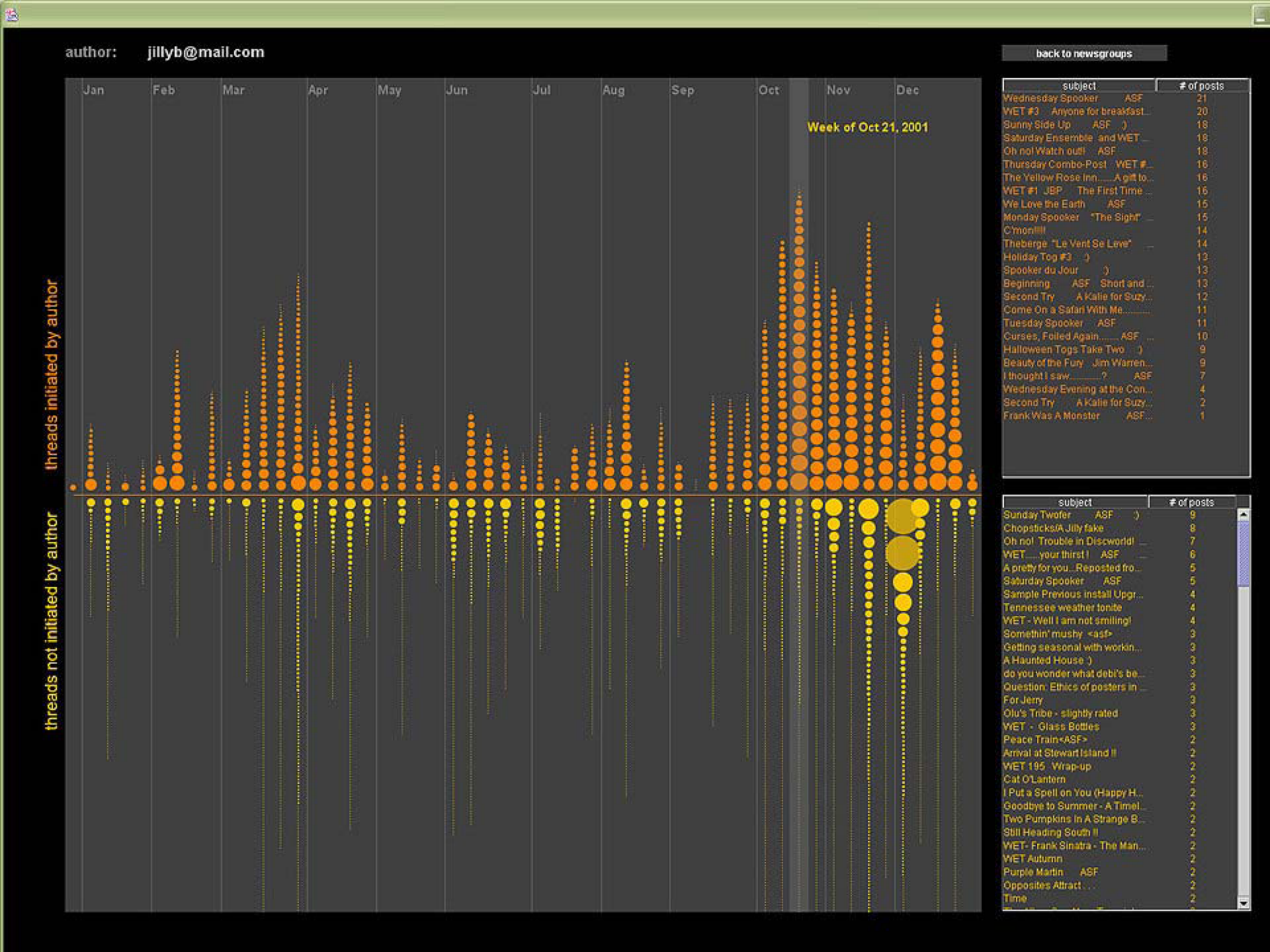
Source: Debate transcripts

Jonathan Corum and Farhana Hossain/The New York Times

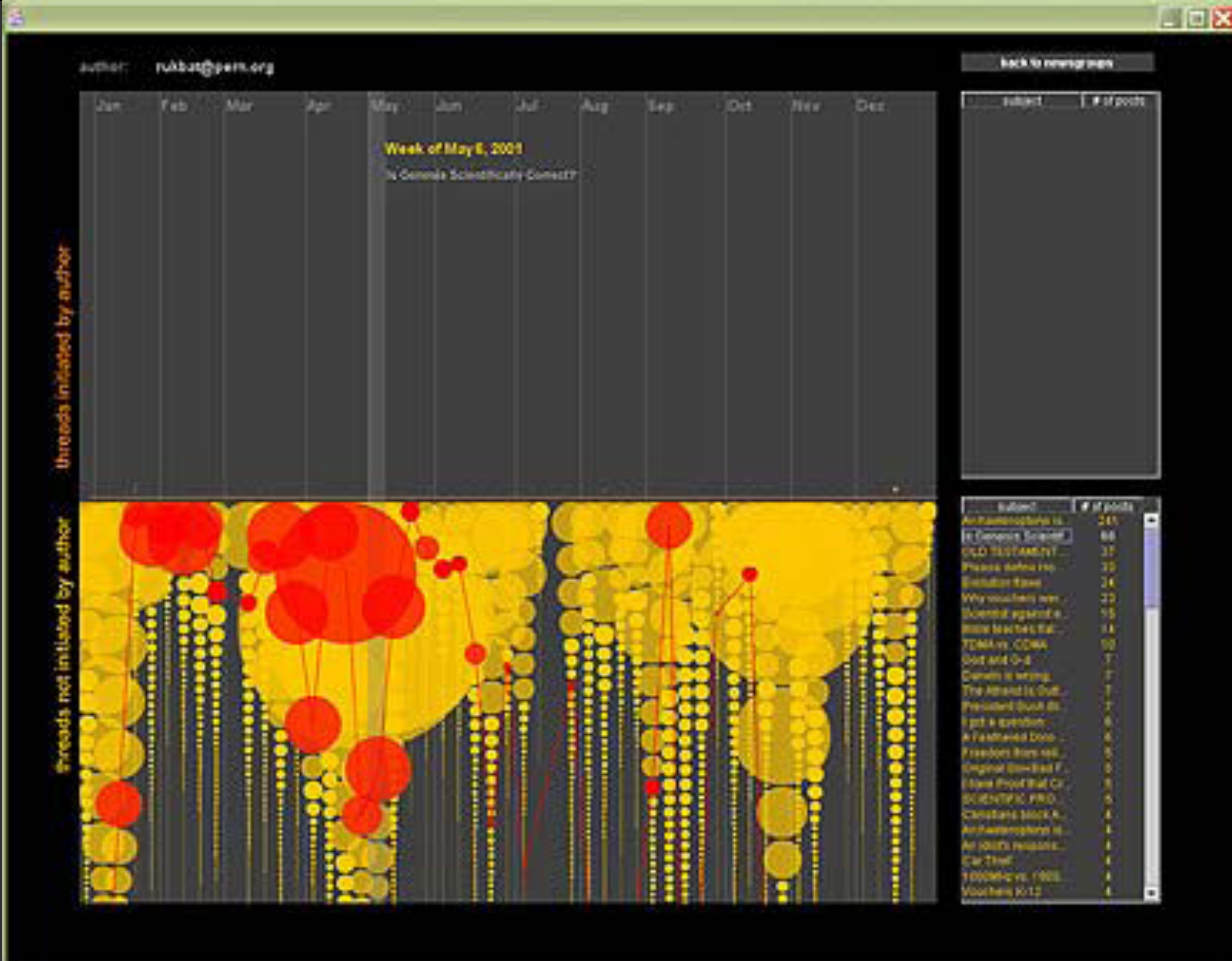
Usenet Visualization [Viegas & Smith]

