Influence Propagation in Adversarial Social Network—Impact of Space and Time

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The goal of a major DoD project (Minerva), currently underway at Arizona State University, is mapping the diffusion and influence of counter-radical Muslim discourse across various parts of the world. The project team include Social Scientists, Ethnographers, Mathematicians and Computer Scientists. Data collection and analysis for the project is being carried out by the team members in four different continents—North America, Europe (Germany, France, Britain), Africa (Niger) and Asia (Indonesia). The objective is to map the size, scope, and spectrum of the social, religious, and political characteristics of radical/counter-radical Muslim networks in Southeast Asia, West Africa, and Western Europe. As a part of this study, we have collected over 800,000 documents from Indonesian web sites and with assistance from the Social Scientists in our team, identified organizations engaged in radical and counter radical activities. Based on agreement and disagreement of their beliefs and practices, we constructed a multi-graph where the nodes represent radical/counter-radical/neutral organizations and a labelled edge represents agreement/disagreement between them. Utilizing this graph, we plan to understand *influence propagation mechanism through these networks and devise strategies to isolate the radical organizations and minimize their influence*.

Social Network Theory provides the framework within which studies on influence propagation through social media can be undertaken. Due to its application in many different domains, influence propagation through Social Networks has emerged as an important area of research in recent times and a significant amount of research in *influence propagation model* has been carried out in sociology, economics and computer science communities [1, 5, 7, 8, 10–13, 15]. Models such as *linear threshold* [5, 14], *independent cascade* [4, 9] and *decreasing cascade model* [8] have been studied in the computer science community and their effectiveness evaluated. *However, all these models do not take into account presence of an adversary in the social network, whose goal is to prevent diffusion of ideas that an opponent is trying to promote.*

We illustrate the point with the help of a simple example. Suppose that the Coca-Cola company comes up with a new Coke (NewCoke) and attempts to sell its product through viral marketing in a social network, such as Facebook, with the slogan *"NewCoke is great."* The influence propagation models studied so far, such as *linear threshold*, *independent cascade* and *decreasing cascade model* provide means to identify the nodes that are *more influential* than others, so that influencing these "important" nodes will result in larger acceptance of the idea that "NewCoke is great" in the social networking community.

However, if Pepsi, an adversary of Coke, wants to confront Coke in an attempt to contain spreading of Coke's message with its own *"Pepsi is better,"* the models such as *linear threshold*, *independent cascade* and *decreasing cascade model* do not have any mechanism to capture impact of adversaries in the influence propagation model. Clearly, influence propagation will be significantly different in *absence* or *presence* of an active adversary.

The adversarial scenario discussed here cannot be modeled by the known diffusion techniques for an important reason. In the traditional diffusion models, each node *u* in the social network is in one of following two states: (i) *u* has adopted innovation *I* and (ii) *u* has not adopted innovation *I* but *u* is open to the idea of adoption. In presence of an adversary who is not only trying to dissuade *u* adopting innovation *I* but actively trying to persuade *u* to adopt a competing innovation *J*. In this case, each node *u* in the social network graph can be in one of following three states: (i) *u* has adopted innovation *I*, (ii) *u* has adopted innovation *J*, and (iii) *u* has not adopted has not adopted innovation *I* or *J* but is open to the idea of adopting either one of them. This scenario can be visualized by coloring the nodes of the social network graph $G = (V,E)$) with *blue* if they adopted *I*, with *red* if they adopted *J* and with *green* if they have not adopted either *I* or *J*, but open to the idea of adopting either *I* or *J*. As the diffusion process progresses over time, by observing changing color of the nodes of the graph, one can infer if innovation *I* (or *J*) is being adopted by the members of the social network $G = (V,E)$.

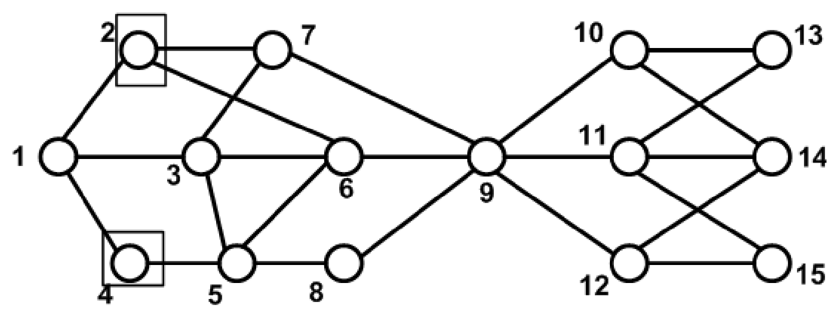

Figure 1: Adversarial diffusion blocking network

The main reason why traditional models of innovation diffusion is inadequate to capture the adversarial scenario is the following. In the traditional models of diffusion, the nodes are either blue or green and green nodes can be used in the diffusion process to change the color of a node from green to blue. As discussed in the previous paragraph, in the adversarial scenario, the colors assigned to the nodes may be blue, green or red. It may be noted that in this case, a red node *will not allow* diffusion of a blue stream through it. Consider the network shown in the Figure 1. Suppose that initially (i.e., at $t = 0$), only two nodes in the network are colored red or blue—the node 2 is colored blue and the node 4 is colored red (the remaining nodes are all green). As the diffusion process progresses over time, more and more nodes change their color from green to blue or green to red. At some point of time during the diffusion process the node 9 will be colored either red or blue.

