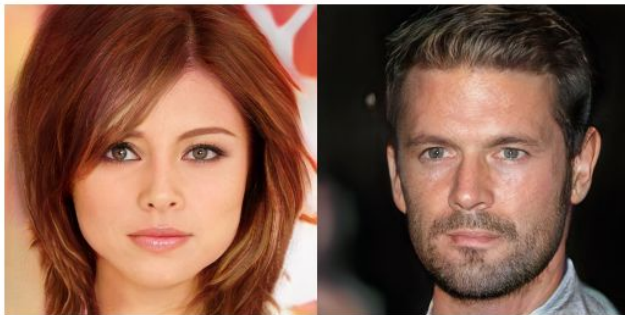


Generative Adversarial Networks

Generating content, Deep Learning style

Publications

Progressive Growing of GANs for Improved Quality, Stability, and Variation



We describe a new training methodology for generative adversarial networks. The key idea is to grow both the generator and discriminator progressively: starting from a low resolution, we add new layers that model increasingly fine details as training progresses. This both speeds the training up and greatly stabilizes it, allowing us to produce images of unprecedented quality, e.g., CelebA images at 1024^2 . We also propose a simple way to increase the variation in generated images, and achieve a record inception score of 8.80 in unsupervised CIFAR10. Additionally, we describe several implementation details that are important for discouraging unhealthy competition between the generator and discriminator. Finally, we suggest a new metric for evaluating GAN results, both in terms of image quality and variation. As an additional contribution, we construct a higher-quality version of the CelebA dataset.

Authors: [Tero Karras](#)

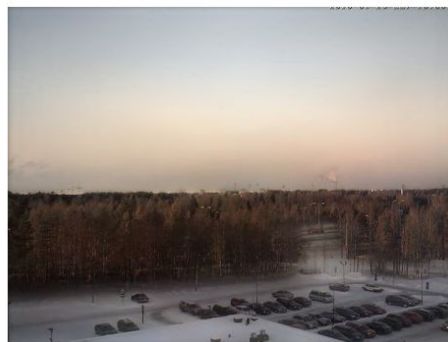
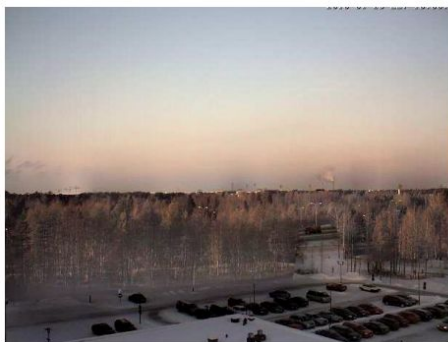
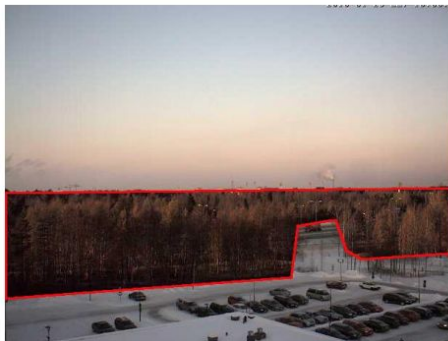
[Timo Aila](#)

[Samuli Laine](#)

Jaakko Lehtinen (NVIDIA and Aalto University)

More usages ...

Blending high resolution images



Text to image synthesis

bright droopy
yellow petals with
burgundy streaks,
and a yellow
stigma.



a flower with
long pink petals
and raised orange
stamen.



