Synthesizing Programs for Images using Reinforced Adversarial Learning

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Motivation

- inverse graphics: In the visual domain, inversion of a renderer for the purposes of scene understanding
- renderer: automatic process of generating a photorealistic or non-photorealistic image from a 2D or 3D model by means of computer programs
- input programs that have sequential semantics, are composed of discrete symbols (e.g., keystrokes in a CAD program), and are long (tens or hundreds of symbols)
- an adversarially trained agent generates visual programs
- executed by a graphics engine to generate images, either conditioned on data or unconditionally
- The agent is rewarded by fooling a discriminator network
- trained with distributed reinforcement learning without any extra supervision
- target distribution of real images: \( p_d \)
- external black box renderer: input \((a_1, \ldots, a_n)\) converted to bitmap (for example a CAD program)
- \( p_d \approx R(p_a) \)
- \( p_a \): policy network or agent (\( \pi \) RNN)
- Generation: \( \pi + R \)
Figure: An execution trace of the SPIRAL agent. The policy outputs program fragments which are rendered into an image at each step via a graphics engine R. The agent can make use of these intermediate renders to adjust its policy. The agent only receives a reward in the final step of execution.
Training Objectives

Wasserstein GAN training for Discriminator:

\[ L_D = -E_{x \sim p_d} D(x) + E_{x \sim p_g} D(x) + R \]  \hspace{1cm} (1)

Generator:

\[ L_G = -E_{x \sim p_g} D(x) \]  \hspace{1cm} (2)

cannot train with naive gradient descent: black box renderer
Training generator

- maximization of the expected return which can be solved using standard techniques from reinforcement learning.
- Use Advantage Actor Critic

\[ L_G = -\sum_t \pi(a_t|s_t; \theta)[R_t - V^\pi(s_t)] \] (3)

- \( R_t = \sum_t^N r_t \)
- Optimizes 2 if

\[ r_t = \begin{cases} 0, & t < N, \\ D(\mathcal{R}(a_1, a_2, \ldots, a_N)), & t = N. \end{cases} \]

**Figure:** generator reward
Conditional generation

- condition the model on auxiliary input
- find a specific program that generates a given image
- supply $x_{target}$ to the policy and to the discriminator networks.
- $p_g = R(p_a(a|x_{target}))$
- $p_d$ becomes a Dirac $\delta$-function centered at $x_{target}$.
- $l_2$ optimal discriminator (however, not unique)

$$-D(x_{target}|x_{target}) + \mathbb{E}_{x \sim p_g}[D(x|x_{target})].$$

**Figure:** generator reward
Distributed Architecture

Figure: IMPALA Architecture
Experiments: Environments

- open-source painting library libmypaint
- The agent controls a brush and produces a sequence of (possibly disjoint) strokes on a canvas $C$
- The state of the environment is comprised of the contents of $C$ as well as the current brush location $l_t$.
- Each action $a_t$ is a tuple of 8 discrete decisions ($a_1, a_2, \ldots, t$) [location, color, etc]
- In a 3d scene, at each time step, the agent has to decide on the object type (4 options), its location on a $16 \times 16$ grid, its size (3 options) and the color (3 color components with 4 bins each)
Results

Figure: A SPIRAL agent is trained to draw digits/alphabets via a sequence of strokes in the libmypaint environment. As training progresses, the quality of the generated images improves, capturing the multi-modality of the dataset, varying brush sizes and digit styles.

(a) MNIST unconditional generation

(b) MNIST reconstruction

(a) Omniglot unconditional generation

(b) Omniglot reconstruction
### Results

<table>
<thead>
<tr>
<th>INPUT</th>
<th>RECONSTRUCTION</th>
<th>RECONSTRUCTION</th>
<th>TRACE</th>
</tr>
</thead>
<tbody>
<tr>
<td>64 x 64</td>
<td>64 x 64</td>
<td>256 x 256</td>
<td>256 x 256</td>
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</table>

![Character images](image_url)
**Figure 10. 3D scene reconstructions.** The SPIRAL agent is trained to reconstruct 3D scenes by emitting sequences of commands for the MuJoCo environment. In each pair, the left image corresponds to the model’s output while the right one is the target. Our method is capable of accurately inferring the number of objects, their locations, sizes and colors.