Online Topic-based Social Influence Analysis for the Wimbledon Championships

Varun R Embar  
IBM Research, India  
varembar@in.ibm.com

Indrajit Bhattacharyya  
IBM Research, India  
indrajbh@in.ibm.com

Vinayaka Pandit  
IBM Research, India  
pvinayak@in.ibm.com

Roman Vaculin  
IBM Research, NY, USA  
vaculin@us.ibm.com

ABSTRACT
Various industries are turning to social media to identify key influencers on topics of interest. Following this trend, the All England Lawn Tennis and Croquet Club (AELTC) is keen to analyze the ‘social pulse’ around the famous Wimbledon Championships. IBM developed and deployed social influence analysis capability for AELTC during the 2014 edition of the Championship. The design and implementation of influence analysis technology in the real world involves several challenges. In this paper, we define various functional and usability criteria that social influence scores should satisfy, and propose a multi-dimensional definition of influence that satisfies these criteria. We highlight the need to identify both all-time influencers and recent influencers, and track user influences over multiple time-scales for this purpose. We also stress the importance of aspect-specific influence analysis, and investigate an approach that uses an aspect hierarchy that annotates tweets with topics or aspects before analyzing them for influence. We also describe interesting insights discovered by our tool and the lessons that we learnt from this engagement.

Categories and Subject Descriptors
H.2.8 [Database Management]: Database Application—Data mining

Keywords
Social Influence Analysis; Wimbledon; IBM; multi-dimensional; aspect-specific; multiple time-scales; online updates

1. INTRODUCTION
The last few years have seen unprecedented adoption of social media forums all over the world. Analyzing social media data has emerged as one of the best ways to gain insight into social trends, individual preferences, and community behavior. Initially, analysis of social media data largely meant analysis of sentiment, brand value, network structure, etc. Of late, a new aspect of social media forums has been gaining attention. Social media platforms provide various modes of interaction between users, and these interactions carry signals of authority or influence of any user over others in the network. This aspect of analyzing influence signals in social media data is called social influence analysis. Its applications are in marketing, law enforcement, social sciences, etc. Recently, social influence analysis has received concerted attention of the research community as well as the industry. In this paper, we present our experience of deploying a social influence analysis platform for the 2014 Wimbledon Tennis Championship.

The Wimbledon Championship is one of the four Grand Slam tennis tournaments, and ranks among the most popular sporting events in the world. In the social and mobile era, the tournament generates large volumes of social conversations throughout the tournament. The All England Lawn Tennis and Croquet Club (AELTC), which organizes the event, has recognized its social footprint and has been particularly keen on analyzing the social buzz and on providing the social media users an immersive experience during the tournament. IBM has been the official technology partner for the tournament since 1990. In 2014, IBM helped AELTC deploy the Social Media Command Center (SMCC) on site at Wimbledon. The SMCC was open for visiting executives, journalists and industry practitioners to get a ‘social perspective’ of the Wimbledon.

Deploying a robust and useful social influence analysis tool in the real world involves many technical challenges. The first and foremost is coming up with a robust, interpretable and useful definition of social influence. It is important to recognize that social media has many unique features of interaction, and simply borrowing notions of influence from other domains is not sufficient. In order to be useful, influence has to be tied to topics. A user who is an influencer for technology may not be an influencer for the arts. The dynamism of social media interactions makes static notions of influence irrelevant. Influence scores need to evolve all the time taking into account new data that becomes available. Moreover, measuring influence at a single time-scale does not reveal all influencers. To take an analogy from literature, we need to be able to detect the likes of Shakespeare who is an ‘all-time’ influencer, and also the likes of Stephen King, who is indeed an influencer but at a significantly smaller time-scale. Finally, the tool needs to be able to handle data at very large volumes and update influence.
scores at (near) real-time. To give an example, about 200 thousand relevant tweets were generated per hour during the final day at Wimbledon 2014.

Before we proceed, we briefly comment about the various existing social influence analysis tools, techniques and services. We survey these approaches in greater detail in Sec. 2. There are many research papers that are relevant for influence analysis. Some of them focus completely on Twitter data [30], while others consider the more general problem of network inference [16]. The main drawbacks of these approaches are that they are offline in nature yielding static influence scores, and typically require non-trivial adaptation for real-life settings. There are several commercial services offering influence analysis, such as Klout, Kred, etc. These typically provide a single influence score that is hard to interpret and act upon. Most such services have also not been deployed for large scale event analysis.

Given this context, one of our main tasks was understanding what constitutes a good definition of social influence of a user. We came up with two sets of requirements, which we called the functional and usability requirements.

The functional requirements state that the definition of influence should cover all the unique features of social media (specifically Twitter) data. Specifically, the influence measure should account for the following:

- the importance of the user in the structure of social network
- the user’s engagement with her followers and other users
- the reach and the speed of the user’s messages in the network

In comparison, the usability requirements state that the influence score should be easy to use and act upon. We elaborate upon its different aspects below.

- The measure should be natural and intuitive. Users who are commonly acknowledged as influencers on any topic should in general score high according to the influence measure. For example, the official Wimbledon Twitter handle and popular tennis star Roger Federer, who tweets frequently and has many active followers, should be natural choices for the top tennis influencers.

- Since the scores will be exposed to the world, they should be easily interpretable. For example, in the case of analyzing node influence in static networks, the pagerank of a webpage has a natural interpretation — it is the probability that a random surfer will be on the webpage at any time. Similarly, the definition of social influence should also have a natural interpretation that is accessible to a typical social user.

- The social influence score should lead to actionable insights. Any user should be able to analyze her influence score and have an understanding of what actions can help in increasing her score. Alternatively, the influence score should help an analyst designing a viral marketing campaign decide which influencers can help propagate the marketing message far and which influencers can spread it quickly.

- The score should be refreshable quickly based on new data. This implies that the score should not be complex. Instead, it should be possible to compute and also update the scores using efficient algorithms.

