Extracting Issue-Based Information System Structures from Online Discussions for Automated Facilitation Agent

Atsuya Sakai, Shota Suzuki, Rafik Hadfi, and Takayuki Ito

***Abstract*— Automated facilitation agents are currently being used to enhance the quality of online discussions. To this end, agents need to extract meaningful text units before applying facilitation rules. The issue-based information system (IBIS) is a viable way to extract and classify text from online discussions. In this paper, we propose a novel approach for text classification by adopting the IBIS system for online discussions. The method starts by identifying the correct IBIS structures and then finds the correct type of nodes in the structures. The approach relies on a Graph Attention Network (GAT) for both tasks in order to directly learn the IBIS structure. That is, the GAT encodes the graph structures and then classifies different structures using an attention architecture. To evaluate the performance of the approach, we conducted a set of experiments on a persuasive essays dataset formatted with the IBIS model. The experimental results show that the proposed approach is able to accurately classify the structures and the text nodes in online discussions.**

***Index Terms*—Natural Language Processing, Machine Learning, Argument Mining, Deep Learning, Social Networks, Conversational Agents, Automated Facilitation**

I. INTRODUCTION

ONLINE discussion support systems are attracting attention as the next-generation approaches to public citizen forums [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. The intelligent consensus-building support systems Collagree [5], [7] and D-Agree [11], [1], [12], [2], [13] were developed and then deployed in several real-world experiments. Collagree and D-Agree provide support functions for human facilitators to coordinate, lead, integrate, classify, and summarize discussions in order to reach a consensus. In social experiments, the systems significantly gathered more opinions than human facilitators and helped the participants recognize the importance of facilitators in identifying crucial societal issues.

In the fields of online discussions and facilitation, the ultimate goal is to create an automated facilitation agent that can adopt the role of human facilitators. Such type of agents usually have several advantages. For instance, it is able to react quickly, facilitate ongoing discussions 24 hours a day, and make fewer mistakes than human facilitators. With this in perspective, we developed an automated agent that can facilitate online discussions in Collagree and D-Agree.

The automated facilitation agent requires a function that extracts the issue-based information system (IBIS) [14] structures from online discussions in order to understand the context of these discussions. The issue-based information system (IBIS) is a viable methodology to structure and understand wicked discussions. The IBIS elements consist of issues stated in the form of a controversial question, positions that are in response to an issue, and arguments containing evidence supporting or opposing a position.

In order to perform the extraction function, an existing feature-based approach is to carry out two subtasks: node classification and link prediction [15]. However, node classification, which classifies submissions only from their text, does not consider the relationships between the submissions. Meanwhile, link prediction, which predicts the relationships between the classified nodes, is time-consuming because of its computational complexity $O(n^2)$ where n is the number of nodes.

To address these problems, we define another two subtasks, structure classification and node classification. Structure classification determines whether or not the structures are correct. This subtask takes less time than link prediction because of the computational complexity $O(n)$. In node classification, the nodes of the structures are classified as elements of the IBIS. Likewise, this subtask is effective because the relationships between the nodes are considered when classifying the nodes.

We propose an approach that directly learns the graph structure for structure and node classification, unlike the existing feature-based approaches. The proposed approach utilizes a graph attention network (GAT) [16], a kind of graph neural network (GNN). The GAT and GNNs encode the graph structure directly using a neural network model. The GAT, which uses attention mechanisms [17], can classify different graph structures, unlike other GNNs. In this respect, the proposed approach can address many kinds of graph structures created from natural language discussions.

To evaluate the proposed approach, we conducted a set of experiments on a persuasive essay dataset [18] formatted with the IBIS. Despite the complexity of the task, the experimental results of structure classification yielded high F1 scores. On the other hand, the experimental results of node classification yielded the highest F1 scores compared with the baselines for the existing feature-based approaches. We concluded that the proposed approach, which directly learns the graph structure, is effective for structure and node classification.

The remainder of this paper is organized as follows. Section II introduces related studies in the fields of GNNs and GAT. In Section III, we define the subtasks of structure classification and node classification and describe in detail the proposed approach, which directly learns the graph structure with a

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GAT. In Section IV, we explain the experimental setup of the dataset of persuasive essays. In Section V, we evaluate the experimental results. In Section VI, we discuss the classification performance of the proposed approach. Section VII concludes this paper.

