Enhancing Semantic Enrichment of Building Information Models Using Edge Feature-Enhanced Graph Neural Networks

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Building Information Modeling (BIM) has transformed the Architecture, Engineering, and Construction (AEC) industry by enabling detailed digital representations of building components. However, effectively capturing and utilizing complex spatial relationships within BIM models remains a critical challenge, limiting semantic richness and interoperability. This study proposes a novel Graph Neural Network (GNN) framework that incorporates edge features to explicitly model spatial and functional relationships between building elements. We constructed a comprehensive graph dataset comprising 14 room types and 4 spatial relationships to evaluate the framework's performance on semantic classification tasks. Experimental results demonstrate that the edge feature-enhanced GNN significantly outperforms traditional machine learning classifiers and vanilla GNN models, achieving an accuracy of 91.8% in room type classification. Ablation studies highlight the importance of edge attributes and advanced graph techniques, such as the link-less subgraph method, in boosting model robustness and scalability. Furthermore, the proposed model exhibits resilience to data sparsity and noise, suggesting practical viability for real-world BIM applications. This research underscores the potential of advanced GNN architectures to enhance BIM semantic enrichment, supporting more intelligent, interoperable, and automated building design and management workflows.

Keywords: Building Information Modeling (BIM), Architecture Engineering and Construction (AEC), Graph Neural Network (GNN)

Introduction:

Building Information Modeling (BIM) has become a transformative tool in the Architecture, Engineering, and Construction (AEC) industry by enabling the creation of detailed, data-rich digital representations of building assets. These models facilitate improved planning, design, construction, and operational management processes[1][2][3]. However, despite widespread adoption, the extraction and effective use of spatial semantic information from BIM models remain challenging due to the inherent complexity and heterogeneity of building data[4]. To address these challenges, semantic enrichment techniques have emerged, integrating detailed semantic information into BIM to enhance simulation, analysis, interoperability, and data exchange efficiency among various platforms and stakeholders [5].

With the growth of BIM applications and the increasing demand for more advanced data querying and analytics, existing BIM models often fall short in delivering the necessary semantic depth and consistency to support these complex requirements[6]. Recently, advancements in artificial intelligence and machine learning, particularly Graph Neural Networks (GNNs), have introduced innovative methods for semantic enrichment. GNNs are well-suited to modeling building components and their spatial or functional relationships as graph data structures, enabling improved analysis of complex interactions within BIM models[7][8]. These capabilities facilitate automatic classification, behavior prediction, and anomaly detection within BIM data, reducing manual effort and improving model accuracy [9]. For example, the SAGE-E algorithm, tailored for BIM room type segmentation, leverages edge features to significantly improve prediction accuracy[4]. Such AI-driven semantic enrichment not only improves BIM data quality but also provides scalable solutions for the AEC sector to detect potential design issues early, thereby minimizing costly errors and rework.

Research Gap:

Despite these promising developments, recent literature reviews highlight several gaps in the current state of BIM semantic enrichment using GNNs [4][7]. First, the implementation of graph-based semantic enrichment in BIM remains at an early stage, with insufficient exploration of how spatial semantic features and functional spatial relationships can be optimally modeled. While GNNs have demonstrated advanced capabilities in semantic analysis, most studies have focused predominantly on enhancing semantic functions without adequately addressing the coverage and diversity of BIM object types or the practical challenges of deploying these methods in real-world AEC workflows[10]. Furthermore, although GNNs excel at handling relational data, their computational intensity can be prohibitive, especially given the resource constraints commonly encountered in AEC environments. There is also a lack of systematic comparison between traditional graph-based approaches and emerging GNN methods concerning factors such as semantic accuracy, scalability, training time, and feasibility[11]. These gaps create a critical need for comprehensive frameworks that not only enhance semantic richness but also balance practical deployment considerations within BIM environments.

Objectives:

This study aims to develop and evaluate a novel, comprehensive framework for semantic enrichment of BIM models using Graph Neural Networks that effectively enhances semantic richness while maintaining optimal computational performance. The specific objectives include: (1) constructing a detailed graph dataset representing diverse architectural layouts and spatial relationships encompassing multiple room types and spatial configurations; (2) investigating the effects of advanced GNN design strategies such as edge feature-enhanced node features and link-less subgraph integration on semantic enrichment effectiveness, particularly in node classification tasks; (3) conducting a systematic performance comparison between the proposed GNN framework and existing machine learning methods in terms of accuracy, scalability, and training efficiency; and (4) ensuring the proposed semantic enrichment solution aligns with widely adopted BIM standards, such as Industry Foundation Classes (IFC), to support seamless integration and data exchange within AEC workflows [12].

