Public Opinion Dynamics in Cyberspace on Russia–Ukraine War: A Case Analysis With Chinese Weibo

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***Abstract*— The intensity and scale of the opinion fightings in cyberspace on the Russia–Ukraine war (RUW) have opened a new chapter in the history of world warfare. This is a magnificent demonstration of social cognitive war fighting with cyber-physical-social systems (CPSS) that would impact our humankind significantly now and for a long time to come, not just on our understanding of wars, but every aspect of our life. Therefore, it is worth of studying the opinion dynamics of the RUW in the cyberspace. This article will start this direction with an analysis of the evolutionary dynamics of the public opinion fighting, only using Chinese Weibo texts as a case study due to the time constraint. It first clusters the Weibo texts into four categories with unsupervised learning method using Latent Dirichlet Allocation and then collects opinions by extracting keywords. Meanwhile, an opinion adversarial evolution algorithm is proposed to dynamically model the dominance degree of an opinion in the evolutionary processes. We release a dataset of Chinese Weibo associated with RUW. The proposed approach of modeling and analyzing data-driven public opinion dynamics provides a new way for accessing opinion warfare in CPSS.**

***Index Terms*— Opinion adversarial evolution, opinion generation, public opinion analysis, Russia–Ukraine war (RUW), semantic emotion.**

I. Introduction

THERE has been a sharp rise in news coverage and public discussion since the outbreak of the Russia–Ukraine war (RUW). NATO[1] condemns in the strongest possible terms Russia's full-scale invasion of Ukraine, and Associated Press (AP)[2] call it "war crimes." Council of the European Union[3] and United Nations calls the RUW as "Russian's invasion of Ukraine," while Indiatimes[4] calls it "Russian attack on Ukraine." People are very active in expressing their opinions in cyberspace, esp. during RUW using Twitter, Chinese Weibo etc. RUW have opened a new chapter in the history of world warfare. This is a magnificent demonstration of social cognitive war fighting with cyber-physical-social systems (CPSS) that would impact our humankind significantly now and for a long time to come, not just on our understanding of wars, but every aspect of our life.

These social data from social media can be leveraged to mine the semantic emotion, the public event's opinions, and the opinion evolution is significant for public opinion understanding [1]. However, the massive amount of social data added daily makes data labeling difficult or even impossible, so that effective data mining cannot be performed with supervised and semisupervised machine learning methods. On the other hand, it is difficult to dynamically explore the interactions of various opinions in the public affair evolution process due to the complexities of these interactions.

The existing social text emotion analysis methods mainly utilize traditional machine learning for emotion recognition or text classification. For example, Habernal *et al.* [2] used support vector machine (SVM) to analyze Czech social media emotion. However, the traditional approaches cannot effectively extract complex semantic information in large-scale social texts. Meanwhile, the existing public opinion investigations mostly classify social texts by artificially building information categories based on *a priori* knowledge. For example, Imran *et al.* [3] identified the microblogs category based on subjective factor to analyze online public opinion during disaster events, which introduces partial human error and affects the subsequent analysis. In addition, the existing methods mostly study the evolution of public opinion based on single feature or separating multiple features. For example, Rudra *et al.* [4] performed opinion evolution in social media based on hashtag attributes, which ignores the interaction of multiple attributes.

To address the above challenges, this article proposes a comprehensive approach for mining the public opinion dynamics on RUW, using Chinese Weibo text as a case. The Robustly Optimized Bidirectional Encoder Representations from Transformers Pretraining Approach (RoBERTa) is used to mine the semantic emotion of the RUW associated social data. A latent Dirichlet allocation (LDA)-based unsupervised text clustering method is employed to determine the number of opinion categories, and keyword extraction is used to generate opinion content. An opinion adversarial evolutionary

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[1]https://www.consilium.europa.eu/en/policies/eu-response-ukraine-invasion/
[2]https://www.pbs.org/wgbh/frontline/interactive/ap-russia-war-crimes-ukraine/
[3]https://www.consilium.europa.eu/en/policies/eu-response-ukraine-invasion/
[4]https://www.indiatimes.com/ukraine-crisis

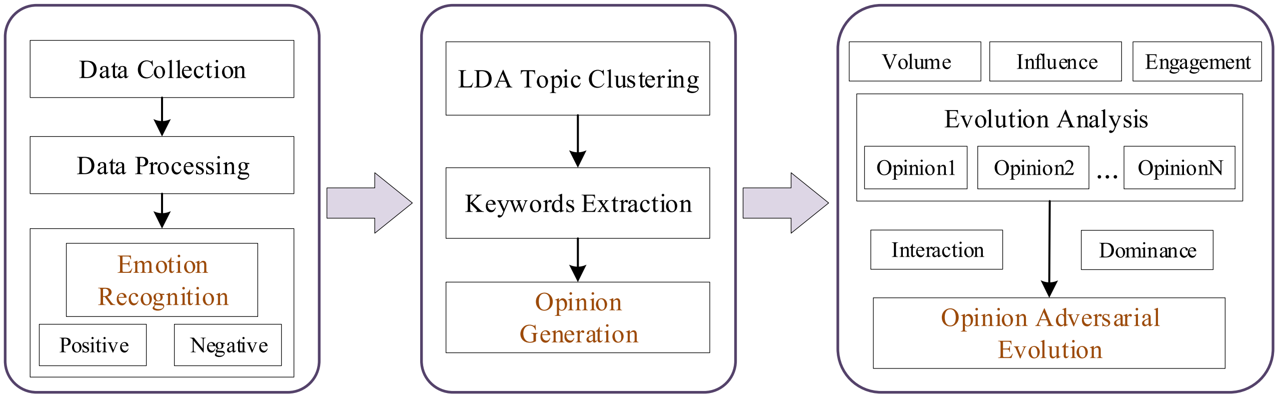

Fig. 1. Overall approach architecture.

algorithm is proposed to dynamically identify the interaction and dominant weights of different opinions in the evolution to achieve opinion evolutionary analysis, considering opinion influence, opinion engagement, and opinion data volume. The following research questions will be answered.