Given these seemingly conflicting requirements that we set for ourselves, we take a multi-dimensional approach for defining social influence. We develop a suite of scores each of which is individually natural, interpretable, actionable and easily computable. Each score covers a subset of the functional requirements, while the suite as a whole covers the entire set. The individual scores are also topic or aspect specific. The final influence score is obtained by aggregating the individual scores in an appropriate fashion. This multi-dimensional nature ensures robustness of the score, and also helps in speeding up computation since the individual scores can be computed in parallel. We use a two-stage approach for aspect-specific influence analysis, where the posts are first annotated and grouped according to a hierarchy of aspects, and then posts in each of the aspects are independently analyzed for influence. Finally, all the scores are online or time-sensitive. Since our data accumulates over time, we analyze influence for every user at every time step at multiple time-scales. Using short term and long term horizons, we identify both all-time influencers and recent influencers.

The rest of this paper is organized as follows. We first discuss existing approaches for influence analysis in Sec. 2. We describe our data, and define the social influence analysis problem and the multi-dimensional influence measure in Sec. 3. Next, the algorithms for computing the influence scores in batch and online fashion and for aggregating the individual scores are described in Sec. 4. A description of the overall system architecture is presented in Sec. 5 before discussing actual data and insights from the Wimbledon engagement in Sec. 6. We end by discussing the impact of the engagement and the lessons that we learnt from it in Sec. 7.

2. RELATED WORK

Analysis of social media data has grown into a vast body of research spanning multiple disciplines and has myriad applications. Among the different social platforms, Twitter has emerged as an important source for social media analysis driven by the Twitter APIs and the rich structure of the tweets. The literature on social network analysis of Twitter data is very broad and an exhaustive survey is beyond our scope. It covers whole range of applications such as information filtering [26], sentiment and opinion analysis [21, 25], detecting emerging topics [22], event detection [27], usage during emergency events [19], analysis of political events [10], and marketing [20]. We will focus on influence analysis in the rest of this section.

Influence Analysis on Twitter Graph: A comprehensive study of influence analysis on Twitter data was carried out by Cha et. al [13]. They considered in-degree, number of retweets, and number of mentions as parameters of influence of a user. They studied the influence of about 6 million users on a population of 54 million users and arrived at three key findings: (i) the in-degree of a node is not necessarily an indicator of top influence, (ii) a top influencer is often an influencer on multiple topics, and (iii) influence profile is not built overnight, but through concerted efforts. An similar analysis was carried out by Ye and Wu [30]. Balshy et.
al [11] conducted influence analysis on Twitter data by looking at the cascade of tiny URLs. They looked at 74 million cascades of tiny URLs among a population of 1.6 million users. Their influence score was a variant of retweet count which roughly looks at ‘tiny URL count’. They concluded that the longer cascades were mostly started by influential users. Other papers have adapted the notion of PageRank and its topic-sensitive variant to the Twitter world. The most notably of these is ‘Twiterrank’ [28]. This approach produces results that are very different from, and sometimes qualitatively better than, those based on counting in-degree, retweets, and mentions.

Relation to Network Inference: The problem of inferring a diffusion network cascade of information through the network was introduced by Gomez-Rodriguez et. al [16] and has evolved into a rich body of research[16, 24, 17, 23, 15]. The idea is to model the cascade as a result of a diffusion process over the network defined by the influence relationships between the nodes. However, such an approach has not so far been used for analysis of real world events, or in an online setting.

Commercial Services: There are several companies that offer influence analysis as a commercial service, such as Klout [2], Kred [3], PeerIndex [5], and Twitalyzer [7] to name a few. Klout provides a “klout score” that ranges from 1 to 100. But the algorithm for the computation of the score is not revealed and hence the score is not interpretable. Kred computes two scores (Influence and Outreach) for each user, and have made their algorithms public. Their influence score reflects the trust reposed on a user by others and Outreach reflects the user’s generosity in spreading other user’s messages. Klout and Kred have reported influence analysis of some events, but only in offline settings. The klout-like scores change slowly over time. Twitalyzer combines a user’s Klout score with analysis of their most recent activities to provide a dynamic view of the user’s influence.

Our main innovation in the context of these myriad tools, techniques and services is that we address the problem of online influence analysis considering topics and multiple time-scales. We also focus on developing a score that is multi-dimensional and interpretable. Among the individual scores in our suite, we introduce a new measure based on the network inference literature that captures the rate at which the user’s tweets diffuse over her network of followers. Such a score has not previously been explored for influence analysis on Twitter. We also adapt this score to consider topics and to work in an online setting. This multi-dimensional approach proved extremely effective in terms of robustness and the richness of insights that it provided.

3. PROBLEM DEFINITION AND SOCIAL INFLUENCE SCORES

In this section, we formally define the online social influence analysis problem based on the Wimbledon requirement. We begin by discussing Twitter data from the perspective of influence analysis, then formally define the representation of the data that we used for our analysis, and formalize the problem of identifying influential users based on this representation. Finally, we address the definition of user-specific influence scores. While it is possible to generalize our approach to deal with data from other social media applications, we will not dwell further on this topic here.

3.1 Influence Cues in Twitter

The two different aspects of Twitter data relevant for influence analysis are (a) the follower graph and diffusion of tweets over it and (b) the content of the tweets.

Follower graph and Tweet diffusion: Each user in Twitter is identified by her unique id or handle. The Twitter network consists of all users and the ‘follow’ relation between them. We will call the directed graph induced on the Twitter users by the follow relations the follower graph. A typical user broadcasts a message of her interest by posting (or tweeting) the message on the Twitter network. This tweet then becomes visible to all her followers. The followers can retweet the message in turn if they wish, which will then be visible to their followers. The follower graph grows when users choose to become followers of other users. A users acquires followers because of various reasons, but mostly because she is either a celebrity or an expert, whose tweets are of interest to others.

Clearly, the number of followers of any user is an indication of her influence in the network. Higher order notions of ‘centrality’ of the user in the follower network provide deeper insight into this influence. Additionally, the rate at which tweets of the user spread over the network via retweets is also indicative of her influence.

