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Text Visualization

Lecture in: “Visualization and Visual Data Analysis”

thanks @ Elena Sofie Rudkowsky

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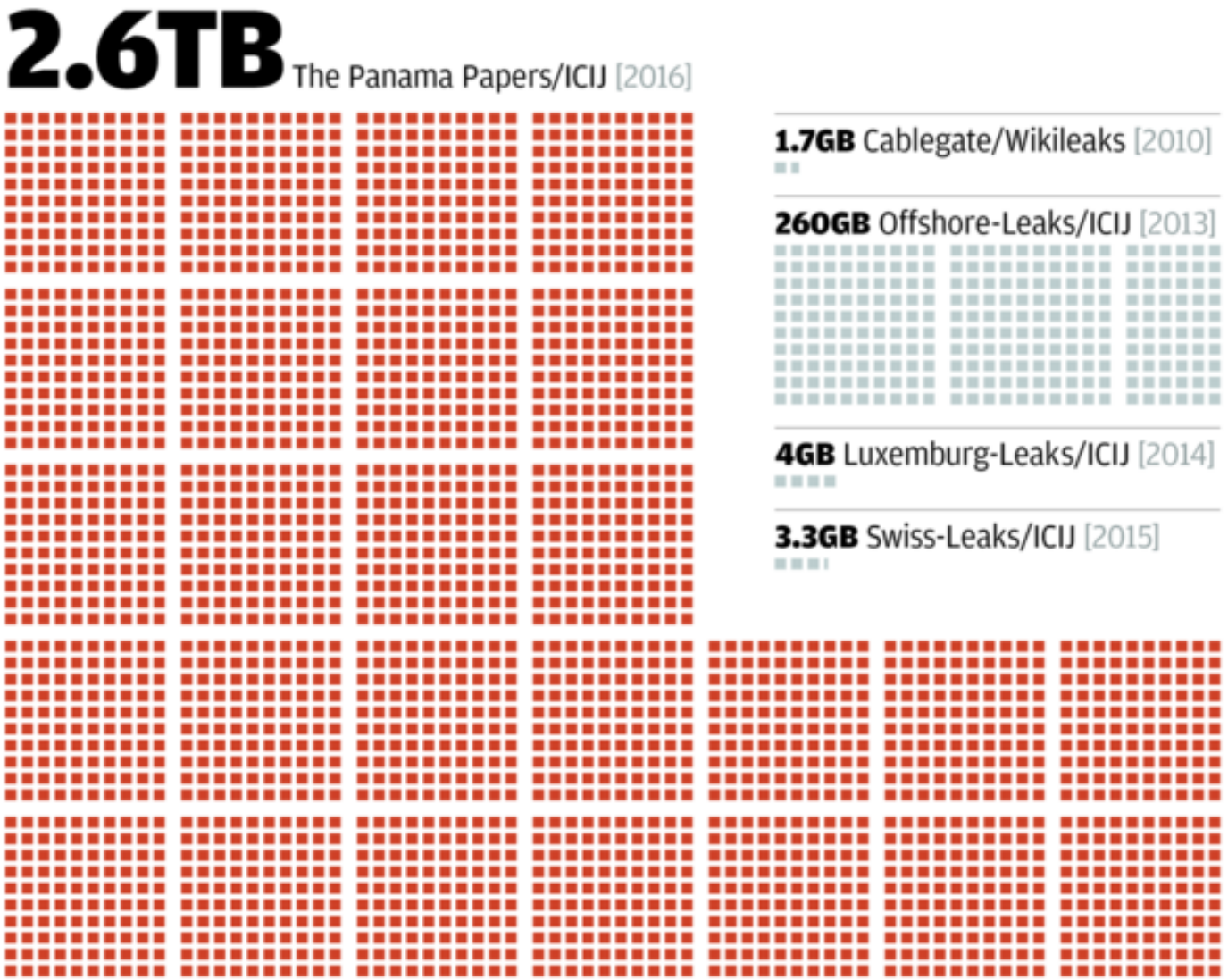
Introductory Example:

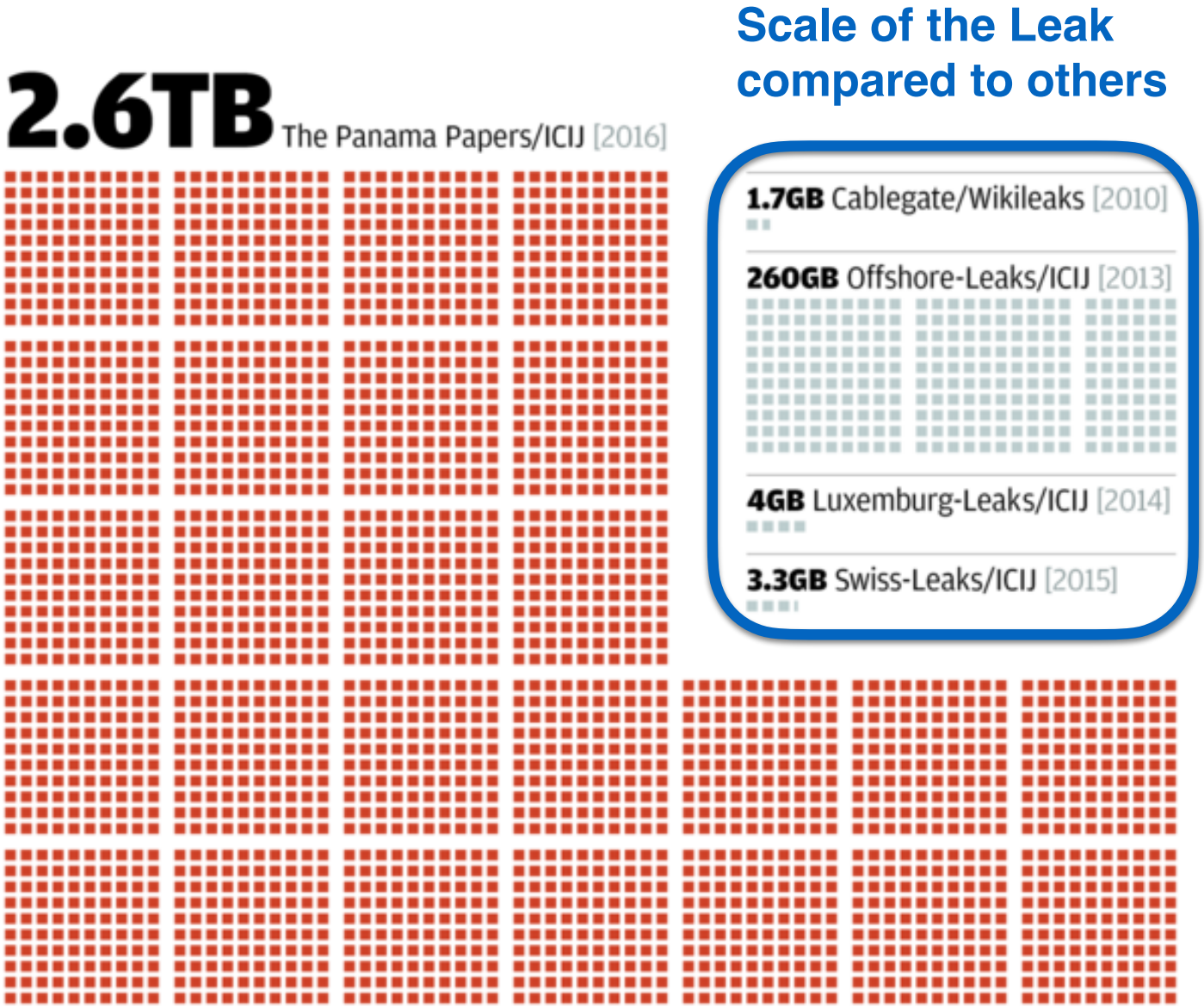
Panama Papers

Panama Papers



http://www.computerworld.com/article/3053601/security/consider-the-panama-papers-breach-a-warning.html

Panama Papers



http://www.computerworld.com/article/3053601/security/consider-the-panama-papers-breach-a-warning.html

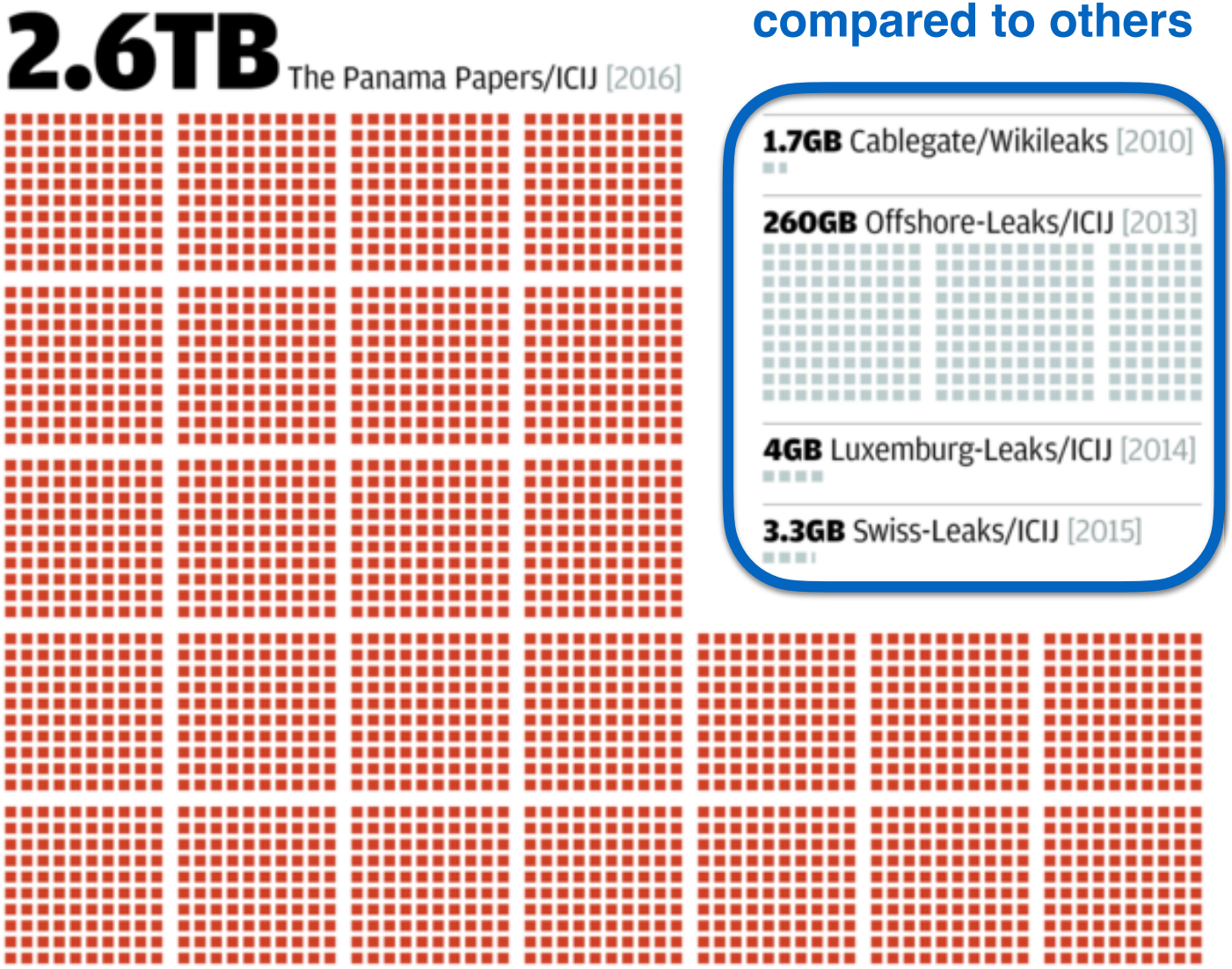
Panama Papers

Mossack Fonseca
- law office in Panama
- 214,000 letterbox companies in 21 tax havens

Letterbox Company
- address for tax purposes, money laundering…
- business carried on elsewhere/nowhere

Prominent Owners
- Iceland: Prime Minister Gunnlaugsson
- Russia: Circle around president Putin
- Syria: Network around president al-Assad
- ….

Scale of the Leak compared to others

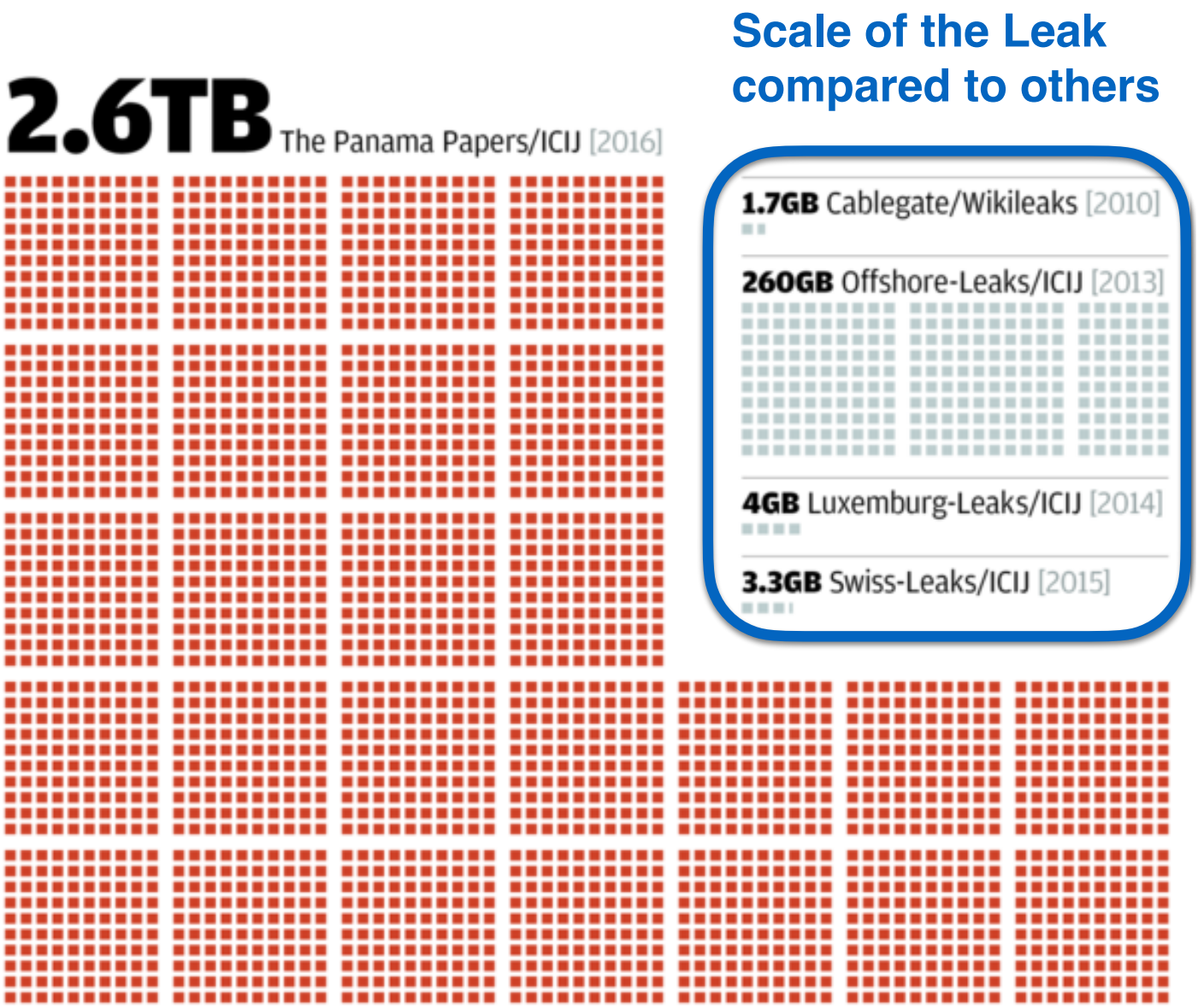


http://www.computerworld.com/article/3053601/security/consider-the-panama-papers-breach-a-warning.html

Panama Papers

Analysis

- **400 journalists** from 80 countries
- **11.5 million documents** (PDFs, emails, text files, database format files, images…)
- **1 year research**
- **text analysis software** like Nuix



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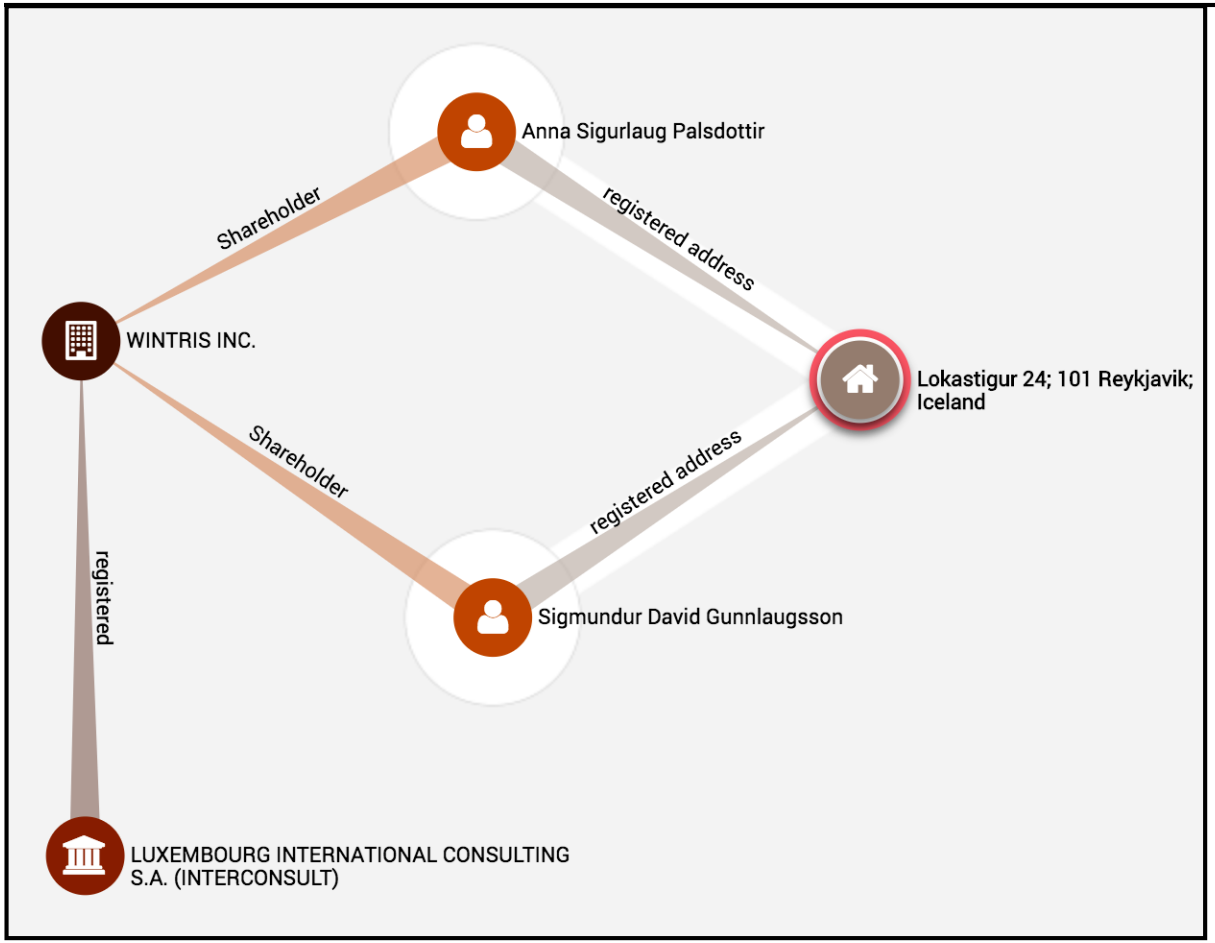
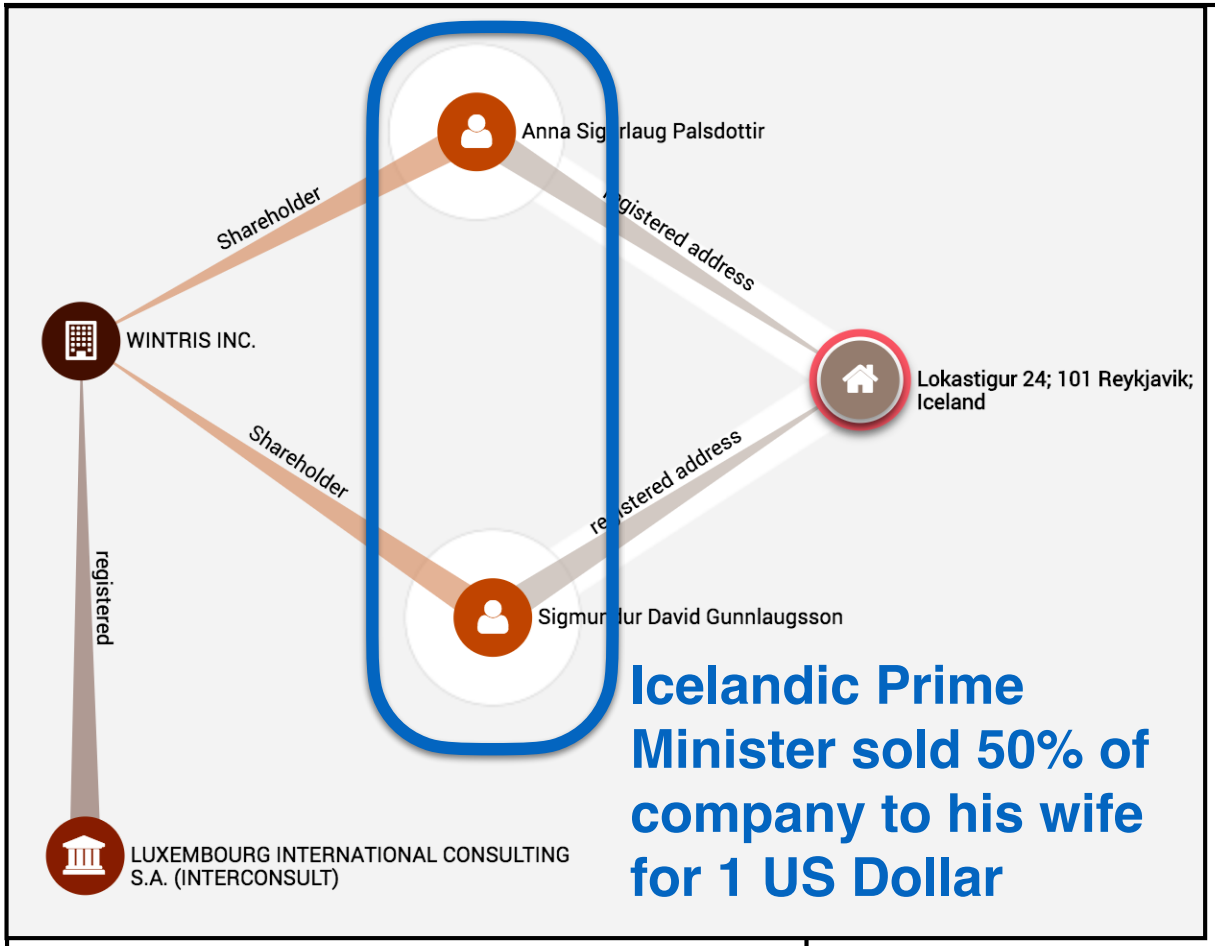
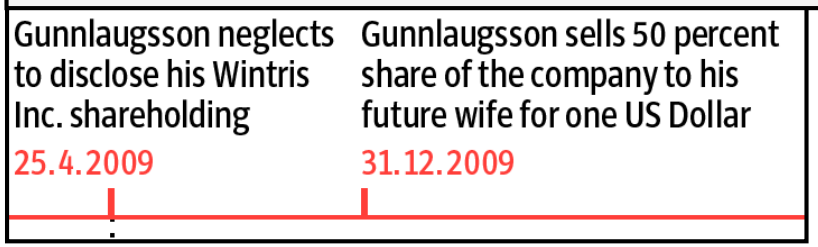
Panama Papers



https://panamapapers.icij.org/the_power_players/
http://panamapapers.sueddeutsche.de/articles/56fec0cda1bb8d3c3495adfc/

