Sentiment Analysis of Posts and Comments in the Accounts of Russian Politicians on the Social Network

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Abstract—Russian politicians are increasingly using social networks publishing a lot of texts. One of the important issues in the context of the analysis of political online communication is the choice of negative and positive topics in publications as well as the reaction of the audience. In order to analyze the main patterns of this process we have collected the data from the social network Vkontakte. Our sample covers the period from 1 January, 2017 to 25 April, 2019, in total 46293 posts and 2197063 comments in 23 politician’s accounts. To build the classifier we used two text corpora: Rubtsova’s corpus and RuSentiment corpus. The algorithm of sentiment analysis was implemented on the basis of bidirectional recurrent neural network. Using Rubtsova’s corpus we provided the accuracy of 91% and using RuSentiment we provided the accuracy of 84% (accuracy is calculated as the proportion of correctly identified cases from the test sample). We found that the markup of data significantly differs when different corpora were used. The most adequate results in the analysis of posts and comments, in our opinion, are obtained by using an ensemble of models based on the both corpora. As a result of classification, we identified a number of patterns. Thus, the number of likes and views of posts is higher for the posts classified as positive, and the number of reposts is higher for the posts classified as negative. We also found that the number of comments is higher for the posts with a negative sentiment, and the average sentiment of comments on positive posts is more positive than the average sentiment of comments on negative posts.

I. INTRODUCTION

The Internet has fundamentally transformed the mechanisms for discussing political issues, and democratic participation [1]. Nowadays the key messages are delivered to audiences online, and politicians are discovering new platforms every year. During 2007-2008 Barack Obama’s team made a breakthrough using a variety of online technologies for political purposes: the election campaign involved a lot of digital channels: websites, email newsletters, Facebook, Twitter, MySpace and Youtube [2]. In Russia, a kind of an innovator in online presence was Dmitry Medvedev, a President who actively used Twitter and did not refuse the social networks even after the incident, when his account with 2.5 million followers was hacked [3]. Gradually, blog adoption in politics became typical of not only Federal politicians but also regional leaders [4]. The concept of political marketing existed since the 70s [5] and now, in the era of Internet presence, it is very topical. Today, it is the marketing approach that allows consultants and press services to determine the key values of target audiences [6] to form the appropriate image [7] and brand of the leader or party [8]. In recent years, social media marketing (SMM) is increasingly being used in political communication, which includes the promotion, positioning and formation of loyalty to the leader in a social network, develop meaningful strategies for account management. Publishing content in the accounts of well-known politicians remains a part of the communication strategy, and sometimes the entire teams of PR specialists work on it. Accounts in social networks could be considered as media outlets actively used for agenda-building and influence on the audience [9]. One notable challenge for strategic communication in this context is the use of positive and negative content. On the one hand, a positive agenda is demanded by a large part of the audience, some Russian media, for example, Lenta gave users the opportunity to simply turn off the bad news with the toggle switch [10]. In recent years, Russian pro-government politicians have mainly focused on a positive agenda in order to prevent downgrade of ratings of the President [11] and the Deputy Prime Ministers [12]. The promotion of the positive agenda is implemented not only through the media, but also through state corporations [13]. On the other hand, negativity can also be effective, as such content is often used in political communication for demonstrative statements and provocations.

But what online content strategy politicians have to choose to be as effective as possible in terms of engagement? In this article, we use data collected form the most popular accounts of Russian politicians on the most visited Russian social network “Vkontakte” [14] and implement machine learning algorithms and sentiment analysis to determine the impact of sentiment on the mechanisms of feedback from the audience. “Vkontakte” is the most popular social network in Russia. It is similar in functionality to Facebook, there are various communities, public communication between users is based on posts and comments, likes and reposts are also used. Since March 2017, “Vkontakte” posts also have views metric.

