电子科技大学
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Information Diffusion and External Influence in Networks

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Outline:

- Background and Motivation
- Model
  - Proposed Model
  - Infer parameters
- Experiments
- Conclusion

Background and Motivation

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Background :

Social network : a role in the diffusion of the information(Fig.1).

Application : **recommend system(Fig.2), viral transmission,…**

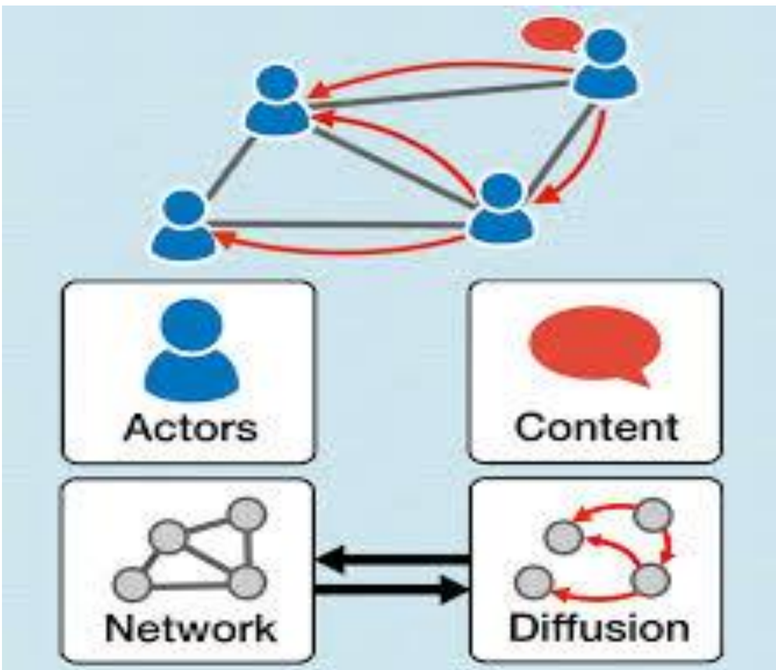


Fig.1

Fig.2

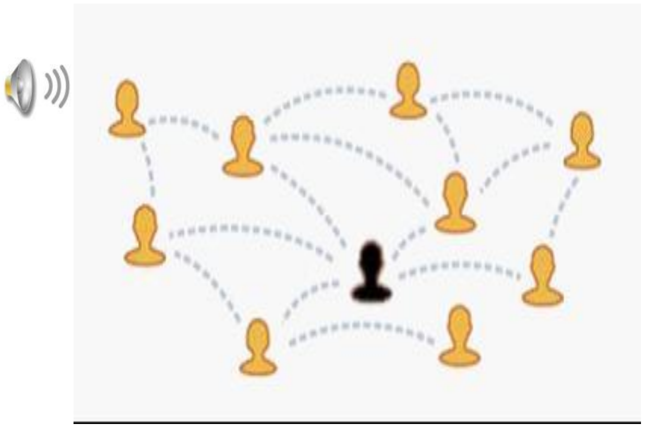
Background and Motivation

Background :

Message pass :

- From a node to another via edges (mostly)
- Through the influence of external sources.

Motivation



Study the process of information diffusion

From a node to another via edges (mostly)

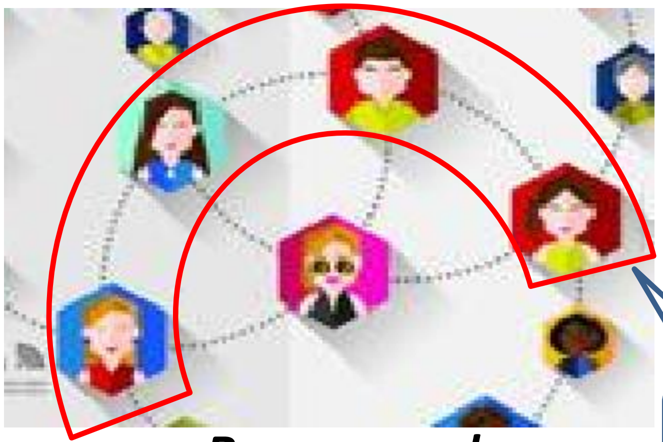
Through the influence of external sources.

Model (*target*)

Background and Motivation

Motivation

Advertisement (External exposures)



Recommend (Internal Exposures)

How to infect ?

How to infect ?

Buy balabala (infection)

