Generating Topological Structure of Floorplans from Room Attributes

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ABSTRACT
Analysis of indoor spaces requires topological information. In this paper, we propose to extract topological information from room attributes using what we call Iterative and adaptive graph Topology Learning (ITL). ITL progressively predicts multiple relations between rooms; at each iteration, it improves node embeddings, which in turn facilitates generation of a better topological graph structure. This notion of iterative improvement of node embeddings and topological graph structure is in the same spirit as [5]. However, while [5] computes the adjacency matrix based on node similarity, we learn the graph metric using a relational decoder to extract room correlations. Experiments using a new challenging indoor dataset validate our proposed method. Qualitative and quantitative evaluation for layout topology prediction and floorplan generation applications also demonstrate the effectiveness of ITL.

CCS CONCEPTS
• Computing methodologies → Scene understanding; Hierarchical representations.

KEYWORDS
topological structure generation, floorplans, graph learning, graph convolutional network

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1 INTRODUCTION
Indoor home modeling enables practical applications such as virtual home tours, indoor navigation, and house design. Augmenting raw models with topological information enhances their value by providing semantic-level knowledge of room identity and arrangement. This, in turn, facilitates indoor understanding (e.g., style classification) and more home-related applications such as remote home shopping (through similarity-based search) and pricing.

Motivated by the lack of large-scale floorplan topology information in real estate listing websites (e.g., Airbnb, Zillow, Apartments), we propose to extract it using available, or derivable, room-level signals encoded into a graph convolutional network (GCN). Topological information of a floorplan can be easily embedded in a graph, where nodes represent rooms and edges encode relations between them. Room adjacency (Fig. 1) is characterized as having a spatial connection; the spatial connection can be either visual (if there

Figure 1: Spatial versus visual edges. Spatial edges are defined by room-room adjacency, while visual connections represent a sub-set of the spatial edges when two rooms share a door or an opening (e.g., kitchen is spatially adjacent, but not visually connected to the master bedroom). From room attributes, the proposed method automatically learns both types of topology information (i.e., spatial and visual), which can be used in applications like floorplan generation.
is a door or opening between rooms) or non-visual (if there is no door or opening). In other words, spatial connectivity provides the information about "which room is adjacent to which room", while visual connectivity provides information about "which room connects which room". To handle the multiple relationships and predict both connection types, we propose the multi-relational GAT as an extension to GAT [31]. Here, we treat each relation as a sub-graph and then fuse the information with a weighted summation of both.

We propose an iterative and adaptive learning mechanism to progressively predict multiple relationships between rooms with given or precomputed attributes in an indoor environment. Note that conventional similarity metric learning approaches (e.g., [5]) cannot simply be applied to our application due to high levels of similarity between our nodes (e.g., two similar non-adjacent bedrooms). Also, current similarity metric learning approaches can be extended to multi-relational graphs only when the graph-structure is available. Thus, we progressively learn the graph metric using a relational decoder to make better use of the containment relationship between the spatial and visual edges (i.e., visual edges should be a subset of spatial edges).

Our contributions are:

- First data-driven method (to our knowledge) to automatically generate floorplan topology using room attributes. Multi-relational (MR) GAT and MR decoder are proposed to model the containment relationship between edges.
- We propose a new iterative learning mechanism to predict multiple relations between graph nodes from scratch, in the absence of any initial topology structure.
- We demonstrate the effectiveness of the proposed method for indoor applications (i.e., realistic floorplan generation) by employing HouseGAN [19] on the outputs of our method.

2 RELATED WORK

2.1 Topological relationships of 2D/3D floorplans

The topological relationships inherent to 2D floorplans have been widely studied in different fields from different perspectives [11]. To assist in the task of navigation, Portugal and Rocha [23] derived a topological graph-based representation from a grid map of floorplan. Lin et al. [17] merged a topology graph and a grid model to boost the efficiency of spatial analysis and to provide positional information. Nauata et al. [19] showed that the spatial connectivity of room boosts the performance of floorplan generation task. In [13], room connectivity provided by users are used as constraints to generate floorplans. More recently, [1] proposed a layered-graph representation, 3D Scene Graph, to facilitate the holistic understanding of indoor spaces.