RQ1: How to identify text emotion and opinion categories in social media using unsupervised approach?

RQ2: What are the interactions and the dominant factors of various opinions in the evolution process?

The primary contributions of this article are as follows.

1) A comprehensive public opinion analysis approach is proposed to analyze the dynamics of public opinion in cyberspace including emotion recognition, opinion extraction and evolutionary analysis.
2) An opinion adversarial evolutionary algorithm is proposed to dynamically identify the interactions and the dominant factors among different opinions in the evolution.
3) A public dataset of Russian–Ukrainian war-related Chinese Weibo is released, with this link (https://github.com/upcbdipt/RUW-Dataset).

The remainder of this article is organized as follows. Section II discusses related work. Section III presents the approach for public opinion analysis. Sections IV–VI describe the data collection and processing, opinion clustering and mining, and opinion adversarial evolution. Section VII concludes this article and opinions out important future work.

II. Related Work

Social media has become the primary means that people obtain information and share opinions [5]–[9]. In particular, daily social media data flood dramatically when major public affairs arise. It provides useful sources for mining users' opinions on these public events [10]–[13].

Text emotion mining usually maps text into vectors, and then uses machine learning methods for emotion recognition [14]. Chen *et al.* [15] construct classifiers with a Naive Bayesian (NB) algorithm and optimize them using the LDA topic model to achieve emotion classification of microblog texts. Muhammad *et al.* [16] propose a lexicon-based social media emotion classification system. The system captures emotion features from both local context and global context perspectives with social media data. However, the social emotional classification effect of the traditional model is limited because of semantic complexity, which will affect the emotion mining effect and the subsequent analysis.

The pretrained models [pretrained language models (PLMs)] is a new approach emotion mining. A generic emotion classification model is first trained using a large-scale corpus, and then the pretrained model is fine-tuned using social text to effectively improve the accuracy of social text emotion classification. Nguyen *et al.* [17] proposes a large-scale PLM Bidirectional Encoder Representations from Transformers for Tweet (BERTweet) for English blog texts, which achieved good emotion classification results. Malla and Alphonse [18] integrates RoBERTa, BERTweet, and Bidirectional Encoder Representations from Transformers for COVID-Twitter (CT-BERT) based on majority voting techniques to identify blog text emotion during the COVID-19.

Opinion analysis [19] mainly includes identifying the number of opinion categories and keywords extraction. Large number of new social texts added daily makes labeling difficult, and unsupervised clustering methods are mostly used in identifying the number of opinions. By retrieving global and local data of opinion distribution patterns, Jose and Babu [20] proposes a novel spam clustering method based on the LDA topic model. Zhang *et al.* [21] proposes an unsupervised clustering method based on contrast learning to address categories overlapping in their representation space.

The class clusters are obtained after clustering, then the text is divided into words, and the keywords are extracted by ranking the relevance of the words to the class clusters [22]. Devika and Subramaniyaswamy [23] proposes a semantic graph-based keyword extraction method (SKEM) and used a ranking method to extract keywords from Twitter. Harakawa and Iwahashi [24] proposes a method to detect communities of tweets with similar opinions and rank the communities by importance measures to extract keywords that are highly relevant to the number of COVID-19 infections.

The opinion evolution is mainly used for analyzing the time-series changes of a variable through data statistics or neural networks. Zhuang *et al.* [25] used the LDA to extract information about comment opinions and predicted the emotion evolution of social text using an autoregressive moving average model (ARMA). Reyero *et al.* [26] built a semantic

TABLE I
EXAMPLE OF BLOG ATTRIBUTES

Opinions	Content	Retweets	Comments	Likes
China evacuation of nationals from Ukraine	Shenzhen students in Ukraine want to return home early to eat snail powder.	2	11	14
Progress of Russia-Ukraine negotiations	Ukraine says that the negotiation process will be decided tonight.	191	513	3473
SWIFT and Russia	The United States issued a joint statement on the 26th to exclude some Russian banks from SWIFT.	3	32	121

network based on user tags to detect the opinions discussed in the society, and studied the evolution of the political landscape during the presidential elections in Argentina based on opinions evolution. However, it is difficult to effectively analyze the features of opinion evolution considering only one variable. Zhu *et al.* [27] propose a model that incorporates opinion evolution into the process of opinion dissemination. The model considered different communication intentions and elucidated the impact of user opinion evolution on information dissemination in online social networks. Liu *et al.* [28] obtain the key nodes of public attention and opinion propagation by hot events' detection and user influence calculation to analyze the evolution of public opinions related to the COVID-19. However, when multiple opinions are analyzed for their evolution, the interaction among each opinion should be taken into account. Separating each opinion for individual analysis does not truly describe the evolutionary process of that opinion as they have interactions, which may negatively affect the effectiveness of evolutionary analysis.

III. Approach

We propose a comprehensive public opinion analysis approach to analyze the dynamics of public opinion, as shown in Fig. 1. First, the RUW associated texts in Chinese Weibo are collected and processed to recognize social emotion regarding RUW. Second, an LDA-based unsupervised learning is employed to determine the number of opinions on the RUW issue. Also, keywords are extracted to form the content of public opinions. Finally, incorporating the opinion influence, opinion engagement, and opinion data volume, an adversarial evolutionary analysis is performed to identify the interactions and the dominant factors among different opinions in the evolution.

