

# Study on the Evolution of Users' Interests on Social Q&A Community with WBTM: A Case Study of Quora

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## Abstract

This paper analyzes the users' interests and their evolution characteristics of on the social Q&A Community, so as to guide the personalized recommendation and advertising on Quora *Film and Television* topics. The data obtained by crawler were divided and cleaned according to the period, and the question and answer text within the period was endowed with user behavior data, and BTM (Biterm Topic Model) was adopted to conduct Topic mining and Topic identification. To improve the effect of mining topics, we propose a new model – Weight Biterm Topic Model (WBTM) by weighting the question answering text with user behavior data. The results show that our model has higher coherence values. Finally, the trend chart of theme evolution is drawn and analyzed by means of thermal map to make personal suggestions on recommendation and advertising of Quora *Film and Television* and other topics.

## 1. Introduction

The social Q&A platform is an emerging knowledge sharing platform developed based on Web 2.0. This platform has no clear organizational structure and allows users to ask questions or answer at any time according to their needs[1]. The core of the social question and answer platform is user participation. The role of users is vague and not clearly defined. They can be information generators or consumers of information. Moreover, with the popularization of the Internet, online Q&A communities have exploded and become important knowledge sharing platforms, such as Quora and StackOverflow in the United States, and Zhihu in China[2]. The online Q&A community provides a platform to create and share knowledge by posting and answering questions. The topics on the platform cover a wide range of topics through questions, opinions, experiences, and comments. By posting or searching questions and collecting answers, users can quickly learn

and adopt knowledge related to their areas of concern, most of which are first-hand answers from domain experts[3]. As a result, people will become more and more accustomed to obtaining topics or news they are interested in from online social platforms, which makes user personalized recommendations an important online service. However, on the one hand, the accuracy of topic mining on the social question and answer platform still needs to be improved. On the other hand, there are relatively few studies on the evolution of user interest under a topic on the social question and answer platform.

At present, Quora is a relatively popular social question and answer platform in foreign countries, established in 2009. At the beginning of its establishment, it adopted the invitation registration system, attracting elites from all walks of life. One year later, it will be officially open to the public. Users can log in to Quora with their social networking site accounts to prevent the corresponding content from being searched through search engines. As an online knowledge sharing community, Quora implements the idea of IT flattening and maps people's actual social life to the Internet through online social networks. People co-author content on the Q&A website Quora and find satisfactory answers to their questions. It allows users to editing and answering questions collaboratively, which brings together a large number of questions and answers, providing a good research context for mining user interests and analyzing evolutionary laws in the platform.

Therefore, this paper selects Quora, a popular social question-and-answer platform, and hopes to identify Quora's user interests from the perspective of topics by using the topic mining model. On this basis, this paper considers the combination of auxiliary data such as the number of views in the question and answer in the topic to add weight to the text data. The weighted text data in our experiments show great optimization in the result of topic classification. Finally, this paper analyzes and processes the topic evolution trend under the topic and uses content analysis to analyze the evolution trend, which is very helpful for understanding current user discussion hotspots and further tracking hot topics in the social Q&A platform. It has very good guiding significance for user personalized recommendation, advertisement placement and public opinion supervision.

## **2. Related work**

At present, researches on socialized question-and-answer platforms are widely distributed, and related researches are distributed in exploring the growth mode of knowledge quality[3], user interaction mechanism research[4], opinion leader generation[5] and detection[6], opinion extraction[7] and Interest preference mining[2] and many other aspects.

### **2.1 Topics mining related research**

In terms of topic mining and interest preference acquisition of social question and answer platforms, Jiang[8] et al. used upvote number to study user interest preferences under the topic of Climate Change. Here, this paper hopes to obtain user interest under a topic and study its evolution trend through topic mining. At present, more researches are carried out based on user text information through methods of identifying and analyzing topics under certain real topics, such as the Latent Dirichlet Allocation (LDA) model proposed by Blei[9] et al. in 2003. For different situations, some scholars have improved the model and tried to apply it to various short text topic mining fields. The classic improved models include ATM[10], Twitter-LDA[11], Labeled-LDA[12] and other models.

However, the LDA model ignores the relevance of text topics between documents. For short texts on social question answering platforms such as Quora, its sparse co-occurrence mode will lead to more serious data sparse problems[13]. A simple and popular way is to aggregate tweets posted by a single user into a document before training LDA, and re-aggregate short text into pseudo-long text[14]. Zhao[11] et al. provided another solution, that is, assuming that a short text document has only one topic, this also causes the model to lose the ability to capture multiple topics in a document.

Therefore, Yan[15] et al. proposed a way to expand the hypothesis, that is, since there is correlation between short text documents, and because the traditional topic model modeling cannot well consider the correlation between short text documents when it comes to the problem of data sparseness, we can consider extending the correlation assumption between documents to the entire corpus space to establish a Biterm Topic Model (BTM). BTM increases the possibility of

vocabulary belonging to other topics through assumptions, so that the effect of the BTM model in short text becomes better, and the effect of topic mining in ordinary text is also quite good. Based on the above discussion, in order to more accurately describe the topic heat of the short text document topic, this paper considers BTM as the basis, adopting the combination of the user's text information and the user's views number under the topic to add weight on the vocabulary to improve the effect of topic mining.

## **2.2 Topics evolution related search**

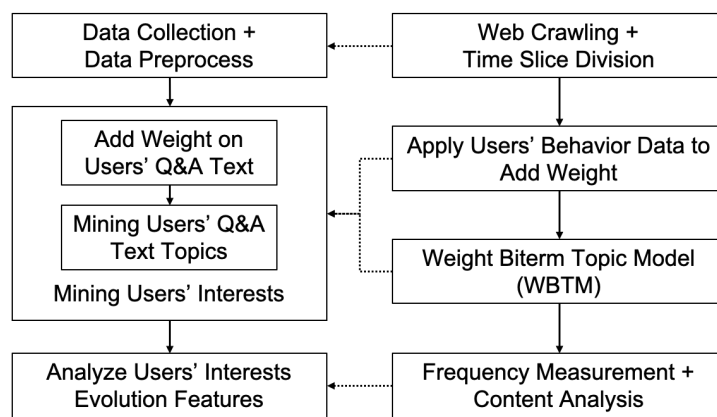
In the topic evolution research of the social question and answer platform, Maity[16] et al. used all the content under Quora as the research background, adopted the method of crawling topic tags to obtain topic popularity and used regression analysis to predict the evolution trend; Barua sorted out the relationship between hot topics and analyzed their evolutionary trends by classifying the topics in StackOverflow through the LDA model[17]; Zou[18] et al. used LDA as a topic mining tool to analyze the NFRs (Non-functional requirements) to classify topics and obtain the occurrence rate of each topic to indicate its popularity, thereby making an evolutionary trend and conducting a qualitative analysis. The above research mainly takes all topics in the entire platform as a research perspective. This paper hopes to study the user's interest and evolution trend of social question and answer platforms from the perspective of topics in the platform. In addition, the above research did not adopt a topic mining model that is more suitable for the platform to study user interests and their evolutionary trends.

To sum up, at this stage, there are deficiencies in the selection of topic mining methods and the analysis of evolution characteristics for the evolution of user interest in social question and answer platforms. This paper will fully consider the characteristics of the social question and answer platform to choose a more appropriate method to identify the topic under the topic in the platform. On this basis, the frequency measurement method will be used to evaluate the popularity of the topic evolution in the time dimension, and then use The content analysis method reasonably analyzes its trend and puts forward some suggestions on the personalized recommendation strategy of the social question and answer platform and advertising.

