ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

Review Paper on Spreading Process in Multilayer Network

Nandini, Dr. Janak Kumar B. Patel, Tejender Rawat

M.Tech Student, Dept. of ECE, ASET, Amity University, Haryana, India

Professor, Dept. of ECE, ASET, Amity University, Haryana, India

Assistant Professor, Dept. of ECE, ASET, Amity University, Haryana, India

ABSTRACT: Many systems can be designed as sets of interconnected networks or networks with multiple types of connections, they are called multilayer networks. Spreading processes such as an information propagation among users of online social networks or we can say that the diffusion of pathogens among individuals through their contact network are fundamental phenomena occurring in these networks. Information diffusion in single networks has received considerable attention from different disciplines for over a decade and spreading processes in multilayer networks is still a young research area presenting various challenging research issues. In this paper, we review the models, results and applications of multilayer spreading processes and discuss some upcoming research directions.

KEYWORDS: Multilayer network, multiplex, interconnected, spreading processes, information diffusion.

I. INTRODUCTION

Many real-world systems can be designed as networks i.e., set of interconnected entities. In some cases the connections between such entities represent communication channels. They indicate that information items available at one of the entities can be transferred (propagated) to some neighbour entities. A typical example is represented by online social networks, where information can be transferred from one user account to the other through. For example: Friendship or following connections but several scenarios exist where the nodes of the network are not human beings (e.g. computer networks and Internet of things) and the items traversing the network are not text messages but for instance viral agents, rumours, behaviours, pathogens or digital viruses. These all are the examples of spreading processes.
Here we focus on the practically relevant topic of spreading processes in multilayer networks a generic term that we use to represent to a number of models involving multiple networks, called interconnected networks [1] or multiple types of relationships, called multiplex networks [2]. Multilayer networks are also known as interdependent, multidimensional, multiple, multi-sliced, multilevel networks, and networks of networks [3]. Historically, networks were first inspected from the multilayer approach by sociologists in works such as in the late 1930s, and research continued in subsequent years [4]. Some of these works also contain discussions on spreading processes.

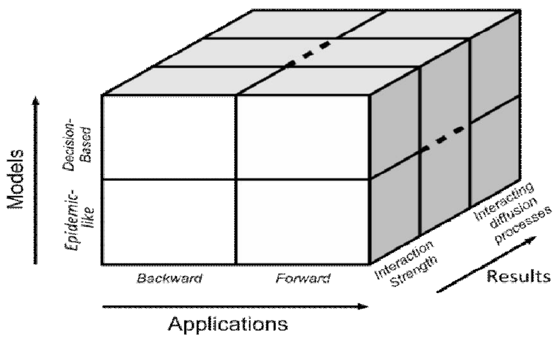

Figure 1: *Three main dimensions for analysing spreading processes in multilayer networks: (i) how to model the spreading processes, (ii) what results we can obtain using these models and (iii) how these results can be exploited in real applications. [5]*

When single networks are involved, it is clearly known that for all the processes above the structure of the network plays an important role on the outcomes of the process. For example, behaviour spreading can stall when it enters a tightly-knit community within the network [5]. The same is valid when multilayer networks are involved, but the effect of the layer structures and the interdependence may vary from the single-network case. Now days, the study of spreading processes in multilayer networks is latest and rapidly evolving research area facing challenging issues. In this paper, I have given a homogeneous overview of current results on the effect of multiple layers and the other network features on the spreading of various types of items, and identify unexplored areas.
To this end, we analyse the topic of spreading processes in multilayer networks according to three main aspects:

i. How spreading process can be designed.
ii. What results can be obtained from these models.
iii. How these results can be exploited in real applications.

II. REVIEW AND CLASSIFICATION OF EXISTING SPREADING MODELS

Existing models are categorized in two groups:

2.1 EPIDEMIC-LIKE MODELS

Epidemic-like models are used for modelling disease and influence spreading. The probability that a node becomes infected by a spreading process is determined by its neighbours or adjacent nodes [10]. The spreading process starts with an initial infected set of nodes, called seeds. The infected node diffuses the infection to a susceptible neighbour with infection rate 'b'. The infected nodes can recover after time 't' from the moment of infection, as in the susceptible-infected-recovered (SIR) model and also- change their state back to susceptible as in the susceptible-infected-susceptible (SIS) model.

2.2 DECISION-BASED MODELS

Decision-based models are also called threshold models and are based on the idea that an agent may decide to adopt a particular behaviour depending on the behaviour of its neighbours [11].
Existing decision-based studies follow two different approaches:

(a) Informational effects and (b) Direct-benefit effects.

