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Cannabidiol tweet miner: a framework for identifying misinformation In CBD tweets.

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CANNABIDIOL TWEET MINER: A FRAMEWORK FOR IDENTIFYING MISINFORMATION IN CBD TWEETS

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ABSTRACT

CANNABIDIOL TWEET MINER: A FRAMEWORK FOR IDENTIFYING MISINFORMATION IN CBD TWEETS

Jason Turner

May 31, 2023

As regulations surrounding cannabis continue to develop, the demand for cannabis-based products is on the rise. Despite not producing the psychoactive effects commonly associated with THC, products containing cannabidiol (CBD) have gained immense popularity in recent years as a potential treatment option for a range of conditions, particularly those associated with pain or sleep disorders. However, due to current federal policies, these products have yet to undergo comprehensive safety and efficacy testing. Fortunately, utilizing advanced natural language processing (NLP) techniques, data harvested from social networks have been employed to investigate various social trends within healthcare, such as disease tracking and drug surveillance. By leveraging Twitter data, NLP can offer invaluable insights into public perceptions around CBD, as well as the marketing tactics employed by those marketing such loosely-regulated substances to the general public.

Given the lack of comprehensive clinical CBD testing, the various health claims made by CBD sellers regarding their products are highly dubious and potentially perilous, as is evident from the ongoing COVID-19 misinformation. It is therefore critically important to efficiently identify unsupportable claims to guide public health policy and action. To this end, we present our proposed framework, the Cannabidiol Tweet Miner (CBD-TM), ment, that are also absent from personal conversations. Through our tech-

which utilizes advanced natural language processing (NLP) techniques, including text mining and sentiment analysis, to analyze the similarities and differences between commercial and personal tweets that mention CBD. CBD-TM enables us to identify conditions typically associated with commercial CBD advertising, or conditions not associated with positive senti-nical contributions, including NLP, text mining, and sentiment analysis, we can effectively uncover areas where the public may be misled by CBD sellers.

Since the rise in popularity of CBD, advertisements making bold claims about its benefits have become increasingly prevalent. The COVID-19 pandemic created a new opportunity for sellers to promote and sell products that purportedly treat and/or prevent the virus, with CBD being one of them. Although the U.S. Food and Drug Administration issued multiple warnings to CBD sellers, this type of misinformation still persists. In response, we have extended the CBD-TM framework with an additional layer of tweet classification designed to identify tweets that make potentially misleading claims about CBD's efficacy in treating and/or preventing COVID-19. Our approach harnesses modern NLP algorithms, utilizing a transformer-based language model to establish the semantic relationship between statements extracted from the FDA's website that contain false information and tweets conveying similar false claims.

Our technical contributions build upon the impressive performance of deep language models in various natural language processing and understanding tasks. Specifically, we employ transfer learning via pre-trained deep language models, enabling us to achieve improved misinformation identification in tweets, even with relatively small training sets. Furthermore, this extension of CBD-TM can be easily adapted to detect other forms of misinformation. Through our innovative use of NLP techniques and algorithms, cept drift can occur, leading to changes in the topics being discussed. We observed significant changes within the CBD Twitter data stream with thewe can more effectively identify and combat false and potentially harmful claims related to CBD and COVID-19, as well as other forms of misinfor-mation.

As the conversations surrounding CBD on Twitter evolve over time, con-emergence of COVID-19, introducing a new medical condition associated with CBD that would not have been discussed in conversations prior to the pandemic. These shifts in conversation introduce concept drift into CBD-TM, which has the potential to negatively impact our tweet classification models. Therefore, it is crucial to identify when such concept drift occurs to maintain the accuracy of our models.

To this end, we propose an innovative approach for identifying potential changes within social network streams, allowing us to determine how and when these conversations evolve over time. Our approach leverages a BERT-based topic model, which can effectively capture how conversations related to CBD change over time. By incorporating advanced NLP techniques and algorithms, we are able to better understand the changes in topic that oc-cur within the CBD Twitter data stream, allowing us to more effectively manage concept drift in CBD-TM. Our technical contributions enable us to maintain the accuracy and effectiveness of our tweet classification models, ensuring that we can continue to identify and address potentially harmful misinformation related to CBD.

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CHAPTER 1

INTRODUCTION

In contemporary public policy debates, cannabis is often promoted as a medicinal remedy. Cannabidiol (CBD), a non-psychoactive compound of cannabis with no side effects like tetrahydrocannabinol (THC), has emerged as a multi-billion dollar industry that is utilized to treat a wide range of conditions, including epilepsy, insomnia, neurological disorders, and certain mental illnesses [4]. However, unlike conventional medications, CBD has not undergone similar clinical trials, and it is still not thoroughly regulated by the U.S. Food and Drug Administration (FDA). Despite this, only four cannabinoid drugs have been approved by the FDA, and all necessitate a prescription, with no endorsement for marketing cannabis for the treatment of any disease [5].

Since CBD-based supplements are available in diverse forms, including tinctures, topical ointments, pills, and candy, they have not undergone the same rigorous testing as other medications. As a result, there may be disparities between the medical conditions for which CBD is marketed and the rationale for which individuals use CBD [6]. To address this potential imbalance, Twitter, which provides a vast corpus of both personal and commercial tweets regarding CBD, can be used as a helpful platform for tracking such discrepancies. In this study, Twitter data was utilized to identify the reasons why certain users use CBD (see Figure 1.1).

In light of the need to accurately understand the marketing of cannabidiol (CBD) and to curb misinformation about unregulated substances, we present the Cannabidiol Tweet Miner (CBD-TM) framework that employs cutting-edge text mining techniques in social networks. This approach provides a powerful tool for public health experts to distinguish between personal and commercial assertions regarding CBD and similar substances.

The CBD-TM framework offers a practical and accessible solution for public health officials. It allows for the easy retrieval of data, which is both cost-effective and

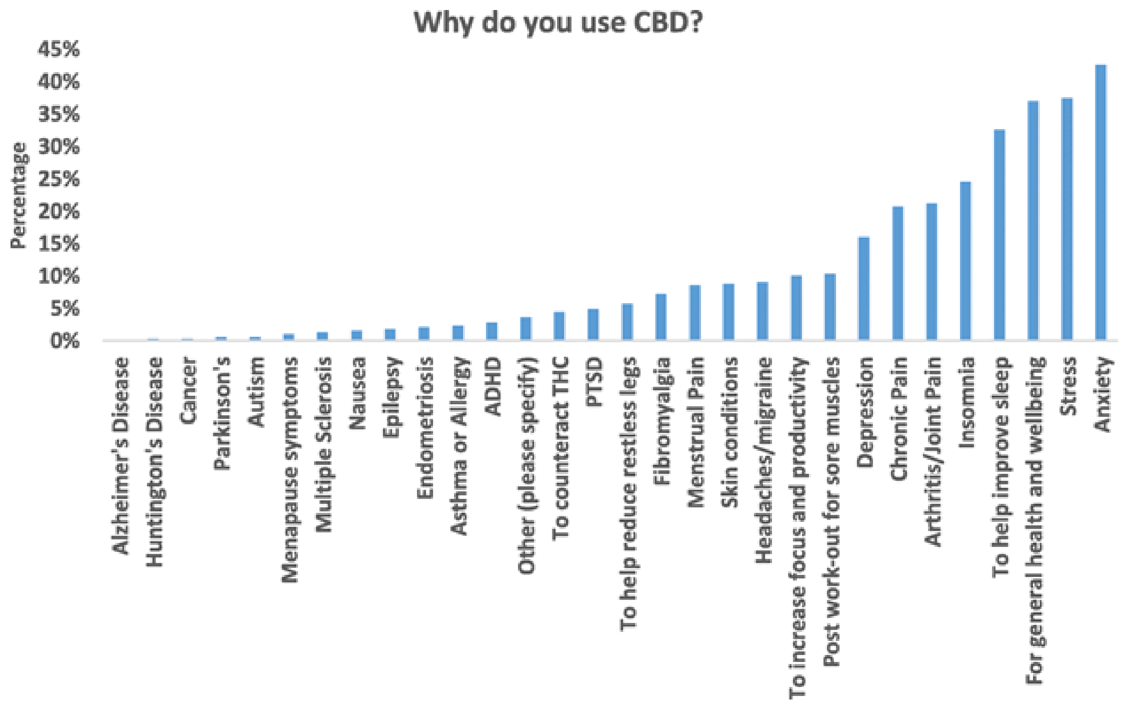

Figure 1.1: Reasons for cannabidiol use among 397 adult cannabidiol users who were allowed to respond to more than one option leading to a total of 1622 responses. Y-axis represents percentage based on total responses (Moltke and Hindocha 2021).

less constrained than information gathered from traditional sources such as surveys or data from governmental and healthcare entities. By utilizing state-of-the-art natural language processing (NLP) algorithms, CBD-TM can efficiently identify and analyze tweets that contain false or misleading information.

Moreover, the potential applications of the CBD-TM framework extend beyond just CBD. The system can be easily adapted to investigate misinformation in other loosely regulated substances. By leveraging the power of modern NLP algorithms, public health experts can gain invaluable insights into the marketing practices of these substances, and take necessary steps to address inaccuracies and ensure that accurate information is disseminated to the public.

1.1 CBD in Online Conversations

Levinson and Gibson define social media as a relationship between sociology and technology that creates an environment where people can share experiences and develop networks, either official or unofficial [7]. The number of people actively participating in social media has increased year-on-year. According to the Global Digital Report [8]:

- The number of internet users worldwide in 2019 was 4.4 billion, up 9.1% year-on-year.
- The number of social media users worldwide in 2019 was 3.5 billion, up 9% year-on-year.
- The number of mobile phone users in 2019 was 5.1 billion, up 2% year-on-year

More recently, increasing popularity and usage of CBD products has spurred the FDA to [9]

> *...be concerned at the proliferation of products asserting to contain CBD that are marketed for therapeutic or medical uses although they have not been approved by FDA. Often such products are sold online and are therefore available throughout the country. Selling unapproved products with unsubstantiated therapeutic claims is not only a violation of the law, but also can put patients at risk, as these products have not been proven to be safe or effective. This deceptive marketing of unproven treatments also raises significant public health concerns, because patients and other consumers may be influenced not to use approved therapies to treat serious and even fatal diseases.*

Medical cannabis has grown into a major point of discussion in public policy, and especially in online social media discourse [10, 11]. Social media and the internet in general are rife with ads making unsubstantiated claims about CBD's health benefits. For example [12]:

- "CBD has been demonstrated to have properties that counteract the growth of [and/or] spread of cancer."
- "CBD was effective in killing human breast cancer cells."
- "CBD has also been shown to be effective in treating Parkinson's disease."
- "CBD has been linked to the effective treatment of Alzheimer's disease ...."

- “CBD is being adopted more and more as a natural alternative to pharmaceutical-grade treatments for depression and anxiety.”
- “CBD can also be used in conjunction with opioid medications, and a number of studies have demonstrated that CBD can in fact reduce the severity of opioid-related withdrawal and lessen the buildup of tolerance.”
- “CBD oil is becoming a popular, all-natural source of relief used to address the symptoms of many common conditions, such as chronic pain, anxiety … ADHD.”
- “What are the benefits of CBD oil? .... Some of the most researched and well-supported hemp oil uses include .... Anxiety, depression, post-traumatic stress disorders, and even schizophrenia .... Chronic pain from fibromyalgia, slipped spinal discs ... Eating disorders and addiction ....”
- “[V]ets will prescribe puppy Xanax to pet owners which can help in certain instances but is not necessarily a desirable medication to give your dog continually. Whereas CBD oil is natural and offers similar results without the use of chemicals.”
- “For dogs experiencing pain, spasms, anxiety, nausea or inflammation often associated with cancer treatments, CBD (aka cannabidiol) may be a source of much-needed relief.”

Waxing interest in CBD as medicine is already a documented phenomenon. An earlier study observed rising interest in CBD oil from 2014 to 2018 [13]. Tran and Kavuluru used CBD-related Reddit posts and comments submitted to the FDA regarding these posts to determine what conditions are commonly being treated with CBD [11]. Figure 1.2 is one of many examples of CBD advertised as a prevention/treatment of the COVID-19 virus. We expect further investigation into how interest in CBD is shared and proliferated on social media, and to what extent it is contaminated with misinformation, to have significant positive effects on public health and likely other sectors, as is becoming apparent with the circulation of COVID-19 misinformation on social media.

Figure 1.2: Example of a Tweet Promoting CBD as a Prevention/Treatment of CBD.

1.2 Thesis Statement

The promotion of unregulated substances and dissemination of misinformation on social networks poses grave health risks and raises ethical concerns for the public and public health policy makers. Misinformation has been found to spread more rapidly and widely than accurate information, resulting in real-world negative consequences such as promoting ineffective or even dangerous "treatments" and vaccine hesitancy [14].

Given the vast volume and frequency of online posts, it is not feasible to manually identify each post as reflecting personal usage, commercialization/promotion, or misinformation without the aid of modern technology. This study demonstrates that combining data extracted from online social networks, text mining, and machine learning methods can enable the identification and understanding of the usage and promotion of loosely regulated substances, such as CBD, on social media. The main contributions of this research are:

1. The development of a novel framework for analyzing the differences between commercial and personal CBD tweets, facilitating the identification of areas of concern where the public may be misled about CBD's health benefits;
2. The extension of the framework to identify misinformation related to CBD by capturing commercial tweets promoting CBD as a cure or prevention for the COVID-19 virus; and
3. A temporal analysis of the Twitter CBD data stream to identify and understand the concept drift occurring as CBD tweets evolve over time. These changes in the historic CBD Twitter data stream may indicate changes in sentiment as public awareness of CBD, advertising practices, cannabis regulation, and other factors evolve, all of which may impact the performance of machine learning models used on this data stream.

1.3 Organization

The chapters in this thesis are arranged and presented as follows:

- Chapter 2: This chapter provides a comprehensive review of previous research on health-related conversations and misinformation on social media. We analyze the methods that have been used in previous studies, including the challenges researchers faced and the solutions that were implemented. Additionally, we provide background information on modern NLP techniques such as transformer models and BERT that have been used in analyzing social media data. This review lays the foundation for the work presented in this thesis.
- Chapter 3: This chapter presents CBD-TM, a novel framework that leverages advanced NLP techniques to analyze personal and commercial CBD-related tweets. Our system can distinguish between tweets reflecting personal use of CBD and those promoting the substance and its uses. We analyze the language used in each

group to uncover the differences between marketing and actual usage of CBD. Furthermore, sentiment analysis is performed on both corpora of tweets to identify potential areas where individuals express dissatisfaction. The work presented in this chapter has been published in the prestigious Journal of Medical Internet Research and was previously presented at the MeFDATA 2020 conference, highlighting the significance of our contributions to the field of natural language processing.

- Chapter 4: In this chapter, we present our extended CBD-TM framework, which explicitly identifies false claims related to CBD and COVID-19 in commercial CBD tweets. Leveraging state-of-the-art transformer-based language models, we are able to identify contextually and semantically similar tweets to previous violators as quoted on the FDA website, reducing the need for extensive training data. Furthermore, we conduct a detailed exploration of subtopics related to COVID-19/CBD misinformation, tweet origins (commercial or personal), and how these tweets circulate over time. Our technical contributions, which include the innovative use of NLP techniques and algorithms, have been published in the reputable JMIR Infodemiology journal and presented at the prestigious Research!Louisville 2021 conference.
- Chapter 5: The surging popularity of CBD has resulted in rapidly evolving conversations, posing significant challenges for machine learning models trained on outdated data. In this chapter, we propose a novel method for tackling this challenge by examining the dynamic nature of CBD-related discussions on Twitter. We collect and analyze a vast corpus of 3.7 million English tweets that reference CBD over a decade-long period (2011-2021) to detect and address concept drift in the CBD Twitter data stream, specifically pertaining to identifying commercial CBD tweets. These conversational changes were detected by leveraging a BERT-based topic model, which enabled us to identify and track emerging topics and trends over time. This work was presented at the prestigious 2023 International Workshop on Semantic Computing for Social Networks and Organization Sci-

ences (SCSN 2023), and provides valuable insights into how advertising and perceptions of CBD have evolved over time, in conjunction with changing cannabis laws and use.

- Chapter 6: This concluding chapter provides a comprehensive summary of the important contributions and results of this thesis, highlighting the innovative use of advanced NLP techniques and methods, including the CBD-TM framework, the identification of false claims related to CBD and COVID-19, and our method for addressing concept drift in the CBD Twitter data stream. We also discuss future work, which includes building resilient CBD tweet classifiers that can effectively adapt to the rapidly evolving conversations related to CBD, detecting tweets that contain misinformation faster and with more precision/accuracy, and applying the CBD-TM to other loosely regulated substances. These advancements have the potential to inform public health policies and interventions aimed at promoting safe and informed use of CBD and other health-related products.
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CHAPTER 2

LITERATURE REVIEW AND BACKGROUND

In recent years, social media platforms like Twitter have become valuable sources of information on various health-related topics, including the use of cannabidiol (CBD) as a potential treatment option for various health conditions. However, with the increase in the volume of CBD-related tweets, the spread of misinformation has become a growing concern. This is where natural language processing (NLP) techniques come into play. NLP is a field of computer science that focuses on the interaction between computers and natural language. In the context of social media data analysis, NLP can help identify patterns in the language used to discuss CBD and distinguish between accurate and inaccurate information. In this literature review chapter, we will explore the current state of research on NLP techniques applied to tweets referencing CBD. Specifically, we will focus on sentiment analysis (Section 2.2), health misinformation (Section 2.3), transformer-based language models (Section 2.4), and concept drift (Section 2.5). Through a comprehensive analysis of existing research in these areas, this chapter aims to provide valuable insights into how NLP can be leveraged to combat the spread of misinformation surrounding CBD on social media platforms like Twitter.

2.1 Health Conversations and Social Media

The first online social network was the Bulletin Board System (BBS), which was created in 1978. BBSs allowed users to connect with each other and share messages and files. In the 1980s, AOL (America Online) became one of the most popular BBSs. AOL offered a variety of features, including chat rooms, email, and news groups. In the early 2000s, social networking websites like Facebook and MySpace became popular. These websites allowed users to create profiles, connect with friends, and share photos and videos. In 2004, Facebook was launched, and it quickly became the most popular social networking website in the world. Twitter was launched in 2006, and it quickly became a popular way for people to share short messages and updates with their followers. In 2016, Twitter had over 300 million active users. Figure 2.1 shows a timeline of online social networks.

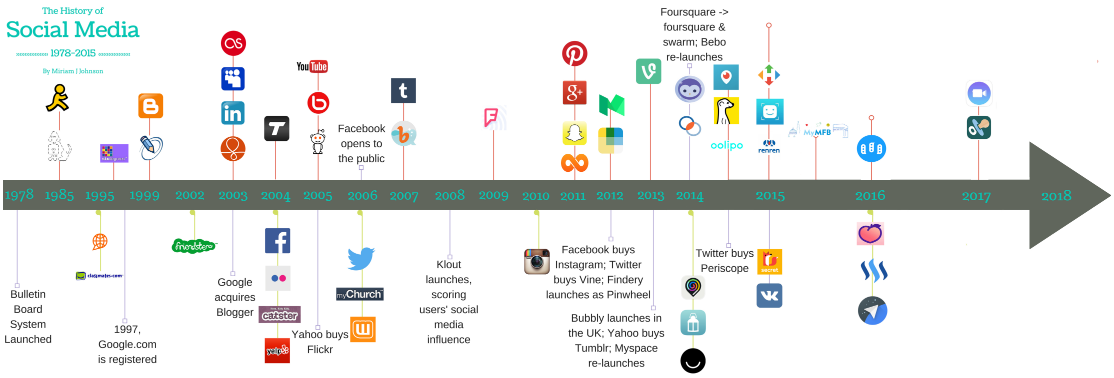

Figure 2.1: Timeline of Modern Social Networks[1].

Users customarily turn to social media to discuss a variety of health- and healthcare-related topics, including specific diseases, advertised drugs, and healthcare costs [15]. Thanks to users supplying this kind of information, social networking sites have served as an excellent source of public health data. Parker, et al. detected seasonality in conditions such as allergies, influenza, and ice cream headaches by using a corpus of medical-related tweets and Wikipedia [16]. During the first months of the COVID-19 pandemic in the United States, industry reports showed that digital media use increased tremendously as lockdowns kept people at home [17]. However, the pandemic has also highlighted social media's disadvantages: users are also spreading panic, fear, and mis-information about COVID-19 [18].

Social capital, the sum of actual and potential resources derived from a network of relationships, is one of the attractive benefits afforded by social media [19]. Ellison, et al. report that social media use is positively associated with two basic forms of social capital – bonding (connections made within a homogenous group) and bridging (connections made among people of differing occupational or organizational backgrounds) – which subsequently leads to increased self-esteem and satisfaction with life [20]. Cheng, et al. employed Twitter to identify who can be considered a local expert on a given topic [21]. They accomplished this by calculating a local rank on a topic for a given user, based upon both an authority on a given topic as well as their perceived authority locally on that same topic.

Novel data streams (NDS) are content generated by users themselves, as with social media and web search data [22]. Such content excludes traditional data sources like electronic health records, disease registries, and vital statistics. When looking at NDS, trying to determine what is factual, false, or somewhere in the gray area is a difficult task. Manually analyzing NDS for factual value and sentiment changes would be both time-consuming and yield inaccurate results. As mentioned previously, our proposed framework addresses this, helping public health experts understand the differences between personal and commercial claims about unregulated substances, in a far more practical way than using surveys, government data, or data from healthcare providers.

2.2 Sentiment Analysis

Researchers have been evaluating sentiment of cannabis through monitoring social networks. Daniulaityte, et al. developed machine learning models to identify marijuana (and synthetic marijuana) tweets from personal entities, along with positive/negative/neutral sentiment [23]. These researchers observed the highest F-scores of .7062 by using an SVM classifier on an annotated set of tweets related to cannabis from personal entities. Similarly, Cortes, et al. built a sentiment classifier on a corpus of Spanish tweets containing marijuana references [24]. Their machine learning approach calculated positive/negative/neutral sentiment using an SVM classifier and achieved F-scores of 0.58. More recently, word embeddings have been incorporated into machine learning models for computing sentiment. Liu, et al. used a word2vec model in their drug sentiment classification models, and trained sentiment classification models on a corpus of annotated drug reviews from AskAPatient.com [25].

It was observed that the sentiment models that used word embeddings outperformed those that did not use word embeddings. Similarly, Jiménez-Zafra, et al. saw improvements in sentiment models that used word embeddings [26]. Their goal was to explore the sentiment toward drugs and physicians in two corpora of text. They noticed the best results using SVM models that used word2vec on balanced training sets. However, it performed better in identifying physician sentiment than computing drug sentiment. Tran, et al. analyzed cannabis sentiment by examining the emoji characters used in reactions to the Facebook posts of High Times Magazine, a pro-cannabis publication, as well as using a proprietary sentiment analysis tool from Google [27]. Using this approach, they successfully built associations between words and emoji characters through collecting and analyzing Facebook posts.

Nguyen, et al. also took a non-machine learning approach to researching marijuana sentiment on Twitter [28]. They collected marijuana-related tweets, disregarded the tweets that were authored by less influential users, and manually annotated the tweets on a Likert scale via crowdsourcing, and segmented by demographics. The demographics were applied to the dataset through a proprietary service. They observed more pro-marijuana attitudes among African-Americans and in youth/younger adults. Krauss, et al. also based their marijuana sentiment analysis on crowdsourced tweets [29]. With the goal of exploring the preferences between marijuana and alcohol on Twitter, they collected tweets mentioning alcohol and marijuana, then annotated the tweets through crowdsourcing. They concluded that 54% of the tweets normalized marijuana and alcohol, 24% showed preference to marijuana over alcohol, 2% showed a preference for alcohol over marijuana, 7% showed negative sentiment on both alcohol and marijuana, and 13% demonstrated no sentiment toward either substance.

The VADER (Valence Aware Dictionary and sEntiment Reasoner) model is a rule-based sentiment analysis tool that is designed to evaluate the positive, negative, or neutral sentiment of a piece of text, including tweets. The model uses a lexicon of words and phrases that have been previously scored based on their sentiment polarity (positive or negative), intensity, and context. VADER analyzes the text for negations, amplifiers, and emoticons and assigns a sentiment score ranging from -1 (most negative) to +1 (most positive), with 0 representing neutral sentiment [30]. VADER has several advantages when it comes to analyzing sentiment in tweets. For one, tweets often use informal language, slang, and non-standard vocabulary, which can be difficult for other sentiment analysis tools to interpret. However, VADER is specifically designed to handle this type of language and has been shown to perform well in analyzing sentiment in tweets [31]. Another advantage of VADER is that it does not require extensive training on large datasets of labeled data, which can be time-consuming and expensive. Instead, VADER uses a pre-existing lexicon of sentiment scores that have been manually annotated by human raters, making it easy to use and deploy for a wide range of applications [30].

VADER has been used in a number of studies to analyze sentiment in tweets. For example, one study used VADER to analyze tweets related to the 2012 US presidential election and found that VADER was able to accurately identify the overall sentiment of the tweets [32]. Another study used VADER to analyze tweets related to the Ebola outbreak and found that VADER was able to identify changes in sentiment over time as the outbreak progressed [33].

2.3 Health Misinformation

Misinformation has been shown to spread faster and farther than accurate information on social media [14]. Chou, et al. define health misinformation as any health-related claim of fact that is verifiably false according to scientific consensus [34]. The ongoing COVID-19 pandemic has underscored the gravity of the misinformation problem. In Italy alone every day in March 2020 an average of 46,000 news posts on Twitter were inaccurate and linked to misinformation about the crisis [35]. For example, many social media users spread rumors about 5G technology causing the pandemic, or that mosquito bites can transmit the virus. Users have suggested the ingestion of chloroquine, drinking cow urine, or drinking hot water as cures. A rumor that neat alcohol can cure COVID-19 resulted in hundreds of poisoning deaths in Iran [36].

Researchers have had success employing supervised machine learning techniques on data to detect and explore COVID-19 misinformation. Choudrie, et al. achieved accuracies above 86% in identifying misinformation using decision tree and convolutional neural network model classifiers [37]. They extended this study by conducting interviews with older adults to understand how this demographic processes online misinformation. Al-Rakhami and Al-Amri built a tweets classifier to identify COVID-19 misinformation using a large set of tweets that were annotated for this specific project [38]. hey were able to build a reliable model for identifying tweets containing misinformation, while also demonstrating the rigors and costs of the annotation process. Serrano, at al. used the transformer-based language models to identify YouTube videos containing COVID-19 related misinformation via the comments posted to the videos [39]. They built a text classifier to identify conspiracy-related content, and concluded that YouTube videos containing misinformation also contain user comments with a high percentage of conspiracy-related content. Kumar, et al. built a multi-label tweet classifier system by using a RoBERTa-large transformer language model to identify COVID-19 misinformation [40]. The model used was able to identify the four classes of Irrelevant, Conspiracy, True Information, and False Information and achieved a F1 score of 76%.

Researchers have also employed unsupervised machine learning techniques in COVID-19 misinformation research. Sear, et al. used Latent Dirichlet Allocation to quantify and analyze Facebook posts regarding COVID-19 vaccines [41]. They observed that anti-vaccine posts exhibit a broad range of topics compared to the pro-vaccine posts. Haupt, et al. conducted a non-machine learning based approach for describing COVID-19 misinformation on Twitter [42]. They manually segmented their collection of tweets into categories based on misinformation or unverified information. After further user account-level segmentation it was revealed that these types of posts were mostly coming from personal accounts. Dhiman and Toshniwal provided an unsupervised framework for analyzing COVID-19 misinformation on Twitter by generating semantic-based clusters to identify influential content related to COVID-19 [43]. Kwok et al performed LDA and sentiment on a corpus of tweets from Australian Twitter users making COVID-19 reference within their tweet [44]. The researchers in this study were able to segment the COVID-19 conversations into three topics: attitude, advocating for infection control, and misconceptions/complaints. It was also observed that an overall positive sentiment towards the COVID-19 vaccine was detected within the tweets.

2.4 Transformer-Based Models

In recent years, natural language processing (NLP) has undergone a major transformation thanks to the development of the Transformer language model. First introduced in a groundbreaking paper by Vaswani et al. in 2017 [2], the Transformer has quickly become the go-to deep learning model for NLP tasks. What makes the Transformer so powerful is its innovative attention mechanism, which enables it to focus on the most relevant parts of the input sequence, allowing it to capture long-range dependencies and perform well on a wide variety of NLP tasks. Unlike earlier NLP models that relied on recurrent neural networks, the Transformer can process text sequences in parallel, making it significantly faster and more efficient.

The Transformer architecture was specifically designed to address the shortcomings of previous models in tasks such as language translation [2]. The model follows an encoder-decoder structure (see Figure 2.2), wherein the encoder converts the text input into a vector representation. Each vector corresponds to a word in the sequence and is based on the context of the nearby terms, providing crucial contextual information. The decoder portion of the Transformer architecture is similar to the encoder, but it can convert a vector into a sequence of text.

