Global and Local Feature Learning for Ego-Network Analysis

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TIR Workshop

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Outline

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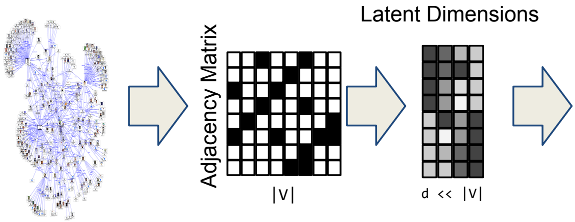
Graph Embedding

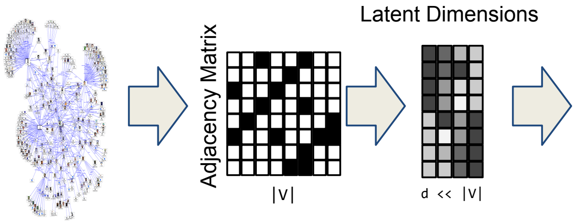


- Anomaly Detection
- Attribute Prediction
- Clustering
- Link Prediction
- ...

Given graph G with a set of nodes $V = \{v_1, \ldots, v_n\}$

$$f : v_i \mapsto y_i \in \mathbb{R}^d,\ d \ll |V|$$

- Methods based on eigen-decomposition of the Adjacency Matrix
- Methods inspired by NLP and Deep Learning



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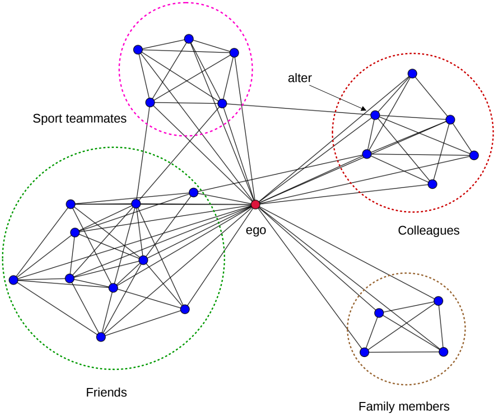
- **Methods inspired by NLP and Deep Learning**

What is an Ego Network?

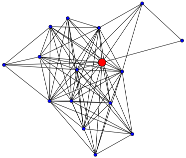
- Social graphs have been divided to several subgraphs (ego-networks) [1]
  - extracting features for nodes
  - detecting distinct neighborhood patterns
  - study social relationships
- Ego-network [1]
  - ego
  - alters
  - social circles



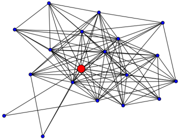
An ego-network with four social circles

Local Neighborhood Analysis

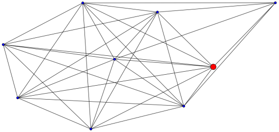
- Neighborhood around each ego has a different pattern [2]



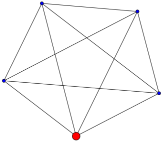
(a) Linked neighbors



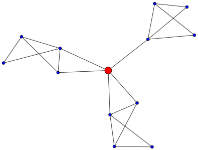
(b) Strongly linked



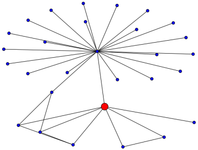
(c) Dense



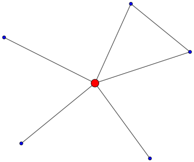
(d) Complete



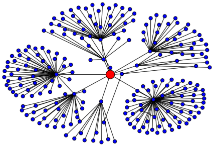
(e) Powerful ego node



(f) Strong ego neighbor



(g) Less cohesive star



(h) Star

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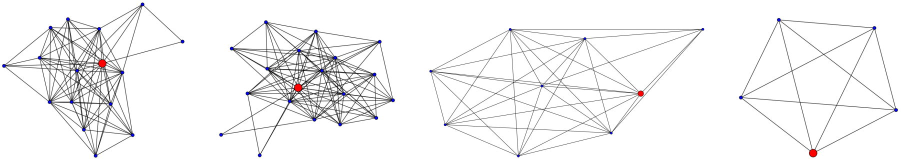
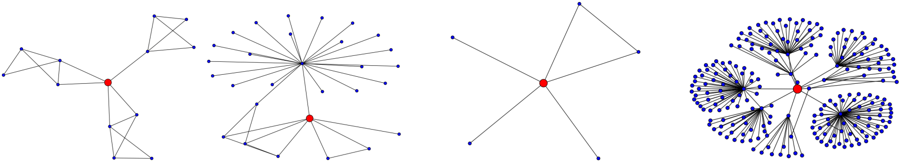