Show correspondence patterns in text forums

Initiate vs. reply; size and duration of discussion



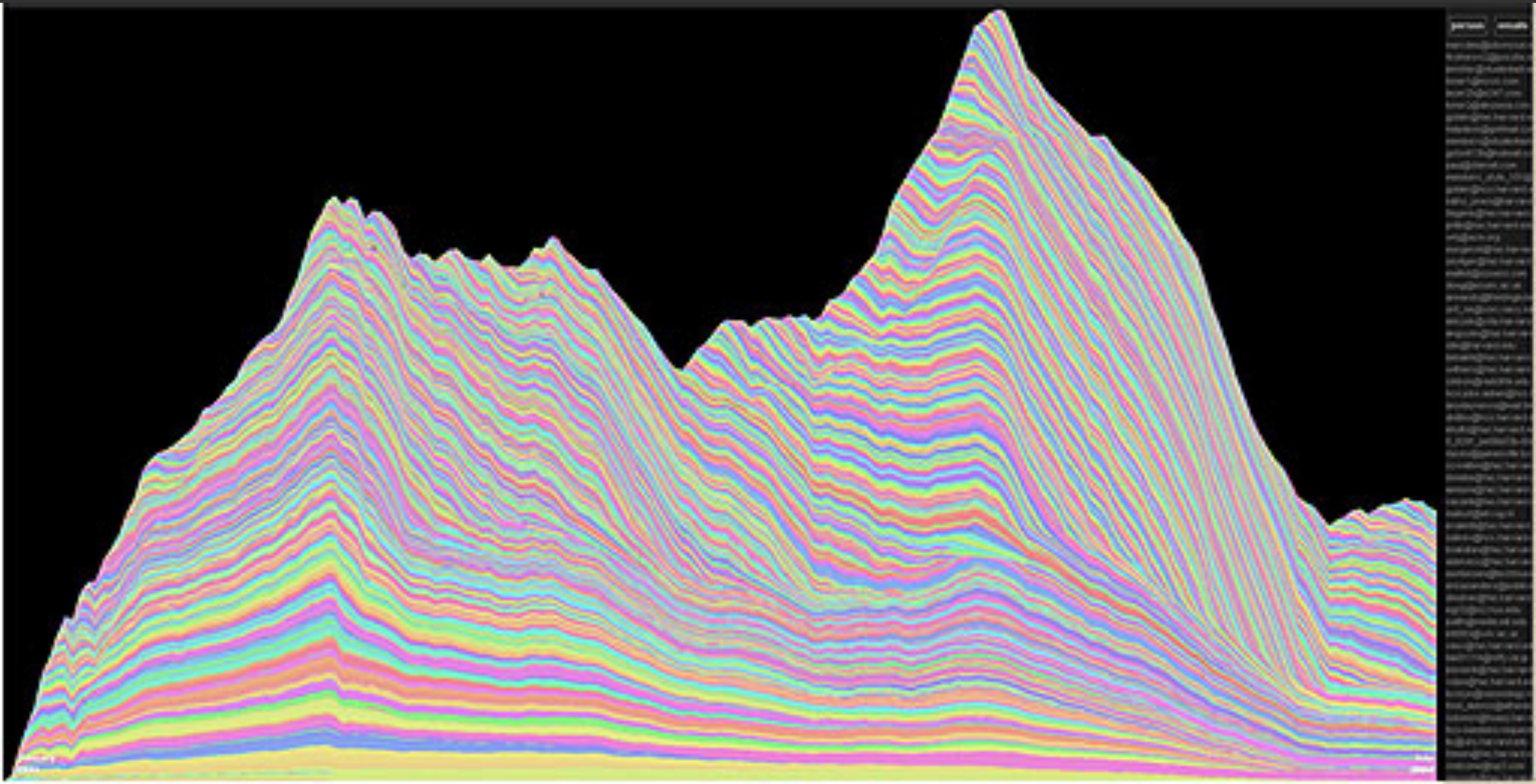
author: jillyb@mail.com
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of Oct 21, 2001
threads initiated by author
threads not initiated by author
subject
# of posts
Wednesday Spooker ASF 21
WET #3 Anyone for breakfast... 20
Sunny Side Up ASF :) 18
Saturday Ensemble and WET ... 18
Oh no! Watch out!! ASF 18
Thursday Combo-Post WET #... 16
The Yellow Rose Inn.......A gift to... 16
WET #1 JBP The First Time ... 16
We Love the Earth ASF 15
Monday Spooker "The Sight" ... 15
C'mon!!!!! 14
Theberge "Le Vent Se Leve" ... 14
Holiday Tog #3 :) 13
Spooker du Jour :) 13
Beginning ASF Short and ... 13
Second Try A Kalie for Suzy... 12
Come On a Safari With Me.......... 11
Tuesday Spooker ASF 11
Curses, Foiled Again....... ASF 10
Halloween Togs Take Two :) 9
Beauty of the Fury Jim Warren... 9
I thought I saw..........? ASF 7
Wednesday Evening at the Con... 4
Second Try A Kalie for Suzy... 2
Frank Was A Monster ASF... 1
subject
# of posts
Sunday Twofer ASF :) 9
Chopsticks/A Jilly fake 8
Oh no! Trouble in Discworld! ... 7
WET.....your thirst ! ASF ... 6
A pretty for you...Reposted fro... 5
Saturday Spooker ASF 5
Sample Previous install Upgr... 4
Tennessee weather tonite 4
WET - Well I am not smiling! 4
Somethin' mushy <asf> 3
Getting seasonal with workin... 3
A Haunted House :) 3
do you wonder what debi's be... 3
Question: Ethics of posters in ... 3
For Jerry 3
Olu's Tribe - slightly rated 3
WET - Glass Bottles 3
Peace Train<ASF> 2
Arrival at Stewart Island !! 2
WET 195 Wrap-up 2
Cat O'Lantern 2
I Put a Spell on You (Happy H... 2
Goodbye to Summer - A Timel... 2
Two Pumpkins In A Strange B... 2
Still Heading South !! 2
WET- Frank Sinatra - The Man... 2
WET Autumn 2
Purple Martin ASF 2
Opposites Attract . . . 2
Time 2



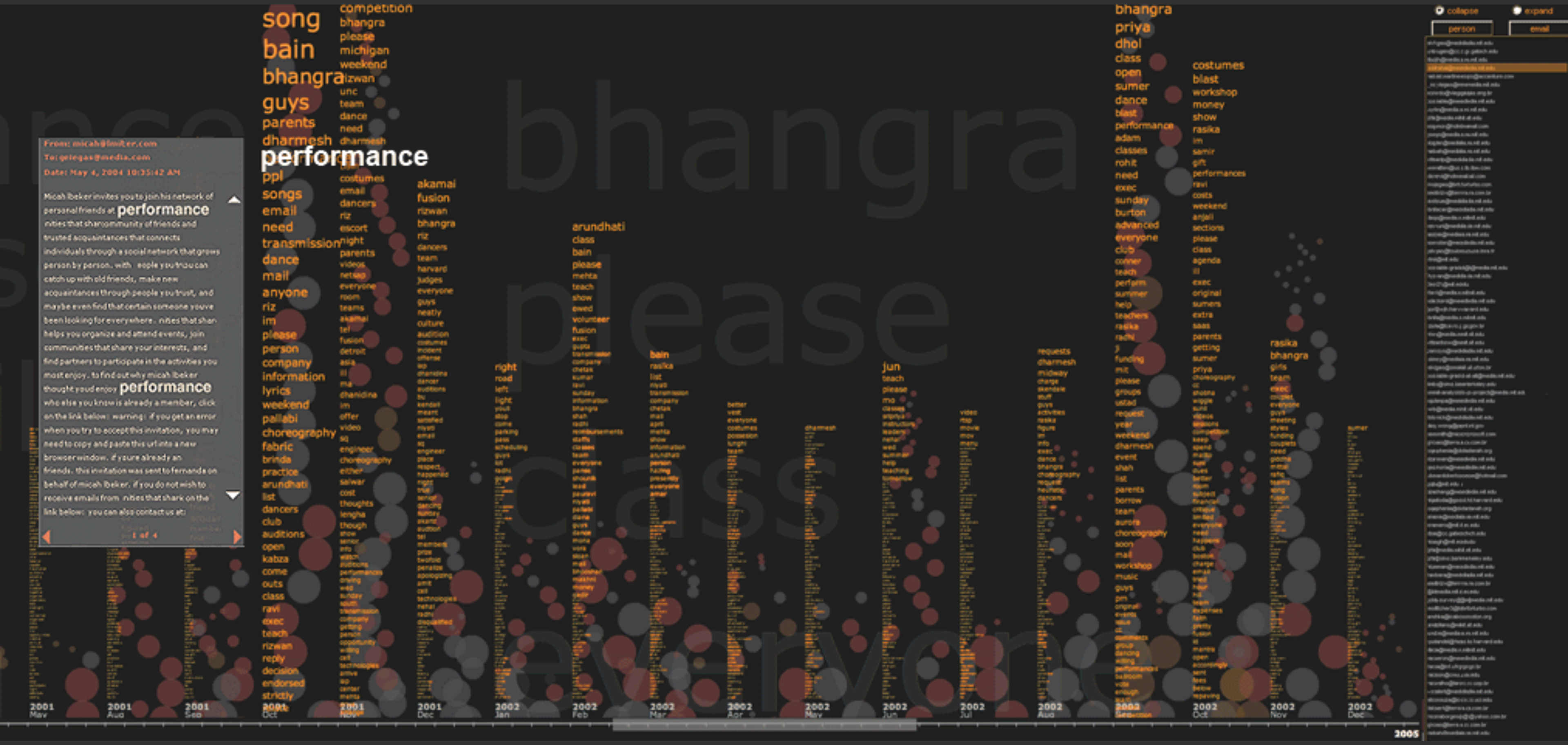
author:
rukbat@pern.org
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of May 6, 2001
Is Genesis Scientifically Correct?
threads initiated by author
threads not initiated by author
subject
# of posts

