

Generative Adversarial Networks

Deep Learning — Unit 9

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Slides available at jonkrohn.com/talks

August 18th, 2018

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4 “Quick, Draw!” Implementation

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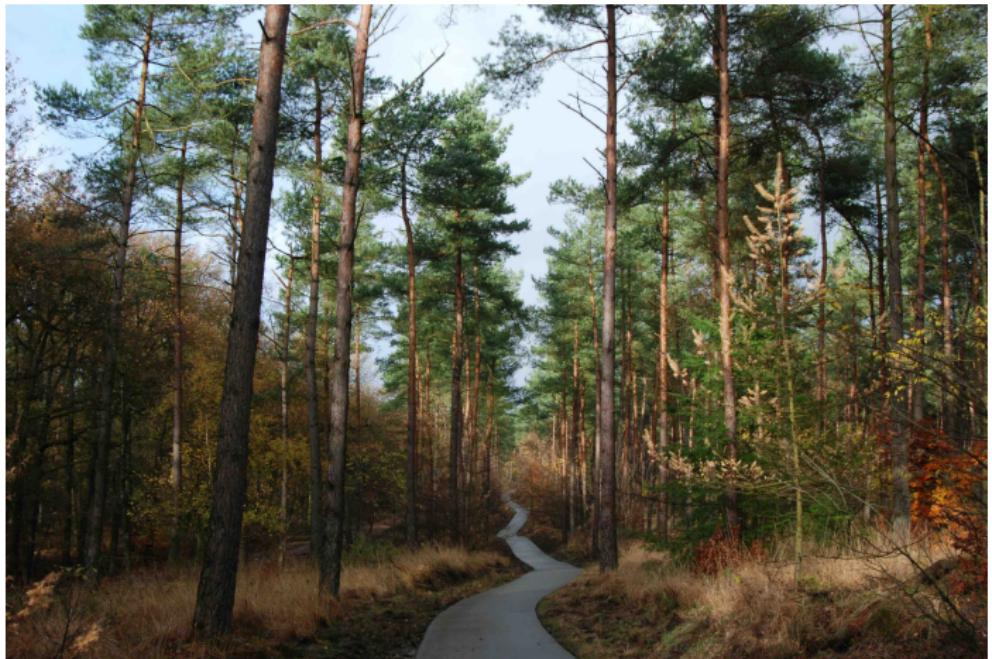
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Progress Check

Your Deep Learning Project V



Progress Check

Your Deep Learning Project V

Where are you at with respect to the following?

① Splitting your data

- training set (80% — for optimizing parameters)
- validation set (10% — for hyperparameters)
- test set (10% — don't touch yet!)

② Building and assessing architecture

- get above chance (simplifying problem, if necessary)
- do existing performance benchmarks exist?
- if not, use a simple architecture as benchmark

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① build a machine-vision architecture to classify images,
e.g.:

- [Fashion MNIST]
- one of dozens of “image” data sets from [CrowdFlower]
- one of the *Computer Vision* data sets from [Luke de Oliveira’s post]

② build a natural language processing architecture to classify text, e.g.:

- Yelp or Amazon sentiment [datasets] from [Zhang et al.]
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GANs

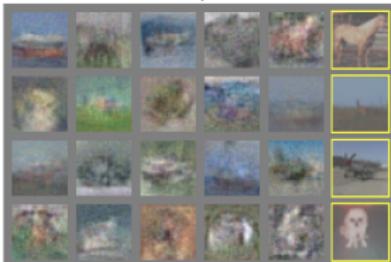
Goodfellow et al. (2014)



a)



b)



c)



d)

DCGANs

Radford et al. (2016)

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(a) Generated by LSGANs.

