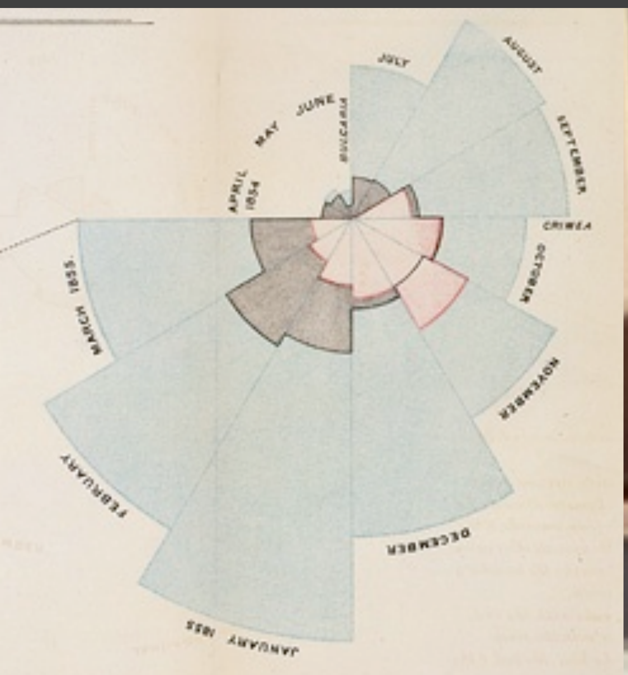
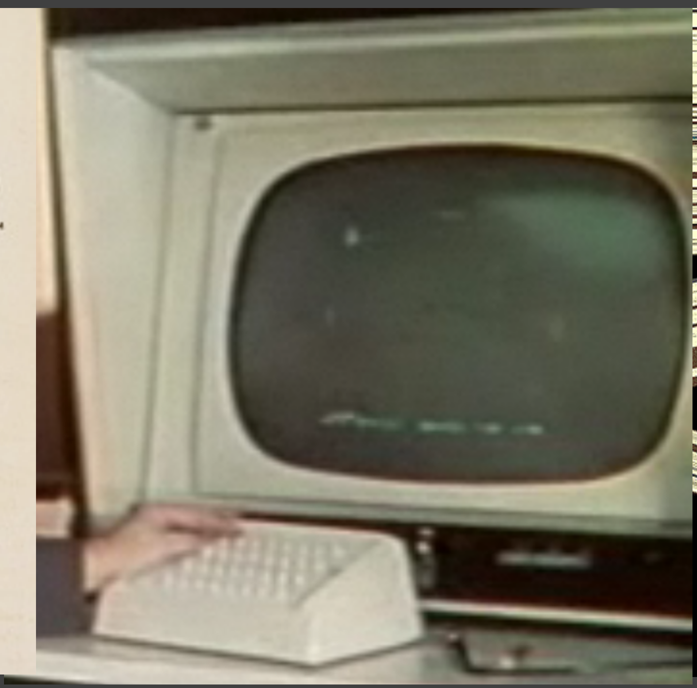
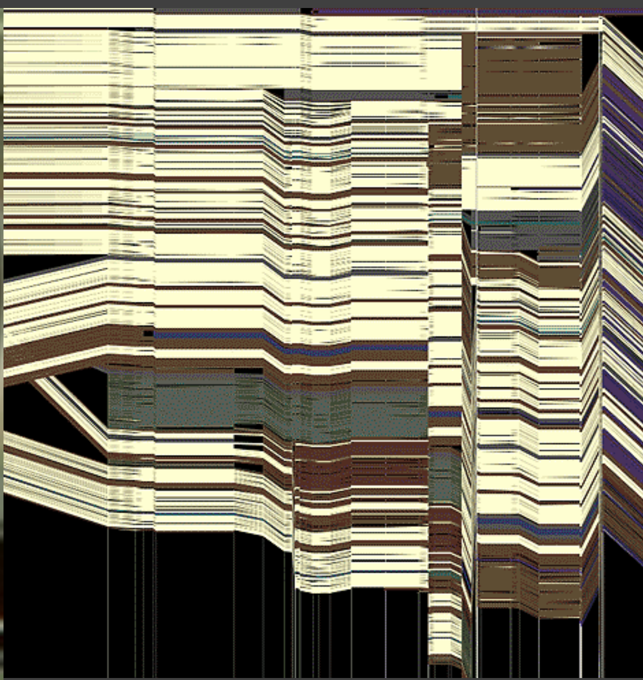
CSE512 :: 4 Mar 2014

Text Visualization







Jason Chuang University of Washington

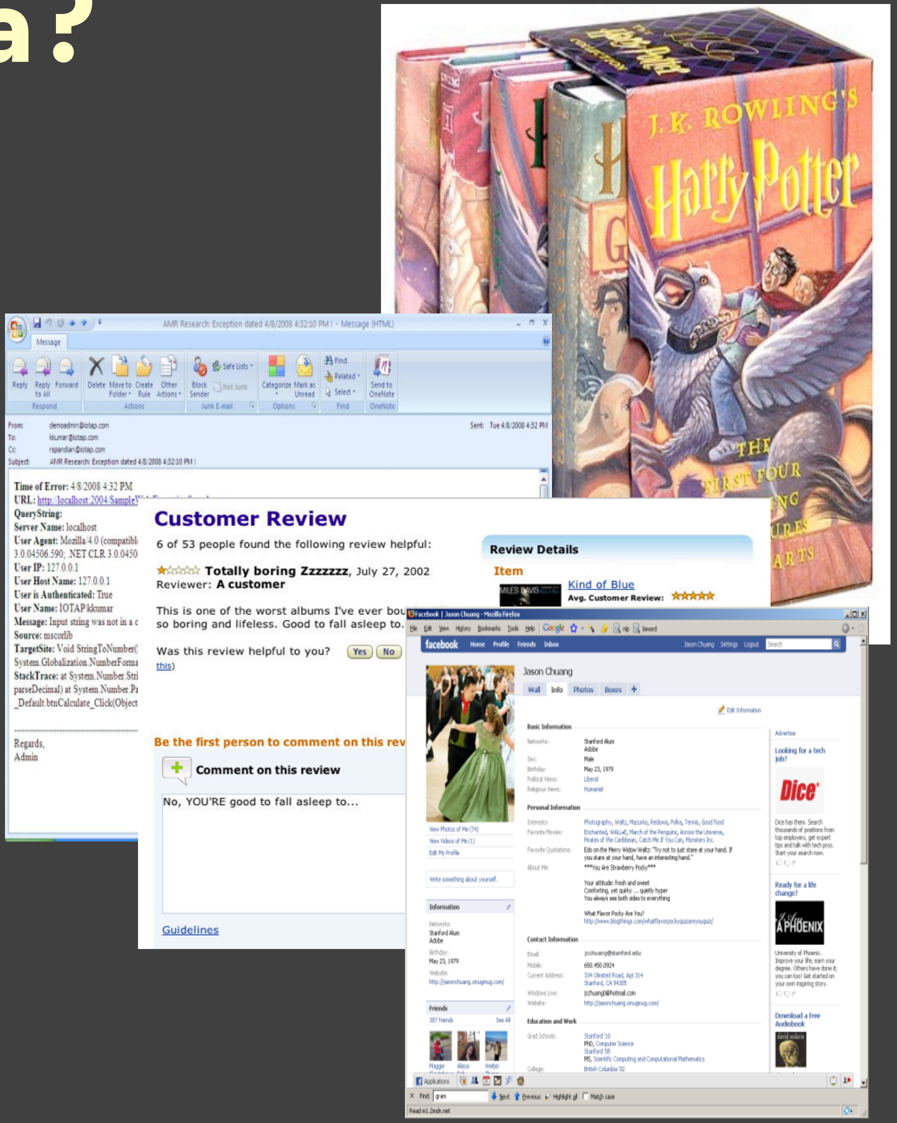
Text visualization:
What-Why-How

What is text data?

Documents
Articles, books and novels
E-mails, web pages, blogs

Text Snippets
Tweets, SMS messages
Tags, comments, profiles

And More...
Computer programs, logs
This slide!
Collections of documents



Why visualize text?

Understanding – read a document

Summaries – get the “gist” of a document

Clustering – group together similar contents

Quantify – convert to numerical measures

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

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 [New York Times]

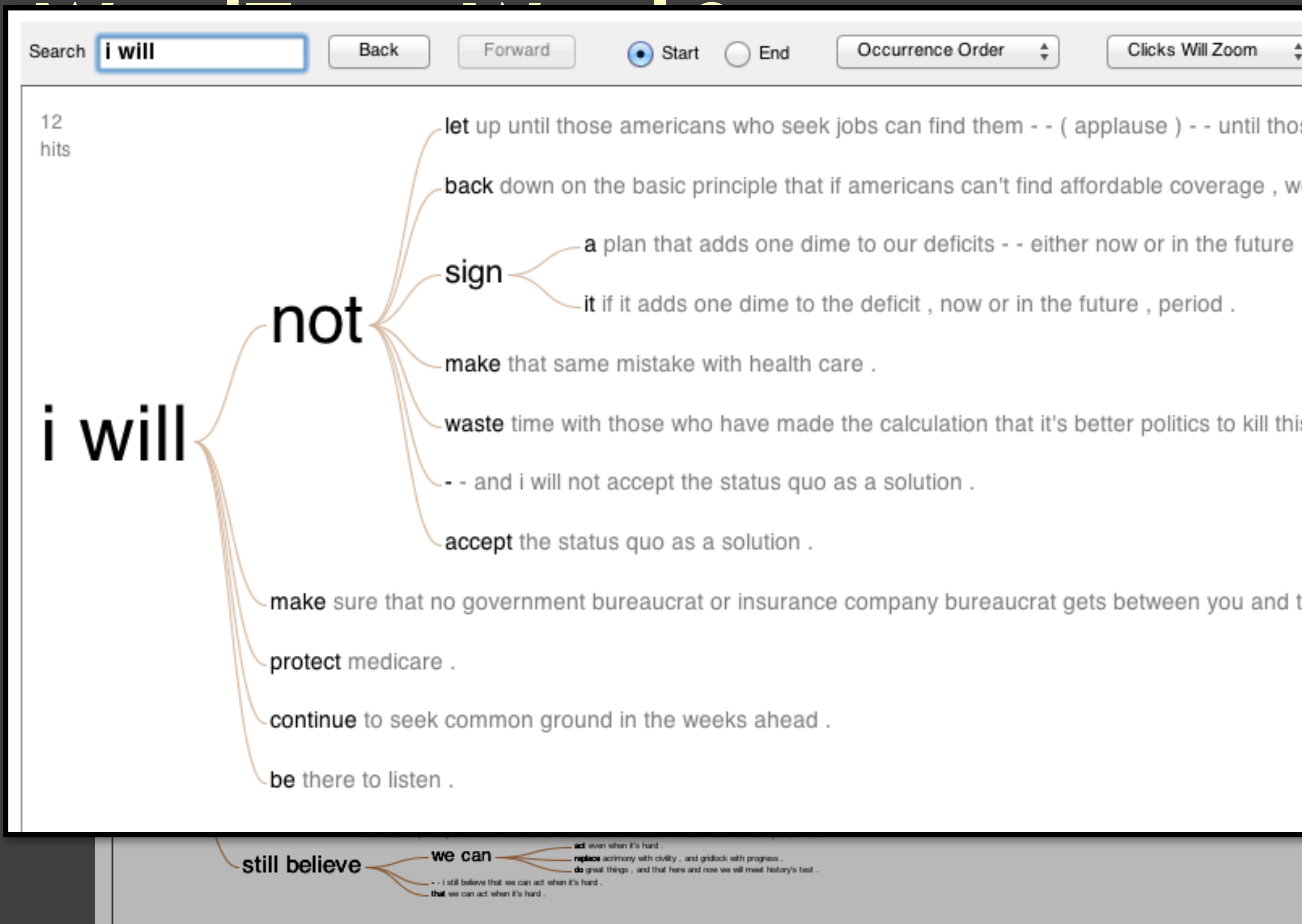
economix.blogs.nytimes.com/2009/09/09/obama-in-09-vs-clinton-in-93

Bill Clinton 1993

Barack Obama 2009

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

WordTree: 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 thos
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

A Double Gulf of Evaluation

Many (most?) 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?

Topics

Summarizing with Words
Visualizing Themes in a Document Collection
Quantifying Textual Content
Performing Text Analysis

Summarize with Words

Words are (not) nominal?

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.*

2. Stemming

   Group together different forms of a word.

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

   Lemmatization? *goes, went, gone* → *go*

3. Ordered list of terms

Tips: Tokenization and Stemming

Well-formed text to support stemming?

txt u l8r!

Word meaning or entities?

#berkeley → *#berkelei*

Reverse stems for presentation.

Ha appl made programm cool?

Has Apple made programmers cool?

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

WordCount (Harris 2004)

http://wordcount.org

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

Creator: Anonymous
Tags:

Edit Language Font Layout Color

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

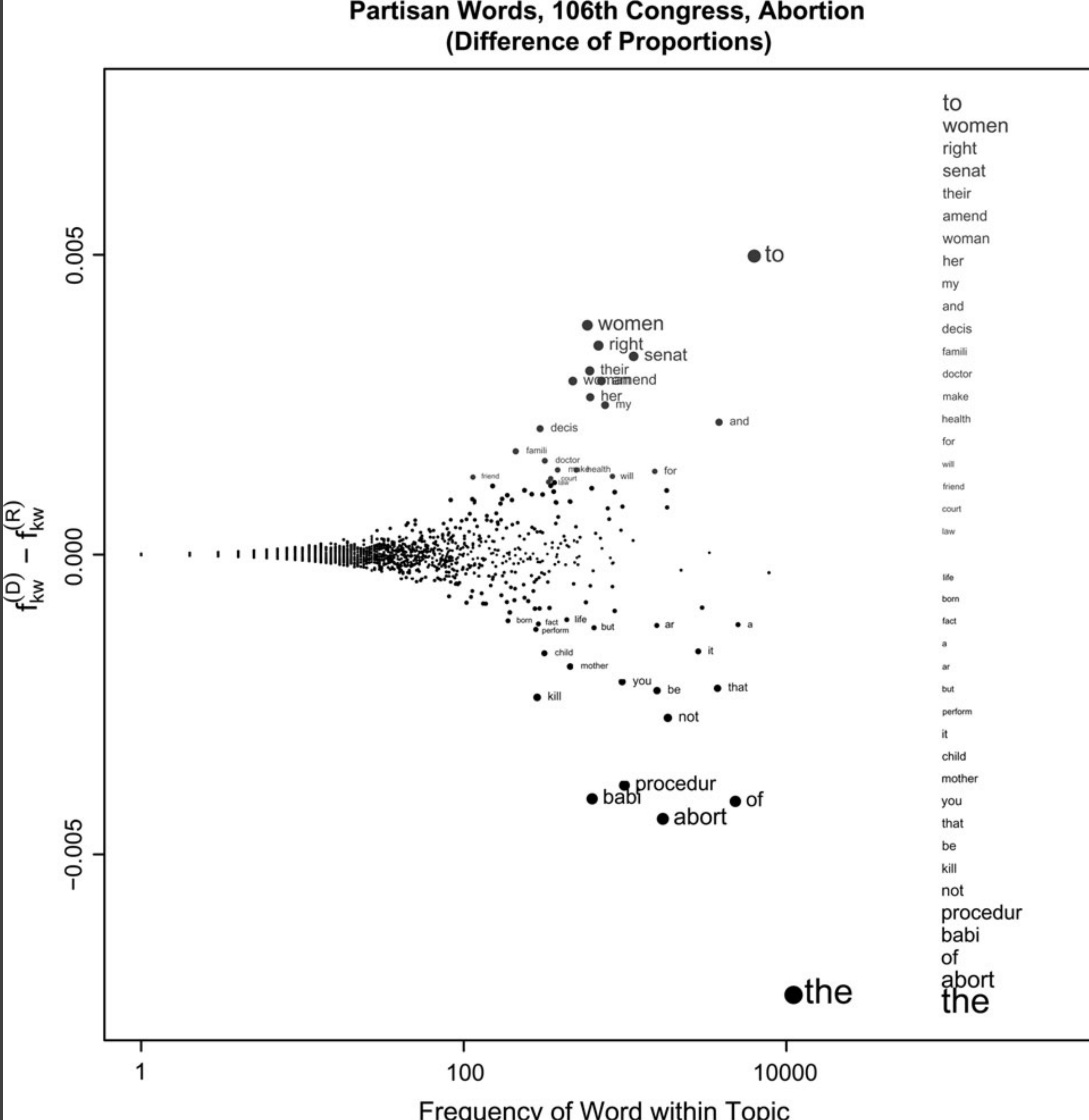
Keyword Weighting

Term Frequency

tf_{td} = count(t) in d

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

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


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
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

Keyword Weighting

Term Frequency

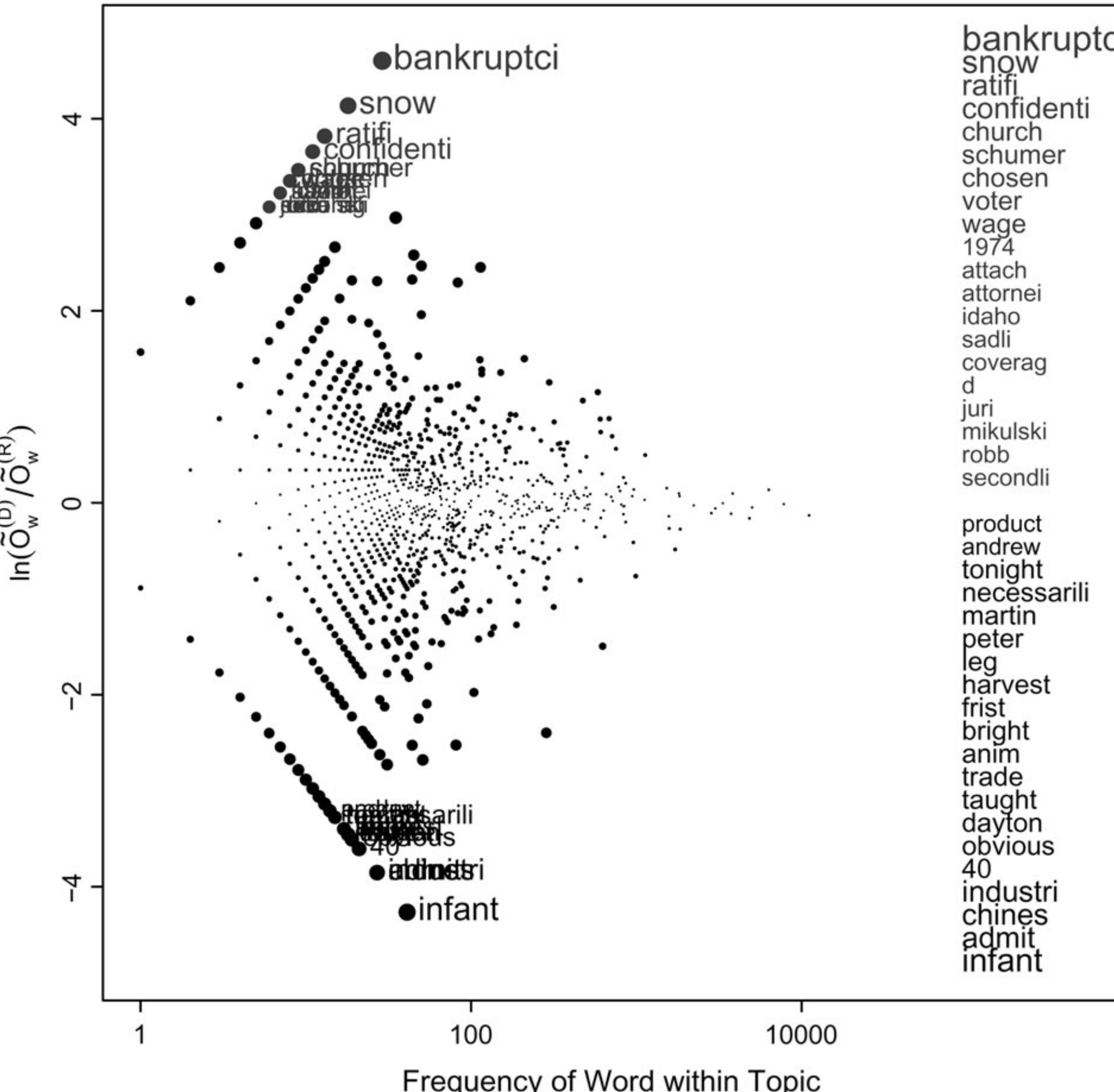
tf_{td} = count(t) in d

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

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



Keyword Weighting

Term Frequency

tf_{td} = count(t) in d

TF.IDF: Term Freq by Inverse Document Freq

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

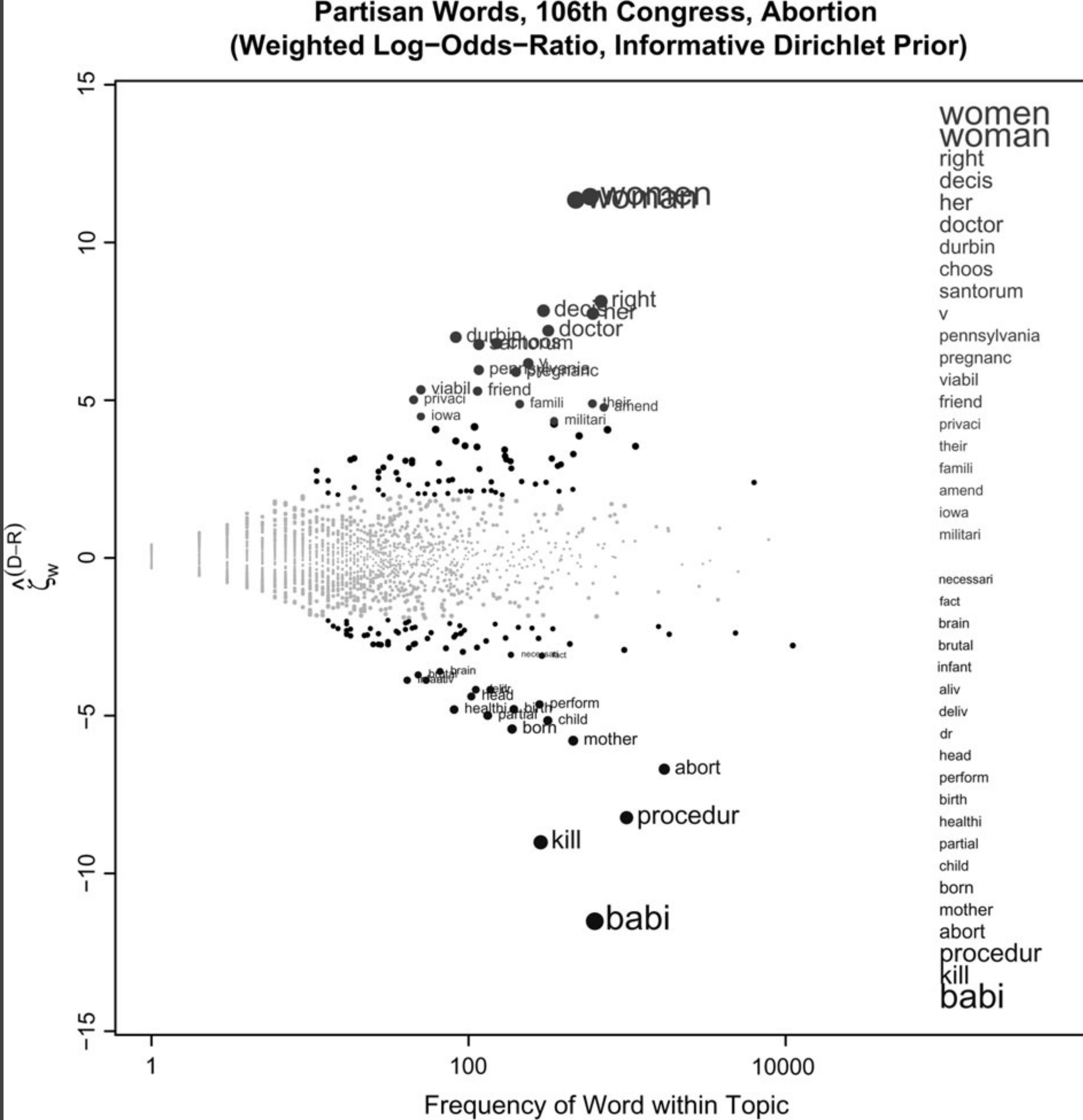
df_t = # docs containing t; N = # of docs

G^2: Probability of different word frequency

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

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

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


Partisan Words, 106th Congress, Abortion
(Weighted Log−Odds−Ratio, Informative Dirichlet Prior)
$\hat{\zeta}_w^{(D-R)}$
Frequency of Word within Topic
15
10
5
0
−5
−10
−15
1
100
10000
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

Limitations of Frequency 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

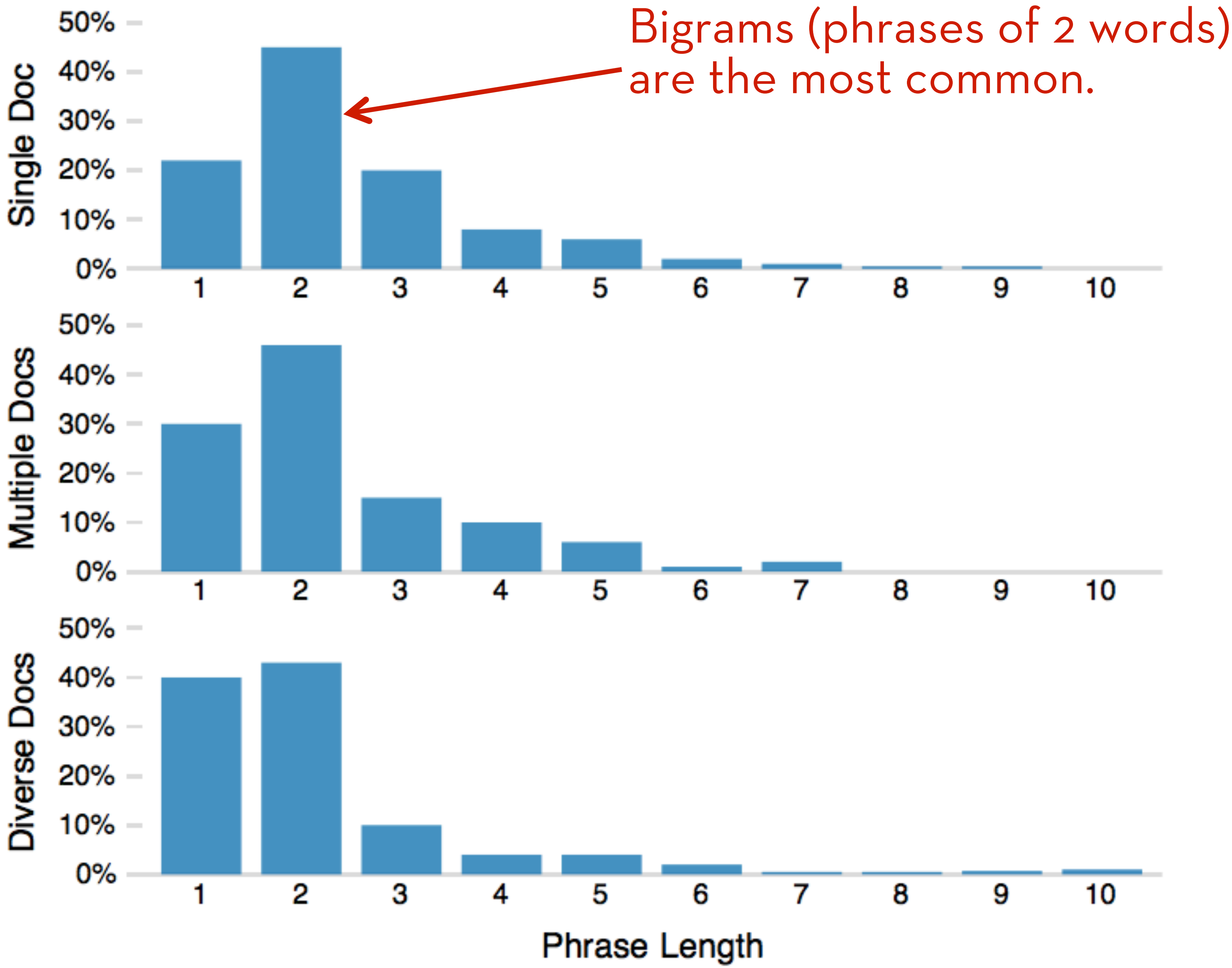
How do people describe text?

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

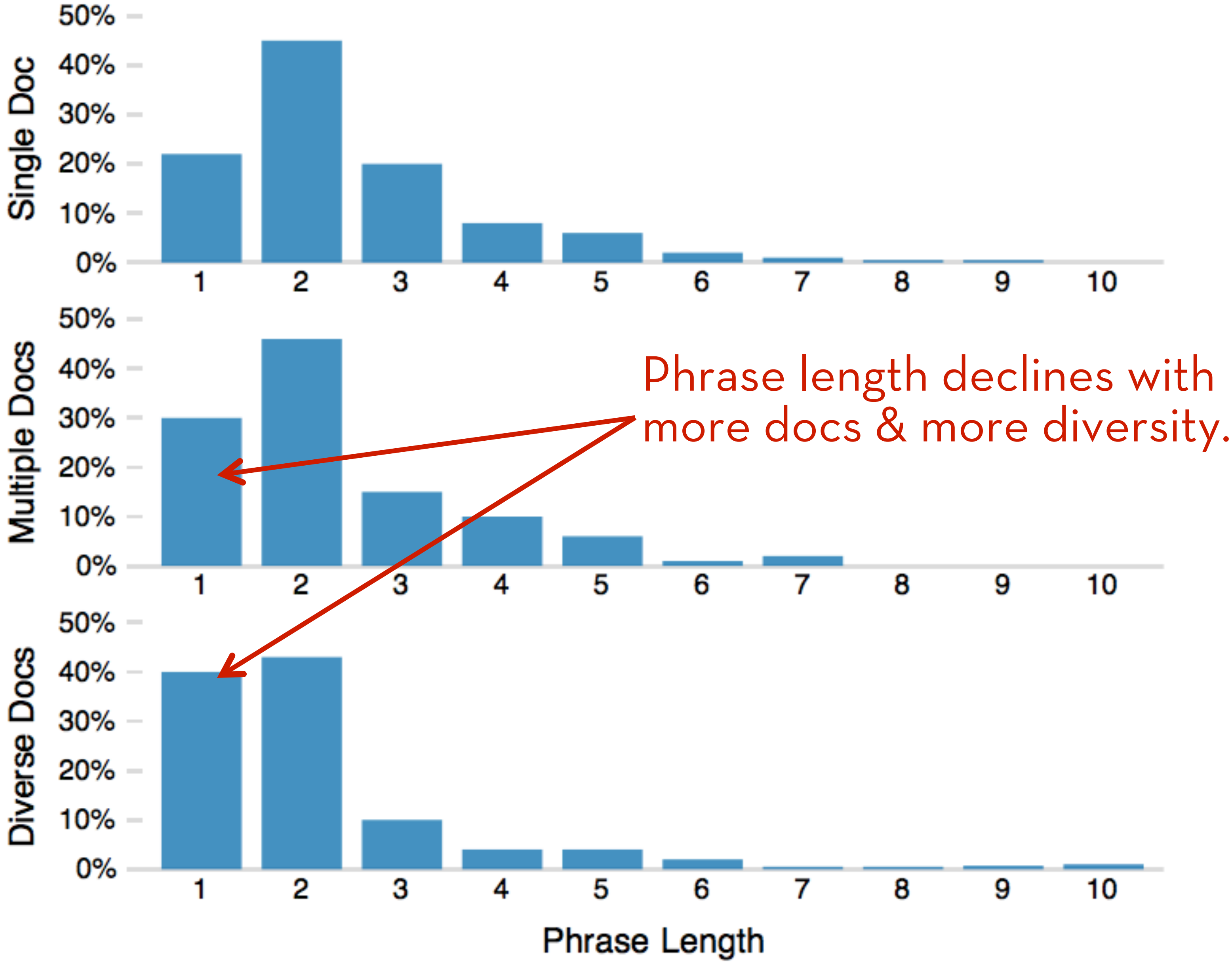
Students were given 3 documents in sequence; they then described the collection as a whole.