### 3. Methodology

#### 3.1 Data collection and data preprocess

In order to analyze the identification and evolution trend of user interest in social question and answer platforms, this paper roughly follows the general paradigm of data collection, data preprocessing, data mining and data analysis to design the research technical route (shown in **Fig. 1**).



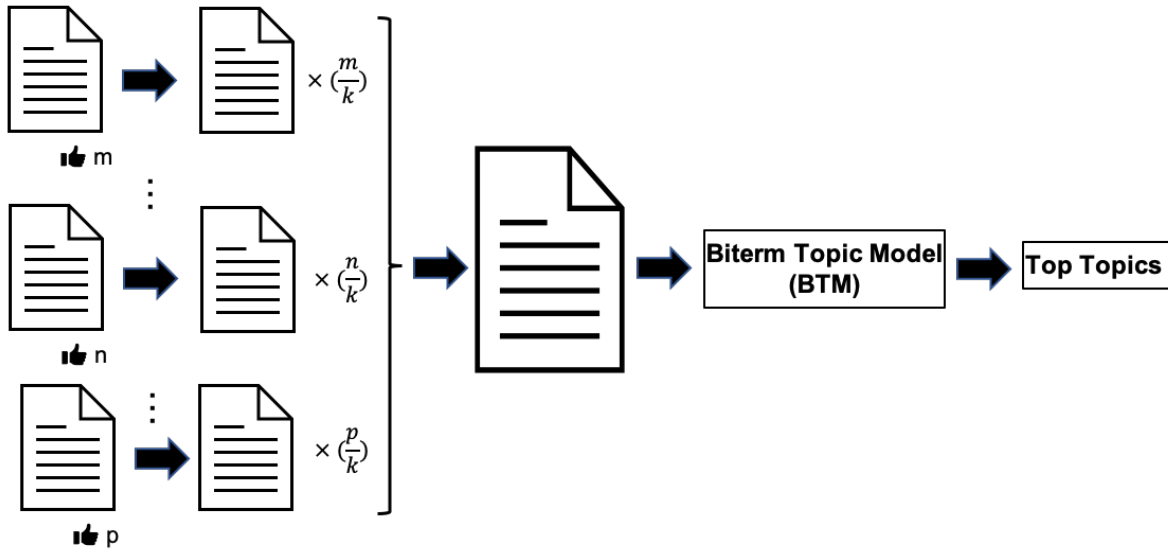
**Figure 1.** Architecture of Research on the Evolution of Users' Interests of Online Q&A Community

First of all, in terms of research content, this paper selects the social question and answer platform Quora as the research scene, but there are many topics under Quora, and selecting the right topic has a profound impact on the research of user interests or topic evolution. The topic that is more suitable for evolution analysis should have the characteristics of faster evolution and more obvious characteristics of evolution, and the topic of *Film and Television* fits these conditions.

Subsequently, with the help of Python web crawler and database manipulation technology, this paper collected and preprocessed all the Q&A texts from December 17, 2018 to April 14, 2019 under the topic of *Film and Television* in Quora. Among them, the preprocessing work is mainly to use the NLTK package in Python to remove stop words and number punctuation in English, and all lowercase. Then, it is necessary to set the length of the time slice based on the evolution law under the topic to prepare for the analysis of user interest evolution.

### 3.2 Proposed model based on original BTM

In terms of user interest topic recognition, this paper combines user behavior data to weight the question and answer text. The original BTM did not consider the influence of user behavior on the topics heat. Therefore, we propose a new model – Weight Biterm Topic Model (WBTM) by replicating text with respect to the number of upvotes to show the weight of certain answer or question (shown in **Fig. 2**).



**Figure 2.** Architecture of Adding Weight on Text Collected from Online Q&A Community.

As shown in the figure,  $k$  is the threshold of replication, and the text collected from Quora will be replicated once when this text upvoted  $k$  times. After combining those text into a whole document with weight on certain text, BTM will be applied to classify them into different topics. Comparing our experiment results on coherence values of topics, the WBTM show great improvement on this respect.

Besides, through experiments, the weighting parameters and the number of divided topics that BTM need to set are determined. The data under each time slice is based on the theme of the *Film and Television* drama. The categories are subject to identification and induction.

Finally, the frequency measurement method was used to identify the user interest topics in each time slice. The topic to which the document belongs is determined according to the number of topics corresponding to the maximum topic probability distribution in each document, and the topic popularity is expressed by counting the occurrence frequency of each topic in all documents. Then, according to the changing trend of the theme in the seventeen weeks, this paper will use heatmap to draw the evolution trend chart, and on this basis, use content analysis to study the characteristics of the theme evolution, and summarize the topic evolution trend of the social question and answer platform, and some suggestions on Quora's personalized recommendations on this topic.

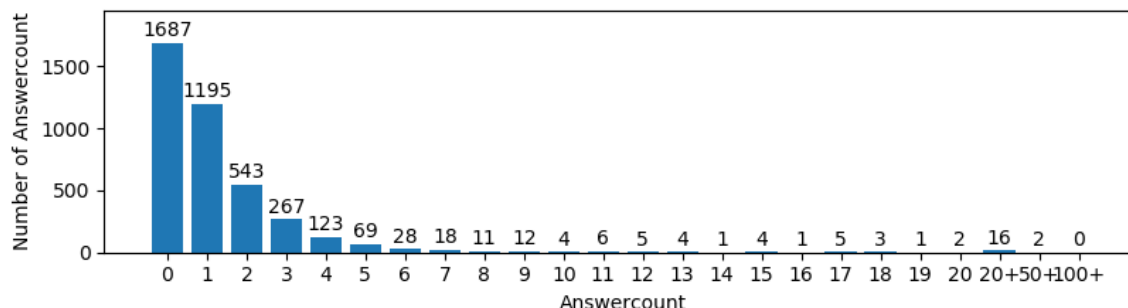
## 4. Experiment Setting

### 4.1 Data preparation

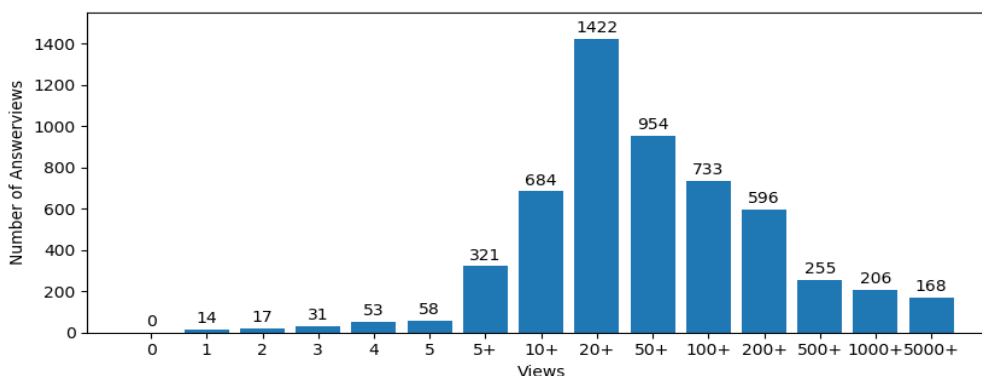
This paper uses Python as the crawler language. After logging into Quora with the help of webdriver in selenium, select the 'All Questions' option under *Film and Television* to enter the list of questions under the topic. Most of the questions are arranged in chronological order from the present to the past. This paper uses BeautifulSoup in bs4 to analyze the links of all questions in the webpage from December 17, 2018 to April 14, 2019 (17 weeks in total) and save them to the MySQL database. Next, by visiting each question link in MySQL, this paper uses the method of simulating login and analyzing the webpage to extract (1) the link of the question; (2) the title of the question; (3) the total number of answers to the question; (4) the last time of following this question; (5) the text information of the answer to this question (pictures, videos and other information are not considered); (6) the time of the answer; (7) the number of views of the answer is saved in the MySQL database.

