A Practical Algorithm for Topic Modling with Provable Guarantees

Sanjeev Arora
Rong Ge
Yoni Halpern
David Mimno
Ankur Moitra
David Sontag
Yihcen Wu
Michael Zhu

Presented by: Vanush Vaswani and Kristy Hughes

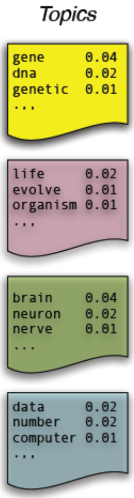
Information Overload

Effective Organisation

Topics


transportation
parking
system
mobility
regional
transit
travel
safe
safety
management
movement
network
trucks
trips
mode
people
priority
demand
impacts
workforce
innovation
education
industry
skills
training
technology
research
economy
clusters
systems
institutions
improving
industries
metropolitan
entrepreneurs
commercial
industrial
residential
retail
areas
mixed
activity
district
existing
office
districts
surrounding
environmental
concentration
plan
community
station
adopted
special
opportunity
existing
part
located
study
figure
rail

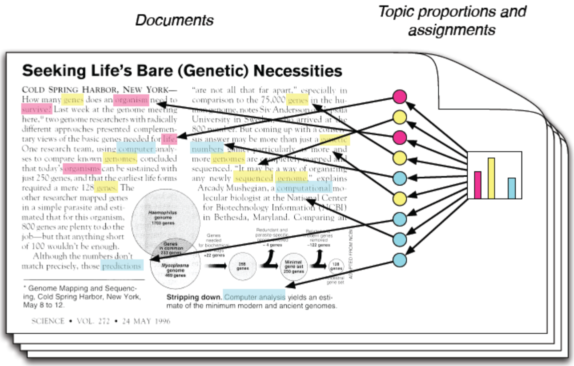
Topics



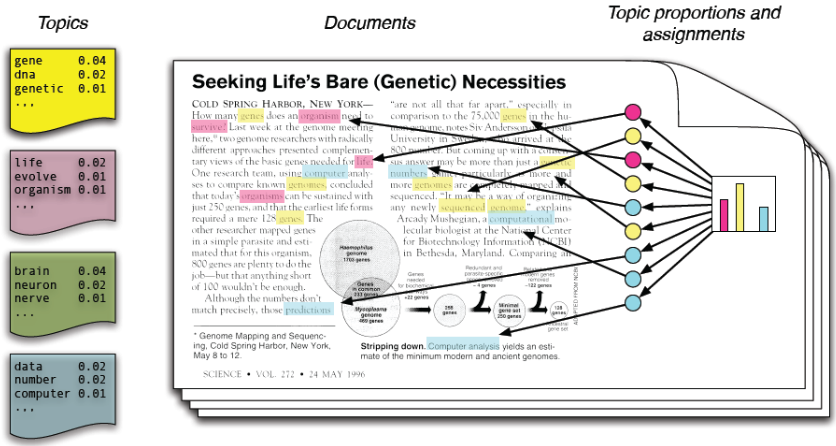
Topics are distributions over words

Documents

Documents have distribution of topics

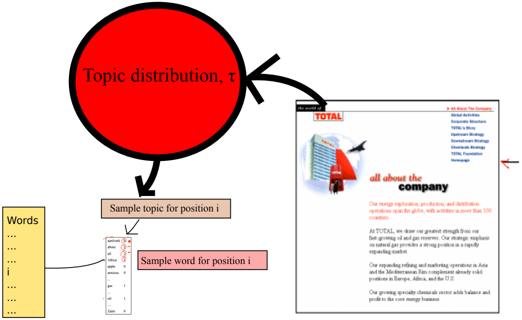


Topic Modelling



Task

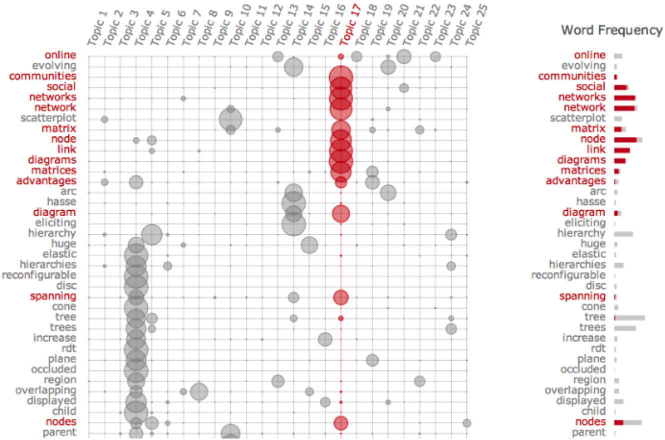
- Assume documents are generated by probabilistic model with unknown variables
- Infer hidden structure onto document
- Situate new document into model