A popular approach to extract topological relationships is detecting high-level information from grid maps [15, 23, 27, 29, 35]. The main problem is that grid maps are often unavailable or difficult to obtain in some applications. We argue that it is too restrictive to ask the user or designer to provide such detailed information including both room attributes and connections. This huge drawback can be addressed by extracting topological relationships from room attributes, which is largely unexplored in the literature. By contrast, we propose to leverage the underlying relational information between rooms to learn topological information from room attributes. The learned topological information can then facilitate indoor understanding (e.g., LayoutGMN [21]) and more home-related applications such as floorplan generation (e.g., HouseGAN [19], HouseGAN++ [20]).

2.2 Graph neural networks

GNNs model graph dependencies via message passing between nodes, and have been thoroughly studied [28, 32, 39]. Recently, GNNs have gained increasing attention in various domains, including knowledge graphs [25, 26, 40], recommendation systems [37, 38], and other computer vision tasks [33, 34]. Multi-relational (MR) GNNs are more intuitive for indoor related tasks, as floorplans typically encode multi-relational connectivity between rooms. To handle multi-relational graphs, R-GCN [25] extends GCN with relation-specific linear transformation. W-GCN [26] utilizes relation-specific learnable weights during information aggregation. COMP-GCN [30] gains extra information by jointly embedding both nodes and relations in a relational graph.

The aforementioned methods are mainly designed for knowledge graph with clean graph structure. However, learning floorplan topology is fundamentally different from these tasks as the graph structure is completely unknown or severely missing. Most of the aforementioned works fail to pass messages along the model when structural information is missing. To directly adopt these MR-GNNs on floorplan topology learning task, we first need to add initial structures (e.g., fully connected graphs, kNN graphs), which will introduce noise to the graph and lead to inaccurate predictions. Rather than using regular MR-GNNs directly, we extend GAT to multi-relational (MR) GAT for message passing and adopt a MR-decoder to utilize the containment relationship among edge types and learn more precise room connections.

2.3 Iterative graph learning

Most GNN methods [4, 16, 31] are only applicable when the graph structure is available and clean. To address this limitation, researchers have explored methods [8, 12, 34] to automatically generate and iteratively update the graph with (previously) unknown structure. More recently, [5] cast the graph learning problem as similarity metric learning and proposed to iteratively learn the graph structure and embeddings. Though promising performance was shown on knowledge graphs, it is less effective on floorplan graphs, where connections are not determined only by similarity of two nodes. For example, bedrooms in a house usually have similar embeddings; however, they are rarely visually connected, and their spatial connectivity is not guaranteed.

3 PROBLEM DEFINITION

In this paper, our goal is to predict a set of topological relations between the nodes of a graph representing an indoor environment. More specifically, we start with a set of given node attributes (room attributes in our case) and the goal is to predict spatial and/or visual connectivity between the given nodes. Our final learned graph embeddings can be used to infer topological structure of indoor environments from scratch, i.e. no links provided, or to complete
the topology of partial layouts. In this section, we first introduce the dataset we are using, then go over three problem definition including graph structure generation, graph structure completion, and the application of floorplan generation.

3.1 Floorplan dataset

The Zillow Indoor Dataset (ZInD)\(^1\) [6] provides 360° panoramas, room layouts, and floorplans collected from 1,575 real unfurnished homes. In total, it contains 2,737 floorplans, from which we retrieved 1,217 and constructed graphs containing nodes and multi-relational edges. The data statistics are summarized in Table 1. More details (e.g., node and edge distributions) of the dataset are provided in the supplementary material.

We then represent each floorplan as a graph. Each node in a floorplan represents a room, and edges represent the connectivity between two rooms. We define two types of edges, spatial and visual (Fig. 1). Spatial edges are defined by room-room adjacency in a floorplan, while visual connections represent a sub-set of the spatial edges when two rooms share a door or an opening. We represent nodes using four types of room features:

- **Basic room information** (Set 1): room type, number of doors, windows, and openings of the room.
- **Distance-based features** (Set 2): perimeter and area of the room, maximum length and width of walls, and ratio between room area and its bounding box area.
- **Shape descriptors** (Set 3): we use the chain code [9] to represent the shape of a room. The chain code is extracted by traversing the boundary of the object and recording the direction of each step.
- **Image features** (Set 4): extracted from panoramas using embeddings from a scene classification model [6].

