Learning Distributed Representations of Users for Source Detection in Online Social Networks

The European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases 2016

Simon Bourigault, Sylvain Lamprier and Patrick Gallinari

Learning Distributed Representations of Users for Source Detection in Online Social Networks
The European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases 2016
Simon Bourigault, Sylvain Lamprier and Patrick Gallinari

Contents

- Background
- Related Work
- Theory
- Evaluation
- Result
- Criticism

Contents

1. Background
2. Related Work
3. Theory
4. Evaluation
5. Results
6. Criticism

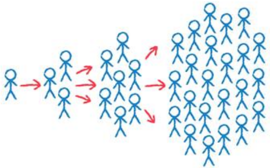
Background

Background

Field

- Social Networks
- Network Diffusion
- Source Detection

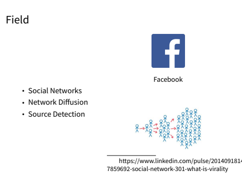
Facebook



https://www.linkedin.com/pulse/2014091814-7859692-social-network-301-what-is-virality

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└Background
└Field



The field of source detection

Contributions

- Introducing representation learning approach to the field of source detection delivering a robost model that handles data sparsity well
- Does not require the influence graph to be known
- Tested on real life data and surpassing other baseline approaches
- Provides an extension that further improves the results

Contributions

- Introducing representation learning approach to the field of source detection delivering a robost model that handles data sparsity well
- Does not require the influence graph to be known
- Tested on real life data and surpassing other baseline approaches
- Provides an extension that further improves the results

- a

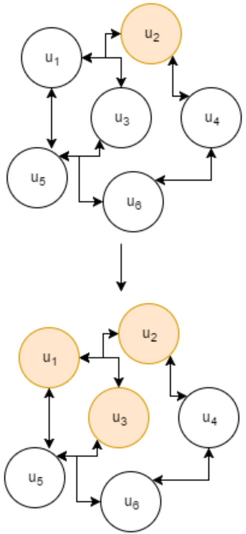
Related Work

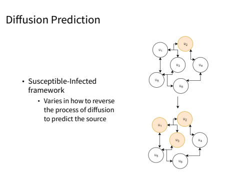
Related Work

- a

Diffusion Prediction

- Susceptible-Infected framework
  - Varies in how to reverse the process of diffusion to predict the source

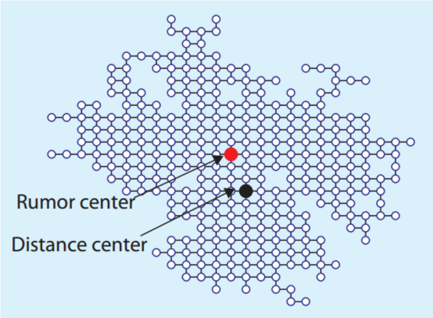




As classically done in the field of diffusion modeling, existing approaches for source detection are based on the Susceptible-Infected framework defined on a given known graph of diffusion G = (U, E). When a user u in U becomes infected at time t, each neighbor v in the graph becomes infected at time t + du,v, with du,v being drawn from some delay distribution [4,5,16,19,20,22]. The various methods mainly differ in their way of reversing the process of diffusion to predict the most probable source when some infections are observed.

Rumor centrality

- Detecting sources of computer viruses in networks: theory and experiment
    - Shah, D. and Zaman, T.

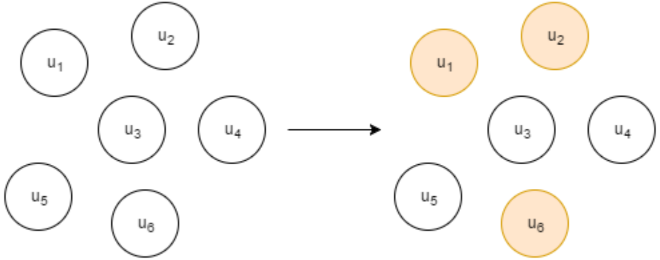


The work of [20] was the first one to introduce the key concept of rumor centrality, a measure rendering the likelihood, for any content emitted from a node u in U, to spread over a given subset of infected users