Background and Motivation

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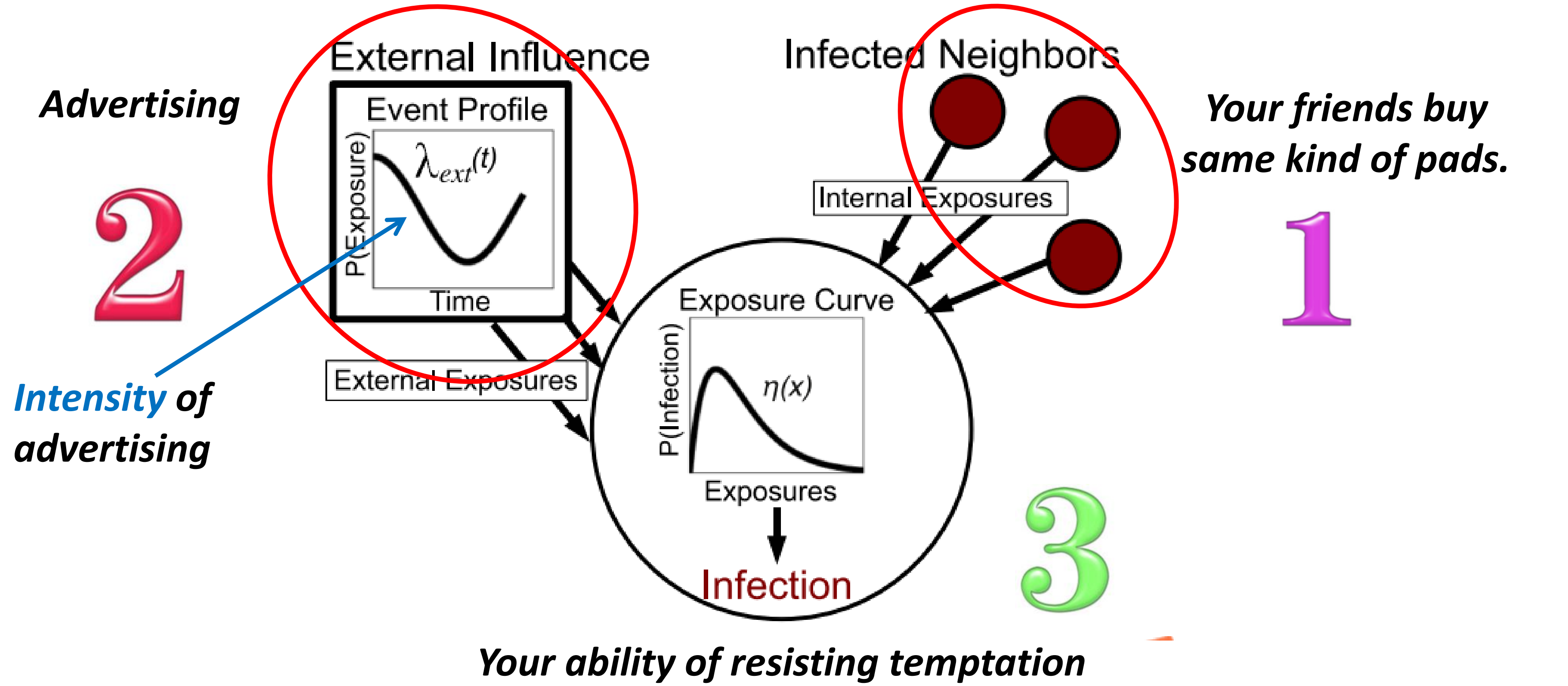
Detail :



Key points:

- External Influence and Infected Neighbors both ***develop exposures***.
- A node is infected with ***different probability*** according to the number of exposures.

Proposed Model(Exposures)

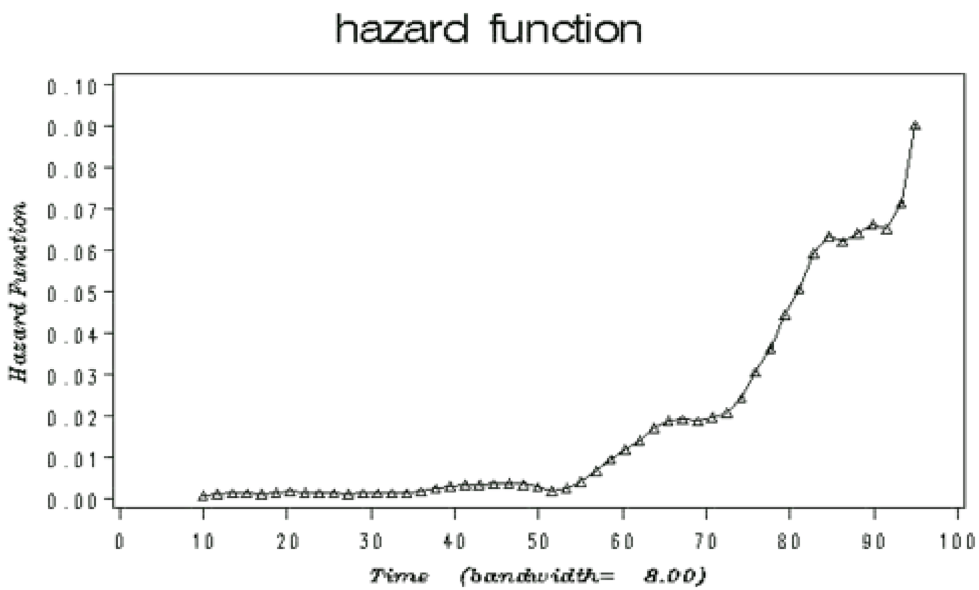
Internal Exposures (introduce a function):

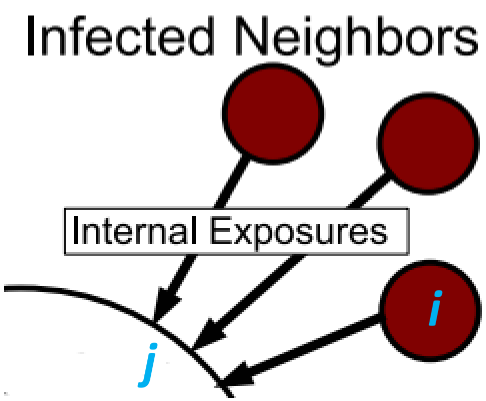
Hazard function : describe a ***distribution*** of the ***length of time*** it takes for an event to occur.

$$h(t) = \frac{N(t)}{M(t)}$$

N(t): *the number of people with* ***infection*** *at t.*

M(t): *the number of people with* ***no infected*** *at t.*





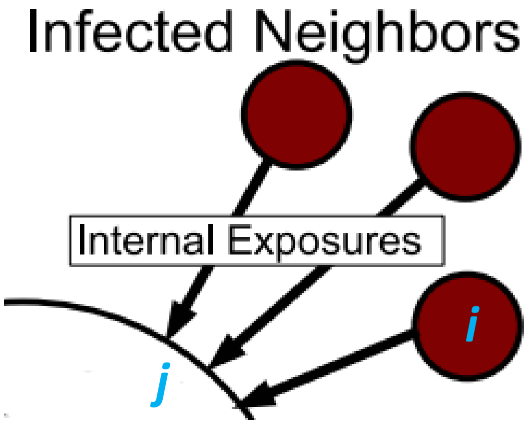
Proposed Model(Exposures)

λ_{int} : internal ***hazard*** function

$$\lambda_{int}(t)\,dt \equiv P\left(i \text{ exposes } j \in [t, t+dt) \middle| \, i \text{ hasn't exposed } j \text{ yet}\right)$$

λ_{int} :*function of the frequency* with which nodes ***check-up*** on each other.

t : the amount of time that has passed since node ***i*** was infected.