TODO: Redo pic

Word-topic Matrix

Extracted: Word-topic matrix



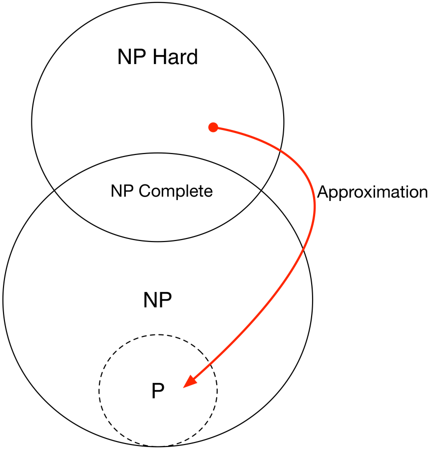
Aim: Find document-topic matrix

Anchor Words

- Word-topic distributions are separable
- There is a word unique to each topic
- Indicates document is partially about that topic
- Can learn parameters in polynomial time provided there is a large enough number of documents

Approximate Inference & Provable Guarantees

- Document-topic inference:
  - NP-hard
- Approximate techniques
- Provably polynomial-time?



Algorithm

Input: Corpus $\mathcal{D}$, Number of topics K

Output: Word-topic matrix A, topic-topic matrix R

1. Compute word-word co-occurrence matrix
2. Normalize the matrix
3. Find anchor words
4. Recover topics

Assumptions:

- Topics may be correlated
- Word-topic distributions are separable

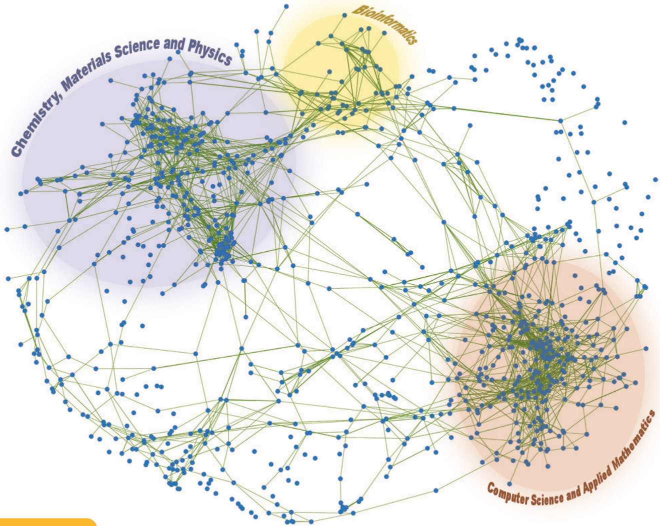
Contributions

1. Anchor Selection
   - Combinatorial rather than ILP
   - Stable in the presence of noise
   - polynomial sample complexity
2. Recovery step
   - Previous matrix-inversion approach sensitive to noise
   - Replaced with Gradient-based inference
3. Empirical comparison of algorithms

