2014

Web of Parody

DETECTION OF DERIVITIVE WORKS

WEESE_000

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1 Introduction

1.1 Overview

Since the introduction of Web 2.0, the user experience on the World Wide Web has ever since changed. Web 2.0 focuses on user participation, folksonomies, services, and dynamic data (O'reilly, 2009), namely a social experience. This leads to peer to peer interaction on multiple levels. Users are able to share, collaborate, and create, which has led to numerous studies on user behavior and content. This research focuses on derivative content. Derivative content or work can be defined as any content that was created based on inspiration or imitation from another work. This can include songs, movies, news articles, plays, essays, videos, and many other types of media. YouTube was chosen as the platform for the basis of this study.

1.2 YouTube

YouTube has become one of the most popular user driven-video sharing platforms on the Web. In a study on the impact of social network structure on content propagation, Yoganarasimhan watched how YouTube propagated based on the social network a video was connected to (i.e. subscribers) (Yoganarasimhan, 2012). He shed light on the traffic YouTube receives such that "In April 2010 alone, YouTube received 97 million unique visitors and streamed 4.9 billion videos" (Yoganarasimhan, 2012). According to recent reports from the popular video streaming service, YouTube's traffic and content has exploded. YouTube, in 2011, streamed over 4 billion videos per day, 3 billion hours of video is watched per month, and over 800 million unique user visits per month (Statistics, 2012). Not only that, YouTube videos are also finding their way to social sites like Facebook (500 years of YouTube video watched every day) and Twitter(over 700 YouTube videos shared each minute) (Statistics, 2012). This leads to many research opportunities like the Web of Derivative Works. With over 100 million people that like/dislike, favorite, rate, comment, and share YouTube videos, there is a plethora of relations to make (Statistics, 2012).

1.3 Problem Statement

The targeted problem for this study is detecting source parody pairs in YouTube, where the parody is a derivative work of the source. Differentiating a source from its parody is a fairly easy task; however, solving the same problem analytically presents a high level of complexity. Preliminary work shows that by analyzing only video information and statistics, identifying correct source/parody pairs can be done with decent performance. This can be improved by doing analysis directly on the video itself, such as Fourier analysis and lyric detection; however, this analysis is computationally expensive. Other information can be gained by studying the social aspect of YouTube. For the social aspect, how users interact by commenting on videos is considered. The novel contribution from this research is that, to our knowledge, parody detection has not been applied in the YouTube domain, nor by analyzing user comments. The hypothesis for this study is that by extracting features from YouTube comments, performance in identifying correct source/parody pairs. The approach of this research is to gather source/parody pairs from YouTube, annotating the data, and constructing features using out of the box toolkits for a proof of concept.

The structure of this report is as follows. The background section will discuss related works and supporting methodology. The experimental design section will discuss data collection, feature construction, and the experimental setup. Afterword, results are discussed, along with a discussion on future work and conclusions.

2 Background

2.1 Related Work

2.1.1 YouTube Social Network

YouTube is a large, content driven social network, interfacing with many social networking giants like Facebook and Titter (Wattenhofer, Wattenhofer, & Zhu, 2012). Considering the size of the YouTube network, there are numerous research areas, such as content propagation, virality, sentiment analysis, and content tagging. Recently, Google published work on classifying YouTube channels based on Freebase topics (Simmonet, 2013). Their classification system worked on mapping Freebase topics to various categories for the YouTube channel browser. Other works focus on categorizing videos with a series of tags using computer vision (Yang & Toderici, 2011). However, analyzing video content can be computationally expensive. To expand from classifying content based on content, this study looks at classifying YouTube content based from social aspects like user comments. Wattenhofer did large scale experiments on the YouTube social network to study popularity in Youtube, how users interact, and how YouTube's social network relates to other social networks (Wattenhofer, Wattenhofer, & Zhu, 2012). By looking at user comments, subscriptions, ratings, and other related features, they found that YouTube differs from other social networks in terms of user interaction (Wattenhofer, Wattenhofer, & Zhu, 2012). This shows that methodology in analyzing social networks like Twitter may not be directly transferable to the YouTube platform. Diving further into the YouTube social network, Siersdorfer studied the community acceptance of user comments by looking at comment ratings and sentiment. Further analysis of user comments can be made over the life of the video by discovering polarity trends (Krishna, Zambreno, & Krishnan, 2013).

