Text Mining On Ukraine Russia War

Advanced-Data and Network Mining

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Introduction

The Ukraine-Russia war started in February 2022 and continues to date. Researchers have been using machine learning methods to analyze sentiments, extract trending topics, and understand global impacts on other economies. This study focuses on applying text mining techniques to Ukraine-Russia War Twitter data, with the primary aim of understanding the sentiments of people and extracting the most trending topics on Twitter.

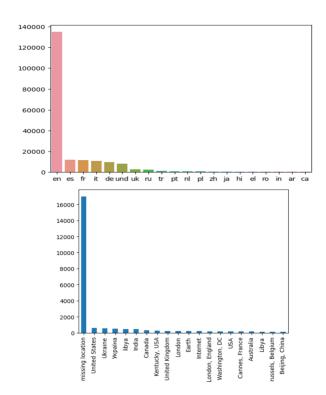
Methodology

The study follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which is a widely used framework for data mining projects. The CRISP-DM methodology consists of six stages: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

- a. Business Understanding: The first stage of the CRISP-DM methodology involves defining the problem to be solved and understanding the project's goals. In this study, the goal is to apply Text Mining techniques to the Ukraine-Russia War Twitter Data to understand the sentiments of people a year after the war began and extract the most trending topics over Twitter regarding the war.
- b. Data Source: The data source for this study is the Kaggle dataset on the Ukraine-Russia crisis, which is updated daily with the most recent tweets on the conflict. The dataset includes 1.2 million rows of tweets with information on the tweet's language, location, user, and text.
- c. Data Understanding: The data understanding stage involves exploring and visualizing the data to gain insights into the data's characteristics. In this study, exploratory data analysis is performed using Python libraries such as Matplotlib and Seaborn. The analysis includes:

Tweets by Language: The number of tweets in different languages is analyzed, and the majority of tweets are in English. Therefore, the study focuses only on tweets in English.

Tweets by Location: As the majority of tweets are missing location information, this is not useful for the analysis.



Top Retweeted Tweets: The top ten retweeted tweets are displayed, and most of them are about the involvement of Putin, Ukraine, and China, or about Biden getting elected, and a few are of people criticizing the war.

Top 10 retweeted tweets

retweetcoun	text	
9932	My daughter and I surviving the night in Ukraine. We are real people at war with crazy dictator and we need the world's support right now/niv#StandWithUkraine https://l.co/FydmY40ACj	39981
986	24 kidnapped Ukrainian children from #Russia-occupied Donetsk region are passed to adoptive families in Novosibirsk, 3600 km away from homeln/nSecrecy of adoption will never let them learn were their parents killed, sent to concentration camps or deported ninffrussialsate/oriststate https://t.co/nx790/VUBy	18239
832	Situation in #Ultraine: #ICC judges issue arrest warrants against Vladimir Vladimirovich Putin and Maria Alekseyevna Lvova-Belovain-Read more 1 in https://t.co/SOMCTX.usy5	4294
777	I want to thank again every American who voted for Biden. When you were celebrating Trump is no longer a threat to humanity, I was drinking champagne for the historical moment too. But Ittle did I know that moment would save soo many lives in #Ukraine. You & your @POTUS are * https://t.co/DoappUXSjw	2012
769	Sergel is a hero \triinDuring a battle in #Bakhmut, he dragged 9 wounded men to safety, applied 3 tourniquets, saved a dying soldier AND was firing his rifle in combat. \triinSergel was trained by Sons of Liberty International (@OfficialSOU) trainer Jason \triin\triVitraine\triin\trii\triin\tr	2443
707	Shocking! This is an actual freight train moving over a twisted, "bendy" railway track linking Ohio and Indiana in the USA!! Ivinit's like a 4th world country. IninAmerica should fix its sh*thole infrastructure rather than waging endless wars. IninRRussia #Ukraine #China https://t.co/EPsRrca9pL	149323
614	Pay attention to the IR leader's beard, it is full of execution ropes. This is the real face of the regime that has killed many people in Wiran, Syria, Iraq, Yemen, #Ukraine, etc. Help the people of Iran to overthrow it.in#MahsaAmini in@ZelenskyyUa In@EUCouncil in@zelin@cnin@apin@cnin@apin@UN https://t.co/A3SLINQWIV	179526
582	On this day in 2014, a #Russiajn Buk shot down a passenger aircraft #MH17 flying at 10 km from Amsterdam to Kuala Lumpur over #Donetsk region in eastern #Ulleraine, IrinAll 283 passengers and 15 crew were killed Irin https://t.co/020x27pHJy	7128
563	us Glory to Ukraine and it's Soldiers us/nAUkraine/War https://t.co/S4fWhnuxqu	20976
563	THREAD: Proof that you are a Nazi if you don't #StandWithUsraine us	30429

