Introduction to Deep Generative Models

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MuseGAN

Learn about our recent work on using GAN to compose pop song at https://salu133445.github.io/musegan/

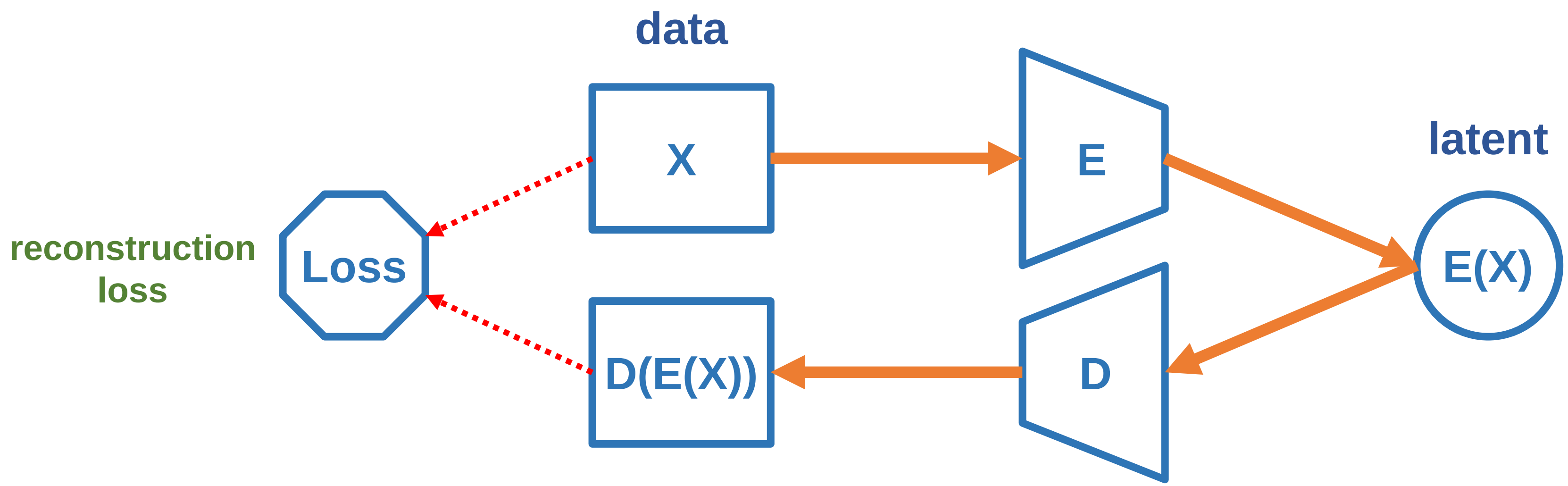
Hao-Wen Dong, Wen-Yi Hsiao, Li-Chia Yang and Yi-Hsuan Yang. 2017. MuseGAN: Symbolic-domain Music Generation and Accompaniment with Multi-track Sequential Generative Adversarial Networks. arXiv preprint arXiv:1709.06298.

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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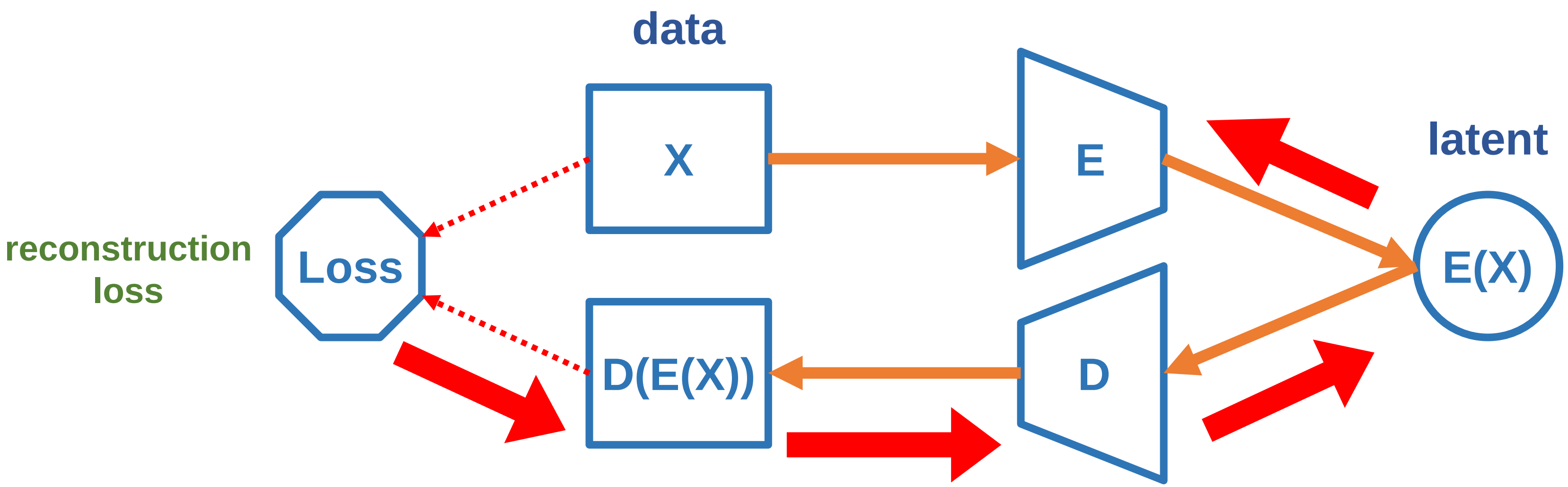

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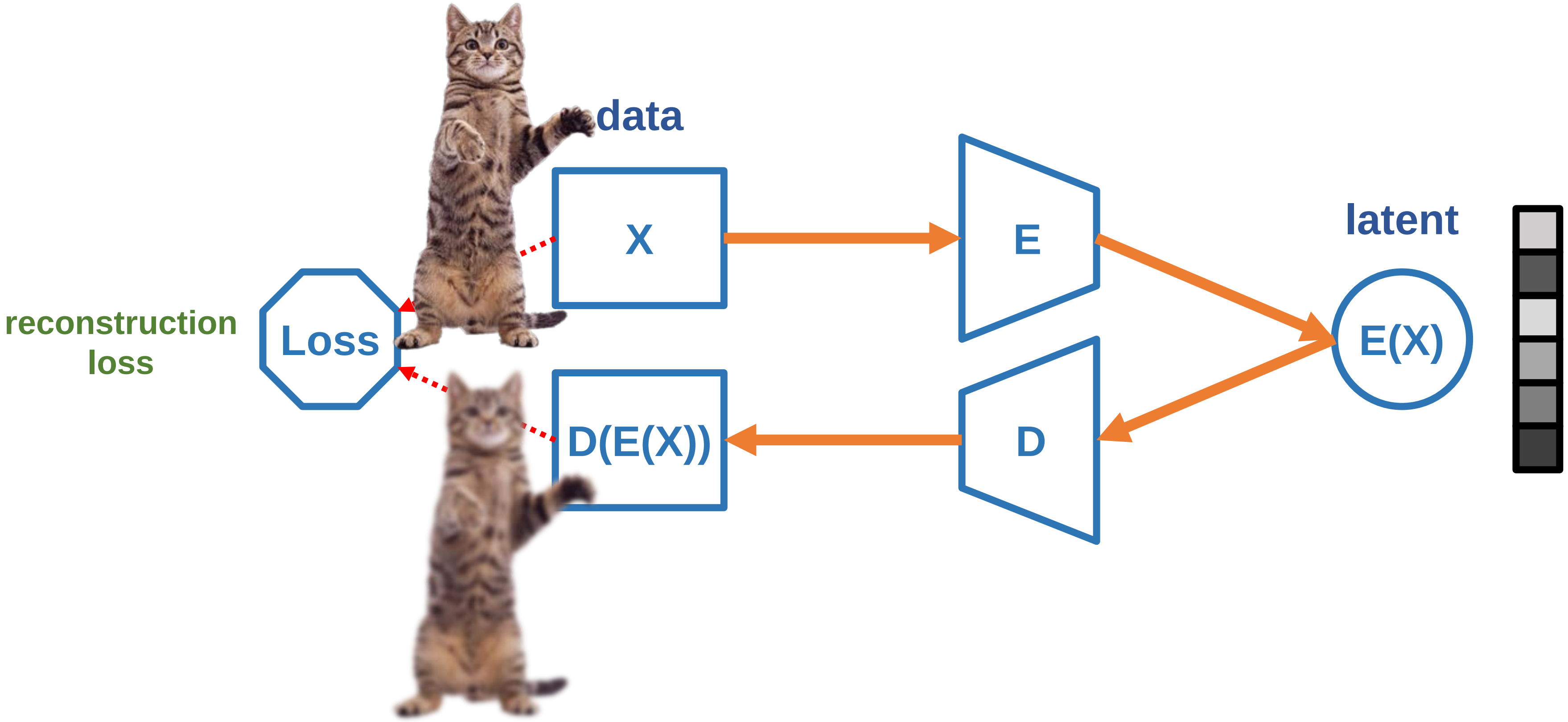
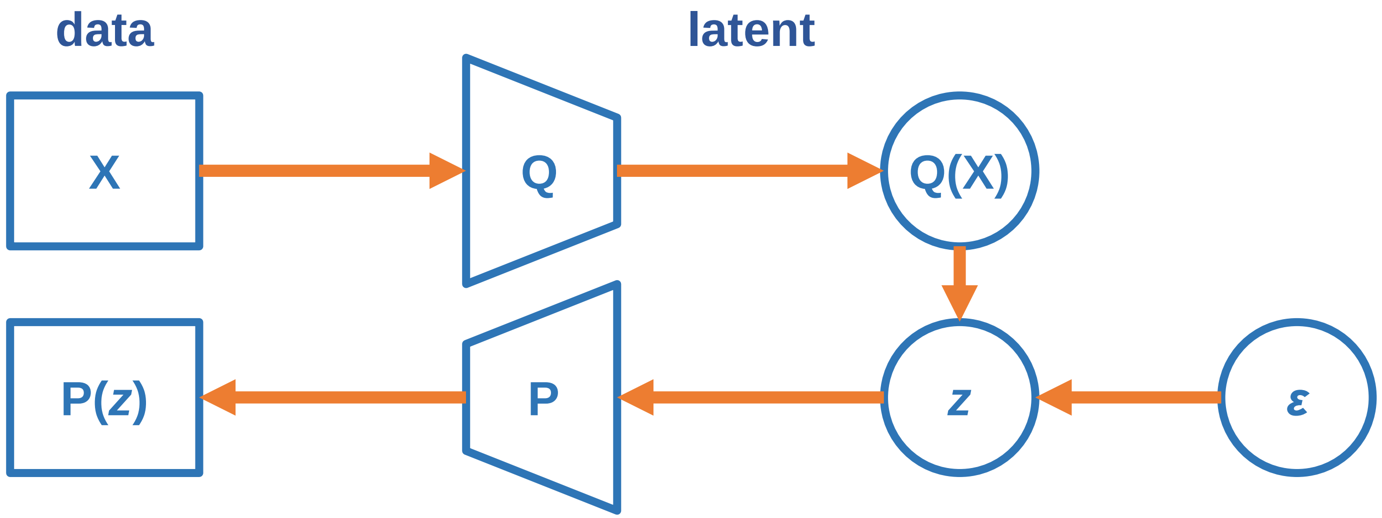


VAE (Variational Autoencoder)

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



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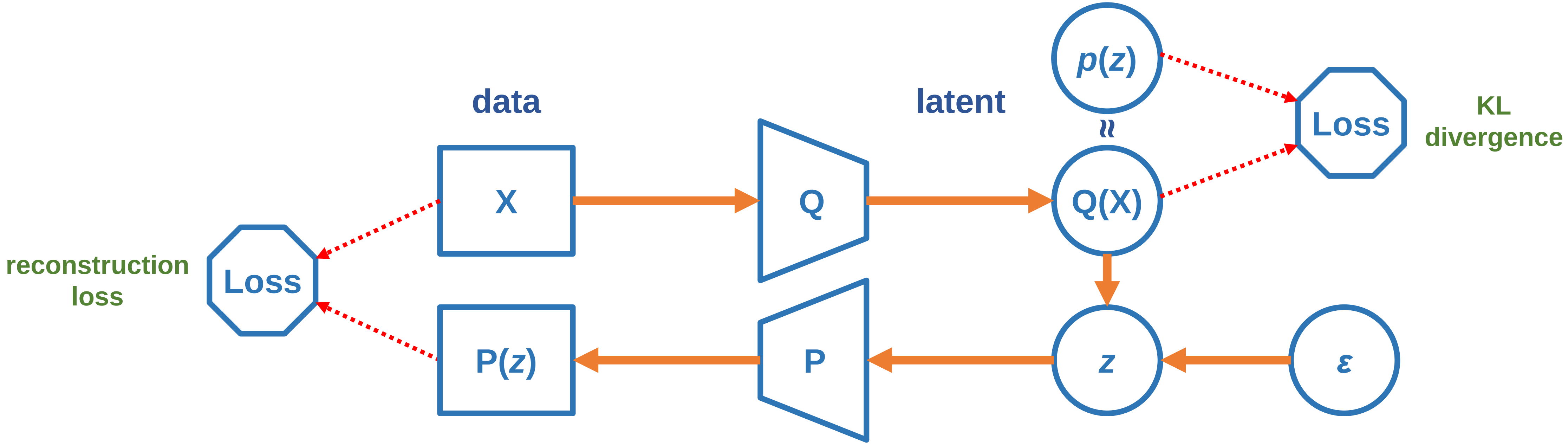

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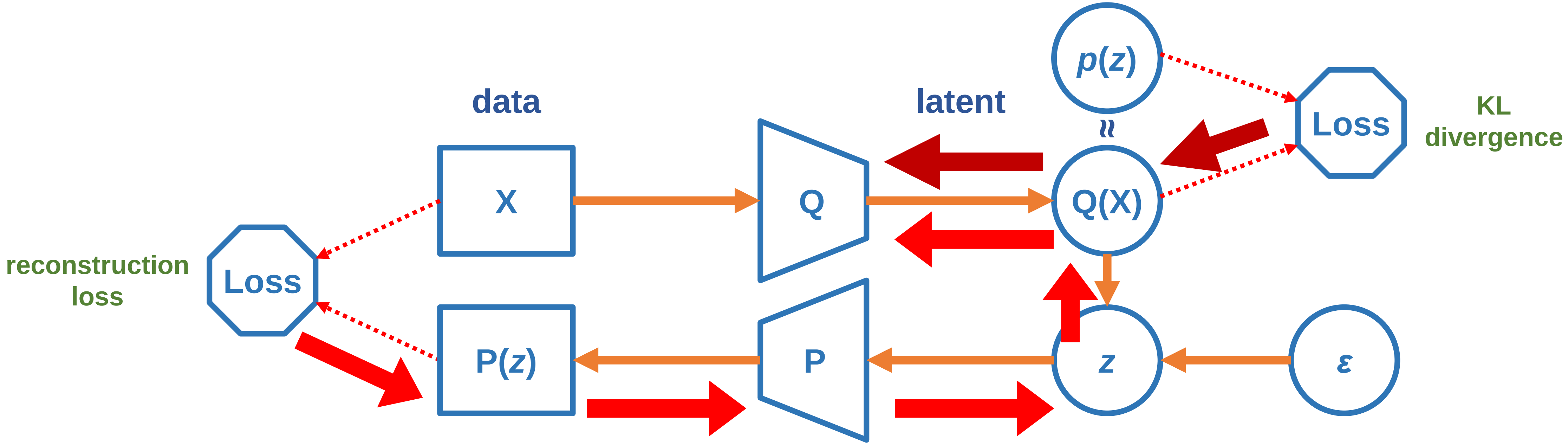

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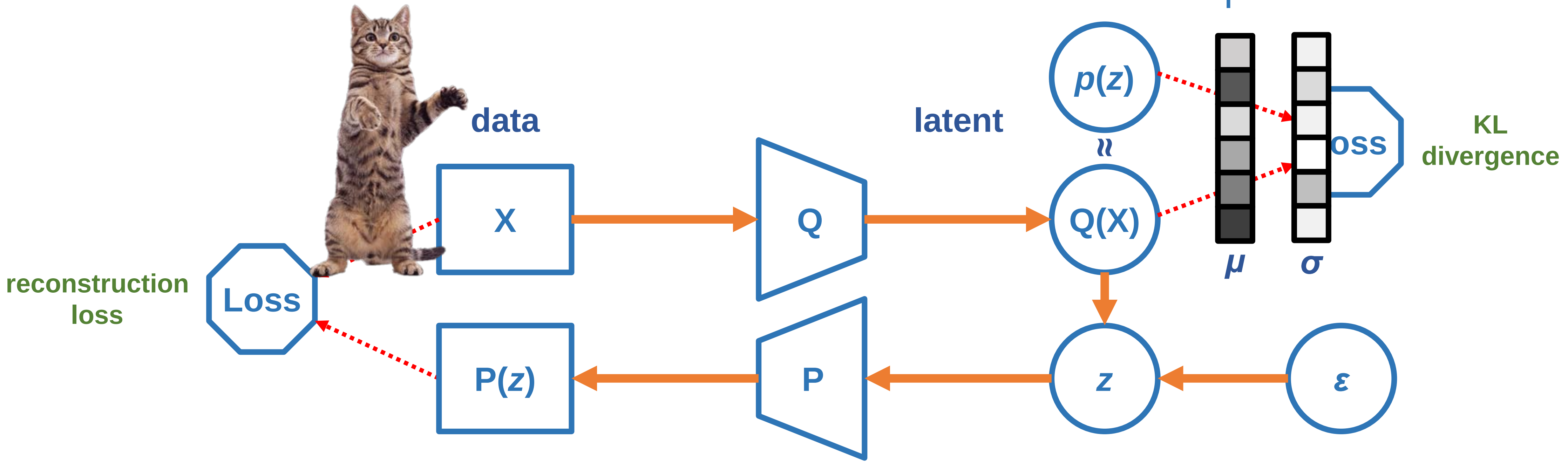

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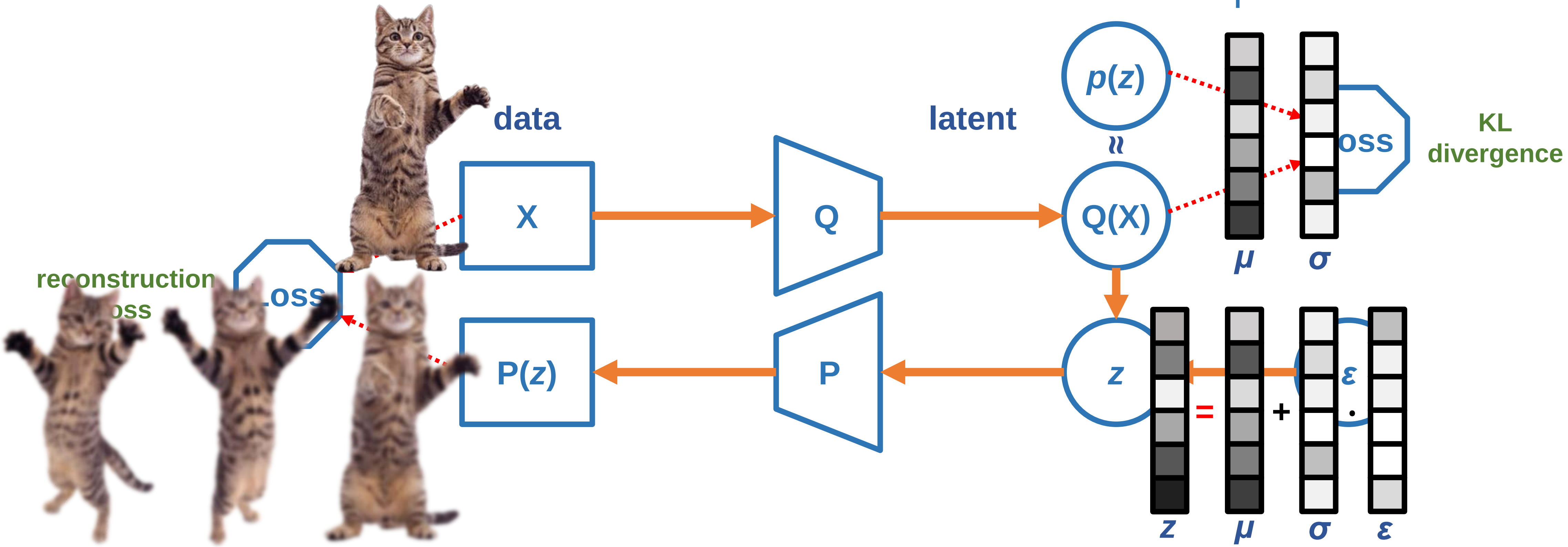

