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Topic Modeling and Sentiment Analysis of US' Afghan Exit Twitter Data: A Text Mining Approach

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Abstract.

The withdrawal of US troops from Afghanistan and the subsequent collapse of the Afghan government threatens the lives, security, and human right of many people. Twitter and other social media platforms took the lead in opinion and sentiment sharing, allowing researchers to make a real-time assessment that may help authorities develop early response strategies. In this study, 362,566 tweets relating to the exit of the US troops from Afghanistan collected between August 11 and 27, 2021, are analyzed using text mining techniques, including sentiment analysis and word cloud analysis. The analysis shows diverse topics on social media related to the fallout, and the general reaction regarding the crisis was negative.

1. Introduction

Social media have taken over the globe by storm and shrunk the world's dimensions with a fair bit of communication between people across multiple social networking platforms such as Twitter and Facebook. As informal as these communications are, they convey the mood and sentiment of the persons involved in the discussion. Twitter has provided an advantage to academic research with rich datasets which can be easily mined and analyzed (see Naseem et al. [27]; Tiwari et al. [41]). Data from Twitter have been used to make predictions on diverse events from crime (see Gerber [15]), the stock market (see Bollen et al. [8]), political campaigns, referendums, and elections (see Gayo-Avello. [14]). Others include hostile media effect (see Shin and Thorson [39]), opinion polls (see O'Connor et al. [29]), public health and well-being (see Addo et al. [3]), news coverage of

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wars (see Aday [1]), media violence and aggression, movie sales, and gender and climate issues (see Addo et al. [2]; Martins et al. [22]). Twitter, in particular, provides an amazing topical memory as in author-annotated hashtags and trends in public perception. Researchers can mine and rely on this to identify valuable insights into topical issues.

The early to mid-parts of 2021 have seen major news headlines, including COVID_19 and related climate and employment topics. One of the most topical issues, however, has to do with Afghanistan. Even though Afghanistan has been on the news since its invasion by the Soviets (December 25, 1979 - February 15, 1989), the exit of the American troops and allied forces in 2021 after two decades of war and the fall of Kabul to the Taliban flooded social media platforms and all news channels causing the world to come to a standstill.

The world was divided in opinion. Some people were for and others against, while others were in a fix about the exit of Americans. This generated varied reasons from individual and organizational perspectives. People express their opinions and disambiguate their soppiness. These large and unorganized data do not provide any trends from which stakeholders can make decisions. However, sentiment analysis offers a practical means to evaluate divergent opinions from the public to reach conclusions that can inform policy decisions (see Ruz et al. [35]). Sentiment analysis computationally identifies and classifies opinionated data according to the polarity (positive, negative, and neutral) (see Vashisht and Sinha [42]). Sentiment Analysis thus has transfigured the way information is perceived and interpreted today.

Approaches to sentiment analysis vary, including lexicon and rule-based techniques, machine learning-based techniques, hybrid techniques, ontology-based approaches, and recently emoticons; a technique that exploits the graphical cues in the text (Emojis) to determine the sentiments (Bhadane et al., 2015) (see Devika et al. [13])(see Akpatsa et al. [5]).

Although there were many studies on sentiment analysis using tweets, none to date is dedicated to the news storms about Afghanistan in 2021. As unique as these related geopolitical tweets are away from the everyday political and customer response tweets, no study has so far looked into the public opinions expressed on social media on the fall of Kabul. Existing studies have also failed in many instances to compare multiple machine learning classification algorithms (see Manguri et al. [21]). Those that come close relied on data samples that are not large enough to generalize opinions from the growing netizens (see Andoh et al., [6]; Rustam et al. [34]). Exploring the large dataset (tweets) to identify trends, keywords, and themes with multiple techniques will be newsworthy and have academic relevance. Also, the current study focuses on answering questions relating to themes, public concerns, and sentiments regarding the return of the Taliban through social media analytics. It is also important to evaluate the performance of several supervised machine learning classifiers. This is yet to be found in any existing literature. This, we believe, will inform researchers on the machine learning algorithm best to apply. The study in this regard identifies algorithms with suitable metrics to evaluate the performance of supervised machine learning classifiers on the US war in Afghanistan-related tweets. Data presented in this study are tweets collected between August 11, 2021, and August 27, 2021, using several relevant hashtags (#) and keywords related to the crisis.

