CADOps-Net: Jointly Learning CAD Operation Types and Steps from Boundary-Representations

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Ilya Arzhannikov[◆] Gleb Gusev[◆] Djamila Aouada[★]

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[★]SnT, University of Luxembourg

Motivation

The parametric nature of CAD models allows engineers and designers to iterate over the parameters of existing CAD models to edit and adapt them to new contexts.

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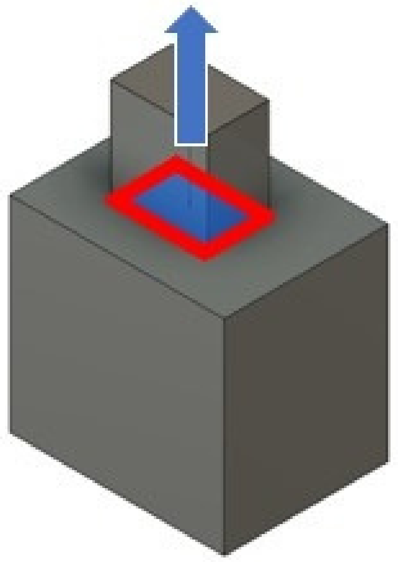
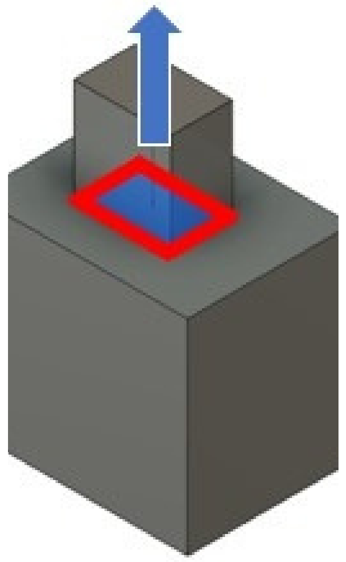
BUT

This is only possible if the final shape of the CAD model comes with its **design history**.

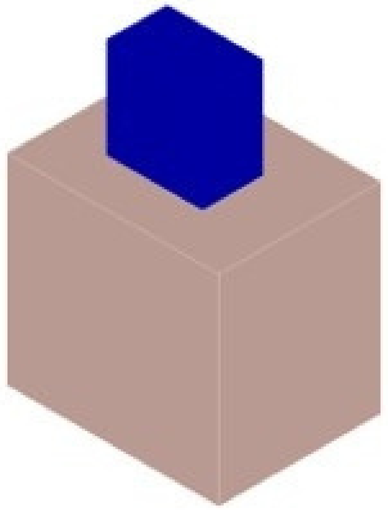
Problem Formulation

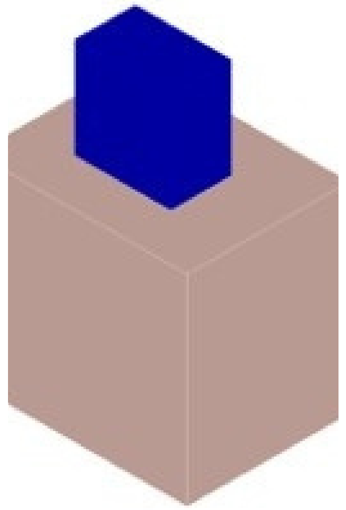
CAD construction history



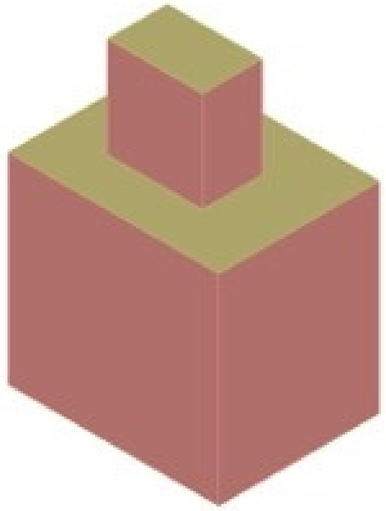


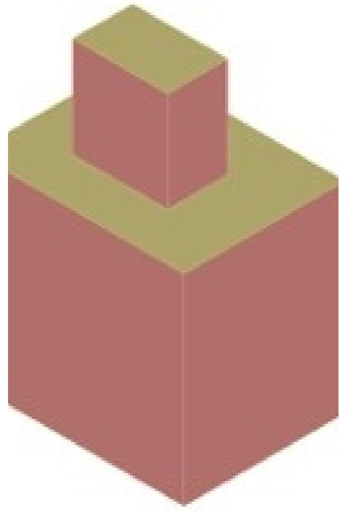
CAD operation step





CAD operation type





Problem Formulation

CAD construction history

CAD operation step

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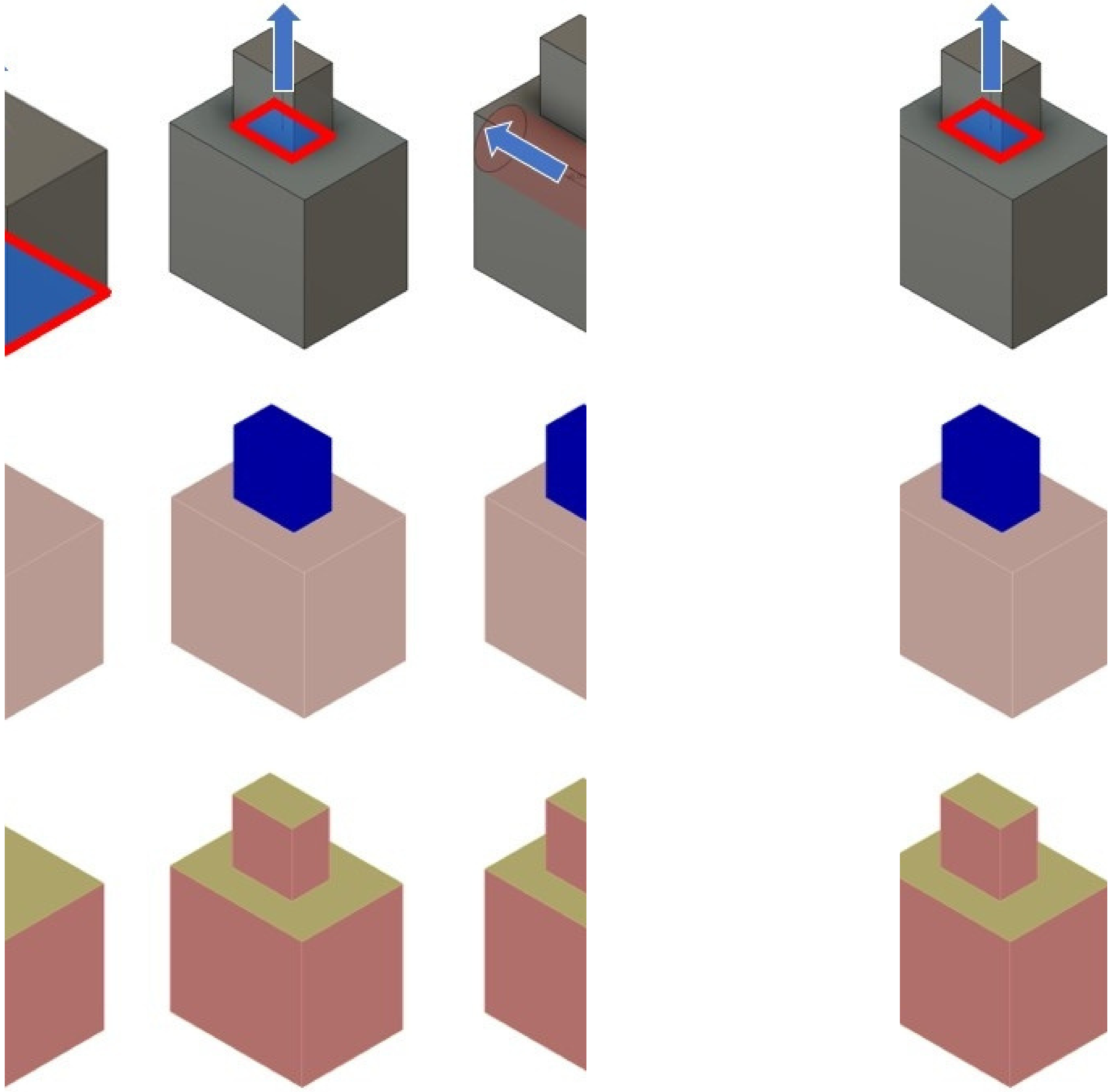

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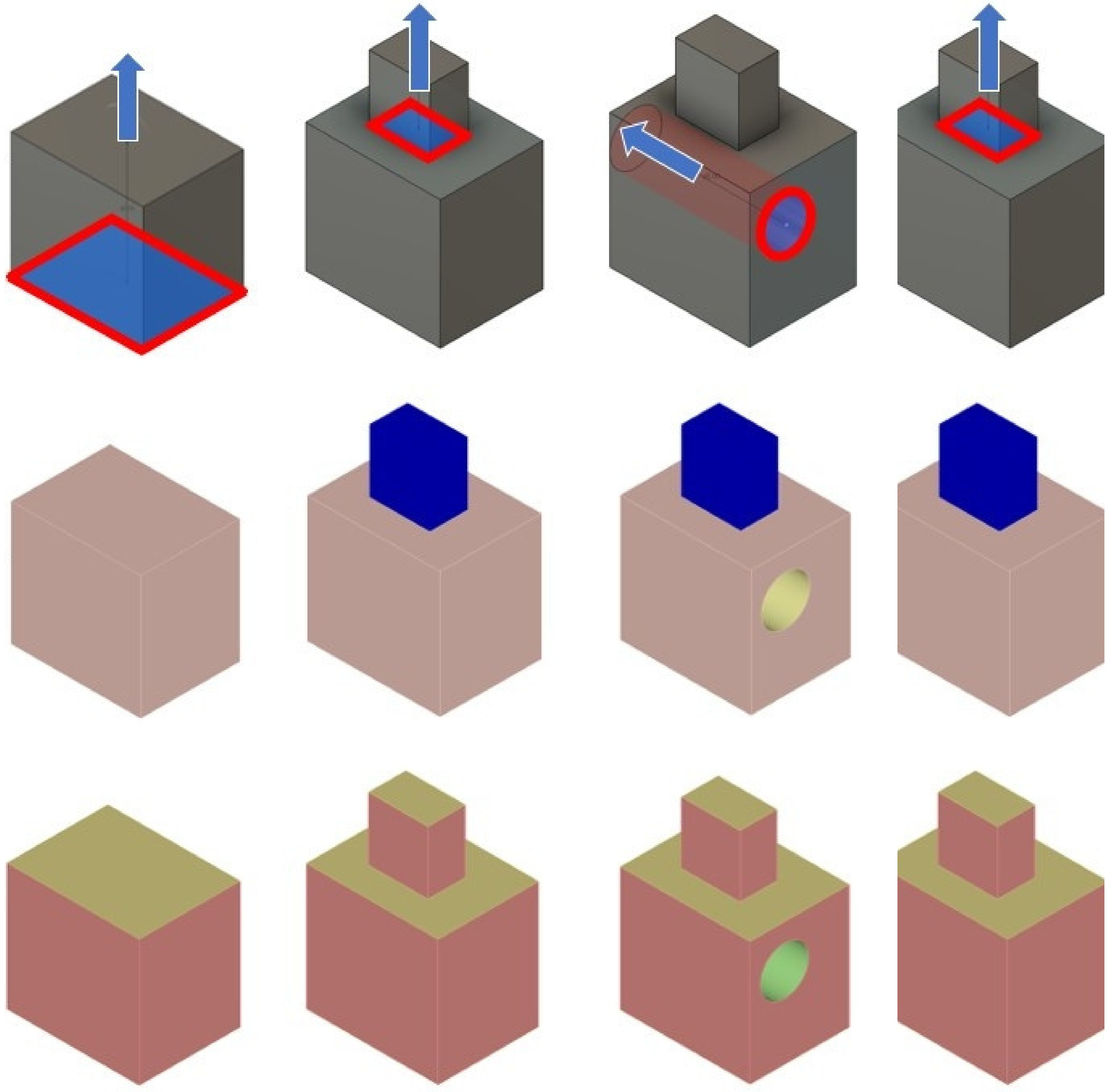