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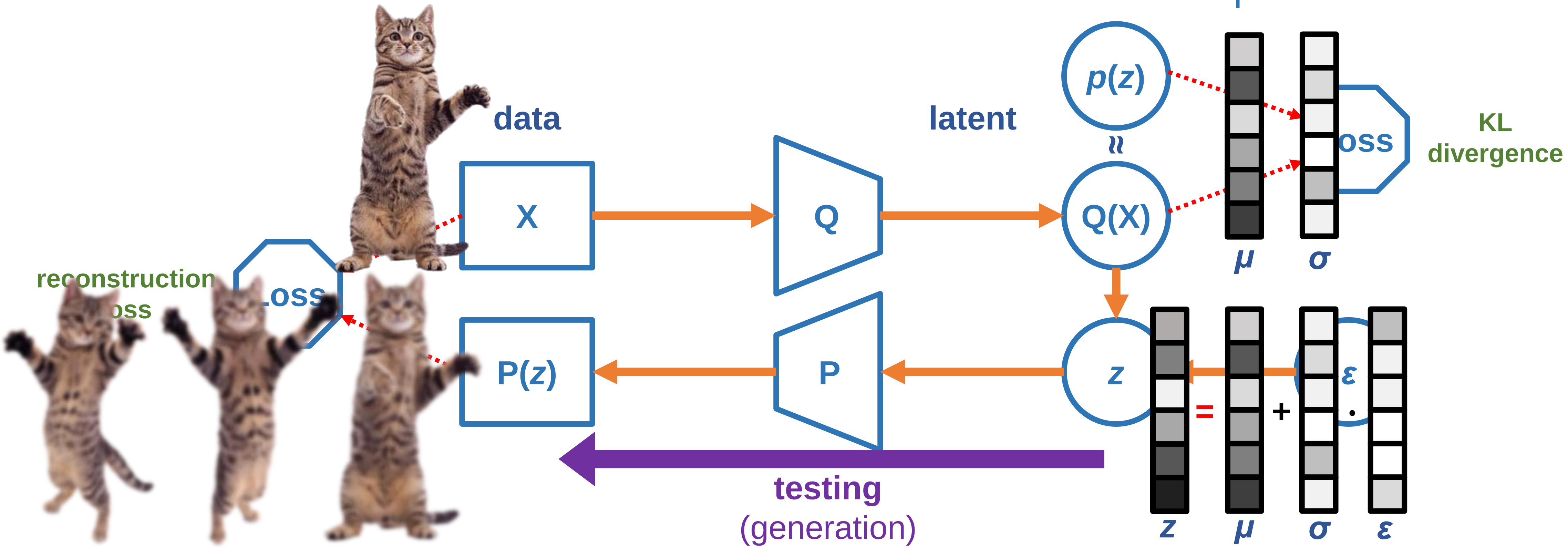
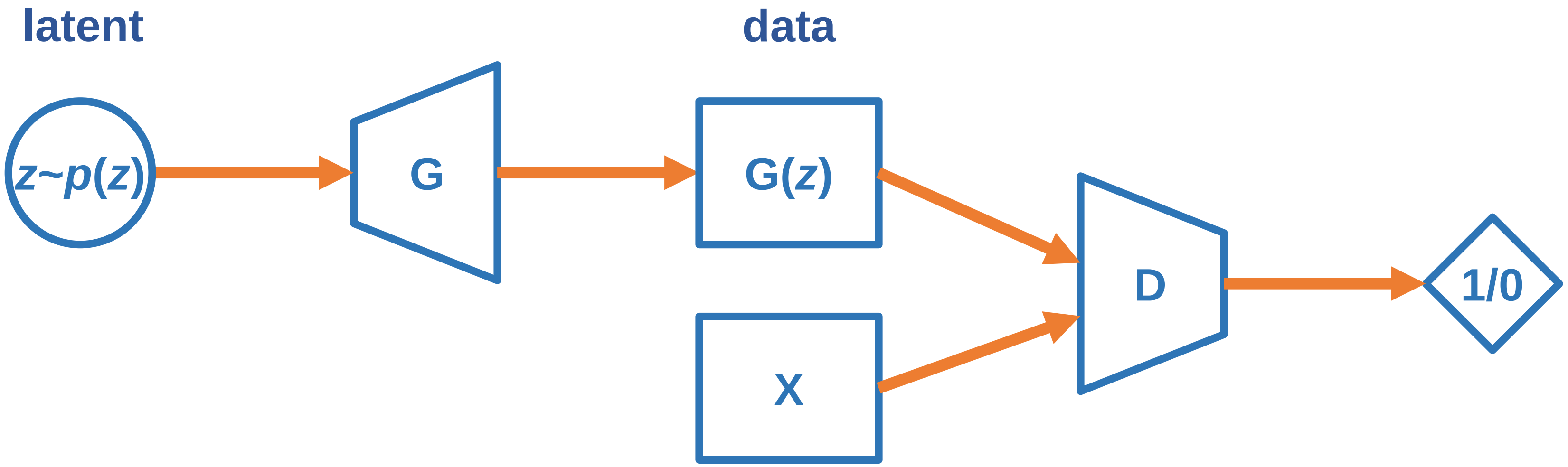


GAN (Generative Adversarial Network)

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



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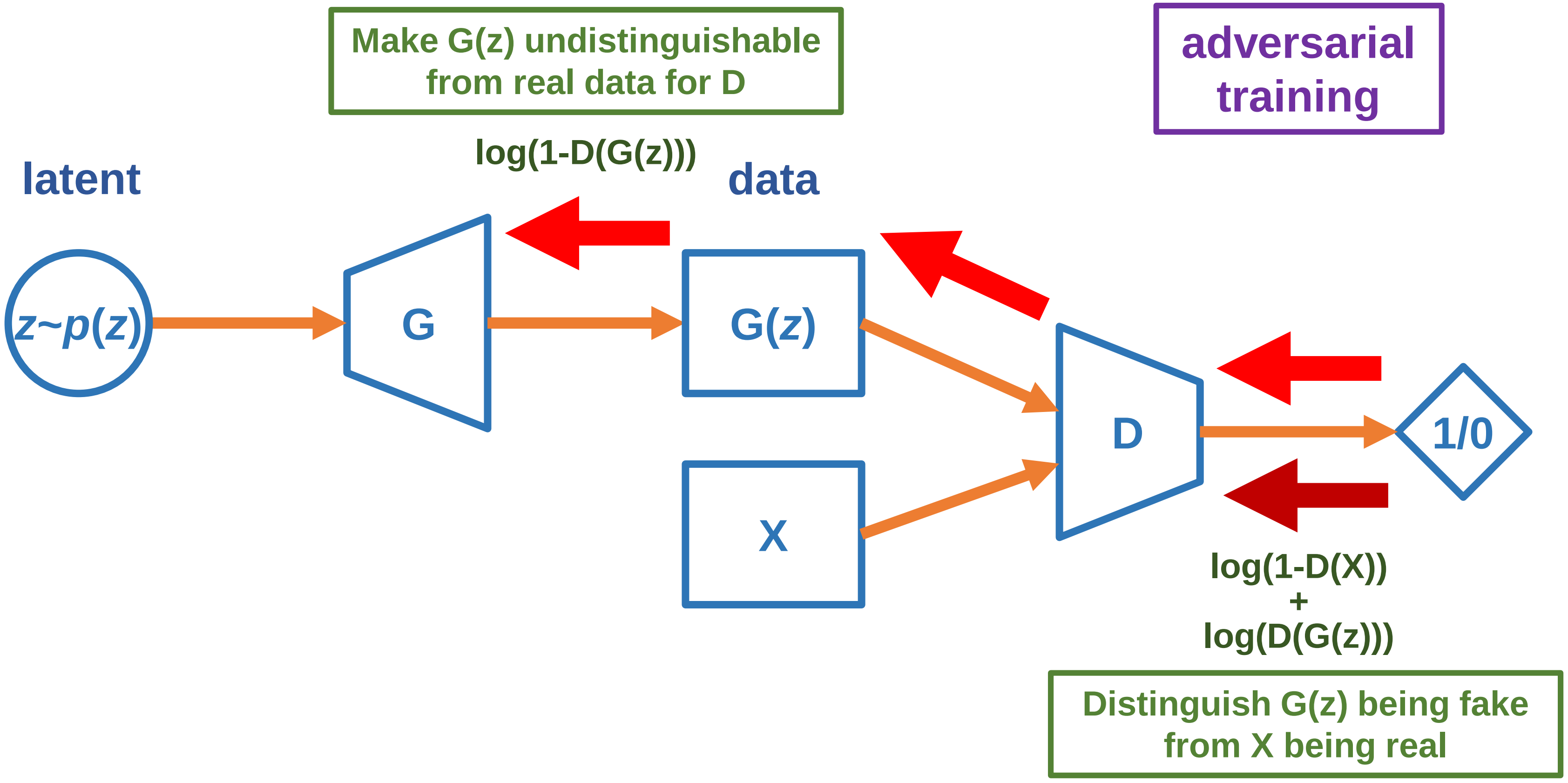

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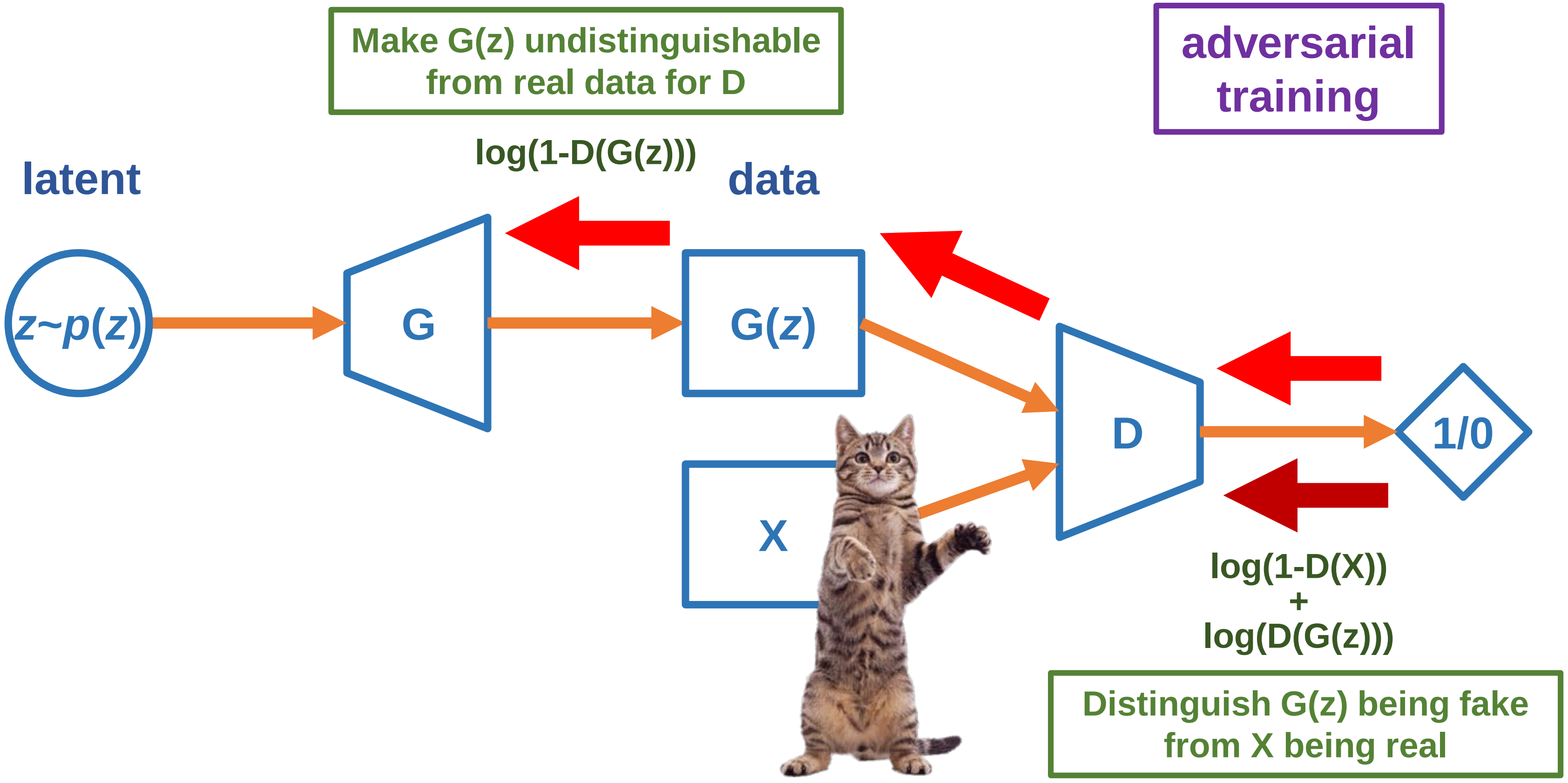

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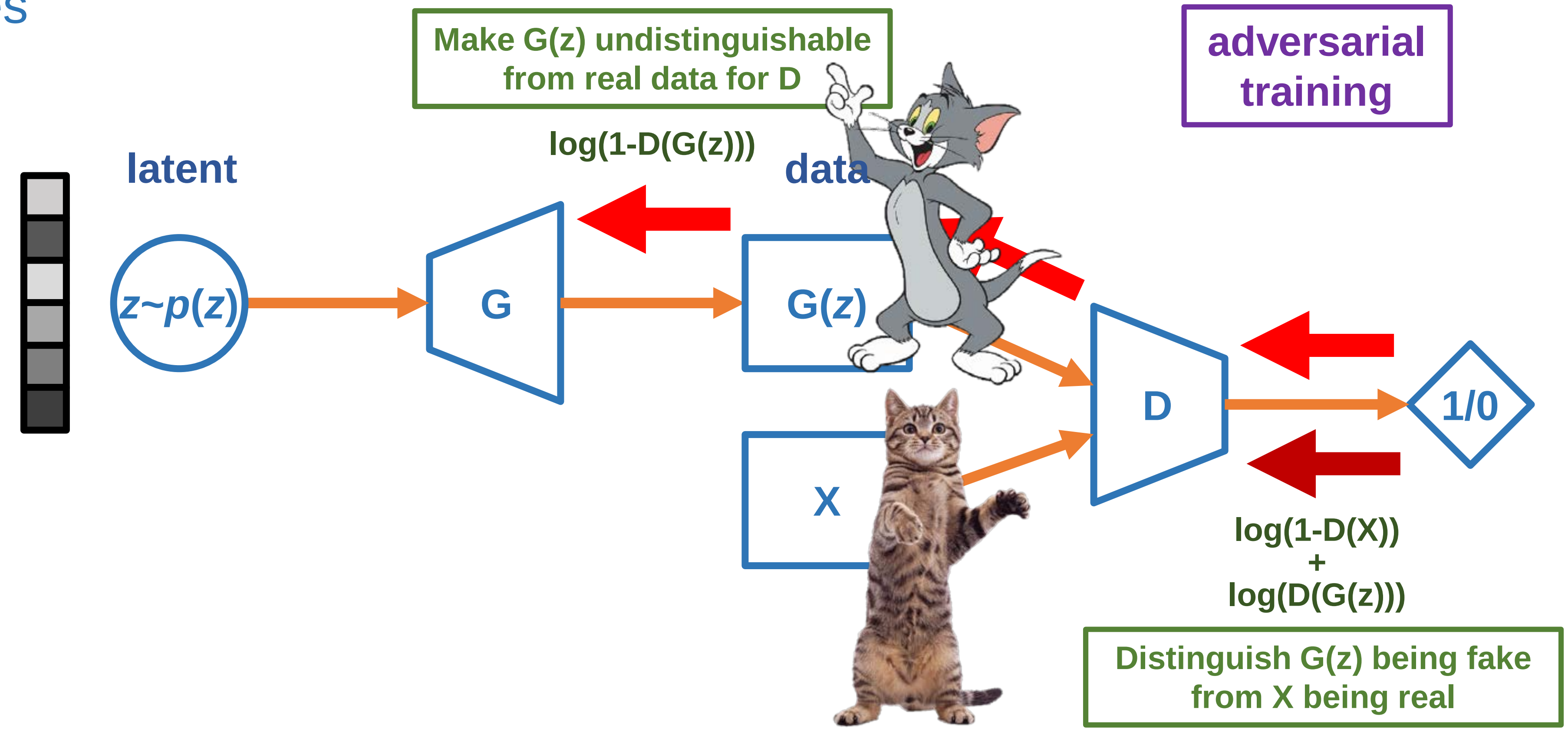

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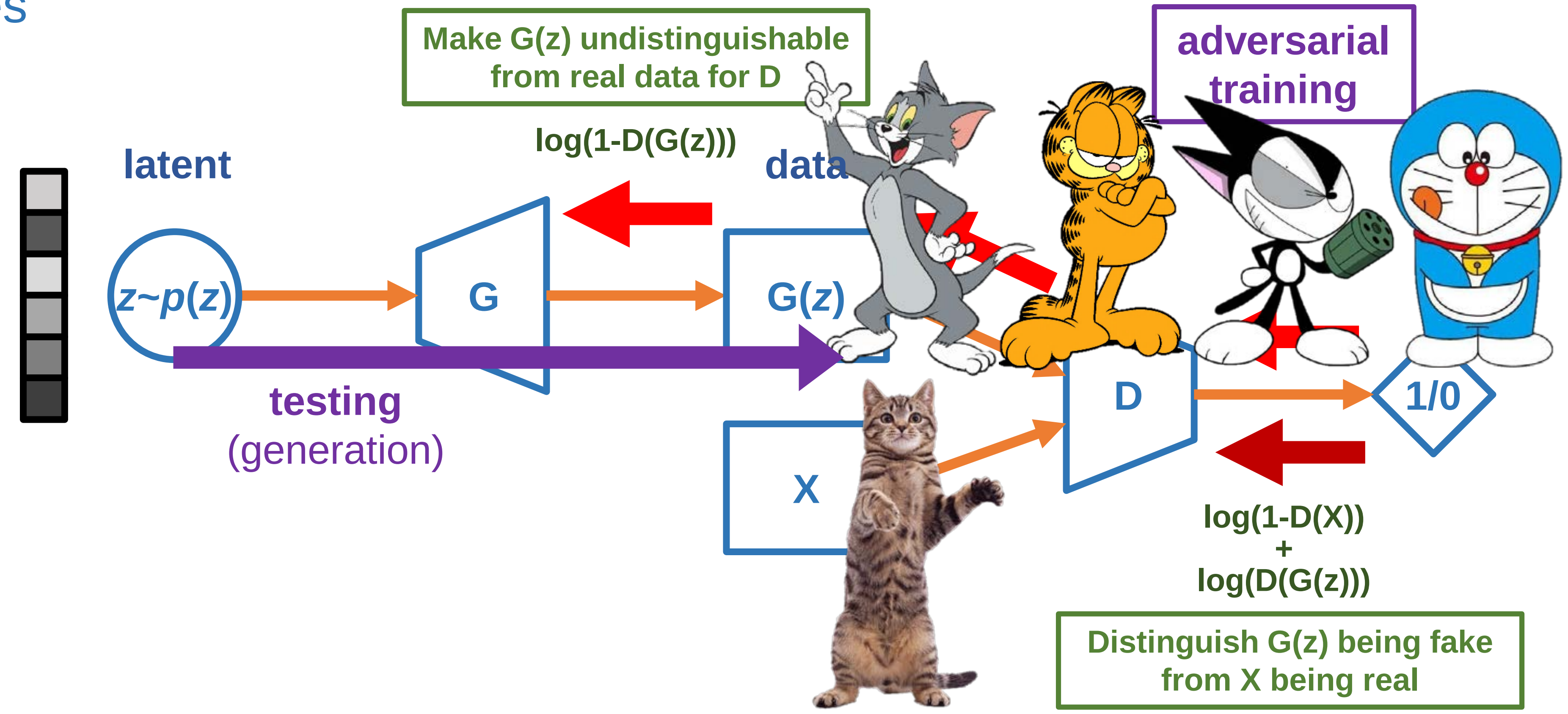
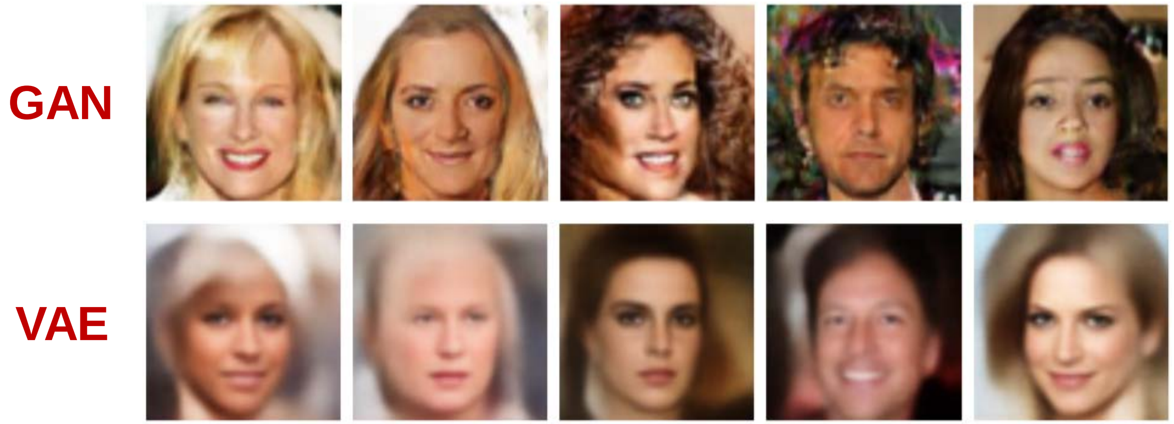


