On Unifying Deep Generative Models

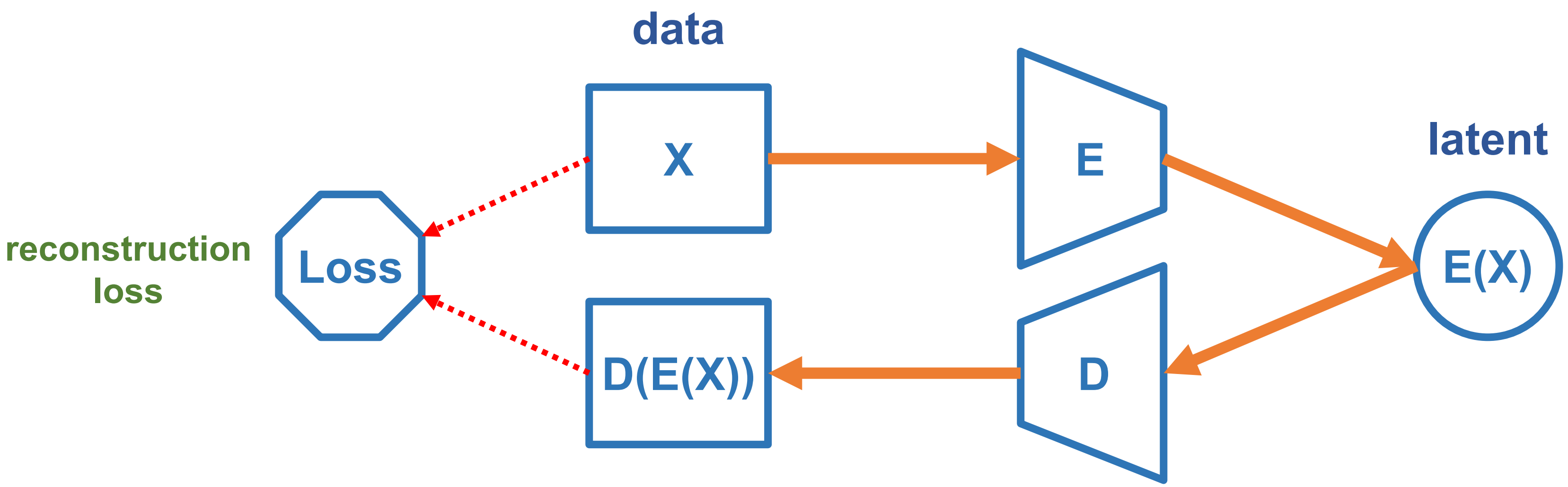
Herman Dong, 2017.8.15

Outline

- **Brief introduction to deep generative models**
  - AE (Autoencoder)
  - VAE (Variational Autoencoder)
  - GAN (Generative Adversarial Networks)
  - AAE (Adversarial Autoencoder)
  - VAE/GAN
  - ADA (Adversarial Domain Adaption)
- **Reformulation**
  - Graphical model representation
  - Connection to Wake-sleep Algorithm

AE (Autoencoder)

- minimize **reconstruction loss**



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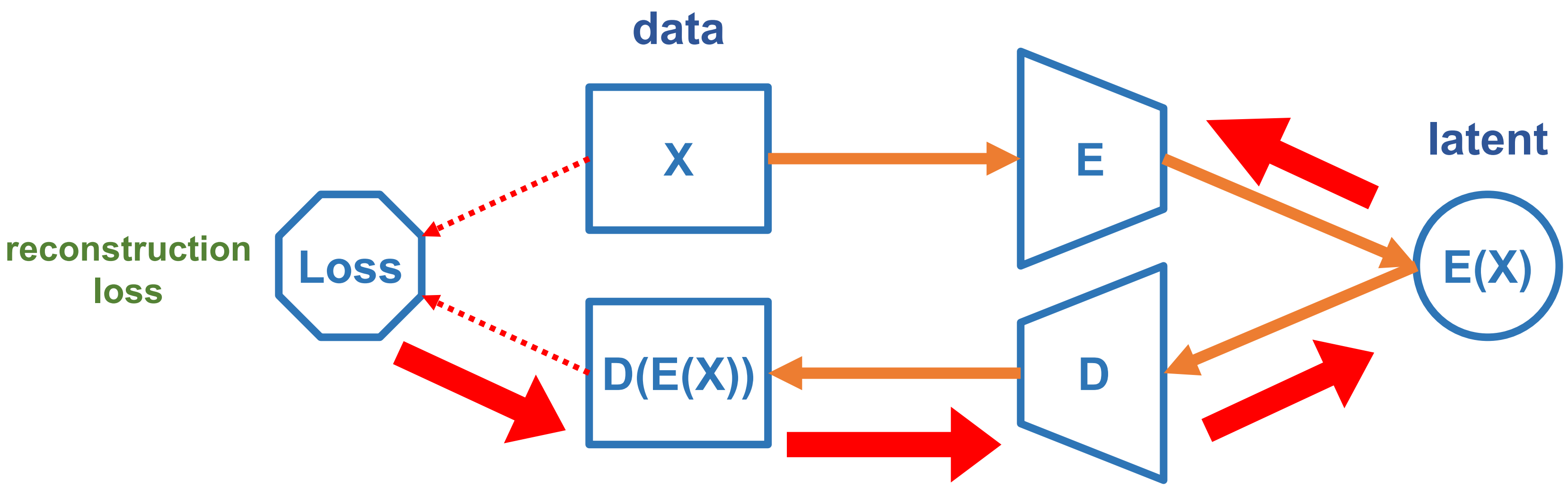

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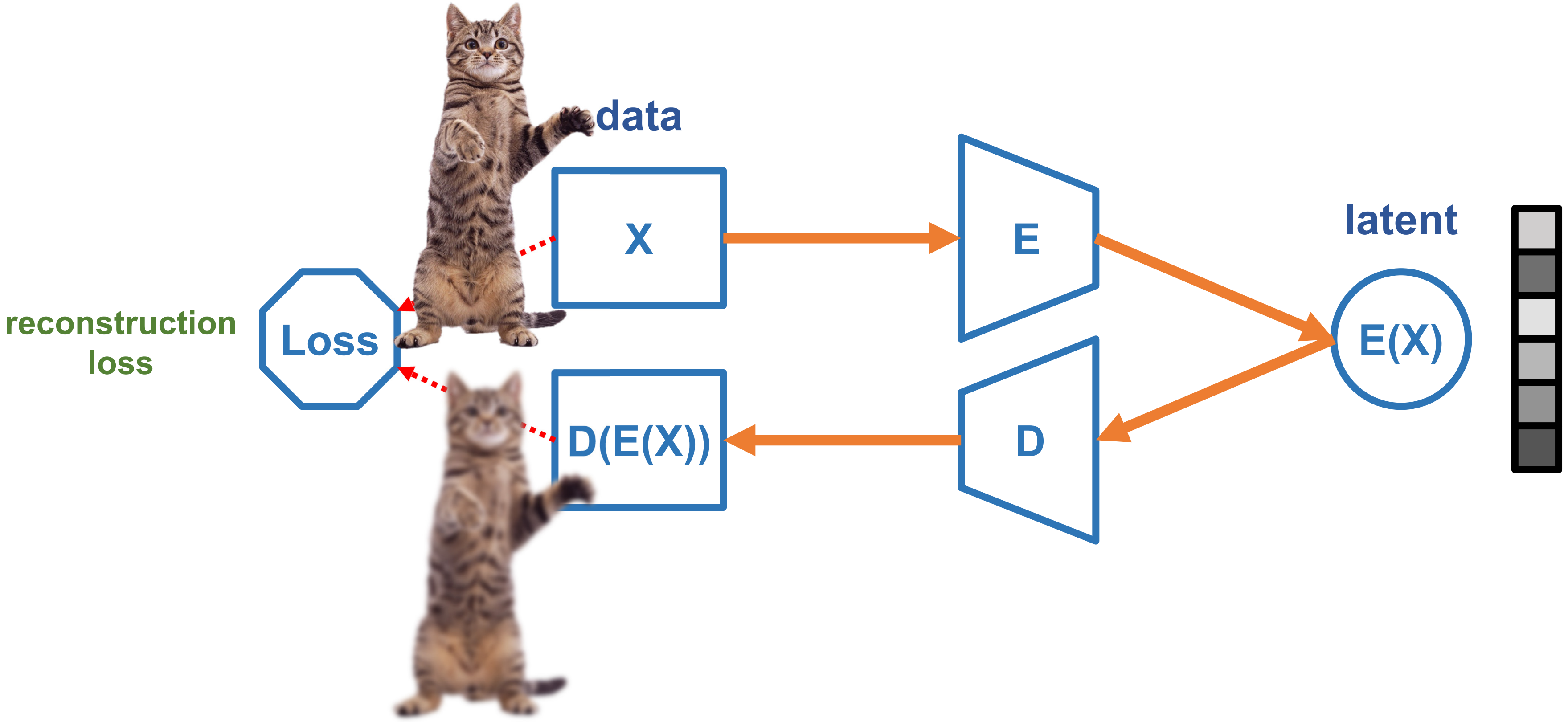
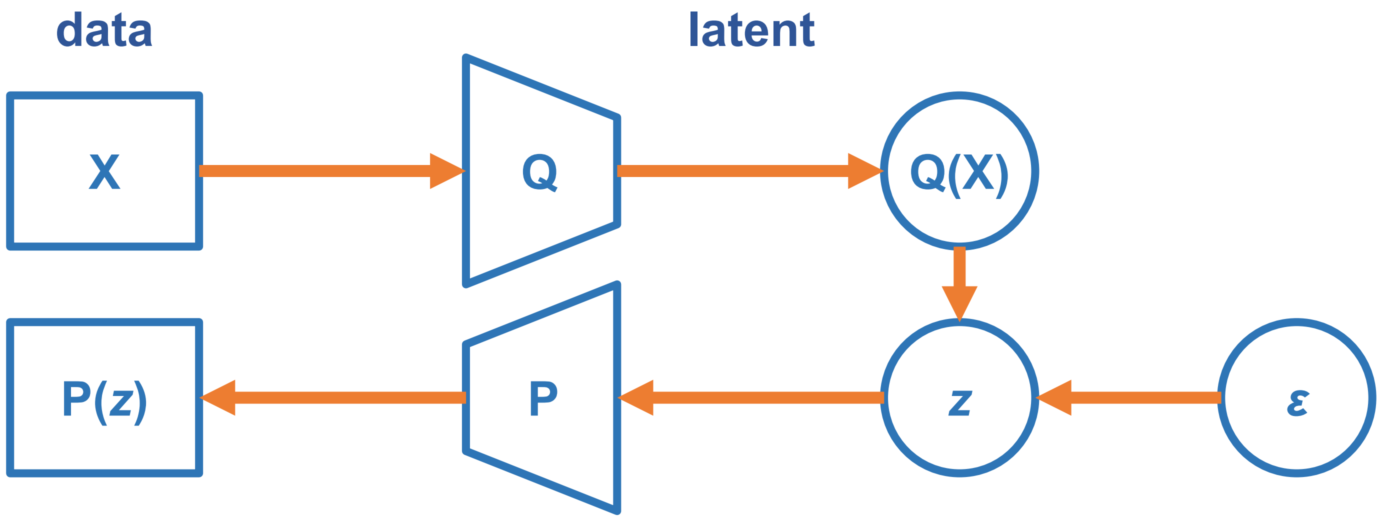


VAE (Variational Autoencoder)

- minimize **reconstruction loss**
- minimize **distance** between encoded latent distribution and prior distribution



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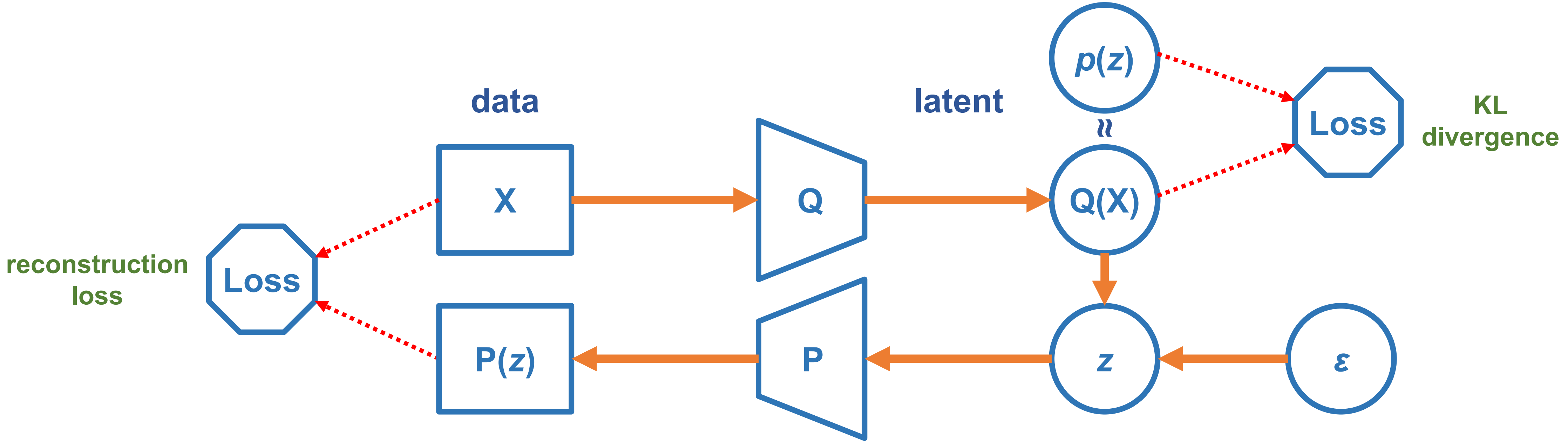

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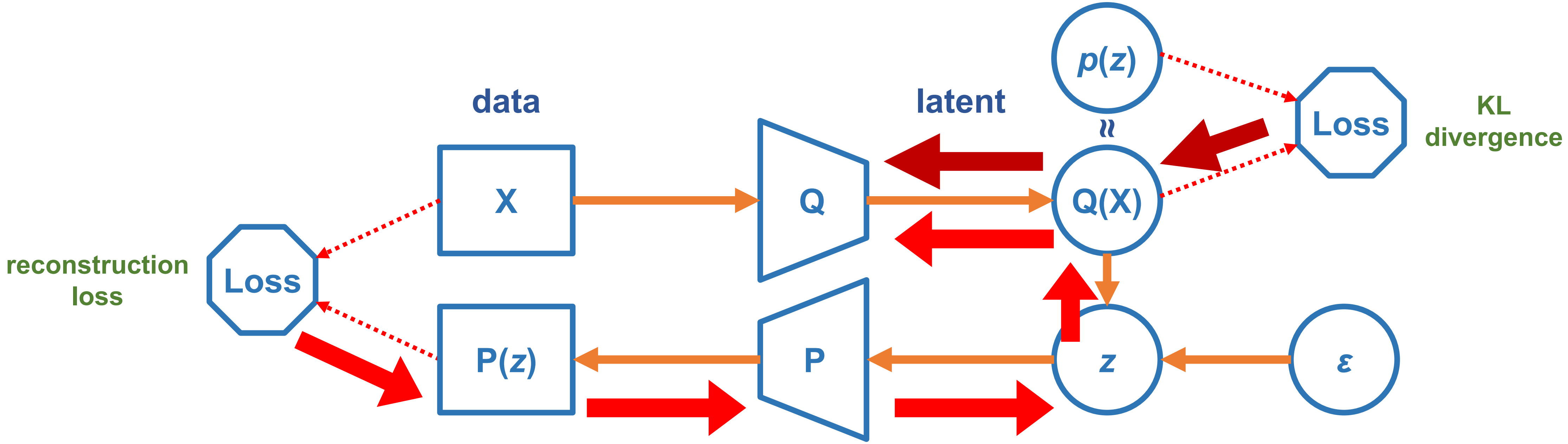

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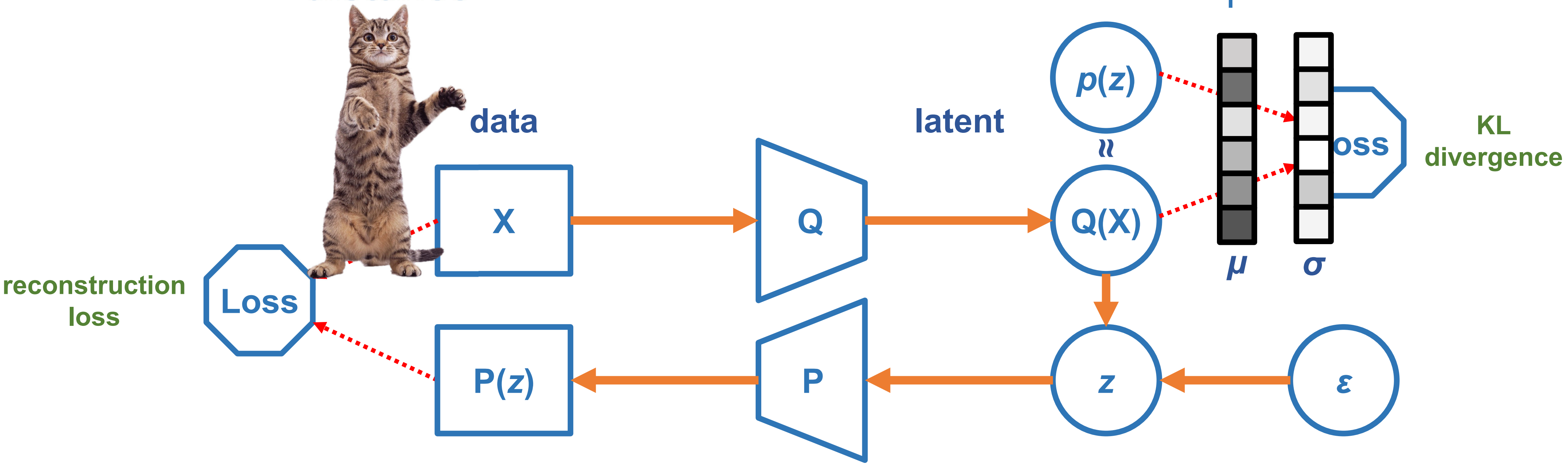

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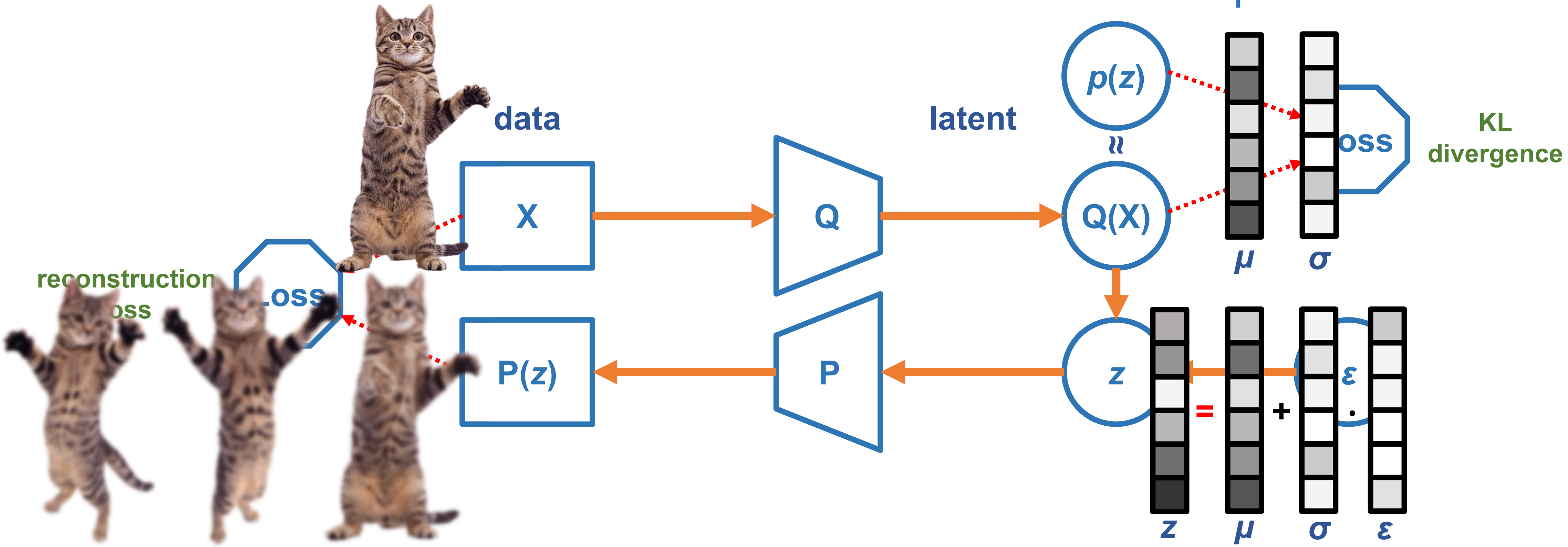

