The Use Of The Twitter Graph For Analyzing User Emotion For Businesses

Gerasimos Rompolas[1], Konstantina Karavoulia[1]

[1]Computer Engineering and Informatics Department, University of Patras, Patras 26504, Greece

Abstract

Nowadays, more and more people are using online social media to express their thoughts and opinions on a variety of topics that interest or concern them. Through social networking platforms, people have the ability to communicate directly and share knowledge with people all around the world. Twitter is one of the most popular social media, used by millions of users daily. In particular, people use it to express their opinion directly and freely on whatever concerns them, thereby generating a large amount of data. The abundance of this information and its multifaceted importance, emphasizes how important is to find ways of collecting and analyzing such data in order to extract valuable knowledge. Such data, are a valuable source of information whose extraction can help individuals or even businesses in the decision-making process. The present research focuses on the study of user communication about a brand on Twitter, and in particular on exploiting user feelings about this brand effectively. In more detail, this work promotes the efficient modeling and management of the business-consumer relationship by studying the interactions of users who are discussing a specific brand name. The purpose of this research work is to provide an efficient tool that will enable businesses to use technological and automated tools in order to effectively manage the emotional state of consumers in relation to their brand. Consumer feedback and expressed emotions may be utilized by companies for making decisions regarding marketing research, competitive business intelligence and online reputation management.

Keywords

community detection, emotion estimation, graph clustering, multilayer graphs, social networks

1. Introduction

It is widely known that the evolution of the Web 2.0 has led into a new era, where the social networks have gained a crucial role in people's lives. More specific, in the recent years, Twitter has been one of the most popular networks that has been broadly utilized in a wide plethora of research studies that are trying to extract and analyze users' activity with the intention of finding valuable trends or patterns [1]. Such trends or patterns have been proved to be valuable information for businesses.

On the one hand, users nowadays are informed regarding businesses' products and services through the social networks and they tend to interact with other users to exchange information, opinions and discuss about products. On the other hand, businesses through the social networks tend to promote and advertise their products or services to a wide range of consumers. Businesses have also gained the capability to observe the impact of their products through consumers' opinions as well.

Therefore, the study of the interactions of consumers and the relationships they develop with brand names on social networks, has become vital for businesses. Consumers' thoughts and opinions about a brand name affect their behavior and consequently their brand perception. According to [2, 3] the consumers trust others' opinions, thus the electronic word-of-mouth (eWOM) has a major role on how users perceive a brand name. The users are no longer receivers of information but they have become transmitters. Thus, there is a considerable need from businesses to assess their relationships with the customers by developing efficient quality and quantitative metrics on the social networks [4], in order to be able to create and maintain their customer relationships.

Although there are several tools that look into the problem of social media networks and their interconnections, in this work we focus on the extraction of emotional information in order to relate it to the loyalty of the users to a specific brand. So, the scope of this research work is to provide a valuable tool for the efficient modelling and management of the business-consumer relationships by analysing the interactions of users who are discussing a specific brand name.

The rest of this paper is organized as follows. Section 2 presents the related work regarding multilayer graphs, graph signal processing (GSP), and emotional analysis over online social networks. The main concepts of our system architecture are covered in Section 3. In Section 4, we present our experimental results on the performance of our proposed methodology based on a variety of metrics. Finally, in Section 5, we conclude the paper by outlining our findings and discussing on the future work.

CIKM'21: 30th ACM International Conference on Information and Knowledge Management, November 01–05, 2021, Virtual Event, QLD, Australia
robolas@ceid.upatras.gr (G. Rompolas); kkaravoulia@ceid.upatras.gr (K. Karavoulia)

2. Related Work

Multilayer or multiplex graphs constitute a graph class where vertices can be connected with multiple edges as long as they have distinct labels [5]. Operations on such graphs include embedding [6] and core decomposition [7]. Moreover, clustering in such graphs can be spectral through convex aggregation [8], local graph convolution [9], or through the respective Laplacian [10]. Applications include brain circuit study [11], unmixing of hyperspectral images through adaptive non-negative matrix factorization [12], and race car trajectory planning for transportation networks [13]. Multilayer graphs can also model social networks facilitating the solution of problems such as link prediction [14], higher order vertex centrality [15], account behavior prediction [16], suspicious activity detection [17], and stable community detection [18].