the flower shown
has a blue petals
with a white pistil
in the center



Image completion



Real

Input



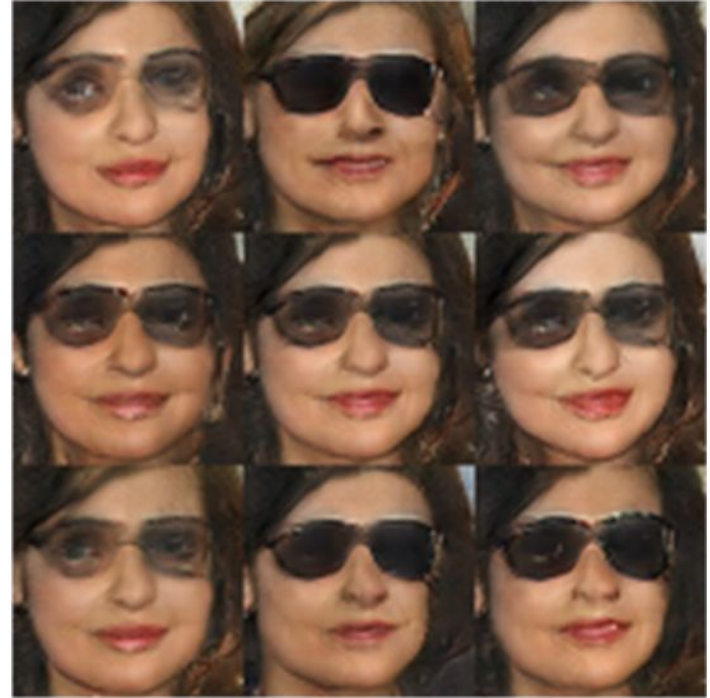
Generating videos



Image to image translations



Vector Space Arithmetic



Retail item generation



What are some recent and potentially upcoming breakthroughs in deep learning?



Yann LeCun, Director of AI Research at Facebook and Professor at NYU

Answered Jul 28, 2016 · Upvoted by Joaquin Quiñero Candela, studied Machine Learning and Gokul Krishnan, M.Sc Computer Science & Machine Learning, ETH Zurich (2018)

There are many interesting recent development in deep learning, probably too many for me to describe them all here. But there are a few ideas that caught my attention enough for me to get personally involved in research projects.

The most important one, in my opinion, is adversarial training (also called GAN for Generative Adversarial Networks). This is an idea that was originally proposed by Ian Goodfellow when he was a student with Yoshua Bengio at the University of Montreal (he since moved to Google Brain and recently to OpenAI).

This, and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion.

What are GANs?

What are GANs?

How do we say if something is part of a group or not?

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
18.303797, 16.037155, 20.368163, 16.665176, 13.573404,
15.139798, 16.515108, 5.441134, 13.283509, 16.787477,
18.294751, 25.165056, 16.328220, 12.926385, 20.027098,
14.360396, 15.171232, 13.447607, 20.654171, 20.809167,
22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
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18.294751, 25.165056, 16.328220, 12.926385, 20.027098,
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22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067

Can 1 be part of this set?

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
18.303797, 16.037155, 20.368163, 16.665176, 13.573404,
15.139798, 16.515108, 5.441134, 13.283509, 16.787477,
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20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067

Can 1 be part of this set?

How about 15?

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
18.303797, 16.037155, 20.368163, 16.665176, 13.573404,
15.139798, 16.515108, 5.441134, 13.283509, 16.787477,
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22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067

Can 1 be part of this set?

How about 15?

... or 24?

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
18.303797, 16.037155, 20.368163, 16.665176, 13.573404,
15.139798, 16.515108, 5.441134, 13.283509, 16.787477,
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22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067

Can 1 be part of this set?

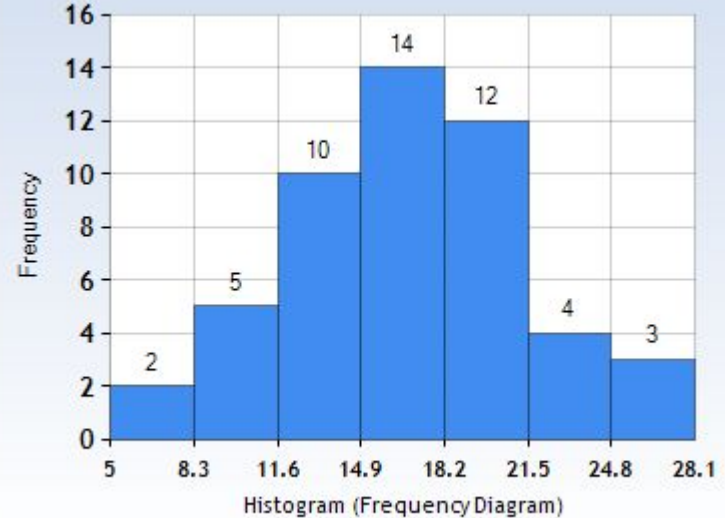
How about 15?

