CSE 316 Final Project Part 1:

Reaction Paper

Brian Gauch

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**1 Introduction**

This purpose of this paper is to summarize and analyze several papers about the spread of social contagions. After analyzing these papers, we will brainstorm some possible continuations to the summarized research, generalizations of models, and applications.

**2 Summaries**

**2.1 Clash of the Contagions: Cooperation and Competition in Information Diffusion**

This paper is about the interactions between contagions, namely how the preceding sequence of contagion exposures affects the probability of spreading a new contagion. It focuses on Twitter, so that a node is a Twitter user and a contagion is a linked URL. It groups contagions into clusters so that a large number of contagions can be analyzed without the number of possible sequences becoming unmanageable. It finds that the preceding contagions – what we shall call the “context” – has on average a 71% influence on the probability of spreading a contagion. If the context was similar to the current contagion, the context made it more likely for the contagion to spread (due to the user sharing the material). Unrelated, more viral contagions in the context made a user less likely to share the current contagion. It was suggested that this information could be used by social network services to sell advertisements that take advantage of these effects.

**2.2 Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter.**

It has been long believed that there are “simple” social contagions, which infect with some probability after one or more exposures, and “complex” social contagions which are more likely to infect after multiple exposures. This paper provides evidence for the existence of complex social contagions, and shows that the complexity of contagions varies, based on the how controversial it is. With their dataset, a node is a Twitter user and a contagion is a hashtag. The paper terms the probability of adopting after one or more exposures “stickiness”, and the relative marginal probability of adoption/infection after repeated exposure “persistence”. Political hashtags were the most controversial, whereas idioms such as #cantlivewithout were the least controversial.

**2.3 A simple model of herd behavior**

This paper explores models similar to the model of herd behavior we discussed in class, where an agent bases their decisions partially on the actions of other agents due to the belief that the others have the same payoffs and may have private information. Based on the similarity, the age, and the number of citations of this paper, I would posit that what we discussed in class was based off of this paper, and this paper is canon in the area.

This paper explores models that are more general than our red ball vs blue ball example in class. It handles decision-making in an infinite decision space (in the interval from 0 to 1). Agents receive a signal with probability alpha, and the signal is the location of the correct decision with probability beta. The correct decision is the same for every agent, and choosing an incorrect decision has payoff 0, while choosing the correct decision has some positive payoff z. The paper varies its assumptions and shows which assumptions lead to what conclusions. It is mostly concerned with finding necessary mechanisms to limit herding to limit or remove negative herding externalities.

If an agent’s action always reveals its signal, as is the case when agents receive signals according to a Gaussian distribution and receive payoffs based on the distance of their choice from the mean of the distribution, then there is no negative herding externality. Problems arise when there are too many false signals from signal-less agents guessing, or when agents do not act on a signal even if they get one, essentially destroying their information for all future agents.

In the case with exact signals and one correct choice (the main case discussed), there are a number of ways to limit the influence of agents who receive no signal. One way is to have a predetermined guess which indicates that an agent has no clue. The first few agents, if they have no signal, might as well make this guess since they will guess correctly with probability 0 no matter what they guess. Another way is to have no predetermined guess, but to somehow punish agents for following someone else’s choice, so that agents will not follow until two people have received a correct signal.

**3 Critiques**

**3.1 Clash of the Contagions: Cooperation and Competition in Information Diffusion**

Although this paper avoids drawing unsupported conclusions, its suggestion that social network services could take advantage of context implies a belief in a causal relation between context and probability of contagion spread. It is worth considering that because Twitter users have control over their sources of contagions, they can somewhat select which contagions they are exposed to, which affects the context. That is, there may be a hidden variable, user long-term interest in contagions in a certain cluster, which affects both the probability of a user being exposed to a contagion and the probability of the user spreading the contagion. In order for us to be sure that the correlation between context and spread is causal, the user must have no control over their exposure to contagions. It so happens that mistaking long-term interest for contextual (short-term) interest, due to treating the correlation as causation, would not have very great adverse effect on advertising policy. Showing related articles would still be good, just for another reason.

**3.2 Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter.**

Only the 500 most popular hashtags were studied. It is possible that the most successful contagions spread differently than less successful ones.

