VISUALIZING TEXT

Petra Isenberg

RECAP

STRUCTURED DATA

0.103	0.176	0.387	0.300	0.379
0.333	0.384	0.564	0.587	0.857
0.421	0.309	0.654	0.729	0.228
0.266	0.750	1.056	0.936	0.911
0.225	0.326	0.643	0.337	0.721
0.187	0.586	0.529	0.340	0.829
0.153	0.485	0.560	0.428	0.628

UNSTRUCTURED DATA

(TODAY)

VISUALIZING TEXT

TEXT IS DIFFERENT

COMMON

UNSTRUCTURED (MOSTLY)

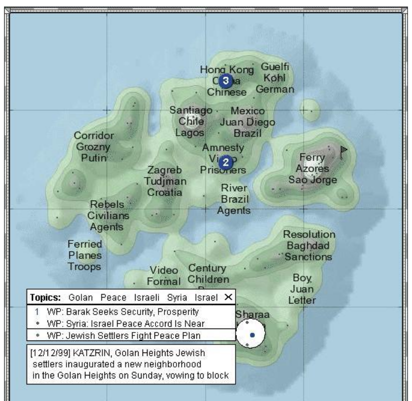
HIGH-DIMENSIONAL (10,000+)

BIG!

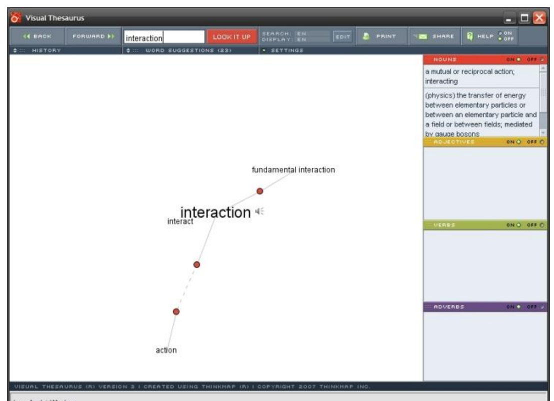
TEXT?

WHY

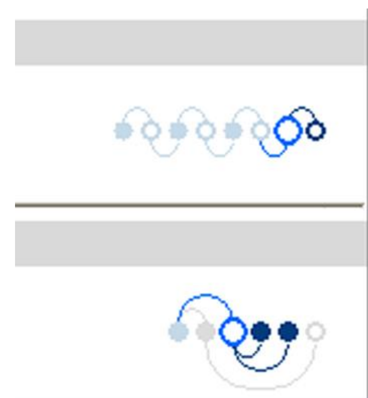
- To assist information retrieval
- To enable linguistic analysis
- To augment analytics on mixed data



Themescape



Visual Thesaurus



Thread Arcs

WHY

UNDERSTANDING: GET THE “GIST” OF A DOCUMENT

GROUPING: CLUSTER FOR OVERVIEW OR CLASSIFICATION

COMPARE: COMPARE DOCUMENT COLLECTIONS, OR INSPECT EVOLUTION OF COLLECTION OVER TIME

CORRELATE: COMPARE PATTERNS IN TEXT TO THOSE IN OTHER DATA, E.G., CORRELATE WITH SOCIAL NETWORK

WHAT IS TEXT

DOCUMENTS

- ARTICLES, BOOKS AND NOVELS
- COMPUTER PROGRAMS
- E-MAILS, WEB PAGES, BLOGS
- TAGS, COMMENTS

COLLECTION OF DOCUMENTS

- MESSAGES (E-MAIL, BLOGS, TAGS, COMMENTS)
- SOCIAL NETWORKS (PERSONAL PROFILES)
- ACADEMIC COLLABORATIONS (PUBLICATIONS)
- EVEN WHOLE LIBRARIES, WEBSITES, SOCIAL NETWORKS

DIFFICULT DATA

TOO MUCH DATA

- Millions of blog posts,
- Hundreds of thousands of news stories,
- 183 billion emails,
- ... **per day**

NOISY DATA

- 70-72% of email is spam
- Text contains section headings, figure captions, and direct quotes
- ….

ONCE YOU HAVE THE DATA...

Most meaning comes from our minds and common understanding.

"How much is that doggy in the window?"

- how much: social system of barter and trade (not the size of the dog)
- "doggy" implies childlike, plaintive, probably cannot do the purchasing on their own
- "in the window" implies behind a store window, not really inside a window, requires notion of window shopping

(Hearst, 2006)

LANGUAGE IS AMBIGUOUS

- Words and phrases can have many meanings, determined by context and world knowledge.
- Interesting language is often figurative:
  – You are a couch potato.
  – They fought like cats and dogs.
  – Opportunity knocked on the door

VISUAL CONSIDERATIONS

Supporters of Martin, who has been jailed without trial for more than two years, are calling on Prime Minister Stephen Harper to ask Mexican president Felipe Calderon to release Martin text is not preattentive under a section of the Mexican constitution that allows the government to expel undesirables from the country. Martin's supporters believe she has no chance of a fair trial in Mexico. Neither does Waage.

VISUAL CONSIDERATIONS

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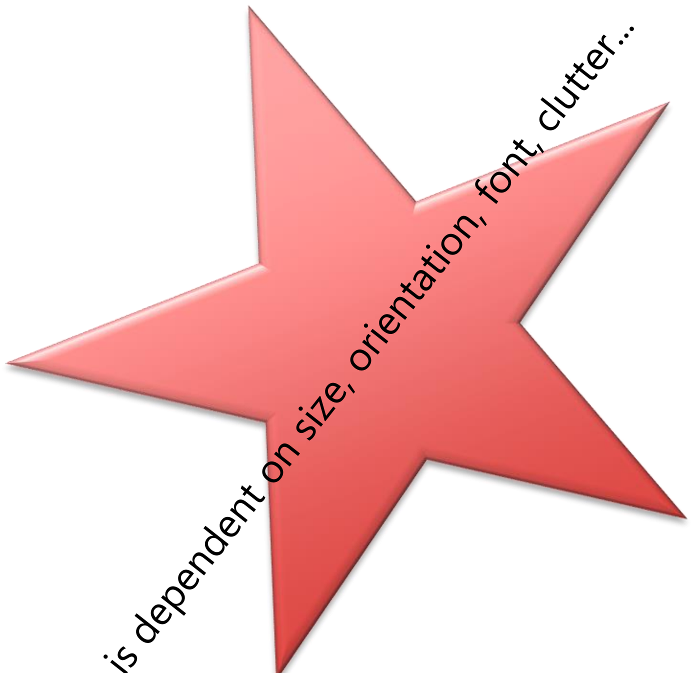


Text readability is dependent on size, orientation, font, clutter…

VISUALIZING LANGUAGE IS ALSO EASY!

SO much data available for analysis

(Mostly) readily computer readable

Simple techniques can give instant summaries

OUTLINE

TEXT AS DATA

VISUALIZING DOCUMENT CONTENT

EVOLVING DOCUMENTS

DOCUMENT COLLECTIONS

TEXT AS DATA

Words are
the basic
unit of data.

WORD-LEVEL ATTRIBUTES

WORD LENGTH

PART OF SPEECH (NOUN, VERB, ADJECTIVE, ETC.)

FORMAT (*ITALIC*, <u>UNDERLINE</u>, ETC.)

LANGUAGE (ENGLISH? LATIN? JAPANESE?)

FREQUENCY / DIFFICULTY (IS IT COMMON?)

SENTIMENT (POSITIVE OR NEGATIVE CONNOTATION)

SYNONYMS / ANTONYMS / ETYMOLOGY (OTHER MEANINGS? ROOTS?)

ENTITIES (e.g. “Calgary”, “Obama”, “Telus”)

… AND MANY MORE

AGGREGATION

REPETITION
PLAGARISM
SHARED ENTITIES
AUTHOR STYLE

COLLECTION

- DOCUMENT
- SECTION
- PAGE
- PARAGRAPH
- SENTENCE
- WORD

TENSE
SENTIMENT
SENTENCE LENGTH
READING LEVEL

LINGUISTIC METHODS

- Word Counting
- Word Scoring
- Stemming
- Stop Word Removal
- Part of Speech Tagging
- Parsing
- Word Sense Disambiguation
- Named Entity Recognition
- Semantic Categorization
- Sentiment Analysis
- Topic Modeling (some caveats)

NAMED ENTITY RECOGNITION

IDENTIFY AND CLASSIFY NAMED ENTITIES IN TEXT:

- JOHN SMITH IS A PERSON
- SOVIET UNION IS A COUNTRY
- 2500 UNIVERSITY DR IS AN ADDRESS
- (555) 867-5309 IS A PHONE NUMBER

ENTITY RELATIONS: HOW DO THE ENTITIES RELATE?

DO THEY CO-OCCUR IN A DOCUMENT? IN A SENTENCE?

TEXT PROCESSING

TOKENIZATION: SEGMENT TEXT INTO TERMS

ENTITIES? "SAN FRANCISCO", "O'CONNOR", "U.S.A."

REMOVE STOP WORDS? "A", "AN", "THE", "TO", "BE"

N-GRAMS? CAN TAKE WORDS IN 2-WORD GROUPS (BI-GRAMS), 3-WORD (TRI-GRAMS), ETC.

STEMMING: GROUP TOGETHER DIFFERENT FORMS

ROOTS: VISUALIZATION(S), VISUALIZE(S), VISUALLY ➞ VISUAL

LEMMATIZATION: GOES, WENT, GONE ➞ GO

FOR VISUALIZATION, SOMETIMES NEED TO REVERSE STEMMING FOR LABELS

SIMPLE SOLUTION: MAP FROM STEM TO THE MOST FREQUENT WORD

RESULT: ORDERED STREAM OF TERMS

TEXT PROCESSING

"The quick brown fox jumps over the lazy dog."

TOKENIZE (N=1)
[The], [quick], [brown], [fox], [jumps], [over], [the], [lazy], [dog].

TOKENIZE (N=1), REMOVE STOPWORDS, STEM
[quick], [brown], [fox], [jump], [over], [lazy], [dog]

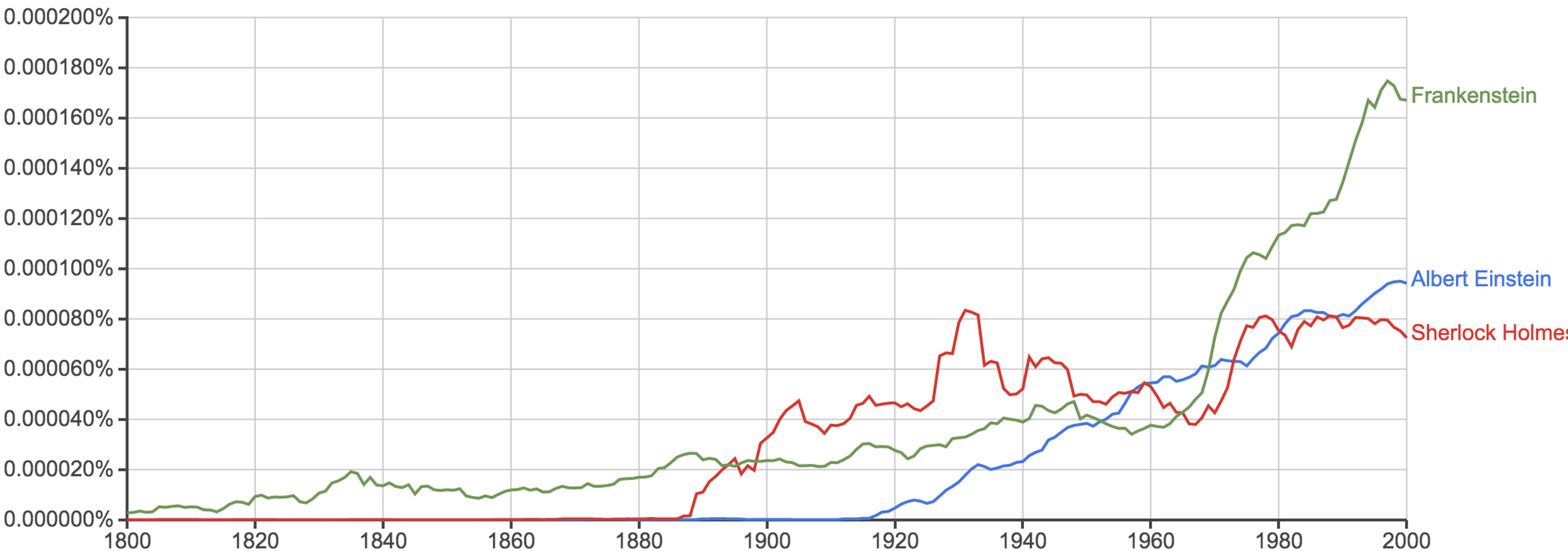
TOKENIZE (N=2)
[the quick], [quick brown], [brown fox], [fox jumps], [jumps over], [over the]…

TOKENIZE (N=5)
[the quick brown fox jumps], [quick brown fox jumps over], [brown fox jumps over
…

Google Books Ngram Viewer

Graph these comma-separated phrases: Albert Einstein,Sherlock Holmes,Frankenstein ☐ case-insensitive

between 1800 and 2000 from the corpus English with smoothing of 3. Search lots of books



(click on line/label for focus)

NLTK (NATURAL LANGUAGE TOOLKIT)

Tokenize and tag some text:

NLTK.org
Python

```
>>> import nltk
>>> sentence = """At eight o'clock on Thursday morning
... Arthur didn't feel very good."""
>>> tokens = nltk.word_tokenize(sentence)
>>> tokens
['At', 'eight', "o'clock", 'on', 'Thursday', 'morning',
'Arthur', 'did', "n't", 'feel', 'very', 'good', '.']
>>> tagged = nltk.pos_tag(tokens)
>>> tagged[0:6]
[('At', 'IN'), ('eight', 'CD'), ("o'clock", 'JJ'), ('on', 'IN'),
('Thursday', 'NNP'), ('morning', 'NN')]
```

Identify named entities:

```
>>> entities = nltk.chunk.ne_chunk(tagged)
>>> entities
Tree('S', [('At', 'IN'), ('eight', 'CD'), ("o'clock", 'JJ'),
           ('on', 'IN'), ('Thursday', 'NNP'), ('morning', 'NN'),
       Tree('PERSON', [('Arthur', 'NNP')]),
           ('did', 'VBD'), ("n't", 'RB'), ('feel', 'VB'),
           ('very', 'RB'), ('good', 'JJ'), ('.', '.')])
```

DOCUMENT CONTENT

TAG CLOUDS

WORD COUNT

additional air analysis analysts annotation applications approach asked author average based build chart citizen clustering collaborative collection comments commentspace community complete condition contributions crowd crowdsourcing data datasets design different discussion evidence example experiment experts explanations explore features figure filtering generated group help hypotheses hypothesis identify including indicating information interactive interface knowledge links members microtasks multiple novice number oaen observations organize participants phases pp proceedings process produced prompt provide quality questions rate redundant requires responses results score sense share showing similar site social source specific state strategies study support systems tags tasks tools understanding used users views visualization web work workers

http://tagcrowd.com/

THESIS WESLEY WILLETT

TAG CLOUDS

WORD COUNT

www.jasondavies.com/wordcloud/

THESIS WESLEY WILLETT

WHAT'S PROBLEMS DO YOU SEE WITH TAG CLOUDS?

