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Soft introduction to Generative Adversarial Networks (GANs)

Appsilon tech talks | Michał Maj | 24/10/2018

Agenda

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- Difference between **discriminative** and **generative** algorithms.
- What are **GANs** ?
- Use cases of GANs.
- Building Vanilla DCGAN in Keras.
- Why it is hard to train a GAN ?

Discriminative and generative algorithms

Let’s start with a ConvNet for satellite imagery classification (from previous tech talk). As you can remember our task looked like this: we wanted to predict class (ship or non-ship), or to be more specific the probability that the image belongs to the specific class, given the image. Each image was composed of a set of pixels that we were using as features / inputs. Mathematically speaking we were using set of features X (pixels) o get the conditional probability of Y given X:

$$p(y|x)$$

This is an example of **discriminative** algorithm.

Discriminative and generative algorithms

Generative algorithms on the other hand are doing something completely opposite. In our example, assuming that the class of an image is ship how should the image look like, so what value should each pixel have? This time we're generating distribution of X (pixels) given Y(class) or joint probability:

$$p(x|y) \text{ or } p(x,y)$$

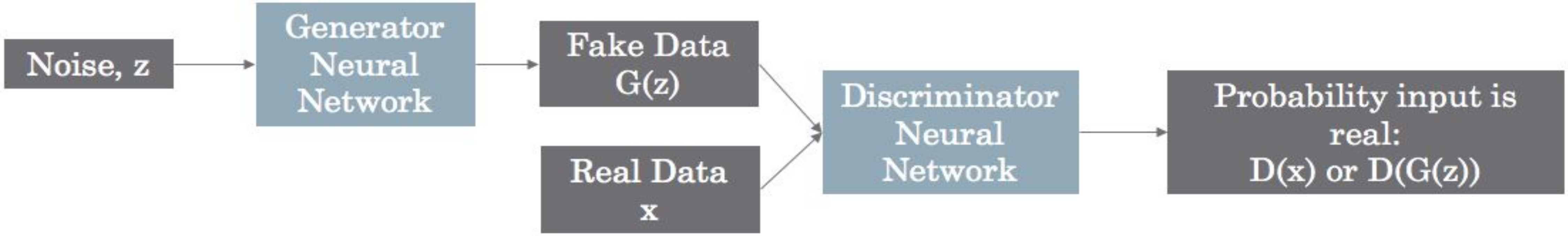
What are GANs ?

Generative adversarial networks, introduced in 2014 by Ian Goodfellow, are **generative algorithms** comprised of **two deep neural networks** “playing” a zero-sum game **against each other**.

There are many different “flavours” of GANs and depending on the task we will use different networks to build our GAN. For example DCGAN (**Deep Convolutional Generative Adversarial Networks**) is a GAN designed for basic image generation.

What are GANs ?

First network is called **generator** and it’s basically responsible for creating new instances of data from random noise. Second network is called **discriminator** and it “judges” if the data generated by generator is real or fake having real data to compare.



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Use cases of GANs

- Data augmentation - e.g. create new instances of data to train your model, alternative to bayesian methods like Gibbs sampling

"NVIDIA showed amazing example of this approach in action: they used GANs to augment dataset of medical brain CT images with different diseases and showed that the classification performance using only classic data augmentation yielded 78.6% sensitivity and 88.4% specificity. By adding the synthetic data augmentation the results increased to 85.7% sensitivity and 92.4% specificity."

