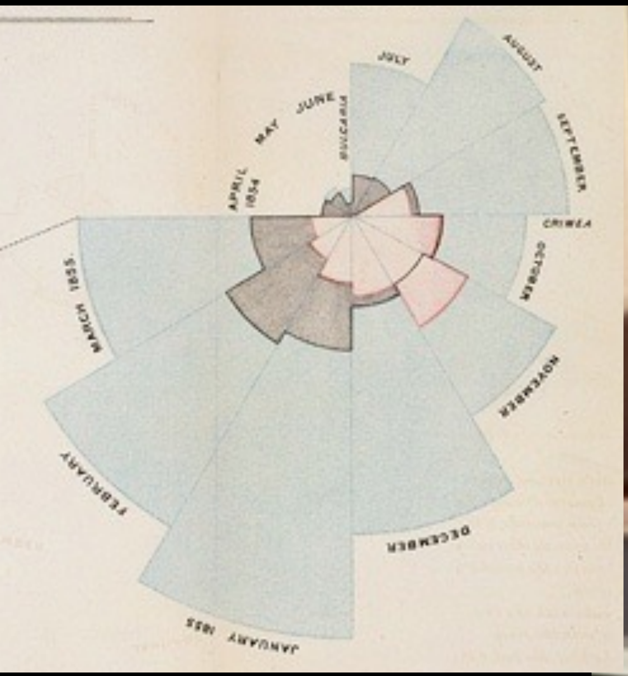
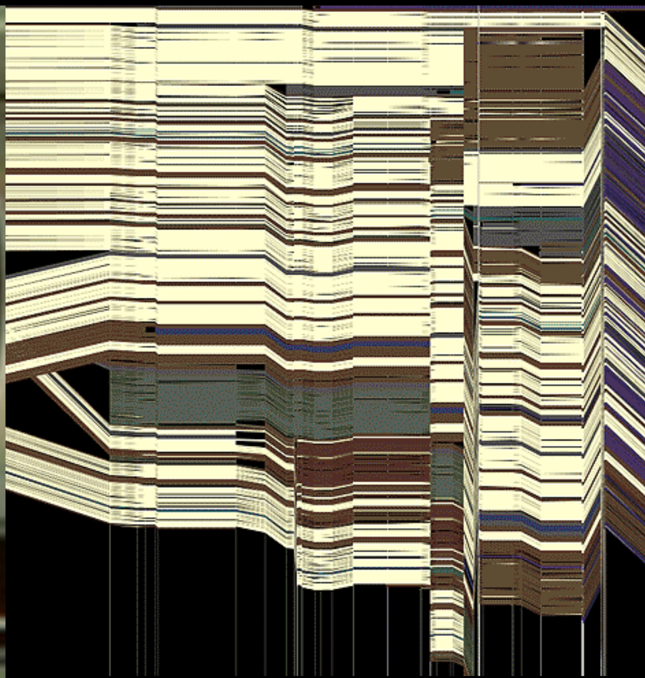
CSE 512 - Data Visualization

Text Visualization





Jeffrey Heer University of Washington

Why Visualize Text?

Why Visualize Text?

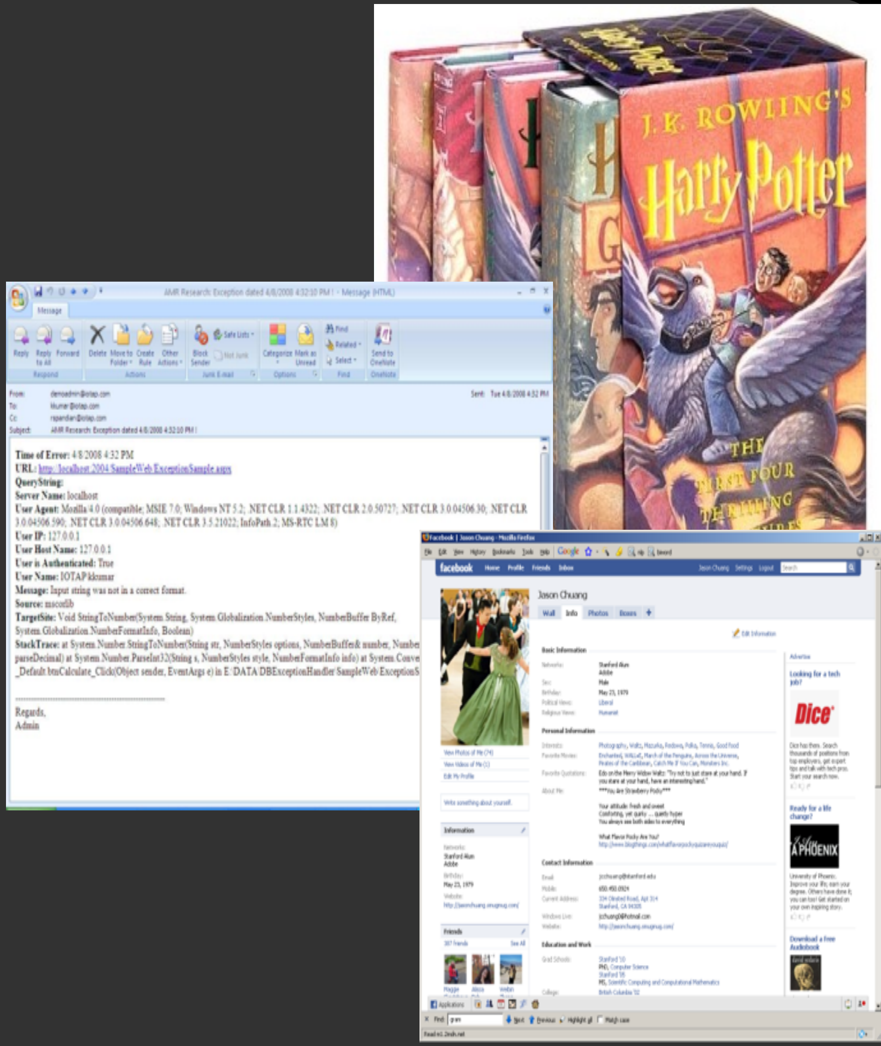
Understanding – get the "gist" of a document

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]

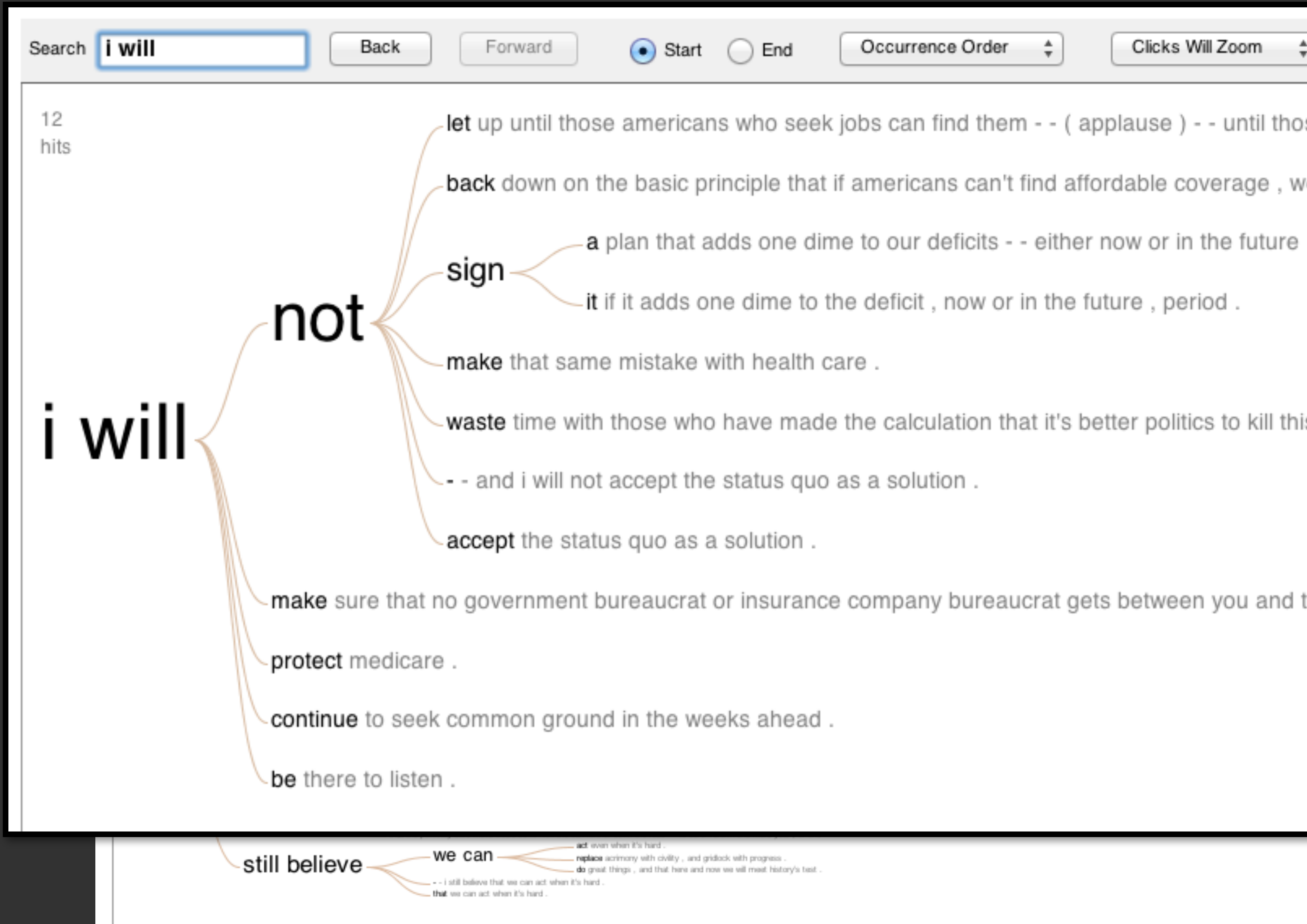
economix.blogs.nytimes.com/2009/09/09/obama-in-09-vs-clinton-in-93

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

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

Evolving Documents

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, San Francisco, 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? *#gocard, @stanfordfball, Beat Cal!!!!!!!!*

   Entities? *San Francisco, 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)

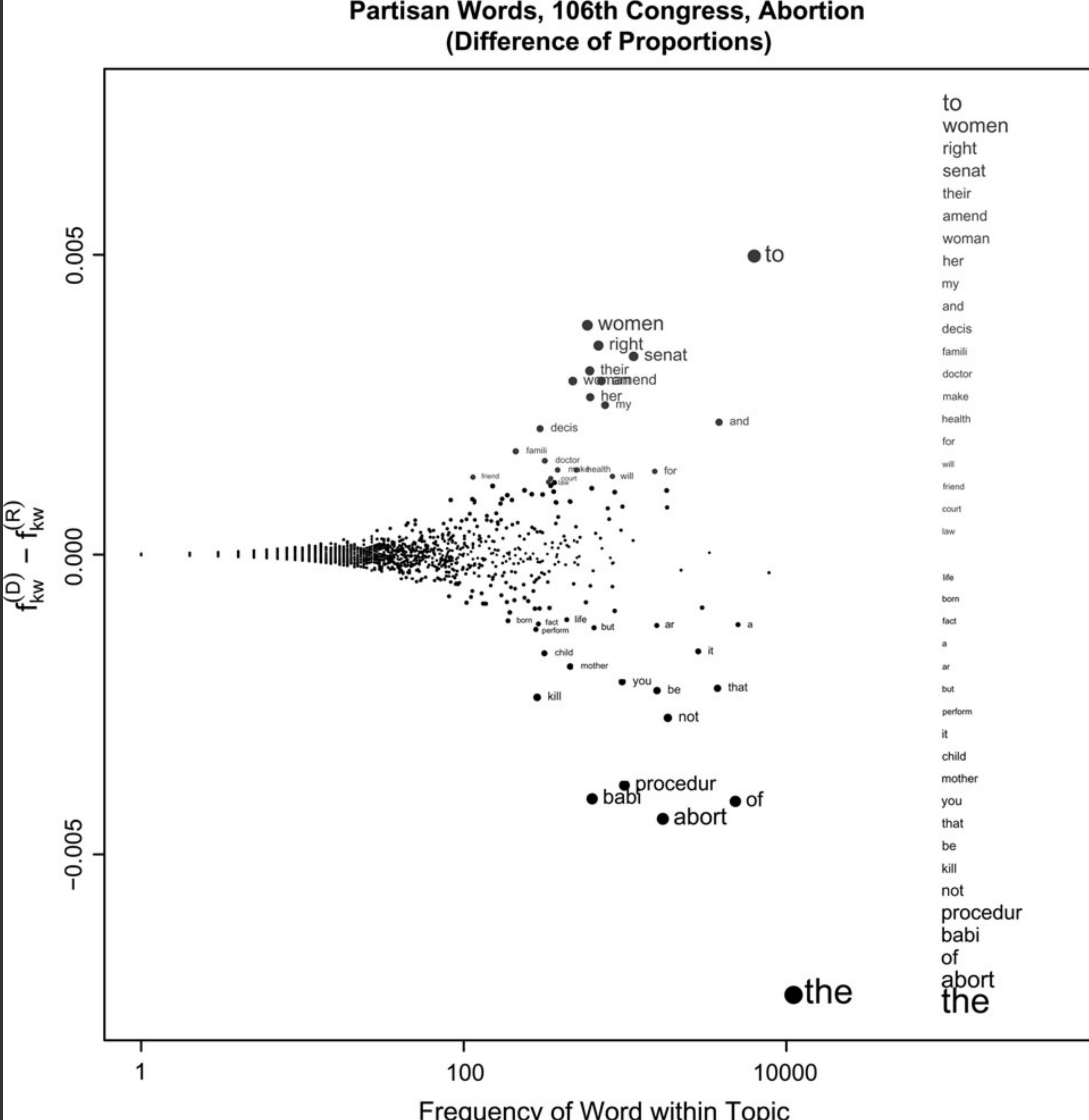
Inaccurate size encoding (long words are bigger)

May not facilitate comparison (unstable layout)

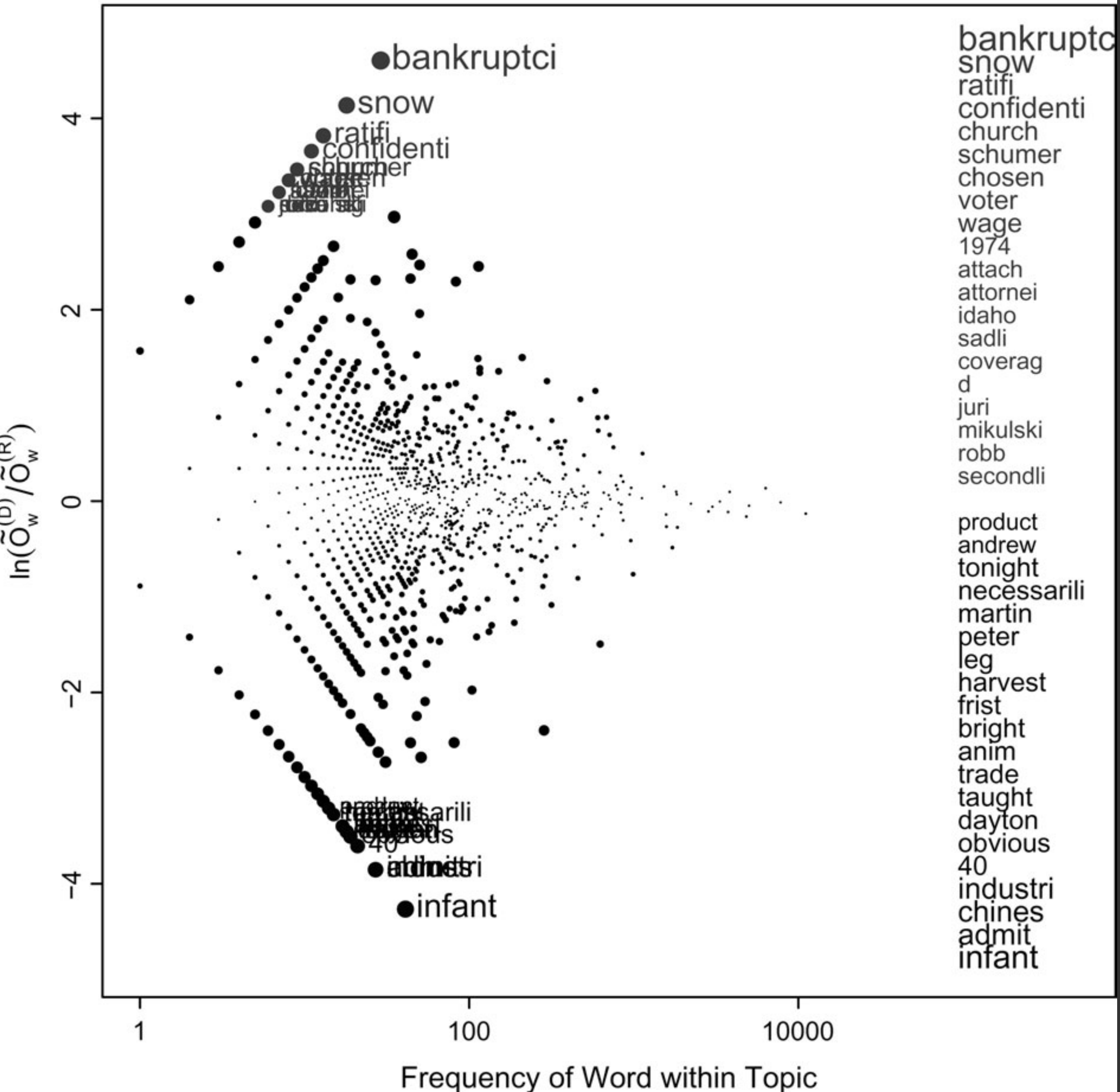
Term frequency may not be meaningful

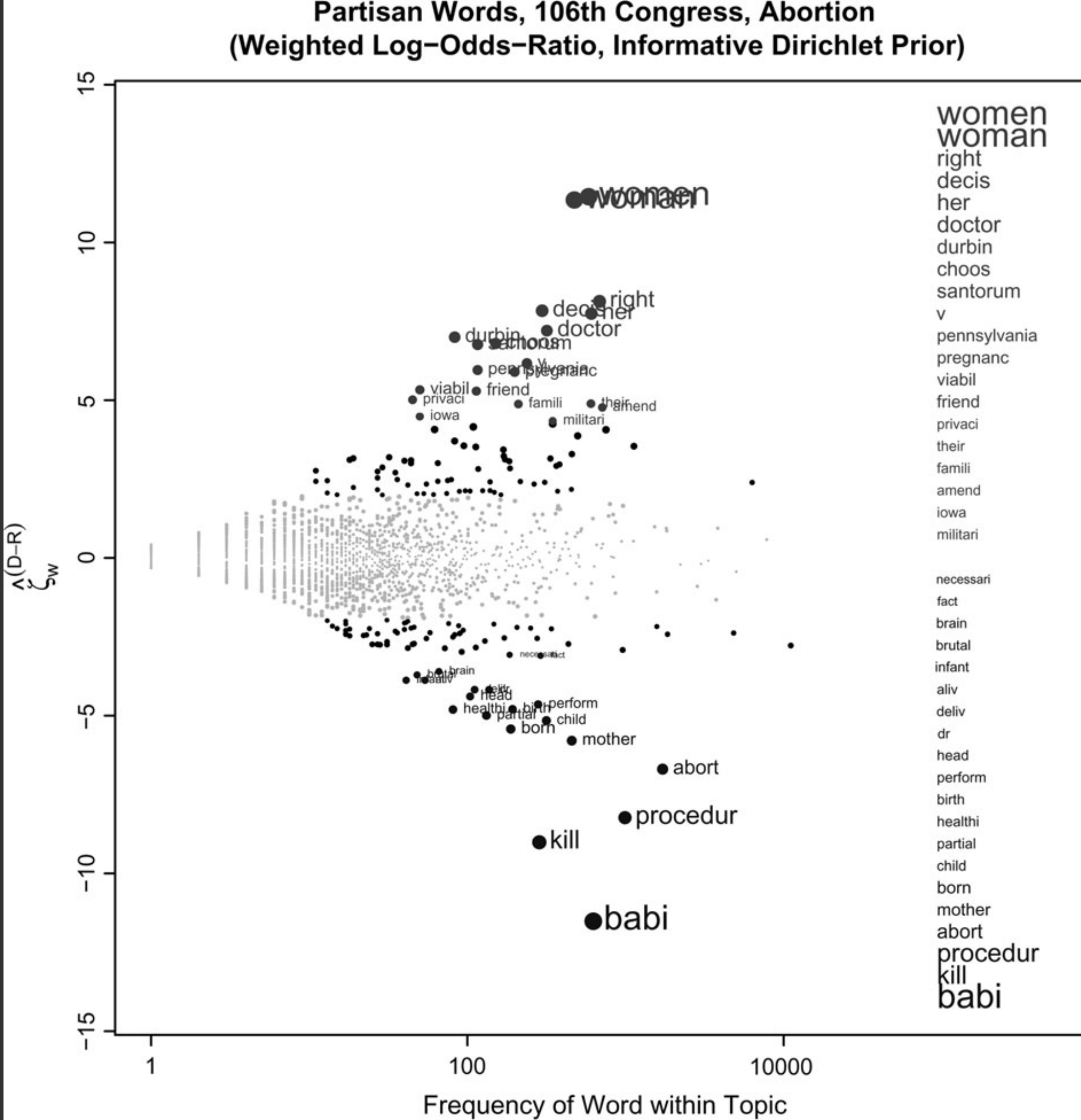
Does not show the structure of the text

Given a text, what are the best descriptive words?


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

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

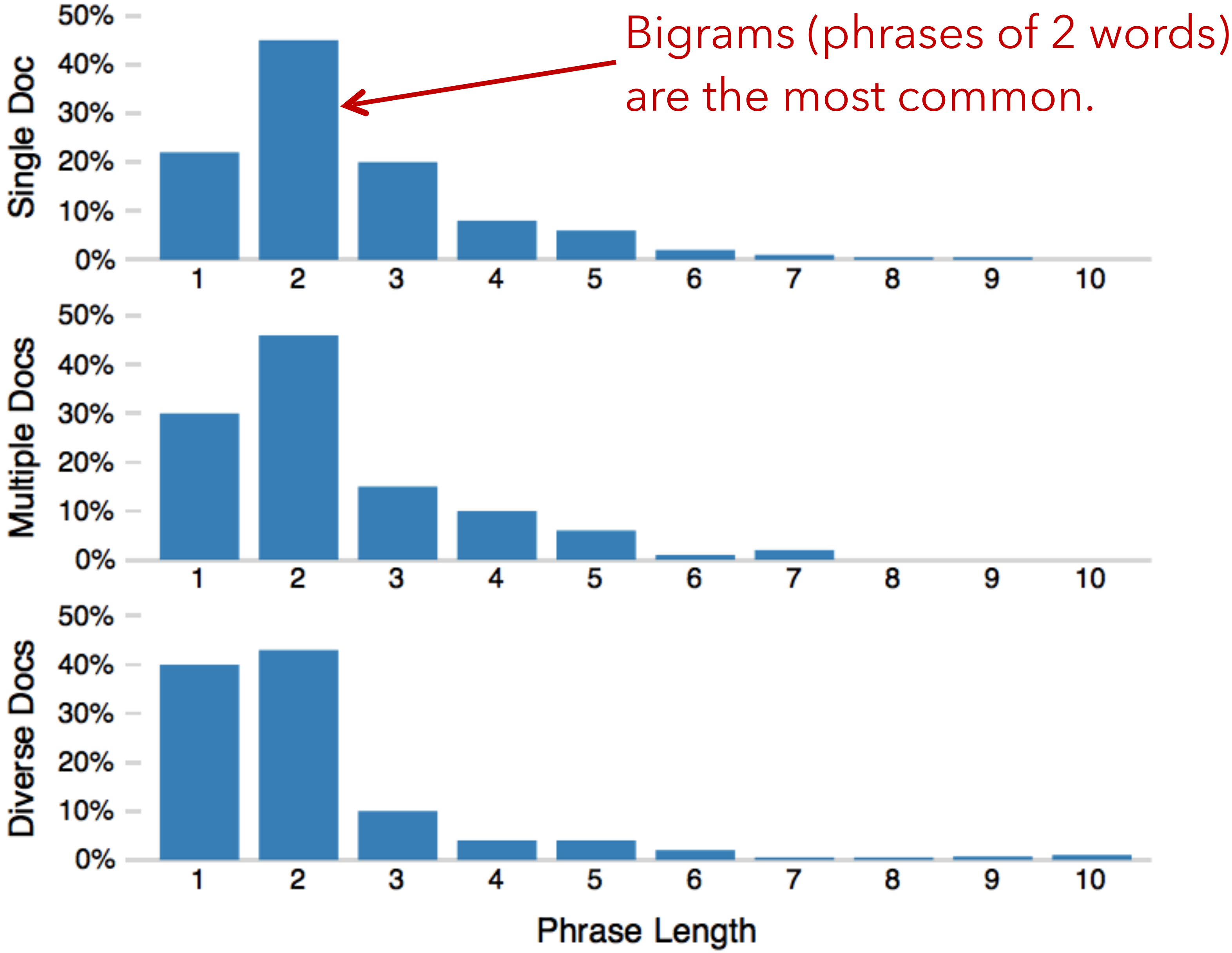
How do people describe text?