(a) Linked neighbors (b) Strongly linked (c) Dense (d) Complete

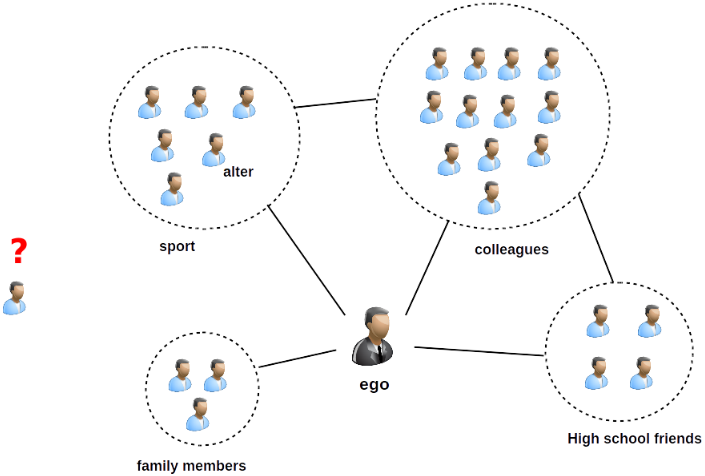


(e) Powerful ego node (f) Strong ego neighbor (g) Less cohesive star (h) Star

- Finding a vector representation for each ego-network
- Social circle detection and prediction

Social Circle Prediction

- Predicting the social circle for a new added alter to the ego-network



Outline

1. Introduction
   - Graph Embedding
   - Ego-Network Analysis
2. Contributions
3. State-of-the-art
4. Approach
5. Experimental Results
6. Future Work
7. References

Our Contributions

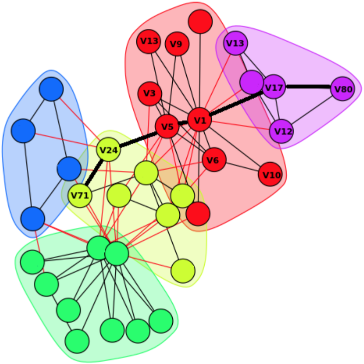
- We introduce local vector representations for egos to capture neighborhood structures
- We apply local vectors to the circle prediction problem
- We replace global representations by local to improve the performance

Outline

Vector Representation for Social Graphs

- DeepWalk [3]
  - walks globally over the graph and samples sequences of nodes
  - treats all these sequences as an artificial corpus
  - feeds the corpus to a Skip-Gram based Word2Vec [5]

$$v_{71} \rightarrow v_{24} \rightarrow v_{5} \rightarrow v_{1} \rightarrow v_{17} \rightarrow v_{80} \rightarrow$$
$$v_{92} \rightarrow v_{2} \rightarrow v_{3} \rightarrow v_{1} \rightarrow v_{12} \rightarrow v_{73} \rightarrow$$
$$v_{37} \rightarrow v_{34} \rightarrow v_{9} \rightarrow v_{1} \rightarrow v_{10} \rightarrow v_{94} \rightarrow$$
$$v_{73} \rightarrow v_{64} \rightarrow v_{5} \rightarrow v_{1} \rightarrow v_{12} \rightarrow v_{1} \rightarrow$$
$$v_{75} \rightarrow v_{14} \rightarrow v_{6} \rightarrow v_{1} \rightarrow v_{13} \rightarrow v_{61} \rightarrow$$



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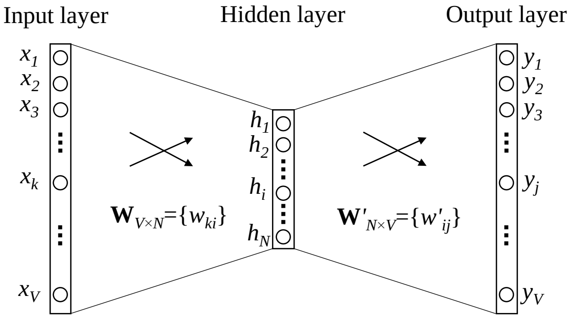
  - Word2Vec: Having the sequence of words $\{w_1, w_2, \ldots, w_{t-1}, w_t, w_{t+1} \ldots, w_n\}$, language models aims to maximize $P(w_t | w_1, \ldots, w_{t-1})$.