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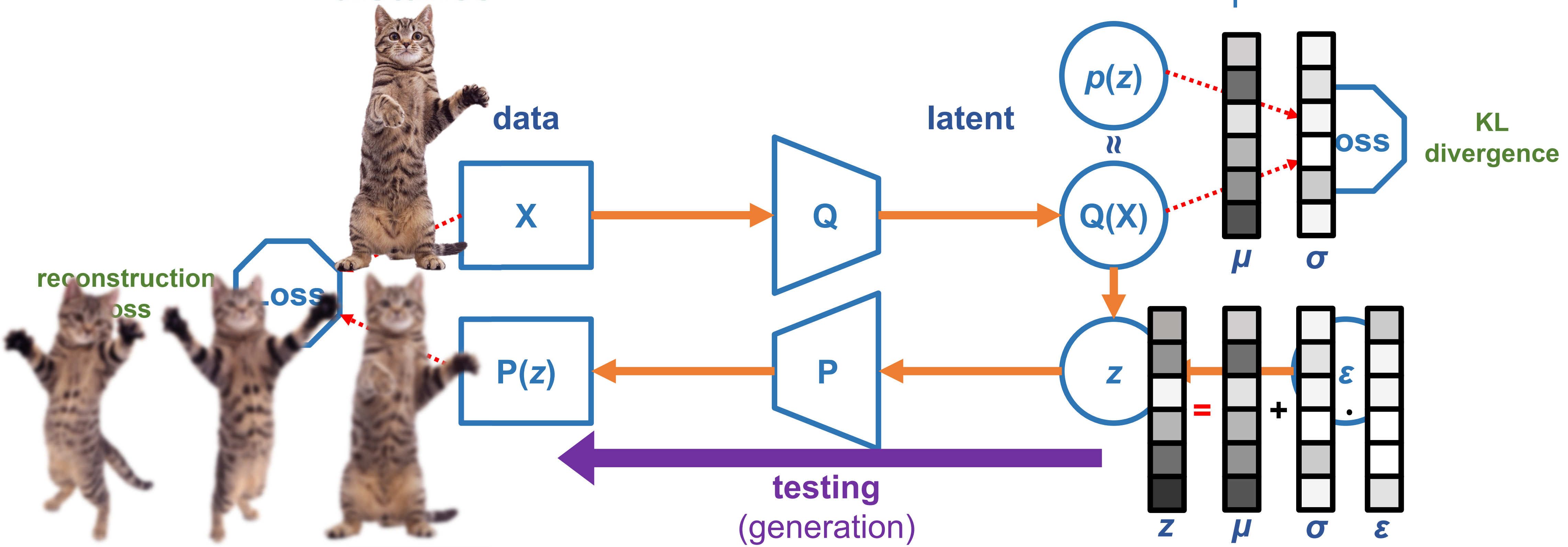
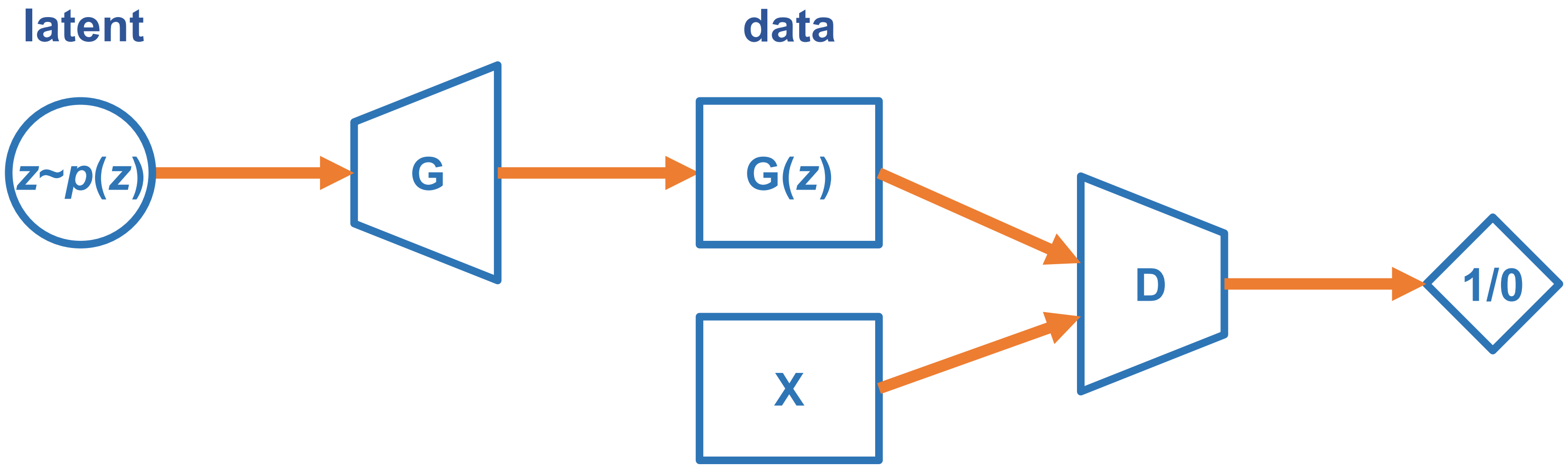


GAN (Generative Adversarial Network)

- minimize **distance** between the distribution of real data and generated samples



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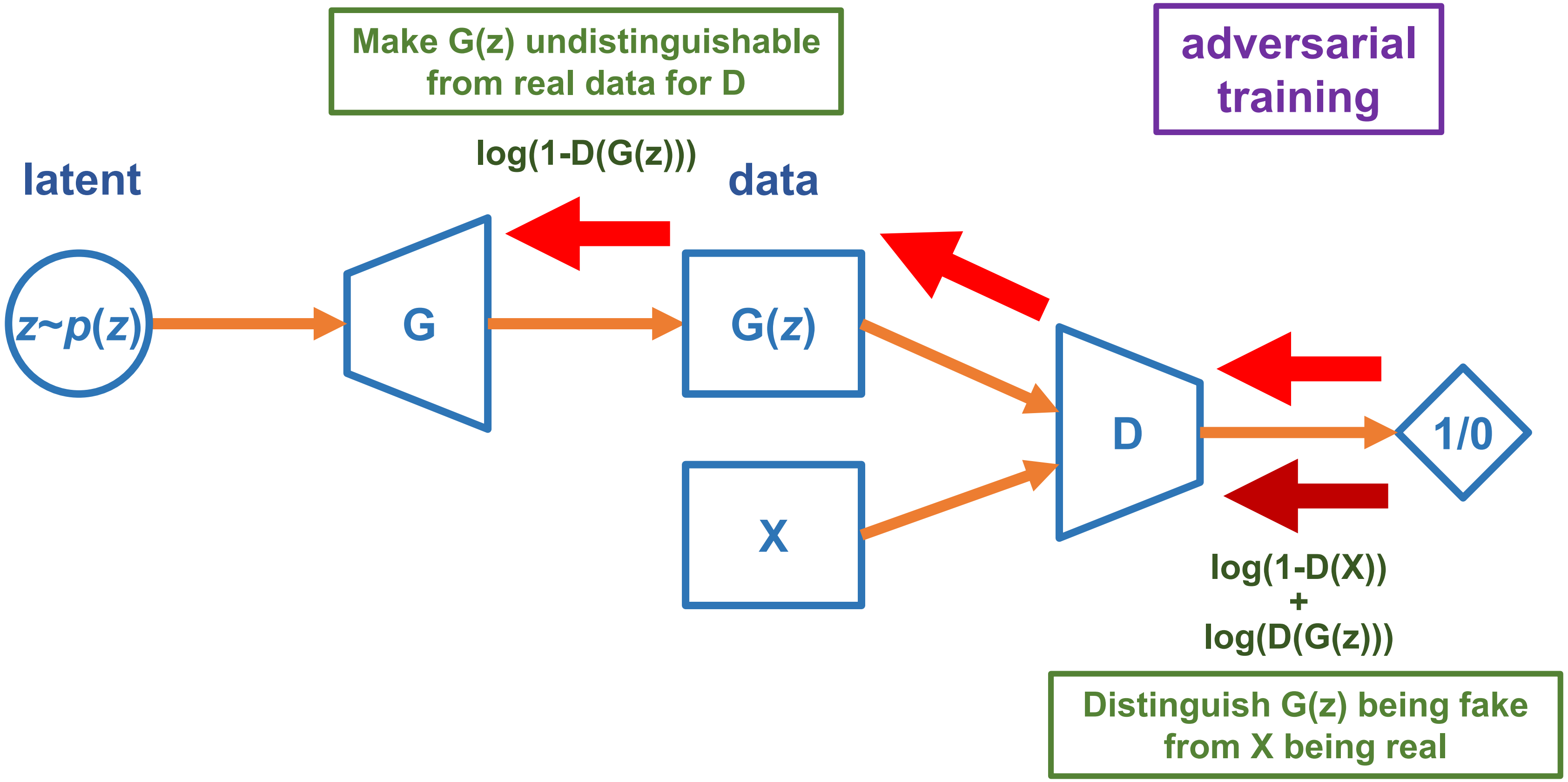

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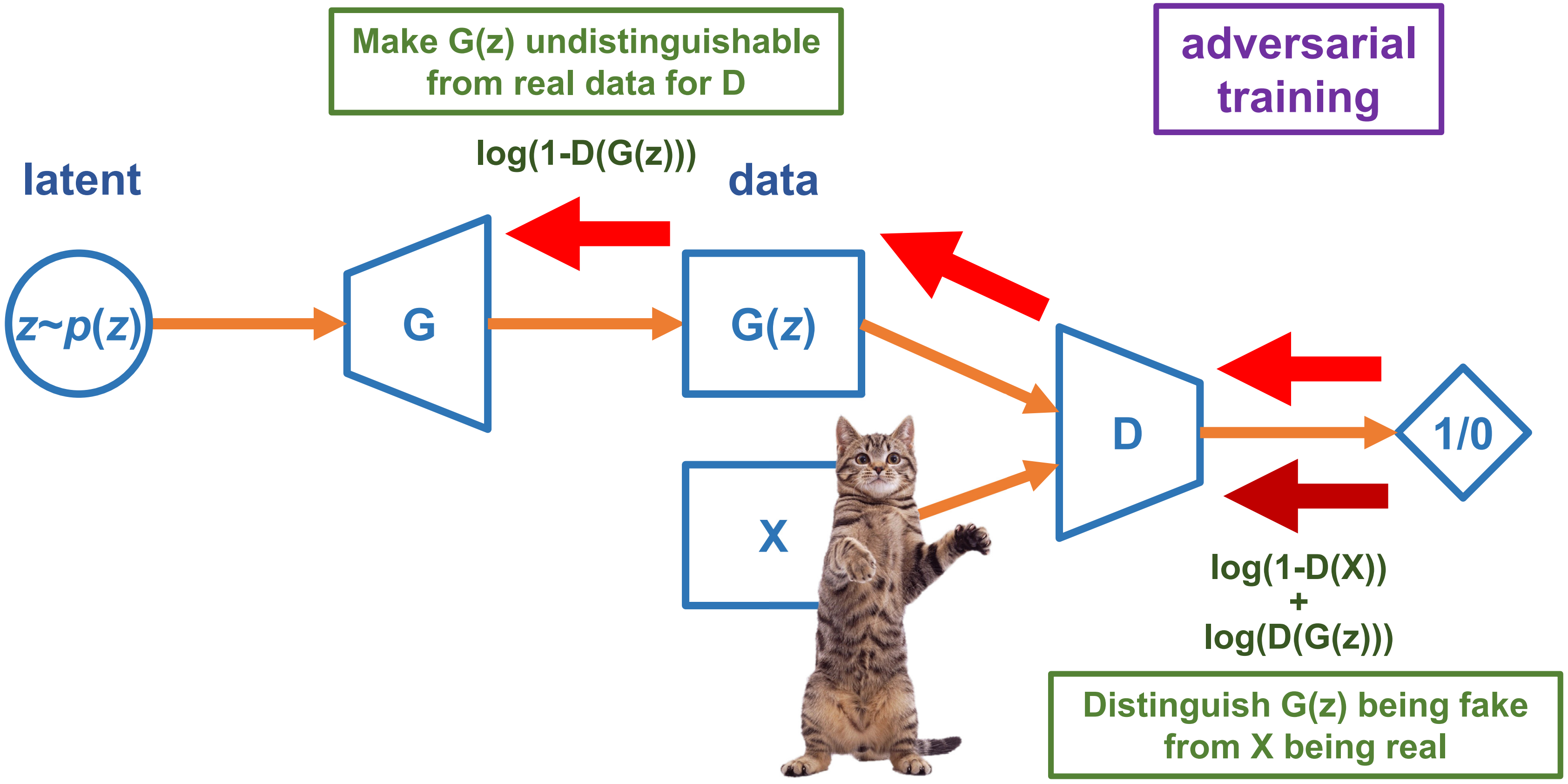

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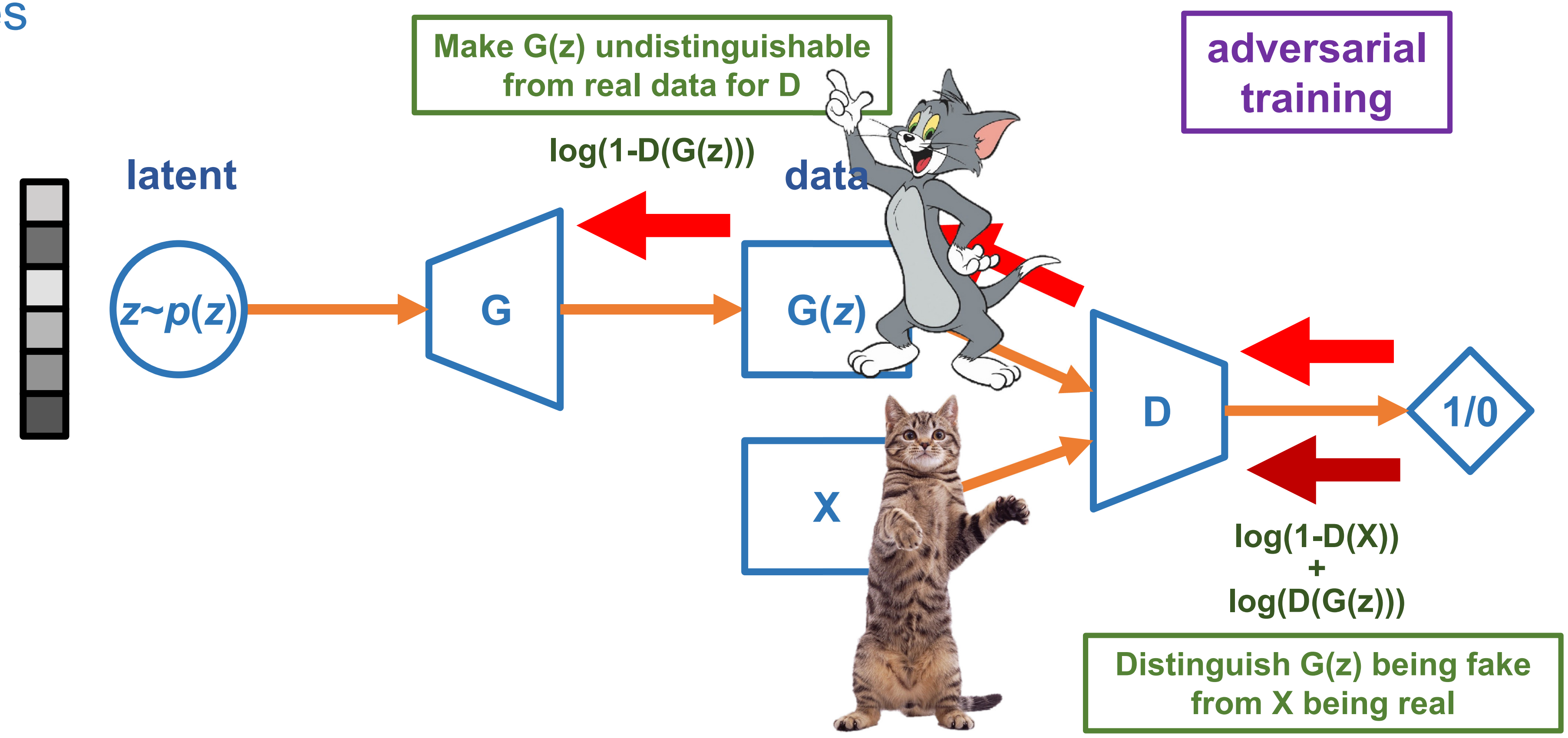

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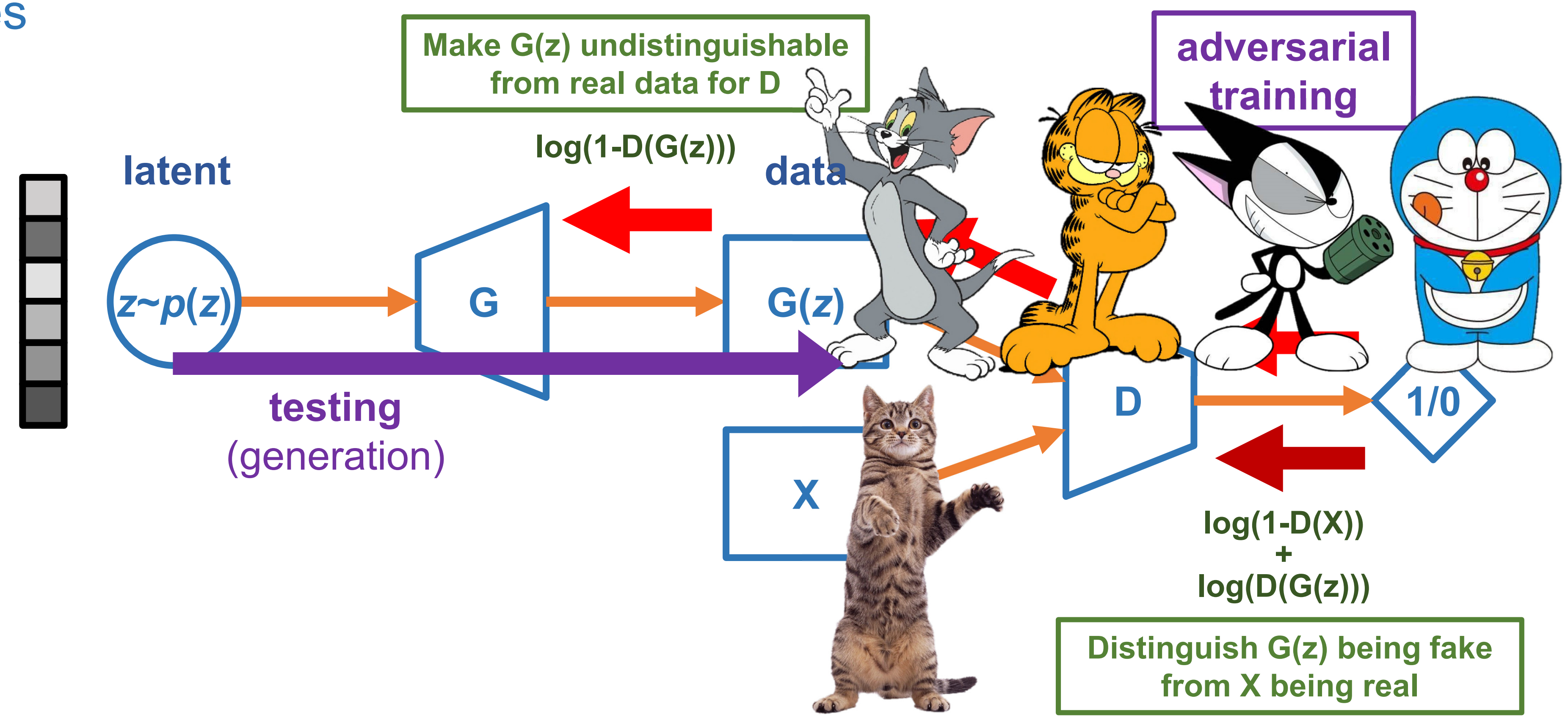
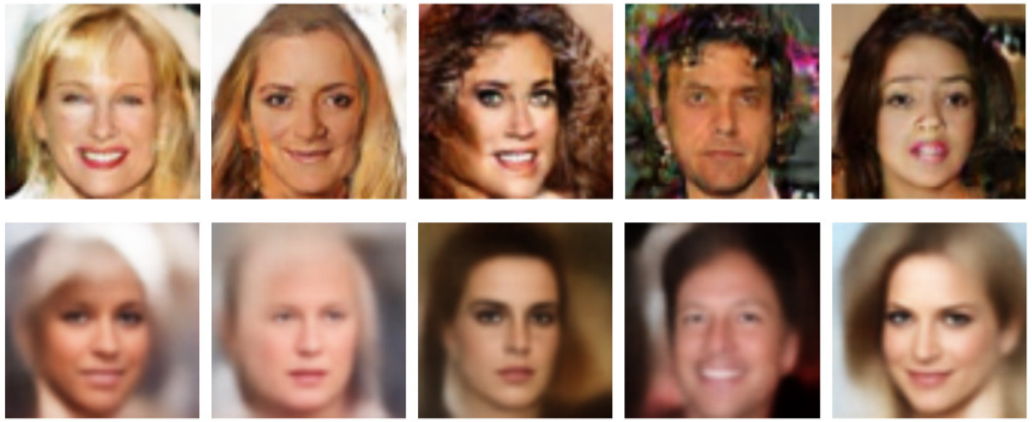


GAN vs VAE

- **GAN**
  - Generator aim to **fool the discriminator**
  - Discriminator aim to **distinguish generated data from real data**
  - output images are **sharper**
  - **higher diversity, lower stability**
- **VAE**
  - Objective: **reconstruct real data**
  - using pixel-to-pixel loss
  - output images are **more blurred**
  - **lower diversity, higher stability**

GAN

VAE



A. B. L. Larsen, S. K. Sønderby, and O. Winther. Autoencoding beyond pixels using a learned similarity metric. arXiv preprint arXiv:1512.09300, 2015.

