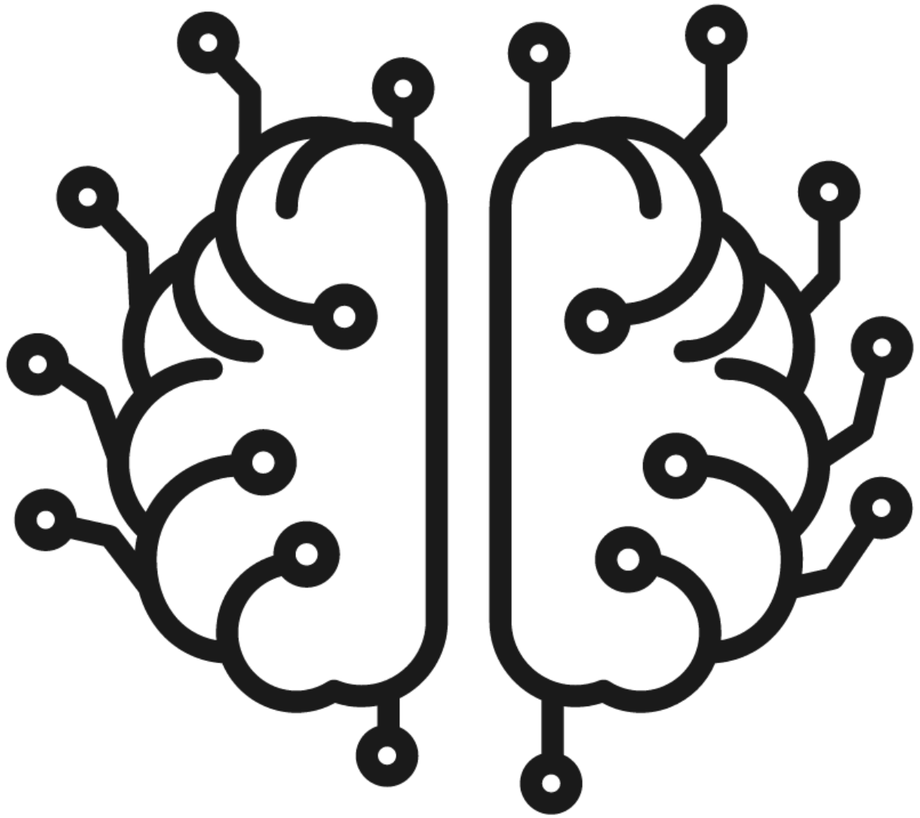
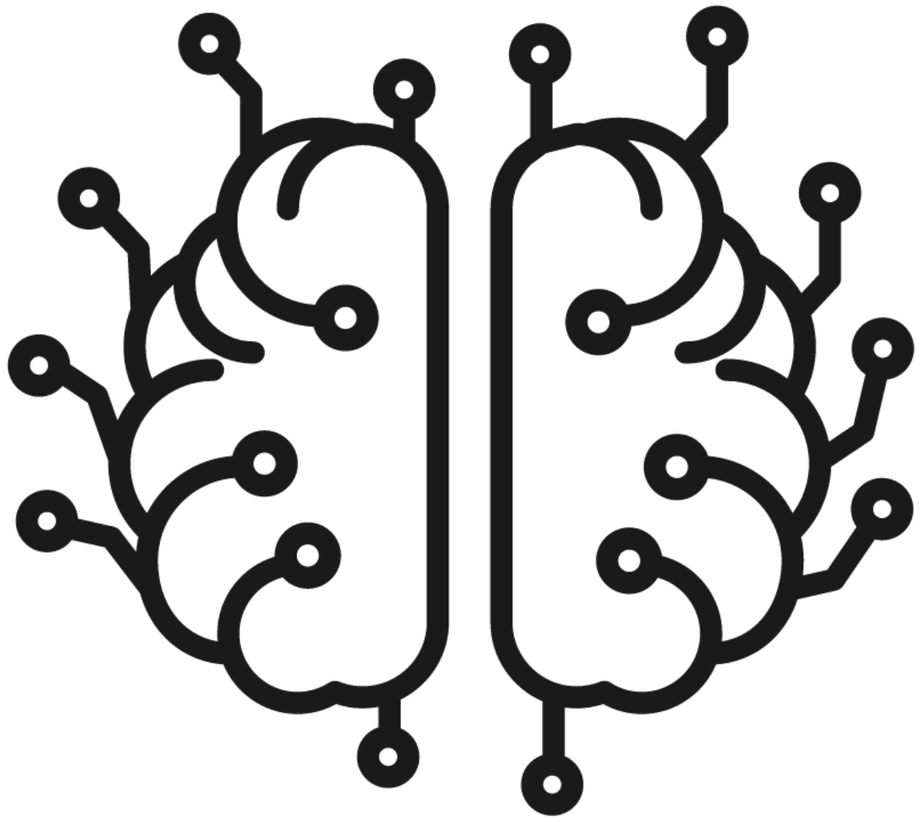
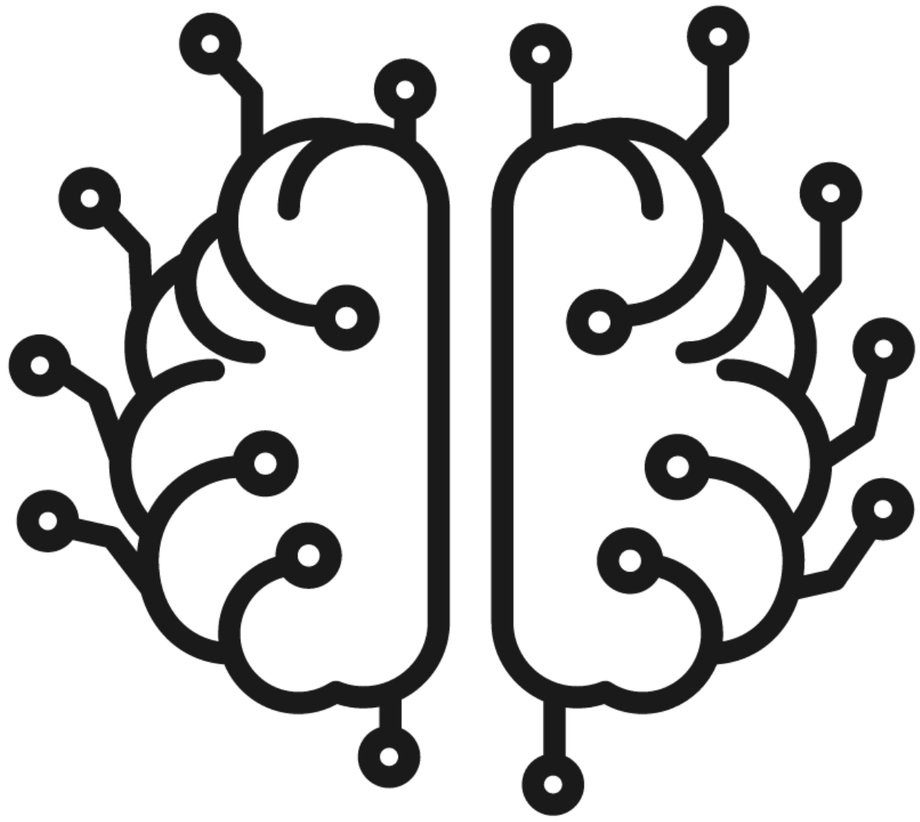
Generative adversarial networks

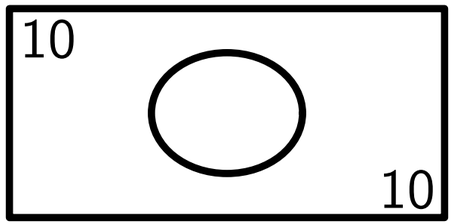
Generative Adversarial Nets

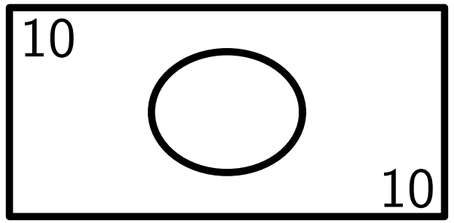
Ian J. Goodfellow, Jean Pouget-Abadie[*], Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair[†], Aaron Courville, Yoshua Bengio[‡]
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

