Artifacia | AI Meet

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Generative adversarial networks and their applications

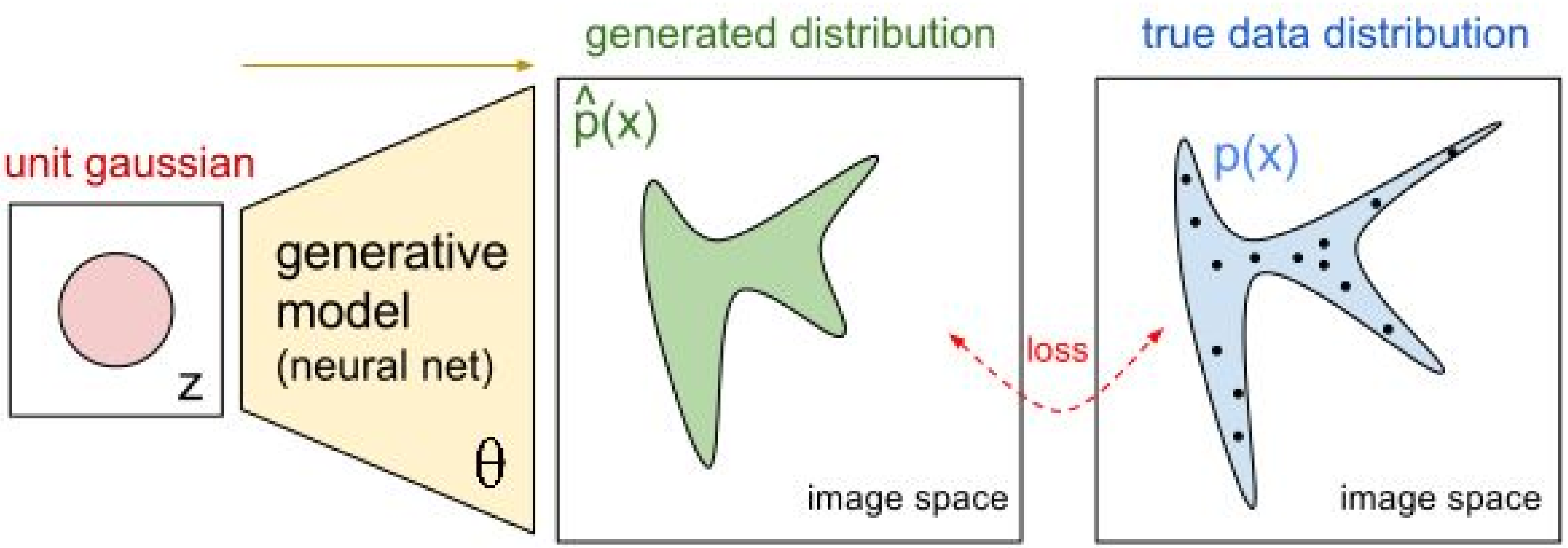
by Vijay Veerabadran, Research Engineer (CV) , Artifacia
(@vijayvee)

Meet agenda

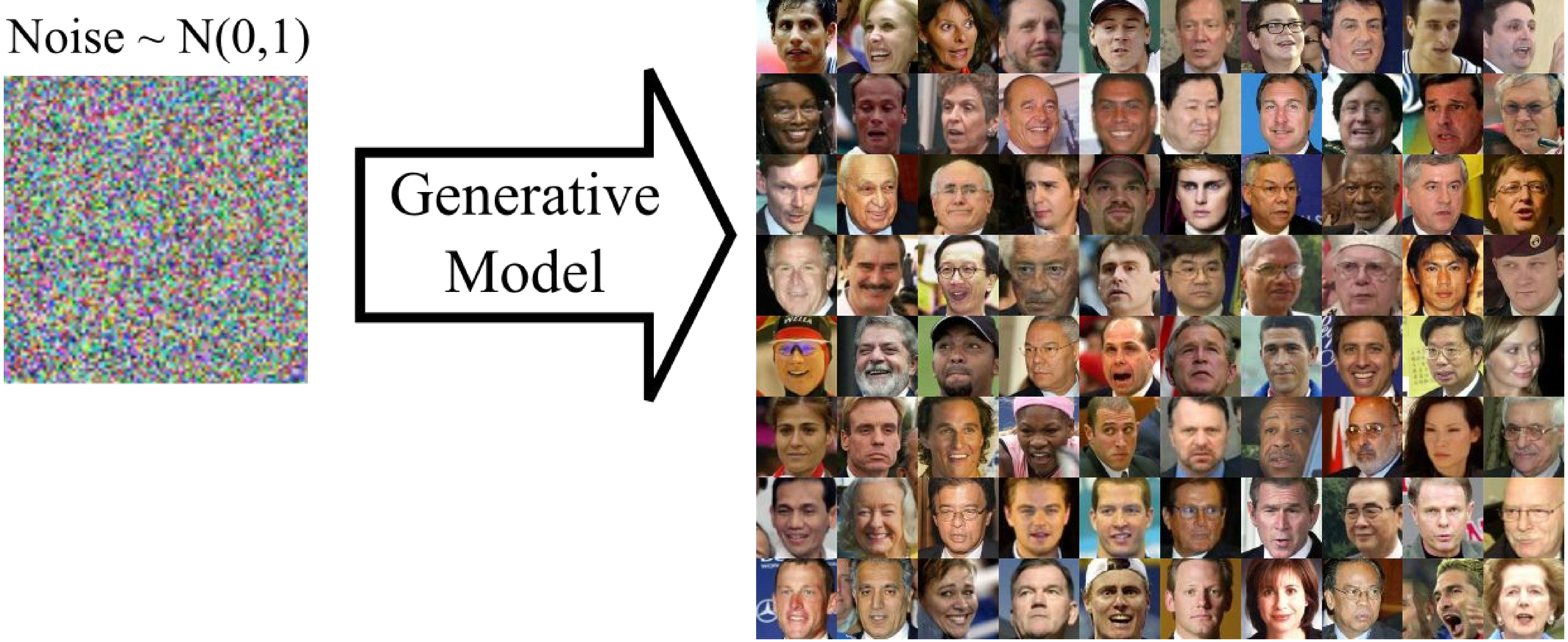
- Phase 1 : Introduction to generative models and GANs
- Phase 2 : Types of GANs
- Phase 3 : Applications of GANs
- Phase 4 : Limitations of GANs
- Phase 5 : GAN Hacks

