uOttawa

Generative Adversarial Nets

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GANs

Basic approach

Generative models

Discriminative models

How do GANs work

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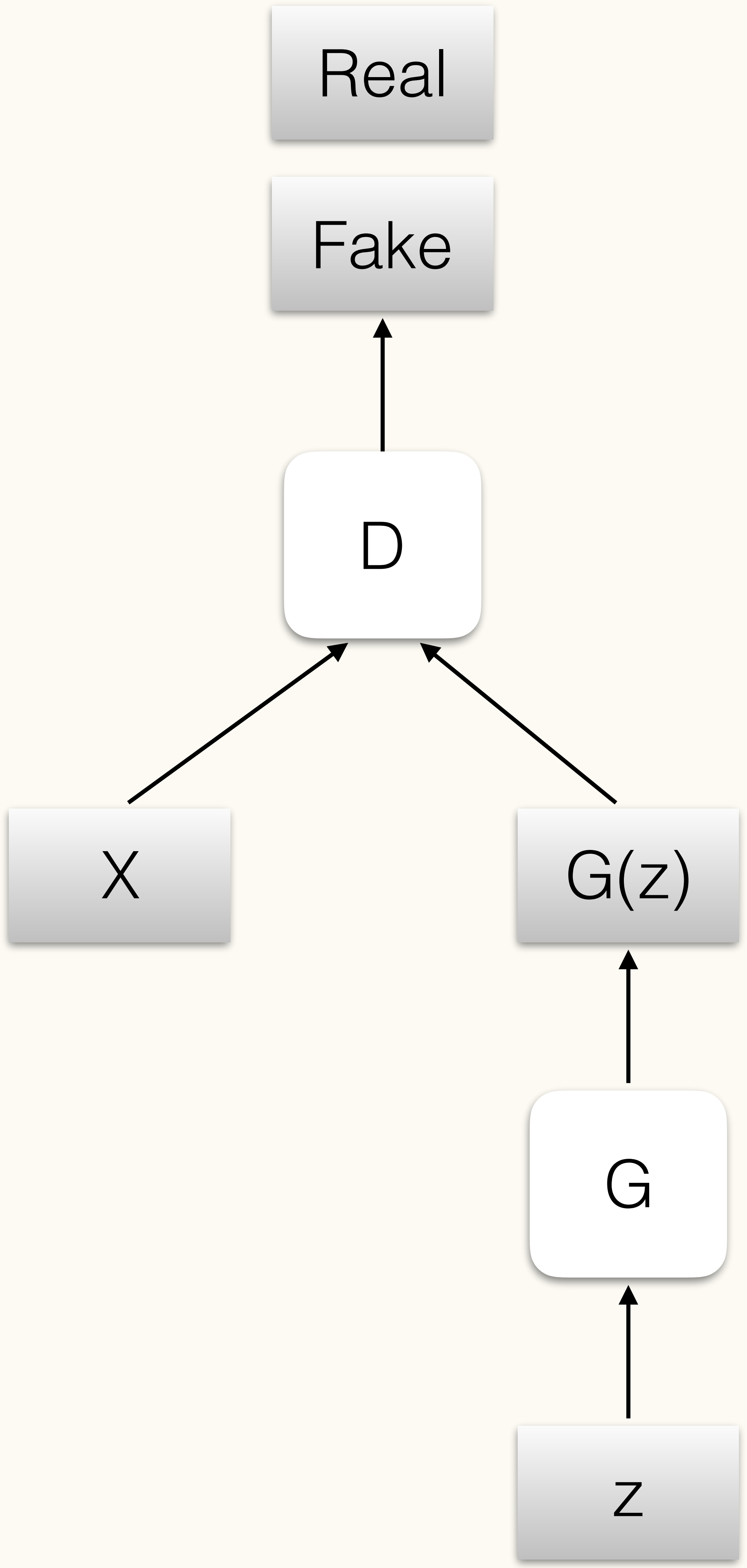
Basic approach

Purpose:
Train a desire Generative Model

Idea:
Add a Discriminative Model

Basic approach



Basic approach

Set up **a game** between two neural nets

- the **generator** creates samples
- the **discriminator** classifies these samples as real or fake
- both **train together** together or in turns?

我觉得这边讲的时候可以把Generator和Discriminator的互相作用这一块着重讲一下：G的作用是尽可能生成可以以假乱真的图片，D的作用是尽可能分辨出图片的真伪。随着G生成的图片越来越真实，又会激励D的分辨能力变强；反之，D的分辨能力变强，又会激励G生成的图片更加可以以假乱真。G和D构成的是一个动态的“博弈过程”。

