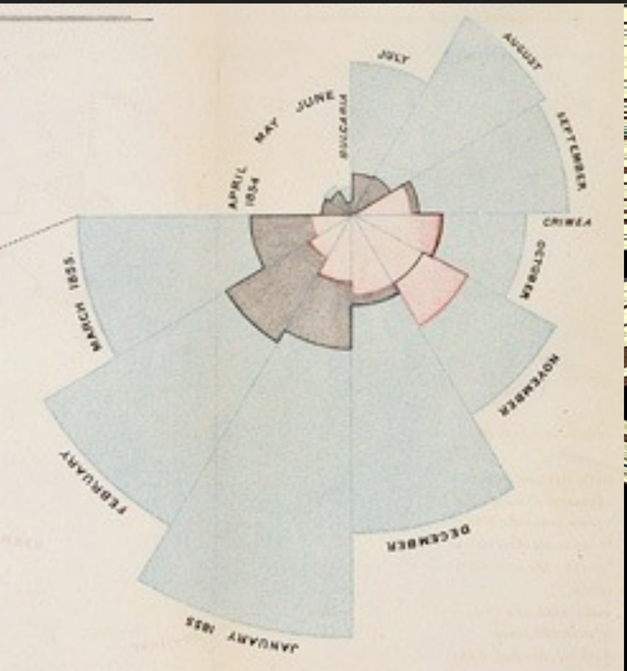
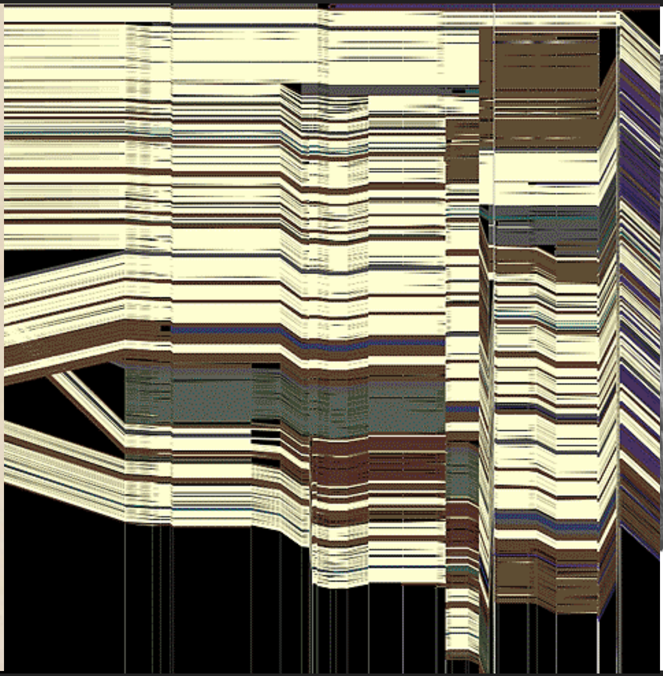
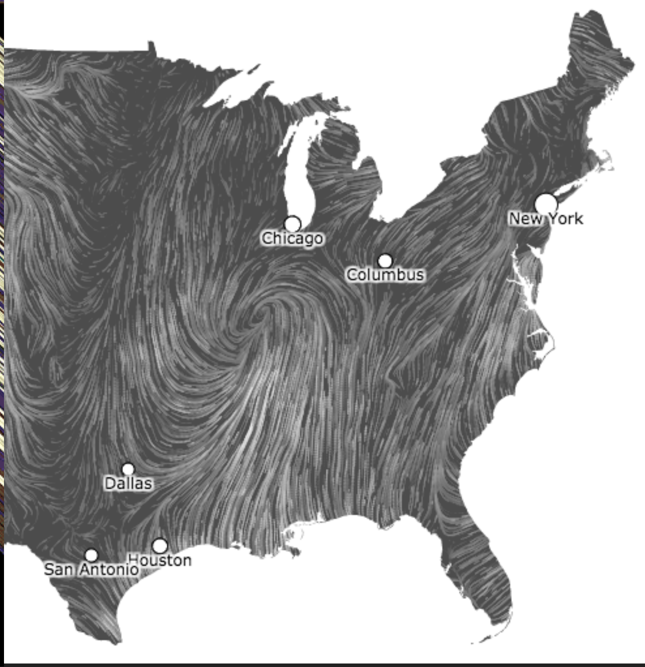
CSE 412 - Intro to Data Visualization

Text Visualization







Jane Hoffswell 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 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.

Example:
Health Care Reform

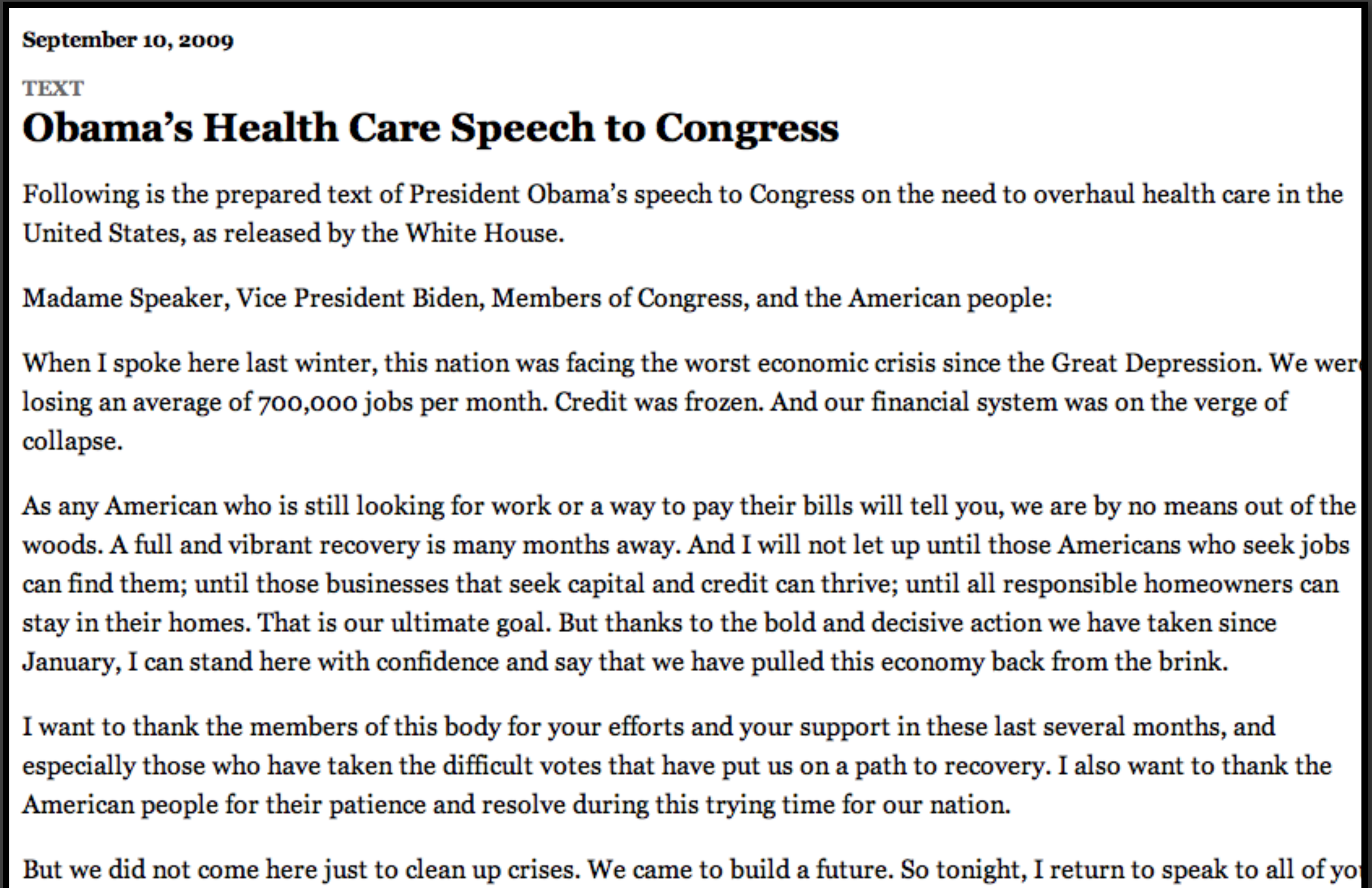
Example: Health Care Reform

Background

Initiatives by President Clinton (1993)
Overhaul by President Obama (2009)

What questions might you want to answer?
What visualizations might help?

Obama on Health Care, 2009



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 were losing an average of 700,000 jobs per month. Credit was frozen. And our financial system was on the verge of collapse.

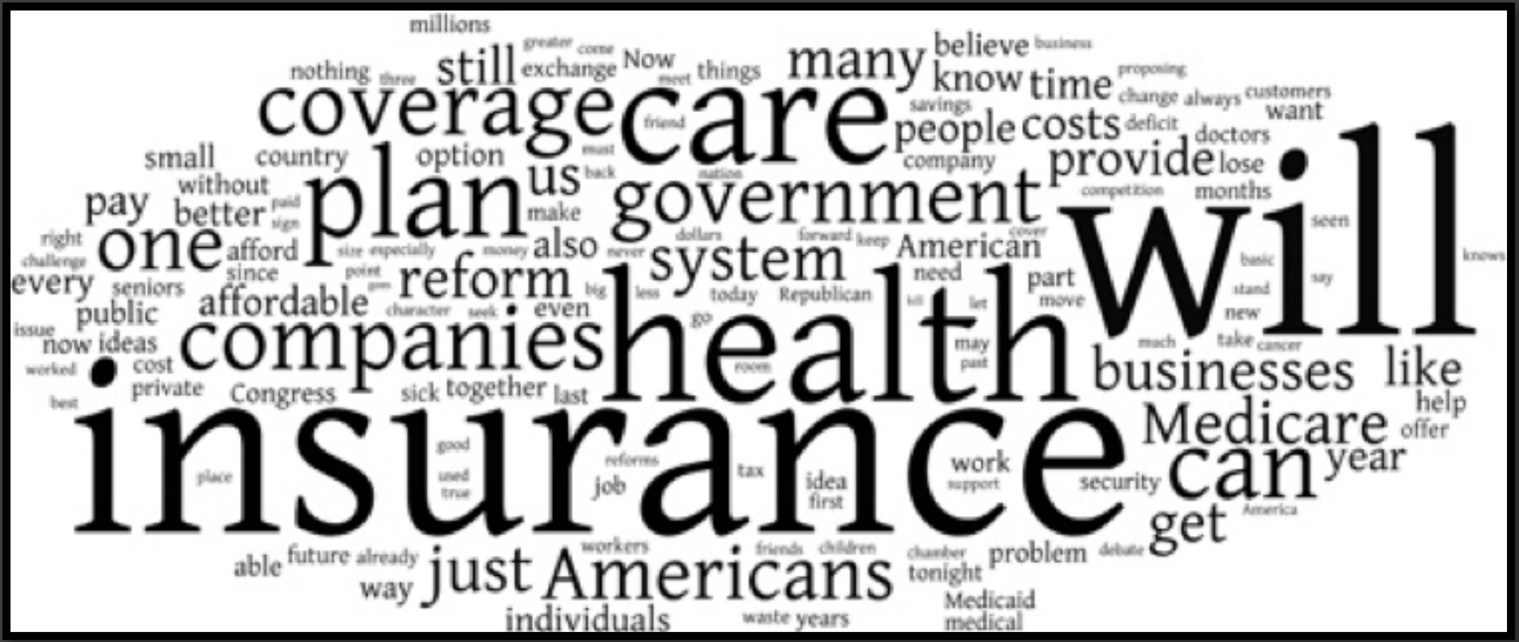
As any American who is still looking for work or a way to pay their bills will tell you, we are by no means out of the woods. A full and vibrant recovery is many months away. And I will not let up until those Americans who seek jobs can find them; until those businesses that seek capital and credit can 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.

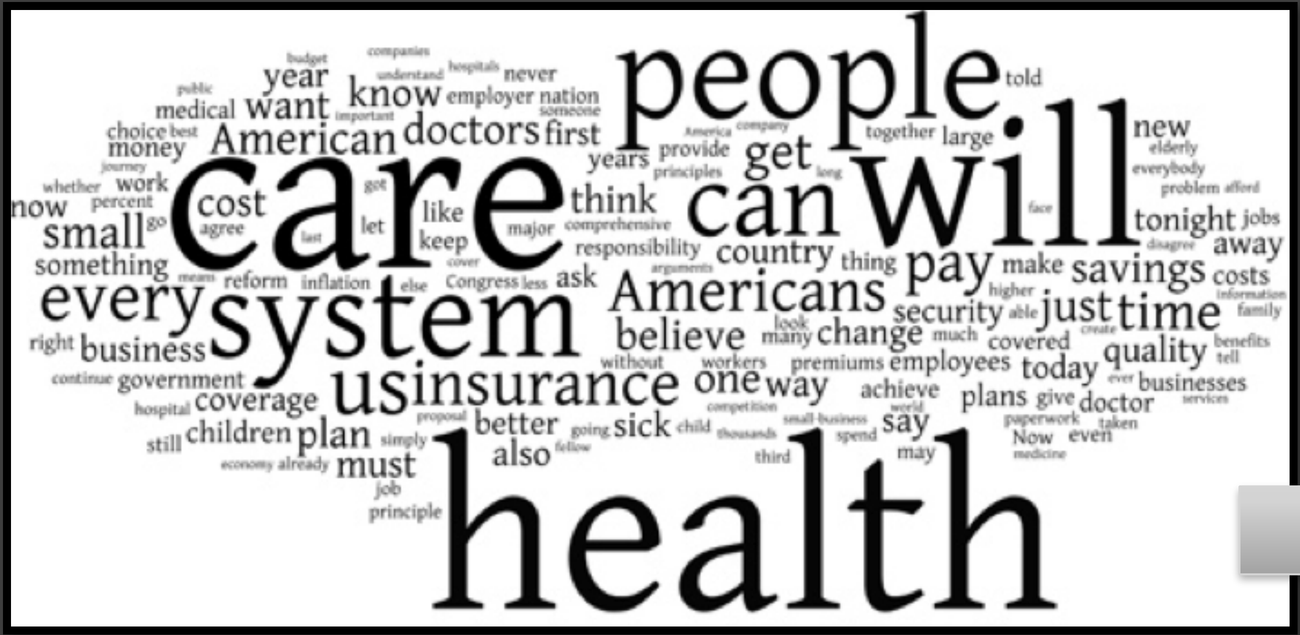
But we did not come here just to clean up crises. We came to build a future. So tonight, I return to speak to all of yo

Tag Clouds: Word Count

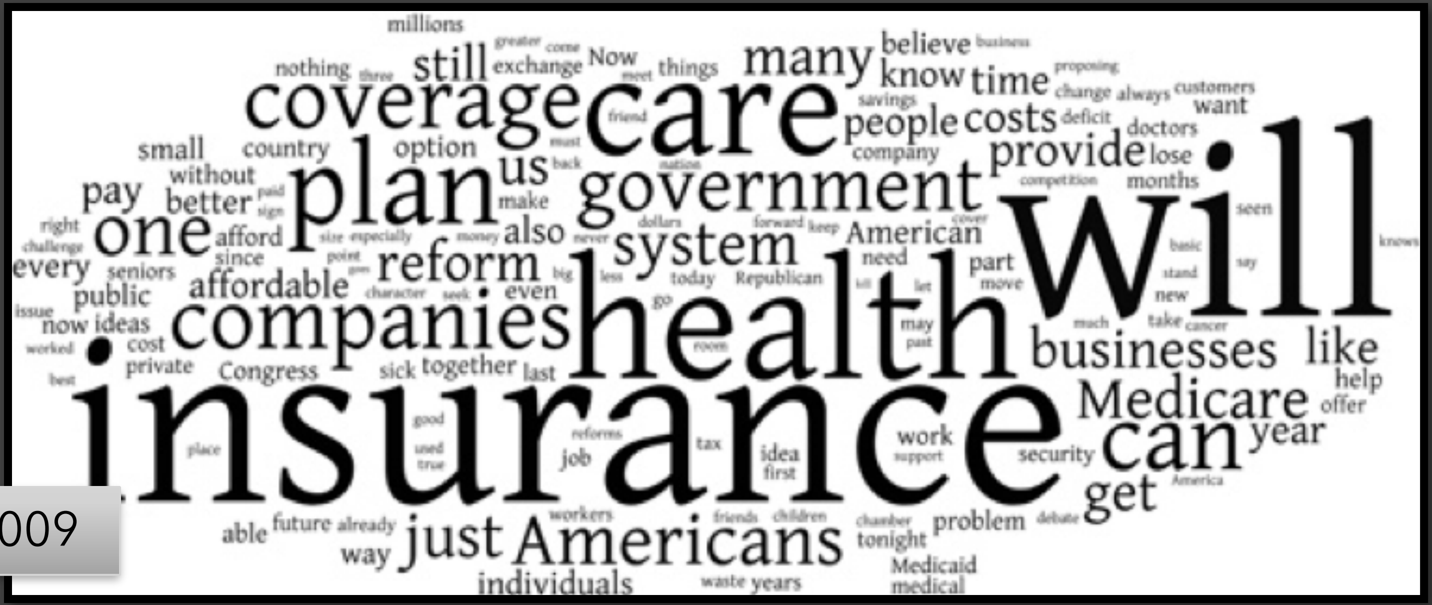
President Obama’s Health Care Speech to Congress [NY Times]



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



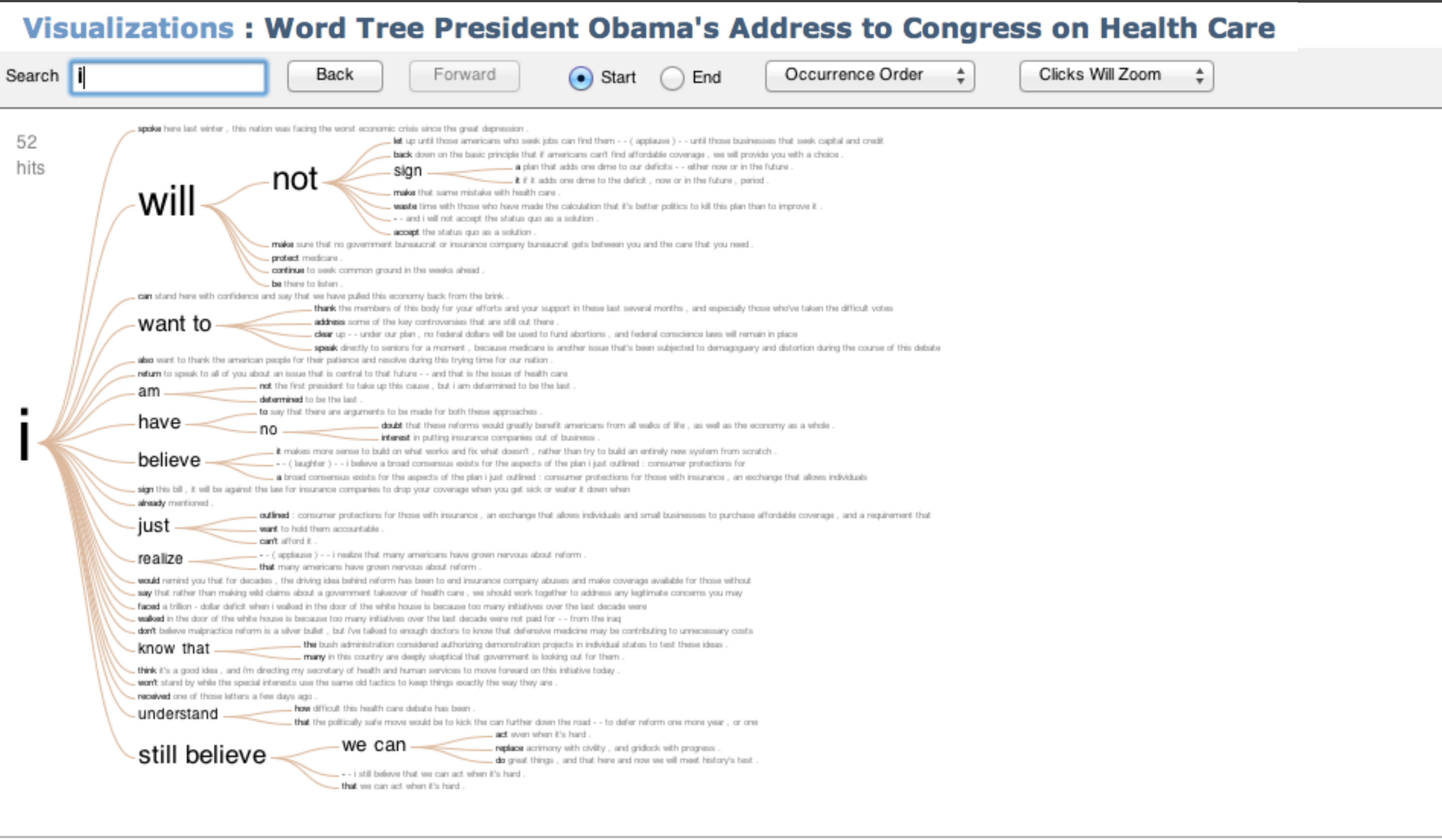
Bill Clinton 1993



Barack Obama 2009

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

Word Tree: Word Sequences



Visualizations : Word Tree President Obama's Address to Congress on Health Care

i

spoke here last winter , this nation was facing the worst economic crisis since the great depression .