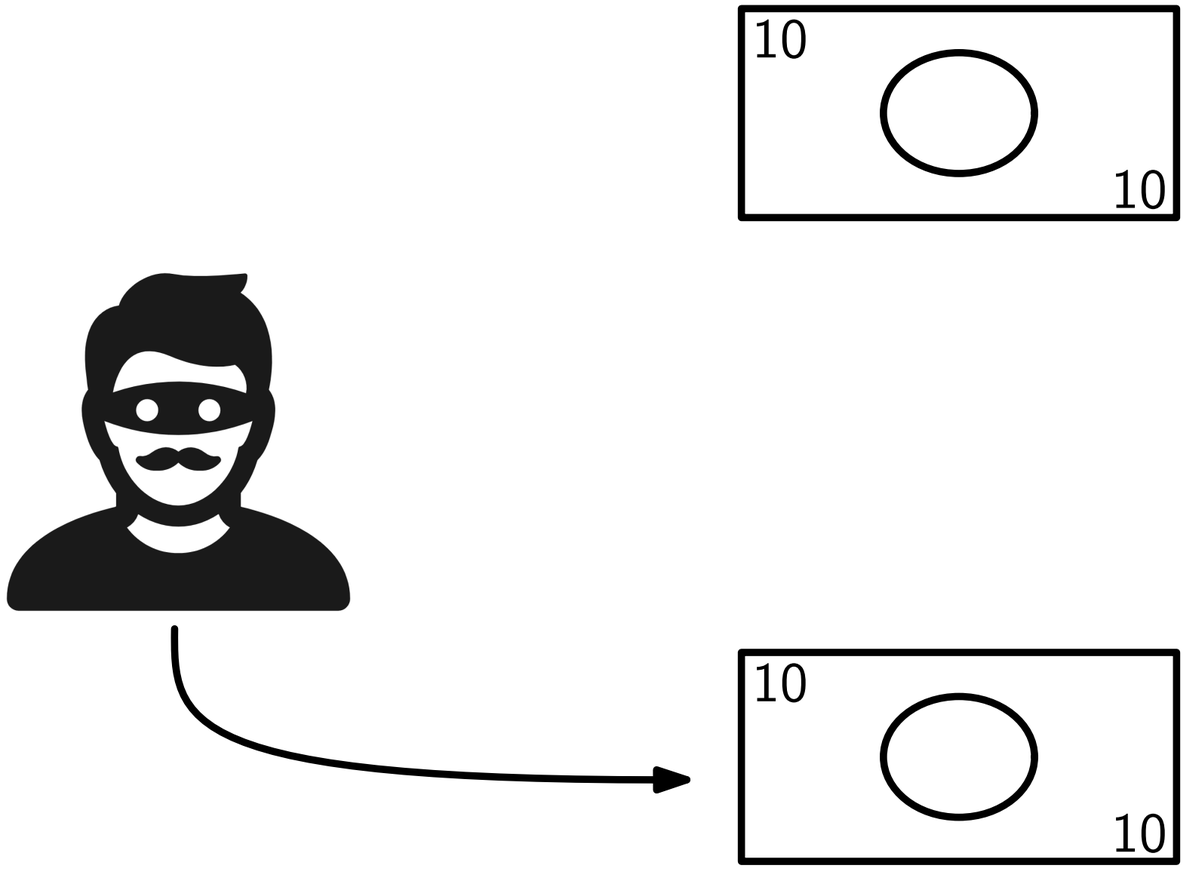


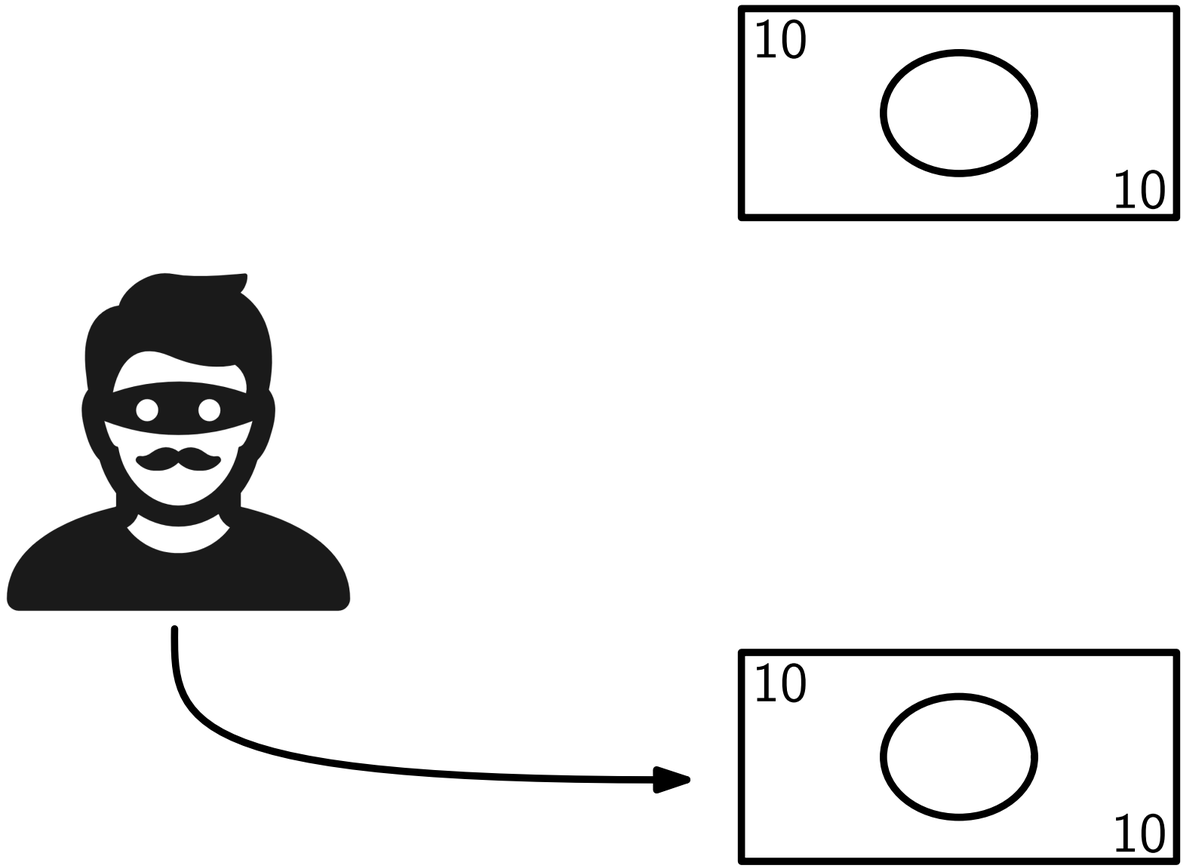


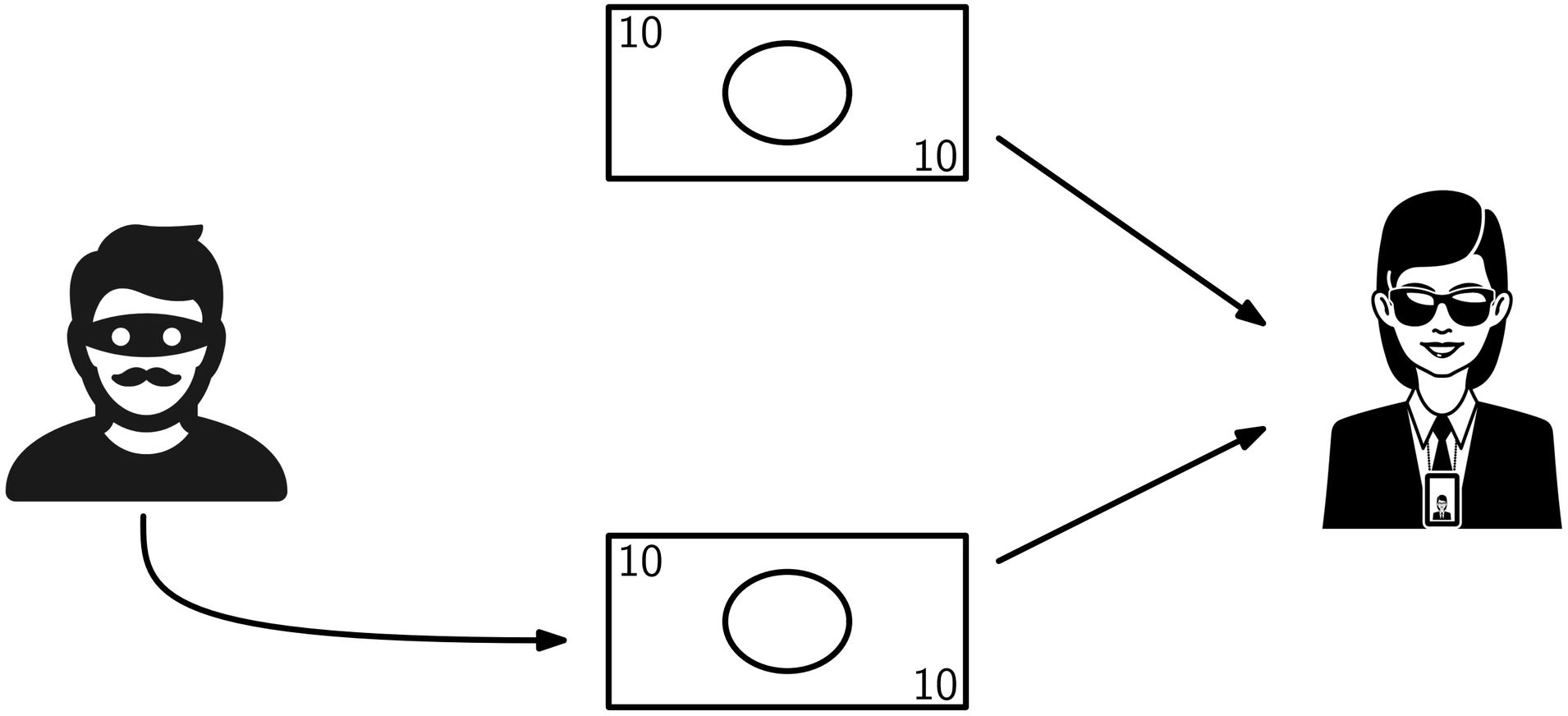


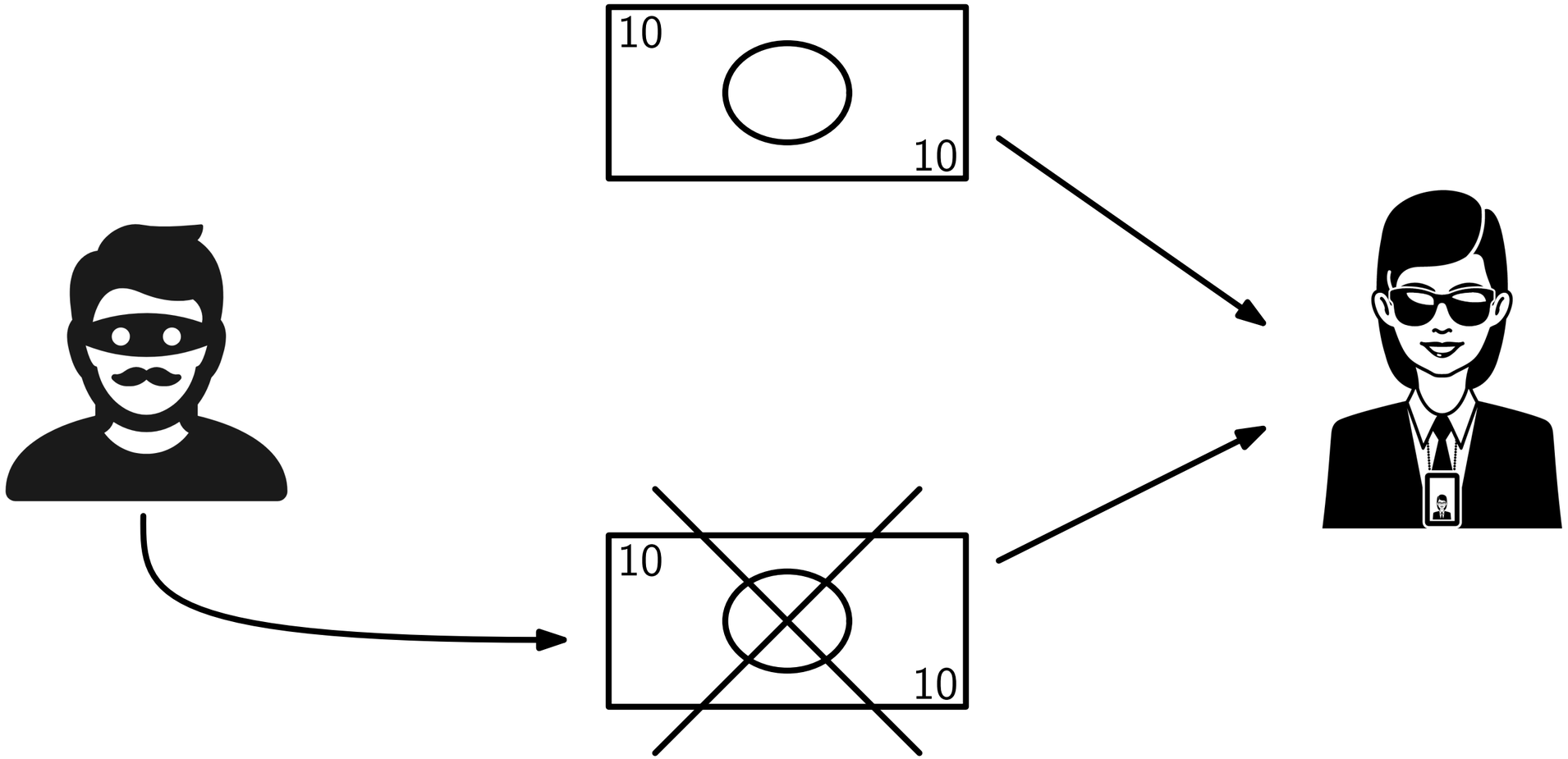

10
10

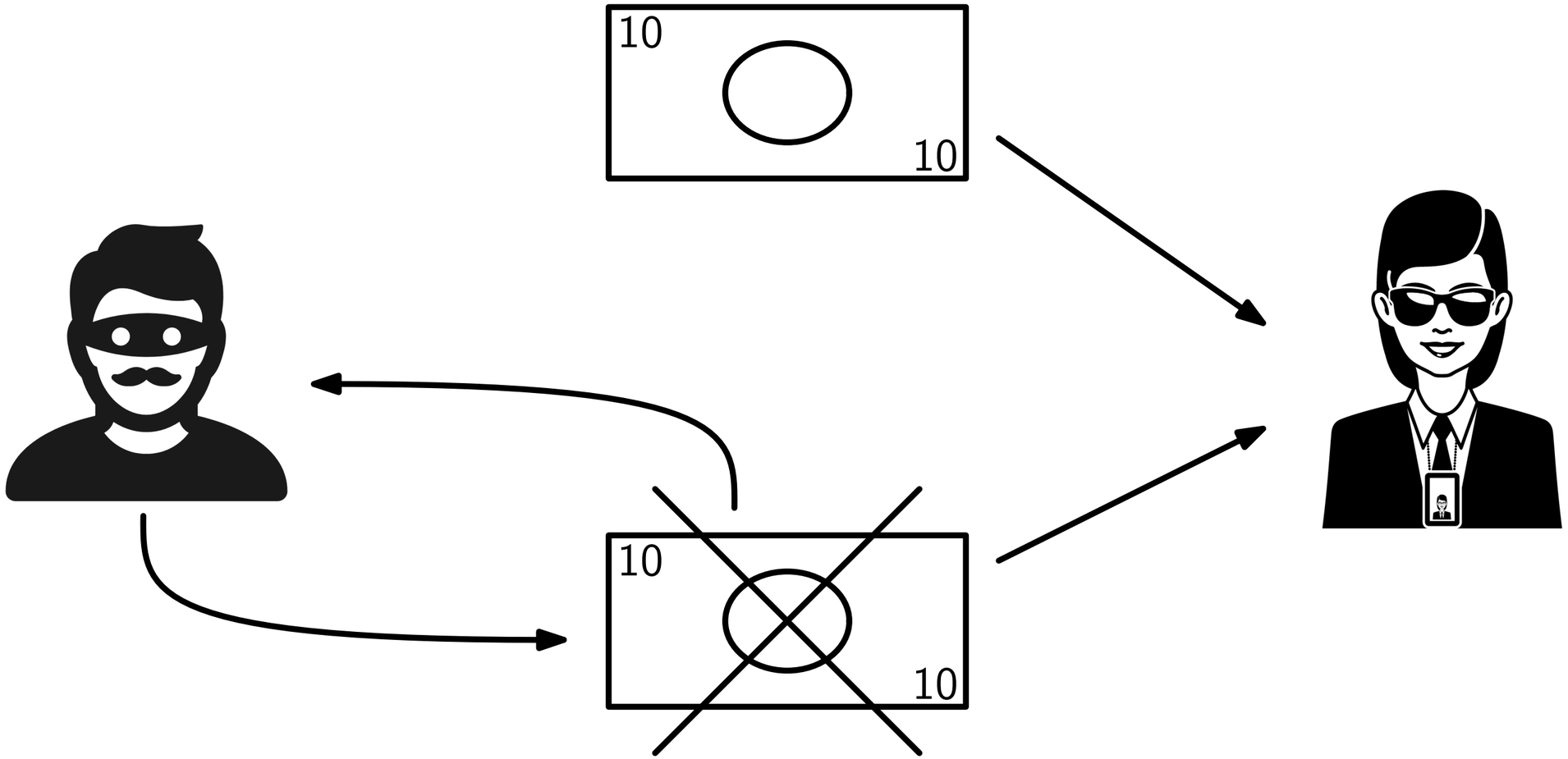

10
10

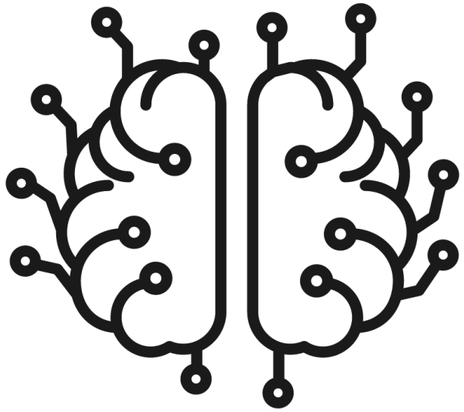

10
10
10
10

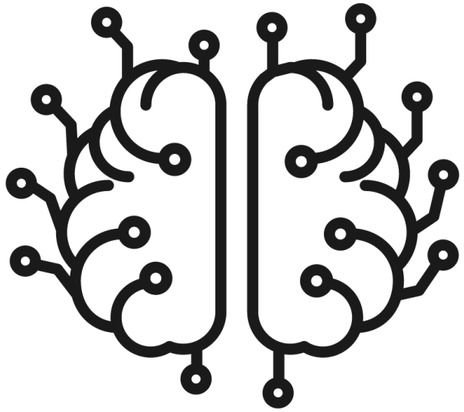

10
10
10
10


10
10
10
10

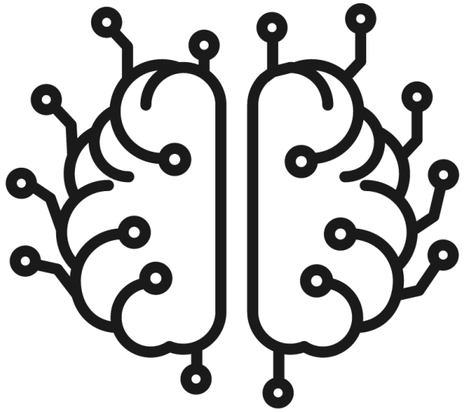

10
10
10
10

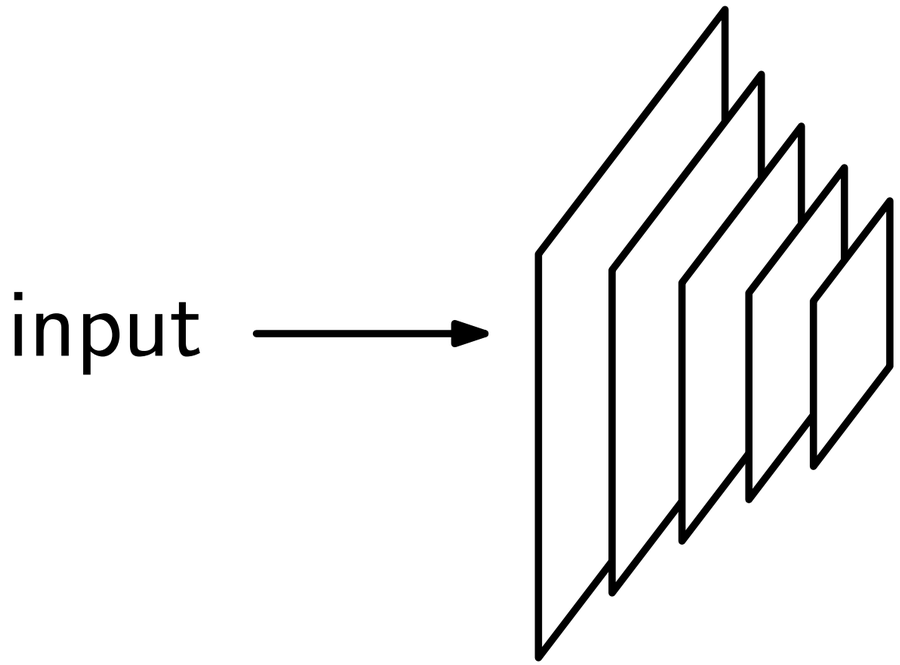

10
10
10
10

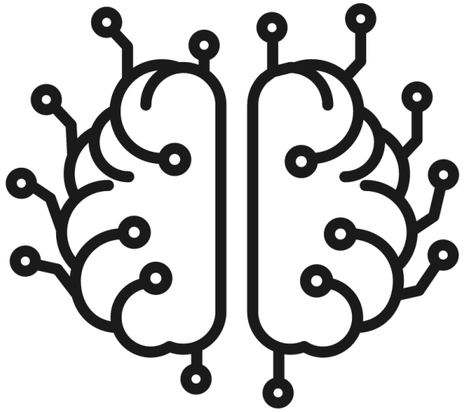


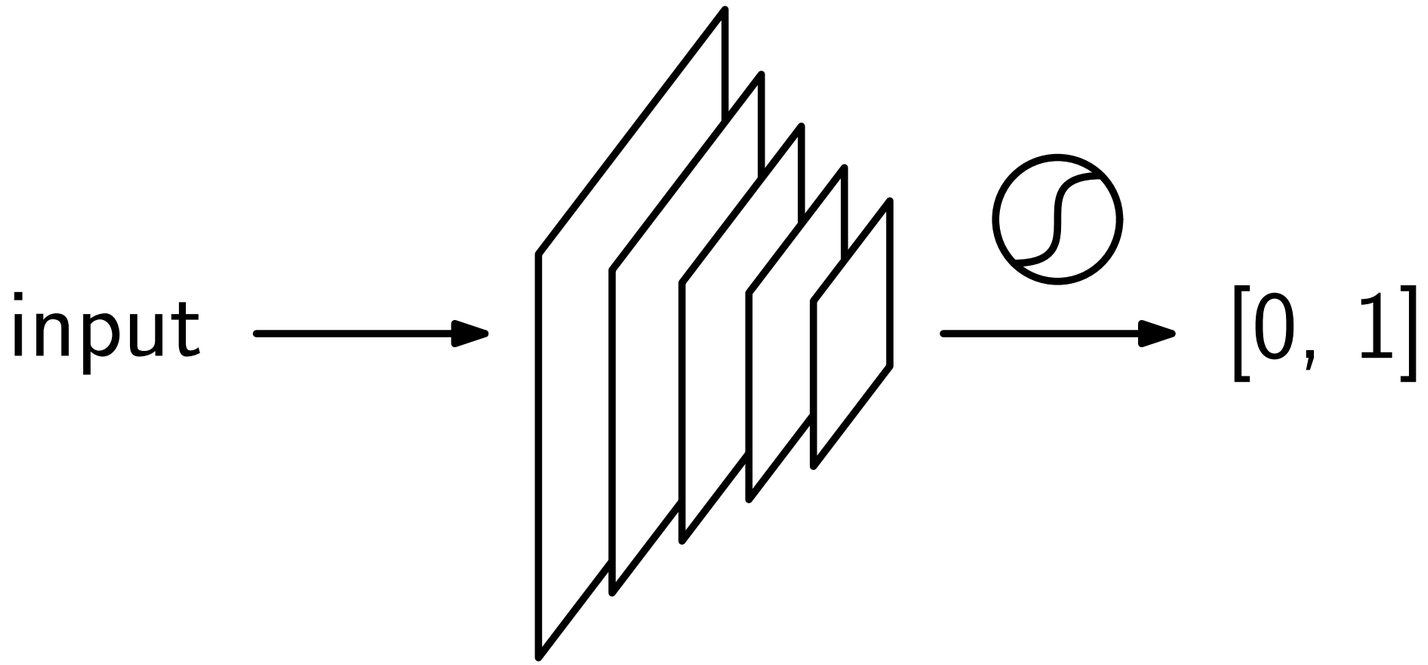


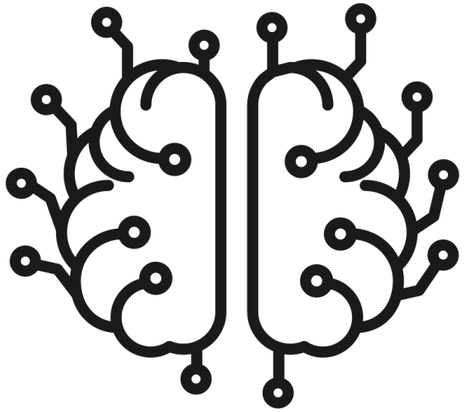
