Deep Convolutional Generative Adversarial Networks

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Summary

Summary

GAN Principle

- Generator $\mathcal{G}$: Generates images of good quality starting from a noise vector z
- Discriminator $\mathcal{D}$: Distinguishes between real and fake images

The GAN objective

$$\min_{G} \max_{D} \quad \mathbb{E}_{x \sim p_{\text{data}}}[\log \mathcal{D}(x)] \; + \; \mathbb{E}_{z \sim p_z}[\log (1 - \mathcal{D}(\mathcal{G}(z)))]$$

DCGAN Ideas

- Replace fully connected layers : Convolutions of kernel size 1
- Replace pooling layers : Strided convolutions
- Upsampling : Transposed convolutions
- Batch Normalization
- Rectified Linear Units activations

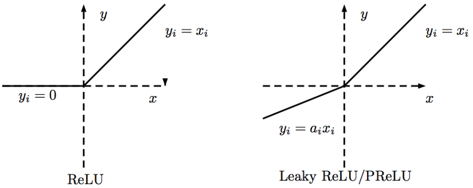


Figure – ReLU [4] and LeakyReLU [2] activations.

Data

- 20,580 dog images from ImageNet [1]
- 64×64 image size
- High variety, much harder than generating faces

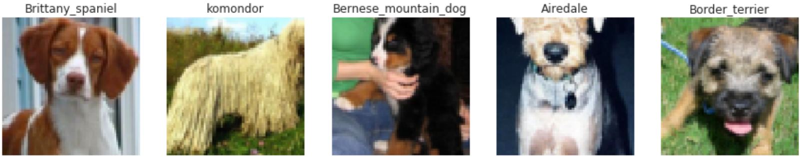


Figure – Pre-processed training data samples.

Fréchet Inception Distance (FID)

Fréchet Distance

For two multivariate Gaussians $X_1 \sim \mathcal{N}(\mu_1, \Sigma_1)$, $X_2 \sim \mathcal{N}(\mu_2, \Sigma_2)$:

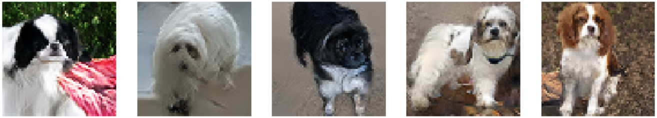
$$d^2(X_1, X_2) = \|\mu_1 - \mu_2\|^2 + \mathrm{Tr}(\Sigma_1 + \Sigma_2 - 2\sqrt{\Sigma_1 \Sigma_2}).$$

- Metric to evaluate GANs
- Use an hidden layer of the Inception [7] network :
  - X_1 = activations on the real data
  - X_2 = activations on the fake data
- Slow to compute and not a perfect indicator of performance

FID Visualisations

(a) DCGAN, FID = 56

(b) DCGAN, FID = 79



(c) BigGAN, FID = 13

Figure – Example of generated dogs for models with different FIDs

Summary

DCGAN Discriminator

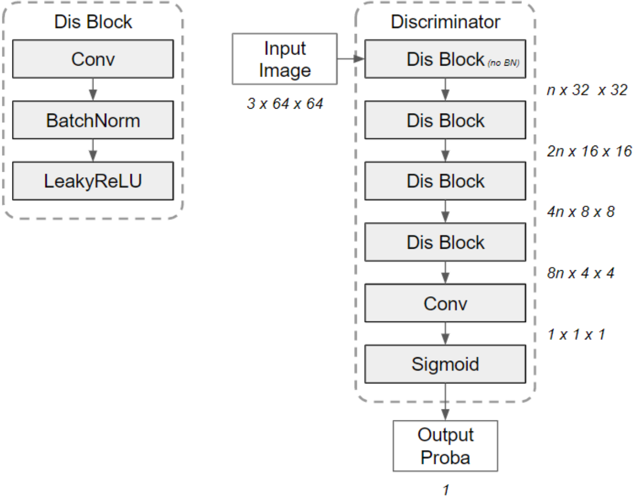


Figure – Architecture of the DCGAN discriminator.