(a) INFORMATIONAL EFFECTS

Here decision is based on the indirect information about the decisions of others. Granovetter presented the first decisionbased model, called as Linear Threshold Model (LTM) [11]. In LTM each node chooses a threshold value and adopts a new behaviour if and only if at least a fraction T_{LTM} of its neighbours has already adopted the new behaviour. Based on LTM, Watts studied the roles of thresholds and network structure on information diffusion.

(b) DIRECT BENEFIT EFFECTS

Direct benefit effects approach assumes that there are direct results from copying the decisions of others [12]. Given a payoff matrix for choosing two possible behaviours A and B, each node is playing a game with its neighbours across all layers. In every single round, all nodes update their strategies based on the whole result (i.e., the sum of all the payoffs collected in all layers). Lower bound for the success of a new behaviour, defined as the eventual adoption of the new behaviour across all nodes in the network.

III. METHODOLOGY

We introduce the concepts of multilayer network and spreading processes in multilayer networks, and the main methods and variables used to study such processes. We consider that the reader is already familiar with the concept of graph (Graph, G=V, E). A monoplex network is a graph. A multilayer network is a data structure made of multiple layers, where each layer is a monoplex network.
During designing of this basic model several attributes can be added to nodes and edges. Example, we can introduce a temporal dimension and make a distinction between node on layer 2 at time 't0' and the same node at time 't1' and then we can add edges among these extended nodes. Connections between nodes on the different or same layers represent channels through which different types of items can propagate and giving rise to spreading processes. Basically,

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

spreading process can refer to the diffusion of pathogens, rumours, behaviours, or the coverage of a news headline in different newsgroups and weblogs. For example, in the case of spreading of some behaviour in a community, people usually choose which behaviour to adopt. On the other side, in the case of epidemics model there is no decision made by the individuals who are infected. In the current section, we present the key concepts that may arise in the analysis of spreading processes.

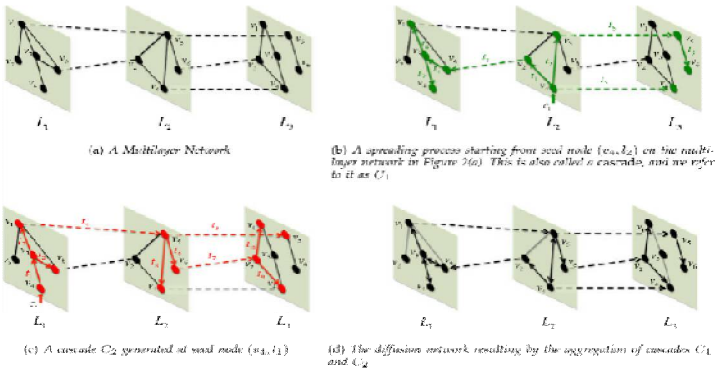

Figure 2:*Spreading processes in multilayer networks [13]*

The evidence left from the spreading of a particular piece of information over a monoplex network is called (information) cascade [6]. This concept can be extended for multilayer networks. It also generates an implicit network. Therefore we will sometimes distinguish between a diffusion network (i.e., the actual connections traversed during the spreading process) and an underlying (multilayer) network. A diffusion network is defined by the sequence of nodes traversed by a certain piece of information or other item. In a multilayer network a cascade can be represented as a set of tuples where t represents the timestamp when the propagated item passed from node 'u' in layer 'l_u' to node 'v' in layer 'l_v'. We call seed the first node of the tuple with the minimum timestamp. While this is the minimum amount of information needed to meaningfully describe a spreading process, specific models reviewed in augment these tuples with additional parameters (i.e., a state space and a set of rules for state-transition) providing more details about the cascade.

This can be resulted by presenting the main dependent variables used in different spreading studies. The so-called epidemic threshold [7], [8] is one of the key observations in epidemic-like models, and indicates a value of transmissibility above which the diffusion involves the whole (or most of the) network, e.g., the diffusion network is a giant component of the underlying network. It is known that in monoplex networks the value of the epidemic threshold is closely related to the largest eigenvalue of the network's adjacency matrix. Furthermore, recent work suggests that the epidemic threshold in a multiplex network cannot be larger than the epidemic thresholds of individual layers [9]. In the context of interacting spreading processes in multilayer networks, two types of thresholds have recently been introduced, called survival threshold and absolute-dominance threshold: they measure if a spreading process will survive and whether it can completely remove another competing process. Another dependent variable is the infection size, generally defined as the number or fraction of nodes in the diffusion network, i.e., those reached by the spreading process. Similar terms such as outbreak size or cascade size have also been used in the literature to refer to this quantity. The Infection rate, representing the average rate of being in contact over a link, is also a frequently studied dependent variable.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

3.1 DIFFERENT POSSIBILITIES FOR SPREADING AN ITEM FROM ONE LAYER TO ANOTHER IN A MULTILAYER NETWORK

	Same Node	Other Node
Same Layer	(unused)	The cascade spreads to a different node on the same layer
Other Layer	The cascade switches layer but remains on the same node	The cascade continues spreading on a different node on another layer

Figure 3:*Different possibilities for spreading an item from one layer to another in a multilayer network [21]*

One of the important ideas of spreading processes in multilayer networks is the fact that items can also spread from one layer to another.
There are four possibilities for an item to traverse a multilayer network.

