XAI: Cluster Variational Inference Reports

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1 Derivation of the ELBO for a Variational Autoencoder

In a Variational Autoencoder (VAE), we aim to maximize the marginal log-likelihood of the observed data x, denoted $\log p(x)$, over a dataset. However, computing $p(x) = \int p(x,z)\,dz = \int p(x|z)p(z)\,dz$ directly is intractable due to the integral over the latent variable z. Variational inference introduces an approximate posterior $q(z|x)$ to address this. The Evidence Lower Bound (ELBO) provides a tractable objective to optimize. Here, we derive it.

1.1 Starting Point: Marginal Log-Likelihood

Consider the marginal log-likelihood of the data:

$$\log p(x) = \log \int p(x,z)\,dz. \tag{1.1}$$

Since this integral is intractable, we introduce a variational distribution $q(z|x)$ over the latent variables z, which approximates the true posterior $p(z|x)$.

1.2 Introducing $q(z|x)$

Using the definition of expectation, we rewrite $\log p(x)$ by incorporating $q(z|x)$:

$$\log p(x) = \log \int p(x,z)\frac{q(z|x)}{q(z|x)}\,dz = \log \mathbb{E}_{q(z|x)}\left[\frac{p(x,z)}{q(z|x)}\right]. \tag{1.2}$$

1.3 Applying Jensen's Inequality

Since the logarithm is a concave function, Jensen's inequality states that $\log \mathbb{E}[f(z)] \geq \mathbb{E}[\log f(z)]$ for any random variable z and function $f(z)$. Applying this:

$$\log p(x) = \log \mathbb{E}_{q(z|x)}\left[\frac{p(x,z)}{q(z|x)}\right] \geq \mathbb{E}_{q(z|x)}\left[\log\frac{p(x,z)}{q(z|x)}\right].$$

This lower bound is the ELBO, denoted $\mathcal{L}(x)$:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)} \left[\log \frac{p(x,z)}{q(z|x)} \right]. \tag{1.3}$$

Equality holds when $q(z|x) = p(z|x)$, but since $p(z|x)$ is intractable, we optimize $q(z|x)$ to make the bound as tight as possible.

1.4 Expanding the ELBO

Now, expand the joint distribution $p(x,z) = p(x|z)p(z)$ inside the expectation:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)} \left[\log \frac{p(x|z)p(z)}{q(z|x)} \right]. \tag{1.4}$$

Using the linearity of expectation:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)} \left[\log p(x|z) + \log p(z) - \log q(z|x) \right]. \tag{1.5}$$

This splits into:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)} \left[\log p(x|z) \right] + \mathbb{E}_{q(z|x)} \left[\log \frac{p(z)}{q(z|x)} \right]. \tag{1.6}$$

1.5 Rewriting with KL Divergence

Recognize that the second term is the negative Kullback-Leibler (KL) divergence between $q(z|x)$ and $p(z)$:

$$\mathbb{E}_{q(z|x)} \left[\log \frac{p(z)}{q(z|x)} \right] = -\mathbb{E}_{q(z|x)} \left[\log \frac{q(z|x)}{p(z)} \right] = -D_{\mathrm{KL}}(q(z|x) \| p(z)).$$

Thus, the ELBO becomes:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)} \left[\log p(x|z) \right] - D_{\mathrm{KL}}(q(z|x) \| p(z)). \tag{1.7}$$

1.6 Interpretation

- The first term, $\mathbb{E}_{q(z|x)} \left[\log p(x|z) \right]$, is the expected log-likelihood of the data under the generative model, often interpreted as a reconstruction term when $p(x|z)$ is parameterized (e.g., as a Gaussian or Bernoulli distribution). - The second term, $-D_{\mathrm{KL}}(q(z|x) \| p(z))$, is a regularization term that encourages $q(z|x)$ to be close to the prior $p(z)$, typically a standard normal $\mathcal{N}(0, I)$.

1.7 Relation to $\log p(x)$

To confirm, relate $\mathcal{L}(x)$ back to $\log p(x)$:

$$\log p(x) = \mathbb{E}_{q(z|x)} \left[\log \frac{p(x,z)}{q(z|x)} \right] + D_{\mathrm{KL}}(q(z|x) \| p(z|x)). \tag{1.8}$$

Since $D_{\text{KL}}(q(z|x)\|p(z|x)) \geq 0$ (KL divergence is non-negative), we have:

$$\log p(x) = \mathcal{L}(x) + D_{\text{KL}}(q(z|x)\|p(z|x)) \geq \mathcal{L}(x). \tag{1.9}$$

This shows $\mathcal{L}(x)$ is indeed a lower bound on $\log p(x)$, tightened by minimizing the KL divergence to the true posterior.