will not let up until those americans who seek jobs can find them - - (applause) - - until those businesses that seek capital and credit

will not back down on the basic principle that if americans can't find affordable coverage , we will provide you with a choice .

will not sign a plan that adds one dime to our deficits - - either now or in the future .

will not sign it if it adds one dime to the deficit , now or in the future , period .

will not make that same mistake with health care .

will not waste time with those who have made the calculation that it's better politics to kill this plan than to improve it .

will not - - and i will not accept the status quo as a solution .

will not accept the status quo as a solution .

will make sure that no government bureaucrat or insurance company bureaucrat gets between you and the care that you need .

will protect medicare .

will continue to seek common ground in the weeks ahead .

will be there to listen .

can stand here with confidence and say that we have pulled this economy back from the brink .

want to thank the members of this body for your efforts and your support in these last several months , and especially those who've taken the difficult votes

want to address some of the key controversies that are still out there .

want to clear up - - under our plan , no federal dollars will be used to fund abortions , and federal conscience laws will remain in place

want to speak directly to seniors for a moment , because medicare is another issue that's been subjected to demagoguery and distortion during the course of this debate

also want to thank the american people for their patience and resolve during this trying time for our nation .

return to speak to all of you about an issue that is central to that future - - and that is the issue of health care

am not the first president to take up this cause , but i am determined to be the last .

am determined to be the last .

have to say that there are arguments to be made for both these approaches .

have no doubt that these reforms would greatly benefit americans from all walks of life , as well as the economy as a whole .

have no interest in putting insurance companies out of business .

believe it makes more sense to build on what works and fix what doesn't , rather than try to build an entirely new system from scratch .

believe - - (laughter) - - i believe a broad consensus exists for the aspects of the plan i just outlined : consumer protections for

believe a broad consensus exists for the aspects of the plan i just outlined : consumer protections for those with insurance , an exchange that allows individuals

sign this bill , it will be against the law for insurance companies to drop your coverage when you get sick or water it down when

already mentioned .

just outlined : consumer protections for those with insurance , an exchange that allows individuals and small businesses to purchase affordable coverage , and a requirement that

just want to hold them accountable .

just can't afford it .

realize - - (applause) - - i realize that many americans have grown nervous about reform .

realize that many americans have grown nervous about reform .

would remind you that for decades , the driving idea behind reform has been to end insurance company abuses and make coverage available for those without

say that rather than making wild claims about a government takeover of health care , we should work together to address any legitimate concerns you may

faced a trillion - dollar deficit when i walked in the door of the white house is because too many initiatives over the last decade were

walked in the door of the white house is because too many initiatives over the last decade were not paid for - - from the iraq

don't believe malpractice reform is a silver bullet , but i've talked to enough doctors to know that defensive medicine may be contributing to unnecessary costs

know that the bush administration considered authorizing demonstration projects in individual states to test these ideas .

know that many in this country are deeply skeptical that government is looking out for them .

think it's a good idea , and i'm directing my secretary of health and human services to move forward on this initiative today .

won't stand by while the special interests use the same old tactics to keep things exactly the way they are .

received one of those letters a few days ago .

understand how difficult this health care debate has been .

understand that the politically safe move would be to kick the can further down the road - - to defer reform one more year , or one

still believe we can act even when it's hard .

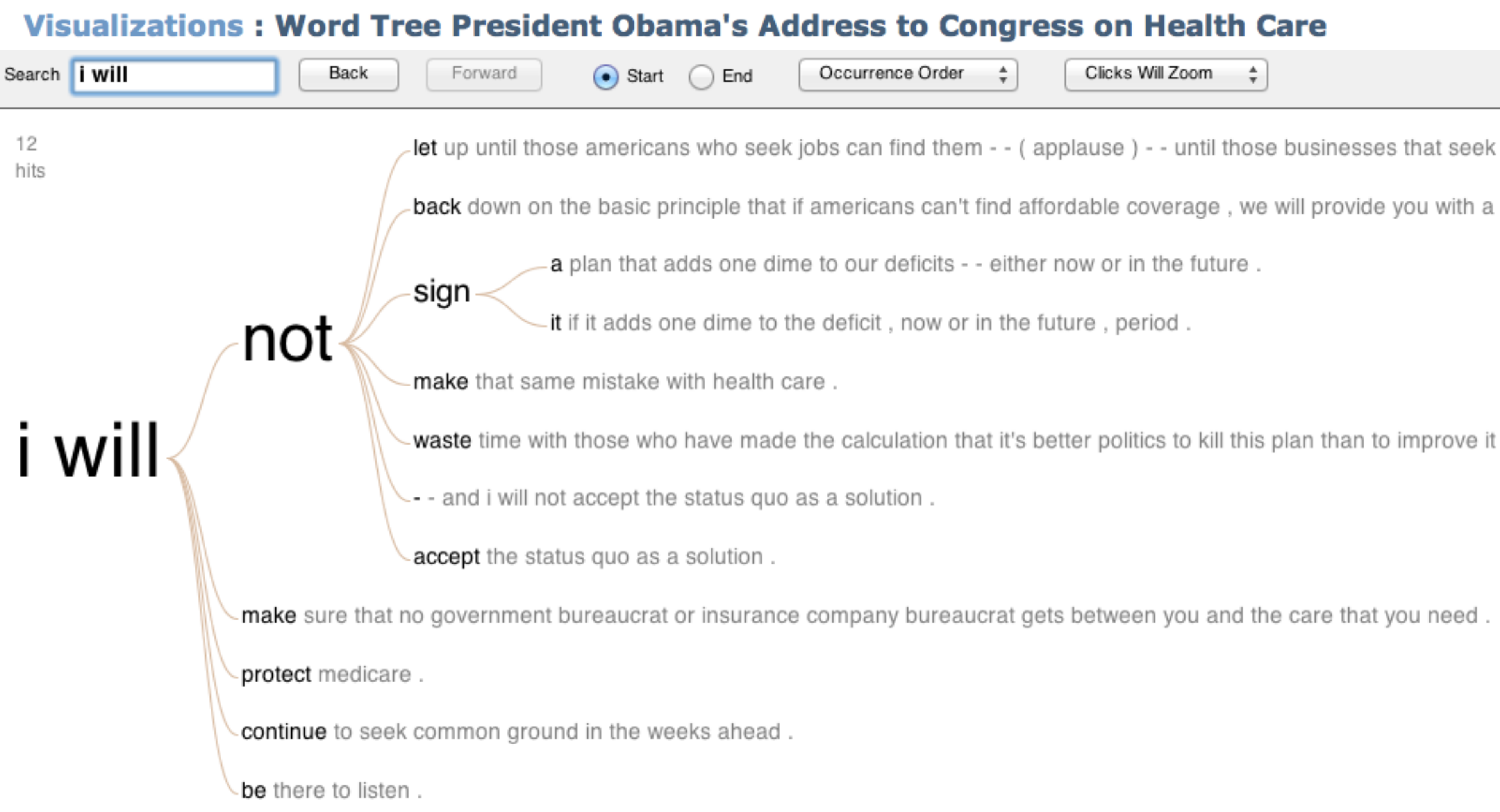
still believe we can replace acrimony with civility , and gridlock with progress .

still believe we can do great things , and that here and now we will meet history's test .

still believe - - i still believe that we can act when it's hard .

still believe that we can act when it's hard .

Word Tree: Word Sequences



Visualizations : Word Tree President Obama's Address to Congress on Health Care

Search: i will

● 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 those businesses that seek
  - back down on the basic principle that if americans can't find affordable coverage , we will provide you with a
  - 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 this plan than to improve it
  - - - 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 the care that you need .
- protect medicare .
- continue to seek common ground in the weeks ahead .
- be there to listen .

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 as Data

Taxonomy of Data Types (?)

1D (sets and sequences)
Temporal
2D (maps)
3D (shapes)
nD (relational)
Trees (hierarchies)
Networks (graphs)

Are there others?

The eyes have it: A task by data type taxonomy for information visualization
[Shneiderman 96]

Unstructured Text

Words have meanings and relations

Correlations: *Hong Kong, Puget Sound, Bay Area*

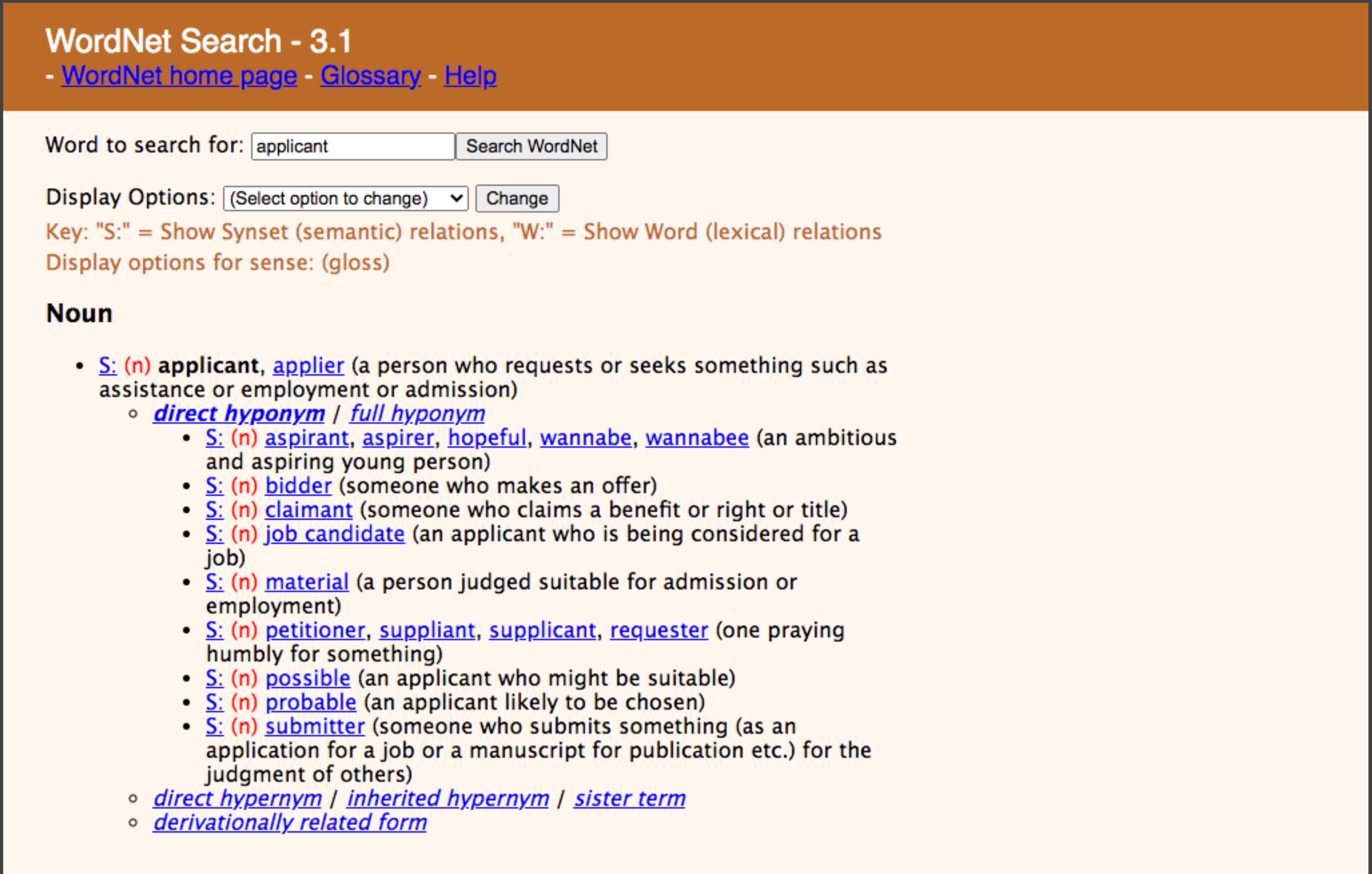
Order: *January, February, March, April, May, June*

Membership: *Tennis, Running, Swimming, Hiking, Piano*

Hierarchy: *Person > Applicant > Job Candidate, Submitter*

Antonyms & synonyms

WordNet: Structure, Relations



WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: applicant [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss)

Noun

- S: (n) **applicant**, applier (a person who requests or seeks something such as assistance or employment or admission)
  - ***direct hyponym*** / *full hyponym*
    - S: (n) aspirant, aspirer, hopeful, wannabe, wannabee (an ambitious and aspiring young person)
    - S: (n) bidder (someone who makes an offer)
    - S: (n) claimant (someone who claims a benefit or right or title)
    - S: (n) job candidate (an applicant who is being considered for a job)
    - S: (n) material (a person judged suitable for admission or employment)
    - S: (n) petitioner, suppliant, supplicant, requester (one praying humbly for something)
    - S: (n) possible (an applicant who might be suitable)
    - S: (n) probable (an applicant likely to be chosen)
    - S: (n) submitter (someone who submits something (as an application for a job or a manuscript for publication etc.) for the judgment of others)
  - *direct hypernym* / *inherited hypernym* / *sister term*
  - *derivationally related form*

Text Processing Pipeline

Tokenization

Segment text into terms.

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

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

Entities? *Washington State, Seattle, U.S.A*

Text Processing Pipeline

Tokenization

Segment text into terms.

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

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

Entities? *Washington State, Seattle, U.S.A*

Stemming

Group together different forms of a word.

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

Lemmatization? *goes, went, gone* → go

Text Processing Pipeline

Tokenization

Segment text into terms.

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

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

Entities? *Washington State, Seattle, U.S.A*

Stemming

Group together different forms of a word.

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

Lemmatization? *goes, went, gone* → go

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, e.g., term counts

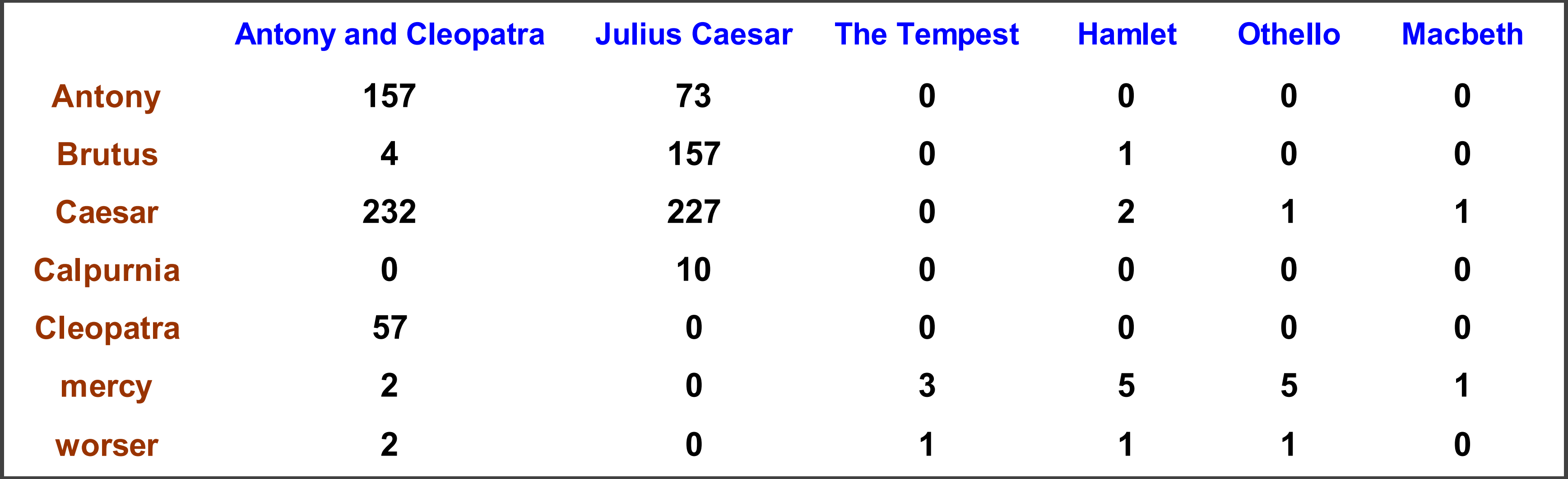
Aggregate into a document-term matrix

Document vector space model

Document-Term Matrix

Each document is a vector of term weights

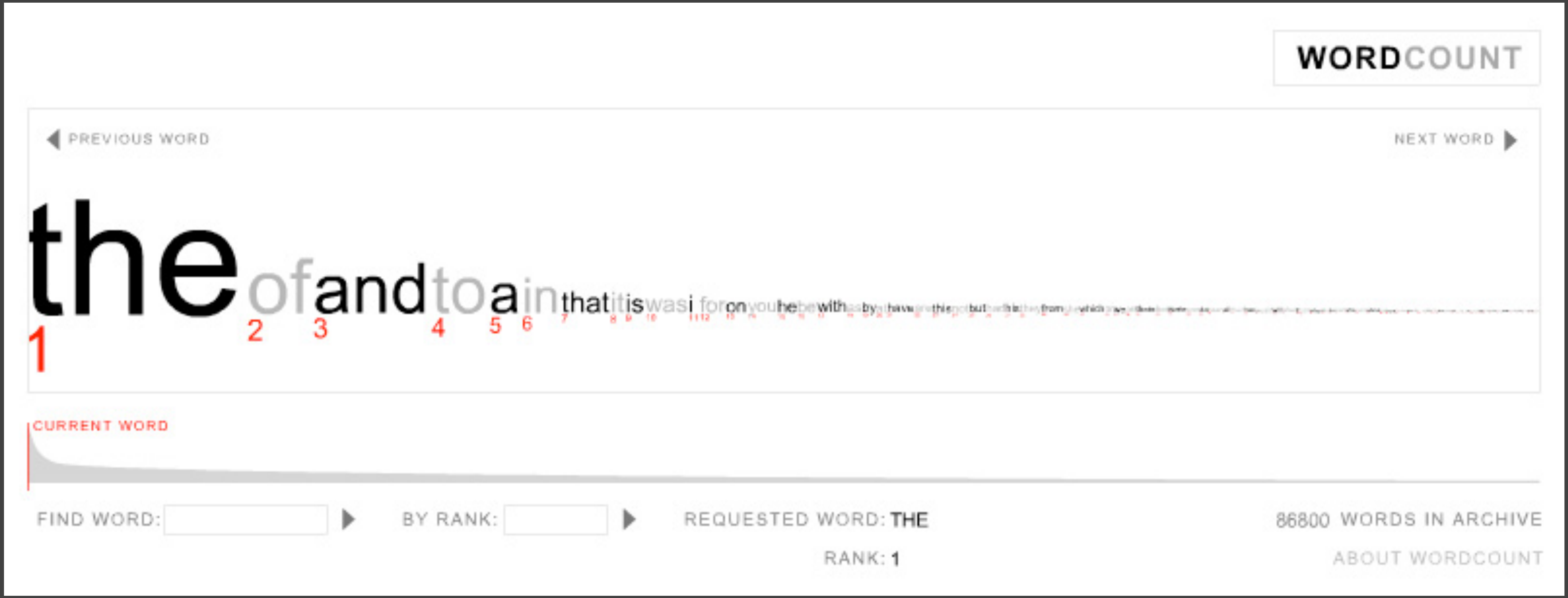
Simplest weighting is to just count occurrences



	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]

