Information Transfer in Social Media

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Plan of presentation

- Approaches to characterizing influence
- Using transfer entropy: what is the difference from previous studies?
- Notations and definitions of transfer entropy
- Sampling problems and solutions
- Experiments on synthetic data
- Experiments with Twitter dataset

Recent approaches to influence measuring

- Methods based on explicit causal knowledge
  - Pagerank score
  - Passivity score
  - Using the size of cascade trees
- Algorithms working without knowing the relationship structure
  - Transfer entropy

Notations

$S_X = \{t_j : 0 < t_1 < t_2 \ldots\}$ - timing of tweets

$$B_X(a,b) \equiv \begin{cases} 1 & \text{if } \exists t_j \in S_X \cap (b,a], \\ 0 & \text{otherwise.} \end{cases}$$ - binned variable (I)

$\delta \in \mathcal{R}$ - bin width; T - considered time period

$$P(B_X(t,t-\delta) = X_t) \equiv \frac{1}{T-\delta} \int_{\delta}^{T} dt [B_i(t,t-\delta) = X_t]$$ - probabilities over the binned variables (II)

$$P(B_X(t,t-\delta_0) = X_t, B_X(t-\delta_0, t-\delta_0-\delta_1) = X_{t-1}, \ldots)$$ - joint probability distribution (III)

$$P(X_t^{(t-k)}), \quad where \quad X_t^{(t-k)} = \{X_t, X_{t-1}, \ldots, X_{t-k}\}$$ - simplified written form of joint probability distribution (IV)

Definition of Transfer Entropy

$$H(A|B) = -\sum_{A,B} P(A,B) \log P(A|B)$$ - conditional entropy (I)

$$T_{X \to Y} = H(Y_t | Y_{t-1}^{(t-k)}) - H(Y_t | Y_{t-1}^{(t-k)}, X_{t-1}^{(t-l)})$$ - information transfer (II)

↑ level of uncertainty with knowing Y's history of activity

↑ level of uncertainty with knowing Y's and X's history of activity

Sampling problems and their solutions

- Absence of sufficient data ⟶ To set a minimal level of activity
- Heavy tail in the distribution of the response times ⟶ To set the bins of equal size
- Bias connected with «binned» approach to data modelling ⟶ To use a class of binless entropy estimators

Experiments with synthetic data

Model I

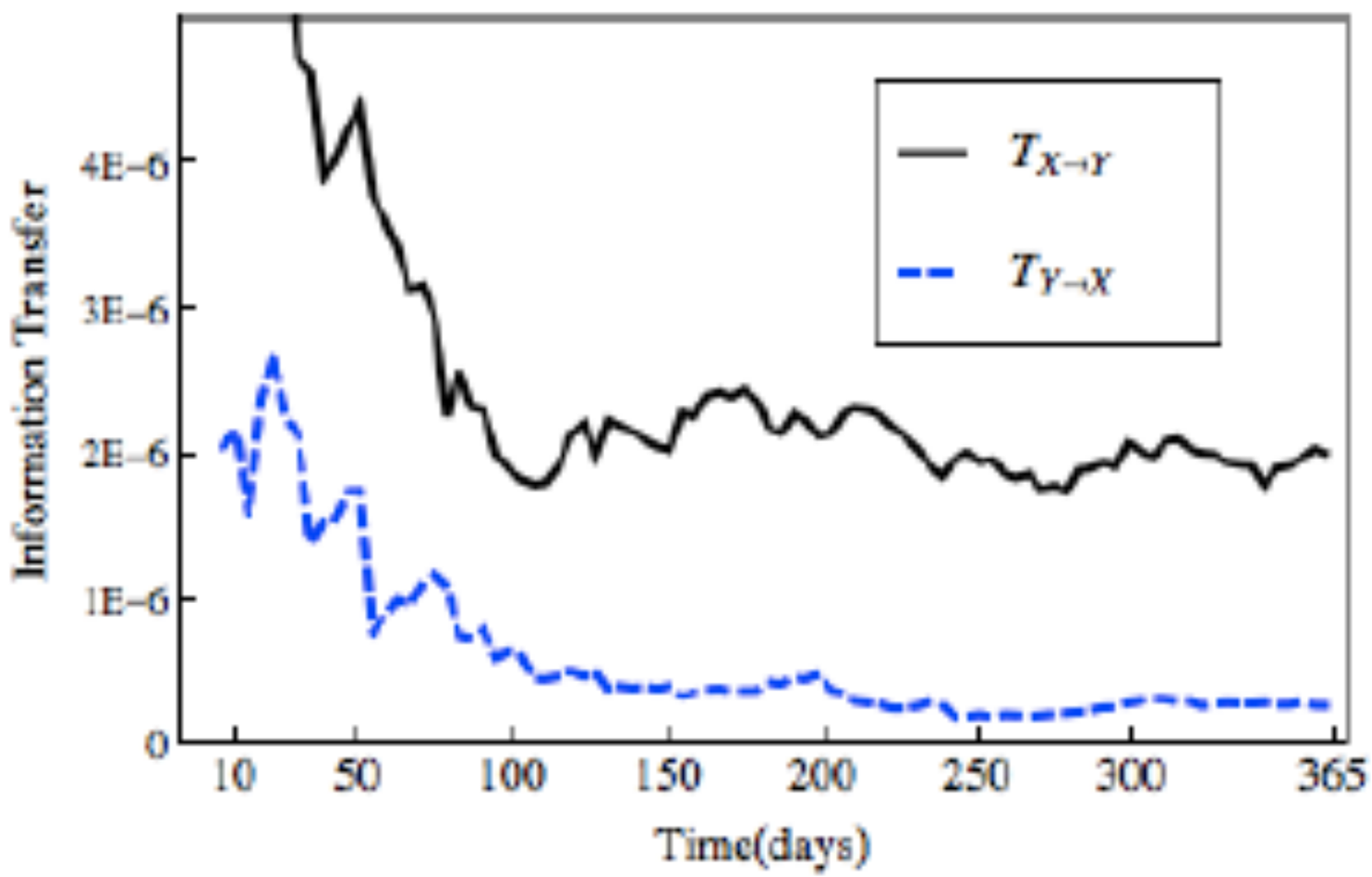
$\lambda_Y(t|S_X^t) = \mu + \gamma \sum_{t_i \in S_X^t} g(t - t_i)$ - Poisson distributed user activity

