International Journal of Multimedia and Ubiquitous Engineering
Vol. 9, No. 11 (2014), pp. 373-384
http://dx.doi.org/10.14257/ijmue.2014.9.11.36

Public Opinion Sensing and Trend Analysis on Social Media: A Study on Nuclear Power on Twitter[1]

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Abstract

Due to their popularity and rapid propagation capability, social media have become important communication channel on public opinions because they work as a main virtual space to raise new public issues, discussion on these issues, and make opinion directions on them. With the recognition of the importance of social media, many enterprises and governments try to use social media as marketing tools or public opinion sensing tools. Nuclear power has become one of trending public issues in Korea after Fukushima nuclear disaster. Nuclear power is a double-edged sword because it is the most efficient way to generate electricity currently and it also has dangerous potential risk such as radiation leakage. Governments and policy makers need to monitor public opinion on nuclear power continuously because it can be changed depending on related events. In this study, we aim to propose an approach to sense public opinions on nuclear power and to analyze their trend based on opinion mining techniques. Also we propose a measure to trace the changes on directions of public opinion on nuclear power. To show the usefulness of the proposed approach, we had gathered tweets on nuclear power in Korean from 2009 to 2013. After classification of tweets from 2009 to 2011, sentimental dictionary including positive and negative terms had been constructed. The performance testing using tweets from 2012 to 2013 showed that the proposed approach can be applied in practice.

Keywords: *Public Opinion Mining, Sentiment Analysis, Nuclear Power*

1. Introduction

Due to the interest and popularity of social media such as Twitter and Facebook, the boundary between real world and virtual world became ambiguous, and they are used as tools for expressing personal opinions and information sharing on social issues including politics, economics, culture, and government-related issues. Social media has also changed the role of citizens from information consumers to prosumers who can initiate new issues and influence the directions of public opinions. However, as a shadowy aspect of social media, there are some drawbacks on online public opinion on social media such as fraudulent and biased messages, witch hunting, extrusion of personal information, and information distortion on social issues.

Social conflict levels within countries can be influenced by social media in the countries which have matured internet infrastructure such as Korea, EU and USA. In the case of Korea, social conflict level is ranked as the second among 27 OECD countries in a cross-country

[1] The initial version of this paper has been presented at the 4th International conference on Circuits, Control, Communication, Electricity, Electronics, Energy, System, Signal and Simulation (CES-CUBE 2014).
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ISSN: 1975-0080 IJMUE

survey on social conflict level in 2010 [22]. The economic loss due to social conflict in Korea is estimated as 7.5 ~ 22.4 million US dollar. If social conflict level in Korea can be reduced by 10%, it is estimated that GDP per person can be improved additional 1.8~5.4%, and if that can be reduced as the average of OECD, GDP improvement is estimated as 7~21%. Also, the countries which have weakness on conflict management have limitations to overcome economic risk and recession and to deploy policies [20]. So, many governments have interests on social media as spaces for communication and participation of citizens and strategic tools to deploy country policies [7]. Based on such needs, there are related researches on public opinion trend analysis, information diffusion analysis, and election prediction [12], [26].

Nuclear power is a country-level political issue in many countries. Some people focus on the economic benefits of nuclear power, but some people highlight risks of nuclear power. To construct nuclear power facilities, governments need to make consensus nationwide and get agreement from people who live in adjacent areas of intended construction place. To make and deploy long-term national nuclear power policy, government officers need to sense and monitor public opinions on nuclear power. Without such efforts, the cost to resolve related conflicts can grow seriously. Traditional survey-based public opinion monitoring on nuclear power has limitation in terms of cost and time delay. Social media-based opinion monitoring can be complementary approach for the traditional approach [6, 8].

In this study, we aim to suggest and verify public opinion approach on nuclear power. To show the usefulness of the proposed approach, we use tweets on ‘nuclear power’ issue in Korea from 2009 to 2013. Tweets from 2009 to 2011 are used to construct a sentiment dictionary on nuclear power and those from 2012 to 2013 are used to test the performance of the proposed approach. Also, a measure called NOI (Nuclear Opinion Index) is proposed to trace the temporal changes on public opinion on nuclear power. The paper is organized as follows. In section 2, we will review issues on nuclear power generation and literatures on public opinion mining on social media. In section 3, the proposed approach will be suggested. Section 4 presents experimental results to show the usefulness of the suggested approach. Section 5 will include some conclusion remarks and further research issues.

