Graph Generation

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Goal: generate fake objects (e.g. images) similar to real ones
Idea: play an adversarial game with two agents

I. Goodfellow et al., *Generative Adversarial Nets*. in Proc. of NIPS, 2014, pp. 2672--2680.

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Generator: maps noise z to a fake object x
Discriminator: maps object x to probability of real/fake
Game: The generator tries to fool the discriminator
The discriminator tries to detect the fake objects

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

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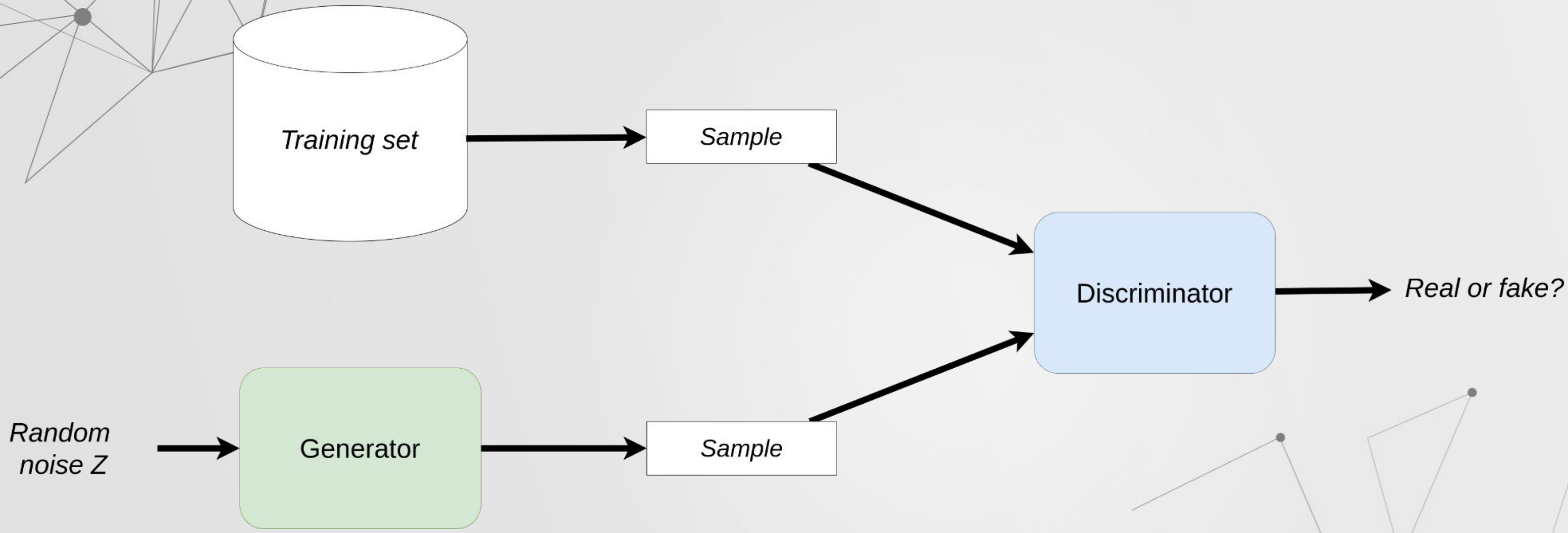
01 Generative Adversarial Networks (GANs)



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The **Discriminator** wants to **max:**

- Recall that D(x) is in [0, 1]
- **First term**:
  → large if D(x) is close to 1
  → assign high probability to real objects

I. Goodfellow et al., *Generative Adversarial Nets*. in Proc. of NIPS, 2014, pp. 2672--2680.

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The **Discriminator** wants to **max:**

- Recall that D(x) is in [0, 1]
- **First term**:
  → large if D(x) is close to 1
  → assign high probability to real objects
- **Second term**:
  → large if 1-D(G(z) is close to 1
  → large if D(G(z)) is close to 0
  → assign low probability to fake objects

I. Goodfellow et al., *Generative Adversarial Nets*. in Proc. of NIPS, 2014, pp. 2672--2680.

01 Generative Adversarial Networks (GANs)

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

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01 Generative Adversarial Networks (GANs)

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

The **Generator** wants to **min:**

- **Second term**:
  → small if 1-D(G(z) is close to 0
  → small if D(G(z) is close to 1
  → fool the discriminator into assigning high probability to fake objects

I. Goodfellow et al., *Generative Adversarial Nets*. in Proc. of NIPS, 2014, pp. 2672--2680.

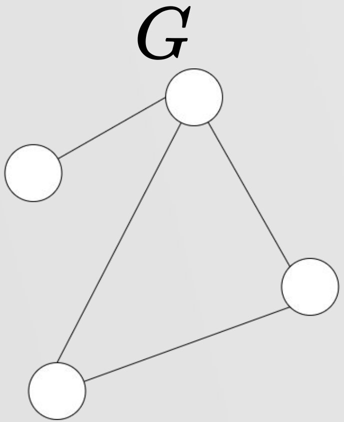
02 Learning social Graph using topologies using GANs

Learning Social Graph Topologies using Generative Adversarial Neural Networks

Sahar Tavakoli[1], Alireza Hajibagheri[1], and Gita Sukthankar[1]

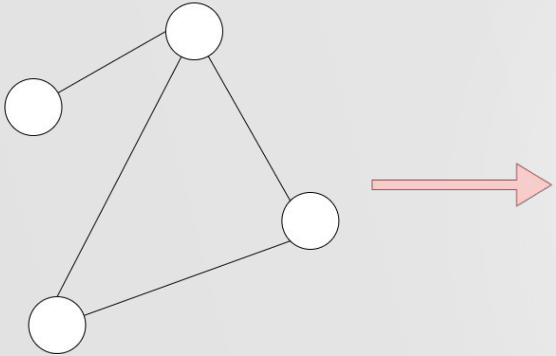
[1]University of Central Florida, Orlando, Florida
sahar@knights.ucf.edu,alireza@eecs.ucf.edu,gitars@eecs.ucf.edu

02 Learning social Graph using topologies using GANs



02 Learning social Graph using topologies using GANs

G

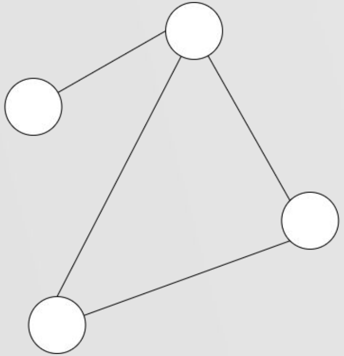


$Adj(G)$

0	1	0	0
1	0	1	1
0	1	0	1
0	1	1	0

02 Learning social Graph using topologies using GANs

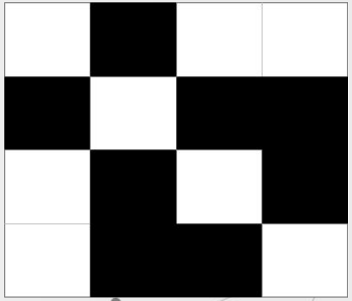
G



$Adj(G)$

0	1	0	0
1	0	1	1
0	1	0	1
0	1	1	0

Img



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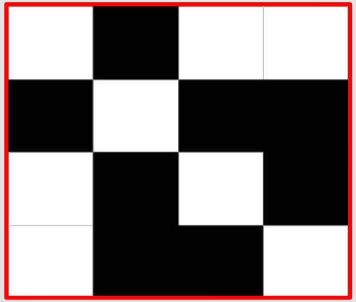
Img



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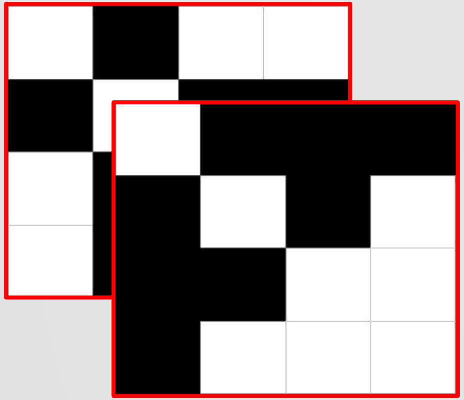

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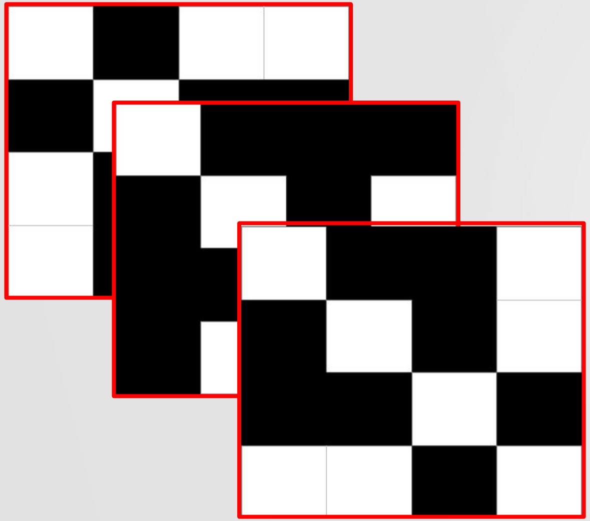
Img



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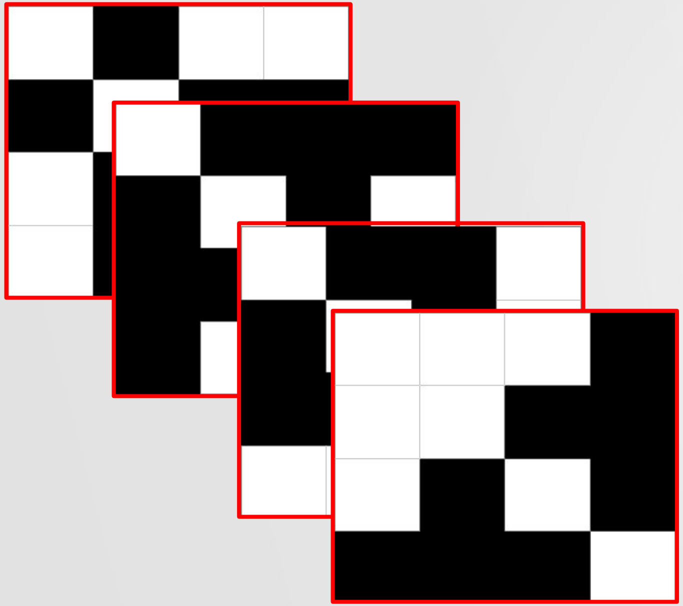

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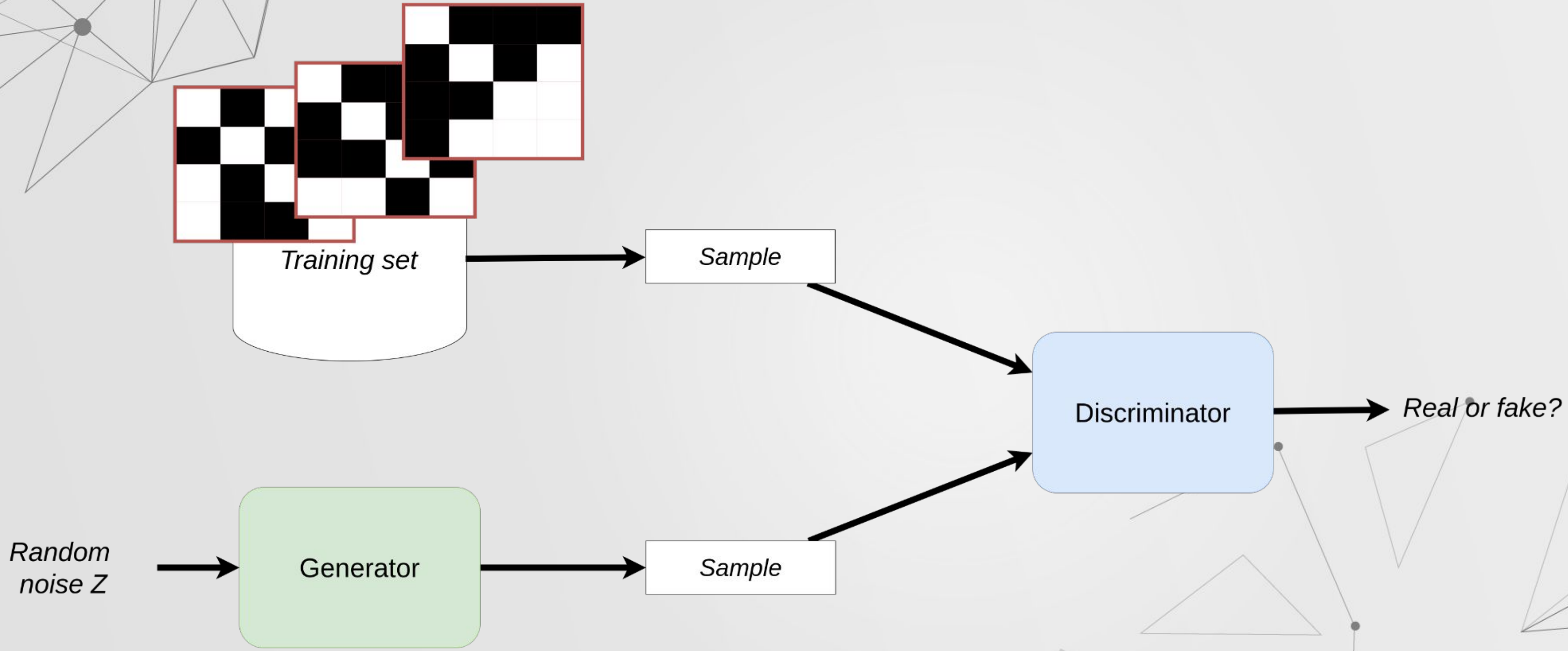