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


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

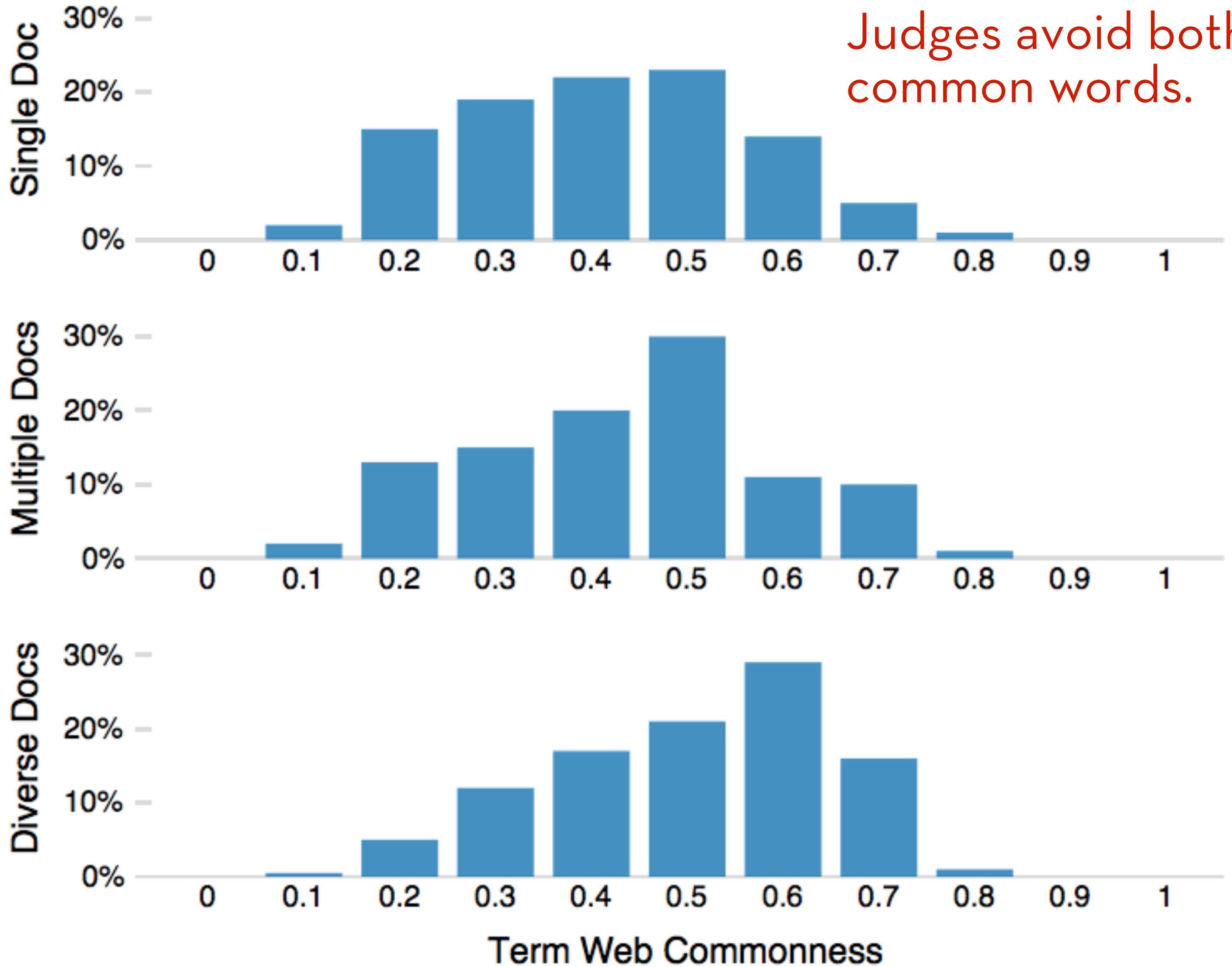
Term Commonness

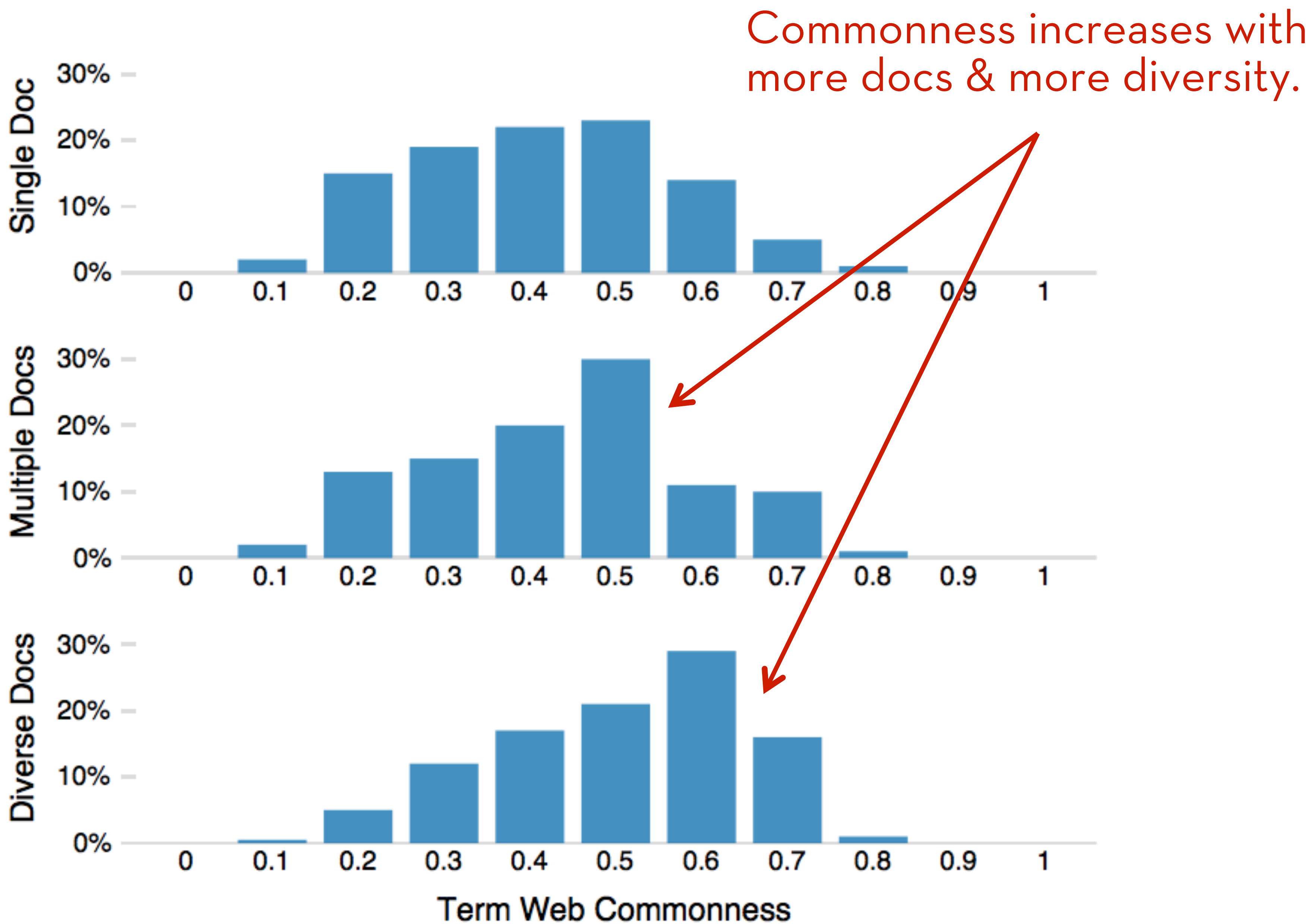
$$\log(tf_w) \; / \; \log(tf_{the})$$

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

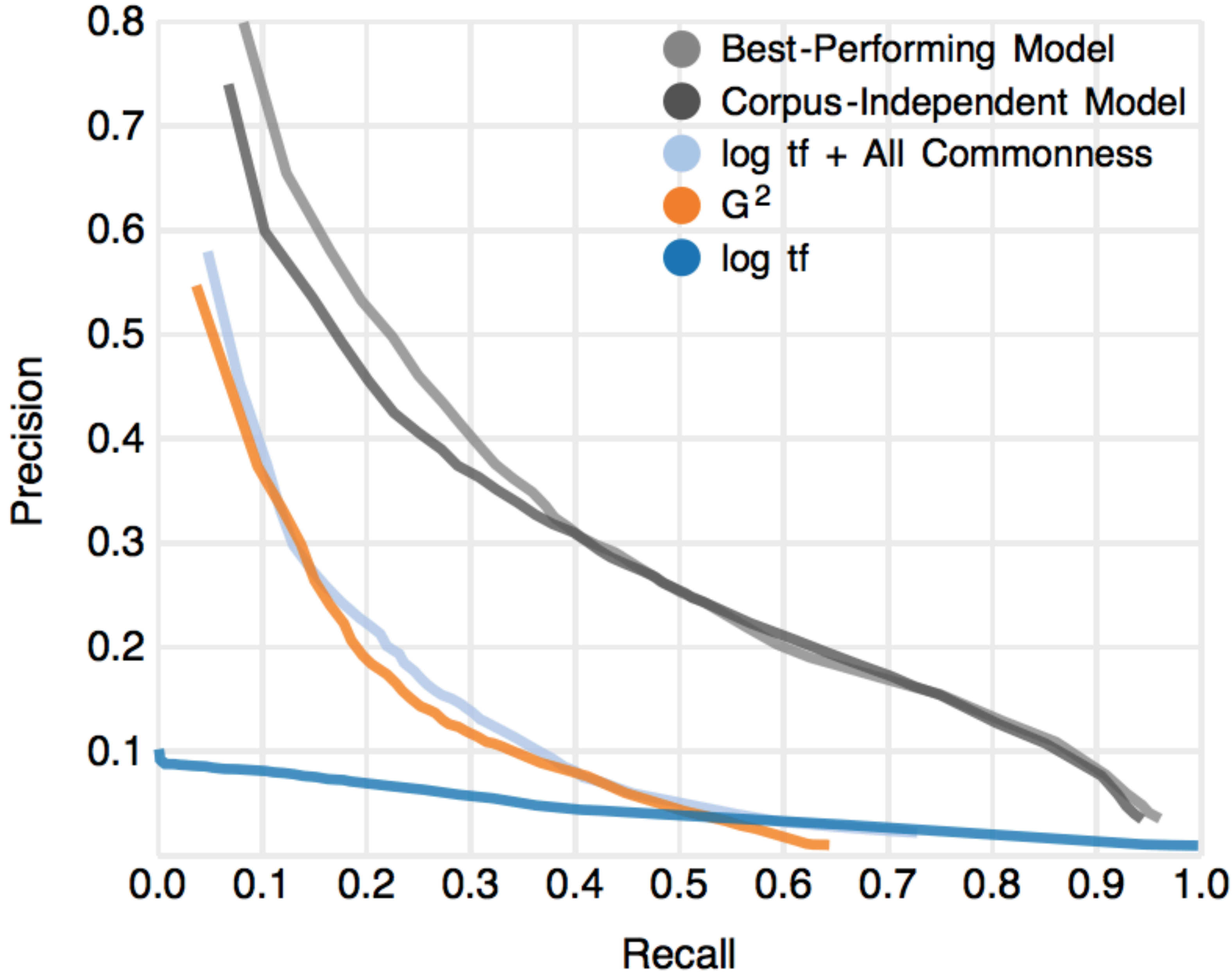
Measured across an entire corpus or across the entire English language (using Google n-grams)

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

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.

CHAMILA JAYAWEERA/BOEING

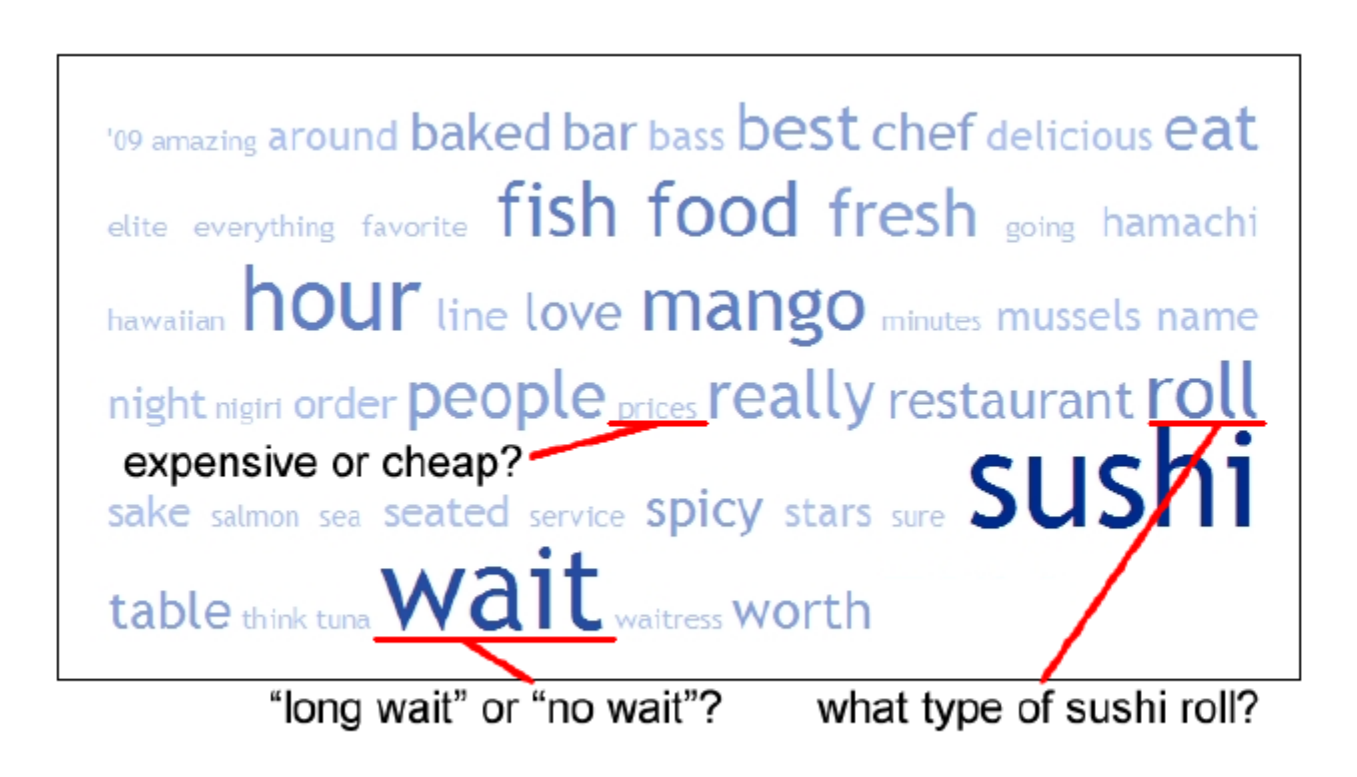
The Water Check team rolls in a large metal frame, which they affectionately call their "spray tree," over a Super Hornet inside a St. Louis hangar.

"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.

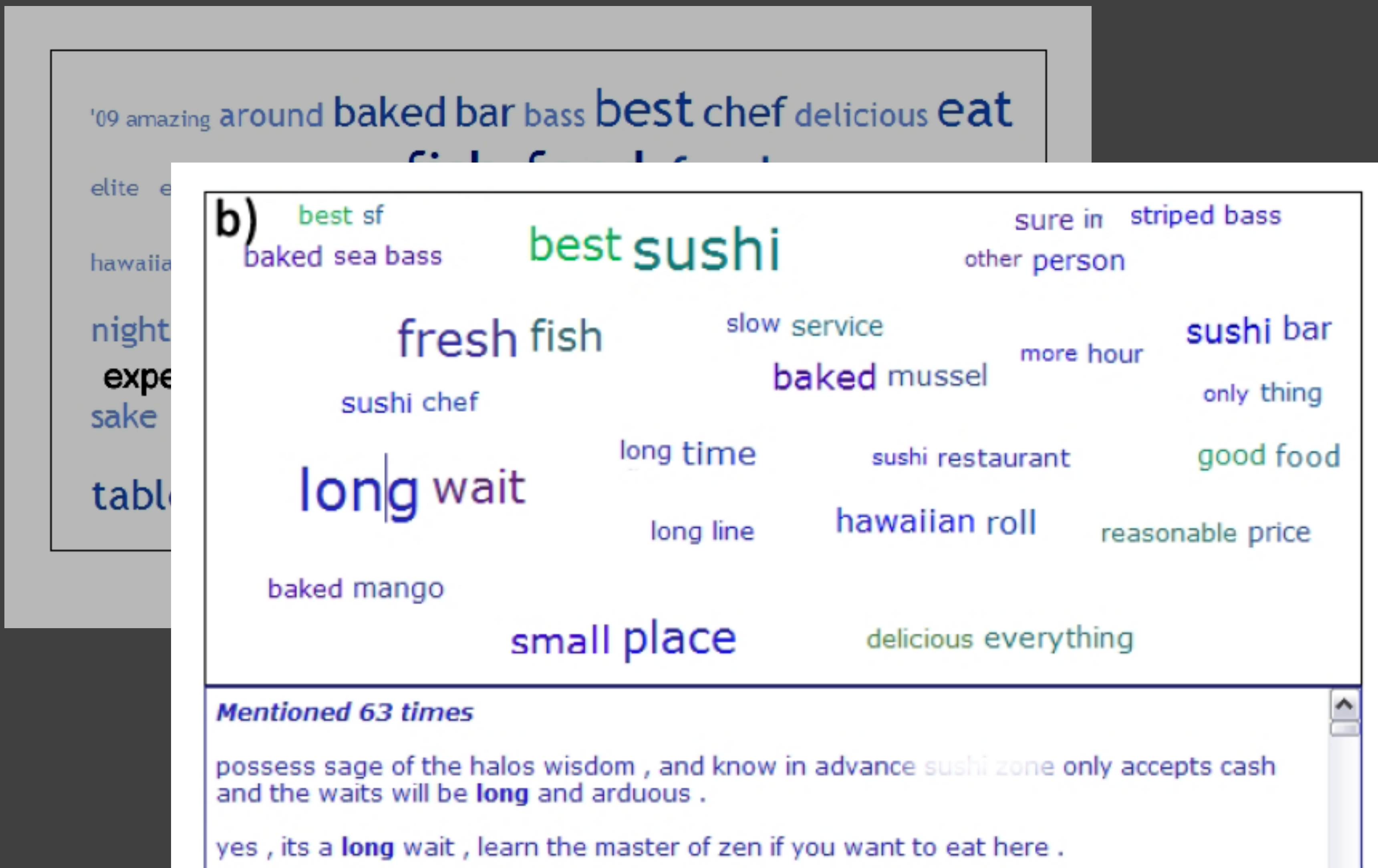
To find out moreabout how the process works and watch the action unfold, click above to see the video story.

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 pilot
Navy	sea-based fighter
sure	
Water	
moisture	
watch	
enormous	
stay	
want	

Yelp: Review Spotlight [Yatani 2011]



Yelp: Review Spotlight [Yatani 2011]



Tips: Descriptive Keyphrases

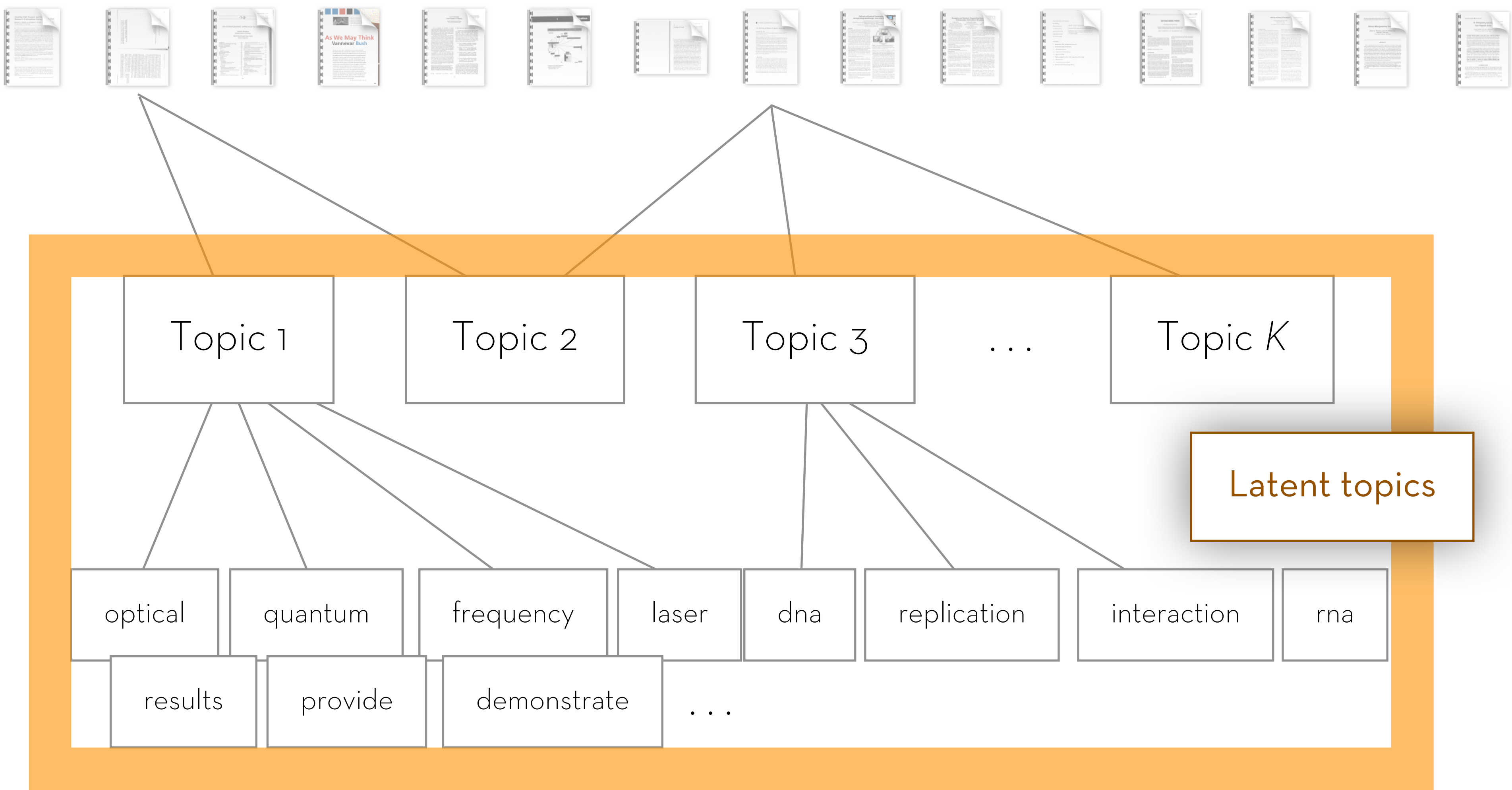
- Understand the limitations of your language model.
  - Bag of words:
    - Easy to compute
    - Single words
    - Loss of word ordering
- Select appropriate model and visualization
  - Generate longer, more meaningful phrases
  - Adjective-noun word pairs for reviews
  - Show keyphrases within source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

Visualize Themes in a Document Collection

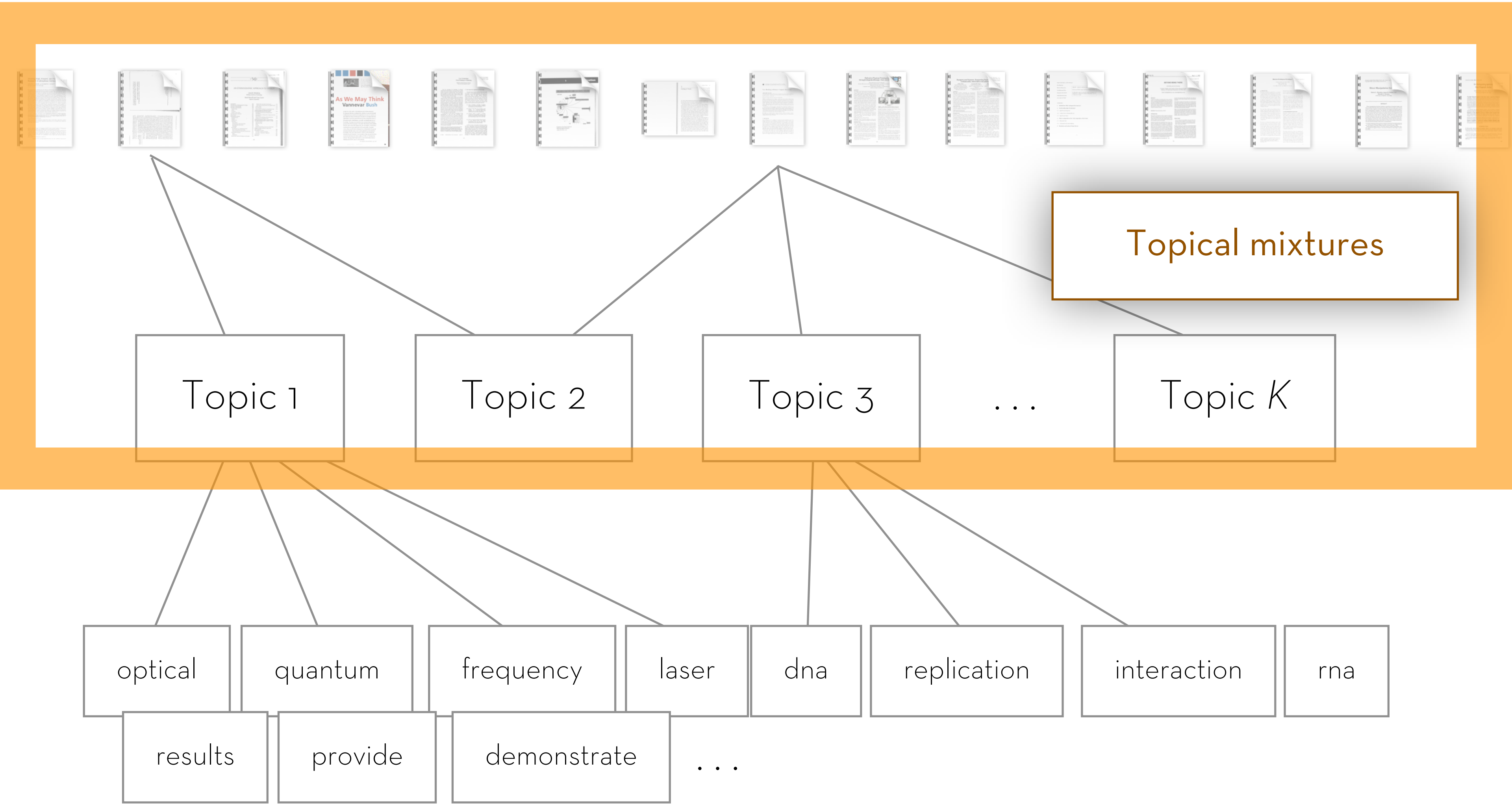
Topical Analysis

- Large document collections
  - Too large to manually read the source documents
  - Deeper analysis than the most common theme
- Statistical topic modeling
  - Analysis of word relationships
  - Extract *latent topics* belonging to the documents

Statistical Topic Modeling



Statistical Topic Modeling



Computational Linguistics

[Hall et al. 2008]

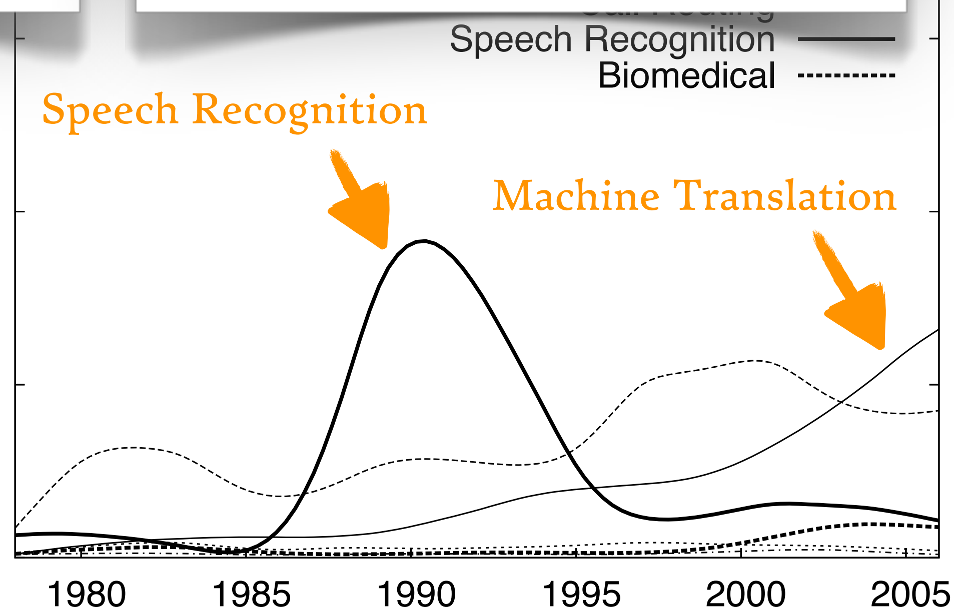
ACL conferences and journals
14,000 papers over 40 years

Sta
46 la

His
Topi
Rise and fall of research areas

Speech Recognition
speech, recognition, word, system, language, data, speaker, error, test, spoken, ...

Stats Machine Translation
english, word, alignment, language, source, target, sentence, machine, bilingual, mt, ...



Computational Linguistics

[Hall et al. 2008]

ACL conferences and journals
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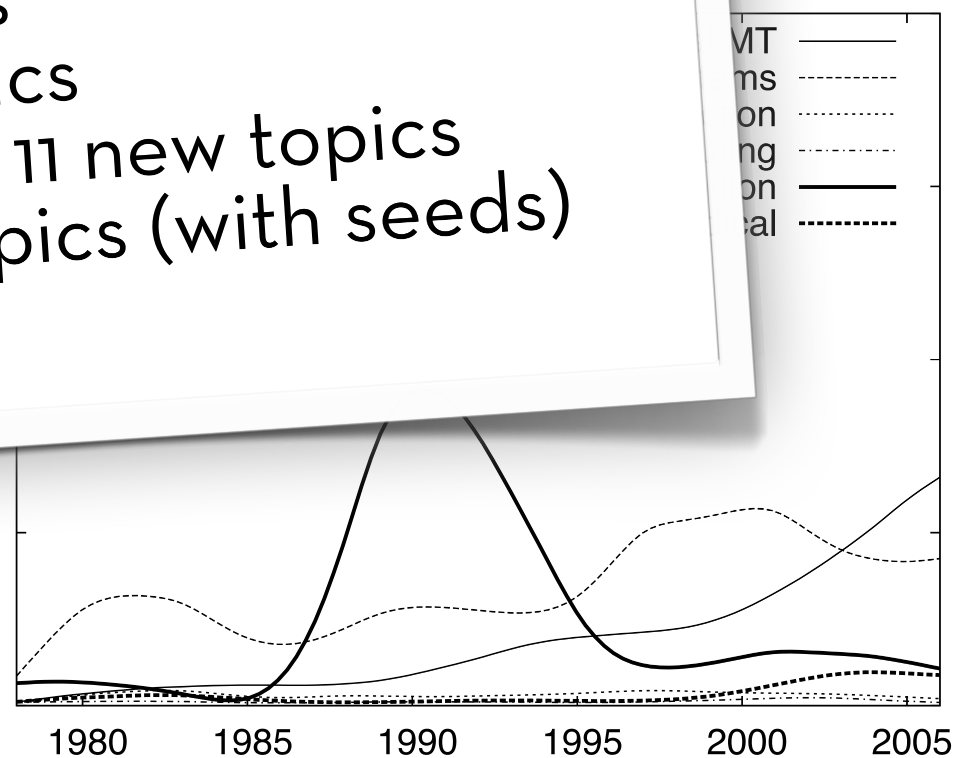
Topi
Rise

Generate 100 latent topics
Retain 36 topics
Remove 64 topics
Manually insert 11 new topics
Re-generate topics (with seeds)
Label topics



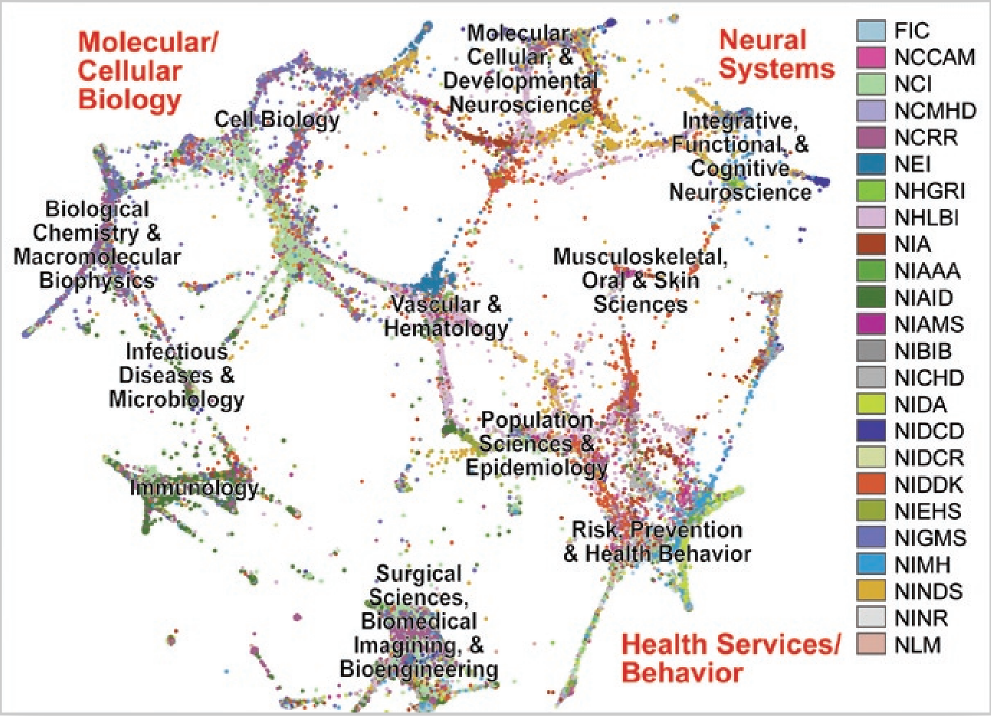
NIH Grants & Funding Agencies

[Talley et al. 2011]

Biomedical research
110,000 NIH grant awards
220,000 MEDLINE journal articles

Statistical topic modeling
700 latent topics

Clustering & correlations
Project areas & Funding institutes
Trends in research funding
Changes in research topics

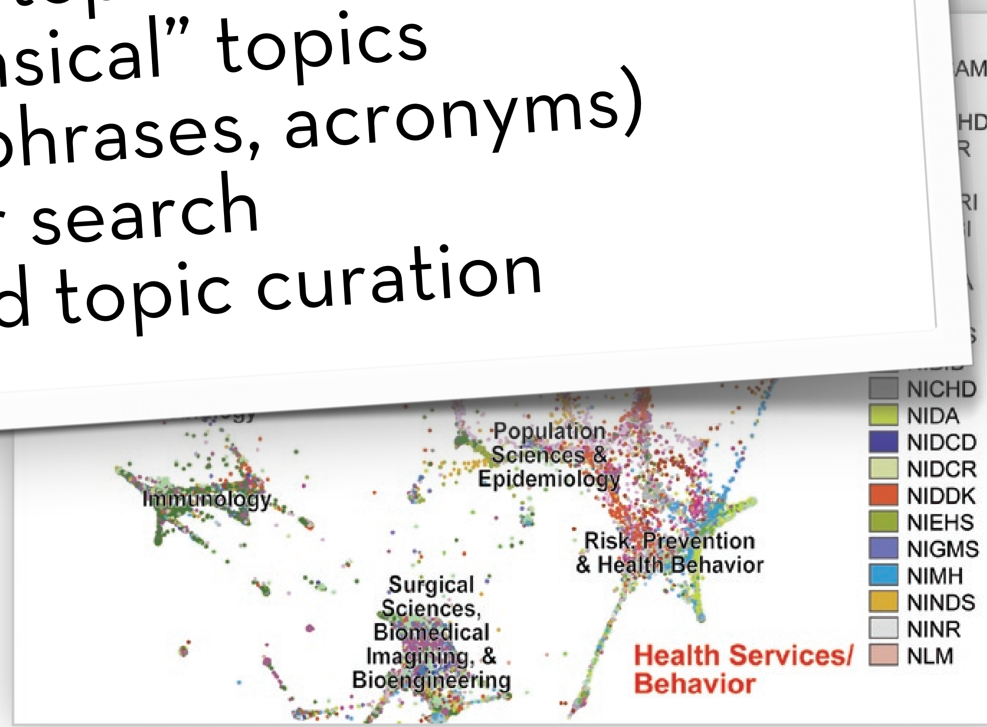


NIH Grants & Funding Agencies

[Talley et al. 2011]

Biomedical research
110,000 NIH grant awards
220,000 MEDLINE journal

Generate 700 latent topics
Remove 15% “nonsensical” topics
Modify vocabulary (phrases, acronyms)
Extensive parameter search
Expert validation and topic curation



List of Words

Anaphora Resolution	resolution anaphora pronoun discourse antecedent pronouns coreferen
Automata	string state set finite context rule algorithm strings language symbol
Biomedical	medical protein gene biomedical wkh abstracts medline patient clinica
Call Routing	call caller routing calls destination vietnamese routed router destinatio
Categorial Grammar	proof formula graph logic calculus axioms axiom theorem proofs laml
Centering*	centering cb discourse cf utterance center utterances theory coherence
Classical MT	japanese method case sentence analysis english dictionary figure japar
Classification/Tagging	features data corpus set feature table word tag al test
Comp. Phonology	vowel phonological syllable phoneme stress phonetic phonology pron
Comp. Semantics*	semantic logical semantics john sentence interpretation scope logic fo

[Hall et al. 2008]