2.1.2 Language in Derivative Works

The language of derivative works is the focus of this research. Derivative works employ different literary devices, such as irony, satire, and parody. As seen in Figure 1, irony, satire, and parody are interrelated. Irony can be described as appearance versus reality. In other words, the intended meaning is different the actual definition of the words (Editors, 2014). For example, the sentence "We named our new Great Dane 'Tiny'." is ironic since Great Dane dogs are quite large. Satire is generally used to expose and criticize weakness, foolishness, corruption, etc. of a work, individual, or society by using irony, exaggeration, or ridicule (Editors, 2014). Parody has the core concepts of satire; however, parodies are direct imitations of a particular work, usually to produce a comic effect.

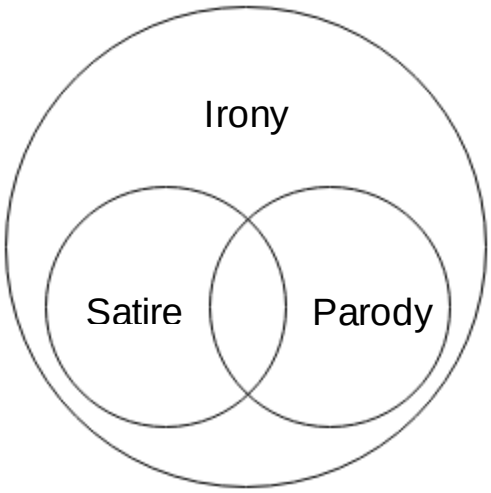

Figure 1 Literary devices used in derivative works.

2.1.3 Irony, Satire, and Parody Detection

As described in section 2.1.2, satire is used for ridiculing original works, such as news articles. Detecting such articles can be a daunting task and remains relatively untapped. Baldwin and Burfoot introduce methodology in classifying satirical news articles as being either true (the real or original news article) or satirical (Burfoot & Baldwin, 2009). In a variety of cases, satire can be subtle and difficult to detect (Burfoot & Baldwin, 2009). Features focused on were mainly lexical, for example, the use of profanity and slang and similarity in article titles. In most cases, the headlines are good indications of

satires, but so are profanity and slang since satires are meant for ridicule (Burfoot & Baldwin, 2009). Semantic validity was also introduced by using named entity recognition (Burfoot & Baldwin, 2009). This refers to detecting whether or not a named entity is out of place or used in the correct context.

Similar features can also be found in parodies. Sarah Bull focused on an empirical analysis on non-serious news, which includes sarcastic and parody news articles (Bull, 2010). Semantic validity was studied by calculating the edit distance of common sayings. This expands beyond just parody as many writings use "common phrases with new spins" (Bull, 2010). Unusual juxtapositions and out of place language was also shown to be common in parody text, for example "Pedophile of the Year" (Bull, 2010). This also leads to a comparison of the type of language used in parody and satirical articles. Non-serious text tends to use informal language with frequent use of adjectives, adverbs, contractions, slang and profanity, where serious text have a more professional approach (Bull, 2010). In contrast to serious text, parodies can also be personalized (use of personal pronouns) (Bull, 2010). Punctuation was also seen an indicator as serious text rarely use punctuation like exclamation marks. (Tsur, Davidov, & Rappoport, 2010; Bull, 2010).

As seen in Figure 1, irony encompasses both satire and parody, but can also be more problematic to detect without a tonal reference or situational awareness. As mentioned in (Reyes, Rosso, & Veale, 2012), it is "unrealistic to seek a computational silver bullet for irony." In an effort to detect verbal irony in text, (Reyes, Rosso, & Veale, 2012) focus on four main properties: signatures (typographical elements), unexpectedness, style (textual sequences), and emotional scenarios. Properties of irony detection clearly cascade down to the sub domains of parody and satire.

2.2 Class Imbalance Problem

Drummond and Holte discuss the class imbalance problem as cost in misclassification. Class imbalance occurs when there is a significantly large number of examples of a certain class (such as

positive or negative) over another. As the imbalance increases, algorithms like Naïve Bayes that are somewhat resistant to the class imbalance problem suffers performance (Drummond & Holte, 2012). Instead of using different algorithms to overcome class imbalance, the authors suggest generalizing the data to create a more uniform distribution to help overcome class imbalance (Drummond & Holte, 2012). There are various methods to create a more uniform distribution of classes in a data set. YouTube has millions of videos with a fraction of those being source/parody pairs. In order to keep the dataset in this study from becoming imbalanced, source/parody pairs were filtered to give a true to false class ratio of 2:1.

