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Material Prediction For Design Automation Using Graph Representation Learning

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Introduction

Background, Motivation, and Contribution

Motivation, Goal, and Contribution

Motivation

- Successful material selection is critical in design automation;
- But requires time and expertise of designers;
- We have huge datasets of past designs; can we leverage them?

Goal

- Learn best design practices from existing Computer-aided Designs (CADs)
- Help guide and automate design processes for designers of various expertise

Contribution

- A systematic procedure to represent CAD models as assembly graphs
- A GNN model for predicting materials on new assemblies
- A scalable baseline for future works

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Background

Graph Neural Networks,
Autodesk Fusion 360 Dataset

Graph Neural Networks

Combination Aggregation

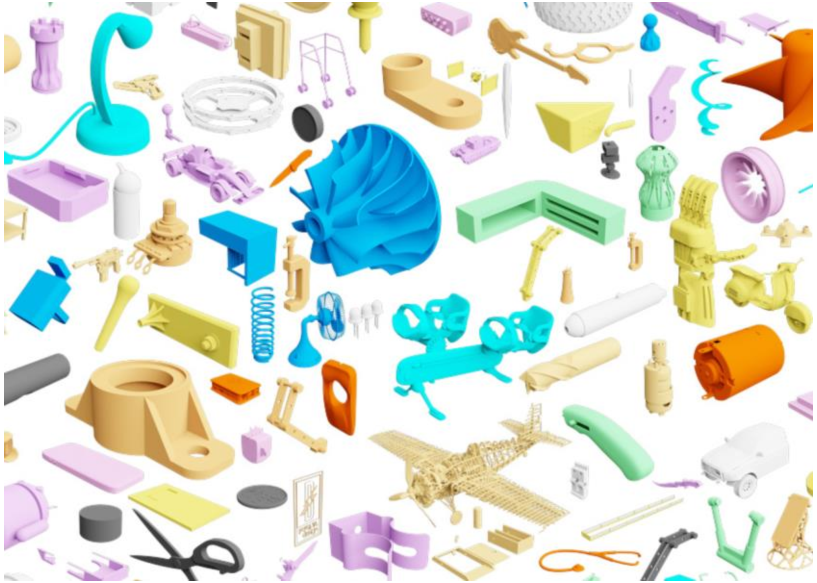
$$h_v^{(k)} = f_\theta^{(k)}\left(h_v^{(k-1)}, g_\phi^{(k)}\left(\left\{h_v^{(k-1)}, h_u^{(k-1)}, e_{uv} : u \in N(v)\right\}\right)\right)$$

$$a_v^{(k)} = LSTM(\{h_u^{(k-1)}, u \in N(v)\}), \quad h_v^{(k)} = ReLU(W^{(k)}[h_v^{(k-1)} || a_v^{(k)}])$$

GraphSAGE

GNNs use a neighborhood aggregation approach, where representation of node is iteratively updated by aggregating representations of neighboring nodes and edges.

Autodesk Fusion 360 Assembly Dataset



- **Content**: 2D and 3D geometry data derived from parametric CAD models
- **Source**: Designs submitted by users of Autodesk Fusion 360 to the Online Gallery
- **Application**: Provide insights for learning how people design
- **Motivation**: Large and scalable

Ref: https://github.com/AutodeskAILab/Fusion360GalleryDataset

03
Methodology

Framework,
Graph Representations of CAD,
Feature Encoding,
Building the Learning Framework