Panama Papers





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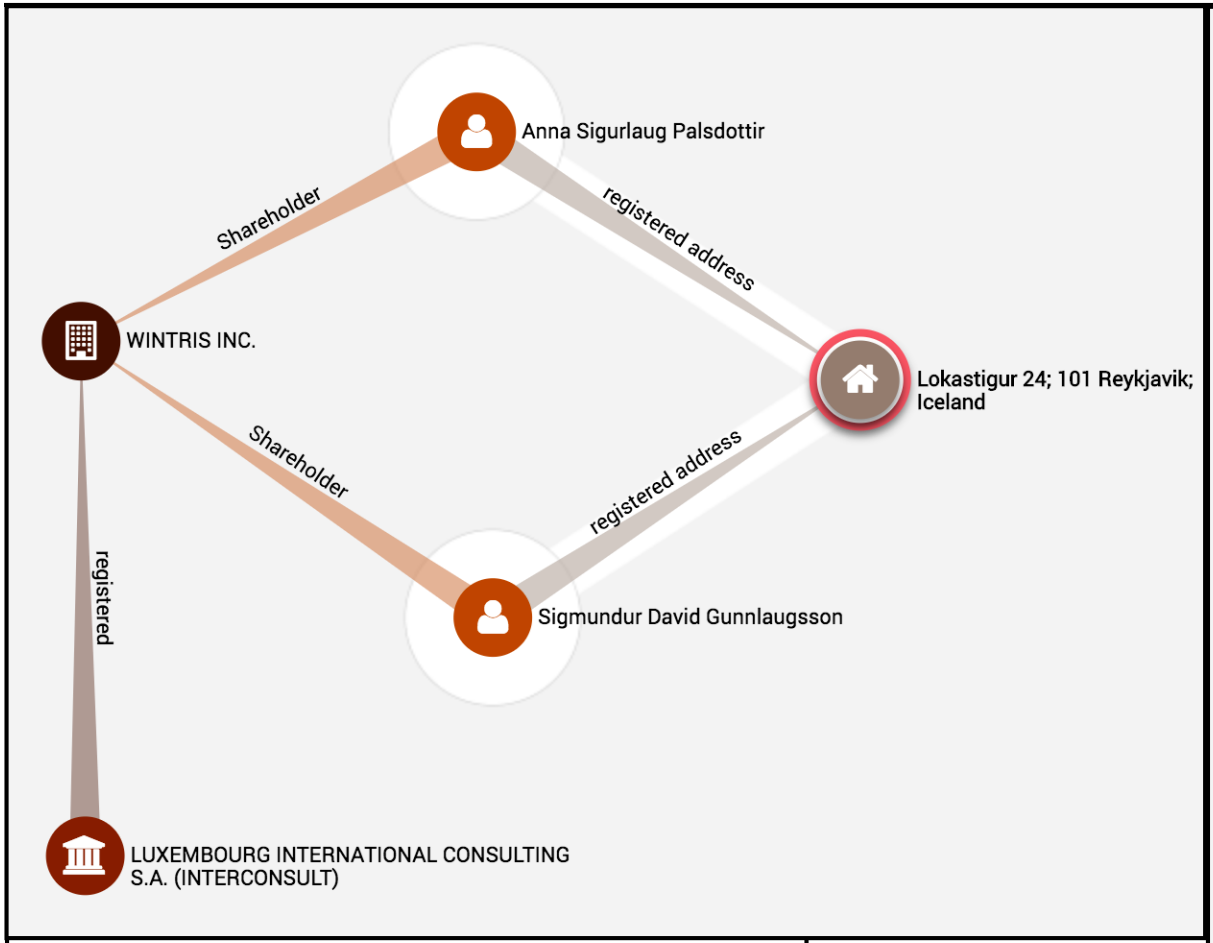
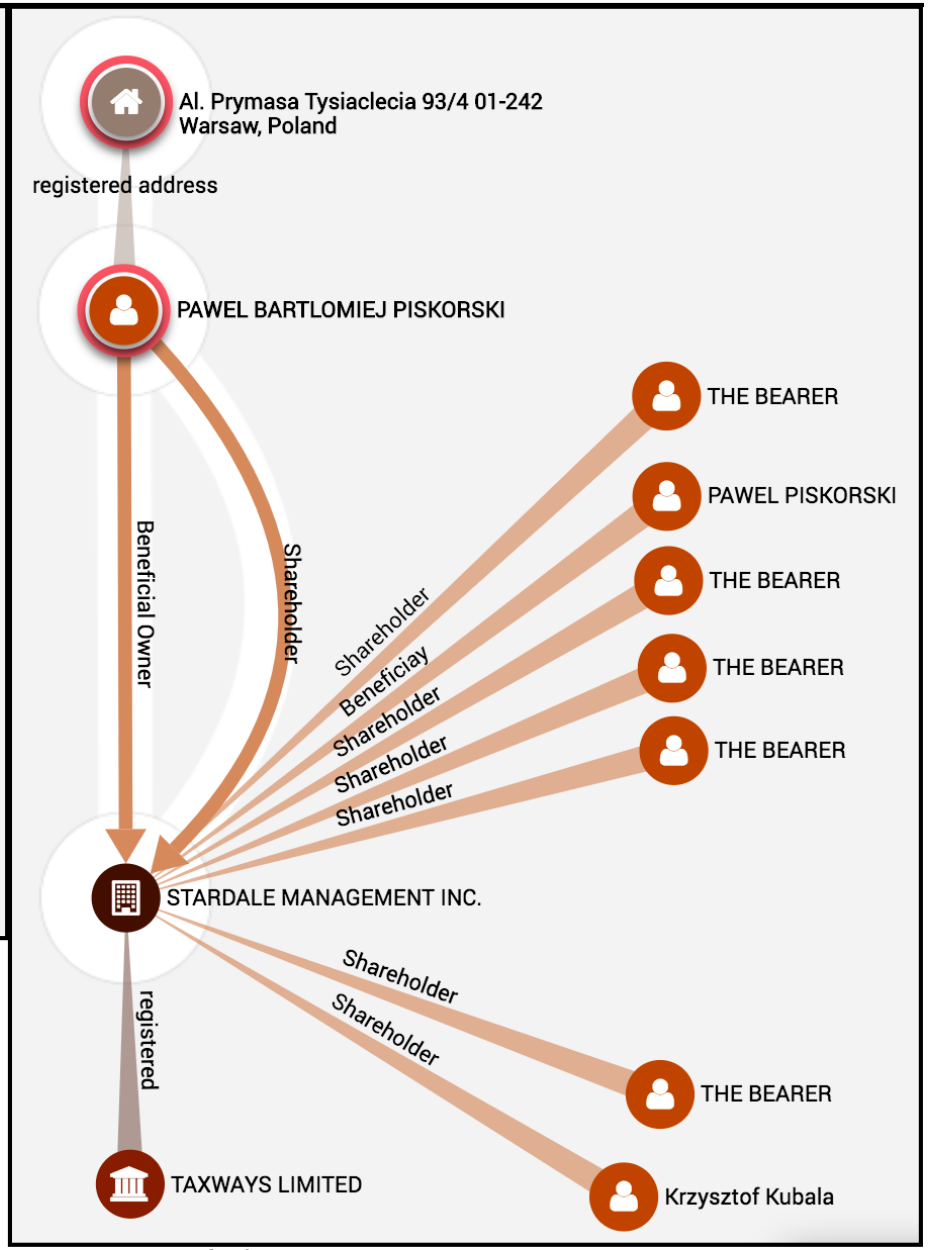
Panama Papers



Gunnlaugsson neglects to disclose his Wintris Inc. shareholding
25.4.2009

Gunnlaugsson sells 50 percent share of the company to his future wife for one US Dollar
31.12.2009



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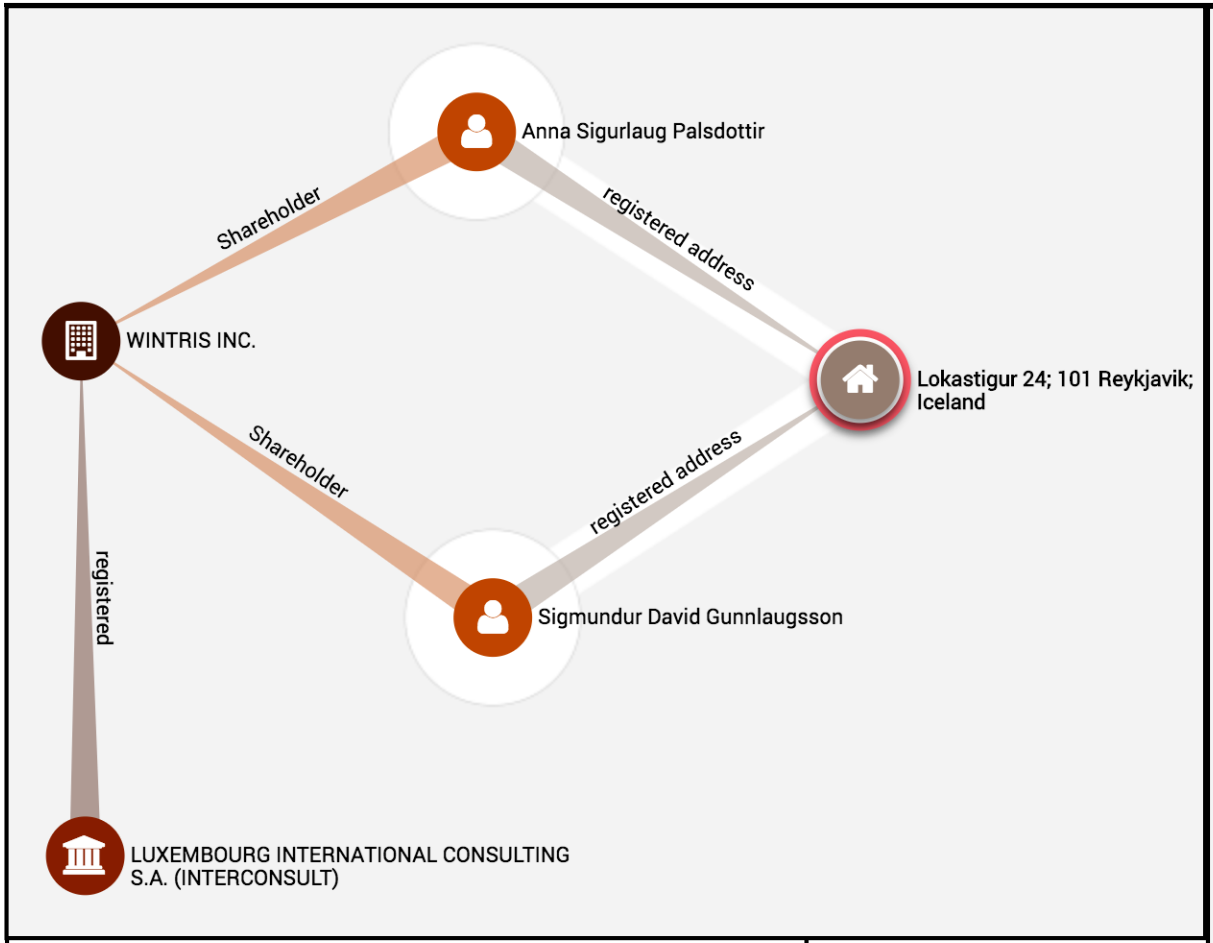
Panama Papers



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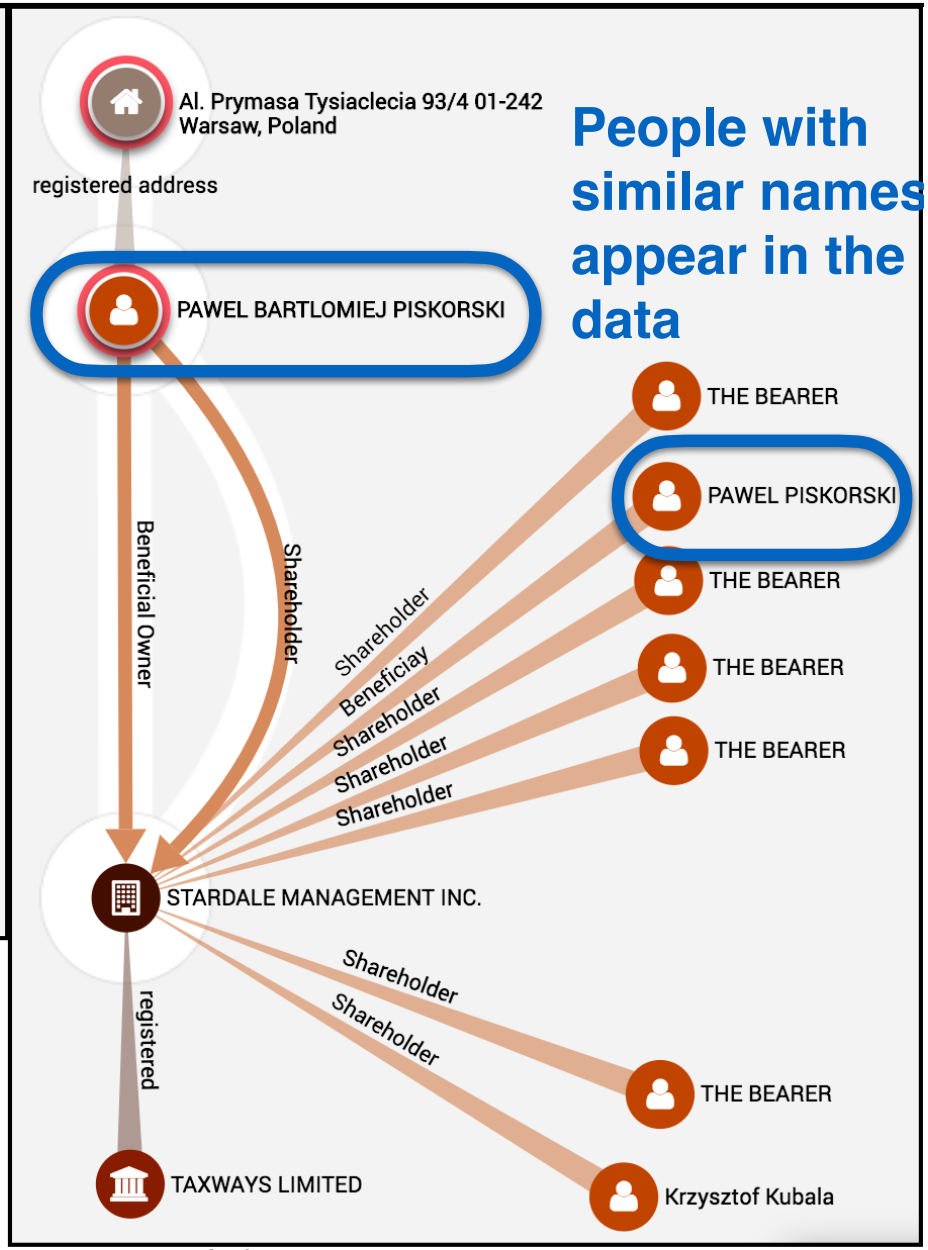

https://panamapapers.icij.org/the_power_players/
http://panamapapers.sueddeutsche.de/articles/56fec0cda1bb8d3c3495adfc/

Question:

What can be extracted out of textual data?

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Agenda

- From Text to Structure
  - POS Tags and Parsing Trees
  - Bag-of-Words
  - Distributed Word Embeddings
  - Topic Models
  - Named Entities
  - Sentiment Analysis
  - Temporal Events
  - Deep Learning
- Projects

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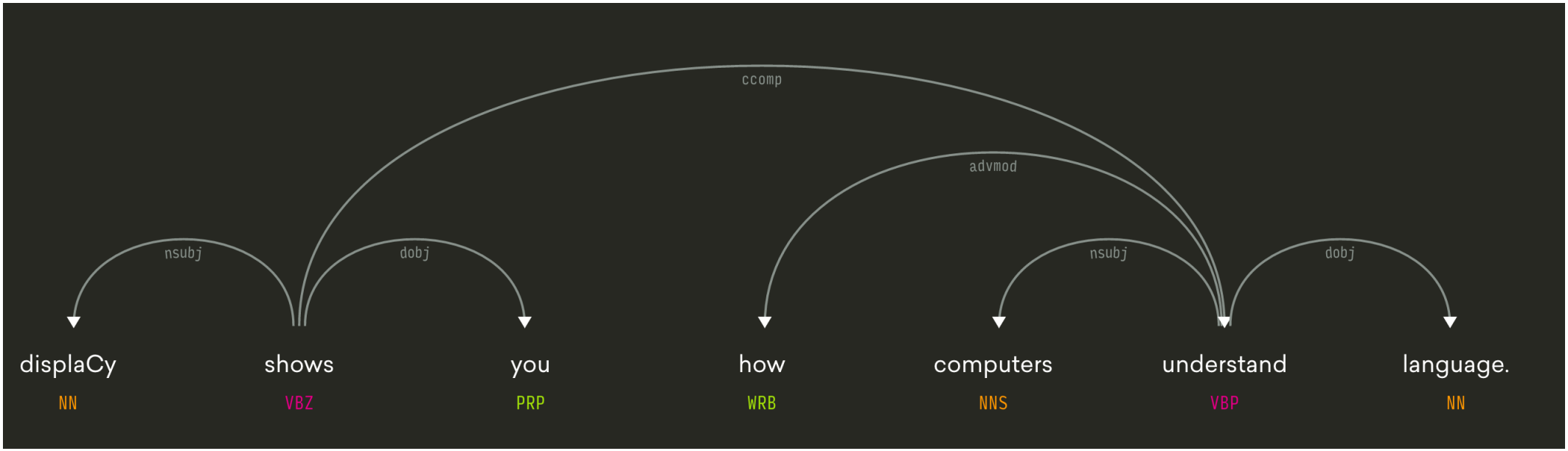
From Text to Structure

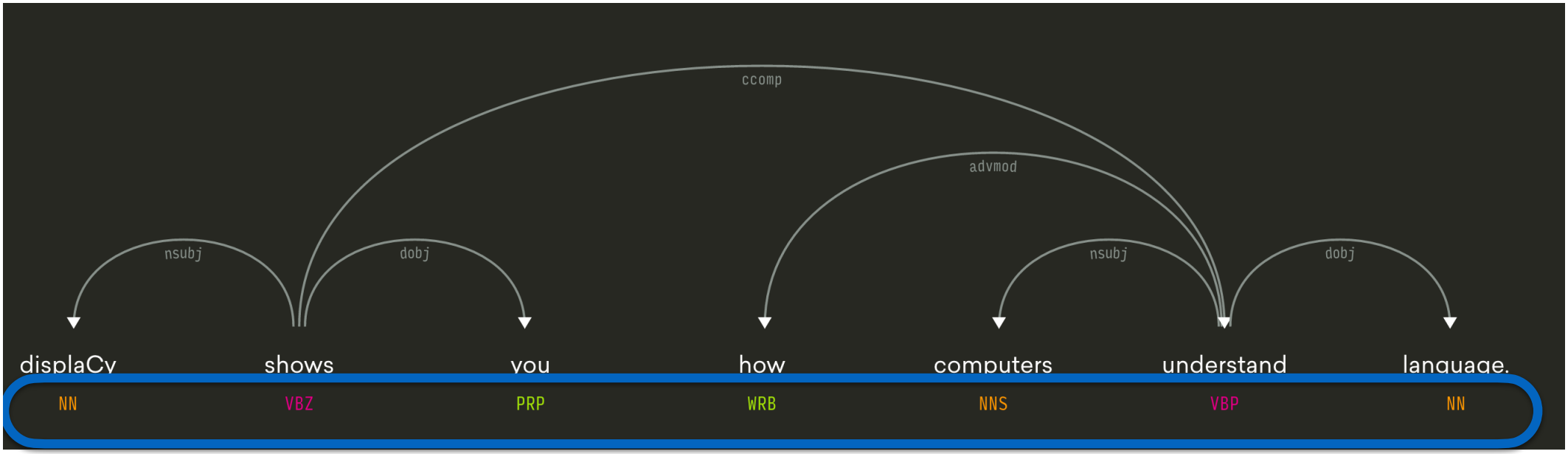
POS Tags and Parsing Trees

POS Tags and Parsing Trees



https://demos.explosion.ai/displacy/

POS Tags and Parsing Trees

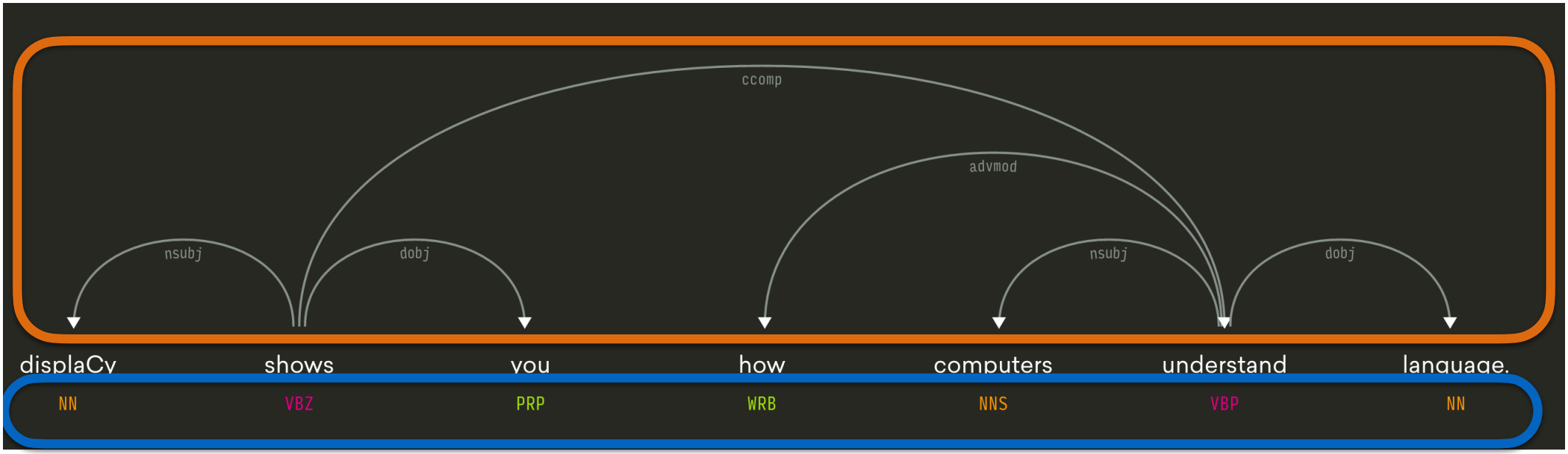


Part-of-speech Tags (POS Tags)
mark verbs, nouns, adjectives etc.

https://demos.explosion.ai/displacy/

POS Tags and Parsing Trees

Parsing (or Syntax) Trees show the syntactical structure of language like object, subject…



Part-of-speech Tags (POS Tags) mark verbs, nouns, adjectives etc.

https://demos.explosion.ai/displacy/

Question:

Are POS Tags and Syntax Trees interesting for Pattern Detection?

POS Tags and Parsing Trees

Mostly not interesting for text mining (pattern detection) in document collections!

POS Tags and Parsing Trees

Mostly not interesting for text mining (pattern detection) in document collections!

Mostly not interesting for text mining (pattern detection) in document collections!

https://www.facebook.com/NewYorkMag/videos/10154081648719826/

Mostly not interesting for text mining (pattern detection) in document collections!

TABLE 1

SENTENCE SIZE

Number of sentences spoken by each speaker and sentence word count statistics. Number of words in a sentence is shown by average and 50%/90% cumulative values for all, stop and non-stop words.

speaker	number of sentences	sentence size								
		all			stop			non-stop		
Hillary Clinton	1,206	15.7•	21	43	9.0•	12	26	7.0•	9	19
Donald Trump	1,970	10.9•	15	36	6.6•	9	22	4.6•	6	16
total	3,176	14.8	19	40	9.5	11	25	7.5	9	19

Fields with • (e.g. 155•) link to data files and Wordles. Hover over the field to show these links. See analysis.

TABLE 2

PART OF SPEECH COUNT

Count of words categorized by part of speech (POS).

	part of speech									
	n+v+adj+adv		nouns (n)		verbs (v)		adjectives (adj)		adverbs (adv)	
Hillary Clinton	7,636•	2,173	3,581•	1,117	2,322•	799	1,306•	543	427•	97
	40.5%	28.5%	46.9%	31.2%	30.4%	34.4%	17.1%	41.6%	5.6%	22.7%
Donald Trump	8,158•	1,752	3,639•	953	2,375•	588	1,621•	550	523•	83
	37.9%	21.5%	44.6%	26.2%	29.1%	24.8%	19.9%	33.9%	6.4%	15.9%
total	15,794•	3,008	7,220•	1,635	4,697•	1,102	2,927•	886	950•	127
	39.1%	19.0%	45.7%	22.6%	29.7%	23.5%	18.5%	30.3%	6.0%	13.4%

Fields with • (e.g. 155•) link to data files and Wordles. Hover over the field to show these links. See analysis.

http://mkweb.bcgsc.ca/debates2016/

Bag-Of-Words (BOW)

Word Cloud


MakeAmericaGreatAgain
DONALD
TRUMP
GREAT
THANK
AMERICA
PRESIDENT
FoxNews
make
people
POLL
NEED
MEDIA
TIME
TWITTER
country
DRUDGE
NEW
VOTE
BORDER
SUPPORT
IMMIGRATION
SPEAKING
love
REPORT
ILLEGAL
DEBATE
WIN
Jeb
truth
DANSCAVINO
PBS
MR
RIGHT
BIG
TALK
DON
TONIGHT
Daniel
GOING
know
SCAVINO
OREILLYFACTOR
IOWA
DAY
job
want
election
DEAL
LOOK
today
TELL
watch
crowd
INTERVIEWED
AMERICAN
TRUE
STOP
THINK
RUNNING
NATION
Veterans
amazing
FOX
Jr
MAN
REALLY
LEAD
GOOD
HOPE
MCCAIN
THINGS
BETTER
MORNING
SEANHANNITY

Word Cloud

^ All nouns in debates, colored by contributing speaker (Clinton: blue, Trump: red, spoken by both: grey).

^ All verbs in debates, colored by contributing speaker (Clinton: blue, Trump: red, spoken by both: grey).

http://mkweb.bcgsc.ca/debates2016/

Word Frequencies over Time

Patterns of Speech: 75 Years of the State of the Union Addresses
(Data Story, Washington Post 2011)

‘health care’

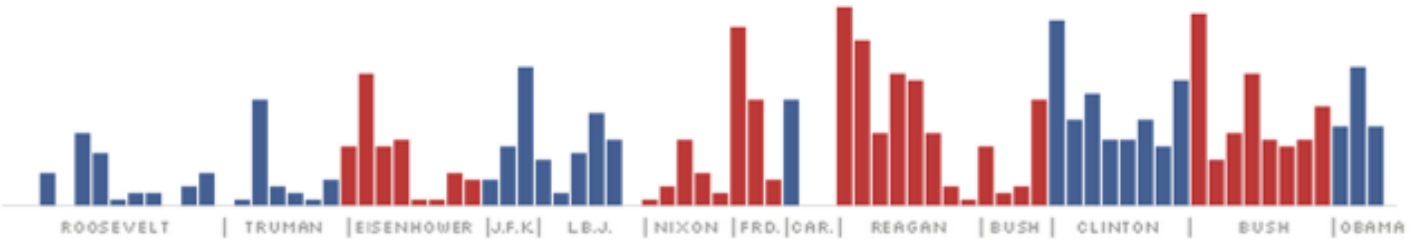
The expansion of health insurance coverage remains unpopular with nearly half the country, but Mr. Obama defended the health care law in his 2011 speech, though he added that he was willing with Republicans to improve it. In 1994, Mr. Clinton promoted his plan, which collapsed that year.

HEALTH CARE

‘tax’

Presidents have used the word every year since 1981, when Mr. Reagan uttered it 30 times, detailing his plan to reduce taxes and government spending.

TAX, TAXED, TAXES, TAXING



Word Frequencies over Time

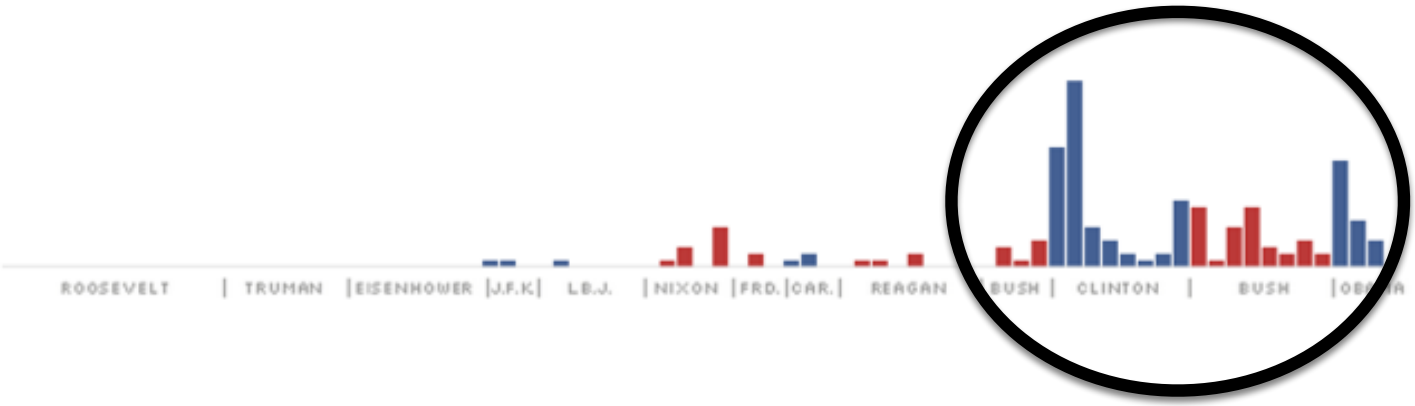
Patterns of Speech: 75 Years of the State of the Union Addresses
(Data Story, Washington Post 2011)

'health care' became popular late

'health care'

The expansion of health insurance coverage remains unpopular with nearly half the country, but Mr. Obama defended the health care law in his 2011 speech, though he added that he was willing with Republicans to improve it. In 1994, Mr. Clinton promoted his plan, which collapsed that year.

