Information Spread in Social Networks

Srinivasan Venkatramanan
Department of ECE, Indian Institute of Science, Bangalore
vsrini@ece.iisc.ernet.in
www.ece.iisc.ernet.in/∼vsrini
Research Advisor: Prof. Anurag Kumar, Department of ECE, IISc. *anurag@ece.iisc.ernet.in*

Abstract

There is recent surge of interest in understanding human social behavior, thanks to the proliferation of online social networks. With the advent of high speed mobile Internet and availability of low cost smart phones, humans generate huge volumes of data pertaining to their social behavior. Thus we have access to both the network structure and the dynamic processes on these networks. One of the most important processes that needs our attention, is the process of information diffusion on such systems. This requires us to revisit theories of collective behavior in the new context, and helps us understand collective decision making such as voting behavior (politics), product adoption (viral marketing), etc. In this work, we focus on a well-known model for information diffusion, namely the threshold model. We study the problem of influence maximization, using some insights derived from the threshold model. We then obtain a mean-field characterization of the threshold model, which will be useful in predicting the behavior of large scale social systems. Motivated by the mean-field limits, we then look at a multi-layered epidemic in a mobile opportunistic network, where we are interested in studying co-evolution of popularity and the availability of content. We finally consider competition between several social contagions (contents), in a timeline-based social network.

Influence Maximization in Social Networks

In a social network, the nodes represent people or organizations and the links represent the interaction between them. These interactions can be weighted and/or directed. These networks play a crucial role in spread of information/influence among the people involved. This has significant consequences in product adoptions, voting behavior in elections, understanding civic unrest, etc. From a viral marketing perspective[1], it might be of interest to find the set of *influential players*, whose network effect (the total spread of information) is maximum. In this work, we focus on a specific model of information diffusion, namely the Linear Threshold (LT) model introduced by Kempe et al. [2]. We analytically characterize the expected influence in the network for a given seed set of influencers, and show an equivalence in terms of acyclic path probabilities (APP) in a Markov chain. We use this insight to derive optimal initial seed set for several toy networks such as star, ring, etc. and regular networks with homogeneous or degree-based influence. We show the relation between our approach and using PageRank [3] to compute the most influential set of nodes. We finally propose an algorithm for influence maximization, G1-sieving, which performs on par with the benchmark algorithms [2], [4] and is significantly faster.

1) *Srinivasan Venkatramanan and Anurag Kumar, "Information Dissemination in Socially Aware Networks Under the Linear Threshold Model", Proceedings of NCC 2011, IISc. Bangalore.*
2) *Srinivasan Venkatramanan and Anurag Kumar, "New Insights from an Analysis of Social Influence Networks under the Linear Threshold model", arXiv:1002.1335*
3) *Srinivasan Venkatramanan and Anurag Kumar, "G1-Sieving:Maximizing Influence Spread with Insights from Linear Threshold Model", in preparation, 2013.*

Mean Field Threshold Model for Information Spread

Large scale, heterogeneous social systems are in general analytically intractable. With some assumptions of homogenity, we can still capture certain key aspects of such systems, by studying their mean-field behavior. In this work, we look at a homogeneous version of the LT model, with the thresholds arising from a general distribution (as against uniform distribution in [2]). The threshold distribution captures the variation in the levels of susceptibility in the population [5]. We derive the fluid limits of the homogeneous LT model using Kurtz's theorem [6]. Thus, we have a characterization of the average trajectory of influence, as against the usually considered expected terminal influence. We observe that the threshold distribution features in the fluid limit, in the form of a hazard function. We use this to show an equivalence between the homogeneous LT model with exponential distribution of thresholds and the well-known SIR epidemic model[7]. We finally demonstrate the accuracy of the fluid approximation, and show how it can be used to solve certain optimization problems in information spread.

1) *Srinivasan Venkatramanan and Anurag Kumar, "Co-evolution of Content Popularity and Delivery in Mobile P2P Networks", In Proceedings of IEEE INFOCOM 2012 (mini-Conference), Orlando,FL*
2) *Srinivasan Venkatramanan and Anurag Kumar, "Mean Field Characterization of the Linear Threshold Model of Influence", in preparation, 2013*

COEVOLUTION OF POPULARITY AND CONTENT SPREAD IN MOBILE OPPORTUNISTIC NETWORKS

With huge demand for high-bandwidth multimedia content on mobile nodes carried by end-users, there is a growing necessity to deliver the content in a device-to-device (D2D) [8] opportunistic manner. Also, for a newly released content, the popularity of the content is evolving, and hence the number of nodes interested in the content increases with time. One problem of interest is to tune the content delivery process to meet the evolving demand [9]. We consider such a framework, and study the co-evolution of popularity and the spread of content in an opportunistic setting. We propose an application framework for such a system, which can be implemented in practice. We use epidemic models to characterize the popularity evolution and content spread. We then study the problem of optimal control, where we intend to deliver the content to as many interested nodes, as early as possible. In order to do so, we can use the nodes not yet interested in the content, to cache the content and act as relays [10]. These relay nodes help increase the availability of the content in the system, and could also become interested in the content at later point of time. Thus there is a tradeoff between minimizing the delay to deliver the content, and the number of relays used in the process. We demonstrate that a time-threshold based open-loop control is optimal in this setting, using extension of theories from cooperative and competitive dynamical systems[11].

1) *Srinivasan Venkatramanan and Anurag Kumar, "Spread of Content and Influence in Mobile Opportunistic Networks", submitted to IEEE Transactions on Mobile Computing, 2012, under revision*
2) *Srinivasan Venkatramanan and Anurag Kumar, "Co-evolution of Content Popularity and Delivery in Mobile P2P Networks - Tech Report", arXiv:1107.5851*

COMPETITION OVER TIMELINE IN SOCIAL NETWORKS

Most online social networks (Facebook, Twitter, etc.) use a reverse chronological timeline interface to display contents to the end-user. With users becoming immune to traditional online advertising (sponsored search slots, banner ads, etc.) there is growing interest in social advertising, i.e., exploiting user interactions on a social network. Due to scarce user attention, there is competition between content creators over the timeline space[12]. In this work, we study a non-cooperative game among content creators over the limited attention of a particular user, and use queueing techniques to model the occupancy of a single user's timeline. We characterize the Nash equilibrium rates of content creation, and study its variation with parameters such as the timeline size (modeling limited user attention), and the number of content creators (modeling player competition). We show that the competition intensity (equilibrium rates of content generation) is maximum when the number of content creators equal the size of the timeline. We then study the effect of content sharing among users in the network incorporating threshold models for sharing behavior.

1) *Eitan Altman, Parmod Kumar, Srinivasan Venkatramanan, and Anurag Kumar, "Competition over Timeline in Social Networks", presented at the Workshop on Social Network Analysis and Algorithms (SNAA), co-held with IEEE/ACM Intl. Conference on Advances in Social Network Analysis and Mining (ASONAM), Niagara Falls, Canada, 2013*

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