Topic Modeling: Mallet

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What is Mallet

Mallet is a Java-based topic-modeling LDA (Latent Dirichlet Allocation) algorithm that aims to provide a simple way to analyze large volumes of unlabeled text (http://mallet.cs.umass.edu/topics.php). Different from other topic modeling tools like Gensim, Mallet uses an implementation of Gibbs sampling, a statistical technique meant to quickly construct a sample distribution, to create its topic models.

Installing Mallet (Environment variable)

Read carefully the Mallet installation TIPS file.

File path with blanks

Wherever you install Mallet, remember that Mallet will bomb if the full installation file path contains blanks. Thus, C:\Program files\Mallet will cause Mallet to fail. But not C:\Mallet_Installation\Mallet.

The same is true for the directory where the TXT corpus files are stored. You do not need to have these files under the Mallet subdirectory. But wherever you store your TXT files, do not leave any blanks in the full directory path of your corpus files. Thus, C:\My Text Corpus\ will cause Mallet to fail. But not C:\MyTextCorpus\ or C:\My_Text_Corpus\

Installing JAVA

Mallet also requires JAVA. Read carefully the JAVA installation TIPS file.

Topic modeling and LDA

A topic-modeling tool takes a text corpus and looks for patterns in the use of words. For large amounts of text, topic modeling provides a quick way to get “the lay of the land”, to get a sense of what the corpus is all about. This “distant reading” of a corpus is not a substitute for “close reading”, but it is a good start, like statistics’ EDA (Exploratory Data Analysis).

Topic models are computer programs that extract topics from texts. A topic, for these computer programs, is a list of words that occur in statistically meaningful ways. A text can be anything: a novel, a university mission statement, a newspaper editorial, an email, a blog post, a book chapter, a journal article, a diary entry. This text is unstructured, i.e., it does not contain any computer-readable annotations (tags) that tell the computer the semantic meaning of the words in the text.

Topic Modeling and LDA are often cited together. But LDA is a special case of topic modeling created by Blei et al. (2002). Among the many topic modeling approaches, LDA is by far the most popular. The myriad variations of topic modeling have resulted in an alphabet soup of techniques and programs to implement them that might be confusing or overwhelming to the uninitiated; ignore them for now. They all work in much the same way.

Number of Topics

How do you know the number of topics to use? Is there a natural number of topics? What we have found is that one has to run the train-topics with varying numbers of topics to see how the composition file breaks down. If we end up with the majority of our original texts all in a very limited number of topics, then we take that as a signal that we need to increase the number of topics; the settings were too coarse. (For more see Griffiths and Steyvers 2004).

What Mallet Output Looks Like

It is important to note that MALLET includes an element of randomness, so the keyword lists will look different every time the program is run, even if on the same dataset.

Keys File (NLP-Mallet_Output_Keys.csv) and visualization (NLP__input.xlsm)