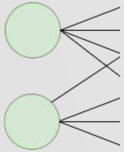
02 Learning social Graph using topologies using GANs

Generator

INPUT

$$I \in \mathbf{R}^{100}$$

$$I \sim N(0,1)$$



100
neurons

02 Learning social Graph using topologies using GANs

Generator

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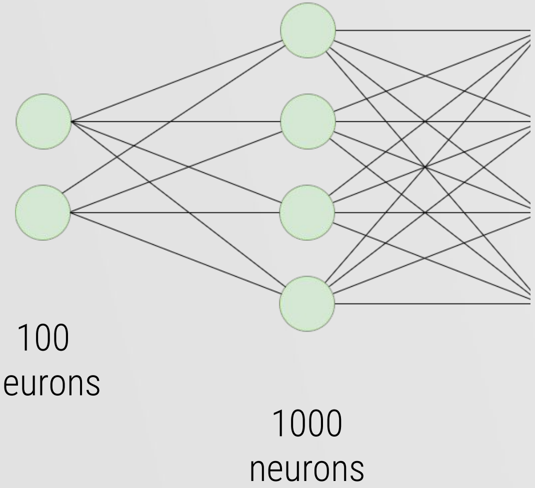

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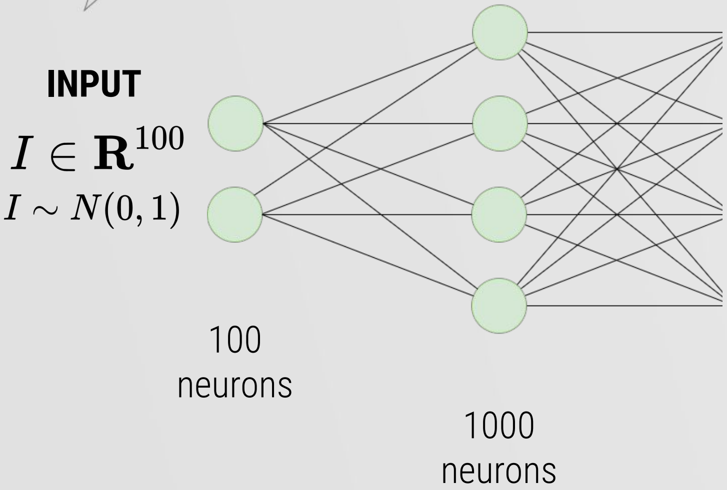
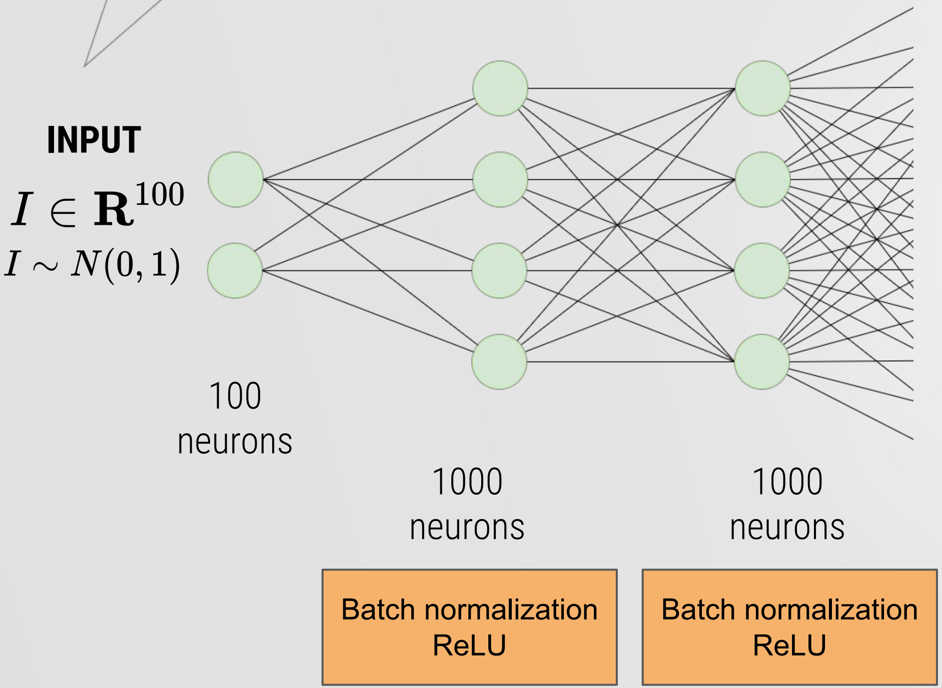
Generator



Batch normalization
ReLU

02 Learning social Graph using topologies using GANs

Generator



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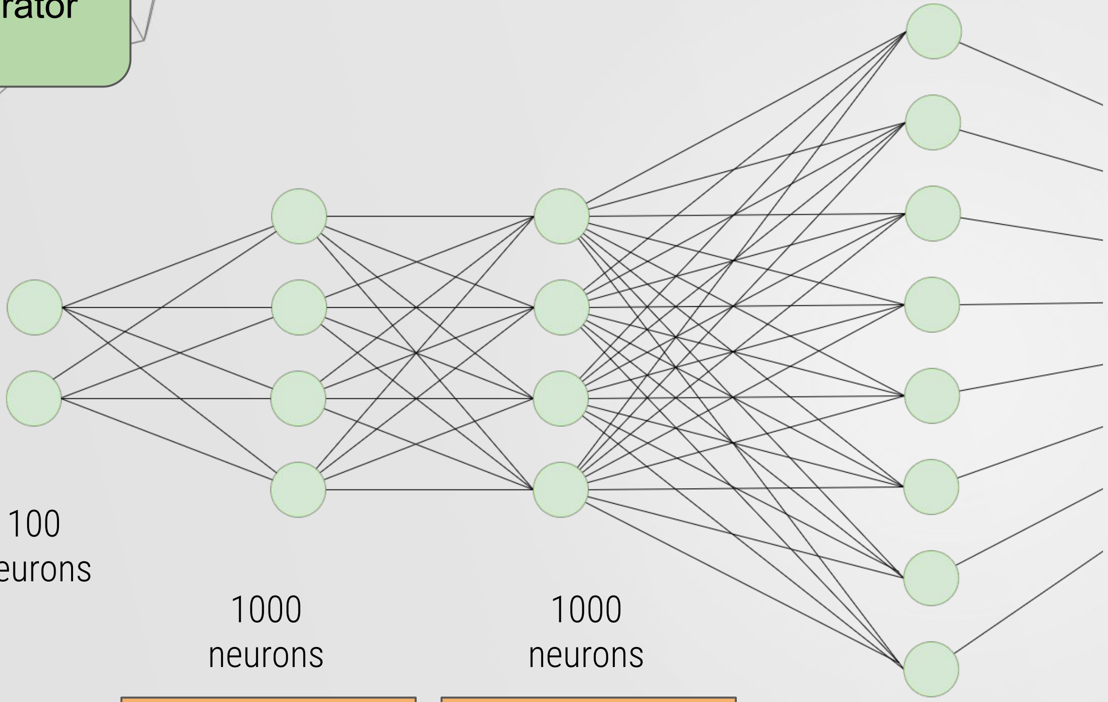


100 neurons

1000 neurons

1000 neurons

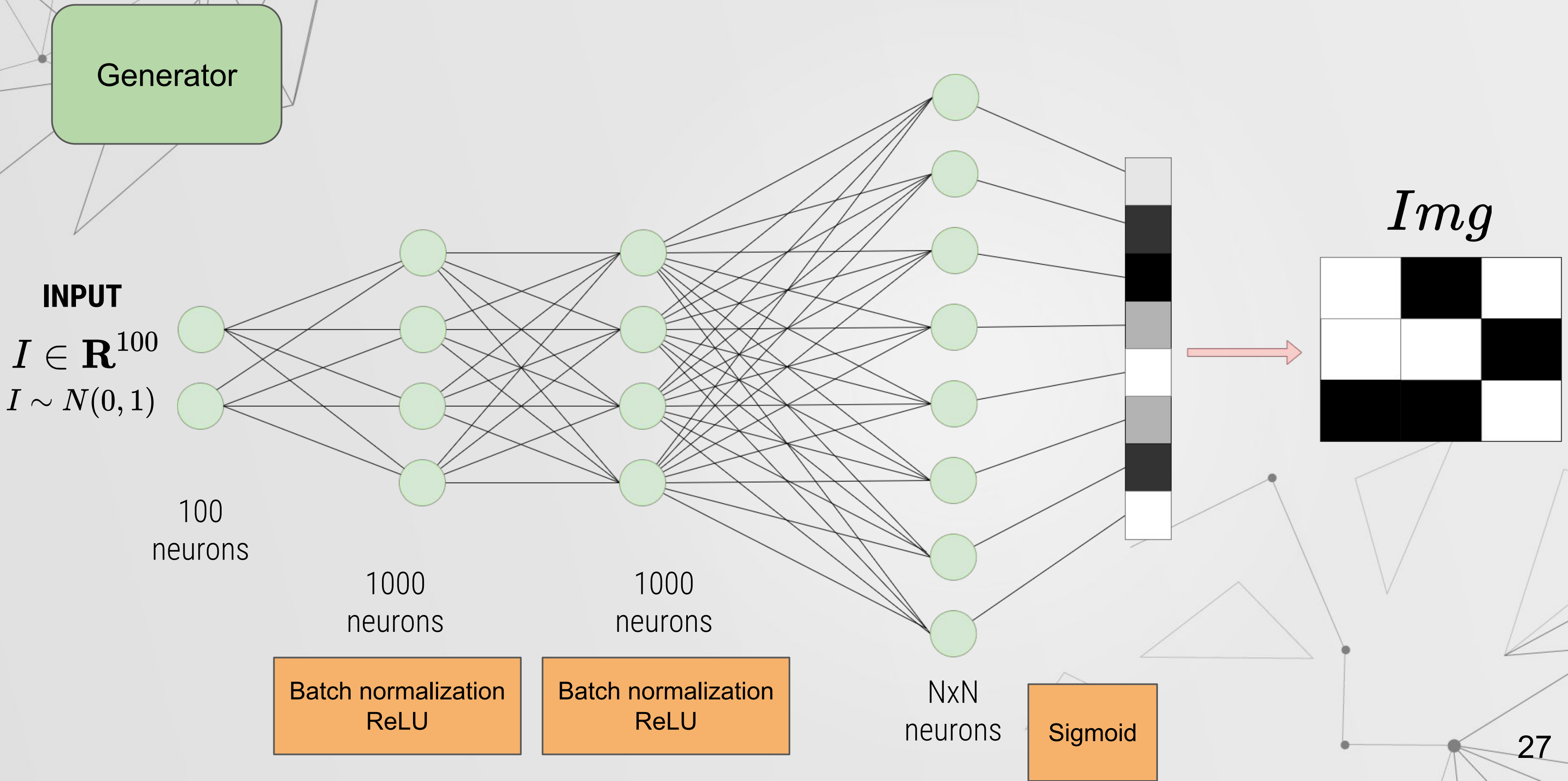
NxN neurons

Batch normalization ReLU

Batch normalization ReLU

Sigmoid

02 Learning social Graph using topologies using GANs



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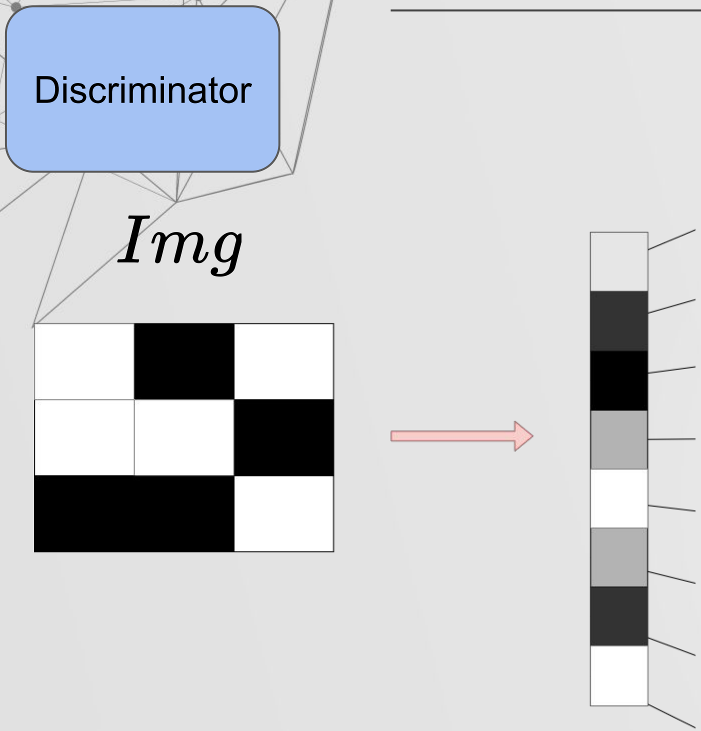