Generative models

- A model that can generate seemingly natural data samples



Generative adversarial networks



Analogy to counterfeit currency

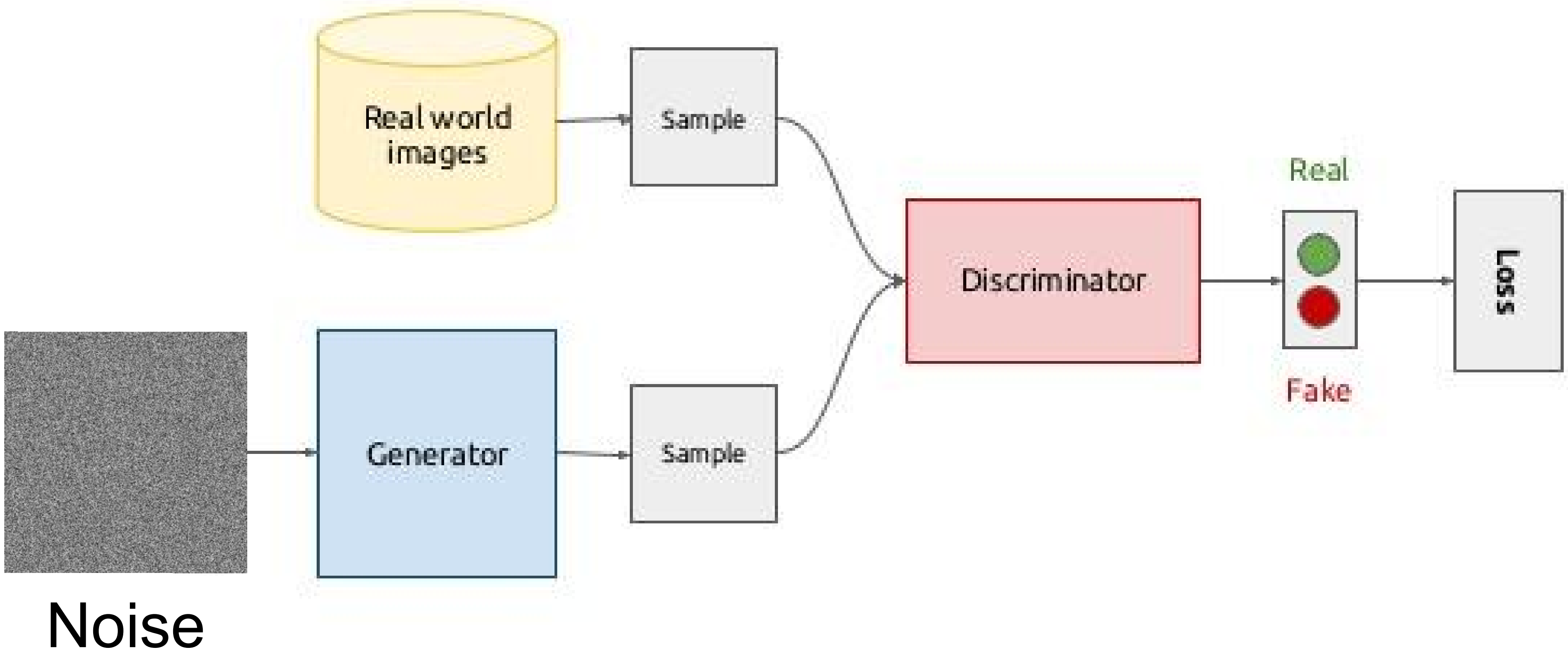
Generator

Discriminator

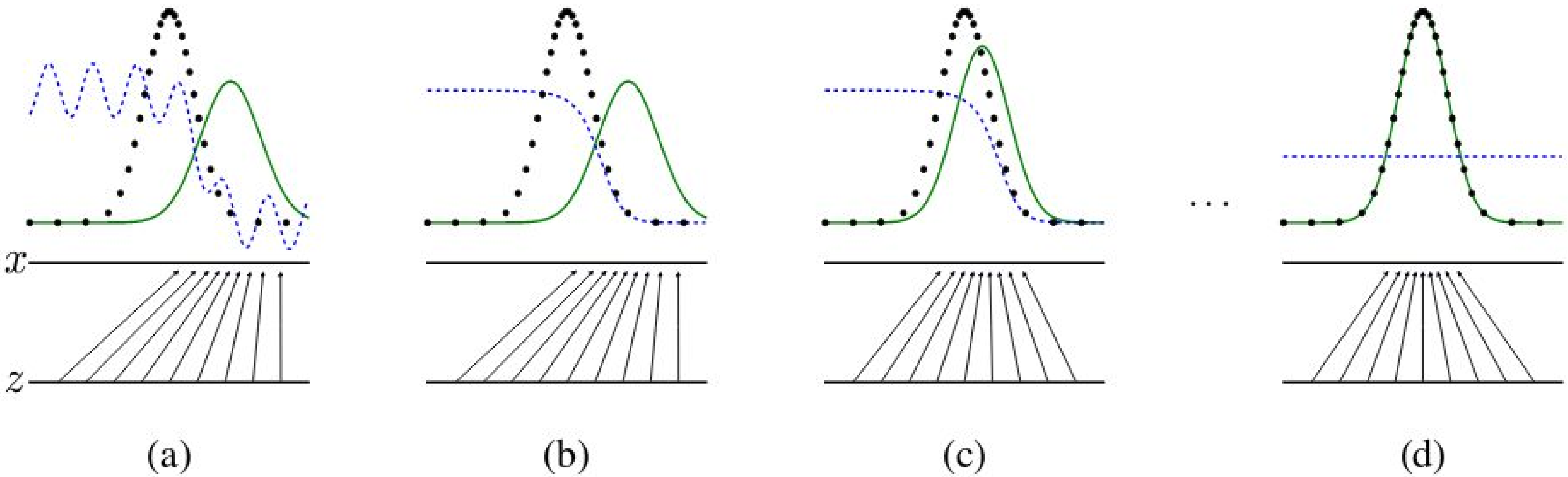
Motivation

- Necessity is the mother of invention
- Previous approaches used for modeling were based on Maximum Likelihood Estimation, Variational Autoencoders etc.
- Huge intractable probabilistic computations
- Need for a more tractable and easily trainable model leads to the inception of GANs