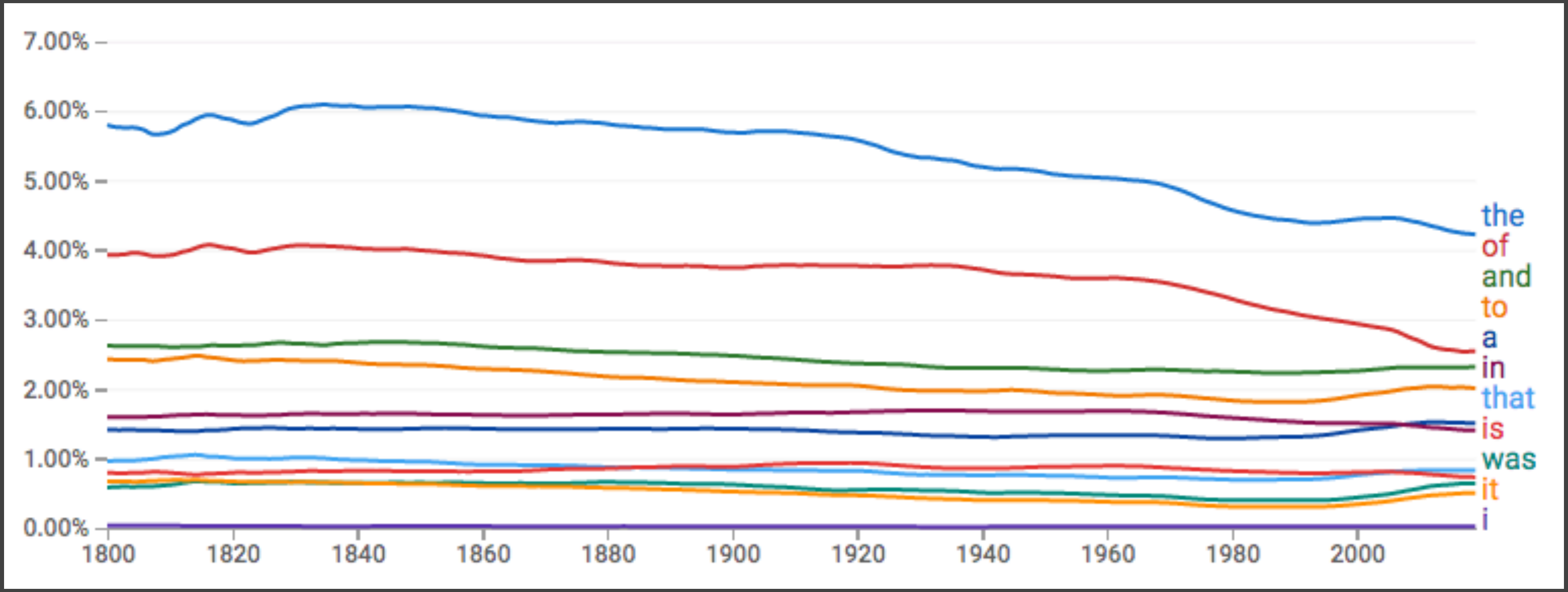


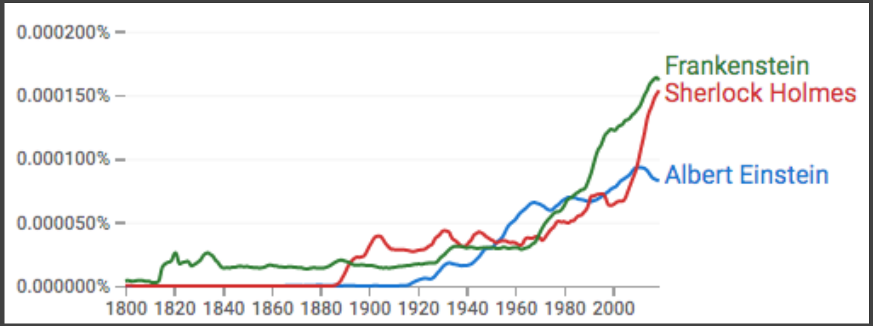
REQUESTED WORD: THE

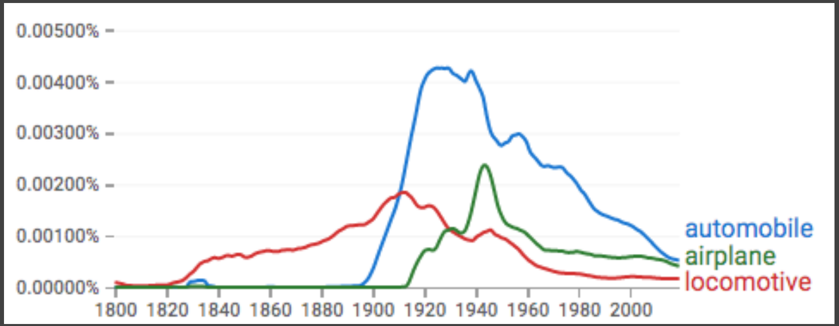
RANK: 1

86800 WORDS IN ARCHIVE

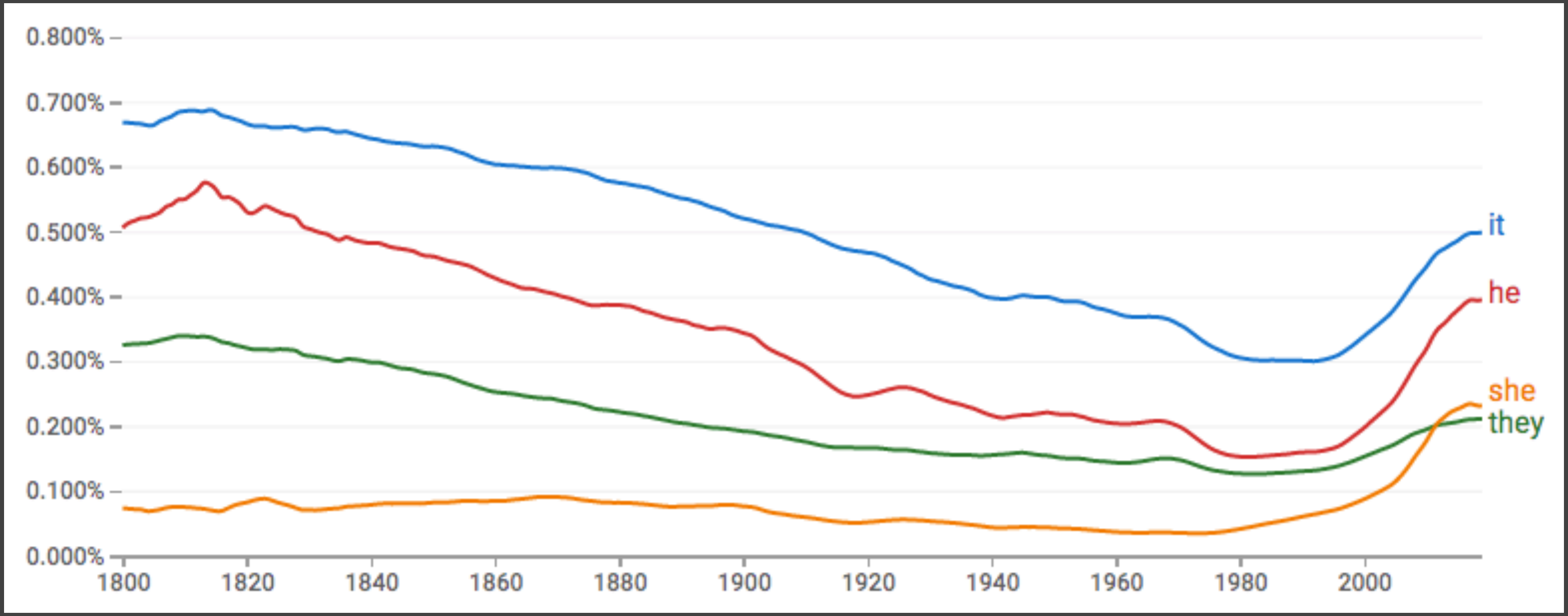
Google Ngram Viewer







Google Ngram Viewer

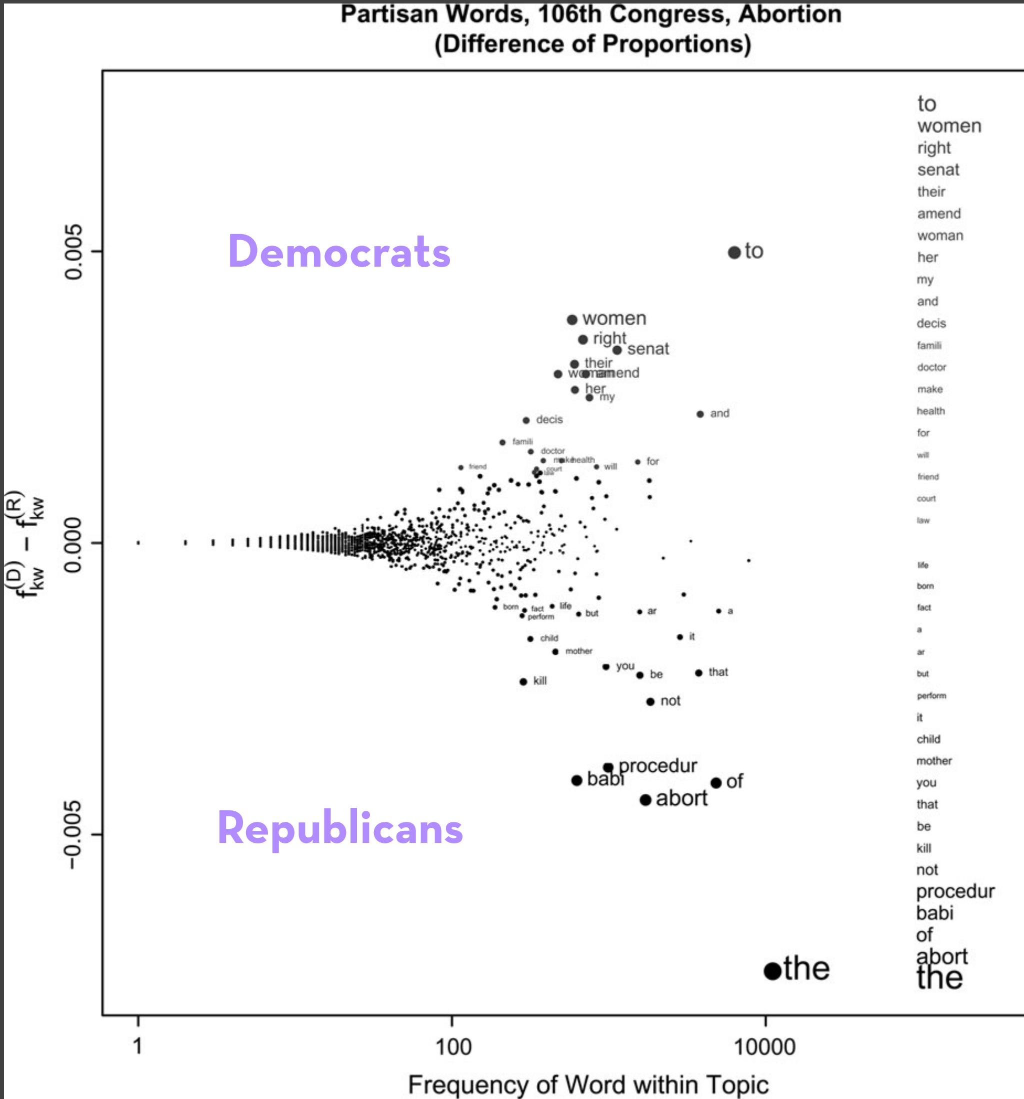


Given a text, what are the best descriptive words?

Lexical Feature Selection [Monroe et al. '08]

Top 20 words labeled

Visualize proportion relative to the word frequency in overall document collection



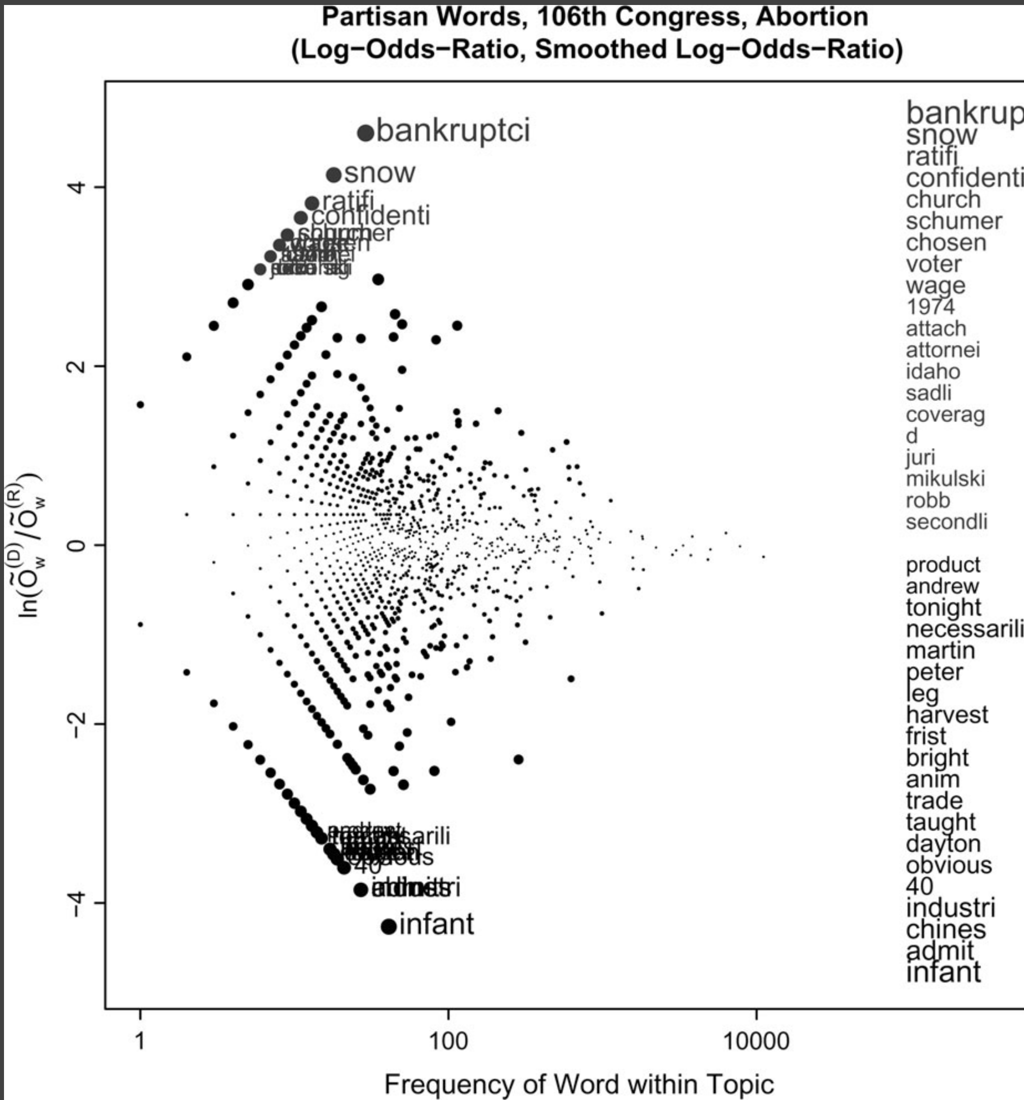
Lexical Feature Selection [Monroe et al. '08]

Top 20 words labeled

Log-odds-ratio

Symmetric display between two parties

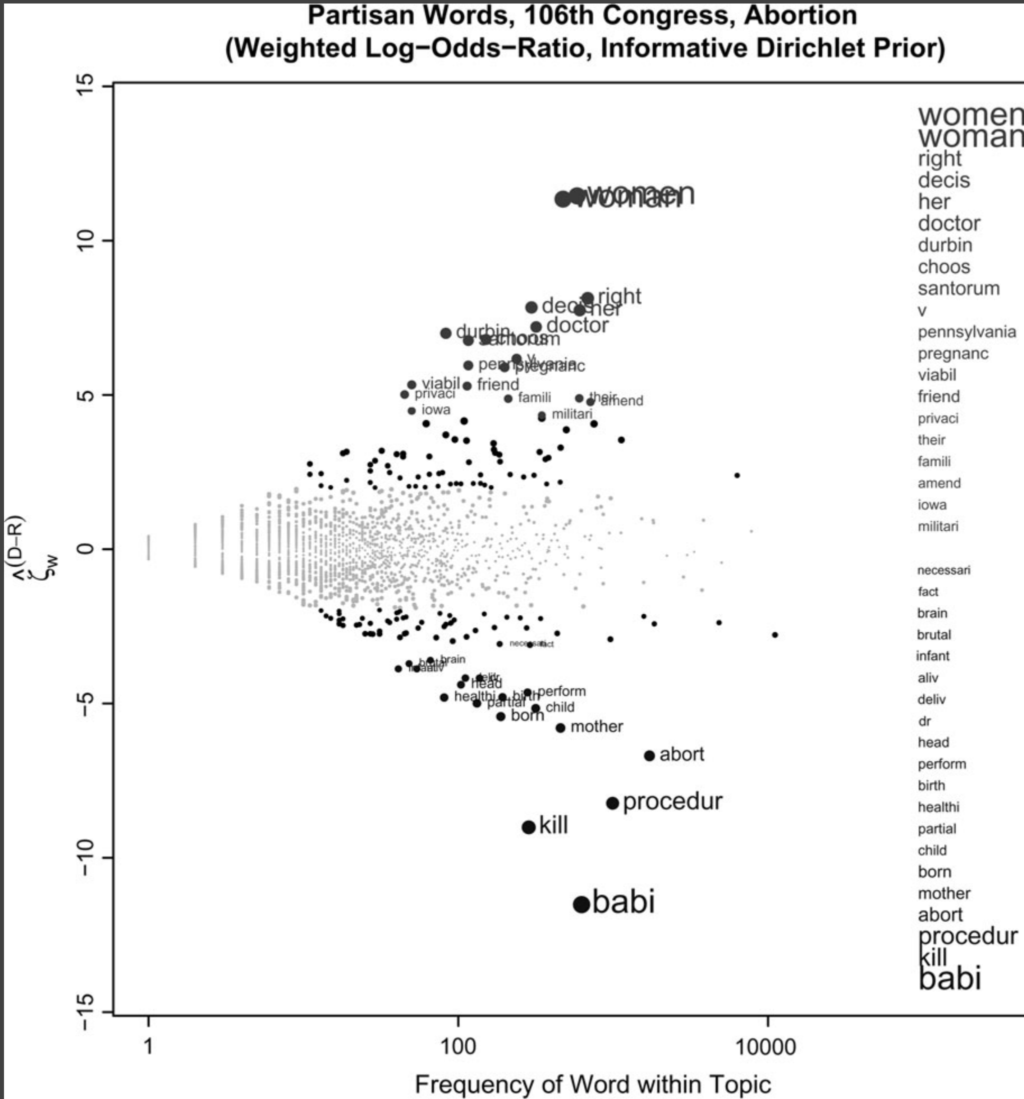
Words only spoken by a particular party (and not the other party)



Lexical Feature Selection [Monroe et al. '08]

Top 20 words labeled

Leverage word priors: expected distribution of words (across many Senate topics)



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

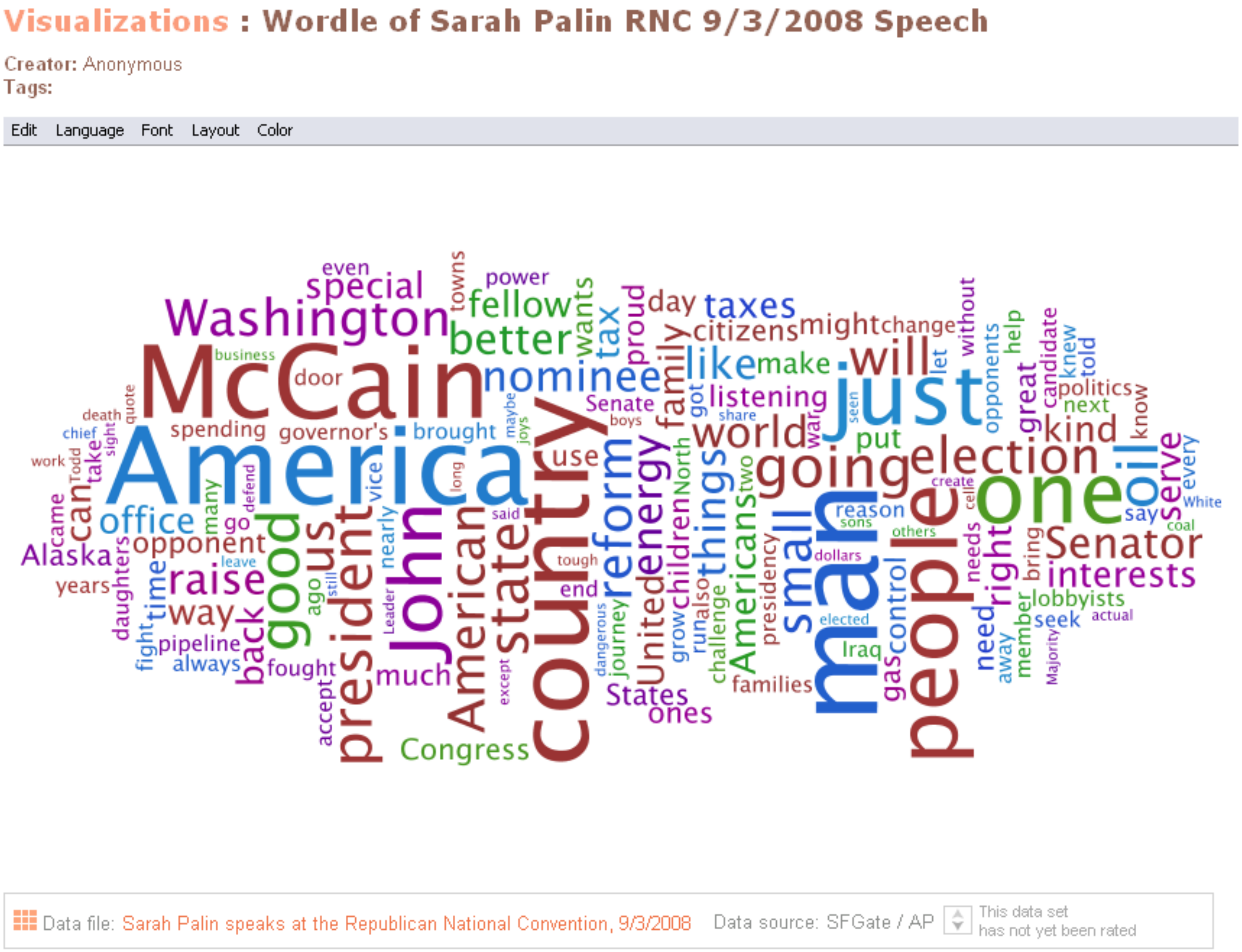
A “bag of words” ignores information

Grammar / part-of-speech

Position within document

Recognizable entities

Bag of Words Model: Word or Tag Clouds



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

Creator: Anonymous
Tags:

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 overview and initial query formation.