DCGAN Generator

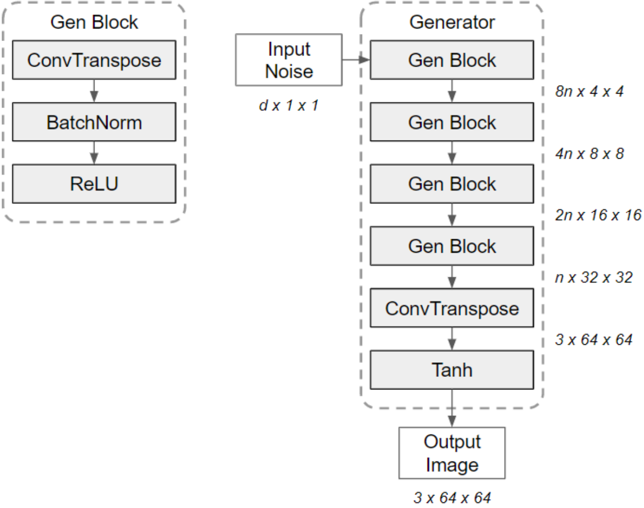


Figure – Architecture of the DCGAN generator.

Algorithm 1 DCGAN training

for $\mathcal{I}_{\text{real}}$ in batch(data) **do**
  # Update discriminator
  $p_{\text{real}} = \mathcal{D}(\mathcal{I}_{\text{real}})$
  $\text{Loss}_{\text{real}} = \mathrm{BCE}(p_{\text{real}}, 1)$
  sample $z \sim \mathcal{N}(0, 1)$
  $\mathcal{I}_{\text{fake}} = \mathcal{G}(z)$
  $p_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}})$
  $\text{Loss}_{\text{fake}} = \mathrm{BCE}(p_{\text{fake}}, 0)$
  Back-propagate $\text{Loss}_{\text{fake}} + \text{Loss}_{\text{real}}$

  # Update generator
  sample $z \sim \mathcal{N}(0, 1)$
  $\mathcal{I}_{\text{fake}} = \mathcal{G}(z)$
  $p_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}})$
  $\text{Loss} = \mathrm{BCE}(p_{\text{fake}}, 1)$
  Back-propagate Loss
end for=0

First Experiments

Table – Influence of the learning rate and batch size.

Batch size	Discriminator lr	Generator lr	**FID**
128	2×10^{-4}	2×10^{-4}	67.9
64	1×10^{-3}	1×10^{-3}	60.2
64	5×10^{-4}	5×10^{-4}	66
64	5×10^{-4}	1×10^{-3}	**56.5**

Table – Influence of the latent dimension d and model size n

d	n	epoch length	**FID**
100	128	44s	**56.5**
256	128	44s	62.2
100	64	11s	78

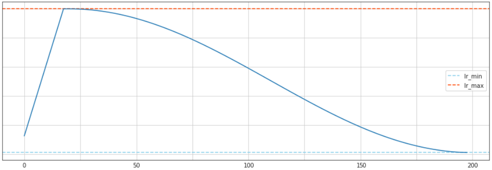
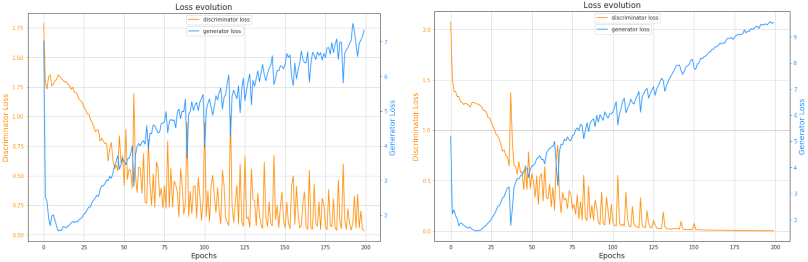


Figure – Cosine learning rate scheduling.

Table – Adding a learning rate scheduler

Discriminator lr	Generator lr	FID
$5 \times 10^{-4} \rightarrow 1 \times 10^{-5}$	$1 \times 10^{-3} \rightarrow 1 \times 10^{-5}$	58
$1 \times 10^{-3} \rightarrow 1 \times 10^{-5}$	$2 \times 10^{-3} \rightarrow 1 \times 10^{-5}$	**55.5**
$1 \times 10^{-3} \rightarrow 1 \times 10^{-4}$	$2 \times 10^{-3} \rightarrow 2 \times 10^{-4}$	57.8
$2 \times 10^{-3} \rightarrow 2 \times 10^{-5}$	$4 \times 10^{-3} \rightarrow 4 \times 10^{-5}$	58.7



(a) Without Scheduling (b) With Scheduling

Figure – Influence of adding a cosine learning rate scheduling on the generator loss (blue) and discriminator loss (orange).

