Deep Learning for Computer Vision

GAN Improvements

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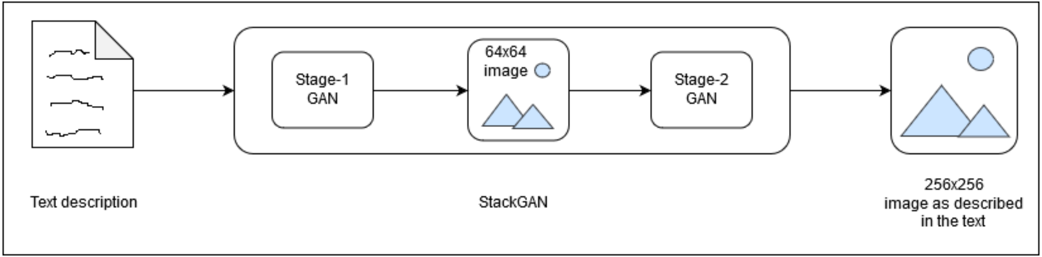
StackGAN[1]

Generate 256 x 256 photo-realistic images conditioned on text descriptions



[1]Zhang et al, StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks, ICCV 2017

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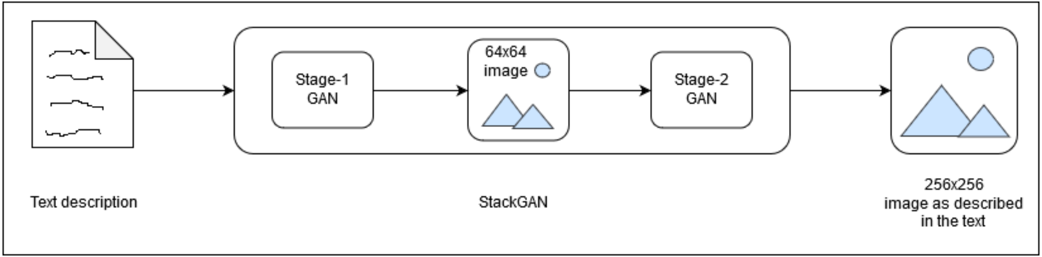

- **Stage 1:** Generate 64×64 images, low details

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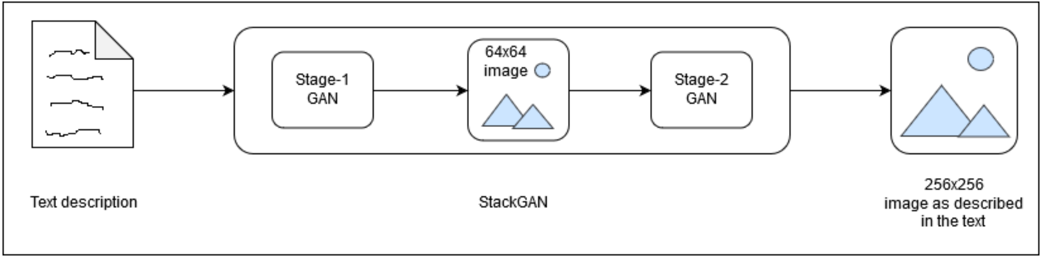
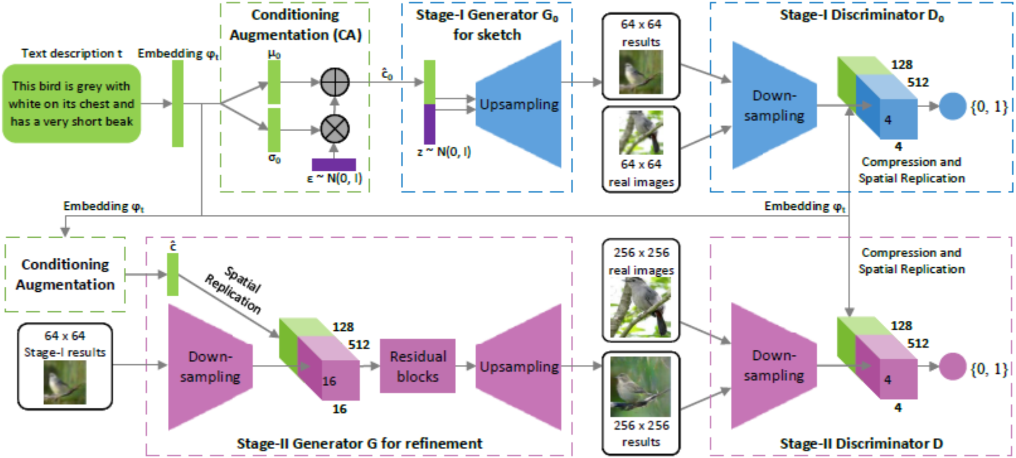


