

Information Diffusion on Social Networks

FDMS

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1 Information Diffusion

- Diffusion on Networks
- Tasks
- Challenges
- Diffusion Models

2 The Independent Cascade Model

- Learning
- Limits
- Extensions

3 Deep-Learning for Diffusion

- Embedded IC
- Predictive models
- Recurrent Neural Networks for Diffusion

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Information Diffusion

- Diffusion on Networks
- Tasks
- Challenges
- Diffusion Models

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The Independent Cascade Model

3

Deep-Learning for Diffusion

Diffusion on Networks

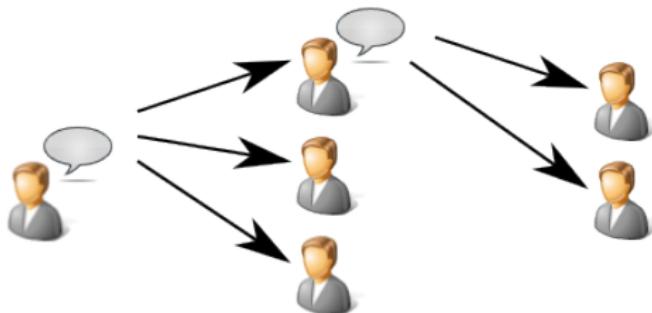
Fundamental Process on Networks:

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



Diffusion on networks

Diffusion = Iterative message passing process



- ⇒ Defines a diffusion **Cascade**
- Tree structure

- 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

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
- ⇒ Temporality is crucial to distinguish influence (diffusion) from homophily (recommendation)
- If one observe relations of precedence between events: influence

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
 - ⇒ 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
 - ⇒ 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]

Source Users

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix} + \xrightarrow{f_{\theta}} \{0, 1\}$$

Content

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

Diffusion Tasks

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

Source Users

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

$$\xrightarrow{f_{\theta}} \mathbb{N}$$

Content

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

Diffusion Tasks

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

Source Users

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

Content

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

$$f_\theta \longrightarrow$$

Final Users

$$\begin{pmatrix} 1 \\ 1 \\ 0 \\ \dots \\ 1 \\ 1 \\ 1 \end{pmatrix}$$

Diffusion Tasks

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

Source Users

$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

Content

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

$$f_\theta \longrightarrow$$

Infected Users per Step

$$\begin{pmatrix} 1 & 2 & \dots & T-1 & T \\ 1 & 1 & \dots & 1 & 1 \\ 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 1 & \dots & 1 & 1 \\ 1 & 1 & \dots & 1 & 1 \end{pmatrix}$$

Diffusion Tasks

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].

Infected Users

$$\begin{pmatrix} 1 \\ 1 \\ 0 \\ \dots \\ 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} + \text{Content} \xrightarrow{f_{\theta}} \begin{pmatrix} 1 \\ 0 \\ 0 \\ \dots \\ 0 \\ 1 \\ 0 \end{pmatrix}$$

Source Users

Content

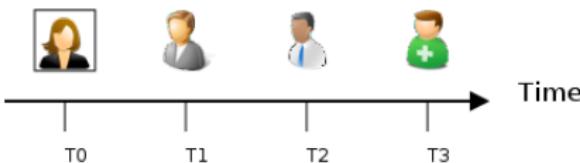
f_{θ}

The diagram illustrates a machine learning model for source prediction. It shows two vectors: one for 'Infected Users' and one for 'Content'. These are combined (indicated by a plus sign) and passed through a function f_{θ} to produce a vector for 'Source Users'. The 'Content' vector is represented as a column of weights $\omega_1, \omega_2, \dots, \omega_{d-1}, \omega_d$.

- 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]
 - ...

- 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**)



- ⇒ We only know who participated in what and when
- ⇒ 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

- 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

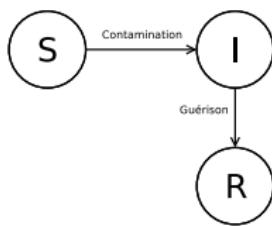
Evolution of the rate of users $i(t)$ that have adopted a product at time t :

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

- 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.