2. Literature Review

Social media has become an inherent part of the daily lives of modern society. Platforms such as Facebook, Instagram, and Twitter have transformed the way we communicate and socialize on the Internet as they allow sharing of content that reaches a wide range of viewers around the globe (see Saurel [37]). The rapid growth of social networks has generated large volumes of textual content online. Consequently, there has been a surge in the literature that seeks to explore topics such as online reviews, public opinion, and sentiments about evolving events and how they impact our social lives (see Chen et al. [10]; Tiwari et al. [41]; Yadav et al. [45]). In academia, researchers have used Natural Language Processing-based methods as a practical tool for text mining and interpreting opinions and events, topical issues (see Mehta and Pandya [23].

Twitter provides a massive platform where instant messages are posted daily (see Adwan et al. [4]). According to recent statistics, Twitter has over 330 million active users, with over 192 million daily users with several million tweets per day (see Ilyas et al. [17]). Analyzing these data has become a gold mine for the research community. It provides valuable insights for governments and policy-makers who need to understand people's views on a particular topic or event to develop early response strategies (see Adwan et al. [4]; Dahal et al. [12]; Mujahid et al. [26]).

Most previous work done on social media analysis focuses on using text mining approaches such as word frequencies, sentiment analysis, and topic modeling to discover trends and popular themes that dominate social media discussions (see Boon-Itt and Skunkan [9]; Chen et al. [10]; Dahal et al. [12]; Xue et al. [44]). For example, this work (see Boon-Itt and Skunkan [9]) uses sentiment analysis on Twitter data to gain insights into Covid-19 trends and share general sentiments and opinions to reveal meaningful themes of concern shared by the public on Twitter. The analysis shows that Twitter is a good platform for understanding public concerns and awareness about evolving events.

Researchers have also used Twitter sentiment analysis to extract a variety of public opinions and sentiments expressed during crisis events such as civil wars and natural disasters (see Ruz et al. [35]; Yao and Wang [46]). Identifying such emotions is important for understanding the situation's dynamics and its emotional impact on those affected. This paper (see Öztürk and Ayvaz [30]) investigates the public discourse on the Syrian refugee crisis, which has affected many people and has become a widely discussed, polarized topic on social media worldwide. A related study shows that extracting sentiments during a disaster can help authorities to develop more critical situational awareness and other programs to manage future events (see Neppalli et al. [28]). The study further demonstrates how users' sentiments change based on their location and proximity to the disaster point. A study is also conducted to evaluate the public sentiment and opinion on Brexit by collecting over 16 million tweets (see Ilyas et al. [17]). The authors use Python VADER library to perform sentiment analysis and Gensim library's using Latent Dirichlet Allocation (LDA) algorithm for topic modeling. The analysis revealed the most popular daily topics of discussion on Twitter and found a positive correlation between Twitter sentiment towards Brexit and the pound sterling exchange rate

Along with topic modeling, sentiment analysis has become a popular research theme in artificial intelligence. A review of existing literature indicates that various Twitter sentiment analysis research uses traditional machine learning algorithms to predict sentiment from tweets [18], [33], [34]. These approaches treat sentiment analysis problems as a text classification task. These algorithms provide good accuracies with fewer computational resources and are regarded as the baseline learning methods in sentiment analysis of Twitter data (see Rachman and others [31]).

