Inferring Graphics Programs from Images

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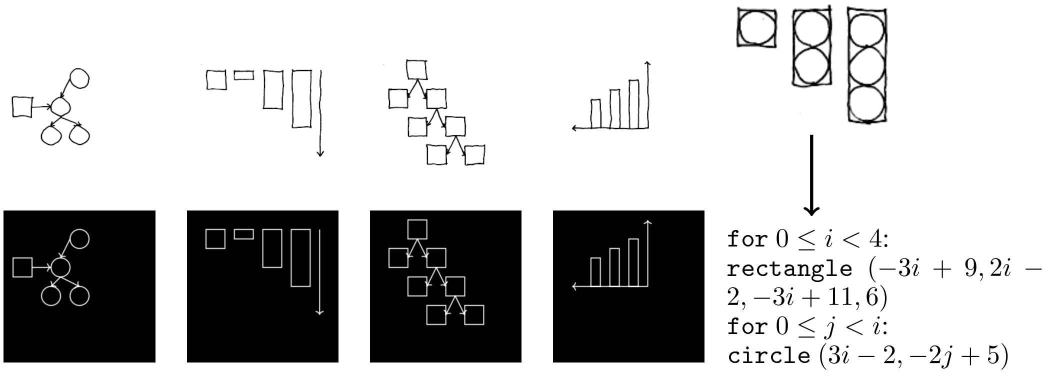
Abstract

1 Introduction

How could an agent go from noisy, high-dimensional perceptual input to a symbolic, abstract object, like a computer program? Here we consider this problem within a graphics program synthesis domain. We develop an approach for converting natural images, such as hand drawings, into executable source code for drawing the original image. The graphics programs in our domain draw simple figures like those found in machine learning papers (see Fig.1). [The use of 'graphics programs / visual programs' in the paper title, title of this section, and the body of this section feels too broad. 'Graphics program' could conjur a lot of different ideas (esp. 3D graphics); don't want to set the reader up to expect one thing and then be disappointed that what you've done isn't that. You bring up diagram-drawing later in the intro; I think it should be made clear sooner (and certainly mentioned explicitly in the abstract, when you get around to writing that).]



```
for $0 \le i < 4$:
rectangle $(-3i + 9, 2i - 2, -3i + 11, 6)$
for $0 \le j < i$:
circle $(3i - 2, -2j + 5)$
```

(a)

(b)

Figure 1: (a): Model learns to convert hand drawings (top) into LATEX (bottom). (b) Synthesizes high-level *graphics program* from hand drawing.

High dimensional perceptual input may seem ill matched to the abstract semantics of a programming language. But programs with constructs like recursion or iteration produce a simpler *execution trace* of primitive actions; for our domain the primitive actions are drawing commands. Our hypothesis is that the execution trace of the program is better aligned with the perceptual input, and that the trace can act as a kind of bridge between perception and programs. We test this hypothesis by developing a model that learns to map from an image to the execution trace of the graphics program that drew it. With the execution trace in hand, we can bring to bear techniques from the program synthesis

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community to recover the latent graphics program. [This is an *excellent* explanation! I would add maybe one more sentence / citation to elaborate on what you mean by ‘techniques from the program synthesis community’, as this will be an unfamiliar concept to some readers, I imagine.]

We develop a hybrid architecture for inferring graphics programs. Our approach uses a deep neural network infer an execution trace from an image; this network recovers primitive drawing operations such as lines, circles, or arrows [and their parameters?] . For added robustness, we use the deep network as a proposal distribution for a stochastic search over execution traces. Finally, we use techniques in the program synthesis community to recover the program from its trace. [This paragraph is all about making things a bit more specific, so you really need more specifics about program synth here.]