$g(\Delta t) = \min(1, \left(\frac{1\ \text{hour}}{\Delta t}\right)^3)$ - time dependence of the influence

γ - the strength of influence of X

μ - constant rate of background activity

Transfer Entropy for data generated according to Model 1



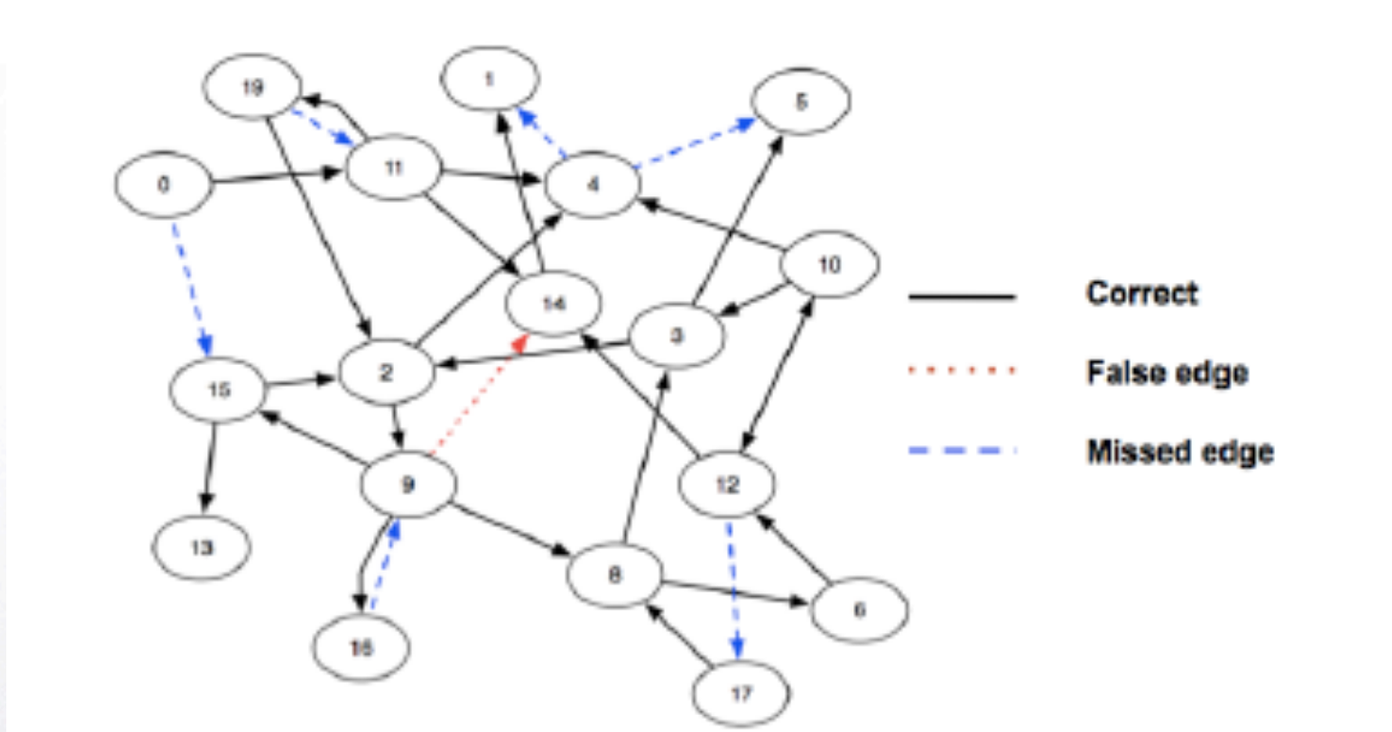
Experiments with synthetic data

Model II

$$\lambda_Y(t|S^t_{\mathcal{N}(Y)}) = \mu + \sum_{X \in \mathcal{N}(Y)} \gamma_X \sum_{t_i \in S^t_X} g(t - t_i)$$