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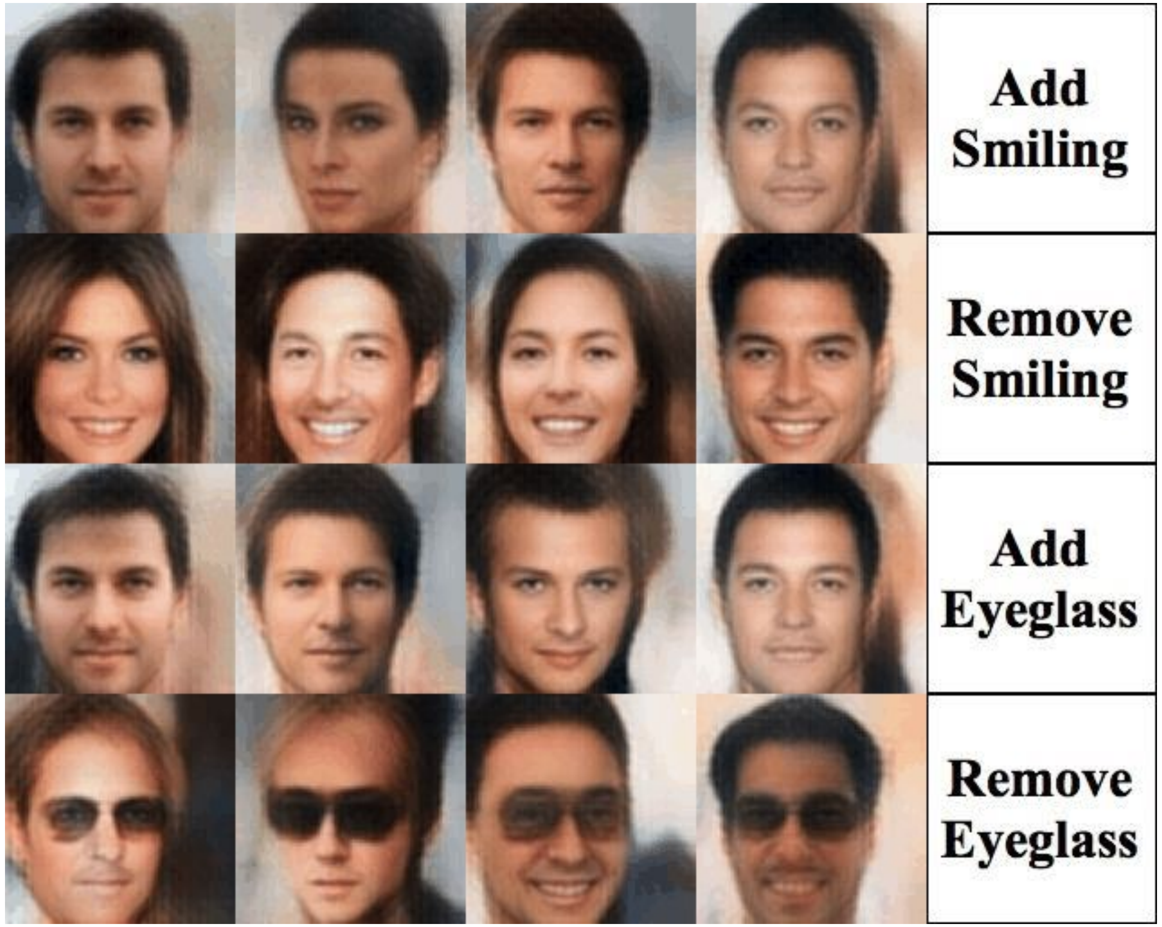
Use cases of GANs

- Image generation - e.g. Disney is generating new textures for animations
- Anomaly detection - GAN learns the predictor distribution so it can detect outliers and anomalies
- Domain adaptation

Source:
https://www.google.com/url?q=https://medium.com/@alexrachnog/gans-beyond-generation-7-alternative-use-cases-725c60ba95e8?fbclid%3DIwAR2c81U-rmlb3FFWq_s56dafuCV-tvOgjqHtcOt0KAwm34I8Z3JJHX6XHZk&sa=D&ust=1547052892635000&usg=AFQjCNFWNEG79Y71yW3V9JVMcH3JOhoK2A

Use cases of GANs

- Data manipulation



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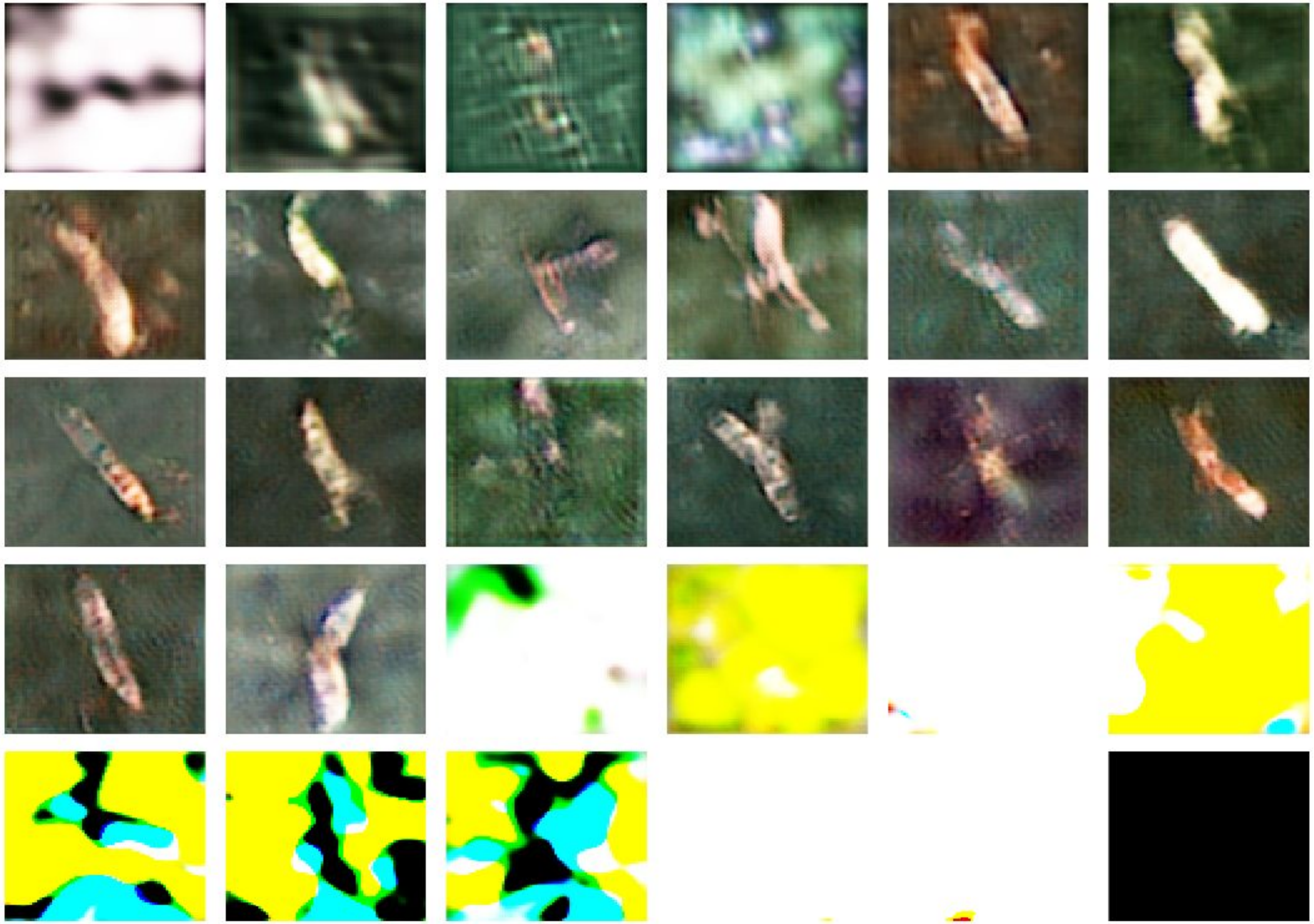
https://medium.com/@jonathan_hui/gan-whats-generative-adversarial-networks-and-its-application-f39ed278ef09

