Inappropriate behavior detection in YouTube comments

Ivanov Mikhail

May 2024

Abstract

The work shows several approaches to detect offensive/toxic behaviour in comments provided by users on YouTube platform, and distinguish those from meaningful or thoughtful. That said, the key idea is to find some pattern in such way of acting hostile to other users.
The project is placed here https://github.com/Mishquad/nlp_project

1 Introduction

This research focuses on a crucial task: distinguishing between two categories in Russian-language comments on YouTube: inappropriate (bots/trolls) and genuine/thoughtful comments.

Bots, essentially automated systems, often serve specific agendas, such as promoting advertising or targeted propaganda. Trolls, on the other hand, are individuals who aim to provoke hatred and pointless arguments within comment sections, typically with messages unrelated to the video topic.

Identifying bots is relatively straightforward—they operate based on predefined algorithms with some obvious text-pattern. However, detecting trolls presents a more complex challenge due to the nuanced nature of human behavior, making it difficult to formalize.

Comment sections across various platforms frequently encounter disruptive users, whether intentional or unwitting, who contribute to the spread of hatred or clutter the information space. These users, in turn, can be broadly categorized into two groups: individuals acting independently or at the behest of others, and automated programs known as bots, which are becoming increasingly sophisticated with advancements in text generation technology.

This research proposes multiple approaches to filter out noise (such as bots and trolls) from genuine user interactions in YouTube comments. By employing these methods, author aims to contribute to the development of more effective moderation strategies, fostering a healthier online environment where genuine discussions can exist without interference from disruptive elements.

As for object of the study, the choice fell on Yuri Dud's YouTube channel with interview of russian enterpreneur Oleg Tinkov. The video has 27 million views as of 01.05.2024 and 95 thousand comments, which is supposedly enough to reflect ongoing sentiment and text-patterns.

1.1 Team

Ivanov Mikhail prepared this document and is the author of the report.

2 Related Work

Previous studies offer valuable insights into this domain: [Skowronski (2019)] provides a foundational perspective, proposing a program utilizing supervised learning on Reddit data to detect bots and trolls comments. Author gathered data for 393 known bots plut 167 more from the botwatch subreddit, data for trolls was collected via Reddit Transparency report. Researcher selected DecisionTreeClassifier from scikit-learn package. His study resulted in Recall = 74%, Precision = 58%, Accuracy = 92%. For normal users the model perfomed quite well: 95% Precision and Recall.

[Varol et al. (2017)] conducted a comprehensive analysis using classical machine learning techniques, achieving promising results in bot detection on Twitter. Their study incorporates models like Random Forests and visualizations through t-SNE projections, enhancing understanding and visualization of bot messaging-behavior. Data consisted of 1150 features split into 5 categories: User-Based, Friends, Content and Language, Sentiment, Network. Authors gathered data from 15000 verified bots and 16000, which yielded in 2.6 million tweets produced by bots and 3 million tweets by human users. Researchers achieved AUC metric at 0.9 for human accounts and 0.7 for bot messages. They also showed that manual annotation for bot-markings is quite sophisticated task as bot algorithms evolve.

In a similar vein, [Chu et al. (2012)] introduced entropy calculations to discern human from offensive robotic behavior, complementing traditional machine learning approaches. Their experiment is based on 8 million tweets, 500k users. It is worth mentioning their approach to define bots as authors manually messaged to suspicious accounts and parsed their response. If the answer lacked meaningful information – they marked the user and all its messages as bot. Also they showed that bots tend to have very little amount of friends/friend requests and large number of followed accounts. They reached Averaged Precision at 0.96. Meanwhile, [Kudugunta and Ferrara (2018) and Mazza et al. (2019)] explored neural network architectures to tackle similar challenges related to propaganda-bots, showcasing the diverse methodologies employed in this field. Both groups of scientists used LSTM and VAE architectures as their baseline with some specific modification based on author's view on the issue. Their data consisted of almost 10 million tweets unevenly divided in human's account favor. Both papers showed that their solutions provide better quality that classic ML algorithms, reaching around 0.9 F-1 metric in both.