input



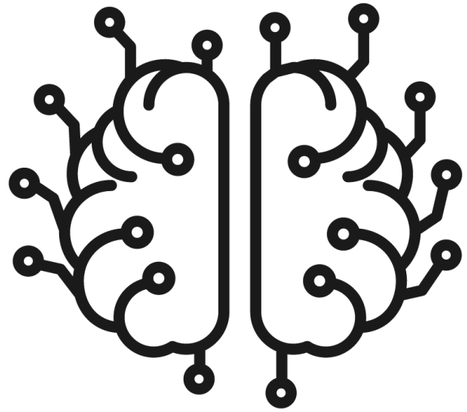

input



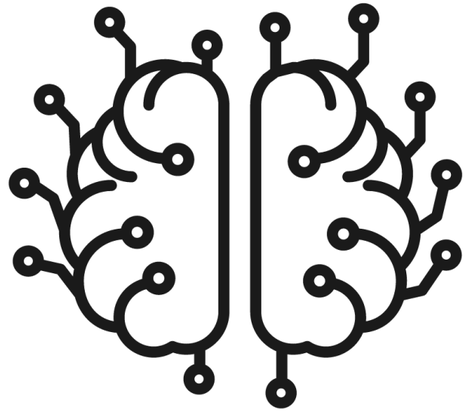

input
[0, 1]



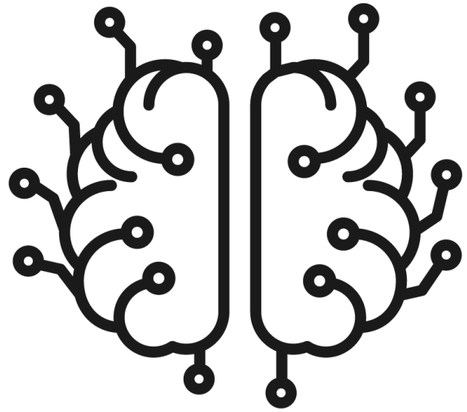
input $p \in \mathbb{R}^n$



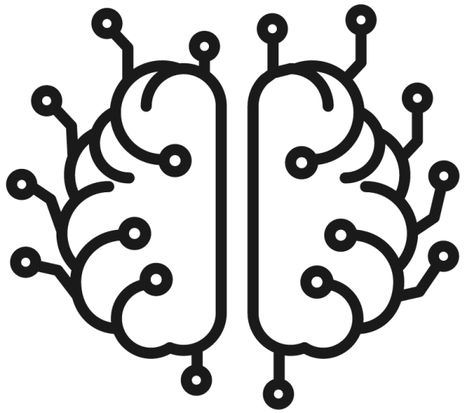
input $p \in \mathbb{R}^n \longrightarrow$ latent code $z \in \mathcal{Z}$



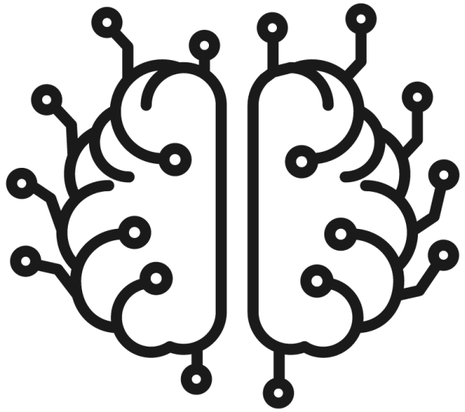
input $p \in \mathbb{R}^n \longrightarrow$ latent code $z \in \mathcal{Z} \longrightarrow [0, 1]$



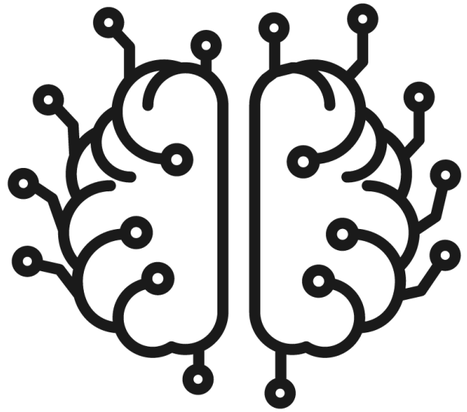
input $p \in \mathbb{R}^n$ ⟵ latent code $z \in \mathcal{Z}$