然后我觉得在这边可以把总的一个核心公式加上：min max...那个，然后再用数学方法解释一下G和D的作用。

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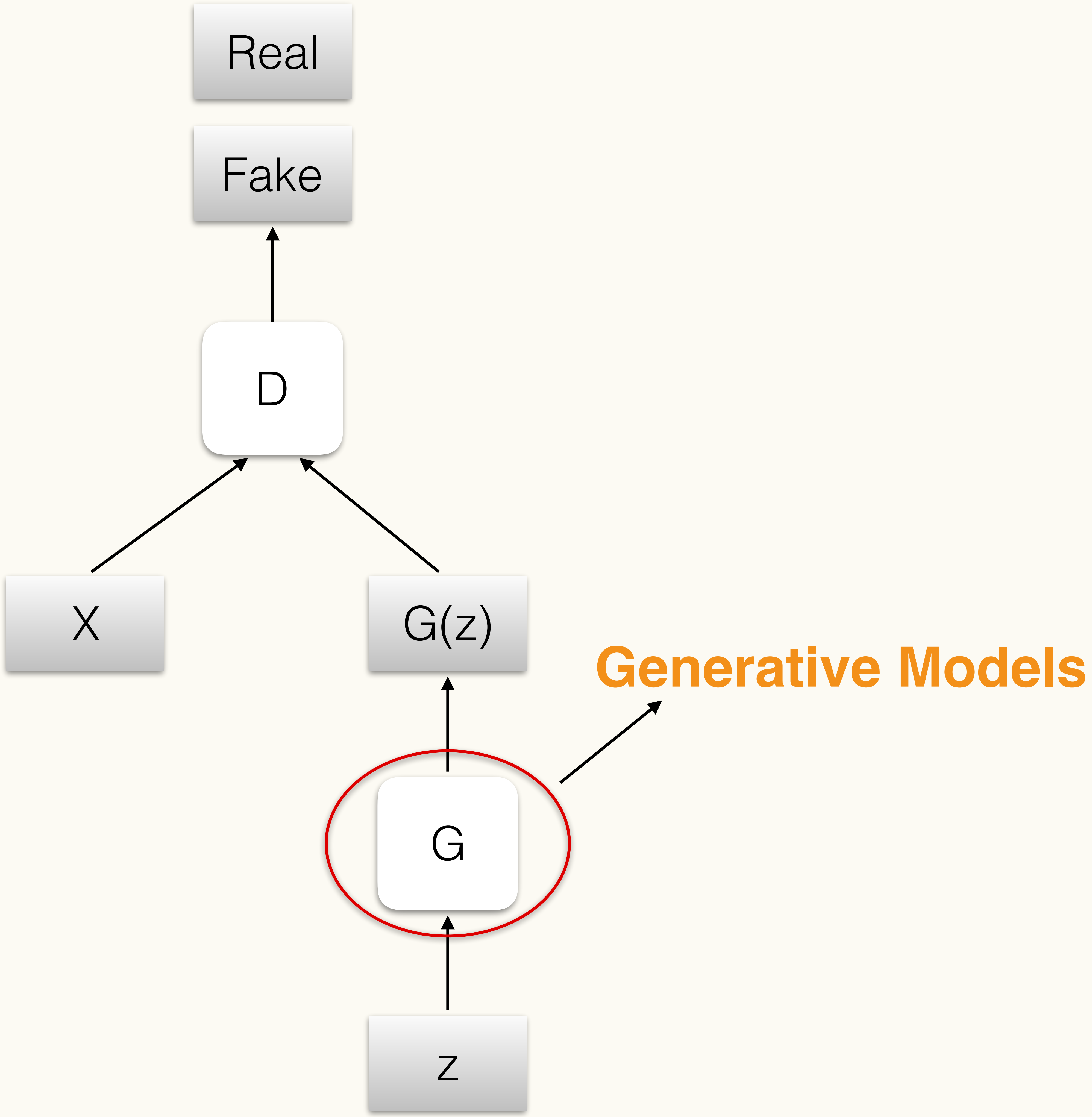
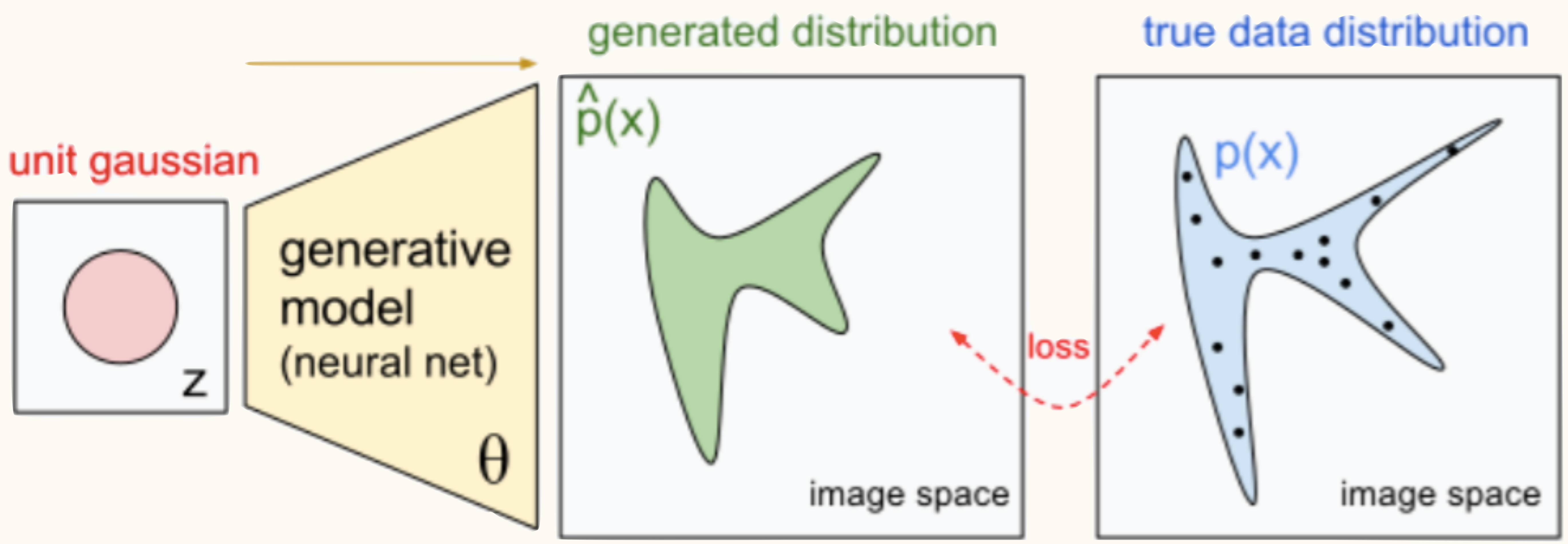