Summary

Feature Matching Idea

- One of the ideas of [6]
- New objective for the generator
- Generator trained to generate images that has features matching those of the real data
- Use the discriminator to extract features, noted $f_{\mathcal{D}}$

Feature Matching objective

$$\min_{G} \quad \|\mathbb{E}_{z\sim p_z}[f_{\mathcal{D}}(\mathcal{G}(z))] - \mathbb{E}_{x\sim p_{\text{data}}}[f_{\mathcal{D}}(x)]\|_2^2$$

Feature Matching Algorithm

Algorithm 2 DCGAN training with Feature Matching

for $\mathcal{I}_{\text{real}}$ in batch(data) **do**
  # Update discriminator
  [...] (Same as algo. 1)

  # Update generator
  sample $z \sim \mathcal{N}(0, 1)$
  $\mathcal{I}_{\text{fake}} = \mathcal{G}(z)$
  $x_{\text{fake}} = f_{\mathcal{D}}(\mathcal{I}_{\text{fake}})$
  $x_{\text{real}} = f_{\mathcal{D}}(\mathcal{I}_{\text{real}})$
  Average x_{fake} and x_{real} over the batch axis
  Loss $= \mathrm{MSE}(\bar{x}_{\text{fake}}, \bar{x}_{\text{real}})$
  Back-propagate Loss
end for=0

DCGAN Discriminator with Feature Matching

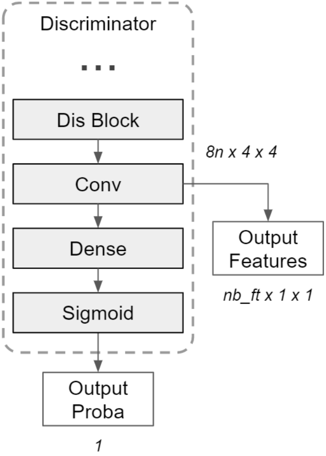


Figure – Adding feature matching to the DCGAN discriminator.

DCGAN with Feature Matching Results

Table – Influence of adding feature matching to our DCGAN.

Feature Matching	**FID**
Without	**55.5**
With	55.9

Summary

Conditional GAN Idea

- Introduced in [3]
- Use class knowledge in the GAN training

Conditional GAN objective

$$\min_G \max_D \quad \mathbb{E}_{x \sim p_{\text{data}}}[\log \mathcal{D}(x|y)] \; + \; \mathbb{E}_{z \sim p_z}[\log (1 - \mathcal{D}(\mathcal{G}(z|y)))]$$

Conditional GAN Algorithm

Algorithm 3 Conditional GAN training

for $\mathcal{I}_{\text{real}}, y_{\text{real}}$ in batch(data) **do**

Update discriminator

$p_{\text{real}} = \mathcal{D}(\mathcal{I}_{\text{real}}, y_{\text{real}})$

$\text{Loss}_{\text{real}} = \mathrm{BCE}(p_{\text{real}},\ 1)$

sample $z \sim \mathcal{N}(0, 1)$

sample $y_{\text{fake}} \sim \mathcal{U}([\![0, c]\!])$

$\mathcal{I}_{\text{fake}} = \mathcal{G}(z, y_{\text{fake}})$

$p_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}}, y_{\text{fake}})$

$\text{Loss}_{\text{fake}} = \mathrm{BCE}(p_{\text{fake}}, 0)$

Back-propagate $\text{Loss}_{\text{fake}} + \text{Loss}_{\text{real}}$

Update generator

sample $z \sim \mathcal{N}(0, 1)$

sample $y_{\text{fake}} \sim \mathcal{U}([\![0, c]\!])$

$\mathcal{I}_{\text{fake}} = \mathcal{G}(z, y_{\text{fake}})$

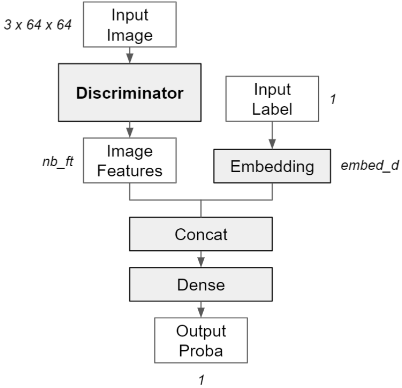
$p_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}}, y_{\text{fake}})$

