

Query Selection
based on Latent
Space Sampling

Benjamin Killeen

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- **Big data** facilitates supervised learning.

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- **Big data** facilitates supervised learning.



Figure: ImageNet examples [2].

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- **Big data** facilitates supervised learning.
- Labels are necessary for **specialized** tasks.

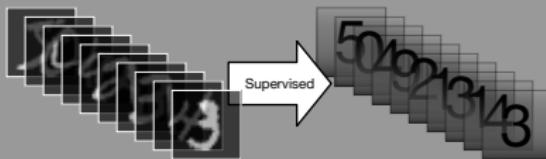


Figure: MNIST classification [1].



Figure: ImageNet examples [2].

Unsupervised Learning

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- Understanding the underlying **structure** of data.

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- Understanding the underlying **structure** of data.
- Avoids the high **cost** of labeling.

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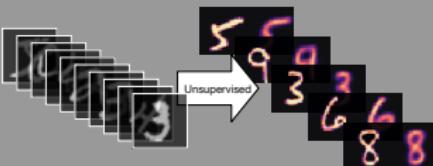


Figure: latent space learned by an auto-encoder.

Semi-supervised Learning

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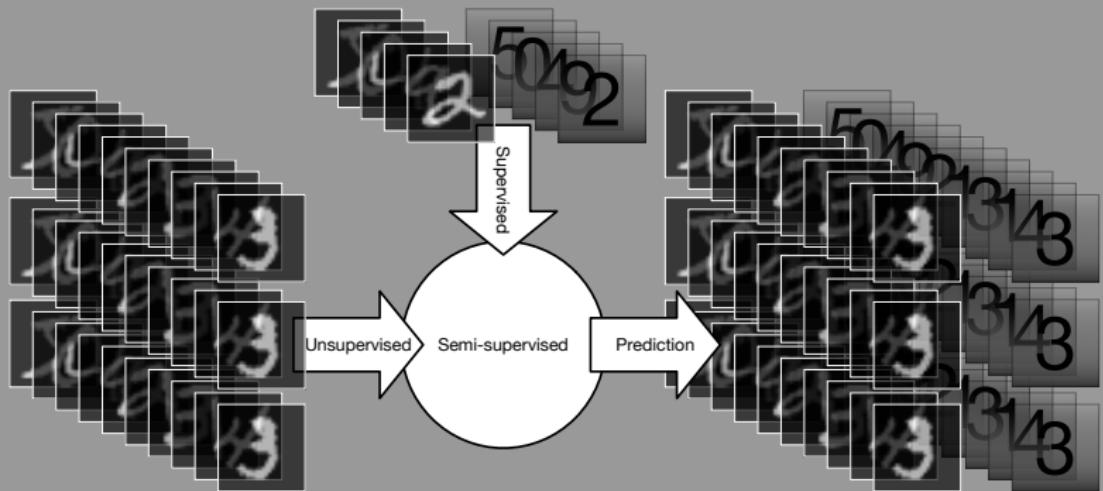


Figure: semi-supervised learning.

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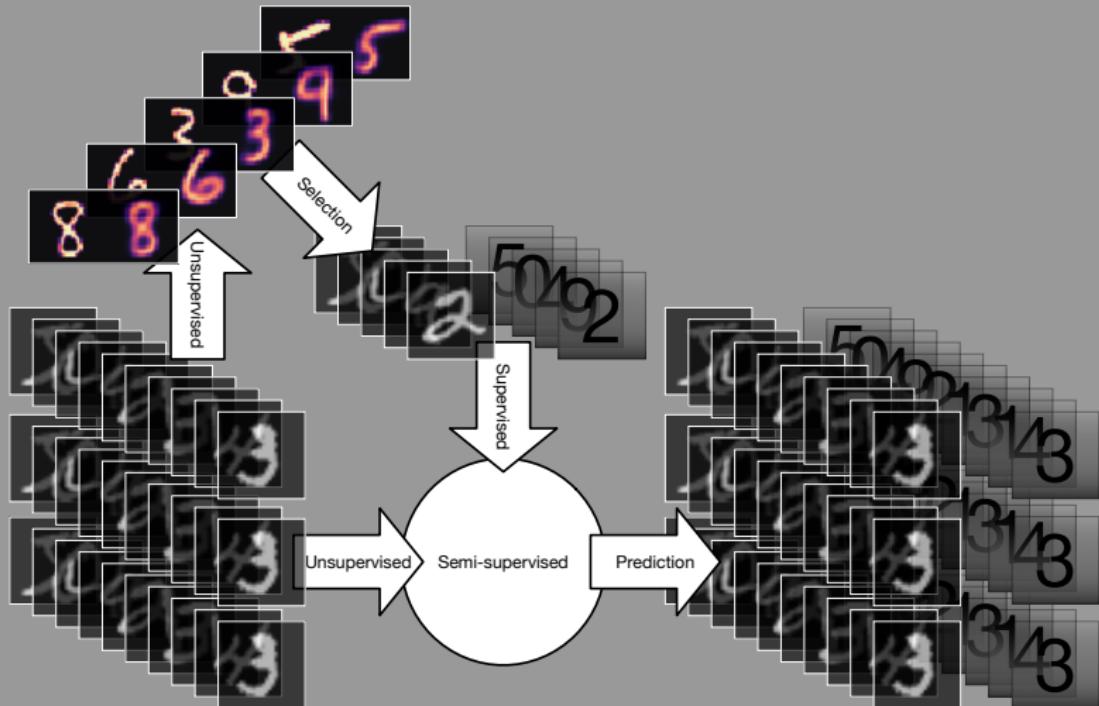


Figure: semi-supervised learning.

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- Supervised learning excels where **labels are available.**

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- Supervised learning excels where **labels are available.**
- Many domains require **starting from scratch** with absolutely no labels.

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- Supervised learning excels where **labels are available.**
- Many domains require **starting from scratch** with absolutely no labels.
- e.g. scientific image analysis.

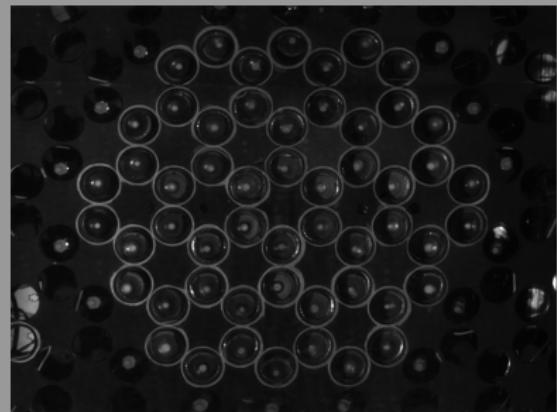


Figure: gyroscope tracking [3].

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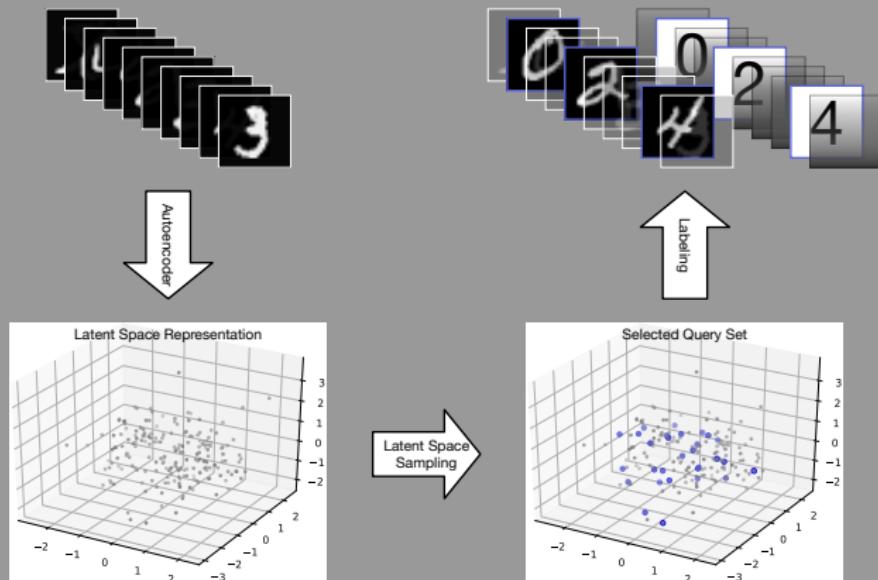


Figure: high-level overview

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- **Goal:** explore learned latent space \mathbb{R}^L representations for optimal query selection.

