Generative models of online discussion threads

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Background

Tutorials given at:

ICWSM 2019
AAAI International Conference on Web and Social Media
Munich (Germany)

ASONAM 2018
IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining
Barcelona (Spain)

Outline

Theoretical session (90)

- Introduction to online discussions
- Statistical modelling of online discussion threads
- Applications and open research challenges

Short break (5’)

Practical session (45’)

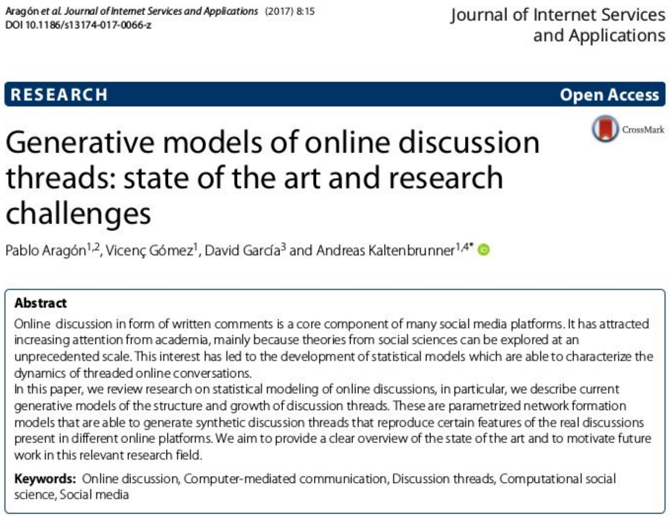
Questions and answers (10’)

Theoretical Session

Theoretical session

Based on the survey paper:

Aragón, P., Gómez, V., García, D., & Kaltenbrunner, A. (2017). Generative models of online discussion threads: state of the art and research challenges Journal of Internet Services and Applications, 8(1), 15.



Aragón et al. Journal of Internet Services and Applications (2017) 8:15
DOI 10.1186/s13174-017-0066-z

Journal of Internet Services and Applications

RESEARCH Open Access

Generative models of online discussion threads: state of the art and research challenges

Pablo Aragón[1,2], Vicenç Gómez[1], David García[3] and Andreas Kaltenbrunner[1,4*]

Abstract
Online discussion in form of written comments is a core component of many social media platforms. It has attracted increasing attention from academia, mainly because theories from social sciences can be explored at an unprecedented scale. This interest has led to the development of statistical models which are able to characterize the dynamics of threaded online conversations.
In this paper, we review research on statistical modeling of online discussions, in particular, we describe current generative models of the structure and growth of discussion threads. These are parametrized network formation models that are able to generate synthetic discussion threads that reproduce certain features of the real discussions present in different online platforms. We aim to provide a clear overview of the state of the art and to motivate future work in this relevant research field.

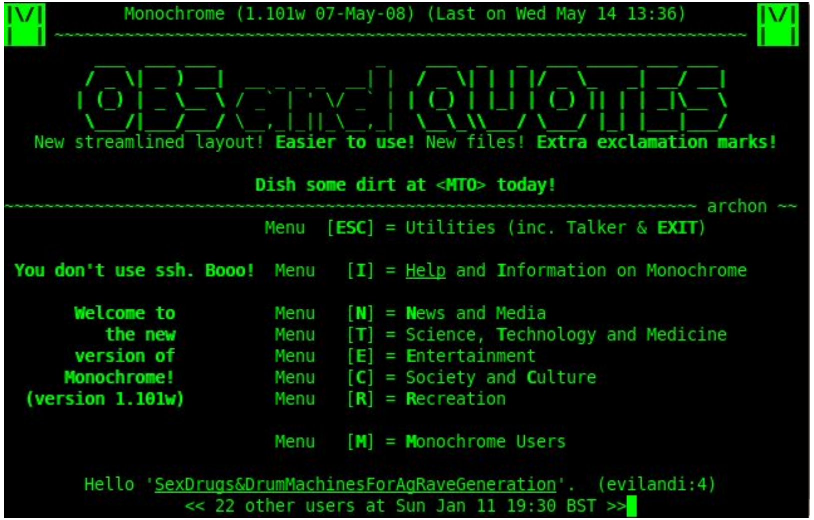
Keywords: Online discussion, Computer-mediated communication, Discussion threads, Computational social science, Social media

https://link.springer.com/article/10.1186/s13174-017-0066-z

Introduction and review of previous work

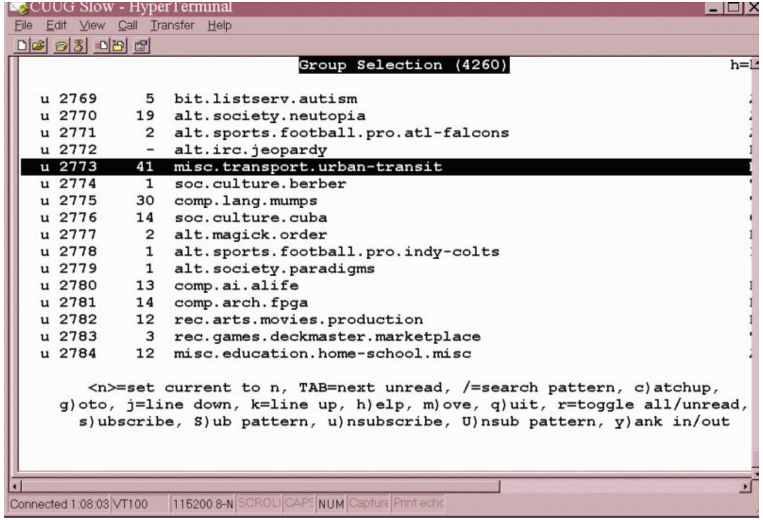
A long time ago in a galaxy far, far away....

Bulletin Board Systems



Source: wikipedia.org

Usenet



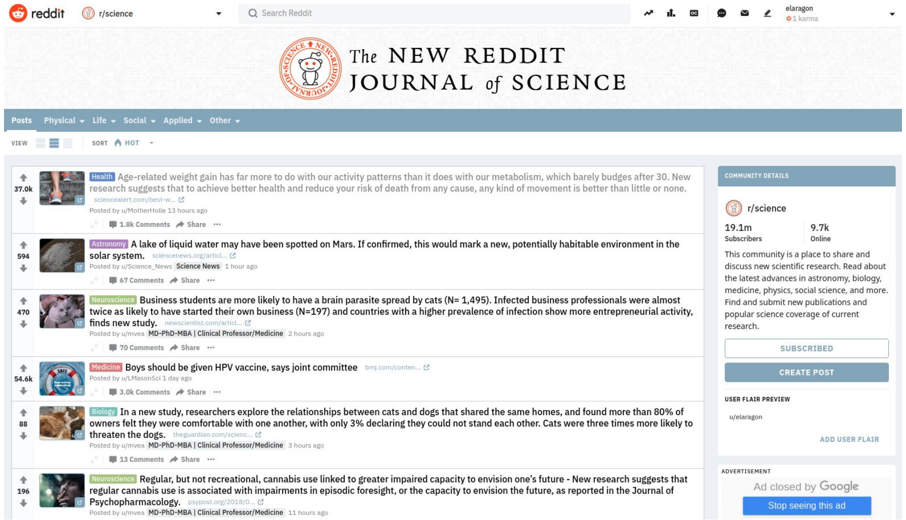
Source: thehistoryoftheweb.com

May the online discussions be with you

Web-based Forums

Reddit

Source: phpbb.com



Source: reddit.com

May the online discussions be with you

Online discussion is a main feature of almost every social media platform.

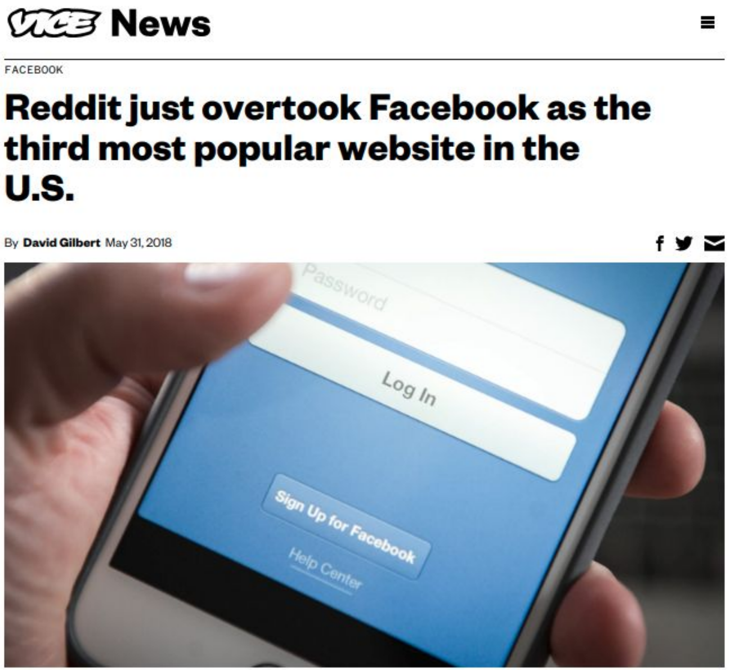
Source: get5ocial.com

Reddit: A New Hope

Online discussion is a main feature of almost every social media platform.

Online discussion is:

- Increasingly popular



https://news.vice.com/en_us/article/ywebqj/reddit-just-overtook-facebook-as-the-third-most-popular-website-in-the-us

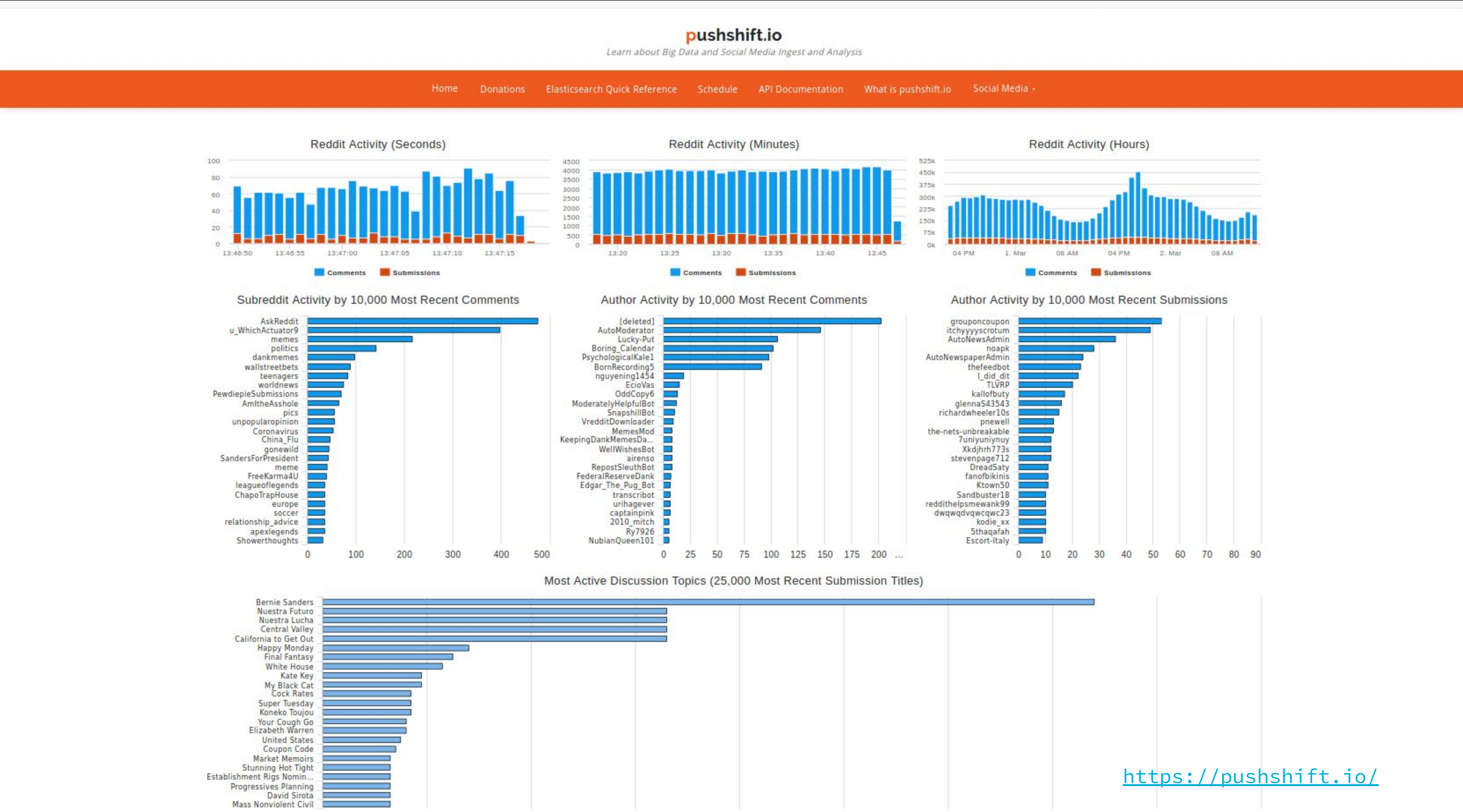
Reddit: A New Hope

Online discussion is a main feature of almost every social media platform.

Online discussion is:

- Increasingly popular
- Very engaging

https://thenextweb.com/contributors/2018/04/19/reddit-now-active-users-twitter-engaging-porn



https://pushshift.io/

Reddit: A New Hope (for research too)

Article	Task	Dataset	Methods
Horne et al. [24]	Predict high scoring comments, assess the impact of thread moderation	Reddit dataset [46], 11 top subreddits	Linear regression, sentiment analysis
Fang et al. [9]	Predict final score of comments	Reddit, three chosen subreddits	Recurrent neural networks (RNN)
Zayats, Ostendorf [54]	Predict final score of comments	Reddit, three chosen subreddits	RNN with long short term memory (LSTM)
Hessel et al. [20]	Given a pair of submissions, predict the one with higher final score	Reddit dataset [46], 6 image-based subreddits	Image description (convolutional neural networks), LSTM
Stoddard [44]	Determine inherent quality of posts and to predict high-scoring posts	Hacker News; Reddit dataset [46], 5 top subreddits	Poisson processes
Lakkaraju et al. [29]	Predict popularity of resubmitted content	Reddit, unique dataset of resubmitted images	Poisson regression
Aragón et al. [3]	Review of the models of discussion trees	Reddit, Slashdot, Meneame, Barrapunto, etc.	Review
Medvedev et al. [33]	Model structure and predict dynamics of discussion trees	Reddit, dataset [46]	Stochastic Hawkes processes

Table 1 Short summary of the articles with studies on Reddit, presented in Section 3

Medvedev, A. N., Lambiotte, R., & Delvenne, J. C.
The anatomy of Reddit: An overview of academic research.
In Dynamics on and of Complex Networks. Springer, 2019.