Besides, advances in deep learning models for sentiment analysis have received significant attention by overcoming challenges associated with conventional models (see LeCun et al. [19]). The success of deep learning models is based on their ability to easily integrate pre-trained word embeddings, which often leads to superior performances(see Goldberg [16]). The current state-of-the-art Twitter sentiment analysis uses deep learning to model complex linguistic information from textual data (see Akpatsa et al. [5]; Minaee et al. [24]). Classification is done using models such as Convolutional Neural Networks (CNNs), attention-based Bidirectional LSTM, and recently, Google BERT (see Jianqiang et al. [18]; Ramadhani and Goo [32]; Roy and Ojha [33]; Severyn and Moschitti [38]). These works demonstrate the effectiveness of deep learning models on social media data analysis as they automatically detect features from unstructured data with less human intervention.

In connection with previous works, our study applies sentiment analysis and topic modeling methods to analyze tweets related to the end of the US-Afghan war. The study also uses the TextBlob annotation approach and TFIDF and Word2vec feature extraction methods to evaluate the performance of various machine learning classifiers for sentiment analysis. To the best of our knowledge, this research is among a few (if any) that seek to provide valuable insights from tweet content related to the aftermath of the US troop withdrawal from Afghanistan. Findings can be a worthy source of information to help governments and international organizations understand social media trends and the public views on the situation in Afghanistan.

3. Research Methodology

3.1. Data collection

Our data collection approach uses Twitter Streaming API and Python script to access tweets related to the US war in Afghanistan and the troops' exit from August 11, 2021, to August 27, 2021. This period coincides with the time the Taliban gained control over Afghanistan following the departure of the last US troops.

This period is important in examining public discourse related to the fallout from the Taliban's return to the seizure of the country swaths. Tweets were collected using related keywords and metadata such as language, source, date range, and location. Since our focus was on the crisis in Afghanistan, we used several relevant hashtags (#) and keywords such as #Afghanistan, #Taliban, #Afghan, #AfghanLivesMatter, #KabulHasFallen, #kabulAirport, #Jihadist, #Jihad, #AfghanWar, #kabul, #AfghanWomen, #AshrafGhani, to collect comprehensive tweets dataset for our analysis. Over 500000 randomly filtered tweets were collected using the Twitter streaming API during the study period. Table 1 shows sample subsets from the collected tweet dataset, including user_location, date, text, and hashtags.

Table 1: Sample tweets from the collected dataset.

user_location	date	text	hashtags
Washington DC	8/19/2021 23:59	Shocker. Afghanistan: Taliban carrying out a door-to-door manhunt, report says #afghanistan https://t.co/iB6dyX1VcK	[‘afghanistan’]
NaN	8/19/2021 23:59	@JoeBiden drop bass, not bombs big homie #Afghanistan #Talibans	[‘Afghanistan’, ‘Taliban’]
West Bengal	8/19/2021 23:59	“Burqa prices have risen in the markets of #Afghanistan’s provinces. According to Aqla, in the past, he could buy a ... https://t.co/rlDrH7295s	[‘Afghanistan’]
York, England	8/19/2021 23:59	The US and the UK carved up #Afghanistan in the 80s to get more heroin to minorities, and militants. I guess the c... https://t.co/UE4YmiyzZH	[‘Afghanistan’]
World	8/19/2021 23:59	@WhiteHouse @JoeBiden .@JoeBiden will NEVER admit that #USArmy NEVER had or will have any right to invade... https://t.co/7JpPYQ9Qgm	[‘USArmy’]

3.2. Data preprocessing

Social media data is highly susceptible to many irregularities as most tweets contain usernames, empty spaces, stopwords, symbols, URLs, special characters, emojis, hashtags, etc. These features introduce unnecessary computational complexity while offering very little or no contribution to the analysis.

This study uses various NLTK techniques to clean and preprocess the collected tweets to improve the data quality. All texts were converted into lowercase form, while background noises such as white space, punctuations, numbers, hashtags, URLs, and special characters were also removed. Converting all text to lowercase reduces the complexity of the feature set as the same words (e.g. ‘Good’ and ‘good’) are seen differently by a learning algorithm. Other preprocessing procedures include removing hyperlinks, targets (@username), and common English stopwords, which do not add valuable information for analysis. Table 2 presents samples of the raw tweets and cleaned tweets (all stopwords removed and selected stopwords removed). The decision to remove selected tweets is to avoid changing the original meaning of the tweets.

