

【ICML2019】Ian Goodfellow自注意力GAN的代码与PPT

专知 今天

【导读】谷歌研究人员Han Zhang和Ian Goodfellow在ICML2019提出的“自注意力生成对抗网络”（SAGAN），将自注意力机制引入到卷积GAN中，作为卷积的补充，在ImageNet多类别图像合成任务中取得了最优的结果。最近在ICML2019作者公开PPT和论文代码。

Self-Attention Generative Adversarial Networks

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【SAGAN的PPT下载】

后台回复“**SAGAN**”就可以获取《**自注意力生成对抗网络**》PPT下载链接~

论文PPT

在这篇论文中，我们提出自注意力生成对抗网络（Self-Attention Generative Adversarial Network，SAGAN）。SAGAN允许对图像生成任务进行注意力驱动、长相关性的建模。传统的卷积GAN生成的高分辨率细节仅作为在低分辨率特征图上的空间局部点的函数。在SAGAN中，可以使用来自所有特征位置的线索来生成细节。此外，鉴别器可以检查图像的远端部分的高度详细的特征彼此一致。此外，最近的研究表明，生成器条件会影响GAN的性能。利用这些发现，我们将谱归一化到GAN生成器中，并发现这改进了训练动态。我们提出的SAGAN达到了state-of-the-art的结果，将Inception score从当前最高的36.8提高到52.52，并且在具有挑战性的ImageNet数据集上将Frechet Inception

distance从27.62降低到18.65。注意力层的可视化表明，生成器利用与对象形状相对应的邻域，而不是固定形状的局部区域。

Which GAN paper are we talking about?



What did we do?

- Add Self-Attention blocks to Generator and Discriminator
- Spectral Normalization (Miyato et al., ICLR, 2018) in both Generator and Discriminator
- Different learning rate for Generator and Discriminator (TTUR: Heusel et al., NIPS, 2017)

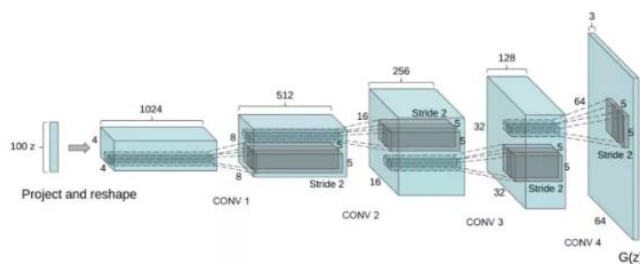
What were the results?

Model	Inception Score	Intra-FID	FID
AC-GAN	28.5	260	\
SNGAN-projection	36.8	92.4	27.62
Our SAGAN	52.52	83.7	18.65

Comparison of SAGAN and AC-GAN (A. Odena et al., ICLR, 2017),
SNGAN-projection (T. Miyato et al., ICLR, 2018) on ImageNet

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What's wrong with convolutions?



DCGAN (Radford et al, ICLR, 2016)



Improved GAN
(Salimans et al, NIPS, 2016)

- + Excel at synthesizing image classes with few structural constraints
- Fail to capture geometric or structural patterns

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What is Self-Attention?

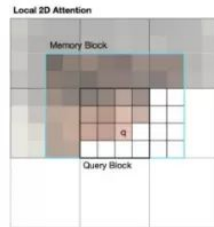
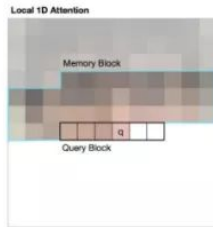


Image Transformer
(Parmar et al, ICML, 2018)

Non-local Neural Networks
(Wang et al, CVPR, 2018)

+ Models long-range dependencies more efficiently

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Self-Attention in GANs

$$y_i = \frac{1}{C(x)} \sum_j f(x_i, x_j) g(x_j)$$

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Self-Attention in GANs

$$y_i = \frac{1}{c(x)} \sum_j f(x_i, x_j) g(x_j)$$

Single output location \downarrow
 y_i
 $\sum_j f(x_i, x_j)$
 Normalizing constant
 $f(x_i, x_j)$
 "relevance" of x_j to x_i
 $g(x_j)$
 learned function of a location

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Self-Attention in GANs

$$y_i = \frac{1}{c(x)} \sum_j f(x_i, x_j) g(x_j)$$

$$f(x_i, x_j) := \exp(\langle \theta(x_i) | \phi(x_j) \rangle)$$

$$\Rightarrow \frac{1}{c(x)} \sum_j f(x_i, x_j) \text{ is a "softmax"}$$

$g(x_j)$ is just an embedding lookup

代码实现

TensorFlow实现

<https://github.com/brain-research/self-attention-gan>

依赖环境

python 3.6

TensorFlow 1.5

数据

Download Imagenet dataset and preprocess the images into tfrecord files as instructed in improved gan. Put the tfrecord files into ./data

训练

The current batch size is $64 \times 4 = 256$. Larger batch size seems to give better performance. But it might need to find new hyperparameters for G&D learning rate. Note: It usually takes several weeks to train one million steps.

```
CUDA_VISIBLE_DEVICES=0,1,2,3 python train_imagenet.py --generator_type test  
--discriminator_type test --data_dir ./data
```

