

IWAE vs. VAE

Tighter Bounds, Richer Latents?

Cedric Damais, Yacine Benihaddadene, Amine Mike El Maalouf,
Leon Ayral, Oscar Le Dauphin

GAIMD
EPITA

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The Goal: Latent Variable Inference

The Objective: Given data x , we want to learn the posterior distribution of the latent variables z :

$$p(z|x) = \frac{p(x|z)p(z)}{p(x)}$$

- $p(x|z)$: Likelihood (Decoder)
- $p(z)$: Prior (e.g., $\mathcal{N}(0, I)$)
- $p(x)$: Marginal Likelihood (The Evidence)

The Problem: Intractability

We can't simply use Bayes Formula because $p(x)$ is intractable. To calculate the denominator $p(x)$, we must marginalize out z :

$$p(x) = \int p(x|z)p(z) dz$$

Standard VAE: The Objective

Goal: Maximize marginal log-likelihood $\log p(x)$.

Since $p(x)$ is intractable, VAE ($K = 1$) maximizes the **ELBO**:

$$\log p(x) \geq \mathcal{L}_{\text{VAE}} = \mathbb{E}_{z \sim q} \left[\log \frac{p(x, z)}{q(z|x)} \right]$$

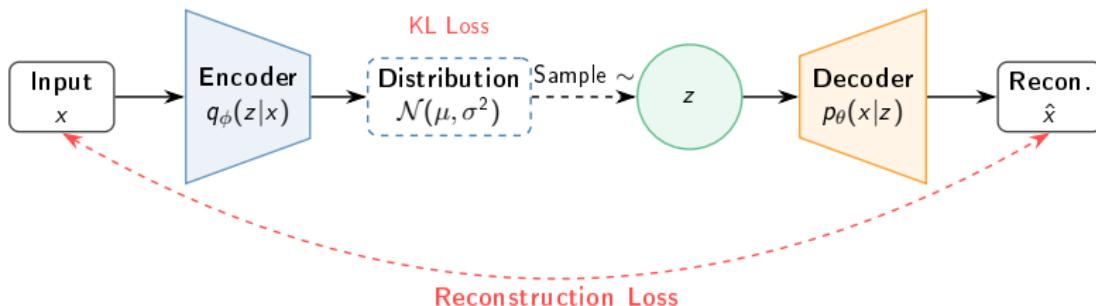
The Problem: The "Gap"

The bound is strictly lower than the evidence due to the KL divergence:

$$\log p(x) - \mathcal{L}_{\text{VAE}} = \text{KL}(q(z|x) || p(z|x))$$

- If $q(z|x)$ is too simple \rightarrow **Loose Bound**.
 - Loose bound \rightarrow Risk of **Posterior Collapse**.

Model Architecture



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Novelty 1: Strictly Tighter Bounds

Theorem (Burda et al., 2015): The IWAE bound \mathcal{L}_K is monotonically increasing with K .

$$\mathcal{L}_1 \leq \mathcal{L}_2 \leq \cdots \leq \mathcal{L}_K \leq \cdots \leq \log p(x)$$

Why?

Using Jensen's Inequality on the concave log function:

$$\mathbb{E} \left[\log \left(\frac{1}{K} \sum w_i \right) \right] \leq \log \left(\mathbb{E} \left[\frac{1}{K} \sum w_i \right] \right) = \log p(x)$$

Implication:

- As $K \rightarrow \infty$, the estimator converges to the true marginal likelihood $\log p(x)$.
- Even with a finite K , we are guaranteed a better objective



Novelty 2: Richer Implicit Posteriors

The IWAE Solution: Weighting as Filtering

Normalized Weight: $\tilde{w}_i = \frac{w_i}{\sum_{j=1}^k w_j}$ where $w_i = \frac{p(x, z_i)}{q(z_i|x)}$

$$\underbrace{\tilde{q}(z|x)}_{\substack{\text{Implicit} \\ \text{Multi-modal}}} \approx \sum_{i=1}^k \tilde{w}_i \delta(z - z_i)$$

$$\nabla \mathcal{L}_k = \mathbb{E}_{\epsilon} \left[\sum_{i=1}^k \tilde{w}_i \nabla_{\theta} \log w(x, z_i, \theta) \right]$$

Why Sampling More Helps? (The Mechanics)

Case $K = 1$ (Risky)

If we draw just **one** bad sample

z_1 :

$$w_1 \approx 0$$

$$\log(w_1) \rightarrow -\infty$$

Gradient Explodes

Case $K > 1$ (Hedging)

If we draw many bad samples,
but just **one good one**:

$$\log(0 + 0 + \dots + w_{\text{good}})$$

$$\approx \log(w_{\text{good}}) > -\infty$$

Stable Training

The Insight: The sum acts as a safety net. The Encoder is allowed to make mistakes, as long as it gets it right *once*.