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)

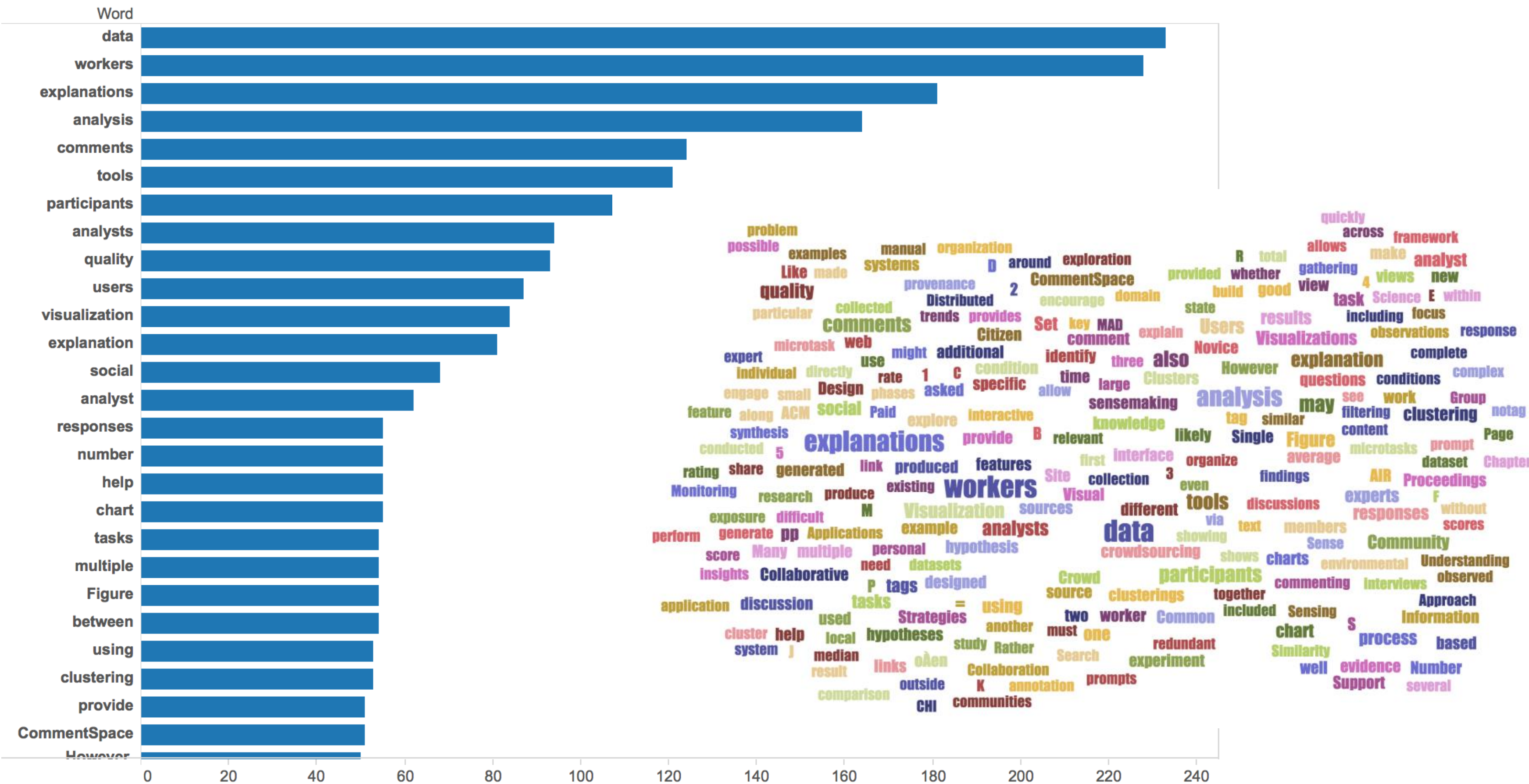
MAY NOT FACILITATE COMPARISON (UNSTABLE LAYOUT)

- ORDER USUALLY MEANINGLESS (USUALLY ALPHABETICAL OR RANDOM)

TERM FREQUENCY MAY NOT BE MEANINGFUL

DOES NOT SHOW THE STRUCTURE OF THE TEXT

WORD COUNTS



Word
data
workers
explanations
analysis
comments
tools
participants
analysts
quality
users
visualization
explanation
social
analyst
responses
number
help
chart
tasks
multiple
Figure
between
using
clustering
provide
CommentSpace
However
0
20
40
60
80
100
120
140
160
180
200
220
240

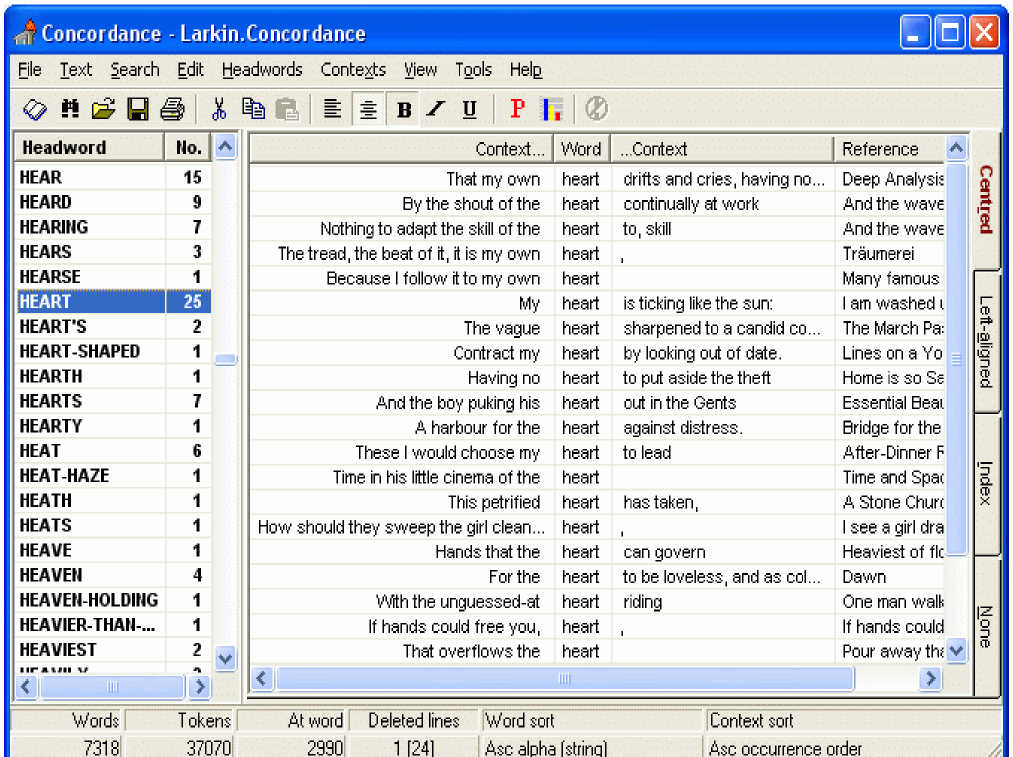
WORDCOUNT

JONATHAN HARRIS

http://wordcount.org

CONCORDANCE

WHAT IS THE COMMON LOCAL CONTEXT OF A TERM?



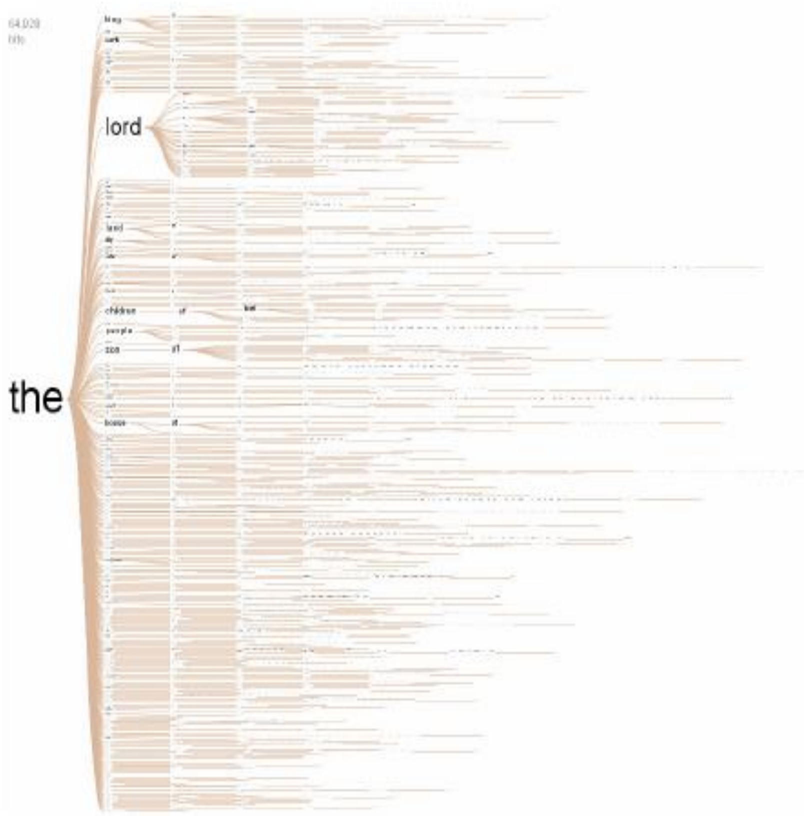
WORD TREES

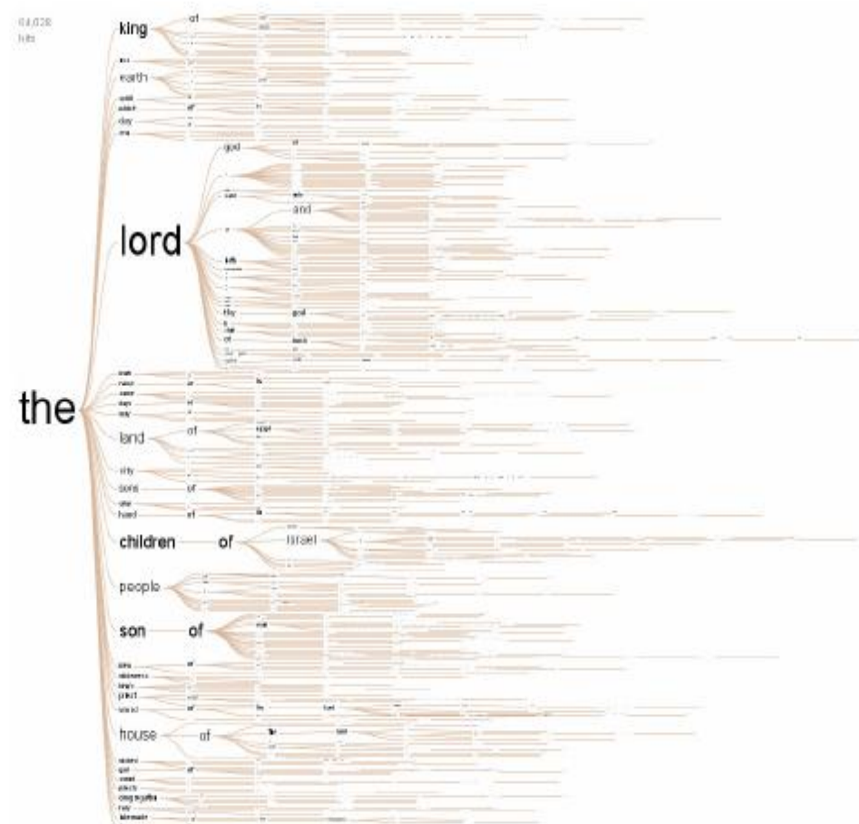
- cats are better than dogs
- cats eat kibble
- cats are better than hamsters
- cats are awesome
- cats are people too
- cats eat mice
- cats meowing
- cats in the cradle
- cats eat mice
- cats in the cradle lyrics
- cats eat kibble
- cats for adoption
- cats are family
- cats eat mice
- cats are better than kittens
- cats are evil
- cats are weird
- cats eat mice

