Self-Attention Generative Adversarial Networks

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Introduction

- Image synthesis
  - Remarkable progress: Emergence of GANs
  - GANs based on deep convolutional networks
    - SOTA ImageNet GAN Miyato and Koyama,2018
    - Self-attention
  - Self-Attention Generative Adversarial Networks(SAGANs)
    - Enforcing good conditioning of GAN generators using the spectral normalization technique
    - Inception Score (IS) from 36.8 to **52.52** and reducing Frechet Inception Distance (FID) from 27.62 to **18.65**

Related Work

- Generative Adversarial Networks
  - Great success in various image generation tasks
    ; image-to-image translation, image super-resolution and text-to-image synthesis
  - Known to be unstable and sensitive to the choices of hyperparameters
  - Attempt to stabilize the GAN training dynamics and improve the sample diversity
  - Limiting spectral norm of the weight matrices in the discriminator
- Attention Models
  - Capture global dependencies
  - Self-attention as a non-local operation

Background

- Spectral Normalization
  - Controls the Lipschitz constant by literally constraining the spectral norm of each layer

Spectral Norm of Matrix A (L2 Matrix Norm of A)

$$\sigma(A) := \max_{\mathbf{h}:\mathbf{h}\neq 0} \frac{||A\mathbf{h}||_2}{||\mathbf{h}||_2} = \max_{||\mathbf{h}||_2 \leq 1} ||A\mathbf{h}||_2 \tag{1}$$

- Equivalent to the largest singular value of A

$$||g||_{Lip} = sup_h \sigma(\nabla g(\mathbf{h})) = sup_{\mathbf{h}} \sigma(W) = \sigma(W), where, g(\mathbf{h}) = W\mathbf{h} \tag{2}$$

$$||f||_{Lip} : ||f||_{Lip} \leq ||\mathbf{h}_L \mapsto W^{L+1}\mathbf{h}_L||_{Lip} \cdot ||a_L||_{Lip} \cdot ||\mathbf{h}_{L-1} \mapsto W^L \mathbf{h}_{L-1}||_{Lip}$$

$$\cdots ||a_1||_{Lip} \cdot ||\mathbf{h}_0 \mapsto W^1\mathbf{h}_0||_{Lip} = \prod_{l=1}^{L+1} ||\mathbf{h}_{l-1} \mapsto W^l \mathbf{h}_{l-1}||_{Lip} = \prod_{l=1}^{L+1} \sigma(W^l) \tag{2.1}$$

Background

- Spectral Normalization
  - Normalize the spectral norm of the weight matrix W so that it satisfied the Lipschitz constraint $\sigma(W) = 1$

$$\bar{W}_{SN}(W) := W/\sigma(W) \tag{3}$$
$$\sigma(\bar{W}_{SN}(W)) = 1 \tag{3.1}$$

- The Hinge Version of the Adversarial Loss

$$\begin{aligned} V_D(\hat{G}, D) = \mathbb{E}_{x\sim q_{data}(x)}[\min(0, -1 - D(\mathbf{x}))] \\ +\mathbb{E}_{x\sim q_{data}(x)}[\min(0, -1 - D(\hat{G}(\mathbf{z})))] \end{aligned}$$

$$V_G(G, \hat{D}) = -\mathbb{E}_{\mathbf{z}\sim p(z)}[\hat{D}(G(\mathbf{z}))] \tag{4}$$

Self-Attention Module

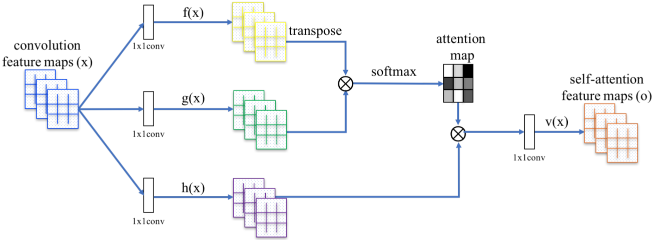
$$\beta_{j,i} = \frac{exp(s_{ij})}{\sum_{i=1}^{N} exp(s_{ij})}, \quad where \ s_{ij} = \mathbf{f}(\mathbf{x}_i)^T \mathbf{g}(\mathbf{x}_j) \tag{5}$$

$$\mathbf{o} = (\mathbf{o_1}, \mathbf{o_2}, ..., \mathbf{o_j}, ..., \mathbf{o_N}) \in \mathbb{R}_{CxN},$$

$$where, \mathbf{o}_j = \mathbf{v}\left(\sum_{i=1}^{N} \beta_{j,i}\mathbf{h}(\mathbf{x}_i)\right), \ \ \mathbf{h}(\mathbf{x_i}) = \mathbf{W_h x_i}, \ \ \mathbf{v}(\mathbf{x_i}) = \mathbf{W_v x_i} \tag{6}$$

$$\mathbf{y_i} = \gamma \mathbf{o_i} + \mathbf{x_i} \tag{7}$$

Self-Attention Generative Adversarial Networks



Hinge version of the adversarial loss

$$L_D = -\mathbb{E}_{(x,y)\sim p_{data}}[min(0, -1 + D(x, y))]$$
$$-\mathbb{E}_{z\sim p_z, y\sim p_{data}}[min(0, -1 - D(G(z), y))]$$

$$L_G = -\mathbb{E}_{z\sim p_z, y\sim p_{data}} D(G(z), y), \tag{8}$$

Techniques to Stabilize the Training of GANs

- Spectral normalization in the generator as well as in the discriminator
- The two-timescale update rule (TTUR)
    - Spectral normalization (SN) for both generator and discriminator
        - Restricting the spectral norm of each layer
        - Does not require extra hyper-parameter tuning
        - Computational cost is relatively small
    - Imbalanced learning rate for generator and discriminator updates
        - Regularization of the discriminator often slows down the GAN's learning process
        - Using separate learning rates (TTUR)
        - Produce better results given the same wall-clock time

Experiments

- Evaluation metrics
  - Inception Score (IS) and Frechet Inception Distance (FID)
- Network structures and implementation details
  - Evaluating the proposed stabilization techniques
  - Self-attention mechanism
  - Comparison with the state-of-the-art

Conclusion

- Self-Attention Generative Adversarial Networks (SAGANs)
  - The self-attention module
  - Spectral normalization and TTUR