Theory

Theory

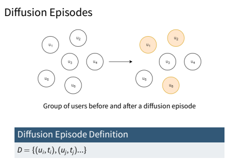
Diffusion Episodes



Group of users before and after a diffusion episode

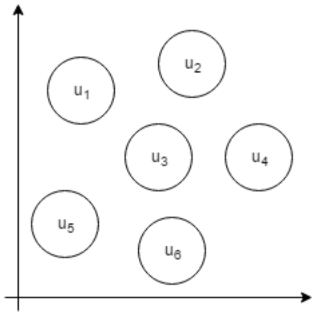
Diffusion Episode Definition

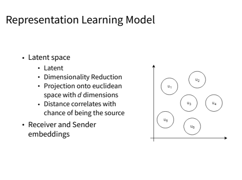
$D = \{(u_i, t_i), (u_j, t_j) \ldots\}$



Representation Learning Model

- Latent space
    - Latent
    - Dimensionality Reduction
    - Projection onto euclidean space with *d* dimensions
    - Distance correlates with chance of being the source
- Receiver and Sender embeddings





Latent space models were introduced by Hoff et al. (2002), and have since been expanded to include model-based clustering (Handcock et al., 2007) and dynamic networks (Sewell and Chen, 2015). Latent space models are similar to a logistic regression predicting whether or not a tie will occur between each pair of people in the network. The models include a random effect - a position in the latent space - for every person. The latent positions are usually constrained to lie in a low-dimensional, Euclidean space to make the model easier to fit and to interpret. A tie is more likely between 2 people who are closer in the latent space.

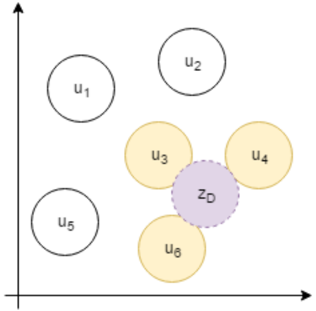
Source Prediction Model

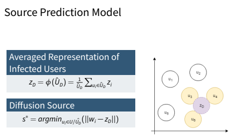
Averaged Representation of Infected Users

$$z_D = \phi(\hat{U}_D) = \frac{1}{\hat{U}_D} \sum_{u_i \in \hat{U}_D} z_i$$

Diffusion Source

$$s^* = argmin_{u_i \in U/\hat{U}_D}(||w_i - z_D||)$$

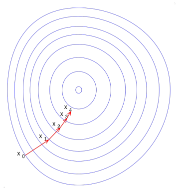




Making 2 latent spaces, one for receiver and one for sender
Finding the source is finding the sender closest to the averaged representation of infected users

Learning Step

- Stochastic Gradient Descent



Update Step

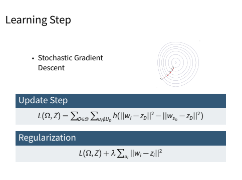
$$L(\Omega, Z) = \sum_{D \in \mathscr{D}} \sum_{u_i \notin U_D} h(||w_i - z_D||^2 - ||w_{s_D} - z_D||^2)$$

Regularization

$$L(\Omega, Z) + \lambda \sum_{u_i} ||w_i - z_i||^2$$

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└Theory
└Learning Step



learning 2 embeddings Omega and Z

Learning Step

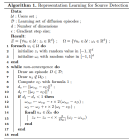
Algorithm 1. Representation Learning for Source Detection

Data:
$\mathcal{U}$: Users set ;
$\mathcal{D}$: Learning set of diffusion episodes ;
d : Number of dimensions
ϵ : Gradient step size;
Result:
$Z = \{\forall u_i \in \mathcal{U} : z_i \in \mathbb{R}^d\}$; $\Omega = \{\forall u_i \in \mathcal{U} : \omega_i \in \mathbb{R}^d\}$;

foreach $u_i \in \mathcal{U}$ **do**
  initialize z_i with random value in $[-1, 1]^d$
  initialize ω_i with random value in $[-1, 1]^d$
end
while *non-convergence* **do**
  Draw an episode $D \in \mathcal{D}$;
  Draw $u_j \notin \mathcal{U}_D$;
  Compute z_D with formula 1 ;
  $d_s \leftarrow ||\omega_{s_D} - z_D||^2$;
  $d_j \leftarrow ||\omega_j - z_D||^2$;
  if $d_j - d_s < 1$ **then**
    $\omega_{s_D} \leftarrow \omega_{s_D} - \epsilon \times 2\,(\omega_{s_D} - z_D)$;
    $\omega_j \leftarrow \omega_j + \epsilon \times 2\,(\omega_j - z_D)$;
    forall $u_x \in \hat{\mathcal{U}}_D$ **do**
      $z_x \leftarrow z_x - \epsilon \times \frac{2}{|\hat{\mathcal{U}}_D|}\,(\omega_j - \omega_{s_D})$
    end
  end
end