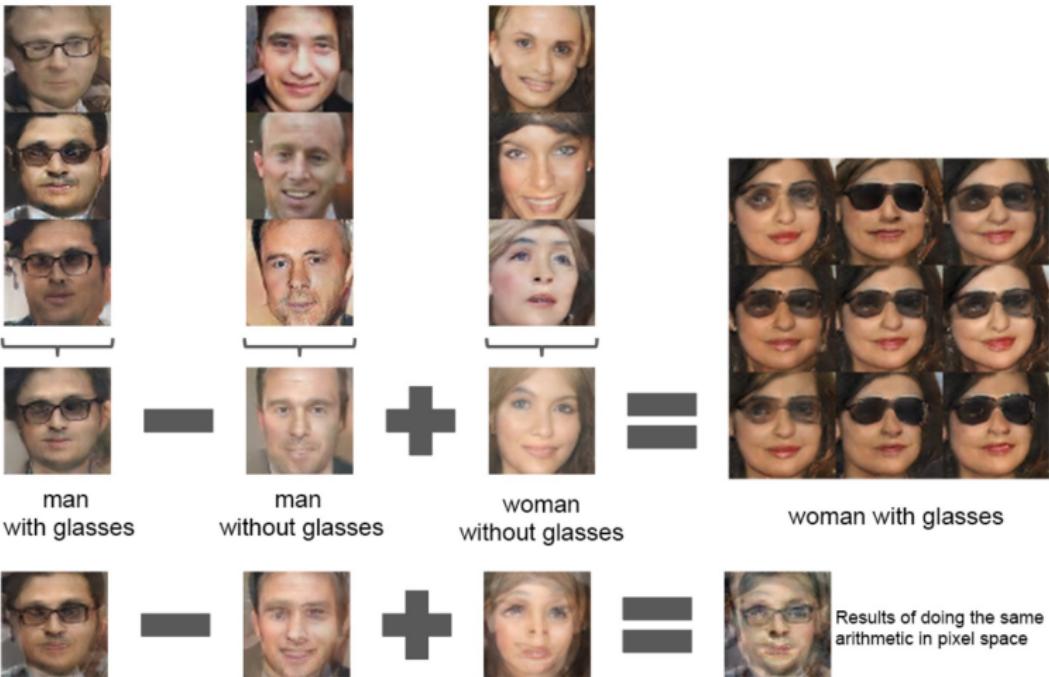


(b) Generated by DCGANs (Reported in [13]).

Figure 5: Generated images on LSUN-bedroom.

DCGANs

Radford et al. (2016)



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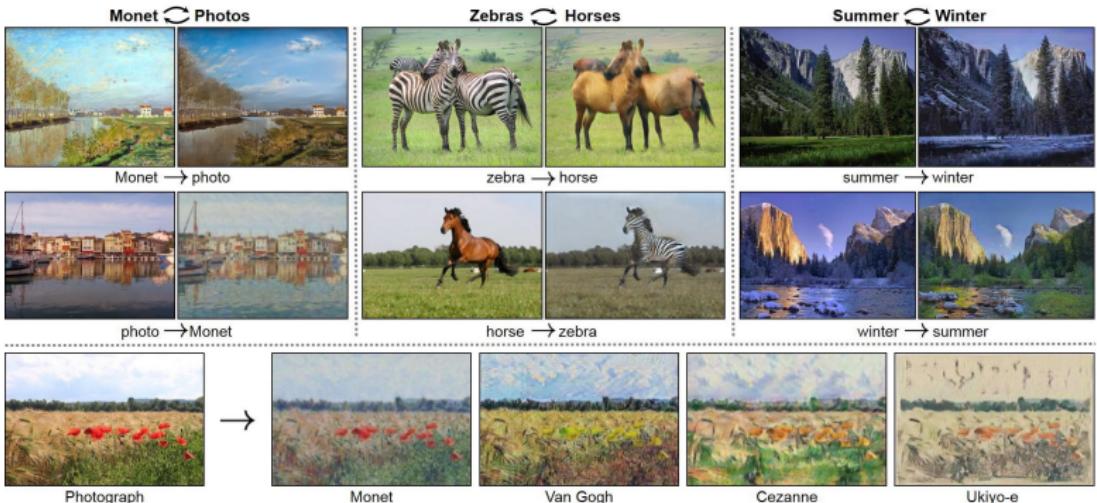
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CycleGANs

Zhu et al. (2017)



<https://junyanz.github.io/CycleGAN>

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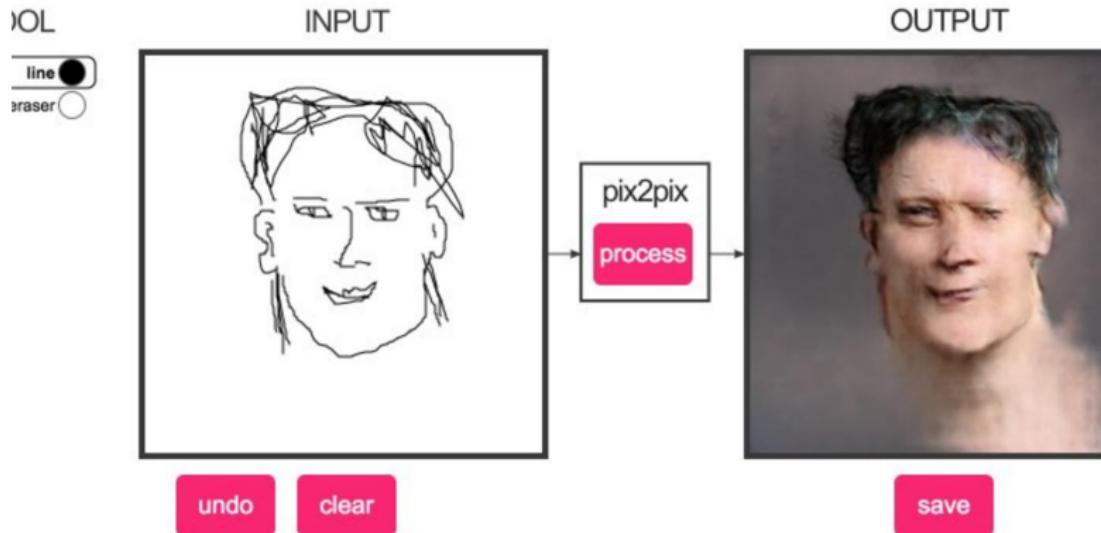
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pix2pix