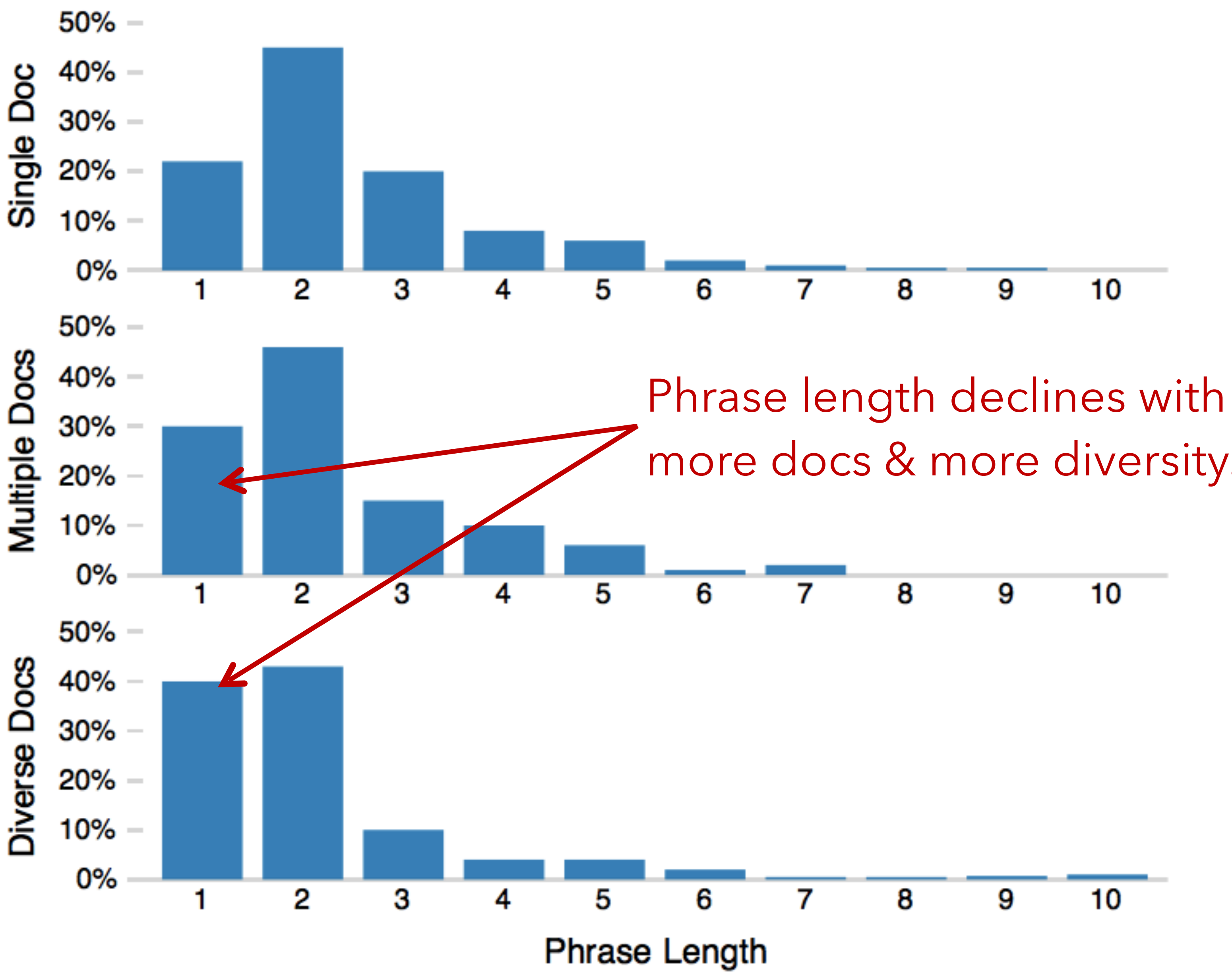
We asked 69 subjects (graduate students) to read and describe dissertation abstracts.

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.

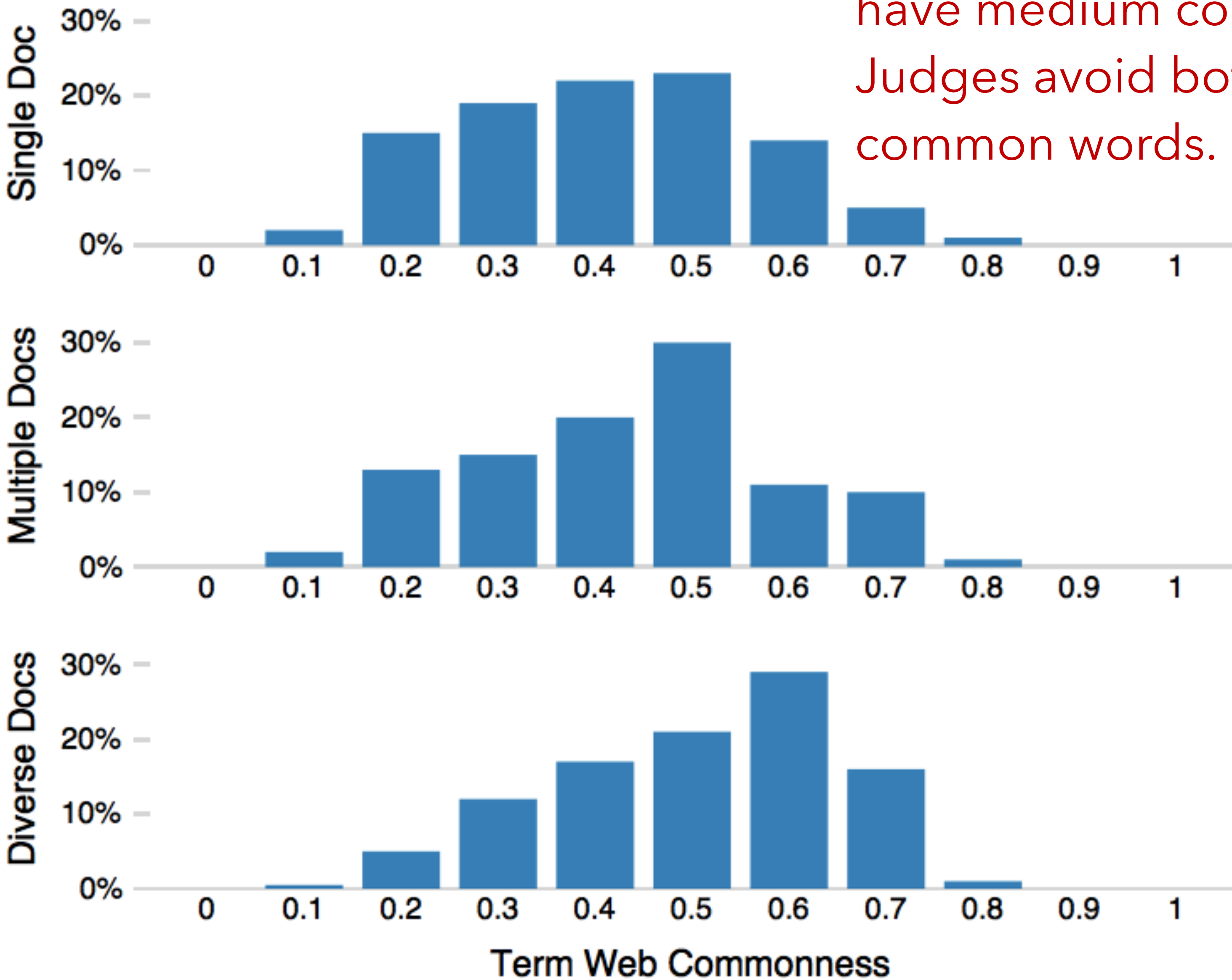
Term Commonness

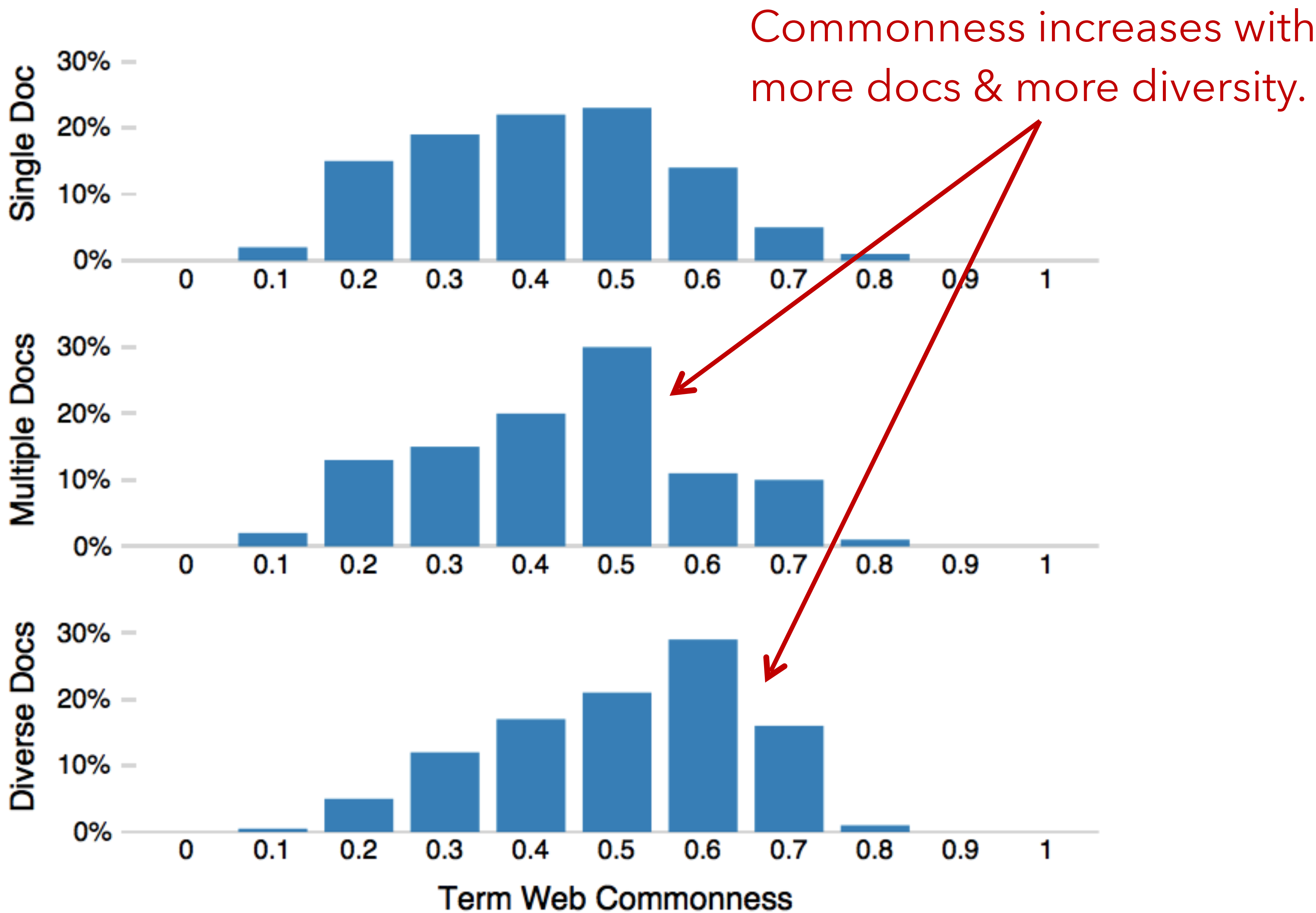
$$\log(tf_w) \;/\; \log(tf_{the})$$

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)

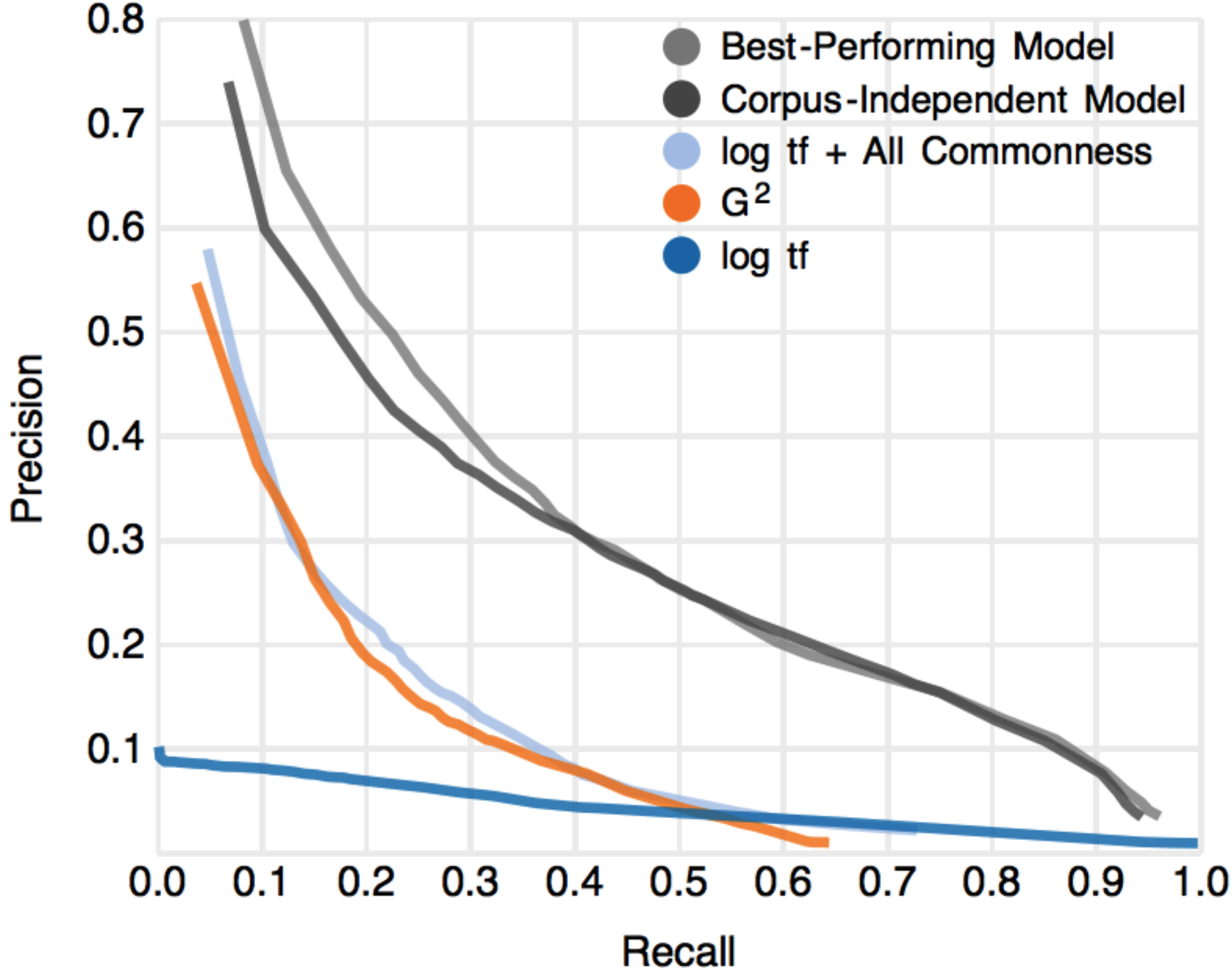
Selected descriptive terms have medium commonness. Judges avoid both rare and common words.





Commonness increases with
more docs & more diversity.
Single Doc
Multiple Docs
Diverse Docs
30%
20%
10%
0%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Term Web Commonness

Scoring Terms with Freq, Grammar & Position



A fighter jet rain check

Story and video by Chamila Jayaweera

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.

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.

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

fighter
F/A
Hornet
Super
Boeing
-18
rain
St.
jet
Louis
15-inch-per-hour
douse
hangar
water-tight
Check
Baxter
sea-based
aircraft
Rich
seep
click
Navy
sure
Water
moisture
watch
enormous
stay
want

Regression Model

Super Hornet
F/A -18
fighter jet
Boeing engineers
special process
rain check
electronics suite
Program experts
simulated rain
ultimate customers
enormous hangar
water-tight integrity
Rich Baxter
15-inch-per-hour rate
video story
aircraft
U.S. Navy fighter pilots
Super Hornet final assembly manager
U.S.
Navy fighter
fighter pilot
sea-based fighter

Yelp Review Spotlight (Yatani 2011)

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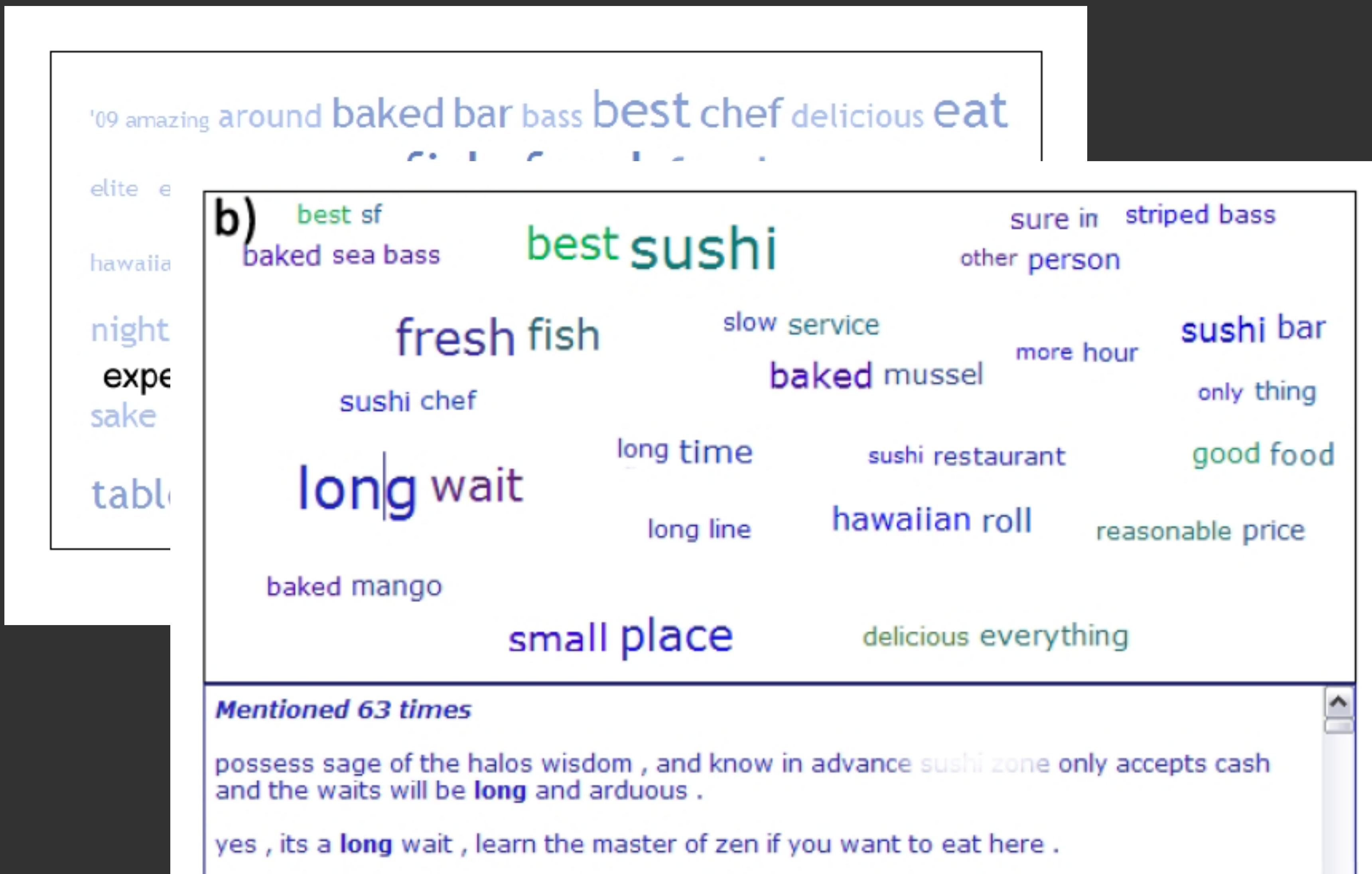


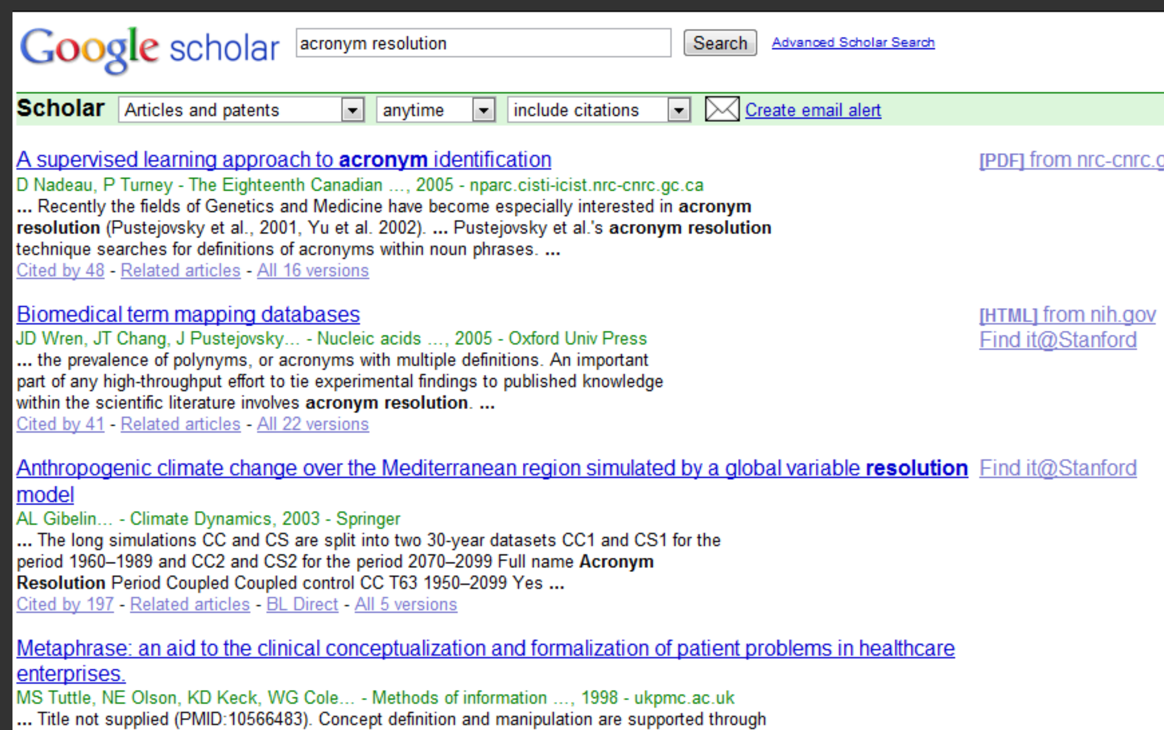
Tips: Descriptive Phrases

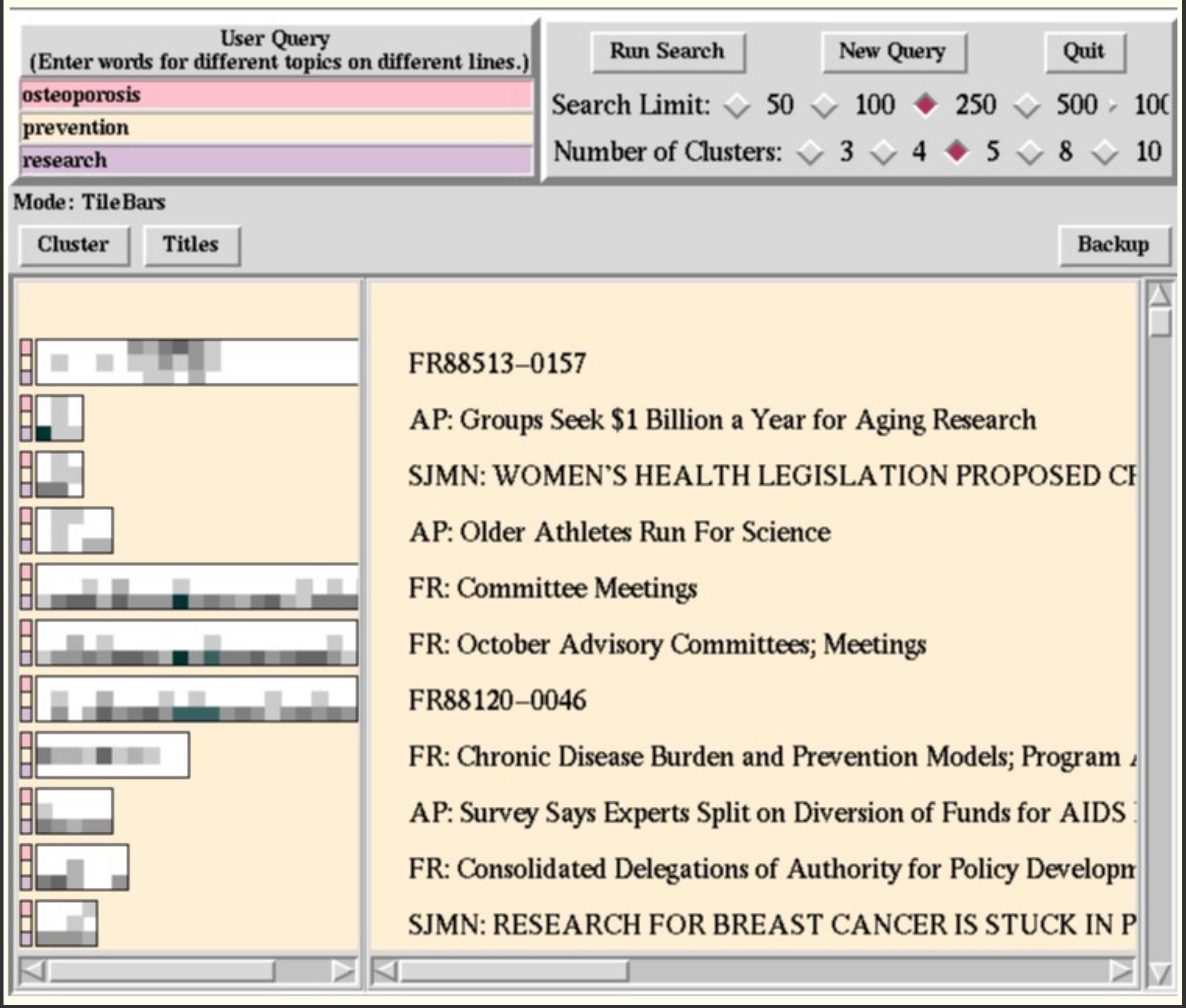
- Understand the limitations of your language model.
  - Bag of words:
    - Easy to compute
    - Single words
    - Loss of word ordering
- Select appropriate model and visualization
  - Generate longer, more meaningful phrases
  - Adjective-noun word pairs for reviews
  - Show keyphrases within source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

