A Data Driven Network Analysis of Coffee Consumer Brand Identities and Sentiments*

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Abstract

Coffee is one of the most-consumed products worldwide and is provided by both well-known large companies and small boutique stores. Of the many popular beverages on the market, coffee appears unique in the sense that people often find identity and feel strong loyalty toward their coffee brand of choice, claiming to be a "small coffee shop person", a "Starbucks person", an "artisanal coffee person", etc. To understand the sentiments toward, commonalities between, and sub-communities within the coffee drinker culture, this study considers tweets about two major coffee brands: Starbucks and Dunkin'. Ten thousand tweets are collected regarding each brand and textually broken down into significant words. For each tweet, metadata is collected regarding the tweet and the user who posted the tweet. Using the tweet metadata, derived attributes of tweets, and sentiment scoring, networks are created by connecting tweets based on their textual commonalities. Network analysis is performed to investigate similarities and differences between the two brands and their respective consumers' sentiments and attributes. Community detection algorithms further identify sub-communities amongst the two brands. The results of this analysis provide insights into these brands and their similarities and differences along with their sub-communities, while the methodology acts as a template for similar analyses of other brands or consumer products to follow.

Key words: Coffee, Consumer, Brand Identity, Brand Loyalty, Network, Twitter, Culture, Sentiment, Text Analysis, Community Detection, Social Network.

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Introduction

Coffee is one of the most-consumed products worldwide and has developed into a major international market. Over the past few decades, the consumption of coffee has changed from a purely practical activity into a cultural and personal experience. Both large-scale coffee houses such as Starbucks and local single-store coffee shops continue to boom in popularity and patron loyalty. World consumption of coffee is currently projected to increase from roughly 9.9 billion kilograms in the 2020/21 coffee year to 10.2 billion kilograms in the 2021/22 coffee year (ICO [7]). With this growing market and increase in popularity, consumers have begun to find identity in their chosen coffee brands. A sense of pride is established in a person's claim to being a Starbucks loyalist or a small-shop artisanal coffee connoisseur. Hence, several distinct groups of coffee-drinkers have naturally formed. And with the advent of third wave coffee, a higher emphasis is being placed on higher quality coffee. As marketers now try to bring this higher quality coffee to the masses, opinions toward tried-and-true establishments with often loyal followings might be subject to change.

The mass consumption of coffee has led to many studies regarding coffee in terms of its consumption and marketplace. A 2018 investigation into the existing research done regarding coffee consumption found that most researchers looked into the sustainability and ethical aspects of coffee consumption (Samoggia and Riedel [12]). Following that topic, the next most researched area revolved around "consumer behavior towards coffee-house brands, mainly Starbucks" (Samoggia and Riedel [12]). This area of research aligns with the focus of this study. The investigation herein uses text and network analytics of Twitter data to understand consumer identities and sentiments toward two of the largest coffee brands in the United States: Starbucks and Dunkin'. Additionally, through tweets posted about each of these brands, this study aims to identify common attributes of the critics and proponents of the two brands, respectively and comparatively, and how these consumers interact and relate. Finally, the study aims to understand sub-communities related to each brand. By investigating all of this, a deeper understanding into the sentiments, similarities, and differences regarding the two brands will be attained.

Before diving into the details of the project objective, a deep literature review is performed to understand the applications and background of the topic and what methodology could be considered. Furthermore, researching previous studies aids in understanding limitations to the study and provides motivation for why this research is important. The literature review provides use cases for the study and a foundation of previous work to grow off of.

One application of this study is to understand marketing directions that a company (namely, Starbucks or Dunkin') could follow to better reach out to both their loyal fans and their critics. By targeting these two groups in unique ways, marketing efforts can be optimized. Understanding consumer perceptions of brands is an essential component of marketing strategy that marketing managers have long relied on to guide marketing strategy (John et al. [8], Lehmann et al. [9]). Because of this, developing improvements to perceptual mapping techniques, a method of visualizing how customers rank a company holistically and comparatively with other companies, have been a priority for marketing researchers (Bijmolt and van de Velden [2]). However, manually collecting data about consumer perceptions has historically been very difficult and expensive due to the need for recruiting study participants and maintaining participant attention and cooperation throughout the study (Steenkamp and Van Trijp [13]). Considering these challenges, the rise of social media has laid a pathway for new methods of data collection.

Social media has redefined the marketing landscape by changing how information about consumer perceptions is collected. Now, marketers can examine consumer opinions by collecting textual evidence about thoughts toward and interactions with the product. Not only can marketers absorb information about their consumers, they can also use social media to distribute messages to their consumers about their products and services. To investigate this, a 2021 study analyzed the Twitter networks of two multi-brand retailers to investigate network activities and network patterns based on centrality measures (Watanabe et al. [17]). The study utilized network statistics to examine the ego networks (brand-centered) and whole networks (hashtag networks) produced via social media communications (Watanabe et al. [17]). The findings revealed that although brands are able to deliver messages through digital platforms, they have limited control over the communication within networks, and thus cannot govern the spread of information (Watanabe et al. [17]). This suggests that marketing teams need to dive deeper into optimizing their methodology for effectively spreading information on social media. One way to do this would be through the collection of consumer thoughts regarding their product and producing material targeted at certain attributes of groups. This project applies the findings of the aforementioned literature toward the analysis of sentiments regarding Starbucks and Dunkin' and whether negative or positive sentiments are clustered together based on group attributes. This could validate the use of market segmentation strategies in favor of or against a "one size fits all" approach. A sample application would be the determination of characteristics of individuals in different groups and utilizing their differences to curate unique messages for advertising to various types of consumers.

While marketers may not be able to control the inter-communications of their consumers regarding their product, it is clear that social media has revolutionized how information in a networked environment is received and disseminated. In particular, Twitter has generated a great deal of attention for its ability to broadly propagate information to a large audience. Information diffusion, the process of how information is spread and interacted with, has been widely studied in the field of network science. Information is often diffused in conjunction with a major event such as an earthquake or a political demonstration (Sakaki et al. [11], Beguerisse-Díaz et al. [1]). Studies following the dissemination of information after a major event map the network of tweets, mentions, and retweets to identify the popularity and measure influence. While this may seem straightforward, tweets are not always indicative of a user's connection with a topic or their community identity due to the noise produced by many personal messages, jokes, and fanfares. Therefore, there is a need to transform into a more structured network in terms of "community" (Myers et al. [10]). This idea is important to keep in mind as a limiting reagent to the study here, as analyzing Twitter networks must be done carefully and very analytically to filter through the noise and gain true insights.

Although the detection of communities may be challenging, understanding the sentiments of consumers has the potential to provide valuable insights about the consumer perspectives on products. Sentiment analysis has long been used in the commercial space, especially for product reviews and predicting future buying behaviors. One study on this topic compared tweets containing two different hashtags related to weight loss (#thinspiration and #fitspiration) in order to understand how users' views on health and fitness differed for each group (Tiggemann and Zaccardo [15], Tiggemann et al. [16]). Analysis of the sentiments of each set of tweets showed that on average, both #thinspiration and #fitspiration tweets were mildly positive in sentiment but that #fitspiration tweets were significantly more positive than #thinspiration tweets (Tiggmann & Zac-cardo 2018). This is consistent with the findings that much of the text on #fitspiration Instagram imagery is positive, suggesting that the text may be the source of inspiration that people feel (Tiggemann and Zaccardo [15], Tiggemann et al. [16]). Considering this study, it is established that sentiments can be evaluated and useful in comparing tweets on two different yet similar topics. This validates the basis of this research topic.

Sentiment analysis also plays a role in building quantitative measures of users' attitudes towards brands as well as underlying business components such as product, website, support and customer service. Another study analyzed the opinion of 19 million Twitter users towards 62 popular industries, encompassing 12,898 enterprise and consumer brands via sentiment analysis of 330 million tweets over a period of one month (Hu et al. [5]). The study found that users tended to be more positive or negative when interacting with brands than in general on Twitter and that the sentiments towards brands between and within industries varied greatly (Hu et al. [5]). For example, airline industries produce very high negative sentiments and automotive industries provide high positive sentiments (Hu et al. [5]). By analyzing sentiment towards topics associated with users' brand interaction tweets, the authors found that highly negative topics included "Fox News" while highly positive topics include "Video Games" and "Music" (Hu et al. [5]). The results of this study suggest that evaluating sentiments about products on Twitter produce valuable insights and it is important to compare brands within the same industry. Again, this solidifies the direction of this research project.