1.8 Final ELBO Formula

The ELBO, as used in VAEs, is:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)}\left[\log p(x|z)\right] - D_{\text{KL}}(q(z|x)\|p(z)). \tag{1.10}$$

In practice, $q(z|x)$ is parameterized (e.g., as $\mathcal{N}(\mu(x), \sigma^2(x))$) by an encoder network, and $p(x|z)$ by a decoder network, with the KL term often computed analytically when $p(z) = \mathcal{N}(0, I)$.

2 Starting Point: The Final ELBO

We begin with the Evidence Lower Bound (ELBO) for a Variational Autoencoder (VAE) where the latent variable is composed of z and c, i.e., the joint latent representation is (z, c). The approximate posterior is factorized as $q(z, c|x) = q(c|z)q(z|x)$, and the prior is factorized as $p(z, c) = p(z|c)p(c)$. The ELBO is given by:

$$\mathcal{L}(x) = \mathbb{E}_{q(z,c|x)}\left[\log p(x|z, c)\right] - D_{\text{KL}}(q(z, c|x)\|p(z, c)) \tag{2.1}$$

Our goal is to expand this expression using the specified factorizations.

2.1 Step 1: Expand the Reconstruction Term

The first term is the expected log-likelihood of the data x under the approximate posterior:

$$\mathbb{E}_{q(z,c|x)}\left[\log p(x|z, c)\right]$$

Given $q(z, c|x) = q(c|z)q(z|x)$, this expectation is over both z and c, where $z \sim q(z|x)$ and $c \sim q(c|z)$. For continuous variables, this is a double integral:

$$\mathbb{E}_{q(z,c|x)}\left[\log p(x|z, c)\right] = \iint q(z|x)q(c|z) \log p(x|z, c)\, dz\, dc$$

We compute this iteratively:

- **Inner Integral**: For a fixed z,

$$\mathbb{E}_{q(c|z)}\left[\log p(x|z, c)\right] = \int q(c|z) \log p(x|z, c)\, dc$$

- **Outer Integral**: Then over z,

$$\mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(x|z,c)\right]\right] = \int q(z|x)\left[\int q(c|z)\log p(x|z,c)\,dc\right]dz$$

This nested form reflects the sampling process: first z from $q(z|x)$, then c from $q(c|z)$.

2.2 Step 2: Expand the KL Divergence Term

The second term is the KL divergence:

$$D_{\text{KL}}(q(z,c|x)\|p(z,c)) = \iint q(z,c|x)\log\frac{q(z,c|x)}{p(z,c)}\,dz\,dc$$

Substitute the factorizations: - $q(z,c|x) = q(c|z)q(z|x)$, - $p(z,c) = p(z|c)p(c)$.
Thus:

$$D_{\text{KL}}(q(z,c|x)\|p(z,c)) = \iint q(c|z)q(z|x)\log\frac{q(c|z)q(z|x)}{p(z|c)p(c)}\,dz\,dc$$

Split the logarithm:

$$\log\frac{q(c|z)q(z|x)}{p(z|c)p(c)} = \log q(c|z) + \log q(z|x) - \log p(z|c) - \log p(c)$$

So:

$$D_{\text{KL}}(q(z,c|x)\|p(z,c)) = \iint q(c|z)q(z|x)\left[\log q(c|z) + \log q(z|x) - \log p(z|c) - \log p(c)\right]dz\,dc$$

Separate into four integrals:

1. $\iint q(c|z)q(z|x)\log q(c|z)\,dz\,dc = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log q(c|z)\right]\right]$,
2. $\iint q(c|z)q(z|x)\log q(z|x)\,dz\,dc = \mathbb{E}_{q(z|x)}\left[\log q(z|x)\right]$ (since $\int q(c|z)\,dc = 1$),
3. $-\iint q(c|z)q(z|x)\log p(z|c)\,dz\,dc = -\mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(z|c)\right]\right]$,
4. $-\iint q(c|z)q(z|x)\log p(c)\,dz\,dc = -\mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(c)\right]\right]$.

