Latent Dirichlet Allocation models considering emojis

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0.0.1 abstract

XXX write later XXX

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1 Introduction

Latent Dirichlet Allocation(LDA) is a popular hierarchical Bayesian model that is widely used as a topic modeling method. LDA exploit statistical inference to discover latent topic of text data, however, the method depends on the number of observations - words. This dependency on observed words lead LDA to its systematic limit is when there exists data sparcity with short text data. New communication medium such as Social Network Service(SNS) and User Generated Content(UGC) platform increased the amount of text data usage, however, the size of the document is limited to a couple hundred words. Hence, LDA model is known for its low performance on these short online text due to the data sparcity.

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The use of Emoji character - a pictographic information that carries class of feelings - with other text data is a unique characteristic of online messages. Conventionally, Emoji characters have been considered as a noise and were deleted prior to applying LDA technique. In contrast with the previous procedure, this paper propose the idea of incorporating Emoji characters to enhance the performance of the LDA method on short online texts.

The use of Emoji characters have three main benefits. First, it may reduce the systematic problem of LDA with data sparcity. All Emoji characters have name and keywords associated with the contextual meaning that it conveys. By translating Emoji characters into its English name or related keywords will increase the observation, and thus lead to better LDA results. Second, each Emoji character has a couple of pre-determined topic dimension set by the official organization. This information could be used as an auxiliary information during the topic matching process. Lastly, Emoji character itself is an abstract of emotion and symbolic representation. Thus, it is natural to take the output of LDA containing Emoji translation to sentiment analysis.

The `emoji` package in `R` was written to help the above analysis.

2 LDA

LDA is a popular method to infer semantics to model a document as a mixture of latent topics.

LDA is a topic modeling method that allows words observed in documents to be explained by unobserved topics and that each word's creation is attributable to one of the document's topics.

was performed on twitter messages scraped online.

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LDA is based on the two following principles:

1. Every document is a mixture of topics
2. Every topic is a mixture of words

To illustrate, a news paper document may contain several topics such as "politics", "economy", "spots", "entertainment", and etc. For a given topic "politics", common words may be "government", "trump", "president", "congress", and etc.

LDA assumes that the probability of documents are random mixture over unseen topics, and document i having topic k follows a Dirichlet distribution with some parameter α. That is, if the probability of document i having topic k is denoted as $\theta_{i,k}$, then $\theta_i \sim Dir(\alpha)$. The second assumption says each topic is a mixture of words, and that the distribution of n^{th} word will follow a multinomial distribution conditioned on the topic z. The probability of word given a topic is denoted as β. Then β has a Dirichlet distribution with parameter η.

1. $\theta_i \sim Dir(\alpha), i = 1, \ldots, M$
2. $\theta_{i,k}$ is the probability that document $i \in \{1, \ldots, M\}$ has topic $k \in \{1, \ldots, K\}$.
3. z is word's topic drawn from a Multinomial distribution with parameter θ, i.e. $z \sim Multi(\theta)$
4. $\beta_k \sim Dir(\eta), k = 1, \ldots, K$
5. $\beta_{k,v}$ is the probability of word $v \in \{1, \ldots, V\}$ in topic $k \in \{1, \ldots, K\}$
6. w is a word drawn from a Multinomial distribution with parameter Z and β, i.e., $w \sim Multi(z, \beta)$.

The marginal distribution of word w given hyper parameter α and β is obtained by the following equation:

$$p(w|\alpha, \beta) = \int p(\theta|\alpha)(\prod_{v=1}^{V} \sum_{z_v} p(z_v|\theta) p(w_v|z_v, \beta)) d\theta$$

where

Graphical display of LDA is given in Figure 1.

2.1 LDA Equation goes here

As indicated in the above section, LDA assumes that documents are represented as random mixtures over latent topics and each topic is characterized by a distribution over words. Therefore, the frequency of each word influence the outcome of the LDA.

