Sentiment Analysis On Tweets Over Natural Disaster

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Abstract---**The accomplishment of any item straightforwardly relies upon its client's opinions. So how might we know whether or not the item is effective? By using sentiment analysis, we know whether the item is effective or not. With the help of sentiment analysis, we can analyze individuals' viewpoints, opinions on any subject, administrations and so on. Examination of social media gives critical data to first responders in quite a while of natural disasters. The Sentiment analysis is tied in with distinguishing the sentiments, suppositions, mentalities. With the help of sentiment analysis people also can identify the positive and negative opinions towards the disasters. In this paper, we analyze the sensations of people who are impacted by a natural disaster that is let out of Twitter information from various recharge papers. We have taken total 20 papers regarding this topic. By study all those papers we have understood that the additional determinations of the sentiment values, fuzzy logic could be presented. Consequently, it is seen that the sentiment analysis with the assistance of fuzzy logic will help us for taking powerful outcomes in this point. We have also presented a comparative study of all those papers.**

Keywords—Sentimental Analysis, Twitter, Natural Disaster

1. INTRODUCTION

Social media have drawn in a huge number of clients to impart sentiments about their routines. The developing act of online media administrations helps following sentiment changes less complex and speedier [1][2]. With the rapid expansion of online media somewhat recently, the web has most certainly changed to enlarge that these days billions of individuals all around the world are uninhibitedly permitted to coordinate various proceedings like sharing, posting, collaborating. Social media can be utilized to redesign an area and preparation for disaster. Nowadays in times of any natural disaster, individuals will generally utilize social media for many reasons like watching out for family and friends, searching for help, assemble news about the disaster.

A natural disaster is a devastating event that occurs suddenly and makes the fear of injury, loss of property, and separation of home [52]. Numerous disasters are there like earthquakes, landslides, volcanic eruptions, Tsunami, cyclones, avalanches and floods that harm the environment as well as individuals [11]. Inside the period between 2000 to 2019, EM-DAT recorded 7,348 disasters[1], which asserted a total of approximately 1.2 million lives. It was affected more than 4.30 billion individuals. Natural disasters kill an average of 60,000 individuals each year all around the world. For the duration of several natural disasters in recent years, Twitter has been found to assume a significant part as an extra mode for lots-to-many emergencies correspondence.

Twitter has become a significant tool for dispersing data during natural disasters, due to the continuous idea of updates and the way that are publicly accessible. One of the most famous interpersonal organization locales is Twitter [4]. Twitter messages were likewise utilized in numerous different fields, for example, financial exchange forecast [5], disaster management [6], and understudies' opportunity for growth [7]. Various investigations have been from an assortment of viewpoints to understand how Twitter is important in natural disaster's connected correspondence. Some have argued that it becomes an opportunity for the individuals who are engaged as content creators during news or any social media platform rather than simply serving as consumers (Freeman,2011) [8]. One investigation discovered that Twitter become additionally being used as a way to determine what resources were needed in disaster locations (Gao, et al., 2011) [8]. Twitter Alerts highlight the disaster's situation and offers more advantageous visibility from government and emergency responder. Nowadays thousands and thousands of users are on Twitter and they express their feelings like happiness, sadness, angry as well

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[1] Human cost of disasters.

as celebrations [59][49]. Microblogging website Twitter is extending quickly among all different online social networking websites with about 400 million users. Currently, 500 million tweets are sent out per day and 350,000 tweets per minute[2] [25].
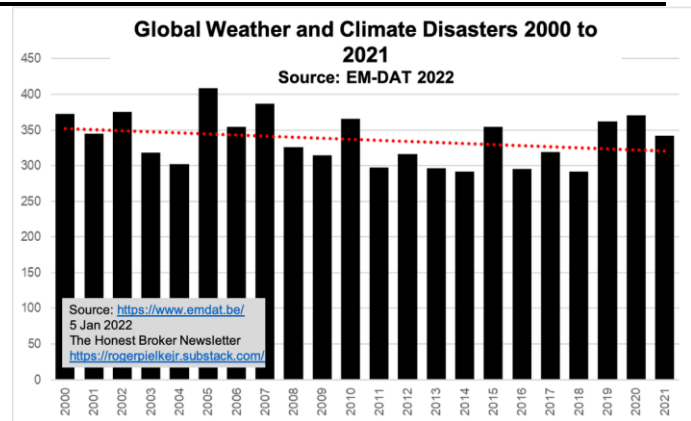
Twitter has been utilized for sentiment analysis in numerous examinations [46][47] for different reasons. The Sentiment analysis is about identifying the feelings, assessment, opinions, attitudes, and thought about this as a way peoples think or detection of positive and negative sentiment towards a topic, person, or entity. Sentiment analysis works by separating a message into topics and then assigning a sentiment score to every topic. Twitter users use to put up their thoughts, emotions, and messages on their profiles called tweets [64][52]. Sentiment analysis of Twitter is based on NLP (natural language processing) fields. Through Sentiment analysis, we can know the trends of individuals on specific topics with their tweets.

