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Social Network Analysis for Online Knowledge Exchange Platform: Evidence from Zhihu

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Abstract: The knowledge exchange platform is an innovative way that empowers online learning for the Internet users to utilize their spare time slots for knowledge sharing and seeking. Many researchers have conducted research on the user interaction and content of the knowledge payment platform. This paper analyzes the user interaction and user comments by analyzing the data of Zhihu live, a major online knowledge exchange platform in China. We employ social network analysis and deep learning method to explore the users' interaction structure in Zhihu live platform and their emotional tendency for knowledge exchange. Particularly, we use social network analysis theory supplemented by social analysis tools Gephi and neural network algorithm, LSTM to achieve our goals. We propose a set of hypotheses from the perspective of a small world phenomenon and users' social engagement in the platform. Our results show that there is a small world phenomenon on core topics and the more frequent users interaction is, the more positive the users' comments are. Theoretically, this study explores the users' knowledge seeking and sharing behavior from the perspective of user interaction and user emotion. Also, our research offers implications to practice that enhancing sociality can be an effective strategy to motivate the desirable users' paid knowledge sharing behaviors in the platform.

Keywords: knowledge payment; social network; sentiment; empirical study

1. INTRODUCTION

In the past few years, knowledge-paying communities have emerged and are growing rapidly. The knowledge-paying community is a mode of content payment. Maxhuni (2016)[1] believes that the development of technology and the emergence of knowledge payment platform promote the spread of knowledge and broaden people's vision. Zhang(2017) [2] investigates the willingness of users to pay for knowledge, and believes that it is affected by many factors such as utilitarian value and hedonic value.Therefore, the success of online education business model and the development of paying users are the key points of industry development. After the knowledge sharing has experienced static knowledge acquisition 1.0 and dynamic knowledge update 2.0, under the dual role of knowledge redundancy and fan economy, enter the knowledge sharing 3.0 stage of paid question and answer and subscription. In China, as of May 2019 the number of Himalayan FM activation users has exceeded 500 million, with 4 million paid users, and Zhihu user base has reached 200 million. The knowledge-paying platform can make full use of people's fragmentation time and achieve the full use of resources. Users can

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participate in content creation and information sharing. The characteristic of payment content is to screen out valuable information and construct a new system of knowledge dissemination. From the perspective of the entire content industry, the knowledge payment market is gradually maturing.

The typical operation process of the knowledge payment platform is as follows. People use the form of paid questions to consume content. The author uses his own fragmented time to share his knowledge and get the corresponding reward. On the platform, people can still use it. The columns are commented on, and others use these comments to understand the quality of the program, and the platform can also make recommendations through comments. If the user feels that a particular section is useful to them, then they can pay for it.

We want to solve two problems. First, what is the user interaction situation of the knowledge paying platform, especially those who publish paid content and get revenue. Here we use the method of social network analysis. Second, what is the commentary on the knowledge-paying platform, and whether it is related to interaction and could affect interaction. Here we use the method of machine learning.

The rest of the article is constructed as follows. First, we review the literature on knowledge payment and commodity comments. Secondly, we explain in detail the limitations of the current research and propose our methods to improve the current research. Finally, we describe our data, analyze the results, and draw conclusions.

2. RELATED LITERATURE

2.1Knowledge payment

Because of its popularity, knowledge payment has attracted the dual attention of the academic community and the industry.

The first is to study the development of knowledge payment. Zhang (2017) [3] divided the development of knowledge payment into three stages: knowledge sharing stage, knowledge payment embryonic stage and knowledge payment development stage. Sun (2019) [4] believes that technology is the main driving force to promote the development of knowledge payment industry.

The second is the study of the content of the knowledge payment platform. Song(2017) [5] believes that the core of knowledge payment platform is knowledge itself. Wang (2013) [6] further explores the topics in the platform and discovers through Quora that the rich diversity of platform topics and answers attracted users to participate spontaneously in topics of interest or popularity. In terms of research on the relationship between content and users, Sharoda (2015) [7] uses quantitative analysis methods to study the user's reputation evaluation method for the Quora platform, and then gives corresponding suggestions for the platform to develop reputation mechanism and produce high-quality topic content. Similarly, Wang (2017) [8] explores the role of incentives, and believes that high-quality knowledge can easily be buried in the shared knowledge of homogenization, which greatly dampens the creative enthusiasm of knowledge producers, and the knowledge sharing without effective incentives eventually tends to be low-quality. Therefore, the development of knowledge payment effectively stimulates knowledge producers, and the production and realization of supply-side cognitive surpluses are positively feedback.