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- **Goal:** explore learned latent space \mathbb{R}^L representations for optimal query selection.
- **Constraint:** $L = 2$

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- **Goal:** explore learned latent space \mathbb{R}^L representations for optimal query selection.
- **Constraint:** $L = 2$
- **Train** multiple auto-encoders:
 - Convolutional [4]
 - Variational (VAE) [5]
 - “t-SNE style” [6]
 - “Variational t-SNE style”

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- **Goal:** explore learned latent space \mathbb{R}^L representations for optimal query selection.
- **Constraint:** $L = 2$
- **Train** multiple auto-encoders:
 - Convolutional [4]
 - Variational (VAE) [5]
 - “t-SNE style” [6]
 - “Variational t-SNE style”
- **Explore** multiple sampling strategies:
 - Distribution based
 - Cluster based (hierarchical)
 - Performance based

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- 3×3 convolution with 64 kernels (3x)
- 2×2 max-pooling
- 3×3 convolution with 32 kernels (3x)
- 2×2 max-pooling
- 3×3 convolution with 32 kernels (3x)
- 2×2 max-pooling
- 1024-node dense layer (2x)
- L -node dense layer, no activation
- 1024-node dense layer (2x)
- 3×3 convolution with 64 kernels (3x)
- 2×2 transpose convolution
- 3×3 convolution with 32 kernels (3x)
- 2×2 transpose convolution
- 3×3 convolution with 32 kernels (3x)
- 2×2 transpose convolution

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■ VAE:

- $2L$ -node dense layer.
- Normal-distribution sampling layer.
- loss: binary cross-entropy with KL divergence from normal $\text{KL}(Z||\mathcal{N})$.

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■ VAE:

- 2 L -node dense layer.
 - Normal-distribution sampling layer.
 - loss: binary cross-entropy with KL divergence from normal $\text{KL}(Z||\mathcal{N})$.
- ## ■ “t-SNE style”
- loss: binary cross, entropy with added $\text{KL}(P||Q)$ for batches of 64

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■ VAE:

- $2L$ -node dense layer.
- Normal-distribution sampling layer.
- loss: binary cross-entropy with KL divergence from normal $\text{KL}(Z||\mathcal{N})$.

■ “t-SNE style”

- loss: binary cross-entropy with added $\text{KL}(P||Q)$ for batches of 64

■ “Variational t-SNE style”:

- $2L$ -node dense layer.
- Normal-distribution sampling layer.
- loss: combination of binary cross-entropy, VAE-like $\text{KL}(Z||\mathcal{N})$, and t-SNE style $\text{KL}(P||Q)$.

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Algorithm 1 Select examples from the encoding Z according to a distribution f .

Require: encoding $Z \in \mathbb{R}^L$, probability distribution $f : \mathbb{R}^L \rightarrow \mathbb{R}$, distance metric $d : \mathbb{R}^{2 \times L} \rightarrow \mathbb{R}$, distance threshold $t \in \mathbb{R}$, $n \in \mathbb{N}$.

```
1:  $Q \leftarrow \{\}$ 
2: while  $|Q| < n$  do
3:   Draw  $z \sim f$ 
4:   for  $z_i \in Z$  do                                ▷ the  $i$ th row of  $Z$ 
5:     if  $d(z, z_i) < t$  then
6:        $Q \leftarrow Q \cup \{i\}$ 
7:     end if
8:   end for
9: end while
10: return  $Q$ 
```

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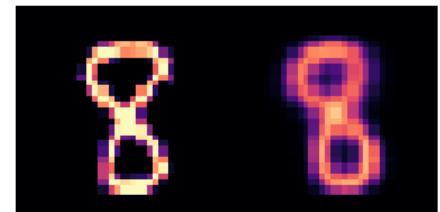
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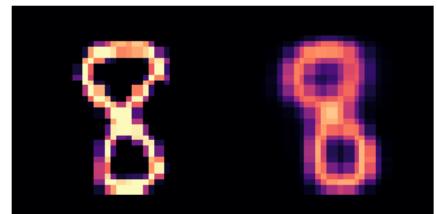
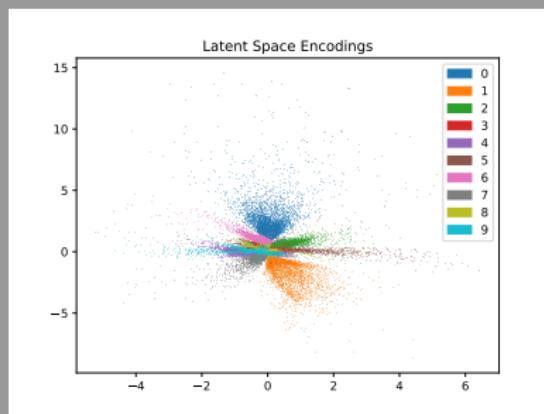
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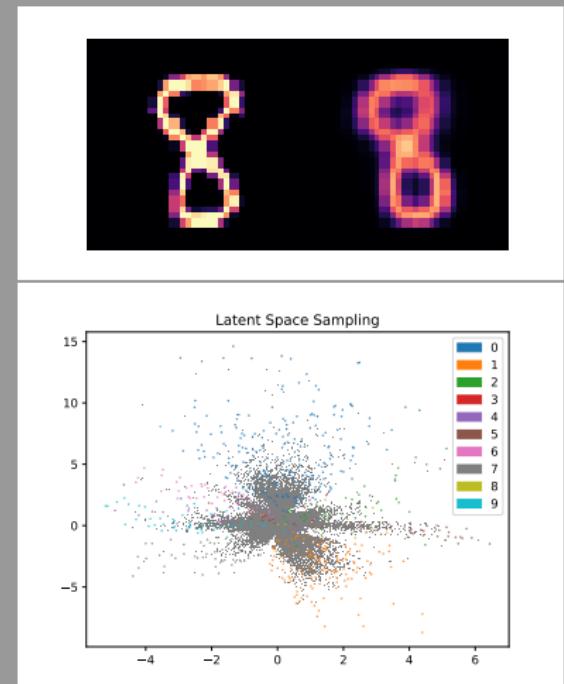
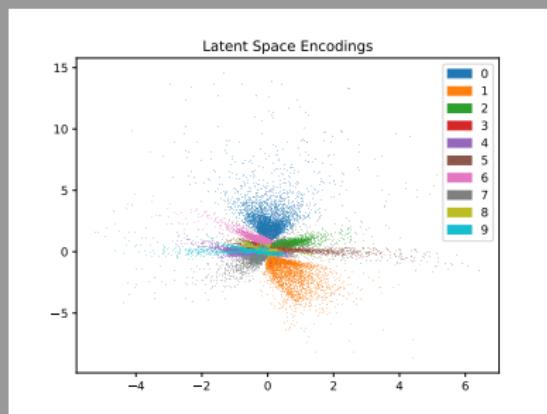
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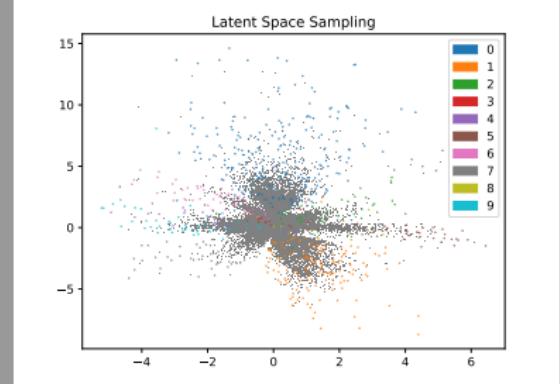
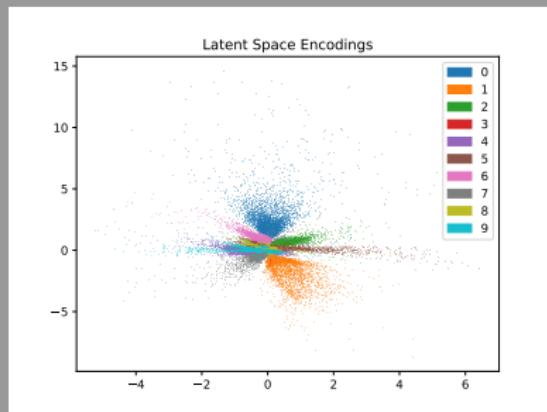
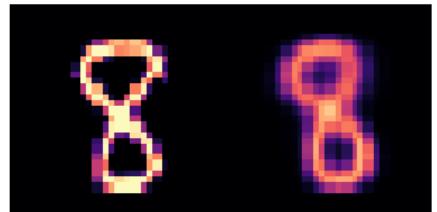
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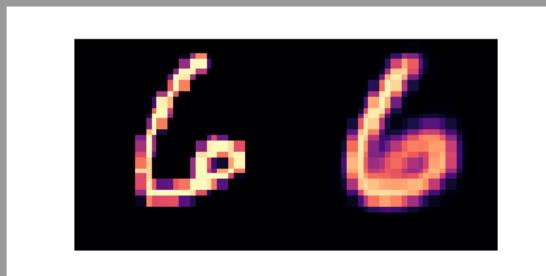
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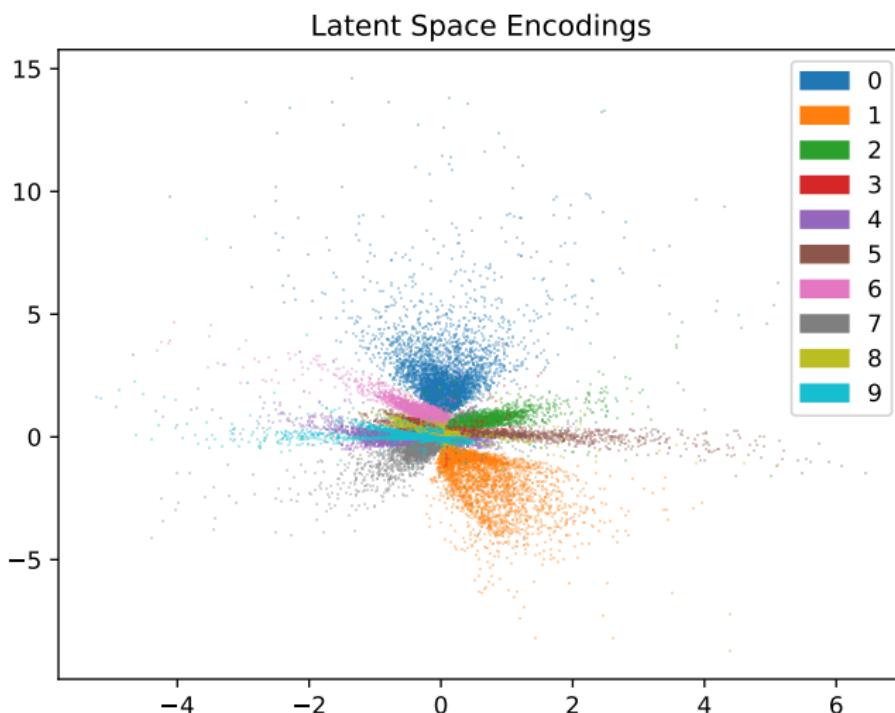
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Uniform Spatial Sampling