However, the absence of labeled data in our context requires innovative approaches. To address this, we propose utilizing topic modeling and Gaussian Mixture Models (GMM) with embeddings from ruBERT—a Russian language model—to identify and categorize users. This methodology draws inspiration from [Gilbert (2019) and Kong (2019)], who leveraged topic modeling, particularly Latent Dirichlet Allocation (LDA), to uncover hidden patterns in textual data. They specifically aimed

to discover if toxic media surge in upcoming US election run is made by bots. Researchers mentioned that LDA could increase Accuracy for about 10% to baseline of 70% varying number of topics and removing manually irrelevant topics.

Additionally, sentiment analysis emerges as a complementary tool for identifying disruptive behavior. Works such as [Ю.В.Рубцова (2014) and Rogers et al. (2018)] provided annotated data for sentiment evaluation, offering valuable resources for detecting bots and trolls based on emotional cues. Authors created a UI to manually tag posts on VK network to find “destabilizing and politics-related” communications to use sentiment analysis in their model. They used MLP classifier upon 20000 posts to distinguish between bots who publish disruptive comments pursuing some political agenda or genuine human thoughts on related topic. Worth mentioning that their approach resulted in worse performance than other studies (about 0.67 F-1 score), scientists claimed that it could be due to complexity of Russian language, since only Cyrillic text was used for modeling.

In light of these insights, our research aims to close the gap between theoretical understanding and practical application, proposing novel methodologies tailored to the unique challenges of Russian-language YouTube comments. By leveraging advanced techniques and drawing upon the rich experience of previous research, we aspire to foster a more constructive and harmonious online environment.

3 Model Description

3.1 Latent Dirichlet allocation

To analyze the corpus with comments, topic modeling is performed using latent Dirichlet allocation from the GenSim package.

3.2 Gaussian mixture models (GMM) and K-means for RuBert embeddings

The second text clustering method is based on K-Means and GMM, which is used for embeddings obtained with RuBert for each comment. Also, after preprocessing (see section 4), only the first 120 words were used in each document. This condition is due to the fact that RuBert has a limited size of the input sequence.

As a vector representation for GMM (and K-means) for a separate comment, the average embedding of RuBert from him was used.

4 Dataset

The data will be comments from YouTube channel "вДудь". On these videos, the journalist interviews famous actors, politicians, etc. The choice fell on this channel for the following reasons:

1. High popularity and as a result a lot of comments.

2. The blogger and his guests have a somewhat outrageous character, which can attract a large number of ill-wishers. It is expected that this may contribute increase in bots and trolls in the comments to this video.

For the analysis of comments, a blog dedicated to interviewing the founder of Tinkoff Bank was chosen. A program that reads data and puts it in a Tab. 1 was implemented. Data includes 93460 observations of comments and replies.

Field name	Description
author_id	Commenter's channel ID
author_url	Address (URL) of the channel of the author of the comment
author_name	Author name
text	Text with comment
reply_count	Number of replies to a comment in a thread
top_level	Depth of comments
publishedAt	Publication date
updateAt	Post update date
likeCount	Number of likes per comment

Table 1: Description of the table with data from YouTube

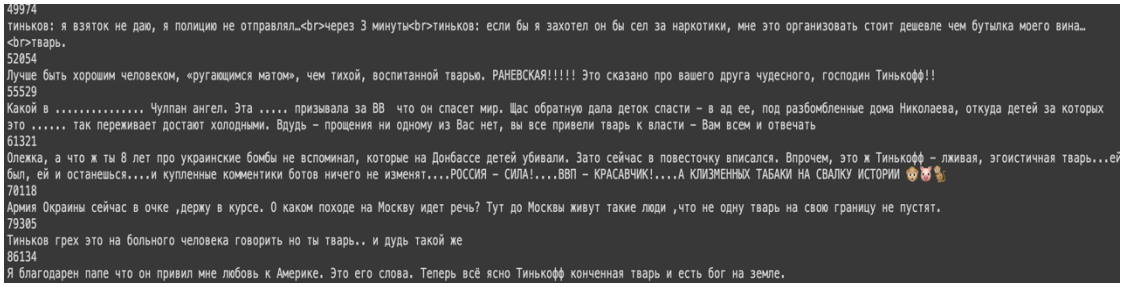
To build a corpus with comments, the following actions are performed:

1. Calculates for each author the number of comments that he wrote under the video.
2. Comments of rare users (commented less than 3 times) are discarded.
3. Delete stop words (English and Russian).
4. Lemmatization (With SpyCy library, file "ru_core_news_sm")

Here are some exerpts from comments to clarify the textual context that is dealt with:
Somewhat positive feedback:

```
4291
Умничка молодец искренне все говорит здоровья я с Украины уважаю вас
4340
Очень уважаю Тинькова! Дай Бог ему здоровья и долгой жизни!
4766
Молодец, Олег! До войны – не уважал. Сейчас – уважаю! Голова у тебя ясная!!! Здоровья тебе и твоей семье!!!!! \n.Крошку Цакхе
5019
Олег, всегда Вас уважаю. Доброго Вам здоровья!
5026
Тиньков а ты подумал про людей которые тебя уважают  твой банк и бренд доверие своих денег
5557
Очень круто! Неожиданно. Интересно. Таких людей, как Олег– один на миллион. Космос. Пожелаем ему здоровья и долголетия. Пусть
внутренней силе. Благодарю за интервью.
5694
Вообще, сильно красуется. Из за непоняток в мозгу бросил свое дело, бросил Родину в трудный час. Не уважаю.
6258
Олег сука бесит.... и в тот же момент я им восхищаюсь и уважаю..
6489
Как же я уважаю Дудя! Он настоящий патриот!
```

And offensive/toxic examples which are the **main objective** of following research:



Yet, it is up to debate if users intentionally tried to provoke hatred or genuinely wanted to express their opinion. In either case, those quotes are violating the rules of YouTube platform.

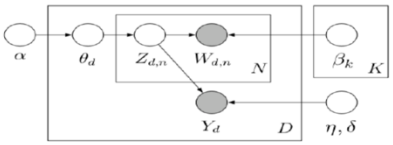
Data was labeled by regular expressions that are found in mentioned related work, plus some of the words that were specific to the context of video-material. Those included all variations of obscenely offensive / abusive / profanity language and words related to the large ongoing political event in Eastern Europe. Examples are shown throughout present research.

5 Experiments

5.1 LDA (Latent Dirichlet Allocation)

Document and response results from following generative process:

1. Draw topic proportions $\theta|\alpha \sim \text{Dirichlet}(\alpha)$.
2. For each word
   (a) Draw topic assignment $Z_n|\theta \sim \text{Multinomial}(\theta)$
   (b) Draw word $w_n|z_n, \beta_{1:K} \sim Multinomial(\beta_{Zn})$
3. Draw response variable $y|z_{1:N}, \mu, \sigma \sim GLM(z, \mu, \sigma)$



A visual representation of the word distribution for each topic is shown in **Fig. 1**.

The class with noise comments was selected after looking at the distribution of words in themes (See Fig. 1). Let's randomly select 10 comments from topic **number 4**. It looks like a topic with information noise and politics-related .

@АНИКС кто сказал, что война бы началась? Кто бы ее начал? Вы что-то перевираете...

@Снежков а я не сомневаюсь бот...иди проспись...

Папе наверное надоело стоять в очереди за колбасой .....

Олег, ничем не отличается от этих коммуняк. Была какая
либо власть, набросился с...

Мы перенесли тогда в 2015 EBV Virus-- это когда иммунитет полностью на нуле, опа...

