A Sliding Window-Based Algorithm for Detecting Leaders from Social Network Action Streams


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Abstract—Influential users or leaders in a social network play important roles in viral marketing by spreading news quickly to a large number of people. Hence, various organizations aim to discover these leaders as campaign targets for advertisement so as to maximize customer reachability. Existing approaches detect leaders from a static social network. However, as social networks are evolving, detecting leaders from dynamic streams of social network data is in demand. In this paper, we propose a sliding window-based leader detection (SWLD) algorithm for discovering leaders from streams of user actions in social networks. Experimental results show that SWLD is accurate, requires short runtime and a small amount of memory space.

Keywords—Web intelligence; social network mining; data stream mining

I. INTRODUCTION

Social network (SN) services (e.g., Facebook, Google+, Twitter) are the platforms to build social community among users who share common interests or real-life connections (e.g., friendships). These services allow users to interact with each other as friends. These users and their connections can be captured in an undirected graph \( G = (V, E) \)—where (i) \( V \) captures users and (ii) \( E \) captures their connections—in which Big social network analytics and mining [7], [9], [10], [13] can be applied for finding useful patterns.

When a user \( u \) shares some interesting information in a social network, some of his friends (say, users \( v_1 \) and \( v_2 \)) may then share the same information (e.g., \( v_1 \) and \( v_2 \) may retweet \( u \)'s tweets). In this action, the user (e.g., \( u \)) who influences other users in the network can be considered as a leader. Finding these leaders from the social network is in demand because they play a vital role in real-life marketing campaigns by distributing news in the network within a short time span. Common techniques to find these leaders include influence path mining, which also mines how influences propagate in a social network. Specifically, for users \( u \) and \( v \) connected in a social network, if a user \( v \) performs an action \( a \) after \( u \) performing \( A \), then \( u \) is considered to be influential as he influences \( v \) to perform \( a \). In such a case, a directed edge \( u \rightarrow v \) denotes the the influence path from \( u \) to \( v \) for that particular action \( a \). A user is considered to be a leader in a network if he influences more than a user-specified number of users.

A recent algorithm [12] for leader discovery uses a static social network graph, together with a static user action log. However, as social networks keep evolving, it is more realistic to use a dynamic graph. Hence, our key contribution of this paper is our proposal of a new algorithm called SWLD, which uses a sliding window for leader detection from dynamic streams of user actions.

The remainder of this paper is organized as follows. The next section presents related works. Section III describes our sliding window-based leader detection algorithm. Experimental results and conclusions are given in Sections IV and V, respectively.

II. RELATED WORKS

Regarding works related to our proposal of a sliding window-based algorithm for leader detection from dynamic streams of user actions in a social network, Matsumura and Sasaki [14] discovered leadership behaviors from human influence networks. Song et al. [6] proposed the InfluenceRank algorithm to detect opinion leaders from blogs; they also found the importance of the propagated information spread through the network. Goyal et al. [2] used a sliding window-based algorithm to discover leaders from community actions. Bodendorf and Kaiser [1] used a text mining approach to detect leaders based on the shared text data in the network. Esslimani et al. [4] detected reliable leaders from behavioral networks by considering the high connectivity and influence propagation potential of users in the network. Lee et al. [8] proposed a network-flow based influence propagation model for static social networks. Braun et al. [3] proposed a tree-based algorithm for mining diverse users from a social network. Leung et al. [11] interactively mined influential friends from social networks that are updated incrementally (than from dynamic streams of user actions). Duan et al. [15] applied a user clustering and sentiment analysis technique to identify opinion leaders. Fariha et al. [5] focused on mining frequent interaction patterns (than users). Recently, the Apriori Probabilistic Path Mining (APPM) algorithm [12] was proposed to mine a static social network graph and
Similarly, \( A \rightarrow B \rightarrow F \rightarrow G \) is one of the 12 length-3 influence paths involving 4 vertices. User \( B \) involves in five length-3 influence paths and leads \( L_3(B) = 2 \) of them (namely, \( B \rightarrow F \rightarrow G \) and \( B \rightarrow F \rightarrow J \rightarrow K \)). So, \( D_3(A) = \frac{2}{12} \). Similarly, \( A \rightarrow B \rightarrow F \rightarrow G \) is one of the 12 length-3 influence paths involving 4 vertices. User \( B \) involves in five length-3 influence paths and leads \( L_3(B) = 2 \) of them (namely, \( B \rightarrow F \rightarrow G \) and \( B \rightarrow F \rightarrow J \rightarrow K \)). So, \( D_3(A) = \frac{2}{12} \).