Overall Framework

Feature Encoding

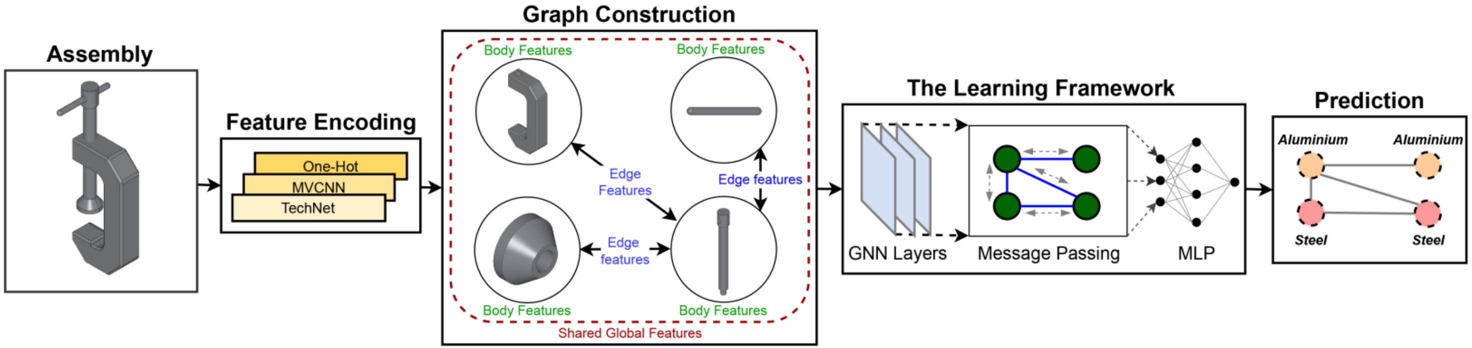
Extract and encode the multi-modal features from the dataset

Graph Construction

Transform assemblies into their graphical representation and attach corresponding features

Representation Learning

Leverage the structural and contextual learning of GNNs to learning expressive representations for material prediction



Assembly Graph Representation of CAD

Nodes

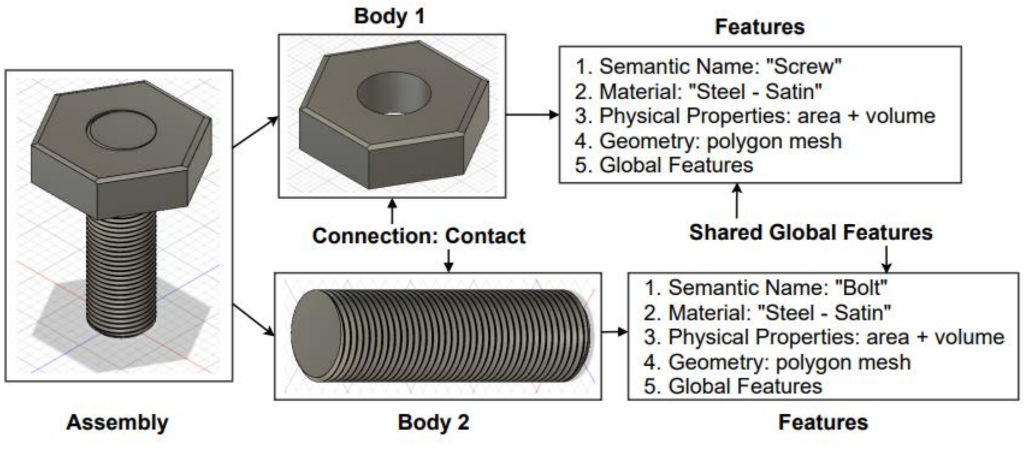
Assembly bodies, each represented as a graph node

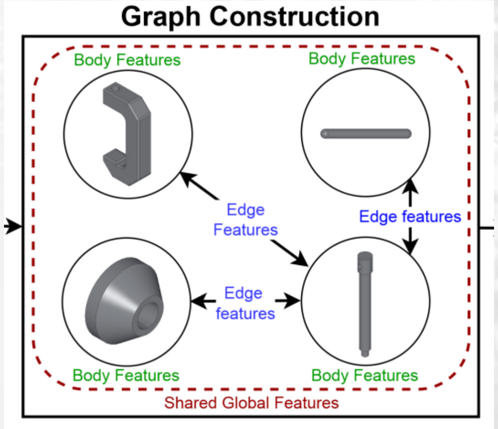
Edges

Structural relationships (e.g., contact / joint / hierarchical)