In this paper, a total of 3849 questions and 6212 answers data were collected through crawlers. After that, a statistical analysis of the number of question answers (**Fig. 3**) showed that most questions only have 0 to 1 answer, and a few questions can get more than 10 Answer. This also shows that there will be a lot of personalized ideas and questions under this theme. But judging

from the distribution of questions with 6 to 20 answers, the downward trend is not very obvious, which also shows that there are many common problems under the topic.



**Figure 3.** The Number of Answer Distribution Under Topic *Film and Television* (Dec 17, 2018 – Apr 14, 2019)



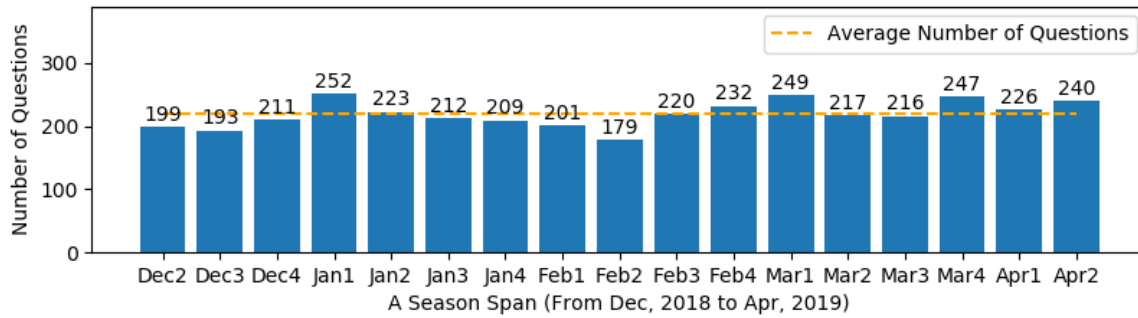
**Figure 4.** The Number of Views in Each Q&A's Distribution Under Topic *Film and Television* (Dec 17, 2018 – Apr 14, 2019)

According to the distribution number of views under each Q&A in the seventeen weeks are in **Figure 4**, after removing the unanswered questions, it can be found that the answer has been increasing from the time the answer is viewed once to the answer is viewed more than 20 times. And the number of answers that have been viewed more than 5 times is growing rapidly. In addition, from the distribution of the histogram, it is roughly in line with the right-skewed distribution, and most of the questions will be viewed 20 to 50 times. In addition, this paper also found that the number of answers that have been viewed more than 1,000 times and 5,000 times is

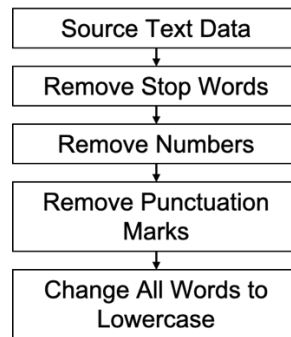


still considerable. This phenomenon indicates that some questions and answers under the topic have attracted more users' attention, and the answers have also been praised by many users, indicating that the topic *Film and Television* has strong reader resonance. Therefore, studying the user's theme preference and theme evolution trend under this topic will have strong help and guiding significance for the improvement of user recommendation effect.

Since the update cycle of British and American dramas and TV shows is one week, this paper sets the time section to one week to analyze the evolution of user interests. Therefore, from December 17, 2018 to April 14, 2019, it is divided into seventeen weeks. The distribution of the number of weekly questions is shown in Figure 5, which shows that the number of questions in a week is 210. Floating up and down, the overall data distribution is relatively stable.



**Figure 5.** The Q&A Distribution in Different Time Section (Dec 17, 2018 – Apr 14, 2019)



**Figure 6.** Data Cleaning Process

Next, the data cleaning process mainly uses the **nltk** package in python to clear the stop words, numbers and punctuation marks in English by using the question and answer data divided by week,

and change them to lowercase (as shown in Figure 6) , and save the organized documents for use in topic mining of next procedure.

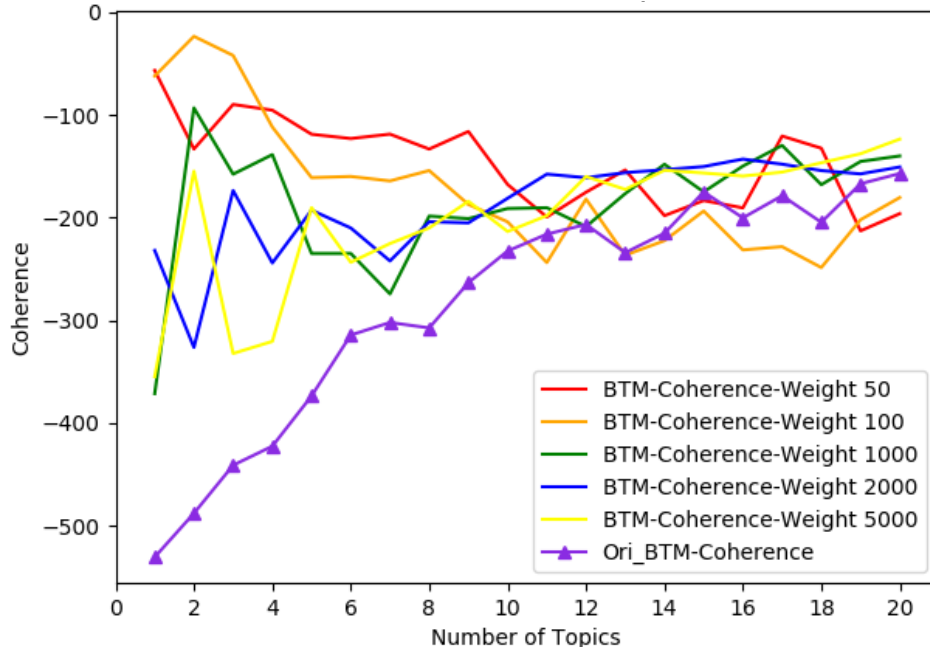
## 4.1 Data mining experiment

When using topic mining models such as BTM to identify topic interest in text data, how to set the number of classified topics is usually a tricky problem. Getting feedback through experimental results and debugging in combination with actual conditions is a powerful way. In addition, considering that the number of views of the text content should be able to reflect the importance of the text, and many answers under the *Film and Television* topic have been viewed more than 1,000 times (shown in **Fig. 4** above). Therefore, this paper considers re-editing and evaluating the text information.

Here, the weighting method of text data in this paper is expanded by answering the number of viewed, that is, first set a threshold value, and the content of the answer under the topic is viewed more than once, and the browsing value will be copied once in the document. Regarding the weight parameters of the weighted text, it is also necessary to debug through the result feedback of the experiment, and judge whether the BTM effect of the weighted text is significantly improved.

How to select the appropriate number of topics in BTM is a key factor, and its value will have a certain impact on the coherence value of the final topic mining and the actual mining effect. Here, the number of iterations of the preliminary tentative model is 20. At the same time, in order to compare the training effect of using unweighted text data and weighted text data and to pre-tune the parameter value of the number of topics in BTM, this experiment feedbacks will be inspected through figures. Therefore, questions and answers data over 50, 100, 1000, 2000, 5000 times will be copied once in different experiment setting.

Using the question and answer data from April 8, 2019 to April 14, 2019 as the training sample, the coherence value of each topic is obtained with the help of the coherence calculation method inside BTM. After averaging the coherence value of each topic, the preliminary experimental results will be shown in Figure 7.