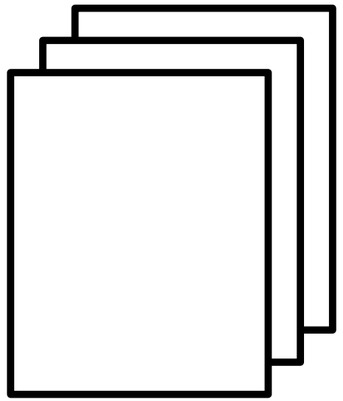
generator



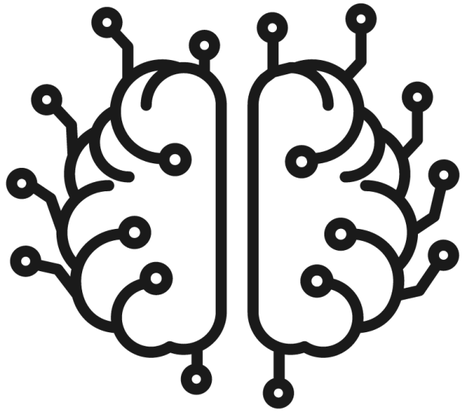
generator



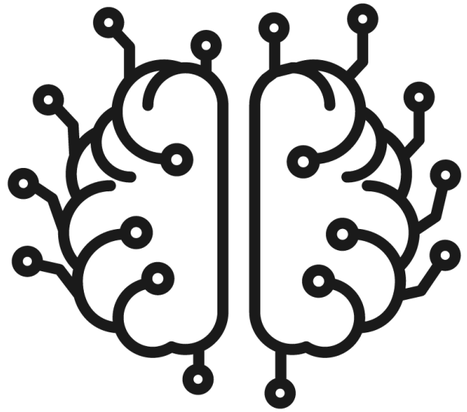
discriminator



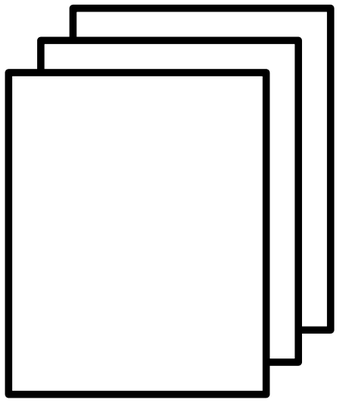
training data



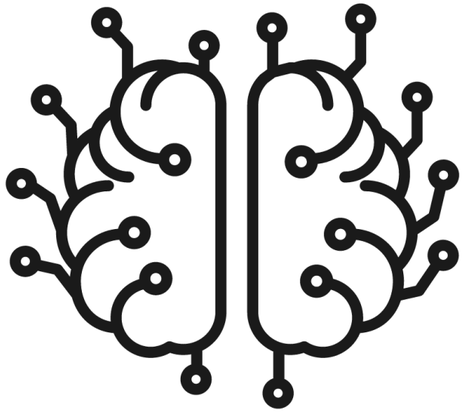
generator



discriminator

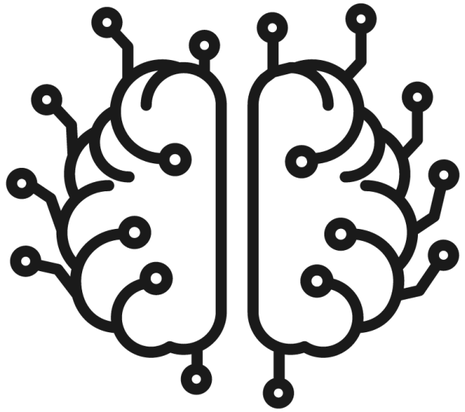


training data

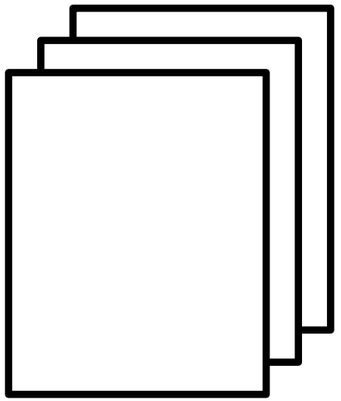


discriminator

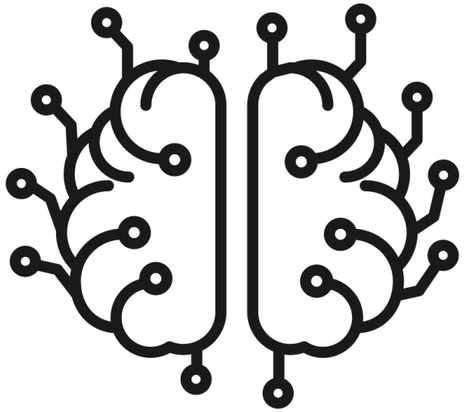
noise



generator

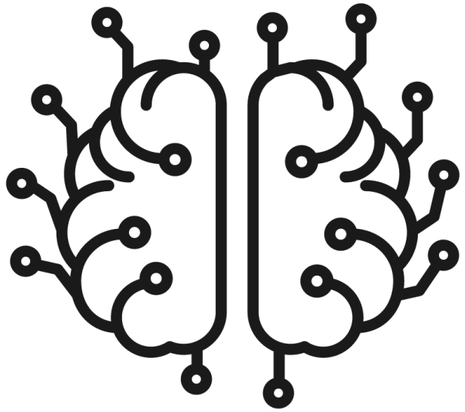


training data



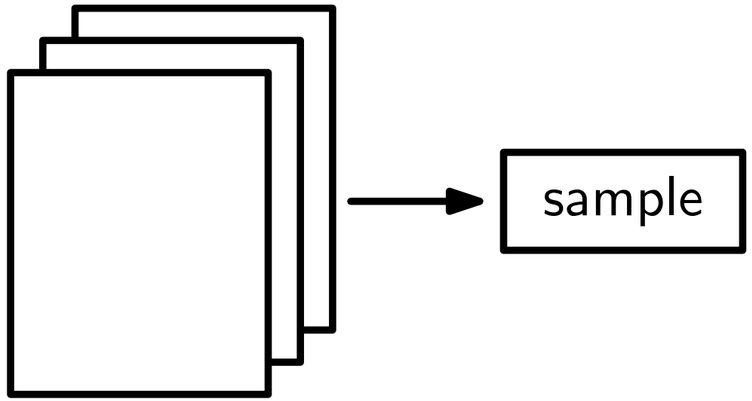
discriminator

noise

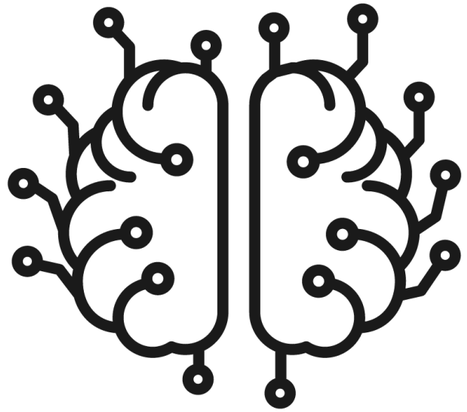


sample

generator

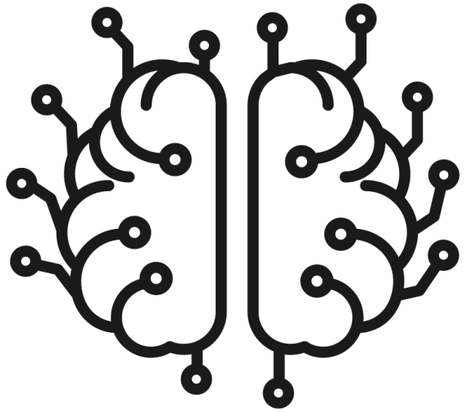


training data

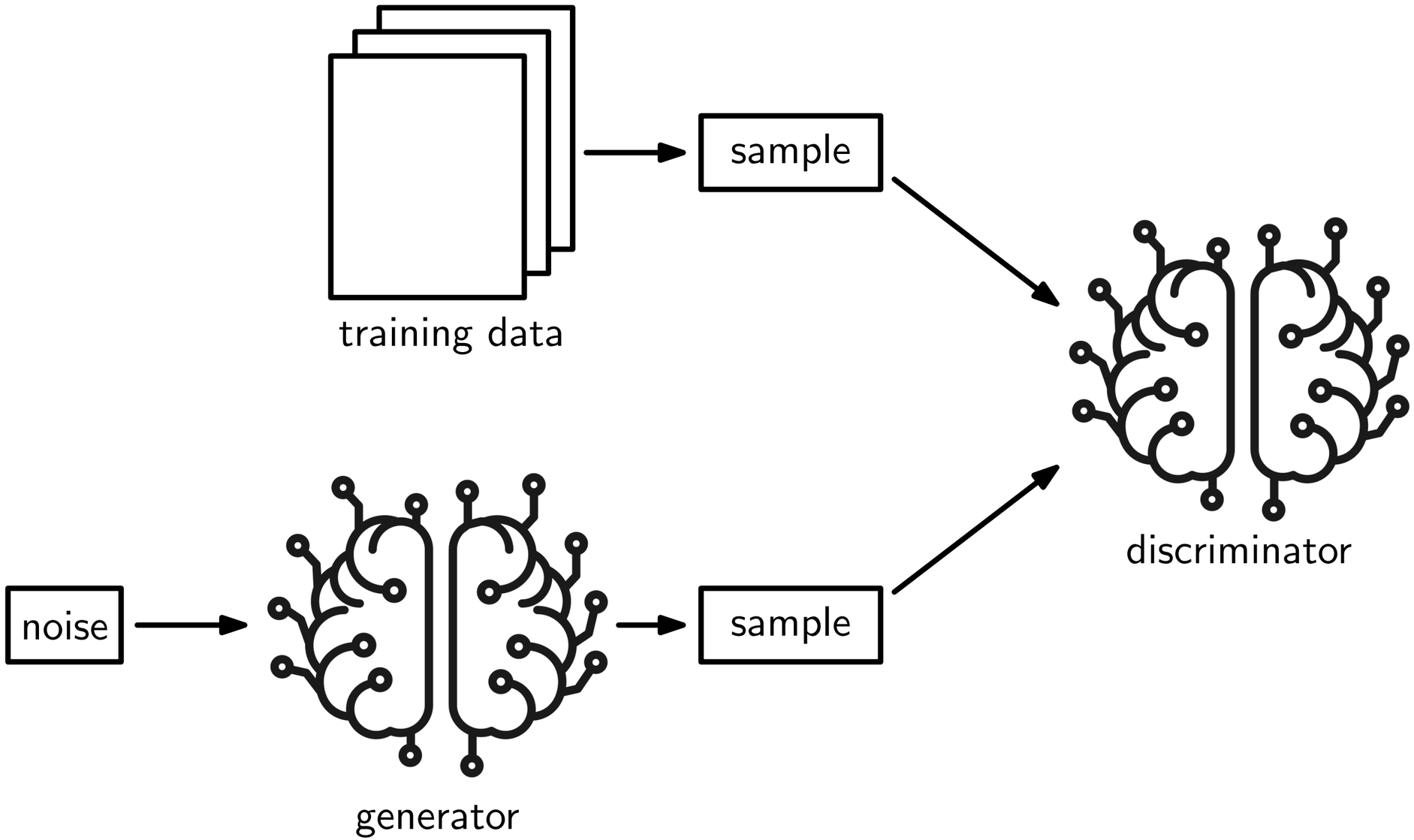


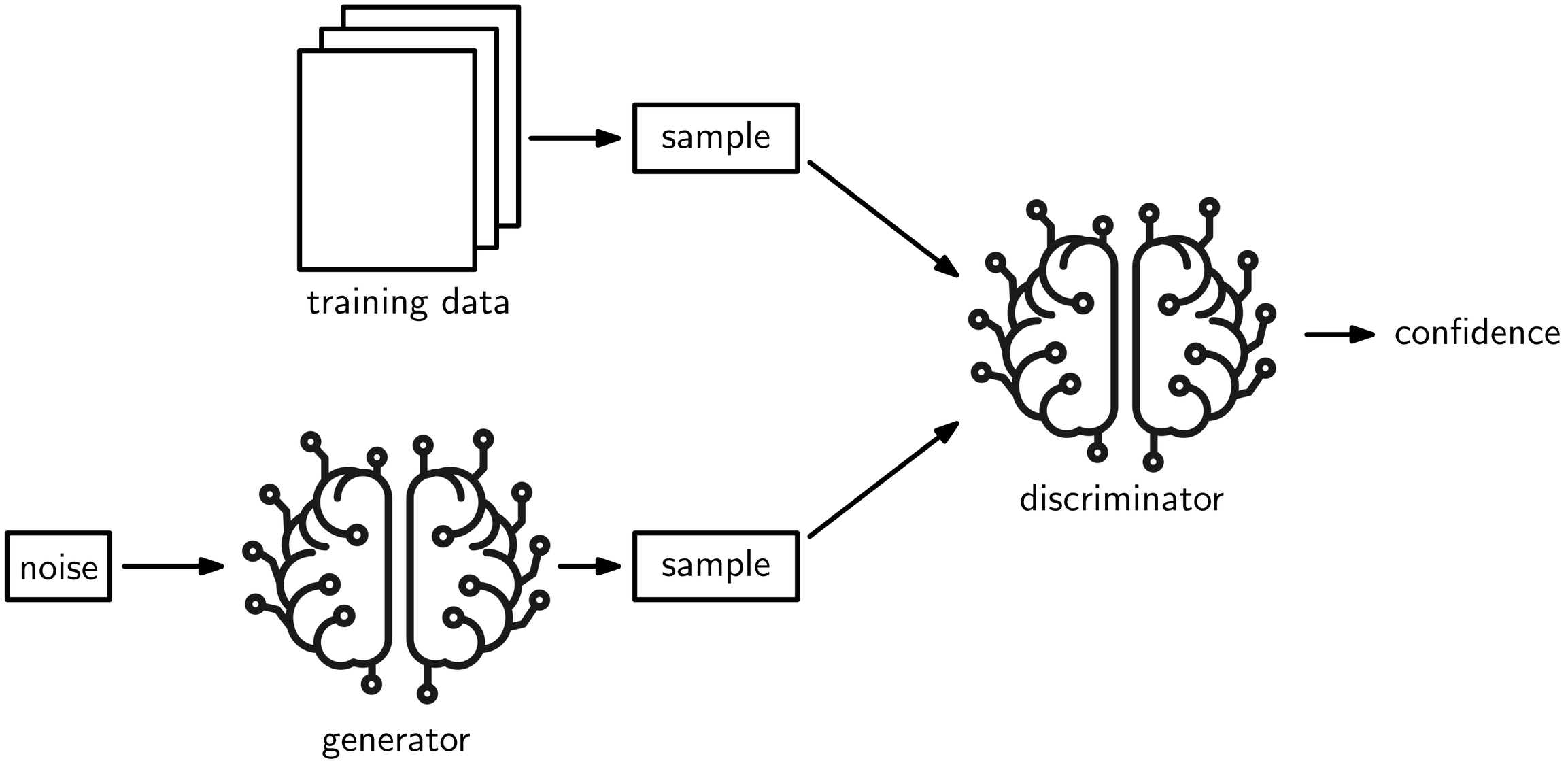
discriminator

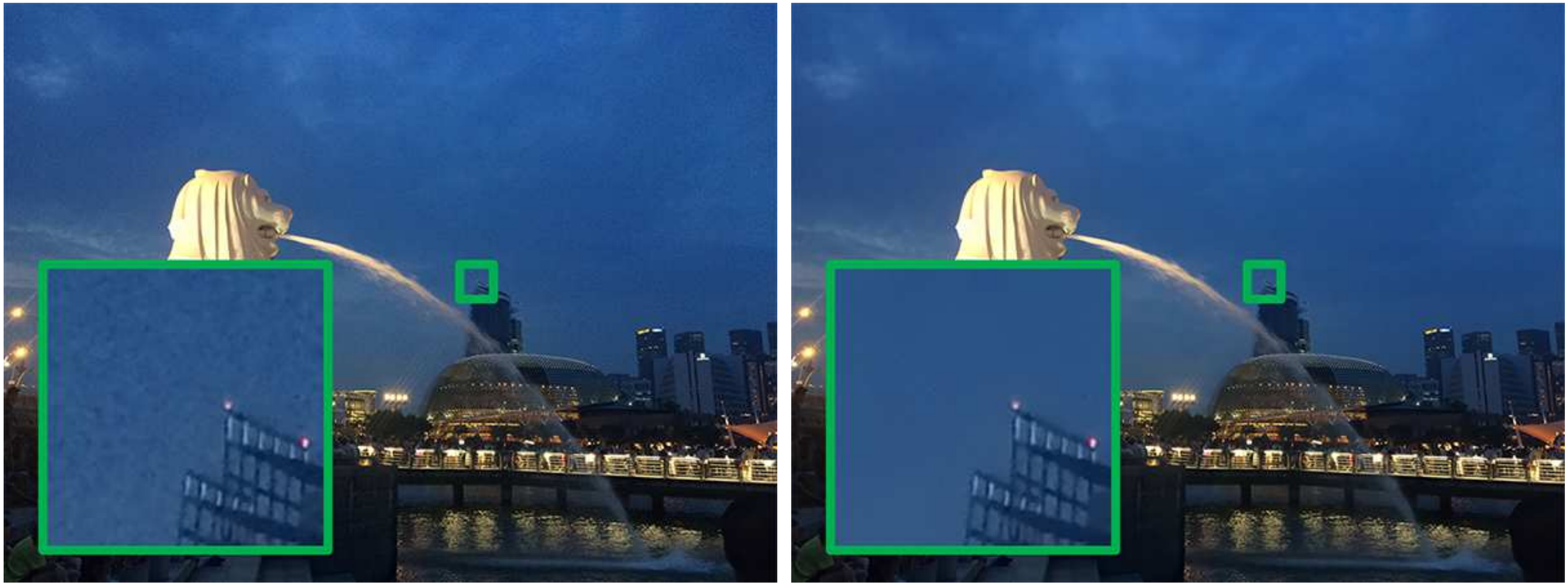
noise



generator


training data
sample
discriminator
noise
generator
sample


training data
sample
discriminator
confidence
noise
generator
sample



Chen et al. *Image Blind Denoising With Generative Adversarial Network Based Noise Modeling* (2018)

Wu et al. *Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling* (2016)

Assignment 1

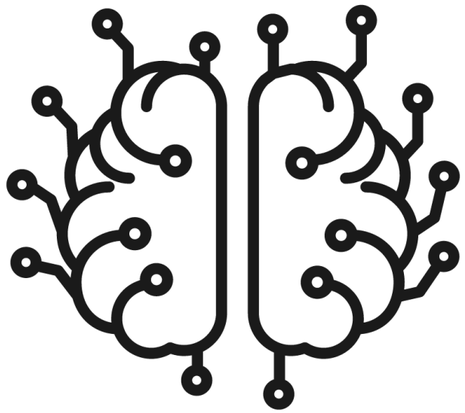
Name three problems we might encounter if we applied GANs to Mario level generation.