Article	Task	Dataset	Methods
Glenski et al. [12, 13]	Collect and assess the dataset of tracks of user actions	Reddit, unique dataset of user interactions	Statistical analysis
Singer et al. [42]	Assess user performance deterioration during activity sessions	Reddit, all comments made in April 2015	Statistical analysis, negative binomial and Poisson regression
Tan and Lee [50]	Study explorers and exploring phenomena of new communities	Reddit, dataset [46]	Statistical analysis, regression, linear classification
Hamilton et al. [18]	Loyalty prediction for newcoming users, patterns of loyal communities	Reddit, all comments made in 2014	User interaction networks, random forest classifiers
Hessel et al. [21]	Study the dynamic of arise of highly-related communities	Reddit, dataset [46]	Statistical analysis
Newell et al. [39]	Study the user migration across platforms during externally caused unrest period	Reddit, dataset [46]	Statistical analysis
Zhang et al. [55]	Classify subreddits along "niche" and "volatile" dimensions, study user retention	Reddit, dataset [46]	Statistical analysis
Das and Lavoie [7]	Model users posting strategies with respect to community feedback	Self-collected Reddit dataset	Machine learning, reinforcement learning, Hierarchical Dirichlet Process
Kumar et al. [28]	Mobilization and attacks between communities	Reddit, dataset [46]	Reply networks, lexical analysis, LSTM, Mechanical Turk
Tan [49]	Genealogy of subreddits	Reddit, dataset [46]	Relational networks

Table 2 Short summary of the articles with studies on Reddit, presented in Section 4

Twitter: The Empire Strikes Back

Twitter is bringing twttr's experiments in threaded conversations to its main app

Sarah Perez

@sarahintampa / 9:39 pm CET • January 8, 2020

https://techcrunch.com/2020/01/08/twitter-is-bringing-twttrs-experiments-in-threaded-conversations-to-its-main-app/

Daily Crunch: Twitter will let you limit replies

Anthony Ha

@anthonyha / 7:03 pm CET • January 9, 2020

https://techcrunch.com/2020/01/09/daily-crunch-twitter-replies/

Twitter opens its 'Hide Replies' feature to developers

Sarah Perez

@sarahintampa / 7:44 pm CET • February 26, 2020

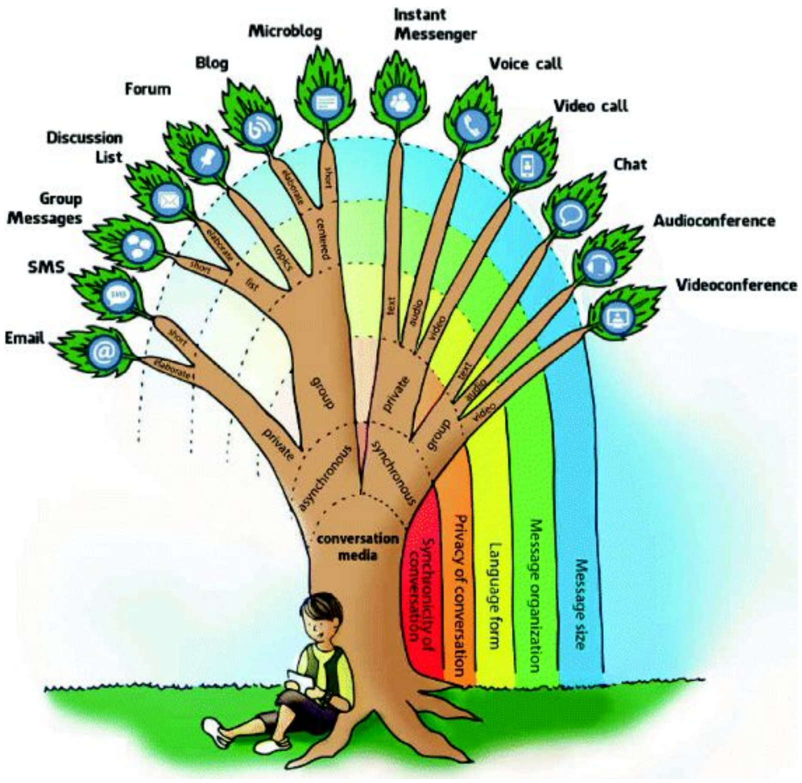
Image Credits: TechCrunch

https://techcrunch.com/2020/02/26/twitter-opens-its-hide-replies-feature-to-developers/

Online discussion platforms

Taxonomy of Internet conversation media

This tutorial covers models of online discussion threads, i.e. conversations from platforms corresponding to asynchronous communication (leafs of the left main branch of the tree)

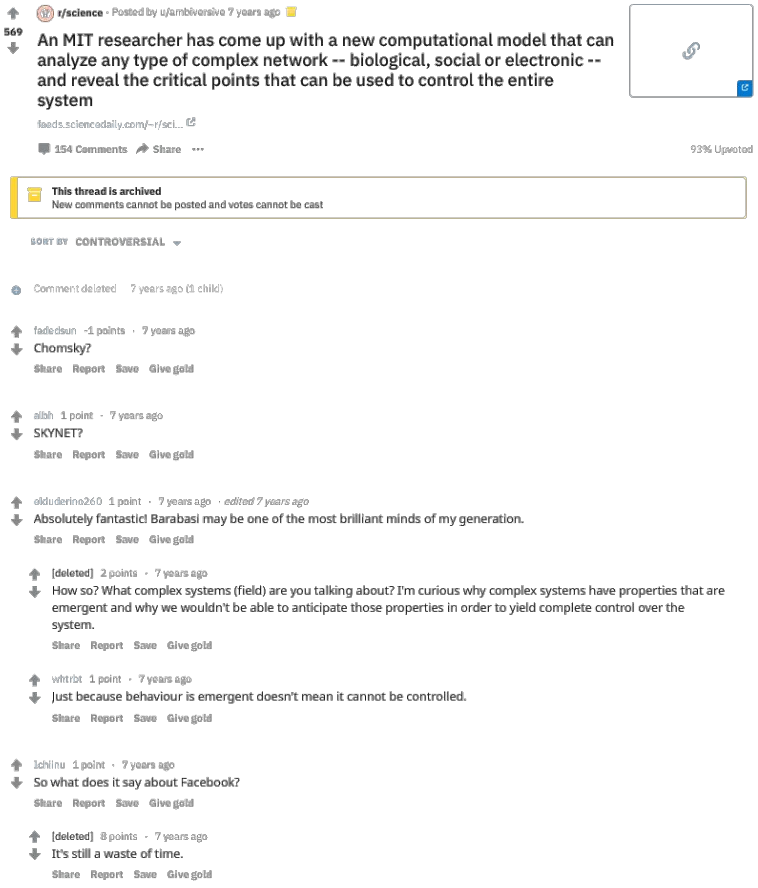


Source: Calvão L, Pimentel M, Fuks H. Internet conversation media: an evolutionary perspective from email to social networks. Rio de Janeiro: UNIRIO; 2016.

Online discussion threads

Asynchronous online communication occur as a exchange of written messages among two or more participants.

Conversations are often represented as **threads**, which are initiated by a user posting a starting message (**post**) and then users send **replies** to either the post or the existing replies

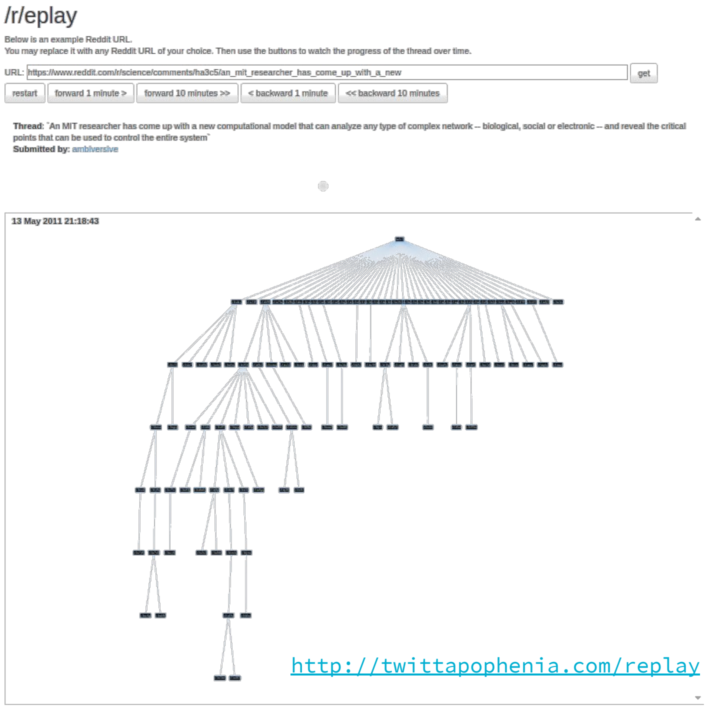


https://www.reddit.com/r/science/comments/ha3c5/an_mit_researcher_has_come_up_with_a_new

Online discussion threads as tree networks

Online discussions threads can be structured as **tree networks:**

- **nodes** correspond to comments
- **edges** represent a reply action.

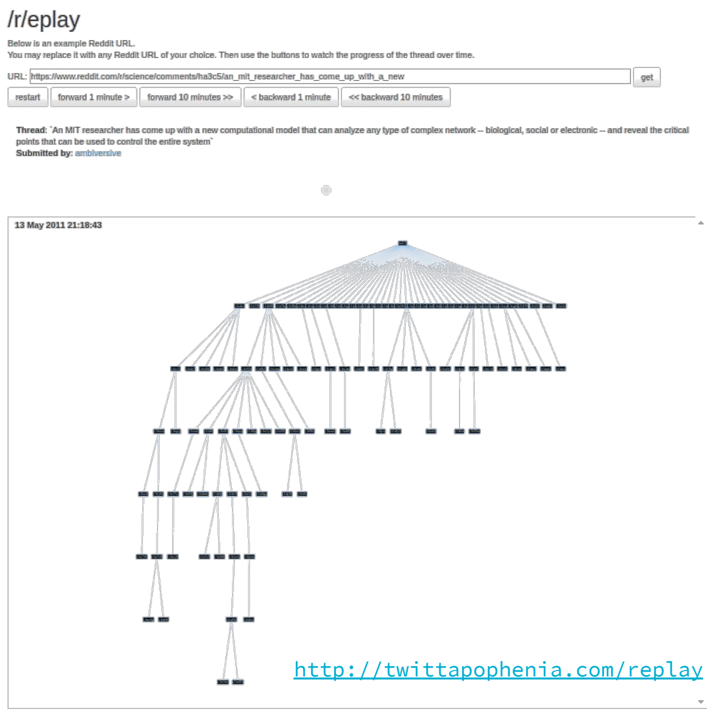


http://twittapophenia.com/replay

@elaragon

Structural properties of online discussion threads

- **Size**: the number of messages,
- **Width**: the maximum number of messages at any reply level,
- **Depth**: the length of the largest exchange of messages,
- **Users**: if the message authorship is known, number of users who authored at least one message.

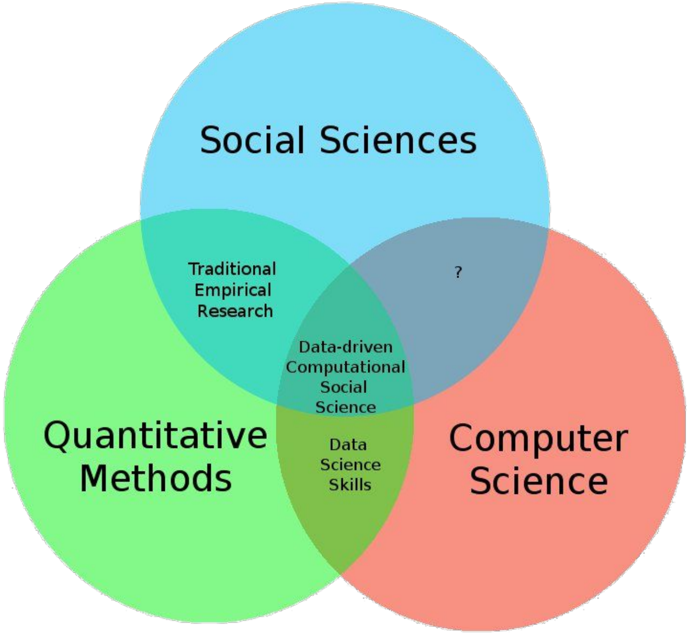


http://twittapophenia.com/replay

The era of Computational Social Science

The collection and analysis of online data (e.g. data from online discussion threads) provide interesting insights on human behavior.

Lazer D, Pentland A, Adamic L, et al (2009).
Life in the network: the coming age of computational social science.
Science (New York, NY), 323(5915), 721.



Source: r-bloggers.com

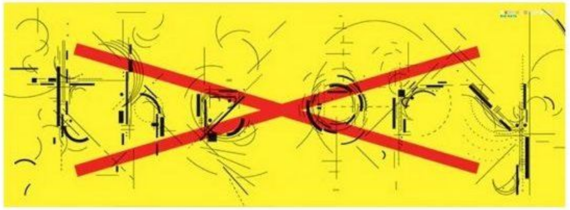
The end of theory?

“With enough data, the numbers speak for themselves”

“But faced with massive data, this approach to science — hypothesize, model, test — is becoming obsolete”

“We can analyze the data without hypotheses about what it might show”

The End of Theory: The Data Deluge Makes the Scientific Method Obsolete



https://www.wired.com/2008/06/pb-theory/

The end of theory? NO!!!

“Finding something unusual or surprising after it has already occurred is neither unusual nor surprising. **Patterns are sure to be found, and are likely to be misleading, absurd, or worse.**”

“**Good research begins with a clear idea of what one is looking for and expects to find.** Data mining just looks for patterns and inevitably finds some.”

The Exaggerated Promise of So-Called Unbiased Data Mining

Opinion: Why ransacking data for hidden patterns often results in misleading—or meaningless—conclusions.

https://www.wired.com/story/the-exaggerated-promise-of-data-mining/

Statistical modelling of online discussion

Statistical and theoretical models are needed to determine the social factors explaining the discussion network structures: the governing mechanisms of the structure of discussion threads.

- What are the structural patterns governing these responses?
- What determines the growth of a conversation?
- Is there a generative model that captures their statistical properties?
- Can we use the model parameters to characterize websites, user behaviour, discussions?

Generative models of online discussion threads

Models of this type are aimed to reproduce the growth of discussion threads through different features (related to human behavior) by **(1) estimating** the statistical significance of their corresponding features and **(2) reproducing** the temporal arrival patterns of messages that form a discussion thread.

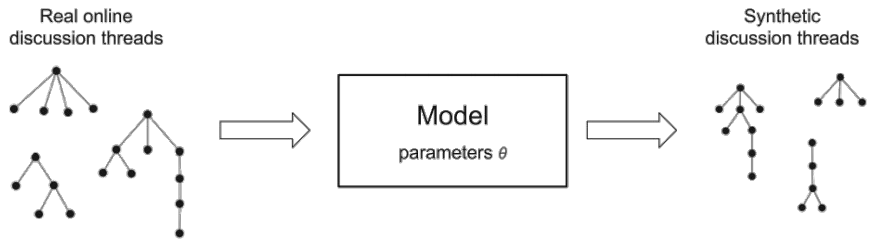


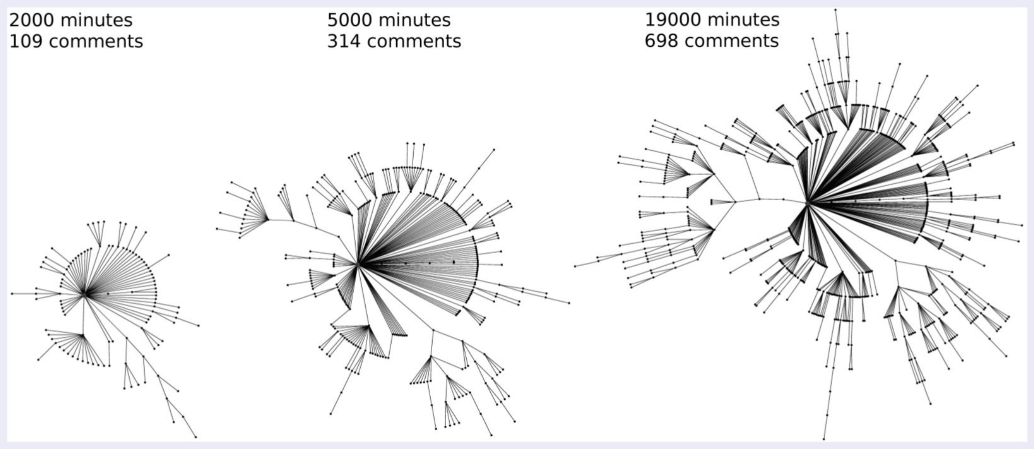
Fig. 4 Modeling approach considered in this review: the model (box in the middle) represents a mechanism or procedure that describes how discussion threads are formed. It is usually governed by a set of parameters θ which are typically learned from real data composed of real discussion threads. This learning step involves some type of optimization. For given parameters θ, the model can be used to generate synthetic threads that reproduce the properties of the real discussion threads

Statistical modelling of online discussion threads

Data-driven modeling of online discussion threads

Unlike descriptive models, generative models:

- Produce instances of the objects of interest
- Provide a mechanism

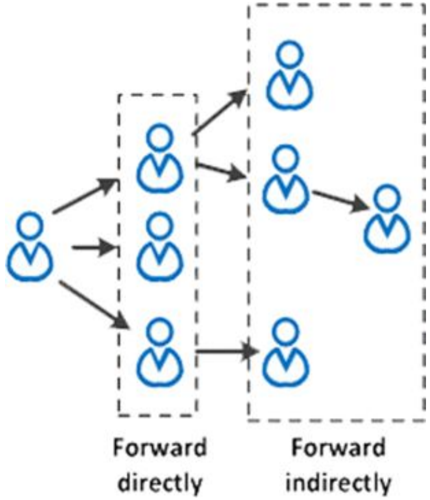


Example of discussion Thread on Slashdot

Data-driven modeling of online discussion threads

This part is **not about modeling Diffusion**

- **Diffusion** is about propagation of Information (little processing)



- **Discussions** are fundamentally different: deliberation, argumentation, ...