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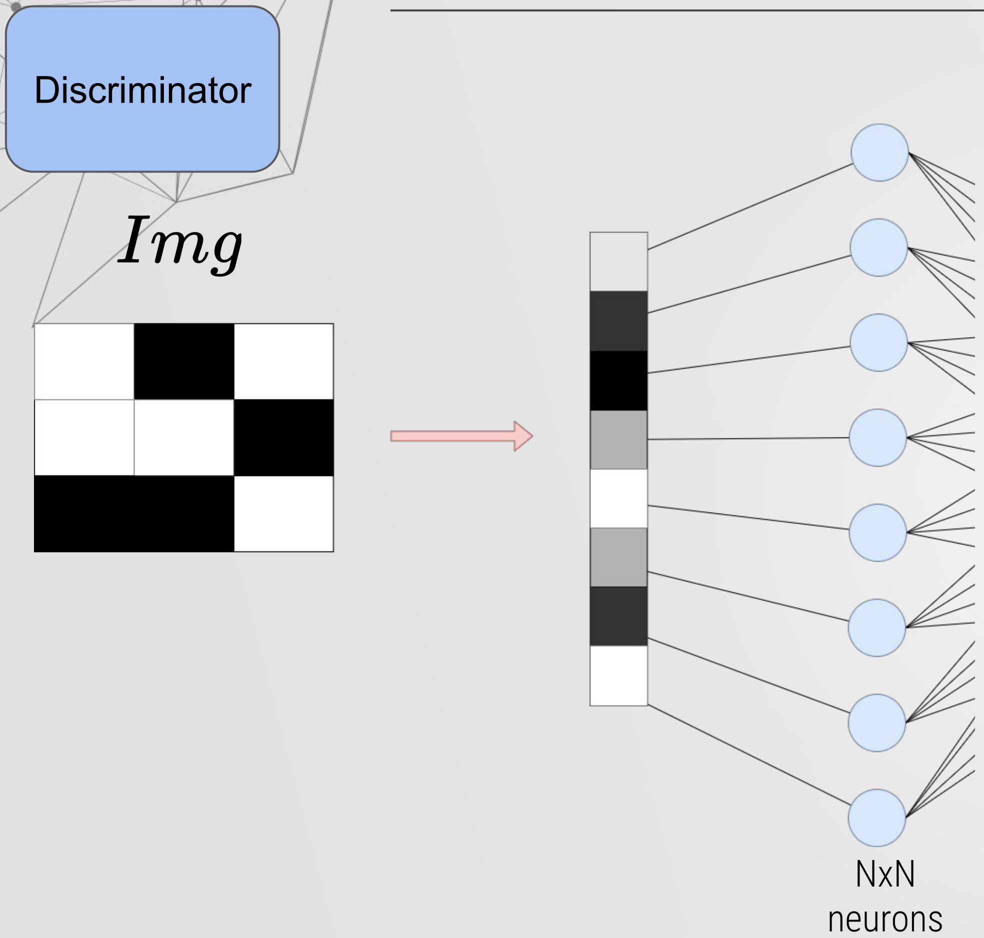

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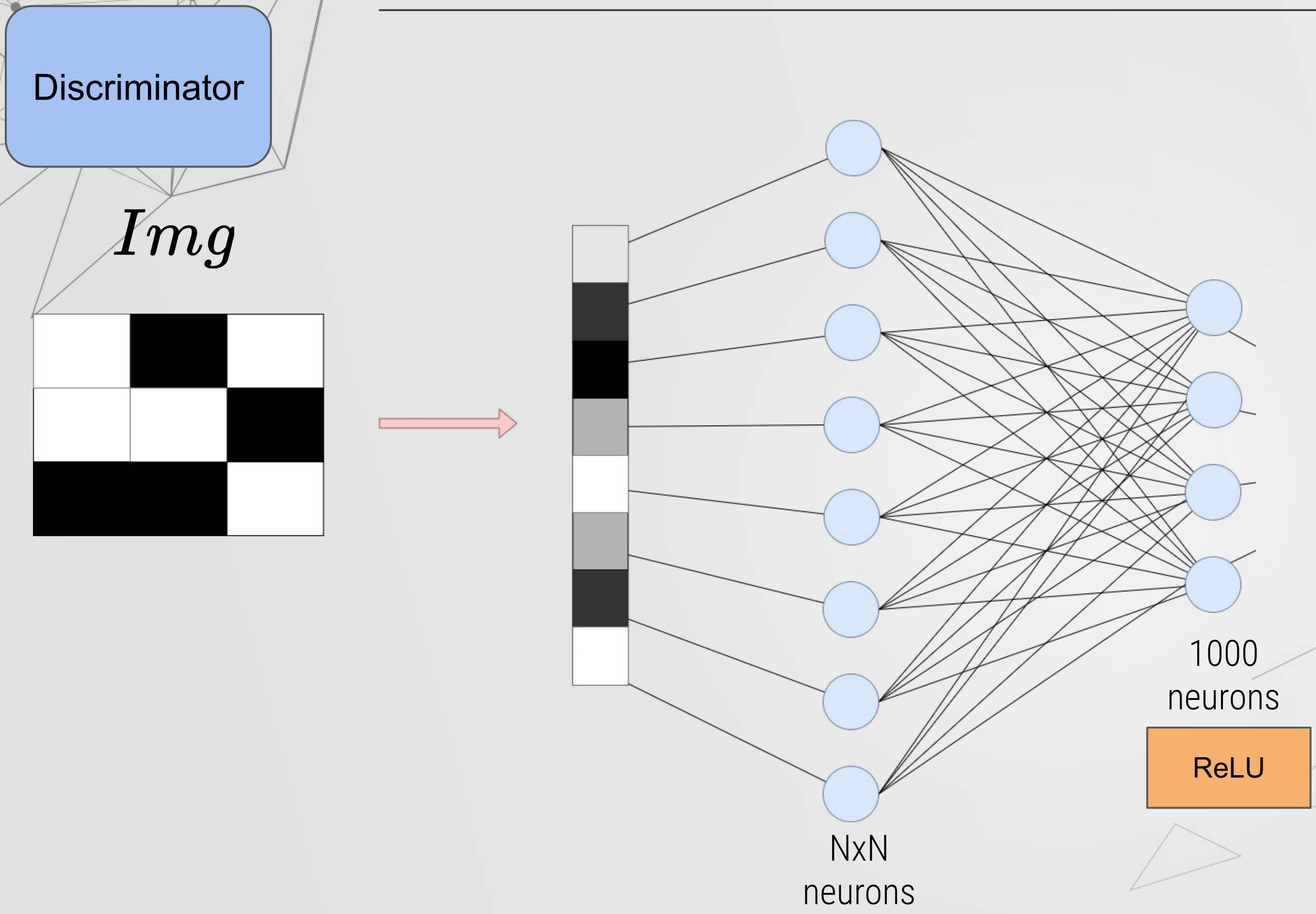

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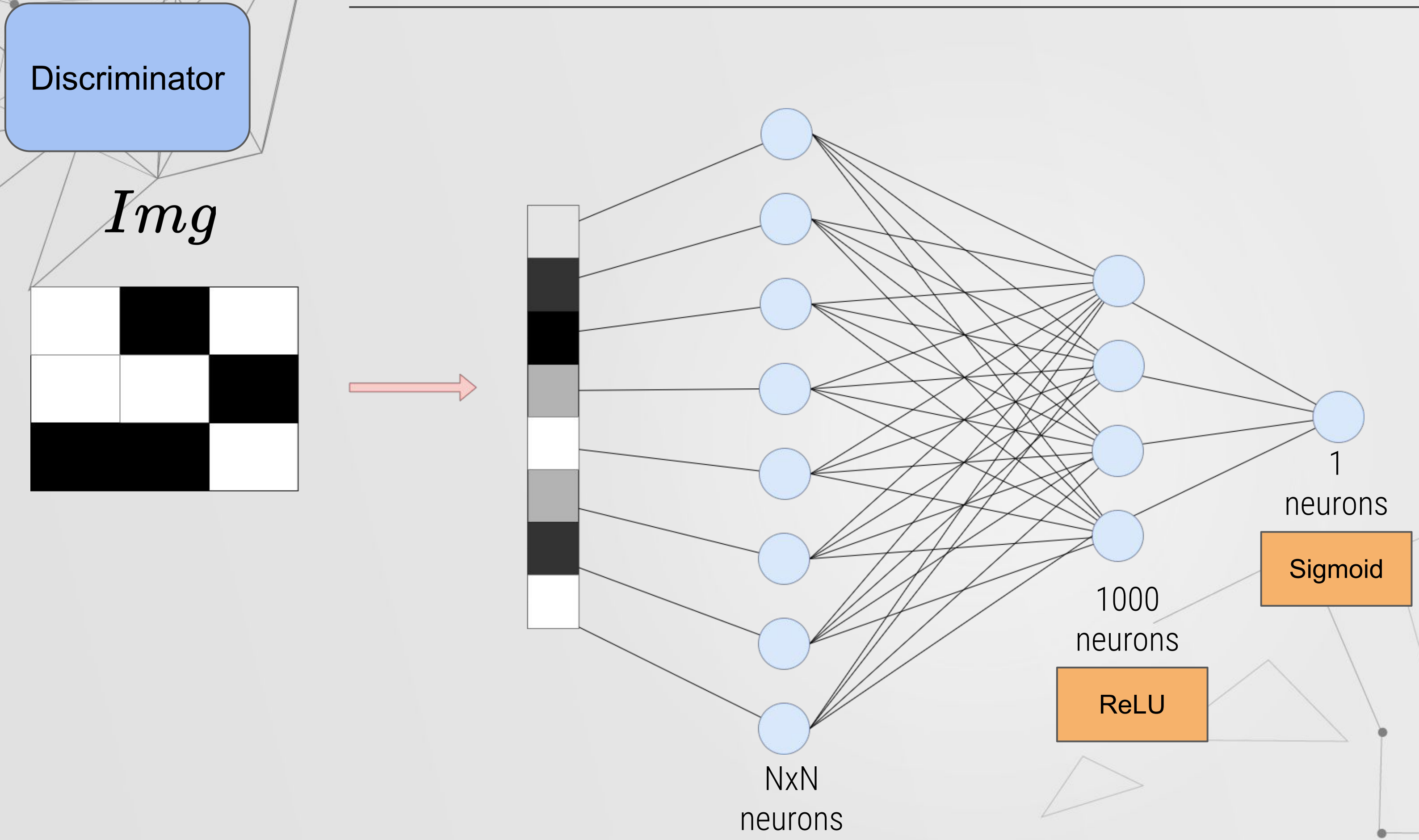

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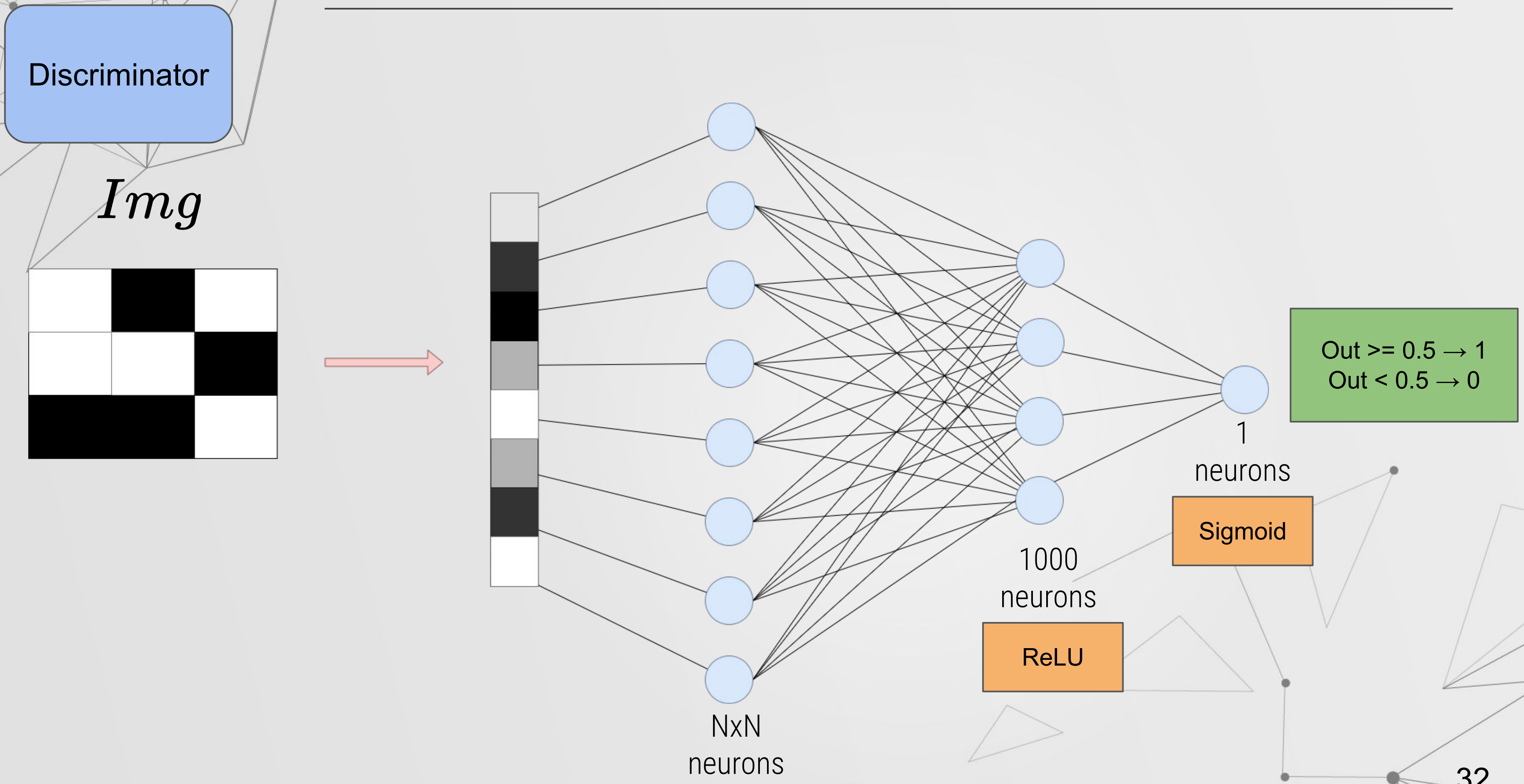