For the public emotion recognition, 5000 Weibo items are labeled to train a binary emotion classification model, where positive and negative semantic emotion from a Weibo content can be obtained. We must point out that the positive emotion not means that Weibo item supports the RUW, but only means the whole content has a positive manner from the semantic analysis point of view.

Since specific opinion categories could not be identified manually and easily, unsupervised clustering is applied to determine the number of opinions toward the RUW. Opinions are then generated by keywords to define opinion categories. In particular, clustering effects of multiple unsupervised models are compared on a public dataset with labels and the best model are used to cluster the collected social text. The clustering results are visualized to determine the number of categories, and keywords are extracted for each category separately. Keywords and press facts are combined to generate corresponding opinions for opinion mining and analysis.

In the opinion evolution, the evolution of each opinion and opinion interaction (adversarial) is analyzed, respectively. The opinions influence is obtained by a weighted sum of the text influence and the users influence. We use the percentage of daily opinion influence over the total influence in a certain time as the opinion engagement. The product of the daily opinion engagement and the volume of opinion data is defined as opinion evolution index, and is used to analyze the trends of each opinion evolution. In addition, considering the interaction and dominance degree of various opinions in the evolution, an opinion adversarial evolution approach is designed. Each opinion engagement in a day is normalized as a weight, and then multiplied and summed with the corresponding opinion volume to obtain event adversarial evolution index, which is used to perform adversarial evolution analysis.

IV. Data Collection and Processing

A. Data Collection

Based on the Scrapy framework, we used a web crawler to collect the Weibo texts during the RUW. The crawler keywords are "China evacuation of nationals from Ukraine," "Progress of Russia–Ukraine negotiations," "SWIFT and Russia," and other words. We collected approximately 150 000 Weibo texts from February 19, 2022 to March 5, 2022. Each text contains blog attributes and user attributes. The blog attributes include the creation time, the collected time, the content of the text, the source of the text, the number of retweets, comments, and likes. The user attributes mainly include a user id, user name, user genders, followers' number, followees number, and user description.

For data preprocessing, we limit the length of the texts within 40–150 characters. Then we remove stop words, special emoticons, duplicate texts, and content-missed texts. After processing, about 100 000 Weibo items are obtained. The example of blog attributes and user attributes is shown in Tables I and II, respectively.

TABLE II
EXAMPLE OF USER ATTRIBUTES

User Id	followers' number	Followees number	Description
1000011415	348	138	Vice Chairman of Shanghai Jiao Tong University EM Alumni Association
1000744910	3	161422	Researcher of traditional Chinese humanistic aesthetics
1180884412	2	5559	Director of Child Psychology Special Committee of National Youth Social Practice Five Education Alliance
90852457	65	216	Shandong Folk Metal Band

TABLE III
PERFORMANCE OF EACH EMOTION CLASSIFICATION MODEL

Models	Public dataset	Our dataset
SVM	74.25%	66.87%
NB	64.76%	56.39%
Bi-LSTM	75.92%	75.46%
Text-CNN	74.46%	72.87%
GPT	80.44%	78.71%
BERT	81.67%	79.43%
ALBERT	77.52%	73.98%
RoBERTa-wwm	**84.81%**	**80.21%**

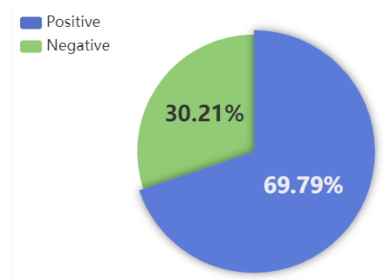

Fig. 2. Emotion classification results of our dataset (RUW-Dataset).

B. Emotion Recognition

Various text classification models can be employed to mine semantic sentiment, such as Generative Pre-Trained Transformer (GPT) [29], Transformer Encoder-based BERT [30], A Lite Bidirectional Encoder Representations from Transformers (ALBERT) [31], and RoBERTa [32].

We first compare the performance of these models on the Weibo data. During the comparison experiments, we invite three graduate students to label the emotion of 5000 Weibo texts. The labels are "positive" and "negative." Also, we demonstrate the validity of the model using the ChnSentiCorp[5] public dataset. The average accuracy of six experiments is used for models' evaluation.

There are similar hyperparameters in each emotion classification model of Table III. The kernel of SVM is radial basis function (RBF), and the smoothing factor of NB is 1e−4. The learning rate, embedding size, batch size, and iterative rounds of both bi-directional long short-term memory (Bi-LSTM) and text convolutional neural networks (Text-CNNs) are 5e−5, 128, 64, 50, respectively. Meanwhile, the hidden layer size of Bi-LSTM is 64 and the convolution kernel size of Text-CNN is [3,4,5]. Moreover, identical parameters are set for each pretrained model (GPT, BERT, ALBERT, RoBERTa-wwm), where the learning rate is 5e−5, the weight decay is 1e−5, the batch size is 64, the number of iterative rounds is 50, and the optimizer is AdamW. The performance of each model is shown in Table III.