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CAD construction history

CAD operation step

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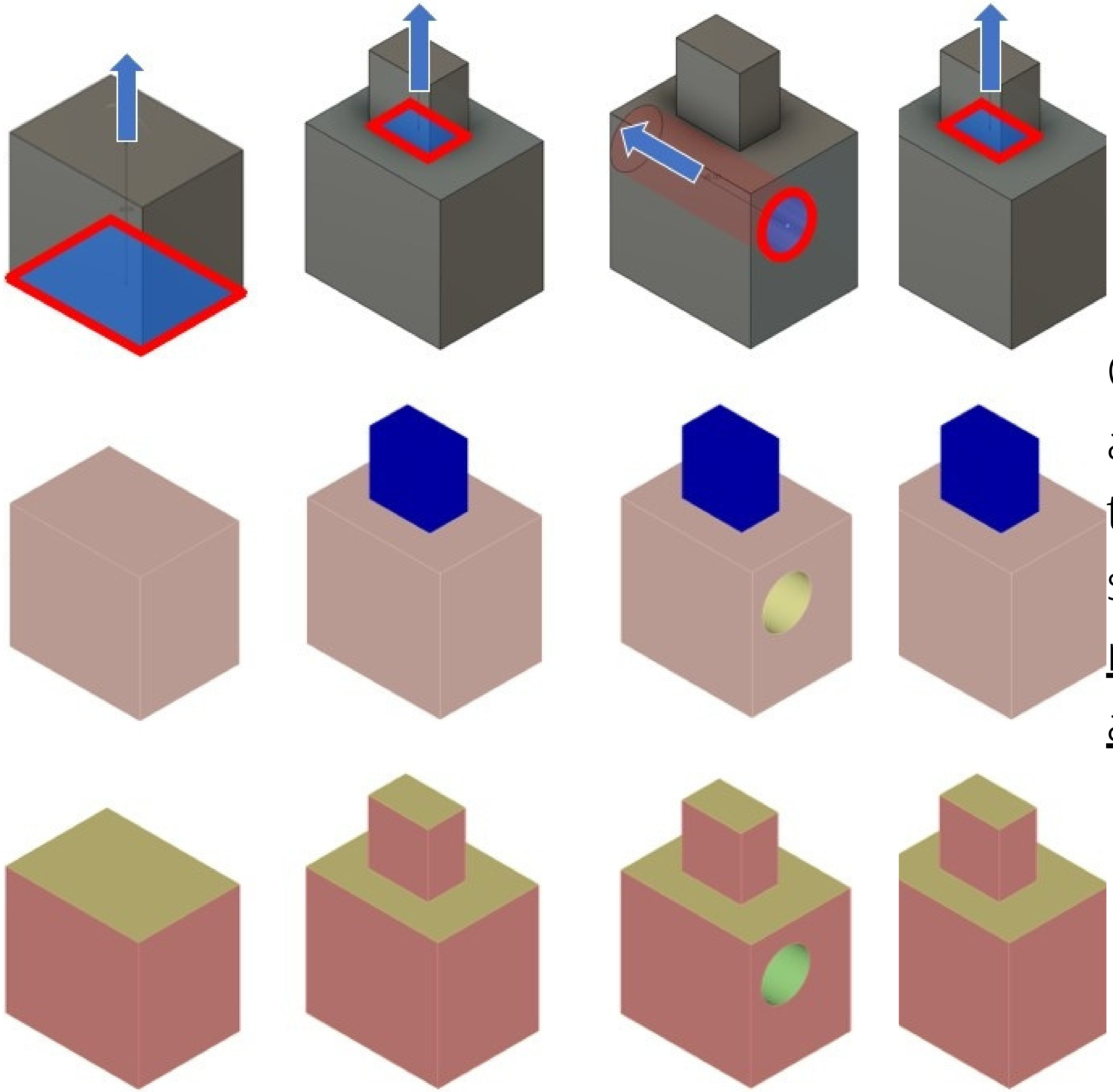

CAD operation steps are unordered and the number of CAD steps in a B-Rep is not known in advance.

Problem Formulation

Input:

B-Rep, $\mathcal{B}$ of f_1, f faces, e_1, e edges and N_c co-edges defined by:

- Face features: $\mathbf{F} \in \mathbb{R}^{N_f \times d_f}$
- Edge features: $\mathbf{E} \in \mathbb{R}^{N_e \times d_e}$
- Co-edge features: $\mathbf{C} \in \mathbb{R}^{N_c \times d_c}$

Output:

- per-face CAD operation types: $\mathbf{T} = [\mathbf{t}_1; \mathbf{t}_2; \ldots; \mathbf{t}_{N_f}] \in \{0, 1\}^{N_f \times k_t}$
- per-face CAD operation steps: $\mathbf{S} = [\mathbf{s}_1; \mathbf{s}_2; \ldots; \mathbf{s}_{N_f}] \in \{0, 1\}^{N_f \times k_s}$

$), \mathbf{1}]$: Number of CAD operation types

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Problem Formulation

Learn mappings Ξ, C and Ξ, (such that:

CAD operation type mapping:

$$\mathbf{\Phi} : \mathbb{R}^{N_f \times d_f} \times \mathbb{R}^{N_e \times d_e} \times \mathbb{R}^{N_c \times d_c} \rightarrow \{0, 1\}^{N_f \times k_t}$$

$$\mathbf{\Phi}(\mathbf{F}, \mathbf{E}, \mathbf{C}) = \mathbf{T}$$

CAD operation step mapping:

$$\mathbf{\Psi} : \mathbb{R}^{N_f \times d_f} \times \mathbb{R}^{N_e \times d_e} \times \mathbb{R}^{N_c \times d_c} \rightarrow \{0, 1\}^{N_f \times k_s}$$

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Table of contents

I Related Works

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face segmentation

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- Graph model with constraints as edges and primitives as nodes.
- Graph neural network architecture

CAD as a language [2]:

- Data serialization protocol to model the geometry and constraints
- Transformer + Pointer Net Backbone

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Only consider 2D sketches not 3D CAD models

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- Models construction history as a language
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Fusion360 [4]:

- Models construction history as a Markov decision process
- Neurally guided search (reinforcement learning)

Zonegraph [5] :

- Graph representation of B-Rep
- Nodes: solid regions formed by extending all B-Rep faces
- Edges: geometric adjacencies between nodes
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Sketch, extrusion, boolean operation only

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- Extract UV-grids for curves and surfaces and face-adjacency graph from B-Reps
- Couples image and graph convolutional neural networks

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- Convolutional kernels with respect to oriented coedges
- Neural network architecture designed to operate directly on B-rep data structures

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[7] Jayaraman, P. K., Sanghi, A., Lambourne, J. G., Willis, K. D., Davies, T., Shayani, H., & Morris, N. (2021). Uv-net: Learning from boundary representations. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 11703-11712).
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Related Works - 3D CAD Datasets

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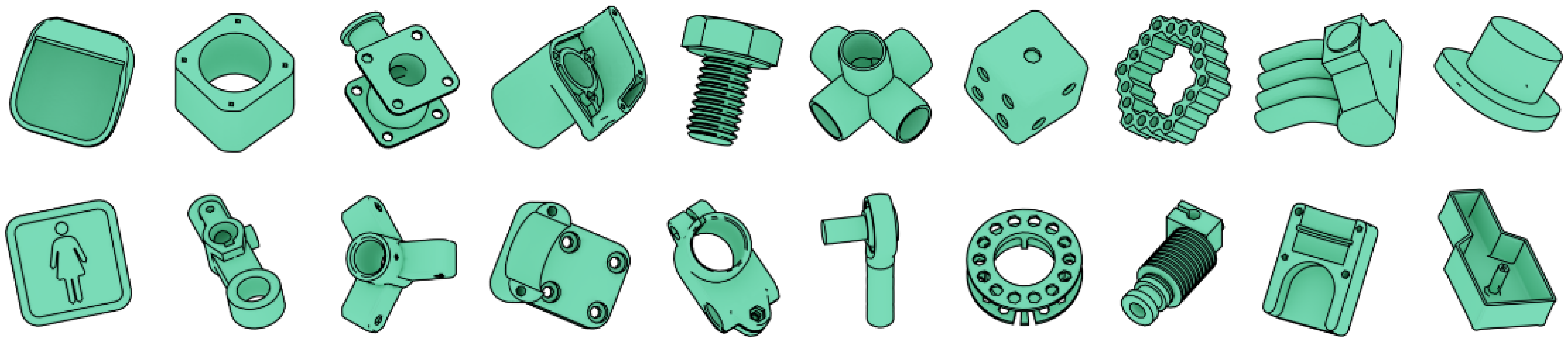
- ABC dataset [1] provides 1M + CAD models with sparse construction history provided in *Onshape proprietary format*.



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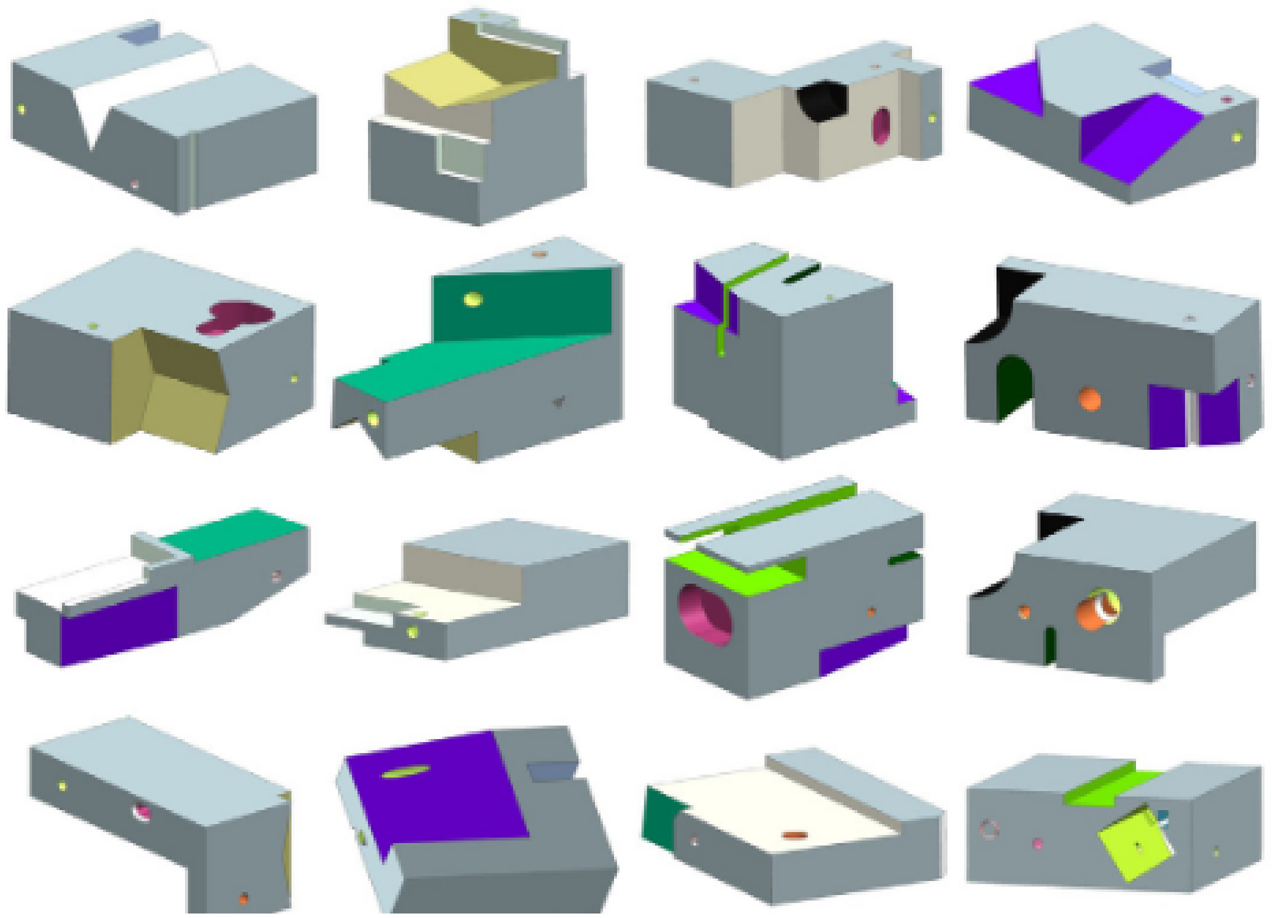
- ABC dataset [1], Onshape proprietary format.
- Both MFCAD [2] and MFCAD++ [3] *synthetic* datasets contain B-Reps and machining feature labels.



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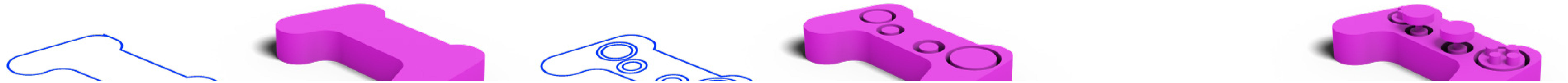
Related Works - 3D CAD Datasets

- ABC dataset [1], *Onshape proprietary format.*
- MFCAD [2] and MFCAD++ [3] datasets, *synthetic.*
- Fusion360 dataset [4] contains 35*k*+ CAD models with their corresponding construction history. However most models are *relatively simple*.