Generative Models

- G trying to recover the **training data distribution**
- The generative model can be thought of as analogous to a team of counterfeiters trying to **produce fake currency** and use it without detection

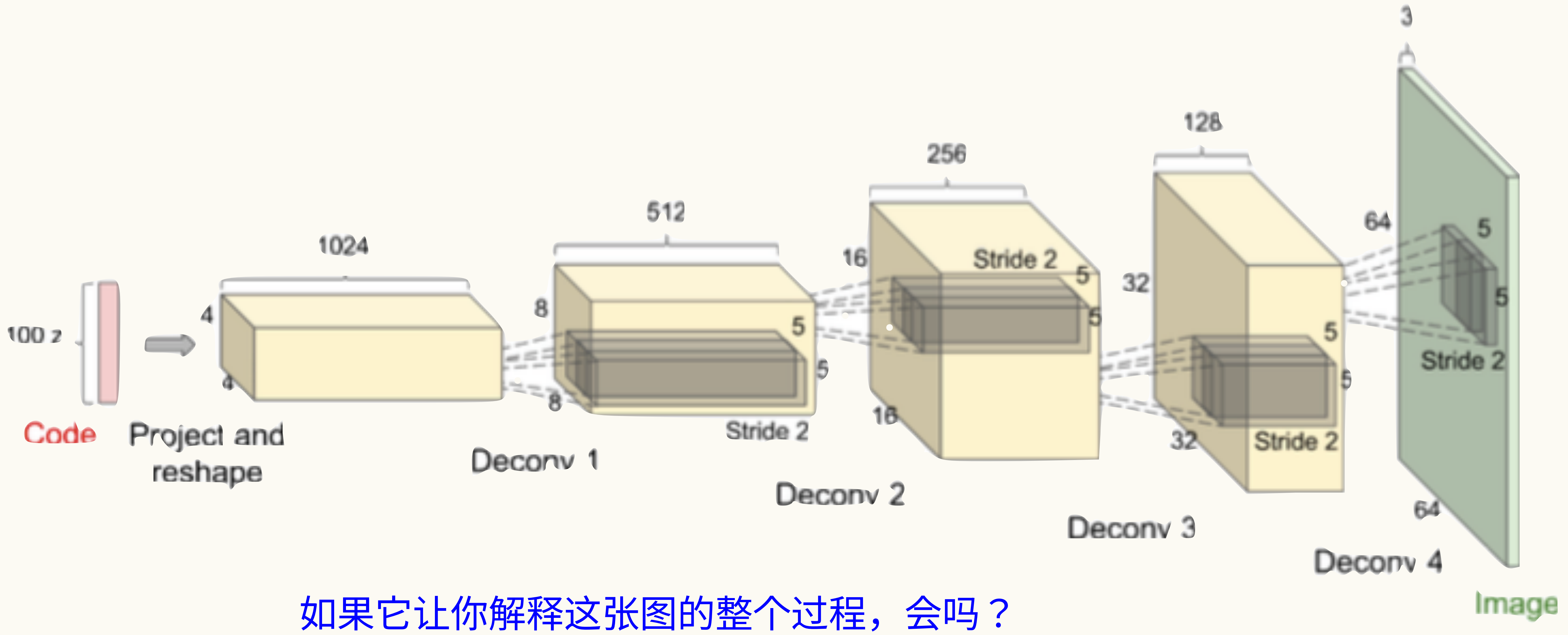
Generative Models

Training Approach



Generative Models

- Upsampling with fractionally-strided convolution
- Opposite of convolutional neural nets