Олег плохо за карму борешься - лукавишь, приписываешь себе заслугу, что ещё в пе...
----------согласен, поэтому СВО необходимо, чтобы вылечить эту раковую
опухоль Украины, на...

Ну,не всем-же иметь таких крутых воров друзей,как у тебя...

@elm tyu как ничего не решают ? Ведь ваши люди поддерживают войну!? Даже родстве... ----------
---
@OffvaniaЯ ЖИВУ В СВОБОДНОЙ ПРЕКРАСНОЙ РОССИИ!!! ПРЕДАТЕЛЯМ НЕТ МЕСТА В НАШЕЙ ВЕ...

Those fragments above are definetely right for our purpose. Except that it requires strict methodology to what consider as “toxic” or “offensive”. Surely, in our specific case there would be 2 categories of comments: related to context of the video and those that are meant to hurt someone. But it is important to consider those, that are both, since large-scale geopolitical event is mostly discussed.

5.2 t-SNE and GMM

t-SNE is used to visualize clusters obtained with GMM. On the Fig. 4 can be seen that part of the data has peeled off from the central cloud, but GMM does not separate these points in any way. A schematic workflow is shown on Fig. 3

The choice of a class with noise comments was chosen after viewing the classified texts. Next, we print 10 randomly selected lines from text that can be considered spam or irrelevant to the topic:

дисс на og buda!. <a href="https://youtu.be/WabZ3hSz2Uo">https://youtu.be/WabZ3h...