The Transformer's ability to capture complex relationships between words and phrases has made it a key tool in a wide range of NLP applications, from language translation to sentiment analysis and question answering. Its ability to process large amounts of data quickly and efficiently has also made it a popular choice among researchers and industry professionals alike.

In 2018, Google revolutionized the field of natural language processing (NLP) with

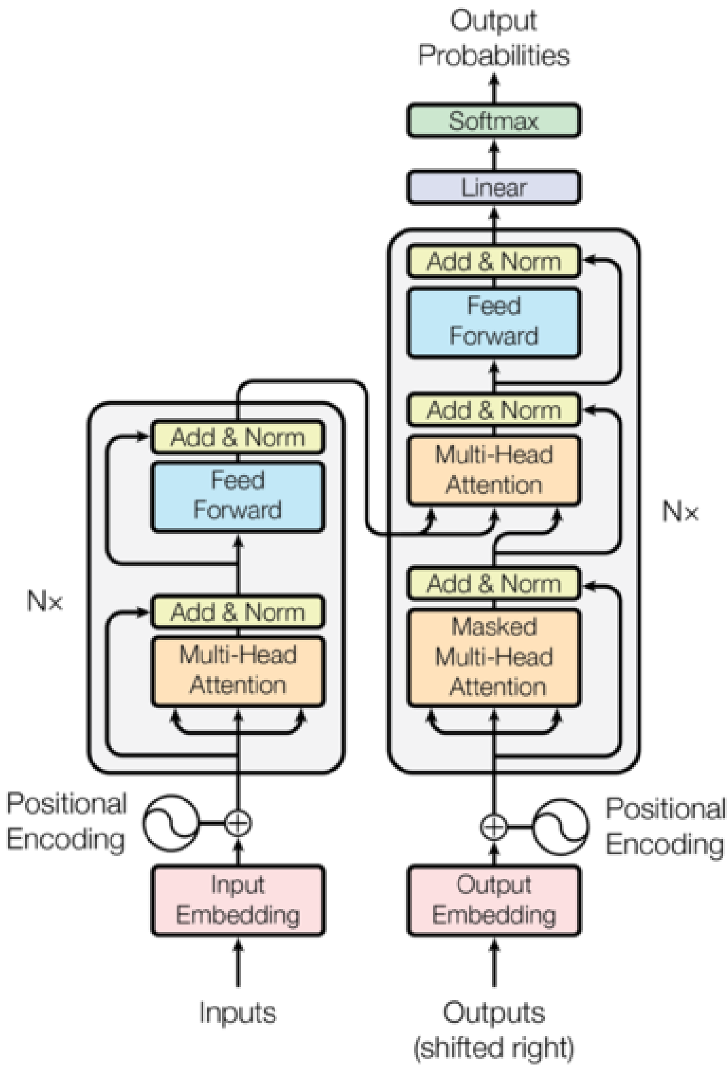

Figure 2.2: The Transformer model architecture [2].

the introduction of Bidirectional Encoder Representations from Transformers (BERT) [45]. BERT is a transformer-based language model that is pre-trained and fine-tuned for a wide range of NLP tasks, including sentiment analysis, question answering, and more. Like its predecessor, the Transformer model, BERT uses an attention mechanism to focus on the most relevant parts of the input sequence, enabling it to capture long-range dependencies and accurately predict outcomes. However, BERT goes a step further by training on the tasks of masked language modeling and next sentence prediction. Masked language modeling involves predicting the missing word in a sentence, while next sentence prediction focuses on understanding the relationships between sentences.

The BERT language model works with two special tokens, the [CLS] token and the [SEP] token, to understand the structure of a given text (see Figure 2.3). The [CLS] token is added to the beginning of the first sentence to classify the entire text as a whole, while the [SEP] token is added at the end of each sentence to separate the sentences. These tokens, along with sentence and positional embeddings, help BERT understand the context and relationships between words and sentences, allowing it to make more accurate predictions about the text. The BERT example using the text "my dog is cute. he likes playing" highlights the model's ability to understand the context of a given piece of text. By adding the [CLS] and [SEP] tokens and using sentence and positional embeddings, BERT is able to understand the structure of the text and the relationships between words and sentences, allowing it to analyze the text in context. For instance, in the example text, the word "playing" could refer to any number of activities, such as playing with a toy or playing fetch. However, by considering the context of the sentence, BERT is able to understand that the word refers to an activity that the dog enjoys, rather than a musical instrument or game.

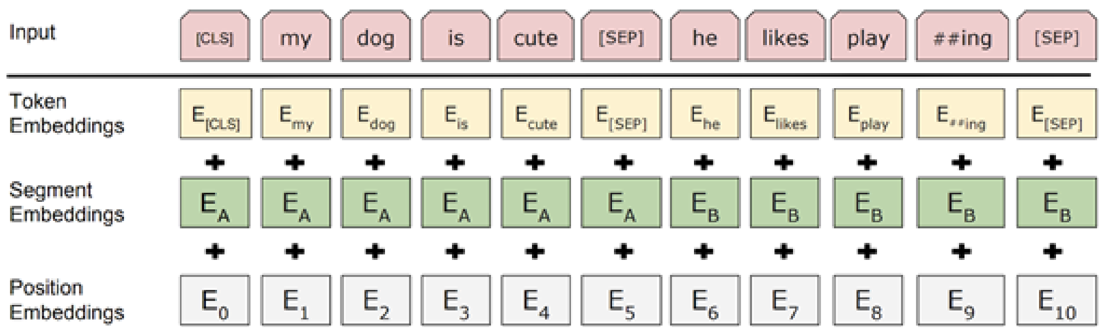

Figure 2.3: BERT input representation (Devlin et al. 2018). The input embeddings are the sum of the token embeddings, the segmentation embeddings, and the position embeddings.

This ability to understand the context of a given piece of text is crucial for natural language processing tasks such as sentiment analysis, language translation, and question-answering. By analyzing text in context, BERT is able to make more accurate predictions and better understand the nuances of language, making it one of the most powerful models in the field of natural language processing. Transformer-based language models can comprehend the meaning of words and phrases similarly to humans by identifying the semantic similarity between pieces of text. Semantic similarity is the task of determining how similar two sentences are, in terms of what they mean. BERT is a pre-trained language model that can be used to measure semantic similarity between sentences. BERT works by first converting each sentence into a sequence of vectors. These vectors represent the meaning of each word in the sentence, as well as the relationship between the words. BERT then uses these vectors to calculate a similarity score between the two sentences. The higher the similarity score, the more similar the two sentences are in terms of their meaning. 2.4 shows an example of semantic similarity, where 'I like cats' is most similar to 'I love dogs', but dissimilar to phrases such as 'I prefer swimming in the ocean'. These models are capable of accurately classifying text for tasks such as sentiment analysis and topic classification, making them valuable for various natural language processing applications. BERT's ability to capture complex relationships between words and sentences has made it a powerful tool in a wide range of NLP applications. Its pre-trained model and fine-tuning capabilities have also made it a popular choice among researchers and industry professionals alike.

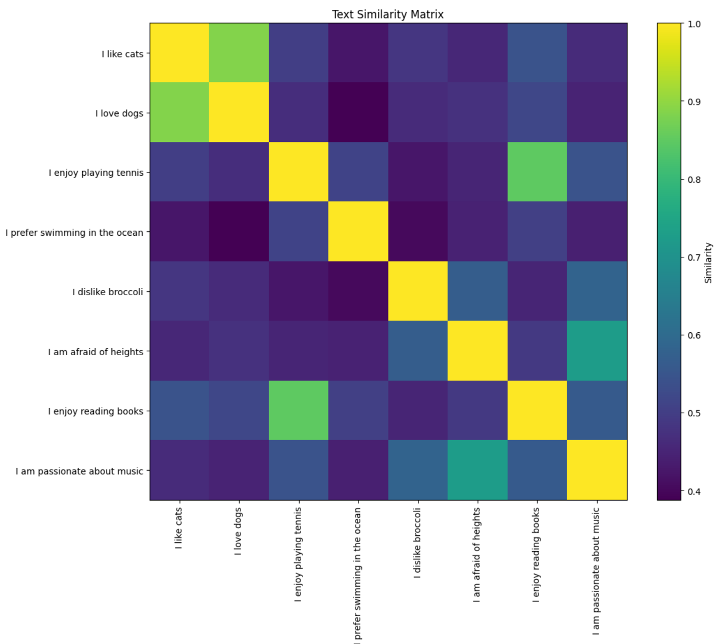

Figure 2.4: Example of use of semantic similarity.

Transformer-based models like BERT have become indispensable tools in the field of natural language processing. These models have achieved state-of-the-art performance in text classification, language translation, auto text summarization, sentiment analysis, question answering, sarcasm detection, and phrase-level information extraction [46, 47, 48, 49]. Recently, BERT and other transformer-based models have been employed in a variety of tasks related to online texts and social networks. In the early stages, detecting fake news became a popular application of these models [50, 51]. The development of FakeBERT by Kaliyar et al. achieved accuracy scores of 98.9% in identifying fake news [52]. Glazkova et al. [53] employed a BERT model to identify COVID-19-related fake news on social networks and achieved F1-scores of 98.69%. Moreover, transformer models have been used to identify mentions of adverse drug reactions in texts [54, 55], as well as to detect subjectivity, polarity, and irony in Italian tweets [56]. Although costly to train initially, they can be transferred and adapted for various NLP tasks.

2.5 Concept Drift

Data streams such as online social networks are certainly subject to concept drift – unforeseeable changes in the underlying distribution of streaming data over time – which can impact the performance of machine learning-based models [57]. It is therefore crucial to detect and address such deviations in the distributions as they occur. It is also important to bear in mind that, where social networks are concerned, concept drift may also represent changes in public opinion.

Concept drift on social networks has been explored by earlier researchers. For example, Costa, et al. proposed using time-window, ensemble-based, and incremental models to detect the presence of concept drift in Twitter streams [58]. Likewise, Abbasi, et al. developed the ElStream framework to detect concept drift in social data streams. The ElStream framework uses different machine- and ensemble- learning methods using majority voting, in which the classifiers can only vote if they cross a certain prediction threshold [59]. Similarly, Lifna & Vijayalakshmi proposed using examining and comparing topics over a sliding window of time as a way to identify potential concept drift in Twitter streams [60]. Nidhi, et al. proposed comparing cluster weights to segments of Twitter data as another way to detect concept drift [61]. (Suprem, Musaev, and Pu 2019) identified the drift in streaming data in tweets related to physical events such as landslides [62]. These researchers generated additional training data for their classification models using alternative yet reliable sources of data, which addressed the concept drift without the associated costs of acquiring additional labeled data.

Some of the research behind concept drift is not only about model performance degradation, but also acknowledging public opinion, which is subject to change over time. Dos Santos, et al. approached concept drift regarding political opinions in Twitter streams by comparing word vectors over a period of time [63]. They were attempting to associate changes in political opinions with specific news-related events. Others compared F-measure, precision, recall, AUC, and accuracy scores on tweet classification models related to vaccine opinions [64]. These researchers observed no drift in the data, and concluded that the model performance was satisfactory at classification tasks over time. More recently, (Bechini et al. 2021) trained a semantic-based classifier using the BERT language model to examined the change in opinions about vaccines within a corpus of Italian tweets; this model outperformed other strategies, such as retraining the ensemble approaches [65].

CHAPTER 3

IMPLICITLY DETECTING MISINFORMATION THROUGH COMPARISON OF TERMS AND SENTIMENT IN PERSONAL AND COMMERCIAL CBD TWEETS

This dissertation chapter explores the potential of text mining in social networks for understanding public perception and marketing of unregulated substances, using CBD as a case study. The chapter begins by highlighting the practical advantages of text mining in social networks for public health researchers and viral marketers alike, and the effectiveness of sentiment analysis in understanding public perception of drugs, diseases, and medical services [66]. We then introduces CBD-TM, a tool for identifying and analyzing the consumption and marketing of CBD in personal and commercial tweets [67, 68]. The chapter describes the methodology used to create two relevant corpora of personal and commercial CBD tweets, including the use of medical, standard, and slang dictionaries to identify frequently occurring medical conditions, symptoms, side-effects, body parts, and other substances referenced in both corpora. We also performs sentiment analysis on the personal CBD tweets using the Valence Aware Dictionary for sEntiment Reasoning (VADER) model, to assess popular claims about the efficacy of CBD as a medical treatment. The chapter concludes by presenting the findings of the study, including medically relevant terms unique to personal or commercial CBD tweets, as well as common terms in both, and an overall positive sentiment in both personal and commercial CBD tweets referencing medical conditions/symptoms. These findings demonstrate the potential of social media data for informing public health research and assessing public claims about unregulated substances, and suggest avenues for further research in this area.

3.1 Introduction of CBD-TM Framework

Our proposed framework, CBD-TM extends the existing CBD research by examining the perceptions of CBD through online discussions, by comparing the terms in tweets reflecting personal use of CBD and tweets reflecting sales and/or promotion of CBD. This approach aids in examining which terms are being used either proportionally or disproportionally. Our methods can be applied to other research that involves analyzing trends in the consumption and advertisement of unregulated substances. Figure 3.1 shows the workflow of CBD-TM from tweet collection, through identification of personal and commercial CBD tweets, and to analysis, which affords the ability to identify the sellers that are potentially misleading the public about CBD's medicinal properties.

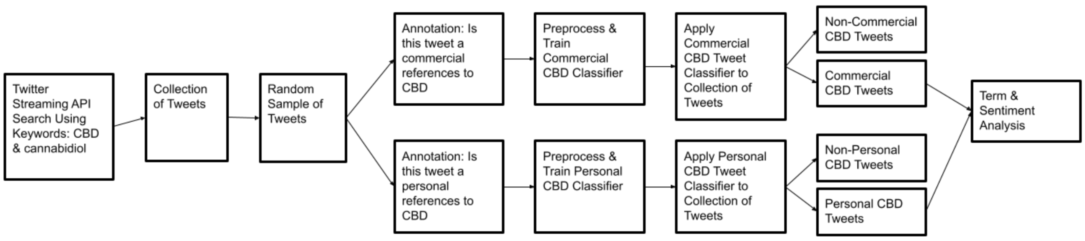

Figure 3.1: Process of identifying and comparing CBD tweets from commercial and personal tweets.

3.2 Collecting Tweets

Between 7 October 2019 and 26 January 2020, we used the Tweepy Python package to search for keywords "CBD" and "cannabidiol" in the Twitter public stream, which provides access to approximately 1% of the public tweets as they are created. We restricted our collection to an approximate 3.5-month period so that we could collect a sufficient number of tweets within a window of time to avoid potential concept drift within the data. We also set filters to collect only original tweets (i.e., no retweets, as retweets replicate content while changing or complicating authorship) and tweets that were written in English. For each tweet that we collected, we kept the full-length tweet text, the time at which the tweet was created, and any geographic information provided. When available, we also retained the unique user identifier, screen name, name, location and time zone provided on the user's profile, Twitter account creation date, number of friends or followers at the time of each tweet, as well as the user-provided description from each profile. This analysis primarily focuses on the full-length tweet text. The resulting dataset consisted of 567,850 tweets.

3.3 Annotating the Training Sample

To ensure accurate and consistent classification of CBD-related tweets, we utilized a one annotator (native English speaking and university educated) to label the tweets in our sample. While using a single annotator can introduce potential biases and limitations, studies have shown that it can still be an effective approach for achieving reliable and consistent labeled data in certain contexts [69, 70]. For example, a study published in the Journal of Medical Internet Research used a single annotator to classify tweets related to vaccine-related discussions and reported high accuracy and consistency in the labeled data [71]. Similarly, a study published in the Journal of Biomedical Informatics used a single annotator to label medical concepts in clinical text data and reported high inter-annotator agreement [72]. We ensured that the annotator was highly knowledgeable in the topic of CBD and had a thorough understanding of our classification criteria. By carefully validating the labeled data and ensuring consistency in the annotation process, we are confident that our models are accurate and effective in automatically extracting personal and commercial CBD tweets from our collection.

To build the models for automatically extracting personal and commercial CBD tweets from our collection of 567,850 tweets, we built two binary classifiers trained on 5,496 tweets. We opted for two binary tweet classifiers over a single multi-class tweet classifier so that CBD-TM could be easily expanded later to analyze other types of CBD tweets (e.g., CBD news articles) by incorporating additional binary classifiers. This sample of tweets was obtained by taking 6,000 random tweets from our collection and removing verbatim duplicates. To annotate the personal CBD tweets – those which appear to come from individuals discussing CBD use, but are not selling it – we determined whether each tweet in the sample represented a post from an individual (i.e., not a "bot") discussing the past, current, and/or future use of CBD. To annotate the commercial tweets, we determined whether each one was a post from an actual non-news entity (that is, not a "bot") selling, advertising, or promoting CBD. Table 3.1 provides some examples of the personal and commercial CBD-related tweets.

Table 3.1: Examples of Personal and Commercial CBD-Related Tweets (usernames/URLS removed for anonymity).

Personal CBD	**Commercial CBD**
CBD products are so good for anxiety, and they don't make you high	Go Away!!!!Pain! We have a variety of CBD products for your needs.... Make sure to ask about our selection your next visit. URL
I've used CBD for anxiety. It is WAY healthier than taking benzodiazepines ...I also use CBD for pain. You know what else is bad for your liver? Tylenol and Ibuprofen	Over time, poor sleep can leave you feeling wrecked..... Could CBD help? URL #cbd #cbdoil #hemp #cannabis #sleep #insomnia
Take some painkillers with sleeping aid like Tylenol or Advil PM or something... any CBD or weed maybe try that too	Chronic Fatigue .... Cannabis CBD THC oil - URL
CBD gummies will not give you the high, but for me personally CBD oil edibles helped with anxiety and menstrual cramps	Our CBD cream combines the relief potential of arnica and natural menthol oil with cocoa butter and the scents of eucalyptus & lavender. This is relief that is crafted for all of your senses. URL

Table 3.2: Example Erroneous Tweets (usernames/URLS removed for anonymity).

Erroneous Tweets
If you live where medical marijuana is legal, get paid $3k a month to critique weed, CBD, edibles and more URL
The FDA is worried about CBD. Should you be concerned? URL
This room is half the size of my cbd apartment....
Flinders Street in Melbourne's CBD has been re-opened following an earlier protest. ... Thanks for your patience during this disruption. #victraffic

Table 3.2 provides examples of tweets related to CBD that were considered irrelevant to both personal and commercial CBD classes. These tweets included news articles, job postings, and references to "CBD" that actually referred to a "central business district," rather than the cannabis extract. During the annotation process, the annotator classified these tweets as neither personal nor commercial CBD-related content to ensure they were not included in the training data for our models.

3.4 Extracting Personal and Commercial CBD Tweets

In order to identify and separate CBD-related tweets from a vast collection of general tweets, we employed a technique called the TF-IDF method, which stands for "term frequency-inverse document frequency." This method allowed us to pinpoint the words and phrases that were most relevant to the classification of each tweet and provided a reliable way of differentiating between personal and commercial CBD-related tweets.

Before training the binary classifiers, we preprocessed the text of the tweets by converting all text to lowercase, normalizing URLs to one consistent string, removing special characters and English stop words, and lemmatizing the tweet text. We then trained two binary classifiers on a random sample of 5,496 tweets, which we selected by removing duplicate texts from approximately 6,000 tweets. The size of the random sample was comparable to that used by Tsapatsoulis and Djouvas to examine the human annotation of tweets for NLP models [73]. We used these classifiers to distinguish between personal and commercial CBD-related tweets.

To create the input matrices for the binary classifiers, we generated a matrix of the term frequency-inverse document frequency (TF-IDF) features based on the words and another matrix based on the characters in tweets. We utilized a range of n-grams from one to three for the matrix of the TF-IDF features based on the words, and a range of n-grams from three to six for the matrix based on the characters in tweets. As shown in Equation 3.1, the term frequency (TF) represents how often a term occurs in a document, while inverse document frequency (IDF) indicates how rare the term is across all documents. To obtain the final TF-IDF, we multiplied the TF and IDF components.

$$TF(t,d) = \frac{number\ of\ times\ t\ appears\ in\ d}{total\ number\ of\ terms\ in\ d}$$
$$IDF(t) = log\frac{N}{1+df}$$
$$TF - IDF(t,d) = TF(t,d) * IDF(t) \tag{3.1}$$

After creating the TF-IDF matrices, we stacked them horizontally, and this served as the input for the binary classifiers. We trained the classifiers on 80% of the annotated sample and tested them on the remaining 20%. The binary classifiers accurately identified personal and commercial CBD-related tweets, which allowed us to separate them from the vast collection of general tweets.

In analyzing the manually annotated tweets, we observed that the amount of personal and commercial CBD-related tweets were imbalanced: the non-personal (negative class) CBD-related tweets occurred 7.7 times more often than the personal (positive class) CBD related tweets, while the non-commercial (negative class) CBD-related tweets occurred 10.2 times more than the commercial (positive class) CBD-related tweets. To achieve a balance in the training set, we down-sampled both positive classes by taking a random sample equivalent in size to the negative class. Tables 3.3 and 3.4 show the class frequencies for both the personal and commercial CBD-related tweet classes before and after down-sampling.

Table 3.3: Training Set Personal CBD Class Counts.

	Pre-Downsampling	**Post-Downsampling**
Personal CBD	631	631
Non-Personal CBD	4,865	631
Total	5,496	1,262

To train the two binary classifiers we performed a five-fold cross-validation grid search using a linear support vector classifier, logistic regression, Gaussian Naive Bayes classifier, and a random forest classifier to find the optimal classification algorithm and

Table 3.4: Training Set Commercial CBD Class Counts.

	Pre-Downsampling	**Post-Downsampling**
Commercial CBD	489	480
Non-Commercial CBD	45,007	489
Total	5,496	978

combination of parameters. The range of parameters are found in Table 3.5. After training the binary classifiers we applied each model to the larger CBD corpora of tweets.

Table 3.5: Algorithm & Parameters Combinations Used in Text Classification Tuning.

Algorithm	**Parameter**	**Range**
Linear Support Vector	Penalty	$\{l_1, l_2\}$
	Loss	{hinge, squared hing}
	regularization parameter	$X_k = 10^{a+(b-a)(k-1)/(n-1)}$,
		k=1,...,n;
Logistic Regression	Penalty	a=0; b=5; n=20
	regularization parameter	$\{l_1, l_2\}$
		$X_k = 10^{a+(b-a)(k-1)/(n-1)}$,
	Solver	k=1,...,n;
Gaussian Naive Bayes	Smoothing	a=0; b=5; n=20
Random Forest	Estimators	{newton-cg,lbfgs,liblinear,ag,saga}
	maximum features	{.99,.75,.5,.25,.1,.01,.001}
		{2,5,10, 100, 1000}
		{1,2,4,8,12,20,30,40}

We employed binary classification algorithms to distinguish between personal and commercial CBD-related tweets. Two separate classifiers were trained independently, each optimized to achieve high classification performance. The optimal personal classifier was based on logistic regression with hyperparameters C=3.36, penalty=none, and solver='newton-cg'. Meanwhile, the commercial classifier was optimized using logistic regression with hyperparameters C=428.13, penalty='l1', and solver='saga'. The hyperparameters of the logistic regression models play a crucial role in optimizing the model's performance. The parameter C determines the regularization strength, where a smaller value of C corresponds to a stronger regularization. The penalty parameter specifies the type of regularization used in the logistic regression model. The solver parameter determines the algorithm used to optimize the logistic regression model's parameters. By tuning these hyperparameters, we were able to develop a model that could effectively classify tweets as either personal or commercial CBD-related.

While we observed a decrease in classification performance on the unbalanced data derived from a smaller validation set, both classifiers were able to achieve AUC scores above 0.80, indicating that they could effectively distinguish between personal and commercial CBD tweets. The performance of the personal and commercial CBD binary classifiers is presented in Appendix I. When applied to the collection of tweets, the personal CBD binary classifier classified 167,755 tweets as personal CBD-related, while the commercial CBD binary classifier classified 143,322 tweets as commercially CBD-related. Our analysis revealed that the logistic regression models performed the best compared to the other three algorithms.

Table 3.6: Personal CBD Logistic Regression Classifier Performance Metrics.

	Balanced Sample				**Unbalanced sample**			
	Prec	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**
Non-Pers. CBD	0.93	0.79	0.85	138	0.94	0.91	0.93	367
Pers CBD	0.79	0.93	0.85	115	0.78	0.83	0.81	133
Accuracy		0.85			Accuracy		0.89	
AUC		0.86			AUC		0.87	

Table 3.7: Commercial CBD Logistic Regression Classifier Performance Metrics.

	Balanced Sample				Unbalanced sample			
	Prec	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**
Non-Comm.CBD	0.92	0.85	0.89	95	0.90	0.93	0.91	367
Comm CBD	0.87	0.93	0.90	101	0.79	0.70	0.74	133
Accuracy		0.89			Accuracy		0.87	
AUC		0.89			AUC		0.82	

Tables 3.6-3.7 show the performance of both logistic regression models on the personal and commercial CBD tweets in the test set. We did not observe any significant differences between validation and testing performance in either model.

3.5 Term Analysis

The methodology employed in this study involved computing term frequencies of the top 1,000 words in both the personal and commercial CBD tweet corpora. The terms were cross-referenced with standard English, medical (SNOMED CT), and/or slang dictionaries to determine their relevance to medical conditions, medical symptoms, body parts, and/or other medications/substances. These terms were then categorized into three groups: health/medical, cannabis-related terms, and other substances. The Scattertext Python package was utilized to generate graphical representations of the frequencies within each group for the personal and commercial CBD tweets [74].

It should be noted that some words were included in multiple groups, such as "high," which is a side-effect of cannabis and a term commonly used in both cannabis- and CBD-related tweets. Additionally, side-effect terms caused by taking a substance, particularly those associated with cannabis, were considered. Moreover, the overall frequency of the top occurring terms was compared with their frequency in either personal or commercial tweet types to produce a visualization of relevant term frequencies.

The visualization of cannabis-related terms revealed that THC-related terms were mentioned in both personal and commercial CBD tweet corpora, with more hashtags containing these references more frequently in the commercial CBD tweets (Figure

A.2). The other substances group included the terms "drink," "melatonin," and "pills," which were mentioned in both personal and commercial CBD tweets (Figure A.3). Kratom and MCT were mentioned more frequently within the commercial CBD tweets and less frequently in the personal CBD tweets. While references to alcohol were slightly more frequent in personal CBD tweets, they were less frequent in commercial CBD tweets. Opioids were infrequently mentioned in both personal and commercial CBD tweet types. In the health and wellness group (Figure A.1), the terms "pain," "sleep," and "anxiety" occurred frequently in both the personal and commercial CBD tweets. Terms related to fitness and nutrition were more common in the commercial CBD tweets. The mean frequency of CBD tweets referencing PTSD was the same within both tweet types. Finally, CBD tweets referencing autism occurred more frequently in personal tweets, but were infrequent in commercial tweets. It is noteworthy that the United States FDA has warned CBD sellers about disseminating misinformation by promoting CBD as a treatment for medical conditions, including autism [75]. The counts of these terms of interest in personal and commercial CBD tweet classes are available in Appendix II.

Our results agree with previous research which found that CBD is associated with anxiety and pain [76]. However, our results allowed us to identify the terms associated with the personal use of CBD versus the terms associated with online marketing, in addition to the general medical terminology associated with CBD.

3.6 Sentiment Analysis and Comparison of Personal and Commercial CBD Tweets

Sentiment analysis is a crucial technique used to assess people's attitudes, emotions, and opinions towards specific subjects. In the context of social media, this technique can be used to analyze users' sentiments towards various products or services, including CBD. One popular model for analyzing sentiment on social media is the VADER sentiment model, which was specifically developed for analyzing sentiment on social network posts [30]. The VADER model is a lexicon- and rule-based model that considers the valence of individual words in a tweet to generate a composite sentiment score. Specifically, the model uses a set of lexical features, such as the presence of capitalized words or emoticons, as well as a rule-based approach to analyze the syntactical and grammatical structures of a sentence. The model then generates a normalized weighted composite score between -1 and +1 for each tweet, known as the compound score, which represents the overall sentiment of the tweet. The compound score takes into account the valence of each word in the tweet, as well as the degree of intensity and polarity of the sentiment.

One of the benefits of using the VADER model for sentiment analysis of CBD-related tweets is its ability to handle the unique language used in social media, including slang, idiomatic expressions, and emojis. The VADER model was specifically designed to handle these types of linguistic features, making it a useful tool for analyzing sentiment on social media platforms. Additionally, the VADER model has been extensively tested and has been shown to outperform other sentiment analysis models in several domains, including political tweets and online reviews [30, 77, 78, 79].

