Diffusion Patterns Of Social Network Posts

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PRESENTER

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Applied mathematician with experience in commercial software development, university teaching (math, programming), inventing (mechatronics and silicate technology) and military service (mandatory).

Current **fields of interest** - complex network analysis in sociology and construction 3D printing.

TEAM

Centre of Applied Big Data Analysis is a team of specialists in technic (programmers, mathematicians) and humanities (sociologists, psychologists). We use statistics, data science and network science approaches to analyse social and psychological data. Some of our projects:

- Studying interconnection between student’s digital trace and educational achievements
- Studying the affect of social media content on real life wellbeing of human
- Studying the structure of extremist, self-harm and suicidal behavior in social network

...

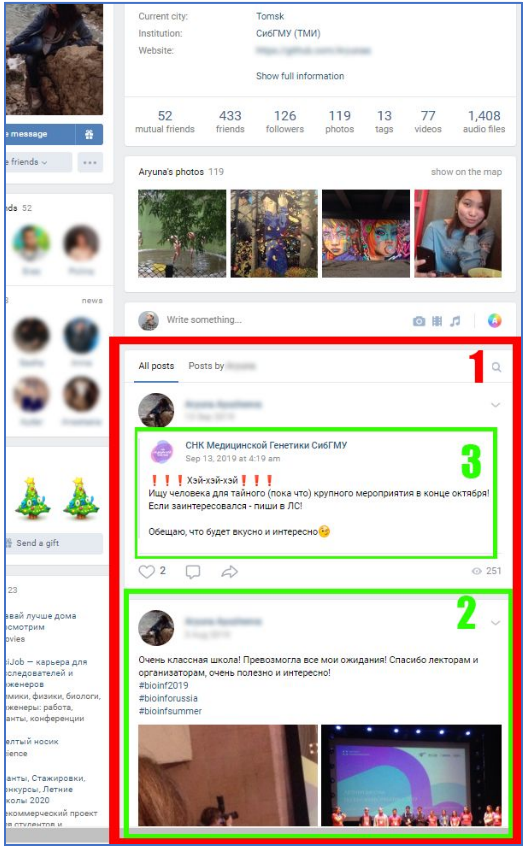
OBJECT DESCRIPTION

Vkontakte is the most popular russian social network with open API and chronological **newsfeed** ordering.

Actors - users and groups.
Links - friendships and subscriptions.

The **unit of information** - post on the wall of user or group, that is visible in **newsfeeds** of friends and subscribers

1. The wall
2. Author's post
3. Repost



PROBLEM DESCRIPTION

What we want to know about spreading?

- **Why?** Is the information viral or does it need social support?
- **What?** The information: is it spreads because it's so effective or it was just started to spread from the best place?
- **Who?** Which actors are make the greatest impact in information spreading?

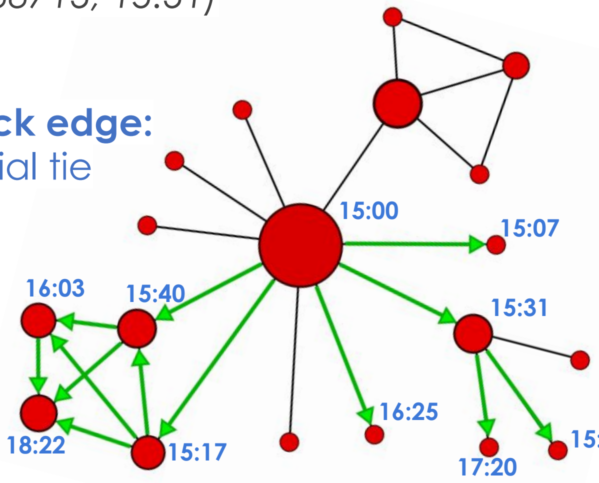
Cascade is a sequence of pairs (actor_id, publication_time):

(38761, 15:00)
(4598, 15:07)
(988713, 15:31)
…

Node: an actor
Time: moment of repost

Black edge: social tie

Green arc: Possible transmission through tie



Cascade combined with **social network** gives **pattern of spreading**

OBJECT FEATURES

What's challenging with our object?