Global Context

Properties of entire assembly, shared across all of its bodies





Feature Encoding

Semantic Names

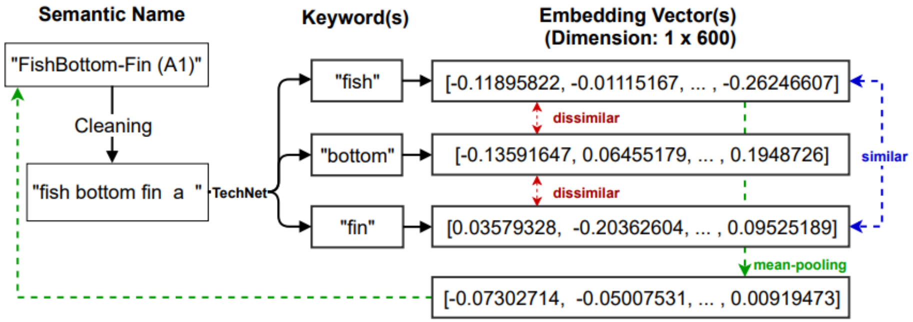
TechNet

Geometric Features

MVCNN

Numerical and Categorical

Standard scaler, One-Hot



Node Features	Semantic Names	Body Names	TechNet
		Occurrence Names	TechNet
	Physical Properties	Area	Standard scaler
		Volume	Standard scaler
	Geometric Information	Geometry	MVCNN, Standard scaler
Edge Features	Assembly Relationship	Connection type (Contact, Joints, *Tree hierarchy*)	One-hot

The Learning Framework

GNN Layers

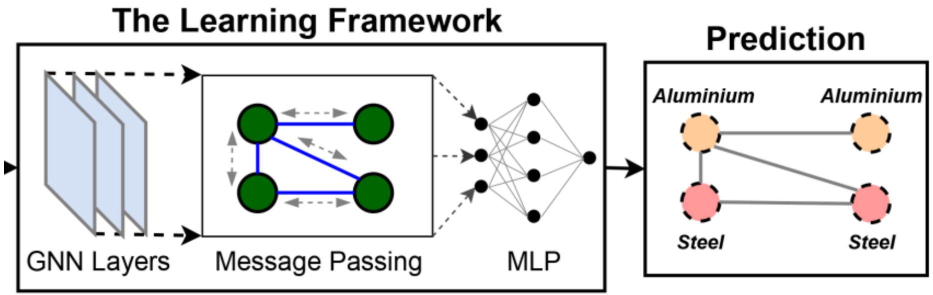
For learning representation embeddings (GraphSAGE)

Message Passing

For neighborhood feature aggregation
(e.g., induce new node embeddings from neighboring nodes)

MLP

For learning and producing classification predictions
(Loss: weighted cross-entropy)



Note: material prediction is formulated as a node-level prediction task

04

Experimental Evaluation

Ablation Experiment,
Fully Algorithm-guided Prediction
Partial Algorithm-guided Prediction
User-guided Prediction

Ablation Experiment – Feature Importance

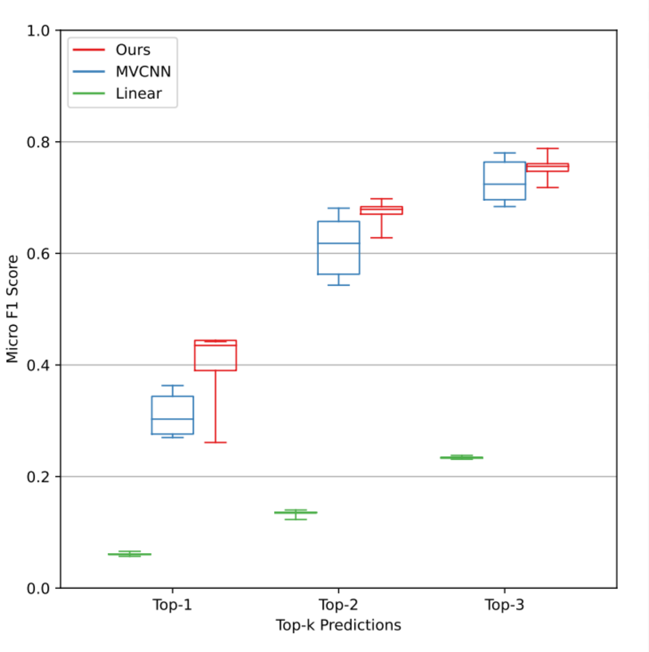
- **Observations**:
1. Semantic names node feature is important
2. Hierarchical edges as introduced by users may cause complications