$\text{Loss} = \mathrm{BCE}(p_{\text{fake}}, 1)$

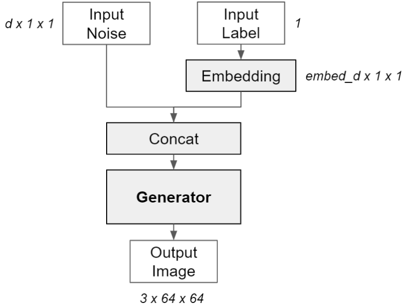
Back-propagate Loss

end for=0

Conditional DCGAN Implementation



(a) Conditional Discriminator



(b) Conditional Generator

Figure – Adding conditioning to the DCGAN architecture.

Projection Discriminator

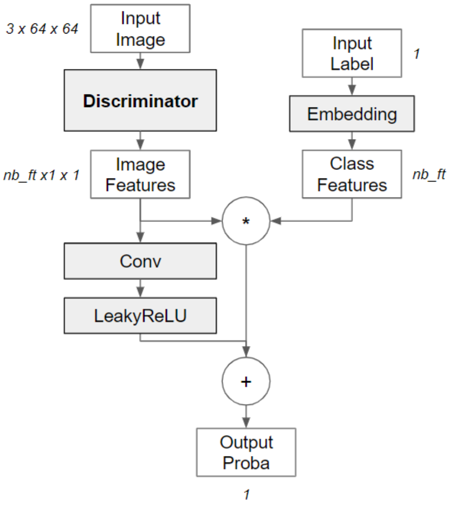


Figure – Architecture of the projection discriminator.

Conditional DCGAN Results

Table – Influence of adding conditioning to our DCGAN.

Conditioning	*nb_ft*	**FID**
Without		**55.5**
With	8	60.3
Projected	1024	62.8

Summary

Auxiliary Classifier GAN Idea

- Introduced in [5]
- Same generator as for the Conditional GAN
- Use the discriminator to predict the class label, noted $\mathcal{D}_c$
- Combination of the two following objectives :

Auxiliary Classifier GAN objectives

$$\min_G \max_D \quad \mathbb{E}_{x\sim p_{\text{data}}}[\log \mathcal{D}(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - \mathcal{D}(\mathcal{G}(z|y)))]$$

$$\max_G \max_D \mathbb{E}_{x\sim p_{\text{data}}}[\log \mathcal{D}_c(x) = y] + \mathbb{E}_{z\sim p_z}[\log \mathcal{D}_c(\mathcal{G}(z|y)) = y]$$

Algorithm 4 Auxiliary Classifier DCGAN training

for $\mathcal{I}_{\text{real}}, y_{\text{real}}$ in batch(data) **do**
  # Update discriminator
  $p_{\text{real}}, p^c_{\text{real}} = \mathcal{D}(\mathcal{I}_{\text{real}})$
  $\text{Loss}_{\text{real}} = \mathrm{BCE}(p_{\text{real}}, 1) + \mathrm{CE}(p^c_{\text{real}}, y_{\text{real}})$
  sample $z \sim \mathcal{N}(0, 1)$
  sample $y_{\text{fake}} \sim \mathcal{U}([\![0, c]\!])$
  $\mathcal{I}_{\text{fake}} = \mathcal{G}(z, y_{\text{fake}})$
  $p_{\text{fake}}, p^c_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}})$
  $\text{Loss}_{\text{fake}} = \mathrm{BCE}(p_{\text{fake}}, 0) + \mathrm{CE}(p^c_{\text{fake}}, y_{\text{fake}})$
  Back-propagate $\text{Loss}_{\text{fake}} + \text{Loss}_{\text{real}}$