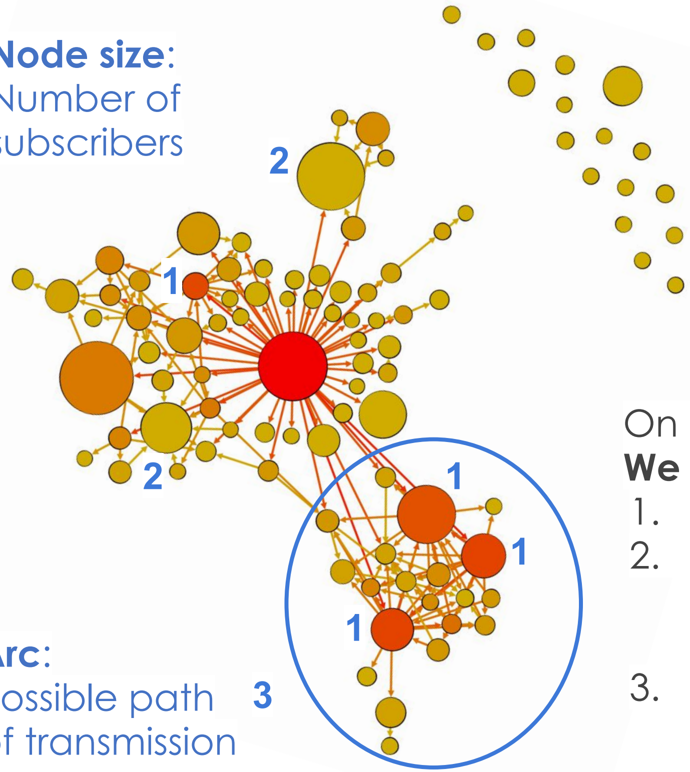
- The **local** (city or region) information cascdes are relatively small (50-400 reposts)
- Social network is **partially relevant**
- Channels of spreading are **partially observable**

That's why it's hard to use many existing approaches

VISUAL APPROACH

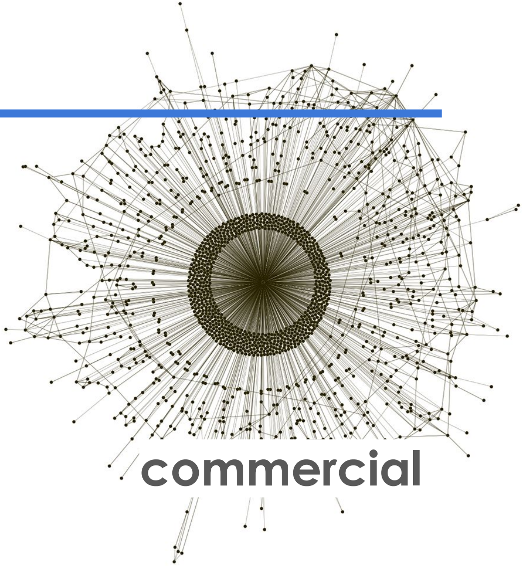
Pattern of spreading

Node size: Number of subscribers

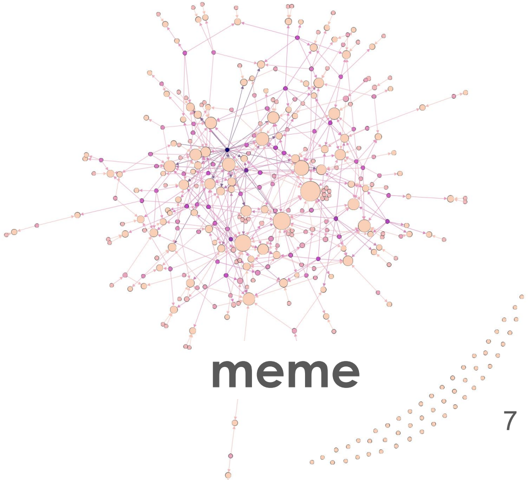


Arc: Possible path of transmission

On the right
We can see that pattern graphs are quite different for commercials and for memes