Each of these three components – the deep network, the stochastic search, the program synthesizer – confers its own advantages. From the deep network, we get a very fast system that can recover plausible execution traces in about a minute [A minute seems slow to me, for deep net inference. Are you talking about training time, here, or...?]. From the stochastic search we get added robustness; essentially, the stochastic search can correct mistakes made by the deep network's proposals. From the program synthesizer, we get abstraction: our system recovers coordinate transformations, for loops, and subroutines, which are useful for downstream tasks [and can help correct some mistakes of the earlier stages?]. [I wonder if this would work even better as a bulleted list...]

2 Related work

attend infer repeat: [1]. Crucial distinction is that they focus on learning the generative model jointly with the inference network. Advantages of our system is that we learn symbolic programs, and that we do it from hand sketches rather than synthetic renderings.

ngpm: [2]. We build on the idea of a guide program, extending it to scenes composed of objects, and then show how to learn programs from the objects we discover.

Sketch-n-Sketch: [3]. Semiautomated synthesis presented in a nice user interface. Complementary to our work: you could pass a sketch to our system and then pass the program to sketch-n-sketch

Converting hand drawings into procedural models using deep networks: [4, 5].

3 Neural architecture for inferring image parses

We developed a deep network architecture for efficiently inferring a execution trace, T, from an image, I. Our model constructs the trace one drawing command at a time. When predicting the next drawing command, the network takes as input the target image I as well as the rendered output of previous drawing commands. Intuitively, the network looks at the image it wants to explain, as well as what it has already drawn. It then decides either to stop drawing or proposes another drawing command to add to the execution trace; if it decides to continue drawing, the predicted primitive is rendered to its “canvas” and the process repeats.

Figure 2 illustrates this architecture. We first pass the target image and a rendering of the trace so far to a convolutional network. Given the features extracted by the convolutionional network, a multilayer perceptron then predicts a distribution over the next drawing command to add to the trace. We predict the drawing command token-by-token, and condition each token both on the image features and on the previously generated tokens. For example, the network first decides to emit the `circle` token conditioned on the image features, then it emits the x coordinate of the circle conditioned on the image features and the `circle` token, and finally it predicts the y coordinate of the circle conditioned on the image features, the `circle` token, and the x coordinate. [There are some more details that are important to provide about this architecture, though possibly in an Appendix: the functional form(s) of the probability distributions over tokens, the network layer sizes, which MLPs share parameters, etc.]

[Planning to move the description of SMC / beam search up here, too?]

`circle`(x, y)	Circle at (x, y)
`rectangle`(x_1, y_1, x_2, y_2)	Rectangle with corners at (x_1, y_1) & (x_2, y_2)
`LINE`$(x_1, y_1, x_2, y_2,$ arrow $\in \{0, 1\}$, dashed $\in \{0, 1\})$	Line from (x_1, y_1) to (x_2, y_2), optionally with an arrow and/or dashed
`STOP`	Finishes execution trace inference

Table 1: The deep network in (2) predicts drawing commands, shown above.

Program$\rightarrow$	Command; $\cdots$; Command
Command$\rightarrow$	`circle`(Expression,Expression)
Command$\rightarrow$	`rectangle`(Expression,Expression,Expression,Expression)
Command$\rightarrow$	`LINE`(Expression,Expression,Expression,Expression,Boolean,Boolean)
Command$\rightarrow$	`for`$(0 \leq$ Var $<$ Expression`) { `Program` }`
Command$\rightarrow$	`REFLECT(`Axis`) { `Program` }`
Expression$\rightarrow$	Z `*` Var `+` Z
Var$\rightarrow$	A free (unused) variable
Z$\rightarrow$	an integer
Axis$\rightarrow$	`X = ` Z
Axis$\rightarrow$	`Y = ` Z

Table 2: Grammar over graphics programs. We allow loops (`for`), vertical/horizontal reflections (`REFLECT`), and affine transformations (Z `*` Var `+` Z).

