Inferring Graphics Programs from Images

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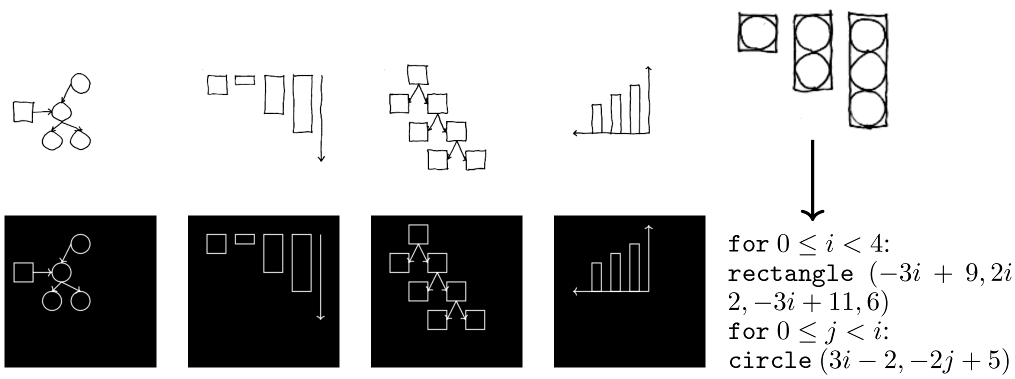
Abstract

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).]



(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 family of techniques, called *constraint-based program synthesis* [**?**], work by modeling a set of possible programs inside of a constraint solver, like a SAT or SMT solver [**?**]. These techniques excel at uncovering high-level symbolic structure, but are not well equipped to deal with real-valued perceptual inputs.

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, along with 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. The program synthesizer discovers constructs like loops and geometric operations like reflections and affine transformations. [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 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 drawing execution traces

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 a 256×256 target image and a rendering of the trace so far to a convolutional network – these two inputs are represented as separate channels for the convnet. Given the features extracted by the convnet, 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?]

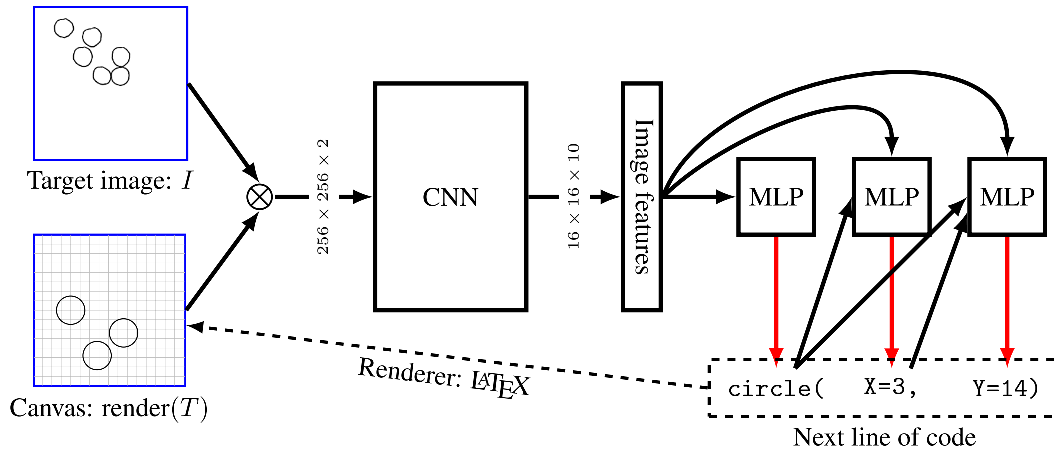


Figure 2: Our neural architecture for inferring the execution trace of a graphics program from its output. Blue: network inputs. Black: network operations. Red: samples from a multinomial. `Typewriter font`: network outputs. Renders snapped to a 16×16 grid, illustrated in gray. [Thoughts on improving 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.]

The distribution over the next drawing command factorizes:

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

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:

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

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.]

This network suffices to "derender" images like those shown in Figure 3. We can perform a beam search decoding to recover what the network thinks is the most likely execution trace for images like these. But, if the network makes a mistake (predicts an incorrect line of code), it has no way

`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.

of recovering from the error. In order to derender an image with n objects, it must correctly predict n drawing commands – so its probability of success will decrease exponentially in n, assuming it has any nonzero chance of making a mistake. For added robustness as n becomes large, we treat the neural network outputs as proposals for a SMC sampling scheme. For the SMC sampler, we use pixel wise distance as a surrogate for a likelihood function; see supplement. Figure 4 compares the neural network with SMC against the neural network by itself or SMC by itself. Only the combination of the two passes a critical test of generalization: when trained on images with ≤ 8 objects, it successfully parses scenes with many more objects than the training data.

3.1 Generalizing to hand drawings

We believe that converting synthetic, noiseless images into a restricted subset of LaTeXhas limited usefulness. A more practical application is one that extends to hand drawings. We train the model to generalize to hand drawings by introducing noise into the renderings of the training target images. We designed this noise process to introduce the kinds of variations found in hand drawings (figure 6). We drew 100 figures by hand; see figure **??**. These were drawn reasonably carefully but not perfectly. Because our model assumes that objects are snapped to a 16×16 grid, we made the drawings on graph paper.