- Nevertheless, diffusion models have been used to model online discussions as baselines.

Data-driven modeling of online discussion threads

This part is **not about Natural Language Processing**

- How much can we understand online discussions without relying on the content?

  Pros: Results are language-independent

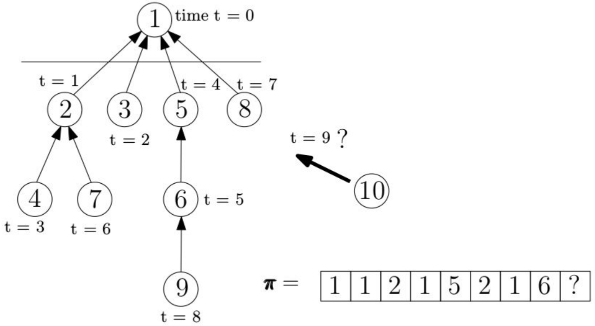
  Cons: Ignoring content may discard important information

- Nevertheless, the work presented here can always be extended, e.g., using content-based features

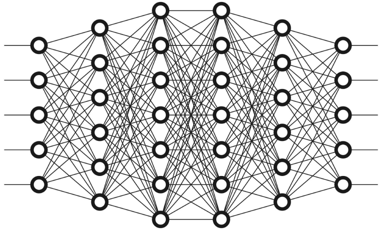
Data-driven modeling of online discussion threads

Two main approaches

1. Model-based **(this tutorial)**



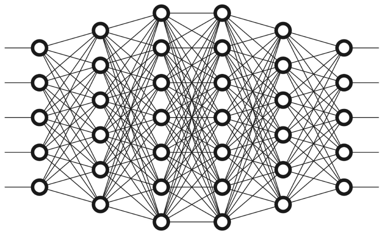
2. Purely data-driven



Data-driven modeling of online discussion threads

1. Purely data-driven are typically

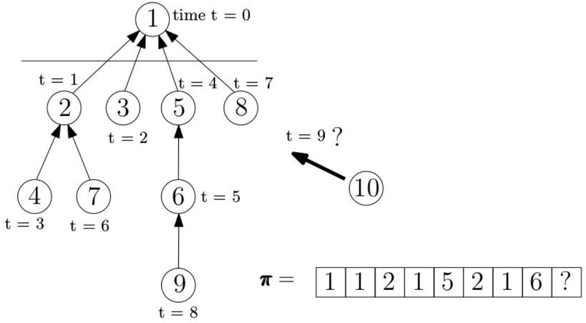
    - originated from the machine learning community
    - “End-to-end”, little prior knowledge is required
    - Learn specific input-output mappings (the final network/thread)
    - Comprise many parameters
    - Main interest is prediction accuracy
    - Black-box, difficult to interpret
    - Nonlinear optimization



Data-driven modeling of online discussion threads

2. Model-based **(this tutorial)**

   - originated from Social sciences, Economy, Computer Science
   - Very structured, explicit prior knowledge
   - Learn a mechanism (thread evolution)
   - Comprise a few parameters adjusted from the data
   - Main interest is understanding
   - “Easily” interpretable
   - “Easier” to optimize



Data-driven modeling of online discussion threads

Some statistical issues regarding model fitting

- Assumptions when modeling sequential data
- Model complexity/comparison
- Evaluation
- Identifiability
- Preprocessing issues : heavy tails, ...

Data-driven modeling of online discussion threads

Modeling sequence data (random variable *x* evolves in time)

- Independence assumption

$$p(x_1, x_2, \ldots, x_T) = p(x_1)p(x_2)\cdots p(x_T) = \prod_{t=1}^{T} p(x_t)$$

- Temporal dependence (first order Markov)

$$p(x_1, x_2, \ldots, x_T) = p(x_1)p(x_2|x_1)p(x_3|x_2)\cdots p(x_T|x_{T-1}) = p(x_1)\prod_{t=1}^{T-1} p(x_{t+1}|x_t)$$

- Temporal dependence (Non-stationary data)

$$p(x_1, x_2, \ldots, x_T) = p_1(x_1)p_2(x_2|p_1)p_3(x_3|x_2)\cdots p_T(x_T|x_{T-1}) = p_1(x_1)\prod_{t=1}^{T-1} p_{t+1}(x_{t+1}|x_t)$$

Data-driven modeling of online discussion threads

Model complexity, comparison and evaluation

- If major interest is **prediction**
  - Use train/test/validation data
  - Make sure data will remain stationary
- If major interest is **interpretability**
  - Consider many observables, e.g.,
    Do not limit to degree distributions

Data-driven modeling of online discussion threads

A simple sanity check before estimating with real data:

1. Generate synthetic data with some known parameter values θ^*
2. Train the model with those data for different initial conditions (parameter initializations θ_0)
3. Check whether the model estimates $\hat{\theta}$ coincide with the known parameter values θ^*

Data-driven modeling of online discussion threads

What if $\hat{\theta}$ does not coincide with θ^* ?

- **Multiple local minima?** different likelihoods and different parameter values (check several random initial conditions)

- **A non-identifiable model?** same likelihood and different parameter values

- **A bug? ...**

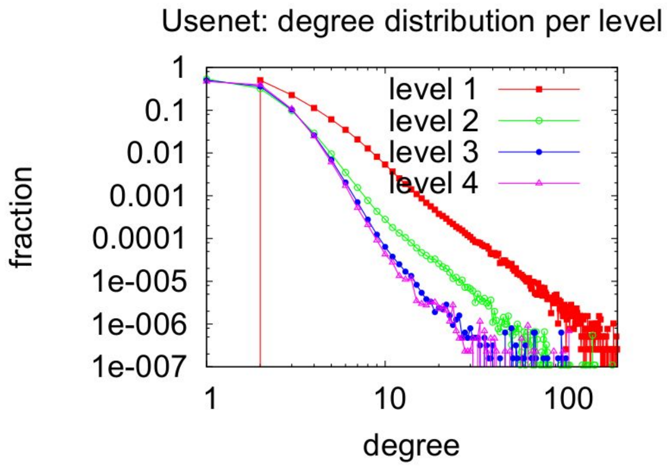
A selection of relevant models of discussion threads

A selection of relevant models of discussion threads

Simplest model: **Branching process** (Galton 1889)

- Start with a root node
- At each discrete time-step:

each node generates *deg* descendants from a pre-specified probability distribution p(*deg*), *deg*=0,1,2,...



Kumar et al. Dynamics of conversations. SIGKDD 2010

A selection of relevant models of discussion threads

Simplest model: **Branching process** (Galton 1889)

- Advantages
  Simple and Easy to estimate. Only requires to fit p(*deg*)

- Disadvantages
  - Not a generative model (~configuration model)
  - Does not consider the order of messages
  - Only captures the Degree distribution p(*deg*)

Discrete-time (structural) models: Kumar et al [2010]

- First proposed generative model of discussion threads

- At each (discrete) time-step
  - Either the thread terminates with probability p_f
  - Or a new comment is attached to an existing comment k with some probability

- This probability depends on two basic features of comment k
  - Its **popularity** (or degree deg_k)
  - Its **novelty** (or elapsed time since posted r_k)

R Kumar, M Mahdian, M McGlohon. Dynamics of conversations. SIGKDD, 2010

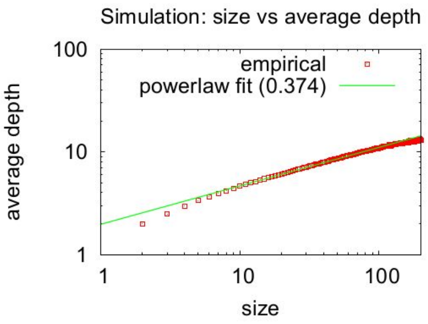
Discrete-time (structural) models: Kumar et al [2010]

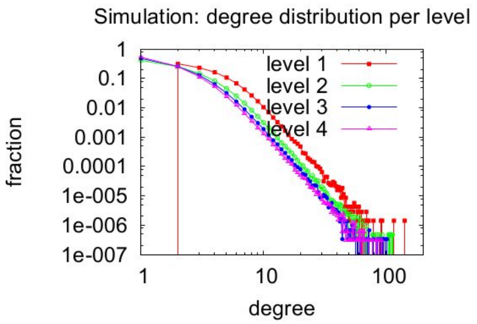
- Popularity and novelty are combined **linearly** to determine which comment receives the reply

$$p(X_t = k|\alpha, \tau, p_f) = \frac{\alpha \deg_k + \tau^{r_k}}{\sum_{k'} \left(\alpha \deg_{k'} + \tau^{r_{k'}}\right) + p_f}$$

- Grid search to find **Maximum likelihood** estimates of α, τ, p_f

- The model reasonably captures empirical observations in USENET

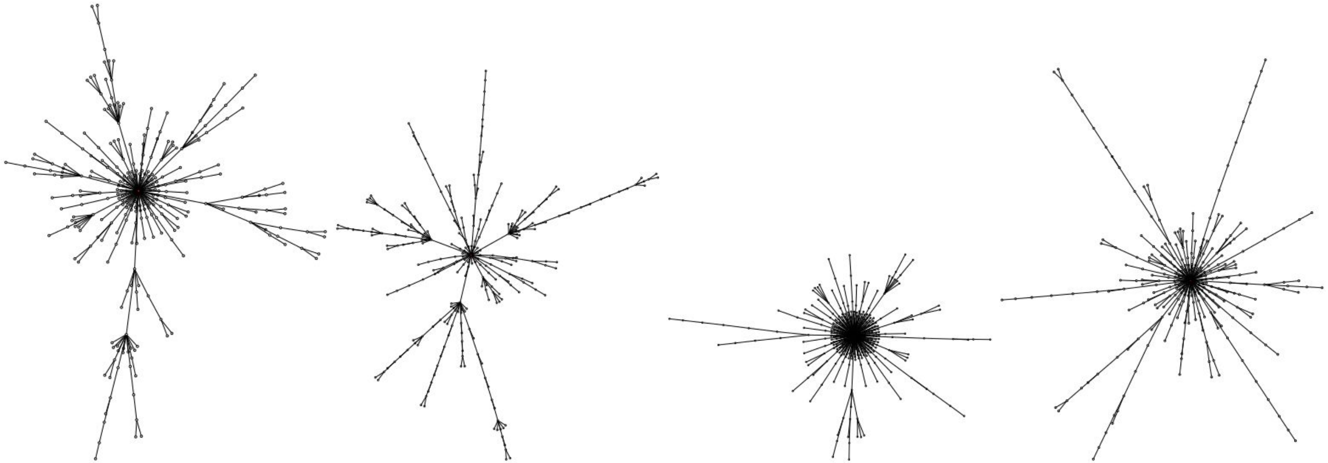




R Kumar, M Mahdian, M McGlohon. Dynamics of conversations. SIGKDD, 2010

Discrete-time (structural) models: Gómez et al. [2013]

- **Observation:** Post replies behave differently to comment replies



(a) Slashdot (b) Barrapunto (c) Meneame (d) Wikipedia

Gómez V., Kappen H. J., Litvak N., Kaltenbrunner A. A likelihood-based framework for the analysis of discussion threads, World Wide Web Journal, 16, 5-6, 2013

Discrete-time (structural) models: Gómez et al. [2013]

- Extends previous models by incorporating the notion of *post bias*
- This probability depends on two basic features of node *k*
  - Its **popularity** (or degree deg_k)
  - Its **novelty** (or elapsed time since posted r_k)
  - Whether it is **root** node or not ($\delta_{0,k}$)

- The discussion is formed according to

$$p(X_t = k|\alpha, \tau, \beta) = \frac{\alpha \deg_k + \tau^{r_k} + \beta\delta_{0,k}}{\sum_{k'} \alpha \deg_{k'} + \tau^{r_{k'}} + \beta\delta_{0,k'}}$$

Gómez V., Kappen H. J., Litvak N., Kaltenbrunner A. A likelihood-based framework for the analysis of discussion threads, World Wide Web Journal, 16, 5-6, 2013

Discrete-time (structural) models: Gómez et al. [2013]

- **Optimization:** Given a dataset comprised of threads $\pi_i,\ i = 1, \ldots, N$, maximize the following log-likelihood function

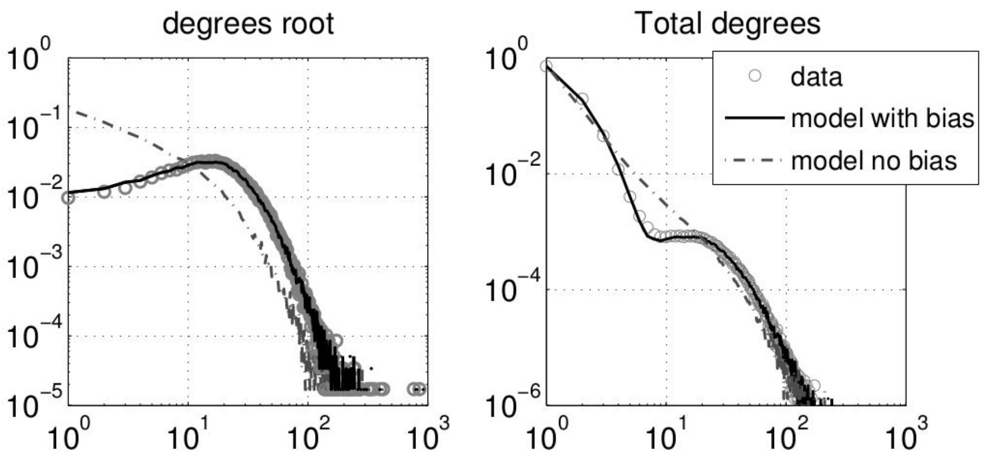
$$\log \mathcal{L}(\Pi|\alpha, \beta, \tau) = \sum_{i=1}^{N} \sum_{t=2}^{|\pi_i|} \log p(X_t = \pi_{i,t}|\alpha, \beta, \tau),$$

where $\pi_{i,t}$ denotes the parent of the comment arriving at time-step *t* in thread *i*

Gómez V., Kappen H. J., Litvak N., Kaltenbrunner A. A likelihood-based framework for the analysis of discussion threads, World Wide Web Journal, 16, 5-6, 2013

Discrete-time (structural) models: Gómez et al. [2013]

- Captures better empirical observations such as degree distributions



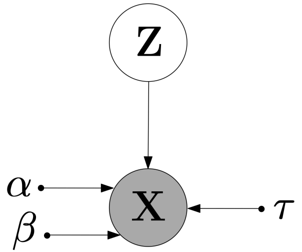
- Which model is better?
  Model comparison is performed using feature ablation

Gómez V., Kappen H. J., Litvak N., Kaltenbrunner A. A likelihood-based framework for the analysis of discussion threads, World Wide Web Journal, 16, 5-6, 2013

Discrete-time (structural) models: Lumbreras et al. [2018]

- **Motivation:** can we discover user roles that are unobserved in our data?