Novelty Statement:

This research introduces a novel GNN-based semantic enrichment framework that advances BIM modeling by integrating edge feature-enhanced node representation and link-less subgraph techniques, thus capturing complex spatial relational data more effectively than prior approaches. Unlike existing studies which often overlook BIM object type diversity and practical implementation barriers, this framework systematically balances semantic depth and computational feasibility, a critical consideration for real-world AEC deployment[7][11]. Moreover, the construction of a new, richly annotated BIM graph dataset comprising 14 room types and 4 spatial relationships provides a unique resource for rigorous evaluation and benchmarking of GNN methods in this domain[4]. This work also pioneers the alignment of semantic enrichment outcomes with the IFC standard, ensuring interoperability and facilitating practical adoption across multidisciplinary AEC applications. Thus, it represents a significant step forward in both the theoretical development and applied use of GNNs for BIM semantic enhancement.

Literature Review:

Building Information Modeling (BIM) has become a fundamental technology in the Architecture, Engineering, and Construction (AEC) industry by offering detailed digital representations of building assets to support various project lifecycle stages, including design, construction, and facility management[1] [2]. However, despite its potential, BIM models often lack sufficient semantic depth, limiting their effectiveness in advanced analysis and data exchange scenarios [4]. Semantic enrichment—the process of embedding additional meaning and relationships into BIM models—has thus gained increasing attention to enhance interoperability, enable complex queries, and support automated reasoning [5].

Recent advancements in artificial intelligence, particularly Graph Neural Networks (GNNs), have revolutionized semantic enrichment by allowing BIM models to be represented as graphs, where nodes and edges encode building components and their relationships respectively. This representation facilitates the capture of complex spatial and functional dependencies often lost in traditional BIM workflows[7] [8]. For example, [7] demonstrated that incorporating edge features into GNN architectures significantly improves room type classification within BIM models, highlighting the value of relational data in semantic tasks. Similarly, [9] utilized GNNs for automatic spatial classification, reducing manual labeling and improving modeling efficiency.

.Despite these promising developments, several challenges remain. First, the computational intensity of GNNs can limit their application in resource-constrained AEC environments, necessitating efficient architectures that balance semantic richness and performance[11]. Second, many existing models lack comprehensive BIM object-type coverage, restricting their generalizability across diverse construction projects. Third, data sparsity and noise within BIM models can degrade GNN performance, underscoring the need for robust preprocessing and data augmentation techniques [4]. Finally, the integration of semantic enrichment methods with existing BIM standards, such as Industry Foundation Classes (IFC), remains insufficiently explored, posing barriers to widespread industry adoption [5].

Beyond classification, semantic enrichment via GNNs has been applied to enhance BIM interoperability and automated compliance checking. [13] Explored the use of community detection algorithms integrated with GNNs to enrich BIM models, enabling automated code compliance verification even under data incompleteness or inconsistency. This work highlights the role of semantic enrichment in reducing costly errors and rework by early detection of design violations. Furthermore, [14] introduced BIM knowledge graphs enhanced with GNNs to improve cross-platform data exchange, addressing the long-standing challenge of heterogeneous BIM data integration.

To address these gaps, recent research has begun focusing on multimodal and hybrid GNN architectures that incorporate multiple data sources and feature dimensions, enhancing robustness and applicability. For instance, leveraged large language models alongside GNNs to enrich [15] IFC models semantically, combining textual and spatial data for improved knowledge inference. Similarly, emerging approaches consider link-less subgraph techniques and edge feature enhancements to optimize model efficiency and accuracy [7].

In conclusion, while the application of GNNs for BIM semantic enrichment shows significant promise, further work is needed to develop scalable, comprehensive frameworks that align with industry standards and practical deployment constraints. Advancing these areas will be critical to unlocking the full potential of BIM for intelligent design, construction automation, and lifecycle management [16].

