Graph Q-Learning for Automatic Assembly in Design-to-Construction

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Abstract

This study tackles construction labor shortages by introducing a robotic brick assembly system using a mobile manipulator. It bridges CAD models and real-world construction through a Design-to-Construction workflow. The proposed Graph Q-Learning (GQL) framework enhances automated brick assembly in complex designs by overcoming the limitations of traditional graph search methods. A Graph Attention Network + Deep Q-Network (GAT-DQN) architecture dynamically models inter-brick relationships, prioritizing structurally critical connections to optimize assembly placement and improve overall stability.

CCS Concepts

• **Applied computing → Computer-aided design**.

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1 Introduction

In recent years, the construction industry has increasingly faced labor shortages, driving the need for robotic integration to maintain efficiency and productivity [Stumm et al. 2016]. This paper presents a novel approach to brick assembly, a critical task in construction, by bridging the gap between computer-aided design (CAD) and physical construction through the adoption of Design-to-Construction with robotic mobile manipulator in graph Q-Learning.

Our research focuses on the use of graph data structures to **enhance the assembly sequence of bricks in complex architectural designs**, thereby optimizing the automatic construction process, such as robotic assembly [Atad et al. 2023], navigation, and planning (**Fig. 1**). Despite the advancements in robotic brick assembly, most existing research has not transitioned beyond laboratory settings to practical, industrial applications[Funk et al. 2022]. The study in [Tian et al. 2022] provides a theoretical framework for assembly planning using physics-based simulations, optimized for industrial settings and complex assemblies with rotational components. However, it **lacks the on-site adaptability** necessary for construction environments. To overcome the limitations of traditional search algorithms like Breadth-First Search (BFS), Depth-First Search (DFS) which often fail to maintain structural integrity in complex arrangements, we employ Graph Q-Learning (GQL) [Nie et al. 2023]. Our GAT-DQN enhances the structural integrity and operational efficiency of automatic brick assembly, significantly outperforming traditional methods like Graph Convolutional Q-Network (GCQN) and standard DQN with GNNs. It demonstrates remarkable adaptability to complex architectural designs, thereby promising to promote automatic construction with contributions to assemble complex brick constructions robustly and efficiently:

- We integrate Graph Attention Networks with the Deep Q-Networks (GAT-DQN) model to specifically address the dynamic and complex challenges in robotic brick assembly without multi-view limitations from the vision-based method.
- We employ robust metrics like the Topological Stability Index and Structural Integrity to guide the continuous optimization of the model, enhancing placement precision, singularity avoidance, and efficiency in decision-making (**Fig. 2**).

2 Method

System. We model the system by employing a Graph Q-Learning (GQL) framework (**Fig. 2**). This framework combines Graph Attention Networks (GAT) with Deep Q-Networks (DQN) to dynamically adjust relationships between nodes (bricks). By graph modeling with information on physical attributes (**supported** and **unsupported** cases depends on reasonable structure designs) and topological relationships of bricks, this integration not only improves decision-making for optimal brick placement but also ensures the structural integrity of the assembly in learning, offering a robust solution to the challenges in complex architectural designs.

After translating the structural model into a graph, each node within this graph represents a brick, and the edges capture the essential spatial and mechanical relationships critical for the stability. We apply a GAT to extract features. $\mathbf{h}_i^{(l)} \in \mathbb{R}^F$ be the feature of node i at

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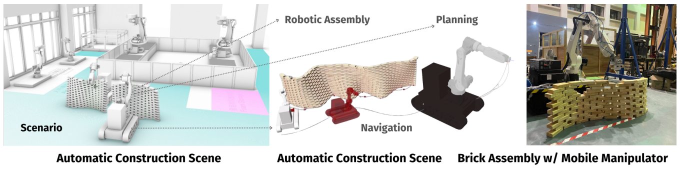

Figure 1: The automatic brick construction scenario for complex designs showcases robotic assembly, navigation, and planning via mobile manipulator.

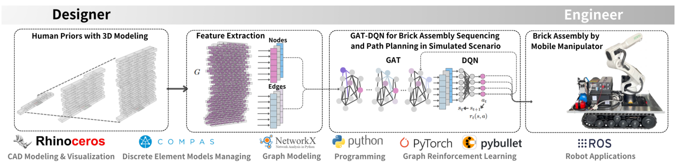

Figure 2: The system leverages graph Q-learning for efficient brick assembly, transforming CAD models into structural graphs. GAT-DQN guides a mobile manipulator, enabling seamless Design-to-Construction integration where designers directly generate executable construction plans.

Table 1: Performance of Graph-Based Models in Brick Assembly. Average results over five independent runs (mean ± standard deviation).

Metric	GAT-DQN	DQN with GNNs	GNNPG	DFS+SC	BFS+SC
Entropy of Action Distribution (H)	**0.92±0.01**	0.87±0.012	0.90±0.01	0.74±0.025	0.55±0.03
Topological Stability Index ($\lambda_{\min}(L)$)	**0.15±0.005**	0.12±0.005	0.11±0.005	0.07±0.007	0.05±0.007
Path Efficiency (P_{eff})	**0.75±0.03**	0.70±0.03	0.68±0.035	0.57±0.05	0.43±0.05
Structural Integrity (S_{integ})	**0.80±0.02**	0.75±0.02	0.74±0.025	0.67±0.04	0.55±0.05
Completion Time (seconds)	**120±5**	135±6	130±5	192±10	180±9
Accuracy of Placement (Success Rate)	**0.98±0.005**	0.95±0.008	0.94±0.007	0.88±0.02	0.75±0.03

layer l (layer $l = 0, \ldots, L-1$): $\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij}^{(l)} \mathbf{W}^{(l)} \mathbf{h}_j^{(l)}\right), \alpha_{ij}^{(l)} = \text{softmax}_j\left(\text{LeakyReLU}\left(\mathbf{a}^{(l)\top}\left[\mathbf{W}^{(l)}\mathbf{h}_i^{(l)} \parallel \mathbf{W}^{(l)}\mathbf{h}_j^{(l)}\right]\right)\right)$.