Email Mountain [Viegas]

Conversation by person over time (who x when).



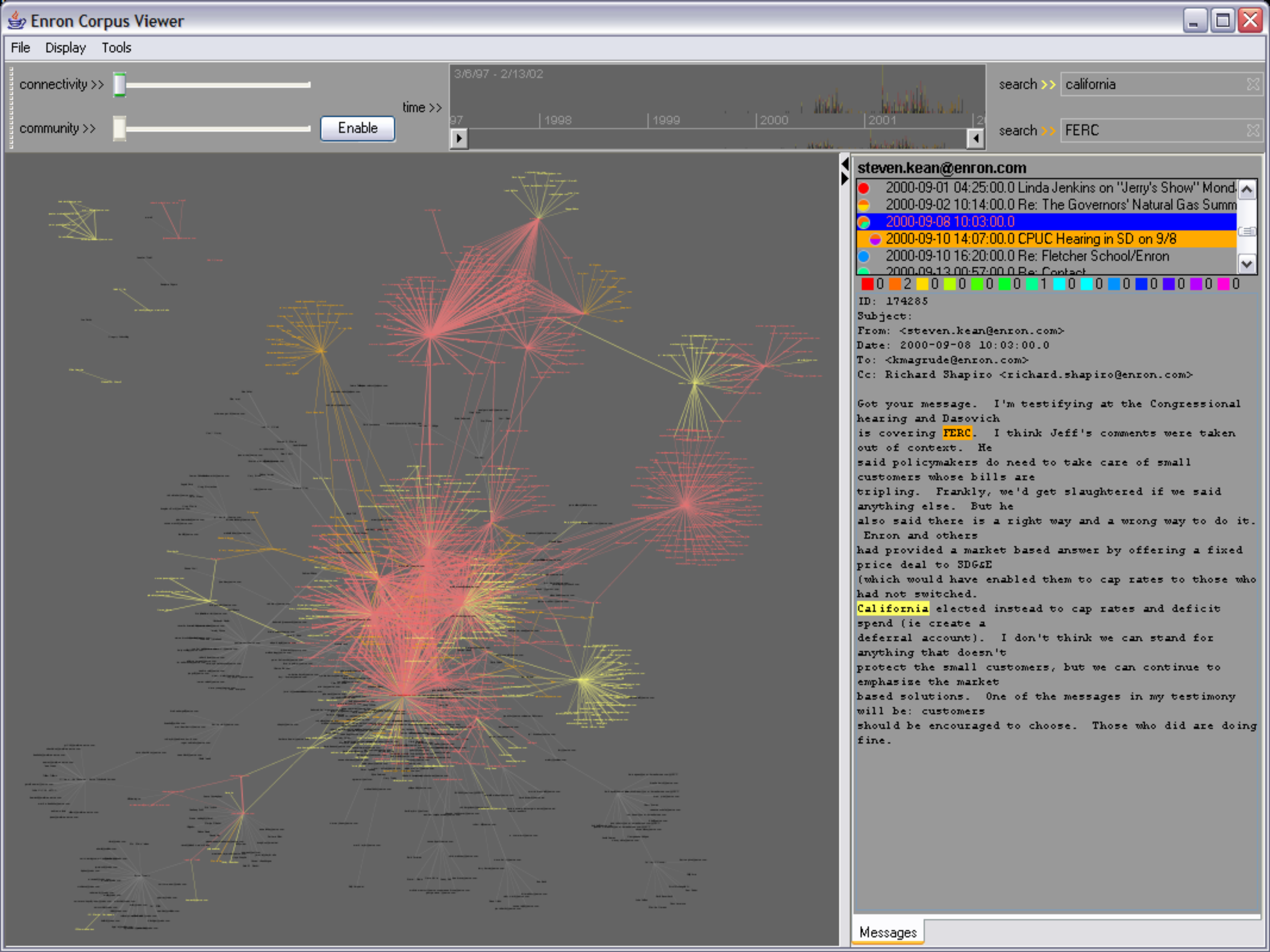
Themail [Viegas]

