

Training Frankenstein's Creature to Stack:

HyperTree Architecture Search

Automate the design of deep neural network architectures for robotics.



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CoSTAR Block Stacking Dataset

The CoSTAR Block Stacking Dataset includes a real robot trying to stack colored children's blocks more than 10,000 times. It is designed to benchmark neural network based algorithms.



HyperTree Architecture Search

Low cost automatic design of multiple-input neural network models with Baysesian Optimization.



rENAS: regression Efficient Neural Architecture Search

Low cost automatic design of multiple-input neural network models with Reinforcement Learning.



Includes:
 vastly different
lighting condition
plush toy
distractors
stacks of 3 or 4
blocks
 object wear
 movable bin
obstacle which
must be avoided
successes and
failures

Joint Data	Angle (radian), velocity (radians/s)20 seconds, 200 frames, 100ms per frame (10 Hz				
Typical Duration					
Labels	stack success/failure/error, action name				
30) Coordinate Poses Rec	corded			
Gripper	RGB camera	Depth camera			
Robot joints	AR tags and ID#	Colored blocks			
	Statistics				
	Blocks	Blocks and Toys			
Attempts	5884	610			
Success	2451	74			
Failures, all kinds	3433	53			
Failures without errors	1233	362			
Failures with errors	2200	170			
Success only subset					
Training	2195	62			
Validation	128	(
—	128				

Overview

Color, depth (resolution 640x480)

Current Version: v0.4

Calibrated Images

Last updated: 09/25/201

Much like how Dr. Frankenstein's creature was assembled from pieces before he came to life in the eponymous book, HyperTrees substitute in and combine parts of other architectures to optimize for a new problem domain. Particular component substitution details can be found in the paper.



		``````````````````````````````````````
LSTM		
Layer IDs 0 - sep 3*3		
2 - average_pooling 3 - max_pooling 4 - identity	5	



rENAS is an extension of ENAS, see paper for details

• An LSTM predicts architectures in a meta-model

• Weights are not discarded, increasing search efficiency

• rENAS extends the so-called "micro search space" of ENAS with a new loss and reward function to minimize error.

• rENAS parameterizes placement and number of reduction cells, which rescale the data width and height by half.





Each row shows key goal time steps from separate stacking attempts. Images sequences are ordered from left to right.



**Dataset Videos and Details:** sites.google.com/site/costardataset



**Abstract, Videos, and Paper:** sites.google.com/site/hypertree-renas 0.65 0.813 0.975 1.138 1.3

**Rotation Error, radians, linear scale** 

Predicting translation and rotation of the gripper independently was more accurate than making those predictions simultaneously. Each mark is a separate HyperTree model with 1 epoch of training.

**Cross-Model Comparison** 

**Distribution of Test Cartesian Error** 

HyperTree Models Ranked By Average Cartesian Error - 200 Epoch Training Rur *final model is for comparison with no epoch limit

5-10 mm

10-20 mm

80-160 mm 160-320 mm 320-2560 mm

20-40 mm

100%

75%

50%

25%



Final rENAS Rotation Cells

#### Results



#### **3D Gripper Translations - Distribution of Cartesian Error** 0-5 mm 5-10 mm 10-20 mm 20-40 mm 40-80 mm 80-160 mm 160-320 mm

	train		15%		4%		22%			33%	13	<mark>% 2</mark> %
HyperTree	val		16%	119	70	1	7%		32%		19%	4%
	test		13%	12%		15%		31%			23%	5%
rENAS	train	<mark>3%</mark> 3%		22	2%			45	%			37%
	val	1%5%		18%					56%			25%
	test	<mark>2</mark> % 7%		15%		16%			40%			19%
0%		%		25	%		50%		75%			10

A high percentage of samples with low error is better. Results compare the predicted gripper positions and orientations against the real robot data in the CoSTAR Block Stacking Dataset. This is done by showing the neural network random time steps in the video and asking it to predict the position and orientation the robot will have at the next goal. (Left) The importance of hyperparameter choice is visible in models 1-9 which were selected from the best of 1100 HyperTree candidates and then trained for 200 epochs.