3 Preliminary Work

3.1 Data

Only information about the YouTube video was collected (video statistics), rather than the video itself. The search for videos was quite limited (search bias in which videos were chosen). Given a well-known or popular parody video, the corresponding known source was found. The problem of multiple renditions of the same source arose and to solve it, only deemed "official" sources were collected (another search bias). The term "official" refers to the video being published (uploaded) by the artistic work's artist or sponsor YouTube channel or account. The collection of known sources and parodies (28 of each) were retrieved using Google's YouTube API and stored into an XML file format for easy access.

3.2 Evaluation of Video Statistics

Four experimental models were created. Each model contained different features which were described in the previous section. The first experiment used only ratio features. The second used ratios plus the publishedAfter feature. The third experiment used only the raw data collected (no ratios) plus the publishedAfter feature; this experiment was used as the baseline used for comparison. The fourth experiment included all features. The best performance was a result of using all features noted in Table

1 (experiment 4) and by oversampling to balance the dataset. This gave a 98% ROC area; however, using the raw data as features, along with the oversampling caused overfitting. A better representative of the preliminary results was an average ROC area of 65%-70%. Note that this is only with features generated from the video statistics.

4 Methodology and Experiment Design

4.1 Data Collection

One challenge to overcome was that there is no parody dataset for YouTube and no concrete way of collecting such data. The final experimentation greatly expanded the preliminary dataset. Kimono Labs, an API for generating crawling templates, was used to generate seeds for crawling YouTube for source and parody videos (Kimono Labs, 2014). The Kimono API allowed quick and easy access to the top 100 songs from billboard.com (the week of November 3rd was used). The song titles were collected and used to retrieve the top two hits from YouTube using the YouTube Data API (API Overview Guide, 2014). Parodies were retrieved in a similar fashion, except the keyword "parody" was added to the YouTube query as well as the number of videos were bumped up to five. This helped reduce the class imbalance problem mentioned in 2.2. Pairs were generated by taking the cross product of the two source videos and the five parody videos, making 1474 videos after filtering invalid videos and videos that were not in English. Information retrieved with the videos included the video statistics (view count, likes, etc.) and up to 2000 comments.

4.2 Data Annotation

A custom annotator was built to allow users to label candidate source/parody pairs as valid or invalid. This was a crucial step in removing pairs that were not true parodies of source videos. Naively, videos could be tagged based on whether the candidate parody video title contains parody keywords

like “parody” or “spoof,” but this generates many incorrect matching with sources. Likewise, if a parody video is popular enough, it also appears in the search results for the corresponding source video. It is also important to note that source lyric videos and other fan made videos were included in the dataset, so as to extend preliminary data beyond “official” videos. Having only two annotators available, pairs that were marked as valid by both annotators were considered to be valid source/parody pairs. In future works, more annotators will be needed and as such, inter-annotator agreement can be verified by kappa statistics and other means. Annotation left only 571 valid pairs (38.74%), which shows the importance of annotating the data versus taking the naïve approach to class labels. The number of pairs used in the final dataset were reduced to 162 valid pairs (about 11%) and 353 invalid pairs (23.95%) after removing videos that did not have a minimum of 100 comments available for crawling.

4.3 Features

Extracting features from video content can come with a high computational overhead. Even though some natural language processing (NLP) tasks can be costly (depending on the size of text), this study focuses on using only features extracted from video information, statistics, and comments. One area of focus were lexical features extracted from user comments per video. Parts of speech tags were generated by two different toolkits: Stanford NLP (Manning, et al., 2014) and GATE’s TwitIE (Bontcheva, et al., 2013). This allows the evaluation of a short-text tagger (TwitIE) and a multipurpose tagger (Stanford NLP). Both were also used to analyze sentiment of user comments. TwitIE was used to produce an average word sentiment, where Stanford NLP was used for sentence level sentiment. Other features include statistical lexical and structural features like punctuation, average word length, and number of sentences. A profanity filter was used to calculate the number of bad words in each set of comments. The number of unrecognizable tokens by the parts of speech taggers was also added as a feature. This hints at the unique language of the user comments where nontraditional English spelling

and internet slang is used. All counts (sentiment, parts of speech, etc.) were normalized to percentages to take into account the difference in the number of comments available between videos. Another large portion of features generated were by using Mallet (McCallum, 2002), a machine learning toolkit for natural language. The built in stop word removal and stemming was used before collecting the top 20 topics for all parodies and sources for each training dataset.