2. Issues on Nuclear Power

Korea is a heavy energy dependent country. For example, the total annual cost of energy import is estimated as 18.5 million dollar which is 36.6% of total annual import amount, 52 million dollar in 2012 [35]. To improve overall productivity at country level in Korea, it is inevitable to secure the supply of electricity economically. Nuclear power is essential portion of electricity supply in Korea because it is the most efficient way to generate electricity currently and it has advantages on low greenhouse gas exhaustion. However, it has fatal potential risk of radiation exposure. Chernobyl disaster in 1986 and Fukushima Daiichi nuclear disaster in 2011 show the impacts and drawbacks of nuclear power. Other weaknesses of nuclear power are high construction cost, difficulties in waste disposal treatment, and demolition cost. Especially, after Fukushima nuclear disaster, citizens in Korea feel a growing sense of insecurity on nuclear power. In addition, negative news such as stops of operation of nuclear power plants and corruptions related on nuclear power increase negative emotion on nuclear power.

Traditionally, public opinion monitoring has been performed using survey-based approach. It is time consuming and expensive. Also, respondents may not have enough information and interest on topics. In addition, there is possibility to express uncertainty on their intention by way of passive participation. In practice, a survey result by a Korean institution in 2011 showed that 27.5% of respondents felt unsafety of unclear power, 31.0% of them distrusted government on nuclear power issue, and 35.2% of them did not support government nuclear power policy [28]. However, another survey result by a foreign institution is quite different. By a survey of Asahi newspaper, 70% of Korean thought that nuclear power is unsafe, 89% of them did not trust government on nuclear power issue, and 64% of them did not support government nuclear power policy [32]. The two cases show that the survey results can be changed by the intention of survey institutes and sampling method. So, in this study, we try to propose complementary way to monitor public opinion on nuclear power using social media.

3. Public Opinion and Social Trends

Due to the popularity of social media, the power on policy decision making is shifted from mass media and major politicians to citizens. Social media can work as new cheap direct communication channels between governments and citizens. So, there are trials to use social media as new tools to establish public agenda setting and to evaluate the results of policy execution. For example, USA government established 'Cash for Clunkers Program' in which government supported car renewals as an economic activation policy in 2009. The initial planned execution period of the program was 4 months and the government prepared required budget based on rough demand forecasting. However, due to the unexpected good response, the budget was exhausted within one week and the government needed to prepare additional budget in a rush. However, Google predicted the respond level based on the number of related terms in Google search, and forecasted budget exhaustion time. Base on the results, Google predicted the need for additional budget accurately [4, 30]. In additional, there are many researches to sense and monitor social trends and public opinion using social media [6, 23]. Some researches focused on political election result prediction based on Twitter information [2, 3], and others aims to monitor customer sentiment on a certain brand [33]. Another study tried to prediction movie performance based on tweets on movies [13, 14]. Based on online search behaviors, there are trials to trace disease and disasters [29], and to predict unemployment rate in USA [11]. Public opinion monitoring using social media can contribute to reduce social cost and to improve the quality of citizens' lives based on systematic monitoring and accurate prediction of social trends [7].

4. Opinion Mining

As a part of text mining, opinion mining refers to the use of natural language processing, text analysis and computational linguistics to identify and extract subject information from source material. As a subpart of opinion mining, sentimental analysis tries to measure emotional scores of source documents, which include classification of positive or negative documents [5]. Even though traditional text mining tries to find relevant 'facts' in source documents, opinion mining challenges identifies 'attitude' of authors on certain subjects and issues [10].

In opinion mining, various techniques can be applied depending on characteristics of texts and languages. In the case of Korean language, it is difficult to identify positive or negative sentences because there are difficulties in identifying sentence structures using morphological analyzers, and emotional directions could completely change based on context and combined ending [19]. Many opinion mining studies mainly use the number of word frequencies regarding grammars, and try to build sentimental dictionaries to meet a certain context and purpose [8, 9, 34]. Some researches classify based on sentence structure, relationships between sentences, patterns on sentence component using PMI (Pointwise Mutual Information), Navie Bayes, and SVM (Support Vector Machine), and try to apply general term dictionaries such as WordNet and SentiWordNet [9, 16, 24, 25, 36]. Natural language processing techniques based on machine learning are studied in computational linguistics, and made progresses in morphological analyzers, sentimental analyzers, and sentimental ontologies [1, 17, 18, 21, 31].