- **Stage 1:** Generate 64×64 images, low details
- **Stage 2:** Take Stage 1 output, generate 256×256, high detail and photo realistic, images
- Both stages conditioned on same textual input

[1]Zhang et al, StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks, ICCV 2017

StackGAN: Two-stage Network[2]



[2]Zhang et al, StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks, ICCV 2017

Loss Functions

Scores from Discriminator:

$$s_r \leftarrow D(x, h) \qquad \{\text{real image, correct text}\}$$
$$s_w \leftarrow D(x, \hat{h}) \qquad \{\text{real image, wrong text}\}$$
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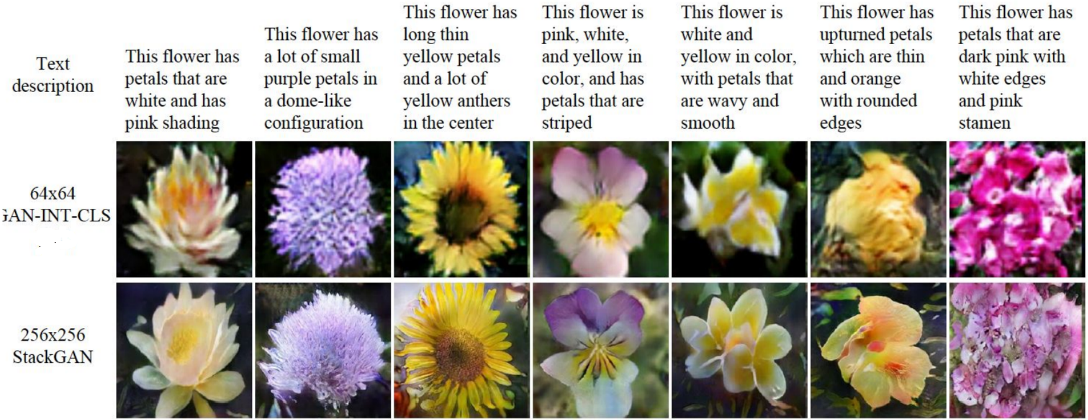
Then alternate maximizing:

$$\mathcal{L}_D \leftarrow \log(s_r) + (\log(1 - s_w) + \log(1 - s_f))/2$$

and minimizing:

$$\mathcal{L}_G \leftarrow \log(1 - s_f) + \lambda D_{KL}(\mathcal{N}(\mu_0(\phi_t), \Sigma_0(\phi_t))||\mathcal{N}(0, I))$$

StackGAN: Sample Results[3]



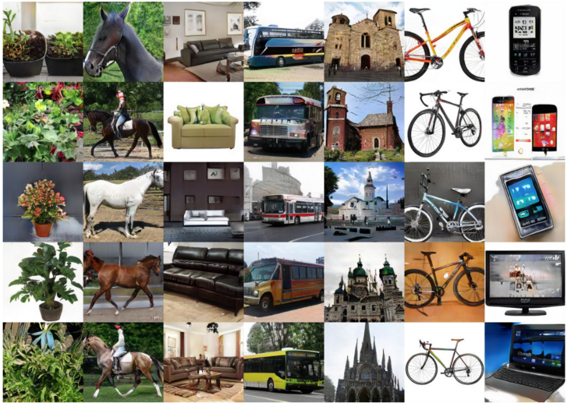
[3] Zhang et al, StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks, ICCV 2017; Reed et al, GAN-INT-CLS: Generative Adversarial Text to Image Synthesis, ICML 2016