4.4 Experiment

Experimentation was setup using a 10 fold cross validation with 90% of the data used for training and 10% used for testing. All features were generated per video automatically with the exception of a few features like title similarity, which requires both videos to construct the feature. Topic features were constructed by training the topic model in Mallet using the training data sets and then using that model to infer the topics for the test datasets. Two data configurations were used to test whether or not the occurrence of "parody" would introduce a bias to classification. A synset was created for removing these occurrences: {parody, parodies, spoof, spoofs}. The data configurations were then combined with different feature arraignments to test the impact of using Stanford NLP, TwitIE, and video statistics. All classification tasks were done using the machine learning tool We ka (Hall, et al., 2009).

5 Results

Results were averaged across all 10 folds. The f-measure, standard deviation, and standard error can be found for each feature configuration in Table 3,Table 4, and Table 5. On average, the best performing inducers were MLP and IB1 at 90%-93% f-measure. J48 performed well, but after looking at the pruned tree, the model tended to overfit. With the addition of features from user comments, performance increased significantly when compared to the preliminary work which used only video

statistics. Stanford NLP is shown to produce more relevant features than the TwitIE parts of speech tagger (Table 3 and Table 4). When the TwitIE features were removed (see Table 4), performance was relatively unaffected (1%-2% at most). Logistic is an exception to this analysis as it dropped 6.59%; however, this is taken as an intrinsic property of the inducer and requires further investigation. The removal of the video statistic features, however, did reduce performance for most inducers, showing that the popularity of a video helps indicate the relation between a parody and its source. Removing the parody synset did not have a heavy impact on performance. This is an important find, such that the word "parody" does not degrade classification of source/parody pairs.

The most influential features were seen by using feature subset selection within Weka. This showed that source and parody topics were most influential in the classification task. However, some topics clusters tend to overfit to popular videos or artist, especially for source videos. Generic clusters were also formed for things like music, humor, appraisal (users liked the song), and hate. A few unexpected topics also appeared, which show that current events also make it into the trending topics of the videos, for example: Obama, Ebola, and religion. Other feature analysis concluded that personal nouns were not relevant. This contradicts related work in 2.1.3. Lexical features that were relevant included verbs, symbols, periods, adjectives, average word length in parody comments, and undefined or unrecognized tokens. Sentiment also showed promise during feature selection, though further experiments and dataset expansion will be needed to achieve more insightful feature selection.

6 Summary and Future Work

The original hypothesis of this study holds. After introducing features extracted from comments, classification of source/parody pairs improved. The hypothesis also held after removing the parody synset. This generalizes the approach and makes it applicable to other domains, such as improving search, classifying news articles, plagiarism, and other derivative work domains. The proof of concept in

this study leaves many possible directions for future research, including domain adaptation and feature expansion. Features left for future work include named entity recognition (this can help detect original authors of works), unusual juxtapositions and out of place language (Bull, 2010), sentence structure beyond punctuation (Reyes, Rosso, & Veale, 2012), and community acceptance of comments to supplement sentiment analysis (Siersdorfer, 2010).

7 Acknowledgements

I would like to thank my RPE committee for the support of this project, Dr. William H. Hsu for the original research domain, and Tracy Hsu for helping with data annotations.

8 Appendix

Feature	Description
ratingOne and ratingTwo	The average rating of each video
commentCountOne and commentCountTwo	The number of comments for each video
dislikeCountOne and dislikeCountTwo	The number of dislikes for each video
durationOne and DurationTwo	The length of play time for each video in seconds
favCountOne and favCountTwo	The favorite count of each video
keyWordsCountOne and keyWordsCountTwo	The number of key words for each video
categoriesCountOne and categoriesCountTwo	The number of categories for each video
likesCountOne and likesCountTwo	The number of likes for each video
viewCountOne and viewCountTwo	The number of times each video has been viewed
avgRatingRatio	The ratio of average ratings
commentCountRatio	The ratio of the number of comments
dislikeCountRatio	The ratio of the number of dislikes
durationRatio	The ratio of video length in seconds
favCountRatio	The ratio of the number of times favorited
keyWordsCountRatio	The ratio of the number of keywords
categoriesCountRatio	The ratio of the number of categories
likesCountRatio	The ratio of the number of likes
viewCountRatio	The ratio of the number of views
publishedAfter	This is a boolean value attribute. This is true if the first video in the pair is published on YouTube after the second video in the pair.
classifier	This is the feature used to label each instance. The values it can take on are source, parody, and negative. That is, an instance is labeled as source if the first video in the pair is the source of the second video, parody if the first video in the pair is a parody of the second video, and negative if the first video is neither a parody nor source of the second video in the pair.