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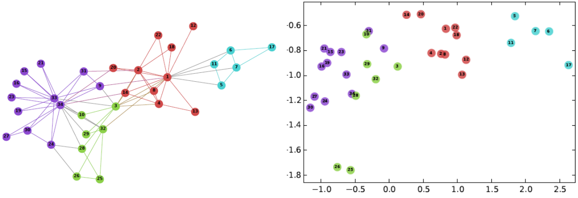
  - given sequence of nodes $\{v_1, v_2, \ldots, v_{t-1}, v_t, v_{t+1}, \ldots, v_n\}$ it maximizes: $\sum_{t=1}^{n} \log Pr(v_t|v_{t+c}, \ldots, v_{t_1}, v_{t+1}, \ldots, v_{t-c})$
  - $\mathrm{glo}\colon V \rightarrow \mathbb{R}^d$

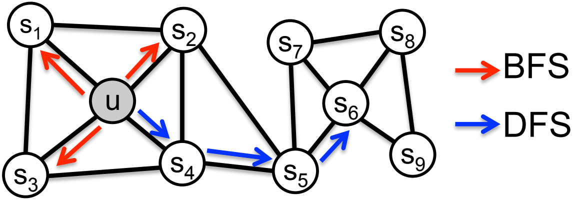


Input Output

Zachary's karate club embedding [2]

Vector Representation for Social Graphs

- node2vec [4]
  - similar to DeepWalk with two additional parameters
  - hyper-parameters $p \in \mathbb{R}^+$ and $q \in \mathbb{R}^+$ control random walks
  - $q > 1$ and $p < \min(q, 1)$ walk locally (BFS)
  - $p > 1$ and $q < \min(q, 1))$ walk explorative (DFS)



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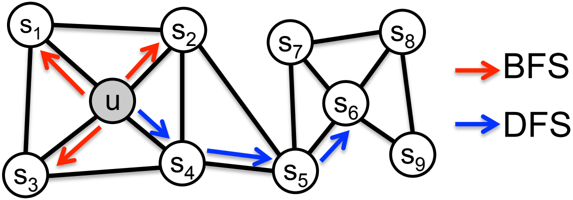
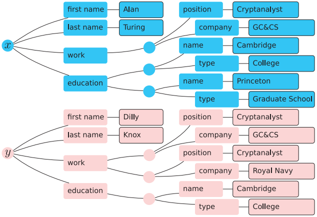


- Even the local walk can exceed the ego-network

Social Circle Prediction by McAuley et al. [1]

ALGORITHM 2: Update memberships node x and circle k.

Data: node x whose membership to circle C_k is to be updated
Result: updated membership for node x
initialize $\ell_x^k(0) := 0$, $\ell_x^k(1) := 0$;
construct a dummy node x_0 with the communities and features of x but with $x \notin C_k$;
construct a dummy node x_1 with the communities and features of x but with $x \in C_k$;
for $(c, f) \in \mathtt{dom}(types)$ **do**
    // c = community string, f = feature string
    $n := types(c, f)$;
    // n = number of nodes of this type
    if $S(x) = c \wedge Q(x) = f$ **then**
        // avoid including a self-loop on x
        $n := n - 1$;
    end
    construct a dummy node y with community memberships c and features f;
    // first compute probabilities assuming all pairs (x, y) are non-edges
    $\ell_x^k(0) := \ell_x^k(0) + n \log p((x_0, y) \notin E)$;
    $\ell_x^k(1) := \ell_x^k(1) + n \log p((x_1, y) \notin E)$;
end
for $(x, y) \in E$ **do**
    // correct for edges incident on x
    $\ell_x^k(0) := \ell_x^k(0) - \log p((x_0, y) \notin E) + \log p((x_0, y) \in E)$;
    $\ell_x^k(1) := \ell_x^k(1) - \log p((x_1, y) \notin E) + \log p((x_1, y) \in E)$;
end
// update membership to circle k
$types(S(x), Q(x)) := types(S(x), Q(x)) - 1$;
$z \leftarrow \mathcal{U}(0, 1)$;
if $z < \exp\{T(\ell_x^k(1) - \ell_x^k(0))\}$ **then**
    $S(x)[k] := 1$
else
    $S(x)[k] := 0$
end
$types(S(x), Q(x)) := types(S(x), Q(x)) + 1$;



