An Evaluation of Performance and Competition in Customer Services on Twitter: A UK Telecoms Case Study

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ABSTRACT

With an increasing number of consumers using social media platforms to share both their satisfaction and displeasure about the products and services they use, organisations with a customer service focus are recognising the importance of genuine – and rapid – engagement with their customers. In turn, consumers judge organisations on the quality of customer service and degree of responsiveness to queries. This paper presents an extensible framework for evaluating direct engagements of customer service teams with customers. Furthermore, it measures indirect engagement with industry sector rivals, competition and their patterns, and intensity. By applying graph analysis of these Twitter interactions, our framework was used to generate analytical measures and visual representations for a case study based on seven major UK telecoms companies. With a dataset consisting of 15,000 tweets and 3,500 user profiles, the results provide sustained evidence for indirect engagements between business rivals, with customer queries as the trigger for those competition, with competition more intense between companies in same industry sub-domain.

KEYWORDS

Customer services, Twitter, reply chains, graph construction, social network analysis, social media

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1 INTRODUCTION

The online news and social networking service Twitter has become one of the most popular social platforms for a variety of demographics across the world. It provides a rich, constantly updating, corpus of big social data to study a range of complex socio-cultural issues, from life event detection [4] and identifying multilingual communities [2], through to providing deeper insight into personality and behaviour [15]. Unsurprisingly, Twitter is increasingly being used by organisations to communicate with their customers, due to the fast and convenient medium of engagement [13], using a variety of sophisticated human and automated approaches [22, 24]. In 2016, a survey was carried out on 5,450 people who follow small or medium-sized enterprises (SME) on Twitter [21]; the key results show that 83% of people that received a reply felt better about the SME, and 68.7% have made at least one purchase from an SME because of Twitter.

However, this medium could serve as an indicator to underlying issues of performance, management and even strategic matters [9]; in many instances, the majority of complaints deal with product and service-related issues [8]. Many studies have been conducted to explore aspects of customer services experiences in various business domains, such as travel and telecoms [12, 14, 20, 23, 25]. News agencies are not far from social media analysis, they use it to uncover users interests so they can provide more focused contents [16]. While various domains have long applied network analysis techniques – especially for crime detection and prevention [17, 18] – only recently has work has been conducted to see how users relate to brands via network structures [7], how information shared by companies disseminate and their types [19], and what type of engagements from companies was found to be of effect on customers perception of the brand [11]. A very common approach in conducting such studies was using sentiment analysis, mainly to measure consumer's perception and satisfaction [1, 25].

However, the novel framework presented here aimes to provide quantitative insights that can produce holistic views of customer service accounts and interactions. Rather than focusing on individual posts and their sentiment, the framework helps in identifying important post conversations that can then be interrogated further by analysts or decision makers. With the high volume of activity on Twitter, the framework helps to easily identify key issues further analysis. Furthermore, by using streaming and RESTful data, this approach can be applied to live data to catch problematic conversations before they reach certain thresholds.

The remainder of this paper is organised as follows: in Section 2, we introduce the methodology; Section 3 presents the results and key visual representations; Section 4 provides the main discussion; Section 5 concludes the paper with a discussion of potential extensions and wider application of this work.

2 METHODOLOGY

Inspired by the approach taken by Cogan et al. [6], this study consists of two main steps: the data collection phases and the graph construction. The data collection runs iteratively to obtain reply chains, process them and save them to a database. Once the data collection phase is completed, a large graph that includes all reply nodes and edges is constructed to conduct the initial analysis. The NetworkX Python package [10] was used for the graph construction, while Gephi [3] provided a range of tools for visualisation.

2.1 Case Study: UK Telecoms Industry

The dataset contains tweets and related replies for seven well-known UK telecoms companies: BT, EE, giffgaff, O2, Sky, Virgin Media and Vodaphone. The choices were intended to represent companies of various sizes, history and range of services provided. While a few companies were found with one account on Twitter, some of them have multiple accounts alongside the primary Twitter account. In those instances, the dedicated customer services accounts were indicated in the biography of the companyâĂŹs other accounts. Therefore, as the focus of the study is on customer services on Twitter, data were collected from either companyâĂŹs primary account or its dedicated customer services one (N.B. names throughout the paper refer to Twitter account handles rather than official company brand names).