II. Related Work

A. Discussion Support Systems

Discussion Support Systems are currently being used to gather opinions and lead to enhanced decision-making across the Web [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [19]. For example, the Collagree platform was deployed for city planning [20], [7], [5]. The CoLab platform was tested worldwide to address global climate change [19]. The Deliberatorium processes ideas by following an argumentation map for a given discussion [21]. Such systems are even used for the implementation of sustainable goals [22]. For instance, the D-Agree platform was employed to collect opinions about Sustainable Development Goals in Afghanistan [2], [23]. Discussion Support Systems commonly rely on conversational agents [24], [25], [26] by combining natural language parsing techniques [27], [28] and Artificial Neural Networks [29], [30]. Such agents are expected to process natural language and make judgments when interacting with humans. Herein, we focus on argumentative discussions and how to extract their structures using Artificial Neural Networks. There are several formal methodologies to reason about arguments [31], [32], [33] but we choose to adopt the issue-based information system (IBIS) [14], [34] for its practicality when combined with Artificial Neural Networks. IBIS consist of issues stated in the form of questions, positions that respond to the issues, and arguments that support or attack the positions. We propose to take advantage of the compact form of IBIS to train Artificial Neural Networks to recognize the different components of a discussion. This task is paramount to any discussion support system that targets argumentative discourse.

B. Graph Neural Networks

Graph Neural Networks (GNNs) encode graph structures directly using a neural network model. GNNs were originally developed by [35]. They showed that neural networks can process structured domains such as medical and technical diagnosis, molecular biology, chemistry, speech, text processing, and many others. They pointed out that standard neural networks and feature-based approaches are usually believed to be inadequate for dealing with complex structures represented as lists, trees, and graphs of variable sizes and complexities. They also mentioned that the current neural networks do not efficiently classify structures of different sizes. In their attempts to classify those complex structures, [36] presented the first GNN capable of directly processing graphs as opposed to feature-based approaches. They introduced a GNN that can extend recursive neural networks and applied the GNN to directed, undirected, labeled, and cyclic graphs. Their study found that valuable information is lost when traditional machine learning techniques attempt to cope with graphical data structures with a preprocessing procedure that transforms the graphs into simpler representations such as vectors or sequences of reals. The loss of the information may result in poor performance and generalization. Additionally, many approaches based on GNNs, such as a recurrent GNN [37], a convolutional GNN [38], [39], a variational graph autoencoder [40], and a spatio-temporal graph neural network [41], have been proposed in order to enhance performance and generalization in many fields of applications. These GNN-based approaches have proven to be capable of learning many kinds of complex graph structures.

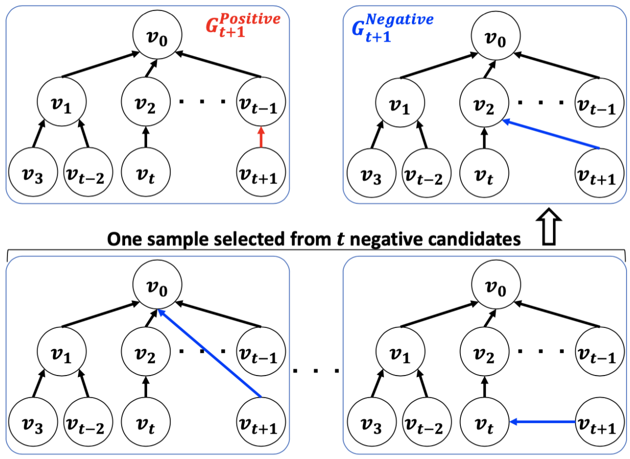

Fig. 1. A positive sample is the correct IBIS structure. A negative sample is selected from t negative candidates excluding the positive sample.

C. Graph Attention Network

A GAT [16] can classify different graph structures because of its attention-based architecture. On the other hand, conventional GNNs cannot, because they compute the eigendecomposition of the graph Laplacian, and their learned filters depend on the Laplacian eigenbasis in encoding graph structures [42]. GATs have achieved state-of-the-art classification across four established graph-based benchmark datasets: Cora, Citeseer, Pubmed, and protein-protein interaction (PPI) [16]. The research has shown that the GAT attains large predictive power by observing the entire neighborhood.

Although the existing research [16] focused on tasks in the fields of citation networks and biochemistry, the proposed approach is for structure and node classification, which, to our knowledge, has yet to be done. Whereas existing research [16] applied a GAT to semi-supervised learning, a noteworthy finding of our research is that the proposed approach is also suitable for supervised learning.