The third is the study of the willingness of users of knowledge payment platform to pay. Work(2007) [9] and Kim(2009) [10] find that perception level of convenience and price would affect users' willingness to use the knowledge payment platform. Many scholars have also made a fine-grained analysis of it. Li (2014) [11] points out in the research on the influencing factors of free customers' willingness to pay for instant messaging value-added services, that network externalities and virtual social capital can directly affect customer perceived value, which indirectly affects customers' willingness to pay, while perceived value has a direct positive impact on customers' willingness to pay. Li (2018) [12] found the willingness to pay is directly affected by the paid attitude, subjective norms and the control factors of perceived behavior; the paid attitude is perceived by quality, experience and trust.

At present, most of the research on the users of knowledge payment platform focuses on the willingness of users to pay. However, the knowledge payment platform has been developing, and the interaction between users is also increasing, which directly affects the choice of knowledge payment products. Because users with similar hobbies tend to be connected. For example, if one of them tends to pay for a certain type of knowledge, the person associated with him will be influenced by him to be interested in such products or buy them directly. Then the user interaction of knowledge payment platform and the purchase of knowledge payment products by user interaction need to be paid close attention to by researchers.

2.2 Online reviews

Knowledge-paying product is a kind of commodity sold online, which is regulated by the demand and supply of both suppliers and demanders. The demands of users are largely affected by commodity reviews. Reviews of online goods have been studied by a lot of people. Pee(2016) [13] believes that reviews of online goods are conducive to information dissemination and promoting user purchase decisions. And also, according to a survey, Stefan(2019) [14] think online merchants are paying more and more attention to online reviews. Many researchers look at online reviews from a variety of fields. Zhang (2001) [15] studies the comments of ordinary customers and industry experts respectively, the results show that the online comments of ordinary customers are more likely to be trusted by consumers and show a positive correlation, while the comments of industry experts show the opposite trend. Lin et al.(2007) [16] analyzes and explores the interaction between book comments and purchase intention, and the conclusion shows that the comprehensiveness and integrity of book comments are positively related to purchase intention. Liu(2015) [17] investigates the factors influencing the perceived usefulness of review and considers that qualitative reviews are very important. Through text mining and sentiment analysis, Cheng(2019) [18] find that Airbnb users make reservation decisions through comments from others, among which "location", "amenities" and "host" are the three most important attributes for users. Besides, Saba(2016) [19] interviews people and even find that the more negative the comment, the more useful it is.

Although the knowledge payment platform is in a period of rapid development, but the current development is not mature enough, the quality of the knowledge products or services provided by the platform is difficult to guarantee, the user experience is poor, and the piracy problem is serious. The content of the platform is vulgarized, homogenized, over-commercialized and so on, which is caused by the simple pursuit of short-term benefits. Among them, user comments can solve the product problems on the platform to a certain extent, and users who have used paid products can make corresponding evaluations of the products according to the advantages and disadvantages of the products. Users who have not purchased the product can refer to these comments before purchasing. The emotional tendency of product comments represents the degree of user love for the product. We believe that the relevant comments on the knowledge payment platform need to - paid attention to by researchers.

3. MODEL BUILDING

In this article, we try to solve this problem: the influence of user interaction and comments on knowledge diffusion efficiency of knowledge payment platform.

Exploring the user interaction of knowledge payment platform can be divided into two aspects. One is to explore whether there is a small-world phenomenon in the user interaction of the knowledge payment platform as a whole, and whether the user interaction is the same for different knowledge payment products. The small world phenomenon shows that there is a close connection in the network structure. The most famous experiment is a six-degree separation experiment, which shows that there are at most five people between any two people in the world (Peter et al.2003) [20]. The small world network has two basic characteristics: a short characteristic path length and a high average aggregation coefficient and it can promote corporate innovation, information flow diffusion, and personal creativity(Verspagen et al.2004; Schilling et al.2007; Uzzi et al.2005) [21,22,23]. Therefore, the small-world phenomenon can be used to explore the dynamic attributes, structural characteristics and evolution mechanism of the knowledge payment network.The second is to explore whether there are opinion leaders in user interaction and what characteristics these leaders have. Lazarsfeld(1948) [24] points out that opinion leaders are active elements in social networks. They influence the behavior of other users and thus promote the evolution of the network structure. Therefore, it is necessary to care about opinion leaders in the network. Thus we have hypotheses H1a and H1b.