2.2 Removing Stop Words

Stop words are a group of natural language words that are essential in construction of grammatical structure of English. For example, words such as "a", "an", "the", "that", "these", "my", "his", "most", "with", and *et cetera* is an example of stop words. Although these words are crucial elements of English structure, however, these stop words are less important when it

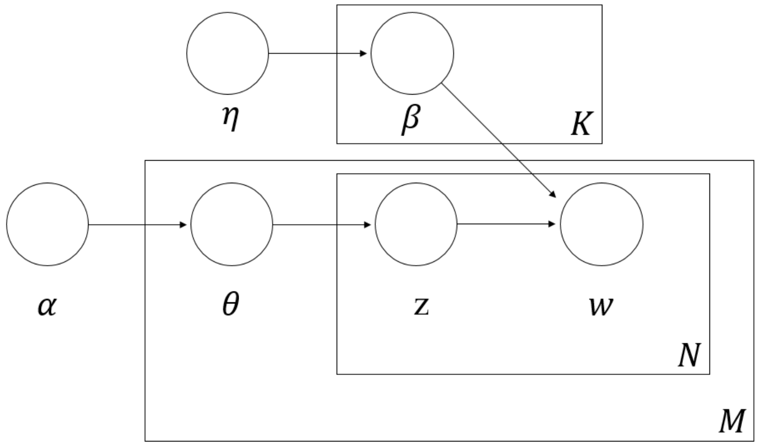


Figure 1: Graphical Model representation of LDA

comes to the purpose of delivering the meanings. Also, high frequency and abundance nature of these stop words makes little value in helping text mining techniques, and thus be filtered out.

2.3 Stemming

Due to structural and grammatical reasons of English, a family of words that are driven from a single root word is used in different forms. For example, words such as “stems”, “stemmer”, “stemming”, and “stemmed” are all based on a root word “stem”. These different form of words with the same root word may cause difficulties applying some text mining techniques. Therefore, stemming procedure should be introduced to reduce inflectional forms of a word to a word in its root form. The `tm` package is again used for the stemming process and its code is given as the following.

3 Application

3.1 Data Set and exploratory data analysis

Two samples of twitter messages with the following hash-tag #inlove and #hateher were scraped. The data set contains 944 #inlove messages, 1145 #hateher messages, and 1195 #marchscience messages. The proportion of Twitter messages containing Emoji characters per hashtag is illustraited in Table 1. 52.7% of the #inlove message strings, 29.3% of the #hateher message strings, and 7.8% of #marchscience message strings have one or more emoji information.

Table 1: Proportion of Twitter messages with Emoji

	#inlove	#hateher	#marchscience
Proportion	0.5275	0.2926	0.07782

For hashtag #inlove, total number of 1188 Emojis were used from 182 unique emojis. For hashtag #hateher, 695 Emojis from 112 unique Emojis were used. For hashtag #sciencemarch, 202 Emojis from 102 unique Emojis were used (Note that there may be multiple Emojis per Twitter message). Top 5 frequently used Emojis per hashtag is given in Table 2.

#inlove	Emoji	Count	#hateher	Emoji	Count	#marchscience	Emoji	Count
U+1F60D	😍	297	U+1F602	😂	154	U+1F52C	🔬	13
U+2764	❤️	164	U+1F644	🙄	88	U+1F30E	🌎	11
U+1F495	💕	47	U+1F621	😡	40	U+1F44D	👍	9
U+1F618	😘	40	U+1F612	😒	38	U+1F680	🚀	8
U+2728	✨	26	U+1F62D	😭	36	U+1F30D	🌍	7

Table 2: Five most popular Emoji for each hastags

It is interesting to see “Face with tear of joy” as the most popular Emoji for hashtag #hateher. Although the name itself contains the word “joy”, some users of this Emoji adopted this pictogram to express their mixed feeling of love and hate at