In this study, we used the VADER model to analyze the sentiment of personal CBD tweets. We converted each tweet's compound score into a 3-level categorical variable based on the threshold recommended by Hutto & Gilbert [30, 80], which allowed us to categorize each tweet as having positive, neutral, or negative sentiment. This approach provided us with a comprehensive understanding of the public's sentiment towards CBD and allowed us to compare the sentiment conveyed in personal CBD tweets to the sentiment expressed in commercial CBD tweets.

In order to accurately assess the sentiment of tweets related to specific conditions and symptoms, we aggregated and calculated the mean compound scores and sentiment category frequencies (positive, negative, neutral) for tweets containing relevant terms. However, we also recognized that the VADER sentiment model partially relies on a dictionary score, and that certain terms related to illness, such as "pain" or "cancer", could potentially bias the overall sentiment score of a tweet. To account for this, we conducted additional analyses to determine whether including or excluding these medical terms of interest affected the VADER scores. Specifically, we computed the VADER sentiment scores both with and without these terms, and compared the mean scores using a t-test to determine whether any individual term biased the overall sentiment of a tweet [30].

For example, the VADER sentiment score of the tweet "CBD really helps my pain" is -0.171, while the VADER sentiment score for "CBD really helps my" is 0.4391, indicating that the inclusion of the word "pain" had a strong negative influence on the overall sentiment score of the tweet (Table 3.8). This approach allowed us to obtain a more accurate assessment of sentiment for CBD-related tweets, and highlights the benefit of using the VADER model over other sentiment models for social media data, as it is specifically designed to handle informal language and contextual nuances often found in social media posts [30, 77].

Table 3.8: Term-level VADER Sentiment Scores for "CBD really helps my pain"

Term	**CBD**	**really**	**helps**	**my**	**pain**
Vader Score	0	0	0.3818	0	-0.5106

Sentiment analysis was conducted on both personal and commercial CBD-related tweets that referenced any of seventeen predefined terms related to specific conditions and symptoms. The sentiment scores were computed using the VADER model, which is based on the valence scores of each word in the tweet, and produces a normalized weighted composite score between -1 and +1 for each tweet. Since many terms related to illness may influence the overall sentiment of a tweet, the VADER sentiment scores were computed both with and without medical terms of interest. To determine whether any individual term of interest biased the overall sentiment assigned to a tweet, the mean VADER scores were compared using a t-test.

Additionally, we computed the term-level sentiment for each of the individual terms of interest, and observed non-neutral sentiment for some terms where the VADER score of the individual term may influence the sentiment score and polarity of the entire tweet. For example, Table 3.9 contains a list of terms for which we observed non-neutral sentiment. By calculating the sentiment for each personal and commercial CBD tweet referencing any of the seventeen terms of interest, both in the original tweet text and with the term of interest removed, we were able to assess how sentiments about the condition itself might affect the sentiment score.

Our proposed framework's results suggest that most CBD users are satisfied with it as a treatment for a variety of advertised conditions, with the exception of autism. Negative sentiment was observed in personal CBD tweets referencing autism, while commercial tweets marketed it multiple times as an autism treatment. The use of the VADER model in this study allowed for a comprehensive analysis of the sentiment expressed in CBD-related tweets, and the inclusion of specific medical terms enabled a more nuanced understanding of the sentiment related to specific conditions and symptoms.

The sentiment analysis results of CBD tweets were presented in Table 3.10. We processed each tweet through the VADER sentiment model to obtain the normalized weighted composite score between -1 and +1, known as the compound score. As we observed in Tables 3.7 and 3.8, some medical terms related to illness may influence

Table 3.9: Medical Related Terms with Non-Neutral Sentiment.

Term	**Vader Compound Score**
anxiety	-0.1779
anxious	0.2500
calm	0.3182
calming	0.4019
cancer	-0.6597
depression	-0.5719
energy	0.2732
pain	-0.5106
pains	-0.4215
stress	-0.4215

the overall sentiment of a tweet, such as the word "pain" that has a negative VADER sentiment score alone. Therefore, we removed the medical terms from the tweets to assess the sentiment of CBD regarding the condition, without the VADER sentiment score of the condition itself affecting the overall VADER sentiment score of the tweet.

The sentiment analysis revealed that commercial CBD tweets were typically positive, with occasional neutral sentiment. Personal CBD tweets were mostly positive, with some neutral and negative sentiment observed throughout. These results align with previous research that found a generally positive sentiment towards CBD use [81]. Overall, our analysis demonstrated that the VADER sentiment model is a useful tool for evaluating sentiment in CBD-related tweets and is capable of detecting nuanced sentiments.

In Appendix III-IV, we present evidence of a statistically significant difference in the mean sentiment score of personal CBD tweets with the term of interest compared to those without for 11 out of the 17 examined terms. Similarly, in commercial CBD tweets, there was a statistical difference in the mean sentiment score with the term of interest compared to without for 12 of the 17 examined terms. This confirms that the sentiment score and polarity of the tweet can be influenced by the sentiment score of a single word. We also observed a statistical difference in the mean sentiment score of commercial CBD tweets compared to personal CBD tweets for 11 of the 17 examined terms, both with and without the term of interest included. This finding suggests that while the sentiment towards CBD is generally positive, in cases where there is a significant difference in sentiment scores between personal and commercial CBD tweets, the mean sentiment score of commercial CBD tweets is higher than that of personal CBD tweets. We provide visual examples of how the distribution of the sentiment score changes when the term of interest ("pain") is removed from the tweet in Figures 3.2 and 3.3.

In our analysis of CBD-related tweets, we observed a mixture of positive and negative sentiments in personal tweets that reference CBD's relationship with autism. Figure 3.4 shows that these tweets had a more negative sentiment compared to other personal CBD tweets. Interestingly, the sentiment of personal CBD tweets did not change when the term "autism" was removed. Despite being negative, the mean sentiment score of these tweets was -0.042, which is considered neutral by the authors of the VADER model. However, a plurality of 46

As shown in Appendix II, removing the term of interest from a tweet often resulted in a change in the sentiment polarity. This indicates that the sentiment score and polarity of a tweet can be influenced by a single word. Our analysis also revealed that there was a statistical difference in the mean sentiment score between personal and commercial CBD tweets for some of the examined terms. For example, the mean sentiment score of commercial CBD tweets was higher than that of personal CBD tweets for 11 of the 17 terms examined, both with and without the term of interest included. Figures 3.2 and 3.3 provide an example of how the distribution of the sentiment score changes when the term of interest ("pain") is removed from a tweet.

It is worth noting that the VADER model is partially based on a dictionary score, and that many terms related to illness can influence the overall sentiment of a tweet. Therefore, we also computed the VADER sentiment scores with and without medical terms of interest, and compared the mean VADER scores using a t-test to determine whether any individual term of interest biased the overall sentiment assigned to a tweet.

In conclusion, our analysis of CBD-related tweets using the VADER sentiment model provided insights into the sentiments expressed by Twitter users regarding CBD and specific conditions. The VADER model's ability to assign sentiment scores to individual words and phrases allowed us to evaluate the influence of specific terms of interest on the overall sentiment score of a tweet.

Table 3.10: Example CBD Tweets and Their Associated Vader Sentiment Score/Category

Tweet	Tweet Type	Vader Score	Sentiment Categaory
Quality, safety, good price and bio-availability are what best describes our products. Studies have shown that #CBD has helped to relieve pain, increased reduction of cancer cells, and helping many common sleep disorders. Read more here: https://t.co/spcvpUM4oa https://t.co/d5iaDoQ5DA	Commercial	0.904	Positive
Evidence CBD may reduce cytokine storm and inflammation in COVID-19 https://t.co/LnKUqJWPig	Commercial	0	Neutral
"Do you know your #cannabinoids? Here's a guide for different #ailments and the cannabinoids that can help Heal with #CBD in 2020 Come by and talk to our specialists for all your #CBDneeds Shop in-store or online https://t.co/tcP5HtVLAL #miwellness-cbd #hemp #cannabiscommunity https://t.co/SrdP2BZkmI"	Commercial	0.402	Positive
Help keep your children calm and it's good for the Corona virus for you all world CBD organic is the best stay alive keep your children alive and calm especially if autism no more... https://t.co/UMb3bIFXVX	Commercial	0.945	Positive
"Pain! Pain! Go Away!!!! We have a variety of CBD products for your needs. Make sure to ask about our selection your next visit. https://t.co/VxkXFlvbIU"	Commercial	0.537	Positive
@offlineweebu Take some painkillers with sleeping aid like Tylenol or Advil PM or something. If you got any CBD or weed maybe try that too.	Personal	0.361	Positive
"Would anyone recommend CBD infused water or go straight to the CBD oil? #CBD #SlowSunday #SundayThoughts #fitness #cbdoil #cbdlife #cbdhealth"	Personal	0.671	Positive
is cbd snake oil elixir or does it actually work	Personal	0.000	Neutral
my observations of using cbd oil for the last 4 weeks to temper the tag-team depression & insomnia: it does bloody nothing! the closest thing to snake oil? (it's literally oil!)	Personal	-0.875	Negative
glad to know my "holy shit cbd is snake oil" conspiracy theory is turning out to be true https://t.co/khjfdi4rmh	Personal	-0.296	Negative

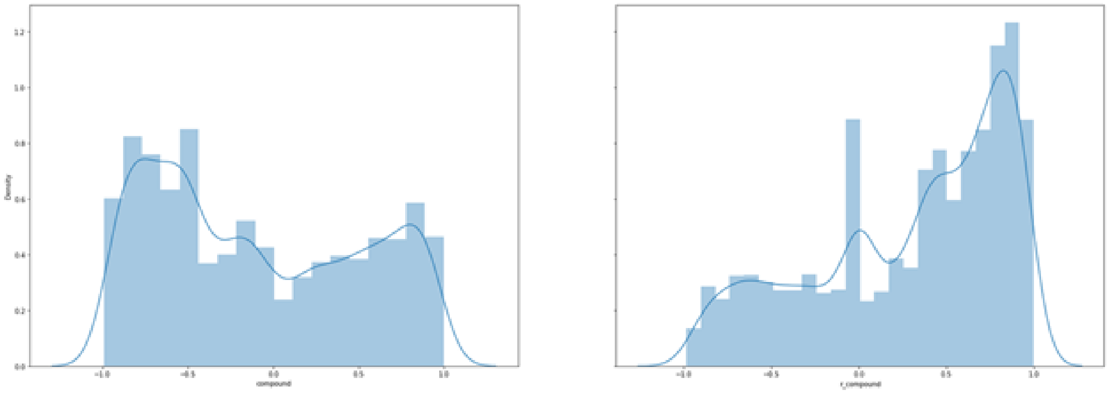

Figure 3.2: Distribution of Sentiment Scores of Personal Tweets Referencing the Term "Pain".

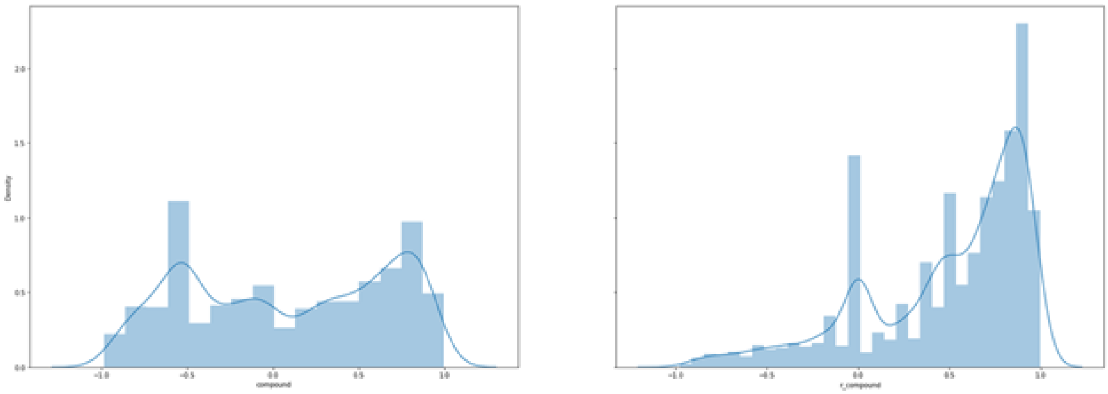

Figure 3.3: Distribution of Sentiment Scores of Commercial Tweets Referencing the Term "Pain".

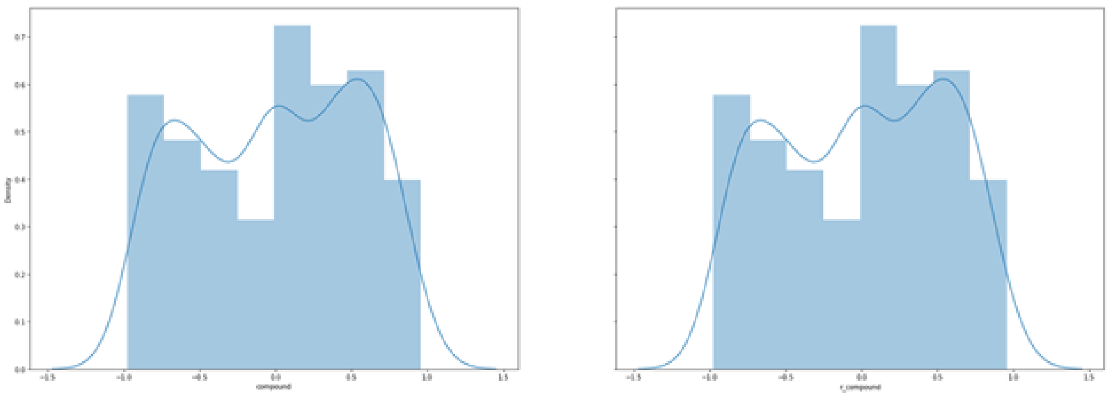

Figure 3.4: Personal CBD Sentiment Autism.

Table 3.11 shows tweets which CBD-TM identified as CBD-related which contained the word "autism." These personal CBD tweets sometimes favored and sometimes disfavored CBD as a treatment for autism. In the commercial CBD tweets referencing autism, we observed both implicit and explicit claims regarding CBD's ability to treat autism. CBD-TM thus works well in contexts where the efficacy claims of medications and supplements are both validated and refuted.

Table 3.11: Examples of Personal and Commercial Tweets Referencing CBD and Autism.

Personal Autism CBD Tweets	Commercial Autism CBD Tweets
@user @user He's ...on a thc/cbd tincture. It's helped his autism beautifully	10 Best CBD Oils For Autism - URL 10-bestcbd-oils-for-autism-40/
@user I use CBD for my C-PTSD and the overstimulation that comes from Autism ... it's kinda hard to function ... It works better than any antipsychotic I've ever been on.	CBD INFUSED ... BOTTLES @ FRUIT PASTELS, THESE ARE IDEAL FOR KIDS WITH ADHD, AUTISM ETC #THECBDCHEMIST #GOOD-NIGHTSLEE
I see a lot of ppl on my timeline ... claiming CBD can "cure" autism is bad and so is anyone knowingly peddling the idea what is wrong with you people URL	COMPANY_NAME® Announces Autism Hope Alliance Sponsorship URL #cannabis #hemp #cbd #vape #cbdoil #natural #anxiety #pain #stress #health #pharma #wellness #beauty #domains URL
@user @user @user if you work somewhere that lies about curing autism with cbd oil you should feel bad	People use CBD to treat everything from epilepsy and autism to chronic pain and anxiety. URL

3.7 Discussion

The CBD-TM framework offers a valuable tool for identifying and analyzing public social media data related to CBD usage and commercialization. The use of binary tweet classifiers to differentiate between personal and commercial CBD tweets is a novel approach to studying the perceptions of CBD in online discussions. Given the lack of FDA-approved medication for CBD and the potential safety and efficacy concerns associated with its usage, the framework provides a useful methodology for tracking the use of CBD as a treatment for various medical conditions and symptoms.

One of the notable findings of this study is the infrequent but concerning promotion of CBD as a treatment for autism and Alzheimer's despite the FDA's warnings against doing so. This highlights the importance of monitoring and regulating the advertising and promotion of unregulated substances like CBD.

The comparison of term frequencies and sentiment in personal and commercial CBD tweets provides a comprehensive understanding of how CBD is discussed and marketed online. The framework's ability to analyze and visualize the data in this way extends previous research on the topic and offers a valuable approach for examining the consumption and advertising of unregulated substances more broadly.

CHAPTER 4

DETECTING TWEETS CONTAINING CANNABIDIOL-RELATED COVID-19 MISINFORMATION USING TRANSFORMER LANGUAGE MODELS AND FDA WARNING LETTERS

Misinformation can take many forms on social media, and in some cases has been used to market products to consumers. Since the beginning of 2020, the COVID-19 pandemic has supplied a new medical condition for companies to exploit, seeking to profit from the crisis at the expense of public health [82]. While some misleading posts regarding COVID-19 have been about the effectiveness and/or safety of masks and vaccines and the origins of the virus, others have focused on false information about the abilities of alternative products in treating and/or preventing COVID-19, which have not been demonstrated to be safe or effective. For example, since the start of the pandemic some cannabidiol (CBD) sellers have claimed that CBD can prevent and/or cure COVID-19. Although the consumption of CBD by humans is typically well-tolerated, misinformation about its effectiveness for treating COVID-19 is widespread and poses a danger to public health. Therefore it is essential that this type of content be efficiently identified so its social and public health impacts can be minimized.

Our methods and results speak to the recent efforts of other researchers to use social networks to analyze misinformation in ways that directly relate to the potential problem of CBD misinformation.

- Ferrand et al. analyzed responses to queries from common digital assistants such as Siri, Alexa, and Google for misinformation regarding vaccines [83].
- Chen et al. collected social network posts from Weibo regarding cancer, and observed 30% of the posts contained misinformation [84].
- Ahmed et al. collected tweets referencing COVID-19 and 5G, and performed graph analysis to identify and analyze how misinformation was being dissemi-

nated online [85].

- Allem et al. observed unsubstantiated health claims related to cannabis on Twitter in their study [66].
- Perhaps most applicably, Rovetta and Bhagavathula also observed an abundance of COVID-19 misinformation in their analysis of tweets [86].

To address potential social media misinformation surrounding CBD, it is important to develop methods for gathering and classifying text corpora. Previous studies using the internet and social media have described personal and commercial discourses surrounding CBD. Narayanan et al. used internet-based data sources to examine CBD trends via Google searches, concluding that interest in CBD oil increased significantly from 2014 to 2018 [13]. Tran and Kavuluru used CBD-related posts from Reddit, and comments submitted to the FDA regarding these posts, to examine the conditions that are commonly being treated with CBD [11]. They examined both corpora of texts for medical conditions and methods of use in posts and comments using the term "CBD," along with any indication of therapy implied in the two corpora.

There have also been non-machine learning approaches to researching marijuana sentiment on Twitter, such as the work done by Nguyen et al. [28]. Their study collected marijuana-related tweets, disregarded the tweets authored by less influential posters, manually annotated the marijuana tweets on a Likert scale via crowdsourcing, and segmented them by demographics applied to the dataset through a proprietary service. The researchers observed more pro-marijuana attitudes among African-Americans, youths, and younger adults. In another example of a research approach that did not rely primarily on machine learning, Krauss et al. based their marijuana sentiment analysis on crowdsourced tweets [29]. They aimed to examine the preferences between marijuana and alcohol on Twitter by collecting tweets containing alcohol and marijuana references, and then annotated the tweets via crowdsourcing. They concluded that 54% of the tweets normalized marijuana and alcohol, 24% showed preference for marijuana over alcohol, 2% showed a preference for alcohol over marijuana, 7% showed negative sentiment on both alcohol and marijuana, and 13% demonstrated no sentiment towards either substance.

As explained in chapter 3, we have demonstrated the ability to build a tweet classifier capable of identifying commercial CBD tweets, some of which contain false claims about the benefits of CBD. The FDA defines “misinformation” as that which misleadingly represents the product as able to mitigate, prevent, treat, diagnose, or cure a condition or disease, such as COVID-19 [87]. In order to train our classification model, we annotated a sample of tweets as to whether each tweet contained misinformation, according to the FDA’s guidelines. While annotating data is often required in machine learning tasks, there are monetary, time, and labor costs. While researchers prefer the annotated data to be available promptly and at low cost, the qualifications and competency of those annotating the training data must also be considered.

Our proposed extension continues to build upon the CBD-TM framework which was developed to identify commercial CBD tweets, described in chapter 3. The results, explained in chapter 5, show that by using another relatively small annotated sample of tweets, along with quotes taken from the FDA website, we can identify commercial CBD tweets containing misinformation.

4.1 Addressing Misinformation

Twitter is a source of a measurable amount of health-related misinformation related to smoking products, drugs, vaccines, and diseases [88]. Misinformation has been shown to spread faster and farther than accurate information on social media [14]. The ongoing COVID-19 pandemic has underscored the gravity of the misinformation problem. In Italy alone, every day in March 2020 an average of 46,000 news posts on Twitter were inaccurate and linked to misinformation about the crisis [35]. While there is no scientific evidence to support their claims, influential Twitter users like former President Donald J. Trump and celebrity Joe Rogan have suggested the ingestion of chloroquine and its derivative hydroxychloroquine are effective treatments for COVID-19 [89]. While the Food and Drug Administration (FDA) warned against improperly consuming these substances in July of 2020, there were still dozens of documented deaths and poisonings are associated with their use, including at least one person who ingested fish tank cleaner containing chloroquine after being exposed to online misinformation [90, 91, 92]. Further, a widespread rumor that neat alcohol could cure COVID-19 resulted in hundreds of poisoning deaths in Iran [36]. Not only has misinformation dissuaded consumers from seeking effective treatments, it has encouraged dangerous treatments that could potentially be lethal.

Misinformation regarding unregulated and/or loosely regulated substances such as CBD is not a new concept [12]. Allem, et al. confirmed that misleading claims about cannabis often take place in online conversations [66]. While there have been some preliminary studies suggesting cannabis may be beneficial in treating the effects of the COVID-19 virus, cannabis is not an FDA-approved treatment [93]. Still, many online CBD retailers claim CBD improves the immune system's ability to fight the COVID-19 virus, while others claim CBD can reduce lung inflammation in those with active COVID-19 infections [94, 95, 96]. Because these claims are about unregulated or loose regulated substances, and are not supported by research, they are violations of the Food, Drug, & Cosmetic (FD&C) Act. The FDA has consequently made numerous attempts to warn online retailers making such claims about their products, sending warning letters to retailers advertising non-alcohol and/or essential oil based sanitizers [96, 87, 96]. These letters specify the policies that the retailers are violating, explain why the retailers' claims are inaccurate, include example statements taken directly from the retailers' own advertisements, and explain associated penalties for not removing the claims.

To better understand how online CBD sellers are misleading the public on Twitter about the benefits of CBD for COVID-19, we retrospectively collected tweets from January 2020 to April 2021 that reference both CBD and COVID-19. From this collection we extracted the commercial tweets via the commercial tweet classifier we previously developed [68]. The resulting set of commercial CBD tweets mentioning COVID-19 were then annotated to determine whether they contained misinformation regarding CBD and COVID-19, according to the FDA's definition and existing examples.

Researchers have been working diligently since the beginning of the COVID-19 pandemic to curb online misinformation related to the virus. Researchers within the field of medicine have suggested that online social network users should engage in discussions, but recommend limiting time spent online and to make sure one gets their news from trusted sources [97]. Roozenbeek, et al. conducted a traditional survey-based approach to examine COVID-19 misinformation to determine which groups are the most susceptible [98]. Through several questions related to demographics and stance on COVID-19 topics, the researchers learned that the trust in scientists was high overall, and having quantitative skills was associated with decreased susceptibility to COVID-19 misinformation. Shahi, et al. also analyzed a corpus of tweets making COVID-19 references and observed that companies and celebrities often circulate misinformation through indirect methods, such as "likes" and "retweets" [99]. The analysis in this study also showed that companies and celebrities contributed to 70% of the “false” and “partially false” categories of misinformation.

Researchers have had success employing supervised machine learning techniques on data to detect and explore COVID-19 misinformation. Choudrie, et al. achieved accuracies above 86% in identifying misinformation using decision tree and convolutional neural network model classifiers [37]. These researchers extended this study by conducting interviews with older adults to ascertain how this demographic processes online misinformation. Al-Rakhami and Al-Amri built a tweets classifier to identify COVID-19 misinformation, using a large set of tweets that were annotated for this specific project [38]. They were able to build a reliable model for identifying tweets containing misinformation, and also demonstrated the rigors and costs of the annotation process. Serrano, Papakyriakopoulos, and Hegelich employed the transformer-based language models to identify YouTube videos that contain COVID-19 misinformation by examining the comments posted to the videos [39]. These researchers built a text classifier to identify comments of a conspiracy-related nature, and concluded that YouTube videos containing misinformation also have a high percentage of user comments mentioning conspiracy theories. Similarly, Kumar, et al. built a multi-label tweet classifier system using a RoBERTa-large transformer language model to identify COVID-19 misinformation [40]. The model was able to identify the four classes of Irrelevant, Conspiracy, True Information, and False Information and achieved an F1 score of 76%.

Unsupervised machine learning techniques have also been employed in COVID-19 misinformation research. Sear, et al. used Latent Dirichlet Allocation (LDA) to quantify and analyze Facebook posts regarding COVID-19 vaccines [41]. It was observed that the anti-vaccine posts exhibit a broad range of topics compared to the pro-vaccine posts. Kouzy, et al. conducted a non-machine learning based approach for describing COVID-19 misinformation on Twitter [42]. Here, these researchers manually segmented their collection of tweets into categories based on misinformation and/or containing unverified information. After further user account-level segmentation it was revealed that these types of posts were mostly coming from personal accounts. Dhiman and Toshniwal provided an unsupervised framework for analyzing COVID-19 misinformation on Twitter by generating semantic-based clusters to identify influential content related to COVID-19 [43]. Kwok, et al. performed LDA and sentiment on a corpus of tweets from Australian Twitter users making COVID-19 references [44]. These researchers were able to segment the COVID-19 conversations into three topics: attitude, advocating for infection control, and misconceptions/complaints. It was also observed that these tweets expressed an overall positive sentiment towards the COVID-19 vaccines.

4.2 Sentence-T5 Language Model

"Sentence-T5: Scalable Sentence Encoders from Pre-trained Text-to-Text Models" by Ni et al. [100] proposes a new model architecture for generating highly informative sentence representations that can be used in a variety of natural language processing (NLP) tasks. The model is based on the T5 transformer, which is a pre-trained text-to-text transformer model that has achieved state-of-the-art performance on several NLP benchmarks.

The Sentence-T5 model consists of two stages for generating sentence representations. In the first stage, the T5 encoder is used to encode the input sentence into a fixed-length vector. This vector is then used to generate a set of candidate sentence representations. In the second stage, a subset of these candidate representations is selected using an attention-based mechanism that assigns a weight to each representation based on its relevance to the target task. This attention-based mechanism ensures that the selected sentence representation is highly informative for the downstream task.

Compared to other transformer-based models such as BERT [45], which is designed to generate context-dependent word representations, Sentence-T5 is specifically optimized for generating sentence-level representations that are invariant to context. This makes it particularly useful for tasks that require understanding the meaning of a sentence, rather than just the meaning of individual words.

The authors demonstrate the effectiveness of the Sentence-T5 model for a wide range of sentence-level tasks, including sentiment analysis, natural language inference, and paraphrase identification. For example, Wang et al. [101] leveraged Sentence-T5 to generate sentence representations for neural machine translation, and their model outperformed several other state-of-the-art models on the WMT14 English-German and WMT16 English-Romanian translation tasks. Similarly, Ravanbakhsh et al. [102] utilized Sentence-T5 as a sentence encoder for entity matching tasks, and found that their model achieved superior performance on several benchmark datasets. In yet another application, Duan et al. [103] employed Sentence-T5 to generate sentence representations for semantic textual similarity tasks, and showed that their model outperformed several other state-of-the-art models on benchmark datasets.

The scalability of Sentence-T5 makes it a promising tool for real-world NLP applications that require processing large volumes of text data. The model is able to generate accurate representations for large datasets quickly and efficiently, which can greatly reduce the time and computational resources required for training models from scratch. This is due to the benefits of transfer learning, where the pre-trained Sentence-T5 model can be fine-tuned on specific downstream tasks, leading to significant improvements in performance with a relatively small amount of additional training data.

The Sentence-T5 model is a powerful tool for generating highly informative sentence representations that can be used in a wide range of NLP tasks. The model's scalability and ability to generate representations that are invariant to context make it a promising solution for real-world NLP applications. The benefits of transfer learning, where pre-trained models can be fine-tuned on specific downstream tasks, offer significant advantages in terms of reducing the amount of training data required and speeding up the development of NLP systems.

