Chapter 26
Influence and Information Flow in Online Social Networks

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ABSTRACT

This article introduces a new method to discover the role of influential people in online social networks and presents an algorithm that recognizes influential users to reach a target in the network, in order to provide a strategic advantage for organizations to direct the scope of their digital marketing strategies. Social links among friends play an important role in dictating their behavior in online social networks, these social links determine the flow of information in form of wall posts via shares, likes, re-tweets, mentions, etc., which determines the influence of a node. This article initially identities the correlated nodes in large data sets using customized divide-and-conquer algorithm and then measures the influence of each of these nodes using a linear function. Furthermore, the empirical results show that users who have the highest influence are those whose total number of friends are closer to the total number of friends of each node divided by the total number of nodes in the network.

1. INTRODUCTION

In the most basic sense, a network is any collection of objects in which some pairs of these objects are connected by links. In a network of objects, objects can be people or computers, which we refer to them as nodes of the network. Have the people in the network adapted their behaviors to become more like their friends, or have they sought out people who were already like them (Easley, 2010)?

Over the course of human history, the collections of social ties among friends have grown steadily in complexity. When people live in neighborhoods or attend schools, the social environment already favors opportunities to form friendships with others like oneself (Easley, 2010). If influence is the capacity to have an effect on someone, then who are the influential people in an Online Social Network? According

DOI: 10.4018/978-1-7998-9020-1.ch026

to (Rashotte, 2011), social influence is defined as change in an individual's thoughts, feelings, attitudes, or behaviors that results from interaction with another individual or a group of people. Influence has long been actively studied in marketing, sociology, communication and political sciences (Althoff, 2017). Online Social Networks(OSNs) have revolutionized the power of social influence exponentially (Aral, 2012). Popular social networks such as Facebook, Google+, Twitter provide platforms allowing user to share information about things that users like or dislike (Romero, 2011). The availability of such interactions among users created a new platform for digital marketing such as brands to run their promotional activities and political parties to run their campaigns (Linyuan, 2011; Bond, 2012).

There have been extensive studies in measuring the social influence. Klout is a website and mobile app (Klout, 2014) that uses social media analytics to measure social influence of its users. To determine the social influence or *Klout score*, which is a numerical value between 1 and 100, Klout measures the size of a user's social media network and correlates the content created to measure how other users interact with that content. Klout uses 35 variables such as Follower/Follow ratio, unique re-tweeters, unique messages re-tweeted and username mention count. However, several objections to Klout's methodology have been raised regarding the process by which scores are generated. Critics have pointed out that Klout scores are not representative of the influence a person really has, highlighted by Barack Obama, President of the United States, having a lower influence score than a number of bloggers.

In our research, similar to scoring mechanism in Klout, we assign numerical value to each user as a result of measuring social influence. But, the range of ranks are proportional to the number of nodes in a network but not a fixed range from 1 to 100 as it is the case in Klout. We are using large datasets from Location Based Social Networks (LBSN) (Leskovec, 2014; Leskovec, 2010; Yang, 2010). These are analogous to popular OSNs like Face book, but content is generated from these in form of check-ins rather than wall posts.

LBSN does not only mean adding a location to an existing social network, but also consists of the new social structure made up of individuals connected by the interdependency derived from their locations in the physical world as well as their location-tagged media content (check-ins), such as photos, video, and texts. Furthermore, these check-ins can influence nodes already in the network to visit these locations. Our primary attribute of measuring influence is this location-tagged content. We are using two LBSNs, Gowalla and Brightkite's data sets in our research. These datasets have very few properties at each node such as edge count, check-ins count but not any other attributes like gender, location, education and etc. This limits our research observations, after deducing influence value, to be read based on these properties. Thus, our approach, implementation and results are focused on mean and median of edge count or check-ins count of each node.

We only focus on users who are highly co-related. It means that the differences among properties of these users are minimal. We have a divide-and-conquer algorithm to identify these targeted users and eliminate users with properties having extreme values. This idea of co-related users results in measuring the influence more accurately. For example, a user who has 8000 friends may have higher influence value compared to a user who has 80 friends despite running through various influence algorithms.

Here we are interested in connectedness at the level of behavior - the fact that each individual's actions have implicit consequences on the outcomes of everyone in the system (Easley, 2010). We investigate prediction of people's behavior and influences in OSN. Our focus is on how different nodes can play distinct roles in information flow through an OSN.

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