1. **Same-node Inter-layer**: When a cascade switches layer but remains on the same node. Example: When a facebook post is shared on twitter by the author of the same post.
2. **Other-node Inter-layer**: When a cascade continues spreading to another node in another layer. Example: Exchanging mails between users with different mail accounts (like Gmail and yahoo).
3. **Other-node Intra-layer**: The cascade continues spreading through the same layer. Example: retweeting a post in Twitter.
4. **Same-node Intra-layer**: This layer is generally not considered meaningful approach and therefore omitted in all the spreading studies.

Magnani and Rossi introduced a model when same individuals can have multiple nodes (e.g, accounts) on the same network.

3.2 SPREADING DYNAMICS ON MULTILAYER NETWORKS

The dynamics of spreading processes such as speed or pattern of spreading are influenced by the properties of underlying multilayer network. Here we discuss the effect of various properties considered in the literature for interconnected networks and multiplex networks.
Aggregating different layers into a single network is one possible way to study multiplex networks [13][18][19]. Example: In [14][20] the authors reduce a multilayer network to a weighted monoplex network, so that the epidemic threshold and infection size of Susceptible Infected Recovered (SIR) and Susceptible Infected Susceptible (SIS) models on the multiplex networks are studied by looking at reduced graph. However, disregarding the inherent multiplex nature of a system could lead to loss of information and wrong conclusions. We will be focused on work that explicitly considers the multiplex nature of the systems.

a. INTERCONNECTED NETWORKS

The dynamics of spreading processes in interconnected networks can be affected by spectral properties of the combinatorial supra-Laplacian of underlying graph [15][16]. This matrix and consequently its properties are strongly affected by inter-layer coupling, i.e., interaction (or coupling) strength between layers. In particular, shows that changing the second eigen value of algebraic connectivity of an interconnected network has two distinct regimes (layers are decoupled or indistinguishable) and a structural transition phase between them.
Most of the works on spreading processes in interconnected networks studied the impact of inter-layer connections, in terms of Interaction strength between layers and Interlayer pattern. Then we review these works.

i. Interaction Strength between Layers
ii. Inter-Layer Pattern
iii. Multidimensional Epidemic Threshold

b. MULTIPLEX NETWORKS

Various topics about spreading processes are addressed in multiplex networks. Here we review some of the most relevant works. Some sections are mostly focused on the role of network structure, while other are focused on the properties of spreading processes.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

i. Intra-Layer Structure
ii. Layer Similarity
iii. Partially Interconnected Multiplex Networks
iv. Layer-Switching Cost
v. Spreading Velocity
vi. Interacting Spreading Processes
vii. Diffusion of Innovations
viii. Resource Constraints

IV. PROBLEMS FACED

i. EMPIRICAL STUDY OF INFORMATION DIFFUSION

This issue is challenging when one tries to gather data on both the spreading process and the structure of the underlying multilayer network. There are no works based on real datasets on the information diffusion in a multilayer networks and the totality of existing works on multilayer spreading are based on simulation or analytic studies. Real-world multilayer networks are sometimes large and non-trivially observable so not even a single company or institution has full control over all layers.

ii. TIME-VARYING NETWORKS

Many real-world networks exhibit a mutable structure i.e., nodes and links change over time. Both types of dynamics i.e, dynamics of spreading processes and the dynamics of underlying networks are considered in this field. Time-varying multilayer networks is more difficult to study.

iii. OUT-BREAK DETECTION

Out-break detection is a technique for the detection of spreading of an information (or virus) in a network as quickly as possible. The problem of outbreak detection is worth exploring in the area of multilayer networks.

V. CONCLUSION

More than 20 nodes in network layer are considered which are connected through highly efficient routers and a wireless LAN 802.11. Different sensors are also used to diagnose the network efficiency and the load present at the nodes of the network. Here different scenarios to determine the highest efficiency of the network are presented using different routing algorithms.

TheSpreading processes in multilayer networks have a large number of applications, such as understanding the dynamics of cascades, maximizing the influence of information in the context of viral marketing, or selecting a subset of nodes in a network to place sensors in order to detect the spreading of a virus or information as quickly as possible.