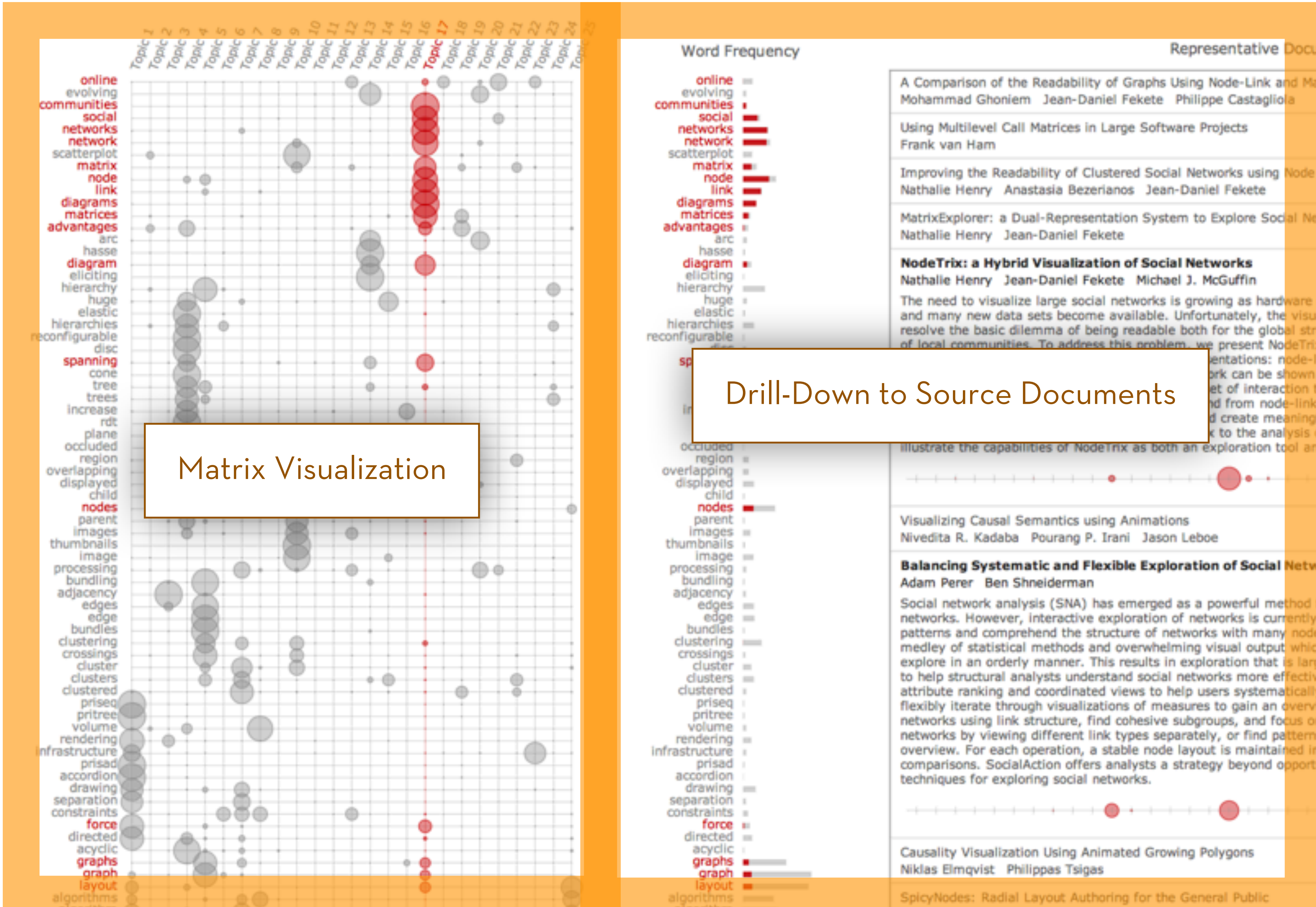
Topic Words: vegf angiogenesis vascular_endothelial_growth_factor angiogenic e
antiangiogenic anti_angiogenic vegf_a tumor_angiogenesis vegfr2 growth signalin

Title Words: angiogenesis, vegf, vascular_endothelial_growth_factor, angiogenic,
neovascularization, angiopoietin, signaling, vegfr, vascular, human

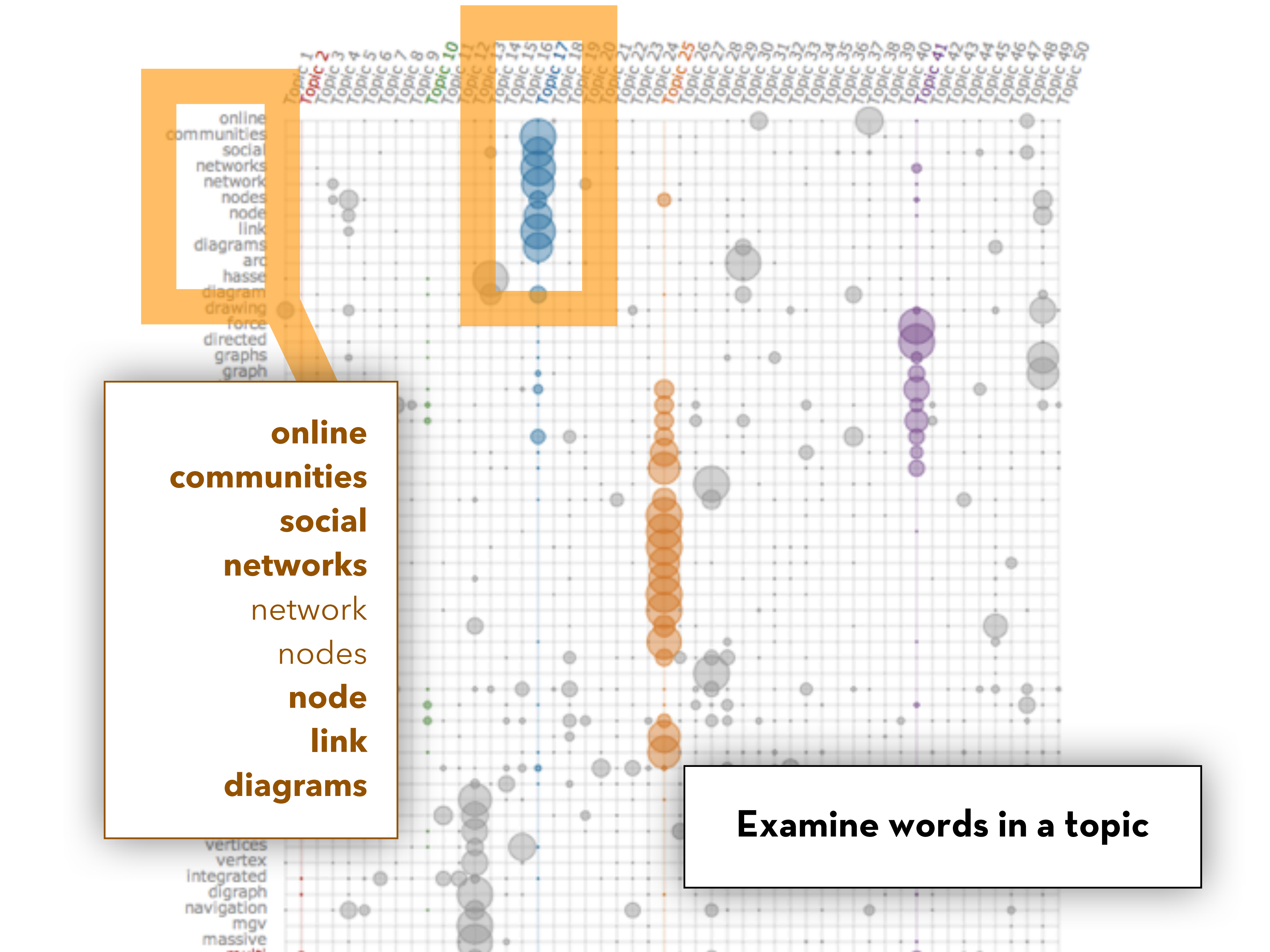
Phrases: vascular_endothelial_growth_factor vegf, vegf angiogenesis, vegf recept

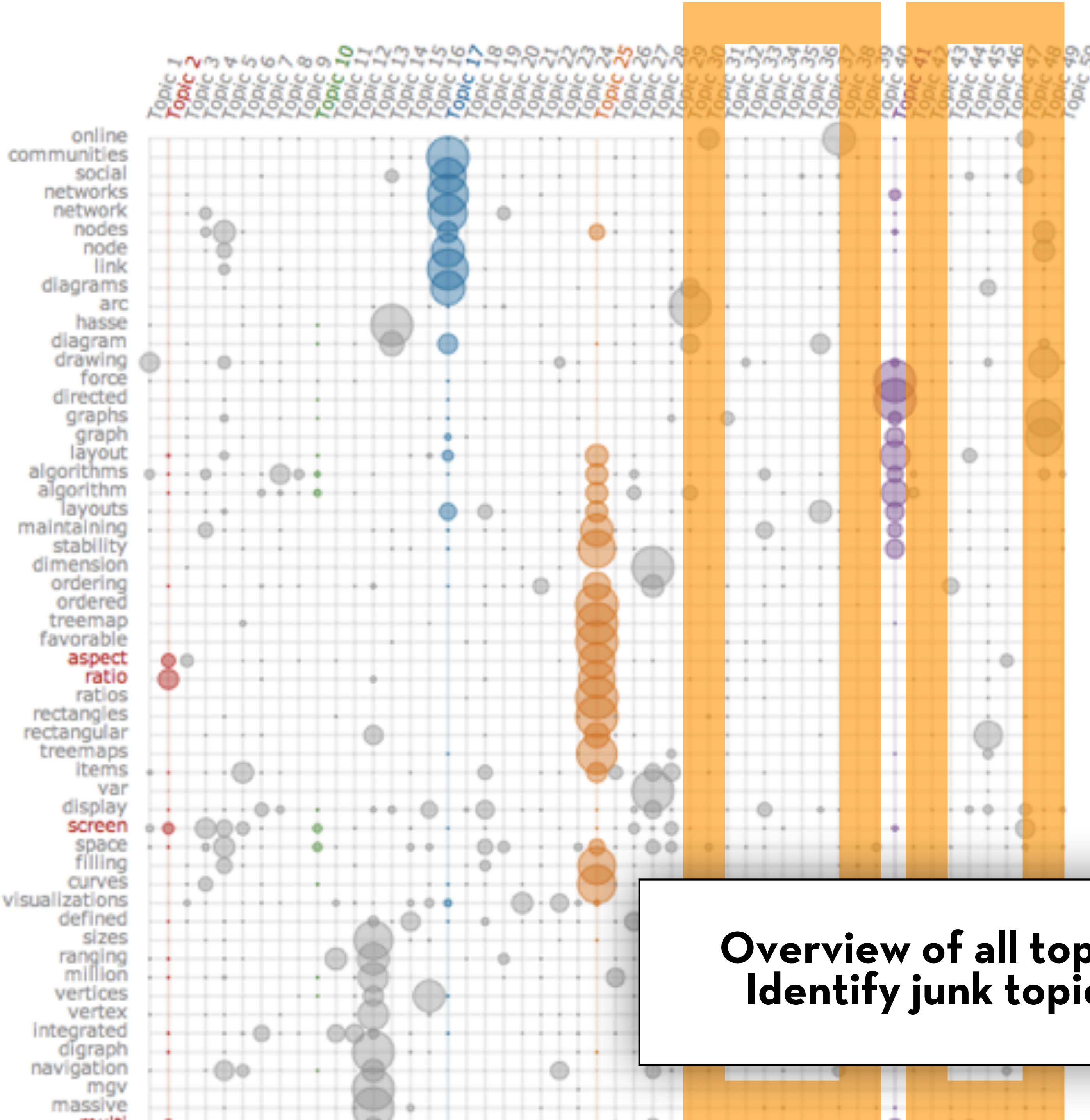
[Talley et al. 2011]

Termite | Topic Model Visualization

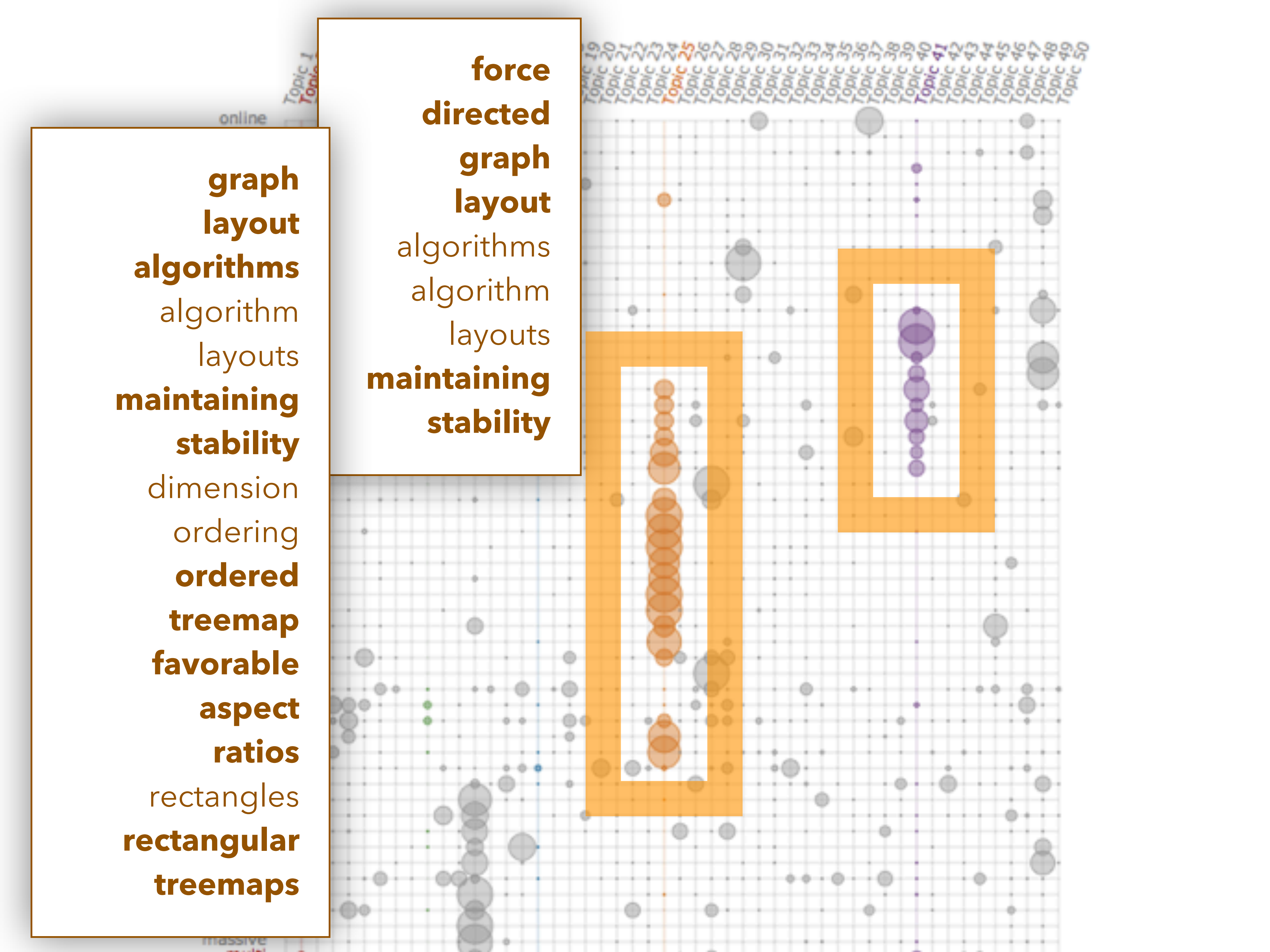


Topics
All papers published in IEEE InfoVis Conference
(16 years, 372 papers, 50 latent topics)
Word frequency per topic
Words
online
communities
social
networks
network
nodes
node
link
diagrams
arc
hasse
diagram
drawing
maintaining
stability
dimension
ordering
ordered
treemap
favorable
aspect
ratio
ratios
rectangles
rectangular
treemaps
items
var
display
screen
space
filling
vertices
vertex
integrated
digraph
navigation
massive


online
communities
social
networks
network
nodes
node
link
diagrams
arc
hasse
diagram
drawing
force
directed
graphs
graph
vertices
vertex
integrated
digraph
navigation
mgv
massive
online
communities
social
networks
network
nodes
node
link
diagrams
Examine words in a topic



Overview of all topics
Identify junk topics



graph
layout
algorithms
algorithm
layouts
maintaining
stability
dimension
ordering
ordered
treemap
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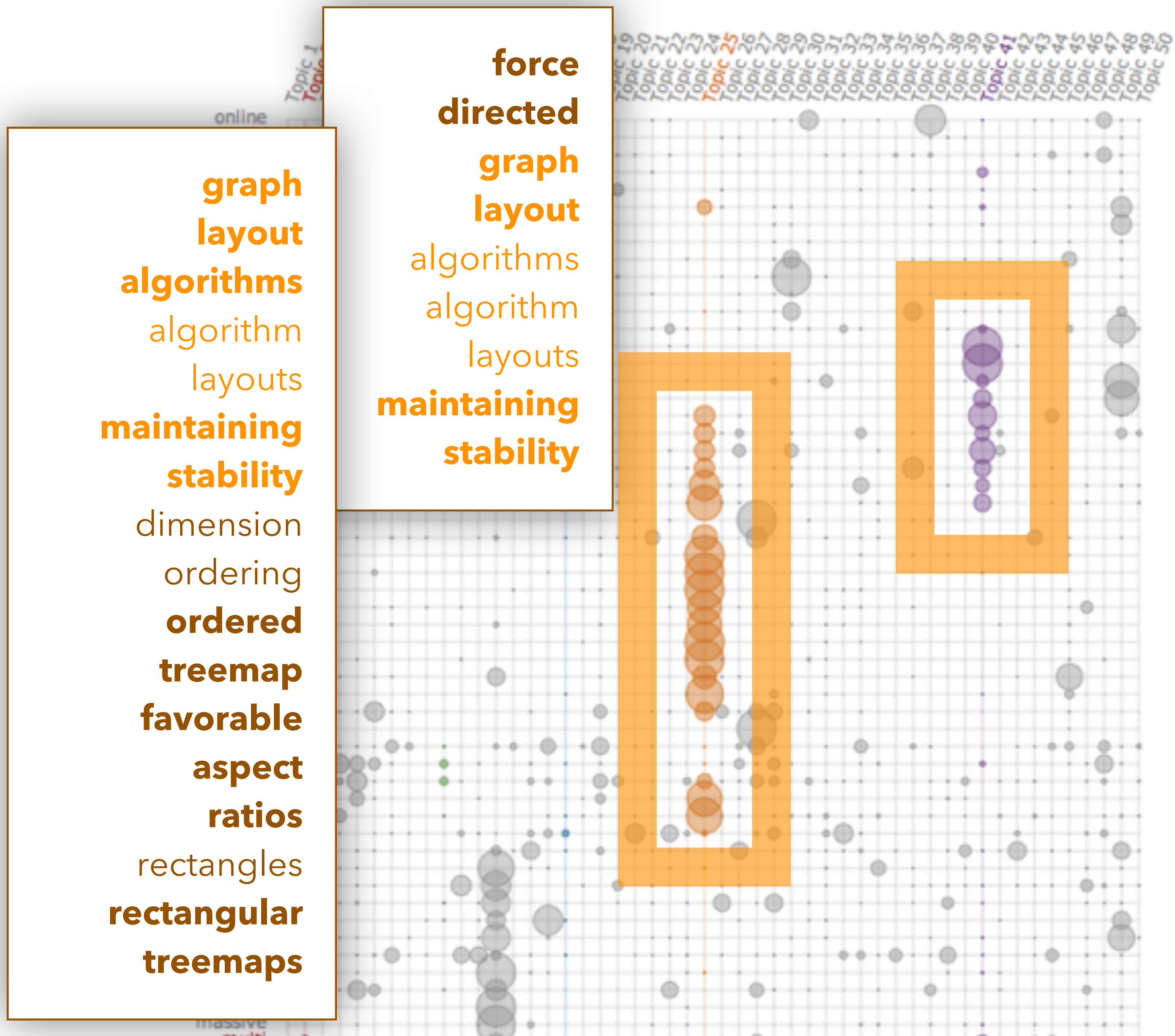
layouts
maintaining
stability


online
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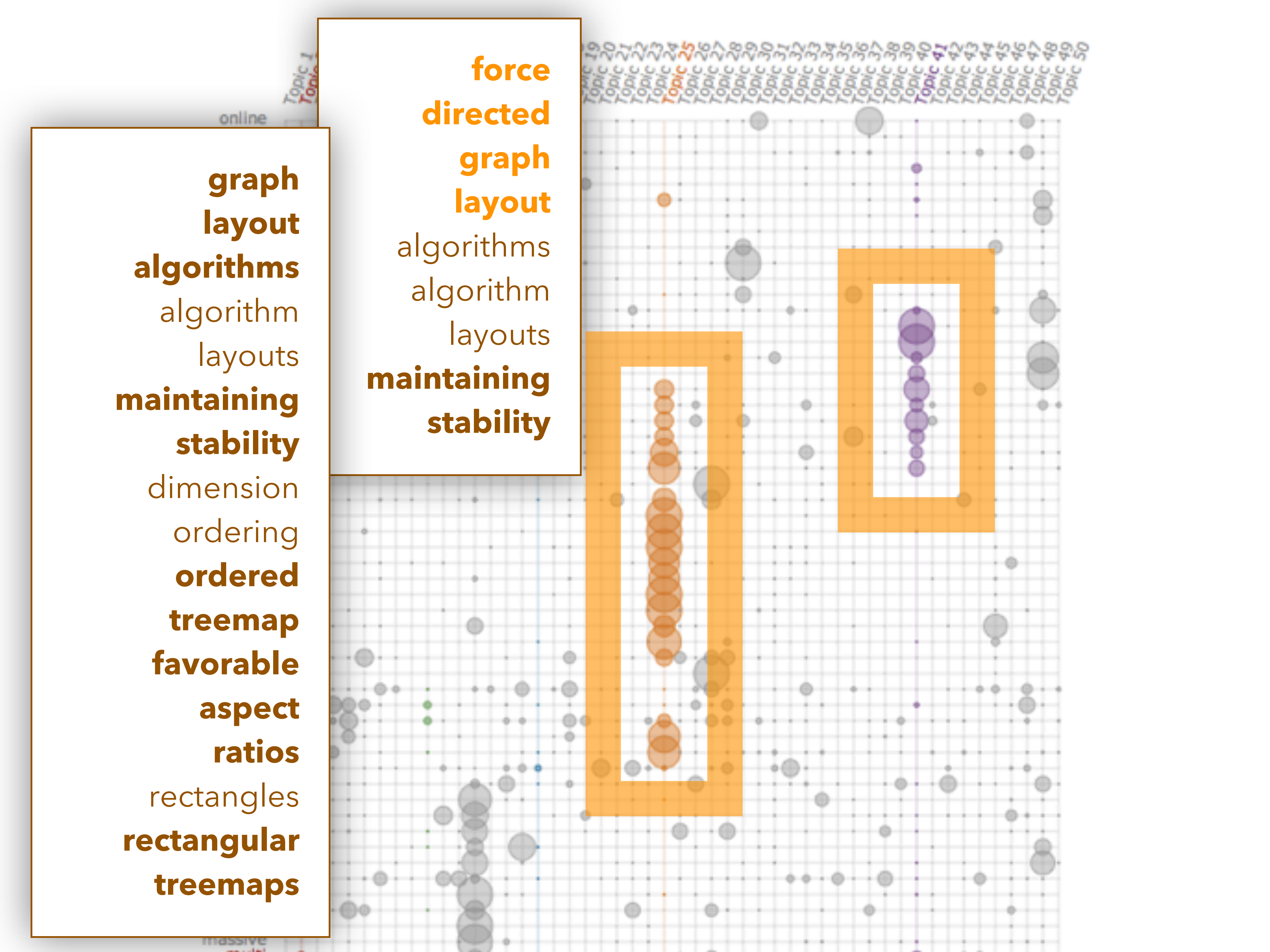
treemaps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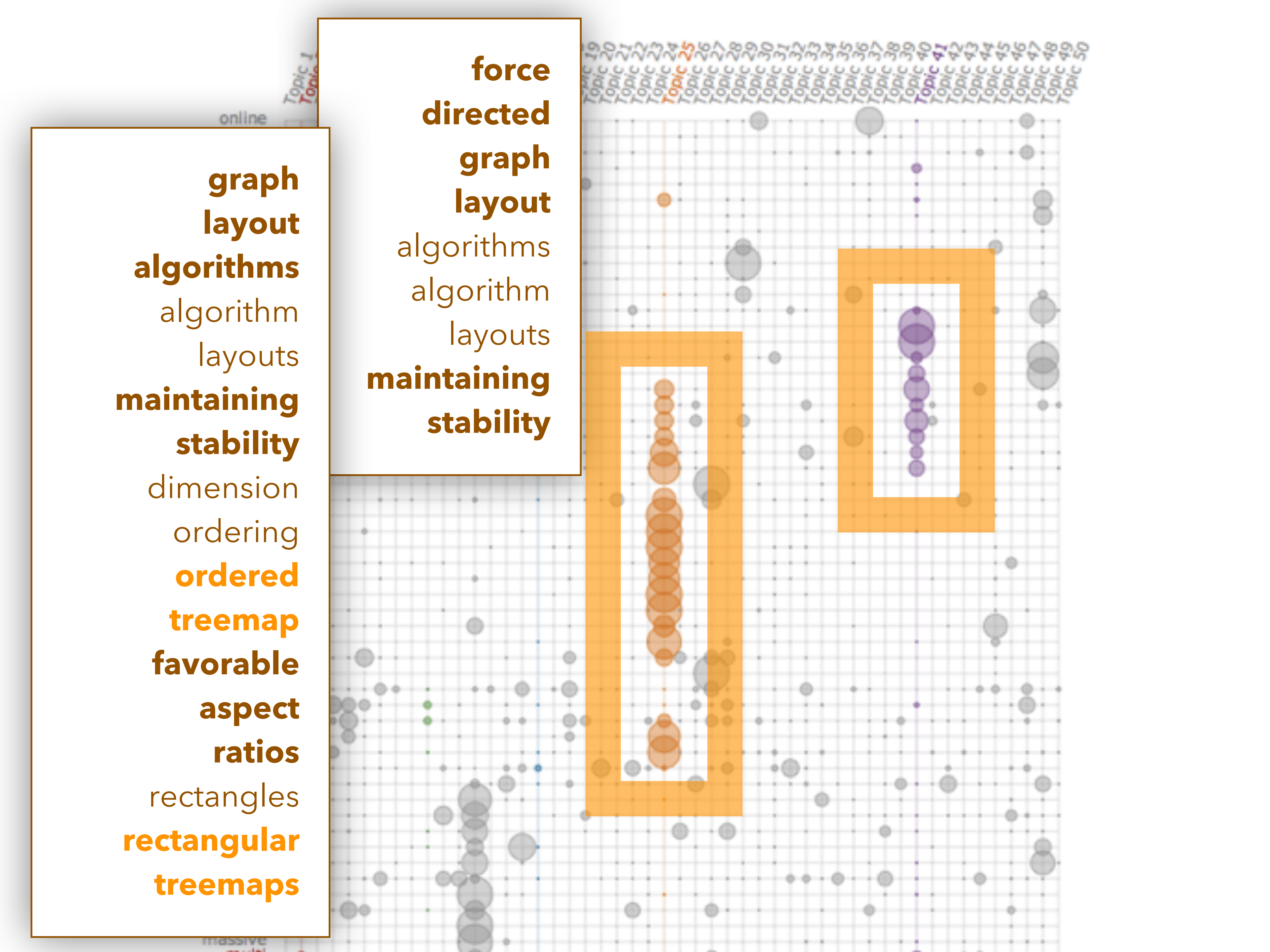
force
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ordered
treemap
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aspect
ratios
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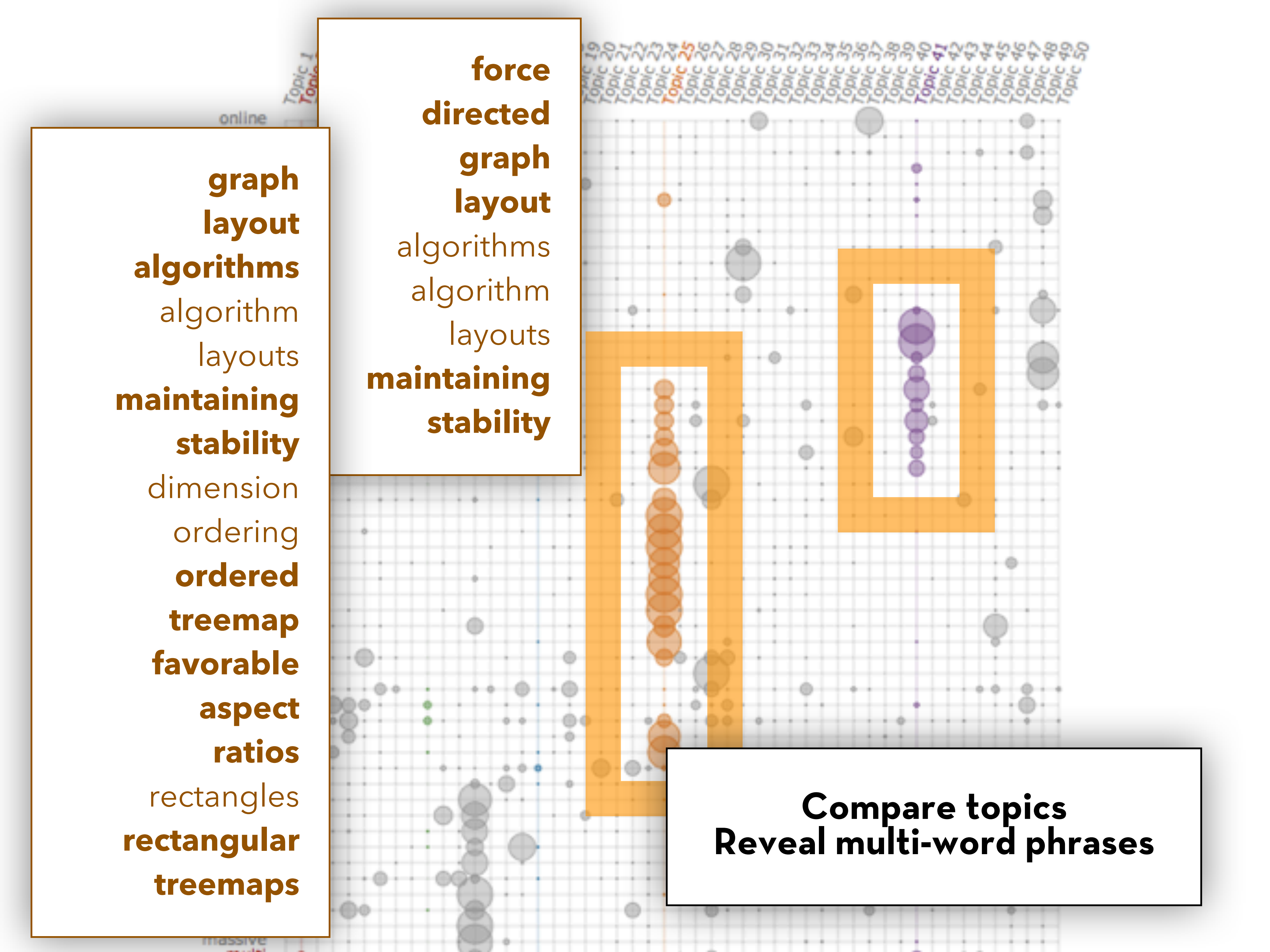
rectangular
treemaps
online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treemaps
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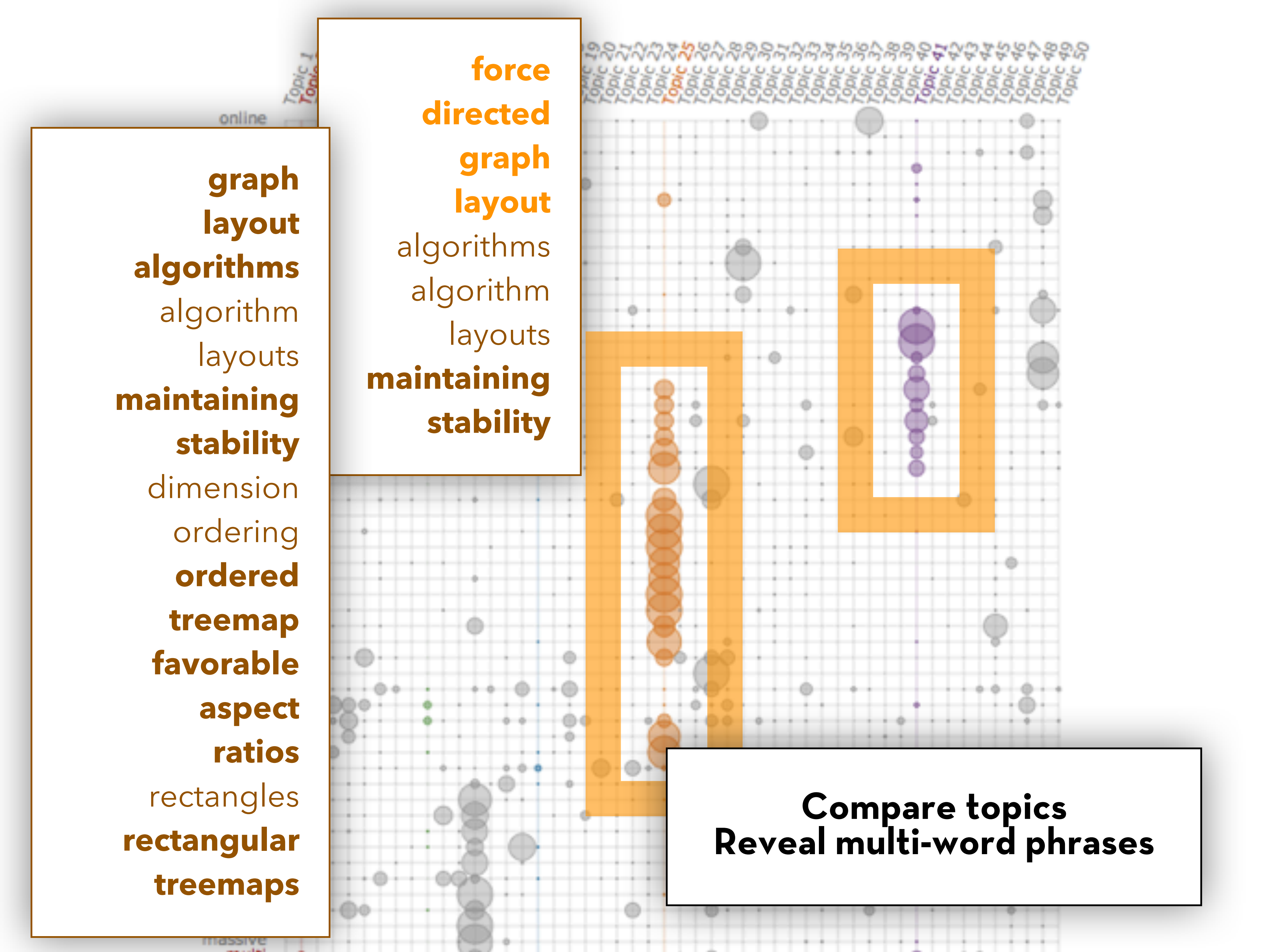
Compare topics
Reveal multi-word phrases