2.2 Streaming

To ensure we were able to collect as much data as possible, the data collection comprised of three steps. First, a stream endpoint is opened to catch activities of accounts under investigation, those accounts will be referred to as 'watched' or 'CS' (customer service) accounts. The Twitter Streaming API[1] is designed to return tweets created by the user, their retweets, replies directed to their tweets, and retweets of their tweets. However, the stream does not include tweets mentioning the user, and replies/retweets by protected users.

2.3 Reply Chains

Returned statuses from the Streaming API may represent reply to statuses that have not been collected previously. It was found that most missing statuses were either posted before the data collection started, mentions, or that the user account is protected. Naturally, this issue could have a huge impact on the quality of the analysis. Therefore, once statuses are returned from the stream endpoint, they are processed to identify missing replied-to posts, and the REST API is used to collect them. This process runs recursively for newly collected replies until no further replies are available. Unavailable statuses are often results from either deletion or protected accounts.

An analysis of changes on the graph after the second phase of data collection shows that there were increases in the number of nodes and edges by 43% and 62%, respectively. This increase in connections has resulted in merging 176 components into others, which improved connectivity of the graph and, thus, accuracy of the dependent analyses.

2.4 Graph Construction

2.4.1 Main Graph. Graph construction is the foundation of the analysis presented in this paper. First, a base graph[2] is generated containing all replies and the needed data. Nodes represent post IDs, while edges indicate replying direction. Other information of statuses are added as attributes to nodes. The information used in this study are screen name of the user, timestamp of the reply, text, and 'watched' entity, to identify CS accounts; an example graph is shown in Figure 1. Properties of this graph are constrained by how replies relate to each other. In other words, no edge is expected to have weight value other than 1. Also, no reply status can have outdegree greater than 1, however some nodes may have an outdegree of 0. Node with outdegree=0 can be root nodes, i.e. first post of conversation, or they were directed to unavailable statuses. On the other hand, indegree of nodes can be 0 or more. Special case nodes are those with indegree and outdegree equal to 0. Those are isolated/floating nodes and must be removed before we perform the analysis – these nodes do not benefit the analysis as they are not part of any conversation. Furthermore, they will be seen as connected component by themselves, which impacts upon the accuracy of results.

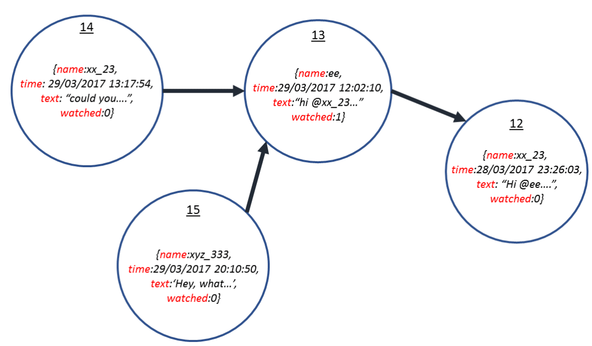

Figure 1: Example of a reply chain graph

2.4.2 Users' Graph. Because most of the analysis focus on relationships between reply posts, they were applied on the base graph. Nevertheless, to allow examination of the relationships between users, another graph is generated from the base graph. This process is carried out by iterating through edges linking reply posts, extracting users' information, and constructing users graph accordingly. In the context of this study, only two attributes are used: screen names and 'watched' values. While nodes represent screen names, 'watched' valued are added as attribute of nodes. For edges, their weights indicate number of replies sent from origin node (sender)

[1]https://developer.twitter.com/en/docs

[2]The terms 'main graph' and 'base graph' are used interchangeably.

to target node (receiver), therefore, the user graph is directed. Applying this process on the example in Figure 1 results in the users graph shown in Figure 2.

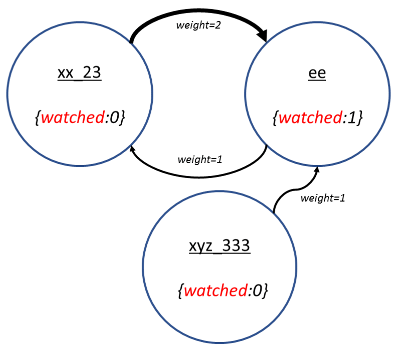

Figure 2: Example of users' graph extracted from base graph

To examine relationships between users, five network graph properties are measured. There were no special case nodes or edges in this graph, as observed in the base graph. Graph properties that are used in analysing this graph and their contextual interpretations are shown in Table 1.