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└─Theory
  └─Learning Step


Learning Step

Extensions

Inclusion of User Importance

$$z_D = \sum_{u_i \in \hat{U}_D} \frac{e^{\alpha_i}}{\sum_{u_j \in \hat{U}_D} e^{\alpha_j}} z_i$$

Integration of Content

$$z_D = \frac{1}{|\hat{U}_D|} \sum_{u_i \in \hat{U}_D} z_i + < w_D, \theta >$$

Extensions
Inclusion of User Importance
$z_D = \sum_{u_i \in \hat{U}_D} \frac{e^{\alpha_i}}{\sum_{u_j \in \hat{U}_D} e^{\alpha_j}} z_i$
Integration of Content
$z_D = \frac{1}{|\hat{U}_D|} \sum_{u_i \in \hat{U}_D} z_i + < w_D, \theta >$

Evaluation

Evaluation

- We have evaluated specific parts and the overall system

Datasets

	Users	Links	Episodes	Density
Artificial	100	262	10 000	2 %
Lastfm	1984	235 011	331 829	5 %
Weibo	5000	20 784	44 345	0.08 %
Twitter	4107	128 855	16 824	1 %

Dataset Statistics

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└Evaluation
└Datasets

Datasets

	Users	Links	Episodes	Density
Artificial	100	262	10 000	2 %
Lastfm	1984	235 011	331 829	5 %
Weibo	5000	20 784	44 345	0.08 %
Twitter	4107	128 855	16 824	1 %

Dataset Statistics

Baseline Approaches

- OutDeg
  - Ranks sources by their out-degree
- Jordan Center
  - Predicted source is the node with the minimum longest distance to any infected
- Pinto's
  - Assumes infection delays follows a Gaussian law

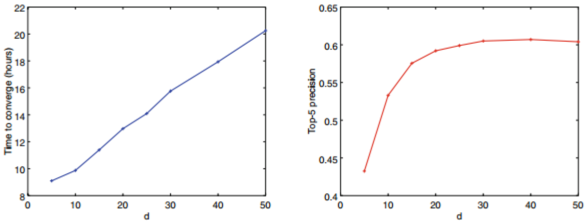
Baseline Approaches

- OutDeg
  - Ranks sources by their out-degree
- Jordan Center
  - Predicted source is the node with the minimum longest distance to any infected
- Pinto's
  - Assumes infection delays follows a Gaussian law

OutDeg: This simple baseline was used in [5]. First, we find all the "possible sources" i.e. all users who can reach every infected one through a series of hops in the graph. Then, we rank these possible sources by their out-degree, the higher one being the most likely source.
Jordan Center: The use of a Jordan Center as a source estimator was studied in [14]. Because our experimental context is not exactly the same as [14], we slightly adapt its formulation: the predicted source is the one with the minimum longest distance to any infected user.
Pinto's: The model described in [16], based on the assumption that infection delays follow a Gaussian law. It uses a heuristic based on the extraction of a tree subgraph.

Training the Model

- Value of $d = 30$



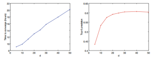
Convergence time and performance for various values of d on the Weibo dataset

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└Evaluation
└Training the Model

