Extended Abstract

Motivation Computer-Aided Design (CAD) programs are the fundamental building blocks for a variety of scientific and engineering fields that requires precise modeling criteria. However, automating CAD designs have been challenging, because there is a limited amount of data available for training a fully supervised model. In this project, we explore the potential of using Reinforcement Learning to address this issue, by training a CAD agent to reconstruct the CAD command sequence from geometric rewards. By scaling up this approach, we can essentially leverage large-scale 3D or 2D data to train a CAD generator generating diverse assets with the full CAD command sequence.

Method We use Proximal Policy Optimization (PPO) to train a RL agent that predict the CAD commands given an input 3D shape. We develop a factorized policy distribution that is capable of outputting both discrete and continuous actions in order to accommodate the action space of CAD generation. Specifically, we model a categorical distribution over the discrete choices and a Gaussian distribution for the continuous parameters given a specific discrete action choice. We develop a custom policy network architecture to accommodate the above policy factorization. The factorized policy distribution has closed-form standard deviation and entropy terms, making it easy to integrate it into a traditional PPO pipeline. For the rewards, we use a combination of two rewards that both account for the geometric and formatting errors of the constructed CAD program w.r.t. the input shape. Specifically, the geometric rewards measures the intersection-over-union (IOU) between the current CAD reconstruction and the input shape. A higher IOU implies that the two shapes are geometrically close to each other and vice versa. A formatting reward is assigned to punish an episode whenever it fails to convert the current CAD command sequence into a valid CAD shape. This happens when either invalid parameters are predicted or the CAD executions fail. In these cases, a negative reward is added.

Implementation We implement a custom environment that builds the CAD program using the Open Cascade Paviot (2022). For the policy network, we sample points on both the current CAD shape and the ground truth shape and pass them through a PointNet Qi et al. (2016). Together with the current CAD command sequence, the encoded features are passed through the discrete head network to predict logits for the categorical distribution over the discrete actions. Finally, concatenate learned embeddings for each discrete action with the point features and the action sequence to output the continuous distributions for each discrete action choice. The PPO algorithm is implemented on top of TianShou Weng et al. (2022) framework.

Results We conducted overfitting experiments where a specialized agent is fitted to reconstruct one CAD shape using the abovementioned pipeline. We conducted two sets of experiments. The first set uses a toy setting to validate the effectiveness of using RL for CAD modeling, and the second experiment leverages the entirety of the above pipeline to train an RL agent for CAD modeling. The validation experiment was able to output a CAD sequence that reconstructs the rough geometry of the input shape. However, details are still missing, potentially due to the insensitivity of rewards to the details. The full experiment was only able to output correct geometry when the CAD sequence was short. This is potentially due to that we did not initialize our policy network from imitation learning, making the initial exploration phase difficult.

Discussion & Conclusion This project investigates the potential of using RL algorithms for CAD command sequence generation. Specifically, we developed a novel factorized action policy to accommodate the hybrid action space of CAD modeling, as well as designed specific rewards to encourage the RL to learn to reconstruct the input shape. Experimentally, the validation experiment shows the promise in this direction for further investigation. For future steps, we would like to pre-trained the action policy network with supervised training, so that the policy network starts from more informative knowledge about the CAD command sequence. We believe that pre-training would help the performance of RL for CAD generation. Further, we would like to incorporate more semantically informative rewards using other modalities such as images or segmentation masks to encourage the RL agent to fill in the details as well. Curriculum training could also be considered to encourage the RL agent to learn the rough geometry first before attending to the geometric details.

Learning CAD Program Generation using Reinforcement Learning

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Abstract

This project investigates the potential of using RL algorithms for CAD command sequence generation. Specifically, we developed a novel factorized action policy to accommodate the hybrid action space of CAD modeling, as well as designed specific rewards to encourage the RL to learn to reconstruct the input shape. Our experiment demonstrates initial progress towards this direction, with the RL agent capable of reconstructing the 3D shapes with only geometric and format rewards – without using the full CAD command history as training data. By further expanding upon this project, we could enable large-scale training on 3D shape dataset using RL algorithms, alleviating the data bottleneck of CAD models with full modeling history.