Document Content

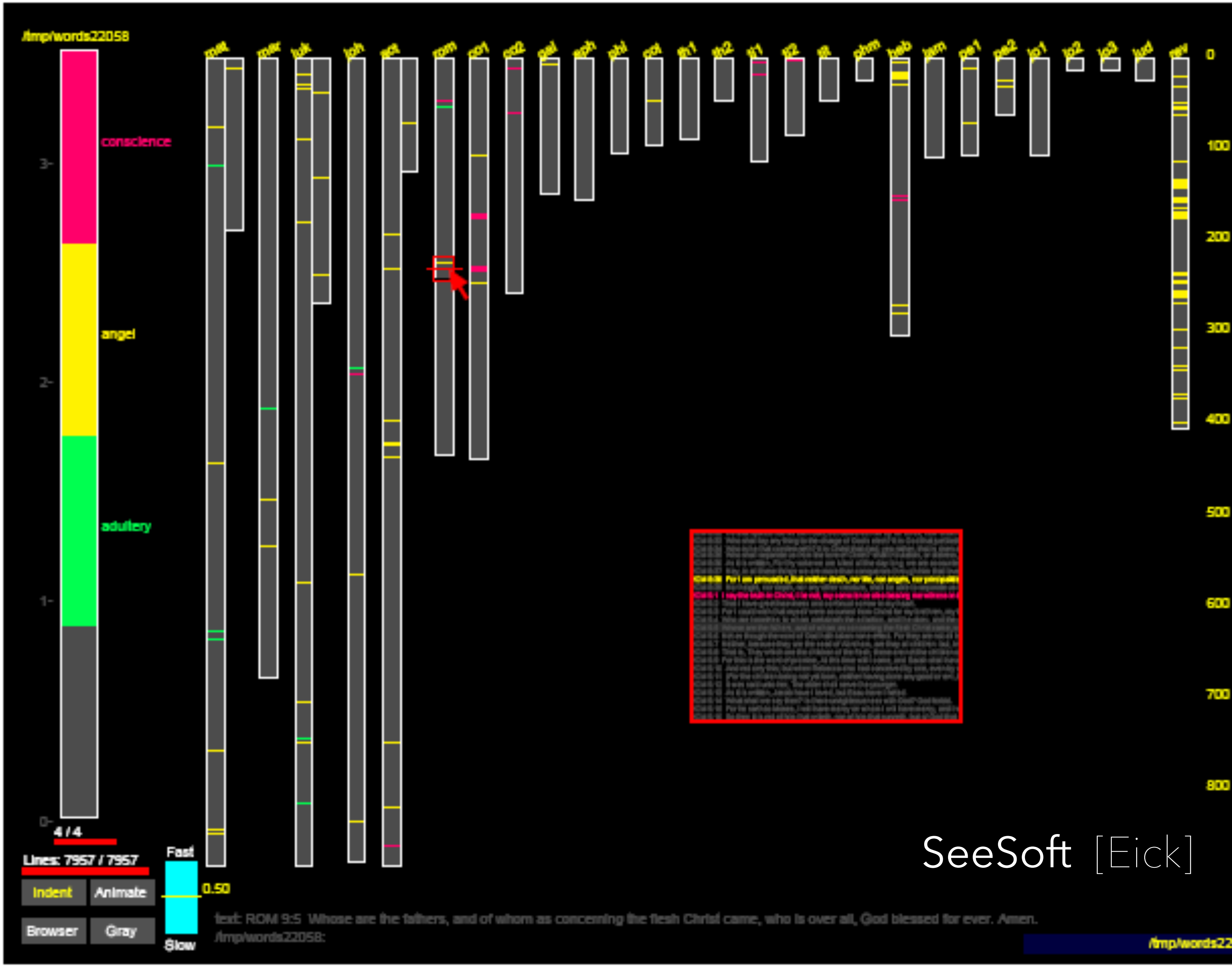
Information Retrieval

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

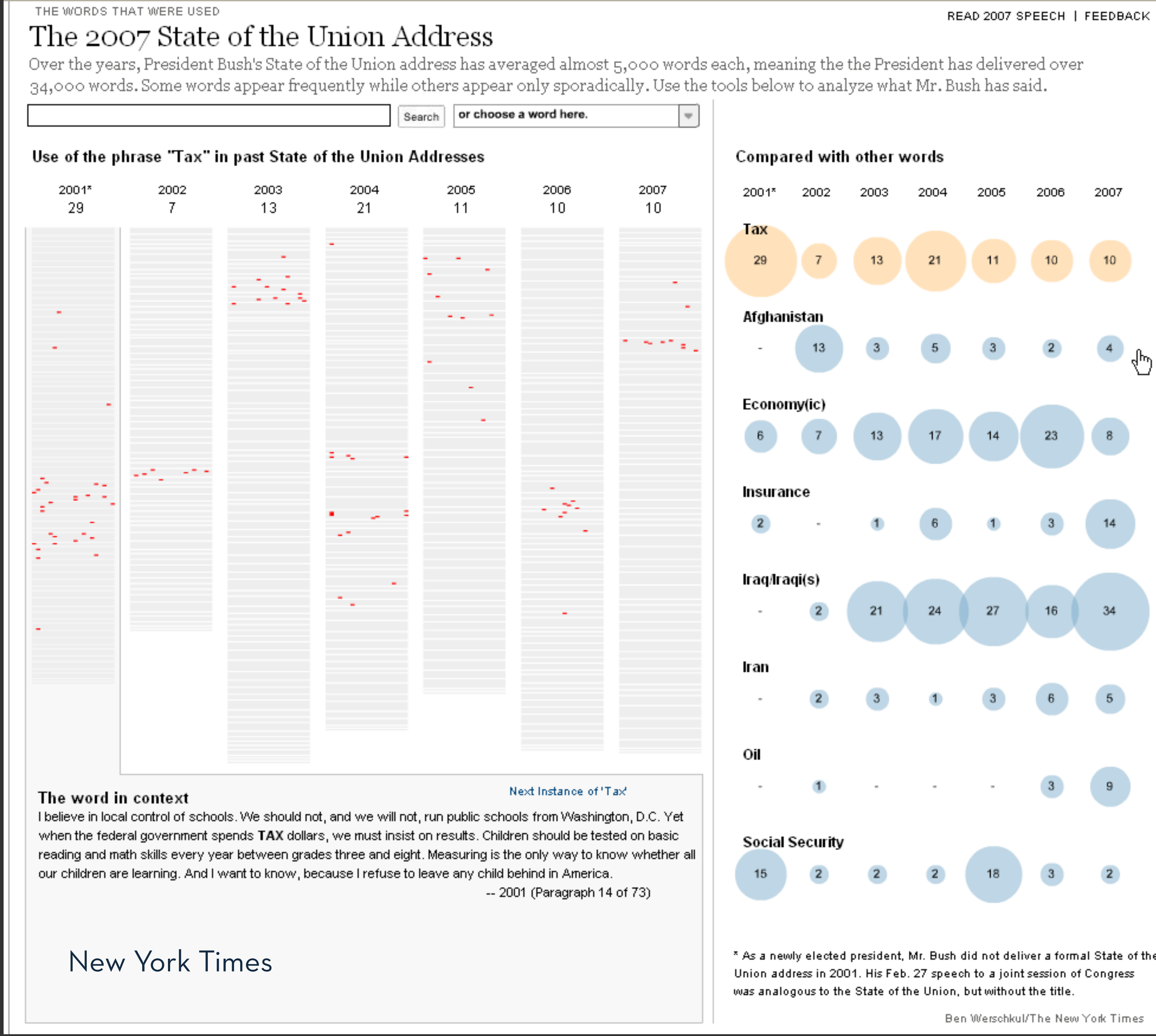




TileBars [Hearst]



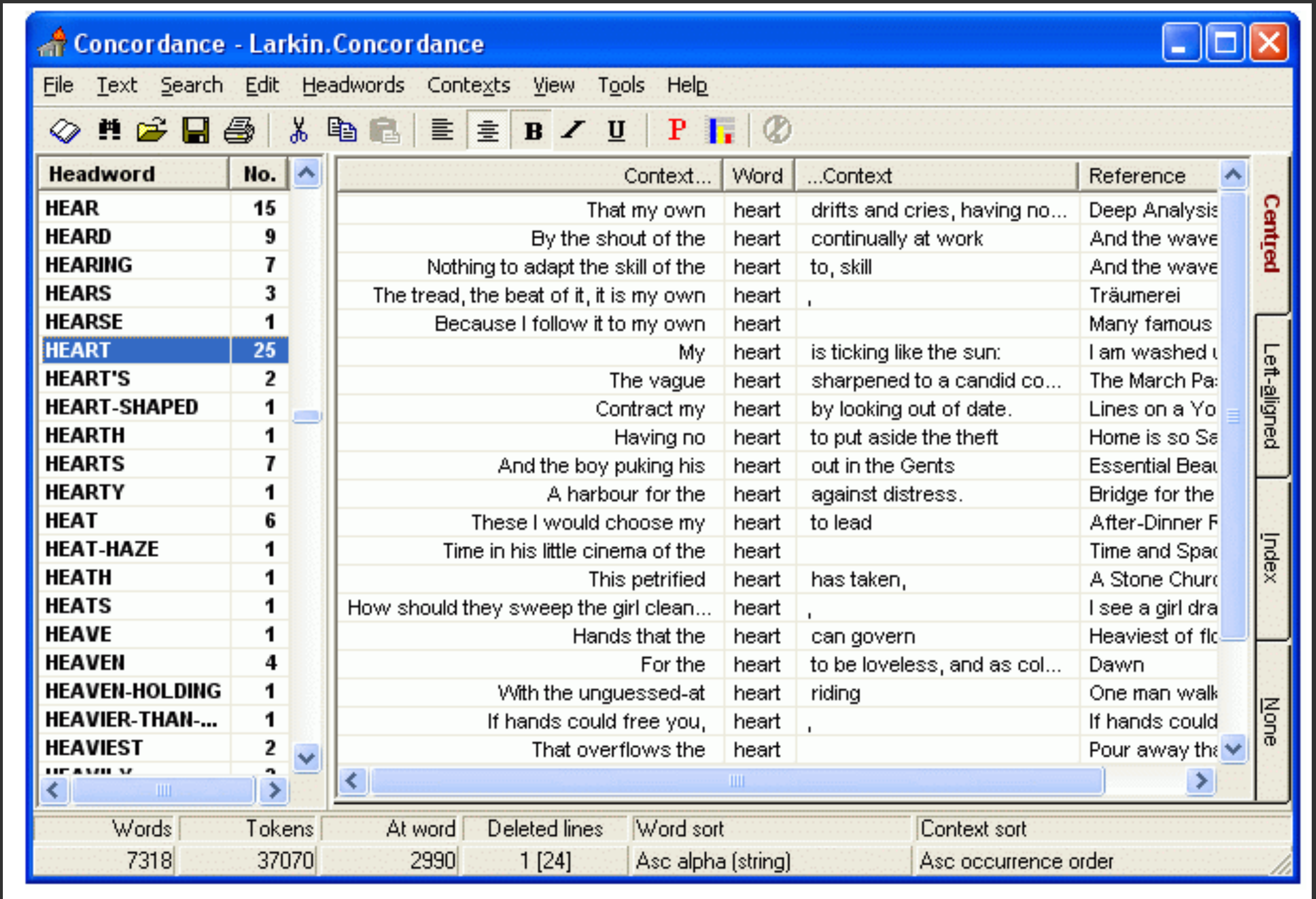
SeeSoft [Eick]

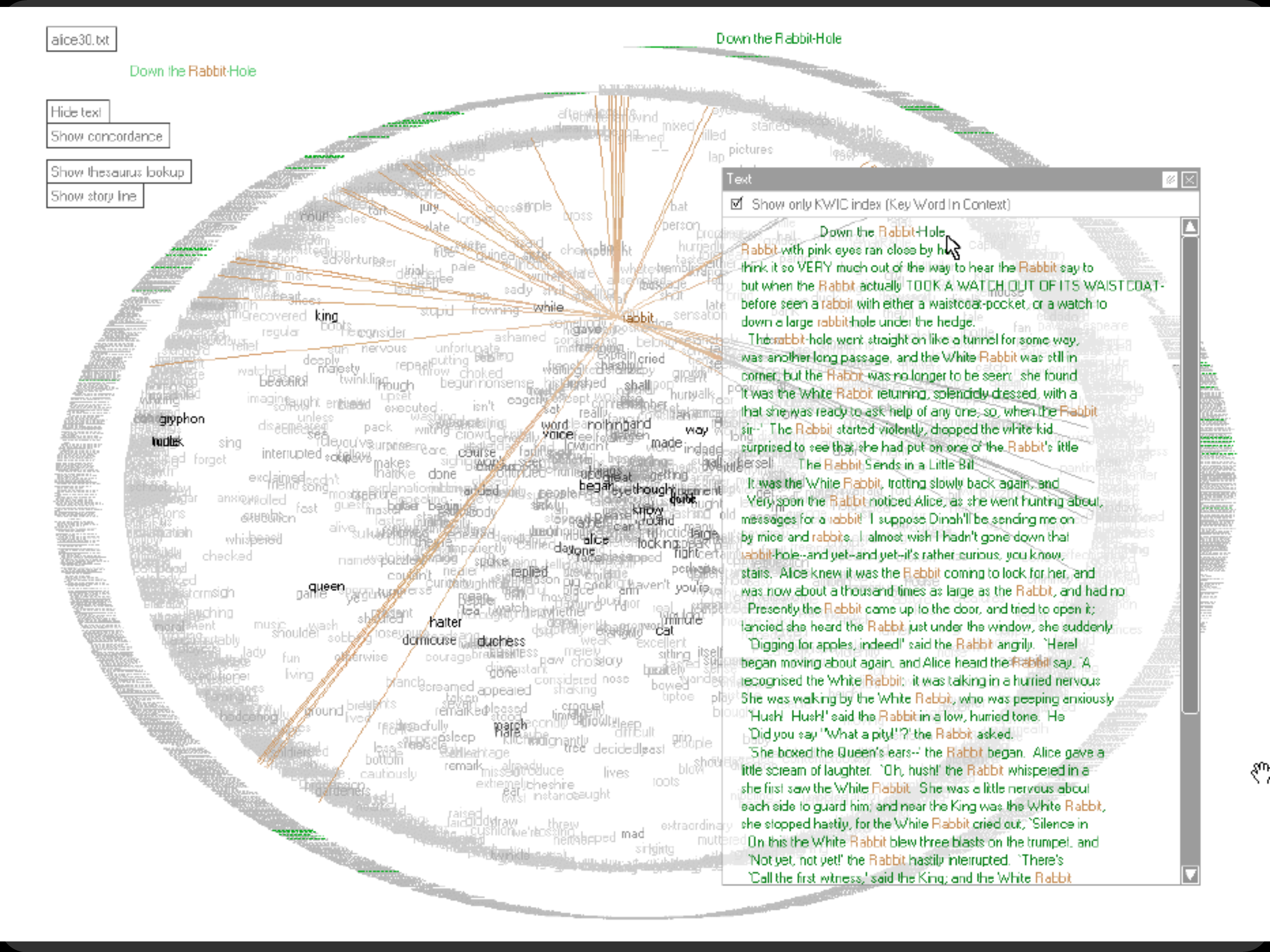


New York Times

Concordance

What is the common local context of a term?

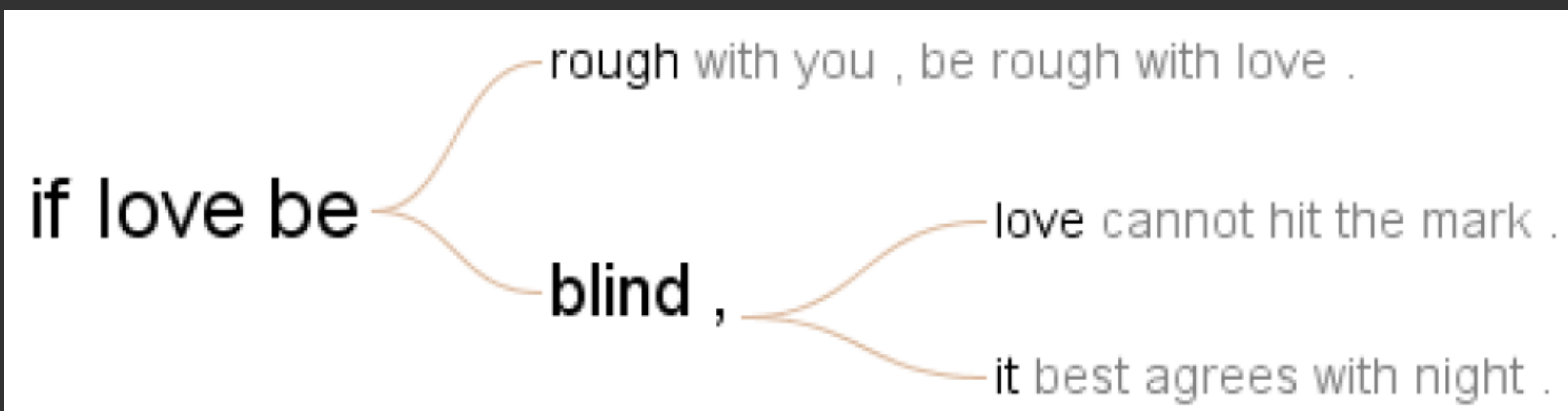



alice30.txt
Down the Rabbit-Hole
Hide text
Show concordance
Show thesaurus lookup
Show story line
Down the Rabbit-Hole
Text
Show only KWIC index (Key Word In Context)
Down the Rabbit-Hole
Rabbit with pink eyes ran close by her
think it so VERY much out of the way to hear the Rabbit say to
but when the Rabbit actually TOOK A WATCH OUT OF ITS WAISTCOAT-
before seen a rabbit with either a waistcoat-pocket, or a watch to
down a large rabbit-hole under the hedge.
The rabbit-hole went straight on like a tunnel for some way,
was another long passage, and the White Rabbit was still in
corner, but the Rabbit was no longer to be seen: she found
It was the White Rabbit returning, splendidly dressed, with a
that she was ready to ask help of any one; so, when the Rabbit
sir--' The Rabbit started violently, dropped the white kid
surprised to see that she had put on one of the Rabbit's little
herself. The Rabbit Sends in a Little Bill
It was the White Rabbit, trotting slowly back again, and
Very soon the Rabbit noticed Alice, as she went hunting about,
messages for a rabbit! I suppose Dinah'll be sending me on
by mice and rabbits. I almost wish I hadn't gone down that
rabbit-hole--and yet--and yet--it's rather curious, you know,
stairs. Alice knew it was the Rabbit coming to look for her, and
was now about a thousand times as large as the Rabbit, and had no
Presently the Rabbit came up to the door, and tried to open it;
fancied she heard the Rabbit just under the window, she suddenly
`Digging for apples, indeed!' said the Rabbit angrily. `Here!
began moving about again, and Alice heard the Rabbit say, `A
recognised the White Rabbit: it was talking in a hurried nervous
She was walking by the White Rabbit, who was peeping anxiously
`Hush! Hush!' said the Rabbit in a low, hurried tone. He
`Did you say "What a pity!"?' the Rabbit asked.
`She boxed the Queen's ears--' the Rabbit began. Alice gave a
little scream of laughter. `Oh, hush!' the Rabbit whispered in a
she first saw the White Rabbit. She was a little nervous about
each side to guard him; and near the King was the White Rabbit,
she stopped hastily, for the White Rabbit cried out, `Silence in
On this the White Rabbit blew three blasts on the trumpet, and
`Not yet, not yet!' the Rabbit hastily interrupted. `There's
`Call the first witness,' said the King; and the White Rabbit

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

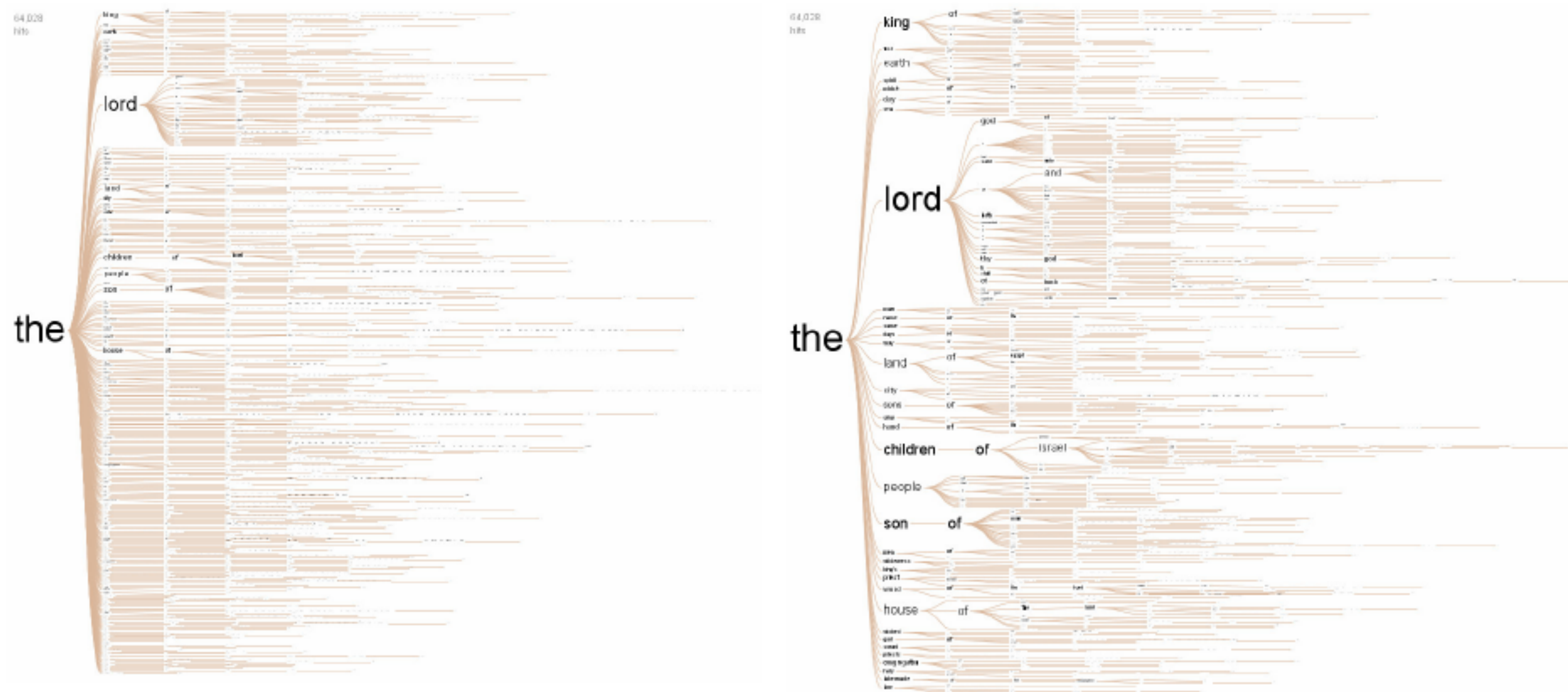
if love be blind , love cannot hit the mark .

if love be blind , it best agrees with night .

