

How People Affect Each Other on Social Networks?



Zhiping (Patricia) Xiao
University of California, Los Angeles

Background

Motivation

Paper List

Problem Settings & Models

Opinion Dynamics Models

Data-Driven Analysis

The End

Background

My previous works:

- | Infer opinion from relation;
- | Infer opinion from text content of posts / tweets.

More:

- | Spread existing opinions;
- | Influence some others' opinions.

Besides, nobody is satisfied with the social media environments nowadays. But we don't know what treatments can be applied yet.

Opinion dynamics models:

- | Predicting Opinion Dynamics via Sociologically-Informed Neural Networks (KDD'22)
- | (*) A model for the influence of media on the ideology of content in online social networks (Physical Review Research'20)

Data-Driven Analysis:

- | The effect of wording on message propagation: Topic- and author-controlled natural experiments on Twitter (ACL'14)
 - | (*) Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement (Journal of Marketing Research'20)
- (*) Some other related aspects:
- | Integrating explanation and prediction in computational social science (Nature'21)

Problem Settings & Models

Code: https://github.com/mayaokawa/opinion_dynamics

- | Data unavailable, crawler script provided;
- | Using Neural Networks to model opinion dynamics models.
- | **NOT** considering network structure (e.g. follower-followee relations).

The idea:

- | Use Neural ODE framework to learn the parameters of the social dynamical systems.
- | Not using VAE for learning (i.e. NOT modeling a trajectory).

From step t to step $t + 1$, consider a single user x_u , given an opinion dynamics model f which predicts it as \tilde{x}_u , it says,

$$\tilde{x}_u(t + 1) = x_u(t) + \int_t^{t+1} f(\mathbf{X}(t)) dt;$$

where \mathbf{X} can be all nodes' opinions in theory (but always select some in practice). f includes some learnable parameters.

Then, they use an MLP net g to model the dynamical system:
code here

$$\hat{x}_u(t + 1) = g(\mathbf{X}(t))$$

- | Note that: their code mentioned “attention” but there is no attention mechanism (https://github.com/mayaokawa/opinion_dynamics/blob/main/modules.py#L35)

Then the loss is computed as:

$$\mathcal{L}_{all} = \mathcal{L}_{data}(\hat{X}_U(t); X_U(t)) + \mathcal{L}_{ode}\left(\frac{\partial g(\mathbf{X}(t))}{\partial t}; f(\mathbf{X}(t))\right) + \mathcal{L}_{reg}(\theta);$$

where:

- | \mathcal{L}_{data} : the difference (Cross Entropy Loss) between ground truth ($X_U(t)$) and predicted result ($\hat{X}_U(t)$)
- | \mathcal{L}_{ode} : the difference (MSE loss) between the SINN model's gradient ($\frac{\partial g}{\partial t}$, fetched via `torch.autograd.grad`), and the ODE gradient ($f(\mathbf{X}(t))$)
- | \mathcal{L}_{reg} : regularization on the parameters of f , usually sum of their ℓ_1 norms (note that for different versions of opinion dynamics models, f are different, and there will be different ways of computing \mathcal{L}_{reg}).

Opinion dynamics: the study of how opinions emerge and evolve through exchanging opinions with others.

Problem Settings in General:

- | Set of users U
- | Each person u holds opinion $x_u(t) \in [-1;1]$ on a specific subject at time t .
- | Users' opinions will affect each other. These models use math formula to model how opinions are updated from t to $t+1$.
- | There are many models with different **update rules**. (i.e. different versions of f as we mentioned in previous pages)

DeGroot: simple, basic

$$x_u(t+1) = x_u(t) + \sum_{U=U} a_{uv} x_v(t);$$

where $U=U$ denotes all other users in the system and a_{uv} is the strength of the interactions between u and v .

It models *assimilation* (i.e. tendency of moving opinions towards others) well.

ODE version in SINN:

$$\frac{dx_u(t)}{dt} = \sum_{U=U} a_{uv} x_v(t) = \sum_{U=U} \mathbf{m}_u^T \mathbf{q}_v x_v(t)$$

Friedkin-Johnsen (FJ) model: allows for stubbornness

$$x_u(t+1) = s_u \prod_{v=u} x_v(t) + (1 - s_u)x_u(0);$$

where $s_u \in [0;1]$ denotes a user's susceptibility to persuasion. The greater s_u is, the more open-minded a person is.