2. SENTIMENTAL ANALYSIS

Humans express their feelings regularly, which are called emotions. Researchers are utilizing various strategies including Machine Learning to prepare machines on the best way to comprehend human emotions. This is called Sentiment Analysis. Sentiment Analysis is the field that attempts to enable machines to comprehend the emotions of the users. It's deciding if a piece of text is positive, negative, or neutral [49][64]. It also focuses on feelings and emotions like anger, happiness, sadness, and intentions like interested or not interested [52].

Many disasters like floods, earthquakes, etc that people get a fear injury, loss of property, and separation of home. Also, natural disaster regularly leaves a few financial harms afterward, the seriousness of which relies upon the impacted populace's flexibility and the framework accessible [11]. Emotional state about disaster victims in the disaster occasion and their activities [61]. Every year natural disasters affected many people. Natural disasters influence 218 million individuals and guarantee 68,000 lives each year. Over the most recent 25 years, there have been very nearly 7,000 natural disasters that have killed over 1.35 million individuals[3].

The following diagram depends on information kept by EM-DAT in Belgium, which is generally seen as a legitimate hotspot for information on worldwide calamities[4].

Global Weather and Climate Disasters 2000 to 2021
Source: EM-DAT 2022

Source: https://www.emdat.be/
5 Jan 2022
The Honest Broker Newsletter
https://rogerpielkejr.substack.com/

Sentiment analysis is a grouping of the extremity of a given message in the archive, sentence, or stages. The opinion of individuals can be examined utilizing Sentiment Analysis (SA) [15]. The Sentiment investigation is tied in with recognizing the sentiments, appraisals, suppositions, mentalities, and considered this a way people groups think or location of positive and negative opinions towards a topic, individual, or element. As indicated by [63][17], Sentiment Analysis is a course of separating the client's feelings, sentiments, or assessment and group them into positive, negative or neutral [18]. The people those who get affected during natural, through sentimental analysis we can know their opinion, feelings and emotion. During the situation of disaster, the people who get affected, through sentiment analysis we can know their opinion, feelings and emotion.

Various examinations disclosed that because of the accessibility of web indexes and online media sites [19][20][21] like Google, Twitter and Facebook, individuals approach a monstrous measure of information than ever before [63][18]. Twitter has turned into the main device for scattering information during natural disasters [22], because of the persistent thought of update this is the way that is freely open. It's also significant in natural disaster-related correspondence. Twitter Alerts feature what is happening as well as what to do or what not to do. It offers additional invaluable permeability from government and crisis responder [50]. There are three level of sentimental analysis [57]:

• **Document level:** The point here is to decide the general opinion of a whole record [57]. The Document Level Sentiment Analysis utilizing assessment digging is utilized for extraction of the client opinion on the record. For instance, given an item survey, the undertaking is to decide if it offers positive or negative viewpoints about the item. This level views at the record as a solitary element, hence it isn't extensible to various reports.

• **Sentence level:** This degree of investigation is extremely near emotional arrangement. The assignment at this level is restricted to the sentences and their offered viewpoints [57]. Particularly, this level decides if each sentence conveys a positive, negative, or neutral opinion. This type is utilized for surveys and remarks that contain one sentence and composed by the client

• **Entity and aspect level:** Rather than exclusively examining language develops for example archive, section, sentences; this level gives better grained examination to every perspective. It straightforwardly checks out the assessments for various angles themselves. The point of view level is more troublesome than both document and

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[2] https://www.dsayce.com/social-media/tweets-day/
[3] Center for Research on the Epidemiology of Disasters
[4] Global Weather and Climate Disasters 2000 to 2021.
Graph of the Week #1

sentence. It comprises a few sub-issues. It tracks down various accessible opinions [57].