Progressive GAN[4]

- Generates high-resolution images at 1024×1024 resolution
- **Key idea:** Grow both generator and discriminator progressively

[4] Karras et al, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

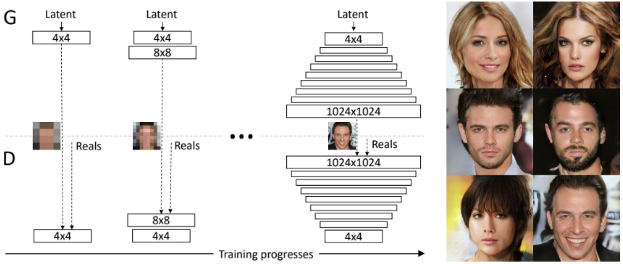
Progressive GAN[4]



- Generates high-resolution images at 1024×1024 resolution
- **Key idea:** Grow both generator and discriminator progressively
- **Other contributions:** Minibatch standard deviation, equalized learning rate and pixel-wise feature vector normalization in generator

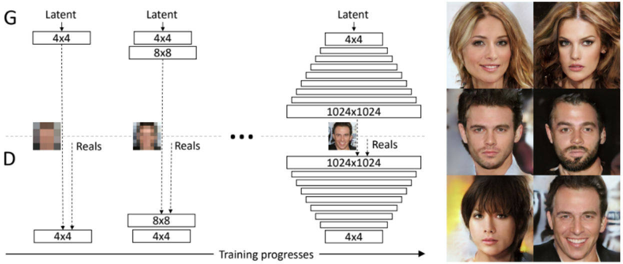
[4]Karras et al, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

Progressive GAN: Multi-scale Architecture



- Generator first produces 4×4 images until this reaches some kind of convergence

Progressive GAN: Multi-scale Architecture



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- Then task increases to 8×8 images, and so on until 1024×1024

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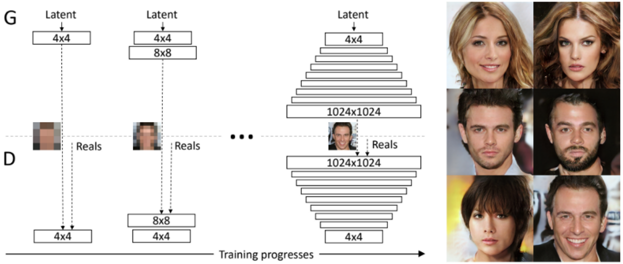
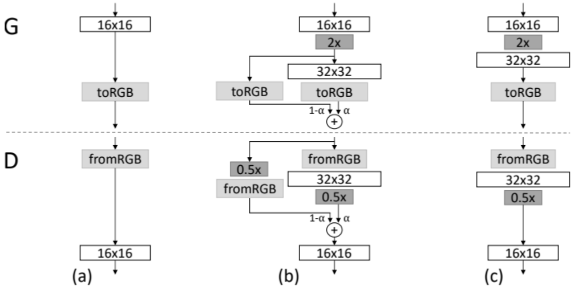


- Generator first produces 4×4 images until this reaches some kind of convergence
- Then task increases to 8×8 images, and so on until 1024×1024
- Allows for stable training of high-resolution images