Note that all room attributes are invariant to translation and rotation. Features in Sets 1 and 4 are also invariant to scale, while the other two are not. Fig. 2 shows an example of a floorplan, input attributes and constructed graphs from the dataset. Detailed description of topology and attribute extraction are in the supplementary material. In our work, we assume all these room-level attributes are given. This is the input to our system, and our goal is to predict the layout. In practice, these room attributes can be derived from the panorama images, either manually (e.g., [2, 6]) or automatically from SOTA algorithms for scene classification (e.g., [14, 18]) and room layout estimation (e.g., [3, 22, 36]). In Table 3 we study the effect of the different attributes.

3.2 Graph structure generation

The goal of graph structure generation is to predict different types of connections (i.e., visual, wall, and spatial connections) given only room attributes and without any structure information. The adjacency matrix of the input graph is an identity matrix, meaning that each room is connected to itself and not to any other rooms in the floorplan. The dataset is split across graphs. We use 700 floorplan graphs for training, 200 floorplans for validation, and the rest (i.e., 317 floorplans) for testing. All edges in training graphs are in the training set, and the model is asked to predict unseen links (i.e., all edges) for test graphs.

3.3 Graph structure completion

Given room attributes and partial spatial structure information, the goal is to complete the spatial connection (i.e., the rooms are connected or not) and predict the specific type of the connection (i.e., the rooms are connected by door (visual) or wall). Let \(A\) be the adjacency matrix of the graph generated from original spatial edges of a floor plan; we randomly remove a subset of spatial edges (e.g., 20% - 80% of edges) and use the remaining observations to generate an incomplete adjacency matrix \(\tilde{A}\). We use the same data split as graph structure generation task (i.e., 700 graphs for training, 200 for validation and 316 for testing). All edges in training graphs are used for training. We then evaluate on a fixed set of 20% of connections that was not observed.

3.4 Indoor application using generated topology

The proposed learned representation includes rich information about an indoor environment. We show how this topological information can benefit the challenging task of home layout generation, from room-level attributes. As demonstration, we use HouseGAN [19], which takes in room attributes and room spatial information. We replace the ground truth (GT) room connections with our estimated graph topology, and show that it can generate compatible results with using the GT. Following [19], results are evaluated in terms of realism, diversity, and compatibility. Qualitative result

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\(^1\)https://github.com/zillow/zind
shows the realism of generate floorplan. Diversity and compatibility are measured by the Frechet Inception Distance (FID) scores and graph edit distance [24] (GED), respectively. We show a significant performance boost on HouseGAN [19] by adopting the topological information generated from the proposed method. Note that we do not train end-to-end, as HouseGAN only includes a single edge type (i.e., spatial edges), whereas our model predicts both spatial and visual connectivity. For floorplan generation task, we fine-tune the pre-trained HouseGAN model with our dataset and follow the same setting as in HouseGAN. Since the room types in HouseGAN are different from ours, we map our room types to match theirs.

4 METHODOLOGY
The goal of this paper is to use relational information between graph nodes to predict its topology, when very little to no topological information is available. By comparison, traditional approaches assume a percentage of edges are available and aim to predict the rest. The architecture of our proposed model is shown in Fig. 3. Our architecture allows us to jointly predict both visual and spatial edges. We first generate an incomplete graph with an identity adjacency matrix from a floor plan. The incomplete graph is then fed into an iterative encoder, which recursively updates graph topology and node embeddings. With node embeddings as the input, the multi-relational (MR) decoder then learns more precise room connections by leveraging the containment relationship between spatial and visual edges (i.e., visual edges should be a subset of spatial edges).