Group terms to form KL-like expressions: - First and third: $\mathbb{E}_{q(z|x)}\left[D_{\text{KL}}(q(c|z)\|p(z|c))\right]$ doesn't directly apply due to mismatched conditionals, so we compute the full form later.
Instead, recompute directly:

$$D_{\text{KL}} = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log\frac{q(z|x)q(c|z)}{p(z|c)p(c)}\right]\right]$$

Factor:

$$= \mathbb{E}_{q(z|x)}\left[\log q(z|x) - \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right] + \mathbb{E}_{q(c|z)}\left[\log\frac{q(c|z)}{p(c)}\right]\right]$$

The last term is:

$$\mathbb{E}_{q(c|z)}\left[\log \frac{q(c|z)}{p(c)}\right] = D_{\mathrm{KL}}(q(c|z)\|p(c))$$

So:

$$D_{\mathrm{KL}}(q(z,c|x)\|p(z,c)) = \mathbb{E}_{q(z|x)}\left[\log q(z|x) - \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right] + D_{\mathrm{KL}}(q(c|z)\|p(c))\right]$$

2.3 Step 3: Combine into the ELBO

Substitute both terms into the ELBO:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(x|z,c)\right]\right] - \mathbb{E}_{q(z|x)}\left[\log q(z|x) - \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right] + D_{\mathrm{KL}}(q(c|z)\|p(c))\right]$$

Distribute the expectation:

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(x|z,c)\right] - \log q(z|x) + \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right] - D_{\mathrm{KL}}(q(c|z)\|p(c))\right]$$

3 Explaining the Inequality

In probabilistic modeling, such as variational autoencoders (VAEs), we often encounter expectations of KL divergences over latent variables. Here, we explain why the inequality

$$\mathbb{E}_{q(z|x)}\left[D_{\mathrm{KL}}(q(c|z)||p(c))\right] \geq D_{\mathrm{KL}}(q(c|x)||p(c))$$

holds, where:

- x is the observed data,
- z and c are latent variables,
- $q(z|x)$ is the approximate posterior distribution of z given x,
- $q(c|z)$ is the conditional distribution of c given z,
- $q(c|x) = \int q(c|z)q(z|x)\,dz$ is the marginal distribution of c given x,
- $p(c)$ is a prior distribution over c, assumed to be independent of x and z.

3.1 Definition of KL Divergence

The Kullback-Leibler (KL) divergence between two distributions p and q over a variable u is defined as:

$$D_{\mathrm{KL}}(p(u)||q(u)) = \int p(u) \log \frac{p(u)}{q(u)} \, du$$

It measures the difference between $p(u)$ and $q(u)$ and is always non-negative ($D_{\mathrm{KL}} \geq 0$), with equality if and only if $p(u) = q(u)$ almost everywhere.

3.2 Left-Hand Side: Expected KL Divergence

The left-hand side, $\mathbb{E}_{q(z|x)} [D_{\mathrm{KL}}(q(c|z)||p(c))]$, is the expectation of the KL divergence between $q(c|z)$ and $p(c)$ over z drawn from $q(z|x)$:

$$\mathbb{E}_{q(z|x)} [D_{\mathrm{KL}}(q(c|z)||p(c))] = \int q(z|x) D_{\mathrm{KL}}(q(c|z)||p(c)) \, dz$$

Substitute the definition of KL divergence:

$$D_{\mathrm{KL}}(q(c|z)||p(c)) = \int q(c|z) \log \frac{q(c|z)}{p(c)} \, dc$$

So:

$$\mathbb{E}_{q(z|x)} [D_{\mathrm{KL}}(q(c|z)||p(c))] = \int q(z|x) \left[\int q(c|z) \log \frac{q(c|z)}{p(c)} \, dc \right] dz$$

This represents the average divergence between $q(c|z)$ and $p(c)$, where $q(c|z)$ varies with z, and the expectation accounts for the distribution of z given x.

3.3 Right-Hand Side: Marginal KL Divergence

The right-hand side, $D_{\mathrm{KL}}(q(c|x)||p(c))$, is the KL divergence between the marginal distribution $q(c|x)$ and $p(c)$:

$$D_{\mathrm{KL}}(q(c|x)||p(c)) = \int q(c|x) \log \frac{q(c|x)}{p(c)} \, dc$$

First, compute $q(c|x)$ by marginalizing over z:

$$q(c|x) = \int q(c, z|x) \, dz = \int q(c|z) q(z|x) \, dz$$

Thus:

$$D_{\mathrm{KL}}(q(c|x)||p(c)) = \int \left[\int q(c|z) q(z|x) \, dz \right] \log \frac{\int q(c|z) q(z|x) \, dz}{p(c)} \, dc$$

This measures the divergence between the averaged distribution $q(c|x)$ and $p(c)$.