如果它让你解释这张图的整个过程，会吗？

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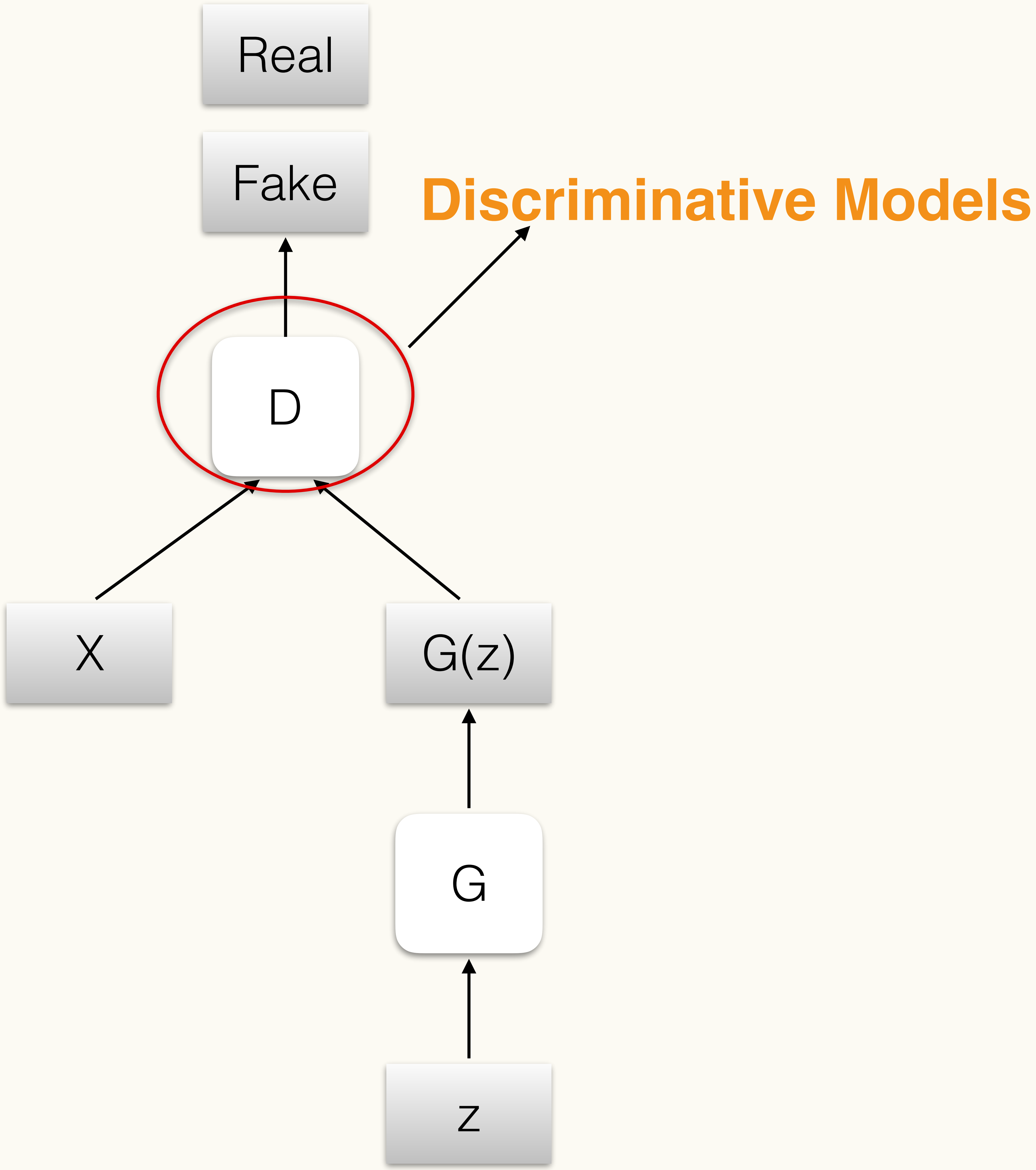

Discriminative Model

- learns to determine whether a sample is from the model distribution or the data distribution
- estimates the **probability** that a sample came from the training data rather than G
- $$D(x) = \frac{P_{data}(x)}{P_{data}(x) + P_{model}(x)}$$ 这个公式需要稍微解释一下吗？

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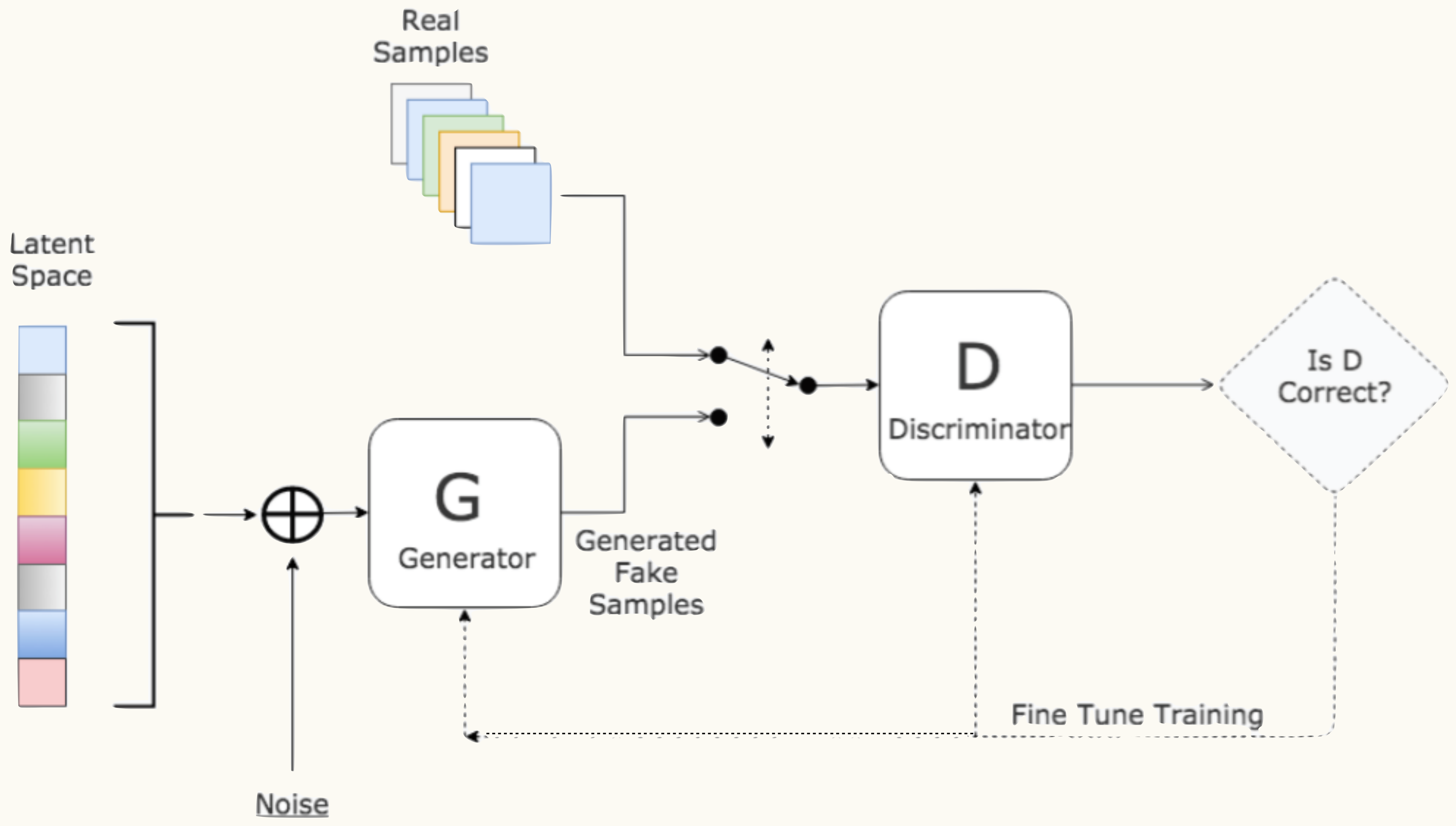
Minimax Game



