Shape Synthesis from Sketches via Procedural Models and Convolutional Networks

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Procedural Modeling

Procedural Modeling

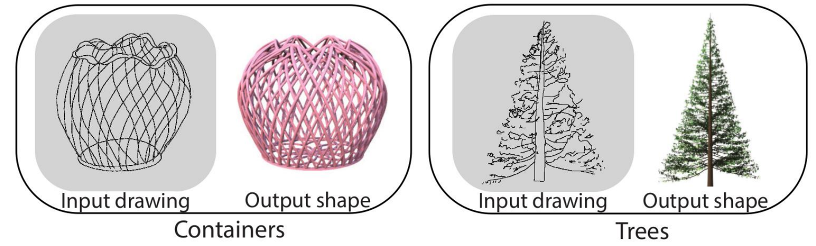
Synthesize 2D or 3D models with a set of parameters.

Figure 1: Procedurally Modeled Chairs (from Sven Havemann, Wikipedia)

Idea: Learn to translate human sketches to Procedural Modeling parameters.

Human Sketches

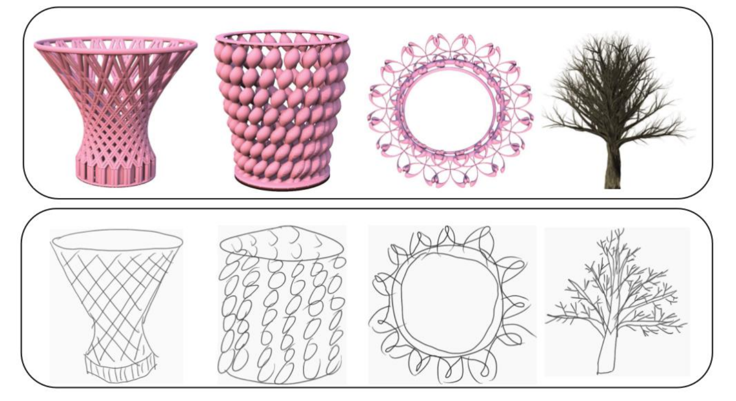
A challenge of this approach is dealing with dramatic abstractions, simplifications, and exaggerations humans make when drawing objects.



A Convolutional Neural Network Architecture

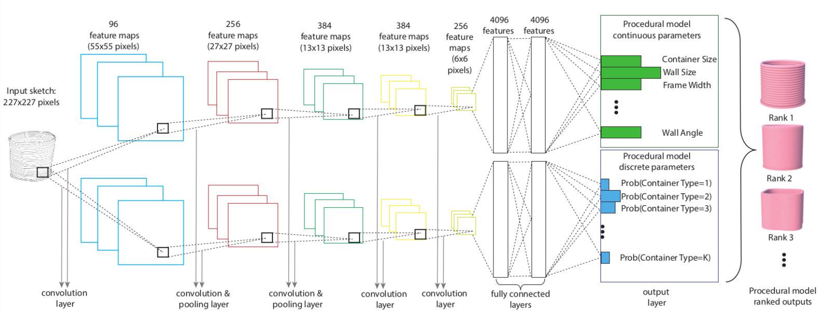
The Data

With a user study and careful curation of generated sketches, a synthetic dataset can be created for a model.



CNN Architecture

Composed of two distinct AlexNet CNN architectures.



One with additional layer for regression of continuous parameters, the other with additional layer for classification of discrete parameters.

Pre-training

AlexNet pre-trained on ImageNet gives significant performance increase for free.

Image classification is a similar task, similar visual features will be useful for sketch $\rightarrow$ shape parameter task.

The network can then be fine tuned by training end to end.

Regression and Classification Layers

The regression layer estimates a normalized parameter c within the range $[0,1]$ using a sigmoid.

$$O_c = \frac{1}{1 + \exp(-\mathbf{w}_c \cdot \mathbf{h}_L - b_c)}$$

The classification layer estimates probabilities of each value of a discrete parameter D_r using a softmax.

$$P(D_r = d) = \frac{\exp(\mathbf{w}_{d,r} \cdot \mathbf{h}_L + b_{d,r})}{\exp(\sum_{d'} \mathbf{w}_{d',r} \cdot \mathbf{h}_L + b_{d',r})}$$

Loss Functions

Loss function for C continuous parameters over S sketches in training data. Uses L^2 loss with L^2 regularization.

$$E_{\text{reg}}(\theta_1) = \sum_{s=1}^{S} \sum_{c=1}^{C} \mathbf{1}_{\delta_{c,s}} ||O_{c,s}(\theta_1) - \hat{O}_{c,s}||^2 + \lambda_1 ||\theta_1||^2$$

Loss function for R discrete parameters over S sketches in training data. Uses logistic loss with L^2 regularization.

$$E_{\text{class}}(\theta_2) = \sum_{s=1}^{S} \sum_{r=1}^{R} \log(P(D_{s,r} = \hat{d}_{s,r} \mid \theta_2)) + \lambda_2 ||\theta_2||^2$$

Results

At Runtime

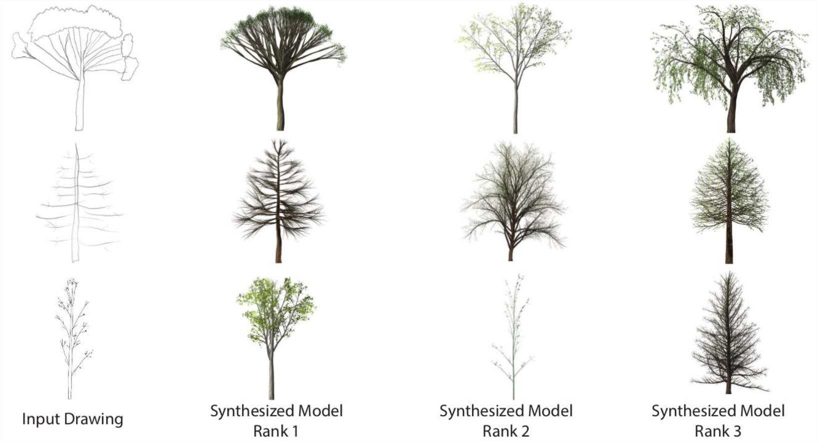
GPU execution can predict PM parameters given a sketch in 1 to 2 seconds.

This is fast enough for near-interactive use.

Method	Containers	Trees	Jewelry	Average
Nearest neighbors (Fisher)	33.3%	26.7%	46.7%	35.6%
Nearest neighbors (CNN)	26.7%	33.3%	40.0%	33.3%
SVM (Fisher)	33.3%	46.7%	60.0%	46.7%
SVM (CNN)	40.0%	33.3%	53.3%	42.2%
Single CNN	66.7%	60.0%	80.0%	68.9%
No pretraining	20.0%	13.3%	20.0%	17.8%
Our method	**80.0%**	**73.3%**	**86.7%**	**80.0%**

Figure 2: Top-3 classification accuracy for discrete parameters

Results


Input Drawing
Synthesized Model
Rank 1
Synthesized Model
Rank 2
Synthesized Model
Rank 3

Results