H1 a: there is a small-world phenomenon on the knowledge payment platform and the interaction between users of different knowledge payment products is different.

H1 b: community opinion leaders have an impact on the knowledge product demand of other users.

Kim (2004) [25] believes that emotional (opinion) can be described by four parts: theme, intention holder, emotion description term and praise and criticism tendency, that is, opinion holders express some kind of praise and criticism tendency for the theme of emotional description. The user comments of knowledge paying products can affect the behavior of users to a certain extent, that is, affect the interactive behavior of users. emotional analysis can be carried out through online comments, and the tendency of users to comment can be measured from the results of emotional analysis. Based on this, we propose H2.

H2: the user's comments represent their emotional preference for the product and affect user interaction.

In order to describe the emotional tendency of user comments, we use the LSTM model in machine learning to perform the operation on the content of the comments.

The long-short term memory model was proposed by Hochreiter and Schimidhuber to improve the traditional recurrent neural network model[26]. The model is a special recurrent neural network model, based on the standard recurrent neural network model and adds long and short time memory cells. The adoption of the LSTM model is better in terms of text classification (Graves et al. 2005) [27] and handwriting recognition (Graves et al. 2009) [28] than simple recurrent neural networks.

As shown in the Figure 1 below, we first convert the text into a word vector. For Chinese, we first use the jieba package for word segmentation, use the word2vec algorithm to convert them into vectors, input these vectors into the LSTM model, after neural network training, finally get the value.

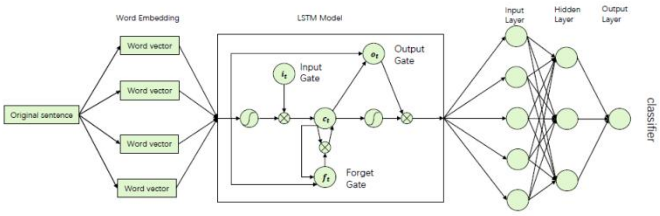

Figure 1. LSTM schematic diagram

4. EMPIEICAL STUDY

4.1Data

The data comes from zhihu live, which is a very hot knowledge payment platform. We write the python program and use the API of the website to get the corresponding data. We obtain information about the all the columns on the zhihu live platform, including the price of the column, the content of the column comments, the number of column comments, and the following relationship of anchors. As of November 21, 2018, there were 17 fields in the live, 6554 columns, and 2,875 speakers in Table 1.

Zhihu live anchors will pay attention to each other, and this kind of attention behavior produces the social interaction on the platform, and we can explore the social scene in the knowledge payment platform by analyzing the interaction behavior among them. Platform users can pay to listen to the live columns, and make corresponding comments. Other users can refer to these comments when purchasing the column. We believe that these comments represent the emotional tendency of users to the column, and this emotional tendency will in turn affect their buying behavior.

Table 1. Overall parameters

Number of topics	Number of columns	Number of anchor s	Number of comments
17	6554	2875	183674

The Zhihu live section has different themes. Specifically, there are 17 topics on the platform in Table 2. We get the corresponding user interaction information, column information and corresponding comment information according to different topics. We use the social network analysis tool Gephi to analyze user interactions and use LSTM to analyze comments.

Table 2. Different topics parameters

Topics	Number of columns	Topics	Number of columns	Topics	Number of columns
Legal	159	Food	55	Medical health	254
Internet	773	Business	141	Art	260
Education	1325	Design	197	MMT	411
Financial economy	588	Lifestyle	529	Reading writing	262
Science & Technology	265	Physical education	160	Career	852
Travel	132	Psychology	191		

4.2Results

We use Gephi, a visual tool for social network analysis. The nodes represent the anchors on the platform, and the connections between the nodes represent the mutual attention between the anchors. The corresponding social network diagram is drawn and the corresponding parameters in the network are obtained. We have a social network map of 17 fields and a maximum k-core map. Parameters such as the number of nodes, the number of edges, the average, and the network diameter in the network are obtained. As shown in the following Figure 2 to Figure 5, the social network map corresponding to the legal and Internet fields and the maximum k-core map are shown. In a k-core network, the minimum degree of each node is k. The largest k-core of the social network formed by the columns in the legal field is 3, and the Internet domain is 8. The larger the k-core, the more compact the network structure and the more frequent the user interaction. Correspondingly, the user interaction in the field of Internet is more frequent than that in the field of law.