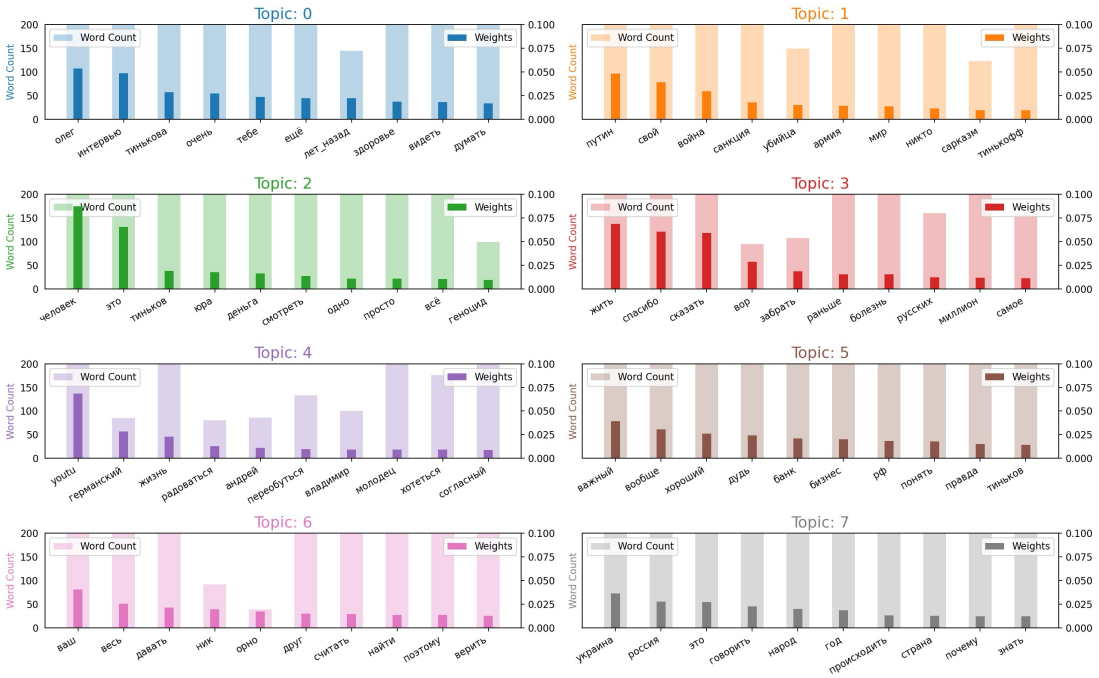


Figure 1: Distribution of words in topics

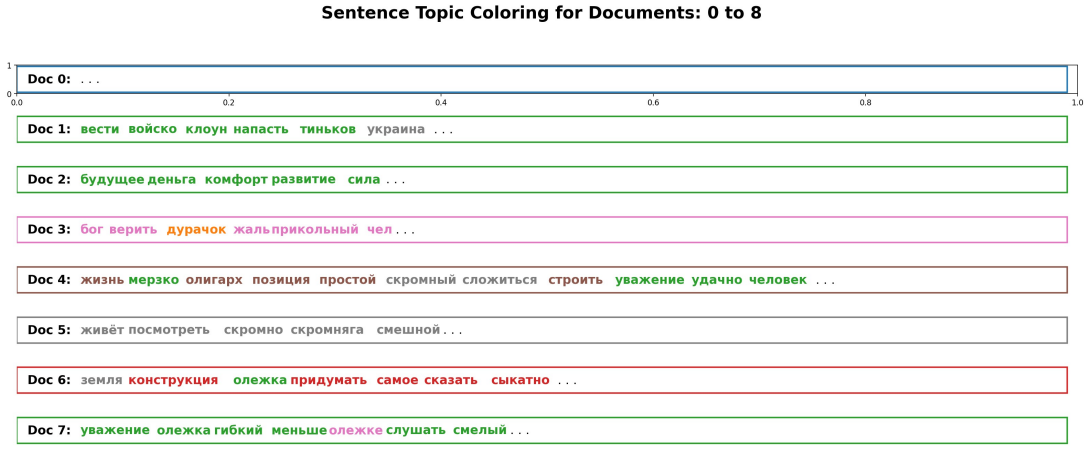


Figure 2: Some documents

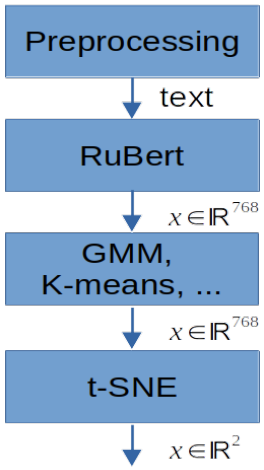


Figure 3: workflow

То самое Младше !7 в Нике ...

Реаниматолог о важности кислорода и тканевого дыхания, о роли Синтезита в этих п...

От каких вопросов Украинцам у них происходит сбой в программе?На что они не смог...
----------https://youtu.be/JoYL1MZmXbs вот...

Когда Закончится Война ..
<a href="https://youtu.be/DfOOS2F1F44">...
----------C0чнbIe Шк0дницЫ в Никке

 рассеивает солнечный свет, чт... ----------
----------это наконец здесь
https://youtu.be/7RTfXNvy8ck...

Тоже рады что Юра вернулся
<a href="https://youtu.be/jk2t5ucbJzc">http...
----------peskov is a coward and a murderertoo! I don’t think he is a wonderful person aft... ----------

5.3 t-SNE и K-means

For K-means similar Fig.5 is built previous t-SNE projection, but with markup after K-means.

