Modeling Peer Influence in Time-Varying Networks

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Introduction

Motivation

Human behavior

- complex dynamics (e.g., bursty)
- influenced by peers

Applications

- detection of bots in online platforms
- sustainability of social and collaboration networks

Related Work

Activity-driven approach by Perra *et al.* [1]

- time-varying networks
- activity potential a_i

Community extension by Laurent *et al.* [2]

- memory, closure processes
- community structures, strong and weak ties

Limitations

- activity potential is fixed and intrinsic
- no dependencies or external influences

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Model

Peer Influence Model Definition

Peer influence p_i

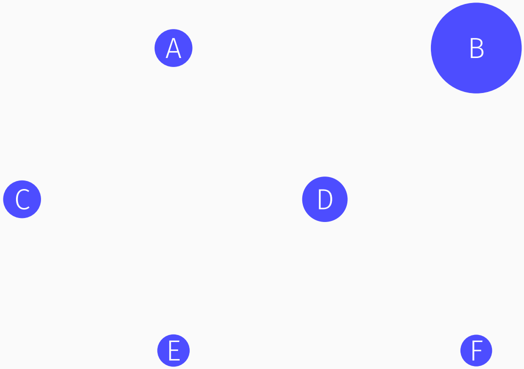
- number of active neighbors
- strong ties are more influential
- upper bound q

Activation probability

- mapping active neighbors onto probability
- requirements (critical threshold, saturation)

Peer Influence Model Illustration

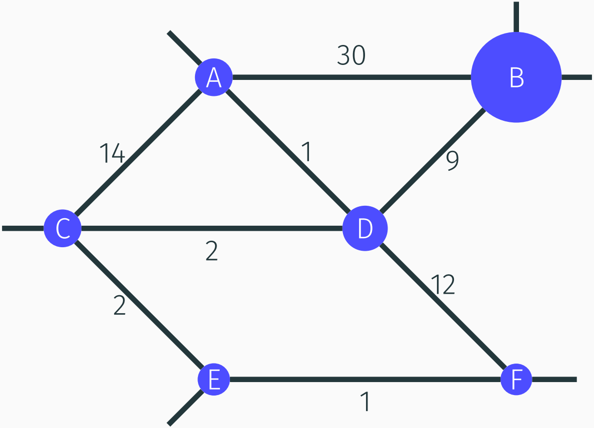
Initial situation



$t = 0$

Peer Influence Model Illustration

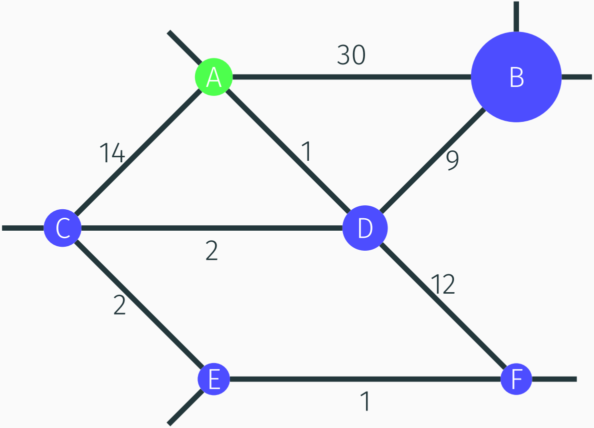
Situation at the beginning of iteration x