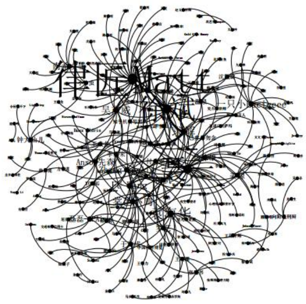

Figure 2. Global topology in legal topic

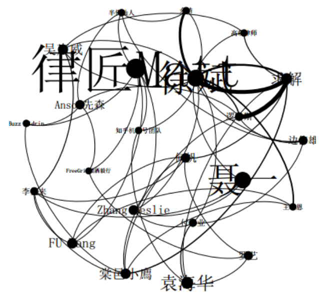

Figure 3. The largest k-core network in legal topics

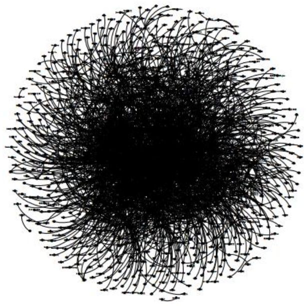

Figure 4. Global topology in Internet topics

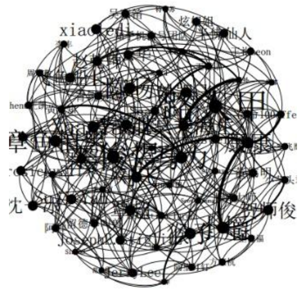

Figure 5. The largest k-core network in Internet topics

The corresponding parameters in the social network diagrams in various fields are shown in the Table 3.

Table 3. Social network parameters of different topics

Topics	Node	Edge	Average degree	Network diameter	k-core
Legal	231	288	1.247	5	3
Internet	872	2181	2.501	13	8
Education	1366	3437	2.516	14	7
Financial economy	618	1294	2.094	11	8
Science & Technology	494	881	1.783	12	5
Travel	338	519	1.536	7	5
Food	170	194	1.141	3	3
Business	277	353	1.274	4	3
Design	372	588	1.581	8	5

Topics	Node	Edge	Average degree	Network diameter	k-core
Lifestyle	786	1676	2.132	13	5
Physical education	289	450	1.557	5	4
Psychology	306	625	2.042	13	7
Medical health	347	598	1.723	10	4
Art	380	607	1.597	7	4
MMT	555	1134	2.043	17	5
Reading writing	397	612	1.542	8	4

The number of nodes represents the number of lives in this field. The larger the number of nodes, the more the number of lives in this field. Edge and average degree are used to measure interactions in the network. For a given number of nodes, the greater the number of edges, the higher the interaction in the network. The higher the average, the more frequently the nodes in the network interact. The network diameter represents the farthest distance between two nodes in the network.

As can be seen from the above table, the number of lives in education and career is the highest, exceeding 1,000. Explain that these two areas on the platform are hot. On average, the links in Internet, education, financial economy, lifestyle, psychology, MMT, and career are more closely related and the average value exceeds 2, indicating that one node is connected to two nodes on average. For the rest of the field, the network average is over 1, indicating that there is a small world phenomenon on the platform. For the indicator of network diameter, the fields of education, internet, financial economy, science and technology, lifestyle, psychology, MMT and career are large, and to some extent, the interaction between these fields is relatively close.

Our results show that the Internet, education, financial economy, lifestyle, psychology, MMT and career as core topics in the Figure 6 to Figure 12. Because the networks indicator in these areas are larger than other areas. These areas interact more frequently, indicating that these areas are hot topics that users are currently paying close attention to. In order to explore whether there are opinion leaders in the network, we analyze these core topics and choose the k-core network for exploring opinion leaders.