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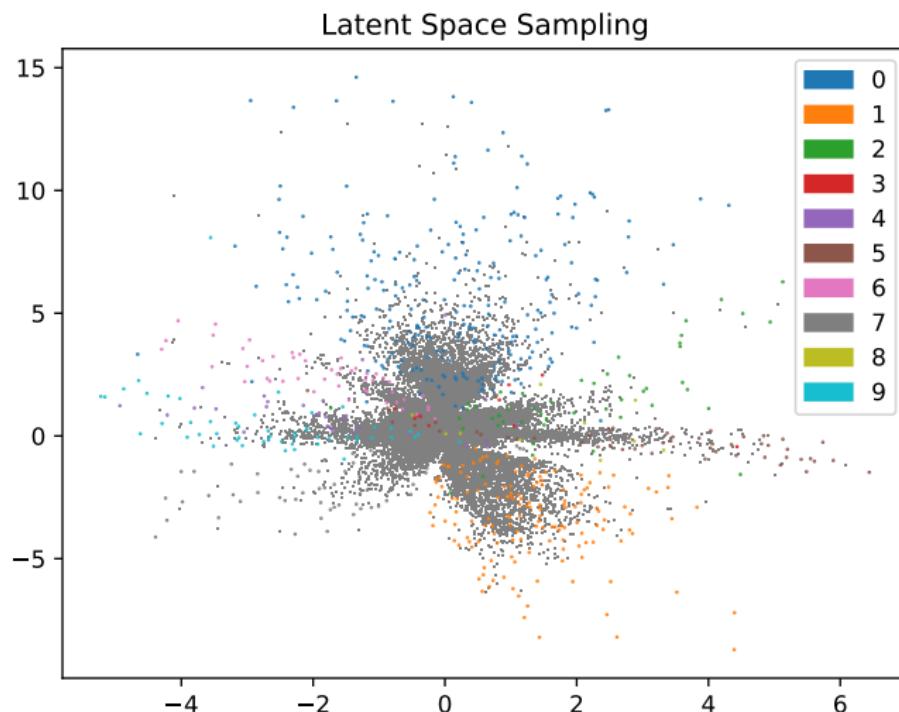
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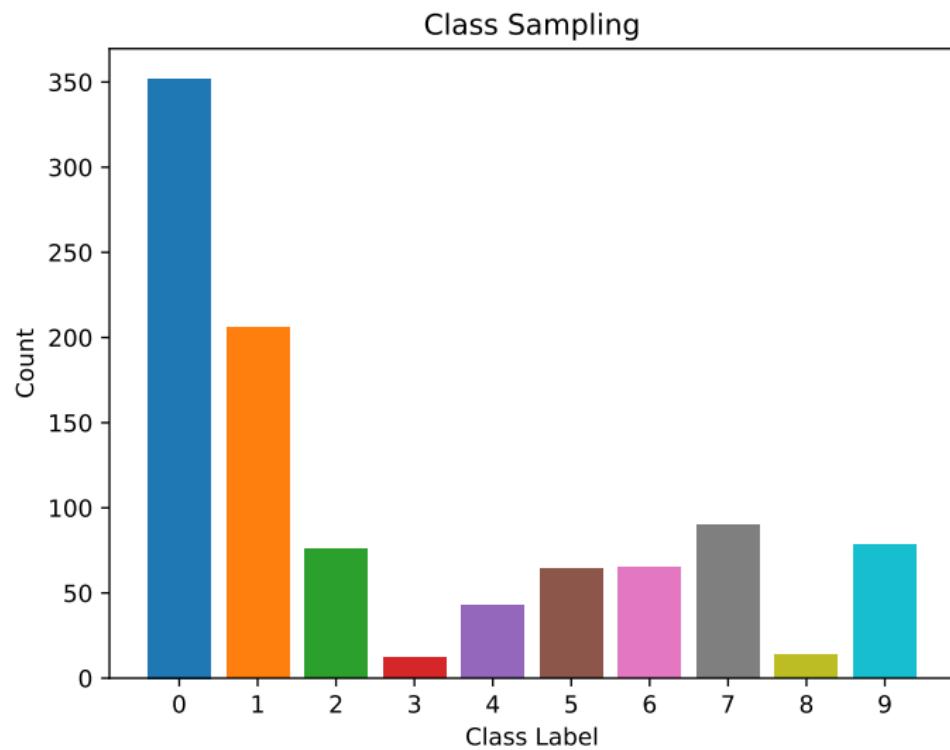
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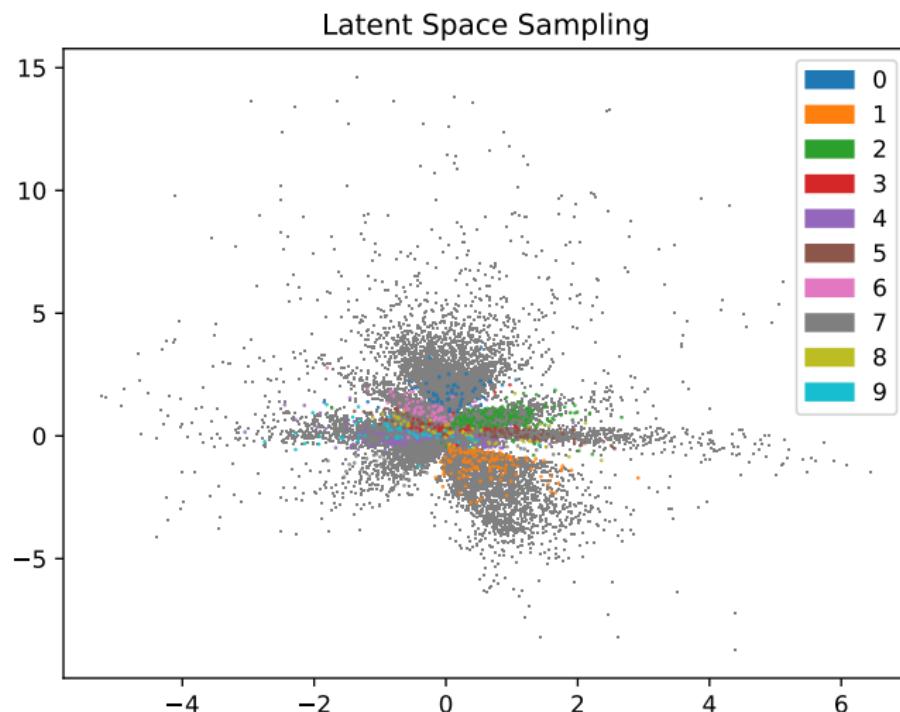
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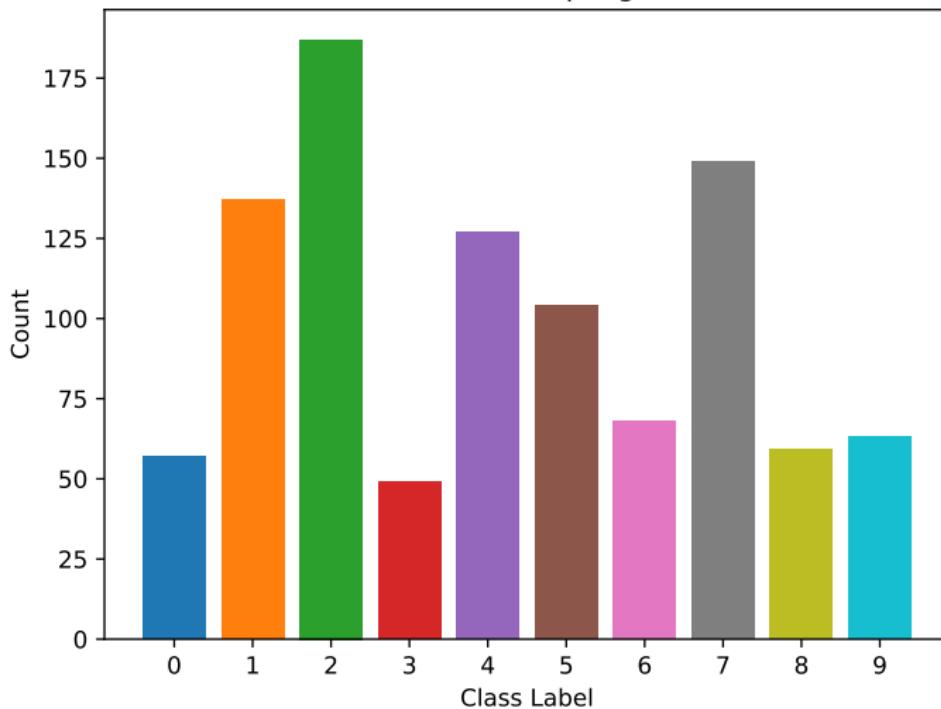