→ Can also be applied on information diffusion on networks

Evolution of the system

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

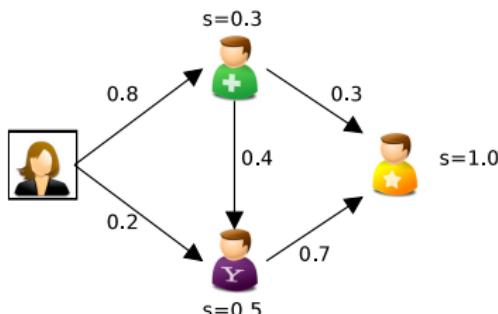
- p : transmission probability
- r : probability of cure

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:

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

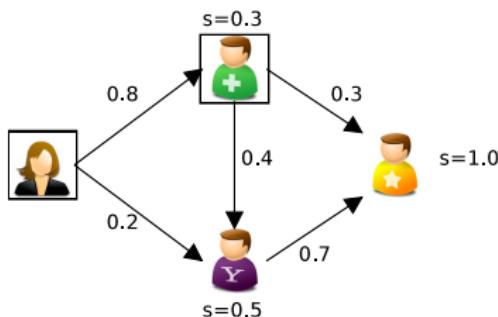


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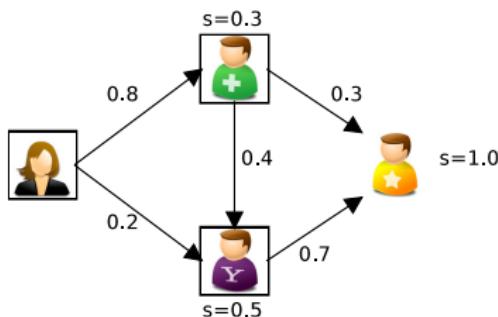


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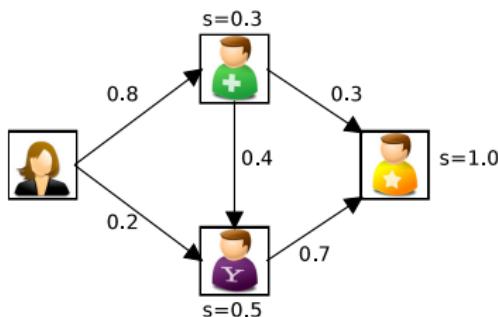


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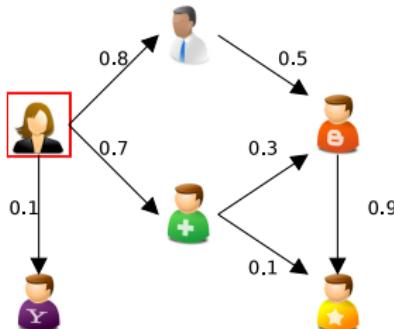
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The Independent Cascade Model (IC)

- Micro-model of diffusion

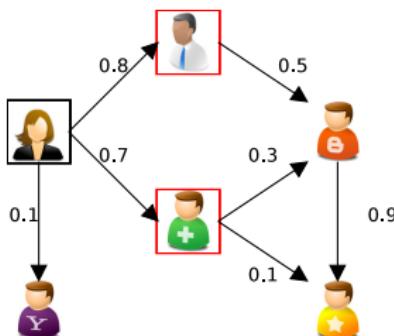
- Hypothesis: influences are independent events
- Infection probabilities $\theta_{u,v}$ are defined on every edge of the graph
- After its infection, a user u gets a unique chance to infect each of its successors in the network for the next step



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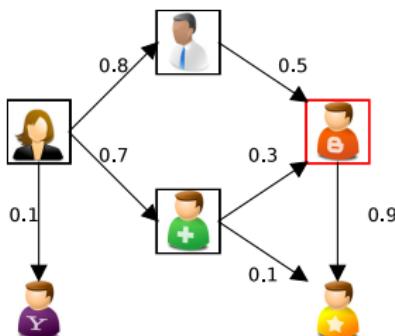
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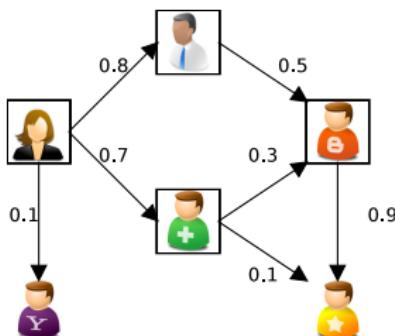
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- Hypothesis: influences are independent events
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- Continuous time
 - Saito 2009 (CTIC), Gomez-Rodriguez 2011 (NetRate)...
- Inclusion of content
 - Barbieri 2013 (TIC)
- Inclusion of users profiles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

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2 The Independent Cascade Model

- Learning
- Limits
- Extensions

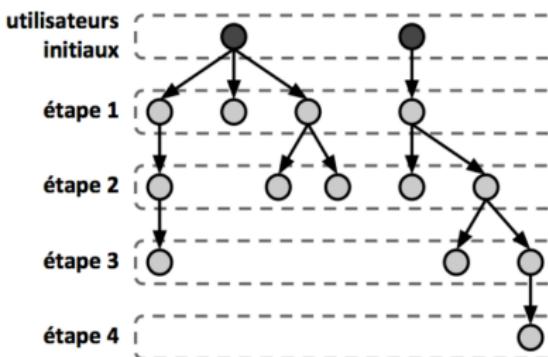
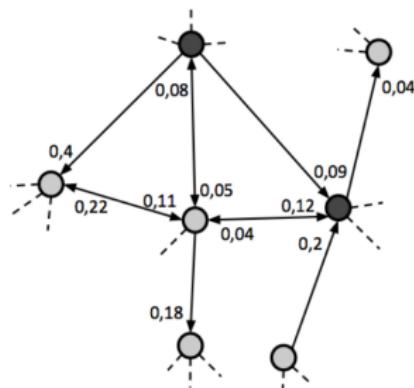
3 Deep-Learning for Diffusion