5. Proposed Approach and Experimental Design

The proposed procedure for public opinion mining on nuclear power consists of four phases: (1) crawling and cleansing on social media data, (2) sentimental term extraction, (3) construction of a sentiment dictionary, and (4) tweets sentiment classification. The detail of such experimental procedure is shown in Figure 1

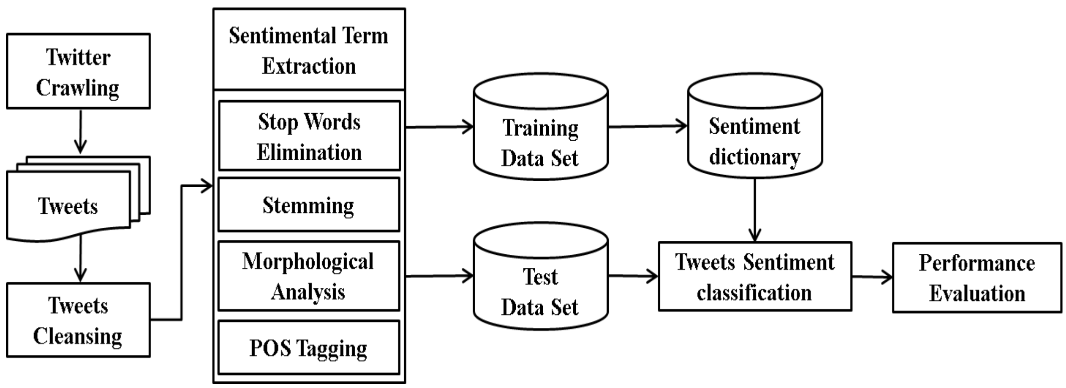

Figure 1. Experimental Procedure

5.1. Crawling and Cleansing on Social Media Data

In this study, we gathered Korean tweets from 2009 to 2013 which include ‘nuclear’ or ‘nuclear power’ in Korean using a crawling tool, LocoySpider[3]. Twitter, with its great number of users having different opinions and real time update, is a useful tool to sense public opinion [15].

Among the crawled tweet, irrelevant tweets are identified and removed for next analysis. Also tweets on neural news articles and tweet from government institutes are removed because our purpose is to identify social opinions rather than government announcement. Finally, the final data set consists of 237 tweets in 2009, 914 tweet in 2010, 5,705 tweets in 2011, 5,081 tweets in 2012, and 4,655 tweets in 2013 (refer Table 1 and Figure 2).

Table 1. Number of Tweets by Month (2009~2013)

	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Total
09	-	-	2	2	7	16	23	46	33	20	25	63	327
10	67	8	9	7	17	34	82	106	111	120	198	155	914
11	309	359	1874	740	448	241	191	170	226	355	424	368	5705
12	334	458	676	245	248	412	761	625	457	297	371	197	5081
13	198	206	423	534	463	672	553	585	328	510	183	-	4655

