

AI approaches for next generation telecommunication networks

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Computer networks are an important example of distributed dynamic systems which are omnipresent in our daily life. The strategic importance and intrinsic constraints of such systems imply the need for distributed control, especially at the routing level, to make the network behavior adaptive to changes in topology, data traffic, services, etc.. Therefore, the control and machine learning communities have always been interested in the field of computer communications. Already in the 1950's, Bellman and Ford applied dynamic programming to the problem of routing optimization in networks.^{1,2} While the Bellman-Ford routing algorithm implements distributed control, it offers limited adaptivity, so that its performance degrades considerably in rapidly changing scenarios. Over the years, people have explored more adaptive versions of the original Bellman-Ford algorithm, encountering, however, several difficulties. More recently, researchers have investigated new routing algorithms which provide better adaptivity, building on advances in machine learning. In 1987, Nedzelnitsky and Narendra developed an approach based on stochastic learning automata.³ In 1994, Boyan and Littman proposed Q-routing,⁴ an adaptation of the Bellman-Ford algorithm which uses ideas from the Q-learning algorithm developed in the context of reinforcement learning. In 1998, Di Caro and Dorigo proposed AntNet,⁵ which was derived from the Ant Colony Optimization (ACO) metaheuristic,⁶ and implements a distributed Monte Carlo sampling system to learn routing decisions.

Despite the very good performance shown by these and many other adaptive routing algorithms, current network technology still relies on mainly static algorithms. Internet routing algorithms such as RIP and BGP are derived from the basic Bellman-Ford algorithm. They have capabilities to deal with infrequent topological changes (e.g. caused by network failures), but do not provide traffic adaptivity. The main strategy to deal with traffic fluctuations and provide guaranteed quality of service is overprovisioning of network resources, making fully adaptive routing algorithms unnecessary in practice.

However, this status-quo is now changing rapidly. Advances in wireless technology, such as Bluetooth and WiFi, allow for more freedom when setting up or changing a data network (e.g., users can move freely across the network and create local ad hoc multi-hop networks), while the introduction of new communication models and user services, such as peer-to-peer networking and voice-over-IP, leads to new and changing demands in terms of data traffic. Networks are becoming increasingly dynamic and heterogeneous. And since these new networks are more user-centered, their characteristics are determined by the users, rather than by a central authority, such that overprovisioning is no longer an effective option. This evolution is expected to accelerate, increasing the need for new, dynamic control algorithms. These algorithms should learn about the current network and user context, adapt decision policies to it, and even self-tune internal parameters. This is the approach advocated in the view of *autonomic communications*.⁷

While the arrival of new generation networks and autonomic communications renews the case for adaptive routing, it poses a challenge which goes beyond what earlier developed learning routing algorithms can deal with. The mobility of network nodes and the changes in data traffic patterns due to the appearance of new services leads to different network modes, defined by characteristics such as bandwidth, connectivity, etc.. The network mode can evolve over time, or different network modes can coexist in the same heterogeneous network. Moreover, constraints imposed by the network technologies add further complexity. We believe one approach to deal with these challenges is to integrate several learning and behavior paradigms to create a fully adaptive, multi-modal controller. We followed this approach in the area of mobile ad hoc networks (MANETs), which are networks consisting of wireless, mobile hosts communicating in multi-hop fashion without the support of any infrastructure. MANETs are a paradigmatic example of the dynamic new generation networks. The algorithm we proposed, AntHocNet,⁸ is an ACO inspired routing algorithm. However, it contains several elements not present in other ACO routing algorithms such as the earlier mentioned AntNet. Specifically, it combines ACO based Monte Carlo sampling and learning with an information bootstrapping process, which is typical for dynamic programming and some reinforcement learning approaches. Operating the two learning mechanisms at different speeds allows to obtain an adaptivity, robustness and efficiency which neither of the subcomponents could offer alone. Moreover, the balance between the use of proactive and reactive behaviors allows both to anticipate and to respond in timely fashion to disruptive events. AntHocNet's innovative design, which sets it apart from other MANET routing algorithms, has been shown to give superior performance over a wide range of simulation scenarios with different characteristics in terms of mobility, data traffic, etc.. We believe that the good performance of AntHocNet for MANETs is an indication that such an integrated approach can be the way to go to provide adaptivity in dynamic multi-modal networks. However, a more fundamental challenge is to bring these challenging environments back to machine learning research, where it offers an opportunity to study difficult but real distributed dynamic environments and to support the implementation of the new algorithms needed to drive the progress of network development.

References

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