Learning Generative Models of Tissue Organization with Supervised GANs
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code and data: https://github.com/phyihan/supervised-gan

Motivation
A key step in understanding spatial organization of cells and tissues is the ability to construct generative models that accurately reflect that organization. We wish to build holistic generative models of cellular structures visible in high-res microscopy images.

Overview

In the first stage, we synthesize a label "image" given a noise "image" as input, which then provides supervision for EM image synthesis in the second stage. The full model naturally generates label-image pairs.

Notation: \( x \), image; \( y \), label; \( z \), latent noise vector/image.

Generative Pipeline

\[
\begin{align*}
\text{Gaussian noise } z & \quad \rightarrow \\
\text{Label generator } G_y & \quad \rightarrow \\
\text{Output1: Structural label } y & \quad \rightarrow \\
\text{Image generator } G_x & \quad \rightarrow \\
\text{Output2: EM image } x & \quad \rightarrow \\
\end{align*}
\]

Value function: \[ \min_{G_y} \max_{G_x} V(G, D), \]
where \[ V(G, D) = V_y(G_y, D_y) + V_x(G_x, D_x) \] and
\[
V_y(G_y, D_y) = \mathbb{E}_{y \sim p(y)} \left[ \log D_y(G_y(y)) + D_x \left[ \log \left(1 - D_x(G_x(G_y(y))) \right) \right] \right].
\]

For SGAN: \[ V_y(G_y, D_y) = \mathbb{E}_{y \sim p(y)} \left[ \log D_y(G_y(y)) + D_x \left[ \log \left(1 - D_x(G_x(y)) \right) \right] \right]. \]

For DSGAN: We add a reconstructor \( \hat{G}_y \) and solve \[ \min_{G_y} \max_{G_x} V_y(G_y, D_y) + V_x(G_x, D_x). \]

Results

We introduce fully-convolutional generator and multiscale discriminators.

Evaluation

Segmentation Accuracies

The diverseness of generated samples is measured by the ‘Birthday Paradox’.

Conclusion

We explore methods towards supervised GAN training, where the generative process is factorized and guided by structural labels. New modifications for both generators and discriminators are also proposed to alleviate mode collapse and allow fully-convolutional generation. Finally, we demonstrate by extensive evaluation that our supervised GANs can synthesize considerably more accurate images than unsupervised baselines.