02 Learning social Graph using topologies using GANs

Results:

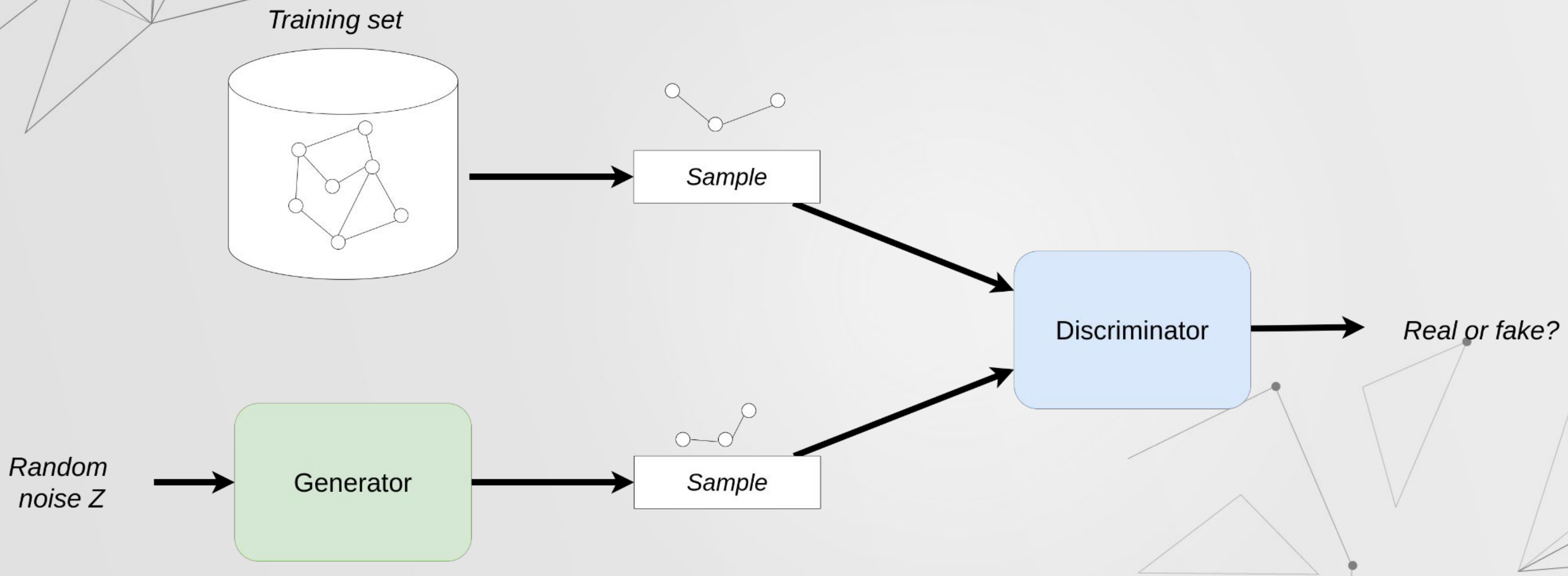
- **Comparison** of several **features** between original and generated graph. (Nb nodes, nb.edges, avg. degree, diameter, assortativity, etc ..)
- On several **social interaction networks** (Karate club, Football, Dolphins, Enron)

03 NetGAN

NetGAN: Generating Graphs via Random Walks

Aleksandar Bojchevski [*1] Oleksandr Shchur [*1] Daniel Zügner [*1] Stephan Günnemann [1]

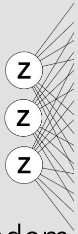
03 NetGAN



Training set
Sample
Discriminator
Real or fake?
Random
noise Z
Generator
Sample

03 NetGAN

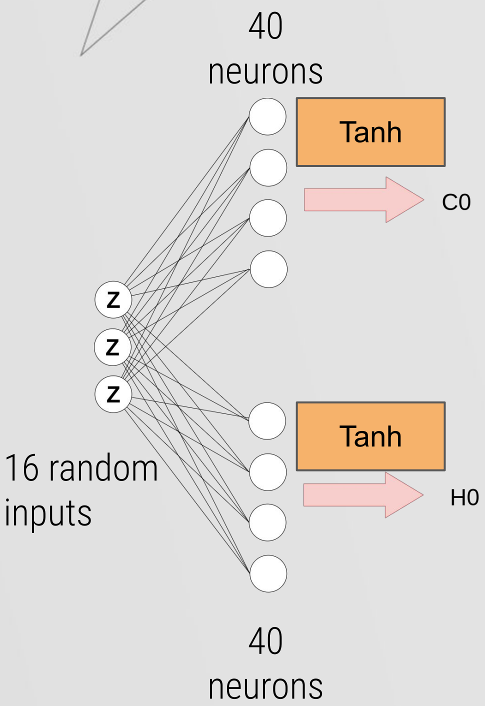
Generator



16 random inputs

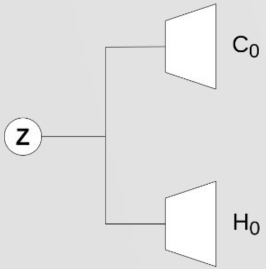
03 NetGAN

Generator

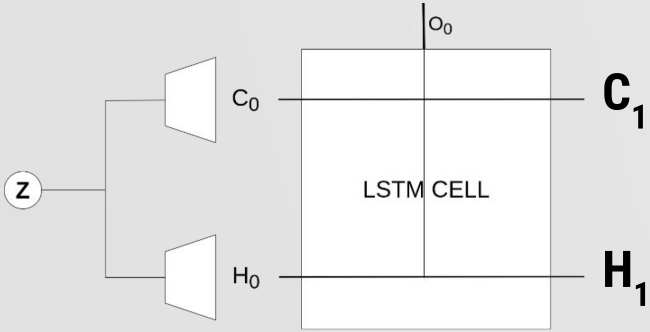


03 NetGAN

Generator



03 NetGAN

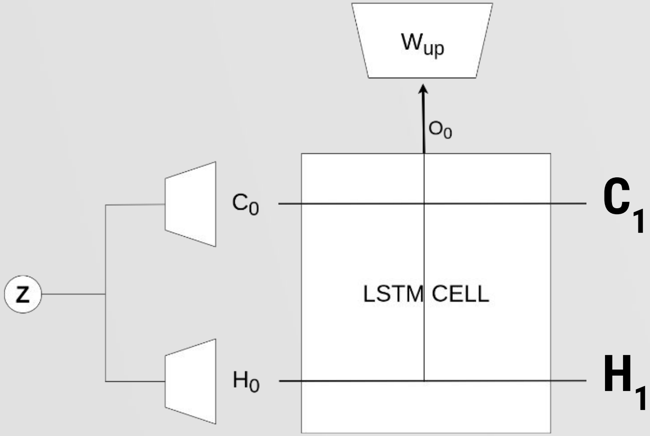


LSTM cell

Generator

03 NetGAN

W_{up}



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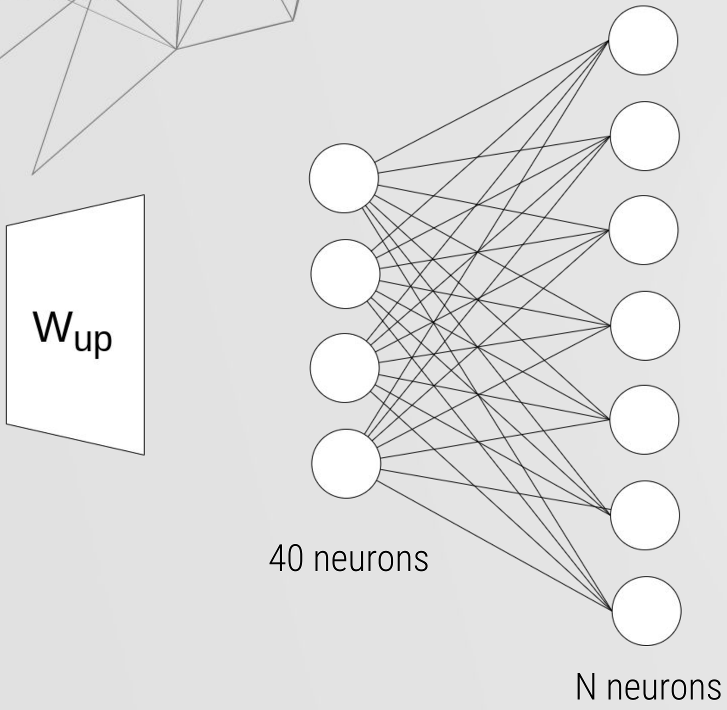

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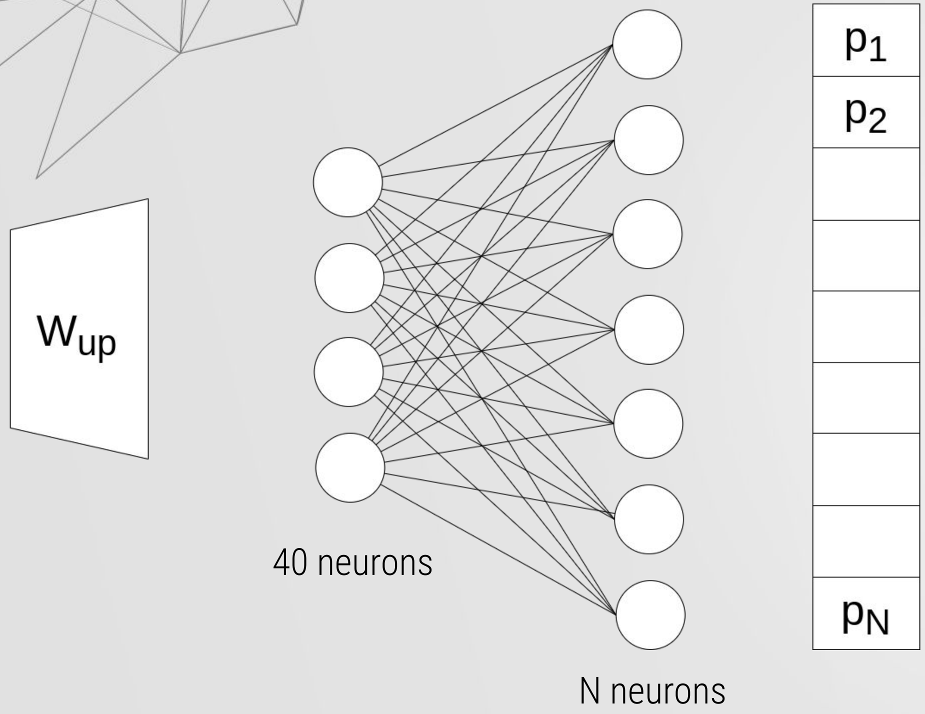

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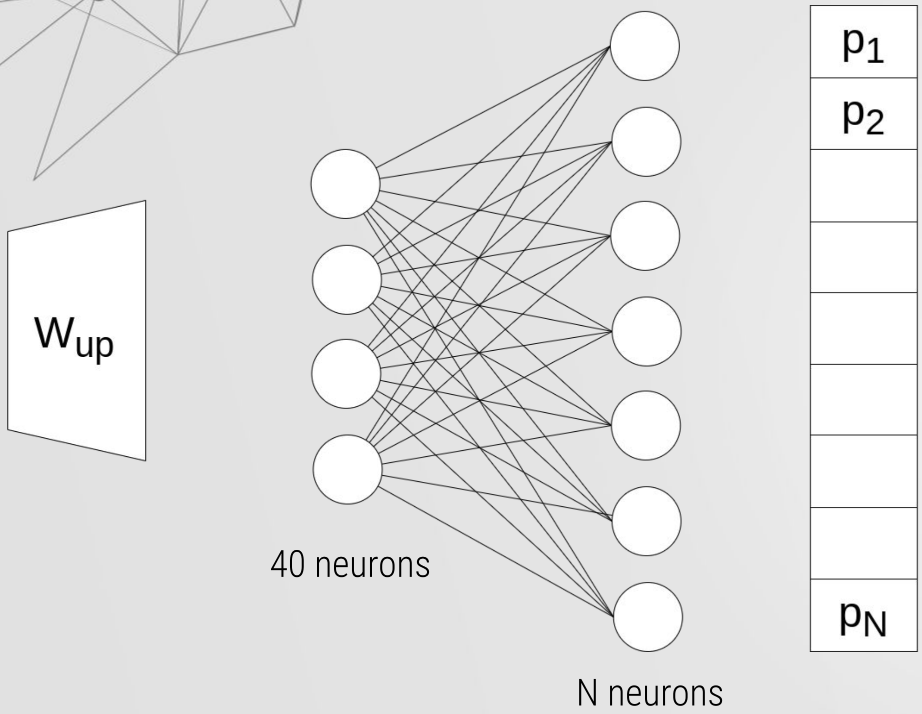
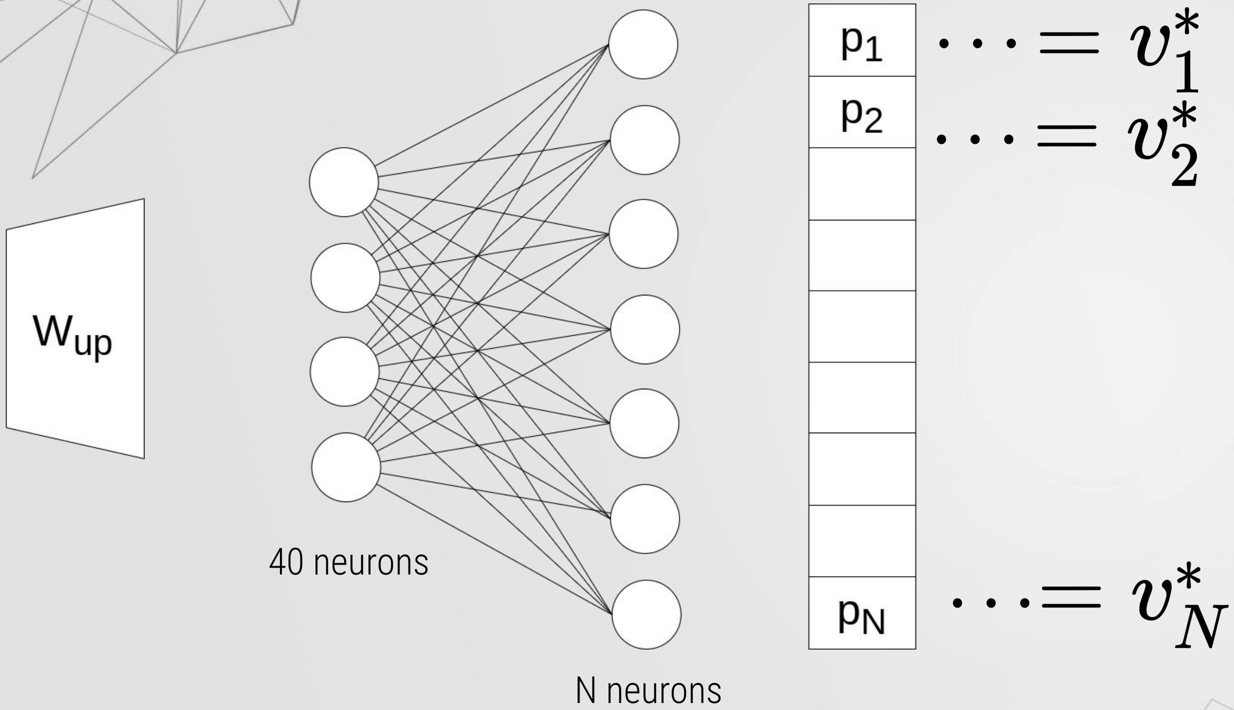