HEALTH CARE



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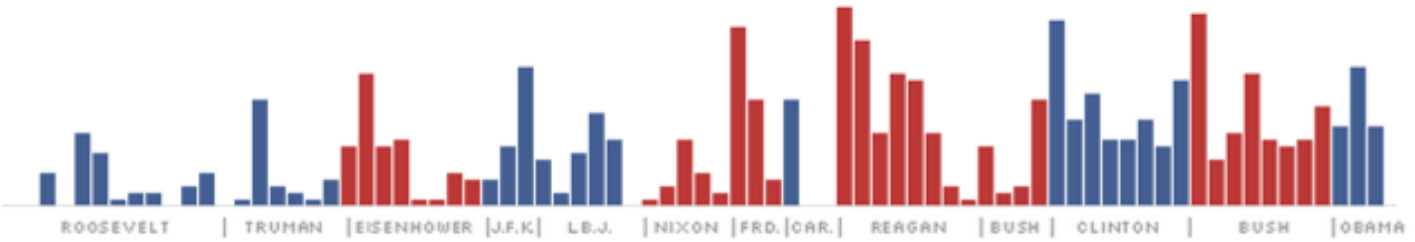
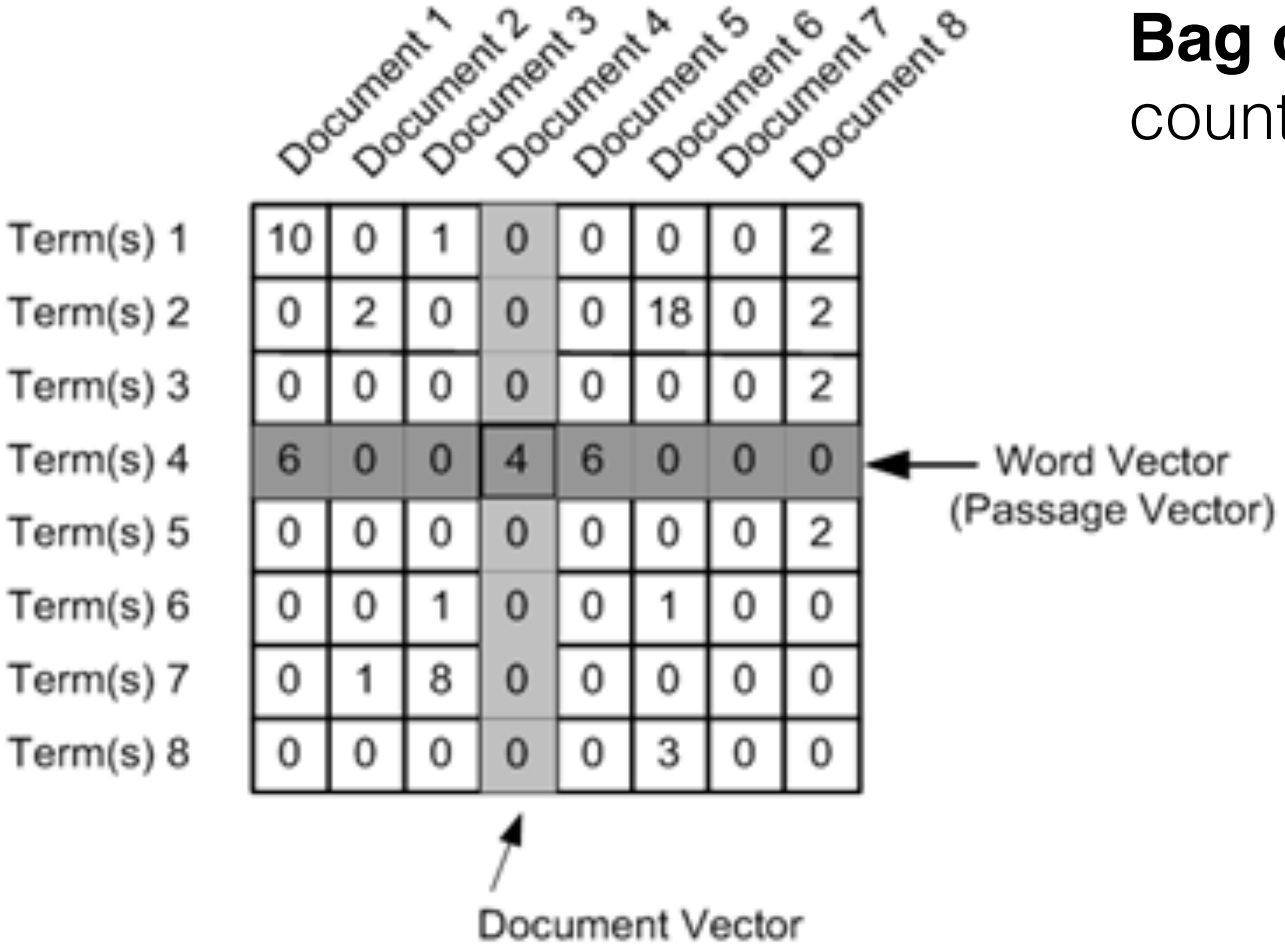
TAX, TAXED, TAXES, TAXING

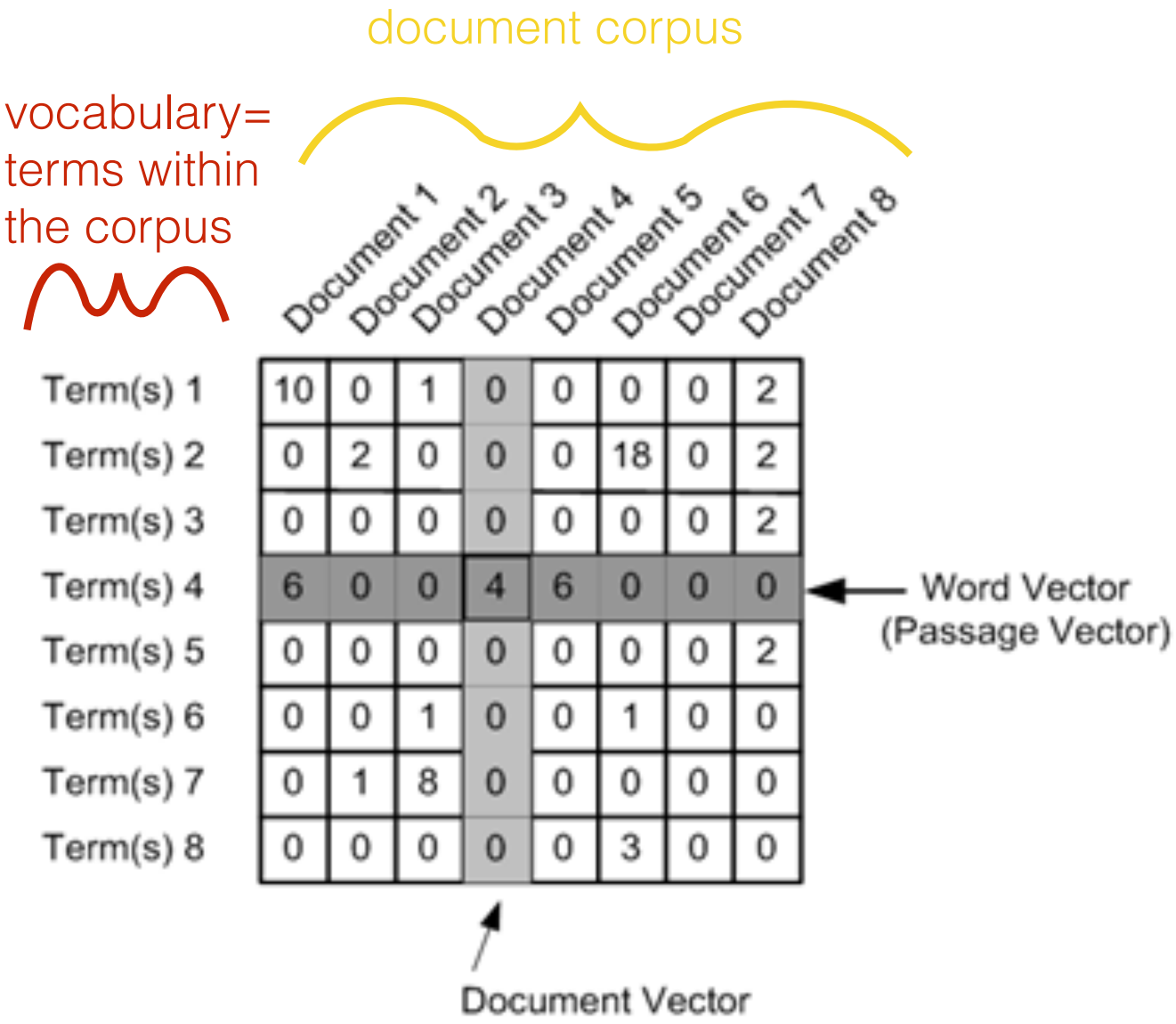


Document Term Matrix

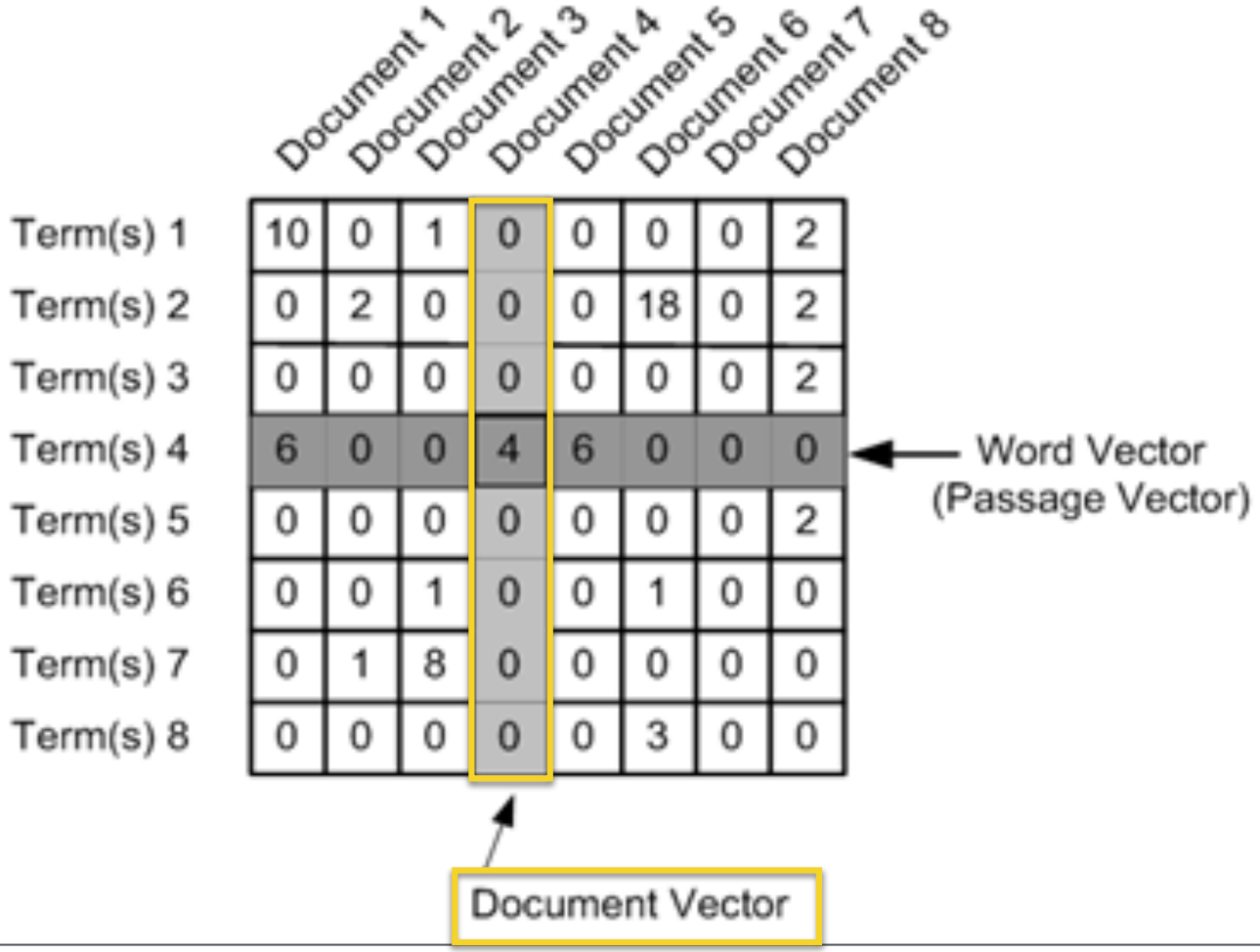


Bag of Words (BOW)
counts words per document

Document Term Matrix



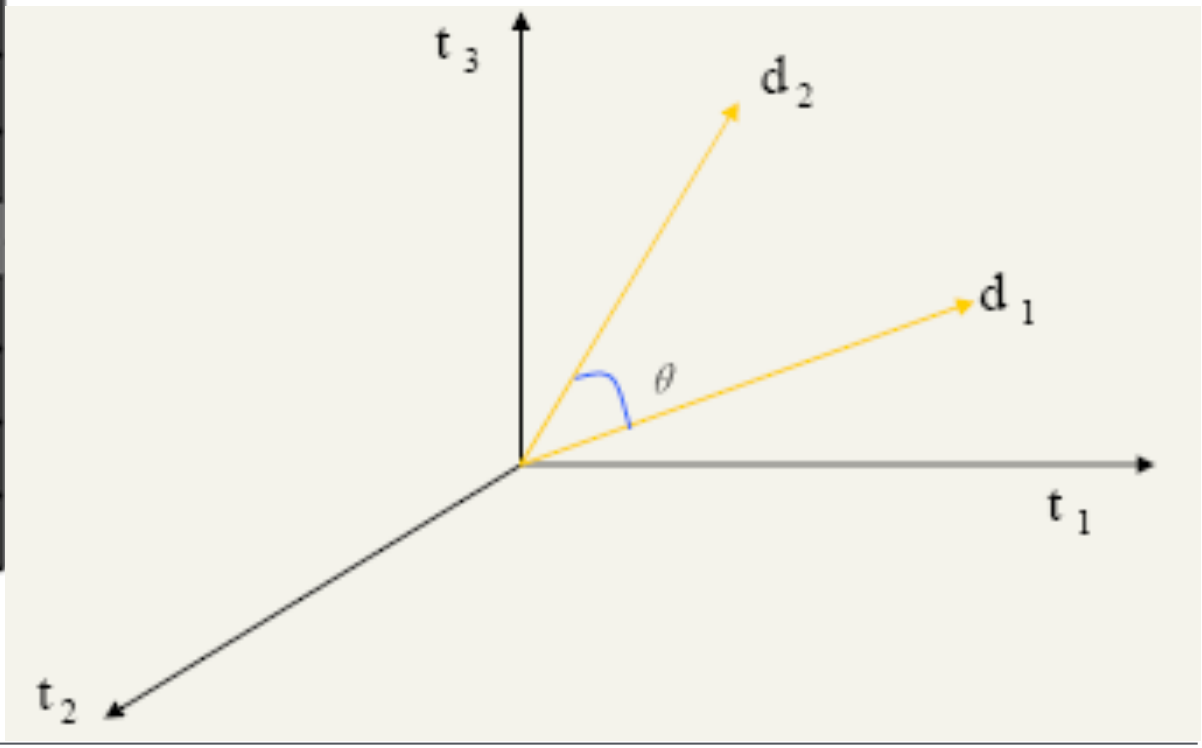
Document Term Matrix



Document Term Matrix

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

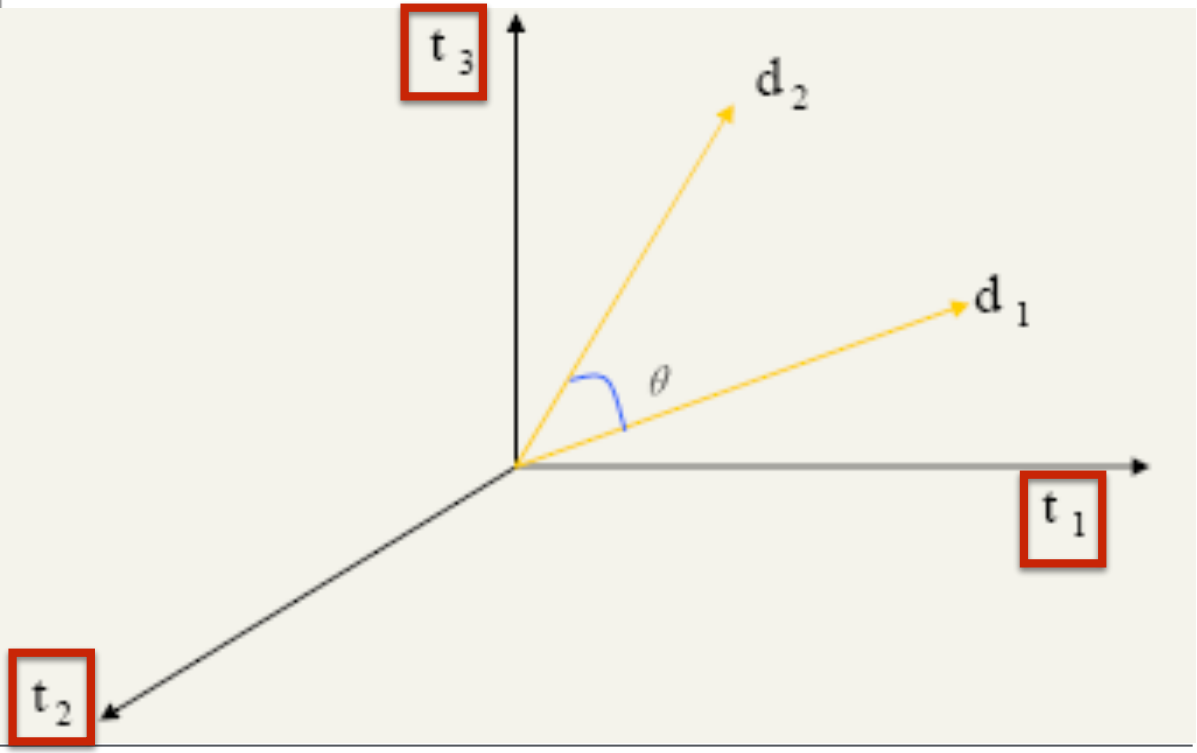
Document Vector



Document Term Matrix

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Document Vector

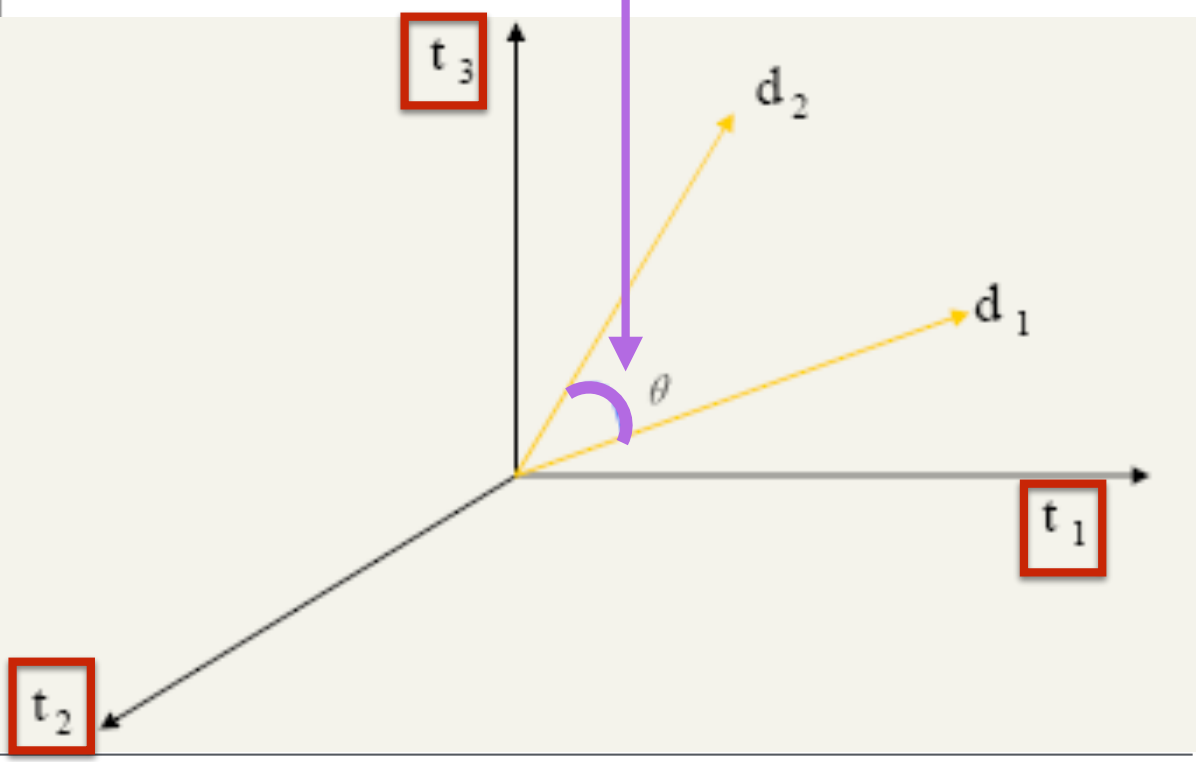


Document Term Matrix

Cosine Similarity = θ (angle)
Distance between Document Vectors

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Document Vector

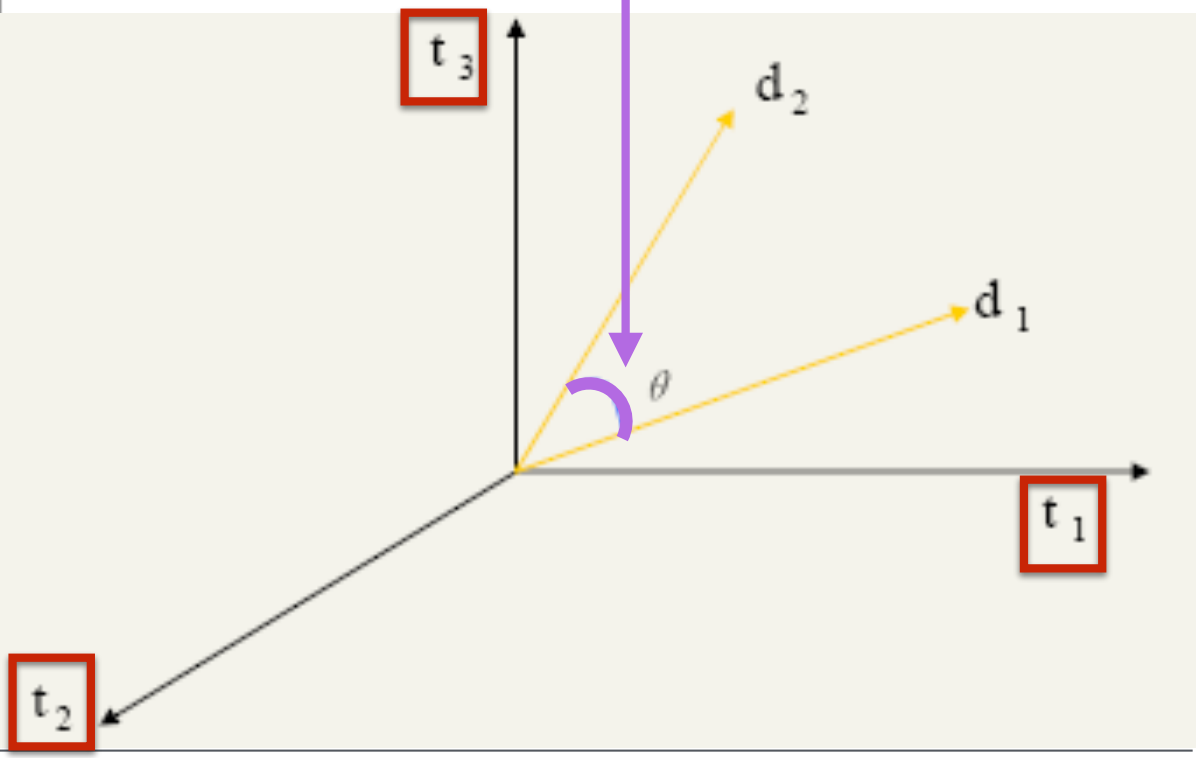


Document Term Matrix

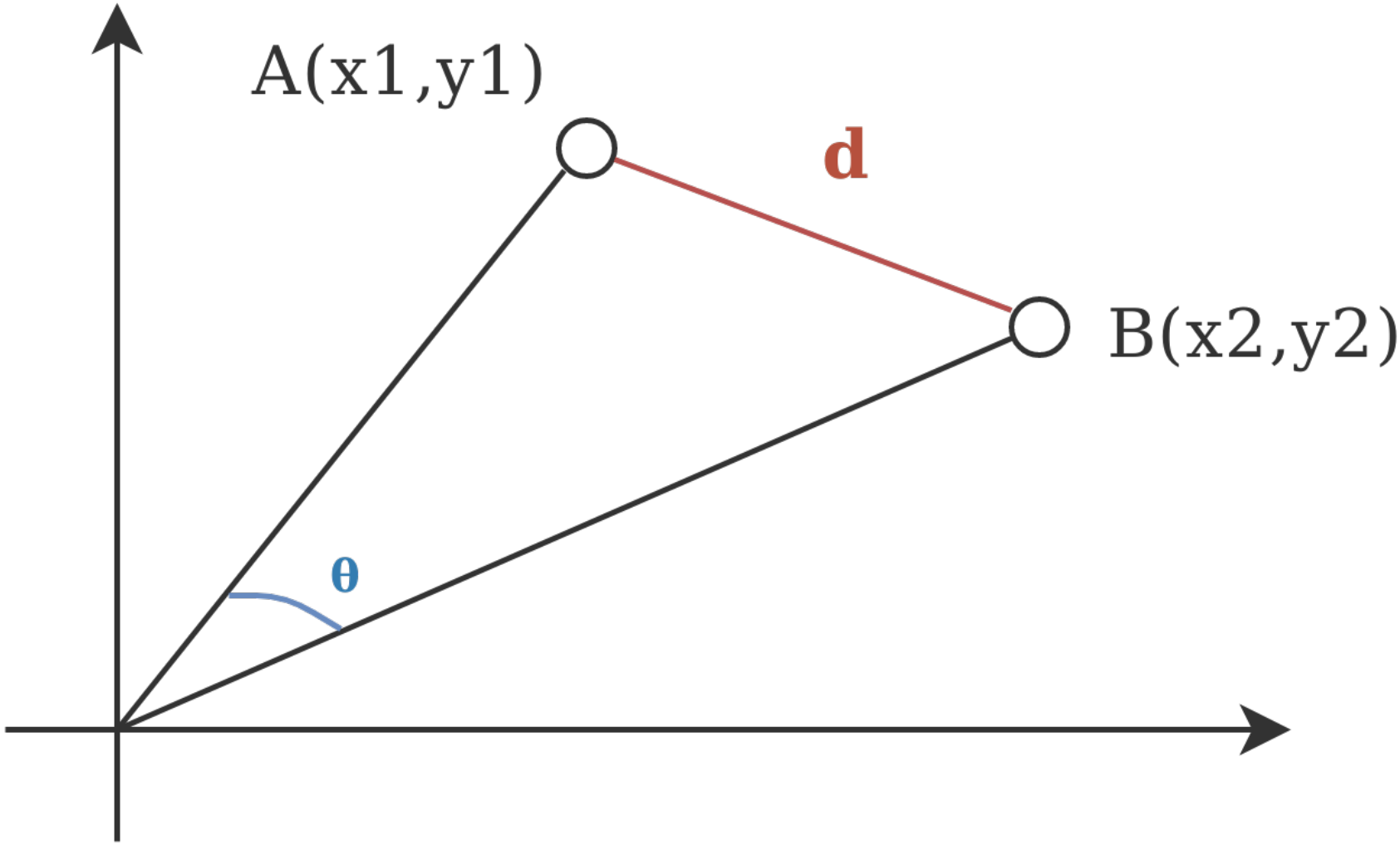
Cosine Similarity - Why not using Euclidean Distance (Similarity)?

