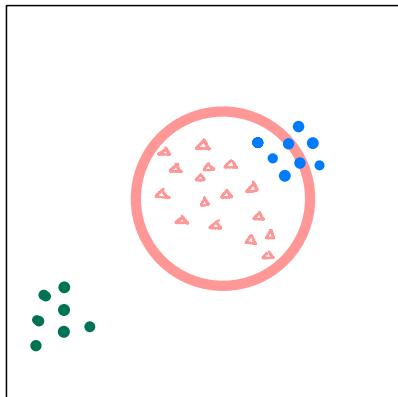


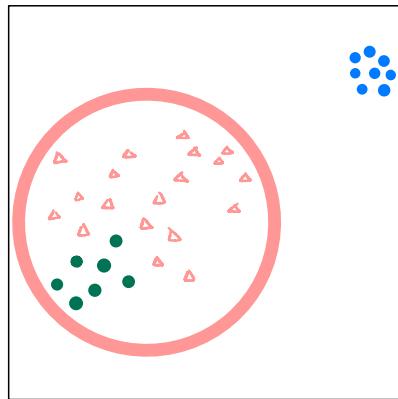
# Intuition for Bias from Latent Space

△ : normal data  
● : labeled anomaly 1  
● : labeled anomaly 2  
x : fake normal

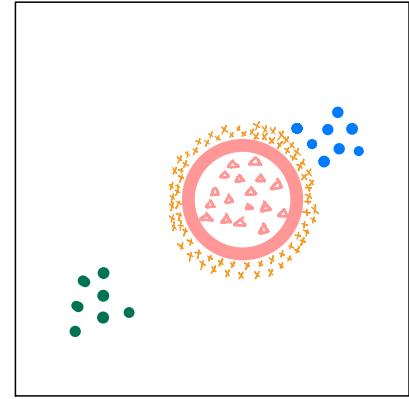
Unsupervised



Semi-supervised with ●



$\min H(z)$   
↑  
or regularize the normal sphere  
↑  
self-supervised with X



# A Unified Objective for Anomaly Detection<sup>1</sup>

---

Principle

$$\max \text{KL} (p_n(x, z) \parallel p_a(x, z))$$

$$\bullet = \max \underbrace{I_n(x, z)}_{\text{mutual info}} - \underbrace{H_n(z)}_{\text{entropy}} + \underbrace{E_{p_n(x)} [H(p_n(z|x), p_a(z|x))]}_{\text{Cross-entropy}}$$

[Can we gain an "unbiased" estimate  
for that w/ limited skewed data?]

Lower Bound for Unsupervision

$$\geq \max I_n(x, z) - H_n(z)$$

# A Unified Objective for Anomaly Detection

Principle

$$\max \text{KL} (P_n(x, z) \parallel P_a(x, z))$$

$$= \max \underbrace{I_n(x, z)}_{\text{mutual info}} - \underbrace{H_n(z)}_{\text{entropy}} + \underbrace{E_{P_n(x)} [H(P_n(z|x), P_a(z|x))]}_{\text{Cross-entropy}}$$

Connection to AE

$$\max I_n(x, z)$$

$$= \max H_n(x) - H_n(x|z)$$

$$= \max E_{x \sim P_n(x)} E_{z \sim P_n(z|x)} [\log P_n(x|z)]$$

reconstruction likelihood  $\Rightarrow$  goal of AE

# A Unified Objective for Anomaly Detection

Principle

$$\max \text{KL} (P_n(x, z) \parallel P_a(x, z))$$

$$= \max \underbrace{I_n(x, z)}_{\text{Mutual info}} - \underbrace{H_n(z)}_{\text{entropy}} + \underbrace{E_{P_n(x)} [H(P_n(z|x), P_a(z|x))]}_{\text{Cross-entropy}}$$

Connection to SVDD

$$\max I_n(x, z); \text{ then } \max -H_n(z)$$

Step 1 for  $I_n(x, z)$ : pretrain using autoencoder

Step 2 for  $-H_n(z)$ : minimizing empirical variances.

$$H_n(z) \propto \log \sigma^2 \text{ if } z \text{ is isotropic Gaussian}$$

$$\text{Thus, } \min H_n(z) \Rightarrow \min_{x \in \text{normal}} \|\phi(x; \theta) - c\|^2$$

Heuristic for SAD:  $\max H_a(z) \Rightarrow \max_{x \in \text{anomalies}} \|\phi(x; \theta) - c\|^2$