The distribution over the next drawing command factorizes:

$$\mathbb{P}_\theta[t_1 t_2 \cdots t_K | I, T] = \prod_{k=1}^{K} \mathbb{P}_\theta[t_k | f_\theta(I, \text{render}(T)), \{t_j\}_{j=1}^{k-1}] \qquad (1)$$

where $t_1 t_2 \cdots t_K$ are the tokens in the drawing command, I is the target image, T is an execution trace, θ are the parameters of the neural network, and $f_\theta(\cdot, \cdot)$ is the image feature extractor (convolutional network). The distribution over execution traces factorizes as:

$$\mathbb{P}_\theta[T|I] = \prod_{n=1}^{|T|} \mathbb{P}_\theta[T_n | I, T_{1:(n-1)}] \times \mathbb{P}_\theta[\texttt{STOP}|I, T] \qquad (2)$$

where $|T|$ is the length of execution trace T, and the `STOP` token is emitted by the network to signal that the execution trace explains the image.

We train the network by sampling execution traces T and target images I for randomly generated scenes, and maximizing (2) wrt θ by gradient ascent. Training does not require backpropagation across the entire sequence of drawing commands: drawing to the canvas 'blocks' the gradients, effectively offloading memory to an external visual store. In a sense, this model is like an autoregressive variant of AIR [1] without attention.

[I like that you make this connection, but it could be made more precisely. Specifically, (1) the architecture isn't *really* recurrent (it uses no hidden state cells), so it'd be good to use a different term or drop this part of the point: (2) training of recurrent nets is also typically fully-supervised (Most RNNs lack latent variables per timestep)—if you're thinking about AIR specifically, maybe just say that, and (3) it's like an autogressive AIR *without attention*.] [Something related to this that's also cool to point out: training this model doesn't require backpropagation across the entire sequence of drawing commands (drawing to the canvas 'blocks' the gradients, effectively offloading memory to an external (visual) store, so in principle it might be scalable to much longer sequences.]