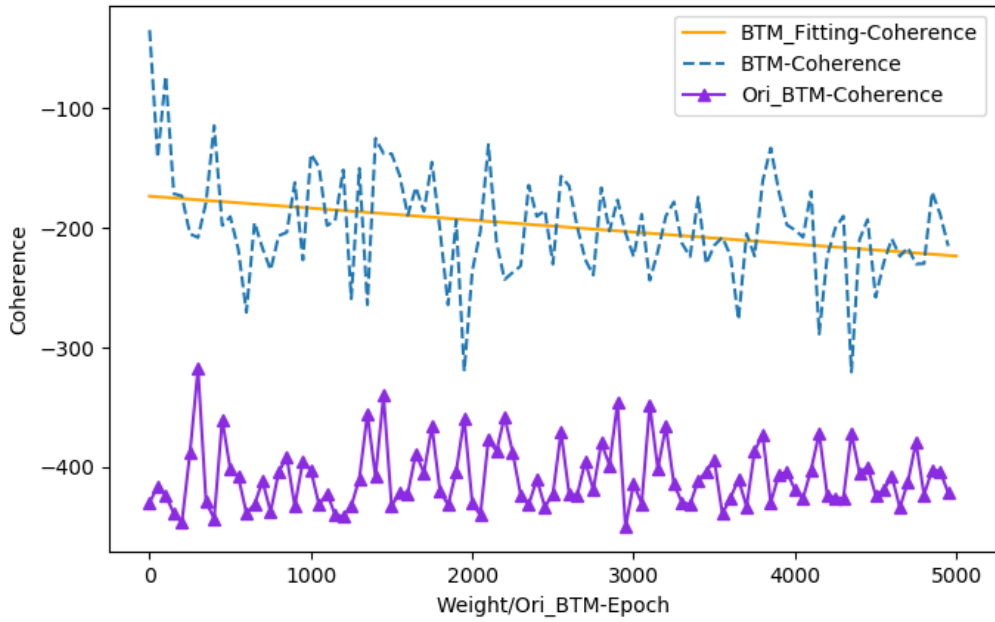
**Figure 7.** Example Comparison of Weighted and Unweighted Text Topic Mining Coherence Values Under Different Number of Topics

Through experimental comparison (as shown in **Fig. 7**), it is found that the coherence value of topic classification for unweighted text is not very high at the beginning, and it gradually increases as the number of topics increases. It can also be found here that as the weight value increases, the coherence value of the weighted text will approach the unweighted text. The reason for this is that when the weight threshold is set higher, the number of weighted texts will be less, closing to the case of unweighted text. But what is surprising is that its coherence value will be better than the value of unweighted text when the number of topics is less than 10 regardless of the weight setting.

Taking into account the reality that the number of questions for *Film and Television* topics in short text documents such as Quora will be about 200 and the number of questions and answers will be about 700 in the next week, the model here should be set within 10.

As to the threshold value of replicating text to add weight, this paper selects the number of topic categories at 6, and sets the replicating threshold value from 50 to 5000 with step size of 50, that

is, from the answer being watched once and then being copied once to the answer being watched more than 5000 times and then being copied again (was shown in **Fig. 2**). From the experimental results in Figure 8, it can be seen that the coherence value of WBTM shows a downward trend after being fitted by a linear function, and the weight threshold falls faster in the interval of 50-500, but the overall effect is better than the effect of unweighted text. Here, we set the weight threshold  $k$  as 100.



**Figure 8.** Example Comparison of Weighted and Unweighted Text Topic Mining Coherence Values Under Certain Number of Topics

## 5. Experiment results and analysis

With the help of BTM after improving the text content, this paper classifies the topics of the seventeen-week data and obtains the top 10 hot words in each topic ranked according to the probability value. Through the common sense of British and American dramas and TV program knowledge and the matching of entries in Wikipedia, this paper combines the classification method of film and television dramas, and divides the themes under Film and Television into *Feature*; *Affectional*; *War*; *Comedy*; *SciFi*; *Animation*; *Thriller*; *Criminal*; *Plot*; *Actor*; *TV Show*, totally 12 themes. After that, you can add corresponding tags to the weekly topic classification results. Here,

this paper selects the topic classification results from April 8, 2019 to April 14, 2019 (shown in **Table 1**) to demonstrate the classification effect (detailed in **Appendix 1**).

**Table 1.** Result of Topic Mining (Apr 8, 2019 – Apr 14, 2019)

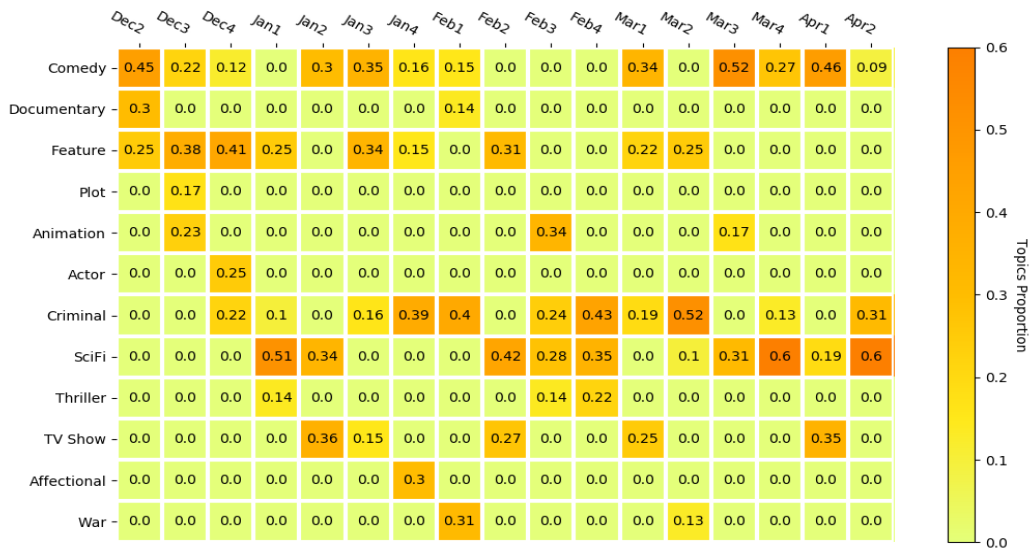
Topic No. (Topic Tags)	Topic1 (Comedy)		Topic2 (Criminal)		Topic3 (SciFi & The Avengers)		Topic4 (SciFi)	
Topics Top Words & Words Weight Value	episode	0.04	people	0.045	thanks	0.015	standard	0.028
	guy	0.039	career	0.044	<b>world</b>	0.014	<b>fiction</b>	0.028
	<b>family</b>	0.038	episode	0.042	frank	0.014	examine	0.028
	mantain	0.035	city	0.041	<b>paul</b>	0.013	structure	0.028
	quo	0.028	<b>weapon</b>	0.041	harris	0.013	informative	0.028
	<b>adult</b>	0.028	<b>cop</b>	0.041	invisible	0.013	drama	0.028
	change	0.026	<b>firing</b>	0.041	<b>hemsworth</b>	0.013	cast	0.028
	phenomenon	0.026	<b>shooting</b>	0.041	bana	0.013	<b>chikills</b>	0.017
	<b>simpson</b>	0.026	<b>criminal</b>	0.041	liam	0.013	<b>jessica</b>	0.017
	favourite	0.026	<b>police</b>	0.041	jordan	0.013	<b>hero</b>	0.017
Topics Frequency	55		182		262		95	
Topics Proportion	9%		31%		44%		16%	

For the case where the topic belongs to multiple subjects, it is necessary to select the more popular topic words and set them as the keywords under the topic by using the vocabulary popularity of the topic under the theme. When encountering special topics such as artist affair, film and television debuts and focusing on certain classic movies, hot topics will be added after the corresponding topics, just like Topic3 in **Table 1**, but may not be in the above 12 topics Label.