$$\mathbf{1} - \sigma_{x,y} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} \begin{array}{l} \textit{first name : Dilly} \\ \textit{last name : Knox} \\ \textit{first name : Alan} \\ \textit{last name : Turing} \\ \textit{work : position : Cryptanalyst} \\ \textit{work : location : GC\&CS} \\ \textit{work : location : Royal Navy} \\ \textit{education : name : Cambridge} \\ \textit{education : type : College} \\ \textit{education : name : Princeton} \\ \textit{education : type : Graduate School} \end{array}$$

$$\mathbf{1} - \sigma'_{x,y} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \begin{array}{l} \textit{first name} \\ \textit{last name} \\ \textit{work : position} \\ \textit{work : location} \\ \textit{education : name} \\ \textit{education : type} \end{array}$$

- A Probabilistic Classifier
- Time Complexity $O(n^3)$

Outline

Local Representations using Paragraph Vector

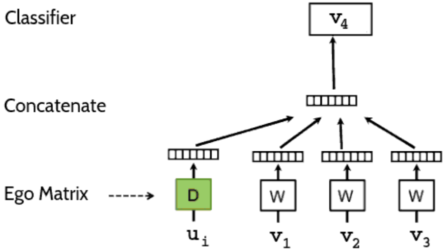
- walking locally over an ego-network to generate sequence of nodes
- treating this sequence as an artificial paragraph
- applying Paragraph Vector [6] to learn vector representation

Local Representations using Paragraph Vector

- walking locally over an ego-network to generate sequence of nodes
- treating this sequence as an artificial paragraph
- applying Paragraph Vector [6] to learn vector representation
- given an artificial paragraph $v_1, v_2, v_3, \ldots, v_t, \ldots, v_l$ for ego u_i, it maximizes the average log probability:

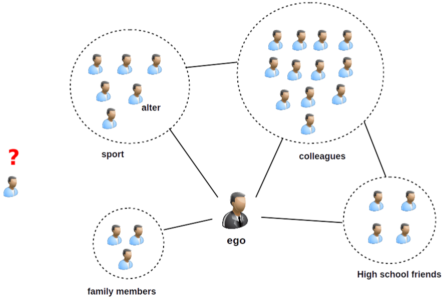
$$\sum_{t=1}^{l} \log Pr(v_t | u_i, v_{t+c}, \ldots, v_{t-c})$$

- $\text{loc}\colon U \rightarrow \mathbb{R}^d$



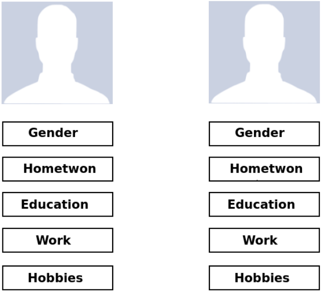
Social Circle Prediction

- Setting
  - social network $G = (V, E)$ with egos U and alters $V \setminus U$
  - profile information $(v.\,\mathrm{feat}_1, \ldots, v.\,\mathrm{feat}_f)$ for every $v \in V$
- Input/Output
  - predict social circles $c \colon V \setminus U \to \{C_1, \ldots, C_k\}^*$ given several samples
- Approach
  - Feature selection (users' profile information, graph embeddings)
  - A Neural Network Classifier



Incorporating Profile Information

- Similarity of ego's and alter's profile as a feature

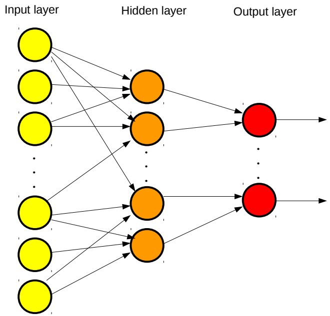


  - ego's profile feature: $u.\text{feat}_1, \ldots, u.\text{feat}_f$
  - alter's profile feature: $v.\text{feat}_1, \ldots, v.\text{feat}_f$
  - $\text{sim}(u, v) = (b_1, \ldots, b_f)$, where

$$b_i = \begin{cases} 1 & \text{if } u.\text{feat}_i = v.\text{feat}_i, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Social Circle Prediction