Content of Tweets: The other unique feature of Twitter data is the content of the tweets. The tweets are short — 140 characters including spaces. As a result of this brevity, tweets are almost always directed towards a very small set of topics, usually just one. A user also has the option of adding interpretable structure in the content of her tweet. She may refer to other users using their handles. These are called mentions. She may also include labels in her Tweet, called hashtags, which then become available for reuse by her followers and other users.

Using such interpretable structure, it is relatively easy to annotate tweets with additional inferred structure, such as higher level topics. First, these annotations can be used for focused or topic-specific influence analysis, for example counting references to specific topics or to specific users. Secondly, these provide an additional indication of any user’s influence through the mentions. Often (but not always), a retweet of a message can be regarded as an endorsement or expression of interest towards the original tweet. Therefore, such annotations carry signals of social influence in the network.

These features highlight the uniqueness of Twitter data from the perspective of influence analysis. In network data such as tele-communication call detail records (CDRs) and emails in the Enron archive for example, the communications are directed. Telephone calls occur between two users, and emails between a sender and small set of recipients. In contrast, Twitter messages are broadcast. Also, unlike in Twitter, there is no specific notion of responding to a phone call, while email responses go back to the sender. As regards content, annotation of phone calls and emails, even assuming that they are acceptable from the privacy viewpoint, is significantly harder to perform at any acceptable combination of accuracy and computational complexity. Thus, any existing approach of user influence analysis in such networks
is not suitable for Twitter. It calls for approaches tailored specifically to handle its unique features, which we address in this paper.

3.2 Influence Analysis: Problem Definition

Having informally identified the various sources of user influence in Twitter data, we now formally define the influence analysis problem. We do this in three parts. We define the representation of annotated Twitter data, the hierarchy of aspects which are used for annotating the data, and then the task of analyzing this annotated data for user influence.

**Annotated Twitter Data:** Let us denote the Twitter follower graph as \( G_f = (U_f, E_f) \) over users \( U_f \) and containing directed follow edges \( (u, v) \in E_f \) denoting that user \( u \) follows user \( v \). Twitter data is made available for analysis through third party providers such as GNIP\(^1\). Such data does not include the follower graph \( G_f \) or the set of all users \( U_f \). Instead, it only contains a collection of tweets.

The data for our problem consists of tweets collected and annotated over a sequence of time intervals or epochs. We represent this data as \( D = \{D_t\}_{t=1}^{T} \), where \( D_t \) is the data from the \( t^{th} \) epoch and there are \( T \) epochs in all. In practice, each epoch may correspond to an hour or a day, and the duration \( T \) may span several days, weeks or months. The data \( D_t = \{D_{t,a}\}_{a=1}^{A} \) for each epoch is grouped according to topics or aspects belonging to a given set of aspects \( A \). We will separately discuss the design of the aspect set. The representation of annotated Twitter data, the hierarchy of aspects which are used for annotating the data, and then the task of analyzing this annotated data for user influence.

**Top Influencers:** Assume that we are given an appropriate definition \( I(u, D) \) of the influence of an user \( u \) based on a set of tweets \( D \) in our representation. Let \( U(D) \) denote all relevant users for tweets \( D \), i.e. the unique users who appear as the user \( u_i \) or in the retweet \( r_i \) or mention \( m_i \) attributes of any tweet \( d_i \in D \). Let \( D_{t,a} = \{d_{t,a}\}_{d=1}^{D} \) denote the accumulated data for aspect \( a \) from the first epoch as the start epoch \( (t_s = 1) \) up to epoch \( t \) as the end epoch \( (t_e = t) \). Given such aspect-annotated tweets and the definition of \( I(u, D) \), our task for every epoch \( t \) is two-fold. First, we need to identify the all-time top influencers over all epochs starting from \( t=1 \), e.g. since the beginning of the Wimbledon tournament. For this, we need to compute the influence of each individual user \( u \in U(D) \) for tweets \( D \in \{D_{t,a}\} \) and then find the top-k influencers for each aspect \( a \in A \) for each epoch \( t \).

This definition cannot find users who are very influential for some time segment of the tournament, but are not influential over the entire tournament. Therefore, we also need to find the recent top influencers. This implies addressing the same problem as above with a start epoch \( t_s \neq 1 \). For Wimbledon, we needed to find influencers for the last 24 hours.

3.3 Defining Social Influence

We now come to the important task of defining social influence \( I(u, D) \) of a user \( u \) based on a collection of tweets \( D \). The definition must capture the different features of social media data. We call these functional requirements. These require the social influence definition to capture (a) the importance of the user in the follower graph, e.g. in terms of number of followers and centrality, (b) her engagement with her followers and other users, in terms of mentions, retweets, etc., and (c) the reach of the users message in the network, in terms of the volume of her tweets and how readily the followers respond to her tweets.

Additionally, there are various requirements elaborated in Section 1 related to the consumption or usage of the influence score by broad spectrum of analysts and users. We refer to these as usability requirements. These require the score to be natural and intuitive, interpretable, actionable and refreshable at (near) real-time.

It is difficult to come up with a single social influence score that satisfies all the above requirements. Instead, we focus on developing different influence scoring functions, each of which is individually natural, intuitive, interpretable. Each

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\(^1\)https://gnip.com/
score individually covers a subset of the functional requirements, while ensuring that together the scores cover all the functional requirements. One advantage of such a multi-dimensional definition is that these score are simple and independent of each other, so that they can be computed efficiently and in parallel.

Formally, we define $K$ influence scores $\{I_1(u, D), \ldots, I_K(u, D)\}$ for each user, which are finally aggregated. We discuss aggregation techniques at the end of this section. We later demonstrate in the paper that this multi-dimensional nature also makes the definition robust. It is essential for a user to score well across multiple dimensions to emerge as influential. In other words, while it is possible for a user who is truly not influential to 'fool' an individual dimension, fooling many dimensions simultaneously is unlikely.

Specifically, we consider 5 different dimensions of social influence:

**Follower strength:** This is a network-centric measure and refers to the number of followers of a user. We denote this as $I_f(u, D)$. Recall that the number of followers of a user $u$ is available as an attribute in tweets posted by $u$. Therefore $I_f(u, D) = d_i$, where $d_i$ is the latest post by user $u$ in $D$.