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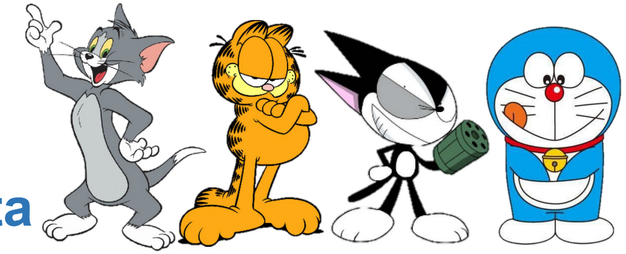
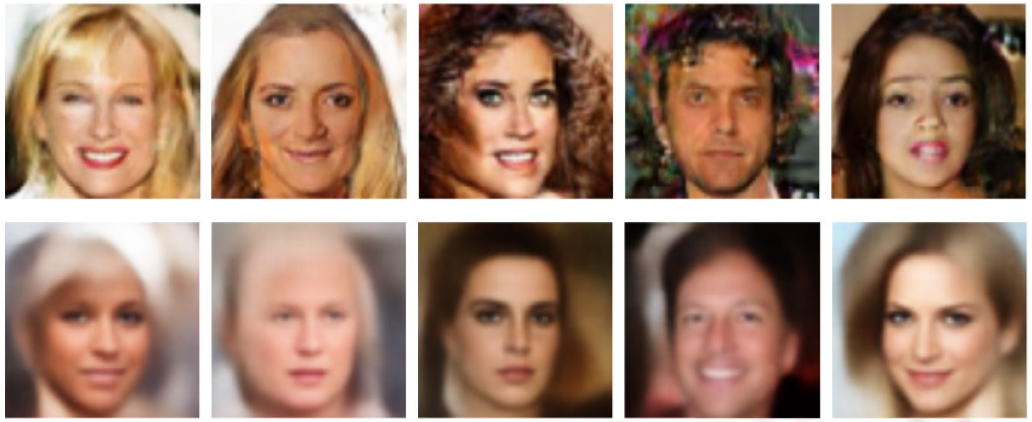


GAN

VAE



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AAE (Adversarial Autoencoder)

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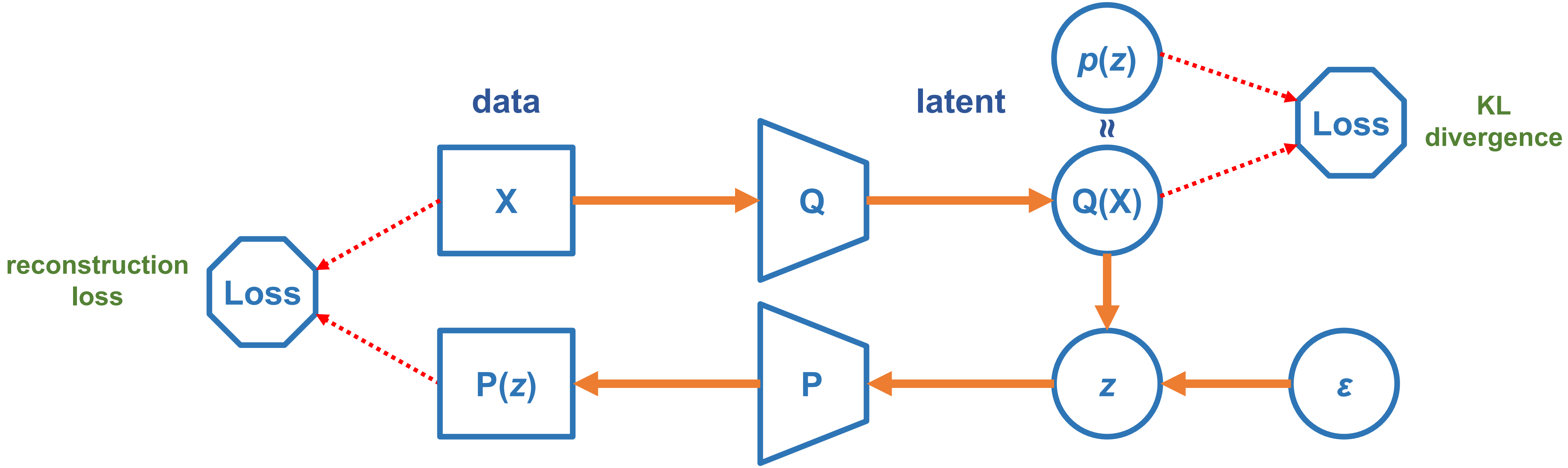

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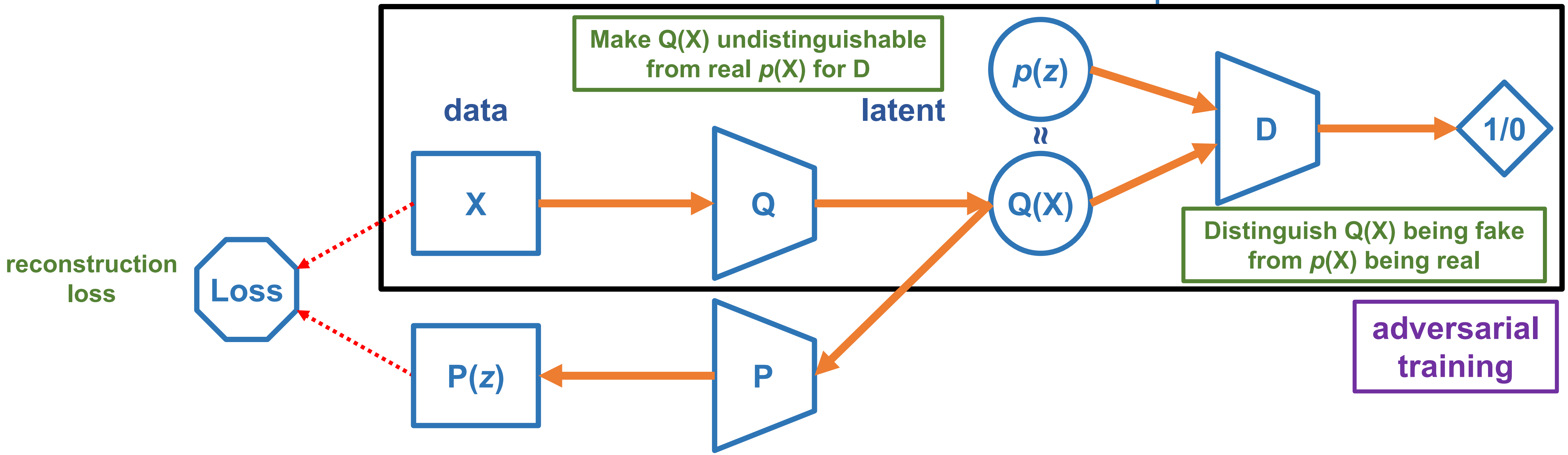

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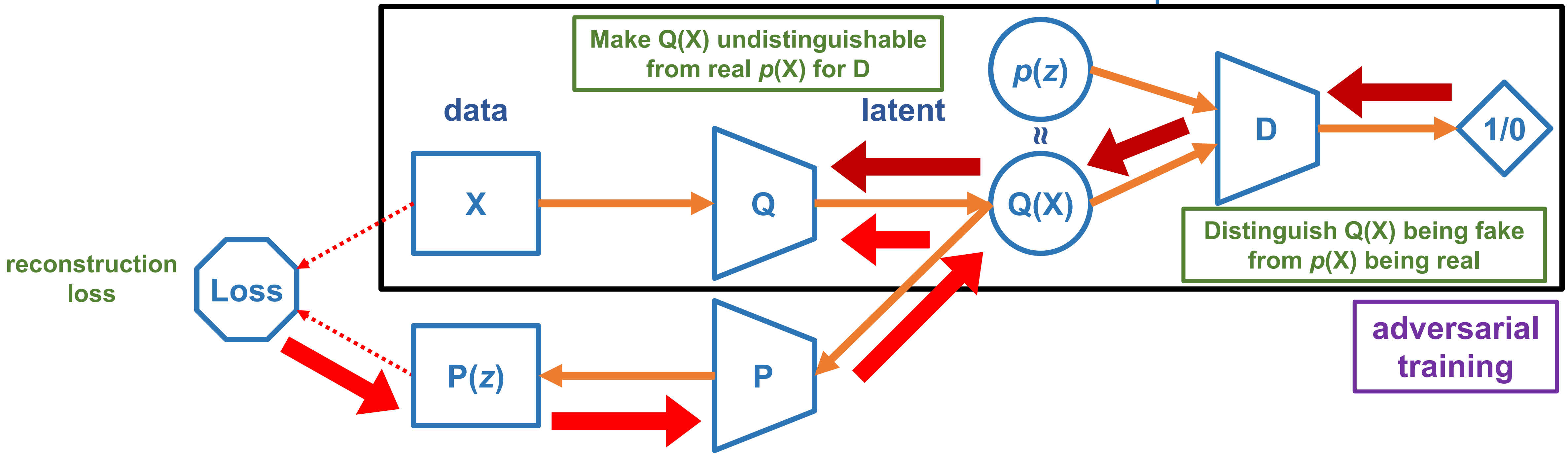
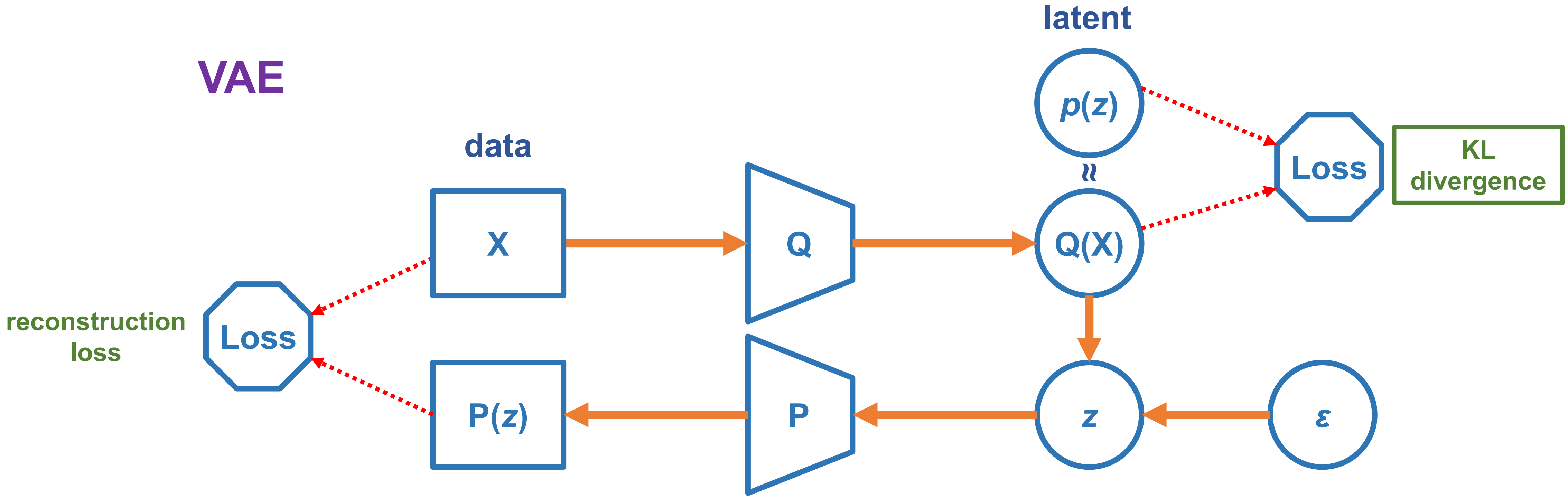


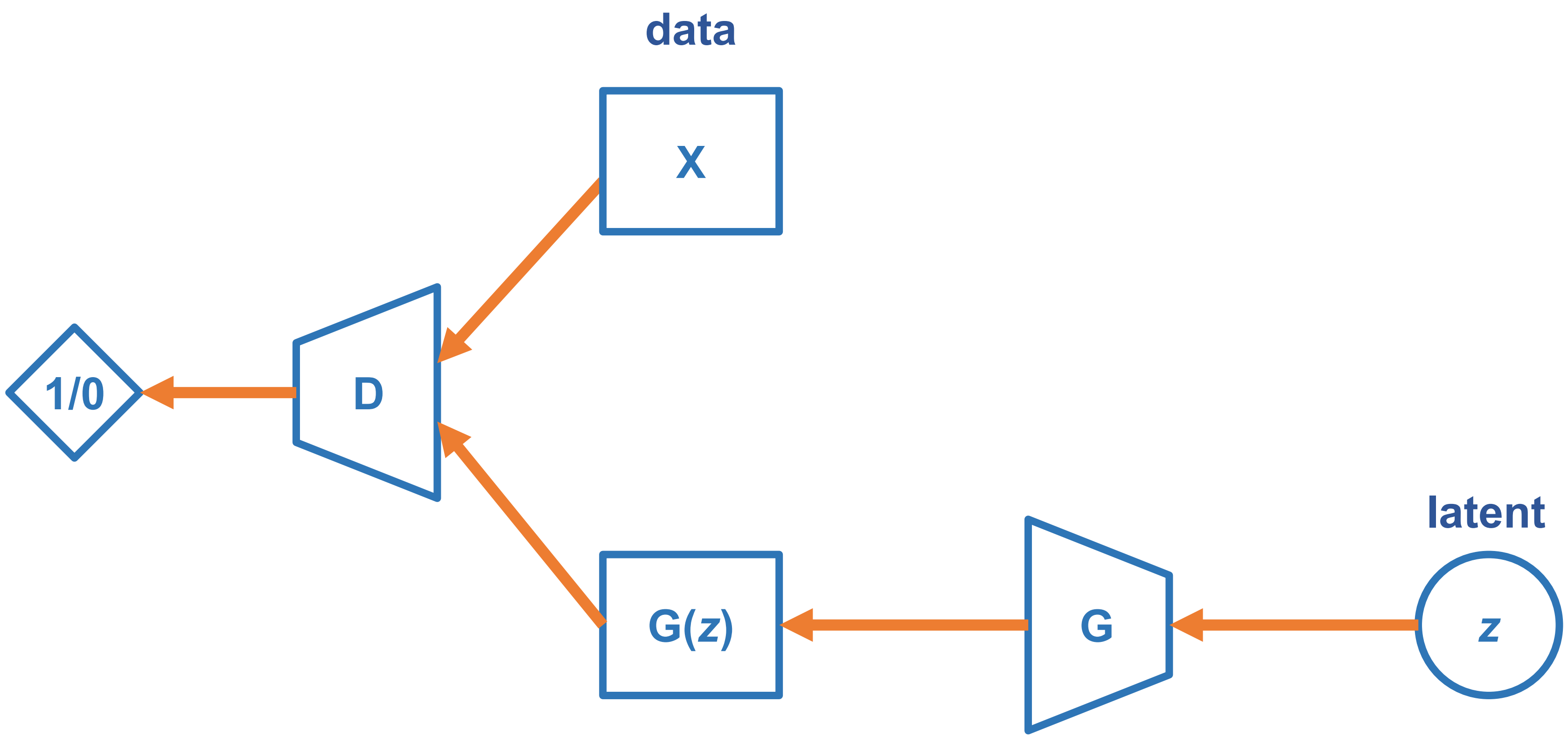
VAE/GAN

VAE

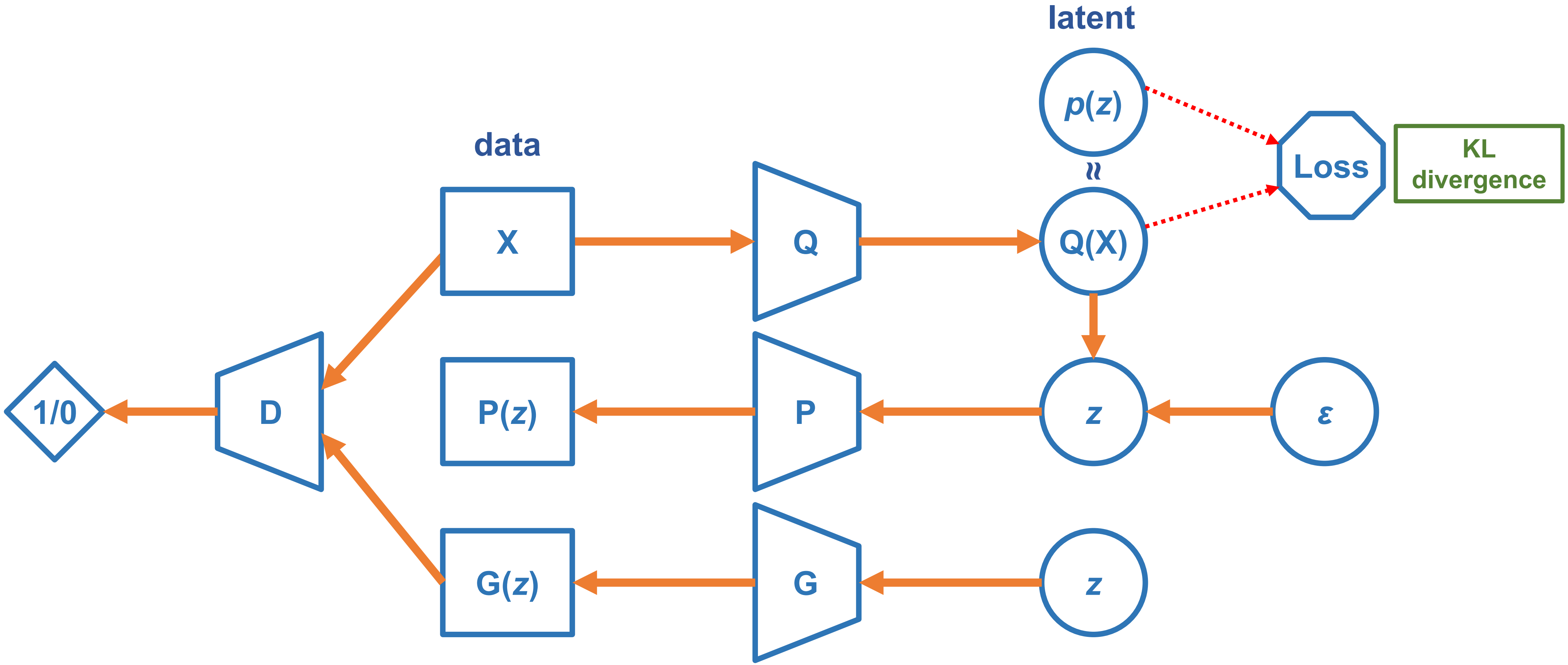

latent
data
p(z)
≈
Loss
KL divergence
X
Q
Q(X)
reconstruction loss
Loss
z
P(z)
P
ε

VAE/GAN

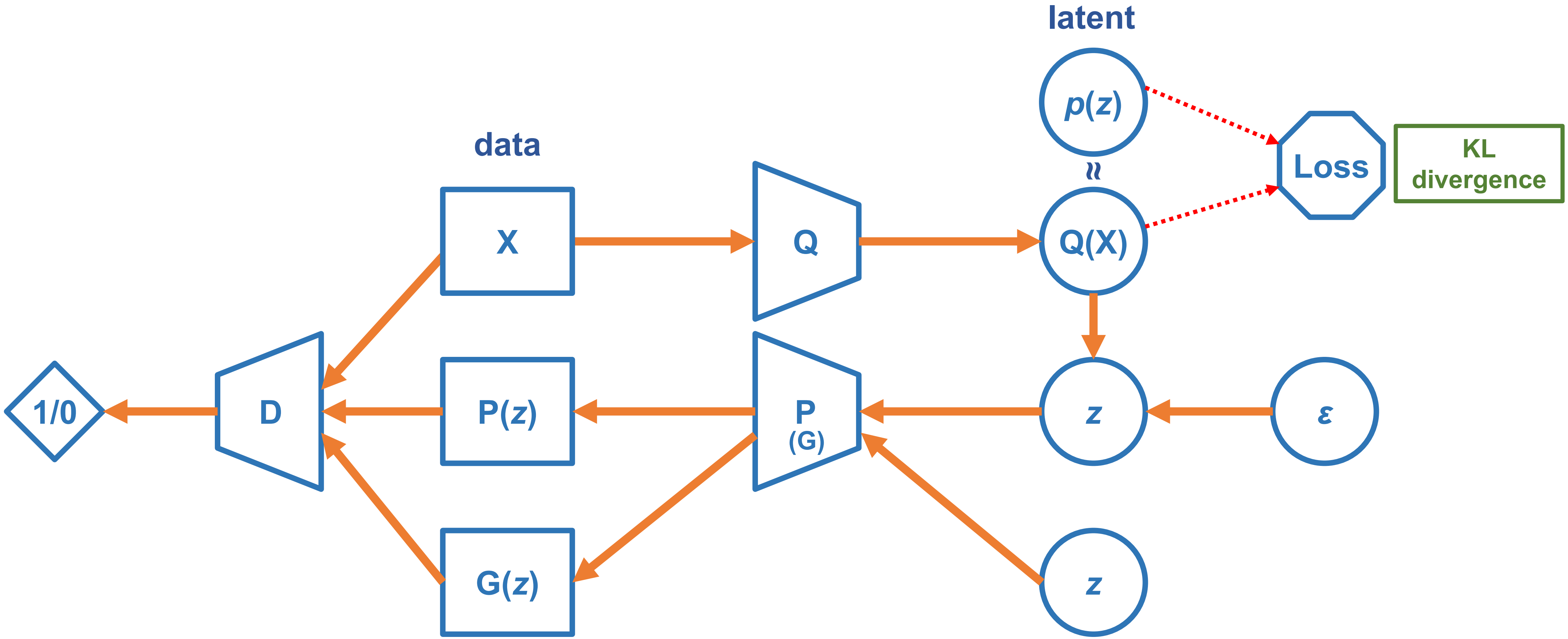
GAN



VAE/GAN



VAE/GAN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Loss
KL divergence
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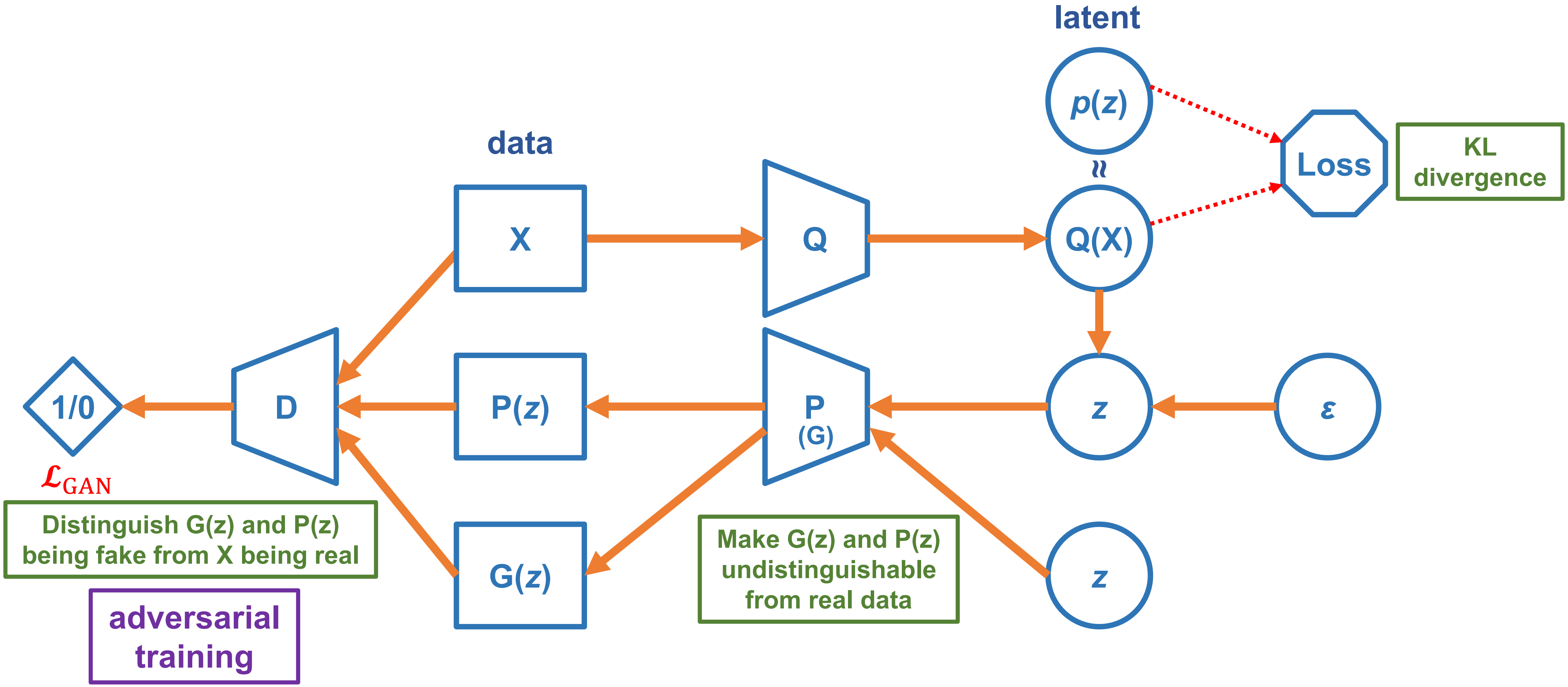
z

