The Web as an Adaptive Network: Coevolution of Web Behavior and Web Structure

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ABSTRACT

Much is known about the complex network structure of the Web, and about behavioral dynamics on the Web. A number of studies address how behaviors on the Web are affected by different network topologies, whilst others address how the behavior of users on the Web alters network topology. These represent complementary directions of influence, but they are generally not combined within any one study. In network science, the study of the coupled interaction between topology and behavior, or state-topology coevolution, is known as 'adaptive networks', and is a rapidly developing area of research. In this paper, we review the case for considering the Web as an adaptive network and several examples of state-topology coevolution on the Web. We also review some abstract results from recent literature in adaptive networks and discuss their implications for Web Science. We conclude that adaptive networks provide a formal framework for characterizing processes acting 'on' and 'of' the Web, and offers potential for identifying general organizing principles that seem otherwise illusive in Web Science.

Categories and Subject Descriptors

H.1.2 User/Machine Systems: Human information processing; J.4 Social and Behavioral Sciences: Sociology

General Terms
Design, Experimentation, Human Factors, Theory

Keywords
Networks, User Behavior, Adaptive, Structure, Dynamics, Simulation

1. Web Behavior and Web Structure

Recently, there have been great advances in what is known about the structure of the Web, and the dynamics of behaviors on the Web. Some notable examples of complex topologies found on the Web includes small world network structure [1], power law scaling [2], preferential attachment [3] and community structure [4]. Examples of how differences in these topologies might affect behavior include the influence of social networks on content browsing behavior [5], or 'meme propagation' [6], i.e., information contagion, [7], information cascades on blogs [8], distribution of messages [9, 10] and the spread/adoption of innovations [11]. Some studies are able to contrast behaviors on one topology with that of another: e.g. small world versus lattice [12]. Within general topologies, some studies are interested in identifying influential nodes, i.e. 'critical/control nodes' in a complex network, that can trigger large cascades to spread information [13-15].

Of course, it is well-understood that the topology of these networks is not static [16, 17]. Studies of topology change, or 'topological evolution', in the Web include evolution of Web-scale social networks [16, 18], link prediction [19], changes in community structure/group membership [4, 20], and the effects of follower recommender algorithms [21, 22]. So, topology affects behavior, and topology is not static. However, each of these different examples brings its own domain-specific assumptions about how topology changes. For example, network topology might change by the rule that well-connected individuals become more well-connected over time (preferential attachment), or that 'friends of mine become friends of each other' (clique formation) governed by the principle of homophily [23]. Moreover, most of this work views topological change as an exogenous process, having a one-way influence on behavior.

The reality is that not only is behavior on the Web affected by the topology of the Web, but reflexively, the topology of the Web is affected by behaviors on the Web. That is, topology change is not an extrinsic process but the result of the distributed action of agents or users on the network. This two-way coevolution of structure and behavior on the Web is the topic of this paper and we will discuss several examples below.

On the one hand, since there is still a lot more that could be learned about how structure affects behavior and, separately, how behavior affects structure, this two-way coupled interaction of both processes might seem a step too far; If we don't have appropriate tools or theory to handle such complications, perhaps we should leave well alone and continue with a reductionist approach to each process separately. But to understand the underlying governing processes, we argue that we must address the reflexive nature of this relationship between structure and behavior. In fact, in some ways, study of each of the independent processes leaves ‘loose ends’ – what should we assume about the behaviors that affect structure, and what should we assume about the structures that affect behaviors. Whereas, when we put these processes together, it offers the potential that each provides a framework for understanding the context of the other. This transition from separate processes to coupled processes also causes us to view the Web as a complex adaptive system and not merely as a complex network or network science subject.

Fortunately, appropriate tools and theory are rapidly developing in the science of complex networks in general. *Adaptive networks* [24, 25] is a rapidly developing field that specifically addresses this two-way interaction of behavior and network structure, or ‘state-topology coevolution’. In this paper we discuss the merits of taking an adaptive networks perspective of the Web and the opportunity for expanding Web Science territory. We review some abstract results from recent literature in adaptive networks and discuss their implications for Web Science. We conclude that adaptive networks provide a formal framework for characterizing processes on the Web, and offers potential for identifying general organizing principles such as self-organization, robustness/resilience, and global adaptation that seem otherwise illusive in Web Science [26-28].

