


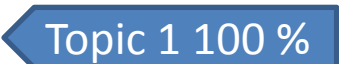




Latent Topics in Microposts



Andrés García-Silva, Victor Rodriguez-Doncel, Oscar Corcho: ***Semantic Characterization of Tweets Using Topic Models: A Use Case in the Entertainment Domain. International Journal on Semantic Web and Information Systems (IJSWIS) , 9 (3)***

Introduction to Topic Models

Document Collection (sentences) :

- I teach math and science  Topic 1 100 %
- I prefer science and literacy  Topic 1 100 %
- Spring and autumn are my favourite seasons  Topic 2 100 %
- The weather during winter and autumn is awful  Topic 2 100 %
- They learn about spring in science class  Topic 1 60 %  Topic 2 40 %

LDA will discover the topics in this sentences (or documents).
However you should define the number of topics.

For 2 topics LDA would produce something like this:

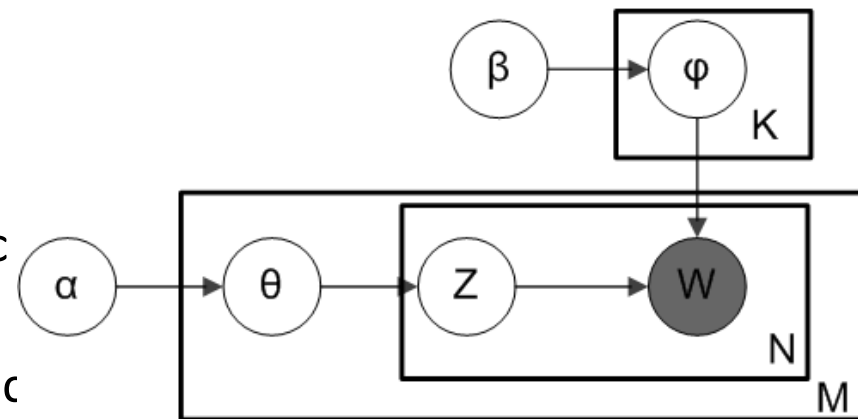
Topic 1={math 15%, science 30%, literacy 15%, teaching 10%, class 10%..}

Topic 2={spring 30%, autumn 30%, winter 10%, season 10% weather 10%..}

LDA – Latent Dirichlet Allocation

Allows sets of observations (words) to be explained by unobserved groups (Topics) that explain why some parts of the data are similar.

- M: Documents
- N: Words
- K: Topics
- θ_i : topic distribution for document i
- ϕ_k : is the word distribution for topic k
- $z_{i,j}$: is the topics for the j -th word in the doc
- $w_{i,j}$: is the j -th word in the doc i
- α : Dirichlet prior on the per-document topic distributions.
- β : Dirichlet prior on the per-topic word distribution



$$p(\theta, \phi, \mathbf{z} | \mathbf{w}, \alpha, \beta)$$

Bayesian Inference problem



Blei, David M.; Ng, Andrew Y.; [Jordan, Michael I](#) (January 2003). Lafferty, John. ed. "[Latent Dirichlet allocation](#)". [Journal of Machine Learning Research](#) **3** (4–5): pp. 993–1022.