[3] www.locoy.com

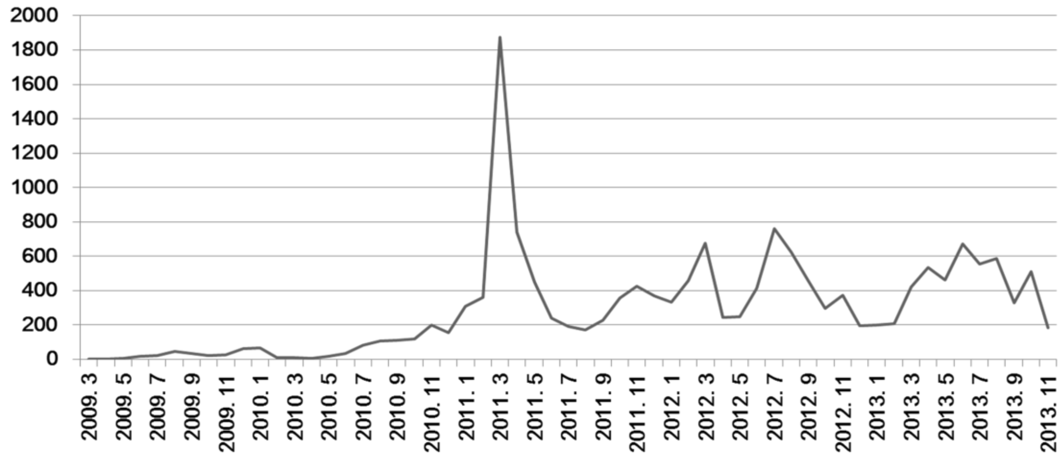

Figure 2. The Number of Tweets

The number of tweets on nuclear power is relatively small in 2009. There were three good news on nuclear power in Korea during 2009 and 2010 (refer Table 2). First, on December 28 2009, there was the first nuclear power plant export to UAE. There were two additional export news in 2010. The most important event during the period was Fukushima nuclear accident in March 2011. The number of tweets in March 2011 made a peak. After the event, there wss a good news (Nuclear Security Summit in Korea) in 2012 and several bad news on stops of operations at nuclear power plants during 2012 and 2013. Depending on the events, the monthly tweets made fluctuation.

5.2. Sentimental term Extraction

Due to Korean language characteristics including many variations on roots, importance of distinguish postposition and ending, and compound nouns with space, natural language processing in Korean is more difficult than that in English. Especially, in social media, users use composite terms and abbreviations more frequently, and include many sentences which do not follow grammar rules. So, it requires more effort to extract sentimental terms in social media. In this study, we use text mining package tm[4] in R and KoNLP (Korea Natural Language Processing)[5] which provides functionalities to parse Korean sentences.

Table 2. Important Events on Nuclear Power during 2009 and 2013

Year	date	Event
2009	December 27	First nuclear power plant export to UAE
2010	March 30	First research nuclear reactor export contract to Jordan

[4] Ingo Feinerer [aut, cre], Kurt Hornik [aut], Artifex Software, Inc. [ctb, cph] (2014). tm: Text Mining Package. R Package Version 0.6. http://CRAN.R-project.org/package=tm
[5] Heewon Jeon (2013). KoNLP: Korean NLP Package. R Package Version 0.76.9. http://CRAN.R-project.org/package=KoNLP

	June 15	MOU on nuclear power plant between Turkey and Korea after a summit meeting
2011	March 11	Fukushima nuclear accident
2012	March 26 and 27	Nuclear Security Summit
	July	Stop of operation at Youngkoyang nuclear power plant
2013	March, August, and November	Stops of operation at nuclear power plants

Potential sentimental terms are extracted though stop words elimination, stemming, morphological analysis and POS (Part of Speech) tagging. In stop words elimination, the special characters such as twitter tags (for example, ‘@’ and ‘#’), punctuation marks, URL (started with ‘http://’), and numbers are removed as stop words. Finally, only nouns are extracted potential sentimental terms.

In the previous study, nouns and emoticons are more frequently used to express emotion than adjectives due to the limitation of the number of characters in Twitter [19]. Also, in our case, representative nouns such as ‘export’, ‘safety’, ‘Mafia’, and ‘disaster’ are used frequently to express users’ emotion. These are the reasons why we consider nouns first as potential sentimental terms.

The followings are several examples of English-translated tweets. First two tweets are examples of positive tweets, and the next two tweets are negative tweets.

(1) a. “South Korea has a high level of nuclear safety systems” http://xxx/xxxxx

b. “Do you know that Republic of South Korea exports ‘nuclear technology’ as well as ‘nuclear safety’?” http://xxx/xxxx

(2) a. #xxxx “Government's safety ignorance of nuclear, more serious than Fukushima.

b. It is fraud of the nuclear mafia!” RT@xxxx

5.3. Construction of a Sentiment Dictionary

Sentimental classification is usually based on the number of positive terms and negatives terms in sentences. The referential positive terms and negative terms are stored in sentiment dictionary. So, the construction of sentimental dictionary is an important part in sentimental analysis. Previous constructed sentiment dictionaries can be used or a new sentiment dictionary can be constructed using gathered sentences [27]. In this study, we use latter to reflect contexts of nuclear power domain.