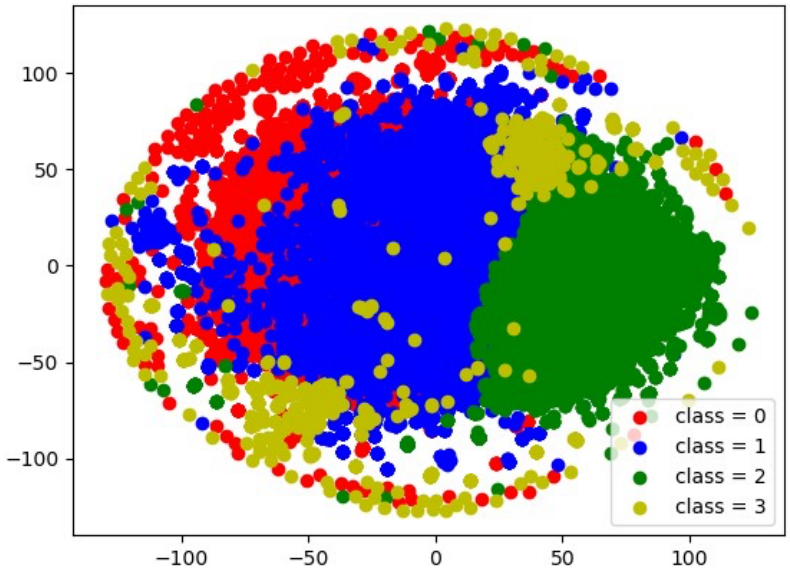


Figure 4: t-SNE и GMM (Noise comments: class 3)

The choice of a class with noise comments was chosen after viewing the classified texts. Eight randomly selected points from informational noise:

Z...

Если бы мы не вели войска в Украину она бы напала на нас а Тиньков он клоун...

Если бы мы не вели войска в Украину она бы напала на нас а Тиньков он клоун...

В деньгах силах. Есть деньги, есть комфорт, есть развитие, есть будущее....

Если бы мы не вели войска в Украину она бы напала на нас а Тиньков он клоун...

В деньгах силах. Есть деньги, есть комфорт, есть развитие, есть будущее.... ----------

---

В деньгах силах. Есть деньги, есть комфорт, есть развитие, есть будущее.... ----------
---
В деньгах силах. Есть деньги, есть комфорт, есть развитие, есть будущее....

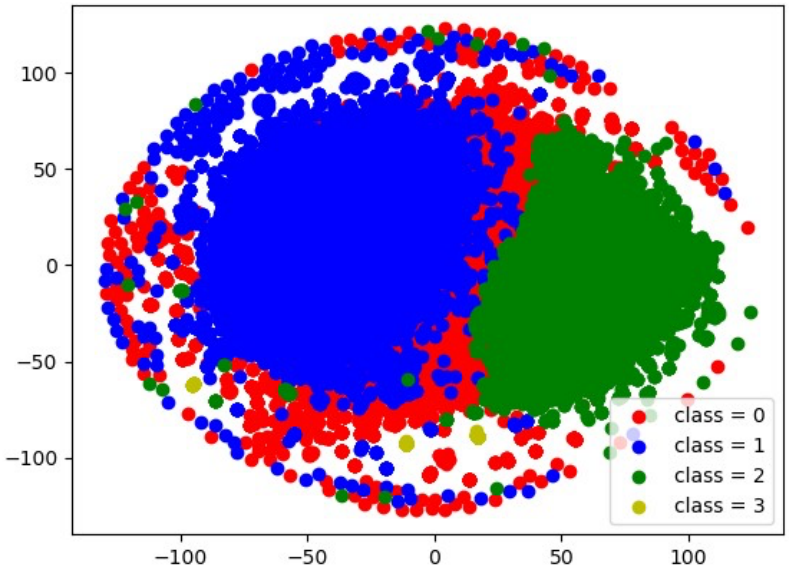


Figure 5: t-SNE и K-means (Noise comments: class 3)

5.4 t-SNE with points on the periphery

It was previously noted that after projecting data onto a two-dimensional plane using t-SNE, some of the points are peeled off (Fig.4). Perhaps these points represent some irregular data, in other words outliers. These emissions may be related to the informational noise of trolls and bots. Separate points on the periphery. To do this, we will take points only outside the circle of some radius (see Fig 6).

We also present 10 randomly selected lines from the text classified in this way:

Не важно что и как в Украине, не важно вообще нечего, что там происходило и прои...
----------P...

<a href="https://youtu.be/Krcr9IQ0Q_w?t=9039">https://youtu.be/Krcr9IQ0Q_w?t=903... ----------
---
Eres un ı´dolo Ayumi.Monster

mejores.<...