1 Introduction

CAD programs refer to computer-aided design programs, which are the fundamental building blocks for a variety of scientific and engineering fields. Specifically, it represents 3D objects through sequences of geometric instructions, commonly referred to as CAD commands, which defines editable geometric components and operations. Despite the emergence of various 3D modeling software (e.g., AutoCAD, SketchUp, Rhino, and FreeCAD), the design workflow persists as a technically challenging and labor-intensive process: it is time-consuming and requires specialized expertise from designers and/or engineers. In the design phase, they use CAD drawings for their precision and ease of editability. During manufacturing, these drawings are converted into constraint-based parameter tables, and for simulation, they yield boundary-representation (B-Rep) data or textual geometry descriptions. While the full design history is not used for downstream applications, current CAD software requires experts to design and modify the model, while the CAD programs need to be frequently updated by communicating with the users. Therefore, it is desirable to develop a toolbox with which the expert, or even the non-expert, can easily design the CAD models by using simple instructions and illustrations to make the ideas in their mind easily come true.

With the advance of machine learning and AI generative models for 3D content, there are many works that generates 3D shapes from text, images, and other user-friendly inputs. However, in contrast to the fast development in 3D generative methods in other shape representations such as point clouds Zeng et al. (2022), voxels Ren et al. (2024), meshes Shen et al. (2024), and implicits Park et al. (2019), CAD program generation achieved limited success. So far, CAD program generation is mainly limited to supervised training using full history CAD programs. While this approach treats CAD programs essentially as text and thereby leverages the success of LLM pre-training, it achieved only limited generation performance primarily due to the limited amount of training data, making the training of large-scale neural networks capable of diverse output infeasible.

The goal of this project is to learn a policy network, which can act as a CAD program generative model, that is able to perform CAD program generation using reinforcement learning. The motivation behind such an approach is to be able to optimize the policy network on shapes without ground truth CAD programs using heuristic rewards, and therefore leverage existing large-scale 3D shape dataset such as ShapeNet Chang et al. (2015) and Objaverse Deitke et al. (2022). Hopefully, this can help the policy network to generate a greater variety of shapes without a groundtruth CAD program.

2 Related Work

CAD generation is a long-standing topic in computer graphics and machine learning. It can mainly be categorized into two sub-directions for research.

BREP-based Shape Generation BREP 3D models are depicted as graphs, incorporating both geometric primitives (e.g., parametric curves and surfaces) and topological primitives (e.g., vertices, edges, and faces) that trim and stitch surface patches to form solid models Xu et al. (2024a). Earliest works focused on BREP classification and segmentation, using a graphical neural network Willis et al. (2021); 10. (2020); Jayaraman et al. (2023), custom convolution kernels Lambourne et al. (2021), and hierarchical graph structures Jones et al. (2022, 2021); Bian et al. (2023) to leverage the graph properties of these shapes.

For generation tasks, previous approaches used predefined template curves and surfaces Sharma et al. (2020); Smirnov et al. (2021); Wang et al. (2022, 2020); Li et al. (2018). Specifically, PolyGen Nash et al. (2020), the pioneer work in this area, uses a pointer network Vinyals et al. (2017) with Transformers Vaswani et al. (2023) to generate n-gon meshes, which can be treated as a special case of BREP shapes with planar faces and straight edges. SolidGen Jayaraman et al. (2023) and BrepGen Xu et al. (2024a) can generate the entire BREP shape. SolidGen Jayaraman et al. (2023) first synthesizes vertices and then constructs them with the edge topology. BrepGen Xu et al. (2024a) progressively denoises the faces, edges, and vertices utilizing Diffusion models Ho et al. (2020). Although B-rep is a direct representation of the boundary of the CAD model, and these generative methods are able to obtain better performance because there is more data in this format; the generated results do not contain the modeling history of the generation, limiting their abilities to perform downstream editing or manipulation of the generated shapes.

CAD Program Generation The second area are methods that try to generate the full modeling history along with the final CAD program.

