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# SIMULATION OF STANCE PERTURBATION

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## ABSTRACT

In this work we use Agent Based Modelling (ABM) to determine when & why intentional social influence operations are likely to succeed. We propose ABM as an evaluation method for intentional stance perturbations in social networks. We do so by developing and verifying an evaluation criterion for stance perturbations, then developing a co-evolutionary Social Influence (SI) model, and finally expounding on an analysis of parameters effecting stance perturbations.

## 1 CONTRIBUTIONS

The main contributions of this work are:

1. The definition and verification of an evaluation criterion for intentional stance perturbations. This makes use of the ratio of the desirable stance flip rate to the undesirable stance flip rate. For instance, in the Covid19 case, stance flips from anti-vax to pro-vax are desirable and undesirable flips are from pro-vac to anti-vac.
2. To develop a co-evolutionary SI model to capture both endogenous perturbations, wherein new nodes are introduced to the network with strategically selected links and stances, & exogenous perturbations, wherein the stances of existing nodes in the network are targeted.
3. The analysis of parameters effecting stance perturbation, along with the conditions required for successful interventions. The main parameters of interest follow from the perturbation mechanics. For exogenous node stance changes these detail the change in distribution of node stances. For endogenous node additions, these include the new node stances and the method of link allocation.
4. The validation of our ABM on a set of stylised facts drawn from empirical findings which are noted in the related work. The facts are related to several relevant social phenomena, including confirmation bias, tipping points for social conventions & rarity of stance flips.

## 2 RELATED WORK

ABM has a rich history in social network analysis. Will et al. (2020) categorized such studies into those that investigate endogenously emerging networks, exogenously imposed networks & co-evolutionary networks. Endogenous studies look at how the agent network changes over time, while keeping individual agent states constant; that is, they model change in network structure as a function of the existing network and the set of agent states. Conversely, exogenous studies keep the network structure constant and model changes in agent states based on this structure. The co-evolutionary approach is a hybrid of both and models the interplay between agent states and network structure. Despite being a closer fit to genuine SI processes, this approach is relatively understudied (Will, Groeneveld, Frank, and Müller 2020). Differing timescales between endogenous & exogenous effects complicate the matter.

Ng and Carley (2022) demonstrated that endogenous & exogenous features are equally important in predicting pro / anti vaccine stance flips on Twitter. The SI model used to make this prediction is an exogenous one based on Friedkin and Johnsen (1990), which keeps the influence network constant and models the change in stance. In contrast, the Hopfield SI model adapts a co-evolutionary approach for simulation of stance change (Macy, Kitts, Flache, and Benard 2003).

ABM has been used to highlight the vulnerability of the SI model to manipulative actors. An addition of as little as 2-4% well positioned bots is capable of tipping the majority opinion (Ross, Pilz, Cabrera, Brachten, Neubaum, and Stieglitz 2019). Of note is the variance in estimations of tipping points, with empirical evidence for the theory of tipping points suggesting that 25% of users must commit to certain language use before it gains traction (Centola, Becker, Brackbill, and Baronchelli 2018). This motivates investigation of a wide variety of environmental conditions in the simulation of intentional stance perturbation.

## 3 METHODOLOGY

In Friedkin's exogenous model, the influence weight matrix **W** is static and pre-calculated from self reports (Friedkin and Johnsen 1990). The model relates influence to stances **y** at time t: $y(t) = AWy(t-1) + (I-A)y(1)$ , where the diagonal matrix **A** gives a susceptibility score to interpersonal influence for each actor. In Hopfield's co-evolutionary model, **W** is not fixed and so there is an additional reverse relation between **y** & **W** for each pair of actors i & j (Macy, Kitts, Flache, and Benard 2003): $w_{ij,t+1} = (1-\lambda)w_{ijt} + \lambda y_{jt} y_{it}$. This introduces a new parameter for consideration; $\lambda$, the rate of structural learning. However, the dimensions of the **W** matrix are still kept constant. Formalizing structural perturbations for actor addition or removal requires extending these models for various actor link allocation schemes.

We use the dataset from the study by Ng and Carley (2022). It contains 1.3M tweets from 679k Twitter users over a 40 day period after the Pfizer-Biotech's vaccine announcement. The dataset is heavily skewed towards the pro-vax stance, with a 90:10 split between pro-vax & anti-vax users. Only 1% of Twitter users flipped their stance in this period. We use this dataset to validate that stance flip from the ABM are sufficiently rare under heavily skewed stance distributions.

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