Information Diffusion on Social Networks

SMART Summer School 2017

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LIP6 - UPMC

MLIA Team

1. Information Diffusion
   - Diffusion on Networks
   - Tasks
   - Challenges
   - Diffusion Models

2. The Independent Cascade Model
   - Learning
   - Limits
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3. Deep-Learning for Diffusion
   - Embedded IC
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   - Recurrent Neural Networks for Diffusion

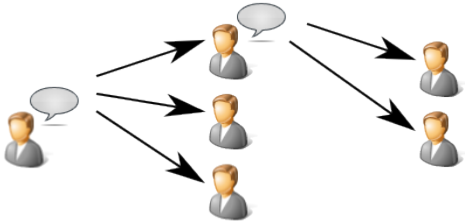
1. Information Diffusion
   - Diffusion on Networks
   - Tasks
   - Challenges
   - Diffusion Models
2. The Independent Cascade Model
3. Deep-Learning for Diffusion

Diffusion on Networks

Fundamental Process on Networks:

- Capture of the dynamics
- How information transits on the network ?

Diffusion = Iterative message passing process



$\Rightarrow$ Defines a diffusion **Cascade**

- Tree structure

Diffusion on Networks

- Diffusion Items
  - Word of mouth / viral marketing
  - Virus or diseases
  - News, opinions, rumors, ..
  - Topics / videos / hashtags / links
  - Language models / expressions
  - Behaviors
  - Errors / Problems
  - ...
- Diffusion Episode = Set of linked events that occur on the network through time

Diffusion

The study of diffusion dynamics has a long history:

- Agricultural practices (1943)
  - Study about the adoption of a new kind of hybrid corn by 259 Iowa's farmers
  - Conclusion: the relationships network plays an important role for the adoption of new products
- Medical practices (1966)
  - Study about the adoption of new drugs by Illinois' doctors
  - Conclusion: Word of mouth is more effective than scientific studies in convincing the doctors
- Psychological effects of opinions on the entourage of persons (1958)
- Contagion of obesity (2007)
  - Having an overweight friend increases our probability of becoming obese by 57% !

Homophily vs. Influence

- Homophily
  - Two connected users tend to have similar behaviors
- Influence
  - The behavior of a user has an impact on the future behavior of his neighborhood

$\Rightarrow$ Temporality is crucial to distinguish influence (diffusion) from homophily (recommendation)

  - If one observe relations of precedence between events: influence

Diffusion vs. Recommendation

Consider a network of product reviewing by users:

- Object of the diffusion: a Product
  - Nodes = Users
  - Infection of a node = a user likes the product
  - Influence relationships between users

    $\Rightarrow$ When a product is liked by this user, it then tends to be liked by these other ones in the future

- Object of the diffusion: a User
  - Nodes = Products
  - Infection of a node = an item has been liked by the user
  - Temporal recommendation

    $\Rightarrow$ When somebody liked this product, she then tends to like these related others in the future

Diffusion Tasks

Buzz prediction - Will the content impact an important number of users ? [Chen et al.,2013]

$$\underbrace{\begin{pmatrix} 1 \\ 0 \\ 0 \\ \ldots \\ 0 \\ 1 \\ 0 \end{pmatrix}}^{\textit{Source Users}} + \overbrace{\begin{pmatrix} \omega_1 \\ \omega_2 \\ \ldots \\ \omega_{d-1} \\ \omega_d \end{pmatrix}}^{\textit{Content}} \xrightarrow{\quad f_\theta \quad} \{0, 1\}$$

Diffusion Tasks

Volume prediction - How many users will be eventually infected? [Tsur and Rappoport, 2012]

$$\begin{array}{c} \textit{Source Users} \\ \begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix} \\ + \\ \textit{Content} \\ \begin{pmatrix} \omega_1 \\ \omega_2 \\ \dots \\ \omega_{d-1} \\ \omega_d \end{pmatrix} \end{array} \xrightarrow{\qquad\qquad f_\theta \qquad\qquad} \mathbb{N}$$

Diffusion Tasks

Infection prediction - Which users will be eventually infected? [Bourigault et al., 2016]

$$\begin{array}{ccc} \textit{Source Users} & & \\ \begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix} & \xrightarrow{\quad f_\theta \quad} & \begin{array}{c} \textit{Final Users} \\ \begin{pmatrix} 1 \\ 1 \\ 0 \\ \dots \\ 1 \\ 1 \\ 1 \end{pmatrix} \end{array} \\ + & & \\ \textit{Content} & & \\ \begin{pmatrix} \omega_1 \\ \omega_2 \\ \dots \\ \omega_{d-1} \\ \omega_d \end{pmatrix} & & \end{array}$$

Diffusion Tasks

Spread prediction - How will evolve the spread of the content?

$$
\begin{array}{c}
\textit{Source Users} \\
\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix} \\
+ \\
\textit{Content} \\
\begin{pmatrix} \omega_1 \\ \omega_2 \\ \dots \\ \omega_{d-1} \\ \omega_d \end{pmatrix}
\end{array}
\xrightarrow{\quad f_\theta \quad}
\begin{array}{c}
\textit{Infected Users per Step} \\
\begin{array}{ccccc} 1 & 2 & \dots & T-1 & T \end{array} \\
\begin{pmatrix}
1 & 1 & \dots & 1 & 1 \\
0 & 0 & \dots & 0 & 1 \\
0 & 0 & \dots & 0 & 0 \\
\dots & \dots & \dots & \dots & \dots \\
0 & 1 & \dots & 1 & 1 \\
1 & 1 & \dots & 1 & 1 \\
1 & 1 & \dots & 1 & 1
\end{pmatrix}
\end{array}
$$

Cascade prediction - Which links will follow the content?