Our SWLD algorithm consists of two phases. In the first phase, regardless of the size of the stream of the action log, SWLD captures contents of the action log in a sliding window of size \( \pi \). Hence, SWLD ensures there are at least \( M \) user actions to be kept in the sliding window, where \( M \) is a user-specified threshold. As SWLD uses a sliding window, it requires much smaller memory space than that for the entire action log.

In the second phase, SWLD calculates the leading degree count \( D_n(u) \). To speed up the mining process, SWLD avoids enumerating all influence paths by scanning the propagation graph once to detect both forward neighbors \( FN(u) \) and backward neighbors \( BN(u) \) and compute their associated forward result \( FR[u][n] \) and backward result \( BR[u][n] \) for each user \( u \). Here, for a directed edge \( u \rightarrow v \) in the propagation graph, (i) \( v \) is a forward neighbor of \( u \) (i.e., \( v \in FN(u) \)) and (ii) \( u \) is a backward neighbor of \( v \) (i.e., \( v \in BN(u) \)).

The forward result \( FR[u][n] \) is a 2-dimensional structure capturing \( L_n(u) \), i.e., frequency of length-\( n \)-length influence paths such that user \( u \) starts the propagation paths; the backward result \( BR[u][n] \) is a similar 2-dimensional structure except that it captures the frequency of length-\( n \)-length influence paths such that user \( u \) ends the propagation paths. Here, \( FR[u][1] = |FN(u)| \) and \( BR[u][1] = |BN(u)| \).

Example 2: In Figure 1, \( FN(F) = \{G, I, J\} \) and \( BN(F) = \{B, C, E\} \). Hence, \( L_1(F) = FR[F][1] = 3 \) and \( BR[F][1] = 3 \). Similarly, as \( BN(I) = \{F\} \), \( BR[I][1] = 1 \).

After computing \( FR[u][1] \) and \( BR[u][1] \) without generating and storing any influence paths, the remaining entries in these two structures can be computed by summing the frequencies of length-(\( n-1 \)) paths as follows:

\[
L_n(u) = FR[u][n] = \sum_{v_i \in FN(u)} FR[v_i][n-1];
\]

\[
BR[u][n] = \sum_{v_i \in BN(u)} BR[v_i][n-1].
\]

Afterwards, \( N_n(u) \) can then be computed as follows:

\[
N_n(u) = FR[u][n] + BR[u][n] + \sum_{i=1}^{n-1} (BR[u][i] \times FR[u][n-i]).
\]

Example 3: Continue with Example 2. As \( FN(F) = \{G, I, J\} \), (i) \( FR[G][1] = 1 \), (ii) \( FR[I][1] = 0 \), and (iii) \( FR[J][1] = 1 \). So, \( L_2(F) = FR[F][2] = 14+0+1 = 2 \).

To a further extent, \( L_3(B) = FR[B][3] = FR[F][2] = 2 \) because \( FN(B) = \{F\} \).

Similarly, (i) \( FR[F][3] = 0 \), (ii) \( BR[F][1] = 3 \), (iii) \( BR[F][2] = 2 \), and (iv) \( BR[F][3] = 0 \). So,
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when detecting length-1 influential users. Figure 4(d) shows the recall for detecting length-2 influential users. The results show that the recall for SWLD with $\pi=12$ hours was almost the twice that for SWLD with $\pi=4$ hours.

V. CONCLUSIONS

In this paper, we proposed an algorithm called SWLD, which uses a sliding window for leader detection. Specifically, SWLD detects the most influential users, who can initiate and participate in lots of influence paths, from dynamic streams of actions performed by users in a social network. The algorithm avoids the expensive enumeration of all possible influence paths by using a dynamic programming approach to compute frequency counts of length-$n$ influential users based on those of length-$(n-1)$ influential users and capturing the results in two 2-dimensional structures. Experimental results show that SWLD is accurate, requires short runtime and a small amount of memory space.

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