According to this definition, for each aspect, all users who posted on that aspect are assigned some follower strength. However, this definition is not specific to any aspect or even Wimbledon. Imagine a Hollywood celebrity, with a huge number of followers tweeting about Wimbledon. Her follower score will suggest that she is an influencer, even if none of her followers are interested about Wimbledon. Additionally, the followers may not all be active. We investigate this further in Sec. 6.

**Activity:** This captures the number of tweets posted by a user. We denote this as $I_a(u, D)$ and define $I_a(u, D) = \sum_{d_i \in D} \delta(u = u)$, where $\delta(a = b)$ is the indicator function which evaluates to 1 if the argument is true and to 0 otherwise. This indicates the volume of the user’s activity in the network.

**Engagement:** This is the number of retweets and mentions of a user. This is denoted as $I_e(u, D)$ and we define $I_e(u, D) = \sum_{d_i \in D} \delta(r_i, u = u) + \sum_{m \in \Gamma(u)} \delta(m = u)$. This is indicative of the popularity of the user in tweets by other users.

**Authority or Network centrality:** This captures the centrality of a specific user in an user graph. To capture centrality of a user in a graph, we use the popular PageRank score used for ranking web-pages on the internet [12]. We denote this as $I_c(u, D)$, and define $I_c(u, D) = p(u, G(D))$, where $\hat{G}(D)$ is a graph over users reconstructed from tweet set $D$, and $p(u, G)$ denotes the PageRank score of a vertex $u$ in a graph $G$. The graph over users may be the follower graph, retweet graph or mention graph. In our work, we used the engagement graph considering retweets and mentions. Note that the follower graph is not directly observed in our data. We discuss reconstruction of the follower graph and other graph construction in Section 4). Also note that when the tweets $D$ correspond to different aspects, we get aspect-specific measures of PageRank.

**Response rate or Timeliness:** None of the scores above consider the temporal nature of tweet diffusion over the network. While the engagement score captures the volume of response to a user, it is also informative from the perspective of influence analysis to measure how quickly a user’s tweets reach her followers. A user who can regularly, consistently and quickly draw a response from a large number of other users is clearly very influential in the network. To capture this, we define response rate as the rate at which other users respond to the user’s tweets in the form of retweets. We denote this as $I_r(u, D)$. Assuming that the delays $(t_v - t_u)$ between a tweet by user $u$ and its retweet by user $v$ follow an exponential distribution $f(t_v|t_u; \alpha_{uv}) = \alpha_{uv} \exp(-\alpha_{uv}(t_v - t_u))$ with transmission rate parameter $\alpha_{uv}$, we define $I_r(u, D; t)$ to be the expected number of retweets for a single tweet by user $u$ by all other users within a delay $t$. Under the assumption of the exponential distribution, this leads to the following definition:

$$I_r(u, D; t) = \sum_{v \in U} (1 - \exp(-\hat{\alpha}_{uv}(D)t)) \quad (1)$$

where $\hat{\alpha}_{uv}(D)$ is the estimate of parameter $\alpha_{uv}$ from tweets in $D$. This problem has been studied in the context of network inference [16] but not for influence analysis in Twitter. (We discuss estimation of $\alpha_{uv}$ parameters in Section 4.2). A very significant aspect of this score is its predictive nature — it captures future reach of a user’s tweets over the network.

We next investigate how well the scores satisfy the requirements that we had stated upfront. Individually, the metrics are natural and intuitive in that any true influencer is expected to score well according to these metrics. They are easily interpretable by a lay-person. In terms of computational complexity, some are easier to compute than others, and we will show analytically in the next section that all of them admit efficient algorithms that generate good approximations if not the exact scores. Thus, the scores satisfy all our usability requirements.

The scores also satisfy the functional requirements. The follower graph is covered by follower strength, network centrality and response rate scores, user activity and engagement are covered by the activity, engagement and timeliness scores, and readiness of followers is covered by the response rate score.

It is worth mentioning that the Klout score of each user is also available in our data as an attribute of each tweet. However, like the follower attribute, this does not have any relevance for any specific subset of tweets, e.g. those relevant for Wimbledon. We will show in our experiments that this score on its own is not very useful for us.

**Aggregating Influence Scores:** Earlier in the section, we have highlighted the advantages of multi-dimensional influence analysis. However, this approach comes with a challenging overhead. These multiple influence scores need to be aggregated to produce a single influence score for each user. We believe that this in itself is a challenging research problem, that can build upon existing work in rank aggregation [14]. Formally, for each user $u \in U$ we have 5 influence scores $I_a(u)$, $I_f(u)$, $I_e(u)$, $I_c(u)$ and $I_r(u)$. The task is to compute an aggregate score $I^*(u)$ for user $u$. We discuss algorithms for this in Sec. 4.4

### 4. ALGORITHMS

In this section, we present the algorithms for computing the influence scores defined in Section 3.3. Recall that one of the key usability requirements is to have efficient algorithms for computation of the scores. Given the scale of tweets for an event like Wimbledon, the computation of the influence
scores at the end of epoch $t$ should be ‘incremental’ in the sense that it should not mean discarding the computations done on data $D_{t-1}$ and redoing the computation on $D_t$. In this section, we will consider such online algorithms for influence scores. We have seen in the previous section that we are required to compute influence scores over different subsets of tweets. For example, for each aspect, we need to compute scores on the all-time data and on the recent data. In this section, we define the algorithms to compute each of the scores $I(u, D)$ over a generic set of tweets $D$. The same algorithm is then run on different tweet collections as required.

**User Graph Construction:** For many of the influence scores, the algorithms require a graph over users as one of the inputs. As mentioned in Section 3.1, even the follower graph is not directly observed in the data available to us. As a result, such graphs need to be reconstructed from the data. Before moving on to algorithms for computing influence scores, we first address this problem.