Source Users

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix} \xrightarrow{f_\theta} \{0,1\}^{|R|}$$

$$+$$

Content

$$\begin{pmatrix} \omega_1 \\ \omega_2 \\ \dots \\ \omega_{d-1} \\ \omega_d \end{pmatrix}$$

with R the set of relationships

Diffusion Tasks

Source prediction - Who are the sources of a given content ? [Shah and Zaman, 2010].

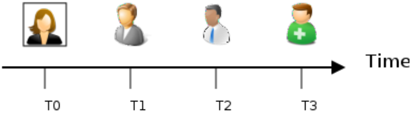
$$\underbrace{\begin{pmatrix} 1 \\ 1 \\ 0 \\ \dots \\ 1 \\ 1 \\ 1 \end{pmatrix}}_{}^{\textit{Infected Users}} + \overset{\textit{Content}}{\begin{pmatrix} \omega_1 \\ \omega_2 \\ \dots \\ \omega_{d-1} \\ \omega_d \end{pmatrix}} \xrightarrow{f_\theta} \overset{\textit{Source Users}}{\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix}}$$

Diffusion Tasks

- Other tasks
  - Link Detection - Which are the main diffusion links of the network? [Gomez-Rodriguez et al., 2011]
  - Opinion Leaders Detection - Who are the most influential users of the network ? [Kempe et al., 2003]
  - Diffusion Maximization - To whom should one give a content to maximize its spread ? [Kempe et al., 2003]
  - Firefighter Problem - How to stop the diffusion of a content ? [Anshelevich et al., 2009]
  - ...

Diffusion on networks

- Challenges
  - The diffusion cascade is usually hidden
    - We do not know who influenced whom
  - What we get is the dated (first) participation of users to the diffusion (diffusion **episode**)



$\Rightarrow$ We only know who participated in what and when

$\Rightarrow$ Model the diffusion dynamics of a network = Learning problem of influence relationships from incomplete data

- Challenges
  - Complex dynamics for rare events
    - Difficult learning
    - Stochastic models rather than deterministic ones
  - Influence distributions depend on the content
    - Different behaviors w.r.t. different contents
    - *e.g.*, Paul can have a strong influence on Pierre for sport but few for politics
  - Closed World Hypothesis rarely valid
    - Diffusion can take place on various media simultaneously
  - Inter-dependency / concurrency of diffusion processes
    - Some process can be impacted by others
  - Dynamicity of the network
    - New users / New relationships
    - Evolution of the influence relationships through time

Diffusion Models

- Models Macro : global statistics on the diffusion (size, speed)
  - Bass : adoption of a product
  - SIR : virus diffusion
- Models Micro : focus on users of the network *[Kempe et al., 2003]*
  - Linear Threshold (LT) : Receiver-centric
  - Independent Cascade (IC) : Transmitter-centric

The Bass model

Bass, 1969
Evolution of the rate of users $i(t)$ that have adopted a product a time t :

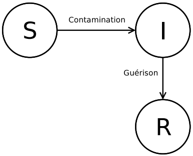
$$\frac{\partial i}{\partial t}(t) = \underbrace{p \times (1 - i(t))}_{\text{Spontaneous Adoptions}} + \underbrace{q \times (i(t) \times (1 - i(t)))}_{\text{Word of Mouth}}$$

- p : Probability that a user adopts a product from ads
- q : probability that a user adopts a product from a neighbor

  - Bass reports values $p = 0.03$ and $q = 0.38$ on average

The model SIR

Epidemiological model. Each user can be in 3 different states.



- *Susceptible* : not infected by the disease;
- *Infected* : infected by the disease;
- *Recovered* : cured and immunized.

Evolution of the system

$$\begin{cases} \frac{\partial S}{\partial t} = -p.SI \\ \frac{\partial I}{\partial t} = p.SI - r.I \\ \frac{\partial R}{\partial t} = r.I \end{cases}$$

- p : transmission probability
- r : probability of cure

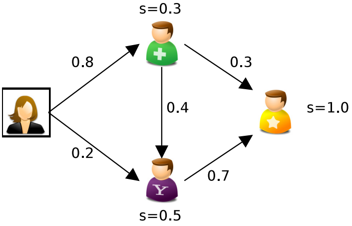
$\rightarrow$ Can also be applied on information diffusion on networks

The Linear Threshold Model *[Granovetter, 1973]*

Micro-model of diffusion

- Hypothesis: Additive Influence
- Links associated to influence weights $\theta_{i,j}$
- Nodes associated to (stochastic) thresholds γ_j
- Iterative model:

$\Rightarrow$ User *j* is infected at step *t* if: $\sum_{i \in Preds(j,t)} \theta_{i,j} \geq \gamma_j$



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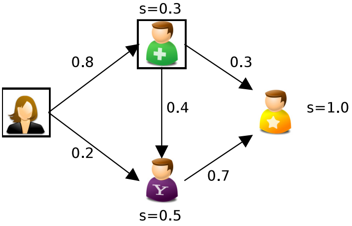

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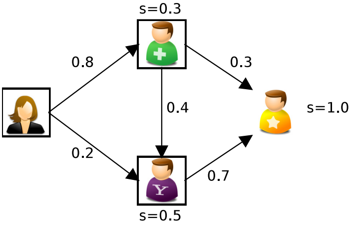