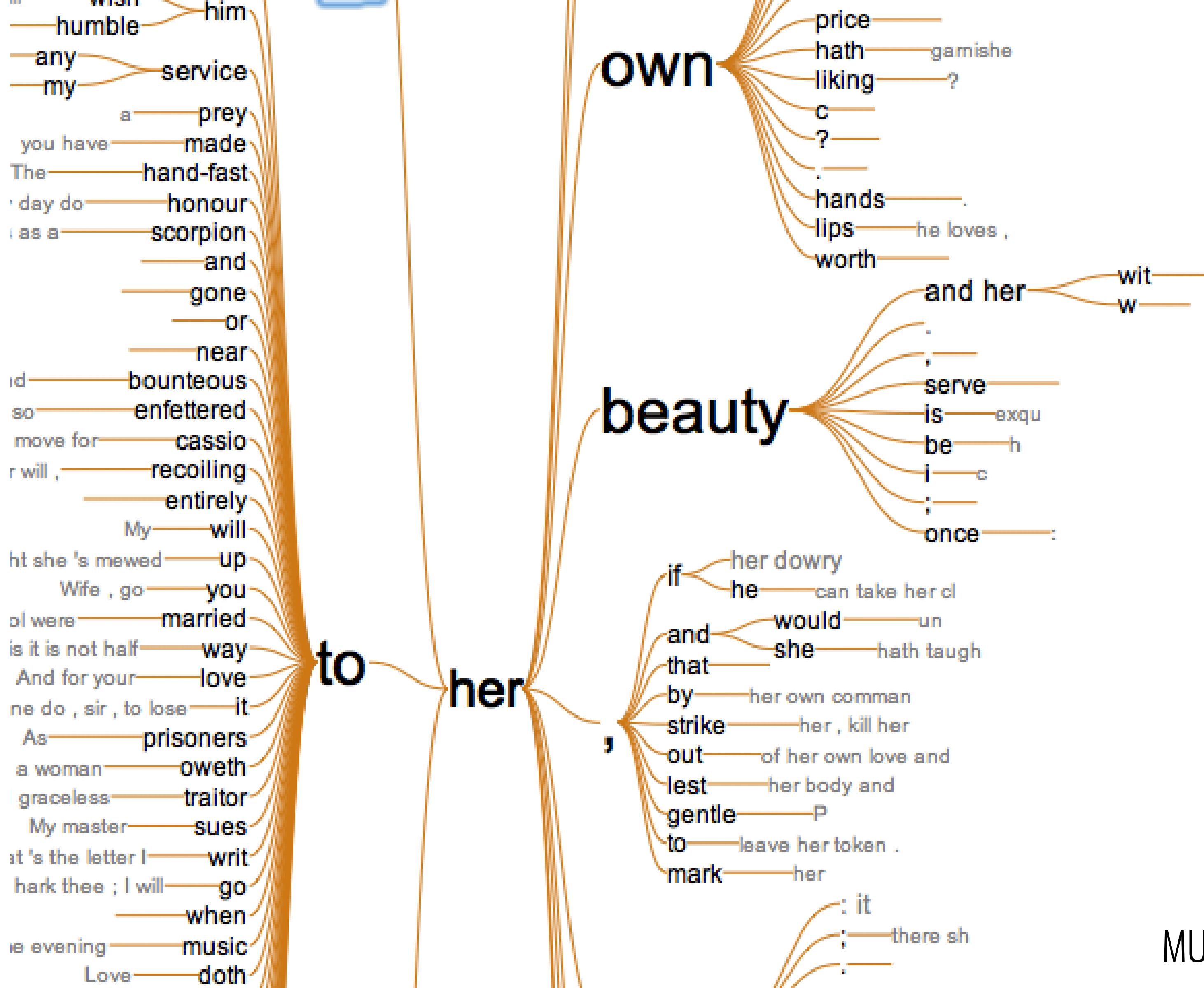
WATTENBERG & VIÉGAS 2008


31 hits
love the
lord
thy god
with all
thine heart , and with all thy soul ,
and with all thy might .
that thou mayest live .
thy heart , and with all thy soul , and with all thy
mind
strength , a
, and
keep his charge , and his statutes , and his judgments , and his commandments , alway .
to walk ever in his ways ; then shalt thou add three cities more for thee , beside these three : 19
that thou mayest obey his voice , and that thou mayest cleave unto him : for he is thy life , and t
to walk in his ways , and to keep his commandments and his statutes and his judgments , that thou mayest liv
your god
, and to
serve him with all your heart and with all your soul , 11 : 14 that i will give you the rain of your la
walk in all his ways , and to keep his commandments , and to cleave unto him , and to serve hi
to walk in all his ways , and to cleave unto him ; 11 : 23 then will the lord drive out all these nations from
with all your heart and with all your soul .
.
,
all ye his saints : for the lord preserveth the faithful , and plentifully rewardeth the proud doer .
hate evil : he preserveth the souls of his saints ; he delivereth them out of the hand of the wicked .
because he hath heard my voice and my supplications .
name of the lord , to be his servants , every one that keepeth the sabbath from polluting it , and taketh hold of my covenant
good , and establish judgment in the gate : it may be that the lord god of hosts will be gracious unto the remnant of joseph
evil ; who pluck off their skin from off them , and their flesh from off their bones ; 3 : 3 who also eat the
truth and peace .
other ; or else he will hold to the one , and despise the other . ye cannot serve god and mammon .
6 : 25 therefore i say unto
16 : 14 and the pharisees
uppermost
rooms at feasts , and the chief seats in the synagogues , 23 : 7 and greetings in the markets , and to be called of
seats in the synagogues , and greetings in the markets .
father
; and as the father gave me commandment , even so i do .
hath bestowed upon us , that we should be called the sons of god : therefore the world knoweth us not , because it knew him
brotherhood .
world , the love of the father is not in him .
brethren .
children of god , when we love god , and keep his commandments .

FILTER INFREQUENT RUNS



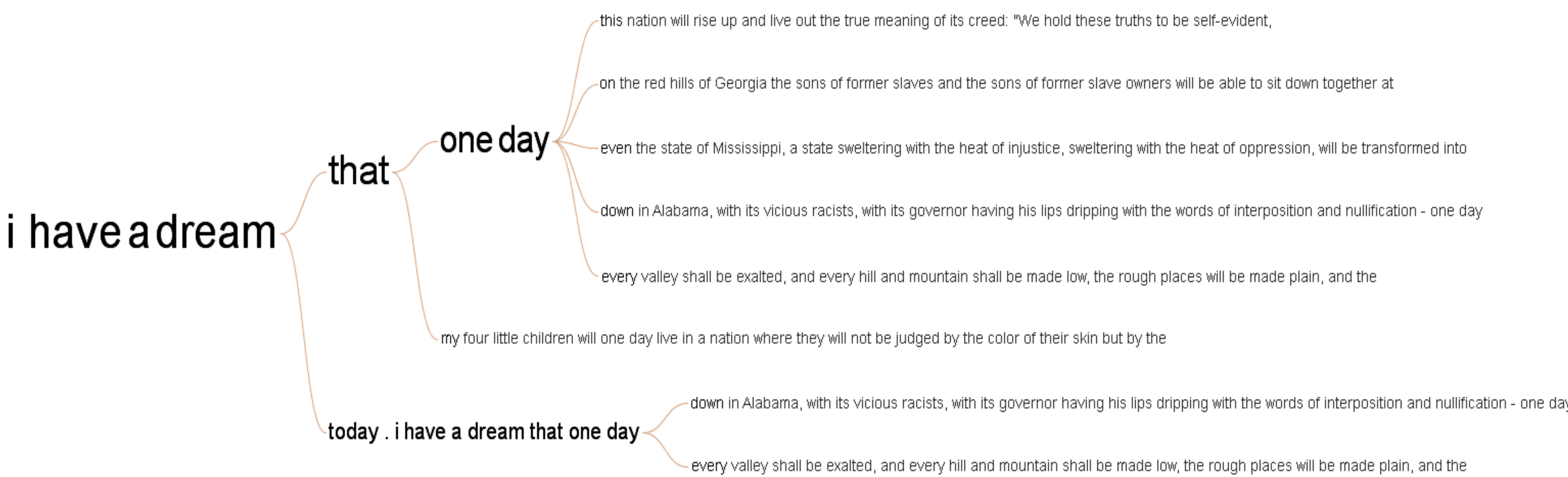




WORDSEER

MURALIDHARAN & HEARST

RECURRENT THEMES IN SPEECH



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

LOOK FOR SPECIFIC LINKING PATTERNS IN THE TEXT:

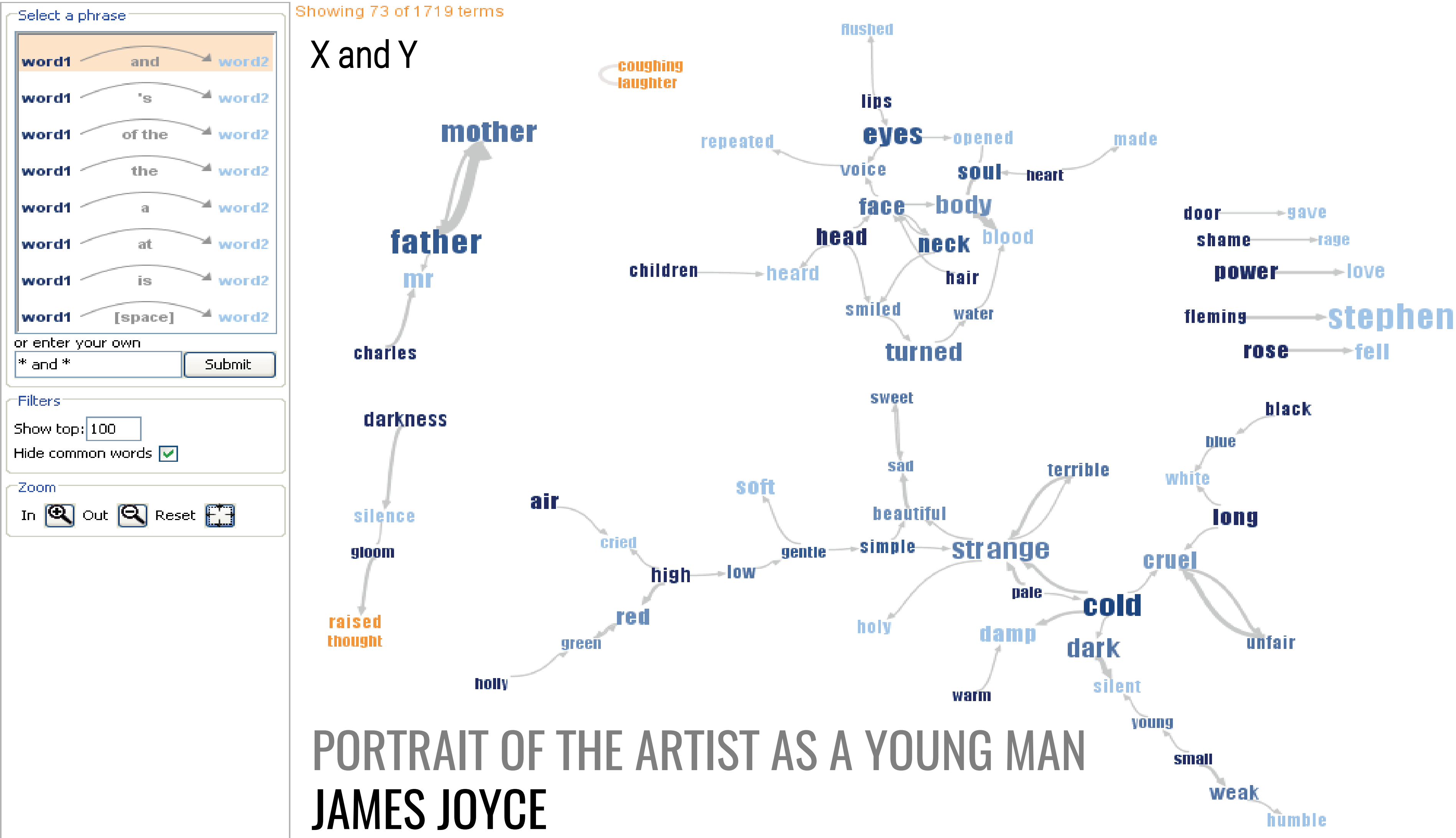
- ‘A AND B’, ‘A AT B’, ‘A OF B’, ETC
- COULD BE OUTPUT OF REGEXP OR PARSER