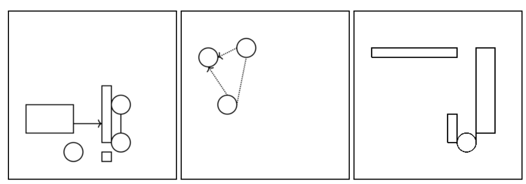
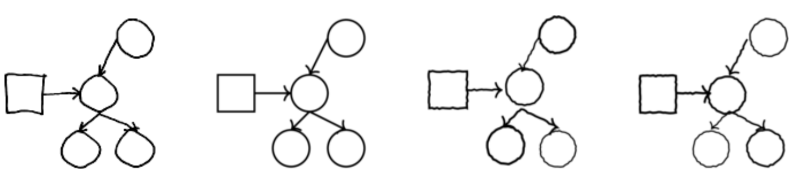


Figure 3: Network is trained to infer execution traces for figures like the three shown above.



(a) (b) (c) (d)

Figure 5: (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).
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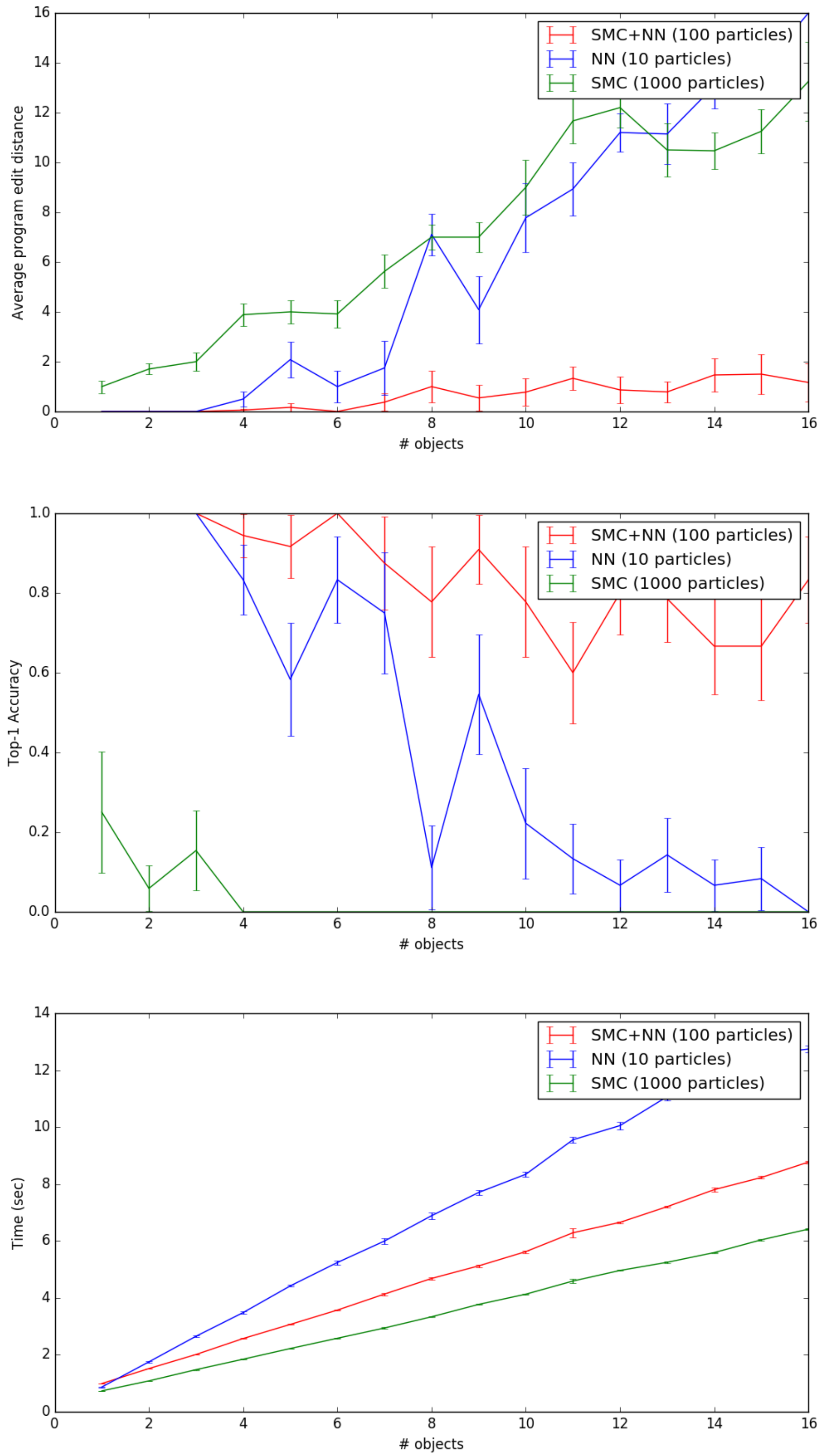
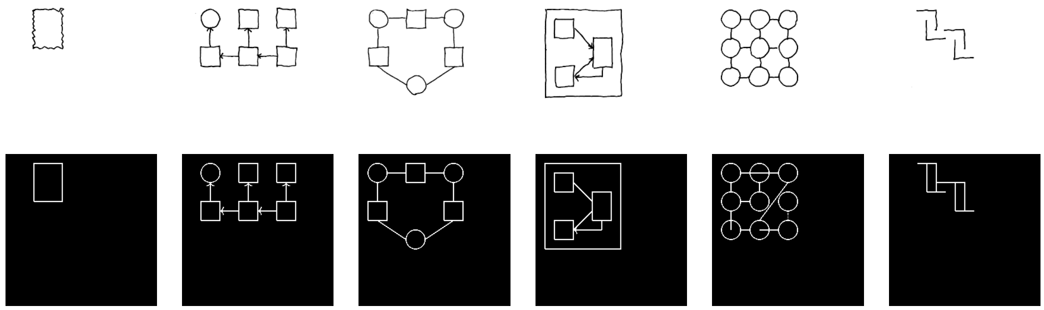