Before diving more into the basis of this project, the world-wide nature of coffee as an industry was investigated to confirm the international nature of this consumer product. One study looked at the dynamics of the international coffee trade network using data from the World Trade Organization from 1996 to 2017 (Sujaritpong et al. [14]) . They found that more than 82% of countries participated in the coffee trade network but only 3% of countries controlled more than 90% of international trade (Sujaritpong et al. [14]). Understanding the vast nature of the coffee industry is important to validate that this topic is a good representation of how tweets can be used to understand consumer sentiments toward products. Thus, the methodology of this study could be replicated with other major consumer products to gain insights about them.

With a review of literature validating the ideation of this project, a firm objective can be stated. This research study aims to understand and compare consumer sentiments and identities surrounding two popular coffee brands: Starucks and Dunkin'. Several questions are sought to be answered. Are there distinguishable communities in a coffee-based social network? If so, what characteristics do they share? Are Starbucks/Dunkin' drinkers more/less positive/negative? Is there an "influencer" effect on coffee brand preference? These questions will be answered through a network analysis of ten thousand tweets about each of the two brands. For each tweet, metadata is collected regarding the tweet user's follower counts, the tweet's retweet counts, and more. Then, text analysis is used to clean the tweets and to score each tweet's sentiment (negative, neutral, positive). Next, a network is created connecting tweets by their textual commonalities. Network analysis is performed to understand each brand's clientele and investigate commonalities and differences between the brands and their consumers' sentiments and attributes. Finally, a community detection algorithm is used to investigate sub-communities of each brand. The results provide insight into these brands and a template for similar analysis of other brands.

Methods

This study utilizes Twitter data to investigate the coffee-drinking communities of Starbucks and Dunkin'. In order to explore these two groups, data in the form of tweets is collected, cleaned, and analyzed.

Data Collection

Twitter is a well-known platform in which users express themselves via a posted statement of 280 characters or less. Because of this, Twitter provides a vast amount of information on an endless spectrum of topics and gives insights into social opinions regarding these different topics. Therefore, to understand the consumer opinions and sentiments surrounding Starbucks and Dunkin', tweets are collected about these two brands using the Twitter API "Tweepy".

For this study, 10,000 tweets containing the word "Starbucks" and 10,000 tweets containing the word "Dunkin" were collected. In addition to the actual text content of the tweets, metadata about each tweet was also collected. This metadata included the tweet's creation time, hashtags and user mentions, retweet and favorite counts, along with user information such as user id, name, screen name, friend count, follower count, status count, and whether or not the user is verified. The 20,000 tweets and their metadata were saved in csv form for use in the analysis.

Text Analysis

Text Cleaning

Before using the data for analysis, the collected tweets required cleaning and preparation. A function was defined to quickly handle this task. The function took each tweet in the dataset and performed the following actions: 1) conversion of all text to lowercase, 2) removal of any URLs (i.e. any string containing "http" or "www." prefixes), 3) removal of user mentions through the deletion of any "@" symbols and the attached text, 4) removal of all punctuation, 5) removal of non-alpha-numeric characters, and 6) removal of any stand-alone number (ex: "0", "00", etc.) or words containing numbers. These actions were performed to isolate only words of meaning or significance.

After the initial cleaning, all words in each tweet were tokenized. Tokenization is a method of breaking down a piece of text into smaller units, which allows for more manageable text analysis. First, tweets are broken down into words. For instance, "I love coffee" would become "I" "love" "coffee". Then, all stop words are removed from these tokenized words. Stop words are commonly-used words such as "the", "as", or "and". Python's Natural Language Toolkit (NLTK) includes a tokenization package containing a list of the most-common stop words in the English language. This analysis used NLTK's list of stopwords to remove these commonly-used words from each tweet. After this, the tweet words were lemmatized to reduce each word to its core, or root, word. Doing this aids in word comparability across different tweets so that words with the same root and same meaning are understood to be the same. For example, the words “dog” and “dogs” reference the same root idea, so the lemmatization change of “dogs” to “dog” allows for recognition of this.

Besides the standard text cleaning processes, further steps were taken for the specific needs of this research. Twitter is a heavily utilized tool for brand advertising and marketing. Therefore, tweets were removed if they were suspected to be ads or promotional content. Additionally, an early stage of text analysis revealed that a large number of tweets appeared to be about the unionization of Starbucks employees due to unfair working conditions and wages, and were mostly tweeted by various news accounts. Tweets regarding the unionization of Starbucks employees were removed in order to mitigate any bias introduced on consumer feelings towards Starbucks and Dunkin’ due to this incident. Also, tweets posted by the official Starbucks and Dunkin’ brand accounts were removed to lessen bias on text analysis. Next, bot-like tweets were removed according to suggested filters outlined in the official Twitter API documentation, and tweets from users with fewer than 10 followers were dropped. Finally, tweets by users with a high tweet frequency were also dropped. A user was considered a “high-frequency tweeter” if they tweeted more than 50 times during the data collection period. Lastly, tweets with less than 3 words were removed.

Text Analysis

With the tweet data cleaned and filtered, it was then transformed into a Term Document Matrix (TDM) which tracks the term (or word) frequency of each term/word by each document. Each ‘document’ in this case is an individual tweet. The Starbucks and Dunkin’ TDMs were utilized to show the top ten words and top ten hashtags used in each coffee company’s tweets as shown in Table 1. An interesting observation of these top words shows that ‘starbuck’ is actually a top word in the Dunkin’ tweet set, occurring a total of 504 times. Additionally, the top ten hashtags for Dunkin’ tweets lose relevance to coffee beyond the top four hashtags, whereas this is not the case for Starbucks. It’s seen that both brands’ tweets are mainly concerned with coffee and drinks. However, words such as ‘safety’, ‘crime’, and ‘drug’ are prevalent in the Starbucks tweets as shown in the Figure 1 wordcloud and Table 1.

Table 1: Top ten words and hashtags found in each sub-network.

Words		Hashtags	
Dunkin	**Starbucks**	**Dunkin**	**Starbucks**
dunkin	starbuck	dunkin	starbucks
donut	drink	sb19	retail
coffee	get	coffee	seattle
like	coffee	dunkindonuts	coffee
get	store	felip_bulan	crime
go	like	feliponglobalspin	starbuckssummer
starbuck	go	jobs	news
im	close	donbelle	shopeemy
ice	im	globalspin	primeday
one	today	hiring	business

Note that Table 1 was not the first iteration of this table. As mentioned previously, an earlier stage of analysis showed that the top hashtags for Stabucks tweets included hashtags such as '#unionstrong' and '#unionsforall'. Additionally, Dunkin' tweets contained '#giveaway' in its top hashtag and both Dunkin' and Starbucks had '#ad' in their top hashtags. This is important to note as the cleaning and filtering process intentionally attempted to remove non-consumer concepts from the tweet base. Thus, Starbucks and Dunkin' topics such as unionization and advertisements do not appear in the tweet base for the network analysis.

In order to further gauge common words in the Starbucks and Dunkin' tweet collections, word clouds were created for both tweet sets as seen in Figures 1 and 2.

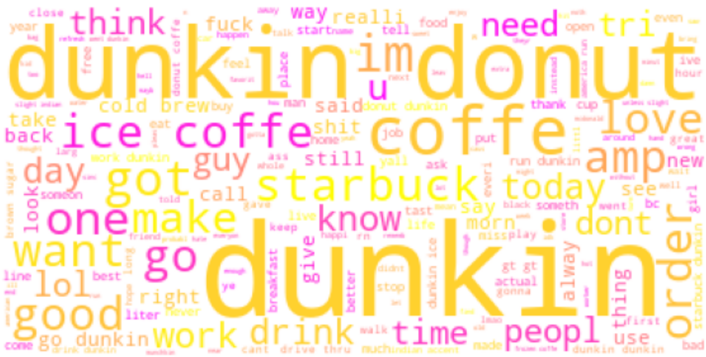

Figure 1: Word cloud from tweets about Dunkin'.

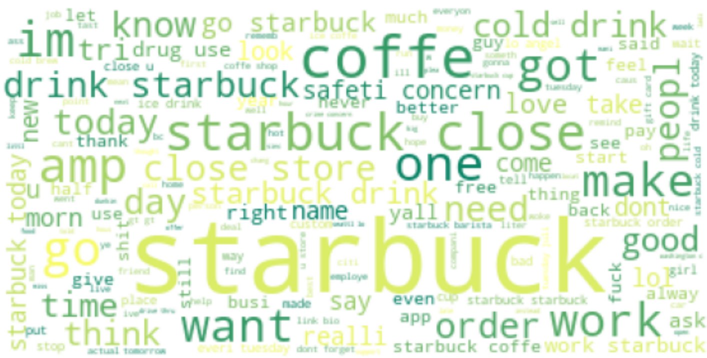

Figure 2: Word cloud from tweets about Starbucks.