TABLE 1. FEATURE ABLATION RESULTS, MICRO-F_1 SCORE

NODE ABLATION	EDGE ABLATION	
NODE	NONE	HIERARCHICAL
BODY NAME	0.384 ± 0.02	0.416 ± 0.03
OCCURRENCE NAME	0.399 ± 0.01	0.423 ± 0.01
SEMANTIC NAMES	0.317 ± 0.05	0.373 ± 0.07
BODY PHYSICAL PROPERTIES	0.413 ± 0.02	0.425 ± 0.01
OCCURRENCE PHYSICAL PROPERTIES	0.415 ± 0.02	0.392 ± 0.06
BODY GEOMETRY	0.394 ± 0.02	0.420 ± 0.00
GLOBAL FEATURES	0.393 ± 0.04	0.429 ± 0.01
NONE	0.404 ± 0.02	0.425 ± 0.01

Fully Algorithm-guided Prediction

- **Description**: Predicting the material IDs of all bodies inside an assembly
- **Application**: To fully automate material selection without user input ground truths



Partial Algorithm-guided Prediction

- **Description**: Same as fully algorithm-guided prediction, but introducing ground truths labels into a portion of assembly graphs (i.e., context nodes)

- **Application**: Simulating scenarios in which designers have access to material labels of parts of their assemblies

		Number of Layers							
		1	2	3	4	5	6	7	8
Context Nodes %	0.1	0.402	0.397	0.398	0.403	0.442	0.425	0.404	0.400
	0.2	0.386	0.421	0.414	0.435	0.416	0.450	0.389	0.385
	0.3	0.381	0.393	0.415	0.460	0.476	0.469	0.466	0.431
	0.4	0.402	0.399	0.435	0.462	0.475	0.477	0.474	0.459
	0.5	0.393	0.407	0.436	0.452	0.482	0.464	0.482	0.475

User-guided Prediction

Top-k	Material Class			F_1 Score	
	Tier 1	Tier 2	Tier 3	Micro-(F_m)	Weighted (F_w)
1	✗	✗	✗	0.417 ± 0.04	0.392 ± 0.03
	✓	✗	✗	0.546 ± 0.01	0.527 ± 0.01
	✓	✓	✗	0.736 ± 0.03	0.746 ± 0.03
	✓	✓	✓	0.731 ± 0.04	0.757 ± 0.03
2	✗	✗	✗	0.677 ± 0.01	0.630 ± 0.01
	✓	✗	✗	0.684 ± 0.10	0.677 ± 0.07
	✓	✓	✗	0.841 ± 0.11	0.851 ± 0.09
	✓	✓	✓	0.897 ± 0.01	0.903 ± 0.01
3	✗	✗	✗	0.754 ± 0.01	0.704 ± 0.01
	✓	✗	✗	0.781 ± 0.12	0.763 ± 0.10
	✓	✓	✗	0.889 ± 0.12	0.891 ± 0.12
	✓	✓	✓	0.953 ± 0.01	0.954 ± 0.01

- **Description**: Same as fully algorithm-guided prediction, but introducing ground truths categories into assembly graph nodes
- **Application**: Avoid the limitation of innovation by allowing the user to input their design information into the learning framework, thereby leading the design process

05

Conclusion

Conclusion and Future Efforts

Conclusion and Future Efforts

Conclusion

A unified framework that:
1. Contributes to design automation
2. Predicts material of assembly parts through graph representation learning
3. Integrates a systematic workflow for feature extraction and encoding
4. Supports three experiments tailored to the needs of various designers

Limitations and Future Efforts

- **Class imbalance**: data augmentation
- **Additional features**: functional and behavioral
- **Future directions**: graph and edge predictions, similarity search, etc.

Thank you!

(Note: Elliot and Bodia can add)