$$\sigma((p_1 + g)/\tau) = v_1^*$$

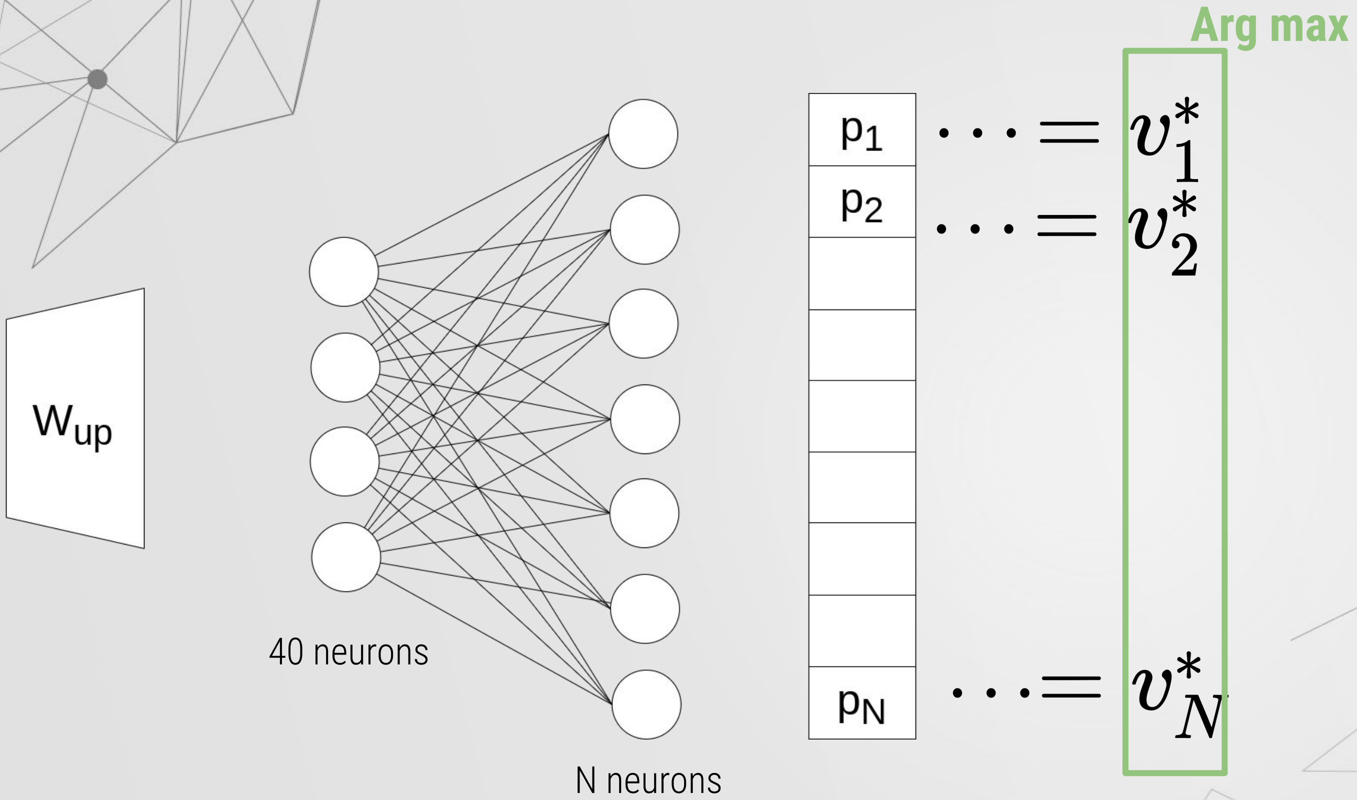
Temperature param

i.i.d. Sample from Gumbel dist.

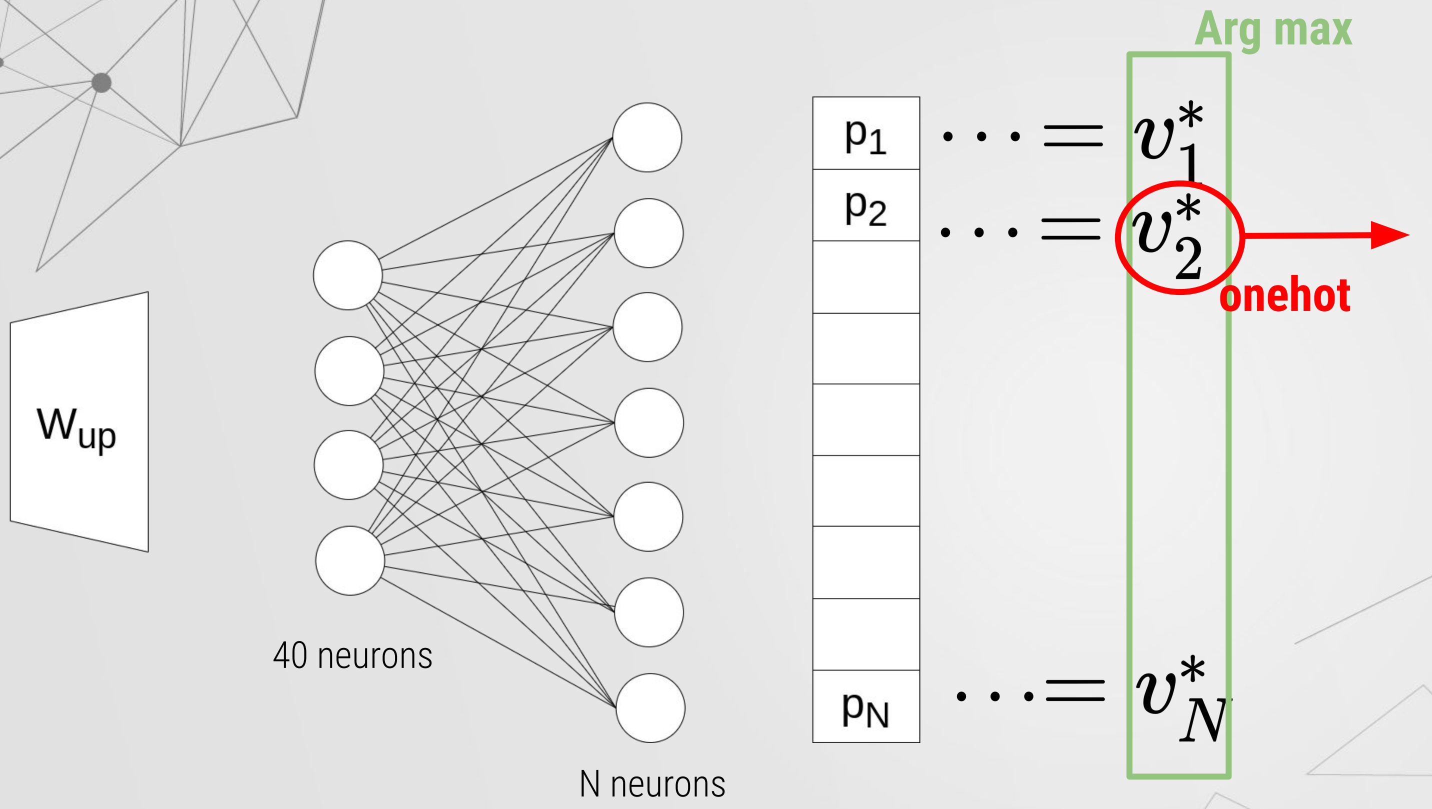
03 NetGAN



03 NetGAN

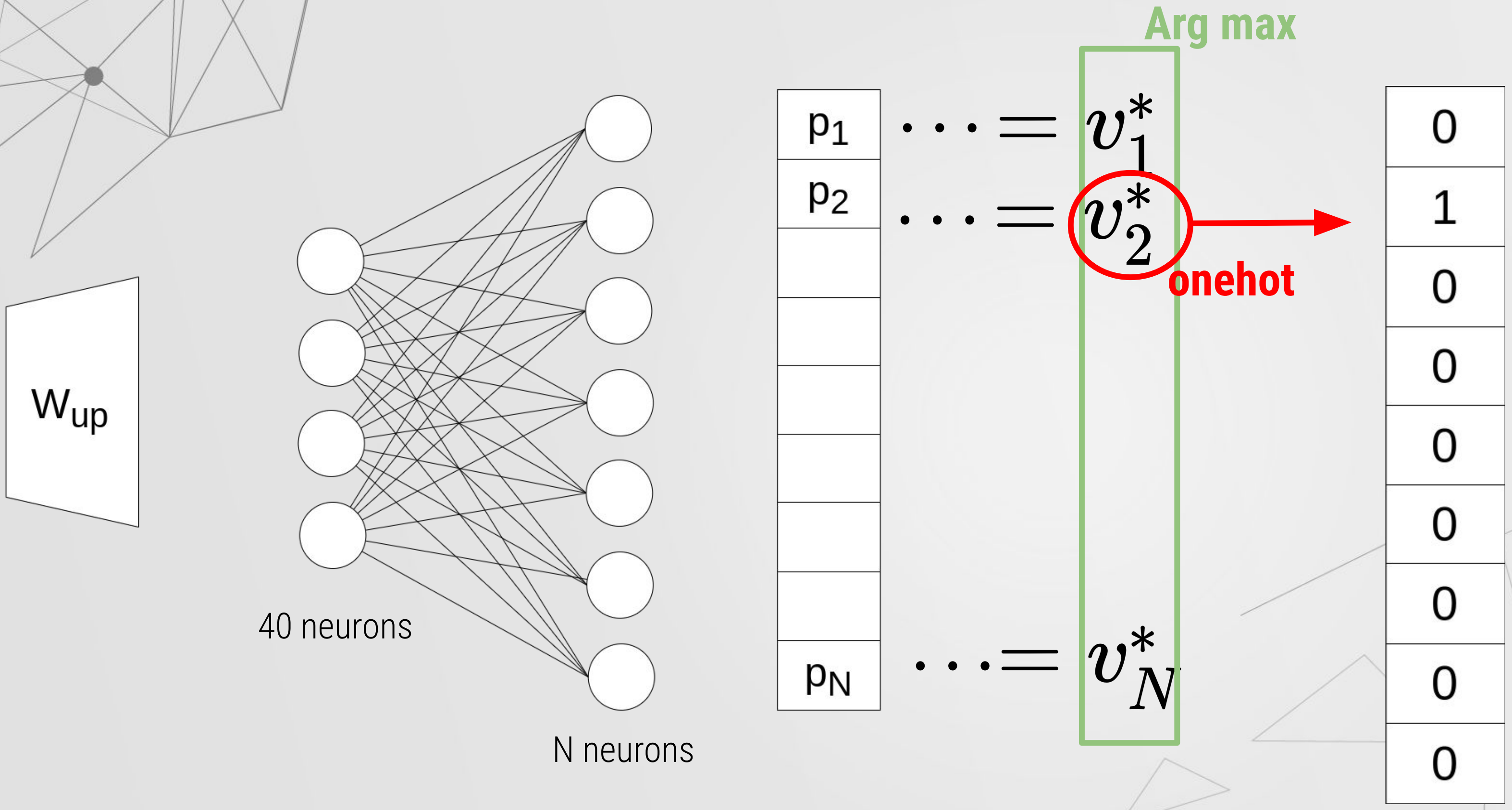

Arg max
W_{up}
40 neurons
N neurons
p_1 $\cdots = v_1^*$
p_2 $\cdots = v_2^*$
p_N $\cdots = v_N^*$