4.3 Commercial CBD Tweets During the COVID-19 Era

The Snscrape Python package is a third-party library that allows users to scrape Twitter data, including tweets, user profiles, and search queries, without the need for an API key [104]. It is different from using the traditional Twitter API in that it does not require authentication or API credentials, making it a more accessible and cost-effective option for data scraping. One of the advantages of Snscrape is that it allows users to retrieve historical tweets that are not available through the Twitter API. This can be useful for researchers and data scientists who need to collect large amounts of Twitter data for analysis. We used the Snscrape Python package to collect English language tweets from the Twitter.com website from January 1, 2020 through April 28, 2021 by searching for tweets using the following keywords: (CBD or cannabidiol) and (COVID-19, COVID, corona). While this method does not provide full access to Twitter's historic data, it does afford the ability to collect thousands of historical tweets retrospectively after an unexpected event has occurred, such as the pandemic. Using this method of historical Tweet searching we were able to collect 37,526 tweets from a 484-day period.

To extract the commercial CBD tweets referencing COVID-19, we used a model previously developed in chapter 3. The model was trained on an earlier collection of CBD tweets for the purpose of identifying those that reflect the commercial sales, promotion, and/or marketing of CBD. Applying the commercial CBD tweet classifier to the historical tweet collection resulted in 4,937 tweets that were classified as commercial CBD tweets referencing COVID-19.

We pulled specific FDA warning letters to understand what types of statements the FDA flags as misinformation. Based on our previous experience, we were aware of CBD-infused sanitizers. However, the FDA's CBD/COVID-19 warning letters did not include CBD-infused hand sanitizers, so we included the warning letters sent to advertisers of non-alcohol and essential oil sanitizer products for making false claims, as guidance in our misinformation annotation process [105, 106, 96, 107, 92, 108, 109, 94]. Figure A.4 is an example of one of the warning letters the FDA issued a seller for misleading the public on the benefits of CBD as a treatment for COVID-19. The extracted commercial CBD/COVID-19 tweets were annotated for misinformation (Y/N) according to the FDA's definition of misinformation by three university-trained, non-medical, professional annotators; discrepancies were decided by a majority vote to determine the overall label of the tweet.

Table 4.1: Five example quotes of CBD and COVID-19 misinformation.

Statement
Firstly, the research performed to date has shown that CBD can reduce a number of pro-inflammatory cytokines (numerous different types of substances, such as interferon, interleukin, and growth factors, which are secreted by certain cells of the immune system and have an effect on other cells) including IL-6, the one reduced by other drugs being studied for COVID-19. CBD was also shown to reduce interleukin (IL)-2, IL-1α and β, interferon gamma, inducible protein-10, monocyte chemoattractant protein-1, macrophage inflammatory protein-1α, and tumor necrosis factor-α – all of which are associated with the pathology of severe cases of COVID-19. In addition to reducing these pro-inflammatory cytokines, CBD has also been shown to increase the production of interferons, a type of signaling protein that activates immune cells and prevents viruses from replicating
there has been an increased interest in CBD and Covid-19 to treat lung problems and symptoms (mental or physical) associated with the coronavirus
CBD oil may help to prevent getting infected by strengthening your immune system. It has also been proven to offer relief to some of the symptoms.
By using CBD oil, you can keep inflammation at bay, retain a healthy or even higher than average white blood cell count, stay calm and relaxed (which is best for a strong immune system), and prevent catching a virus or infection beforehand.
Is CBD an Anti-Viral Agent for Coronavirus, Influenza, MERS, and Sars Plus Key Antiviral Supplements?

The warning letters on the FDA website provide some of the misleading quotes that sellers used within their advertisements that the FDA deemed dishonest. Some of the example quotes taken from these letters are shown in Table 4.1. Along with the FDA's definition of misinformation, these quotes provided a guideline for annotating the collection of tweets as to whether they contained misinformation. Table 4.2 displays select examples of the non-misinformation and misinformation tweets encountered during the annotation process.

Table 4.2: Examples of annotated commercial CBD/COVID-19 tweets.

Misinformation	**Non-Misinformation**
#CBD is readily available for anyone who want to build-up their immune to help guard against the #coronavirus . It's your responsibility to protect &; take care of yourself, not the government. Order Now	Could CBD offer treatment options for COVID-19? Read more at https://t.co/IReD02EMjL Global Go does not endorse the use of any product for medicinal purposes. Please consult with a physician before using any such products. #CBDtrials #hempresearch #hempnews #covid19
I've ordered a 4 month supply of #CBD to help fortify my immune system &; guard against the #CoronaVirusUpdates #COVID19 . What have you done to protect yourself? Order Now	First day of the week… First day of the month of June! Would you like to try something new? #Covid19 #SanFrancisco #SanFranciscobayArea #helpingthecommunity #Realestate #HartFordproperties #CBD Source:
#COVID19 attacks the inside of body/lungs which are internal so topical solutions will not mitigate what's happening inside your body/lungs. Ask me about #CBD. #cbdoil https://t.co/VKhutUztfS	Online sales for cannabidiol (#CBD) products continue to #flourish despite in-store slowdowns amid the COVID-19 #pandemic. #CSPDailyNews
#CBDL Could Double On Product Launch News. CBD Hand Sanitizer Could Help Stop Spread Of Covid-19. [Read Now] LINK #USA #Stocks #Bonds #Equities #Gold #Silver #Bitcoin #CryptoCurrency #Investing #Trading #Options #1Author #USStocks #StockMarket	New post (Iowa Down To One Medical CBD Manufacturer Due To COVID-19 Pandemic) has been published on Buy Premium CBD and CBG Products ǀ 100% Natural Cannabinol Store ǀ Buy CBD Oils, Gummies, Topicals, Pet CBD and more -

In the present study, we used a transformer language model to encode each of the commercial CBD tweets that we collected. Specifically, we used the Sentence-

T5 model as it is a state-of-the-art language model that has outperformed other models in semantic textual similarity [100]. We also computed the encoding for each of the statements containing misinformation taken from the FDA website into vectors of size 768. We then calculated the cosine similarity (Equation 4.1) between the encoding vectors of the tweets (A) and the encoding vectors of the misinformation quotes taken from the FDA warning letters (B).

$$cosine\ similarity = S_C(A, B) := cos(\theta)\frac{A \cdot B}{||A||||B||} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{4.1}$$

Equation for cosine similarity.

Figure A.5 provides a graphical representation of how we isolated tweets making false claims using the quotes taken from the FDA warning letters to find tweets that were contextually similar using cosine similarity. Using cosine similarity as distance of similarity, we expected that the shortest cosine distances should contain more misinformation i.e., tweets that were contextually similar to the FDA's samples. Conversely, we expected tweets with the longest cosine distances to contain less misinformation. Using these points, we identified a threshold at which we could confidently identify sets of tweets as mostly containing misinformation due to their semantic similarity to an established example of misinformation.

To further illustrate the flexibility of this extension of our framework we applied our approach to a corpus of tweets collected in 2019 using only the terms "CBD" and "cannabidiol," and misleading quotes taken from FDA warning letters regarding autism and Alzheimer's disease (A.6). In doing so, we show that by simply changing the quotes of known misinformation and the corpus in which misinformation is suspected, we can arrange these tweets in an order from most to least similar.

4.4 Analysis of Misinformation

After annotating the tweets for misinformation, we observed that approximately 19% (938) of the 4,937 tweets contained misinformation related to both CBD and COVID-19. An analysis of the misinformation n-grams indicated that "immune systems" was one of the most frequent themes (Table 4.3). We observed an increase in CBD/COVID-19 conversations beginning in February 2020. Misinformation related to CBD and COVID-19 peaked during March 2020, and while it appeared to have tapered down, it did not stop.

Table 4.3: Top n-grams in the CBD/COVID-19 misinformation tweets.

Term	**frequency**	**Term**	**frequency**
immune	257	natural	119
cbdoil	244	wellness	114
system	187	boost	112
immune system	181	oil	99
products	157	hand	96
help	152	sanitizer	92
hemp	139	cbdproducts	88
health	129	cbd products	85
virus	127	hand sanitizer	83
new	127	use	81
cbd cbdoil	125	immunity	78

4.5 Detecting Misinformation

Using 27 select misleading quotes taken from the FDA warning letters and converting that into vector form, then converting each of the tweets into vector form, we calculated the cosine similarity. Using the cosine distance, we then counted the number of tweets that were labeled as misinformation compared to the tweets that were considered non-misinformation. We observed that the nearest tweets indeed contained misinformation while the most distant tweets did not (Table 4.4).

We calculated the cosine distance between the sentence vector of each of the 27 statements that we extracted from the FDA warning letters, along with each of the

Table 4.4: Measuring the cosine distance between sentence vectors of statement #0 and the tweets.

Tweet	Position	Misinfo	Cosine Distance
With the growing concern of the COVID-19 virus we understand the importance of boosting the immune system. CBD is a natural way to do that. The Healing Leaf wants to help make CBD more available and lessen costs for those interested. Please come in or call and place your orders! https://t.co/ymBokl4nTY	Most Similar	Yes	0.069577
CBD may reduce cytokine storm and inflammation in COVID-19\nhttps://t.co/3G1B0tLQxn	2nd Most Similar	Yes	0.077852
They snuck a shipping ban on vape products into the last covid relief bill. All vape products. CBD, nicotine, delta 8, doesn't matter.	2nd Most Distant	No	0.296933
Final point: When COVID hit, we LOWERED our prices and never put them back up. Funny how reddit and Review haters never use their real names and 9/10 when you find out their real name - they run for the hills or perhaps just back to Mam's house and their keyboard....	Most Distant	No	0.297551

tweets, so that we could determine a cosine distance threshold in which we collected the most tweets that contained CBD/COVID-19 misinformation while minimizing false positives (non-CBD/COVID-19 misinformation). Figures 4.1 and 4.2 show a consistent observation that as the cosine distance increased, the number and percentage (recall) of the tweets containing misinformation captured increased. Figure 4.3 indicates that as the cosine distance increased, the precision of the tweets containing misinformation decreased. However, if the cosine distance was too small, few to no misinformation tweets were captured and not all FDA statements performed equally at capturing misinformation tweets.

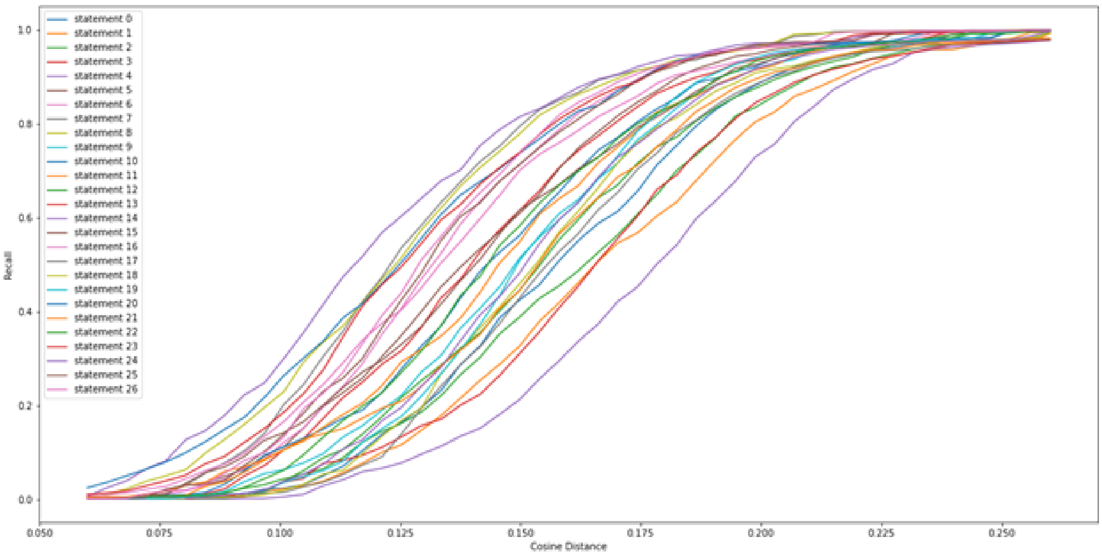

Figure 4.1: Cosine distance vs proportion of misinformation tweets captured.

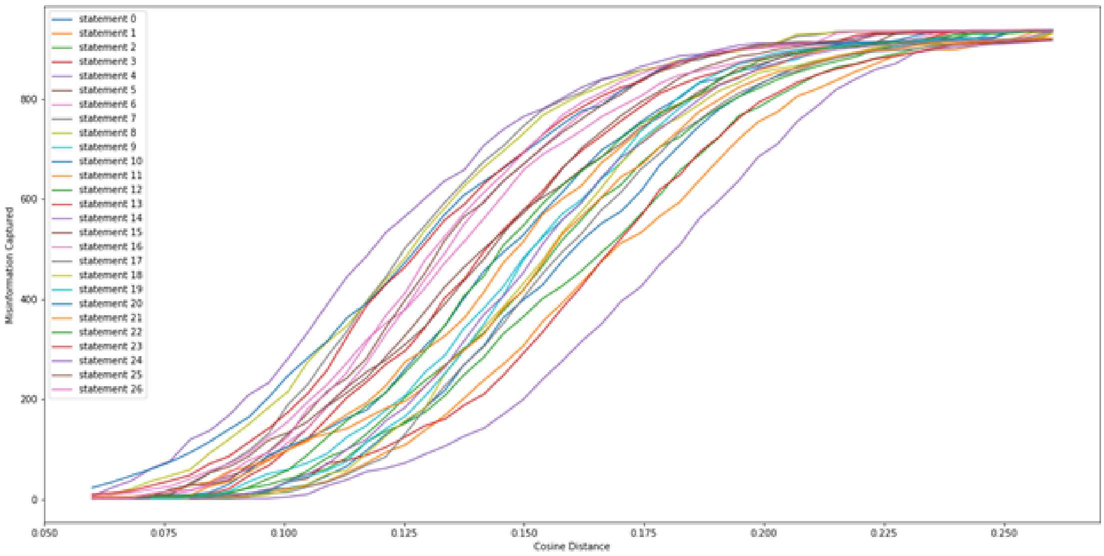

Figure 4.2: Cosine distance vs number of misinformation of tweets captured.

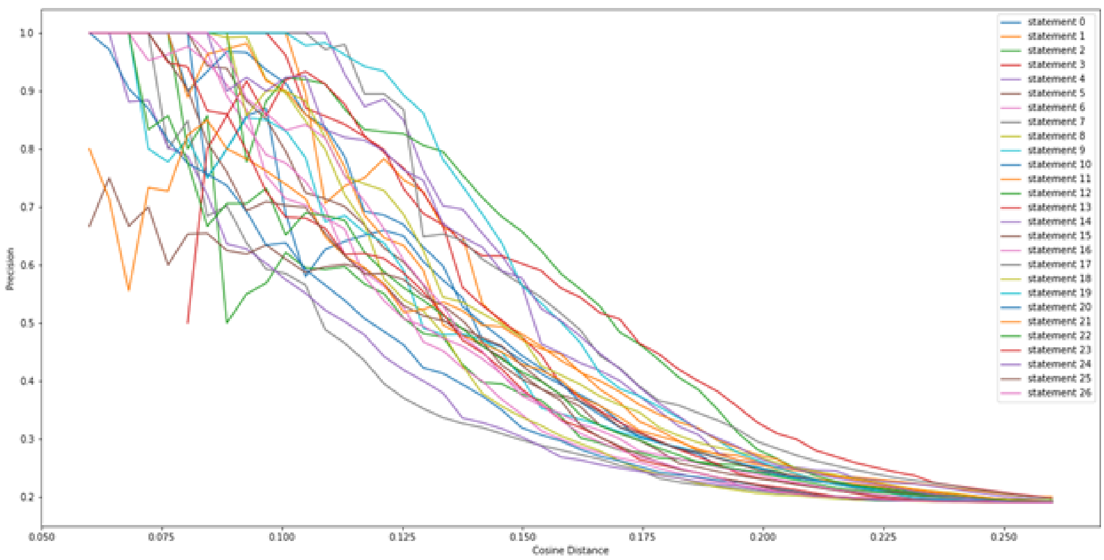

Figure 4.3: Cosine distance vs misinformation precision of tweets captured.

We also examined the top-five performing FDA statements for capturing high amounts of misinformation with a high precision (Table 5.6). Figures 4.4-4.6, are equivalent to figures 4.1-4.3, but with only the statements in Table 5.6 displayed. From these figures we can see that at a cosine distance between 0.10 and 0.13, we were able to capture between 22%-29% of the 938 misinformation tweets, with a precision of above 80%. Specifically, statement #8 was able to capture 323 tweets at a cosine distance of 0.105 and 84.8% (274) of these tweets were labeled as misinformation. These 274 tweets captured represent 29.2% of the 938 of misinformation in our dataset.

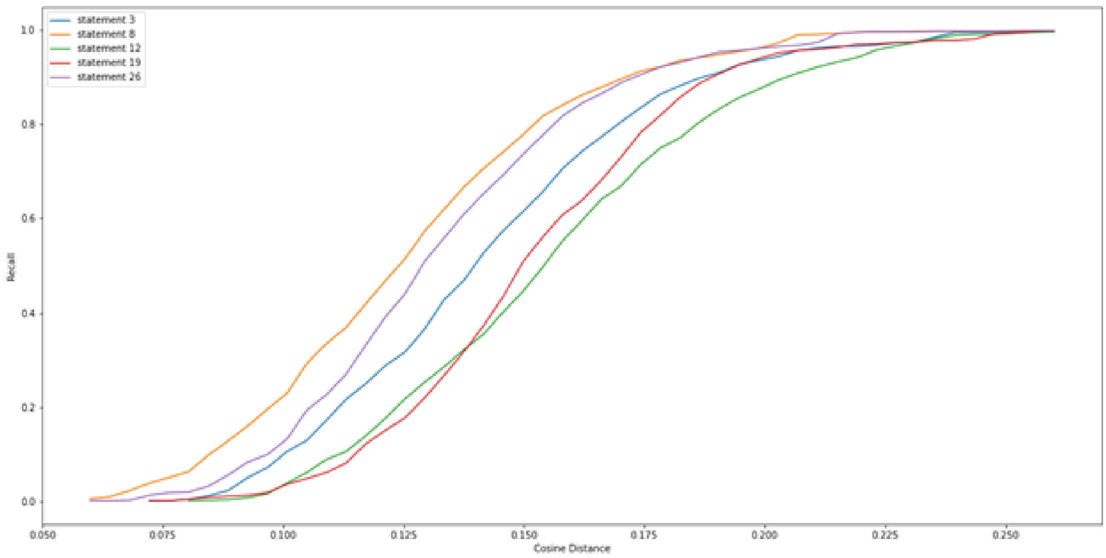

Figure 4.4: Cosine distance vs percentage of misinformation tweets captured.

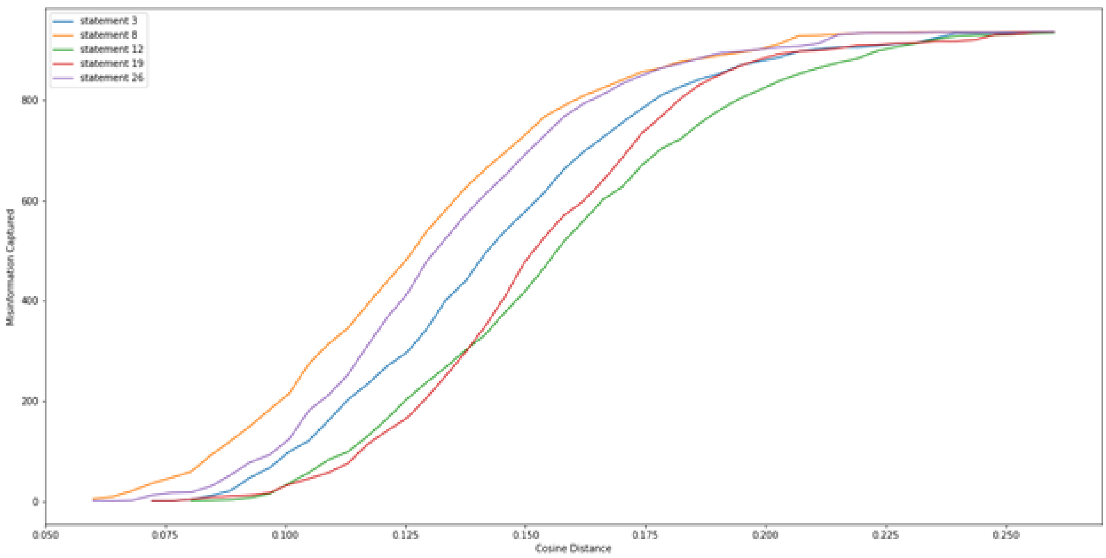

Figure 4.5: Cosine distance vs number of misinformation of tweets captured.

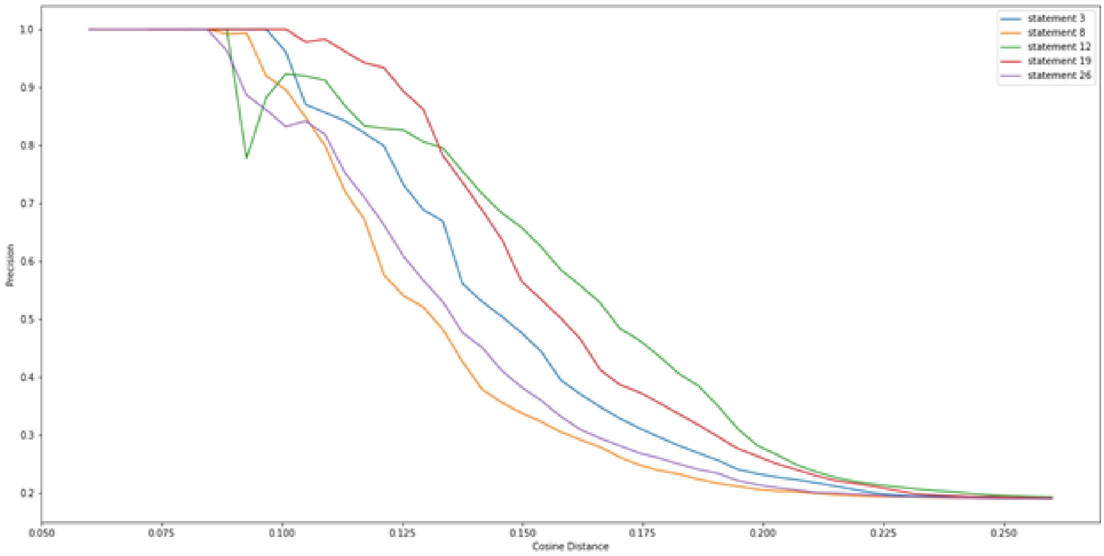

Figure 4.6: Cosine distance vs misinformation precision of tweets captured.

4.6 Application to Other Forms of Misinformation

Our proposed framework demonstrates its versatility by identifying false claims about CBD and two other medical conditions, which suggests that this approach could potentially be a quick and easy way to detect other forms of misinformation on Twitter. Specifically, we extracted quotes from an FDA warning letter regarding misinformation surrounding CBD, autism, and Alzheimer's disease, and utilized these statements to identify semantically similar tweets from a corpus collected in 2019 which referred to CBD or cannabidiol. To narrow down the tweets, we only kept those that mentioned autism, dementia, or Alzheimer's disease. As shown in Table 4.5, tweets that were most similar to the misinformation samples made false claims that CBD could alleviate the symptoms of autism and Alzheimer's disease, while the most dissimilar tweets did not make any false claims about CBD's ability to treat these conditions.

Table 4.5: Most similar and most distant tweets to misinformation quotes regarding Alzheimer's disease.

FDA Misinformation Quote	**Most Similar Tweet**	**Most Distant Tweet**
CBD oil may have neuroprotective properties and may protect against neurological conditions, such as Parkinson's and Alzheimer's disease.	@FlippyO @FrontByrner @DrSeanMackey @supportprop @andrewkolodny On the up side, some evidence suggests THC and CBD may be neuroprotective, so there's a rationale for some MMJ for you. Alzheimer's prophylaxis	@marysuewriter do not believe he was the co-owner and while the store is definitely shitty, the sign did not say CBD cures autism
Possible uses for CBD include helping with skin problems such as acne, autism, ADHD, and even cancer. It's often used in conjunction with traditional treatments to provide extra help. Children can use high amounts of CBD safely and without any risk. 0.092163	CBD is recommended as a treatment for conditions such as seizures, depression and anxiety, and symptoms such as sleeplessness, inflammation, acne, and pain. It has also proven to be effective in treating autistic children.\nSource: https://t.co/e7ZpneP2cy https://t.co/ReBzFyyO18	4)Sydney is demonstrating that she understands what effectual customer demands are, which is going straight to the source to demand change. She didn't see a phone number she could call on the sign that promoted CBD as a cure-all for autism, so she went in to ask for one

4.7 Discussion

Misinformation about COVID-19 can have devastating consequences, potentially leading people to misunderstand how the virus spreads and the risks it poses. This misinformation can then be communicated to others, who may also spread it, putting themselves and others in danger. In light of these risks, this study highlights the prevalence of misleading information about CBD and COVID-19 and offers an effective approach to identifying and addressing this problem. This approach can be used by government entities and social network and message board administrators to minimize the harmful effects of false advertising.

Allem et al. confirmed that misleading claims regarding cannabis (the plant in which CBD is extracted) take place in online conversations [66]. Through analyzing a subset of historical tweets, we observed that misinformation regarding CBD and COVID-19 has occurred throughout the COVID-19 pandemic. Much of this misinformation alleged an improved immune system and reduction in inflammation pains with CBD use. We also observed several instances of tweets promoting the sale of CBD-infused hand sanitizers. While there have been some preliminary studies on the benefits of cannabis in treating the effects of the COVID-19 virus, findings are uncertain and at the time of this writing cannabis is not an approved treatment by the FDA [93]. Thus, claiming that CBD products can unequivocally treat or prevent COVID-19 is a US federal violation. In the US, the FDA has made numerous attempts to warn online retailers making false claims about their products [87]. In many cases, these retailers claim CBD improves the immune system's ability to fight the COVID-19 virus, while others claim CBD can reduce lung inflammation in those infected with COVID-19.

Our study presents an innovative methodology to detect tweets disseminating misleading information about CBD and COVID-19. Specifically, we employ a quote-based approach by utilizing the warning letters as the reference to identify tweets that exhibit semantic and contextual similarities based on cosine distance of sentence vectors. Our approach significantly reduces the time required to identify tweets containing false claims related to health conditions and enhances the confidence level of flagging such tweets. In the event of extensive or future access to Twitter data, our misinformation tweet classifier can efficiently recognize current tweets and potential violations in near-real-time. Additionally, the proposed methodology can be adapted to identify other types of misinformation that could potentially endanger public health and safety.

In our study, the presence of 'bots' on Twitter was not explicitly acknowledged. However, we addressed this implicitly by initially filtering tweets to include only those containing references to commercialization or sales of CBD. The model used in this study was trained on a dataset of CBD-related tweets prior to the COVID-19 pandemic. Consequently, the terms "COVID," "COVID-19," "corona," and "coronavirus" were not associated with "CBD" and "cannabidiol" at the time of training. We suspect that the health-related terms associated with CBD have evolved over time, rendering the overall CBD Twitter datastream subject to concept drift. Further research should investigate the temporal evolution of the CBD Twitter datastream to identify periods when the conversations have shifted, as such concept drift can adversely affect machine learning models. In a recent study on concept drift in Twitter datastreams, Bechini et al. used a semantic-based classifier based on the BERT language model to examine changes in opinions about vaccines within a corpus of Italian tweets. The transformer-based model outperformed other strategies, such as retraining ensemble approaches, suggesting that it could be robust against temporal changes in identifying commercial tweets [65].

Our proposed extension of the CBD-TM model showcases the efficacy of utilizing cosine similarity between quotes obtained from FDA warning letters to identify tweets containing false claims regarding CBD and COVID-19. Moreover, we demonstrate that making simple modifications to this extended framework could enable the identification of other types of misinformation on Twitter, including false claims about CBD as a treatment for Alzheimer's disease and autism. Given the harmful impacts of COVID-19 misinformation on social media, we anticipate that our approach for detecting misinformation will be beneficial for public health stakeholders and other allied sectors.

CHAPTER 5

ON THE EXPLANATION OF TEMPORAL CHANGES IN CBD TWITTER DISCOURSE BETWEEN 2011-2021

This chapter presents a historical analysis of ten years of anglophone Cannabidiol (CBD) tweets, using temporal topic modeling. The study proposes a classification method that distinguishes commercial and non-commercial tweets, in order to better understand how topics change over time. The conversation surrounding CBD topics is influenced by cannabis laws, policies, and consumers, and these topics evolve in response to changes in these areas. While social media platforms such as Twitter capture social information and facilitate the spread of information, misinformation is also a social threat. Therefore, this study aims to identify changes and underlying continuities in the CBD conversation on Twitter.