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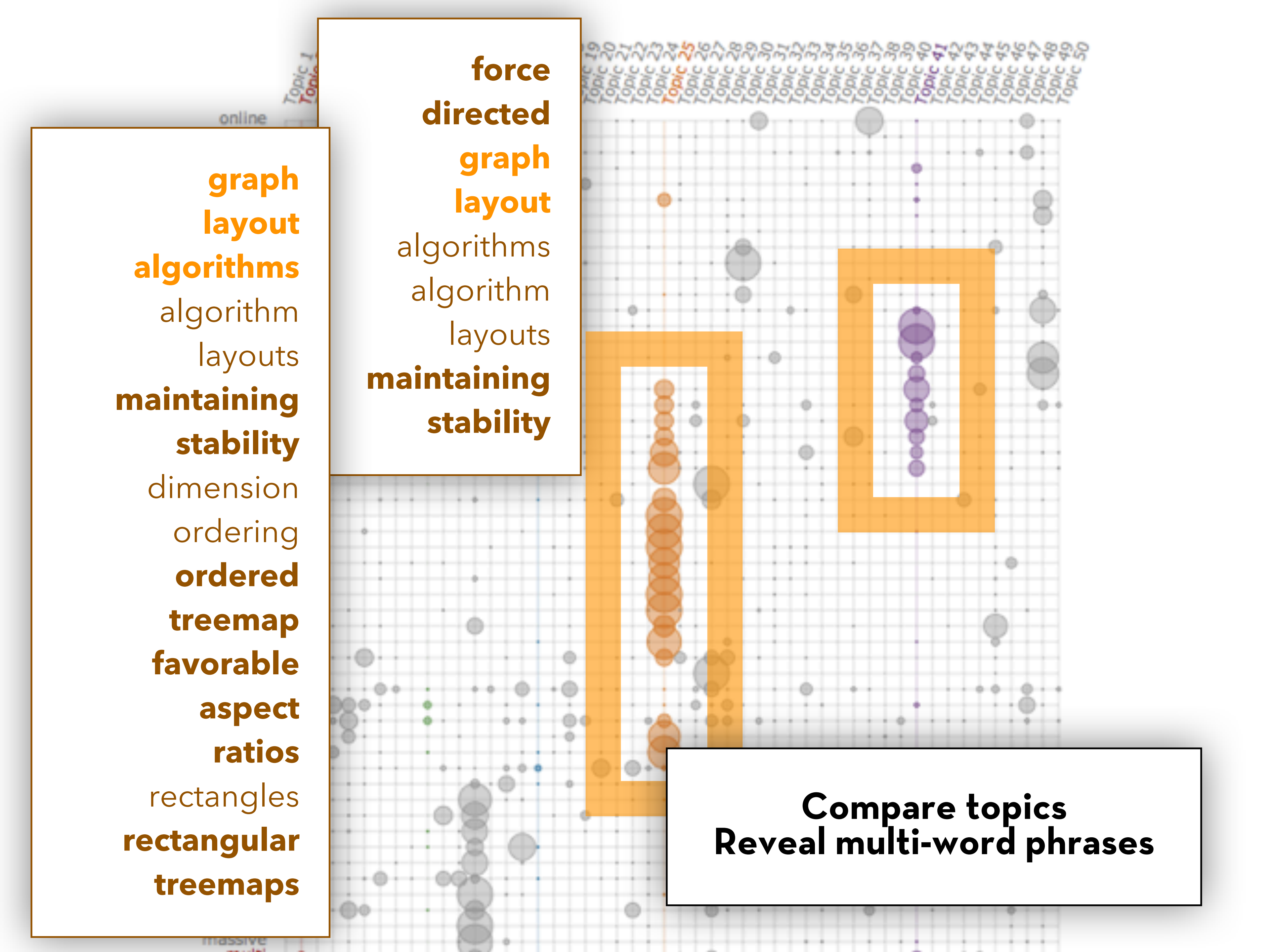
Compare topics
Reveal multi-word phrases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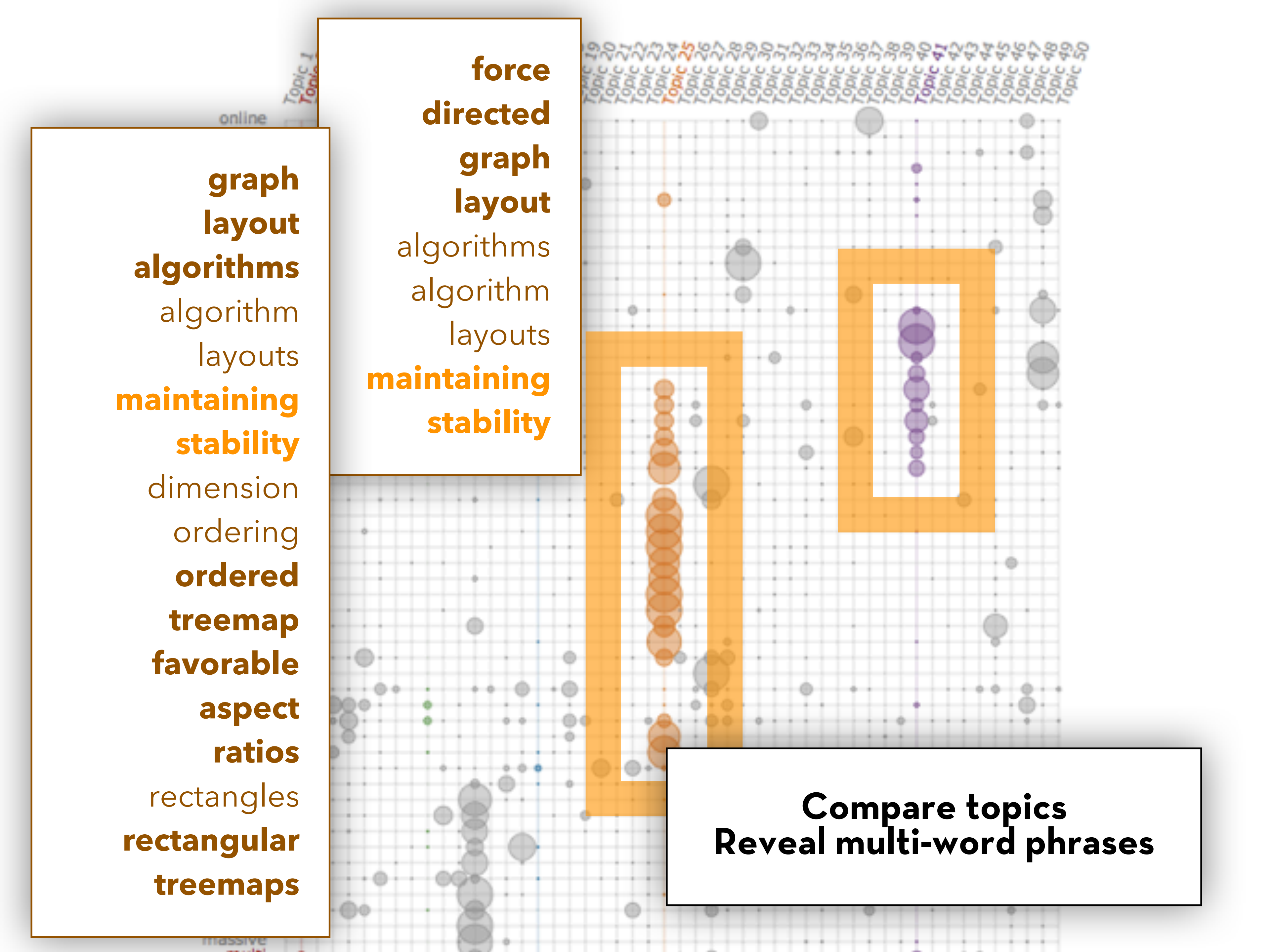
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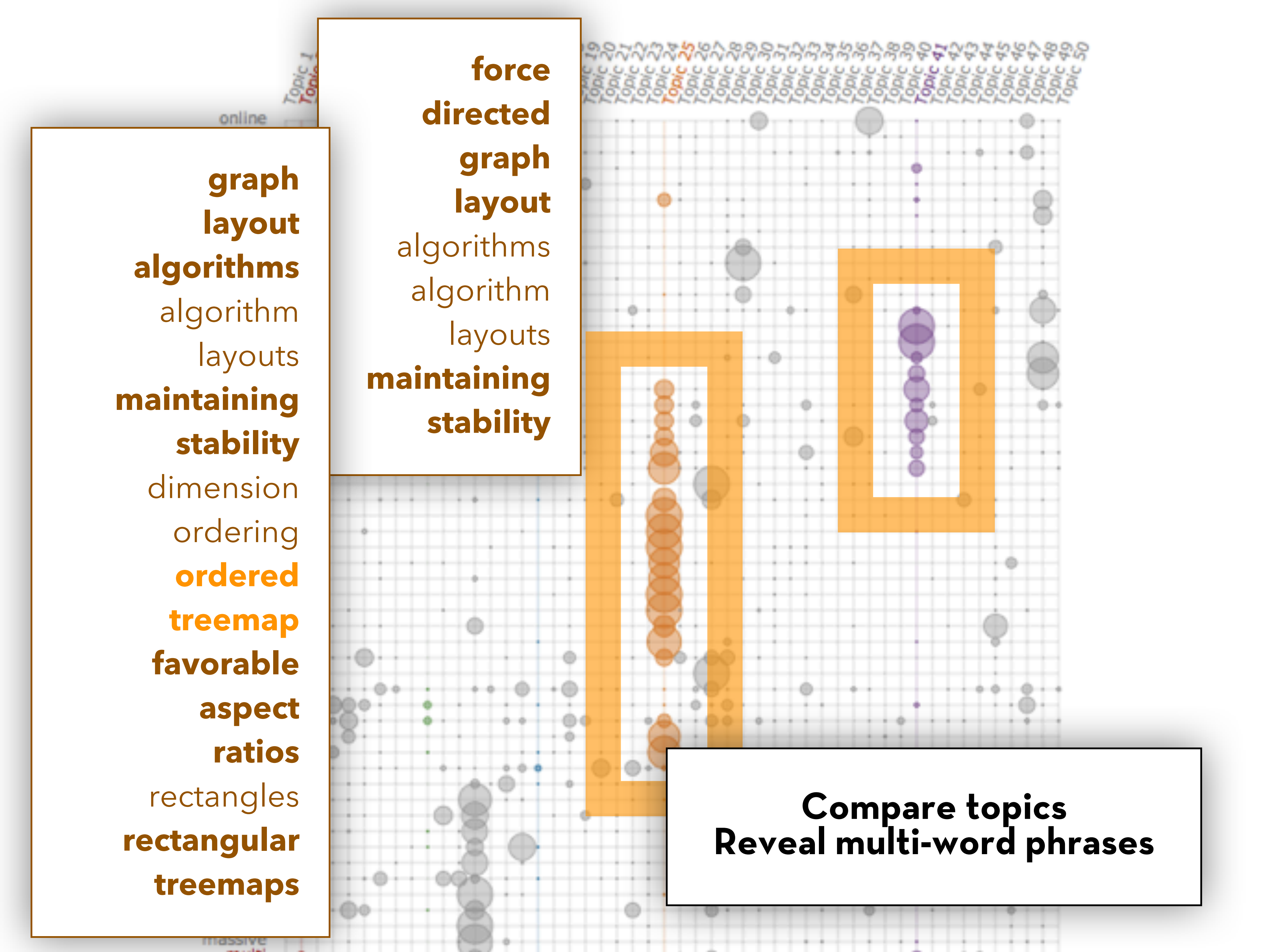
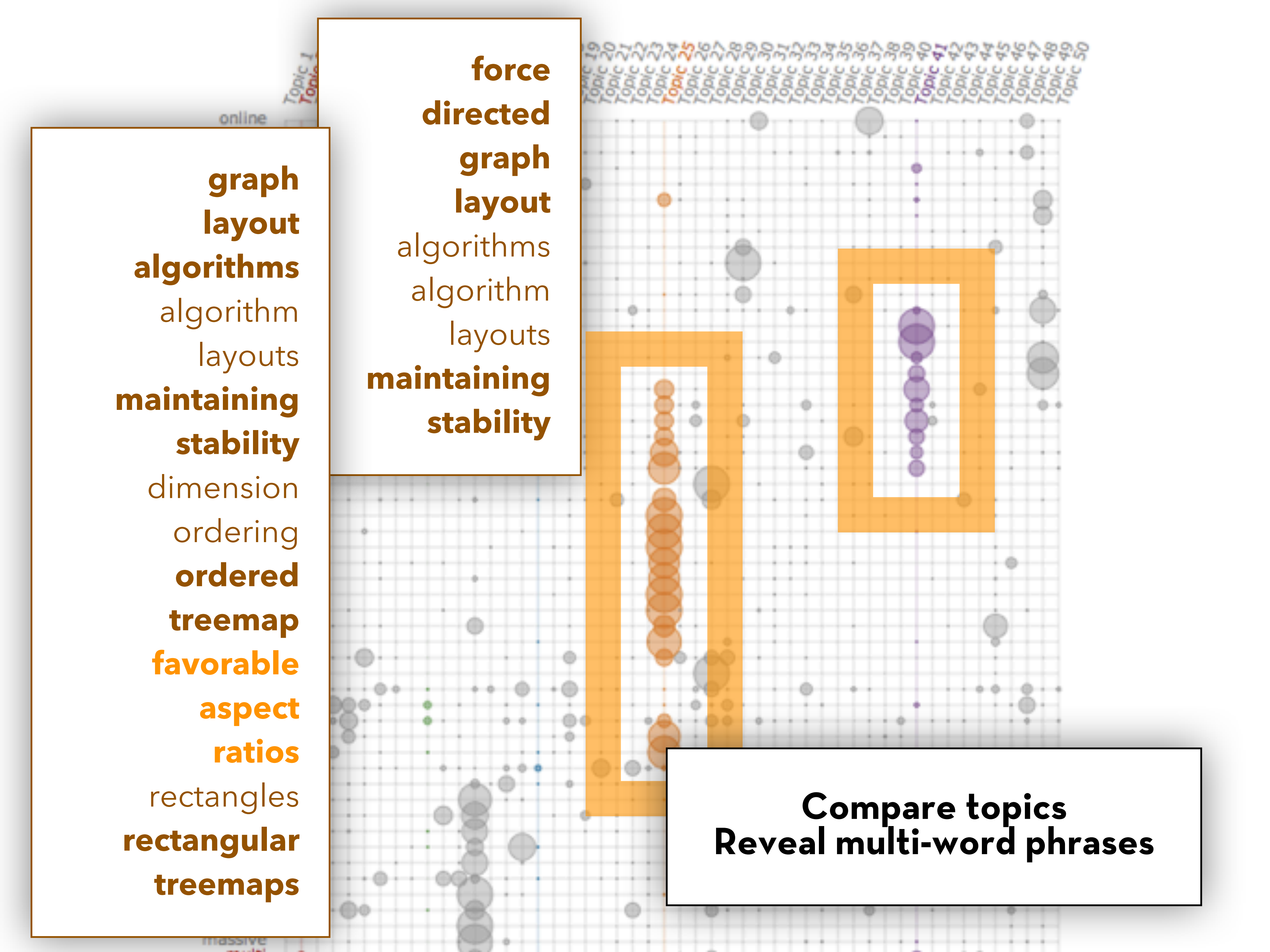
Reveal multi-word phrases



Compare topics
Reveal multi-word phrases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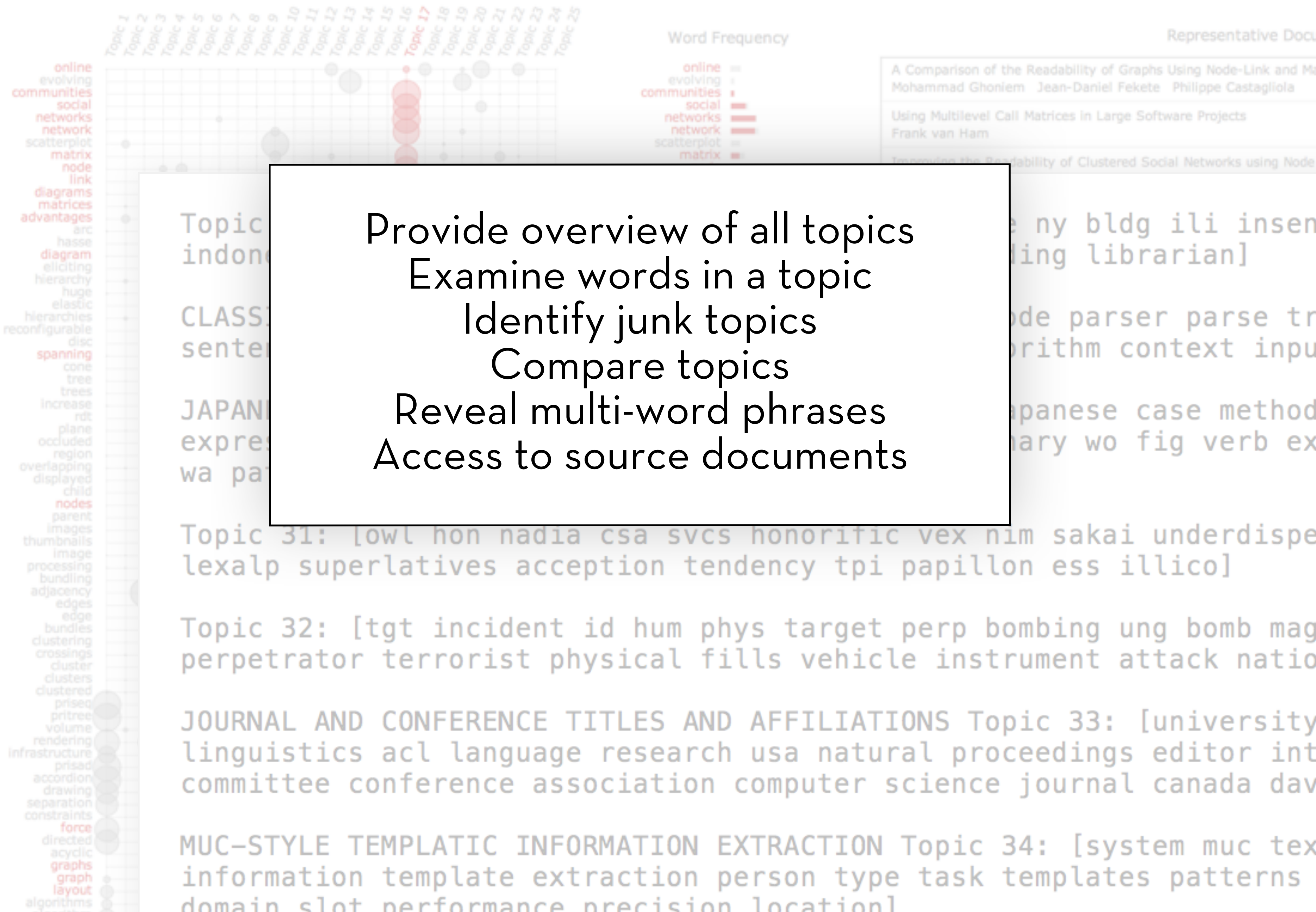
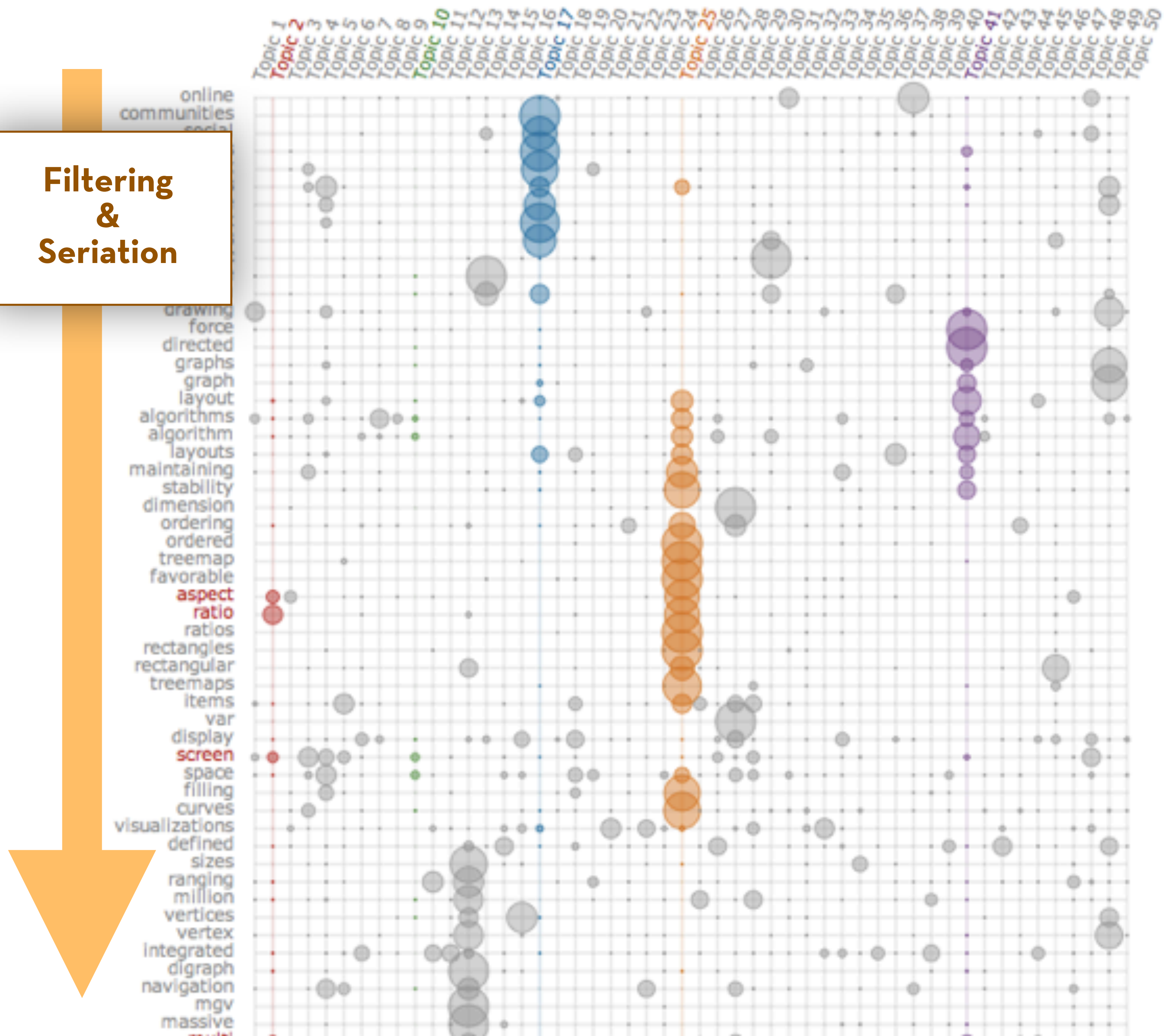
Compare topics
Reveal multi-word phrases

Termite | Topic Model Visualization



Provide overview of all topics
Examine words in a topic
Identify junk topics
Compare topics
Reveal multi-word phrases
Access to source documents

Filtering & Seriation



Filtering: What words to show?

Frequent words are not necessarily discriminative
data, visualization, information, visual, techniques, users, visualizations, ...

Saliency
Score for word w based on frequency and distinctiveness

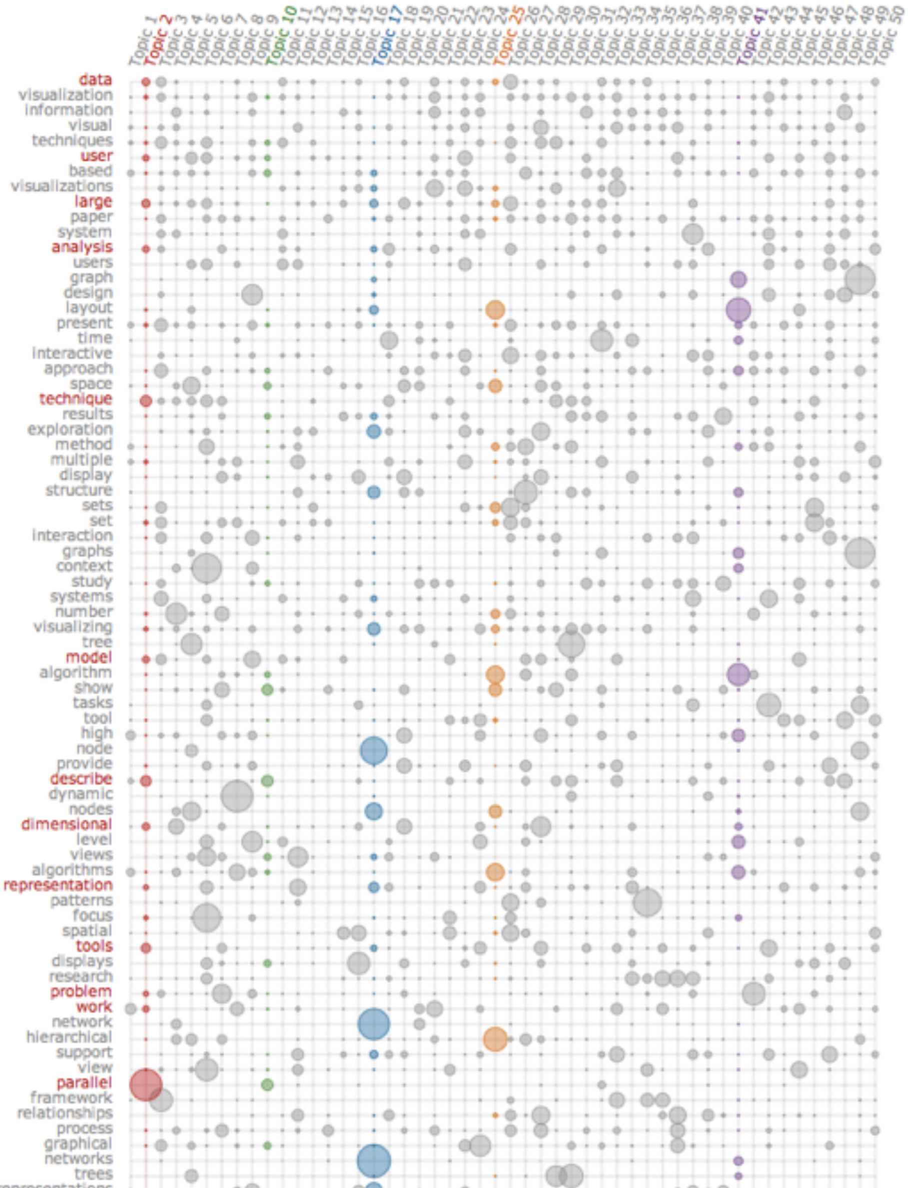
$$\text{saliency}(w) = \text{frequency}(w) \times \text{distinctiveness}(w)$$

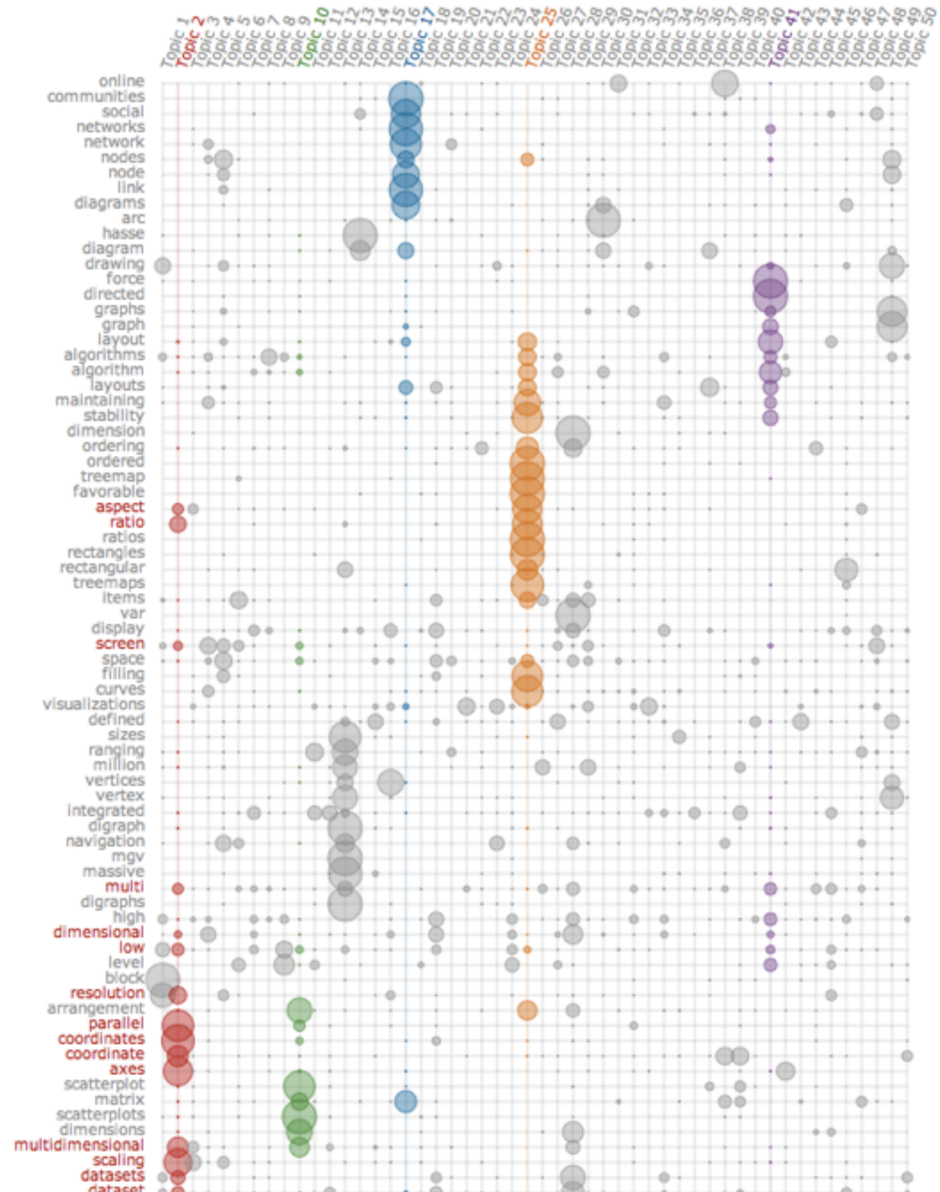
Distinctiveness
Knowing a word w, how much does it tell us about a topic?

$$\text{distinctiveness}(w) = \text{KL}(\, P(T|w) \,||\, P(T)\,)$$

$P(T|w)$ = generating topic T for a given word w
$P(T)$ = generating topic T for a randomly-selected word in the corpus

Seriation: How to show the words?





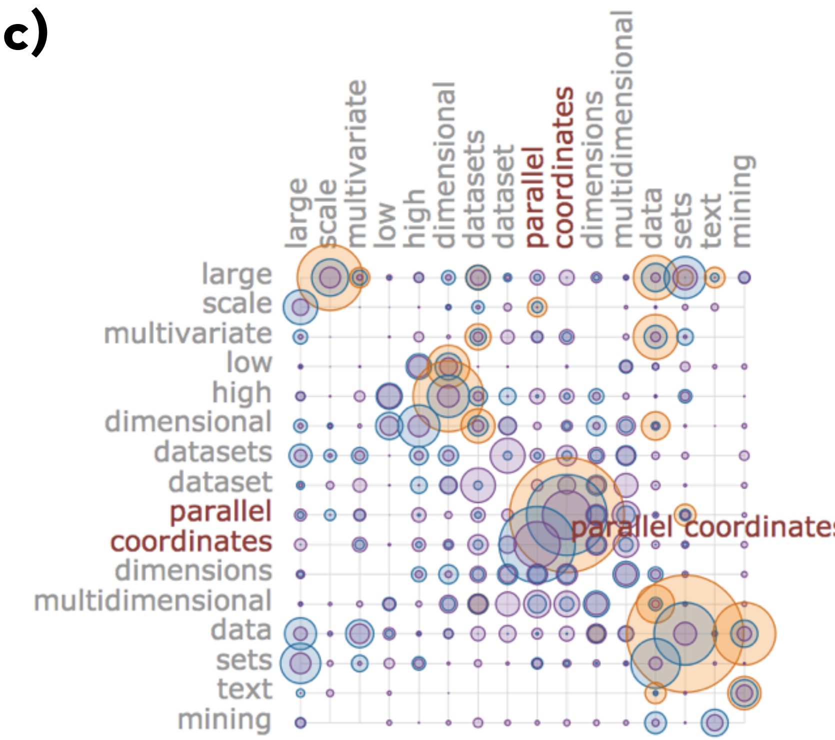
Seriation: How to show the words?

Clustering of related words
large, node, networks, social, link, diagrams, online, dataset, communities, ...

Preservation of reading order
online communities, social networks, node link diagrams, large datasets, ...

Word similarity matrix (asymmetric)
document co-occurrence
sentence co-occurrence
collocation (word transition probability)

Text seriation
based on bond energy algorithm
accepts asymmetric similarity matrices
aware of salient terms
early termination



Seriation: How to show the words?

Clustering of related words
large, node, networks, social, link, diagrams, online, dataset, communities, ...

Preservation of reading order
online communities, social networks, node link diagrams, large datasets, ...

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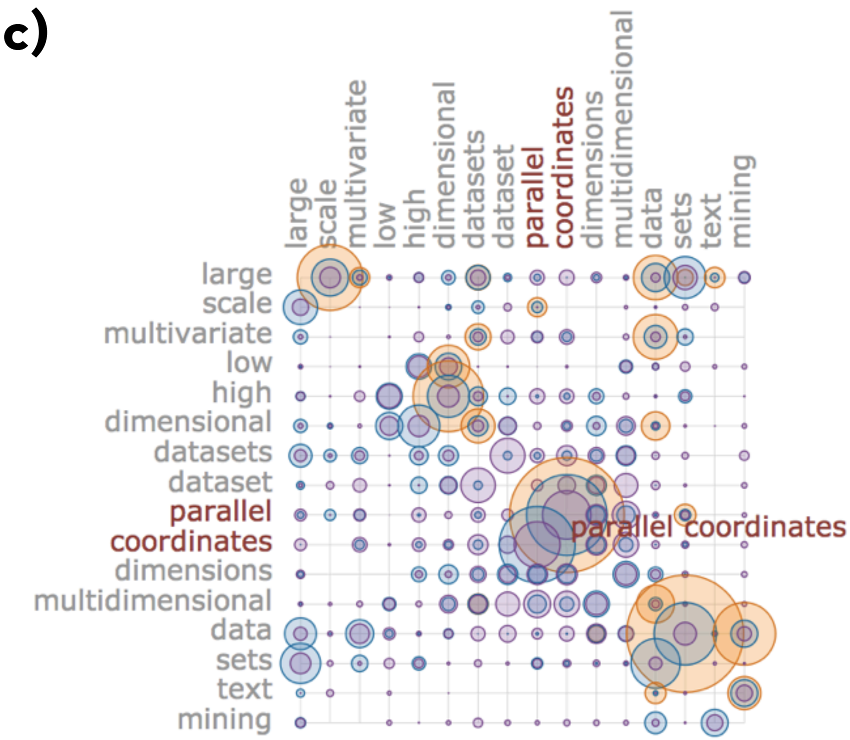

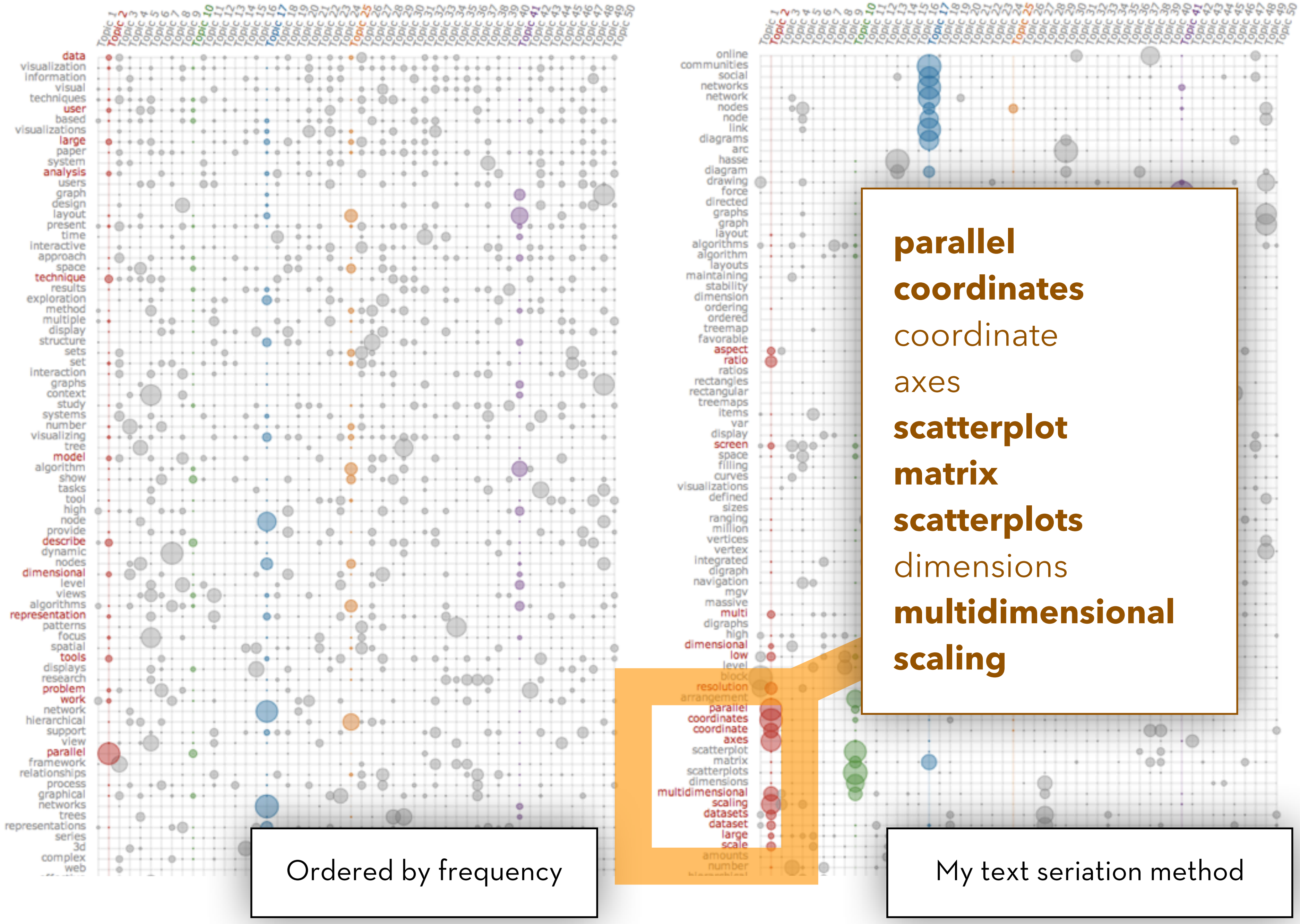
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coordinate
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matrix
scatterplots
dimensions
multidimensional
scaling
Ordered by frequency
My text seriation method

Quantify Textual Content

London Riot 2012

Select a rumour to see how unsubstantiated claims are spread on Twitter before being confirmed or denied

Rioters attack London zoo and release animals

Rioters cook their own food in McDonald's

Police 'beat a 16-year-old girl'

London Eye set on fire

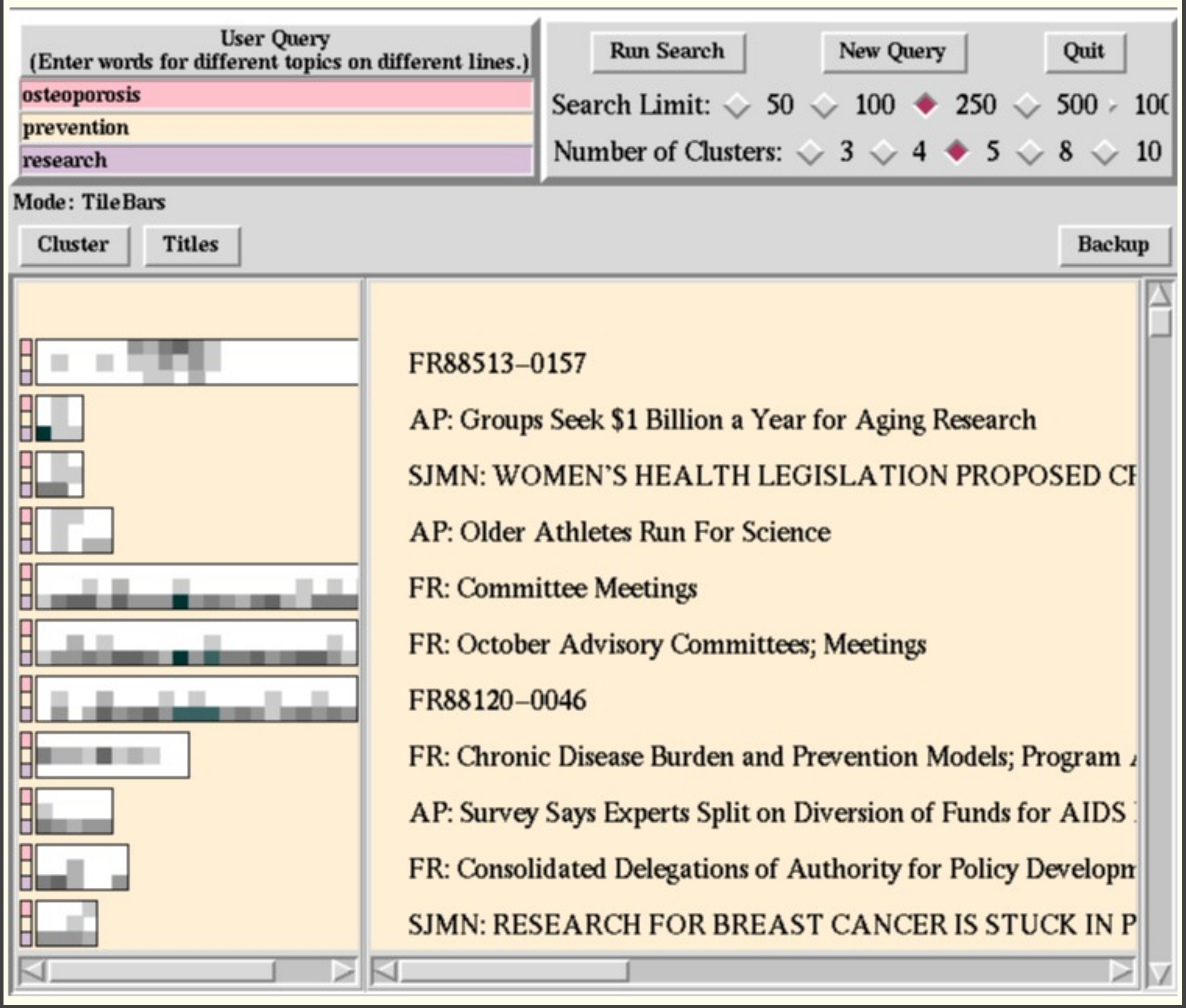
Rioters attack a children's hospital in Birmingham

Army deployed in Bank

Miss Selfridge set on fire

How riot rumors spread?