03 NetGAN



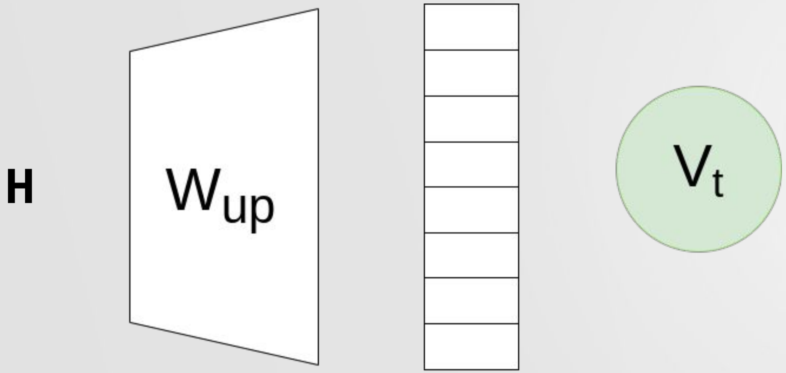
Arg max
W_{up}
40 neurons
N neurons
p_1
p_2
p_N
$\cdots = v_1^*$
$\cdots = v_2^*$
$\cdots = v_N^*$
onehot

03 NetGAN



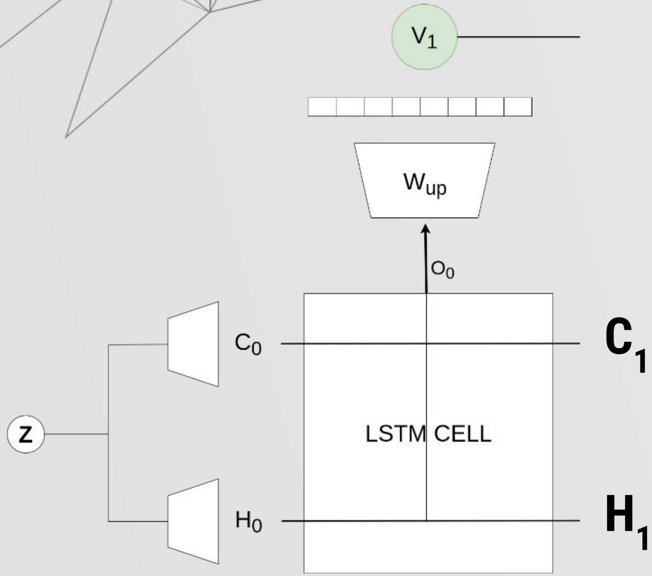
Arg max
W_{up}
40 neurons
N neurons
p_1
p_2
p_N
$\cdots = v_1^*$
$\cdots = v_2^*$
$\cdots = v_N^*$
onehot
0
1
0
0
0
0
0
0
0