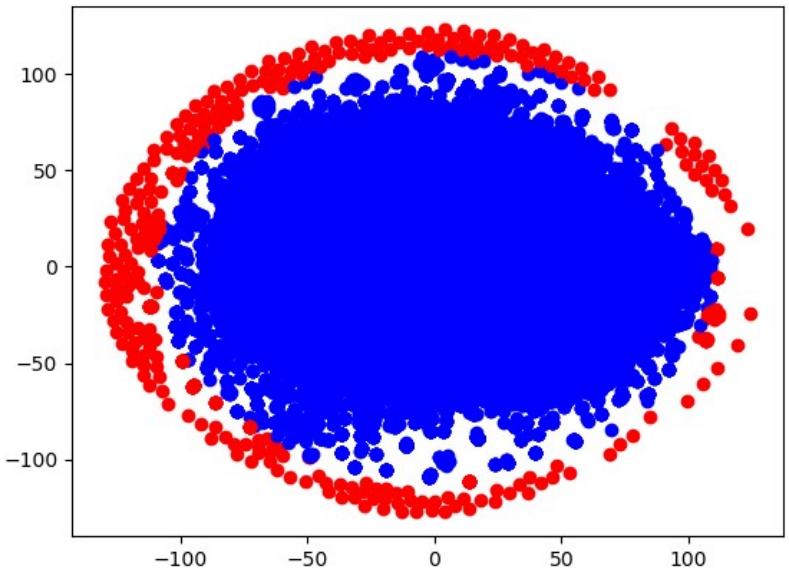


Figure 6: t-SNE and selection of points on the periphery of a circle

---
<a href="https://www.youtube.com/watch?v=Y3hNyPKuEUU&ab_channel=NEMAGIA">htt... ----------
---
<a href="https://www.youtube.com/watch?v=Y3hNyPKuEUU&ab_channel=NEMAGIA">htt...
----------То самое Младше !8 в
  нuke ...
----------То самое Младше !8 в
  нuke ...
----------Карателu.

Неужели мозги вы заржавили,
Дорогой
украинский сосед?

Вы н...

Топ...

5.5 Experiment Setup

The Fig. 3 shows a general scheme for clustering and visualizing data using RuBert, GMM (K-means), t-SNE.

The following parameters have been set for LDA:

- Number of topics: 8
- Number of iterations: 100
- α: symmetrical
- Number of passes through the body during training:10
- Number of documents to be used in each training block: 10

Then, ruBERT embeddings were applied to the text and classified (0 for non-offensive/toxic, 1 for the opposite) using kNN with hyperparameter search and CatBoostClassifier with default parameters. Then experiment was conducted on data that was labeled by regex and that which was topic-modelled by LDA, also on the combination of both.

6 Results

CatBoost showed a bit higher performance: 0.74 F-1 score against 0.68 F-1 score by kNN. The Tab. 2 shows the number of comments that were filtered by one of the four methods. Only the comments of authors who wrote more than two times participated in the clustering. Similar statistics for authors only are presented in the Tab. 3.

Fig. 1-5 shows the clustering results.

models	class_size
total	22661
GMM	976
out_circle	436
kmeans	413
lda	2185

Table 2: General statistics on toxic comments

models	number_of_authors
total	4267
GMM	319
out_circle	58
kmeans	255
lda	1455

Table 3: General statistics for toxic authors

Work	Model (Models)	Specification	F-1	Accuracy
[Skowronski (2019)]	DecisionTreeClassifier	Classic ML	0.65	0.92
[Kudugunta and Ferrara (2018) and Mazza et al. (2019)]	Neural network	VAE, LSTM, custom architectures	0.9	0.94
[Ю.В.Рубцова (2014) and Rogers et al. (2018)]	MLP Classifier	Sentiment analysis	0.67	0.81
Present research	CatBoost	RuBERT embeddings, clustering topics as features (LDA and K-means)	0.74	0.85

Table 4:Results of some related works and present research

7 Conclusion

Three approaches were used to identify troll/bot comments that are aimed to provoke other users or offend them. The first is topic modeling with LDA. The second method of parsing messages is based on the use of embeddings obtained from RuBert. Further, for this vector representation, the GMM and K-means clustering methods were used. Based on the hand review of the data for the corresponding clusters, a conclusion was made about the class number to which the noise messages correspond. The third

approach is tdistributed stochastic neighbor nesting (t-SNE) applied to RuBert embeddings. Noise comments were considered points lying on the periphery of a circle of a given radius.

