Generative Adversarial Nets

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Outline

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1. Introduction
   - Background
   - Motivation
2. Method
3. Experiments
4. Analysis
5. Code Implementation

Introduction: Overview

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Retrieved from https://paperswithcode.com/method/gan.

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  - Performance problem: requires feedback loops, less able to leverage piecewise linear units.

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- We want to sidestep difficulties such as intractable probabilistic computations and leveraging piecewise linear units.

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Retrieved from https://zhuanlan.zhihu.com/p/33752313.

Method: Annotations

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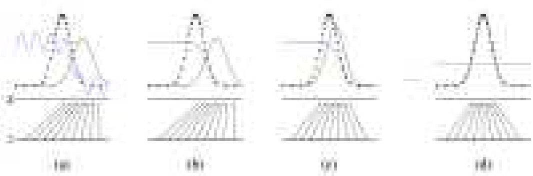
- $G\left(\mathbf{z};\theta_g\right)$ is the function representation of generator (multilayer perceptron) with parameters θ_g, differentiable. $D\left(\mathbf{x};\theta_d\right)$ similars.
- $p_{\mathbf{z}}\left(\mathbf{z}\right)$ is the prior of input noise

POV: Minimax gaming

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$



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[1] Early in learning, when G is poor, rather than training G to minimize $\left[\log\left(1 - D\left(G\left(\mathbf{z}\right)\right)\right)\right]$, we can train G to maximize $\left[\log\left(D\left(G\left(\mathbf{z}\right)\right)\right)\right]$.

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- $g\_loss = \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}\left[\log\left(1 - D\left(G\left(\mathbf{z}\right)\right)\right)\right]$[1]

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Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from noise prior $p_g(z)$.
  - Sample minibatch of m examples $\{x^{(1)}, \ldots, x^{(m)}\}$ from data generating distribution $p_{\text{data}}(x)$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(x^{(i)}\right) + \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right) \right].$$

  end for

- Sample minibatch of m noise samples $\{z^{(1)}, \ldots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

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Experiments

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Model	MNIST	TFD
DBN [3]	138 ± 2	1909 ± 66
Stacked CAE [3]	121 ± 1.6	2110 ± 50
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  - Cross validation $\rightarrow \sigma$

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  - Less computational cost
  - Model can accept multiple types of functions (differentiable)
  - Is able to represent very sharp, even degenerate distributions
- Disadvantages
  - Required synchronization between G and D (to avoid mode collapse)
  - Highly sensitive to the hyperparameter selections

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Input Format

```python
dataloader = torch.utils.data.DataLoader(
    datasets.MNIST(
        "../../data/mnist",
        train=True,
        download=True,
        transform=transforms.Compose(
            [transforms.Resize(opt.img_size), transforms.ToTensor(), transforms.Normalize([0.5], [0.5])]
        ),
    ),
    batch_size=opt.batch_size,
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- Each sample is a 28 $\times$ 28 pixel, 1 channel (grayscale) image
- ToTensor() + Normalize([0.5], [0.5]): each pixel's value is mapped to the range of [-1, 1]

Input Format (Cont.)

```
# Sample noise as generator input
z = Variable(Tensor(np.random.normal(0, 1, (imgs.shape[0], opt.latent_dim))))
```

- For each mini-batch, it generates 64 (batch size) 100-dim (latent dimension) Gaussian noises ($\mu = 0, \sigma = 1$) as noise prior $p_g\left(\mathbf{z}\right)$

Misc.

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Output Format

```python
print(
    "[Epoch %d/%d] [Batch %d/%d] [D loss: %f] [G loss: %f]"
    % (epoch, opt.n_epochs, i, len(dataloader), d_loss.item(), g_loss.item())
)

batches_done = epoch * len(dataloader) + i
if batches_done % opt.sample_interval == 0:
    save_image(gen_imgs.data[:25], "images/%d.png" % batches_done, nrow=5, normalize=True)
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- For each mini-batch, it uses BCELoss to calculate d_loss (loss for discriminator) and g_loss (loss for generator)

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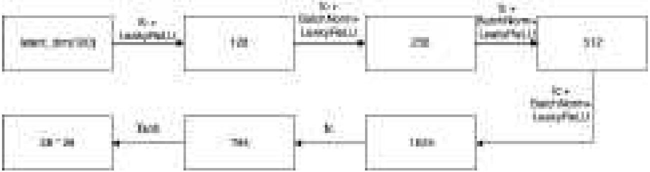
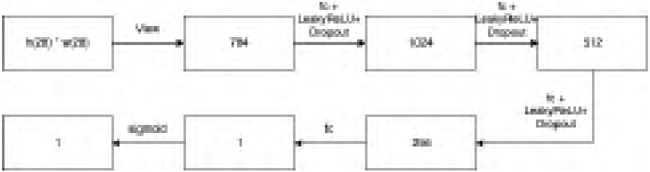
- For each mini-batch, it uses BCELoss to calculate d_loss (loss for discriminator) and g_loss (loss for generator)
- For every 400 batches (sample interval), it saves the first 25 generated images (28×28 pixel, 1 channel grayscale)