Once the node 9 changes its color from green to say, blue, it will not allow the diffusion of red color through it to the any node to its right side. Accordingly, the nodes 10 through 15 will never have an opportunity to turn red, and most likely the entire right side of the node 9 will eventually turn blue. The traditional models of diffusion have no mechanism to capture this aspect of an adversarial scenario.

From the discussion in the preceding paragraphs, it is clear that current models of innovation diffusion are inadequate to capture some key features of an adversarial scenario and new models are needed. The complexity of the problem is further acerbated by two additional dimensions - *time* and *space*. In Figure 2 we present some results of our analysis of the data collected as part of the Minerva project. The figure shows how influence of various radical and counter-radical groups evolved over time and space in Indonesia.

As discussed earlier, studies on influence propagation model in adversarial scenario is fairly limited, and studies on influence propagation model in adversarial scenario that evolves over time and space is almost non-existent. Currently, we are exploring mathematical modeling tools, such as a *Markov decision process, Pebbling Games* [2, 6] and *Petri Nets* [3] as possible candidates. However, none of these tools seem to be able to capture the complexity and nuances of this challenging problem. Clearly, further research is essential to study the impact of time and space on influence propagation model. From that perspective, the proposed meeting could not possibly have come at a more appropriate time.

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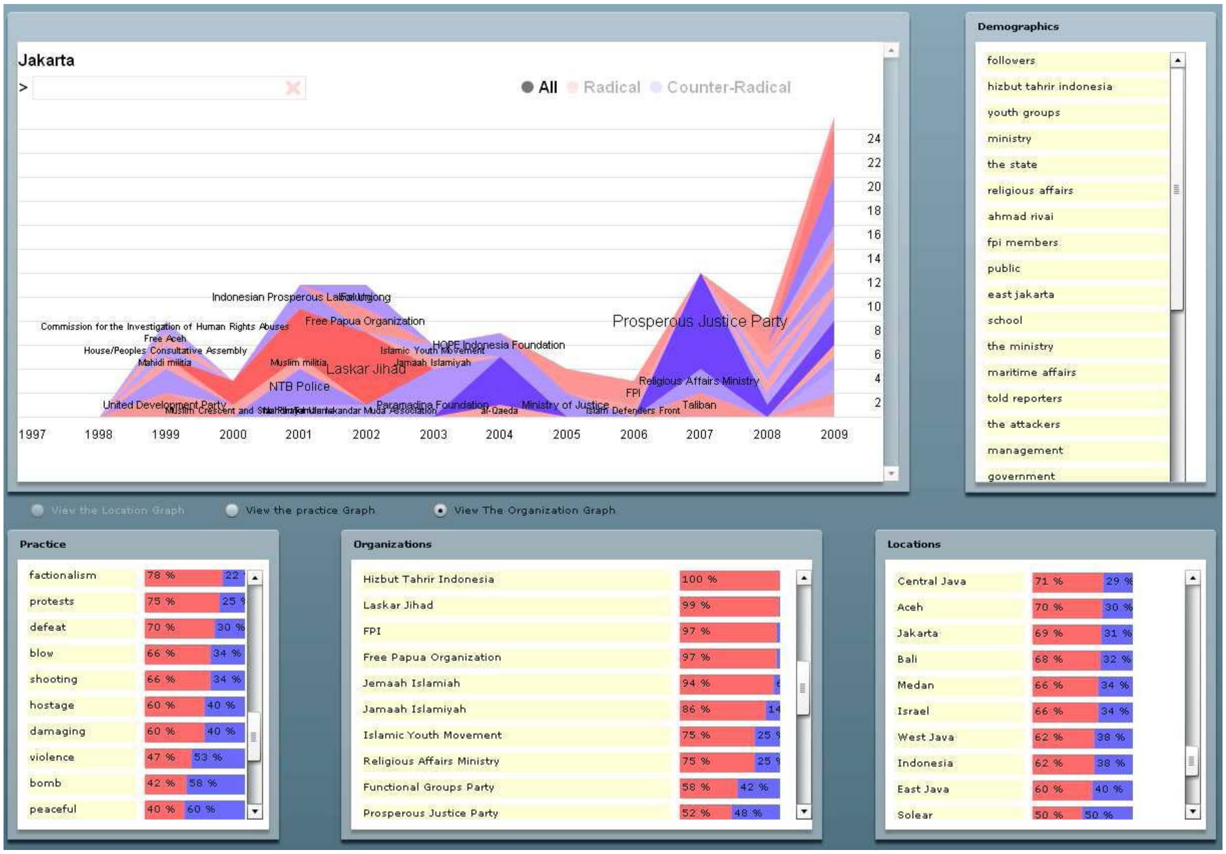

Figure 2: Influence of radical and counter-radical groups as they evolve over time and space in Indonesia