III. Proposed Approach

A. The Issue-Based Information System

Our methodology departs from the the Issue-Based Information System (IBIS), which is a practical way to structure arguments in discussions [43], [34]. As illustrated in Figure 2, IBIS categorizes sentences into issues, positions, and arguments. IBIS generally uses issues to identify questions, or problems. To these issues, IBIS associates positions, ideas, or answers. Finally, pros and cons are attached to the positions.

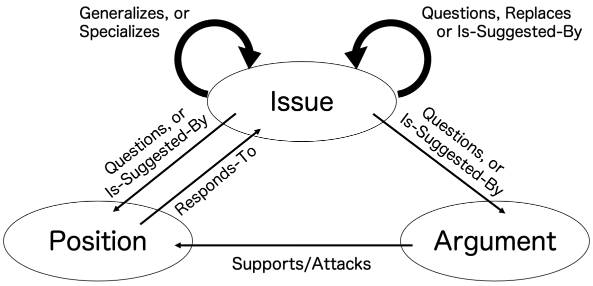

Fig. 2. Issue-Based Information System (IBIS)

In the following, the IBIS model will be used to model argumentative structures in online discussions.

B. Structure Classification

The main structure classification task relies on an IBIS structure represented as a graph, as shown in Figure 3.

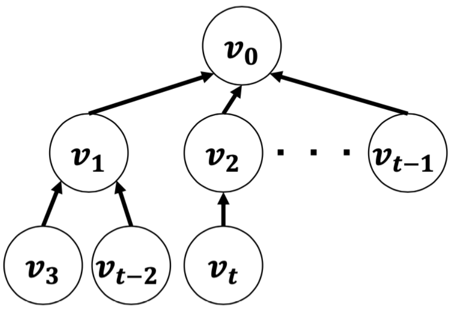

Fig. 3. The IBIS structure represented as a graph consisting of several nodes and their relationships.

The graph is represented as a tuple (G_t, V_t, E_t) with

$$G_t = (V_t, E_t)$$
$$V_t = \{v_0, v_1, \ldots, v_{t-1}, v_t\}$$
$$E_t = \{(v_0, v_1), (v_0, v_2), \ldots, (v_1, v_{t-2}), (v_2, v_t)\}$$

where t is time when message v_t is posted in the discussion. The goal of the structure classification task is to classify whether the structures consisting of G_t and v_{t+1} are correct or not. In order to train models, we prepared both positive and negative samples. A positive sample is the correct IBIS structure $G_{t+1}^{positive}$ as shown in Figure 1, and a negative sample $G_{t+1}^{negative}$ is selected from t negative candidates except for $G_{t+1}^{positive}$, as shown in Figure 1.

The proposed approach uses the GAT to classify whether G_{t+1} is positive or negative with consideration of the whole structure. Following the prior study [16], the layer computes a linear combination of the features considering the neighbors' features:

$$\boldsymbol{h}_i' = \sigma\left(\sum_{j\in\mathcal{N}_i} \alpha_{ij}\boldsymbol{W}\boldsymbol{h}_j\right) \tag{1}$$

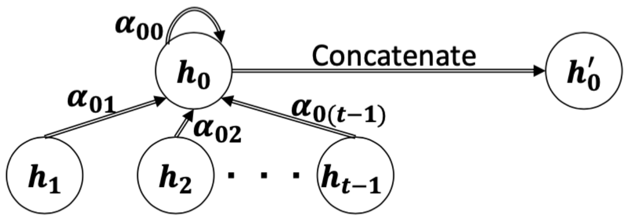

Fig. 4. The single layer computes a linear combination of features and concatenates the outputs. The layer performs the computation for all nodes.

where σ is an activation function, $\mathcal{N}_i$ is the first-order neighbors of node i including a self-loop, α_{ij} is an element of an attention weight vector, $\boldsymbol{W}$ is a weight matrix for shared linear transformation, and $\boldsymbol{h}_j$ is the features of v_j. α_{ij} is calculated by the softmax function [44]:

$$\alpha_{ij} = \frac{\exp(a(\boldsymbol{W}\boldsymbol{h}_i, \boldsymbol{W}\boldsymbol{h}_j))}{\sum_{k\in\mathcal{N}_i}\exp(a(\boldsymbol{W}\boldsymbol{h}_i, \boldsymbol{W}\boldsymbol{h}_j))} \tag{2}$$

where $a : R^{F'} \times R^{F'} \to R$ is an attention mechanism which calculates the importance of node j's features to node i's features. The resulting single layer of the proposed approach is shown in Figure 4. Lastly, the proposed approach minimizes the cross-entropy loss in order to tune the weights of the model according to:

$$\mathcal{L}_{structure-classification} = -\sum_{i\in 2N}\sum_{c\in C} t_{ic}\ \ln(h_{ic}') \tag{3}$$

where N is the number of correct structures in a dataset, C is the set of classes of structures $\{Positive, Negative\}$, t_{ic} is ground truth of the i-th graph, and h_{ic}' is the output of the i-th input graph.