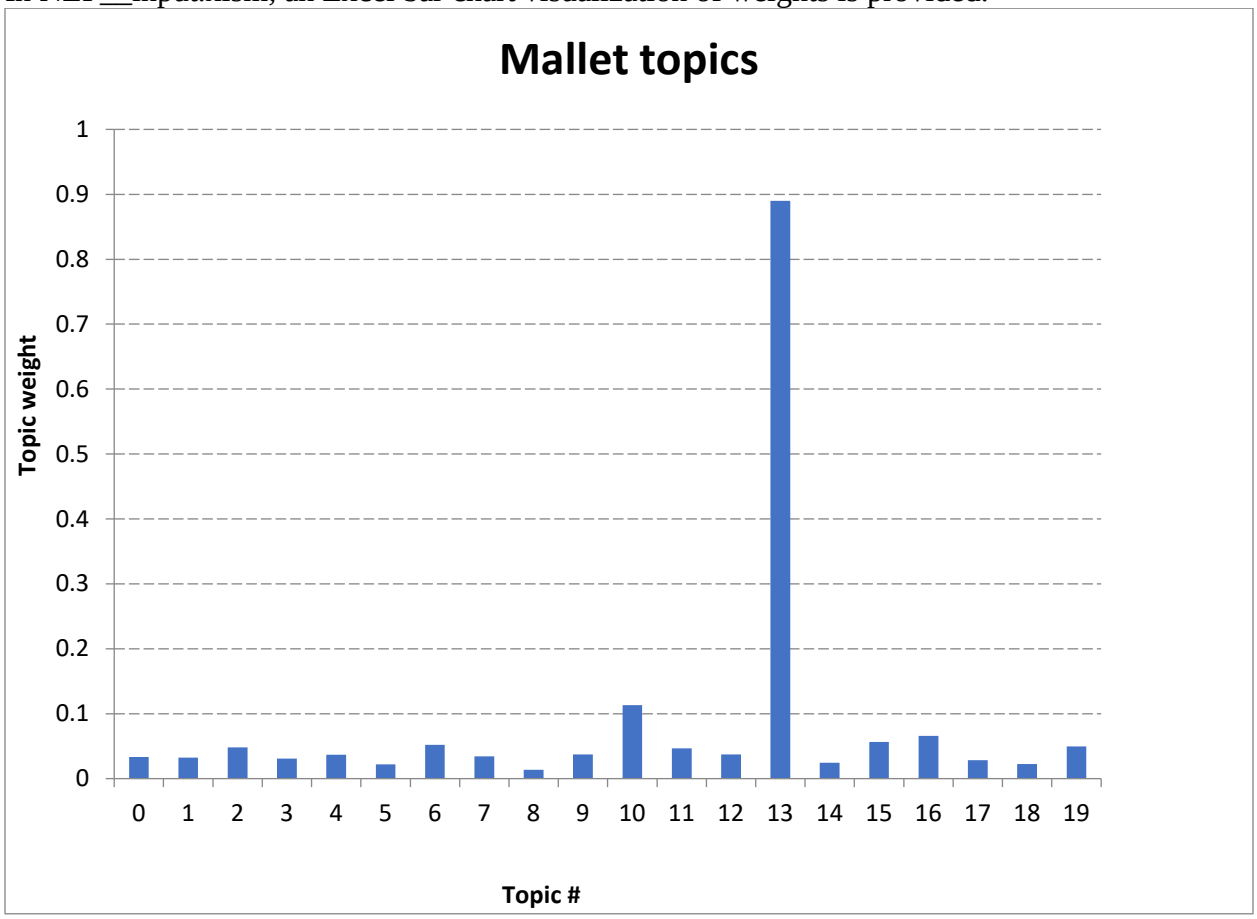
Using the sample-data EN in Mallet, this is what the keys file output looks like.

0	1.78908	hawes army richard law stage asia kabhi romance top-grossing consecutive single recognised female role debut degree films appeared actress opposed
1	1.45624	hindi indian life accomplishments markets character teenage female psychology independent stability uranus's relative adaptations sightings habitat disease blamed bounties fossil
2	3.82601	yard earned thylacine survived storey sunderland gen years union neutrality spent columns movie established biggest gaya koi science heroine kehna
3	2.44352	rings kentucky kinetic kya service support park graduated wilderness extended due dark incomplete relative names obtained mainland tazzy thylacinus inept
4	2.56565	england years team union forces energy punjab co-owner boyfriend regular news namaste success fiction naa kal award members called americans
5	3.96024	war norway theorem film zinta national echo american gunnhild system wadia performer online bbc overseas salaam women acclaim veer-zaara star-crossed
6	4.4393	rings acting test battle including gilbert early critical grant maj launched years world confederate equipartition series league premier portrayal lead
7	3.17539	rings gunnhild standards parks yard dust king ness noted naa performance graduating forest helping peers caused commercialism ideals based educational
8	0.23648	protecting living common extinct thylacine inaugural eventually society recorded etchings
9	1.92177	australian zinta tasmanian south record test hill mother cinema alvida top-grossing play image changing types subsequently filmfare dil made films

Column 1: contains the topic number, as many as specified in the parameter “Number of Topics” (topic 0, 1, 2, …);
Column 2: gives an indication of the weight of that topic across all the documents analyzed; it is the Dirichlet parameter for the topic;

Column 3: The list of words in column 3 are key words that belong to each topic, one topic per line.

In NLP__input.xlsm, an Excel bar chart visualization of weights is provided.



