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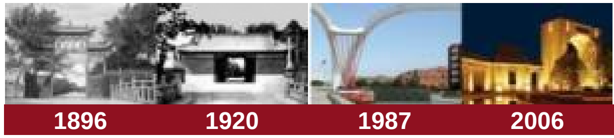

Modeling Information Diffusion in Multi-Sensitive Networks

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Time Line:

6 weeks reading papers

6 weeks proposing a new model and trying to prove it

Introduction:

Information Diffusion in online social networks

Epidemic spread model

Learning algorithms

Considering this phenomenon:

Sometimes the famous answerers (e.g. Zhang Jiawei and Ma Qianzu) answered a question totally wrong form the professional perspective, but still received lots of likes. Public sees that you have lots of fans, than they think that your answer is right, and vote for it.

So, that’s what I’m going to find. I think the rate of information diffusion will change with the number of edges a transmit node have. If a node has more edges than others, it has more “fans”, and gets more popular. Then, information provided by the popular node has a stronger ability to propagate than the “unknown” one. Meanwhile, the diffusion rate will attenuate with transmitting time growing.

it’s the first work to establish a theoretical framework under which the impact of the shape of infection rate with consideration of the infected node’s edges on the information diffusion dynamics is discussed!

Diffusion Models for Multi-Sensitive Networks

Overview:

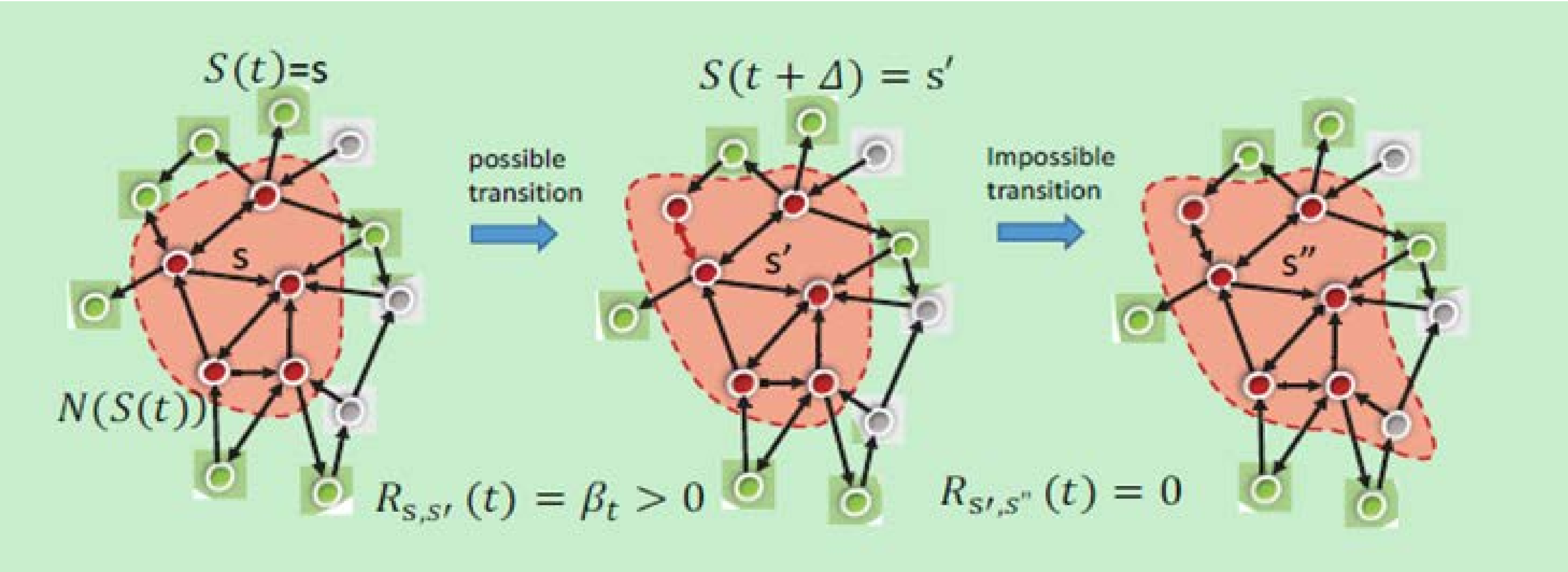
$$\mathrm{G} = (\mathrm{N}, \mathrm{E})$$