The role of social media in social change has been a persistent focus in media studies, and this chapter acknowledges the importance of continuity by contrasting the overall concept drift in keywords with an analysis of associated topics. The use of topic modeling has been shown to be an effective tool in mining tweets. This chapter finds that while keywords and specific medical issues drifted over time, the overall strategy of marketing CBD as a medical product remained consistent. Thus, this study illustrates the process of conceptual drift in anglophone CBD topics between 2011 and 2021.

To better understand how CBD topics respond to social stimuli, this chapter proposes a classification model that distinguishes between commercial and non-commercial tweets. Changes in the classification confidence can help detect changes in the conversation. This study demonstrates how the CBD conversation on Twitter has evolved over time, and how the classification model can be used to identify changes and monitor trends.

This chapter highlights the importance of monitoring social media conversations surrounding CBD topics. It is crucial to identify and address misinformation in these conversations, especially given the potential impact on public health. This study also demonstrates the potential of temporal topic modeling and classification models in understanding the evolution of social media conversations.

5.1 Introduction

Studying CBD on social media platforms like Twitter is essential because they capture social information and provide a venue for the spread of misinformation. Misinformation is a potential social threat, whether intentional or otherwise, and has been studied extensively [110, 111]. By analyzing tweets that promote CBD, we can better understand how misinformation circulates on Twitter, and better understand its effects on public perceptions and policies. Media theorists have studied Twitter as both an advertising environment and an agent for the process of social change [112].

Here, we explain the process of concept drift in anglophone CBD topics between 2011 and 2021. By visualizing temporal topic changes, we demonstrate how the CBD topics respond to social stimuli. Focusing on concept drift as a process of social change captures the underlying continuity of CBD marketing strategies and their relationship to broader social, political, and economic factors.

Studying the changes and continuities in the CBD conversation on Twitter over a 10-year period allowed us to shed light on the evolving trends and strategies in CBD marketing and the spread of misinformation on social media platforms. The insights gained from this study can inform policy decisions and contribute to a better understanding of the complexities of the CBD industry.

5.2 Logistic Regression & Concept Drift

Concept drift is a fundamental challenge in machine learning that arises when the statistical properties of the data change over time. This phenomenon makes it difficult for machine learning models to adapt to changes in the environment and can cause a decline in model performance over time [113]. In the context of a tweet classifier, concept drift can significantly affect the accuracy and reliability of the model's predictions, especially when the data distribution changes significantly over time. A relevant use-case for this concept is the commercial CBD tweet classifier that was trained on 2019 data (chapter 3) and is being used to classify tweets that reflect sales or promotions of CBD from 2011-2021. During this period, the landscape for CBD marketing and sales underwent significant changes, including changes in federal and state regulations, which have had a significant impact on the market for CBD products. In the US, the legal status of cannabis and related products, including CBD, has changed dramatically over the past decade. In 2011, the use of cannabis was illegal under federal law, and only a handful of states had legalized it for medical use. However, by 2019, several states had legalized cannabis for medical and recreational use, and the federal government had passed the Farm Bill, which legalized the production and sale of hemp-derived CBD products [114]. These changes in the regulatory environment are likely to have had a significant impact on the language and sentiment of tweets related to CBD sales and promotions, making it difficult for a classifier trained on data from 2019 to accurately classify tweets from earlier years. For instance, before the passage of the Farm Bill, tweets promoting CBD might have been more cautious in their language and focused on the potential health benefits, while post-legalization tweets might have been more promotional and focused on the product's availability and ease of access. As a result, a classifier trained on data from 2019 may suffer from concept drift. To address this challenge, it may be necessary to periodically retrain the model with new data to ensure that it remains accurate and relevant in the face of changing trends and regulatory environments.

The method proposed by Haque et al. [115] provides a means of detecting concept drift in tweets between 2011 and 2021 using a logistic regression model that was trained on 2019 data. Building upon this approach, this chapter proposes a hybrid ensemble-based method that combines an ensemble of base models with a meta-model that employs model confidence to detect concept drift. This method adapts the ensemble of base models by dynamically adding or removing models based on their individual performance and uses the meta-model to analyze the model's confidence level for detecting changes in the data distribution. The central idea is to employ the logistic regression model, which was utilized for tweet classification in chapter 3, on new incoming tweets and track changes in the data distribution via its confidence scores.

To classify commercial CBD tweets, one can utilize the logistic regression model trained on 2019 data directly to classify tweets between 2011 and 2021. The model's performance can be monitored over time by examining its confidence scores. A significant decrease in confidence scores indicates that the model's performance is declining due to concept drift. Given that CBD policies have undergone changes during this period, the distribution of commercial CBD tweets may have also changed significantly, leading to concept drift. In this context, monitoring the confidence scores of the model provides a concrete and effective method to detect and handle concept drift. If concept drift is detected, it is necessary to train a new model or adapt the existing model to the new data distribution.

5.3 BERT-Based Topic Modeling

Topic modeling is a widely used technique in natural language processing that aims to uncover latent themes or topics within large collections of unstructured text data. The goal of topic modeling is to identify patterns of co-occurring words that frequently appear together across documents and group them into distinct topics that provide meaningful insights into the underlying content. Various topic modeling methods exist, including Latent Dirichlet Allocation (LDA) [116], Non-negative Matrix Factorization (NMF) [117], and probabilistic Latent Semantic Analysis (pLSA) [118]. Despite the effectiveness of these methods, they often struggle with certain aspects of the data, such as handling short or noisy text, identifying synonyms, and capturing the full context of the text. BERT-based topic modeling methods aim to overcome these limitations by leveraging the power of pre-trained language models such as BERT (Bidirectional Encoder Representations from Transformers) [45] to better understand the nuances of the text data and generate more accurate and coherent topics. BERT-based methods have shown promising results in various natural language processing tasks, including sentiment analysis, question answering, and named entity recognition, and are expected to further improve the quality of topic modeling results [119].

BERT is a pre-trained neural network architecture that learns contextual relationships between words in a given text corpus [45]. The model is trained on a large amount of text data, learning to predict the likelihood of a word appearing in a given context based on the other words around it. This allows the model to encode contextual information, capturing the meaning of a word based on its surrounding words [120]. The BERT language model can be used for a wide range of natural language processing tasks, including text classification, named entity recognition, and question answering across a variety of languages [121]. In terms of semantic similarity, BERT can be used to calculate the degree of similarity between words, phrases, or sentences. This is achieved by using the model's output to produce a vector representation of each piece of text, which can then be compared using a similarity metric such as cosine similarity [122].

The BERT language model captures the semantic meaning of polysemous words (words with multiple meanings). Yenicelik et al. created a dataset of sentences containing polysemous words and then examined the representations of these words in BERT using various techniques [123]. They found that BERT captures different senses of polysemous words in a relatively separable manner, with each sense occupying its own region in the BERT embedding space. They also showed that the context in which a polysemous word appears can significantly affect how BERT represents the word.

The schematic diagram depicted in Figure 5.1 provides a depiction of the pipeline of the BERTopic model [124]. BERTopic utilizes a pre-trained BERT model to produce dense vector embeddings for every document in the corpus [3]. These embeddings encode the semantic meaning of the text by representing each word in a continuous vector space. In addition, BERTopic incorporates dimensionality reduction methods such as Uniform Manifold Approximation and Projection (UMAP) to lower the dimensionality of the embeddings, thus increasing the efficiency and effectiveness of the clustering process. For clustering similar documents based on their embeddings, BERTopic utilizes density-based clustering algorithms, such as Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), that can manage clusters of different densities, which is suitable for text clustering. BERTopic extracts topics by identifying the most representative documents within each cluster. Coherence, which is computed based on the pairwise cosine similarity between document embeddings, is used to evaluate the representativeness of the documents. The most representative documents are then subjected to extractive summarization algorithms, generating a summary for each topic. Based on their embedding similarity to the representative documents of each topic, the documents are then assigned to one or more topics, with any document that is not sufficiently similar to any topic being assigned to an "outlier" topic. BERTopic also provides a range of visualization tools, such as topic keyword visualizations, document visualizations, and topic hierarchy visualizations, to enable users to investigate and comprehend the resulting topics. This approach has been utilized in the topic model analysis of a variety of social network studies [125, 126].

The utilization of BERT-based topic models for extracting insights from short and unstructured text exhibits significant potential. The efficacy of BERT-based models can be attributed to their ability to capture the semantics of individual tokens, leveraging the neural network's pre-training to understand the contextual meaning of words and phrases. By applying this BERT-based topic model to a corpus of text related to CBD over a period of time, we can gain insights into how conversations related to CBD have changed over time. One way to analyze the changes in the usage of CBD over time is by clustering related pieces of text into specific topics such as the health benefits of CBD or legal and regulatory issues. By examining how the frequency and content of these clusters change over time, we can identify the evolving trends in the usage of CBD. For instance, we can track the changes in the usage of CBD for health benefits and how the legal and regulatory issues have affected it, especially with the introduction of new legislation. By leveraging the notion of semantic similarity, we can gain a more

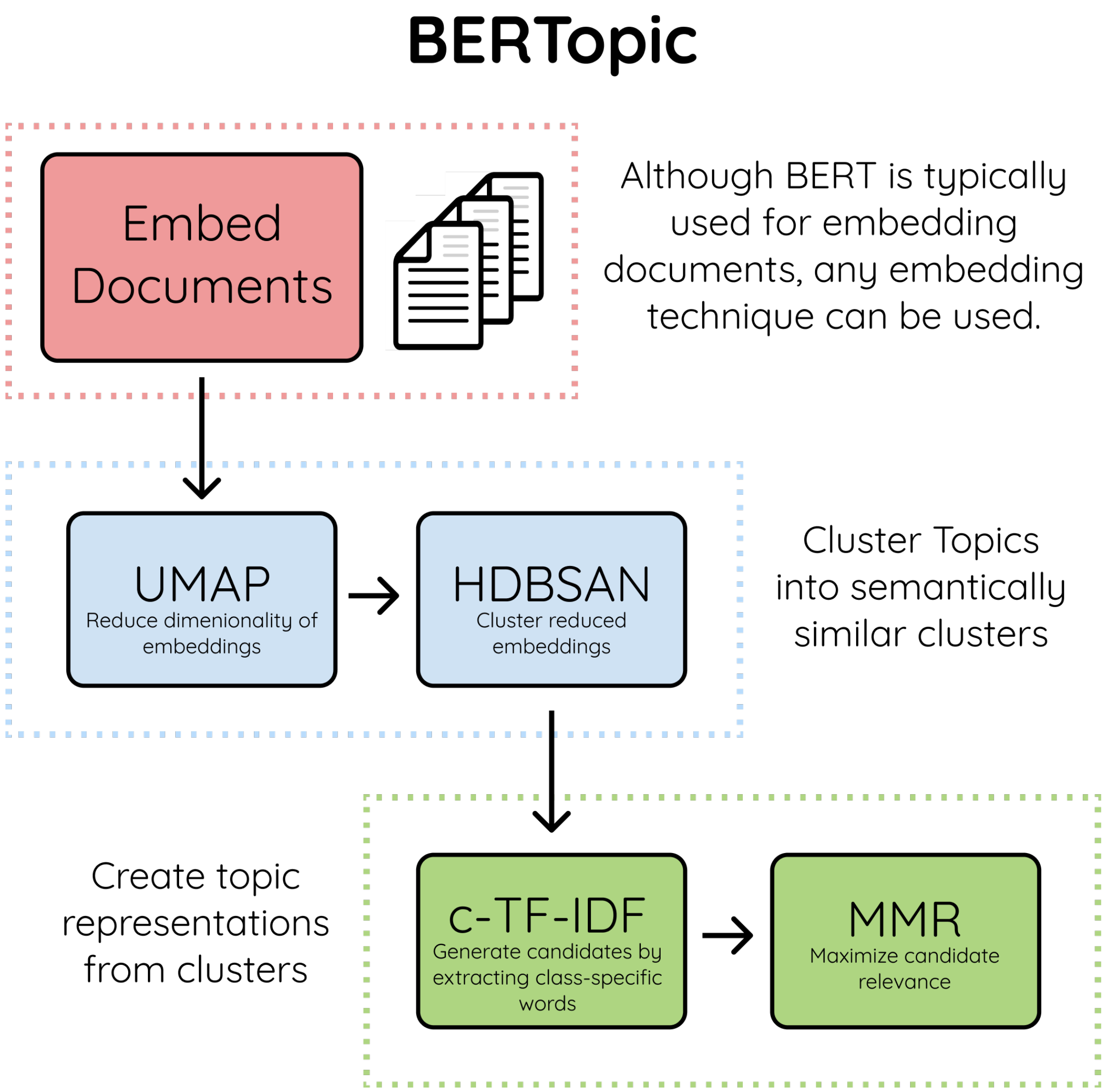

Figure 5.1: Pipeline of BERTopic Model [3]

nuanced understanding of how conversations related to CBD have evolved over time.

5.4 Methods for Detecting Changes in CBD Conversations

The data presented in Figure 5.2 indicates a significant increase in the number of tweets mentioning CBD since 2011, with the largest increases occurring in 2015 and 2017. This growth in CBD-related tweets suggests a growing interest in CBD among Twitter users over the years. The distribution of the number of CBD-related tweets collected in recent years has been somewhat variable, with a peak in 2020 and a decrease in 2021. This trend may reflect the impact of various external factors on Twitter usage, such as changes in CBD legislation, social media trends, or global events. Nonetheless, the overall trend highlights a consistent increase in interest in CBD among Twitter users. As social media platforms continue to play an increasingly important role in shaping public perceptions of health-related topics, the data presented in this study serves as a valuable contribution to the emerging field of social media analytics. Further research is needed to explore the underlying reasons for the observed trends and to investigate the potential impact of social media on public health beliefs and behaviors.

The distribution of the CBD-related tweets corpus, as illustrated in Figure 5.2, highlights the importance of monitoring and analyzing social media conversations around CBD. This information can be useful for businesses, policymakers, and public health professionals in gaining insights into consumer perceptions and behaviors related to CBD. By leveraging social media analytics tools such as SnsScrape and data visualization techniques, researchers can generate meaningful insights into public perceptions of health-related topics and inform evidence-based decision-making. As the use of social media continues to grow, it is likely that social media analytics will play an increasingly important role in public health research and policy.

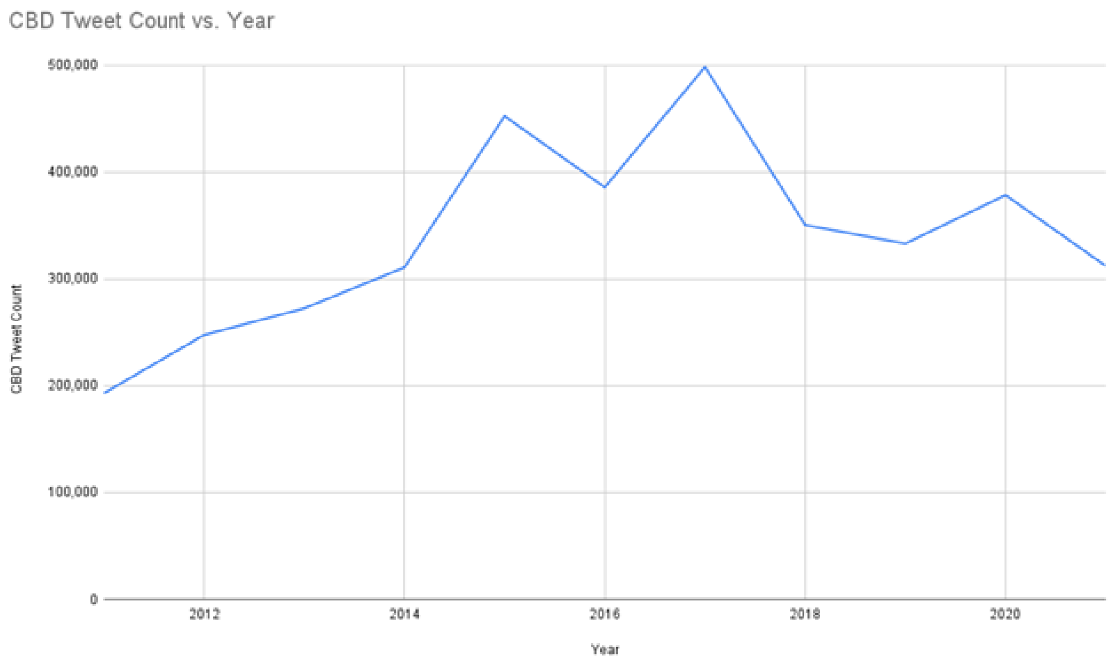

Figure 5.2: Collection of CBD Tweets 2011-2021

The use of logistic regression model, along with confidence scores, provides a valuable tool for unsupervised concept drift detection [115]. Confidence is a measure of the probability or likelihood of a specific classification or outcome for a given input. This measure is obtained by applying the logistic function to the linear combination of the input features and their corresponding coefficients. The logistic function transforms the output of the linear combination into a value between 0 and 1, representing the probability of the positive class. The higher the probability is to 1, the greater the model's confidence that the input belongs to the positive class, and vice versa. The confidence of the logistic regression model is often utilized to make decisions based on the predicted outcome. For instance, in binary classification problems, a threshold value can be set for the predicted probability to classify the input as positive or negative. The threshold value can be adjusted to increase the sensitivity or specificity of the model based on the desired trade-off between false positives and false negatives. The confidence of the logistic regression model reflects the degree of certainty the model has in its predictions and can be a valuable metric for assessing the model's performance and making decisions based on its predictions.

By monitoring changes in confidence over time, we can identify shifts in the underlying data stream, which can save time and resources in data analysis. The logistic regression model assigns probabilities to each data point in a given data stream. For example, a commercial CBD tweet classifier generates probabilities for whether a tweet belongs to the commercial CBD category or the non-commercial CBD category [67]. Ideally, these probabilities are concentrated towards either end of the sigmoid function, indicating a high degree of alignment between the words in the tweet and the keywords used in the model. However, when the probabilities are close to 0.5, it suggests that the model is unable to confidently classify the tweet, possibly due to insufficient alignment between the words in the tweet and the keywords in the model. By tracking the confidence scores produced by the logistic regression model over time, we can identify changes in the underlying data stream and, therefore, detect concept drift.

To detect concept drift, the historical tweet dataset is divided into chunks, with each chunk representing one month of CBD tweets. The average confidence scores for each chunk are recorded and plotted over time. Significant changes in confidence are identified as changes of more than 5% from the previous month. This approach offers a reliable and cost-effective way to detect concept drift in data streams without the need for explicit supervision. Therefore, the logistic regression model's confidence score plays a crucial role in unsupervised concept drift detection, making it a valuable tool in data analysis.

The BERTopic model is a powerful tool that utilizes semantic similarity to create topics. This method involves encoding each piece of text in the corpus into a vector representation using the pre-trained BERT model. These vector representations are then clustered together using HDBSCAN to create clusters of similar documents. After clustering, all documents within each cluster are combined to create a single document representing that cluster. A bag-of-words representation is then used to count the frequency of each word in each cluster, which allows us to determine the distinguishing features of each cluster and the words that are unique to each.

To determine the importance of each word within a cluster, the class-based TF-IDF method is applied. This method treats all documents within a single cluster as a single document and calculates the importance of each word within the cluster using TF-IDF. The importance score of each word within a cluster is obtained by multiplying the cluster-based term frequency (TF) and inverse document frequency (IDF).

One of the key advantages of using the BERTopic model is that it requires minimal preprocessing of text. This is because the BERT model is pre-trained on large amounts of raw text data and has already learned to understand the context and meaning of words and phrases within a sentence or paragraph. However, some preprocessing is still necessary to reduce noise in the data. This includes removing URLs, Twitter usernames, and non-alphabetic characters, as well as converting the text to lowercase. By using the BERTopic model, we can effectively analyze large amounts of text data and identify important topics and themes without the need for extensive preprocessing.

To conduct a comprehensive analysis of Twitter discourse surrounding CBD, we leveraged the BERTopic model in two distinct yet complementary ways. First, we applied the model to yearly chunks of the tweet collection that specifically mentioned CBD, allowing us to examine the prominent topics and themes that were prevalent within each calendar year. Second, we randomly selected a proportional sample of 250,000 tweets that mentioned CBD from across all years between 2011 and 2021 to which to apply the model. This approach was necessitated by the computational intensity of the BERTopic model, which rendered it impractical to process the entire dataset of over three million tweets in a single iteration. By analyzing the randomly selected subset in tandem with the yearly chunks, we were able to identify broader trends and patterns within the data stream, while still retaining a granular view of the most salient topics within each calendar year. Overall, this multi-pronged approach enabled us to effectively navigate the computational challenges posed by the size and complexity of the dataset, and to derive deeper insights into the evolving discourse surrounding CBD on Twitter.

5.5 Results

In this study, we aimed to detect instances of concept drift in the dynamic and continuously evolving Twitter data stream. To achieve this, we employed a commercial classifier, CBD, which was trained on data from the year 2019, as detailed in Chapter 3. Subsequently, we classified each tweet using the CBD classifier and recorded the corresponding model confidence score. We analyzed the classifier's confidence in distinguishing between tweets related to commercial CBD and those that are not, to identify any variations in the data distribution over time.

Figure A.7 displays the graphical representation of the results. The non-commercial CBD tweets exhibited a consistent and stable level of model confidence over time. However, the classifier's confidence levels for tweets related to commercial CBD gradually declined as the temporal distance from the training year (2019) increased. This observation suggests the presence of constant concept drift within the data stream.

Overall, our results demonstrate that the use of CBD classifier enables the detection of concept drift in the dynamic and continuously evolving Twitter data stream. These findings highlight the importance of regular monitoring and updating of the classifier to account for such drift and ensure optimal performance.

The year 2013 (as depicted in Figure A.8) witnessed a substantial increase in Twitter references to three essential cannabis components - CBD, THC, and CBN. This trend emerged alongside media coverage from reputable news outlets such as CNN and ABC, reporting on the use of CBD to alleviate seizures in children [127, 128]. The association of CBD with medical therapy gained momentum in 2014 when Kannaway, a subsidiary of Medical Marijuana, Inc., launched its direct sales program in the United States. Kannaway became the premier publicly traded hemp corporation in the country, pioneering the direct sales of CBD, the first to legally convey CBD across state lines and international borders, and the first to patent CBD products as "antioxidants and neuroprotectants" [129].

Our findings suggest that the media coverage of CBD as a potential therapy for seizures and the direct sales program by Kannaway played a crucial role in the significant upsurge in Twitter references to CBD, THC, and CBN in 2013. This increase demonstrates the influence of media and commercial activities on public awareness and perception of cannabis components. Furthermore, Kannaway's direct sales program in the United States set a precedent for the legal sale and distribution of CBD products, which paved the way for the widespread availability of CBD products in the market.

Through an examination of year-to-year changes in Twitter references to hemp-related compounds, our analysis revealed a shifting set of keywords. Notably, keywords such as Alzheimer's, dementia, multiple sclerosis, Crohn's disease, migraines, Parkinson's, and ALS began appearing more frequently over time. However, despite the changing terminology, misinformation and its sources - hemp companies - persisted (Figure A.12).

While these shifts in keywords may initially appear to be a form of concept drift, they demonstrate an underlying consistency in the propagation of unsubstantiated medical claims by hemp companies. These companies relentlessly peddle their products to the public, heedless of the potential consequences. Our findings suggest that the increasing frequency of medical conditions associated with hemp-related compounds in Twitter references is likely the result of the continuous promotion of such compounds as remedies by hemp companies, rather than a true shift in the data distribution. This underscores the need for caution in accepting such claims and for greater regulation of the hemp industry to ensure public safety.

In the years 2016-17, we observed a noticeable shift in the medical topics associated with CBD, as the focus moved towards less regulated concerns such as anxiety, pain management, ADHD, depression, and inflammation. These issues are often chronic, multifactorial, and symptomatically treated, which makes them ideal targets for wellness marketing strategies. It is worth noting that these topics have persisted and remained in circulation through 2021, underscoring the enduring prevalence of CBD in the realm of health and wellness.

As shown in Figure A.14, the top 10 terms of the top 8 topics in 2019 provide insight into the current state of Twitter discussions surrounding CBD. These topics illustrate how the use of CBD as a remedy for health concerns continues to be prevalent and relevant. Thus, our findings emphasize the need for further research on the efficacy of CBD for the treatment of such conditions, as well as the regulation of its use for therapeutic purposes. This will ensure the safety and well-being of those who use these products.

In order to extract the main themes and subject matters from the tweets regarding hemp-related compounds from the years 2011-2012 (proportionally sampled by year), we utilized the BERTopic model. This model generated numerous topics, but due to their excessive volume, we condensed them down to 25, retaining only the most relevant and representative themes for further analysis. To better understand the interrelatedness and organization of the various themes within the dataset, we employed the clustering of BERT embeddings. Figure A.16 visually represents the hierarchical structure of the topics, which enables a more nuanced and detailed understanding of the relationships between the various themes. This approach facilitates a more comprehensive analysis of the tweets and provides valuable insights into the dominant topics of discussion during this period.

To investigate the medical aspects of hemp-related compounds, we identified topics within the top 10 term representation generated by the BERTopic model (Figure A.17). These topics comprised a diverse set of terms such as pain, arthritis, cancer, tumor, breast, epilepsy, seizures, Alzheimer, anxiety, PTSD, stress, and MS. We conducted a close examination of these topics to gain a comprehensive understanding of the medical issues that have been linked to hemp-derived compounds and the language used to describe them within the dataset. This analysis provided us with valuable insights into the medical concerns associated with these compounds.

After conducting an analysis of the topics generated by the BERTopic model, we observed a discernible temporal pattern concerning the association between CBD and health-related terminology (Figure A.18). Specifically, we noted that the co-occurrence of CBD-related discussions with medical conditions did not emerge until 2014, reached its peak in approximately 2015, and then experienced a notable decline in 2016. However, this trend has persisted and undergone fluctuations in subsequent years. Our findings suggest that the relationship between CBD and medical terminology has been evolving over time, with a peak in interest during the mid-2010s. It is important to note, however, that while the frequency of CBD-related discussions with medical conditions has varied over time, they continue to be a prevalent topic of discussion in the Twitter sphere.

One limitation encountered while analyzing temporal changes in the discourse around CBD is the persistent presence of references to Central Business Districts (CBDs), particularly in Australia. Within the sample, commercial recommendations for coffee and lunch spots in CBDs and complaints of traffic congestion were prevalent. Additionally, an analysis of the most active accounts tweeting about CBD indicated that they are CBD brand ambassadors and accounts dedicated to horror movie appreciation, reflecting the diverse interests and industries associated with the CBD acronym.

5.6 Conclusion

In this chapter, our main objective was to detect instances of concept drift in the constantly evolving Twitter datastream using the commercial CBD classifier, which was trained on data from the year 2019. This study holds significant importance as accurate and timely identification of concept drift is a crucial problem in real-time data processing. To accomplish this, we classified each tweet using the aforementioned classifier and recorded the corresponding model confidence score, which was then graphically plotted. The model's confidence in distinguishing between tweets related to commercial CBD and those unrelated to the same was analyzed to detect and analyze any variations in the data distribution over time.

The findings of this chapter provide valuable insights into the evolving discourse surrounding commercial CBD tweets and the impact of misinformation in the CBD industry. By using advanced natural language processing techniques, we were able to identify and track changes in commercial and non-commercial CBD tweets over a 10-year period. The observed gradual, perceptible decline in the classifier's confidence levels for tweets related to commercial CBD as the temporal distance from the training year (2019) increased, suggests the presence of constant concept drift within the data stream. This finding highlights the need for continuous monitoring and adaptation of machine learning models to keep pace with the ever-evolving data distribution.

Overall, this chapter contributes to the growing body of research on concept drift detection and adaptation in real-time data processing, with specific focus on the CBD industry. The insights gained from this study can be used to inform policy decisions and help businesses to better navigate the complex and rapidly changing landscape of social media discourse surrounding CBD.

The chapter uncovered an intriguing finding that the underlying logic of marketing CBD as a medical product remained consistent, despite a shift in keywords used in commercial tweets over time. The analysis further revealed that the CBD industry heavily relied on cherry-picked medical studies to make bold claims about CBD as a treatment for various medical conditions; many of these claims are not supported by current medical practice.

An unsupervised approach using logistic regression confidence was utilized to detect concept drift, revealing that the misinformation in commercial CBD tweets caused a significant shift in the topic modeling algorithm. Conversely, non-commercial CBD tweets remained consistent over time, possibly indicating that CBD misinformation may not impact consumer conversations on a large scale.

To gain further insight, the study also utilized BERT topic modeling to describe how the CBD Twitter discourse changed over time. The results showed an evolving nature of CBD conversations on Twitter, with notable changes in language and the topics of discussion. Overall, our study highlights the importance of monitoring changes in CBD tweets and the potential impact of misinformation in the CBD industry. Further research is needed to determine the broader impact of commercial CBD misinformation beyond Twitter, and to develop effective strategies to combat the spread of CBD misinformation.