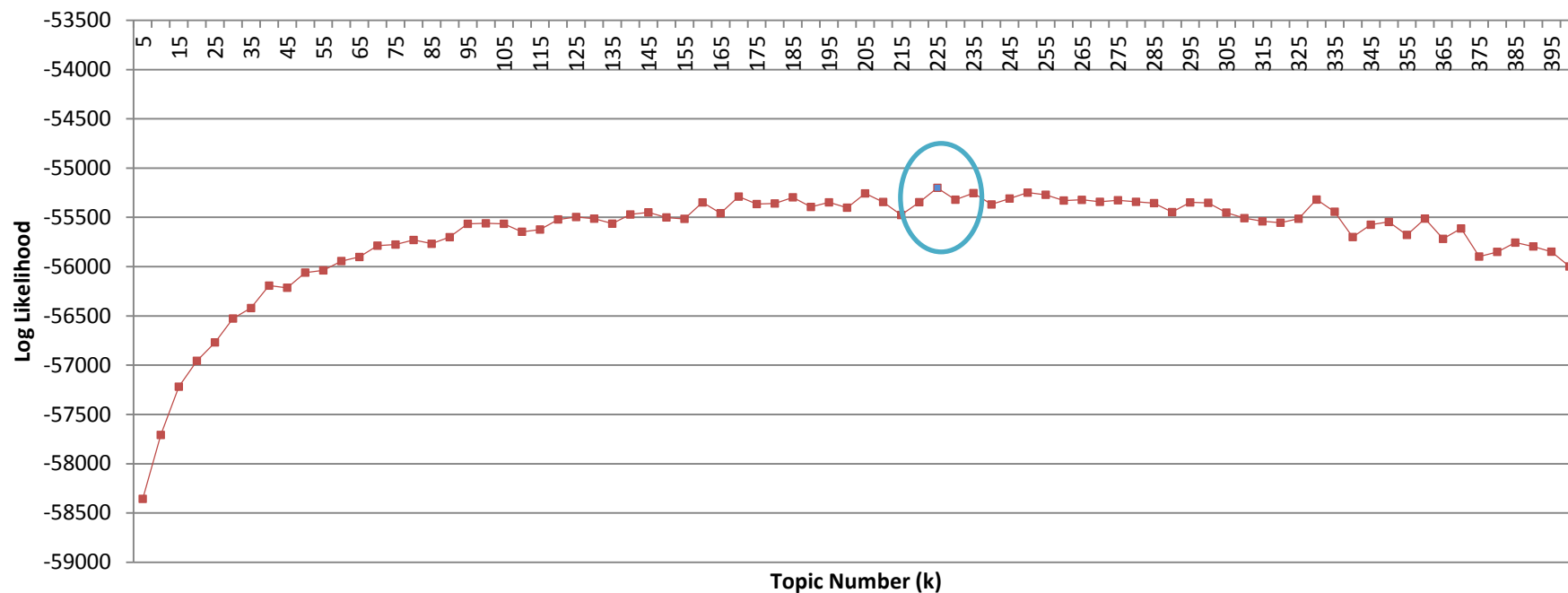


Topic Models: Tweets



- 144 theatre plays announced in TimeOut London.
- We collected ~7000 geo-localized (London) tweets

Finding the best K





Topic Models: Tweets



- $K = 225$

"Jamie Parker as Henry V at #TheGlobe was AMAZING. He said 'Cry God for Harry, England & St.Geooorge!' Then we won 6 Gold medals! #Olympics" ok

Topic 46, 0.379

"v";0.202
"henry";0.195
"globe";0.061
"parker";0.028
"jamie";0.025
"watch";0.023

Topic 51, 0.324

"v";0.100
"henry";0.094
"england";0.040
"bbc";0.033
"olympics";0.033
"crown";0.033

Topic 55, 0.0549

"amazing";0.065
":)";0.061
"many";0.061
"see";0.051
"seen";0.041
"times";0.041



Topic Models: Tweets



"Tonight I'm going to see a play I've never seen before... 'A Midsummer Night's Dream'."

Topic 94, 0.286

"night";0.157
"dream";0.153
"midsummer";0.134
"theatre";0.046
"open";0.046
"air";0.042

Topic 56, 0.197

"see";0.115
"going";0.054
"tonight";0.051
"today";0.038
"tomorrow";0.036
"off";0.035

"Regent's Park Open Air Theatre's A Midsummer Night's Dream. Absolutely brilliant."

Topic 94, 0.696

"night";0.157
"dream";0.153
"midsummer";0.134
"theatre";0.046
"open";0.046
"air";0.042

Topic 92, 0.178

"night";0.080
"last";0.070
"great";0.061
"show";0.040
"saw";0.040
"loved";0.036

How can we use these models?

Opinions

"Jamie Parker as Henry V at #TheGlobe was AMAZING. He said 'Cry God for Harry, England & St.Geooorge!' Then we won 6 Gold medals! #Olympics" ok

"Regent's Park Open Air Theatre's A Midsummer Night's Dream. Absolutely brilliant.

Expectations

"Tonight I'm going to see a play I've never seen before... 'A Midsummer Night's Dream'."