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Proposed Model(Exposures)

Excepted number of ***internal*** exposures:

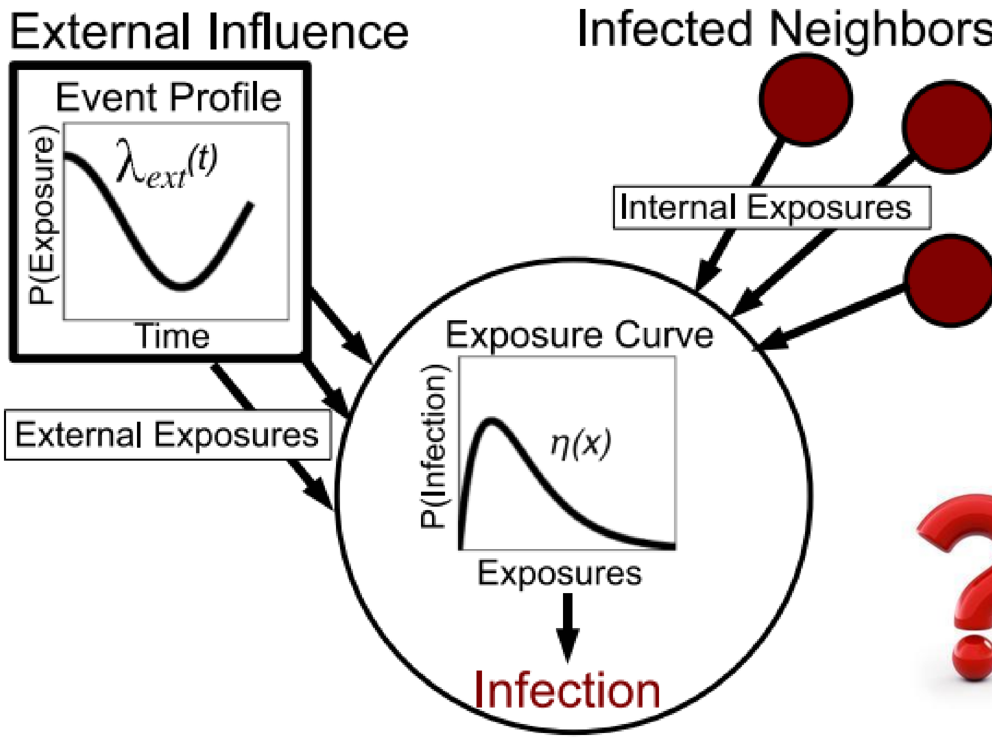
Node ***i*** has received by ***t*** :

$$\Lambda_{int}^{(i)}(t) = \sum_{j;j \text{ is } i\text{'s inf. neighbor}} P(j \text{ exposed } i \text{ before } t)$$

$$= \sum_{j;j \text{ is } i\text{'s inf. neighbor}} \left[1 - \exp\left(-\int_{\tau_j}^{t} \lambda_{int}(s - \tau_j)ds\right)\right]$$

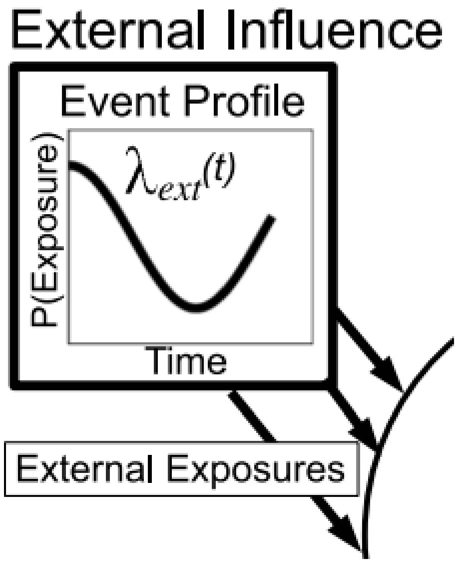
where τ_i is the ***infection time*** of node ***j***

Proposed Model(Exposures)



Proposed Model(Exposures)

External exposures:



$\lambda_{ext}(t)$: the source various in intensity over time called ***event profile***.

$$\lambda_{ext}(t)\,dt \equiv P(i \text{ receives exposure} \in [t, t+dt))$$

The ***probability :***

(receive ***n*** external exposures within $T \bullet \Delta t$)

$$P_{exp}(n; T \cdot \Delta t) = \binom{T}{n} (\lambda_{ext} \cdot \Delta t)^n \cdot (1 - \lambda_{ext} \cdot \Delta t)^{T-n}$$

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Proposed Model(Exposures)

The ***probability :***

(receive ***n*** external exposures within $T \bullet \Delta t$)

$$P_{exp}^{(i)}(n;t) \approx \binom{t/dt}{n} \left(\frac{\Lambda_{ext}(t)}{t} \cdot dt \right)^{n} \cdot \left(1 - \frac{\Lambda_{ext}(t)}{t} \cdot dt \right)^{t/dt-n}$$