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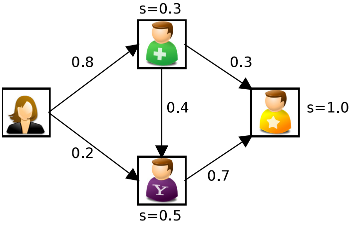
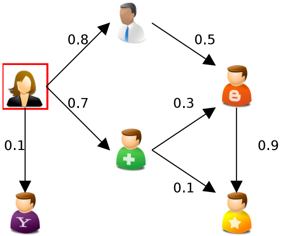


The Independent Cascade Model (IC)

- Micro-model of diffusion
  - Hypothesis: influences are independent events
  - Infection probabilities $\theta_{u,v}$ are defined on every edge of the graph
  - After its infection, a user *u* gets a unique chance to infect each of its successors in the network for the next step



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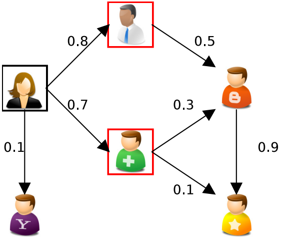

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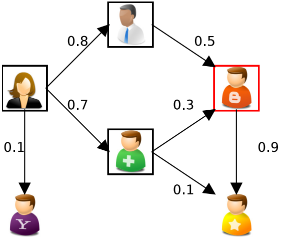

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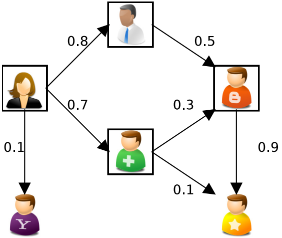


IC Extensions

- Continuous time
  - Saito 2009 (CTIC),Gomez-Rodriguez 2011 (NetRate)...
- Inclusion of content
  - Barbieri 2013 (TIC)
- Inclusion of users profiles
  - Guille 2012, Saito 2011...
- Concurrent Diffusions
  - Myers 2012, Bharathi 2007...
- etc...

IC: Learning the Influence Relationships

Which inputs ?

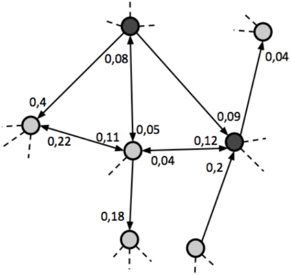
- Training set of episodes
  - Diffusion episode = List of timestamps of infection
- Graph of the network
  - Explicit relationships can help to drive the learning but...
    - Sometimes no available relationship
    - Explicit relations do not always correspond to the main influence relationships of the network [Ver Steeg et al., 2013]

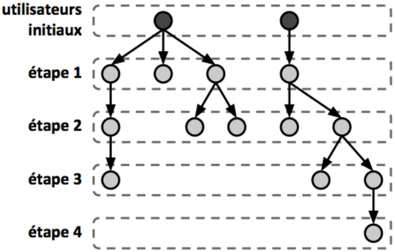
  $\Rightarrow$ Diffusion Link detection approaches: e.g., NetInf [Gomez Rodriguez et al., 2010]
    - Search of the maximum spanning tree for each episode
    - Selection of the n links the most used by the trees

  $\Rightarrow$ Or use the complete graph of the nodes if possible ($n \times (n-1)$ relations)
    - Can be restricted to links with at least one example of possible diffusion in the training set

IC: Learning the Influence Relationships

- Independent Cascade Model (IC)
  - Inference from an influence graph with probabilities defined on edges





- Infection probability for v at step t = Probability that at least one user infected at step $t-1$ succeeds in influencing v:

$$P_t(v) = 1 - \prod_{u \in Preds(v) \wedge t_u = t-1} 1 - \theta_{u,v}$$

IC: Learning the Influence Relationships

$\Rightarrow$ Find parameters $\theta_{u,v}$ maximizing the model likelihood according to a training set of diffusion episodes $\mathcal{D}$

[Saito et al., 2008] :

$$L(\mathcal{D};\theta) = \prod_{D\in\mathcal{D}} \prod_{u\in D} P_{t_u^D}(u) \prod_{\substack{(u,v),u\in D\wedge v\in Succs(u)\wedge \\ ((v\notin D)\vee(v\in D\wedge t_v^D>t_u^D+1))}} 1-\theta_{u,v}$$

with $P_{t_u^D}(u) = 1 - \prod_{v\in Preds(u)\wedge t_v^D=t_u^D-1} 1-\theta_{v,u}$

Or equivalently:

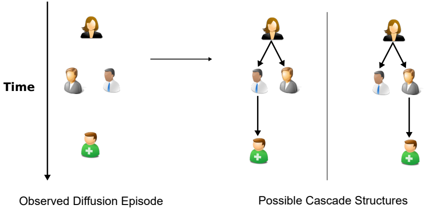
$$\log\left(L(\mathcal{D};\theta)\right) = \sum_{D\in\mathcal{D}} \sum_{u\in D} \log P_{t_u^D}(u) + \sum_{\substack{(u,v),u\in D\wedge v\in Succs(u)\wedge \\ ((v\notin D)\vee(v\in D\wedge t_v^D>t_u^D+1))}} \log\left(1-\theta_{u,v}\right)$$

$\Rightarrow$ Difficult to maximize

Missing Information

Diffusion Episodes

- One only know *when* each user was infected
- Missing information: *who* infected *whom*