- Assign each user *u* to a role *k*
- Each role is characterized by parameters $\alpha_k, \beta_k, \tau_k$ (popularity, root bias, and novelty)
- **Problem:** From threads and user data
  - Estimate user-role membership
  - Learn role parameters $\alpha_k, \beta_k, \tau_k$



A Lumbreras, B Jouve, J Velcin, M Guégan. Role detection in online forums based on growth models for trees. Social Network Analysis and Mining 7 (1), 49

Discrete-time (structural) models: Lumbreras et al. [2018]

- **Challenges:**
  - Role membership is a latent variable (nonconvexity)
    - Expectation-Maximization algorithm
  - Model order parameter (number of roles)
    - Bayesian Information Criterion (BIC)

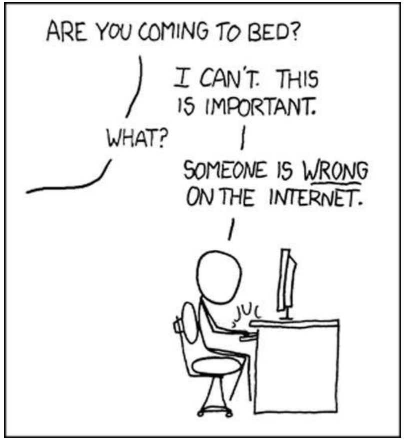
- The proposed model improves the predictions over special roles whose parameters are far from the other roles

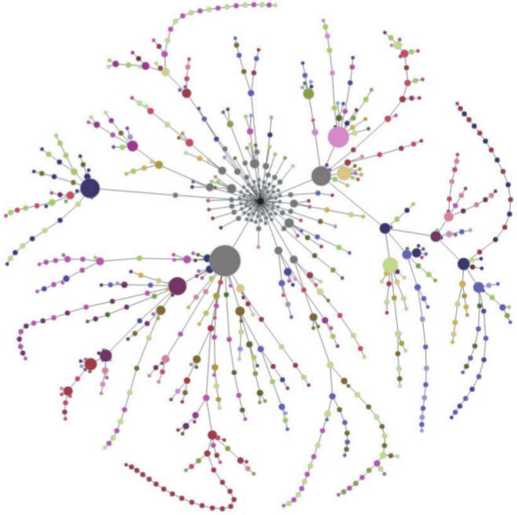
A Lumbreras, B Jouve, J Velcin, M Guégan. Role detection in online forums based on growth models for trees. Social Network Analysis and Mining 7 (1), 49

Discrete-time (structural) models: Aragón et al. [2017]

- **Observation:** Users tend to reply comments that reply to their previous comments

- Can we capture this effect by minimally *extending* an existing model?



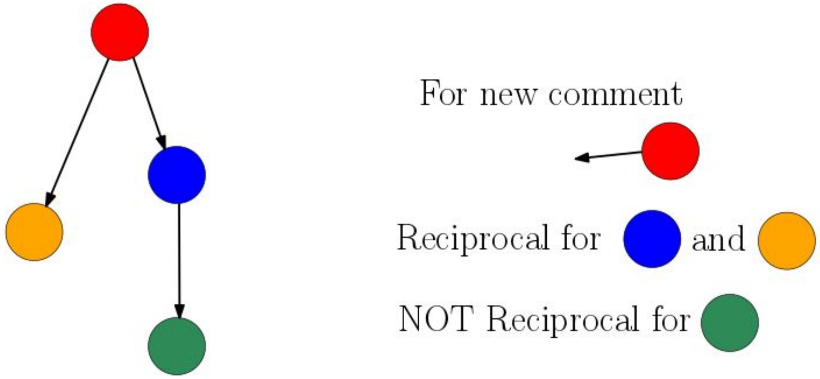


(b) Thread in 2015.
https://www.meneame.net/story/2484585

Aragón P, Gómez V, Kaltenbrunner A. To thread or not to thread: The impact of conversation threading on online discussion. ICWSM, 2017

Discrete-time (structural) models: Aragón et al. [2017]

- A new feature: **reciprocity**
- A comment *c* from author *A* is defined to be reciprocal when *c* is a reply to a reply to a comment made by the same author *A*



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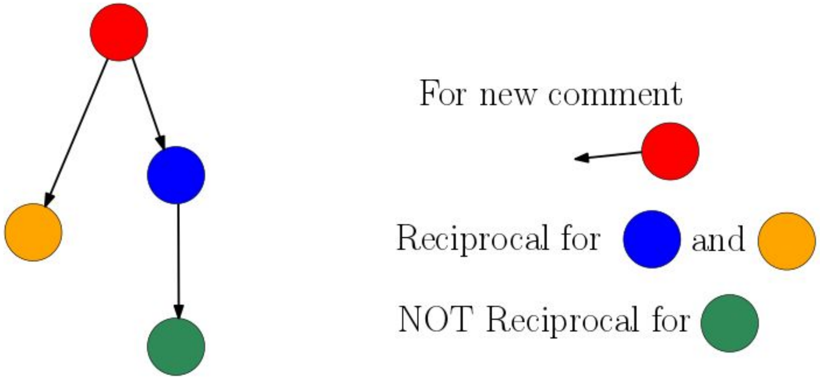
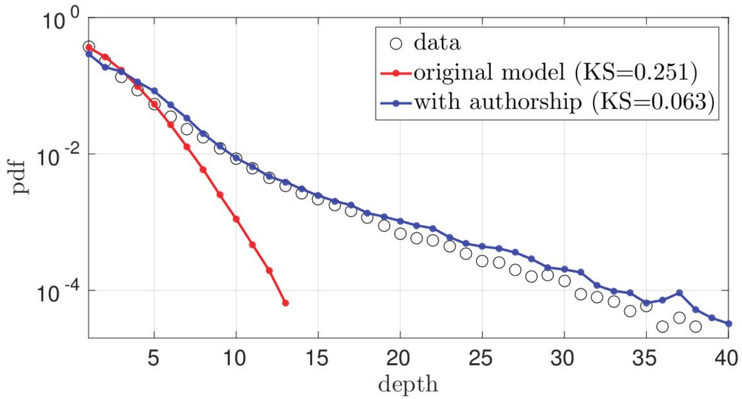


Aragón P, Gómez V, Kaltenbrunner A. To thread or not to thread: The impact of conversation threading on online discussion. ICWSM, 2017

Discrete-time (structural) models: Aragón et al. [2017]

- Thread structure and **authorship** are mutually influenced
  - **New feature:** the structure depends on the authorship
  - **New process:** the authorship depends on the structure

- Reproduces better the distribution of depths (long chains)



Aragón P, Gómez V, Kaltenbrunner A. To thread or not to thread: The impact of conversation threading on online discussion. ICWSM, 2017

Discrete-time (structural) models: A unifying view

- Multinomial logit model

$$P(X_t = k|\boldsymbol{\theta}) = \frac{\exp \boldsymbol{\theta}^T \mathbf{x}_k}{\sum_{k'} \exp \boldsymbol{\theta}^T \mathbf{x}_{k'}}$$

$$\begin{aligned} \mathbf{x}_k &\text{ is the feature vector of node } k : \\ x_{k,1} &: \text{number of replies} \\ x_{k,2} &: \text{(log) elapsed time} \\ x_{k,3} &: \text{is } k \text{ root?} \\ &\vdots \end{aligned}$$

- Learning and inference: convex likelihood function

  Similar idea introduced recently for general networks:

Jan Overgoor, Austin R. Benson, Johan Ugander. Choosing to Grow a Graph: Modeling Network Formation as Discrete Choice. The WebConf (WWW) 2019

Discrete-time (structural) models: A unifying view

- Similar to an Exponential random graph model (ERGM)

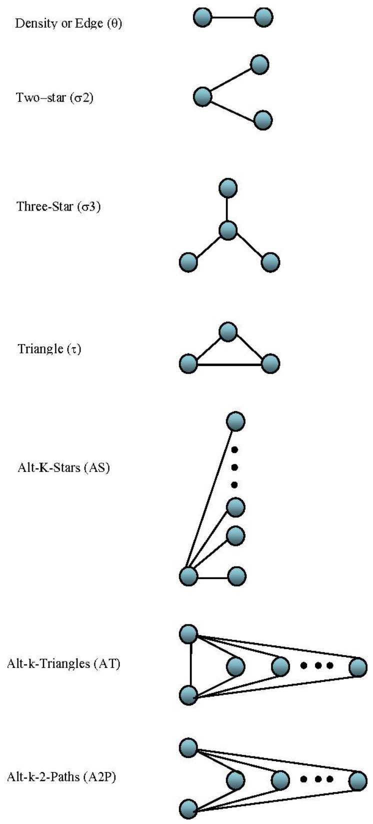
$$P(X = x|\boldsymbol{\theta}) = \frac{\exp \boldsymbol{\theta}^T \mathbf{z}(x)}{\sum_{x'} \exp \boldsymbol{\theta}^T \mathbf{z}(x')}$$

In ERGMs:

- $\mathbf{z}(x)$ vector of features of the entire graph x
- Normalization sums over **all** possible graphs

In our case:

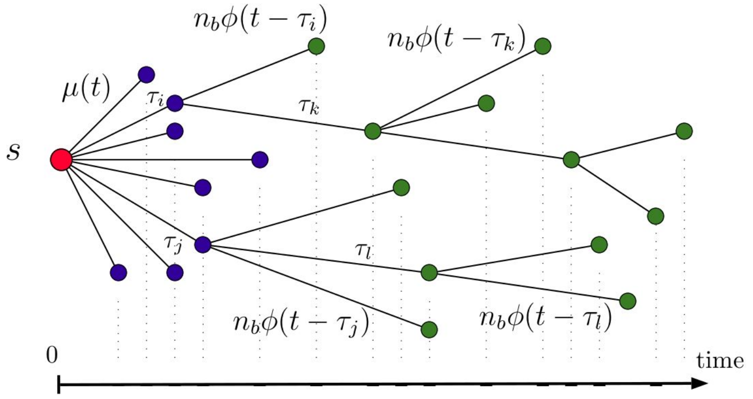
- Features are defined for each node
- The graph (thread) evolves in time



A selection of relevant models of discussion threads

Continuous-time models

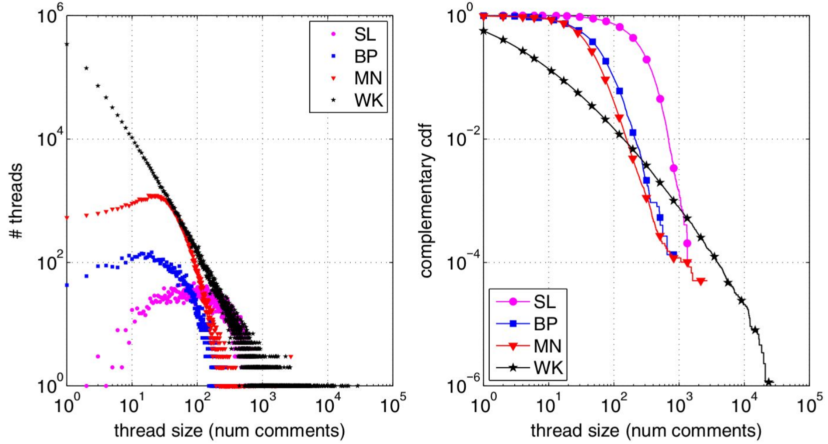
- Captures the exact timing, no only the thread structure
- Assume that no two events can occur at the same time
- Theoretical framework
  - Point processes



Medvedev et al. Modelling structure and predicting dynamics of discussion threads in online boards. Journal of Complex Networks (2018)

Continuous-time models

- **Observation:** conflicting studies report significant differences in the thread lifespan/size



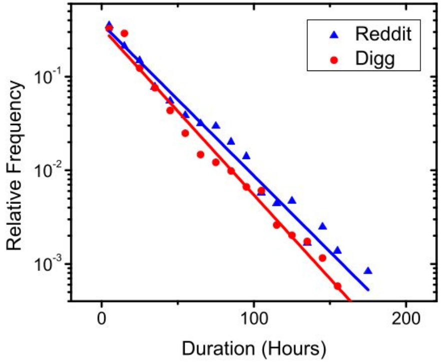
- SL : Slashdot
- BP : Barrapunto
- MN : Meneame
- WK : Wikipedia

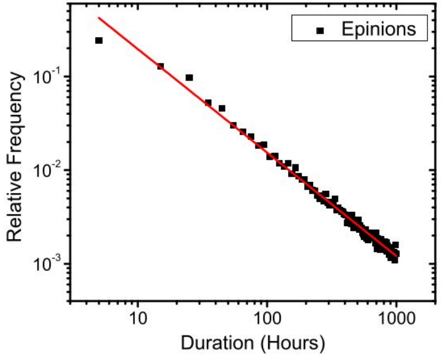
Gómez V., Kappen H. J., Kaltenbrunner A. Modeling the Structure and Evolution of Discussion Cascades. Hypertext 2011

Continuous-time models: Wang et al. [2012]

- **Observation:** conflicting studies report significant differences in the thread lifespan/size

- Are these differences explained by the different platform algorithms (exposure durations)?





Wang C, Ye M, Huberman BA. From user comments to on-line conversations. In: Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining. 2012.

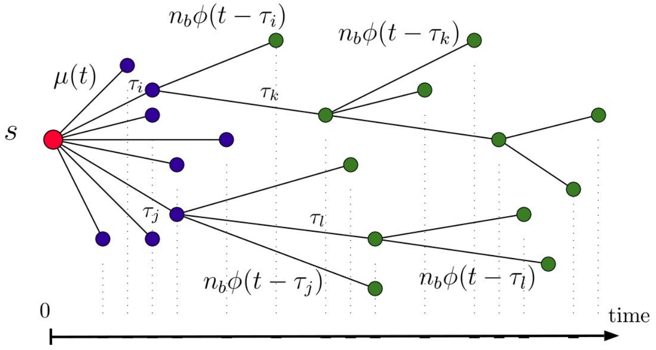
Continuous-time models: Wang et al. [2012]

- Assumptions
  - Distribution of Waiting times between comments is fixed
  - Mean-field: users share the same microscopic behaviors
- Findings
  - Lifespan (dynamics)
    - Suggest different exposure durations (platform algorithms) as the origin of the discrepancies
  - Structure
    - A simple Yule process
    - Degree distribution is **independent** of exposure durations

Wang C, Ye M, Huberman BA. From user comments to on-line conversations. In: Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining. 2012.

Continuous-time models: Medvedev et al. [2018]

- **Motivation:** combine **structure** and **continuous-time** to predict commenting activity and final size of a thread



- Self-exciting Hawkes process

$$\lambda(t) = \mu(t) + n_b \sum_{i:\tau_i<t} \phi(t-\tau_i),$$

$\lambda(t)$ rate function
$\mu(t)$ background (root) intensity
$\phi(t)$ memory kernel
n_b branching number

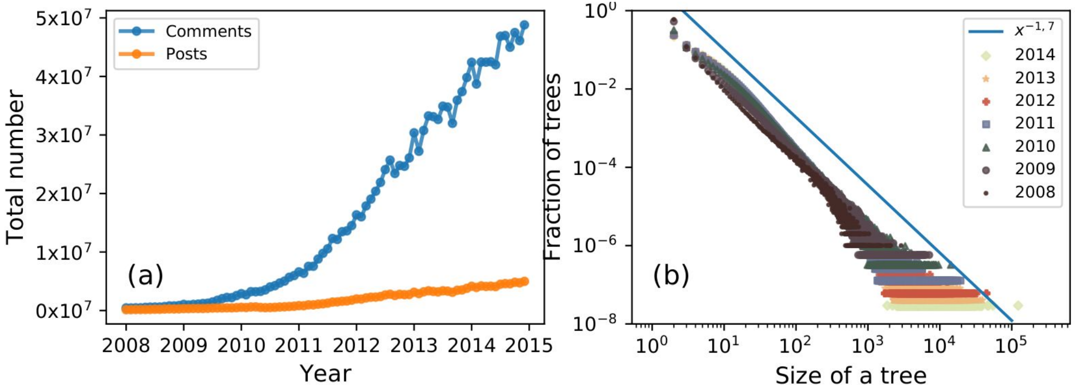
Medvedev, Alexey N., Jean-Charles Delvenne, and Renaud Lambiotte. Modelling structure and predicting dynamics of discussion threads in online boards. Journal of Complex Networks (2018)

Continuous-time models: Medvedev et al. [2018]

- Dataset: Reddit.com (all posts from Jan 2008 to Jan 2015)

~ 150 million posts

~ 1.4 billion comments

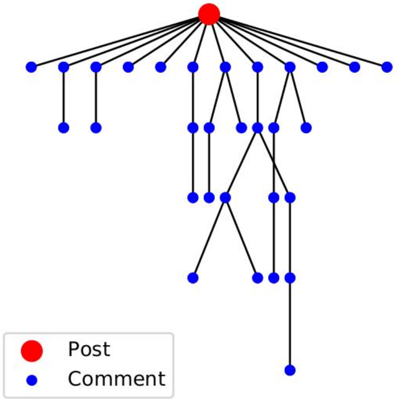


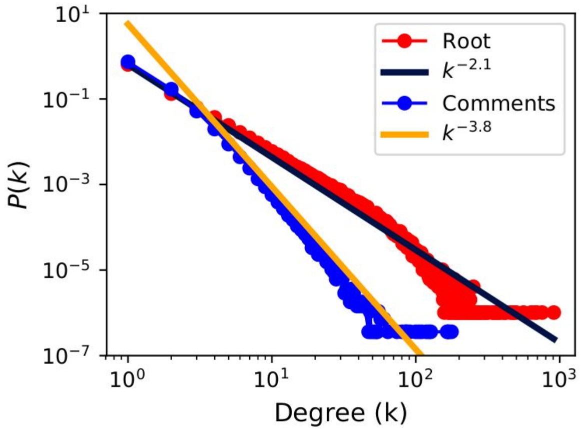
a) Total number of submissions; b) Tree size distribution.

