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CFIN: A community-based algorithm for finding influential nodes in complex social networks

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Abstract

Influence maximization (IM) problem, a fundamental algorithmic problem, is the problem of selecting a set of *k* users (refer as seed set) from a social network to maximize the expected number of influenced users (also known as influence spread). Due to the numerous applications of IM in marketing, IM has been studied extensively in recent years. Nevertheless, many algorithms do not take into consideration the impact of communities to influence maximization and some algorithms are non-scalable and time-consuming in practice. In this paper, we proposed a fast and scalable algorithm called community finding influential node (CFIN) that selects k users based on community structure, which maximizes the influence spread in the networks. The CFIN consists of two main parts for influence maximization: (1) seed selection and (2) local community spreading. The first part of CFIN is the extraction of seed nodes from communities which obtained the running of the community detection algorithm. In this part, to decrease computational complexity effectively and scatter seed nodes into communities, the meaningful communities are selected. The second part consists of the influence spread inside communities that are independent of each other. In this part, the final seed nodes entered to distribute the local spreading by the use of a simple path inside communities. To study the performance of the CFIN, several experiments have been conducted on some real and synthetic networks. The experimental simulations on the CFIN, in comparison with other algorithms, confirm the superiority of the CFIN in terms of influence spread, coverage ratio, running time, and *Dolan-Moré* performance profile.

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