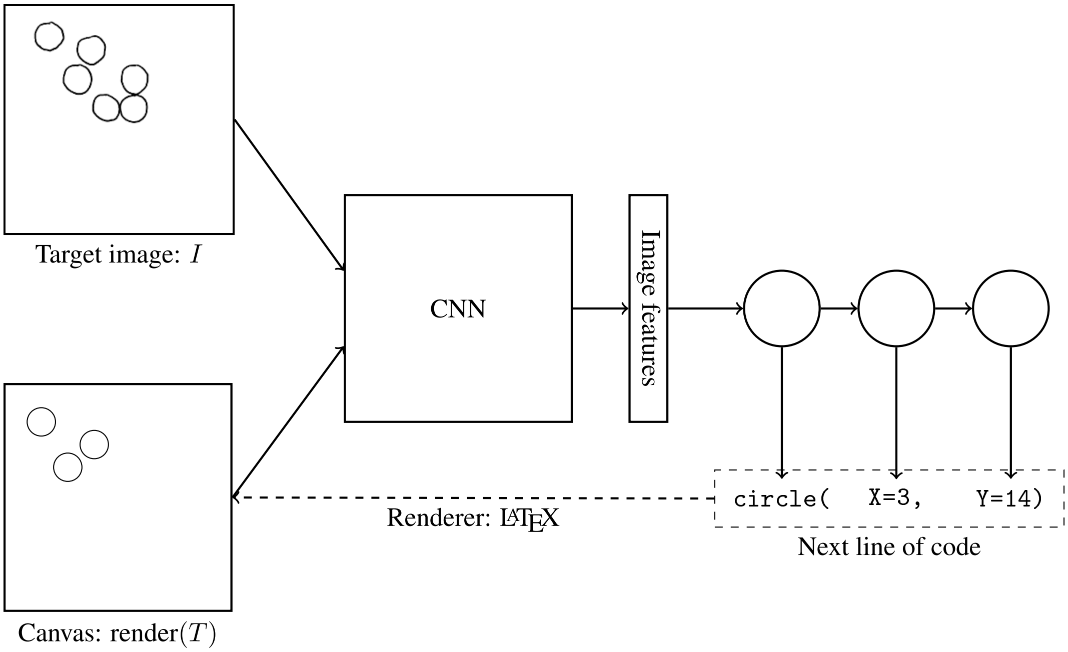


Figure 2: Our neural architecture for inferring the execution trace of a graphics program from its output. [Thoughts on improving this figure: (1) Convnet diagrams typically show the sequence of layers, if possible (space might not permit it here, but those thin arrows just aren't doing it for me). (2) Are the target image / canvas convolved down independently, or jointly (i.e. starting as a 2-channel image)? That's an important detail that's not clear with the current figure/explanation. (3) The three circles downstream from 'Image Features' are supposed to be MLPs, I assume(?), but it took me a little while to parse that. Having some visual way of clearly separating network operations from data (color, perhaps) would go a long way.]

4 Generalizing to hand drawings

5 Synthesizing graphics programs from execution traces

6 Neural networks for guiding SMC

Let $L(\cdot|\cdot) : \text{image}^2 \to \mathcal{R}$ be our likelihood function: it takes two images, an observed target image and a hypothesized program output, and gives the likelihood of the observed image conditioned on the program output. We want to sample from:

$$\mathbb{P}[p|x] \propto L(x|\text{render}(p))\mathbb{P}[p] \tag{3}$$

where $\mathbb{P}[p]$ is the prior probability of program p, and x is the observed image.

Let p be a program with L lines, which we will write as $p = (p_1, p_2, \cdots, p_L)$. Assume the prior factors into:

$$\mathbb{P}[p] \propto \prod_{l \leq L} \mathbb{P}[p_l] \tag{4}$$

Define the distribution $q_L(\cdot)$, which happens to be proportional to the above posterior:

$$q_L(p_1, p_2, \cdots, p_{L-1}, p_L) \propto q_{L-1}(p_1, p_2, \cdots, p_{L-1}) \times \frac{L(x|\text{render}(p_1, p_2, \cdots, p_{L-1}, p_L))}{L(x|\text{render}(p_1, p_2, \cdots, p_{L-1}))} \times \mathbb{P}[p_L] \tag{5}$$

Now suppose we have some samples from $q_{L-1}(\cdot)$, and that we then sample a p_L from a distribution proportional to $\frac{L(x|\text{render}(p_1, p_2, \cdots, p_{L-1}, p_L))}{L(x|\text{render}(p_1, p_2, \cdots, p_{L-1}))} \times \mathbb{P}[p_L]$. The resulting programs p are distributed according to q_L, and so are also distributed according to $\mathbb{P}[p|x]$.