These wordclouds provide interesting insights into the words posted in reference to the two topics. A careful scan of the words shows that while many words reflect consumer ideology such as opinions and drink choices, many words stray from this topic.

Sentiment Analysis

Sentiment analysis is a commonly used natural language processing and computational linguistics task for quantifying general attitudes based on text. Typically, sentiment analysis algorithms assign a score to a piece of text which classifies the text as positive, neutral, or negative. VADER (Valence Aware Dictionary and sEntiment Reasoner) is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media (Hutto and Gilbert [6]). An important thing to note is that sentiment analysis was conducted prior to the steps taken in the Text Cleaning section above. This is because VADER sentiment analysis uses many of the elements of text which were removed from the tweets such as punctuation, capitalizations, emoticons, emojis, and more. VADER is also able to handle sentiment-laden slang ('nah', 'meh') as well as various spellings of established English words ('sux', 'rox'). VADER also considers sentiment-laden initialisms and acronyms ('lol', 'omg').

The VADER implementation in Python returns four scores. The first three scores (positive, neutral, negative) are ratios of words in a text that fall in each category. These scores do not necessarily convey the sentiment of the text but rather the presentation and unique style of the author. In other words, "some writing styles may reflect a penchant for strongly flavored rhetoric, whereas other styles may use a great deal of neutral text while still conveying a similar overall (compound) sentiment" (Hutto and Gilbert [6]). The last score is the compound score which can be thought of as a "normalized weighted composite score" and conveys actual sentiment of a text (Hutto and Gilbert [6]). This score is most commonly used by researchers to gauge mood and attitudes. For the purposes of this research, only compound scores are used. The raw compound score value ranges from -1 to 1. Once the continuous compound score is obtained, the values are discretized or binned as follows: a compound score greater than or equal to 0.05 is categorized as positive, a compound score less than 0.05 and greater than -0.05 is categorized as neutral, and a compound score less than or equal to -0.05 is categorized as negative. This method of categorization is suggested by the creators of VADER (Hutto and Gilbert [6]).

Network Nodes, Edges, & Attributes

With the data collected and cleaned, nodes and edges were constructed from the tweets and their attributes. A typical way to build networks using Twitter data is to consider each individual Twitter user to be nodes, and to connect nodes based on if users follow each other. However, this study is interested in the relationship between words used in relation to and sentiments felt toward the topics of Starbucks and Dunkin'. Therefore, each individual tweet was established as a node, and nodes were connected based on their similar use of words. To do this, several steps were taken and several node and edge attributes were established or derived.

As stated, each tweet was established as its own node. Each node was given several attributes, as described here and summarized in Table 2. The first attribute of each node is the list of unique words contained in each tweet (filtered/cleaned as discussed above). Then, the total number of unique words included in each tweet is added as another attribute. Next, each node was given a label of either "Starbucks" or "Dunkin'" based on which keyword they were collected under. The sentiment of each tweet (negative, neutral, positive) as derived and discussed in the Sentiment Analysis section above was also included as a node attribute.

Additionally, two metrics about the tweet's popularity were included as individual attributes: number of retweets and number of favorites. Also, the number of followers of the user who posted the tweet was added as an attribute. This follower count was analyzed and used to mark each tweet as being posted by an "influencer" or not. Influencers in social media are those who have many followers and therefore can influence their followers' opinions. Since there is no strict rule on what defines an influencer in terms of a precise number of followers, this study considered users with follower counts in the top 10% of the data set to be influencers.

The final attribute was derived for each node from the node's degree and word count. This attribute is considered to be a "normalized degree" attribute of the node, and is discussed in detail in the Investigation of Network Attributes section below. All of these node attributes are summarized in Table 2.

Table 2: Summary of node attributes.

Node Attribute	Attribute Description
Content	List of unique words contained in each tweet
Number of Words	Count of unique words of each tweet
Brand	"Starbucks" or "Dunkin"
Sentiment	"Negative", "Neutral", or "Positive"
Retweets Count	Number of retweets received by tweet
Favorites Count	Number of favorites received by tweet
Followers Count	Number of followers of user who posted the tweet
Influencer	"Yes" or "No" (based on user follower count)

Nodes must be connected by edges based on some similarity or inherent connection. For the networks considered here, an edge between two nodes was added if the two nodes contained a minimum of four similar words. In other words, tweets were connected based on their textual similarity with a threshold of four words defining similarity between two tweets. Based on this creation of edges, two inherent edge attributes were established for each edge: the number of common words shared between the two nodes, and a list of the common words shared between the nodes. Thus, all nodes were created with many attributes and were connected to each other based on textual similarity.

Network Analysis

With the network nodes and edges created and many inherent and derived attributes added, the Twitter data was ready for analysis. Three networks were considered: the complete network of all tweets, the subnetwork of only tweets collected on the topic of Starbucks, and the subnetwork of only tweets collected on the topic of Dunkin'. By analyzing the complete network along with the subnetworks, both overall and comparative analytics could be performed to best understand the similarities and differences between the tweets about the two coffee brands.

To analyze these networks, several steps were taken. First, the networks' nodal attributes were investigated through visual exploration and correlation analysis. Next, the basic network metrics such as node and edge count and centrality measures were found and investigated. The degree distribution of the complete network was also plotted in several ways for a deeper analysis of this measure. Following this, the networks were visually investigated through plotting of each network's giant connected component using different attributes for node sizing and comparison. The giant connected component (GCC) was used as a way to understand the interactions between the largest group of connected tweets of each coffee brand. Approximately 96% of each network's nodes were contained within their respective GCCs. Therefore, it was decided that utilizing the GCCs would provide an adequate representation of the networks for analysis.

All of these network analysis methods were used to understand the similarities and differences between the two coffee networks. The analysis techniques were primarily performed using Python's NetworkX package. The results of the network analysis are discussed in the Results section below.

Community Detection

In order to detect any sub communities within the Dunkin' and Starbucks tweeters, the Louvain Algorithm was used on the Starbucks network data, the Dunkin' network data, and the complete network data. The results of the community detection on the complete network data are discussed in the Results section. This community detection algorithm introduces a greedy method which strives to optimize modularity when generating communities (Blondel et al. [3]). Modularity is a metric described as the density within each community with respect to edges outside the communities. The Louvain Algorithm begins by assuming each node is its own community and then assigns similar nodes into the same communities upon each iteration. Using this algorithm, communities are discovered within the complete network of all tweets.

Results

Investigation of Network Attributes

Relationships between Node Attributes

The investigation on network attributes first looks at correlations between node attributes of a given network. Correlation matrices were examined for the complete network, the Starbucks network, and the Dunkin' network. The correlation matrix for the entire network can be found in Table 3. The correlation matrix for the entire network reveals that the strongest correlation is between the attributes of retweet_count and favorite_count. The second highest correlation of 0.33 exists between attributes degree and num_unique_words. A similar outcome is present in the individual Starbucks and Dunkin' correlation matrices. For Starbucks, the correlation between degree and num_unique_words is 0.22 and for Dunkin' the correlation is 0.47.

This outcome is expected due to the chosen edge creation method discussed previously. The number of similar words two tweets have determines whether a link forms between the two nodes. The higher the number of unique words a tweet has, the higher the likelihood of that tweet sharing similar words with other tweets. Therefore, lengthier tweets are more likely to receive new links. Due to this high positive correlation between degree and num_unique_words, degree was normalized by num_unique_words. This was done in order to lessen the effect of preferential attachment to longer tweets seen in the network.

Table 3: Correlation matrix of node attributes across the complete network.

Pairwise Correlations						
Node Attributes	user_followers_count	retweet_count	favorite_count	num_unique_words	normalized_degree	degree
user_followers_count	1.00					
retweet_count	0.052	1.00				
favorite_count	0.0063	0.9	1.00			
num_unique_words	0.0085	0.018	0.0083	1.00		
normalized_degree	0.028	0.016	0.00067	0.038	1.00	
degree	0.029	0.018	0.0017	**0.33**	0.86	1.00

Comparisons can be made between the individual Starbucks and Dunkin' correlation matrices as well. The attributes of retweet_count and favorite_count are more highly correlated for Starbucks (0.97) than for Dunkin' (0.84) which could suggest that Starbucks tweets are more likely to get 'boosted' (ie. they are more likely to be both favorited and retweeted). The retweet_count and user_followers_count are more highly correlated for Dunkin' (0.12) than Starbucks (0.062). For Dunkin' tweets, it seems that a user's number of followers has a greater impact on the number of retweets the tweet gets. On the other hand, Starbucks tweets do not necessarily need to have high follower counts to get high retweet counts. This could be due to the fact that Starbucks is simply tweeted about at a higher magnitude than Dunkin' is and thus a non-influential user with a low follower count can get a 'hit' tweet. Or, an influential user or celebrity could tweet about Starbucks and not receive much attention from it since Twitter is already saturated with Starbucks related content.