Medvedev, Alexey N., Jean-Charles Delvenne, and Renaud Lambiotte. Modelling structure and predicting dynamics of discussion threads in online boards. Journal of Complex Networks (2018)

Continuous-time models: Medvedev et al. [2018]

- Differentiates direct replies from comments to comments

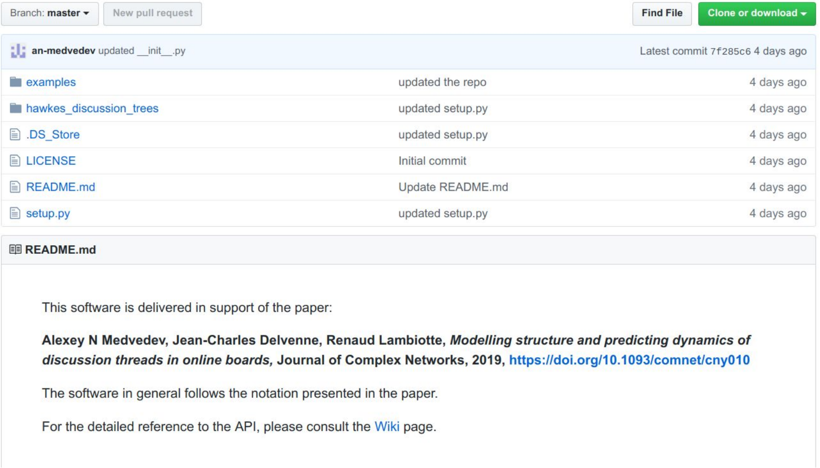




Medvedev, Alexey N., Jean-Charles Delvenne, and Renaud Lambiotte. Modelling structure and predicting dynamics of discussion threads in online boards. Journal of Complex Networks (2018)

Continuous-time models: Medvedev et al. [2018]

- GITHUB repository



https://github.com/an-medvedev/hawkes-discussion-trees

Medvedev, Alexey N., Jean-Charles Delvenne, and Renaud Lambiotte. Modelling structure and predicting dynamics of discussion threads in online boards. Journal of Complex Networks (2018)

Misc. model : Backstrom et al. [2013]

- **Motivation:** can we predict...
  - the number of comments a discussion thread will receive?
  - whether a user who has participated will later contribute another comment to it?

- Considers the arrival pattern (precise sequence of arrivals of the first few participants)

focused thread		*expansionary thread*	
Mary:	Anyone there	James:	we're engaged!
Mary:	?	Dina:	congrats!
Don:	me	Fred:	congrats!
Pat:	not me	Mia:	great!!!
Don:	v funny	Moe:	great!
Pat:	i know	James:	Thanks guys :)
. . .	. . .	. . .	. . .
Length-2 arrival pattern: 0,1		*Length-2 arrival pattern: 1,2*	
Length-5 arrival pattern: 0,1,2,1,2		*Length-5 arrival pattern: 1,2,3,4,0*	

Backstrom L, Kleinberg J, Lee L, Danescu-Niculescu-Mizil C. Characterizing and curating conversation threads: expansion, focus, volume, re-entry. WSDM (2013)

Misc. model : Backstrom et al. [2013]

- A **linear regression** model
  (strictly speaking not a generative model)
- Additional features
  - *Social influence*: #links previous to comment, ...
  - *Novelty*: elapsed continuous time
  - *Text-based features*: ‘agree’, ‘comment’, ...
  - *Misc. features*: #words, #characters, ...

- Captures the fraction of long path-like trees but not large irregular trees

Backstrom L, Kleinberg J, Lee L, Danescu-Niculescu-Mizil C. Characterizing and curating conversation threads: expansion, focus, volume, re-entry. WSDM (2013)

A selection of relevant models of discussion threads

Model	Features	Time	Datasets	Evaluation
Kumar et al.	Popularity, Novelty, Reciprocity	Discrete	Y! Groups, Usenet, Twitter	Size, Depth, Degree
Wang et al.	Popularity	Continuous	Digg, Reddit, Epinions	Size
Gómez et al.	Popularity, Novelty, Root-bias	Discrete	Slashdot, Barrapunto, Wikipedia, Menéame	Size, Depth, Degree
Backstrom et al.	Novelty, Arrival patterns, Text expressions, Social influence	Continuous	Facebook, Google+, Wikipedia	Size
Nishi et al.	Popularity, Segment lengths	Discrete	Twitter	Size, Depth, Shapes
Lumbreras et al.	Popularity, Novelty, Root-bias, User Role	Discrete	Reddit	Size, Depth, Degree
Aragón et al.	Popularity, Novelty, Root-bias, Reciprocity	Discrete	Menéame	Size, Depth, Degree
Medvedev et al.	Novelty	Continuous	Reddit	Size,Timing

Applications and open research challenges

Main areas of application

- Comparison among online discussion platforms
- Prediction of user behavior
- Evaluation of platform design
- Use of models in software tools

Application I: Comparison of online discussion platforms

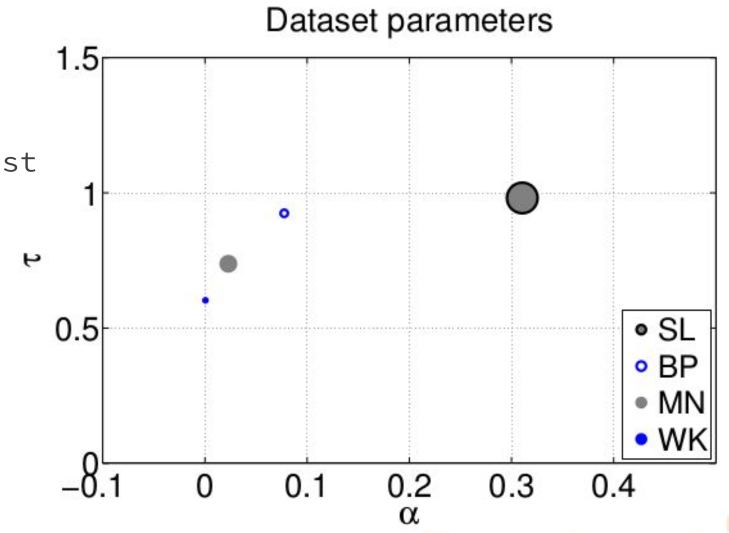
Most straightforward application:

- interpretation of the parameters of generative models
- i.e. the quantification of the relevance of each model feature.
- allows to compare platforms of different nature.
- can be used as well on the same underlying platform.

Application I: Comparison of online discussion platforms

Compare platforms of different nature.

- **Popularity** **(α)** Comments with many replies are more appealing (pref. attachment)
- **Root bias** **(β)** Point size: Distinction between the post (the initial node) and the comments
- **Novelty** **(τ)** Older comments gradually become less attractive than newer ones (smaller τ ⇔ larger impact)



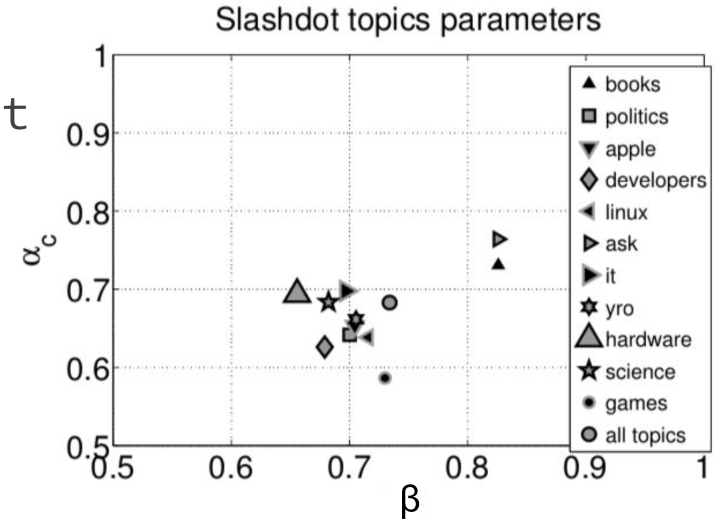
Gómez V., Kappen H. J., Litvak N., Kaltenbrunner A.
A likelihood-based framework for the analysis of discussion threads,
World Wide Web Journal, 16, 5-6, 2013, pp 645-675.

Application I: Comparison of online discussion platforms

Compare parameters in the same underlying platform

- to compare different user communities
  - e.g in different language versions
  - or different spheres of interest
- allows then to measure the impact of a specific topic or cultural aspect.

Gómez V., Kappen H. J., Kaltenbrunner A. (2011) Modeling the Structure and Evolution of Discussion Cascades, HT2011, Eindhoven, The Netherlands.



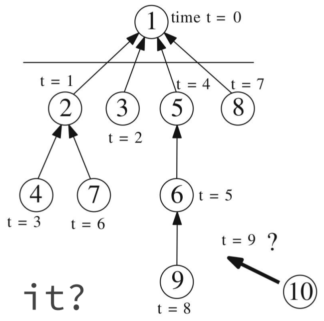
Application I: Comparison of online discussion platforms

Other noteworthy findings.

- **Kumar et al. [2010]** **Usenet:** Political groups exhibit greater degree of preferential attachment (popularity), groups with fewer users are more affected by novelty
  Twitter: novelty is prominent in threads about topics with a stronger sense of time, e.g. sports.
- **Backstrom et al. [2013]** **Facebook vs. Wikipedia:** content- based features are stronger in a peer production online environment like Wikipedia.

Application II: Prediction of user behavior

- Features in models for the structure of online discussion can also serve to predict behavior.
- All of these generative models have inherently the capability to be used to predict the future evolution of an online discussion given its state at a given point in time.
- **Questions to be asked:**
  - What size will the discussion reach?
  - Where will the next comment reply to?
  - Reentry prediction: Will a user who has participated in a thread contribute another comment to it?

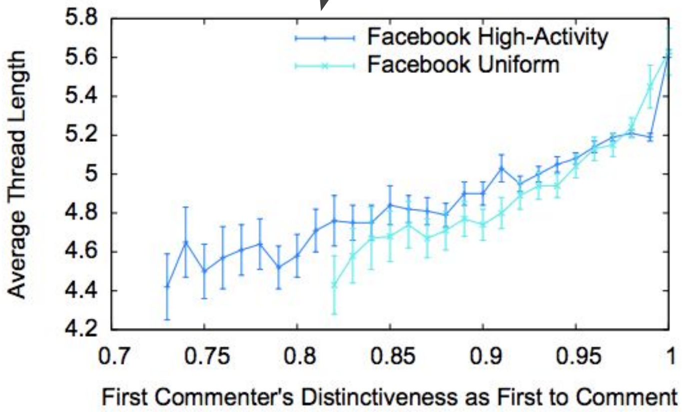


Application II: Prediction of user behavior

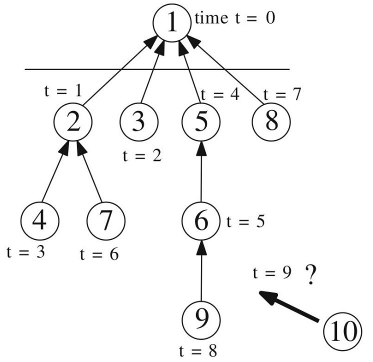
Example: Reentry and size prediction?

- **Backstrom et al. [2013]** Predictive model which considers early sequences of threads to infer the final **thread size** and **reentry probability**.

		AUC (x-val)
FB (after 5 comments)	Pos.-% bias baseline	.500
	Text baseline	.520
	Our features	**.808**
FB (after 9 comments)	Pos.-% bias baseline	.500
	Text baseline	.525
	Our features	**.855**
Wiki (after 5 comments)	Pos.-% bias baseline	.500
	Text baseline	.494
	Our features	**.644**



Application II: Prediction of user behavior



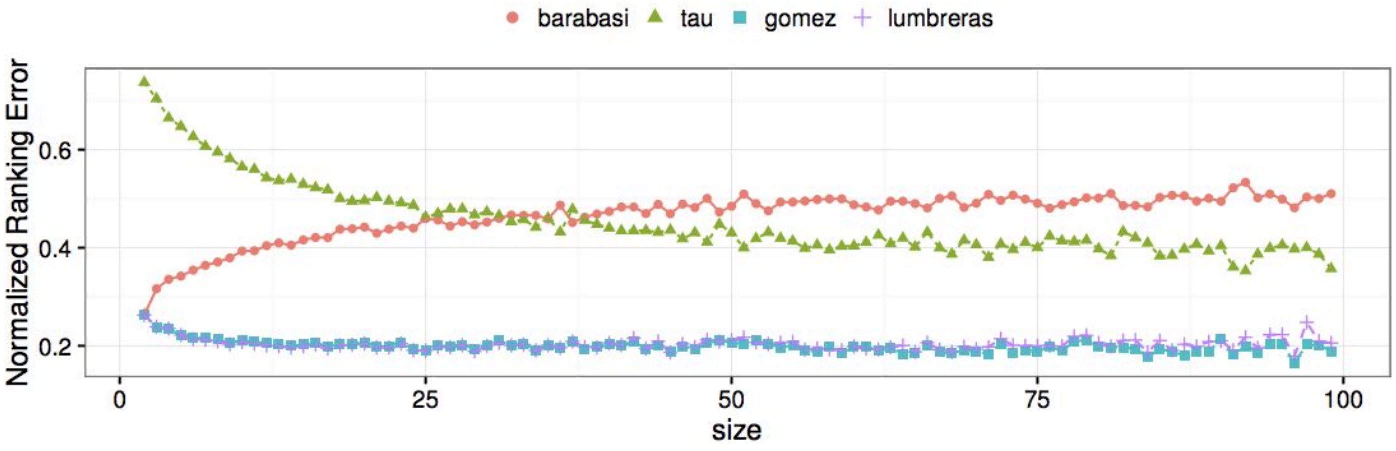
Example: Where will the next comment reply to?

- **Lumbreras [2016]** compares normalized prediction error of different models per thread size.