或者也可以在这边写那个总的核心公式，跟着图一起解释。

Minimax Game

Loss Function

$$J^{(D)} = -\frac{1}{2} E_{x \sim P_{data}} \log D(x) - \frac{1}{2} E_x \log(1 - D(G(z)))$$

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

What is the problem?

Non-Saturating

Minimax Game

$$J^{(D)} = -\frac{1}{2}E_{x\sim P_{data}} \log D(x) - \frac{1}{2}E_x \log(1 - D(G(z)))$$

$$J^{(G)} = -\frac{1}{2}E_z \log D(G(z))$$

When the Discriminator is too smart,
G still has a learning signal

ALGORITHM

Minimax Game

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

end for

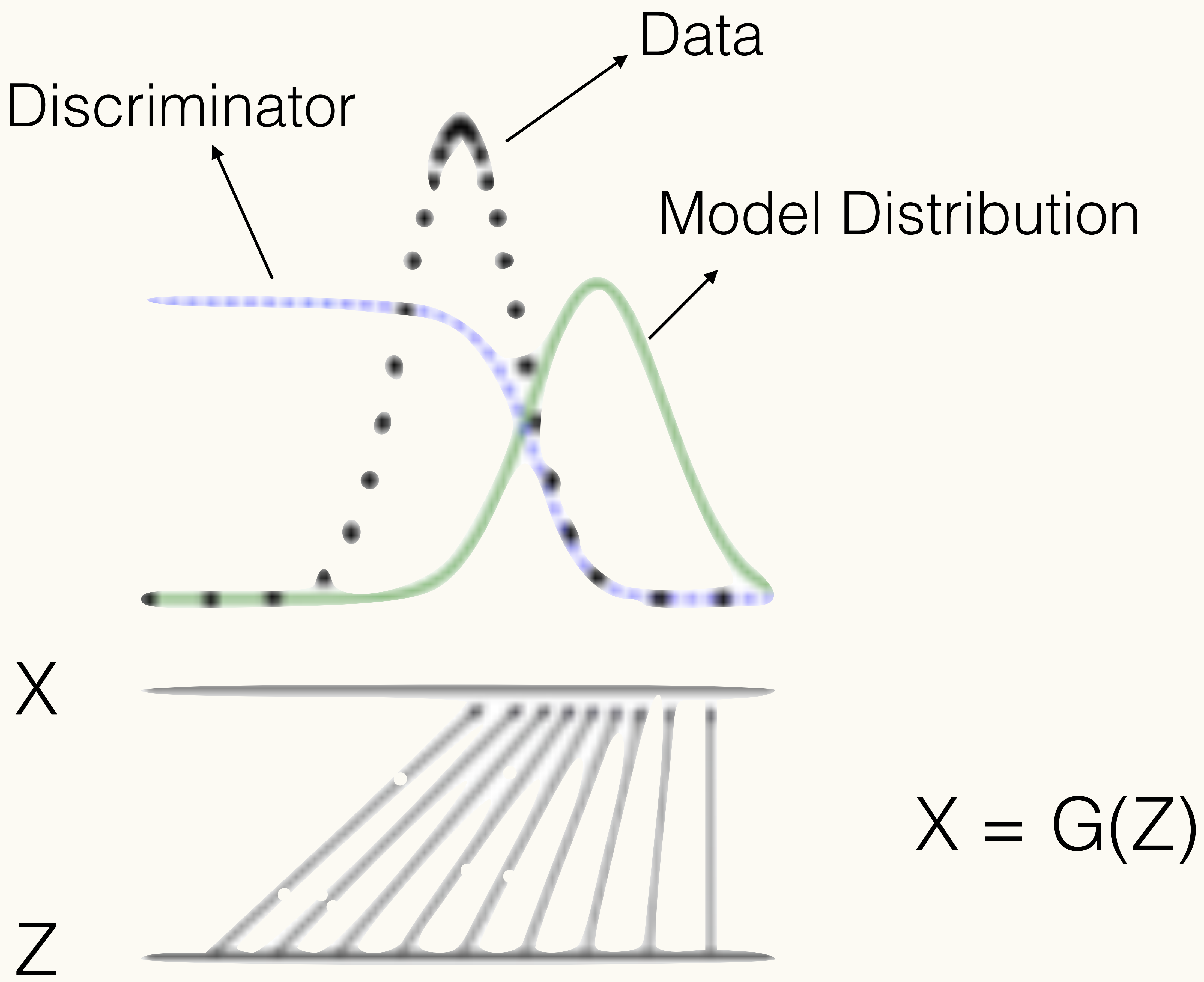
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