Generative Adversarial Nets - Ian et al



Generative Adversarial Nets - Ian et al



Training stages of a GAN

Black dotted: True data

Green solid: Generated data

Blue dotted: Discriminator loss

Adversarial loss

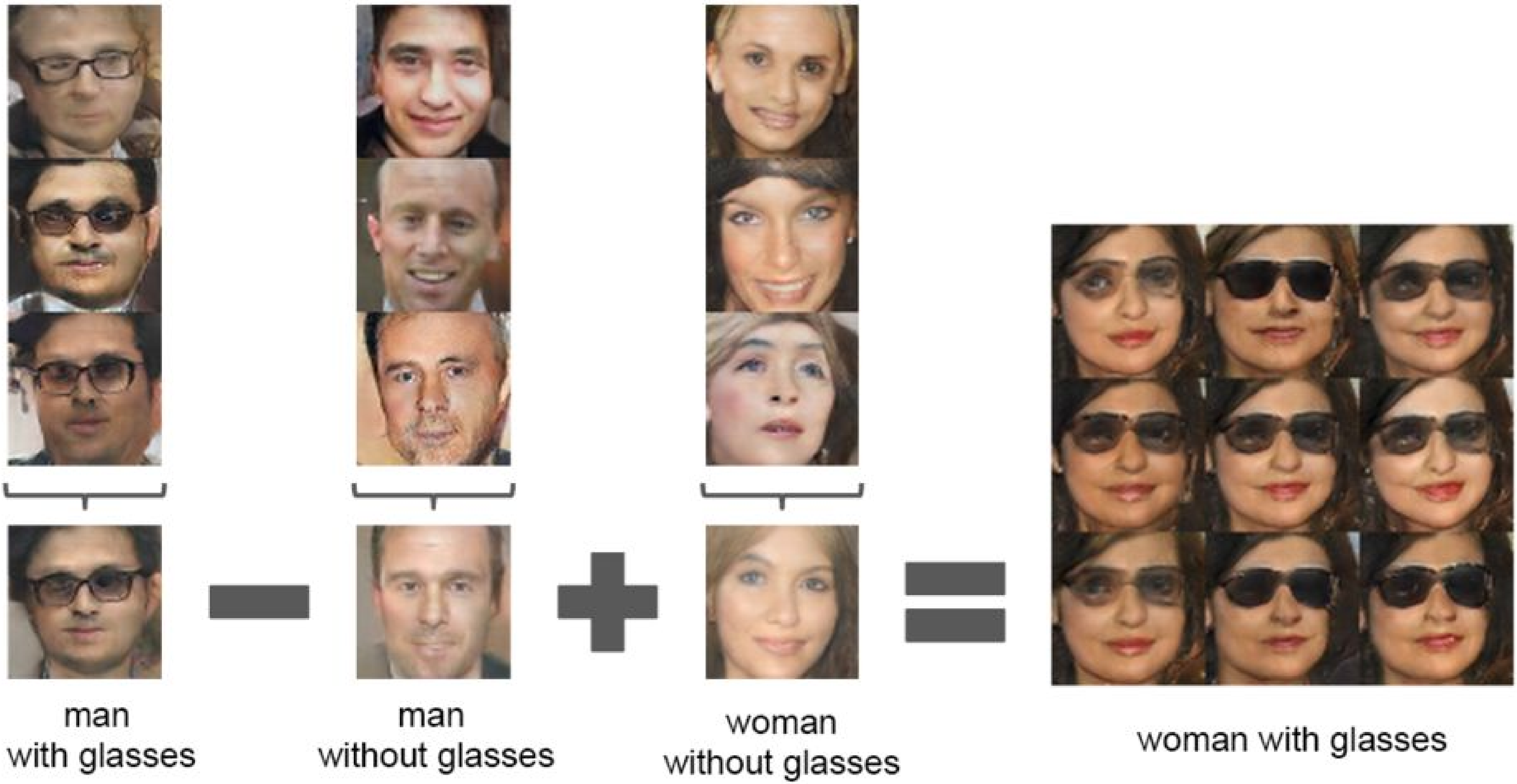
- Loss function proposed in Goodfellow's paper introducing GANs