Weaknesses

Sub-optimal visual encoding (size vs. position)

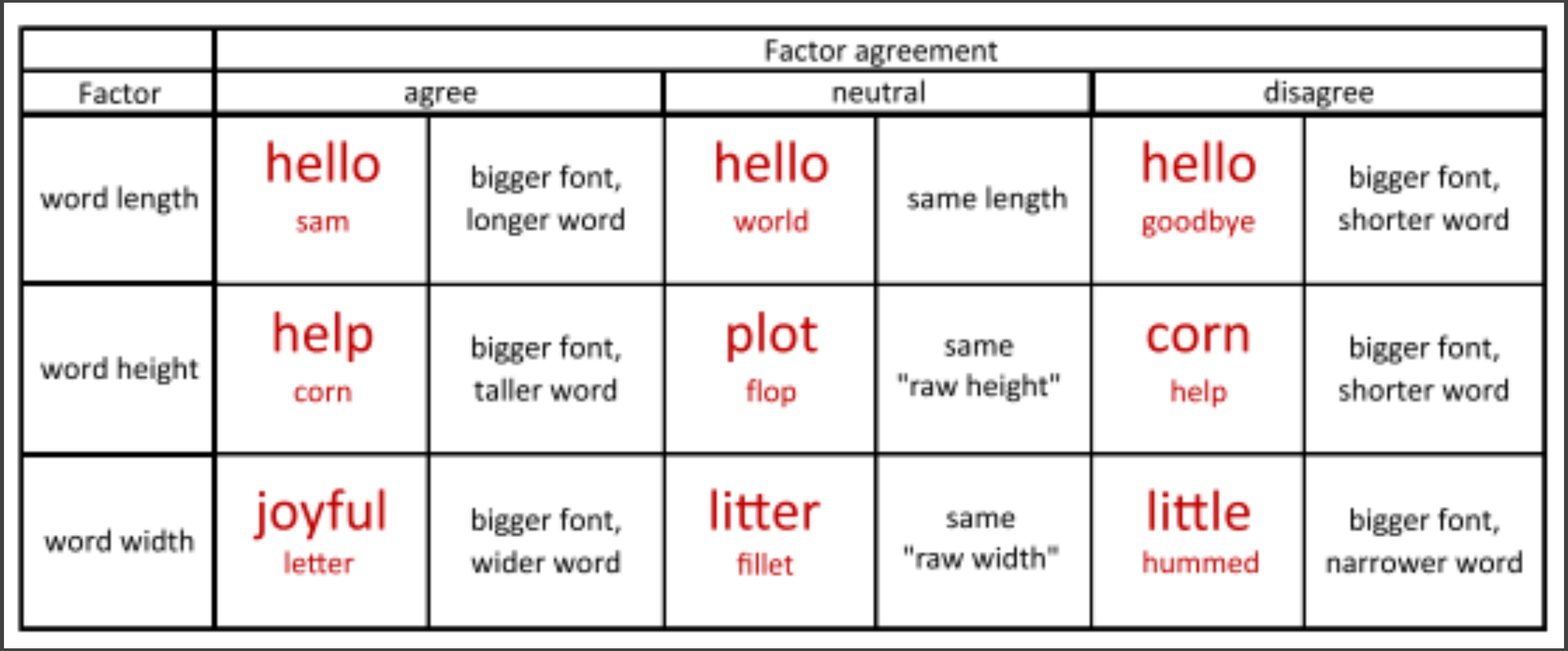
Inaccurate size encoding (long words are bigger)

May not facilitate comparison (unstable layout)

Term frequency may not be meaningful

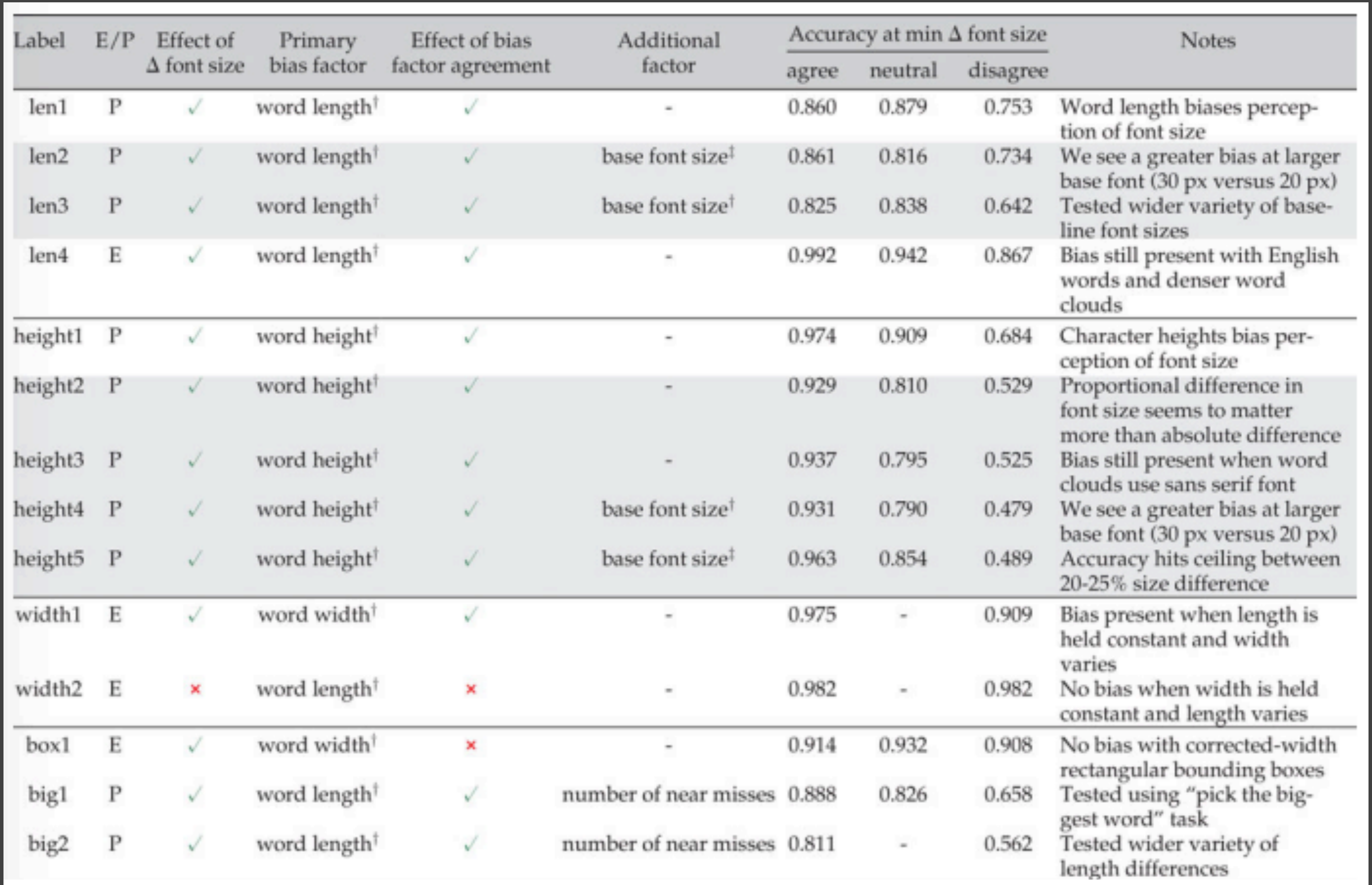
Does not show the structure of the text

Size: Perceptual Biases [Alexander et al. '18]



	Factor agreement					
Factor	agree		neutral		disagree	
word length	hello sam	bigger font, longer word	hello world	same length	hello goodbye	bigger font, shorter word
word height	help corn	bigger font, taller word	plot flop	same "raw height"	corn help	bigger font, shorter word
word width	joyful letter	bigger font, wider word	litter fillet	same "raw width"	little hummed	bigger font, narrower word

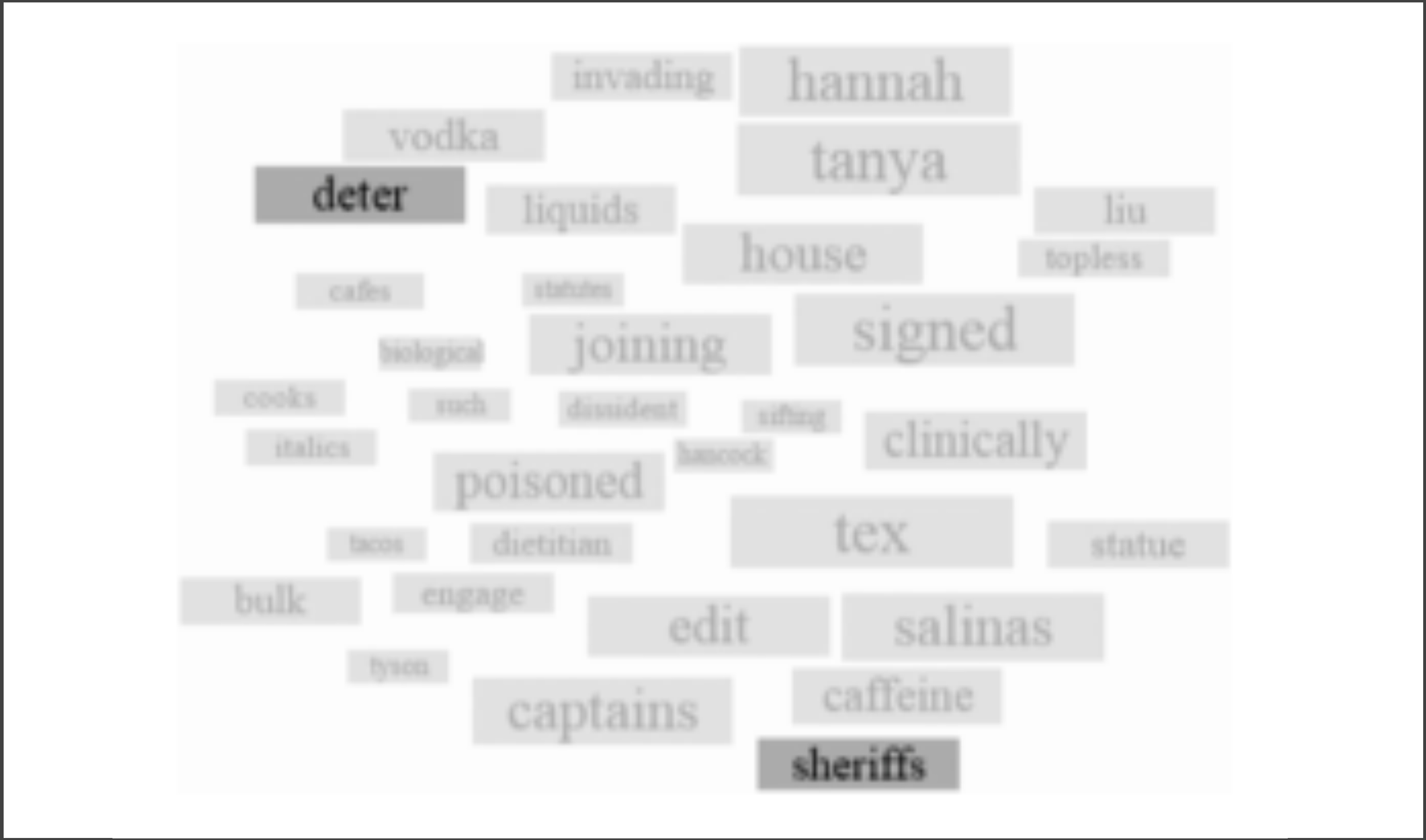
Size: Perceptual Biases [Alexander et al. '18]



Label	E/P	Effect of Δ font size	Primary bias factor	Effect of bias factor agreement	Additional factor	Accuracy at min Δ font size			Notes
						agree	neutral	disagree	
len1	P	✓	word length†	✓	-	0.860	0.879	0.753	Word length biases perception of font size
len2	P	✓	word length†	✓	base font size‡	0.861	0.816	0.734	We see a greater bias at larger base font (30 px versus 20 px)
len3	P	✓	word length†	✓	base font size†	0.825	0.838	0.642	Tested wider variety of baseline font sizes
len4	E	✓	word length†	✓	-	0.992	0.942	0.867	Bias still present with English words and denser word clouds
height1	P	✓	word height†	✓	-	0.974	0.909	0.684	Character heights bias perception of font size
height2	P	✓	word height†	✓	-	0.929	0.810	0.529	Proportional difference in font size seems to matter more than absolute difference
height3	P	✓	word height†	✓	-	0.937	0.795	0.525	Bias still present when word clouds use sans serif font
height4	P	✓	word height†	✓	base font size†	0.931	0.790	0.479	We see a greater bias at larger base font (30 px versus 20 px)
height5	P	✓	word height†	✓	base font size†	0.963	0.854	0.489	Accuracy hits ceiling between 20-25% size difference
width1	E	✓	word width†	✓	-	0.975	-	0.909	Bias present when length is held constant and width varies
width2	E	×	word length†	×	-	0.982	-	0.982	No bias when width is held constant and length varies
box1	E	✓	word width†	×	-	0.914	0.932	0.908	No bias with corrected-width rectangular bounding boxes
big1	P	✓	word length†	✓	number of near misses	0.888	0.826	0.658	Tested using "pick the biggest word" task
big2	P	✓	word length†	✓	number of near misses	0.811	-	0.562	Tested wider variety of length differences

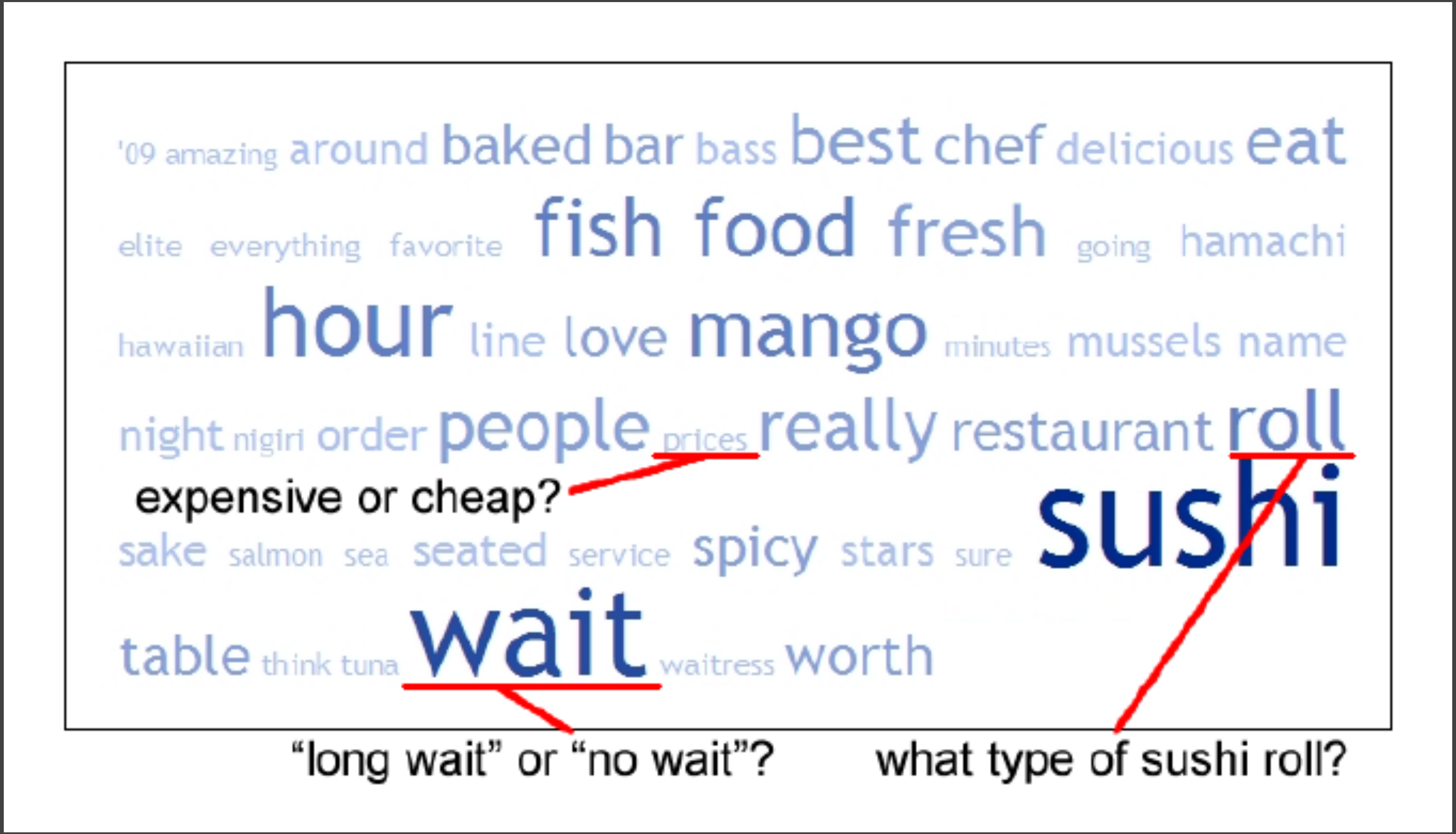
Size: Perceptual Biases

[Alexander et al. '18]