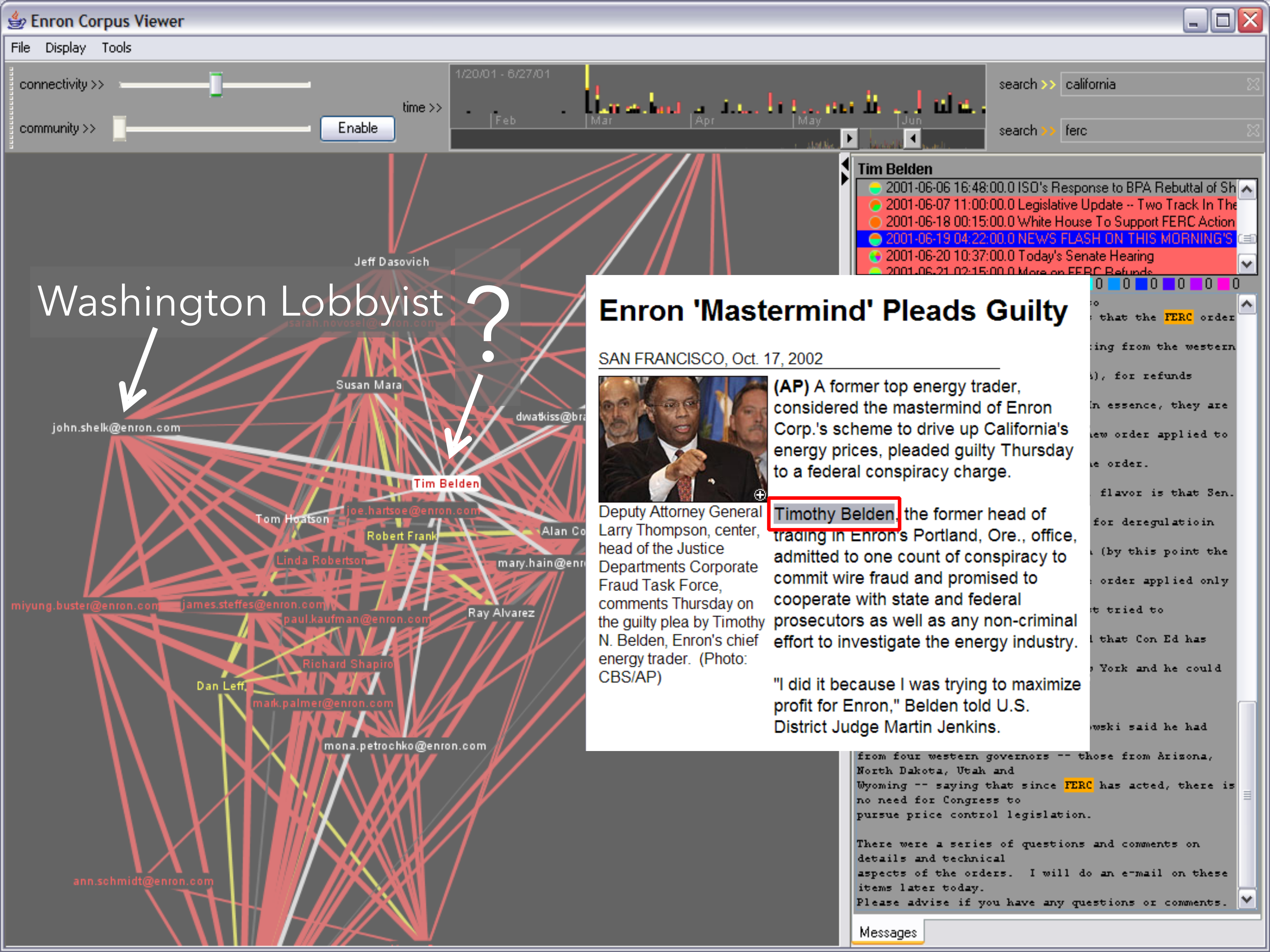


One person over time, TF.IDF weighted terms

Enron E-Mail Corpus

[Heer]


Enron Corpus Viewer
File Display Tools
connectivity >>
community >>
Enable
time >>
3/6/97 - 2/13/02
1998
1999
2000
2001
search >> california
search >> FERC
steven.kean@enron.com
2000-09-01 04:25:00.0 Linda Jenkins on "Jerry's Show" Mond
2000-09-02 10:14:00.0 Re: The Governors' Natural Gas Summ
2000-09-08 10:03:00.0
2000-09-10 14:07:00.0 CPUC Hearing in SD on 9/8
2000-09-10 16:20:00.0 Re: Fletcher School/Enron
0 2 0 0 0 0 1 0 0 0 0 0 0 0
ID: 174285
Subject:
From: <steven.kean@enron.com>
Date: 2000-09-08 10:03:00.0
To: <kmagrude@enron.com>
Cc: Richard Shapiro <richard.shapiro@enron.com>
Got your message. I'm testifying at the Congressional
hearing and Dasovich
is covering FERC. I think Jeff's comments were taken
out of context. He
said policymakers do need to take care of small
customers whose bills are
tripling. Frankly, we'd get slaughtered if we said
anything else. But he
also said there is a right way and a wrong way to do it.
Enron and others
had provided a market based answer by offering a fixed
price deal to SDG&E
(which would have enabled them to cap rates to those who
had not switched.
California elected instead to cap rates and deficit
spend (ie create a
deferral account). I don't think we can stand for
anything that doesn't
protect the small customers, but we can continue to
emphasize the market
based solutions. One of the messages in my testimony
will be: customers
should be encouraged to choose. Those who did are doing
fine.
Messages



Enron Corpus Viewer
File
Display
Tools
connectivity >>
community >>
Enable
time >>
1/20/01 - 6/27/01
Feb
Mar
Apr
May
Jun
search >>
california
search >>
ferc
Tim Belden
2001-06-06 16:48:00.0 ISO's Response to BPA Rebuttal of Sh
2001-06-07 11:00:00.0 Legislative Update -- Two Track In The
2001-06-18 00:15:00.0 White House To Support FERC Action
2001-06-19 04:22:00.0 NEWS FLASH ON THIS MORNING'S
2001-06-20 10:37:00.0 Today's Senate Hearing
Washington Lobbyist
?
Jeff Dasovich
Susan Mara
john.shelk@enron.com
dwatkiss@bra
Tim Belden
Tom Hoatson
joe.hartsoe@enron.com
Robert Frank
Alan Co
Linda Robertson
mary.hain@enr
miyung.buster@enron.com
james.steffes@enron.com
paul.kaufman@enron.com
Ray Alvarez
Richard Shapiro
Dan Leff
mark.palmer@enron.com
mona.petrochko@enron.com
ann.schmidt@enron.com
Enron 'Mastermind' Pleads Guilty
SAN FRANCISCO, Oct. 17, 2002
Deputy Attorney General Larry Thompson, center, head of the Justice Departments Corporate Fraud Task Force, comments Thursday on the guilty plea by Timothy N. Belden, Enron's chief energy trader. (Photo: CBS/AP)
(AP) A former top energy trader, considered the mastermind of Enron Corp.'s scheme to drive up California's energy prices, pleaded guilty Thursday to a federal conspiracy charge.
Timothy Belden, the former head of trading in Enron's Portland, Ore., office, admitted to one count of conspiracy to commit wire fraud and promised to cooperate with state and federal prosecutors as well as any non-criminal effort to investigate the energy industry.
"I did it because I was trying to maximize profit for Enron," Belden told U.S. District Judge Martin Jenkins.
from four western governors -- those from Arizona, North Dakota, Utah and Wyoming -- saying that since FERC has acted, there is no need for Congress to pursue price control legislation.
There were a series of questions and comments on details and technical aspects of the orders. I will do an e-mail on these items later today.
Please advise if you have any questions or comments.
Messages

Document Collections

Named Entity Recognition

Label named entities in text:

John Smith -> PERSON

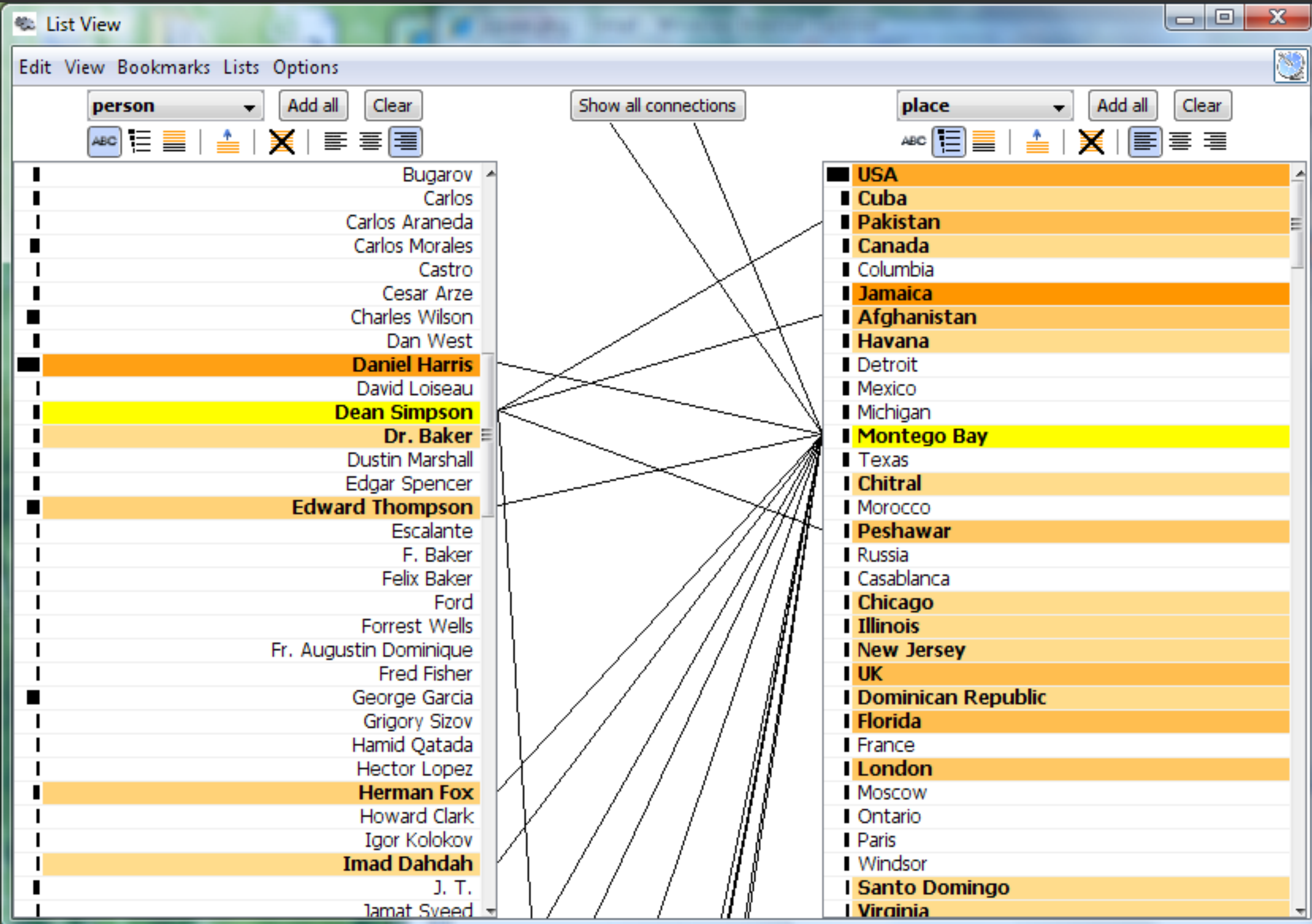
Soviet Union -> COUNTRY

353 Serra St -> ADDRESS

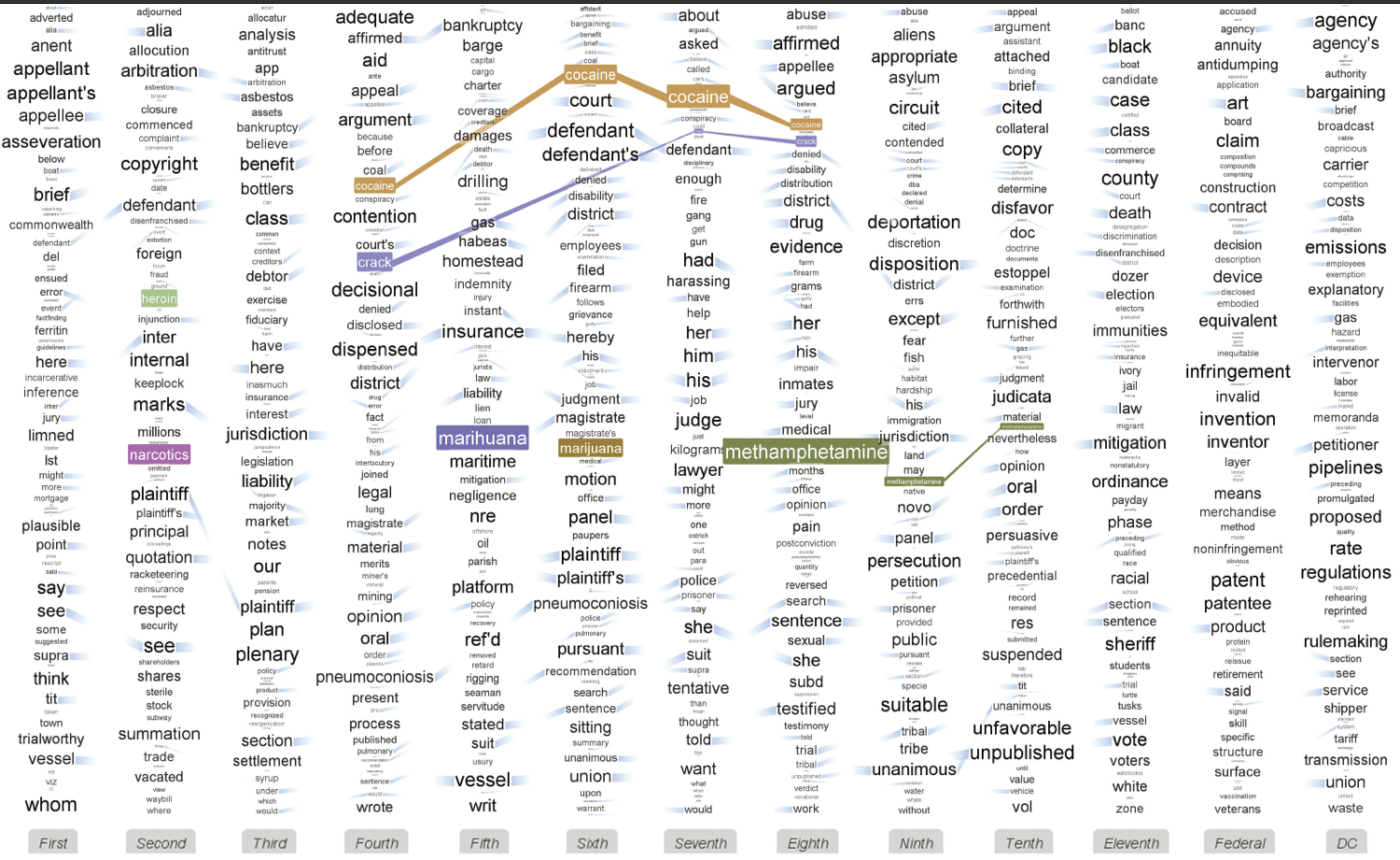
(555) 721-4312 -> PHONE NUMBER

Entity relations: how do the entities relate?

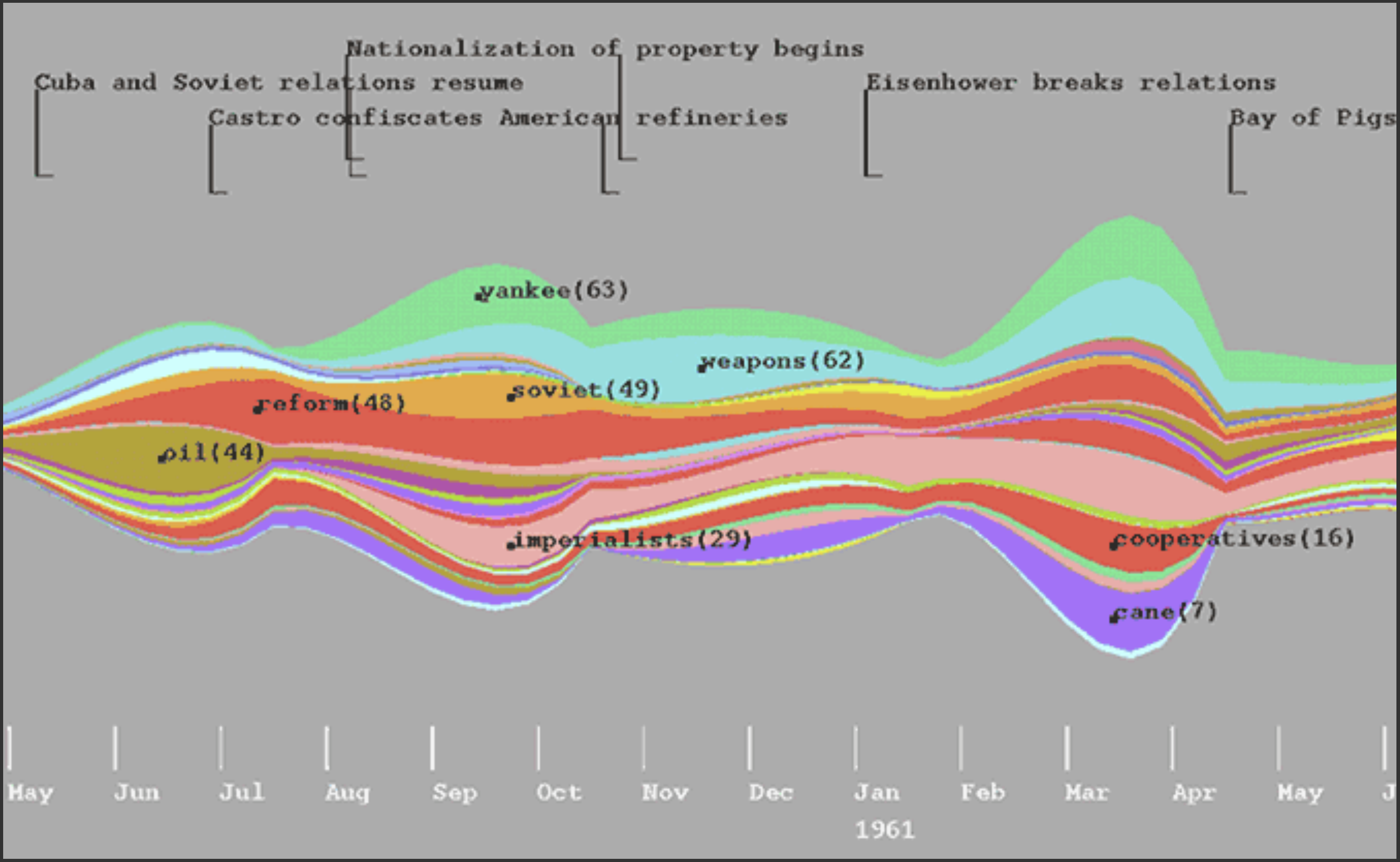
Simple approach: do they co-occur in a small window of text?