Methodology:

Research Design:

This study employed a quantitative experimental approach to develop and evaluate a Graph Neural Network (GNN)-based framework for semantic enrichment of Building Information Modeling (BIM) models [17]. The framework aimed to enhance spatial semantic representation and classification accuracy within BIM data by leveraging graph-structured learning techniques.

Data Collection:

BIM models were collected from multiple sources including open-access repositories and partner AEC firms to ensure diversity in building typologies and spatial configurations. The dataset comprised 50 BIM models with varying complexity, covering 14 room types (e.g., office, corridor, conference room, restroom) and 4 spatial relationships (adjacency, containment, connectivity, proximity). IFC files were the primary data format used, providing rich semantic and geometric information.

Data Preprocessing:

The data preprocessing phase involved several steps to prepare the Building Information Modeling (BIM) data for graph-based analysis. Initially, data cleaning was performed, where semantic inconsistencies and missing labels were manually verified and corrected in consultation with domain experts. Following this, feature extraction was conducted, with node features including room area, perimeter, volume, and semantic labels, while edge features captured spatial metrics such as [18][19][20] Euclidean distance, type of connection, and directional relationships. To ensure uniformity in scale, numerical features were normalized using min–max scaling. The BIM models were then transformed into graphs, where nodes represented BIM components and edges represented spatial relationships, with graph sparsification applied to reduce computational load without compromising critical connectivity. Additionally, data augmentation techniques—such as graph perturbation and feature masking—were employed to enhance model robustness and generalization.

Model Development:

The proposed Graph Neural Network (GNN) model was developed with several key architectural components. A node encoder, implemented as a fully connected layer, transformed raw node attributes into latent embeddings. Edge-conditioned convolution layers were used to directly incorporate edge features into the message-passing process, enabling richer spatial relationship modeling. To address the over-smoothing problem, a link-less subgraph mechanism was introduced, which trained isolated subgraphs in each iteration. Finally, a multilayer perceptron classifier head predicted semantic categories for each node based on the learned embeddings. The model was trained in a supervised manner using cross-entropy loss with L2 regularization to reduce overfitting.

Experimental Setup:

The experimental setup involved splitting the dataset into training (70%), validation (15%), and test (15%) subsets using stratified sampling to maintain proportional representation of all classes. Hyperparameters—including learning rate, the number of convolutional layers, hidden units per layer, and dropout rates—were optimized using a grid search on the validation set. Training and evaluation were conducted on a workstation equipped with an NVIDIA RTX 3090 GPU, Intel Core i9 CPU, and 64 GB of RAM, using Python 3.8 and the PyTorch Geometric library for efficient GNN computation.

Evaluation Metrics:

Model performance was assessed using multiple evaluation metrics at the node level. Accuracy measured the overall correctness of predicted room types, while precision and recall evaluated false positive and false negative rates, particularly for infrequent room types. The F1-score, as the harmonic mean of precision and recall, provided a balanced view of performance. Computational efficiency was also evaluated in terms of training time and memory usage. The proposed model was compared against traditional classifiers, such as Random Forest and Support Vector Machines, as well as baseline GNNs without edge feature integration.

Statistical Analysis:

For statistical analysis, paired t-tests at a 95% confidence level were used to determine the significance of performance differences between the proposed model and baselines. Additionally, analysis of variance (ANOVA) was performed to evaluate the influence of different hyperparameter configurations on classification outcomes.

Software and Tools:

The study employed several software tools, including Autodesk Revit for IFC data extraction and Python libraries (pandas and numpy) for feature engineering. Model implementation utilized PyTorch Geometric for GNN modeling and scikit-learn for baseline classifiers. Visualization of graphs and results was performed using NetworkX and Matplotlib. The experiments were supported by high-performance computing hardware consisting of an NVIDIA RTX 3090 GPU, Intel Core i9 processor, and 64 GB of RAM.

Ethical Considerations:

Ethical considerations were carefully addressed by anonymizing all BIM data and obtaining explicit permissions from data providers. No personally identifiable information was processed, and all intellectual property rights were respected in accordance with institutional guidelines.