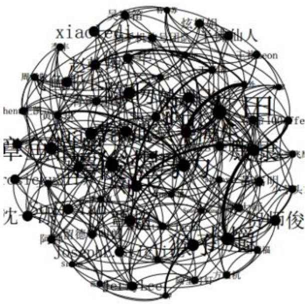

Figure 6. The largest k-core network in the Internet topics

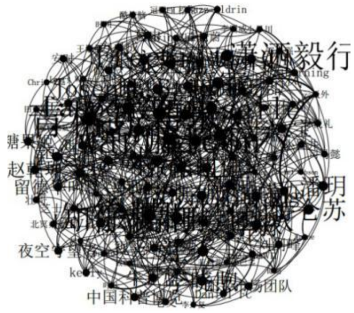

Figure 7. The largest k-core network in the education topics

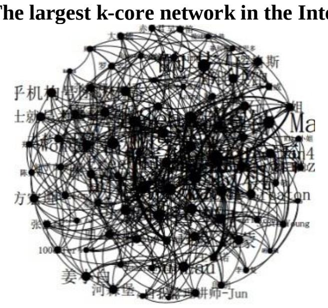

Figure 8. The largest k-core network in the career topics

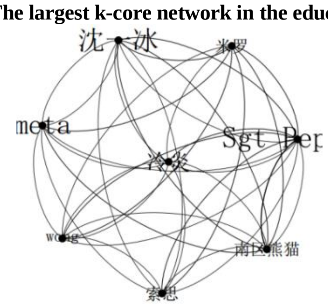

Figure 9. The largest k-core network in the financial topics

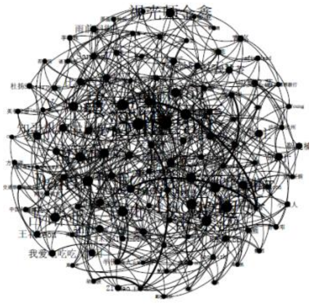

Figure 10. The largest k-core network in the lifestyle topics

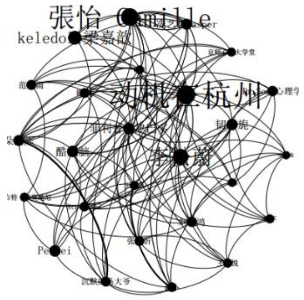

Figure 11. The largest k-core network in the psychology topics

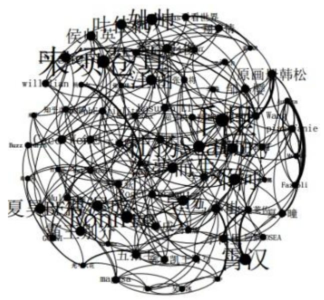

Figure 12. The largest k-core network in the MMT topics

For these core topics, the results show that some of the k-core networks are more intensive and some are sparse. In order to better explore the opinion leaders in the network, three relatively sparse networks, networks in the Internet, financial economy and psychology topic, are selected and analyzed. The top three nodes of the size of the degree in the networks and the relevant data is shown in the Table 4 to Table 6.

Table 4. The top five nodes in the Internet topic

ID	In-degree	Out-degree	Degree	Closeness centrality	Betweenness centrality
passerby	10	41	51	0.319	32162.948
horsepower	24	23	47	0.248	17908.959
bei-ming	26	16	42	0.275	22539.686
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horsepower	24	23	47	0.248	17908.959
bei-ming	26	16	42	0.275	22539.686

Table 5. The top five nodes in the financial economy topic

ID	In-degree	Out-degree	Degree	Closeness centrality	Betweenness centrality
sgt-pepper	6	6	12	0.875	13.166
shen-yi-bing	6	4	10	0.636	6.5
leng-yan	2	7	9	1.0	2.666
sgt-pepper	6	6	12	0.875	13.166
shen-yi-bing	6	4	10	0.636	6.5
leng-yan	2	7	9	1.0	2.666
sgt-pepper	6	6	12	0.875	13.166
shen-yi-bing	6	4	10	0.636	6.5
leng-yan	2	7	9	1.0	2.666

Table 6. The top five nodes in the psychology topic

ID	In-degree	Out-degree	Degree	Closeness centrality	Betweennes s centrality
dong-ji-zai-han	13	10	23	0.8125	63.316
fei-li-pu-jin-ba	16	1	17	1.0	4.583
lisongwei	12	4	16	1.0	13.0
dong-ji-zai-han	13	10	23	0.8125	63.316
fei-li-pu-jin-ba	16	1	17	1.0	4.583
lisongwei	12	4	16	1.0	13.0
dong-ji-zai-han	13	10	23	0.8125	63.316
fei-li-pu-jin-ba	16	1	17	1.0	4.583
lisongwei	12	4	16	1.0	13.0