Let $G = (V, E)$ be an undirected graph, where $V$ is a set of $N$ nodes with node attributes $X = \{x_1, x_2, ..., x_N\}, x_i \in \mathbb{R}^{1 \times F}$. $F$ is the feature dimension of each node. The true adjacency matrix $A \in \mathbb{R}^{N \times N}$ is formulated from edges $E$, where $R$ is the number of relation types in the graph. Suppose the initial adjacency matrix $A^0$ has missing or incomplete information. The objective of the model is to complete the graph topology by exploiting potential relationships based on room attributes. Specifically, an iterative encoding function is applied to transform the initial features $X^0$ to a new feature representation. The multi-relational decoding function, which takes the new feature representations as input, is then used to predict the probability of whether or not an edge exists between pairs of nodes $(u_i, u_j)$, as well as the edge type.

We predict multiple types of edges (i.e., spatial and visual edges). Since visual edges are a subset of spatial edges, we split spatial edges into two exclusive sets: door (i.e., visual) connectivity and wall connectivity. We then jointly predict all three types of edges to fully explore and utilize the containment relationship among them.

4.1 Iterative encoder
The iterative encoder recursively augments the initial graph topology and node embeddings to improve the performance of downstream prediction tasks. The initial node embeddings $X^0$ and adjacency matrix $A^0$ are the input of our iterative encoder. $X^0$ is the original node (room) attributes, and $A^0$ is set to either an identity matrix or an incomplete adjacency matrix. In each iteration $k$, we first update the graph topology from $A^k \in \mathbb{R}^{N \times N}$ to $A^{k+1} \in \mathbb{R}^{N \times N}$ using a multi-relational scoring function, then compute new node embeddings $X^{k+1} \in \mathbb{R}^{N \times F}$ based on $X^k \in \mathbb{R}^{N \times F}$ and $A^{k+1}$. Inspired by [26], we extend GAT [31] to multi-relation GAT (MR-GAT) for message passing, where we treat each relation as a subgraph and then conduct weighted summation on all the subgraphs. The process of each iteration block can be expressed as:

$$
A^{k+1} = h_{edge}(X^k, A^k), \\
X^{k+1} = h_{node}(X^k, A^{k+1}),
$$

where $h_{edge}$ and $h_{node}$ denote the function to update graph topology and node embeddings, respectively.

4.1.1 Updating graph topology. Previous approaches (e.g., [5, 7]) that model the graph structure learning problem as similarity metric learning have shown promising performance on knowledge graphs. However, these methods are unable to cope with the floor-plan graphs, in which connections are not determined only by the similarity of two nodes. Moreover, similarity metric learning can only generate a single matrix to represent one type of room relationship given the node embeddings, and hence cannot be applied to multi-relational graphs. Instead, we use a multi-relational scoring function to make better use of the containment relationship between spatial and visual edges. Specifically, we decompose spatial connectivity into door (visual) and wall connectivity and predict them separately. Then spatial edges can be calculated by summing up door and wall edges. The prediction of door and wall edges can further be restricted by the binary cross-entropy loss applied on spatial edges. Therefore, the probability $a^k_{i,j,r}$ that node $i$ and $j$ are connected by relation $r$ (i.e., door, wall, or spatial) at the $k$-th
iteration is updated by:
\[
a_{i,j,r}^{k+1} = \begin{cases} 
  f\left(\tilde{x}_i^k, \tilde{x}_j^k, a_{i,j,r}^k\right), & r \in \{\text{door, wall}\} \\
  \frac{\exp\left(g(\tilde{x}_i, \tilde{x}_j)\right)}{\sum_{j \in N(i,r)} \exp\left(g(\tilde{x}_i, \tilde{x}_j)\right)}, & r \in \{\text{spatial}\}
\end{cases}
\]  
(2)

where \(x_i\) and \(x_j\) are the embeddings of node \(i\) and \(j\). The scoring function \(f(\cdot)\) is implemented with three fully-connected layers.

