

Analysis of the attacker and defender GAN models for the indoor navigation network

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ABSTRACT: Evacuation research relies heavily on the efficiency analysis of the study navigation networks, and this principle also applies to indoor scenarios. One crucial type of these scenarios is the attacker and defender topic, which discusses the paralyzing and recovering operations for a specific indoor navigation network. Our approach is to apply the Generative-Adversarial-Neural network (GAN) model to optimize both reduction and increase operations for a specific indoor navigation network. In other words, the proposed model utilizes GAN both in the attacking behavior efficiency analysis and the recovering behavior efficiency analysis. To this purpose, we design a black box of training the generative model and adversarial model to construct the hidden neural networks to mimic the human selection of choosing the critical nodes in the studying navigation networks. The experiment shows that the proposed model could alleviate the selection of nodes that significantly influence network transportation efficiency. Therefore, we could apply this model to disaster responding scenarios like fire evacuation and communication network recovery operations.

1. INTRODUCTION

1.1 A general introduction of deep learning models

The indoor navigation network is crucial for many application scenes like indoor routing and emergency evacuation, and the research results from these studies could significantly reduce the total evacuation time and egress routes' length (Scholz and Schabus, 2014, Zlatanova et al., 2013, Liu and Zlatanova, 2011, Krūminaitė and Zlatanova, 2014, Gozick et al., 2011, Kirkko-Jaakkola et al., 2013). Therefore, many researchers committed contributions to investigate the robustness for this specific type of navigation networks (Freitas and Chau, 2020, Alattas et al., 2017, Fellner et al., 2017, Snelder et al., 2012, Santos et al., 2010).

The graphs studies usually are in the form of networks, which are widely used for processing several critical graphs and applications like transportation network analysis and a significant loss. This approach originated from the graph

convolution network, which uses deep networks to extract global and local graphs. The specific graphs for this approach are widely used along with this approach and promising for many fields. They can still conclude several layers of deep learning networks, consisting of millions of parameters for a specific model. To mitigate the specific challenges brought by the indoor navigation environment, we have to tune these models for our specific usage.

Fortunately, we could refer to many existing methods that could efficiently handle the challenges of introducing deep learning techniques for indoor navigation networks. One of the most heavily studied solutions is based on the generative adversarial network (GAN) framework (Liu et al., 2019, Suárez et al., 2017, Martin Arjovsky, 2017, Qiyue Li 2020, Jonas Adler 2018, Cao et al., 2019). Thus, we follow this approach due to its advantages in taking both the global and local processing information features.