One potential future direction for research is to develop more sophisticated algorithms for identifying concept drift within large-scale text datasets such as social media. This may include investigating new methods of unsupervised and semi-supervised learning that can adapt to rapidly evolving language use and provide early warning systems for detecting new forms of misinformation related to loosely regulated substances such as CBD. Further research is also needed to develop more effective approaches for distinguishing commercial and non-commercial tweets, as well as identifying subtopics within broader topics to gain deeper insights into how conversations on social media are evolving over time. This type of research could be valuable for understanding how public opinion and discourse on sensitive topics are shaped and influenced through social media, and could have implications for fields such as public health, social policy, and crisis management.

CHAPTER 6

CONCLUSION

This thesis presents CBD-TM, an innovative framework designed to mine Twitter data for references to CBD, a popular health and wellness product derived from cannabis. Our framework employs advanced natural language processing techniques to analyze a vast corpus of CBD-related tweets, providing valuable insights into the evolving discourse surrounding CBD. This research is highly significant as it contributes to the growing body of knowledge on the social and cultural factors that influence the use and perception of CBD. Furthermore, it presents a promising approach for monitoring and understanding the emergence of potentially harmful misinformation about CBD on social media platforms.

Our framework's technical contributions leverage state-of-the-art NLP techniques and algorithms, allowing us to extract nuanced insights from the vast amount of data available on social media platforms. The insights gained from our approach have the potential to inform public health policies and interventions aimed at promoting safe and informed CBD use, as well as helping to combat the spread of harmful misinformation related to CBD.

Importantly, the CBD-TM framework can be adapted and applied to other health and wellness products, providing a powerful tool for mining social media data to gain insights into the perceptions and usage of a wide range of products. Through our technical contributions and innovative use of NLP techniques and algorithms, we aim to provide valuable insights that can be leveraged to promote safe and informed health and wellness practices.

Chapter 3 explains how we gathered a corpus of CBD-related tweets during the latter part of 2019 and utilized it to create two binary classifiers – one for detecting commercial CBD tweets, and another for identifying personal CBD tweets. These classifiers were then applied to the entire corpus, allowing us to compare the frequently used terms in commercial CBD tweets against those in personal CBD tweets, thus providing a deeper understanding of the marketing and usage patterns surrounding CBD on Twitter. We also conducted sentiment analysis using the VADER model to investigate the overall sentiment of tweets mentioning CBD. This research is particularly significant as CBD has gained widespread attention for its perceived health benefits, but the regulations surrounding its marketing and usage remain in flux. Analyzing the usage patterns and sentiment of CBD tweets can therefore aid in understanding the public perception of CBD, and can inform the development of future regulations and policies in this area.

As detailed in chapter 4, we used the commercial CBD tweet classifier described in chapter 3 to analyze a collection of tweets referring to CBD and COVID-19. Because misinformation concerning CBD and COVID-19 has become increasingly prevalent on social media platforms, and has the potential to cause serious harm, this research is important. We developed a methodology for identifying tweets that contain such misinformation by leveraging transformer language models and warning letters issued by the FDA. We were thereby able to quickly identify tweets that are semantically similar and contain similar misinformation, providing a means to combat the spread of false claims about the health benefits of CBD related to COVID-19. This research has important implications for the development of automated tools for detecting and curbing the spread of misinformation on social media platforms.

Chapter 5 provides valuable insights into the temporal evolution of the discourse on CBD on Twitter. Applying the commercial CBD tweet classifier to a larger collection of tweets allowed us to identify concept drift in the CBD Twitter datastream over time. Understanding the evolution of this discourse is crucial for researchers and policymakers to design effective interventions to address the emerging concerns related to CBD use. Using a BERT-based topic model to explain the temporal changes in CBD discourse further enriches our understanding of how the CBD-related conversations evolved and the important shifts that occurred over time. The findings of this study could be useful for public health organizations, social media companies, and policymakers who are interested in monitoring the discourse on CBD and regulating the marketing and sale of

CBD products.

The CBD-TM framework presented in this thesis provides a strong foundation for future research in the field of text mining on Twitter data related to health and wellness products. This study contributes to the growing body of knowledge on CBD and its usage patterns, the public perception of CBD, and the spread of misinformation related to CBD on social media platforms. However, there are several areas that warrant further investigation.

One area of future research is the detection of commercial CBD-related tweets over time despite concept drift. Although the commercial CBD classifier described in chapter 3 provided insights into marketing patterns, it is limited to a specific timeframe. As social media platforms and the CBD market continue to evolve, the usage patterns and marketing tactics employed by CBD sellers will also change. Therefore, a more robust and dynamic classifier is needed that can adapt to the concept drift in the CBD Twitter datastream. Advanced machine learning techniques, like deep learning and ensemble learning, could be utilized to develop more accurate and reliable classifiers.

There is also room for further growth in the development of more advanced approaches for sentiment analysis. While the VADER model (mentioned in chapter 3) provided valuable insights into the overall sentiment of CBD tweets, it is a rule-based model that may not accurately capture the nuances of human emotions. Machine learning-based sentiment analysis techniques, such as deep learning and neural networks, could be used to develop more advanced sentiment analysis models that can accurately detect the complex emotions expressed in tweets.

Early detection of misinformation related to CBD is an important area for future research. As described in chapter 4, our work provided a methodology for identifying tweets containing potentially harmful medical misinformation related to CBD and COVID-19. However, there is a need for more advanced approaches that can identify misinformation related to other health and wellness products. Additionally, our study focused on detecting misinformation after it had already been spread on social media platforms. A future direction could entail the development of tools and algorithms that can detect misinformation at an earlier stage, thereby mitigating the spread of false claims about the health benefits of health and wellness products.

Our CBD-TM framework presented in this thesis provides a solid foundation for future research on text mining Twitter data related to health and wellness products. The future work in detecting commercial tweets over time despite concept drift, developing more advanced approaches for sentiment analysis and early detection of misinformation has significant implications for public health organizations, social media companies, and policymakers. The insights gained from this research could inform the development of effective interventions aimed at promoting safe and informed use of health and wellness products, as well as regulations and policies related to the marketing and sale of these products.

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APPENDIX

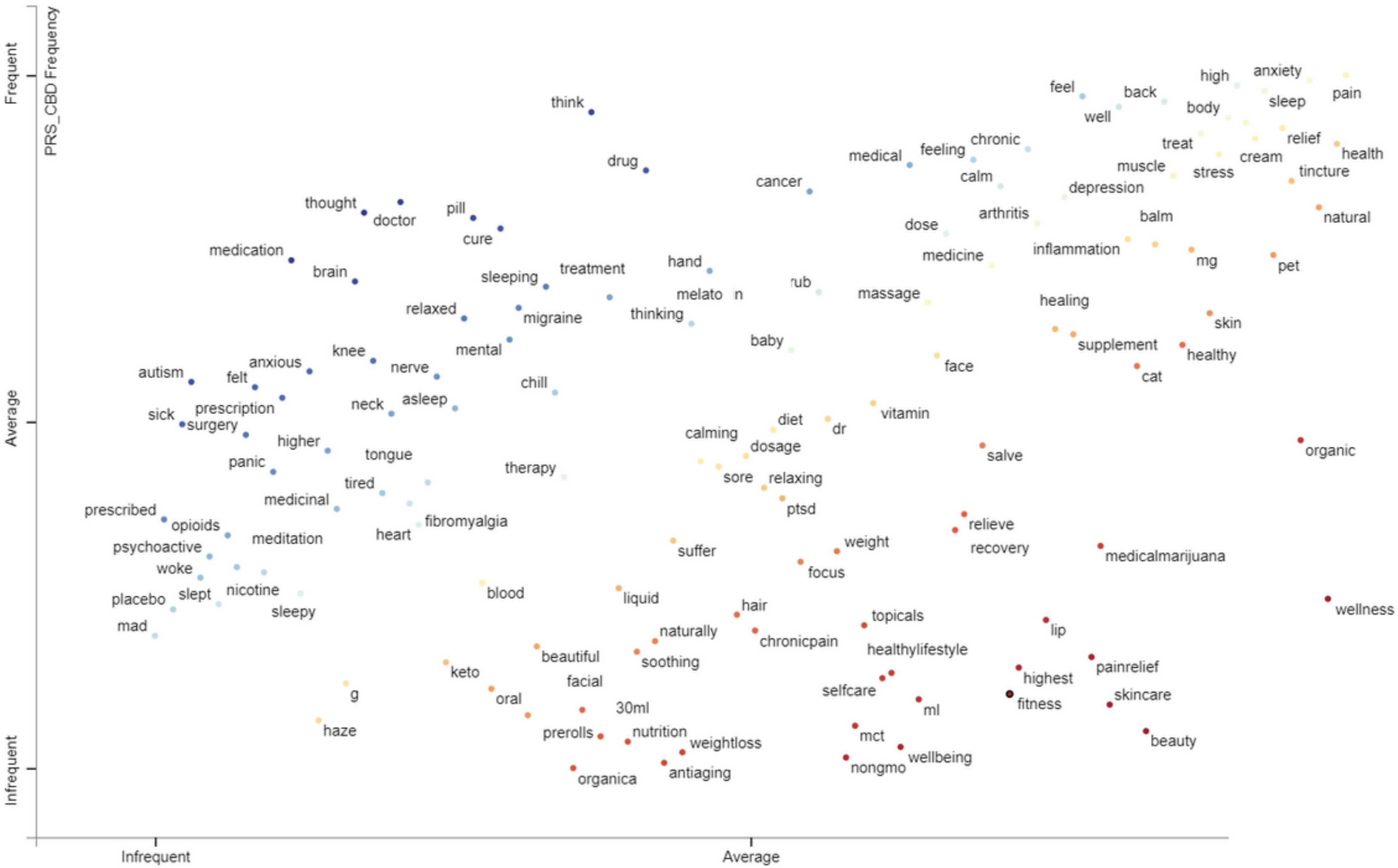


Figure A.1: Medical/Health/Wellness-Related Term Frequency per Class.

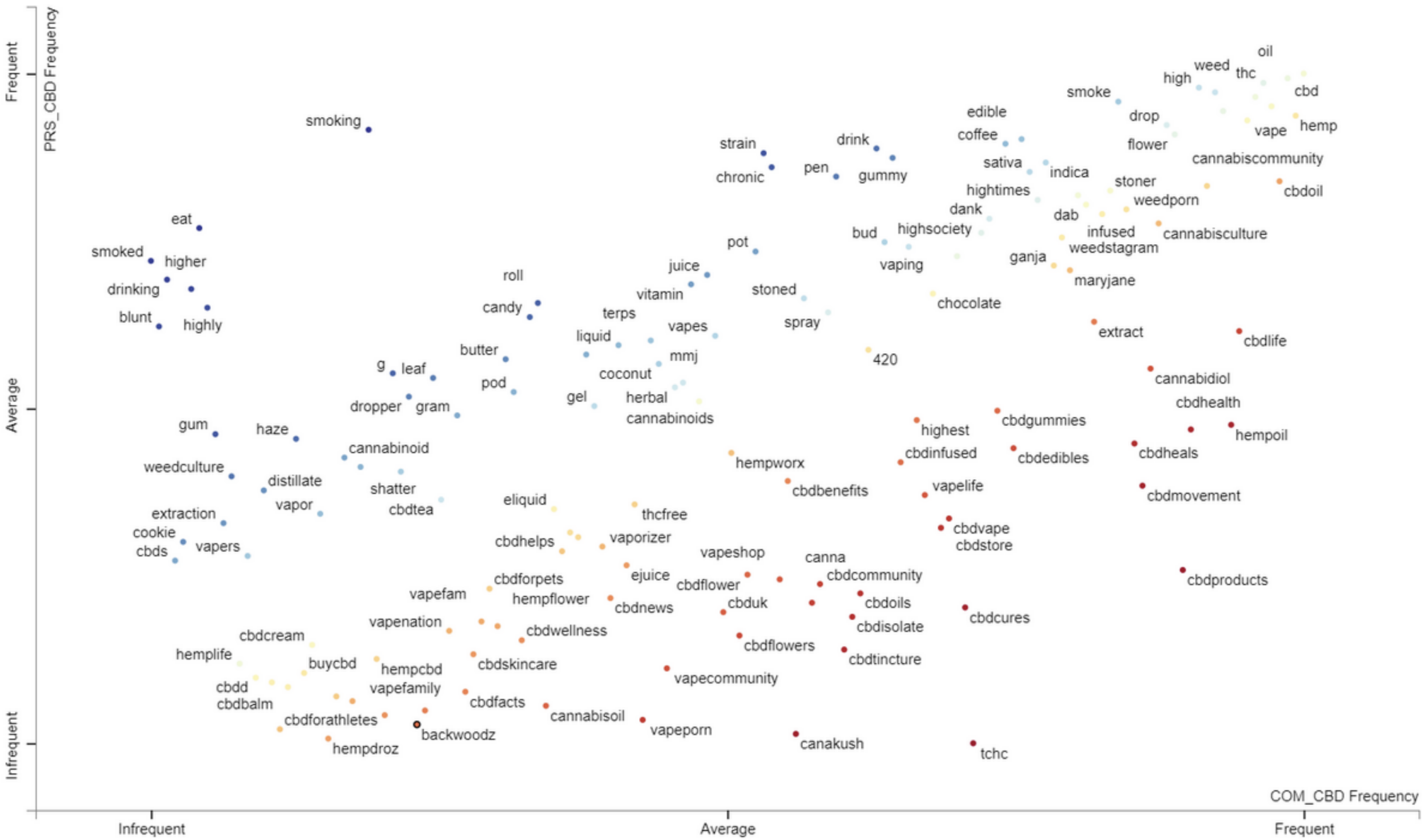
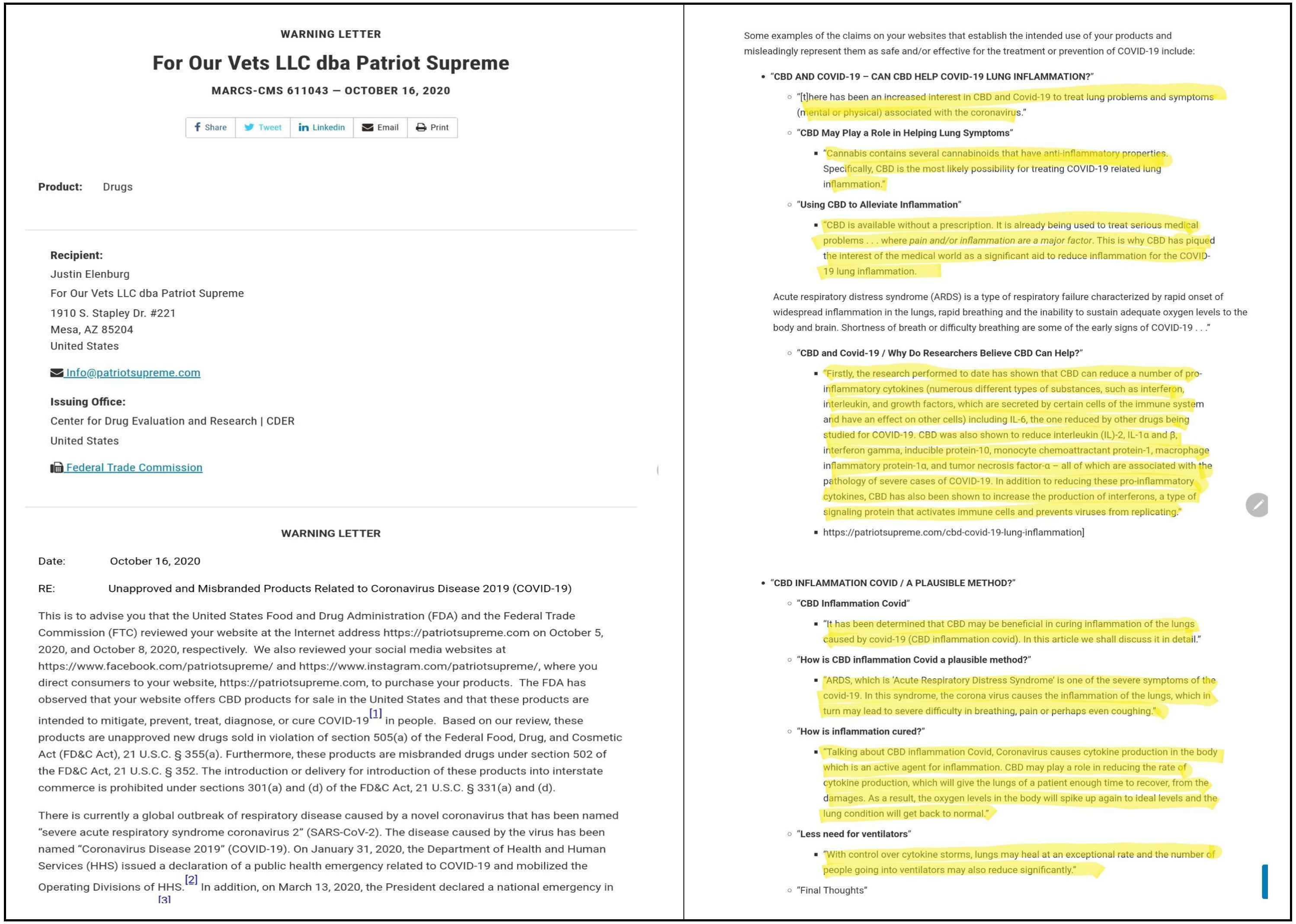


Figure A.2: Cannabis-Related Term Frequency per Class.

Figure A.3: Other Substances Term Frequency per Class.



WARNING LETTER

For Our Vets LLC dba Patriot Supreme

MARCS-CMS 611043 — OCTOBER 16, 2020

Share | Tweet | Linkedin | Email | Print

Product: Drugs

Recipient:
Justin Elenburg
For Our Vets LLC dba Patriot Supreme
1910 S. Stapley Dr. #221
Mesa, AZ 85204
United States

Info@patriotsupreme.com

Issuing Office:
Center for Drug Evaluation and Research | CDER
United States

Federal Trade Commission

WARNING LETTER

Date: October 16, 2020

RE: Unapproved and Misbranded Products Related to Coronavirus Disease 2019 (COVID-19)

This is to advise you that the United States Food and Drug Administration (FDA) and the Federal Trade Commission (FTC) reviewed your website at the Internet address https://patriotsupreme.com on October 5, 2020, and October 8, 2020, respectively. We also reviewed your social media websites at https://www.facebook.com/patriotsupreme/ and https://www.instagram.com/patriotsupreme/, where you direct consumers to your website, https://patriotsupreme.com, to purchase your products. The FDA has observed that your website offers CBD products for sale in the United States and that these products are intended to mitigate, prevent, treat, diagnose, or cure COVID-19[1] in people. Based on our review, these products are unapproved new drugs sold in violation of section 505(a) of the Federal Food, Drug, and Cosmetic Act (FD&C Act), 21 U.S.C. § 355(a). Furthermore, these products are misbranded drugs under section 502 of the FD&C Act, 21 U.S.C. § 352. The introduction or delivery for introduction of these products into interstate commerce is prohibited under sections 301(a) and (d) of the FD&C Act, 21 U.S.C. § 331(a) and (d).

There is currently a global outbreak of respiratory disease caused by a novel coronavirus that has been named "severe acute respiratory syndrome coronavirus 2" (SARS-CoV-2). The disease caused by the virus has been named "Coronavirus Disease 2019" (COVID-19). On January 31, 2020, the Department of Health and Human Services (HHS) issued a declaration of a public health emergency related to COVID-19 and mobilized the Operating Divisions of HHS.[2] In addition, on March 13, 2020, the President declared a national emergency in [3]

Some examples of the claims on your websites that establish the intended use of your products and misleadingly represent them as safe and/or effective for the treatment or prevention of COVID-19 include:

- **"CBD AND COVID-19 – CAN CBD HELP COVID-19 LUNG INFLAMMATION?"**
  - "[t]here has been an increased interest in CBD and Covid-19 to treat lung problems and symptoms (mental or physical) associated with the coronavirus."
  - **"CBD May Play a Role in Helping Lung Symptoms"**
    - "Cannabis contains several cannabinoids that have anti-inflammatory properties. Specifically, CBD is the most likely possibility for treating COVID-19 related lung inflammation."
  - **"Using CBD to Alleviate Inflammation"**
    - "CBD is available without a prescription. It is already being used to treat serious medical problems . . . where *pain and/or inflammation are a major factor*. This is why CBD has piqued the interest of the medical world as a significant aid to reduce inflammation for the COVID-19 lung inflammation.

Acute respiratory distress syndrome (ARDS) is a type of respiratory failure characterized by rapid onset of widespread inflammation in the lungs, rapid breathing and the inability to sustain adequate oxygen levels to the body and brain. Shortness of breath or difficulty breathing are some of the early signs of COVID-19 . . ."

  - **"CBD and Covid-19 / Why Do Researchers Believe CBD Can Help?"**
    - "Firstly, the research performed to date has shown that CBD can reduce a number of pro-inflammatory cytokines (numerous different types of substances, such as interferon, interleukin, and growth factors, which are secreted by certain cells of the immune system and have an effect on other cells) including IL-6, the one reduced by other drugs being studied for COVID-19. CBD was also shown to reduce interleukin (IL)-2, IL-1α and β, interferon gamma, inducible protein-10, monocyte chemoattractant protein-1, macrophage inflammatory protein-1α, and tumor necrosis factor-α – all of which are associated with the pathology of severe cases of COVID-19. In addition to reducing these pro-inflammatory cytokines, CBD has also been shown to increase the production of interferons, a type of signaling protein that activates immune cells and prevents viruses from replicating."
    - https://patriotsupreme.com/cbd-covid-19-lung-inflammation]

- **"CBD INFLAMMATION COVID / A PLAUSIBLE METHOD?"**
  - **"CBD Inflammation Covid"**
    - "It has been determined that CBD may be beneficial in curing inflammation of the lungs caused by covid-19 (CBD inflammation covid). In this article we shall discuss it in detail."
  - **"How is CBD inflammation Covid a plausible method?"**
    - "ARDS, which is 'Acute Respiratory Distress Syndrome' is one of the severe symptoms of the covid-19. In this syndrome, the corona virus causes the inflammation of the lungs, which in turn may lead to severe difficulty in breathing, pain or perhaps even coughing."
  - **"How is inflammation cured?"**
    - "Talking about CBD inflammation Covid, Coronavirus causes cytokine production in the body which is an active agent for inflammation. CBD may play a role in reducing the rate of cytokine production, which will give the lungs of a patient enough time to recover, from the damages. As a result, the oxygen levels in the body will spike up again to ideal levels and the lung condition will get back to normal."
  - **"Less need for ventilators"**
    - "With control over cytokine storms, lungs may heal at an exceptional rate and the number of people going into ventilators may also reduce significantly."
  - "Final Thoughts"

Figure A.4: Example warning letter taken from the FDA website.

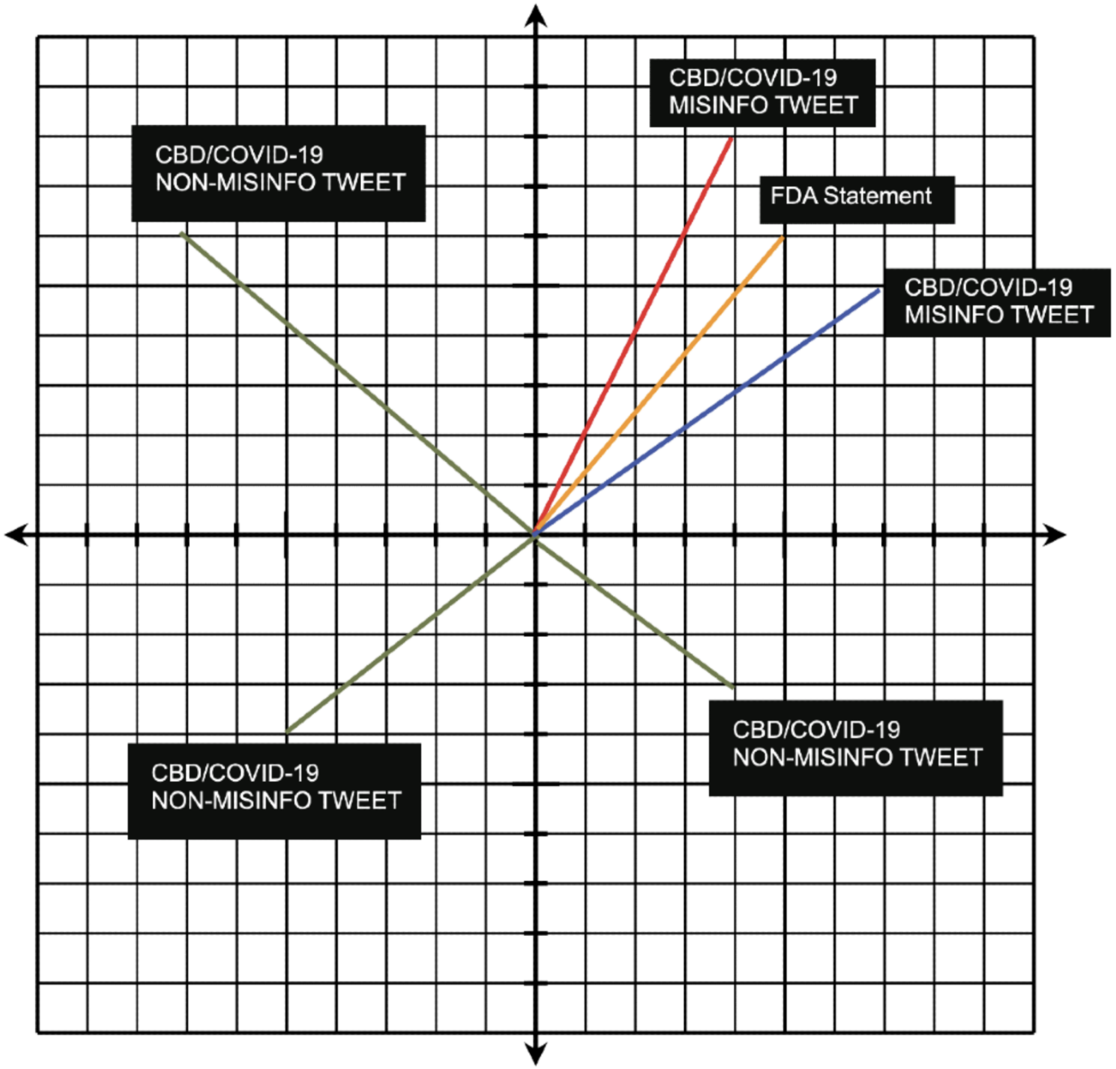


Figure A.5: Representation of contextual similarity between CBD tweets and quotes from FDA warning letters.

An official website of the United States government Here's how you know

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FDA NEWS RELEASE

FDA, FTC warn company marketing unapproved cannabidiol products with unsubstantiated claims to treat teething and ear pain in infants, autism, ADHD, Parkinson's and Alzheimer's disease

FDA is also working quickly to evaluate regulatory policies related to cannabis and cannabis-derived ingredients like CBD

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For Immediate Release: October 22, 2019

Español

Today, the U.S. Food and Drug Administration and the Federal Trade Commission posted a joint warning letter to Rooted Apothecary LLC, of Naples, Florida, for illegally selling unapproved products containing cannabidiol (CBD) online with unsubstantiated claims that the products treat teething pain and ear aches in infants, autism, attention-deficit/hyperactivity disorder (ADHD), as well as Parkinson's and Alzheimer's disease, among other conditions or diseases.

"Cannabis and cannabis-derived compounds are subject to the same laws and requirements as FDA-regulated products that contain any other substance. We are working to protect Americans from companies marketing products with unsubstantiated claims that they prevent, diagnose, treat, or cure a number of diseases or conditions. This is especially concerning when companies are peddling unproven CBD products for use in vulnerable populations like infants and children," said Acting FDA Commissioner Ned Sharpless, M.D. "We've sent numerous warning letters that focus on matters of significant public health concern to CBD companies, and these actions should send a message to the broader market about complying with FDA requirements. As we examine potential regulatory pathways for the lawful marketing of cannabis products, protecting and promoting public health through sound, science-based decision-making remains our top priority. We appreciate the FTC joining us on these and other actions to protect consumers from fraudulent CBD products."

As described in the warning letter issued to Rooted Apothecary, the company used product webpages, through its online store and social media websites, to make unfounded claims about its CBD products, and some of the products were also unlawfully marketed as dietary supplements. The agency has determined that CBD products cannot be marketed as dietary supplements.