A Style-Based Generator Architecture for Generative Adversarial Networks

Tero Karras
NVIDIA
tkarras@nvidia.com

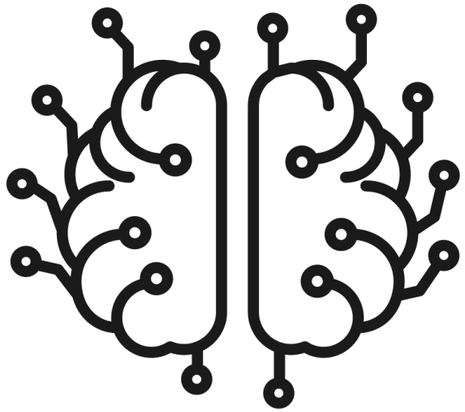
Samuli Laine
NVIDIA
slaine@nvidia.com

Timo Aila
NVIDIA
taila@nvidia.com

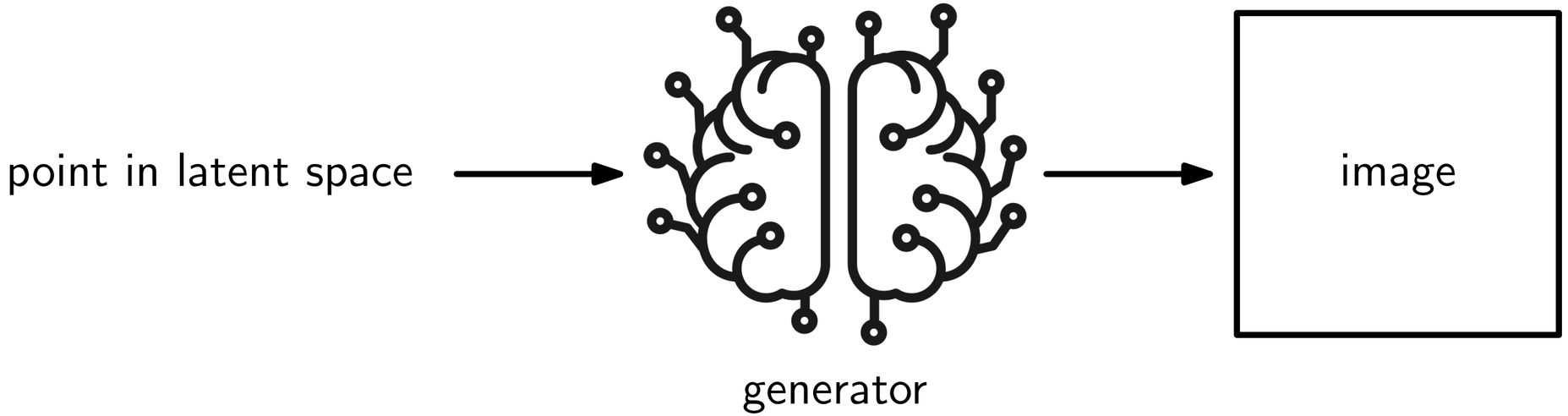


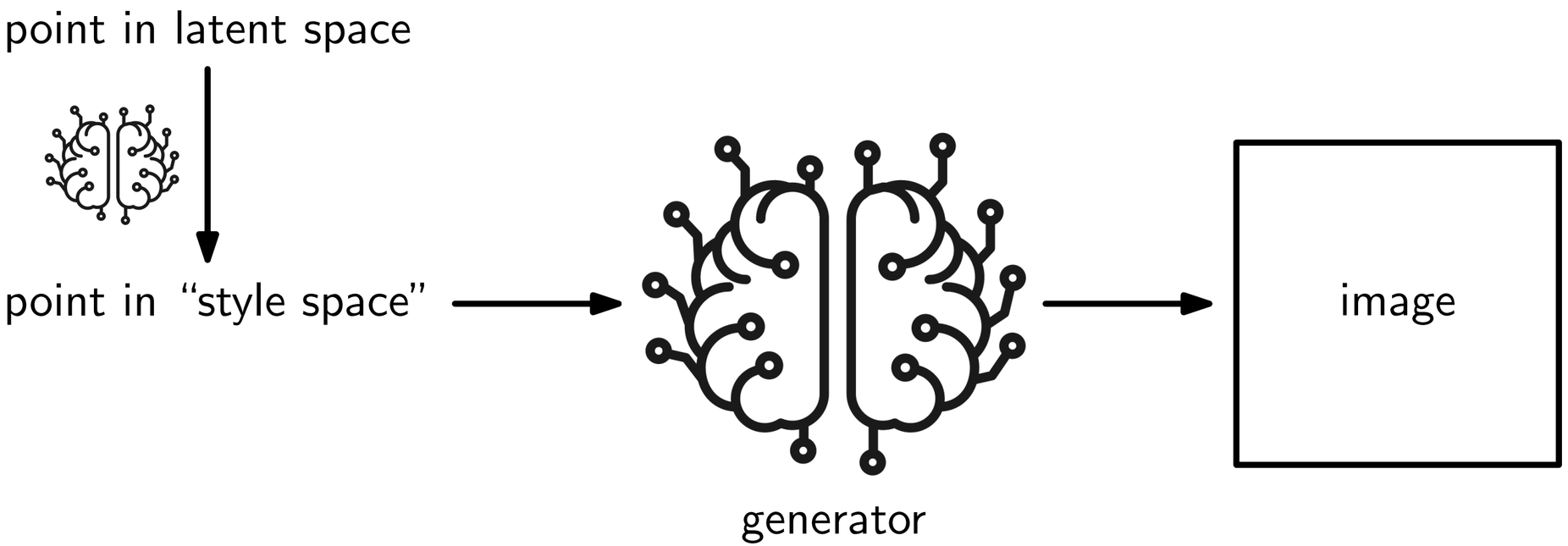
generator

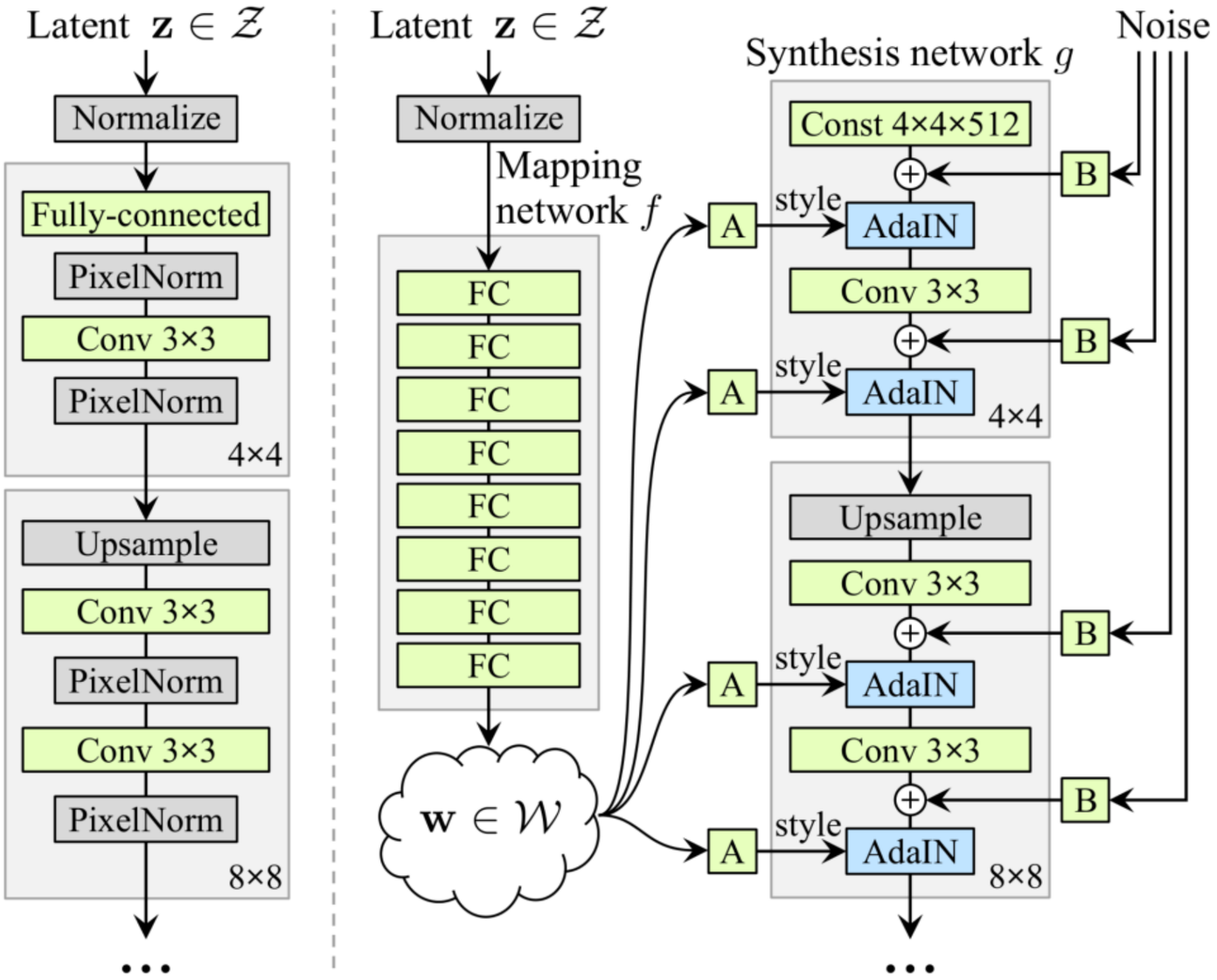
point in latent space



generator


point in latent space
image
generator

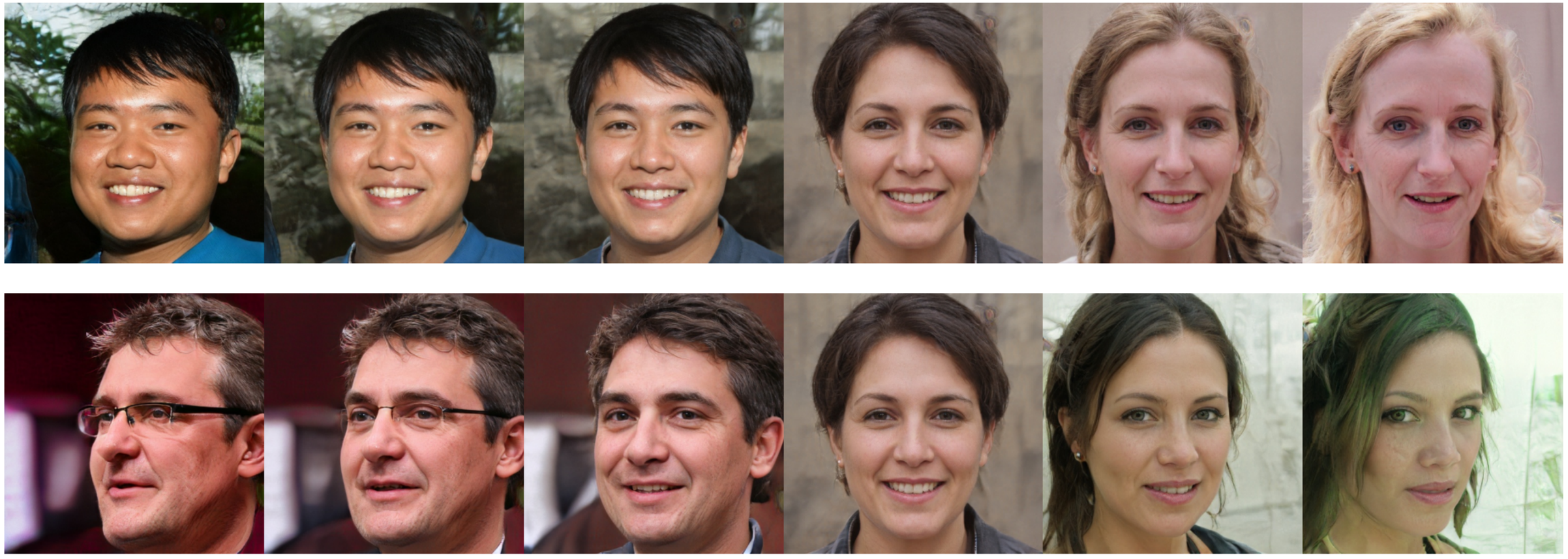

point in latent space
point in "style space"
generator
image



(a) Traditional

(b) Style-based generator

Source B
Source A
Coarse styles from source B
Middle styles from source B
Fine from B



$\psi = 1$ $\psi = 0.7$ $\psi = 0.5$ $\psi = 0$ $\psi = -0.5$ $\psi = -1$

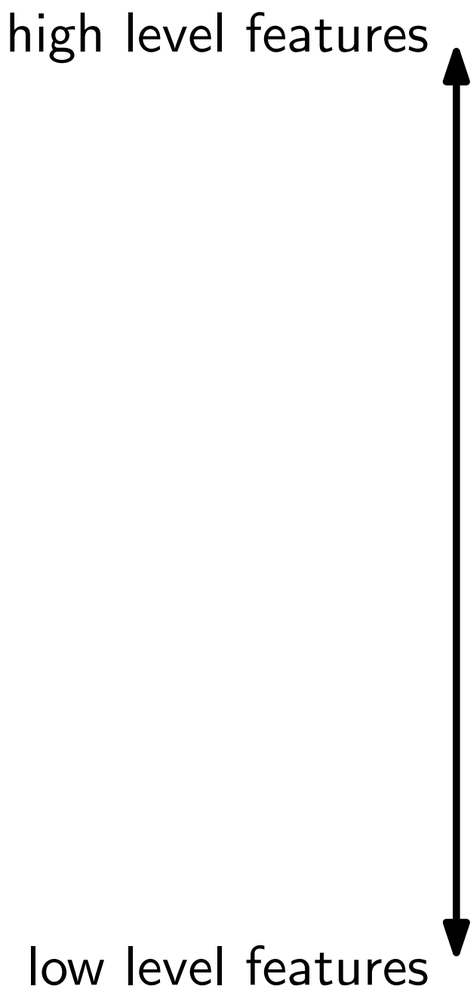
Assignment 2

Name three things we could use style-based GANs for in games.

Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks

Chuan Li and Michael Wand

Institut for Informatik, University of Mainz, Germany


high level features
low level features

high level features

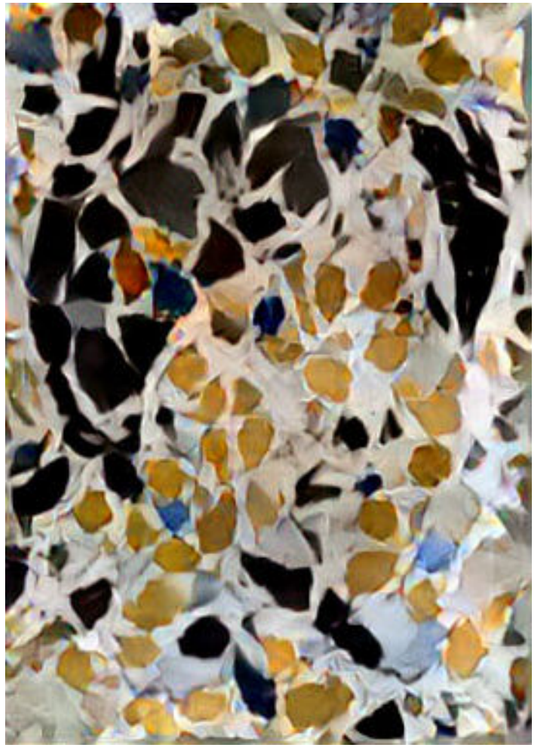
low level features

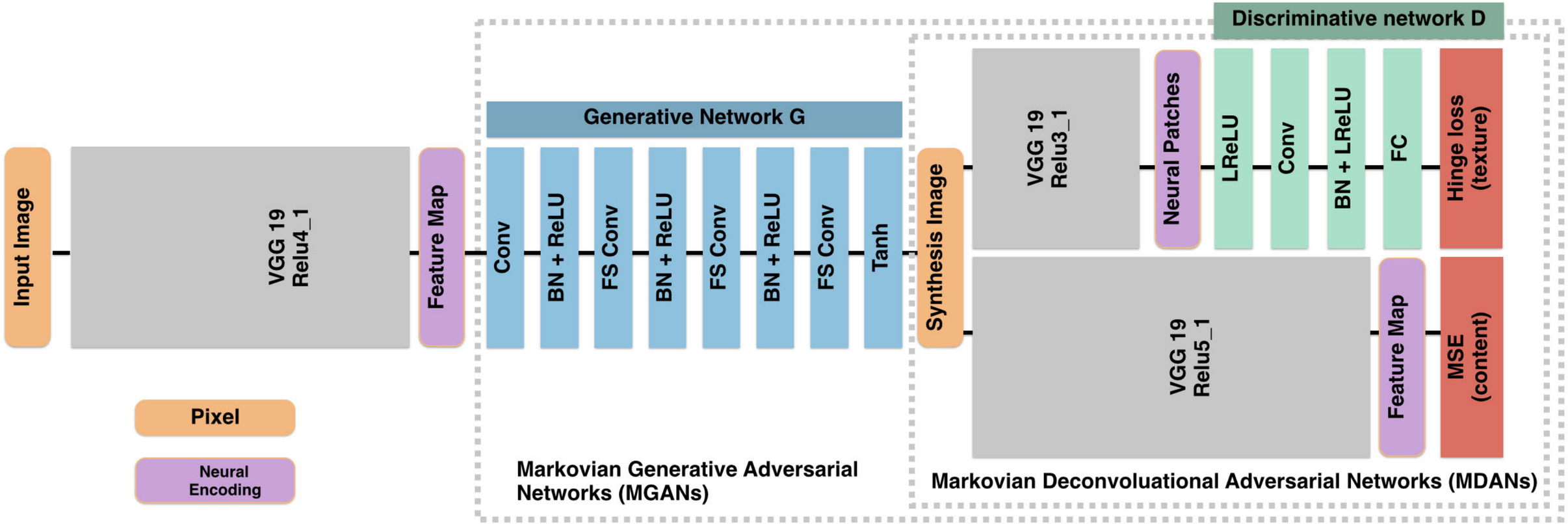
high level features

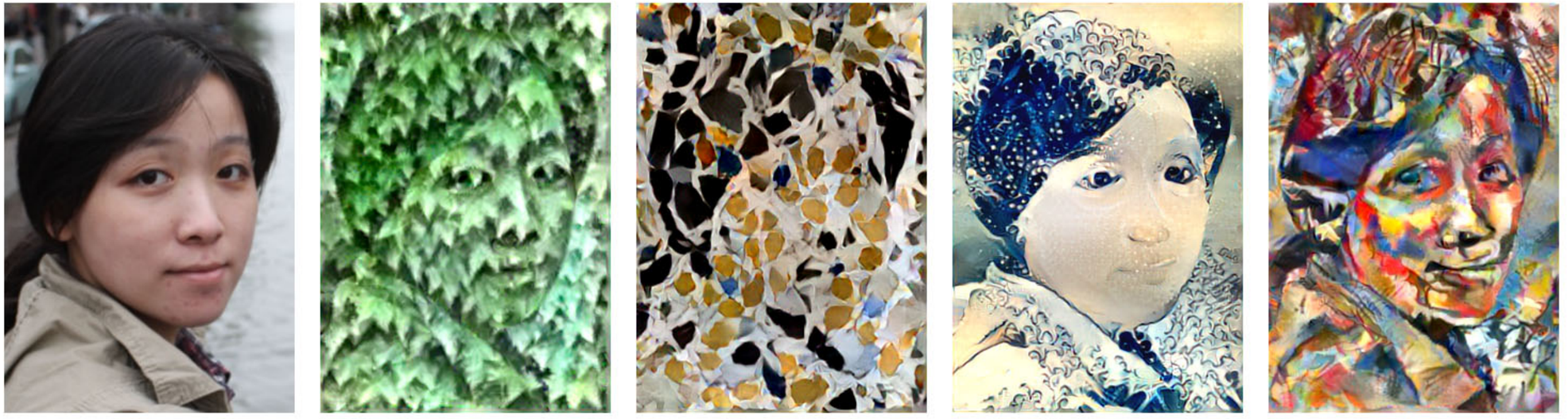
low level features

high level features

low level features




Input Image
VGG 19
Relu4_1
Feature Map
Generative Network G
Conv
BN + ReLU
FS Conv
BN + ReLU
FS Conv
BN + ReLU
FS Conv
Tanh
Synthesis Image
Discriminative network D
VGG 19
Relu3_1
Neural Patches
LReLU
Conv
BN + LReLU
FC
Hinge loss
(texture)
VGG 19
Relu5_1
Feature Map
MSE
(content)
Pixel
Neural
Encoding
Markovian Generative Adversarial
Networks (MGANs)
Markovian Deconvoluational Adversarial Networks (MDANs)



Assignment 3

Name three things we might use texture synthesis for in games.