C. Node Classification

The goal of the node classification task is to classify nodes $v_0, v_1, ..., v_{t+1}$ into the IBIS elements, of the IBIS as shown in Figure 5. In order to perform node classification, the proposed approach uses the GAT and classifies each node in V_{t+1} as an issue, position, or argument with consideration for the overall structure. The layer computational rule is the same as structure classification in Subsection III-B. Finally, the proposed approach minimizes the cross-entropy loss according to:

$$\mathcal{L}_{node-classification} = -\sum_{i\in N}\sum_{c\in C} t_{ic}\ \ln(h_{ic}') \tag{4}$$

where N is the number of sentences in a text, C is the set of classes of nodes $\{Issue, Position, Argument\}$, t_{ic} is the ground truth of the i-th node, and h_{ic}' is the output of the i-th node.

IV. Experiments

A. Dataset

To evaluate the proposed approach, we conducted a set of experiments on a dataset of persuasive essays [18] formatted into the IBIS. The dataset consisted of 90 English discussions.

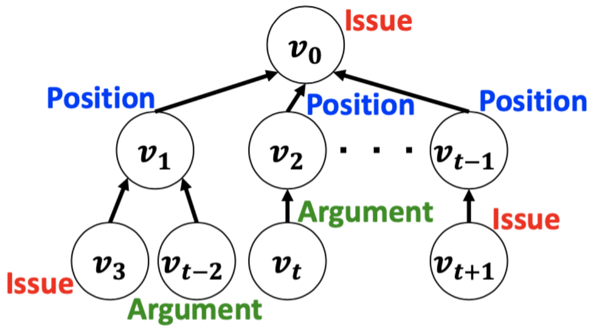

Fig. 5. Each node is classified as an IBIS element.

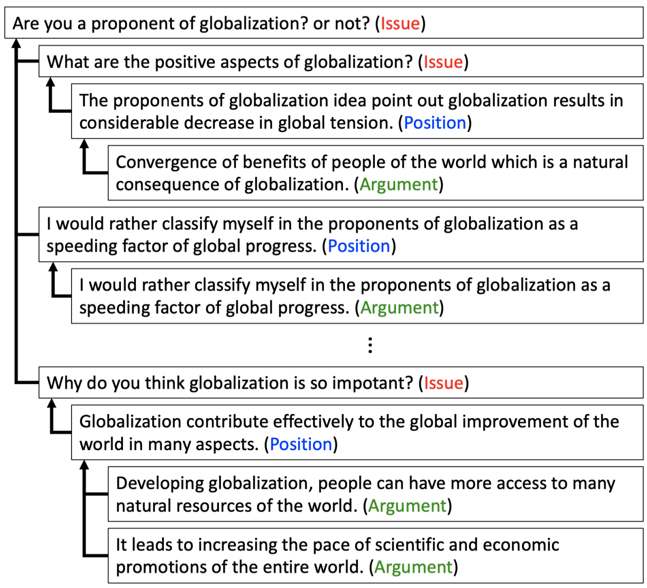

Fig. 6. A discussion in the dataset consists of several submissions about the topic and their reply relationships. The submissions are annotated with the IBIS types (indicated in parentheses).

An example discussion in the dataset is shown in Figure 6. In order to evaluate generalization, we randomly split the dataset into training data, validation data, and test data. The number of discussions, sentences, and tokens are shown in Table I.

B. Baselines

The proposed approach for structure classification was compared with an existing feature-based approach [15] based on bidirectional long short-term memory (Bi-LSTM) [45] for link prediction. The proposed approach cannot be compared with existing feature-based approaches for structure classification because such approaches cannot handle graph structures.

The proposed approach for node classification was compared with several baselines for the existing feature-based approaches. In particular, we performed the same task with three machine learning approaches: support vector machine (SVM) [46], random forest (RF) [47], and gradient boosting (GB) [48].