Isola et al. (2017)



<https://>



NYC DATA SCIENCE
ACADEMY

StackGAN

Zhang et al. (2017)

Text description	This bird is red and brown in color, with a stubby beak	The bird is short and stubby with yellow on its body	A bird with a medium orange bill white body gray wings and webbed feet	This small black bird has a short, slightly curved bill and long legs	A small bird with varying shades of brown with white under the eyes	A small yellow bird with a black crown and a short black pointed beak	This small bird has a white breast, light grey head, and black wings and tail
64x64 GAN-INT-CLS [22]							
128x128 GAWWN [20]							
256x256 StackGAN							

Figure 3. Example results by our proposed StackGAN, GAWWN [20], and GAN-INT-CLS [22] conditioned on text descriptions from CUB test set. GAWWN and GAN-INT-CLS generate 16 images for each text description, respectively. We select the best one for each of them to compare with our StackGAN.

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[“celebrity” latent-space interpolation]

Latent-Space Interpolation

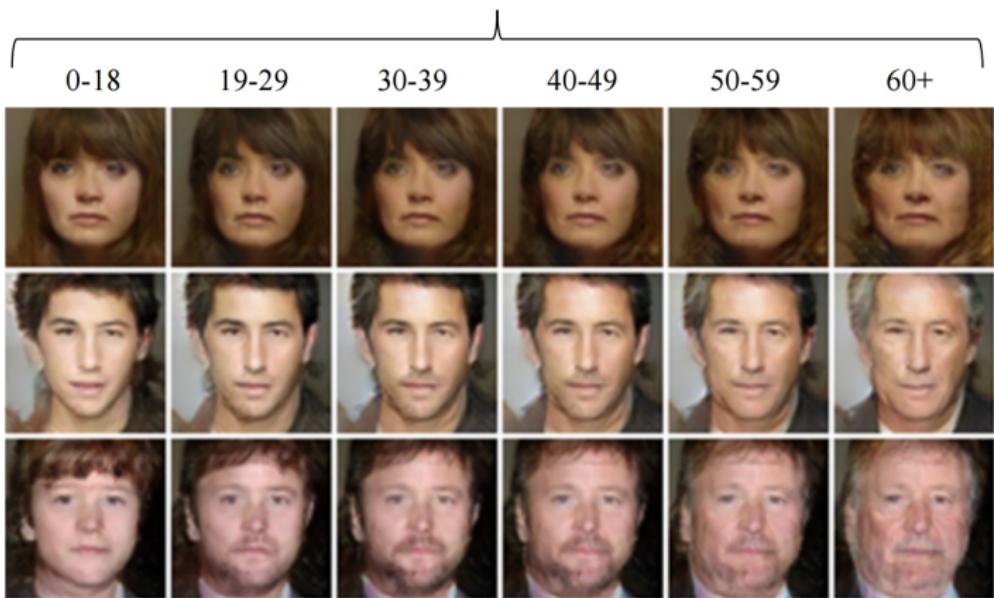
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Face Aging



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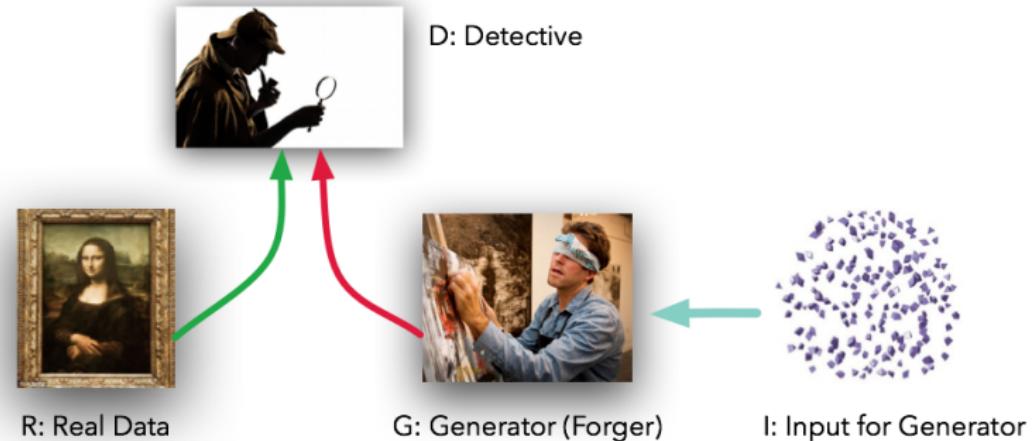
Goodfellow et al. (2014)