Building Vanilla DCGAN in Keras



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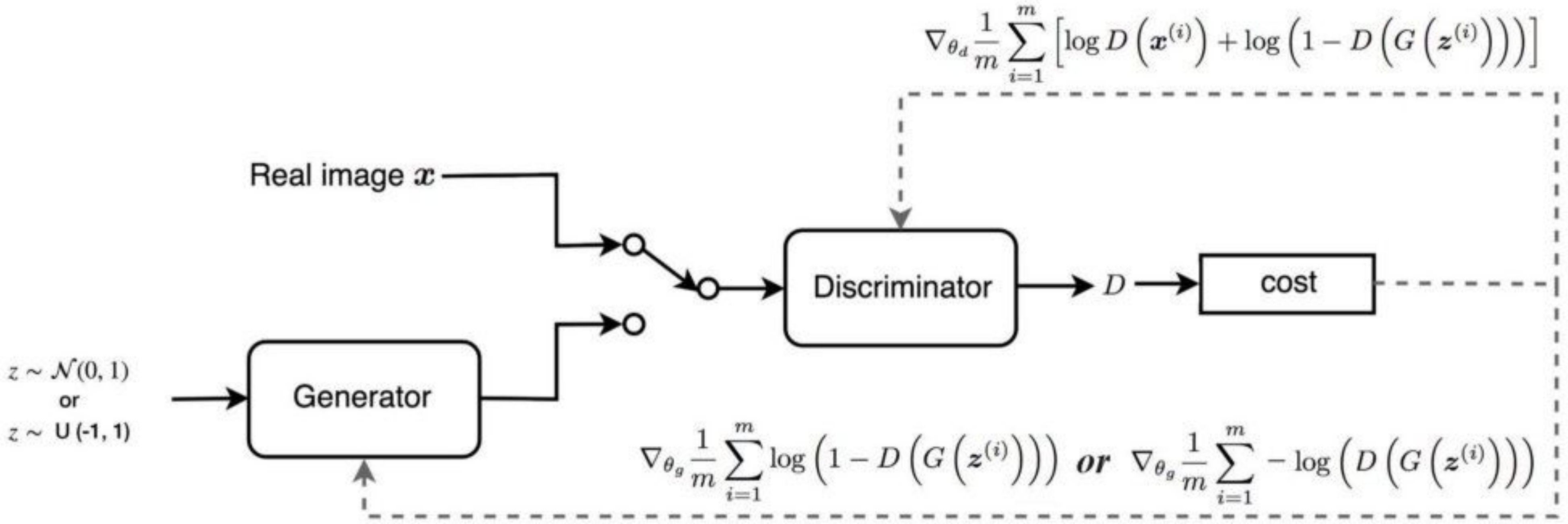
Why it is hard to train a GAN

- There's no fixed minimum of a loss function (it changes in each iteration)
- Discriminator gets too successful (vanishing gradient problem for generator)
- Complicated goal:

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



Source: https://medium.com/@jonathan_hui/gan-why-it-is-so-hard-to-train-generative-advisory-networks-819a86b3750b

Resources

https://poloclub.github.io/ganlab/

https://medium.com/@alexrachnog/gans-beyond-generation-7-alternative-use-cases-725c60ba95e8?fbclid=IwAR2c81U-rmlb3FFWq_s56dafuCV-tvOgjqHtcOt0KAwm34I8Z3JJHX6XHZk

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Questions?