... or 24?

Is 15 more likely to be in this set compared to 24?

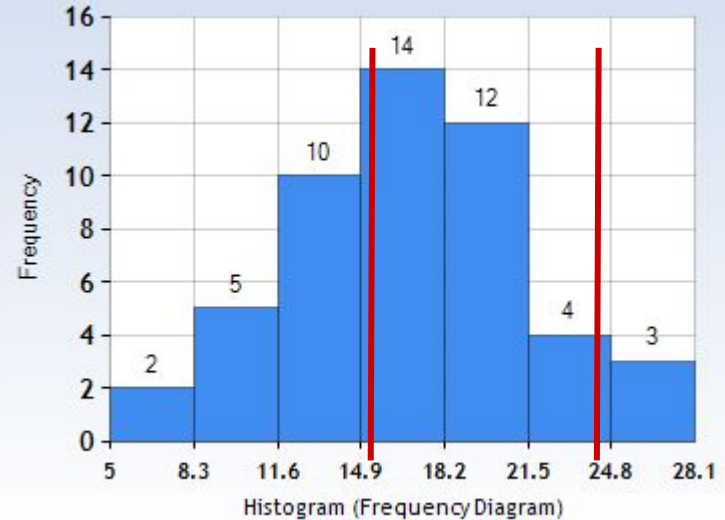
Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
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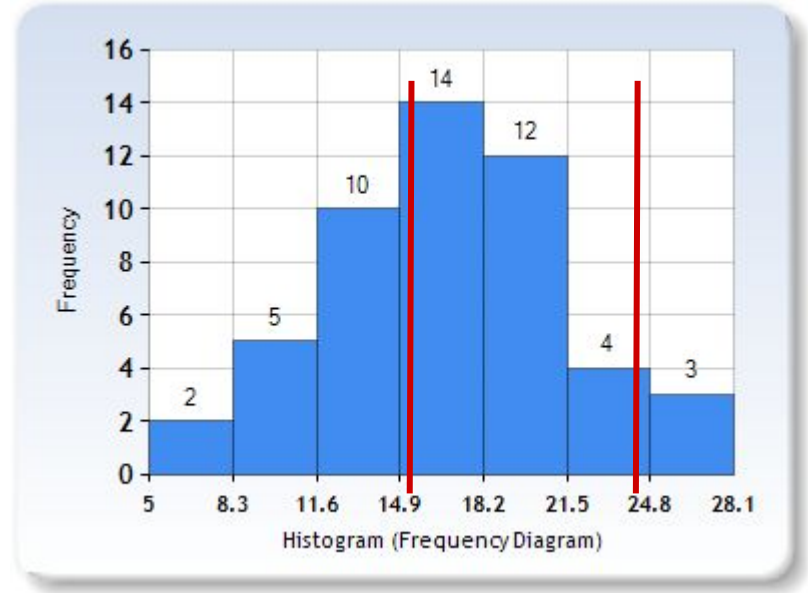
Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
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22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
20.389758, 11.593847, 15.781812, 25.418625, 21.020760,
12.751493, 5.676766, 16.448069, 17.550310, 18.291067



Eg.