Our last challenge was to classify each tweet according to a 'common senseunderstanding' of its main role as a communicative act. Did it support, oppose, query or comment on a rumour? In addition to an algorithmic analysis by our academic partners, each tweet was independently coded by three sociology PhD students in order to enable us to check for reliability. All the results were then subject to final review for quality assurance purposes. These categories could then be used to colour code each tweet so that readers get an overall picture of what direction the dialogue is taking.

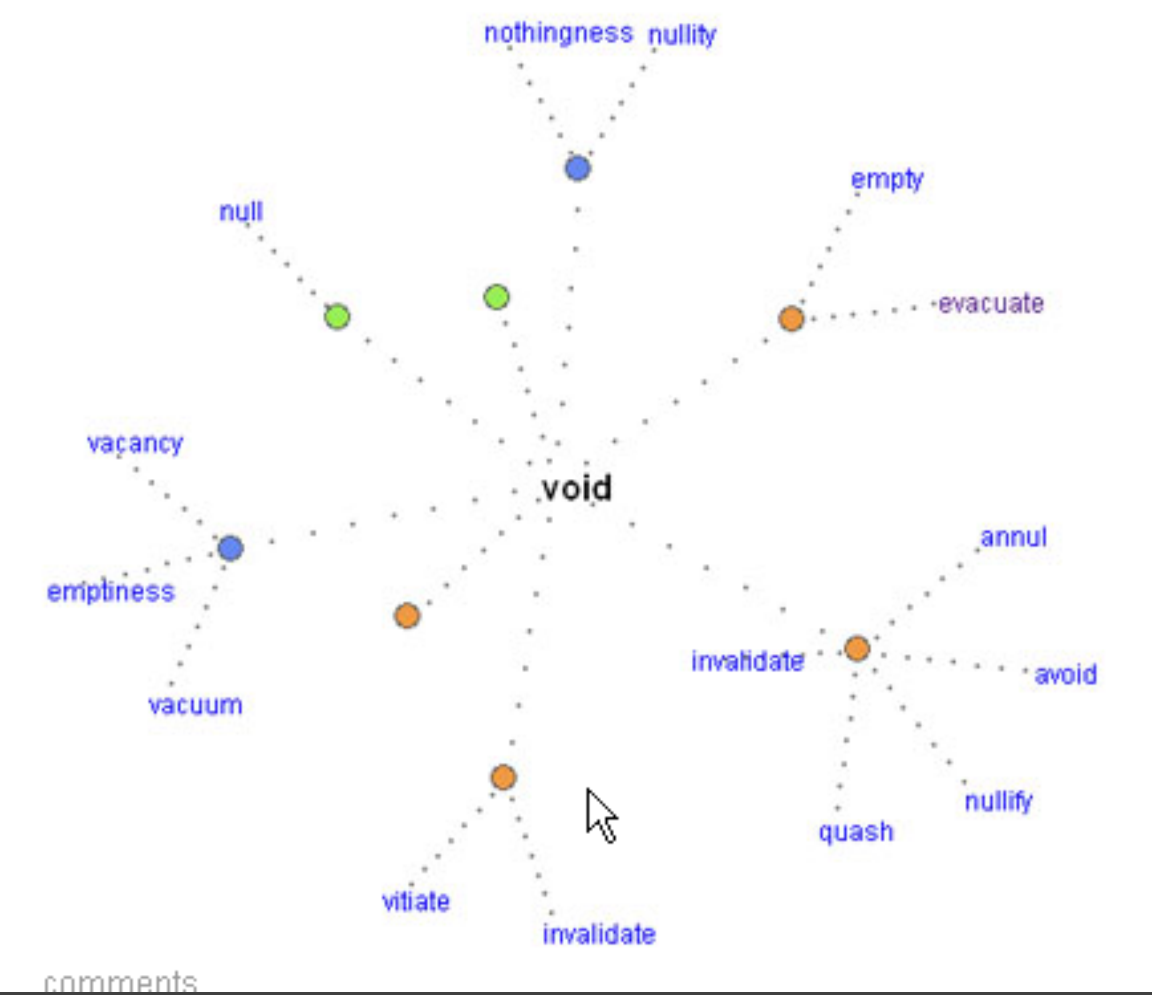


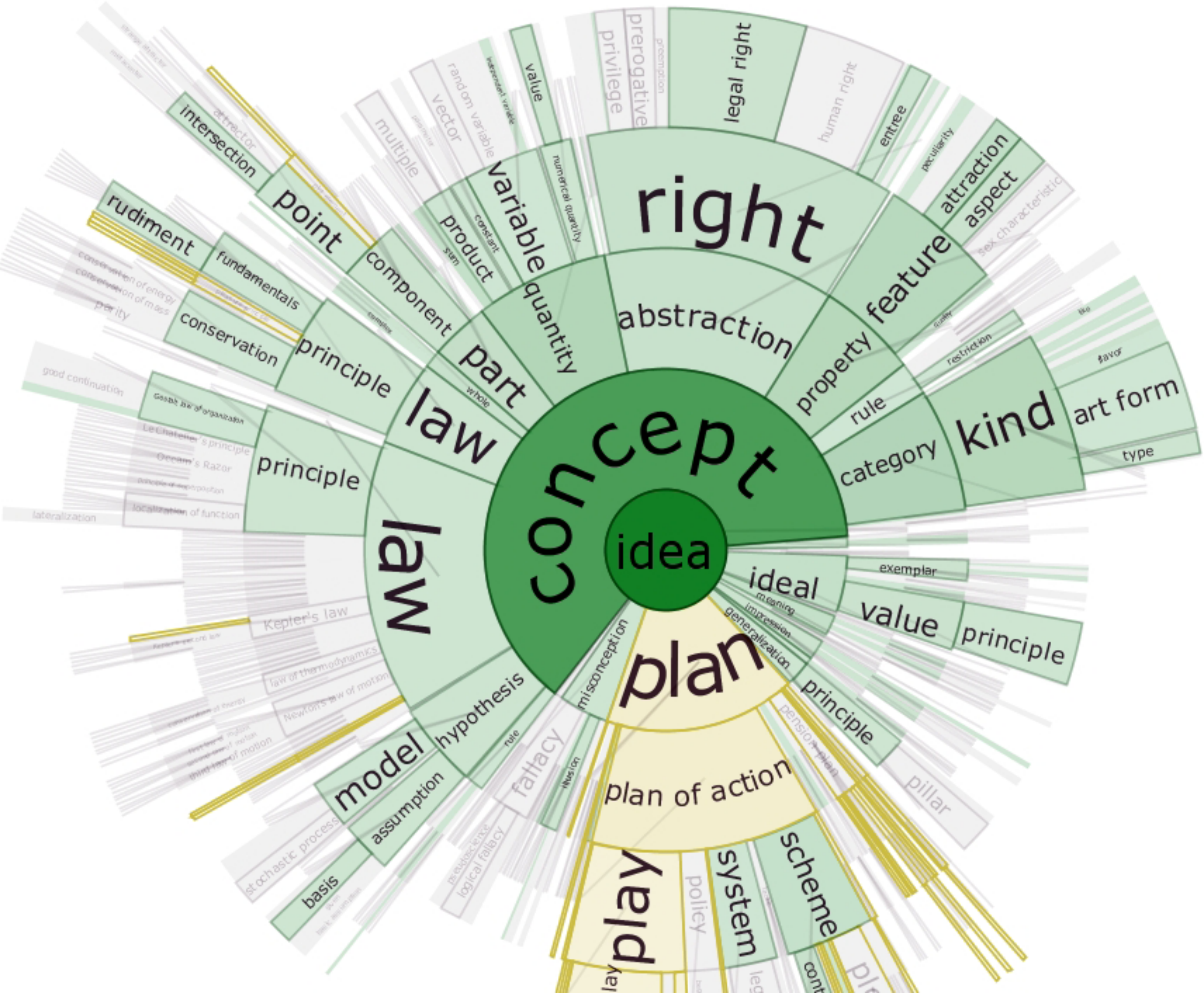
TileBars [Hearst]

LIWC: Linguistic Inquiry & Word Count

Psychological Processes				
Social processes	social	Mate, talk, they, child	455	
Family	family	Daughter, husband, aunt	64	.87
Friends	friend	Buddy, friend, neighbor	37	.70
Humans	human	Adult, baby, boy	61	
Affective processes	affect	Happy, cried, abandon	915	
Positive emotion	posemo	Love, nice, sweet	406	.41
Negative emotion	negemo	Hurt, ugly, nasty	499	.31
Anxiety	anx	Worried, fearful, nervous	91	.38
Anger	anger	Hate, kill, annoyed	184	.22
Sadness	sad	Crying, grief, sad	101	.07
Cognitive processes	cogmech	cause, know, ought	730	
Insight	insight	think, know, consider	195	
Causation	cause	because, effect, hence	108	.44

Visual Thesaurus [ThinkMap]




idea
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rule
legal right
human right
privilege
prerogative
variable
product
component
point
intersection
rudiment
fundamentals
conservation
model
assumption
basis
plan of action
play
policy
system
scheme
art form
type
attraction
aspect
entree
exemplar
fallacy
pillar
Kepler's law
stochastic process
multiple
vector
random variable
value

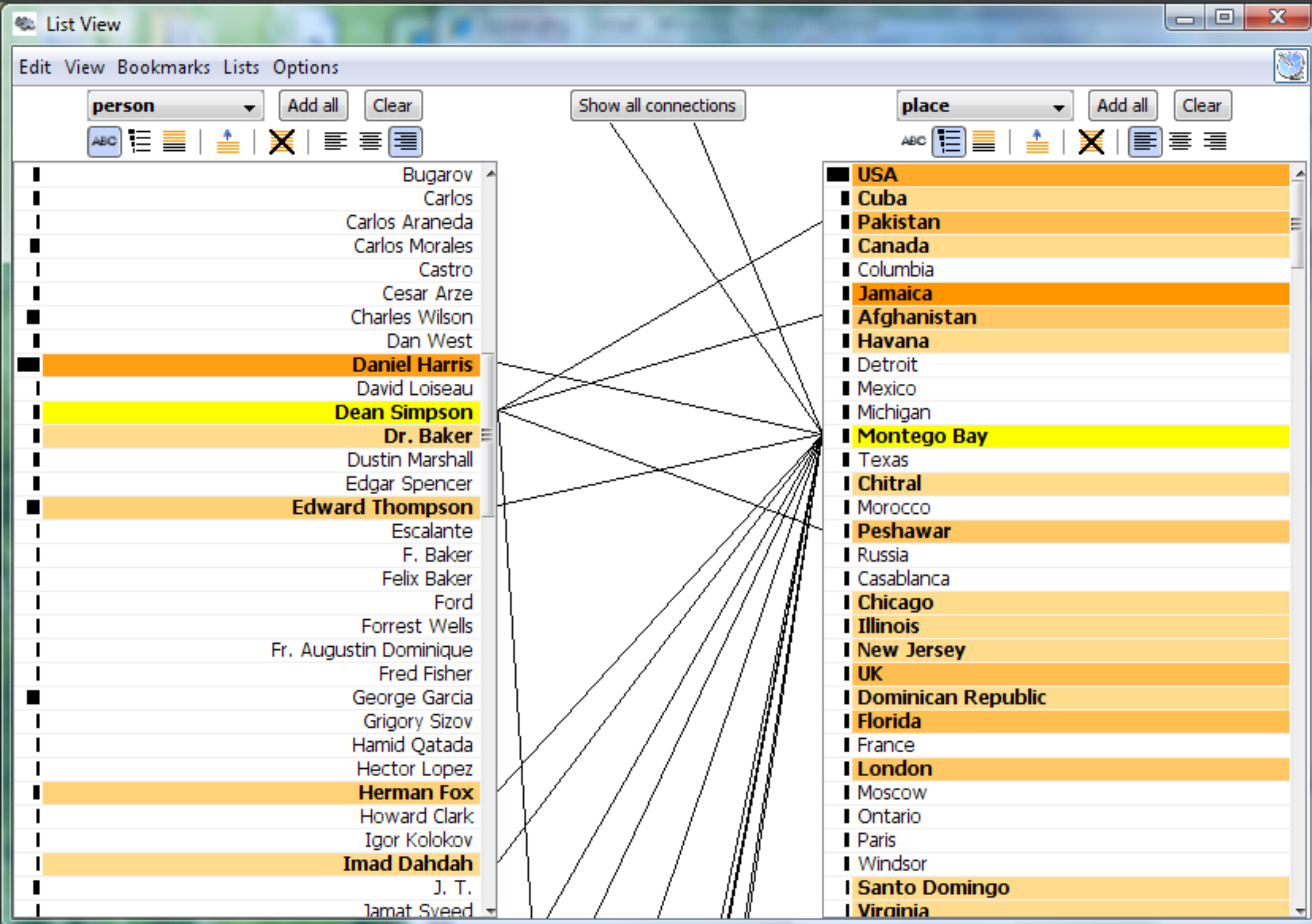
Named Entity Recognition

Identify and classify 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
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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
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Cuba
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Canada
Columbia
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Detroit
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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

Doc. Similarity & Clustering

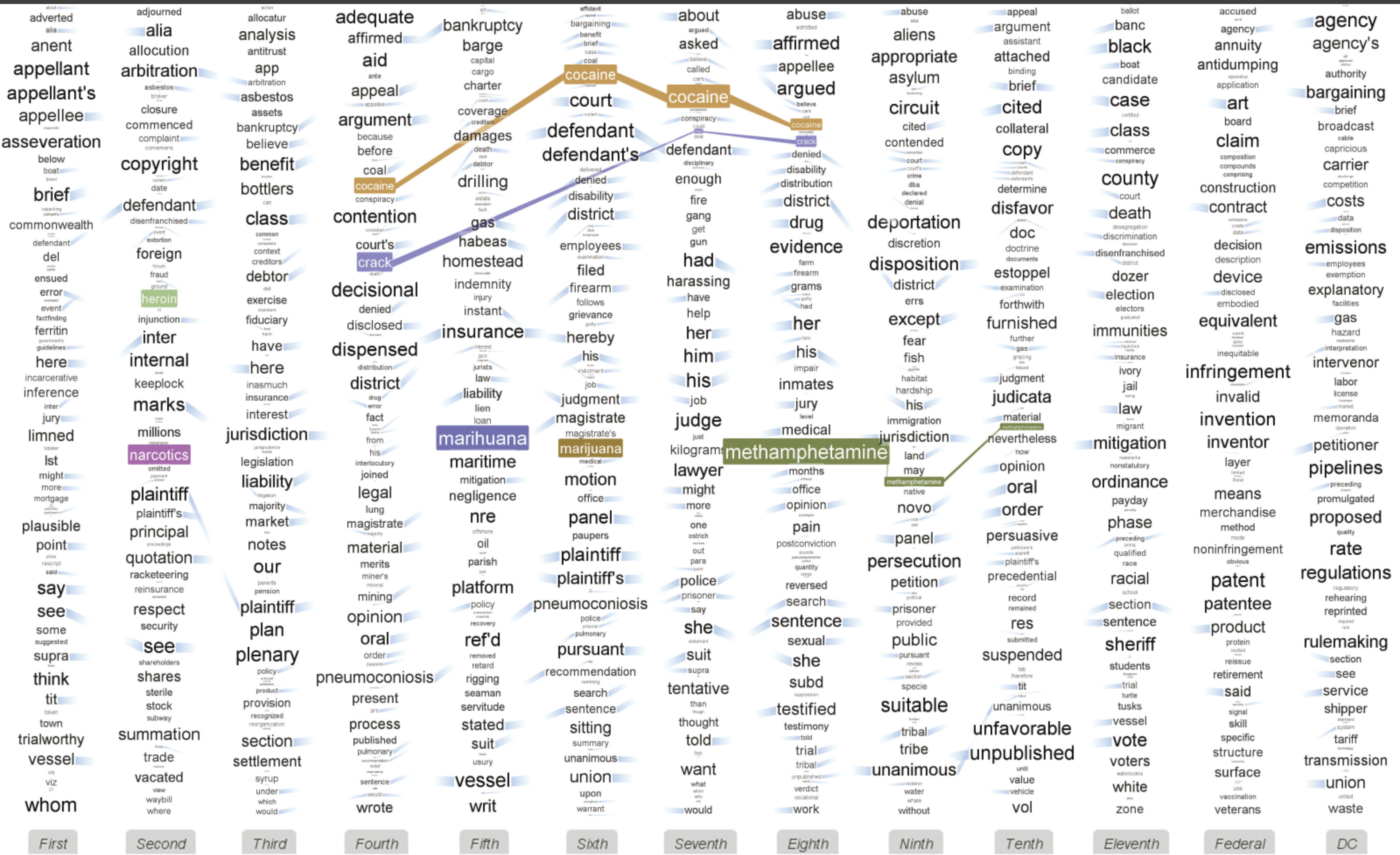
In vector model, compute distance among docs

- For TF.IDF, typically cosine distance
- Similarity measure can be used to cluster

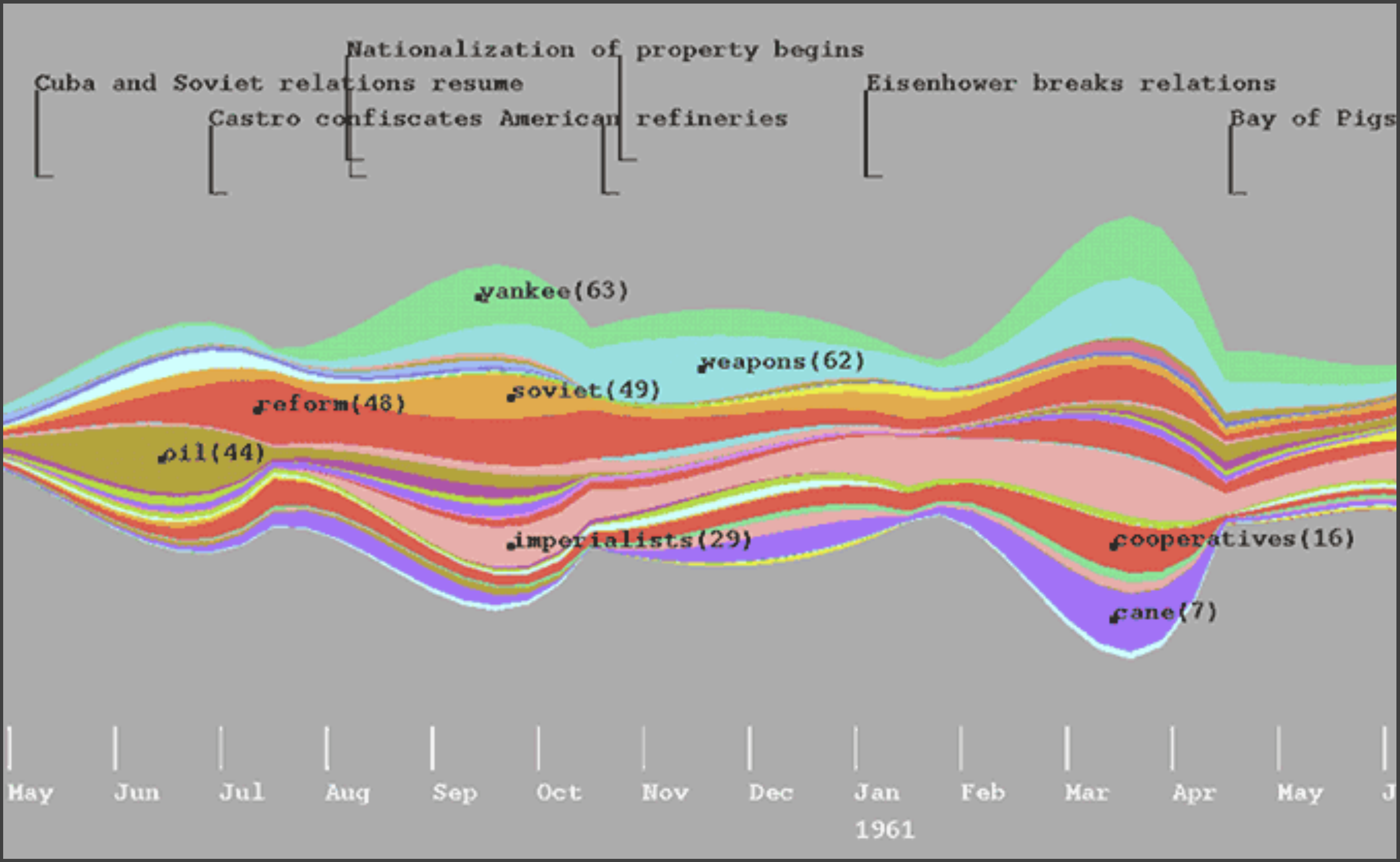
Topic modeling approaches

- 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

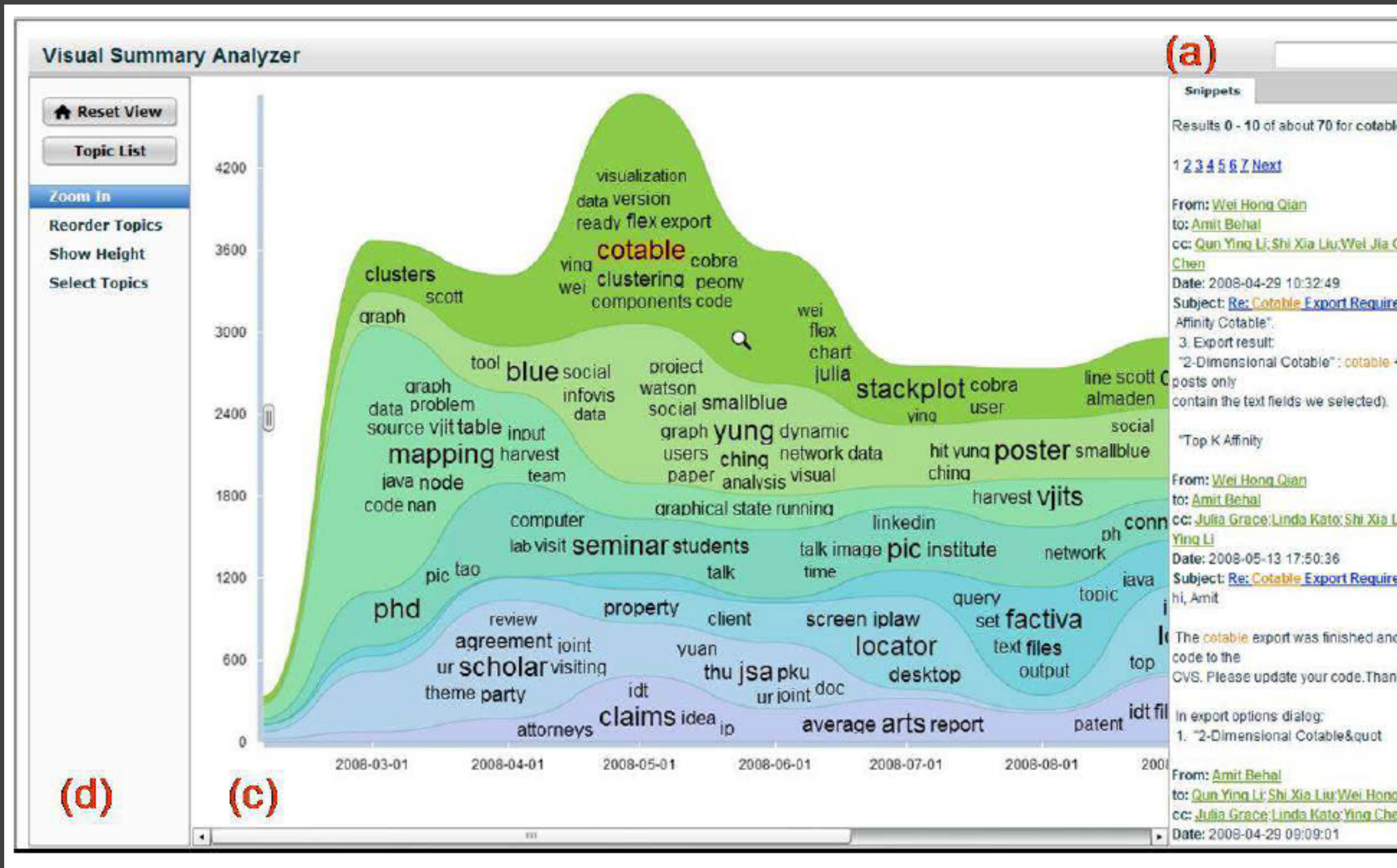
Parallel Tag Clouds [Collins et al 09]

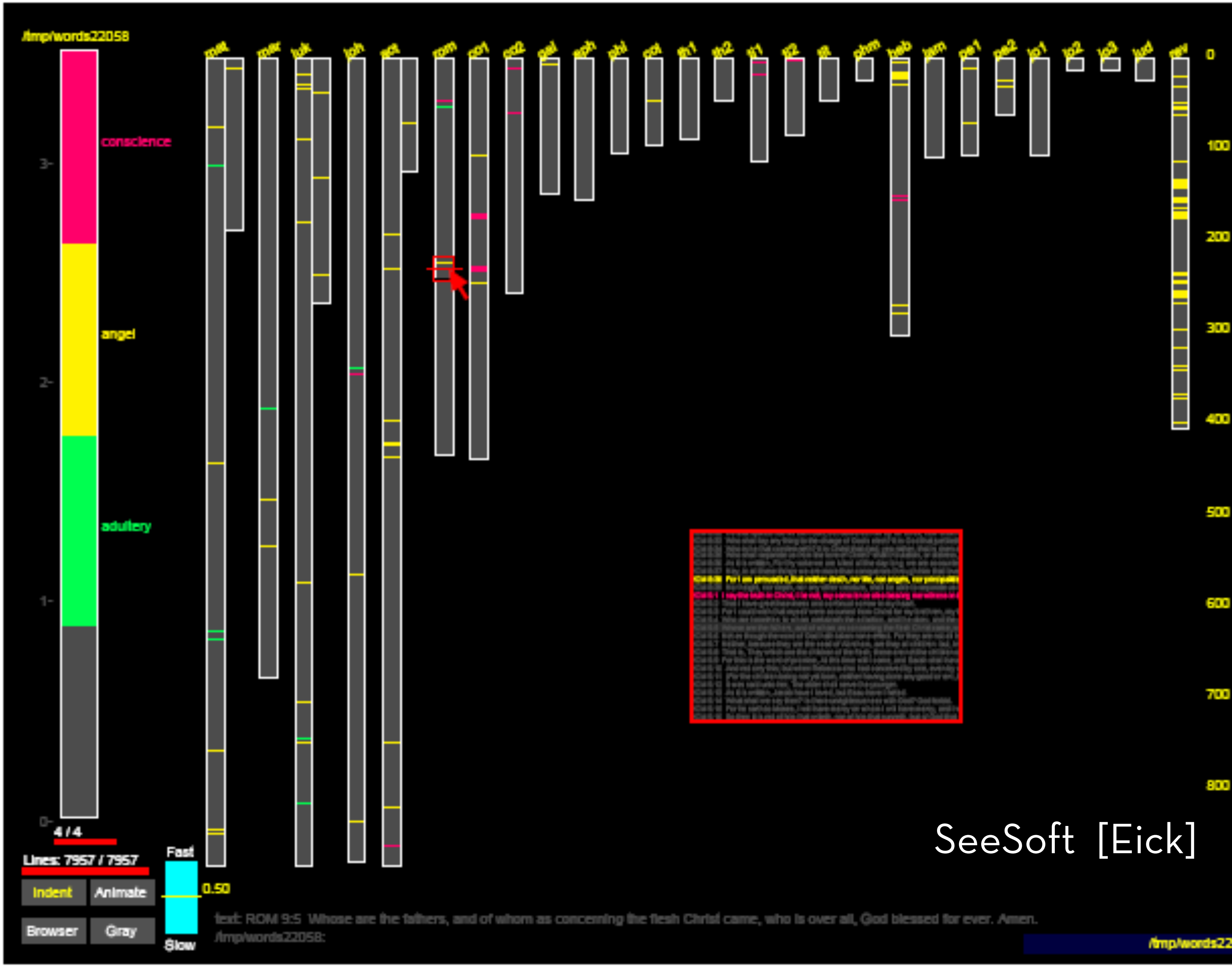


ThemeRiver [Havre et al 99]



TIARA [Wei et al. 09]





SeeSoft [Eick]

THE WORDS THAT WERE USED

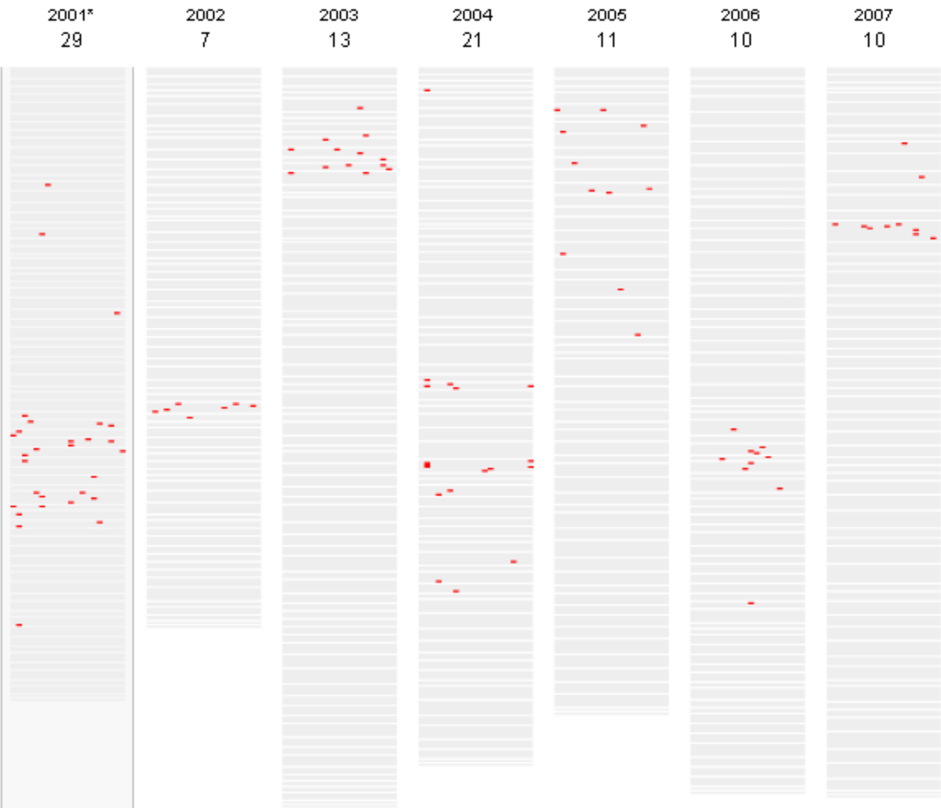
READ 2007 SPEECH | FEEDBACK

The 2007 State of the Union Address

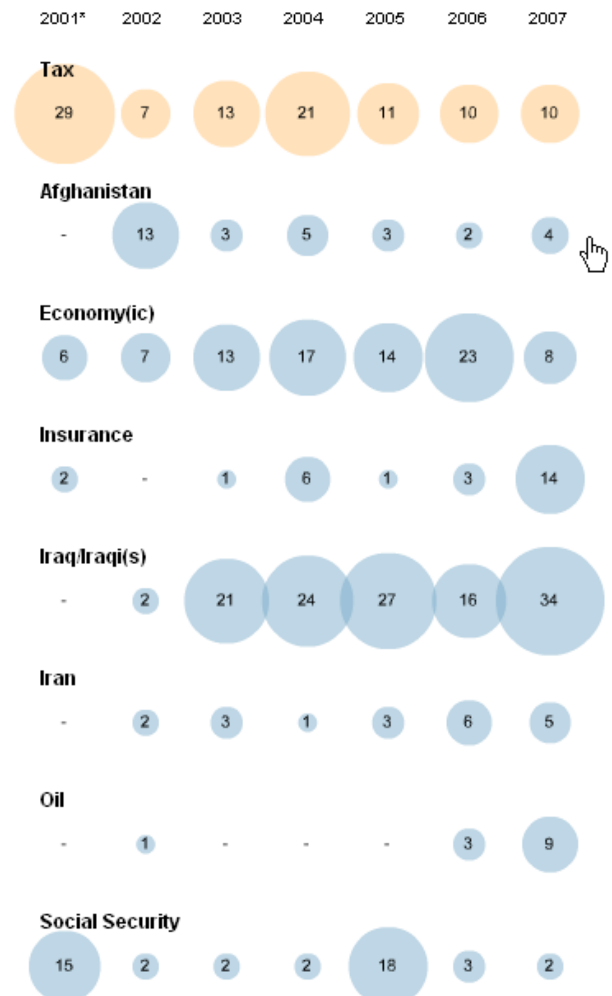
Over the years, President Bush's State of the Union address has averaged almost 5,000 words each, meaning the the President has delivered over 34,000 words. Some words appear frequently while others appear only sporadically. Use the tools below to analyze what Mr. Bush has said.