3.3 LDA on a raw data set

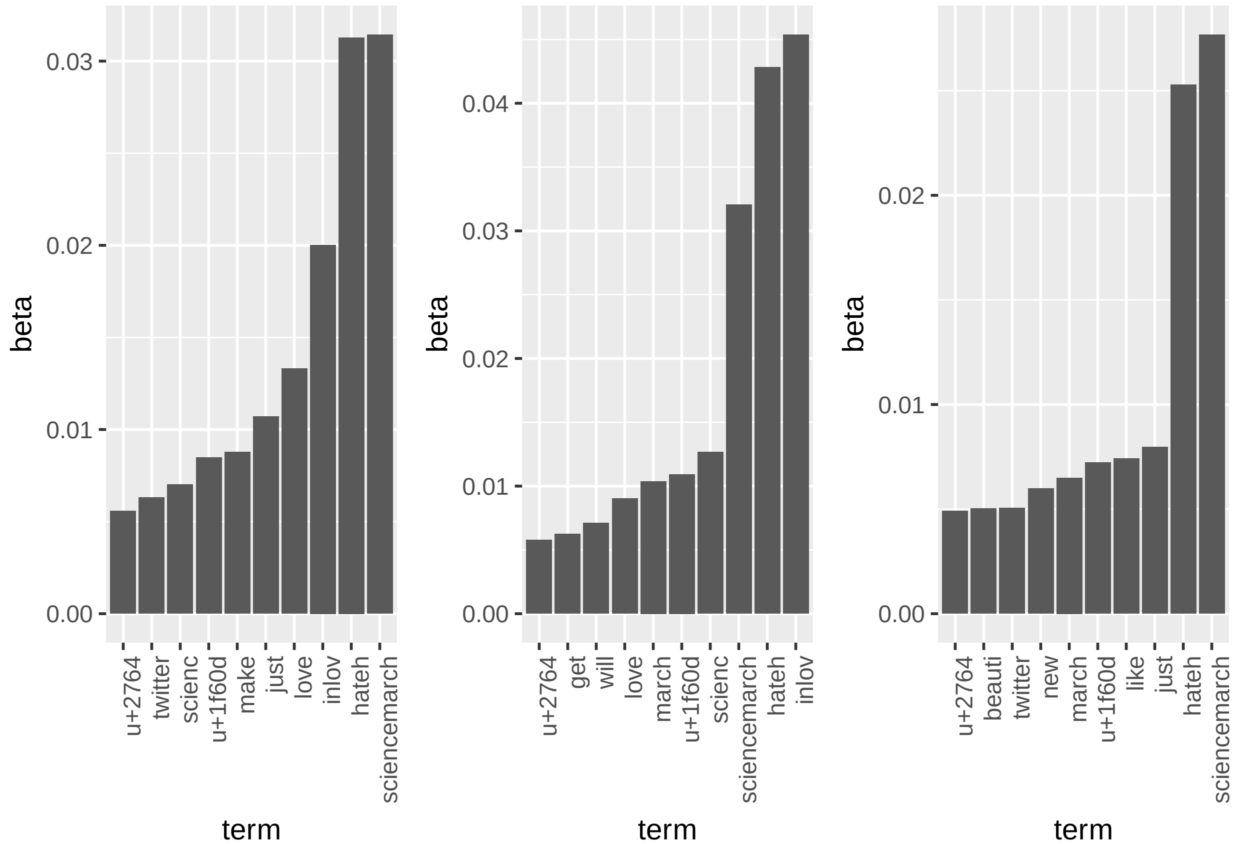
The second case was to run LDA on a raw data set. Stemming and stop word deletion were performed. Different number of topic dimensions were tested and the result of 4 topic dimension with 10 terms are provided in Table 3. Describe the output.

Table 3: Output LDA with the raw data

Topic 1	Topic 2	Topic 3
sciencemarch	inlov	sciencemarch
hateh	hateh	hateh
inlov	sciencemarch	just
love	scienc	like
just	u+1f60d	u+1f60d
make	march	march
u+1f60d	love	new
scienc	will	twitter
twitter	get	beauti
u+2764	u+2764	u+2764

Table 4: Word prob. given topic

1.term	1.beta	2.term	2.beta	3.term	3.beta
sciencemarch	0.03144	inlov	0.04538	sciencemarch	0.02768
hateh	0.03128	hateh	0.04284	hateh	0.02529
inlov	0.02003	sciencemarch	0.03207	just	0.007963
love	0.01332	scienc	0.01267	like	0.007421
just	0.01071	u+1f60d	0.01094	u+1f60d	0.007232
make	0.008777	march	0.01038	march	0.006499
u+1f60d	0.008472	love	0.009037	new	0.005988
scienc	0.007018	will	0.007123	twitter	0.005049
twitter	0.006312	get	0.006249	beauti	0.005037
u+2764	0.005584	u+2764	0.005768	u+2764	0.004917