Progressive GAN: Fading in New Layers



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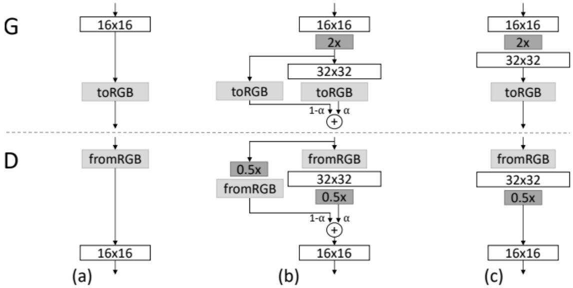

- Methodology similar to ResNets
- In figure (b), generator G:
  - **Nearest neighbor interpolation** of upsampled 16×16 layer's output, i.e. 32×32 is added to a 32×32 output layer
  - $\alpha \times$ new output layer $+ (1 - \alpha) \times$ projected layer; $\alpha \in \{0, 1\}$

Progressive GAN: Other Contributions

- **Minibatch standard deviation:** Standard deviation for each feature in each spatial location over a minibatch computed and averaged; this is concatenated to all spatial locations at a later layer of discriminator. Why?

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- **Pixelwise feature vector normalization in generator G:** Normalize feature vector in each pixel of G after each convolutional layer using:

$$b_{x,y} = \frac{a_{x,y}}{\sqrt{\frac{1}{N}\sum_{j=0}^{N-1}(a_{x,y}^{j})^2 + \epsilon}} \tag{1}$$

where $\epsilon = 10^{-8}$, N is number of feature maps, $a_{x,y}$ and $b_{x,y}$ are original and normalized feature vectors in pixel (x, y) respectively

Progressive GAN: Results[5]

Mao et al. (2016b) (128×128) Gulrajani et al. (2017) (128×128) Our (256×256)

[5]Karras et al, Progressive Growing of GANs for Improved Quality, Stability, and Variation, ICLR 2018

StyleGAN[6]

- ProGAN generates high-quality images, but control of specific features is very limited

[6]Karras et al, A Style-Based Generator Architecture for Generative Adversarial Networks, CVPR 2019

StyleGAN[6]

- ProGAN generates high-quality images, but control of specific features is very limited
- **StyleGAN:** Automatically learned, unsupervised separation of high-level attributes (pose and identity), stochastic variation (hair) and scale-specific control attributes

[6] Karras et al, A Style-Based Generator Architecture for Generative Adversarial Networks, CVPR 2019

How StyleGAN works: Intuition

- **Coarse** resolution of up to 82 - affects pose, general hair style, face shape, etc

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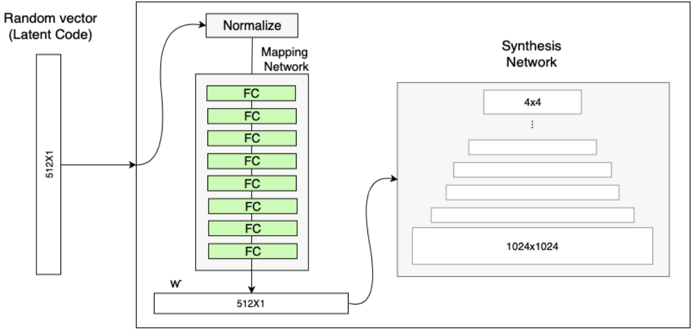
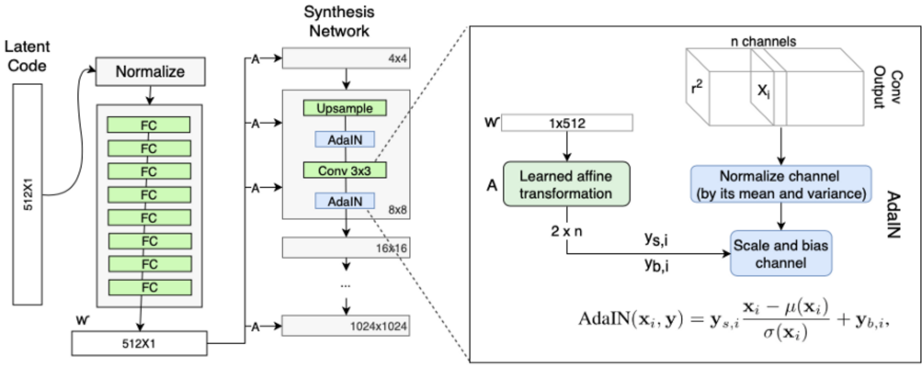
- **Coarse** resolution of up to 82 - affects pose, general hair style, face shape, etc
- **Middle** resolution of 162 to 322 - affects finer facial features, hair style, eyes open/closed, etc
- **Fine** resolution of 642 to 10242 - affects color scheme (eye, hair and skin) and micro features