### 4.1.2 Updating node embeddings
MR-GAT is employed to handle multi-relation message passing, which measures the various types of relationships differently during aggregation and learns the weights adaptively during network training. Specifically, the encoder treats a multi-relation floorplan graph as multiple single-relation subgraphs, where each subgraph represents a specific type of connection (i.e., door or wall connection). For each subgraph with relation \(r\), we then conduct self-attention on the nodes to indicate the importance of node \(j\)'s features to node \(i\). We first apply an attention mechanism \(g(\cdot)\), which is the same as [31], on the concatenated features of node \(i\) and \(j\) to compute the attention coefficient, then use the softmax function to normalize it across all choices of \(j\) in each relation \(r\). The attention coefficients can be expressed as:
\[
\beta_{i,j,r} = \text{softmax}_j(r(g(\tilde{x}_i, \tilde{x}_j))),
\]
(3)
where \([\cdot, \cdot]\) represents concatenation operation, and \(N(i,r)\) denotes sets of rooms that are connected with node \(i\) by relation \(r\) (i.e., wall or door connection). Hence the output of each subgraph can be expressed as:
\[
\tilde{x}_i^{r'} = \sum_{j \in N(i,r)} \beta_{i,j,r} \tilde{x}_j W_r,
\]
(4)
where \(W_r\) is the weight matrix of linear transformation for relation \(r \in \{\text{wall, door}\}\).

Then we extend GAT to MR-GAT by performing weight summation on subgraphs of different relations \(r\). The MR-GAT determines how much weights to give to each subgraph when fusing the GAT embeddings for a node. Hence, the embeddings of node \(i\) can be updated by:
\[
\tilde{z}_i^r = \sigma\left(\sum_r a_r \sum_{j \in N(i,r)} \beta_{i,j,r} \tilde{x}_j W_r\right),
\]
(5)
where \(a_r\) denotes the attention coefficient for each subgraph \(r\) and is learnt during training. As shown in Fig. 4, this process is essentially matrix multiplication. For each subgraph \(A^{k+1}\), we first conduct self-attention on the nodes. Then the attention-weighted adjacency matrix \(\tilde{A}^{k+1}\) will be the weighted sum of the output subgraphs, and can be written as:
\[
\tilde{A}^{k+1} = \sum_r a_r \tilde{\beta}_r A^{k+1}.
\]
(6)

In matrix form, the node embedding update can be expressed as:
\[
X^{k+1} = \sigma\left(\tilde{A}^{k+1} X^k W^k\right).
\]
(7)

### 4.2 Link prediction decoder
Similarly, we take advantage of the containment relationship between spatial and visual edges and apply the same MR decoder for the link prediction task by decomposing spatial connectivity into door and wall connectivity, and then predicting them separately. After the iterative encoder, the model splits into two decoder branches, which predict door and wall edges separately. The two decoders have the same structure, each containing three fully-connected layers. Then, the door and wall predictions are fused to obtain the probability of whether two nodes are connected (i.e., spatial edges). Furthermore, we found that the initial features \(X^0\), which contain node-wise room properties (e.g., room shape), help to improve the prediction performance. Hence, we add a long skip connection by concatenating the initial features \(X^0\) and the output of the encoder \(X^{k+1}\). Hence, the probability that two nodes are connected by relation \(r\), \((r \in \{\text{spatial, door, wall}\})\), can be computed by:
\[
p_r = \text{mr. dec}(X^{k+1}, X^0, A^{k+1}).
\]

The whole process of our method is described in Alg. 1.

### 4.3 Loss function
We jointly predict all three types of edges by combining the loss function of each task at the end of every iteration during training. Therefore, the loss function \(L\) of the proposed model can be expressed as:
\[
L = \sum_{i=1}^{K} \left(L_{\text{vis}}^{(k)} + \lambda_1 L_{\text{wall}}^{(k)} + \lambda_2 L_{\text{spa}}^{(k)}\right)
\]
where \(L_{\text{vis}}^{(k)}\), \(L_{\text{wall}}^{(k)}\), and \(L_{\text{spa}}^{(k)}\) denote the binary cross-entropy loss for visual (door), wall, and spatial connectivity, respectively. \(\lambda_1\) and \(\lambda_2\) are non-negative hyperparameters. We set \(\lambda_1 = \lambda_2 = 1\) in our experiments. Sensitivity analysis for these two hyper-parameter is shown in the Supplementary material.

### 5 EXPERIMENTS
To evaluate our framework, we compare it with a variety of baselines on graph structure generation and completion. We further report results on floorplan generation as one of the applications of the proposed method. Ablation studies are conducted to show the
Algorithm 1: Iterative learning of the multi-relational topology of a floor plan graph.