Sentimental Analysis can be classified into two categories [24]:

- **Machine Learning Approach**
- **Lexicon-based Approach**

Machine learning is a method of data analysis. With machine learning, clients input a lot of information into an algorithm, which empowers the PC to settle on suggestions and choices in light of that information [65].

The lexicon-based approach makes use of the sentiment lexicon with data regarding which words and expressions are positive and which are negative. It counts the number of positive and negative words of any text. Assuming the number of positive is more than negative, it will return as a positive opinion. If each is the same then it will return as a neutral opinion. It consists of two classifications such as corpus-based approach and dictionary-based approach [24]. For the corpus-based approach, it collects the dictionary from a basic set by the use of statistical technique and it does not depend on a predefined dictionary. There is a huge number of texts that might have a positive or negative set of words [67]. As for the dictionary-based approach, it creates a dataset of positive and negative words from a basic set of words along with synonyms and antonyms.

3. RELATED WORK

Public had started using twitter in order to share their opinion or emotions specifically about disaster event through their post. Many articles have been written about sentiment analysis.

Go et. al. [3] in their paper, their motivation was to make a calculation that can precisely group messages on Twitter as positive or negative according to a given term. Their supposition that will be that they involving machines to group feeling in Twitter messages accomplishes high precision concentrate on abilities.

Qaiser et. al. [9] in their paper, plan to dissect individuals' perspectives about the impact of development on employment and movements in headways and build a machine learning classifier to orchestrate the sentiments. In their review, they saw that 65% of individuals hold pessimistic sentiments concerning that impact.

Pak et. al. [13] had focused a task on sentiment analysis using the most popular microblogging platform Twitter. They additionally perform etymological analysis of the gathered corpus and decipher the discoveries Phenomenon. With the help of corpus, they set up a sentiment classifier to decide positive, negative, and neutral feelings of documents

In their paper, Greaves et. al. [14] utilized opinion examination procedures to classify online free-text remarks by patients as one or the other positive or negative depictions of their medical services. They used machine learning to know patients' unstructured remarks about their consideration.

In Younis's [56] work, an open-source approach, all through which, Twitter Microblogs information had been gathered, pre-handled, dissected also pictured utilizing open-source apparatuses to perform text mining also sentiment analysis.

Saif et. al. [29] had introduced their paper a novel methodology of adding semantics as extra highlights into the preparation set for sentiment analysis. They also apply these methods to predict sentiment for three different Twitter datasets: a general Stanford Twitter Sentiment (STS) dataset, a dataset on the Obama-McCain Debate (OMD), and one on Health Care Reform (HCR).

In their paper, Neppalli et. al. [12] performed sentiment analysis of tweets posted on Twitter eventually of the shocking Hurricane Sandy and envision online clients' opinions on a topographical guide revolved around the hurricane. They also showed the changes of users' sentiments as indicated by not exclusively to their areas yet additionally founded on the distance from the disaster.

Shalunts et. al. [26] had introduced in their paper the fundamental usage of the resulting advancement and models to sentiment analysis of online media data in German, covering information gathered during the Central European surges of 2013.

In their paper, Balahur et. al. [48] understood that news opinion mining is not quite the same as that of other text types. So, they distinguished three subtasks that should be tended to the definition of the target; separation of the good and bad news content from the good and bad sentiment communicated on the objective; and examination of plainly stamped assessment that is communicated unequivocally, not requiring translation or the utilization of world information. And also, they recognized three unique potential perspectives on paper articles: author, reader, and text.

Zaki et. al. [62] paper was based on the ATHENA project. They extend the Crisis Information Processing Center part by utilizing administered learning procedure of the machine learning approach with the consolidation of the RUP/SOMA system.

Beigi et. al. [16] examined in their paper the relationship between web-based media, disaster relief, and situational mindfulness. And also clarified how web-based media was utilized in these settings with the focus on sentiment analysis.