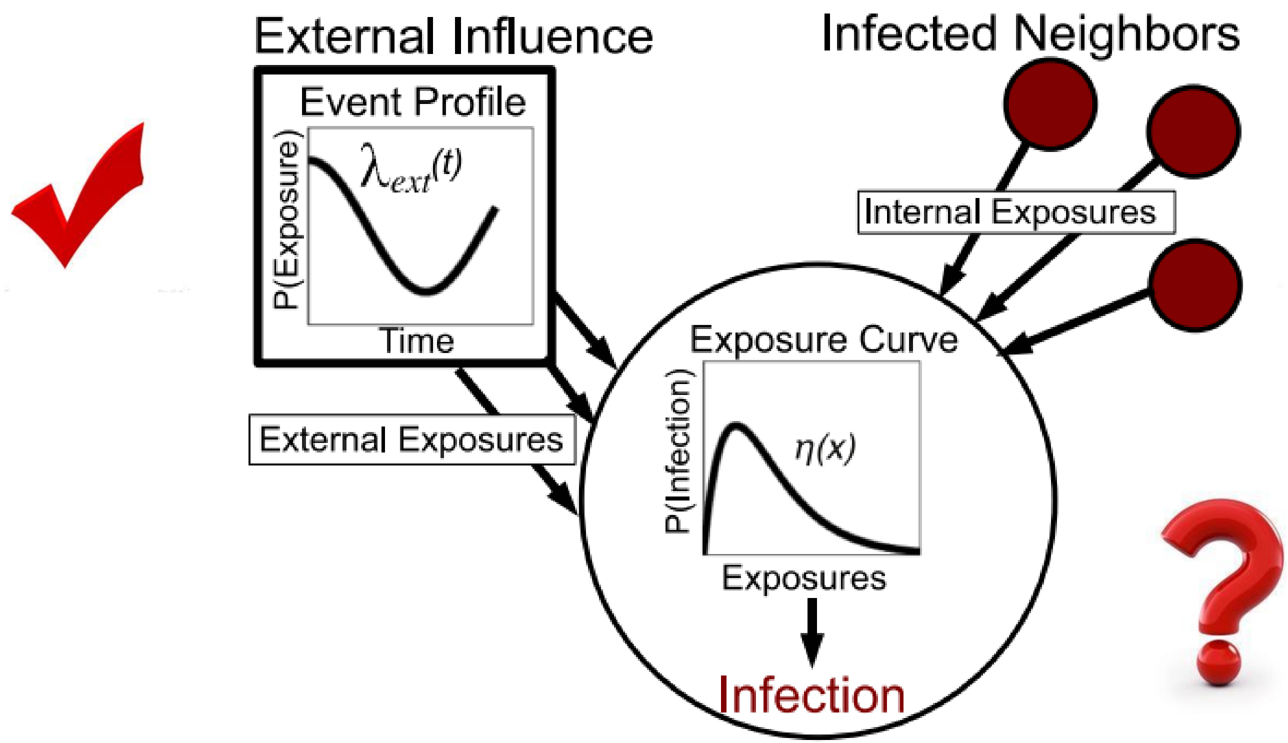
where $\Lambda_{ext}(t) \equiv \int_0^t \lambda_{ext}(s)ds.$ (average)

$\lambda_{ext}(t) + \lambda_{int}^{(i)}(t)$

$$P_{exp}^{(i)}(n;t) \approx \binom{t/dt}{n} \left(\frac{\Lambda_{int}^{(i)}(t) + \Lambda_{ext}(t)}{t} \cdot dt \right)^{n} \times \left(1 - \frac{\Lambda_{int}^{(i)}(t) + \Lambda_{ext}(t)}{t} \cdot dt \right)^{t/dt-n}$$

Exposures = *internal exposures* + *external exposures*

Proposed Model(Exposures)

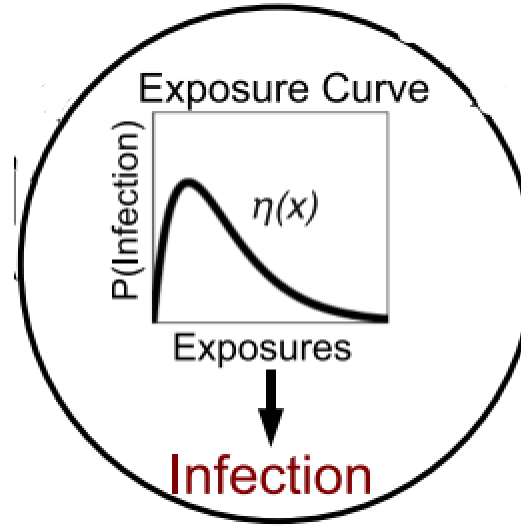


Proposed Model(infection)

Exposure curve:

$$\eta(x) \equiv$$
$$P(\text{node } i \text{ is infected immediately after } x^{th} \text{ exposure})$$

How to define the exposure curve ?



Some properties:

- *No exposure , no infection.*
- *Only one max infection rate.*
- ***Two factors:***
  - *Measure of how infectious a contagion.*
  - *Measure of the contagion's enduring relevancy.*

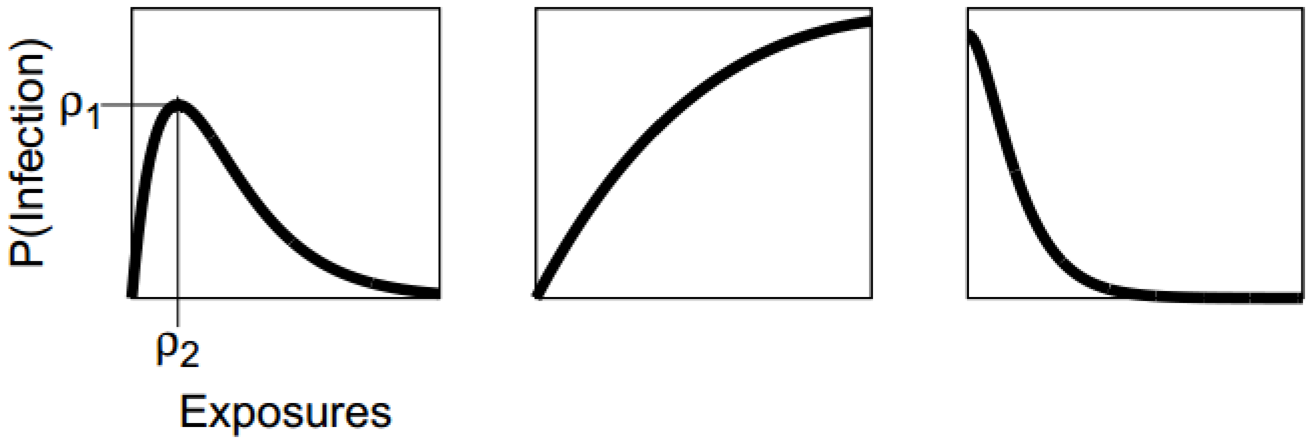
Model

Proposed Model(infection)

Exposure curve:

$$\eta(x) = \frac{\rho_1}{\rho_2} \cdot x \cdot \exp\left(1 - \frac{x}{\rho_2}\right).$$

- *Measure of how infectious a contagion----- ρ_1*
- *Measure of the contagion's enduring relevancy----- ρ_2*