$$\mathrm{S(t)} = (S_1(t), S_2(t), \dots, S_n(t)) \in \{0,1\}^n$$

$$\mathrm{N}\big(\mathrm{S(t)}\big) = \{\mathrm{j} \in \mathrm{N} \backslash \mathrm{S(t)} \mid \exists (\mathrm{i,j}) \in \mathrm{E}, \mathrm{i} \in \mathrm{S(t)}\}$$

$$\partial(\mathrm{S(t), j}) = \{(\mathrm{i,j}) \in \mathrm{E} \mid i \in S(t), j \in N(S(t))\}$$

$$p_i = \beta \times \big|\partial\big(s(t,i)\big)\big|$$



$S(t)$=s
$S(t+\Delta) = s'$
possible transition
Impossible transition
s
s′
s″
$N(S(t))$
$R_{s,s'}(t) = \beta_t > 0$
$R_{s',s''}(t) = 0$

Diffusion Models for Multi-Sensitive Networks

Model of Time-sensitive information diffusion:

$$\mathrm{m(t)} = \int_0^t \beta ds$$

$$\{S(t_1), S(t_2), \dots, S(t_r)\}$$

$$\{\breve{S}(m(t_1)), \tilde{S}(m(t_2)), \dots, \tilde{S}(m(t_r))\}$$

$$p_i = \beta \times \left|\partial\left(s(t,i)\right)\right| = \alpha \times t^{\gamma} \times |\partial(s(t,i))|$$

Diffusion Models for Multi-Sensitive Networks

Model of Edge-sensitive information diffusion:

For a homogeneous network

$$\mathrm{\beta} = \mathrm{\alpha} |\partial(\mathrm{s(t)})|^{\gamma}$$

$$|\partial(\mathrm{S(t)})| = \sum_{j \in N(S(t))} |\partial(\mathrm{S(t,j)})|$$

$$\mathrm{E}(V_t) == \alpha |\partial(s(t-1))|^{1+\gamma}$$

Continue

$$\mathrm{E}(\left|\partial\left(\mathrm{s}(\mathrm{t}-1)\right)\right|) = \mathrm{m} \times \frac{N - |s(t-1)|}{N-1} \times |s(t-1)|$$

$$\mathrm{s}(\mathrm{t}) = \mathrm{s}(\mathrm{t}-1) + V_t$$

$$\mathrm{E}(V_t) = \alpha\left(\mathrm{m} \times \frac{N - |s(t-1)|}{N-1} \times |s(t-1)|\right)^{1+\gamma}$$