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

True data

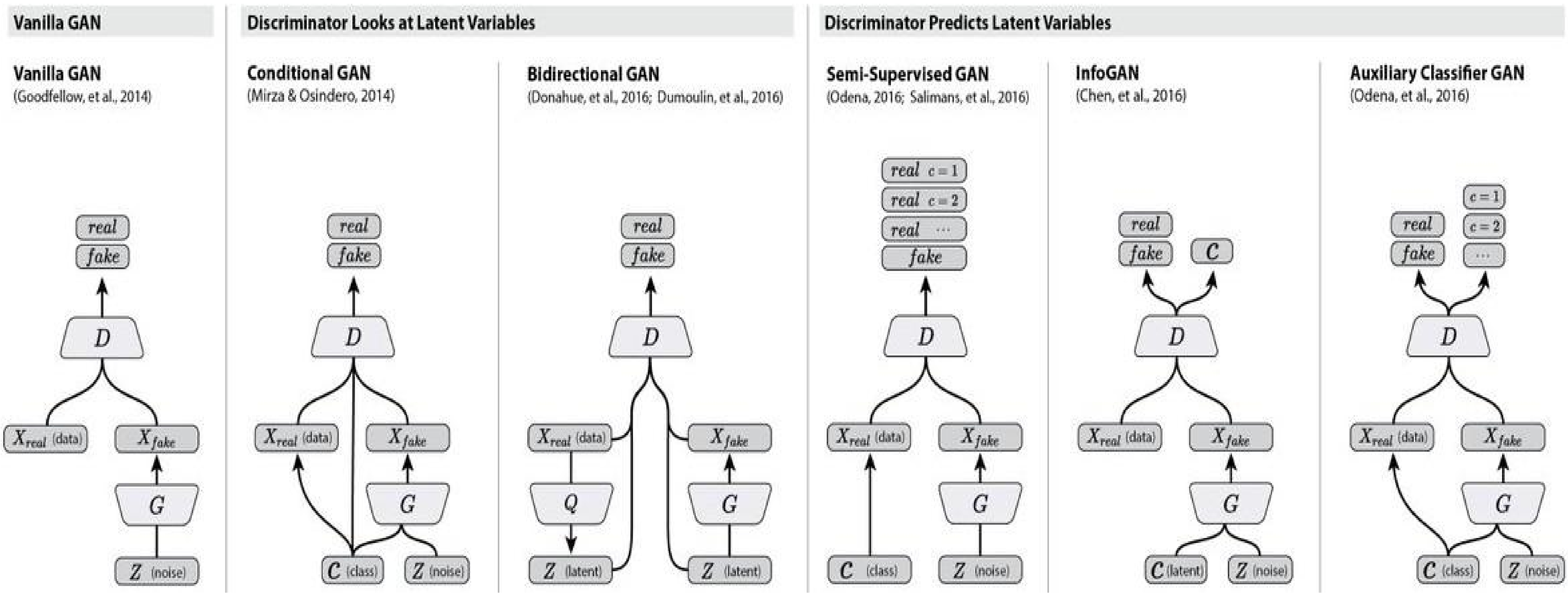
Noise provided for generating data

Bonus! - Vector space arithmetic of GANs

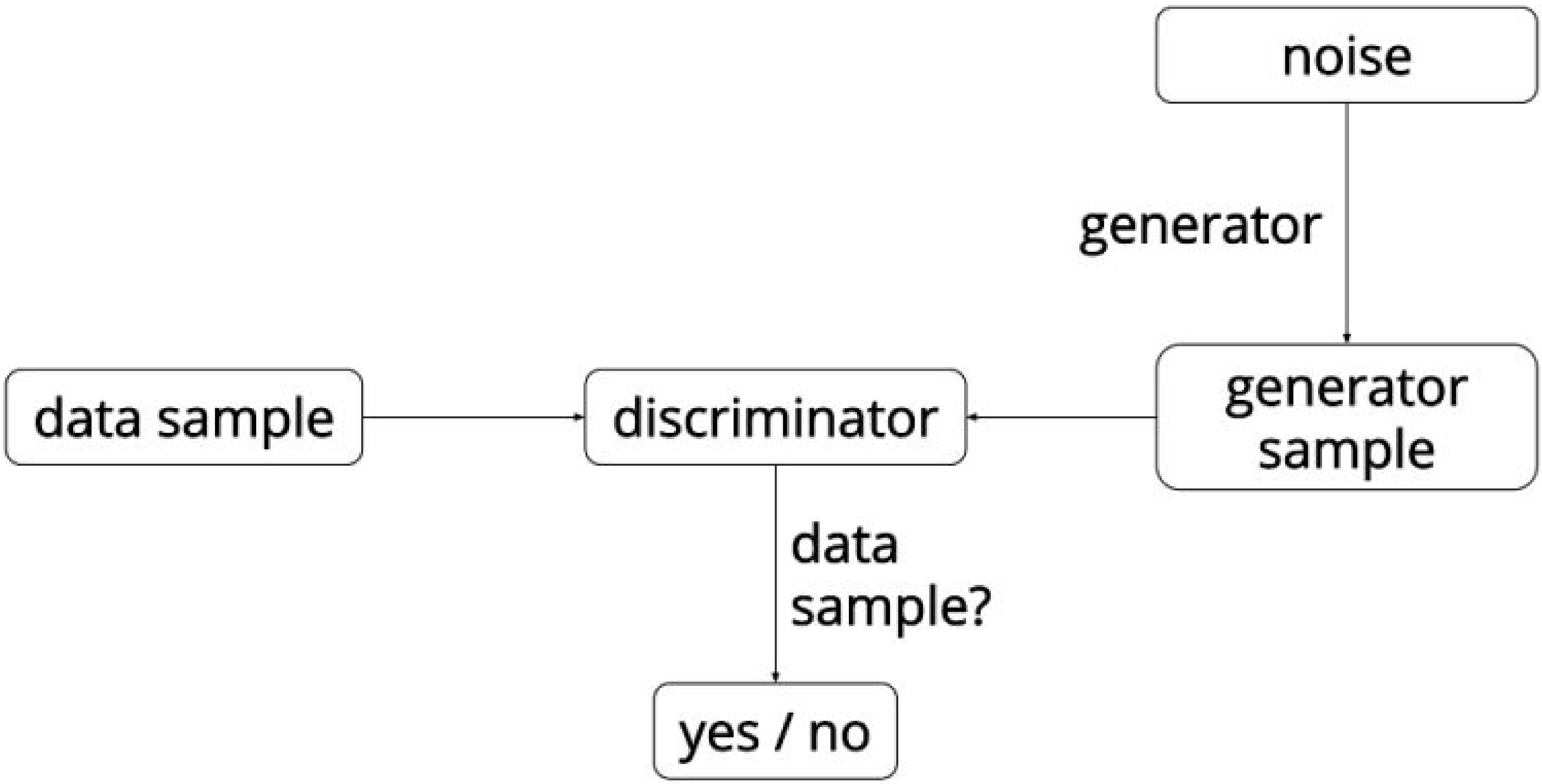