As a result, the analysis of texts that were marked as noise (with bots and trolls), we can conclude that thematic modeling showed the worst. There is a lot of information in his texts that does not look like the work of trolls and bots. And yet, it is worthwhile considering for detecting toxic comments.

Methods based on RuBert embeddings showed very good results. Approach based on the identification of noise points at the t-SNE boundary performance showed good results. This method does not require additional analysis of classes like all other methods. The only thing it selected is less than all the points (objects) for the noise class. This is due to the choice of a large circle radius. The following experiments were not successful in the work:

- Detect GMM points that lie far from the centers of Gaussians of each class.
- Build a classification model on labeled data via pure LDA.

Overall, according to Table 4, present research provides comparable (to related researches) quality for classic ML modeling, but not as good as builiding own neural network architecture with manual tagging with larger amount of data. That's definetely what could be a 'low-hanging fruit'.

References

[Chu et al., 2012] Chu, Z., Gianvecchio, S., Wang, H., and Jajodia, S. (2012). Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING*.

[Ю.В.Рубцова, 2014] Ю.В.Рубцова (2014). Построение корпуса текстов для настройки тонового классификатора. *Программные продукты и системы*.

[Gilani et al., 2017] Gilani, Z., Farahbakhsh, R., Tyson, G., and Crowcroft, L. W. J. (2017). Of bots and humans (on twitter). *Conference: 9th IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*.

[Varol et al., 2017] Varol, O., Ferrara, E., Davis, C. A., Menczer, F., and Flammini, A. (2017). Online human-bot interactions: Detection, estimation, and characterization. *arXiv*.

[Rogers et al., 2018] Rogers, A., Romanov, A., Rumshisky, A., Volkova, S., Gronas, M., and Gribov, A. (2018). Rusentiment: An enriched sentiment analysis dataset for social media in russian. *Proceedings of COLING*.

[Kudugunta and Ferrara, 2018] Kudugunta, S. and Ferrara, E. (2018). Deep neural networks for bot detection. *Information Sciences*.

[Kong, 2019] Kong, B. (2019). Analysing russian trolls via nlp tools. *The Australian National University*.

[Gilbert, 2019] Gilbert, E. C. E. (2019). Hybrid approaches to detect comments violating macro norms on reddit. *https://arxiv.org/abs/1904.03596*.

[Mazza et al., 2019] Mazza, M., Cresci, S., Avvenuti, M., Quattrociocchi, W., and Tesconi, M. (2019). Rtbust: Exploiting temporal patterns for botnet detection on twitter. *WebSci*.

[Pierre, 2019] Pierre, S. (2019). Russian troll tweets: Classification using bert. *towardsdatascience.com*.

[Rogers et al., 2018] Rogers, A., Romanov, A., Rumshisky, A., Volkova, S., Gronas, M., and Gribov, A. (2018). Rusentiment: An enriched sentiment analysis dataset for social media in russian. *Proceedings of COLING*.

[Skowronski, 2019] Skowronski, J. (2019). Identifying trolls and bots on reddit with machine learning. *towardsdatascience.com*.

[Alsmadi and O'Brien, 2020] Alsmadi, I. and O'Brien, M. J. (2020). How many bots in russian troll tweets? *Information Processing and Management*.

[Tardelli et al., 2022] Tardelli, S., Avvenuti, M., Tesconi, M., and Cresci, S. (2022). Detecting inorganic financial campaigns on twitter. *Information Systems*.