Training the Model

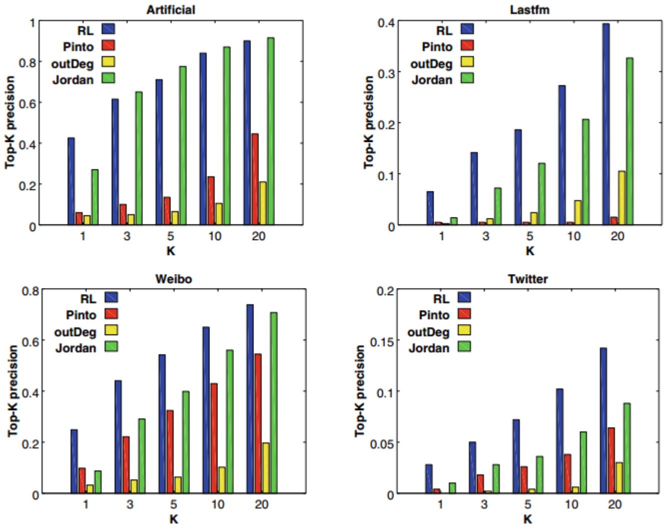
- Value of $d = 30$



Convergence time and performance for various values of d on the Weibo dataset

Results

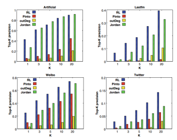
Results



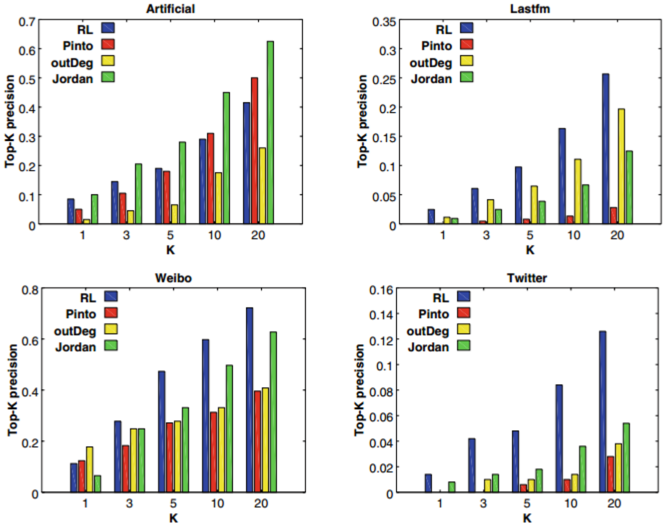
Source detection with full cascades

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└─Results



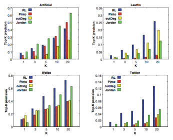
Source detection with full cascades



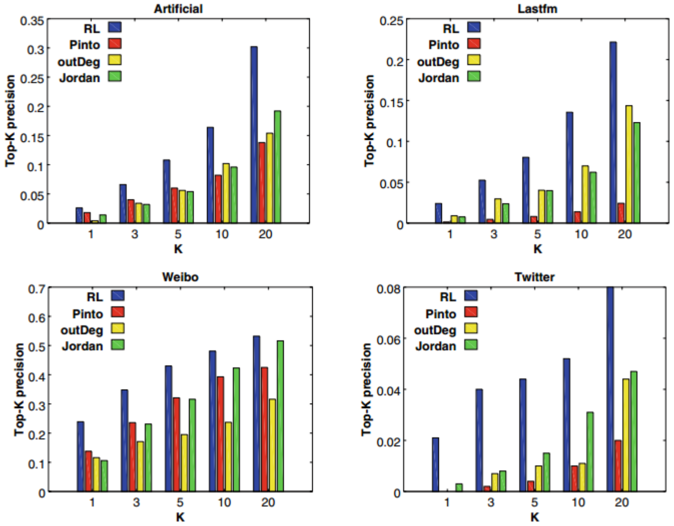
Source detection with partial cascades (20%)

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└─Results



Source detection with partial cascades (20%)

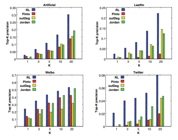


Source detection with partially observed cascades (20%)

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data

└─Results



Source detection with partially observed cascades (20%)

Top-K	1	3	5	10	20
Twitter					
RL	0.020	0.042	0.058	0.099	0.141
RL w/weights	0.021	0.047	0.073	0.107	0.154
Gain	3 %	10 %	25 %	8 %	9 %
Lastfm					
RL	0.052	0.12	0.166	0.2545	0.374
RL w/weights	0.065	0.1335	0.175	0.2605	0.378
Gain	25 %	11 %	5 %	2 %	1 %
Weibo					
RL	0.31	0.51	0.59	0.72	0.82
RL w/weights	0.31	0.50	0.60	0.75	0.84
Gain	0 %	−2.3 %	+0 %	+4 %	+1 %

Source detection with user weights

2017-01-26

Sentiment Knowledge Discovery in Twitter Streaming Data
└Results

Source detection with user weights

Top-K	1	3	5	10	20
RL	0.028	0.05	0.072	0.102	0.142
RL w/content	0.043	0.069	0.099	0.128	0.179
Gain	56 %	38 %	38 %	26 %	26 %

Source Detection with Content Integration on the Twitter dataset

Top-K	1	3	5	10	20
RL	0.028	0.05	0.072	0.102	0.142
RL w/content	0.043	0.069	0.099	0.128	0.179
Gain	56 %	38 %	38 %	26 %	26 %

Source Detection with Content Integration on the Twitter dataset

Criticism

Criticism

Criticism

- Inconsistent reference strategy. Did not always refer to their figures and formulas
- Latent Space
  - Missing flow between concept and construction of representation model
  - No reference to the picture
- Size of dataset
- High concept, low technical
- Results of Content Integration for Twitter dataset

Criticism

- Inconsistent reference strategy. Did not always refer to their figures and formulas
- Latent Space
  - Missing flow between concept and construction of representation model
  - No reference to the picture
- Size of dataset
- High concept, low technical
- Results of Content Integration for Twitter dataset