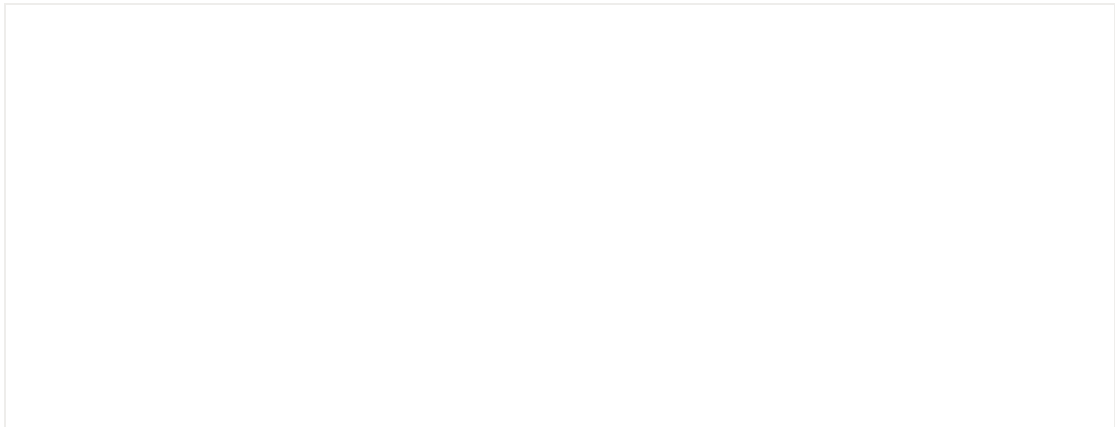
评价

```
CUDA_VISIBLE_DEVICES=4 python eval_imagenet.py --generator_type test --  
data_dir ./data
```

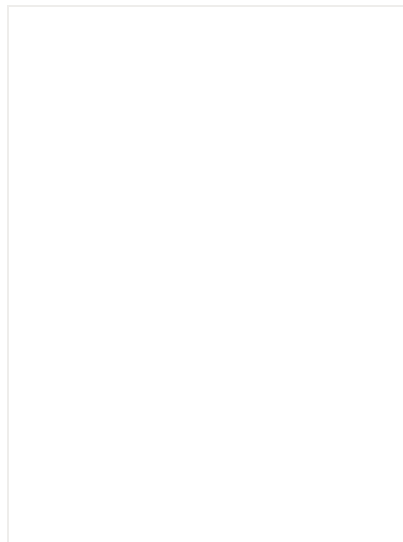
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专·知

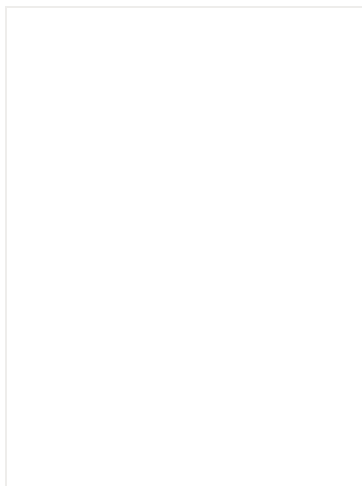
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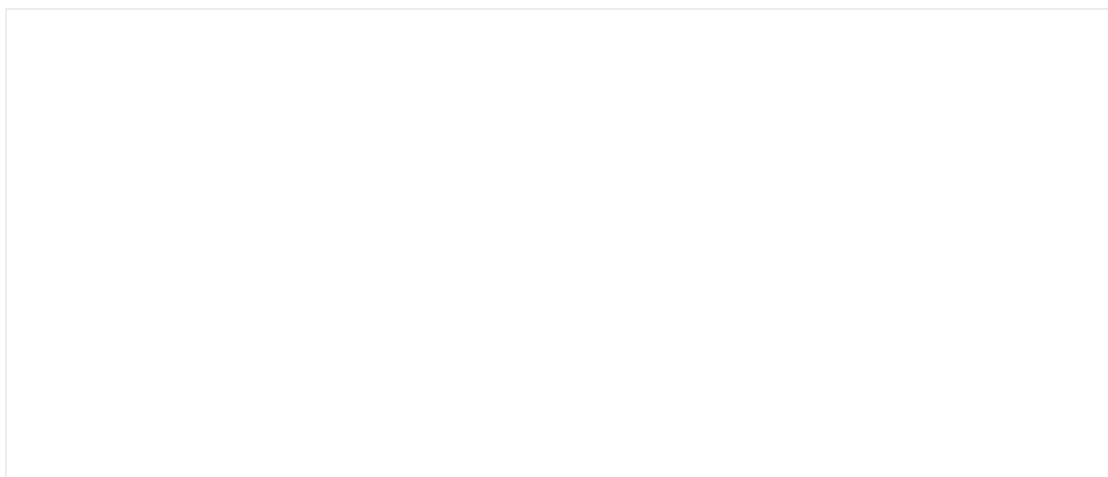
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