Yao et. al. [10] paper proposed an area explicit sentiment analysis approach explicitly for tweets posted during hurricanes (DSSA-H). They also found that every classifier i.e., RE and DANN outperform baseline classifiers and that DSSA-H outperforms high-acting general sentiment class tactics when classifying sentiments of tweets posted at some point of hurricanes.

Zaki et. al. [28] goal of their work was to survey existing flood calamity the executives, dissecting their joining with opinion investigation and SOA. They also talk about how an SOA technique can be viably planned and carried out in flood catastrophe the board structure by utilizing sentiment analysis.

Alfarrarjeh et. al. [51] this paper proposed an original system for geo-spatial sentiment analysis of disaster-related online media information objects. Their system tended to three kinds of difficulties: the error and disparity related with a different message and picture sentiment classifiers, the geo-sentiment inconsistency among information objects in a nearby topographical region, and seeing arranged

suppositions from intelligent media data objects i.e., message and picture. They investigated Twitter and Flickr datasets at the hour of Hurricane Sandy.

In their paper, Ragini et. al. [53] proposed a major information-driven methodology for disaster reaction through sentiment analysis. And their results show that lexicon-based methodology was appropriated for examining the necessities of individuals during the disaster.

Schulz et. al. [45] paper, we could see the orderly assessment of a methodology for sentiment analysis on miniature posts that permits distinguishing seven inclination classes.

The goal of Haque et. al. [66] paper was to dissect the feelings on a theme that are extricated from Twitter and finish up a comment i.e., positive or negative of the characterized subjects. And they had carried out a more straightforward method to dissect opinions on any interest or theme.

Howells et. al. [41] paper proposes a model for sentiment analysis of web-based media network information. The target of their paper is to recommend, that in consolidating social bots with information mining and fuzzy logic, it was conceivable to fabricate a profoundly productive instrument that won't just track down an objective populace, yet will impart and incite the objective for much more data.

Kaur et. al. [23] describe in their paper about a Twitter dataset that had been utilized for sentiment analysis of people's perspectives connected with coronavirus (COVID-19) was an imperative issue nowadays over the world and also different nations were impacted by this pandemic. They used machine learning techniques and sentiment analysis models such as Naive Bayes, Support Vector Machine, Logistic Regression, and Random Forest Classifier to analyze the sentiments of the people.

The motto of Chintalapudi et. al. [35] paper was to examine tweets by Indian netizens during the COVID-19 lockdown. The information included tweets gathered on the dates between 23 March 2020 and 15 July 2020 and also the text has been marked as fear, sadness, anger, and joy. They also separately calculated the accuracy of every sentiment, where the Bidirectional Encoder Representations from Transformers (BERT) model produced 89% accuracy and the other three models produced such as logistic regression (LR) 75%, support vector machines (SVM) 74.75%, and long-short term memory (LSTM) 65%.

4. METHODOLOGY

Machine Learning allows the computer to examine new tasks without being programmed to perform them. Machine learning automatically detects sentiment without human help. Machine learning gives maximum accuracy and its capacity is verified in solving the tasks of sentimental analysis. They can be classified into three groups: supervised technique, unsupervised technique and semi-supervised[5]. With the supervised technique, we get every textual data along with their polarity, objectivity, and subjectivity [65]. The supervised technique needs two sets

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[5]

https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

of data for testing and training [27]. The unsupervised techniques find out the hidden collection of data without the need for human help and suggested if it is not able to have an advanced set of labeled documents to categorize the rest of the things [58]. Semi-supervised learning works by information researchers taking care of a limited quantity of marked preparing information to an algorithm.

Deep learning is a type of machine learning algorithm that trains computers to do what comes easily to human beings. In deep learning algorithm computers learn to execute any task from any images, audios and texts. Deep learning uses multiple algorithms in a progressive chain of activities to work out complicated problems and allows to tackle huge number of information, accurately and with less human interaction. Sometimes deep learning and machine learning utilized interchangeably. Deep learning is undoubtedly machine learning but deep learning is more advanced than machine learning. Machine learning sometime makes mistake and they need human input to correct it or to change the output and force the model to learn it [33]. However, in deep learning [32], the neural network learns by itself to correct through its advanced algorithm chain [34][54]. Deep Learning algorithms have been utilized for a few Big Data areas like PC vision [30][31] and discourse acknowledgment [36] [38] it is as yet flawless with regards to Big Data examination [39].