VAE/GAN


latent
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Loss
KL divergence
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Q(X)
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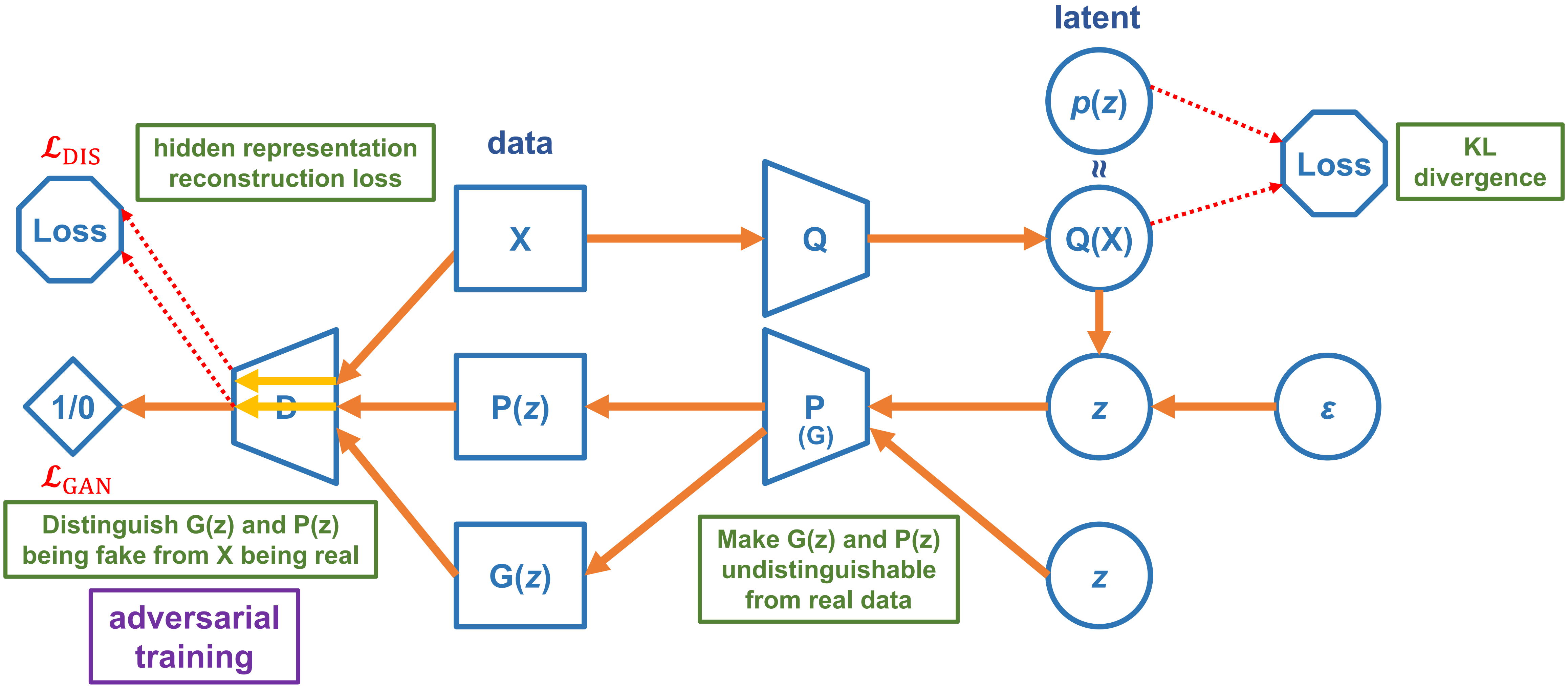
$\mathcal{L}_{\text{GAN}}$
Distinguish G(z) and P(z) being fake from X being real
G(z)
Make G(z) and P(z) undistinguishable from real data
z
adversarial training

VAE/GAN


latent
p(z)
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Q(X)
Loss
KL divergence
$\mathcal{L}_{\text{DIS}}$
hidden representation reconstruction loss
data
X
Q
Loss
1/0
D
P(z)
P
(G)
z
ε
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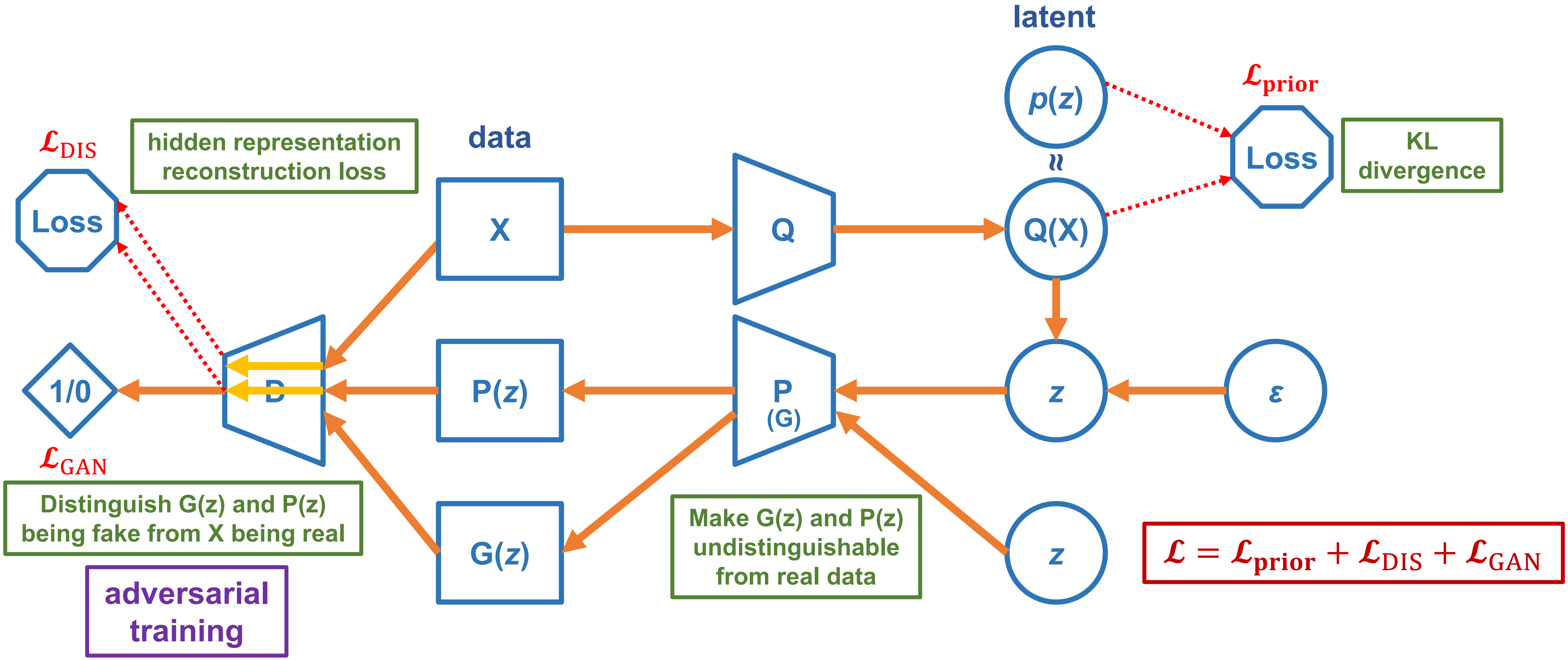
latent
$\mathcal{L}_{\text{prior}}$
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Loss
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data
Loss
X
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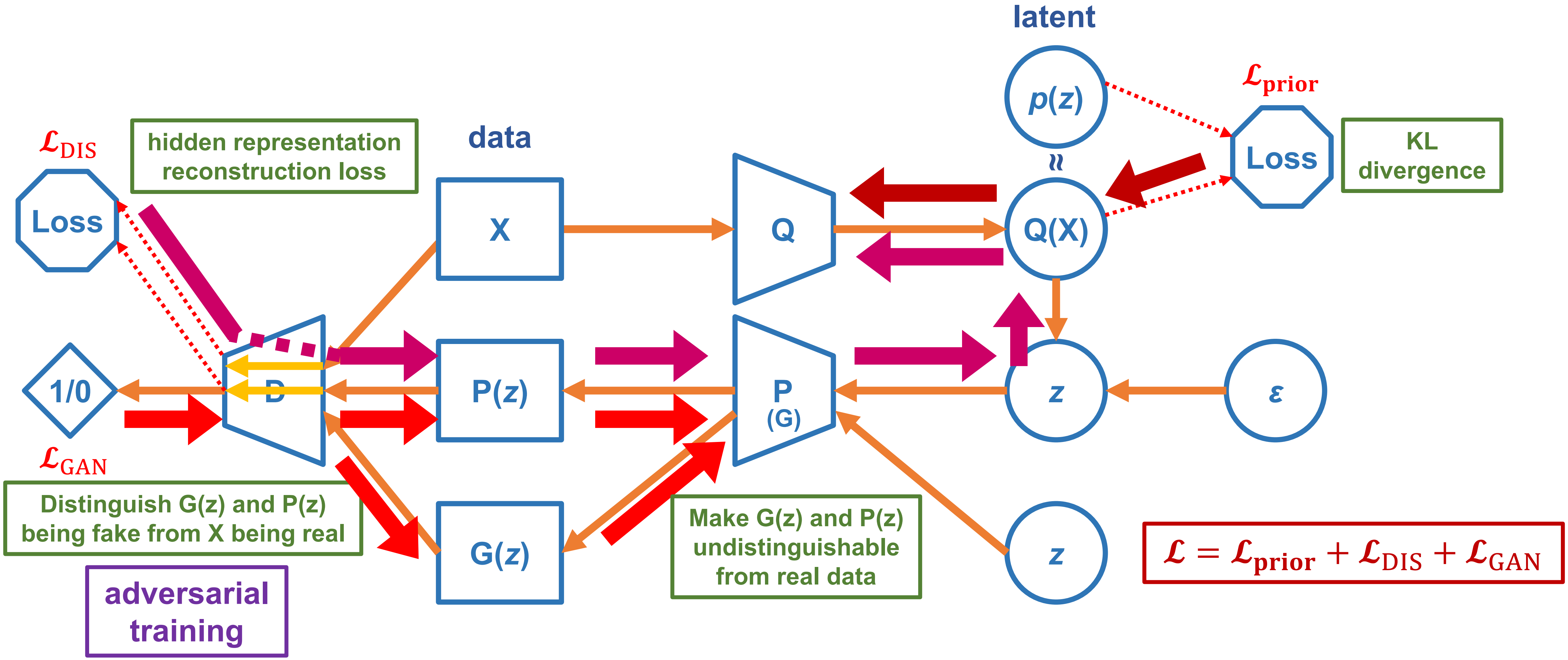
VAE/GAN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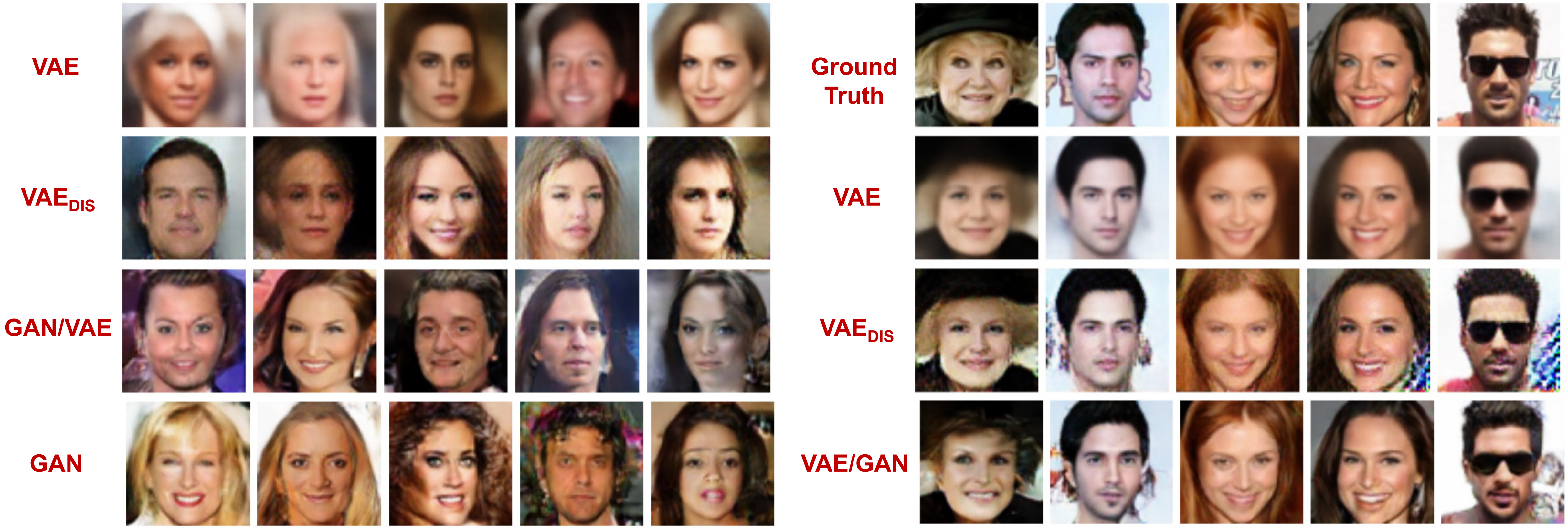

Generation test **Reconstruction test**

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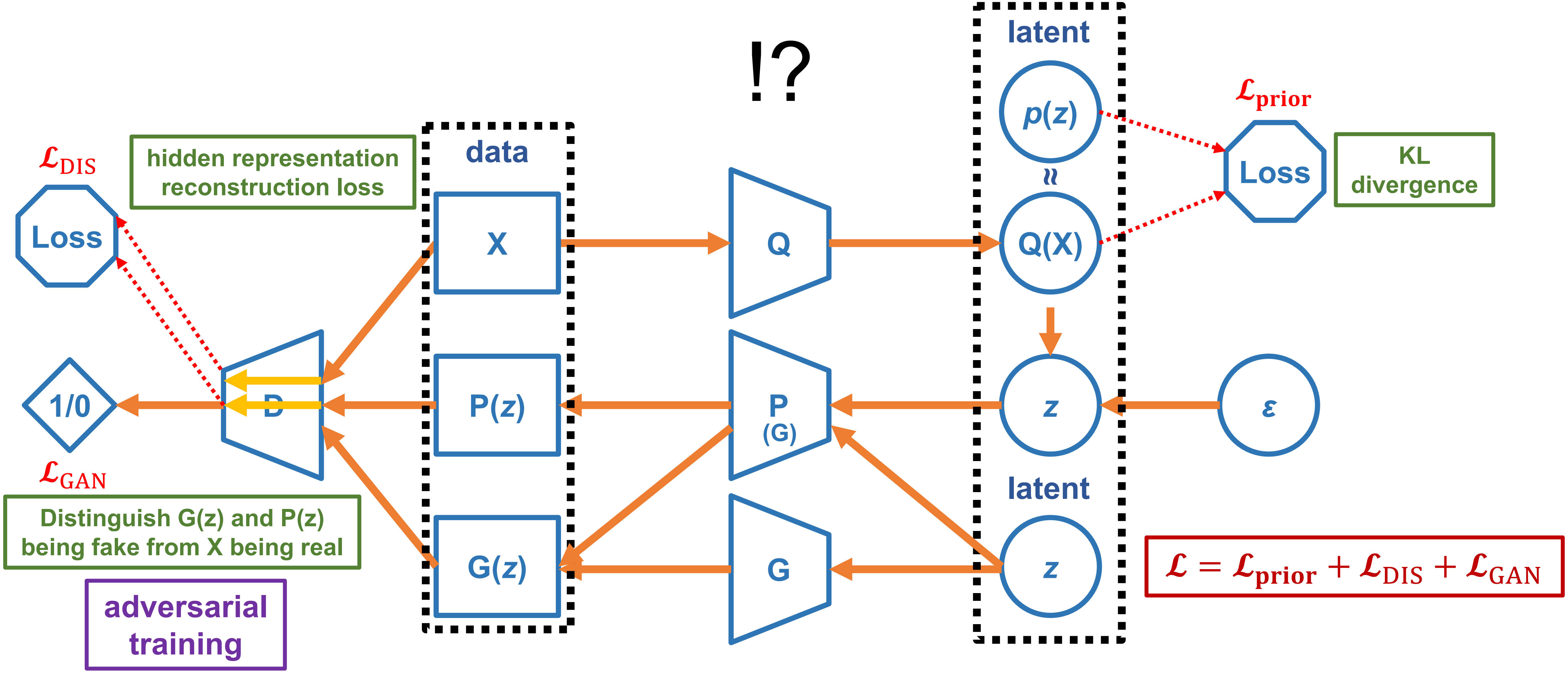
VAE/GAN


!?
latent
$p(z)$
$\wr$
Q(X)
z
latent
z
$\mathcal{L}_{\text{prior}}$
Loss
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ε
data
X
P(z)
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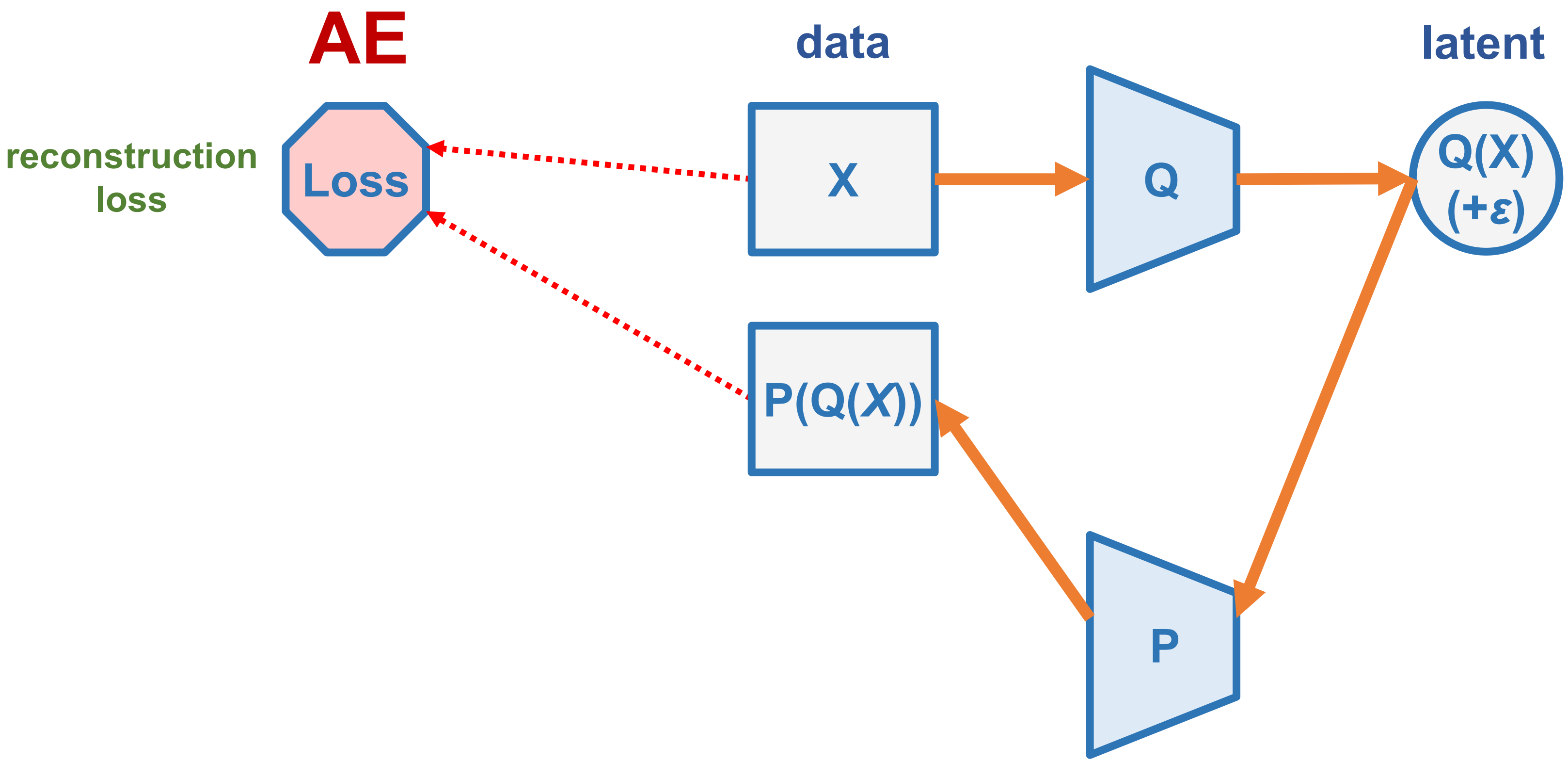