Figure 4: Using the model to parse latex output. The model is trained on diagrams with up to 8 objects. As shown above it generalizes to scenes with many more objects. Neither the stochastic search nor the neural network are sufficient on their own.



(a) Noisy input (b) A graphical model (c) A figure from a deep learning textbook (d) Near miss (e) Failing on a Ising model (f) Illusory contours

Figure 6: Example drawings above model outputs. See also Fig. 1

4 Synthesizing graphics programs from execution traces

Although the execution trace of a graphics program describes the parts of a scene, it fails to encode higher-level features of the image, such as repeated motifs, symmetries or reflections. A *graphics program* better describe structures like these, and we now take as our goal to synthesize simple graphics programs from their execution traces.

We constrain the space of allowed programs by writing down a context free grammar over a space of programs. Although it might be desirable to synthesize programs in a Turing-complete language like Lisp or Python, a more tractable approach is to specify what in the program languages community is called a Domain Specific Language (DSL). Our DSL (Table 2) encodes prior knowledge of what graphics programs tend to look like.

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

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

Given the DSL and a trace T, we want a program that evaluates to T and also minimizes some measure of program cost:

$$\text{program}(T) = \underset{\substack{p \in \text{DSL} \\ p \text{ evaluates to } T}}{\arg\min} \ \text{cost}(p) \tag{3}$$

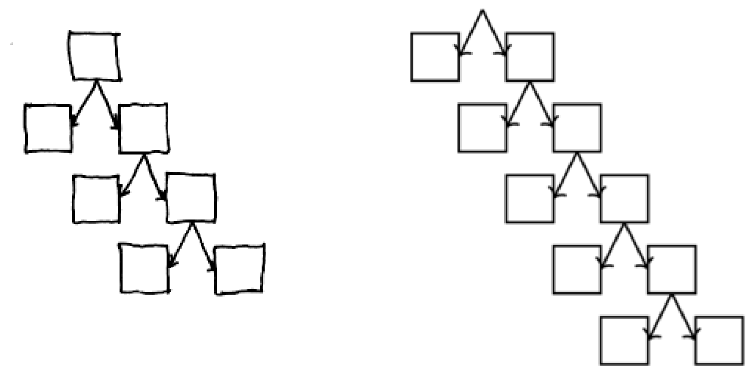
An intuitive measure of program cost is its length. We define the cost of a program to be the number of statements it contains, where a statement is a "Command" in Table 2.

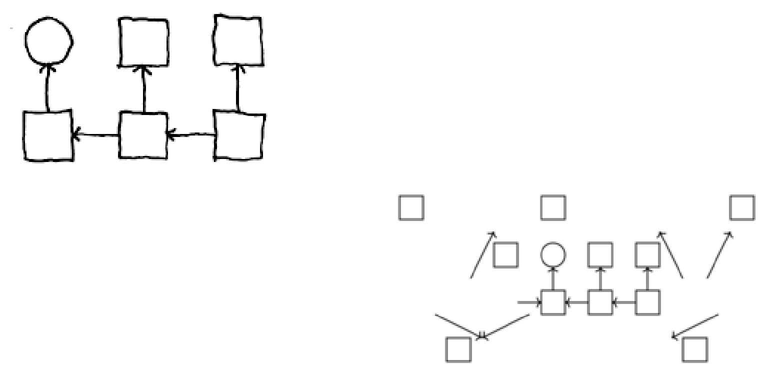
The constrained optimization problem in equation 3 is intractable in general, but there exist efficient-in-practice tools for finding exact solutions to program synthesis problems like these. We use the state-of-the-art Sketch tool [**?**]. Describing Sketch's program synthesis algorithm is beyond the scope of this paper; see supplement. At a high level, Sketch takes as input a space of programs, along with a specification of the program 's behavior and optionally a cost function. It translates the synthesis problem into a constraint satisfaction problem, and then uses a quasiboolean solver to find a minimum cost program satisfying the specification. In exchange for not having any guarantees on how long it will take to find a minimum cost solution, it comes with the guarantee that it will always find a globally optimal program.

