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Automatic space type classification of architectural BIM models using Graph Convolutional Networks

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Abstract: The instantiation of spaces as a discrete entity allows users to utilize BIM models in a wide range of analyses. However, in practice, their utility has been limited as spaces are erroneously entered due to human error and often omitted entirely. Recent studies attempted to automate space allocation using artificial intelligence approaches. However, there has been limited success as most studies focused solely on the use of geometric features to distinguish spaces. In this study, in addition to geometric features, semantic relations between spaces and elements were modeled and used to improve space classification in BIM models. Graph Convolutional Networks (GCN), a deep learning algorithm specifically tailored for learning in graphs, was deployed to classify spaces via a similarity graph that represents the relationships between spaces and their surrounding elements. Results confirmed that accuracy (ACC) was +0.08 higher than the baseline model in which only geometric information was used. Most notably, GCN was able to correctly distinguish spaces with no apparent difference in geometry by discriminating the specific elements that were provided by the similarity graph.

Keywords: BIM, semantic enrichment, graph learning, semantic relational information

1. INTRODUCTION

Building Information Modeling (BIM) made it possible to recognize spaces represented only by geometric occlusal planes in 2D drawings as individual objects. The instantiation of space allows individual spaces to express property, and users can utilize building information in a wide range, such as legal review, energy analysis, and evacuation path analysis.

However, it was challenging to ensure semantic consistency of spatial information due to errors and omissions by the manual BIM modeling process. In addition, since spatial information in most BIM models used in practice was often not entered at all, there was a problem that users had to manually modify and specify space labels to utilize building information.

Recent studies have attempted to explore ways to automate space allocation using artificial intelligence (AI) algorithms, increasing the potential applicability of BIM. [1] conducted spatial classification using a Naive Bayes classifier, and [2] derived 82% classification accuracy by learning spatial geometry using a machine learning algorithm. Such existing approaches proved the superiority of machine learning approaches compared to rule-based approaches. However, they had a limitation in that they could not correctly distinguish similar spaces by focusing only on the geometric features.

Since space is a semantic concept perceived by the walls, slabs, and ceilings, it is necessary to include relational information in the AI learning process [3]. Individual spaces often show similarity in the relationship between elements and adjacent spaces, so the AI model should reflect these characteristics by expressing the similarity of each topologically linked space in the form of a network graph.

This study attempted to construct an outstanding AI model for automatic space classification by using graphs of semantic relations between individual BIM spaces and elements in the model learning process. Graph Convolutional Networks (GCN) was used for graph learning in this study. GCN has proven its high performance with a semi-supervised learning algorithm that classifies node information and neighbor node information based on weight sharing and local feature learning of convolution operations [4].

The 12-story office building (BIM model) was used for GCN training. 9 highly utilized space types were selected for analysis, and 17 element types were used to build space-element graphs and learn the GCN model. In addition, to prove the effectiveness of utilizing the relational information in the space classification, the Multi-Layer Perceptron (MLP) was trained as geometric features of space and used as a baseline model to compare and analyze GCN results.

2. RESEARCH BACKGROUND

2.1. GRAPH CONVOLUTIONAL NETWORKS (GCN)

GCN is a model that trains information of nodes and neighboring nodes based on weight sharing and local feature learning through convolution operation [4]. GCN also utilizes both labeled and unlabeled data for training in a semi-supervised learning method, so that high learning accuracy can be derived even if the amount of labeled data is insufficient.

GCN training process is composed of an adjacency matrix representing the relationship between edges and a node feature matrix describing the characteristics of a node. A neural network is created using the learning variables and nonlinear functions of nodes in the graph and neighboring nodes.

Error! Reference source not found. presents the training process of GCN. The adjacency matrix is expressed as $N \times N$, and the node feature matrix is described as $N \times F$, where N is the number of nodes and F is the number of features. The adjacency matrix and the node feature matrix are multiplied in the first hidden layer. At this time, only the relationship with the connection of the adjacent matrix is reflected in the results. In the second hidden layer, the adjacency matrix is multiplied once more while the relationship of the adjacency matrix is already reflected in the node feature matrix. That is, as the number of hidden layers increases, the relationship between each node is reflected more.

As the number of layers increases, GCN has a characteristic that the over-smoothing problem occurs, in which the accuracy decreases as the embedding values become similar to each other. Therefore, this study tried to derive the optimal performance by configuring the GCN in two layers. As a nonlinear function, an activation function such as ReLU (Rectified Linear Unit) was used in the first layer. In the second layer, training was performed using softmax for space type classification.