GSP is an emerging field [19][20] with numerous applications including graph partitioning with methods such as spectral clustering as in [21], submodular computation [22], graph dimensionality reduction [23], higher order iterative methods [24], multi-view [25], and vertex search [26]. Additionally, GSP covers the scenario where a neural network architecture such as marginalized graph autoencoders [27], tensor stack networks (TSNs) [28], or graph neural networks (GNNs) [29] is applied to a graph for processing purposes such as clustering or community structure discovery [30].

Social media in general and Twitter in particular offer numerous opportunities for observing the emotional evolution of human interaction [31]. The recent bibliography abounds with approaches ranging from employing information diffusion patterns in conjunction with textual information [32] and transformers applied on tweets for deep text mining [33] to neural network architectures [34] and ensemble classification [35]. Applications include among others cryptocurrency price prediction based on emotional attributes [36], the behavioral dynamics of product customers on Twitter [4], the impact of Twitter collective sentiment on the price of energy stocks [37], and well being [38]. Finally, an extensive review of current emotional analysis techniques for Twitter is [39].

3. Methodology

In Figure 1, an overview of our proposed model architecture is depicted. Initially, in order to apply our model it is necessary to crawl the corresponding data; in our case we need to collect data regarding a brand name. Then we proceed with the graphs construction, where we are building the different graph layers that are needed to construct a multilayer graph. Since the multilayer graph construction has been completed, we proceed with the partitioning of our network graph into two smaller subgraphs based on the type of relationships between the users.

Then, we are analysing both of these graphs independently and we are applying a scalable community detection algorithm to further divide them based on the multilayer network structure. And finally, we are doing a community emotion analysis on each cluster in order to gain further insights of the attributes and emotions that characterize each one of the extracted communities. Each one of the aforementioned steps, are being further analysed in the following sections.

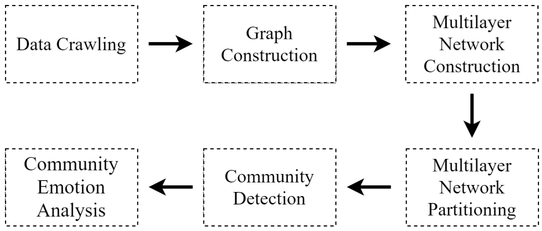


Figure 1: Architecture Overview

3.1. Data crawling

We collect data by crawling the Twitter. We are interested in customers-business relationships, therefore we select those tweets that include either the brand name or the hashtag of the the brand name. Thus we extract users that are potential customers since they possess basic brand awareness.

3.2. Graph Construction

A Twitter graph has nodes that represent the users and edges that usually represent the follow relationships between them. However, we are interested to represent the users' interactions in a more detailed manner than representing only the follow relationships. Therefore, we consider three types of interactions:

1. Mentions (MT)
2. Retweets (RT)
3. Replies (RP)

For each type of interactions we construct a directed graph $G_k(V, E)$, where V is the vertex set, which contains all the network users, E is the edge set and $k \in \{MT, RT, RP\}$. We consider a directed edge from the node v_i to v_j if the user i re-tweets, mentions or replies to the user j.

3.3. Creating a multilayer graph

According to the Section 3.2, we have constructed three independent network graphs, one for each user interaction. Therefore, since each network has its own structure and its own characteristics that define it, an appropriate mechanism to represent this information are the multilayer graphs [40, 41]. A multilayer graph can capture the several interactions that can exists among the nodes of each layer, without losing any information.