Search | or choose a word here.

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



Compared with other words



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)

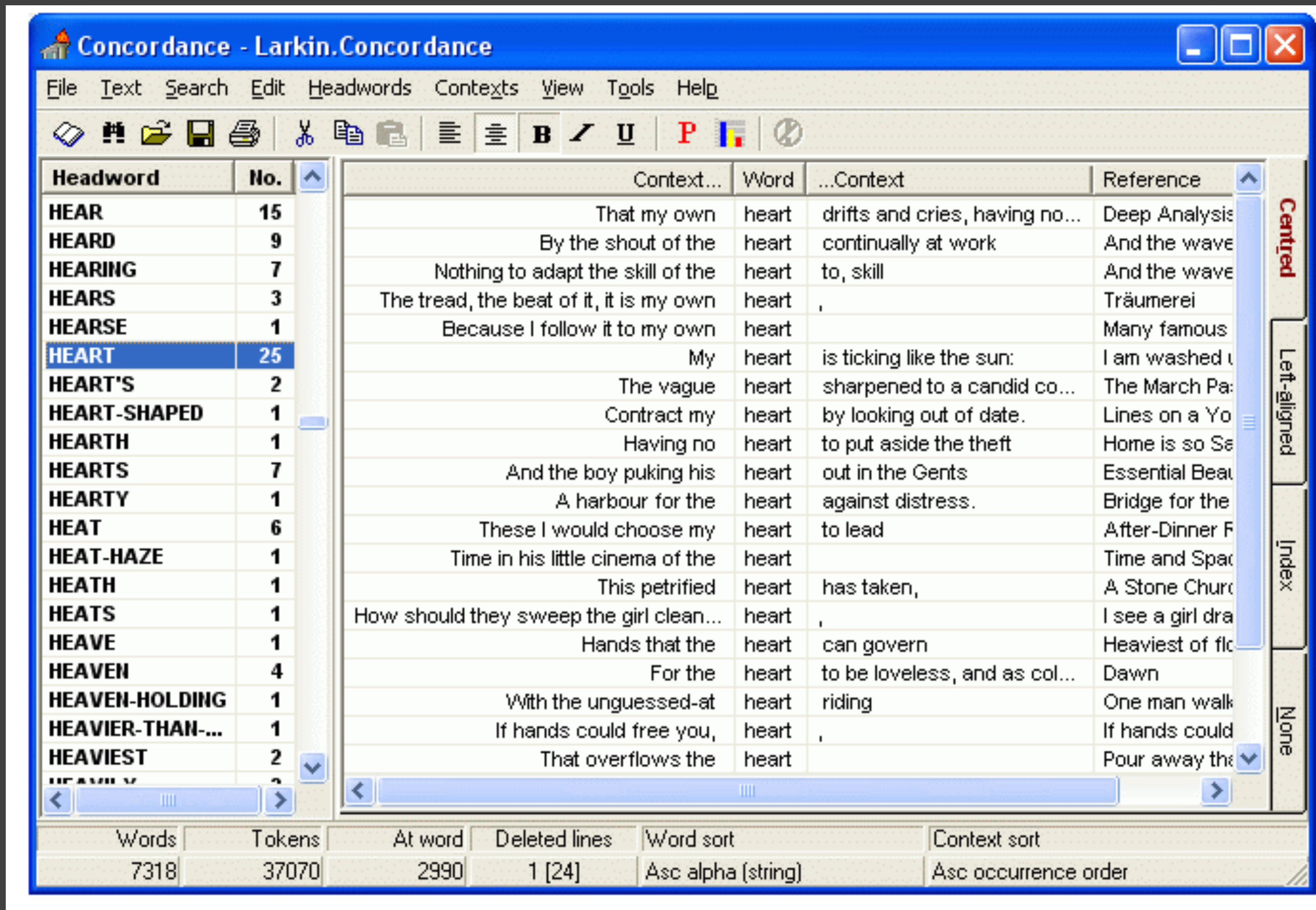
* As a newly elected president, Mr. Bush did not deliver a formal State of the Union address in 2001. His Feb. 27 speech to a joint session of Congress was analogous to the State of the Union, but without the title.

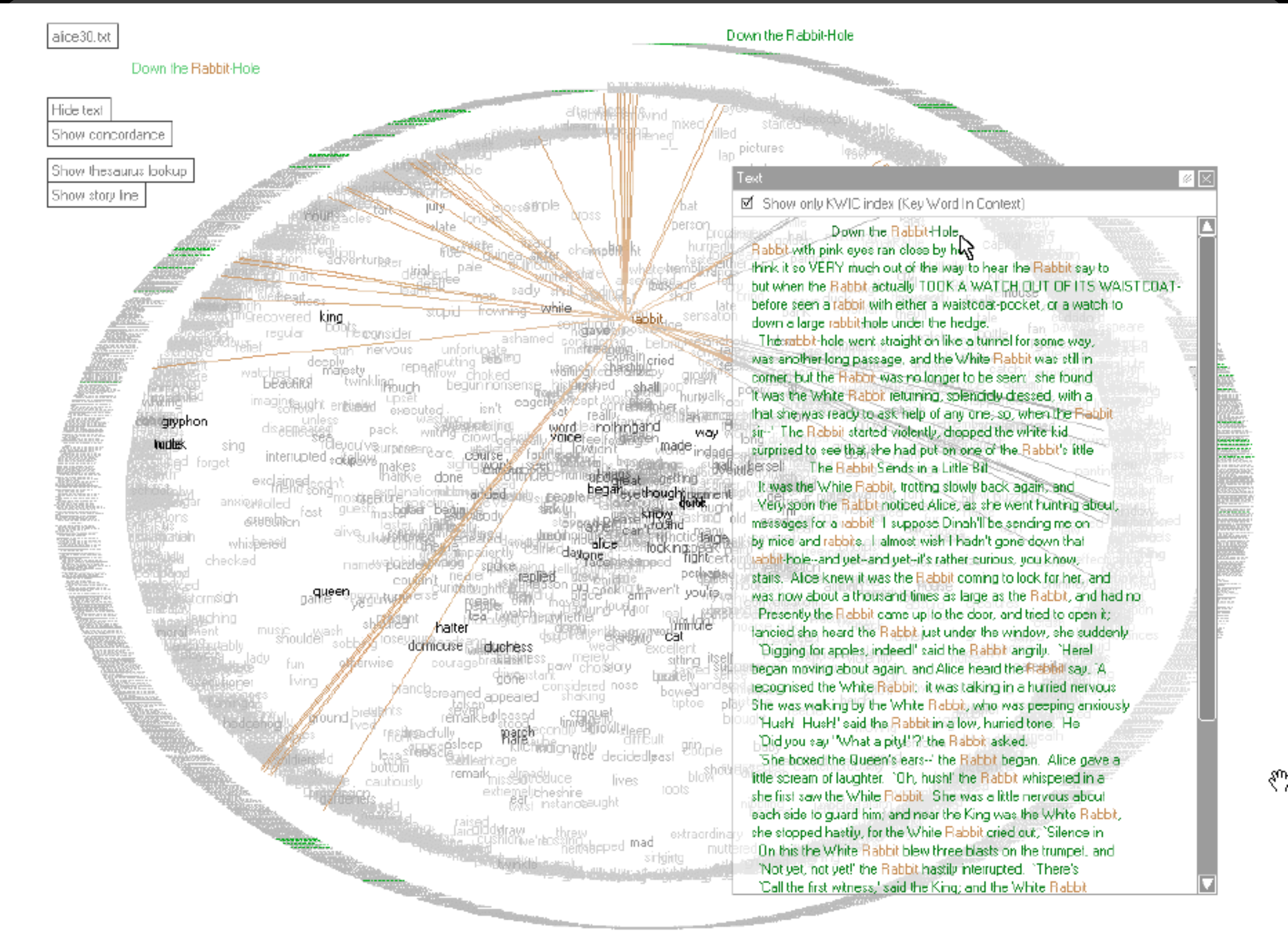
Ben Werschkul/The New York Times

New York Times

Concordance

What is the common local context of a term?

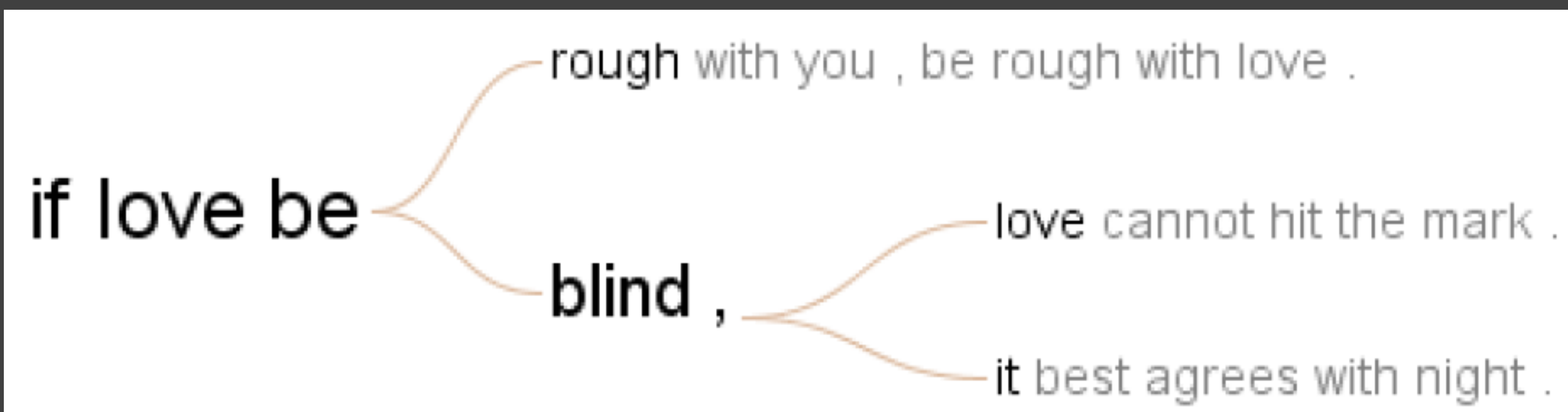



alice30.txt
Down the Rabbit-Hole
Hide text
Show concordance
Show thesaurus lookup
Show story line
Down the Rabbit-Hole
Text
Show only KWIC index (Key Word In Context)
Down the Rabbit-Hole
Rabbit with pink eyes ran close by her
think it so VERY much out of the way to hear the Rabbit say to
but when the 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
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 .

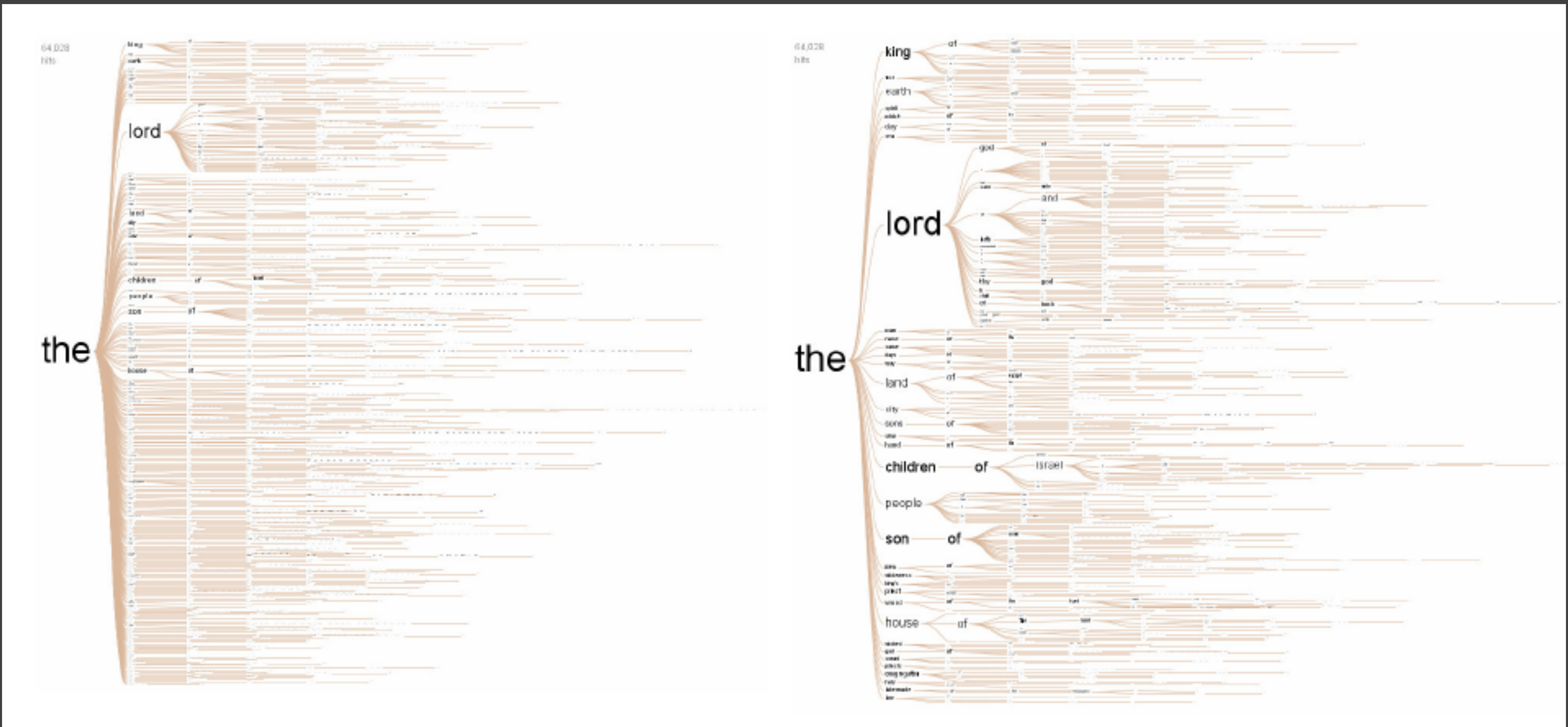
if love be blind , love cannot hit the mark .

if love be blind , it best agrees with night .

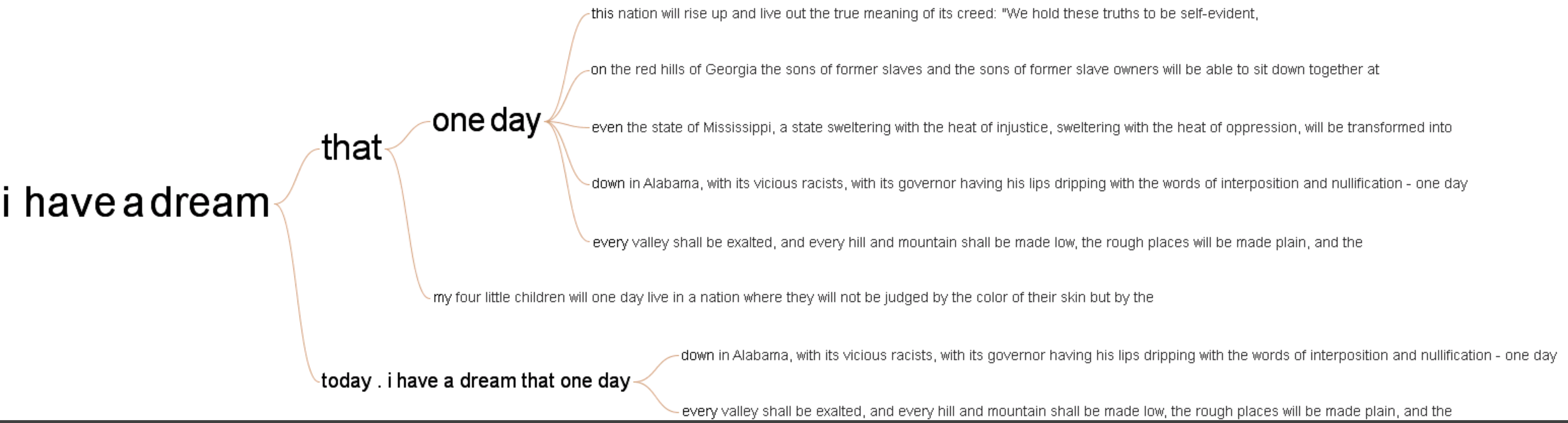


WordTree (Wattenberg et al)

Filter infrequent runs



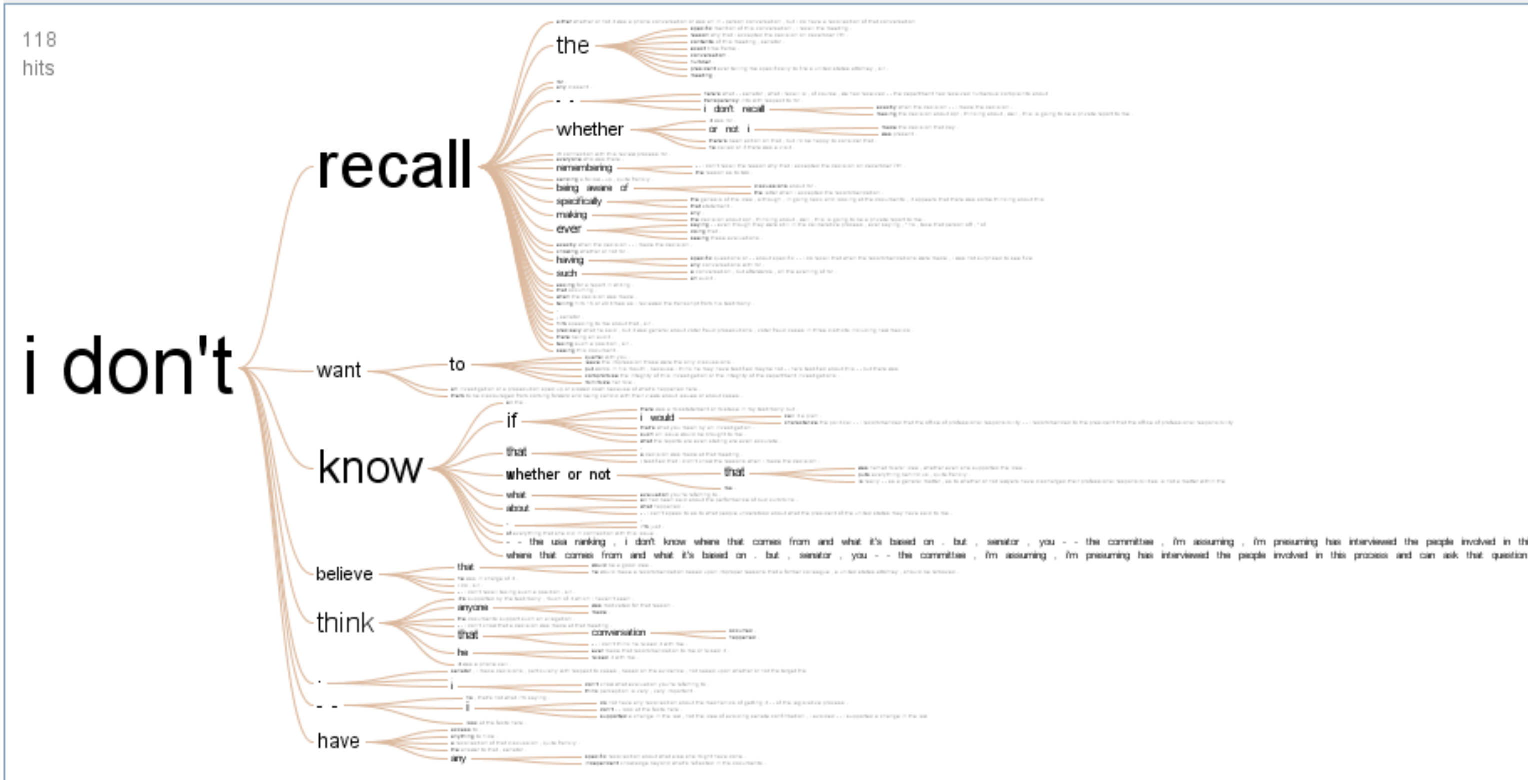
Recurrent themes in speech



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

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data sets
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data format & style
about Many Eyes
FAQ
blog

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contact
report a bug

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terms of use

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

Endings and Job Progressions

- Word Transition Probability

Glimpses of structure

Concordances show local, repeated structure
But what about other types of patterns?

For example

Lexical: <A> at <B>

Syntactic: <Noun> <Verb> <Object>

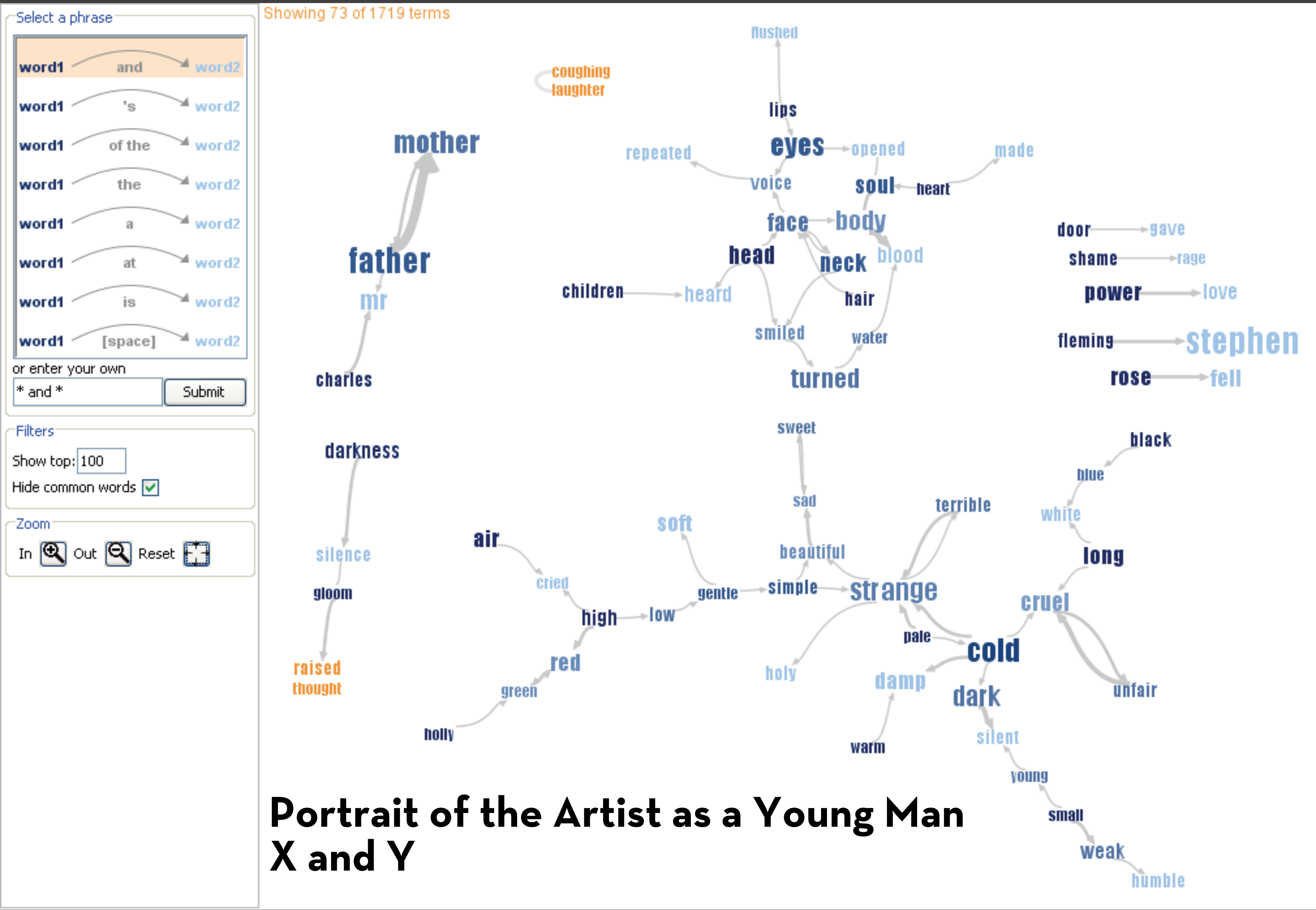
Phrase Nets [van Ham et al 2009]

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.

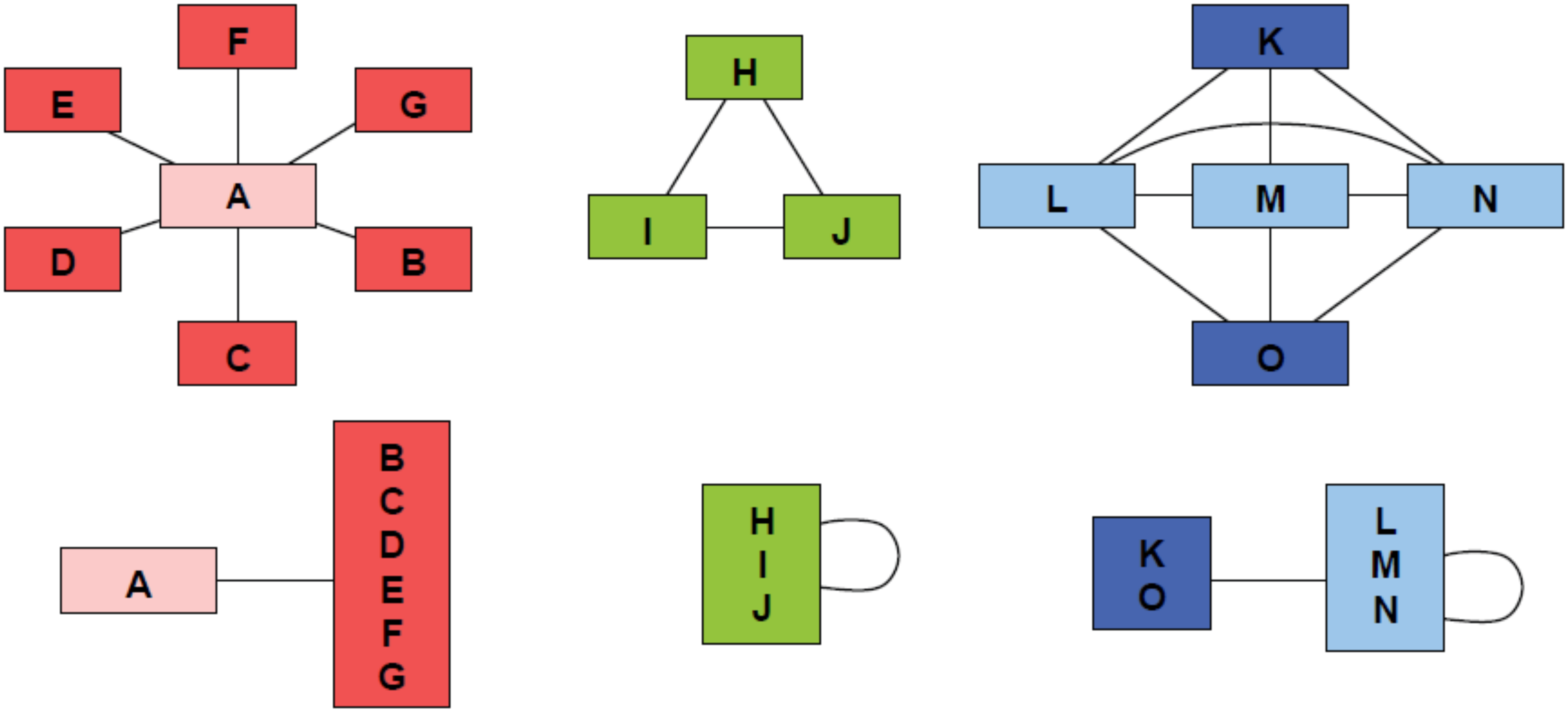
Visualize extracted patterns in a node-link view

- Occurrences → Node size
- Pattern position → Edge direction



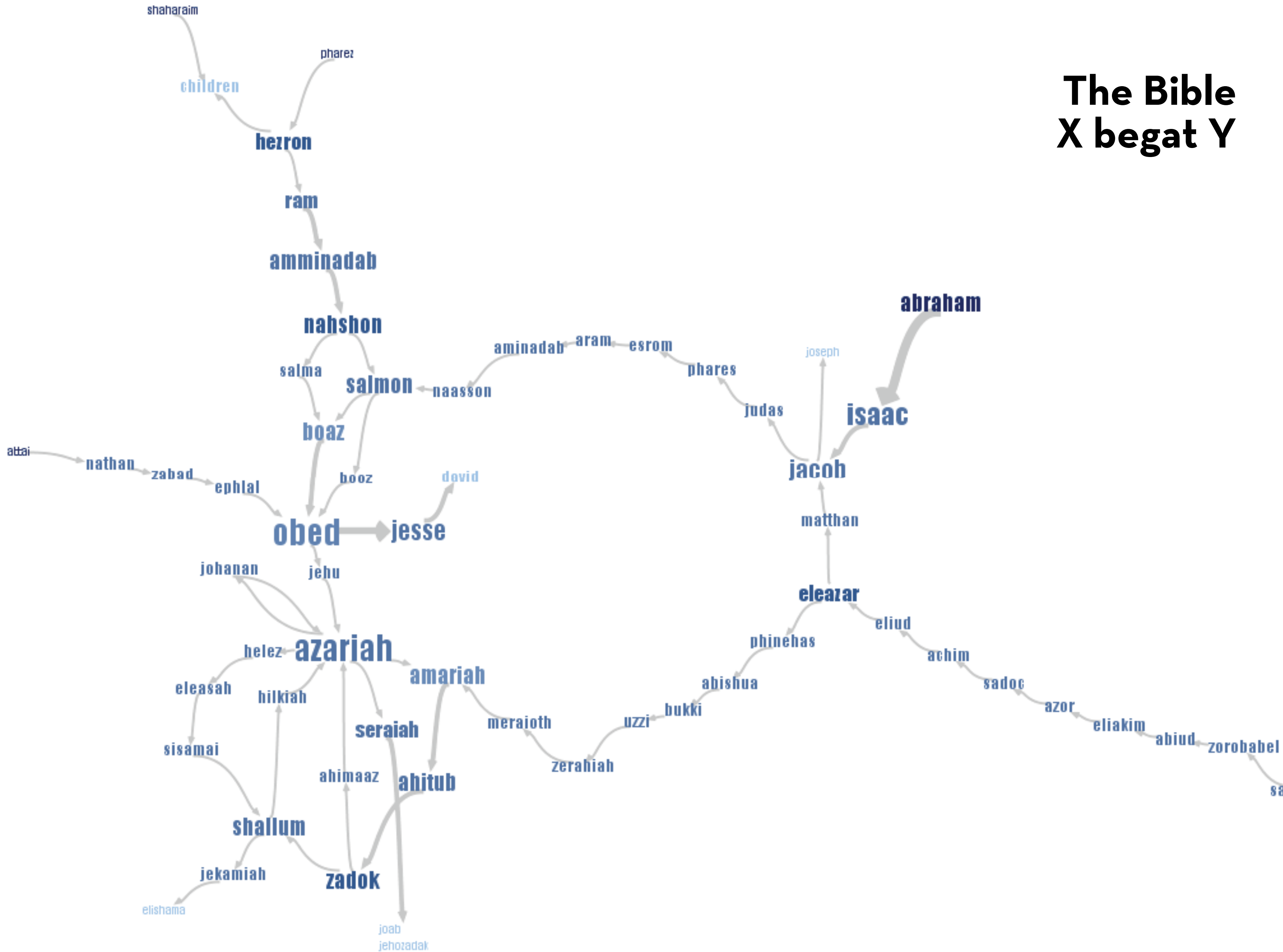
Portrait of the Artist as a Young Man
X and Y

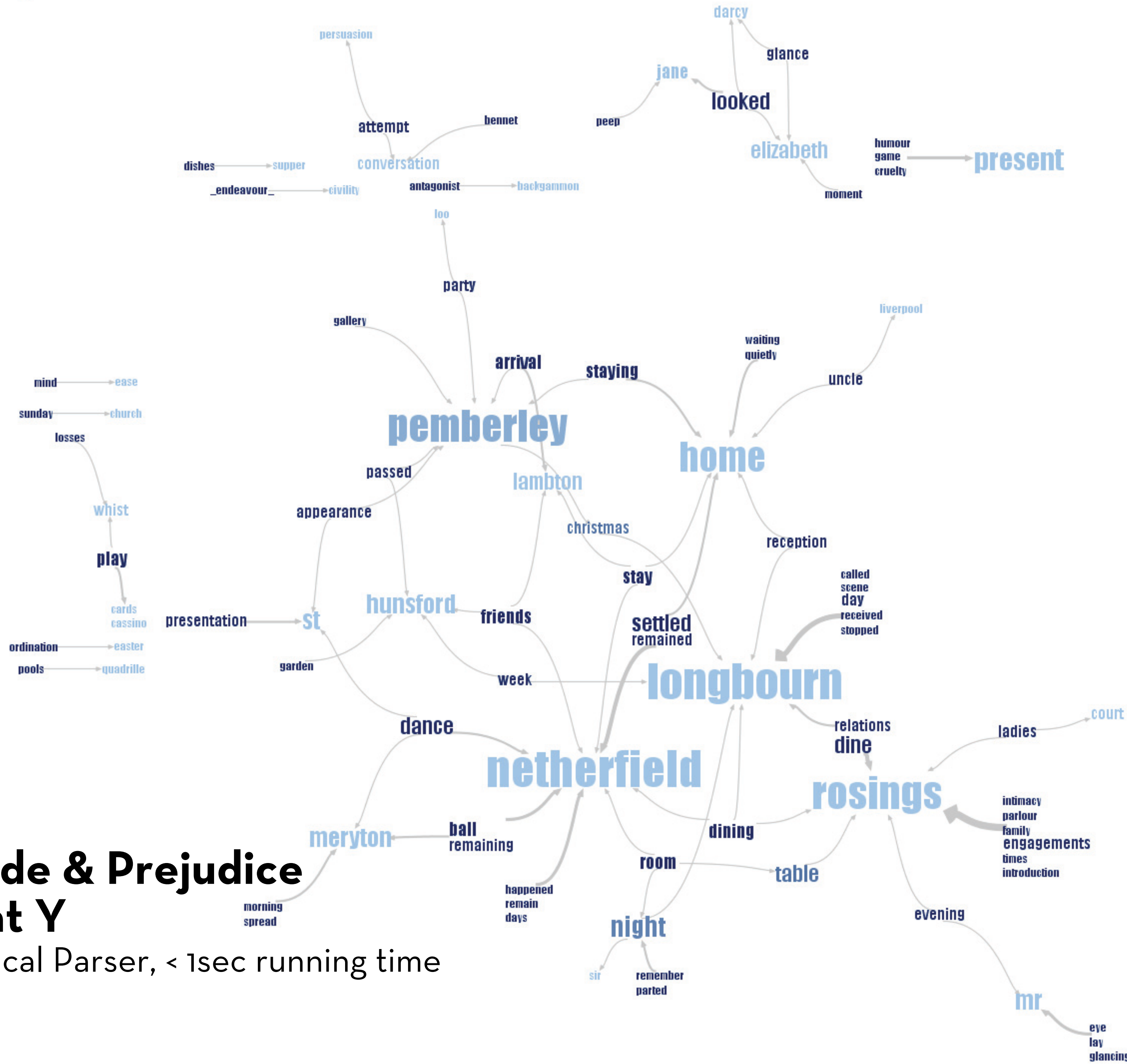
Node Grouping



(a) (b) (c)