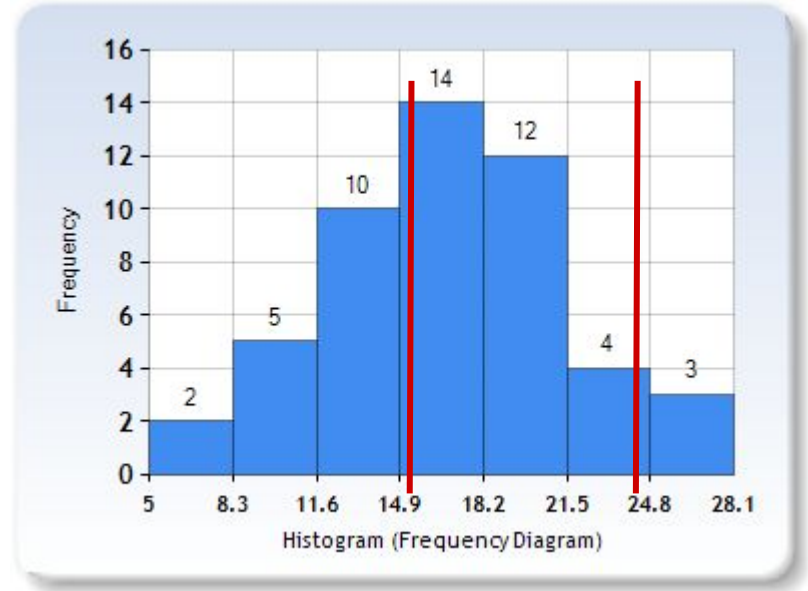
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16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
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12.751493, 5.676766, 16.448069, 17.550310, 18.291067



Is 15 more likely to be in this set compared to 24?

Eg.

26.784374, 16.221426, 23.969908, 18.128964, 13.310599,
16.169977, 10.518126, 19.088016, 11.662497, 12.075612,
18.459770, 16.673500, 18.325148, 9.600440, 22.215492,
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22.041561, 8.681153, 8.919257, 21.681817, 14.043993,
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12.751493, 5.676766, 16.448069, 17.550310, 18.291067



Is 15 more likely to be in this set compared to 24?

YES!

Is 15 more likely to be in this set compared to 24?

Eg.

Is **x** more likely to be in this set compared to **y**?

How to determine this?

Is **x** more likely to be in this set compared to **y**?

How to determine this?

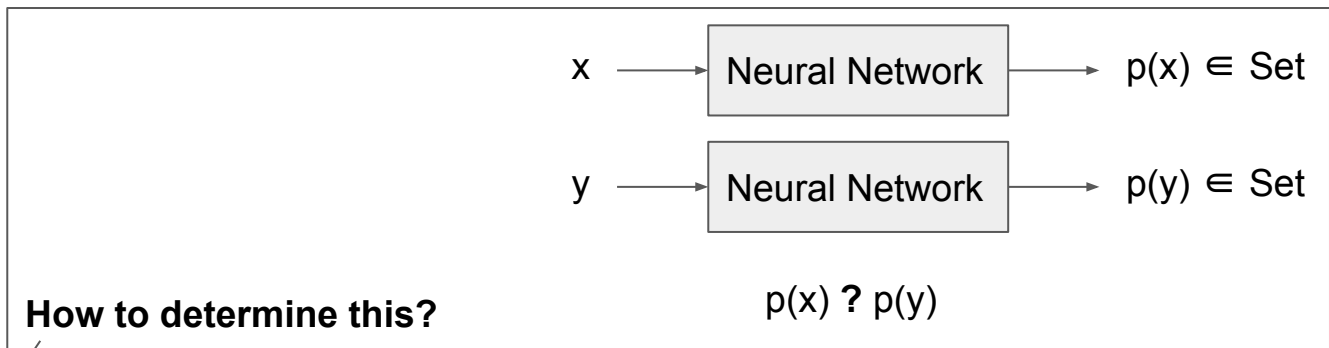
Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

How to determine this?

Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?



Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

How to determine this?

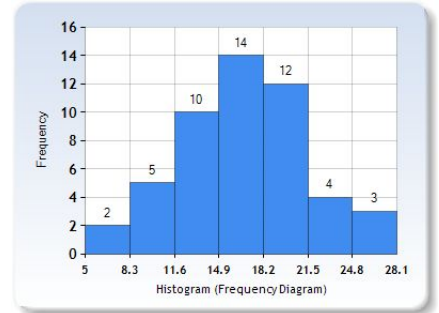
Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

How to determine this?

Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

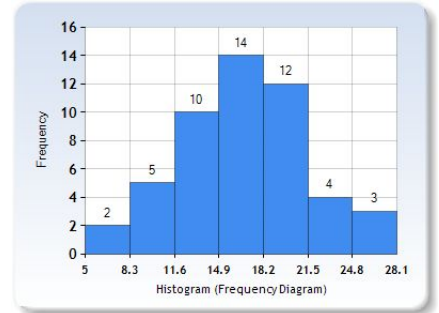


How to determine this?

Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

Normal Distribution with mean 16 and standard deviation of 5.



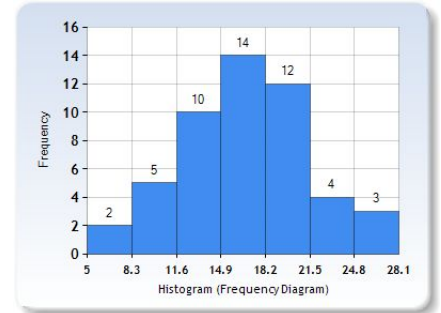
How to determine this?

Is **x** more likely to be in this set compared to **y**?

How to generate plausible candidates for this?

Normal Distribution with mean 16 and standard deviation of 5.

What is the data distribution function?



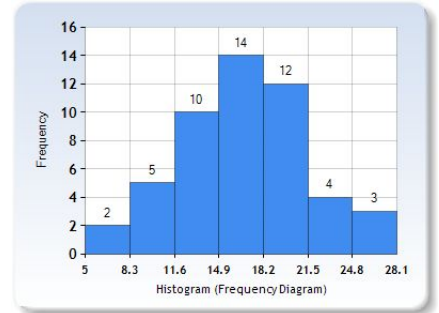
How to determine this?

Is **x** more likely to be in this set compared to **y**?

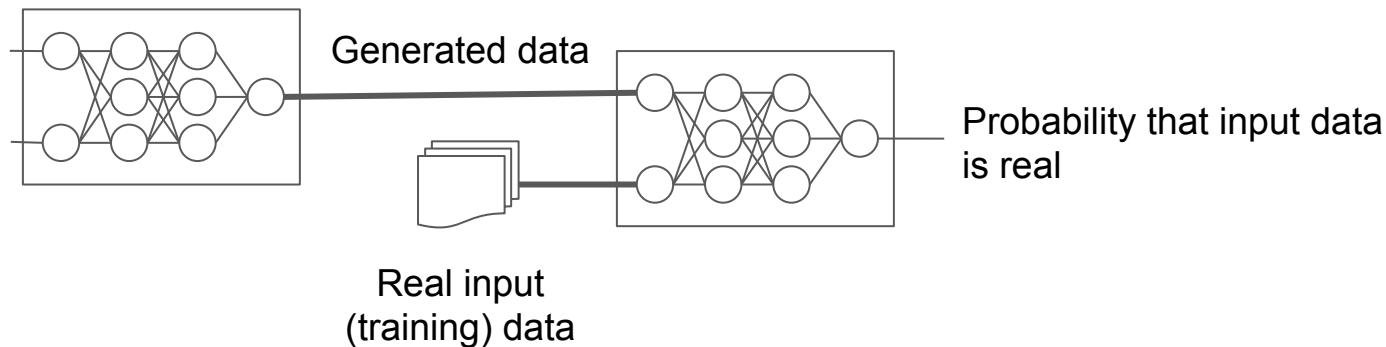
How to generate plausible candidates for this?

Normal Distribution with mean 16 and standard deviation of 5.