When this paper analyzes the evolution of weekly topics, it also needs to merge and simplify similar topics. In **Table 1**, in the experimental environment, WBTM separates the two SciFi topics because one topic is simply talking about some SciFi movies, and the other topic is discussing SciFi because *The Avengers* is about to be released, which set off a small climax of discussion. But in order to facilitate the drawing and theme evolution analysis, this paper chooses to merge

the two topics into *SciFi & The Avengers* here. Similar processing will also exist in the labeling work of the topic classification in the previous weeks.

Finally, with the help of the frequency measurement method, the appearance frequency statistics of each topic in **Table 1** can be obtained, and the proportion of each topic in all documents can be obtained. Here, this paper uses this ratio to indicate the popularity of each topic in all discussions this week. The value will be reflected in the topic heat proportion in Table 1, and the value and the color depth in the heat map are shown in **Figure 9**. Therefore, this paper draws a heat map of the theme evolution trend from December 17, 2018 to April 14, 2019 for a total of seventeen weeks (shown in **Fig. 9**), which represents the evolution of each topic in the time dimension during each week, and each row represents the evolution of the popularity of each topic in the seventeen weeks.



**Figure 9.** Heatmap of Topics Evolution Trend (Dec 17, 2018 – Apr 14, 2019),

Based on the analysis of the evolution of the topics in **Figure 10** from December 17, 2018 to April 14, 2019, this paper finds the following rules for the Film and Television topics in Quora:

The topic is updated quickly. Although the subject matter may still belong to one category, the specific content will change greatly. The general life cycle is about one to two weeks. This paper believes that the reason for this is British and American dramas and TV shows. The update frequency is fast, and the occurrence of events has a certain chance. For example, some news of certain artists may generate a hot topic of the week.

It takes a certain amount of time for a topic to become a hot topic, usually about a week, and then it will be replaced by a new topic; in addition, there will be a certain delay from the occurrence of a hot event in reality to becoming a hot topic, such as in *Deadpool*. After the PG13 version was released in North America on December 12, 2018, SciFi related to *Deadpool* became a hot topic of discussion two weeks later, which happened to be in the time period before the release of *Deadpool* in North America and before the release in mainland China. This paper believes that the reason for this is that it takes time for users to discuss topics. The hot topics discussed under the current topic may have become hot topics before this time period. This also shows that if you need to recommend content to users. At this time, it is necessary to combine some hot issues in real life to predict in advance.

Among the 17-week evolution themes, *Comedy*, *SciFi* and *Criminal* topics appeared more frequently, and they were the mainstream of discussion under this topic. Therefore, the system can pay attention to Film and Television topics. The users of the corresponding topic promote relevant content. Because there are not many sitcoms currently being updated, most Comedy content may be biased towards classic comedies and TV shows. In this way, the content recommendation for the *Comedy* topic is very simple. If the content is selected from the classic comedy content of the past, the probability of being liked will increase accordingly. The topic of *Criminal* will often discuss issues such as film and television situations and plots. The topics are more likely to evolve into topics such as *Thriller* and *Character* (movie characters) in the next week. *SciFi* (*science fiction*) topics will discuss some new topics other than classic sci-fi movies, because there are a lot of movies and TV works currently being updated, when recommending user content, you need to consider the current hot works being updated and the new products that will be shown to make recommendations.

Here, although this paper uses the *Film and Television* topic in Quora as an entry point to study the evolution of user interest, the experience here can be extended to similar topics, such as *Movies*, *Television Series* and other film and television drama topics. The personalized recommendation and advertising of drama topics have a good reference.

## 6. Conclusion

For the research on the evolution of user interest in social question-and-answer platforms, this paper uses Quora as a study case and uses topic of *Film and Television* as an entry point. Through Python web crawler technology, database manipulation technology and data cleaning toolkit, the time section is set to one week according to the update cycle of British and American dramas and TV shows. Based on the paper's understanding and discussion of the LDA model and BTM, this paper finally chooses WBTM as the topic mining method and weights the text data based on the number of user's answers viewed as a parameter. The experimental results prove that the effect of weighted text is better than that of weighted text. It is better to determine the number of WBTM topics at 3-6. The parameter of weighted text is set to be copied once when the answer is viewed more than 100 times. This is also an important improvement and innovation of this paper. Afterwards, through the topic mining of the weekly empowered text data for seventeen weeks, this paper finally obtained the weekly user interest topics and hot vocabulary, and the topics were summarized and classified.

Through the top words under each topic, the discussion content of the topic can be evaluated and classified. After that, based on the occurrence frequency of the topic in each question and answer document in each week, the popularity of the topic can be identified, and the corresponding value can be obtained. The heat of the topics discussed each week is indicated by the color shades through the heat map, and then a topic evolution trend chart can be obtained by chronologically from the past to the future according to the horizontal axis.

Finally, this paper combines the theme evolution trend from December 17, 2018 to April 14, 2019, and qualitatively analyzes the evolution trend of Film and Television topic and believes that the evolution of Film and Television topic is relatively fast. In addition, through a specific analysis of the 17-week data, this paper also believes that there will be a certain delay in the generation of topic hotspots from reality to the platform, and the main topics of the discussion are *Comedy*, *SciFi* and *Criminal* subject matter. As a result, the system can promote relevant content to users who follow the corresponding topic under the Film and Television topic. The content recommendation for *Comedy* topics can select the pushed content from the classic comedy content of the past, and its probability of being liked will increase accordingly. The topic of *Criminal* will often discuss



issues such as film and television situations and plots. The topics are more likely to evolve into topics such as *Thriller* and *Character* (movie characters) in the next week. When recommending user content on *SciFi* topics, you can consider currently updating hot works and upcoming new products for recommendation.

In summary, this paper conducts topic mining on user interests under the topic of *Film and Television* in Quora and optimizes the topic recognition effect of BTM by weighting text data. In the subsequent analysis of the evolution trend of user interests, through qualitative analysis of the topic, some suggestions were put forward for Quora to make personalized recommendations and advertising on the topic. However, this paper did not perform quantitative modeling and analysis on the subsequent theme evolution trends to obtain quantifiable laws, which will also become the next important breakthrough direction in the evolution of user interests.

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## Appendix 1

Table 1 2018.12.17-2018.12.23 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Feature & Criminal	Topic1	girl	0.018	69	16%
		character	0.017		
		<b>murderer</b>	0.017		
		favourite	0.016		
		obscure	0.013		
		historical	0.013		
		event	0.013		
		<b>breaking</b>	0.012		
		<b>pinkman</b>	0.012		
		<b>jesse</b>	0.012		
Feature & Adventure	Topic2	sure	0.059	39	9%
		imposed	0.058		
		<b>silverlake</b>	0.055		
		<b>tonto</b>	0.05		
		actor	0.049		
		man	0.047		
		silted	0.046		
		workshop	0.046		
		character	0.043		
		real	0.043		
Documentary	Topic3	movie	0.048	126	29%
		<b>throne</b>	0.043		
		great	0.041		
		delegate	0.03		
		<b>polish</b>	0.03		
		important	0.03		
		wikipedia	0.03		
		<b>henry</b>	0.03		
		explain	0.03		
		france	0.03		
Comedy	Topic4	piece	0.025	75	17%
		<b>parent</b>	0.022		
		<b>ben</b>	0.022		
		plan	0.022		
		<b>greg</b>	0.022		
		<b>byrnes</b>	0.022		
		propose	0.022		
		wikipedia	0.022		
		<b>focker</b>	0.022		

		learn	0.022		
Comedy	Topic5	time	0.017	84	22%
		sound	0.015		
		age	0.015		
		home	0.012		
		experience	0.01		
		<b>guy</b>	0.009		
		<b>prarie</b>	0.009		
		<b>foley</b>	0.009		
		<b>horse</b>	0.009		
		<b>companion</b>	0.009		