GAN vs VAE

- **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**



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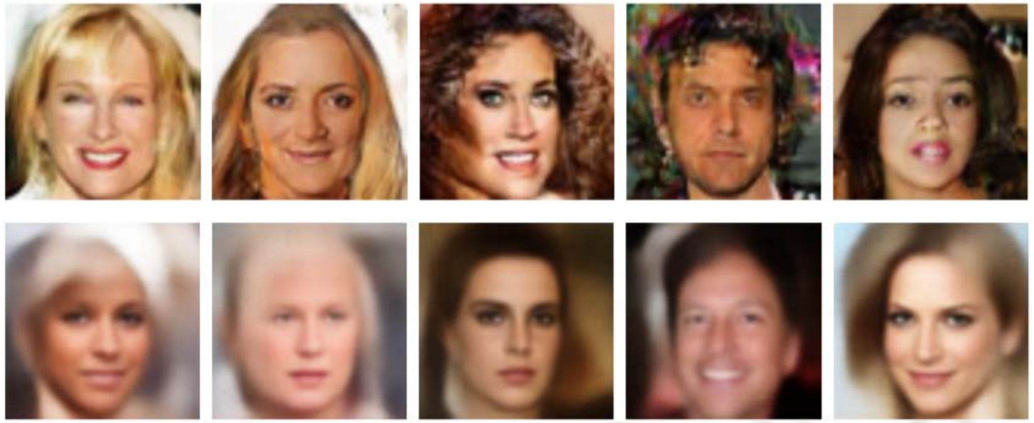
GAN

VAE



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AAE (Adversarial Autoencoder)

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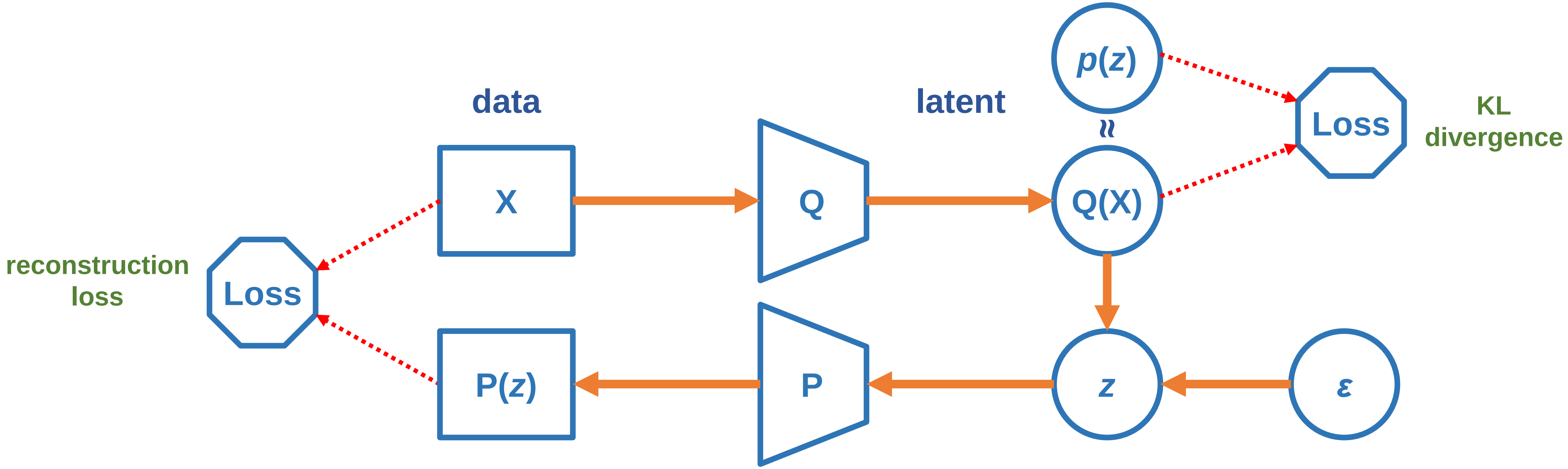

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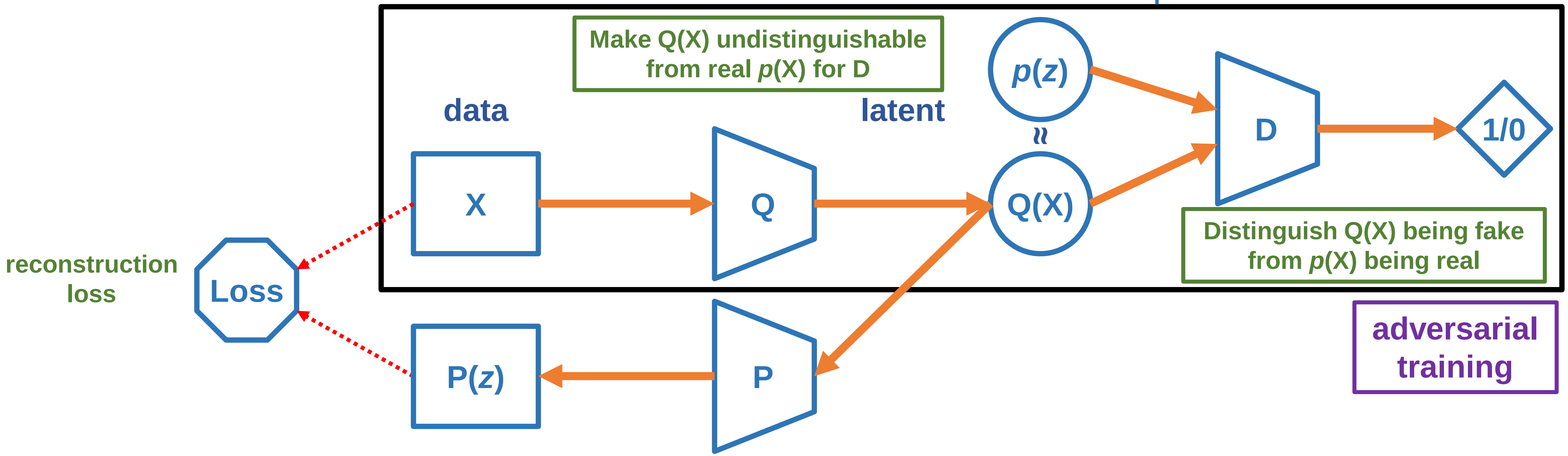

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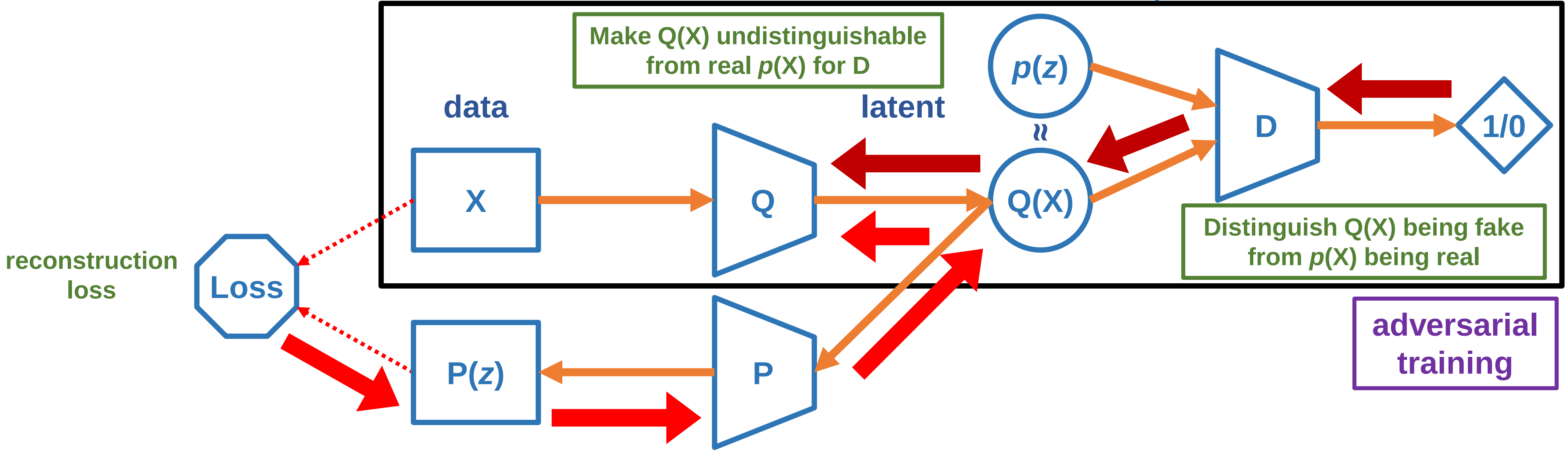
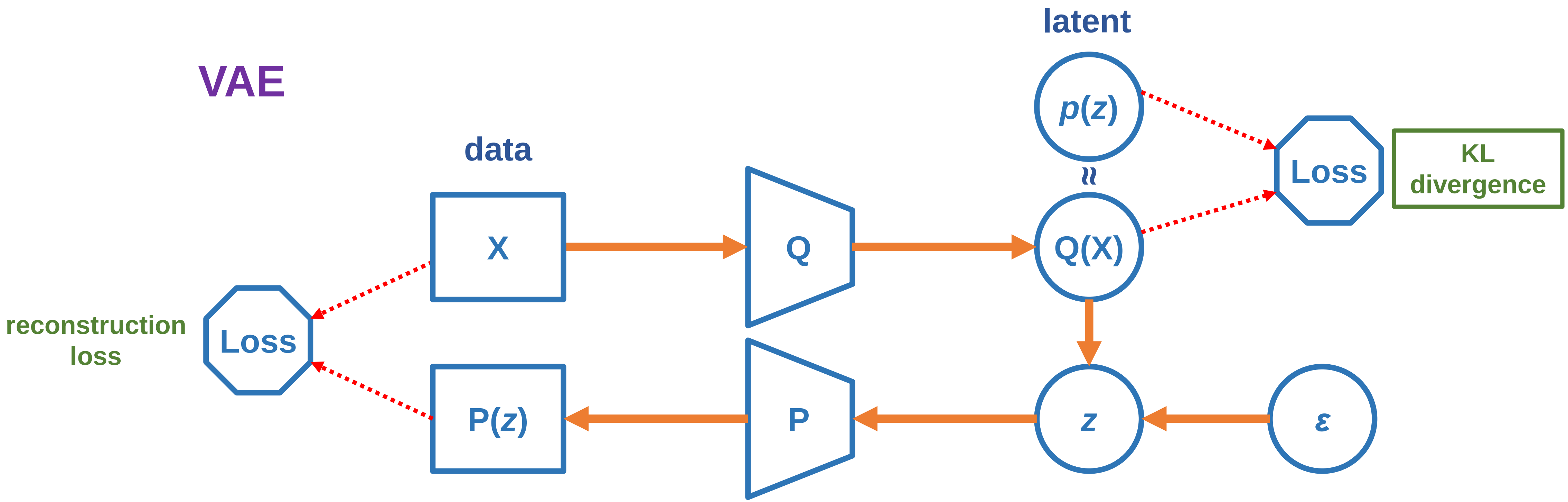


VAE/GAN

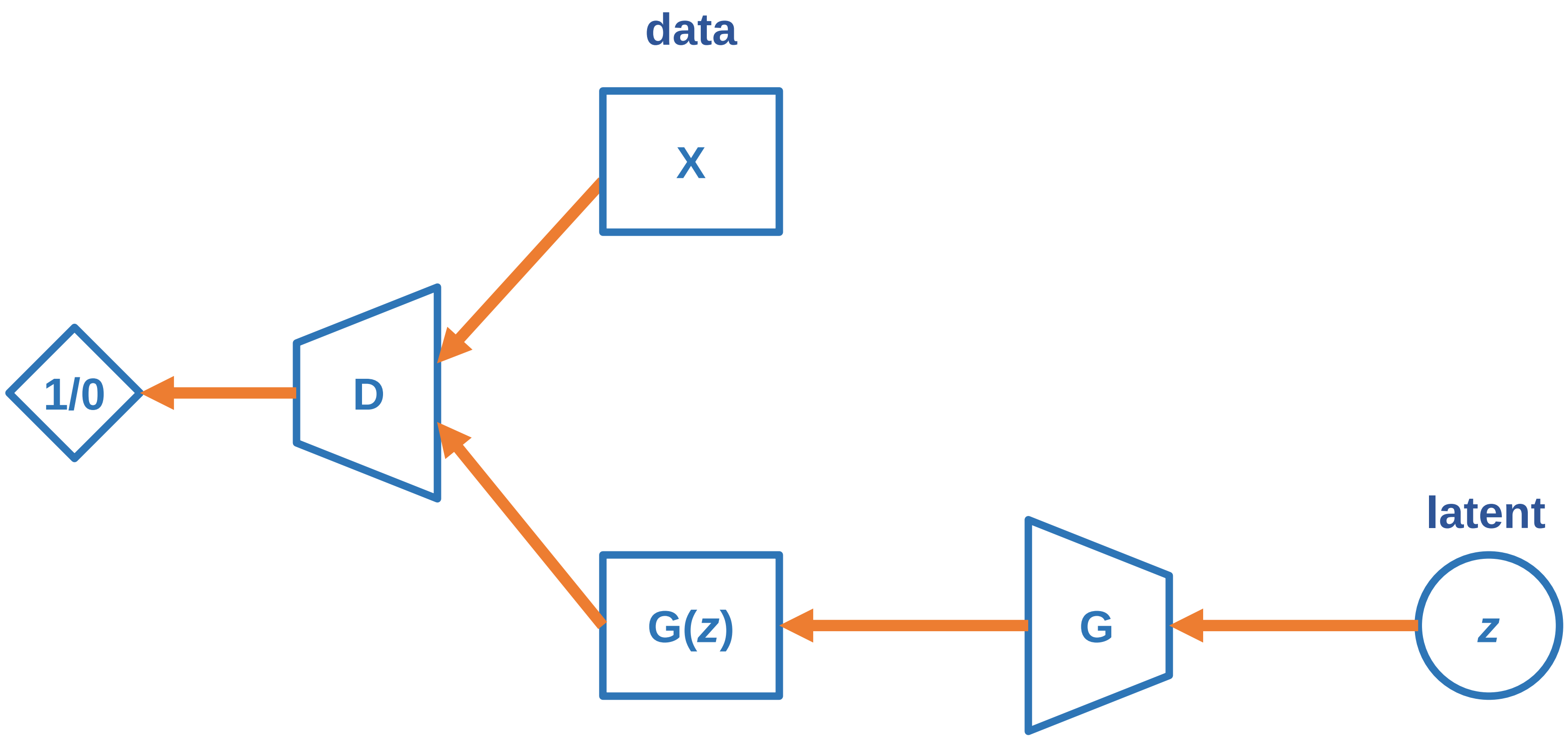
VAE



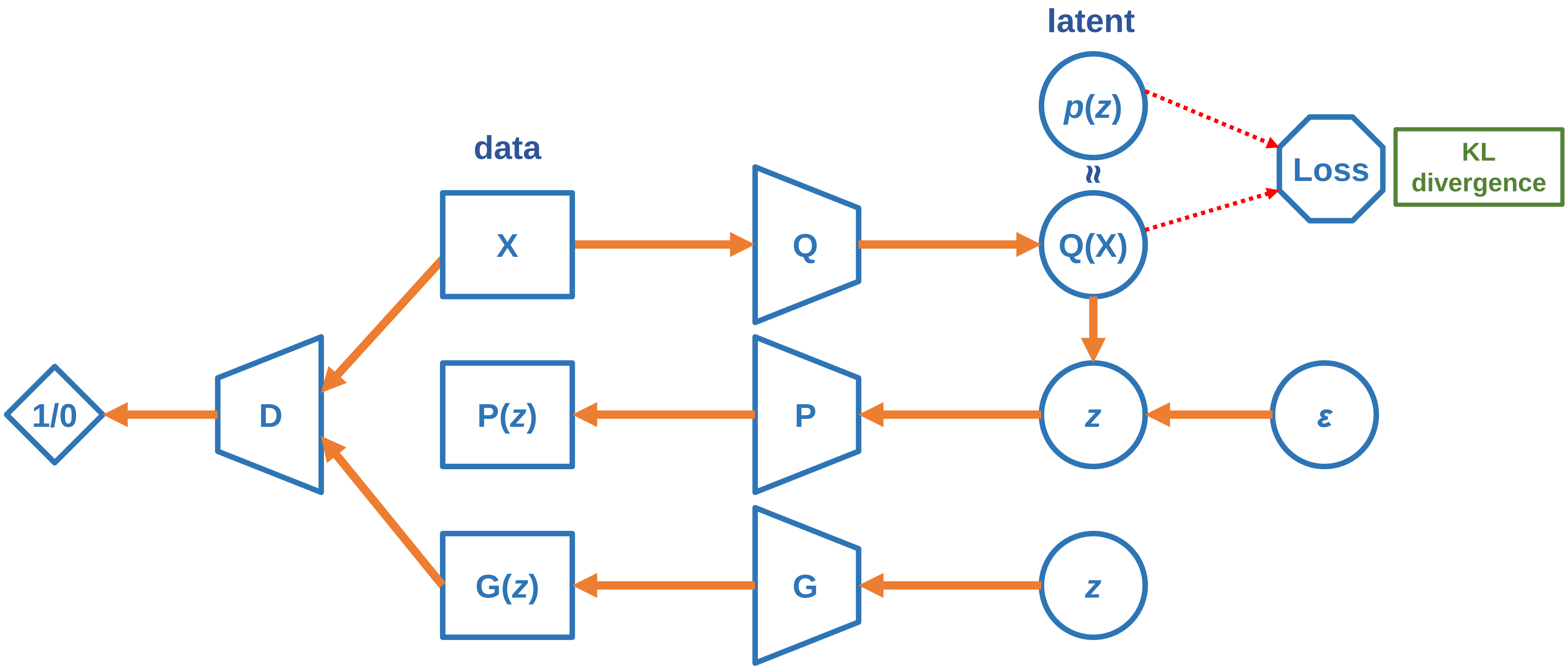
latent
p(z)
≀
data
X
Q
Q(X)
Loss
KL divergence
reconstruction loss
Loss
P(z)
P
z
ε