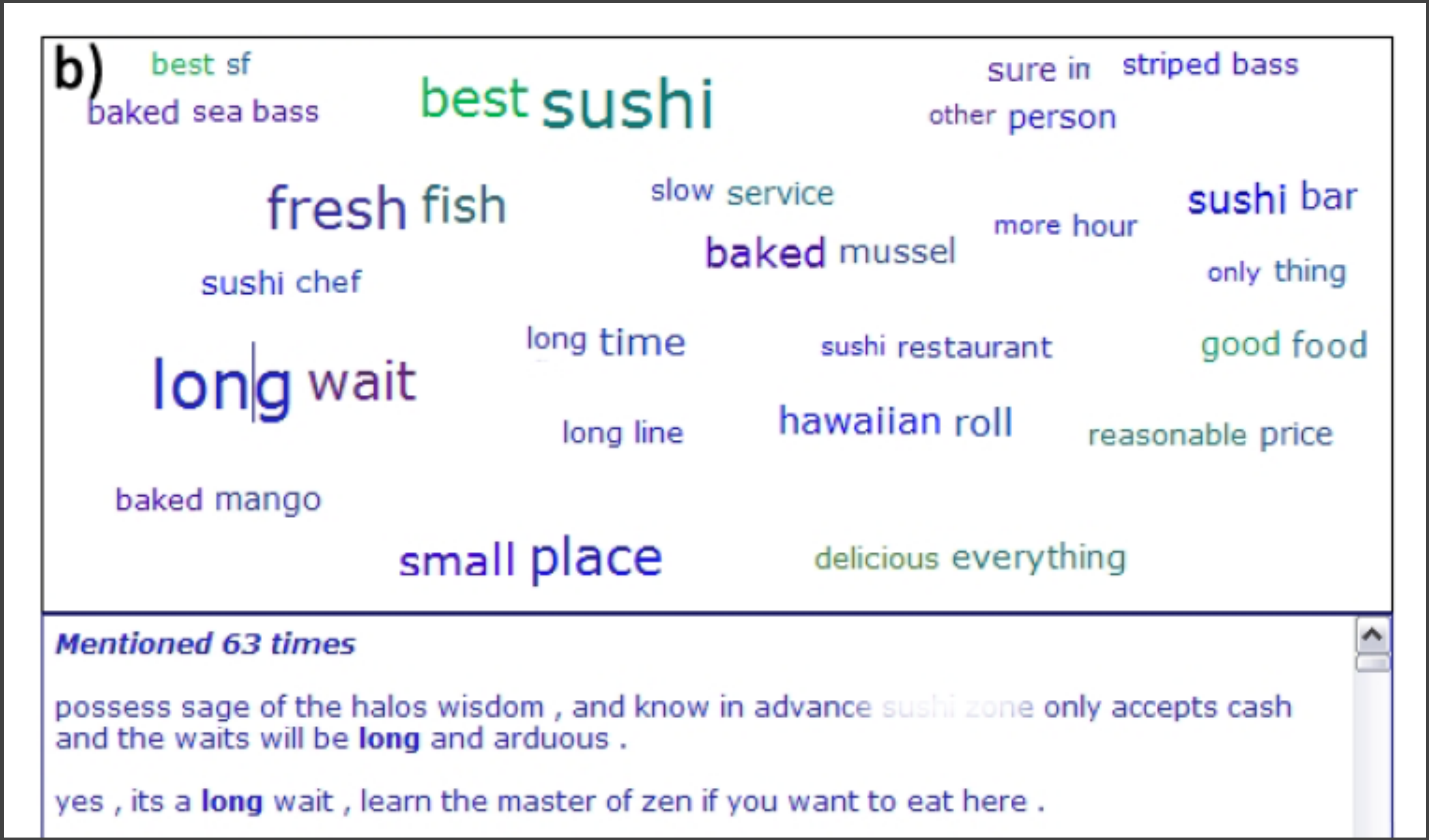
Yelp Review Spotlight

[Yatani et al. '11]


'09 amazing around baked bar bass best chef delicious eat
elite everything favorite fish food fresh going hamachi
hawaiian hour line love mango minutes mussels name
night nigiri order people prices really restaurant roll
expensive or cheap?
sake salmon sea seated service spicy stars sure sushi
table think tuna wait waitress worth
“long wait” or “no wait”?
what type of sushi roll?

Yelp Review Spotlight

[Yatani et al. '11]



Mentioned 63 times

possess sage of the halos wisdom , and know in advance sushi zone only accepts cash and the waits will be **long** and arduous .

yes , its a **long** wait , learn the master of zen if you want to eat here .

Descriptive Phrases

Understand the limitations of your language model.

Bag of words: (1) easy to compute, (2) single words, (3) loss of order

Select appropriate model and visualization

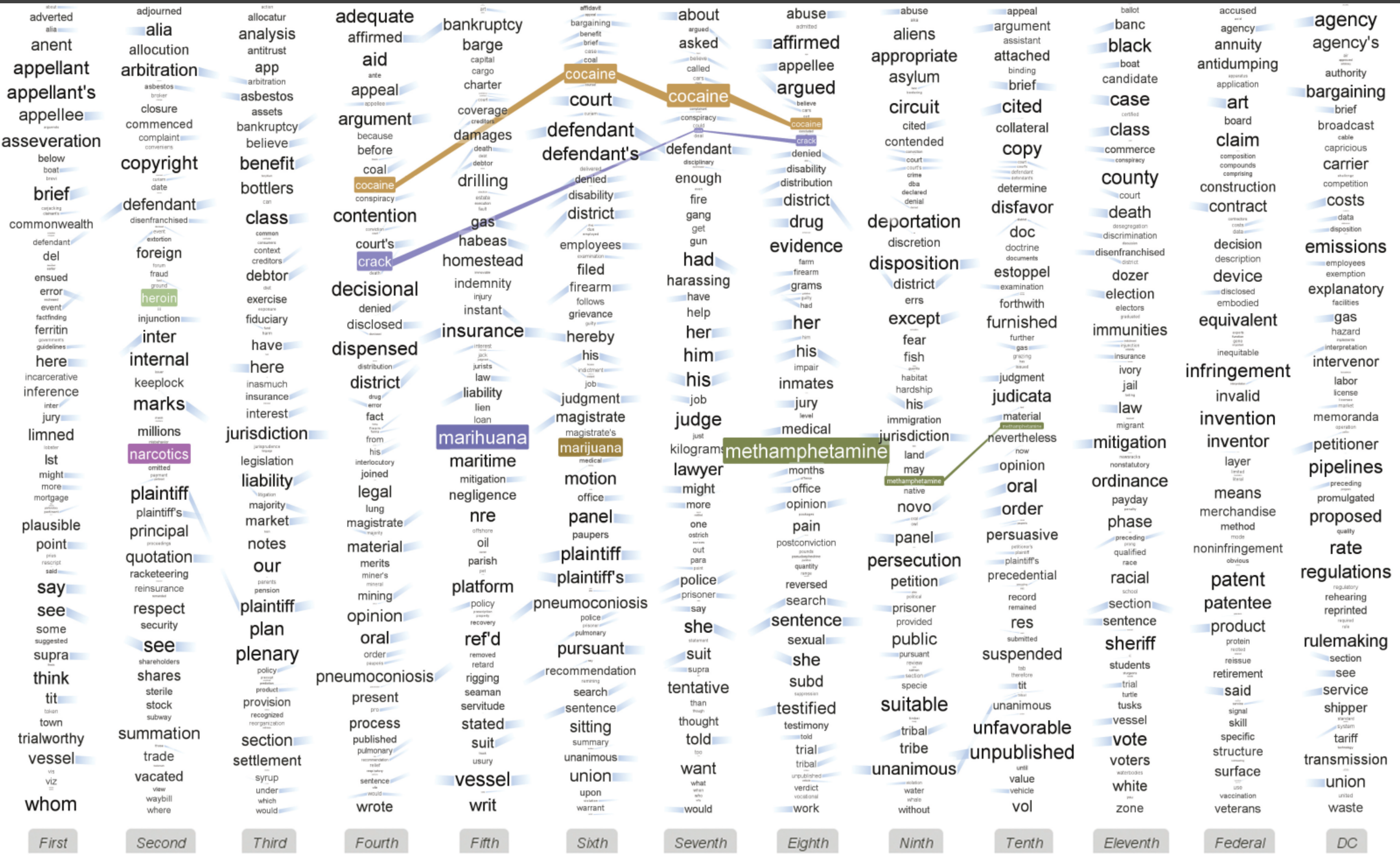
Generate longer, more meaningful phrases

Adjective-noun word pairs for reviews

Show keyphrases within source text

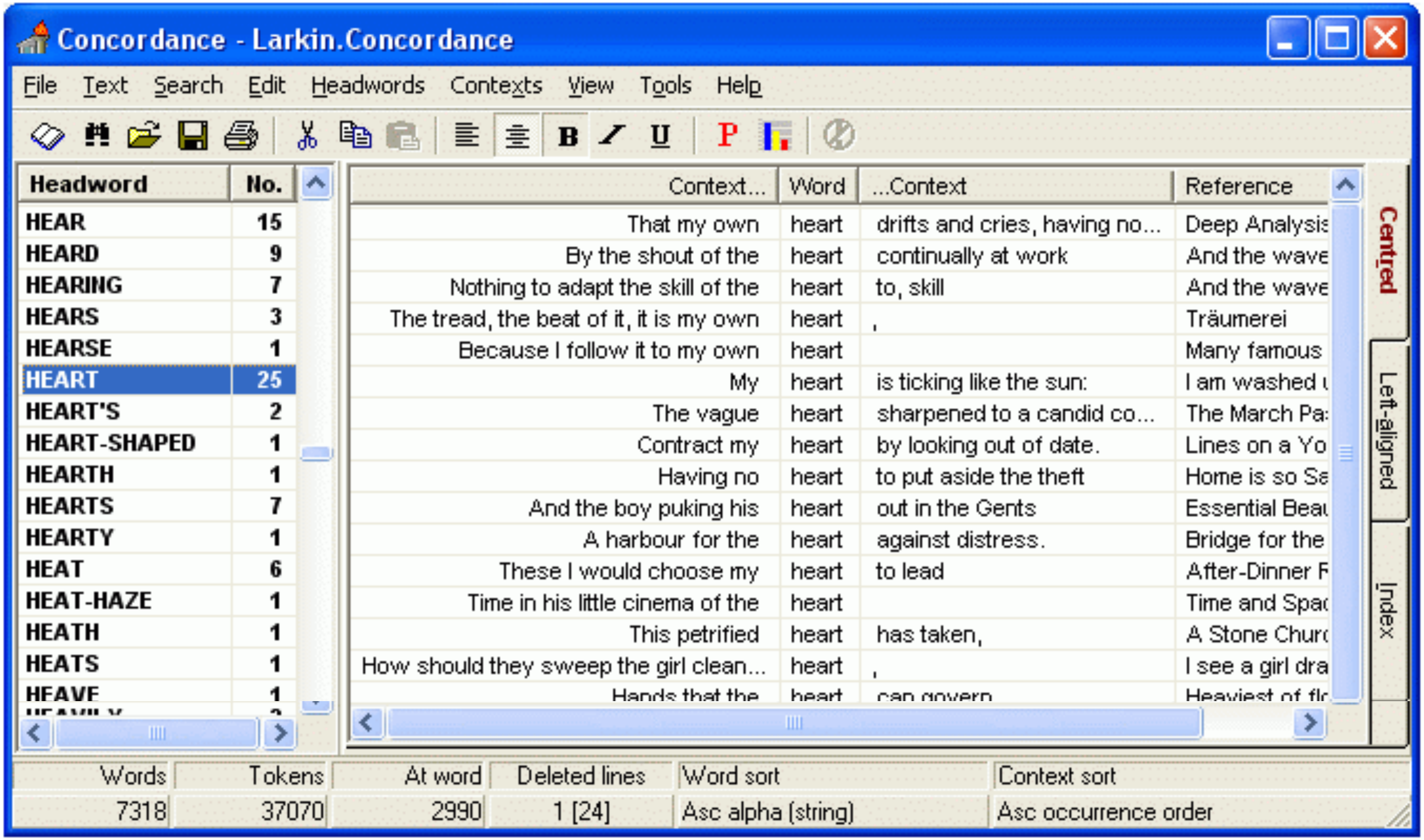
Parallel Tag Clouds

[Collins et al. '09]



Context and Structure

Concordance



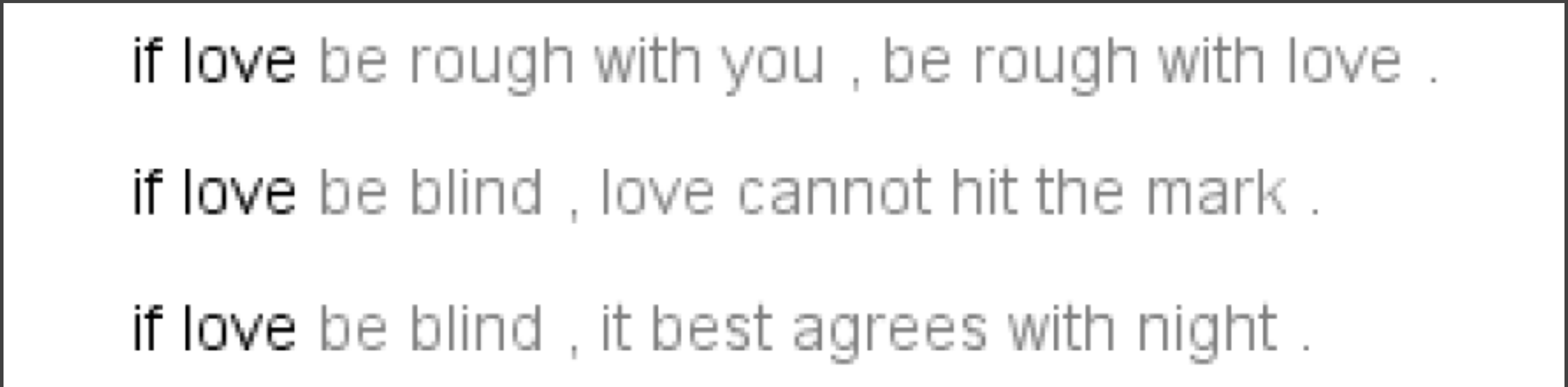
Headword	No.
HEAR	15
HEARD	9
HEARING	7
HEARS	3
HEARSE	1
HEART	25
HEART'S	2
HEART-SHAPED	1
HEARTH	1
HEARTS	7
HEARTY	1
HEAT	6
HEAT-HAZE	1
HEATH	1
HEATS	1
HEAVE	1

Context...	Word	...Context	Reference
That my own	heart	drifts and cries, having no...	Deep Analysis
By the shout of the	heart	continually at work	And the wave
Nothing to adapt the skill of the	heart	to, skill	And the wave
The tread, the beat of it, it is my own	heart	,	Träumerei
Because I follow it to my own	heart		Many famous
My	heart	is ticking like the sun:	I am washed u
The vague	heart	sharpened to a candid co...	The March Pa:
Contract my	heart	by looking out of date.	Lines on a Yo
Having no	heart	to put aside the theft	Home is so Sa
And the boy puking his	heart	out in the Gents	Essential Beau
A harbour for the	heart	against distress.	Bridge for the
These I would choose my	heart	to lead	After-Dinner R
Time in his little cinema of the	heart		Time and Spac
This petrified	heart	has taken,	A Stone Churc
How should they sweep the girl clean...	heart	,	I see a girl dra
Hands that the	heart	can govern	Heaviest of flo

Words	Tokens	At word	Deleted lines	Word sort	Context sort
7318	37070	2990	1 [24]	Asc alpha (string)	Asc occurrence order

Context & Structure

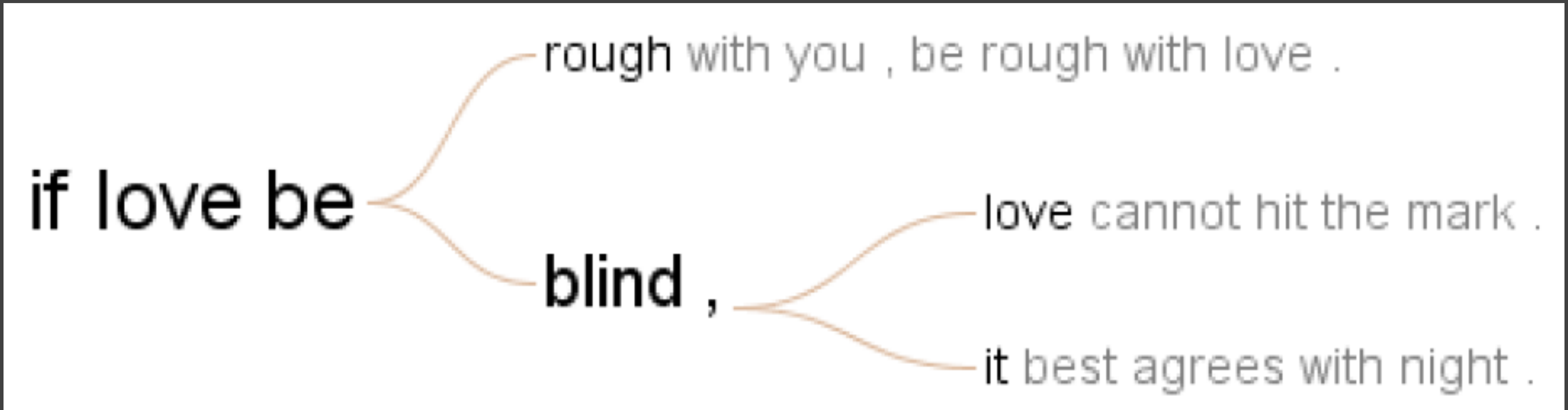
[Wattenberg et al. '08]



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 .



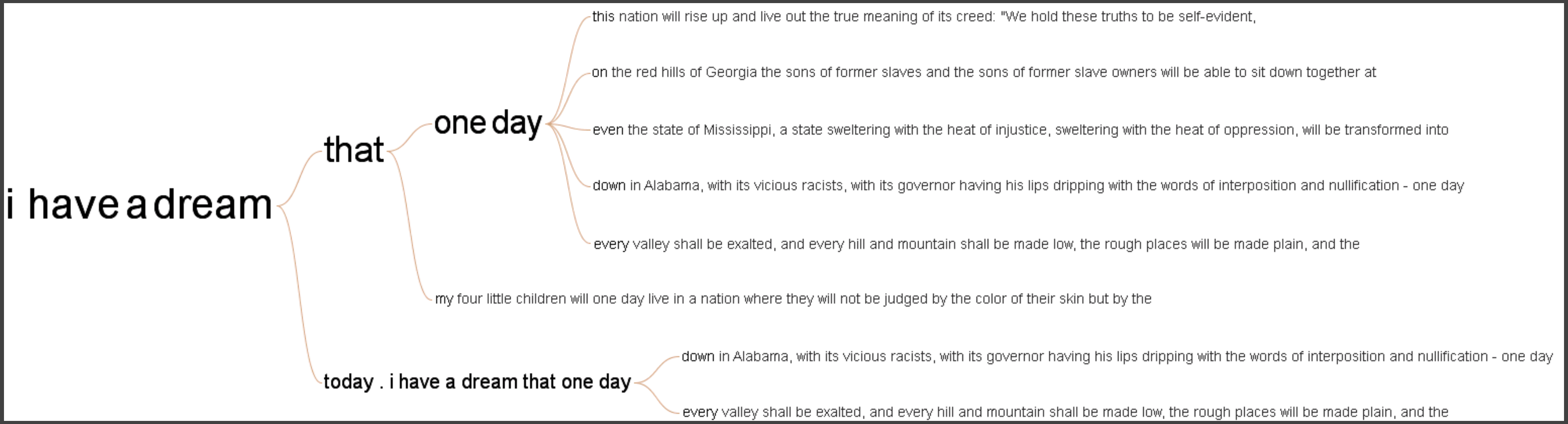
if love be
rough with you , be rough with love .
blind ,
love cannot hit the mark .
it best agrees with night .