Basic Statistics

Correlation matrices only take numeric node attributes into account. Therefore, frequency tables were used to inspect categorical node attributes such as sentiment and influencer_status. These frequencies were converted to percentages in order to get the percentage frequencies of the desired sub groups. For example, Table 4 displays the percentage of positive, neutral, and negative tweets posted by influencers and non-influencers for the respective networks. As shown in the table, 33.4% of Starbucks' influencer tweets are positive. This is roughly 15% less than the percentage of Dunkin's influencer tweets that are positive (48.6%). This could suggest that Dunkin' influencers have more positive attitudes when tweeting. Moreover, a higher percentage of Starbucks' influencer tweets are negative (30.1%) compared to Dunkin's negative influencer tweets (21.4%). This is roughly an 8% difference between the two brands, further affirming the idea that influential users tweeting Starbucks-related content may have more negative views and opinions.

Table 4: Frequency of tweets' sentiments by influencer status within the three networks.

Percentage Frequency – Sentiment by Influencer Status						
	Dunkin'		**Starbucks**		**Complete Network**	
	Infl.	Non-Infl.	Infl.	Non-Infl.	Infl.	Non-Infl.
positive	48.6%	44.7%	33.4%	41.1%	40.3%	42.9%
neutral	30.0%	31.1%	36.4%	32.6%	33.5%	31.7%
negative	21.4%	24.2%	30.2%	26.5%	26.2%	25.4%

A possible explanation for this could be that at the time of data collection, controversial stories involving Starbucks were circulating in the media. The impacts of Starbucks current events are discussed in more detail in the Community Detection section below. This could also have a marginal effect on the general sentiments of Starbucks tweets. Figure 3 shows that Dunkin' tweets have a higher frequency of positive tweets than Starbucks, and that Starbucks has a higher frequency of negative tweets than Dunkin'.

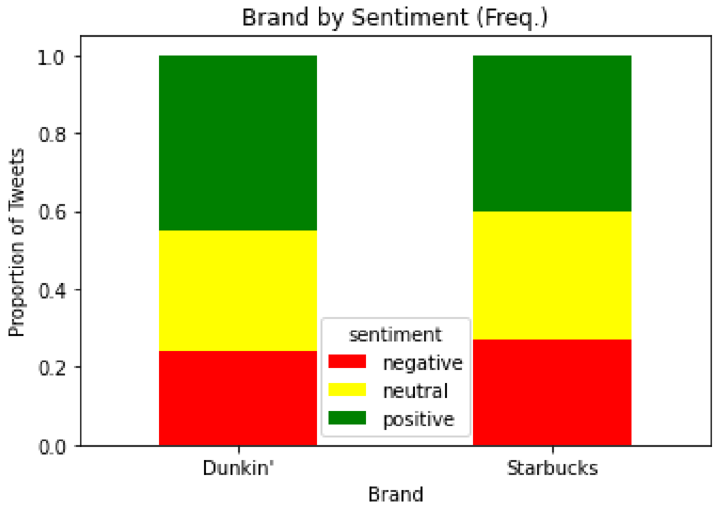

Figure 3: Bar graph showing the proportion of each group of tweets (Starbucks and Dunkin') assigned each of the three options of sentiments: positive (green), neutral (yellow), or negative (red). It appears that the proportions between the two brands are very similar but that Starbucks tweets have more negative and less positive tweets than Dunkin' tweets.

Investigation of Network Metrics

The overall network has 11,167 nodes and 302,028 edges. The Starbucks network has 5,411 nodes and 178,923 edges, whereas the Dunkin' network has 5,411 nodes and 97,487 edges. The centrality metrics can help identify key players in the coffee drinking network. Across degree centrality, closeness centrality and between centralities, node 'D4276' stood out as the top node across all three measures. In terms of top nodes within each network, the Starbucks network appeared to be more heterogeneous than Dunkin's network.

Table 5 illustrates the centrality matrix for the entire network. Closeness centrality has the highest score overall, with the mean of 0.29 and median of 0.3.

Table 5: Centrality measures for the complete network of all tweets.

Complete Network			
	Degree (normalized)	Closeness Centrality	Between Centrality
Min	8.96 e-05	8.96 e-05	0
Max	0.095	0.436	0.026
Mean	0.005	0.292	0.0001
Median	0.001	0.300	7.196e-06

Table 6 illustrates the centrality matrix for the Starbucks network. The centrality matrix is fairly similar with the overall network.

Table 6: Centrality measures for the Starbucks sub-network.

Starbucks Network			
	Degree (normalized)	Closeness Centrality	Between Centrality
Min	0	0	0
Max	0.102	0.430	0.037
Mean	0.011	0.294	0.0003
Median	0.003	0.307	2.019e-05

Table 7 illustrates the centrality matrix for the Dunkin' network. The centrality matrix is fairly similar compared to the other two networks.

Table 7: Centrality measures for the Dunkin' sub-network.

Dunkin' Network			
	Degree (normalized)	Closeness Centrality	Between Centrality
Min	0	0	0
Max	0.162	0.474	0.041
Mean	0.007	0.304	0.0004
Median	0.002	0.314	1.427e-05

The histogram and cumulative distribution of degree indicate a power law distribution, although there is some amount of nonlinearity for each network. The complementary cumulative distribution function (cCDF) examines how often the random variable is above a particular level. Both the cCDF and its logarithmic scale demonstrates pareto distribution.

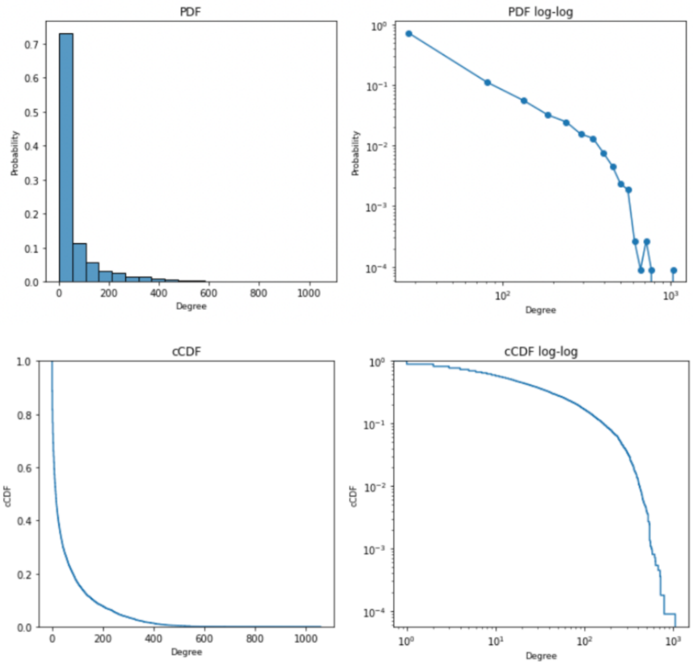

Figure 4: Degree distribution for the complete network of all tweets.

Network Plots

Networks are plotted to understand the relationships between the two coffee brands through visual analysis and consideration of different attributes of the networks and their components. First, the complete network of all nodes (Starbucks and Dunkin' together) is built using NetworkX's spring layout algorithm for positioning the nodes. According to the NetworkX documentation, this "algorithm simulates a force-directed representation of the network treating edges as springs holding nodes close, while treating nodes as repelling objects, sometimes called an anti-gravity force" (Hagberg et al. [4]). The algorithm analyzes these forces and moves the nodes into positions to give a balanced equilibrium. The complete network of all tweets plotted positionally based on the spring layout algorithm is shown in Figure 5.