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Document Vector



Document Term Matrix



https://cmry.github.io/notes/euclidean-v-cosine

Is counting good enough?
Ideas for improvement?

Term Frequency - Inverse Document Frequency (TF-IDF)

Term Frequency - Inverse Document Frequency

We introduce a new weight
- consisting of two parts!

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Document Vector

term frequency (how often does the term appear in the current document?) normalised according to document length

document frequency (how many documents contain the term?)

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$ = number of occurrences of i in j

df_i = number of documents containing i

N = total number of documents

Term Frequency - Inverse Document Frequency

If a term appears in many documents
(term is not interesting & weight = low)

df = high
N/df = low
log(N/df) = low
weight = low

df = low
N/df = high
log(N/df) = high
weight = high

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Document Vector

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

$tf_{i,j}$ = number of occurrences of i in j
df_i = number of documents containing i
N = total number of documents

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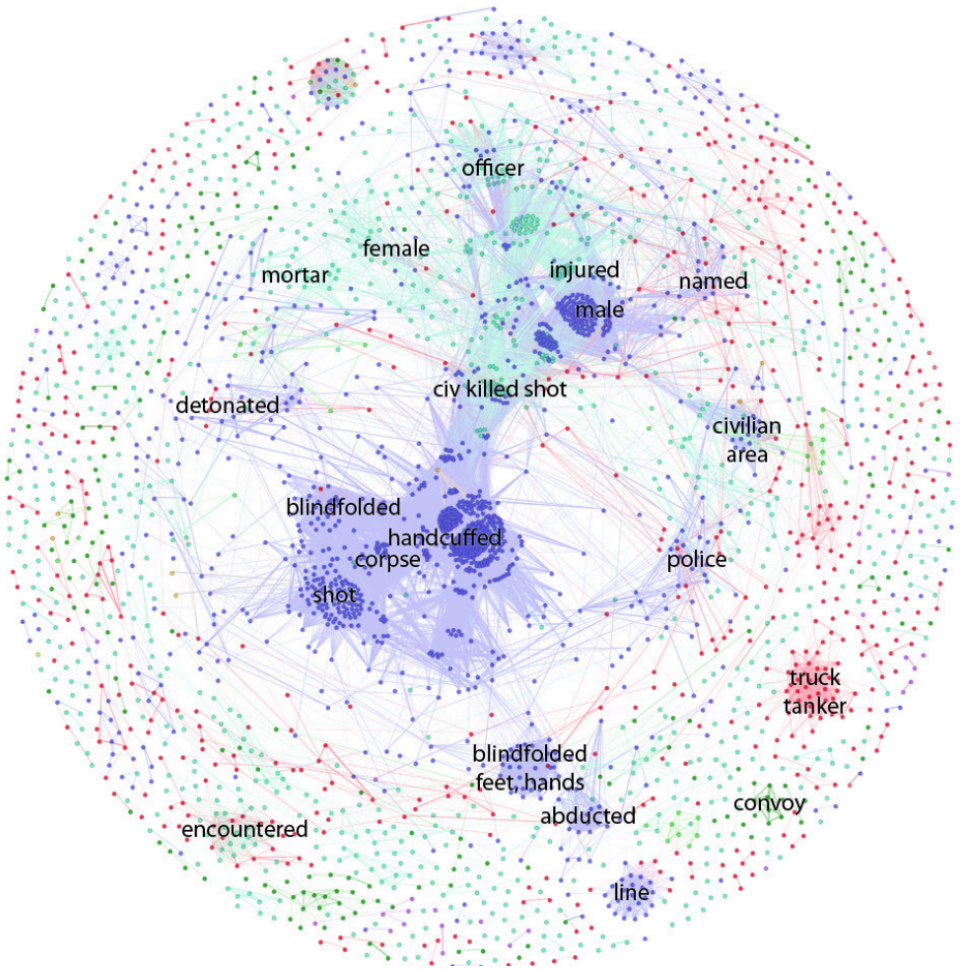
Document Term Matrix Visualization:

WikiLeaks Iraq War Logs

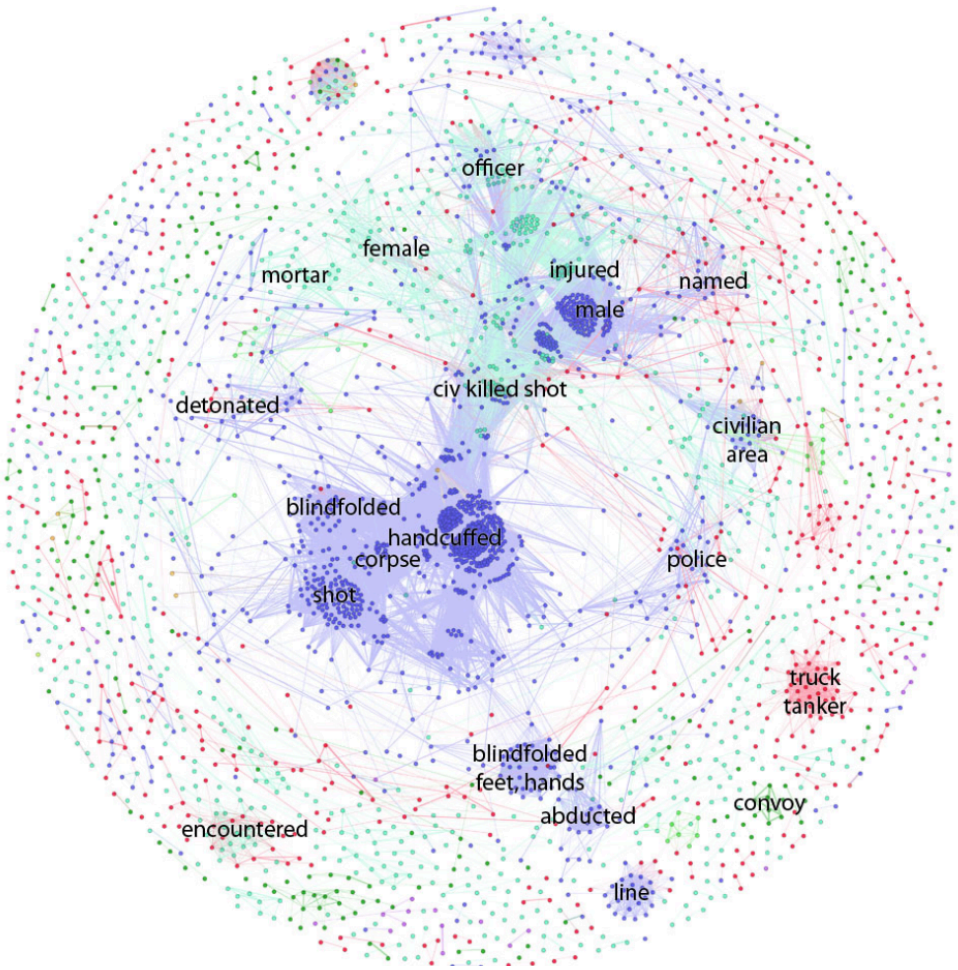
How could we visualize such a matrix?

Overview Project: WikiLeaks Iraq War Logs



http://jonathanstray.com/a-full-text-visualization-of-the-iraq-war-logs

Overview Project: WikiLeaks Iraq War Logs

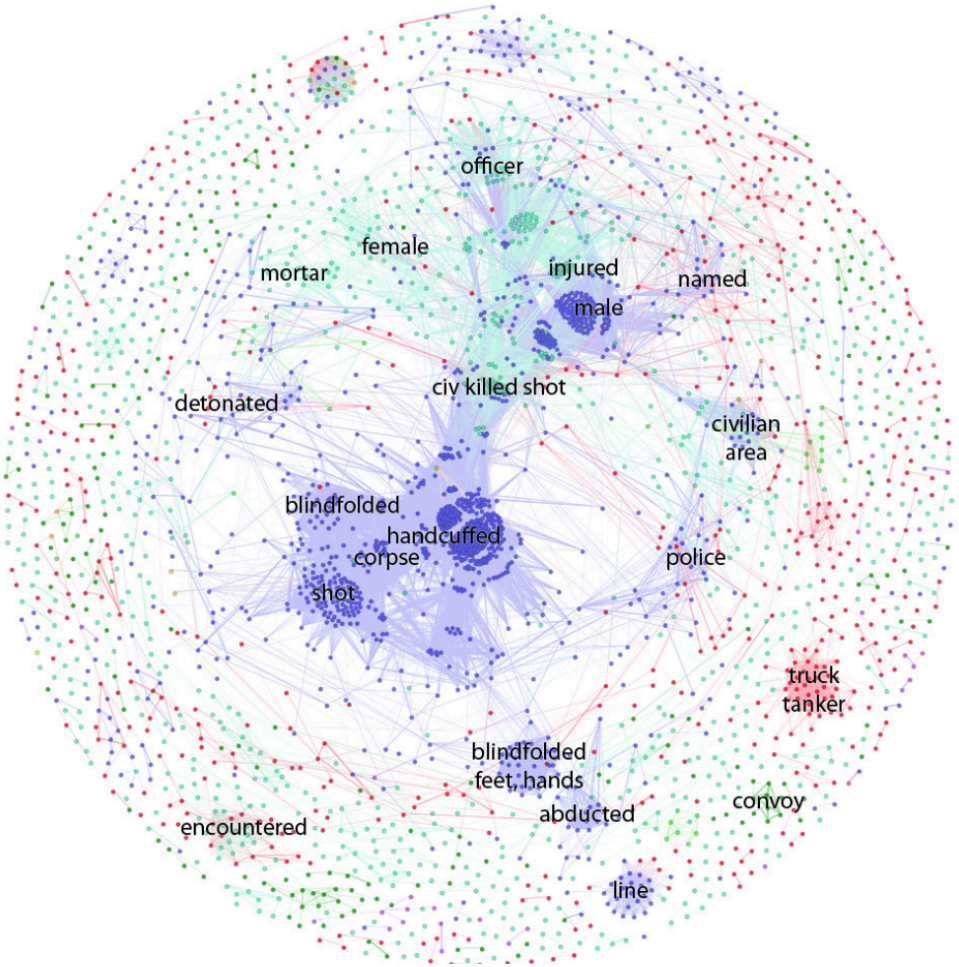


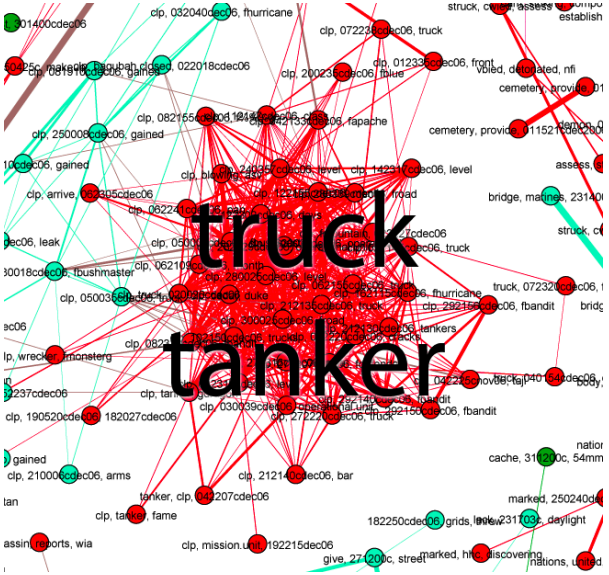
~ 400,000 war reports

visualized as keyword clusters according to TF-IDF (cosine similarity)

http://jonathanstray.com/a-full-text-visualization-of-the-iraq-war-logs

Overview Project: WikiLeaks Iraq War Logs





Red signifies that the military coded these reports as "explosive hazard"

Each point is a incident

http://jonathanstray.com/a-full-text-visualization-of-the-iraq-war-logs

Can you think of any Limitations of the TF-IDF Modeling Approach?

Limitations of TF-IDF

- **no syntactic or semantic relationships** of words or passages
- **words** are treated independently and are **not comparable**
- **topics** (word concepts) are **not reflected** very well
- stop word removal needed (or other **preprocessing** steps) in order **to achieve meaningful results**

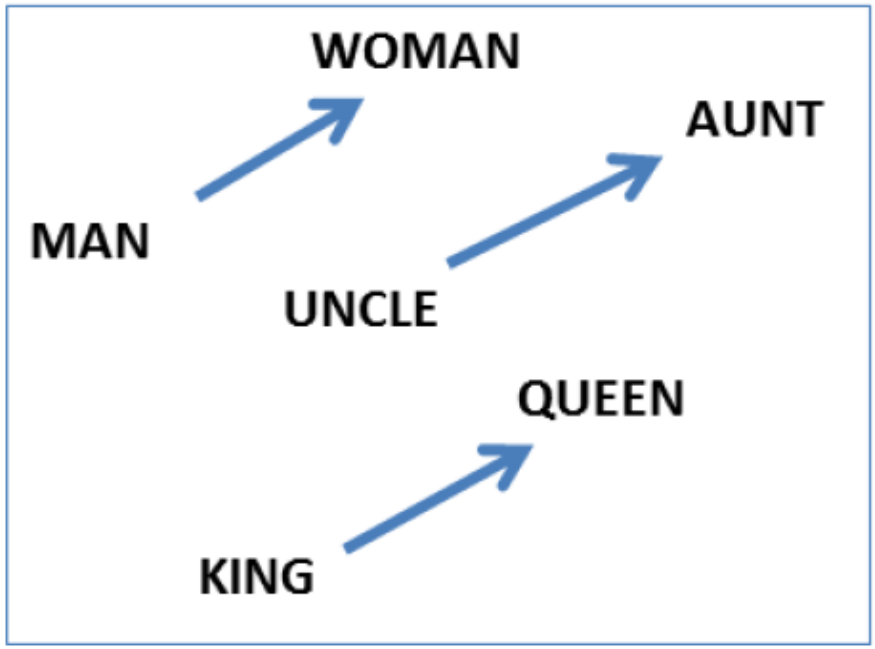
Distributed Word Embeddings

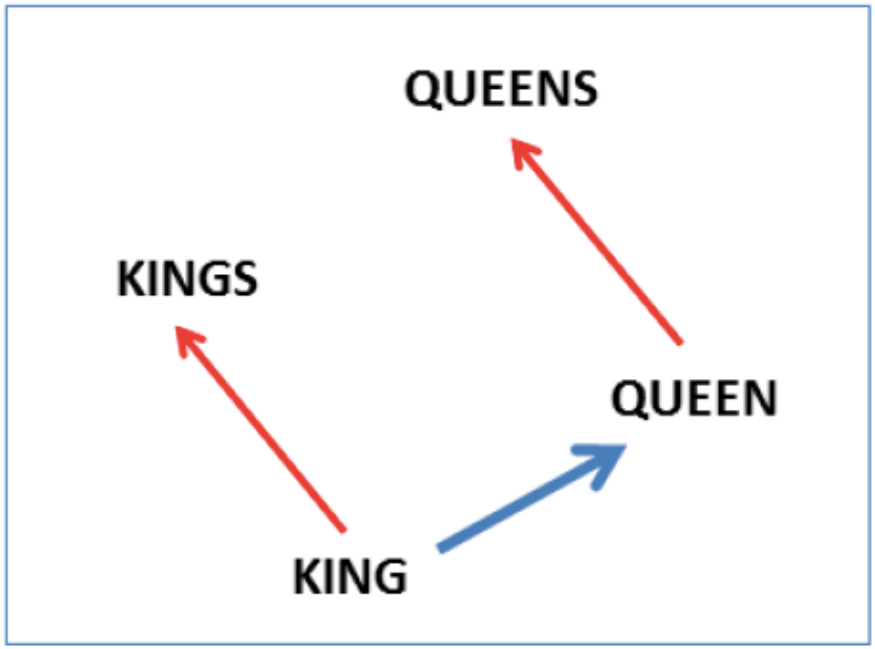
some versions:
word2vec/glove/fasttext/bert/elmo/GPT-2

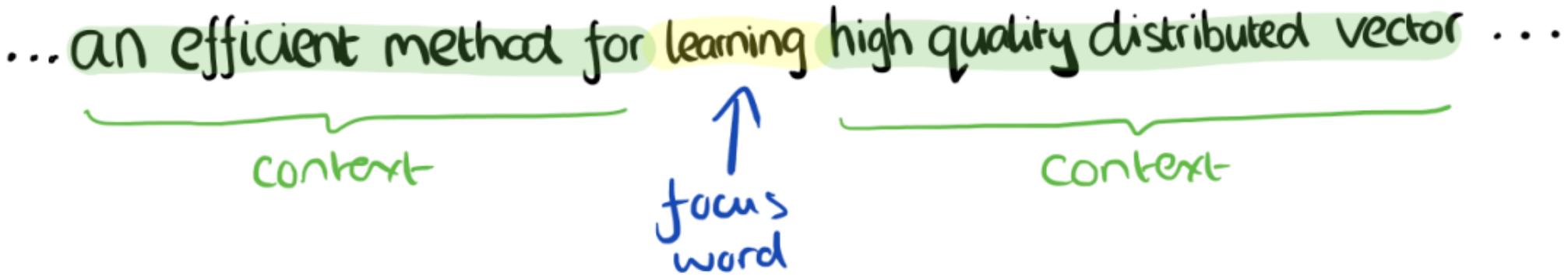
Words as distributions according to their context

- a word is a representation of all its context windows within a corpus (**context = N-gram** of which a word is part)
  See Google N-gram viewer: https://books.google.com/ngrams
- similar **words** tend to have similar representations —> **comparable**
- **syntax** as well as **semantics** is reflected
- no document vectors are created, only word vectors

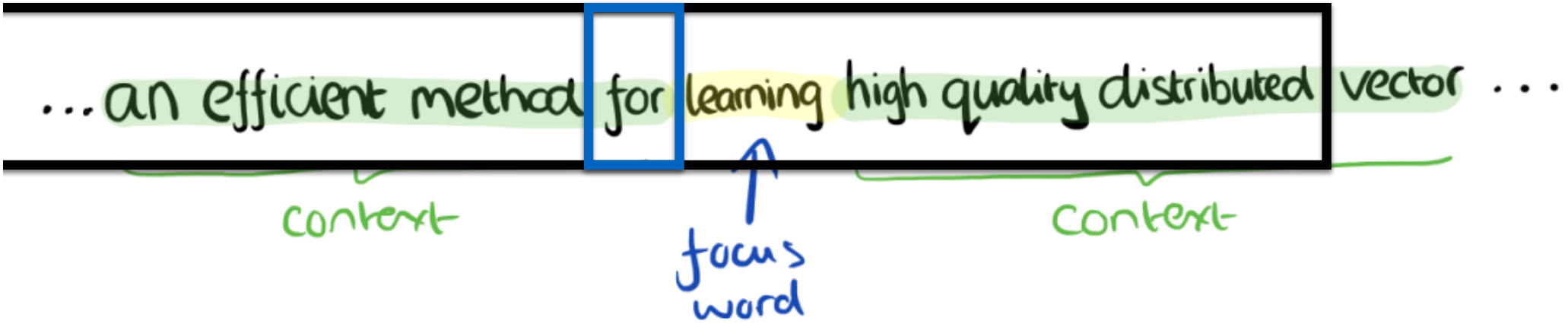
Efficient estimation of word representations in vector space
Tomas Mikolov et al., ICLR Workshop, 2013







https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/



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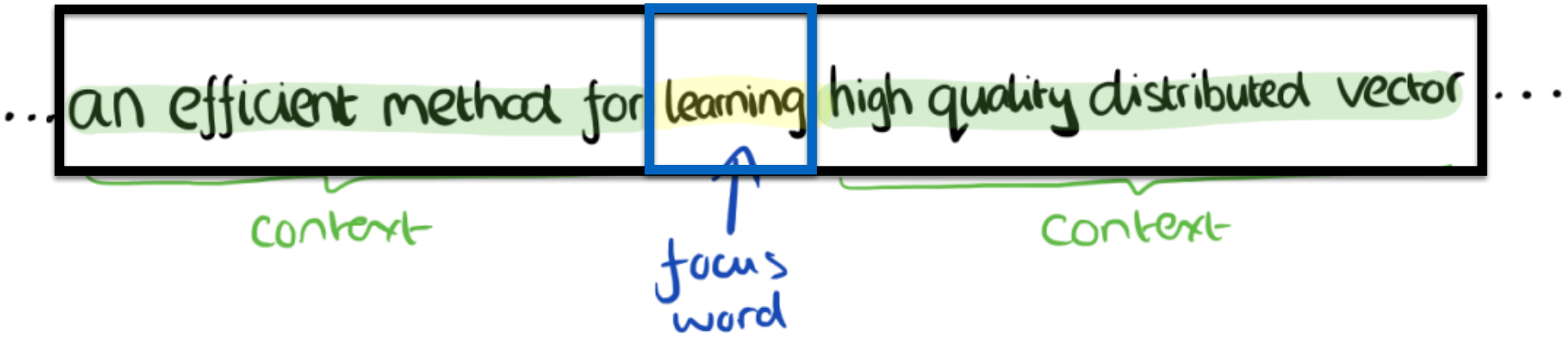

https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

We try to predict the current focus word with a Neural Network

https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

First: Our **output reflects** the relation between all words within the vocabulary (**Co-Occurrences**).

After a dimensionality reduction (from maybe 10,000 words in vocabulary to 100 dimensions) we receive something related to **“concepts”** like…..

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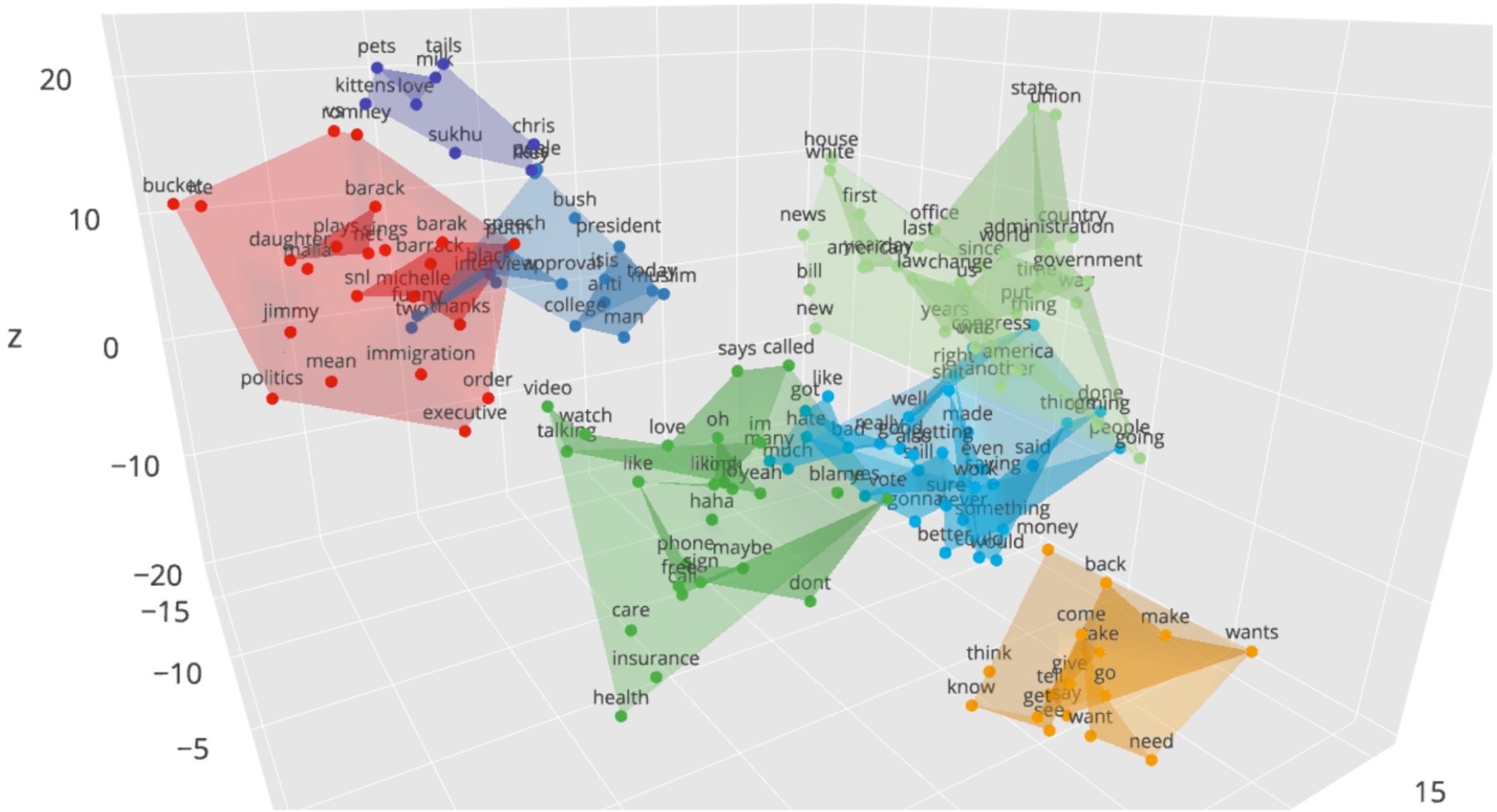
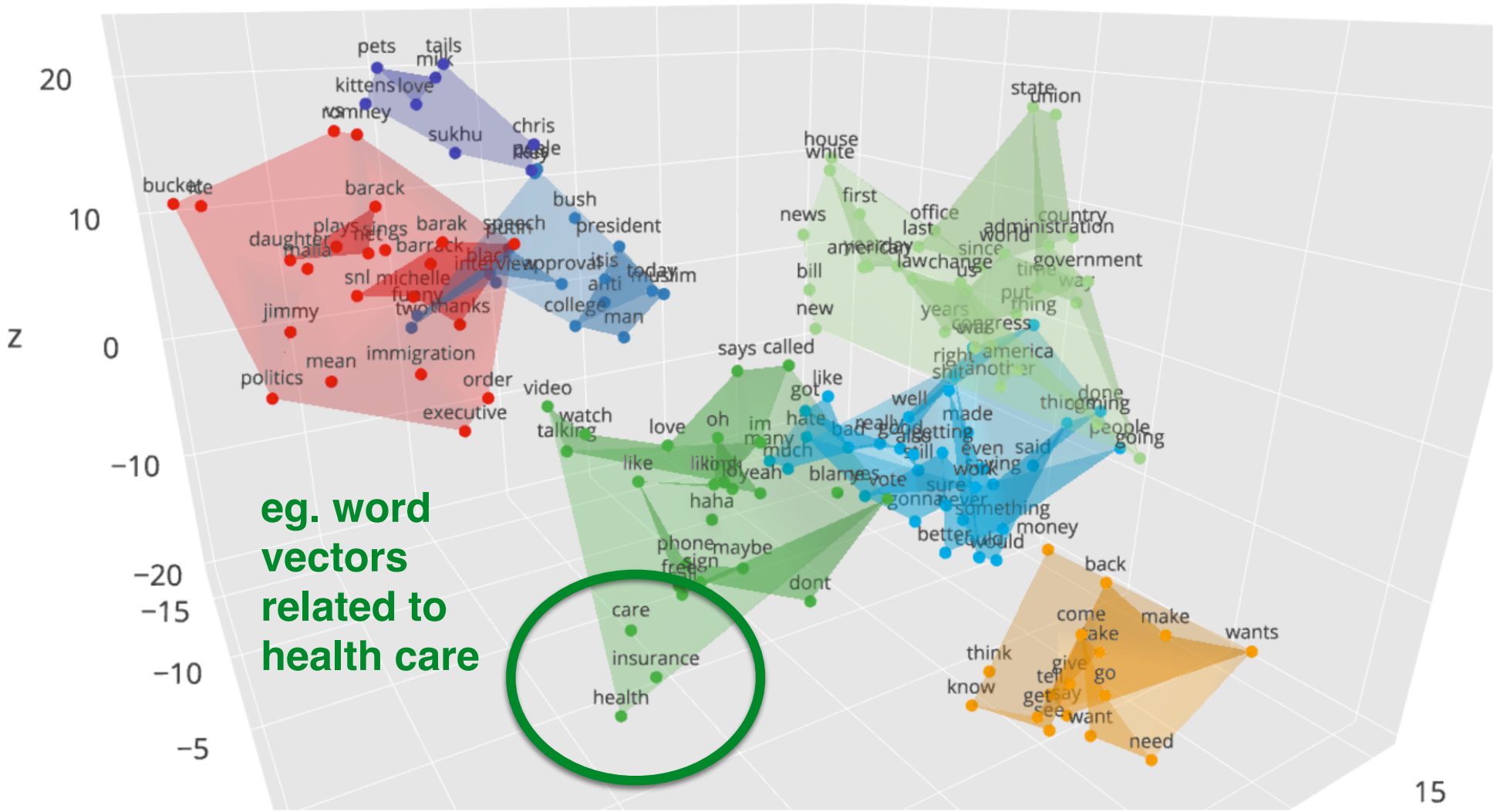
https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