Existing CAD program generation methods are used for reverse engineering the full CAD program from input point clouds and/or images, text inputs. Point clouds are the most well-studied input modality in CAD reconstruction. The seminal work on point cloud-based CAD reconstruction, DeepCAD by Wu et al. (2021), proposed encoding CAD sketch-and-extrude sequences as special tokens. Beyond that, DeepCAD also proposed the first large-scale dataset of 180k hand-crafted CAD modeled scraped from the OnShape online repository. Subsequent works Chen et al. (2025); Khan et al. (2024a); Xu et al. (2022); Dupont et al. (2024); Ma et al. (2023) adopted the same CAD representation and trained on the same DeepCAD dataset. More recently, CAD-Recode Rukhovich et al. (2024) introduced a paradigm shift by representing CAD models as Python code, providing greater expressiveness and flexibility, and released a new training dataset of approximately 1 million procedurally generated CAD samples. More recently, works Chen et al. (2025); You et al. (2024); Yuan et al. (2024); Wang et al. (2025); Khan et al. (2024b) have explored CAD reconstruction from other input modalities, such as single- or multi-view images and natural language descriptions. These approaches extend the DeepCAD dataset by rendering synthetic views or generating textual captions for existing CAD models. Among them, CADCrafter Chen et al. (2025) proposes an unified framework that handles both single- and multi-view inputs using a latent diffusion model Rombach et al. (2021) to sample from the latent space of DeepCAD. For text-to-CAD generation, Text2CAD Khan et al. (2024b) uses a vision-language model (VLM) to generate captions for CAD programs in the DeepCAD dataset and trains an autoregressive model to predict the corresponding sketch-and-extrude sequences given these text inputs. Finally, with the advance of Multimodal LLMs OpenAI et al. (2024); Liu et al. (2024); Grattafiori et al. (2024), works such as CAD-GPT Kapsalis (2024) and CAD-MLLM Xu et al. (2024b) takes in multimodal input conditioning to reconstruct the desired CAD programs. They both fine-tune existing Multimodal LLMs on DeepCAD programs with multimodal annotations.

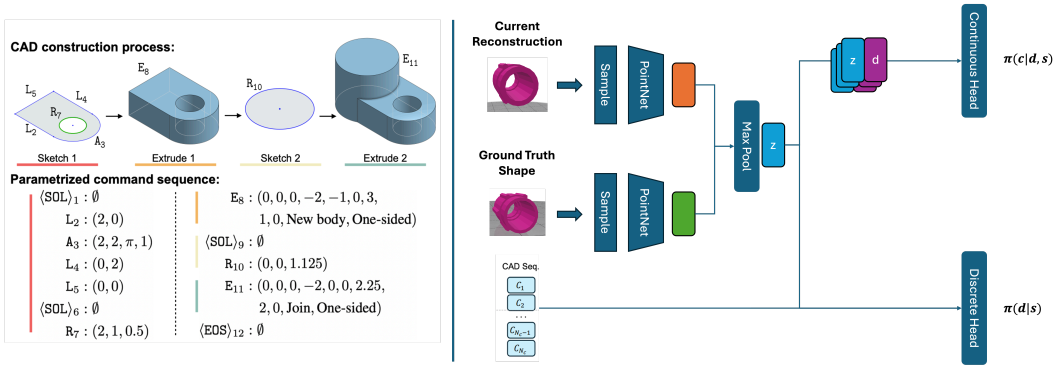


Figure 1: **Method Overview.** (Left) Example of a CAD construction process adopted from Deep-CAD Wu et al. (2021) using the sketch-extrude paradigm. (Right) The proposed factorized policy network that separates the discrete actions ($\pi(d|s)$) and the continuous actions ($\pi(c|d,s)$).

A pioneering work in this area is DeepCAD Wu et al. (2021). In this work, the authors proposed to focus on the type of CAD programs built solely with sequences of sketch-extrude operations, and proposed a dataset containing CAD programs with modeling history. Building on the task setup of DeepCAD, many works Xu et al. (2022); Ma et al. (2023); Khan et al. (2024a); Chen et al. (2025); Dupont et al. (2024); You et al. (2024); Ma et al. (2024) improves upon it by extending the method to more tasks such as CAD prediction from images You et al. (2024), voxels Lambourne et al. (2022), and texts Khan et al. (2024c); Wu et al. (2024). However, all of these works rely on full supervision using the DeepCAD dataset, fundamentally limiting the scale and variety of their generated CAD programs. In our work, we will also focus on generating CAD programs in this paradigm. However, in contrast to these methods, which require supervision on the modeling history, reinforcement learning allows us to update the policy network using 3D shapes without CAD modeling history.

Past literature also tried to use unsupervised learning approaches to directly generate CAD programs in the sketch-extrude paradigm Li et al. (2024); Jones et al. (2023). However, these approaches typically only allows for a limited sequence length, and thereby restricting the representation power of these methods. For us, however, the policy network can generate the operations in an auto-regressive manner; therefore, in theory, achieve infinite-length CAD operations.