StyleGAN: Mapping Network



- Encodes input vector into an intermediate vector to control different visual features
- 8 fully connected (FC) layers, output w is of same size as input layer, i.e. 512×1

StyleGAN: Adaptive Instance Normalization



$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i}\frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

- Transfers w (from mapping net) to generated image
- Module is added to each resolution level of synthesis network, defines the visual expression of features in that level

SPADE[7]

Key Idea

- Previous methods directly feed semantic layout as input to network

[7] Park et al, Semantic Image Synthesis with Spatially-Adaptive Normalization, CVPR 2019

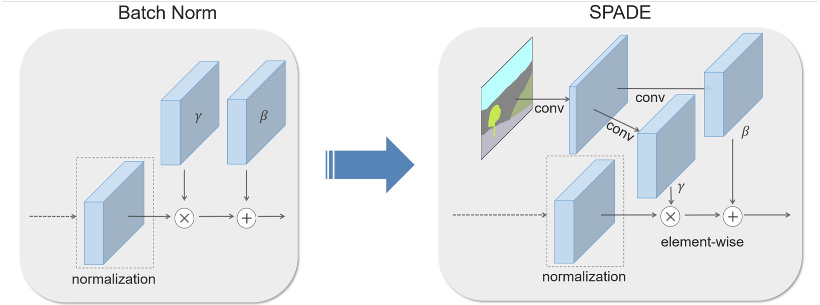
SPADE[7]

Key Idea

- Previous methods directly feed semantic layout as input to network
- **Spatially-adaptive normalization:** Input layout for modulating activations in normalization layers through a spatially-adaptive, learned transformation

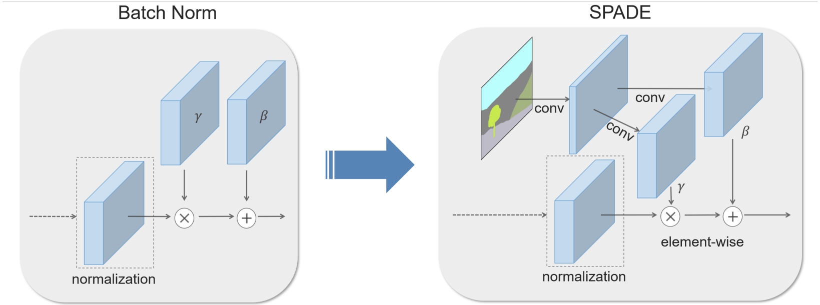
[7] Park et al, Semantic Image Synthesis with Spatially-Adaptive Normalization, CVPR 2019

SPADE: Methodology



- Batch Normalization gives us affine layers

SPADE: Methodology



- Batch Normalization gives us affine layers
- In SPADE, affine layer is learned from semantic segmentation map (or any other computer vision task)