TABLE I
CALCULATED STATISTICS OF EXPERIMENTAL DATASET.

	Training	Validation	Test
Number of discussions	54	18	18
Number of sentences	1,238	420	413
Number of tokens	15,359	5,216	5,009
Average sentences/text	22.93	23.33	22.94
Average tokens/sentence	12.41	12.42	12.13

TABLE II
PARAMETERS SET FOR PROPOSED APPROACH IN BOTH THE STRUCTURE CLASSIFICATION AND NODE CLASSIFICATION EXPERIMENTS.

Parameter	Value
Number of GAT layers	1
Number of layer dimensions	256
Number of hidden attention heads	4
Number of output attention heads	4

C. Model Settings

In order to perform structure and node classification by directly learning graph structures, we implemented the proposed approach in Python. We used PyTorch [49], an open-source machine learning framework that accelerates the path from research prototyping to production deployment. In addition, we used PyTorch Geometric [50], a library for geometric deep learning. We used the stochastic gradient descent [51] as an optimizer and the stochastic gradient descent with warm restarts (SGDR) [52] as a method for adjusting the learning rate. The representative parameters of the model for both structure and node classification are shown in Table II, and the representative parameters for model training are shown in Table III and Table IV. The neural network models, such as the proposed approach and Bi-LSTM, were trained on a Quadro RTX 8000 GPU. The machine learning models such as SVM, RF, and GB were trained on a Intel Xeon Gold 6234 CPU. The time taken to train the models on the GPU and CPU is shown in Table V.

D. Features

The proposed approach and the baselines embed each text into a vector representation in order to build the features. The following features, referenced from [18], were utilized:

- Lexical features are binary unigrams and 2K most frequent dependency word pairs.
- Indicator features are forward, backward, thesis, and rebuttal Indicators. In addition, the features contain binary values if first-person Indicators are present.
- Embedding features are word embeddings with the bidirectional encoder representations from transformers (BERT) [53].

E. Evaluation Methods

In the structure and node classification experiments, we evaluated the proposed approach and the baselines with the precision, recall, and F1 score values [54]. The F1 score is the harmonic average of precision and recall:

$$F1\ Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \quad (5)$$

TABLE III
PARAMETERS SET FOR PROPOSED APPROACH IN STRUCTURE CLASSIFICATION EXPERIMENTS.

Parameter	Value
Epochs	3000
Batch size	256
Learning rate	0.001
Dropout	0
Momentum for SGD	0.9
Number of first restart for SGDR	100

TABLE IV
PARAMETERS SET FOR PROPOSED APPROACH IN THE NODE CLASSIFICATION EXPERIMENTS.

Parameter	Value
Epochs	10000
Batch size	18
Learning rate	0.2
Dropout	0.1
Momentum for SGD	0.9
Number of first restart for SGDR	5000

TABLE V
TIME TAKEN FOR MODEL LEARNING.

Device	Model	Time [m]
3*GPU	GAT for structure classification	40
	GAT for node classification	5
	Bi-LSTM	10
3*CPU	SVM	540
	RF	5
	GB	20

In addition, in the structure classification experiments, we evaluated the performance on the basis of the inference duration. In this respect, a shorter prediction time is required for the automated facilitation agent to react quickly.

V. RESULTS AND EVALUATION

A. Structure Classification

The results of the structure classification experiments are shown in Table VI. The proposed approach yielded F1 scores of 0.674 for correct structure classification and 0.629 for incorrect structure classification. Meanwhile, the baseline (Bi-LSTM) attained a precision of 0.508 in link prediction.

In addition, the durations of the inference are shown in Table VII. The results show that the proposed approach takes only 3.841×10^{-5}[s] to classify one IBIS structure. In contrast, the baseline requires 1.374[s] to identify links in the same IBIS structure.

These results indicate that the proposed approach for structure classification identifies the IBIS structures more accurately and rapidly than the baseline for link prediction. In addition to learning links between two node features, directly learning the graph structures enhances the proposed approach. The proposed approach solves the problem of the computational complexity of the baseline and performs well as the extracting function for the automated facilitation agent.

B. Node Classification

The results of the node classification experiments are shown in Table VIII. The proposed approach yielded F1 score values of 0.989 in issue classification, 0.962 in position classification, and 0.989 in argument classification.

TABLE VI
EXPERIMENTAL RESULTS OF STRUCTURE CLASSIFICATION. THE VALUES ARE PRECISION, RECALL, AND F1 SCORE.