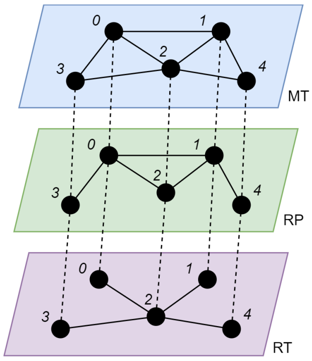


Figure 2: Users' interactions as a multiplex multilayer graph

Furthermore, in order to focus to the most interactional users we maintain only on the common ones among all the layers. We combine the three layers into a multiplex network. Multiplex networks have the same entities in every layer but different connections between them. Thus, we transform the three different interaction graphs G_k as defined in Section 3.2 into a multiplex multilayer Twitter graph $G(V, E, D)$, where V is the vertex set, E is the edge set and $D \in \{MT, RT, RP\}$.

3.4. Multilayer network partitioning

Upon the construction of the multilayer networks, we proceed with its partitioning into two smaller multilayer sub-networks, based on the type of the users' communication relationships. More specific, we separate our initial network into a sub-network $G_{UU}(V, E, D)$ that represents the interactions between users who communicate about the brand name, and into another sub-network $G_{UA}(V, E, D)$ that represents the user interactions with the official brand name accounts on Twitter.

3.5. Community Detection

Subsequently, we apply on the multilayer graph the MULTITENSOR[42] community detection algorithm. The algorithm takes as input the adjacency matrix of a multilayer network and returns for every node of the network the probability distributions of the node for each community. We also defined as input to the algorithm the number of communities $K = 2$. Hence, in our case, after the execution of the algorithm two distributions are being produced for every node, one for each community. Although the algorithm supports the nodes to be assigned to more than one community, we use hard node assignments in our approach, where a node belongs to a single community. Therefore, we apply the MULTITENSOR algorithm to each one of the two networks, in order to extract two communities from each case.

3.6. Community Emotion Analysis

In order to gain further insights from our extracted communities and translate them into meaningful information, we use the state-of-the-art NRC Emotion Lexicon[43, 44] that categorizes the emotions in the following emotions {*anger, anticipation, disgust, fear, joy, sadness, surprise, trust*} and sentiments {*positive, negative*}. Based on the above affect categories we quantify the emotions of the tweets at a finer granularity level.

4. Experimental Results

Our experiments were performed independently in both of the extracted multilayer networks, that were created by our methodology as described in Section 3.4.

4.1. Implementation

For the implementation of our system we used Python 3.8.0 as the programming language. The python library Tweepy[1] was used as a wrapper to access the Twitter API[2] to retrieve data from Twitter. The MULTITENSOR[3] library was used as well, with regards to the multilayer tensor factorization for community detection.

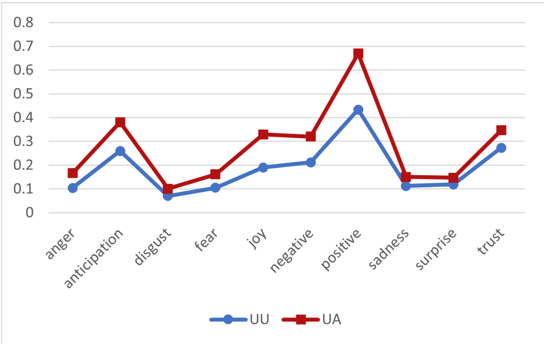
4.2. Data description

For our implementation, we selected the Adidas sportswear brand name. Thus we collected Tweets that included the word Adidas or the hashtag #Adidas for the time interval from 09-07-2019 till 29-07-2019. We maintained only the tweets that were in the English language. Moreover, we filtered out users mentions, the RT abbreviation symbol that denotes a retweet, hyperlinks, numbers, symbols and punctuation as well.