Examples of the unsupported claims made by the company include:

- "Instead of synthetic chemical[s] that can have safety concerns, this blend uses the best of nature to help calm the inflammation and pain of teething, while also promoting sleepiness for your little one."
- "No matter what age, ear aches are a terrible, no good way to live each day! Our main priority was safety, effectiveness . . . as we formulated this for the entire family including our precious little ones. When the pain is bad, this roller goes to work for soothing pain, inflammation, and to battle against the bacterial/viral critters to blame."
- "Increasing evidence suggests that CBD oil is a powerful option for pain . . . anxiety . . . and autism . . . It seems like an attractive and safe option for children."
- "CBD oil may have neuroprotective properties and may protect against neurological conditions, such as Parkinson's and Alzheimer's disease."
- "[P]ossible uses for CBD include helping with skin problems such as acne, autism, ADHD, and even cancer. It's often used in conjunction with traditional treatments to provide extra help. Children can use high amounts of CBD safely and without any risk."

Additionally, under the Federal Trade Commission Act, it is unlawful to advertise that a product can prevent, treat, or cure human disease unless the advertiser possesses competent and reliable scientific evidence, including, when appropriate, well-controlled human clinical studies, substantiating that the claims are true at the time they are made. More generally, to make or exaggerate such claims, whether directly or indirectly, through the use of a product name, website name, metatags, or other means, without rigorous scientific evidence sufficient to substantiate the claims, violates the FTC Act. The FTC is concerned that one or more of the efficacy claims cited may not be substantiated by competent and reliable scientific evidence. These products are also misbranded under the Federal Food, Drug, and Cosmetic (FD&C) Act, because the products' labels and product information fail to include adequate directions for use. Drugs in the United States must contain directions explaining how a consumer can use a drug safely for its intended purpose. Under the law, there is an exemption for this labeling requirement for prescription drugs that have FDA-approved applications in effect. However, none of Rooted Apothecary's products are FDA-approved.

The FDA and FTC have requested responses from Rooted Apothecary within 15 working days stating how the company will correct the violations. Failure to correct the violations promptly may result in legal action, including product seizure and/or injunction. Violations of the FTC Act may result in legal action seeking a Federal District Court injunction or administrative cease and desist order, and an order also may require that a company pay back money to consumers.

The FDA continues to be concerned about the proliferation of products claiming to contain CBD that are marketed for therapeutic or medical uses that have not been approved by the agency. The FDA approval process ensures that drugs on the market are safe and effective for their intended therapeutic uses. CBD is marketed in a variety of product types, such as oil drops, capsules, syrups, teas and topical lotions and creams. The FDA has not approved any CBD products other than one prescription human drug product to treat rare, severe forms of epilepsy. There is very limited information for other marketed CBD products, which likely differ in composition from the FDA-approved product and have not been evaluated for potential adverse effects on the body.

The FDA continues to explore potential pathways for various types of CBD products to be lawfully marketed. An important component of this work is obtaining and evaluating information to address outstanding questions related to the safety of CBD products while

Figure A.6: FDA Warning Letter to CBD Seller Regarding Alzheimer's Disease Misinformation.