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]
 - ⇒ 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
 - ⇒ 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 :

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

IC: Learning the Influence Relationships

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

[Saito et al., 2008] :

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

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

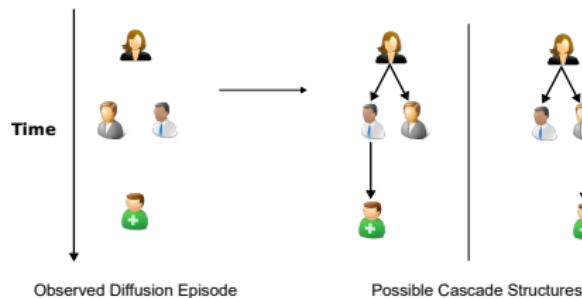
Or equivalently:

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

⇒ Difficult to maximize

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

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

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

with \mathbf{Z} containing all hidden (binary) transmission outcomes.

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

$$\text{with } \hat{P}_{t_u^D}(u) = 1 - \prod_{v \in \text{Preds}(u) \wedge t_v^D = t_u^D - 1} 1 - \hat{\theta}_{v,u}$$

Thus:

$$Q(\theta; \hat{\theta}) = \sum_{D \in \mathcal{D}} \Phi^D(\theta; \hat{\theta}) + \sum_{\substack{(u,v), u \in D \wedge v \in \text{Succs}(u) \wedge \\ ((v \notin D) \vee (v \in D \wedge t_v^D > t_u^D + 1))}} \log(1 - \theta_{u,v})$$

with

$$\Phi^D(\theta; \hat{\theta}) = \sum_{\substack{(u,v) \in D^2, \\ v \in \text{Succs}(u) \\ \wedge t_v^D = t_u^D + 1}} \frac{\hat{\theta}_{u,v}}{\hat{P}_{t_v^D}(v)} \log(\theta_{u,v}) + (1 - \frac{\hat{\theta}_{u,v}}{\hat{P}_{t_v^D}(v)}) \log(1 - \theta_{u,v})$$

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

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

\Rightarrow By canceling $\frac{\partial Q(\theta; \hat{\theta})}{\partial \theta}$, we get:

$$\theta_{u,v}^* = \frac{\sum_{D \in \mathcal{D}_{u,v}^?} \hat{\theta}_{u,v}}{|\mathcal{D}_{u,v}^?| + |\mathcal{D}_{u,v}^-|}$$

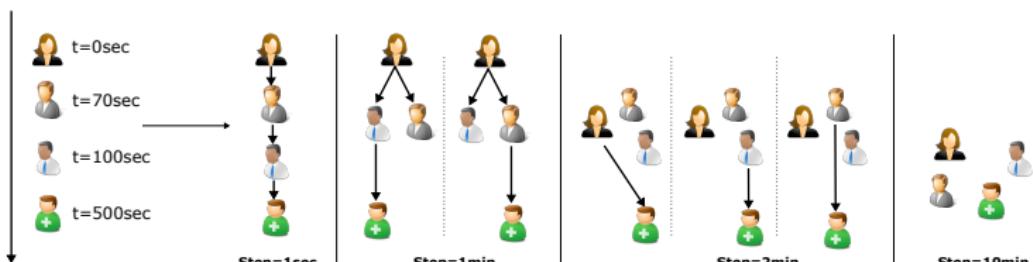
$$\mathcal{D}_{u,v}^? = \{D \in \mathcal{D} | (u, v) \in D^2 \wedge t_v^D = t_u^D + 1\}$$

$$\mathcal{D}_{u,v}^- = \{D \in \mathcal{D} | u \in D \wedge ((v \notin D) \vee (v \in D \wedge t_v^D > t_u^D + 1))\}$$