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- ABC dataset [1], *Onshape proprietary format*.
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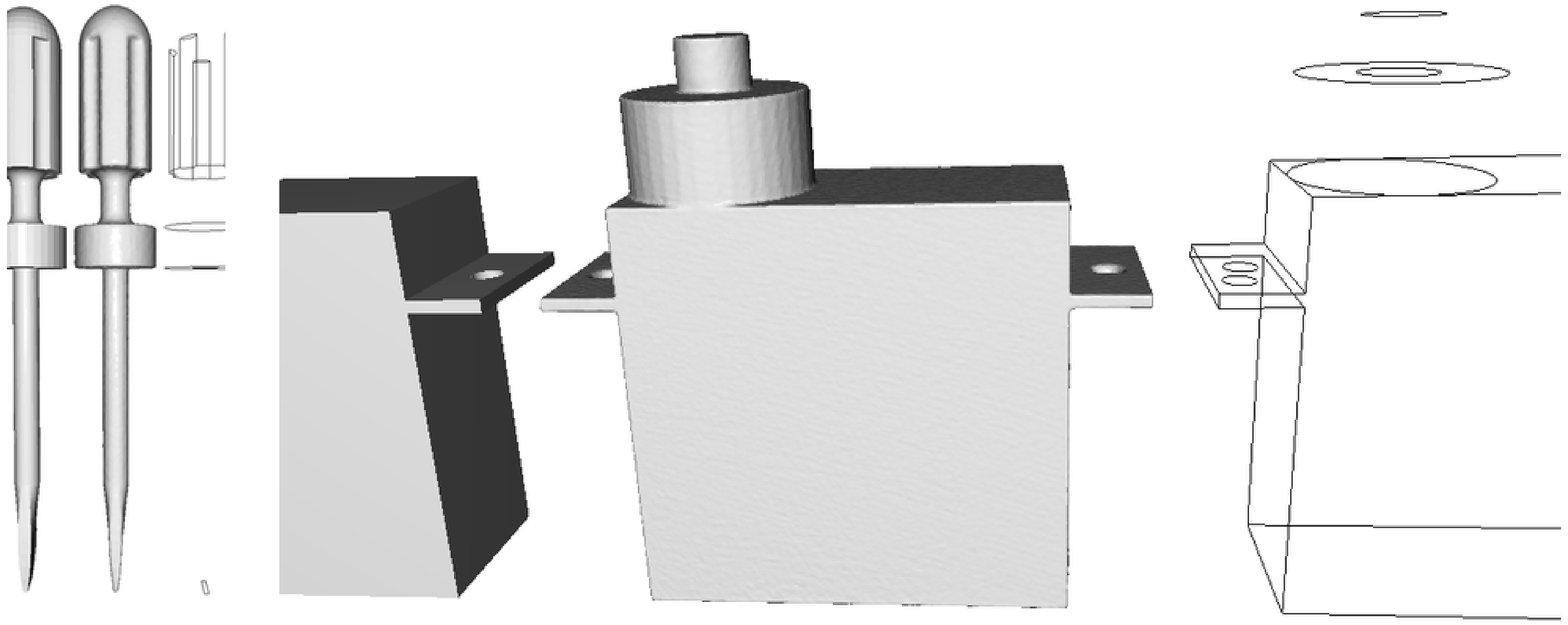
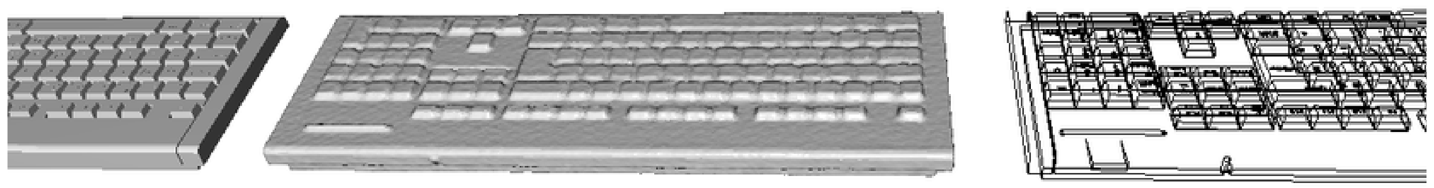
- Fusion360 dataset [4], *relatively simple models*.
- CC3D dataset [5] offers 50k+ pairs of industrial CAD models as triangular meshes and their corresponding 3D scans, but *without construction steps and B-Reps.*





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[5] Cherenkova, K., Aouada, D., & Gusev, G. (2020, October). Pvdeconv: Point-voxel deconvolution for autoencoding cad construction in 3d. In 2020 IEEE International Conference on Image Processing (ICIP) (pp. 2741-2745). IEEE.

II Contributions

Contributions

- A neural network, **CADOps-Net**, to learn the segmentation of faces into CAD operation **types** and **steps** from **B-Reps**.
- **A joint learning** method within an end-to-end model.

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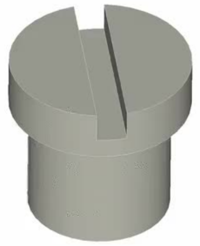
- **Novel dataset, CC3D-Ops**, with **~37k** B-Reps and corresponding per-face CAD operation type and step annotations.

- Evaluation on **two datasets** and **compared** to recent **SOTA** methods.

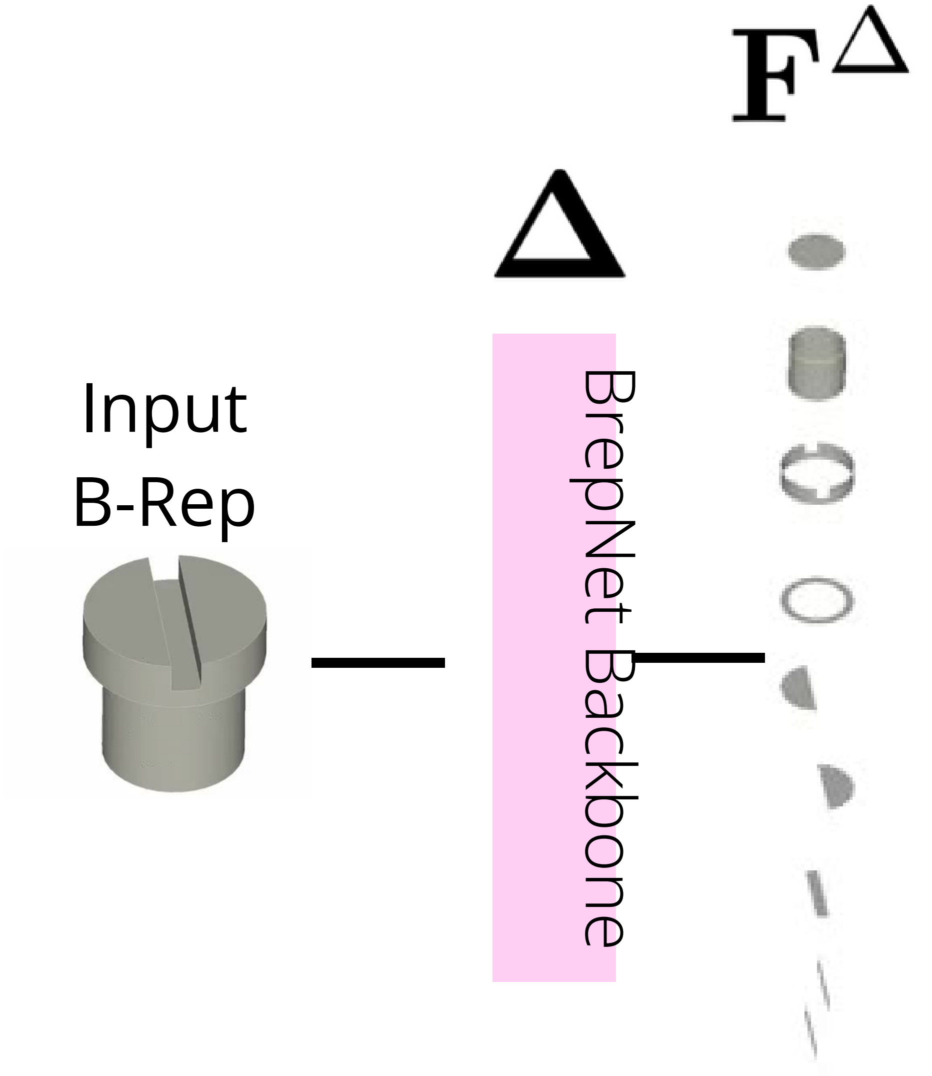
- Possible downstream application: **CAD sketch recovery** from B-Reps.