Table 3. Example of Terms in a Sentiment Dictionary

Polarity	Terms
Positive	Safety, Export, Creative, Clean, Economic, Powerful Nation, Clean Energy, Respect, Profit, Green Growth, Advanced Country, Technology, Excellent, Green, Alternative Energy, Efficiency......
Negative	Disaster, Ignorance, Nuclear Power Mafia, Unrest, Radiation Leak, Fraud, Irresponsibility, Destruction, Tsunami, Opposition, Impeachment, Suspicion, Corruption, Conceit, Opacity, Imprisonment, Dilemma, Catastrophe, Scapegoat……

The tweets from 2009 to 2011 are used to construct a sentimental dictionary. Nouns are extracted after potential sentimental term extraction. Three human evaluators are classified positive, negative, and neutral terms separately. The terms which assigned in positive or negative terms by all of three evaluators are finally assigned as positive or negative terms. The number of positive terms is 1,012 term and that of negative terms is 3,291 (refer Table 3). We can find that the number of negative terms is greater than that of positive terms.

5.4. Tweets Sentiment Classification

The tweets between 2012 and 2013 are used to evaluate the performance of sentimental classification. Sentimental classification is based on sentimental scores of tweets. The sentimental score of a tweet is calculated based on the number of positive terms and the number of negative terms in the tweet. The range of sentimental score is between -1 and 1. Tweets are classified as positive tweets when sentimental scores are greater than 0, and as negative tweets when those are less than 0. The tweets with 0 sentimental scores which mean that there are no positive terms and negative terms, or the number of positive terms and negative terms are the equal.

$$Sentimental\_Score(t) = \begin{cases} \dfrac{N(Positive\_tems(t)) - N(Negative\_terms(t))}{N(Positive\_terms(t)) + N(Negative\_terms(t))} \\ \quad \text{when } N(Positive\_terms(t)) + N(Negative\_terms(t) \neq 0 \\ 0 \quad \text{otherwise} \end{cases} \qquad (1)$$

6. Experimental Results

The performance of proposed approach is tested using tweets between 2012 and 2013. The prediction accuracy is shown in Table 4. In the case of positive tweets, accuracy rates are 51.57% for 2012 tweets and 50.55% for 2013 tweet. Accuracy rates on negative tweets are relatively higher than positive tweets. It is 61.19% for 2012 tweets and 64.08% for 2013 tweets. However the accuracy rates on neutral tweets are relative lower those on positive or negative tweet. It is 38.96% for 2012 neutral tweets and 21.67% for 2013 neutral tweets. The reason is that we focus on positive or negative tweets and construct only positive and negative dictionaries without a neutral dictionary.

Table 4. Sentimental Prediction Accuracy

Sentiment	2012		2013	
	Accuracy Rate	No. of Tweets	Accuracy Rate	No. of Tweets
Positive	51.58%	948	50.55%	991
Negative	61.19%	2067	64.08%	2289
Neutral	38.96%	2066	21.67%	1375

7. Public Opinion Index of Nuclear Power

To trace the temporary changes of public opinion on nuclear power, we define Nuclear Opinion Index (NOI) as follows (refer <formula 2>). NOI is determined based on the number of positive tweets, negative tweets, and total tweets of the month. Based on NOIs, we can trace the change of public opinion on nuclear power at a specific period.

$$Nuclear\,Opinion\,Index(m) = \frac{N(Positive\_tweets(m)) - N(Negative\_tweets(m))}{N(Total\_tweets(m))} \times 100 + 100 \quad (2)$$

Figure 3 shows the changes of NOIs during 2009 and 2013. Based on a positive news on export of nuclear technology, public opinion on nuclear power was positive until 2010. However, it turned to negative from Fukushima Daiichi nuclear disaster and was still located in negative until the end of 2013. The NOI chart visualizes the changes of public opinion on nuclear power.