Composition File (NLP-Mallet_Output_Composition.csv)

The composition file has as many lines as documents imported (one document per line) and several columns, column 1, document number, column 2, document name and directory path, column 3, the topic number corresponding to the number in column 1 in the keys file followed by a column of numbers with the proportion of words in the document corresponding to that topic. Pairs of columns follow on each row for each computed topic: topic, proportion, topic, proportion, topic, proportion, topic, proportion, …

#doc	name	topic	proportion	...									
0	file:/C:/Test/Mallet/sample-data/web/en/elizabeth_needham.txt	5	0.227882	7	0.167171	6	0.145144	2	0.137362	4	0.070618	3	0.069068
1	file:/C:/Test/Mallet/sample-data/web/en/equipartition_theorem.txt	5	0.264542	2	0.14755	6	0.136072	7	0.12561	0	0.089303	4	0.079177
2	file:/C:/Test/Mallet/sample-data/web/en/gunnhild.txt	7	0.304076	5	0.207537	2	0.102312	6	0.098657	3	0.089247	4	0.062049
3	file:/C:/Test/Mallet/sample-data/web/en/hawes.txt	6	0.171536	5	0.144941	0	0.135988	2	0.128626	4	0.126635	3	0.125702
4	file:/C:/Test/Mallet/sample-data/web/en/hill.txt	6	0.267914	9	0.207684	4	0.132723	3	0.131745	7	0.097549	2	0.070714
5	file:/C:/Test/Mallet/sample-data/web/en/shiloh.txt	6	0.286084	3	0.176164	0	0.143444	5	0.109715	4	0.090072	2	0.085792
6	file:/C:/Test/Mallet/sample-data/web/en/sunderland_echo.txt	2	0.220222	6	0.18421	0	0.121407	5	0.106394	4	0.086736	9	0.08145
7	file:/C:/Test/Mallet/sample-data/web/en/thespis.txt	6	0.235398	5	0.223156	2	0.164104	4	0.104008	3	0.09472	0	0.064472
8	file:/C:/Test/Mallet/sample-data/web/en/thylacine.txt	9	0.180357	2	0.16682	1	0.132135	7	0.13032	5	0.128931	6	0.125566
9	file:/C:/Test/Mallet/sample-data/web/en/uranus.txt	7	0.230675	6	0.186825	4	0.111347	9	0.09878	2	0.098048	3	0.08748
10	file:/C:/Test/Mallet/sample-data/web/en/yard.txt	7	0.227867	2	0.203386	5	0.167821	6	0.142086	4	0.091845	0	0.07155
11	file:/C:/Test/Mallet/sample-data/web/en/zinta.txt	5	0.23079	9	0.140692	2	0.140078	0	0.120587	6	0.099088	4	0.093481

Document # 0 (the first document loaded into MALLET), elizabeth_needham.txt has topic 5 as its principal topic, with 22.7%; topic 7 with 16.7%, topic 6 at 14.5% and so on in decreasing weight; equipartition_theorem.txt (document # 1) and zinta.txt (document # 11) also have topic 5 as their largest topic, at 26.4% and 23% respectively. The topic model suggests a connection between these three documents that you might not at first have suspected.

Gensim vs. Mallet

The Python package Gensim has an LDA topic modeling implementation available in the NLP Suite. Genism has excellent visualization of topics. The Mallet LDA algorithm, however, typically gives a better quality of topics; Mallet is also faster. Mallet has no visualization options. The NLP Suite builds this visualization using Excel charts.

References

Blei, David M., Andrew Y. Ng, and Michael I. Jordan. 2002. "Latent Dirichlet Allocation." *Advances in Neural Information Processing Systems*, 14.

Griffiths, T. L. and M. Steyvers. 2004. "Finding scientific topics". *Proceedings of the National Academy of Science*, 101, 5228-5235.

Sievert, Carson and Kenneth Shirley. 2014. "LDAvis: A Method for Visualizing and Interpreting Topics." Pp. 63–70 in Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces. Baltimore, Maryland, USA: Association for Computational Linguistics.

TIPS_NLP_Topic modeling Mallet installation.pdf
TIPS_NLP_Topic modeling Gensim.pdf