- If this information was available, the maximization problem would be easy

$\Rightarrow$ An Expectation-Maximization algorithm (EM) was proposed by Saito in 2008 for solving the problem

Expectation-Maximization for IC [Saito et al., 2008]

1. Expectation (E) of the log-likelihood according to current parameters $\hat{\theta}$

$$Q\left(\boldsymbol{\theta};\hat{\boldsymbol{\theta}}\right) = E_{\mathbf{Z}|\mathbf{X},\hat{\boldsymbol{\theta}}}\left[L\left((\mathbf{X},\mathbf{Z});\boldsymbol{\theta}\right))|\hat{\boldsymbol{\theta}}\right]$$

with **Z** containing all hidden (binary) transmission outcomes.

$$P(z^D_{u,v}=1|D) = \frac{\hat{\theta}_{u,v}}{\hat{P}_{t^D_v}(v)} \quad \text{and} \quad P(z^D_{u,v}=0|D) = 1 - \frac{\hat{\theta}_{u,v}}{\hat{P}_{t^D_v}(v)}$$

with $\hat{P}_{t^D_u}(u) = 1 - \prod_{v\in Preds(u)\wedge t^D_v = t^D_u - 1} 1 - \hat{\theta}_{v,u}$

Thus:

$$Q\left(\theta;\hat{\theta}\right) = \sum_{D\in\mathcal{D}} \Phi^D\left(\theta;\hat{\theta}\right) + \sum_{\substack{(u,v),u\in D\wedge v\in Succs(u)\wedge\\ ((v\notin D)\vee(v\in D\wedge t^D_v > t^D_u+1))}} \log\left(1-\theta_{u,v}\right)$$

with

$$\Phi^D\left(\theta;\hat{\theta}\right) = \sum_{\substack{(u,v)\in D^2,\\ v\in Succs(u)\\ \wedge t^D_v = t^D_u+1}} \frac{\hat{\theta}_{u,v}}{\hat{P}_{t^D_v}(v)} \log(\theta_{u,v}) + \left(1 - \frac{\hat{\theta}_{u,v}}{\hat{P}_{t^D_v}(v)}\right) \log(1-\theta_{u,v})$$

2. Maximization (M) of the log-likelihood expectation :

$$\hat{\boldsymbol{\theta}} \leftarrow \arg\max_{\boldsymbol{\theta}} \left(Q\left(\boldsymbol{\theta}, \hat{\boldsymbol{\theta}}\right)\right)$$

$\Rightarrow$ By canceling $\dfrac{\partial Q\left(\theta; \hat{\theta}\right)}{\partial \theta}$, we get: $\theta^*_{u,v} = \dfrac{\sum\limits_{D \in \mathcal{D}^?_{u,v}} \dfrac{\hat{\theta}_{u,v}}{\hat{P}_{t^D_v}(v)}}{|\mathcal{D}^?_{u,v}| + |\mathcal{D}^-_{u,v}|}$

$$\mathcal{D}^?_{u,v} = \{D \in \mathcal{D} | (u,v) \in D^2 \wedge t^D_v = t^D_u + 1\}$$
$$\mathcal{D}^-_{u,v} = \{D \in \mathcal{D} | u \in D \wedge ((v \notin D) \vee (v \in D \wedge t^D_v > t^D_u + 1))\}$$

Limits of IC

- Closed-world Hypothesis
  - External world can be represented as an additional node [Gruhl et al., 2004]
- Diffused content not taken into account
  - Influence distributions do not depend on what is diffused
- Information on nodes not taken into account
  - User profiles
  - Current user activities
- Time Discretization
  - Diffusion proceeds in steps

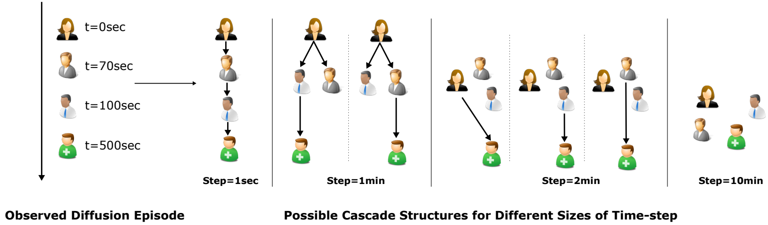
IC : Time Discretization

- IC learning requires to gather events per time period for learning
  - Infection of v by u only possible at step $t_u^D + 1$

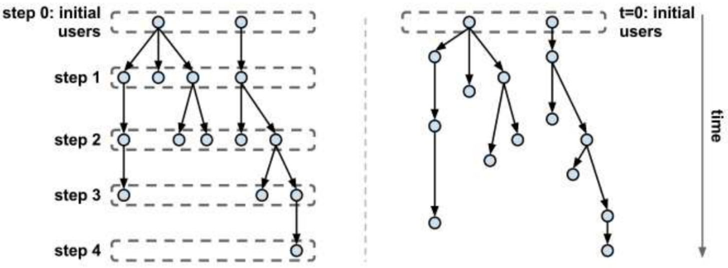
$\Rightarrow$ Too long steps : too many events in the same steps (no possible influence)

$\Rightarrow$ Too short steps : many "holes" in the diffusion process

  - Isolated users with no possible explanation
  - Even if we remove empty steps, very strong assumptions on the diffusion:



Continuous Time Diffusion



Modèle Independent Cascade

Processus de diffusion plus réaliste

- Two main variants of IC propose to consider continuous time delays of infection:
  - NetRate [Gomez-Rodriguez et al., 2011]
  - CTIC [Saito et al., 2009]

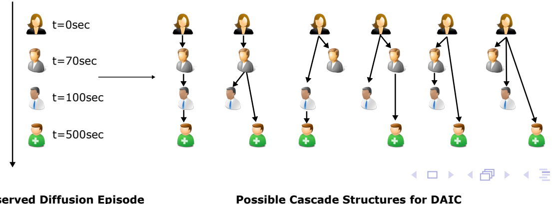
Continuous Time Diffusion

- NetRate [Gomez-Rodriguez et al., 2011]
  - Definition of probability distributions which decrease with time (Exponential, Power, Raighley, etc.)
    - *e.g.*, Exponential Distribution: $f(t_j|t_i;\theta_{i,j}) = \theta_{i,j}\exp^{-\theta_{i,j}(t_j-t_i)}$
  - Only one parameter per link to control:
    - Influence strength
    - Influence delay
  - $+$ Convex optimization problem
  - $-$ Every infection happens, some after a maximal time T
    - The choice of T can be difficult
  - $-$ A slower influence does not necessarily imply a less frequent one
- CTIC [Saito et al., 2009]
  - 2 types of parameters per link
    - Influence probability $k \in]0,1[$
    - Delay parameter $r \in \mathbb{R}^+$
  - Probability density that i infects j at time t_j^D:

    $f(t_j|t_i;k_{i,j};r_{i,j}) = k_{i,j}r_{i,j}\exp^{-r_{i,j}(t_j^D-t_i^D)}$
  - $+$ A more flexible model
  - $-$ But more complex to optimize $\Rightarrow$ EM algorithm

Learning Diffusion Models in Practice

- Continuous Time Diffusion
  - Very effective when infection delay regularities can be observed but...
  - Such regularities are rarely observed from social data
  - ⇒ The variability on delays can strongly limit the ability of extracting influence tendencies
- Relaxation of IC: Delay-Agnostic IC [Lamprier et al., 2015]
  - No time discretization
  - Uniform time delays
  - \+ More flexible than IC ($\times$10 more effective on social data)
  - \+ More realistic than continuous models (performs at least as well as CTIC on social data)
  - \+ Greatly simpler than CTIC
  - – Infection times cannot be predicted



DAIC

Log-likelihood of DAIC:

$$\mathcal{L}(\theta;\mathcal{D}) = \sum_{D\in\mathcal{D}} \left(\sum_{v\in D} \log P_{t_v^D}(v) + \sum_{v\notin D}\sum_{u\in D} \log(1-\theta_{u,v}) \right)$$

with $P_{t_v^D}(v) = 1 - \prod_{u\in Preds(v)\wedge t_u^D < t_v^D} 1-\theta_{u,v}$

Update-rule for DAIC :

$$\theta^*_{u,v} = \frac{\sum_{D\in\mathcal{D}^+_{u,v}} \frac{\hat{\theta}_{u,v}}{\hat{P}_{t_v^D}(v)}}{|\mathcal{D}^+_{u,v}| \ + \ |\mathcal{D}^-_{u,v}|}$$

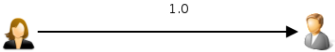
With:

$$\mathcal{D}^+_{u,v} = \{D\in\mathcal{D} | (u,v)\in D^2 \wedge t_v^D > t_u^D\}$$
$$\mathcal{D}^-_{u,v} = \{D\in\mathcal{D} | u\in D \wedge v\notin D\}$$

Avoid overfitting with IC and DAIC

Learning bias of IC (increased with DAIC):

Observed Diffusion Episode



Infered probabilities

Avoid overfitting with IC and DAIC

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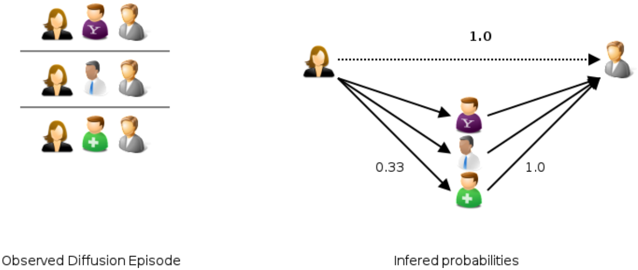
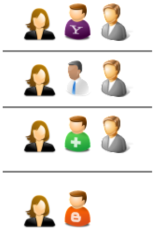


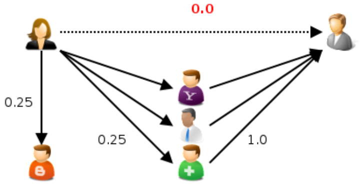
- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0$ ...