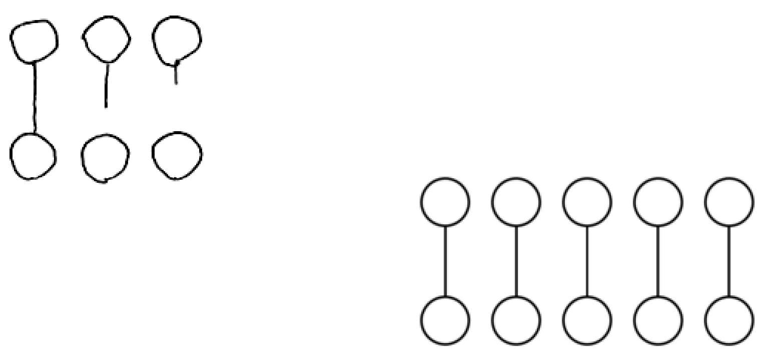
Why synthesize a graphics program, if the execution trace already suffices to recover the objects in an image? Within our domain of hand-drawn figures, graphics program synthesis has several important uses:

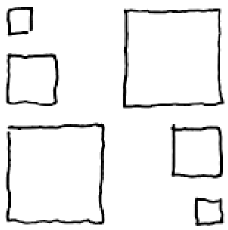
4.1 Extrapolating figures

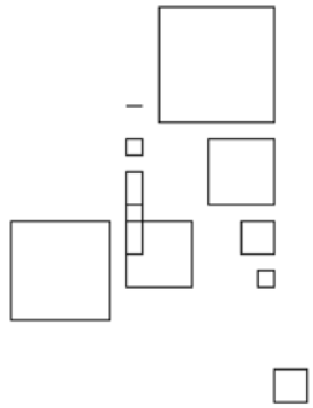
Given the source code of a graphics program, we can automatically tweak the program to make natural-feeling changes to the figure. For example, we can change all of the circles to squares, were make all of the lines be dashed. We can also **extrapolate** figures by increasing the number of times that loops are executed.

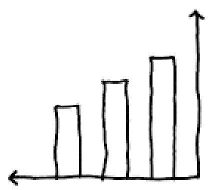


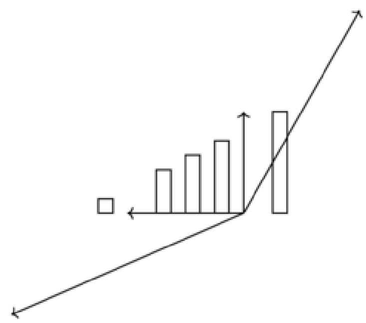


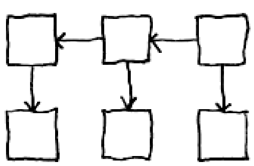


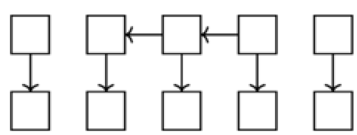


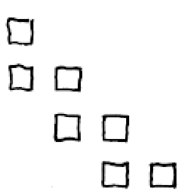


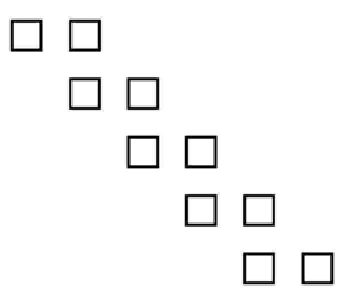


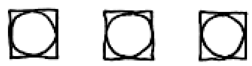


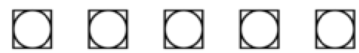


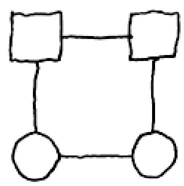


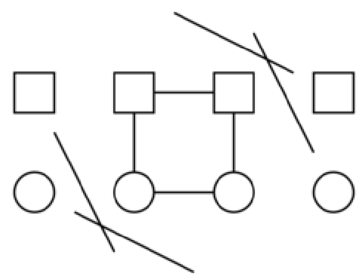


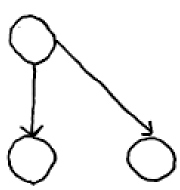


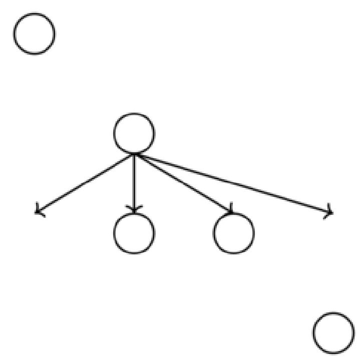


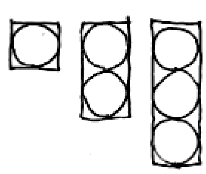


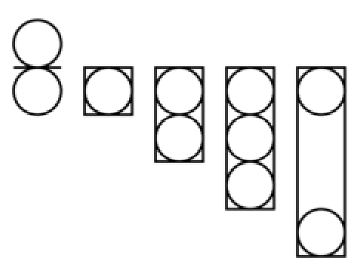


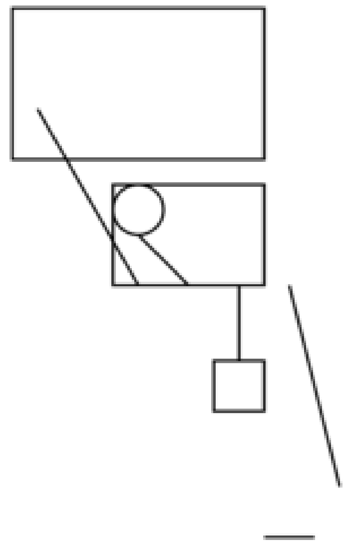












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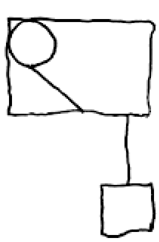

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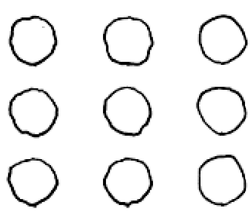