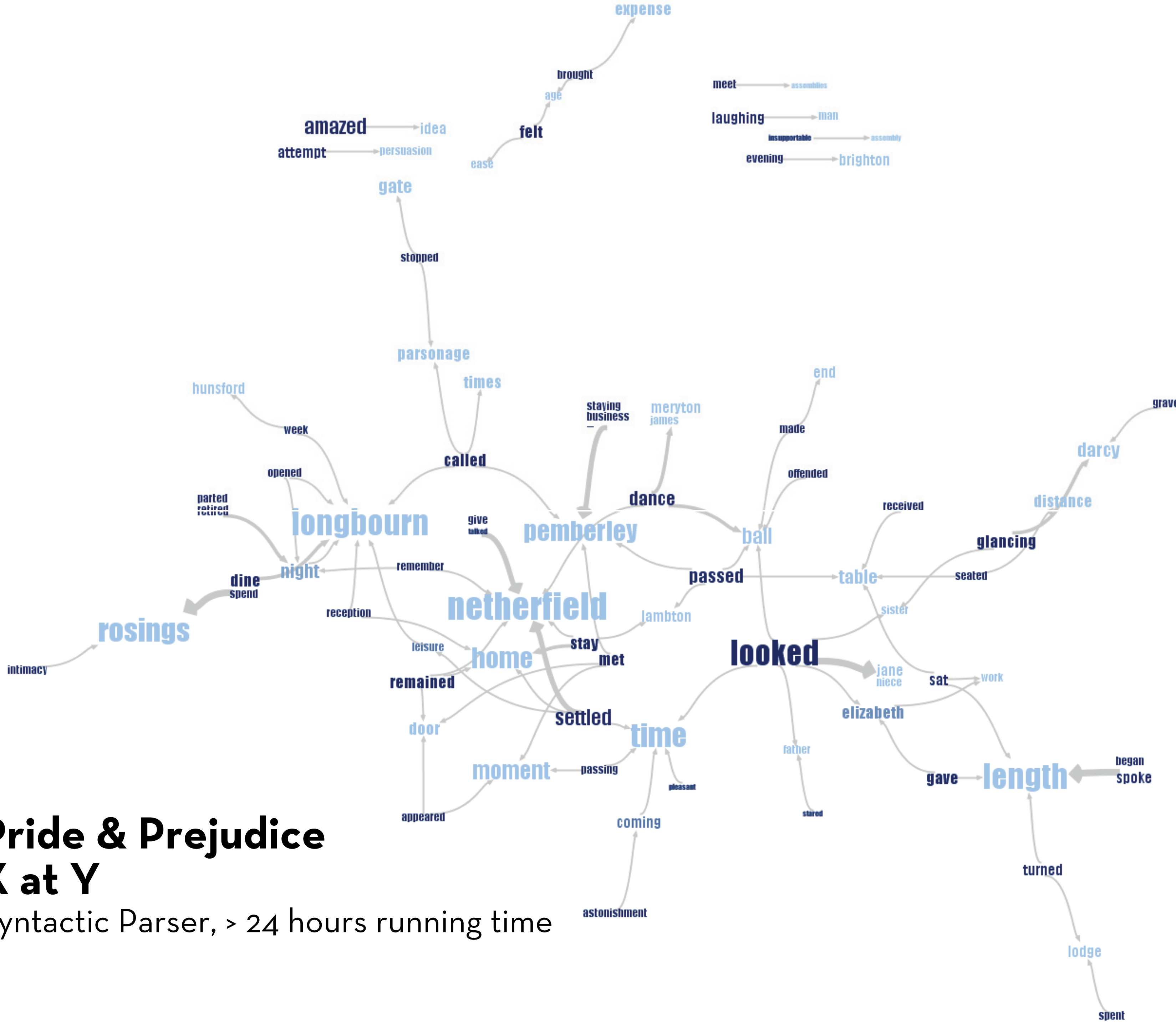
The Bible
X begat Y





Pride & Prejudice
X at Y

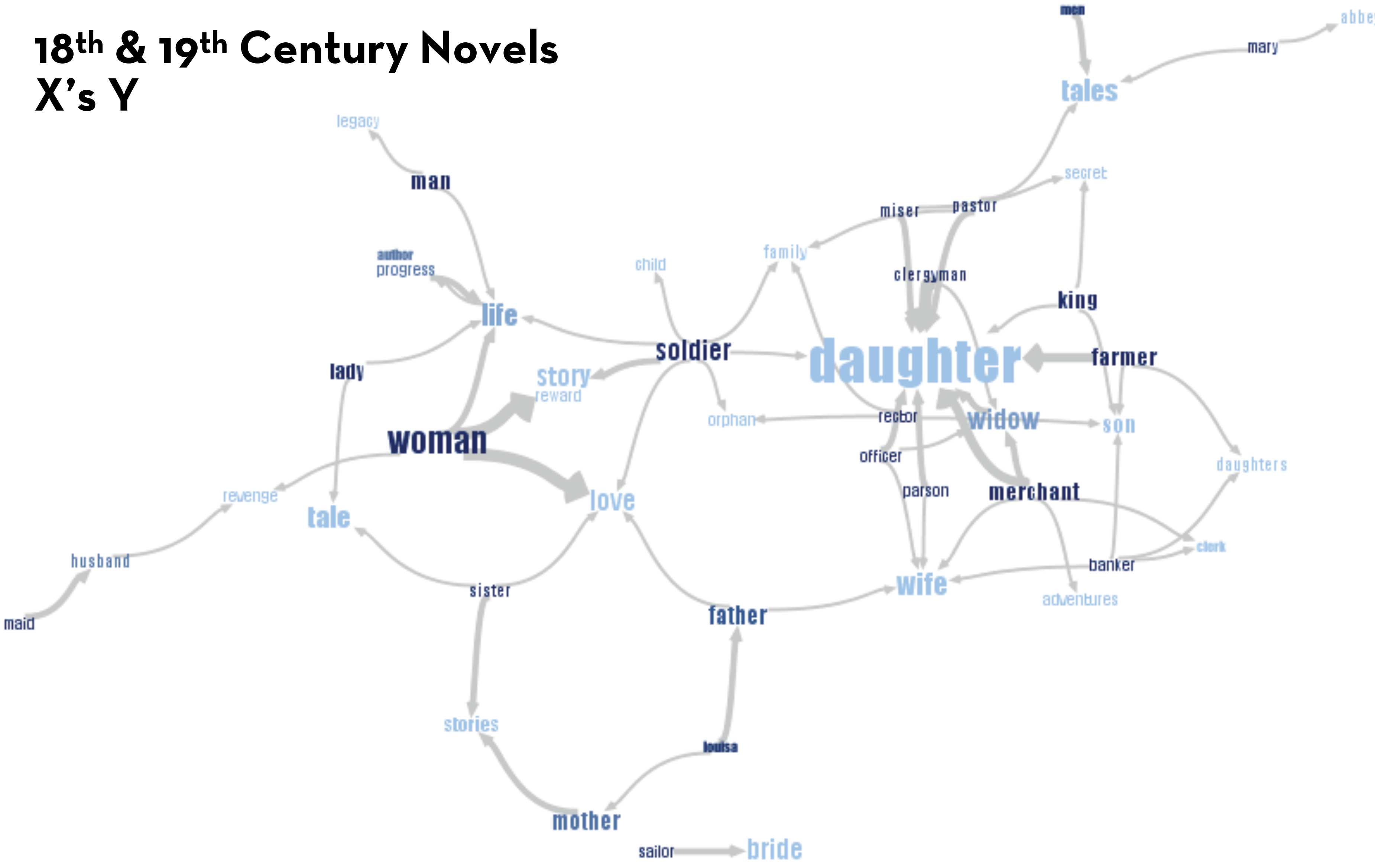
Lexical Parser, < 1sec running time



Pride & Prejudice
X at Y

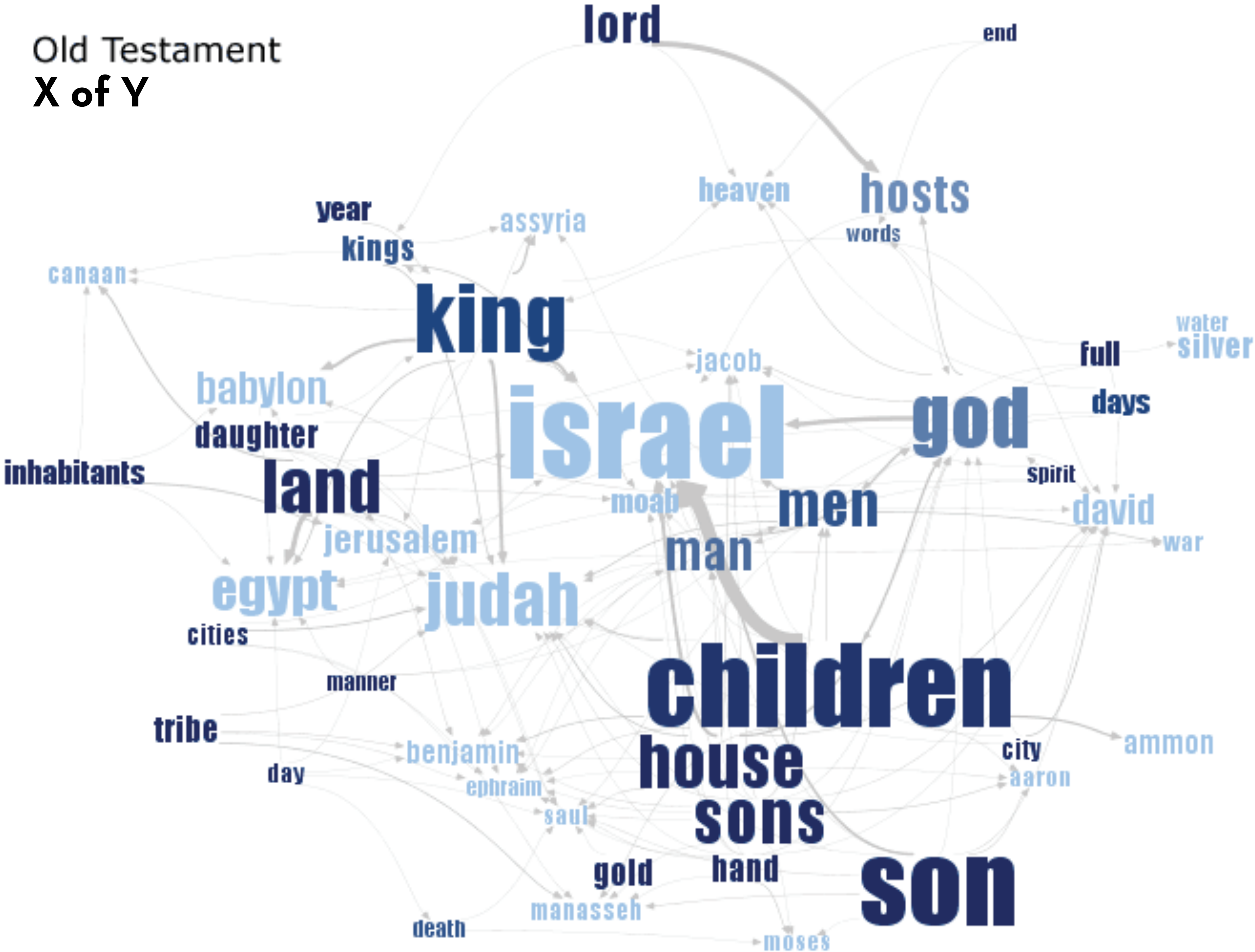
Syntactic Parser, > 24 hours running time

18th & 19th Century Novels
X's Y



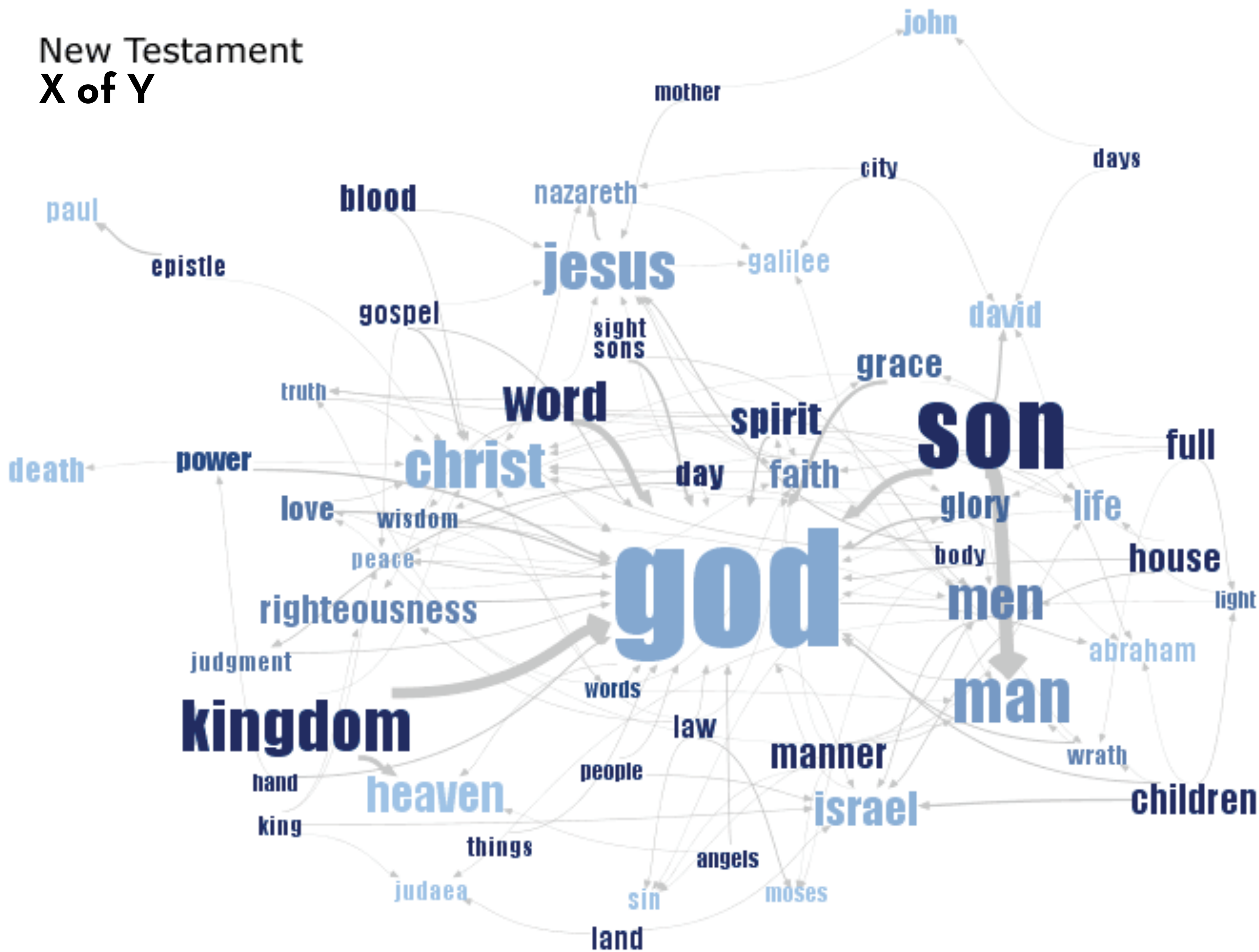
Old Testament

X of Y



New Testament

X of Y



Text Visualization 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

Determine your **analysis task**.

Understand abstraction of your **language models**.

Match analysis task with appropriate tools and models.

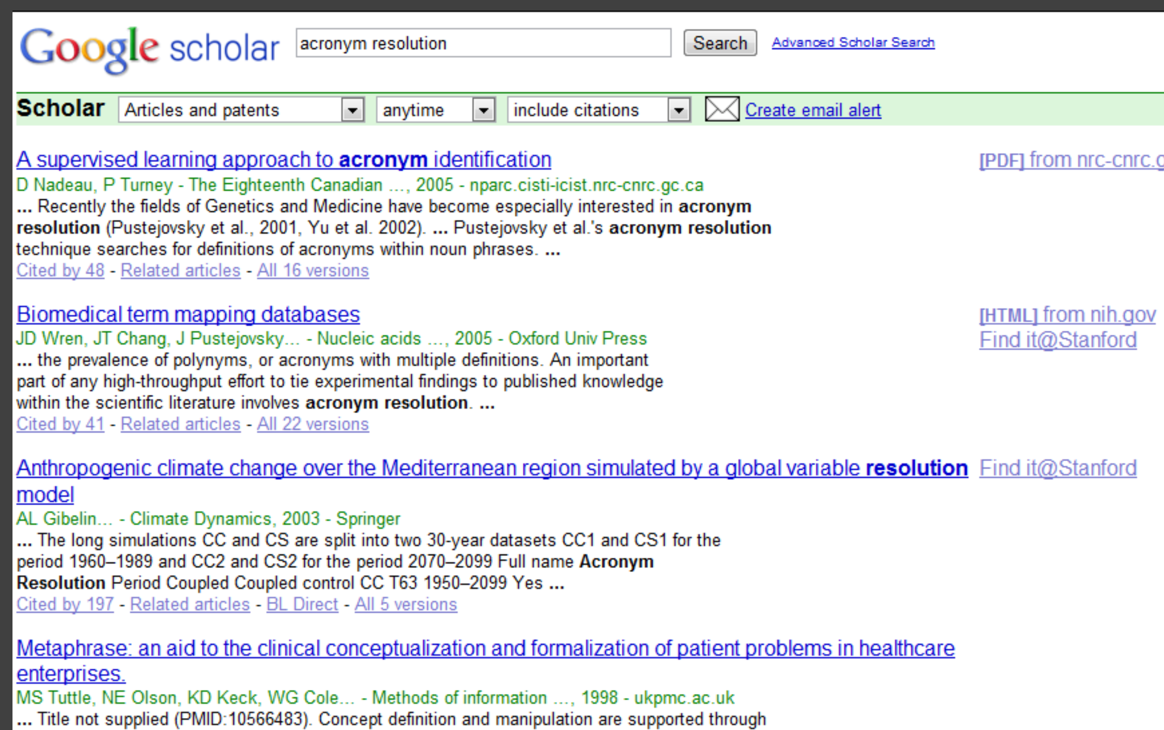
Perform Text Analysis

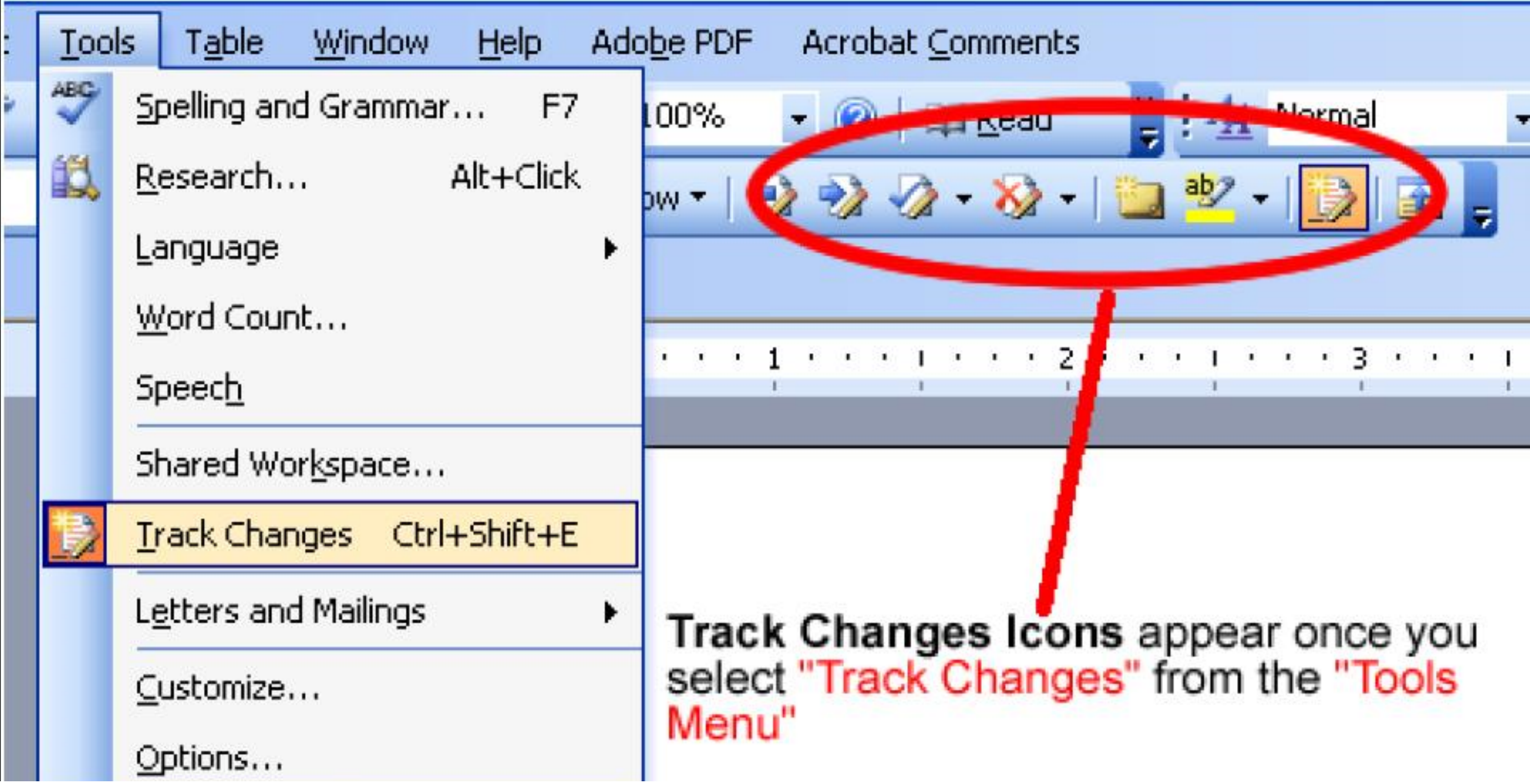
Information Retrieval

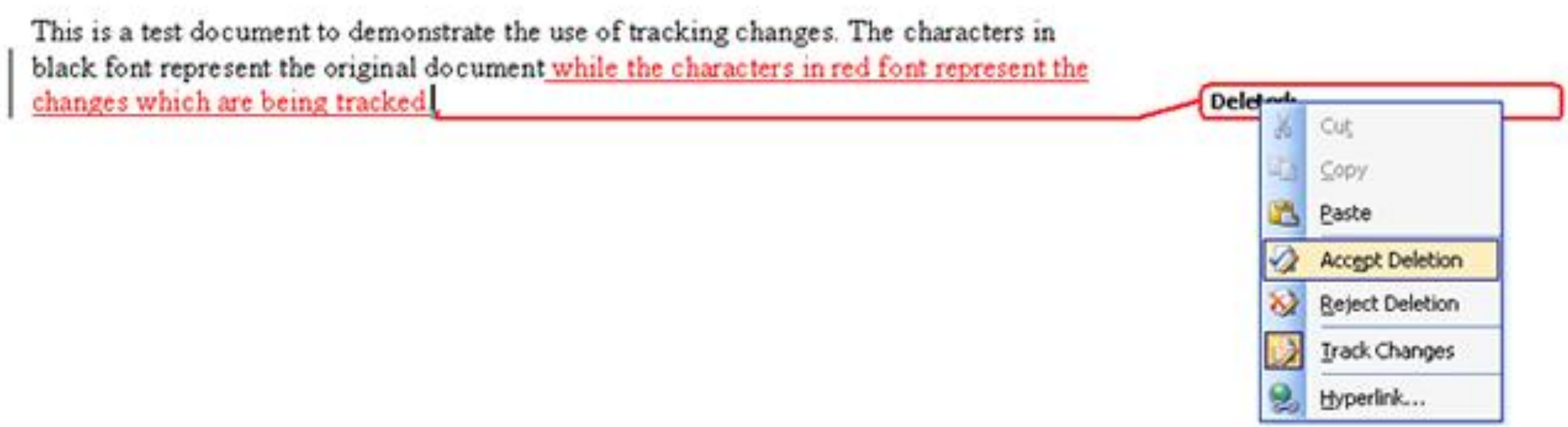
Search for documents

- Match query string with documents

Contextualized search




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

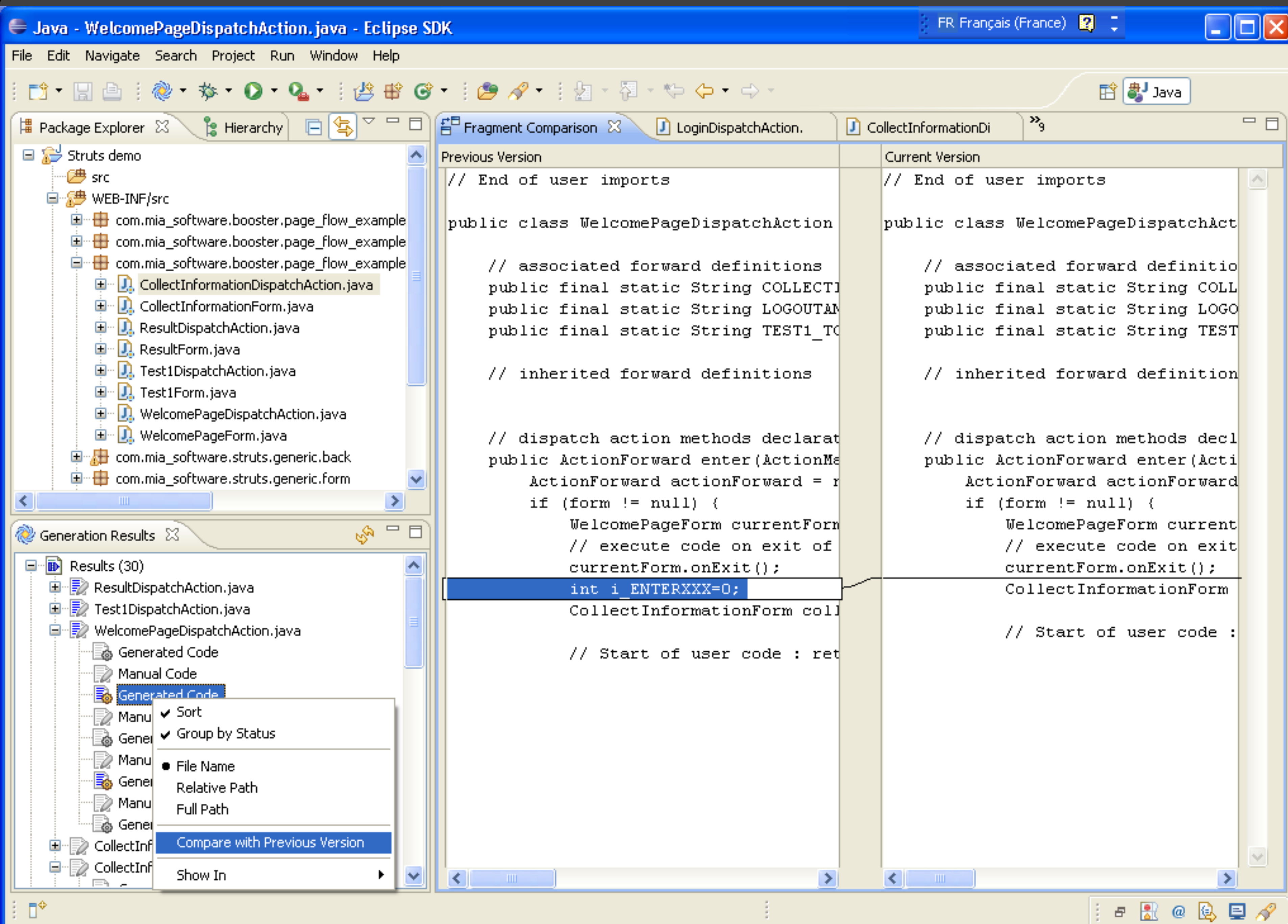
Revision history

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 LOGOUTAI
public final static String TEST1_TC
// inherited forward definitions
// dispatch action methods declarat
public ActionForward enter(ActionMa
ActionForward actionForward = r
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

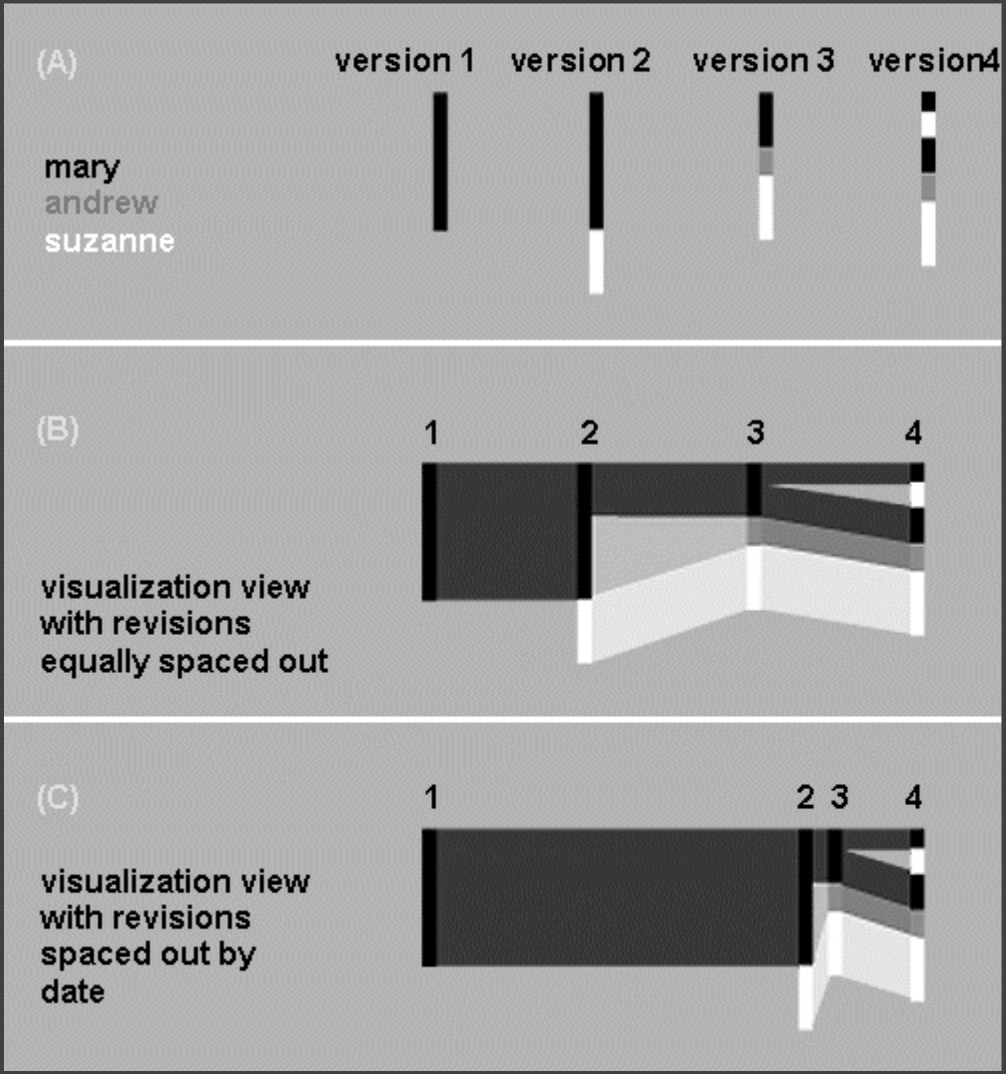
Files Changed:

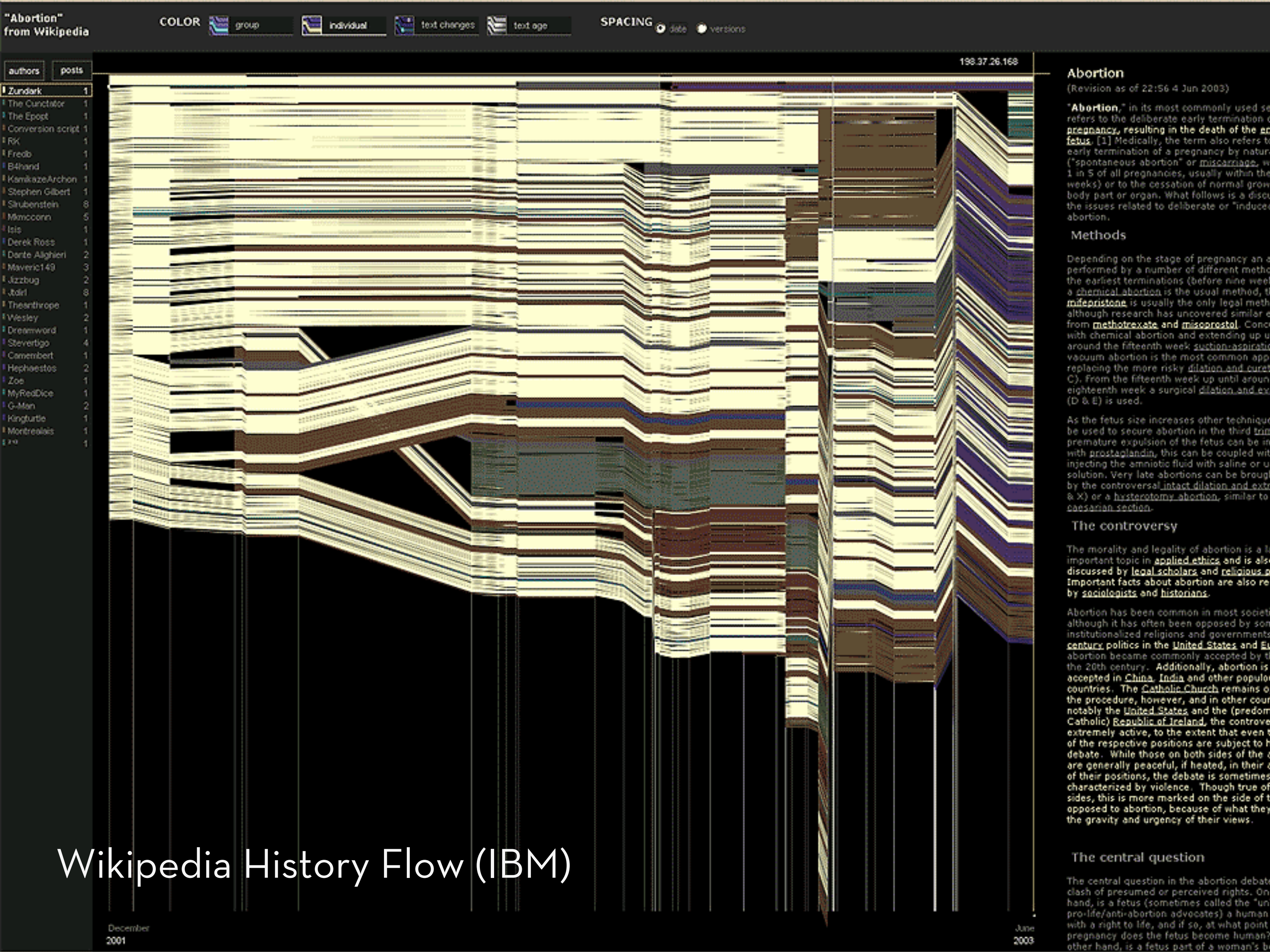
1. sshconsole.js: 1 change [1]