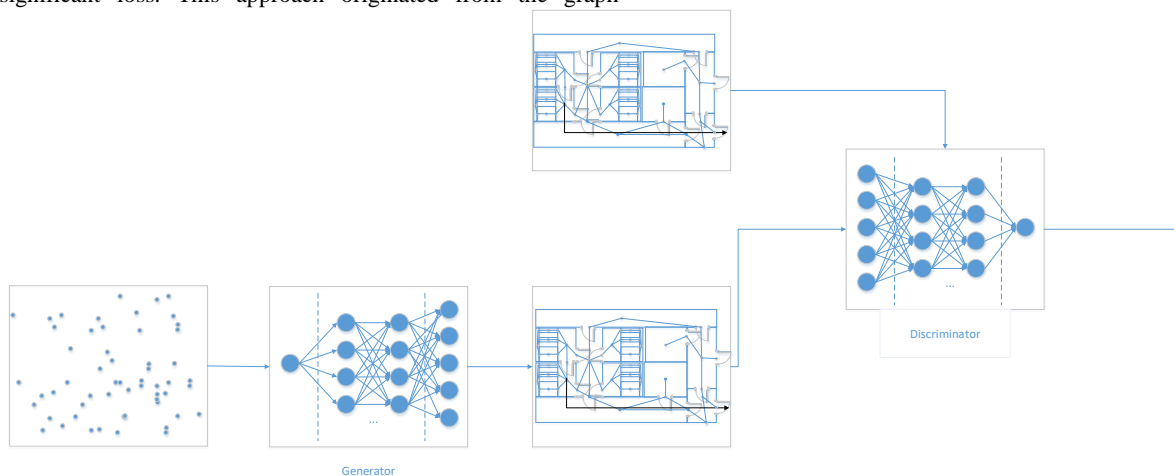


Figure 1. The demonstration of the GraphGAN for our approach

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Along with our approach, we utilize the GAN that uses a generator and discriminator to study the connection features of the navigation graphs in figure 1 (Hou et al., 2019, Suárez et al., 2017, Adler and Lunz, 2018). Although our current investigation solution is premature and naïve, we still believe it could extract critical features from the whole navigation network that will influence the network's connectivity status. As a GAN framework, one part of this model is named the 'generator'; the other network is named the 'discriminator.' The first one that is in charge of generating objects as realistic as the studying examples; while the latter one act like judges, who will distinguish the fake pictures of networks, which are previously generated by the generator. Using the generator and discriminator, we can identify fake objects like pictures that are very like the actual pictures generated by a selected optimizer. For our purpose, we use the generator and discriminator function as the attacking and defending of the critical nodes of the navigation networks (Freitas and Chau, 2020, Duan and Lu, 2014, Zlatanova et al., 2013, Liu and Zlatanova, 2011, Krūminaitė and Zlatanova, 2014).

2. THE MECHANISM OF GRAPHGAN FOR INDOOR NAVIGATION NETWORK ANALYSIS

We build this model because we are inspired by the GraphGAN project from GitHub: <https://github.com/hwwang55/GraphGAN/tree/3f1c3f7db6b8b5102eea899659d4c52f64c4288c>, which is shown in figure 2. The composition mechanism is quite straight, and we inherit the main schema of this GraphGAN framework. Thus, we establish the generator with a softmax mechanism to minimize the logarithm result between the produced graphs and the learning graph layers. On the contrary, the introduced discriminator aims to maximize the logarithm result between the provided graph results mixed with the original graphs and the generator-produced graphs. The detail foundation theory and proving detail could be found in the original GraphGAN paper and is generally demonstrated in figure 2.

The detail softmax mechanism is a graph softmax operation. This graph softmax is implemented by the Adam optimizer both across the generator and discriminator. Besides, there are three modes for the GraphGAN operations: link-prediction, node classification and recommendation. The first one is the process of generating fake edge by the generator and identification by the discriminator; while the second one is the process of generating different groups of edges that have labels to distinguish them; and the last one is to utilize the connectivity relationship to find recommendations between different nodes. We currently only consider the former two types of operations.

The detail operation flow is:

1. Use the word2vec libraries to embed the comparative similarity rate between different graph structures;
2. Then use the previously produced embedding matrix to compute the generated graph edges for link prediction and node groups;
3. Generate the output matrixes by executing the Tensorflow loops.

Figure 2 shows that the working performance of the generator. As in the left part of this figure, we could easily perceive that the accessible nodes selected by the generator does not overlap with any of the existing target learning nodes. Thus, under this circumstance, the generator fails to achieve the link generation

purpose, and we name this situation as the underperformance. While for the central part, the generated nodes set is partially overlapping the existing target node set, and we name this situation as the approaching truth situation. For the last part of the figure, due to the selection set of the generator is nearly overlapping with the whole truth nodes set, thus the performance of using adversarial training for generator is achieved.

The most critical settings of Tensorflow based GraphGAN structures are the outer iterations and inner iterations for the computing process because these settings determine the studying result of the GraphGAN softmax layers on the input graph connection matrixes.

Following this approach, without drowning with the tedious work of tuning hyper-parameter for our model, we can concentrate on optimizing the mechanism of generator and discriminator for identifying the indoor navigation networks.

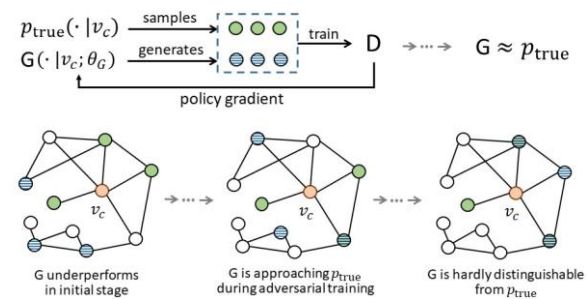


Figure 2. The mechanism of the GraphGAN (by courtesy of Hongwei Wang, etc..)