List View
Edit View Bookmarks Lists Options
person
Add all
Clear
Show all connections
place
Add all
Clear
ABC
Bugarov
Carlos
Carlos Araneda
Carlos Morales
Castro
Cesar Arze
Charles Wilson
Dan West
Daniel Harris
David Loiseau
Dean Simpson
Dr. Baker
Dustin Marshall
Edgar Spencer
Edward Thompson
Escalante
F. Baker
Felix Baker
Ford
Forrest Wells
Fr. Augustin Dominique
Fred Fisher
George Garcia
Grigory Sizov
Hamid Qatada
Hector Lopez
Herman Fox
Howard Clark
Igor Kolokov
Imad Dahdah
J. T.
Jamat Syeed
ABC
USA
Cuba
Pakistan
Canada
Columbia
Jamaica
Afghanistan
Havana
Detroit
Mexico
Michigan
Montego Bay
Texas
Chitral
Morocco
Peshawar
Russia
Casablanca
Chicago
Illinois
New Jersey
UK
Dominican Republic
Florida
France
London
Moscow
Ontario
Paris
Windsor
Santo Domingo
Virginia

Parallel Tag Clouds [Collins et al.]



Theme River [Havre et al.]



Similarity & Clustering

Compute vector distance among docs

For TF.IDF, typically cosine distance

Similarity measure can be used to cluster

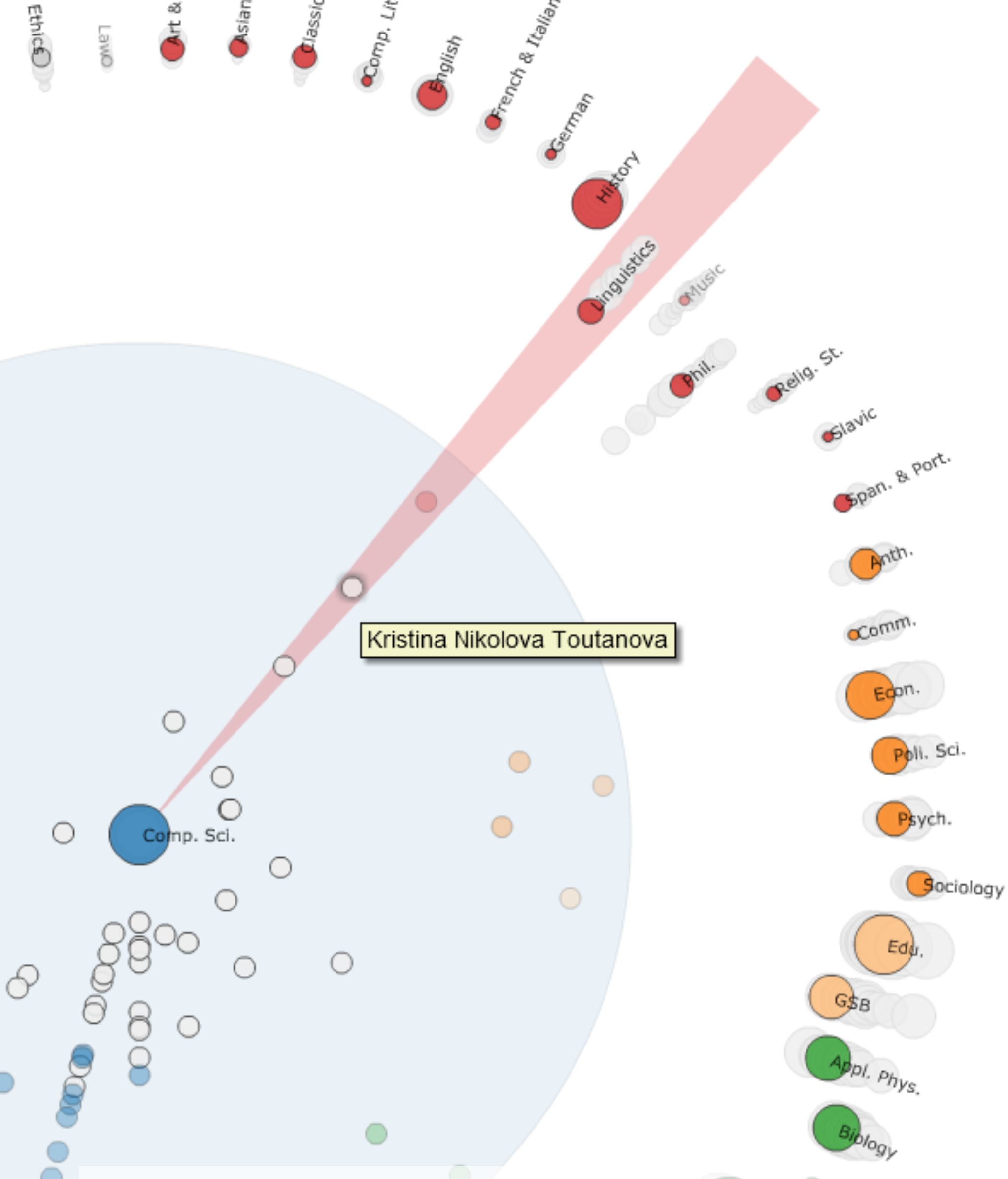
Topic modeling

Assume documents are a mixture of topics

Topics are (roughly) a set of co-occurring terms

Latent Semantic Analysis (LSA): reduce term matrix

Latent Dirichlet Allocation (LDA): statistical model



Effective statistical models for syntactic and semantic disambiguation

Student: Kristina Nikolova Toutanova
Advisor: Christopher D. Manning

Computer Science (2005)

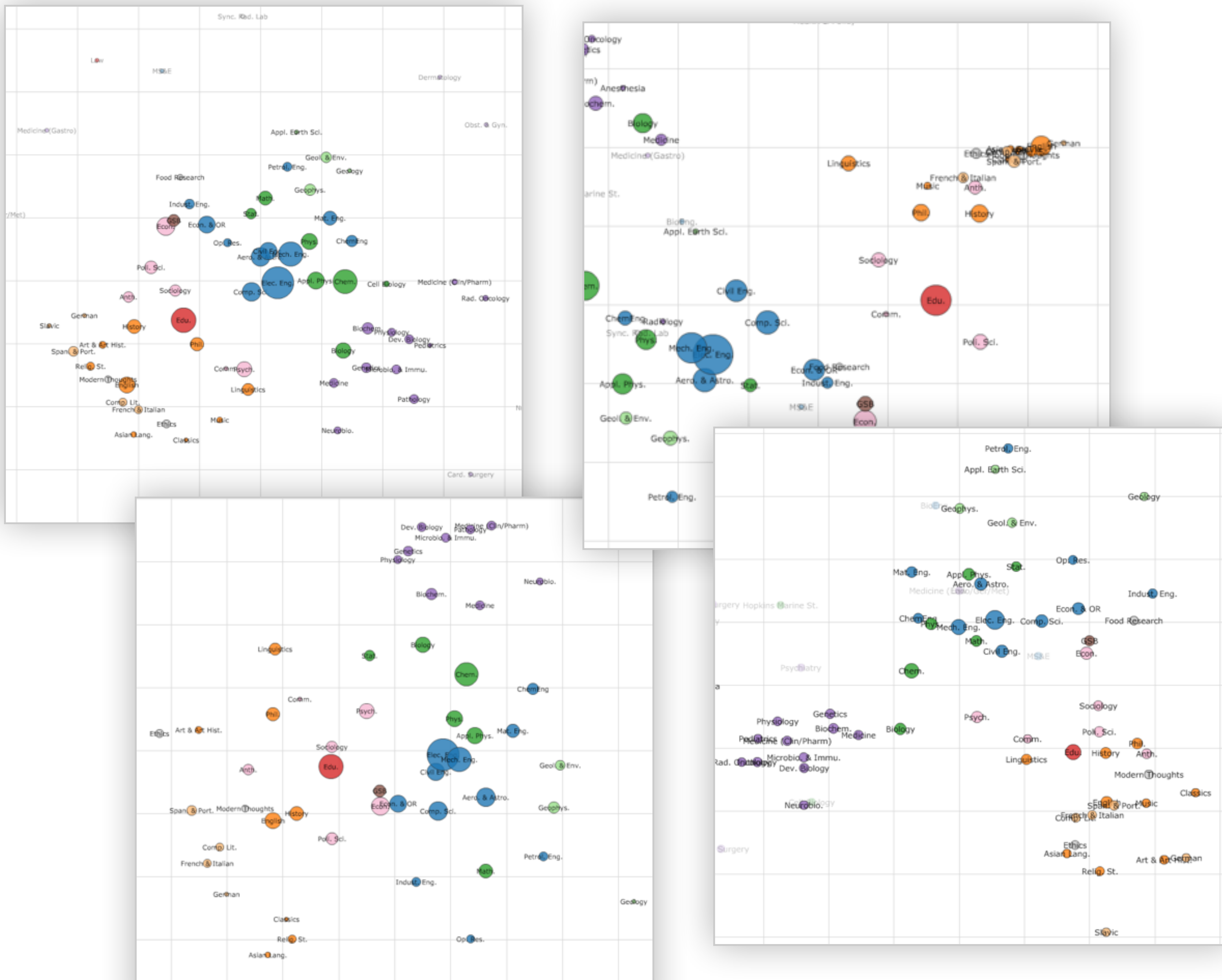
Keywords: Syntactic, Semantic, Tree kernels, Parsing