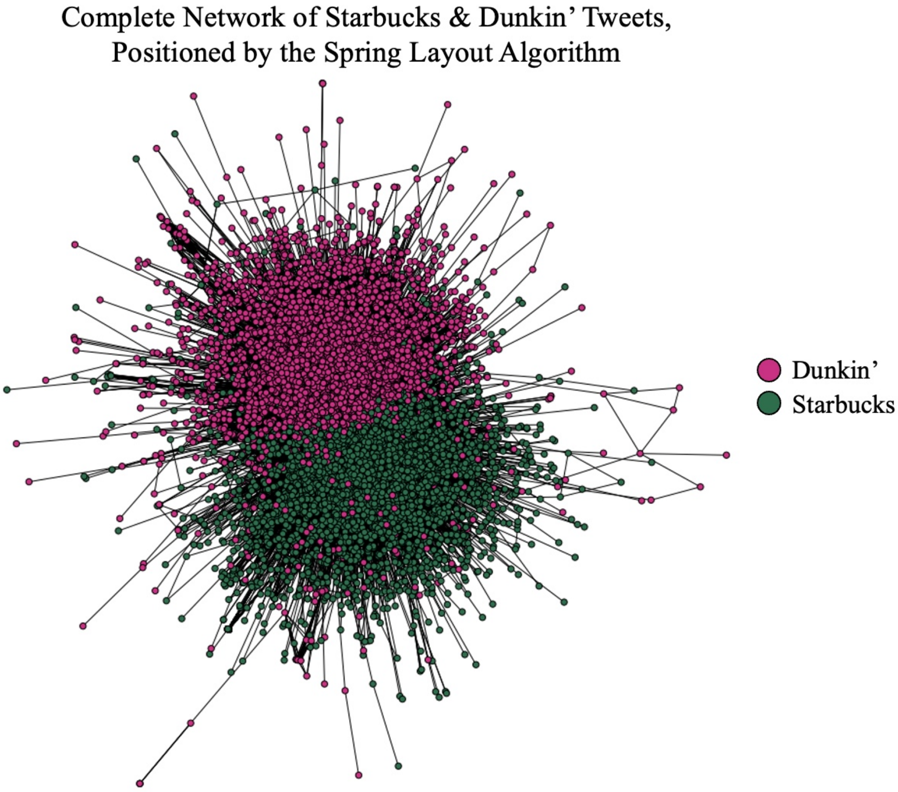

Figure 5: The complete network of Starbucks and Dunkin' tweets, with nodes positioned using NetworkX's spring layout algorithm. The Dunkin' tweets (pink) and the Starbucks tweets (green) form distinct clusters on the plot, indicating that they do have inherent differences.

Figure 5 shows that there is a clear grouping of Dunkin' tweets versus Starbucks tweets. While there appears to be some cross-pollination of Dunkin' tweets existing in the Starbucks grouping and vice versa, overall it's clear that the two brands' tweets form distinct groups as recognized by the spring layout algorithm. This suggests that there are certain similarities amongst tweets posted about each coffee brand, and differences amongst tweets posted on the differing brands.

To further investigate the differences between the two groups of tweets, the complete network of all tweets is split into two subnetworks: one containing all tweets collected on the topic of Starbucks, and one containing all tweets collected on the topic of Dunkin'. The topic-specific subnetworks will be plotted side-by-side using different metrics for node sizing and coloring to understand different metrics of the overall network and the two subnetworks.

First, the distribution of centrality measures of the nodes in each sub-network can be visualized. To do this, the two subnetworks are plotted side-by-side with nodes sized respectively to a centrality measure: betweenness centrality (Figure 6) closeness centrality (Figure 7), and degree centrality (Figure 8).

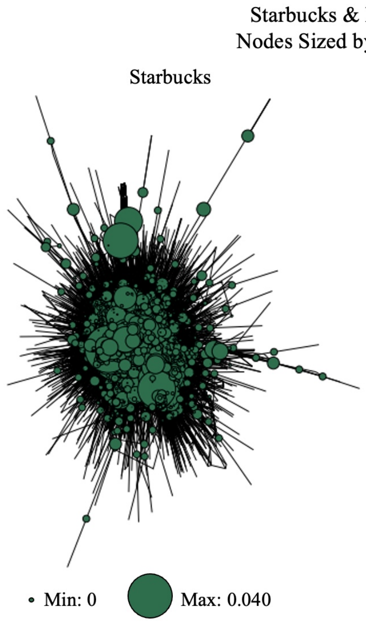

Figure 6: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by betweenness centrality.

Betweenness centrality indicates a node's importance in the flow of information. If a node has a high betweenness centrality, that means it is on many of the shortest paths between two other nodes and therefore is critical for many pairs of nodes to "talk" to each other. The similar distribution of node sizes and the maximum and minimum values seen in Figure 6 suggests that the betweenness centralities of the two networks are very similar. The prevalence of a few very large nodes and many very small nodes indicates the presence of a power law distribution of this measure.

Next, the closeness centralities of the nodes within the two networks are considered.

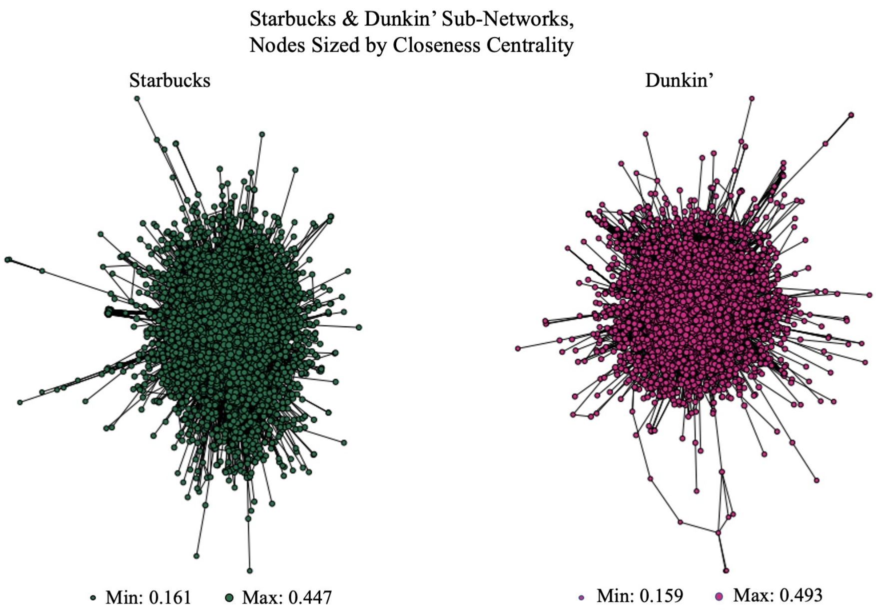

Figure 7: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by closeness centrality.

Figure 7 shows that there seems to be a somewhat uniform distribution of closeness centralities for both of the networks. Additionally, the minimum and maximum closeness centralities are very similar between the two networks. Each node's closeness centrality measure indicates the average shortest path length between a node and all other nodes. In a social network, this can be correlated to the speed at which information spreads within the network. Therefore, the fact that the distribution of closeness centralities of the Starbucks and the Dunkin' networks are so similar suggests that these two networks have similar speeds of information distribution.

Next, the degree centralities of the two networks are considered.

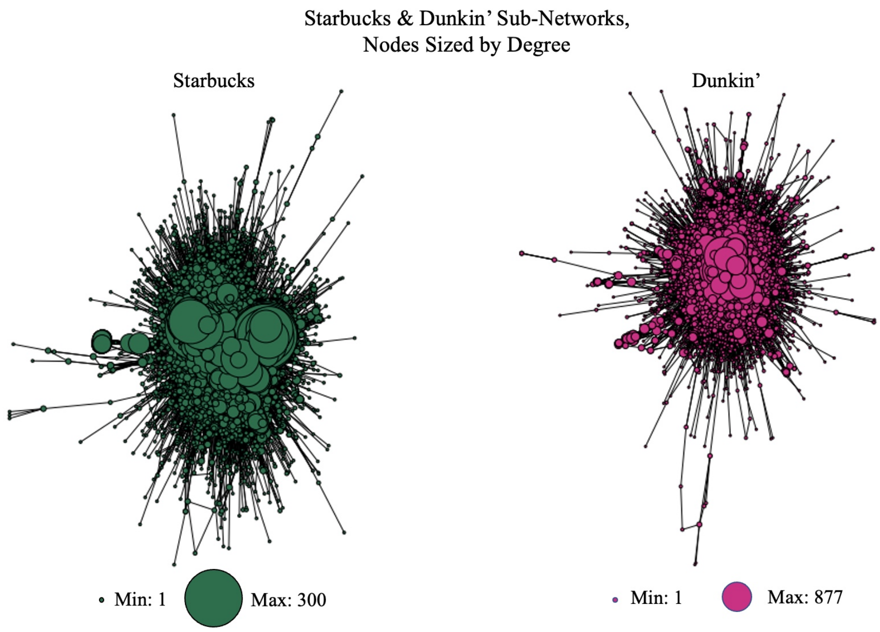

Figure 8: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by degree centrality.

Figure 8 shows the Starbucks and Dunkin' networks side-by-side with the nodes sized proportional to each node's degree. A node's degree indicates how many edges it is connected to. By visualizing the distribution of degree in each network, it appears that the Starbucks network has a smaller difference between maximum degree and minimum degree, as the proportionate sizing of largest-to-smallest node is bigger in the Starbucks network as compared with the Dunkin' network. It's seen that the maximum degree of the Dunkin' network is almost three times that of the Starbucks network, indicating that the Dunkin' network's highest-degree node has many more connections to nodes in the Dunkin' network than the Starbuck network's highest-degree node has within its respective network.