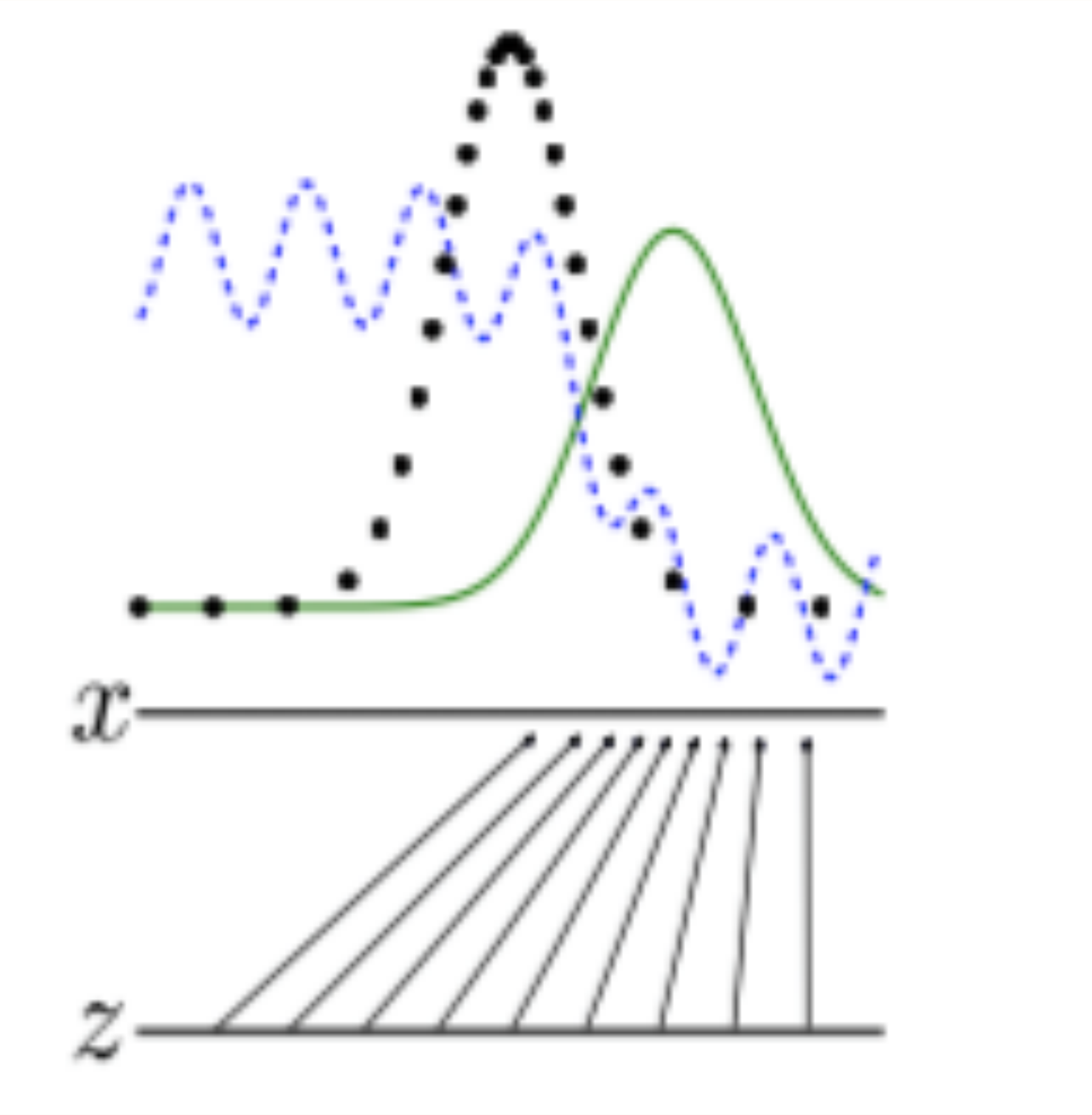
end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Minimax Game