Table 1 Features of the Preliminary Experiment

Feature	Description
sentenceCount	Number of sentences from comments
Stanford NLP Sentiment	Sentiment of comment sentences which range from very negative to very positive.
avgCommentSentiment	Average word sentiment from TwitIE
badWordCount	Percentage of words that are profanity
Penn Treebank NLP	The parts of speech tags in the Penn Treebank generated by Stanford NLP
Penn Treebank TwitIE	The parts of speech tags in the Penn Treebank generated by TwitIE
Punctuation	Punctuation marks
WordCount	Number of words in comments
averageWordLength	Average length of words in comments
Top 20 Mallet Topics	The top 20 topics generated by mallet for source videos and for parody videos.
Views	Number of views the video received
Likes	Number of likes for the video
dislikes	Number of dislikes for the video
favCount	Number of times the video was favorited
commentCount	Number of comments the video has
titleSimularity	The edit distance of the parody and source video titles.

Table 2 Features of the final experiment. Note that each are unique to the source video and the parody video except titleSimularity which is for both.

Average F-Measure: Stanford NLP, TwitIE, and Video Statistics						
Inducer	**With Parody Synset**			**Without Parody Synset**		
	AVG F Measure	STD	STD-ERR	AVG F Measure	STD	STD-ERR
IB1	91.01%	2.87%	0.91%	91.39%	3.17%	1.00%
J48	90.78%	4.11%	1.30%	85.67%	5.99%	1.89%
JRip	86.60%	5.06%	1.60%	82.14%	5.58%	1.76%
Logistic	87.95%	2.87%	0.91%	88.29%	3.72%	1.18%
MLP	91.35%	3.36%	1.06%	90.44%	2.64%	0.83%
NaiveBayes	82.37%	4.21%	1.33%	80.18%	3.87%	1.22%

Table 3 Results for the Stanford NLP, TwitIE, and video statistics feature set.

Average F-Measure: Stanford NLP and Video Statistics						
Inducer	**With Parody Synset**			**Without Parody Synset**		
	AVG F Measure	STD	STD-ERR	AVG F Measure	STD	STD-ERR
IB1	92.59%	2.96%	0.94%	93.15%	3.19%	1.01%
J48	90.70%	4.21%	1.33%	85.05%	4.88%	1.54%
JRip	85.80%	4.57%	1.45%	86.16%	4.96%	1.57%
Logistic	86.80%	4.65%	1.47%	81.73%	5.10%	1.61%
MLP	90.28%	3.65%	1.16%	90.09%	3.06%	0.97%
NaiveBayes	82.55%	4.50%	1.42%	78.50%	3.69%	1.17%

Table 4 Results for the Stanford NLP and video statistics feature set.

Average F-Measure: Stanford NLP						
Inducer	**With Parody Synset**			**Without Parody Synset**		
	AVG F Measure	STD	STD-ERR	AVG F Measure	STD	STD-ERR
IB1	92.39%	2.87%	0.91%	92.94%	3.19%	1.01%
J48	88.50%	3.41%	1.08%	86.87%	4.25%	1.34%
JRip	84.06%	3.83%	1.21%	81.63%	4.80%	1.52%
Logistic	82.94%	6.41%	2.03%	81.73%	5.03%	1.59%
MLP	88.73%	2.87%	0.91%	87.71%	3.08%	0.97%
NaiveBayes	78.51%	4.70%	1.48%	75.14%	4.11%	1.30%

Table 5 Results for the Stanford NLP feature set.