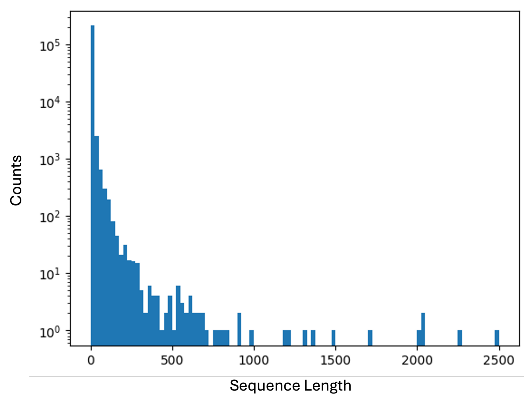
3 Method

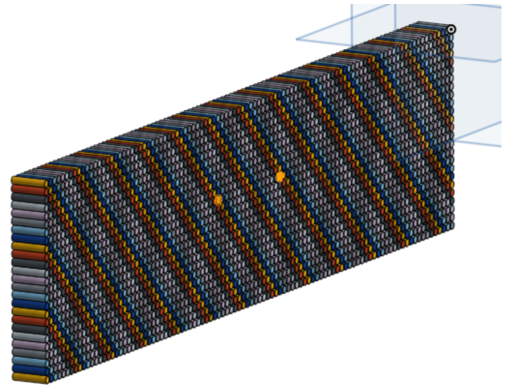
We detail our approach to using reinforcement learning for CAD program generation below. Specifically, Sec. 3.1 details the sketch-extruce CAD construction process we adopt for this paper. In Sec. 3.2 we present our data preparation process together with statistics of the datasets. Finally, in Sec. 3.3 and Sec. 3.4, we outline how we adopt Proximal Policy Optimization (PPO) Schulman et al. (2017) for CAD program generation as well as the rewards we use to training PPO.

3.1 CAD Representation for Neural Networks

CAD programs consist of two levels of representation. When users are designing a CAD model, they will perform a sequence of operations in a CAD software to create a solid shape. Typically, different CAD software contains a different set of operations. For example, users may draw a set of closed curves and lines on a 2D plane, and then perform extrusions on faces formed by the curves to convert them into 3D shapes. Other common operations include sweeping, revolving, and lofting, all of which define 3D shapes using 2D faces on the sketch. Additionally, different 3D primitives created this way are further processed by other operations such as a boolean union, difference, or intersection to create the final desired 3D model (see Fig. 1 (left)). We refer to such a specification as a CAD command sequence.

As the users are creating the CAD models using a sequence of commands, the CAD software builds a kernel representation of the CAD program, widely known as the boundary representation (or BREP) Xu et al. (2024a); Lambourne et al. (2021). BREP describes a solid purely by the topology and geometry of its outer shell: vertices store points, edges link the vertices following pre-defined





(a) Sequence Length Histogram of the DeepCAD Dataset.

(b) The CAD program with the longest sequence length in the DeepCAD dataset.

Figure 2: The DeepCAD Dataset

curves, and faces are formed by patching together edge loops on analytic or spline surfaces. While BREP is usually the output format for standard industry software, shapes represented this way cannot be as easily edited by casual users as the CAD command sequence.

In this work, we aim for a generative model of CAD command sequences. Specifically, following prior works Wu et al. (2021); Xu et al. (2022), we adopt the sketch-extrude paradigm for CAD modeling. While previous works use full supervised learning to learn how to generate CAD programs from human demonstrations, in this project we explore the usage of reinforcement learning to automatically discover CAD command sequence from 3D geometric rewards.

3.2 Data Preparation

This project requires both a CAD dataset with a full CAD modeling command sequence. To this end, we will use the DeepCAD dataset Wu et al. (2021), which contains around 120k CAD programs from the OnShape Repository, filtered to only contain sketch-extrude types of operation. The sequence length of shapes in the dataset varies, but with most of the shapes ranging between 1-4 operations in total. See Fig. 2 for the sequence length statistic (left) as well as the CAD program in the DeepCAD dataset with the longest sequence length (right).

DeepCAD dataset consists mostly of mechanical parts designed for engineering purposes. To increase the diversity of the data shapes, we also consider other datasets. While we did not have time to explore other datasets besides the DeepCAD dataset, to train the RL policy on shapes without groundtruth CAD operations, we also consider adopting the large-scale ShapeNet dataset Chang et al. (2015), which contains clean 3D models with manually verified category and alignment annotations. It covers 55 common object categories with about 51,300 unique 3D models. ShapeNet has been used for many 3D machine learning tasks due to its combination of variety, cleanness, and annotation richness. Thus, it will be a good starting point for this project to test the feasibility of fine-tuning the policy network for the generation of more complex shapes.