The experiments show that SVM, NB cannot perform well because they cannot fully learn the complex text features of social media data. The transformer-based pretrained model outperforms the traditional deep learning models Bi-LSTM and Text-CNN on both datasets. We believe that the pretrained models have been trained with a large-scale corpus and possess stronger feature extraction capability. The GPT model uses only one-way linguistic information and is slightly less effective than BERT for text classification tasks. Compared with BERT, RoBERTa-wwm leverage a dynamic full-word masking strategy, which is more suitable for Chinese short text classification tasks. This model achieves the best performance in both datasets. Therefore, RoBERTa with the whole word masking (RoBERTa-wwm) is used in the subsequent analysis for Weibo texts emotion recognition.

The RoBERTa-wwm is fine-tuned with 5000 labeled Weibo texts to recognize other Weibo texts semantic emotion. The classification result is shown in Fig. 2.

The result shows that positive emotions are as high as 69.79% and negative emotions are 30.21%. The following analysis focuses on both positive and negative aspects.

V. OPINION CLUSTERING AND MINING

A. Method

For the public opinion mining, the clustering performance of some unsupervised models are first compared based on a subset of the THUCNews [33] dataset, and the best model is selected for Weibo texts clustering. The Weibo texts are clustered with 4, 6, 8, 10 classes, respectively, and the best number of opinion classes is determined by visualizing the clustering results. We also extract keywords for each category of opinion based on people's positive and negative semantic emotions, and summarize the content of opinions by combining with actual events.

B. Model Comparison

THUCNews dataset is composed of historical data of Sina News from 2005 to 2011, with 14 categories and 1000 data items in each category. We verify the clustering effect of four unsupervised clustering models, namely LDA [34], K-means

[5]Chnsenticorp data https://github.com/duanruixue/Chnsenticorp

TABLE IV
CLUSTERING EXPERIMENT RESULTS (THE NUMBER IS THE CLUSTER AMOUNT)

Model	Four	Six	Eight	Ten-
LDA	**0.6965**	**0.685**	**0.6138**	**0.6431**
K-Means	0.4357	0.364	0.2977	0.2726
BIRCH	0.5412	0.3563	0.2561	0.2115
GSDMM	0.6017	0.5735	0.5138	0.4343

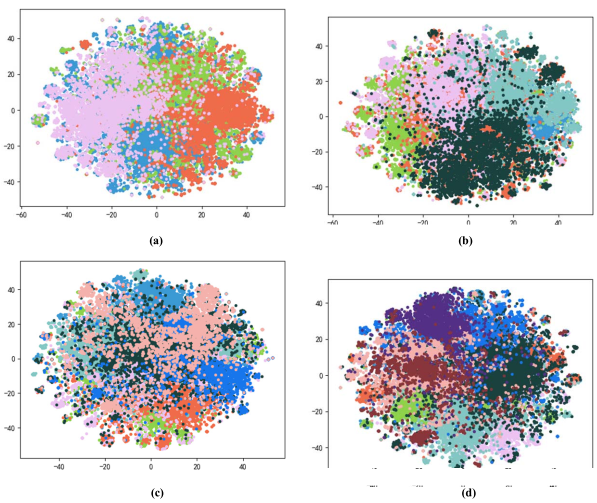

Fig. 3. Positive text clustering results. (a) Four Categories. (b) Six Categories. (c) Eight Categories. (d) Ten Categories.

[35], balanced iterative reducing and clustering using hierarchies (BIRCH) [36], and GSDMM [37]. A model accuracy is used as the evaluation criteria, as shown in Table IV.

Since the correspondence between class clusters and labels is not known in the unsupervised clustering results, each class cluster is ranked with the true labels and the maximum value of all combinations is used as the accuracy. The LDA model achieved the best results and is used for opinion clustering.

C. Results and Analysis

1) Clustering Results Analysis: The collected Weibo data are clustered and analyzed using the LDA model and visualized by dimensionality reduction using T-distributed stochastic neighbor embedding (TSNE) with category numbers as 4, 6, 8, and 10, respectively. The results are shown in Figs. 3 and 4.

The visualization results show that the clustering of four and six categories are better the other categories.

2) Keyword Extraction and Opinion Generation: The keywords are extracted from different semantic emotions in these four and six categories for further analysis, respectively. The keywords are divided into each category using Jieba library. The relevance of keywords and opinions is obtained according to LDAvis [38], whose formula is shown as follows:

$$r(w, t \mid \lambda) = \lambda \log(\phi_{tw}) + (1-\lambda)\log\left(\frac{\phi_{tw}}{P_w}\right) \tag{1}$$

where ϕ_{tw}, P_w are the occurrence probability of keyword w in opinion t, w, respectively. r is the correlation between keyword w and opinion t in the condition λ, $\lambda \in [0, 1]$, which is used to measure the weight of ϕ_{tw} and P_w.

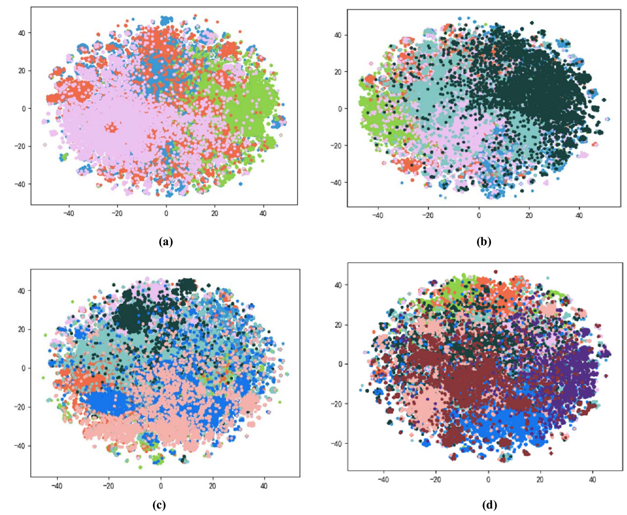

Fig. 4. Negative text clustering results. (a) Four Categories. (b) Six Categories. (c) Eight Categories. (d) Ten Categories.

