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

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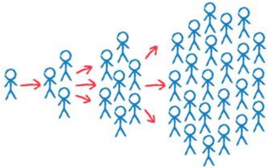
Contents

Background

Field

Facebook

- Social Networks
- Network Diffusion
- Source Detection



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

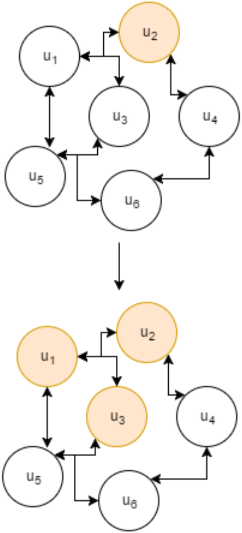
Contributions

- 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

Related Work

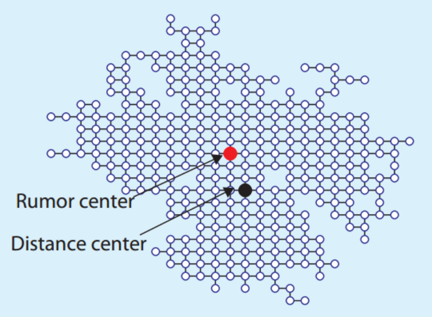
Diffusion Prediction

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



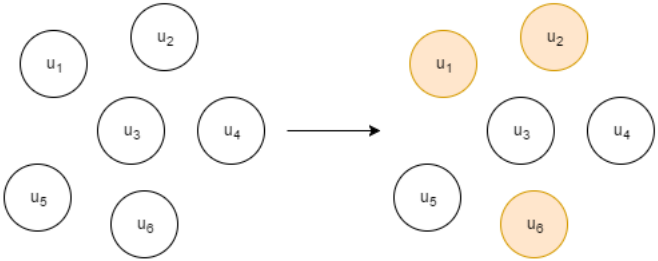
Rumor centrality

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



Theory

Diffusion Episodes



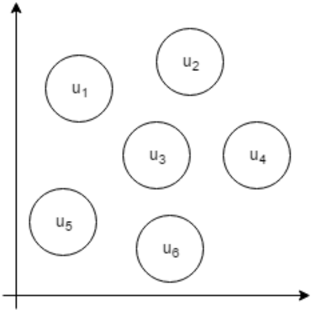
Group of users before and after a diffusion episode

Diffusion Episode Definition

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

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



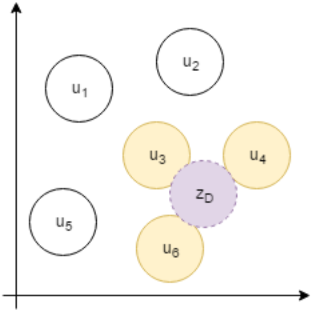
Source Prediction Model

Averaged Representation of Infected Users

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

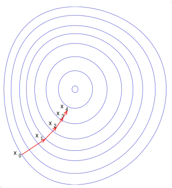
Diffusion Source

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



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

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

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

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

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 %

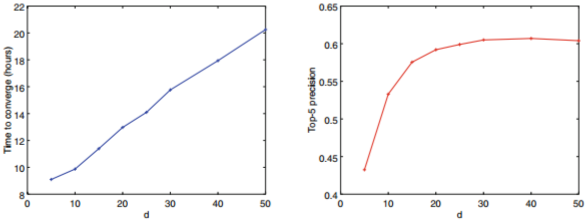
Dataset Statistics

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

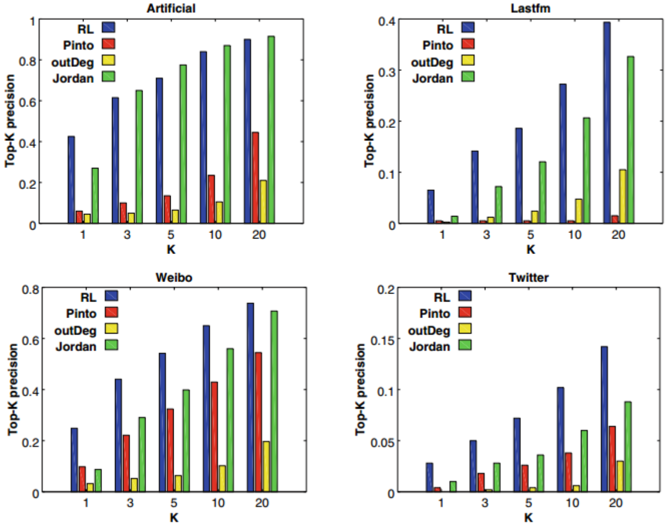
Training the Model

- Value of $d = 30$

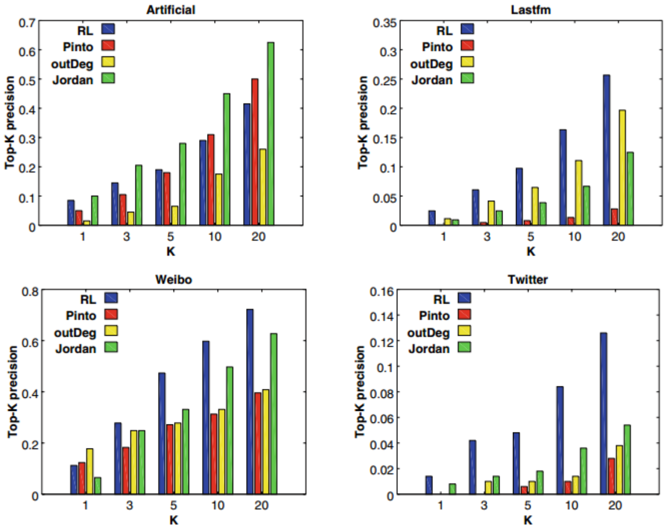


Convergence time and performance for various values of d on the Weibo dataset

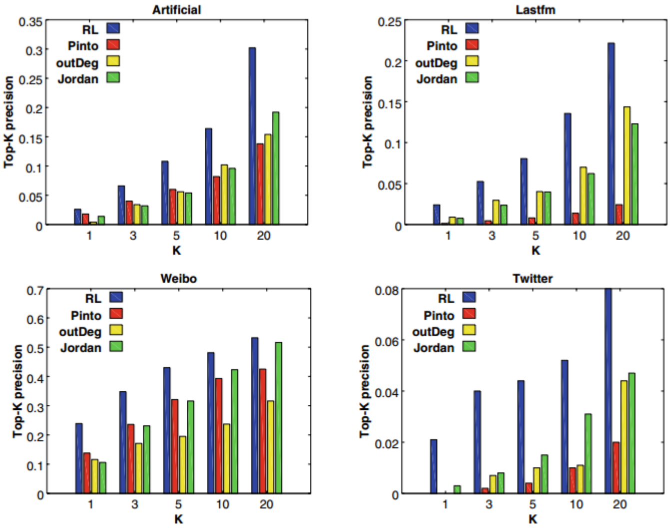
Results



Source detection with full cascades



Source detection with partial cascades (20%)



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

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

- 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