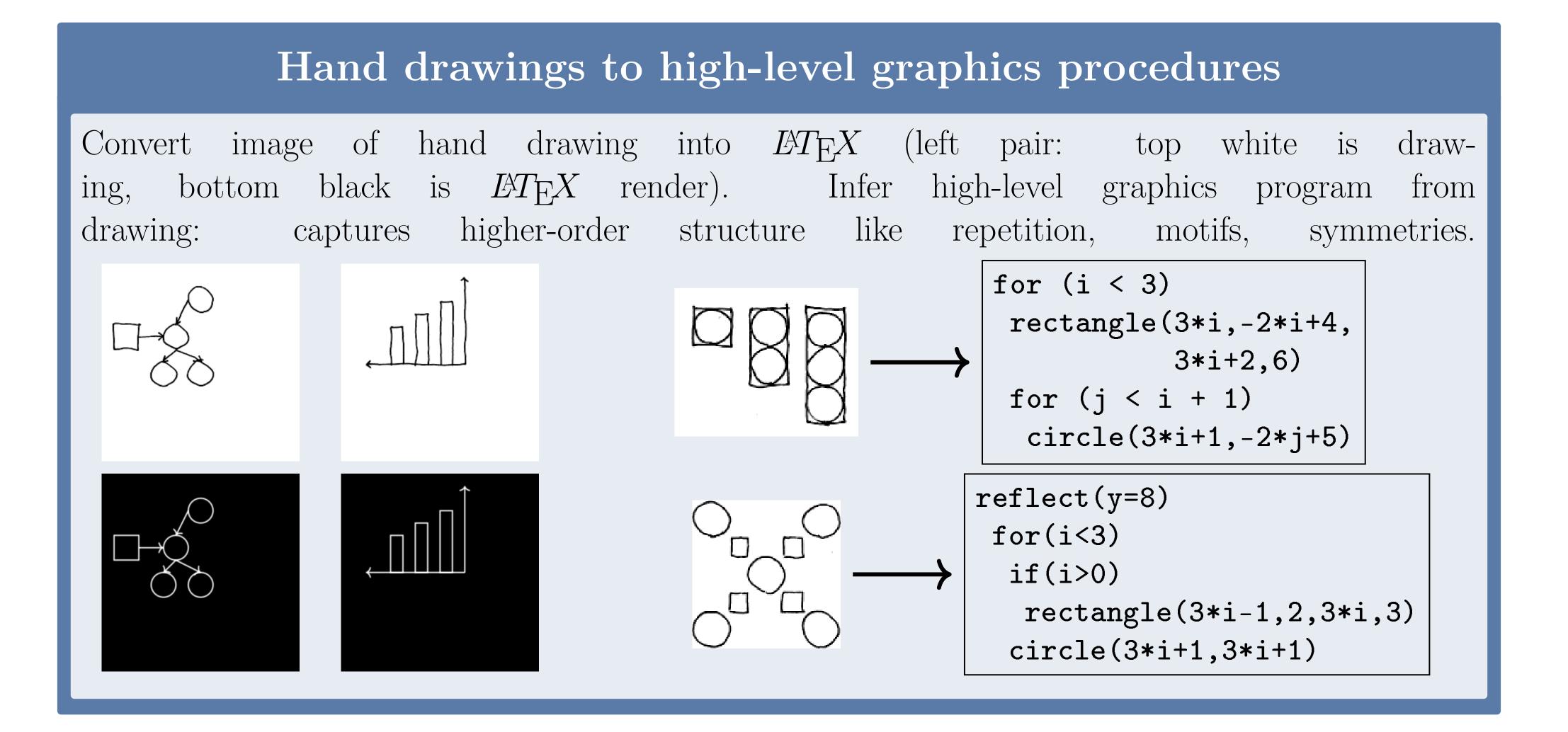


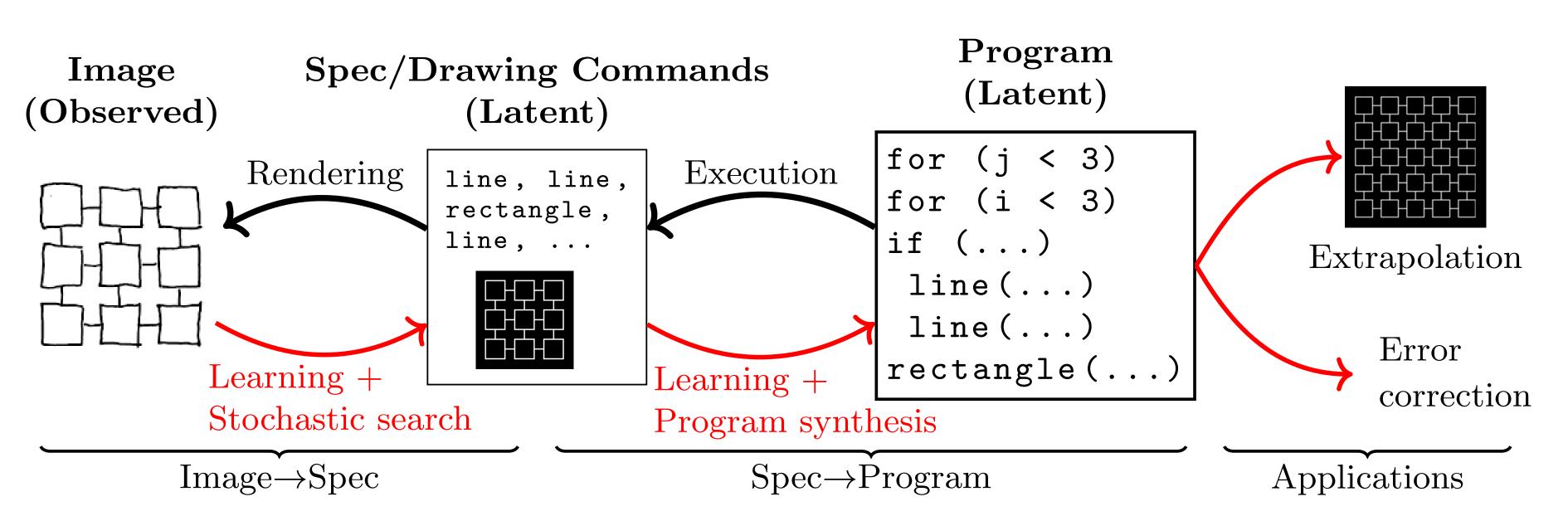
# Learning to Infer Graphics Programs