TransNet: Translation-Based Network Representation Learning for Social Relation Extraction

用于社交关系提取的基于转移的网络表示学习

Cunchao Tu[1,2], **Zhengyan Zhang**[1], **Zhiyuan Liu**[1,2*], **Maosong Sun**[1,2]

[1]Department of Computer Science and Technology, State Key Lab on Intelligent Technology and Systems, National Lab for Information Science and Technology, Tsinghua University, Beijing, China

[2]Jiangsu Collaborative Innovation Center for Language Ability, Jiangsu Normal University, Xuzhou, China

What Does “Translation” Mean?

We may familiar with :

Network Representation Learning

What Does “Translation” Mean?

“Translation” here means the movement that changes the position of a vector in representation space.

What Is Social Relation Extraction？

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Formally, we define the problem of SRE as follows. Suppose there is a social network $G = (V, E)$, where V is the set of vertices, and $E \subseteq (V \times V)$ are edges between vertices. Besides, the edges in E are partially labeled, denoted as E_L.

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Finally, given the overall network structure and the labeled edges in E_L, SRE aims to predict the labels over unlabeled edges in E_U, where $E_U = E - E_L$ represents the unlabeled

What We Have Got here?

Now, We have already got a baby step for :

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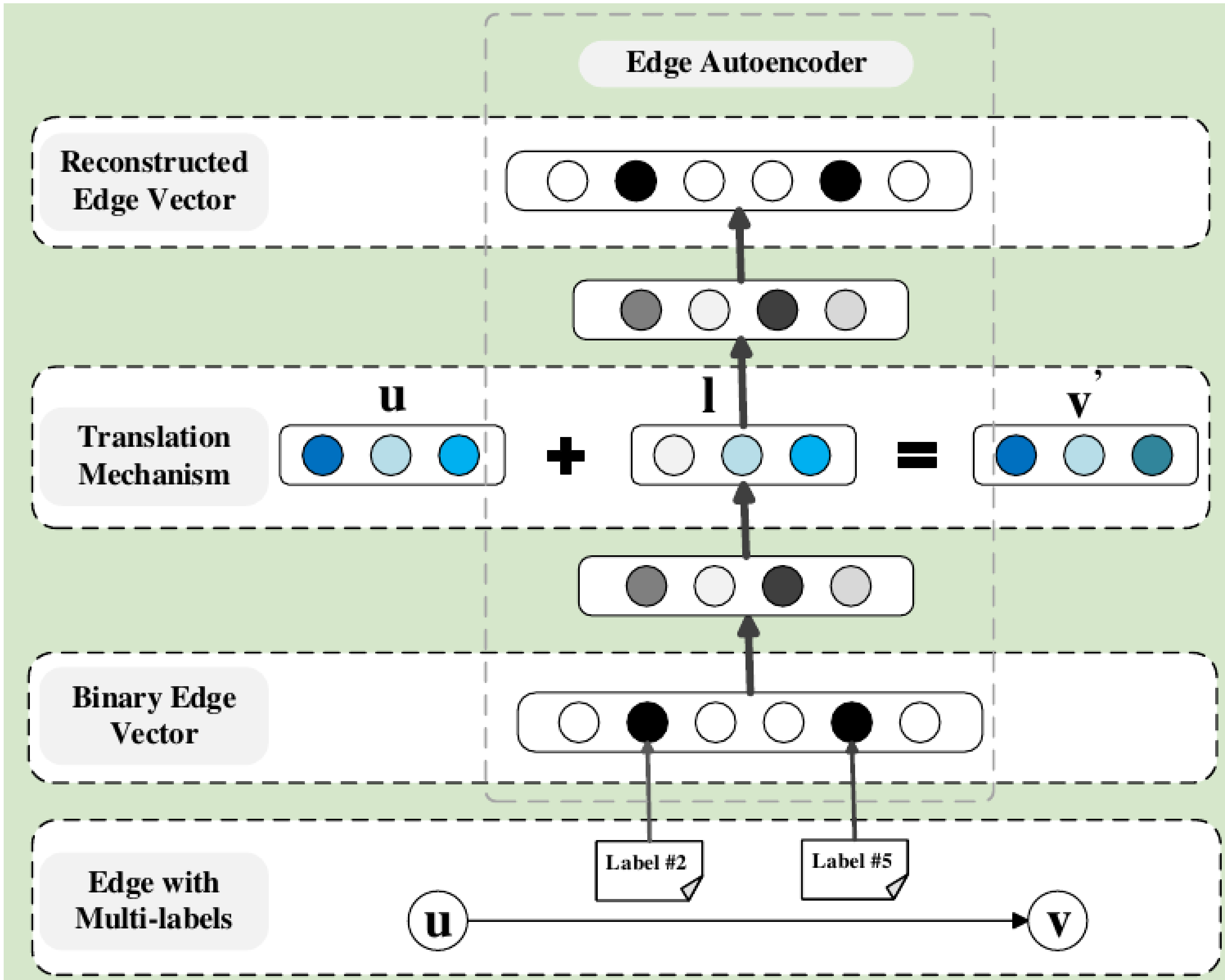
Then, let’s go for a more detail about “main work”