  # Update generator
  sample $z \sim \mathcal{N}(0, 1)$
  sample $y_{\text{fake}} \sim \mathcal{U}([\![0, c]\!])$
  $\mathcal{I}_{\text{fake}} = \mathcal{G}(z, y_{\text{fake}})$
  $p_{\text{fake}}, p^c_{\text{fake}} = \mathcal{D}(\mathcal{I}_{\text{fake}}$
  $\text{Loss} = \mathrm{BCE}(p_{\text{fake}}, 1) + \mathrm{CE}(p^c_{\text{fake}}, y_{\text{fake}})$
  Back-propagate Loss
end for=0

DCGAN Discriminator with an Auxiliary Classifier

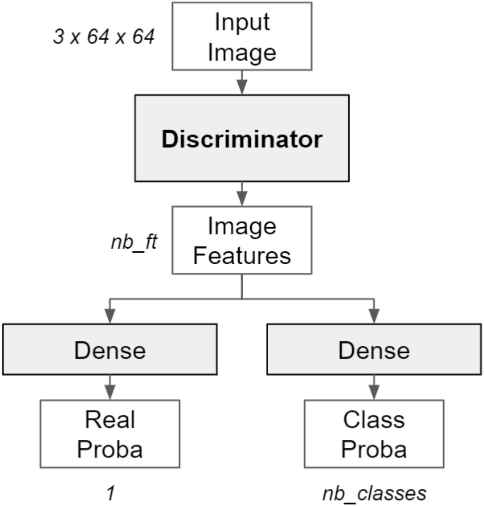


Figure – Adding an auxiliary classifier to the DCGAN discriminator.

Auxiliary Classifier DCGAN Results

Table – Influence of adding an auxiliary classifier to our DCGAN.

Auxiliary classifier	**FID**
Without	**55.5**
With	57.9

Summary

Training Evolution

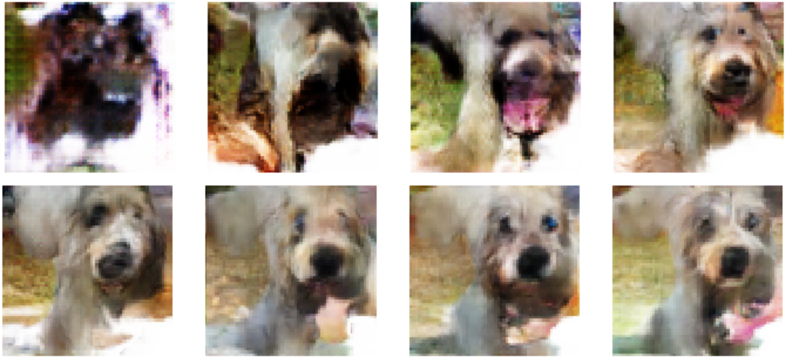


Figure – Evolution of the output for a fixed noise during the training.

Best Generated Dogs

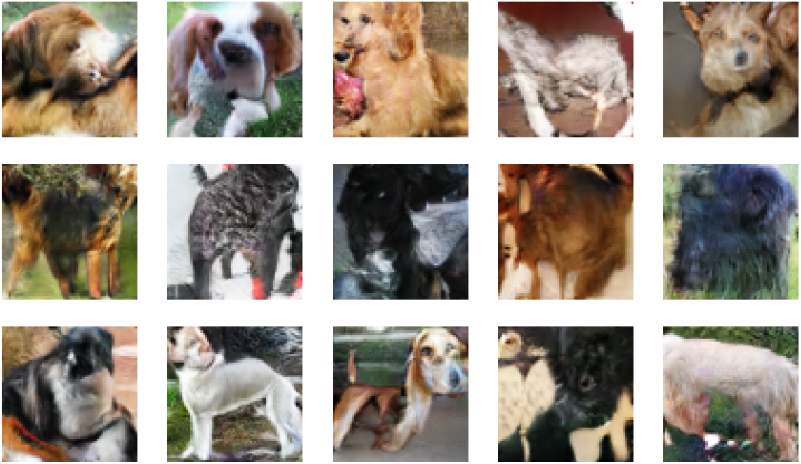


Figure – Generated dogs for the best model, achieving an FID of 55.5.

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[3] Mehdi Mirza and Simon Osindero.
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[4] Vinod Nair and Geoffrey E. Hinton.
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In *Proceedings of the 27th International Conference on International Conference on Machine Learning*, ICML'10, page 807–814, Madison, WI, USA, 2010. Omnipress.

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