While this may provide interesting insights, an investigation into the nodes with highest and lowest degrees in each network showed that tweets with a higher word count typically have higher degree as well. This makes sense considering the method in which edges were formed between nodes. Since edges were formed between nodes based on two tweets containing four or more similar words, tweets with greater number of words would have greater chances of forming edges with other nodes. Therefore, the standard degree measure counting the number of edges connected to each node is somewhat misleading for this study. Considering this, a new pseudo-degree measure was established.

A "normalized degree" metric was derived by dividing a node's degree by its number of words. In this way, a node's "ability" to gain higher degree by just having more words was somewhat nullified through normalization. The normalized degree of each node in the Starbucks and Dunkin' networks was plotted as node size in Figure 9.

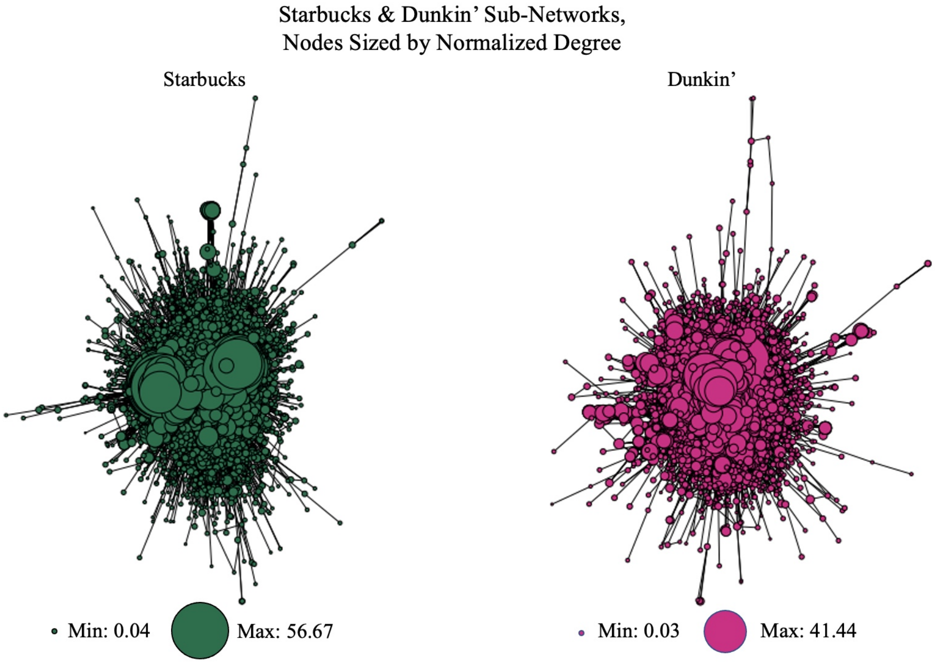

Figure 9: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by normalized degree centrality.

Here, it's seen that the Starbucks network tends to have greater disparity between the maximum normalized degree and the minimum normalized degree than that seen in the Dunkin' network. This indicates that there may be some tweets in the Starbucks network that tend to carry more weight or common ideology within its network as compared with the tweets in the Dunkin' network.

While the centrality measures and normalized degree provide insight into the connectivity of the plot, more insights into the attributes of the Starbucks and the Dunkin' networks can be established by considering the other node attributes, for example, the "influencer" nodes. Figure 10 shows the network plotted with the influencer nodes identified.

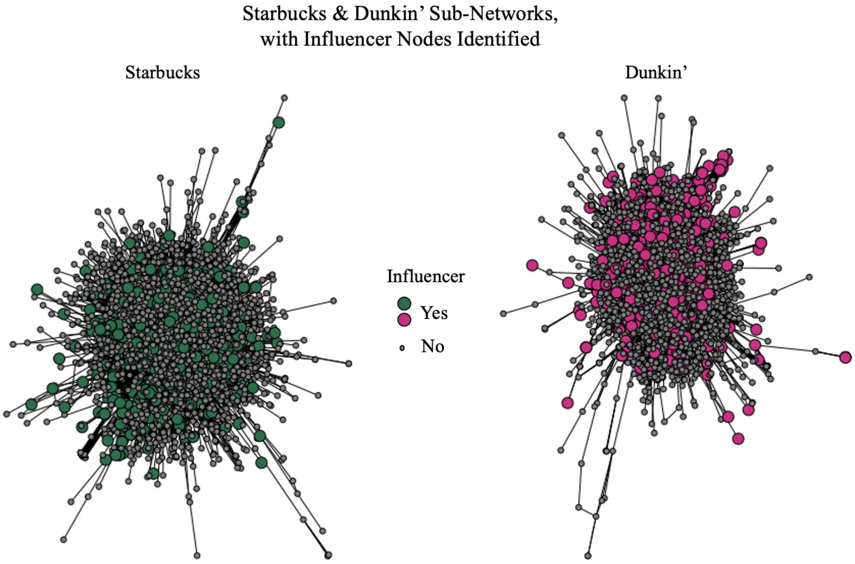

Figure 10: Starbucks and Dunkin' networks plotted side-by-side with influencer nodes identified with coloration and sizing. It appears that influencer nodes do not form any obvious clusters but are instead spread out fairly-uniformly throughout their respective networks.

There does not appear to be obvious clustering of influencer nodes grouping together. This may suggest that influencers cover a wide range of topics and influence not only many people but many different types of people. Also, it appears that the distribution of influencers in the Starbucks and the Dunkin' networks are similar in terms of their interconnections and quantity.

To further dive into the role that users' number of followers play, Figure 11 shows the networks with nodes sized by the number of followers that the user who posted each tweet has.

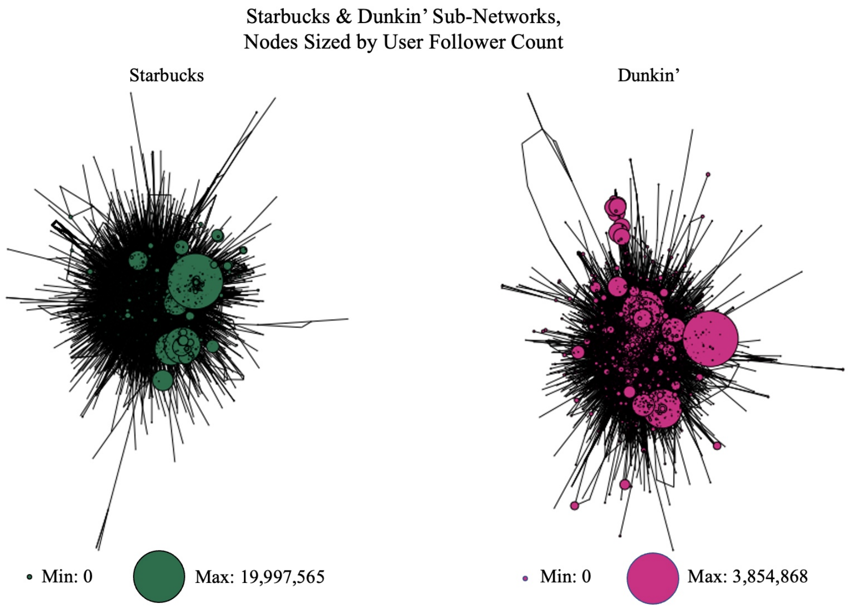

Figure 11: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by user follower count. A power law distribution is noted with there being a few very large nodes and many very small nodes.

Figure 11 shows that there are very few tweets whose user has a huge number of followers, but the tweets with the most followers actually have millions. These tweets would have a great amount of influence to the network of coffee drinkers and could spread opinions quickly. For example, the tweet with the most number of followers in the Starbucks network was posted by the Wallstreet Journal. Not only does this user have 19 million followers, but it is overall a well-known information source that has a major influence in the world. It's seen that the tweet posted by the user with the most followers in the Dunkin' network was posted by Barstool Sports, another well-known and very popular source. Clearly, the few tweets posted by those with many followers will have a great influence on opinions. That being said, most tweets are posted by users with fewer followers but are still important in influencing their own circle of followers.

Next, the popularity attributes of the tweets in the networks can be shown using two different metrics: the number of favorites received by the tweet (Figure 12) and the number of retweets received by the tweet (Figure 13).