Main Work

In this work, we focus on the problem of incorporating rich relation information on edges into NRL.

Main Work


Edge Autoencoder
Reconstructed Edge Vector
Translation Mechanism
u
l
v'
Binary Edge Vector
Edge with Multi-labels
Label #2
Label #5
u
v

Translation Mechanism

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the translation mechanism among u, v and e can be formalized as

$$\mathbf{u} + \mathbf{l} \approx \mathbf{v}'. \tag{1}$$

head vertex

tail vertex

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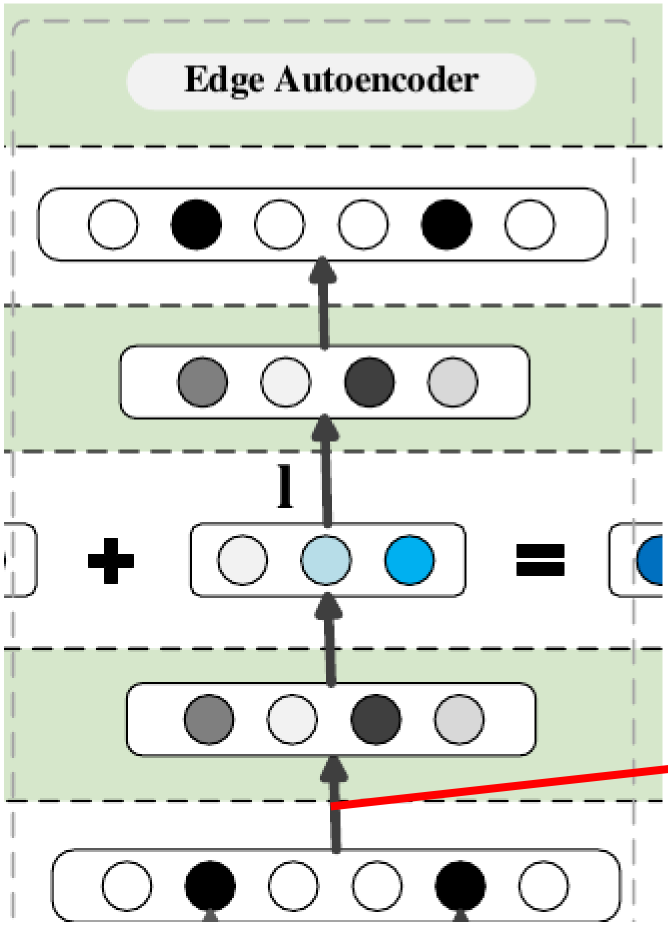
With the above definitions, for each (u, v, l) and its negative sample $(\hat{u}, \hat{v}, \hat{l})$, the translation part of TransNet aims to minimize the hinge-loss as follows:

$$\mathcal{L}_{trans} = \max(\gamma + d(\mathbf{u} + \mathbf{l}, \mathbf{v}') - d(\hat{\mathbf{u}} + \hat{\mathbf{l}}, \hat{\mathbf{v}}'), 0), \qquad (2)$$

where $\gamma > 0$ is a margin hyper-parameter

Edge Representation Construction

we employ a deep autoencoder to construct the edge representations.