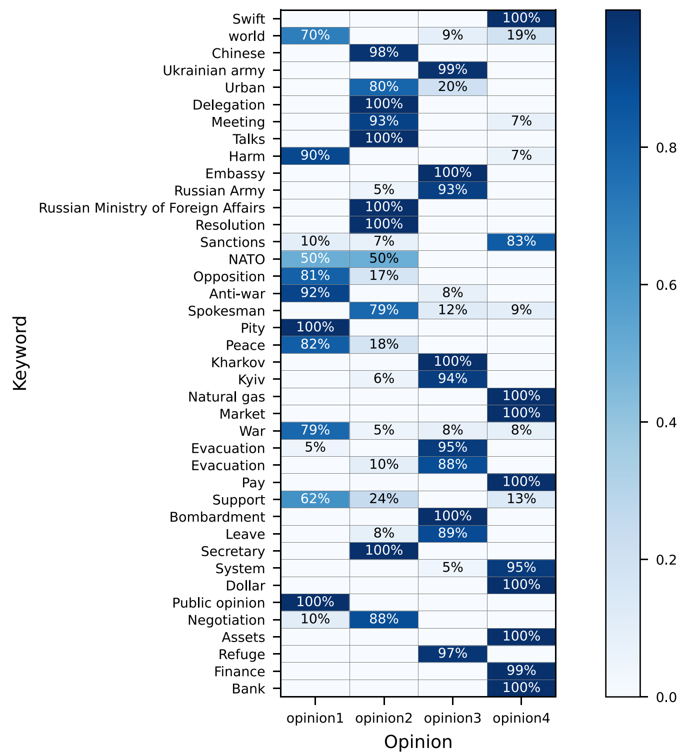

Fig. 5. Positive semantic keywords extraction clustered into four categories.

a) Semantic keywords extraction for positive emotion: We use the LDA model to cluster texts of positive semantic sentiment with the number of category clusters of 4. After obtaining the label of texts, we extract and take out the top10 keywords of each class cluster according to the correlation between keywords and the class clusters. The correlation of keywords is normalized between each class cluster, which is shown in Fig. 5. The keyword weights below 5% are not shown in Fig. 5.

TABLE V
EXAMPLES OF POSITIVE SEMANTIC OPINION INFORMATION

Category	Content	Weibo items
1	Whether NATO has indirectly entered the war.	12872
2	There is no need for Russia to hold talks with Ukraine in third...	12815
3	On February 27, local time, the UN Security Council held a meeting...	9098
4	On the matter of using swift to sanction Russia...	28289

Fig. 5 shows that the dominant keywords in *opinion1* are "opposition," "war," and "peace," in *opinion2* are "Russia," "Ukraine," "negotiation," in *opinion3* are: "shelling," "Kiev," "evacuation," and in *opinion4* are: "financial, sanctions, swift." To further investigate the meaning of these keywords, the extracted keywords are input into the Google search page and extracting opinions in combination with press facts, four opinions are obtained as follows:

1) opposition to war, hope for peace;
2) Russia–Ukraine negotiations;
3) Russian shelling of Kiev and evacuation of foreigners;
4) financial and oil sanctions.

To further explore whether the opinions we get are accurate or not, we will extend the experiment using six categories clustering. We get the following opinions:

1) NATO's eastward expansion, Russian strategic deterrence;
2) United Nations (UN) mediation;
3) Russian shelling of Kiev;
4) evacuation of foreigners;
5) financial and oil sanctions;
6) Russia–Ukraine negotiations.

The analysis found that the extracted opinions from the two classifications are very similar. In the experiment of clustering into six categories, the data volume of "UN mediation" and "Russian shelling of Kiev" is less than other categories. Considering the clustering into four categories is more effective, the final opinions can be classified into four categories as follows:

1) NATO's eastward expansion;
2) oppose war and hope for peace;
3) evacuation of foreigners;
4) financial, oil and other multifaceted sanctions.

Each type of opinion information (example) is shown in Table V.

b) Negative semantic keyword extraction: The same negative semantic keyword extraction is performed with four categories, and the visualization is shown in Fig. 6.

From the results of negative semantic LDA visualization in Fig. 6, it can be seen that in *opinion1*, the dominant keywords are: "opposition, war, support, peace," in *opinion2* the dominant keywords are: "UN," "mediation," "conference," and in *opinion3* the dominant keywords are: "Russian army," "shelling," "Kiev," "evacuation," etc. After the Russian shelling of Kiev, countries launched evacuation operations as well as actively promoted the Russian–Ukrainian negotiations, so in *opinion3*, the keywords "evacuation" and "negotiation" occupy a certain proportion; in *opinion4*, the keywords that occupy a dominant position are: "financial," "sanctions," and "swift."