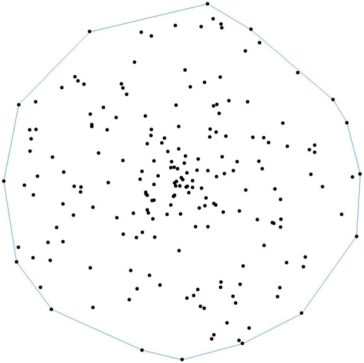
Word-word co-occurrence matrix

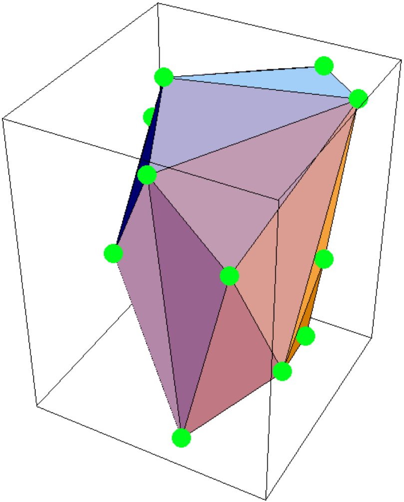
	bank	California	Canada	career	careers	employers	employment	federal	human	job	jobs	listings	openings	opportunities	positions	recruiters	resources	resume	resumes	retirement	search	state	texas	unemployment	work
bank	--																								
California		--																							
Canada	1		--																						
career	3	3		--																					
careers			2	9	--																				
employers		2		11	7	--																			
employment	3	26	22	66	10	16	--																		
federal	1	1	5		1		11	--																	
human		4	12	1	1			4	--																
job	34	14	2	49	8	13	92	13	2	--															
jobs		18	6	62	11	27	204	19	2	74	--														
listings		4	2	15	4	9	68	2	55	44		--													
openings		4		7	2	9	28			49	30		--												
opportunities	4	8	3	51	9	13	181	9		84	106	25	19	--											
positions		1		8	2	10	19			16	20	9	13	21	--										
recruiters				10	4	3	9			5	4	2	2	5	2	--									
resources		4	12		1			4	74	3	2						--								
resume		4	3	5		2	3	1	1	10	3			1	2	1		--							
resumes				8	3	3	11			5	16	1		8	5			15	--						
retirement		1	1						3			2		1						--					
search			3	4	6			10			18	6		6	2			3	1		--				
state			4	1			18		1	12	7	6		3			1			2		--			
texas	2			1			18			12	6		1	2						9			--		
unemployment																						2	2	--	
work			2	1		3	3	2		2	8	2	4	7	5				1			1	2		--

Words as vertices



Convex Hull





Computing Convex Hull

- Efficient for 2 dimensions - $\mathrm{O}(n \log n)$
- Inefficient for $n > 2$ dimensions
- Complexity depends on method and approximation used
- Previous method: ILP
- New method: Recursive greedy
  1. Compute subspace span of current convex hull
  2. Find point furthest from this sub-span
  3. Add point to convex hull
  4. Repeat until K points found

TODO: Work out how the whole convex hull - words as vertices work. I think what we have here is wrong because there is no approximation

Topic Recovery Task

- Recovers the topics
- Represented as topic-word distributions
- Topic uniquely identified by anchor word

Previous method

1. Discard rows not containing anchor words from word-word co-occurrence matrix (Q)
2. Permute matrix into a diagonal matrix
3. We know that $Q = ARA^T$ where A is the word-topic matrix and R is the TODO matrix
4. Solve $Q = ARA^T$ using matrix inversion

TODO: what the hell does R represent?!?!

Word-word co-occurrence probability matrix

For an anchor word (row) in the co-ocurrence matrix

$$Q_{s_k,j} = \sum_{k'} p(z_1 = k' | w_1 = s_k) p(w_2 = j | z_1 = k')$$

= 1 because of the anchor word property

$$= p(w_2 = j | z_1 = k) = C_{i,k}$$

For any other row

$$\bar{Q}_{i,j} = \sum_k p(z_1 = k | w_1 = i) p(w_2 = j | z_1 = k)$$

But this is clearly a convex combination of anchor words

$$\bar{Q}_{i,j} = \sum_k C_{i,k} \bar{Q}_{s,k}$$

New method

- Row normalize Q into $\bar{Q}$
- Recover A and R using Bayes rule

$$p(w_1 = i | z_1 = k) = \frac{p(z_1 = k | w_1 = i) p(w_1 = i)}{\sum_i p(z_1 = k | w_1 = i') p(w_1 = i')}$$

1. Introduction
2. Topic Modelling
3. Algorithm
4. Efficiently Finding Anchor Words
5. Topic Recovery via Bayes' Rule
6. **Experimental Results**
7. Conclusion

Experiments

TODO: overview of the experiments run

Metrics

TODO: Metrics

Documents

TODO: Talk about semi-synthetic documents, real documents and the need for both

Results

TODO: describe results. Iterate through each experiment, and each document type, reporting the computed metrics for each. This may need to be split up into more slides by either experiment or document type

Summary

TODO: Put the paper's conclusion into dot point form

Comments

TODO: Do we need to comment on the paper?
Are there things that we wish they had reported but didn't?
Are there things that we really liked that they reported?
Check the marking guidelines about what exactly we need here

Future Work

TODO: They didn’t have a future work section but they really should have. We can make one up and maybe comment that they didn’t put a future work section

Thanks!

Any questions please email either of us:

Vanush Vaswani
vvas****@uni.sydney.edu.au

Kristy Hughes
khug2372@uni.sydney.edu.au