Measure	Interpretation
Indegree	Number of users that sent reply to the node
Weighted Indegree	Total number of received replies
Outdegree	Number of users that have received a reply from the node
Weighted Outdegree	Total number of sent replies
Edge Weight	Number of replies between the connecting nodes

Table 1: User-user centrality measures interpretation

2.5 Connected Components

The base graph consists of many number of subgraphs, each of which represent related replies, i.e. one conversation entity. Investigating connected components plays a major role in identifying conversations for accounts. They are used to measure size of conversation, their depths, and to identify shared conversations between watched accounts. To extract conversations that user or users were engaged in, the process iterates through nodes in each component and examine the 'name' attributes. As soon as the search is matched, no further nodes are examined. Then, the component is either analysed on the fly, or returned if more intensive analysis is required.

In the base graph, the number of connected components reflect conversations, while in the users' graph, connected components show the users' communities. Therefore, in the base graph many components should be expected, depending on activity of the watched accounts. However, in the users' graph, the number of components should not exceed the number of watched accounts, although there might be exactly one component due to common customers.

3 RESULTS

3.1 Accounts Activity

An overall evaluation was carried to measure accounts activity. As shown in Figure 3, *@virginmedia* was found the most active CS account by far. As the focus of this section is on customer service, it is necessary to investigate post types to examine the purposes of these accounts. The result shows that replies were at least 83.5% of accounts activity. This confirms that all chosen accounts are primarily used to interact with customers, handling requests and queries. Therefore, the resulting analyses will be based on replies only.

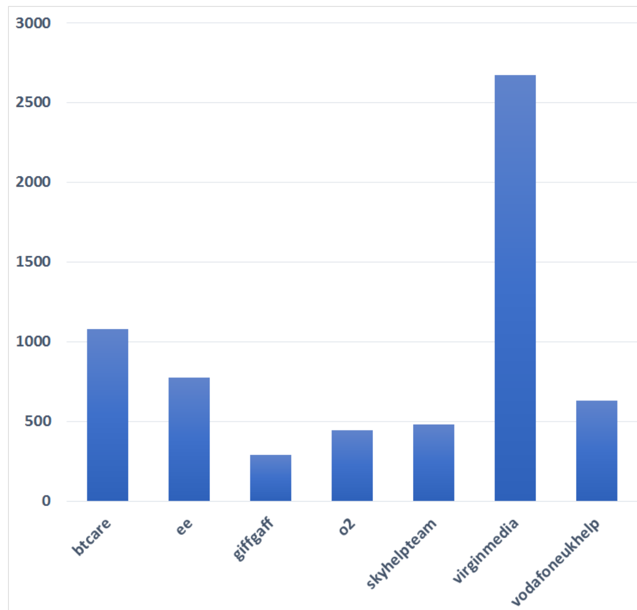

Figure 3: Total activity

3.2 Interaction and Users

Although the indicated "working hours" of CS accounts is important to evaluate activity, it is valuable to measure posts that are directed to those accounts from other users and examine them in line with CS accounts. Audience and their relations with the accounts can be analysed directly from the main graph (i.e. post-post). However, as user details are embedded inside post nodes, observing such relationships will not simple task to accomplish. Therefore, a user-user graph was built from the main graph. The resultant graph contains 3,521 user nodes and 5,938 edges, as shown in Figure 4. Although post-post relationship cannot have weight higher than one, user-user edge weight indicates number of posts in one direction, which explains the reduction in number of nodes and edges.

Based on Table 1, summary of the graph is presented below in Table 2. The table says that *@virginmedia* received that highest

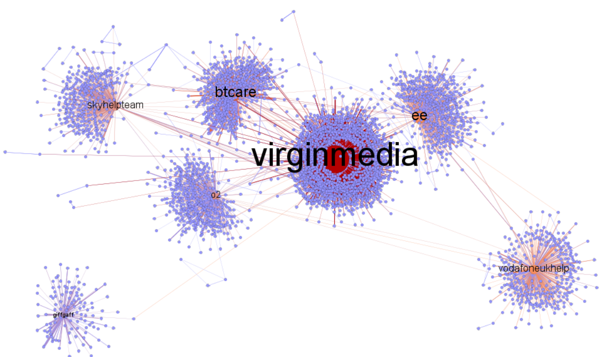

Figure 4: User-user graph

number of replies from 866 users with an average of 3.05 per user. Also, the same account scored highest in number of recipients. The difference between indegrees and outdegrees shows that apart from *@o2*, all accounts have outdegrees bigger that their indegrees. Additionally, the total number of sent replies is found to be more than the number of received replies; this may reflect that those replies were directed to non-reply posts.

