Chapter 1
Random Walk Algorithms: Definitions, Weaknesses, and Learning Automata-Based Approach

Abstract Random walk algorithms are used to problem-solving, modeling, and simulation in many types of networks including computer networks, social networks, and biological networks. In real-world problems, the non-intelligent models of random walk may not be used as a problem-solving method. Recently, intelligent models of random walk have been reported in the literature. These models try to extend the basic versions of random walk to design a novel problem-solving method. The learning mechanism of these models is based on learning automata. In these models, the design of feedback systems given by the theory of learning automata is used to design intelligent models of random walk. In this chapter, we discuss about the weaknesses of non-intelligent models of random walk as a problem-solving method in real-world applications. We also give the required information about random walk algorithms and the theory of learning automata.

Keywords Random walk algorithm · Networks · Feedback systems · Learning automata

1.1 Introduction

A random walk is one of the simplest dynamical processes that can occur on a network. Random walk algorithms on networks have attracted considerable interest because they are applicable for problem-solving and also easy to interpret. The random walk algorithms also can be used to approximate many natural processes. Different types of random walk algorithms are reported in the literature. They have yielded important insights into a huge variety of applications (Fig. 1.1). Some of these applications are explained as below.

- **Web computing**: Random walk algorithms have been applied to rank web pages and sports teams, optimize searches, investigate the efficiency of network navigation, characterize cyclic structures in networks, and coarse-grain networks to highlight mesoscale features such as community structure [1, 2].

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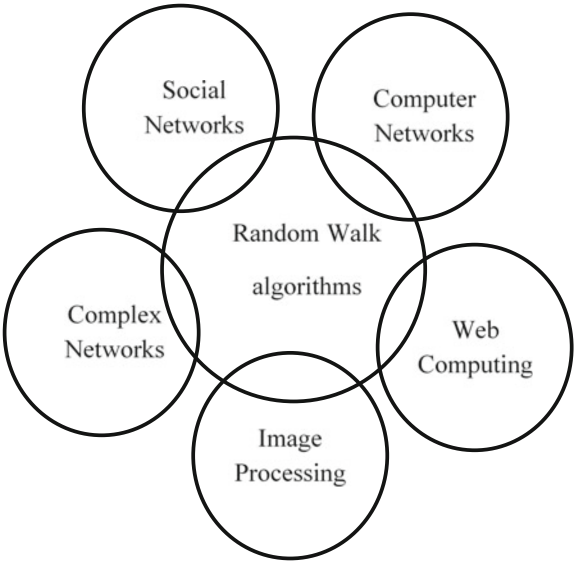

Fig. 1.1 Applications of random walk algorithms

- **Complex networks**: Another interesting application of random walk algorithm is to calculate the centrality of actors in complex networks when there is no knowledge about the full network topology but only local information is available [3–5].
- **Computer networks**: In computer networks such as peer-to-peer networks, the random walk algorithms are used to design efficient search algorithms. Since the scale of these networks is very large, designing an appropriate search algorithm for them is a challenging problem. Many algorithms such as those reported in [6–10] utilize intelligent models of random walk.
- **Social networks**: In the context of complex social networks, random walks have proven to be useful tools and several algorithms have been proposed for structural properties of the networks [11–13]. Among them, the restricted dynamics of Self-Avoiding Random Walks (SAW) [6] in the application of community detection is proposed. Based on this algorithm, random walker visits only at most once each vertex [14].
- **Image Processing**: Random walk algorithms are applied in image segmentation to determine the label of objects which associate with each pixel. With the aid of random walk, a small number of pixels with user-defined (or predefined) labels, one can analytically and quickly determine the probability that a random walker starting at each unlabeled pixel will first reach to one of the pre-labeled pixels. This algorithm is typically referred to as the random walker segmentation algorithm [15].

In the other hand, a learning automaton is an adaptive decision-making unit in which the performance is improved by learning how to choose the optimal action from a finite set of allowed actions considering repeated interactions with a random environment. Learning automata are a type of machine learning algorithm called reinforcement learning. Recently, different versions of intelligent random walk algorithms based on learning automata are reported in the literature. In this book, we summarize the recent approaches for implementing an intelligent random walk based on learning automata.

1.2 Basic Concepts

In this section, in order to provide basic information for the remainder of this book, we present a brief overview of random walk algorithms, k-random walk algorithms, and theory of learning automata.

1.2.1 Random Walk Algorithms

Random walk algorithms have attracted considerable attention because they are easy to interpret. In the following, we will describe the behavior of random walk algorithms in the networks. In a random walk on a graph, the graph and a starting node are given. During a walk on the graph, we select a neighbor of the node at random manner. After selecting the neighbor, we move to the neighbor. Then, we select a neighbor of the node at random, and move to it. During this procedure, a sequence of nodes is constructed which determine a traverse for the graph [16–18].

