Learning Neurosymbolic Generative Models via Program Synthesis

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Generative Models and Global Structure

Full Image

¼ of Image

Baseline Completion
Our Approach: Global Structure as Programs

```plaintext
\{ for i = 1..3
  for j = 1..6
    draw(i*2, j*2, )
  \}
```
Application to Image Completion

Full Image

Third Image

Baseline Completion
(No representation of global structure)

Our Completion
Learning via Program Synthesis - Phase 1

```
for i = 1..3
    for j = 1..1
        draw(i*2, j*1, )
    ...
```
Learning via Program Synthesis - Phase 1

```
for i = 1..3
    for j = 1..1
        draw(i*2, j*1, )
    . . .
```

```
for i = 1..3
    for j = 1..6
        draw(i*2, j*2, )
    . . .
```
Learning via Program Synthesis - Phase 1

for i = 1..3
    for j = 1..1
        draw(i*2, j*1,
            ...
        )

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for i = 1..3
    for j = 1..6
        draw(i*2, j*2,
            ...
        )
Learning via Program Synthesis - Phase 2
Our approach (Synthesis-Guided Generative Model, SGM) significantly **outperforms the baseline in 5 out of 6 experiments** in image completion (as well as in all image generation experiments).

(Scores for GLCIC/CycleGAN represent Fréchet Inception Distance, scores for VED represent negative log likelihood).
Experimental Results

Original Image (Synthetic)  Original Image (Facades)
Experimental Results

Original Image (Synthetic)

Original Image (Facades)

SGM (GLCIC, Synthetic)

SGM (GLCIC, Facades)
Experimental Results

- Original Image (Synthetic)
- SGM (GLCIC, Synthetic)
- Baseline (GLCIC, Synthetic)
- Original Image (Facades)
- SGM (GLCIC, Facades)
- Baseline (GLCIC, Facades)
Future Work

• More expressive programs
• Better ways of incorporating program structure
• Domains beyond images