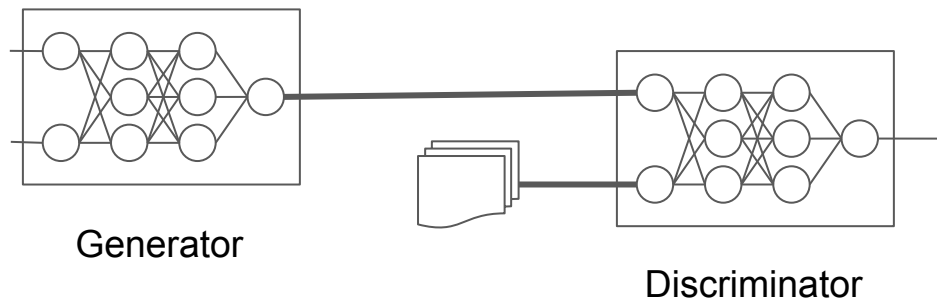
What is the data distribution function *so that we can sample new values?*



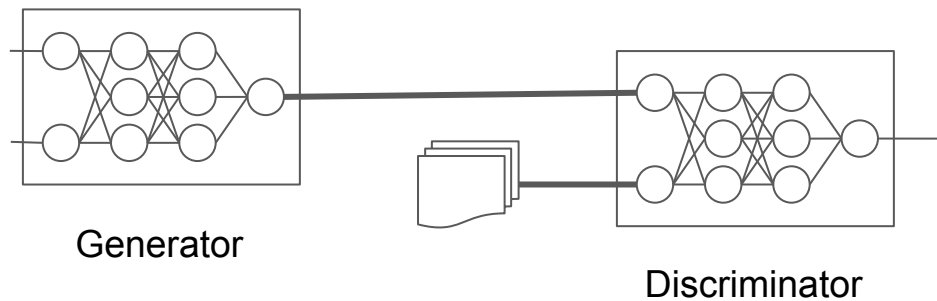
Architecture. Generating new data



Architecture. Generating new data

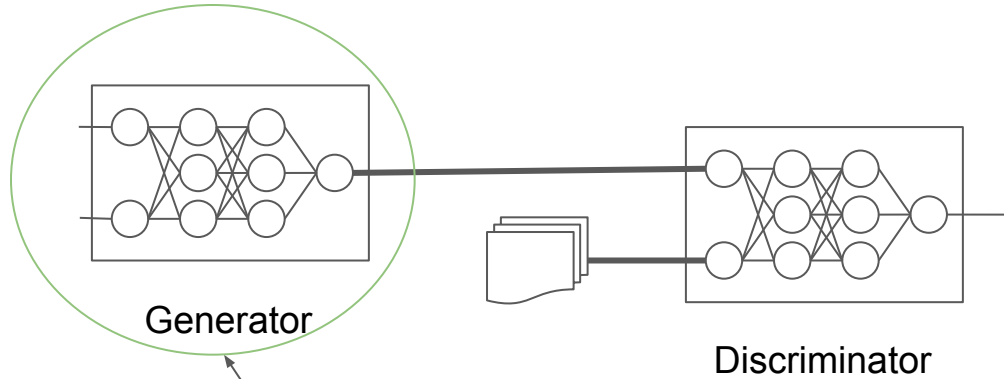


Architecture. Generating new data



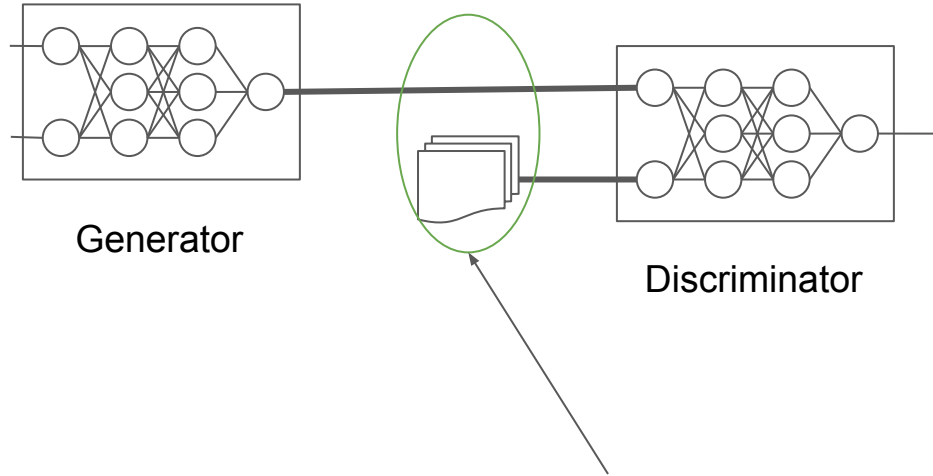
Generative Adversarial Network (GAN)