Table 2: Sample tweets from the collected dataset before and after preprocessing.

Raw tweets	Tweets after all stopwords cleaned	Tweets after selected stopwords cleaned.
What's happening in Afghanistan is not an excuse for you woke Twitter warriors to be Islamophobic while giving your... https://t.co/wnL2VPZRgE.	Whats happening afghanistan excuse woke twitter warriors islamophobic giving your.	Whats happening Afghanistan not excuse woke twitter warriors islamophobic giving your.
To those pointing to chants of "death to America" as an excuse to do something, I want to ask you an honest question https://t.co/dTRR8bTWwz.	Those pointing chants death America excuse something, want ask honest question.	Those pointing chants death America excuse something, want ask honest question.
Couldn't believe this ___ heart wrenching ♡ situation right now in #Kabul https://t.co/AGDxYekZmB	Couldn't believe this heart wrenching situation right kabul.	Couldn't believe this heart wrenching situation now Kabul.
(OPINION) What the Taliban takeover might mean for the "struggle for the soul of Islam." https://t.co/jLKTvZYLhK https://t.co/U5O2m6lRgZ	(opinion) what taliban takeover might mean struggle soul islam.	(opinion) what taliban takeover might mean struggle soul islam.

3.3. Assigning sentiment

We perform sentiment analysis on the dataset using TextBlob, which is a lexicon and rule-based sentiment analysis tool, to assign sentiment scores to the processed tweets. TexBlob is specifically tailored to sentiments expressed on social media. Textblob is mostly used to carry out sentiment analysis task using its inbuilt classifier which is pre-trained on movie review datasets. It requires fewer computational resources to implement, while its simple structure allows it to become one of the most popular and easier to use python library for sentiment analysis for both beginners and experienced researchers in the recent past (See Akpatsa et al. [6]). Besides, TextBlob offers other important features such as a spelling corrector which is mostly required to normalize text data. Fundamentally, TextBlob employs two key metrics: polarity and subjectivity in its sentiment analysis processing (see Loria [20]). The sentiment value is based on the polarity score of the text in the range of -1 and 1. Text with a polarity score less than 0 is assigned a negative sentiment, a polarity score equal to 0 is assigned a neutral sentiment, and a polarity score greater than 0 is assigned a positive sentiment (see Sohangir et al. [40]). On the other hand, subjectivity is a float within the range [0.0, 1.0], where 0.0 is very objective, and 1.0 is very subjective.

Figure 1 shows sample tweets with polarity and subjectivity scores. TextBlob identifies the statement in the first example as having a neutral polarity and maximum objectivity, which makes sense, given that the tweet contains a definite trend regarding

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TextBlob('kabul afghanistan internal state department cable warned kabul collapse').sentiment
Sentiment(polarity=0.0, subjectivity=0.0)

TextBlob('great pledge norway prime minister submit afghanwomen safe the world').sentiment
Sentiment(polarity=0.65, subjectivity=0.625)