lll Proposed Approach

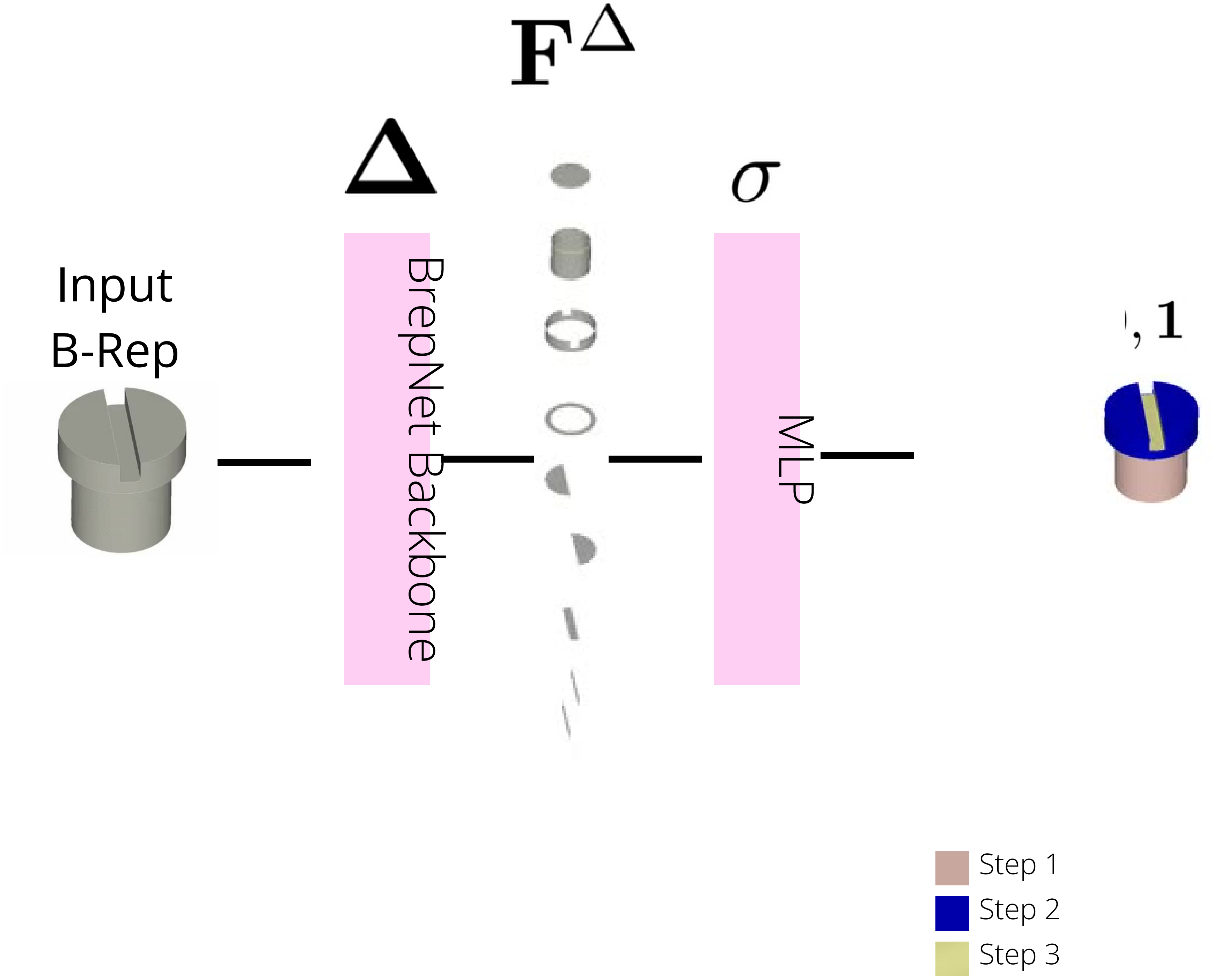
Input
B-Rep



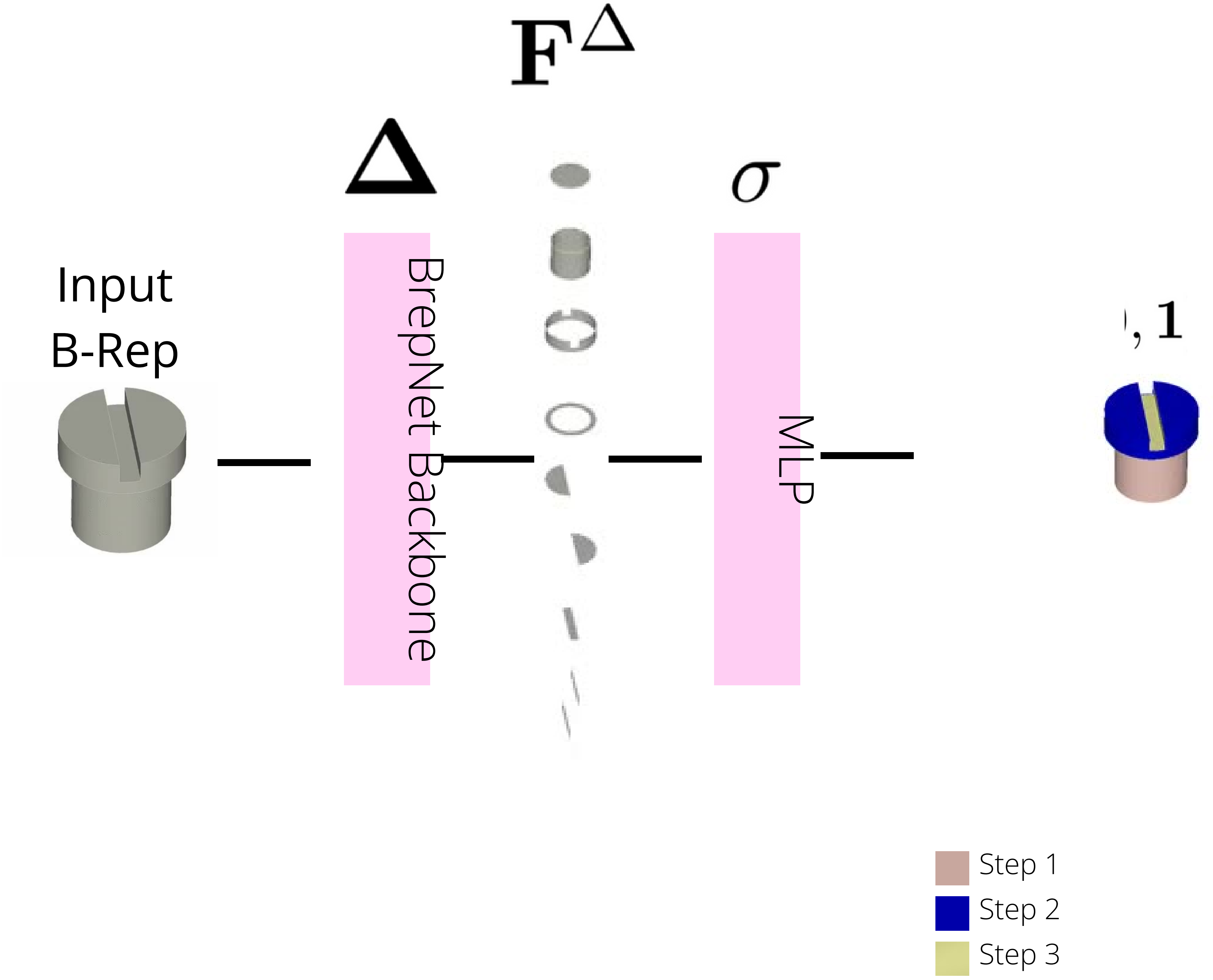
Extract face embeddings: $\mathbf{F}^{\Delta}$



Predict per face operation step labels:$, \mathbf{1}$

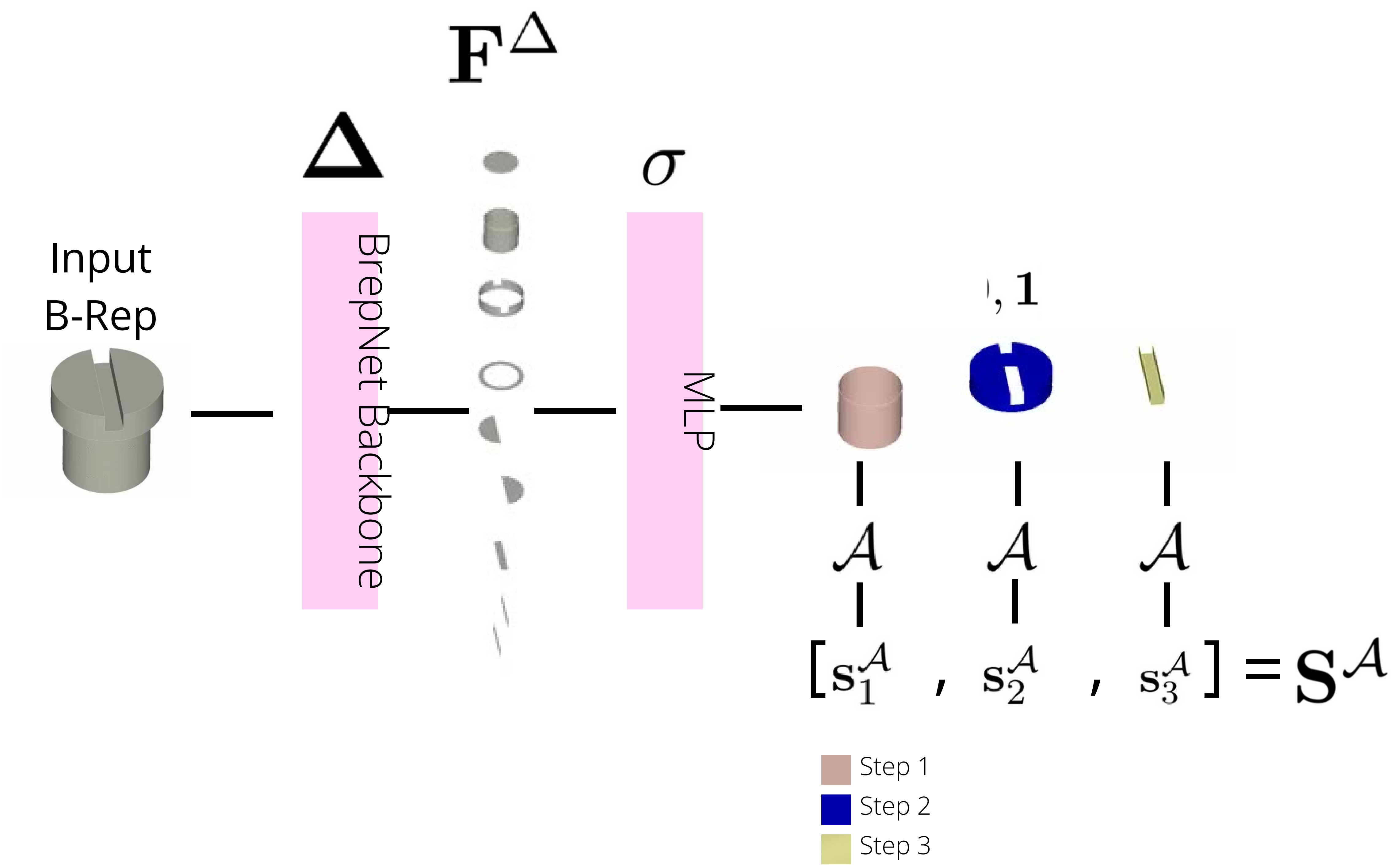


Predict per face operation step labels:



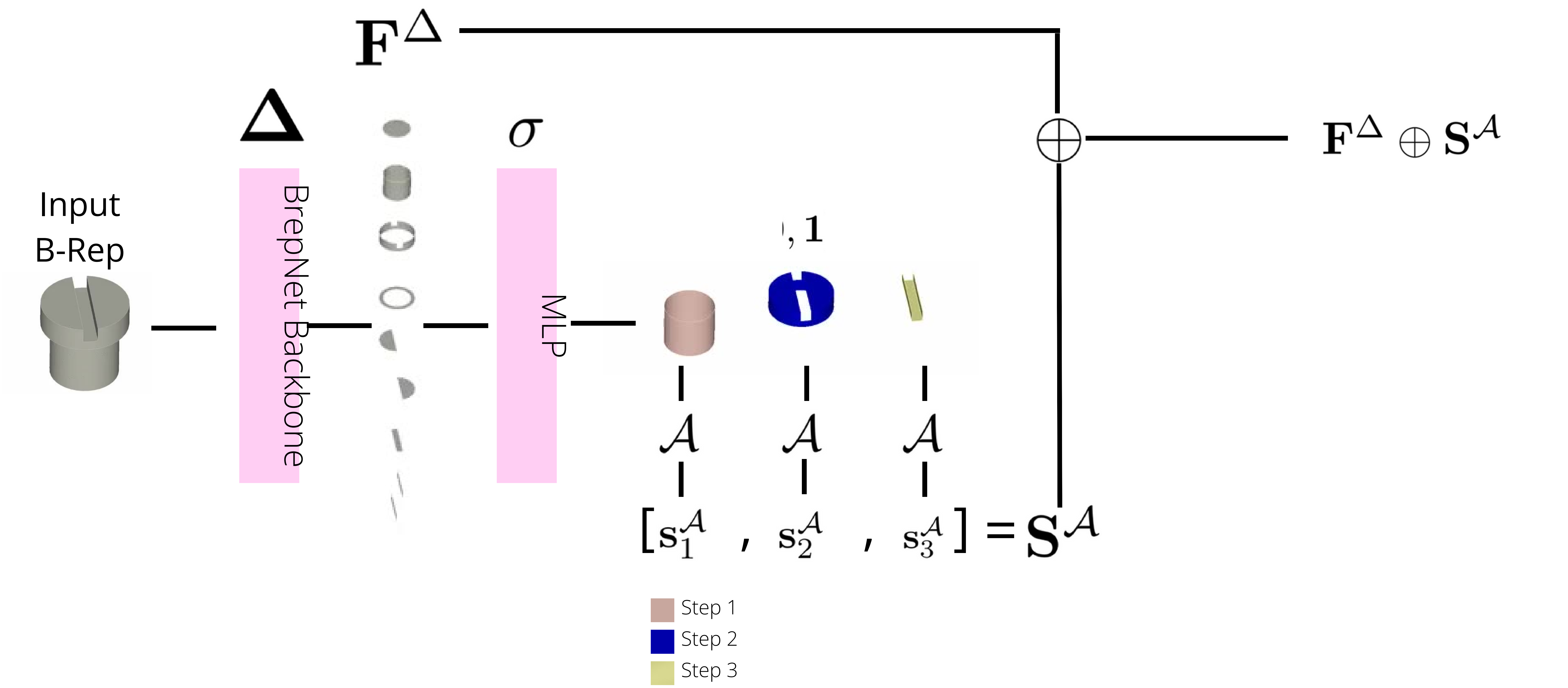
Use **Hungarian matching** to identify the correspondance between the ground truth and prediction CAD step labels.