- activity distribution for many users

Recovered network structure for Model II



Working with Twitter dataset

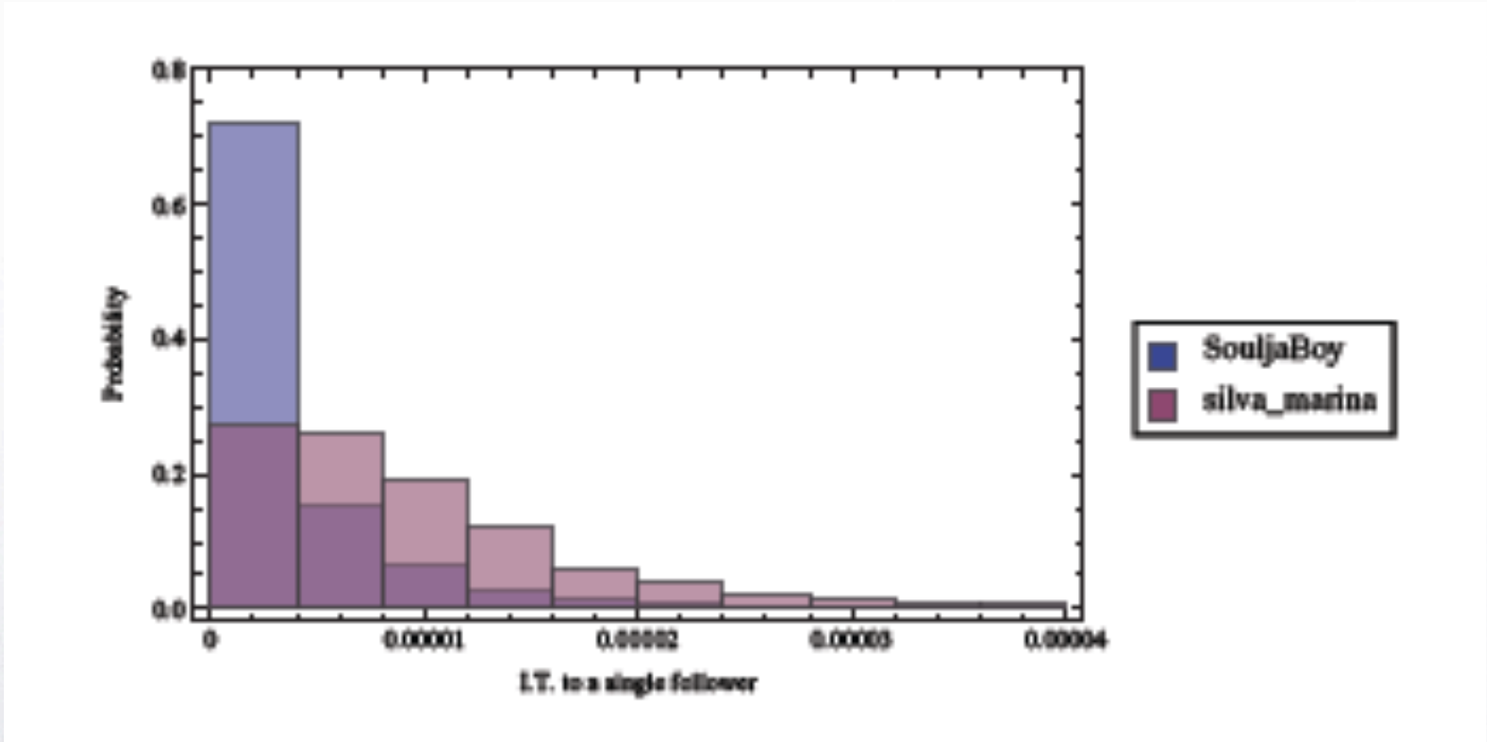
70 000 distinct URLs
3 500 000 tweets
800 000 users
Time period (T) = 3 weeks

Active user tweeted > 10 tweets for three weeks

δ_0 - 1 sec
δ_1 - 10 min
δ_2 - 2 hours
δ_3 - 24 hours

How can we use the information transfer meaningfully?

Probability distribution of outgoing transfer entropy
for SouljaBoy and silva_marina



Conclusions

- Information transfer based approach works without knowing the maps of the relationships $\longrightarrow$ recovering the network structure and finding influentials
- For better estimation many effects impact are taken into account
- Synthetic data based experiments showed rather good results of recovering nertwork structure
- Twitter data analysis proved to be more certain tool for finding the influentials and provided the idea that influence changes through times

Thank you for your attention!