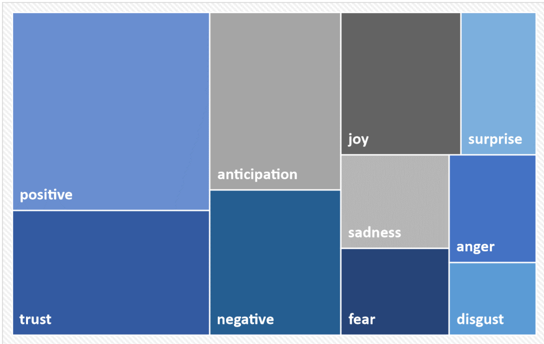
4.3. The User-User interaction network

The User-User network is composed of $N = 3618$ users and 12620 interactions. If we define the density of the

[1] $https://github.com/tweepy/tweepy$
[2] $https://developer.twitter.com/$
[3] $https://github.com/cdebacco/MultiTensor$



(a) Emotional comparison between the two networks



(b) Tree-map of the overall emotions

Figure 3: Aggregated network emotions over the different types of interaction networks, where the User-Adidas network has more emotional information

edges as:

$$d(V,E) = \frac{|E|}{N(N-1)} \tag{1}$$

where N is the number of nodes and E the number of edges, then we get the following information regarding the network structure of each layer:

D	E	d
Mentions (MT)	11929	0.09116
Replies (RP)	3287	0.02512
Retweets (RT)	4439	0.03392

Table 1
Description of the User-User network structure

There were two communities created, where the first one had 1707 nodes and the other 1911. We used the cosine similarity to evaluate the quality of the clusters. The cosine similarity is defined as:

$$CS = \frac{1}{N}\sum_{i=1}^{N} \frac{\overline{u}_i^0 \overline{u}_i}{|\overline{u}_i^0||\overline{u}_i|} \tag{2}$$

where $|\overline{u}|$ denotes the Euclidean norm. We also computed the L_1 metric as follows:

$$L_1 = \frac{1}{2N}\sum_{i=1}^{N} ||\overline{u}_i^0 - \overline{u}_i||_1 \tag{3}$$

The value of $CS = 0.99$ which is value near 1, while $L_1 = 0,020$. Therefore the quality of the clustering is very good.

4.4. The User-Adidas interaction network

The User-Adidas network consists of $N = 1514$ users, including 16 accounts of the Adidas Company and 4463 interactions. There were two communities created where the first one had 357 nodes and the other 1157 accordingly. Table 4.4 shows respectively some structural information of the network. We can notice that although the User-Adidas network has much fewer nodes, it seems to be a more dense network than the User-User network. Furthermore, the clustering quality was very good in this case as well, with $CS = 0.98$ and $L_1 = 0.017$.

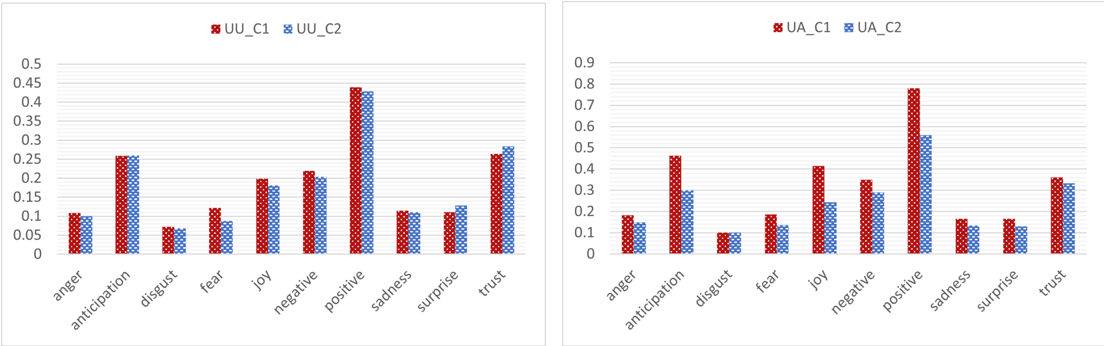
D	E	d
Mentions (MT)	4618	0.20160
Replies (RP)	268	0.01170
Retweets (RT)	156	0.00681

Table 2
Description of the User-Adidas Network structure

4.5. Emotional Analysis

Upon the communities extraction from both of the multilayer networks, we proceeded the emotions quantification of each community. The Figure 3 shows our aggregated results. Initially, we measured the mean values of all the users' emotions mentioned in Section 3.6 over each one of the multilayer graphs. It is interesting to notice that although the Adidas network has less nodes and less interactions it is a more emotional information. Moreover, we also distinguished the overall emotions that users express regarding the brand name. In our case, the anticipation, the joy and the trust emotions and the sentiments are the most dominant ones, as they have the largest mean values, Figure 3.