Table 2 2018.12.24-2018.12.30 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Comedy	Topic1	time	0.015	84	22%
		drama	0.012		
		<b>comedy</b>	0.012		
		big	0.011		
		book	0.009		
		<b>sherlock</b>	0.009		
		day	0.008		
		suggest	0.008		
		think	0.008		
		scenario	0.008		
Plot	Topic2	<b>film</b>	0.032	67	17%
		<b>stroytelling</b>	0.016		
		challenge	0.014		
		<b>visual</b>	0.014		
		director	0.014		
		speaking	0.014		
		device	0.014		
		<b>fun</b>	0.014		
		recent	0.014		
		creative	0.014		
Animation & Character	Topic3	<b>actor</b>	0.014	87	23%
		<b>character</b>	0.014		
		thing	0.013		
		called	0.012		
		person	0.01		
		mind	0.008		
		<b>cartoon</b>	0.008		
		girl	0.008		

		great	0.008		
		real	0.007		
Feature & Criminal	Topic4	episode	0.018	148	38%
		<b>bad</b>	0.017		
		face	0.016		
		moment	0.012		
		scene	0.011		
		died	0.011		
		<b>role</b>	0.01		
		<b>beraking</b>	0.009		
		romance	0.009		
		expecting	0.009		

Table 3 2018.12.30-2019.01.06 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Criminal & Actor	Topic1	time	0.015	137	21%
		drama	0.012		
		<b>comedy</b>	0.012		
		big	0.011		
		book	0.009		
		<b>sherlock</b>	0.009		
		day	0.008		
		suggest	0.008		
		think	0.008		
		scenario	0.008		
Actor	Topic2	featured	0.025	163	25%
		woman	0.023		
		thought	0.022		
		young	0.02		
		<b>penny</b>	0.017		
		<b>shirley</b>	0.017		
		<b>laverne</b>	0.017		
		marshall	0.017		
		recent	0.017		
		<b>news</b>	0.017		
Feature & Character	Topic3	rick	0.018	265	41%
		time	0.017		
		episode	0.016		
		question	0.011		
		actor	0.01		
		<b>jackson</b>	0.01		
		meant	0.01		

Comedy & Actor	Topic4	percy	0.01	78	12%
		mean	0.01		
		teach	0.01		
		happy	0.032		
		old	0.032		
		star	0.031		
		think	0.027		
		winkler	0.027		
		student	0.026		
		high	0.026		
		fonzie	0.026		
		wit	0.026		
		henry	0.026		

Table 4 2019.01.07-2019.01.13 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Thriller	Topic1	home	0.034	115	14%
		american	0.032		
		horror	0.032		
		long	0.032		
		toddler	0.032		
		mom	0.032		
		bloody	0.032		
		hidden	0.032		
		belly	0.032		
		corpse	0.032		
Feature & Cult	Topic2	human	0.048	201	25%
		godfrey	0.048		
		reggio	0.048		
		experience	0.047		
		produced	0.047		
		concentrate	0.047		
		philip	0.047		
		glass	0.047		
		musical	0.047		
		koyanisqaasti	0.047		
SciFi & Deadpool	Topic3	fred	0.07	193	24%
		recreate	0.068		
		savage	0.067		
		bedroom	0.064		
		hero	0.063		
		deadpool	0.062		

		<b>version</b>	0.06		
		kidnap	0.048		
		movie	0.044		
		princess	0.043		
SciFi & Starwar	Topic4	best	0.039	217	27%
		movie	0.033		
		<b>adlibbed</b>	0.028		
		<b>carbonite</b>	0.028		
		<b>empire</b>	0.027		
		<b>strike</b>	0.027		
		leia	0.027		
		choose	0.027		
		han	0.027		
		frozen	0.027		
Criminal & Thriller	Topic5	scene	0.055	79	10%
		upset	0.04		
		needle	0.04		
		<b>murdered</b>	0.04		
		<b>jesse</b>	0.04		
		<b>andrea</b>	0.04		
		<b>breaking</b>	0.04		
		<b>bad</b>	0.04		
		brock	0.04		
		inside	0.04		

Table 5 2019.01.14-2019.01.20 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
SciFi & Deadpool	Topic1	movie	0.025	324	34%
		say	0.016		
		scene	0.016		
		<b>pg</b>	0.016		
		<b>version</b>	0.015		
		<b>deadpool</b>	0.014		
		princess	0.014		
		break	0.014		
		bedroom	0.014		
		savage	0.014		
TV Show & Comedy	Topic2	sex	0.015	290	30%
		written	0.013		
		character	0.012		
		main	0.011		
		<b>stern</b>	0.01		



		<b>prank</b>	0.01		
		potter	0.01		
		wizard	0.01		
		porkies	0.01		
		convince	0.01		
TV Show	Topic3	kind	0.011	343	36%
		read	0.01		
		say	0.01		
		<b>bengi</b>	0.01		
		<b>kya</b>	0.01		
		<b>fav</b>	0.01		
		<b>karna</b>	0.01		
		<b>ka</b>	0.01		
		<b>bhi</b>	0.01		
		<b>mai</b>	0.01		

Table 6 2019.01.21-2019.01.27 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Comedy & Character	Topic1	green	0.047	72	16%
		<b>chandler</b>	0.041		
		<b>schwimmer</b>	0.041		
		<b>cast</b>	0.04		
		<b>joey</b>	0.039		
		<b>leblanc</b>	0.036		
		<b>aniston</b>	0.035		
		<b>kudrow</b>	0.035		
		<b>rachel</b>	0.035		
		<b>best</b>	0.035		
Scene & Criminal	Topic2	movie	0.016	71	16%
		<b>story</b>	0.013		
		<b>dark</b>	0.011		
		<b>criminal</b>	0.01		
		people	0.01		
		<b>scene</b>	0.01		
		believe	0.01		
		english	0.009		
		thing	0.009		
		time	0.009		
TV Show	Topic3	lot	0.016	68	15%
		used	0.016		
		actor	0.013		
		sinatra	0.012		

		ncis	0.012		
		<b>superbowl</b>	0.012		
		<b>football</b>	0.012		
		loop	0.012		
		downtown	0.012		
		parking	0.012		
Feature	Topic4	movie	0.017	153	40%
		series	0.016		
		actor	0.014		
		people	0.012		
		<b>tom</b>	0.01		
		funny	0.01		
		<b>bombadil</b>	0.01		
		certain	0.009		
		juvenil	0.009		
		giant	0.009		
Comedy	Topic5	member	0.031	91	20%
		fear	0.02		
		near	0.019		
		day	0.016		
		<b>sitcom</b>	0.016		
		way	0.016		
		run	0.016		
		cast	0.016		
		loyal	0.016		
		left	0.016		

Table 7 2019.01.28-2019.02.03 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Affectional	Topic1	time	0.047	205	30%
		<b>ancient</b>	0.046		
		<b>love</b>	0.045		
		culture	0.045		
		language	0.045		
		<b>platonic</b>	0.045		
		understanding	0.045		
		code	0.045		
		space	0.045		
		exist	0.045		
Feature		watch	0.016	268	39%
		follow	0.015		
		like	0.013		