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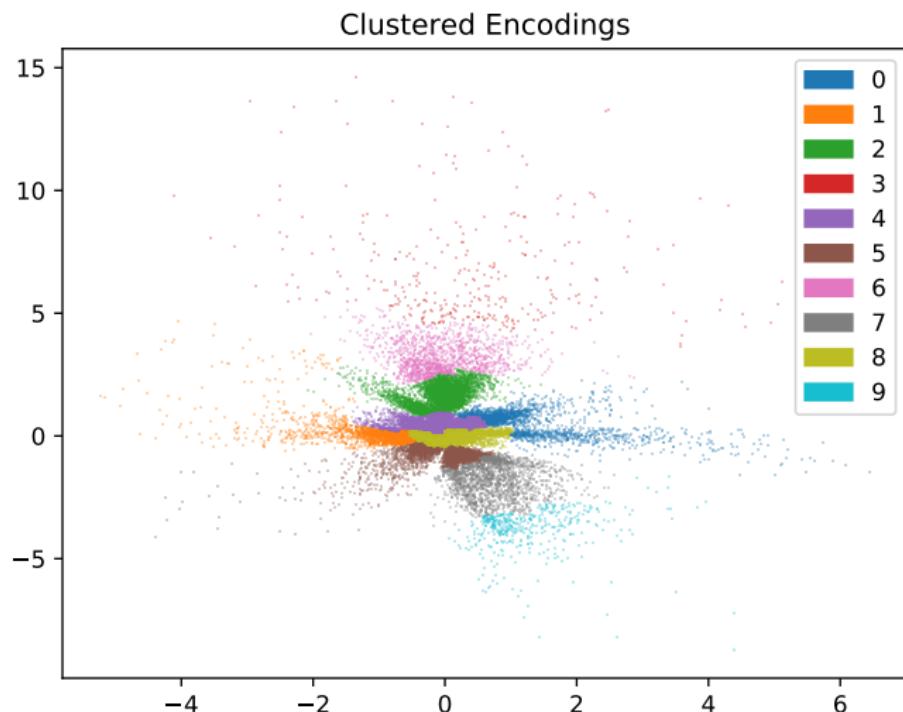
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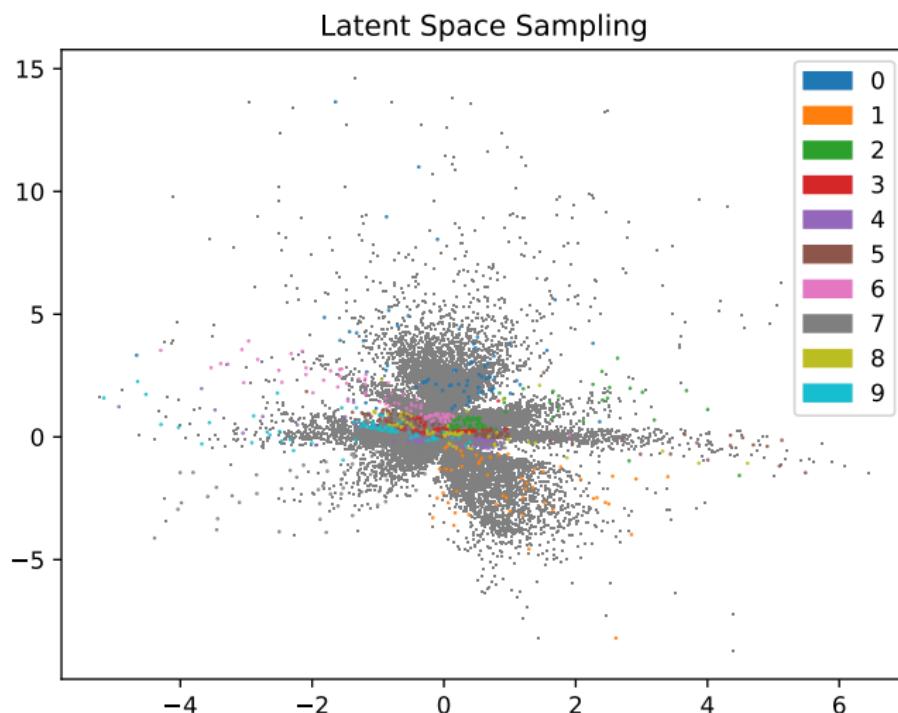
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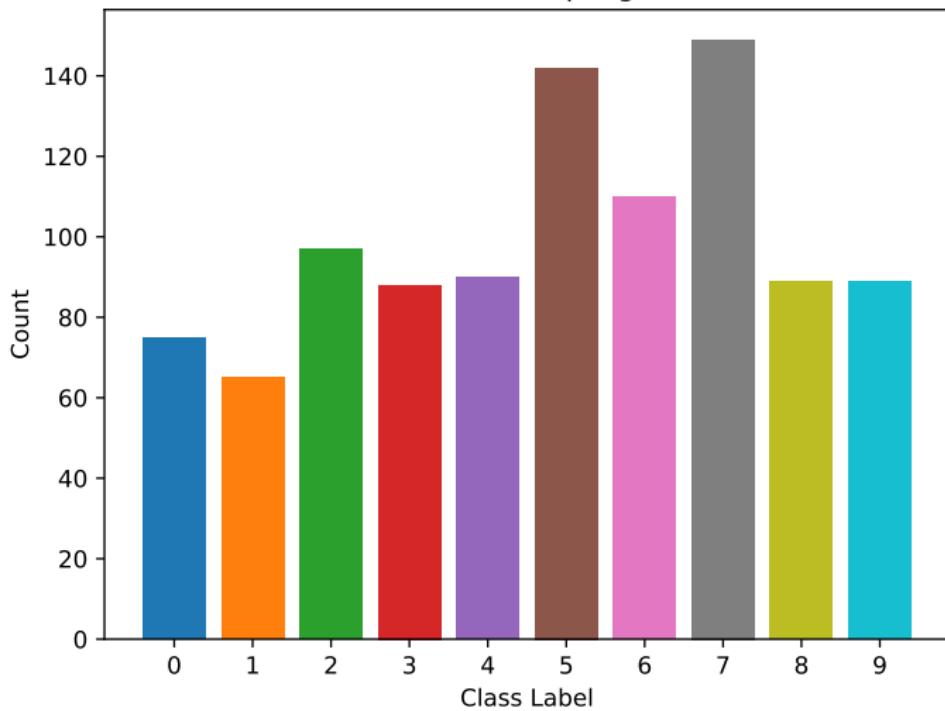
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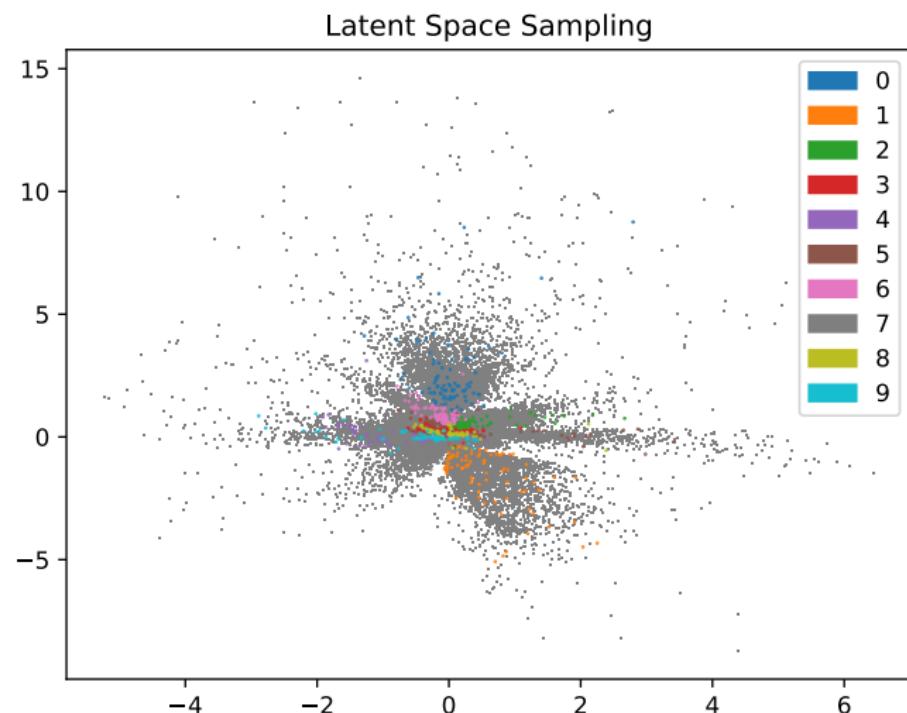