2. ADAPTIVE NETWORKS

Adaptive networks is a recent term recognizing the importance of ‘state-topology coevolution’, both in general terms (Fig. 1) and in many domains from economics to epidemiology [24, 29-31]:

> *Complex network research has so far addressed mostly either "dynamics on networks" (state transition on a network with a fixed topology) or "dynamics of networks" (topological transformation of a network with no dynamic state changes). In many real-world complex biological and social networks, however, these two dynamics interact with each other and coevolve over the same time scales. Modelling and predicting state-topology coevolution is now recognized as one of the most significant challenges in complex network science.* [32]

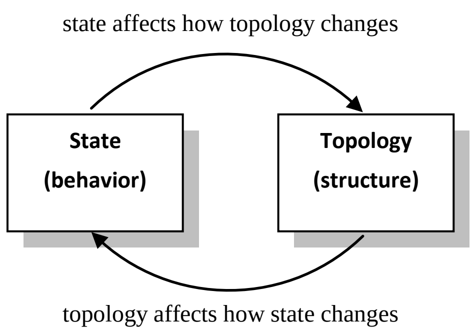

Figure 1. State-topology coevolution is the basis of adaptive networks (see [25]).

Many general network science studies address how topology affects behavior, e.g. how the level of cooperation in games on networks is affected by a scale-free, lattice or community structure. Others address topological evolution [33]. But in some cases these use purely topological rules to govern this topological evolution [34]. For example, the notion that friends of mine become friends of each other is a topological rule of closure, and for preferential attachment the current degree of a node is sufficient to determine the probability of new links [3]. In contrast, the idea that people might tend to make links with co-operators (or break links with defectors) is a rule about how behavioral state affects topology [35]. It is the latter kind of topological change, that which is driven by behavioral states (themselves determined by current topology, and so on), that constitutes an adaptive network (Fig. 1) [1, 36-38].

Models of opinion networks [39, 40] provide a simple example to make the concept of an adaptive network more concrete. Such models concern how opinions are spread by connections on a network. They involve two governing processes social adjustment (change in behavior) and social segregation (change in connections) [41]. In general, it is natural to assume that the first process acts to update the node states by ‘infection’ of opinions, while the latter changes links to be in contact with like-minded actors, e.g. to support homophily [23, 42]. Both processes will reduce the number of social links between actors of differing opinions (either by changing opinions or by changing links) creating self-reinforcing loops in social structure and behavior [43-45]. Different separations of timescales between the two processes (e.g. fast change of opinions/slow change of links, or vice versa) can result in the formation of homogenous communities with a uniform opinion [41] or cause the network to split into two distinct homogenous groups (‘assortative mixing’) [46].

We discuss some other representative examples of adaptive networks research (not yet connected with Web Science research) in more detail:

1. The dynamics of epidemic spreading or ‘epidemics’ is frequently modeled as non-adaptive networks. The nodes in these models are multi-type of usually either ‘infected’ or ‘not infected’ and connected nodes indicate the opportunity for transfection. However, more recent models also incorporate adaptive changes to topology – i.e. individuals can adjust their social ties to others to move away from infected individuals [47]. This is shown to sometimes affect the robustness or resilience of a network to infection [47, 48].
2. Some adaptive networks models simulate the action of playing games between agents on a network, and examples of this include models of cooperation that involve dynamic linking or ‘active linking’ [30, 49]. Individuals in these models are able to adjust both their strategy and their social ties, and self-organize based on self-interest. The emerging social network was shown to support high levels of co-operation when individuals were able to adjust their social ties in an adaptive network, compared to when they not able to adjust their ties on a static network. Recent work has also shown that individual differences between agents (diversity) actions on an adaptive network can change the topology further, which in this context of co-operative games resulted in even higher levels of cooperation [35].
3. Other studies of games on networks allow individuals to adjust their social ties in a continuous-valued fully-connected network [50, 51]. For example, this might represent how user’s perceptions of others change over time [50] or the probability of interaction [52] between two

players. These changes are equivalent to changing the (effective) strength of a connection or the weighting of a game between two players. This work then shows that, under the conditions studied, when users adjust the strength of those ties selfishly (i.e. to maximize their individual utility) they necessarily adjust them in a manner dynamically equivalent to Hebbian learning [53,52] in a neural network. Thus the network as a whole can exhibit associative memory and distributed optimization behavior merely through the decentralized, self-interested action of the individual actors selfishly modifying connections.

Each of these models addresses adaptive network dynamics and behavior, but the implications of such models for the Web Science domain have not yet been addressed.