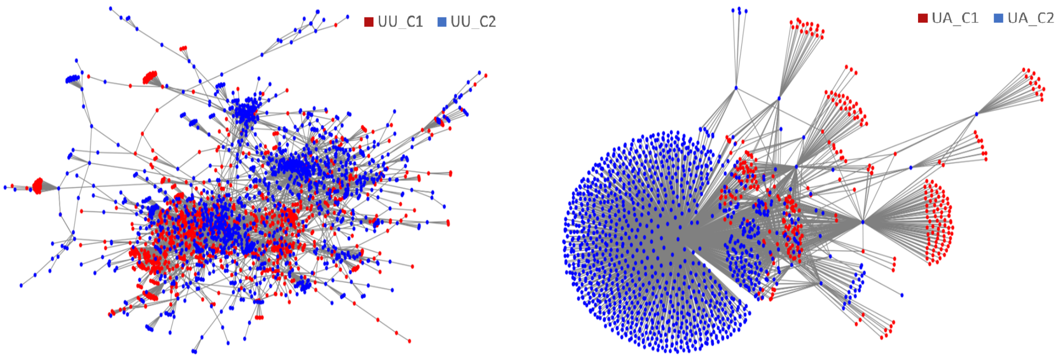
We also measured the mean values of all the emotions over each one of the extracted communities for each multilayer network. In the case of the User-User network we



(a) User-User Network

(b) User-Adidas Network

Figure 4: Aggregated community emotions, where the User-User Network does not show any particular difference, in contrast to the User-Adidas Network



(a) User-User Network

(b) User-Adidas Network

Figure 5: Visualisation of the networks partitioning into communities

observe that the emotional differences between the clusters are not significant, as we can notice from the Figure 4(a) that for each emotion the mean values are almost equally. Applying the same approach for the User-Adidas network we observe that the emotions of the two clusters are significantly different, Figure 4(b). Thus, in this case the community detection algorithm has achieved a better separation of the users, regarding their emotions.

In order to further validate our results, we used the T-test [45] to compare the mean values of the clusters with respect to emotions. In the case of the User-User network the value of the T-test was 0.111, which indicates the similarity of the extracted communities. While in the case of the User-Adidas network the value of the T-test was 1.009, that proves that the two clusters are quite different with respect to emotions.

Moreover, a visual representation of the two graphs can verify our findings. In Figure 5, the two different multilayer networks are depicted, where each user is labelled to its respective community. The Figure 5(a) refers to the User-User network where it is clear that the network is separated to two clusters of different emotions, while the Figure 5(b) refers to the User-Adidas one, where the clusters do not show significant differences.

5. Conclusions

In this work we focused on the users' communication for the Adidas brand name. Two different networks were examined, that represent different types of interactions among the users. The first one represents the users' interactions and the second one the interactions with the Adidas accounts. We used multilayer graphs to represent these interactions. We then applied a community detection algorithm to determine user communities. Finally, we examined the users' emotions so that we can differentiate each network in two sub-networks based on the emotions.

Through our methodology, we reached to the following conclusions. The interactions among the users does not provide us with as much valuable information as the interactions between the users and the brand name accounts. The community detection algorithm achieved a better emotion separation based on the latter interactions. Furthermore, among all the emotions that were analysed through this work, we were able to distinguish some particular ones as the most notable, such as the anticipation, the joy and the trust emotions and the sentiments.

As a possible future direction, it would be interesting to apply our methodology on the study of how the users' interactions and emotions change over time. Moreover, an additional potential approach could be to focus on the development of prediction models that will take into consideration the users' behavior and emotions in order to predict the future relationships between consumers and businesses.

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