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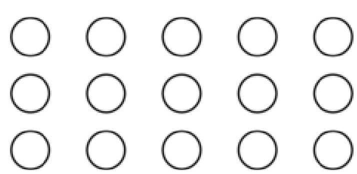

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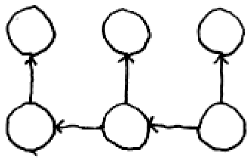

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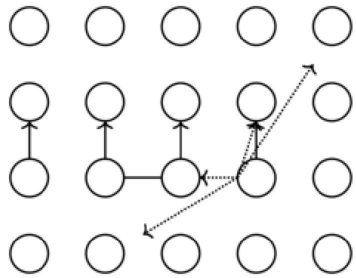

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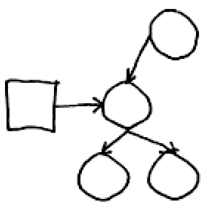

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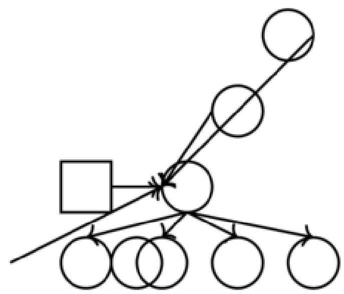

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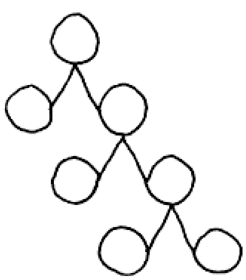

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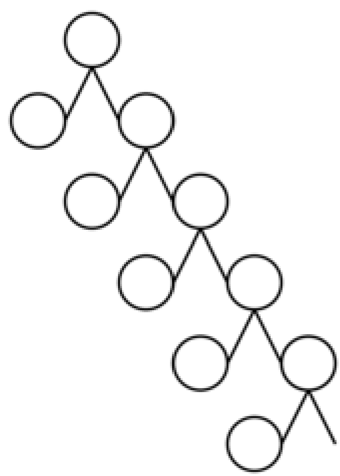

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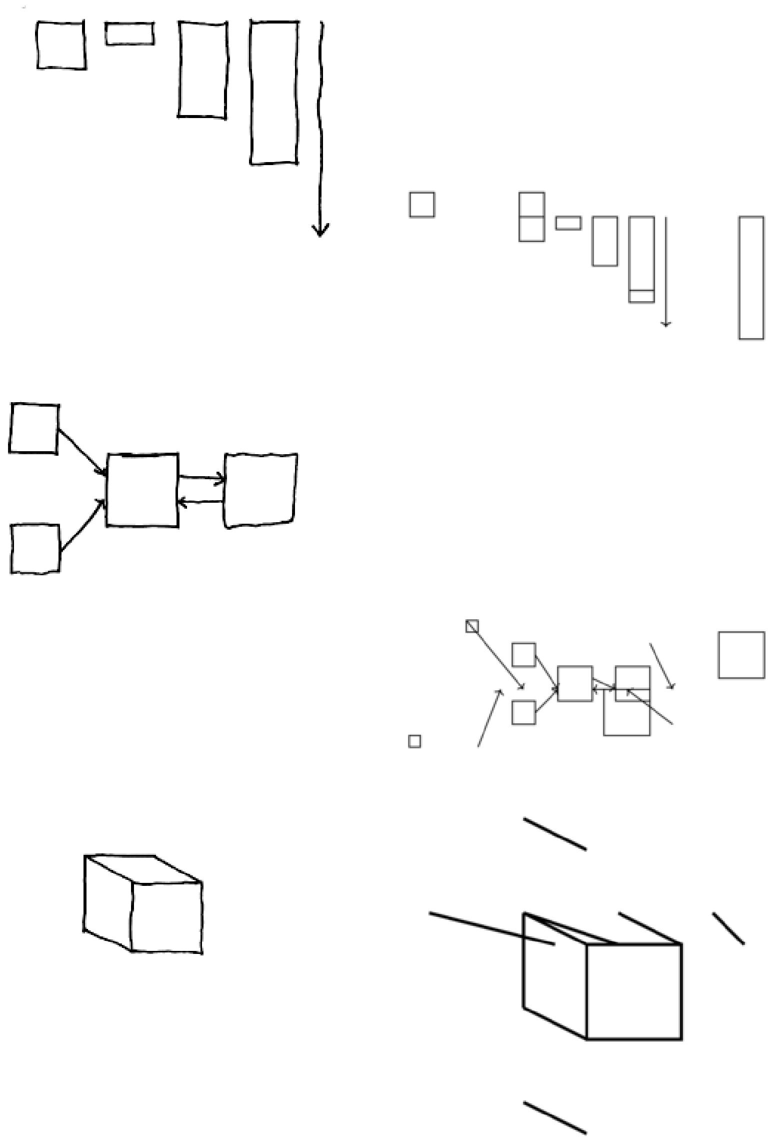


4.2 Modeling similarity between figures

4.3 Correcting errors made by the neural network

Let $L(\cdot|\cdot)$: 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. Write $\hat{T}(I)$ for the trace the model predicts for image I.