TextBlob('devastating heartbreaking scenes coming kabul desperation despair afghanistan').sentiment
Sentiment(polarity=-1.0, subjectivity=1.0)
```

Figure 1: Sample sentiment scores assigned be TextBlob.

Table 3: Sentiment distributions after applying TextBlob.

Collected tweets	Negative	Neutral	Positive
362566	168244	117863	76459

the ongoing situation in Kabul. The statement in the second example is identified as positive in polarity but relatively subjective. In contrast, a negatively charged sentiment is associated with the statement in the third example and is recognized as highly subjective. The words "devastating" and "heartbreaking" have negative connotations, but no factual evidence supports them. After data cleaning and removing the duplicated tweets, the final dataset consisted of 362566 tweets. Table 3 shows the number of negative, neutral, and positive tweet sentiments labeled by TextBlob.

4. Results and Discussions

This section contains a detailed analysis of tweets to discover public sentiments, social media trends, keyword associations, and themes using sentiment analysis techniques. The objective is to answer questions relating to public concerns and opinions regarding the return of the Taliban through social media analytics. We present insights using descriptive textual analytics and data visualization techniques such as exploratory word clouds and n-gram representations from the collected tweets.

4.1 Sentiment analysis

In this study, we collected over 5000000 initial English tweets. A total of 362566 unique tweets were realized after duplicated tweets, and tweets with only emojis, memes, and other special characters were deleted. Of the 362566 tweets, 33% were classified as neutral, 46% as negative, and 21% as positive. Figure 2 visualizes the breakdown of sentiment analysis results of Tweets. As shown in the figure, the negative sentiment is higher than the positive sentiment category. The reason for this is that many have regarded the US military withdrawal as poorly executed, further rendering the security and the human rights of women and children at higher risk. These misgivings have tragically been proved correct by the volume of negative Twitter comments during the study period.

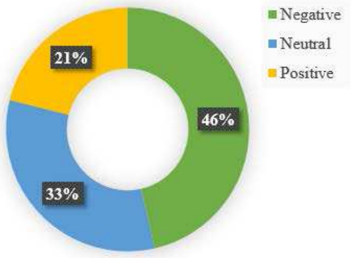

Figure 2: Sentiment Distribution Visualization.

4.2. Exploratory Word Cloud

A word cloud is used to graphically represent salient words in a textual corpus (see Samuel et al. [36]) (see Conner et al. [11]). The word cloud generated from our experiment is shown in Figure 3. From the perspective of Twitter users, the findings from this study indicate words such as “Afghan,” “Afghanistan,” “Taliban,” “Kabul,” and “People” were among the most popular words found in our tweet dataset regarding the situation revolving in Afghanistan during the study period. Along with these search terms, there are words such as “airport,” “evacuation,” “leave,” “kabulairport”, and “explosion.” These words are related to the chaotic scenes at the Kabul airport amidst the desperate attempt by people to escape the country.

Figure 3: Word cloud representation of peoples’ opinions on Twitter about US exit from Afghanistan.

Besides, the frequency of tags such as “afghanlivesmatter,” “afghanwomen,” and “children” in the word cloud could be linked to the fear of the potential threats to fundamental human rights abuse, particularly the rights of women and children under the new regime. The prevalence of words such as “UN,” “EU,” “NATO,” “Pakistan,” “China,” “India,” “help,” and need, “in our Twitter dataset suggest a call for the international bodies and other foreign donors to take action to ensure that Afghanistan affected by hunger and collapsed medical services receive the necessary aids. Finally, some Twitter users highlight the important role of the US government in the Afghanistan war as words such as "USA," "America," "Biden," and "Trump" was noticeable on the generated word cloud. Other relevant keywords are shown in Figure 3

4.3. N-Gram representation

We extended our analysis to obtain the most frequent words and phrases (n-grams) in the collected tweets as discussed by the public. This n-gram representation is a stochastic combination of words representing trends and patterns in the dataset used in this study. We removed keywords such as "taliban", "kabul", "afghanistan", "us", "usa", and "afghan". Besides, the name of some popular politicians such as "Biden," "Trump" were excluded to prevent any potential skewness of the n-gram analysis. After the data preprocessing, we split the tweets into n consecutive word chunks. Next, we merged the chunks of all tweets as a flat list, where $n = [1; 2; 3]$. The analysis of the n-grams helps us understand which words were used the most separately and in combination regardless of the grammatical structure or meaning. The generated frequent words and human-interpretable themes are distinct from each other and form the major subject or the umbrella terms under which most of the sentiments about the happenings in Afghanistan revolve.