Aggregate face features to obtain step embeddings: $\mathbf{S}^{\mathcal{A}}$

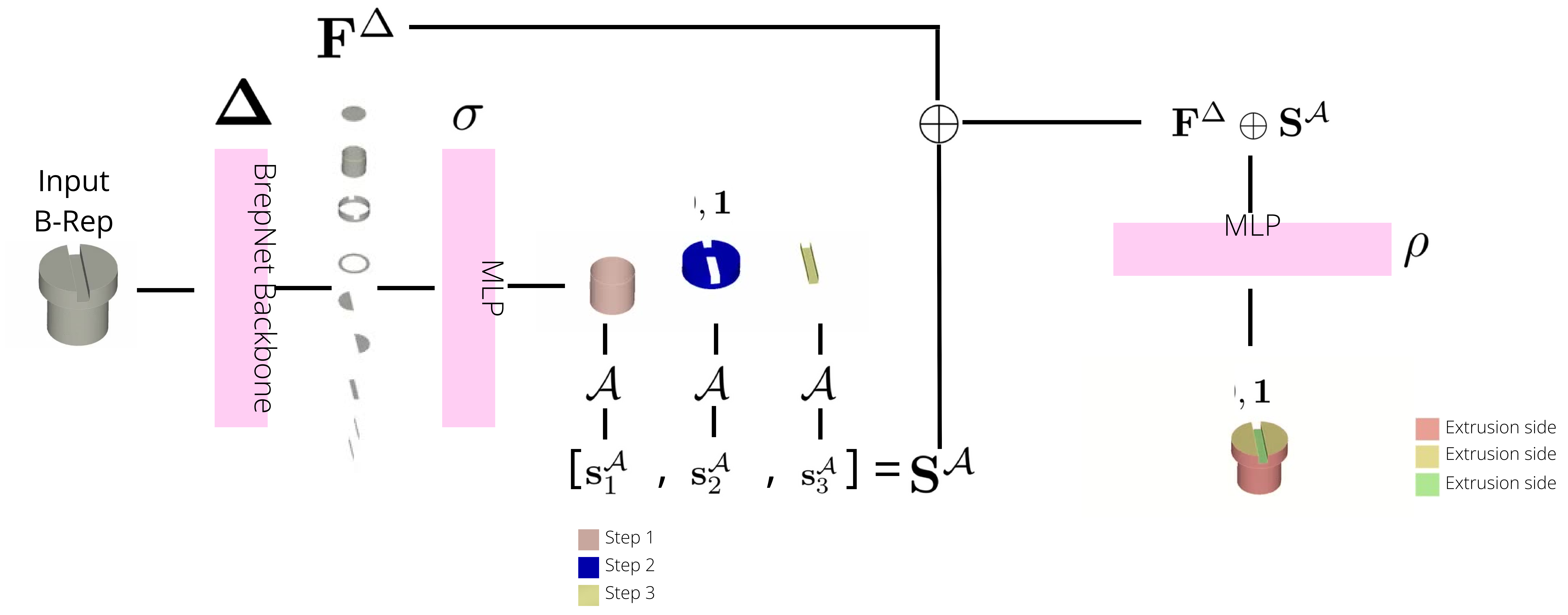


$\mathcal{A}$: Aggregation function

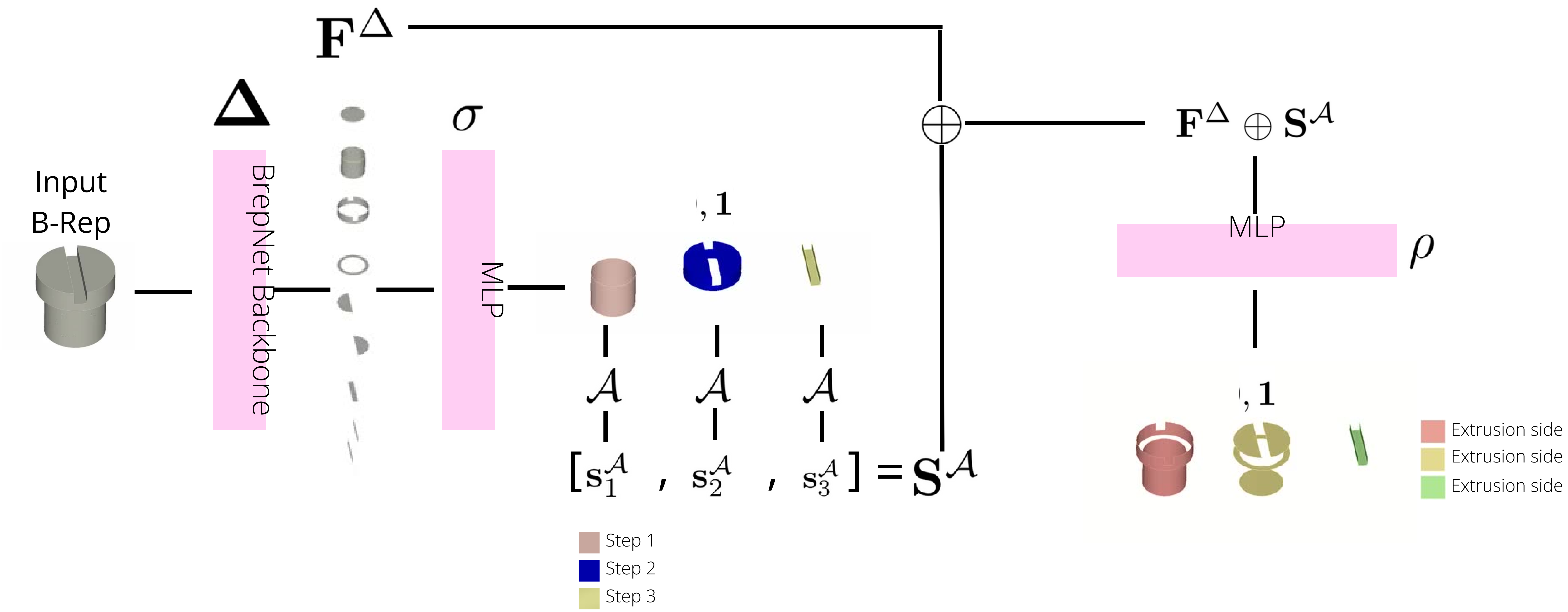
Concatenate face and step embeddings: $\mathbf{F}^{\Delta} \oplus \mathbf{S}^{\mathcal{A}}$



Predict per face operation step labels: , 1



CADOps-Net



$\mathbf{F}^{\Delta}$
$\mathbf{\Delta}$
σ
Input
B-Rep
BrepNet Backbone
MLP
, 1
$\mathcal{A}$
$\mathcal{A}$
$\mathcal{A}$
$[\mathbf{s}_1^{\mathcal{A}}, \mathbf{s}_2^{\mathcal{A}}, \mathbf{s}_3^{\mathcal{A}}] = \mathbf{S}^{\mathcal{A}}$
Step 1
Step 2
Step 3
$\mathbf{F}^{\Delta} \oplus \mathbf{S}^{\mathcal{A}}$
MLP
ρ
, 1
Extrusion side
Extrusion side
Extrusion side

Network Output

CAD Operation Type: $\widehat{\mathbf{T}} \in [\mathbf{0}, \mathbf{1}]^{N_f \times k_t}$

CAD Operation Step: $\widehat{\mathbf{S}} \in [\mathbf{0}, \mathbf{1}]^{N_f \times k_s}$

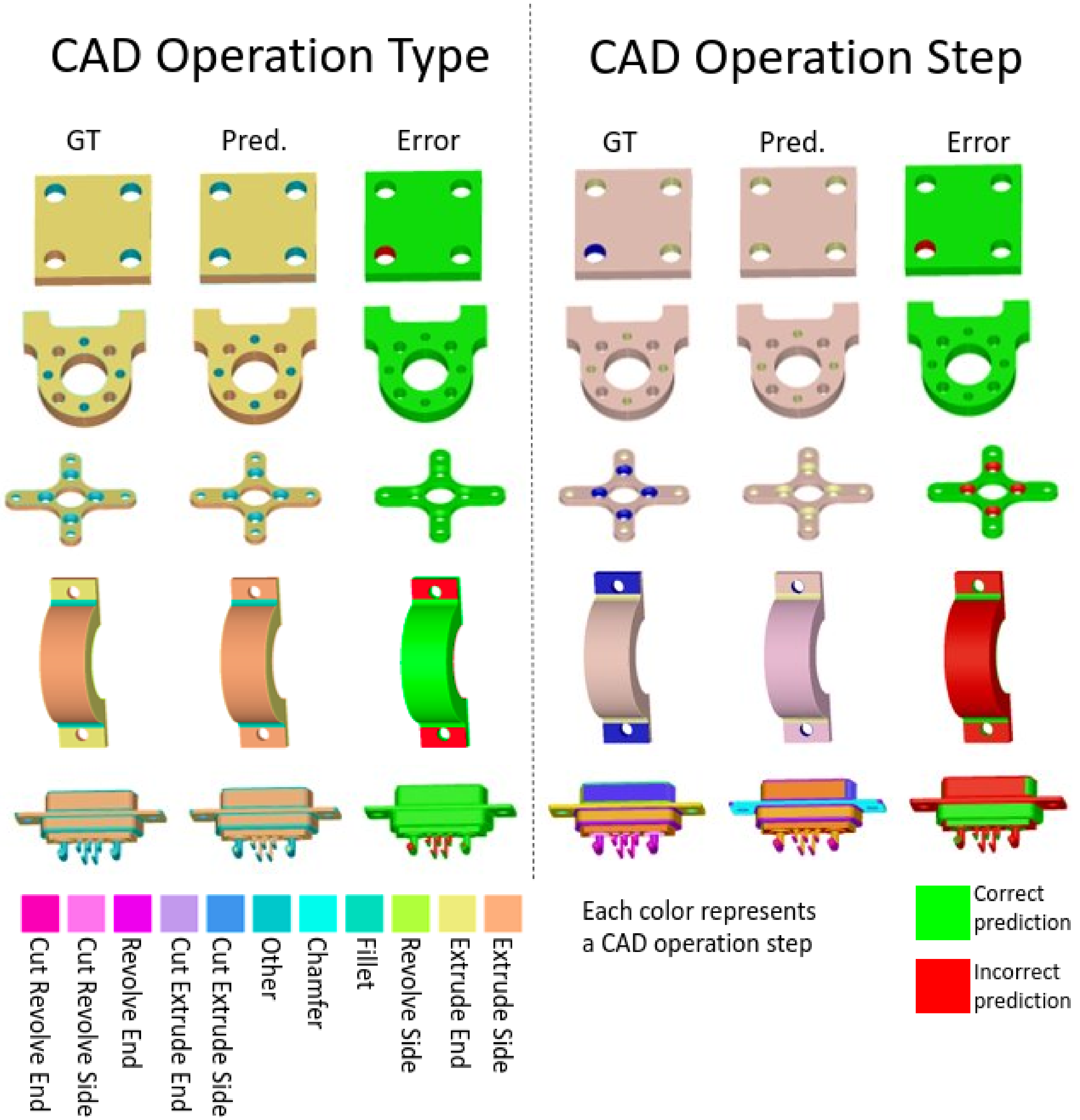
$\mathbf{0}, \mathbf{1}]$: Number of faces

$), \mathbf{1}]$: Number of CAD operation types

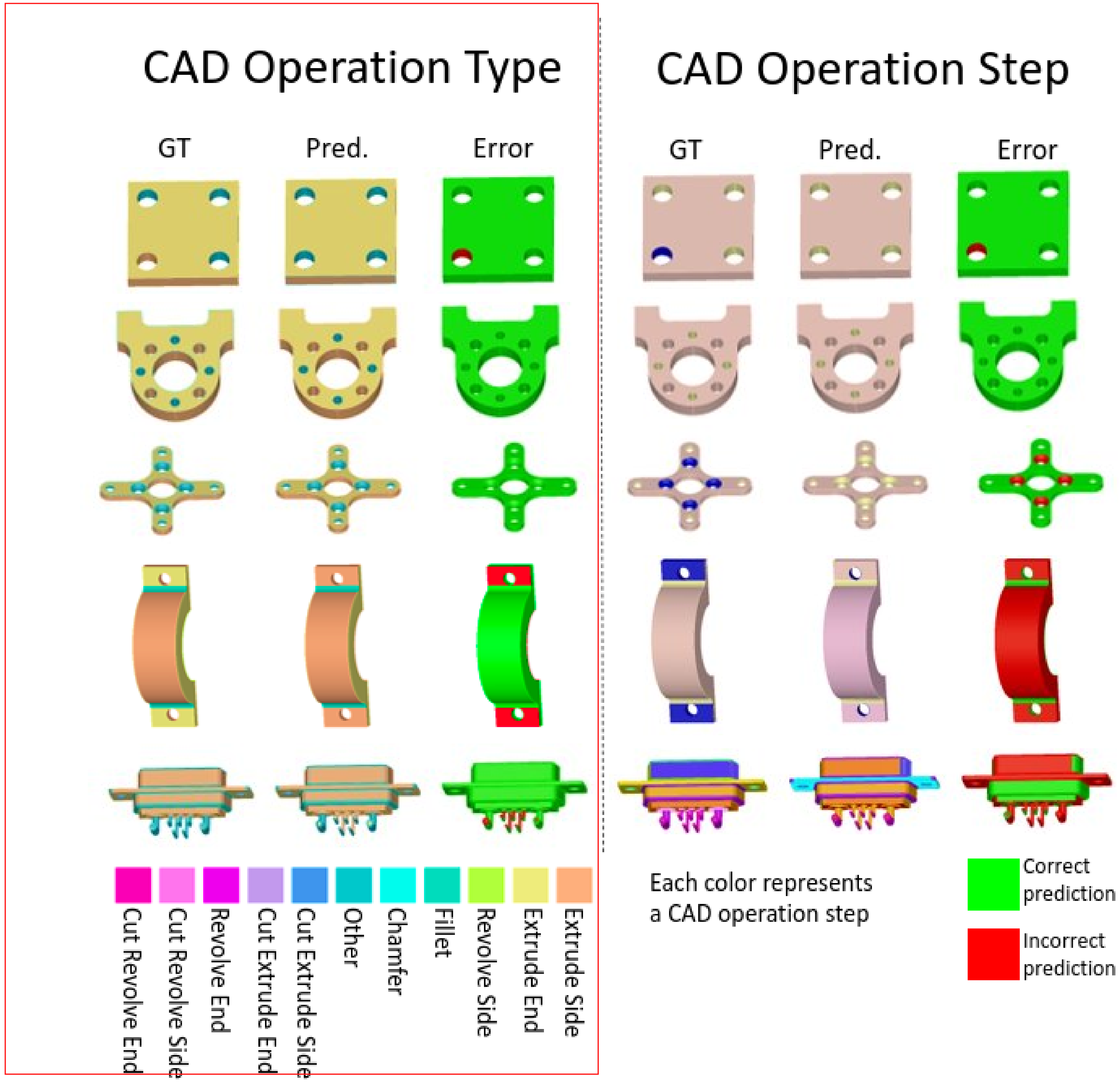
$, \mathbf{1}$: Number of CAD operation types