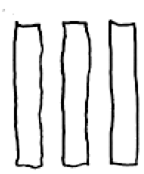
We can extract a few basic features of a program, like its size or how many loops it has, and use these features to help predict whether a trace is the correct explanation for an image.

$$\hat{T}(I) = \arg\max_T L(I|\text{render}(T)) + \theta \cdot \phi\left(\text{program}(T)\right) \tag{4}$$

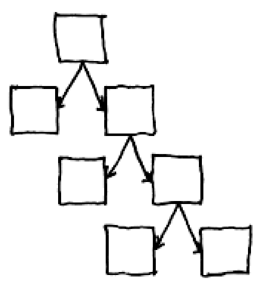
where $\phi(\cdot)$ is a feature extractor for programs. This is equivalent to doing MAP inference in a generative model where the program is first drawn from a log linear distribution $\propto \exp(\theta \cdot \phi(\text{program}))$, than the program is executed deterministically, and then we observe a noisy version of the program's output, where L is the noise model.

5 Preliminary extrapolation results

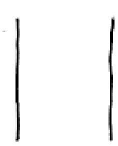
6 Preliminary Synthesis results



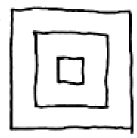
```
Rectangle(0,0,1,6)
Rectangle(2,0,3,6)
Rectangle(4,0,5,6)
```



```
Rectangle(2,9,4,11)
  for (3)
      Line(-2*i + 7,3*i + 3,-2*i + 6,3*i + 1,arrow = True,solid
      Line(2*i + 3,-3*i + 9,2*i + 4,-3*i + 7,arrow = True,solid
      Rectangle(2*i,-3*i + 6,2*i + 2,-3*i + 8)
      Rectangle(-2*i + 8,3*i,-2*i + 10,3*i + 2)
```

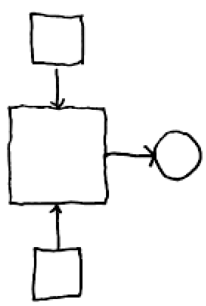


```
Line(0,0,0,5,arrow = False,solid = True)
```

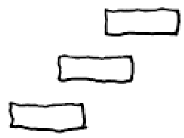


```
Rectangle(0,0,5,5)
Rectangle(1,1,4,4)
Rectangle(2,2,3,3)
```

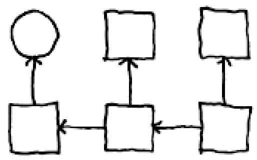
```
Circle(1,1)
```



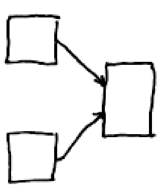
```
Rectangle(0,4,4,8)
      reflect(y = 12)
      Circle(7,6)
      Line(2,2,2,4,arrow = True,solid = True)
      Line(4,6,6,6,arrow = True,solid = True)
      Rectangle(1,0,3,2)
```



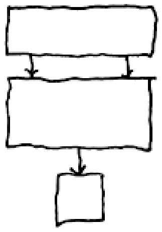
```
Rectangle(2,2,5,3)
Rectangle(0,0,3,1)
Rectangle(4,4,7,5)
```



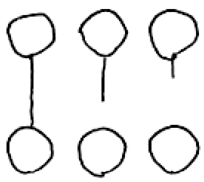
```
Circle(1,5)
  for (2)
      Line(-5*i + 9,-1*i + 2,-7*i + 9,-3*i + 4,arrow = True,soli
      Rectangle(-4*i + 8,4*i,-4*i + 10,4*i + 2)
            reflect(x = 6)
            Line(7*i + 1,-1*i + 2,5*i + 1,-3*i + 4,arrow = True,
            Rectangle(8*i,4*i,8*i + 2,4*i + 2)
```



```
Rectangle(4,2,6,5)
      reflect(y = 7)
      Line(2,6,4,4,arrow = True,solid = True)
      Rectangle(0,5,2,7)
```

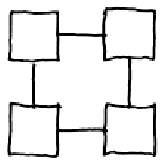


```
Line(3,3,3,2,arrow = True,solid = True)
Rectangle(0,7,6,9)
Rectangle(2,0,4,2)
Rectangle(0,3,6,6)
      Line(1,7,1,6,arrow = True,solid = True)
```

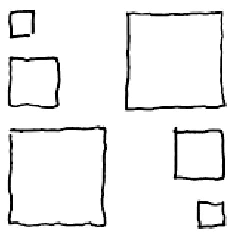


```
for (3)
    Circle(-3*i + 7,1)
    Circle(3*i + 1,6)
    Line(3*i + 1,2,3*i + 1,5,arrow = False,solid = True)
```

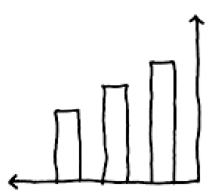
```
    reflect(x = 12)
    Circle(4,1)
    Line(9,1,10,1,arrow = False,solid = True)
    Rectangle(10,0,12,2)
```



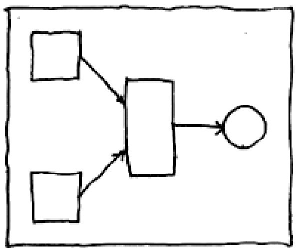
```
    reflect(x = 6)
    Line(5,2,5,4,arrow = False,solid = True)
          reflect(y = 6)
          Line(2,5,4,5,arrow = False,solid = True)
          Rectangle(0,4,2,6)
```



```
for (2)
    Rectangle(0,-3*i + 8,1,-2*i + 9)
    Rectangle(-3*i + 8,5*i,9,8*i + 1)
    Rectangle(-7*i + 7,-2*i + 2,-5*i + 9,4)
```