Types of GANs

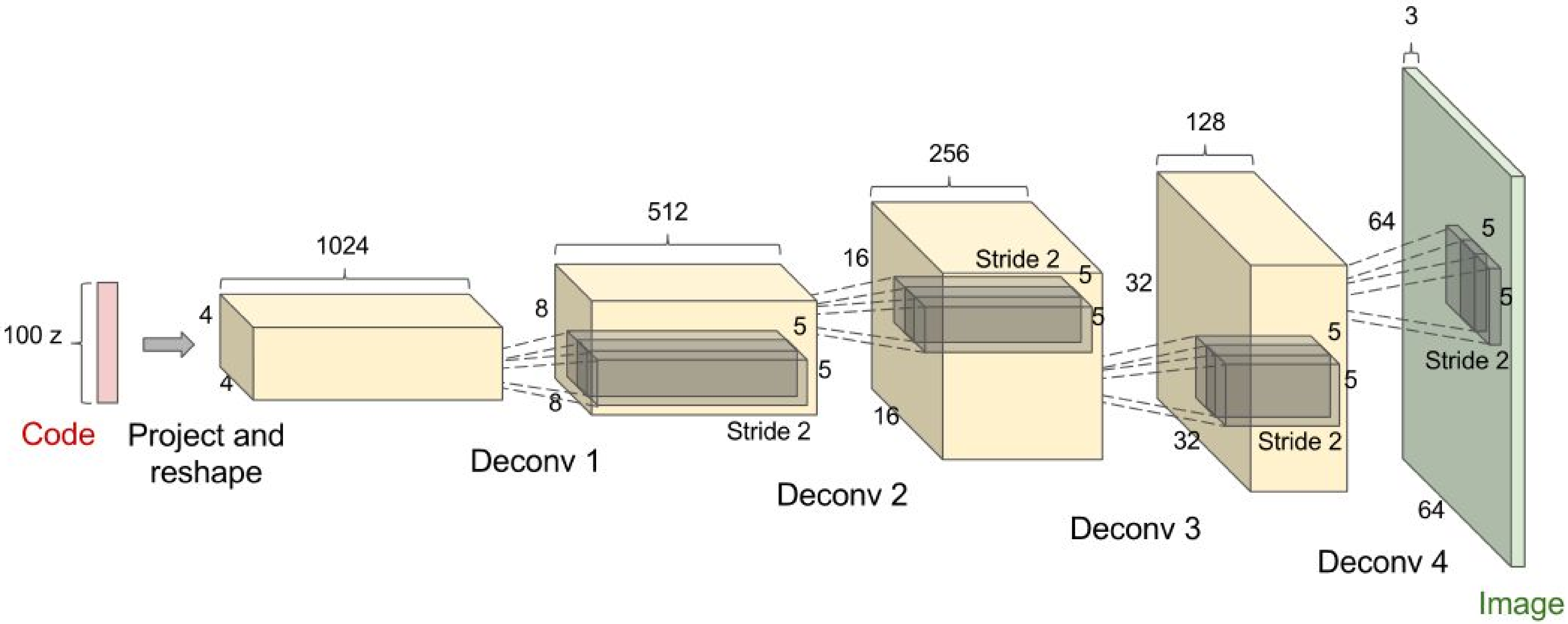
Sub classifications



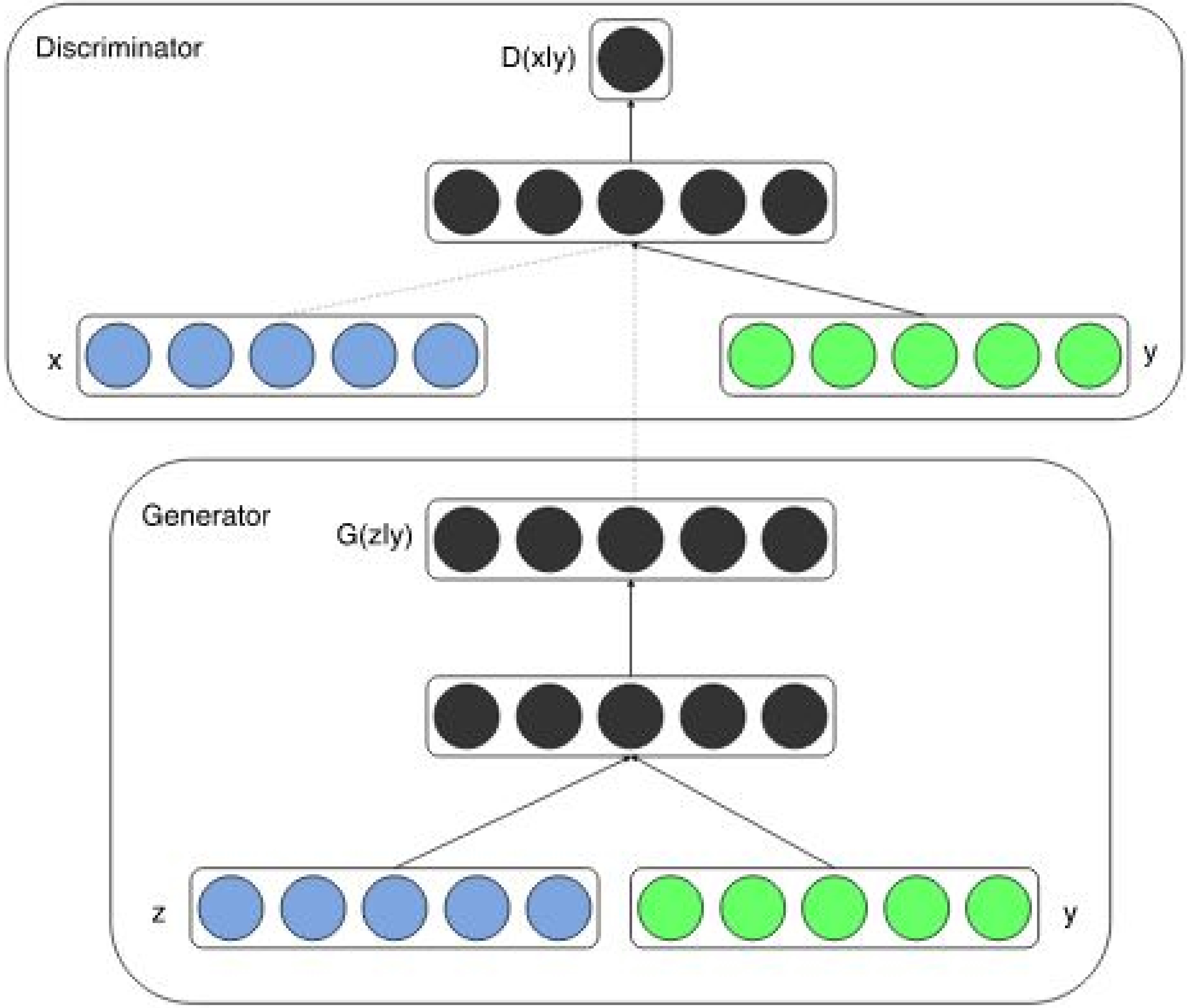
Basic vanilla GAN (T1)



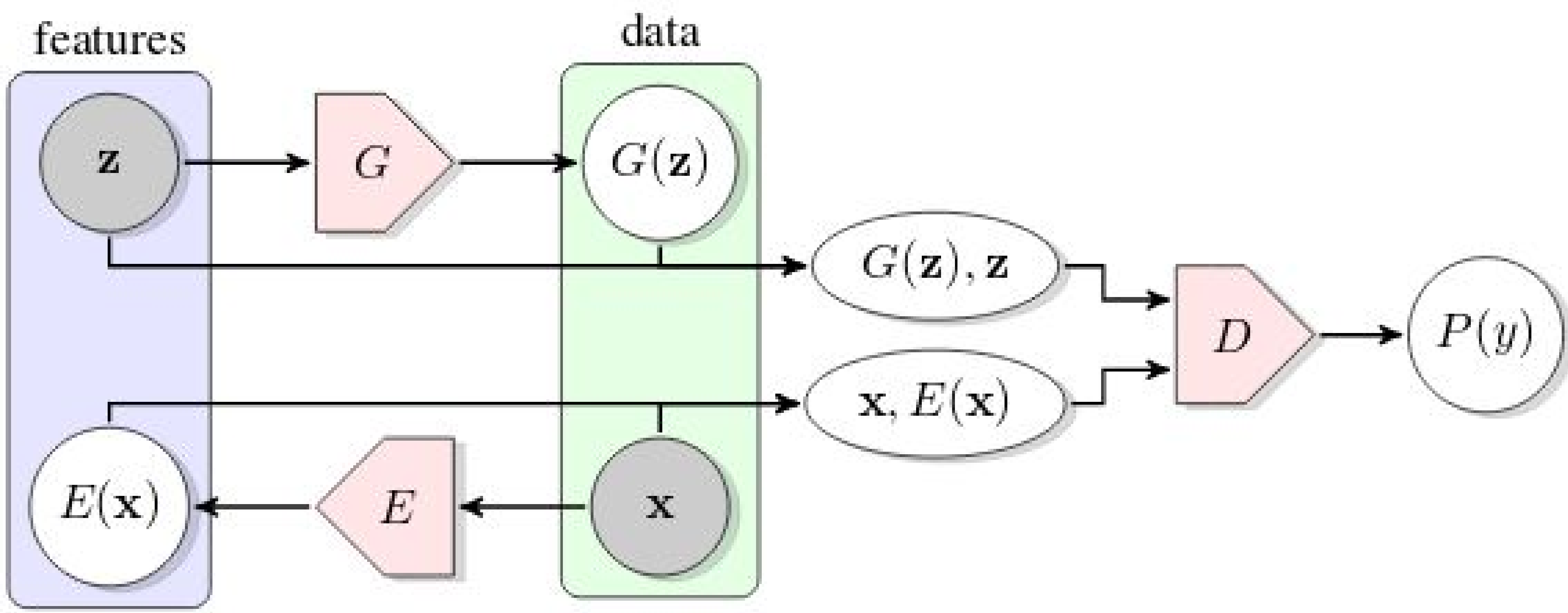
Deep Convolutional GAN (T1)