In the past 10 years the deep learning made development and make new results in many application domains [37], beginning from computer vision, then the voice recognition and recently NLP [42]. Deep learning algorithms try to make comparable conclusions as human could by constantly analyzing data with a given logical structure [40][60]. To accomplished this deep learning utilizes a multilayer structure of algorithms called neural networks.

Fuzzy logic is a way to deal with variable handling that considers various conceivable truth esteems to be handled through a similar variable. Fuzzy logic attempts to tackle issues with an open, uncertain range of information and heuristics that makes it conceivable to get a variety of precise ends. Fuzzy logic is intended to take care of issues by thinking about all suitable data and settling on the most ideal choice given the information. Fuzzy logic frameworks can deal with these intrinsic vulnerabilities [43] and have been utilized as a way to address and display influence relations [44][55]. The development of Fuzzy Logic Systems is simple and justifiable. This framework can work with a data source, whether loose or twisted input data.

Its Architecture contains four parts:
- **Rule Base:** Ongoing improvements in fuzzy theory offer a few successful techniques for planning and tuning fuzzy regulators. The vast majority of these advancements reduce the number of fuzzy rules.
- **Fuzzification:** It is utilized to change over inputs.
- **Inference Engine:** It decides the coordinating level of the current fuzzy contribution for each standard.
- **Defuzzification:** The most fitting one is utilized with a particular master framework to lessen the error.[6]

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[6] https://www.geeksforgeeks.org/fuzzy-logic-introduction/

FUZZY LOGIC ARCHITECTURE
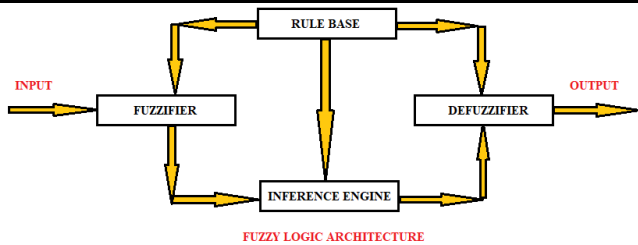
Fuzzy logic works on the idea of choosing the output based on assumptions. It works based on sets and each set show some linguistic variables defining achievable condition of the output. Each possible condition of the input and the stages of change of the state are a part of the set, based upon which the output is predicted. Fuzzy logic requires some mathematical parameters to figure out what is to be considered as unusual error and rate of change of that error [67]. But specific qualities are normally not required until extremely responsive execution is required, where case experimental turning would decide them [67].

5. RESULT ANALYSIS

The table shown below depicts the comparative study of all the paper related to sentiment fields-----

S L N O	Topic name	Author name	Datasets used	Algorithms used	Accuracy percentage
1	Twitter Sentiment Analysis	Alec Go, Lei Huang, Richa Bhayani	Twitter API.	SVM, Naive Bayes	73.913%, 44.9%
2	Sentiment Analysis of Impact of Technology on Employment from Text on Twitter	Shahzad Qaiser, Noorani Yusoff, Farzana Kabir Ahmad, Ramsha Ali	Machine Learning, Rule Based, Lexicon Based	SVM, Decision Tree, Naive Bayes	79.08%, 75.16%, 76.47%
3	Twitter as a Corpus for Sentiment Analysis and Opinion Mining	Alexander Pak, Patrick Paroubek	Twitter API.	N/A	N/A
4	Use of Sentiment Analysis for Capturing Patient Experience From Free-Text Comments Posted Online	Felix Greaves, Daniel Ramirez-Cano, Christopher Millett, Ara Darzi, Liam Donaldson	Machine Learning	Naïve Bayes, Decision Tree, Bagging, Support Vector Machine	88.6%, 80.8%, 82.5%, 84.6%
5	Sentiment Analysis and Text Mining for Social Media Microblogs using Open-Source Tools : An Empirical Study	Eman M.G. Younis	Text Mining	Data Mining	N/A
6	Semantic Sentiment Analysis of Twitter	Hassan Saif, Yulan He, and Harith Alani	Stanford Twitter Sentiment (STS), Obama McCain Debate (OMD), Health Care Reform (HCR)	Baseline	6.47%