These random indoor navigation networks that mainly consist of one hundred nodes. These networks have a maximum of four degrees of connectivity for the nodes in them. Although this setting connectivity degree is not thoroughly studied through the theoretical research, we extract this setting from a complete survey from the observation of realistic buildings from both the Henan university of urban construction number 5 building and the Meiluocheng building shanghai city in figure 3 and 4.

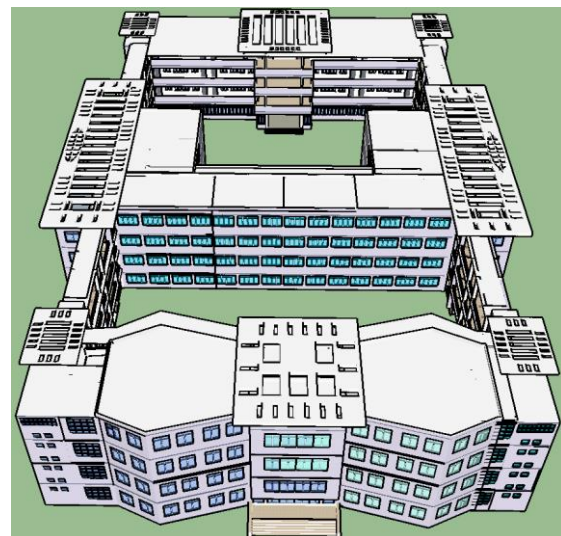


Figure 3. The overview of the Henan University of Urban Construction Number 5 building



Figure 4. The overview of the Meiluocheng building

3. DATASET AND EXPERIMENT RESULTS

3.1 Test platform and configurations

Test platform hardware configuration is 16 core Ryzen 9 3950X with 64GB DDR3000 rams and Geforce GTX 2070; the software platform is Ubuntu 20.04 LTS; the deep learning framework is Tensorflow 2.2 GPU. The detail configuration setting of the GraphGAN model is listed below:

```
# training settings
batch_size_gen = 64
batch_size_dis = 64
lambda_gen = 1e-5
lambda_dis = 1e-5
n_sample_gen = 20
lr_gen = 1e-3
lr_dis = 1e-3
n_epochs = 20
n_epochs_gen = 30
n_epochs_dis = 30
gen_interval = n_epochs_gen
dis_interval = n_epochs_dis
update_ratio = 1

# model saving
load_model = False
save_steps = 10

# other hyper-parameters
n_emb = 128
window_size = 2
multi_processing = False
```

‘batch_size_gen’ parameter determines the batch size for the generator; ‘batch_size_dis’ parameter determines the batch size for the discriminator; ‘lambda_gen’ parameter determines the l2 loss regulation weight for the generator; ‘lambda_dis’ parameter determines the l2 loss regulation weight for the discriminator; ‘n_sample_gen’ parameter determines the number of samples for the generator; ‘lr_gen’ parameter determines the learning rate for the generator; ‘lr_dis’ parameter determines the learning rate for the discriminator; ‘n_epochs’ parameter determines the number of outer loops; ‘n_epochs_gen’ parameter determines the number of inner loops for the generator; ‘n_epochs_dis’

parameter determines the number of inner loops for the discriminator; ‘gen_interval’ parameter determines the sample new nodes for the generator for every generator interval iterations; ‘dis_interval’ parameter determines the sample new nodes for the discriminator for every discriminator interval iterations; ‘update_ratio’ parameter determines the updating ratio when choose the trees; ‘load_model’ parameter determines whether loading existing model for initialization; ‘save_steps’ parameter determines the step saving frequencies; ‘n_emb’ parameter determines the embedding matrix’s mapping node number; ‘window_size’ parameters determine the searching windows size; ‘multi_processing’ parameter determines whether using multi-processing to construct BFS-trees. The BFS-tree here means the breadth first searching tree formed for the specific node.

The experiments are executed on these random networks set with 100 nodes and 4 degrees of the maximum connection degree. We choose these specific node numbers and degree settings because, according to our current study of the existing floor, blueprints of several collected buildings are with these settings.

Because the research of GraphGAN on these navigation networks is scarce and rare, we can only extract several key features favoured from our aspects. A complete, more objective refinery of the raw data from the defined GAN produced results is expected in the following research step.