Top Tweets from Most Followed Account: The top most tweets from the most followed account are displayed, and most of them are about the involvement of Putin, Ukraine, and China, but some are not relevant to the war but are related to countries and their friendships or tourism.

Top most tweets from the most followed user accounts



Word Cloud: A word cloud is formed to find the most used words, and words like Ukraine, Russia, China, Justice4Tigray, Tigray genocide, Ukraine-Russia war, etc. are highlighted.

Top most trending hashtags



d. Data Preprocessing: The data preprocessing stage involves cleaning and transforming the data into a format suitable for analysis. In this study, data cleanup is done in Python using BeautifulSoup and NLTK libraries. The tasks performed include:

Removal of HTML tags and links

- Transforming data into lowercase
- Converting contractions to words (e.g., can't've = cannot have; doin = doing)
- Removal of punctuations
- Filtering stop words
- Lemmatization to convert words to their root word (e.g., eat, ate, eating, eaten = eat)



Tokenization

e. Modeling (Sentiment Analysis): The modeling stage involves selecting and applying a model to the data to predict outcomes. In this study, sentiment analysis is performed using RapidMiner, and the VADER sentiment analysis algorithm is used for scoring and defining polarity. The steps performed include:

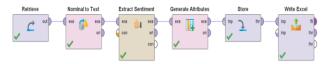
Loading cleaned data set

- Generating sentiments using VADER
- Aggregating polarity
- Balancing the dataset
- Predicting sentiments using the auto model in RapidMiner
- Evaluating the result using Fast Large Margin

Row No.	text	tweetcreate	tweetcreate	tokenised_clean_text
1	Success is gi	2023-03-20	00:00:00	success give seekers video
2	#NSTleader	2023-03-20	00:00:00	nstleader international criminal court iraq war
3	Russia's co	2023-03-20	00:00:00	russia combat losses ukrainewar front incl
4	uaUkraine W	2023-03-20	00:00:00	ukraine war footage follow new videos ukr
5	British Intelli	2023-03-20	00:00:00	british intelligence ukrainerussiawar map
6	Book summe	2023-03-20	00:00:01	book summer camp canada national park go
7	#Russia's se	2023-03-20	00:00:01	russia self delude victimization
8	#Ukraine: Ev	2023-03-20	00:00:01	ukraine everyone hear recent mq incident r
9	In preparatio	2023-03-20	00:00:02	preparation vlads time prison want show t

f. Modeling (Topic Modeling): The topic modeling stage involves extracting topics from the dataset. In this study, LDA (Latent Dirichlet Allocation) is used for topic modeling, and it is implemented in two ways: LDA modeling in Python using Gensim and LDA modeling in RapidMiner. The steps performed include:

- * Running the model in Python
- * Loading cleaned data set
- * Preparing the data using Gensim
- * Building the LDA model
- * Extracting the topics
- * Visualizing the topics using pyLDAvis



Row No.	Score	text	tweetcreate	tweetcreate	tokenised	sentiment
1	0.692	Success is gi	2023-03-20	00:00:00	success give	positive
2	-1.359	#NSTleader	2023-03-20	00:00:00	nstleader int	negative
3	-0.795	Russia's co	2023-03-20	00:00:00	russia comb	negative
4	-0.744	uaUkraine W	2023-03-20	00:00:00	ukraine war f	negative
5	0.538	British Intelli	2023-03-20	00:00:00	british intelli	positive
6	0	Book summe	2023-03-20	00:00:01	book summe	neutral

b. Running the model in RapidMiner

Loading cleaned data set

Applying LDA operator

Extracting topics

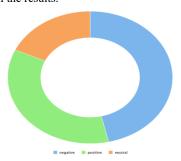
g. Evaluation: The evaluation stage involves assessing the quality of the models and determining whether they meet the project's goals. In this study, the quality of the sentiment analysis and topic modeling models is evaluated using performance metrics such as accuracy, precision, recall, and F1 score.