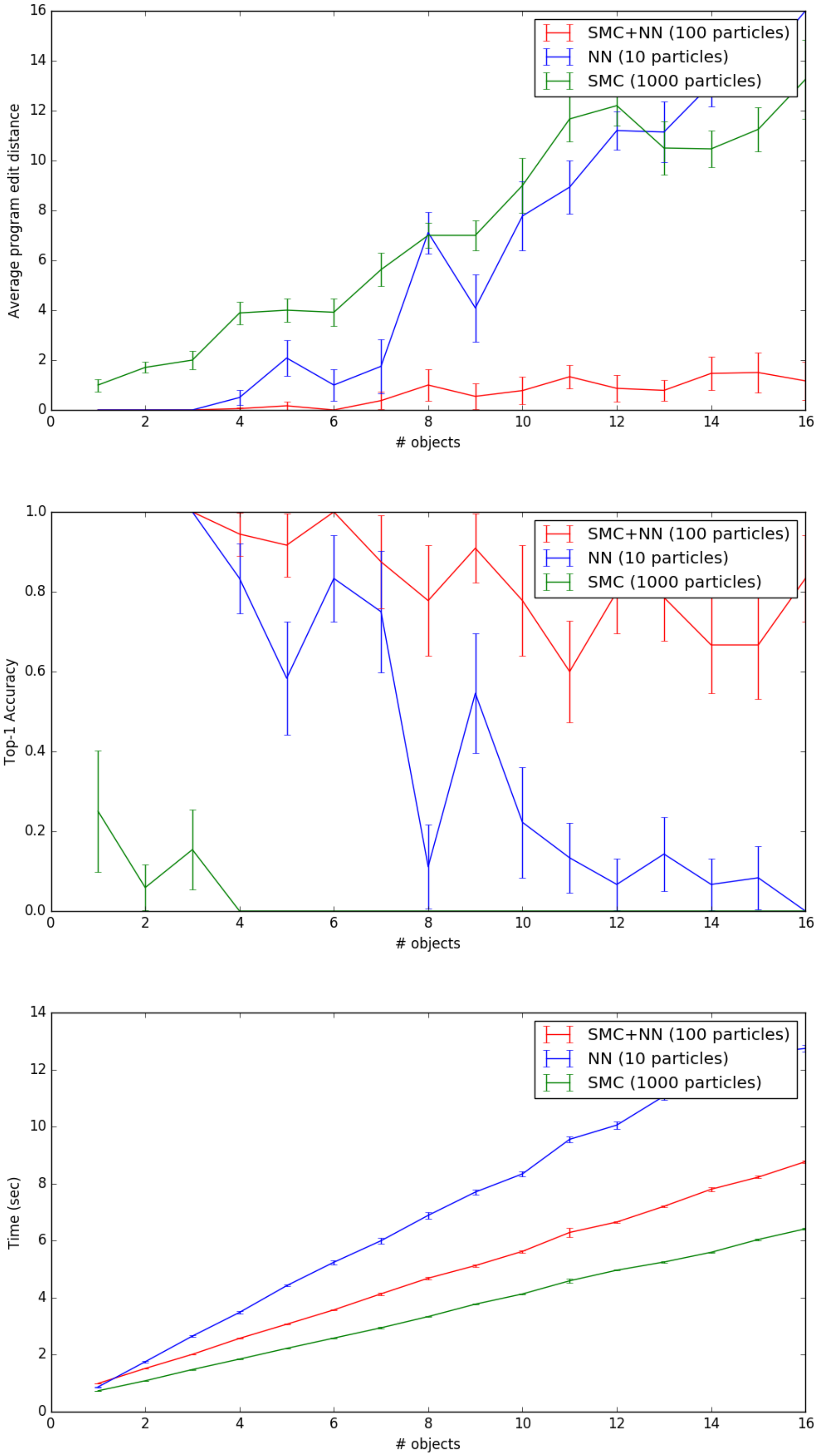
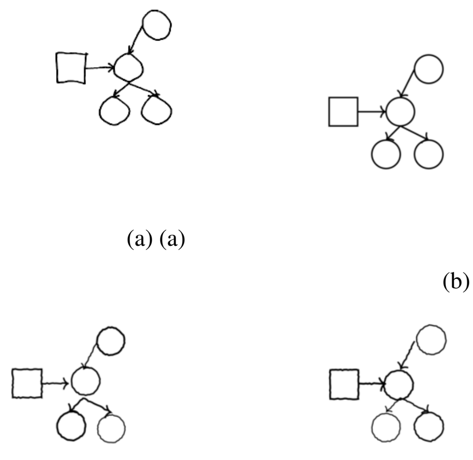


Figure 3: Using the model to parse latex output. The model is trained on diagrams with up to 8 objects. As shown above it generalizes to scenes with many more objects. Neither the stochastic search nor the neural network are sufficient on their own.



(a) (a)

(b) (b)

(c) (c)

(d) (d)

Figure 4: (a): a hand drawing. (b): Rendering of the parse our model infers for (a). We can generalize to hand drawings like these because we train the model on images corrupted by a noise process designed to resemble the kind of noise introduced by hand drawings - see (c) & (d) for noisy renderings of (b).