Measure	ind	w.ind	%	out	w.oud	%
btcare	330	995	3.02	485	1317	2.72
ee	247	432	1.75	470	778	1.66
giffgagg	77	209	2.71	102	247	2.42
o2	293	463	1.58	260	479	1.84
skyhelpteam	147	254	1.73	305	504	1.65
virginmedia	866	2645	3.05	1215	3421	2.82
vodaphoneukhelp	166	403	2.43	302	660	2.19

Table 2: Centrality measures of user-user graph

3.3 Delay

The observation of active hours provides an overall view of account activity. However, calculating delays is important to provide more insights on performance of CS team. As reply nodes in the base graph (post-post) include timestamp attribute, measuring delay was achieved by calculating time differences between end nodes on each edge. Table 3 shows descriptive statistics for CS account delays. Interestingly, *@skyhelpteam* was found with an average delay of 45.04 hours, although rest of the CS accounts' delay ranged between 1.14 and 3.34 hours.

Account	mean	stdev	max	min(sec)
btcare	2.04	16.11	572.46	38
ee	1.46	3.39	19.28	27
giffgagg	1.22	10.25	159.97	73
o2	1.14	2.66	22.48	58
skyhelpteam	45.04	49.16	117.21	44
virginmedia	3.34	9.25	263.98	22
vodaphoneukhelp	1.92	5.01	76.51	50

Table 3: Summary delays statistics

3.4 Conversation Components

As covered in the methodology, each connected component in the post-post graph represent a conversation entity that includes related replies. In this dataset, there were 3,289 conversation components with various number of replies. Observations of their sizes shows that the smallest component consists of one post, while the biggest component contains 81 posts. Furthermore, the number of one-post components was 102, and they were all found belonging to CS accounts. Examining those singular components revealed that they were either original tweets that have no replies or replies with no replied-to post available. As covered earlier, missing replies are those that could not be captured due to a deletion or their posting account being protected. Because they do not have any length, and hence do not represent an examinable conversation, single-node components will be excluded from forthcoming analyses.

Additionally, most common size of connected components was found to be two nodes. They were 1,188 components and the direction of their edges revealed that most of these communications were from CS accounts and directed to customer's post. However, 25 of those conversations were initiated by customers. As they are in two-node components, this shows that those posts have not been answered by CS. Although other means of communications could have been used, such as direct messages, there were no visible sign of such interaction.

3.5 Component Size and Longest Path

It is important to note that the size of connected components does not necessarily reflect length of conversations, although there is a strong correlation between size of component and length of its longest path (0.88). As can be seen in Figure 5, many components measures are positioned in a near perfect diagonal line; interestingly, the longest path in the biggest component (81 nodes/posts) was only 1.

To further explore properties of connected components, the largest 20 components, as shown in Figure 6, were examined. The findings show that components with very high variations in indegree amongst their nodes are mostly originate from CS. Examples of this claim is illustrated by the three big components in the figure. When observed, they were found to featuring advertising tweets. Another observation on the biggest component is that origin node was a post by *@o2* and has an indegree of 80, while rest of the nodes have indegree of zero, i.e. they were not answered. On the other hand, the longest path component was ranked the third biggest component. It was found with a single leaf, and all other nodes along