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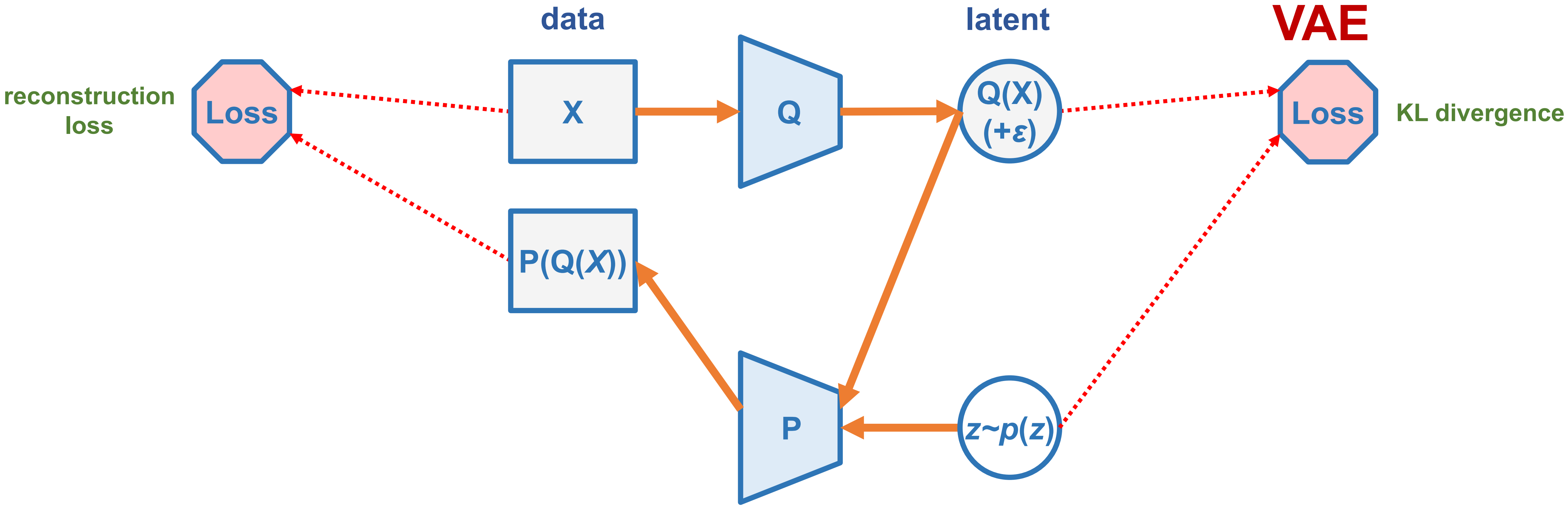

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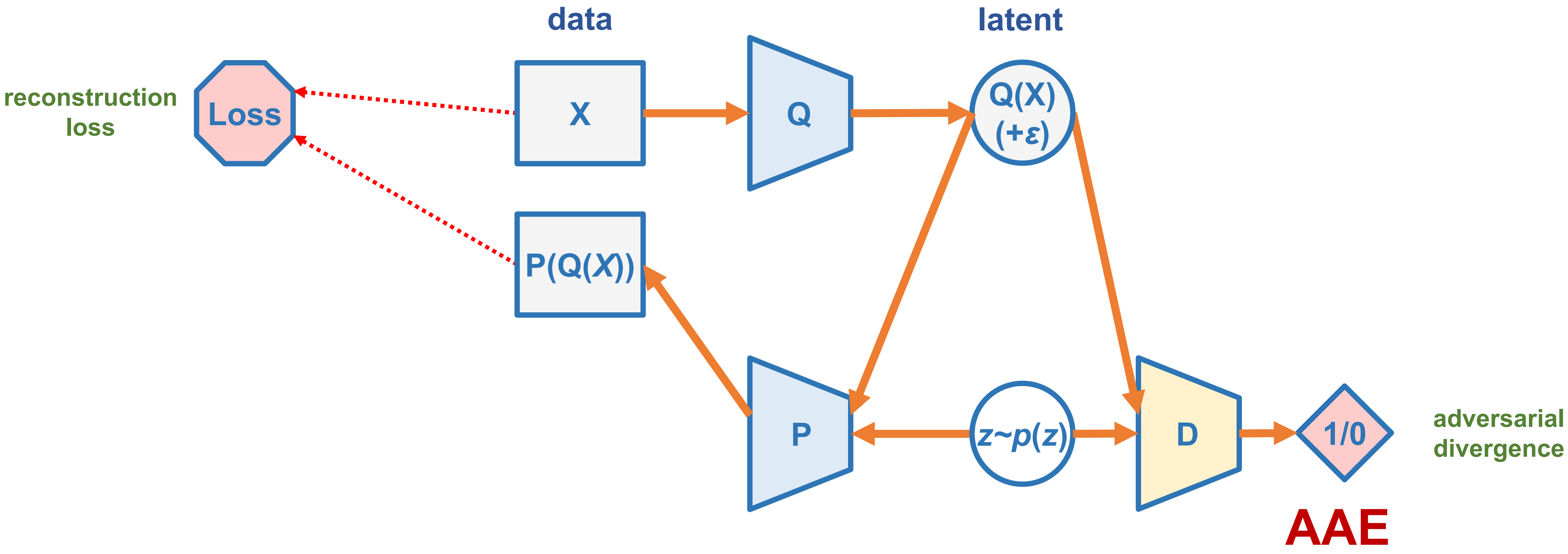

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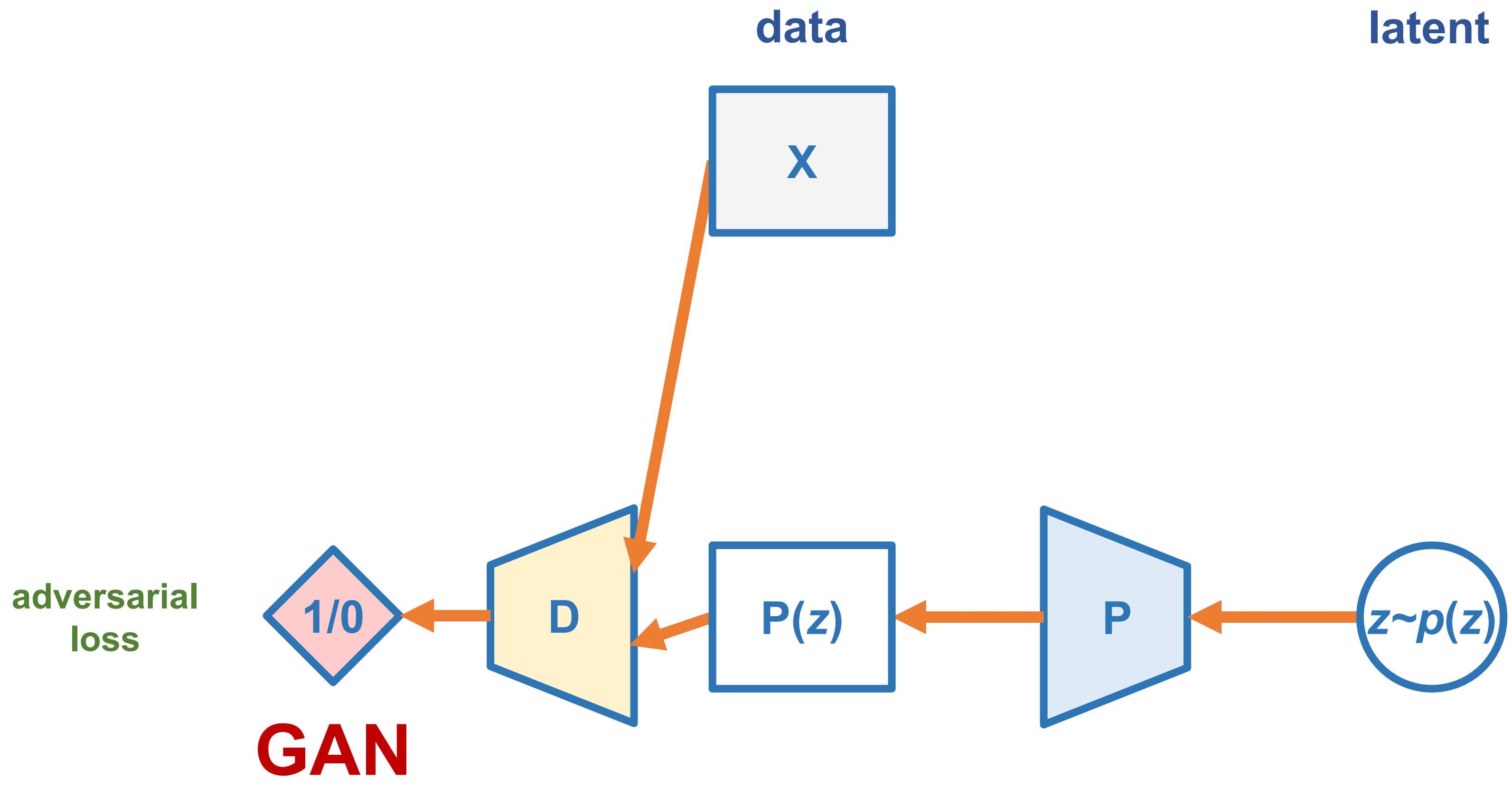

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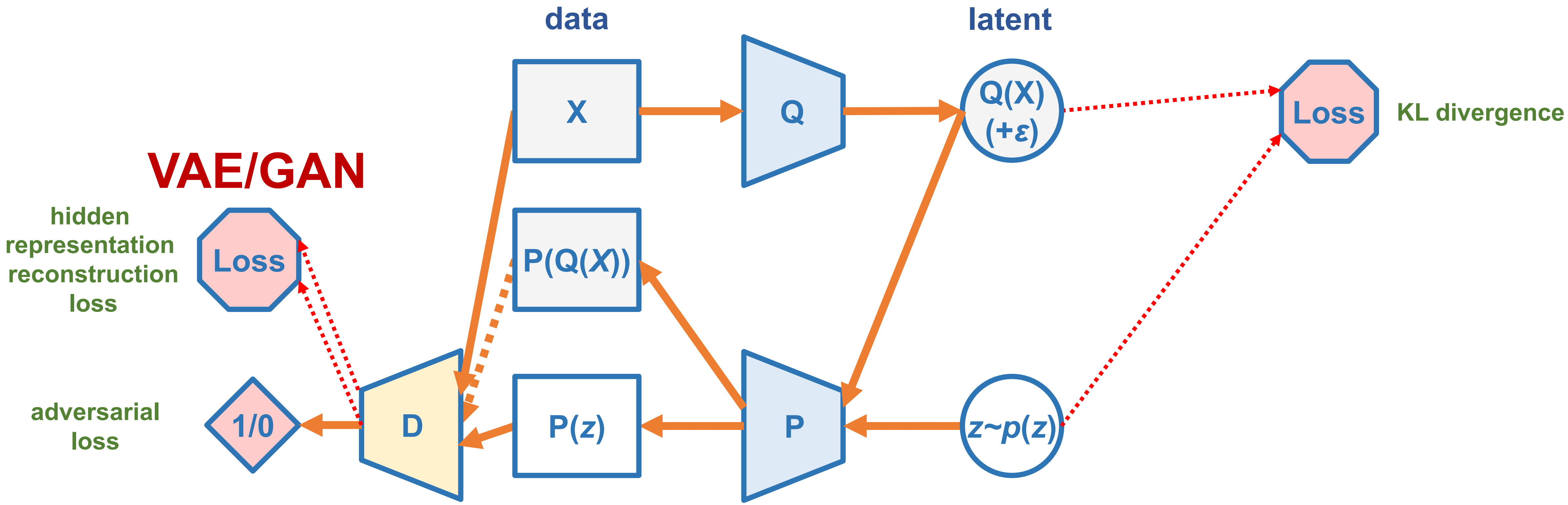

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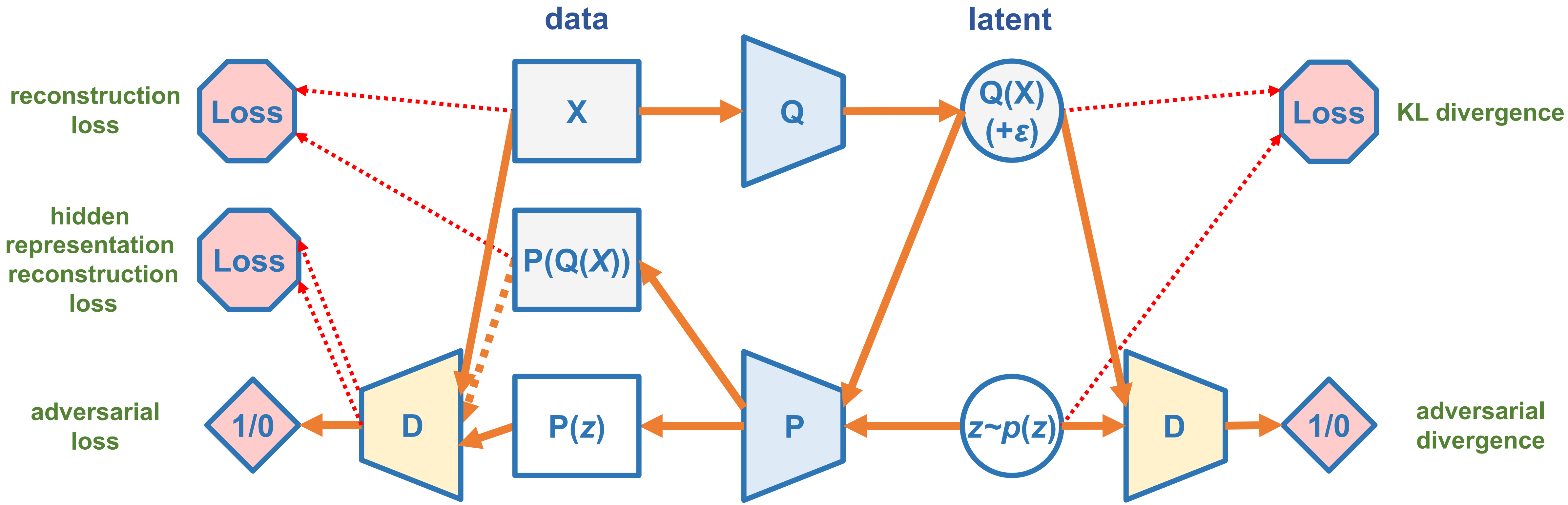
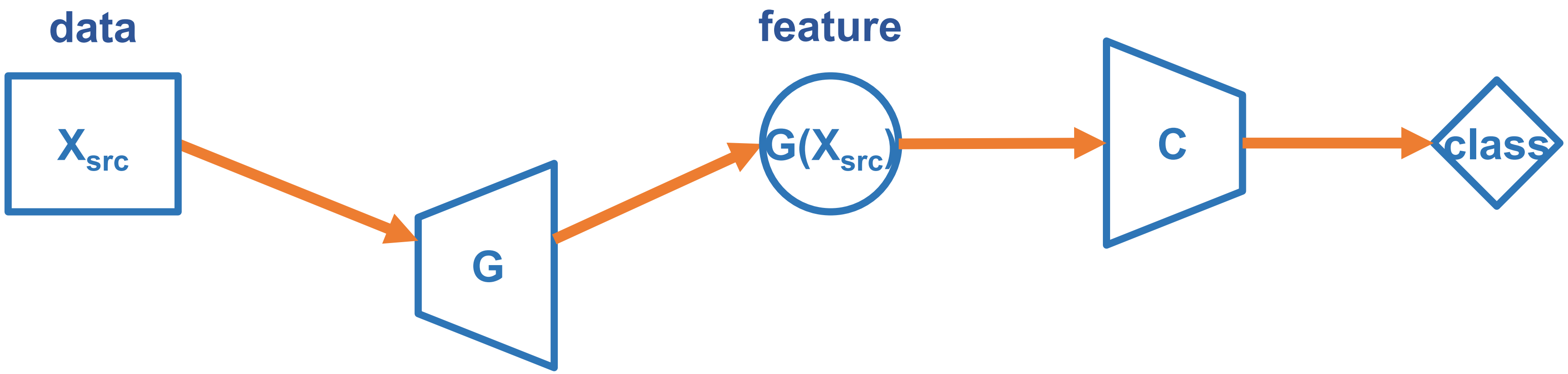


ADA (Adversarial Domain Adaption)

- Goal: given labeled data in source domain, aim to classify unlabeled data in target domain.



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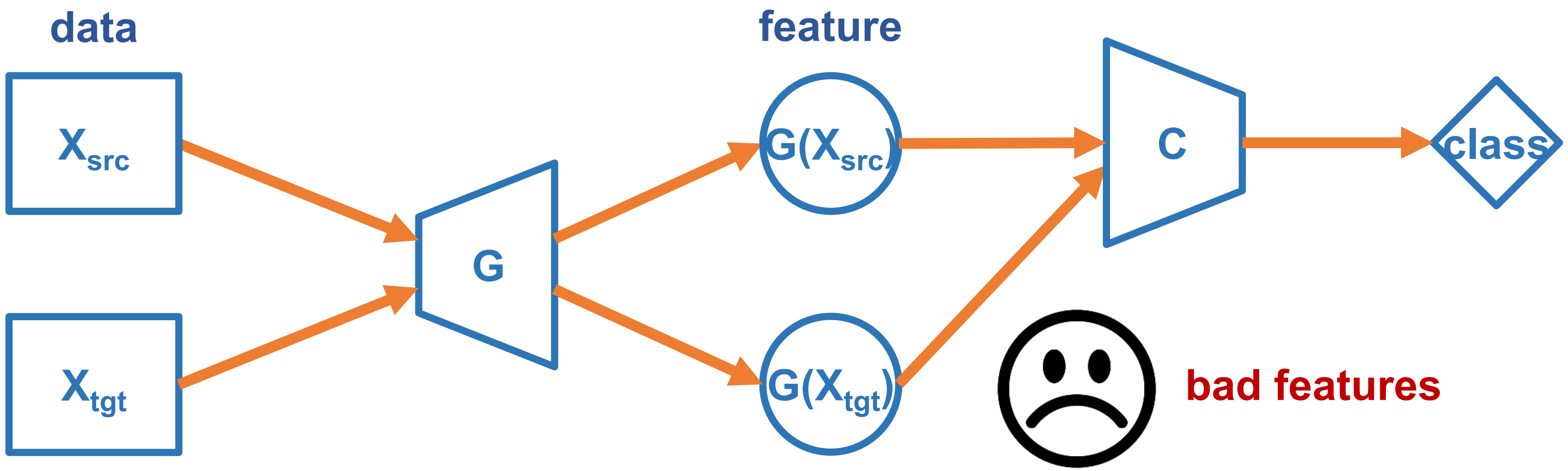