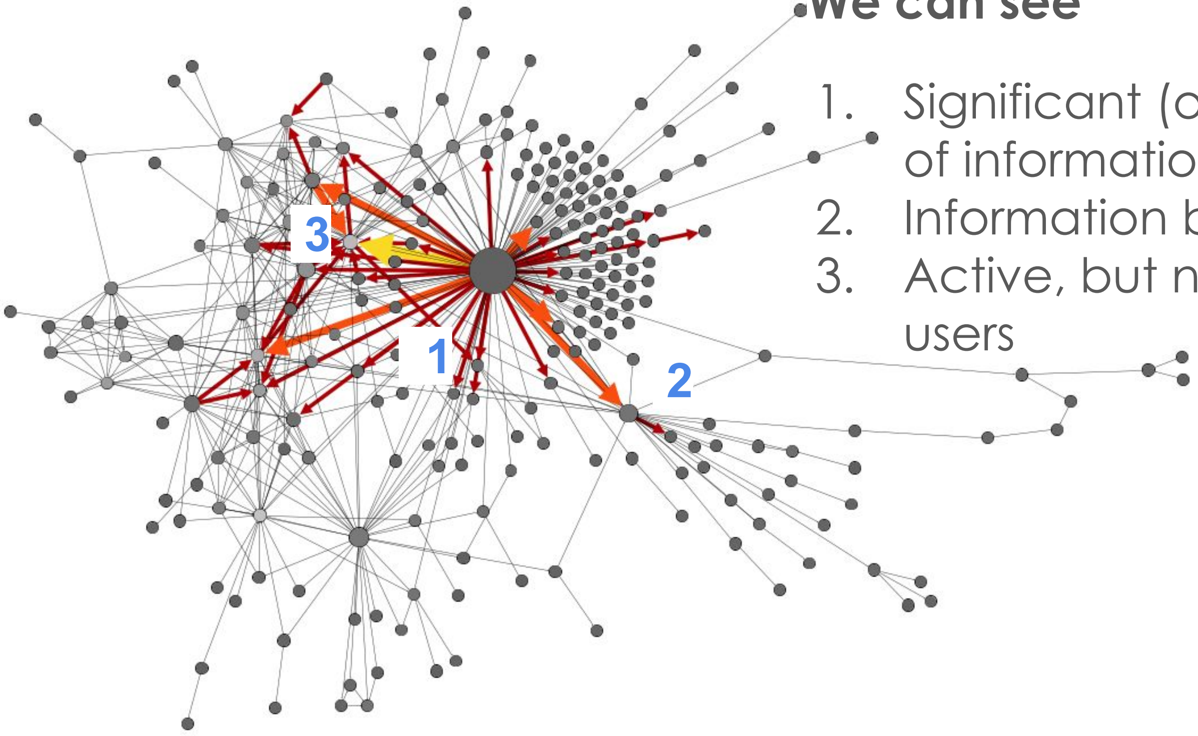


On the left
We can see
1. Significant nodes candidates
2. Outsiders (nodes that have a lot of friends but nobody reposts from them)
3. Clusters of users



VISUAL APPROACH

- Pattern of spreading for multiple cascades



We can see

1. Significant (often used) paths of information spreading
2. Information brokers
3. Active, but non significant users

STATISTICAL APPROACH

All diffusion patterns are result of some stochastic process

Diffusion model for each link between infected **i** and suspicious **j** defines the such function $\mathbf{P_{ij}(t)}$ that at time interval **(t, t+dt)** information spreads through this link with probability $\mathbf{P_{ij}(t)dt}$.

For example, for classic infection SI process $\mathbf{P_{ij}(t)}$ is a **constant** (so-called infection rate θ)

$$\boxed{\frac{dP_j(t)}{dt} = \theta N_j(t)}$$

SI process, where $\mathbf{P_j(t)}$ is a probability for actor **j** to be infected at moment **t**. $\mathbf{N_j(t)}$ - number of **j**'s neighbors, infected at this moment.

DIFFUSION MODEL

θ - the infection rate (**virulence**) through observable tie (θ >= 0)

ρ - the infection rate through unobservable tie (**background**) (ρ >= 0)

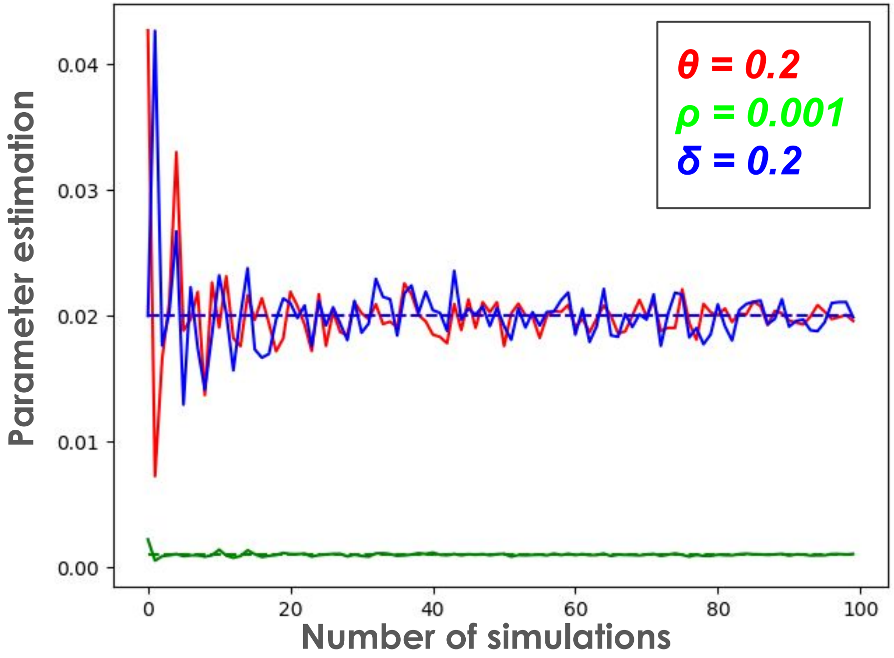
κ - **conformism** (social pressure coefficient) (-1<= κ <= 1)