VAE/GAN

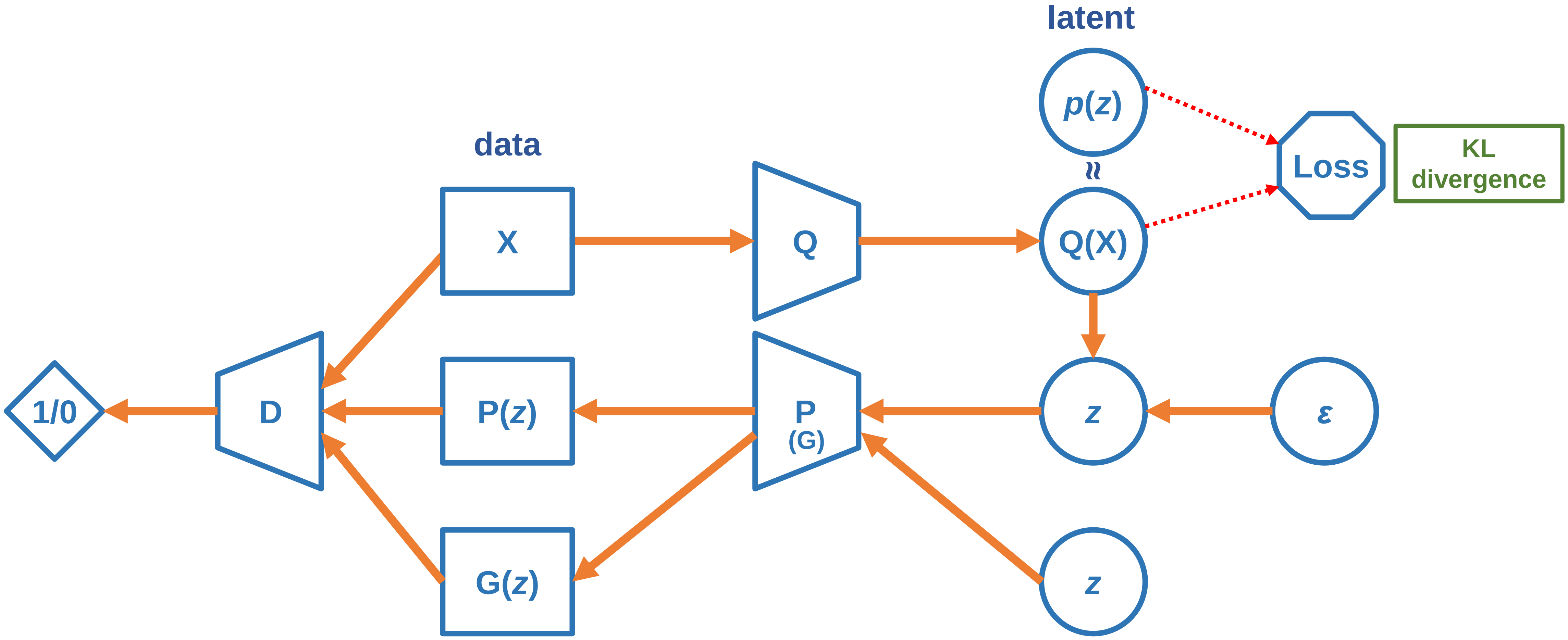
GAN



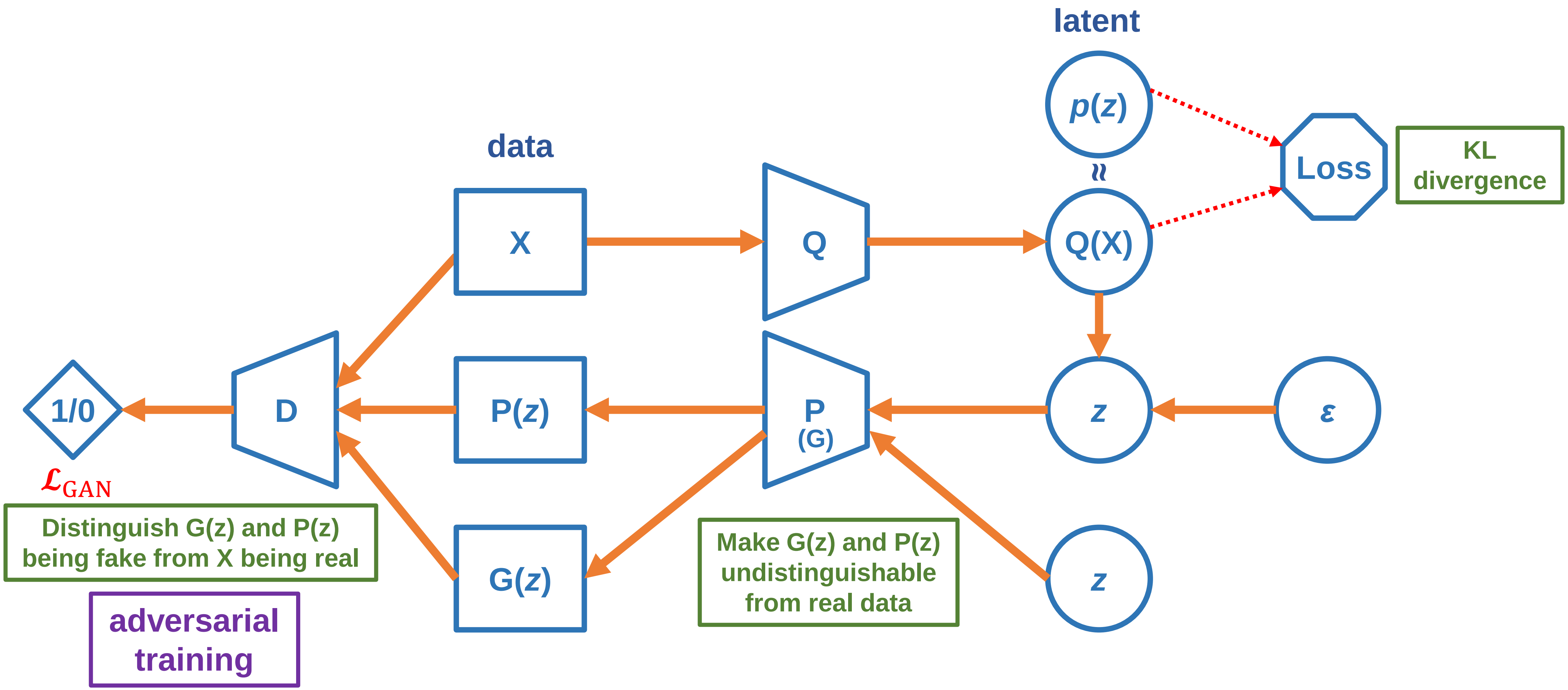
VAE/GAN



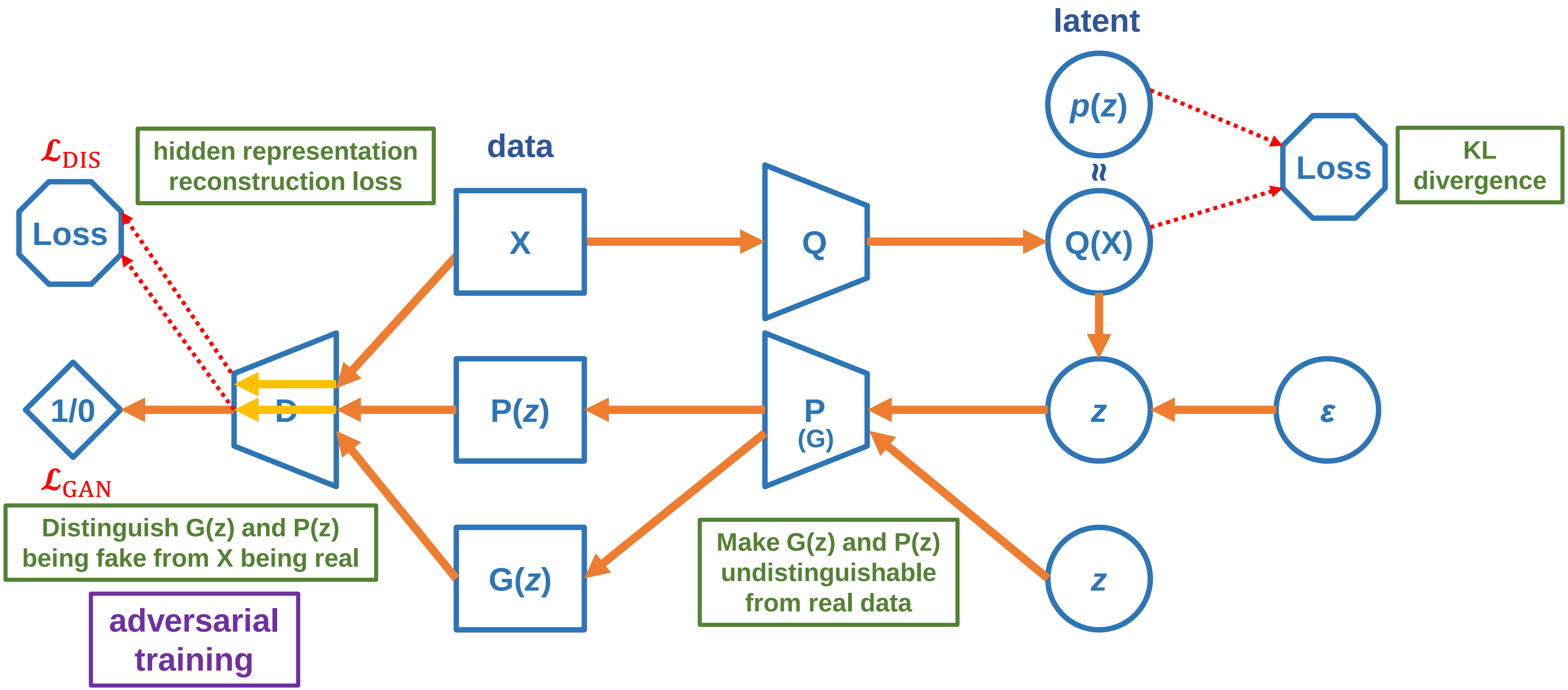
VAE/GAN



VAE/GAN


latent
data
p(z)
≈
Loss
KL divergence
X
Q
Q(X)
z
ε
1/0
D
P(z)
P (G)
$\mathcal{L}_{GAN}$
Distinguish G(z) and P(z) being fake from X being real
adversarial training
G(z)
Make G(z) and P(z) undistinguishable from real data
z

VAE/GAN



latent
$p(z)$
≀
Loss
KL divergence
data
hidden representation reconstruction loss
$\mathcal{L}_{\mathrm{DIS}}$
Loss
X
Q
Q(X)
1/0
D
P(z)
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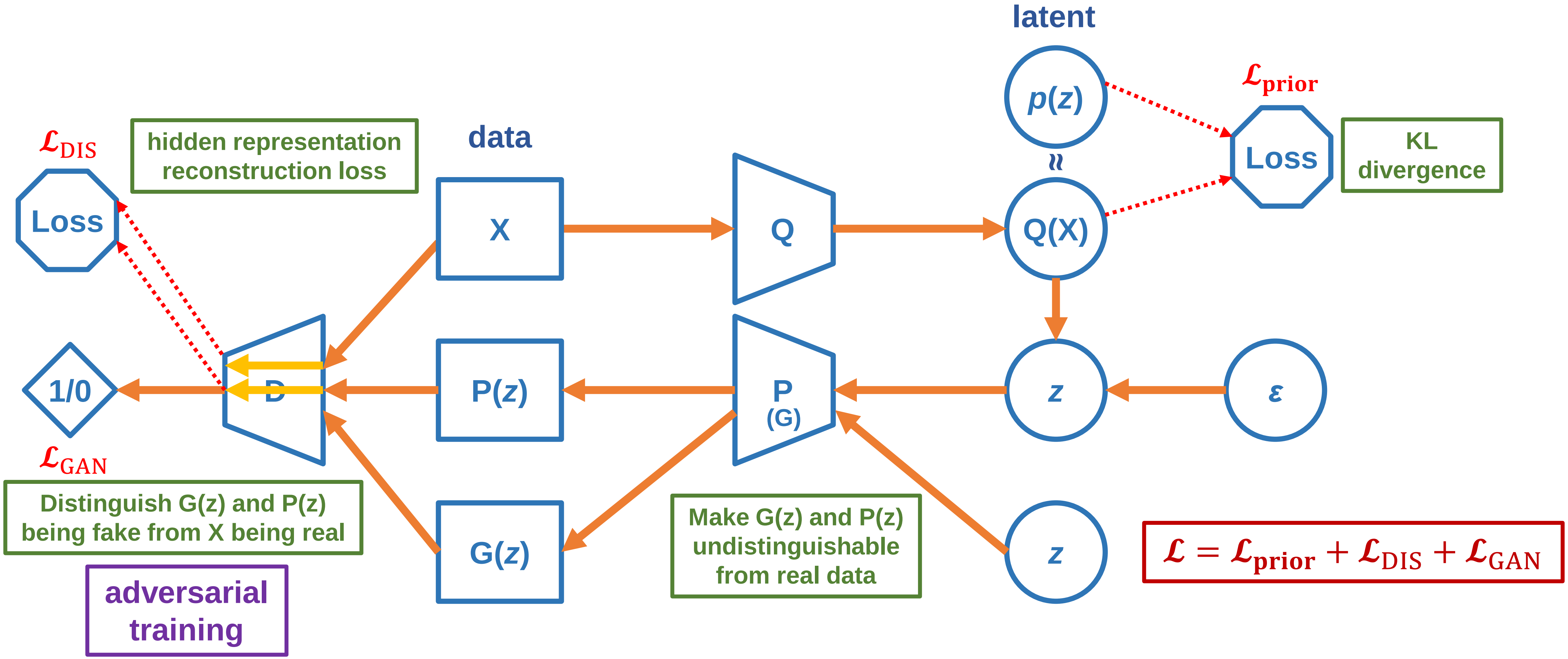
latent
data
$\mathcal{L}_{\text{DIS}}$
hidden representation reconstruction loss
Loss
X
Q
p(z)
≈
Q(X)
$\mathcal{L}_{\text{prior}}$
Loss
KL divergence
1/0
D
P(z)
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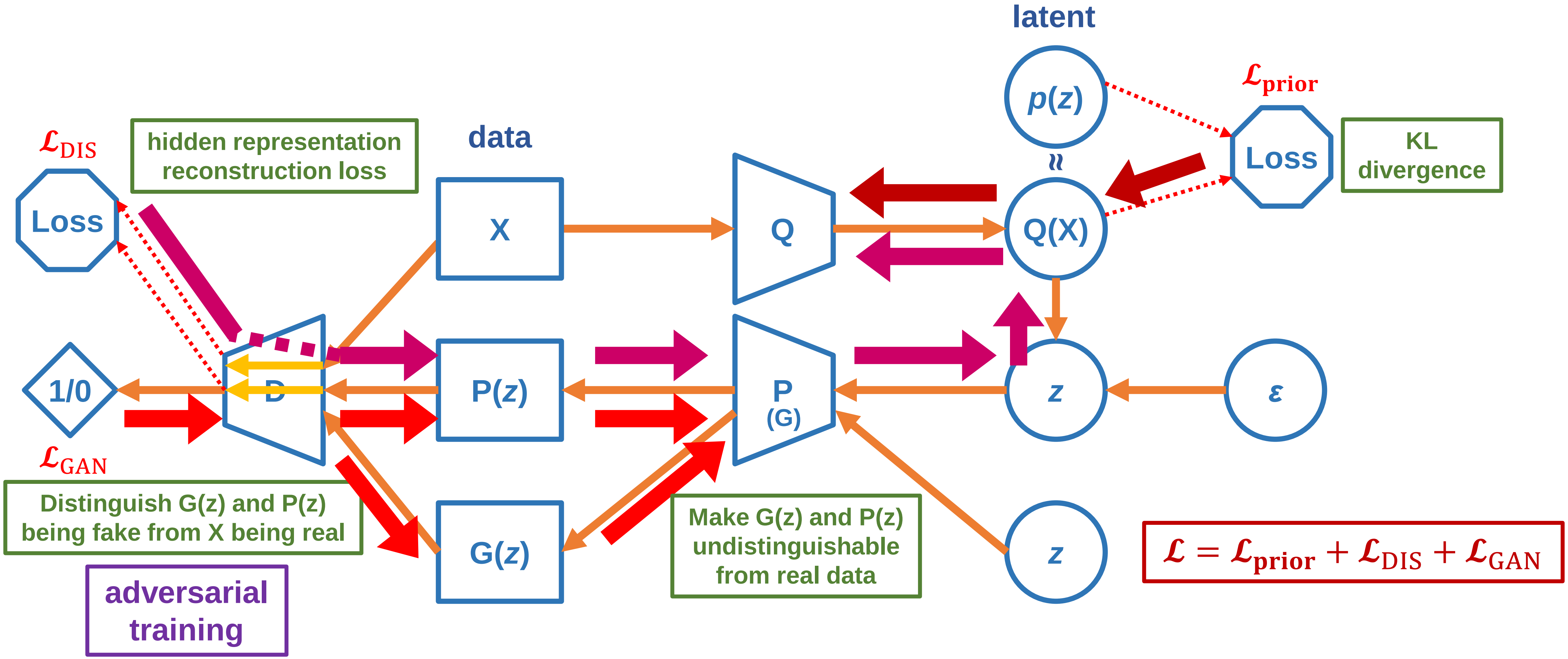
$\mathcal{L} = \mathcal{L}_{\text{prior}} + \mathcal{L}_{\text{DIS}} + \mathcal{L}_{\text{GAN}}$

VAE/GAN


latent
data
$\mathcal{L}_{\text{DIS}}$
hidden representation reconstruction loss
Loss
X
Q
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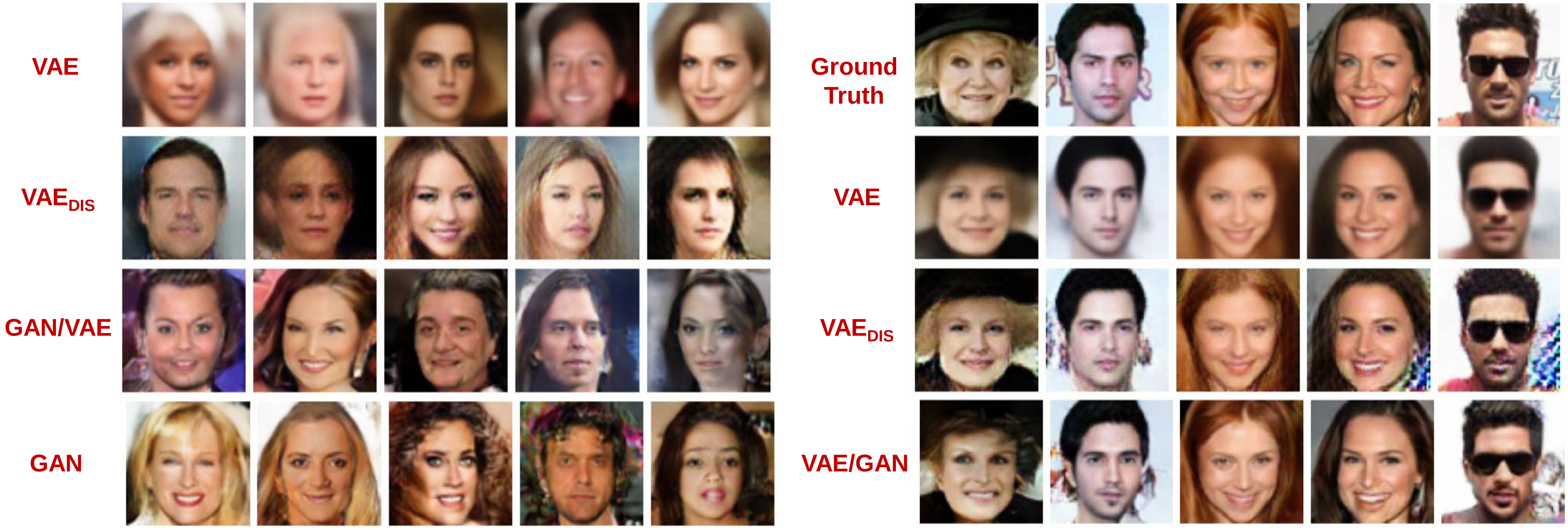

Generation test **Reconstruction test**

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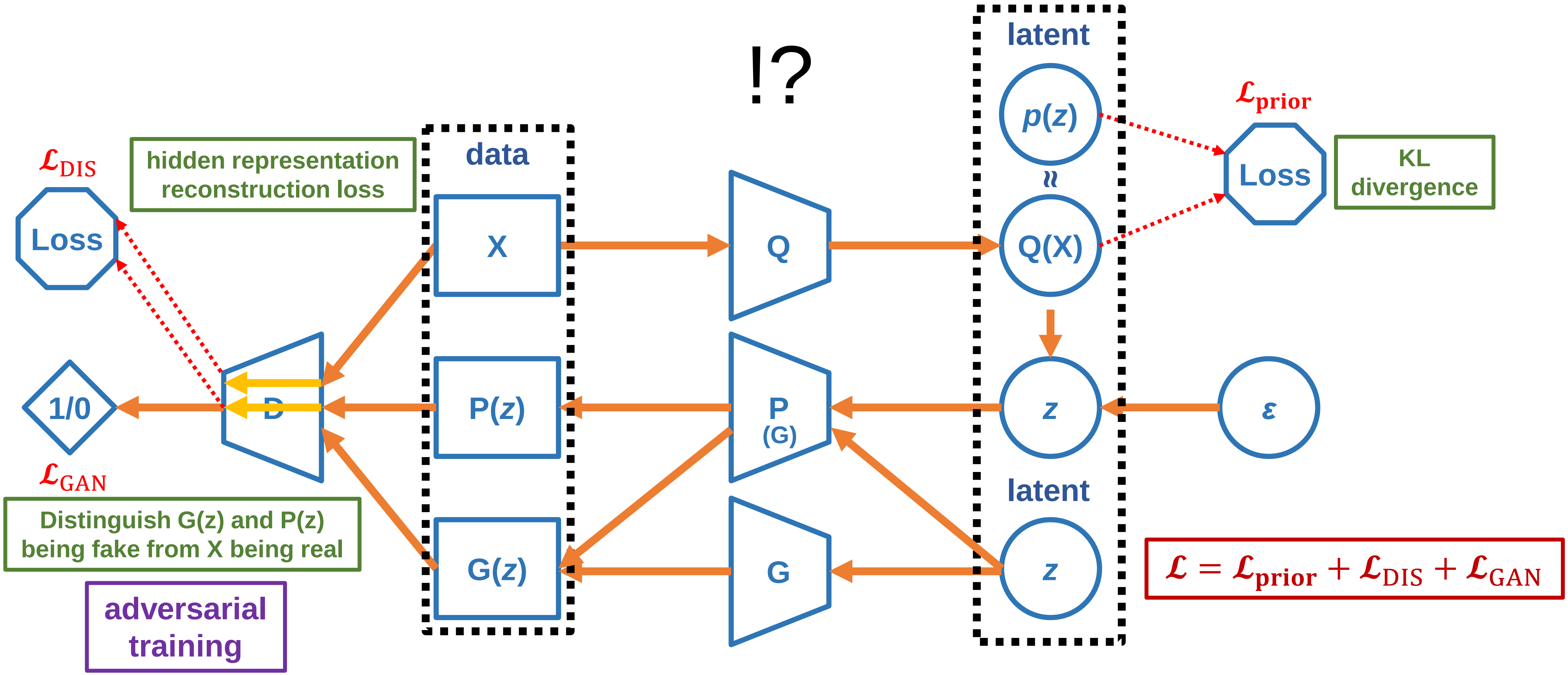
VAE/GAN