Avoid overfitting with IC and DAIC

Learning bias of IC (increased with DAIC):



Observed Diffusion Episode



Infered probabilities

- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0$ ...
- .. and can make more frequent pairs (u, v) converge to $\theta_{u,v} = 0.0$

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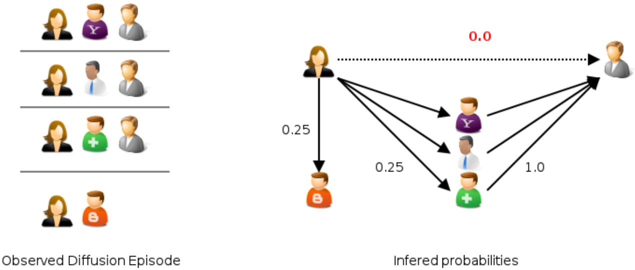

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$\Rightarrow$ Rare users have a great impact on the extracted relationships

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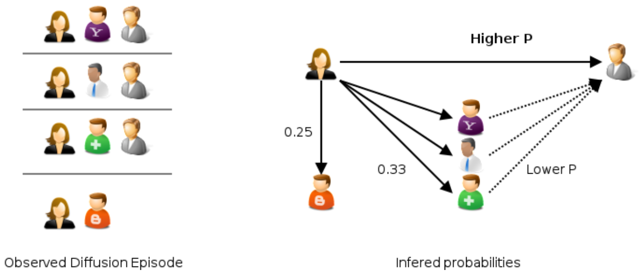

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DAIC Regularization

- Influence is a rare event
  - Very high probabilities for $\theta_{u,v}$ are unlikely

$\Rightarrow$ Introduction of an exponential prior [Lamprier et al., 2015]:

$$p(\theta) = \prod_{\theta_{u,v}} \lambda e^{-\lambda \theta_{u,v}}$$

- Maximum a Posteriori:

$$\theta^* = \arg\max_{\theta} \mathcal{L}(\theta; \mathcal{D}) - \lambda \sum_{\theta_{u,v}} \theta_{u,v}$$

- Favors sparse influence networks

$\Rightarrow$ Adaptation of the Saito's EM

1. Information Diffusion
2. The Independent Cascade Model
3. Deep-Learning for Diffusion
   - Embedded IC
   - Predictive models
   - Recurrent Neural Networks for Diffusion

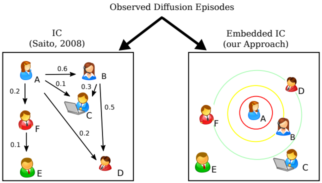
Embedded IC

Representation Learning

Project items in a continuous space in such a way that *relationships* between items are modeled by *distances* (or similarities) between their representations in this space

$\Rightarrow$ Obtain a more compact model

$\Rightarrow$ Infer new relationships

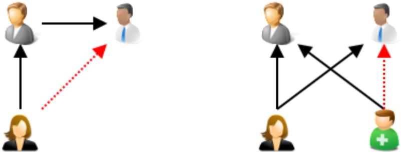


- Each user i is associated to a projection $z_i \in \mathbb{R}^d$
- The transmission probability $\theta_{i,j}$ becomes a function:

$$\theta_{i,j} = f(z_i, z_j)$$

Advantages

- Less parameters, $\mathcal{O}(N)$ rather than $\mathcal{O}(N^2)$
- Inclusion of correlations between links of the network:
  - Transitive relationships (cohesive communities)
  - Similar users tend to impact the same other users (bimodal communities)
  - $\rightarrow$ Naturally modeled by the use of a representation space



Algorithm

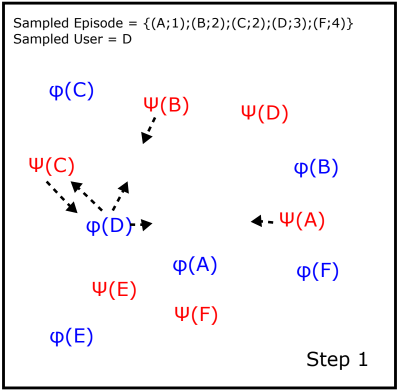
- Influence is an asymmetric relationship
  - Each user i is associated to *two* projections z_i (transmitter projection) and ω_i (receptor projection) in $\mathbb{R}^d$
  - The transmission probability $\theta_{i,j}$ becomes a function:

$$\theta_{i,j} = f(z_i, \omega_j) = \frac{1}{1 + \exp\left(z_i^{(0)} + \omega_j^{(0)} + ||z_i^{(1..d)} - \omega_j^{(1..d)}||^2\right)}$$

- Inter-dependent probability values: no analytic solution for the maximization step

$\rightarrow$ GEM: the maximization is replaced by a step of stochastic gradient ascent

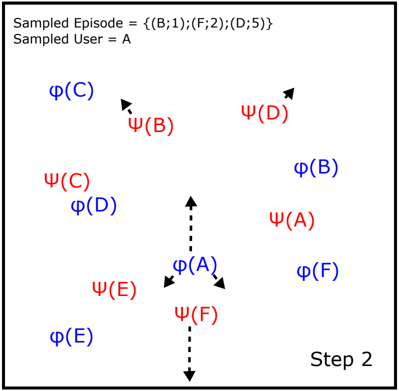
Embedded IC: Example



Iteration 1 :

- Episode : $\{(A, 1); (B, 2); (C, 2); (D, 3); (E, 3); (F, 4)\}$
- User : D (infected)
- Infected predecessors: $\{A, B, C\}$

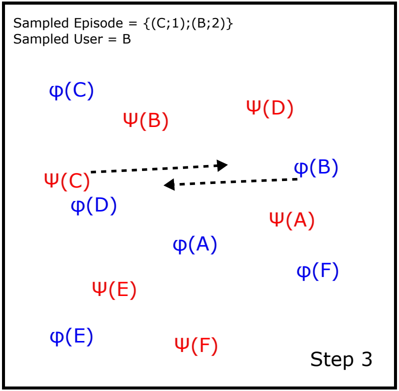
Embedded IC: Example



Iteration 2 :

- Episode : $\{(B, 1); (F, 2); (D, 5)\}$
- User : A (non infected)
- Infected predecessors : $\{B, F, D\}$

