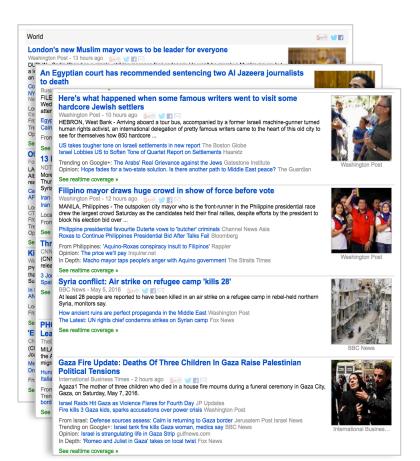
Interpretable Machine Learning: Lessons from Topic Modeling

Michael Paul University of Colorado Boulder

> CHI HCML May 8, 2016

Topic Modeling





united attorney air federal flight states charged plane trade filed airlines nations world pilots court fraud eastern countries indictment airline european international investigation airport nicaragua sales voters government vote percent rebels billion votes campaign share contras democratic sandinista quarter candidate ortega earnings sandinistas state last

chamorro

first

election

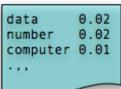
Topic Modeling

Topics

gene 0.04dna 0.02 0.01 genetic

life	0.02
evolve	0.01
organism	0.01
.,,	_

brain	0.04
neuron	0.02
nerve	0.01



Documents

Topic proportions and assignments

Seeking Life's Bare (Genetic) Necessities

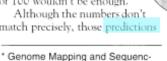
COLD SPRING HARBOR, NEW YORK-How many genes does an organism need to survive? Last week at the genome meeting here, two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known 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

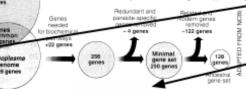
ing, Cold Spring Harbor, New York,

May 8 to 12.



"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson o University in Swed at the arrived at 800 pumber. But coming up with a co sus answer may be more than just a numbers games particularly as more and more genomes are completely 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

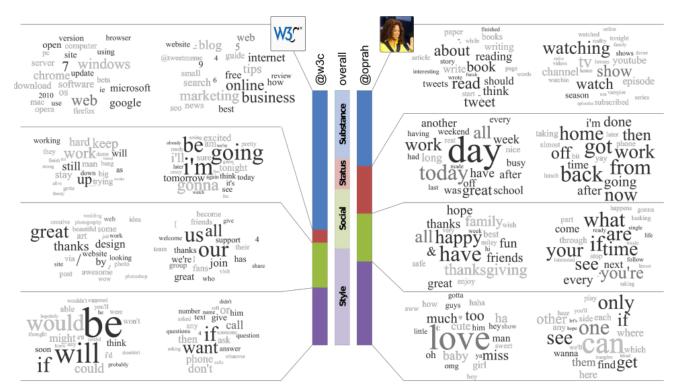


Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes

SCIENCE • VOL. 272 • 24 MAY 1996

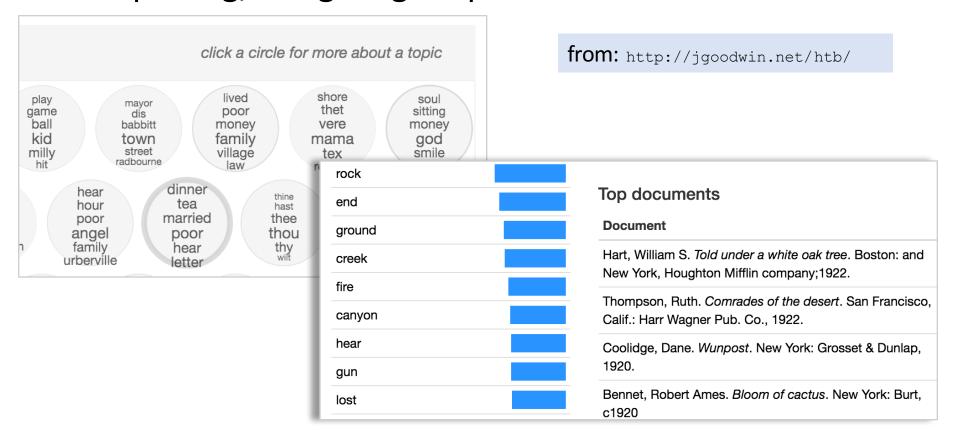
Identifying main themes in text

"What do people talk about on Twitter?"

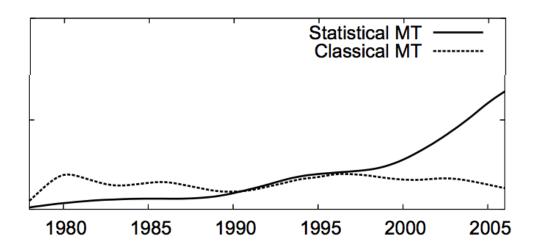


Ramage. Dumais. Liebling (2010) Characterizing Microblogs with Topic Models. ICWSM.