Let us first consider the follower graph $G_f$. Formally, given a collection of tweets $D$, the task is to estimate from $D$ the follower edges $(u, v)$ indicating that user $u$ follows user $v$. The only evidence in the tweets about follower edges are the retweets. This is because a user $u$ retweets user $v$ only if $u$ follows $v$, or in other words, $(u, v)$ is an edge in the follower graph. For any tweet $d_i$ with non-empty $r_v$, we add an edge $(u_i, r_v)$ in the retweet graph $G_r$. Based on this, the retweet edges from a set of tweets $D$ is $E_r(D) = \cup_{d_i \in D} \{(u_i, r_v)\}$. We consider the resultant retweet graph $G_r(D) = \{U, E_r(D)\}$ as also the reconstructed follower graph $G_f(D)$ from tweets $D$.

Alternatively, some scores may require the mention graph $G_m = \{U, E_m\}$, where $(u, v)$ is a mention edge between users $u$ and $v$ if $u$ mentions $v$ in some tweet. Based on this, we construct the mention edges from a set of tweets $D$ as $E_m(D) = \cup_{d_i \in D} \cup_{m \in m_i} \{(u_i, m)\}$. We also consider the engagement graph $G_e = \{U, E_e\}$, where $(u, v)$ is an engagement edge if $u$ has either retweeted or mentioned $v$. This can be obtained simply taking the union of the follower and mention edges.

### 4.1 Updating Follower strength, Activity and Engagement

The definitions of Follower strength, Activity and Engagement scores, as seen in Sec. 3.3, are quite straightforward and the scores can be computed very efficiently. Specifically, for Follower strength $I_f(u, D)$, the algorithm initializes all scores to 0 and makes one pass over all the tweets $d_i \in D$. For each tweet $d_i$, it updates the follower strength $I_f(u_i, D)$ of $u_i$ as $f_i$. At the end of the pass, the follower strengths of all users appearing in $D$ are available.

The algorithms for Activity score $I_a(u, D)$ and Engagement score $I_e(u, D)$ are similar. On scanning each tweet $d_i \in D$, the algorithm for Activity increments $I_a(u, D)$ by 1 and the algorithm for Engagement increments $I_e(r_i, u, D)$ by 1 and $I_e(u_j, D)$ by 1 for all $u_j \in m_i$.

Let us now consider the online settings for these scores, where we have a current score $I(u, D_t')$ for each user at the end of epoch $t$ and it needs to be updated based on a new set of tweets $D_{t+1}$ at epoch $t+1$. A naïve approach is to recompute the score $I(u, D_t')$ from scratch over the aggregated tweets $D_{t+1}$. However, this completely disregards the existing score $I(u, D_t')$, which we would like to reuse and restrict our computation to only the new data $D_{t+1}$. This online or incremental approach turns out to be straightforward for all three scores. The algorithm proceeds exactly as in the batch setting, with the scores for each user initialized to their current scores $I(u, D_t')$ instead of 0 and then scans over the tweets $D_{t+1}$.

### 4.2 Updating Response Rate Scores

We now come to the Response rate score, which is significantly more sophisticated than the three earlier scores. Recall that for computing this score, we need to find the estimate $\hat{\alpha}_{uv}(D)$ of the ‘transmission rate’ parameter $\alpha_{uv}$ between users $u$ and $v$ from a collection of tweets $D$. The only evidence in the tweets about follower edges are the retweets. This is because a user $u$ retweets user $v$ if $u$ follows $v$, or in other words, $(u, v)$ is an edge in the follower graph. For any tweet $d_i$ with non-empty $r_v$, we add an edge $(u_i, r_v)$ in the retweet graph $G_r$. Based on this, the retweet edges from a set of tweets $D$ is $E_r(D) = \cup_{d_i \in D} \{(u_i, r_v)\}$. We consider the resultant retweet graph $G_r(D) = \{U, E_r(D)\}$ as also the reconstructed follower graph $G_f(D)$ from tweets $D$.

Intuitively, $\rho_{uv}(D)$ indicates the total number of times $u$ has retweeted $v$ in $D$, and $\Delta_{uv}(D)$ is the cumulative delay between tweets by $v$ and their retweeters by $v$ in $D$.

Based on this definition of the ML estimate, the batch algorithm for computing the Response rate scores computes $\rho_{uv}(D)$ and $\Delta_{uv}(D)$ from the tweets in $D$, then the estimate $\hat{\alpha}_{uv}(D)$ for each edge in the retweet graph $G_r$, and finally the expectations for each user $u$ over all followers $v$ as in Eqn 1. The second and third operations take $O(E_r(D))$ time. Let us now consider the algorithm for computing $\rho$ and $\Delta$. This algorithm is very similar in spirit to those for the first three scores. It initializes all $\rho$ and $\Delta$ counts to 0, and makes a single pass over the tweets in $D$ and updates the scores. For tweet $d_i \in D$, if it is a retweet, it increments $\rho_{u_i, r_v}(D)$ by 1 and $\Delta_{u_i, r_v}(D)$ by $t_i - r_v$. The correct $\rho_{uv}(D)$ and $\Delta_{uv}(D)$ values for all follower edges are available at the end of the pass. Thus this algorithm takes $O(|D|)$ time and the end-to-time time to compute Response rate scores is $O(|D|) + O(|E_r(D)|)$.

Now we come to the online algorithm, where we have existing values $\rho_{uv}(D_t')$ and $\Delta_{uv}(D_t')$ at the end of epoch $t$ and we need to update the scores based on data $D_{t+1}$ from the next epoch $t+1$. The approach for this is again straightforward. Since $\rho_{uv}(D_{t+1}) = \rho_{uv}(D_t') + \sum_{d_i \in D_{t+1}} \delta(r_v = u)\delta(u_i = u)$, we can use exactly the same algorithm as in the batch setting with the initial scores changed from to $\rho_{uv}(D_t')$. Online computation of $\Delta_{uv}(D_{t+1})$ follows a very similar approach. Once we have the updated $\rho$ and $\Delta$ values for all retweet edges, the Response rates for all users can again be updated in $O(|E_r(D_{t+1})|)$ time.

