

GANs in action

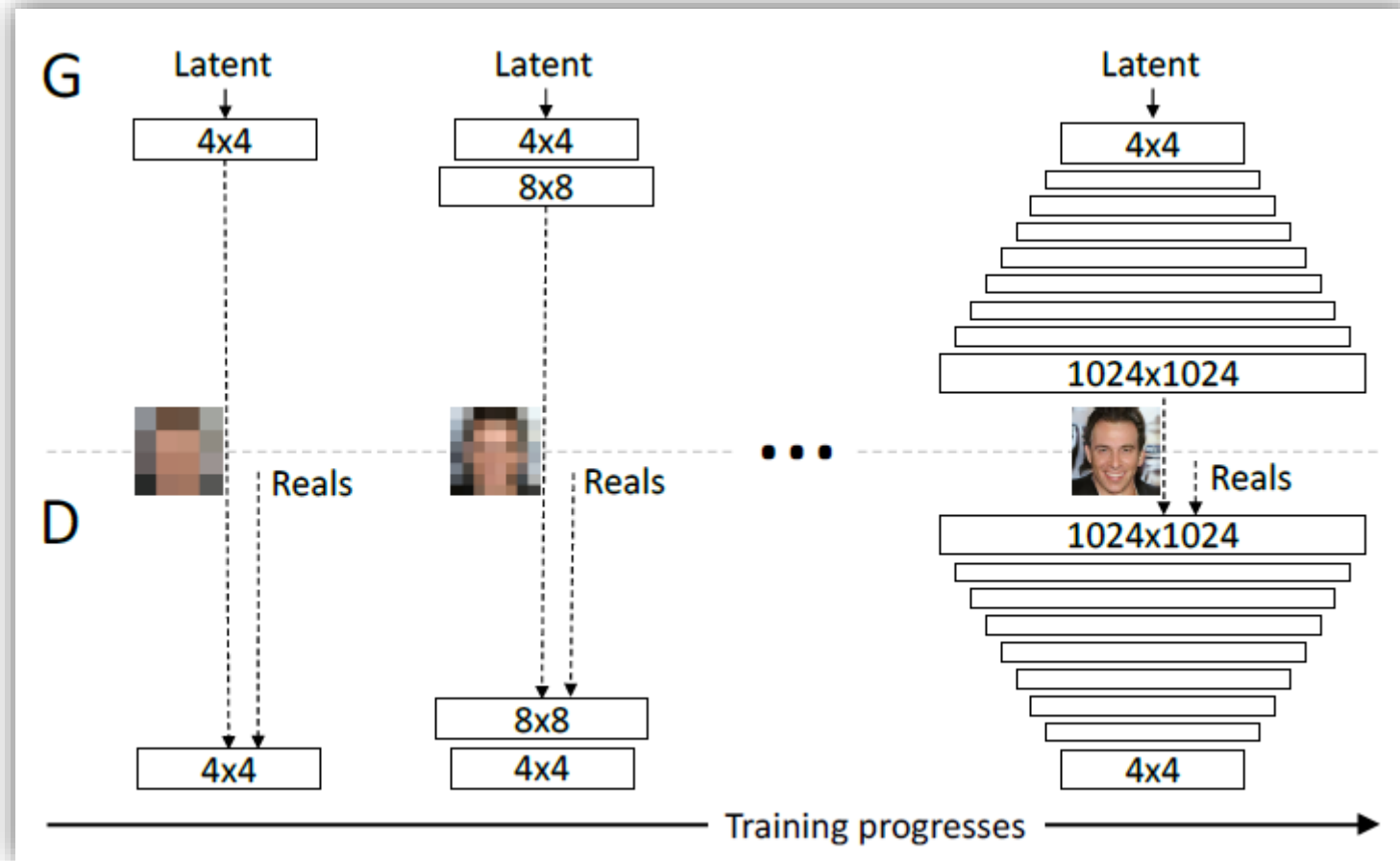
ProGAN

한병찬

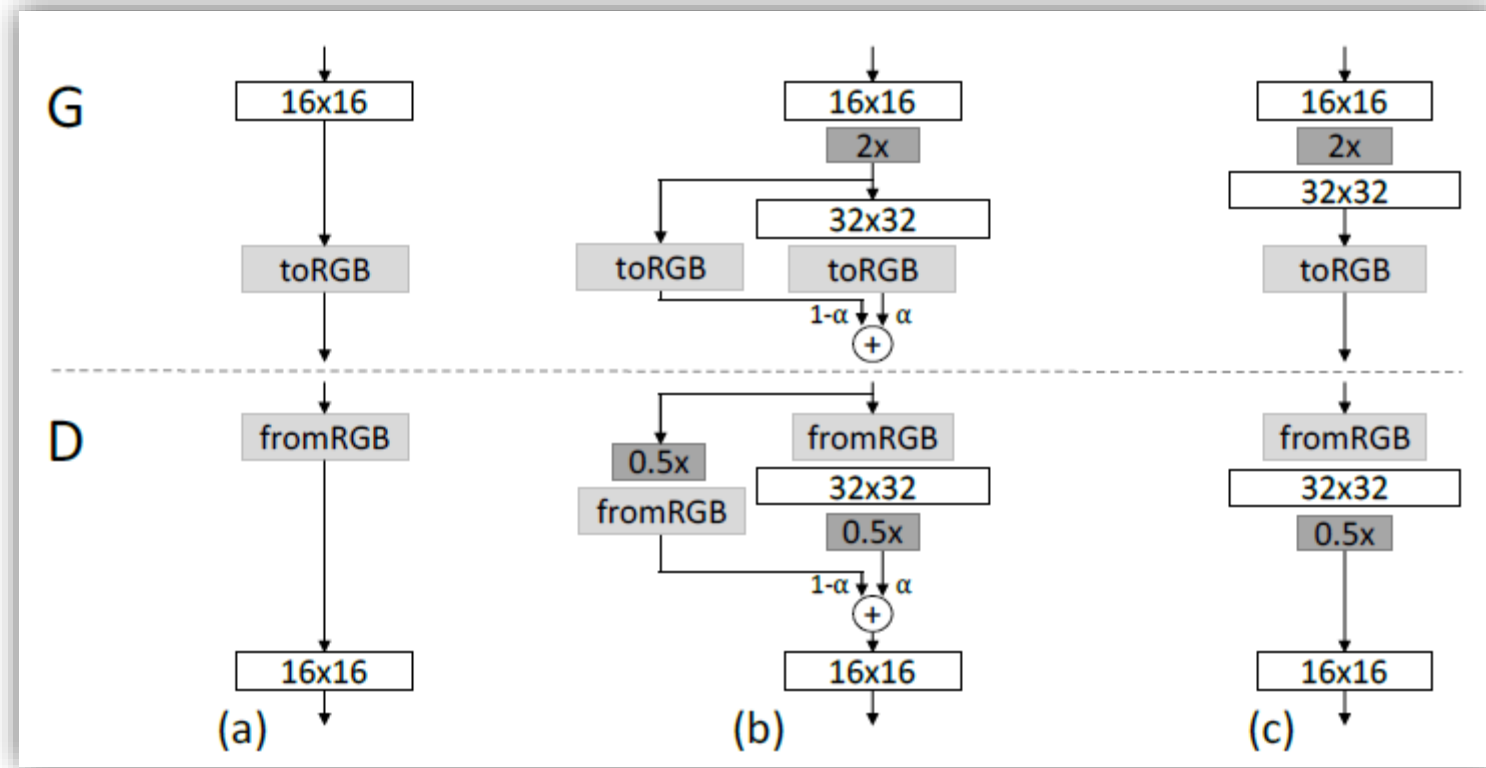
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Progressive structure