from Hand-Drawn Images

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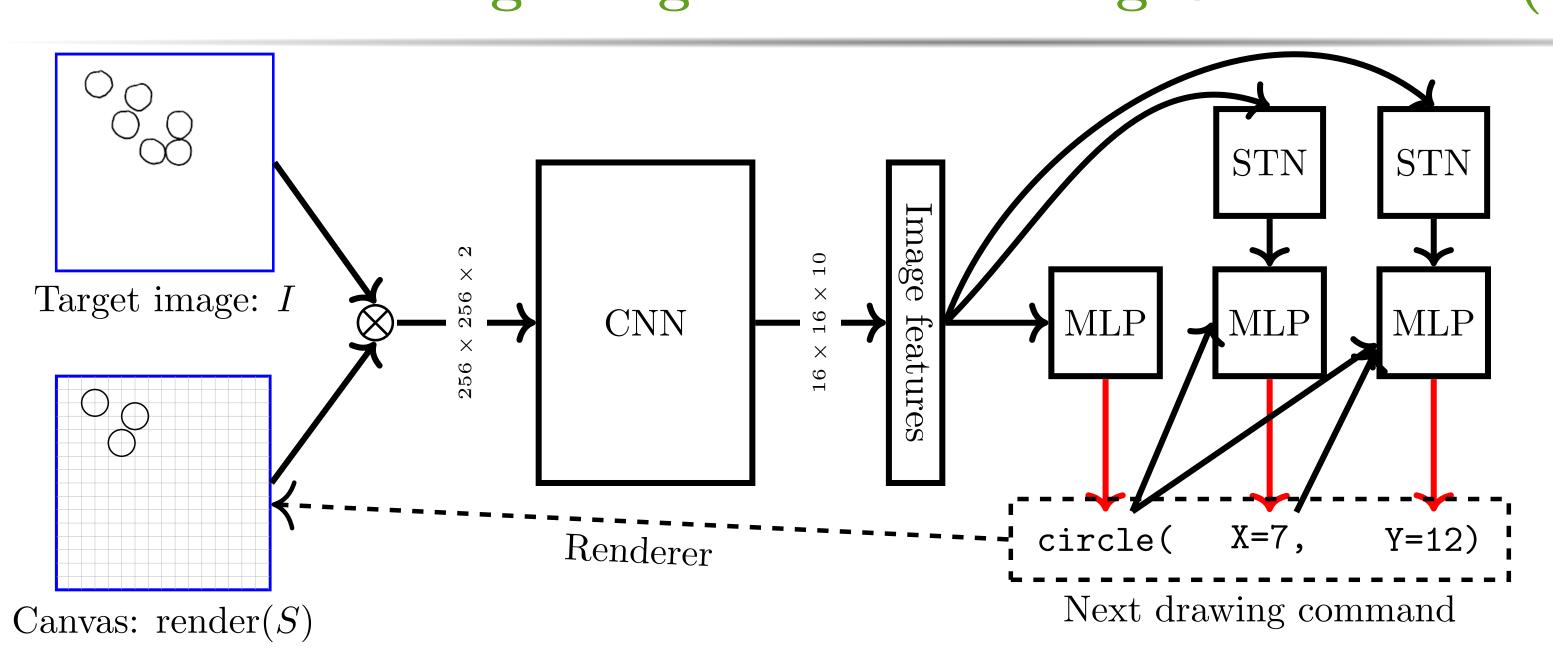