3.3 Factorized Hybrid Action Policy for PPO

After processing the DeepCAD dataset, we delineate how we design our policy network and adopt PPO for CAD generation with reinforcement learning.

As discussed in previous sections, modeling a CAD program requires both discrete actions, such as choosing types of curves to draw (lines, arcs, and circles), and the shape boolean operations to use (union, difference, and intersection), and continuous actions, including the parameters for each CAD modeling command. To this end, we require our action policy network to be able to output both continuous actions and discrete actions.

Below, we formalize the above discussion. Let D be the random variable corresponding to the discrete actions and C be the r.v. corresponding to the continuous actions. Given state s, we wish to model the action distribution $\pi_\theta\left(C, D|s\right)$, that is, the probability of choosing one continuous and discrete action given the current state s. Now, because the continuous actions in CAD programs are only determined after the discrete choices are made, we can factorize the action policy to

$$\pi_\theta\left(C, D|s\right) = \pi_\theta\left(C|D, s\right)\pi_\theta\left(D|s\right). \tag{1}$$

Compared to the left hand side, the right hand side's factorized distribution allows us to separate the prediction of the discrete distribution $\pi_\theta\left(D|s\right)$ and the continuous distributions $\pi_\theta\left(C|D, s\right)$ given a discrete action choice D. Comparing with other approaches to modeling a hybrid action space, such as discretizing the continuous space into fixed bins, this approach losslessly retains the full precision of the continuous parameters. Moreover, while other appaoches such as Hybrid PPO Fan et al. (2019) require a different algorithm to handle hybrid action sequences, the factorized policy can be plugged into any RL algorithms without modifications.

To model the factorized policy, we construct a custom policy network that respects the probability diagram. As shown on the right side of Fig. 1, we first use the information from the state s to predict the discrete action via the discrete head. Then, for each discrete action, we predict a separate continuous distribution (Gaussian in our experiments) that parametrizes $\pi_\theta\left(C|D, s\right)$. Notice that it is crucial to predict one distribution for each discrete action D, since the continuous part of the factorization given in Eq. 1 depends on the discrete action D.

3.4 Reward Design

How to design a reward function so that it can give the policy network meaningful optimization signal becomes one of the keys to the success of PPO training. We adopt two reward functions in our training. The first reward is a geometric one, where we encourage the reconstructed CAD sequence to be as close as possible to the input ground truth shape. To this end, we use intersection-over-union (IOU) as the geometric reward. Specifically, given two shapes S, S', the IOU reward is defined as

$$\mathrm{IOU}(S, S') = \frac{|S \cap S'|}{|S \cup S'|} \tag{2}$$

where $|S \cap S'|$ is the volume of the intersection of S and S' and $|S \cup S'|$ is the volume of their union. Notice that when $S = S'$, their IOU score will be 1, as their intersection and their union will equal exactly. In general, a higher value of IOU indicates a better similarity between the two shapes. Thus, PPO that maximizes this reward will encourage the reconstructed CAD sequence to be as geometrically close as possible to the target.

The second reward term we adopt is similar to the format reward used when training for LLM's reasoning capability DeepSeek-AI et al. (2025). Specifically, because the CAD reconstruction from a sequence of CAD commands sometime will fail to execute, we want to punish the agent from outputting such a command sequence. Therefore, we assign a negative reward $R_{\text{fail}}(S) = -10$ whenever the CAD execution of S fails.

In total, the reward at every environment step consists of the sum

$$R(S, S') = 100 \cdot \mathrm{IOU}(S, S') + R_{\text{fail}}(S). \tag{3}$$

4 Experimental Setup

Following what is described in Sec. 3, we implement a PPO training for CAD generation. Specifically, we implement a custom gym environment that builds the CAD program using the Open Cascade Paviot (2022). At every environment step call, the environment will build the CAD model from the current CAD command sequence and evaluate the aforementioned rewards.