Input: Node embeddings $X^0$, incomplete or unavailable adjacency matrix $A^0$.

Output: Predicting multi-relations of the floorplan graph $P_{\text{spatial}}$, $P_{\text{door}}$, $P_{\text{wall}}$.

$A^0 = \text{identity matrix } I$ if $A^0$ is not available

while $k \leq K$ do

/* Updating graph topology */

if $r \in \{\text{door, wall}\}$ then

$A^{k+1}_{\text{door}} = f(X^k_{\text{door}}, A^k)$

else

$A^{k+1}_{\text{spatial}} = A^{k+1}_{\text{door}} + A^{k+1}_{\text{wall}}$

$A^{k+1} = \left[A^{k+1}_{\text{spatial}}; A^{k+1}_{\text{door}}; A^{k+1}_{\text{wall}}\right]$

/* Updating node embeddings */

$A^{k+1} = \sum_i \alpha_i f_i A^{k+1} X^{k+1} = \sigma(A^{k+1} X^{k+1} W^k)$

/* Downstream task (link prediction) */

$P_{\text{spatial}}$, $P_{\text{door}}$, $P_{\text{wall}} = \text{mr}_\text{dec}(	ext{concat}(X^{k+1}, X^0), A^{k+1})$

Table 2: Generating topology from scratch. We report results with ROC AUC and AP.

|               | Spatial | Wall | Door | Spatial | Wall | Door |
|---------------|---------|------|------|---------|------|------|
| GCN$_{\text{NN}}$ [16] | 73.10   | 54.72 | 82.23 | 73.80   | 54.10 | 80.08 |
| GAT$_{\text{NN}}$ [31] | 73.67   | 54.46 | 83.22 | 74.54   | 54.82 | 83.39 |
| HGCN$_{\text{NN}}$ [4]  | 73.96   | 54.99 | 86.90 | 76.41   | 55.80 | 86.70 |
| MLP            | 73.93   | 56.74 | 83.41 | 74.25   | 55.06 | 83.41 |
| HNN [10]       | 75.21   | 58.33 | 86.27 | 76.59   | 56.87 | 86.23 |
| IDGL+sim [5]   | 72.19   | 56.81 | 83.48 | 73.00   | 56.01 | 81.08 |
| IDGL+dec [5]   | 79.23   | 63.63 | 89.82 | 79.48   | 63.89 | 87.13 |
| Ours           | 81.64   | 65.67 | 91.73 | 81.86   | 65.36 | 91.31 |

The contribution of each attribute set, as well as each component of our method and its limitations. Implementation details are described in the supplementary material.

5.1 Experimental settings

Graph structure generation. We predict different types of connections (i.e., visual, wall, and spatial connections) given only room attributes and without any structure information. Following previous works [4, 5, 16], we evaluate link prediction by measuring area under the receiver operating characteristic (ROC) curve (AUC) and average precision (AP) on the test set.

Graph structure completion. Given room attributes and partial spatial edges (e.g., 20% - 80% of edges), the goal is to complete the spatial connection (i.e., the rooms are connected or not) and predict the specific type of the connection (i.e., the rooms are connected by door (visual) or wall). We evaluate on a fixed set of 20% of connections that was not observed. As with the graph structure generation task, results are reported with ROC AUC and AP.

Floorplan generation. Floorplan generation is a challenging task that highly depends on topological information. We selected the problem of house layout generation and showed how representations learned using our method can improve the state-of-the-art in this task, both qualitatively and quantitatively. Specifically, we fine-tune the pre-trained HouseGAN [19] model with our dataset to generate floorplans. Room attributes and room spatial information are the input of HouseGAN. We replace the ground truth (GT) room connections with our estimated graph topology, and show that it can generate compatible results with using the GT. We follow the same setting as in HouseGAN, and report both qualitative and quantitative results (i.e., the Frechet Inception Distance (FID) scores and graph edit distance [24] (GED)).

5.2 Graph structure generation

Table 2 reports the performance of our method in comparison to other baselines on graph structure generation. For state-of-the-art GNN models, we consider GCN [16], GAT [31], and Hyperbolic Convolutional Networks (HGCN) [4]. We also consider feature-based approaches: Multilayer Perceptron (MLP) and its hyperbolic variant (HNN) [10], which do not utilize the graph structure. Moreover, we compare with IDGL [5] and its variant, which are iterative graph learning methods. We use the same decoder for downstream prediction task for all the methods.