Proposed Model(from *exposures* to *infections*)

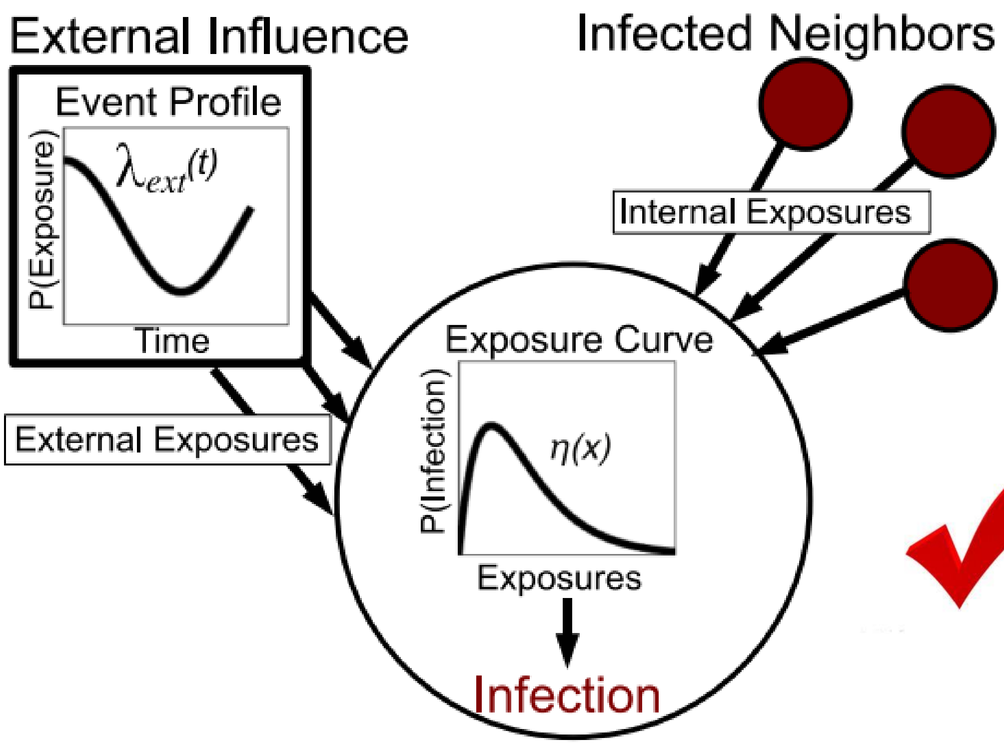
Construct the probability functions :

Idea : The probability of how long time between node i influenced(τ_i) and have infected (t).

$$F^{(i)}(t) \equiv P(\tau_i \leq t) \approx P_{\text{exp}}^{(i)}(n;t)$$

$$\begin{aligned} F^{(i)}(t) &= \sum_{n=1}^{\infty} P[i \text{ has } n \text{ exp. }] \times P[i \text{ inf. } | i \text{ has } n \text{ exp. }] \\ &= \sum_{n=1}^{\infty} P_{exp}^{(i)}(n;t) \times \left[1 - \prod_{k=1}^{n} [1-\eta(k)]\right]. \end{aligned}$$

Model



Finish model, any questions?

Infer parameters

Given :

- Network
- The ***infection times*** for each node

Infer parameters :

- Event profile $\lambda_{ext}(t)$
- Parameters of $\eta(x)$: ρ_1 , ρ_2 .

Idea :

- when the exposures curve is known.

  ⟹ ***infer*** the event profile $\lambda_{ext}(t)$

- when the event profile is known

  ⟹ ***infer*** the exposures curve $\eta(x)$

Infer parameters ($\lambda_{ext}(t)$)

Assume : given

$S(t)$: the number of nodes with uninfected at ***t***.

$$S(t_k) = \sum_{i=1}^{N} P(\text{ node } i \text{ not infected by time } t)$$

$$= \sum_{i=1}^{N} \sum_{n=1}^{\infty} P_{exp}^{(i)}(n; t_k) \prod_{k=1}^{n} [1 - \eta(k)]$$

$$\approx \ldots$$

$$\approx \sum_{i} \exp\left(- \int_{0}^{\Lambda_k + \Lambda_{int}^{(i)}(t_k)} \eta(y) dy \right)$$

Get from data

$$\Lambda_k = \Lambda_{ext}(t) \equiv \int_0^t \lambda_{ext}(s) ds$$

Model

Infer parameters ($\eta(x)$ -- ρ_1, ρ_2)

Assume : given Λ_{ext}

Idea : fix ρ_2, solve for a ρ_1 according to ***maximizes log-likelihood***.

$$F^{(i)}(t) = \sum_{n=1}^{\infty} P[i \text{ has } n \text{ exp. }] \times P[i \text{ inf. } | i \text{ has } n \text{ exp. }]$$

$$= \sum_{n=1}^{\infty} P_{exp}^{(i)}(n;t) \times \left[1 - \prod_{k=1}^{n} [1 - \eta(k)]\right].$$