& Criminal	Topic2	set	0.012		
		<b>breaking</b>	0.01		
		plenty	0.009		
		coffee	0.009		
		listen	0.009		
		lion	0.009		
		<b>bad</b>	0.009		
Feature	Topic3	ancient	0.019	105	15%
		life	0.016		
		series	0.015		
		<b>game</b>	0.013		
		replaced	0.012		
		<b>throne</b>	0.011		
		nostalgia	0.011		
		capture	0.009		
		failure	0.009		
		cristo	0.009		
Comedy & Actor	Topic4	acting	0.06	113	16%
		role	0.06		
		<b>tarrak</b>	0.06		
		<b>metha</b>	0.06		
		<b>ka</b>	0.06		
		<b>ooltah</b>	0.06		
		<b>chashmah</b>	0.06		
		skill	0.06		
		experssion	0.06		
		great	0.06		

Table 8 2019.02.04-2019.02.10 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Comedy	Topic1	work	0.014	101	15%
		right	0.014		
		entertainment	0.014		
		bad	0.013		
		mood	0.013		
		fantasy	0.012		
		happen	0.009		
		<b>comedy</b>	0.009		
		advert	0.009		
		<b>broadcast</b>	0.009		
		death	0.029	260	38%
		<b>villian</b>	0.026		

Criminal	Topic2	line	0.026		
		slaughtere	0.025		
		potty	0.025		
		<b>trigger</b>	0.025		
		<b>cop</b>	0.025		
		action	0.025		
		caused	0.025		
		demand	0.025		
War	Topic3	<b>artillery</b>	0.052	202	30%
		intense	0.052		
		soviet	0.052		
		<b>american</b>	0.052		
		massive	0.052		
		say	0.052		
		affair	0.052		
		number	0.052		
		<b>gun</b>	0.052		
		<b>russian</b>	0.052		
Documentary & Comedy	Topic4	<b>sitcom</b>	0.083	95	14%
		<b>documentary</b>	0.077		
		mood	0.067		
		<b>picturization</b>	0.066		
		style	0.066		
		unlike	0.065		
		make	0.064		
		<b>trust</b>	0.062		
		<b>precise</b>	0.059		
		<b>jiffy</b>	0.056		

Table 9 2019.02.11-2019.02.17 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Comedy	Topic1	<b>shatner</b>	0.029	41	7%
		<b>skywalker</b>	0.029		
		audrey	0.029		
		hepburn	0.029		
		<b>william</b>	0.029		
		dorothy	0.029		
		<b>indiana</b>	0.029		
		<b>jones</b>	0.029		
		luke	0.029		
		lucy	0.029		

Criminal	Topic2	<b>batman</b>	0.013	196	35%
		completely	0.013		
		film	0.013		
		birdman	0.012		
		typical	0.012		
		freeze	0.012		
		<b>terminator</b>	0.012		
		arnold	0.012		
		<b>superhero</b>	0.012		
		<b>lantern</b>	0.012		
War	Topic3	cute	0.057	154	27%
		banoo	0.054		
		dulhann	0.053		
		divyanka	0.05		
		dabmn	0.049		
		rose	0.047		
		acting	0.045		
		<b>mohabbatein</b>	0.044		
		household	0.042		
		favourite	0.042		
Documentary & Comedy	Topic4	thing	0.022	173	31%
		country	0.014		
		<b>orphan</b>	0.014		
		<b>chumlum</b>	0.014		
		ron	0.014		
		rice	0.014		
		week	0.013		
		<b>aesthetically</b>	0.013		
		beautiful	0.013		
		example	0.013		

Table 10 2019.02.18-2019.02.24 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
SciFi	Topic1	carrie	0.034	159	28%
		actor	0.03		
		<b>kirk</b>	0.029		
		neil	0.029		
		patrick	0.029		
		fisher	0.029		
		<b>skywalker</b>	0.029		
		luke	0.029		
		friend	0.029		

		reef	0.029		
Thriller & Criminal	Topic2	mother	0.048	82	14%
		<b>lake</b>	0.046		
		birth	0.046		
		new	0.046		
		jersey	0.046		
		<b>caystal</b>	0.046		
		<b>voorhees</b>	0.046		
		allow	0.046		
		introduce	0.046		
		<b>jason</b>	0.046		
Animation	Topic3	best	0.017	195	34%
		subtitle	0.016		
		enjoy	0.016		
		netfilx	0.012		
		<b>anime</b>	0.012		
		attention	0.012		
		understand	0.012		
		wat	0.012		
		actual	0.012		
		tongue	0.012		
Criminal	Topic4	movie	0.027	139	24%
		mind	0.026		
		deep	0.026		
		<b>matthau</b>	0.022		
		crook	0.021		
		audience	0.021		
		death	0.02		
		bank	0.02		
		<b>robbery</b>	0.02		
		resulting	0.02		

Table 11 2019.02.25-2019.03.03 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
SciFi & Adventure	Topic1	series	0.058	195	25%
		replaced	0.051		
		<b>stargate</b>	0.05		
		half	0.05		
		<b>farscape</b>	0.05		
		tv	0.05		
		cast	0.05		

		sg	0.05		
		death	0.05		
		scene	0.05		
Thriller	Topic2	character	0.057	170	22%
		rewatch	0.05		
		slayer	0.05		
		vampire	0.05		
		firefly	0.05		
		whedon	0.05		
		think	0.05		
		school	0.05		
		creator	0.05		
		joss	0.05		
Criminal	Topic3	work	0.026	73	9%
		jake	0.026		
		prove	0.026		
		detective	0.026		
		talented	0.026		
		cop	0.026		
		peralta	0.026		
		ray	0.026		
		holt	0.026		
		brooklyn	0.026		
Criminal & Thriller	Topic4	actor	0.018	266	34%
		role	0.017		
		netfilx	0.016		
		crime	0.011		
		stalker	0.011		
		new	0.011		
		dirty	0.011		
		perfect	0.01		
		success	0.01		
		thriller	0.01		
SciFi & Captain Marvel	Topic5	man	0.024	75	10%
		started	0.019		
		imperium	0.016		
		captain	0.015		
		jr	0.014		
		iron	0.013		
		marvel	0.012		
		peak	0.012		
		screen	0.012		

		success	0.012		
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Table 12 2019.03.04-2019.03.10 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
SciFi	Topic1	time	0.021	316	34%
		question	0.017		
		clean	0.016		
		april	0.016		
		<b>sabachthani</b>	0.016		
		<b>anatomy</b>	0.016		
		<b>jesus</b>	0.016		
		died	0.016		
		cross	0.016		
		<b>eloi</b>	0.016		
Thriller & Criminal	Topic2	affair	0.027	232	25%
		urinate	0.025		
		club	0.016		
		<b>carson</b>	0.012		
		wife	0.011		
		<b>johnny</b>	0.011		
		<b>friar</b>	0.011		
		roast	0.011		
		camera	0.011		
		tonight	0.011		
Animation	Topic3	looking	0.02	177	19%
		try	0.019		
		<b>case</b>	0.019		
		<b>drama</b>	0.018		
		lost	0.017		
		feel	0.014		
		day	0.012		
		<b>hwang</b>	0.011		
		serial	0.011		
		uncover	0.011		
Criminal	Topic4	california	0.021	207	22%
		way	0.013		
		fun	0.011		
		beautiful	0.011		
		violence	0.011		
		uk	0.011		
		<b>battle</b>	0.011		