3. ADAPTIVE NETWORKS ON THE WEB

Here we detail three examples of adaptive networks in the Web Science domain. In each case we identify the nodes, the links, how topology affects behavior and how behavior affects topology.

Example 1: Information networks. The World Wide Web is, of course, a network of nodes (Web pages) connected by links (hyperlinks), known as the Web Graph [54]. The behavior of interest is the act of visiting a Web page, and the topology of links obviously affects this behavior by facilitating the opportunity to move from one particular page to another quickly and easily (without utilizing search engines). Perhaps slightly less obvious is the opportunity for behavior to affect topology. But this may occur when, for example, disuse causes a link to be removed, or simply by the fact that highly visited sites attract new links. More indirectly, if a lack of visits causes a site to be removed from the Web, the remaining dead links to this site may be subsequently removed.

Example 2: Social networks. Twitter[1] is a micro-blogging social network, where actors can publically post a message (tweet) on their profile page. Nodes in this network are users or news sources, links are uni-directional, and the topology is referred to as the 'follower network'. These one-way social ties directly influence the behavior on the network, i.e. the flow/dissemination of news or tweets. A user may also, of course, decide to break a follower link if the content of tweets is not deemed valuable – behavior affects topology. An interesting augmentation to this basic behavior is the 'retweet' behavior that facilitates the user-filtered propagation of tweets to users that are not directly connected to the source of the tweet. Interestingly, the retweet mechanism provides attribution and preserves provenance of a message. This enables another mechanism by which behavior can then affect topology; specifically, a user receiving a retweeted message may subsequently choose to follow the source directly.

Example 3: Collaborative filtering. Collaborative filtering and recommender systems are now embedded within many commercial systems such as NetFlix[2] and Amazon[3]. The nodes in such systems are not the users but the products (movies, books). Links between products have the meaning that there is a user that likes/has bought/recommends both of these products. The behavior of interest is both the presentation/sampling of a product and the act of recommending or purchasing. The topology of links influences this behavior by enabling such systems to make targeted recommendations to users to buy or sample other products. This completes the coupling between the purchasing behaviors and the topology of the network that made the recommendations that precipitated those purchases.

Direct evidence of structure affecting behavior is provided in a large scale study of social networks [5]. Their analysis of Flikr[4], a photo sharing website, described how the user network of Flikr was involved in content browsing behavior. They found over 80% of the views of content came from users clicking through their social network. Another network study demonstrated that social network structure was affected group affiliation [20]. Recent work by Wei et al has studied a scenario similar to our third example, social recommendation of news, using an adaptive network model [55].

Such examples thus describe a reflexive coupling between structure and behavior that constitutes an adaptive network. Other systems that might similarly offer further examples include ecommerce sites such as eBay[5] (with reputation feedback) and knowledge sharing sites such as Wikipedia[6] (where existing structure affects both knowledge sharing and knowledge accumulation), etc..

4. IMPLICATIONS

Recognizing that the Web contains adaptive networks provides the opportunity to transfer insights from the general adaptive networks research into the Web Science domain. Below we discuss three of the 'hallmarks' of adaptive networks taken from Blasius and Gross [56], each of which has implications for adaptive networks in Web Science.

1. *Robust topological self-organization*. An adaptive networks perspective reinforces the idea that we should think of the Web not just as a network science topic but as a complex adaptive system (CAS) [57, 58] with the accompanying possibility of self-organization and 'order for free' [59], i.e. the emergence of patterns in a distributed system without any central control [60]. Blasius and Gross discuss examples where the adaptive feedback inherent in an adaptive network "enables the agents that form the network to robustly organize into a state with special topological or dynamical properties" such as self-organized criticality and power-law distributions [56].
2. *Spontaneous emergence of hierarchies and division of labor*. Adaptive networks can exhibit cascading behavioral changes that give rise to spontaneous social hierarchies [61] and "classes of topologically and functionally distinct nodes can arise from an initially homogenous population" exhibiting spontaneous division of labor [62]. Such possibilities have implications for understanding on-line community structure, commercial dynamics (e.g. monopoly formation), trust [63, 64], social norms [65], social segregation, rapid evolution of structure (e.g. emergence of Web 2.0 applications to support new behaviors [66]).

[1] Twitter: http://twitter.com/ Accessed 12/5/2011

[2] Netflix: http://www.netflix.com/ Accessed 12/05/2011

[3] Amazon: http://www.amazon.com/ Accessed 12/05/2011. Here we refer to Amazon's "users who viewed this item were also interested in this item" feature rather than the "personal recommender system".