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Infer parameters

Infer $\eta(x)$ ***through max log-likelihood***

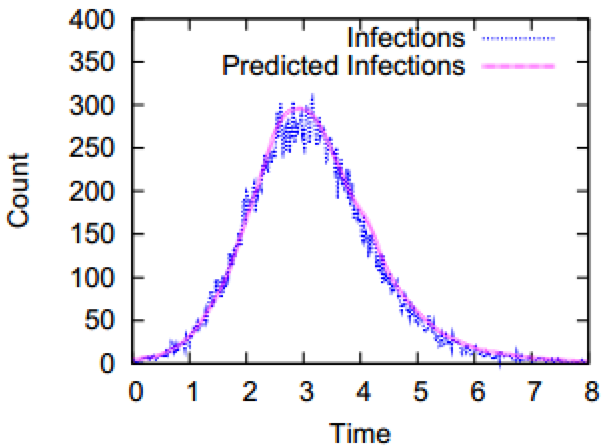
Algorithm 1 Model Parameter Inference

Initialize $\Lambda_{ext}(t)$, ρ^1_{final}, ρ^2_{final}, $\mathcal{L}_{max}$
for $\rho_2 = 1 \rightarrow \rho_{max}$ **do**
  Initialize ρ_1
  while not converged **do**
    $\rho_1 \leftarrow$ Solution to Eq. 12 using ρ_2, $\Lambda_{ext}(t)$
    $\Lambda_{ext}(t) \leftarrow$ Solution to Eq. 10 using ρ_1, ρ_2.
  end while
  $\mathcal{L} \leftarrow \textit{Log-Likelihood}(\Lambda_{ext}(t), \rho_1, \rho_2)$
  if $\mathcal{L} \geq \mathcal{L}_{max}$ **then**
    $\mathcal{L}_{max} \leftarrow \mathcal{L}$
    $\rho^1_{final} \leftarrow \rho_1$
    $\rho^2_{final} \leftarrow \rho_2$
  end if
end for
$\Lambda_{ext}(t) \leftarrow$ Solution to Eq. 10 using ρ^1_{final}, ρ^2_{final}.

Infer $\Lambda_{ext}(t)$ ***through*** $\eta(x)$ ***and*** $S(t)$

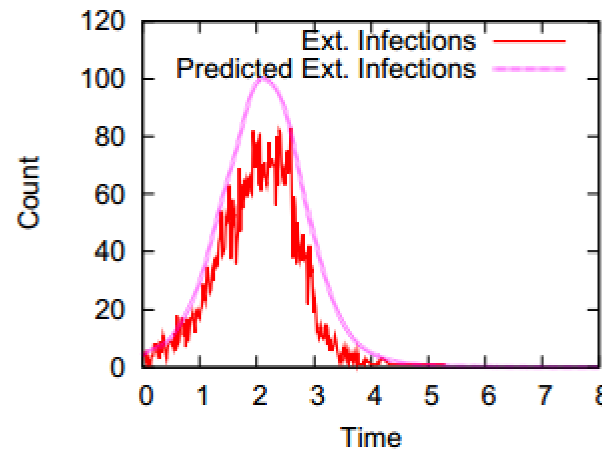
Experiments

Synthetic data ($\lambda_{\text{int}}(t)=t$)

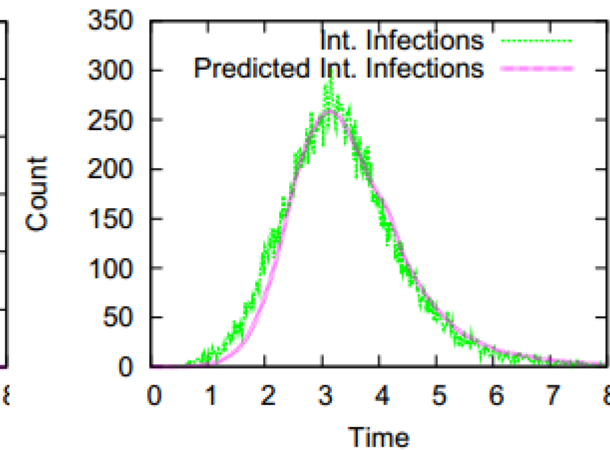


(a) All Infections

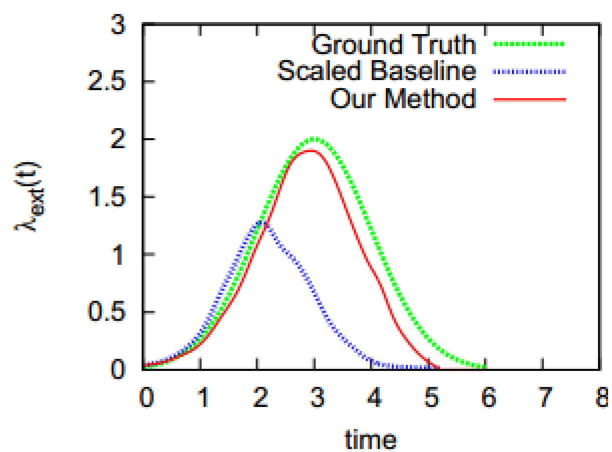
Given (a), infer (b)-(e)