3.4 LDA without Unicode

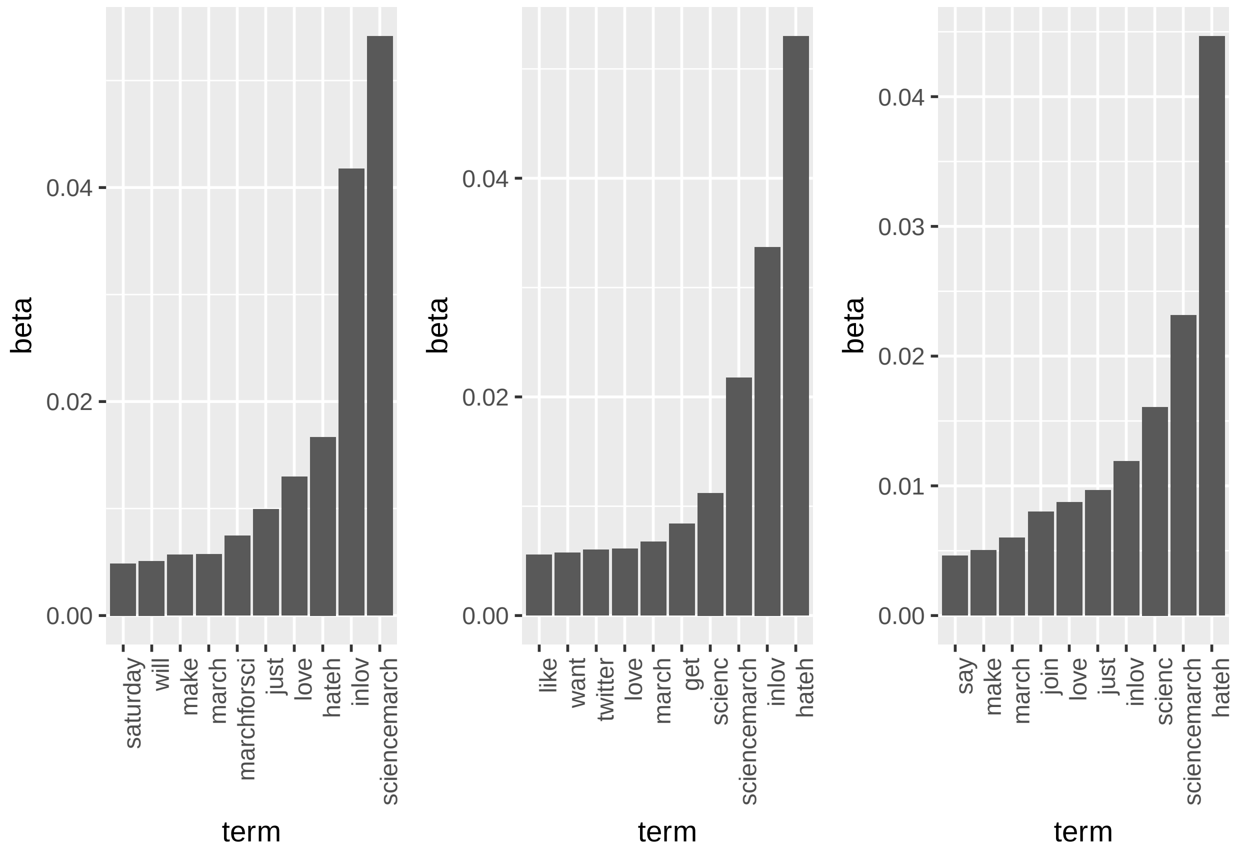
In most text mining examples, LDA is performed after removing the Unicode information. For the first case, therefore, Unicode characters were removed from the raw text data set. Then, the standard procedure of stemming and stop word deletion was performed to enhance the accuracy of LDA. `tm` package was used to conduct the above procedure.

Table 5: Output of LDA with the raw data without the Unicode

Topic 1	Topic 2	Topic 3
sciencemarch	hateh	hateh
inlov	inlov	sciencemarch
hateh	sciencemarch	scienc
love	scienc	inlov
just	get	just

Table 6: Word prob. given topic

1.term	1.beta	2.term	2.beta	3.term	3.beta
sciencemarch	0.05416	hateh	0.053	hateh	0.04467
inlov	0.04176	inlov	0.03371	sciencemarch	0.02315
hateh	0.01669	sciencemarch	0.02177	scienc	0.01608
love	0.01298	scienc	0.0112	inlov	0.01188
just	0.00995	get	0.008392	just	0.009674
marchforsci	0.007475	march	0.006736	love	0.008741
march	0.005744	love	0.006099	join	0.007993
make	0.005686	twitter	0.006017	march	0.005992
will	0.005104	want	0.005735	make	0.005035
saturday	0.004867	like	0.005576	say	0.004625