Abstract:

This thesis focuses on building effective statistical models for disambiguation of sophisticated syntactic and semantic natural language (NL) structures. We advance the state of the art in several domains by (i) choosing representations that encode domain knowledge more effectively and (ii) developing machine learning algorithms that deal with the specific properties of NL disambiguation tasks--sparsity of training data and large, structured spaces of hidden labels. For the task of syntactic disambiguation, we propose a novel representation of parse trees that connects the words of the sentence with the hidden syntactic structure in a direct way. Experimental evaluation on parse selection for a Head Driven Phrase Structure Grammar shows the new representation achieves superior performance compared to previous models. For the task of disambiguating the semantic role structure of verbs, we build a more accurate model, which captures the knowledge that the semantic frame of a verb is a joint structure with strong dependencies between arguments. We achieve this using a Conditional Random Field without Markov independence assumptions on the sequence of semantic role labels. To address the sparsity problem in machine learning for NL, we develop a method for incorporating many additional sources of information, using Markov chains in the space of words. The Markov chain framework makes it possible to combine multiple knowledge sources, to learn how much to trust each of them, and to chain inferences together. It achieves large gains in the task of disambiguating prepositional phrase attachments.

Stanford Dissertation Browser

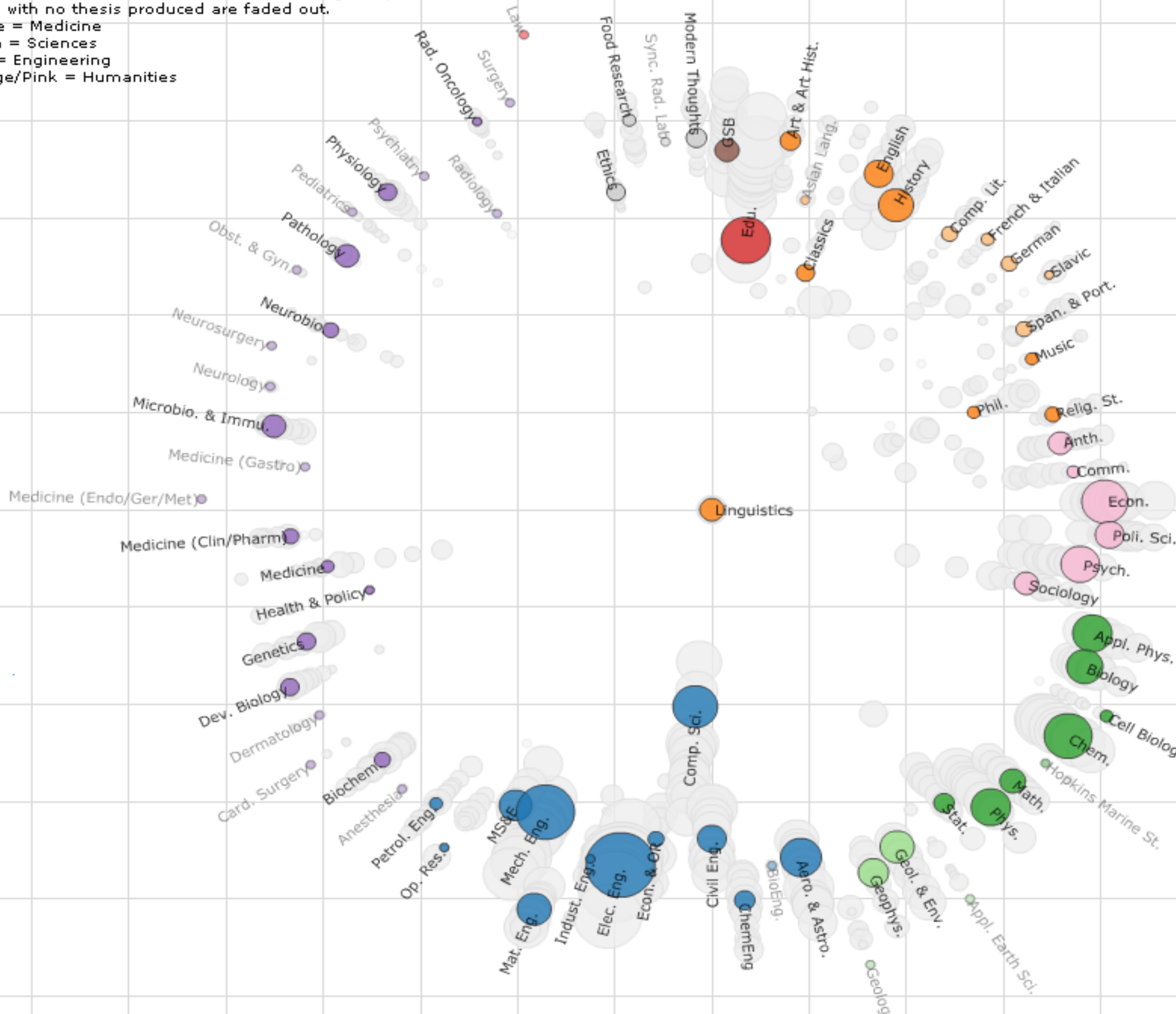
with **Jason Chuang**, Dan Ramage & Christopher Manning