3.4 Applying Jensen's Inequality

To show the inequality, recognize that the KL divergence $D_{\mathrm{KL}}(p||q)$ is a convex function with respect to p. Consider the KL divergence as a functional of the distribution $q(c|z)$. The left-hand side takes the expectation of this convex function over z, while the right-hand side applies the KL divergence to the expected (or averaged) distribution $q(c|x)$.

By Jensen's inequality, for a convex function f and a random variable Z:

$$\mathbb{E}[f(Z)] \geq f(\mathbb{E}[Z])$$

Define $f(q(c)) = D_{\mathrm{KL}}(q(c)||p(c))$, where $q(c)$ is a distribution over c. Here, $q(c|z)$ is a distribution parameterized by z, and $z \sim q(z|x)$. The expectation of $q(c|z)$ over z is:

$$\mathbb{E}_{q(z|x)}[q(c|z)] = \int q(z|x)q(c|z)\,dz = q(c|x)$$

Applying Jensen's inequality:

$$\mathbb{E}_{q(z|x)}\left[D_{\mathrm{KL}}(q(c|z)||p(c))\right] \geq D_{\mathrm{KL}}\left(\mathbb{E}_{q(z|x)}[q(c|z)]||p(c)\right)$$

Substitute $\mathbb{E}_{q(z|x)}[q(c|z)] = q(c|x)$:

$$\mathbb{E}_{q(z|x)}\left[D_{\mathrm{KL}}(q(c|z)||p(c))\right] \geq D_{\mathrm{KL}}(q(c|x)||p(c))$$

This establishes the inequality.

4 Rewriting $q(c|z)$ as $q(c|x)$ in the ELBO

Consider the Evidence Lower Bound (ELBO):

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|z)}\left[\log p(x|z,c)\right] - \log q(z|x) + \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right] - D_{\mathrm{KL}}(q(c|z)\|p(c))\right]$$

Define a modified ELBO, $\hat{\mathcal{L}}(x)$, by replacing $q(c|z)$ with $q(c|x)$:

$$\hat{\mathcal{L}}(x) = \mathbb{E}_{q(z|x)}\left[\mathbb{E}_{q(c|x)}\left[\log p(x|z,c)\right] - \log q(z|x) + \mathbb{E}_{q(c|x)}\left[\log p(z|c)\right] - D_{\mathrm{KL}}(q(c|x)\|p(c))\right]$$

The difference is:

$$\begin{aligned}\mathcal{L}(x) - \hat{\mathcal{L}}(x) = \mathbb{E}_{q(z|x)}\Big[&\mathbb{E}_{q(c|z)}\left[\log p(x|z,c)\right]\\ &- \mathbb{E}_{q(c|x)}\left[\log p(x|z,c)\right]\\ &+ \mathbb{E}_{q(c|z)}\left[\log p(z|c)\right]\\ &- \mathbb{E}_{q(c|x)}\left[\log p(z|c)\right]\\ &- D_{\mathrm{KL}}(q(c|z)\|p(c))\\ &+ D_{\mathrm{KL}}(q(c|x)\|p(c))\Big]\end{aligned} \tag{4.1}$$

Since $q(c|x) = \mathbb{E}_{q(z|x)}[q(c|z)]$, apply Jensen's inequality to the convex KL divergence:

$$\mathbb{E}_{q(z|x)}\left[D_{\mathrm{KL}}(q(c|z)\|p(c))\right] \geq D_{\mathrm{KL}}\left(\mathbb{E}_{q(z|x)}[q(c|z)]\|p(c)\right) = D_{\mathrm{KL}}(q(c|x)\|p(c))$$

Thus, $-\mathbb{E}_{q(z|x)}[D_{\mathrm{KL}}(q(c|z)\|p(c))] \leq -D_{\mathrm{KL}}(q(c|x)\|p(c))$. The first two terms involve expectations of $\log p(x|z,c)$ under different distributions, and the next two involve $\log p(z|c)$, both potentially reducing $\hat{\mathcal{L}}(x)$ if $q(c|z)$ better captures dependencies. Generally, $\mathcal{L}(x) \geq \hat{\mathcal{L}}(x)$, with equality only if $q(c|z) = q(c|x)$ for all z.