Embedded IC: Example

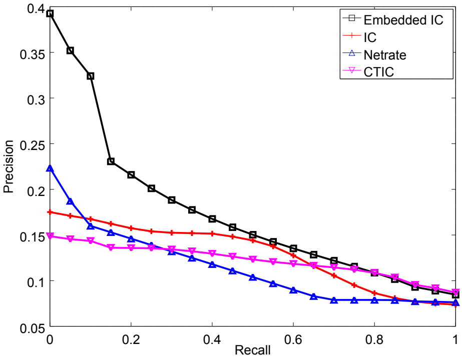


Iteration 3 :

- Episode : $\{(C, 1); (B, 2); \}$
- User : B (infected)
- Infected predecessors : $\{C\}$

Influence links detection

- On the Memetracker corpus:
  - Evaluation on the ability for assigning high transmission probabilities to known relationships
  - Ranking of the links (u_i, u_j) according to $f(z_i, \omega_j)$
  - Precision-Recall curves:



Limits of iterative approaches

- Iterative models effective to describe diffusion processes but...
- ... Low robustness w.r.t. network evolutions [Najar et al., 2012]
- ... Hard to learn for large networks
- ... Over-fitting risks
- ... Complex estimations of infection probabilities (Monte-Carlo simulations [Bòta et al., 2013] or Diffusion kernels [Rosenfeld et al., 2016])

$\Rightarrow$ Non-iterative approaches for diffusion prediction

- Focus on mapping final states from inital ones.
- $C^D = f_\theta(S^D)$, with S^D and C^D respectively the source and final contamination states for the episode D

A first non-iterative approach

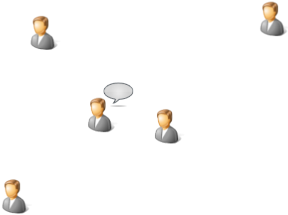
- Discriminative Model from a set of sources [Najar et al., 2012]
    - Input = Binary vector $S^D \in \{0;1\}^{|U|}$, with $S_i^D = 1$ if i is in the sources of D
    - Output = Binary vector $C^D \in \{0;1\}^{|U|}$, with $C_i^D = 1$ if i is in the final infection of D
- Logistic Regression

$$\theta^* = \arg\max_{\theta} \sum_{D \in \mathcal{D}} \sum_{i \in U} C_i^D \log\left(\frac{1}{1+e^{-f_\theta(i,S^D)}}\right) + (1 - C_i^D)\log\left(1 - \frac{1}{1+e^{-f_\theta(i,S^D)}}\right)$$

- Various possible functions f (dot product, neural network, etc...)

a Non-iterative Approach with Representation Learning

- Projection in a continuous latent space [Bourigault et al., 2014]
  - Diffusion modeled as a heat diffusion process in the space



- The temperature $T(u_i, t)$ of u_i at time t renders its propensity of infection
- The heat starts from the source

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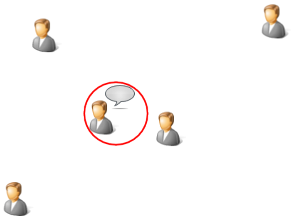

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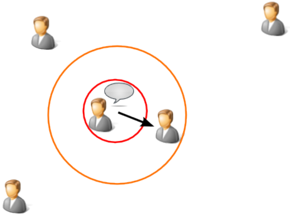

Heat equation :

$$\begin{cases} \frac{\partial T}{\partial t} = \Delta_x T \\ f(x,0) = f_0(x) \end{cases}$$

Solution when the source is at x_0 :

$$T_{x_0}(x,t) = (4\pi t)^{-\frac{n}{2}} e^{-\frac{||x_0 - x||^2}{4t}}$$

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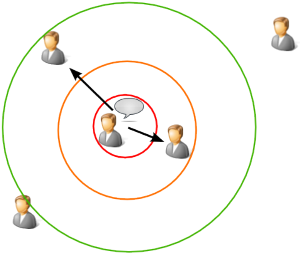

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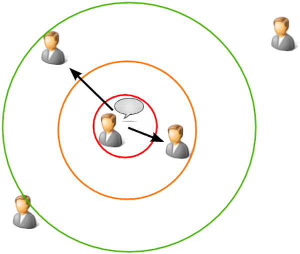


$\rightarrow$ Find a representation $\mathcal{Z}$ of the users such that observed diffusion can be explained as a heat kernel starting from the source

$$\mathcal{U} = (u_1, ..., u_N) \rightarrow \mathcal{Z} = (z_1, ..., z_N) \subset \mathbb{R}^D$$

Diffusion as a heat process

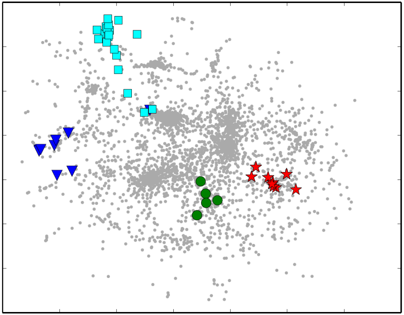
- Projection in a contiunous latent space [Bourigault et al., 2014]
  - For an episode D whose source is s^D:
    - $\forall (u,v), t_u^D < t_v^D \Rightarrow \forall t \; T_{s^D}(u,t) > T_{s^D}(v,t)$
  - In the latent space $\rightarrow$ geometric constraint:
    - $\forall (u,v), t_u^D < t_v^D \Rightarrow ||z_{s^D} - z_u|| < ||z_{s^D} - z_v||$

$\Rightarrow$ Loss Function:

$$\Delta_{rank}(\mathcal{Z}, \mathcal{D}) = \sum_{D \in \mathcal{D}} \sum_{\substack{u,v \\ t^{C}(u) < t^{C}(v)}} max(0, 1 - (||z_{s^D} - z_v||^2 - ||z_{s^D} - z_u||^2)) + \sum_{u,v \in D \times \bar{D}} max(0, 1 - (||z_{s^D} - z_v||^2 - ||z_{s^D} - z_u||^2))$$

Optimization by stochastic gradient descent on $\mathcal{Z}$.