!?
latent
p(z)
≈
Q(X)
z
latent
z
ε
$\mathcal{L}_{\text{prior}}$
Loss
KL divergence
data
X
P(z)
G(z)
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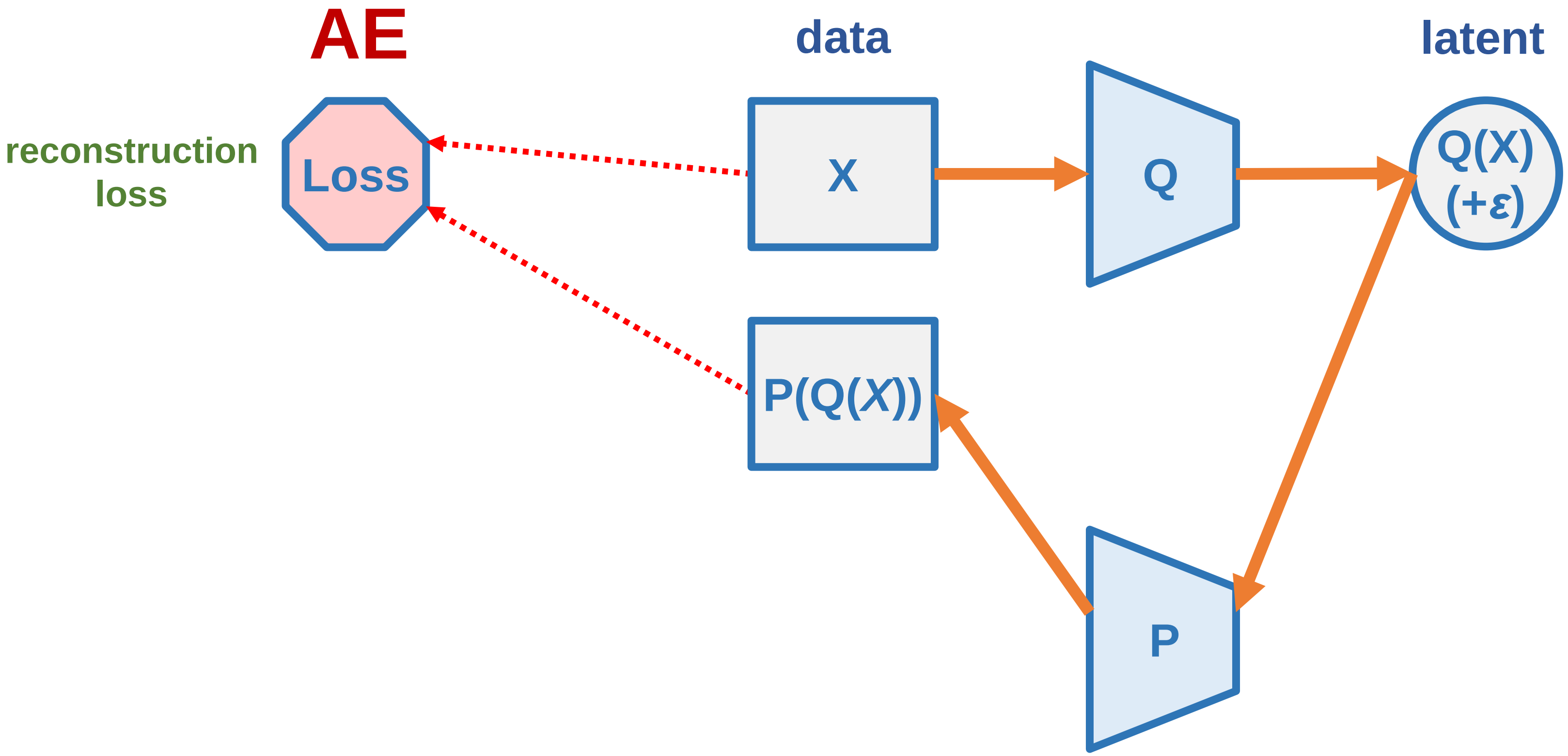
What's going on?



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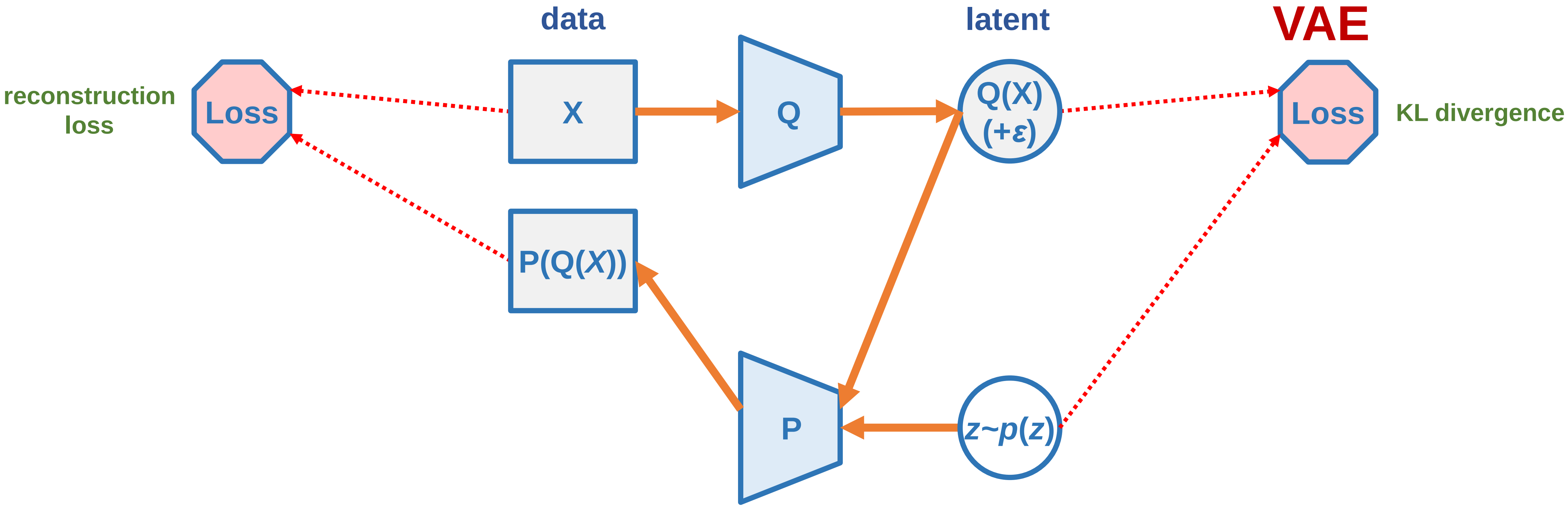

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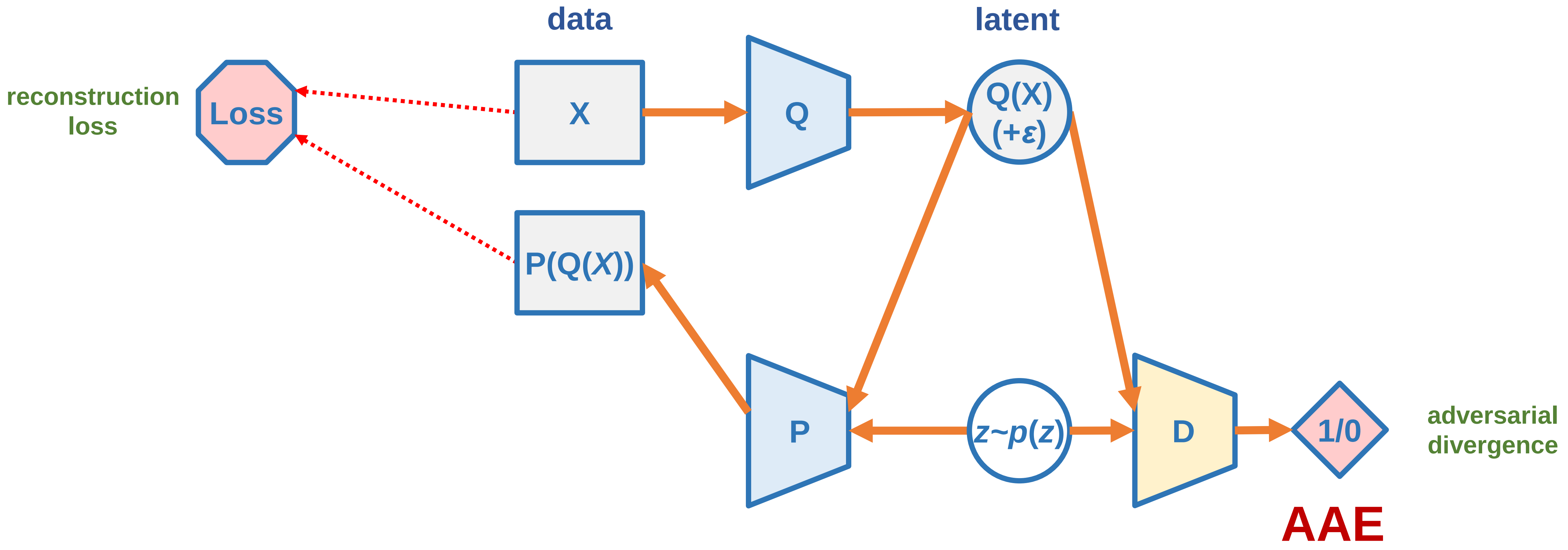

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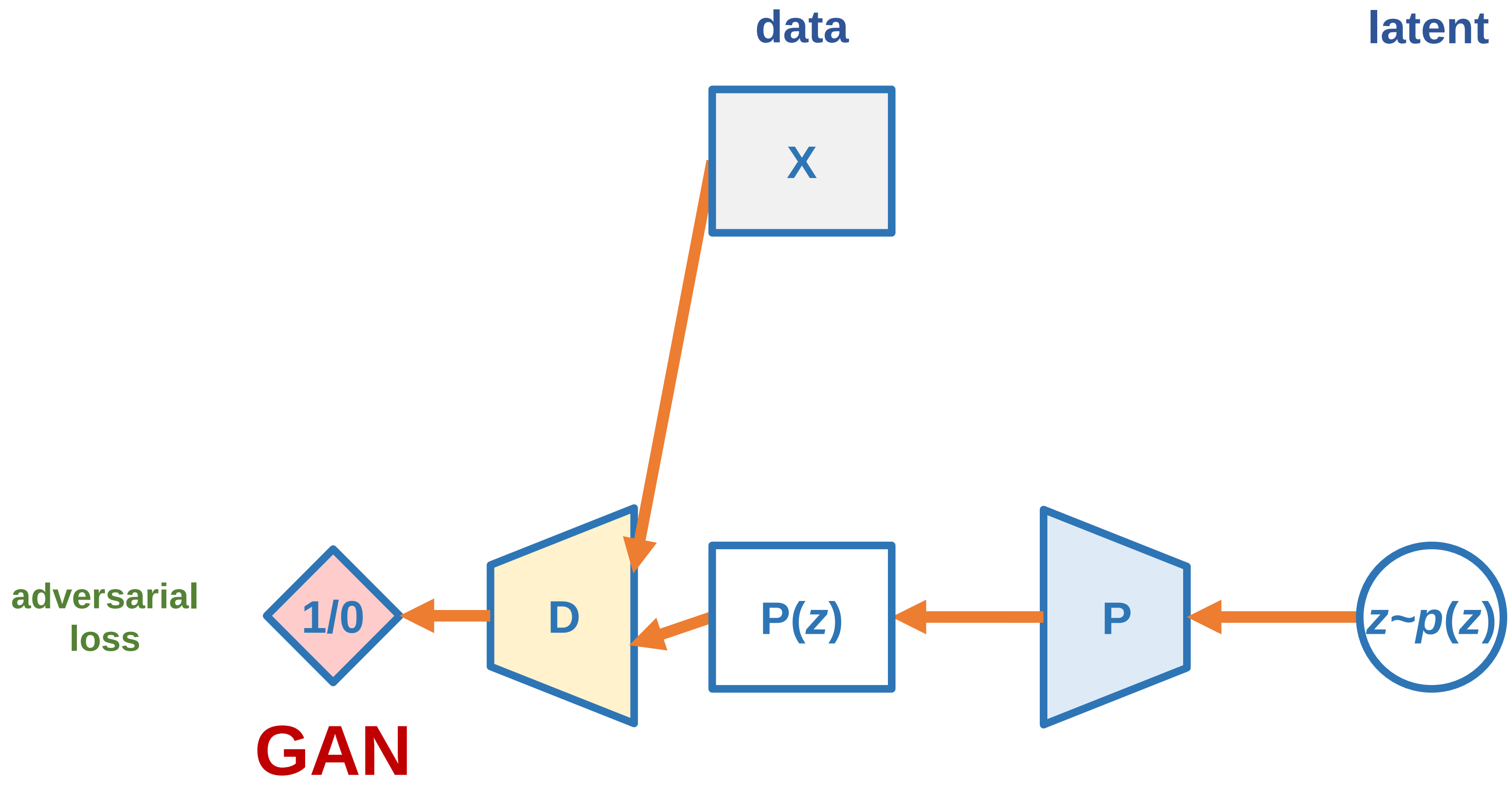

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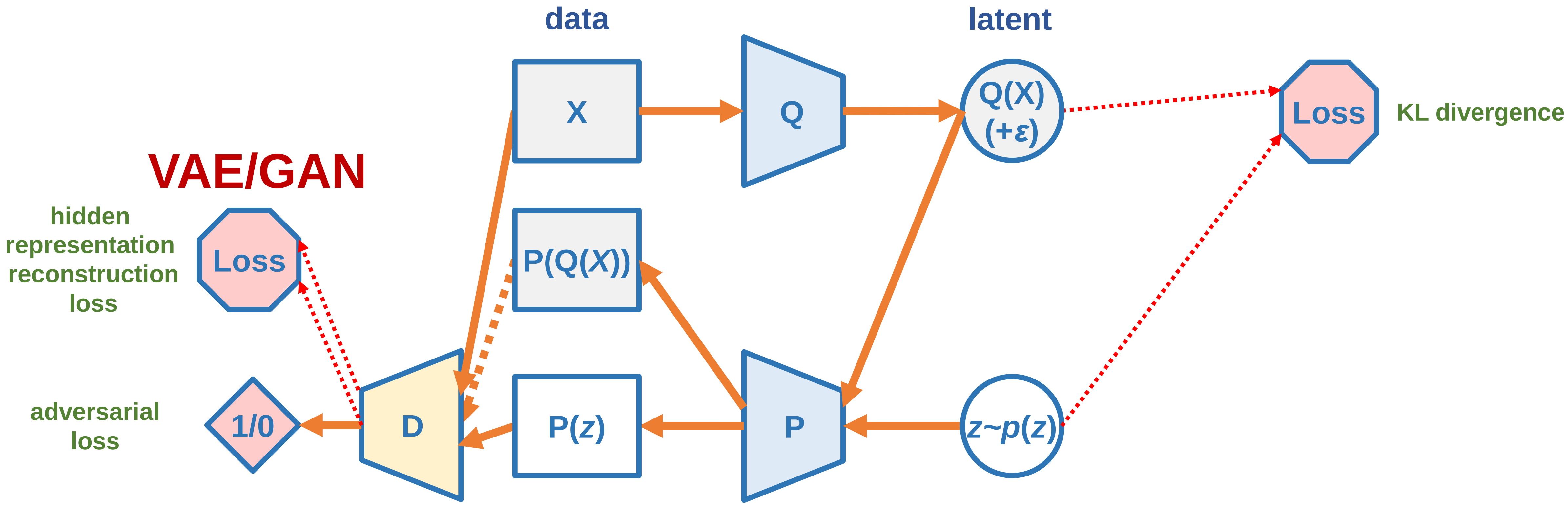

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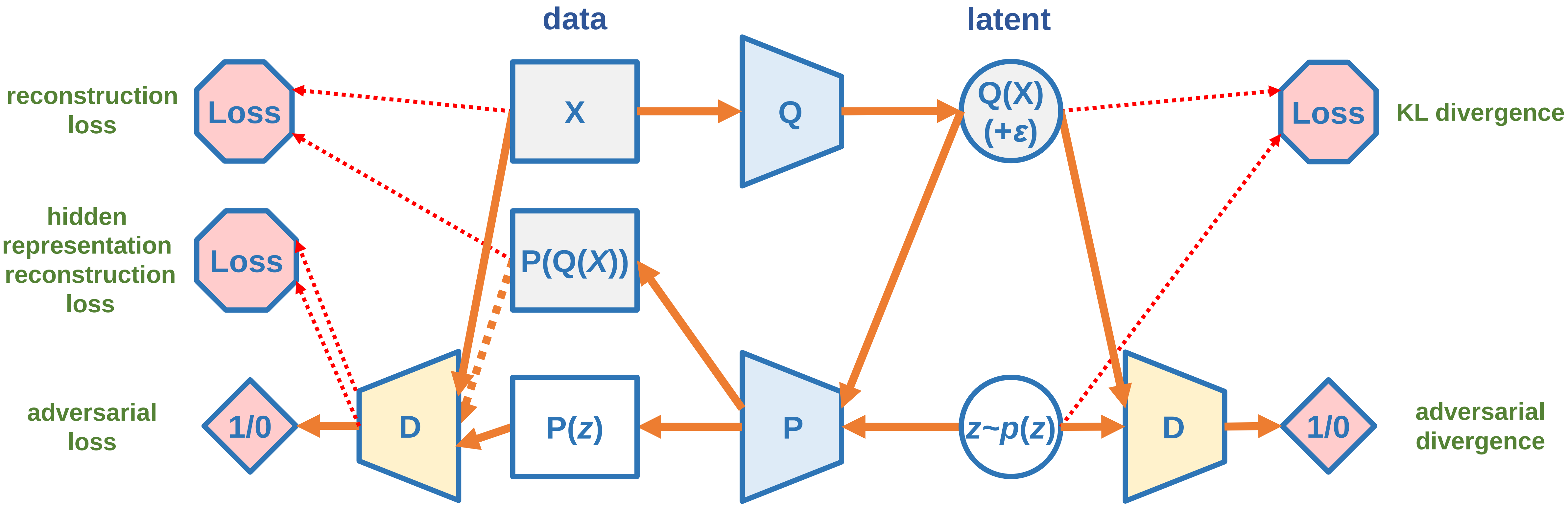
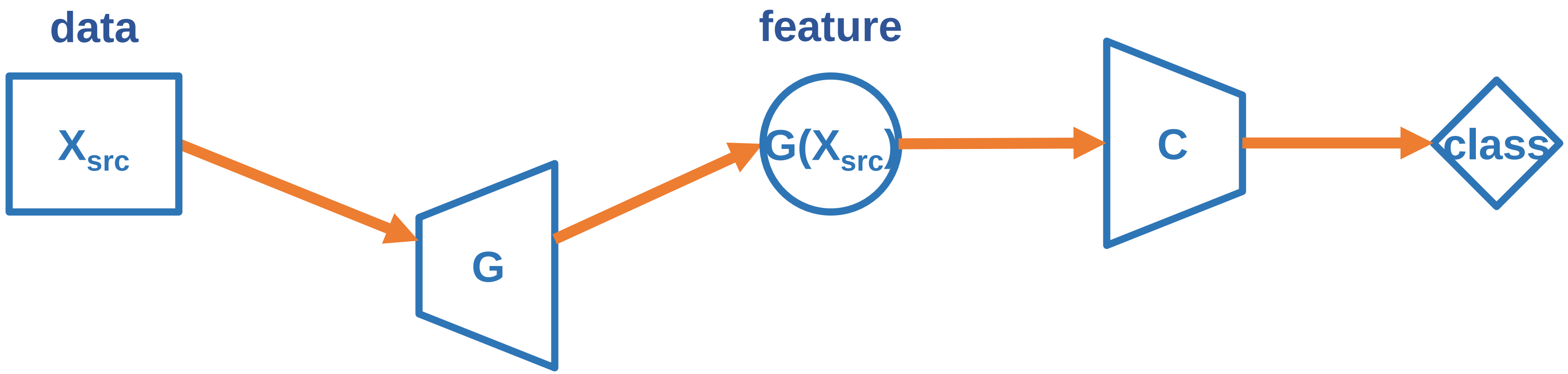


ADA (Adversarial Domain Adaption)