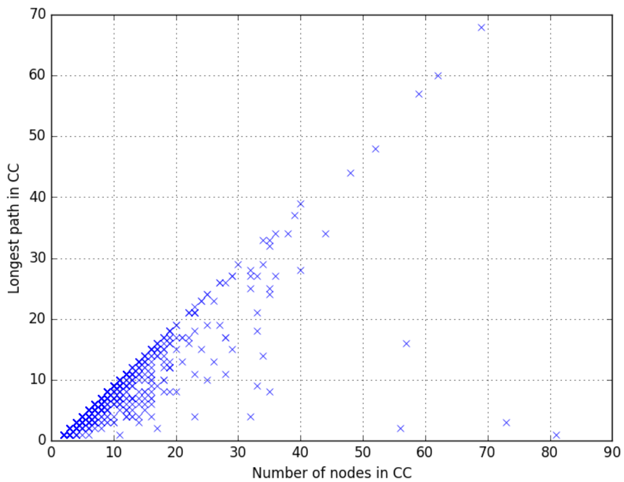

Figure 5: Size of components and their longest paths

the path were found with indegree=1 and outdegree=1, forming what we call a *simple chain*, uniquely coloured in Figure 6. Additionally, 15 of those components were found to have originated from customer accounts, and they all take a semi-simple chain.

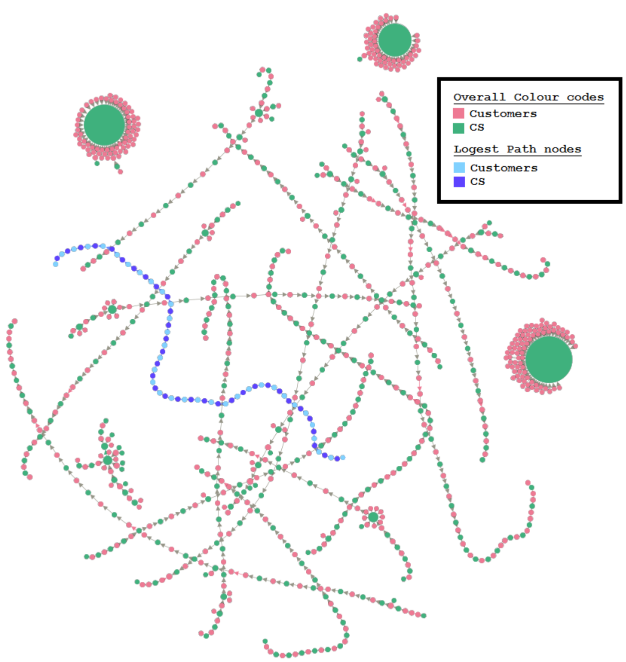

Figure 6: Largest 20 connected components in post-post graph

Generally, simple chains can be identified where the number of edges equals length of the longest path in component. Simple chains account for 80% of the connected components in graph, of which 47% were found with the length of 1. This is in agreement with the results of connected component sizes presented earlier. Finally, Table 4 presents statistics on chains of individual CS accounts.

Name	count	max	min	mean	stdev
btcare	388	19	1	3.46	3.22
ee	324	9	1	1.98	1.43
giffgagg	147	12	1	2.39	1.98
o2	216	11	1	2.53	2.26
skyhelpteam	252	15	1	2.22	1.99
virginmedia	959	68	1	3.78	4.46
vodaphoneukhelp	248	39	1	2.58	3.29

Table 4: Summary statistics on chain length for CS accounts

3.6 Coexistence and Competition

Connected components were utilised to investigate competition amongst CS accounts. This was achieved by first identifying components that include more than one CS account. For each connected component, notes are checked in turn to examine their names. Components with more than one name are then marked as coexistence component. The results show that there were 39 common components, 38 have two CS accounts, and one includes three accounts. The graph presented in Figure 7 shows those components, with each CS account given a colour code for identification as the legend clarifies.

To explore these relationships further, a specific users graph was constructed based on those components. Construction of this graph follows similar steps as used in customer-CS graph. However, as CS accounts do not have direct engagement with each other, edges in this graph are undirected and their weights indicate number of times they appeared together in the same conversation component. The resulted CS-CS graph is shown in Figure 8, where node size indicates degree of node to show how many other CS accounts the node has coexisted with, while darkness of node reflects weighted degree to show the total frequency of coexistence for the node.

The first observation on the graph is that *@giffgaff* account was not found in any common conversation. In contrast, *@o2* was the only account that have shared conversations with all other CS accounts, while *@vodafoneukhelp* was found with the least common conversations. Nevertheless, weighted degree measure shows that *@virginmedia* was the highest in number of common conversations, 21 components, although its degree tells that those conversations were shared with only three other CS teams. The heaviest edge existed between *@virginmedia* and *@btcare*, followed by the edge between *@virginmedia* and *@skyhelpteam*. Also, edges of *@o2* show that it was mostly appeared with *@ee*, and for *@vodafoneukhelp* it was *@ee*.