3.5 LDA with name translated

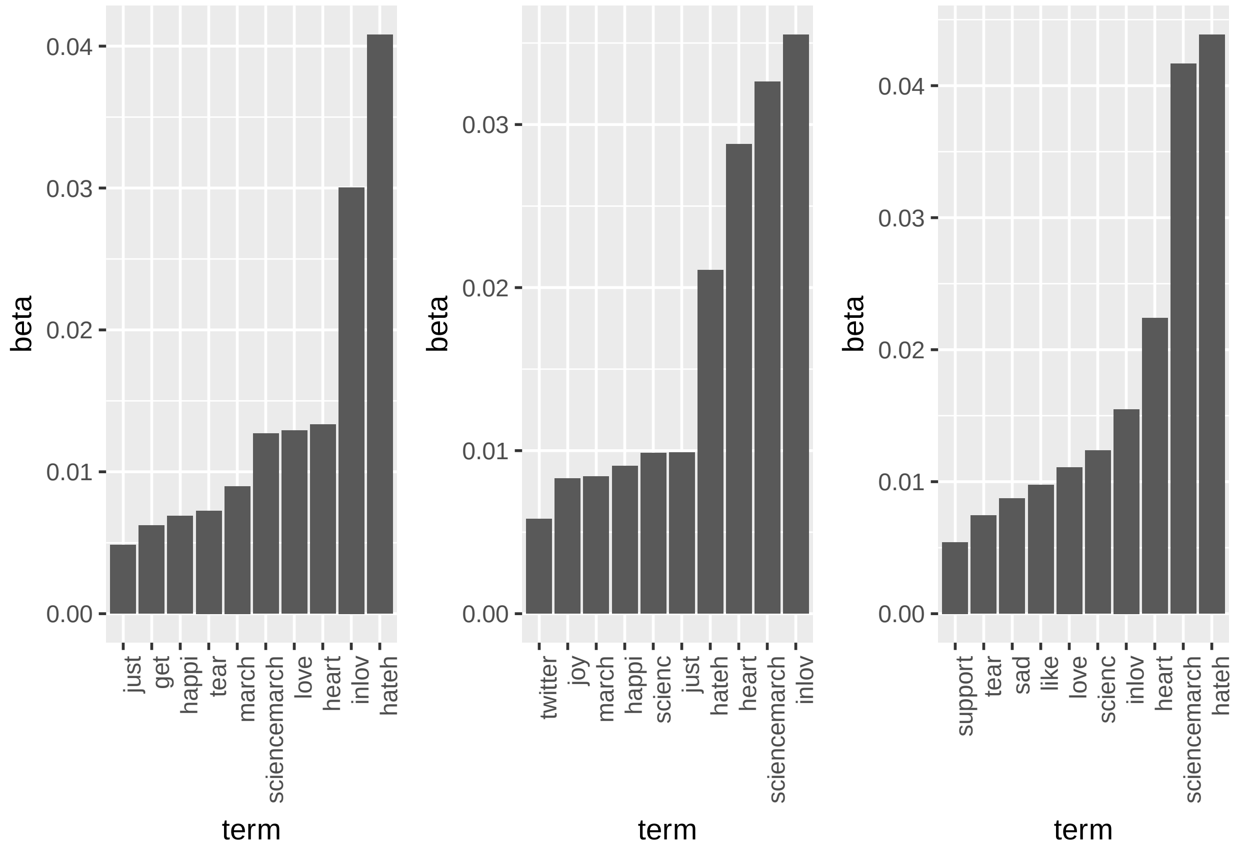
The last case was to perform LDA after translating the Unicode Emoji characters in English. `unicode` package was used to match the Unicode to its name. Then the standard process of stemming and deletion of stop words where performed.