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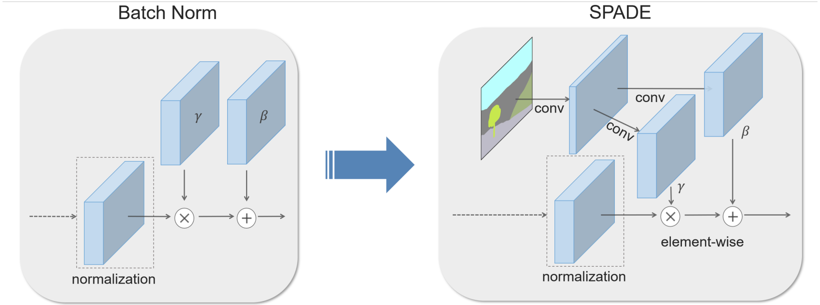
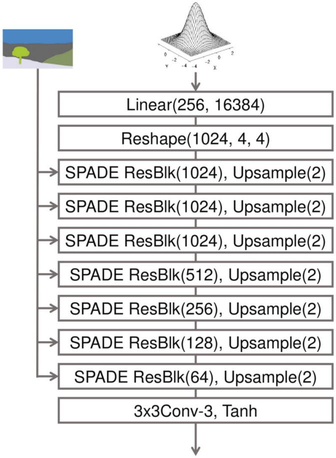
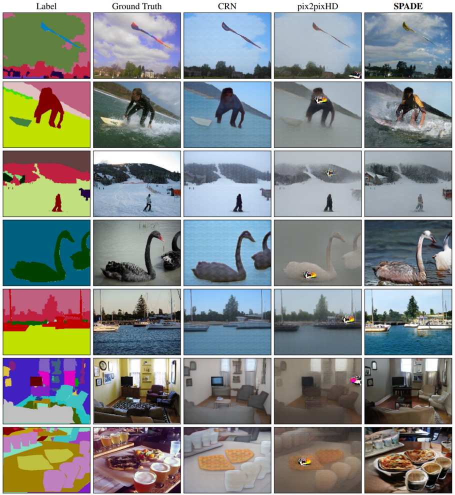


- Batch Normalization gives us affine layers
- In SPADE, affine layer is learned from semantic segmentation map (or any other computer vision task)
- Semantic information is provided via SPADE layers; random latent vector may still be used as input to network, used to manipulate style of generated images

SPADE: Architecture and Results[8]





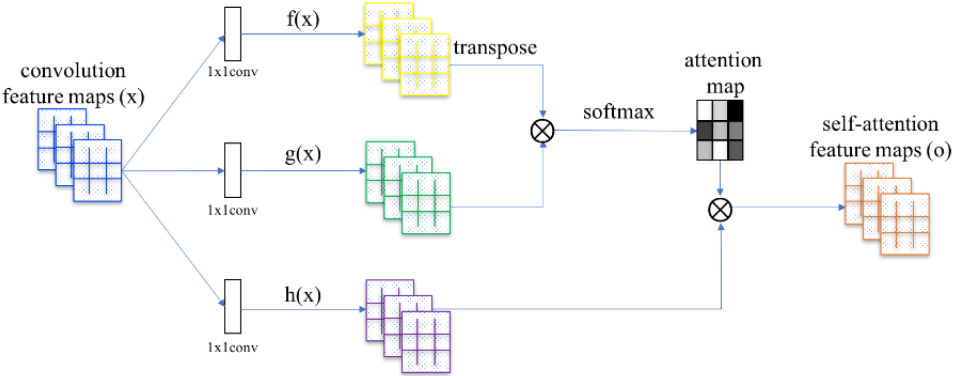
[8]Park et al, Semantic Image Synthesis with Spatially-Adaptive Normalization, CVPR 2019

BigGAN[9]

- Intended to scale up GANs for better high-resolution generation
- Designed for class-conditional image generation (generation of images using both a noise vector and class information as input)
- Multiple design decisions to improve generation quality