IV Experimental Results

Qualitative Results on CC3D-Ops dataset



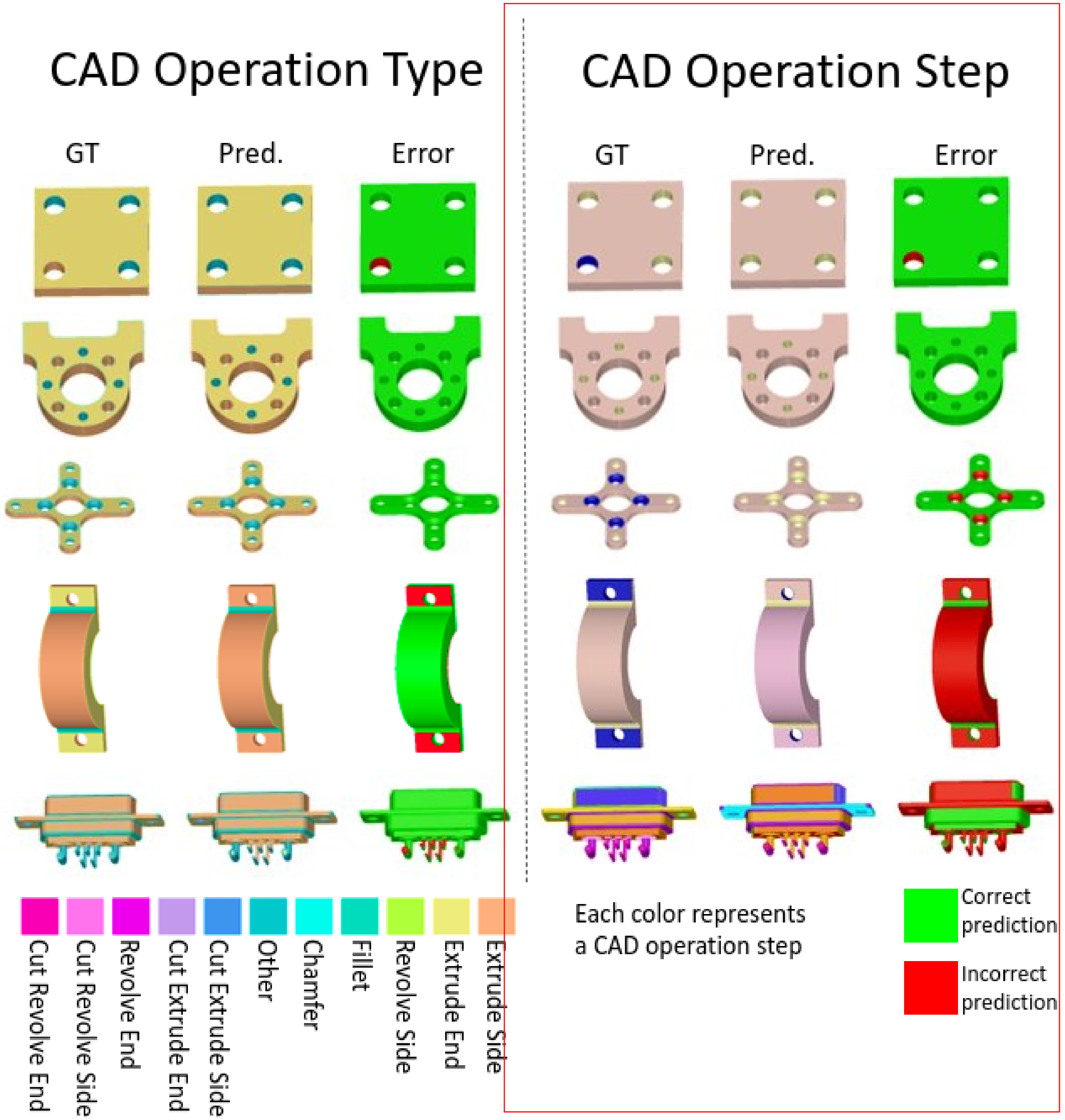
Qualitative Results on CC3D-Ops dataset



Observations:

- Correctness of operation type predictions do not depend on the complexity of the model.

Qualitative Results on CC3D-Ops dataset



Observations:

- Correctness of operation type predictions do not depend on the complexity of the model.
- This does not appear to be the case for the operation step predictions.
- The operation step segmentation task is more challenging as it relates to the construction history.

Quantitative Results - SOTA Comparison

	Model	Operation Type		Operation Step	
		mAcc	mIoU	mAcc	mArea
Fusion360	*CADNet* [5]	88.9	67.9	-	-
	UV-Net [12]	92.3	72.4	-	-
	BRepNet [17]	94.3	81.4	-	-
	Ours w/o JL$^-$	95.5	83.2	80.2	**86.2**
	Ours w/ JL$^+$	**95.9**	**84.2**	**82.5**	86.0
CC3D-Ops	*CADNet* [5]	57.5	26.9	-	-
	BRepNet [17]	71.4	35.9	-	-
	Ours w/o JL$^-$	**76.0**	43.0	48.4	50.7
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- The joint learning strategy provides small improvements for both the operation type and step predictions.

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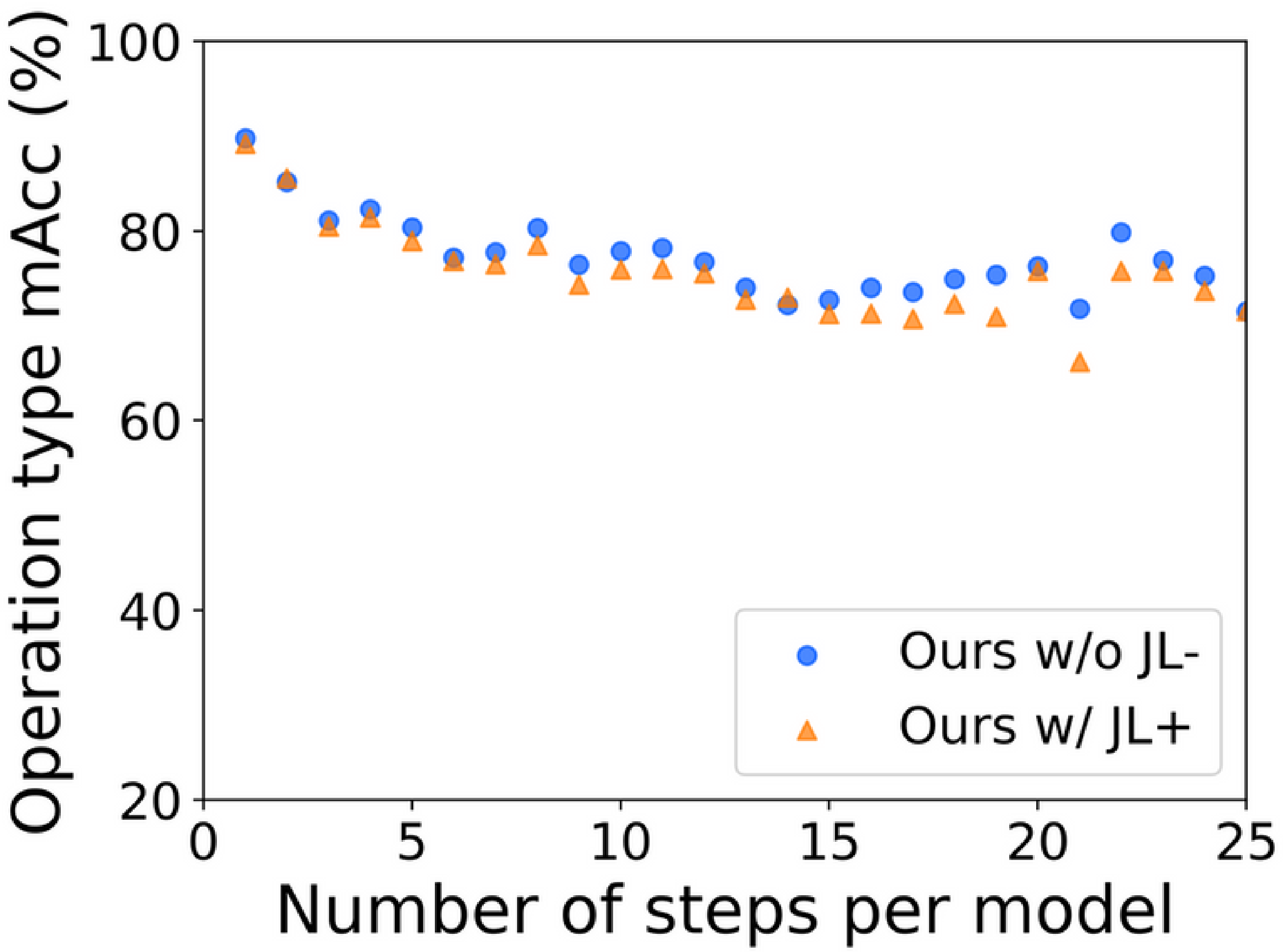
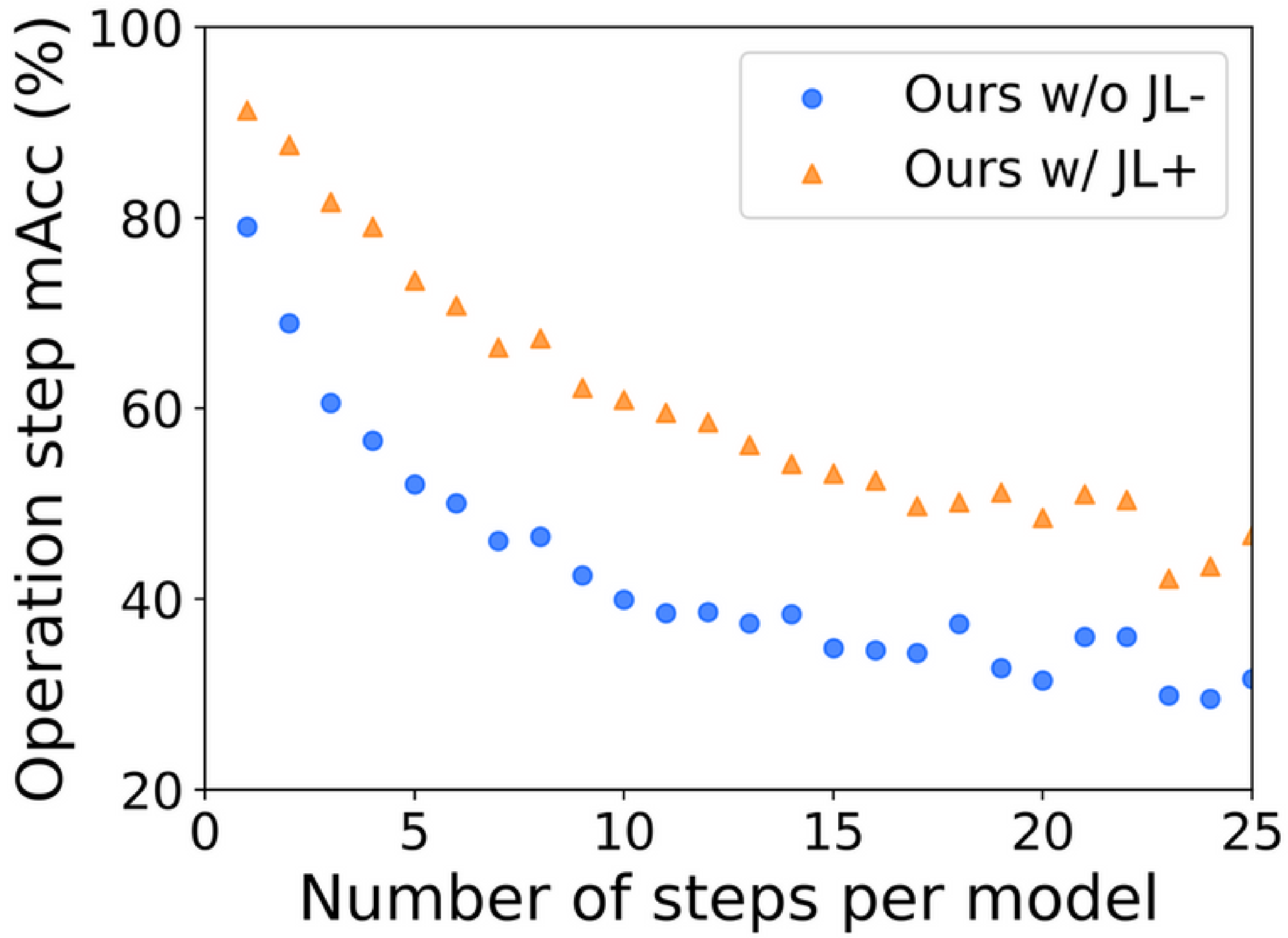
Observations:

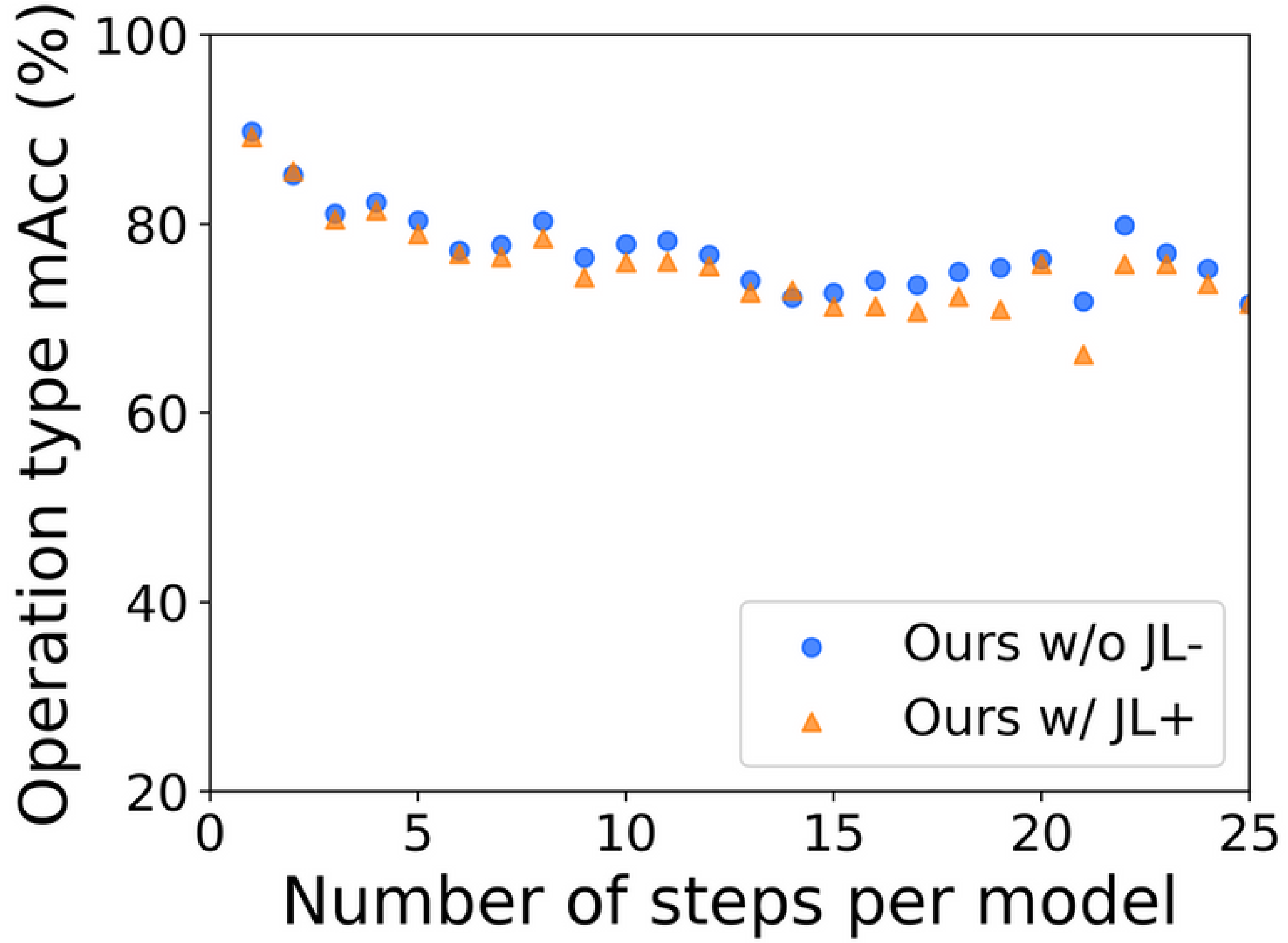
- The joint learning strategy provides **small improvements** for both the operation **type and step** predictions on the **Fusion360** dataset**.**
- The joint learning strategy provides **significant improvements** for the operation **step** predictions on the more complex **CC3D-Ops** dataset.

Quantitative Results

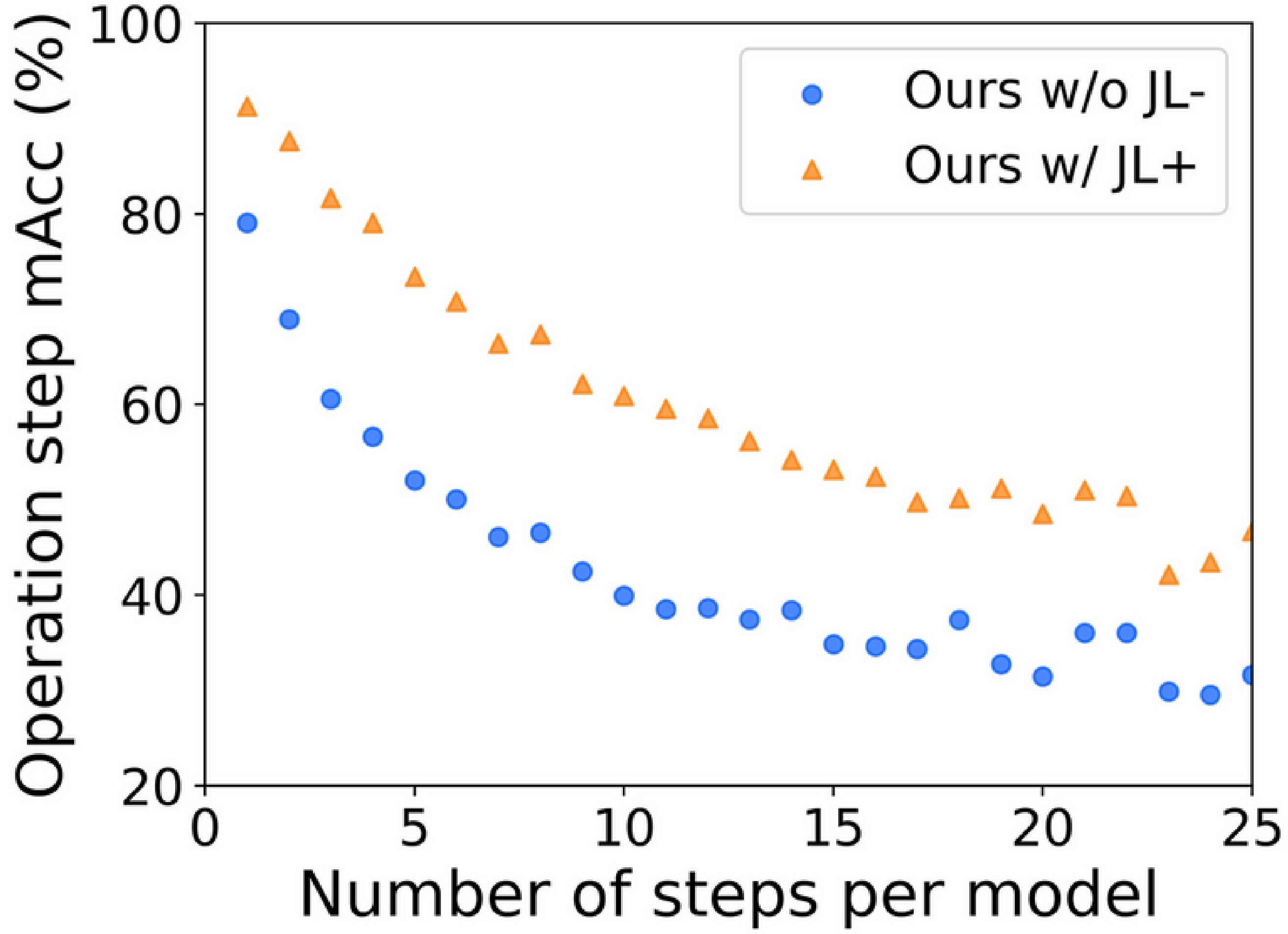




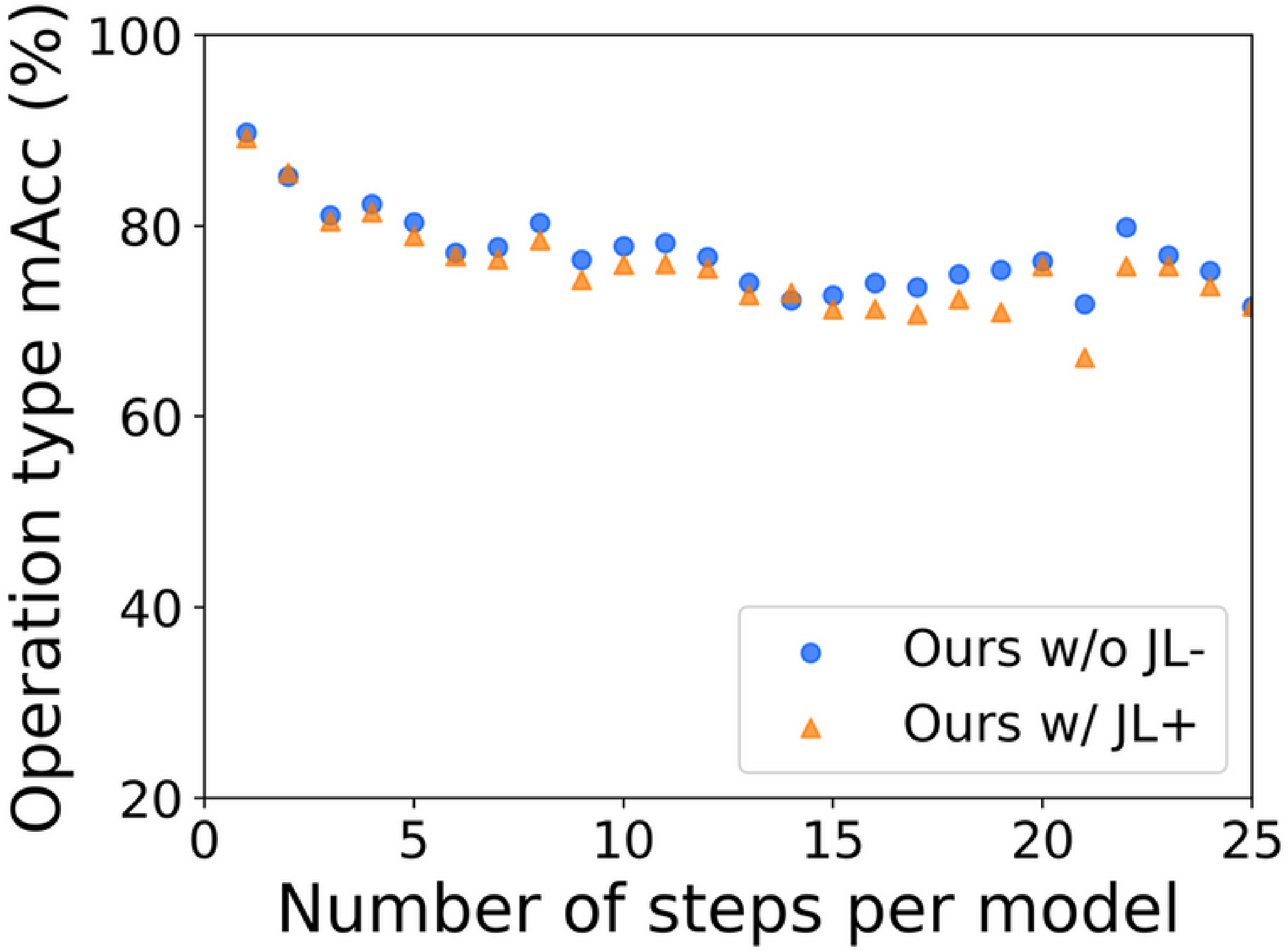
Quantitative Results



Type predictions do not depend on the complexity of the models.