1.2.2 K-Random Walk Algorithms

It is obvious that executing multiple random walk algorithms on a graph result in faster than a single random walk in searching a network. In k-random walk algorithms, we choose a random node in the network and trigger k-random neighbors of that node. All of the triggered nodes repeat this process. Recently, these types of algorithms are used to search in large-scale networks such as peer-to-peer networks and social networks [6–10]. This is because random walk algorithms have very simple logic and faster version of these algorithms may be applied in new generations of large-scale networks reported in Internet of Things (IoT), complex networks, and grid computing.

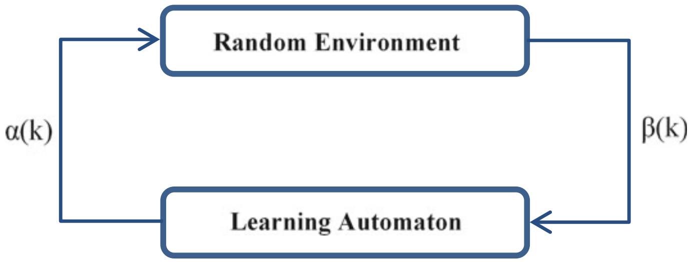

Fig. 1.2 A learning automaton and the relationship with its random environ

1.2.3 Theory of Learning Automata

Learning automata are a type of machine learning algorithms called reinforcement learning. A Learning Automaton (LA) is an adaptive decision-making unit in which the performance is improved by learning how to choose the optimal action from a finite set of allowed actions considering repeated interactions with a random environment [19]. The action is chosen by the LA. In turn, the environment responds to the action taken with a reinforcement signal. The objective of an LA is to find the optimal action from the action set so that the average reward received from the environment is maximized. The relationship between the LA and its random environment is shown in Fig. 1.2. Several learning automata-based algorithms have been proposed in the application of social networks [20–22] and peer-to-peer networks [23–25].

1.3 Random Walk Weaknesses and the Approach of Learning Automata

Random walk algorithms are used to problem-solving, modeling, and simulation in many types of applications. In real-world applications, the random walk algorithms must be tuned considering information about the nature of the application. The performance of non-intelligent models of random walk is low in practical problems because these models do not consider the changes and information about the nature of the practical problems. To solve this problem, in real-world applications, we may use feedback loops to improve the performance of random walk algorithms. Recently, the intelligent models of the random walk are reported in the literature [6, 7]. The rationale behind intelligent models based on random walk algorithms and learning automata is to extend the capabilities of random walk algorithms by the feedback loops of the theory of learning automata.

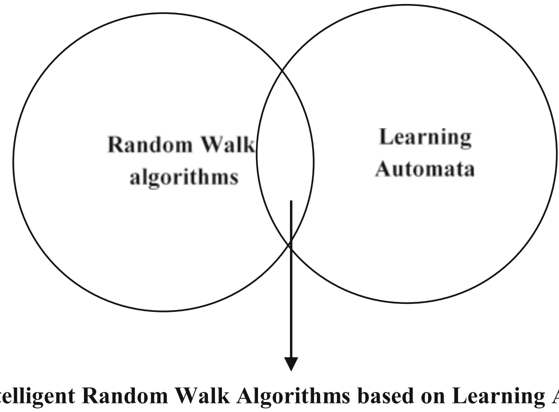

Fig. 1.3 A conceptual diagram for combination of random walk and learning automata

Figure 1.3 shows a conceptual diagram for combination of random walk algorithms and theory of learning automata. In the rest of this section, the main problems of the random walk algorithms in the networks for real-world applications are explained.

- The first problem is to find the optimum value of the k in k-random walk algorithm in every arbitrary network. Choosing a value of k larger than the average number of neighbors of all nodes of the network results in observing useless parts of the network. For example, in a computer network, a large value for k results in generating more traffic in the computer network, because it works like flooding search methods. On the other hand, if k is smaller than the average number of neighbors of all nodes of the network, the probability of selecting desirable parts of the network is decreased. For example, in a computer network, a low value for k results in generating low traffic and limited observation which leads to miss the appropriate nodes.
- The second problem is to determine which neighbors should be selected in each node of the network.

Both above mentioned problems can be solved using feedback system of the theory of learning automata. Intelligent models of random walk based on learning automata may be used to a wide range of real-world applications. As it was previously mentioned, multiple intelligent models of random walk based on learning automata are reported in [6, 7]. These models of random walk try to gradually learn the required information from the nature of the application to improve their efficiency. In the rest of this book, we suggest three intelligent models of the random walk based on learning automata. The proposed models will be implicitly used as prediction models for problem-solving in large-scale complex networks such as peer-to-peer networks and social networks.