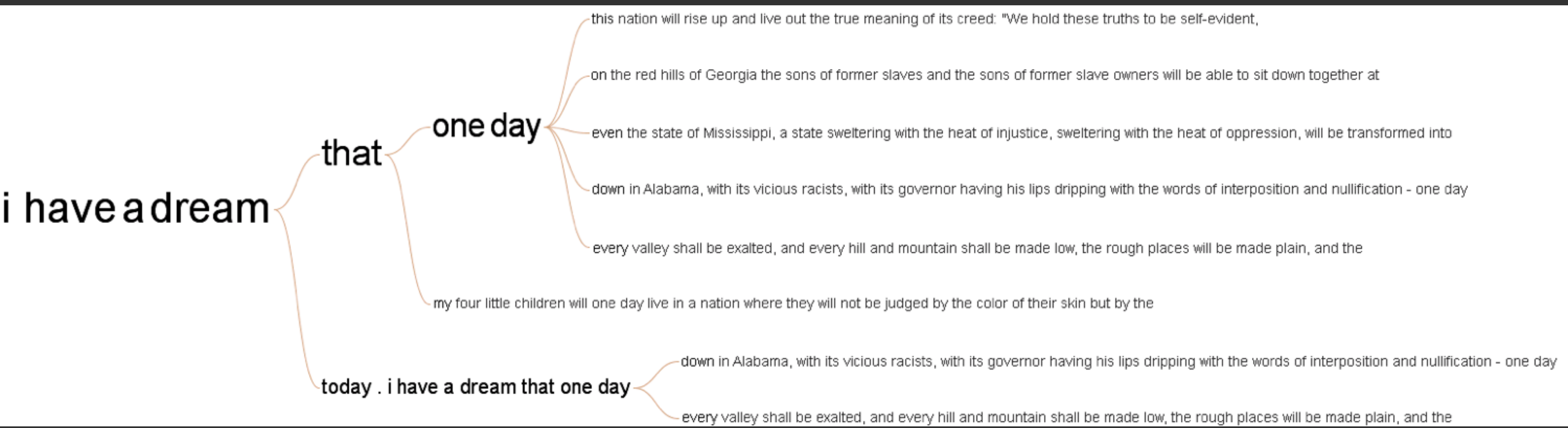


Word Tree [Wattenberg et al.]

Filter Infrequent Runs



Recurrent Themes in Speeches



many eyes

Login

visualizations search

explore
- visualizations
- data sets
- comments
- topic hubs

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

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

contact Us
- contact
- report a bug

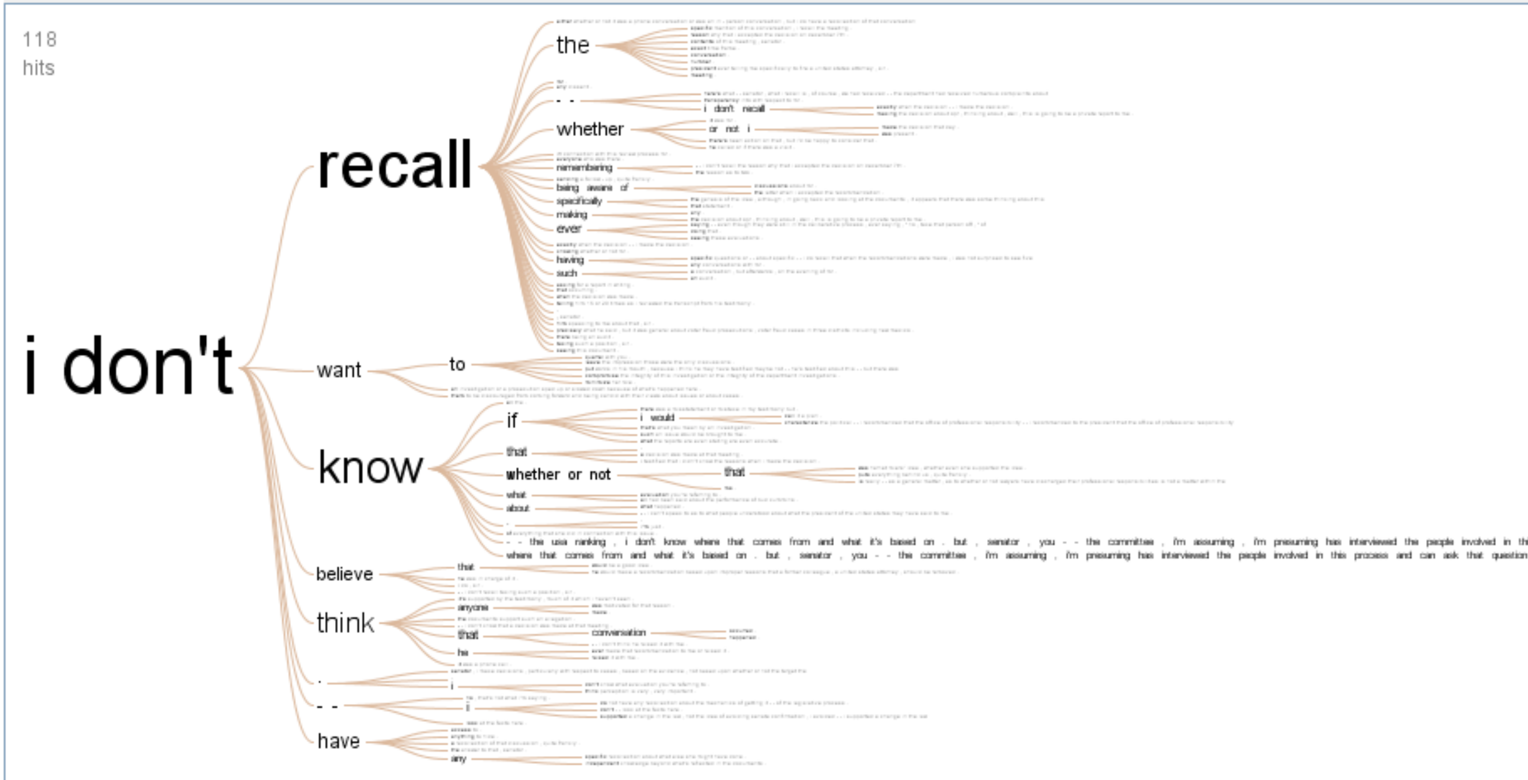
legal
- terms of use

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

Popular Dataset Tags

2007 2008 bible blog books census crime education eharmony election energy food health inauguration internet ireland literature lyrics media music network obama people politics population president prices religion

Glimpses of Structure…

Concordances show local, repeated structure

But what about other types of patterns?

Lexical: <A> at <B>

Syntactic: <Noun> <Verb> <Object>

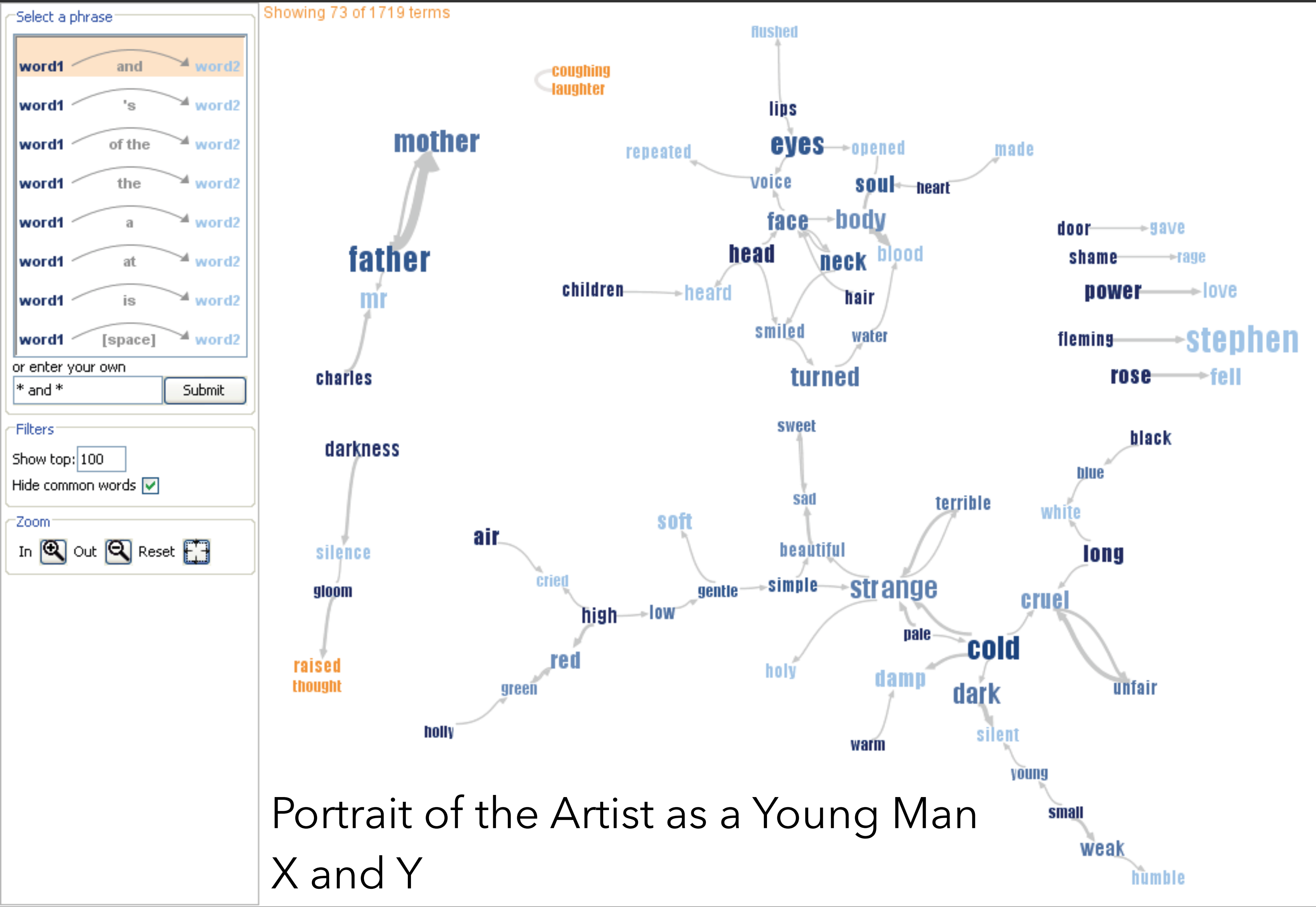
Phrase Nets [van Ham et al.]

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

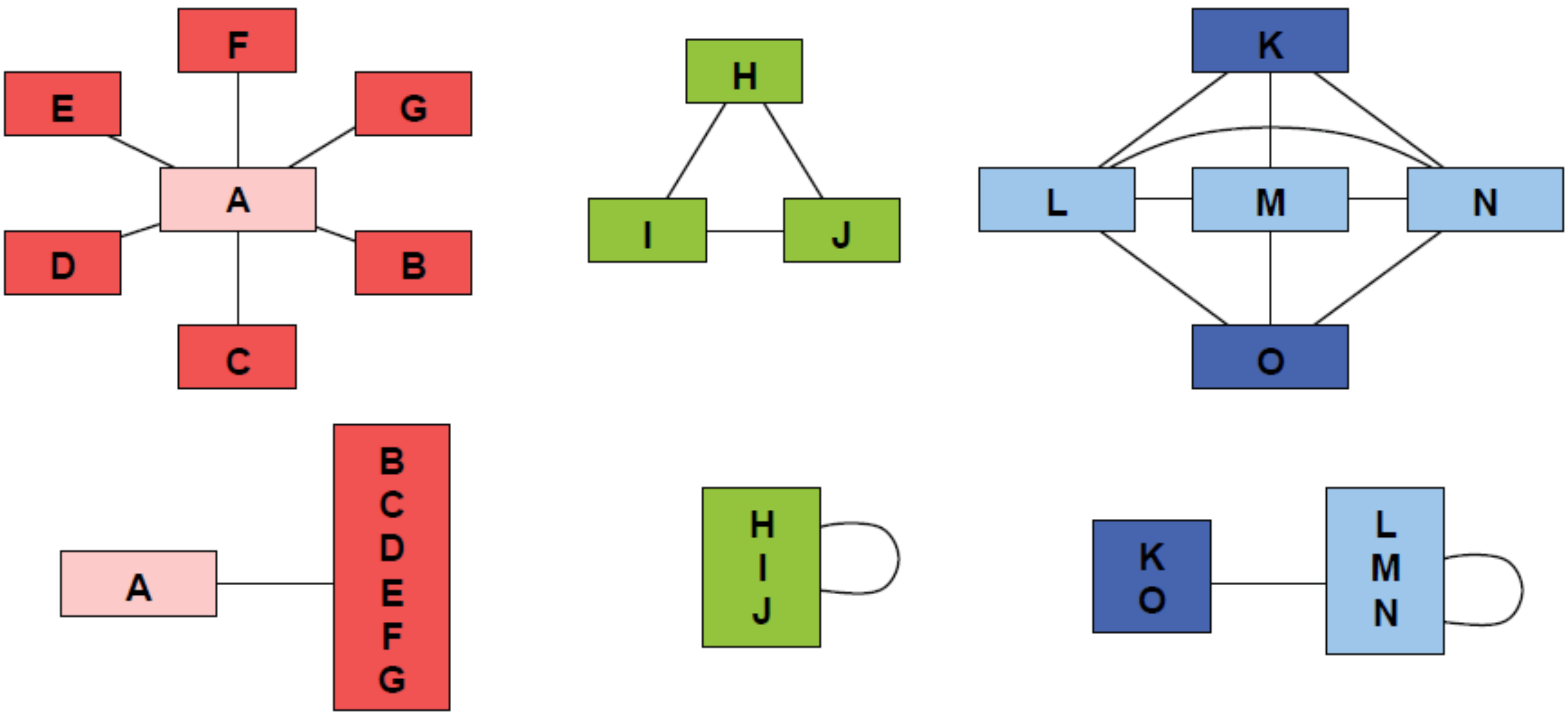
- Occurrences -> Node size
- Pattern position -> Edge direction



Portrait of the Artist as a Young Man

X and Y

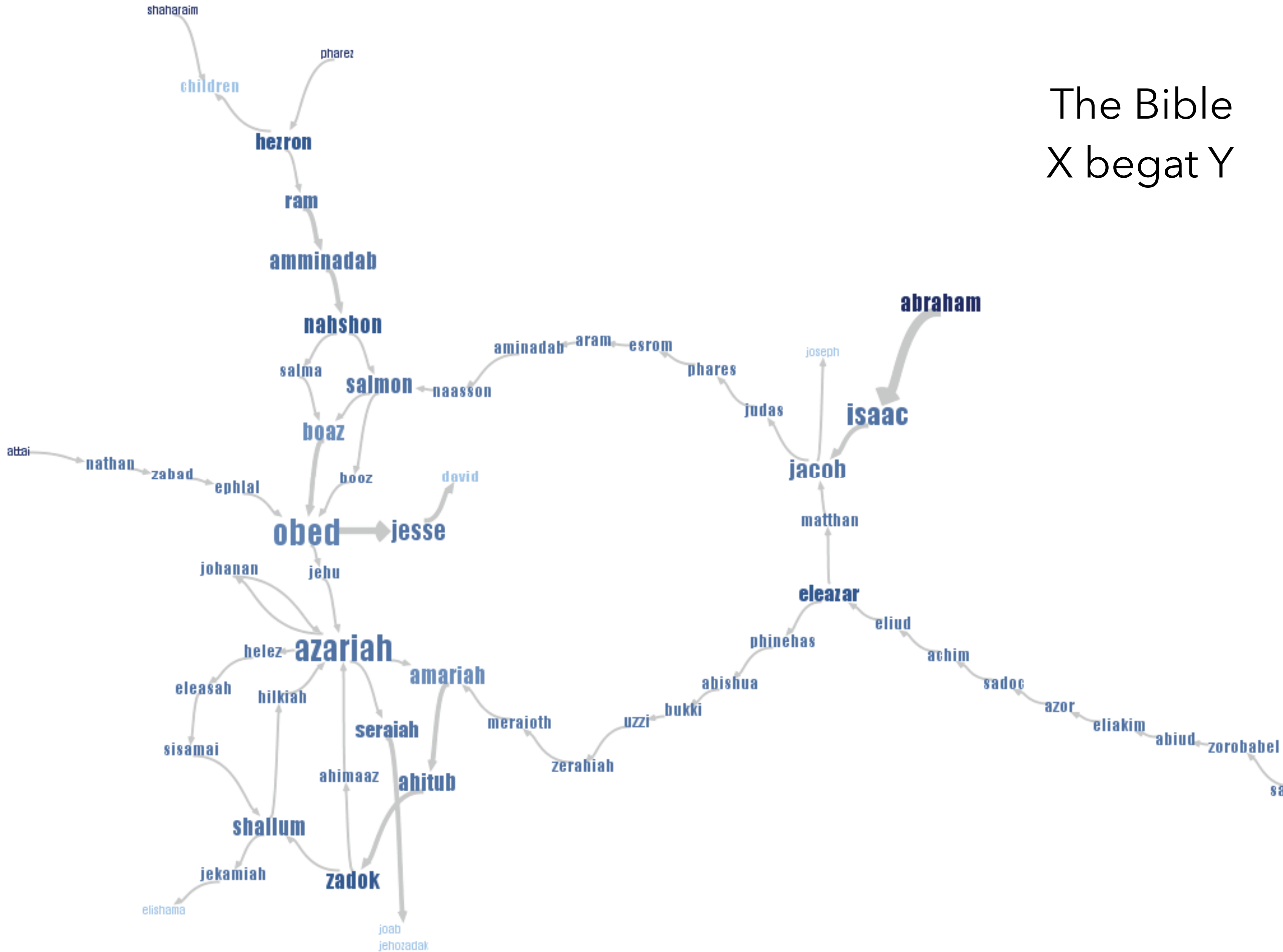
Node Grouping

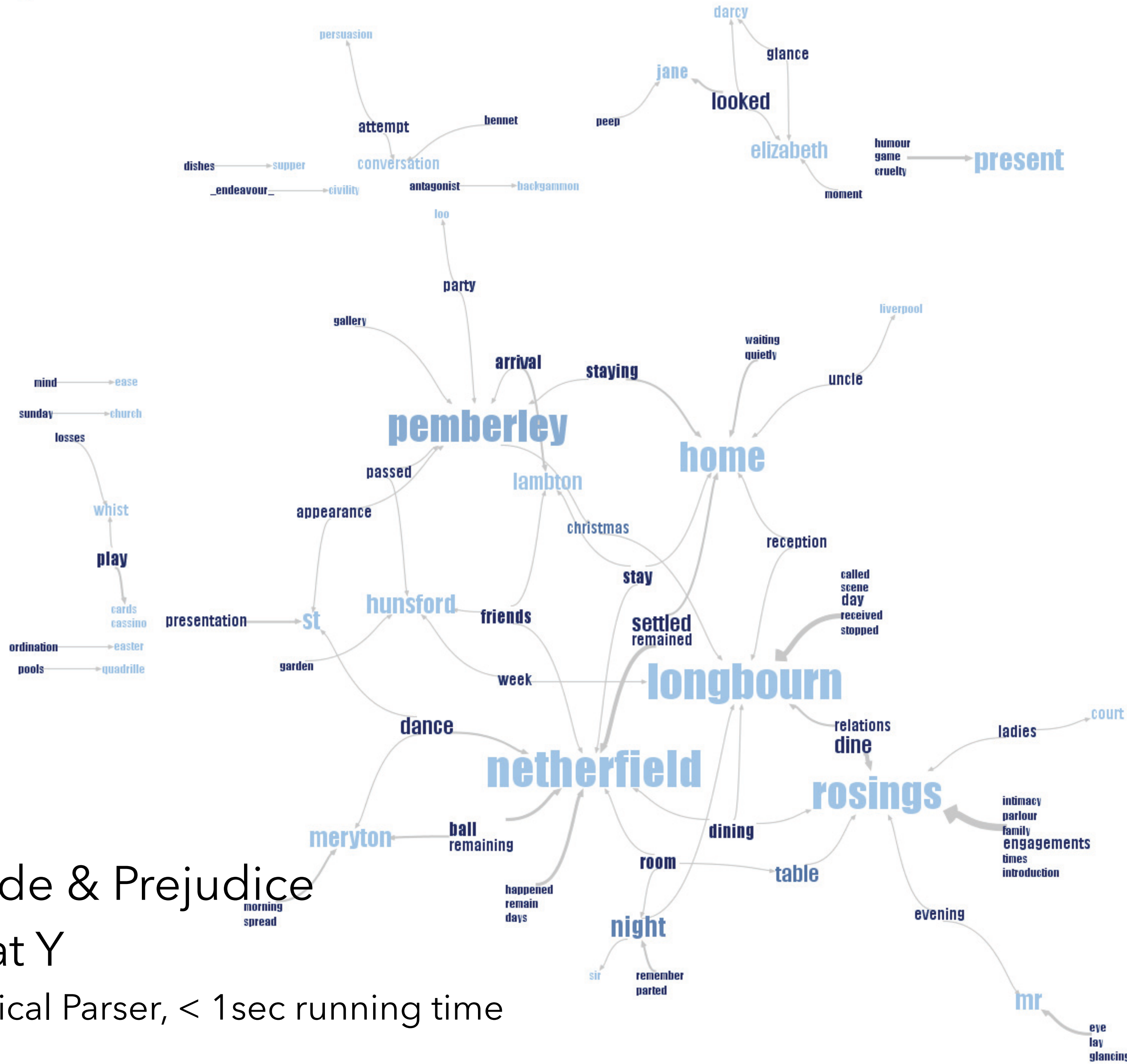


(a) (b) (c)