Evolving Mario Levels in the Latent Space of a Deep Convolutional Generative Adversarial Network

Vanessa Volz
TU Dortmund University
Dortmund, Germany
vanessa.volz@tu-dortmund.de

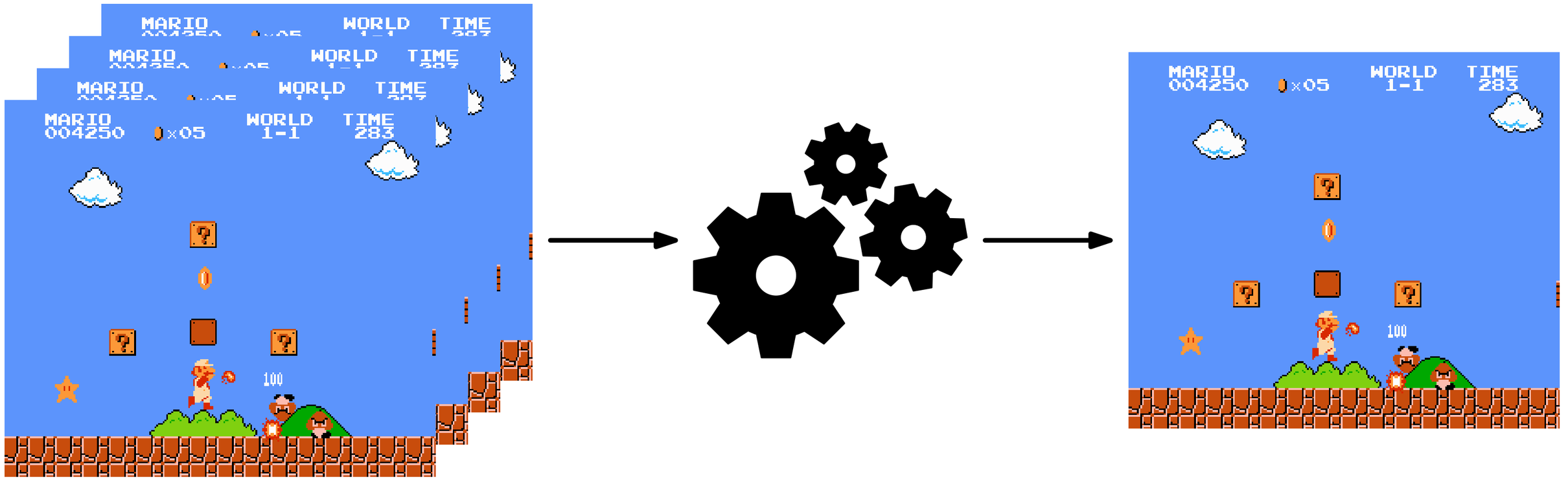
Jacob Schrum
Southwestern University
Georgetown, TX USA
schrum2@southwestern.edu

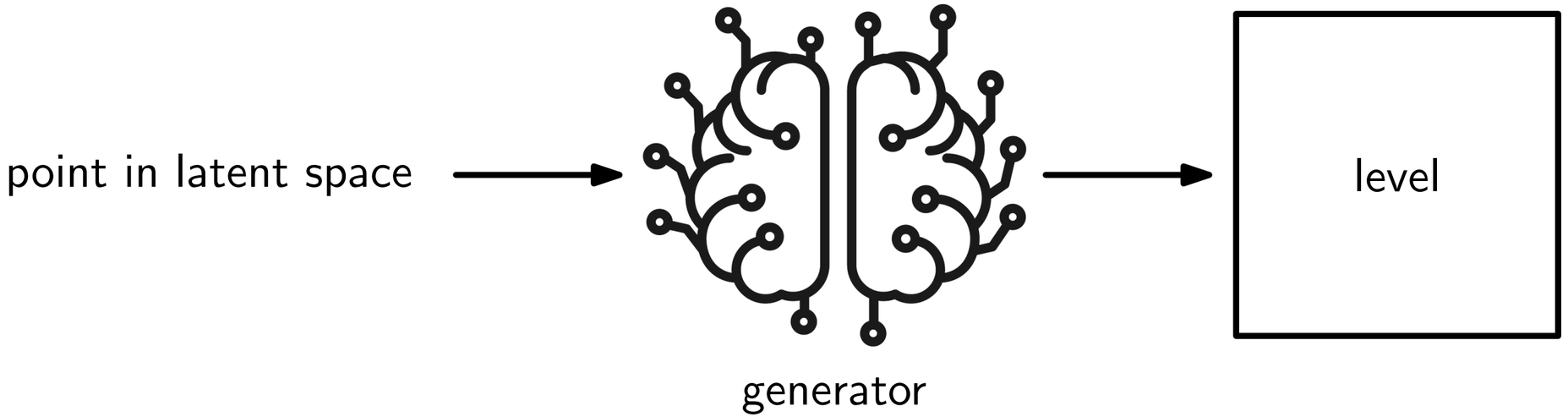
Jialin Liu
Queen Mary University of London
London, UK
jialin.liu@qmul.ac.uk

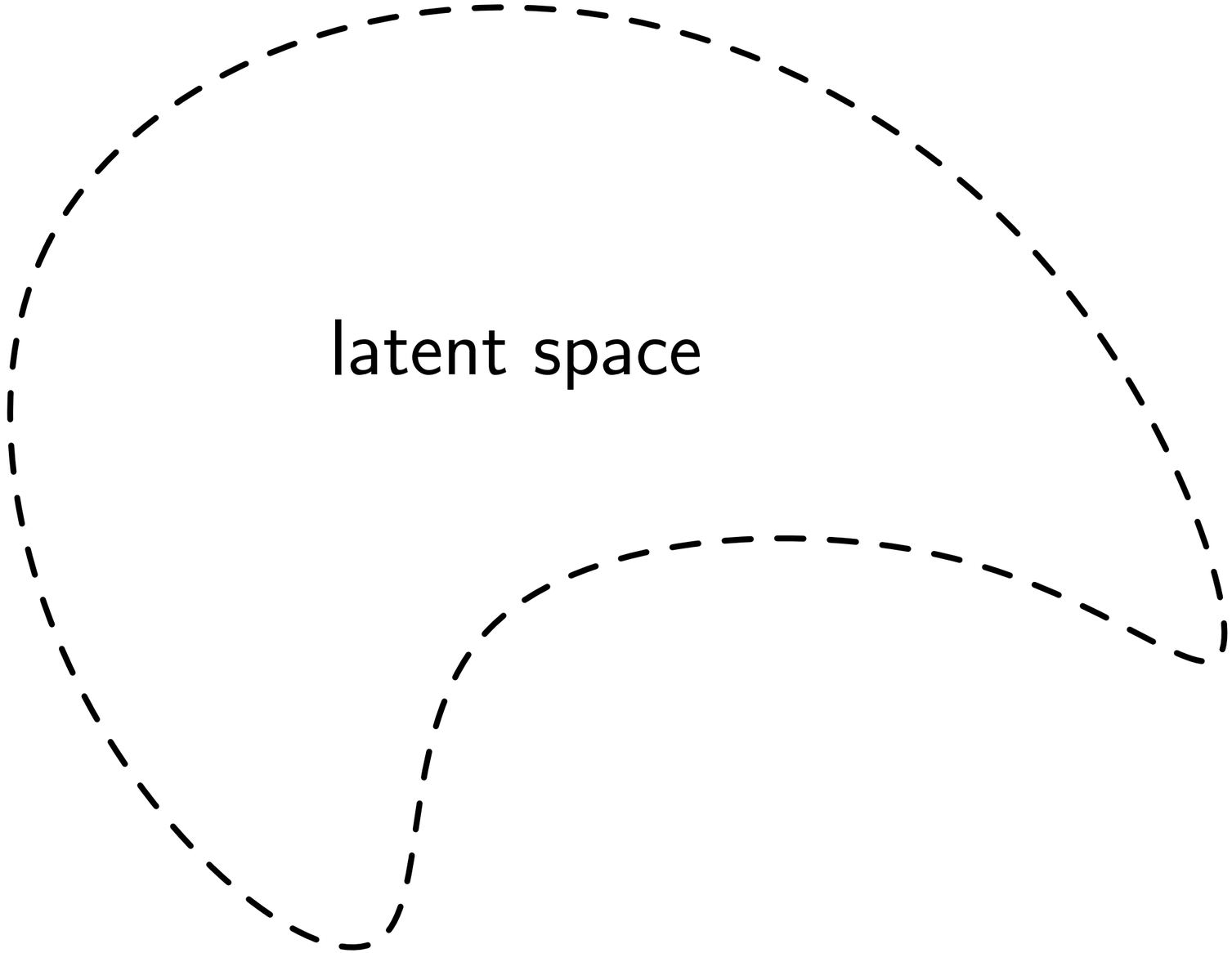
Simon M. Lucas
Queen Mary University of London
London, UK
simon.lucas@qmul.ac.uk

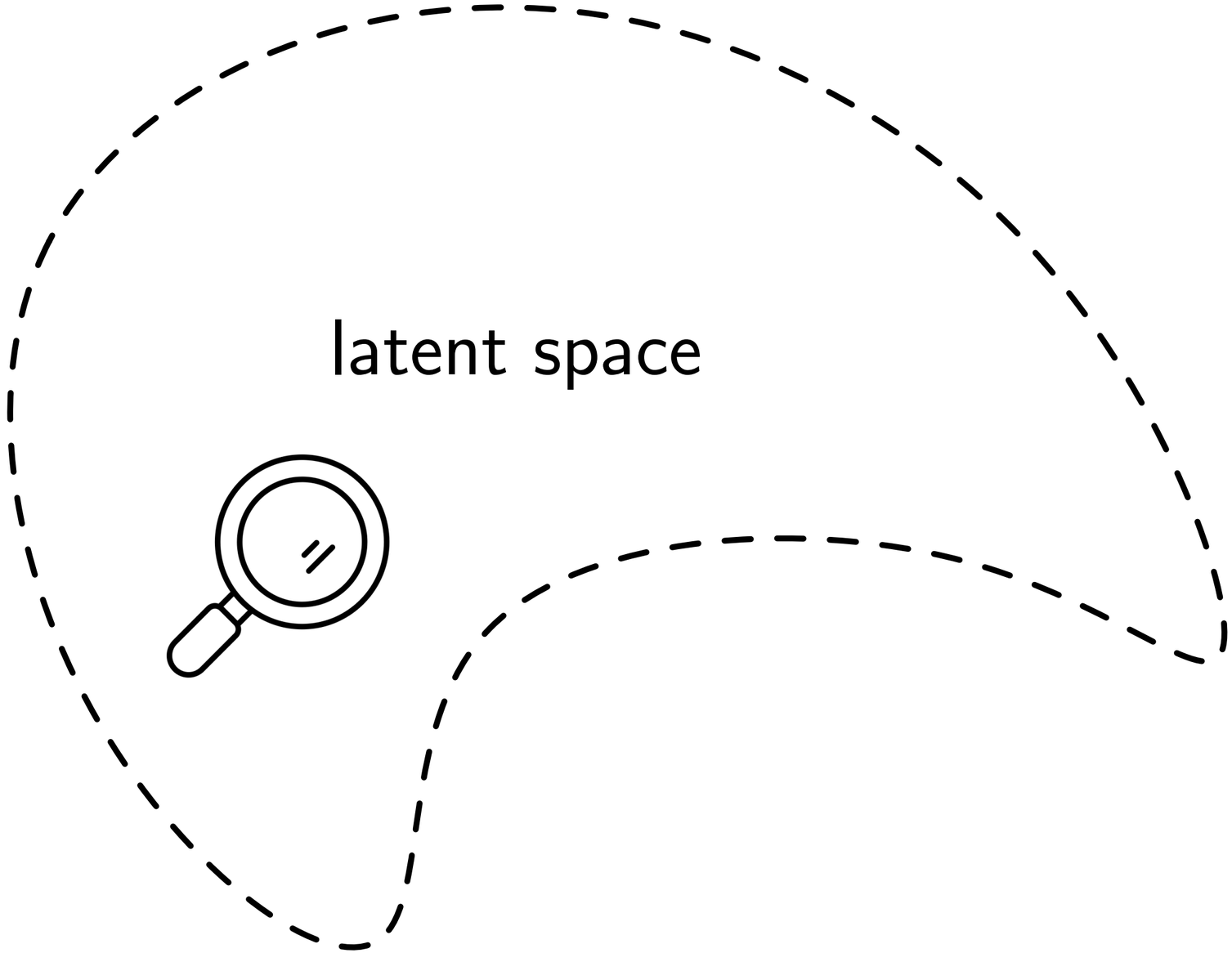
Adam Smith
University of California
Santa Cruz, CA USA
amsmith@ucsc.edu