It models *susceptibilities* to persuasion (i.e., the tendency to defer to others' opinions) well.

ODE version in SINN:

$$\frac{dx_u(t)}{dt} = s_u \prod_{v=u} x_v(t) + (1 - s_u)x_u(0) - x_u(t)$$

Bounded confidence model: models *confirmation bias* (i.e., tendency to focus on information that confirms our preconceptions). A family of model. The most popular variant, the Hegselmann-Krause (HK) model:

$$x_u(t+1) = x_u(t) + \frac{1}{|N_u(t)|} \sum_{v \in N_u(t)} (x_v(t) - x_u(t)) ;$$

where $N_u(t)$ denotes the set of users whose opinions fall within the bounded confidence interval of u at t :

$$N_u(t) = \{v \in U \mid |x_u(t) - x_v(t)| \leq g\}$$

ODE version in SINN:

$$\frac{dx_u(t)}{dt} = \sum_{v \in U} (x_v(t) - x_u(t)) \mathbb{1}_{|x_u(t) - x_v(t)| \leq g}$$

Stochastic Bounded confidence model: incorporating stochastic interactions based on opinion differences. Use $p(z_{uv}^t = 1)$ to model the probability that u and v interact at time t . > 0 means users with similar opinions are more likely to interact and influence each other, and < 0 means the opposite.

$$p(z_{uv}^t = 1) = \frac{\exp(\beta(x_u(t) - x_v(t)))}{\sum_k \exp(\beta(x_u(t) - x_k(t)))};$$

ODE version in SINN:

$$\frac{dx_u(t)}{dt} = \sum_{v \in U} z_{uv}^t (x_v(t) - x_u(t));$$

where: $z_{uv}^t = \text{Softmax}([\log(\mathbf{p}_u^t) + \mathbf{g}_u]_v)$; with $\mathbf{p}_u^t \in \mathbb{R}^U$, \mathbf{g}_u being random noise and β a temperature parameter. When $\beta \rightarrow \infty$, z_{uv}^t approximates one-hot.

$$x_u(t+1) = \frac{1}{|I_u| + w} \left(w x_u(t) + \sum_{v \in I_u} \mathbf{A}_{uv} x_v(t) f(x_u(t); x_v(t)) \right);$$

where I_u is the set of accounts to which account u is receptive to, w is a pre-defined hyper-parameter, \mathbf{A} is the adjacency matrix of the network, f is a function that could be defined like “when [cond] then 1 else 0”.

From paper: *A Model for the Influence of Media on the Ideology of Content in Online Social Networks*

- | Considered network structure;
- | Somewhat more similar to GNN update rules.
- | Note: this update rule is designed for modeling **media** influence. $M; N$ are the sets of media and normal accounts respectively.

- | Efforts were made to bridge the gap between opinion dynamics models and powerful computation tools (e.g. Neural Networks).
- | More and more research works have considered graph structure in modeling social influence.
- | Opinion dynamics models are having strong assumptions in general, bringing about a gap between theory and practice.

The effect of wording on message propagation: Topic- and author-controlled natural experiments on Twitter

- | **Effect of Wording:** Investigate whether a different choice of words affects message propagation, *controlling speaker and the topic*.
- | Measure propagation by #retweet

(*) Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement

- | **Image Content Engagement:** Investigate the influence of image content on social media engagement, empirically.
- | Measure engagement by #retweet and #like

Observation: *it is unexpectedly common for the same user to post different tweets regarding the same URL.*¹

Data:

- | **TAC: Topic- and Author-Controlled** pairs
 - | The previous one: t_1 , the later one: t_2 . Corresponding number of retweets: n_1, n_2 .
 - | How to control author: from the same account.
 - | How to control topic: including the same URL.