Word Tree

[Wattenberg et al. '08]

Recurrent themes in speech structure

Visualization of all occurrences of "I have a dream" in Martin Luther King's historic speech:



i have a dream

that

one day

this nation will rise up and live out the true meaning of its creed: "We hold these truths to be self-evident,

on the red hills of Georgia the sons of former slaves and the sons of former slave owners will be able to sit down together at

even the state of Mississippi, a state sweltering with the heat of injustice, sweltering with the heat of oppression, will be transformed into

down in Alabama, with its vicious racists, with its governor having his lips dripping with the words of interposition and nullification - one day

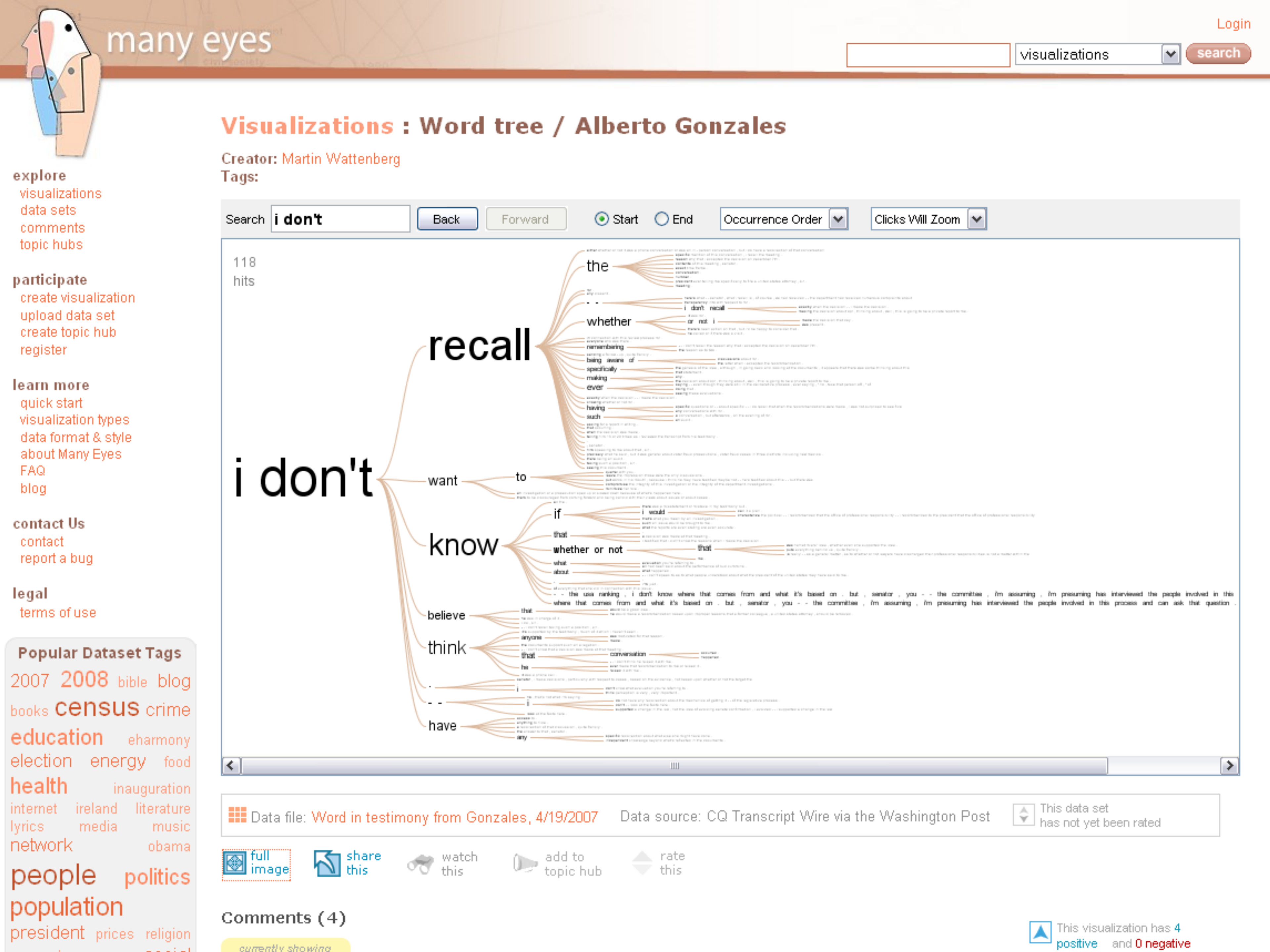
every valley shall be exalted, and every hill and mountain shall be made low, the rough places will be made plain, and the

my four little children will one day live in a nation where they will not be judged by the color of their skin but by the

today . i have a dream that one day

down in Alabama, with its vicious racists, with its governor having his lips dripping with the words of interposition and nullification - one day

every valley shall be exalted, and every hill and mountain shall be made low, the rough places will be made plain, and the



Visualizations : Word tree / Alberto Gonzales

Creator: Martin Wattenberg

Tags:

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

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

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

118 hits

i don't
recall
the
- -
whether
or not i
remembering
being aware of
specifically
making
ever
having
such
want
to
know
if
i would
that
whether or not
that
what
about
- - the usa ranking , i don't know where that comes from and what it's based on . but , senator , you - - the committee , i'm assuming , i'm presuming has interviewed the people involved in this
where that comes from and what it's based on . but , senator , you - - the committee , i'm assuming , i'm presuming has interviewed the people involved in this process and can ask that question
believe
that
think
anyone
that
conversation
he
.
- -
have
any

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

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. '09]

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

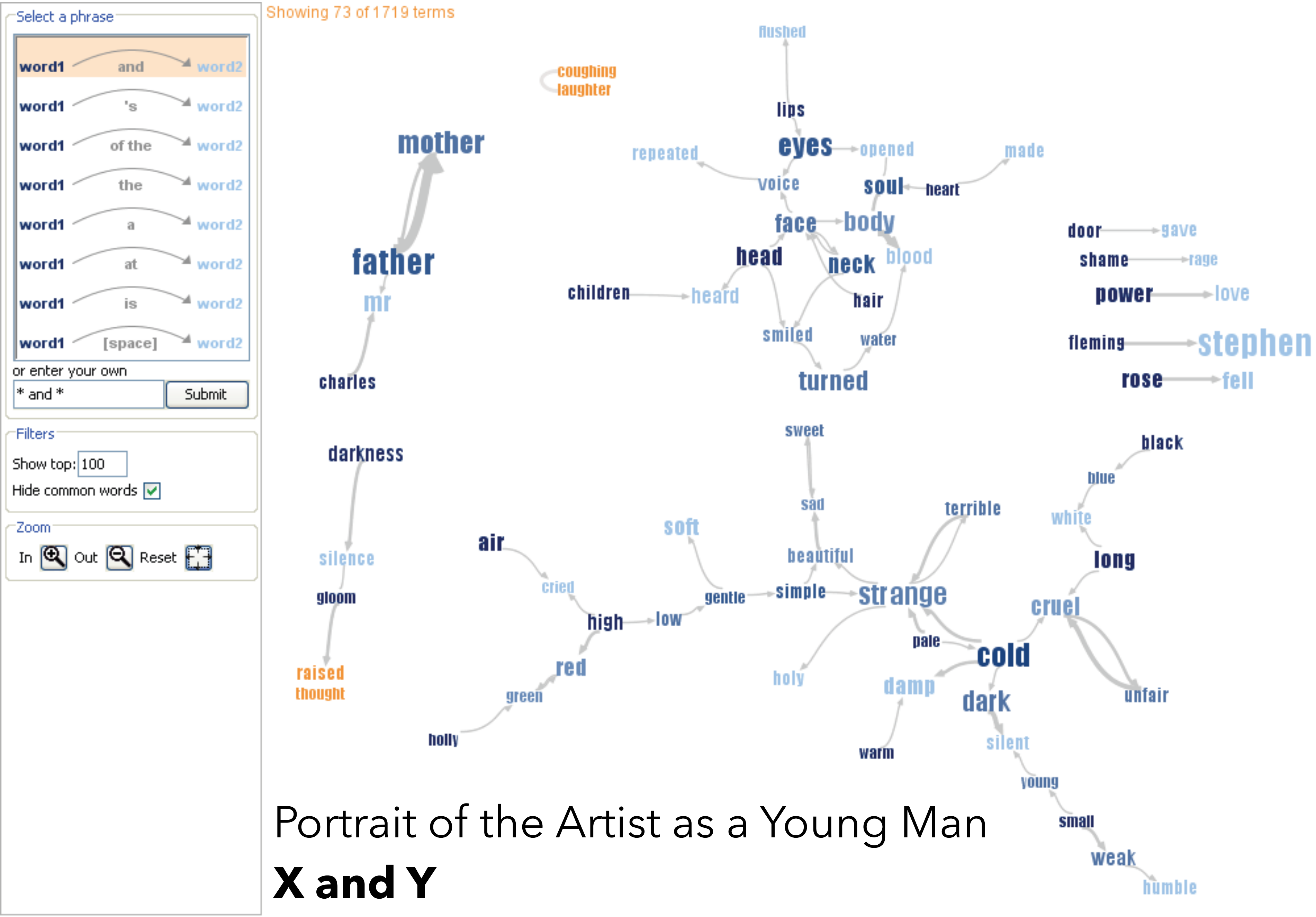
"A and B", "A at B", "A of B", etc.

Could be output of regexp or parser.

Visualize patterns in a node-link view:

Occurrences → Node size

Pattern position → Edge direction



Select a phrase

word1 and word2
word1 's word2
word1 of the word2
word1 the word2
word1 a word2
word1 at word2
word1 is word2
word1 [space] word2