[9] Brock et al, Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019

BigGAN

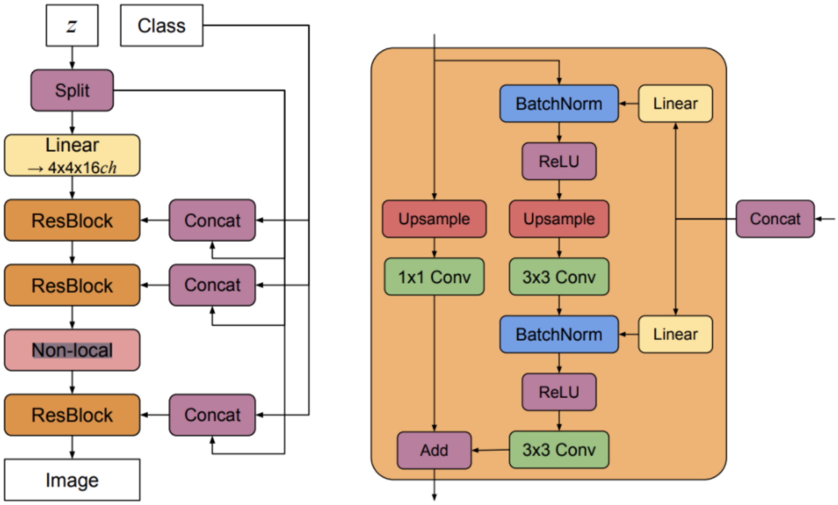


Base model is **Self-Attention GAN (SAGAN)**

Trained using **Hinge Loss:** $\max(0, 1 - t \cdot y)$, where t is target output and y is predicted output

Credit: Zhang et al, Self-Attention Generative Adversarial Networks, ICML 2019

BigGAN: Class-conditional Latents



BigGAN: Other Design Decisions

- **Spectral Normalization:** Normalizes weight matrix W using spectral norm so that it satisfies Lipschitz constraint $\sigma(W) = 1$ (See Miyato et al, Spectral Normalization for Generative Adversarial Networks, ICLR 2018 for details)
- **Orthogonal Weight Initialization:** Initialize weights in each layer to be a random orthogonal matrix (satisfying $W^TW = I$)
- **Skip-z Connections:** Directly connect input latent z to specific layers deep in the network
- **Orthogonal Regularization:** Encourages weights to be orthogonal: $R_\beta(W) = \beta||W^TW - I||_F^2$. Why? Homework!

Credit: Jason Brownlee, MachineLearningMastery.com

BigGAN: Other Tricks/Hacks

- Updates discriminator model twice before updating generator model in each training iteration
- Model weights are averaged across prior training iterations using a moving average (similar to Progressive GAN)
- Large batch sizes of 256, 512, 1024 and 2048 images (best performance at 2048)
- More model parameters: doubled number of channels or feature maps (filters) in each layer
- **Truncation Trick:** Sample from truncated Gaussian (values above a threshold) as input at inference alone

Credit: Jason Brownlee, MachineLearningMastery.com

Homework

Readings

- Wang et al, Generative Adversarial Networks in Computer Vision: A Survey and Taxonomy, arXiv 2020
- Chapter 20 (Deep Generative Models), Deep Learning book
- Code links:
  - Progressive GAN: `https://github.com/tkarras/progressive_growing_of_gans`
  - StackGAN: `https://github.com/hanzhanggit/StackGAN`
  - StyleGAN: `https://github.com/NVlabs/stylegan`
  - BigGAN: `https://github.com/ajbrock/BigGAN-PyTorch`

Questions

- Minibatch Standard Deviation is used in ProgressiveGAN. Why is this useful?
- Orthogonal Regularization of weights is used in BigGAN. Why is this useful?

References

[1] Tero Karras et al. "Progressive growing of gans for improved quality, stability, and variation". In: *arXiv preprint arXiv:1710.10196* (2017).

[2] Han Zhang et al. "Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks". In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 5907–5915.

[3] Andrew Brock, Jeff Donahue, and Karen Simonyan. "Large Scale GAN Training for High Fidelity Natural Image Synthesis". In: *International Conference on Learning Representations*. 2018.

[4] Tero Karras, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2019, pp. 4401–4410.

[5] Taesung Park et al. "Semantic image synthesis with spatially-adaptive normalization". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019, pp. 2337–2346.