## 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)

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

Equivalent to the largest singular value of A

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

$$||f||_{Lip} : ||f||_{Lip} \le ||\mathbf{h}_{L} \mapsto W^{L+1}\mathbf{h}_{L}||_{Lip} \cdot ||a_{L}||_{Lip} \cdot ||\mathbf{h}_{L-1} \mapsto W^{L}\mathbf{h}_{L-1}||_{Lip}$$

$$\cdots ||a_{1}||_{Lip} \cdot ||\mathbf{h}_{0} \mapsto W^{1}\mathbf{h}_{0}||_{Lip} = \prod_{l=1}^{L+1} ||\mathbf{h}_{l-1} \mapsto W^{l}\mathbf{h}_{l-1}||_{Lip} = \prod_{l=1}^{L+1} \sigma(W^{l}) \quad (2.1)$$

# 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

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

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

### Self-Attention Generative Adversarial Networks

#### Self-Attention Module

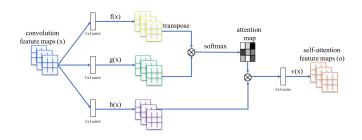
$$\beta_{j,i} = \frac{\exp(s_{ij})}{\sum_{i=1}^{N} \exp(s_{ij})}, \text{ where } s_{ij} = \mathbf{f}(\mathbf{x}_i)^T \mathbf{g}(\mathbf{x}_j)$$
 (5)

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

where, 
$$\mathbf{o}_j = \mathbf{v} \left( \sum_{i=1}^N \beta_{j,i} \mathbf{h}(\mathbf{x}_i) \right), \quad \mathbf{h}(\mathbf{x}_i) = \mathbf{W}_h \mathbf{x}_i, \quad \mathbf{v}(\mathbf{x}_i) = \mathbf{W}_v \mathbf{x}_i$$
 (6)

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

### Self-Attention Generative Adversarial Networks



## Hinge version of the adversarial loss

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

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

## 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