or enter your own

* and *

Submit

Filters

Show top: 100

Hide common words ☑

Zoom

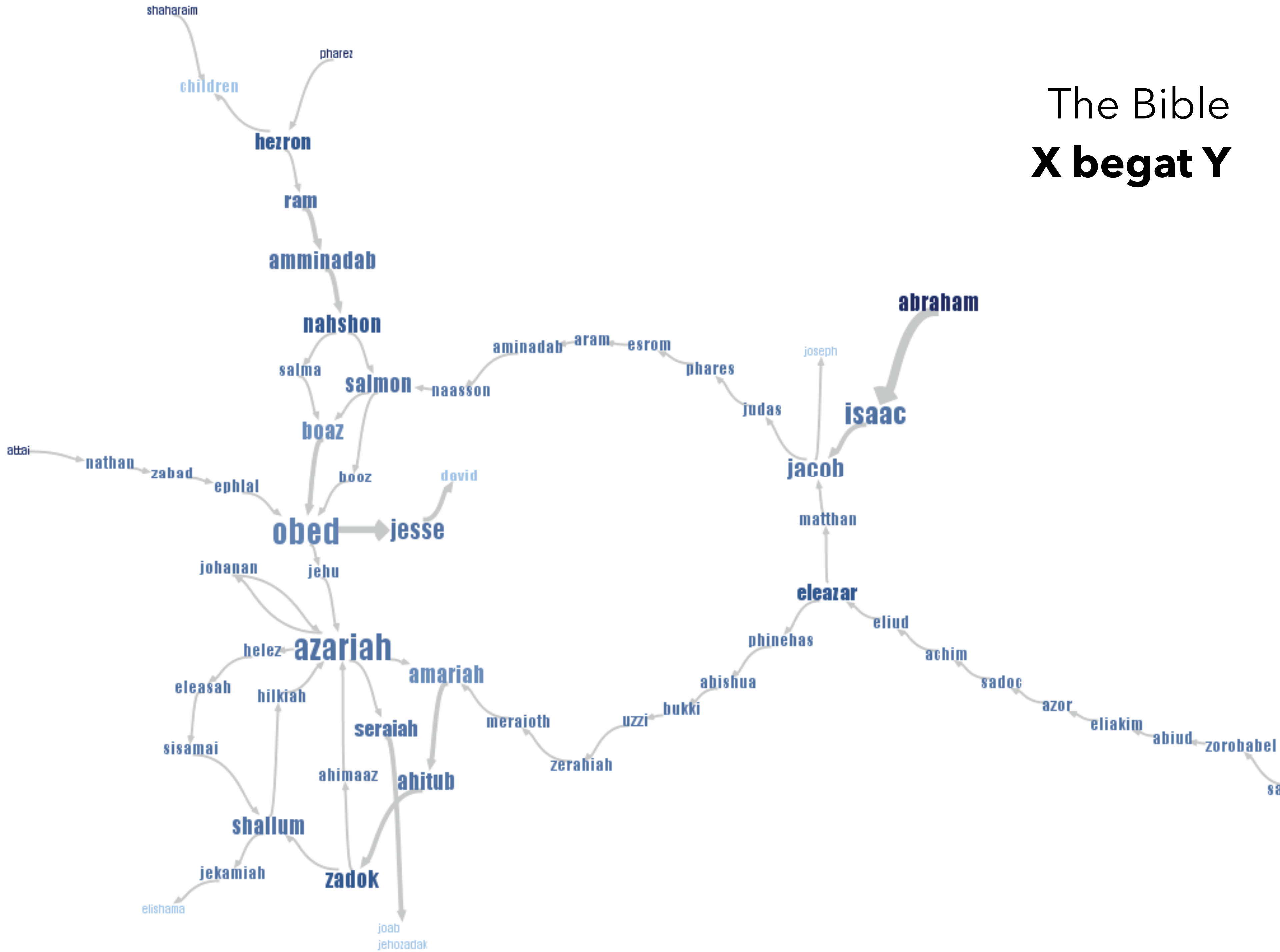
In Out Reset

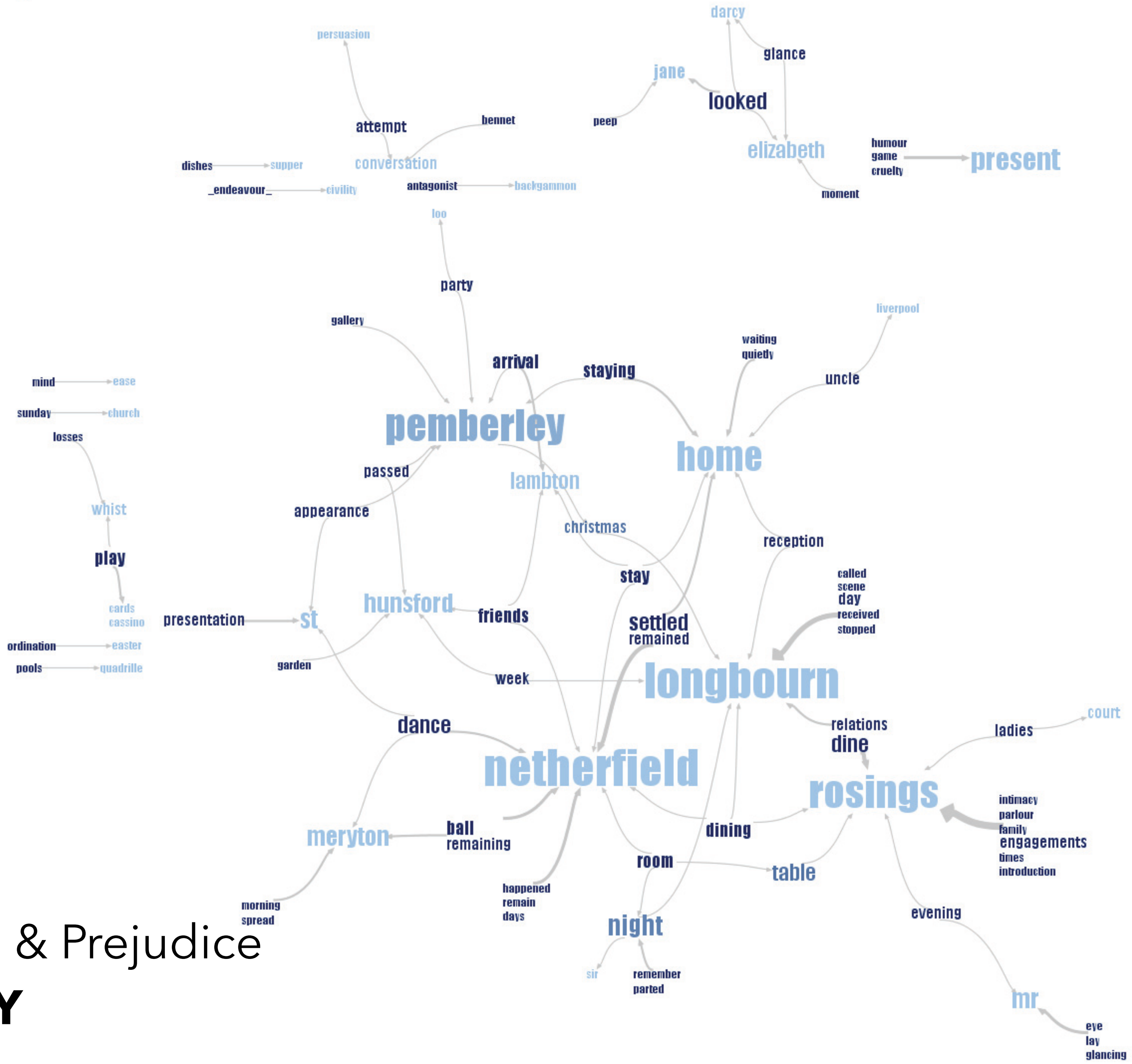
Showing 73 of 1719 terms

Portrait of the Artist as a Young Man

X and Y

The Bible
X begat Y



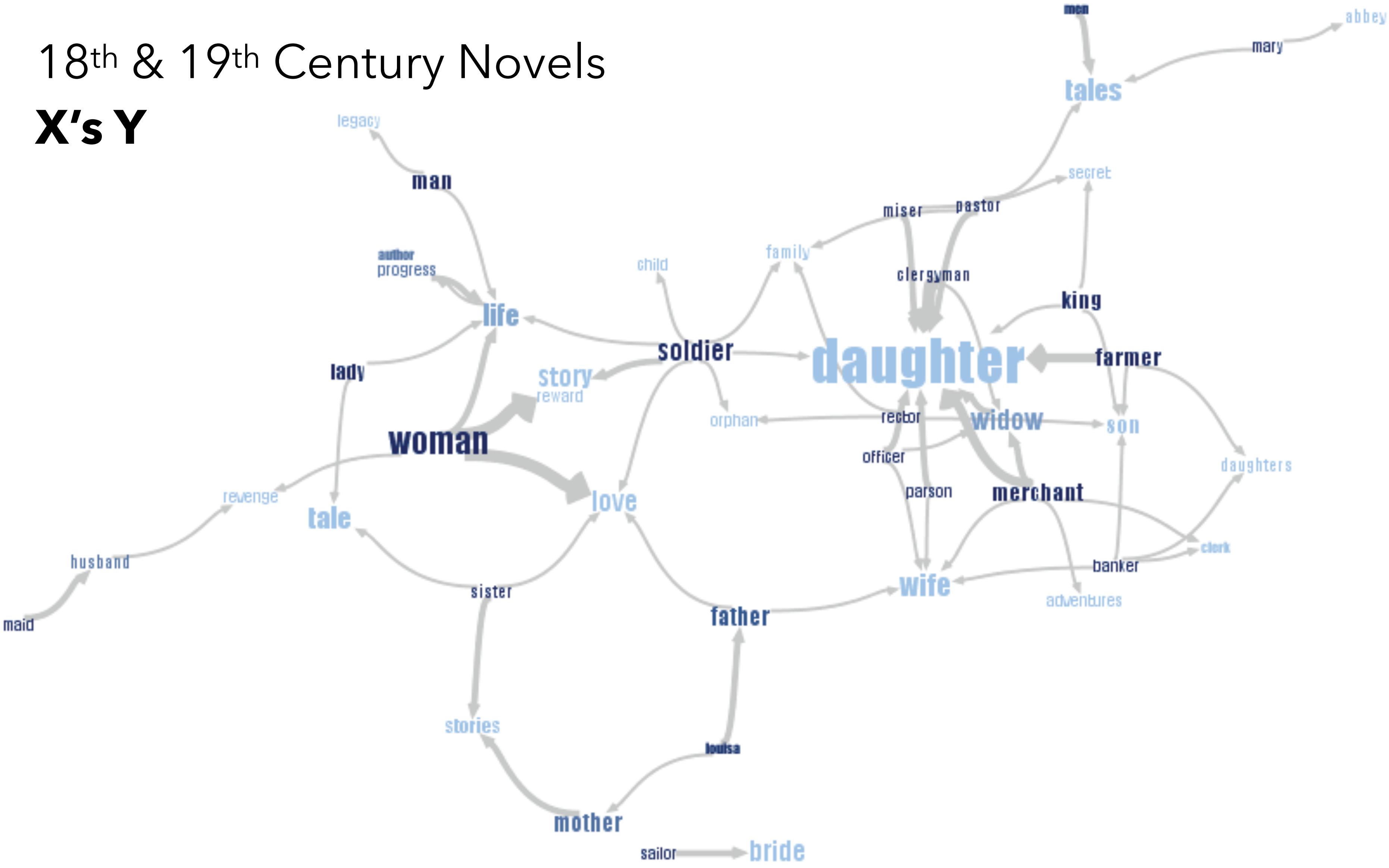


Pride & Prejudice

X at Y

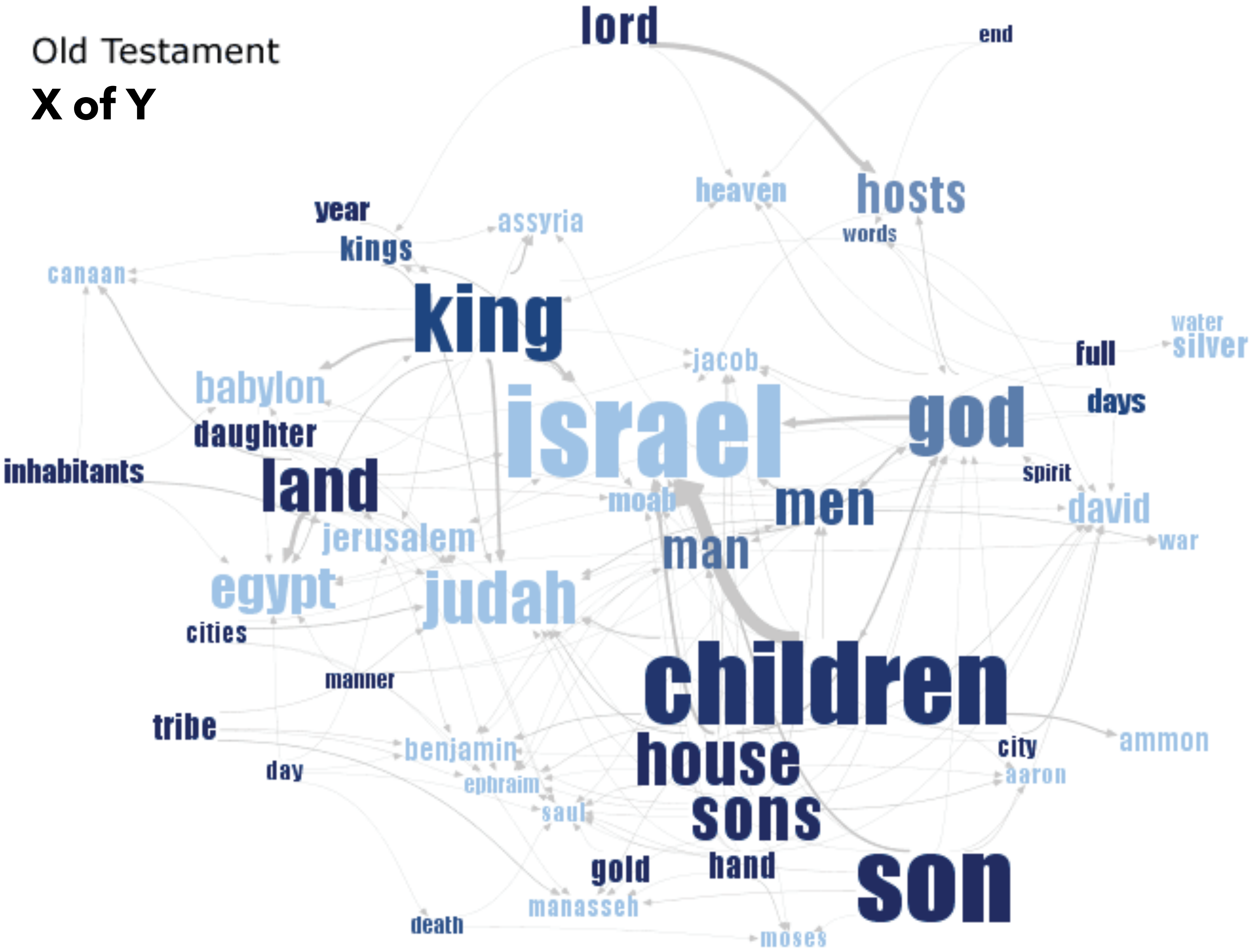
18th & 19th Century Novels

X's Y



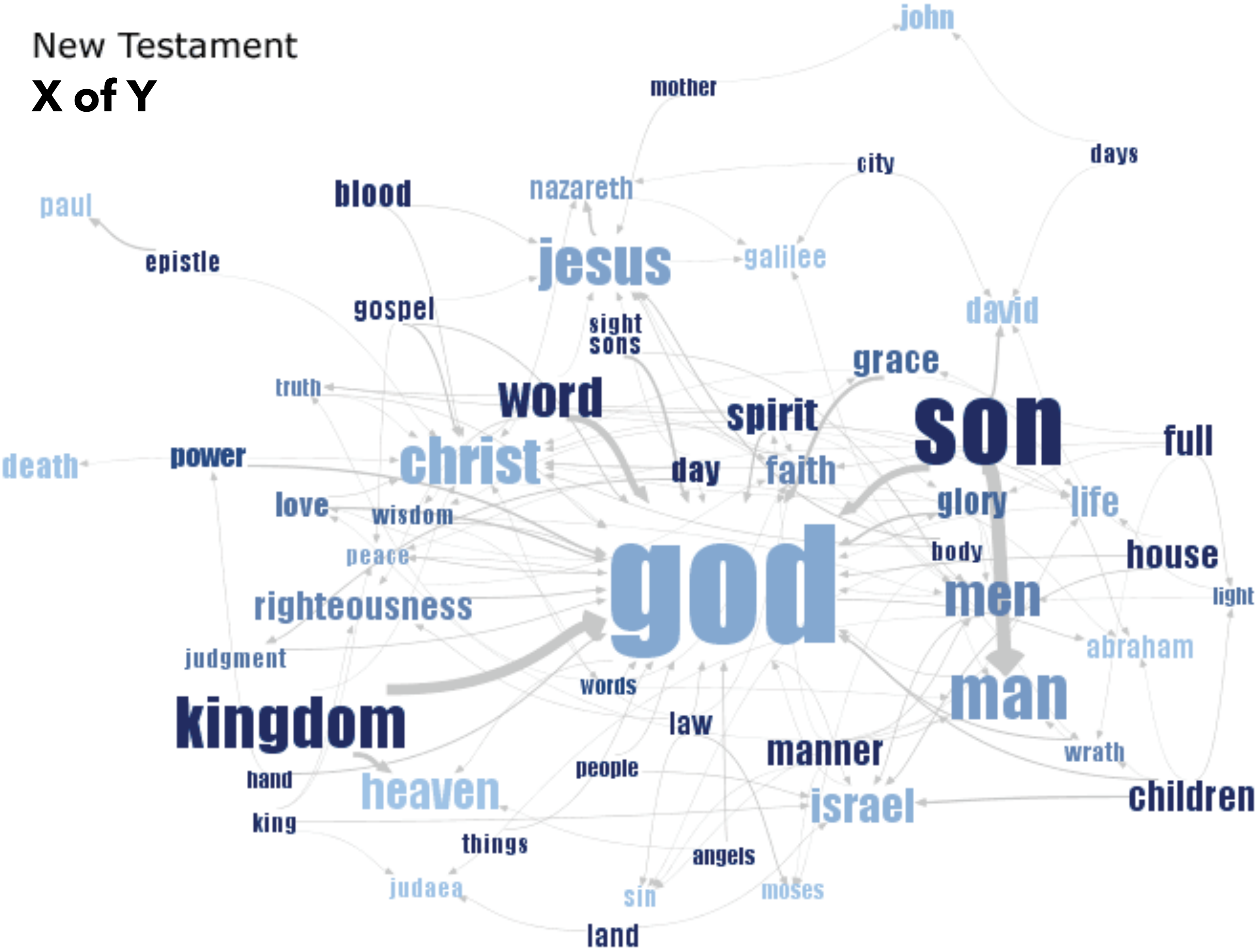
Old Testament

X of Y



New Testament

X of Y



Document Content

Understand Your Analysis Task

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

The Role of Interaction

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

Document Collections

Named Entity Recognition

Label named entities in text:

John Smith -> PERSON

Soviet Union -> COUNTRY

353 Serra St -> ADDRESS

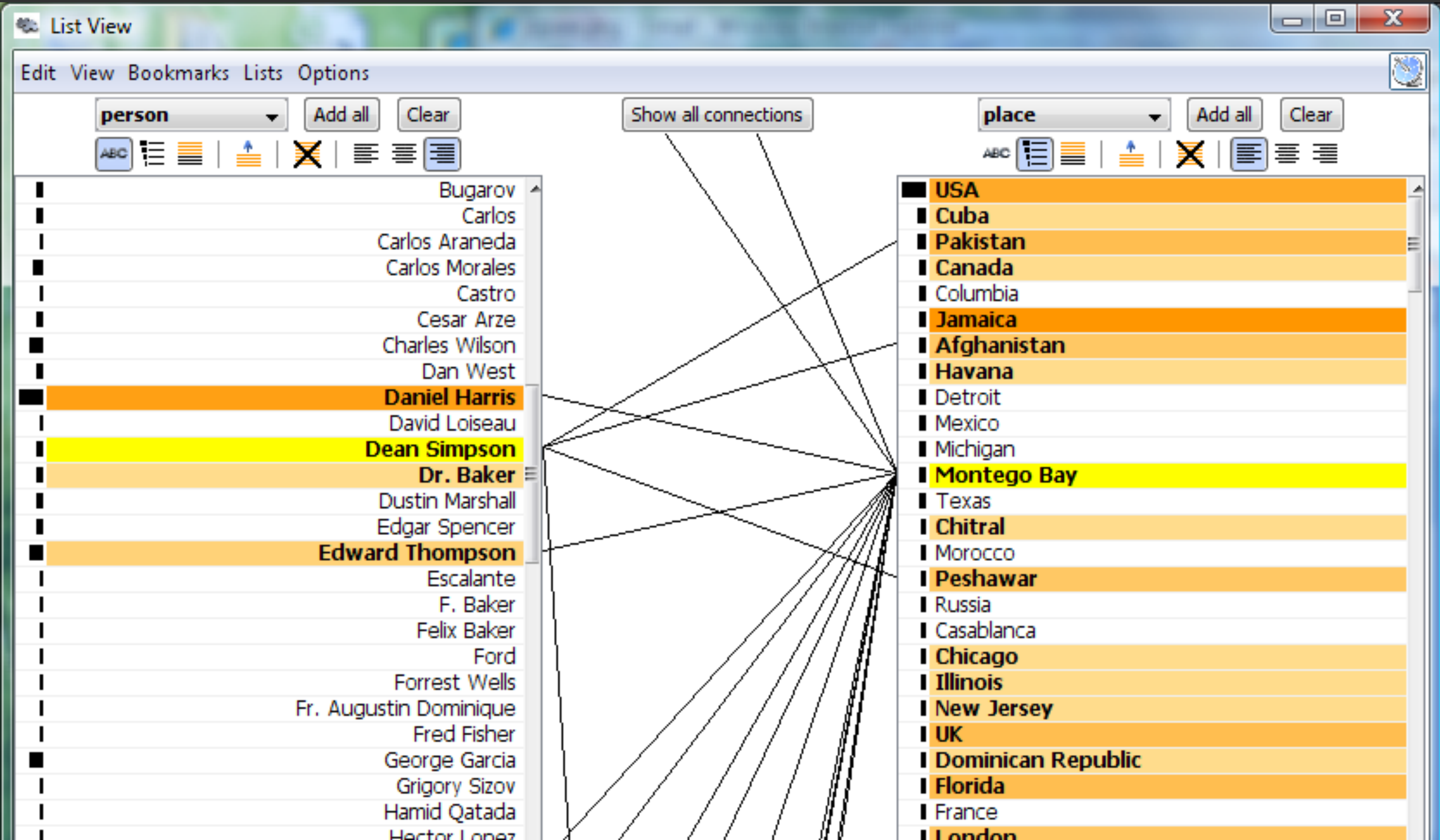
(555) 721-4312 -> PHONE NUMBER

Entity relations: how do the entities relate?

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

Entity Relationships

[Görg et al. '07]

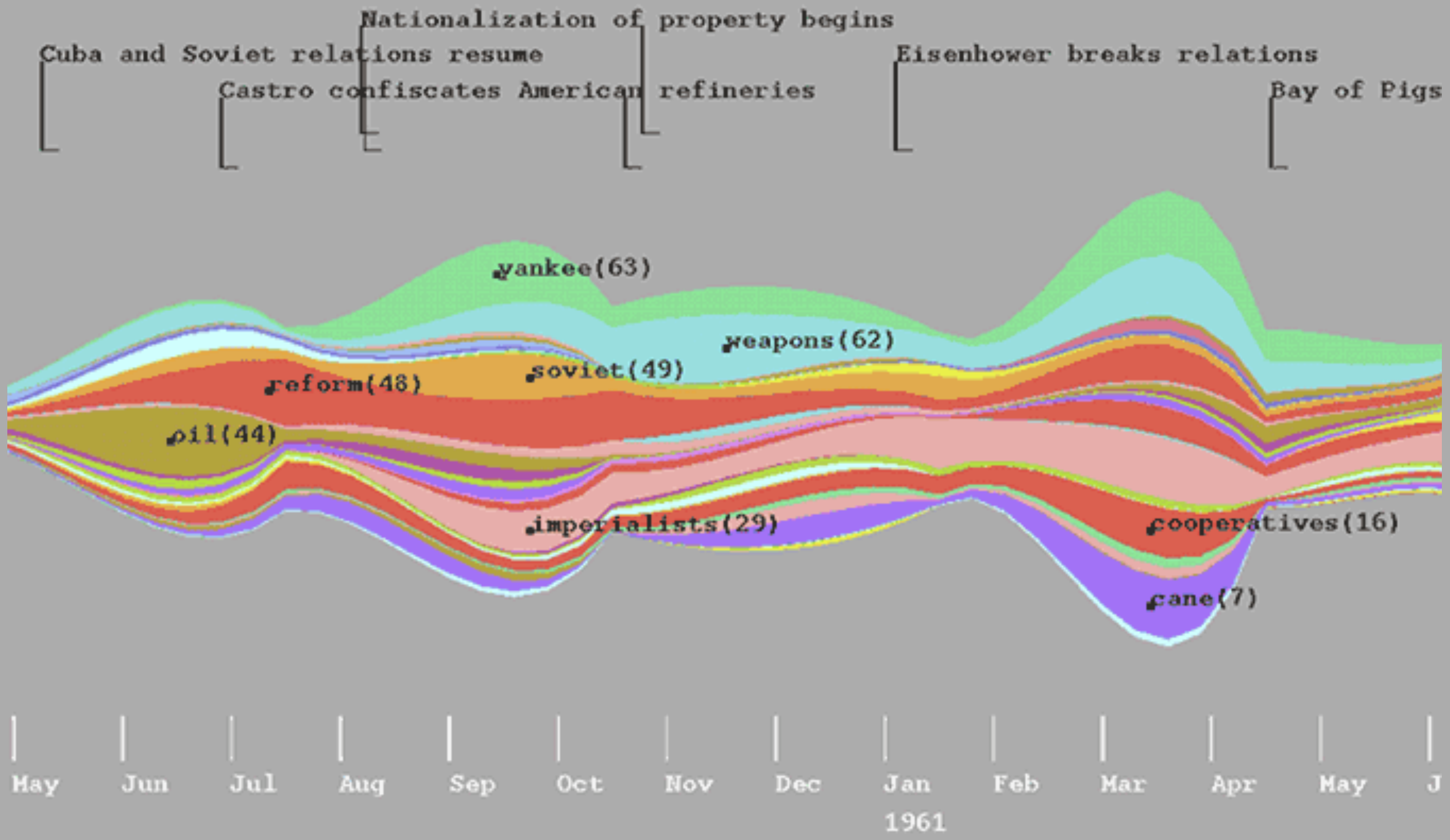


Bugarov
Carlos
Carlos Araneda
Carlos Morales
Castro
Cesar Arze
Charles Wilson
Dan West
Daniel Harris
David Loiseau
Dean Simpson
Dr. Baker
Dustin Marshall
Edgar Spencer
Edward Thompson
Escalante
F. Baker
Felix Baker
Ford
Forrest Wells
Fr. Augustin Dominique
Fred Fisher
George Garcia
Grigory Sizov
Hamid Qatada
Hector Lopez

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

Theme River

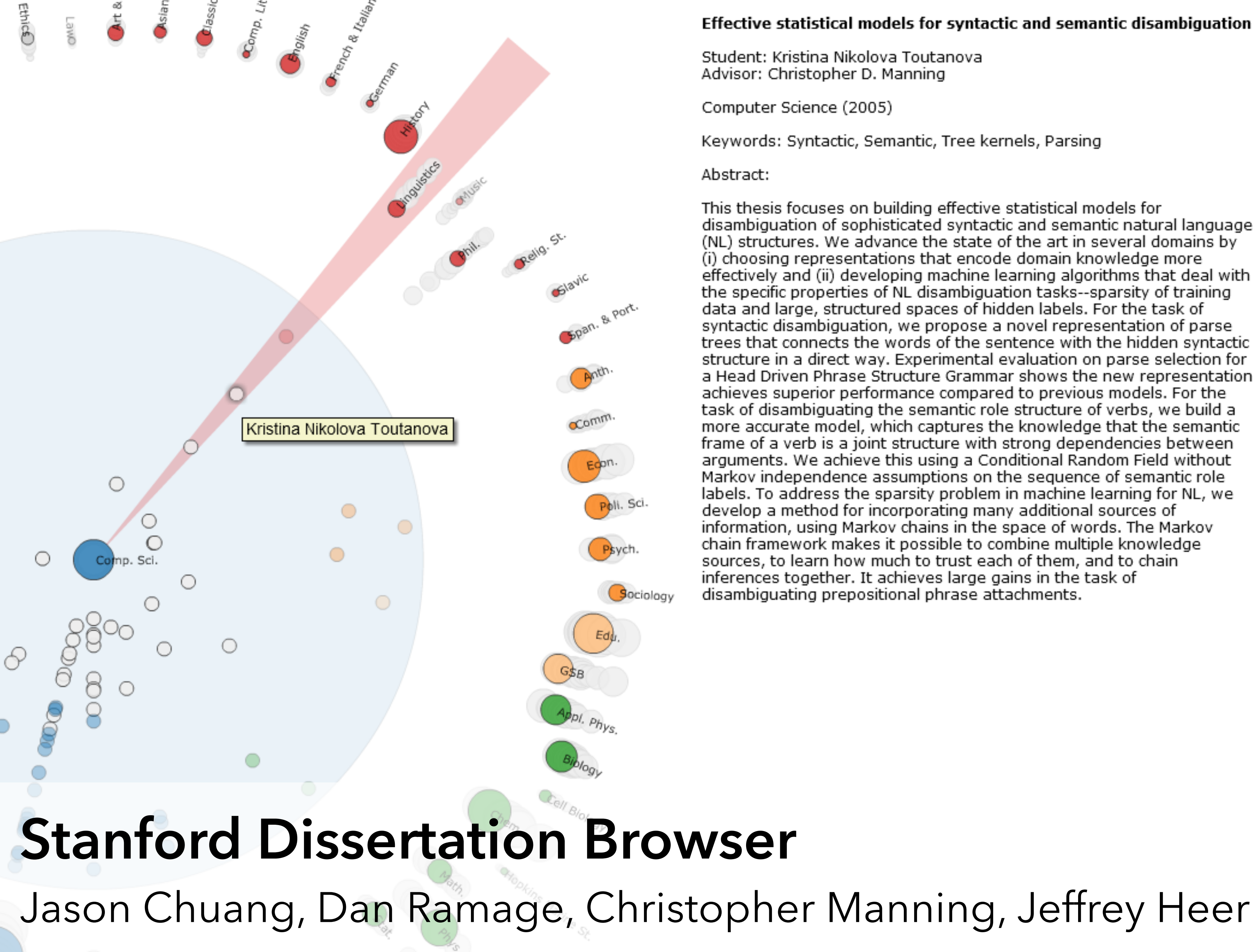
[Havre et al. '00]



Similarity & Clustering

Compute vector distance among docs
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:

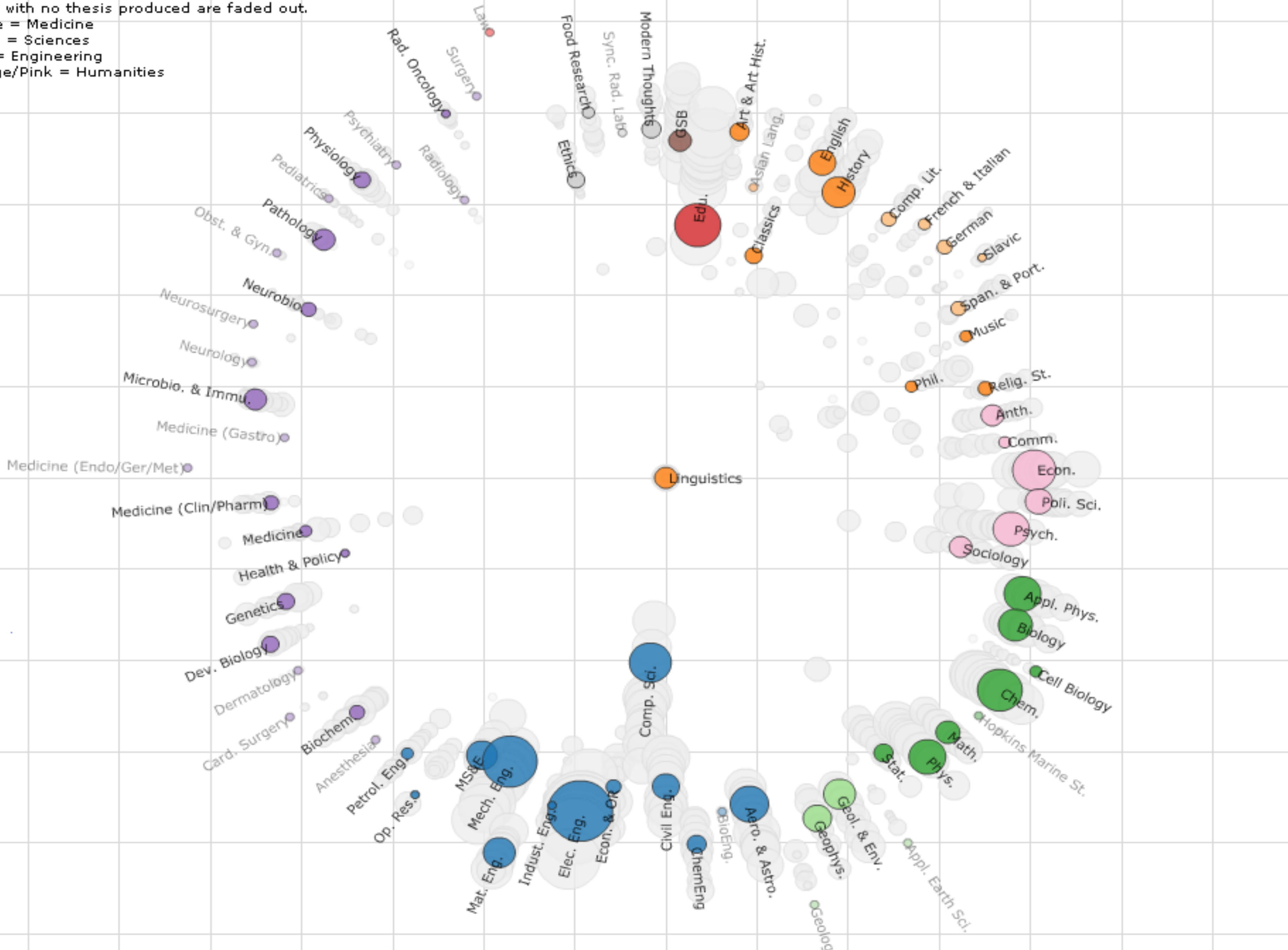
This thesis focuses on building effective statistical models for disambiguation of sophisticated syntactic and semantic natural language (NL) structures. We advance the state of the art in several domains by (i) choosing representations that encode domain knowledge more effectively and (ii) developing 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.