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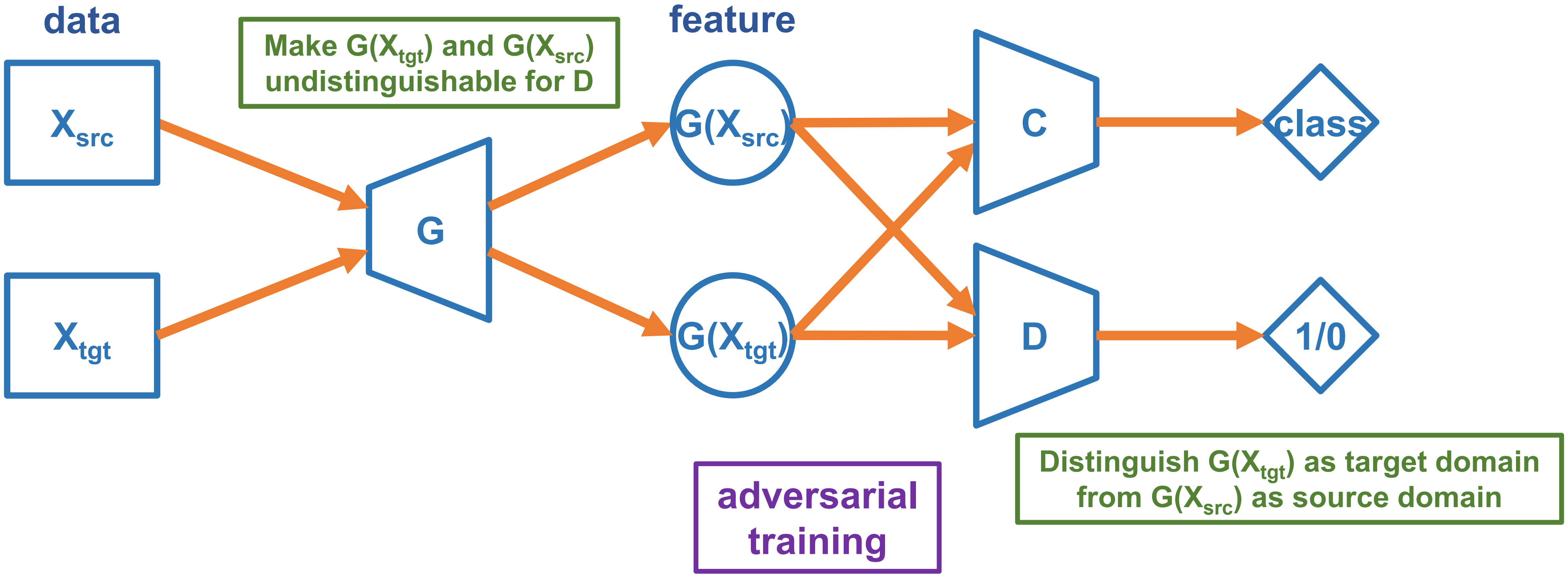

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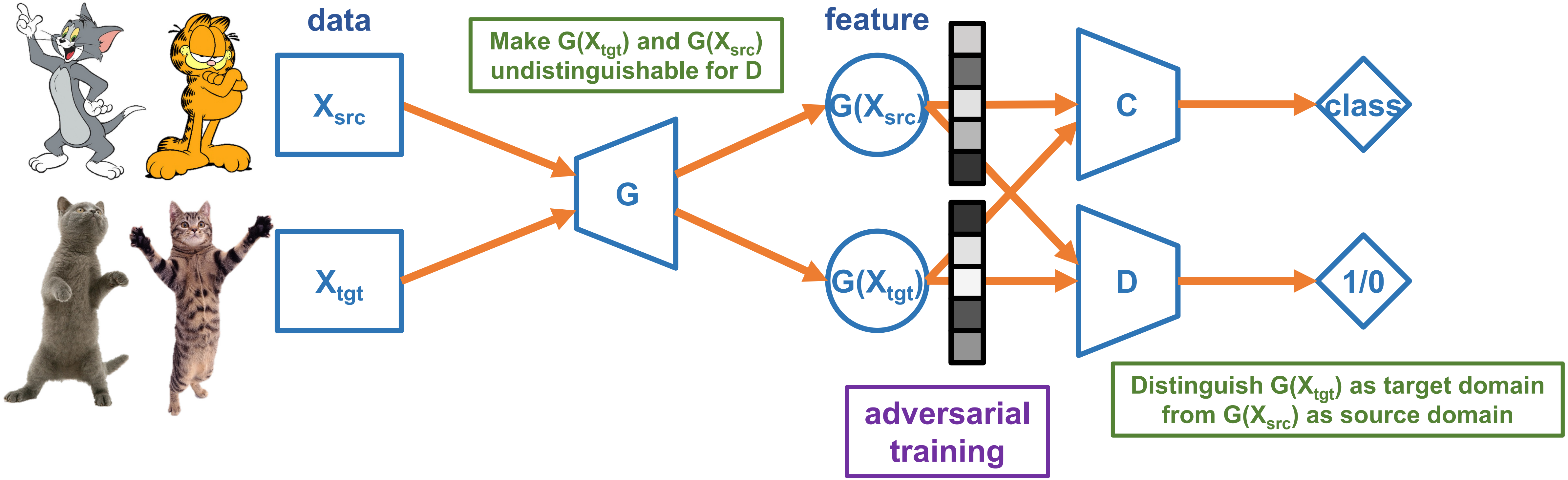

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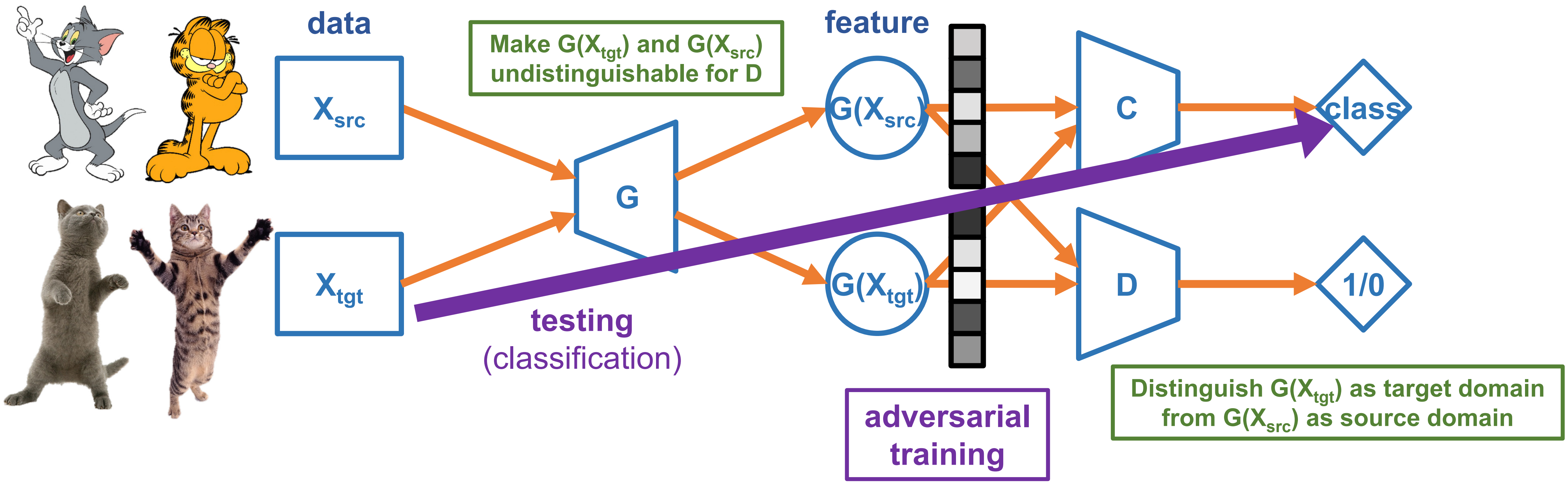

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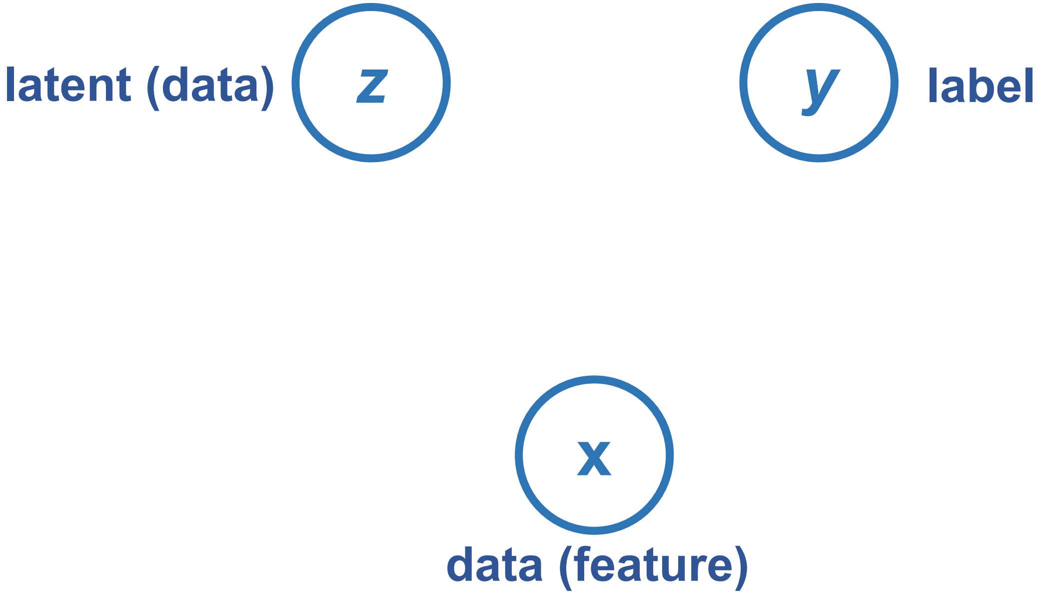

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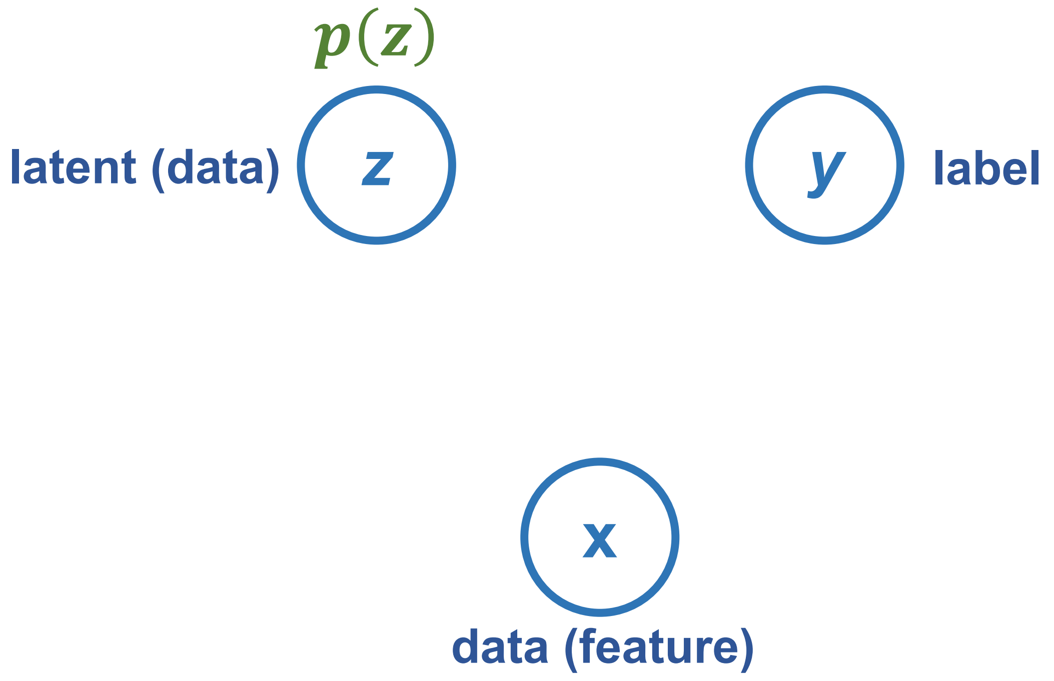
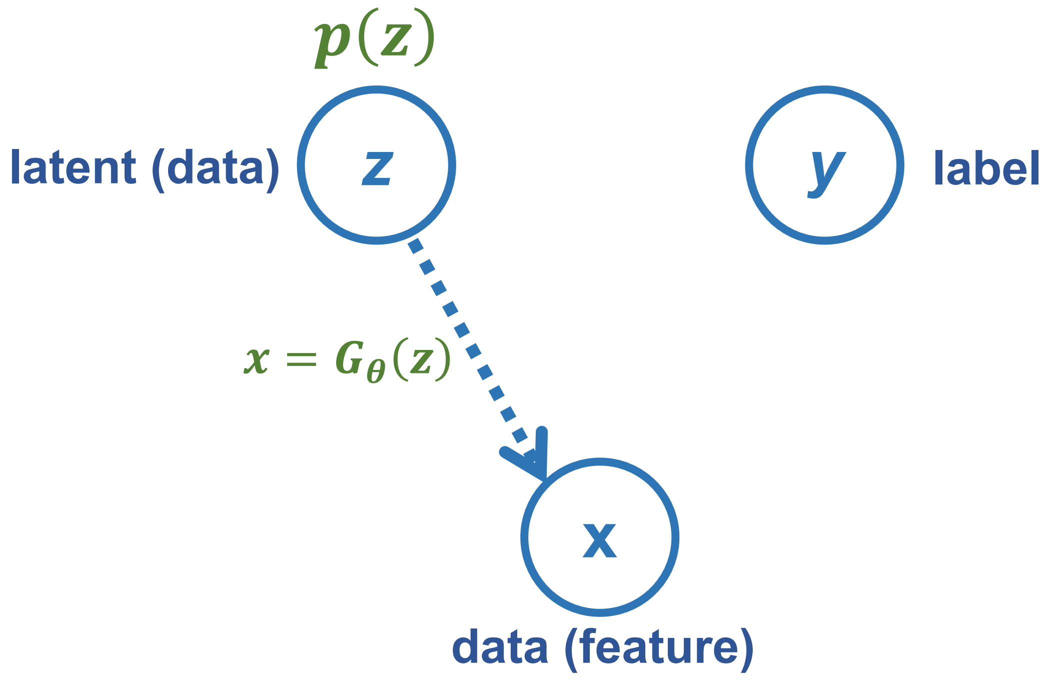


On Unifying Deep Generative Models

- $\boldsymbol{G_\theta} - \theta$ are parameters in generator
- $\boldsymbol{D_\phi} - \phi$ are parameters in generator

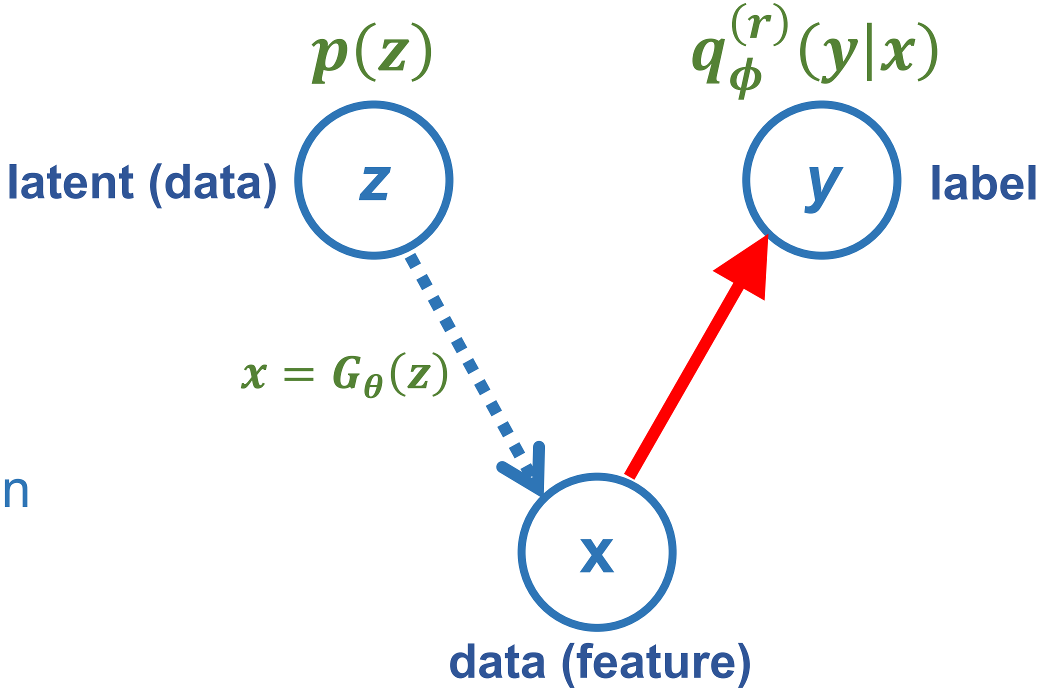


On Unifying Deep Generative Models

- G_θ – θ are parameters in generator
- D_ϕ – ϕ are parameters in generator

- **Solid line** – generative process
- **Dashed line** – inference process
- **Hollow arrow** – deterministic transformation
- **Red arrow** – adversarial mechanism

- $q_\phi^{(r)}(y|x)$ denotes $q_\phi(y|x)$ and $q_\phi(1-y|x)$



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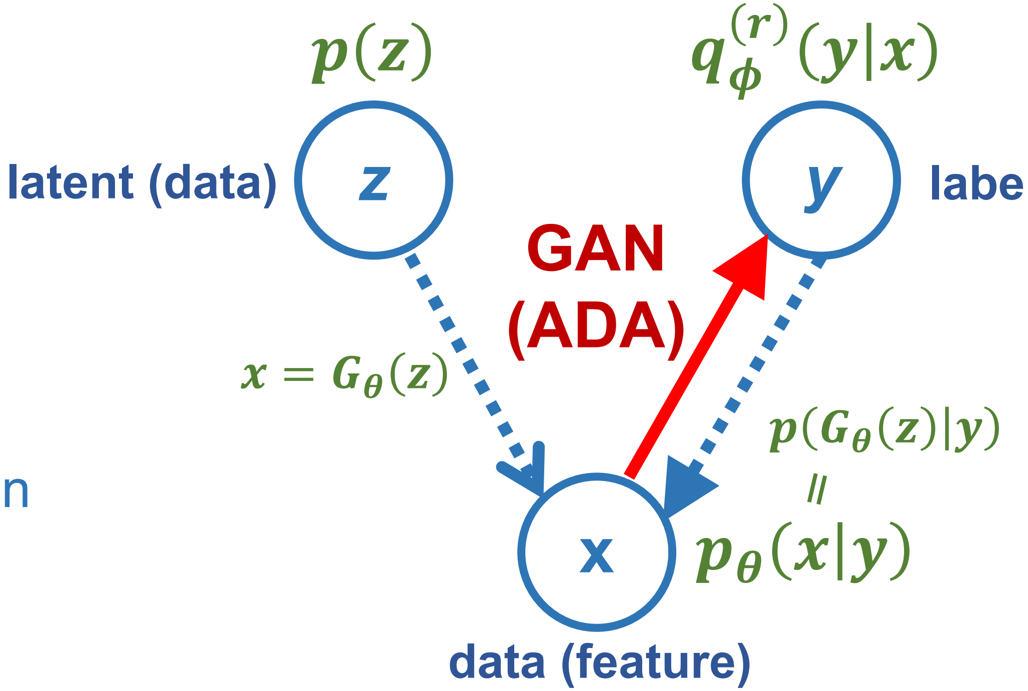

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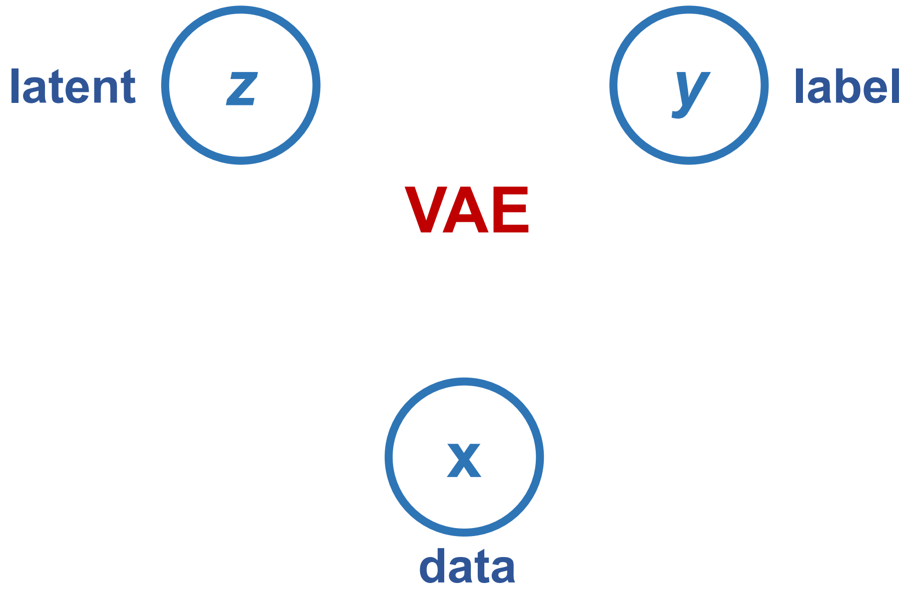

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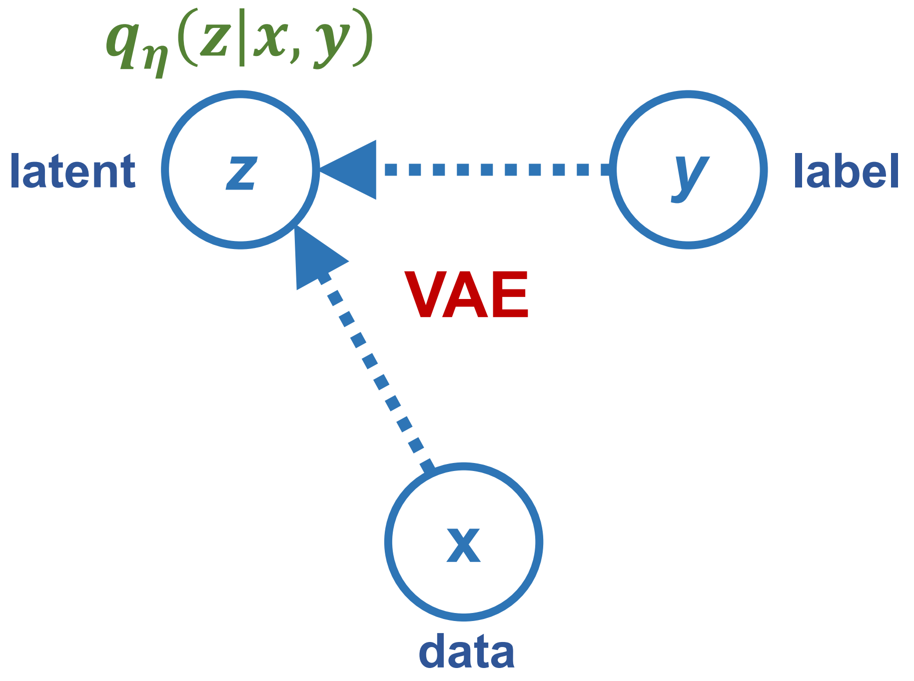