## Two-Stage Pipeline

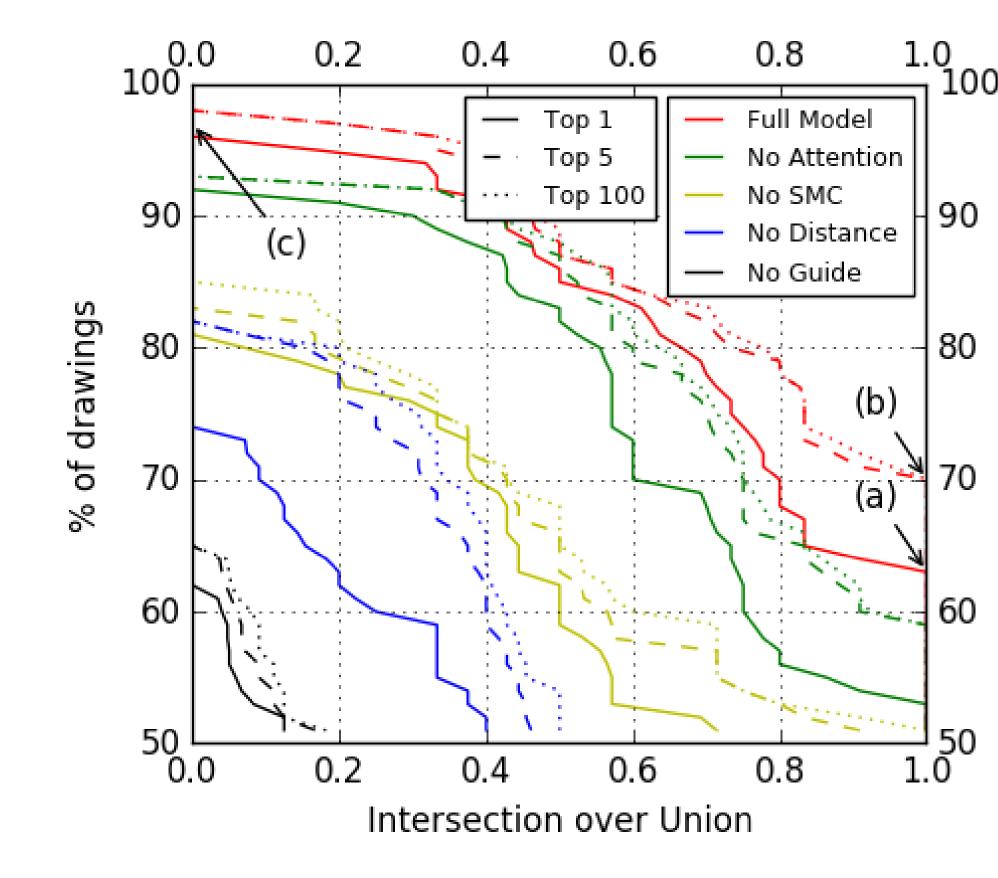


Black arrows: Top-down generative model; Program→Spec→Image. Red arrows: Bottom-up inference procedure. Bold: Random variables (image/spec/program)