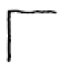


```
Rectangle(4,0,5,4)
  for (2)
      Line(8,0,-8*i + 8,-7*i + 7,arrow = True,solid = True)
      Rectangle(-4*i + 6,0,-4*i + 7,-2*i + 5)
```

226 

```
Circle(10,5)
Line(7,5,9,5,arrow = True,solid = True)
Rectangle(5,3,7,7)
Rectangle(0,0,12,10)
      reflect(y = 10)
      Line(3,2,5,4,arrow = True,solid = True)
      Rectangle(1,1,3,3)
```

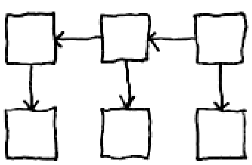
227



228

```
Line(0,0,0,2,arrow = False,solid = True)
Line(0,2,2,2,arrow = False,solid = True)
```

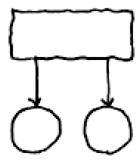
229



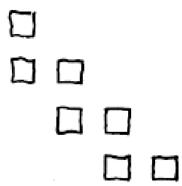
230

```
Line(8,5,6,5,arrow = True,solid = True)
Line(4,5,2,5,arrow = True,solid = True)
  for (3)
      Line(-4*i + 9,4,-4*i + 9,2,arrow = True,solid = True)
      Rectangle(4*i,0,4*i + 2,2)
      Rectangle(-4*i + 8,4,-4*i + 10,6)
```

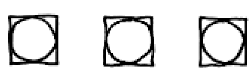
231



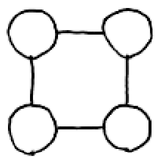
```
Rectangle(0,4,5,6)
      reflect(x = 5)
      Circle(4,1)
      Line(1,4,1,2,arrow = True,solid = True)
```



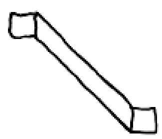
```
Rectangle(0,6,1,7)
  for (3)
      Rectangle(-2*i + 6,2*i,-2*i + 7,2*i + 1)
      Rectangle(-2*i + 4,2*i,-2*i + 5,2*i + 1)
```



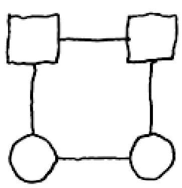
```
for (3)
    Circle(4*i + 1,1)
    Rectangle(4*i,0,4*i + 2,2)
```



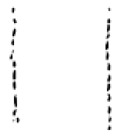
```
reflect(y = 6)
Line(2,1,4,1,arrow = False,solid = True)
      reflect(x = 6)
      Circle(1,1)
      Line(1,2,1,4,arrow = False,solid = True)
```



```
Line(1,5,5,1,arrow = False,solid = True)
Line(1,4,5,0,arrow = False,solid = True)
Rectangle(5,0,6,1)
Rectangle(0,4,1,5)
```

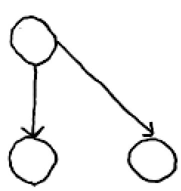


```
for (2)
    Circle(-5*i + 6,1)
    Line(-4*i + 6,-1*i + 2,-1*i + 6,-4*i + 5,arrow = False,solid
    Line(-1*i + 2,-4*i + 6,-4*i + 5,-1*i + 6,arrow = False,solid
    Rectangle(5*i,5,5*i + 2,7)
```

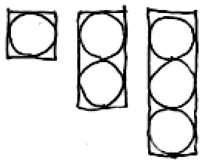


```
Line(0,0,0,5,arrow = False,solid = False)
Line(4,1,4,5,arrow = False,solid = False)
Line(4,0,4,1,arrow = False,solid = False)
```

```
Rectangle(0,0,3,4)
```



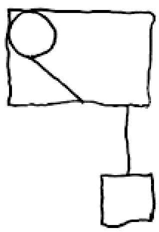
```
Circle(1,1)
  for (2)
      Circle(-5*i + 6,5*i + 1)
      Line(1,5,5*i + 1,2,arrow = True,solid = True)
```



250

```
Circle(7,3)
  for (3)
      Circle(-3*i + 7,5)
      Circle(-3*i + 7,2*i + 1)
      Rectangle(-3*i + 6,2*i,-3*i + 8,6)
```

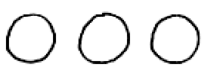
251



252

```
Circle(1,8)
  for (2)
      Line(4*i + 1,-5*i + 7,2*i + 3,5,arrow = False,solid = True
      Rectangle(-4*i + 4,5*i,6,7*i + 2)
```

253



254

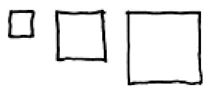
```
Circle(7,1)
Circle(4,1)
Circle(1,1)
```

255

256

```
Line(1,2,1,5,arrow = False,solid = True)
  for (2)
      Line(2,-4*i + 4,-4*i + 6,4,arrow = False,solid = True)
      Line(0,-2*i + 6,-2*i + 2,6,arrow = False,solid = True)
      Line(1,5,2*i + 2,5,arrow = False,solid = True)
```