The Mechanism: Importance Weighting

1. The Definition

- Calculate raw weight:

$$w_i = \frac{p(x, z_i)}{q(z_i|x)}$$

- Normalize:

$$\tilde{w}_i = \frac{w_i}{\sum_{j=1}^k w_j}$$

2. The Intuition

Sample z_i is **Good**
 $\rightarrow p(x, z_i)$ is High
 $\rightarrow \tilde{w}_i \approx 1$

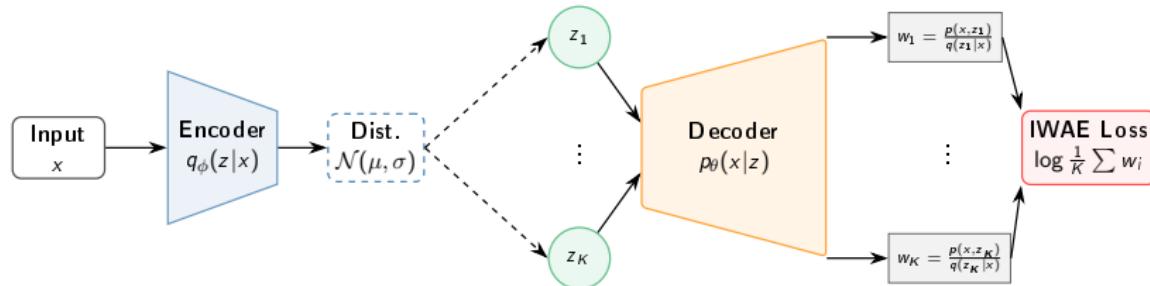
Sample z_j is **Bad**
 $\rightarrow p(x, z_j)$ is Low
 $\rightarrow \tilde{w}_j \approx 0$

Key Result: The Filter Effect

The gradient update effectively **ignores** bad samples:

k

IWAE Architecture



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Experimental Setup

- **Objective:** Compare VAE ($K = 1$) vs IWAE ($K > 1$).
- **Constraint: Identical Architecture** for fair comparison.

Parameter	Value
Dataset	MNIST (Binarized)
Encoder	MLP (784 → 400 → 20)
Decoder	MLP (20 → 400 → 784)
Optimizer	Adam ($\text{lr} = 1e - 3$)
K (Samples)	1, 5, 20, 30, 50, 100

Implementation Detail

Used `torch.logsumexp` to avoid numerical underflow.

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Log-Likelihood

Latent Utilization

K-Analysis

Sample Quality

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Result 1: Estimated Log-Likelihood vs Number of Samples (K)

- Metric: Estimated Log-Likelihood (Higher is better).

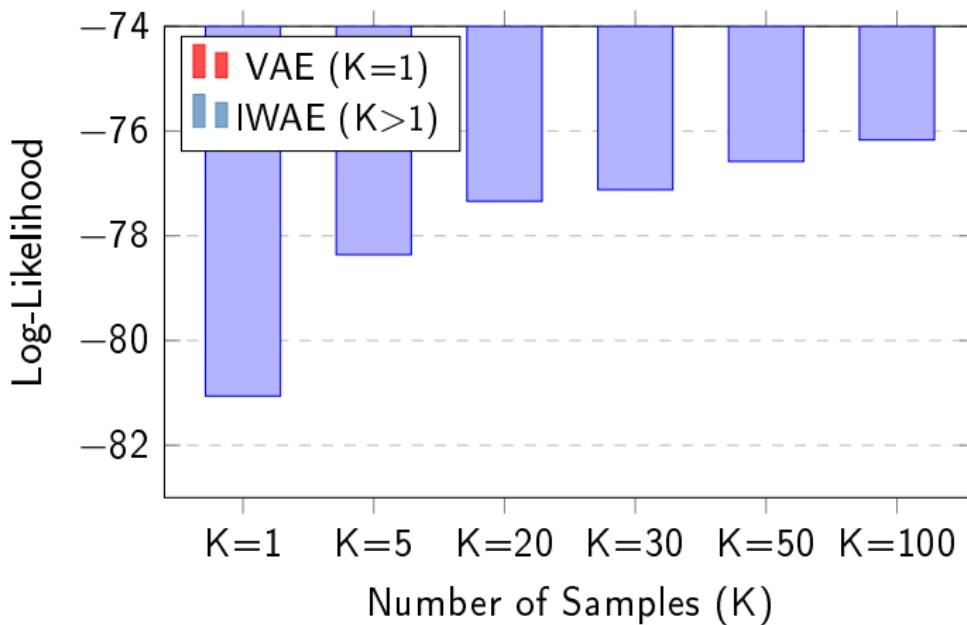


Figure 1: Estimated Log-Likelihood on MNIST Test Set (Higher is Better)