5 Introduction to Gaussian Mixture Models (GMMs)

A Gaussian Mixture Model (GMM) represents data as a weighted combination of K Gaussian distributions. It assumes each data point x is generated from one of K components, with a latent variable z indicating the component assignment.

5.1 Key GMM Formulas

The joint distribution of x and z is given by:

$$p(x, z) = p(z)p(x \mid z)$$

where: - $p(z)$ is the marginal distribution of z, using a 1-of-K representation:

$$p(z) = \prod_{k=1}^{K} \pi_k^{z_k}$$

with mixing coefficients π_k satisfying $0 \leq \pi_k \leq 1$ and $\sum_{k=1}^{K} \pi_k = 1$. - $p(x \mid z)$ is the conditional distribution, where if $z_k = 1$, x follows a Gaussian:

$$p(x \mid z_k = 1) = \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

and generally:

$$p(x \mid z) = \prod_{k=1}^{K} \mathcal{N}(x \mid \mu_k, \Sigma_k)^{z_k}$$

- The marginal distribution of x is:

$$p(x) = \sum_{z} p(z)p(x \mid z) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

- The posterior responsibility $\gamma(z_k)$ of component k for x is:

$$\gamma(z_k) = p(z_k = 1 \mid x) = \frac{\pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(x \mid \mu_j, \Sigma_j)}$$

This represents the probability that x belongs to component k.

5.2 Estimation Methods: MLE and MAP

5.2.1 Maximum Likelihood Estimation (MLE)

MLE maximizes the likelihood $p(x \mid \theta)$, where $\theta = \{\pi_k, \mu_k, \Sigma_k\}$, using the marginal distribution:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

The Expectation-Maximization (EM) algorithm is used: - **E-step**: Compute $\gamma(z_k)$ for each x. - **M-step**: Update θ to maximize the expected complete-data log-likelihood. MLE assumes no prior knowledge, focusing solely on the data, but can overfit with complex models or small datasets.

5.2.2 Maximum A Posteriori (MAP) Estimation

MAP maximizes the posterior $p(\theta \mid x) \propto p(x \mid \theta)p(\theta)$, incorporating priors $p(\theta)$ (e.g., Dirichlet for π_k, Gaussian for μ_k):

$$p(\theta \mid x) = \frac{p(x \mid \theta)p(\theta)}{p(x)}$$

The EM algorithm adapts to maximize this posterior: - **E-step**: Compute $\gamma(z_k)$ as in MLE. - **M-step**: Update θ by balancing the likelihood and prior information. MAP reduces overfitting by regularizing with priors, but requires careful prior specification.

5.3 Comparison

- **MLE** is data-driven, simpler, but prone to overfitting without priors. - **MAP** incorporates prior knowledge, iproving robustness, but depends on prior choice. Both use $\gamma(z_k)$ in EM, but MAP adds regularization via priors on θ.

6 Workflow

For $q(z, c|x) = q(c|x)q(z|x)$ and $p(x, z, c) = p(x|z, c)p(z|c)p(c)$, the ELBO is:

$$\mathcal{L}(x) = \mathbb{E}_{q(c|x)q(z|x)}\left[\log p(x|z,c)\right] + \mathbb{E}_{q(c|x)}\left[\mathbb{E}_{q(z|x)}\left[\log p(z|c)\right]\right] - D_{\mathrm{KL}}(q(c|x)\|p(c)) - \mathbb{E}_{q(z|x)}\left[\log q(z|x)\right]$$

Derivation:

$$\begin{aligned}
\mathcal{L}(x) &= \mathbb{E}_{q(c|x)q(z|x)}\left[\log \frac{p(x|z,c)p(z|c)p(c)}{q(c|x)q(z|x)}\right] \\
&= \mathbb{E}_{q(c|x)q(z|x)}[\log p(x|z,c)] + \mathbb{E}_{q(c|x)}[\mathbb{E}_{q(z|x)}[\log p(z|c)]] \\
&\quad + \mathbb{E}_{q(c|x)}[\log p(c)] - \mathbb{E}_{q(c|x)}[\log q(c|x)] - \mathbb{E}_{q(z|x)}[\log q(z|x)] \\
&= \mathbb{E}_{q(c|x)q(z|x)}[\log p(x|z,c)] + \mathbb{E}_{q(c|x)}[\mathbb{E}_{q(z|x)}[\log p(z|c)]] \\
&\quad - D_{\mathrm{KL}}(q(c|x)\|p(c)) - \mathbb{E}_{q(z|x)}[\log q(z|x)]
\end{aligned} \tag{6.1}$$