#### Parsing Images into Drawing Commands (specs)



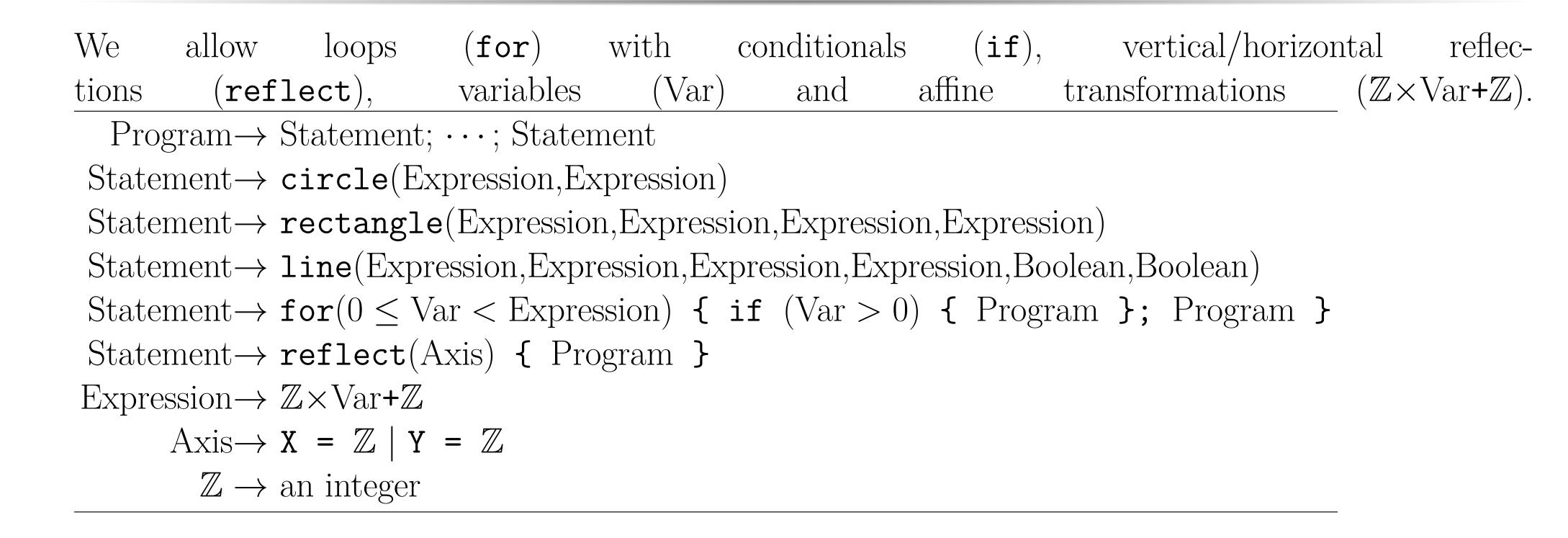
Blue: network inputs. Black: network operations. Red: draws from a multinomial. Typewriter font: network outputs. Renders on a 16 × 16 grid, shown in gray. STN: differentiable attention mechanism. Combined with stochastic search (Sequential Monte Carlo)



(Left) NN outputs vs ground truth on hand drawings (measured by IoU), as we consider larger sets of samples (1, 5, 100).

(a) for 63% of drawings the model's top prediction is exactly correct; (b) for 70% of drawings the ground truth is in the top 5 model predictions; (c) for 4% of drawings all of the model outputs have no overlap with the ground truth. Red: the full model. Other colors: ablations. Model is at ceiling for synthetic ETEX output.

# Domain-Specific Language for Graphics Programs



# Learning & Constraint-Based Program Synthesis

Sketch: state-of-the-art program synthesizer. Solar-Lezama 2008. Solves, for spec S & program p:  $\operatorname{program}(S) = \underset{p \in \mathrm{DSL, s.t. } \ p \text{ consistent w/} \ S}{\operatorname{arg min}} \operatorname{cost}(p)$ 

Learn policy  $\pi_{\theta}$  to accelerate program synthesizer's search.  $\pi_{\theta}(\cdot|S) \in \Delta^{\Sigma}$ , where  $\Sigma \ni \sigma$  a set of synthesis problem (i.e.,  $\sigma \in \Sigma$  is a sketch) Inference strategy: Timeshare according to  $\pi_{\theta}(\cdot|S)$ , like in Levin Search