03 NetGAN



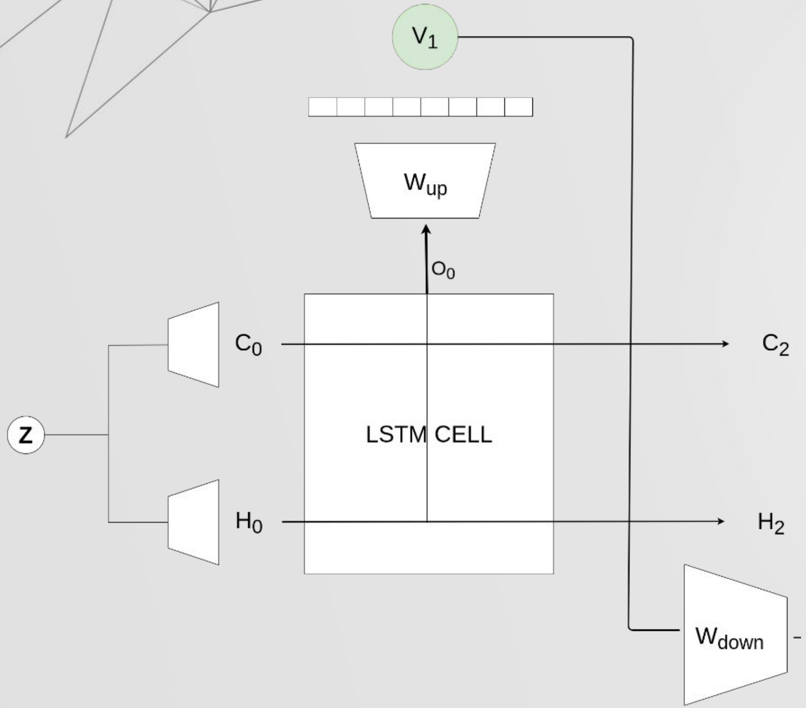
03 NetGAN

Generator



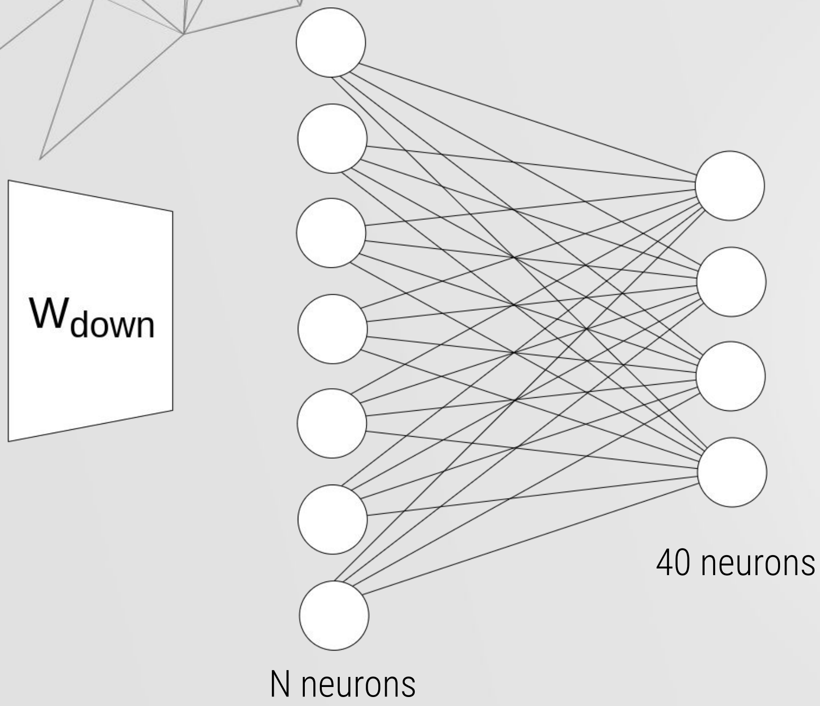
Generator

03 NetGAN



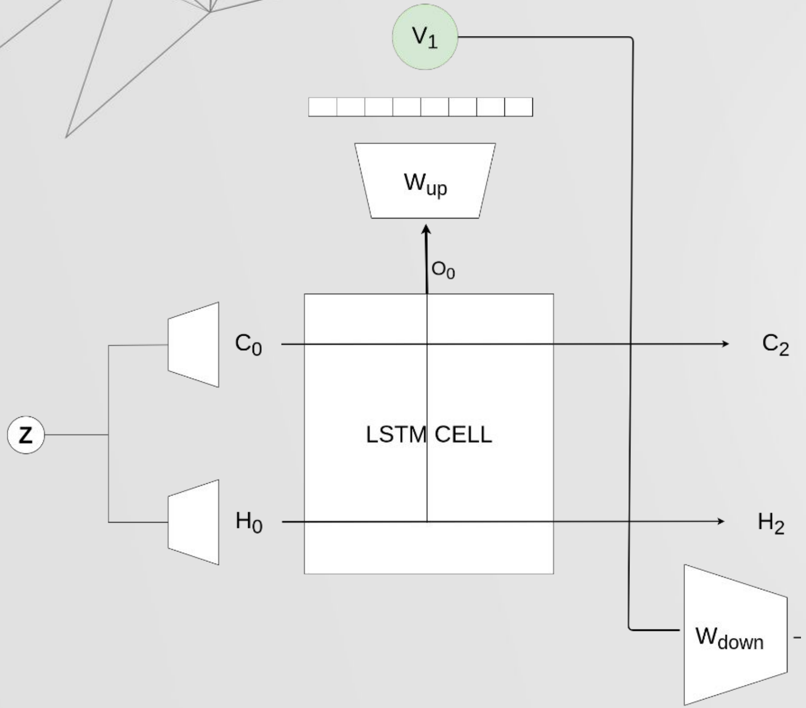
W_{down}

03 NetGAN



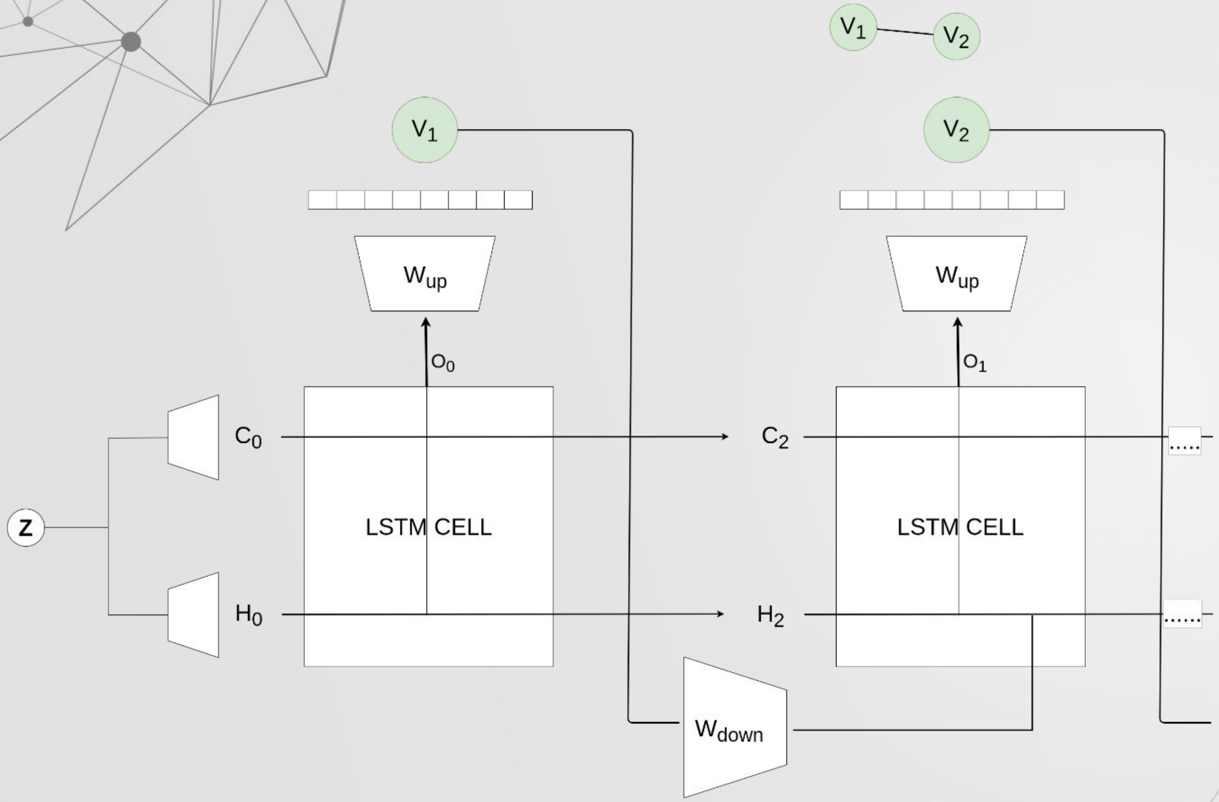
03 NetGAN

Generator



Generator

03 NetGAN



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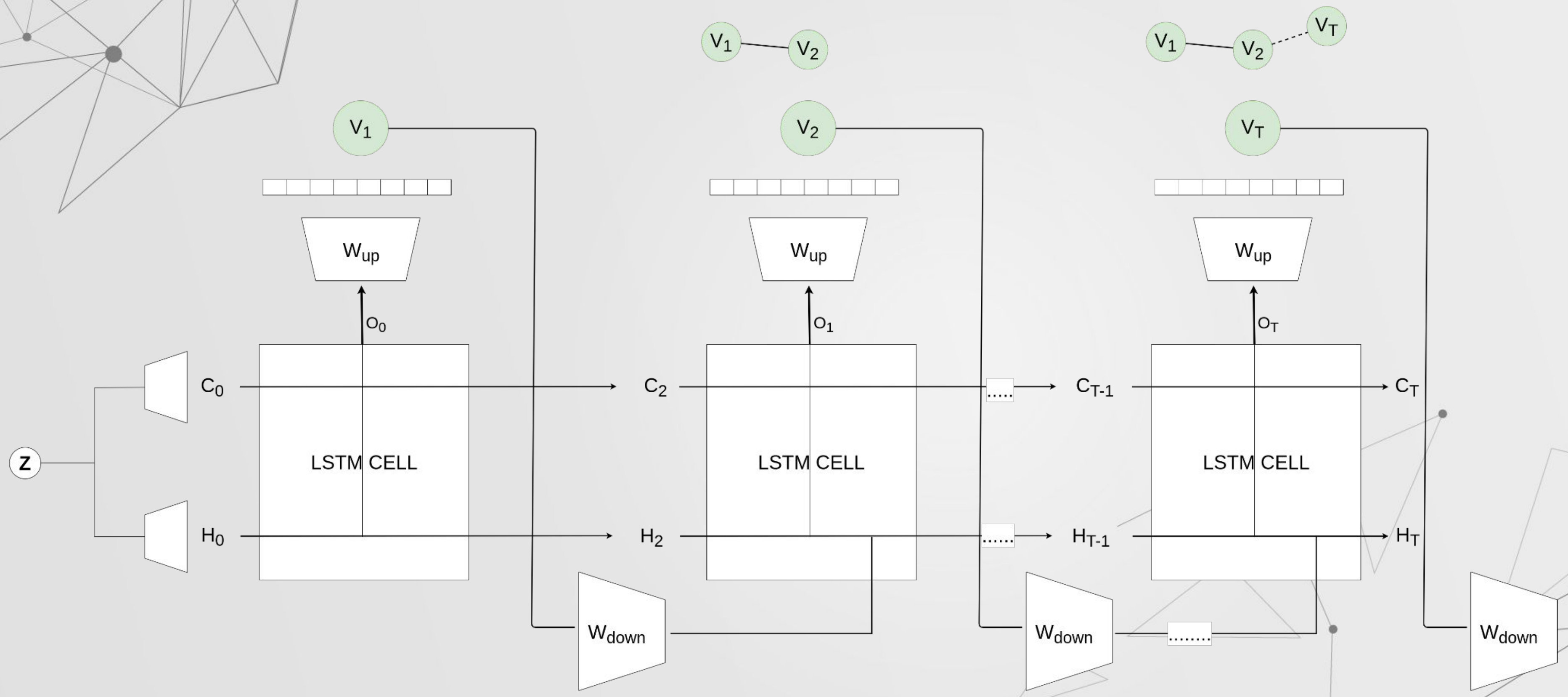
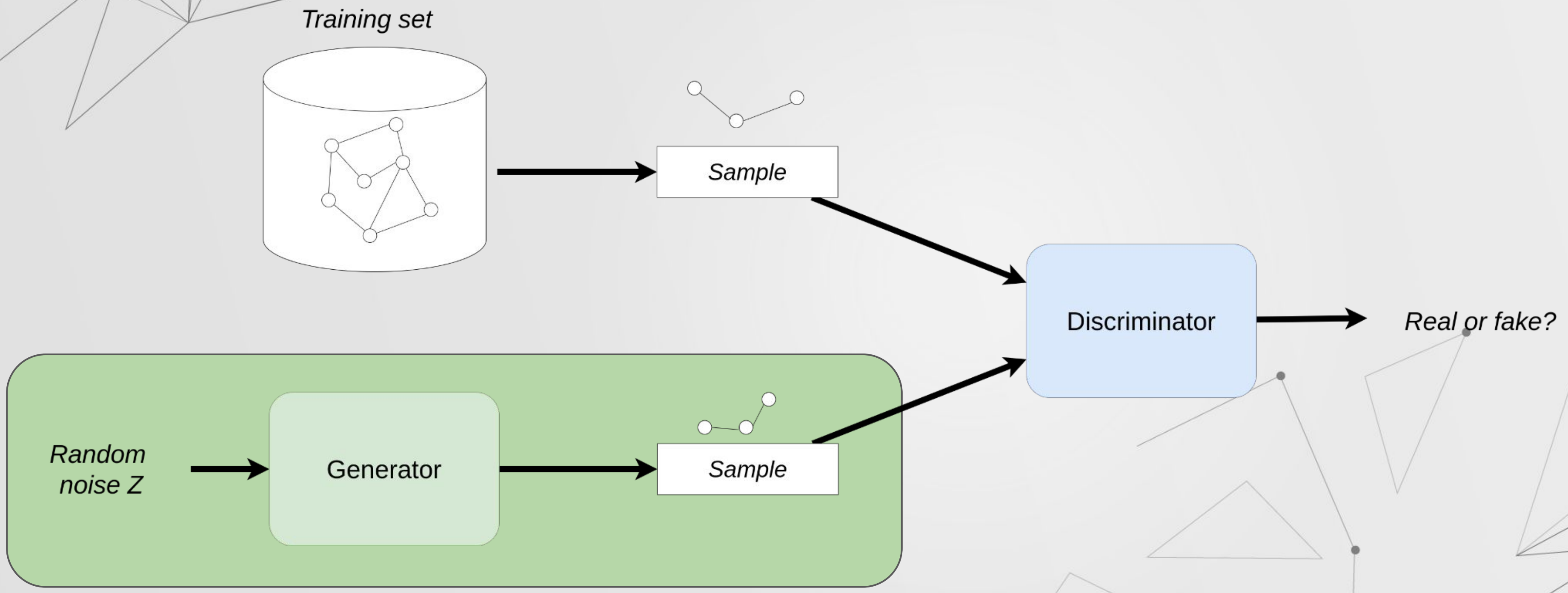
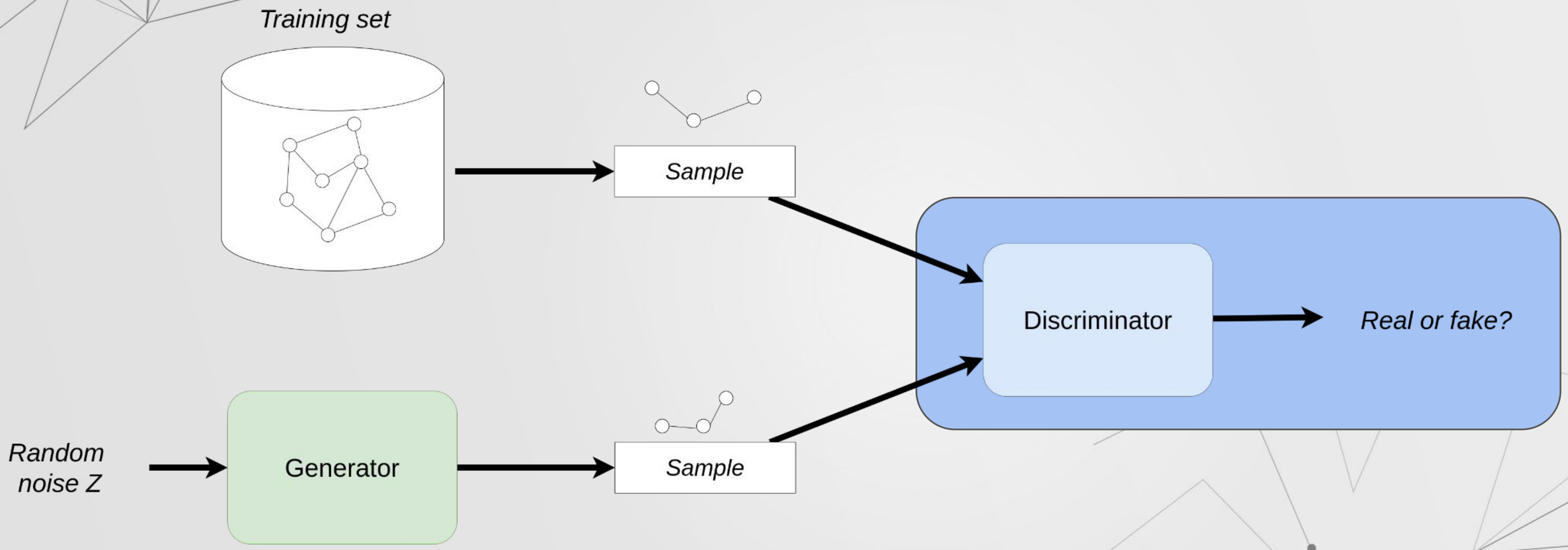


V_1
V_2
V_1
V_2
V_T
V_1
V_2
V_T
W_{up}
W_{up}
W_{up}
O_0
O_1
O_T
C_0
C_2
C_{T-1}
C_T
Z
LSTM CELL
LSTM CELL
LSTM CELL
H_0
H_2
H_{T-1}
H_T
W_{down}
W_{down}
W_{down}

03 NetGAN


Training set
Sample
Discriminator
Real or fake?
Random noise Z
Generator
Sample

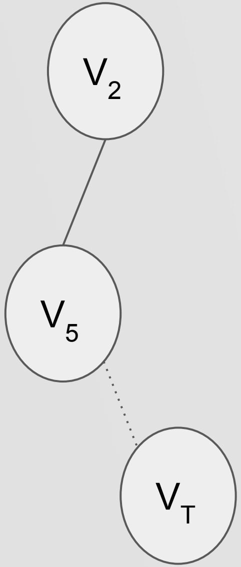
03 NetGAN



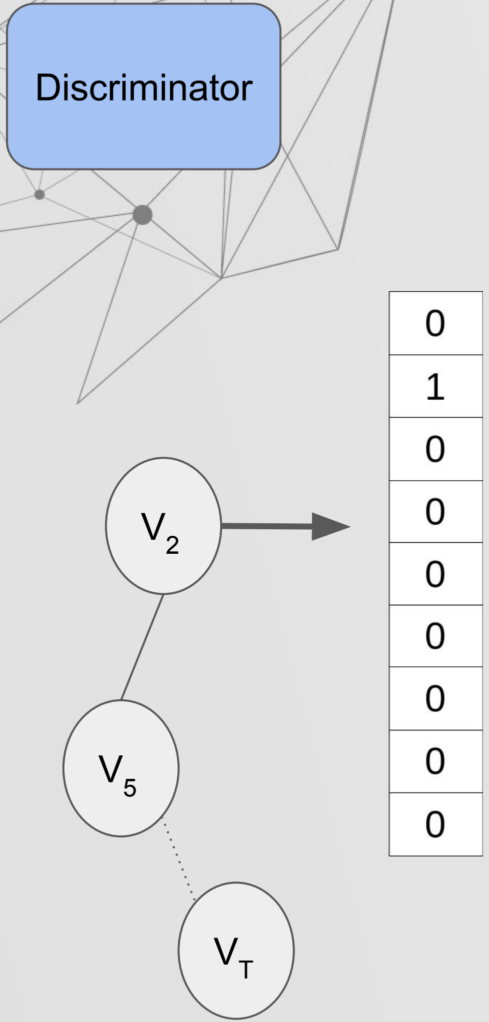
Training set
Sample
Discriminator
Real or fake?
Random noise Z
Generator
Sample