Topic Number	Coefficent	Words in cluster
0	0.03733	jason selena aldean justin trumpets sos burnin heart amnesia keith lyrics car trumpet cry gomez urban derulo picture beginning
1	0.06791	ariana grande bang rude jessie harder zedd gotta free break weeknd love starbucks voice marry ari thought lol magic
2	0.05891	shawn love direction zayn harry omg proud hair niall amazing weeknd perfect louis guys liam video big life boys
3	0.07676	taylor kendrick swift sean lamar hop hip car kanye big driving album message shake lol positive rap eminem gonna
4	0.11248	nigga black white shit week ago bobby type rap lol song bitch zone flex dance racist niggas beat bad
5	0.03017	ellie calvin maroon video harris goulding animals adam maps creepy lyric map leads miss sad eat levine alive tonight
6	0.06159	video sia chandelier ella dance rihanna dancer ghost girl drink dancing voice thought maddie amazing henderson lyrics gonna lyric
7	0.14298	shit song fuck nigga young beat thug lol money drake lyrics dope sounds ass wiz rap niggas yall hard
8	1.38529	song love good amazing great music awesome songs nice voice lyrics don beautiful im time check favorite listen sounds
9	0.05161	la ed fergie sheeran video dangerous pitbull fireball thinking back ebola loud ich ebo dance john official ryan das
10	0.05645	country music video great luke blake soundsofsunday bryan week waves dirt http countrymusic probz mr scotty pop youtu roller
11	0.22741	de la es esta el en http youtu ft version cancion se enrique cancin video lo music una bailando
12	0.03765	chris blame brown calvin ross usher rick harris john newman trey clap boom flame ft beat songz deadmau fault
13	0.02635	happy pharrell williams high tove lo alesso video heroes stay youtu massage drugs http feel minions habits life remix
14	0.05648	people beautiful don wrong skinny fat secrets meghan care feel mary bass girls message nico world colbie vinz pretty
15	0.05188	script imagine dragons band album guys superheroes awesome life fall video bet boy songs centuries remember ve power amazing
16	0.07931	gay god sam people smith girls stay made men women sexist don man gays religion world voice beautiful christian
17	0.93417	video people music don song hate good fuck shit make fucking guys dont stop bad time girl lol doesn
18	0.02447	tinashe john legend ink kid video lindsey guetta usher david youtu http beautiful stirling violin language body xwsyvbyzcx johnlegend
19	0.07614	nicki iggy minaj katy august ass gwen black perry lol booty azalea video big baby rap anaconda butt nash

Table 6 Sample topics from a set of source videos

Topic Number	Coefficent	Words in cluster
0	0.1087	black shit song nigga bitch rap bobby jack miley lil lmao music markiplier ass hot angie guys yall drake
1	0.12842	de la una el es parodia shakira ooh en day se esta fergie song life por te como con
2	0.06403	sad demi cry cried ik je crying de het een die toby song en dit died van ryan dat
3	0.05462	obama secret liberal romney bush states red president chicks country liberals government work god dixie average republicans google war
4	0.0873	fuck give tuesday josh song cute school bird spanish xd nicki day lol boom awesome original friday chainsaw minaj
5	0.05071	song game guys play make awesome xd instalok songs disney good sion nice league style fire great scar lol
6	0.09857	love justin song dad cute direction joey bieber shane kid awesome ki ds guy mom daughter end girl hot nate
7	0.04261	ich das ihr und ist die geil nicht mal der von es aber video cool euch ein parodie gut
8	0.03901	alex richard rolanda guys love funny song roi skinny fat meghan video cute cameron videos bass lol trainor people
9	0.05728	ebola star racist wars la cancer link http spanish google joke man portuguese dubstep africa brazil apple jesus dogs
10	0.13231	bart baker love taylor ariana bang make iggy video stupid song swift funny nicki bass grande fun black hate
11	0.02377	ghost joan rivers ghosts cod musical game na chwytak call rip boobs duty nie jest mayday ops jak mario
12	0.13505	song love country music video good listen movie songs don great joe big pop awesome jason band gwen boy
13	0.04021	jimmy omg katniss love surgery plastic jennifer peeta maddie friends patrick movie girl dance rue guillermo girls bangs kelly
14	0.72347	lol funny love xd video omg haha hilarious good make videos awesome lmao im hahaha watch guy girl wtf
15	0.78652	people don song video make good hate made fuck time dont thing fucking bad god shit feel true didn
16	0.03466	batman superman man germany gay german super fuck spider movie spiderman arnold dc hitler beat kryptonite lol austria dark
17	0.4271	love song amazing good voice video great awesome beautiful sing music cover omg ed job wow perfect singing nice
18	0.06407	la de est le il xd les siete ma che si je video trop di pas qui super sa
19	0.10462	song love minecraft awesome cool good make mine video nice night epic lol creeper zombie game xd play great

Table 7 Sample topics from a set of parody videos

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