VISUALIZE EXTRACTED PATTERNS IN A NODE-LINK VIEW

- OCCURRENCES = NODE SIZE
- PATTERN POSITION = EDGE DIRECTION

van Ham et al

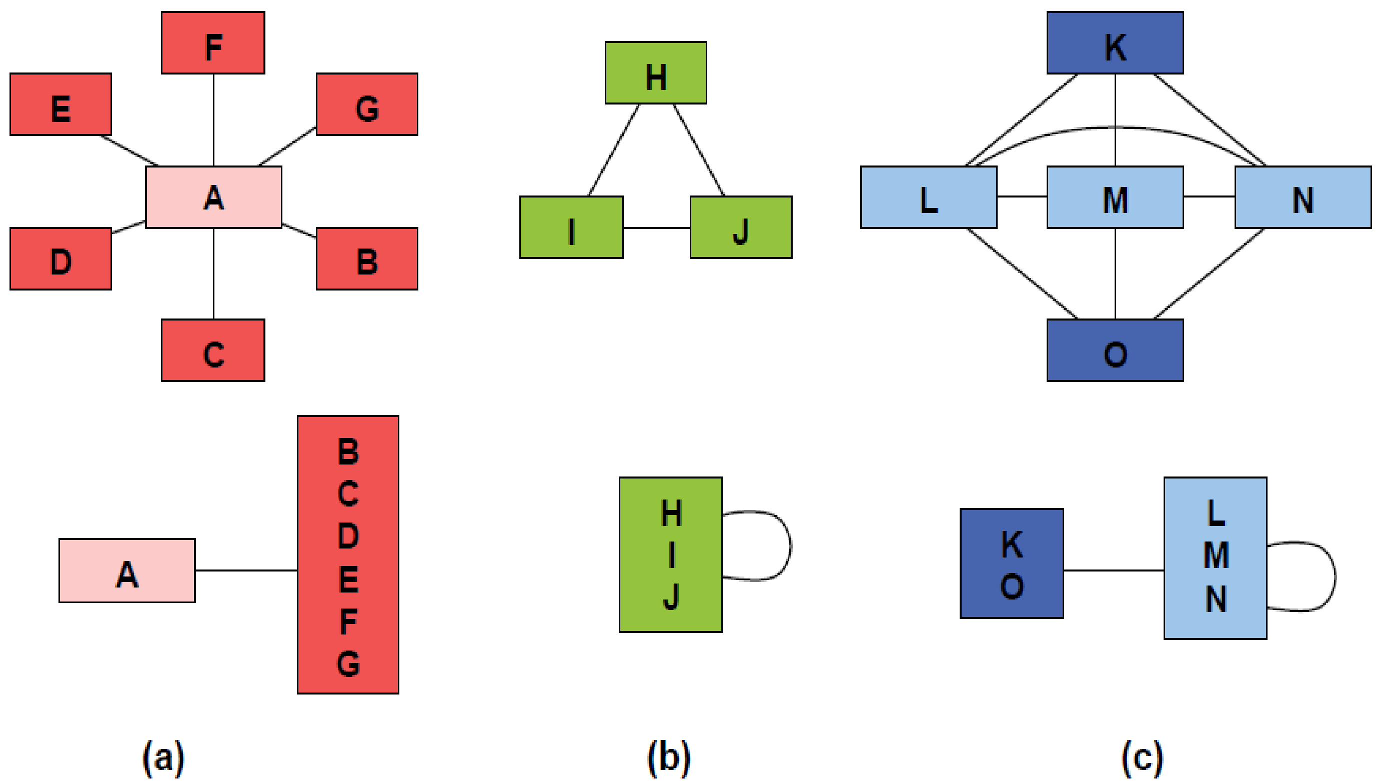
X and Y



PORTRAIT OF THE ARTIST AS A YOUNG MAN

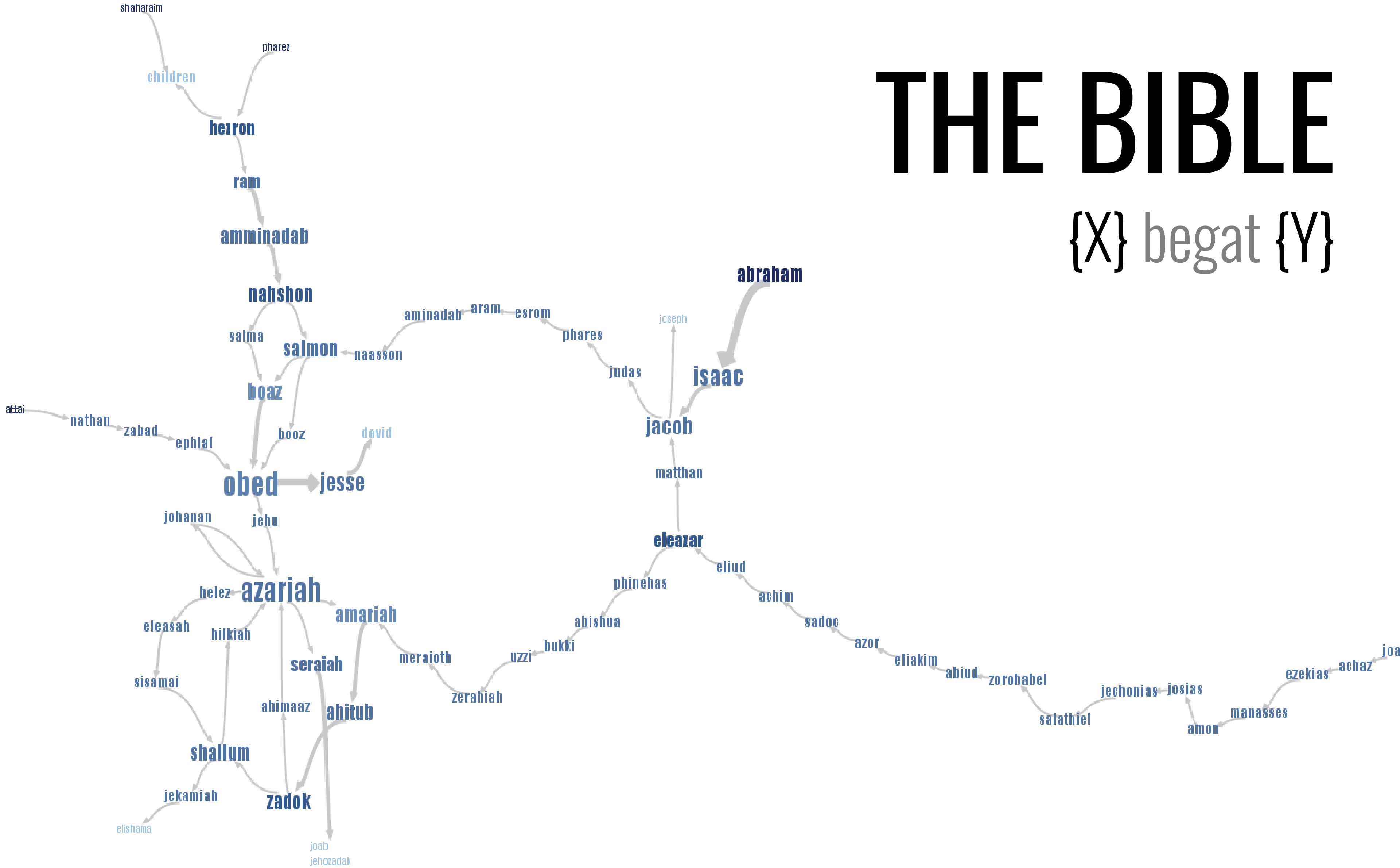
JAMES JOYCE

NODE GROUPING



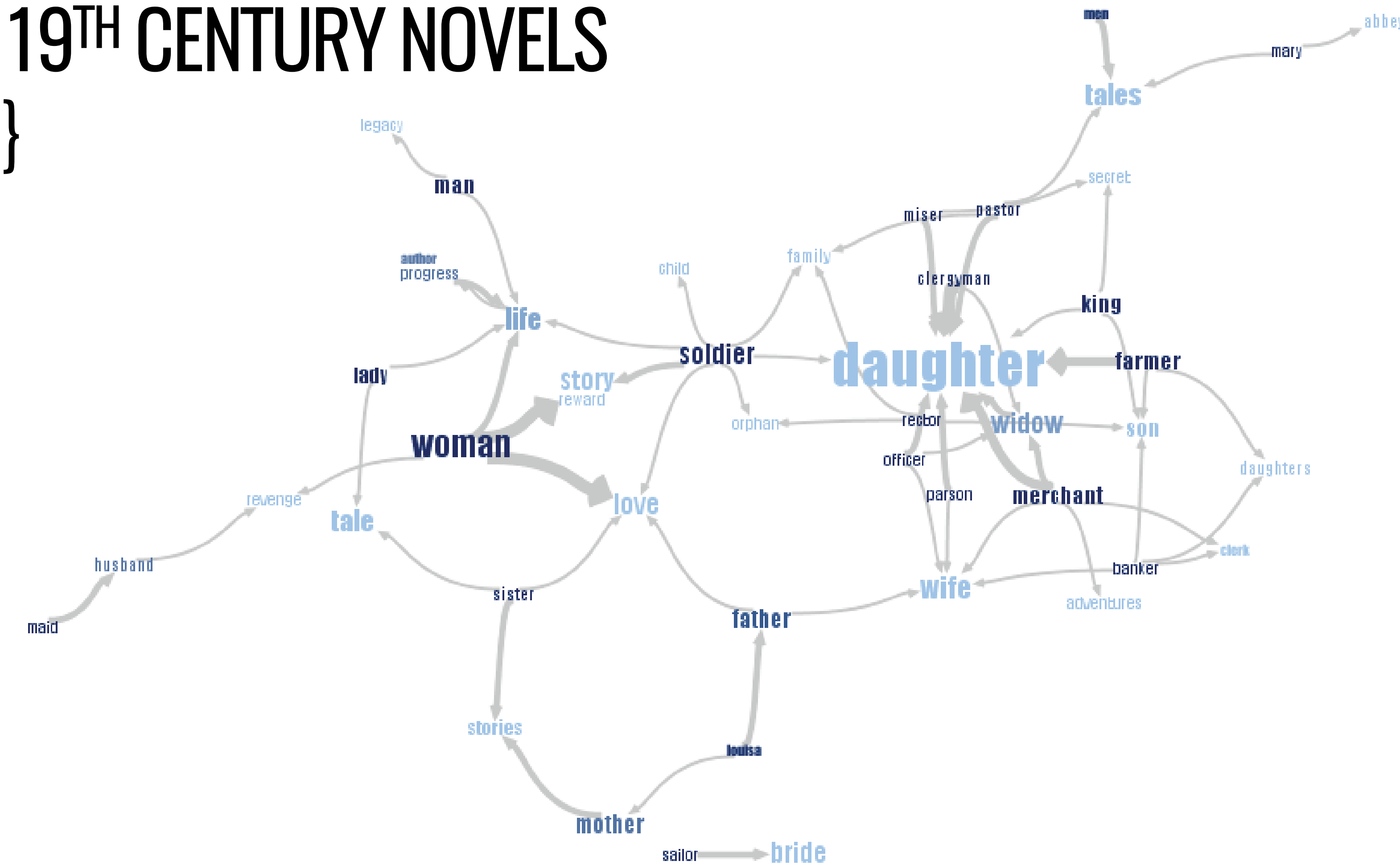
THE BIBLE

{X} begat {Y}



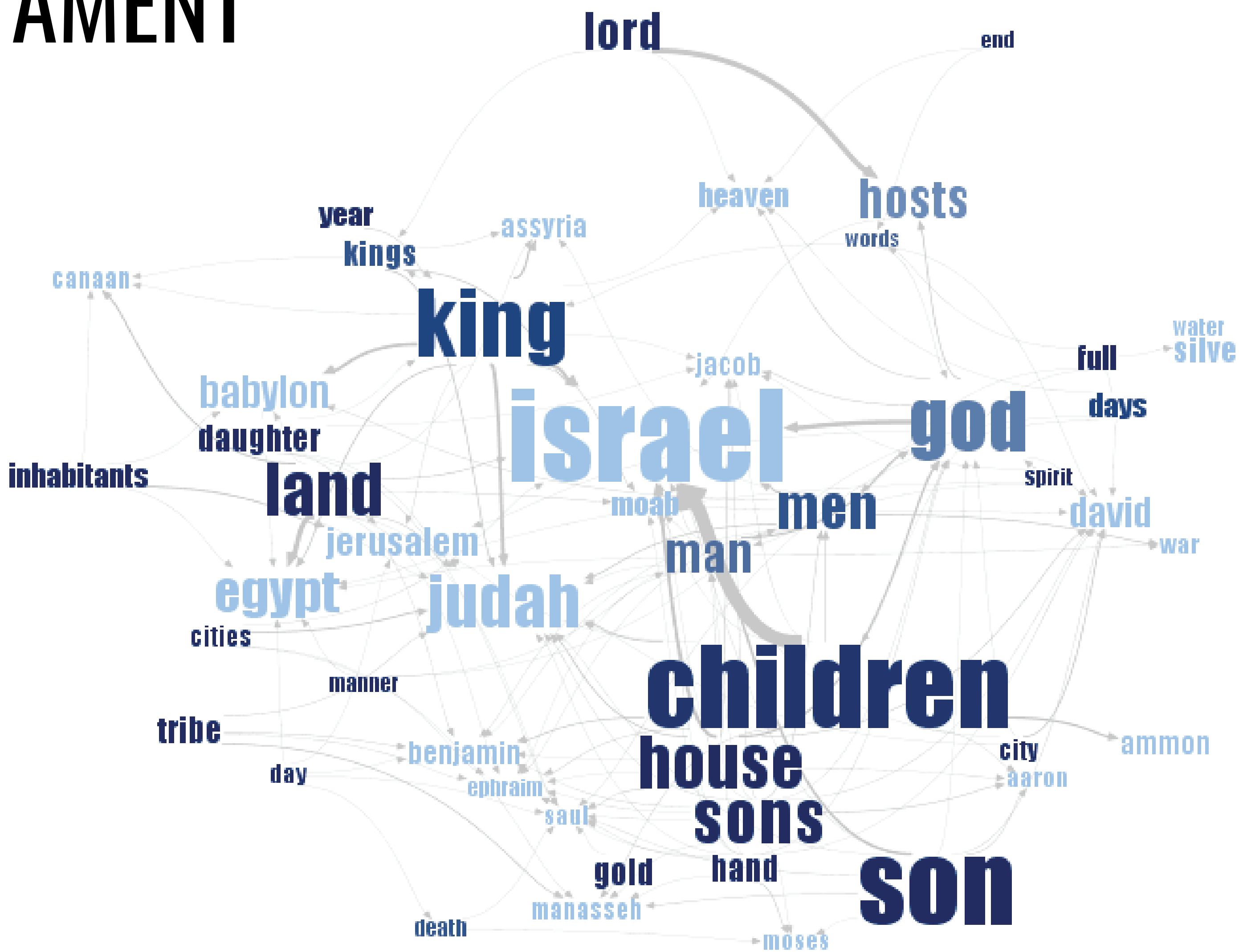
18TH & 19TH CENTURY NOVELS

{X}'s {Y}



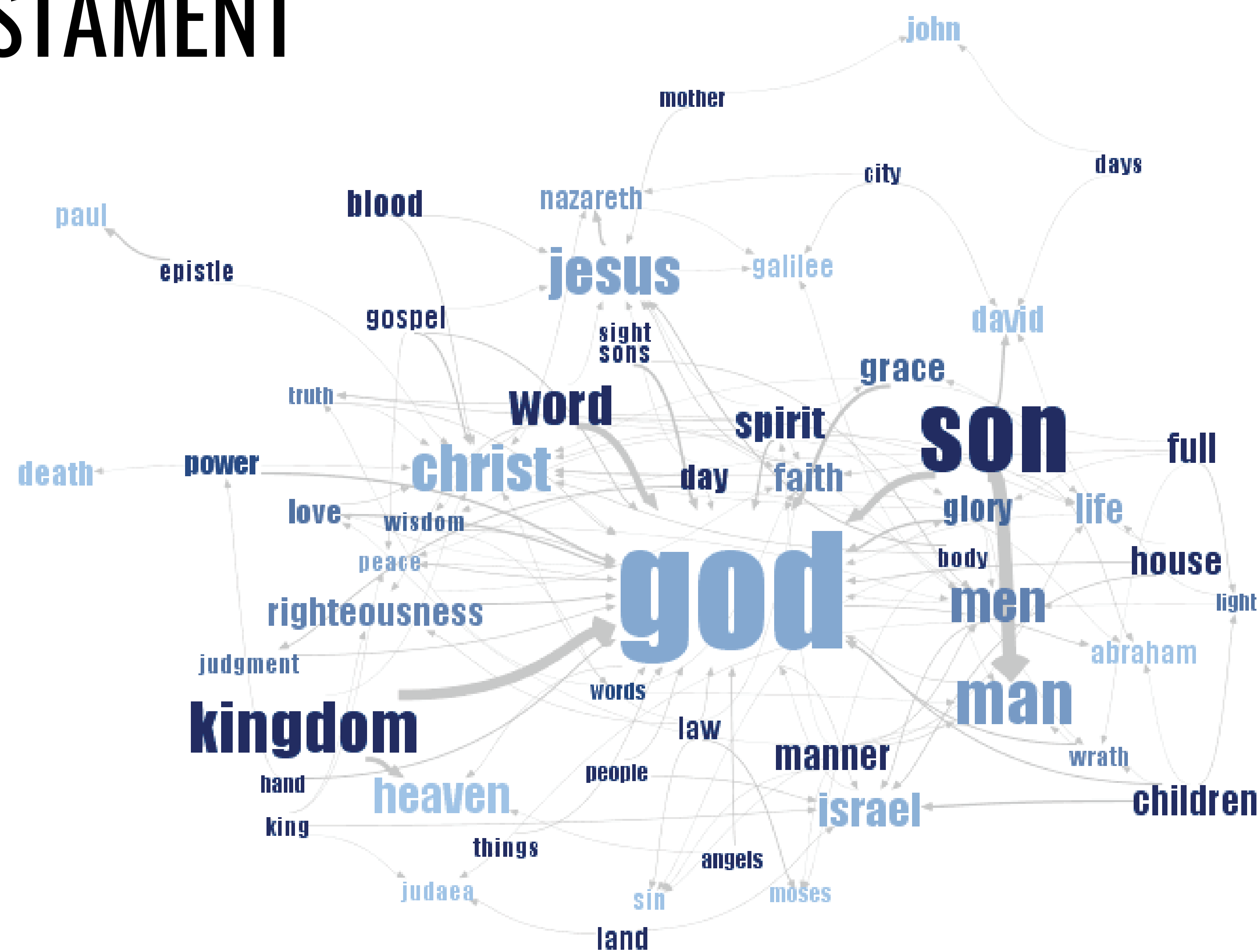
OLD TESTAMENT

{X} of {Y}

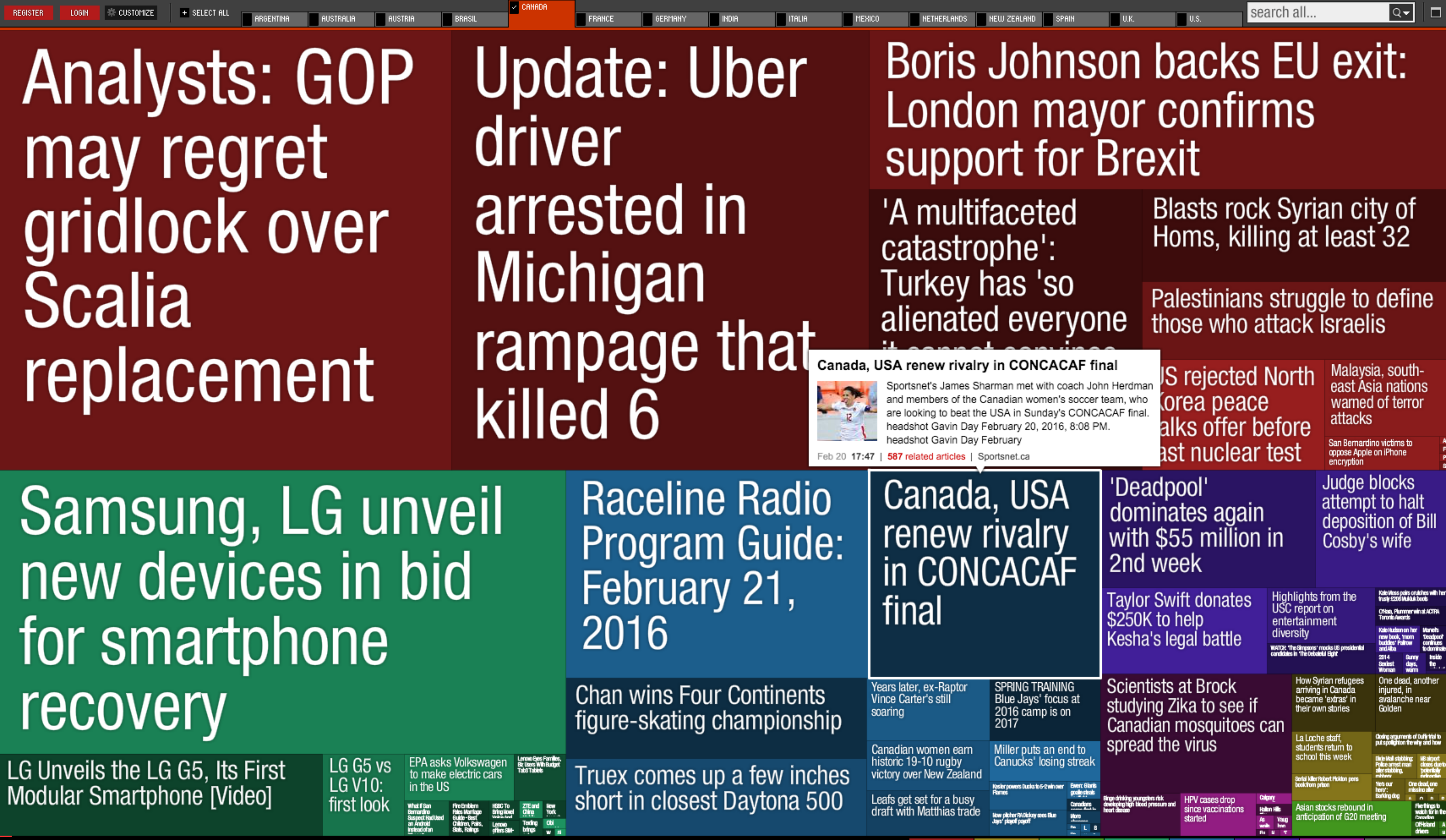


NEW TESTAMENT

{X} of {Y}



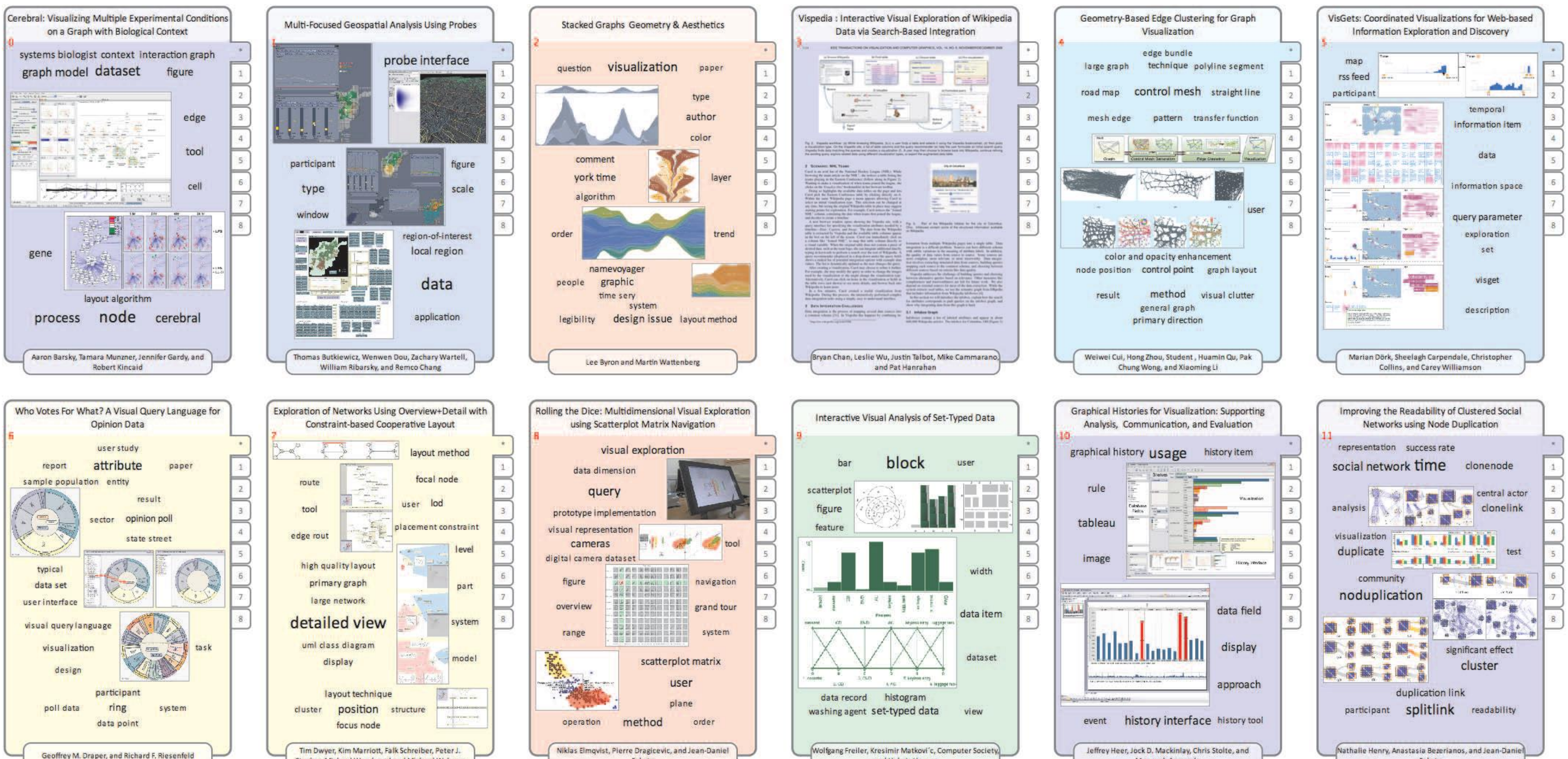
VISUALIZING DOCUMENT COLLECTIONS


REGISTER
LOGIN
CUSTOMIZE
SELECT ALL
ARGENTINA
AUSTRALIA
AUSTRIA
BRASIL
CANADA
FRANCE
GERMANY
INDIA
ITALIA
MEXICO
NETHERLANDS
NEW ZEALAND
SPAIN
U.K.
U.S.
search all...
Analysts: GOP may regret gridlock over Scalia replacement
Update: Uber driver arrested in Michigan rampage that killed 6
Boris Johnson backs EU exit: London mayor confirms support for Brexit
'A multifaceted catastrophe': Turkey has 'so alienated everyone
Blasts rock Syrian city of Homs, killing at least 32
Palestinians struggle to define those who attack Israelis
Malaysia, south-east Asia nations warned of terror attacks
San Bernardino victims to oppose Apple on iPhone encryption
Canada, USA renew rivalry in CONCACAF final
Sportsnet's James Sharman met with coach John Herdman and members of the Canadian women's soccer team, who are looking to beat the USA in Sunday's CONCACAF final. headshot Gavin Day February 20, 2016, 8:08 PM. headshot Gavin Day February
