Influence Maximization

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In an online, connected world where any information about you can be written and exposed, Influence Maximization is a topic regularly practiced and rarely discussed. It can be found applied in some of the most common systems utilized in a connected world since the birth of the World Wide Web. Also, its applications are very attractive to eCommerce companies that are interested in discovering information about their customers to recommend the best products, or social media giants that want to connect their users for a more fluid experience. This networking technology can be used for an abundant of applications that involve research or analysis of desired data.

Before describing the variable applications that Influence Maximization, it is important to understand the characteristics of such technology. For this reason, Influence Maximization is derived from the Influence Maximization Problem that analyzes a graph model in network diffusion to find the shortest possible time [1]. To do this, the S subset should be selected as seed set from the nodes in such a way that under a diffusion model with probability p leading to activating most the number in the given graph [1]. The Influence Maximization Problem has been proven as NP-Hard and was provided an alternative solution consisting of a General Greedy (GG) slgorithm with an optimal approximation of $1-1/e = 0.63123$ [1]. What our Influence Mazimization Problem yields is an efficient way to calculate the best connections possible (based on the social media network graph), but with a difficutly of NP-Hard an alternative was necessary as shown.

Social networks can expand as the best example for the applications of this technology. As discussed by Zhang et. al, mobile social networks are a similar communications system that involves the social relationship of the users. In a similar manner, mobile users can spread information, opinions, ideas, and rumors [15]. This can be traversed using Influence Maximization, however, existing methods of influence maximization are heuristic algorithms based on network topology and greedy algorithms based on spreading [15]. The connection of such techniques still require weight analysis of network nodes, but the traversal still requires too many sequences to be used efficiently.

Social media tyrants are the primary occupants of Influence Maximization. Amongst a variety of companies (such as Facebook, Twitter, WhatsApp, Instagram, etc...) Influence Maximization is incorporated on a model based on network topology that is the result of people's interactions on that social network [7]. Methods of measurement examined by Guo et. al can be divided into three measures titled *node degree*, *shortest path*, and *random walk characteristics* [7]. We have seen network topology algorithms in class such as the Distance Vector (DV) or Link State (LS) algorithms that exhibit shortest path and random walk characteristics respectively. As such, Influence Maximization measures these values to exhibit the best connections for user recommendations or ad direction.

From social network tyrants to eCommerce market rates, Influence Maximization also determines two-sided market rates for merchants. Research involving Inter-temporal pricing conducted

by Chen et. al [4] showed that from the perspective of platform profit maximization the greater the positive network externalities of merchants, the lower the platform charges merchants. This gives merchants an opportunity to redefine their cost margin when allocating the budget available for the cost of production and promotion. Through traversal of an online association of users, companies/merchants now have a better opportunity to create a profitable business.

A different perspective that Influence Maximization can approach is one common concept floating in the internet today: *the Meme*. Unlike a Graphics Interchange Format image, or *GIF*, a meme consists of adding layers to an existing image that can be in the format of text or other graphics for the purpose of a humoristic result. The connection of a Meme with Influence Maximization reverts back to our original Influence Maximization problem. The Influence Maximization Problem aims to find the most influential node set in the network and make it produce the greatest influence through information dissemination [14]. Upon research of LDGIM, Wang et. al discovered that LDGIM has a wider influence spread, faster transmission rte and more stable propagation [14]. Thus, with such a spread of memes throughout a network it can be useful to discover associated user data for other personal or business uses.

Another breakthrough in computing technology is the evolution of a quantum computer that utilizes quantum mechanics principles for much better processing compared to our traditional classical computers. As such, the concept of social computing can be applied to quantum computers for better results based on an analysis by Dinh et. al [6]. The reason quantum computing would be optimal for applying Influence Maximization is due to its NP-Hard difficulty [6]. This way, with social quantum computing the results can be *near-optimal* by proposing a two-phase algorithm that converts the Influence Maximization into a Max-Cover instance and provides efficient quadratic unconstrained binary optimization formulations to solve the Max-Cover instance on quantum annealers [6]. Problem reductions is common practice in computer science, so this method essentially takes an incredibly difficult problem and reduces it to a much easier (and solveable) instance. Results provided by Dinh et. al showed an advantage of social quantum computing over classical simulated computing on different nodes of $n = 10, \ldots, 30$ with weights $w = 0.05$.

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