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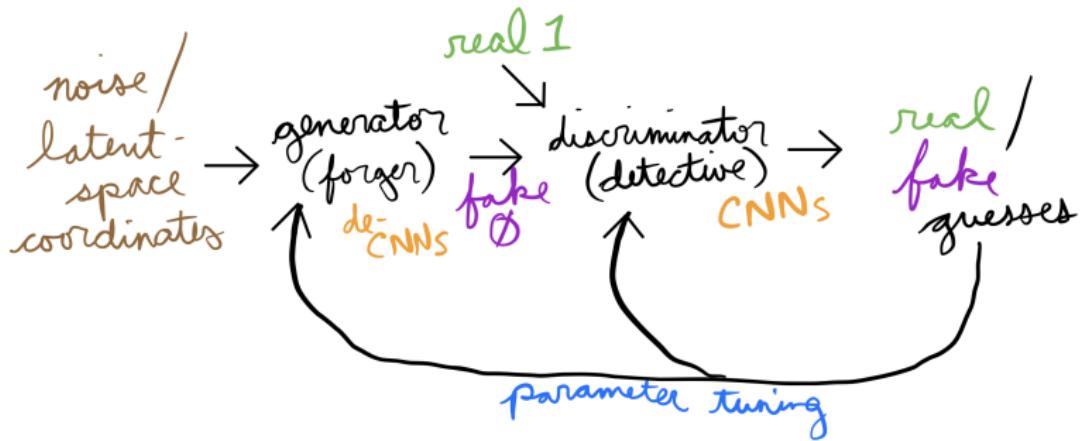
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Goodfellow et al. (2014)

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1-D Gaussian

Approximating a Toy Distribution

[video]

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[Quick, Draw!]

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GANimation

(Requires Adobe Reader)

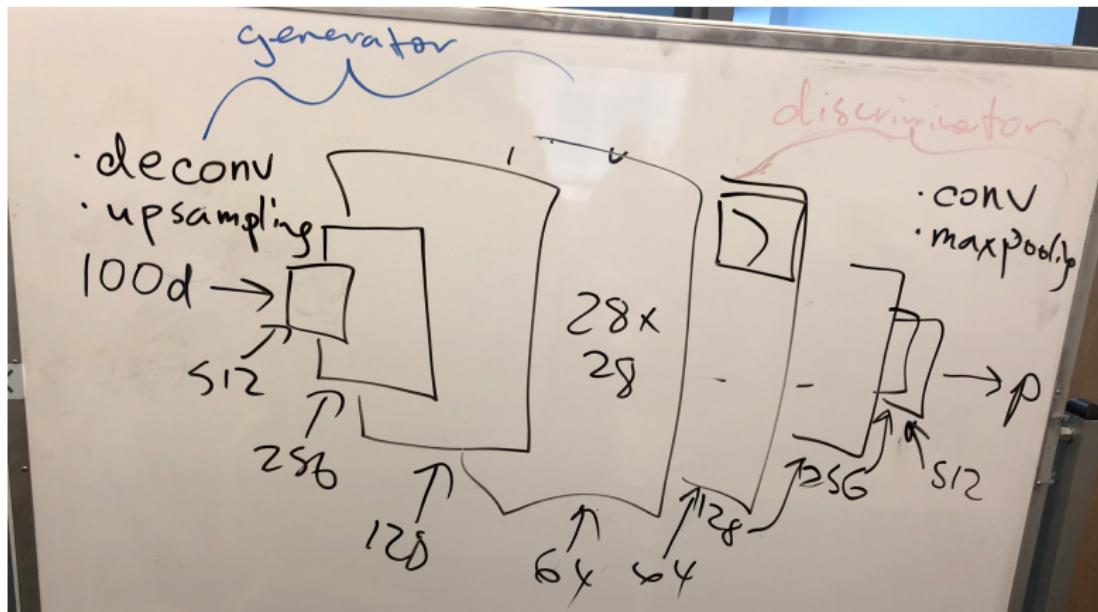
GAN Code

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[notebook]