$$\mathbf{h}^{(1)} = f(\mathbf{W}^{(1)}\mathbf{s} + \mathbf{b}^{(1)}),$$
$$\mathbf{h}^{(i)} = f(\mathbf{W}^{(1)}\mathbf{h}^{(i-1)} + \mathbf{b}^{(i)}), i = 2, \ldots, K.$$

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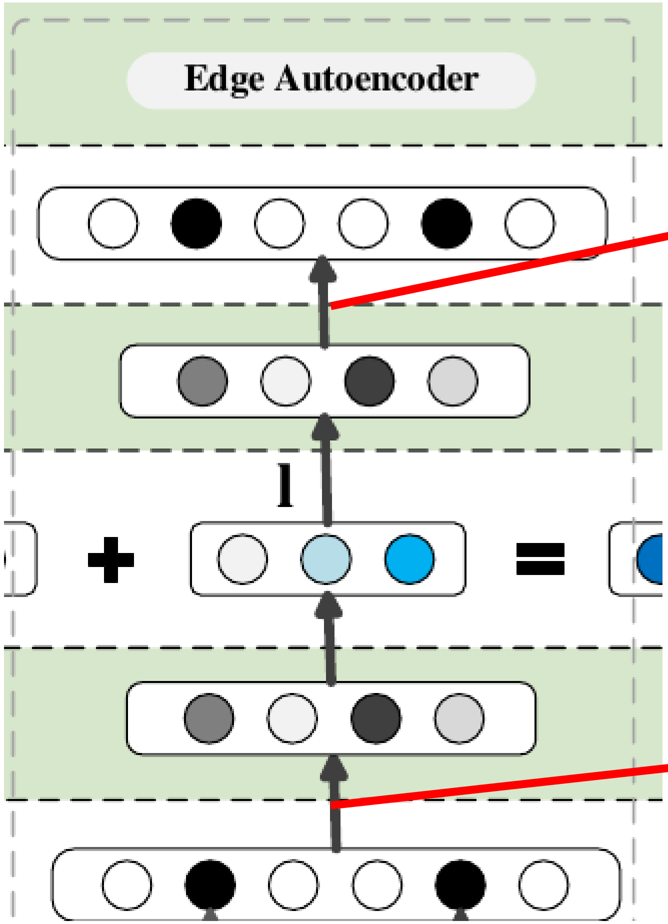

sigmoid activation function

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$$\mathcal{L}_{ae} = ||(\mathbf{s} - \hat{\mathbf{s}}) \odot \mathbf{x}||, \quad (6)$$

where $\mathbf{x}$ is a weight vector and $\odot$ means the Hadamard product. For $\mathbf{x} = \{\mathbf{x}_i\}_{i=1}^{|T|}$, $\mathbf{x}_i = 1$ when $\mathbf{s}_i = 0$ and $\mathbf{x}_i = \beta > 1$ otherwise.

Overall Cost

$$\mathcal{L} = \mathcal{L}_{trans} + \alpha[\mathcal{L}_{ae}(l) + \mathcal{L}_{ae}(\hat{l})] + \eta\mathcal{L}_{reg}. \tag{7}$$

Here, we introduce two hyper-parameters α and η to balance the weights of different parts. Besides, $\mathcal{L}_{reg}$ is an $L2$-norm regularizer to prevent overfitting, which is defined as

$$\mathcal{L}_{reg} = \sum_{i=1}^{K}(||W^{(i)}||_2^2 + ||b^{(i)}||_2^2). \tag{8}$$

One More Thing

Thanks for Listening

Preferences

- [1] 《 TransNet: translation-based network representation learning for social relation extraction[C]International Joint Conference on Artificial Intelligence. AAAI 》
- [2]