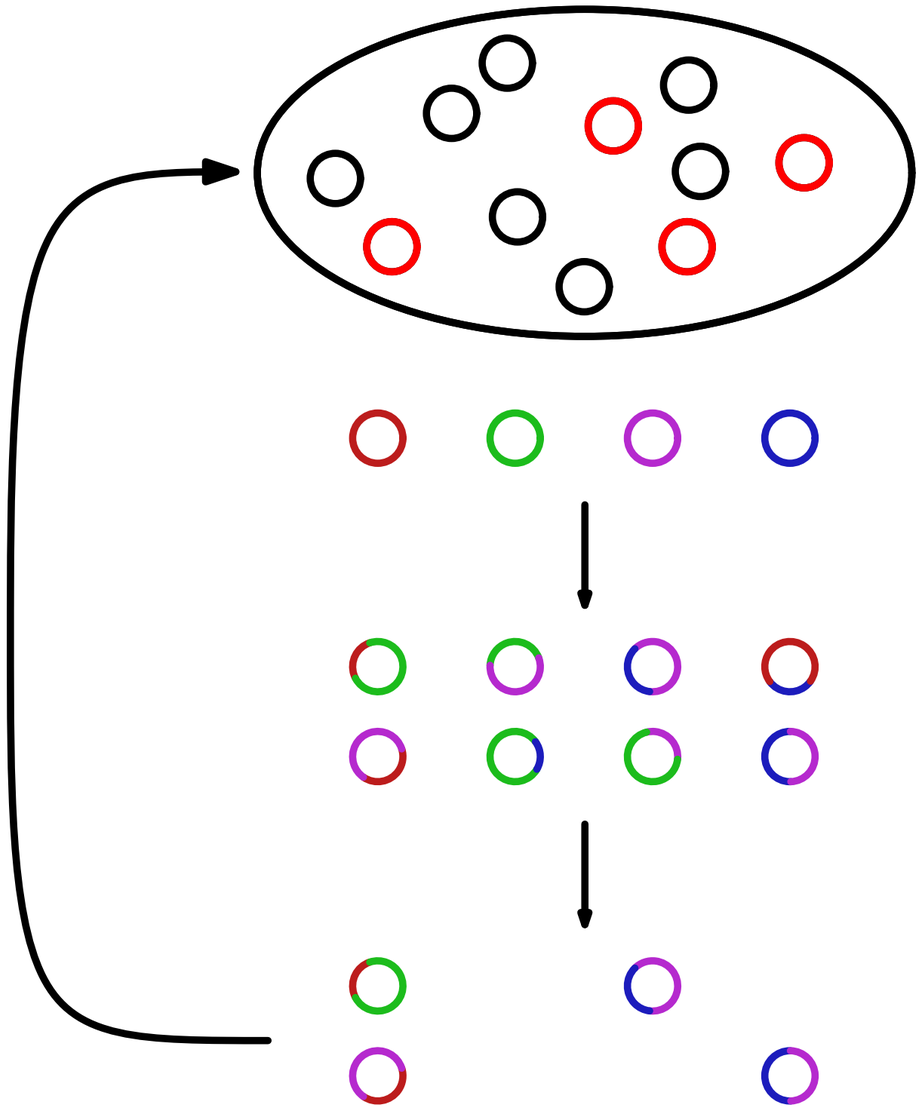
Sebastian Risi
IT University of Copenhagen
Copenhagen, Denmark
sebr@itu.dk


MARIO
WORLD
TIME
MARIO
004250
x05
WORLD
1-1
TIME
283
100


point in latent space
generator
level


latent space


latent space



latent code: $\langle 0.1, 0.8, 0.3, \ldots, 0.5 \rangle$

latent code: $\langle 0.1, 0.8, 0.3, \ldots, 0.5 \rangle$

mutation: $\langle 0.2, 0.1, 0.0, \ldots, -0.2 \rangle$

$$\begin{aligned}
\text{latent code:} \quad & \langle 0.1, 0.8, 0.3, \ldots, 0.5 \rangle \\
& + \\
\text{mutation:} \quad & \langle 0.2, 0.1, 0.0, \ldots, -0.2 \rangle \\
& = \\
\text{offspring:} \quad & \langle 0.3, 0.9, 0.3, \ldots, 0.3 \rangle
\end{aligned}$$

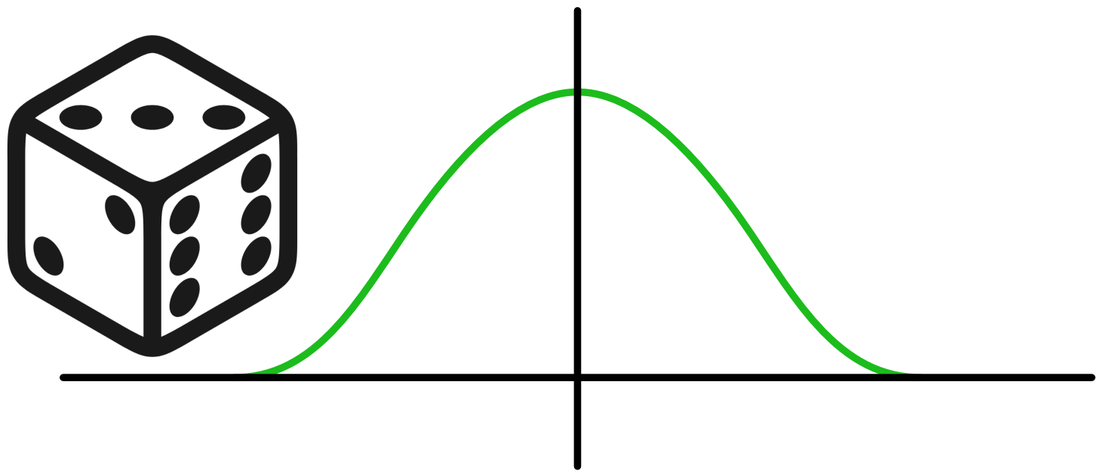
latent code: $\langle 0.1, 0.8, 0.3, \ldots, 0.5 \rangle$

$+$

mutation: $\langle 0.2, 0.1, 0.0, \ldots, -0.2 \rangle$

$=$

offspring: $\langle 0.3, 0.9, 0.3, \ldots, 0.3 \rangle$



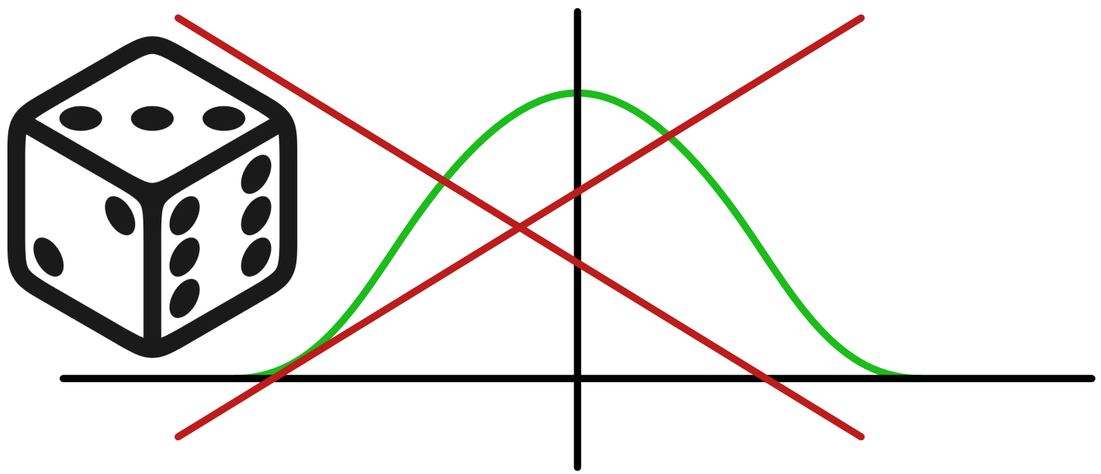
latent code: $\langle 0.1, 0.8, 0.3, \ldots, 0.5 \rangle$

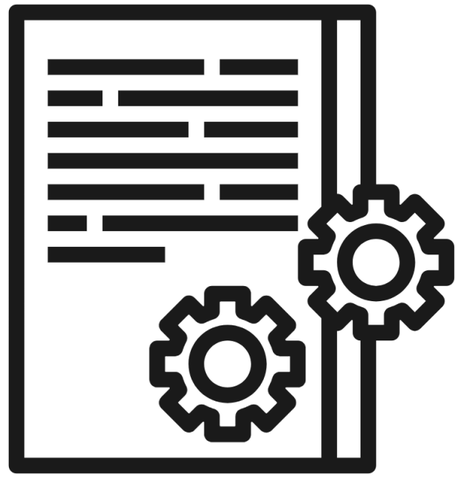
$+$

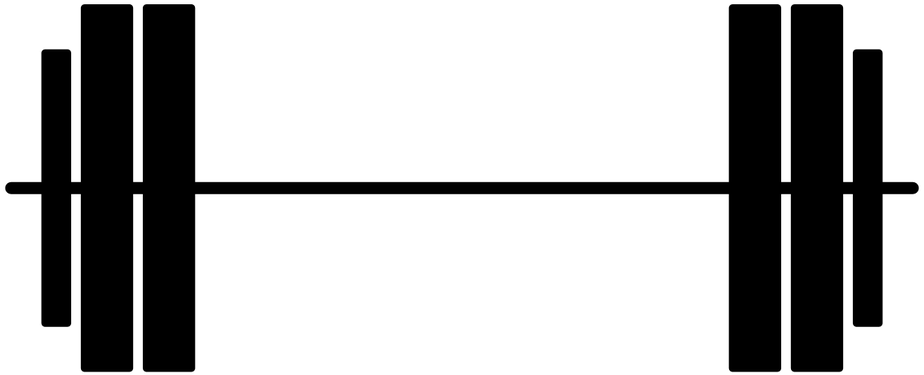
mutation: $\langle 0.2, 0.1, 0.0, \ldots, -0.2 \rangle$

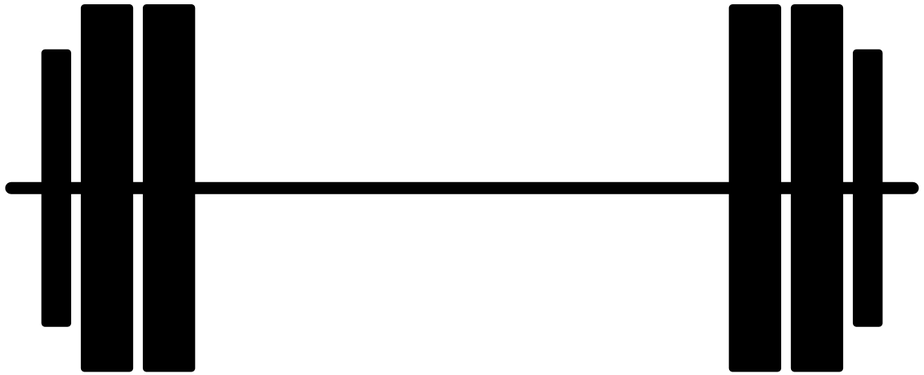
$=$

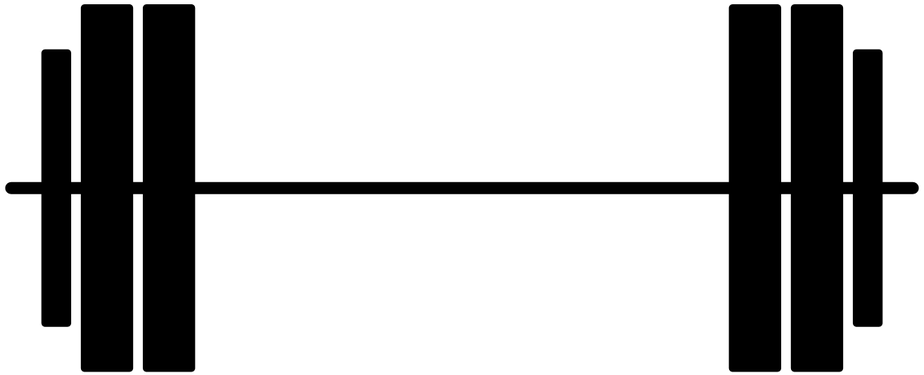
offspring: $\langle 0.3, 0.9, 0.3, \ldots, 0.3 \rangle$





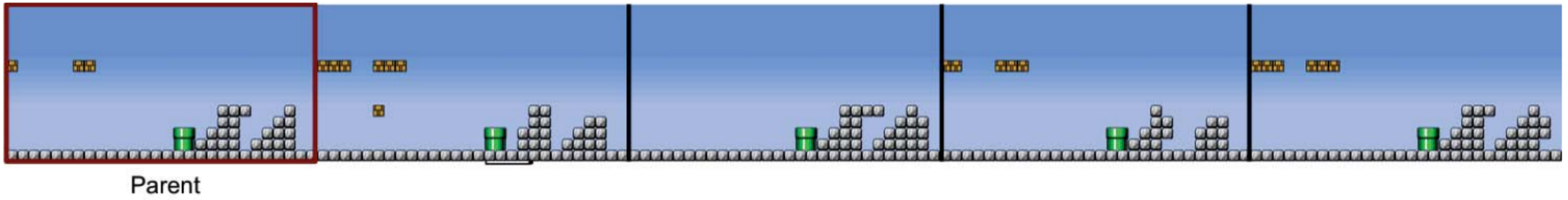




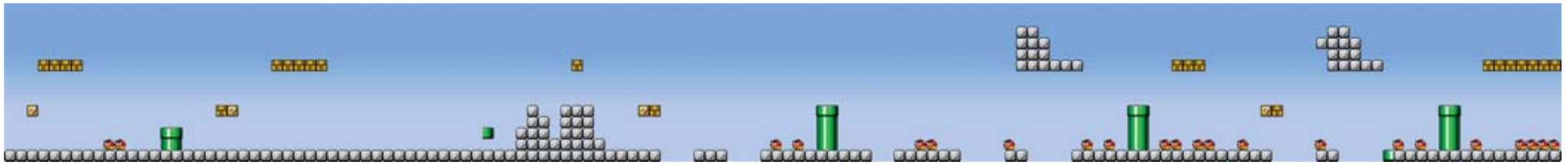


#jumps

(a) Random Sampling



(b) Mutations



Assignment 4

Name three additional statistics that we could use in our agent-based fitness function.