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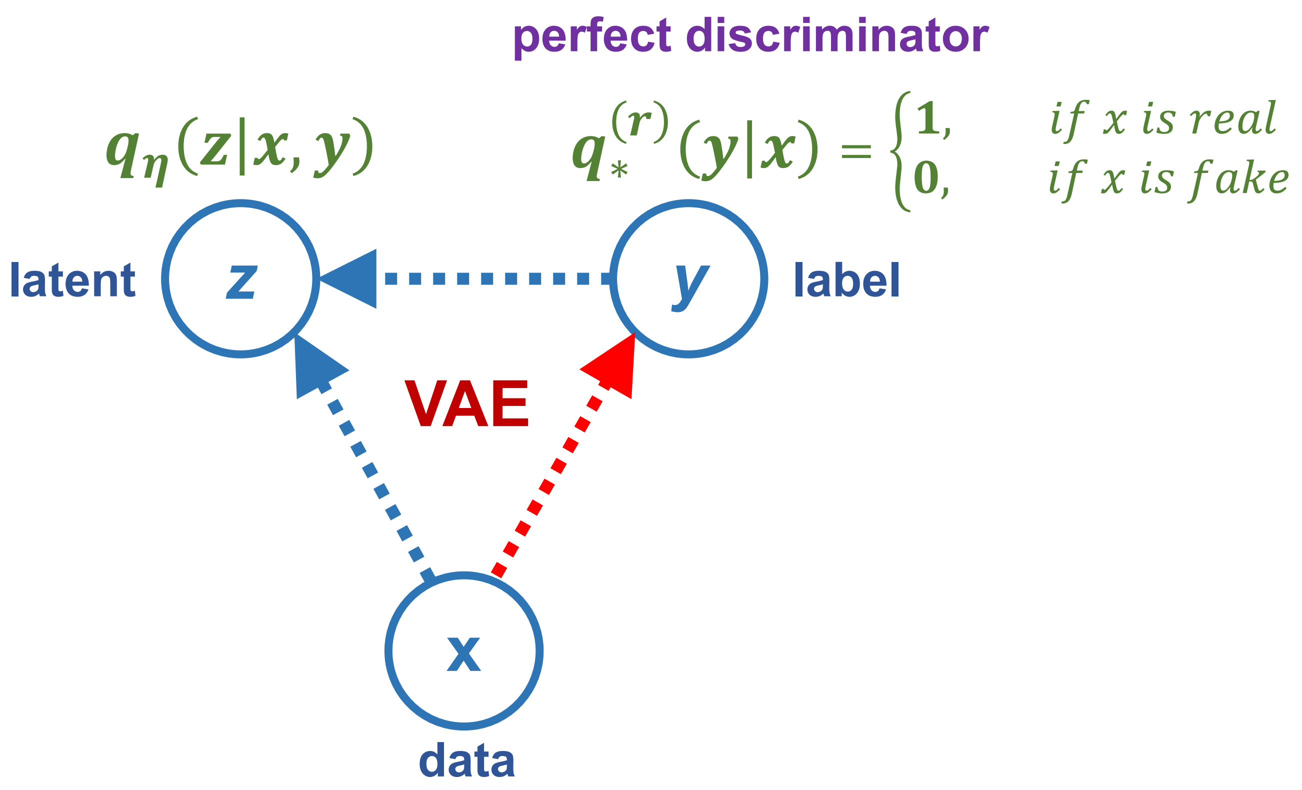

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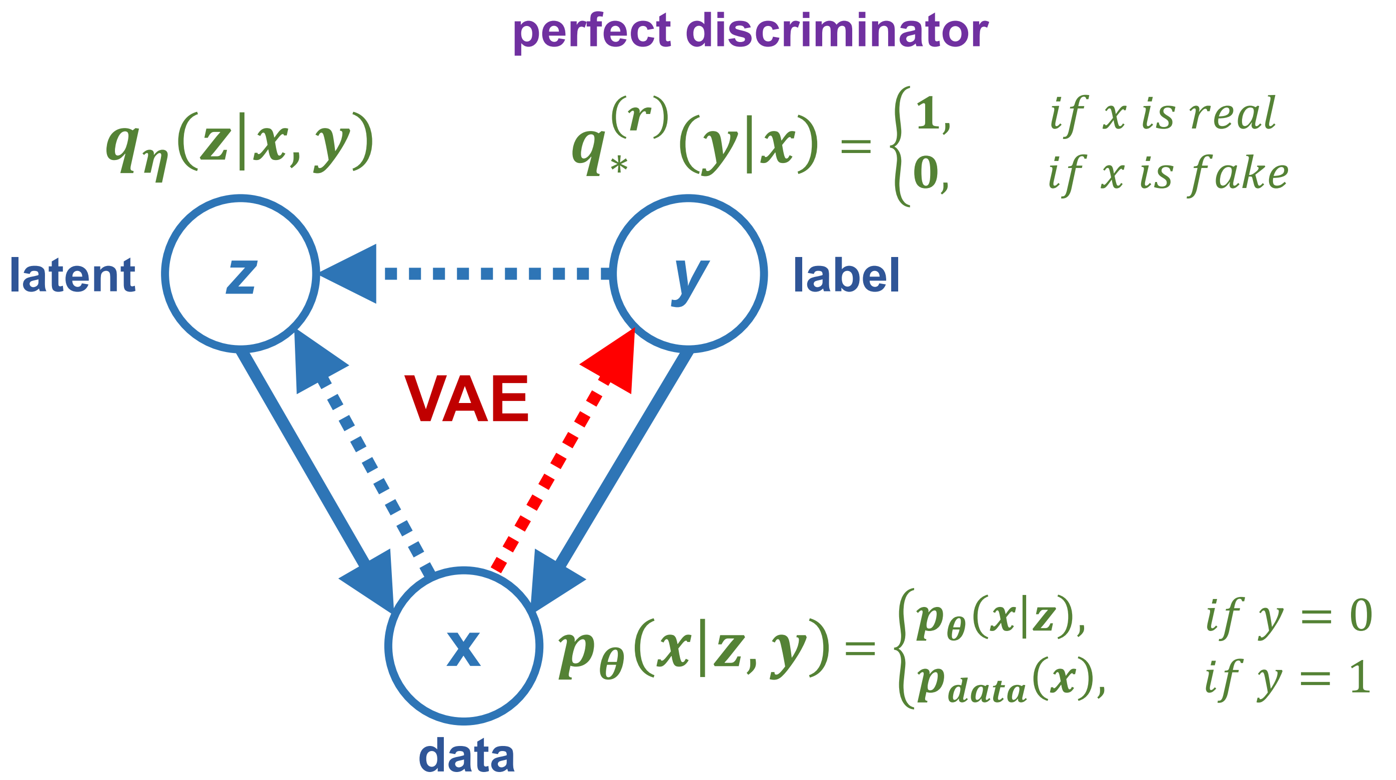
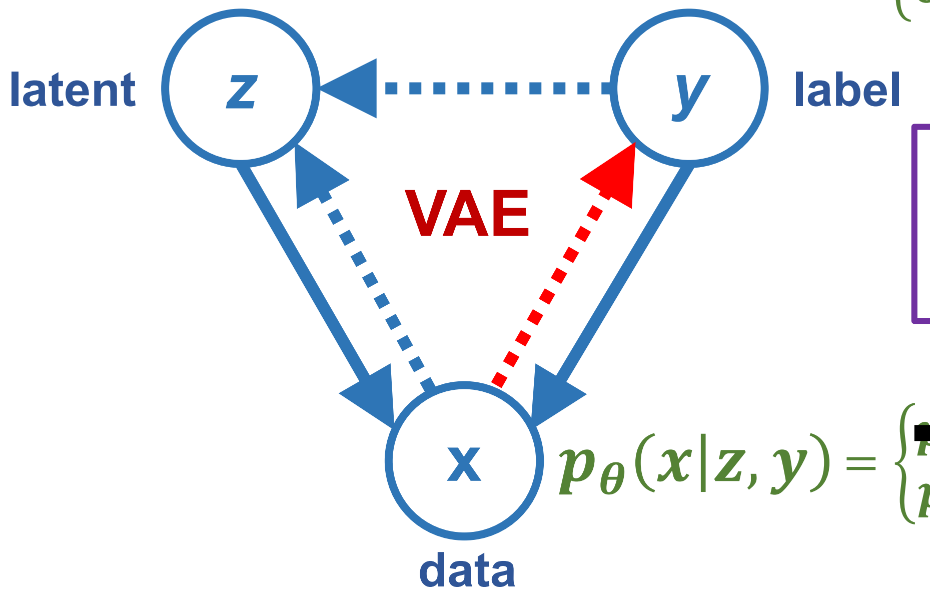


On Unifying Deep Generative Models

perfect discriminator

$$q_*^{(r)}(\boldsymbol{y}|\boldsymbol{x}) = \begin{cases} \mathbf{1}, & if\ x\ is\ real \\ \cancel{\mathbf{0}}, & \cancel{if\ x\ is\ fake} \end{cases}$$

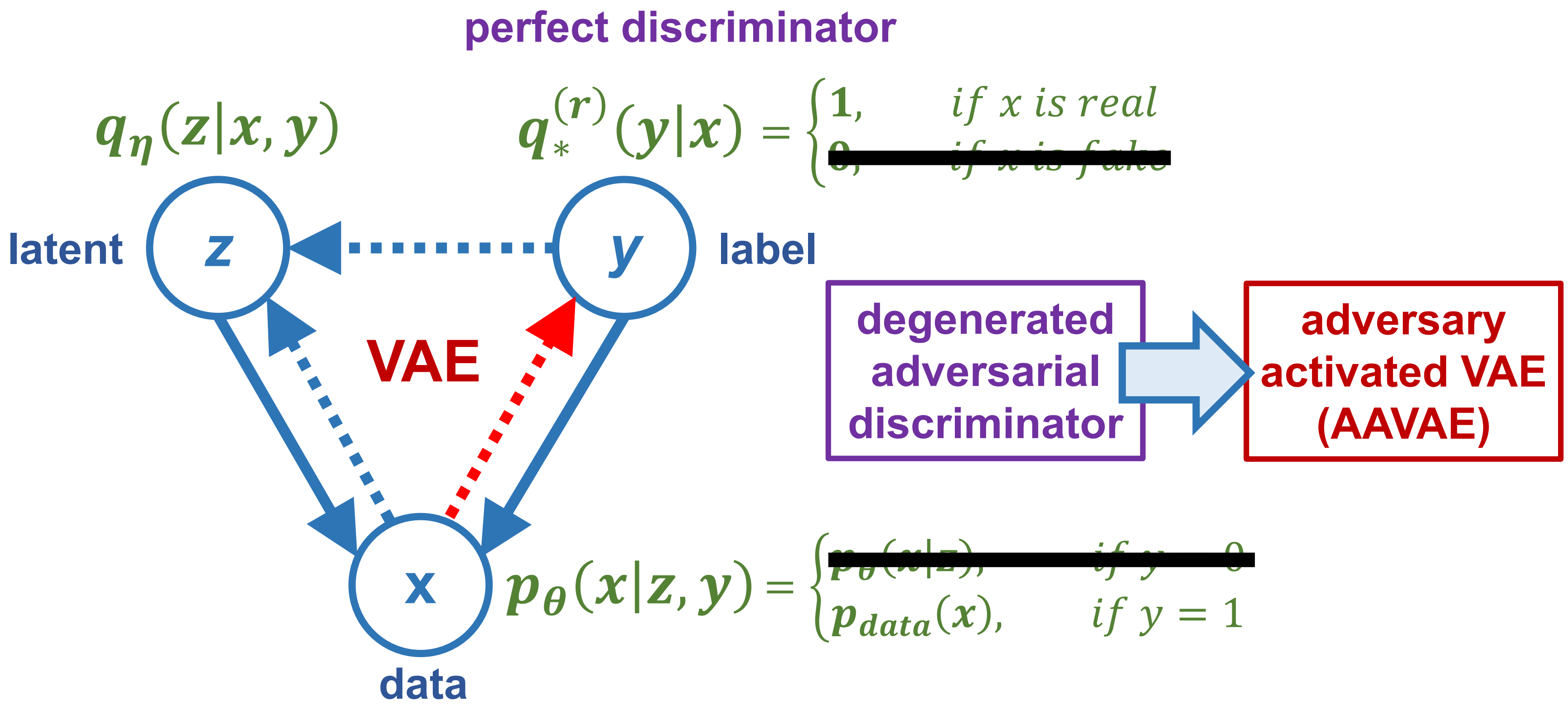
$$q_\eta(\boldsymbol{z}|\boldsymbol{x},\boldsymbol{y})$$



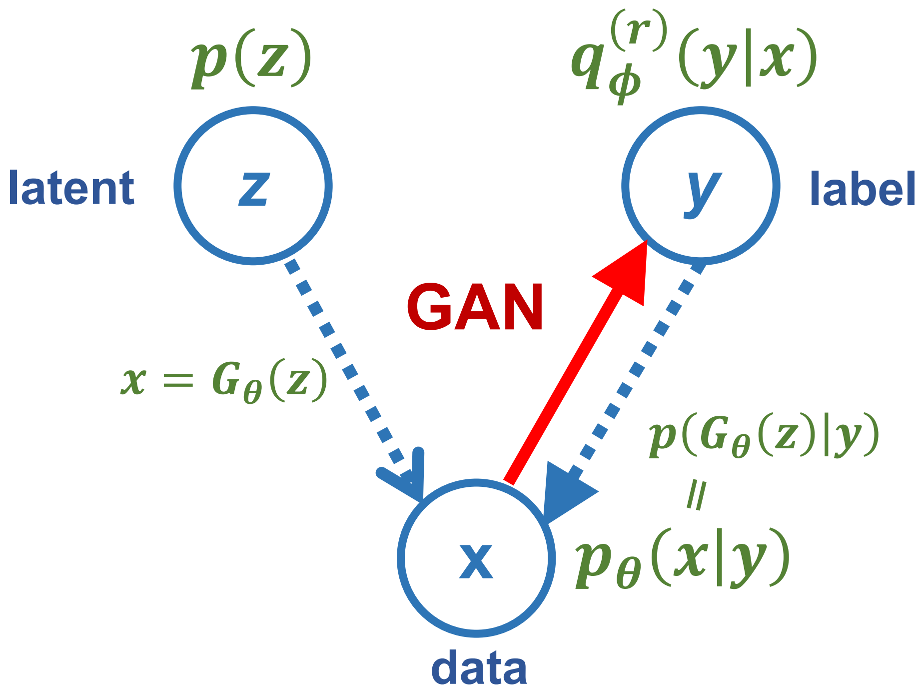
degenerated adversarial discriminator

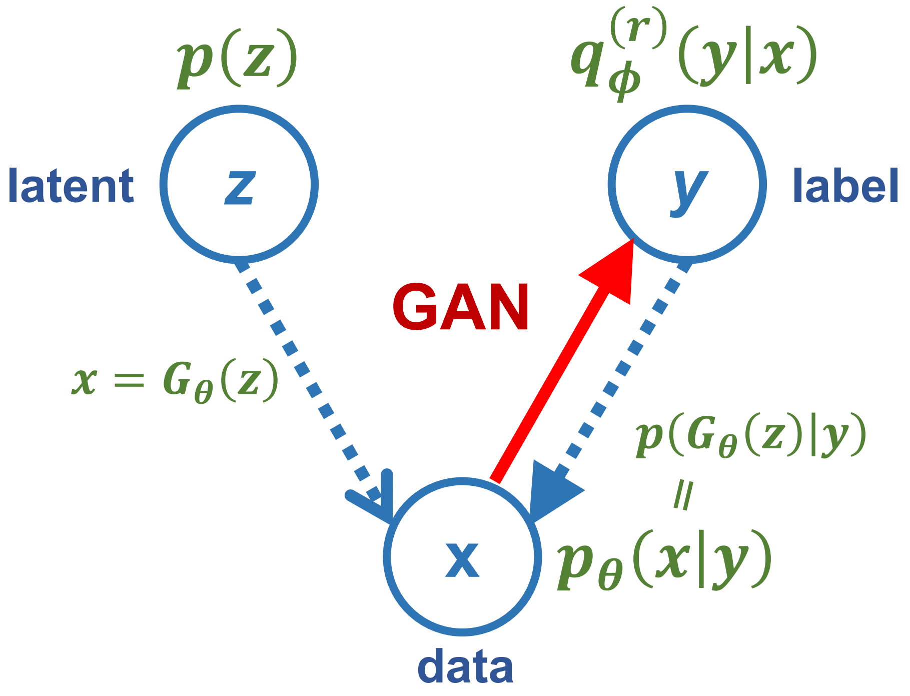
$$p_\theta(\boldsymbol{x}|\boldsymbol{z},\boldsymbol{y}) = \begin{cases} \cancel{p_\theta(\boldsymbol{x}|\boldsymbol{z})}, & \cancel{if\ y = 0} \\ p_{data}(\boldsymbol{x}), & if\ y = 1 \end{cases}$$

On Unifying Deep Generative Models

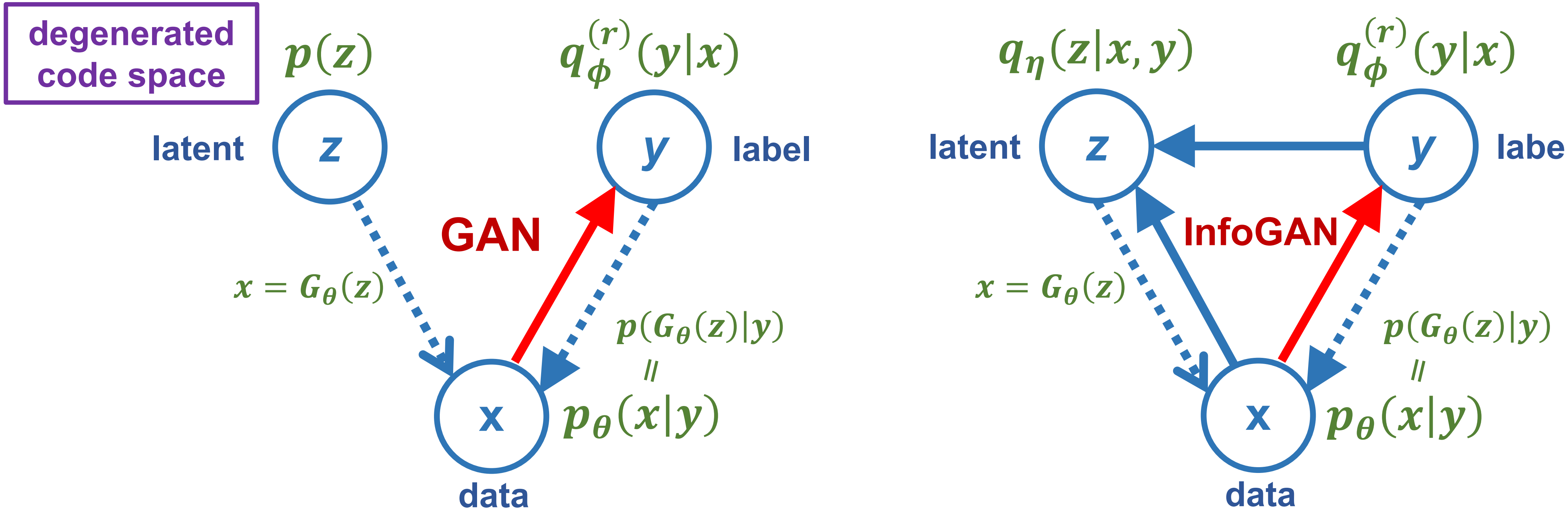


On Unifying Deep Generative Models





On Unifying Deep Generative Models



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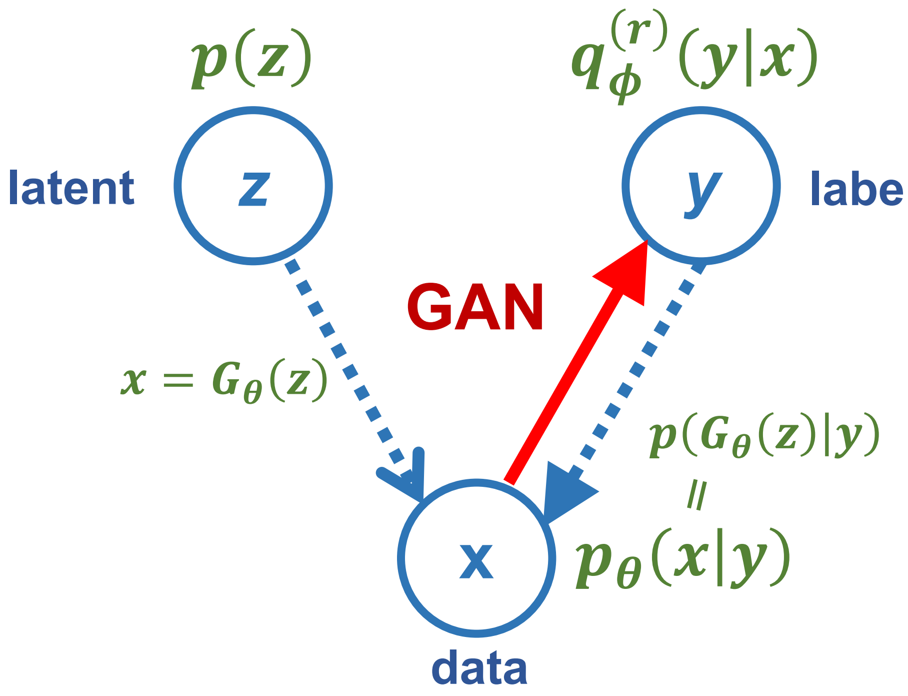