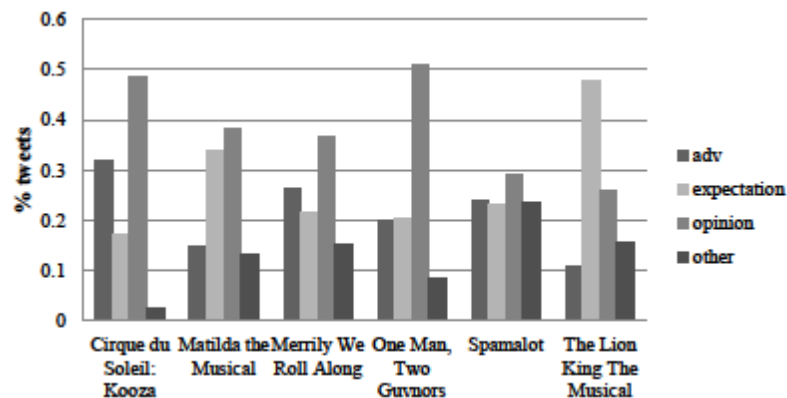
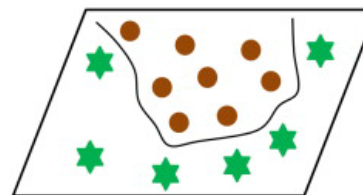
"At the Open Air Theatre for A Midsummer Night's Dream #excited"

Advertisement

"FLASH SALE! Get tickets for 'One Man, Two Guvnors' at The Haymarket Theatre for only £39.99! Buy before time runs out! <http://t.co/CSVpgyfP>"

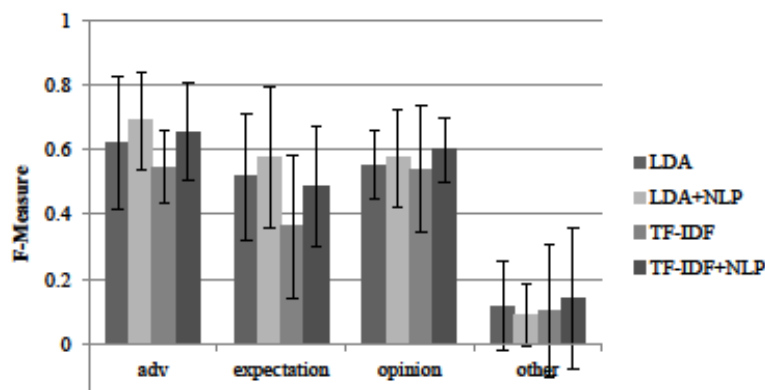


Tweet Classifier

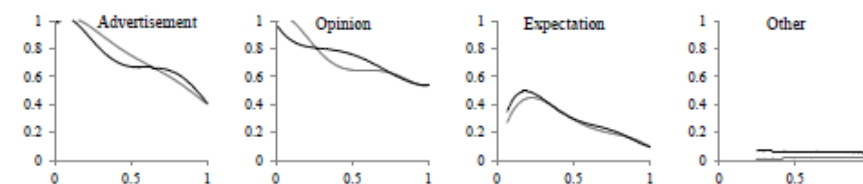


Evaluation of classifiers using precision, recall and f-measure

	P	R	F	P	R	F	P	R	F
	Spamalot			Merrily We Roll Along			Matilda the Musical		
TF-IDF	0.509	0.442	0.444	0.503	0.557	0.493	0.465	0.471	0.435
LDA	0.479	0.496	0.484	0.634	0.608	0.611	0.494	0.563	0.521
TF-IDF + NLP	0.599	0.575	0.573	0.543	0.547	0.524	0.464	0.52	0.49
LDA + NLP	0.617	0.653	0.623	0.565	0.529	0.544	0.506	0.563	0.529
	Cirque du Soleil: Kooza			One Man, Two Guvnors			The Lion King The Musical		
TF-IDF	0.484	0.554	0.488	0.631	0.651	0.597	0.471	0.515	0.423
LDA	0.627	0.635	0.608	0.575	0.583	0.555	0.584	0.621	0.585
TF-IDF + NLP	0.524	0.558	0.5	0.697	0.72	0.695	0.497	0.584	0.526
LDA + NLP	0.594	0.615	0.599	0.708	0.748	0.725	0.617	0.653	0.623



Cirque du Soleil: Kooza



Spamalot

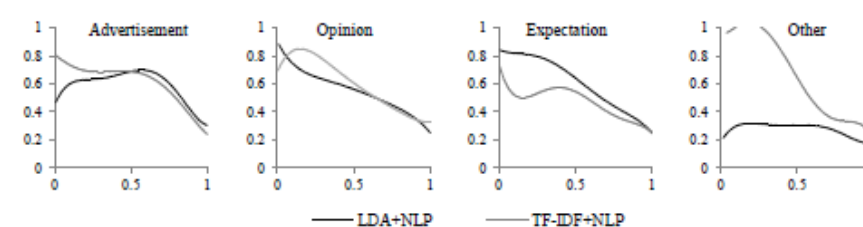


Figure 5. Precision (y-axis) and recall (x-axis) curve per category for two of the shows