### 4.3 Computing Network Centrality

We finally come to the most computationally demanding influence score in our suite, which is the Network centrality score. Recall that for the network centrality score $I_n(u, D)$ for a user $u$ based on data $D$, we need to compute the PageRank $p(u, G_c(D))$ of user $u$ in the engagement graph $G_c(D)$ constructed using tweets in $D$. The PageRank $p(u, G)$ of a vertex in a graph $G$ is defined recursively in terms of the
PageRank of its neighbors $N(u)$ in the graph. In the simplest version, $p(u, G) = \sum_{v \in N(u)} p(v, G)/d(v, G)$, where $d(v, G)$ is the degree of the vertex $v$ in graph $G$. A typical PageRank algorithm starts with some initial values for the PageRanks of all vertices, and then iteratively updates the values for each vertex based on the current PageRanks of its neighbors. The algorithm terminates when there is no significant change in the PageRank values.

There are many scalable open-source implementations of PageRank. We experimented with many of these implementations to determine the right framework for the expected number of users for the Wimbledon data. An Apache Giraph implementation of this algorithm exchanges messages between individual vertices and runs on top of MapReduce. The Jung library has an in-memory implementation that uses a Markov Chain representation for the edges between vertices and uses the power method for computing the stationary distribution. For the expected size of the user graph for our use-case, we found a centralized in-memory framework to be more suitable.

Unlike our other scores, incremental computation of PageRank scores is a very challenging problem that has attracted recent research [18]. However, we were able to compute the PageRank scores from scratch on the accumulated data $D_t^2$ for each epoch in time before the data $D_{t+1}$ for the next epoch arrived. Therefore, we decided to use the batch algorithm for Wimbledon.

### 4.4 Aggregating Influence Scores

Given 5 influence scores $I_a(u)$, $I_f(u)$, $I_e(u)$, $I_r(u)$ and $I_s(u)$, we now address the problem of computing an aggregate score $I^*(u)$ for user $u$. A simple aggregation technique is to directly aggregate the scores for each user, for example, using a linear combination: $I^*(u) = \sum_k I_k(u) \times w_k$. However, this has several issues. Individual scores are not normalized, and the best normalization is not obvious. There are many outlier scores, for example in the case of followers, which would drown all other scores in a linear combination.

A better option is to bypass the actual scores and consider just the ranking of users for each score, where $R_k(u)$ now indicates the rank of user $u$ for the $i^{th}$ influence score. Then, instead of aggregating scores, we aggregate the ranks of individual users.

Optimal rank aggregation is known to be a hard problem, and the individual ranked lists that we need to aggregate are extremely long since they are over all users. A computationally easier approach is Borda’s method [14]. In its simple form, this approach computes the average rank of each user, and then creates the final list by sorting the average rank. This is computationally straightforward but suffers from some drawbacks. For example, consider a user who is top-ranked in all the lists except one, where she has a low rank. This user’s overall rank would be very low in this approach. We considered three different rank scoring functions for each user: (a) Average rank, which is essentially the approach above, (b) Top rank, which considers the best rank for a user, and (c) Average Top-k rank which takes the average of $k$ ($<5$) best ranks for a user. The third approach worked best for us, as we demonstrate in Sec. 6.

### 5. SYSTEM DESIGN

In this section, we briefly describe the architecture of the Social Influence Analysis tool deployed at Wimbledon.

The Influence Analysis (IA) tool was one component of the larger Social Media Analysis framework that IBM deployed at Wimbledon. This larger framework obtained tweets in JSON format from the GNIP Twitter feed every hour, filtered these to extract tweets relevant for Wimbledon, annotated the Wimbledon-related tweets using the Aspect hierarchy, and deposited the hourly batch files in the IA server. The responsibility of the IA tool was to compute the all-time and daily influence scores for every aspect and expose the scores of the top 100 users through Rest APIs at the end of the hour.

Extraction of tweets relevant for Wimbledon was done using a multi-stage algorithm. First, this includes all tweets that contained words and hashtags from a Wimbledon and tennis-specific dictionary, followed by all tweets posted by users from a pre-specified list including all players participating in the Wimbledon tournament, etc. This was followed by a spam-filtering step, where all tweets matching certain regular expressions were filtered out. These steps were extremely crucial for the success of the engagement, but we do not go into further details in this paper.

On the Influence Analysis server, a cron job monitored the arrival of new data batches. When a data batch arrived, this job invoked the modules that compute the individual influence scores in parallel. These modules, on completion, wrote two sets of influence scores, one for the all-time scores and another for the daily scores, in two JSON files, each containing the scores for every user for every aspect. Once all individual scores were available, the scores for each user were aggregated and the top 100 users and their scores were written into database tables. On invocation through the Rest APIs the scores were retrieved from the database. The entire system was deployed on a cloud platform.

The IA tool also included two user interfaces. The external user interface embedded within the Social Media Analysis tool displayed the top 9 all-time influencers and their individual influence scores. Aside from this, there was an internal user interface containing all details about the influence scores, and included the ability to slice and dice according to days and aspects, sort users according to aggregate and individual scores, and view the original tweets of users. This was primarily meant for verifying the accuracy of the ongoing analysis, and diagnosing any surprises that may appear during the course of the tournament. In Sec. 6, we demonstrate the strength of the internal UI with an example insight that we were able to discover through it.

### 6. EXPERIMENTAL RESULTS

In this section, we discuss quantitative details of the Wimbledon engagement, including the data and the influence scores, and the some insights that we derived from the scores.

**Summary of the data:** We first discuss properties of the annotated data for Wimbledon that we were required to analyze for social influence. The 2014 Wimbledon tournament started on Monday, June 23rd, and continued until Sunday, July 6, when the Men’s Singles Final was played.

The aspect hierarchy was hand-crafted ahead of time, and had 3 levels and 23 nodes in total. The highest level contained the General Aspect, while the aspects in the second
level were Broadcasters, Celebrities, Commentators, Grounds, Players, Sponsors, Tennis, Travel and Weather. There were 14 aspects in the third level, all of them under Celebrities.