II. RELATED WORK

In the context of political communication, data from social networks can be used in solving the problems of opinion mining as a significant predictor of public opinion, including the growth of social tension [15] and prediction of election results [16], [17]. Sentiment analysis of a policy-related content in social networks is being actively used to monitor trends [18], [19], analysis of the political agenda, and assessment of the level of support for candidates and parties [20]. Wang & Can et
al. showed how it is possible to start an online wave of positive or negative reactions through the provocation [21]. Working with Twitter data, Stieglitz & Dang-Xuan showed that emotionally charged publications get higher retweetability [22]. Experiments also show interdependency between intensity of publication activity and various events, such as debates [23]. Sentiment analysis of political online communication is also used to model the emotional background of the discussions [24], fact-checking [25], analysis of propaganda trends [26]. Early versions of the sentiment analysis appeared in the late 70's – early 80's [27]. In general, all automatic algorithms can be divided into, firstly, lexical-based, machine learning-based and mixed, and, secondly, ontology based and non-ontology based [28]. There are many sentiment classification algorithms, however, even advanced algorithms tend to reach accuracy about 70% on social media data [29], [30], [31]. Researchers use numerous methods to conduct sentiment analysis, for example, various modifications of the bag-of-words [32], [33], neural networks [34], machine learning [35], conditional random fields and support vector machines [36], deep learning [37]. The automatic sentiment classification for the Russian language is still a challenging task because of low number of open source and ready solutions, as well as the small community and low number and quality of thematic text corpora.

We submit the following research questions:

1) How an accuracy of sentiment classification can be increased?
2) Are there any significant differences in feedback levels depending on the sentiment of the content? (Which posts get more likes, comments, reposts?)
3) How is the positive/negative sentiment in comments related to the positive/negative sentiment in posts?

III. DATA AND METHODOLOGY

A. Text processing

For sentiment classification we used the Russian language corpus of short texts RuTweetCorp (Rubtsova’s corpus) [41] and the corpus of the posts RuSentiment [29]. RuTweetCorp corpus contains texts posted by Twitter users during the period from late November 2013 to late February 2014. There were 226834 records in total, 114911 annotated as positive and 111923 annotated as negative. RuSentiment corpus contains 30521 annotated posts on social network Vkontakte, divided into 5 classes: 6646 posts marked as positive (code "positive"), 3912 marked as negative (code "negative"), 3467 marked as neutral (code "neutral"), 127220 (code "neutral"). We used only the first two classes of posts from this case in order to match the classes in Rubtsova’s corpus. The first step in model building was to develop procedure for text preprocessing. We used standardized procedure [43] that covered all the text data in this study. This consist of the following steps.

1) We replaced the Russian letter “ ¨e” with “е”;
2) The particles “not” and “neither” were converted to the prefix “NOT” to the next word;
3) Links to web resources were excluded from the text;
4) User’s mentions were excluded from the text;
5) Processing of emoticons and emojis was performed. The most popular of them were replaced with the tokens “POSITIVESMILE” or “NEGATIVESMILE”;
6) We deleted all non-letter characters, including punctuation and numbers;
7) Normalization of words was performed with MyStem [44];
8) Any number of consecutive spaces was replaced with a single space;
9) Repeated consecutive words were replaced with a single word;

Taking emoticons in account allows to increase the accuracy of text classification [39]. We conducted a special procedure for processing emoticons and emojis. First of all, emoticons composed of typographic characters were replaced by these tokens. As positive emoticons we considered the following: \{ ; ( ; , = ) ; : ( ; , : ) \} , \{ ; ( ; , = ) ; : ( ; , : ) \} , \{ ; ( ; , = ) ; : ( ; , : ) \} , \{ ; ( ; , = ) ; : ( ; , : ) \} . Further, a similar procedure was applied to the following manually marked emojis, which are used in VKontakte:

- **Positive emojis:**
  - thumbs_up,
  - red_heart,
  - folded_hands,
  - smiling_face_with_smiling_eyes,
  - grinning_face_with_big_eyes,
  - clapping_hands,
  - beaming_face_with_smiling_eyes,
  - flexed_biceps,
  - grinning_face_with_smiling_eyes,
  - winking_face,
  - grinning_face_with_tongue,
  - rose,
  - smiling_face_with_heart_eyes,
  - grinning_face,
  - kiss_mark,
  - tulip,
  - oncoming_fist,
  - hugging_face,
  - OK_hand,
  - victory_hand,
  - face_blowing_a_kiss,
  - hibiscus_face,
  - fire,
  - cherry_blossom,
  - sparkles,
  - handshake,
  - party_popper,
  - two_hearts,
  - raised_fist,
  - sparkling_heart,
  - raised_hand,
  - bouquet,
  - smiling_face,
  - slightly_smiling_face,
  - blue_heart

- **Negative emojis:**
  - rolling_on_the_floor_laughing,
  - grinning_squinting_face,
  - pouting_face,
  - SOS_button,
  - smirking_face,
  - thumbs_down,
  - fearful_face,
  - thinking_face,
  - pile_of_poo,
  - middle_finger,
  - crying_face,
  - loudly_crying_face,
  - person_facepalming,
  - nauseated_face,
  - pensive_face,
  - grinning_face_with_sweat,
  - unamused_face,
  - see-no-evil_monkey,
  - face_screaming_in_fear

It should be mentioned that in the process of checking the effectiveness of various methods of text preprocessing, we also considered the step of filtering the texts with Russian-language stop-words list included in the "nlkt.corpus" package, however, their exclusion reduced the accuracy of the models on the considered corpora. So, this procedure was removed from the list of steps for text preprocessing.