Feb 20 17:47 | 587 related articles | Sportsnet.ca
Samsung, LG unveil new devices in bid for smartphone recovery
Raceline Radio Program Guide: February 21, 2016
Canada, USA renew rivalry in CONCACAF final
'Deadpool' dominates again with $55 million in 2nd week
Judge blocks attempt to halt deposition of Bill Cosby's wife
Taylor Swift donates $250K to help Kesha's legal battle
Highlights from the USC report on entertainment diversity
Chan wins Four Continents figure-skating championship
Years later, ex-Raptor Vince Carter's still soaring
SPRING TRAINING Blue Jays' focus at 2016 camp is on 2017
Scientists at Brock studying Zika to see if Canadian mosquitoes can spread the virus
How Syrian refugees arriving in Canada became 'extras' in their own stories
One dead, another injured, in avalanche near Golden
La Loche staff, students return to school this week
LG Unveils the LG G5, Its First Modular Smartphone [Video]
LG G5 vs LG V10: first look
EPA asks Volkswagen to make electric cars in the US
Truex comes up a few inches short in closest Daytona 500
Canadian women earn historic 19-10 rugby victory over New Zealand
Miller puts an end to Canucks' losing streak
Leafs get set for a busy draft with Matthias trade
HPV cases drop since vaccinations started
Asian stocks rebound in anticipation of G20 meeting
SELECT ALL
WORLD
NATIONAL
BUSINESS
TECHNOLOGY
SPORTS
ENTERTAINMENT
HEALTH
LESS THAN 10 MIN. AGO
MORE THAN 10 MIN. AGO
MORE THAN 1 HOUR AGO