The observation of edges and their weights can provide insight into uncovering more specific service areas within the specific industry or sector. This was found clear when the modularity of the graph was examined [5]. The result has unfolded into two communities, as shown in Figure 9. Also, industry knowledge regarding these following CS teams: *@ee*, *@o2*, and *@vodafoneukhelp* belong to a domain that is mostly focused on mobile services, while

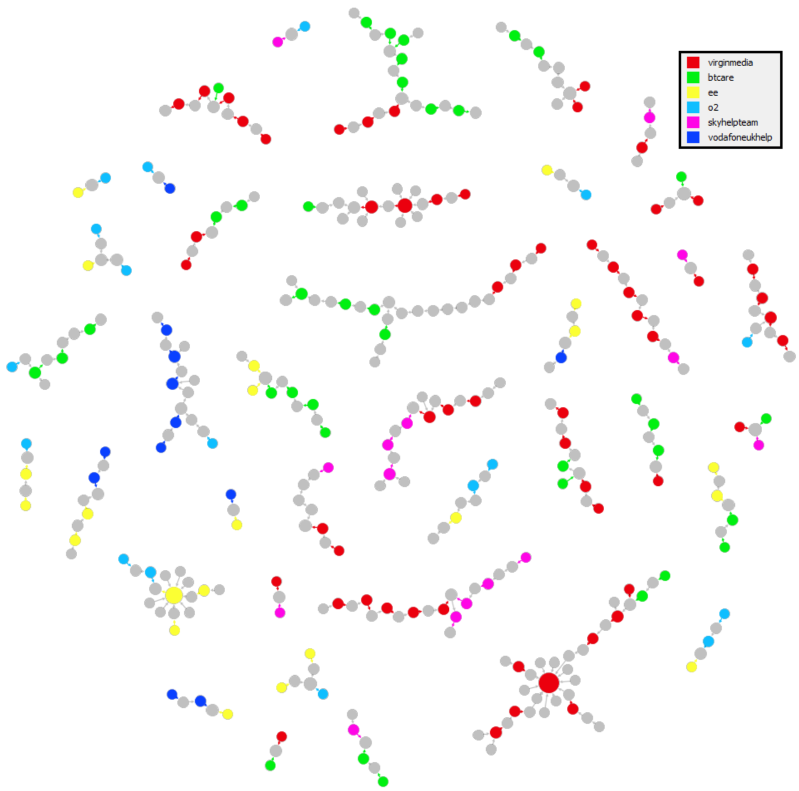

Figure 7: Common connected components

@skyhelpteam, *@virginmedia*, and *@btcare* are mostly known to be focusing on landline and home internet services.