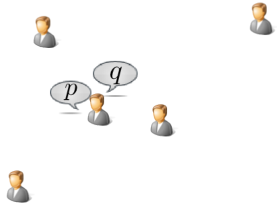
- Projection of users of **Digg** in 2 dimensions :



+ Capture of regularities between extracted relationships ⇒ better generalization
+ Possibility to include the propagated content

Heat Diffusion: Inclusion of the Content

- Hypothesis : The diffused content impacts the diffusion dynamics
  - Translation of the source according to the content



- Similar learning:
  - Simultaneous learning of the translation function f_θ and the projections $\mathcal{Z}$
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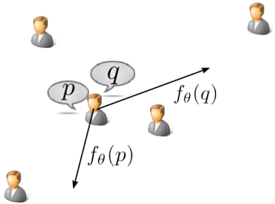

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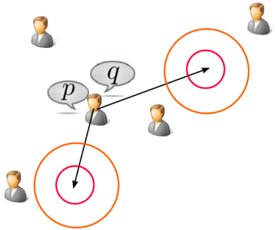

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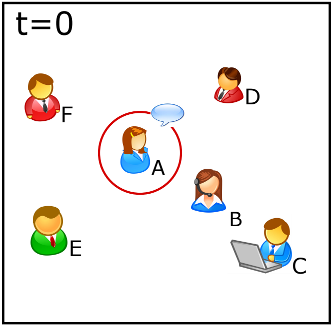
Heat diffusion: iterative version

Chain reaction : Each infected user starts emitting heat from its infection time



⇒ Dynamic model

⇒ Infection time prediction

⇒ Dealing with multiple sources

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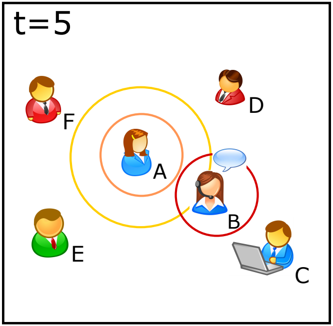

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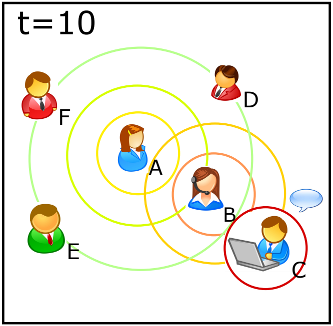

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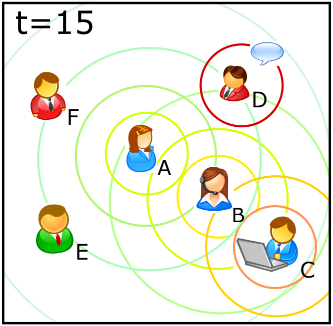

- ⇒ Dynamic model
- ⇒ Infection time prediction
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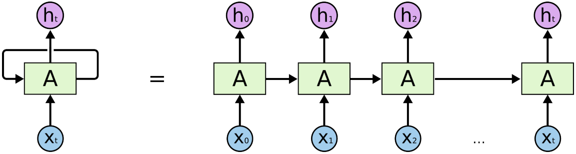
Recurrent Neural Networks for Diffusion

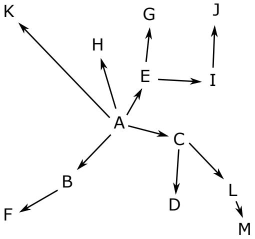


- Diffusion episodes could be seen as sequences
  - Recurrent Neural Networks are well suited for dealing with sequences

  $\Rightarrow$ RNN could be used to consider the history of events to predict the future events

- However, direct application of RNN does not well perform for diffusion

⇒ Not sequences but trees



- Should the prediction of J be impacted by the previous observation of D ?
  - ⇒ Cross-dependence of infections

Recurrent Neural Networks for Diffusion

- RNN based on Attention Learning
  - DeepCas [Li et al., 2017]

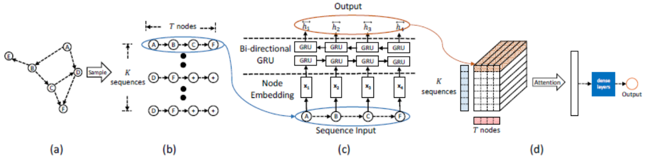
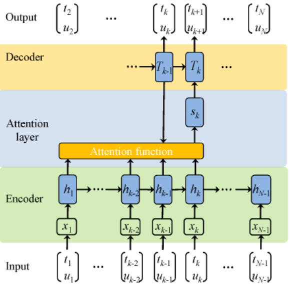


Figure 1: The end-to-end pipeline of DeepCas.

  - CYAN-RNN [Wang et al., 2017]



⇒ RNN IC with MCMC / Variational inference

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