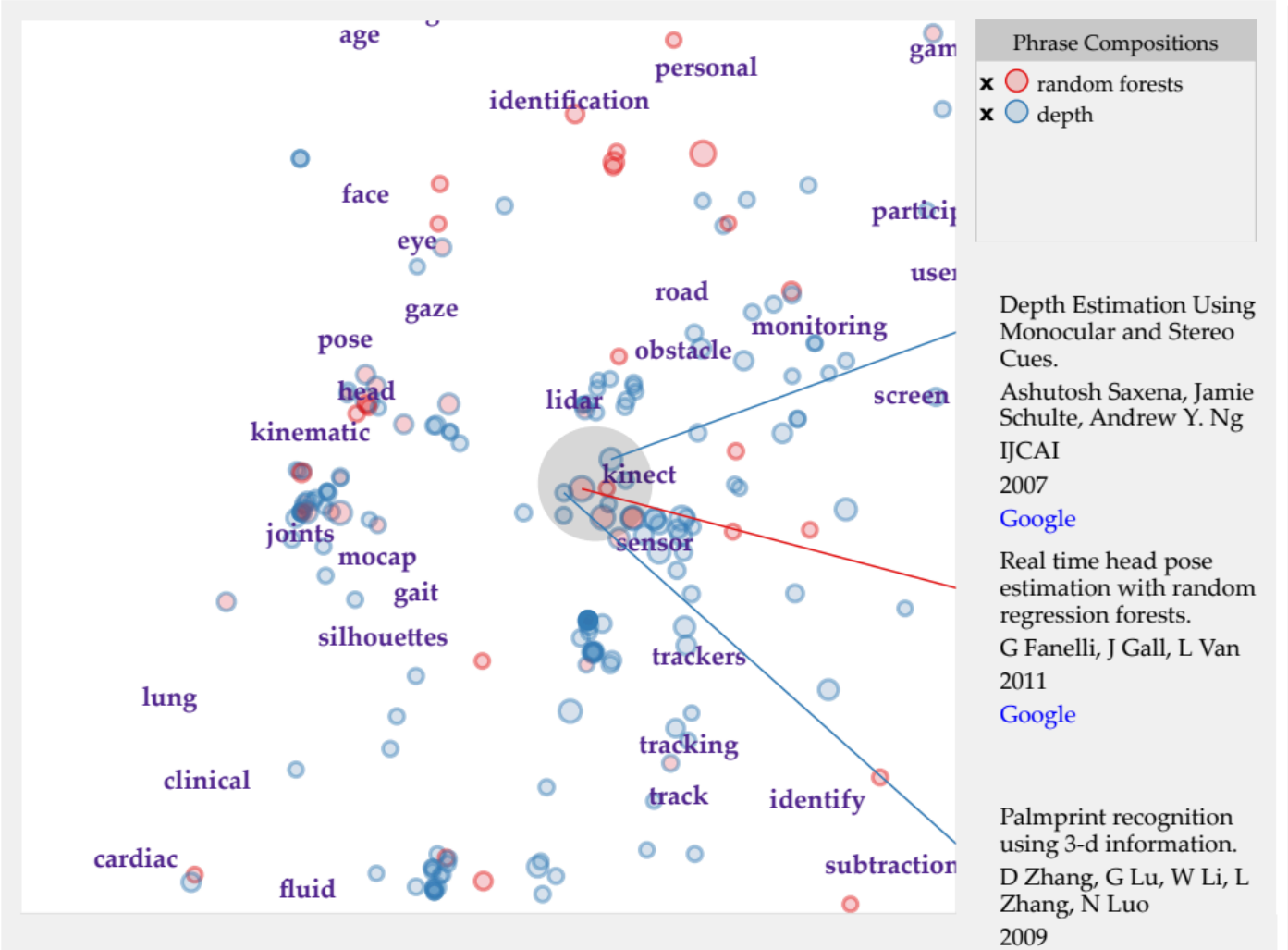
How could we visualize such vector spaces?



https://plot.ly/~KevinAccount/18.embed

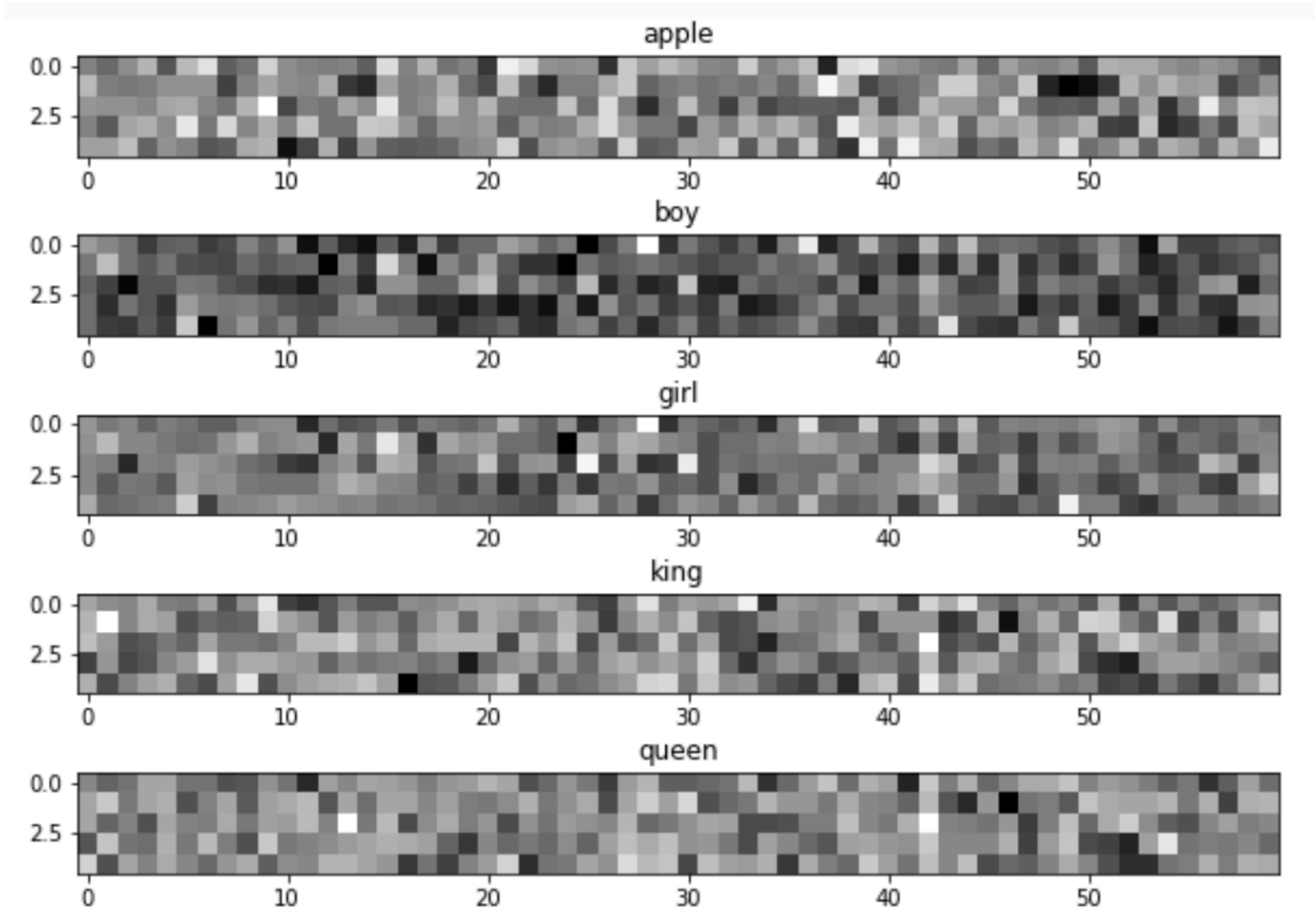


https://plot.ly/~KevinAccount/18.embed



Berger, Matthew, Katherine McDonough, and Lee M. Seversky. "cite2vec: Citation-driven document exploration via word embeddings." *IEEE transactions on visualization and computer graphics* 23.1 (2016): 691-700.

word2vec



https://towardsdatascience.com/visualisation-of-embedding-relations-word2vec-bert-64d695b7f36

What are possible short comings of word2vec?

Limitations of Word 2 Vec

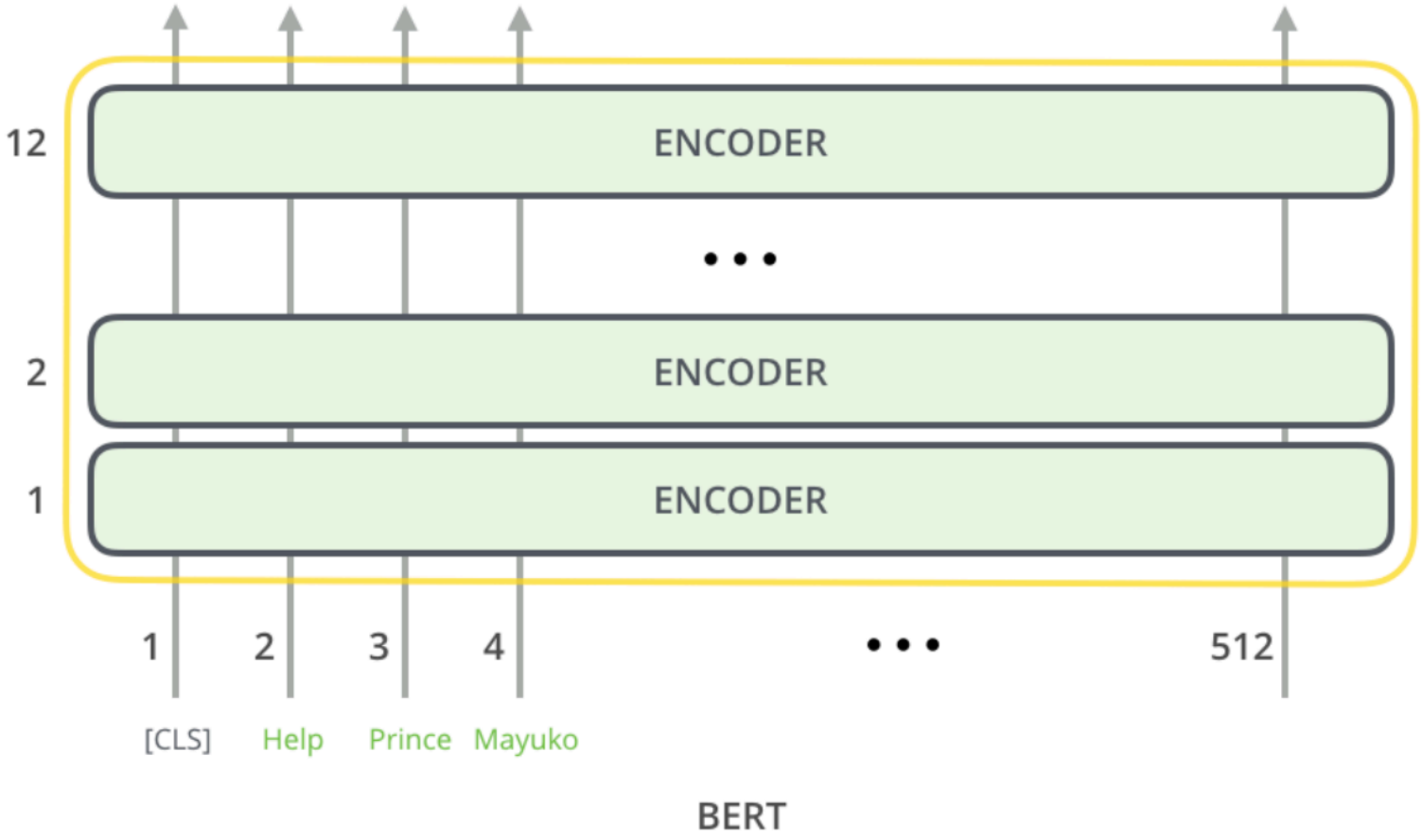
- different contexts get averaged

```
bank vault
bank robber
river bank
```

- how to represent documents? (doc2vec, …)
- cannot handle unknown words

BERT (Bidirectional Encoder Representations from Transformers)

ELMo (Embeddings from Language Models)



https://jalammar.github.io/illustrated-bert/

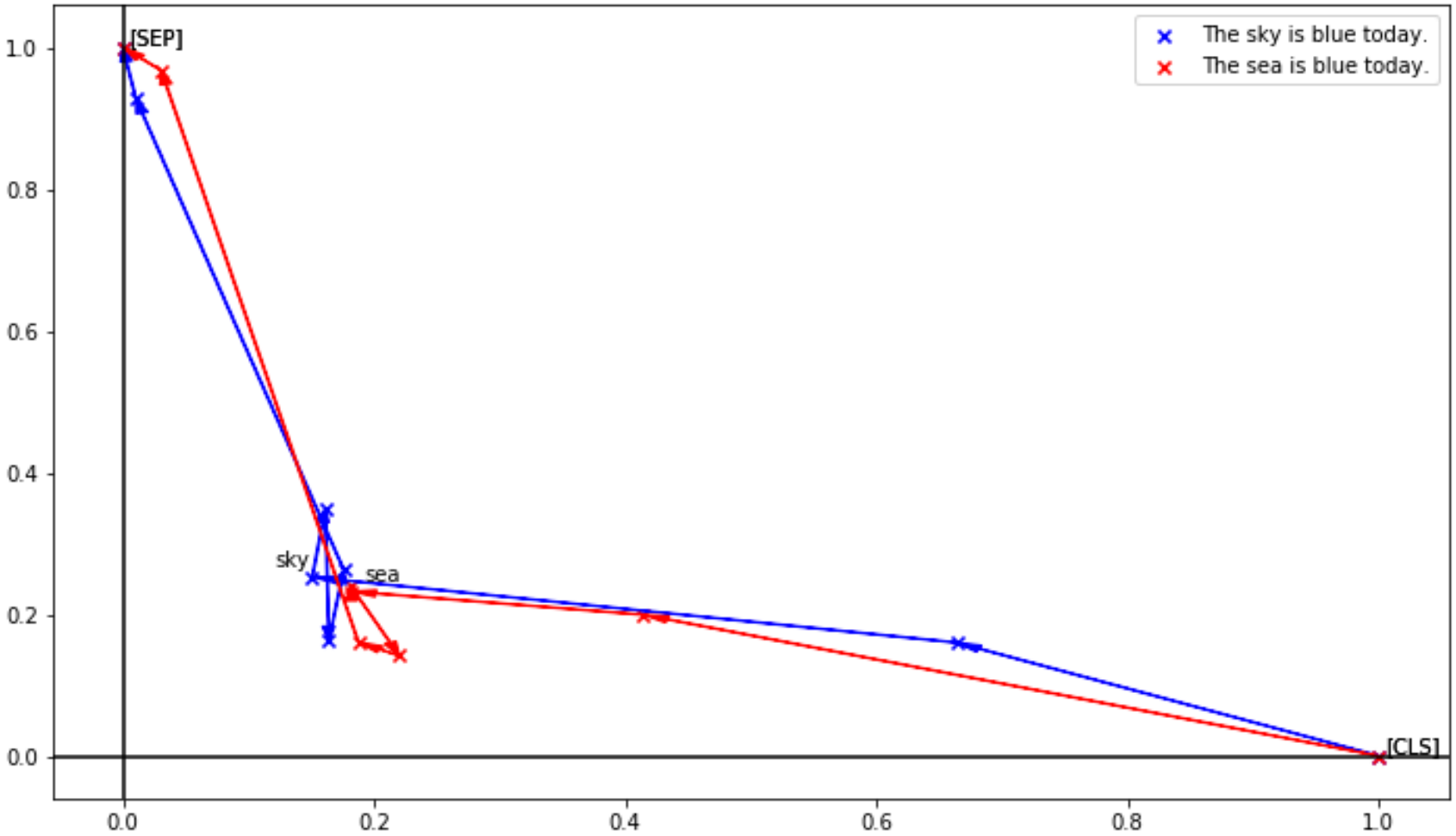
```
First 5 values for each meaning of "bank".

bank vault    tensor([ 2.1319, -2.1413, -1.6260,  0.8638,  3.3173])
bank robber   tensor([ 1.1868, -1.5298, -1.3770,  1.0648,  3.1446])
river bank    tensor([ 1.1295, -1.4725, -0.7296, -0.0901,  2.4970])
```

```
Vector similarity for  *similar*  meanings:  0.94
Vector similarity for *different* meanings:  0.69
```

https://mccormickml.com/2019/05/14/BERT-word-embeddings-tutorial/

```
[CLS] This is a sentence example. [SEP]
```



https://towardsdatascience.com/visualisation-of-embedding-relations-word2vec-bert-64d695b7f36

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[CLS] This is a sentence example. [SEP]
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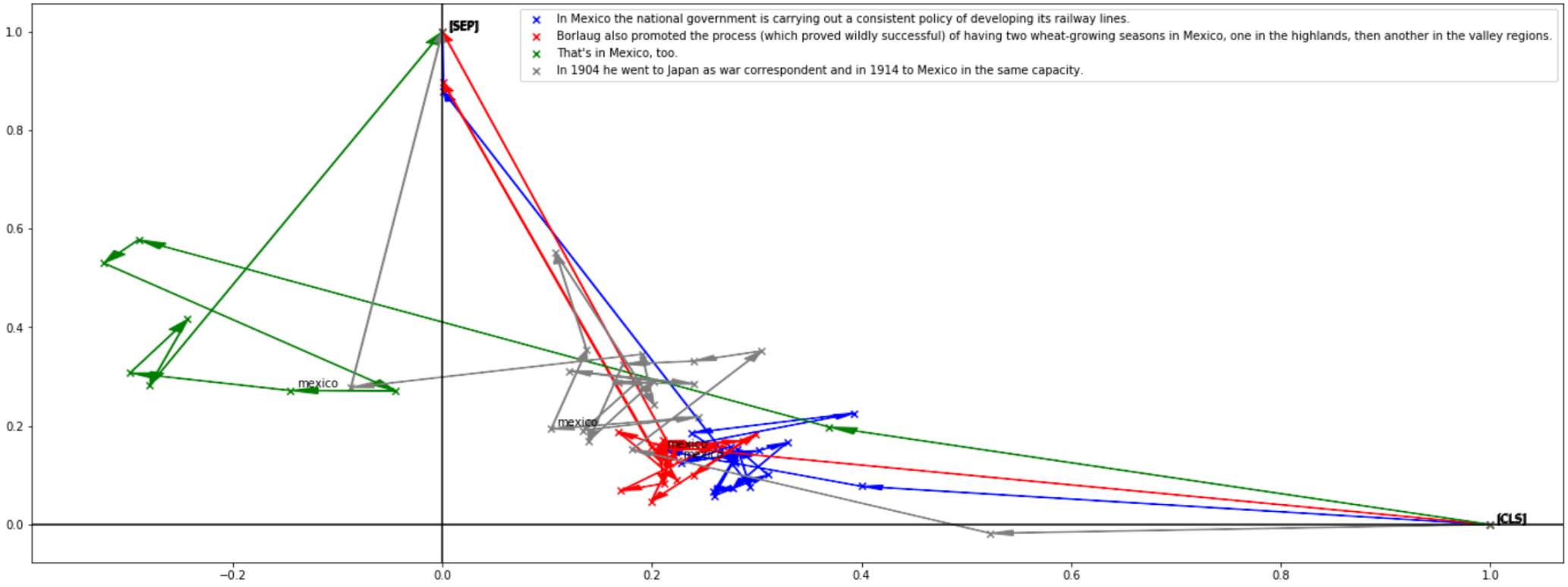

https://towardsdatascience.com/visualisation-of-embedding-relations-word2vec-bert-64d695b7f36

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Topic Modeling

Probabilistic topic models

David Blei, Communications of the ACM 2012

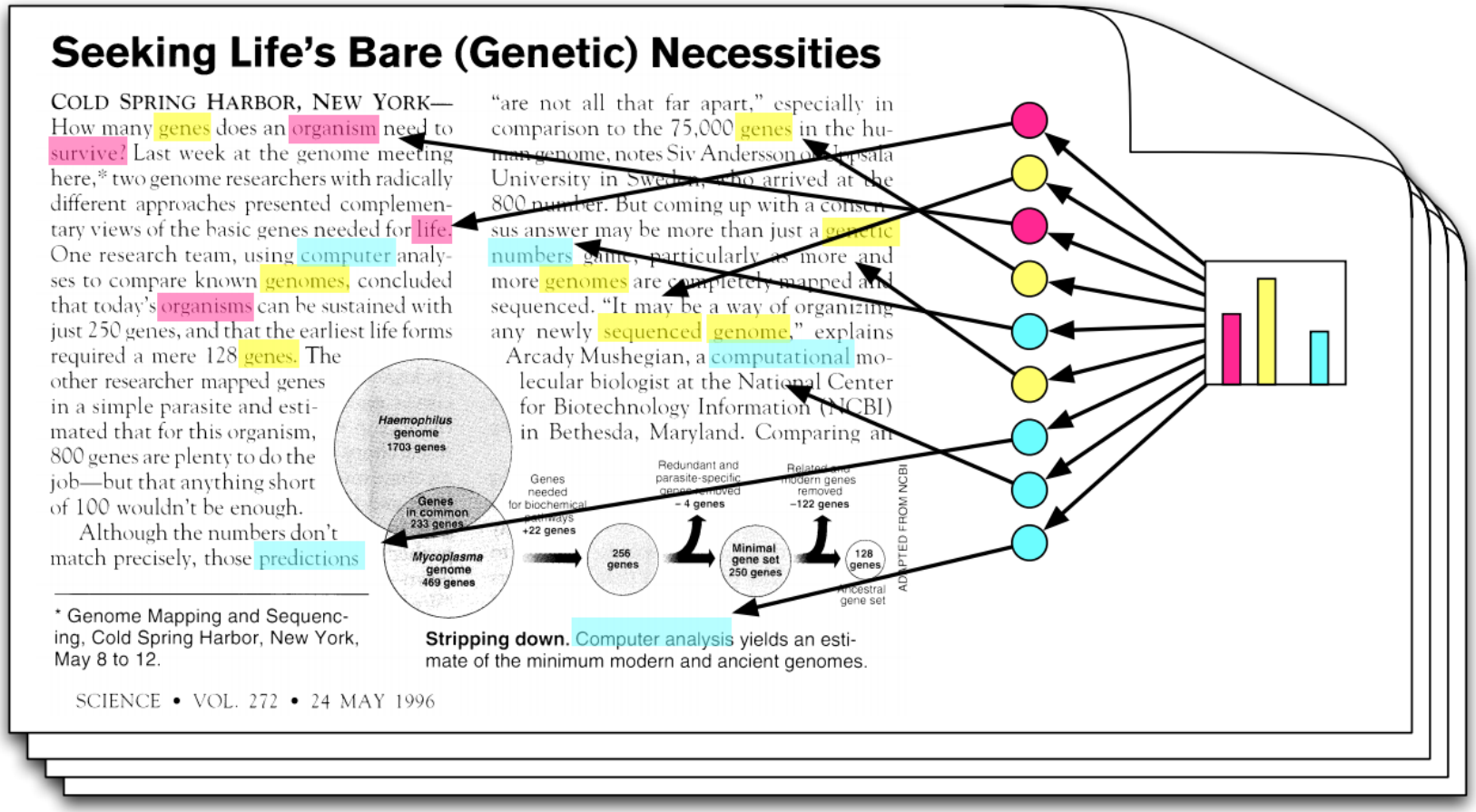
Topics *Documents* *Topic proportions and assignments*

gene	0.04
dna	0.02
genetic	0.01
...	

life	0.02
evolve	0.01
organism	0.01
...	

brain	0.04
neuron	0.02
nerve	0.01
...	

data	0.02
number	0.02
computer	0.01
...	



Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK— How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Input

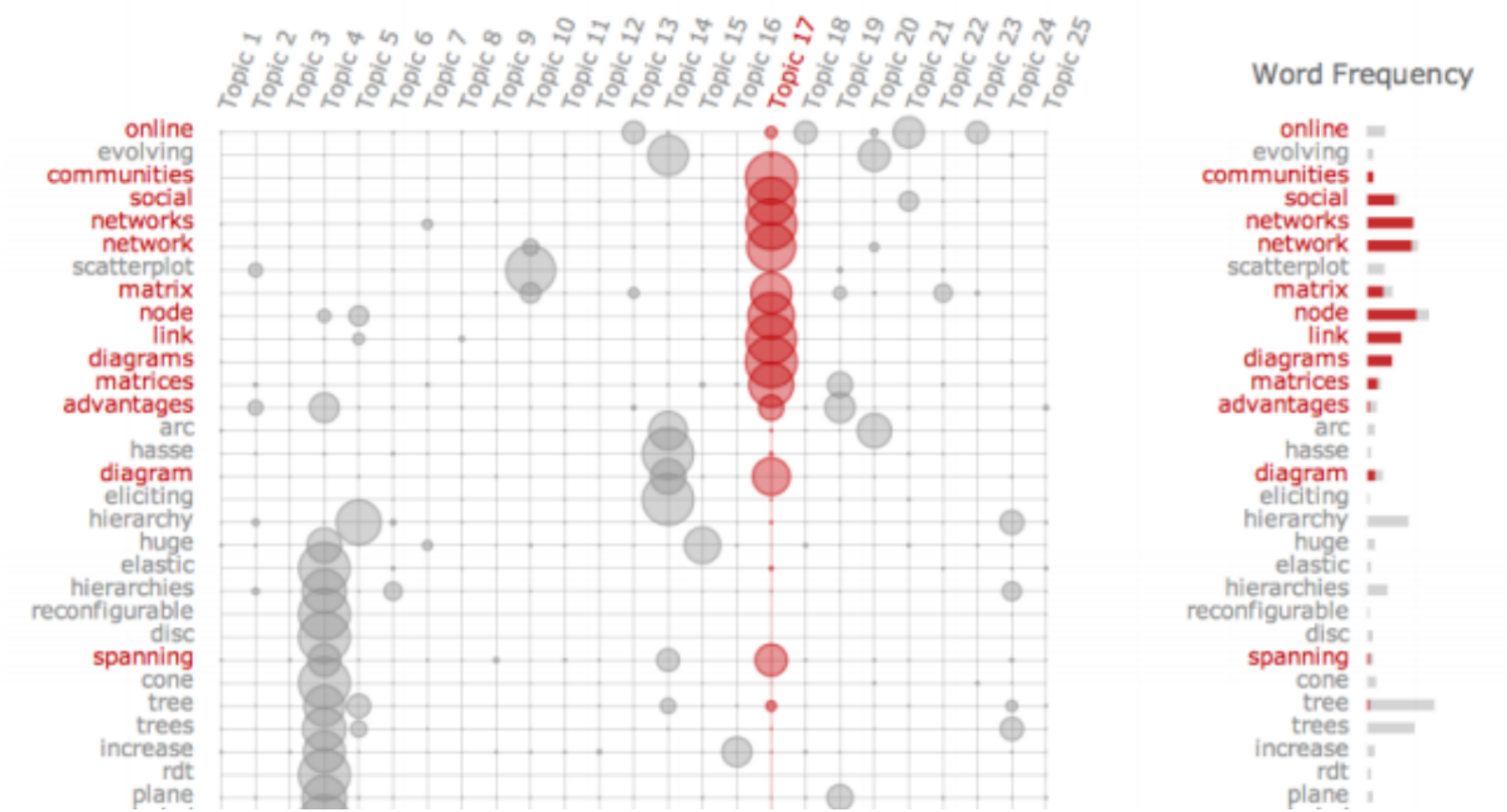
- Corpus = Text Sources (amount=M)
- Number of Topics (N) you want the model to cover

Output: two different kinds of distributions

- N Topic Distributions with probabilities for each word of the vocabulary
- M Text Distributions with probabilities for each of the N topics

Termite: Visualization techniques for assessing textual topic models

Jason Chuang, Christopher D. Manning, Jeffrey Herr; Proceedings of the International Working Conference on Advanced Visual Interfaces 2012



Serendip: Topic model-driven visual exploration of text corpora.
Alexander, E., Kohlmann, J., Valenza, R., Witmore, M., & Gleicher, M. (2014, October). In Visual Analytics Science and Technology (VAST), 2014

Fig. 2. CorpusViewer centers around a re-orderable matrix that provides a variety of ordering, selection, aggregation and annotation features to help users find high-level patterns in the corpus and connect to specific documents and topics. Each row represents a document, each column a topic, and the circle size encodes the proportion. Here, colorings are applied to selected columns in order to connect to other views of topics. In the upper right, a topic is depicted by showing the proportions of its most salient words.

Task-driven comparison of topic models.
Alexander, E., Gleicher, M. *IEEE Transactions on Visualization and Computer Graphics* 22.1 (2015): 320-329.

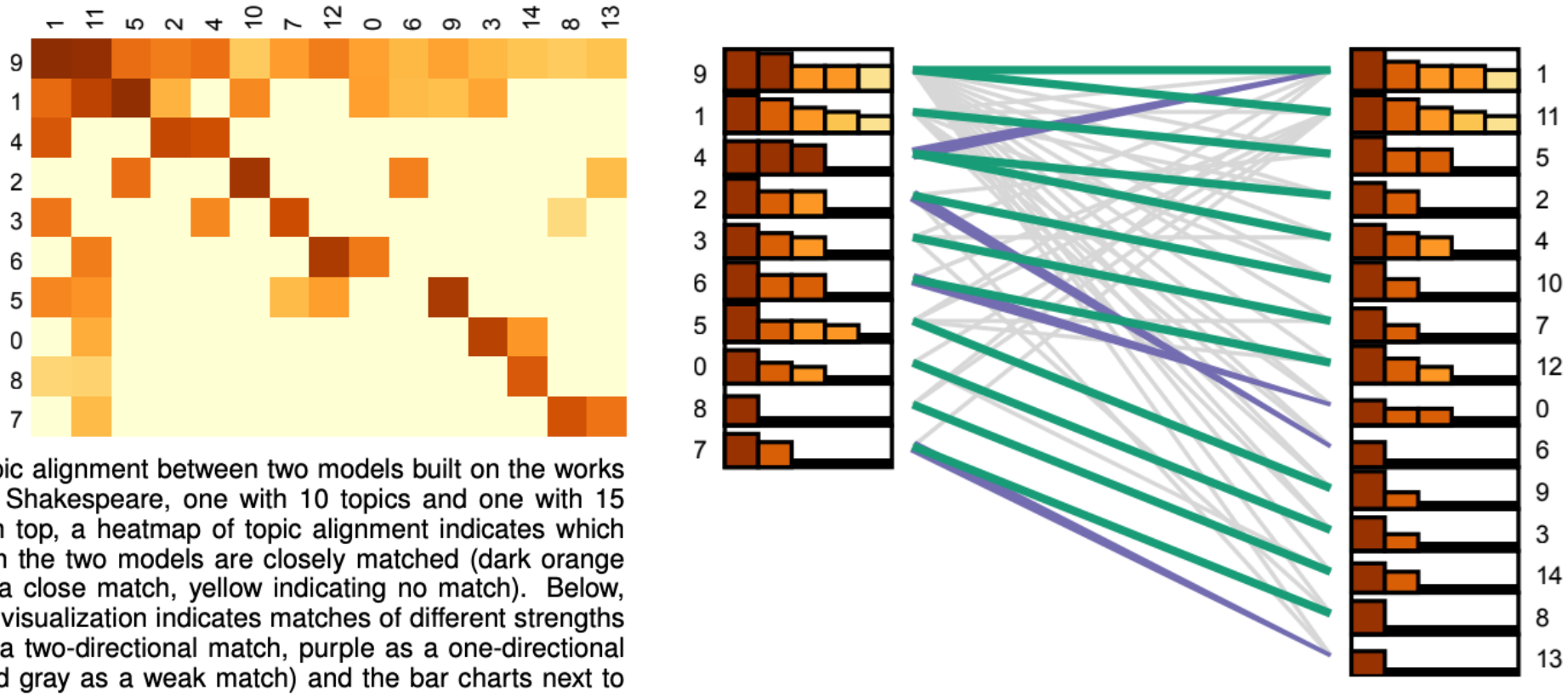


Fig. 2: Topic alignment between two models built on the works of William Shakespeare, one with 10 topics and one with 15 topics. On top, a heatmap of topic alignment indicates which topics from the two models are closely matched (dark orange indicating a close match, yellow indicating no match). Below, a bipartite visualization indicates matches of different strengths (green as a two-directional match, purple as a one-directional match, and gray as a weak match) and the bar charts next to each topic show the strength of the top five matches (with bar height encoding strength and color used to show rank so that ties are salient). Topics exhibiting multiple close matches (e.g. Topic 4 in the 10-topic model) may be instances of merged concepts to explore more closely.

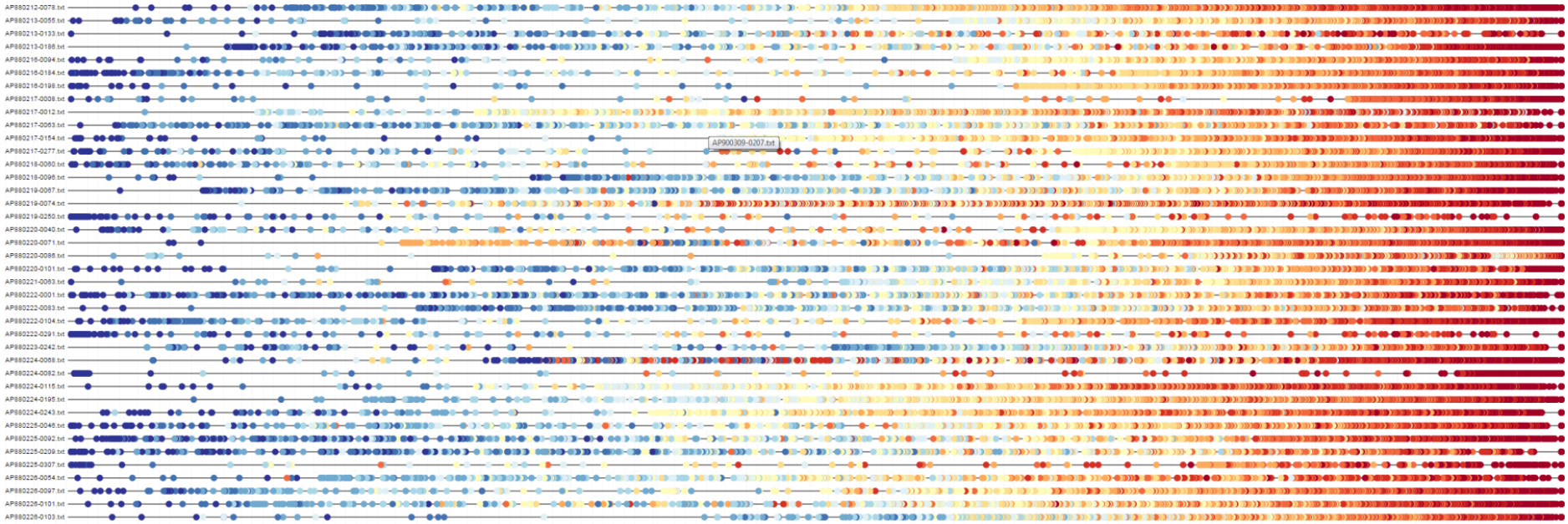
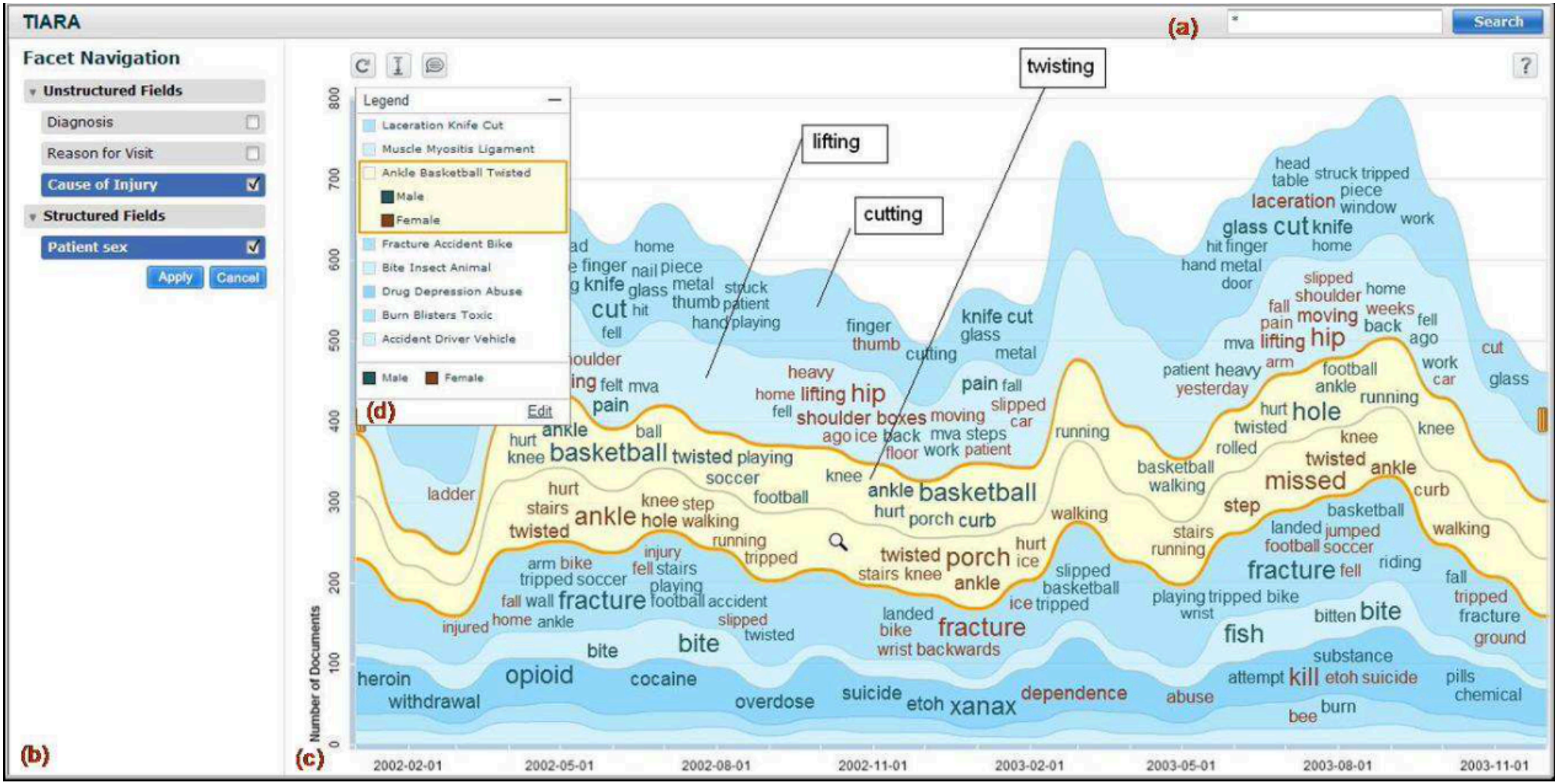


Fig. 1: Buddy plots show consistency of document relationships across topic models by encoding similarity with respect to individual documents. In this figure, each row represents a document, with the rest of the corpus encoded as circular glyphs along the row. Distance from the row's document in one model is encoded using horizontal position, while distance in a second model is encoded using color. This combination of encodings lets us see similarities from two models within one row of glyphs. Deviations in similarity between the two models can be identified as breaks from a smooth gradient. Though the two models seem to correlate well with documents at either extreme (blue documents to the left, red documents to the right), we see dramatic shifts between different classifications for documents in between, identified by breaks in the blue-to-red gradient structure.

Alexander, Eric, and Michael Gleicher. "Task-driven comparison of topic models." *IEEE Transactions on Visualization and Computer Graphics* 22.1 (2015): 320-329.

TIARA: A Visual Exploratory Text Analytic System, Wei et. al, KDD 2010)



Topic Modeling

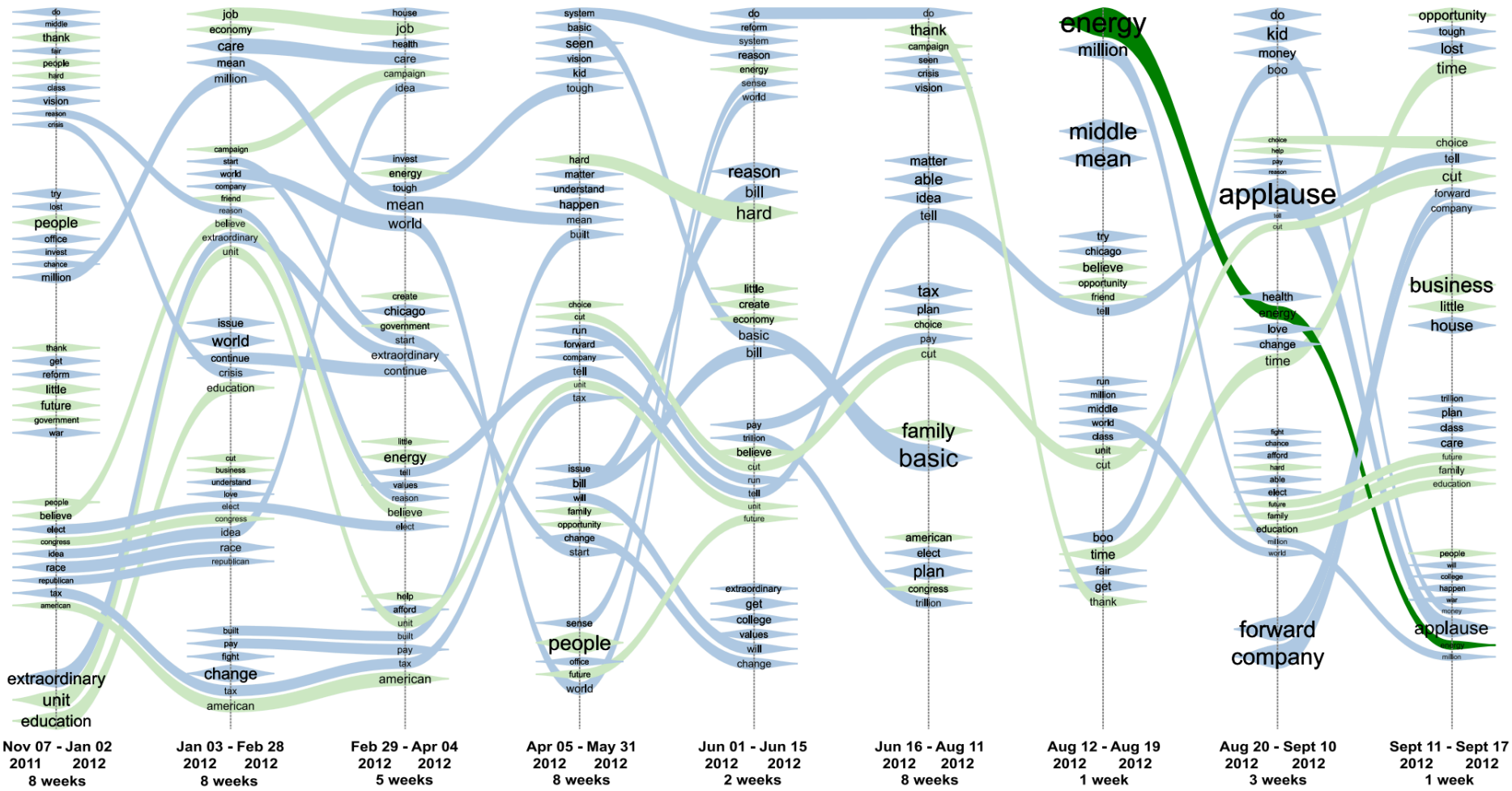
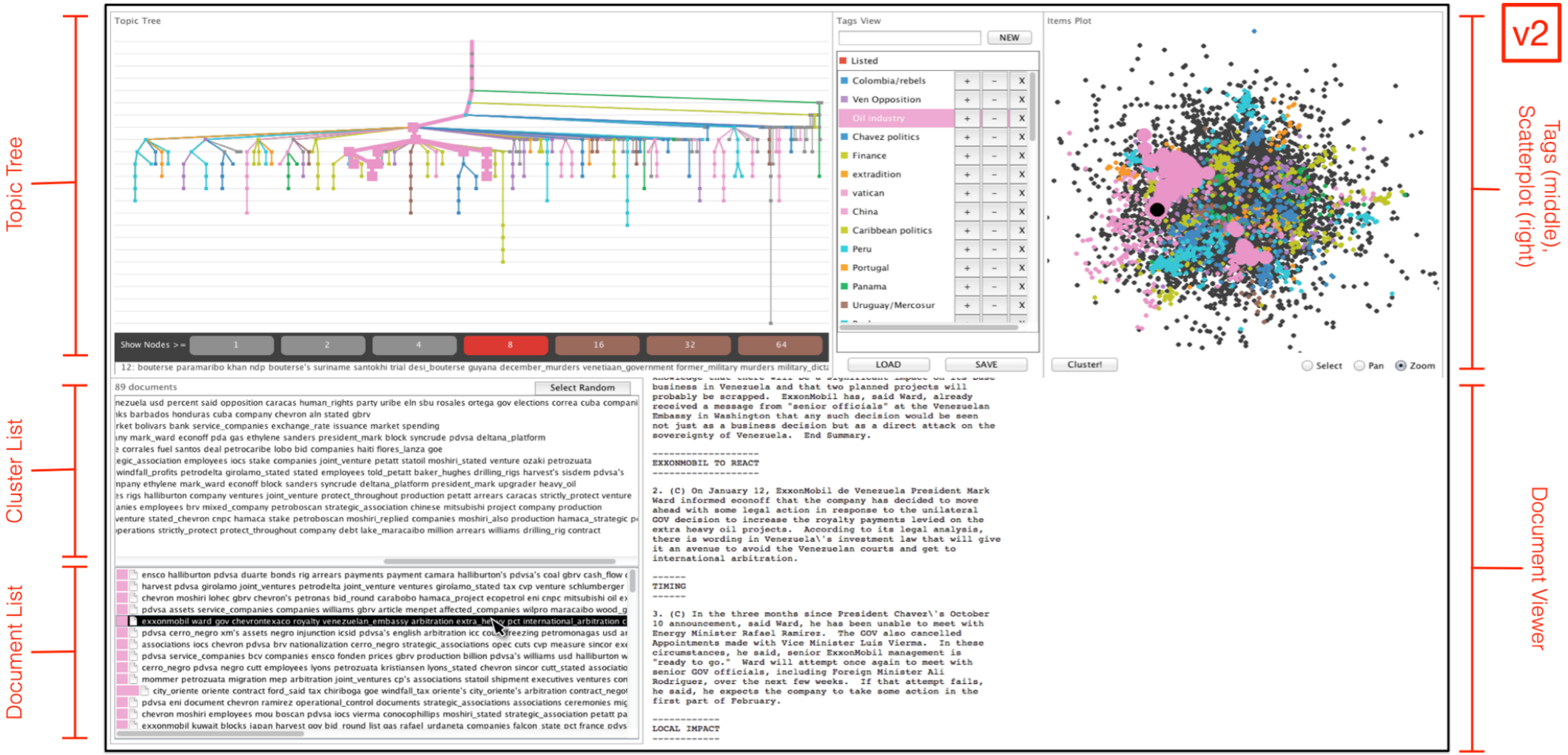


Fig. 1. ThemeDelta visualization for Barack Obama‘ campaign speeches during the U.S. 2012 presidential election (until September 10, 2012). Green lines are shared terms between Obama and Romney. Data from the “The American Presidency Project” at UCSB (http://www.presidency.ucsb.edu/).

Cui, Weiwei, et al. "Textflow: Towards better understanding of evolving topics in text." *IEEE Transactions on Visualization and Computer Graphics* 17.12 (2011): 2412-2421.

Overview: The Design, Adoption, and Analysis of a Visual Document Mining Tool For Investigative Journalists (Brehmer et al., IEEE InfoVis 2014)

old version of the software:



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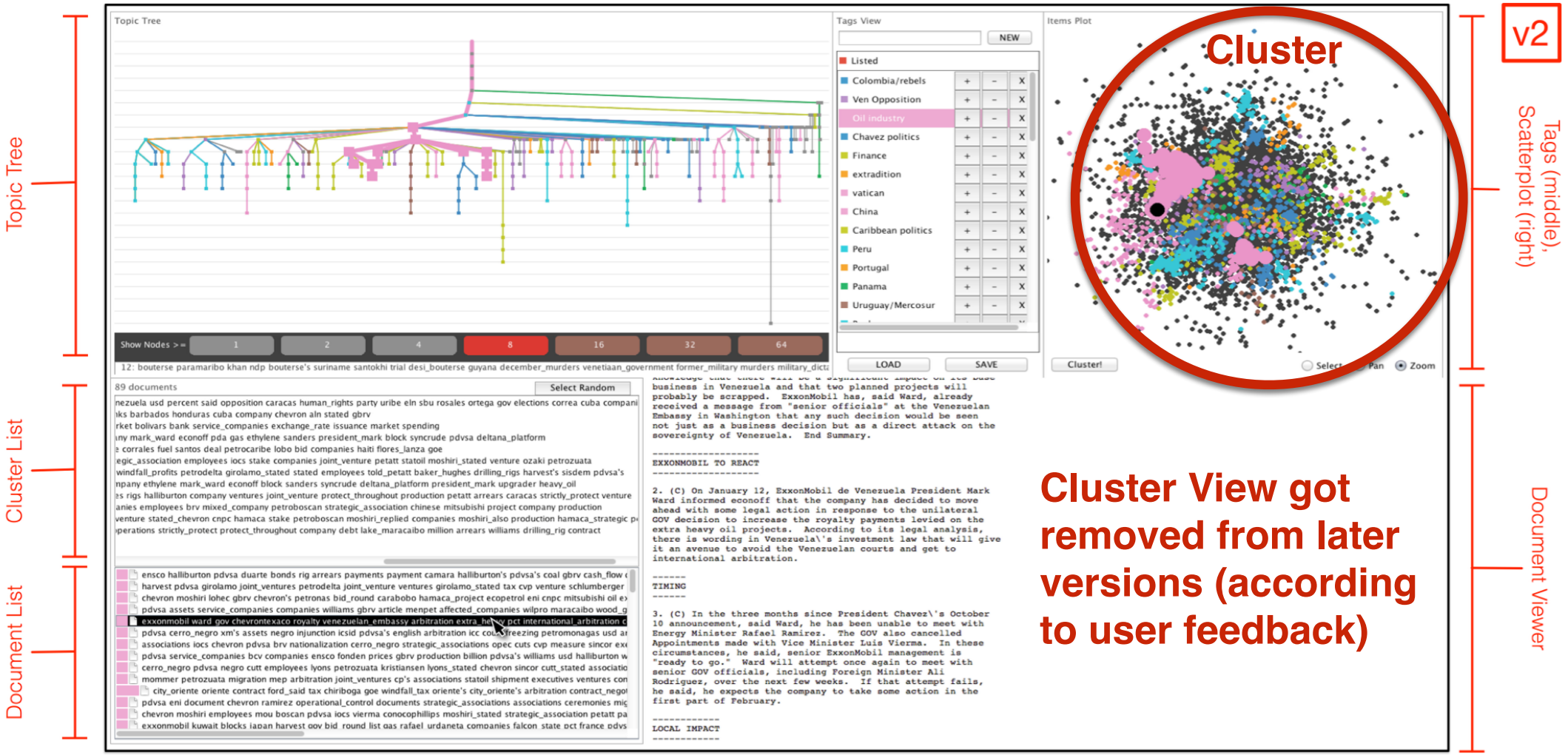