- 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

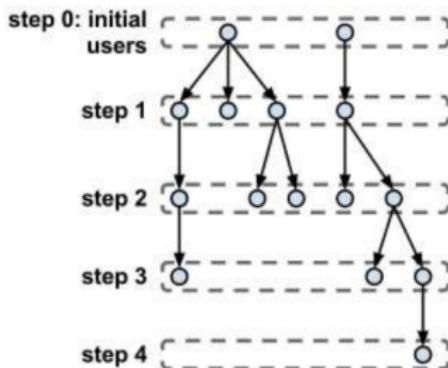
- IC learning requires to gather events per time period for learning
 - Infection of v by u only possible at step $t_u^D + 1$
 - ⇒ Too long steps : too many events in the same steps (no possible influence)
 - ⇒ Too short steps : many "holes" in the diffusion process
 - Isolated users with no possible explanation
 - Even if we remove empty steps, very strong assumptions on the diffusion:



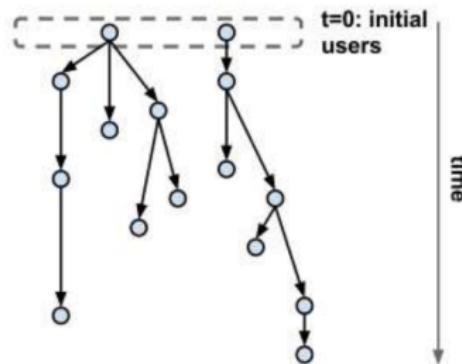
Observed Diffusion Episode

Possible Cascade Structures for Different Sizes of Time-step

Continuous Time Diffusion



Modèle Independent Cascade



Processus de diffusion plus réaliste

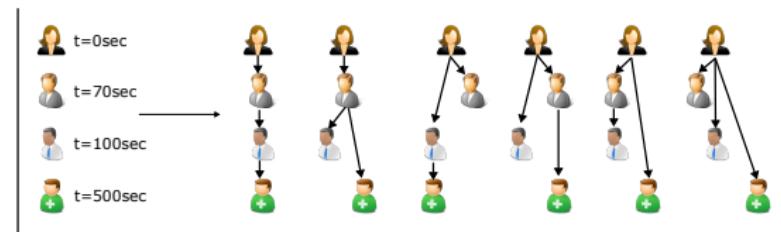
- Two main variants of IC propose to consider continuous time delays of infection:
 - NetRate [Gomez-Rodriguez et al., 2011]
 - CTIC [Saito et al., 2009]

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



Log-likelihood of DAIC:

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

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

Update-rule for DAIC :

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

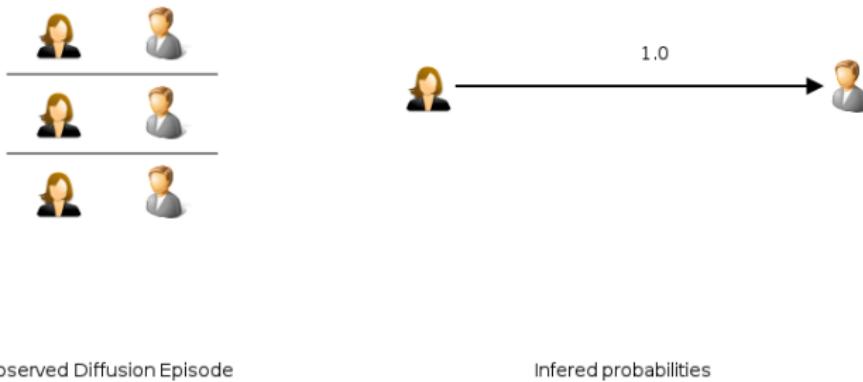
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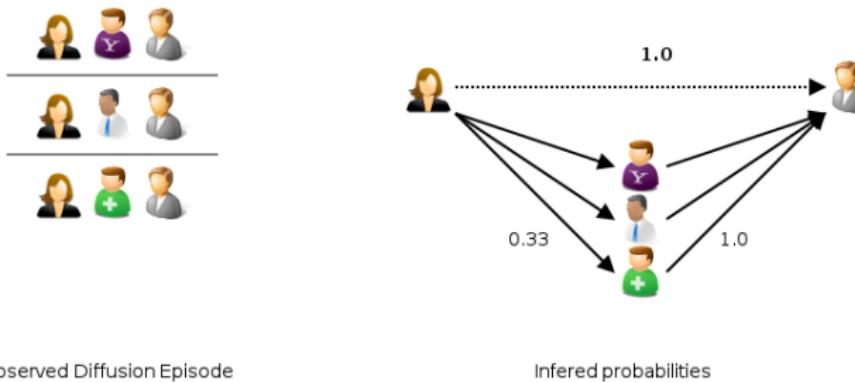
Avoid overfitting with IC and DAIC

Learning bias of IC (increased with DAIC):