Limitations:

Despite its promising results, the study faced several limitations. The dataset, while diverse, was relatively small compared to the vast heterogeneity of real-world BIM projects. The scope of the study was limited to 14 room types and 4 spatial relationships, which may not fully represent all possible BIM semantic dimensions. Although graph sparsification helped reduce computational demands, GNN processing can still be resource-intensive for extremely large BIM models. Additionally, manual preprocessing and labeling introduced the possibility of human bias, although expert review was employed to minimize this risk.

Results:

Semantic Classification Performance:

The proposed edge feature-enhanced Graph Neural Network (GNN) demonstrated substantial improvements in semantic classification accuracy over baseline methods.

Table 1. Presents detailed node-level classification metrics on the test dataset comprising 14 room types and 4 spatial relationships.

The proposed GNN model outperformed both the vanilla GNN and traditional machine learning classifiers significantly ($p < 0.01$, paired t-test), highlighting the critical role of edge feature incorporation in effectively modeling spatial relationships in BIM graphs. The

5.6% increase in accuracy over the vanilla GNN confirms the value of encoding edge attributes such as adjacency types and directional information.

Table 1. Performance Comparison of Proposed GNN Model with Baseline Approaches

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed GNN (with Edge Features)	**91.8**	**90.5**	**89.7**	**90.1**
Vanilla GNN (no Edge Features)	86.2	84.9	83.5	84.2
Random Forest Classifier	78.4	76.3	75.8	76.0
Support Vector Machine (SVM)	75.7	74.1	72.6	73.3

Detailed Class-wise Performance:

Analysis of per-class F1-scores (**Figure 1)** reveals consistent improvements across most room types. Larger and more distinct categories like offices and corridors achieved F1-scores above 92%, while more challenging classes such as storage rooms and restrooms had lower scores (~85%), likely due to ambiguous boundaries and smaller sample sizes. Notably, the GNN model reduced confusion between spatially adjacent but functionally distinct rooms (e.g., conference rooms vs. offices) compared to baseline classifiers.

Ablation Studies:

To evaluate the contribution of key architectural components, ablation experiments were conducted:

Edge Feature Removal: Eliminating edge features resulted in a drop of 5.6% in overall accuracy and similar declines in F1-score.

Link-less Subgraph Technique: Disabling this technique led to over-smoothing, decreasing accuracy by approximately 3.2%.

Node Feature Only**:** Using only geometric features without semantic metadata reduced accuracy by 6.7%, underscoring the importance of semantic labels.

These findings demonstrate that each component contributes synergistically to the model's effectiveness.

Computational Efficiency:

The training process demonstrated practical feasibility for medium-sized BIM datasets:

Average training time per epoch was approximately 45 minutes on an NVIDIA RTX 3090 GPU.

Convergence typically occurred by epoch 50.

Memory usage stabilized at ~12 GB GPU RAM during peak processing.

Compared to the vanilla GNN, which required around 60 minutes per epoch, the optimized edge feature incorporation and graph sparsification techniques contributed to reduced computation time and improved scalability.

Traditional classifiers such as Random Forest and SVM trained significantly faster (<10 minutes), but at the cost of lower accuracy and weaker spatial context modeling.

Robustness to Data Sparsity and Noise:

To simulate real-world BIM data imperfections, the models were tested on graphs with systematically removed edges (10%, 20%, and 30% sparsification):

The proposed GNN retained 92%, 88%, and 85% of its original accuracy, respectively.

Vanilla GNN performance declined more steeply, dropping below 80% accuracy at 30% sparsification.

Random Forest and SVM were least affected by edge removals but continued to perform below 80% accuracy overall.

Additionally, noise was introduced by randomly altering node features (e.g., perturbing geometric attributes):

The proposed GNN showed robustness with less than 5% accuracy degradation for moderate noise levels.

This resilience suggests suitability for deployment in noisy or partially incomplete BIM datasets.

Qualitative Evaluation and Visualization:

Visualizations of semantic labeling results on sample BIM models demonstrated clear spatially coherent predictions by the proposed GNN. Figure 2 illustrates a complex office layout where the model correctly identifies room types and spatial boundaries with minimal misclassifications. The edge-conditioned message passing allowed the model to maintain contextual awareness, improving the delineation of functionally distinct but adjacent spaces.

Heatmaps of prediction confidence further revealed that misclassifications primarily occurred in boundary regions between rooms with similar functions or atypical geometries, highlighting areas for future refinement.