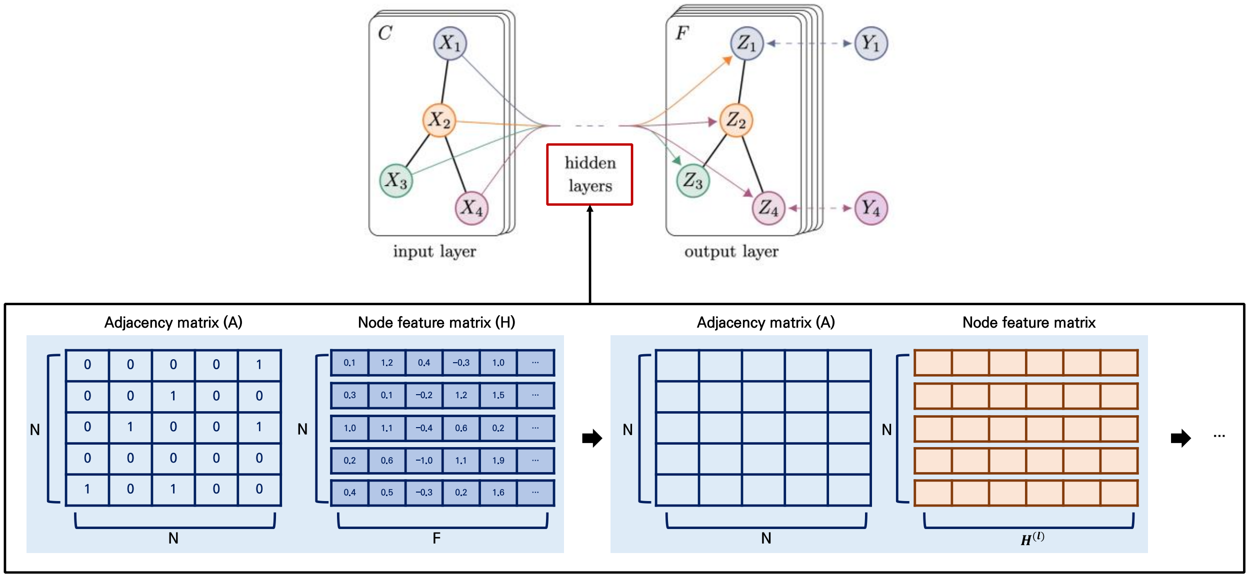

Figure 1. Structure of GCN [4]

2.2. MULTI-LAYER PERCEPTRON (MLP)

A perceptron is a basic unit of an artificial neural network that outputs from multiple inputs to one result. MLP is a network composed of a combination of several perceptrons. It is an artificial neural network model consisting of several hidden layers along with an input layer and an output layer.

In MLP, all values corresponding to the input layer are transferred to the hidden layer. Likewise, all values output from the hidden layer are also transferred to the output layer. An activation function is applied to the output result value at the hidden layer to the output layer process. Unlike single-layer perceptron, which can only learn linear problems, MLP can solve nonlinear problems and is advantageous for predicting continuous values. In addition, it is a representative technique of neural network algorithms and is mainly used for multi-class classification, so it was used as a baseline model for learning geometric features of space.

3. RESEARCH METHODOLOGY

3.1. DATA OVERVIEW

This study used the 'KBIMS office building' for analysis. This building is a 12-story standard IFC model with LOD (Level of Detail) 300 in the detailed design phase and was provided by the buildingSMART Korea. The elements used in this study were initially composed of 13 IFC classes. However, to improve the classification performance of spaces containing specific elements when using relational information in the model training process, the types of elements were subdivided into 17 enumeration types. For example, for *IfcDoor,* as the shape and function were different according to the enumeration type, it was subdivided into ‘single, double, and door, etc.’

presents 247 spaces of 9 types and 9,213 elements of 17 types included in this model.