We can see from the above table that in these three fields, the degree of nodes in the k-core network is much larger than the average degree of nodes in the overall network. Further, we find that the size of each degree is ranked in each field. The degree of the top five nodes is much larger than the node average in the overall network. This shows that there are opinion leaders in these nodes. These nodes are closely related to other nodes and have significant influence in the network. The closeness centrality and betweenness centrality of these nodes are also larger than other nodes, indicating that these nodes occupy a more important position in the network. On the one hand, this is inseparable from the expertise they possess, and on the other hand, their activity on the platform. They can spread knowledge in specific areas for users, and they are also very enthusiastic about the dissemination of knowledge, that is, they are very active on the platform. Therefore, the platform administrator should strengthen the tracking and management of this part of the node users, so as to enhance the activity of other users through them, thereby gaining more profits for the platform.

Combining the data from the diagram and the table above, we conclude that hypotheses H1a and H1b are correct.

To explore the content of the comments on the platform, we employ the LSTM model for sentiment analysis and use Word2vec/Skip-Gram with Negative Sampling (SGNS) to convert words into vectors, which use a widely used hotel review set. This corpus is a real-world data collected from the network platform and is labeled. Therefore, it's appropriate for the sentiment analysis task. The results are shown in the Table 7.

Table7. Social network parameters of different topics

Topics	Emotion score	Topics	Emotion score	Topics	Emotion score	Topics	Emotion score
Legal	0.614	Science & Technology	0.613	Design	0.603	Medical health	0.589
Internet	0.608	Travel	0.607	Lifestyle	0.587	Art	0.620
Education	0.627	Food	0.572	Physical education	0.594	MMT	0.608
Financial economy	0.609	Business	0.598	Psychology	0.582	Reading writing	0.609

When the emotional score is less than 0.5, it indicates that the attitude of people is negative. When the emotional score is greater than 0.5, it indicates that it is positive. The higher the emotional score is, the more positive the attitude is. As can be seen from the above table, in each field, users have a positive attitude towards them, because the emotional scores are greater than 0.5. The emotional scores of the core topics are higher than the rest of the themes, while the emotional scores of other non-core topics are lower, indicating that the emotional scores have a certain relationship with the level of user interaction. The results show that when the interaction of anchors is more frequent, the users' evaluation of the field is higher. Because people can learn more about the field through the programs of anchors attention. In other words, people can use anchors to find more high-quality programs and give a higher rating. Among them, the educational subject has the highest emotional score of 0.627, indicating that the person is most satisfied with the field. Besides, the accuracy of this model is 0.82. It indicates that this model is suitable. Hence, the last hypothesis has been supported.

5. CONCLUSION

The research on user interactions of knowledge payment platform is a breakthrough to promote the development of the platform. We mainly focus on social network and comment emotion in knowledge payment in this paper. We take Zhihu live as an example, and do the structural analysis and semantic analysis. Empirical study have proved that there is a small world phenomenon on the knowledge payment platform. Through social network analysis, we define the core topics of Zhihu live. Subsequently, we use the sentiment analysis to verify the relationship between user comments and user interactions. The study found that users are better rated for those areas where users are closely related. We believe that this article contributes two points: First, we have studied and visualized the social network of the knowledge payment platform, which was lacking in previous research. Second, we analyze the emotional sentiment of users on the platform and filled in the corresponding gaps. Our research serves the purpose of not only optimizing knowledge repositories but also enhancing social engagement.

However, our research contains several shortcomings. First, we only focus on user interaction within the same topic, ignoring user interaction between different domains. Secondly, we do not describe the users' profile of the opinion leader. We believe that the user interaction on Zhihu has an impact on the user interaction of Zhihu live. Last but not least, in the LSTM analysis, we are using a commonly used corpus, but there are only 10,000 statements. So in the future work, we could collect more user data and do deeper analysis, and use a larger corpus to make the results of sentiment analysis more accurate.

6. ACKNOWLEDGEMENT

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