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



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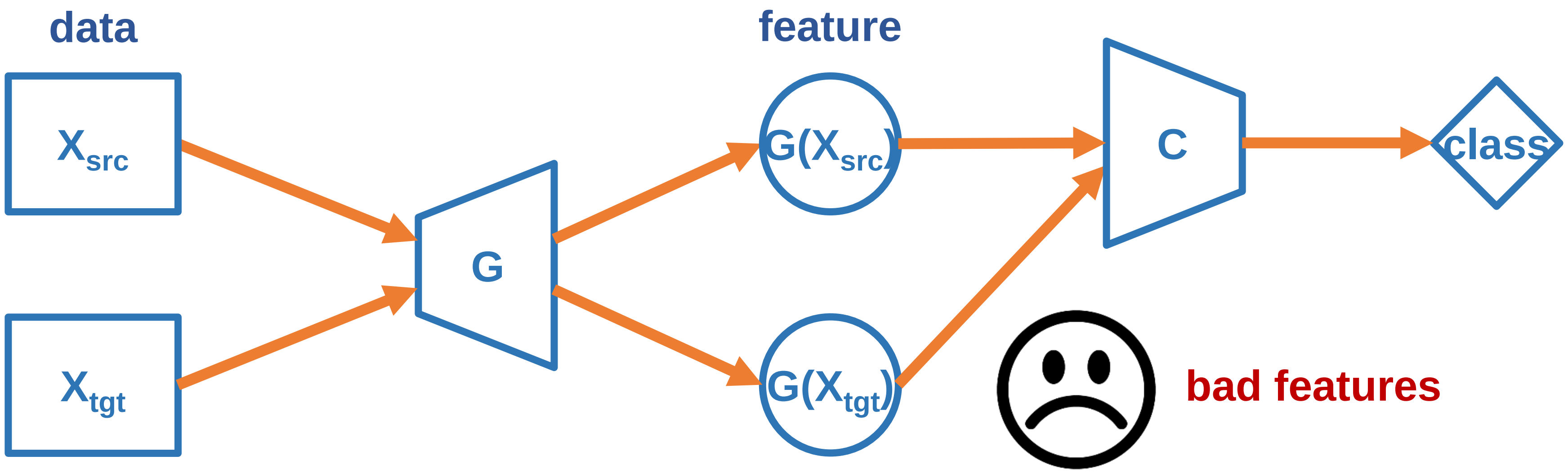

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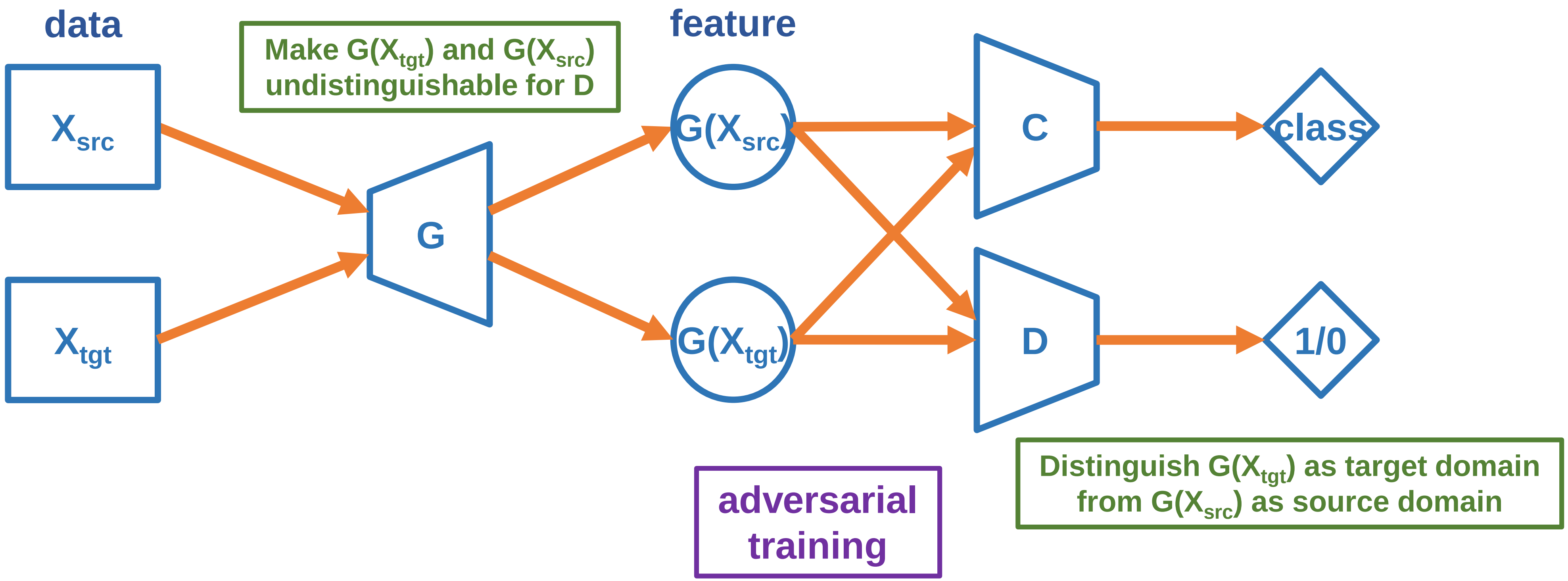

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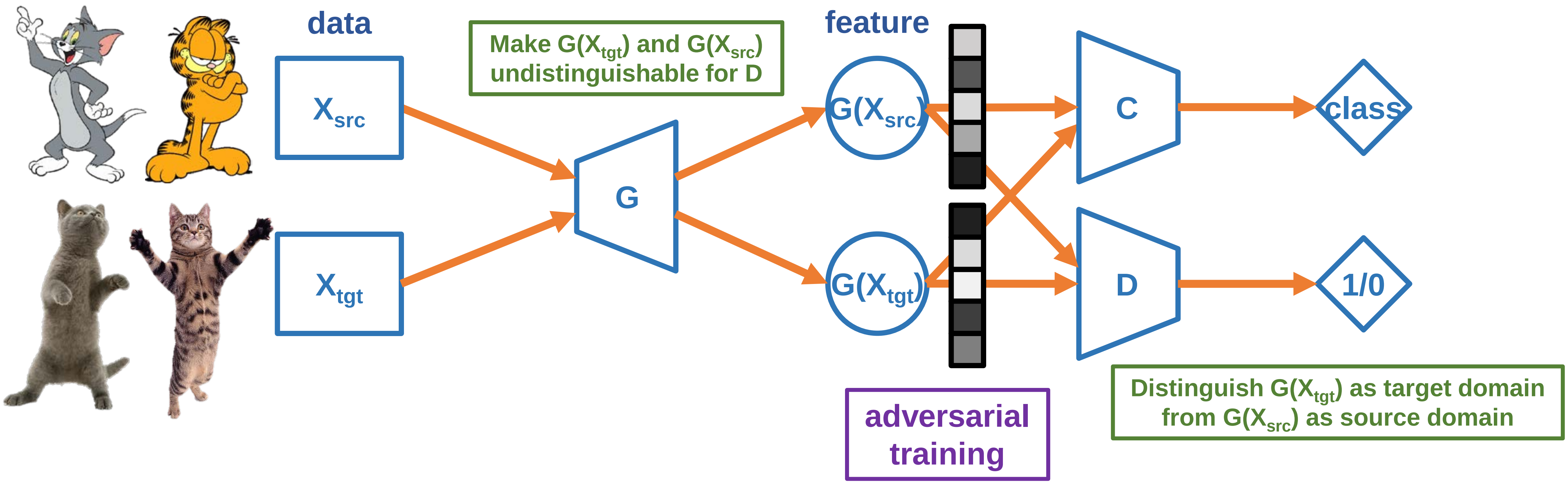

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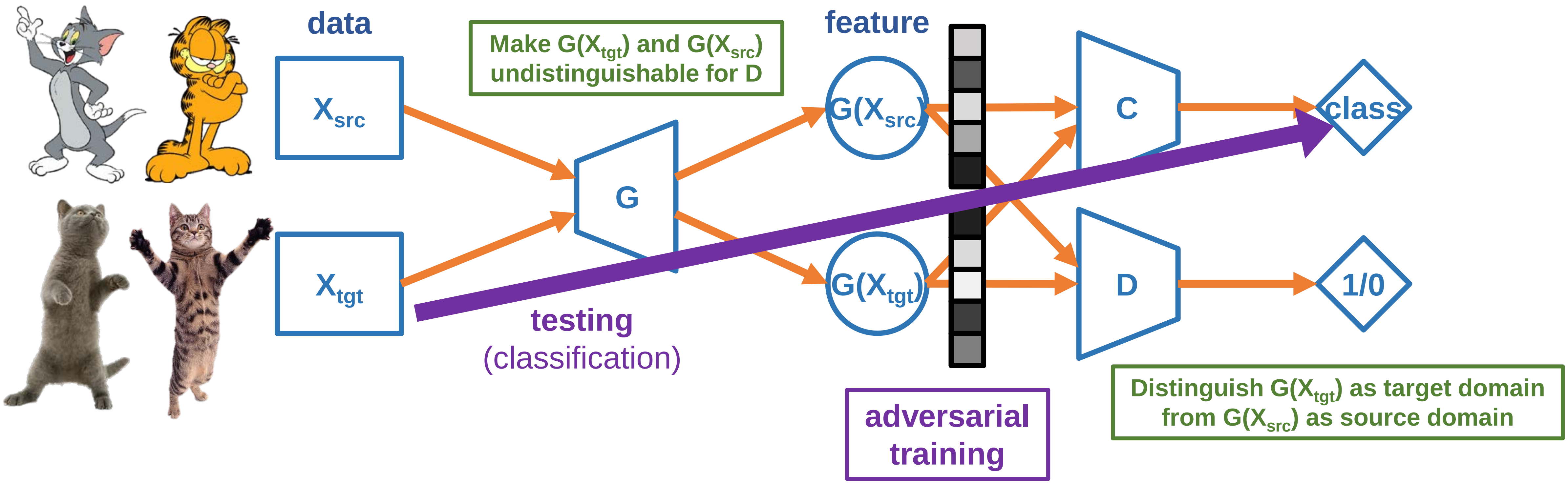
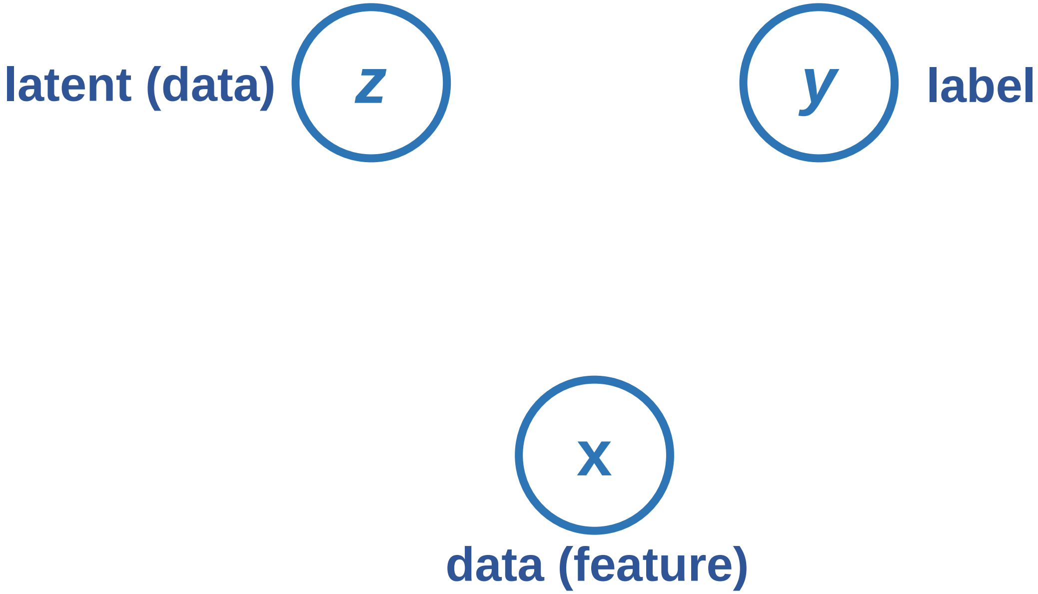


On Unifying Deep Generative Models



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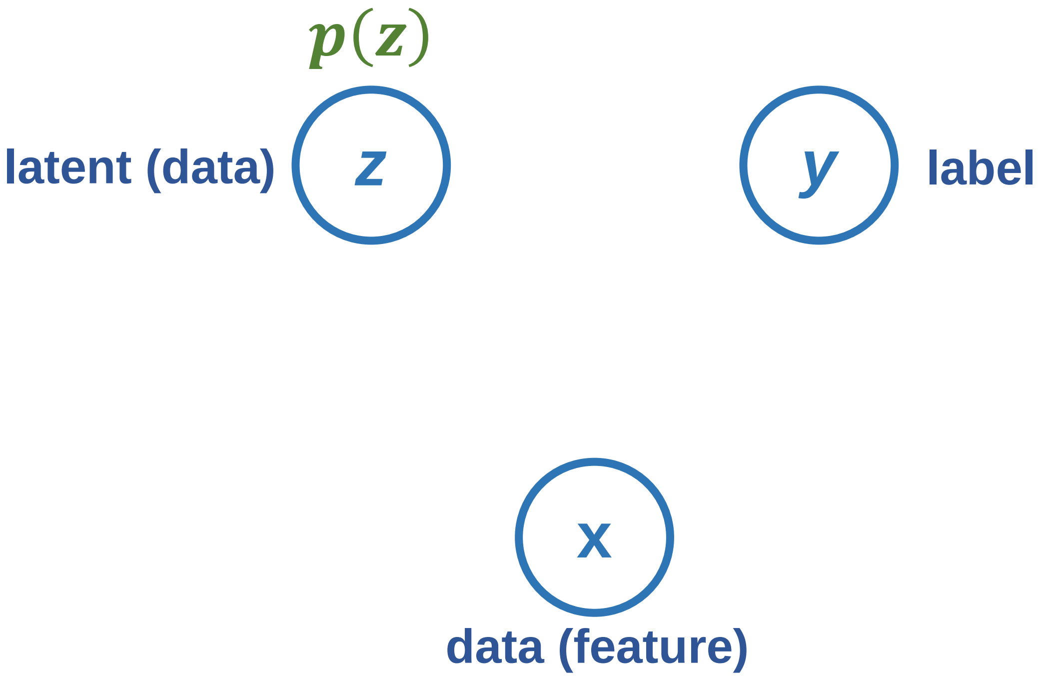
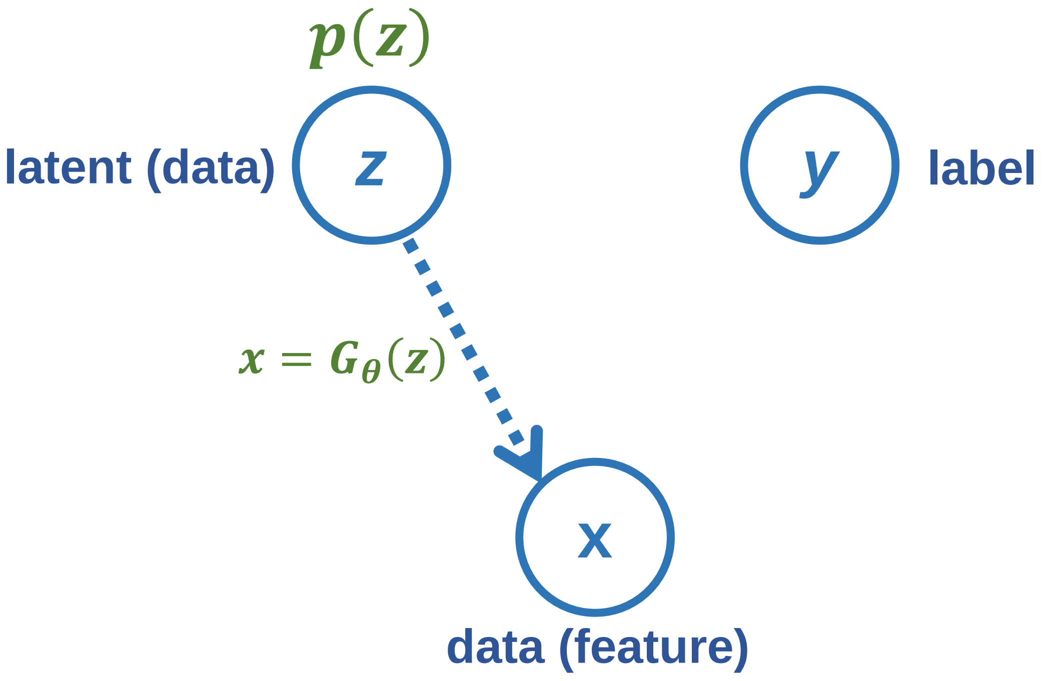


On Unifying Deep Generative Models

- $G_\theta - \theta$ are parameters in generator
- $D_\phi - \phi$ are parameters in generator

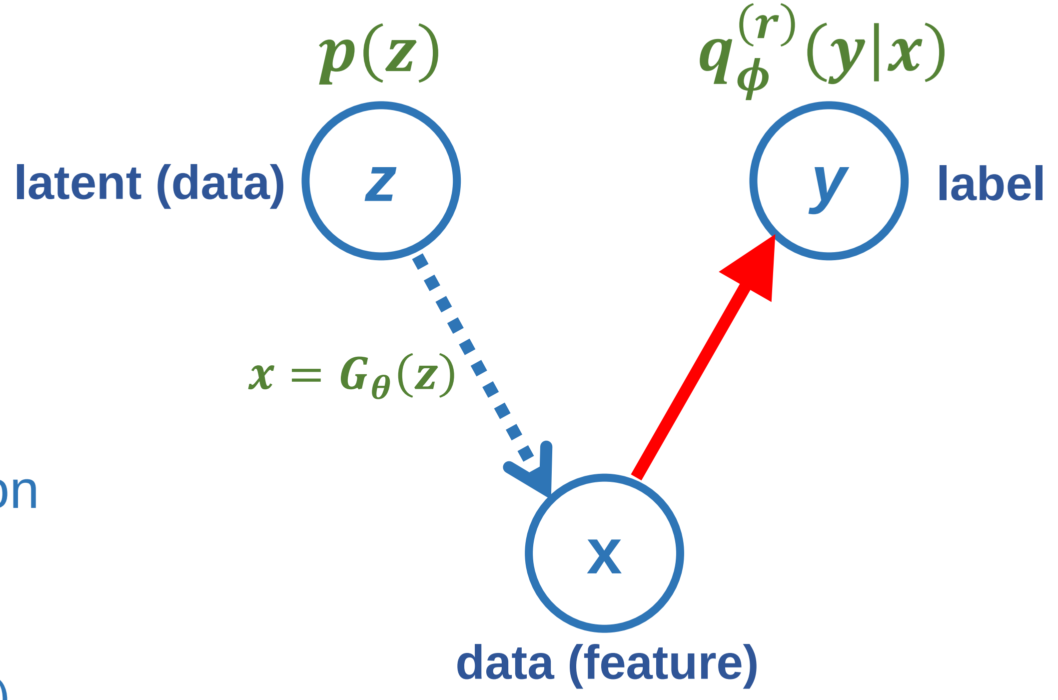


On Unifying Deep Generative Models

- 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 $q_\phi(1-y|x)$



GAN $y = \begin{cases} 1, & if\ x\ is\ real \\ 0, & if\ x\ is\ fake \end{cases}$

ADA $y = \begin{cases} 1, & if\ x\ is\ in\ source\ domain \\ 0, & if\ x\ is\ in\ target\ domain \end{cases}$

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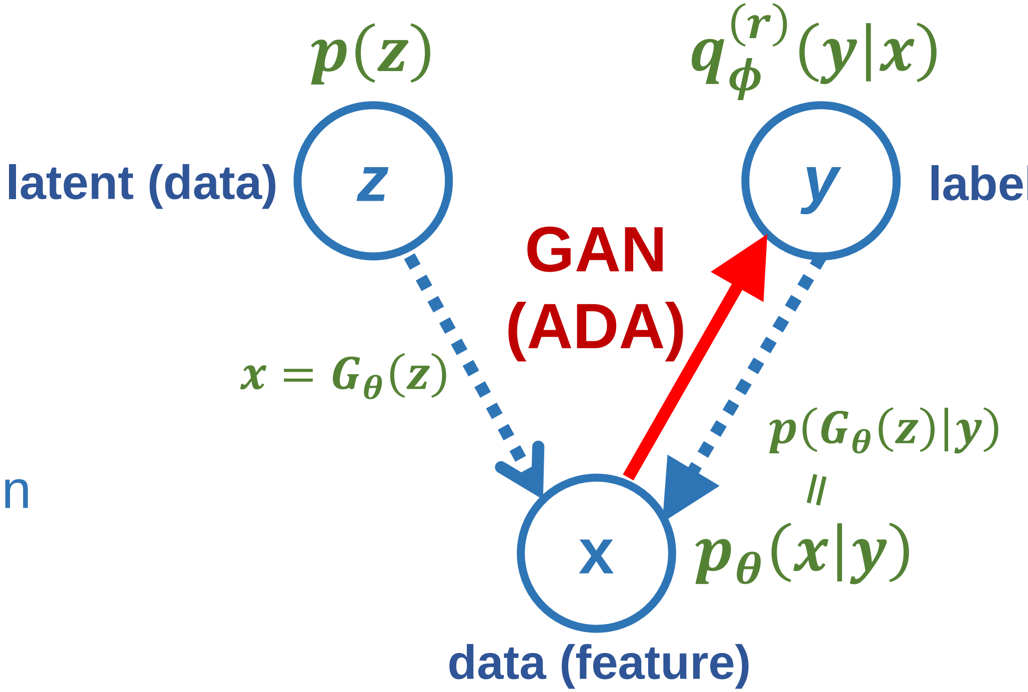