Table 7: Output of LDA with translated Unicode

Topic 1	Topic 2	Topic 3
hateh	inlov	hateh
inlov	sciencemarch	sciencemarch
heart	heart	heart
love	hateh	inlov
sciencemarch	just	scienc

Table 8: Word prob. given topic

1.term	1.beta	2.term	2.beta	3.term	3.beta
hateh	0.04082	inlov	0.03552	hateh	0.04387
inlov	0.03005	sciencemarch	0.03263	sciencemarch	0.04166
heart	0.01333	heart	0.02881	heart	0.02239
love	0.01291	hateh	0.02107	inlov	0.01548
sciencemarch	0.01269	just	0.009882	scienc	0.01236
march	0.008989	scienc	0.009847	love	0.01109
tear	0.007262	happi	0.00907	like	0.00974
happi	0.006902	march	0.008407	sad	0.008726
get	0.006214	joy	0.008298	tear	0.00744
just	0.004859	twitter	0.005808	support	0.005421



4 Conclusion

As the result of the exploratory analysis indicates, user-generated-contents may contain Unicode Emoji characters. These Emoji characters sometimes carry mixture of condensed information that is difficult to express in words. The result of the output from the LDA indicates that words such as "heart" that would have been neglected using the traditional method may be saved when the Unicode characters are translated into meanings.

5 Appendix

6 `emoji` package in R

6.1 Emoji Data Set

Plan to change this part after posting the Emoji package on CRAN

Emoji in a text data is encoded as a sequence of Unicode: an industrial standard that consists encoding, representation, and text expression of writing system. *The Unicode Standard* is distributed by a non-profit organization the *Unicode Consortium*. The current list of Emoji v5.0 is available on the official *Unicode Consortium* website. Example illustration of the Emoji table is attached in Figure 2. Data set of Emoji characters are available in `emoji` package.

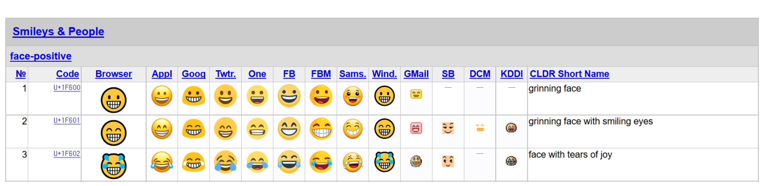


Figure 2: Glimpse of the table of Emoji on the Unicode.org website

6.2 Generate different type of encodings using Python

A script was written R that changes between different encoding environment. Plan to include this feature in the 'emoji' package.\ There are multiple way of encoding Emojis on website or SNS. Unicode, Unicode escape, UTF-8hex, zerox notation, NCR are examples of commonly used encoding. As shown in Figure 2, the initial data set scraped from the *Unicode Consortium* only has Unicode. The most common encoding type for online web page, however, is UTF-8 and Unicode escape. Therefore, the original Unicode sequence should be translated into different encoding types for the data set to be applied. Different types of encoding format were generated from the original Unicode via simple Python code.

6.3 Scoring of Sentiment

The characteristic of Emoji (effectively delivers feelings and moods), naturally leads text mining with Emoji to sentiment analysis. `tidytext` package in R has three general purpose lexicon sets. The `AFINN` score words from -5 to 5 scale, `bing` assigns words in binary category(positive and negative), and `nrc`assigns words with more categories.

6.4 Description of the Emoji Data set

The table should be updated. It is using the v4.0 Emoji list

The complete Emoji data set is saved under the 'data' directory. This complete data set is read and named 'uni_info'. Some Emojis are a combination of two or more basic Emojis. For example, Emoji 'boy: light skin tone' is a combination of 'boy' (U+1F466) and 'light skin tone' (U+1F3FB). Data 'basic_uni_info' is a data set of the basic Emojis. There are many different ways to encode 'Unicode'. The data set includes the following encoding types: 'U+hexadecimal', 'UTF-8 hexadecimal', 'hexadecimal', and 'numeric character reference (NCR)'. The example of the data set is given in Table 9

Table 9: Information of 5 Emoji data set

uni_No	uni_code	uni_name	uni_age	uni_keyws	utf_8_hex	zerox_notation	ncr	PosScore	NegScore
1	U+1F600	grinning face	2012	face	f09f9880	0x1f600	128512	0	0
1	U+1F600	grinning face	2012	face	f09f9880	0x1f600	128512	0	0.5
1	U+1F600	grinning face	2012	face	f09f9880	0x1f600	128512	0.125	0.125
1	U+1F600	grinning face	2012	face	f09f9880	0x1f600	128512	0.125	0.375
1	U+1F600	grinning face	2012	grin	f09f9880	0x1f600	128512	0	0

7 More work

1. Check Stemming - scienc vs. science
2. Check output again. Also, a check aggregation of short messages to avoid data sparsity.
3. LDA explanation
4.