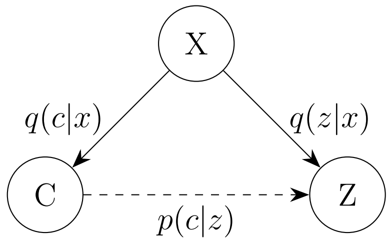

Figure 1: Directed Graphical Model

6.1 Model Formulation

We consider a Variational Autoencoder (VAE) with latent variables z and cluster assignments c. The joint variational distribution is factorized as $q(z, c|x) = q(c|x)q(z|x)$, where x denotes the observed data, assumed to be images of shape $(1, 28, 28)$. The ELBO for this model is derived as:

$$\mathcal{L}(x) = \mathbb{E}_{q(c|x)q(z|x)}\left[\log p(x|z,c)\right] + \mathbb{E}_{q(c|x)}\left[\mathbb{E}_{q(z|x)}\left[\log p(z|c)\right]\right] - D_{\mathrm{KL}}(q(c|x)\|p(c)) - \mathbb{E}_{q(z|x)}\left[\log q(z|x)\right].$$

we analyze each term:

- **Reconstruction Error**:

$$\mathbb{E}_{q(c|x)q(z|x)}\left[\log p(x|z,c)\right]$$

This term represents the reconstruction error, measuring how well the decoder reconstructs the MNIST image x (shape $(1, 28, 28)$) from z and c. Here, $p(x|z, c)$ is typically a Gaussian or Bernoulli distribution over pixel intensities.

- **Latent Prior Alignment**:

$$\mathbb{E}_{q(c|x)}\left[\mathbb{E}_{q(z|x)}\left[\log p(z|c)\right]\right]$$

For $p(z|c) = \mathcal{N}(z|\hat{\mu}_c, \sigma_c^2 I)$, where $\hat{\mu}_c$ represents cluster-specific image data, we have:

$$\log p(z|c) \propto -\frac{1}{2\sigma_c^2}\|z - \hat{\mu}_c\|^2.$$

The posterior $q(c|x) \approx \gamma_c$, resembling GMM weights, classifies x and weighs contributions from image data. This term aligns z with cluster centroids.

- **Cluster Posterior Regularization**:

$$-D_{\mathrm{KL}}(q(c|x)\|p(c))$$

Ideally, $q(c|x) \approx p(c) = \frac{1}{K}$, but maximization of $\mathcal{L}(x)$ drives $q(c|x)$ to adapt to image pixel perturbations, especially in non-significant pixels (e.g., background), enhancing clustering sensitivity.

- **Latent Entropy**:

$$-\mathbb{E}_{q(z|x)}\left[\log q(z|x)\right]$$

This entropy term ensures $q(z|x)$ spreads z evenly across the latent space, preventing collapse to a single class and promoting diversity in latent representations.

6.1.1 Prior Distributions

The prior over cluster assignments $p(c)$ is a uniform categorical distribution:

$$p(c) = \frac{1}{K}, \quad c \in \{1, \dots, K\},$$

where K is the number of clusters. The conditional prior $p(z|c)$ models the latent representation for each cluster c, parameterized as a distribution over images of shape $(1, 28, 28)$. Specifically, z is a latent embedding that, through the generative model, corresponds to a reconstructed image:

$$p(z|c) = \mathcal{N}(z|\mu_c, \sigma_c^2 I),$$

where μ_c and σ_c are cluster-specific parameters learned to represent the image distribution.

6.1.2 Evidence Lower Bound (ELBO)

The ELBO for this model is derived as:

$$\mathcal{L}(x) = \mathbb{E}_{q(c|x)q(z|x)}\left[\log p(x|z,c)\right] + \mathbb{E}_{q(c|x)}\left[\mathbb{E}_{q(z|x)}\left[\log p(z|c)\right]\right] - D_{\mathrm{KL}}(q(c|x)\|p(c)) - \mathbb{E}_{q(z|x)}\left[\log q(z|x)\right].$$

Here, $p(x|z,c)$ is the likelihood of reconstructing x given z and c, typically modeled as a Bernoulli or Gaussian distribution over the $(1, 28, 28)$ image.