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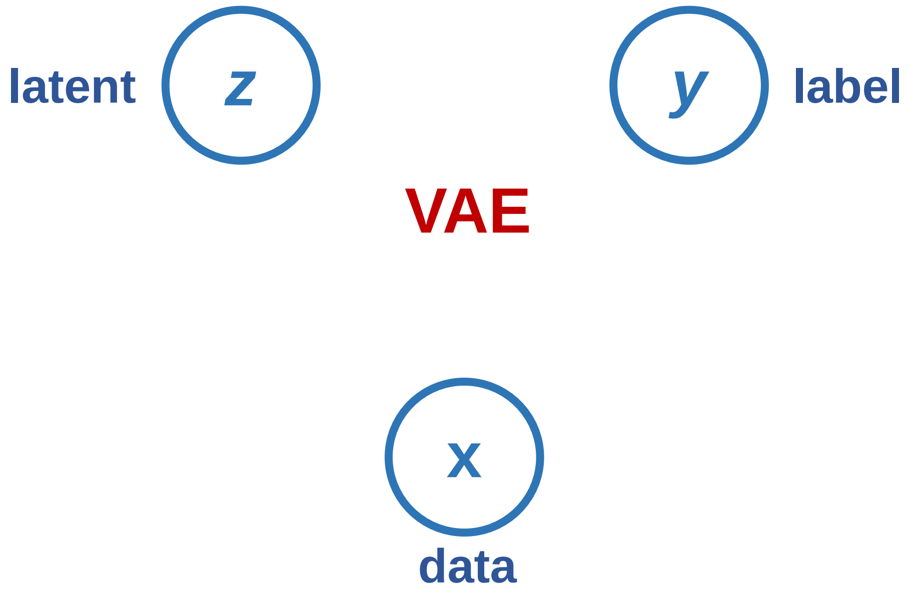
On Unifying Deep Generative Models



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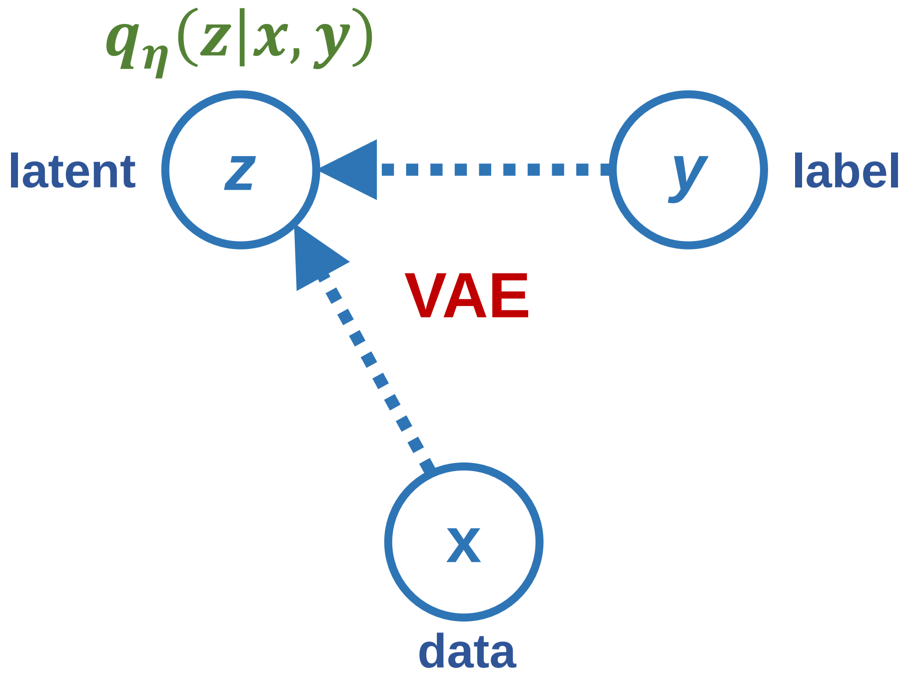

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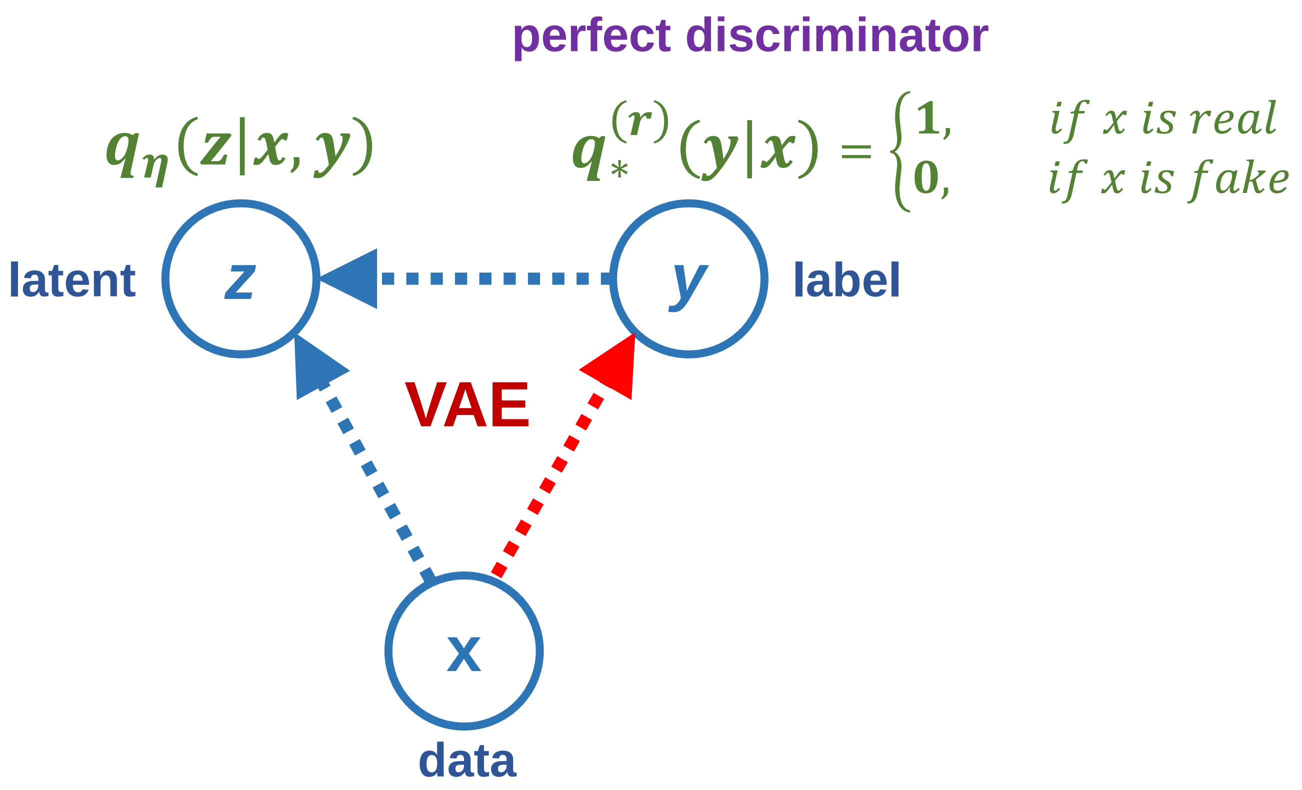

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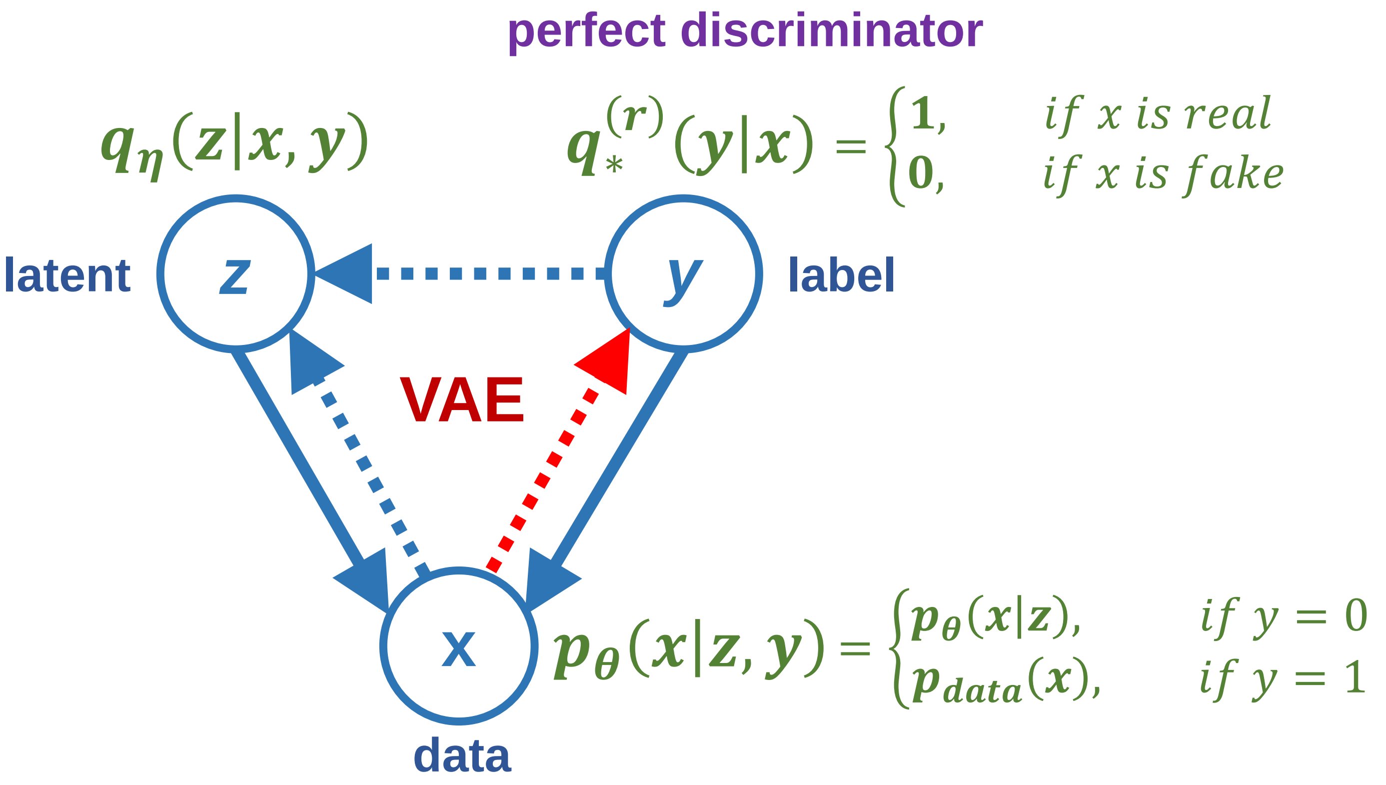
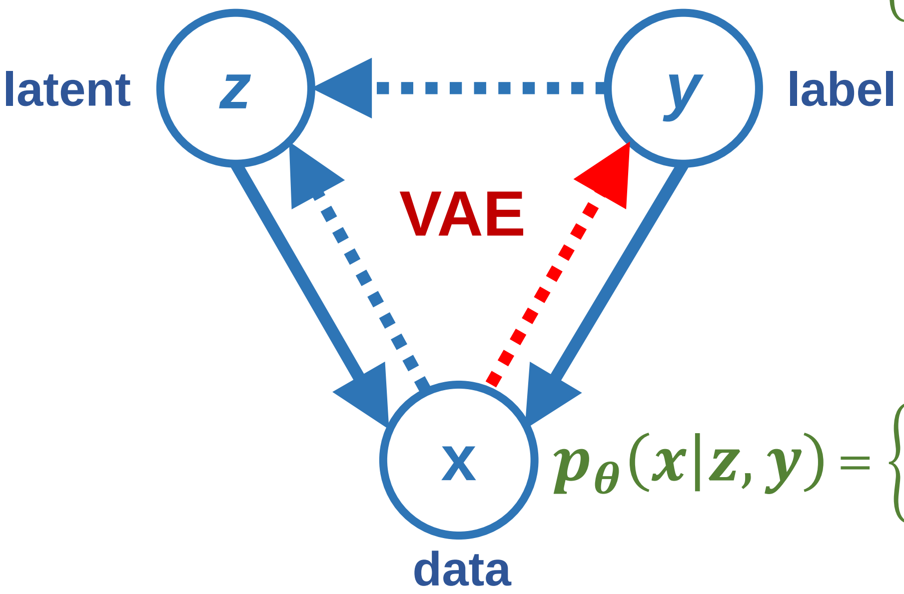


On Unifying Deep Generative Models

perfect discriminator

$$q_\eta(z|x,y)$$

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



degenerated adversarial discriminator

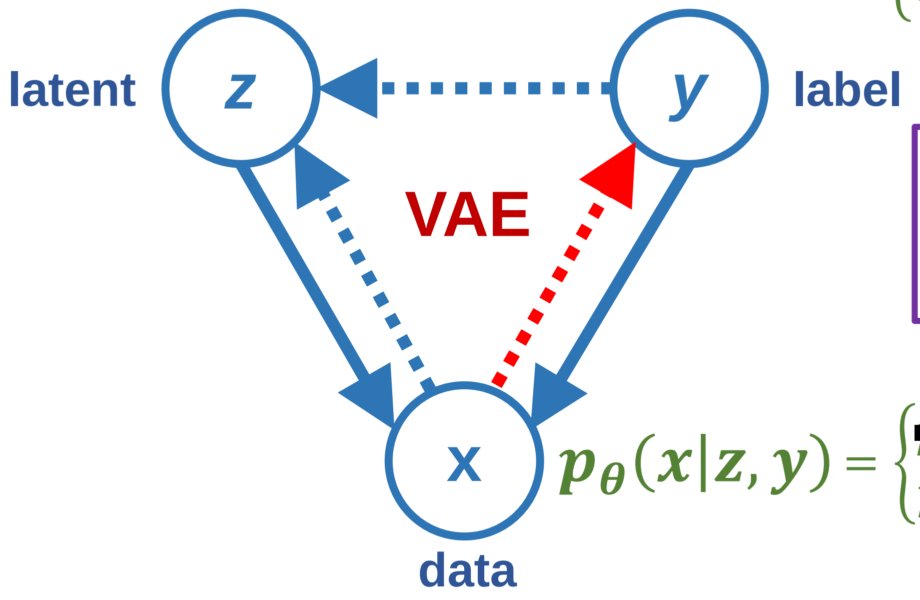
$$p_\theta(x|z,y) = \begin{cases} \cancel{p_\theta(x|z),} & \cancel{if\ y=0} \\ p_{data}(x), & if\ y=1 \end{cases}$$

On Unifying Deep Generative Models

perfect discriminator

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

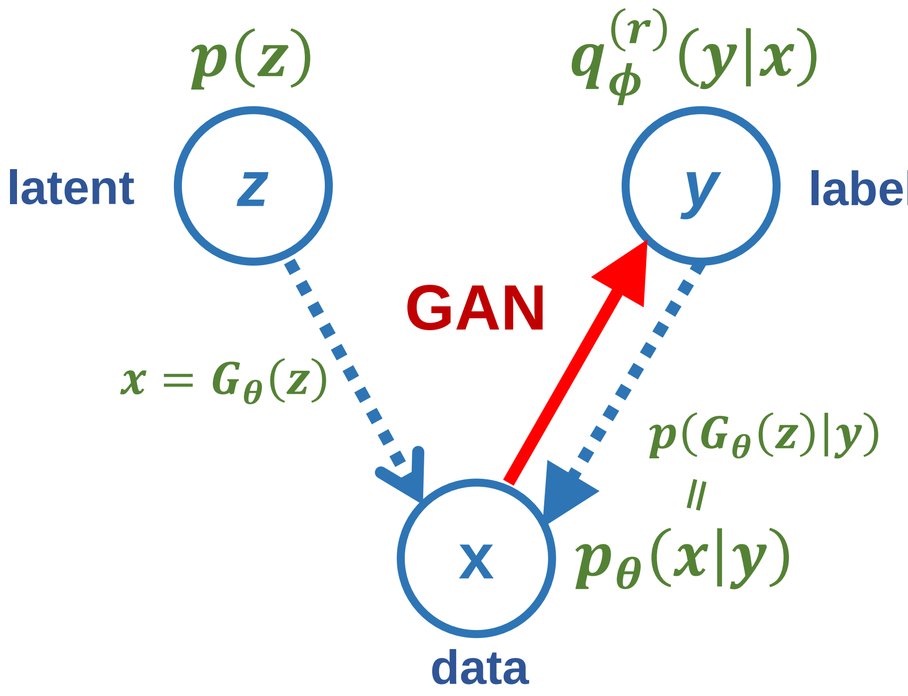
$$q_\eta(z|x, y)$$

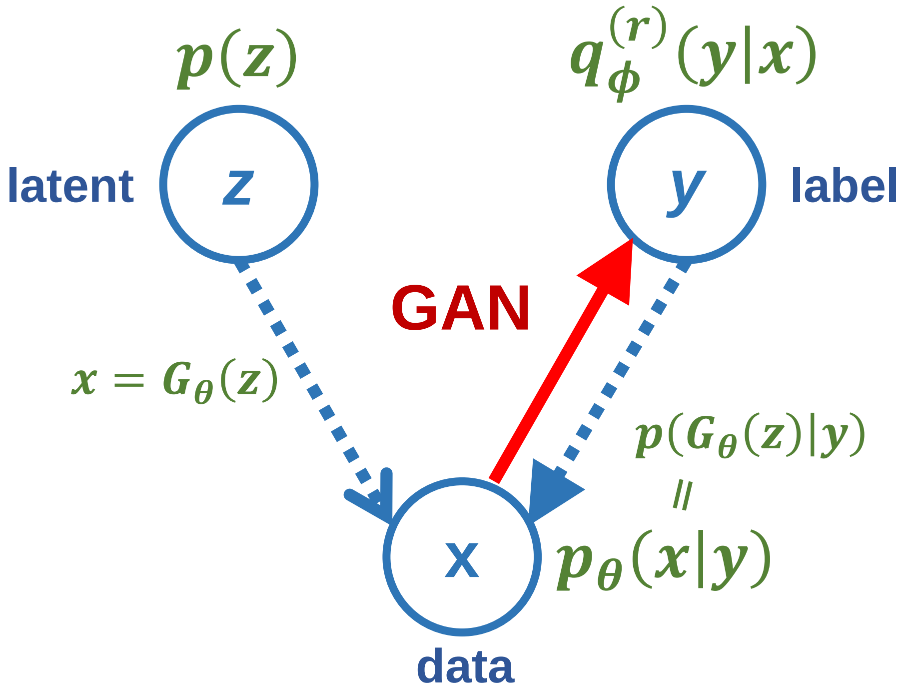


$$p_\theta(x|z, y) = \begin{cases} \cancel{p_\theta(x|z),} & \cancel{if\ y = 0} \\ p_{data}(x), & if\ y = 1 \end{cases}$$