VI. APPLICATIONS

The application areas can be roughly categorized into two classes: (a) FORWARD PREDICTION: Applications that need to guide the network into a particular desired state. Viral marketing and influence maximization fall under this category[17]. (b) BACKWARD PREDICTION: Applications that require predicting how a given piece of information will spread in a network. Outbreak detection, cascade detection and immunization are some examples under this category.

REFERENCES

1. H. Wang, Q. Li, G. D'Agostino, S. Havlin, H. E. Stanley, and P. Van Mieghem, "Effect of the interconnected network structure on the epidemic threshold," Phys. Rev. E, vol. 88, no. 2, Aug. 2013.
2. K.-M. Lee, J. Y. Kim, S. Lee, and K.-I. Goh, "Multiplex networks," in Networks of Networks: The Last Frontier of Complexity, series Understanding Complex Systems, G. D'Agostino and A. Scala, Eds. New York, NY, USA: Springer, 2014, pp. 53–72.
3. J. Gao, D. Li, and S. Havlin, "From a single network to a network of networks," Nat. Sci. Rev., vol. 1, no. 3, pp. 346–356, Jul. 2014.
4. P. Pattison and S. Wasserman, "Logit models and logistic regressions for social networks: II. Multivariate relations," British J. Math. Statist. Psychol., vol. 52 (Pt 2), pp. 169–193, Nov. 1999.
5. D. Easley and J. Kleinberg, Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge, U.K.: Cambridge Univ. Press, 2010.

6. R. Ba~nos, J. Borge-Holthoefer, and Y. Moreno, “The role of hidden influentials in the diffusion of online information cascades,” EPJ Data Sci., vol. 2, no. 6, pp. 1–16, 2013.
7. N. T. J. Bailley, The Mathematical Theory of Infectious Diseases and its Applications. London: Charles Griffin & Company Ltd, 5a Crendon Street, High Wycombe, Bucks HP13 6LE, 1975.
8. H. W. Hethcote, “The mathematics of infectious diseases,” SIAM Rev., vol. 42, no. 4, pp. 599–653, 2000.
9. B. Min and K. Goh. (2013, Jul.). Layer-crossing overhead and information spreading in multiplex social networks, arXiv preprint 1307.2967 [Online]. Available: http://arxiv.org/abs/1307.2967.
10. R. Pastor-Satorras and A. Vespignani, “Epidemic spreading in scale-free networks,” Phys. Rev. Lett., vol. 86, no. 14, pp. 3200–3203, Apr. 2001.
11. M. Granovetter. (1978, May). Threshold models of collective behavior. Am. J. Soc. [Online]. 83(6), pp. 1420–1443. Available: http://www.jstor.org/stable/2778111
12. D. J. Watts, “A simple model of global cascades on random networks,” Proc. Nat. Acad. Sci., vol. 99, no. 9, pp. 5766–5771, Apr. 2002.
13. M. De Domenico, A. Sol_e-Ribalta, E. Cozzo, M. Kivel€a, Y. Moreno, M. A. Porter, S. G_omez, and A. Arenas, “Mathematical formulation of multilayer networks,” Phys. Rev. X, vol. 3, no. 4, p. 041022, Dec. 2013.
14. Y. Sun, C. Liu, C.-X. Zhang, and Z.-K. Zhang, “Epidemic spreading on weighted complex networks,” Phys. Lett. A, vol. 378, no. 78, pp. 635–640, 2014.
15. S. G_omez, A. D_ıaz-Guilera, J. G_omez-Garde~nes, C. J. P_erez-Vicente, Y. Moreno, and A. Arenas, “Diffusion dynamics on multiplex networks,” Phys. Rev. Lett., vol. 110, no. 2, p. 028701, Jan. 2013.
16. P. Domingos and M. Richardson, “Mining the network value of customers,” in Proc. ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2001, pp. 57–66.
17. J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, and N. Glance, “Cost-effective outbreak detection in networks,” in Proc. 13th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2007, pp. 420–429.
18. M. Eslami, H. R. Rabiee, and M. Salehi, “DNE: A method for extracting cascaded diffusion networks from social networks,” in Proc. IEEE Conf. Soc. Comput., 2011, pp. 41–48.
19. R. Banos, J. Borge-Holthoefer, and Y. Moreno, “The role of hidden influentials in the diffusion of online information cascades,” EPJ Data Sci., vol. 2, no. 6, pp. 1–16, 2013.
20. Z. Li and J. Yichuan, “Cross-layers cascade in multiplex networks,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2014, pp. 269–276.
21. M. Magnani and L. Rossi, “The ML-model for multi-layer social networks,” in Proc. Int. Conf. Adv. Social Netw. Anal. Mining, 2011, pp. 5–12.