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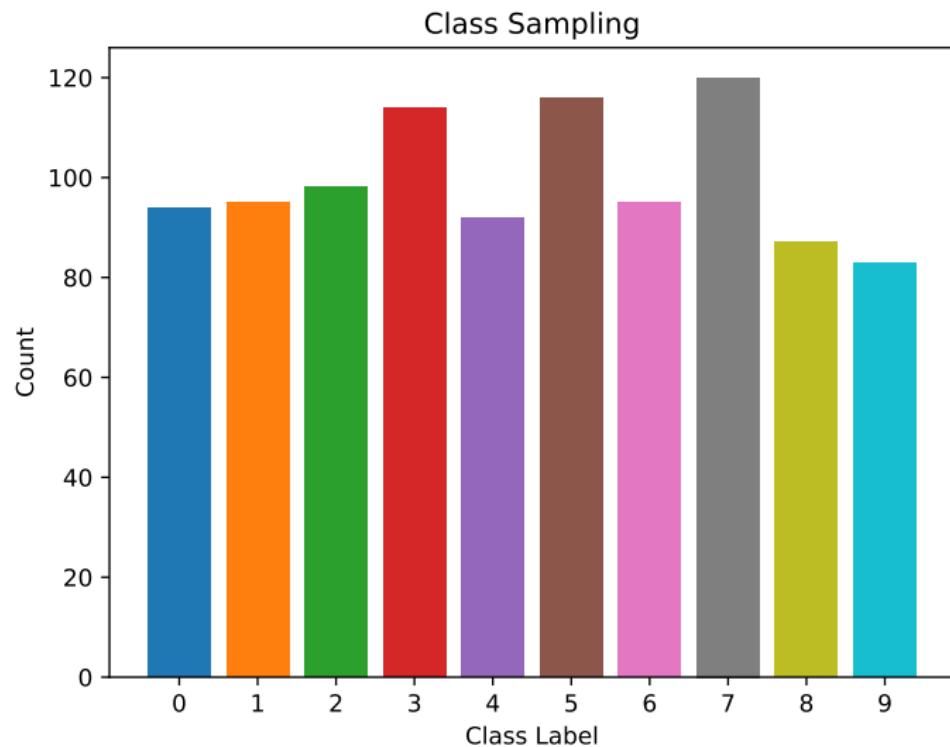
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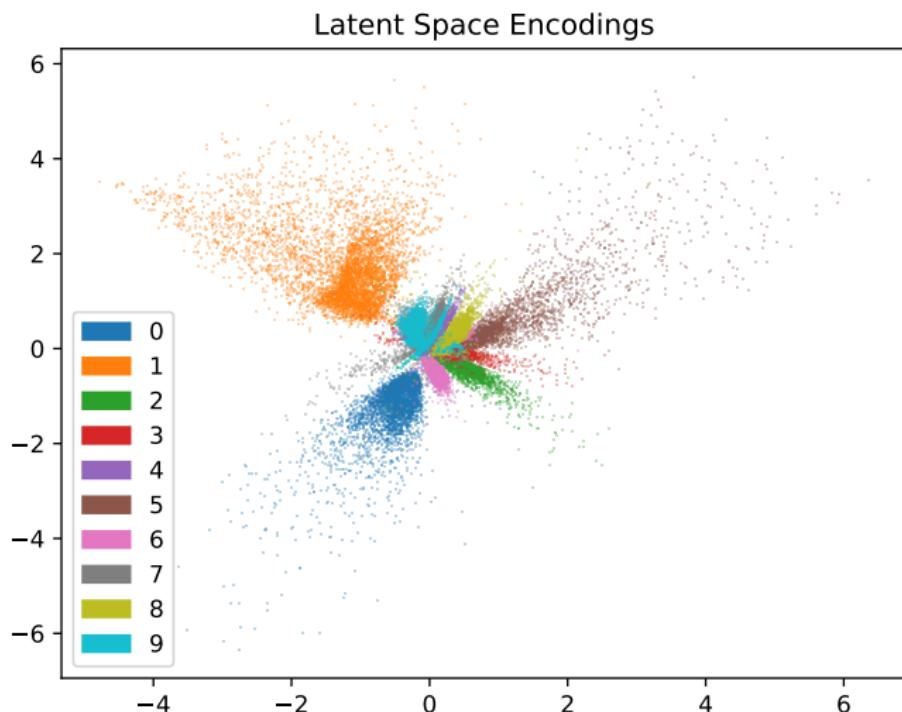
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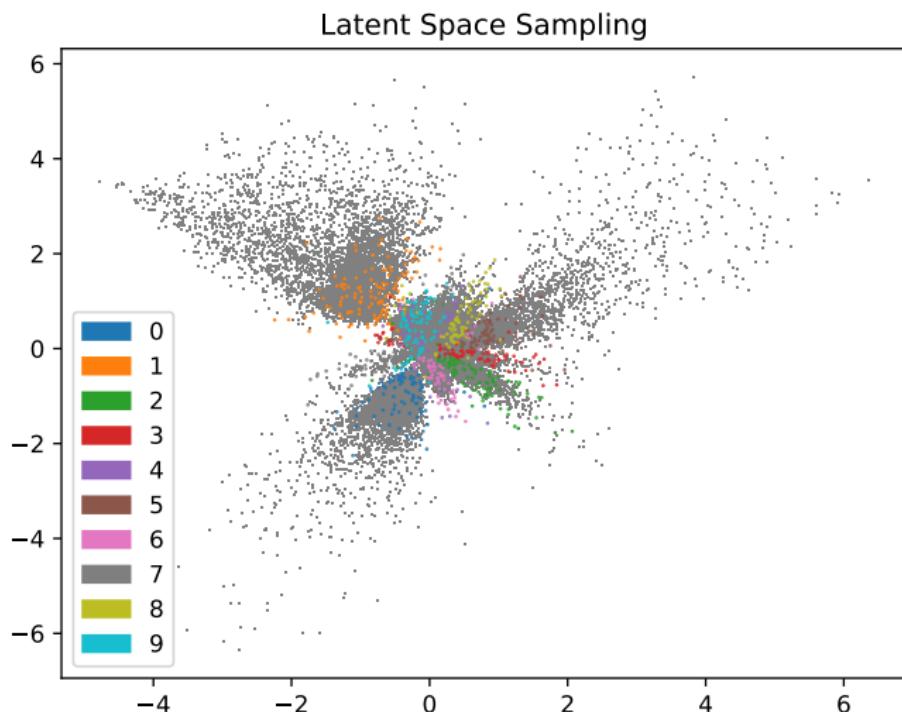
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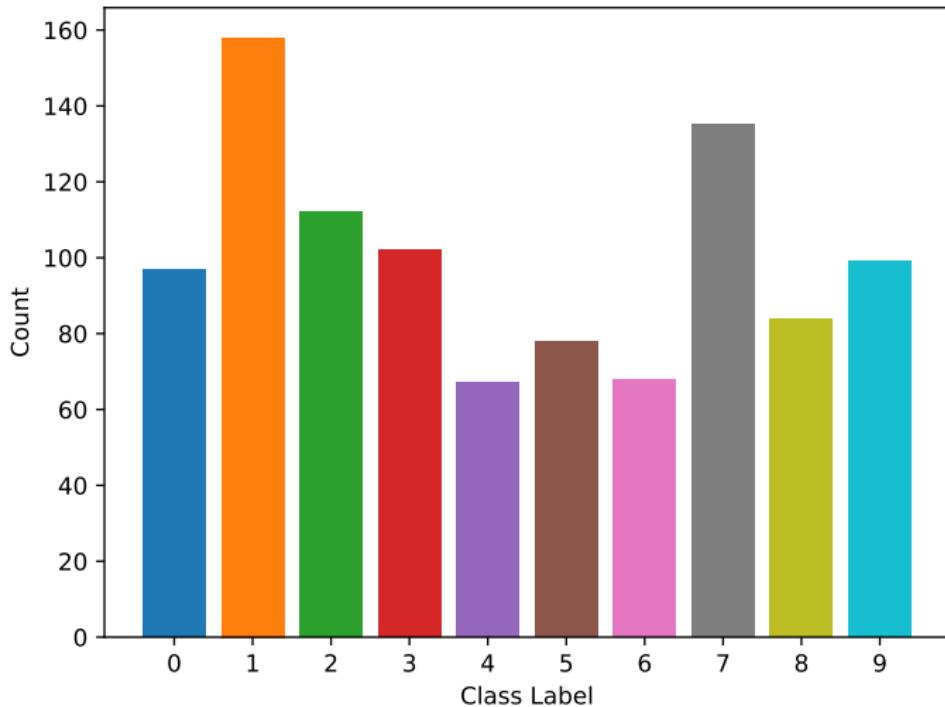
