



15. Text Data Visualization

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- **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 Data



- Documents
 - Articles, books and novels
 - E-mails, web pages, blogs
 - Tags, comments
 - Computer programs, logs
- Collection of documents
 - Messages (e-mail, blogs, tags, comments)
 - Social networks (personal profiles)
 - Academic collaborations (publications)

Where Text Data?









Example: Health Care Reform



September 10, 2009

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 you about an issue that is central to that future – and that is the issue of health care.

I am not the first President to take up this cause, but I am determined to be the last. It has now been nearly a

Tag Clouds: Word Count





Tag Clouds: Word Count







WordTree: Word Sequences





WordTree: Word Sequences





Challenges of Text Visualization



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.





- Text as Data
- Visualizing Document Content
- Evolving Documents
- Visualizing Conversation
- Document Collections





Words are (not) nominal? High dimensional (10,000+) More than equality tests Words have meanings and relations

- Correlations: Hong Kong, San Francisco, Bay Area
- Order: April, February, January, June, March, May
- Membership: Tennis, Running, Swimming, Hiking, Piano
- Hierarchy, antonyms & synonyms, entities, ...

Text Processing Pipeline



1. Tokenization

Segment text into terms.

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

Numbers and symbols? *#gocard, @stanfordfball, Beat Cal!!!!!!!*

Entities? San Francisco, O'Connor, U.S.A.

2. Stemming

Group together different forms of a word.

Porter stemmer? visualization(s), visualize(s), visually \rightarrow visual

Lemmatization? goes, went, gone \rightarrow go

3. Ordered list of terms



Ignore ordering relationships within the text

A document \approx vector of term weights Each dimension corresponds to a term (10,000+) Each value represents the relevance

For example, simple term counts

Aggregate into a document-term matrix Document vector space model

Document-Term Matrix

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- Each document is a vector of term weights
- Simplest weighting is to just count

UCC	un ences					
	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

Tag Clouds



- Strength
 - Can help with 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

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

Creator: Anonymous Tags:

Edit Language Font Layout Color



Data file: Sarah Palin speaks at the Republican National Convention, 9/3/2008 Data source: SFGate / AP 💽 This data set has not yet been rated



Term Frequency

- $tf_{td} = count(t) in d$
- Can take log frequency: $log(1 + tf_{td})$
- Can normalize to show proportion: tf_td / Σ_t tf_td

Partisan Words, 106th Congress, Abortion (Difference of Proportions)







Term Frequency

 $tf_{td} = count(t) in d$

TF.IDF: Term Freq by Inverse Document Freq tf.idf_{td} = log(1 + tf_{td}) × log(N/df_t) df_t = # docs containing t; N = # of docs





Term Frequency $tf_{td} = count(t) in d$

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$\begin{aligned} & \textbf{G}^2 \textbf{: Probability of different word frequency} \\ & \textbf{E}_1 = |\textbf{d}| \times (tf_{td} + tf_{t(C-d)}) \ / \ |\textbf{C}| \\ & \textbf{E}_2 = |\textbf{C}\textbf{-d}| \times (tf_{td} + tf_{t(C-d)}) \ / \ |\textbf{C}| \\ & \textbf{G}^2 = 2 \times (tf_{td} \ \text{log}(tf_{td}/\textbf{E}_1) + tf_{t(C-d)} \ \text{log}(tf_{t(C-d)}/\textbf{E}_2)) \end{aligned}$

Partisan Words, 106th Congress, Abortion (Weighted Log-Odds-Ratio, Informative Dirichlet Prior)



Frequency of Word within Topic

Limitations of Frequency Statistics?



Typically focus on unigrams (single terms)

Often favors frequent (TF) or rare (IDF) terms Not clear that these provide best description

A "bag of words" ignores additional information

- Grammar / part-of-speech
- Position within document
- Recognizable entities

How do people describe text?



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

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

Students were matched to both *familiar* and *unfamiliar* topics; *topical diversity* within a collection was varied systematically.

[Chuang, Heer & Manning, 2010]







Term Commonness

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

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

Measured across an entire corpus or across the entire English language (using Google ngrams)







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A fighter jet rain check

Story and video by Chamila Jayaweera

Have you ever thought about what it takes to make sure that sea-based fighter jets stay dry?

When it comes to the F/A-18 Super Hornet, Boeing engineers in St. Louis use a special process called the Water Check Test to rule out areas where moisture could seep into the aircraft and its electronics suite.

Program experts douse the jet with simulated rain at a 15-inch-per-hour rate for about 20 minutes inside an enormous hangar in St. Louis.

"Our ultimate customers are U.S. Navy fighter pilots, and we want to ensure their safety in flight and on the ground, and water-tight integrity of the aircraft also



CHAMILA JAYAWEERA/BOEING

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

helps increase their effectiveness," said Boeing's Rich Baxter, F/A-18 Super Hornet final assembly manager.

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



 G^2

Regression Model

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

want

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

Yelp: Review Spotlight [Yatani 2011]







b) best sf baked sea bass bes	ass best sushi		sure in striped bass other person						
fresh fish sushi chef	slov	v service baked mussel	more ho	only thing					
long wait	long time	sushi resta	sushi restaurant						
iong wait	long line	hawaiian ro	oll _{re}	easonable price					
baked mango									
small	delicious ev	delicious everything							
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 .									

Tips: Descriptive Keyphrases

Understand the limitations of your language model.

Bag of words

Easy to compute

Single words

Loss of word ordering

Select appropriate model and visualization Generate longer, more meaningful phrases Adjective-noun word pairs for reviews Show keyphrases within source text



Thank You