#	Title	Authors			
7	Sentiment Analysis During Hurricane Sandy in Emergency Response	Venkata K. Neppalli, Cornelia Caragea, Anna Squicciarini, Andrea Tapia, Sam Stehle	Hurricanes Sandy	SVM, SentiStrength	75.91%, 53.54%
8	Sentiment Analysis of German Social Media Data for Natural Disasters	Gayane Shalunts, Gerhard Backfried, Katja Prinz	N/A	N/A	N/A
9	Sentiment Analysis in the News	Alexandra Balahur, Ralf Steinberger, Mijail Kabadjov, Vanni Zavarella, Erik van der Goot, Matina Halkia, Bruno Pouliquen, Jenya Belyaeva	N/A	N/A	N/A
10	SentiFlood: Process Model for Flood Disaster Sentiment Analysis	Ummu Hani' Hair Zaki, Roliana Ibrahim, Shahliza Abd Halim, Khairul Anwar Mohamed Khaidzir, Takeru Yokoi	N/A	N/A	N/A
11	An Overview of Sentiment Analysis in social media and its Applications in Disaster Relief	Ghazaleh Beigi, Xia Hu, Ross Maciejewski and Huan Liu	N/A	SentiStrength	20%
12	Domain-Specific Sentiment Analysis for Tweets during Hurricanes	FANG YAO, YAN WANG	N/A	Machine Learning,	N/A
13	A Review on Service Oriented Architecture Approach in Flood Disaster Management	Ummu Hani' HAIR ZAKI, Roliana IBRAHIM, Shahliza ABD HALIM and Takeru YOKOI	N/A	data mining	N/A

14	Geo-spatial Multimedia Sentiment Analysis in Disasters	Abdullah Alfarrarjeh, Sumeet Agrawal, Seon Ho Kim, Cyrus Shahabi	N/A	N/A	N/A
15	Big data analytics for disaster response and recovery through sentiment analysis	J. Rexiline Ragini, P.M. Rubesh Anand, Vidhyacharan Bhaskar	N/A	Machine Learning, SVM	N/A
16	A Fine-Grained Sentiment Analysis Approach for Detecting Crisis Related Microposts	Axel Schulz, Tung Dang Thanh, Heiko Paulheim, Immanuel Schweizer	N/A	N/A	N/A
17	SENTIMENT ANALYSIS BY USING FUZZY LOGIC	Md. Ansarul Haque, Tamjid Rahman	N/A	Fuzzy	N/A
18	Applying fuzzy logic for sentiment analysis of social media network data in marketing	Karen Howellsa, Ahmet Ertugan	N/A	N/A	N/A
19	COVID-19 Sentimental Analysis Using Machine Learning Techniques	Chhinder Kaur and Anand Sharma	N/A	Support vector machine, Logistic regression, Random Forest classifier, Naive bayes	N/A
20	Sentimental Analysis of COVID-19 Tweets Using Deep Learning Models	Nalini Chintalapudi, Gopi Battineni and Francesco Amenta	N/A	Fine-tuned BERT, LR, SVM, LSTM	N/A

6. CONCLUSION & FUTURE WORK

After a natural disaster, many people posted on Twitter. Hashtags allow gathering all the tweets about the specific topic and make it easier to find what the user searching for. Through the use of fuzzy logic, the sentiment values of tweets can be determined. We can calculate the tweets by having the values of the tweets. This would provide us the level of positive sentiment, negative sentiments, and neutral sentiments. The main goal of our work was to analyze the feelings and opinions of individuals who are impacted by a natural disaster that is extricated from Twitter and other social media. We had study fuzzy logic to analyze feelings on individuals of this topic.

By using fuzzy logic in this topic, we think that we will get more powerful outcomes. The study has found that very little work has been done on fuzzy in sentiment analysis to

date. We wish that we could see much more work on this topic in the future so that we can gain more knowledge and information.

Hope this task would be useful for anybody in any capacity to get together their interests on this point. This was our significant objective of this project and holding on to give much more worthy works in our future work.

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