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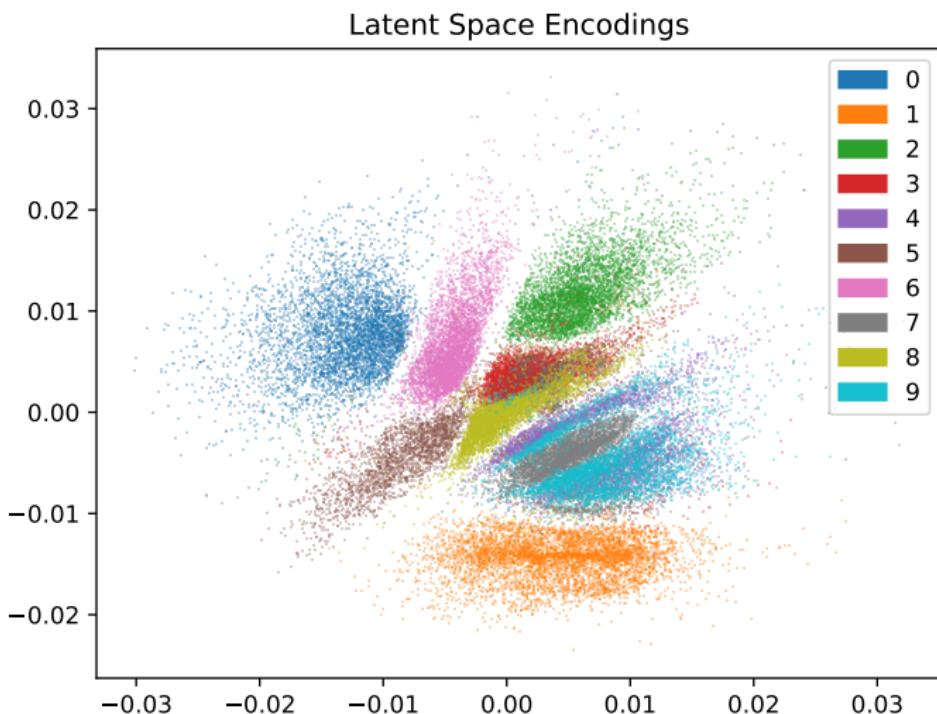
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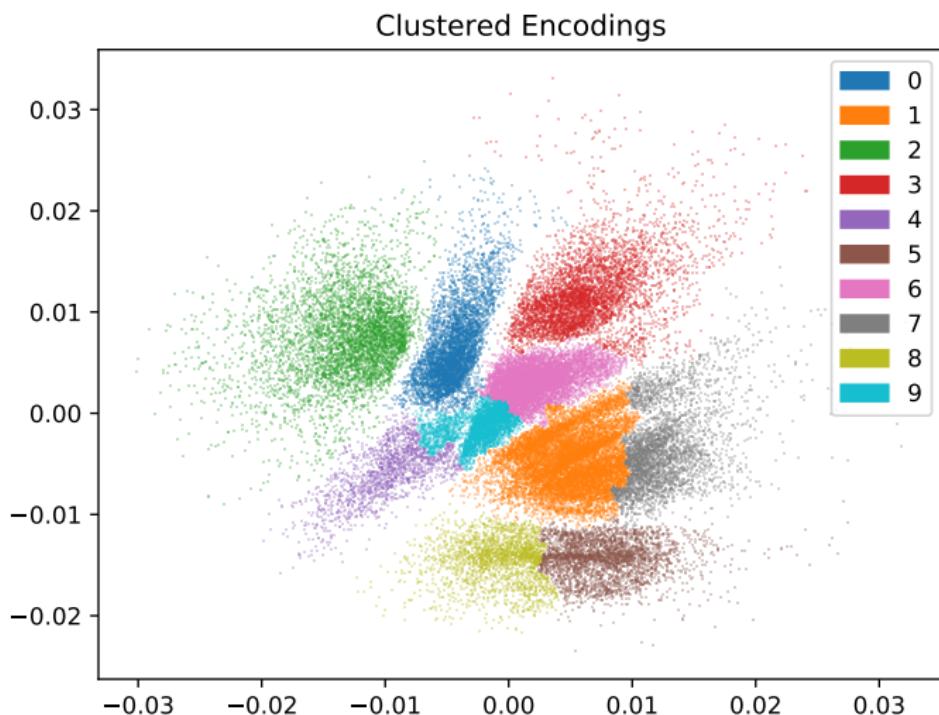
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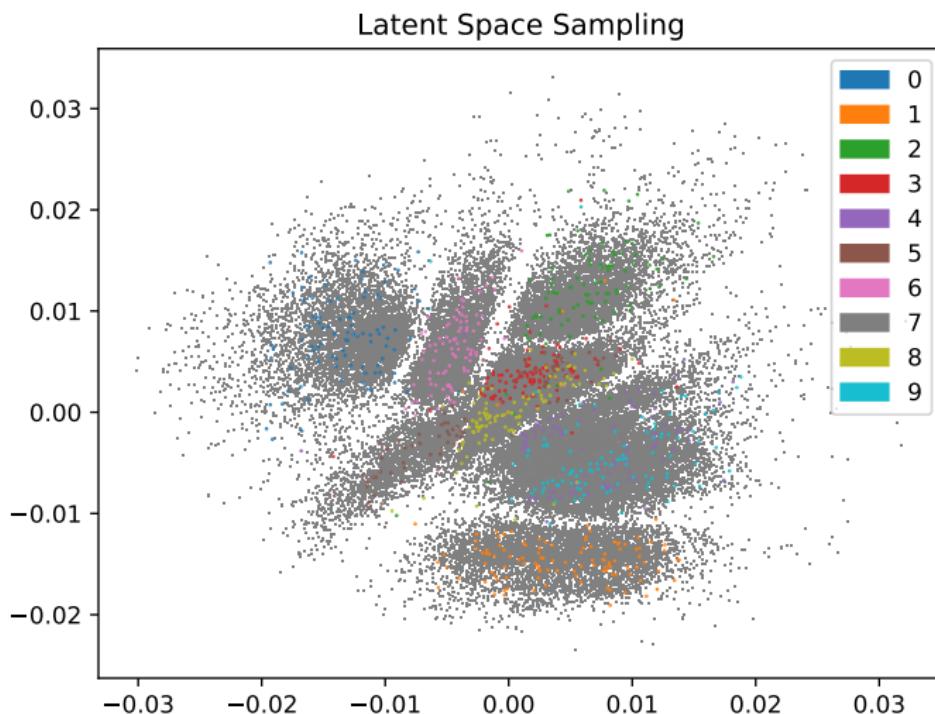
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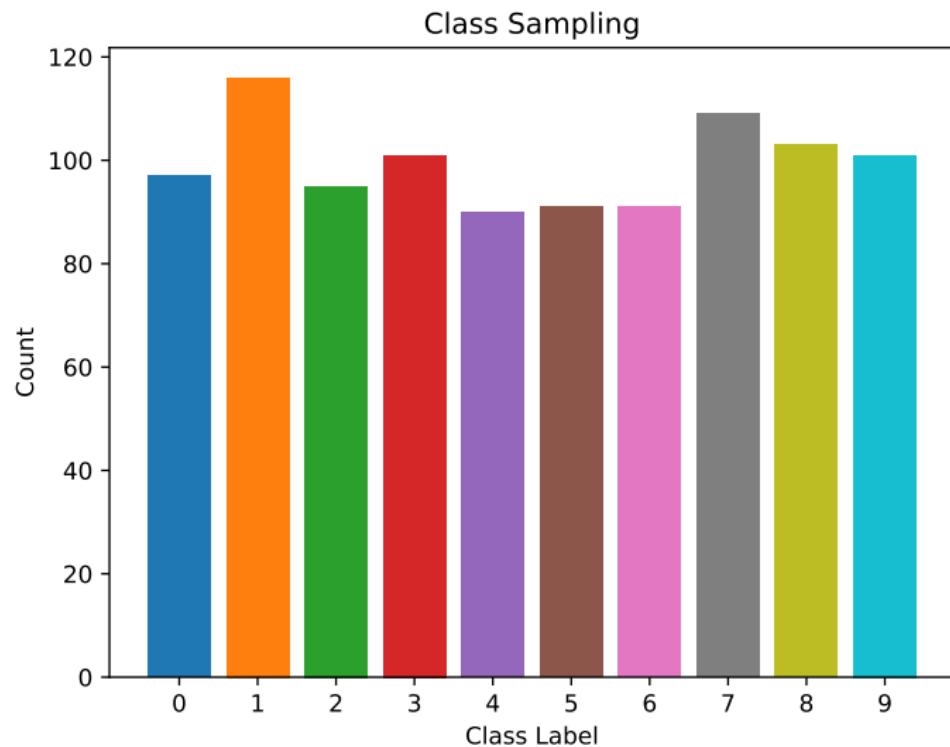