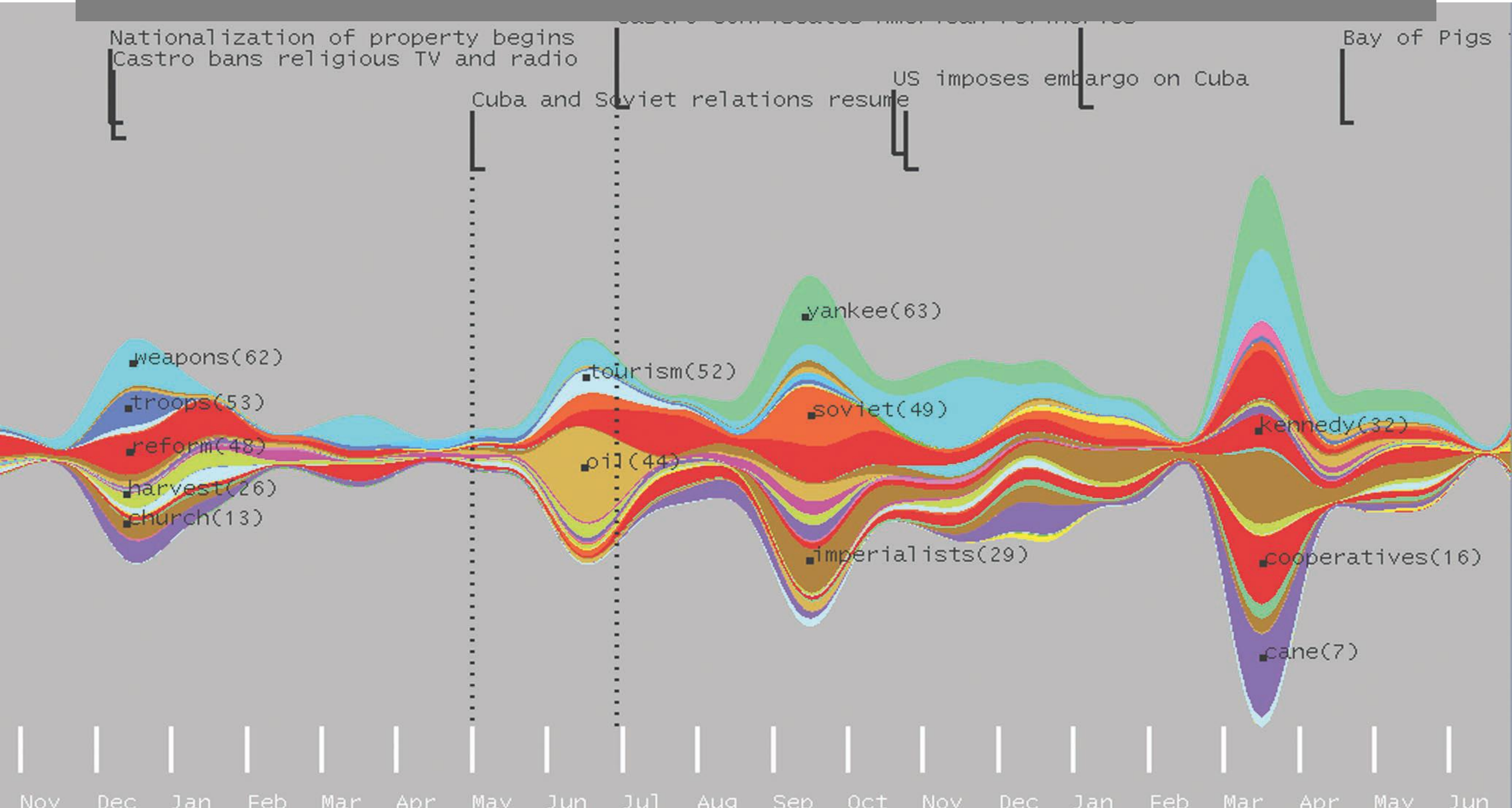
newsmap.jp

DOCUMENT CARDS

SMALL MULTIPLES FOR DOCUMENTS

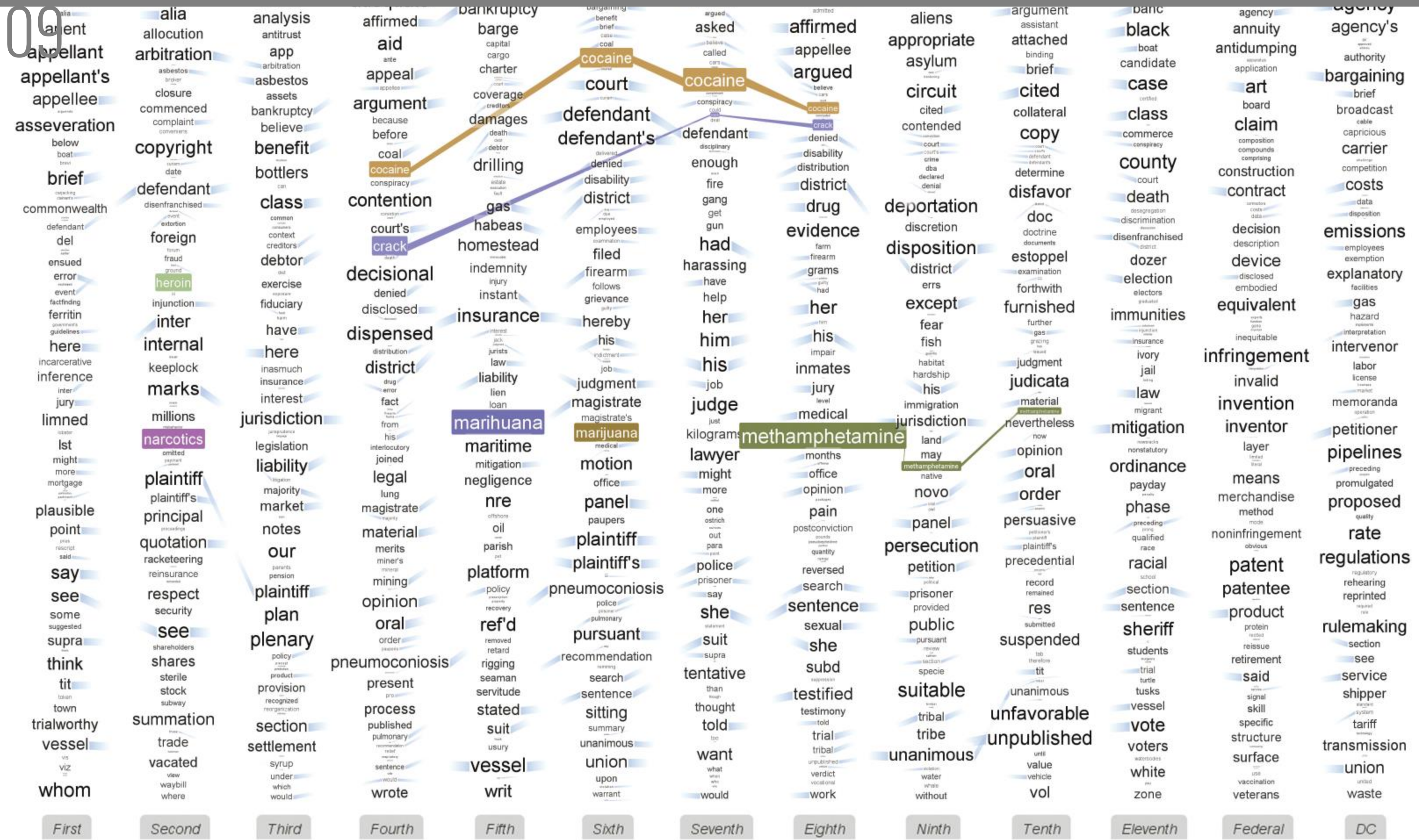


THEMERIVER HAVRE ET AL 1999

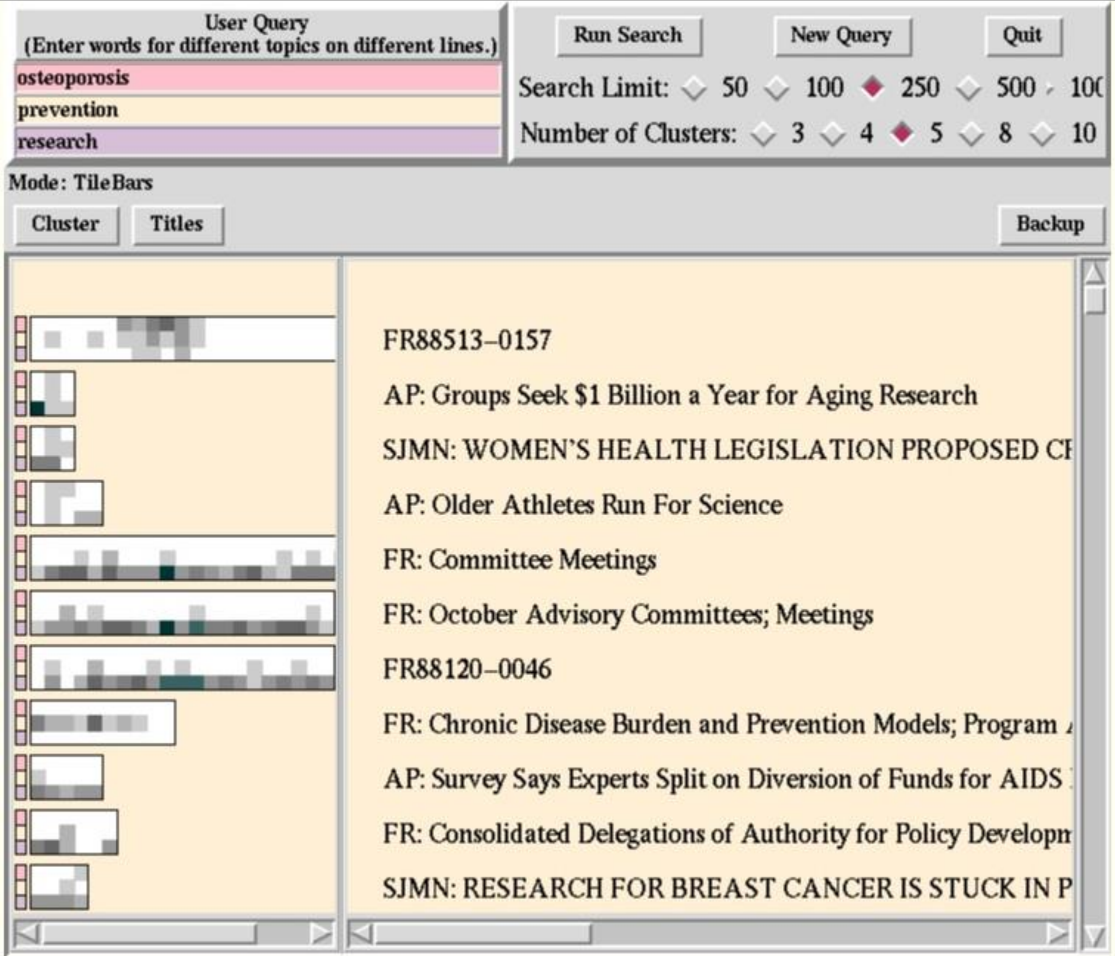


PARALLEL TAG CLOUDS

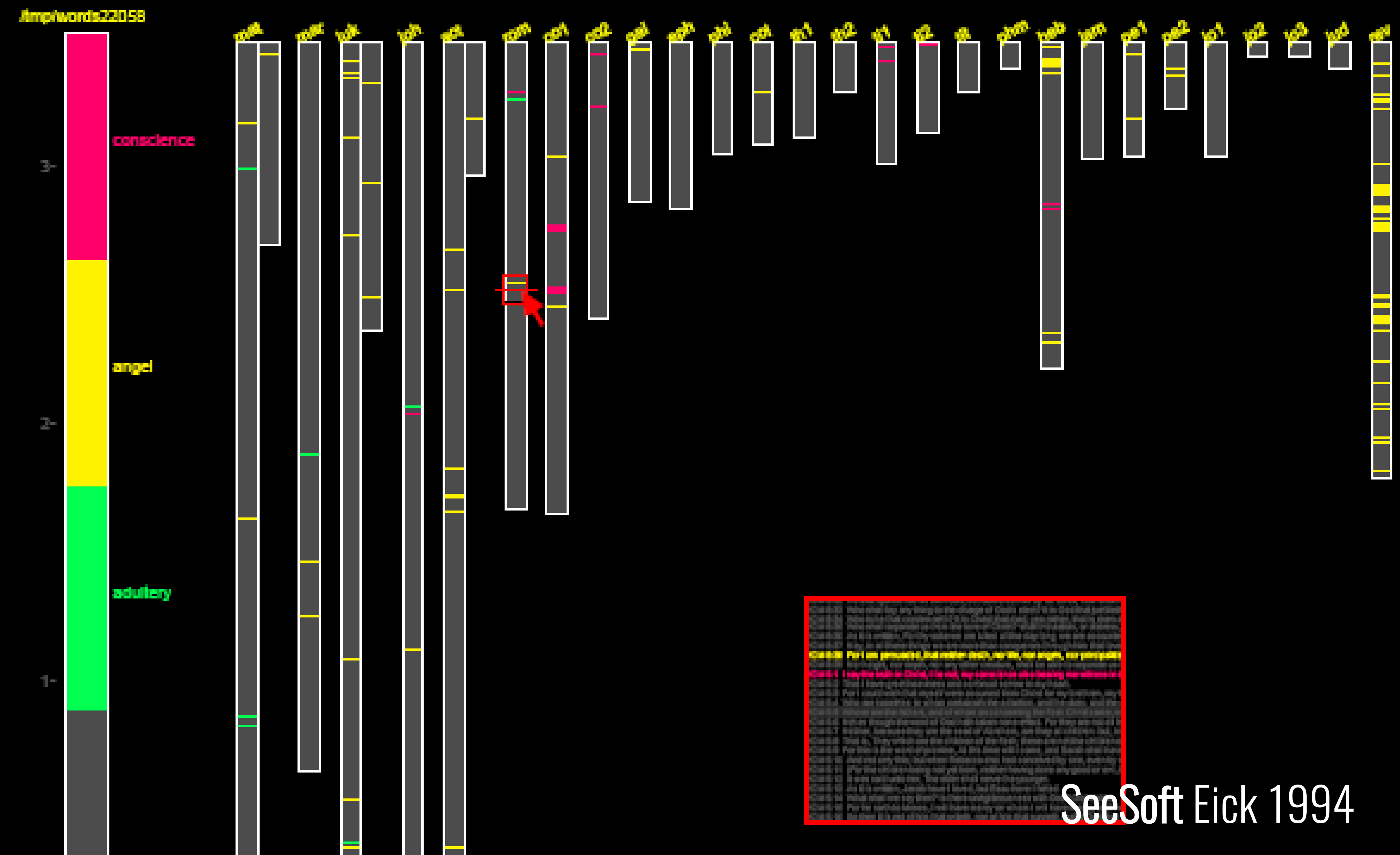
09



SUPPORTING SEARCH



TileBars Hearst 1999



SeeSoft Eick 1994

THE WORDS THAT WERE USED

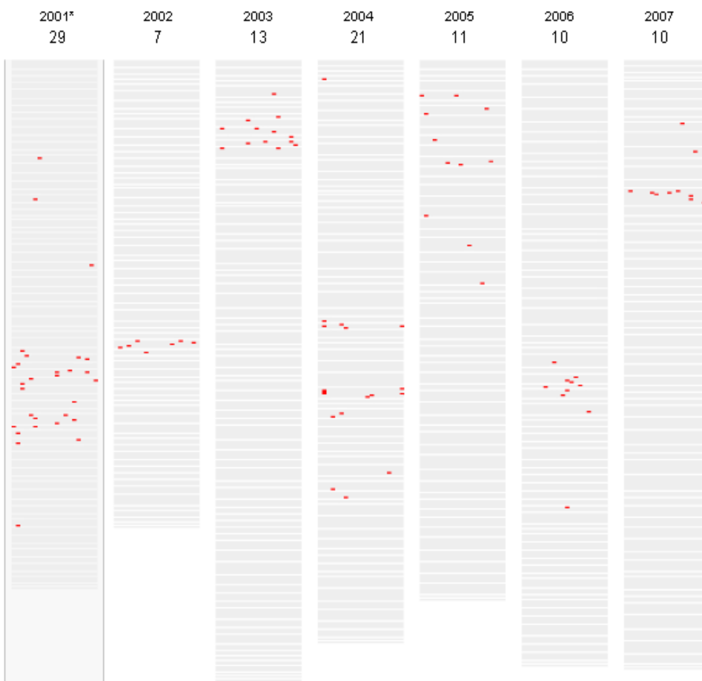
READ 2007 SPEECH | FEEDBACK

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



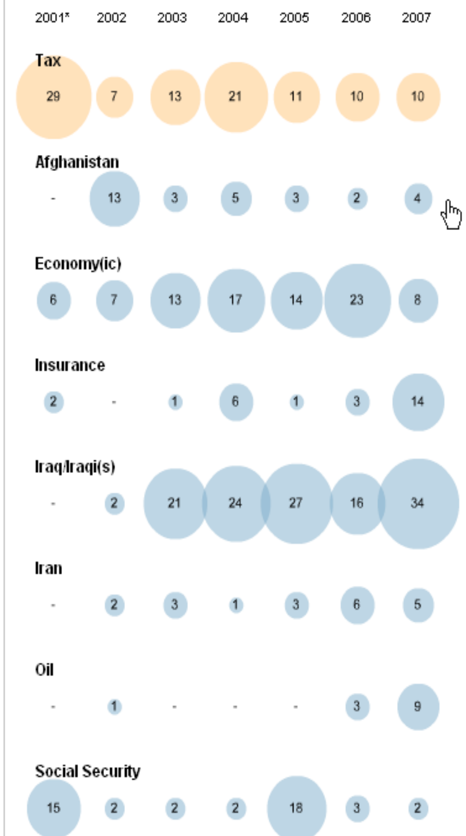
The word in context

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.

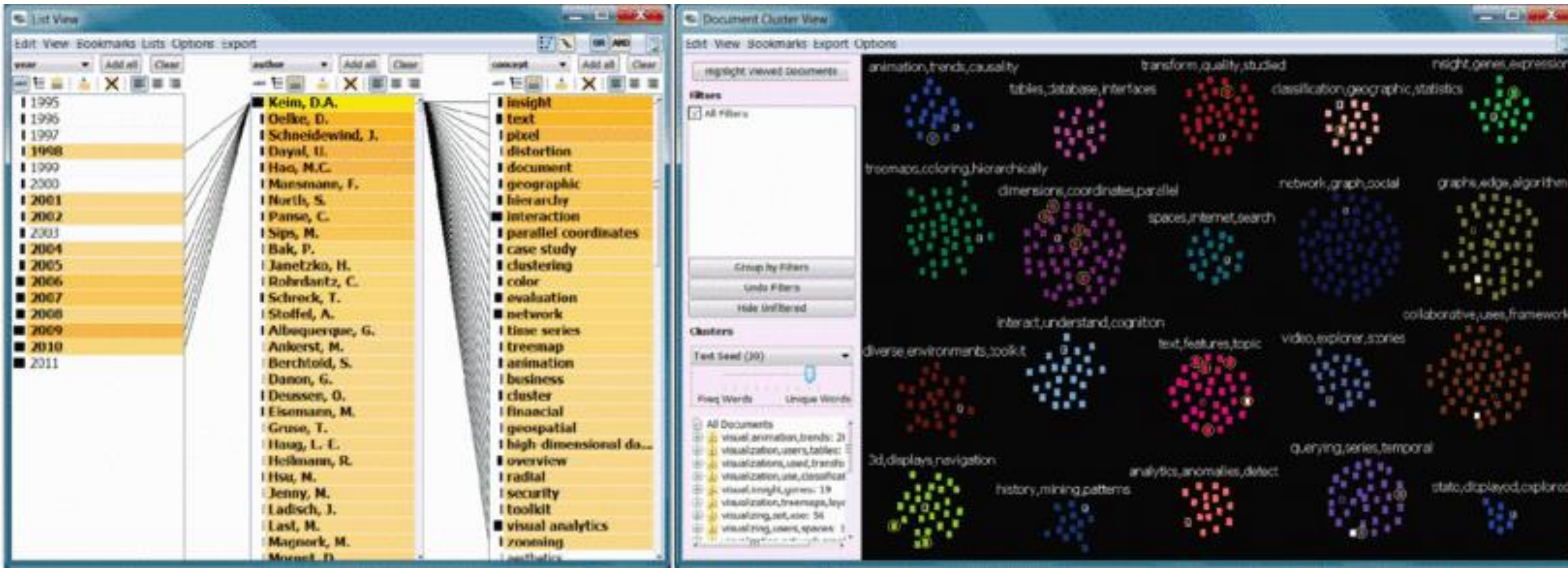
-- 2001 (Paragraph 14 of 73)

Compared with other words

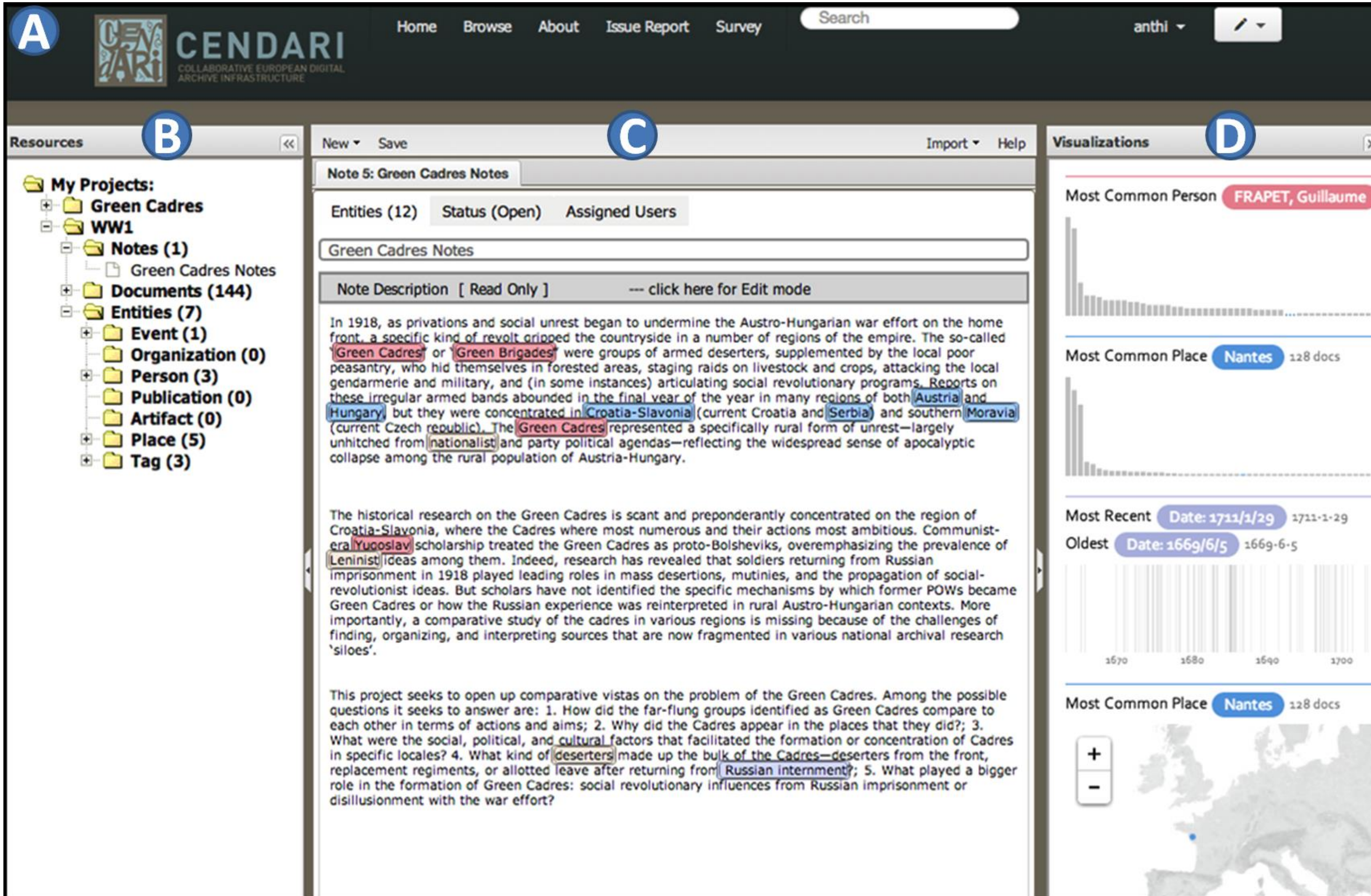


* As a newly elected president, Mr. Bush did not deliver a formal State of the Union address in 2001. His Feb. 27 speech to a joint session of Congress was analogous to the State of the Union, but without the title.

Ben Werschkul/The New York Times


List View
Edit View Bookmarks Lists Options Export
Add all
Clear
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Keim, D.A.
Oelke, D.
Schneidewind, J.
Dayal, U.
Hao, M.C.
Mansmann, F.
North, S.
Panse, C.