$t = x$

Peer Influence Model Illustration

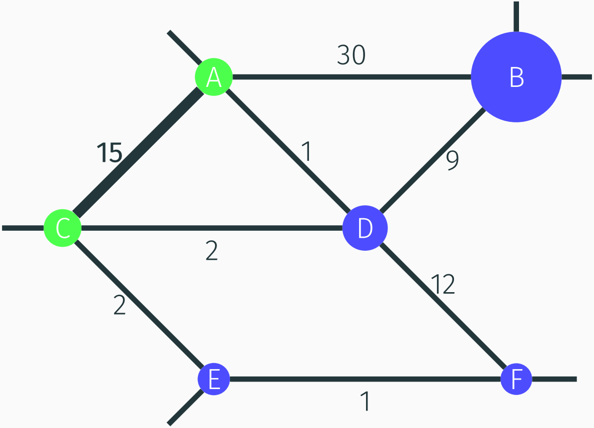
Node becomes active



$t = x$

Peer Influence Model Illustration

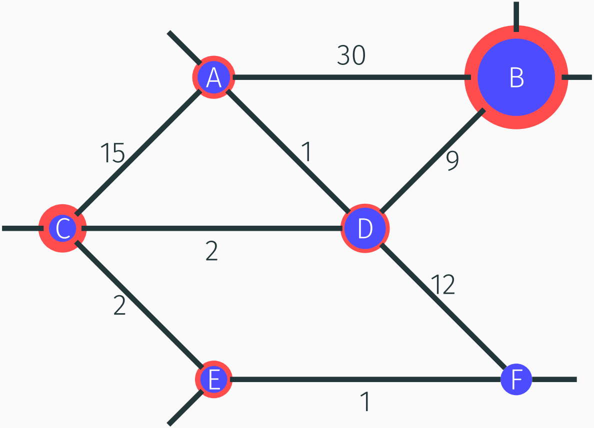
Node interacts with other node



$t = x$

Peer Influence Model Illustration

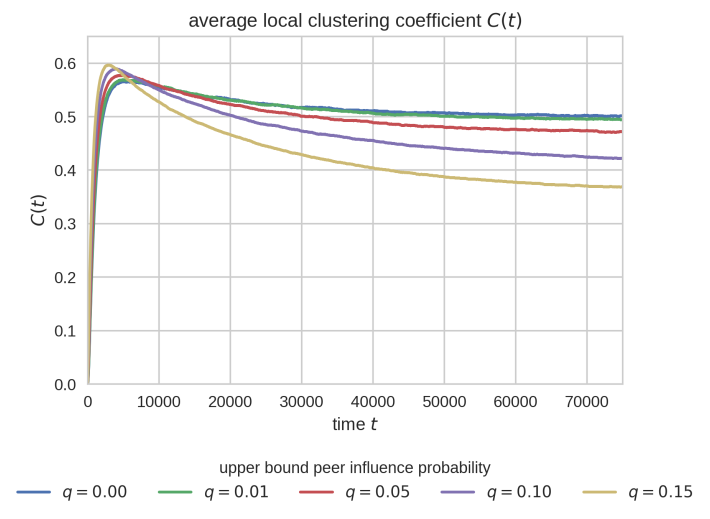
Effects on the neighbors in the next iteration