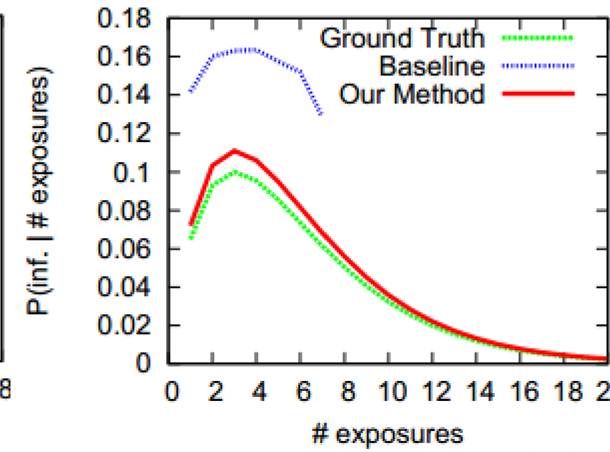
(b) External Infections



(c) Internal Infections



(d) Event Profile $\lambda_{ext}(t)$



(e) Exposure Curve $\eta(x)$

Experiments

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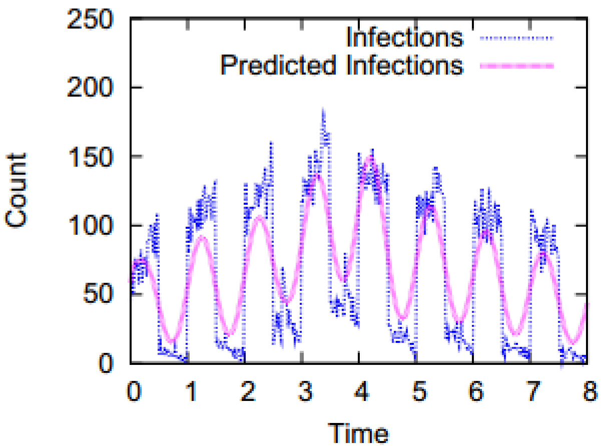
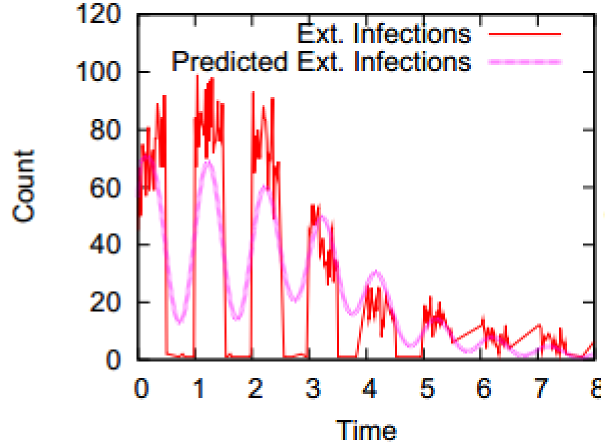
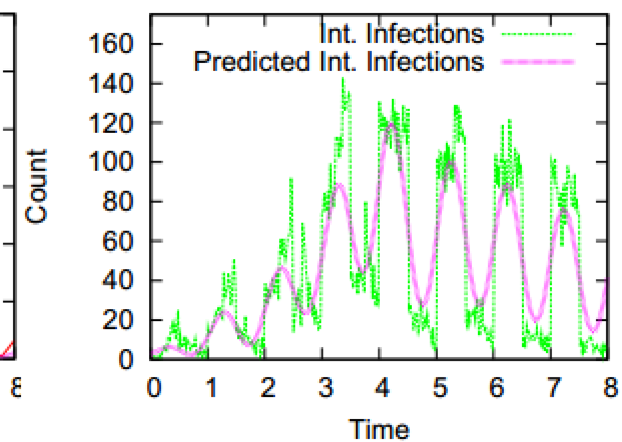
Synthetic data ($\lambda_{int}(t) = \frac{1}{t}$)



(f) All Infections

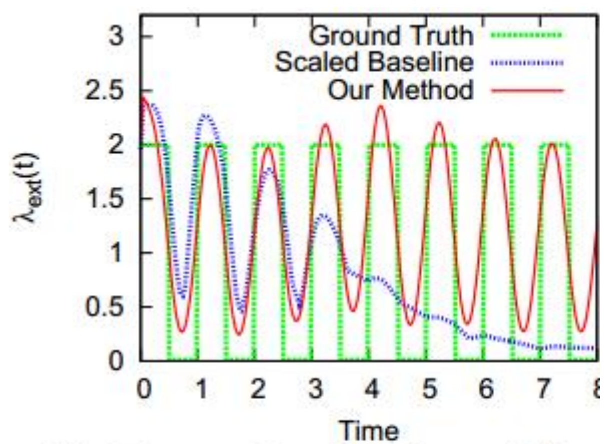


(g) External Infections

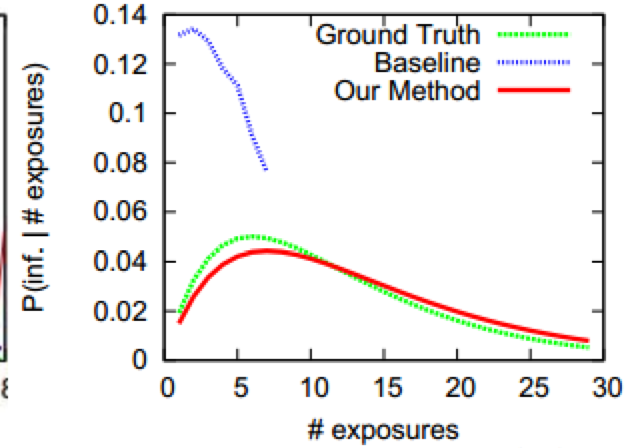


(h) Internal Infections

Given (f), infer (g)-(j)

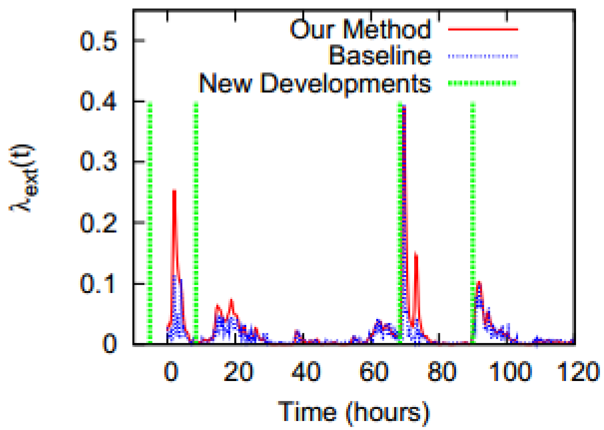


(i) Event Profile $\lambda_{ext}(t)$

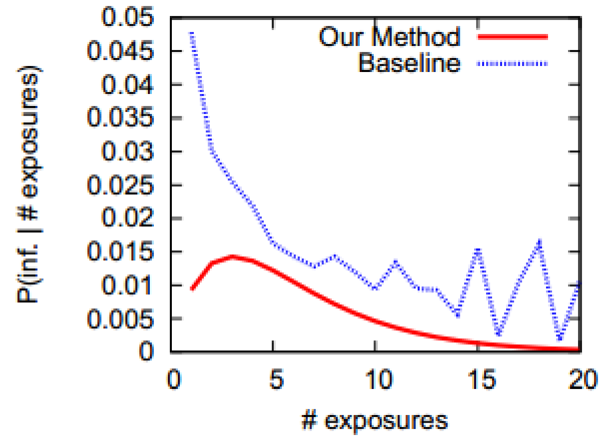


(j) Exposure Curve $\eta(x)$

Real data (Twitter)



(a) Event Profile $\lambda_{ext}(t)$



(b) Exposure Curve $\eta(x)$

Figure 4: The model fitted to a single contagion representing URLs related to the Tucson, Arizona shootings. The green vertical lines designate when four distinct developments related to the shooting event occurred.