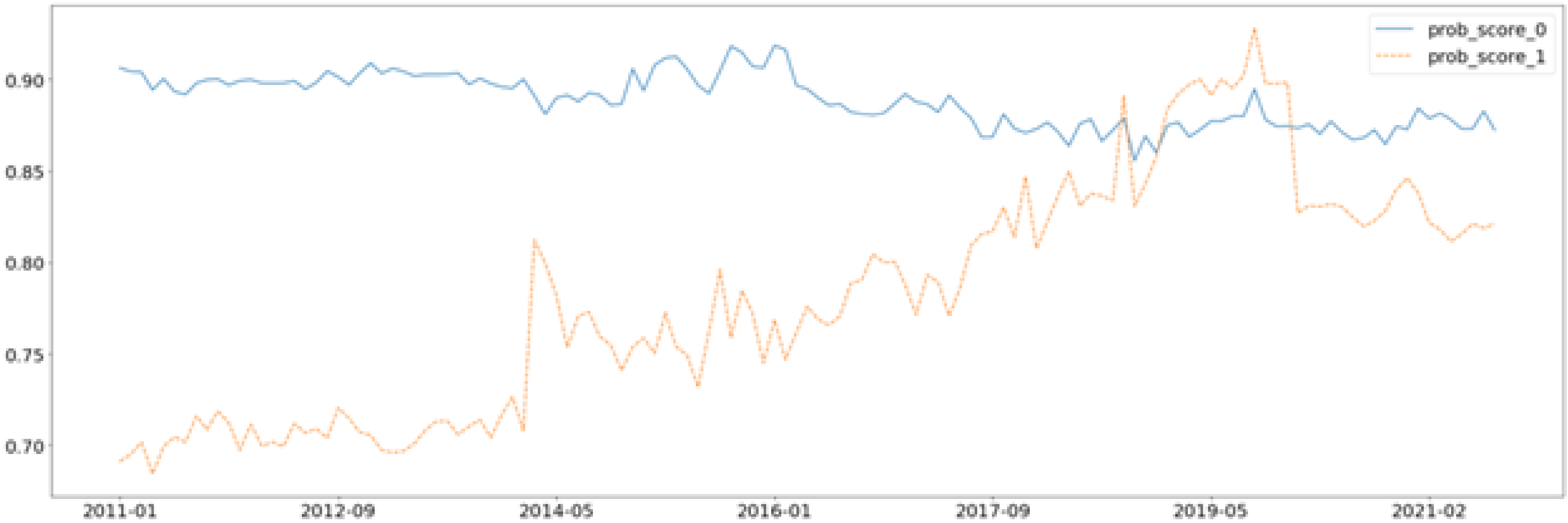

Figure A.7: Logistic Regression Confidence Plotted Over Time

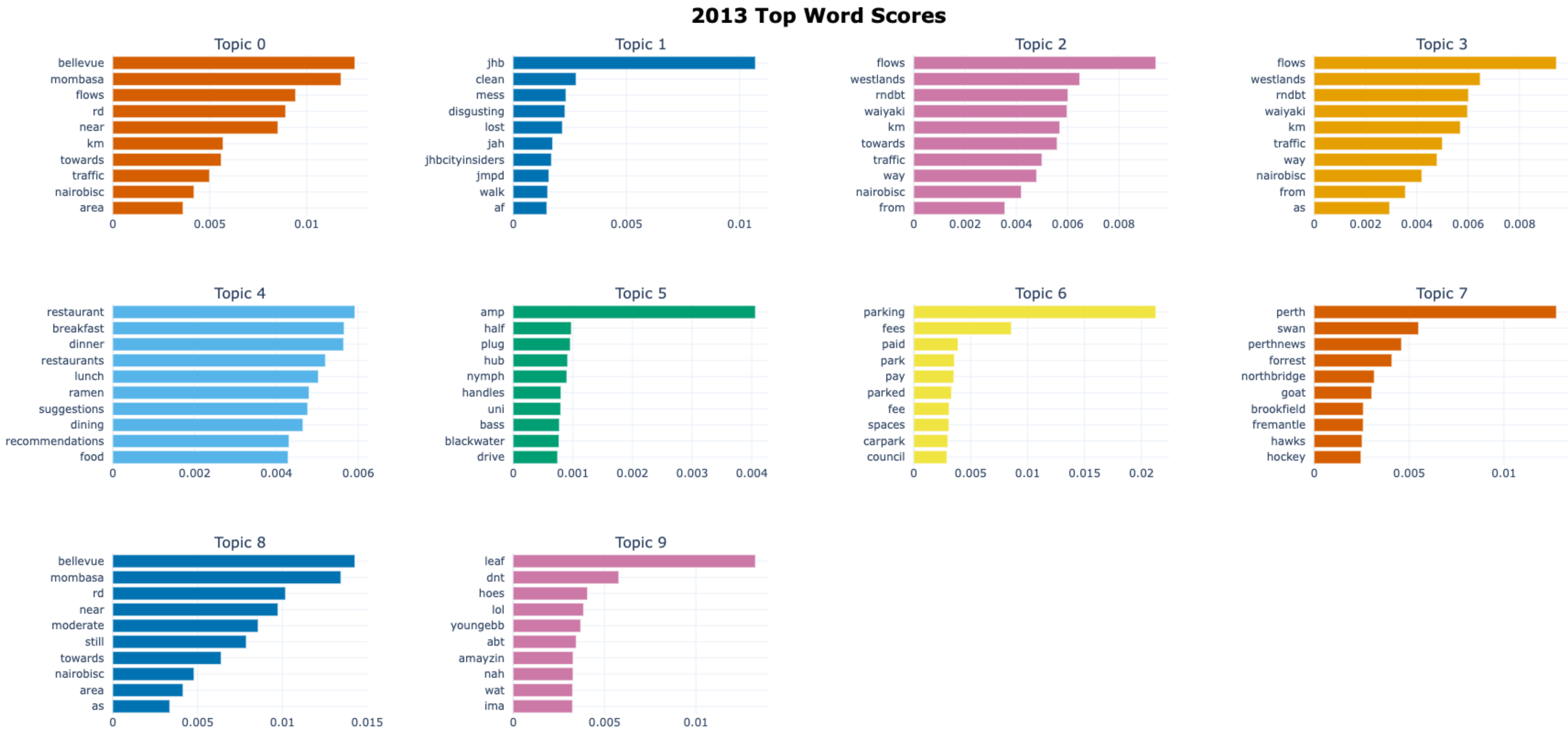

Figure A.8: 2013 BERTopic Model Results

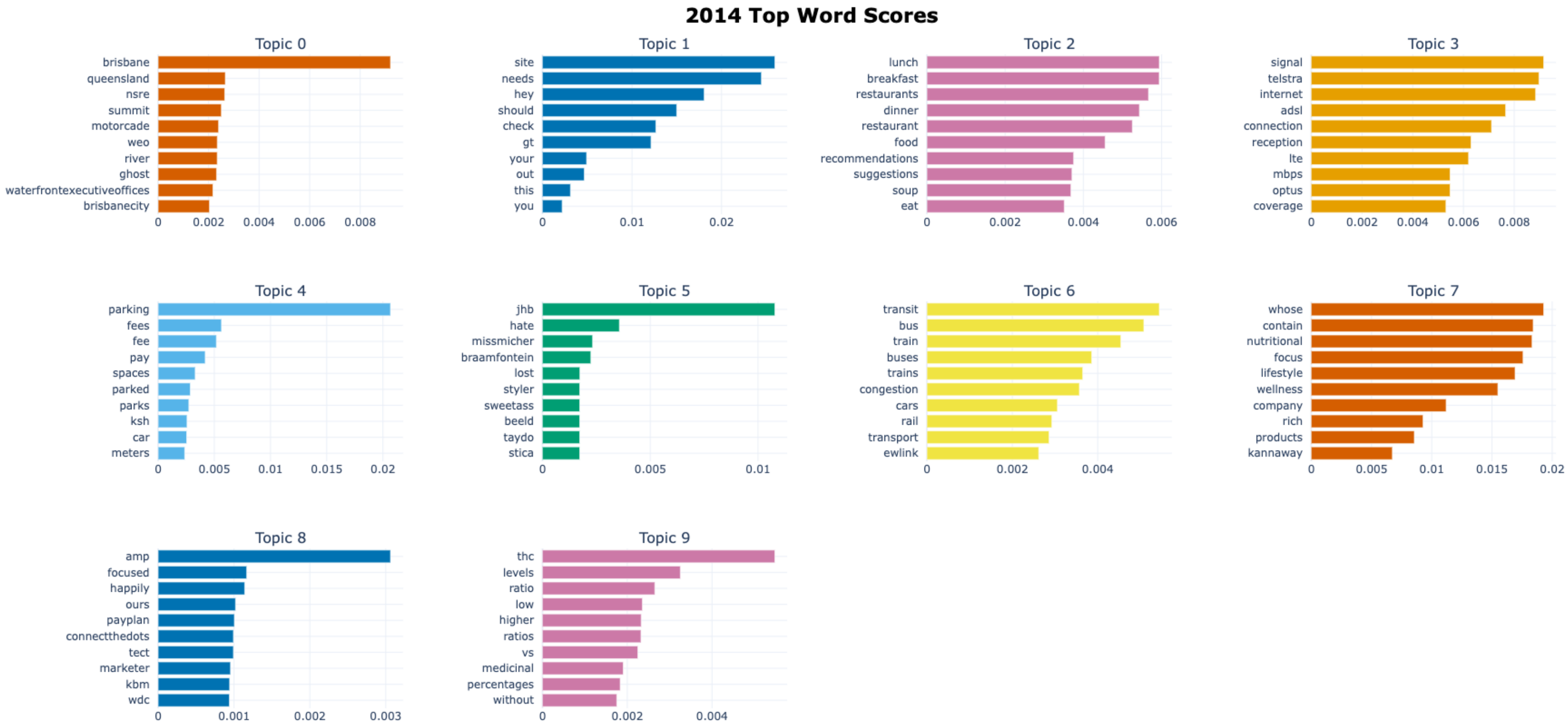

Figure A.9: 2014 BERTopic Model Results

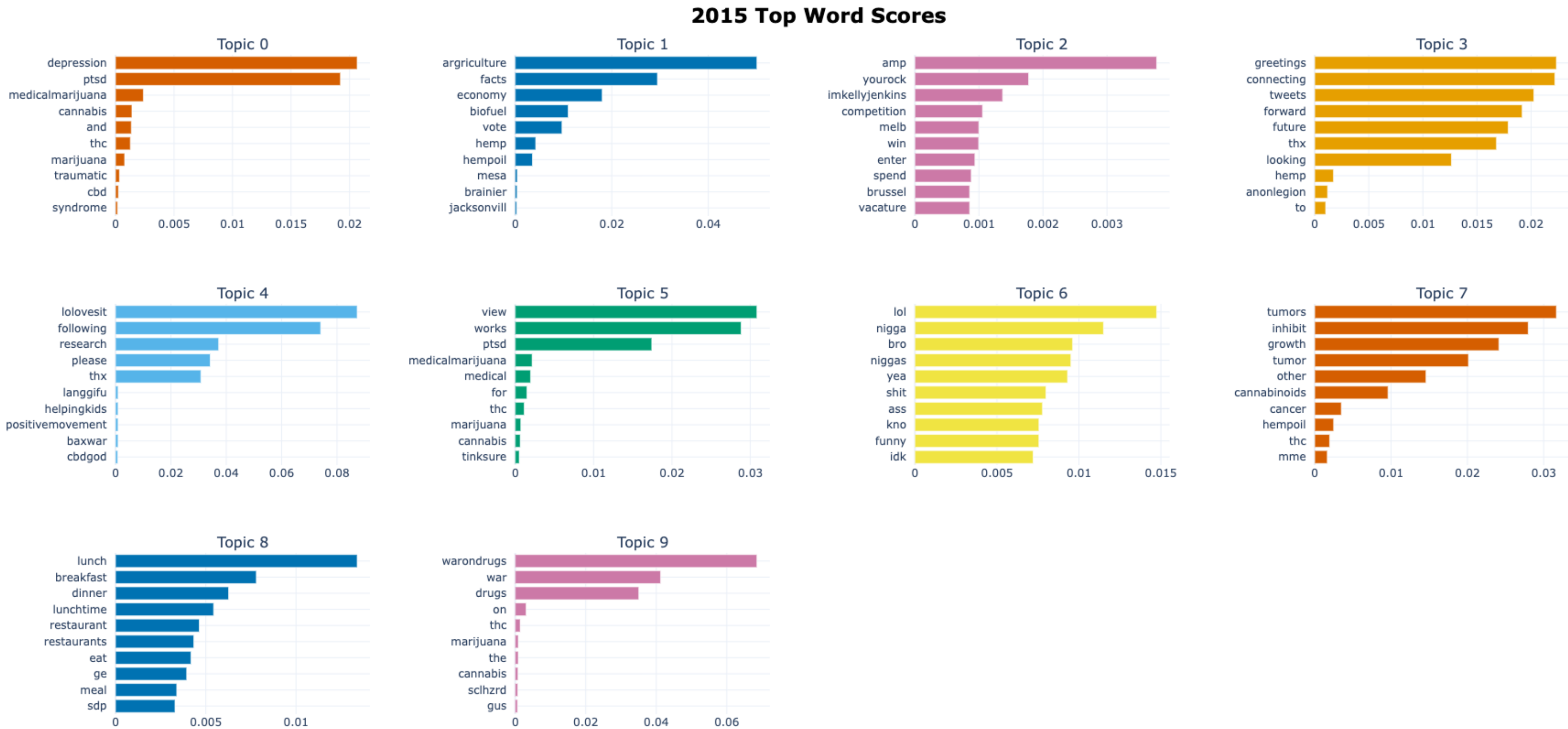

Figure A.10: 2015 BERTopic Model Results

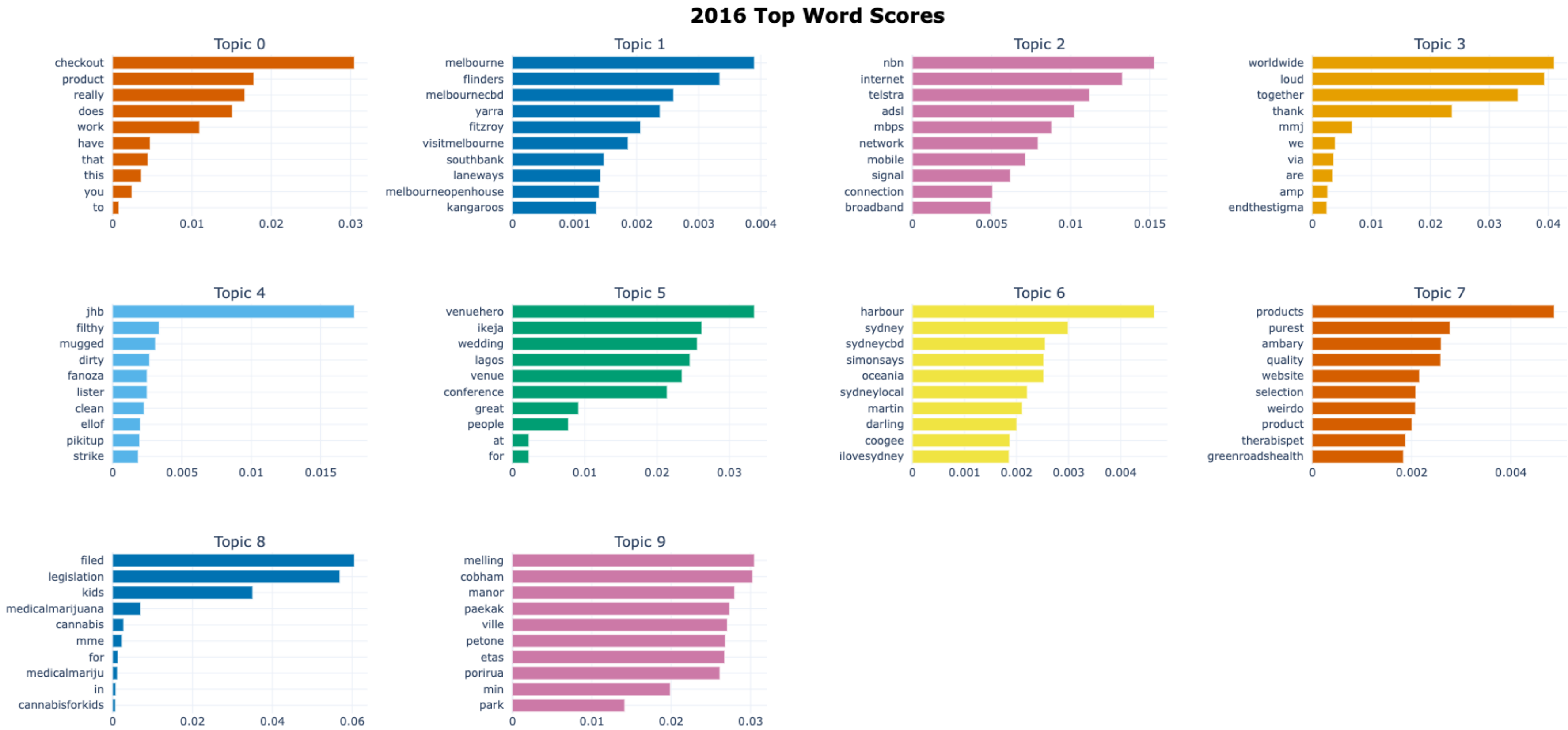

Figure A.11: 2016 BERTopic Model Results

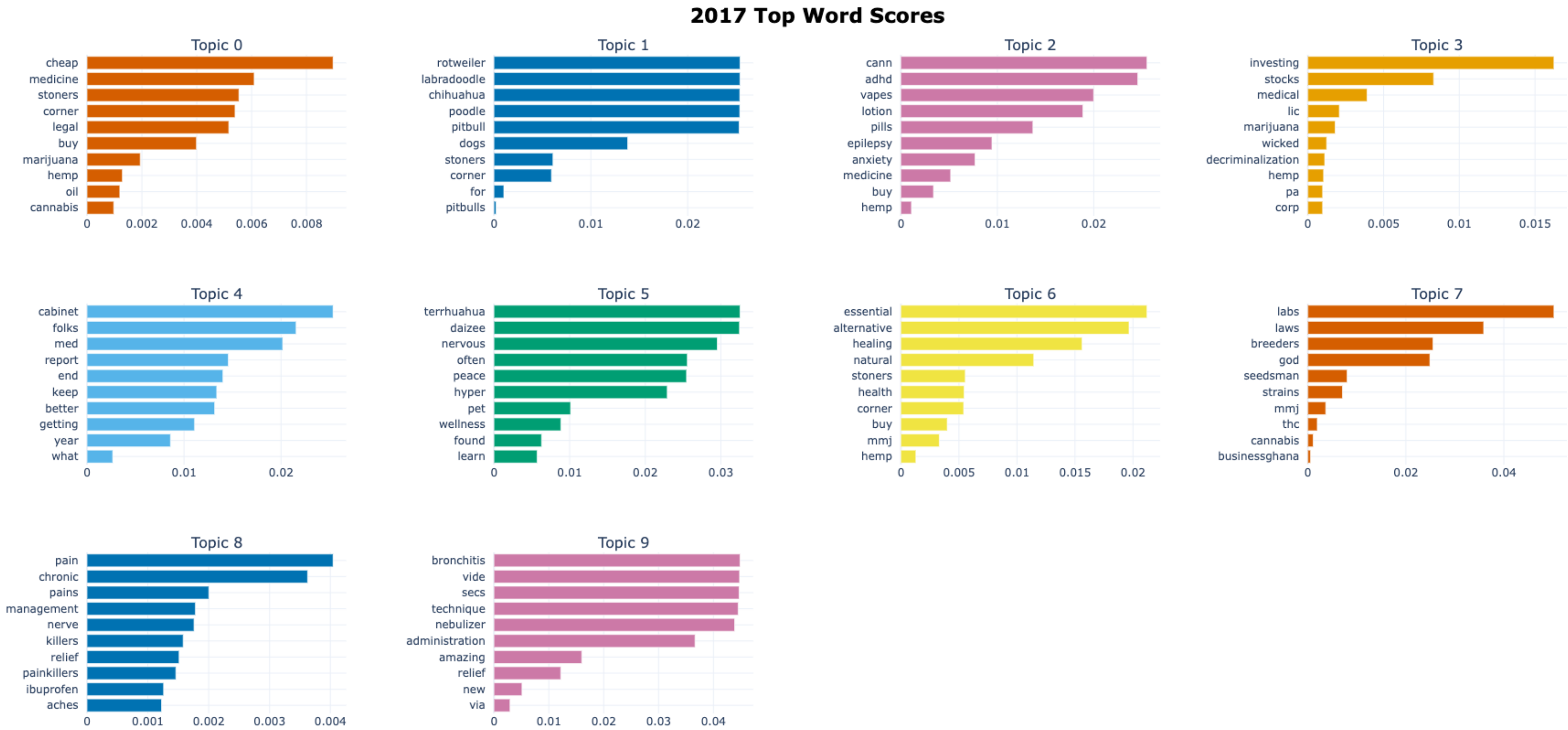

Figure A.12: 2017 BERTopic Model Results

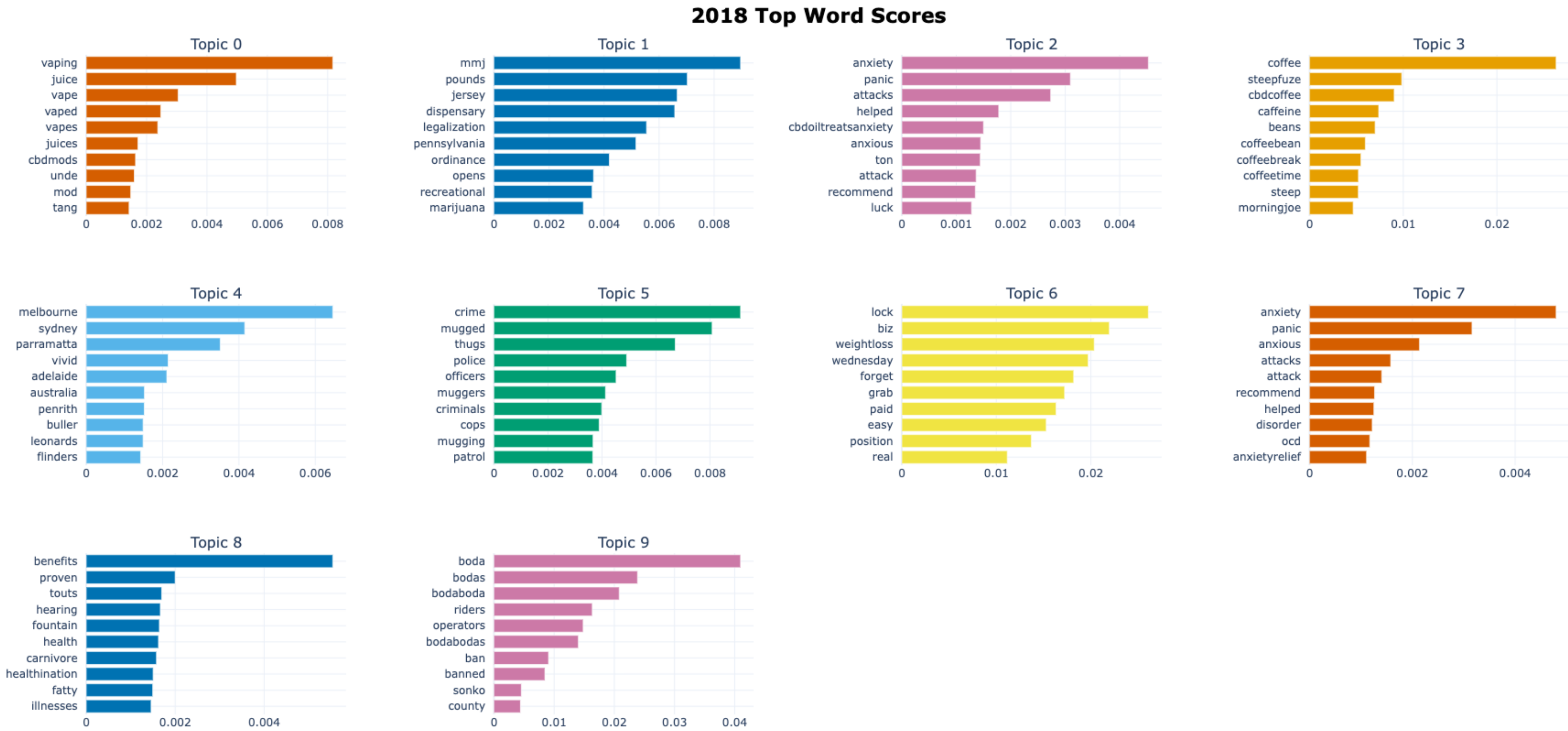

Figure A.13: 2018 BERTopic Model Results

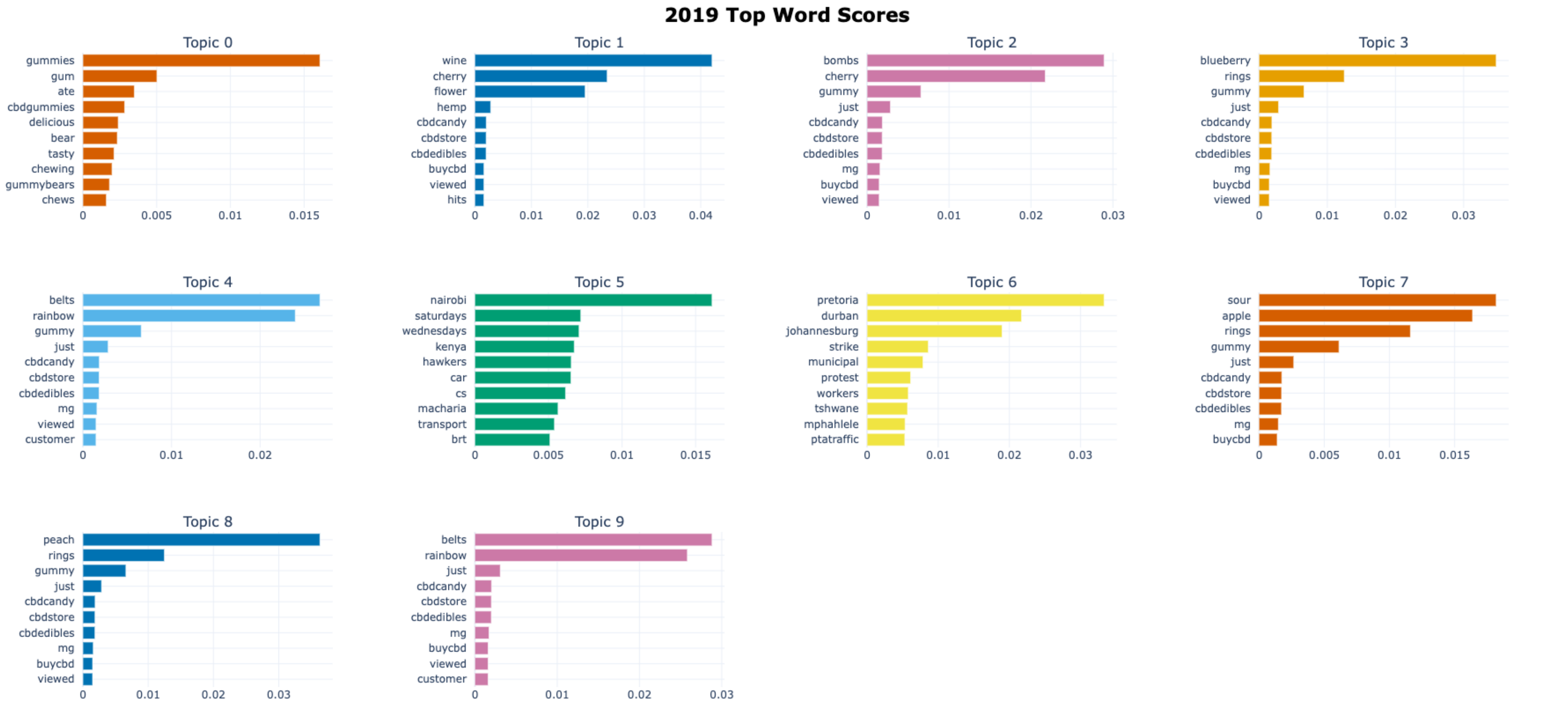

Figure A.14: 2019 BERTopic Model Results

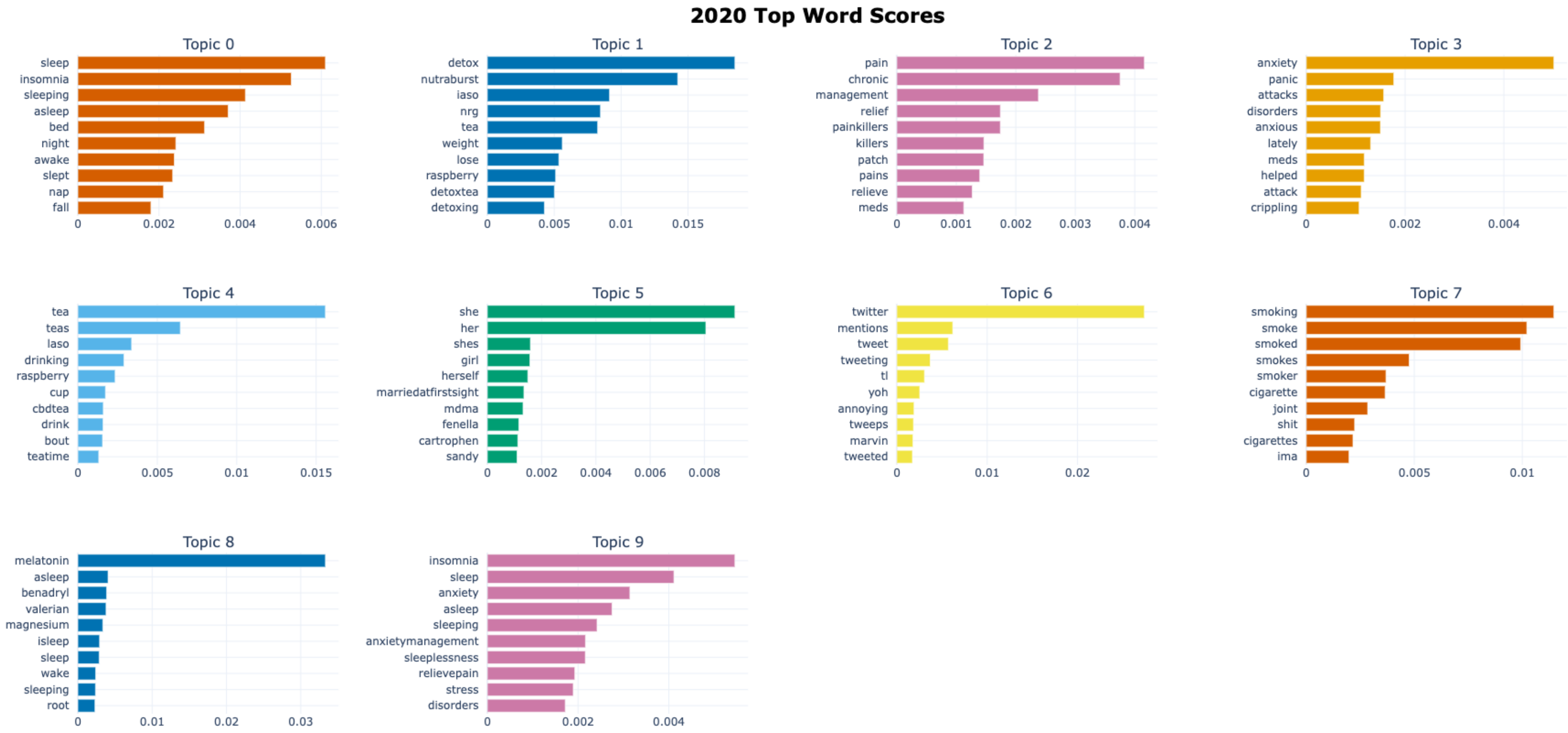

Figure A.15: 2020 BERTopic Model Results

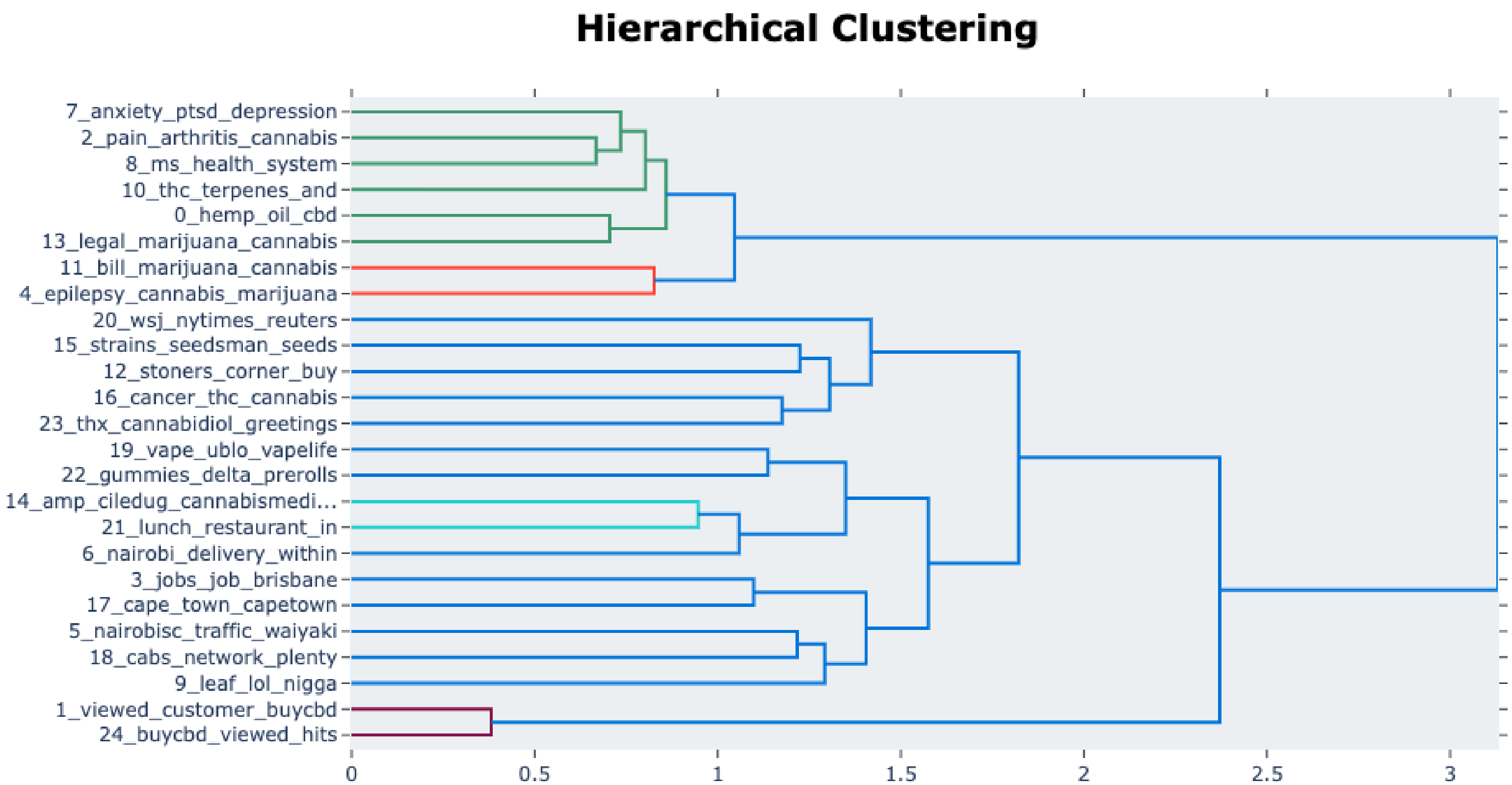

Figure A.16: Hierarchical Cluster of 25 Topics for CBD Tweets 2011-2021

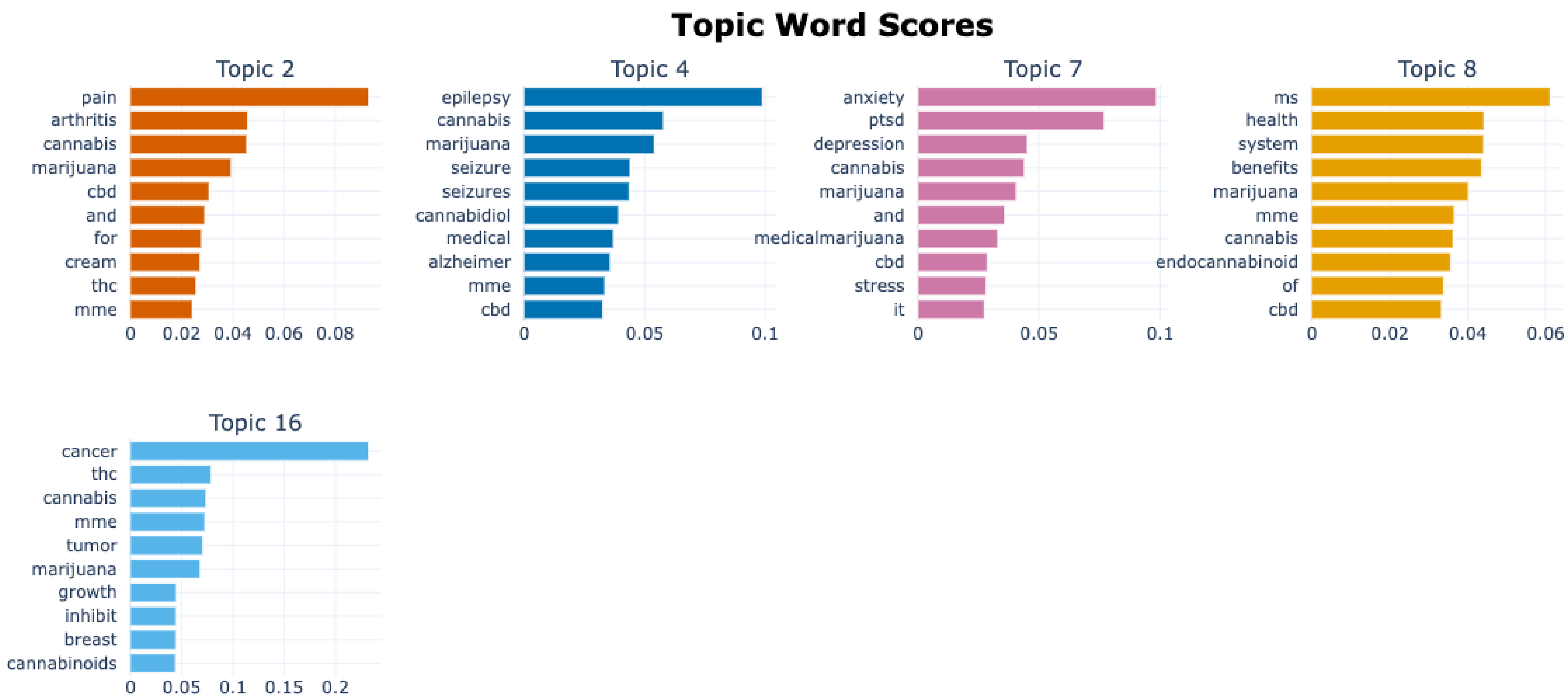

Figure A.17: CBD Topics that Make References to Health/Medical Terms

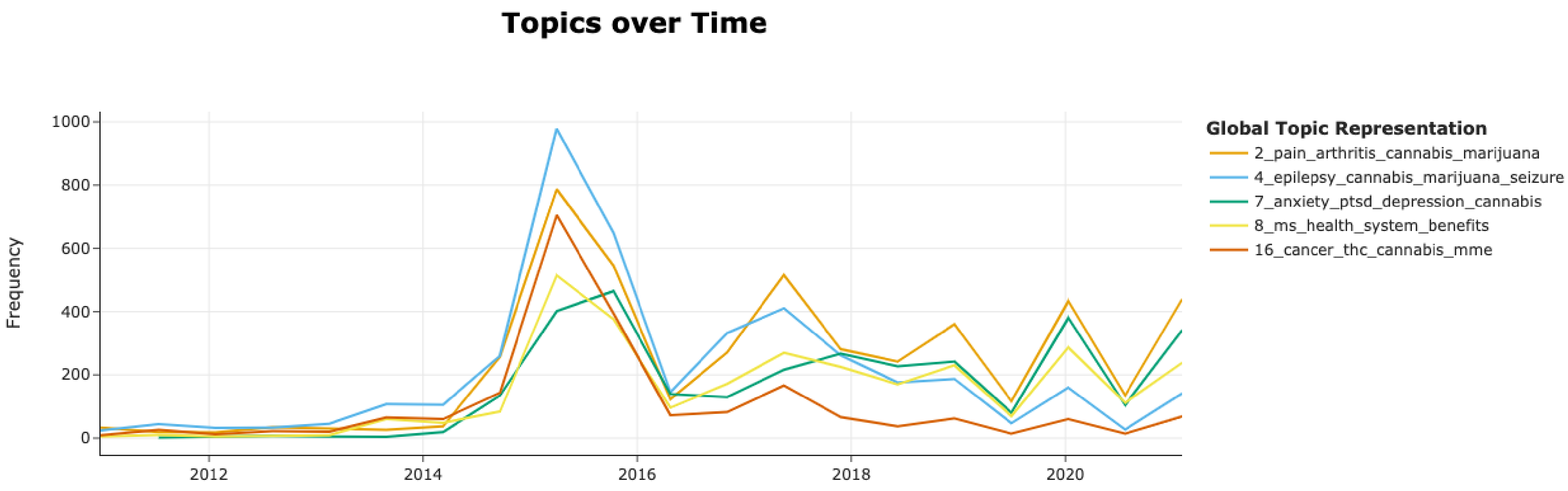

Figure A.18: Plot of the Health/Medical Topics Over Time

Table 5.1: Personal CBD Binary Classifier Performance Metrics.

	GaussianNB				Logistic Regression				Linear Vector		Support		Random Forest			
	Prec	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**
Non-Pers. CBD	0.92	0.8	0.9	138	0.9	0.8	0.9	138	0.91	0.8	0.8	138	0.85	0.8	0.8	138
Pers CBD Accuracy	0.78	0.9	0.8 0.9	115 253	0.8	0.9	0.9 0.9	115 253	0.76	0.9	0.8 0.8	115 253	0.75	0.8	0.8 0.8	115 253

Table 5.2: Commercial CBD Binary Classifier Performance Metrics.

	GaussianNB				Logistic Regression				Linear Vector		Support		Random Forest			
	Prec	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**	**Prec**	**Rec**	**F1**	**Sup**
Non-Pers. CBD	0.91	0.66	0.77	95	0.92	0.85	0.89	95	0.91	0.79	0.85	95	0.78	0.92	0.84	95
Pers CBD Accuracy	0.75	0.94	0.83 0.81	101 196	0.87	0.93	0.9 0.89	101 196	0.82	0.93	0.87 0.86	101 196	0.9	0.75	0.82 0.83	101 196

Table 5.3: Personal and Commercial CBD Sentiment Categorical Counts.

	Personal Tweets							Commercial Tweets						
		With Term			Without Term				With Term			Without Term		
Term	**n**	**pos**	**neu**	**neg**	**pos**	**neu**	**neg**	**n**	**pos**	**neu**	**neg**	**pos**	**neu**	**neg**
anxiety	5,353	2,818	126	2,409	3,125	519	1718	2,924	1,564	44	1,316	1,726	352	846
anxious	515	266	11	238	307	47	161	114	53	4	57	84	5	25
autism	395	180	47	168	180	47	168	27	17	2	8	17	2	8
calm	1,224	1,007	17	200	761	145	318	725	659	9	57	535	80	110
calming	445	399	4	42	324	33	88	389	369	2	18	308	47	34
cancer	986	230	19	737	530	111	345	246	76	0	170	122	44	80
depression	568	164	17	387	307	31	230	326	69	8	249	178	19	129
energy	507	416	9	82	334	57	116	444	421	7	16	357	52	35
fitness	57	48	2	7	37	4	16	128	125	0	3	100	15	13
pain	7,432	2,948	188	4,296	4,985	558	1889	6,287	3,262	113	2,912	4,956	591	740
pains	394	157	11	226	225	19	150	311	168	9	134	219	11	81
ptsd	217	111	14	92	111	14	92	55	33	9	13	33	9	13
skin	618	461	55	102	464	54	100	2,516	2,211	150	155	2,229	136	151
sleep	3,761	2,518	356	887	2,517	356	888	2,980	2,129	322	529	2,131	321	528
stress	1,012	560	18	434	713	45	254	1,407	883	28	496	1,100	36	271
weight loss	8	5	2	1	5	2	1	24	18	3	3	18	3	3
wellness	144	129	2	13	98	18	28	4,216	4,020	38	158	3,106	814	296

Table 5.4: Personal and Commercial CBD Sentiment Score Descriptive Statistics (With & Without Term).

	Personal Tweets					Commercial Tweets				
	With term			Without term		With term			Without term	
Term	**n**	**mean**	**stdy**	**mean**	**stdy**	**n**	**mean**	**stdy**	**mean**	**stdy**
anxiety	5,353	0.074	0.573	0.186	0.557	2,924	0.118	0.568	0.241	0.538
anxious	515	0.048	0.591	0.203	0.566	114	0.08	0.566	0.254	0.529
autism	395	-0.001	0.546	-0.001	0.546	27	0.188	0.557	0.188	0.557
calm	1,224	0.448	0.484	0.258	0.54	725	0.616	0.374	0.452	0.467
calming	445	0.608	0.408	0.41	0.508	389	0.695	0.334	0.513	0.444
cancer	986	-0.369	0.571	0.158	0.559	246	-0.303	0.638	0.167	0.564
depression	568	-0.275	0.573	0.122	0.571	326	-0.353	0.506	0.111	0.525
energy	507	0.469	0.492	0.324	0.541	444	0.681	0.331	0.547	0.421
fitness	57	0.429	0.463	0.263	0.514	128	0.633	0.283	0.464	0.4
pain	7,432	-0.099	0.605	0.293	0.547	6,287	0.088	0.58	0.49	0.44
pains	394	-0.098	0.61	0.169	0.577	311	0.087	0.615	0.342	0.553
ptsd	217	0.037	0.626	0.037	0.627	55	0.2	0.563	0.2	0.563
skin	618	0.42	0.501	0.427	0.501	2,516	0.55	0.371	0.568	0.371
sleep	3,761	0.305	0.522	0.305	0.523	2,980	0.392	0.493	0.394	0.493
stress	1,012	0.116	0.632	0.36	0.567	1,407	0.234	0.596	0.481	0.396
weight loss	8	0.289	0.344	0.289	0.344	24	0.436	0.549	0.436	0.549
wellness	144	0.606	0.431	0.384	0.524	4,216	0.72	0.279	0.505	0.426

Table 5.5: Personal and Commercial CBD Sentiment Score T-Test Results (With & Without Term).

	Pers. w/term vs Pers. w/o term		Com. w/term vs Com. w/o term		Com. w/term vs Pers. w/ term		Com. w/o term vs Pers. w/o term	
Term	**t-statistic**	**P-value**	**t-statistic**	**P-value**	**t-statistic**	**P-value**	**t-statistic**	**P-value**
anxiety	-10.31	<.001	-8.508	<.001	-3.329	0.001	-4.282	<.001
anxious	-4.292	<.001	-2.393	0.018	0.533	0.594	-0.882	0.378
autism	0	0.999	0	0.999	-1.739	0.083	-1.739	0.083
calm	9.151	<.001	7.399	<.001	-8.063	<.001	-8.04	<.001
calming	6.403	<.001	6.486	<.001	-3.374	0.001	-3.087	0.002
cancer	-20.71	<.001	-8.647	<.001	-1.592	0.112	-0.219	0.826
depression	-11.67	<.001	-11.49	<.001	2.06	0.4	0.289	0.773
energy	4.445	<.001	5.254	<.001	-7.679	<.001	-7.019	<.001
fitness	1.812	0.073	3.915	<.001	-3.685	<.001	-2.881	0.004
pain	-41.39	<.001	-43.82	<.001	-18.37	<.001	-23.02	<.001
pains	-6.315	<.001	-5.431	<.001	-3.978	<.001	-4.009	<.001
ptsd	-0.012	0.99	0	0.999	-1.766	0.078	-1.757	0.08
skin	-0.243	0.808	-1.755	0.079	-7.25	<.001	-7.886	<.001
sleep	0.007	0.994	-0.12	0.904	-6.971	<.001	-7.098	<.001
stress	-9.115	<.001	-11.98	<.001	-4.649	<.001	-5.604	<.001
weight loss	0	0.999	0	0.999	-0.708	0.484	-0.708	0.484
wellness	3.937	<.001	27.38	<.001	-4.72	<.001	-3.3.45	0.001

Table 5.6: FDA statements that captured the largest amount of misinformation with the highest amount of precision.

Statement #	**Statement**
3	Firstly, the research performed to date has shown that CBD can reduce a number of pro-inflammatory cytokines (numerous different types of substances, such as interferon, interleukin, and growth factors, which are secreted by certain cells of the immune system and have an effect on other cells) including IL-6, the one reduced by other drugs being studied for COVID-19. CBD was also shown to reduce interleukin (IL)-2, IL-1 α and β, interferon gamma, inducible protein-10, monocyte chemoattractant protein-1, macrophage inflammatory protein-1 α, and tumor necrosis factor- α – all of which are associated with the pathology of severe cases of COVID-19. In addition to reducing these pro-inflammatory cytokines, CBD has also been shown to increase the production of interferons, a type of signaling protein that activates immune cells and prevents viruses from replicating

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Statement #	Statement
8	DML CBD: Immune Boost Pack . . . ALERT: There is no cure or treatment for COVID19. With this in mind, many doctors claim the best defense is to boost the body's immune system. DML CBD aims to help our customers in an attempt to boost the immune system. . . . WHY TO BUY THE BOOST PACK: Studies suggest that CBD can help fight off inflammation, boost the immune system, and help battle against certain harmful bacteria. Some research suggests it can help suppress the cytokine storm inside the body that can cause great illness and sometimes death. . . . NOTE: The cytokine storm is often triggered in patients with COVID19. Please note there is no proven cure or treatment for COVID19 . . . There has never been a more important time than to boost your immune system. To help our customers get a full CBD experience that aims to boost your immune system, we offer the 'DML CBD Immune Boost' package . . ..

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Statement #	Statement
12	What is COVID-19? Coronavirus is referred to as a novel cause for viral pneumonia because it's a virus we haven't seen before and have developed no immunity to. . . . What Happens If You Get Infected and What Can Help? . . . Regardless of the shape you're in at this moment, there may be ways you can prepare and protect your body from developing a more severe response to infection. Explore the solutions included in NoronaPak below! [graphic with the following text] 'Selenium, Cannabidiol (CBD), Vitamin-C, Zinc, Vitamin-D, N-Acetylcysteine' . . . Supplementation with selenium results in changes in the gene expression that is required for protein biosynthesis in lymphocytes, the infection-fighting cells that are crucial to the immune system being able to identify infection and mount an immune response. . . . Selenium is not only important in boosting the immunity of the individual but also to slow the development of more virulent strains of some viral pathogens. . . . CBD may suppress the productions of cytokines in the setting of infection
19	In the wake of the current epidemic, it is now more important than ever to keep your immune system as healthy as can be . . . Here are 5 key ways to strengthen your immune system during the outbreak . . . Take supplements such as CBD

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Statement #	Statement
26	Crush Corona . . . While scientists around the world are working 24/7 to develop a COVID-19 vaccine, it will take many more months of testing before it's approved and available. However, there's something you can do right now to strengthen your immune system. Take CBD . . . CBD can help keep your immune system at the stop of its game. . . . We want everyone to take CBD and take advantage of its potential to help prepare your body to fight a coronavirus infection. So, we're making all of our products more affordable

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Education

- University of Louisville: J.B. Speed School of Engineering Louisville, KY
  - Computer Science - MS, 2009
    - Project Supervisor: Patricia Cerrito, PhD
  - Graduate Certificates: Data Mining & Network & Information Security
- Eastern Kentucky University Richmond, KY
  - Applied Computing (Option: Software Engineering) - MS, 2007
  - Statistics - BS, 2006
  - Computer Science (Concentration: Computer Technology) - BS, 2002
  - Undergraduate Minors: Mathematics, Mathematical Sciences, Computer Electronics
- Hazard Community College & Technical College Hazard, KY
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Journal Articles

- Turner J, Kantardžič M, Vickers-Smith R, Brown A Detecting Tweets Containing Cannabidiol-Related COVID-19 Misinformation Using Transformer Language Models and Warning Letters From Food and Drug Administration: Content Analysis and Identification JMIR Infodemiology 2023;3:e38390 URL: https://infodemiology.jmir.org/2023/1/e38390 DOI: https://doi.org/10.2196/38390
- Turner J, Kantardžič M, Vickers-Smith R Infodemiological Examination of Personal and Commercial Tweets About Cannabidiol: Term and Sentiment Analysis J Med Internet Res 2021;23(12):e27307 URL: https://www.jmir.org/2021/12/

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Conference Proceedings Articles

- J. Turner, M. McDonald and H. Hu, "An Interdisciplinary Approach to Misinformation and Concept Drift in Historical Cannabis Tweets," 2023 IEEE 17th International Conference on Semantic Computing (ICSC), Laguna Hills, CA, USA, 2023, pp. 317-322, doi: https://doi.org/10.1109/ICSC56153.2023.00065
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- Turner, J., & Kantardžič, M. (2017). Geo-social analytics based on spatio-temporal dynamics of marijuana-related tweets. Proceedings of the 2017 International Conference on Information System and Data Mining - ICISDM '17, 28–38. https://doi.org/10.1145/3077584.3077588

Conference Posters

- Turner, Jason "Analysis and Identification of COVID-19 Misinformation Within Commercial CBD Tweets". Research!Louisville 2021, 2021. Louisville, KY
- Turner, Jason "Using SAS Enterprise Miner's Association Node on Patient Diagnoses". SAS M2009 Data Mining Conference, 2009. Las Vegas, NV
- Turner, Jason "Predicting Hospital Length of Stay and Cost using ARIMA and Text Miner". SAS F2009 Business Forecasting Conference, 2009. Cary, NC

Book Chapters

- Neupane, R and Turner, J. "Outcomes Research in the Treatment of Asthma". In Cases on Health Outcomes and Clinical Data Mining: Studies and Frameworks. Cerrito PB, Editor. IGI Publishing. 2010.

Awards/Honors

- 2022 JB Speed School of Engineering CSE Doctoral Award
- Humana Star Award
- F2009 Business Forecasting Conference: awarded 1 of 3 prizes for poster submission
- Eastern Kentucky University Dean's List
- Eastern Kentucky University NSF Computer Science, Engineering, and Mathematics Scholarship