Progressive structure



Progressive structure

Generator	Act.	Output shape	Params
Latent vector	–	$512 \times 1 \times 1$	–
Conv 4×4	LReLU	$512 \times 4 \times 4$	4.2M
Conv 3×3	LReLU	$512 \times 4 \times 4$	2.4M
Upsample	–	$512 \times 8 \times 8$	–
Conv 3×3	LReLU	$512 \times 8 \times 8$	2.4M
Conv 3×3	LReLU	$512 \times 8 \times 8$	2.4M
Upsample	–	$512 \times 16 \times 16$	–
Conv 3×3	LReLU	$512 \times 16 \times 16$	2.4M
Conv 3×3	LReLU	$512 \times 16 \times 16$	2.4M
Upsample	–	$512 \times 32 \times 32$	–
Conv 3×3	LReLU	$512 \times 32 \times 32$	2.4M
Conv 3×3	LReLU	$512 \times 32 \times 32$	2.4M
Upsample	–	$512 \times 64 \times 64$	–
Conv 3×3	LReLU	$256 \times 64 \times 64$	1.2M
Conv 3×3	LReLU	$256 \times 64 \times 64$	590k
Upsample	–	$256 \times 128 \times 128$	–
Conv 3×3	LReLU	$128 \times 128 \times 128$	295k
Conv 3×3	LReLU	$128 \times 128 \times 128$	148k
Upsample	–	$128 \times 256 \times 256$	–
Conv 3×3	LReLU	$64 \times 256 \times 256$	74k
Conv 3×3	LReLU	$64 \times 256 \times 256$	37k
Upsample	–	$64 \times 512 \times 512$	–
Conv 3×3	LReLU	$32 \times 512 \times 512$	18k
Conv 3×3	LReLU	$32 \times 512 \times 512$	9.2k
Upsample	–	$32 \times 1024 \times 1024$	–
Conv 3×3	LReLU	$16 \times 1024 \times 1024$	4.6k
Conv 3×3	LReLU	$16 \times 1024 \times 1024$	2.3k
Conv 1×1	linear	$3 \times 1024 \times 1024$	51
Total trainable parameters			23.1M

Discriminator	Act.	Output shape	Params
Input image	–	$3 \times 1024 \times 1024$	–
Conv 1×1	LReLU	$16 \times 1024 \times 1024$	64
Conv 3×3	LReLU	$16 \times 1024 \times 1024$	2.3k
Conv 3×3	LReLU	$32 \times 1024 \times 1024$	4.6k
Downsample	–	$32 \times 512 \times 512$	–
Conv 3×3	LReLU	$32 \times 512 \times 512$	9.2k
Conv 3×3	LReLU	$64 \times 512 \times 512$	18k
Downsample	–	$64 \times 256 \times 256$	–
Conv 3×3	LReLU	$64 \times 256 \times 256$	37k
Conv 3×3	LReLU	$128 \times 256 \times 256$	74k
Downsample	–	$128 \times 128 \times 128$	–
Conv 3×3	LReLU	$128 \times 128 \times 128$	148k
Conv 3×3	LReLU	$256 \times 128 \times 128$	295k
Downsample	–	$256 \times 64 \times 64$	–
Conv 3×3	LReLU	$256 \times 64 \times 64$	590k
Conv 3×3	LReLU	$512 \times 64 \times 64$	1.2M
Downsample	–	$512 \times 32 \times 32$	–
Conv 3×3	LReLU	$512 \times 32 \times 32$	2.4M
Conv 3×3	LReLU	$512 \times 32 \times 32$	2.4M
Downsample	–	$512 \times 16 \times 16$	–
Conv 3×3	LReLU	$512 \times 16 \times 16$	2.4M
Conv 3×3	LReLU	$512 \times 16 \times 16$	2.4M
Downsample	–	$512 \times 8 \times 8$	–
Conv 3×3	LReLU	$512 \times 8 \times 8$	2.4M
Conv 3×3	LReLU	$512 \times 8 \times 8$	2.4M
Downsample	–	$512 \times 4 \times 4$	–
Minibatch stddev	–	$513 \times 4 \times 4$	–
Conv 3×3	LReLU	$512 \times 4 \times 4$	2.4M
Conv 4×4	LReLU	$512 \times 1 \times 1$	4.2M
Fully-connected	linear	$1 \times 1 \times 1$	513
Total trainable parameters			23.1M

Pixel Normalization

$$b_{x,y} = a_{x,y} / \sqrt{\frac{1}{N} \sum_{j=0}^{N-1} (a_{x,y}^j)^2 + \epsilon}, \text{ where } \epsilon = 10^{-8}$$

```
class PixelNorm(nn.Module):  
    def __init__(self):  
        super(PixelNorm, self).__init__()  
        self.epsilon = 1e-8  
  
    def forward(self, x):  
        return x / torch.sqrt(torch.mean(x ** 2, dim=1, keepdim=True) + self.epsilon)
```

Equalized Learning Rate

$$W \sim N(0, Var(W))$$

$$Var(W) = \sqrt{\frac{2}{n_{in}}} \longrightarrow \sqrt{\frac{2}{k * k * n_{in}}}$$

```
self.scale = (2 / (in_channels * (kernel_size ** 2))) ** 0.5
```

ProGAN