We received fresh batches of tweets every hour. In other words, one epoch corresponded to 1 hour. In totality, the data had about 4.8 million tweets, 1.6 million users, 1.5 million retweets and 6.2 million engagements (retweets and mentions). The volume of data per hour varied greatly over the tournament, peaking every day during the matches, and peaking over days before reaching the largest volume on the last day during the Men’s Singles Final. In Tab. 1, we record this the summary of this temporal pattern for the total number of tweets, the number of users and the number of retweets for the General Aspect. Observe the large range and standard deviation for all 3 characteristics.

<table>
<thead>
<tr>
<th>Table 1: Statistics of the hourly data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tweets</td>
</tr>
<tr>
<td>Min</td>
</tr>
<tr>
<td>14,898</td>
</tr>
</tbody>
</table>

Aggregate analysis of influence scores: We now come to the user influence scores computed on top of this data. As mentioned earlier, we maintained two different running influence scores for each user for each aspect. One was the all-time influence score, which indicates the influence score for the user since the beginning of the tournament to the current hour (or epoch), and the other was the recent or daily influence score, which indicates the influence of the user over the previous 24 hour window. Because of space constraints, here we only present details and analysis for the all time influence score computed at the end of the tournament.

We first provide some aggregate insight on the influence scores in Tab. 2 and Tab. 3 before analyzing user-specific scores. In Tab. 2, we show the correlation among the top-100 influencers (according to the aggregated influence score) for pairs of second-level aspects. Specifically, for each pair of aspects, we report two scores for their top-100 influencers. The Jaccard score is the ratio of the intersection and the union of the two sets. This score stays in the range [0, 1] where higher scores indicate better agreement. We can see that the largest Jaccard score is 0.21. Even when there is overlap, there is very little agreement in terms of ranking. This shows that influencers vary greatly across aspects, and therefore categorizing influencers according to aspects is important. The scores indicate some shared influencers for (Tennis, Grounds) and (Tennis, Players), which is intuitive, and also for (Celebrities, Grounds), which is not as intuitive.

<table>
<thead>
<tr>
<th>Table 2: Kendall Tau (upper triangle) and Jaccard (lower triangle) among top influencers across aspects: Broadcasters, Celebrities, Commentators, Grounds, Players, Sponsors, Tennis and Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Br</td>
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<tr>
<td>Br</td>
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<tr>
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<td>Gr</td>
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<td>Te</td>
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<td>Tr</td>
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<tr>
<td>We</td>
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</tbody>
</table>

Analysis of user-specific influence scores: We next present an analysis of influence scores at the level of users. Naturally, no gold-standard rankings were available for evaluation. But we anecdotally verified the rankings and scores through the duration of the tournament for the different influence scores and for different aspects to the extent possible. In Tab. 4, we show the top-5 users in terms of the individual influence scores for the General Aspect. Observe that Activity and Follower strength on their own did not yield meaningful influencers for Wimbledon. Expectedly, the top users for Activity post in huge volumes without much engagement, and those for Follower strength have millions of followers but are not very relevant for Wimbledon. We also show the top users according to the Klout scores, which we did not use though available in our data. We can see that ranking according to raw Klout scores is not very relevant for Wimbledon. The Engagement, Centrality and Response Rate scores are the most interesting. While there is some overlap in these 3 lists, there are differences as well. Many of the top influencers here, such as the official Wimbledon handle, and popular tennis players Federer, Bouchard, Murray, Djokovic, are natural candidates for appearing at the top of the list. However, there are some surprising names as well. For example, popular boy band One Direction members Liam Payne and Niall Horan are not intimately related to tennis or Wimbledon, but appear at the top in these lists.

<table>
<thead>
<tr>
<th>Table 3: Kendall Tau (upper triangle) and Jaccard (lower triangle) for top influencers across Influence scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
</tr>
<tr>
<td>Br</td>
</tr>
<tr>
<td>Br</td>
</tr>
<tr>
<td>Ce</td>
</tr>
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<td>Gr</td>
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<td>We</td>
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</tbody>
</table>

The influence scores over the duration of the tournament presented many interesting insights. We briefly mention some of them here. Basketball player Shaquille O’Neal was among the top celebrity influencers at the end of the first day (24th hour), by virtue of mentions after he was observed
in the stands, even though he did not tweet about Wimbledon at all. He never appeared among top influencers after that. Similarly, celebrity cricketer Sachin Tendulkar was among the top recent influencers for a few hours on the 10th day (July 2nd). This demonstrates the need for recording the recent influencers, which picks up such notable but temporary trends that are too insignificant in the long term to be picked up by the all-time influence score. Another interesting insight was that Roger Federer’s soccer-related tweets about Wimbledon. This did not show up automatically in our analysis, which did not have a soccer aspect, pointing to the short-coming of having fixed and pre-determined aspects. We were able to pick this up by diagnosing Federer’s influence using the internal user-interface, which proved to be very useful during the course of the engagement.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Activity</th>
<th>Engagement</th>
<th>Followers</th>
<th>Centrality</th>
<th>Response Rate</th>
<th>Klout</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>YSMLive</td>
<td>Wimbledon</td>
<td>Instagram</td>
<td>Wimbledon</td>
<td>Wimbledon</td>
<td>Forbes</td>
</tr>
<tr>
<td>2</td>
<td>onesportmanck</td>
<td>rogerfederer</td>
<td>twitter</td>
<td>rogerfederer</td>
<td>NiallOfficial</td>
<td>guardian</td>
</tr>
<tr>
<td>3</td>
<td>yoursportman</td>
<td>NiallOfficial</td>
<td>geniebouchard</td>
<td>Andy Murray</td>
<td>Real_LiamPayne</td>
<td>CNN</td>
</tr>
<tr>
<td>4</td>
<td>yoursportman</td>
<td>BritishTennis</td>
<td>cmbrk</td>
<td>geniebouchard</td>
<td>BBCSport</td>
<td>CNN</td>
</tr>
<tr>
<td>5</td>
<td>thatsportman</td>
<td>geniebouchard</td>
<td>Real_LiamPayne</td>
<td>DjokerNoles</td>
<td>ESPNTennis</td>
<td>AP</td>
</tr>
</tbody>
</table>