Descriptions



Generator NN Structure

Descriptions

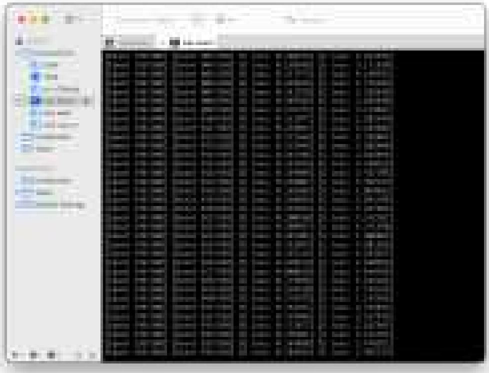


Discriminator NN Structure

Running Result

Ran on server with GeForce RTX 2080 Ti

200 epochs, batch size = 64, learning rate = 0.0002



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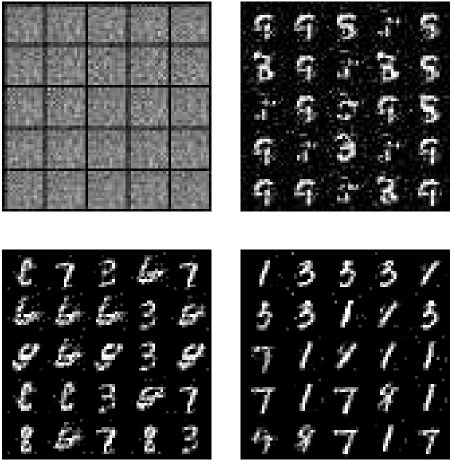
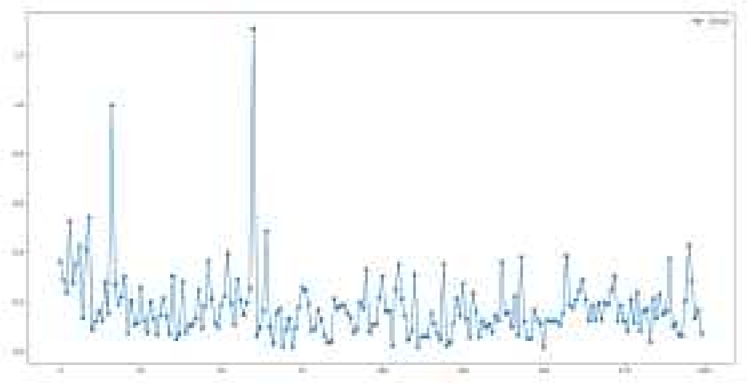


Generated Images for MNIST (patch #0, #46800, #93600, and # 180000)

Running Result



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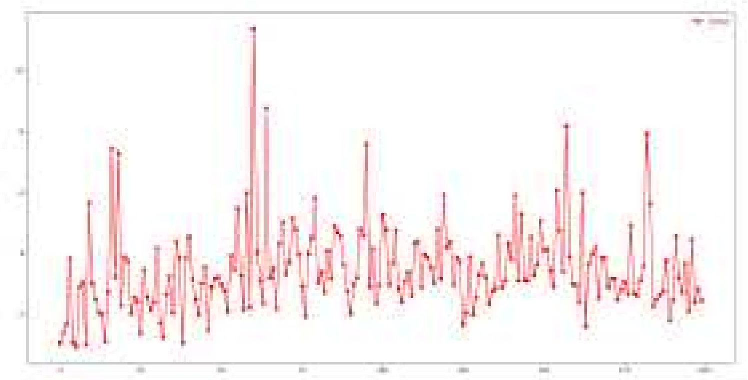

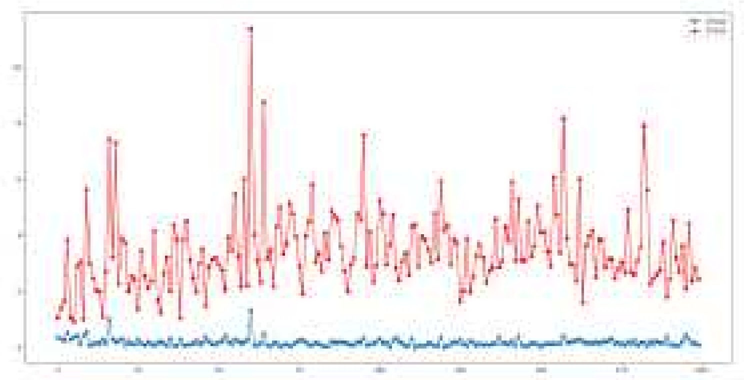

References I

[1] Ian J. Goodfellow **andothers**. "Generative Adversarial Nets". **in***Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*: **byeditor**Zoubin Ghahramani **andothers**. 2014, **pages** 2672–2680.

[2] Ming-Yu Liu, Thomas M. Breuel **and** Jan Kautz. "Unsupervised Image-to-Image Translation Networks". **in***Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*: **byeditor**Isabelle Guyon **andothers**. 2017, **pages** 700–708.