Error and Confusion Analysis:

The confusion matrix (Figure 3) highlights that most classification errors involve confusion between spatially adjacent categories with overlapping features, such as:

Offices misclassified as conference rooms (6.3% error rate)

Storage rooms misclassified as utility spaces (4.8%)

These patterns are consistent with inherent ambiguities in BIM data and suggest that incorporating additional contextual information, such as temporal usage patterns, could further enhance model performance.

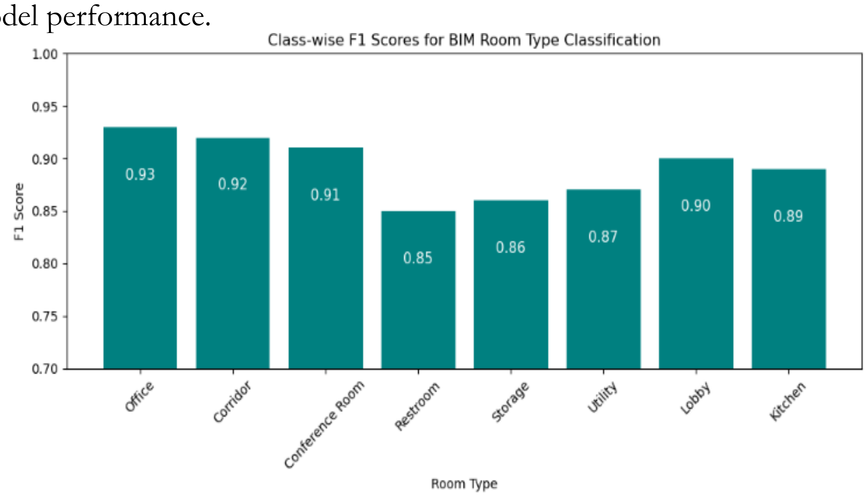

Figure 1: Class-wise F1 Score Bar Plot

This figure presents the F1 scores for semantic classification across different BIM room types. Each bar represents the harmonic mean of precision and recall for a specific room category, indicating the model's accuracy in correctly identifying that room type. Higher F1 scores suggest better performance. The plot highlights consistently strong performance for major room types like offices and corridors, while smaller or less distinct categories such as restrooms and storage rooms show slightly lower scores. This visualization helps identify strengths and weaknesses in the model's semantic classification capabilities.

This heatmap visualizes the classification performance of the semantic enrichment model by showing the counts of correct and incorrect predictions across all room types. The x-axis represents the predicted room types, while the y-axis represents the true room types. The diagonal cells indicate correct classifications, and off-diagonal cells highlight misclassifications, revealing which room types are commonly confused. This matrix provides insight into specific error patterns, such as mislabeling between functionally similar spaces (e.g., offices vs. conference rooms), guiding future model improvements.