- A feed-forward neural network classifier
- Predicting social circle for alter v which belongs to ego-network of ego u
- **Input layer:**
  - **locglo:** $\mathrm{loc}(u) \oplus \mathrm{glo}(v)$
  - **gloglo:** $\mathrm{glo}(u) \oplus \mathrm{glo}(v)$
  - **locgloglo:** $\mathrm{loc}(u) \oplus \mathrm{glo}(u) \oplus glo(v)$
  - **locglosim:** $\mathrm{loc}(u) \oplus \mathrm{glo}(v \oplus \mathrm{sim}(u, v)$
  - **gloglosim:** $\mathrm{glo}(u) \oplus \mathrm{glo}(v) \oplus \mathrm{sim}(u, v)$
  - **locgloglosim:** $\mathrm{loc}(u) \oplus \mathrm{glo}(u) \oplus \mathrm{glo}(v) \oplus \mathrm{sim}(u, v)$



- **Hidden layer:** a single dense layer with ReLU activation units
- **Output layer:** softmax units (same number as circles)
- Ground-truth
  - alter's circle label (family, colleagues, etc)

Outline

Dataset

Table 1: Statistics of Social Network Datasets [7]

		Facebook	**Twitter**	**Google+**
nodes	$\lvert V \rvert$	4,039	81,306	107,614
edges	$\lvert E \rvert$	88,234	1,768,149	13,673,453
egos	$\lvert U \rvert$	10	973	132
circles	$\lvert \mathcal{C} \rvert$	46	100	468
features	f	576	2,271	4,122

Experimental Results

Table 2: Performance (F_1-score) of different embeddings for circle prediction on three dataset. Standard deviation is less than 0.02 for all experiments.

Approach	**Facebook**	**Twitter**	**Google+**
gloglo	0.37	0.46	0.49
locglo	**0.42**	**0.50**	**0.52**
locgloglo	0.37	0.44	0.48
gloglosim	0.40	0.49	0.51
locglosim	**0.45**	**0.53**	**0.55**
locgloglosim	0.38	0.46	0.47
Φ^1, McAuley & Leskovec [1]	0.38	0.54	0.59

Outline

Future Work

- Using embeddings to approximate more complex measures (e.g. shortest-path distance)
- Using embedding to find similar egos
- Learning embedding for directed graphs

Outline

References

McAuley, Julian J., and Jure Leskovec. "Learning to Discover Social Circles in Ego Networks." In NIPS, vol. 2012, pp. 548-56. 2012.

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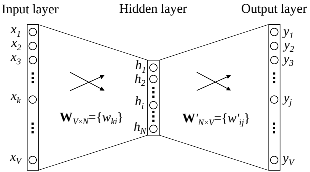
https://snap.stanford.edu/data/

Word2vec [5]

- Language Modeling
    - Distributional Hypothesis in the natural languages: semantically similar words dispose to appear in similar word neighborhoods
- Having the sequence of words $\{w_1, w_2, ..., w_{t-1}, w_t, ..., w_n\}$, language models aims to maximize $P(w_t|w_1, ..., w_{t-1})$.
- In word2vec [2], they defined a fix context length surrounding each word
- with length context c and the sequence of words $\{w_1, w_2, ..., w_{t-1}, w_t, ..., w_n\}$ the goal is to word2vec is to maximize: $\sum_{t=1}^{n} \log P(w_t|w_{t+c}, ..., w_{t-c})$
- The neural network which learns word representations:
    - One hidden layer
    - The number of input layer entries is equal to the vocabulary size of the text
    - The number of units in the hidden layer determines dimensionality of the vectors

Word2vec [5]

- Having a sequence of words $\{w_1, w_2, ..., w_{t-1}, w_t, ..., w_n\}$ and context window with length one
- Predict one target word, given one context word $P(w_t|w_{t-1})$.



- Each input is a one-hot encoding vector
- The probability is computed using the softmax function:
  $h = W^T \times x, \quad u = W'^T \times h, \quad P(w_t|w_{t-1}) = y_t = \frac{e^{u_t}}{\sum_{i=1}^{V} e^{u_j}}$
- After several iterations matrix W will not change

Paragraph Vector

- Given a sequence of paragraphs $p_1, p_2, ..., p_q$ and training words $w_1, w_2, w_3, \ldots, w_t, \ldots w_n$, the idea of Paragraph Vector [6] is to maximize $p(w_t|p_j, w_{t-c}..., w_{t+c}))$
- For example consider 2 paragraphs and window size of 3
  - P_1 : $\boxed{\text{The cat sat}}$ on the mat
  - P_2 : I ate potato crisps for evening snack
  - $p(on|P_1, The, cat, sat)$