3.2 Experiment result types

The first result is named the uniform manifold approximation and projection (UMAP); the second result is the ‘Student-t distribution stochastic neighbor embedding’ (t-SNE in short); the third result is the principal component analysis (PCA) analysis result. The first two types of results show the analyzing data correlations across high dimensional space, and the last one shows the traditional correlations between any combination of selected features.

4. DISCUSSIONS AND EXTENSIVE STUDY OF RESULTS

From the results, we can find that these two networks are producing quite complex results, and the reason we have not provided the loss results of the experiment is due to that the current stage of our research is to testify the working flow of the combination between GraphGAN and the indoor navigation networks, we only committed the loops with the minimum setting of the GraphGAN model. This minimum setting is of 10 epochs for the input simulated graphs, thus the loss results of this simulation mechanism could not provide a complete overview of the total learning performance for this model. Besides, because we have not thoroughly investigated the different setting of the GraphGAN model.

The PCA results demonstrate the different mapping between the generated indoor navigation networks embedding relationships across different groups. The results provided below are these results among classes 1, 2, and 3; 4, 5, and 6; 7, 8, and 9, shown in Figures 5, 6, and 7.

The UMAP results show the graphs have relatively sparse distributions of the network: most of the nodes are distributed along a centric area but without prominent spatial distributions. The results provided are the snapshots of using 5 neighbors, 25

neighbors, and 50 neighbors for this type of data evaluation aspect in Figures 8, 9, and 10.

The analysis result for t-SNE shows step 1003 for the iterations of the Student-t distribution stochastic neighbor embedding features for the iteration between all evaluation nodes in the test graphs, shown in figure 11.

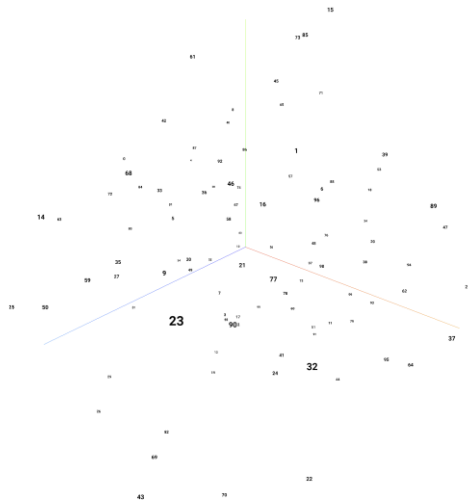


Figure 5. The demonstration of the PCA 1-2-3 result.

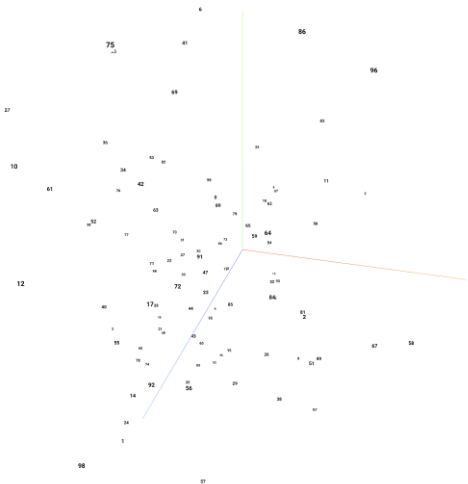


Figure 6. The demonstration of the PCA 4-5-6 result.

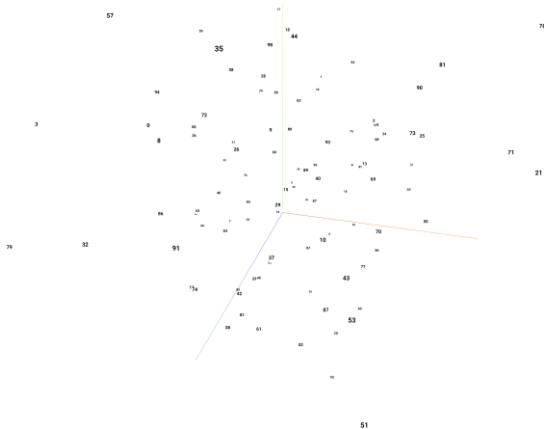


Figure 7. The demonstration of the PCA 7-8-9 result.

