The Effects of Feedback on Human Behavior in Social Media: An Inverse Reinforcement Learning Model
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A model-free case for learning
Do users change behavior in response to social interactions? We first take a model-free view. Given that a user makes a contribution to a certain community, how likely is the user to visit that community again as a function of the resulting social interactions? We use data from reddit.com, a social media website with many constituent communities ("subreddits"). We are interested in changes in activity level after a contribution: how much more (or less) time does the user spend in a community after receiving a given response?

How do social interactions change us? in social media
We are social creatures, and no less so when in front of a computer. However, data from large-scale online social processes provide a unique opportunity to analyze the effects of social interaction. What kinds of social interactions are most influential, and how much do they change our behavior? The semi-structured discourse and high levels of participation found in social media allow us to find answers.

Social media as a game
What is the right way to model observed learning effects in social media? We make an analogy to learning in repeated game playing, studied in behavioral economics. Here, players are determining their (mixed) strategies based on well-defined payoffs from previous rounds of simple games.

Models have been developed to explain observed behavior (e.g. Erev and Roth 1998). These models need some adaptation in order to apply to social media. First, there is no fixed strategy space: communities (our strategies) are created regularly. Users also have strong initial preferences, for instance based on their physical location. Finally and most critically, there are no pre-defined rewards in social media. Determining the motivating effects of different types of feedback is an explicit goal of this work.

In social media

Predicting future behavior
How well can the model predict the future behavior of users, given past actions and the social feedback resulting from those contributions? We compare to a variety of baselines (right) using the Quadratic Scoring Rule (see Gneiting and Raftery 2007). How does the amount of training data per-user affect performance? The plots below show performance on a consistent test set as the number of actions by each user directly before that test set made available to the algorithms is varied. On synthetic data, performance is near-optimal. On real data, the model outperforms many reasonable baselines.

Group dynamics
What does this model of individual learning in response to social feedback say about large groups interacting? One common scenario is the formation of a new community, which faces a catch-22: to keep new participants, those users need social interaction. But users are required to provide interaction! Inspired by reddit's own founding, involving content submitted by the founders under fake accounts, we investigate the possibility of seeding a community so that it becomes self-sustaining.

Inverse reinforcement learning
We see behavior changing over time, and know the type and quantity of the social interactions which may have caused those behavior changes, but are left with a learning problem: given observed behavior, what is the relative contribution to behavior changes of different types of social interactions?

Inverse reinforcement learning (Ng and Russell 2000) seeks to determine, typically with a formal model of the world (i.e. an MDP), an agent's preferences over states of the world given that agent's observed actions and a set of features representing states. Our setting is similar, in that we are learning about an agent's preferences from observed behavior. The main difference is that we make an assumption about the learning process rather than assuming the observed agent is acting optimally.

Surprisingly, the voting score ("karma") of a contribution seems to be more motivating than replies to that contribution (both normalized). The majority of contributions are explained as learned behavior by the model.

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