		<b>throne</b>	0.011		
		<b>war</b>	0.011		
		boring	0.011		

Table 13 2019.03.11-2019.03.17 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Criminal & Sherlock Holmes	Topic1	<b>holmes</b>	0.028	181	29%
		school	0.026		
		produced	0.026		
		fan	0.026		
		<b>law</b>	0.025		
		world	0.024		
		<b>benedict</b>	0.024		
		longer	0.024		
		wife	0.024		
		<b>cumberbach</b>	0.024		
Criminal & Actor	Topic2	<b>series</b>	0.044	143	23%
		watch	0.022		
		favourite	0.021		
		<b>holmes</b>	0.02		
		<b>solomin</b>	0.019		
		fan	0.019		
		music	0.019		
		<b>watson</b>	0.019		
		<b>vasily</b>	0.019		
		youtube	0.019		
Feature & Actor	Topic3	movie	0.047	159	25%
		best	0.029		
		<b>role</b>	0.029		
		version	0.028		
		talkie	0.028		
		<b>eagels</b>	0.028		
		paramount	0.028		
		<b>letter</b>	0.028		
		nominated	0.028		
		<b>jeanne</b>	0.028		
SciFi	Topic4	ca	0.05	61	10%
		urge	0.05		
		people	0.05		
		meet	0.05		
		<b>convention</b>	0.05		

		<b>attendee</b>	0.05		
		<b>firefly</b>	0.05		
		stuff	0.05		
		<b>resist</b>	0.05		
		really	0.05		
Feature & War	Topic5	world	0.018	83	13%
		series	0.015		
		like	0.013		
		actress	0.012		
		<b>sky</b>	0.012		
		scene	0.01		
		<b>normandy</b>	0.008		
		<b>brother</b>	0.008		
		<b>company</b>	0.008		
		<b>hbo</b>	0.008		

Table 14 2019.03.18-2019.03.24 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Animation	Topic1	good	0.045	70	17%
		instantly	0.043		
		<b>maid</b>	0.043		
		<b>datin</b>	0.042		
		<b>programmer</b>	0.042		
		<b>geek</b>	0.042		
		intorvert	0.042		
		<b>miss</b>	0.042		
		<b>kobayashi</b>	0.042		
		<b>dragon</b>	0.042		
Comedy & War	Topic2	character	0.067	81	19%
		popular	0.05		
		actor	0.031		
		homepage	0.031		
		<b>holocaust</b>	0.029		
		toner	0.029		
		video	0.025		
		pop	0.022		
		<b>vudu</b>	0.022		
		base	0.022		
		watch	0.12	130	31%

Documentary & SciFi	Topic3	time	0.1		
		<b>speed</b>	0.096		
		aspect	0.093		
		mankind	0.093		
		<b>future</b>	0.09		
		commercial	0.016		
		<b>hulu</b>	0.016		
		<b>documentary</b>	0.008		
		<b>ai</b>	0.008		
Comedy & SciFi	Topic4	work	0.045	141	33%
		decribed	0.045		
		<b>comedian</b>	0.045		
		screen	0.045		
		battle	0.045		
		<b>monster</b>	0.045		
		<b>seller</b>	0.045		
		<b>peter</b>	0.045		
		depression	0.045		
		manic	0.045		

Table 15 2019.03.25-2019.03.31 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Criminal & Character	Topic1	experience	0.056	96	13%
		tv	0.052		
		<b>depicted</b>	0.052		
		bad	0.052		
		<b>prison</b>	0.051		
		<b>pain</b>	0.051		
		<b>violence</b>	0.051		
		separated	0.051		
		heatache	0.051		
		witnessed	0.01		
Comedy & Actor	Topic2	<b>hazzard</b>	0.045	201	27%
		episode	0.045		
		<b>john</b>	0.045		
		ran	0.045		
		salary	0.045		
		<b>wopat</b>	0.045		
		<b>tom</b>	0.045		
		dispute	0.045		
		pretty	0.045		
		thing	0.045		
		information	0.021	216	29%

SciFi & Actor	Topic3	happens	0.016		
		character	0.014		
		watch	0.014		
		<b>fictional</b>	0.012		
		nature	0.012		
		<b>khardshian</b>	0.012		
		use	0.012		
		project	0.012		
		<b>software</b>	0.012		
SciFi & Star Trek	Topic4	<b>gravity</b>	0.026	226	31%
		<b>star</b>	0.022		
		movie	0.019		
		<b>trek</b>	0.018		
		science	0.018		
		<b>artificial</b>	0.016		
		<b>production</b>	0.014		
		commercial	0.013		
		fiction	0.011		
		cast	0.01		

Table 16 2019.04.01-2019.04.07 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
TV Show & Comedy	Topic1	thing	0.031	102	19%
		<b>comedy</b>	0.027		
		distant	0.026		
		smile	0.021		
		simple	0.021		
		<b>tera</b>	0.021		
		<b>monkey</b>	0.021		
		<b>sharma</b>	0.021		
		<b>mimicry</b>	0.021		
		<b>kapil</b>	0.021		
SciFi & Thriller	Topic2	movie	0.03	104	19%
		like	0.018		
		think	0.018		
		<b>stranger</b>	0.018		
		want	0.017		
		real	0.014		
		<b>thing</b>	0.014		
		body	0.011		

		supes	0.011		
		<b>demodogs</b>	0.011		
Comedy & Affectional	Topic3	movie	0.026	85	16%
		actor	0.025		
		<b>mcluhan</b>	0.017		
		<b>woody</b>	0.016		
		line	0.016		
		theory	0.016		
		<b>annie</b>	0.016		
		<b>alvy</b>	0.016		
		<b>singer</b>	0.016		
		<b>hall</b>	0.016		
TV Show & Host	Topic4	question	0.017	85	16%
		missed	0.015		
		example	0.014		
		<b>jeopardy</b>	0.014		
		<b>diagonsed</b>	0.013		
		probabaly	0.013		
		routine	0.013		
		<b>host</b>	0.013		
		<b>alex</b>	0.013		
		<b>stage</b>	0.013		
Comedy & Thriller	Topic5	movie	0.037	166	30%
		thing	0.021		
		star	0.02		
		<b>miss</b>	0.019		
		based	0.019		
		<b>rodriguez</b>	0.017		
		nanjano	0.017		
		<b>bala</b>	0.017		
		<b>gina</b>	0.017		
		<b>comedy</b>	0.016		

Table 17 2019.04.08-2019.04.14 Results of Topics Mining

Topic Tags	Topic No.	Top Words	Words Weight	Topics Frequency	Topics Proportion
Comedy	Topic1	episode	0.04	55	9%
		guy	0.039		
		<b>family</b>	0.038		
		maintain	0.035		
		quo	0.028		
		<b>adultoriented</b>	0.028		

		change	0.026		
		phenomenon	0.026		
		<b>simpson</b>	0.026		
		favourite	0.026		
Criminal	Topic2	people	0.045	182	31%
		carrer	0.044		
		episode	0.042		
		city	0.041		
		<b>weapon</b>	0.041		
		<b>cop</b>	0.041		
		<b>firing</b>	0.041		
		<b>shooting</b>	0.041		
		<b>criminal</b>	0.041		
		<b>police</b>	0.041		
SciFi & The Avengers	Topic3	thanks	0.015	262	44%
		<b>world</b>	0.014		
		frank	0.014		
		<b>paul</b>	0.013		
		harris	0.013		
		invisible	0.013		
		<b>hemsworth</b>	0.013		
		bana	0.013		
		liam	0.013		
		jordan	0.013		
SciFi & Fantastic Four	Topic4	standard	0.028	95	16%
		<b>fiction</b>	0.028		
		examine	0.028		
		structure	0.028		
		informative	0.028		
		drama	0.028		
		cast	0.028		
		<b>chikills</b>	0.017		
		<b>jessica</b>	0.017		
		<b>hero</b>	0.017		