δ - **decay** (information obsolescence coefficient) (δ >= 0)

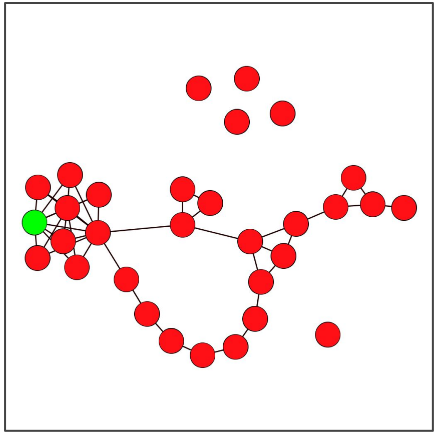
$$\frac{dP_j(t)}{dt} = \rho \sum_{i \in A(t)} e^{-\delta(t-t_i)} + \tau_\kappa(j,t)\theta \sum_{i \in A_j(t)} e^{-\delta(t-t_i)}$$

PRELIMINARY RESULTS

estimations are **consistent** on the set of simulated cascades

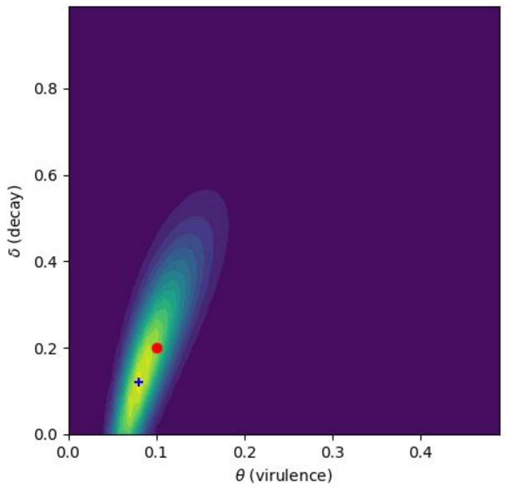


Model network for testing convergence. **Green** node is a **source** of infection



PRELIMINARY RESULTS

Infection rate and **decay** are correlated (obviously)



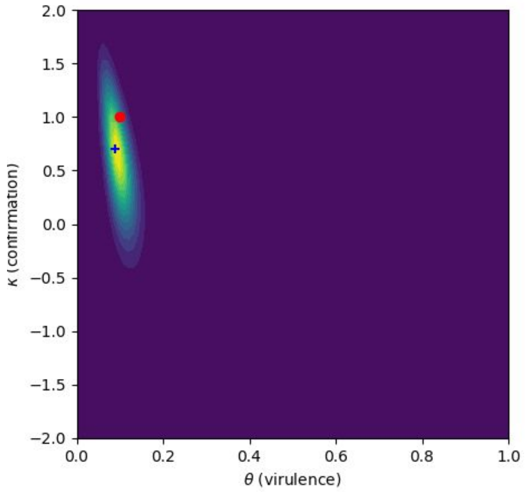
Heatmap of **likelyhood** function
Red dot - true parameters
Green cross - MLE

θ/δ is the probability of spreading through an edge at least once during infinite time. This value tends to have better estimation.

But it is possible to separate **θ** from **δ** on the set of cascades (**δ** is cascade-independent).