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

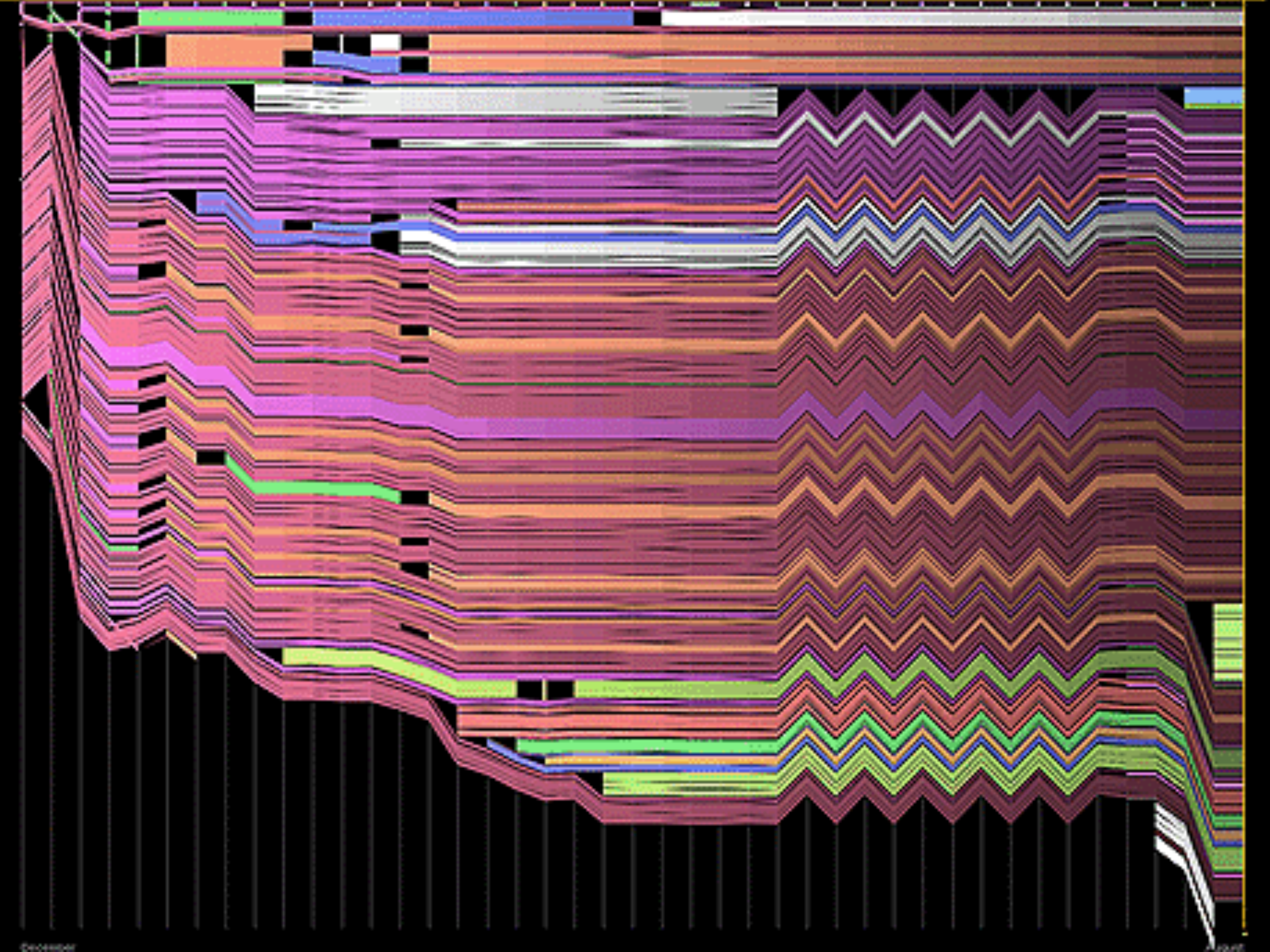
...	50 lines hidden [Expand]		
51	`_term = new VT100(80, 24, "term");`	51	`_term = new VT100(80, 24, "term");`
52	`//_term.debug_ = 1;`	52	`//_term.debug_ = 1;`
53	`_term.curs_set(true, true, _term_box_element);`	53	`_term.curs_set(true, true, _term_box_element);`
54	`_term.noecho();`	54	`_term.noecho();`
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 (Viégas et al)





Wikipedia History Flow (IBM)


December
August

Visualizing Conversation

Many dimensions to consider:

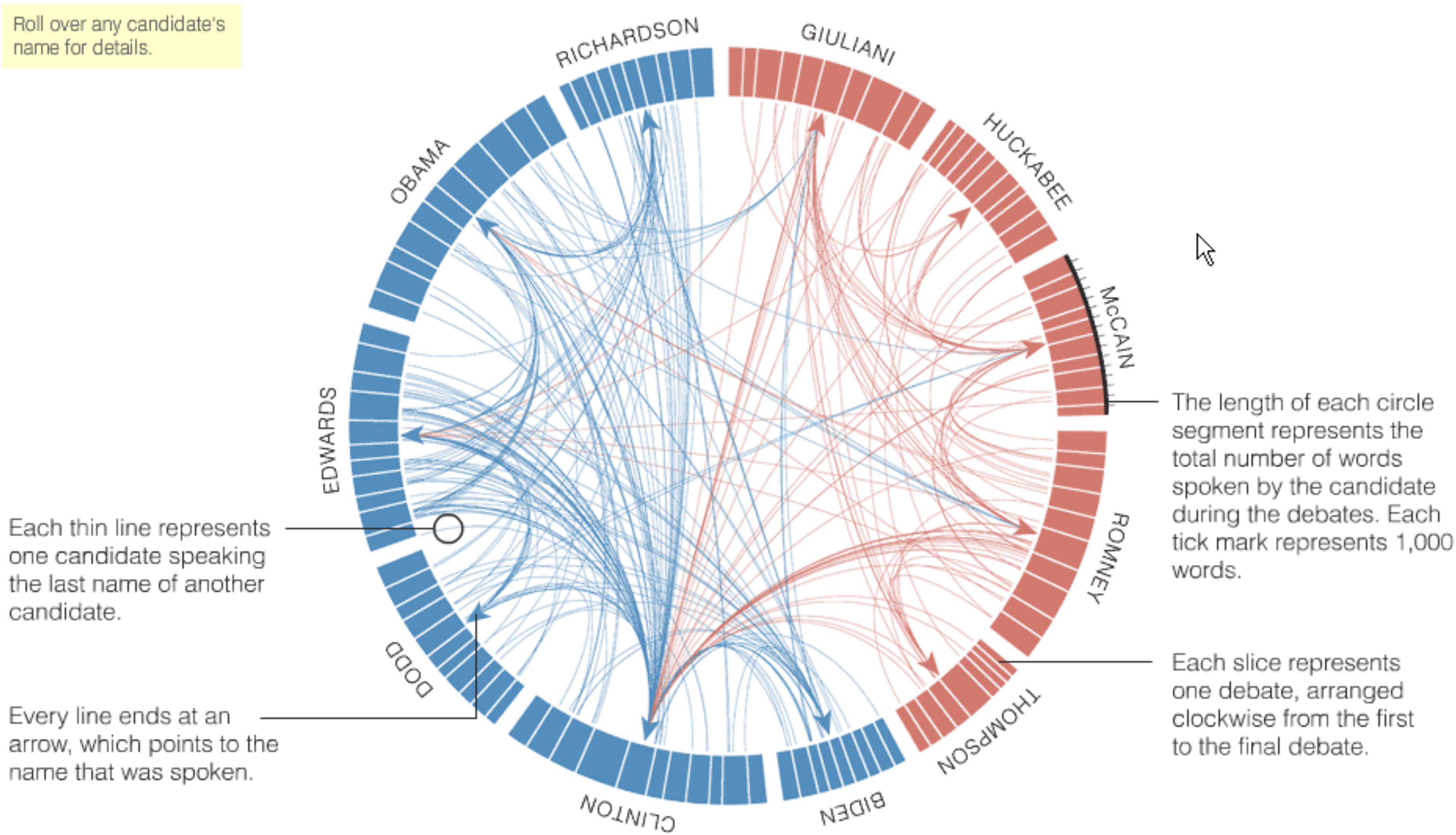
- Who (senders, receivers)
- What (the content of communication)
- When (temporal patterns)

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.

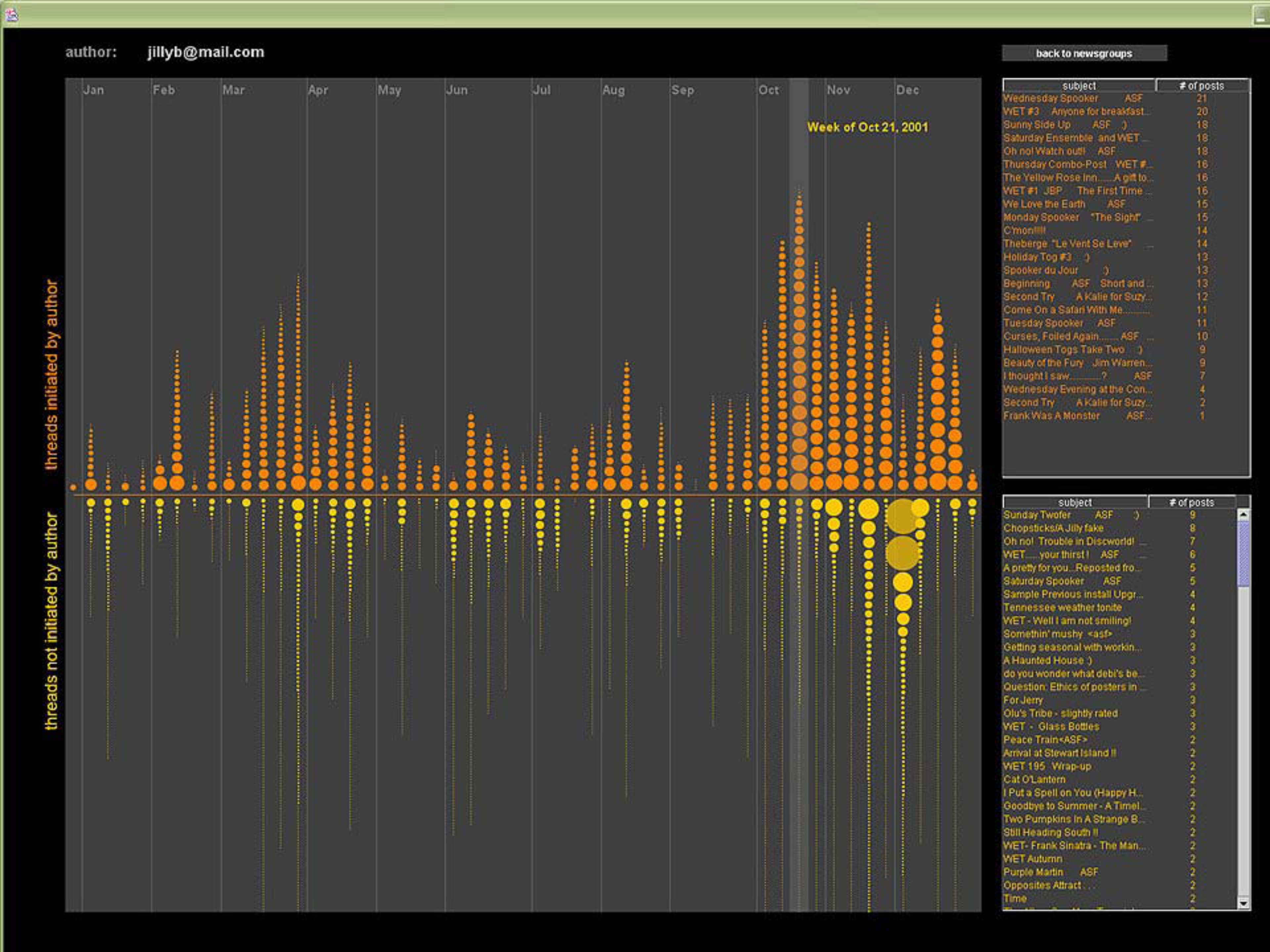


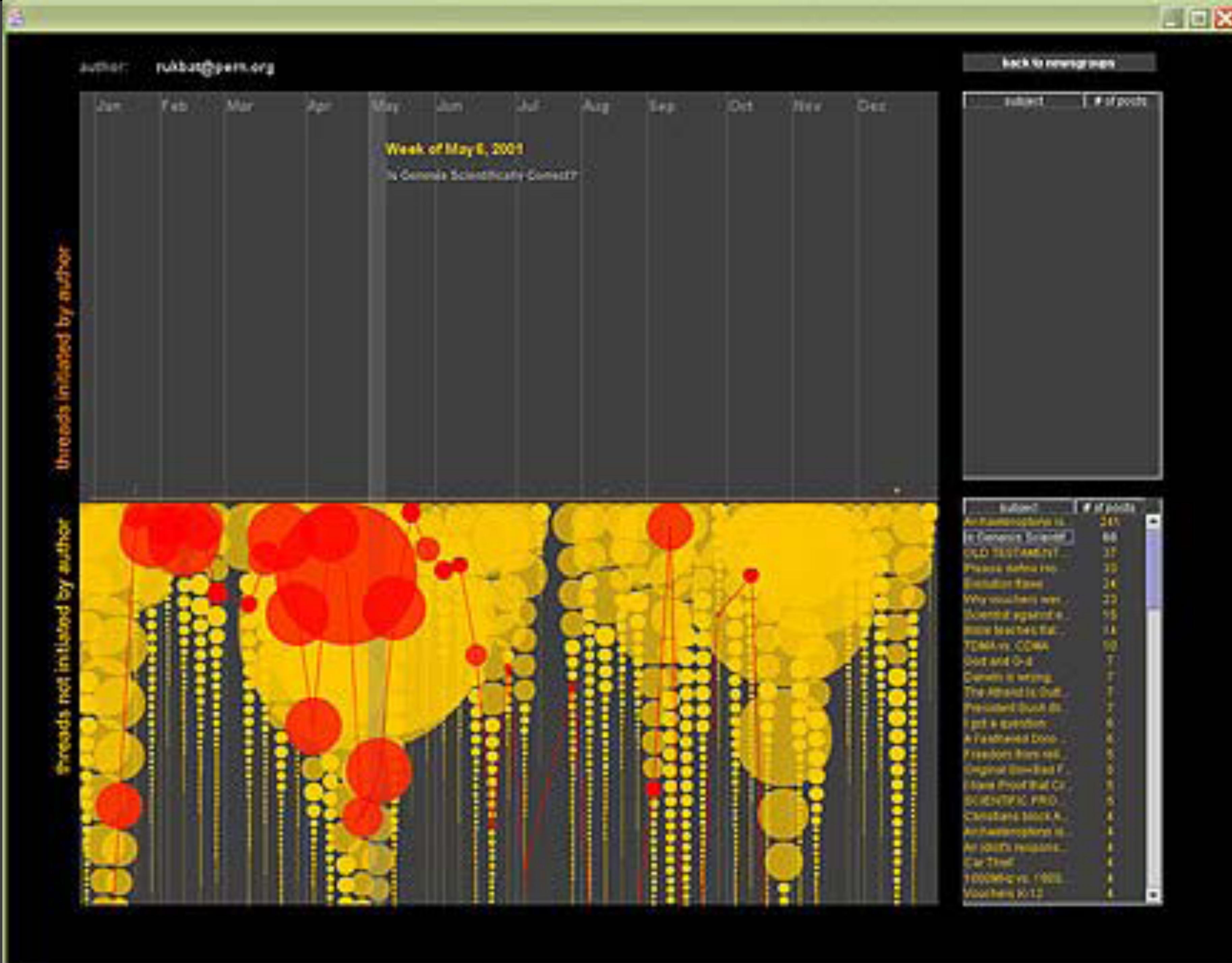
Source: Debate transcripts

Jonathan Corum and Farhana Hossain/The New York Times

Usenet Visualization (Viégas & Smith)

Show correspondence patterns in text forums
Initiate vs. reply; size and duration of discussion

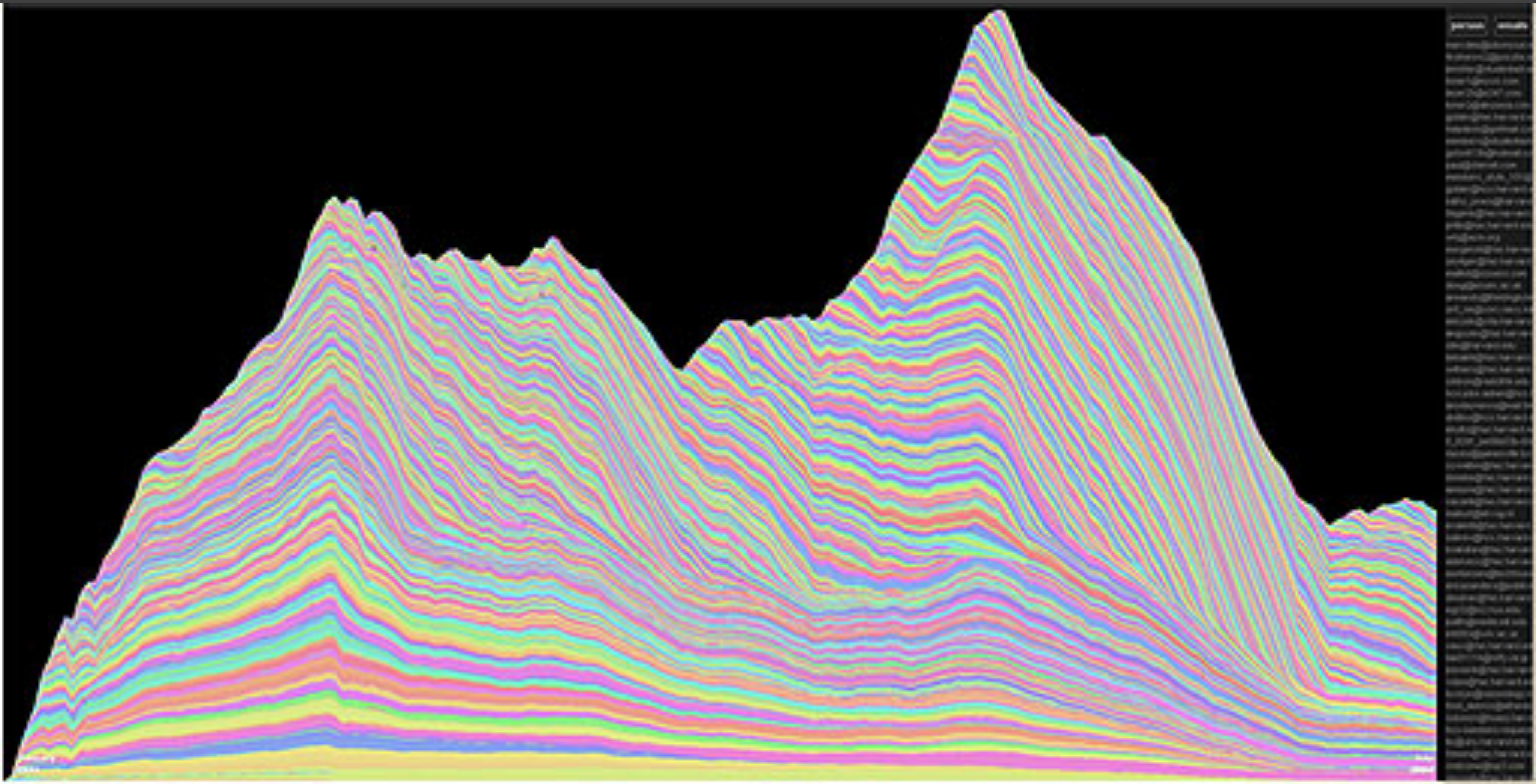

author: jillyb@mail.com
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of Oct 21, 2001
threads initiated by author
threads not initiated by author
subject
# of posts
Wednesday Spooker ASF 21
WET #3 Anyone for breakfast... 20
Sunny Side Up ASF :) 18
Saturday Ensemble and WET...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



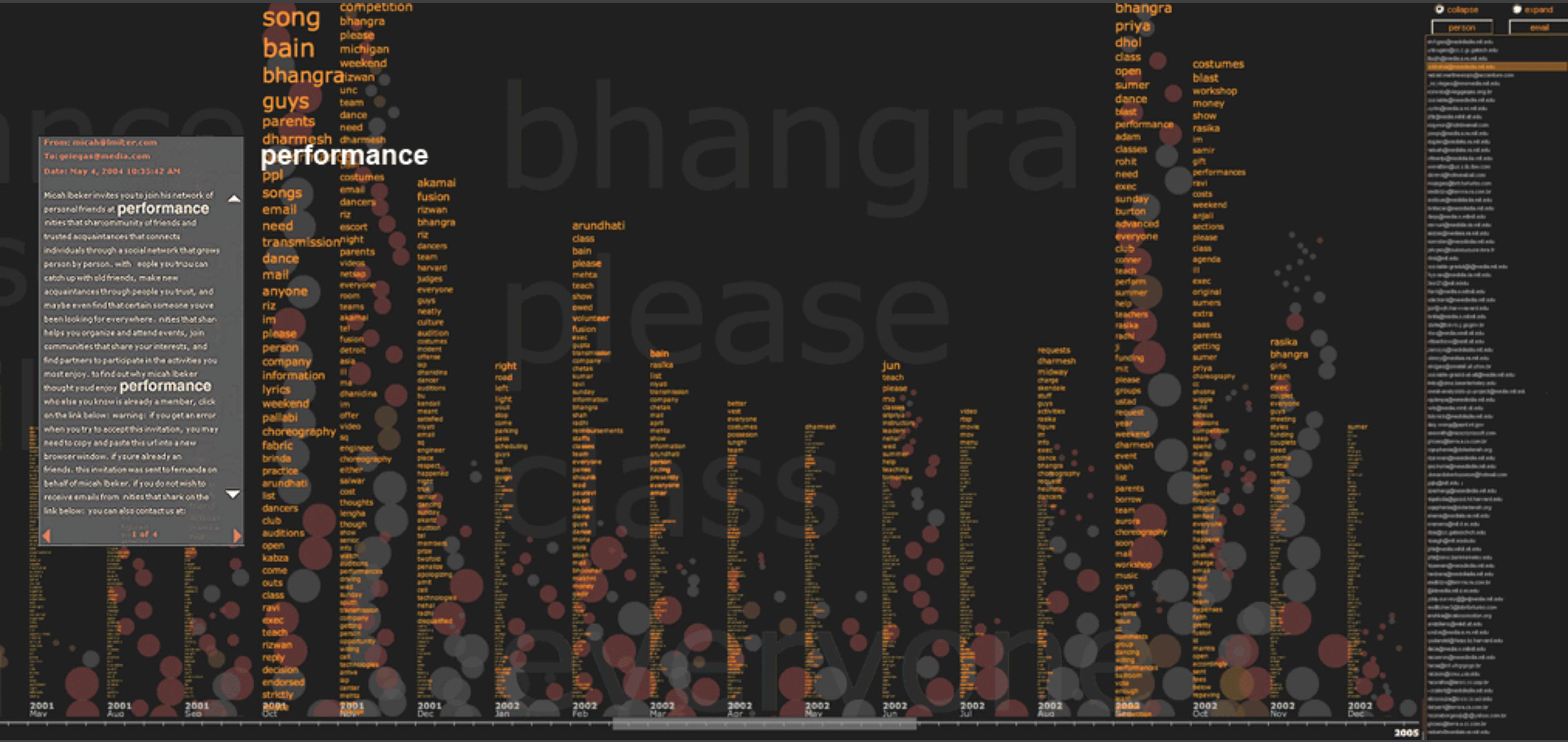
author:
rukbat@pern.org
back to newsgroups
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Week of May 6, 2001
Is Genesis Scientifically Correct?
threads initiated by author
threads not initiated by author
subject
# of posts

Mountain (Viégas)

Conversation by person over time (who x when).



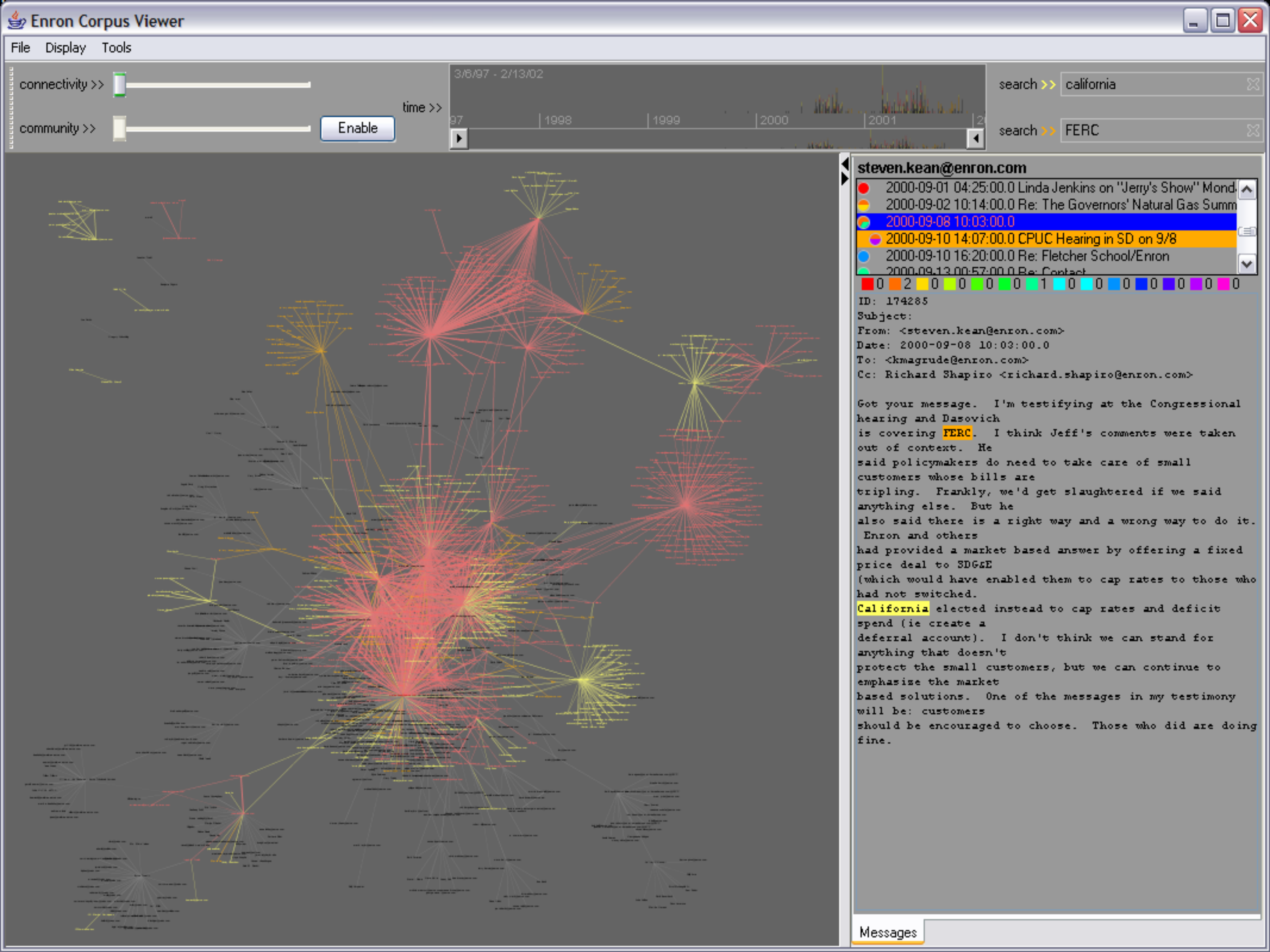
Themail (Viégas et al)

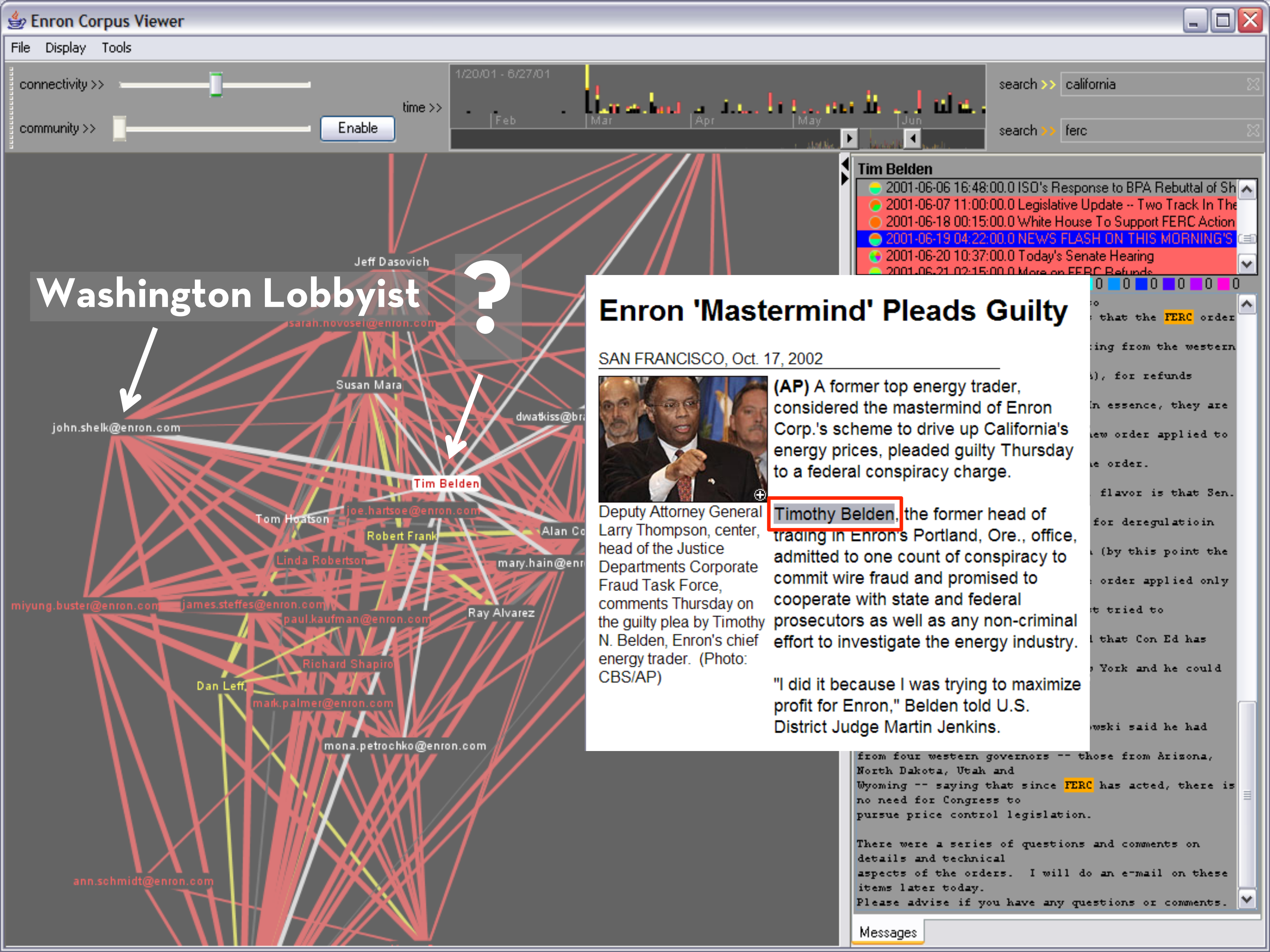


One person over time, TF.IDF weighted terms

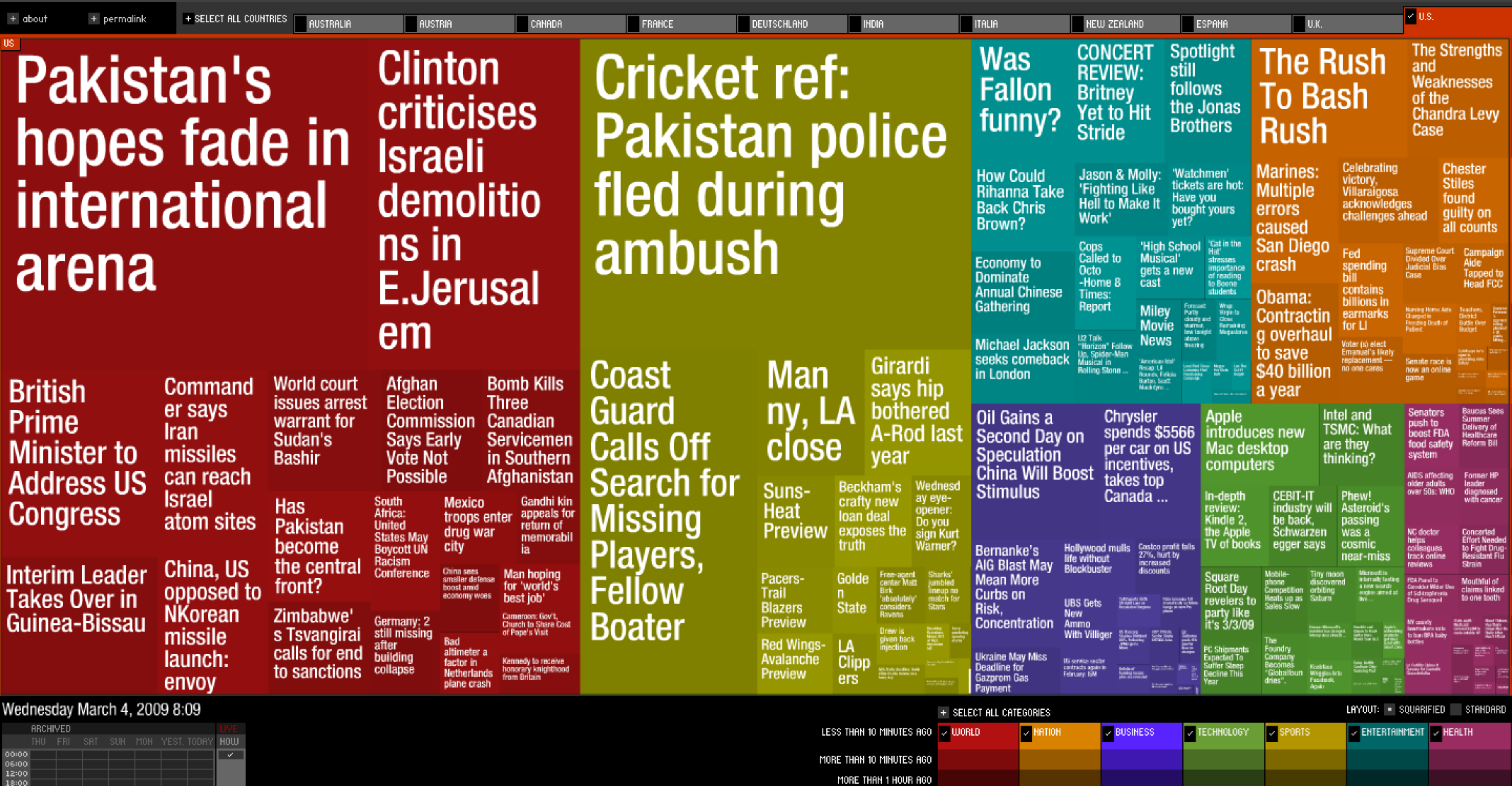
Enron E-Mail Corpus

[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
Washington Lobbyist
?
Jeff Dasovich
sarah.novosel@enron.com
Susan Mara
john.shelk@enron.com
Tim Belden
Tom Hoatson
joe.hartsoe@enron.com
Robert Frank
Linda Robertson
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
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
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



NewsMap: Google News Treemap (Marcos Weskamp)

Tips: Document Contents

Understand your task, and handle high dimensionality accordingly…

- *Visually*: Word position, browsing, brushing + linking
- *Semantically*: Word sequence, hierarchy, clustering
- *Both*: Spatial layout reflect semantic relationships

Role of Interaction:

- Sufficient language model to enable visual analysis cycles
- Allow modifications to the model: custom patterns for expressing contextual or domain knowledge