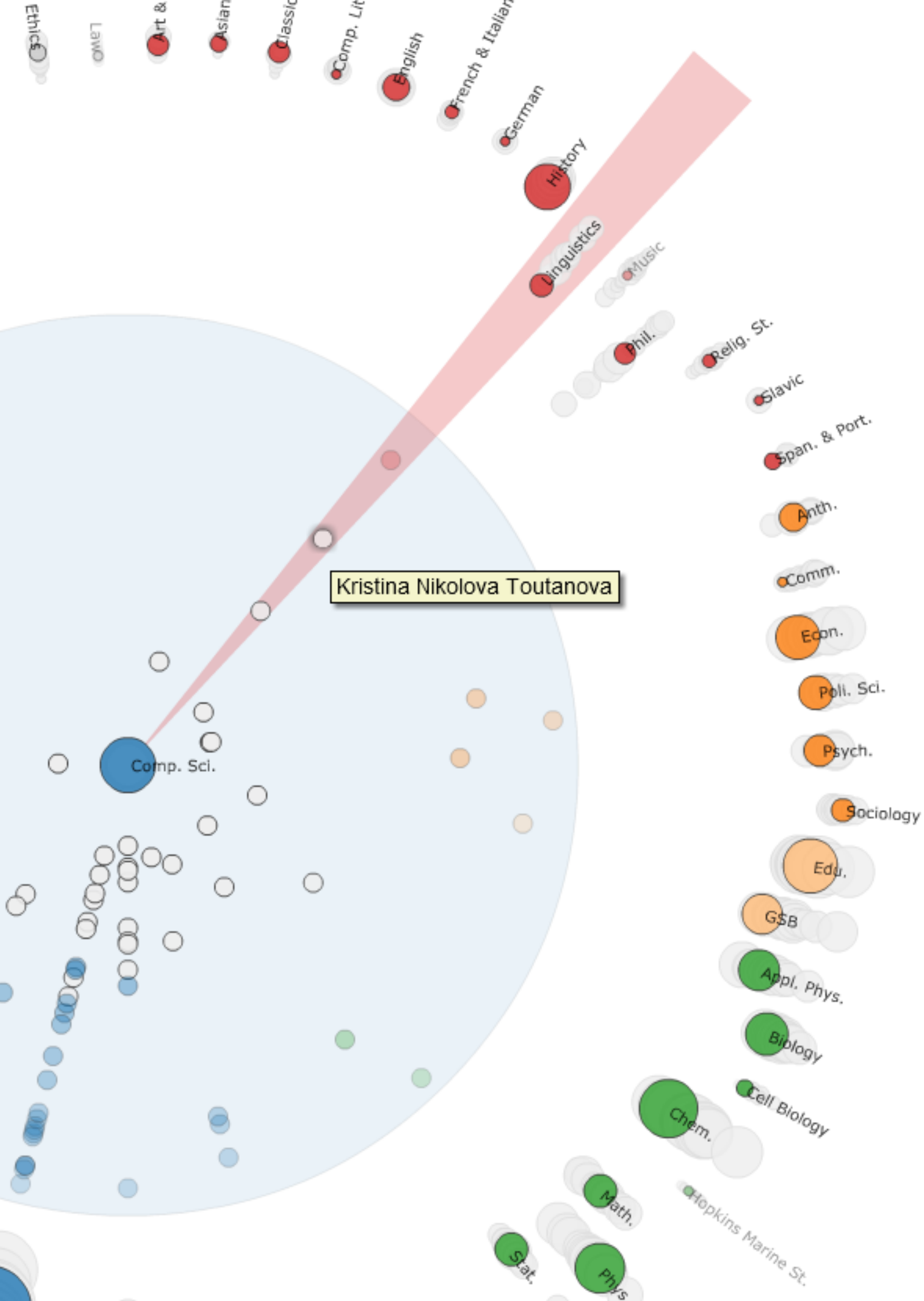
Sync. Rad. Lab
Dermatology
Medicine (Gastro)
Obst. & Gyn.
Appl. Earth Sci.
Geol. & Env.
Petrol. Eng.
Geology
Food Research
Geophys.
Math.
Indust. Eng.
Stat.
Mat. Eng.
Econ. & OR
Op. Res.
Phys.
Chem. Eng.
Mech. Eng.
Poli. Sci.
Elec. Eng.
Appl. Phys.
Chem.
Cell Biology
Medicine (Clin/Pharm)
Sociology
Comp. Sci.
Rad. Oncology
Anth.
German
Edu.
Slavic
History
Art & Art Hist.
Phil.
Span. & Port.
Biochem.
Physiology
Dev. Biology
Pediatrics
Biology
Relig. St.
Comm.
Psych.
Genetics
Microbio. & Immu.
Modern Thoughts
English
Linguistics
Medicine
Comp. Lit.
French & Italian
Pathology
Ethics
Music
Asian Lang.
Classics
Neurobio.
Card. Surgery
Oncology
Anesthesia
Sociology
Civil Eng.
Radiology
Aero. & Astro.
GSB
Econ.
MS&E
Psychiatry
Surgery

Topic Distance Between Stanford Depts

Area of circles denote number of theses in a given year.
Depts with no thesis produced are faded out.
Purple = Medicine
Green = Sciences
Blue = Engineering
Orange/Pink = Humanities



Oh, the humanities!



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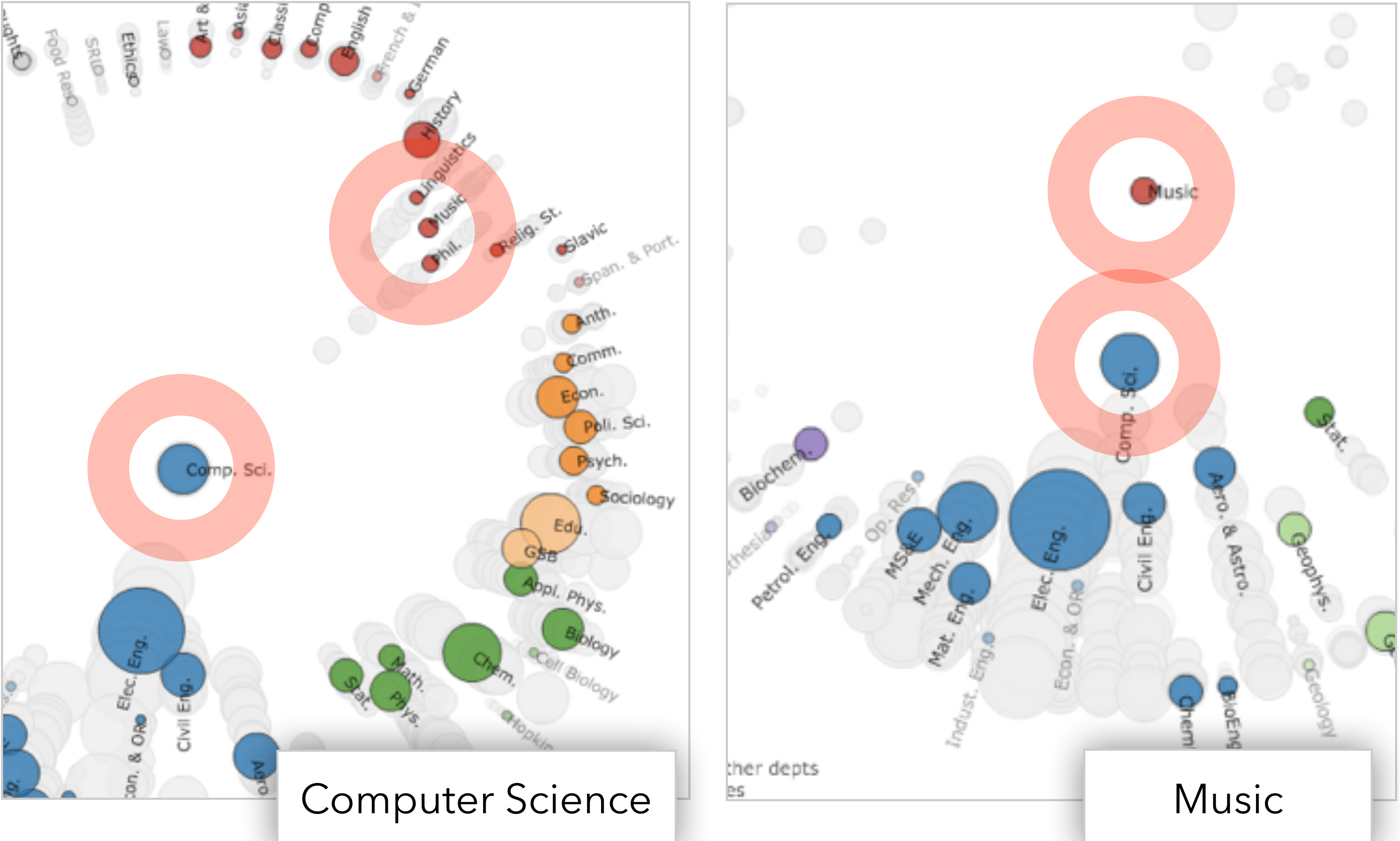

"Word Borrowing" via Labeled LDA

Summary

High Dimensionality

Where possible use text to represent text…

… which terms are the most descriptive?

Context & Semantics

Provide relevant context to aid understanding.

Show (or provide access to) the source text.

Modeling Abstraction

Understand abstraction of your language models.

Match analysis task with appropriate tools and models.

Future: from bag-of-words to *vector space embeddings*