How do we sample p_L from a distribution proportional to $\frac{L(x|\text{render}(p_1,p_2,\cdots,p_{L-1},p_L))}{L(x|\text{render}(p_1,p_2,\cdots,p_{L-1}))} \times \mathbb{P}[p_L]$? We have a neural network that takes as input the target image x and the program so far, and produces a distribution over next lines of code (p_L). We write $\text{NN}(p_L|p_1,\cdots,p_{L-1};x)$ for the distribution output by the neural network. So we can sample from NN and then weight the samples by:

$$w(p_L) = \frac{\mathbb{P}[p_L]}{\text{NN}(p_L|p_1,\cdots,p_{L-1};x)} \times \frac{L(x|\text{render}(p_1,p_2,\cdots,p_{L-1},p_L))}{L(x|\text{render}(p_1,p_2,\cdots,p_{L-1}))} \tag{6}$$

Then we can resample from these now weighted samples to get a new population of particles (here programs are particles), where each program now has L lines instead of $L-1$.

This procedure can be seen as a particle filter, where each successive latent variable is another line of code, and the emission probabilities are successive ratios of likelihoods under $L(\cdot|\cdot)$.

Comments for Dan. Right now I'm not actually sampling from the neural network - instead, I enumerate the top few hundred lines of code suggested by the network, and then weight them by their likelihoods. So actually the form of NN is:

$$\text{NN}(p_L|p_1,\cdots,p_{L-1};x) \propto \begin{cases} 1, & \text{if } p_L \in \text{top hundred neural network proposals} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Do you think this is a problem? The neural network puts almost all of its mass on a few guesses. In order to get the correct line of code I sometimes need to get something like the 50th top guess, so I don't want to literally just sample from the distribution suggested by the neural network.

References

[1] SM Eslami, N Heess, and T Weber. Attend, infer, repeat: Fast scene understanding with generative models. arxiv preprint arxiv:..., 2016. *URL http://arxiv. org/abs/1603.08575*.

[2] Daniel Ritchie, Anna Thomas, Pat Hanrahan, and Noah Goodman. Neurally-guided procedural models: Amortized inference for procedural graphics programs using neural networks. In *Advances In Neural Information Processing Systems*, pages 622–630, 2016.

[3] Brian Hempel and Ravi Chugh. Semi-automated svg programming via direct manipulation. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*, UIST '16, pages 379–390, New York, NY, USA, 2016. ACM.

Algorithm 1 Neurally guided SMC

```
**Input:** Neural network NN, beam size $N$, maximum length $L$, target image $x$
**Output:** Samples of the program trace
Set $B_0 = \{\text{empty program}\}$
**for** $1 \leq l \leq L$ **do**
  **for** $1 \leq n \leq N$ **do**
    $p_n \sim \text{Uniform}(B_{l-1})$
    $p'_n \sim \text{NN}(\text{render}(p), x)$
    Define $r_n = p'_n \cdot p_n$
    Set $\tilde{w}(r_n) = \frac{L(x|r_n)}{L(x|p_n)} \times \frac{\mathbb{P}[p'_n]}{\mathbb{P}[p'_n = \text{NN}(\text{render}(p), x)]}$
  **end for**
  Define $w(p) = \frac{\tilde{w}(p)}{\sum_{p'} \tilde{w}(p')}$
  Set $B_l$ to be $N$ samples from $r_n$ distributed according to $w(\cdot)$
**end for**
**return** $\{p : p \in B_{l \leq L}, p \text{ is finished}\}$
```

[4] Haibin Huang, Evangelos Kalogerakis, Ersin Yumer, and Radomir Mech. Shape synthesis from sketches via procedural models and convolutional networks. *IEEE transactions on visualization and computer graphics*, 2017.

[5] Gen Nishida, Ignacio Garcia-Dorado, Daniel G. Aliaga, Bedrich Benes, and Adrien Bousseau. Interactive sketching of urban procedural models. *ACM Trans. Graph.*, 35(4), 2016.