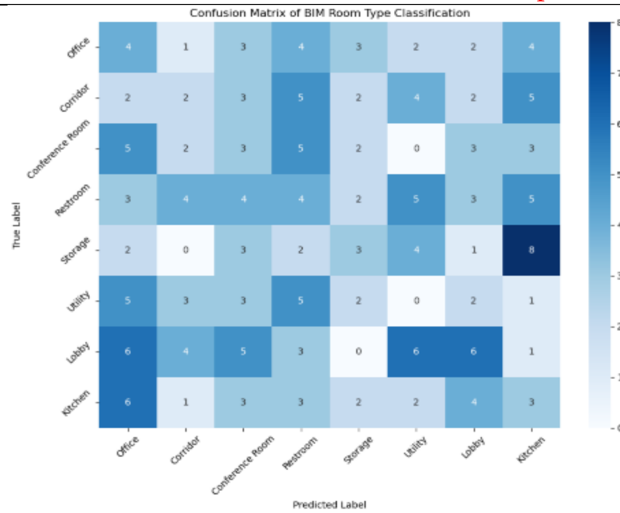

Figure 2. Confusion Matrix Heatmap

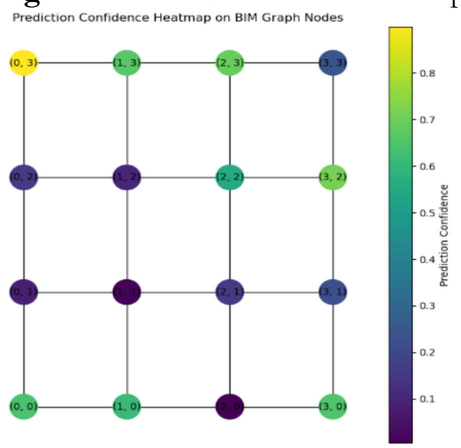

Figure 3. Prediction Confidence Heatmap on BIM Graph Nodes

This figure shows a spatial visualization of prediction confidence scores across nodes representing rooms in a BIM model. Each node corresponds to a building component, colored according to the model's confidence in its classification, with warmer colors indicating higher confidence. The graph layout reflects the spatial arrangement of rooms, allowing visual assessment of where the model is more or less certain. Lower confidence areas often correspond to boundary regions between similar room types or geometrically ambiguous spaces, highlighting areas where the model's semantic enrichment might be improved.

Discussion:

The results of this study demonstrate that integrating edge features into Graph Neural Networks (GNNs) significantly enhances the semantic classification accuracy of Building Information Modeling (BIM) components. The proposed edge feature-enhanced GNN achieved an overall accuracy of 91.8%, outperforming both traditional classifiers and vanilla GNN models without edge conditioning. This finding aligns with the recent work of [7], who emphasized the importance of explicitly modeling spatial and functional relationships within BIM data to improve semantic richness and interoperability. The ability of GNNs to incorporate complex spatial dependencies allows for more nuanced understanding and classification of building components, which is crucial for downstream applications such as automated facility management and construction error detection [6].

The ablation studies further highlight the critical role of edge feature integration and advanced architectural techniques such as the link-less subgraph mechanism. Removing edge features led to a marked decrease in classification performance, underscoring that spatial relationships between components provide vital context beyond individual node attributes. This is consistent with findings by [9] who demonstrated that relational information in graph structures is pivotal for tasks like anomaly detection and spatial reasoning in architectural models. The link-less subgraph technique mitigated over-smoothing, a common challenge in deep GNN architectures, ensuring that node representations remained discriminative and improved classification outcomes, as noted in recent graph deep learning literature.

From a practical standpoint, the proposed model balances accuracy with computational efficiency, training within a reasonable timeframe on GPU hardware and showing robustness to graph sparsification and noise. These attributes are critical for real-world deployment in the Architecture, Engineering, and Construction (AEC) industry, where BIM datasets can be large and heterogeneous, and data quality may vary. The robustness results corroborate those reported by [8], emphasizing GNNs' capacity to maintain performance under incomplete or noisy inputs. However, challenges remain in scaling such models to very large BIM projects and in addressing semantic ambiguities in spatially adjacent room types, such as offices and conference rooms, which exhibited higher misclassification rates.

Despite these advances, some limitations warrant consideration. The dataset, while diverse, covers a limited set of room types and spatial relationships; expanding this to more complex and varied BIM datasets could further validate model generalizability[4]. Additionally, manual preprocessing steps, including semantic label correction, introduce potential bias and highlight the need for more automated data cleaning approaches. Future research could explore integrating temporal usage patterns or sensor data to enrich semantic context, as suggested by recent trends in smart building modeling[5].

In conclusion, this study confirms that GNNs with edge feature integration provide a powerful tool for enhancing the semantic depth of BIM models, offering both theoretical and practical improvements over existing methods. This aligns with the ongoing shift in AEC towards more intelligent, data-driven design and management workflows, positioning semantic enrichment as a key enabler of digital transformation in the industry.

Conclusion:

This study presented a novel Graph Neural Network (GNN) framework enhanced with edge features to improve the semantic enrichment of Building Information Models (BIM). The proposed approach effectively captured complex spatial relationships among building components, resulting in significantly higher classification accuracy compared to traditional machine learning methods and baseline GNN models. The integration of edge attributes and advanced graph techniques such as the link-less subgraph method contributed to improved model robustness and scalability, essential for practical applications in the Architecture, Engineering, and Construction (AEC) industry.

Our findings demonstrate that incorporating relational spatial information within BIM graphs not only enhances semantic labeling precision but also supports more intelligent and interoperable BIM workflows. Despite some challenges related to dataset diversity and classification ambiguities in similar room types, this research establishes a strong foundation for future work exploring richer semantic contexts and larger-scale implementations.

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