| Examples:

author	tweets	#retweets
natlsecuritycnn	t_1 : FIRST ON CNN: After Petraeus scandal, Paula Broadwell looks to recapture 'normal life.' http://t.co/gy7GGuYw	$n_1 = 5$
	t_2 : First on CNN: Broadwell photos shared with Security Clearance as she and her family fight media portrayal of her [same URL]	$n_2 = 29$
ABC	t_1 : Workers, families take stand against Thanksgiving hours: http://t.co/J9mQHilEqv	$n_1 = 46$
	t_2 : Staples, Medieval Times Workers Say Opening Thanksgiving Day Crosses the Line [same URL]	$n_2 = 27$
cactus.music	t_1 : I know at some point you've have been saved from hunger by our rolling food trucks friends. Let's help support them! http://t.co/zg9jwA5J	$n_1 = 2$
	t_2 : Food trucks are the epitome of small independently owned LOCAL businesses! Help keep them going! Sign the petition [same URL]	$n_2 = 13$

At: <https://chenhaot.com/pages/wording-for-propagation.html>

¹ Natural experiments and quasinnatural experiments (DiNardo, 2008)

Three versions of Features:

- | Customize: Combining all 39 features (any feature can be used independently), including “ask people to share (explicitly)”, “1st person singular”, “positive/negative (sentiment)”, “informative” etc. These features are designed according to a lot of previous works.
- | Also consider tagged bag-of-words (“BOW”) features, which includes all the unigram (word:POS pair) and bigram features.

Classifier: L2-regularized logistic regression, SVM

- | A strong baseline: same classifier structure, including more features — time (day and hour) and follower-count, but not using TAC for training. (called : TAC+ff+time)

1. Do the wording effects exist?
 - | Ask 106 humans to predict which version gets more widely spread (via Amazon Mechanical Turk experiment), and achieved an average accuracy of 61.3%.
 - | It is somewhat possible to predict greater message spread from wording.
2. How to determine time-lag (t_1 t_2) and follower thresholds?

$$D = \sum_{0 \leq n_1 < 10} \hat{E}(n_2 | n_1) \cdot n_1$$

By examining D value's when other conditions are different. Here, $\hat{E}(n_2 | n_1)$ is the average value of n_2 over pairs where t_1 are retweeted n_1 times.

Focus on analyzing the following aspects:

- | Effectiveness: measured by attracting more retweets
- | Author Prefer: measured by how often the authors have higher tendency of such feature in t_2 than in t_1
- | Feature coefficients: measured by how well the model performs using that feature set.

Prediction performance:

- | Human: 61.3%
- | : TAC+ff+time: 55.3%
- | Using TAC: 65.6%

Some Findings:

- | @-mentions and 2nd person pronouns are ineffective in promote retweeting, but these features are preferred by authors.

Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement

- | Similar Data Source and Ground Truth: from Twitter and Instagram, use likes and retweets counts as ground-truth engagements.
- | Scope of Data narrowed to mostly commercial posts (sale, airline, etc.).
- | Different Ways of Finding Pairs: Using **propensity score matching** approach to create a pseudo “treatment” (expose to image or not) group and a “control” group (1:1) on the basis of post and account characteristics.
- | Models: logistic regression, multinomial naive Bayes, **linear support vector machine**, and random forest.

Treatment Effect: $\tau_i = Y_i(1) - Y_i(0)$

| Y_i refers to the outcome of whether (1) or not (0)
treatment Y is applied to sample i

When there is a treatment group and a controlled group, we have Averaged Treatment Effect (ATE):

$$\text{ATE} = E[Y(1) - Y(0)]$$

Propensity Score: used to estimate the likelihood that treatment is applied to every sample.

$$P(X) = P(D = 1|X);$$

where D refers to whether or not the treatment is applied.

- | Labeling is hard even to human beings;
 - | e.g. *the Effect of Wording* work find human average accuracy of judging which message is more widespread 61.3%
- | Hard to observe counter-factual pairs;
- | Lack of ground-truth knowledge of the offline world;
- | Most problems are not well-defined. It can be hard to convince your audience what you are studying in the first place.

(*) *Integrating explanation and prediction in computational social science*

| Social Science:

| Pros: Interpretable, Explainable, often invoking causal mechanisms.

| Cons: Fail to predict outcomes of interest, fail to offer solutions to real-world problems, fail to replicate results.

| Computer Science:

| Pros: Good at designing accurate predictive models.

| Cons: Neglecting causal mechanism, doesn't care whether or not the models are interpretable, easily biased.

Thank You All!

Please feel free to discuss with me afterwards.