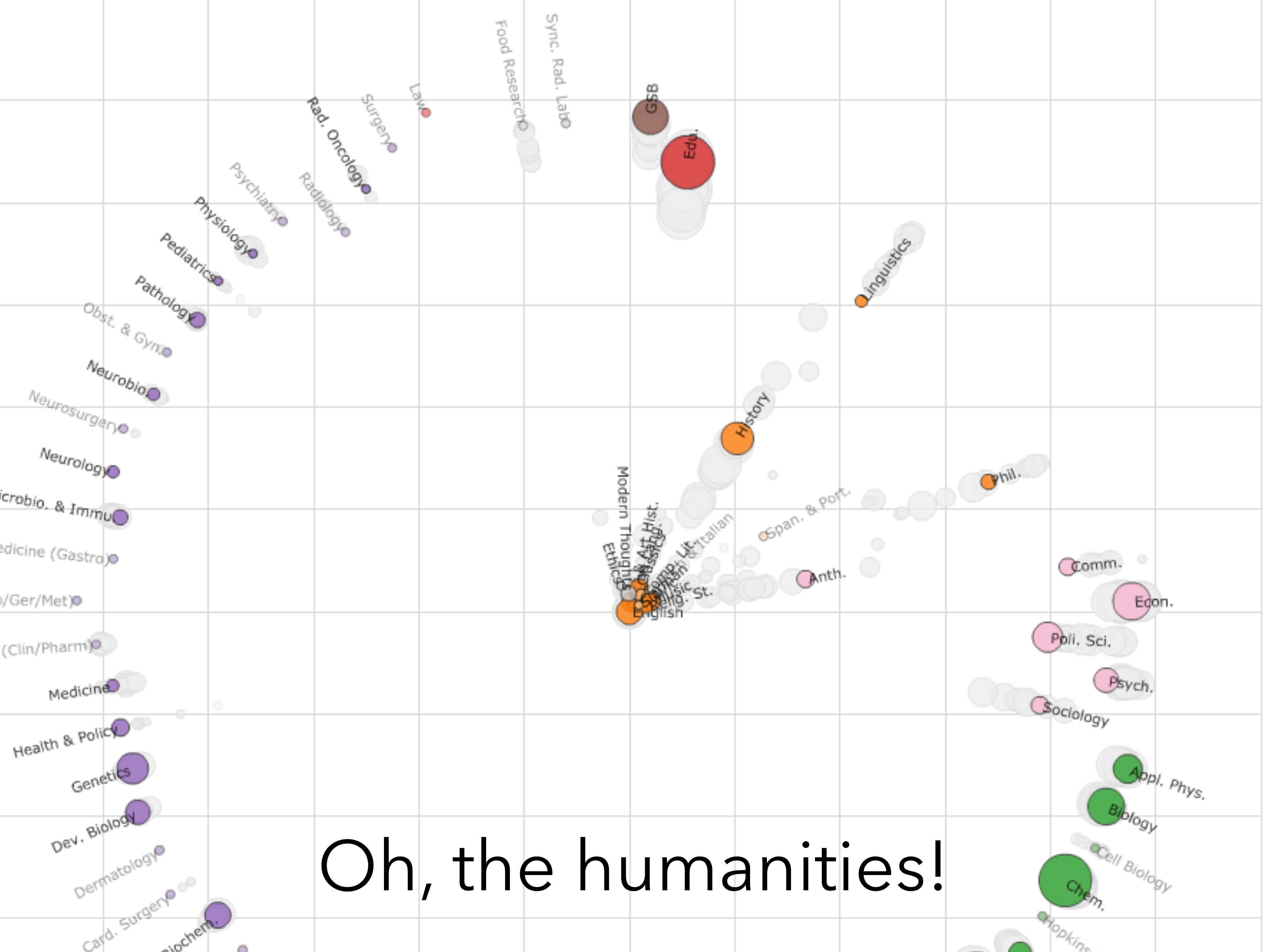
Stanford Dissertation Browser

Jason Chuang, Dan Ramage, Christopher Manning, Jeffrey Heer

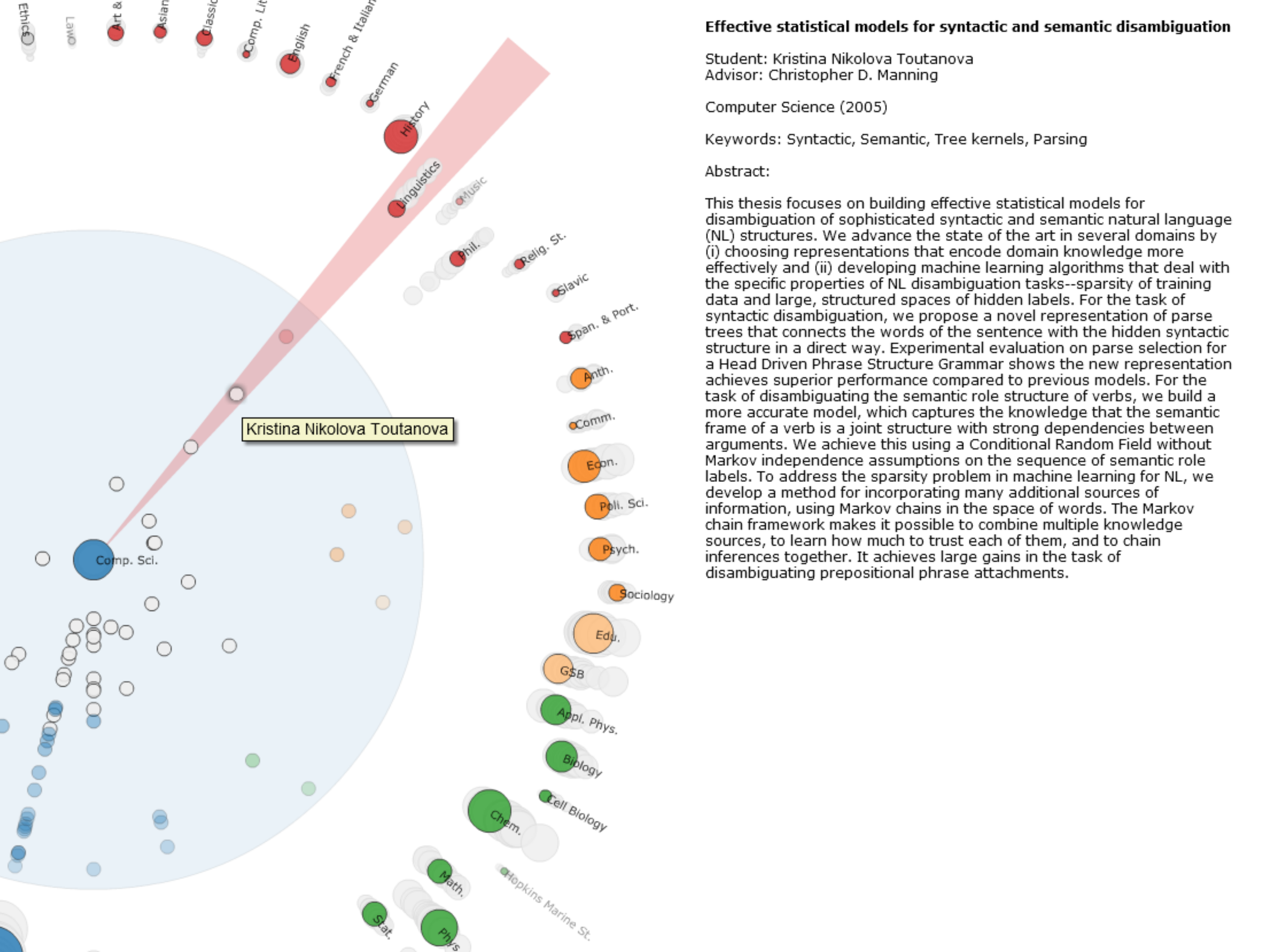
Topic Distance Between Stanford Depts

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

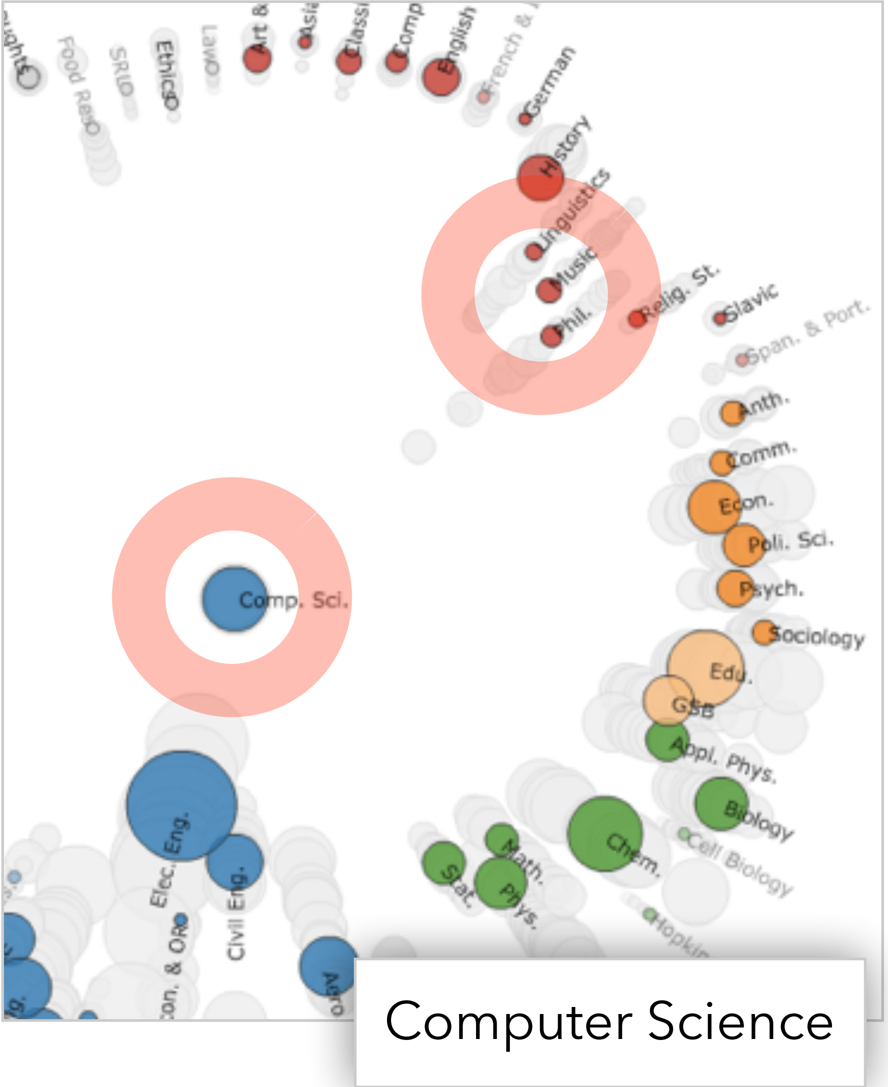
Student: Kristina Nikolova Toutanova
Advisor: Christopher D. Manning

Computer Science (2005)

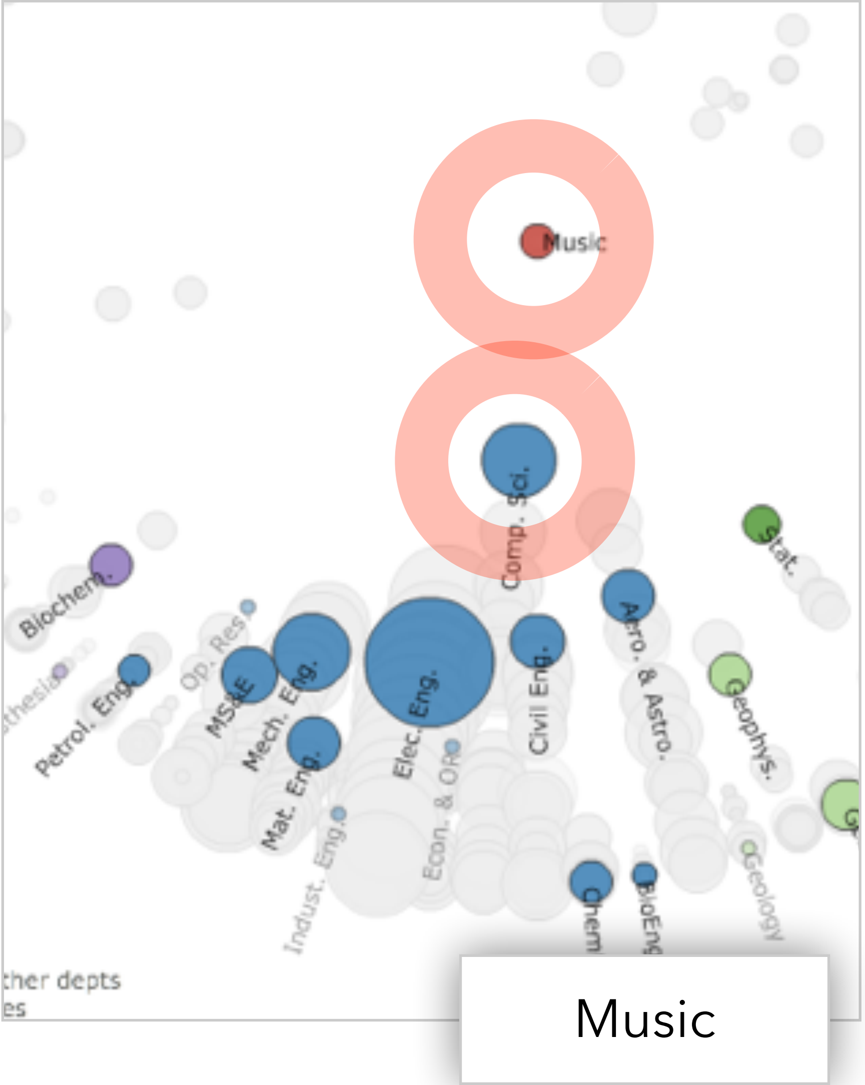
Keywords: Syntactic, Semantic, Tree kernels, Parsing

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.

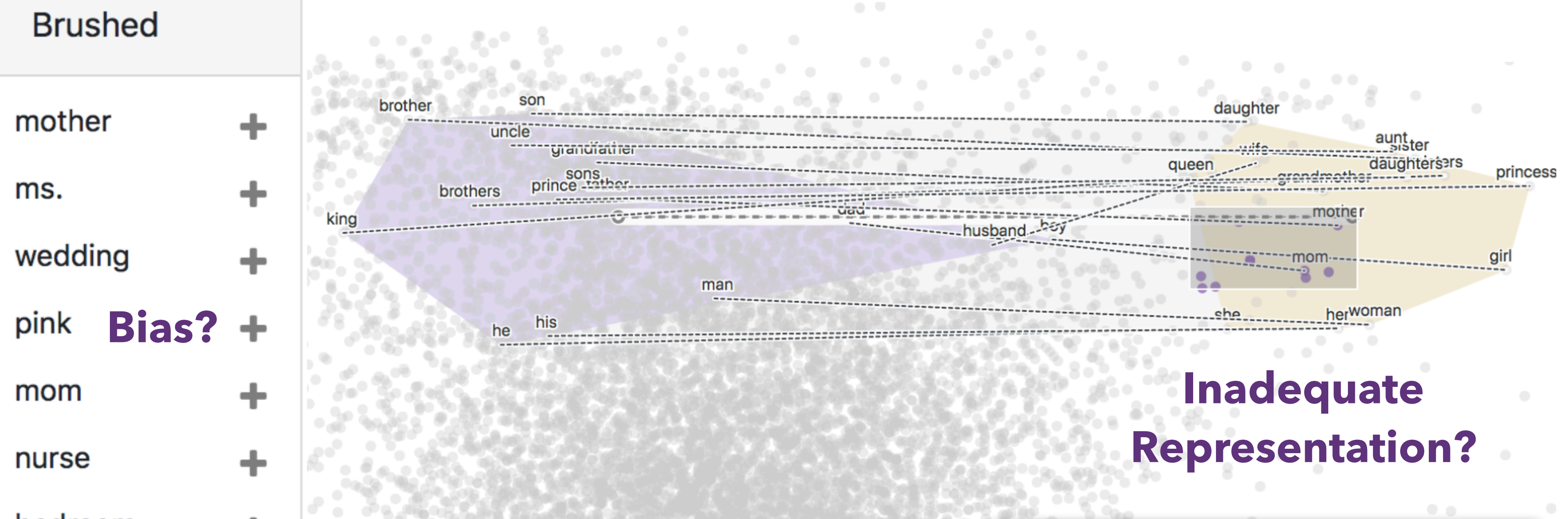


Computer Science



Music

“Word Borrowing” via Labeled LDA

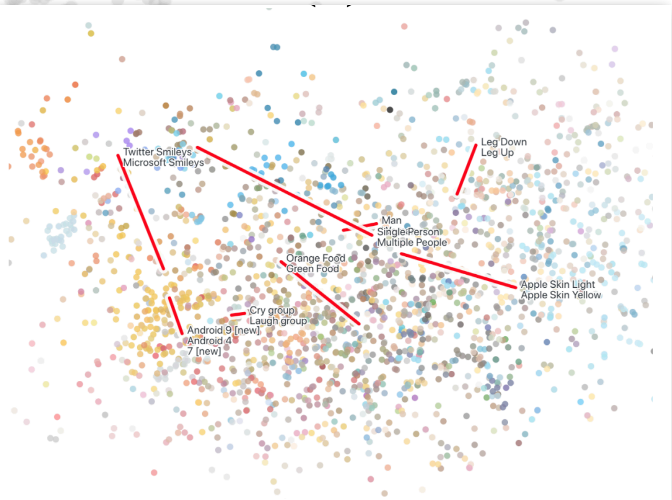


Brushed

- mother +
- ms. +
- wedding +
- pink +
- mom +
- nurse +
- bedroom +
- ladies +
- householder +
- butterfly +

Bias?

Inadequate Representation?



Latent Space Cartography

Visual Analysis of Vector Space Embeddings

Yang Liu, Eunice Jun, Qisheng Li (CSE 512, Spring '18)

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.

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