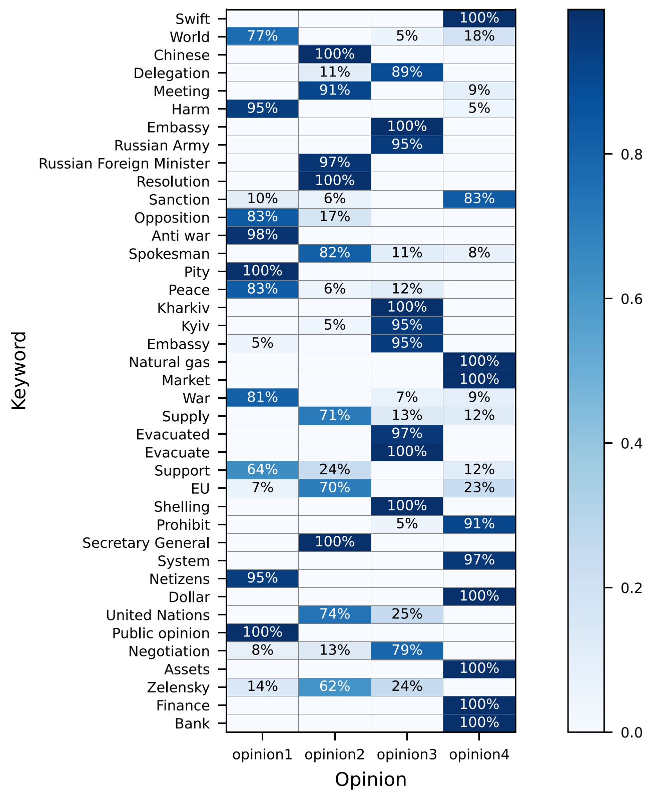

Fig. 6. Negative semantic keywords extraction clustered into four categories.

The extracted keywords are entered into the Google search page and combined with press facts to extract opinions, then four opinions are obtained as follows:

1) support peace and oppose war;
2) UN mediation;
3) Russian shelling of Kiev;
4) financial, oil sanctions.

As the same with positive emotion, keywords extraction is performed for the opinions clustered into six categories (see the Appendix for visualization results), and the following opinions for each category can be obtained:

1) causing World War III;
2) opposition to war, hope for peace;
3) Russia–Ukraine negotiations;
4) Russian forces shell Kiev, evacuation of foreigners;
5) financial, oil sanctions:
6) Chechnya enters war.

The analysis found that opinion 1, 4, and 6 described the same events and had similar keywords, so they are combined into "Russian shelling of Kiev." Comparing the two clustering results and keywords, we finally determined that the four negative semantic opinions are as follows:

1) against war, hope for peace;
2) Russian shelling of Kiev;

TABLE VI
EXAMPLES OF NEGATIVE SEMANTIC OPINION INFORMATION

Category	Content	Weibo items
1	Hope for world peace ...	17229
2	The Ukrainian says Russian shelling has killed at least seven people...	7533
3	Russian troops approach Kiev, Zelensky's government finally relents and demands negotiations...	7954
4	The Americans' sanctions against Russia are mainly financial...	5304

3) UN mediation;
4) financial, oil sanctions.

The information about each type of opinion (examples) is shown in Table VI.

In general, the opinions of "Oppose war and hope for peace" and "Financial, oil sanctions" are presented in both semantic emotions. It shows that whether the people are positive or negative in their emotional attitude, they are all expressing their opinion against war and hope for world peace.

VI. Opinion Evolution Analysis

A. Method

The evolutionary trend of an opinion can be characterized by opinion data volume, opinion engagement and opinion influence. The opinion influence is weighted sum of the Weibo item influence (textDigit) and user influence (userDigit). The Weibo item influence is a weighted sum of comments ($texts_i$.commentsCount), retweets ($texts_i$.retweetsCount), and likes number ($texts_i$.likesCount). Since the above three actions represent different emotional strength (e.g., comments action means that the user strongly agrees with the opinion and is assigned a larger weight), the action weights w_{co}, w_{re}, w_{li} are different. Similar as the Weibo item influence, the user influence is a weighted sum of followers number ($texts_i$.user.followingCount) and historical texts number ($texts_i$.user.textsCount). The details are shown in Algorithm 1.

The concept of date window is introduced for the calculation of opinion engagement. The data collected date as the start date (startDate) when the date range (dateRange) is less than the number of days in the date window. The daily percentage of each opinion influence over the total influence in the date window is defined as the opinion engagement. The details are shown in Algorithm 2. The product of the daily opinion engagement and the volume of opinion data is defined as opinion evolution index, and is used to analyze the trends of each opinion evolution.

B. Analysis

1) Opinion Evolution Analysis: From Section III, we know that there are four positive opinions (*opinion1, opinion2, opinion3, opinion4*): NATO's eastward expansion, opposition to war and hope for peace, countries' evacuation, and financial and oil sanctions from multiple perspectives, respectively. The evolution index of each opinion is obtained using Algorithms 1 and 2.

As shown in Fig. 7, the evolution index of each opinion reaches the highest level in turn, followed by several fluctuations and a gradual decrease. Throughout the evolution of opinions, the evolution index of opinion 1 reaches the highest first, then fluctuates significantly and remains high level for a period of time. The evolution index of opinion 2 and opinion 3 increased to some extent, but remained at a low level.

Algorithm 1 Opinion Influence in a Single Day

1 $Function\ opinionInfluenceInSingleDay(opinion, date)$
2 $texts \leftarrow textsDaily_{date}.opinion$
3 $textDigit, userDigit \leftarrow 0, 0$
4 $for\ i\ in\ texts.count():$
5 $textDigit \leftarrow textDigit$
$+w_{co} * texts_i.commentsCount$
$+w_{re} * texts_i.retweetsCount$
$+w_{li} * texts_i.likesCount$
$//(w_{co} > w_{re} > w_{li})$
6 $userDigit \leftarrow userDigit + w_{ufc}$
$* texts_i.user.followingCount$
$+w_{utc} * texts_i.user.textsCount$
$//(w_{ufc} > w_{ufc})$
7 $opinionInfluence$
$\leftarrow \alpha * textDigit + \beta$
$* userDigit$
8 $return\ opinionInfluence$