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Table 1. Status of spaces and elements in the BIM model

Space			Element		
IFC class	**Enumeration type**	**# of spaces**	**IFC class**	**Enumeration type**	**# of elements**
IfcSpace	Elevator hall	39	*IfcBeam*	Beam	158
			IfcBuildingElement Proxy	Disabled restroom partition	20
	Elevator vestibule	13		Disabled sign	20
				Elevator door	36
	Hallway	11	*IfcColumn*	Column	264
			IfcCovering	Covering	65
	Office room	79	*IfcCurtainWall*	Curtain wall	152
			IfcDoor	Single door	88
	Plant room	14		Double door	87
				Door etc.	40
	Restroom	20	*IfcFlowTerminal*	Flow terminal	140
			IfcFurnishingElement	Furnishing element	251
	Shaft	40	*IfcMember*	Member	6,559
	Stariway	25	*IfcSlab*	Slab	303

		IfcStairFlight	Stair flight	49
Storage	6	*IfcWall*	Wall	899
		IfcWindow	Window	82
Total	**247**	**Total**		**9,213**

3.2. Data preprocessing

The primary data for training the automatic space classification model was the geometric features of individual spaces. The geometric features were extracted using a rule set file mounted in the commercial BIM software (KBim Assess-Lite). As a result, 10 features including area, volume, perimeter, length, width, and height of the bounding-box, aspect ratio, surface area, number of boundary lines, and ax1s (area/volume) were extracted.

3.3. Semantic relational graph extraction

GCN requires two input values for learning, a node feature matrix and an adjacency matrix. In this study, the node feature matrix consisted of geometric features of individual spaces extracted in Section 3.2. The adjacency matrix consisted of the semantic relational information between each space and physically adjacent elements. The extraction process of relational information was as follows:

Bounding boxes of each space were used to extract relational information between space and elements. Specifically, when the bounding boxes of each space and element were projected onto a 2D plane, physical adjacency was extracted, assuming that elements were included in the space if the two projections overlapped (Figure).

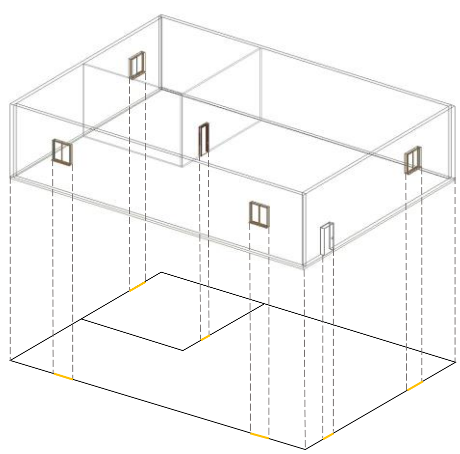

Figure 2. Relational information extraction

The space-element adjacency matrix constructed through the above process was expressed as an undirected graph consisting of 11,313 nodes (space and elements) and 15,199 edges (physical connectivity).

3.4. Relational graph extraction based on similarity.

The relational graph in Section 3.3 was a form in which space and physically adjacent elements were connected. However, for the GCN training, conversion into a graph form constructed as an edge based on the similarity between nodes was required, not a physically adjacent relationship. Therefore, elements adjacent to individual spaces were used as a criterion for deriving similarity, and the graph was reconstructed (Figure).

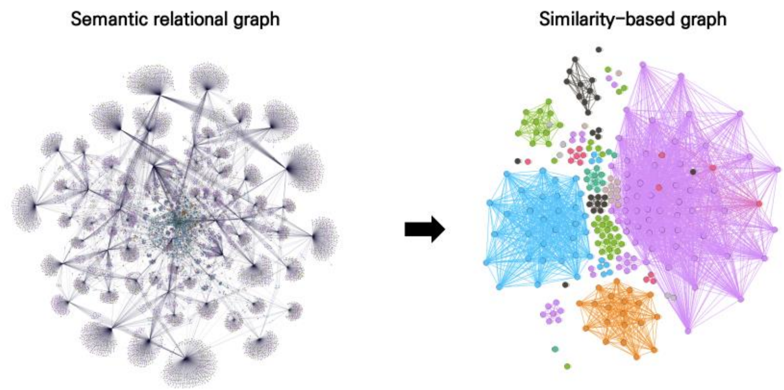

Figure 3. Graph conversion from physical adjacency to similarity

Jaccard similarity technique was used for measuring the similarity between spaces. The Jaccard similarity technique is a technique that measures similarity based on frequency through intersection and union between sets. Specifically, as shown in Equation (1), if n (= $A \cap B$) out of m ($A \cup B$) elements included in an adjacent space are similar, the similarity is derived by calculating them as n/m (= $A \cap B / A \cup B$).

$$J(A,B) = \frac{|A \cap B|}{|A|+|B|-|A \cap B|} \tag{1}$$

As a result of measuring the similarity using the Jaccard similarity technique, a graph consisting of 61,009 edges was constructed according to each similarity value.