### Entire program search space

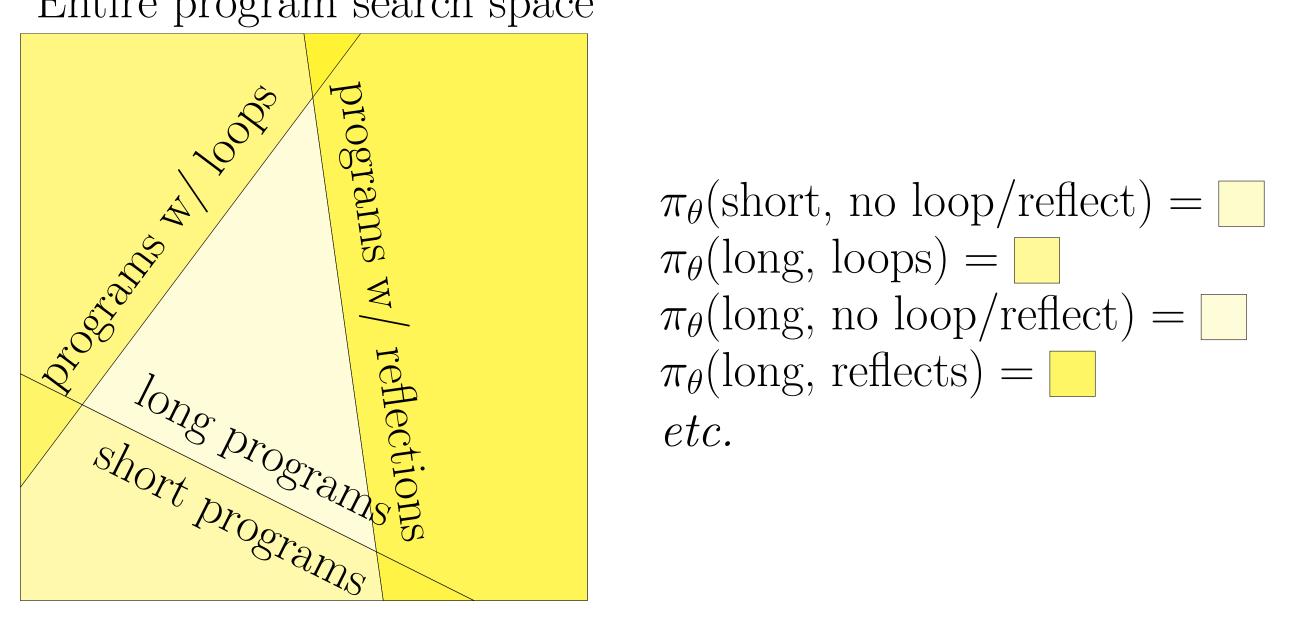
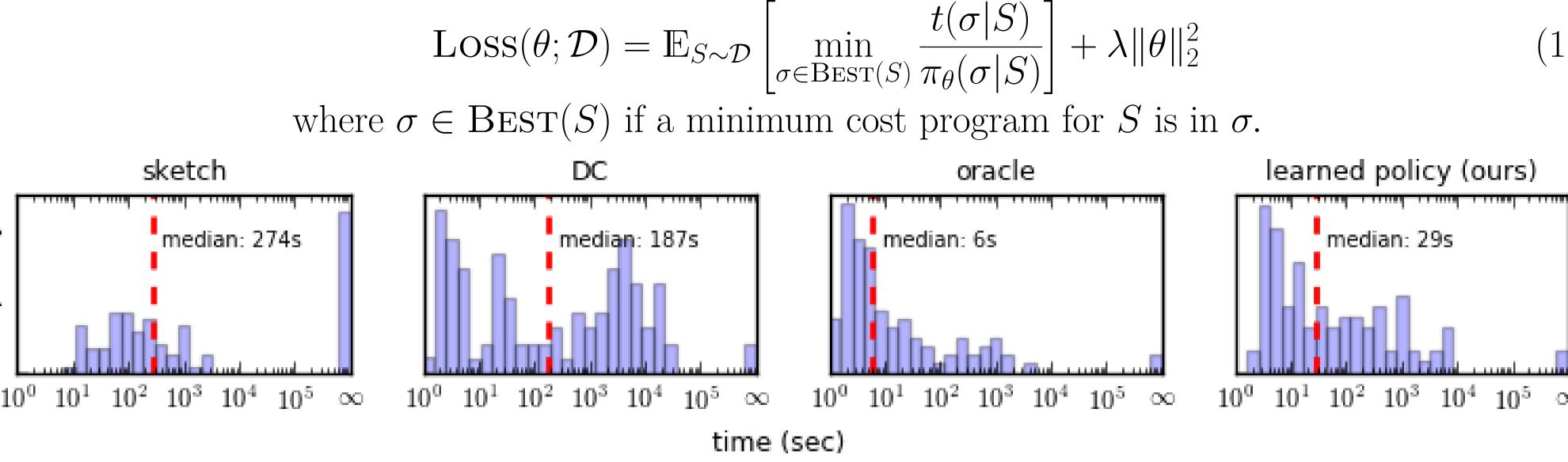