References

1. Bar-Yossef Z, Berg A, Chien S, Fakcharoenphol J, Weitz D (2000) Approximating aggregate queries about web pages via random walks. In: Proceedings of the 26th international conference on very large data bases. ACM, Egypt, pp 535–544
2. Tong H, Faloutsos C, Pan J-Y (2006) Fast random walk with restart and its applications. Sixth International conference on data mining. IEEE, China, pp 613–622
3. da Fontoura Costa L, Travieso G (2007) Exploring complex networks through random walks. Phys Rev E 75:16102
4. Ma T, Xia Z, Yang F (2017) An ant colony random walk algorithm for overlapping community detection. International Conference on Intelligent Data Engineering and Automated Learning. Springer, China, pp 20–26
5. Backstrom L, Leskovec J (2011) Supervised random walks: predicting and recommending links in social networks. In: Proceedings of the fourth ACM international conference on Web search and data mining. ACM, pp 635–644
6. Ghorbani M, Meybodi MR, Saghiri AM (2013) A novel self-adaptive search algorithm for unstructured peer-to-peer networks utilizing learning automata. 3rd Joint conference of AI & Robotics and 5th RoboCup Iran open international symposium. IEEE, Qazvin, Iran, pp 1–6
7. Ghorbani M, Meybodi MR, Saghiri AM (2013) A new version of k-random walks algorithm in peer-to-peer networks utilizing learning automata. 5th Conference on information and knowledge technology. IEEE Computer Society, Shiraz, Iran, pp 1–6
8. Kwok YK (2011) Peer-to-Peer computing: applications, architecture, protocols, and challenges. CRC Press, United States
9. Ghorbani M, Saghiri AM, Meybodi MR (2013) A Novel Learning based Search Algorithm for Unstructured Peer to Peer Networks. Tech J Eng Appl Sci 3:145–149
10. Gkantsidis C, Mihail M, Saberi A (2006) Random walks in peer-to-peer networks: algorithms and evaluation. Perform Eval 63:241–263
11. de Guzzi Bagnato G, Ronqui JRF, Travieso G (2018) Community detection in networks using self-avoiding random walks. Physica A: Stat Mach Appl 505:1046–1055
12. Xin Y, Xie Z-Q, Yang J (2016) The adaptive dynamic community detection algorithm based on the non-homogeneous random walking. Physica A: Stat Mach Appl 450:241–252
13. Barabási A-L, Ravasz E, Vicsek T (2001) Deterministic scale-free networks. Physica A: Stat Mach Appl 299:559–564
14. Rosvall M, Bergstrom CT (2008) Maps of random walks on complex networks reveal community structure. Proc Natl Acad Sci 105:1118–1123
15. Grady L (2006) Random walks for image segmentation. IEEE Trans Pattern Anal Mach Intell 28:1768–1783
16. Malkiel BG, McCue K (1985) A random walk down Wall Street. Norton New York
17. Van Horne JC, Parker GG (1967) The random-walk theory: an empirical test. Financ Anal J 87–92
18. Kallenberg O (2017) Random measures, theory and applications. Springer
19. Narendra KS, Thathachar MA (1989) Learning automata: an introduction. Prentice-Hall
20. Khomami MMD, Haeri MA, Meybodi MR, Saghiri AM (2017) An algorithm for weighted positive influence dominating set based on learning automata. In: 4th International conference on Knowledge-Based Engineering and Innovation (KBEI), IEEE, pp 734–740
21. Khomami MMD, Rezvanian A, Meybodi MR (2018) A new cellular learning automata-based algorithm for community detection in complex social networks. J Comput Sci 24:413–426
22. Ghamgosar M, Khomami MMD, Bagherpour N, Reza M (2017) An extended distributed learning automata based algorithm for solving the community detection problem in social networks. In: Iranian Conference on Electrical Engineering (ICEE), IEEE, pp 1520–1526
23. Saghiri AM, Meybodi MR (2016) A self-adaptive algorithm for topology matching in unstructured peer-to-peer networks. J Netw Syst Manage 24:393–426

24. Saghiri AM, Meybodi MR (2017) A distributed adaptive landmark clustering algorithm based on mOverlay and learning automata for topology mismatch problem in unstructured peer-to-peer networks. Int J Commun Syst 30:e2977
25. Saghiri AM, Meybodi MR (2018) Open asynchronous dynamic cellular learning automata and its application to allocation hub location problem. Knowl-Based Syst 139:149–169