Table 5: Top overall influencers according to different aggregation methods

<table>
<thead>
<tr>
<th>Rank</th>
<th>Activity</th>
<th>Engagement</th>
<th>Followers</th>
<th>Centrality</th>
<th>Response Rate</th>
<th>Klout</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Wimbledon</td>
<td>Wimbledon</td>
<td>Wimbledon</td>
<td>Wimbledon</td>
<td>Wimbledon</td>
<td>Forbes</td>
</tr>
<tr>
<td>2</td>
<td>NiallOfficial</td>
<td>geniebouchard</td>
<td>geniebouchard</td>
<td>Andy Murray</td>
<td>Real_LiamPayne</td>
<td>CNN</td>
</tr>
<tr>
<td>3</td>
<td>rogerfederer</td>
<td>tennisnews</td>
<td>geniebouchard</td>
<td>tennisnews</td>
<td>geniebouchard</td>
<td>CNN</td>
</tr>
<tr>
<td>4</td>
<td>NiallOfficial</td>
<td>Real_LiamPayne</td>
<td>tennisnews</td>
<td>tennisnews</td>
<td>geniebouchard</td>
<td>CNN</td>
</tr>
</tbody>
</table>

7. IMPACT AND LESSONS LEARNT

In this section, we summarize the real-world impact achieved by the Social Influence Analysis engagement at Wimbledon 2014. We also look at the lessons learnt from this engagement and highlight some research challenges that need to be addressed for greater impact in the future.

Impact: The Social Influence Analysis Engine was deployed as part of the Social Command Center (SMCC) developed by IBM to provide insights about the tournament. The deployment proved to be extremely successful according to multiple metrics.

The deployment got prominent coverage in press. At least four prominent broadcasters (CNBC, Bloomberg, Sky News and BBC), 25 independent articles in national and prestigious media outlets (Wall Street Journal, Newsweek, Guardian, Reuters, Forbes, Techweek, London Evening Standard, Computer Weekly, eWeek and others) and many Business and Trade forums reported the innovation [6, 9]. AELTC publicly praised the role of the Social Command Center in the success of Wimbledon 2014. Special tours of the Social Command Center at Wimbledon were conducted for at least 300 executives from industry and press. IBM Leaders appeared in TV programs and wrote popular blogs on the capability [8]. Buoyed by the success of the Wimbledon engagement, the Social Influence Analysis capability became part of an announced solution and has since generated interest from clients. The technology has been used successfully in Proofs of Concepts with clients from different industries. As a follow up after Wimbledon 2014, the same capability was also successfully deployed recently at the Australian Open Tennis Championships 2015 with a minimum of effort, demonstrating the reproducibility of the framework and the generalizability of the algorithms within.

Lessons Learnt: In parallel with the overall success, the Social Influence Analysis engagement with Wimbledon also made us aware of some deficiencies in our analysis, which need to be addressed in the future versions of this framework. We highlight some of the main challenges here.

We used a multi-dimensional approach to influence analysis, which was largely successful. However, the individual influence scores have room for improvement. We found that number of followers was not very useful for aspect-specific analysis. The followers also need to be interested and active in that aspect. Also, some scores will be more useful than others, and we expect this usefulness to be engagement specific. Thus, as the size of the influence suite grows, more work will need to be done around score aggregation.

In summary, our experiments demonstrate that for social influence analysis in a real-world setting an aspect-oriented, multi-dimensional and online approach with multiple temporal resolutions is necessary and useful.

Analysis of influence-aggregation methods: Finally, we do an analysis of different influence aggregation methods. In Tab. 5, we show the top 5 influencers according to different aggregation methods that we discussed in Sec. 4.4. Considering the top-rank for a user does not work very well, as is it not very robust. The average of all ranks is not a good alternative either, since it is unlikely for genuine candidates to rank high across all influence dimensions. Average of top-3 ranks and ranking by weighted average of all scores are much better options. Interestingly, the top 5 users are identical (though reordered) for these two lists.

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A novel aspect of our analysis was the use of multiple temporal windows for online influence analysis. We scored each user for a specific epoch, for all epochs, and also for the most recent epoch. This proved to be extremely useful and necessary for separating out ‘influence blips’ from long-term influence. However, we did not have tools for analyzing influence patterns over time, and had to fall back on manual analysis, which yielded many interesting insights. Integrating time-series analysis techniques to detect patterns and anomalies in influence change over time would be an important area of future work.

The aspect hierarchy used for annotating the tweets was fixed and defined ahead of time using domain knowledge about tennis and Wimbledon and the expected consumers of the insights. While simplicity of deployment and interpretability of the aspects are the main motivations of this approach, it can also be a serious shortcoming. Many of the
leaf-level aspects did not accumulate enough tweets, indicating that they were either not significant or incompletely defined. Additionally, this leaves no room for surprising topics that were not expected ahead of time and yet generated a lot of conversation, such as soccer-related conversation in our case. Specifically, this calls for online topic detection techniques that can identify new topics on the fly and also allow enhancements and modifications for existing topics. While this area has seen some research recently[29], this needs to be tied seamlessly with influence analysis. On a related note, the filtering algorithm determines a fine balance between precision of the analysis and its coverage. Our filtering algorithm was biased towards high precision, resulting in a smaller volume of very related tweets. This also meant that we could not detect many relevant and possibly important tweets. For example, all tweets of yesteryears star John McEnroe were missed because of his unusual language though they were very relevant for Wimbledon.

The network centrality or PageRank score proved to be a key score in our suite. The volume of data for this engagement could be handled by batch algorithms for PageRank. However, this is unlikely to hold true in all scenarios. Therefore, it is important to have online algorithms for PageRank, in spite of their implementation challenges.

In summary, we have presented our online, multi-dimensional approach for topic-specific social influence analysis which was successfully deployed for the Wimbledon 2014 Tennis Championships. The engagement helped us appreciate both the usefulness and the challenges of social influence analysis in a real-world setting. We believe that our experience will benefit us in improving our tool and also the broader social media analysis community in their understanding of an important problem and its real-world demands.

8. REFERENCES