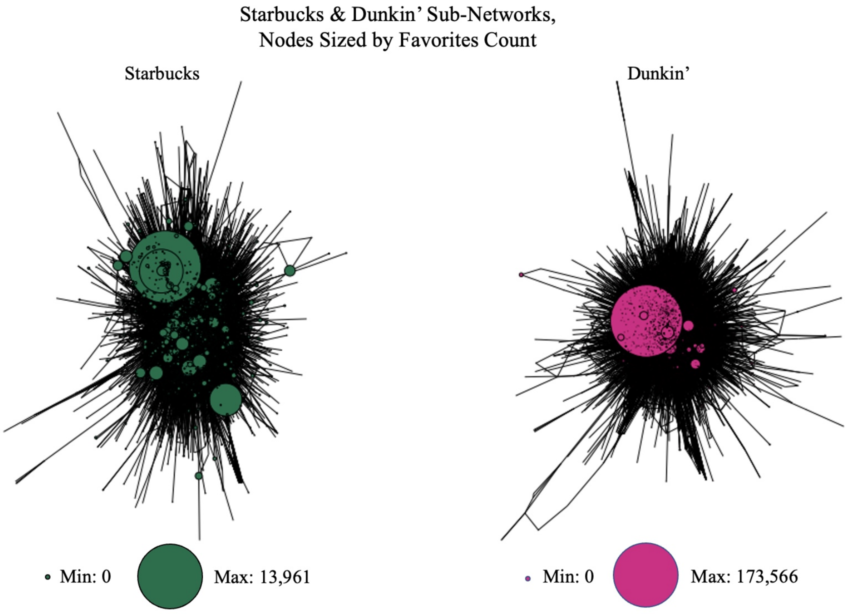

Figure 12: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by number of favorites. A power law distribution is noted with there being a few very large nodes and many very small nodes.

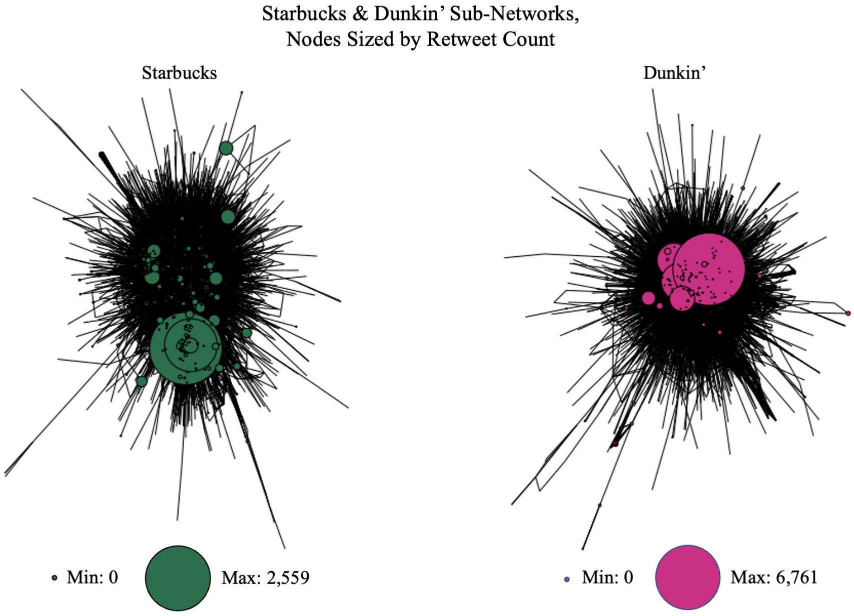

Figure 13: Starbucks (green) and Dunkin' (pink) networks plotted side-by-side with nodes sized by number of retweets. A power law distribution is noted with there being a few very large nodes and many very small nodes.

In terms of number of retweets (Figure 12) and number of favorites (Figure 13), it's seen that one or two major tweets surpass the other tweets by leaps and bounds. The tweet in the Dunkin' network with the most retweets is the same as the tweet with the most favorites. Interestingly, the content of this tweet is actually making fun of Starbucks for its high prices compared with Dunkin'. This shares insight into the interaction between Starbucks and Dunkin' loyalists. Lastly, the sentiment of each node is plotted using color for both the Starbucks and the Dunkin' networks in Figure 14.

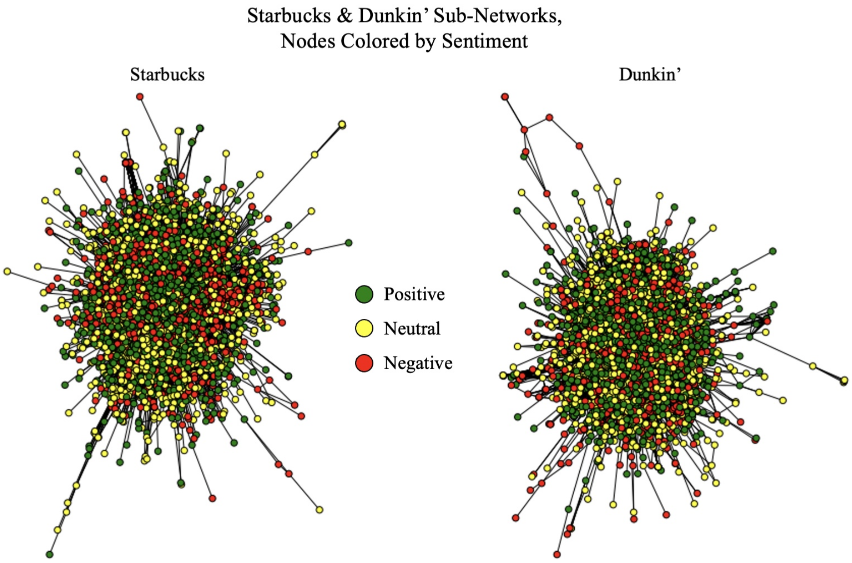

Figure 14: Starbucks and Dunkin' networks plotted side-by-side with tweet sentiment identified by node coloration, where green represents positive tweets, yellow represents neutral tweets, and red represents negative tweets. It appears that sentiments are fairly evenly distributed across both networks and no major positive, negative, or neutral clusters are observed.

While there may be minor groupings of common sentiments within the respective networks, sentiment does not seem to create any significant clusters in the networks. This suggests that positive tweets and negative tweets don't necessarily all share the same words. To understand a tweet's sentiment, one must explore beyond plain words and consider other context clues that VADER uses to assign sentiment, as discussed previously. Also, there does not appear to be a major difference in the proportion or distribution of positive, neutral, and negative tweets posted in the Starbucks versus the Dunkin' networks comparatively. This echoes what was found in the Figure 3 bar graph above.

Overall, the Starbucks and the Dunkin' networks were analyzed using several different attributes and metrics. While the relevance of many of these results have been indicated, further discussion of the greater importance of these findings is included in the Conclusions section to follow.

Community Detection

The Louvain algorithm was used to investigate communities found from the Dunkin' tweet network alone, the Starbucks tweet network alone, and the complete network of all tweets. When community detection was performed on the Dunkin' network alone, over a hundred communities were formed; however, 96.05% of the nodes in the Dunkin' network all belonged to one single community. When performed on the Starbucks network alone, again over a hundred communities formed but there was a clear separation between communities. 81.34% of the nodes belonged to one community, and 17.17% belonged to another community. The remaining nodes were dispersed among the remaining communities. Community detection performed on the complete network validated these communities along with finding additional communities. The community detection resulting from the complete network is shown in Figure 15.

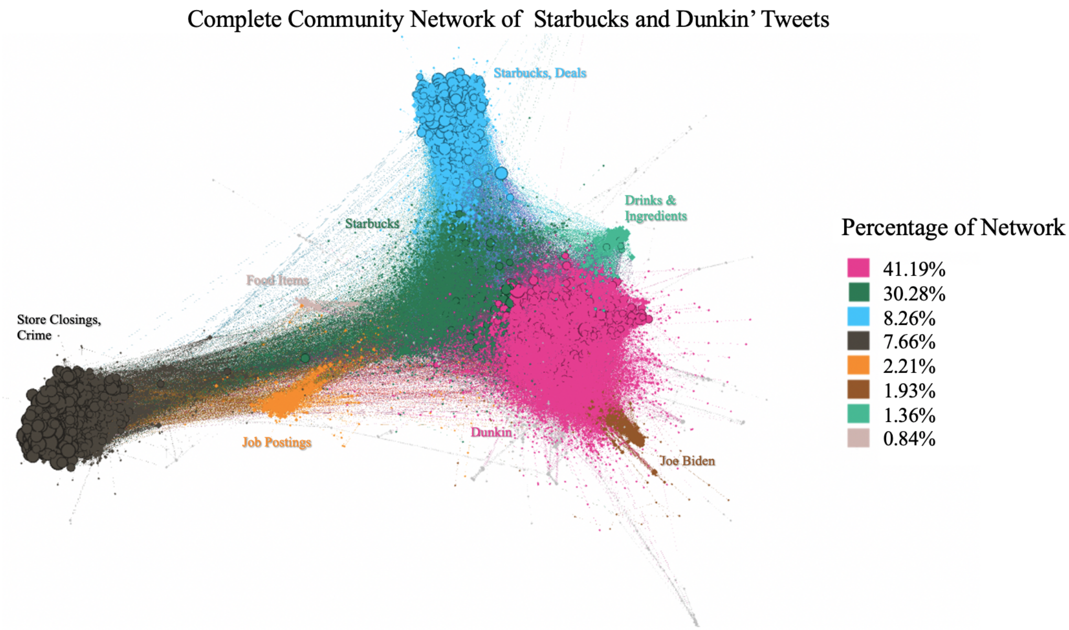

Figure 15: The top eight communities of the complete network of all tweets as found by the Louvain Algorithm.