03 NetGAN

Discriminator

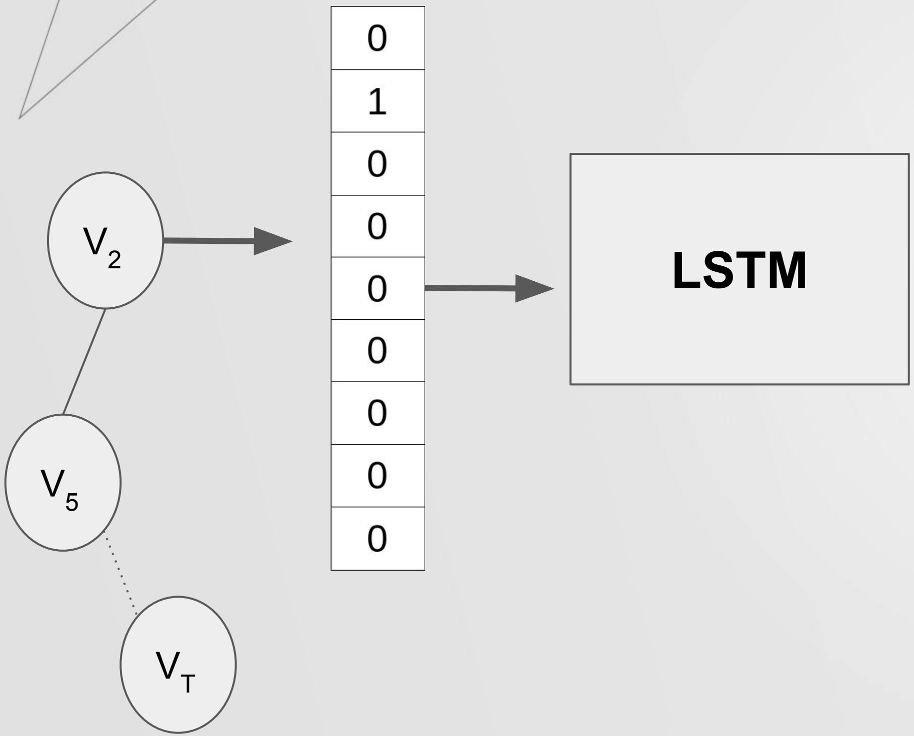


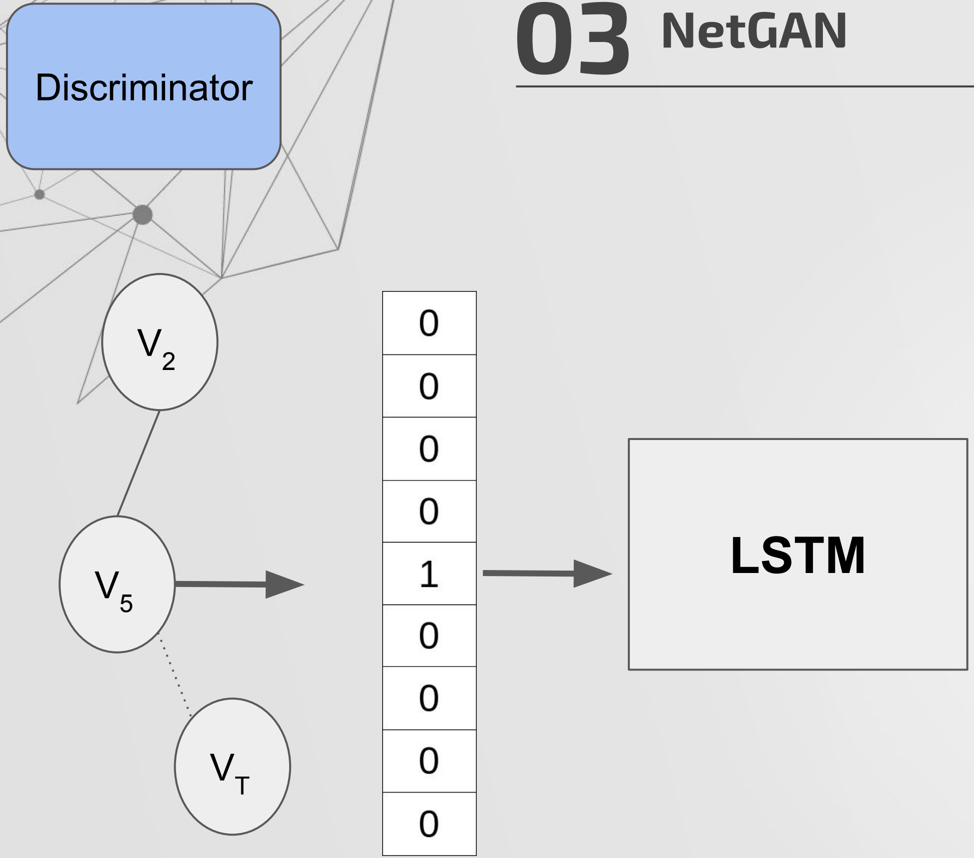
03 NetGAN



Discriminator

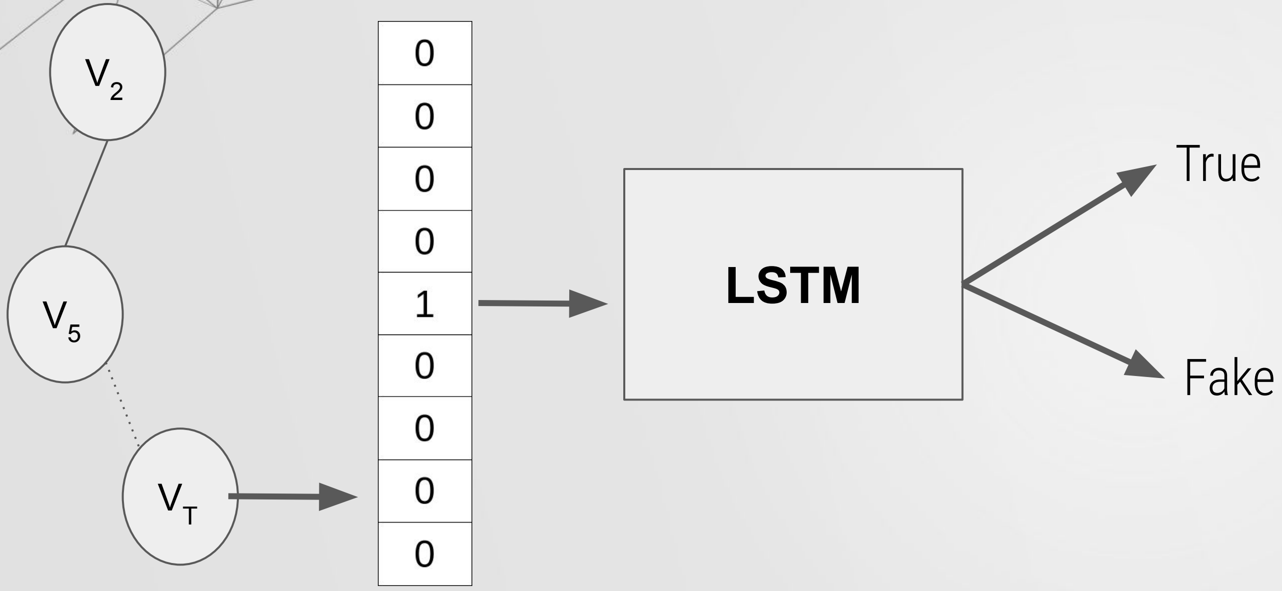
03 NetGAN




Discriminator
V2
V5
VT
0
0
0
0
1
0
0
0
0
LSTM

03 NetGAN

Discriminator



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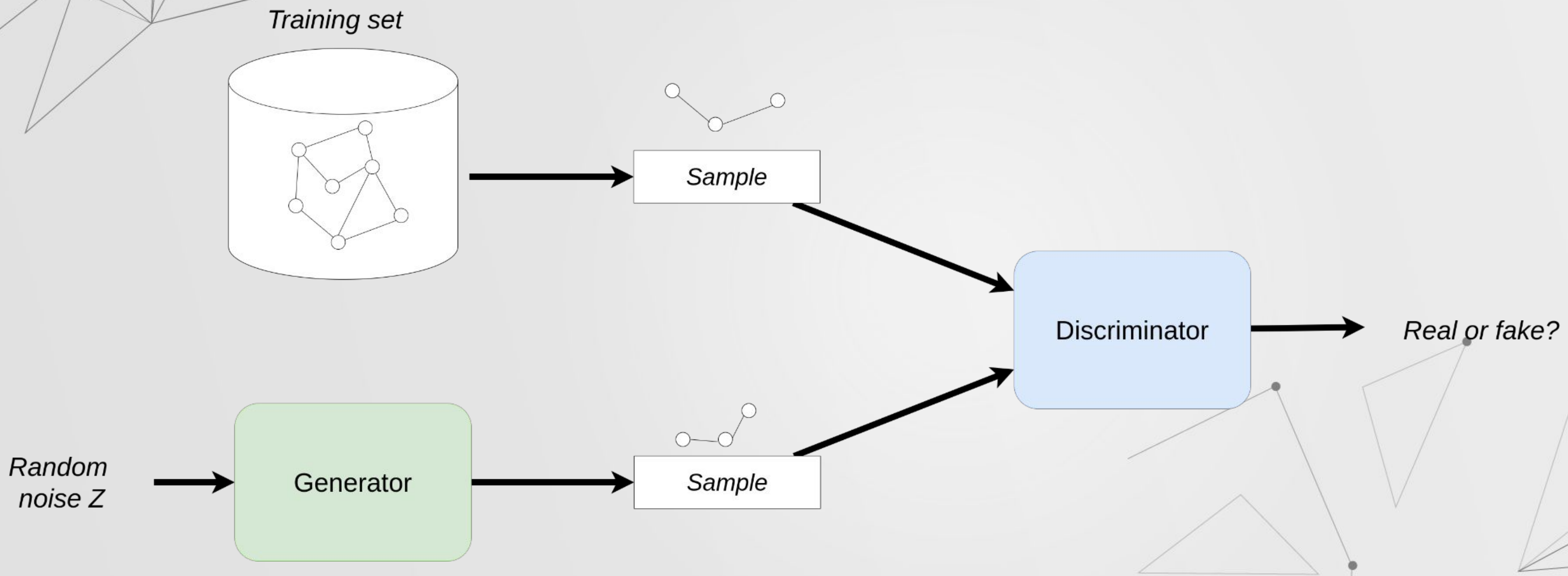
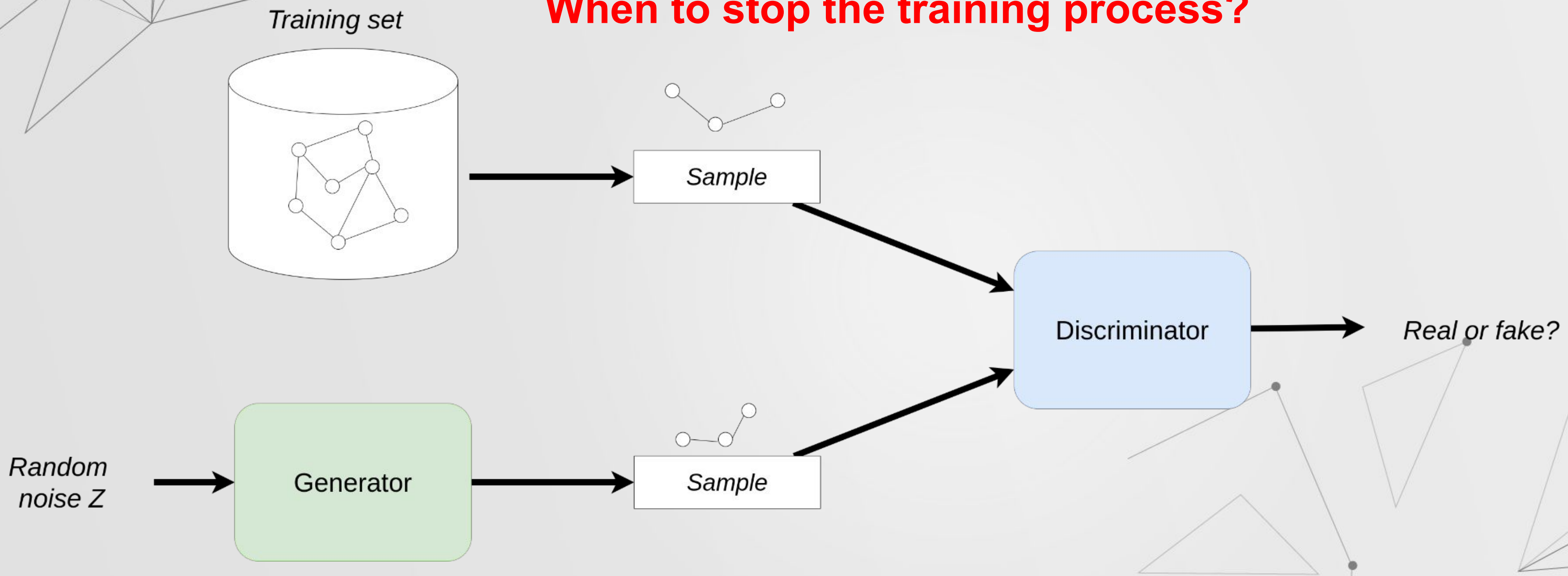

Training set
Sample
Discriminator
Real or fake?
Random
noise Z
Generator
Sample

03 NetGAN

When to stop the training process?



When to stop the training process?

EO-Criterion & VAL-Criterion

When to stop the training process?

<u>EO-Criterion</u> & VAL-Criterion

When to stop the training process?

EO-Criterion:

Stop the training process, when the input graph and the generated graph has an **edge overlapping** specified by the user.

How to build the graph?

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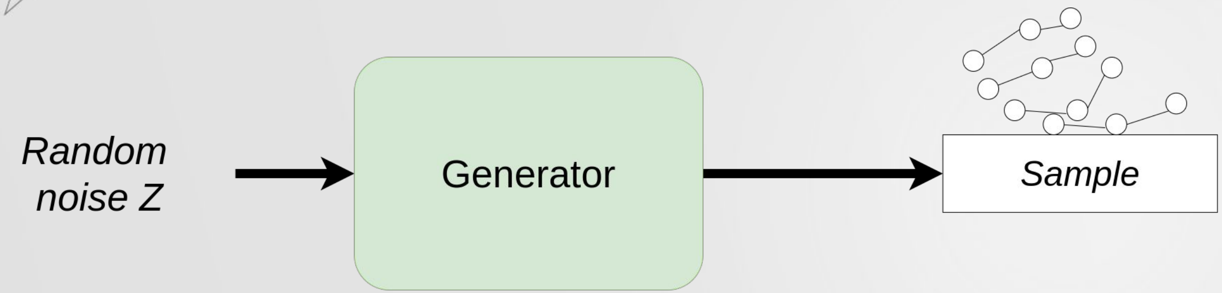
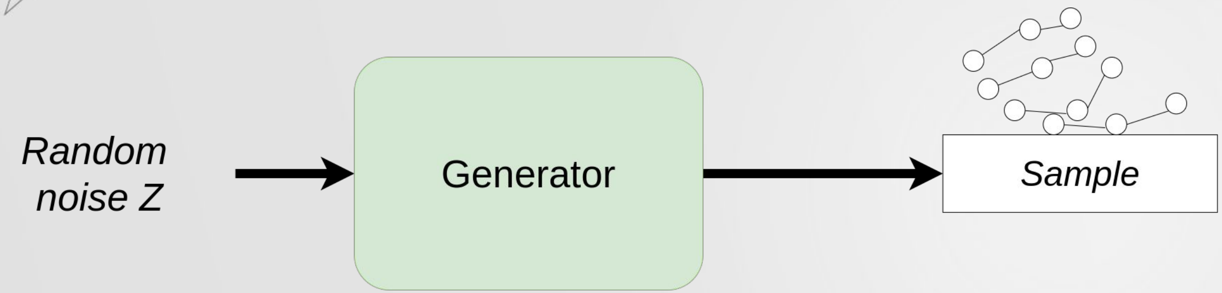


How to build the graph?



0	10	2	0	1
..	..	..	..	2
..	..	..	..	..
..	..	..	..	..
..	..	..	..	..

0	10	2	0	1
..	..	..	..	2
..	..	..	..	..
..	..	..	..	..
..	..	..	..	..

How to build the graph?

1. Symmetrize $$s_{i,j} = s_{j,i} = max(s_{i,j}, s_{j,i})$$

03 NetGAN

0	10	2	0	1
..	..	..	..	2
..	..	..	..	..
..	..	..	..	..
..	..	..	..	..

How to build the graph?

1. Symmetrize $$s_{i,j} = s_{j,i} = max(s_{i,j}, s_{j,i})$$
2. Ensure every node i has at least one edge $$p_{i,j} = \frac{s_{i,j}}{\sum_v s_{i,v}}$$

0	10	2	0	1
..	..	..	..	2
..	..	..	..	..
..	..	..	..	..
..	..	..	..	..

How to build the graph?

1. Symmetrize $s_{i,j} = s_{j,i} = max(s_{i,j}, s_{j,i})$
2. Ensure every node i has at least one edge $p_{i,j} = \frac{s_{i,j}}{\sum_v s_{i,v}}$
3. Continue sampling edges with probability $p_{i,j} = \frac{s_{i,j}}{\sum_{u,v} s_{u,v}}$

04 NetGAN practice

Jupyter Notebook

Code:
https://github.com/mmiller96/netgan_pytorch