The Bible

X begat Y

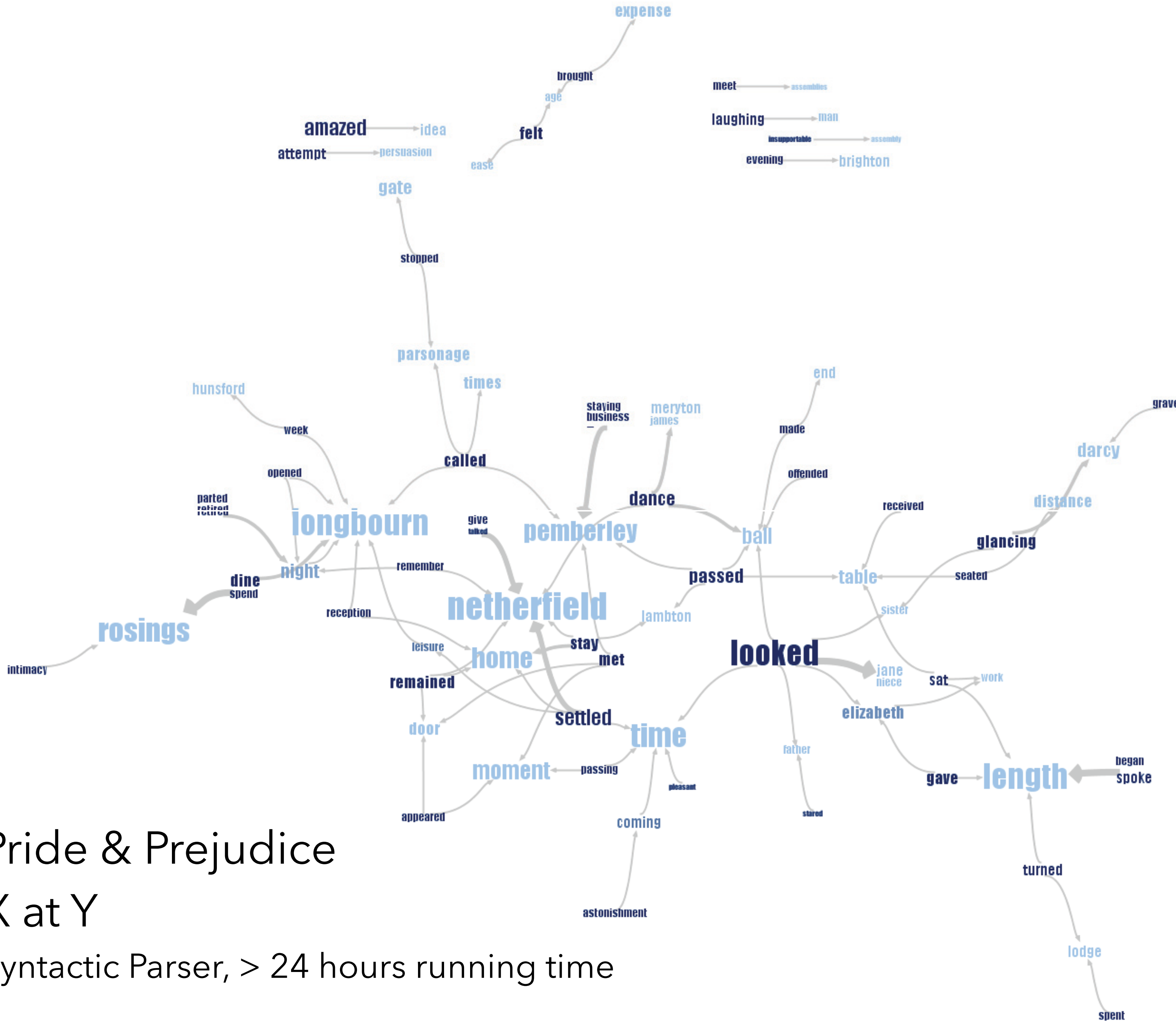




Pride & Prejudice

X at Y

Lexical Parser, < 1sec running time



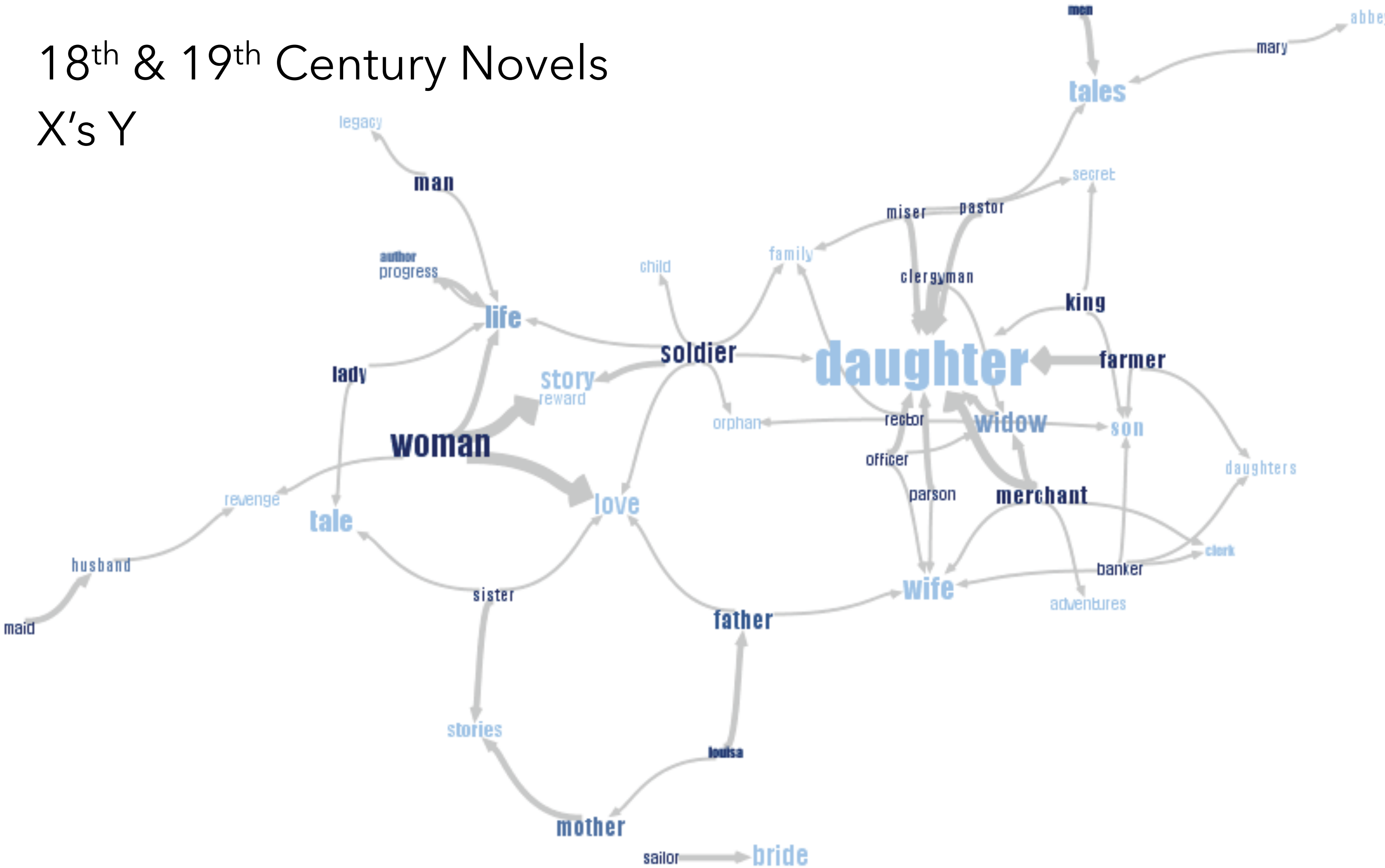
Pride & Prejudice

X at Y

Syntactic Parser, > 24 hours running time

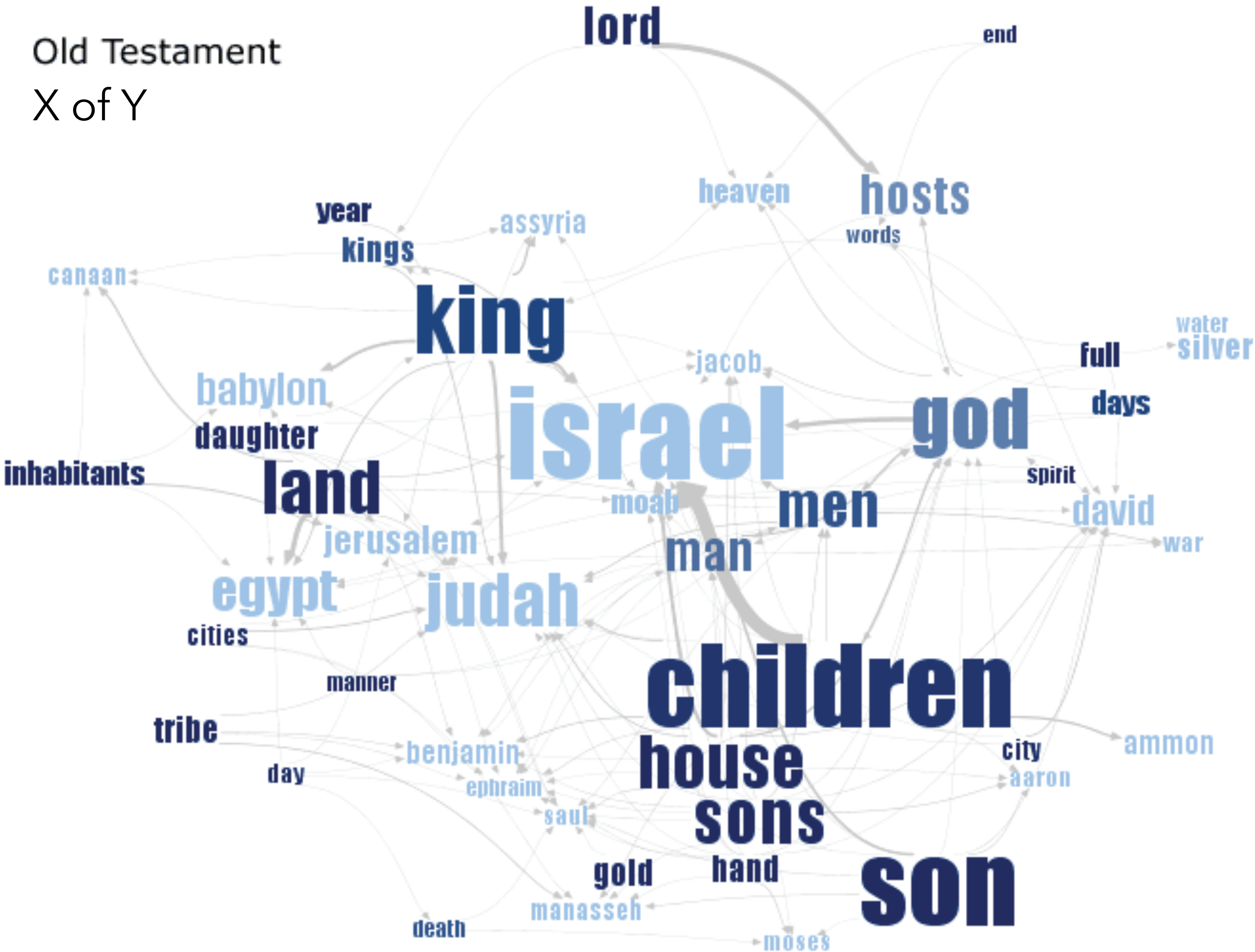
18th & 19th Century Novels

X's Y



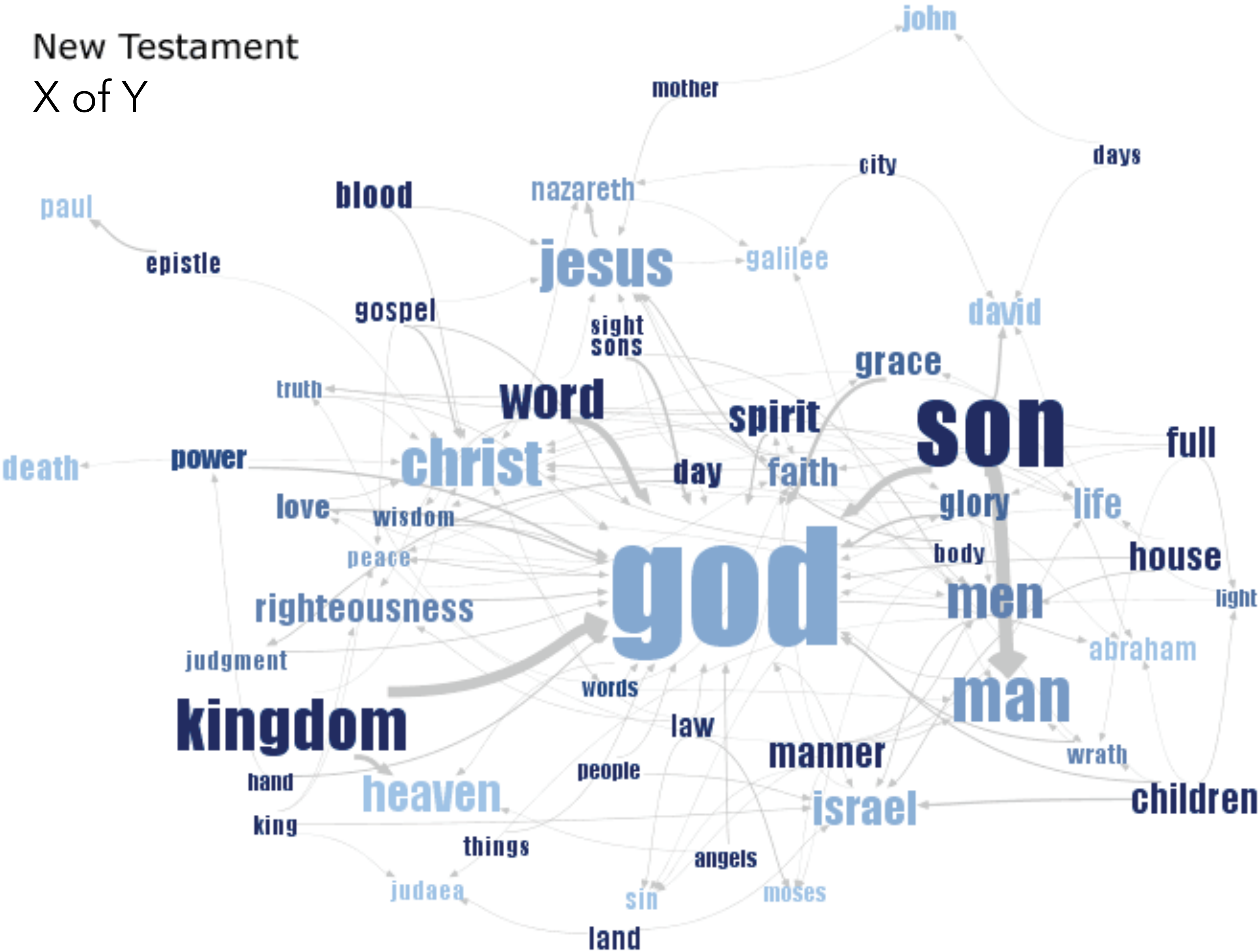
Old Testament

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

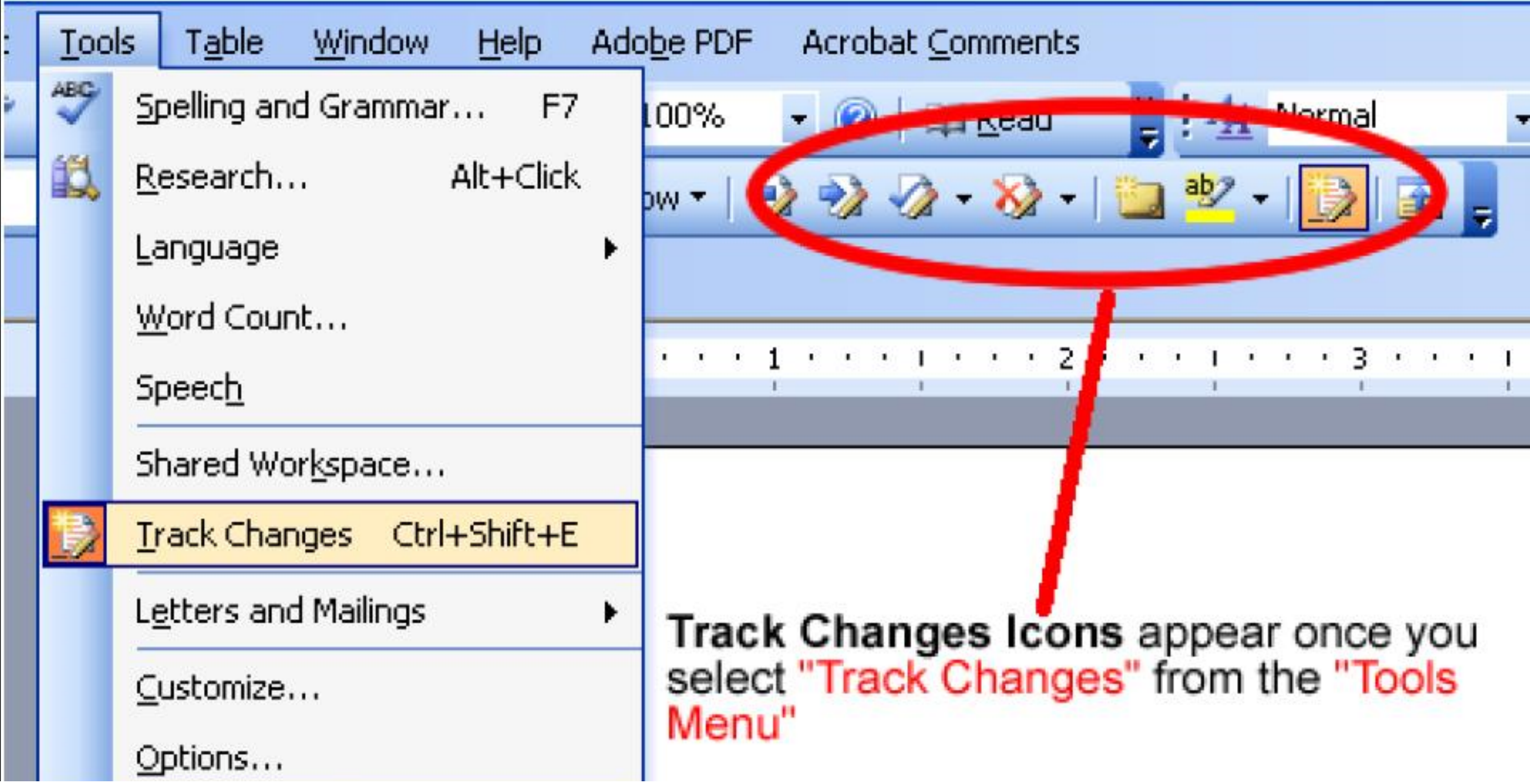
Both: Spatial layout reflects semantic relationships

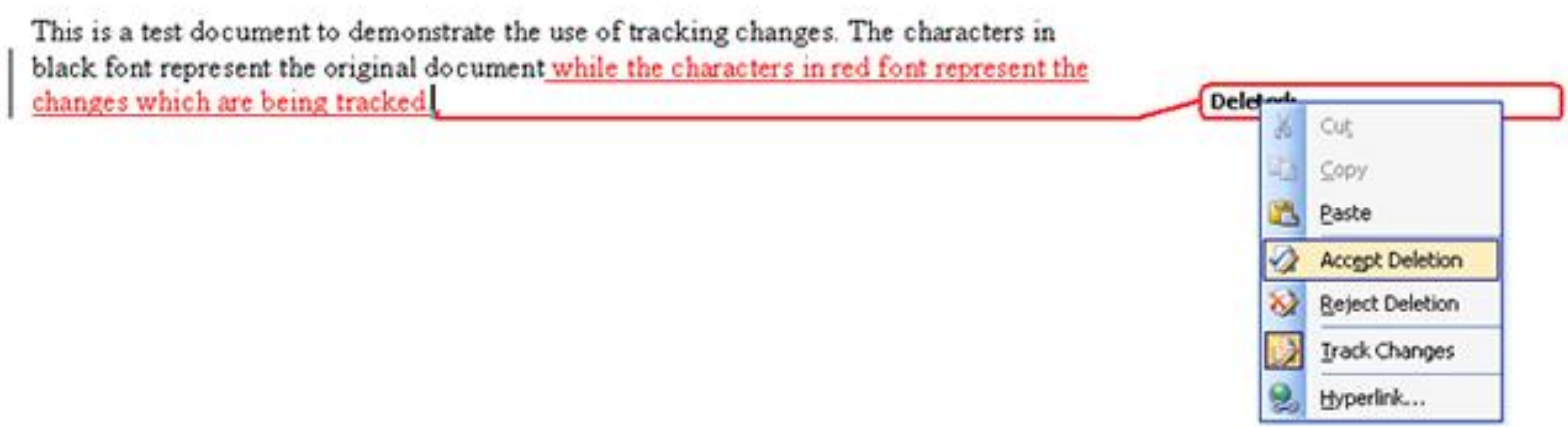
The Role of Interaction

Language model supports visual analysis cycles

Allow modifications to the model: custom patterns for expressing contextual or domain knowledge

Evolving Documents


Tools Table Window Help Adobe PDF Acrobat Comments
Spelling and Grammar... F7
Research... Alt+Click
Language
Word Count...
Speech
Shared Workspace...
Track Changes Ctrl+Shift+E
Letters and Mailings
Customize...
Options...
100%
Normal
Track Changes Icons appear once you select "Track Changes" from the "Tools Menu"


This is a test document to demonstrate the use of tracking changes. The characters in black font represent the original document while the characters in red font represent the changes which are being tracked
Cut
Copy
Paste
Accept Deletion
Reject Deletion
Track Changes
Hyperlink...

Visualizing Revision History

How to depict contributions over time?

Example: Wikipedia history log

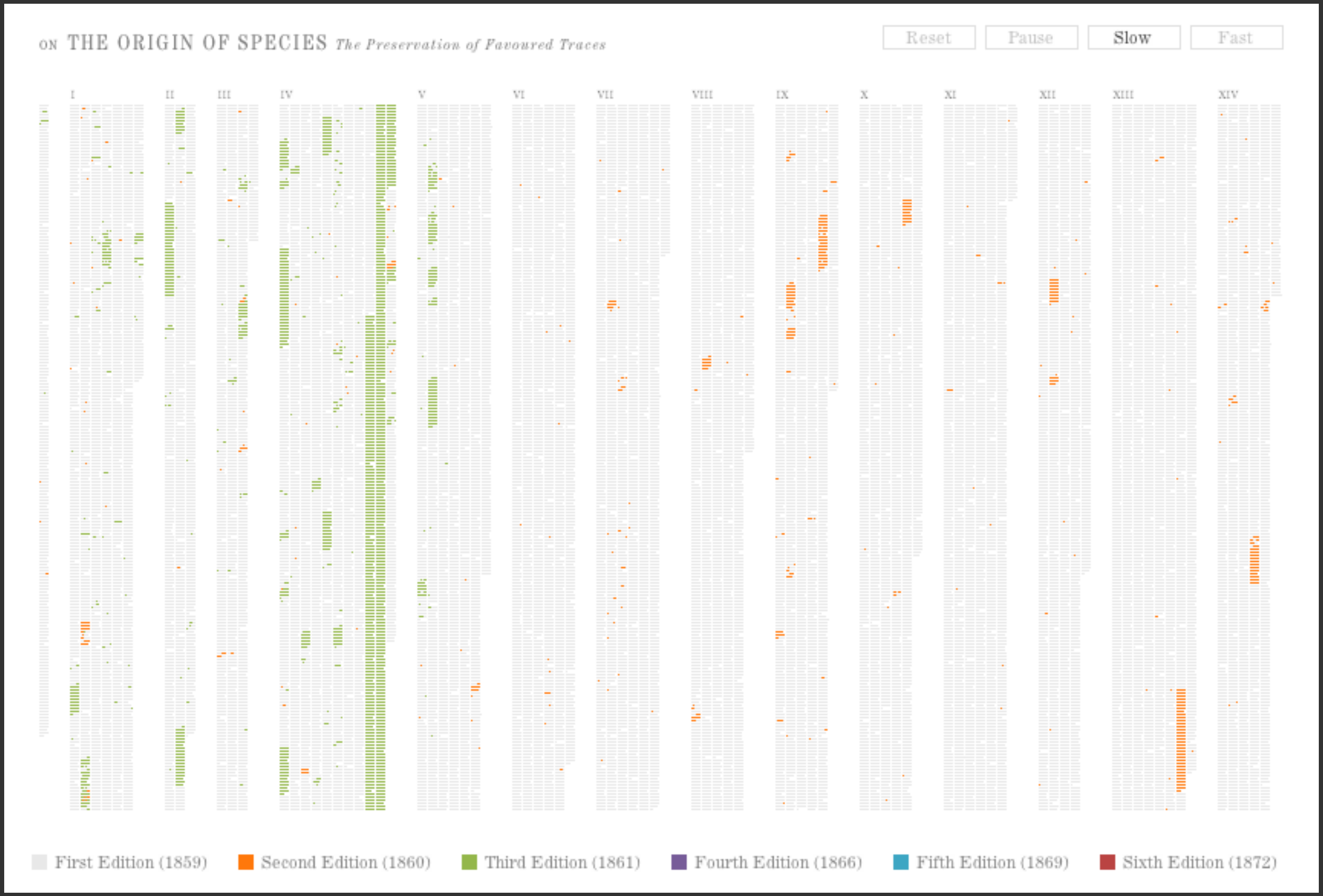
Chocolate

Revision history

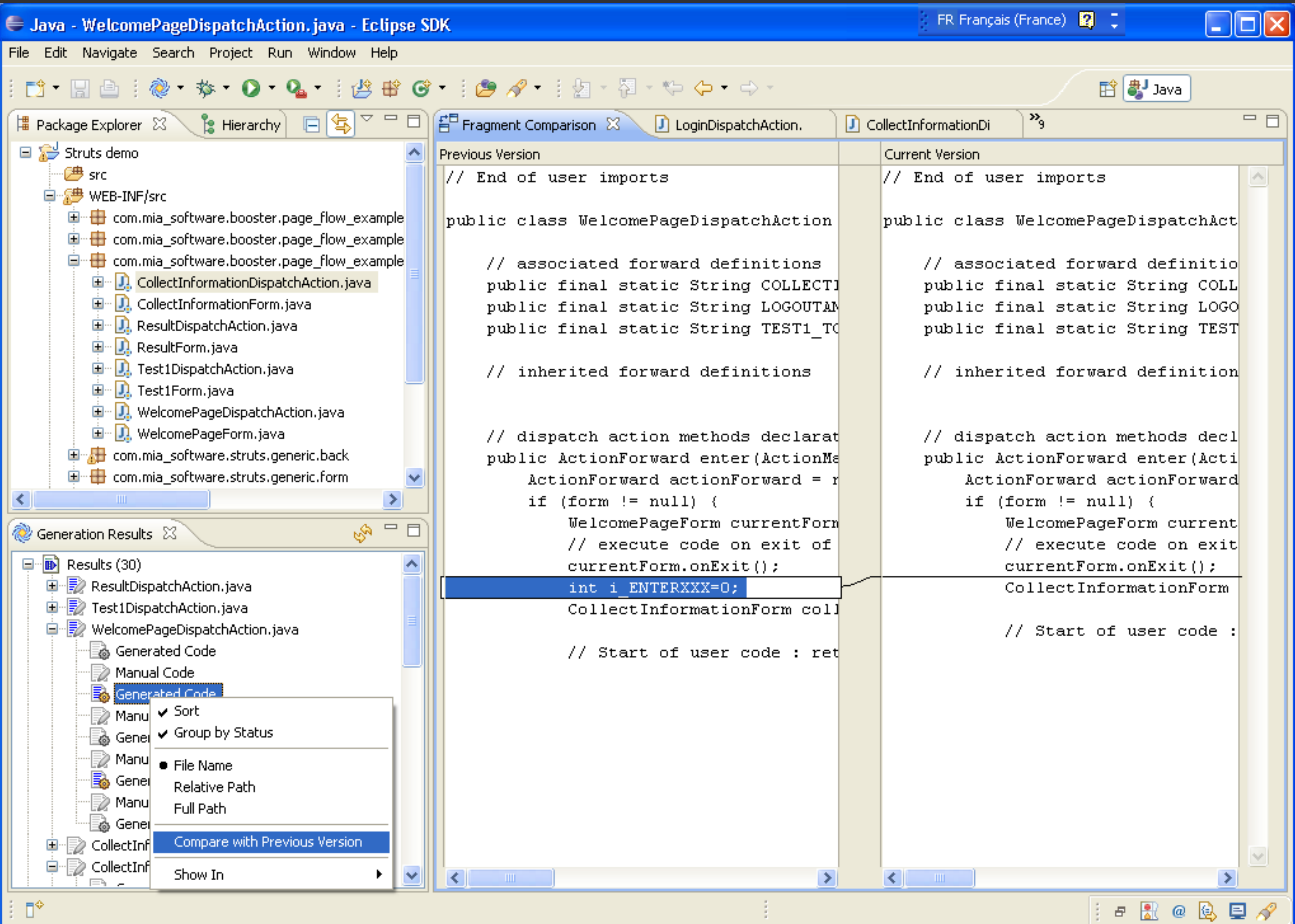
Legend: (cur) = difference with current version, (last) = difference with preceding version, M = minor edit