h. Deployment: The final stage of the CRISP-DM methodology involves deploying the models and implementing the insights gained from the data analysis. In this study, the insights gained from the sentiment analysis and topic modeling models can be used by policymakers and researchers to understand the sentiments of people towards the Ukraine-Russia War and extract the most trending topics over Twitter regarding the war. The models can also be integrated into a web application for real-time analysis and visualization of Twitter data related to the war.

Modeling- Sentiment Analysis

In the Modelling (Sentiment Analysis) stage of the study, the goal is to predict the sentiment of each tweet in the dataset. The sentiment analysis technique used in this study is VADER (Valence Aware Dictionary and Sentiment Reasoner). VADER is a rule-based sentiment analysis tool that is specifically designed for analyzing social media texts. It uses a lexicon of words with associated sentiment scores and rules to identify the sentiment of a given text.

After the sentiment analysis is performed using RapidMiner, the data is balanced by multiplying and dividing it into positive, negative, and neutral sentiments. This ensures that the model has an equal number of tweets for each sentiment category, which helps to avoid bias in the results.



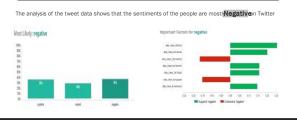
To evaluate the performance of the sentiment analysis model, two algorithms are used - Fast Large Margin and Generalized Linear Model. The Fast Large Margin algorithm shows the highest accuracy and performs the best, followed by the Generalized Linear Model.

Row No.	sentiment	count(sentiment)
1	negative	19466
2	neutral	7616
3	positive	14859

Based on the results, the sentiment of people on Twitter regarding the Ukraine-Russia war is mostly negative. This insight can help in understanding the overall public opinion about the war and can be useful for policymakers and researchers working in this area.

		Standard Deviation		Standard Deviation
Models	Accuracy	(+-)	Classification Error	(+-)
Naïve Bayes	37.4%	0.5%	62.6%	0.5%
Generalized Linear Model	56.0%	0.8%	44.0%	0.8%
Fast large Margin	61.6%	0.7%	38.4%	0.7%
Decision Tree	41.7%	0.7%	58.5%	0.7%
Random Forest	39.1%	0.7%	60.9%	0.7%
Gradient Booster	35.2%	0.5%	64.8%	0.5%

Result Evaluation Using Fast Large Margin



Modeling-Topic Model

In the Modeling (Topic Model) stage of the study, the goal is to extract topics from the Ukraine-Russia War Twitter data. The approach used for this is Latent Dirichlet Allocation (LDA), which is a widely used method for topic modeling in natural language processing.

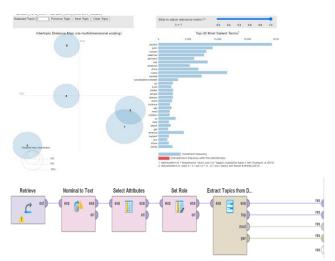
	number_of_topics	coherence_score_C_v	coherence_score_U_mass
0	1	0.281096	-3.121876
1	2	0.565669	-2.679459
2	3	0.371025	-5.075367
3	4	0.520381	-3.592864
4	5	0.479557	-4.640056
5	6	0.451019	-6.827097
6	7	0.414954	-5.044110
7	8	0.422059	-6.048332
8	9	0.467584	-6.339196

LDA assumes that each document is a mixture of topics and that each word in a document is associated with a particular topic. The goal of LDA is to identify the underlying topics that explain the co-occurrence of words in the corpus.