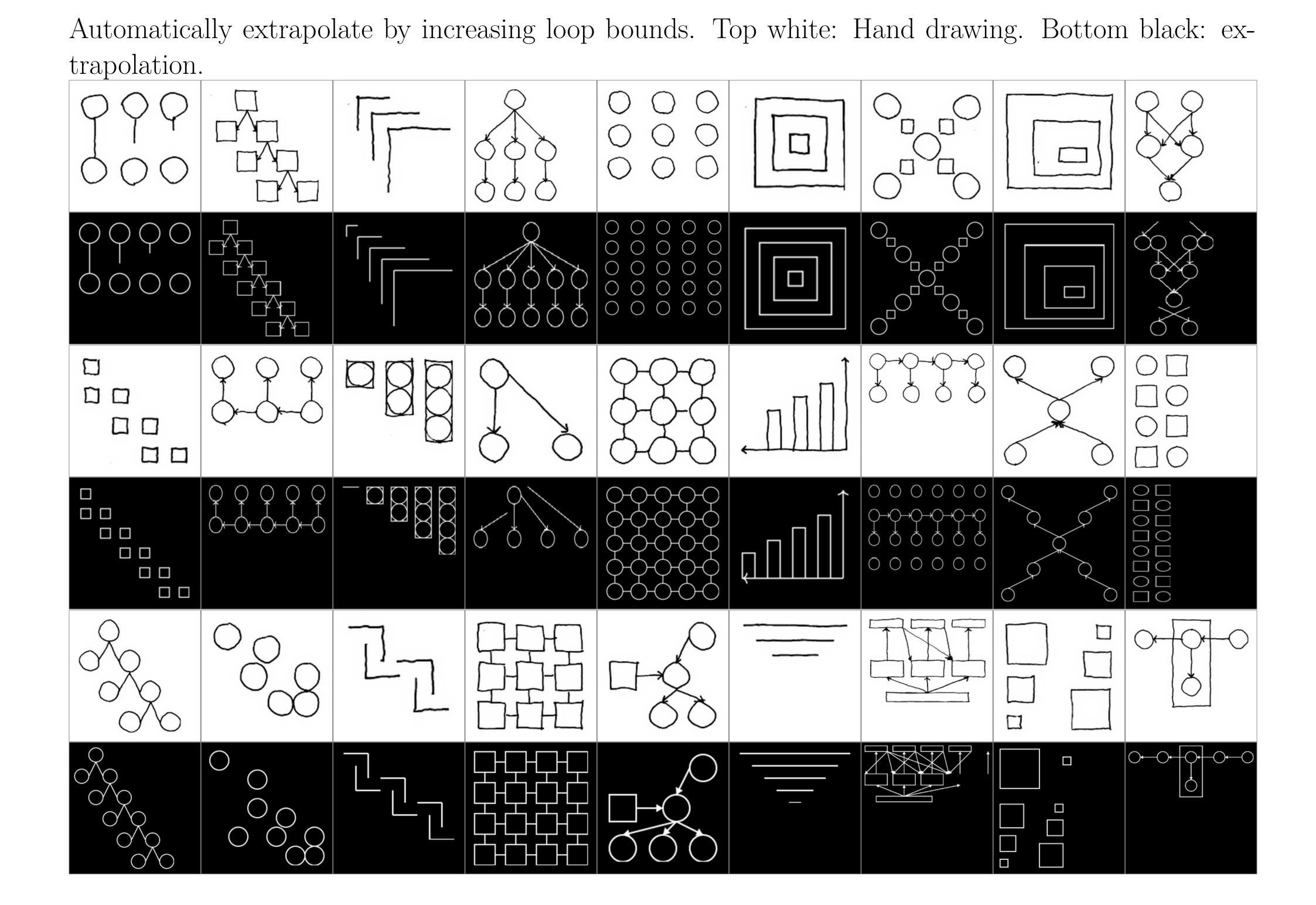
Figure 1: The bias-optimal search algorithm divides the entire (intractable) program search space in to (tractable) program subspaces (written  $\sigma$ ), each of which contains a restricted set of programs. For example, one subspace might be short programs which don't loop. The policy  $\pi$  predicts a distribution over program subspaces: weight assigned by  $\pi$  indicated by shading