Minimax
Game



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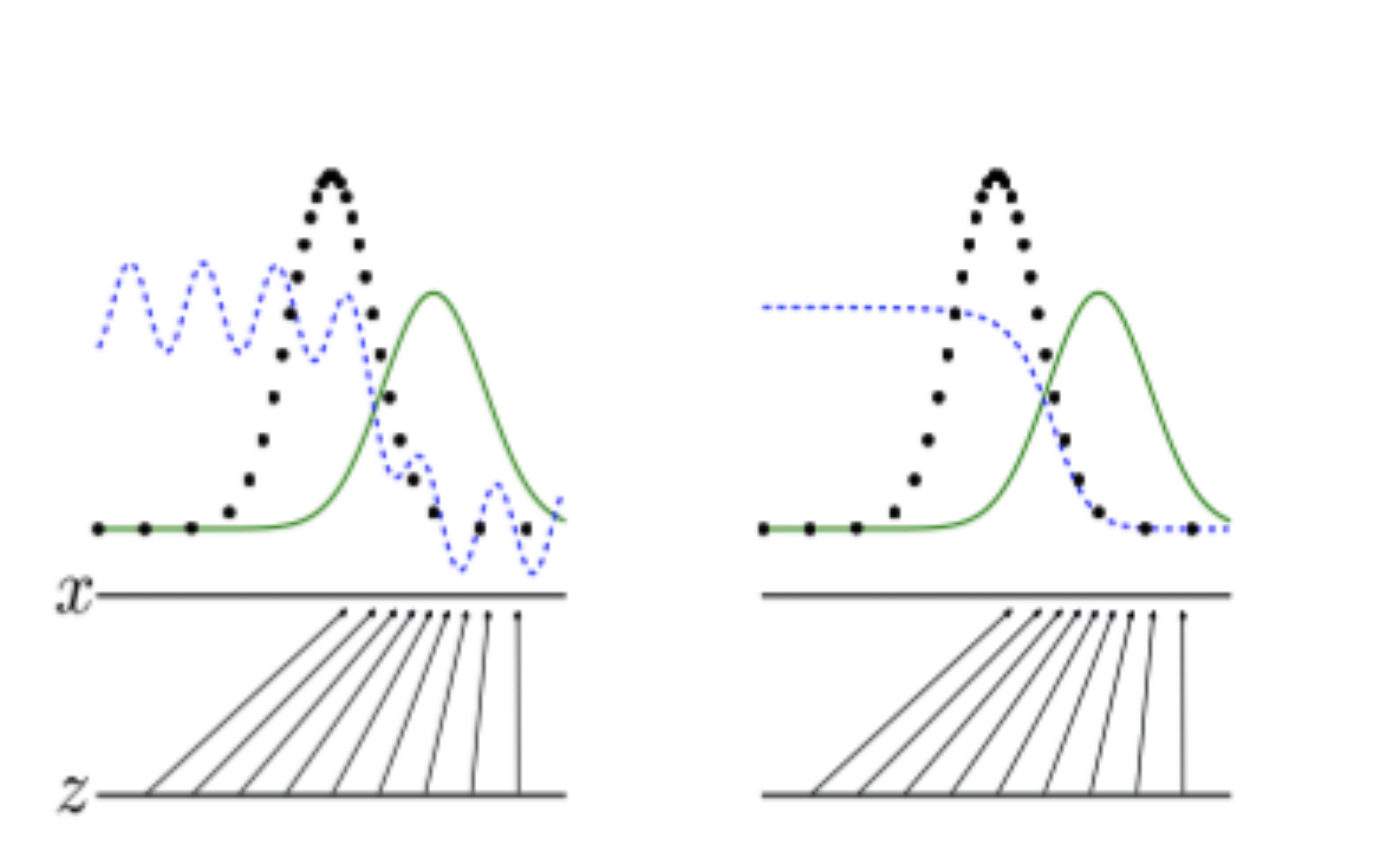

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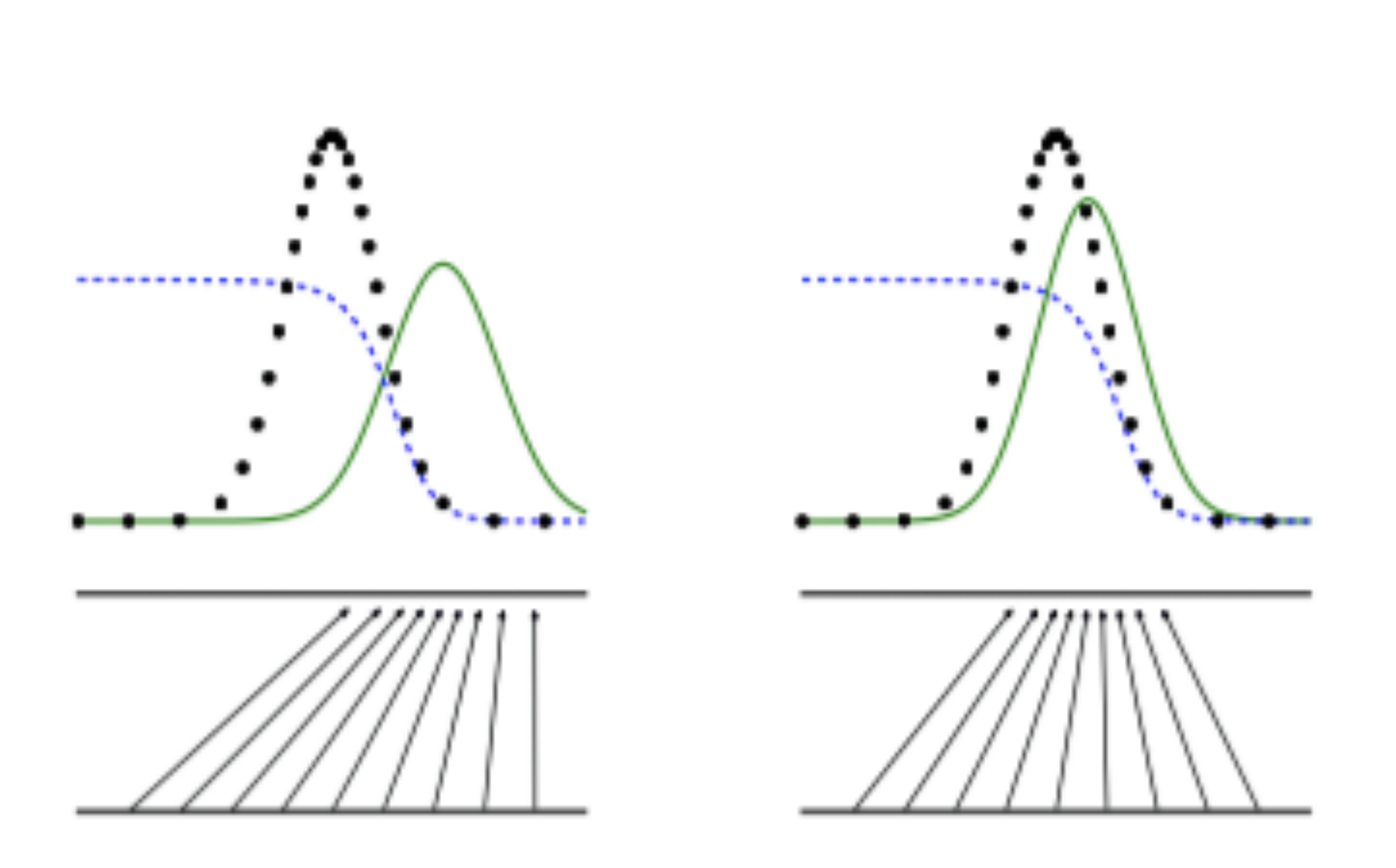