**3.3 A simple model of herd behavior**

This paper makes a number of interesting conclusions with different assumptions, but the payoff schemes seemed too simple. When I am choosing restaurants, if I go to the second best restaurant in town, I get more utility than if I go to the worst restaurant in town. Aside from that, there are a lot of things that can be added to these models, but it is hard to critique what was done in this paper, as it was clearly intended only to lay the groundwork for future research.

**4 Brainstorming**

**4.1 Clash of the Contagions: Cooperation and Competition in Information Diffusion**

It was suggested that infectious URL content could be of later use, and in fact URLs without blocks of ASCII text were culled for this reason. To determine the true power of context versus long-term user interest, we suggest isolating the latter by looking at data over longer period of time if possible (the data used in this study was all tweets in one month) with fewer users if needed.

The first step would be to categorize linked URLS into clusters by looking at their text. These clusters can be thought of as subjects, like sports and politics. Cluster size must be tuned based on the average number of tweets we have data about per user. There are a number of ways to cluster based on page content, and this task is by no means trivial, but it has at least been researched for some time.

The second step would be iterate over all users, and for each user, determine which clusters they are interested in based on what they have read and what they have retweeted, and what clusters these contagions belong to. What we need to actually calculate is the likelihood of a user retweeting a member of a cluster given the number of members of the same cluster they have read and/or retweeted. We should be able to analyze a longer history of contagions than was used in the original study because we are not interested in the sequence, only the number of occurrences.

The third step is to use the result of the previous study, along with the result of the second step, to find the probability of retweeting given context, normalized by long-term probability of retweeting a contagion in that cluster. This should determine the true importance of context.

**4.2 Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter.**

In this study, hashtags were categorized manually, into categories that were also created manually. Human categorizing, or “subject indexing”[4] tends to be robust (and was found to be robust in this case), but is expensive. If some form of automatic subject indexing is used in a future study, more than 500 hashtags could be studied. More categories could also be added, but this should probably be done manually because there are many problems with automatic index term selection.

**4.3 A simple model of herd behavior**

Here we will generalize the Gaussian utility model discussed briefly in the paper, with the addition of personal preferences. Let each agent have utility across choices according to a Gaussian distribution. Let the means of these utility functions be distributed according to a Gaussian distribution. Let the variances of the utility functions be the same for each agent. Let each agent know their own utility function. Let the variance of utility function means be known. Let each agent receive a signal distributed according to their utility function.

Then each agent tries to find center of their utility function and choose that location, but they only have one good signal. Information from the action of a preceding agent has lower value than the information an agent personally receives, because of the probable distance between the utility functions the agents are trying to maximize. The overall distribution of choices will be a Gaussian, centered on the Gaussian of means but with greater variance. This is because personal preferences muddy signals from other agents, but they are individually muddied in a random direction, so that signals still point towards the mean.

In the limit as the number of agents grows, an agent knows before choosing the location of their own signal and the exact location of the mean of the overall utility function, since this is the same as the mean of the choice distribution. An agent then chooses a point between their signal location (their best guess without outside information at maximum of their utility function) and the most likely location of the overall mean. The lower the variance of preferences, the closer the agent’s choice will be to the overall mean choice. The lower the variance of signal locations, the more an agent trusts their own data, and the closer their choice is to their signal location. The weight of others’ choices is further discounted based off of how sure we are that the overall mean is correct – which is based off of how many agents have gone so far. However, even in the limit where an agent is sure of the location of the overall mean, they still choose a point a finite distance from the mean, and in fact may choose a point closer to their signal location than to the overall mean.

The result that self-gathered data is more valuable than another agent’s data (implied by their action) is intuitive and does not require special tie-breaking in the model. Self-gathered data is simply a stronger signal, since your signal about restaurant goodness is based on your utility, while their signal was based off of their utility. You would value your signal more even if the other agent directly told you the signal they received.

We also get the result that personal preferences curbs herding behavior somewhat. This could explain why one does not, in fact, see every person in town go to the same restaurant.

There is more exploration to be done in this direction. Nothing here is formally proven. An actual equation for choice location given signal location, mean choice location, personal utility variance and societal preference variance should be calculated at the very least, for the many-agent limit.

**References**

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