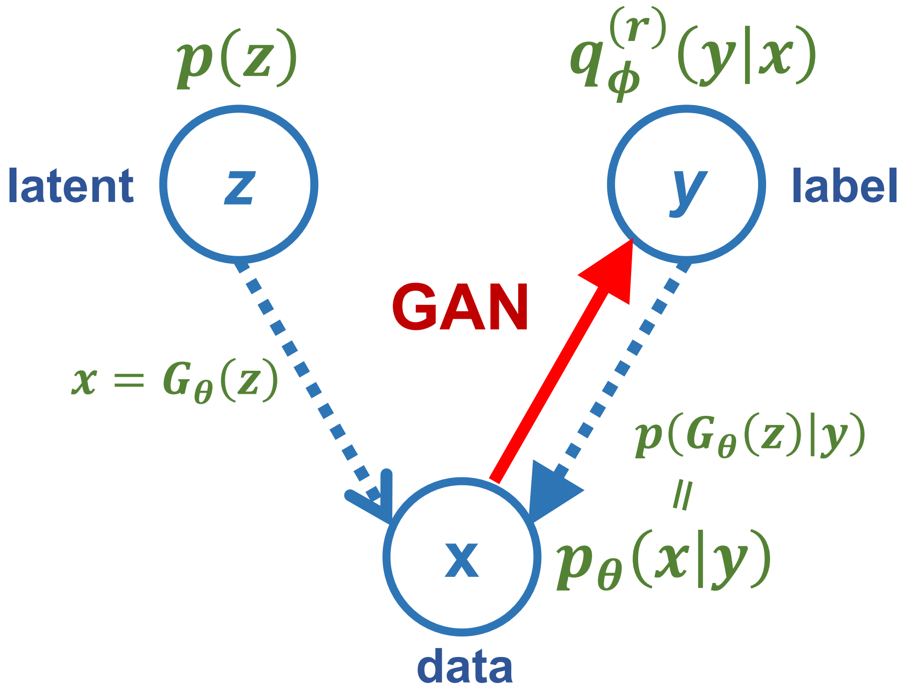

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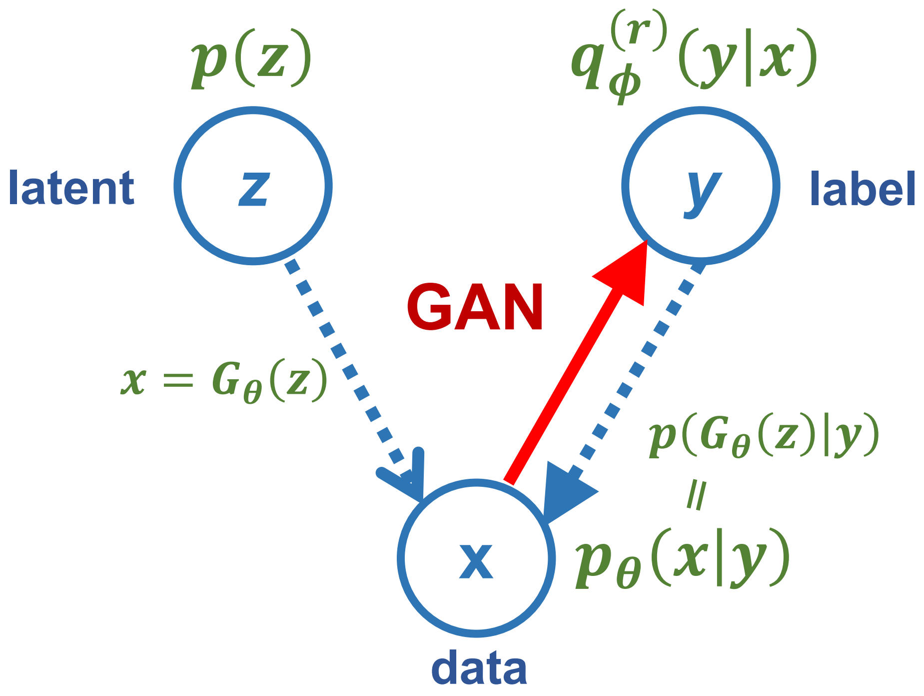
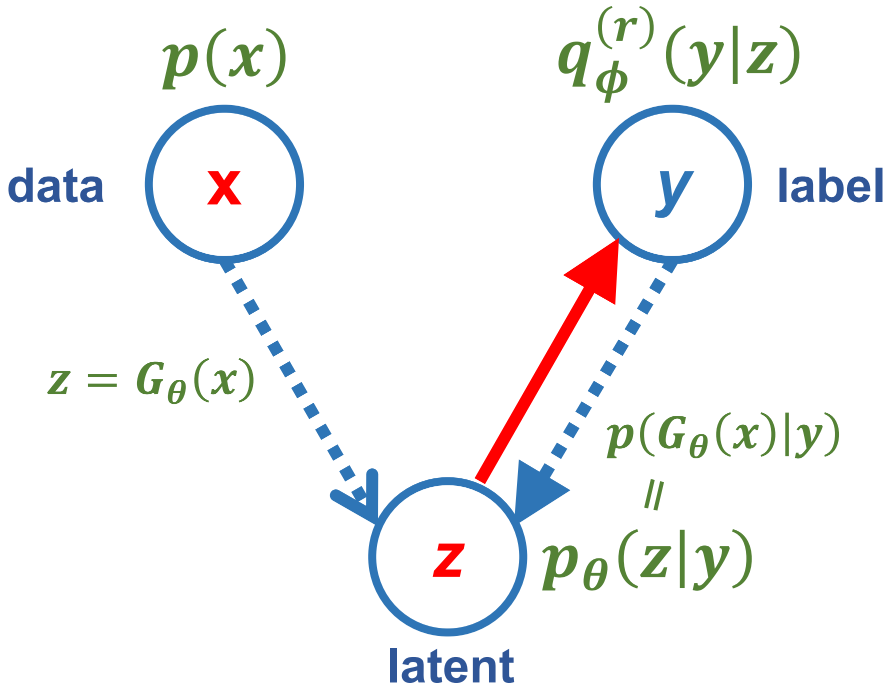
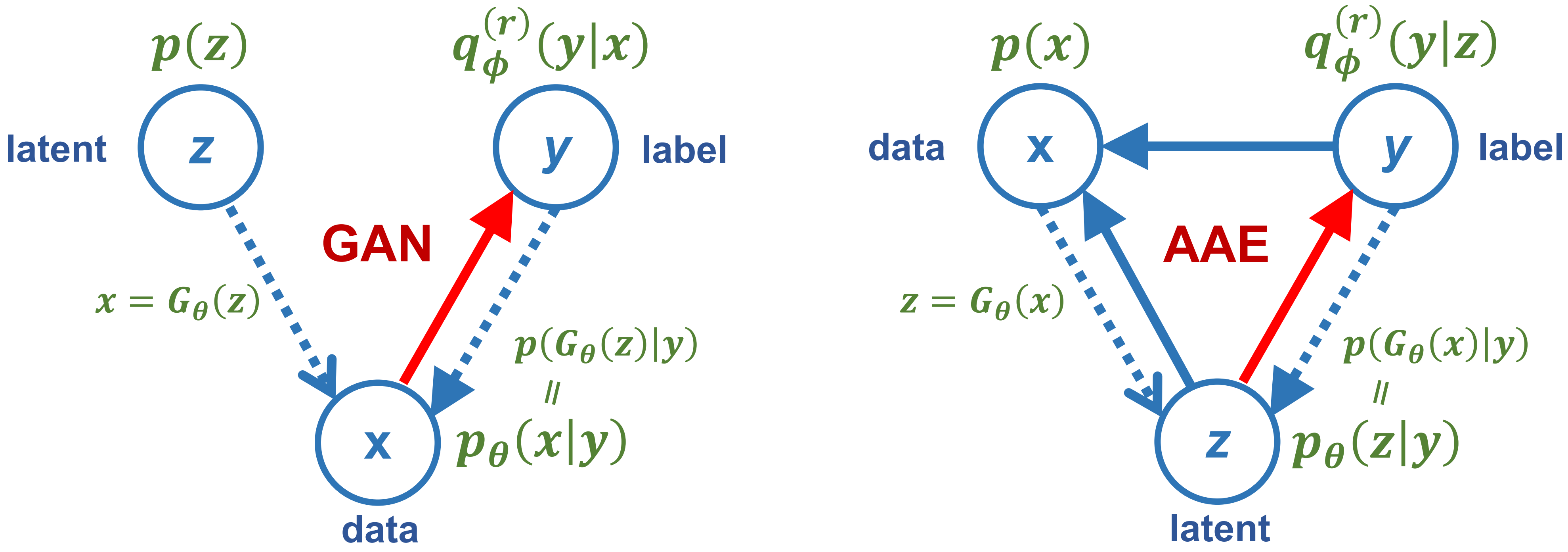
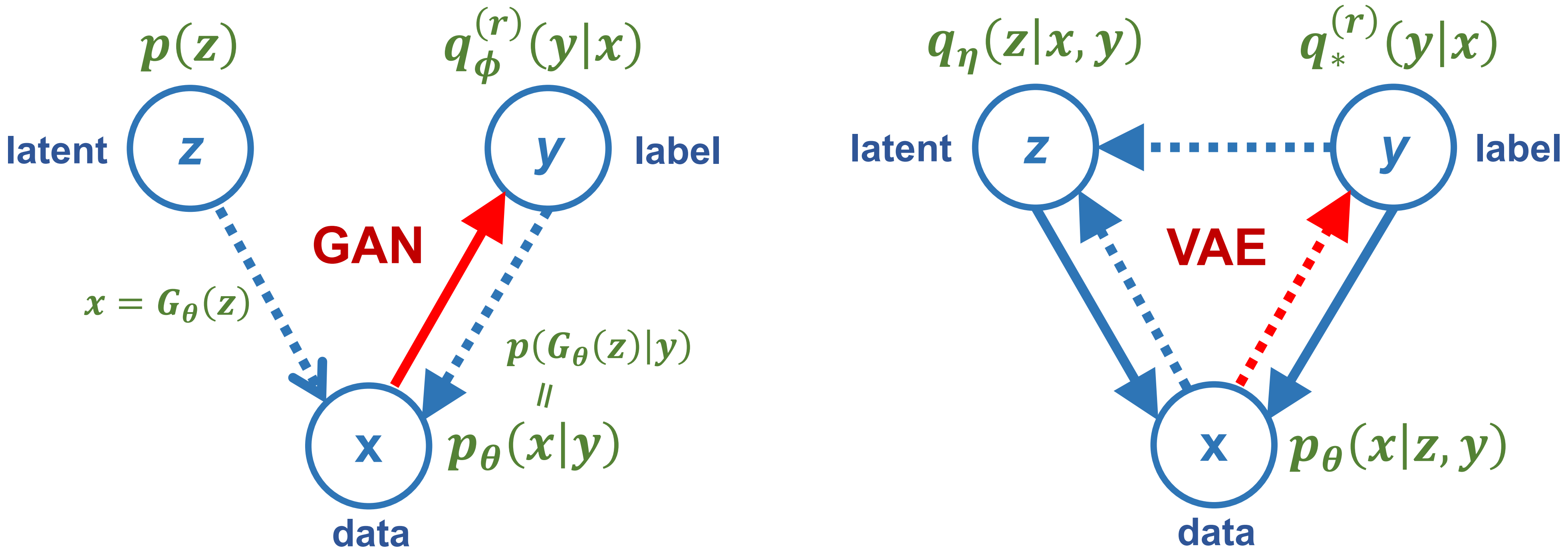




On Unifying Deep Generative Models

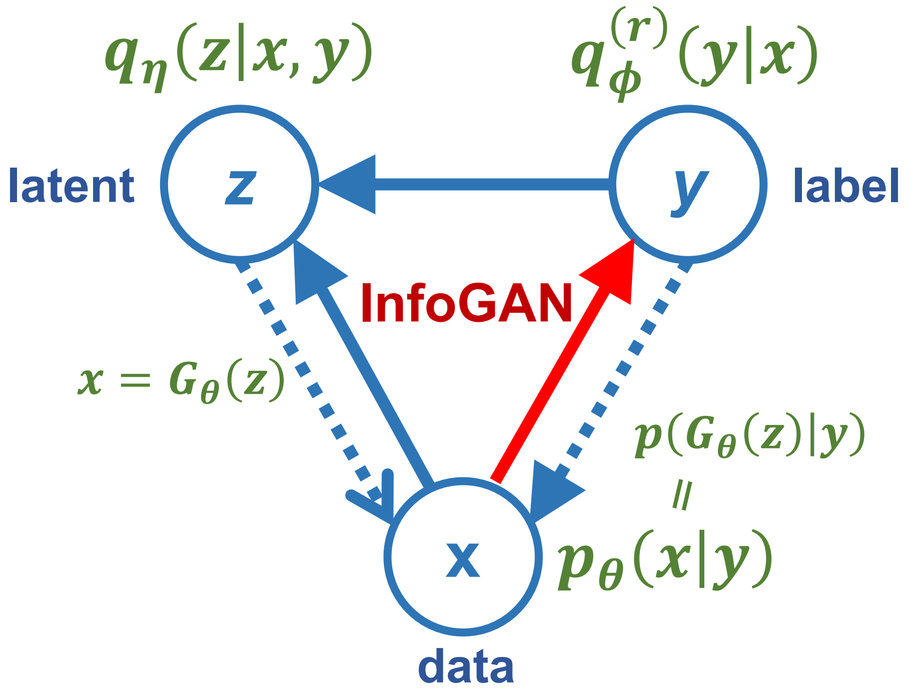


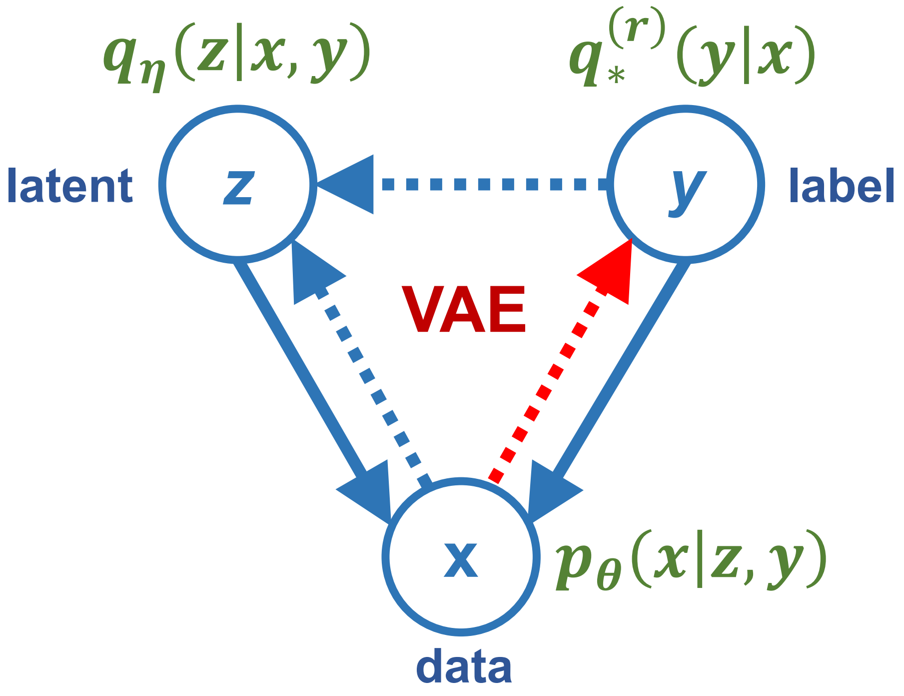
GAN vs VAE



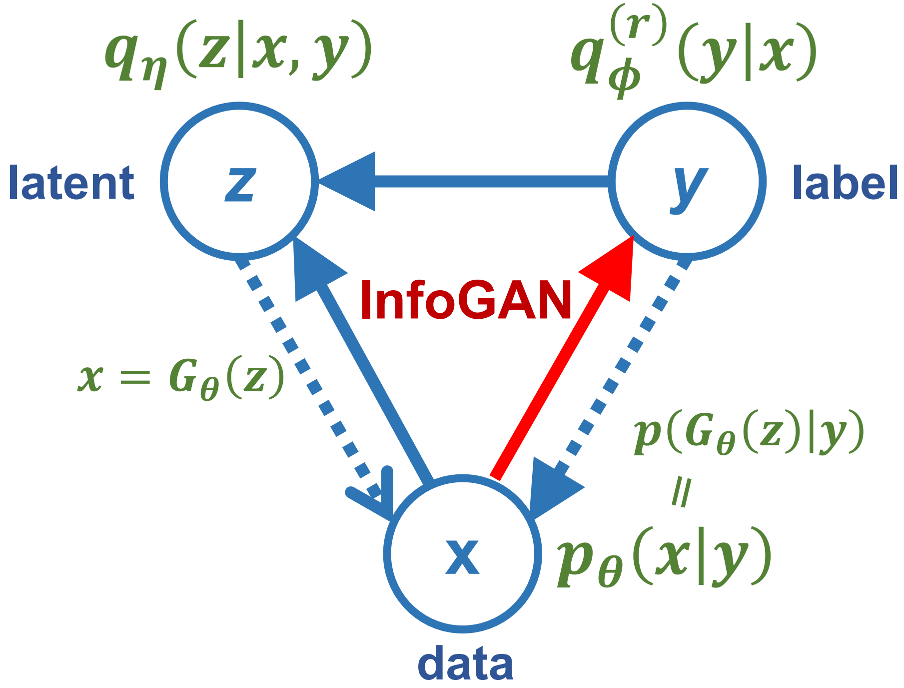
$p(z)$
latent
z
$x = G_\theta(z)$
GAN
$q_\phi^{(r)}(y|x)$
y
label
$p(G_\theta(z)|y)$
$||$
x
$p_\theta(x|y)$
data
$q_\eta(z|x,y)$
latent
z
VAE
$q_*^{(r)}(y|x)$
y
label
x
$p_\theta(x|z,y)$
data

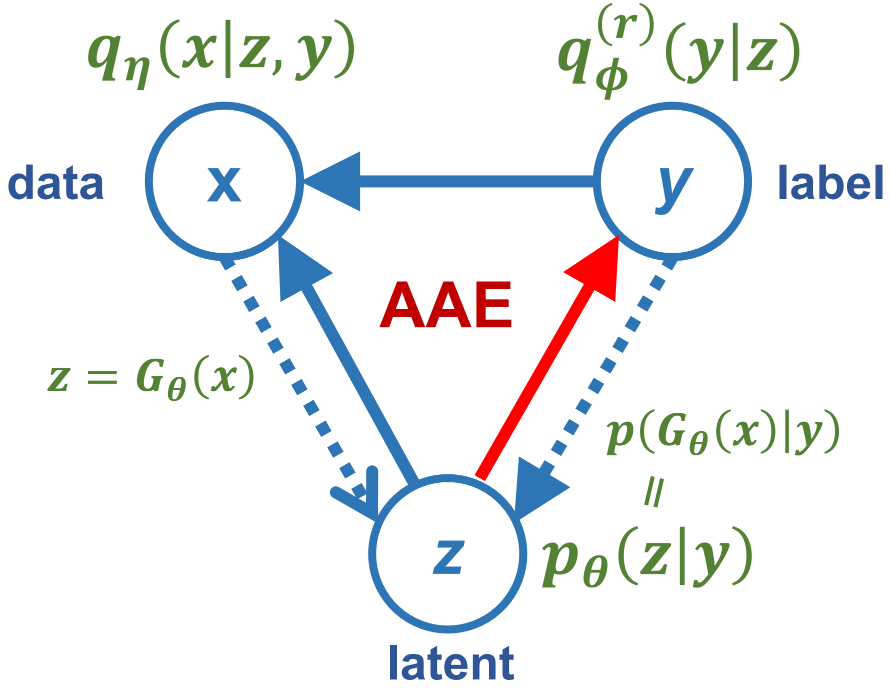
InfoGAN vs VAE





InfoGAN vs AAE





Wake-sleep Algorithm

- $\boldsymbol{h}$ - general latent variables
- $\boldsymbol{\lambda}$ - general parameters
- $\boldsymbol{\theta}$ - generator parameters

$$\text{Wake:} \quad \max_{\boldsymbol{\theta}} \mathbb{E}_{\boldsymbol{q_\lambda(h|x)p_{data}(x)}} [\log p_\theta(x|h)]$$
$$\text{Sleep:} \quad \max_{\lambda} \mathbb{E}_{\boldsymbol{p_\theta(x|h)p(h)}} [\log q_\lambda(h|x)]$$

- In **wake** phase, update $\boldsymbol{\theta}$ by fitting $\boldsymbol{p_\theta(x|h)}$ to $\boldsymbol{x}$ and $\boldsymbol{h}$ inferred by $\boldsymbol{q_\lambda(h|x)}$.
- In **sleep** phase, update $\boldsymbol{\lambda}$ based on generated samples.

- **VAE:** $\boldsymbol{h} \to \boldsymbol{z}, \boldsymbol{\lambda} \to \boldsymbol{\eta}$
- **GAN**: $\boldsymbol{h} \to \boldsymbol{y}, \boldsymbol{\lambda} \to \boldsymbol{\phi}$

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