Differentiable loss ( $\mathcal{D}$  a corpus of synthesis problems):



Time to synthesize a minimum cost program. Sketch: out-of-the-box performance of Sketch. DC: Deep-Coder style baseline that predicts program components, trained like Balog 2016. Oracle: upper bounds the performance of any bias-optimal search policy.  $\infty$  = timeout. Red dashed line is median time

### Extrapolating Drawings



## Error correction

'Top down' influences upon perception: reasoning engine (program synthesizer) can influence agent's percept through higher-level considerations like symmetry and alignment.

$$\hat{S}(I) = \underset{S \in \mathcal{F}(I)}{\operatorname{arg max}} L_{\operatorname{learned}}(I|\operatorname{render}(S)) \times \mathbb{P}_{\theta}[S|I] \times \mathbb{P}_{\beta}[\operatorname{program}(S)]$$

$$\beta^* = \arg\max_{\beta} \mathbb{E} \left[ \log \frac{\mathbb{P}_{\beta}[\operatorname{program}(S)] \times L_{\operatorname{learned}}(I|\operatorname{render}(S)) \times \mathbb{P}_{\theta}[S|I]}{\sum_{S' \in \mathcal{F}(I)} \mathbb{P}_{\beta}[\operatorname{program}(S')] \times L_{\operatorname{learned}}(I|\operatorname{render}(S')) \times \mathbb{P}_{\theta}[S'|I]} \right]$$

where  $\mathcal{F}(I)$  is set of parses output by neural net on image I;  $\mathbb{P}_{\beta}[\cdot]$  is prior over programs parameterized by  $\beta$ ; and expectation is taken over a corpus of program synthesis problems.