Normalized Ranking Error

$$NRE = \frac{r-1}{l-1}$$

$\boldsymbol{r}$ … predicted rank of the actual parent
$\boldsymbol{l}$ … thread length



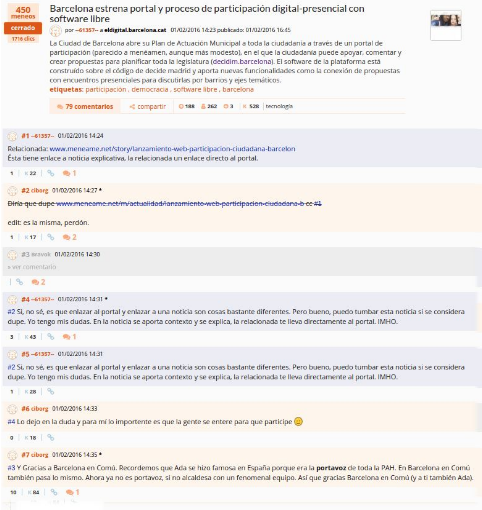
Application III: Evaluation of platform design

- Probably the most useful from a technical point of view.
- Can be used to assess the impact of a given design element on the user interaction patterns on a platform.
- Shows the interdependency between user interaction patterns and platform design elements.
- Can be exploited to help site owners and community managers to create a positive and constructive environment for large scale online discussions.

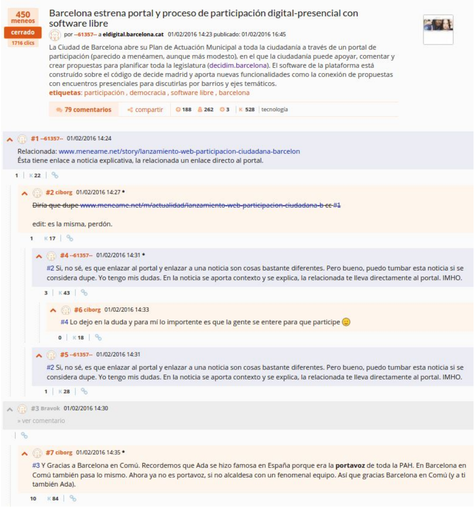
Application III: Evaluation of platform design

Example: Change of how conversation threads are presented

- **Aragón et al. [2017]** analyze the impact of threaded vs. non-threaded conversation views

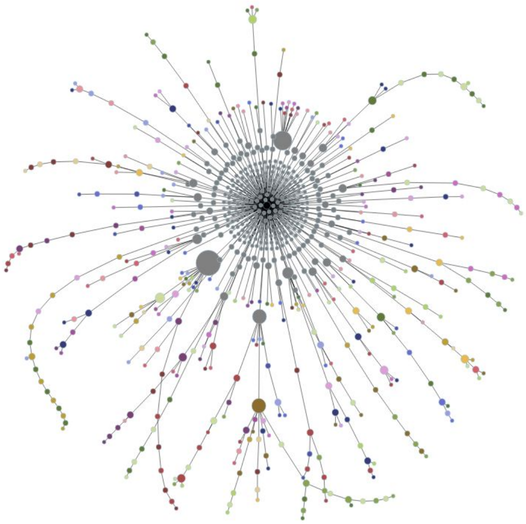


Aragón P., Gómez V., Kaltenbrunner A. (2017) To Thread or Not to Thread: The Impact of Conversation Threading on Online Discussion, ICWSM-17, Montreal, Canada.

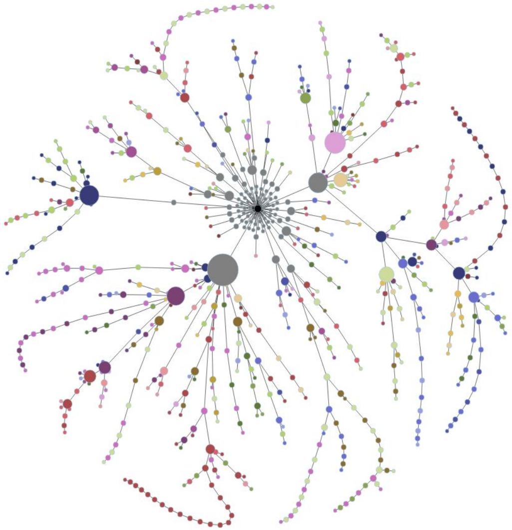


Application III: Evaluation of platform design

Aragón et al. [2017] Visual differences visible



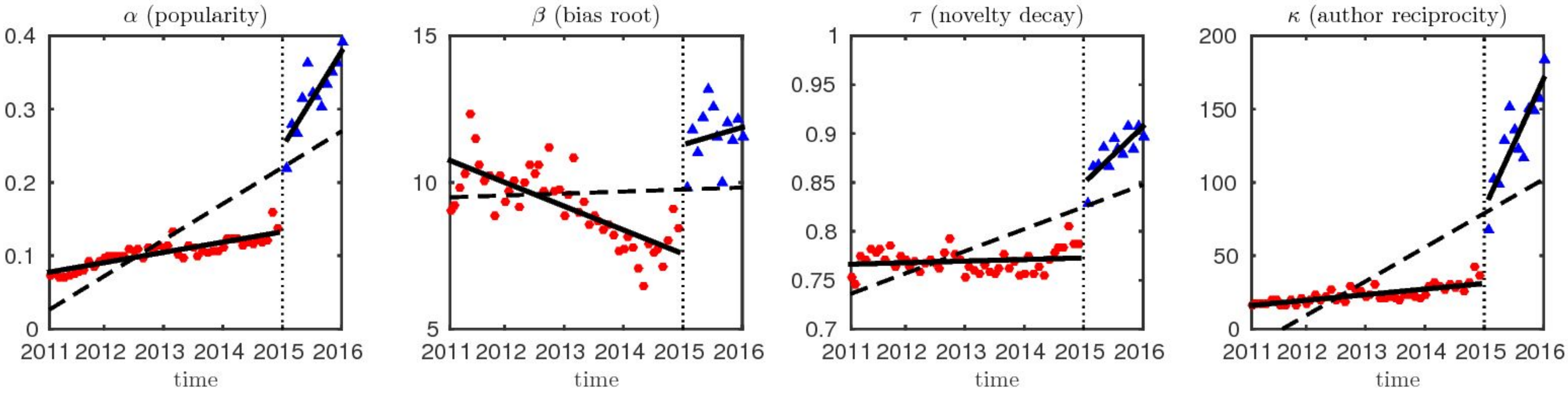
Thread in 2013
(linear view)



Thread in 2015
(hierarchical view)

Application III: Evaluation of platform design

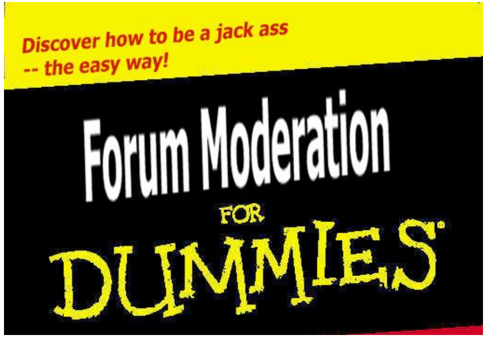
- **Aragón et al. [2017]** Behavioural features of a generative model undergo an notable increase when conversation threading is released (Jan 2015)
- Change in design can be detected with Regression Discontinuity Design applied on model parameters



Application VI: Use of models in software tools

Computer Assisted Forum moderation.

Use model parameters and prediction algorithms to visualize current and possible future states of an online discussion.



Source: http://www.nuk3.com/gallery/comedy/304/Forum-Moderation-For-Dummies.html

Chat boots for online discussion

Current Models already allow to select best comments to reply to.

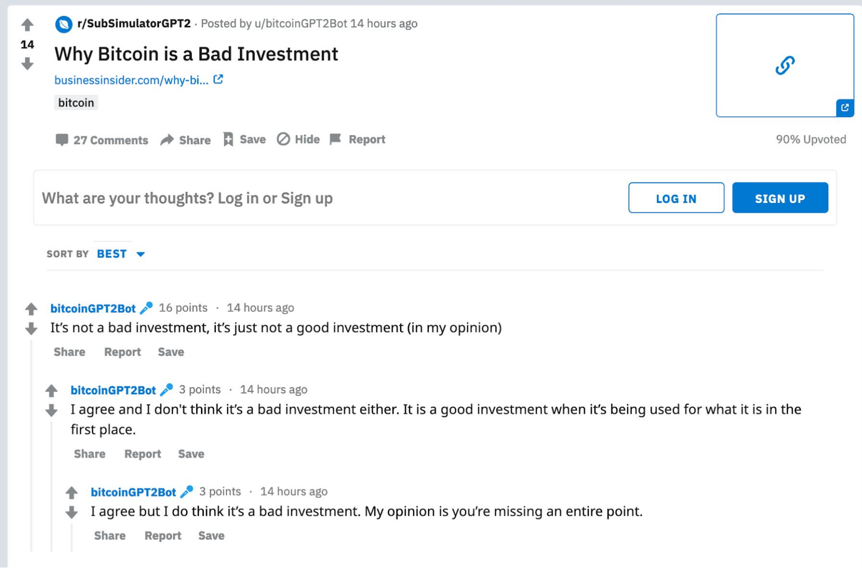
Source https://medium.com/marketing-and-entrepreneurship/10-of-the-most-innovative-chatbots-on-the-web-37f70fb19da3

Chat bots example: r/SubSimulatorGPT2

A subreddit with all posts and comments generated automatically
uses a GPT-2 language model developed by OpenAI.

Similar to /r/SubredditSimulator, which used a simple markov chain model.
GPT-2: more coherent and realistic simulated content.
But no structure or user model

64 different fine-tuned models
Conspiracy, 4chan, bitcoin, etc



Source https://www.reddit.com/user/4chanGPT2Bot/

Link: https://www.reddit.com/r/SubSimulatorGPT2/comments/btfhks/what_is_rsubsimulatorgpt2/

Open challenges

- Competition between discussion threads
- Impact of sub-communities
- The role of content
- Influencing user activity

Challenge I: Competition between discussion threads

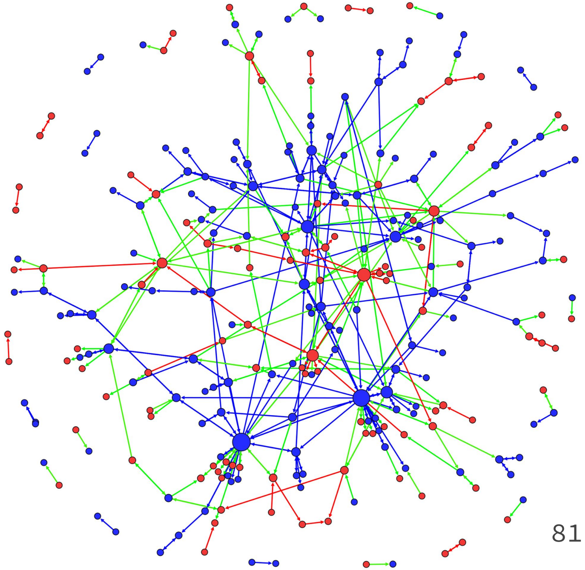
- What determines that a user comments in a particular thread and not in another?
- Is there a global mechanism that can capture how the messages of different users distribute themselves among the different available threads?
- **Possible approaches:**
    - estimate the longevity of discussion threads to minimize the arrival of new comments to old conversations.
    - modeling competition between conversation threads for user attention.

Image source: http://allthingsd.com/20111101/focus-no-willpower-required/

Challenge II: Impact of sub-communities

- Homophily and social influence are features of online interaction that usually induce a segregation or clustering in the community.
- Important because user groups usually evolve into echo chambers, which might favor extremism.
- The problem of identifying groups of users can be viewed as a community detection problem.

- Many existing algorithms but could also motivate new methods to detect communities based on interactions (i.e. comments or votes) which only occur between opposing fractions.



Neff, J. J., Laniado, D., Kappler, K. E., Volkovich, Y., Aragón, P., & Kaltenbrunner, A. [2013]. Jointly they edit: Examining the impact of community identification on political interaction in wikipedia. PloS one, 8(4), e60584.

Example: Comparison of Subreddits

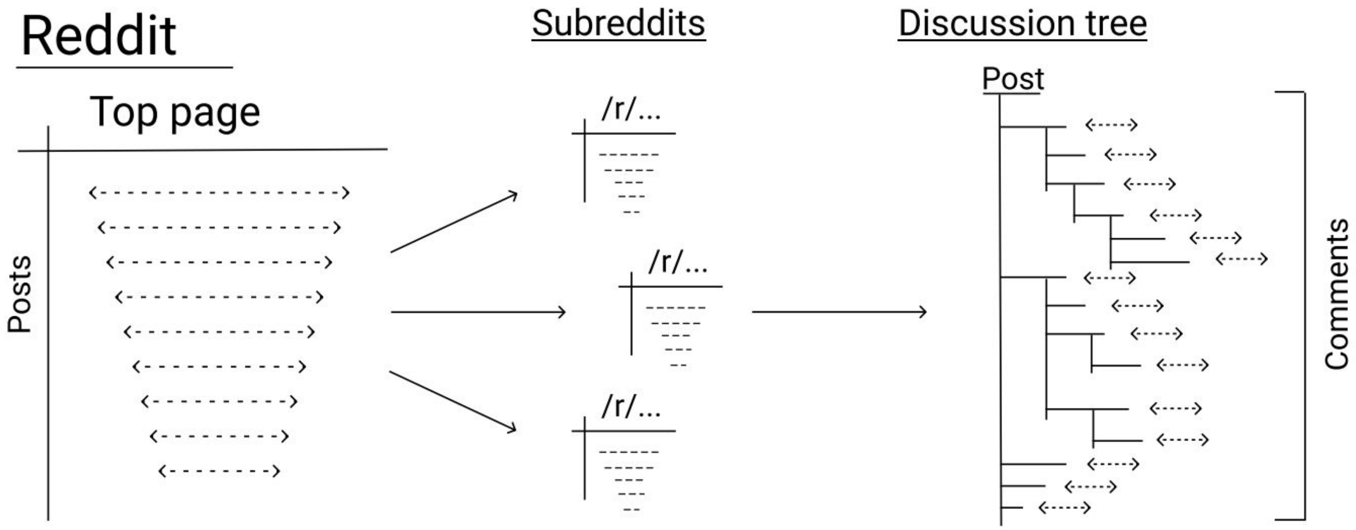
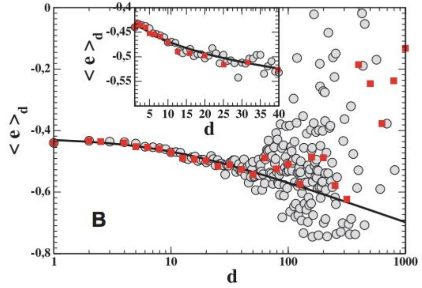


Figure source: **Medvedev, A. N., Lambiotte, R., & Delvenne, J. C.** (2017). The anatomy of Reddit: An overview of academic research. In Dynamics on and of Complex Networks (pp. 183-204). Springer.

Challenge III: The role of content

- Emotional contagion in online discussions is a very present phenomenon
- Example: **Chmiel et al. [2011]** Emotional expressions prolong online discussions.
  - More negative average emotion <*e*> of a user ⇔ longer user activity *d* in thread



- most of the generative models do not include features related to the content
- only **Backstrom et al. [2013]** consider some simple text-based features like the occurrence of certain terms (e.g. 'comment', 'agree') or the number of question/exclamation marks

Chmiel et al. [2011]. Negative emotions boost user activity at bbc forum. Physica A: Stat Mech Appl. 2011;390(16):2936-44.

Challenge III: The role of content

- content of messages can also reveal the emergence and evolution of topics in online discussions.
- Example: **Weninger et al. [2013]** found strong evidence that hierarchical comment threads represent a topical hierarchy in discussion platforms

- text-based features (e.g. text similarity between replies) should allow to better characterize the arrival of new comments in a discussion thread.

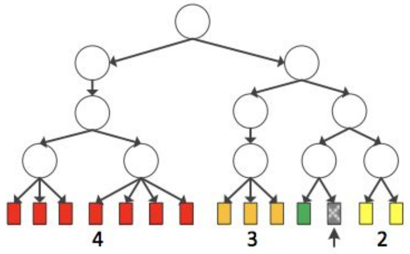


Fig. 4: Illustration of 4 level hLDA output. Green, yellow, orange, red indicate most topically similar to least topically similar.