- Identifying main themes in text
- Exploring/navigating corpora



- Identifying main themes in text
- Exploring/navigating corpora
- Revealing trends in content

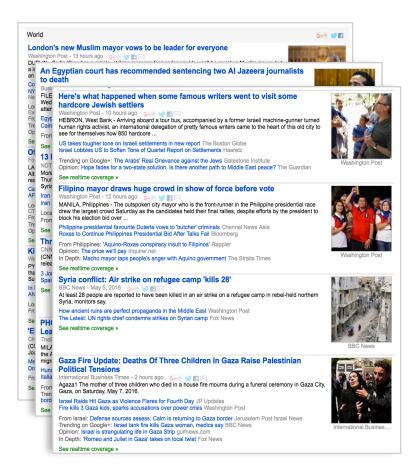


Hall, Jurafsky, Manning (2008) Studying the History of Ideas Using Topic Models. *EMNLP*.

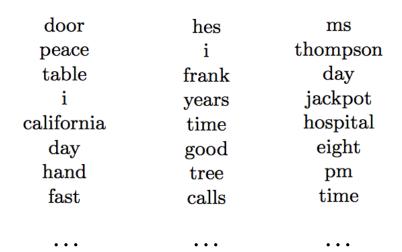
- Identifying main themes in text
- Exploring/navigating corpora
- Revealing trends in content

These uses assume topic models are human-interpretable

Interpretability in Topic Models



Topics aren't always easy to decipher...



Interpretability in Topic Models

How does the topic modeling community deal with interpretability?

Two key areas:

- Evaluation
- Training

Interpretability in Topic Models: Evaluation

How to evaluate the quality of a topic?

Commonly used concept: coherence

Coherent		
space	health	
earth	disease	
moon	aids	
science	virus	
scientist	vaccine	
light	infection	
nasa	hiv	
mission	cases	
planet	infected	
mars	asthma	

Incoherent		
dog	king	
moment	bond	
hand	berry	
face	bill	
love	ray	
self	rate	
eye	james	
turn	treas	
young	byrd	
character	key	

Newman, Lau, Grieser, Baldwin (2010) Automatic Evaluation of Topic Coherence. *NAACL*.

Interpretability in Topic Models: Evaluation

How to evaluate the quality of a topic?

Coherence

• Human judgments: word intrusion

Spot the out-of-place word: nasa

mission

planet

dog

mars

Chang, Gerrish, Wang, Boyd-Graber, Blei (2009) Reading Tea Leaves: How Humans Interpret Topic Models. *NIPS*.

Interpretability in Topic Models: Evaluation

How to evaluate the quality of a topic?

Coherence

- Human judgments: word intrusion
- Metrics based on co-occurrence statistics
 - Similarity of all pairs of words in a topic

$$C(t; V^{(t)}) = \sum_{m=2}^{M} \sum_{l=1}^{m-1} \log \frac{D(v_m^{(t)}, v_l^{(t)}) + 1}{D(v_l^{(t)})}$$

Mimno, Wallach, Talley, Leenders, McCallum (2011) Optimizing Semantic Coherence in Topic Models. *EMNLP*.

Interpretability in Topic Models: Training

How to train topic models in a way that will be more interpretable?

- Priors to incorporate human preferences/constraints
 Andrzeiewski, Zhu, Craven (2009) Incorporating Domain
 - Andrzejewski, Zhu, Craven (2009) Incorporating Domain Knowledge into Topic Modeling via Dirichlet Forest Priors. *ICML*.
- Priors to encourage co-occurrence patterns
 - Mimno, Wallach, Talley, Leenders, McCallum (2011) Optimizing Semantic Coherence in Topic Models. *EMNLP*.
- Interactive topic modeling

Hu, Boyd-Graber, Satinoff, Smith (2013) Interactive Topic Modeling. *Machine Learning*.

Beyond Topic Modeling

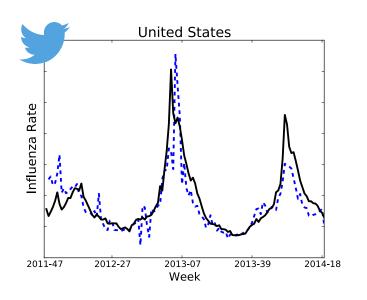
Can other areas of machine learning benefit from the topic modeling approach to interpretability?

Is coherence a desirable property in other types of models?

Beyond Topic Modeling

Poor coherence = poor predictive performance?

Example: Modeling flu prevalence from Twitter



christmas sick flu strong processing snow new want hard better body best coughing festivities eve

Top predictors of regression model

Conclusion

Takeaway:

The topic modeling community has a growing body of research on making models more interpretable

This research should be incorporated into the larger context of interpretable machine learning

What's next?

- Coherence as an evaluation metric for other machine learning models
- Training models to be coherent