Structure	Precision	Recall	F1
Correct	0.658	0.692	0.674
Not correct	0.647	0.613	0.629

TABLE VII
DURATION OF STRUCTURE CLASSIFICATION USING PROPOSED APPROACH AND LINK PREDICTION USING BI-LSTM.

Method	Time [s]
Link prediction	1.374
Structure classification	3.814×10^{-5}

TABLE VIII
EXPERIMENTAL RESULTS OF NODE CLASSIFICATION. VALUES ARE THE SAME AS THOSE IN STRUCTURE CLASSIFICATION; F1 SCORE.

Method	Issues	Positions	Arguments
SVM	0.000	0.000	0.713
RF	0.973	0.679	0.892
GB	**0.989**	0.693	0.908
Proposed approach	**0.989**	**0.962**	**0.989**

To summarize, the results indicate that the proposed approach, which directly learns the graph structure, accurately classifies nodes. Particularly, the F1 score of classifying nodes into positions and arguments was higher than that of the baselines. This result is attributed to the fact that the proposed approach learns the graph structures. Thus, the proposed approach is effective for classifying nodes into positions because the position nodes have relations with both issue and argument nodes. Its high accuracy in addition to its speed of 1.857×10^{-4}[s] enhance the extracting function of the automated facilitation agent.

VI. DISCUSSION

A. Feature Ablation Study

We examined which features were most effective for structure and node classification by conducting a set of feature ablation experiments. We excluded one of three features and conducted experiments on the rest. The results of the ablation experiments are shown in Table IX and X. As shown in Table IX, the indicator feature and embedding feature are most important for structure classification. The lexical feature also supports the proposed approach for structure classification. As shown in Table X, the embedding feature is the most effective for node classification. Specifically, the embedding feature boosts the classification performance of position nodes. The indicator feature and lexical feature improve the classification performance of the proposed approach.

B. Details of Node Classification Performance

Figure 7 shows the confusion matrix of the experimental results in Subsection V-B for analyzing the node classification performance of the proposed approach in detail. Figure 7 indicates that the proposed approach classifies issue nodes

TABLE IX
RESULT OF FEATURE ABLATION FOR STRUCTURE CLASSIFICATION.

Features	Correct	Not correct
All	**0.674**	**0.629**
All - Lexical	0.590	0.415
All - Embedding	0.676	0.005
All - Indicator	0.667	0.000

TABLE X
RESULT OF FEATURE ABLATION FOR NODE CLASSIFICATION.

Features	Issues	Positions	Arguments
All	**0.989**	**0.962**	**0.989**
All - Lexical	0.935	0.867	0.974
All - Embedding	0.644	0.246	0.836
All - Indicator	0.940	0.880	0.976

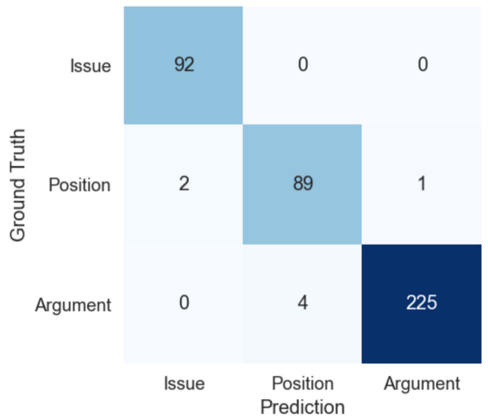

Fig. 7. Confusion matrix of the performance of the proposed node classification method

precisely, though there is room for improvement in classifying position and argument nodes. In order to further improve node classification, the proposed approach should consider additional relevant features.

VII. Conclusion and Future Work

We proposed a classification approach for online discussion data using a graph attention network (GAT). To evaluate the proposed approach, we conducted a set of experiments on a persuasive essay dataset formatted into an IBIS structure. In structure classification experiments, the proposed method yielded high F1 scores and shorter inferring time compared with a link prediction approach. In node classification experiments, the proposed approach also yielded higher F1 scores than those of the existing feature-based approaches. The accuracies of structure and node classification should be improved in future work. An approach that performs structure and node classification simultaneously would be optimal, though developing such an approach would present various challenges.

Acknowledgment

This work was supported by JST CREST Grant Number JPMJCR15E1, Japan and JPMJCR20D1, Japan.

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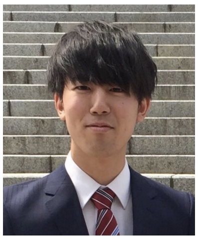

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