Architecture. Generating new data



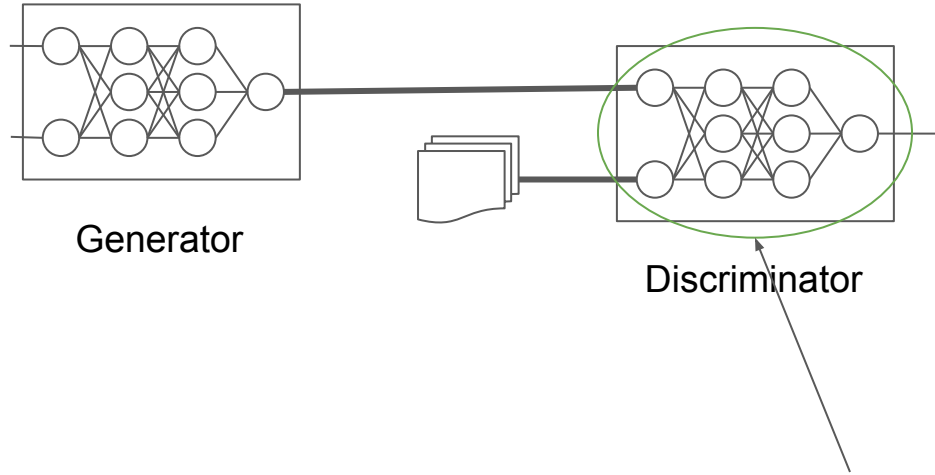
Generative Adversarial Network (GAN)

Architecture. Generating new data



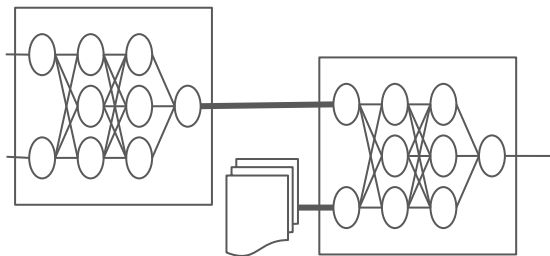
Generative **Adversarial** Network (GAN)

Architecture. Generating new data



Generative Adversarial **Network** (GAN)

GANs. Training. Cost function

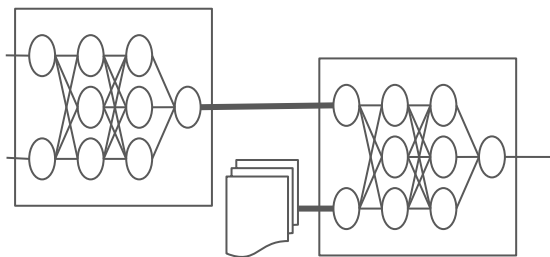


Use SGD-like algorithm of choice on two minibatches
simultaneously:

A minibatch of training examples

A minibatch of generated samples

GANs. Training. Cost function



Use SGD-like algorithm of choice on two minibatches simultaneously:

A minibatch of **training examples**

A minibatch of **generated samples**

$$J^{(D)} = -\frac{1}{2} \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}} \log D(\mathbf{x}) - \frac{1}{2} \mathbb{E}_{\mathbf{z}} \log (1 - D(G(\mathbf{z})))$$

$$J^{(G)} = -J^{(D)}$$

Code example



Google Research Blog

The latest news from Research at Google

TFGAN: A Lightweight Library for Generative Adversarial Networks

Tuesday, December 12, 2017

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[8] Yann LeCun's Quora answer -- <https://goo.gl/qS88pA>

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