As inputs to the policy network, the CAD shapes will first sample points from their surfaces, and be passed through a PointNet Qi et al. (2016) to be encoded as a latent feature. Together with the current CAD command sequence, the encoded feature are passed through the discrete head network parameterized as a 3 layer MLP to predict logits for the categorical distribution over the discrete actions. Finally, concatenate learned embeddings for each discrete action with the point features

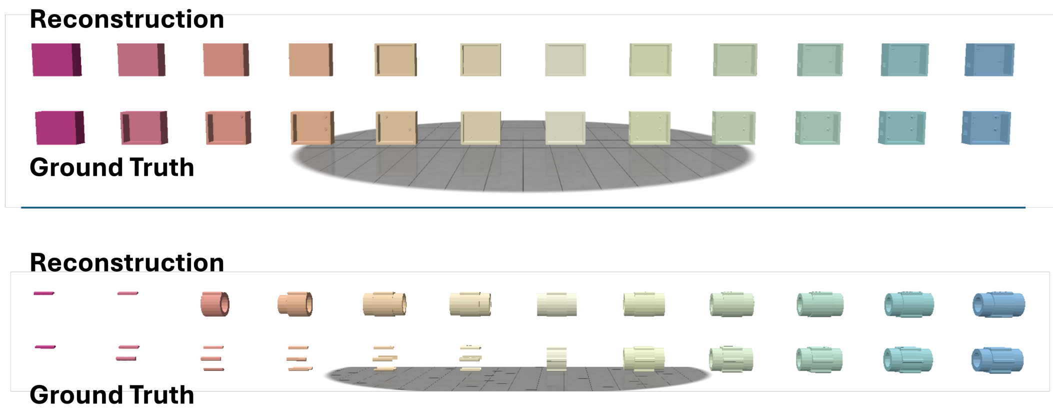


Figure 3: Visualization of the initial results.

and the action sequence to output the means of the continuous actions for each discrete choice. The variance of each continuous distribution is a learnable variable.

The PPO algorithm is implemented on top of TianShou Weng et al. (2022) framework, with a buffer size of 750 steps and a constant learning rate of $1e-3$. We use a clip ratio of 0.2 and an entropy regularization weight of 0.05. We also use advantage normalization and gradient norm clipping to stabilize the optimization.

5 Results

Due to time constraint, we only conducted overfitting experiments where a specialized agent is fitted to reconstruct one CAD shape using the abovementioned pipeline. We conducted two sets of experiments. The first set uses a toy setting to validate the effectiveness of using RL for CAD modeling, and the second experiment leverages the entirety of the above pipeline to train an RL agent for CAD modeling.

5.1 Validation Experiment

The initial experiment was conducted by training an RL algorithm to predict only the discrete actions. To make the RL task easier, we manually created a sequence of actions to take for the agent to reconstruct the entire CAD program. This way, the difficulty of predicting continuous actions is eliminated for now. The agent is trained with Chamfer Distance only w.r.t. to the target CAD program. In this way, supervised pre-training is not used.

Fig. 3 shows the results of a single CAD program overfitting under this setting. Notice that the reconstruction is able to get the overall geometry of the CAD program. However, it misses details such as holes on the side or protrusions at the bottom of the square on the top row, and the outer edges in the bottom row. This is due to the insensitivity of the reward function, a.k.a., Chamfer distance, w.r.t. to small geometric details. However, this do provide a promising starting point for using PPO for CAD modeling.

5.2 Full Experiment

We use the pipeline described in Sec. 3.3 and Sec. 3.4 to train a PPO algorithm to predict the CAD command sequence. Compared to the validation experiment above, the full experiment requires the agent to predict both continuous and discrete actions correctly for the final CAD model to be similar to the input shape. Thus, this setting is much harder compared to the previous one, which resulted in less performant results.

Fig. 4 shows a successful case in which the agent is able to reconstruct the input shape relatively well. In this case, the agent learned to place the primitives correctly at the right orientations and locations,