Avoid overfitting with IC and DAIC

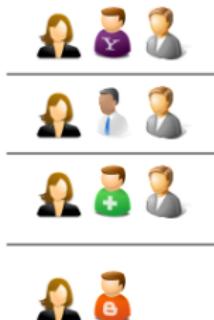
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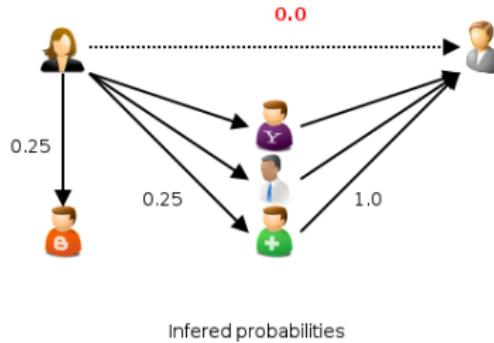
- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0 \dots$

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Learning bias of IC (increased with DAIC):



Observed Diffusion Episode



Inferred probabilities

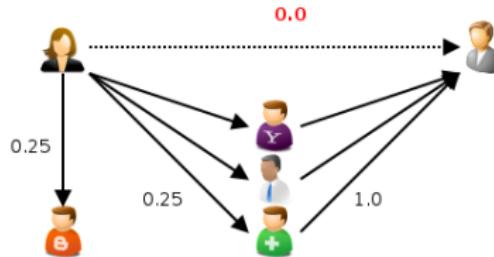
- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0 \dots$
- .. and can make more frequent pairs (u, v) converge to $\theta_{u,v} = 0.0$

Avoid overfitting with IC and DAIC

Learning bias of IC (increased with DAIC):



Observed Diffusion Episode

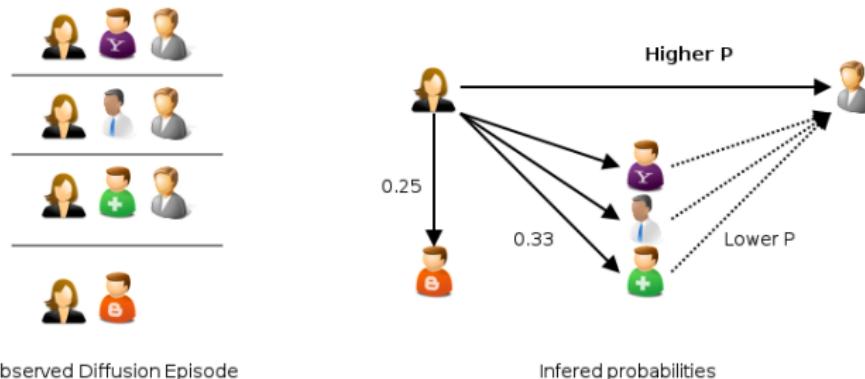


Inferred probabilities

- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0 \dots$
 - .. and can make more frequent pairs (u, v) converge to $\theta_{u,v} = 0.0$
- ⇒ Maximum likelihood reached with several parameters set to 1 (overfitting)
- ⇒ Rare users have a great impact on the extracted relationships

Avoid overfitting with IC and DAIC

Learning bias of IC (increased with DAIC):



- Rare pairs (u, v) can easily obtain $\theta_{u,v} = 1.0 \dots$
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- ⇒ Maximum likelihood reached with several parameters set to 1 (overfitting)
- ⇒ Rare users have a great impact on the extracted relationships

- Influence is a rare event
 - Very high probabilities for $\theta_{u,v}$ are unlikely
- ⇒ Introduction of an exponential prior [Lamprier et al., 2015]:

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

- Maximum a Posteriori:

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

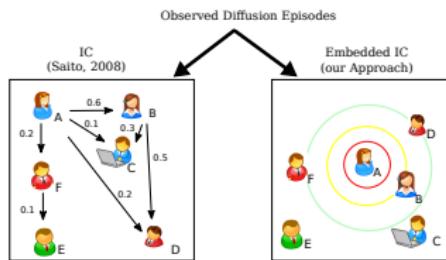
- Favors sparse influence networks
- ⇒ Adaptation of the Saito's EM

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

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

- ⇒ Obtain a more compact model
- ⇒ 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)
- Naturally modeled by the use of a representation space

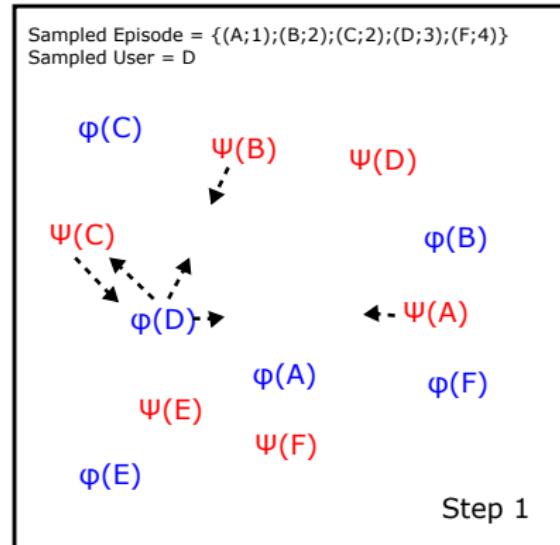


- Influence is an asymmetric relationship
 - Each user i is associated to *two* projections z_i (transmitter projection) and ω_i (receptor projection) in \mathbb{R}^d
 - The transmission probability $\theta_{i,j}$ becomes a function:

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

- Inter-dependent probability values: no analytic solution for the maximization step
- GEM: the maximization is replaced by a step of stochastic gradient ascent

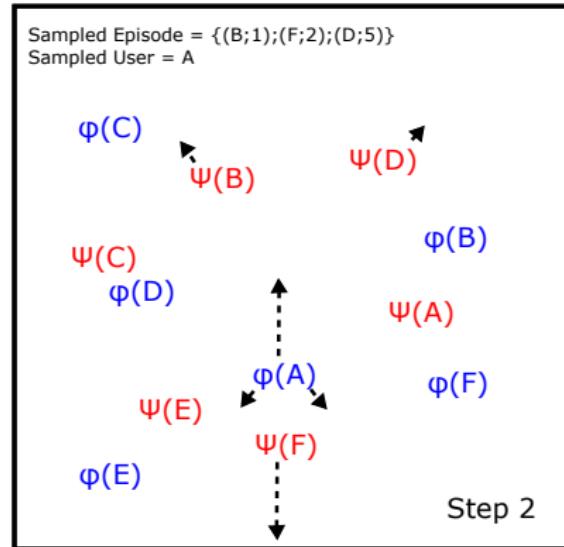
Embedded IC: Example



Iteration 1 :

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

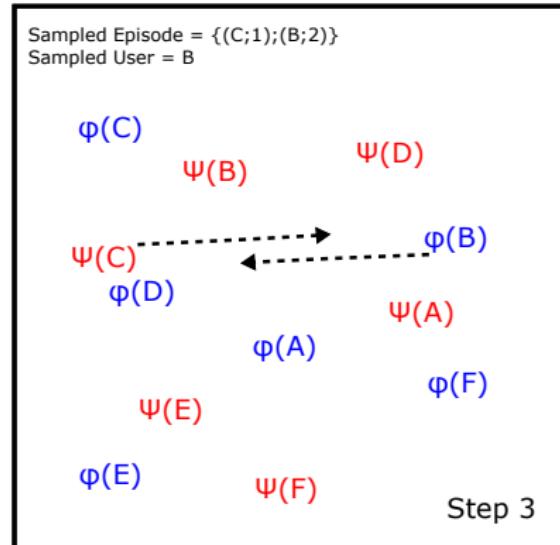
Embedded IC: Example



Iteration 2 :

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

Embedded IC: Example

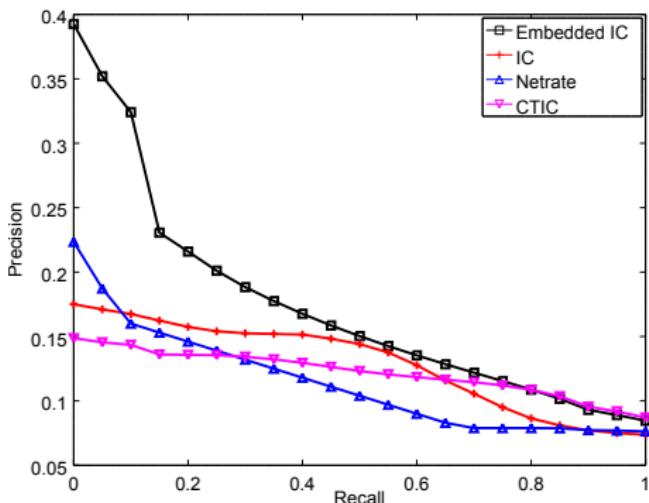


Iteration 3 :

- 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])
- ⇒ Non-iterative approaches for diffusion prediction
- Focus on mapping final states from initial 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

a Non-iterative Approach with Representation Learning

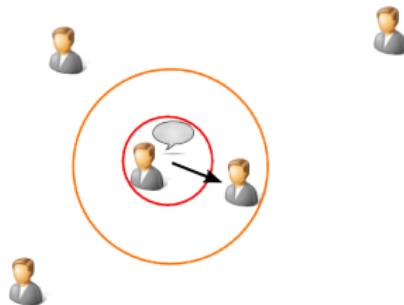
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Heat equation :