[4] Flickr: http://www.flickr.com/ Accessed 30/04/2010

[5] eBay: http://www.ebay.co.uk/ Accessed 12/05/2011

[6] Wikipedia http://www.wikipedia.org/ Accessed 12/05/2011

3. *Complex system-level dynamics*. Adaptive networks (unlike their non-adaptive counterparts) can “give rise to new continuous and discontinuous phase transitions”. Marsili’s model of ‘the rise and fall of a network society’, for example, demonstrated that the move from a sparsely connected network to a more connected one involved a phase transition such that a small change in environment could trigger either a ‘virtuous’ or ‘vicious’ cycle [67]. The implications for Web Science could be important in understanding the stability of services and the possibility of radical reorganization and/or collapse, for example.

In addition, other works in the area of adaptive networks suggests implications for social group dynamics [68], social influence, synchronization, cooperation and network growth [24]; identification of critical point or control nodes [15], and local events and universality [69].

The *structure versus agency debate* [70] at the core of sociology provides a good analogue for the importance of an adaptive networks perspective in Web Science. Specifically, in the modern ‘structuration’ [43] perspective, “social phenomena are treated neither in terms purely of social structure nor in terms purely of human agency, rather a view is adopted which treats structure and agency as influencing each other” [45]. Similar ideas are also current in the field of evolutionary biology where it is recognized that we cannot understand the evolution of an organism independently of its environmental niche, nor can we assume that its environmental niche is fixed, but we must recognize that organisms construct their own niches as a response to selection but thereby also alter their selection [71]. *Social niche construction* develops this idea into the domain of social behaviors, i.e. individuals co-create their social context, which then subsequently affects their social behavior [72, 73]. The analogy is that processes on the Web cannot be properly understood purely in terms of how structure affects behavior, nor in terms of behavior independent of structure, but only as a coupled process of ‘co-constitution’ [26]. Such ‘structurist’ perspectives are evident in the foundations of Web Science: “there is a significant interplay between the social interactions enabled by the Web's design, the scalable and open applications development that is mandated to support these, and the architectural and data requirements of these large scale Web applications” [28].

One of the general organizing principles that appear to be relevant to understanding structure/agency interaction in networks is the notion of self-reinforcing loops [45] – i.e. actors tend promote structural changes in a network that support their current behavior, and structures enable or constrain agent behaviors to those that support (or do not disrupt) the current structure – creating a positive feedback loop. Interestingly, positive feedback between structure and behavior on networks has dynamical consequences that we understand very well in another, largely unrelated, field of complex systems research; computational neuroscience. In neural network research, the idea of changing a link between two neurons to reinforce the current behavioral configuration is called Hebbian learning [53]. This simple positive feedback principle, applied locally to each link based on the current behavior of the pair of nodes it connects, is well-known to produce global, network-level behaviors such as memory, associative learning, generalization and optimization [51]. Previous work shows that when individual agents modify connections of an adaptive network to maximize their own self-interest this causes topological changes that are Hebbian (because Hebbian changes are simply those that produce positive feedback or myopic exploitation of a connection). This means that the global behaviors well-known in neural networks may occur spontaneously in adaptive networks [52]. Such adaptive networks theory has the potential to provide a rigorous foundation for the ‘magics of Web science’ [28]; to properly understand the relationship between micro-processes and macro-phenomenon [28, 74].

5. CONCLUSIONS

Many studies of the Web address how structure affects behavior and some address topological evolution, but few consider the Web as an adaptive network with reflexive coupling between behavior and structure. The study of adaptive networks is an inclusive framework to study both the behavior and topology of networks, and crucially the coupling of the two. We described several different types of Web networks and how they may be characterized as adaptive networks.

Taking an adaptive networks approach to Web Science provides a framework for characterizing processes on and of networks and for understanding the Web as a complex adaptive system. Many concepts, principles and specific results from adaptive networks in other domains have implications for how we understand Web Science phenomenon. The hallmarks of adaptive networks – robustness, self-organization, emergence, division of labour, etc. – each suggest avenues for further research in the context of the Web. In particular, the agency/structure debate in sociology has synergy with adaptive networks concepts and suggests that further cross-disciplinary transfer may be fruitful.

Much work still remains. Our current knowledge of the specific relationships between dynamic processes acting ‘on’ and ‘of’ the Web is limited. But we suggest that adaptive networks provide a formal framework for characterizing such processes, and offers potential for identifying general organizing principles that seem otherwise illusive in Web Science.

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