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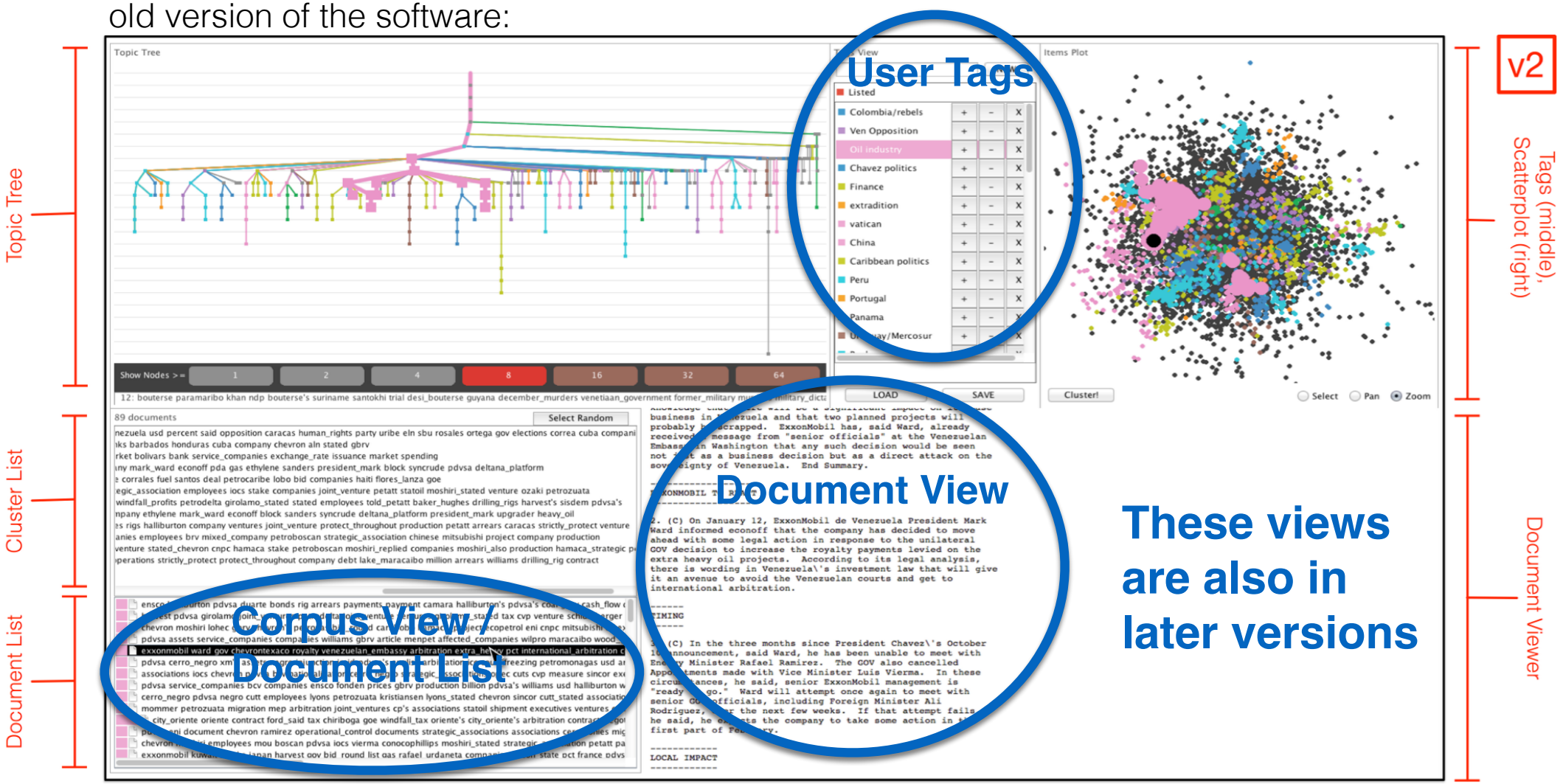

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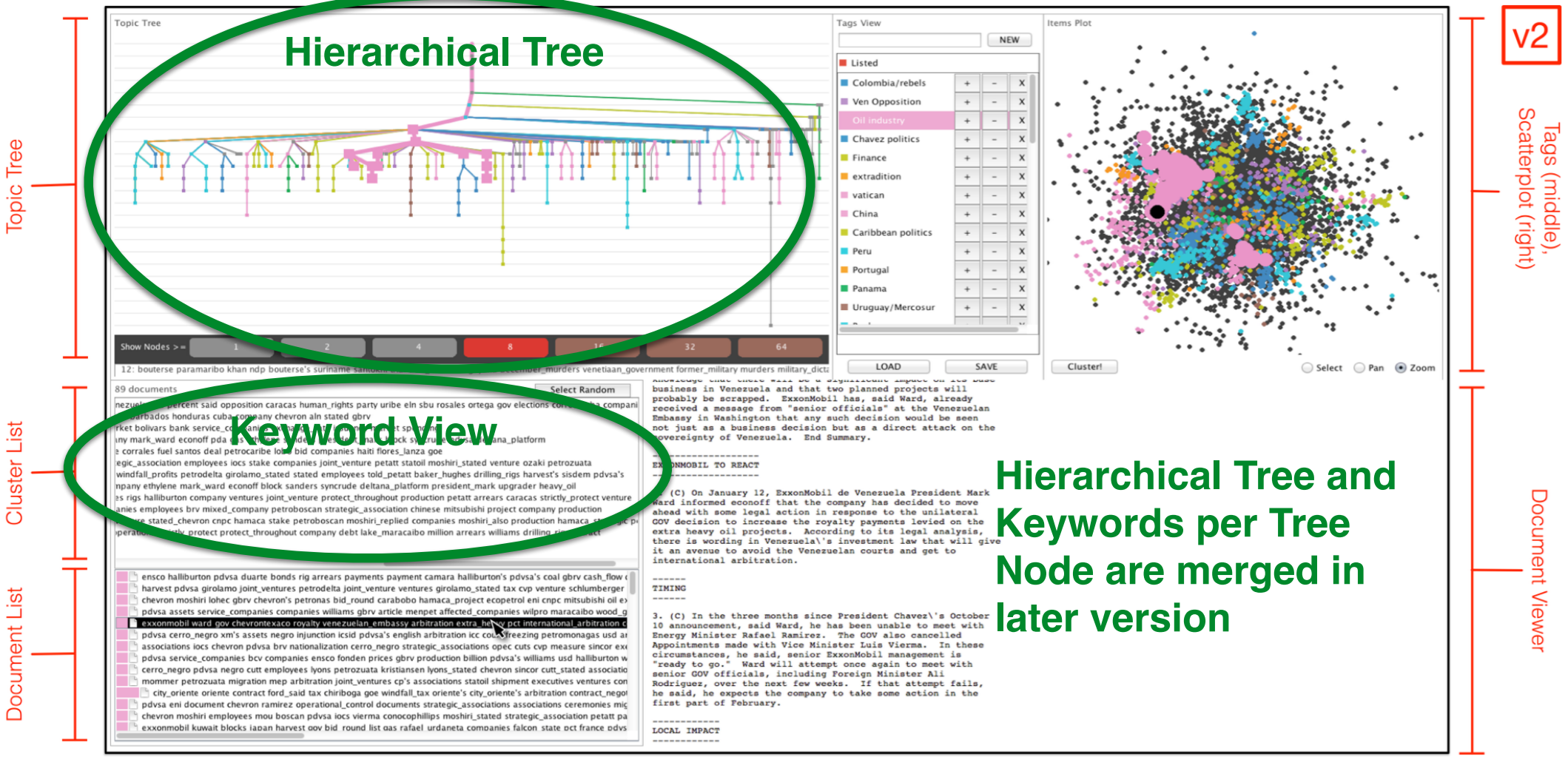
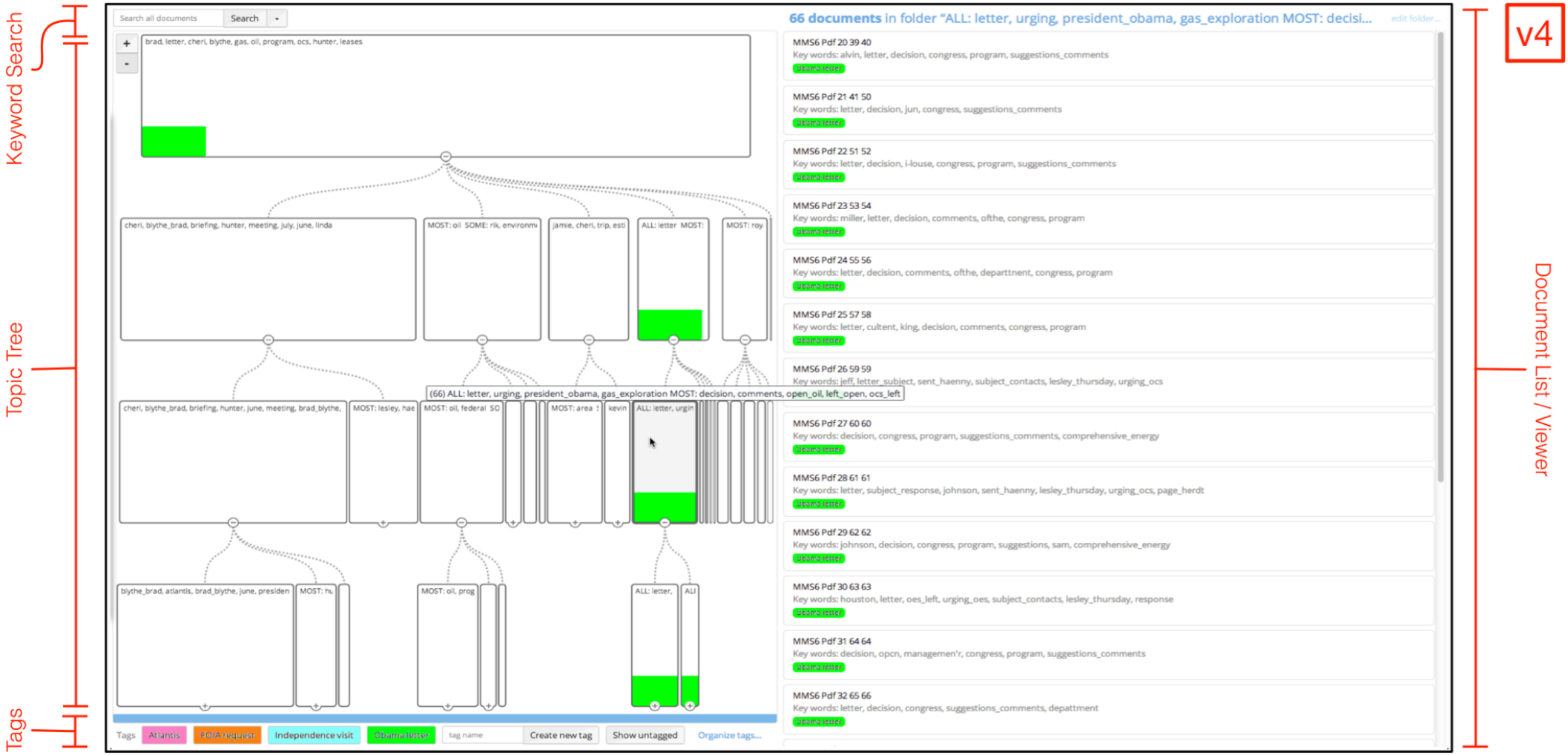
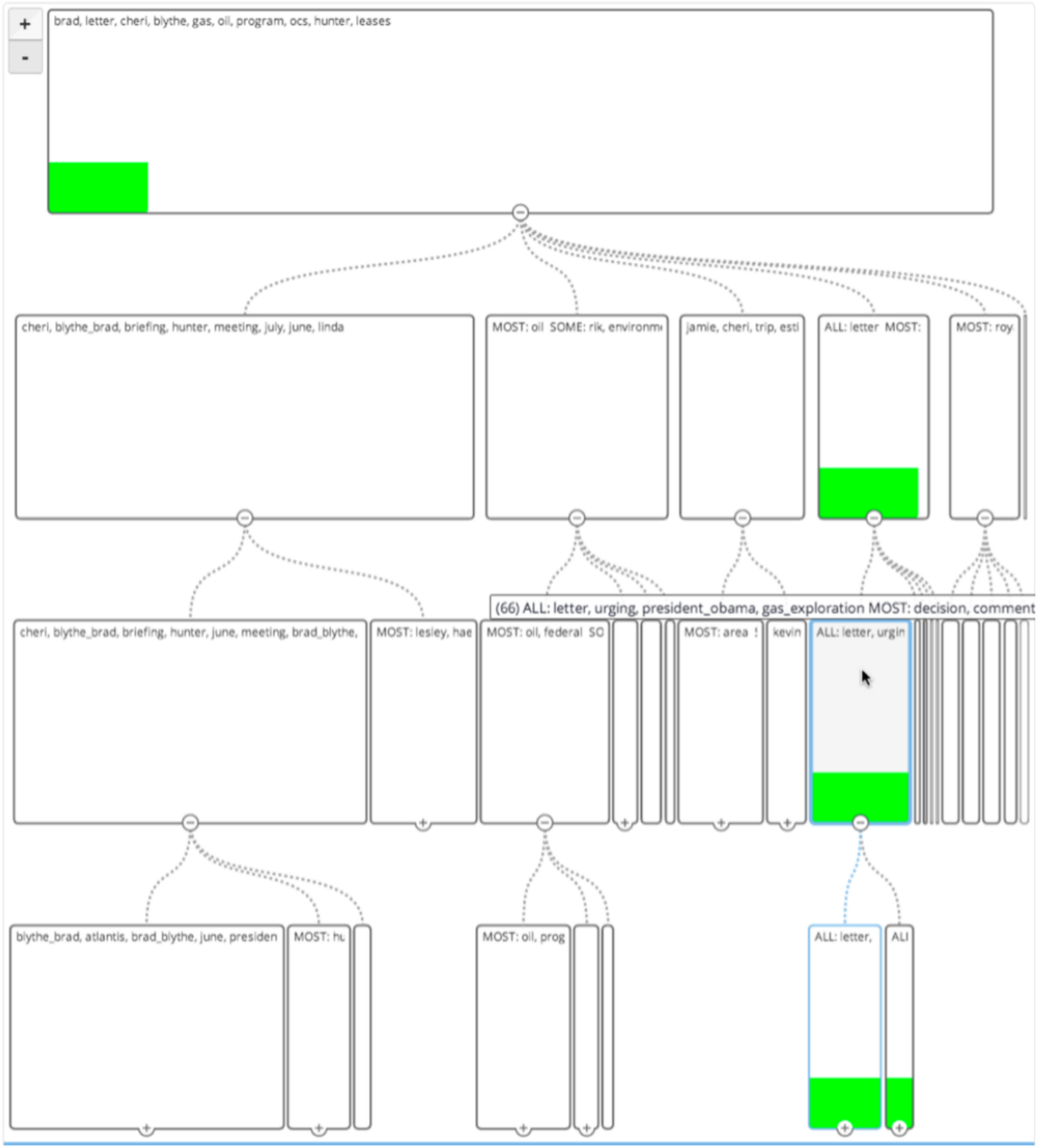


Overview: The Design, Adoption, and Analysis of a Visual Document Mining Tool For Investigative Journalists (Brehmer et al., IEEE InfoVis 2014)

new version focuses on hierarchical tree according to cosine similarity (TF-IDF) of documents:



Topic Modeling



- **Size of nodes** related to number of documents
- **Keywords located** within the corresponding nodes
- **Tags color-coded** according to percentage of fill level within node
- **Tree expandable**

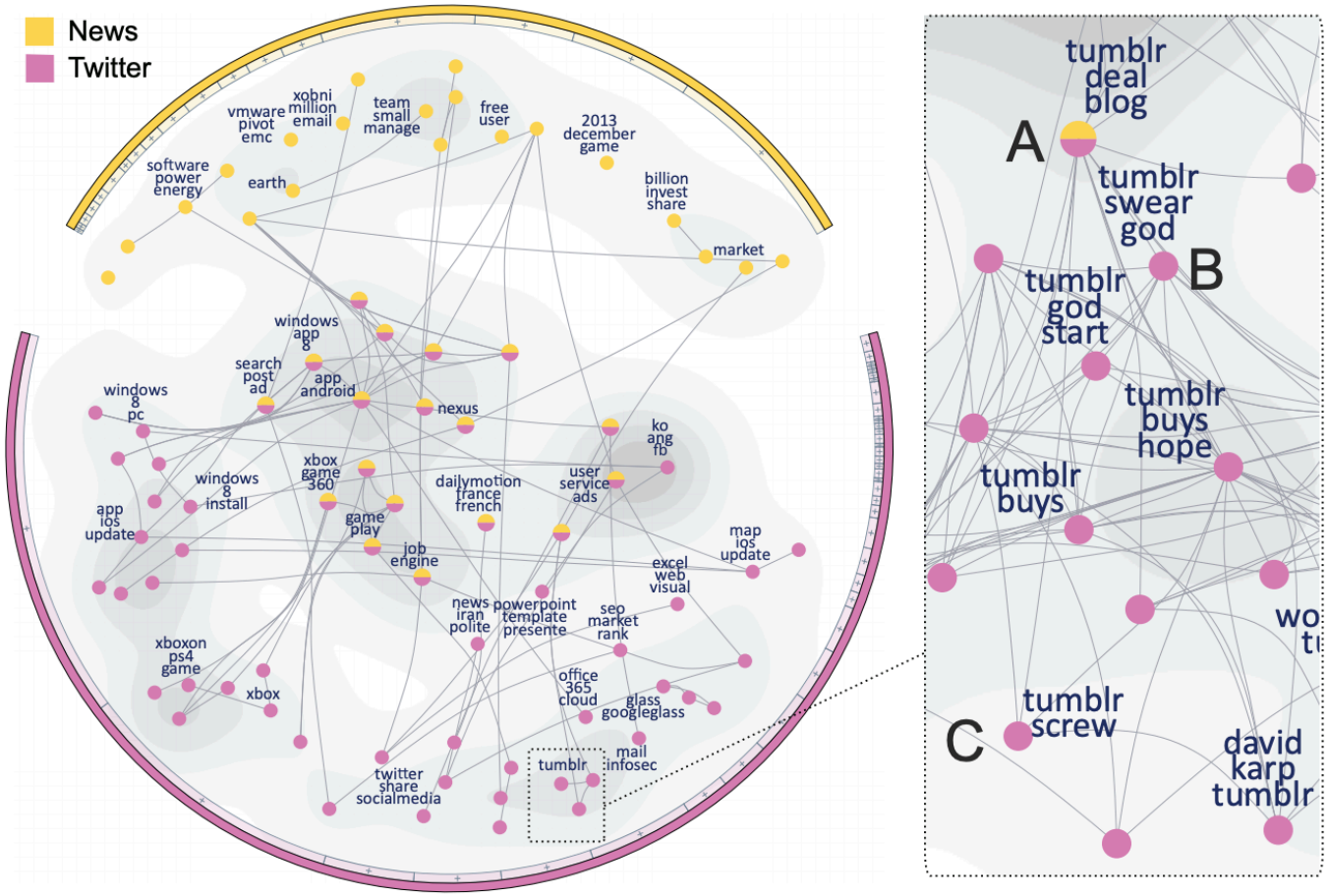


Figure 12. Matching the news corpus with the Twitter corpus: (a) overview; (b) comparison of Tumblr related topics.

Liu, Shixia, et al. "Topicpanorama: A full picture of relevant topics." *2014 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, 2014.

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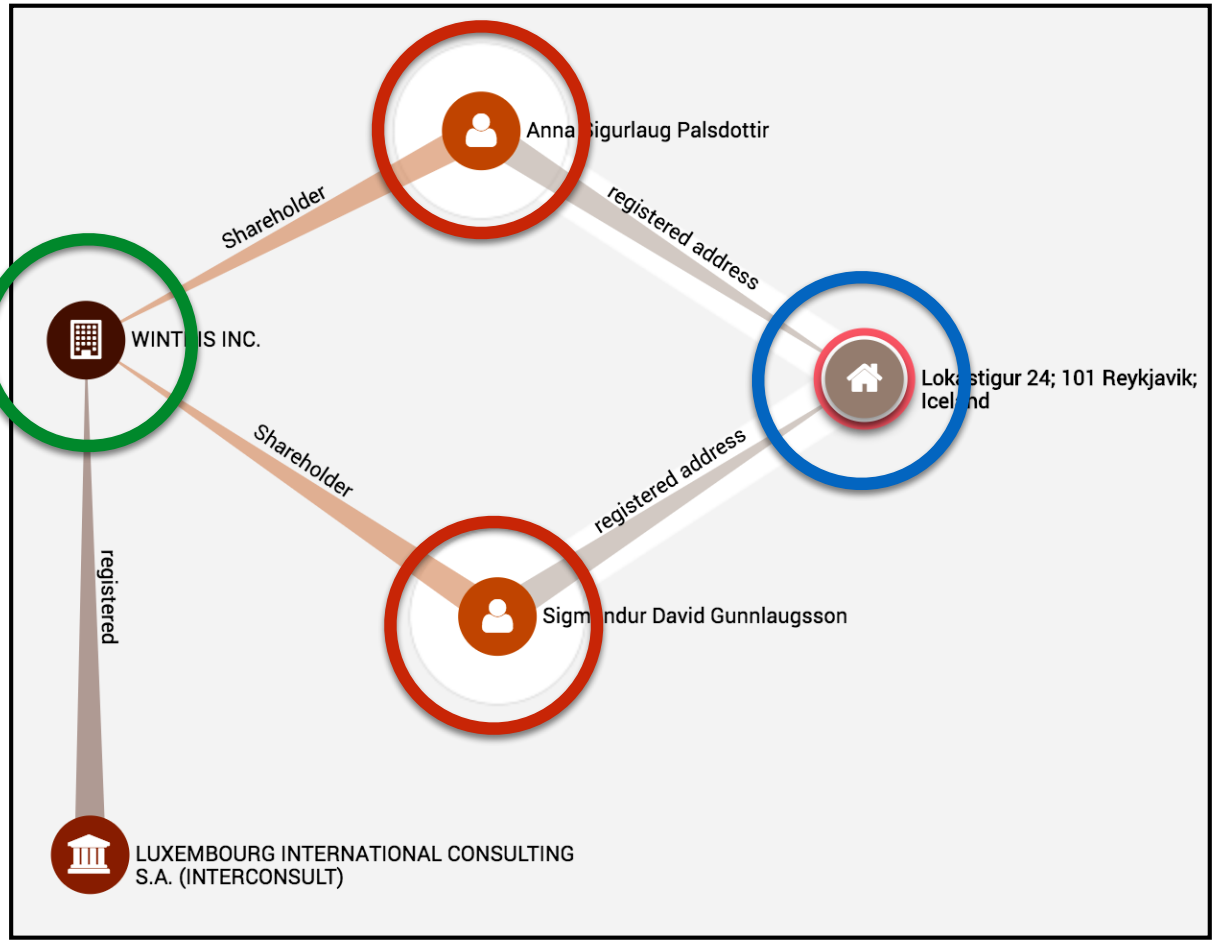
Named Entities

Named Entities are:

- People
- Organizations/Companies
- Locations
- Time Events

Panama Papers Networks use different visual encodings for:

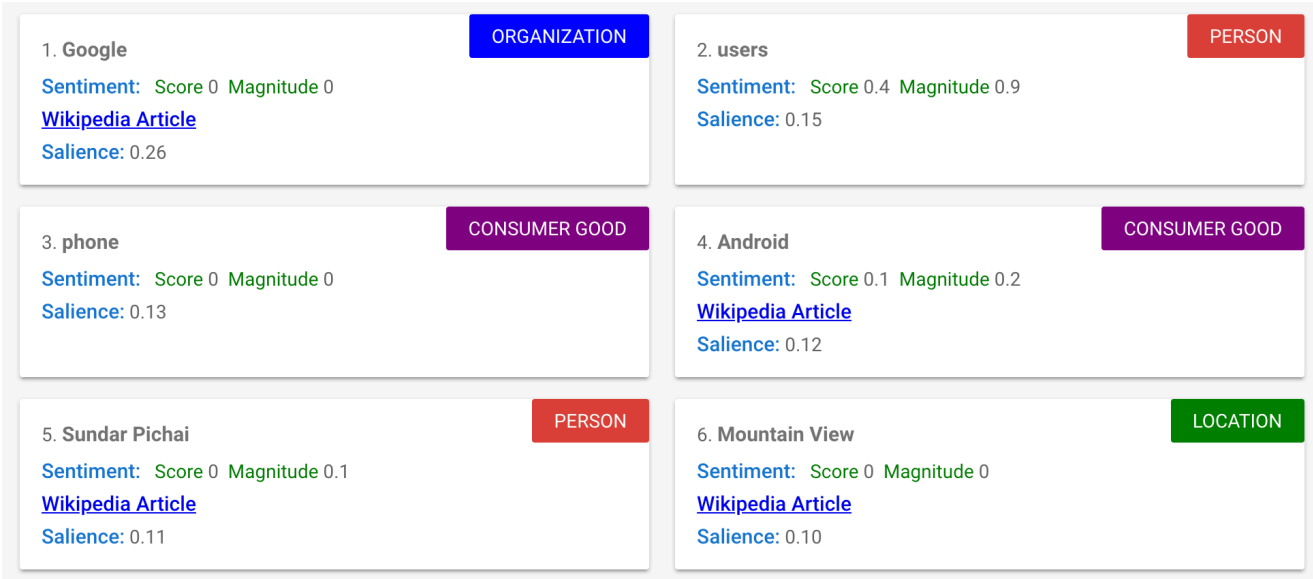
People
Organizations
Locations



What is possible?

⟨Google⟩$_1$, headquartered in ⟨Mountain View⟩$_6$, unveiled the new ⟨Android⟩$_4$

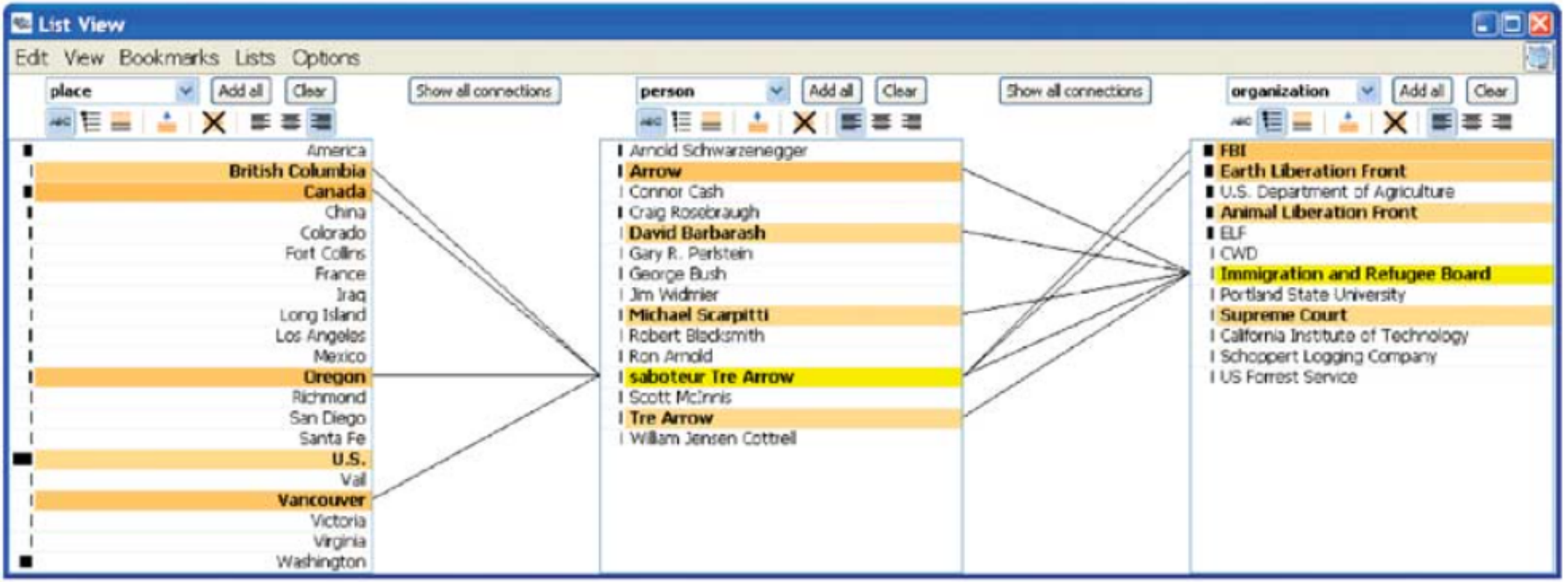
⟨phone⟩$_3$ at the ⟨Consumer Electronic Show⟩$_7$. ⟨Sundar Pichai⟩$_5$ said in his



https://cloud.google.com/natural-language/

Named Entities

Jigsaw: Supporting investigative analysis through interactive visualization, Stasko et. al, Information Visualization, 2008



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Sentiment Analysis

What is Sentiment Analysis?

https://cloud.google.com/natural-language/

What is Sentiment Analysis?