Algorithm 2 Opinion Engagement in a Single Day

1 $Function\ opinionEngagementInSingleDay(opinion, date, dateWindow)$
2 $startDate \leftarrow min(firstDate, date$
$-dateWindow)$
3 $dateRange \leftarrow (startDate, date)$
4 $fordate_i indateRange:$
5 $opinionInfluence_{date_i}$
$\leftarrow opinionInfluenceInSingleDay(opinion, date_i)$
6 $opinionEng \leftarrow softmax(opinionInfluence)_{date}$
7 $return\ opinionEng$

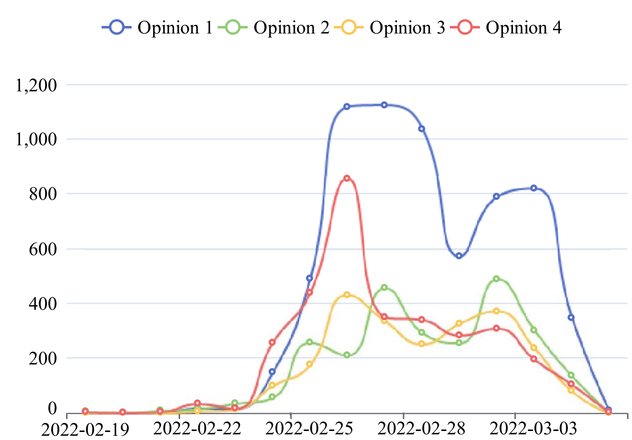

Fig. 7. Evolutional trends of each positive opinion.

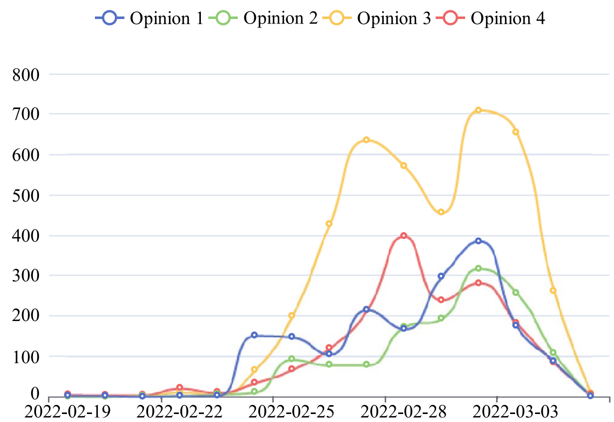

Fig. 8. Evolutional trends of each negative opinion.

The evolution index of opinion 4 showed a faster growth, and then gradually decreases.

The trend of the evolution indexes of the four opinions is consistent with the actual situation. Opinion 1 is the most direct cause of the outbreak of the RUW. NATO's eastward expansion leads to intensification of the conflict. Therefore, at the beginning of the war, the evolution index of opinion 1 gradually increased and tended to be the highest. Moreover, the evolution index of this opinion remained high level throughout the RUW process.

On the other hand, the outbreak of war caused serious damage to people's lives and properties. The general public are displaced and homeless. The compassion from netizens is gradually aroused. As a result, the evolution index of opinion 2 gradually increased. With the further intensification of the conflict, the lives and safety of the expatriates are gradually threatened. The expectation for the evacuation of expatriates has become stronger. Therefore, the evolution index of opinion 3 also gradually increases. However, opinion 2 and opinion 3 are not direct influencing factors of the outbreak of the RUW compared with opinion 1, but only the real impact of the war outbreak. Therefore, the evolution index of opinion 2 and opinion 3 never exceed the level of the evolution index of opinion 1. There is a large gap between them.

Similar to opinion 2 and opinion 3, opinion 4 is also a real impact brought from the outbreak of the RUW, but the evolution index of opinion 4 shows a faster growth at the beginning of the outbreak of war and continues to go up. This phenomenon is inseparable from the reality of the world. The outbreak of the war brought sanctions from multiple perspectives, including financial and oil, to one of the parties in the war. The world has also faced many economic sanctions over the years. Since the netizens empathize with the impact of sanctions, the evolution index of opinion 4 tends to be higher compared to opinion 2 and opinion 3 at first.

The results of the evolutionary trend of negative opinions are shown in Fig. 8. *opinion1, opinion2, opinion3, opinion4* denote the four opinions of opposition to war, shelling of Kiev, UN mediation, and financial sanctions, respectively.

As shown in Fig. 8, the growth trend of the evolution index of opinion 3 is increasing faster and remains consistently at a high level. On the other hand, the growth trend of the evolution index of opinion 1, opinion 2, and opinion 4 is relatively slow and there are several fluctuations.

Among the negative emotions, the evolution index of opinion 3 shows a faster growth trend at the beginning of the war and remains at a high level. The opinion evolution index of opinion 1, also showed a faster growth trend at the beginning of the conflict. This situation indicates that the hearts of netizens who hold negative feelings about RUW are filled with disgust for war. They oppose war and long for world peace. They have high expectations of the United Nations, which maintains international peace and security. They expect the UN to intervene to ease the situation and stop the war.

The emergence of opinion 2 is unexpected, but reasonable. Netizens with negative feelings about the RUW expect the war initiator to shell Kiev and gain strategic advantage as soon as possible. This approach played a crucial role in ending the war as early as possible. Opinion 4 is similar to opinion 4 in positive emotion. Their evolutionary trends are essentially the same, which shows that netizens with positive and negative emotion share the same feeling when faced with sanctions.