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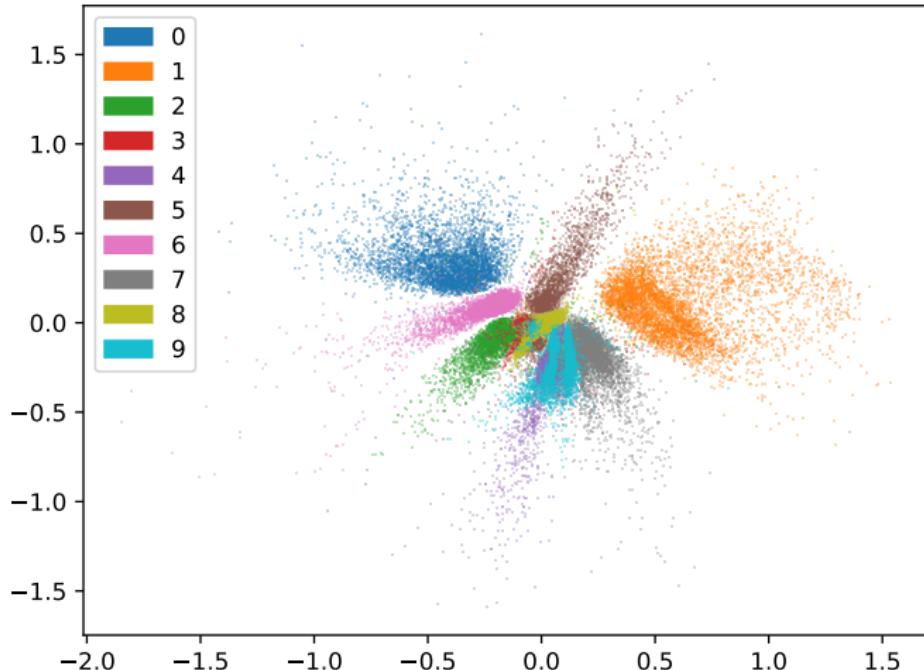
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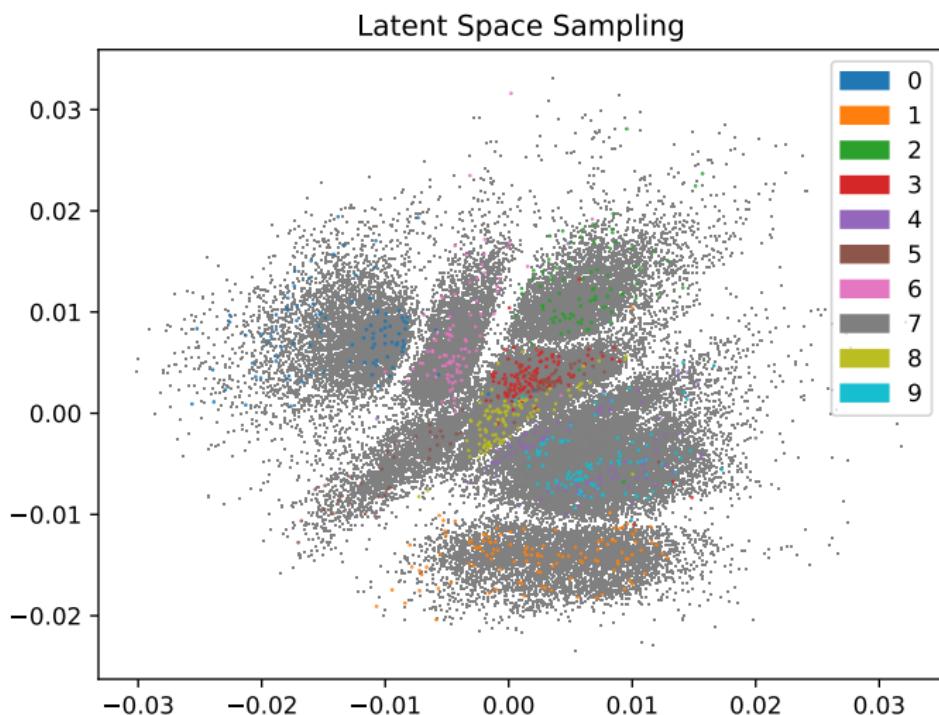
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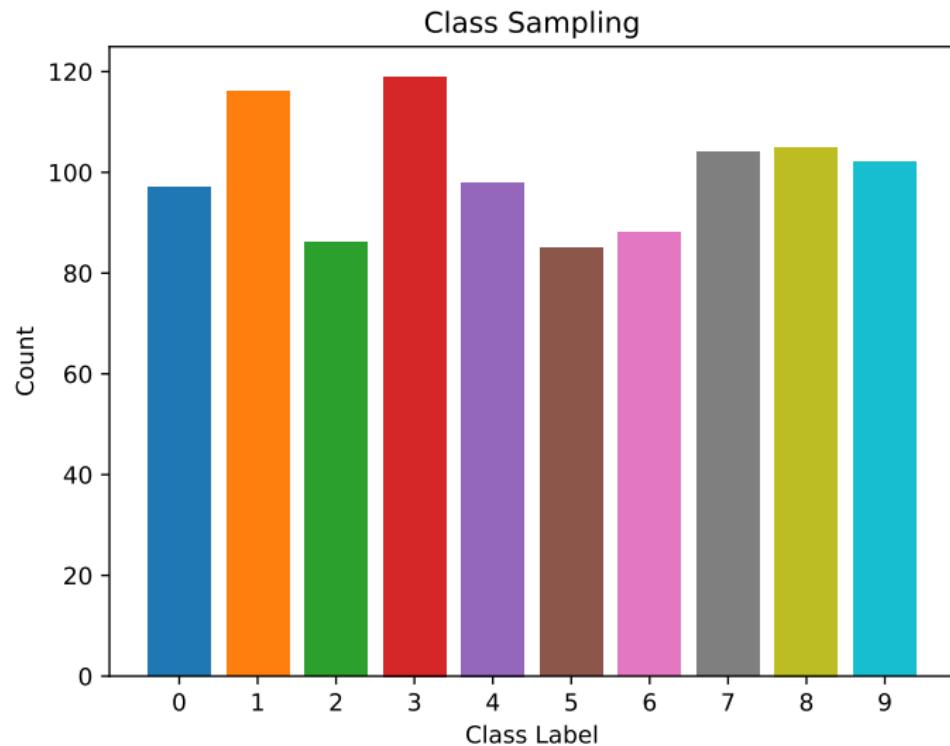
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- Normal sampling inside clusters yields **balanced samples**.

