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Graph Convolutional Networks for Node Classification in Issue-based Information System

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1 Introduction

Issue-based information system (IBIS) is a classic argumentation-based approach to solve wicked problems [1]. One of its fundamental problems is how to automatically classify labels of arguments such as ideas and issues from argumentation structures. Since IBIS-based argumentation can be regarded as graphical data, graph neural networks (GNN) as an efficient method to capture the latent relationships of graphical data, can automatically classify argument labels.

However, in some realistic scenarios, the participants may not strictly follow an IBIS structure to discuss. Thus, it is important to investigate how IBIS structures would influence performances when applying GNN for argument classification. Specifically, we define two types of IBIS structures: strict-IBIS and soft-IBIS which are distinguished by whether the argumentation structures strictly follow IBIS definition. We then perform evaluations on a real English discussion dataset to compare their performances.

2 Problem and Method

There are five elements in IBIS: *Topic* is a theme of one argumentation structure; *Issue* is a sub-subject related to the topic that's being discussed or analyzed; *Idea* is a response to an *Issue* which offers a potential resolution or clarification of the *Issue*; *Pros* and *Cons* are comments in favor of or against an *Idea*. Then, we define strict-IBIS structure and soft IBIS-structure as follows.

Definition 1. strict-IBIS structure: Given a set L of argument labels: $L = \{Topic, Issue, Idea, Pros, Cons\}$ and a set R^{str} of relationships of the labels: $R^{str} = \{(Topic, Issue), (Issue, Idea), (Idea, Pros), (Idea, Cons)\}$, we call an argument structure $G =< V, E >$ follows a strict-IBIS structure if any of its node's labels belongs to L and any of its edge's labels belongs to R^{str}, i.e., $\forall v \in V, v \in L$ and $\forall e \in E, e \in R^{str}$.

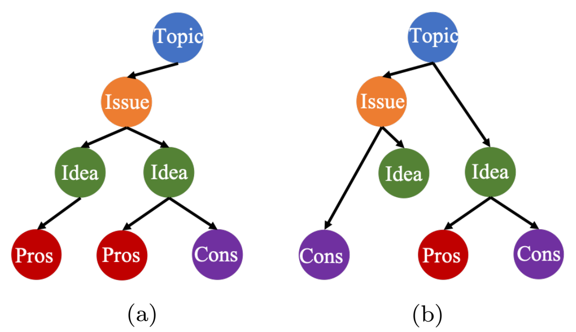

Figure 1. (a) An example of strict-IBIS structure. (b) An example of soft-IBIS structure.

This means the relationships are constrained by the elements of R^{str}. Based on the definition of strict-IBIS structure, we define soft-IBIS whose constraints of the relationship can be weakened. Without losing generality, all pos-

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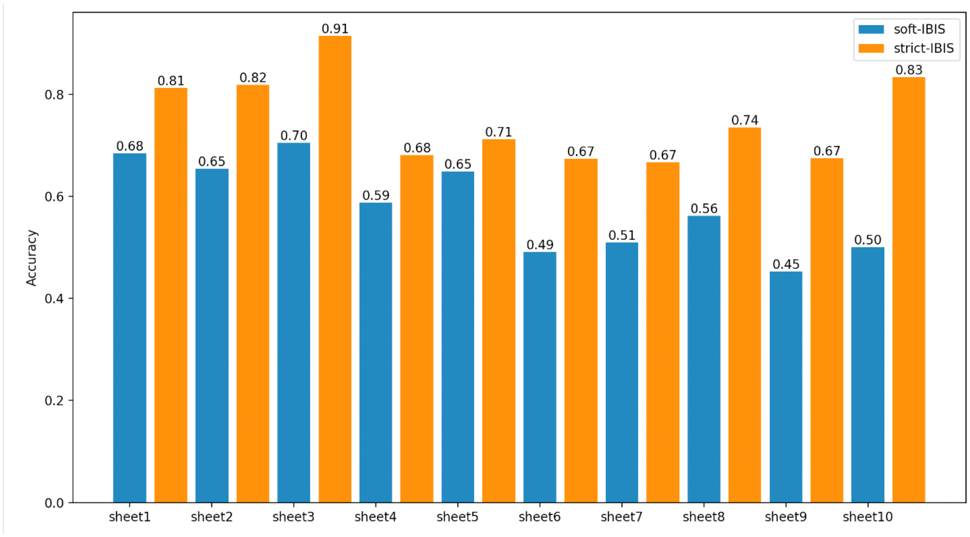

Figure 2. Compare the performances of on strict-IBIS and soft-IBIS structure based dataset.

sible relationships are accepted in soft-IBIS.

Definition 2. soft-IBIS structure: Given a set L of argument labels and $R^{sof} = \{(l^i, l^j)|l^i, l^j \in L\}$, then we call an argument structure $G =< V, E >$ follows a soft-IBIS structure if any of node's label belongs to L and edge's label belongs to R^{sof}.

Figure 1 shows the examples of both the two types of the structures. We then consider both soft-IBIS and strict-IBIS structure-based argument classification tasks, where a convolutional graph network (GCN) [2] represented as follows is used.

$$H^{l+1} = \delta(\widetilde{A}H^l W^l), \qquad (1)$$

where $\widetilde{A}$ is a Laplacian matrix and δ is an activation function. $H^l \in R^{|V|\times d_l}$ is the latent variable in the l-th layer with d_l dimensions. We first use the universal sentence encoder to embed all arguments v as a vector and take it as the first layer H^0 of GCN. Then, the latent variable of H^{l+1} is updated by the latent variable H^l at the previous layer. In the final layer L, it outpts a matrix $H^L \in \mathcal{R}^{|V|\times 5}$ where each row denotes the probabilities of each label for each argument.

3 Experiments

In this section, we use a dataset collected from 10 discussions by 5 negative English speakers. Each discussion denoted as *sheet i* corresponds to one topic. The original data generally follows a soft-IBIS pattern such as the relationship of Topic-Idea exists. Then we process a data cleaning to obtain a strict-IBIS structure based dataset. We evaluate both the two structures-based dataset. The results in Figure 2 show that the average accuracy of the strict-IBIS dataset is 0.75 which is higher than that of soft-IBIS structure which is 0.57. This is because GCN has captured the latent relationships of strict-IBIS structures, however most of the argumentation data in soft-IBIS do not follow strict-IBIS structure, which causes a wrong classification.

References

[1] NOBLE et al. Issue-based information systems for design. 1988.

[2] KIPF et al. Semi-supervised classification with graph convolutional networks, 2016.