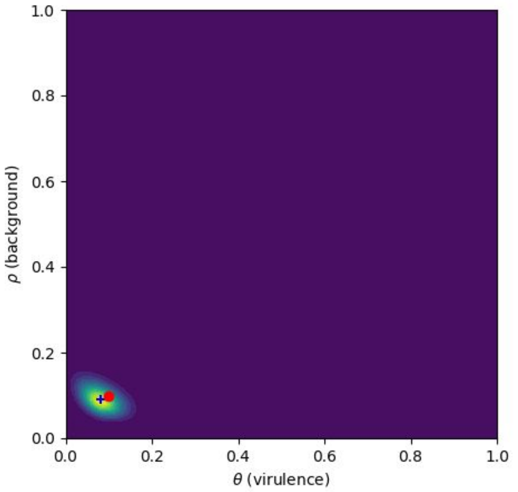
PRELIMINARY RESULTS

conformism is very fuzzy. We keep it away from the model for now



Heatmap of **likelyhood** function
Red dot - true parameters
Green cross - MLE

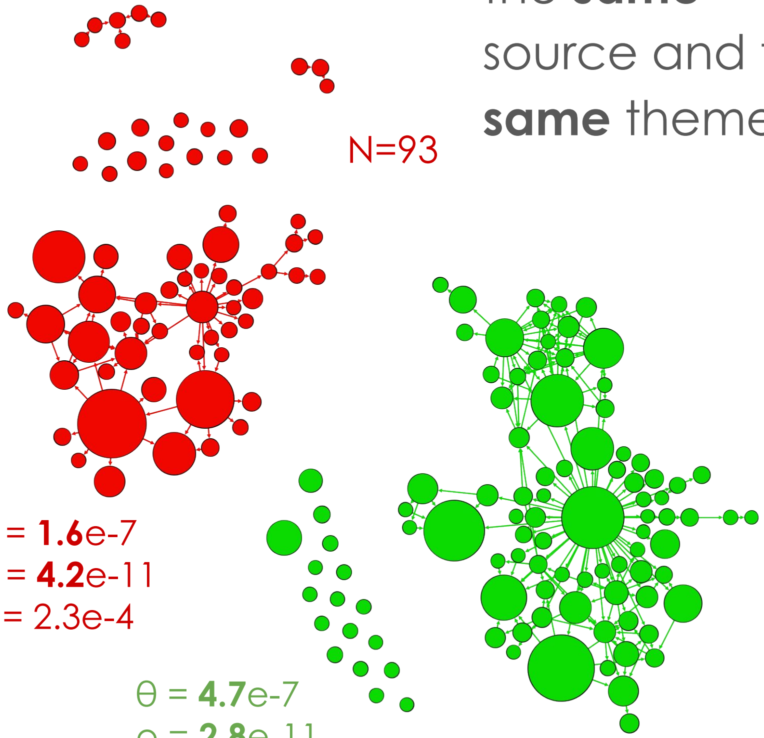
background is separated from **infection rate** surprisingly well



Heatmap of **likelyhood** function
Red dot - true parameters
Green cross - MLE

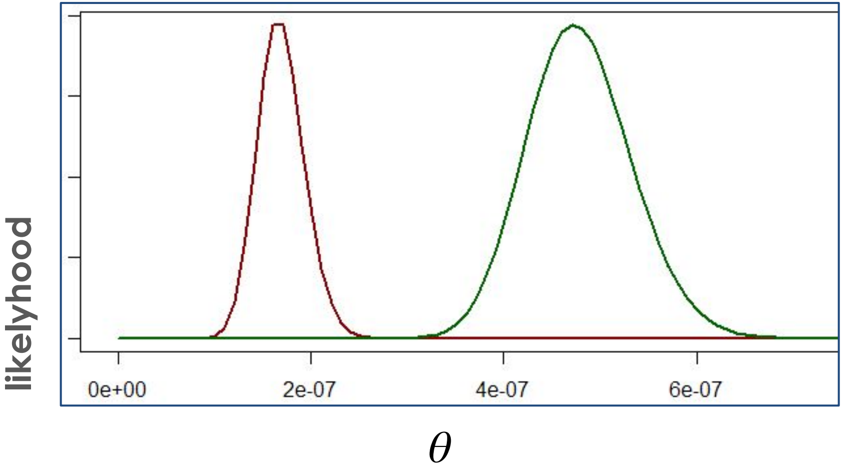
PRELIMINARY RESULTS

the **same** source and the **same** theme



θ = **1.6**e-7
ρ = **4.2**e-11
δ = 2.3e-4

θ = **4.7**e-7
ρ = **2.8**e-11
δ = 2.4e-4



δ is about the same for both cascades. **ρ** is **1.5** times higher for **red**. **θ** is **3** times higher for **green**.

Seems that people like to **spread bad** news but they also like to **manifest good** things.

FURTHER DEVELOPMENT

1. Complete the testing
2. Compare results with existing models
3. Implement parallel calculations and easy-to-use python library
4. Implement the opinion leader detection

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