- (cur) (last) . . 12:01, 20 Aug 2003 . . Dysprosia *(neaten to do, rearrange see also)*
- (cur) (last) . . 11:59, 20 Aug 2003 . . Patrick
- (cur) (last) . . 11:52, 20 Aug 2003 . . 81.203.98.109
- (cur) (last) . . **M** 18:36, 6 Aug 2003 . . Manika *(corrected spelling)*
- (cur) (last) . . 18:32, 6 Aug 2003 . . Daniel Quinlan *(removing obscure heraldry information, belongs on [[heraldry]] if anywhere)*
- (cur) (last) . . 15:21, 6 Aug 2003 . . Rmhermen
- (cur) (last) . . 15:08, 6 Aug 2003 . . Cyp *(Chocolate often has odd shapes.)*
- (cur) (last) . . 19:14, 3 Aug 2003 . . Daniel C. Boyer *("chocolate" as shade of gules in heraldry)*
- (cur) (last) . . **M** 02:00, 30 Jul 2003 . . Evercat *(fmt)*

Animated Traces [Ben Fry]



http://benfry.com/traces/



Java - WelcomePageDispatchAction.java - Eclipse SDK
FR Français (France)
File Edit Navigate Search Project Run Window Help
Java
Package Explorer
Hierarchy
Struts demo
src
WEB-INF/src
com.mia_software.booster.page_flow_example
com.mia_software.booster.page_flow_example
com.mia_software.booster.page_flow_example
CollectInformationDispatchAction.java
CollectInformationForm.java
ResultDispatchAction.java
ResultForm.java
Test1DispatchAction.java
Test1Form.java
WelcomePageDispatchAction.java
WelcomePageForm.java
com.mia_software.struts.generic.back
com.mia_software.struts.generic.form
Generation Results
Results (30)
ResultDispatchAction.java
Test1DispatchAction.java
WelcomePageDispatchAction.java
Generated Code
Manual Code
Generated Code
Sort
Group by Status
File Name
Relative Path
Full Path
Compare with Previous Version
Show In
Fragment Comparison
LoginDispatchAction.
CollectInformationDi
Previous Version
Current Version
// End of user imports
public class WelcomePageDispatchAction
// associated forward definitions
public final static String COLLECTI
public final static String LOGOUTAN
public final static String TEST1_TO
// inherited forward definitions
// dispatch action methods declarat
public ActionForward enter(ActionMa
ActionForward actionForward = n
if (form != null) {
WelcomePageForm currentForm
// execute code on exit of
currentForm.onExit();
int i_ENTERXXX=0;
CollectInformationForm coll
// Start of user code : ret
// End of user imports
public class WelcomePageDispatchAct
// associated forward definitio
public final static String COLL
public final static String LOGO
public final static String TEST
// inherited forward definition
// dispatch action methods decl
public ActionForward enter(Acti
ActionForward actionForward
if (form != null) {
WelcomePageForm current
// execute code on exit
currentForm.onExit();
CollectInformationForm
// Start of user code :

svn diff: sshconsole.js

Diff style: Side-by-side ☐ Enable syntax coloring

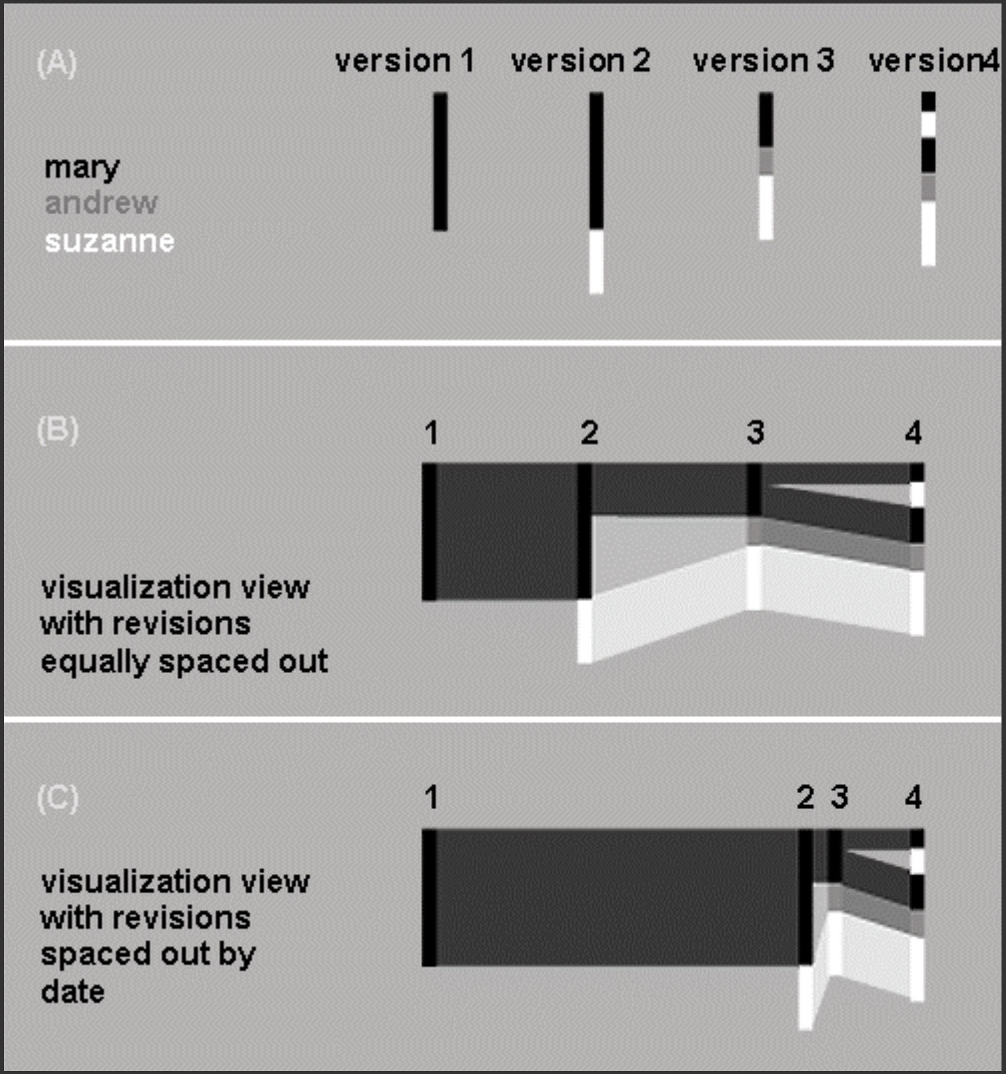
Files Changed:

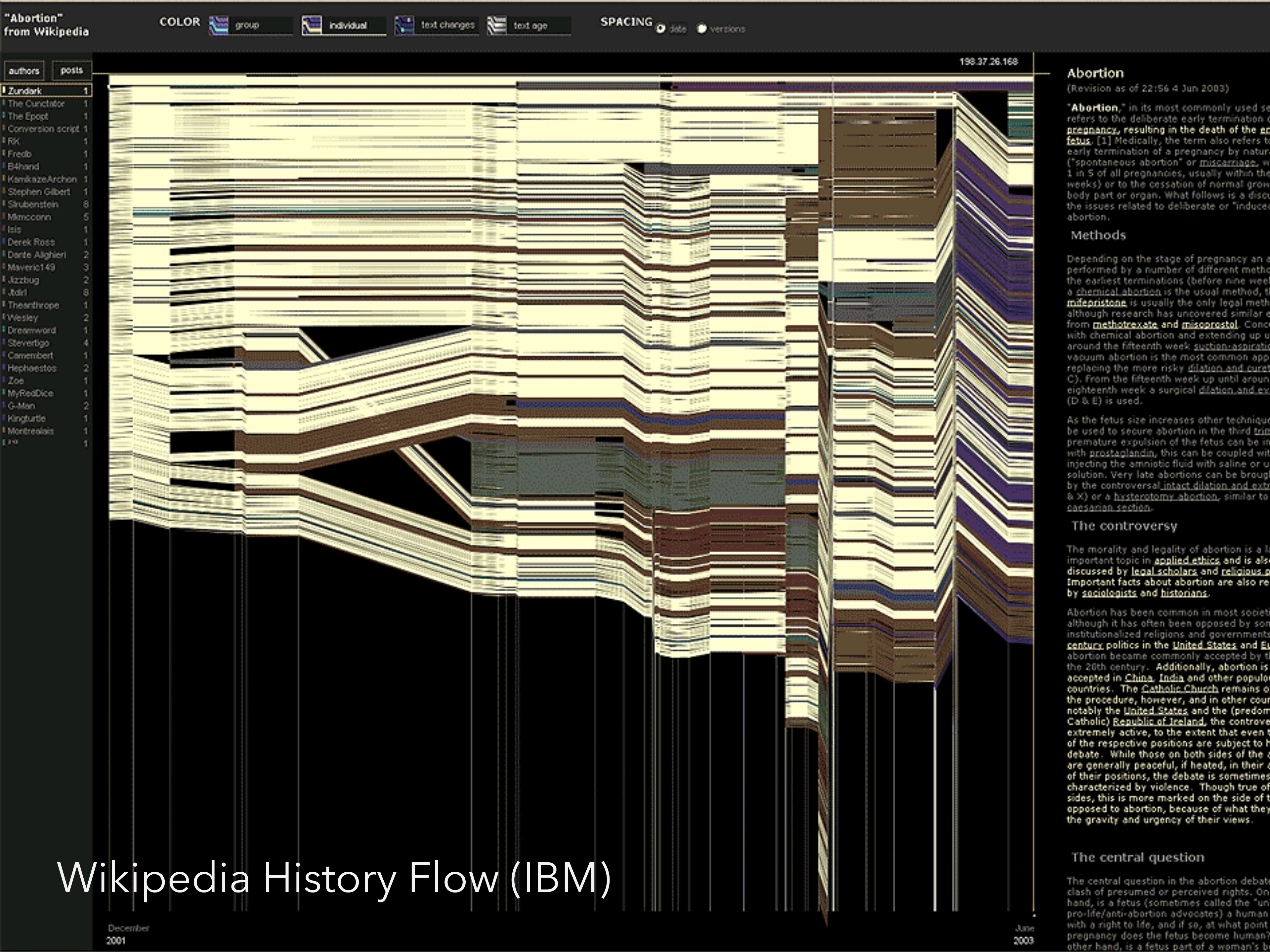
1. sshconsole.js: 1 change [1]

/home/toddw/src/sshconsole-read-only/content/sshconsole.js

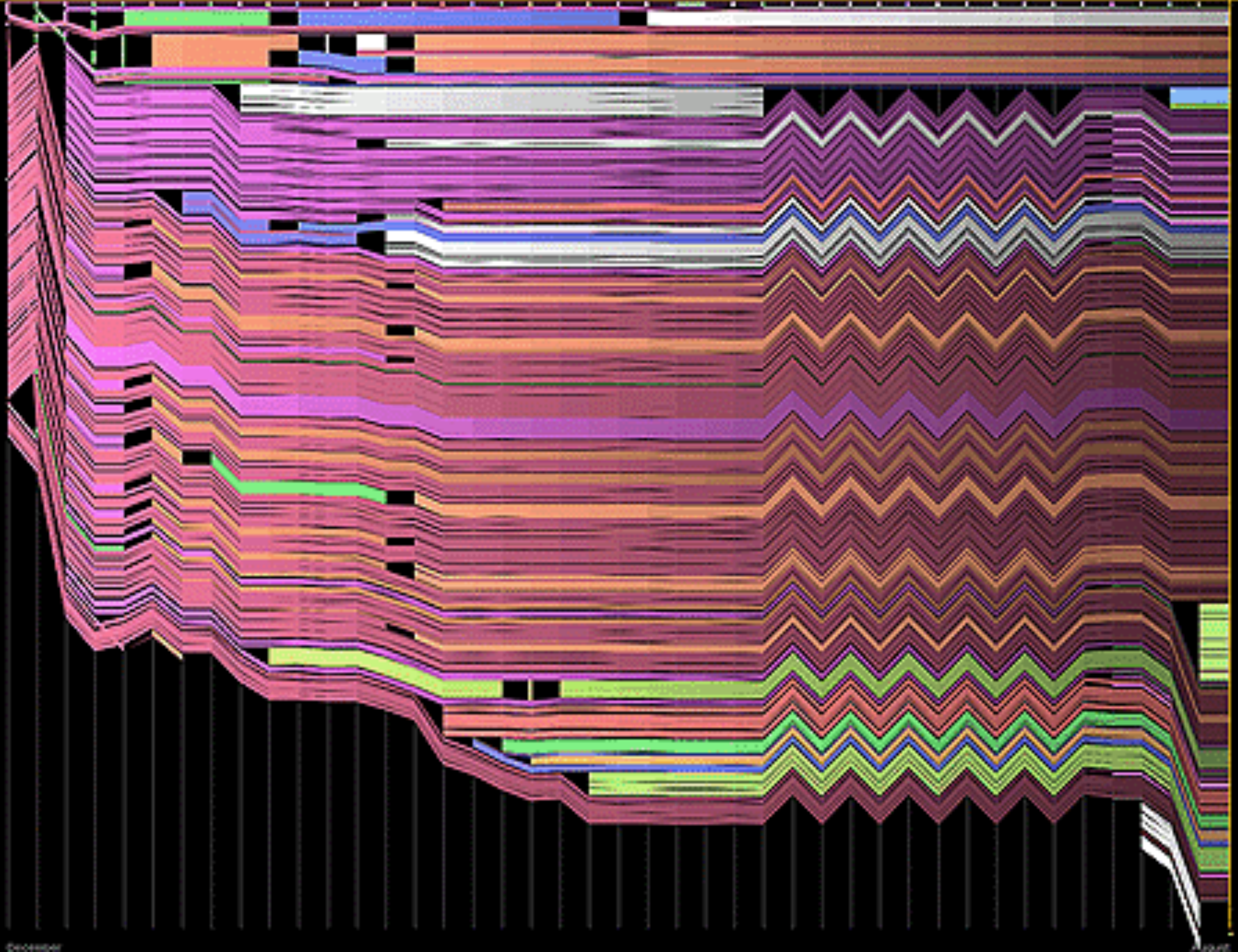
...	50 lines hidden [Expand]		
51	`_term = new VT100(80, 24, "term");`	51	`_term = new VT100(80, 24, "term");`
52	`//_term.debug_ = 1;`	52	`//_term.debug_ = 1;`
53	`_term.curs_set(true, true, _term_box_element);`	53	`_term.curs_set(true, true, _term_box_element);`
54	`_term.noecho();`	54	`_term.noecho();`
55		55	
56	`// Replace the go_getch_ function with our own, this is called`	56	`// Replace the go_getch_ function with our own, this is called`
57	`// for every keypress that is passed through the terminal to the`	57	`// for every keypress that is passed through the terminal to the`
58	`// remote server. The character is already converted into the`	58	`// remote server. The character is already converted into the`
59	`// required VT100 character sequence(s).`	59	`// required VT100 character sequence(s).`
60	`VT100.go_getch_ = function() {`	60	`VT100.go_getch_ = function() {`
61	`var vt = VT100.the_vt_;`	61	`var vt = VT100.the_vt_;`
62	`if (vt === undefined) {`	62	`if (vt === somevalue) {`
63	`return;`	63	`return;`
64	`}`	64	`}`
65	`var ch = vt.key_buf_.shift();`	65	`var ch = vt.key_buf_.shift();`
66	`//dump("go_getch_:: ch: '" + ch + "'\n");`		
67	`if (ch === undefined) {`	66	`if (ch === undefined) {`
68	`return;`	67	`return;`
69	`}`	68	`}`
70	`if (vt.echo_ && ch.length == 1) {`	69	`if (vt.echo_ && ch.length == 1) {`
71	`vt.addch(ch);`	70	`vt.addch(ch);`
		71	`vt.refres();`
72	`}`	72	`}`
73	`if (_ssh_channel) {`	73	`if (_ssh_channel) {`
74	`_ssh_channel.sendStdin(ch);`	74	`_ssh_channel.sendStdin(ch);`
75	`}`	75	`}`
76	`}`	76	`}`
77		77	
78	`var serverTextbox = document.getElementById("sshconsole_server_textbox");`	78	`var serverTextbox = document.getElementById("sshconsole_server_textbox");`
79	`var connectionText;`	79	`var connectionText;`
80	`if ('connectionText' in window.arguments[0]) {`	80	`if ('connectionText' in window.arguments[0]) {`
81	`connectionText = window.arguments[0].connectionText;`	81	`connectionText = window.arguments[0].connectionText;`
82	`} else {`	82	`} else {`
...	174 lines hidden [Expand]		

History Flow [Viegas et al.]





Wikipedia History Flow (IBM)



December

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”

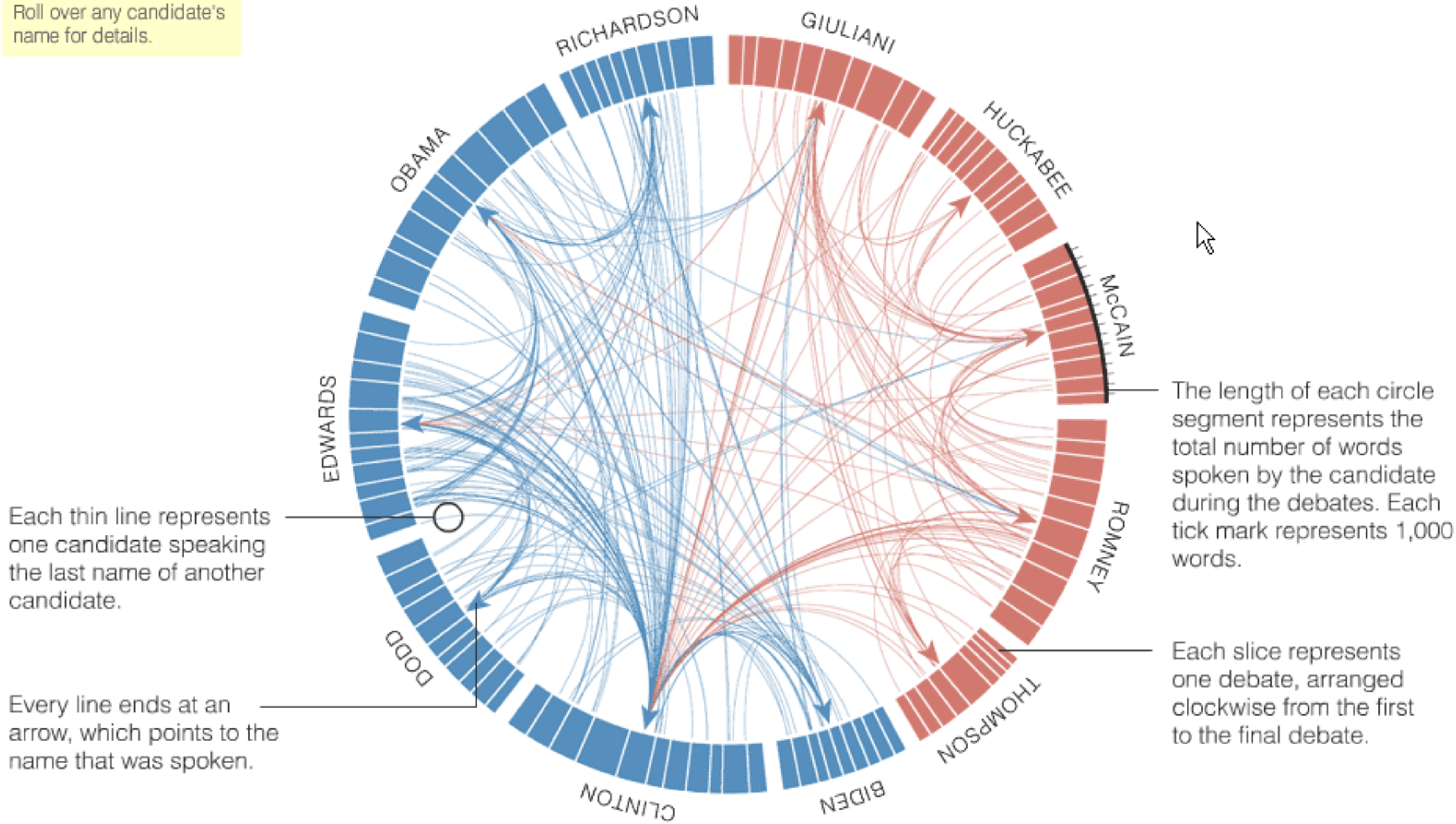
Who x Who -> Social network

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.