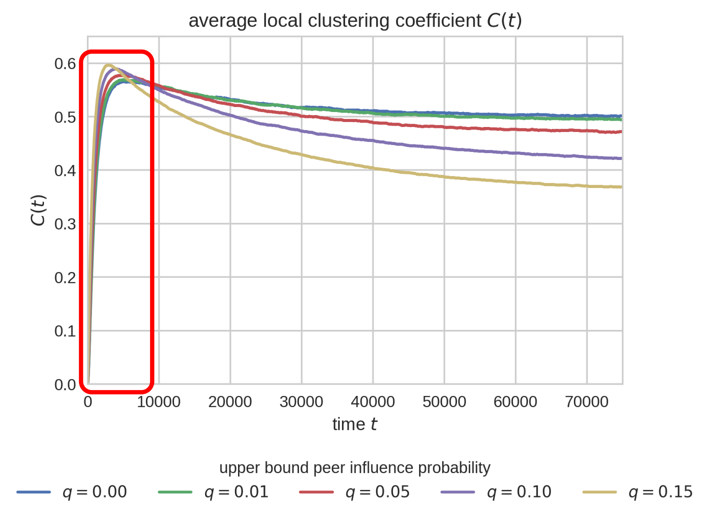
$t = x + 1$

Results

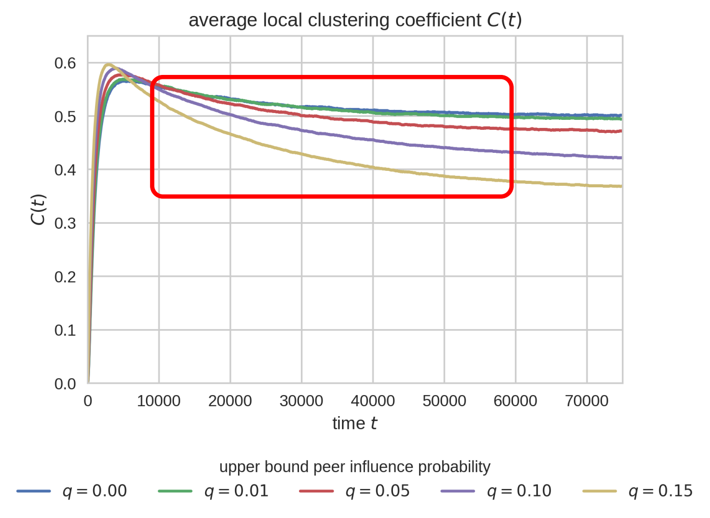
Development of community structures



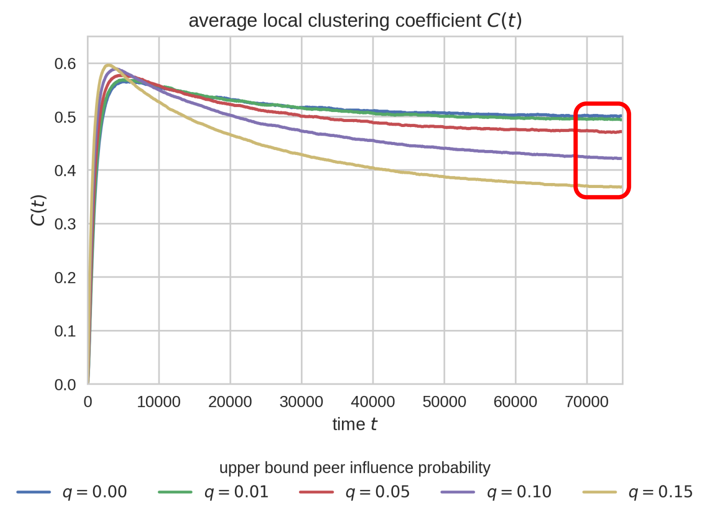
Development of community structures



Development of community structures

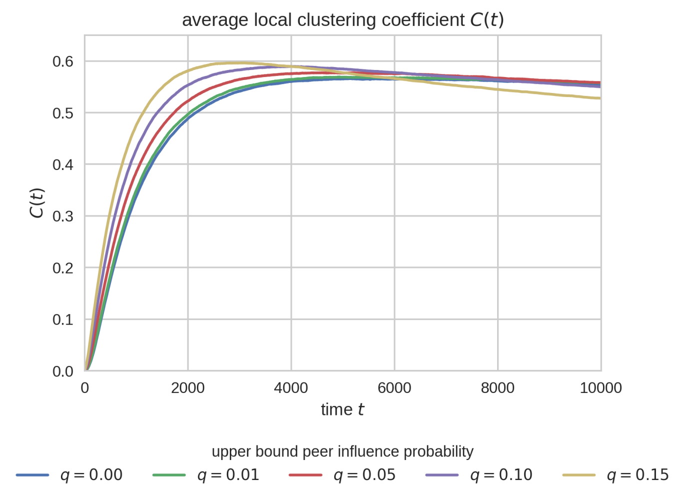


Development of community structures



Time-dependent Network Properties

Initial phase of $C(t)$



Inter-Event Time Distribution

Inter-event times

- time between two consecutive activations
- long tailed distribution

Burstiness

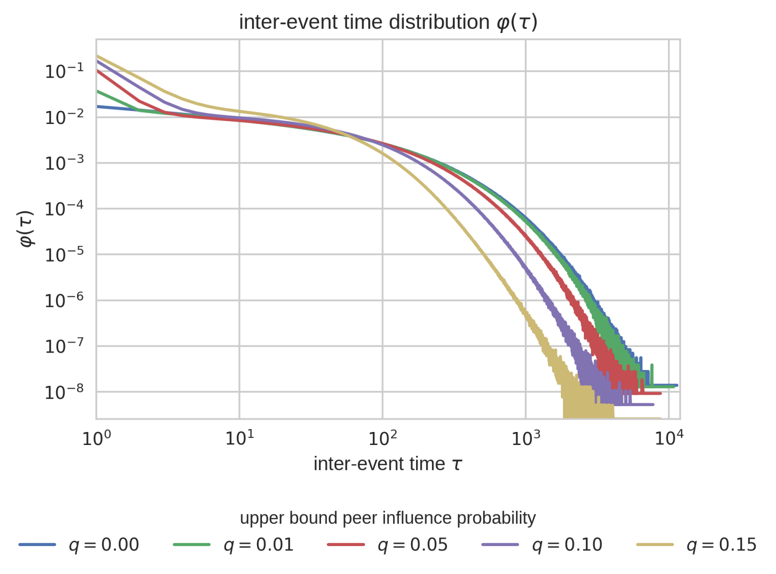
- moments of inter-event time distribution $\varphi(\tau)$
- burstiness parameter $B \in [-1, 1]$