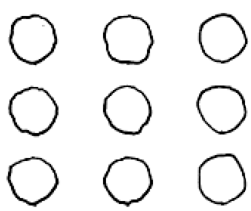
257



258

```
Rectangle(5,0,8,3)
Rectangle(2,1,4,3)
Rectangle(0,2,1,3)
```

259

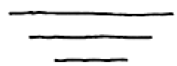


260

```
for (3)
    Circle(-4*i + 9,4)
    Circle(-4*i + 9,1)
    Circle(4*i + 1,7)
```

261

```
Circle(1,5)
Line(1,4,1,2,arrow = True,solid = True)
Rectangle(0,0,2,2)
```



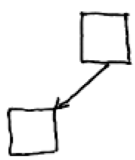
```
Line(0,2,7,2,arrow = False,solid = True)
Line(1,1,6,1,arrow = False,solid = True)
Line(2,0,5,0,arrow = False,solid = True)
```

```
Circle(1,9)
Line(1,8,1,6,arrow = True,solid = True)
Line(1,3,1,2,arrow = True,solid = True)
Line(1,3,1,4,arrow = False,solid = True)
      reflect(y = 6)
      Circle(1,1)
```

268

```
Line(1,2,3,2,arrow = False,solid = True)
Line(2,1,4,1,arrow = False,solid = False)
Line(3,0,5,0,arrow = False,solid = True)
Line(0,3,2,3,arrow = False,solid = False)
```

269



270

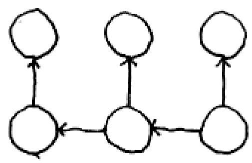
```
Line(4,4,2,2,arrow = True,solid = True)
Rectangle(3,4,5,6)
Rectangle(0,0,2,2)
```

271

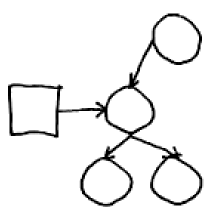
272

```
Line(0,0,0,4,arrow = False,solid = True)
```

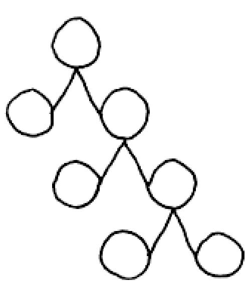
273



```
Line(4,1,2,1,arrow = False,solid = True)
  for (2)
      Line(-4*i + 5,2,-4*i + 5,4,arrow = True,solid = True)
        for (3)
            Circle(-4*j + 9,4*i + 1)
            Line(8,1,3*i + 6,3*i + 1,arrow = True,solid = False)
```

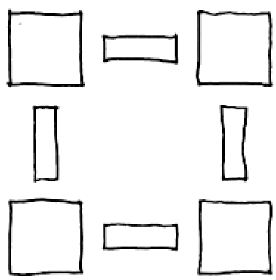


```
Rectangle(0,3,2,5)
  for (2)
      Circle(3*i + 4,1)
      Circle(-2*i + 7,-3*i + 7)
      Line(5,3,-3*i + 7,2,arrow = True,solid = True)
      Line(4*i + 2,3*i + 4,4,4,arrow = True,solid = True)
```

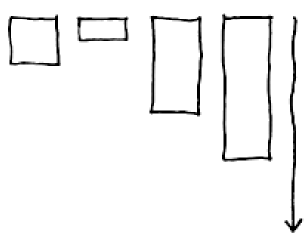


```
Circle(9,1)
  for (3)
      Circle(2*i + 3,-3*i + 10)
      Circle(-2*i + 5,3*i + 1)
      Line(2*i + 2,-3*i + 7,2*i + 3,-3*i + 9,arrow = False,solid
      Line(-2*i + 7,3*i + 3,-2*i + 8,3*i + 1,arrow = False,solid
```

```
Line(5,0,3,0,arrow = True,solid = True)
Line(0,3,2,3,arrow = True,solid = True)
Line(3,2,1,2,arrow = True,solid = True)
Line(2,1,4,1,arrow = True,solid = True)
```

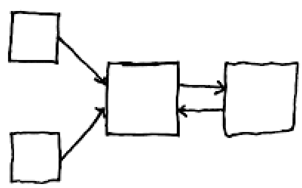


```
reflect(y = 11)
Rectangle(4,9,7,10)
      reflect(x = 11)
      Rectangle(8,0,11,3)
      Rectangle(1,4,2,7)
```

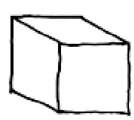


```
Line(12,9,12,0,arrow = True,solid = True)
  for (2)
      Rectangle(-3*i + 6,3*i + 5,-3*i + 8,9)
      Rectangle(9*i,-4*i + 7,9*i + 2,9)
```

```
Line(4,0,0,0,arrow = False,solid = False)
```



```
Line(8,3,9,3,arrow = False,solid = True)
  for (2)
      Line(-6*i + 8,3*i + 3,-3*i + 7,3,arrow = True,solid = True
      Line(5*i + 2,3*i + 1,5*i + 4,3,arrow = True,solid = True)
      Rectangle(9*i,2*i,10*i + 2,3*i + 2)
      Rectangle(-4*i + 4,3*i + 2,-5*i + 7,2*i + 5)
```



```
Line(0,1,0,4,arrow = False,solid = True)
Rectangle(2,0,5,3)
  for (2)
      Line(0,3*i + 1,2,3*i,arrow = False,solid = True)
      Line(-3*i + 3,4,-2*i + 5,3,arrow = False,solid = True)
```

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.

[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.