Sentiment analysis refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information.

https://monkeylearn.com/sentiment-analysis/

Example Sentence:

Google, headquartered in Mountain View, unveiled the new Android phone at the Consumer Electronic Show. Sundar Pichai said in his keynote that users love their new Android phones.

https://cloud.google.com/natural-language/

Sentiment Analysis

1. **Google** — ORGANIZATION
Sentiment: Score 0 Magnitude 0

2. **users** — PERSON
Sentiment: Score 0.6 Magnitude 1.3

3. **phone** — CONSUMER GOOD
Sentiment: Score 0 Magnitude 0

4. **Android** — CONSUMER GOOD
Sentiment: Score 0.5 Magnitude 1

5. **Sundar Pichai** — PERSON
Sentiment: Score 0.1 Magnitude 0.2

6. **Mountain View** — LOCATION
Sentiment: Score 0 Magnitude 0

7. **Consumer Electroni…** — EVENT
Sentiment: Score 0.1 Magnitude 0.1

8. **phones** — CONSUMER GOOD
Sentiment: Score 0.7 Magnitude 0.7

9. **keynote** — OTHER
Sentiment: Score 0.2 Magnitude 0.2

https://cloud.google.com/natural-language/

Updated Sentence:

Google, headquartered in Mountain View, unveiled the new **and very expensive** Android phone at the Consumer Electronic Show. Sundar Pichai said in his keynote that users love their new Android phones.

https://cloud.google.com/natural-language/

Sentiment Analysis

1. **Google** — ORGANIZATION
Sentiment: Score 0 Magnitude 0

2. **users** — PERSON
Sentiment: Score 0.6 Magnitude 1.3

3. **phone** — CONSUMER GOOD
Sentiment: Score -0.8 Magnitude 0.8

4. **Android** — CONSUMER GOOD
Sentiment: Score 0 Magnitude 1.7

5. **Mountain View** — LOCATION
Sentiment: Score 0 Magnitude 0

6. **Consumer Electroni…** — EVENT
Sentiment: Score 0 Magnitude 0

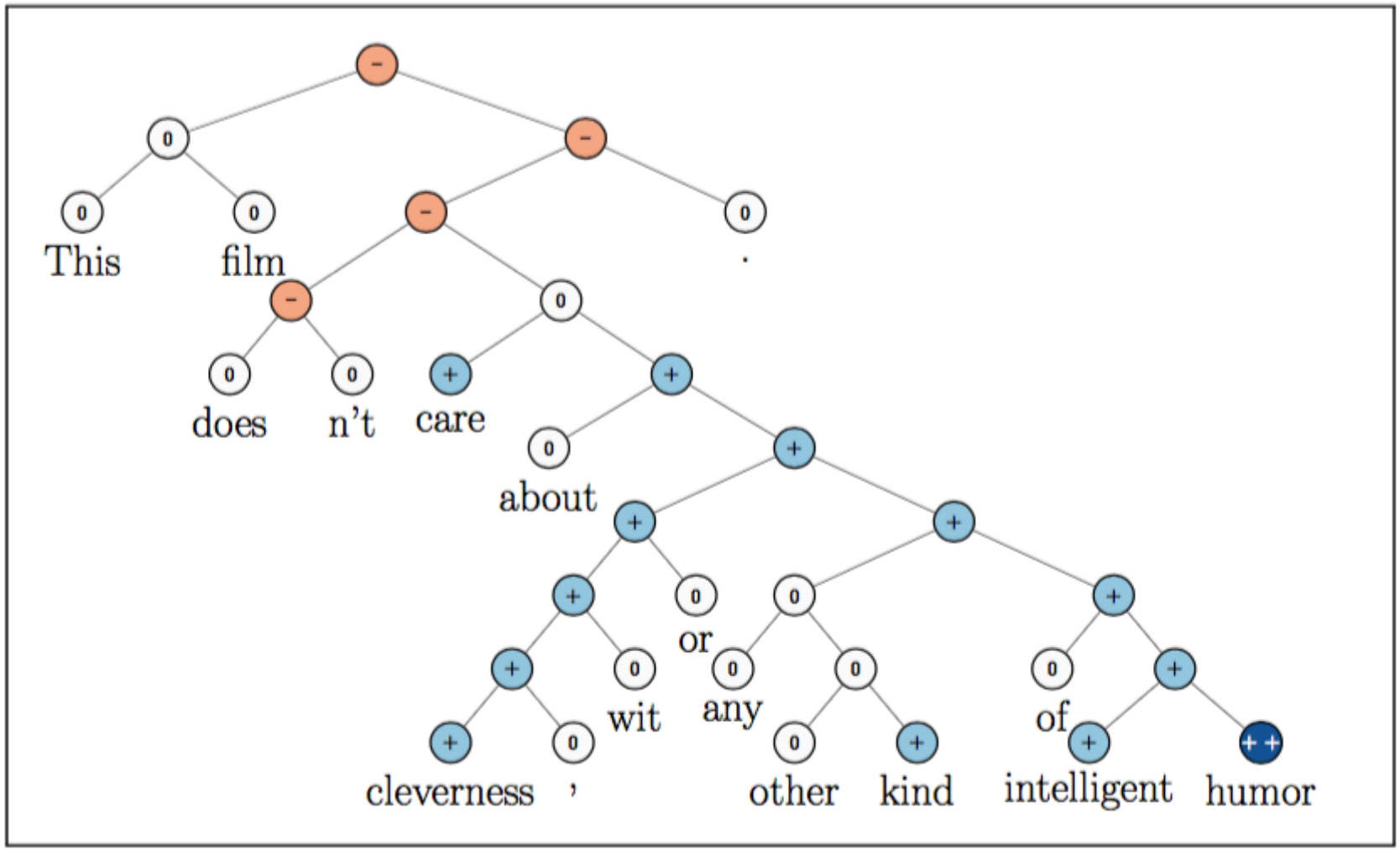
7. **Sundar Pichai** — PERSON
Sentiment: Score 0.1 Magnitude 0.2

8. **phones** — CONSUMER GOOD
Sentiment: Score 0.7 Magnitude 0.7

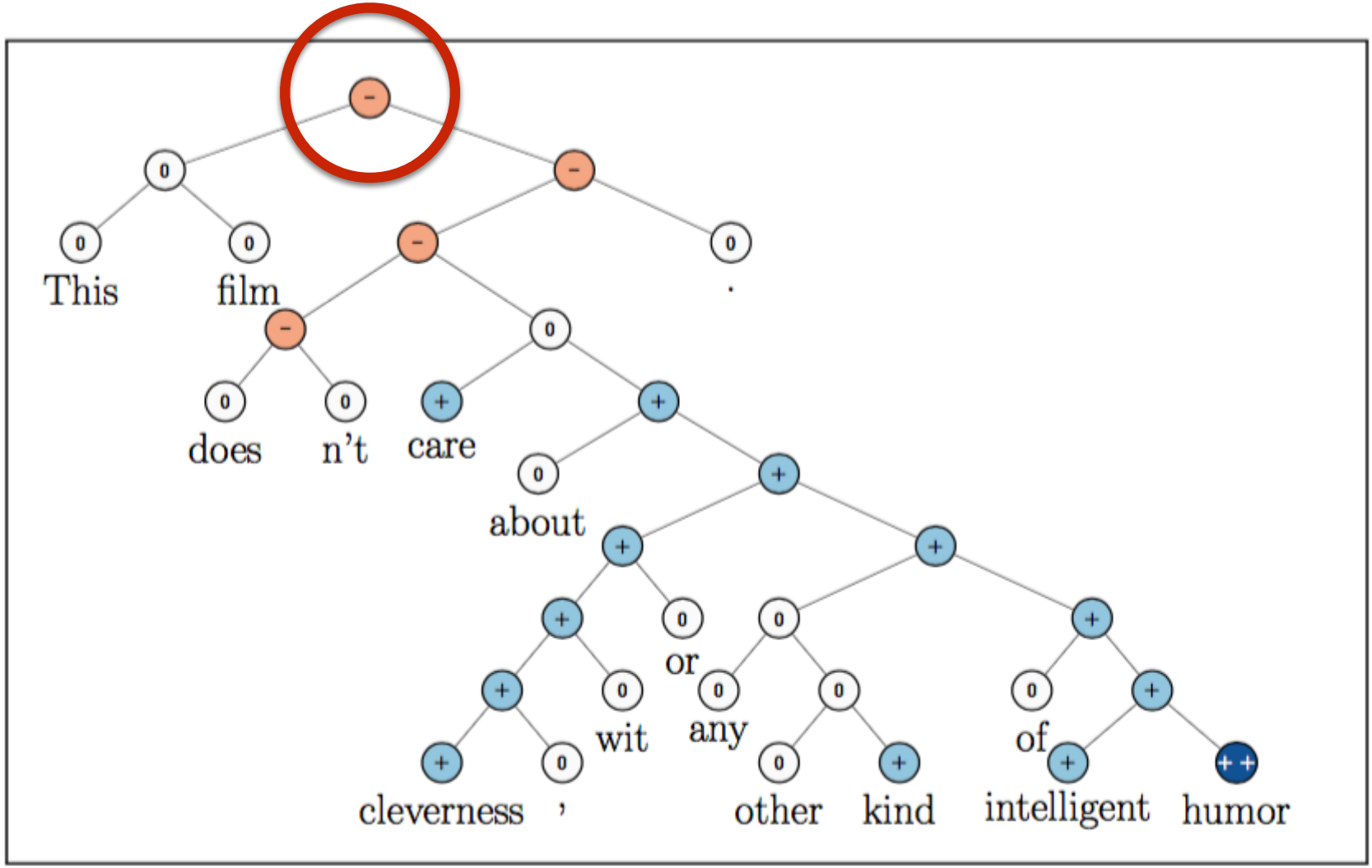
9. **keynote** — OTHER
Sentiment: Score 0.2 Magnitude 0.2

https://cloud.google.com/natural-language/

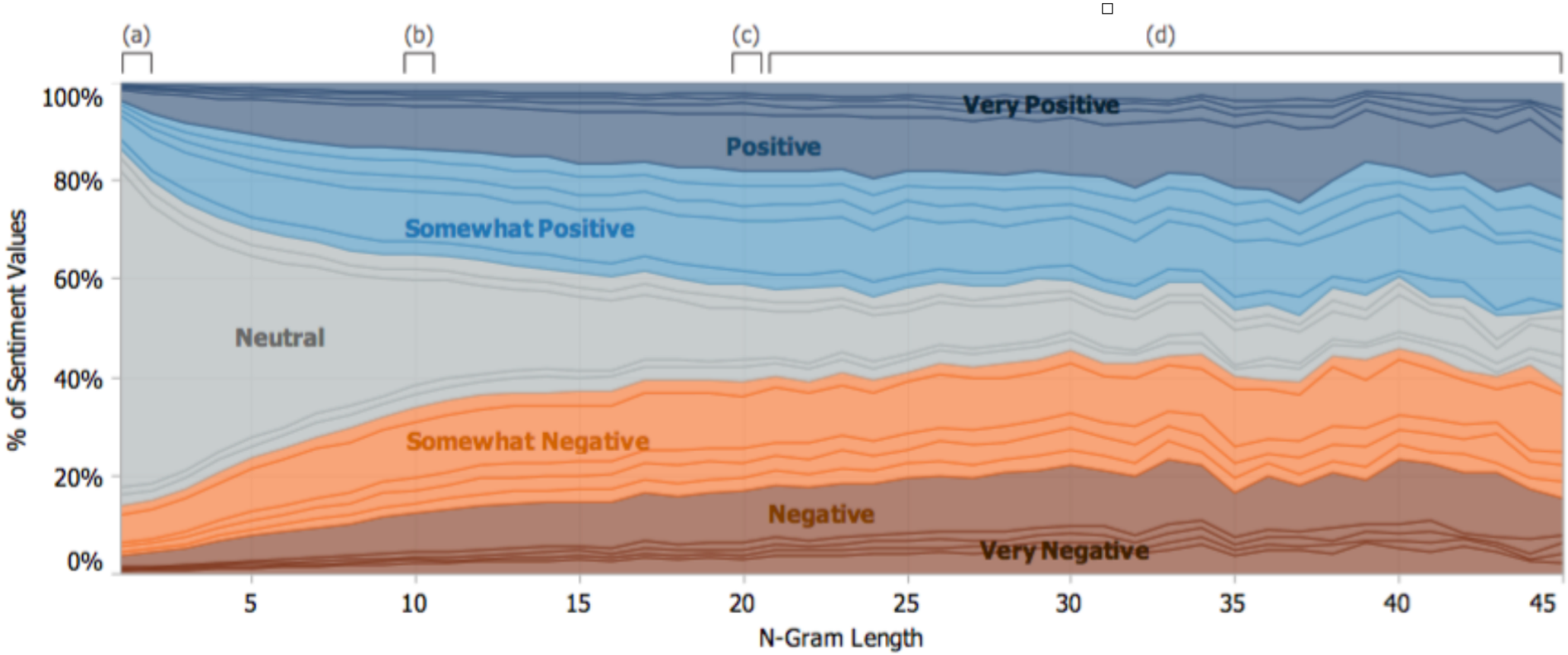
Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank, Socher et al., EMNLP 2013



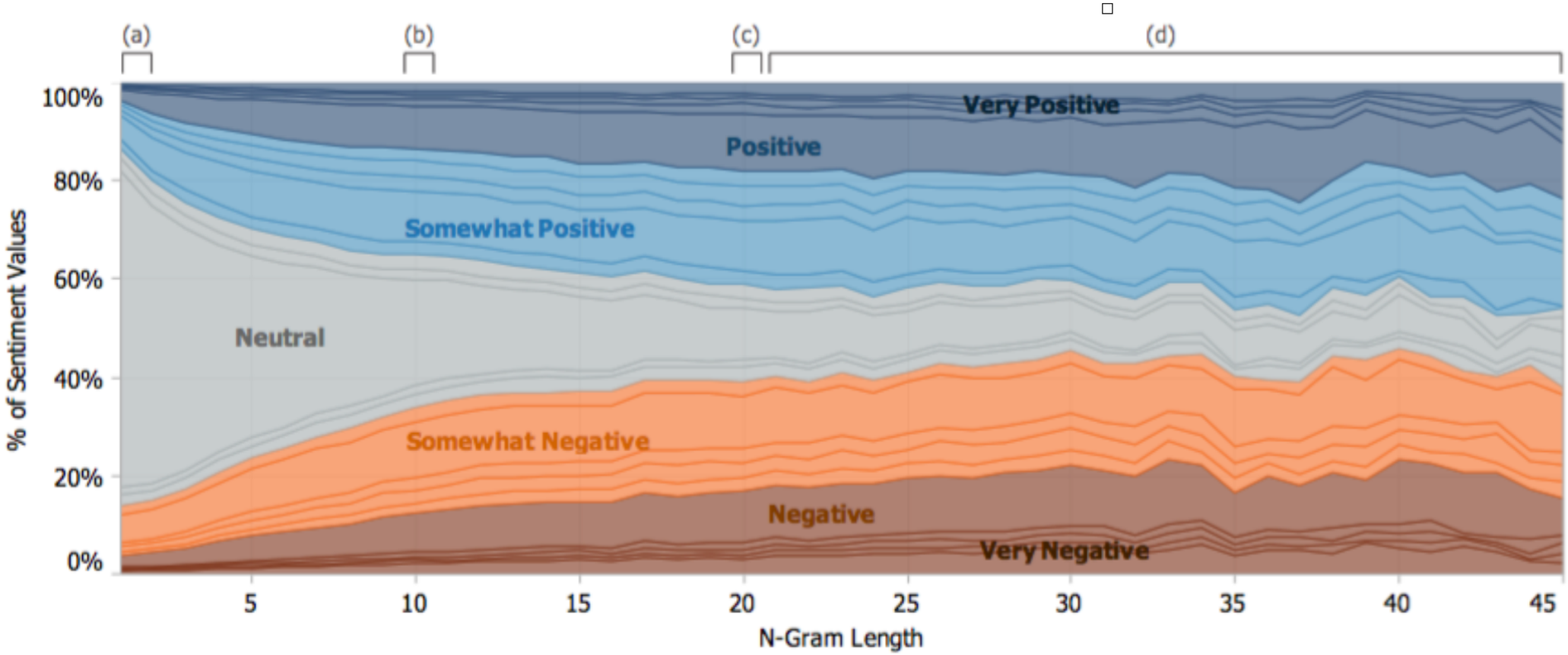
Although more nodes within this sentence have a positive meaning, the sentence is labeled negative!



Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank, Socher et al., EMNLP 2013



The longer a phrase gets, the more likely it is either positive or negative!



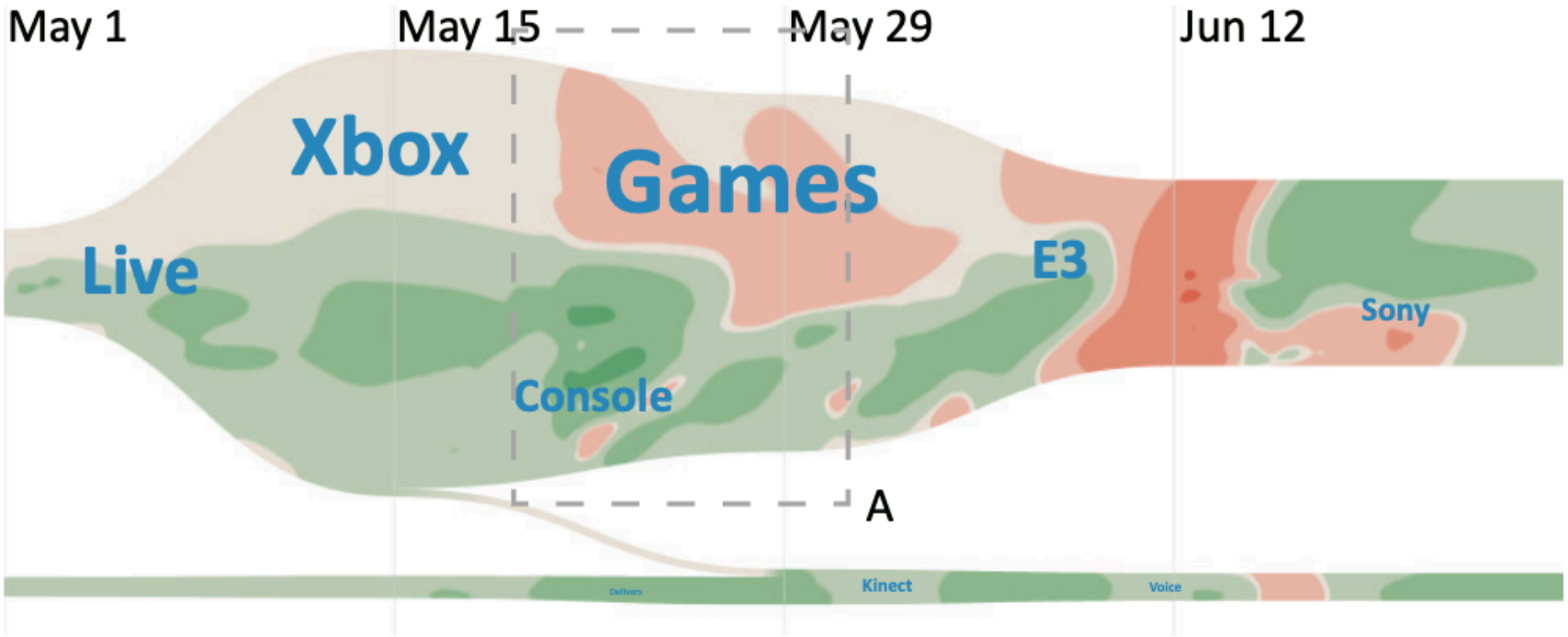


Fig. 7. Opinion diffusion on the Xbox topic from the period between May 15 to 29 when Xbox One was announced.

Wu, Yingcai, et al. "Opinionflow: Visual analysis of opinion diffusion on social media." *IEEE Transactions on Visualization and Computer Graphics* 20.12 (2014): 1763-1772.

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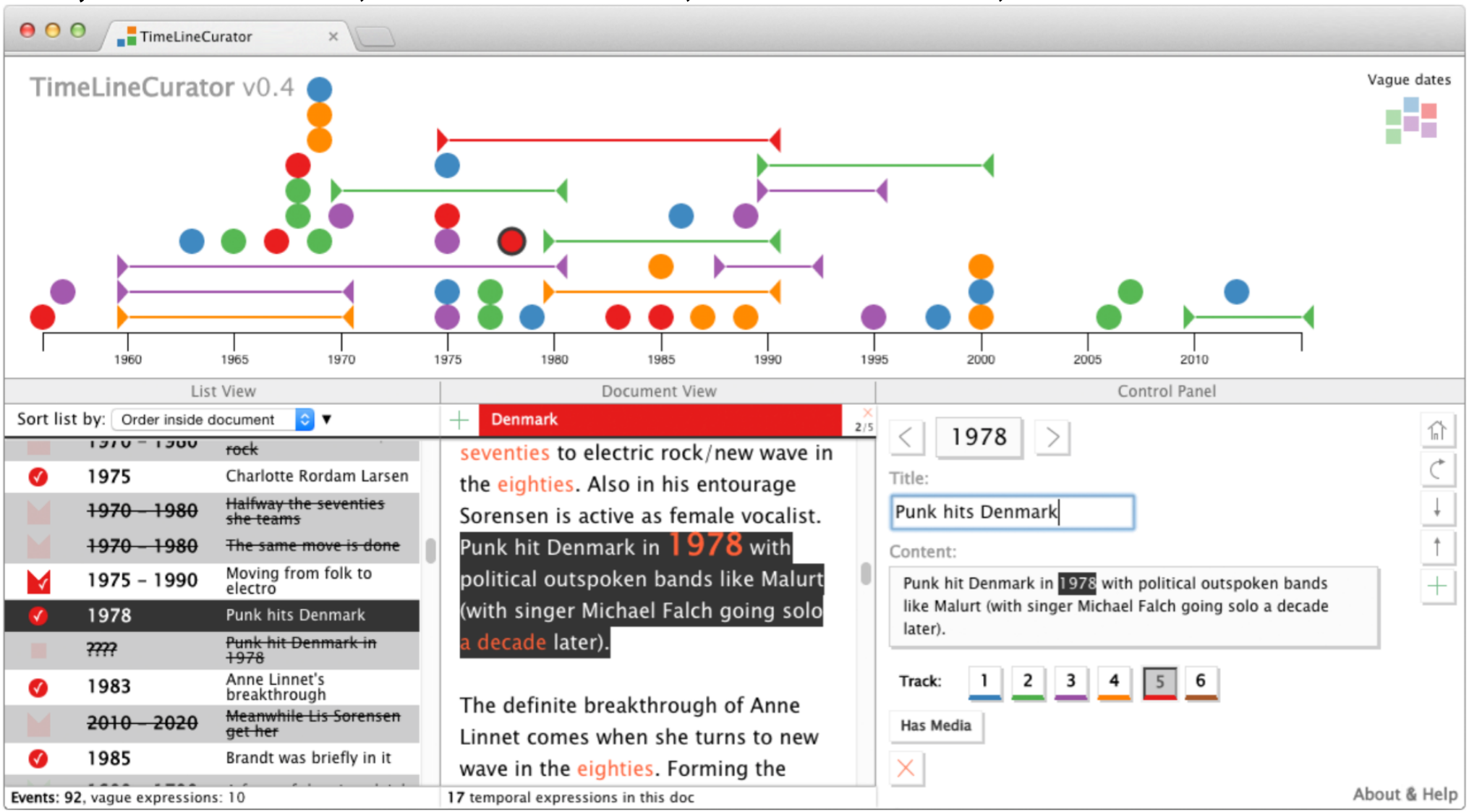
Temporal Events

TimeLineCurator: Interactive Authoring of Visual Timelines from Unstructured Text; Johanna Fulda, Matthew Brehmer, Tamara Munzner; IEEE VAST 2015



Time Events get extracted from an input text source

Time Events get extracted from an input text source and visualised as Timeline

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Deep Learning

Tasks:

POS tagging
Parsing
Named-Entity Recognition
Semantic Role Labeling
Sentiment Classification
Machine translation
Question answering
Dialogue systems
Contextual Embeddings
…

Young, Tom, et al. "Recent trends in deep learning based natural language processing." *IEEE Computational Intelligence Magazine* 13.3 (2018): 55-75.

TABLE VII: **Machine translation** (Numbers are BLEU scores)

Paper	Model	WMT2014 English2German	WMT2014 English2French
Cho et al. [82]	Phrase table with neural features		34.50
Sutskever et al. [74]	Reranking phrase-based SMT best list with LSTM seq2seq		36.5
Wu et al. [162]	Residual LSTM seq2seq + Reinforcement learning refining	26.30	41.16
Gehring et al. [163]	seq2seq with CNN	26.36	41.29
Vaswani et al. [113]	Attention mechanism	28.4	41.0

BLEU Score:

"the closer a machine translation is to a professional human translation, the better it is" – this is the central idea behind BLEU.

https://en.wikipedia.org/wiki/BLEU

Young, Tom, et al. "Recent trends in deep learning based natural language processing." *IEEE Computational Intelligence Magazine* 13.3 (2018): 55-75.

TABLE X: Comparison of ELMo + Baseline with the previous state of the art (SOTA) on various NLP tasks. The table has been adapted from [41]. SOTA results have been taken from [41]; SQUAD [166]: QA task; SNLI [178]: Stanford Natural Language Inference task; SRL [153]: Semantic Role Labelling; Coref [179]: Coreference Resolution; NER [180]: Named Entity Recognition; SST-5 [4]: Stanford Sentiment Treebank 5-class classification;

Task	Previous SOTA	Previous SOTA Results	Baseline	ELMo + Baseline	Increase (Absolute/Relative)
SQuAD	Liu et al. [181]	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Qian et al. [182]	88.6	88.0	88.70 $\pm$ 0.17	0.7 / 5.8%
SRL	Luheng et al. [183]	81.7	81.4	84.6	3.2 / 17.2%
Coref	Kenton et al. [184]	67.2	67.2	70.4	3.2 / 9.8%
NER	Matthew et al. [185]	91.93 $\pm$ 0.19	90.15	92.22 $\pm$ 0.10	2.06 / 21%
SST-5	Bryan et al. [186]	53.7	51.4	54.7 0.5	3.3 / 6.8%

Task	BiLSTM+ ELMo+Attn	BERT
QNLI	79.9	91.1
SST-2	90.9	94.9
STS-B	73.3	86.5
RTE	56.8	70.1
SQuAD	85.8	91.1
NER	92.2	92.8

TABLE XI: QNLI [187]: Question Natural Language Inference task; SST-2 [4]: Stanford Sentiment Treebank binary classification; STS-B [188]: Semantic Textual Similarity Benchmark; RTE [189]: Recognizing Textual Entailment; SQUAD [166]: QA task; NER [180]: Named Entity Recognition.

Young, Tom, et al. "Recent trends in deep learning based natural language processing." *IEEE Computational Intelligence Magazine* 13.3 (2018): 55-75.