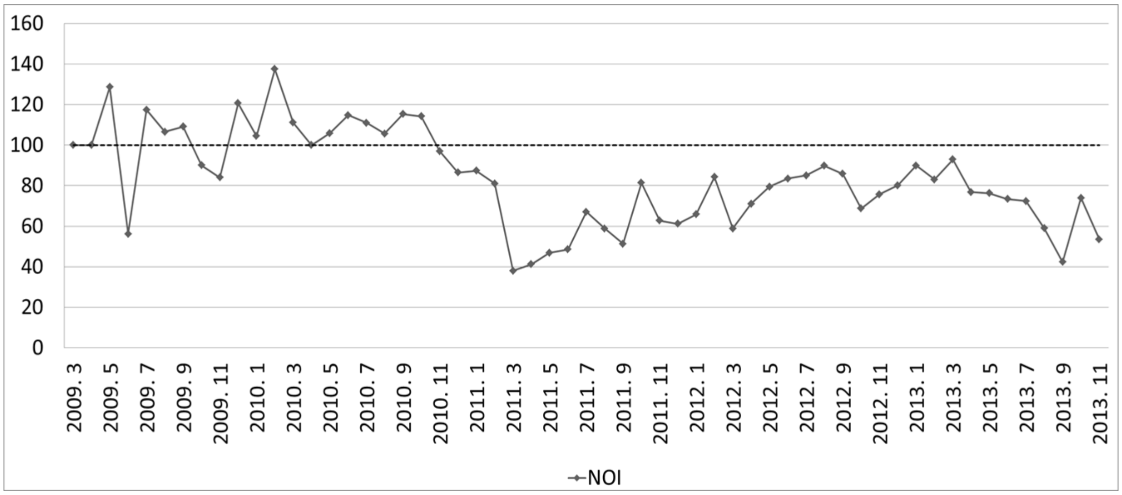

Figure 3. Changes on Monthly Nuclear Opinion Index

8. Conclusion and Future Research Issues

Social media advanced as new communication channels for public opinion because they are open to many citizens, easy to use, and provides online discussion mechanisms. Attempts to use social media to monitor public opinions are in initial stages of studies and practices. In this study, we proposed and evaluated an approach to monitor public opinion on nuclear power using a representative social media, Twitter. We constructed a sentimental dictionary with positive and negative terms using tweets between 2009 and 2011. Sentimental score is proposed to classify tweets sentiment on nuclear power. Based on sentimental score concept, we tried to classify tweets between 2012 and 2013 to show the usefulness of proposed approach. The classification accuracy rates on positive and negative tweets are acceptable. Also, in order to trace temporary changes on public opinions on nuclear power, we proposed NOI (Nuclear Opinion Index) as a way to aggregate tweets' emotions in a certain period. The chart of NOIs from 2009 to 2013 showed the changes of public opinion reflecting important events on nuclear power such as Fukushima Daiichi nuclear disaster.

Traditionally, survey-based approach has been used to monitor public opinion on nuclear power, which is expensive and has time delays. Opinion mining approach based on social media contents can provide complementary approach, which is relatively cheap and with no time delays. Even though we focus on public opinion on nuclear power, the proposed approach can be easily applied to other public opinion cases.

The further research issues are as follows. First, in this study, the sentiment dictionary is constructed based on evaluation of human evaluators. So, it is necessary to minimize human evaluators' participation and to automate sentiment dictionary building process. Another limitation on sentiment dictionary is that it is static. To reflect changes on social issues, sentiment dictionary needs to have self-evolution mechanism. That is, it is necessary to develop automatic update mechanism of sentiment dictionary based on new contents on social media. Secondly, in this study, we only used rooted nouns as potential sentimental terms because they are the most important structural components in tweet sentences. We will try to include other parts of sentences such as verbs and adjectives as potential sentimental terms. Also, it is an interesting research issue to apply the proposed approach other social media such as online communities and news sites. Finally, country level comparison on public opinion on nuclear power is also an interesting research topic.

Acknowledgements

This work was supported by the Nuclear Power Core Technology Development Program of the Korea Institute of Energy Technology Evaluation and Planning (KETEP) granted financial resource from the Ministry of Trade, Industry & Energy, Republic of Korea (No. 201300000003242).

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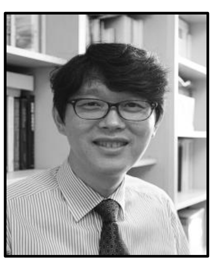

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