Burstiness

q	0.00	0.01	0.025	0.05	0.075	0.10	0.15
μ	198.7	184.6	164.3	132.8	102.4	76.3	37.2
σ	291.3	270.5	241.4	197.4	155.1	118.0	61.2
B	0.189	0.189	0.190	0.196	0.205	0.215	0.244

Table 1: Mean value μ, standard deviation σ, and the resulting burstiness parameter B of the inter-event time distribution $\varphi(\tau)$ for different upper bounds of peer influence q.

Inter-Event Time Distribution



Conclusion

Conclusion

Contributions

- specification of a model
- evaluation on synthetic networks

Limitations/issues

- balancing the effect

Future Work

- improve/simplify mechanism
- real-world data sets
- ...

Questions?

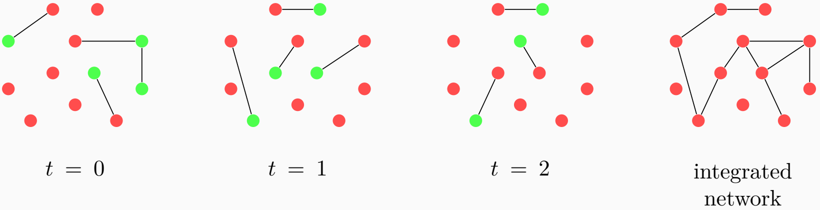
Model Details: Dynamics

For each time step t:

1. Create a new empty network G_t
2. each node v_i in G_t becomes active w. p. $f(a_i, p_i)$
3. active neighbors choose their communication partners and form links with them
4. increment time $t \to t + 1$