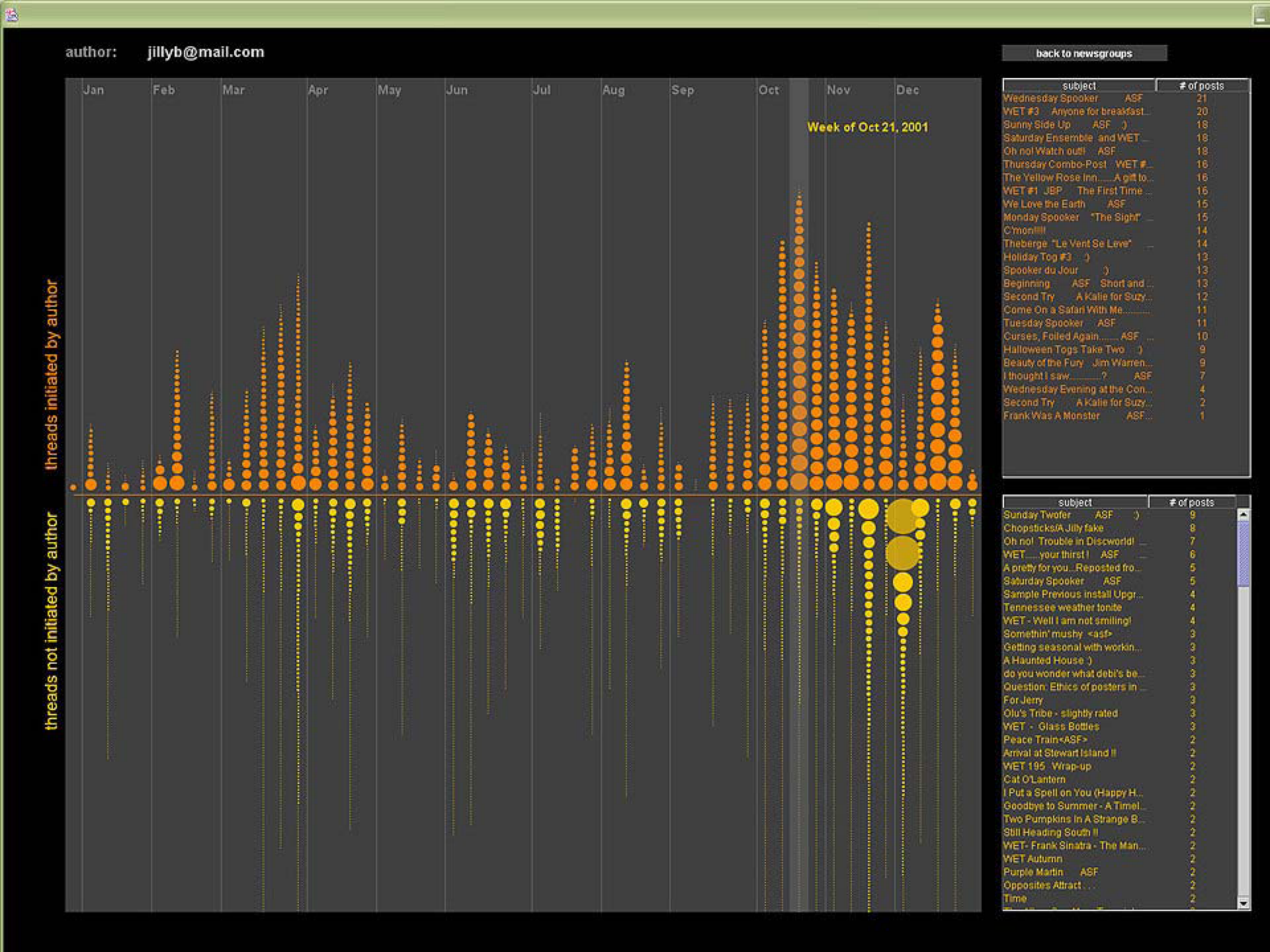
Source: Debate transcripts

Jonathan Corum and Farhana Hossain/The New York Times

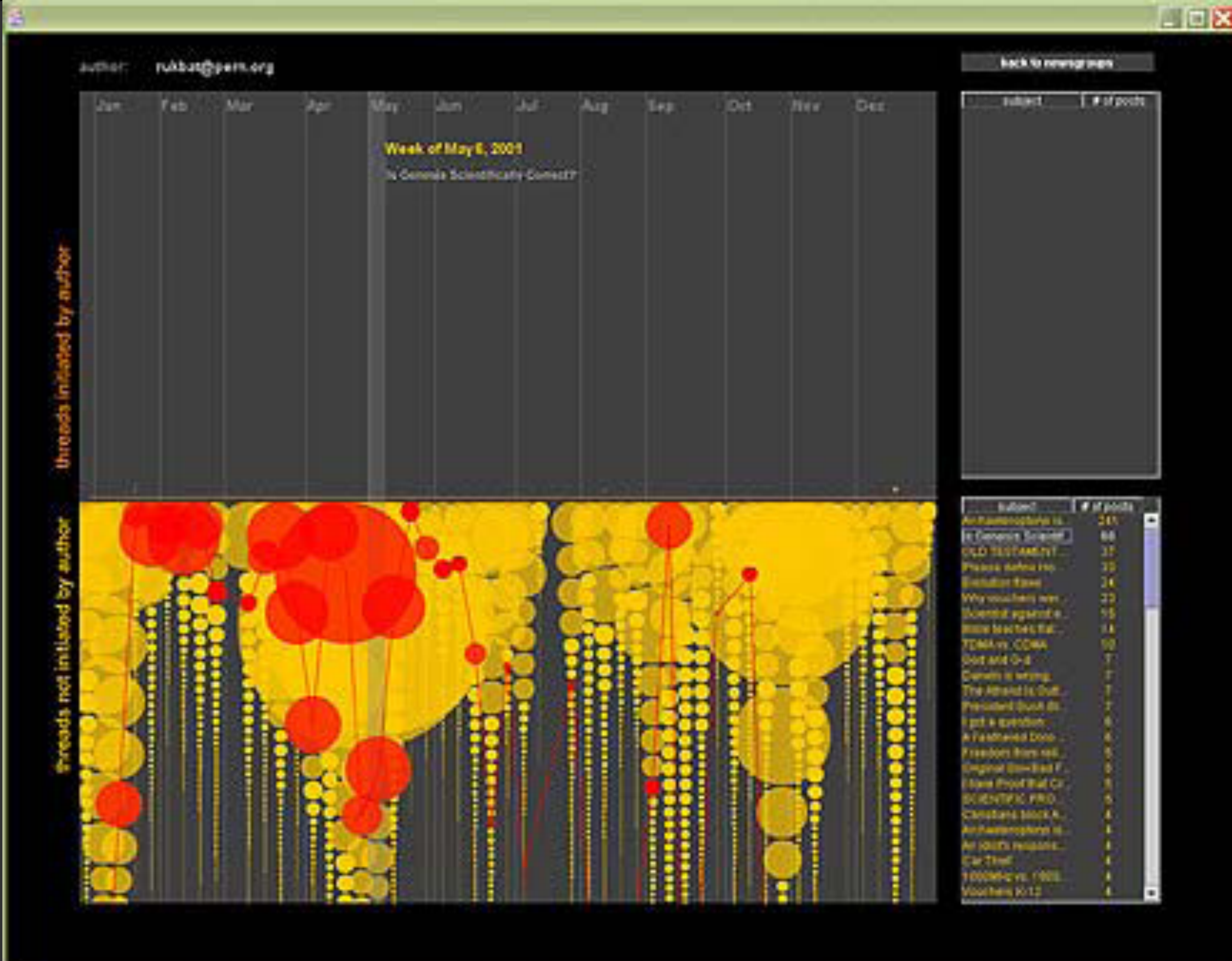
Usenet Visualization [Viegas & Smith]

Show correspondence patterns in text forums

Initiate vs. reply; size and duration of discussion



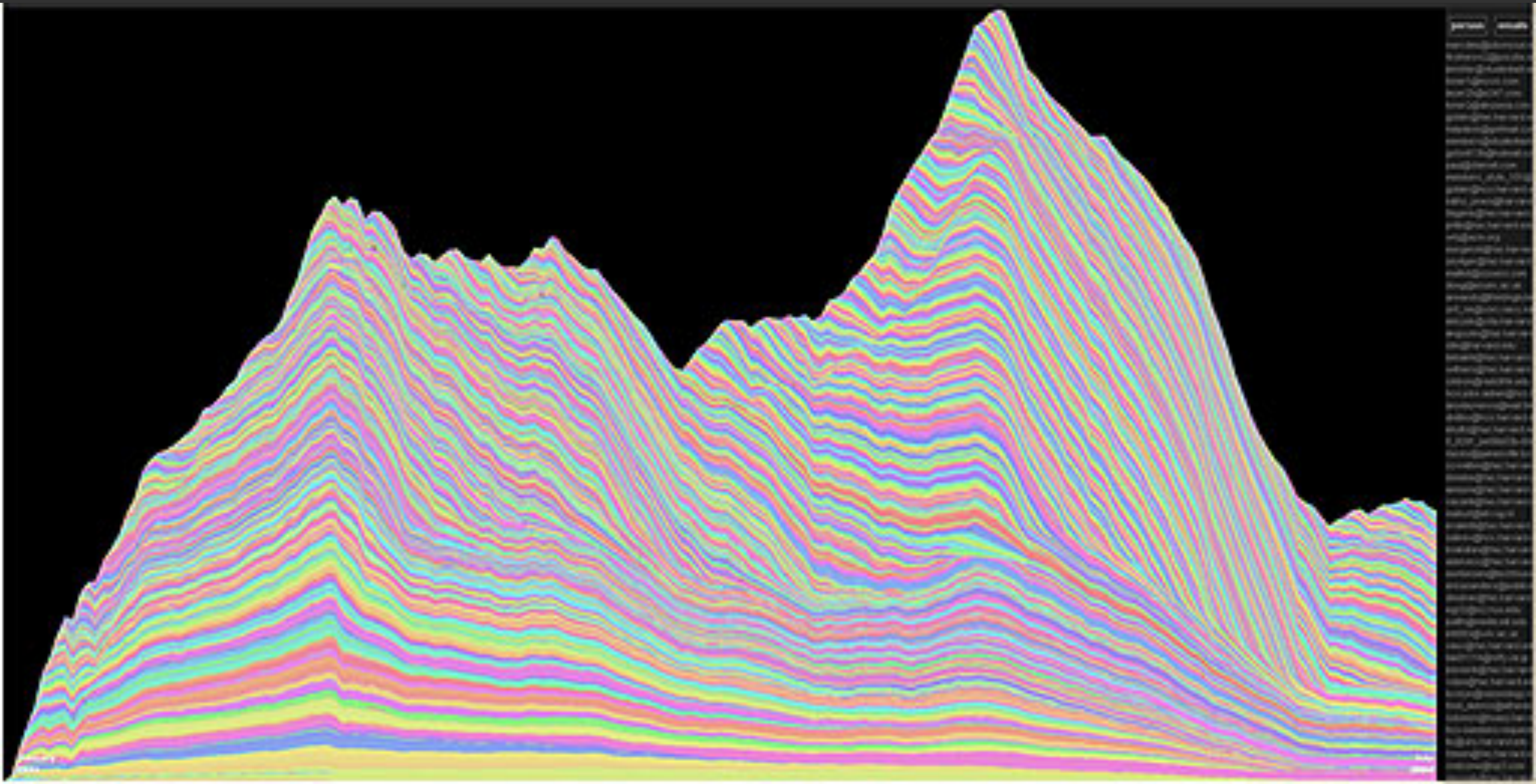
author: jillyb@mail.com
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of Oct 21, 2001
threads initiated by author
threads not initiated by author
subject
# of posts
Wednesday Spooker ASF 21
WET #3 Anyone for breakfast... 20
Sunny Side Up ASF :) 18
Saturday Ensemble and WET... 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



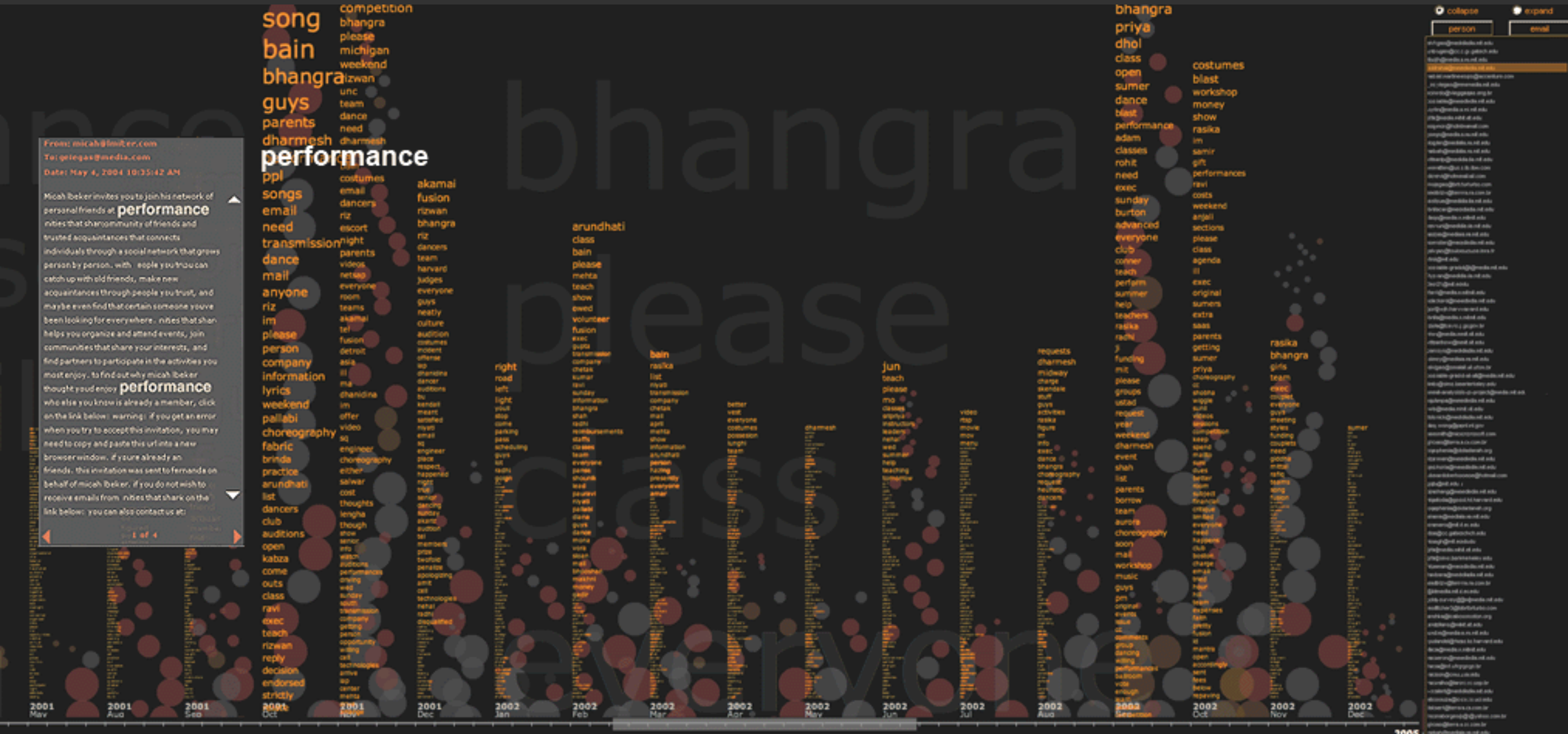
author:
rukbat@pern.org
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of May 6, 2001
Is Genesis Scientifically Correct?
threads initiated by author
threads not initiated by author
subject
# of posts

Email Mountain [Viegas]

Conversation by person over time (who x when).



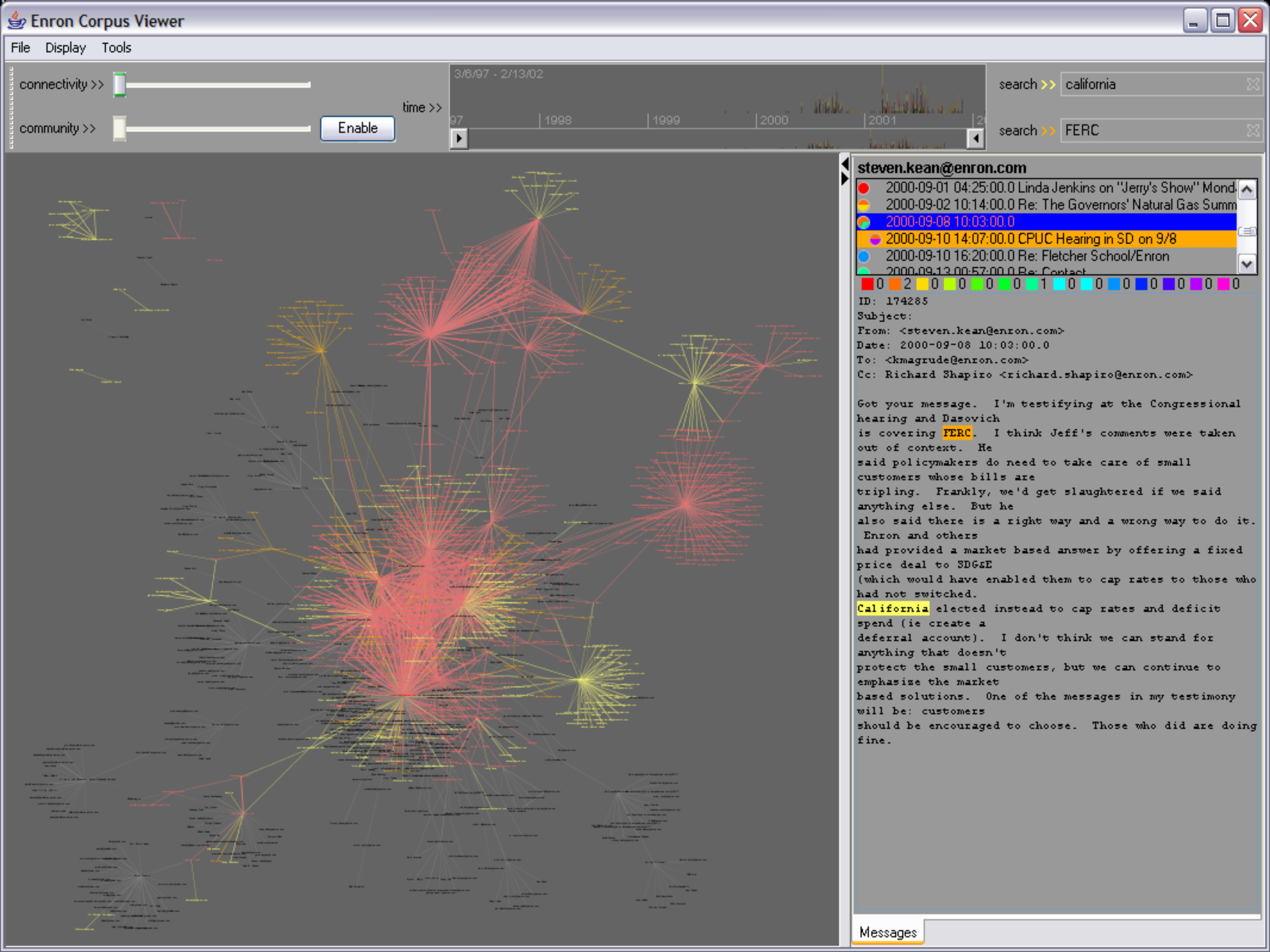
Themail [Viegas]

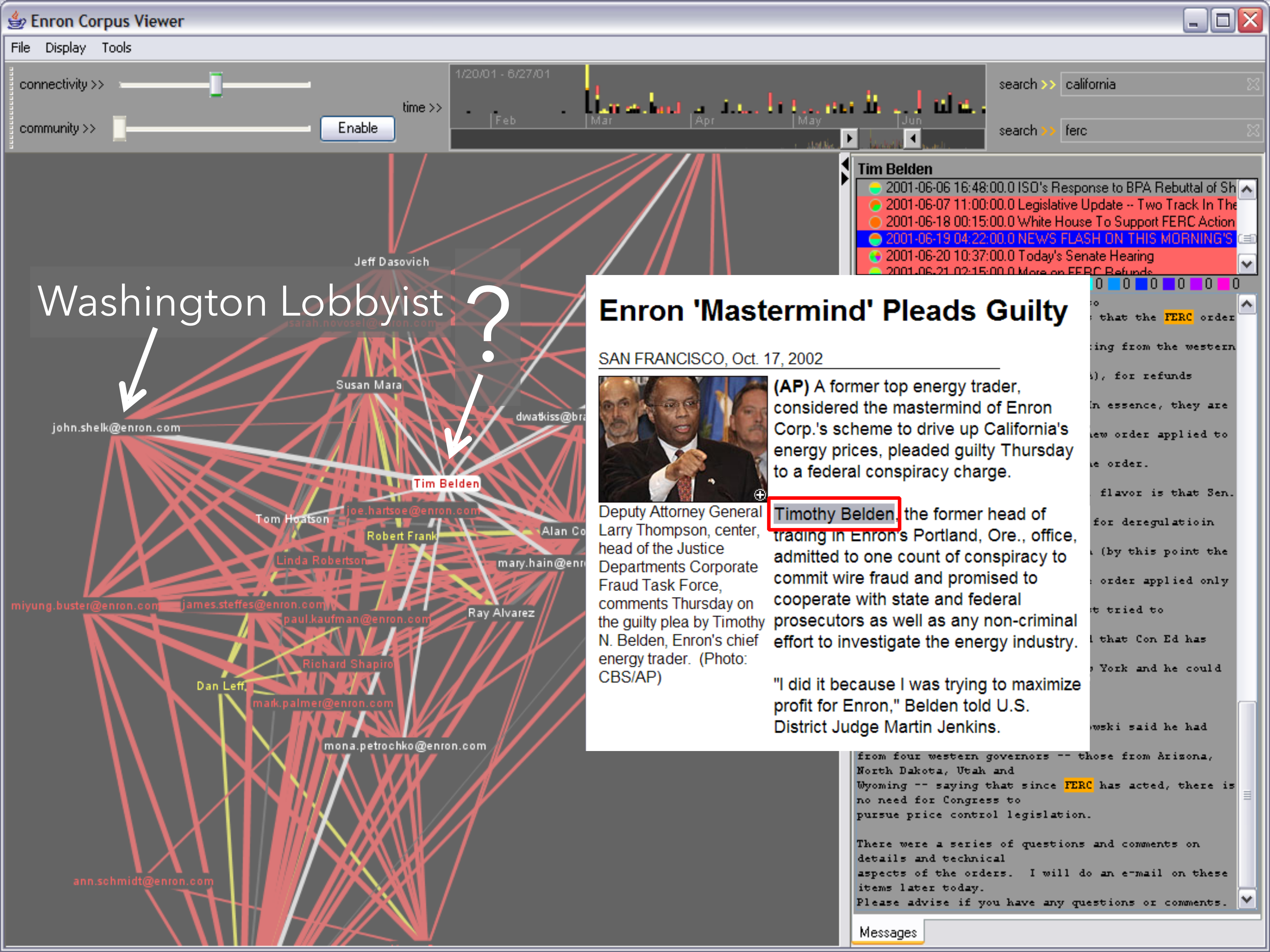


One person over time, TF.IDF weighted terms

Enron E-Mail Corpus

[Heer]


Enron Corpus Viewer
File
Display
Tools
connectivity >>
community >>
Enable
time >>
3/6/97 - 2/13/02
97
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
(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.
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)
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