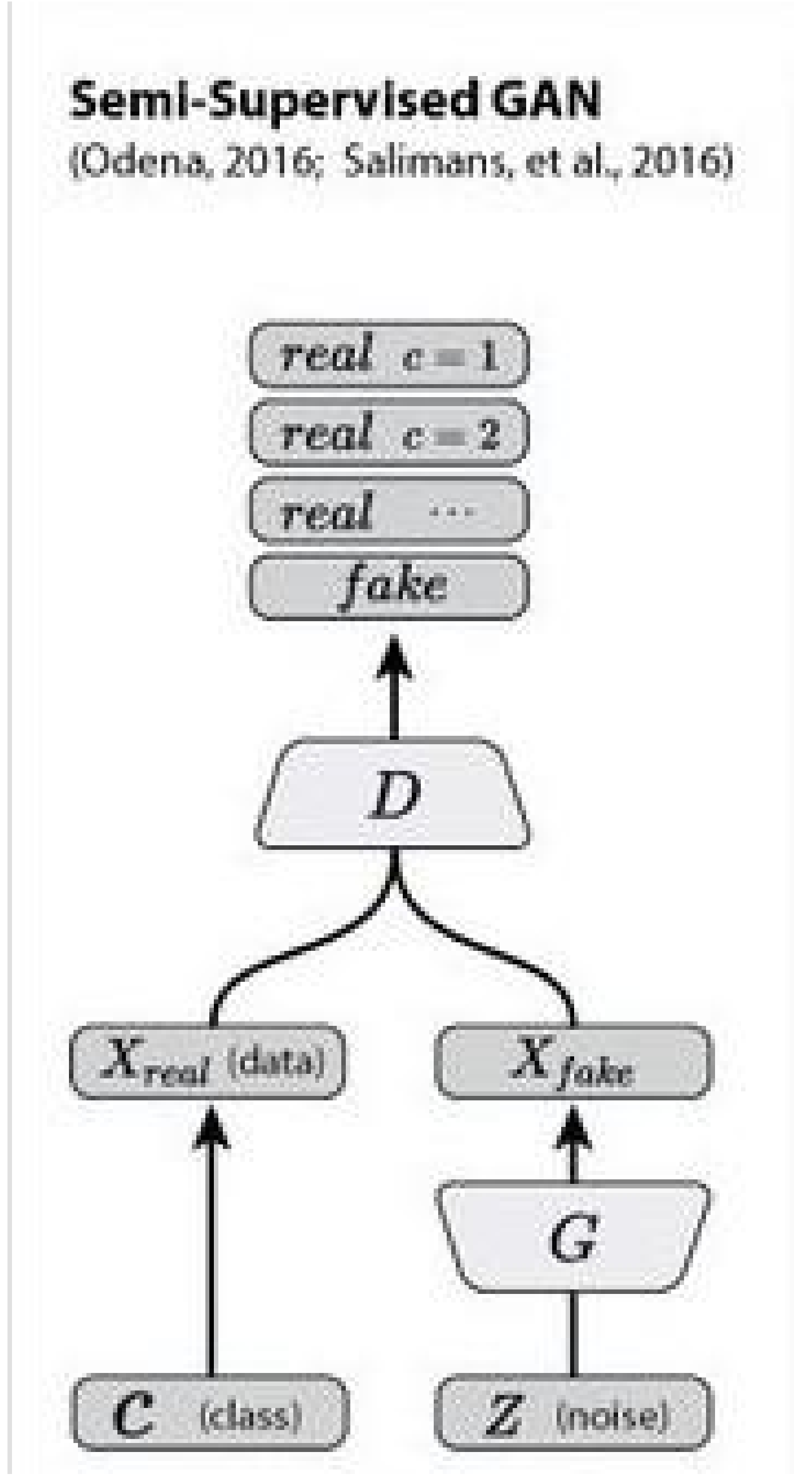
Conditional GAN (T2)



Bidirectional GAN (T2)



Semi-supervised GAN (T3)