Sips, M.
Bak, P.
Janetzko, H.
Rohrdantz, C.
Schreck, T.
Stoffel, A.
Albuquerque, G.
Ankerst, M.
Berchtold, S.
Danon, G.
Deussen, O.
Eisemann, M.
Gruse, T.
Haug, L. E.
Heilmann, R.
Hsu, M.
Jenny, M.
Ladisch, J.
Last, M.
Magnork, M.
insight
text
pixel
distortion
document
geographic
hierarchy
interaction
parallel coordinates
case study
clustering
color
evaluation
network
time series
treemap
animation
business
cluster
financial
geospatial
high dimensional da...
overview
radial
security
toolkit
visual analytics
zooming
Document Cluster View
Edit View Bookmarks Export Options
Filters
All Filters
Group by Filters
Undo Filters
Hide Unfiltered
Clusters
Freq Words
Unique Words
All Documents
animation,trends,causality
tables,database,interfaces
transform,quality,studied
classification,geographic,statistics
insight,genes,expression
treemaps,coloring,hierarchically
dimensions,coordinates,parallel
spaces,internet,search
network,graph,social
graphs,edge,algorithm
interact,understand,cognition
collaborative,uses,framework
diverse,environments,toolkit
text,features,topic
video,explorer,stories
querying,series,temporal
3d,displays,navigation
history,mining,patterns
analytics,anomalies,detect
state,displayed,explored