Per Figure 15, the Dunkin' community contains 41.19% of the network's nodes. This is greater than the Starbucks community which contains 30.28% of the network's nodes. This is because the Starbucks network separates into more sub-communities than Dunkin'. Additionally, there is a clear visual overlap between Dunkin' and Starbucks. Recall from the Text Analysis section that one of the most commonly-tweeted words in Dunkin' tweets was actually 'Starbucks'. This overlap can be attributed to both brands' consumers tweeting about similar topics (coffee, food, drinks) as well as consumers comparing the two brands on Twitter. For example, one of the nodes in the network is a tweet posted by Buzzfeed UK in which they invite users to weigh in on whether individuals prefer to date "Starbucks girls" or "Dunkin' girls".

After the community network is obtained, the top ten words per community are extracted and used to define a label for each community as shown in Table 8. As expected, there is a natural separation of Dunkin' and Starbucks tweets with some overlap between the two. The community most separated from the network is the black cluster "Store Closings, Crime". This community comprises 7.66% of all nodes in the network and shares many connections with the green "Starbucks" cluster. During the data collection period, Starbucks was making headlines after announcing that 16 stores would be closed in 2022 (mainly on the west coast) due to safety concerns, citing increased property crime as the reason. A Starbucks spokesperson stated that the increased crime rate around these stores was not conducive to a safe working environment for its employees. Recall from the Text Analysis section that among the top words in Starbucks tweets were 'store' and 'close'. At the same time this story was making news in the US, Starbucks was also under controversy for the unionization of its employees across the nation due to poor employee treatment and working conditions. The majority of the nodes in the black "Store Closings, Crime" cluster are tweets posted by news or journalism accounts.

Table 8: Top ten words of the top eight communities found by the Louvain Algorithm.

Community							
1 – Dunkin	**2 – Starbucks**	**3 – Starbucks, Deals**	**4 – Store Closings, Crime**	**5 – Job Postings**	**6 – Joe Biden**	**7 – Drinks & Ingredients**	**8 – Food Items**
dunkin	starbuck	starbuck	starbuck	starbuck	dunkin	dunkin	starbuck
donut	get	drink	close	job	donut	cold	sandwich
coffee	like	Tuesday	store	store	go	brew	chicken
like	coffee	today	concern	bio	indian	sugar	menu
get	go	half	crime	link	accent	brown	diarrhea
ice	im	cold	safety	open	slight	cream	pull
starbuck	drink	get	seattle	like	unless	foam	new
im	work	ice	city	barista	biden	good	coffee
go	one	app	drug	click	eleven	new	custom
work	order	every	use	look	joe	starbuck	chai

Another influence of current events on community detection can be seen in the brown "Joe Biden" community. During the period of data collection, a video resurfaced from 2008 of former US Vice President and current US President Joe Biden and gained attention on social media. In the video Biden states "You cannot go to 7-Eleven or a Dunkin' Donuts unless you have a slight indian accent. I'm not joking.". The resurfacing of this video sparked an online community of individuals reporting on and discussing the incident, which was picked up by the Louvain Algorithm as a unique community. Additionally, it could be possible that the formation of the orange "Job Postings" cluster could be a direct effect of the unionization of Starbucks employees. Starbucks was again under fire for firing union organizers and other employees involved in the unionization effort. This could explain why the orange "Job Postings" cluster is connected to other Starbucks sub communities in the network. The orange "Job Postings" cluster is also (less densely) connected to the pink "Dunkin"' cluster. Recall from the Text Analysis section that "#jobs" and "#hiring" were among the top hashtags used in Dunkin' tweets.

In sum, it's clear that the community detection algorithm did a good job in identifying unique factions of the Starbucks and Dunkin' communities. While this may not have provided direct insight into the differences between Starbucks-drinkers and Dunkin'-drinkers, it showed that the coffee brands carried more influence and interest in regards to topics beyond just coffee.

Conclusion

Understanding the Twitter networks between Starbucks and Dunkin' can provide important insights for business executives, marketing specialists and operation managers in the coffee industry. There are many communities in the coffee drinking network and below are the three key findings from this study.

First, there are significant intersections between the Starbucks and Dunkin' communities. This was reflected by the sentiment analysis as well as the top words cited in each online community, as one of the most commonly tweeted words in the Dunkin' tweets was actually 'Starbucks'. Both brands are famous coffee chains and key players in the industry but their business models differ from each other. While Starbucks focuses on creating lofty and welcoming social atmospheres, Dunkin' takes a different approach by leveraging its speed, consistency, and low pricing as its competitive advantage. The difference in the operation models was supported in this study as the tweet with the most retweets in the Dunkin' network was about making fun of Starbucks for its higher prices. However, there were no other significant differentiations to be found from each brand's online presence. The existing overlap may provide a window of opportunity for either company to enter the online marketplace as part of its brand-building efforts.

Second, the influencer effect is worth examining further especially for the Starbucks communities. Overall, influencers within Starbuck's network are 15% less likely to tweet positively and 8% more likely to tweet negatively compared to Dunkin's. This disparity could be exacerbated as some tweets in the Starbucks network tend to carry more weights than Dunkin's. To prevent Starbucks suffering from its potential defamation in the social network, more studies are needed to examine the types and groups of influencers within each network, as potential strange attractors in the network system.

Third, mainstream media remains an important player in influencing social media communications. Coffee brands should not lose sight of this. The tweet with the most number of followers for both Starbucks and Dunkin's networks comes from news outlets (Wallstreet Journal and Barstool Sports). Current events, such as politics and crime news, could also influence community formation for both networks. Media relations has been an important channel for brands to communicate with their stakeholders and based on our analysis, the social media didn't change its prominence in the marketing strategy.

These conclusions reflect interesting observations found from the study. However, further research could be continued in the following ways. First, the study could be expanded to investigate dynamic networks and watch sentiments and attributes of the two brands' networks change over time. For this study, all networks were captured statically which might explain the social network response of time-relative current-affairs such as labor unrest and store closings. The study of dynamic networks might also help understand the changes of communities over time for both Starbucks and Dunkin'. Another potential area of research is to include more brands in the coffee industry. For example, it would be interesting to include a boutique brand like Blue Bottle Coffee as one might see more distinguished communities from the analysis.

This study touches the surface of comparing two consumer brands through network analysis of Twitter data. Similar methodologies and studies could be performed on any number of growing consumer products that may benefit from understanding consumer sentiments and attributes from a social media perspective.

Author Contributions

Anam Khan: This co-author contributed to several portions throughout the project. Primarily, she performed all of the text cleaning, text analysis, text EDA, and sentiment analysis by writing Python scripts and functions for all processes. In addition to this, she calculated several network attribute correlations and statistics. Furthermore, she led the community detection algorithm implementation and visualization creation. She authored all of these sections within the report ("Text Analysis", "Community Detection", "Investigation of Network Attributes"). She also aided in the collection and analysis of articles for the literature review. Additionally, she initiated the project GitHub account. Finally, she handled the initial formatting of the report into the Lyx software system.

Haley Roberts: This co-author contributed to many aspects of the project. She wrote the Python script for collecting tweets from Twitter via the Tweepy API. She also scripted the node, edge, and attribute creation converting the cleaned tweet data and metadata into usable network data. Furthermore, she investigated the network metrics and performed the network plotting based on different attributes and metrics. For the report, she wrote the Abstract and Introduction along with all of the portions related to her main contributions ("Data Collection", "Network Nodes, Edges, & Attributes", "Network Analysis", "Network Plots"). She also aided in the collection and analysis of articles for the literature review. Additionally, she contributed to the organization of the project GitHub account. Lastly, she structured the initial report, provided final editing of all sections, and finalized the formatting of the report in the Lyx software system.

Nuoya Wu: This co-author was involved with various aspects of the project. She aided in the collection and analysis of articles and summarized the collected articles for the literature review section of the Introduction. Additionally, she wrote the "Investigation of Network Metrics" and "Conclusions" sections of the report. Lastly, she edited and proofread the final draft of the report.

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