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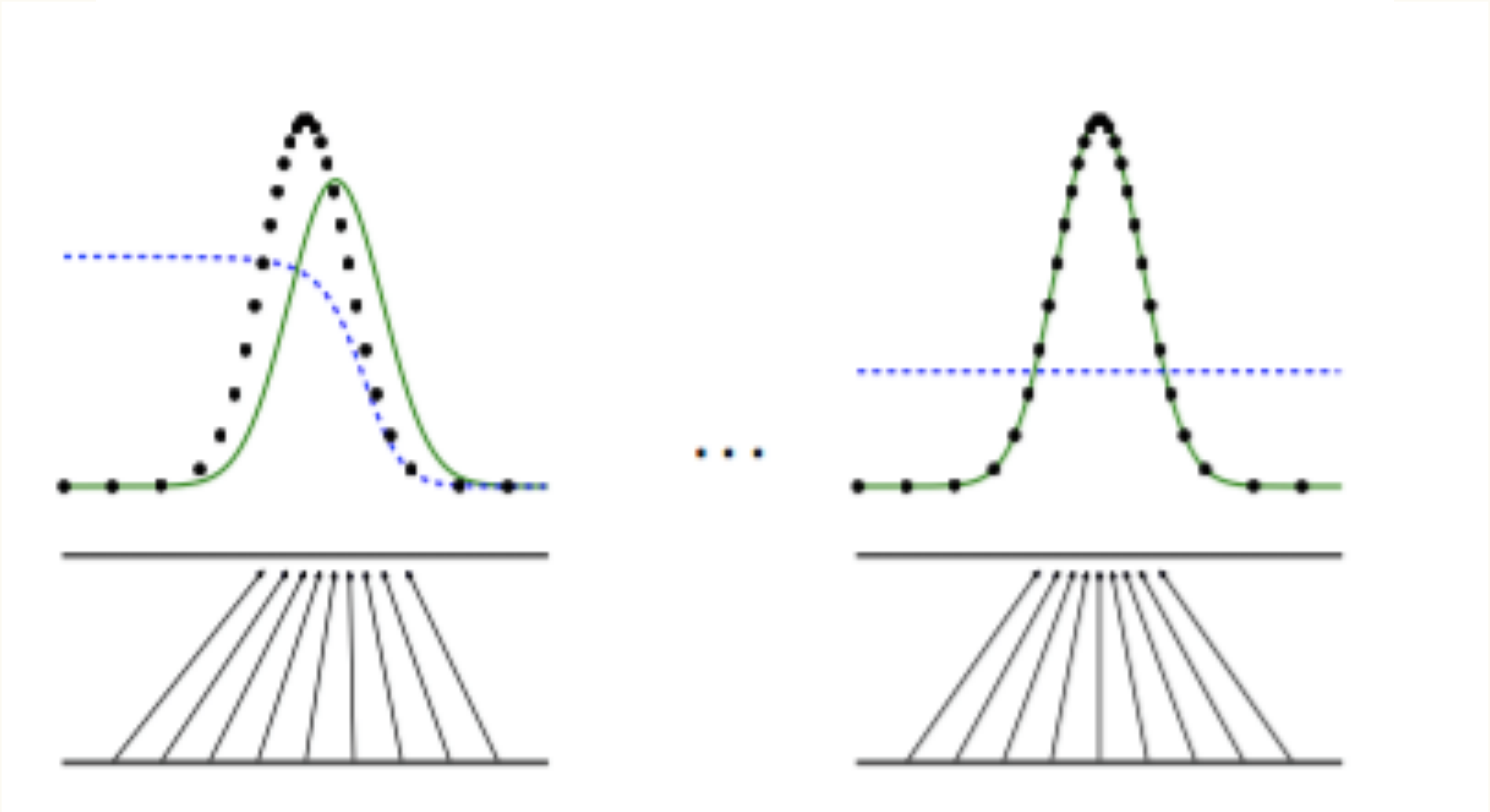

这边需不需要解释一下当Pg=Pdata的时候，min max...=-log 4？
即生成模型能完美地复制数据的生成过程。

Global optimality:

$$P_{data}(x) = P_{model}(x)$$

Thank you!

Questions?