6.1.3 Optimization Insight

When maximizing $\mathcal{L}(x)$, the KL divergence term $D_{\mathrm{KL}}(q(c|x)\|p(c))$ measures the divergence between the variational posterior $q(c|x)$ and the uniform prior $p(c)$. Since $D_{\mathrm{KL}} \geq 0$ and achieves its minimum of 0 when $q(c|x) = p(c)$, the optimal $q(c|x)$ under unconstrained maximization of the ELBO is:

$$q(c|x) = p(c) = \frac{1}{K}.$$

This implies that $q(c|x)$ collapses to the uniform prior, rendering the clustering uninformative unless additional constraints (e.g., regularization or clustering-specific losses) are introduced.

7 Experimental Results

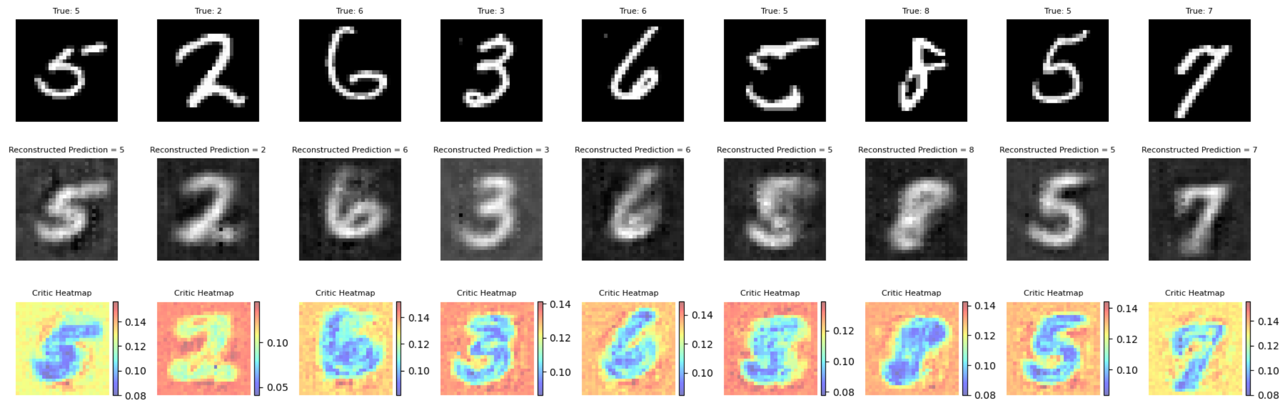

Figure 2: Example of VAE output, reconstruction, and critic heatmap in training set.

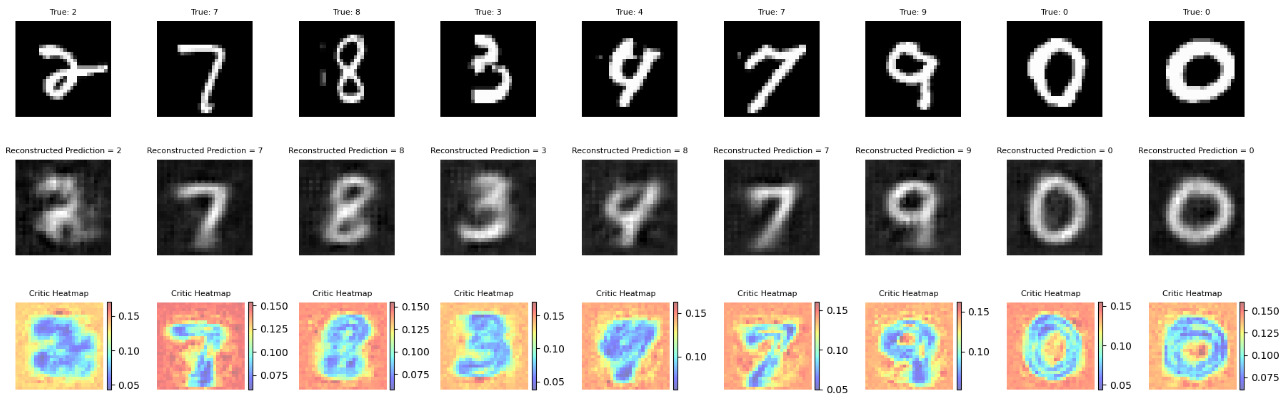

Figure 3: Example of VAE output, reconstruction, and critic heatmap in testing set.

8 Conclusion

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