GCN, GAT, and HGCN need graph structure information to perform message passing. Since the graph topology is inaccessible, we adopt the kNN graph to generate the initial topology and build various GNN$_{\text{NN}}$ baselines (i.e., GCN$_{\text{NN}}$, GAT$_{\text{NN}}$, HGCN$_{\text{NN}}$). The kNN graph is computed based on node attributes, and is constructed during preprocessing before applying a GNN model. We can see that these methods do not perform well when the true graph topology is inaccessible and GNNs are not directly applicable (Table 2). Note that most of existing multi-relational graph methods (e.g., RGCCN [25], WGCN [26], COMP-GCN [30]) fail to handle the task here due to missing initial graph structure for all relations. Like GCN and GAT, initial graph structure is needed for multi-relational graph methods to pass messages along the model. However, kNN cannot provide topological information for different edge types, since the same node embeddings are given. Therefore, we do not compare with those methods.

MLP and HNN are feature-based methods and do not need neighbor information. As shown in Table 2, feature-based methods (i.e., MLP and HNN) may perform better than GNN models when the true graph topology is unavailable. One possible reason is that...
Figure 6: Floorplan generation with different input topology. We compare the output of HouseGAN given different connectivity information (i.e., kNN graph and estimated topology using ITL). The graph topology generated by our method is more faithful to GT, and has lower graph edit distance (GED). For complicated cases (i.e., node $N \geq 10$), ITL can still provide reasonable topology to HouseGAN for generating realistic floorplans. More examples are in the supplementary material.

Table 3: Quantitative results. We evaluate the diversity and compatibility of HouseGAN with different connectivity information. Note: the lower the FID, GED scores, the better.

| Diversity (FID) | Compatibility (GED) |
|----------------|---------------------|
| Fully connected graph | 83.79 | 8.64 |
| kNN graph | 33.56 | 6.53 |
| Estimated topology | 19.68 | 4.71 |
| Ground truth | 17.54 | 4.22 |

the graph structure initialization step used in GNNs is inaccurate and introduces a significant amount of noise.

IDGL iteratively learns graph structure and graph embedding during training. The first IDGL baseline (i.e., IDGL+sim) casts the graph structure learning problem as a similarity metric learning problem. For the baseline of IDGL+dec, we replace similarity metric learning with our proposed topology learning method to update graph structure. Since IDGL cannot handle multi-relation graphs, we only consider spatial edges when updating graph structures. Compare to IDGL baselines, our method consistently achieves better performance on all types of edges.

5.3 Graph structure completion
The results on graph structure completion task are shown in Figure 5. Although feature-based methods (i.e., MLP, HNN) perform better than GNN models (i.e., GCN, GAT) when the graph structure is either unknown or severely missing, its performance remains almost unchanged even if more neighbor information is given. With more observations, GNN models tend to outperform feature-based methods. Iterative learning methods (i.e., IDGL and ours) achieve better results than GNNs and feature-based methods by a large margin and have stable performance with different proportion of observations. Note that the IDGL model we compare with is IDGL+dec, which uses the same topology updating method as ours. Compared to IDGL, our method consistently achieves much better results by adopting a multi-relational message passing mechanism.

5.4 Indoor application using generated topology
Figure 6 shows the qualitative comparison of different graph structure (i.e., kNN graph and ITL graph) usage for floorplan generation. We show that ITL can generate effective and practical floorplan topological information with much lower graph edit distances, which leads to more realistic floorplan generation using HouseGAN [19]. The kNN graph fails to provide compelling topology for HouseGAN, since it predicts connections based on the similarity of room attributes. Rooms generated with kNN graphs tend to be clustered by the room type (e.g., bedrooms are connected to bedrooms, closets are connected to closets).

We demonstrate the importance of topological information for house layout generation tasks in Table 3. Compared to fully connected graph and kNN graph, we observe significant performance boost on HouseGAN by adopting the topological information estimated from ITL. The floorplans generated with ITL are very close to the ones generated with GT graphs in terms of diversity and compatibility, which also shows ITL can provide reasonable topology for indoor applications, and can well replace GT graphics.