The top 20 most frequent n-grams are shown in Table 4 to broaden the scope and meanings of issues being discussed. From the table, words such as "airport," "people," "kabulairport" are unigrams which may be pointing to things that happens at the Kabul airport. Bigrams such as "american government," "20 years", "american troops" could be related to the 20 years of the American military invasion of Afghanistan. Phrases such as "civilian lives," "human rights," "civilian protected," and "women children" point to the potential return of restrictions on the rights of individuals, especially women and children. From the tri-gram, phrases such as "extremely saddest news," "chaos gunshots," "total chaos airport," and "airport gunshots background" underline the enormity of the situation in Afghnistan after the seizure of major population centres by the Taliban. Besides, the frequent words reflect national security breakdown as the Taliban gained full control of major cities, including the presidential palace in the capital city, Kabul.

4.4. Implications

The takeover of the Taliban has sociopolitical and economic implications, sending a strong indication to many other regions, including Mali, one of Africa's countries battling various jihadist groups in its northern and central regions. Somalia also has some of the strongest comparisons to Afghanistan, dealing with the l-Qaeda-affiliated al-Shabab group since the mid-2000 (see Benjaminsen and Ba, [7]; Whitehouse and Strazzari [43]). The increase in foreign militants in India and the associated influx of refugees, the economic impact the takeover has on the economy of the neighboring countries like Pakistan, Iran, Turkmenistan, Tajikistan, Uzbekistan, and India, and questions regarding regional investment projects, including the TAPI gas export pipeline, and security issues among others (see Mohd Saleem et al. [25]). Our work analyzing and making critical inferences from public opinion provides a perfect learning curve and a clue to stakeholders

Table 4: N-gram representation of tweets.

1-gram	2-gram	3-gram
people	20 years	visited un 2014
airport	american government	united states government
kabulairport	presidential palace	eu protect civilians
president	united states	government terrorist negotiation
world	foreign policy	partners including internationals
war	women children	condemn child soldiers
women	air force	extremely saddest news
years	president ashraf	international ngos indifferent
breaking	civilian lives	total chaos airport
government	eu started	chao airport gunshots
military	civilian protected	airport gunshots background
afghanwomen	protected eu	including international ngos
american	human rights	ethiopias government terrorist
situation	international support	un political affairs
help	american troops	ngos indifferent condemn
troops	un political	indifferent condemn childsoldiers
country	shed crocodile	met presidential candidates
today	ashraf ghani	united states embassy
isis	troop withdrawal	united states partners
killed	chaos airport	president ashraf ghani

on the indicators to look out for to avert a similar situation. Key opinions shared before the takeover of Kabul are practical indications that international, regional, and local stakeholders can leverage in strategizing to overt, mitigate or minimize similar future occurrences. Tweets and opinions during and after the takeover provide a concrete basis of geopolitical, social, and economic implications and how to deal with similar situations. These lessons are fundamental learning curves that cannot be overlooked.

5. Conclusion

The study highlights the benefits of mining social media data to understand users' emotional dispositions and opinions during crises. The sentiment analysis technique was used to examine sentiments from public discourse on topical issues relating to the US exit from Afghanistan. The dataset was obtained using Twitter Streaming API and keywords (hashtags) related to the situation in Afghanistan. Various text preprocessing techniques have been used to clean and improve data quality. Afterward, a lexicon-based sentiment approach (TextBlob) was used to find sentiments scores to label the tweets. The analysis shows that tweets with negative sentiments exceeded tweets with positive sentiments, which points to the general disapproval of the 20 years of US government activities in

Afghanistan. A major limitation of this study, however, is that, it does not consider the use of other popular NLP sentiment analysis tools such as Vader, and Flair, with their performances on the dataset cross-validated. Future work will consider leveraging other lexicon-based approaches to social media sentiment analysis to determine which tools perform better on the dataset. It is further recommended that future studies consider classifying tweets based on user_locations to understand the kind of tweets coming from various regions.

Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships that could be interpreted as a potential conflict of interest.

Declaration of Interest: None.

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