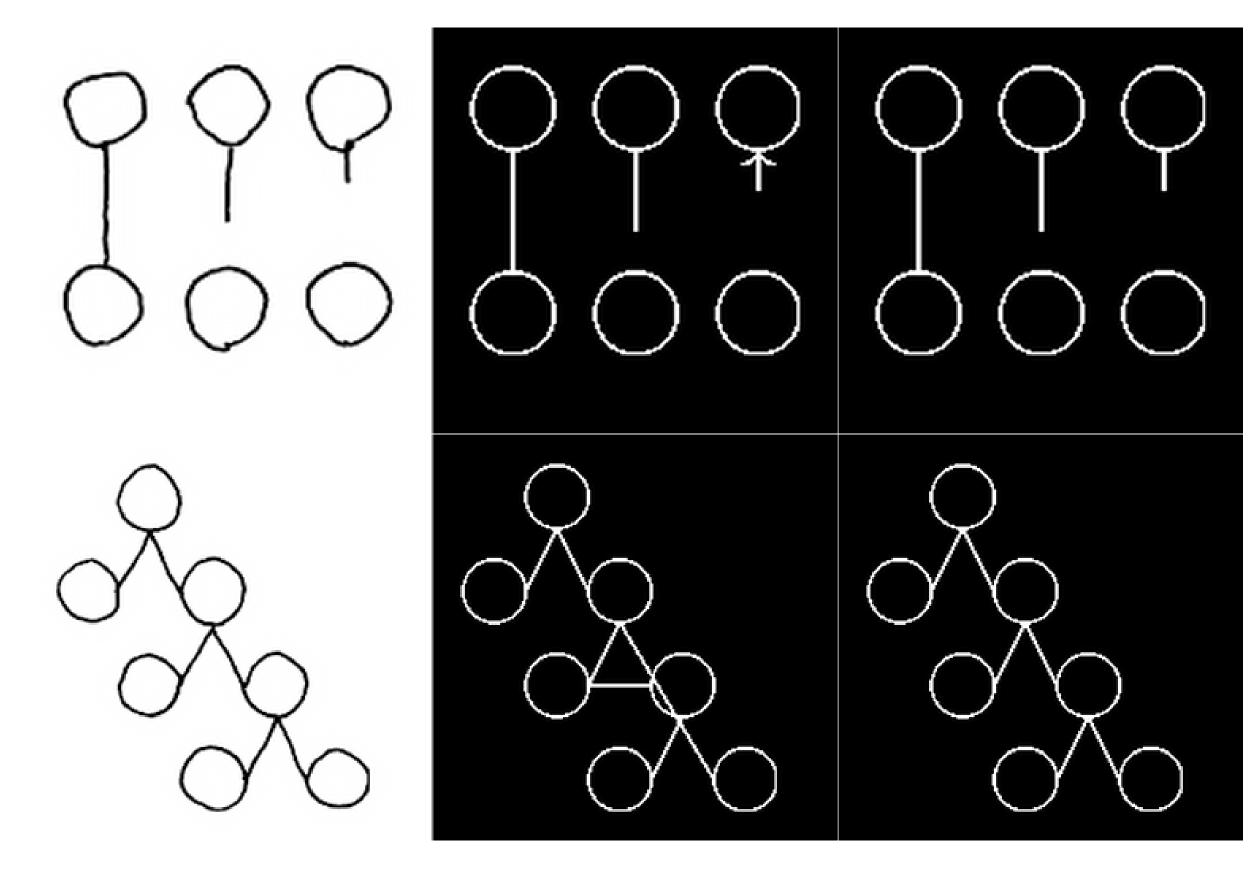


Figure 2: Left: hand drawings. Center: interpretations favored by the deep network. Right: interpretations favored after learning a prior over programs. The prior favors simpler programs, thus (top) continuing the pattern of not having an arrow is preferred, or (bottom) continuing the "binary search tree" is preferred.

## Example System Outputs

Drawing	$\mathbf{Spec}$	Program	Compression factor
	Line(2,15, 4,15) Line(4,9, 4,13) Line(3,11, 3,14) Line(2,13, 2,15) Line(3,14, 6,14) Line(4,13, 8,13)	<pre>for(i&lt;3) line(i,-1*i+6,</pre>	$\frac{6}{3} = 2x$
	Line(5,13,2,10,arrow) Circle(5,9) Circle(8,5) Line(2,8, 2,6,arrow) Circle(2,5) etc; 13 lines	<pre>circle(4,10) for(i&lt;3)   circle(-3*i+7,5)   circle(-3*i+7,1)   line(-3*i+7,4,-3*i+7,2,arroline(4,9,-3*i+7,6,arrow)</pre>	$\frac{13}{6} = 2.2x$
9-0-0	Circle(5,8) Circle(2,8) Circle(8,11) Line(2,9, 2,10) Circle(8,8) Line(3,8, 4,8) Line(3,11, 4,11) etc; 21 lines	<pre>for(i&lt;3)   for(j&lt;3)   if(j&gt;0)   line(-3*j+8,-3*i+7,</pre>	$\frac{21}{6} = 3.5x$
	Rectangle (1,10,3,11) Rectangle (1,12,3,13) Rectangle (4,8,6,9) Rectangle (4,10,6,11) etc; 16 lines	for(i<4) for(j<4) rectangle(-3*i+9,-2*j+6, -3*i+11,-2*j+7)	$\frac{16}{3} = 5.3x$
	Line(3,10,3,14,arrow) Rectangle(11,8,15,10) Rectangle(11,14,15,15) Line(13,10,13,14,arrow) etc; 16 lines	<pre>for(i&lt;3)   line(7,1,5*i+2,3,arrow)   for(j<i+1) if(j="">0)      line(5*j-1,9,5*i,5,arrow)     line(5*j+2,5,5*j+2,9,arrow)   rectangle(5*i,3,5*i+4,5)   rectangle(5*i,9,5*i+4,10) rectangle(2,0,12,1)</i+1)></pre>	$\mathbf{G}$
	Circle(2,8) Rectangle(6,9, 7,10) Circle(8,8) Rectangle(6,12, 7,13) Rectangle(3,9, 4,10) etc; 9 lines	<pre>reflect(y=8) for(i&lt;3)   if(i&gt;0)   rectangle(3*i-1,2,3*i,3)   circle(3*i+1,3*i+1)</pre>	$\frac{9}{5} = 1.8x$