Weninger et al. [2013]. An exploration of discussion threads in social news sites: A case study of the reddit community. In: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. New York: ACM; 2013.

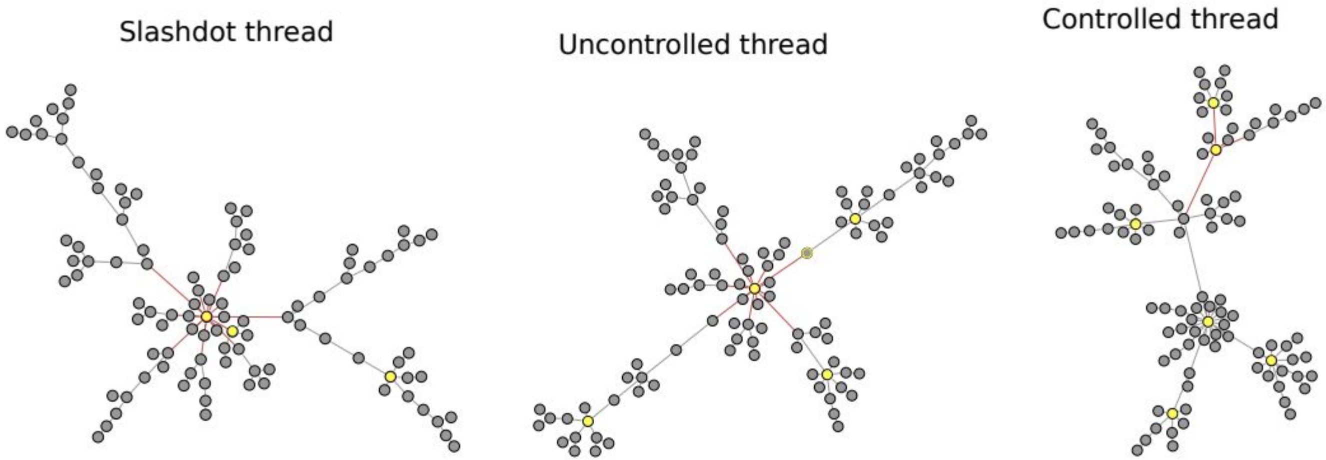
Challenge IV: Influencing user activity

- **Problem**: How to devise strategies to influence, or reshape, user activity?
- **Approach**: learn a policy or control law that guides the user activities in a closed-loop setting.
- Example: **Thalmeier et al [2017]** use the model of **Gomez et al. [2013]** presented here to
  - learn platform dynamics of commenting behavior.
  - then influence it using some control mechanism on the platform.
- Unclear if these computationally demanding methods (also limited by their model assumptions) can be deployed effectively in real platforms.
- Could be very useful for Computer Assisted Forum moderation.

Thalmeier et al [2017]. Action selection in growing state spaces: control of network structure growth. J Phys A Math Theor. 2017;50(3):034006.

Challenge IV: Influencing user activity

Example results from **Thalmeier et al [2017]** maximising a balanced discussion metric (h-index)



Thalmeier et al [2017]. Action selection in growing state spaces: control of network structure growth. J Phys A Math Theor. 2017;50(3):034006.

Challenge IV: Influencing user activity

Goal:

Design platforms to get discussions in the desired form

Example Applications:

- Citizen Participation platforms
- Online news comments

EUROZINE

Platforms are not neutral

Online debate and the rules of interaction

BAPTISTE CAMPION

6 August 2018

ONLY IN EN

Critique of social media tends to focus on the content of online discourse, particularly the impacts of fake news and hate speech. But how do social media platforms themselves determine interaction, and how can users adapt to default functionalities in the interests of constructive debate?

Short break
(5’)

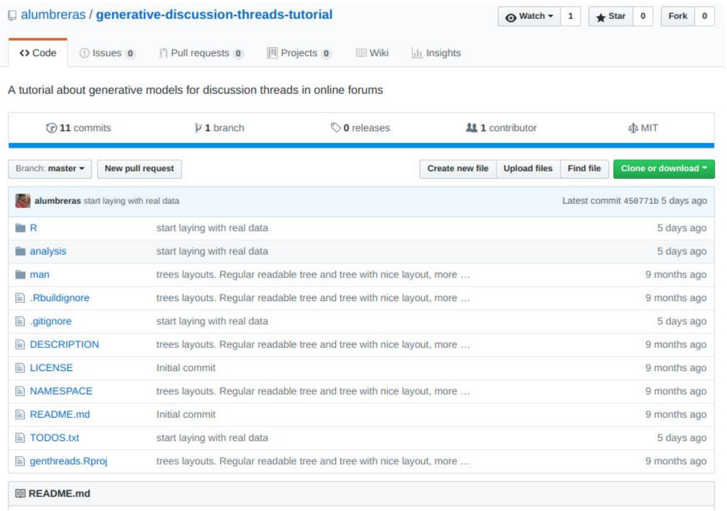
Meanwhile, let’s clone https://github.com/elaragon/generative-discussion-threads

Practical Session

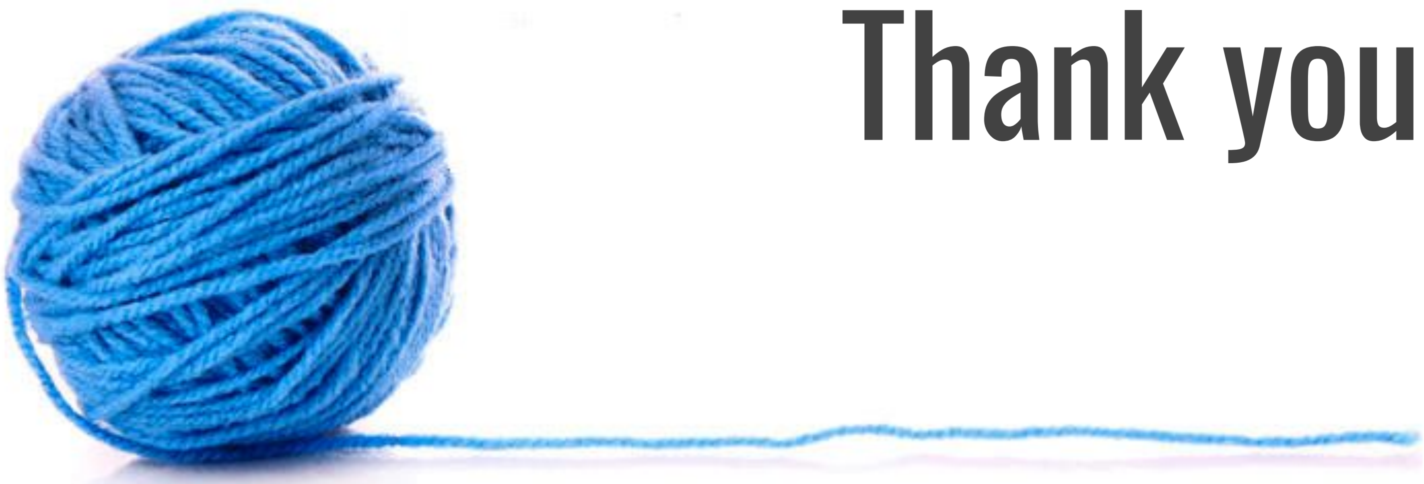
Practical session

Based on the R library for:

Lumbreras, A., Jouve, B., Velcin, J., & Guégan, M. (2017). Role detection in online forums based on growth models for trees. Social Network Analysis and Mining, 7(1), 49.



https://github.com/elaragon/generative-discussion-threads



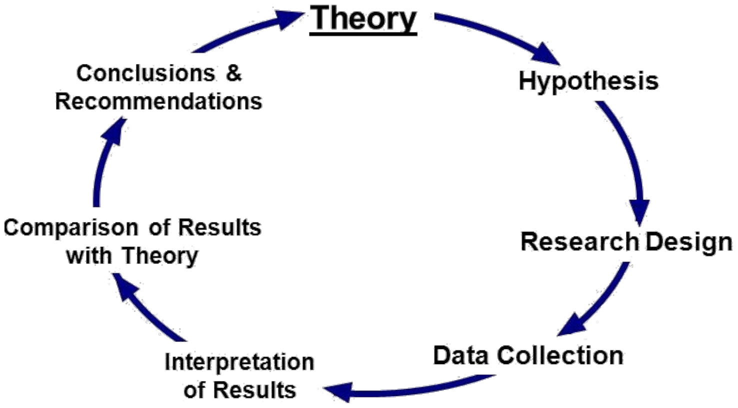
Thank you

Extra slides

Social theories in online discussions

An important fraction of research in online discussion has explored well-known theories from sociology and social psychology, e.g.:

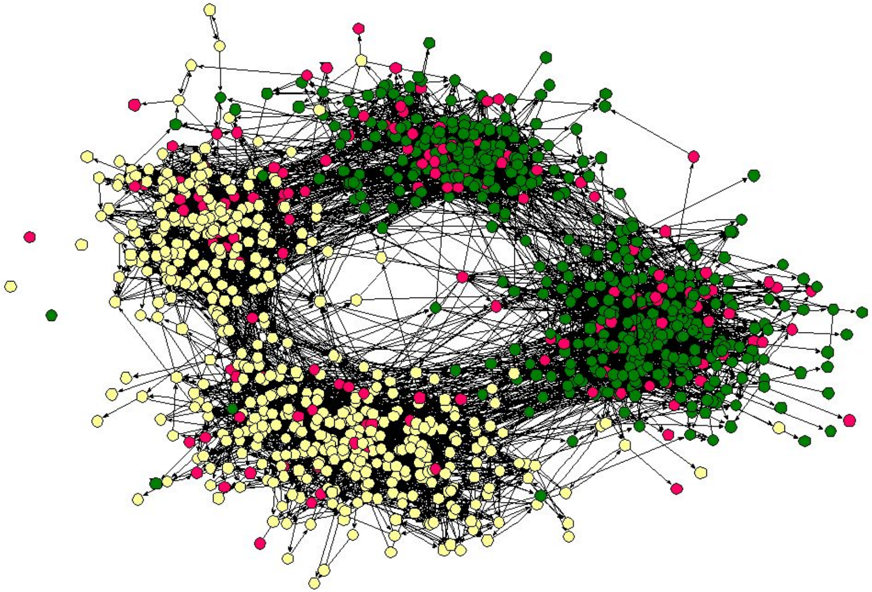
- Homophily
- Social influence
- Emotional contagion



Homophily (I)

“Birds of a feather flock together" is a proverb that captures the principle of homophily: the contact between similar people is more likely than among dissimilar ones

McPherson M, Smith-Lovin L, Cook JM. Birds of a feather: Homophily in social networks. Annu Rev Sociol. 2001; 27(1):415-44. doi:10.1146/annurev.soc.27.1.415.

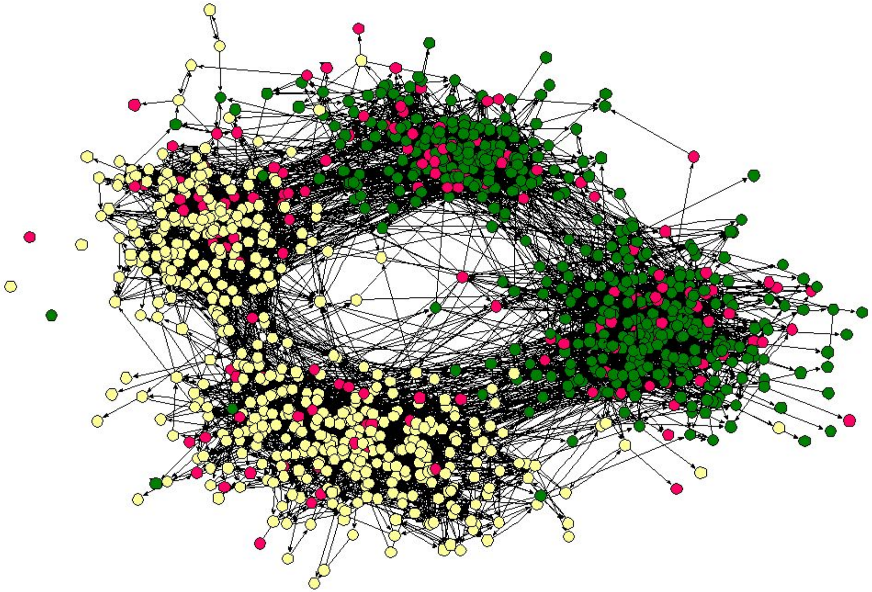


Moody, J. (2001). Race, school integration, and friendship segregation in America. American journal of Sociology, 107(3), 679-716.

Homophily (II)

Homophily in social networks is commonly tested through the topological principle of **assortativity**: the attributes at the ends of social links are correlated.

Newman ME. Mixing patterns in networks. Phys Rev E. 2003; 67(2):026126.



Moody, J. (2001). Race, school integration, and friendship segregation in America. American journal of Sociology, 107(3), 679-716.

Homophily (III)

Online discussion in MSN Messenger exhibits homophily with respect to interests, age, and location.

Singla P, Richardson M. Yes, there is a correlation:-from social networks to personal behavior on the web. In: Proceedings of the 17th international conference on World Wide Web. New York: ACM: 2008. p. 655–64. doi:10.1145/1367497.1367586.

Table 4: Similarities (%) comparing random pairs and messenger pairs

	Word	Query	Main Category	Sub Category	Zip	Age Group	Gender
Baseline	0.51	0.09	15.26	6.23	0.81	34.40	51.67
Messenger	1.00	0.62	16.68	7.59	13.00	64.19	48.74

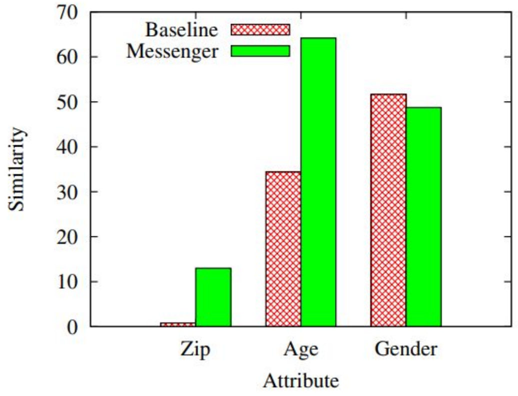


Figure 1: Similarities(%) comparing random pairs and messenger pairs: **personal attributes**

Homophily (IV)

In MySpace, commenting across profiles shows homophily with respect to a wide variety of demographic factors, including ethnicity, religion, age, and marital status.

Thelwall M. Homophily in myspace.
J Am Soc Inf Sci Technol. 2009; 60(2):219-31.

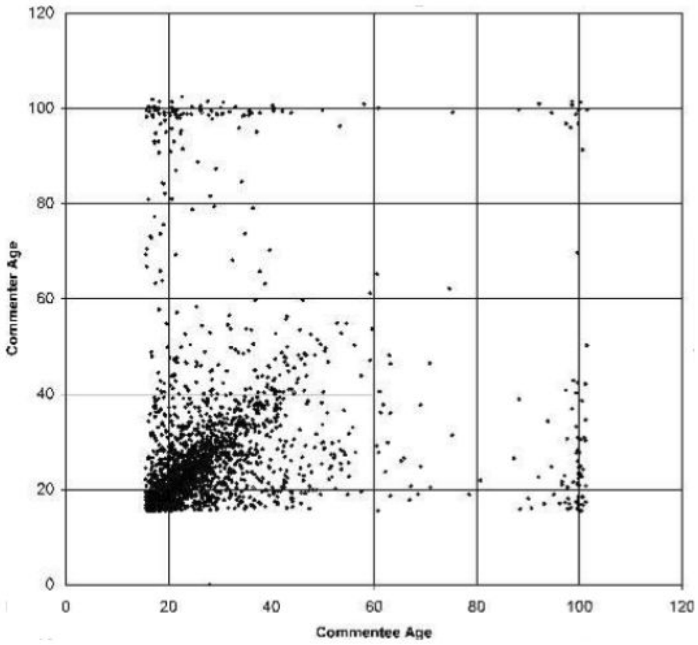


FIG. 2. Listed age of commenter against listed age of commentee. Random jitter of up to +/− half a year has been added to each age to minimise data overlap on the graph.