Topic Ollock 0.091",pxin' + 0.053"gn' + 0.022"canati + 0.093"bgn' + 0.093"ggn' + 0.019"mgn' + 0.019"nsisyararimg' + 0.013"fmg' + 0.013"smg' + 0.011"mgiyyo'
Topic 1 Word 0.068" nesien" + 0.002" hesisciennistate! + 0.004" solde! + 0.004" vold! + 0.004" saj + 10.004" support! + 0.014" blore! + 0.013" cines! + 0.011" los!
Topic 2 North 0.099" hosis' + 0.055" thira' + 0.009" Marine' + 0.055" his + 0.055" breats' + 0.022" family' + 0.021" hosis + 0.000" Marine sosionas' + 0.000" pubrica nationinal + 0.000" reto'
Topic 3 Nord 0.119" Unried + 0.059" bahmut + 0.049" gemany + 0.044" Navi + 0.049" Unaina' + 0.059" carabi + 0.059" noisa' + 0.059" betoy + 0.056" betoy + 0.056" attait + 0.050" aneisa'
Topic 4North 0.029" not" + 0.029" nos!" + 0.029" people + 0.009" brofons! + 0.000" heef! + 0.0009" britise! + 0.004" heid + 0.00

To implement LDA, two approaches are used in this study. The first approach is to run the LDA model in Python using the

Gensim library, which is a popular open-source library for topic modeling in Python. The Gensim library provides a simple interface for implementing LDA models and allows for the selection of a number of topics and other model parameters.



The second approach used in this study is to implement LDA modeling in Rapidminer. Rapidminer is a data mining and machine learning platform that provides a wide range of tools for data preparation, modeling, and evaluation. Rapidminer's LDA operator allows for the selection of the number of topics, alpha, and beta values and provides options for topic modeling based on different approaches such as Gibbs Sampling, Variational Inference, and Expectation Maximization.

Topic #	Topics (RAPIDMINER)
1	Tigraygenocide_war_committed_women_atrocities
2	russian_forces_destroyed_military_near_ukranianarmy
3	russia_china_president_meeting_leader_peace
4	need_peace_make america_see_iraq_never_stop
5	footage attack soldiers horrible near kherson

Once the LDA models are implemented, the topics are extracted, and the results are analyzed to identify the most significant topics in the data. These topics can provide insights into the most discussed themes on Twitter related to the Ukraine-Russia war.

Topic #	Topics (Python with Gensim)
1	putinisawarcriminal_issue_home_arrest_warrant
2	russia_destroy_tank_kill_soldier_kherson
3	president_see_army_army_take_missiles_near country_video
4	people_women_children_still_crimes_genocide
5	putin_go_canada_help_russianwarcrimes

Conclusion

The study shows that the sentiments of people on Twitter regarding the Ukraine-Russia War are mostly negative. The most trending topics over Twitter regarding the war are related to Ukraine, Russia, and China, with hashtags like #Justice4Tigray, #Tigraygenocide, and #Ukraine-Russia war getting highlighted. The study provides valuable insights into public opinion on the war

and can be used by policymakers and analysts to understand the sentiments of people better.

Future Scope

The study can be extended by analyzing the impact of the war on other countries and their economies. The study can also be extended to include other social media platforms like Facebook and Instagram, which could provide more insights into public opinion on the war.

Key Takeaway

The Key learnings and takeaways from the assignment on Text Mining in Ukraine-Russia War:

- Text mining techniques can be used to analyze people's sentiments and extract trending topics related to a particular event or topic.
- The CRISP-DM methodology is useful for organizing the text mining process, including understanding the business problem, selecting appropriate data sources, and preparing and modeling the data.
- Exploratory data analysis is a crucial step in understanding the data better before preprocessing and modeling.
- Preprocessing of social media data is necessary because it is noisy and requires data cleanup. This includes the removal of HTML tags, and links, converting contractions to words, removal of punctuations, filtering stop words, lemmatization, and tokenization.
- Sentiment analysis is a popular text mining technique used to determine the attitude or emotion of a writer towards a specific topic or product. Vader Sentiment Analysis is widely used to determine the polarity of tweets.
- 6. Topic modeling is another text mining technique used to extract topics from a given set of documents (in this case, tweets). LDA (Latent Dirichlet Allocation) is one of the most popular methods used for this purpose.
- The tweet data analysis shows that the people's sentiments are mostly negative on Twitter towards the Ukraine-Russia war.
- 8. Understanding the sentiments of people towards a particular topic can help in making informed decisions and formulating appropriate policies. It can also be useful for businesses to gain insights into consumer opinions and improve their products or services accordingly.

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