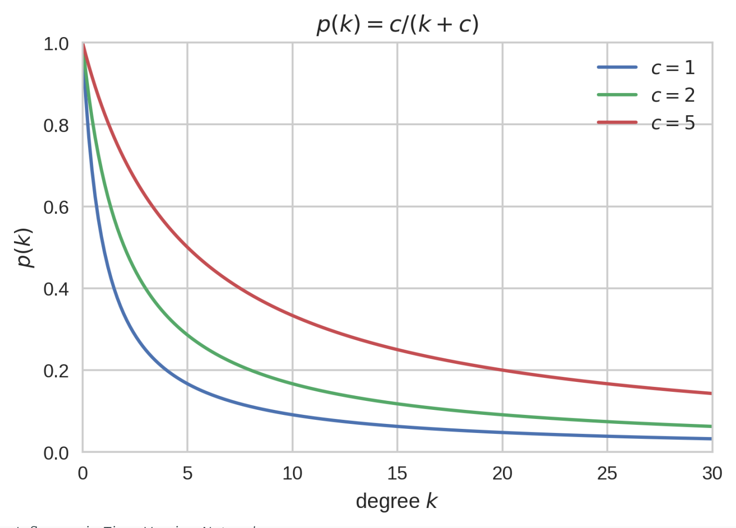
Model Details: Network Generation

time-varying network as sequence of *instantaneous networks*



Model Details: Reinforcement Process

Probability for the formation of a new tie $p(k)$



Model Details: Cyclic Closure Mechanism

Mechanism responsible for the formation of triangles in the network structure

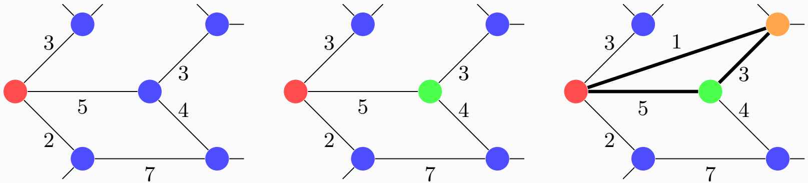
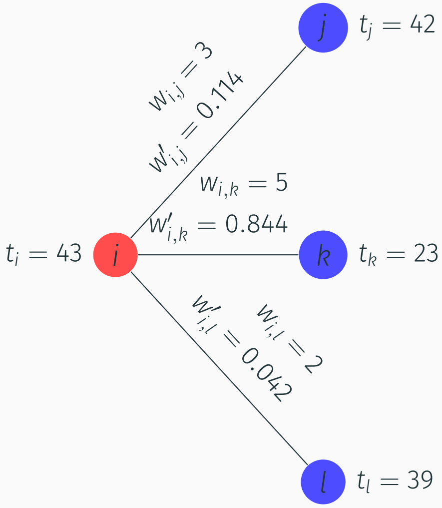


Figure 1: example for the cyclic closure mechanism

Model Details: Peer Influence Mechanism



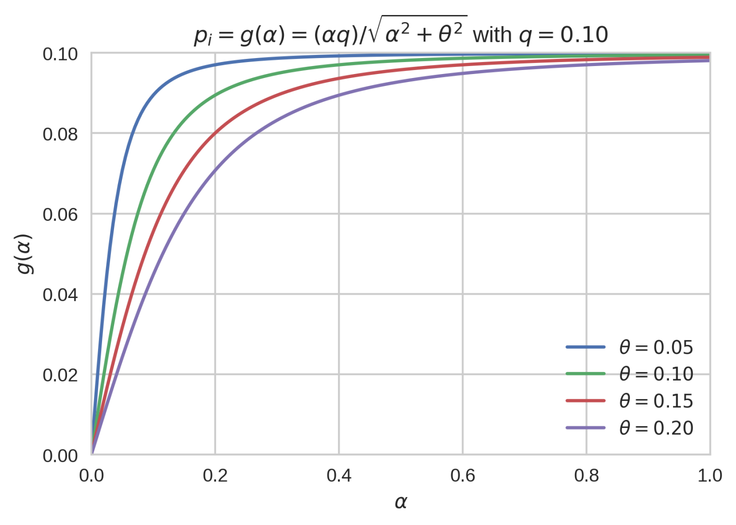
$$w'_{i,j} = \frac{\exp(\beta w_{i,j})}{\sum_{k \in N(v_i)} \exp(\beta w_{i,k})} \quad (1)$$

$$\alpha_i(t) = \frac{\sum_{j \in N(v_i)} \mathbf{1}_{\{t_j = t-1\}} w'_{i,j}}{\sum_{j \in N(v_i)} w'_{i,j}} \quad (2)$$

$$p_i(t) = \frac{\alpha_i(t) q}{\sqrt{\alpha_i^2(t) + \theta^2}} \in [0, q] \quad (3)$$

Model Details: Sigmoid Function

Mapping from fraction of active neighbors onto probability



Model Details: All Model Parameter

Activity-driven framework: n, $f(x)$, ε, Δt, η, m

community extension: p_Δ, p_d, δ, c

Peer influence extension: β, q, θ

Results: Clustering

q	0.00	0.01	0.025	0.05	0.075	0.10	0.15
t_{max}	5,140	4,919	4,839	5,192	4,173	4,044	3,038
C_{max}	0.566	0.569	0.572	0.577	0.582	0.59	0.596

Table 2: The maximum value for the local clustering coefficient $C_{max} = \max C(t)$ and the time to reach the maximum $t_{max} = \arg\max C(t)$, for different values of q.

Burstiness Measures

Coefficient of variation

$$c_v = \frac{\sigma}{\mu} \tag{4}$$

Burstiness parameter by Goh and Barabási [3]

$$B = \frac{c_v - 1}{c_v + 1} = \frac{\sigma - \mu}{\sigma + \mu} \tag{5}$$

References i

- Nicola Perra, Bruno Gonçalves, Romualdo Pastor-Satorras, Ro Vespignani, and Linkalab Cagliari.
  Activity driven modeling of time varying networks.
  Scientific reports, 2:469, 2012.
- Guillaume Laurent, Jari Saramäki, and Márton Karsai.
  From calls to communities: a model for time-varying social networks.
  The European Physical Journal B, 88(11):301, 2015.
- Kwang-Il Goh and Albert-Laszlo Barabási.
  Burstiness and memory in complex systems.
  EPL (Europhysics Letters), 81(4):48002, 2008.