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- Normal sampling inside clusters yields **balanced samples**.
- Are auto-encoders the **best choice** for latent-space representation?

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- Normal sampling inside clusters yields **balanced samples**.
- Are auto-encoders the **best choice** for latent-space representation?
- Distribution of **difficult examples** in latent space.

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- Normal sampling inside clusters yields **balanced samples**.
- Are auto-encoders the **best choice** for latent-space representation?
- Distribution of **difficult examples** in latent space.

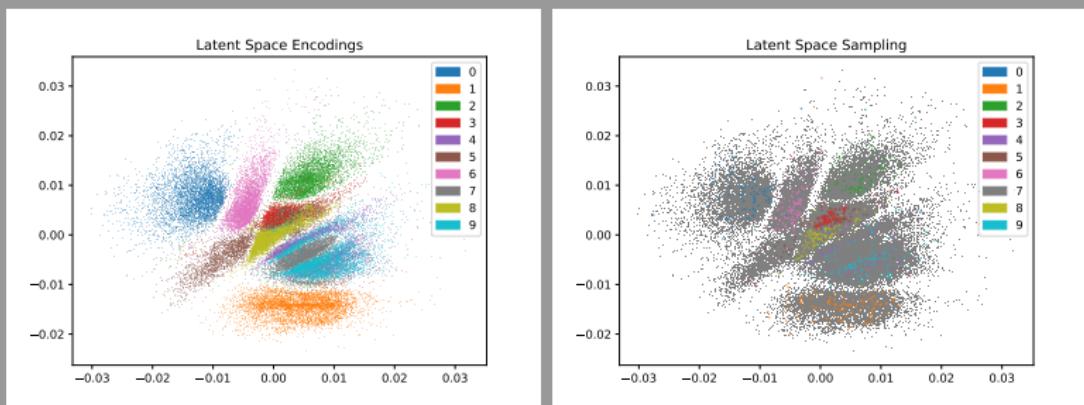


Figure: Visualizing points which are difficult to learn.

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- Transfer learning **without overfitting.**

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- Transfer learning **without overfitting.**
- Evaluate performance of classifiers **trained on query selections.**

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- Transfer learning **without overfitting.**
- Evaluate performance of classifiers **trained on query selections.**
- Explore higher dimensions.

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- Transfer learning **without overfitting**.
- Evaluate performance of classifiers **trained on query selections**.
- Explore higher dimensions.
- Labeling **artificial examples** produced by an auto-encoder.

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