2) Opinion Adversarial Evolution Analysis: In different stages of the evolutionary process, the opinions interact with each other. Each opinion has a different dominant position in the evolutionary process. Therefore, an opinion adversarial evolution algorithm is designed to analyze the adversarial evolutionary trends of event. The normalization operation of the engagement of each opinion reflects the adversarial features of each opinion. Each opinion engagement in a day is normalized as a weight ($\mathrm{opinionEng}_{\mathrm{date}_i}$), and then multiplied and summed with the corresponding opinion volume ($\mathrm{opinionVolume}_{\mathrm{date}_i\mathrm{opinion}_i}$). The sum of the adversarial evolution index ($\mathrm{opinionAdver}_{\mathrm{date}_i\mathrm{opinion}_i}$) of each opinion is the evolution index ($\mathrm{eventAdverEvo}_{\mathrm{date}_i}$) of the war events. All war event evolution indexes constitute the evolutionary trend of war events, as shown in Algorithm 3.

Algorithm 3 Opinion Adversarial Evolutionary Algorithms

$Function\ opinionAdverEvolution(firstDate,\ date,\ dateWindow)$

$dateRange \leftarrow (firstDate, date)$

$for\ date_i\ in\ dateRange:$

$for\ opinion_i\ in\ opinions:$

$opinionEng_{date_i opinion_i} \leftarrow opinionEngagementInSingleDay(opinion_i, date_i, dateWindow)$

$opinionEng_{date_i} \leftarrow softmax(opinionEng_{date_i})$

$for\ opinion_i\ in\ opinions:$

$opinionAdver_{date_i opinion_i} \leftarrow opinionEng_{date_i opinion_i} * opinionVolume_{date_i opinion_i}$

$eventAdverEvo_{date_i} \leftarrow \sum opinionAdver_{date_i opinion_i}$

The visualization results of the RUW adversarial evolution index are shown in Figs. 9 and 10. Both trends show a faster growth at first. It tends to decrease after several fluctuations.

In the evolution trend corresponding to the positive opinion, the adversarial evolution index of opinion 1 still dominates the overall evolution of the event. The increasing and decreasing

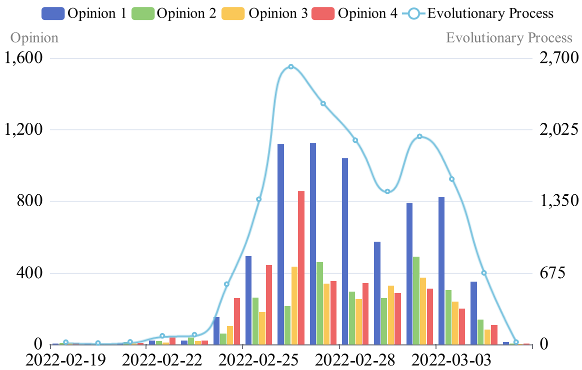

Fig. 9. Adversarial evolutional trends of RUW event (positive).

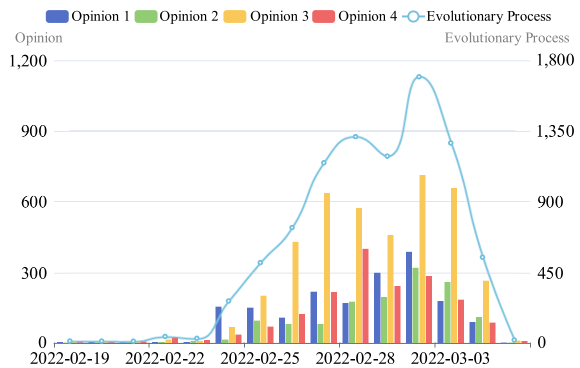

Fig. 10. Adversarial evolutional trends of RUW event (negative).

trend of this opinion's adversarial evolution index directly determines the overall evolutionary trend of the event. The results in the opinion evolution analysis section and the figure of the event evolution trends fully indicate that NATO's eastward expansion is the main influencing factor for the outbreak of war and further intensification of the conflict.

Among the evolution trends corresponding to negative opinions, the adversarial evolution index of opinion 3 dominates the overall evolution of the event. It is the main driving force for the growth and fluctuation of the evolutionary trend of events corresponding to negative opinions. Through the results in the opinion evolution analysis section and the visual display of the above event evolution trend figure, we can conclude that world peace and the UN mediation are the common wishes in the hearts of netizens.

VII. Conclusion and Future Work

The proliferation of public opinions in cyberspace on the RUW has bring a totally new social cognitive war fighting with CPSS that would impact our humankind significantly from now on. Therefore, analyzing opinion dynamics of the RUW in the cyberspace is very important. The purpose of this article is to kick a start on such kind of research. This article proposes a comprehensive approach for exploring the dynamics of online public opinion and their evolutions, using Chinese Weibo on RUW as a case study. First, a semantic emotion recognition is performed on the collected data with the RoBERTa pretrained model. Second, an unsupervised clustering of positive and negative emotion texts is performed with the LDA model. The social data of the two emotions are divided into four categories and the opinion content is generated using keywords extraction. Finally, an opinion adversarial evolution algorithm is proposed to dynamically identify the interactions and dominance degree of each opinion to further understand opinion evolutions.

In the future, we will further expand the scale of data collection and analyze opinion from multiple perspectives. Meanwhile, we will also further study social computing, opinion deduction with reinforcement learning [39]. In addition, we will further design an unsupervised clustering method for complex social texts to improve the opinion recognition effect.

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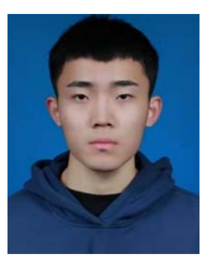

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