Applications of GANs

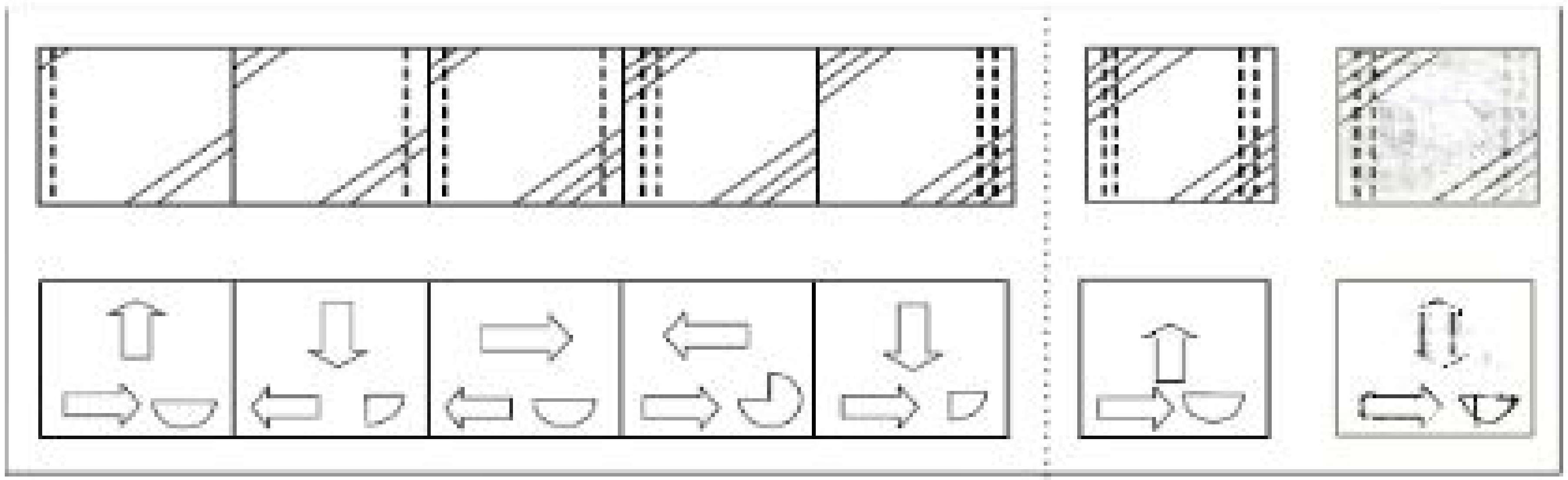
Image generation

PPGNs - High resolution image generation

volcano

Interactive image generation - iGANs

GANs for Diagrammatic Abstract Reasoning



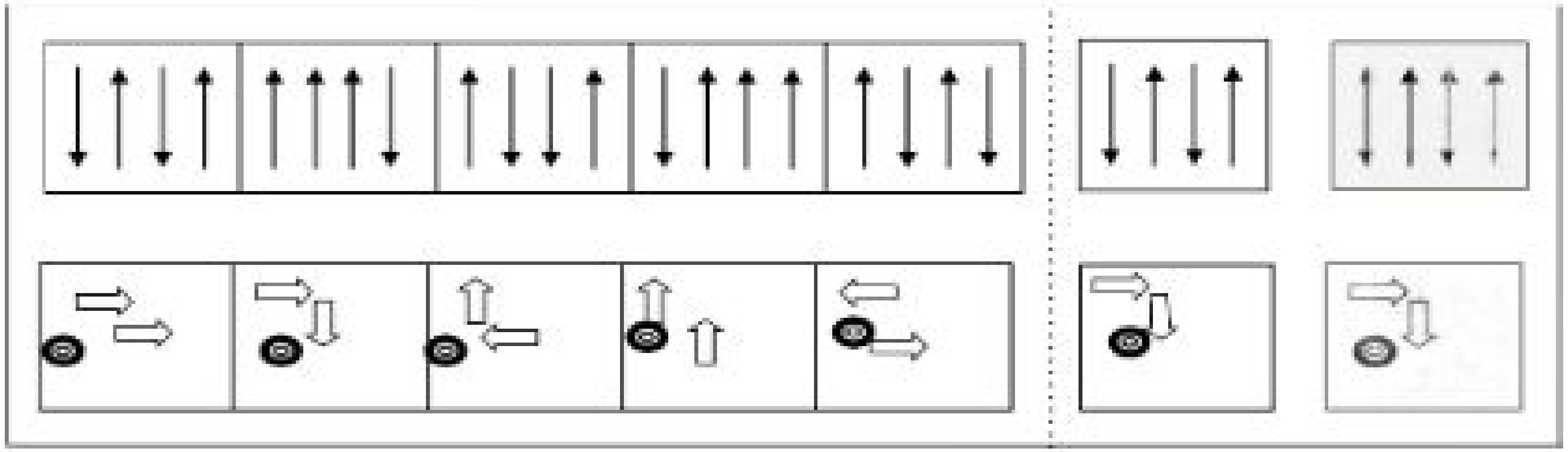


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Image super resolution using SRGANs

(Result of our experiment at Artifacia)