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Latent Utilization

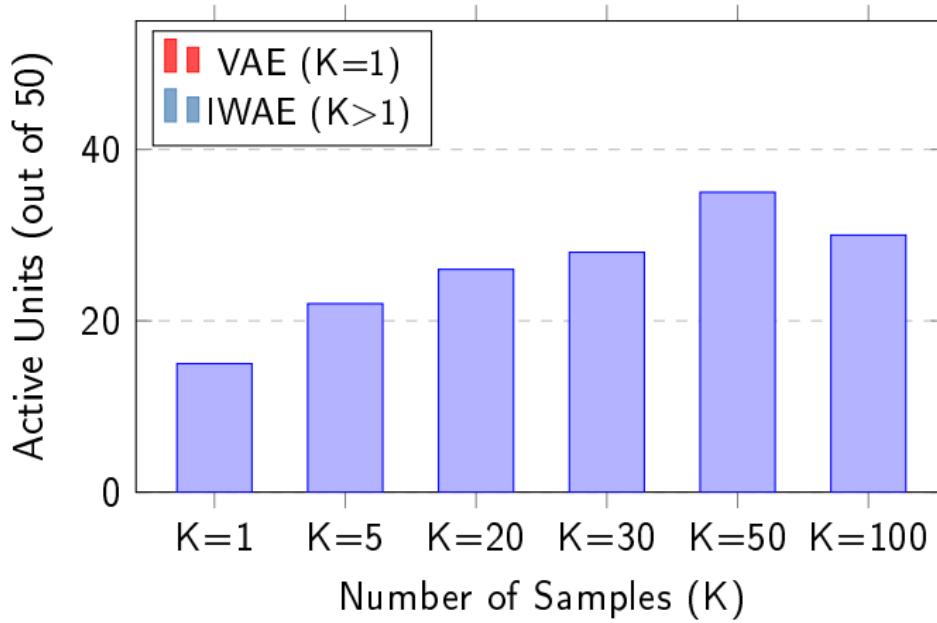
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Result 2: Active Latent Units vs Number of Samples (K)

- **Metric:** Active Units (Dimensions where $\text{KL} > \epsilon$, with $\epsilon = 0.01$).



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Log-Likelihood

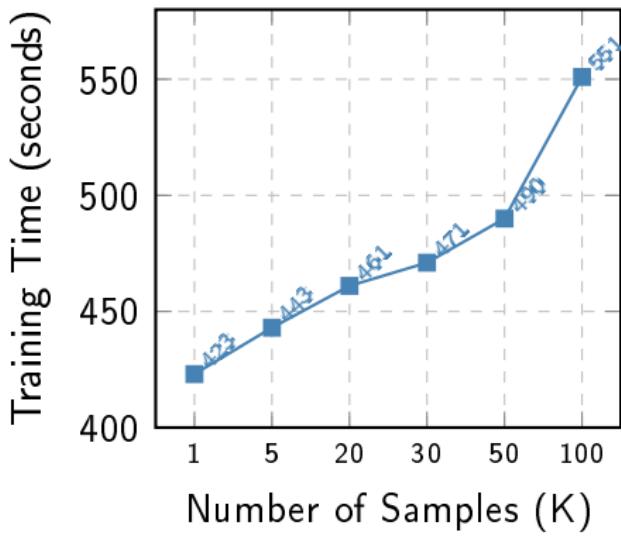
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Result 3: Impact of K on Training Time



Trade-off Analysis:

- **Compute:** Training time scales **sub-linearly** with K ($423s \rightarrow 551s$).
- **Log-Likelihood:** Diminishing returns as K increases.
- **Gradient SNR:** Decreases at high K (encoder neglect).

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Result 4: Sample Quality

VAE (K=1)



IWAE (K=50)



IWAE samples typically show sharper strokes and fewer "averaged" blurry digits.

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Trade-offs Summary

Metric	VAE (K=1)	IWAE (K=50)
Bound Tightness	Loose	Tight
Latent Usage	Risk of Collapse	Rich
Bound Variance	High	Low
Encoder Gradient SNR	High	Low
Sample Quality	Blurry	Sharp
Compute Cost	Low	High ($\times K$)

Thanks!

Q & A