However, the number of edges compared to nodes was significantly higher, and all existing spaces in the BIM model were expressed as connected, which acts as a hindrance to GCN training. [5] removed unnecessary edges in a graph using a threshold and verified that graph performance was the most effective when the threshold was between 0.8 and 1.0. As a result of applying the same method in this study, a graph in which unnecessary edges were effectively removed when the threshold was 0.85 (the number of edges 4,907) was derived, and this was used for model training.

3.5. Deep learning implementation

MLP was trained using only geometric feature values, and GCN was trained using geometric features and similarity-based relational graphs constructed in Section 3.4. Machine learning libraries, Python's 'sikit-learn' and PyTorch's 'deep graph,' were used to implement the model training.

To train the two learning models (MLP, GCN), the ratio of space data collected in Section 3.1 was divided into 6:4 and used as a train set and test set. As a result, 148 spaces were used for model training, and 99 spaces were used for model verification. In addition, accuracy (ACC) and F_1-score were used to evaluate the performance of each learning model.

4. RESULTS

Error! Reference source not found. presents the classification performance of the two deep learning models (MLP, GCN). As a result of verifying the performance of the MLP model that learned geometric information, ACC was 0.86, and F_1-score was 0.71. The overall classification performance of the MLP model was confirmed to be satisfactory, but the elevator vestibule, plant room, and storage showed inferior classification performance compared to other spaces. In particular, it was confirmed that the storage was incorrectly inferred as an elevator hole and stairway. This was due to the lack of data, and the geometric features were not clearly distinguished from other spaces.

ACC of the GCN learning model using semantic relationship information was derived as 0.95 and F_1-score was derived as 0.91. The classification performance of the GCN model with semantic relational information added was superior to the MLP model that learned only geometric features. In particular, the ACC of the elevator vestibule and storage space, which showed abysmal classification performance in MLP, was derived as 1.00 and 0.50 in the GCN model, respectively, showing relatively improved classification performance. In addition, the ACC of the hallway, plant room, and shaft space was slightly improved.

Table 2. Validation results for MLP and GCN

Space	MLP		GCN		Delta values	
	ACC	F_1-score	ACC	F_1-score	ACC	F_1-score
Elevator hall	1.00	0.86	1.00	0.97	0.00	0.11
Elevator vestibule	0.40	0.57	1.00	1.00	0.60	0.43
Hallway	0.75	0.86	1.00	0.89	0.25	0.03
Office room	1.00	0.97	1.00	0.97	0.00	0.00
Plant room	0.33	0.44	0.67	0.80	0.34	0.36
Restroom	1.00	0.94	1.00	1.00	0.00	0.06
Shaft	0.81	0.79	0.94	0.94	0.13	0.15
Stairway	0.90	0.95	0.90	0.95	0.00	0.00
Storage	0.00	0.00	0.50	0.67	0.50	0.67
Average	**0.86**	**0.71**	**0.95**	**0.91**	**0.09**	**0.20**

The GCN model improved ACC by 0.09 and F_1-score by 0.20 compared to the MLP model. In detail, it can be seen that the classification performance of a total of 5 spaces, including elevator vestibule, hallway, plant room, shaft, and storage, had been improved. In particular, the classification performance of elevator vestibule and storage spaces, including specific elements such as elevator doors and single doors, has dramatically improved. On the other hand, in the case of the hallway, plant room, and shaft spaces that do not contain elements differentiated from other spaces, the degree of performance improvement was relatively insignificant.

6. CONCLUSION

This study built an automatic space classification model for increasing the potential applicability of BIM. GCN, trained on geometric and relational information, was proposed to secure outstanding performance for space classification. As a result, the ACC of the GCN model was about 8% higher than the MLP model in which only geometric feature was trained. And it was confirmed that spaces that were difficult to distinguish only by the geometric properties of the space were classified correctly. In addition, although the geometric shape was not significantly differentiated from other spaces, the accuracy of space classification was improved by including specific elements distinguished in the relational information.

However, in the case of the hallway, plant room, and shaft spaces, there was a problem in that the improvement of accuracy was insignificant because the singularities in the relational information could not be trained adequately in GCN training. In other words, due to the lack of data, the spatial characteristics were not reflected in the training process, which served as a performance limitation of the GCN model. More data is required to learn enough about the spaces where the model's classification performance was weak.

Since the approach presented in this study used the similarity of space as a medium for graph connection, space data of several BIM models can be learned simultaneously. That is, graphs are generated based on similarity, multiple BIM models can be used for deep learning without being limited to a single BIM model. Accordingly, future work includes improving the model's performance by accumulating the data from additional BIM models.

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