Homophily (V)

Subjective well-being and happiness has been found in Twitter when analyzing bidirectional reply links.

Bliss CA, Kloumann IM, Harris KD, Danforth CM, Dodds PS. Twitter reciprocal reply networks exhibit assortativity with respect to happiness. J Comput Sci. 2012; 3:388-97.

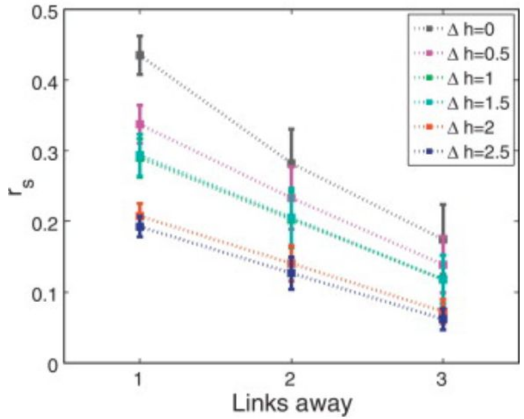


Fig. 9. Average assortativity of happiness for week networks measured by Spearman's correlation coefficients as Δ*h* is dialed from 0 to 2.5, with *α* = 50. As Δ*h* increases, the average correlation decreases. For large Δ*h* the resulting words under analysis have more disparate happiness scores and thus the correlations between users' happiness scores are smaller. Similarly, choosing Δ*h* to be too small (e.g., Δ*h* = 0) could result in an over estimate of happiness–happiness correlations because of the uni-modal distribution of h_{avg} for the labMT words. Thus a moderate value for Δ*h* is chosen (Δ*h* is set to 1 for this study).

Homophily (VI)

The network of political retweets exhibits a highly segregated partisan structure but this is not the case for the user-to-user mention network

Conover M, Ratkiewicz J, Francisco MR, Gonċalves B, Menczer F, Flammini A. Political polarization on Twitter. ICWSM. 2011; 133:89-96.

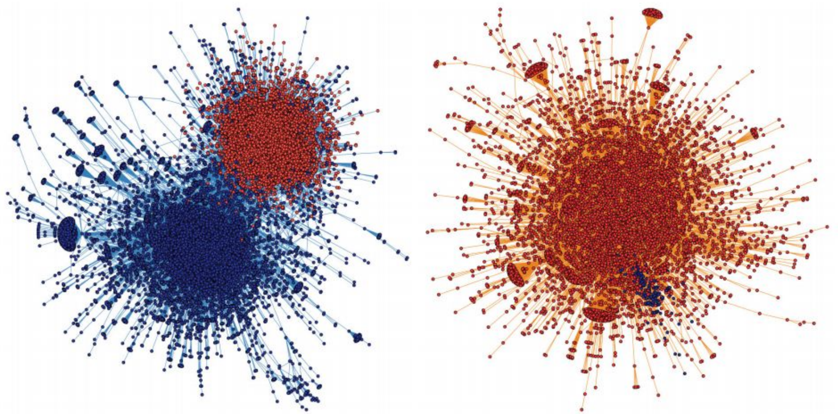


Figure 1: The political retweet (left) and mention (right) networks, laid out using a force-directed algorithm. Node colors reflect cluster assignments (see § 3.1). Community structure is evident in the retweet network, but less so in the mention network. We show in § 3.3 that in the retweet network, the red cluster A is made of 93% right-leaning users, while the blue cluster B is made of 80% left-leaning users.

Homophily (VII)

Interactions with positive connotation (supports and likes) display stronger patterns of homophily with respect to party alignment than the comments, where no homophily is present.

(a) Supports layer, $|V| = 2,740$, $|E| = 16,657$

(b) Likes layer, $|V| = 1,147$, $|E| = 6,386$

(c) Comments layer, $|V| = 1,091$, $|E| = 6,800$

Figure 2. Visualization of Network Layers of Supports, Likes, and Comments Excluding Unaligned Politicians. *Notes*: Colors of the nodes are labeled according to the parties self-reported by politicians. Party colors are reported in Table 1. The networks are drawn using the Fruchterman–Reingold layout algorithm (Fruchterman and Reingold, 1991).

Garcia D, Abisheva A, Schweighofer S, Serdült U, Schweitzer F. Ideological and temporal components of network polarization in online political participatory media. Policy & Internet. 2015; 7(1):46-79.

Homophily (VIII)

Wikipedia editors who display their party alignment on their profile show homophily with respect to this alignment when interacting through their user walls, but not through common discussions in talk pages.

Neff JJ, Laniado D, Kappler KE, Volkovich Y, Aragón P, Kaltenbrunner A. Jointly they edit: Examining the impact of community identification on political interaction in wikipedia. PLoS ONE. 2013; 8(4):e60584

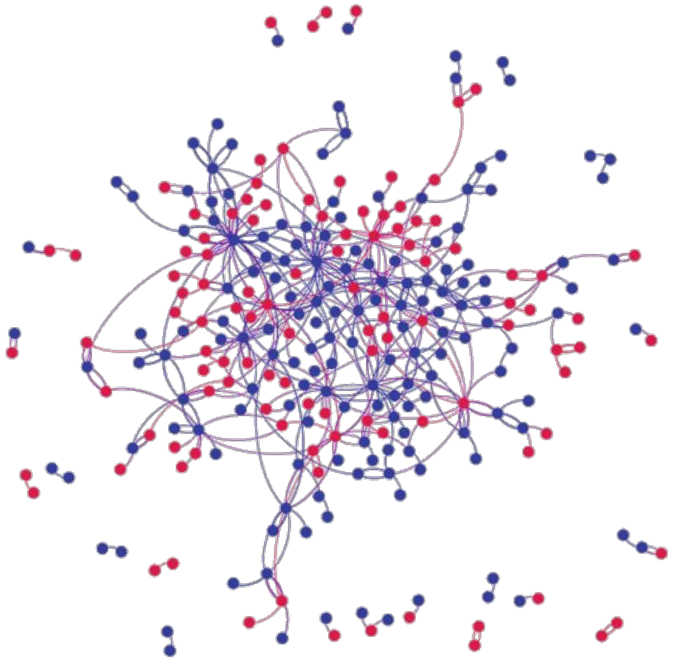


Fig. 2 The reply network in Wikipedia talk pages between Democrats (blue nodes) and Republicans (red nodes) shows no homophily with respect to party alignment. Data from [38]

Social influence (I)

While homophily implies assortativity, a**ssortativity can also be a manifestation of social contagion or peer influence when attributes are acquired** (such as religion or occupation) rather than ascribed (like race or age).

A large fraction of research has focused on social influence for message propagation in online platforms, however, some studies have explicitly evaluated the role of social influence in online discussion.

Social influence (II)

Social influence affected the discussions in an online learning environment: users were more inclined to follow social recommendations made by highly central users than those by peripheral ones.

Figure 1. Class Email Communication Network Structure (n=31)

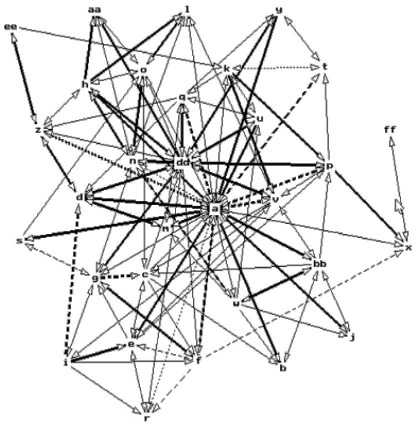
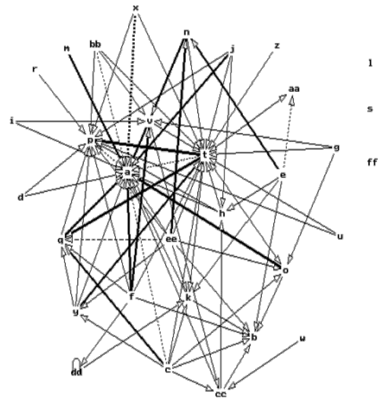


Figure 2. Class Discussion Board Communication Network Structure (n=32)



Cho H, Stefanone M, Gay G. Social information sharing in a CSCL Community. In: Proceedings of the Conference on Computer Support for Collaborative Learning: Foundations for a CSCL Community. Boulder: International Society of the Learning Sciences: 2002. p. 43–50.

Social influence (III)

For the discussions on Twitter about the Haiti earthquake, when the percentage of one's friends joining the discussion increases, the likelihood that the user also participates increases too.

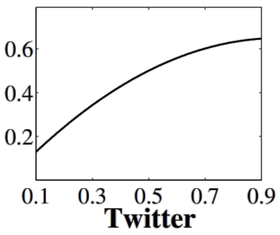


Figure 1: Social influence. The x-axis stands for the percentage of one's friends who perform an action at $t-1$ and the y-axis represents the likelihood that the user also performs the action at t.

Tan C, Tang J, Sun J, Lin Q, Wang F. Social action tracking via noise tolerant time-varying factor graphs. In: Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining. New York: ACM: 2010. p. 1049–58. doi:10.1145/1835804.1835936

Social influence (IV)

A study of the messages by thousands of participants across 16 Google Groups concluded that activity and tenure of discussion within a group were related to the ability to influence others.

Huffaker D. Dimensions of leadership and social influence in online communities. Hum Commun Res. 2010; 36(4):593-617.

Social influence has been also detected on Youtube in a experiment in which the comments of videos were proven to affect the evaluation of the videos' owners.

Walther JB, DeAndrea D, Kim J, Anthony JC. The influence of online comments on perceptions of antimarijuana public service announcements on youtube. Hum Commun Res. 2010; 36(4):469-92.

Emotional contagion (I)

The process by which **individual emotions are triggered by similar emotional states in other individuals**. Recent research has shown that emotional contagion is present:

- in computer-mediated communication as much as in face to face communication

  Derks D, Fischer AH, Bos AE. The role of emotion in computer-mediated communication: A review. Comput Hum Behav. 2008; 24(3):766-85.

- While reading and writing in forum threads

  Garcia D, Kappas A, Küster D, Schweitzer F. The dynamics of emotions in online interaction. Open Sci. 2016; 3:8.

Emotional contagion (II)

Manipulations of the selection of content seen by Facebook users led to their emotions moving in the predicted direction

Kramer AD, Guillory JE, Hancock JT. Experimental evidence of massive-scale emotional contagion through social networks. Proc Natl Acad Sci. 2014; 111(24):8788-90.

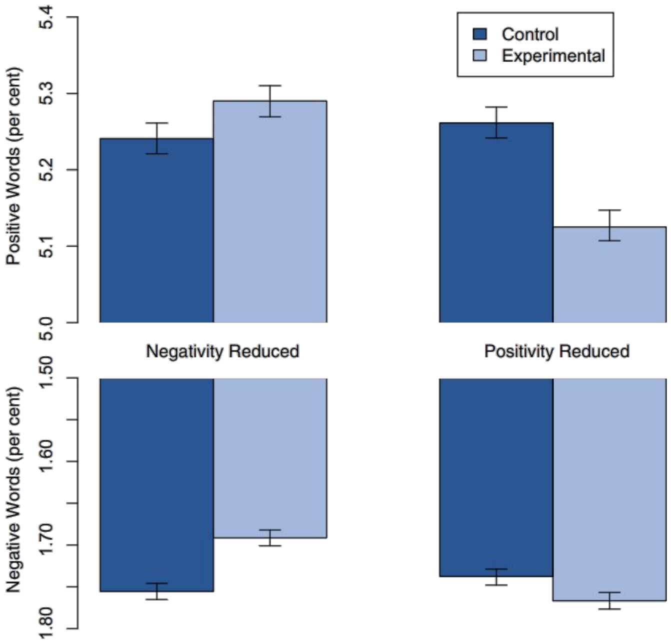


Fig. 1. Mean number of positive (*Upper*) and negative (*Lower*) emotion words (percent) generated people, by condition. Bars represent standard errors.

Emotional contagion (III)

Research on Twitter has shown a strong correlation between stimuli and responses in terms of valence

Ferrara E, Yang Z. Measuring emotional contagion in social media. PLoS ONE. 2015; 10:1–14.

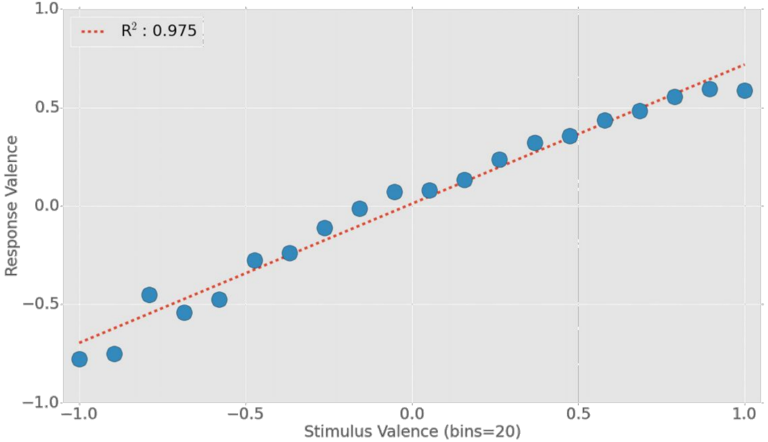
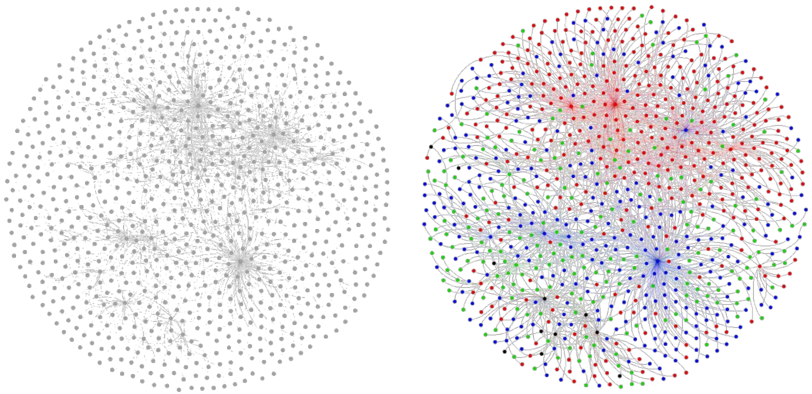


Fig 3. Relationship between stimulus and response valence in Twitter. The emerging linear relationship ($R^2 = 0.975$) suggests that there is a strong correlation between stimuli and responses in terms of valence (difference between positive and negative sentiments in the set of tweets).

Emotional contagion (IV)

The analysis of emotional expression in Weibo (Chinese Twitter) shows asymmetric properties of emotional contagion: Anger seems to be more contagious than joy

Fan R, Zhao J, Chen Y, Xu K. Anger is more influential than joy: Sentiment correlation in weibo. PLoS ONE. 2014; 9:1-8.



(a) An interaction network. (b) Node colored by emotions.

Figure 2. (Color online) The giant connected cluster of a network sample with $T=30$. (a) is the network structure, in which each node stands for a user and the link between two users represents the interaction between them. Based on this topology, we color each node by its emotion, i.e., the sentiment with the maximum tweets published by this node in the sampling period. In (b), the red stands for *anger*, the green represents *joy*, the blue stands for *sadness* and the black represents *disgust*. The regions of same color indicate that closely connected nodes share the same sentiment.

Emotional contagion (V)

In Wikipedia article talk pages, editors tend to interact with editors with a similar emotional style. This might be an effect of emotional contagion and/or emotional and linguistic homophily.

Iosub D, Laniado D, Castillo C, Fuster Morell M, Kaltenbrunner A. Emotions under discussion: Gender, status and communication in online collaboration. PLOS ONE. 2014; 9:1–23.

Fig. 3 Reply network of users on Wikipedia article talk pages. The color of nodes expresses the proportion of words expressing anger (from blue to red). Assortativity observed in this network (e.g. clusters of red nodes) might be explained by either homophily or emotional contagion. Data from [66]