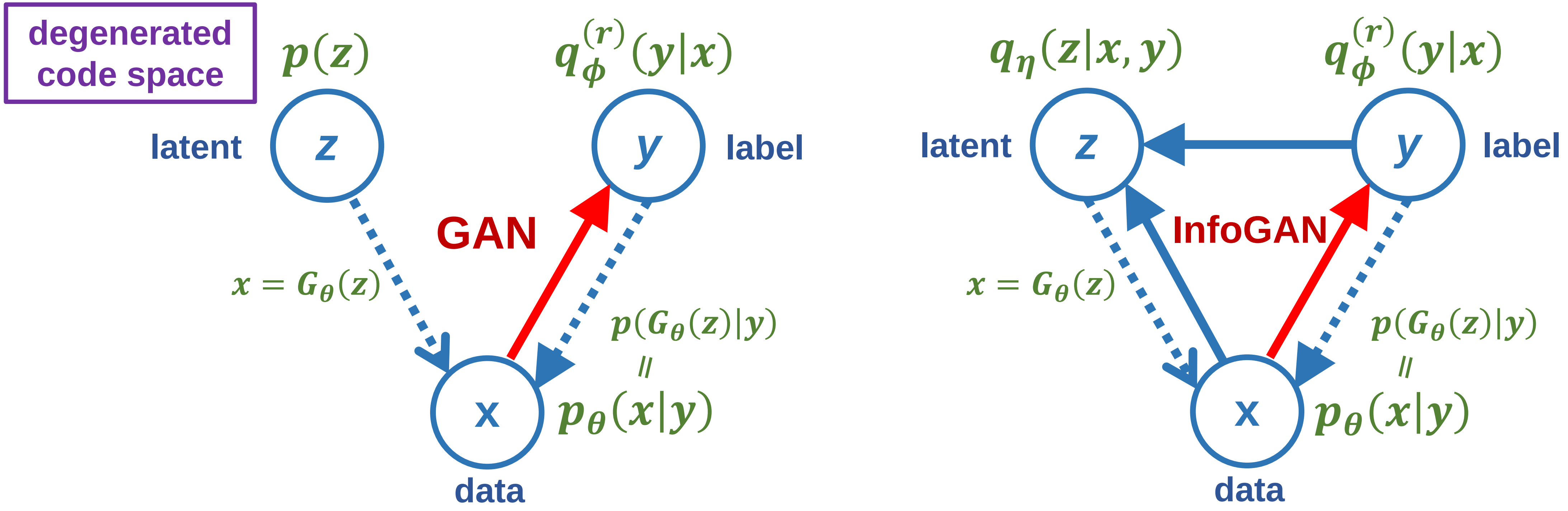
degenerated adversarial discriminator ⇒ **adversary activated VAE (AAVAE)**

On Unifying Deep Generative Models

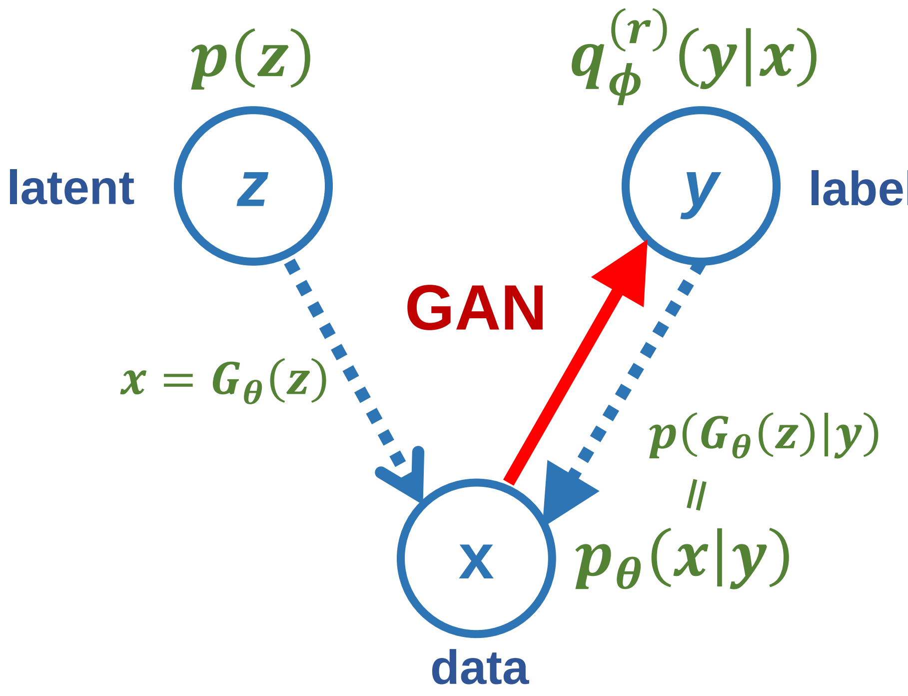


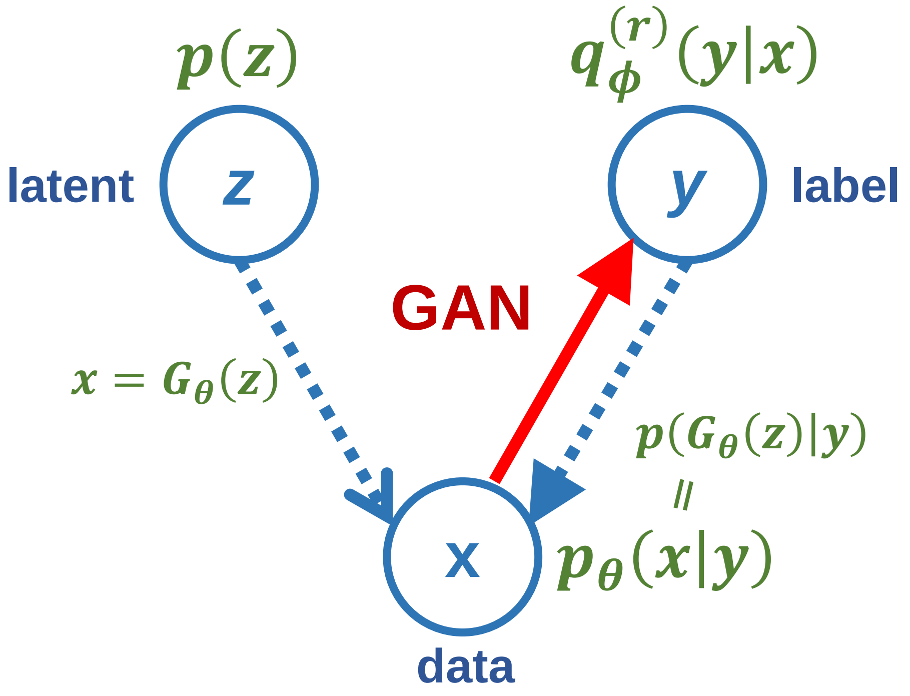


On Unifying Deep Generative Models

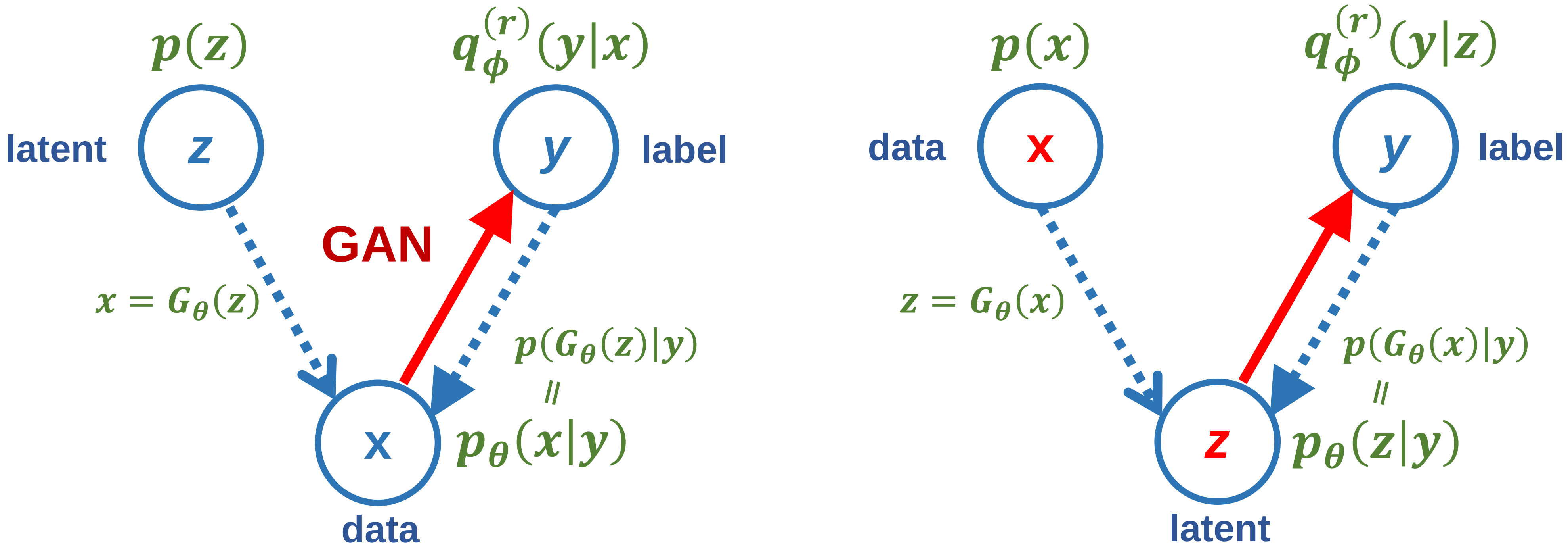


On Unifying Deep Generative Models

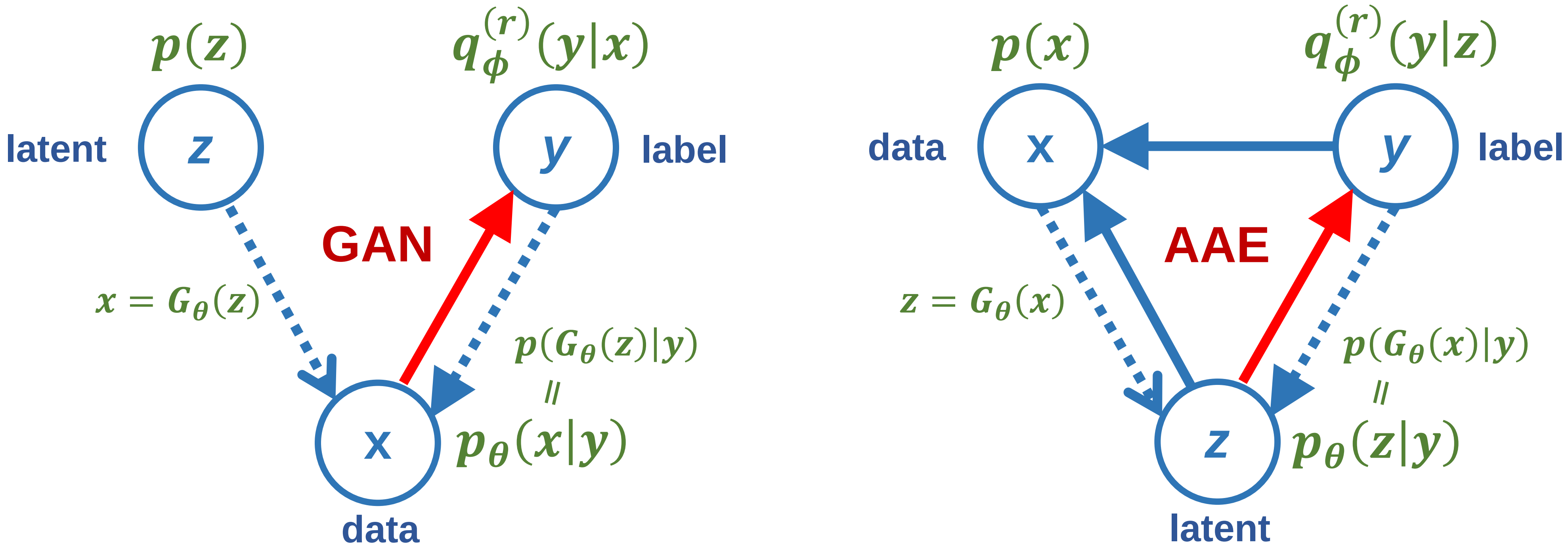




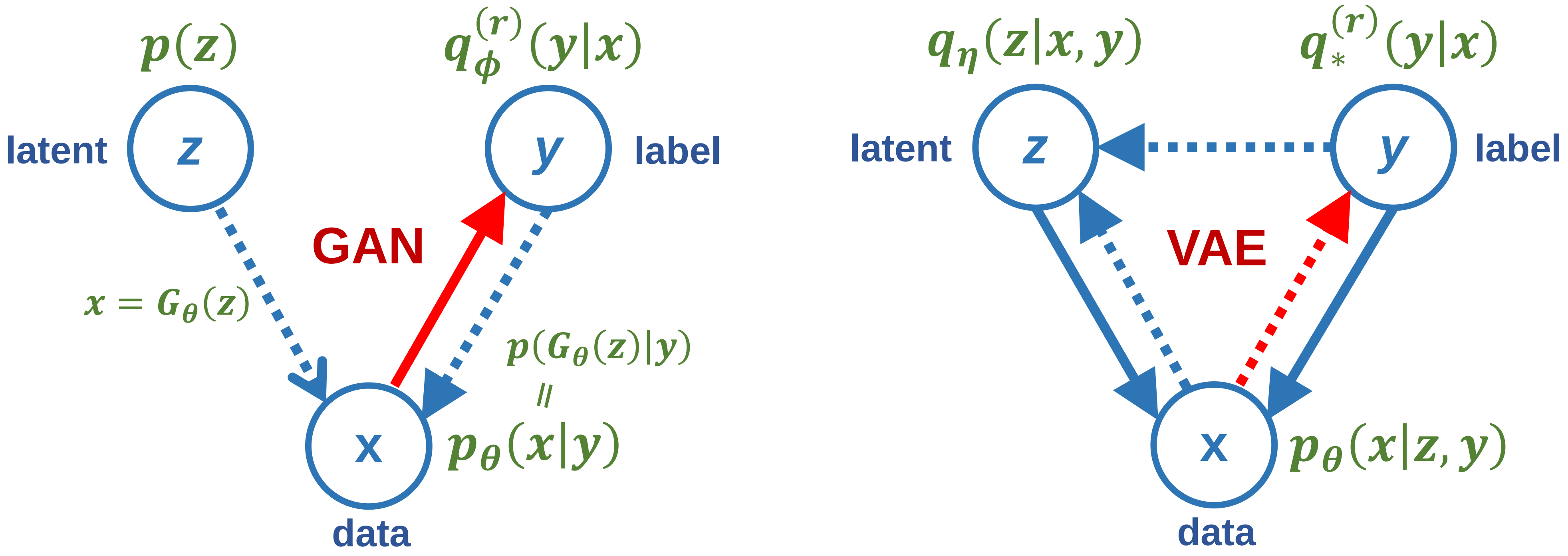
On Unifying Deep Generative Models



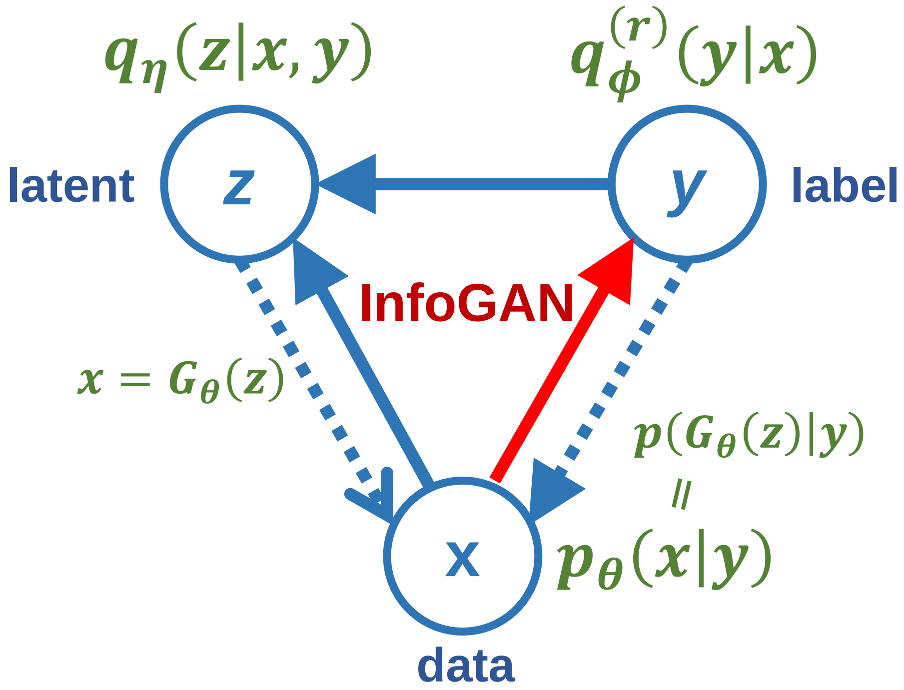
On Unifying Deep Generative Models

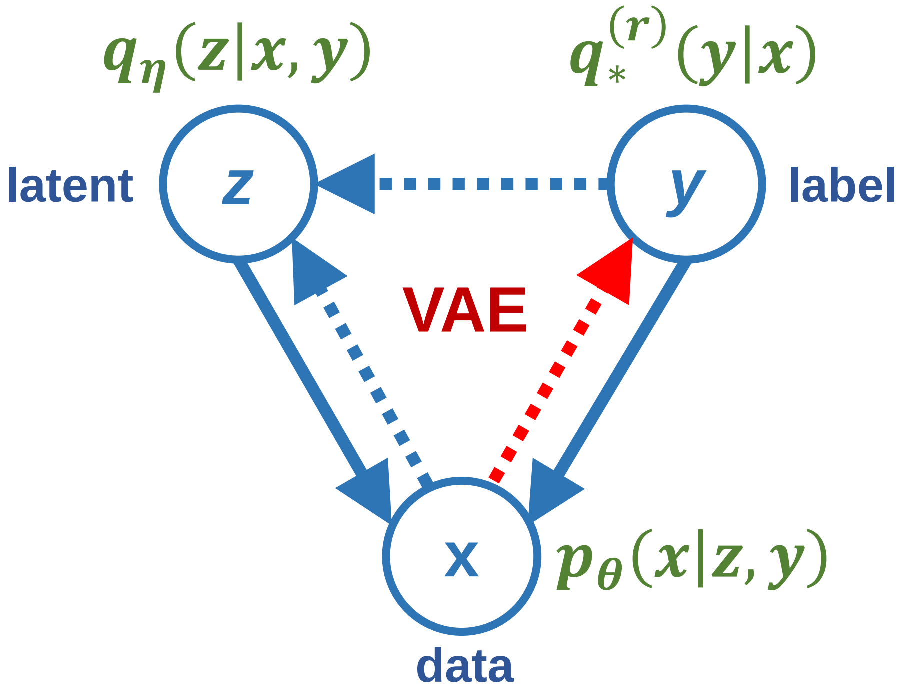


GAN vs VAE

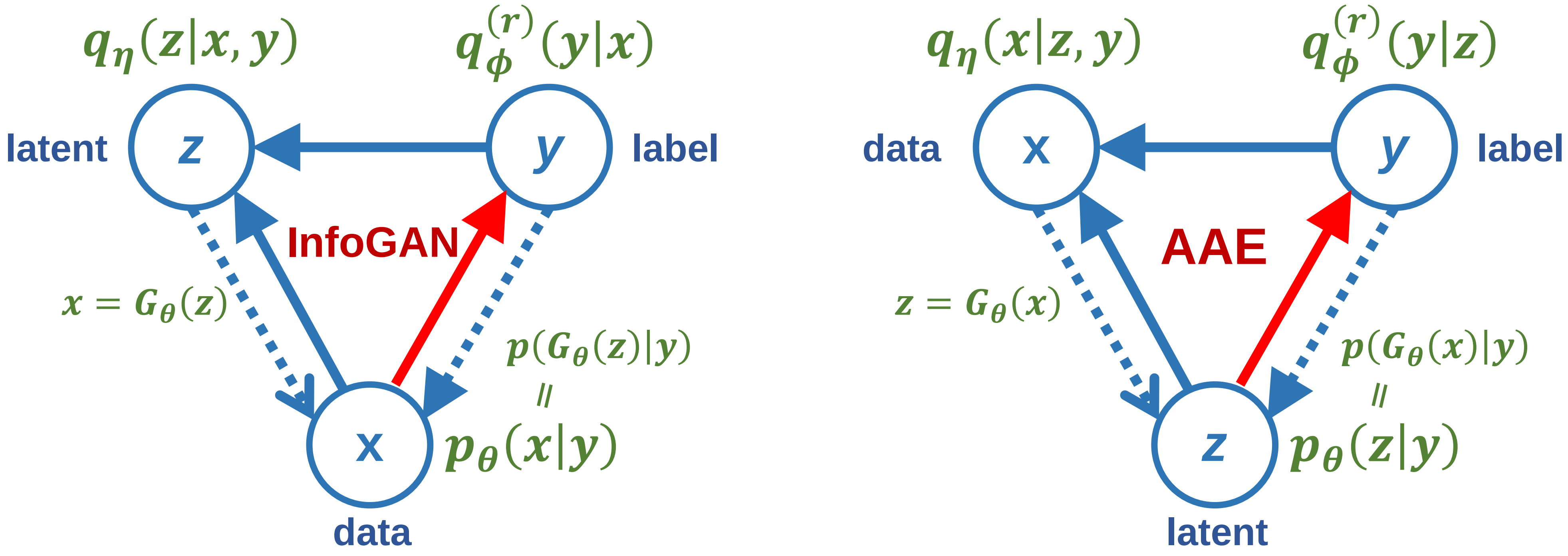

$p(z)$
$q_\phi^{(r)}(y|x)$
latent
z
y
label
GAN
$x = G_\theta(z)$
$p(G_\theta(z)|y)$
$\|$
x
$p_\theta(x|y)$
data
$q_\eta(z|x,y)$
$q_*^{(r)}(y|x)$
latent
z
y
label
VAE
x
$p_\theta(x|z,y)$
data

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

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