B. Sentiment analysis

Traditional word-based sentiment analysis techniques are often not suitable for classifying policy-related content [38]. In order to construct the sentiment classifier based on the Rubtsova’s corpus, we adopted an approach using deep learning models such as convolutional and recurrent neural networks.
As the first alternative, we used the neural network [40], in which the LSTM (Long Short-Term Memory) layer follows the one-dimensional convolution layer (Fig. (1)). As a second alternative, we used a neural network with a bidirectional GRU (Bidirectional Gated Recurrent Unit, BiGRU) layer (Fig. (2)) followed by dense layers. This architecture, in particular, was implemented in the library DeepPavlov [42]. In both neural networks, the first layer is the word embeddings vector representation layer which maps the first 30 words from the preprocessed text to a real-valued vectors from $\mathbb{R}^{64}$. The size of the dictionary, which includes the most common words from the Rubtsova’s corpus, was 30 thousand words. In order to avoid overfitting, we use dropout layers with parameter 0.2 and L2-regularization with parameter $10^{-5}$ in dense layers. We used the following data separation for the neural networks training: 70% of the data used in the training sample, 10% of the data included in the validation sample and 20% – in the test sample. The selection of the number of training epochs was based on accuracy and losses metrics on the validation set. Fig.(3) and Fig. (4): to achieve optimal scores (both loss and accuracy) and to avoid the effect of overfitting CNN+LSTM network had completed 2 epochs of training, and BiGRU network had completed 3 epochs. The performance results of these models on the test set are represented at tables (I) and (II). Since the value of the $F_1$ metric for the BiGRU model was higher, then we decided to use it instead of CNN+LSTM.

We also used BiGRU architecture of a neural network with

Table I. Results for CNN + LSTM model on the test set from Rubtsova’s corpus

<table>
<thead>
<tr>
<th>Class</th>
<th>precision</th>
<th>recall</th>
<th>F1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0.90238</td>
<td>0.91206</td>
<td>0.90719</td>
<td>22196</td>
</tr>
<tr>
<td>Positive</td>
<td>0.91405</td>
<td>0.90458</td>
<td>0.90929</td>
<td>22950</td>
</tr>
<tr>
<td>Macro avg</td>
<td>0.90822</td>
<td>0.90832</td>
<td>0.90824</td>
<td>45146</td>
</tr>
<tr>
<td>Weighted avg</td>
<td>0.90831</td>
<td>0.90825</td>
<td>0.90826</td>
<td>45146</td>
</tr>
</tbody>
</table>

Table II. Results for BiGRU model on the test set from Rubtsova’s corpus

<table>
<thead>
<tr>
<th>Class</th>
<th>precision</th>
<th>recall</th>
<th>F1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0.92094</td>
<td>0.89223</td>
<td>0.90636</td>
<td>22196</td>
</tr>
<tr>
<td>Positive</td>
<td>0.89882</td>
<td>0.92593</td>
<td>0.91217</td>
<td>22950</td>
</tr>
<tr>
<td>Macro avg</td>
<td>0.90988</td>
<td>0.90988</td>
<td>0.90988</td>
<td>45146</td>
</tr>
<tr>
<td>Weighted avg</td>
<td>0.90970</td>
<td>0.90936</td>
<td>0.90970</td>
<td>45146</td>
</tr>
</tbody>
</table>

the RuSentiment corpus. Since this corpus is smaller, compared with the Rubtsova’s one, we used a dictionary containing 15 thousand words, which are the most frequent in the corpus. The table (III) shows that this model is able to recognize only 54.1% of negative replies. Also, because the classes it was trained on were not balanced, model’s predictions should be expected to be biased in the direction of positive sentiment.