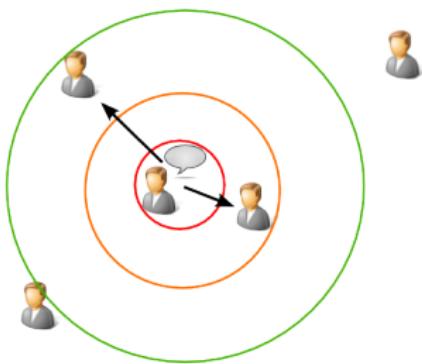
$$\begin{cases} \frac{\partial T}{\partial t} = \Delta_x T \\ f(x, 0) = f_0(x) \end{cases}$$

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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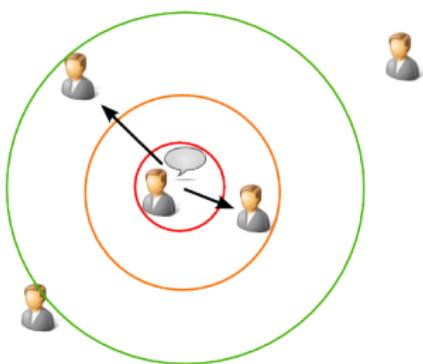
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a Non-iterative Approach with Representation Learning

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



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

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

Diffusion as a heat process

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

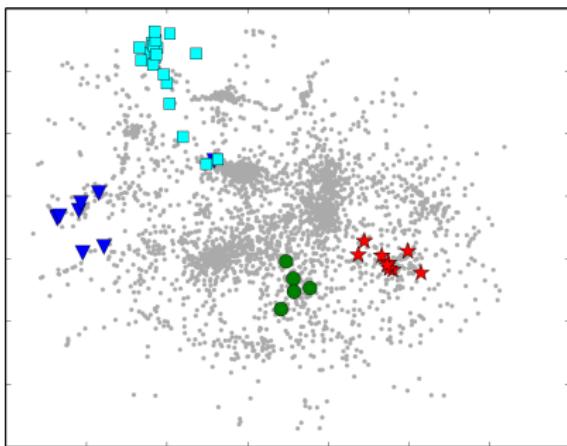
\Rightarrow Loss Function:

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

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

Diffusion as a heat process

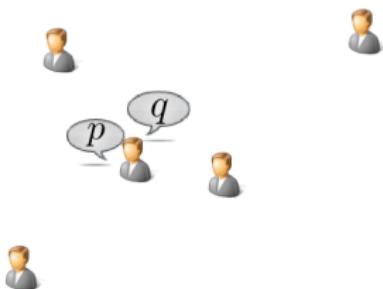
- Projection of users of **Digg** in 2 dimensions :



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

Heat Diffusion: Inclusion of the Content

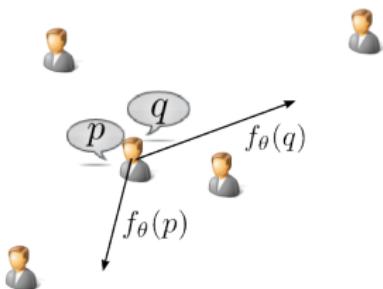
- Hypothesis : The diffused content impacts the diffusion dynamics
 - Translation of the source according to the content



- Similar learning:
 - Simultaneous learning of the translation function f_θ and the projections \mathcal{Z}
 - Optimization by stochastic gradient ascent

Heat Diffusion: Inclusion of the Content

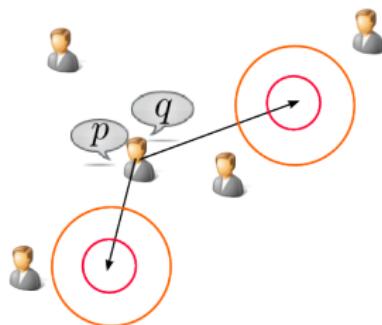
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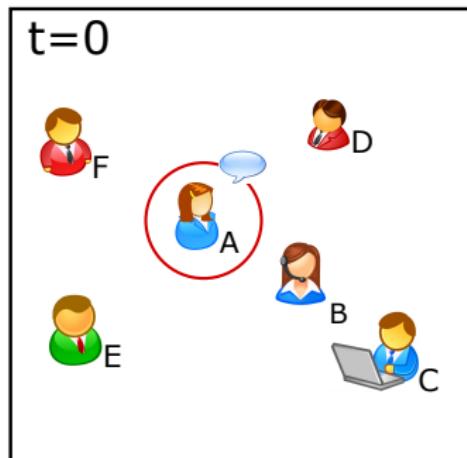
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Heat diffusion: iterative version