Quantitative Results



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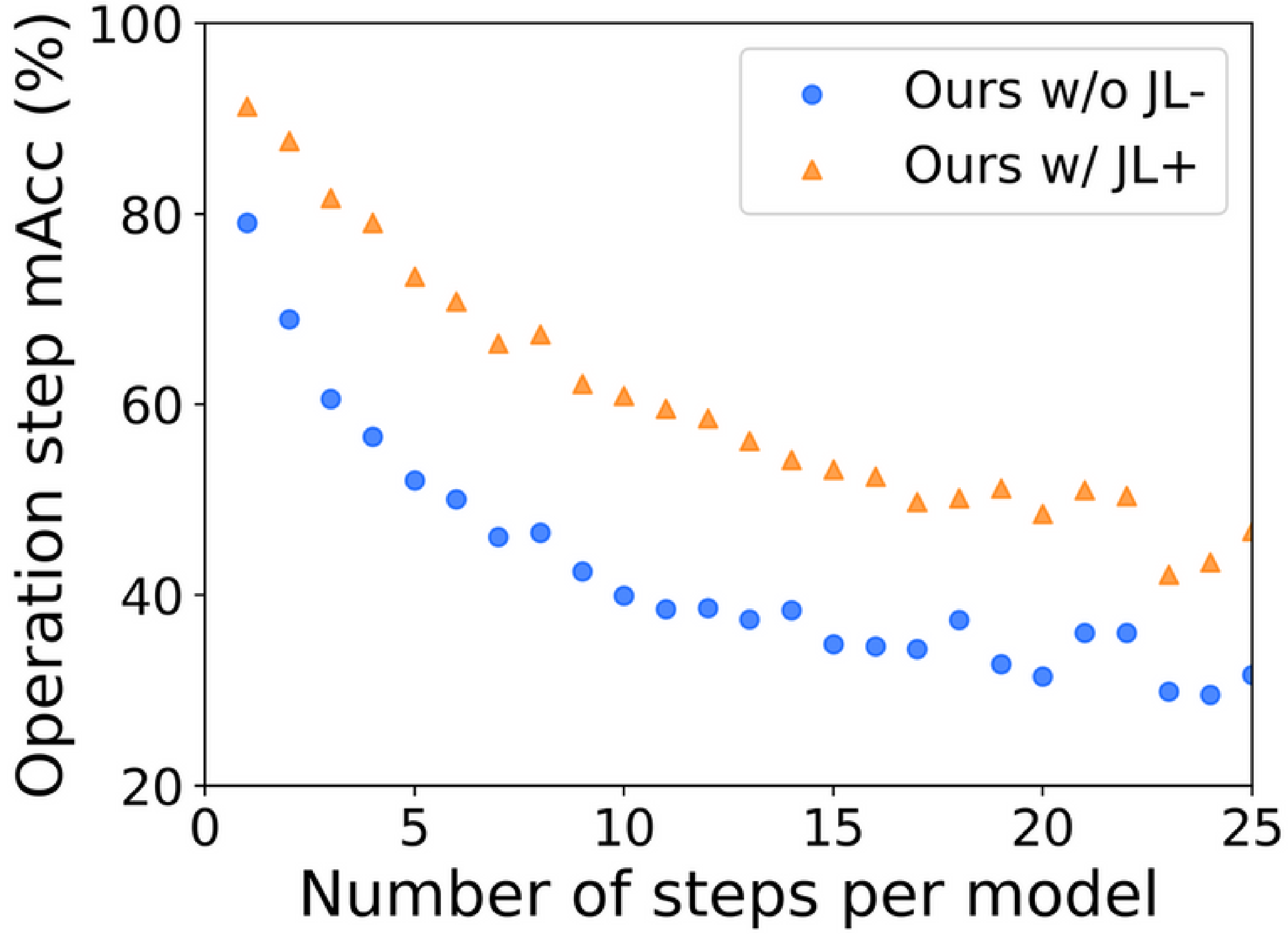
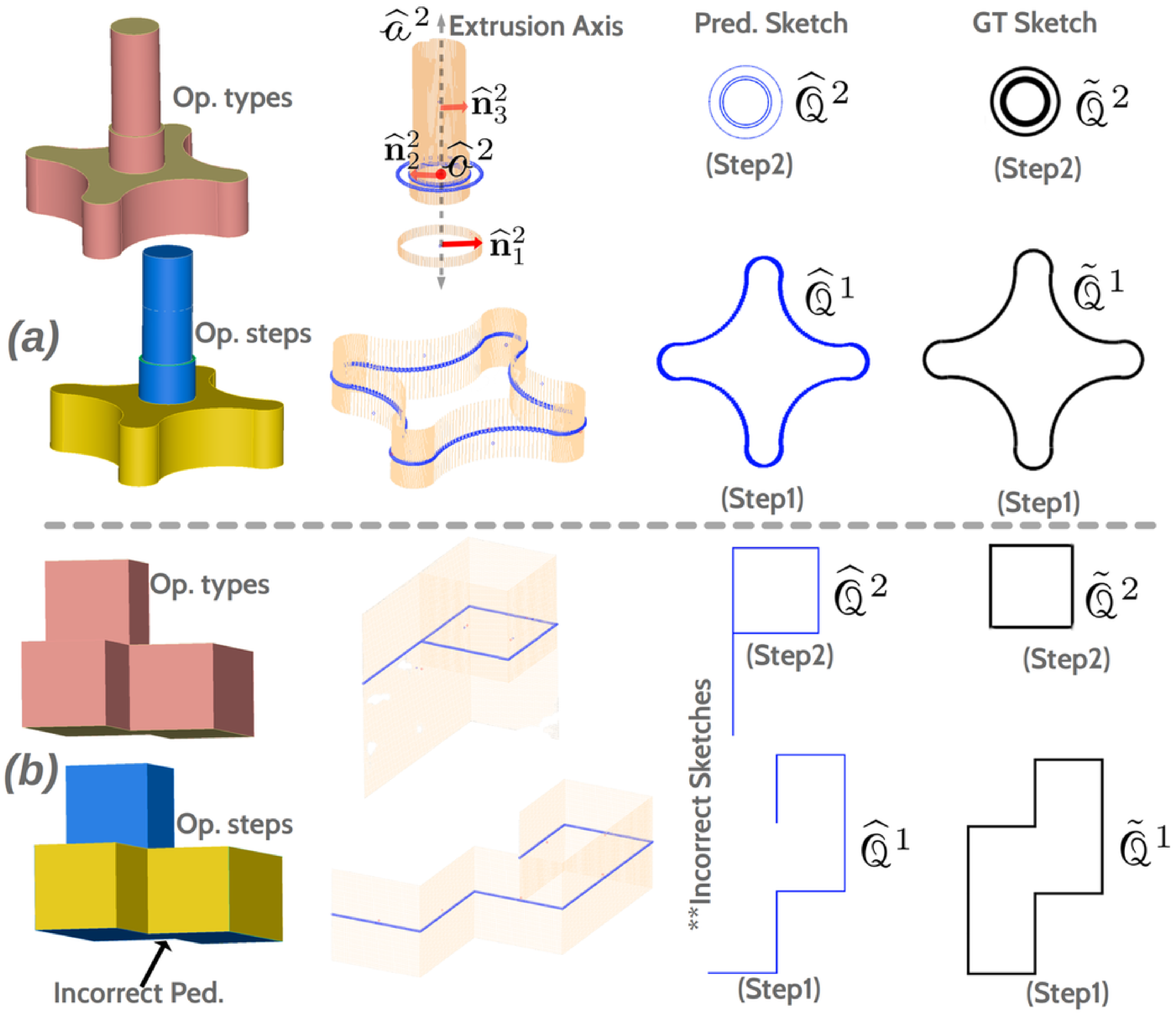


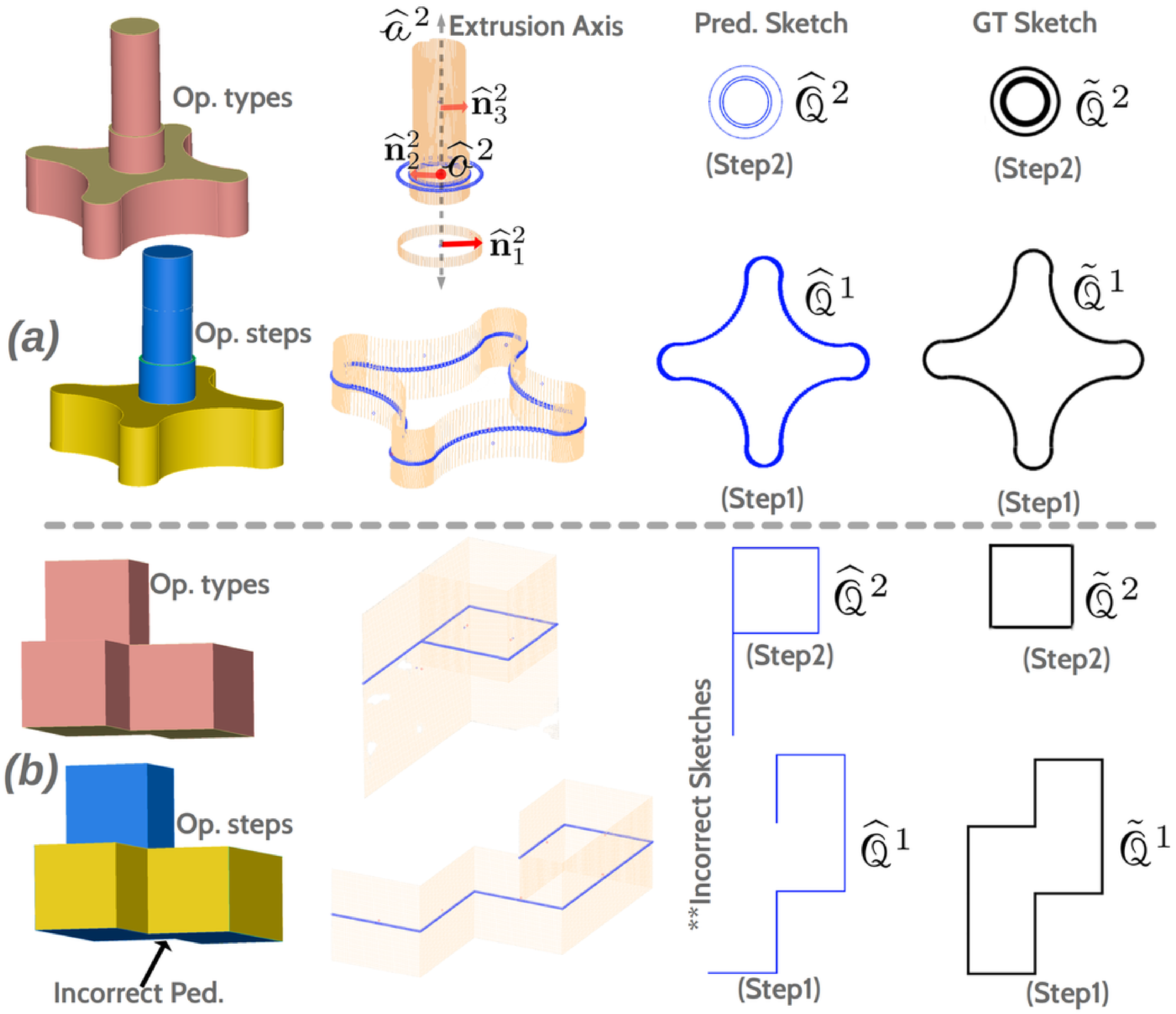
Step predictions mAcc decreases as the number of steps per model increases.

Possible downstream application: Sketch detection



- Demonstrate the relevance of predicting both the operation type and step.

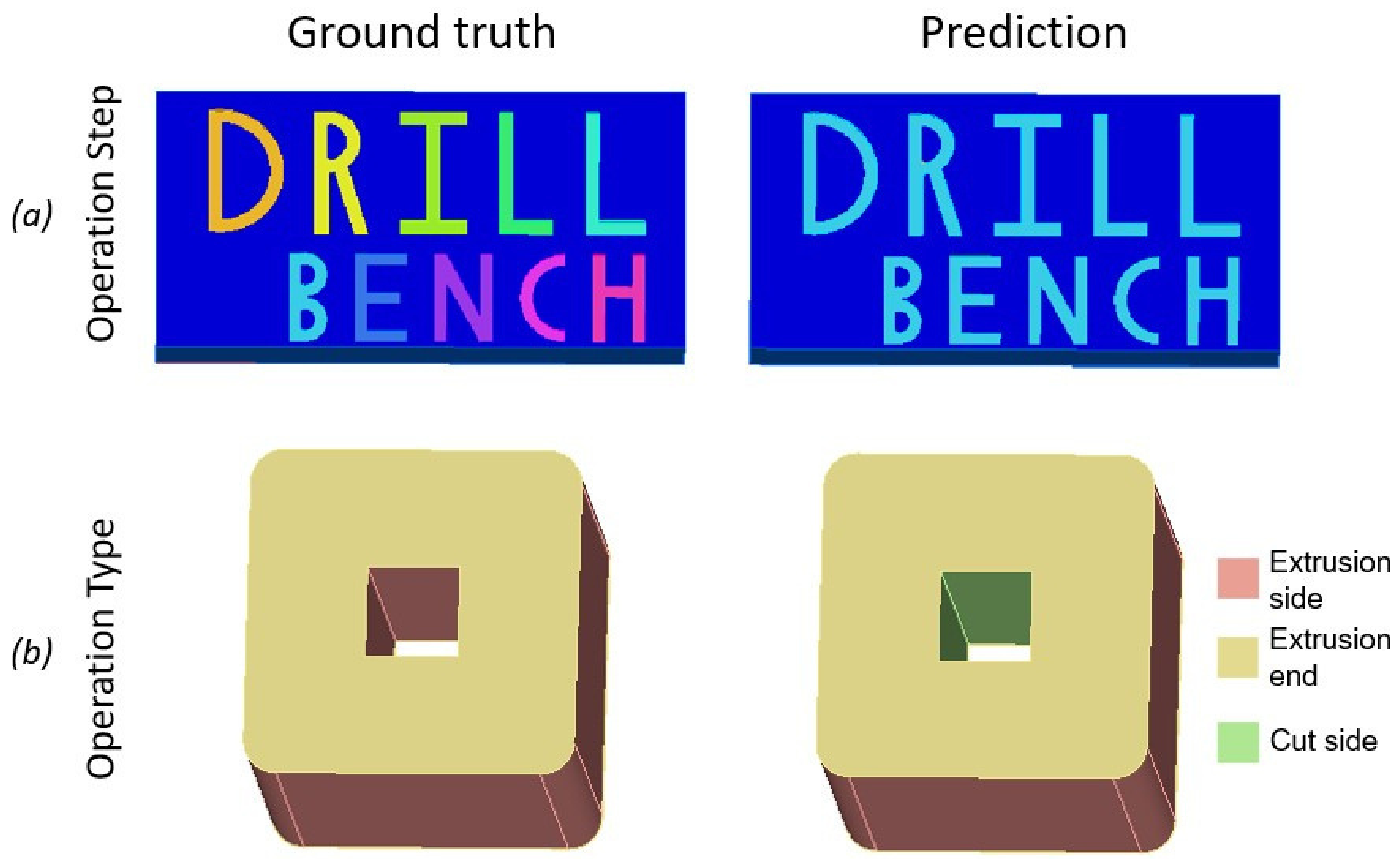
Possible downstream application: Sketch detection



- Demonstrate the relevance of predicting both the operation type and step.
- Propose a simple method to detect sketches on models made from extrusion only.

Limitations

Limitations



- There are **different valid methods** to construct the **same CAD model**.
- CADOps-Net sometimes make valid predictions that are labelled as incorrect.

V Conclusions

Conclusion

- **CADOps-Net**, a neural network that **jointly** learns the CAD operation **type** and **step** segmentation of **B-Rep** faces.

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  - **state-of-the-art** results on the CAD operation **type** segmentation task.

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- **CC3D-Ops dataset** with **B-Reps** and operation **type** and **step** annotations.