JIGSAW



CENDARI NOTE-TAKING ENVIRONMENT 2015

DOCUMENT SIMILARITY & CLUSTERING

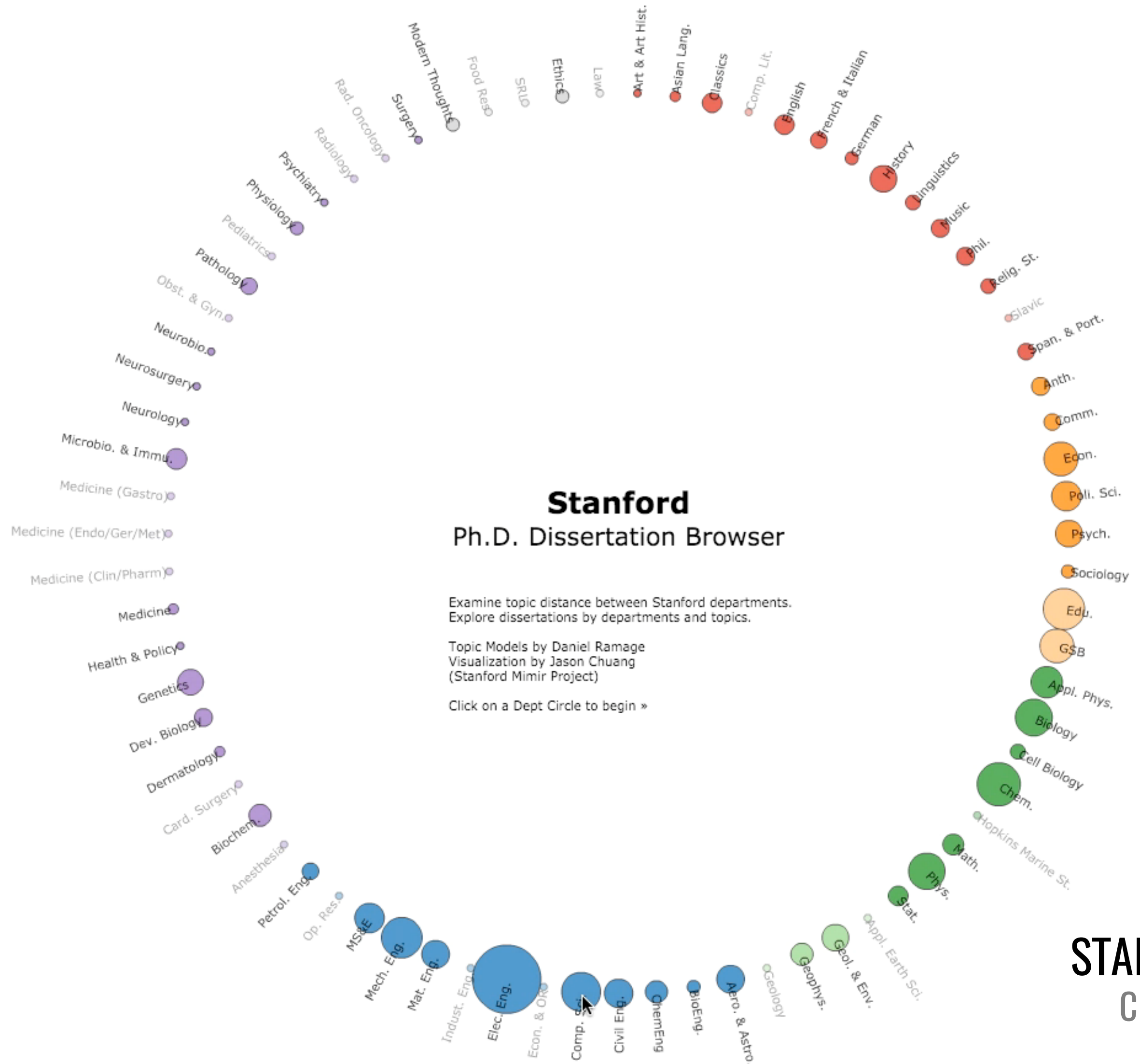
COMPUTE SIMILARITY BETWEEN DOCUMENTS BASED ON THE WORDS THEY SHARE

- **TF-IDF** (TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY) IS COMMON

TOPIC MODELING APPROACHES

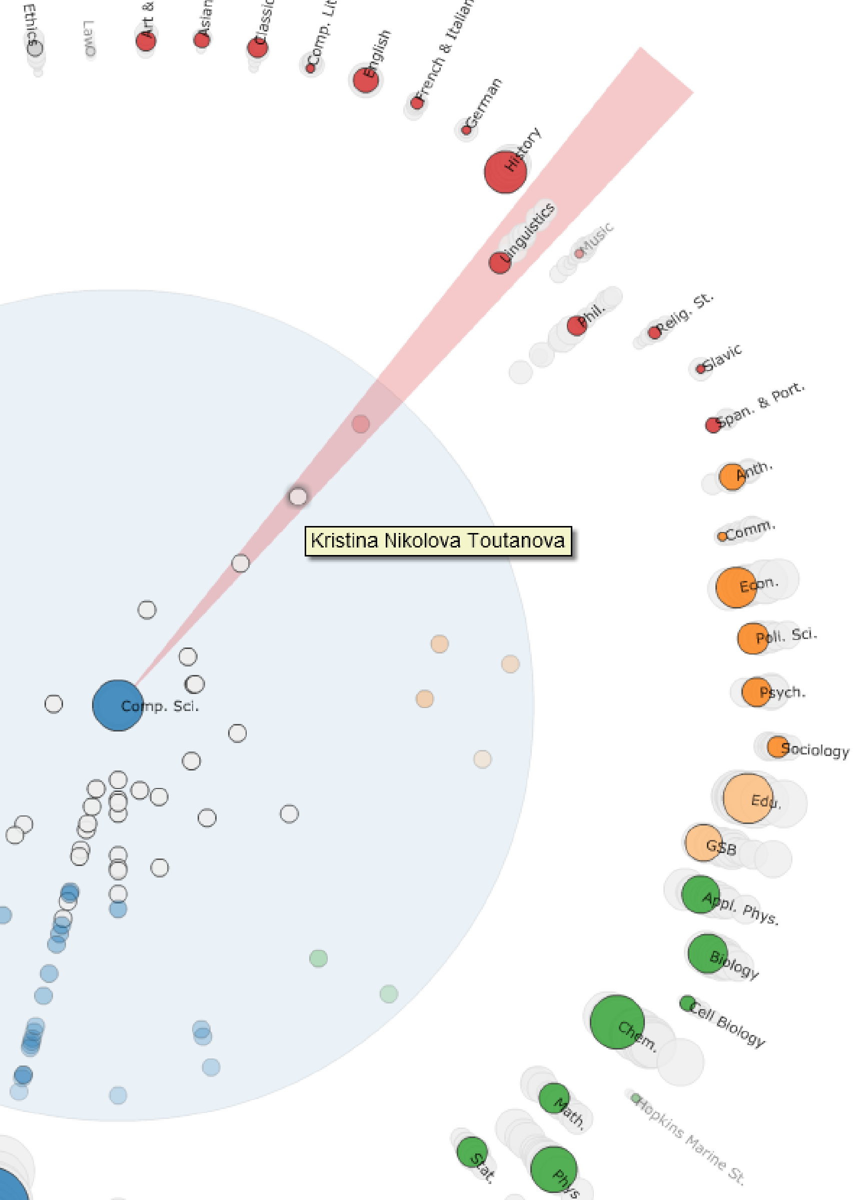
- ASSUME DOCUMENTS ARE A MIXTURE OF TOPICS
- TOPICS ARE (ROUGHLY) A SET OF CO-OCCURRING TERMS
- LATENT SEMANTIC ANALYSIS (LSA): REDUCE TERM MATRIX

- MANY, MANY APPROACHES EXIST



STANFORD DISSERTATION BROWSER

CHUANG, RAMAGE, MANNING & HEER 2012



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

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WARNING

OFTEN, TEXT VISUALIZATIONS DO NOT REPRESENT TEXT DIRECTLY, BUT THEY REPRESENT A MODEL

WORD COUNTS, WORD SEQUENCES, CLUSTERS, ETC.

ASK:

CAN YOU INTERPRET THE VISUALIZATION?

DOES THE MODEL ACCURATELY REPRESENT THE ORIGINAL TEXT?

LESSONS FOR TEXT VISUALIZATION

SHOW SOURCE TEXT (OR PROVIDE ACCESS TO IT)

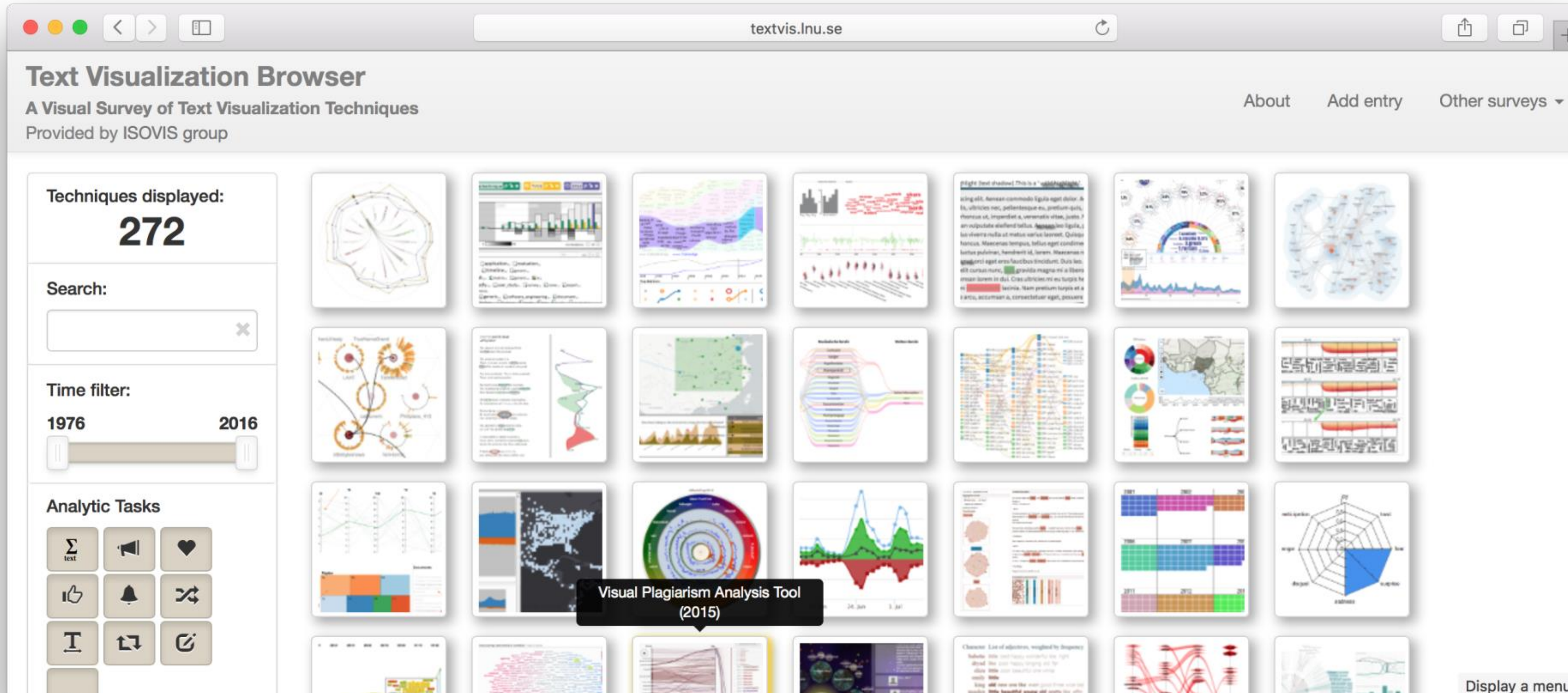
WHERE POSSIBLE, USE VISUALIZATION AS INDEX INTO DOCUMENTS

GROUP DOCUMENTS IN MEANINGFUL WAYS

WILL VIEWERS UNDERSTAND THE CLUSTERS?

WHERE POSSIBLE **USE TEXT TO REPRESENT TEXT**

HUNDREDS OF TOOLS & TECHNIQUES FOR TEXT AT http://textvis.lnu.se/



QUESTIONS?

EXAM

- 2h, Dec 8th
- bring a pencil
- questions from lectures (at least 1 per lecture)
- some creativity questions
- some questions about assessing visualizations

- every student gets individual exam sheet

Introduction to Human-Computer Interaction **Exam on 23/03/2016**

- Time period: 8:00 – 11:00
- Duration of the exam: 180 min
- Number of pages: 8
- Materials allowed: Pencils, erasers

Please write your answers directly on the exam paper.

☐0	☐0	☐0	☐0	☐0	☐0	☐0	☐0
☐1	☐1	☐1	☐1	☐1	☐1	☐1	☐1
☐2	☐2	☐2	☐2	☐2	☐2	☐2	☐2
☐3	☐3	☐3	☐3	☐3	☐3	☐3	☐3
☐4	☐4	☐4	☐4	☐4	☐4	☐4	☐4
☐5	☐5	☐5	☐5	☐5	☐5	☐5	☐5
☐6	☐6	☐6	☐6	☐6	☐6	☐6	☐6
☐7	☐7	☐7	☐7	☐7	☐7	☐7	☐7
☐8	☐8	☐8	☐8	☐8	☐8	☐8	☐8
☐9	☐9	☐9	☐9	☐9	☐9	☐9	☐9

← Encode your student number here, and write the student number again as well as your given name and family name below. If you cannot remember your student number, use the number X you see at the top of the exam sheet in this code +X/Y/Z+.

Student number: ....

Given name: ....

Family name: ....

- The questions with the symbol ♣ can have none, one, or more than one possible correct answers. All other questions have exactly one correct answer.
- Please answer the questions like this: ☒; use a **pencil** (hardness HB), and make clear marks. To correct, clearly erase the wrong mark and put a new one (if needed). If you cannot erase because you did not bring a pencil, make the incorrect box completely black.
- All multiple-choice questions are worth one point. For it to be counted as answered correctly, all correct answers and no incorrect answer have to be selected.
- Do not fold the answer sheet(s), do not write on the back.

Question 1 Student did **NOT** bring a pencil. Do **NOT** fill out yourself.

☐ Student brought a pencil.
☐ Student did not bring a pencil.

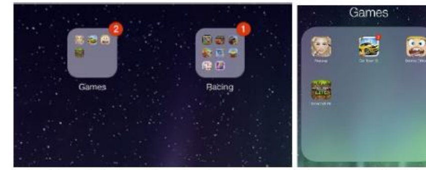
Multiple-Choice Questions:

Question 2 Driving to the supermarket but ending up at work is an example of which type of error

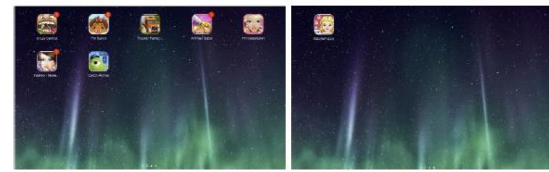
☐ description error
☐ a mistake
☐ capture error
☐ none of the above
☐ mode error

Controlled Experiments

You are a designer for a mobile phone company and are trying to decide which method you want people to use for opening apps in future versions of your mobile UI. You are planning to go with either a single page with folders (Interface 1), or multiple scrolling pages and no folders (Interface 2). The choice needs to be made based on which interaction technique allows the user to open an app the fastest. You decide to run a controlled lab experiment to find out.



Interface 1: The main interface shows a single page with folders of icons (left). Clicking on a folder, opens up the folder to show its contents (right).



Interface 2: The main interface shows a page with icons for apps (left). Swiping the page to the side shows a second page with more icons for apps (right).

Question 21 Write an appropriate **hypothesis** for this study (1 point): ☐w ☐c *Reserved*

....

....

Question 22 Continuing with the example from the previous question: Write an appropriate **null hypothesis** for this study. ☐w ☐c *Reserved*

....

EXAM

- best way to mark a box: ☒
- unacceptable way to mark a box: ☐ ☐ ☐ ☐
- if you make an error – erase your answer

- if you forgot your eraser, mark the box like this ■

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- Christopher Collins (University of Ontario Institute of Technology)
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