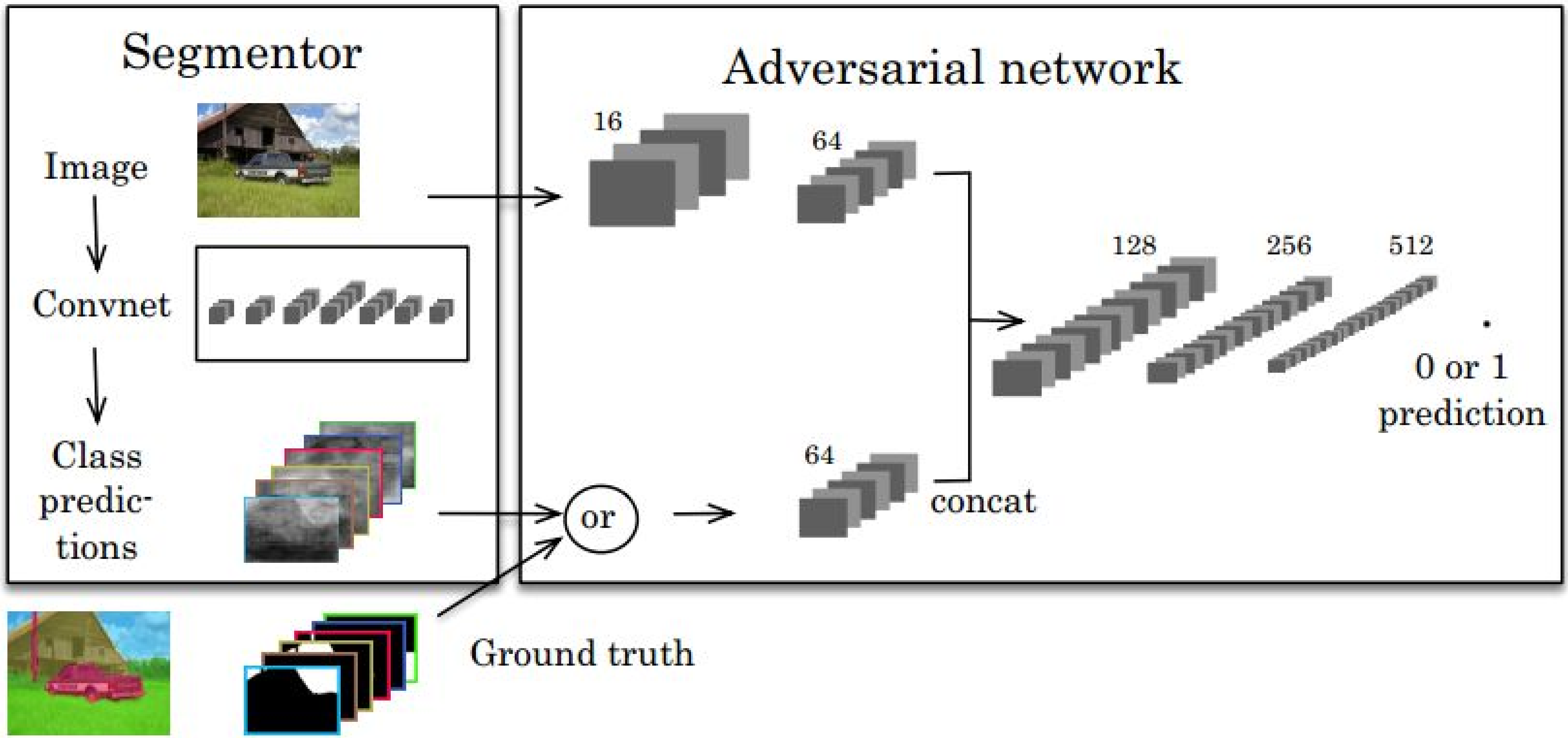
Image inpainting

Input to GAN

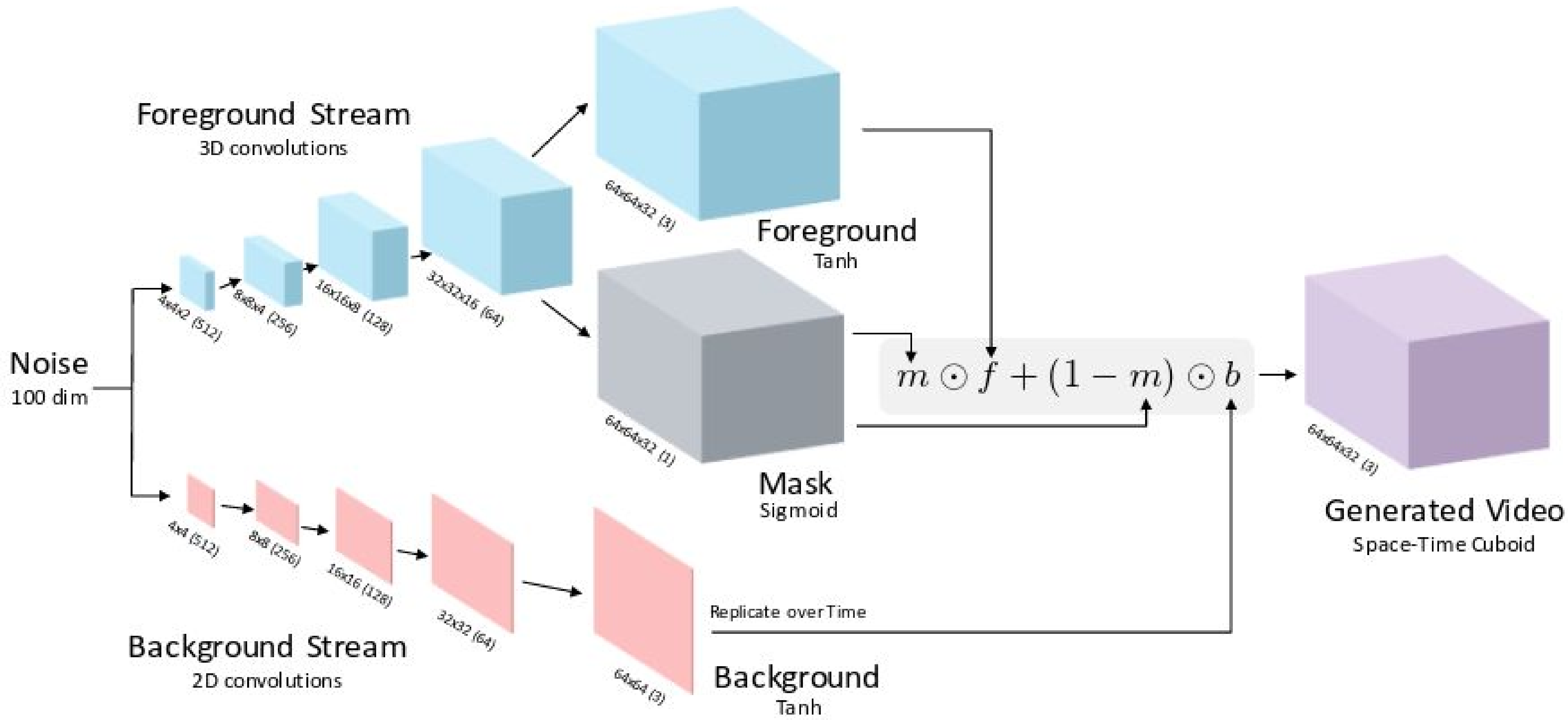
GAN generated output

(Result of our experiment at Artifacia)

Semantic segmentation using Adversarial networks



Video generation using Adversarial networks



Generator network

Impressive text to image results

This small blue bird has a short pointy beak and brown on its wings

This bird is completely red with black wings and pointy beak

A small sized bird that has a cream belly and a short pointed bill

A small bird with a black head and wings and features grey wings

Limitations of GANs

Mode collapse

- Generator keeps generating highly similar looking images
- Happens when the generator is optimized while keeping the discriminator constant for many iterations

Predicting pixels based on context

- GANs are trained to predict all pixels in an image at once
- Giving one pixel and predicting its neighbouring pixels is hence difficult

Difficulty in reaching convergence

- Generator and discriminator losses keep oscillating
- Network does not converge to an optimal solution

Relative strength of the two networks

- Either of the two networks becoming extremely strong relative to the other
- Network never learns beyond this point

Dealing with these issues - GAN Hacks

Normalizing images

- Standard practice of normalizing images by mean normalizing and scaling by stddev should work
- Make sure that the images are normalized to values between -1 and +1
- Paper explaining intuition Sampling Generative Networks

Inverting labels

- While training generator, flip labels sent to the discriminator

- Label of real image is made fake(say class 0) and that of generated image is made real(class 1)

Schedule for training G and D

- People tend to find a fixed (nIter_Gen/nIter_Disc) training schedule

- Better to train G or D based on a loss threshold

- if loss_G > A:
      train_G()
  If loss_D > B:
      train_D()

Noisy D input

- Add noise to inputs of the discriminator
- Label of real image is made fake(say class 0) and that of generated image is made real(class 1)
- Paper explaining intuition: Towards Principled Methods for Training Generative Adversarial Networks

Feature matching

- Modify the loss function of the generator to include intermediate feature activations rather than output

- Forces the generator to generate data that match the statistics of real data

One sided label smoothing

- Technique proposed in the 1980's
- Instead of having hard labels like 0 and 1, smoothen the labels by making them close to 0 and 1
- For example, 0,1 -> 0.1,0.9

References

- Ian's talk on GANs
- Generative Adversarial Networks - Ian et al
- DCGANs
- Conditional GANs
- BiGANs
- Semi-supervised GANs
- PPGN
- iGANs
- Text to image generation
- Improved techniques for training GANs
- GAN Hacks

"What I cannot create, I do not understand"

- Richard Feynman

THANK YOU

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