IV. RESULTS

We investigate the characteristics of the posts published by Russian politicians on the social network VKontakte for
The period from January 1, 2017 to April 25, 2019. There are 46293 posts of 23 politicians and 2197063 of users’ replies to them. We decided to conduct sentiment analysis for each of the models separately (Rubtsova’s corpus and RuSentiment corpus), as well as using both models. By using both models, we mean using the ensemble technique, in which the probabilities of assigning text to a particular class are determined in accordance with the probabilities for each individual model taken with given weights (in our case (0.5, 0.5)). In order to calculate the average sentiment of the politicians posts, we use the following technique: we assign a number +1 to each positive post, -1 to each negative post and 0 to unrecognised (skipped) posts. Unrecognised texts are those consisting of tokens that are not contained in the dictionary of the most frequent words in the corpus. Then we calculate the averages for all posts and comments for the given politicians. The engagement rate is calculated for each post as the sum of the number of likes and comments per thousand views of this post:

\[
\text{Eng. Rate} = \frac{\text{Likes} + \text{Comments}}{\text{Views}} \cdot 1000.
\]

Statistics on the average sentiment as well as on the number of views and the engagement rate are presented in the table (IV). The average sentiment of posts takes values from the

<table>
<thead>
<tr>
<th>Class</th>
<th>precision</th>
<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0.89474</td>
<td>0.54140</td>
<td>0.67460</td>
<td>785</td>
</tr>
<tr>
<td>Positive</td>
<td>0.77968</td>
<td>0.96224</td>
<td>0.86139</td>
<td>1324</td>
</tr>
<tr>
<td>macro avg</td>
<td>0.83721</td>
<td>0.75182</td>
<td>0.76800</td>
<td>2109</td>
</tr>
<tr>
<td>weighted avg</td>
<td>0.82251</td>
<td>0.80560</td>
<td>0.79187</td>
<td>2109</td>
</tr>
</tbody>
</table>
range \([-1, 1]\). If among the texts there is an identical number of positive and negative posts, then the average sentiment will be 0. If most of the posts are positive, then this indicator will be greater than 0. And on the contrary, in a situation when majority of the posts are negative, the average sentiment will be less than 0. As can be seen from the table (IV), most politicians have a positive average sentiment of posts. At the same time, for most of the politicians this indicator calculated on the basis of Rubtsova’s corpus is much higher than that obtained on the RuSentiment corpus. The use of an ensemble of models leads to mid-range results.

The table (V, VI, VII) summarizes the data on classification of the politicians’ posts in accordance with the model built on Rubtsova’s corpus, the model built on the RuSentiment corpus and the model which represents the ensemble of the two mentioned above.

V. Conclusion

Despite the difference in overall assessments of positive, negative and unrecognized texts obtained as a result of the application of various models, the following patterns were identified:

- the number of likes from users is higher for posts classified as positive
- the number of comments is higher for posts with a negative sentiment, and this difference is mainly provided by comments that also have a negative sentiment. The average tone of comments on positive posts is more positive than the average tone of comments on negative posts.
- the number of reposts is higher for posts classified as negative.
- the number of views is higher for positive posts.
- according to the sentiment classifier built on the RuSentiment corpus, the level of engagement rate is higher for negative posts. Inversely, using the classifier built on the RuSentiment corpus, we found the opposite relation. In general, we can say that there is no clear relationship between the tone of posts and engagement rate.

We found that the most adequate results of sentiment classification can be achieved by using an ensemble of the models. Also we showed that a special emoji encoding scheme, taking into account the frequent use of sarcasm, also increased the quality of classification. Another procedure towards improving the quality was inclusion of stop-words. Significant differences in the results obtained from different corpora suggest that more specific corpora are needed for a more reliable classification, high precision and recall. A balance of classes, the specificity of the content are main requirements for such corpora. In terms of strategy, we showed that in general it is possible to influence on the magnitude and sentiment of the feedback from the audience on social media using negative or positive content.

Further, we plan to analyze the dynamic patterns associated with publication activity and sentiment to determine the general trends and identify the characteristics of particular authors. We also plan to describe in detail the topics represented by positive and negative sentiment in posts and comments. Another issue is to understand why there were such significant variations between the results of the models trained on different corpora, and which texts were assigned to opposite classes by the different models.