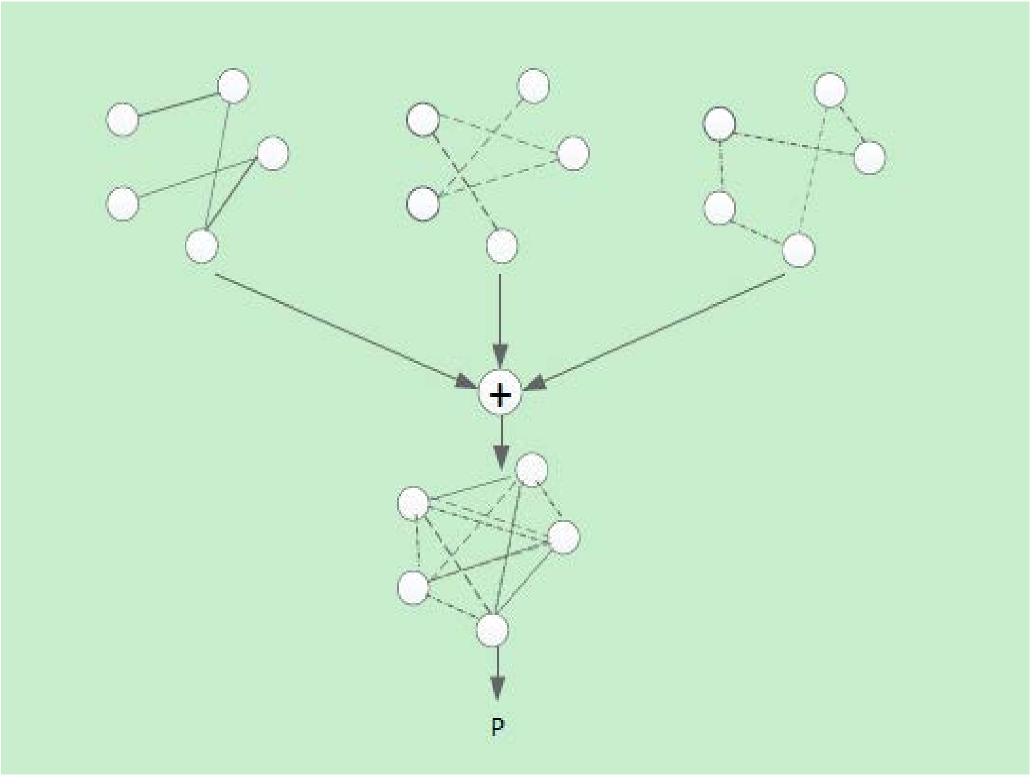
For an inhomogeneous network:

$$p_i = \beta \times \left|\partial\left(s(t,i)\right)\right|$$
$$= \alpha \times \left[\sum_{i\epsilon R_t} \sum_{j\in\tau_t(i,k)} \delta(j,t)\right]^{\gamma} \times \sum_{j\in\tau_t(i,k)} \delta(j,t)$$

$$\mathrm{E}(V_t) = \sum_{i\epsilon R_t} p_i = \alpha \times \left[\sum_{i\epsilon R_t} \sum_{j\in\tau_t(i,k)} \delta(j,t)\right]^{\gamma+1}$$

Model Information Diffusion in Multi-sensitive networks:

$$p_i = \sum_k \mu_k \times (\beta_i^{(k)} \times \sum_{j \in \tau_t(i,k)} \delta(j,t))$$



Diffusion Model Learning From Action Log

The Learning Framework:

$$P(V_t, R_t \backslash V_t) = \prod_{u \in V_t} p_u(t) \prod_{u \in R_t \backslash V_t} (1 - p_u(t))$$

$$\mathrm{L} = \prod_{k} \prod_{t=1}^{T^{(k)}} P({V_t}^{(k)}, R_t \backslash {V_t}^{(k)})$$

Diffusion Model Learning From Action Log

Learning Algorithm:

$$\log(\mathrm{L}) = \sum_t \left\{ \sum_{u \in V_t} log p_u(t) + \sum_{u \in V_t \setminus R_t} \log\left(1 - p_u(t)\right) \right\}$$

$$= \sum_t \left\{ \sum_{u \in V_t} log \sum_k \mu_k \beta_u^{(k)} \sum\nolimits_{j \in \tau_t(u,k)} \delta(j,t) \right.$$

$$\left. + \sum_{u \in V_t \setminus R_t} log \left[1 - \sum_k \mu_k \beta_u^{(k)} \sum\nolimits_{j \in \tau_t(u,k)} \delta(j,t) \right] \right\}$$

Continue

$$\mu_k^{new} = \mu_k^{old} + \eta \frac{\partial logL}{\partial \mu_k}$$

Action Prediction:

$$E(\sum_{u \in R_t} Y_u(t)) = \sum_{u \in R_t} p_u(t)$$

Future Work

·find the theoretical proof of edge-sensitive model

·find the parameters that fits the time-edge-sensitive model best

·learning algorithms