Here, $\mathbf{W}^{(l)} \in \mathbb{R}^{F' \times F}$ and $\mathbf{a}^{(l)} \in \mathbb{R}^{2F'}$ are the *layer-specific* learnable parameters: $\mathbf{W}^{(l)}$: feature projection matrix at layer l,$\mathbf{a}^{(l)}$: attention weight vector at layer l. By indexing $\mathbf{W}$ and $\mathbf{a}$ with the layer superscript (l), we clearly distinguish between the different "learnable weight matrices" used in each GAT layer. The final node embeddings $\mathbf{h}_i^{(L)}$ are then passed to the DQN for decisions. α_{ij} are the attention coefficients determining the significance of node j's features for node i, and $\mathcal{N}_i$ represents the set of neighbors of node i in the graph. The function σ denotes a non-linear activation function, such as sigmoid or ReLU, and $\mathbf{a}'$ is a parameter vector crucial for computing the attention coefficients.

3 Experiments

3.1 Evaluation Metrics.

Several key metrics evaluate the GAT-DQN system's performance in brick assembly and path planning, capturing decision quality, structural stability, learning dynamics, and efficiency: **Entropy of Action Distribution:** $H = -\sum p(a|s) \log p(a|s)$ — measures policy exploration; higher entropy indicates broader strategy search. **Topological Stability Index:** $\lambda_{\min}(L)$ — the smallest eigenvalue of the Laplacian, reflecting assembly graph robustness. **Accuracy of Placement:** $A_{\text{place}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i - x_i')^2 + (y_i - y_i')^2 + (z_i - z_i')^2}$ — measures alignment precision between intended and actual positions. **Path Efficiency:** $P_{\text{eff}} = \frac{1}{\sum_{t=1}^{T} d(\mathbf{x}_t, \mathbf{x}_{t+1})}$ — favors shorter, more direct robot trajectories. **Completion Time:** $T_{\text{comp}} = t_{\text{end}} - t_{\text{start}}$ — total construction time; lower is better. **Structural Integrity:** $S_{\text{integ}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\sigma_i - \overline{\sigma})^2}$ — evaluates variance in stability scores across bricks. These metrics enable a holistic evaluation of learning and robotic control.

3.2 Model Comparisons.

In the evaluation of graph-based models for automatic construction, particularly the brick assembly, mobile navigation and manipulator path planning, the GAT-DQN model demonstrates superior performance when compared to other methods such as DQN with Graph Neural Networks (GNNs), Graph Neural Network Policy Gradient (GNNPG), and DFS/BFS. Our experimental results for average in 5 times of each training, summarized in **Table 1**, reveal that GAT-DQN achieves higher scores across a range of key metrics, improving performance over baselines. GAT-DQN outperforms in metrics such as Path Efficiency ($\mathbf{P_{eff}}$), reflecting a more optimal navigation through the assembly sequence, and Structural Integrity ($\mathbf{S_{integ}}$), indicating a more robust assembly under various load conditions compared to previous methods.

4 Conclusions

Our system applies GQL to robotic construction, using GAT combined with DQN to improve the adaptability and efficiency in planning, navigation, and brick assembly with the mobile manipulator. Initially trained in a simulated environment, the GAT-DQN model learns optimal brick assembly and placement strategies from graph-structured data that models the construction plan. This training focuses on robust policy formulation that accounts for physical constraints and the targeted final structure in automatic assembly.

References

Matan Atad, Jianxiang Feng, Ismael Rodr'iguez, Maximilian Durner, and Rudolph Triebel. 2023. Efficient and Feasible Robotic Assembly Sequence Planning via Graph Representation Learning. *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2023), 8262–8269. https://api.semanticscholar.org/CorpusID:257623086

Niklas Funk, Svenja Menzenbach, Georgia Chalvatzaki, and Jan Peters. 2022. Graph-based Reinforcement Learning meets Mixed Integer Programs: An application to 3D robot assembly discovery. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 10215–10222. doi:10.1109/IROS47612.2022.9981784

Mingshuo Nie, Dongming Chen, and Dongqi Wang. 2023. Reinforcement Learning on Graphs: A Survey. *IEEE Transactions on Emerging Topics in Computational Intelligence* 7, 4 (2023), 1065–1082. doi:10.1109/TETCI.2022.3222545

Sven Stumm, Johannes Braumann, and Sigrid Brell-Çokcan. 2016. Human-Machine Interaction for Intuitive Programming of Assembly Tasks in Construction. *Procedia CIRP* 44 (2016), 269–274. https://api.semanticscholar.org/CorpusID:63263344

Yunsheng Tian, Jie Xu, Yichen Li, Jieliang Luo, Shinjiro Sueda, Hui Li, Karl D. D. Willis, and Wojciech Matusik. 2022. Assemble Them All: Physics-Based Planning for Generalizable Assembly by Disassembly. *ACM Trans. Graph.* 41, 6, Article 278 (nov 2022), 11 pages. doi:10.1145/3550454.3555525