Acknowledgment

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References

TABLE IV. STATISTICS ON POLITICIANS’ POSTS

<table>
<thead>
<tr>
<th>Name</th>
<th>Post count</th>
<th>Avg. sent. Rubtsova</th>
<th>Avg. sent. Rubtsovite</th>
<th>Avg. sent. ensemble</th>
<th>Avg. thousand views</th>
<th>Avg. eng. rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Dmitry Medvedev</td>
<td>798</td>
<td>0.456140</td>
<td>0.155388</td>
<td>0.393484</td>
<td>181.628246</td>
<td>11.662548</td>
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<tr>
<td>2 Alexander Beglov</td>
<td>28</td>
<td>0.642857</td>
<td>0.357143</td>
<td>0.714286</td>
<td>107.953321</td>
<td>29.401820</td>
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<tr>
<td>3 Alexei Navalny</td>
<td>18.11</td>
<td>0.455549</td>
<td>0.101561</td>
<td>0.245495</td>
<td>102.382515</td>
<td>32.315528</td>
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<tr>
<td>4 Ramzan Kadyrov</td>
<td>2247</td>
<td>0.671117</td>
<td>-0.038273</td>
<td>0.409435</td>
<td>58.082514</td>
<td>25.994744</td>
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<tr>
<td>5 Rastam Minnikhanov</td>
<td>2308</td>
<td>0.418977</td>
<td>0.639948</td>
<td>0.694913</td>
<td>33.551016</td>
<td>27.844797</td>
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<td>6 Sergei Sobyanin</td>
<td>2179</td>
<td>0.643414</td>
<td>0.383662</td>
<td>0.615878</td>
<td>28.000022</td>
<td>21.623156</td>
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<td>7 Andrei Vorobov</td>
<td>1132</td>
<td>0.566537</td>
<td>-0.529085</td>
<td>0.659127</td>
<td>19.485459</td>
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<td>8 Vladimir Zhirinovskiy</td>
<td>2328</td>
<td>0.272337</td>
<td>-0.198024</td>
<td>0.048110</td>
<td>19.450439</td>
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<td>9 Naii Magdyeve</td>
<td>37</td>
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<td>0.756757</td>
<td>15.787383</td>
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<td>10 Gennady Zyuganov</td>
<td>433</td>
<td>0.341801</td>
<td>-0.055427</td>
<td>0.125711</td>
<td>13.587981</td>
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<tr>
<td>11 Igor Orlov</td>
<td>104</td>
<td>0.778846</td>
<td>0.432692</td>
<td>0.596165</td>
<td>11.654760</td>
<td>11.721684</td>
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<tr>
<td>12 Oleg Kuvshinnikov</td>
<td>474</td>
<td>0.813464</td>
<td>0.691983</td>
<td>0.873418</td>
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<td>13 Venediam Kondratiev</td>
<td>631</td>
<td>0.559429</td>
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<td>0.458343</td>
<td>8.100658</td>
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<td>14 Ilya Yashin</td>
<td>670</td>
<td>0.385382</td>
<td>-0.085075</td>
<td>0.162687</td>
<td>7.671209</td>
<td>45.627586</td>
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<td>15 Vitaly Milonov</td>
<td>796</td>
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<td>16 Grigory Vavlinsky</td>
<td>329</td>
<td>0.373860</td>
<td>-0.294833</td>
<td>-0.057751</td>
<td>6.519483</td>
<td>43.406006</td>
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<td>17 Anatoly Lokot’</td>
<td>539</td>
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<td>0.307978</td>
<td>0.564007</td>
<td>6.113163</td>
<td>22.806604</td>
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<td>18 Sergey Mironov</td>
<td>1358</td>
<td>0.509573</td>
<td>0.024300</td>
<td>0.266568</td>
<td>5.965062</td>
<td>42.355856</td>
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<td>19 Igor Koshin</td>
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<td>0.690945</td>
<td>0.438976</td>
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<td>20 Vladimir Medinsky</td>
<td>566</td>
<td>0.733216</td>
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<td>21 Dmitry Berdnikov</td>
<td>608</td>
<td>0.736842</td>
<td>0.578947</td>
<td>0.779605</td>
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<td>22 Mikhail Delyagin</td>
<td>23984</td>
<td>0.369830</td>
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<td>0.689485</td>
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<td>35.698497</td>
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</table>

TABLE VI. PARAMETERS CALCULATED USING THE MODEL BASED ON RUBLETVA’S CORPUS

<table>
<thead>
<tr>
<th>Name</th>
<th>Negative</th>
<th>Positive</th>
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<tr>
<td>1 K. Ravi, V. Ravi</td>
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<td>2 V. Ravi</td>
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<td>4.2722</td>
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