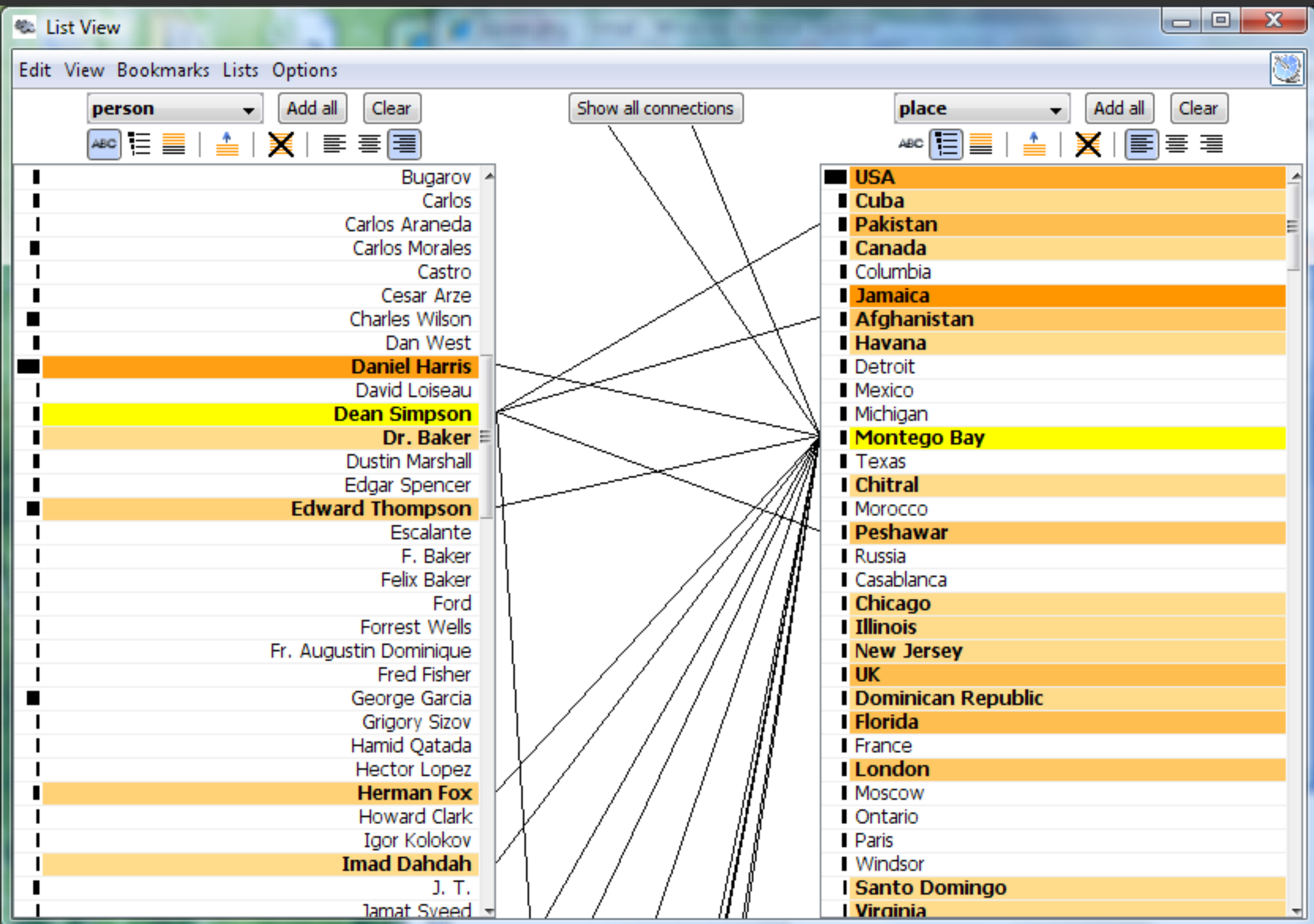
Soviet Union -> COUNTRY

353 Serra St -> ADDRESS

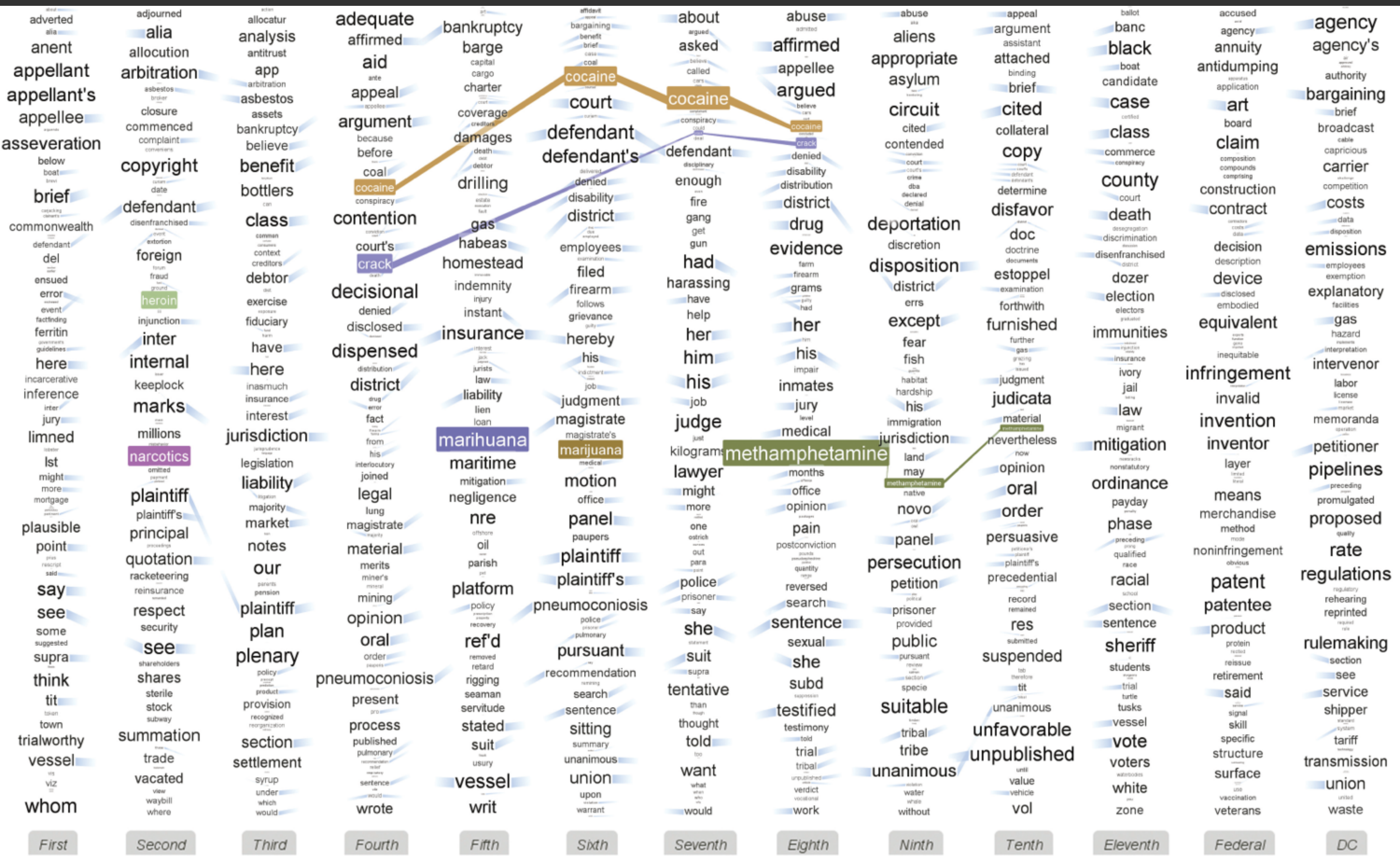
(555) 721-4312 -> PHONE NUMBER

Entity relations: how do the entities relate?

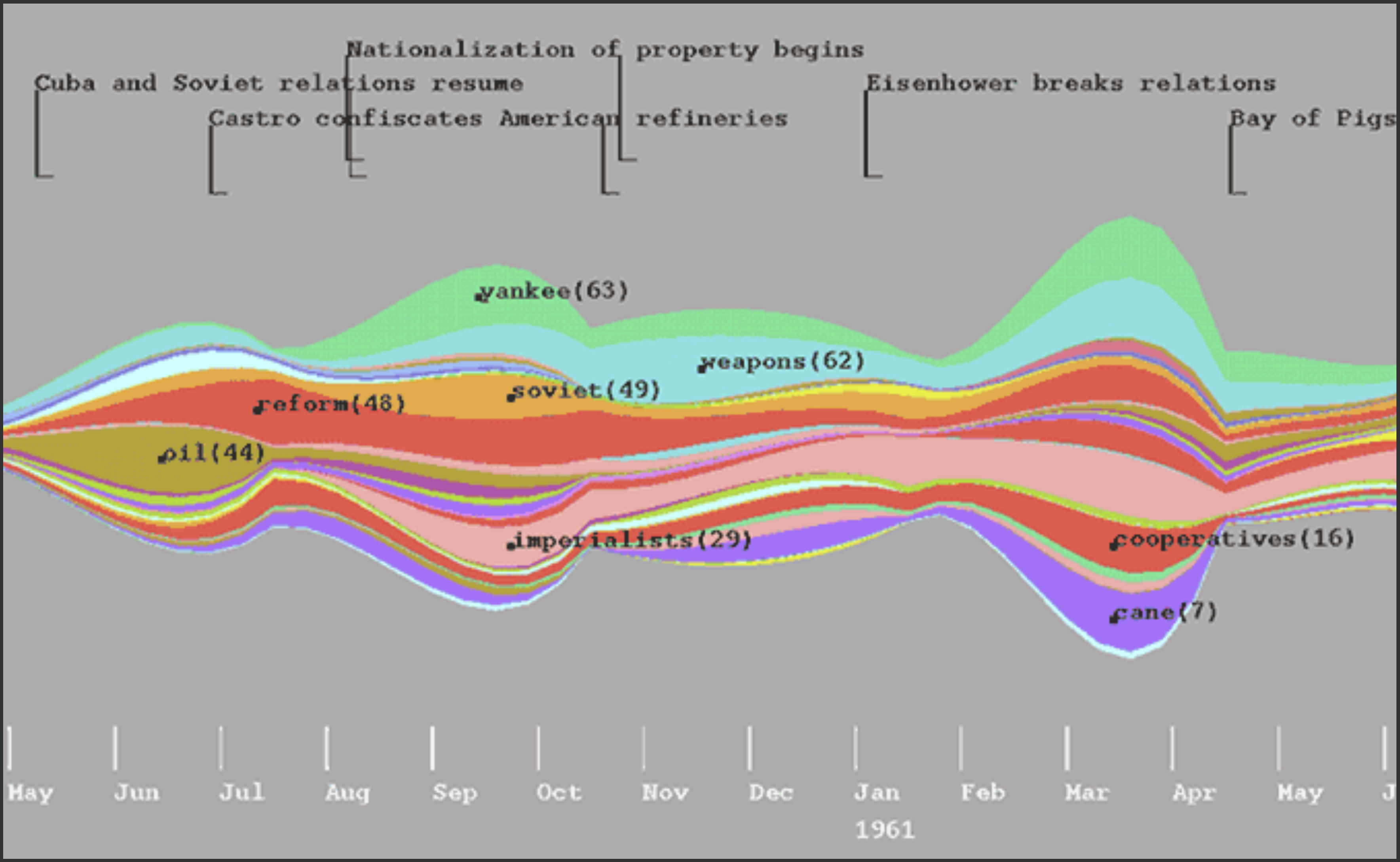
Simple approach: do they co-occur in a small window of text?


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
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

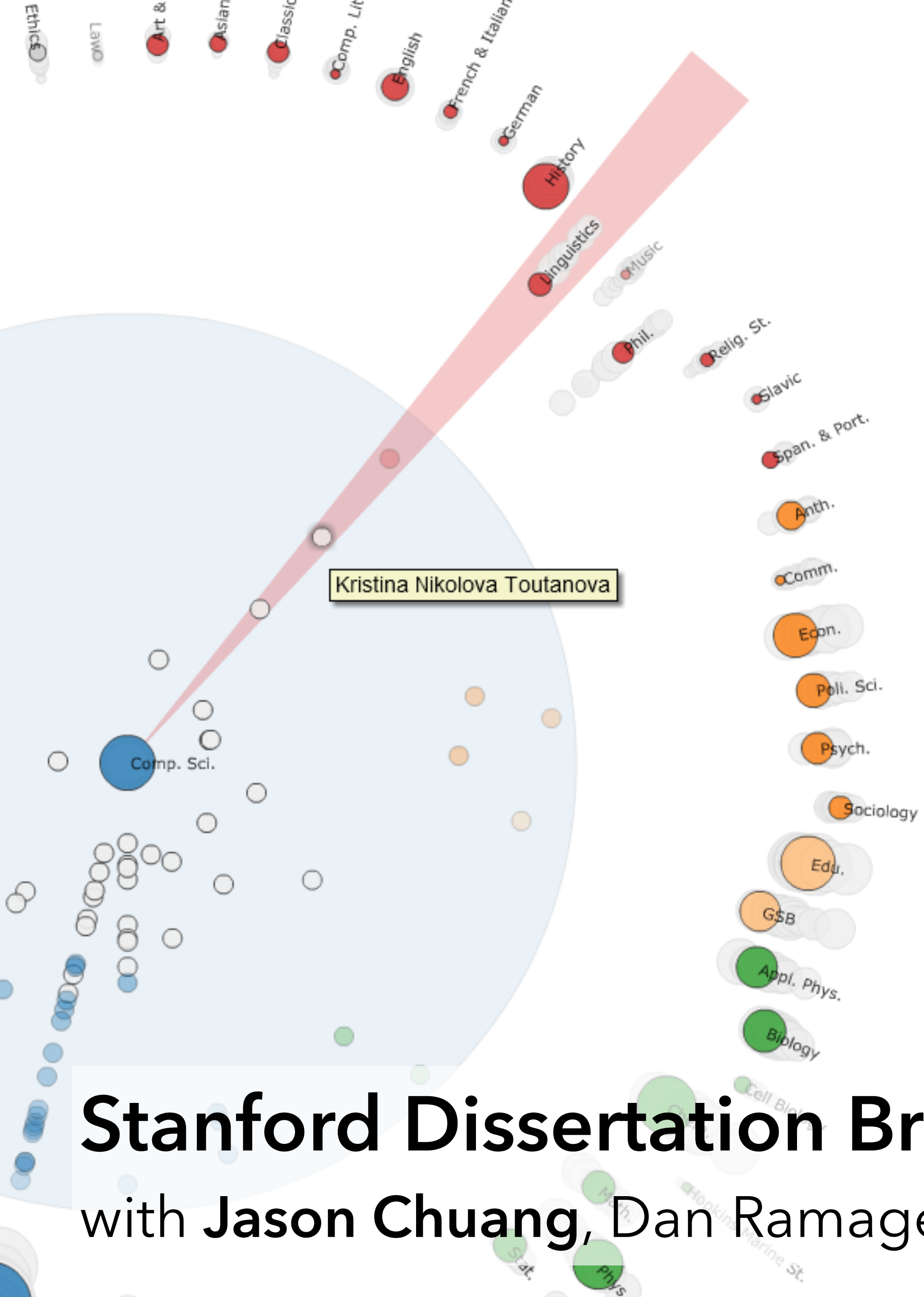
Topic modeling

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.

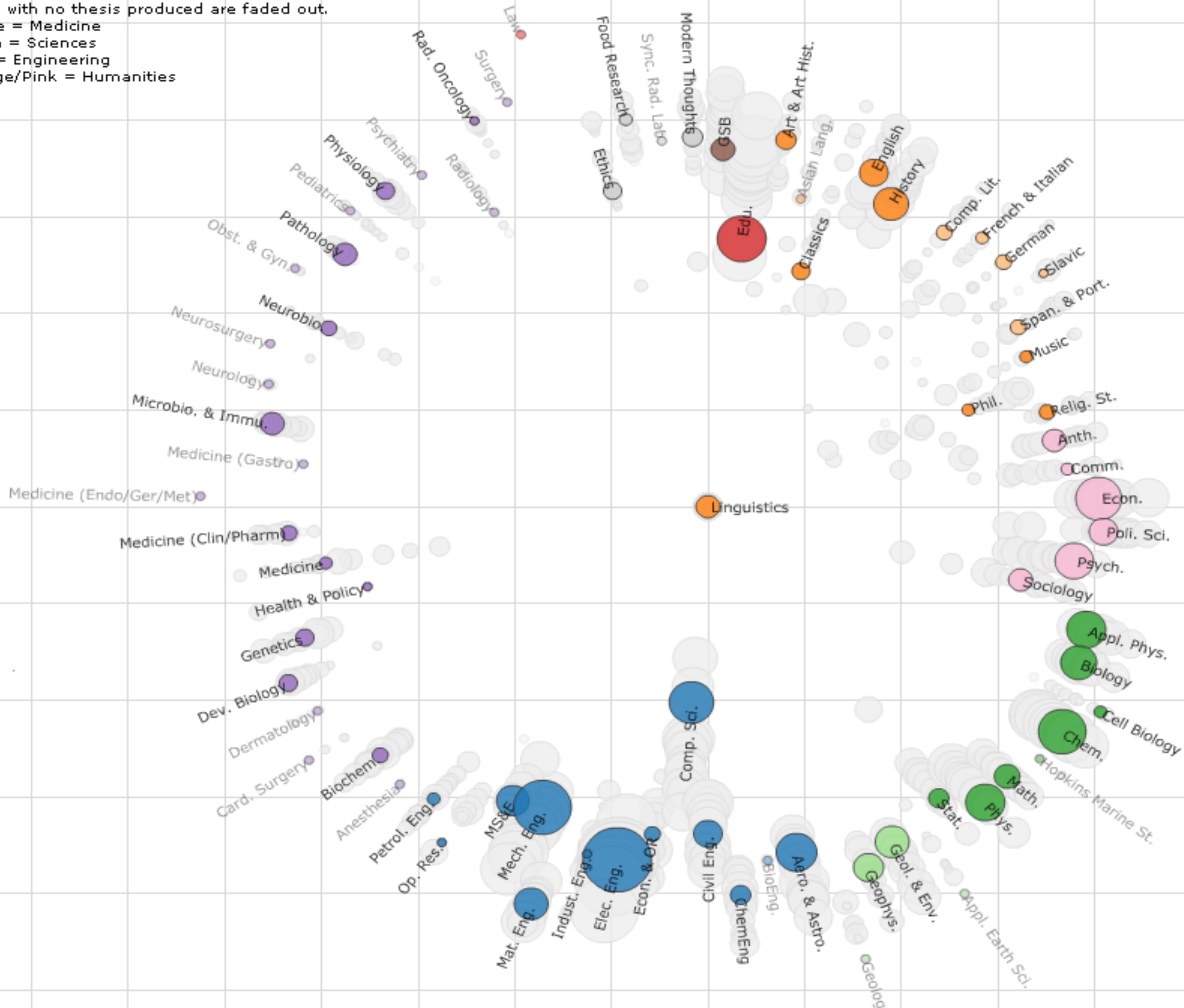
Stanford Dissertation Browser

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

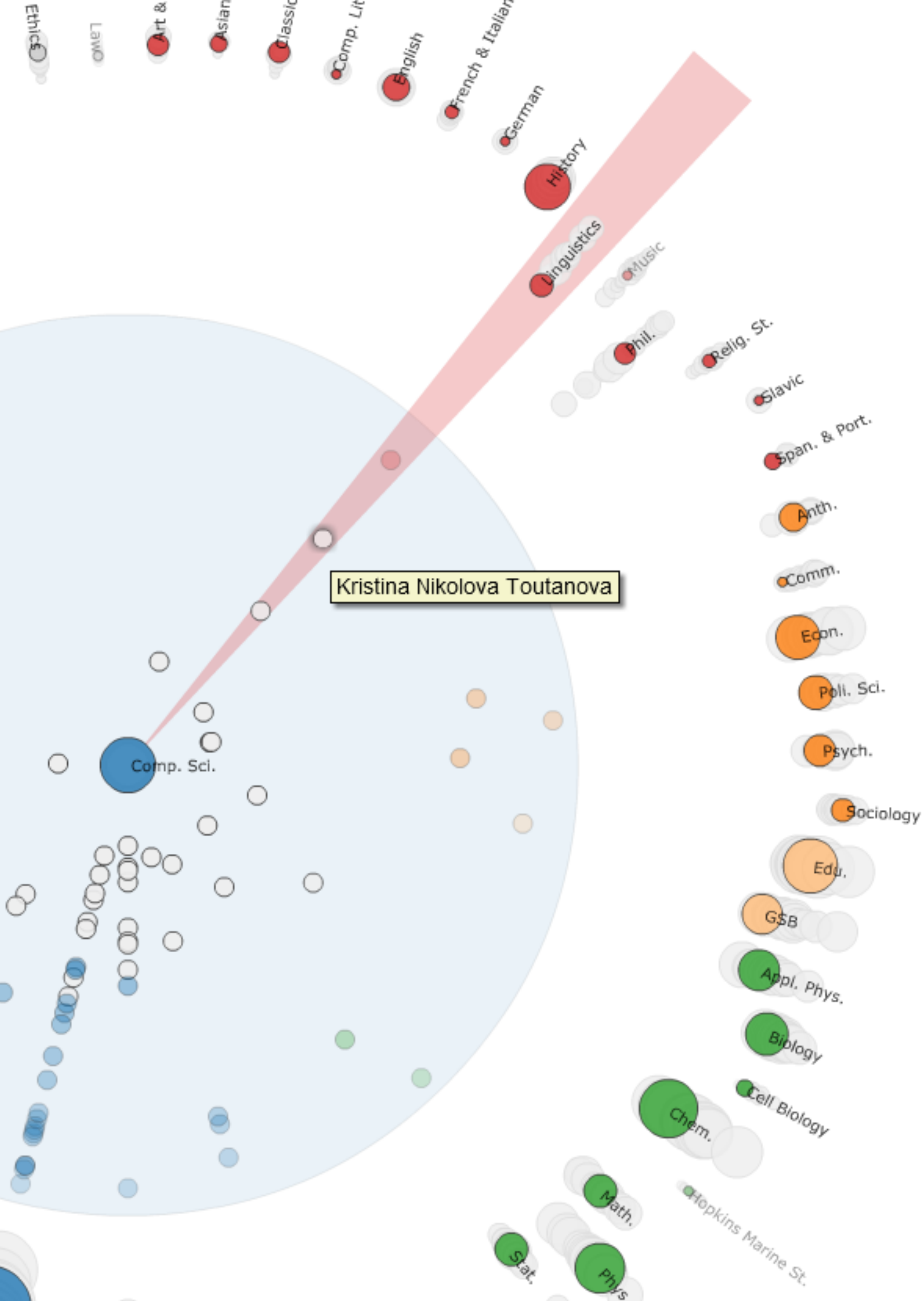
Petrol. Eng.
Appl. Earth Sci.
Geology
Geophys.
Geol. & Env.
Op. Res.
Stat.
Mat. Eng.
Appl. Phys.
Aero. & Astro.
Indust. Eng.
Econ. & OR
Food Research
Elec. Eng.
Comp. Sci.
Mech. Eng.
Math.
Civil Eng.
GSB
Econ.
Chem.
Sociology
Psych.
Poli. Sci.
Genetics
Physiology
Biochem.
Medicine
Biology
Comm.
Edu.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

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!



Effective statistical models for syntactic and semantic disambiguation

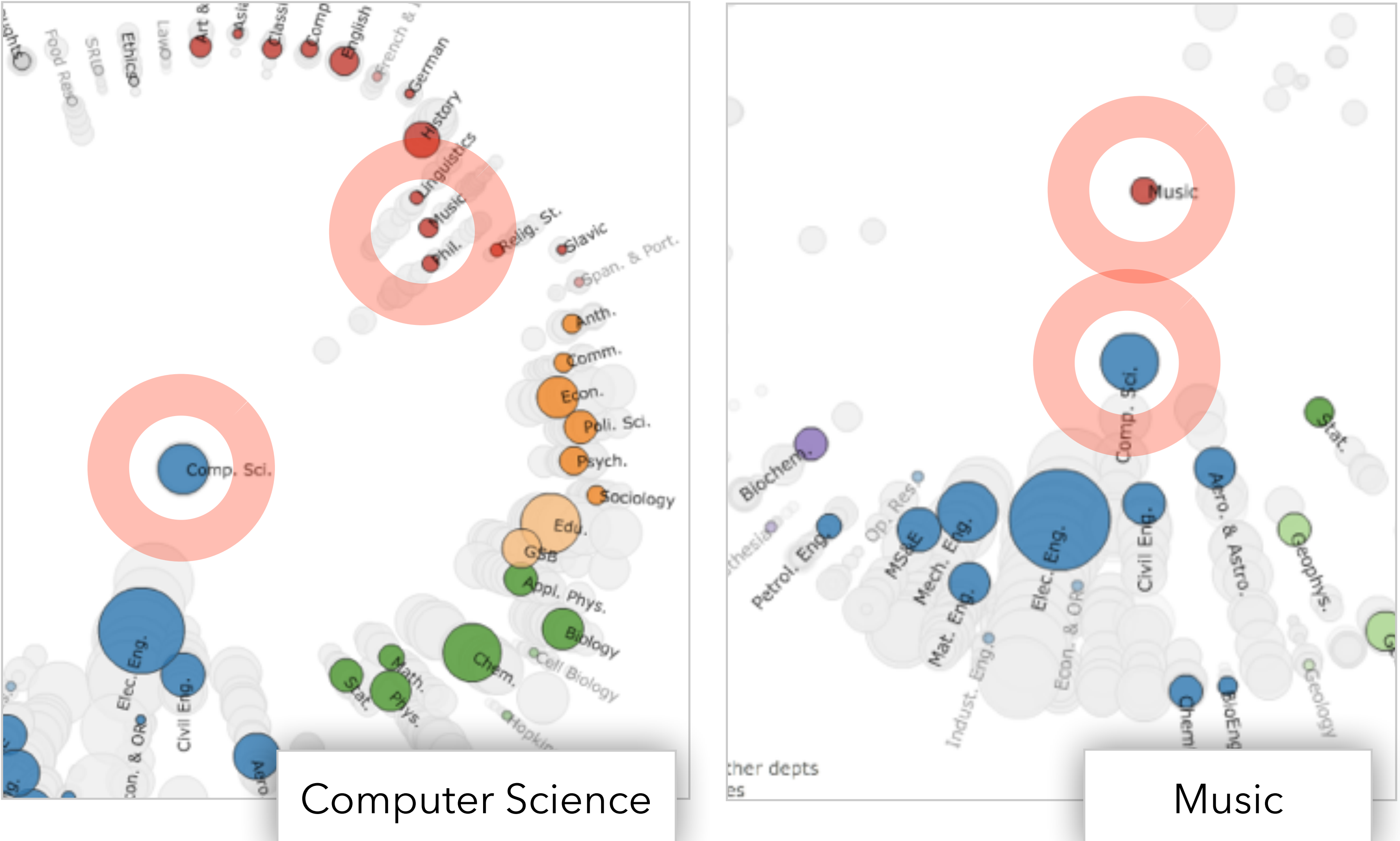
Student: Kristina Nikolova Toutanova
Advisor: Christopher D. Manning

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.



“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*