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Real data (Twitter)

-

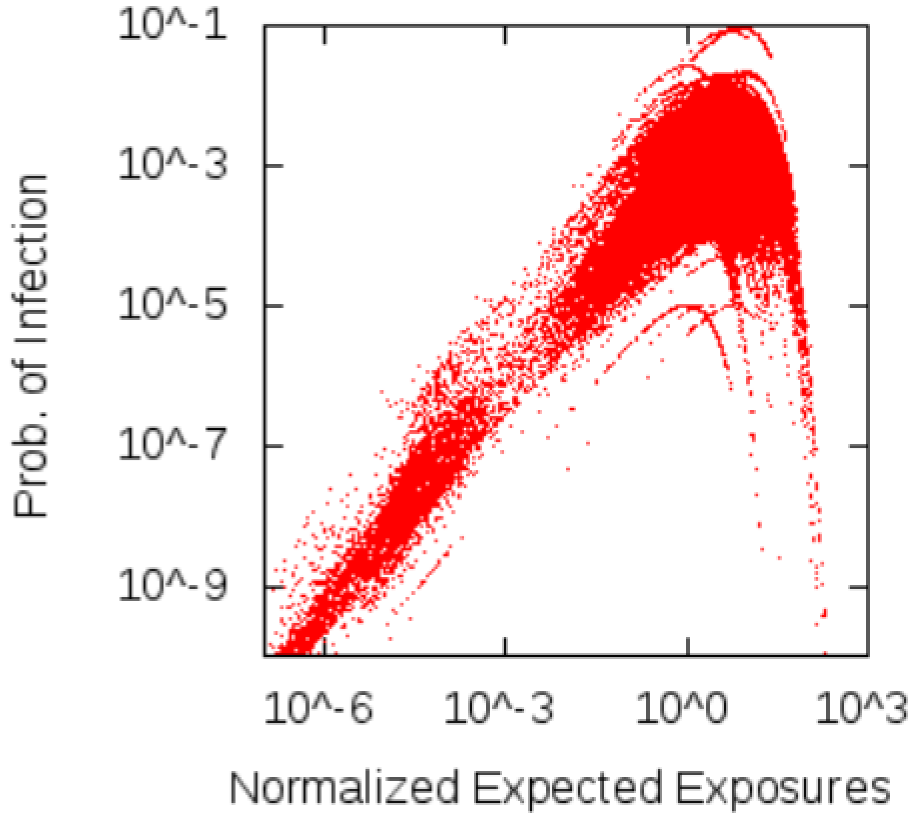
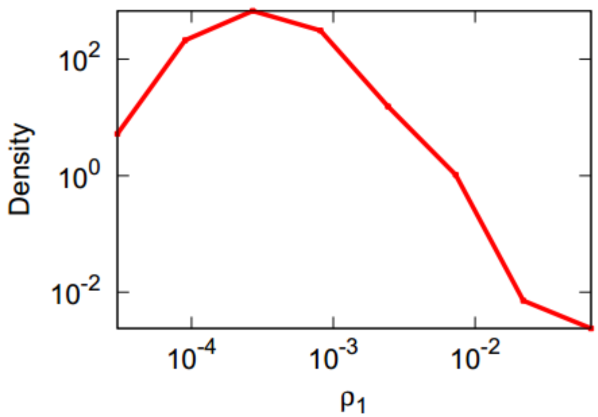
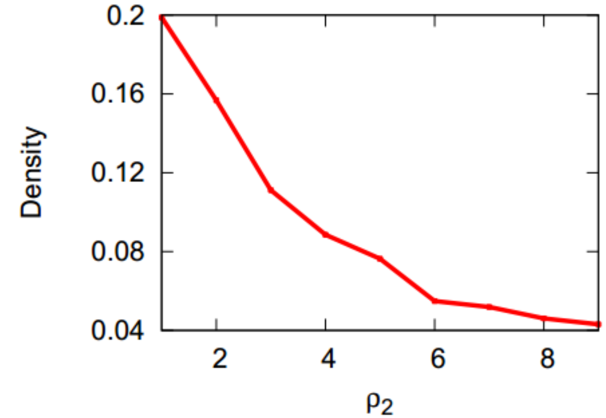


Figure 5: An aggregation of the exposure curves for each URL. Upon the infection of each user, the expected number of exposures received by the user divided by ρ_2 was plotted against inferred infection probability.

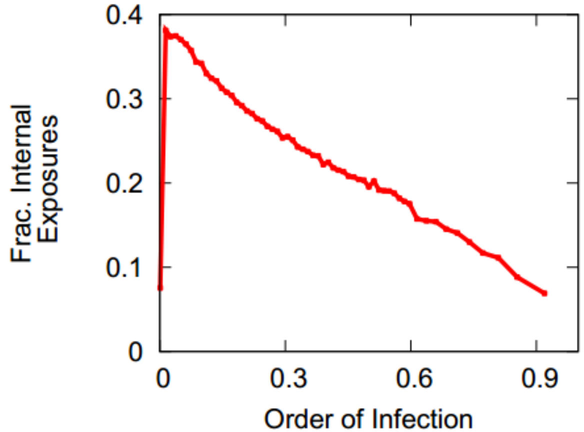
Real data



(a) Distribution of ρ_1



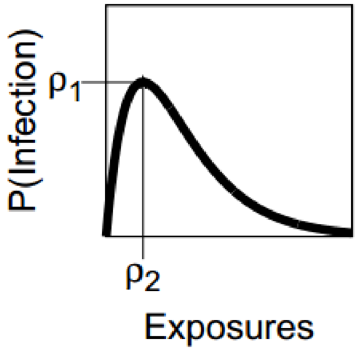
(b) Distribution of ρ_2



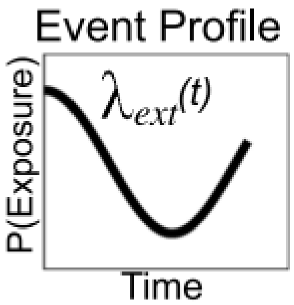
(c) Fraction of Internal Exposures

Conclusion

➢Infer the ***shape*** of influence functions.



➢Capture the ***external influence***.



➢More accurate ***description*** of the real network diffusion process

Thanks

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