5.5 Ablation study
5.5.1 Contribution of each component. Table 4 shows the contribution of each component of our framework. By turning off the
Table 4: Ablation study. We measure the contributions of iterative learning scheme, multi-relation (MR) GAT, and MR prediction.

|                          | Spatial | Wall   | Door   |
|--------------------------|---------|--------|--------|
| ITL                      | 81.64   | 65.67  | 91.73  |
| w/o IL                   | 75.62   | 57.92  | 88.61  |
| w/o MR-GAT               | 80.93   | 65.15  | 90.46  |
| w/o MR decoder           | 78.43   | 61.38  | 89.43  |

Figure 7: Results with different numbers of training iterations. Note that the model with zero iteration directly feeds the node features to the decoder and predicts links.

iterative learning module (IL), we see a consistently large performance drop for ITL, thus indicating IL’s effectiveness. In addition, we ran two additional variants (i.e., w/o MR-GAT and w/o MR prediction) to show the advantages of incorporating multi-relational room connections in both the encoder and the downstream task. In the first variant, we replace the multi-relation GAT in our encoder with vanilla GAT and update only spatial edges during training. The second variant is done by predicting spatial, visual, and wall edges separately. Taking visual edge prediction as an example, the input graph is fed to the encoder and then one single decoder to predict the probability of the visual connectivity of two rooms. The same structure is applied to predict the other two edges as well.

5.5.2 Effect of iteration. Figure 7 shows the link prediction performance of ITL trained with different number of iterations. The performance of the model reaches its peak after two iterations during training, and then gradually decreased. We believe the drop is due to noisy messages beginning to permeate the entire graph and worsening the final prediction. The same phenomenon is also found in [5, 33]. Note that in the proposed method, we do not share weights between blocks. $K$ iteration blocks are stacked together to give the final prediction. During our experiments, we found that not sharing weight gives us better performance (Table 8 in the supplementary material).

5.5.3 Contribution of various room attributes. The contribution and effect of different types of room attributes are shown in Table 5. It shows that each single attribute set can achieve fairly well performance, while the basic room information (i.e., set 1) contributes the most. It also shows that ITL does not require very specific room information to estimate the topology of floorplans and thus can be easily adopted by other indoor applications. Still, with more detailed room information, ITL can achieve even higher performance.

5.6 Limitations

The input of our model is room-level attributes, which include basic room information, distance-based features, shape descriptors, and image features. In this paper, all attributes are derived from human annotations. The attribute extraction process can be found in the supplementary material. In practice, some of these room attributes might be difficult to obtain. One possible solution is to exclude the attributes that are too specific and hard to get. To this end, we study the effect of the different attributes (Table 5 of the main paper). We show that basic room information can achieve fairly well performance. However, with more detailed room information, ITL can achieve even higher performance. Moreover, except human annotation, these attributes may also be extracted from state-of-the-art algorithms for scene classification (e.g., [14, 18]) and room layout estimation (e.g., [3, 22, 36]).

We also inherit other issues associated with ZInD [6]. One issue is our architecture is trained on ZInD empty homes, which may not work as well with regular well-furnished homes. In addition, as discussed in [6], there are ambiguities associated with large open spaces where, to quote [6], “semantic distinctions, such as ‘dining room’, ‘living room’ and ‘kitchen’, are not always geometrically clear”. In other words, room labels may not be consistent across different annotators, and may be another source of errors.

6 CONCLUSION

In this paper, we propose to extract topological information from room attributes using what we call Iterative and adaptive graph Topology Learning (ITL). ITL progressively predicts multiple relations between rooms; at each iteration, it improves node embeddings, which allows for better topological structure learning and vise versa. In contrast to conventional similarity metric learning approaches (e.g., [5]), we learn the graph metric using a relational decoder to make better use of the containment relationship between the spatial and visual edges. Experiments using a new challenging indoor dataset support our design decisions. Qualitative and quantitative evaluation for floorplan generation applications also demonstrates the effectiveness of ITL.
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