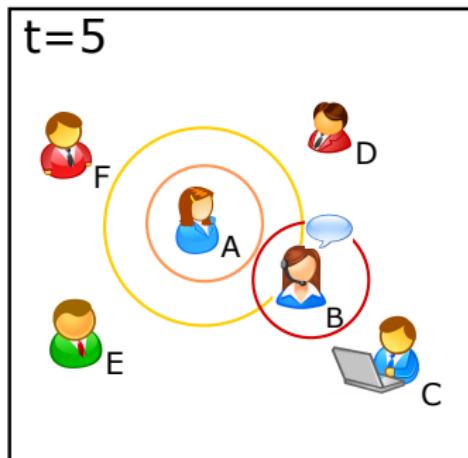
Chain reaction : Each infected user starts emitting heat from its infection time



- ⇒ Dynamic model
- ⇒ Infection time prediction
- ⇒ Dealing with multiple sources

Heat diffusion: iterative version

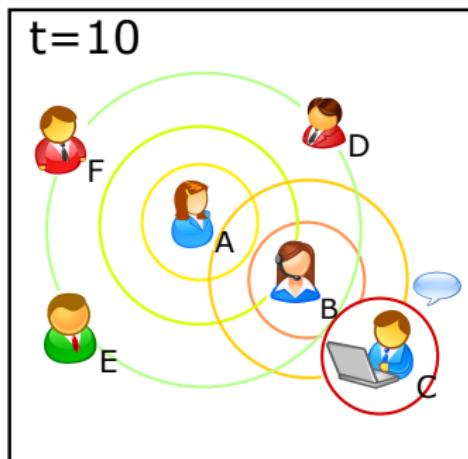
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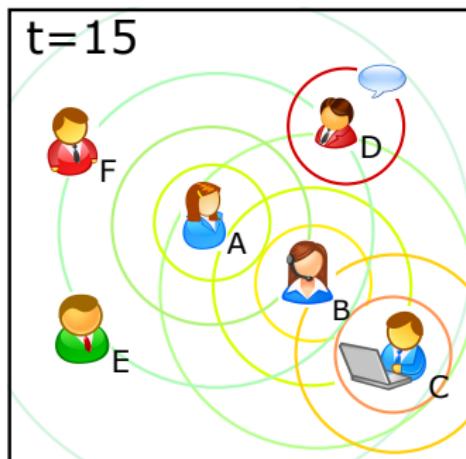
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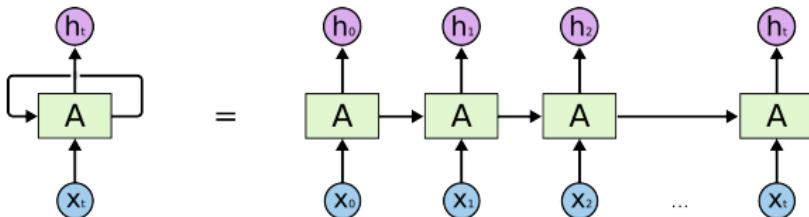
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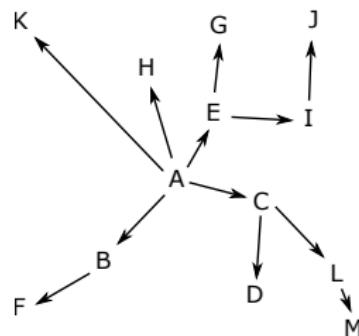
Recurrent Neural Networks for Diffusion



- Diffusion episodes could be seen as sequences
 - Recurrent Neural Networks are well suited for dealing with sequences
 - ⇒ RNN could be used to consider the history of events to predict the future events

Recurrent Neural Networks for Diffusion

- 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]

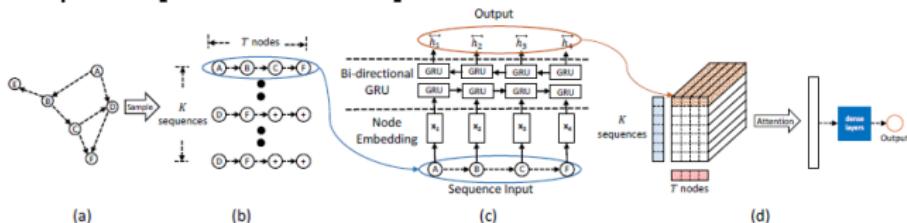
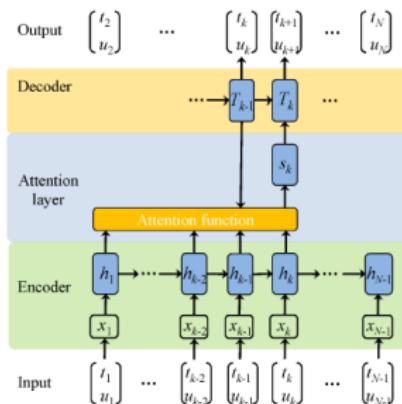


Figure 1: The end-to-end pipeline of DeepCas.

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



⇒ RNN IC with MCMC / Variational inference

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