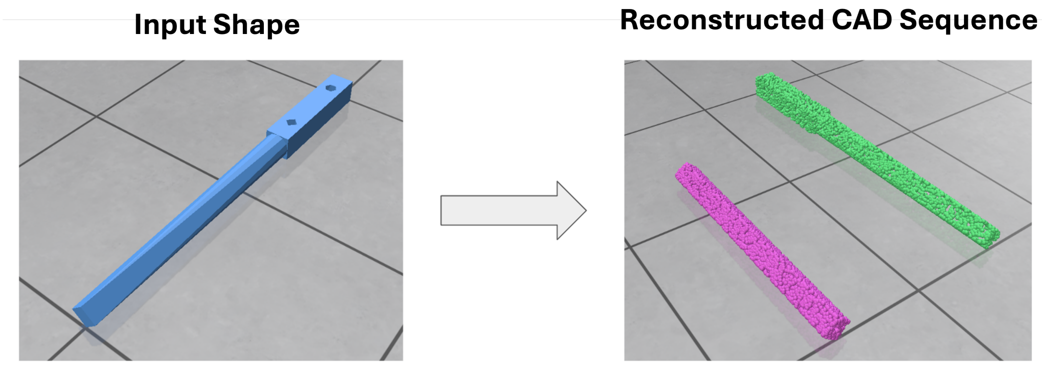


Figure 4: Visualization of results using the full pipeline in Sec. 3.

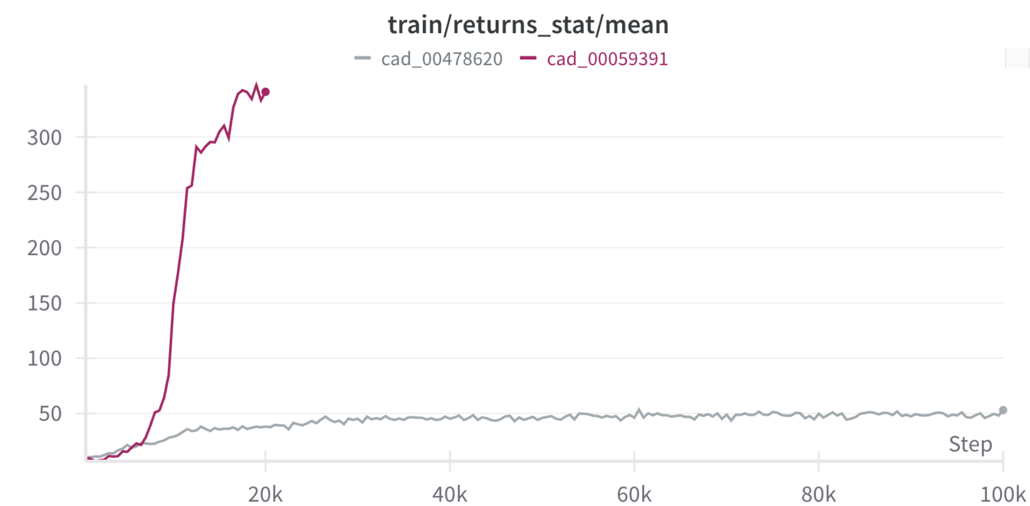


Figure 5: Reward comparison of two runs of different shapes.

as well as choose the correct Boolean operations. However, the results on more complicated shapes the involves either more steps for constructions or negative Boolean operations such as cutting or differencing, faced convergence issues. Specifically, as shown in Fig. 5, the PPO training is stuck at local minima for certain shapes (e.g., shape 00478620 in the figure), because the model did not learn to take the correct step and had a collapsing action distribution. This might be due to it requirement of using a shape intersection shape to obtain the final shape, which might be hard for the RL algorithm to learn, as the initial attempts of doing so would lead to negative rewards. Further investigation is needed in terms of the choice of hyperparamters as well as the RL algorithm for making the convergence better.

6 Discussion & Conclusion

This project investigates the potential of using RL algorithms for CAD command sequence generation. Specifically, we developed a novel factorized action policy to accommodate the hybrid action space of CAD modeling, as well as designed specific rewards to encourage the RL to learn to reconstruct the input shape. While the results are not as high quality as we had wished for, the validation experiment does show the promise in this direction for further investigation. For future steps, we would like to pre-trained the action policy network with supervised training, so that the policy network starts from more informative knowledge about the CAD command sequence. We believe that pre-training would help the performance of RL for CAD generation. Further, as noted in the validation experiment, the geometric reward currently does not reflect the accuracy of small geometric details. Thus, we would like to incorporate more semantically informative rewards using other modalities such as images or segmentation masks to encourage the RL agent to fill in the details as well. Curriculum training could also be considered to encourage the RL agent to learn the rough geometry first before attending to the geometric details.

7 Team Contributions

- **George Nakayama:** Sole author of the project.

Changes from Proposal Due to time and computational budget constraints, we did not have time to implement supervised fine-tuning as described in the proposal. We also did not get a chance to test on ShapeNet and other more large-scale datasets, as we have only conducted overfitting experiments.

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