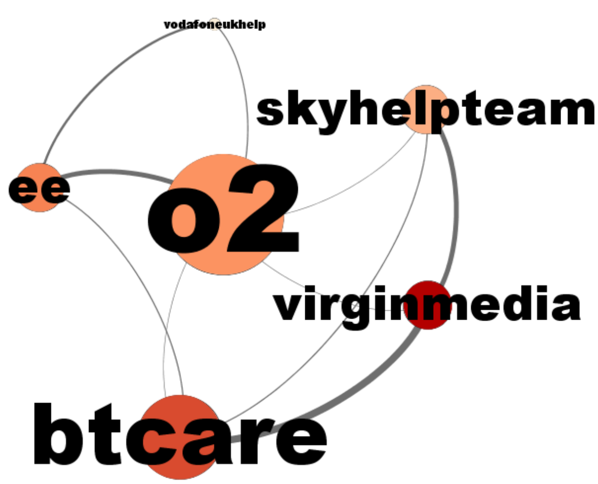

Figure 8: CS-CS coexistence graph

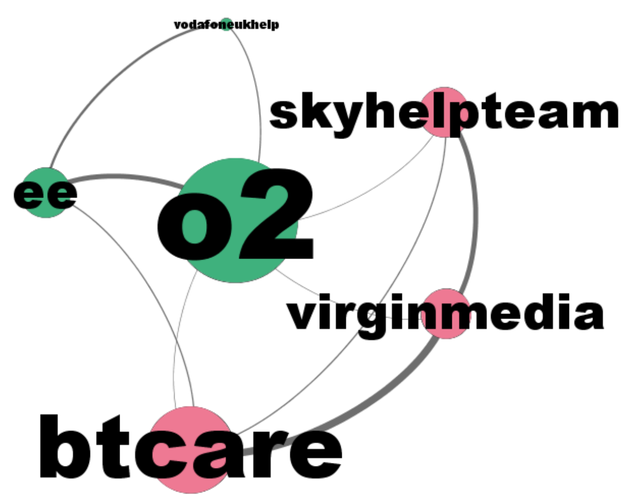

Figure 9: Modularity class graph

Furthermore, using a similar approach that was used in Section 3.3, the delay was measured in those components to evaluate if presence of competitor has influence on how quick CS team response. Interestingly, an improvement of 26%, 43% and 72% were observed for *virginmedia*,*btcare* and *skyhelpteam*, respectively. Rather surprisingly, for the other three companies, the average delay showed a drop by at least 9%.

4 DISCUSSION

Initially, the performance of CS accounts and their popularity on Twitter were measured by an analysis of activity and users. From this perspective, *@virginmedia* was found to have the highest volume of posts, the least diverse in terms of type of posts (99.7% were replies) and with the highest number of customers served.

The average delays of accounts ranged between 1.14 and 3.34 hours, apart from *@skyhelpteam* which was found with an average delay of 45.04 hours. This may indicate a management issue for the team, such as unclear social media strategy or staff resources.

Most CS teams have clearly specified working hours on their account page, apart from *@giffgaff* and *@o2*. Interestingly, these two accounts were found to have the lowest delay. Nevertheless, high availability, i.e. longer activity hours, was not found to significantly improve speed of reply to customers. For example, while *@giffgaff* was observed active for longer hours, *@o2* was found to be faster to reply.

Although the data shows that no CS team has been in a direct engagement with a competitor, analysis of common/shared connected components has uncovered some form of competition amongst CS accounts. Particularly, in the case of *@virginmedia* and *@btcare*, the competition was clear and intense. In all cases, customers were found to be initiators of competing conversations by making use of the Twitter *@-mention* feature to bring different rivals into conversations. In contrast to phone, letter or email, complaints that are made on social media are open for the public to read and follow, and therefore can be potentially damaging to the business reputation if not handled appropriately. Therefore, it was not surprising to see improvement in the speed of response in a few instances where competitors were included in the same conversation. This shows that with the openness of social media platforms, such as Twitter, customers have more chance to obtain better deals or speedy resolution of their problems [8]. In turn, this nature of publicly posted complaints add more pressure on CS teams to improve their social media engagement, especially when business rivals are included by customers [9].

5 CONCLUSIONS

The paper has introduced an extensible framework for evaluating customer service performance and competition between industry rivals on Twitter. We have presented methods on how network graphs properties can be used to make sophisticated evaluations, with the framework being tested on selected accounts in the UK telecoms sector.

Section 2 highlighted two important techniques that need to be applied prior to starting the analysis phase. First, the recursive reply chain data collection is a crucial stage in obtaining accurate results. The importance of this stage stems from the fact that it fills the gaps and improve connectivity of graphs. Second, construction of the initial graph from replies and the removal of floating isolated nodes. In constructing this graph, key information needs to be identified and attached as attributes to nodes. The information used in this study include post *id*, *timestamp*, *screen name*, *text* and *watched* value. However, the framework could easily be extended to include other information such retweets.

The core of this work was to show the importance of connected components in distinguishing users' conversations, as well as analysing competitions and their key features. With the added value of modularity classes, competition analysis has helped in uncovering more specialist communities within the industry sector.

The presented framework could also be used by service providers to reflectively evaluate their social media accounts and interactions, as well as to generate insight into the activities of their key domain competitors; in this way, the presented methods in this study could be used to make real-time observations. Another application would be to identify gaps, competitions, challenges and opportunities in services that can be used in developing strategies for start-ups, for example. The approach could also be applied to other domains or contexts, such non-profit or the public sector. Also, it can be used for groups of users, such as celebrities and their direct and indirect engagements on Twitter. Moreover, with the emerging practice of signing a reply with a team member's initials, this practice can be exploited to further augment this framework's capabilities; this extension could help in estimating team sizes, working shifts and to evaluate performance of individual team members.

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