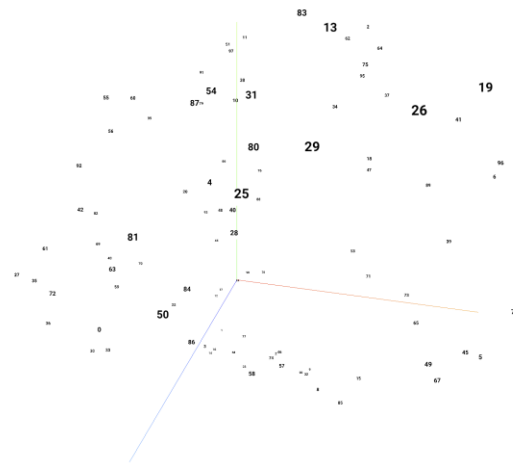


Figure 8. The demonstration of the UMAP 5 neighbors' result.

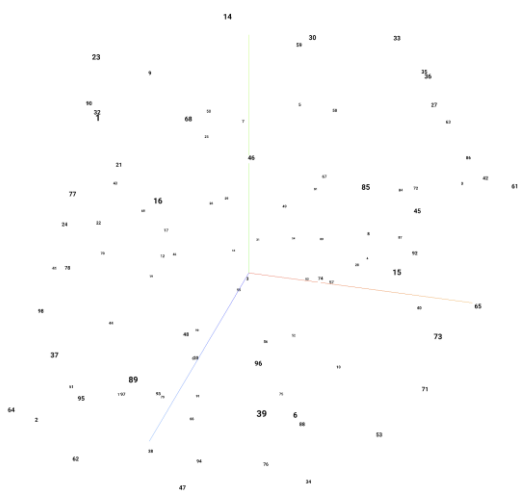


Figure 9. The demonstration of the UMAP 25 neighbors' result.

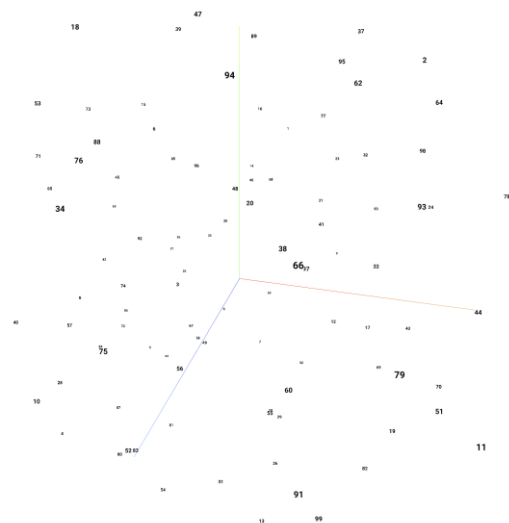


Figure 10. The demonstration of the UMAP 50 neighbors' result.

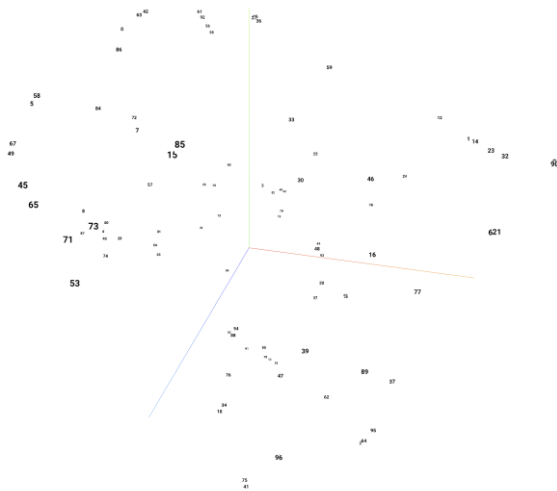


Figure 11. The demonstration of the t-SNE result with 1003 steps of iterations.

5. CONCLUSIONS

Aiming to solve the graph analysis problems by introducing GAN models, we have successfully established a foundational GraphGAN framework for analyzing the critical nodes in indoor navigation works. Although the current solution is naïve and preliminary, it still proposes a promising solution for starting the first step to study more complex and large-scale indoor navigation networks.

To mitigate the current bottlenecks of the proposed solution, we plan to configure the hyper test parameters with more loops, which may exceed 10,000 loops. An extensive set of nodes may exceed 10,000 for the number of nodes and connection degree more significant than 10. However, we still have to pay enough attention to the balance between payouts of data model analysis and efficiency without introducing an overwhelming computational burden on test platforms with acceptable price.

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