Query Selection based on Latent Space Sampling

Benjamin Killeen

Outline

Motivation: Supervised Learning

- **Big data** facilitates supervised learning.

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Figure: ImageNet examples [2].

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

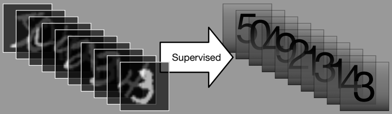

Figure: MNIST classification [1].

Figure: ImageNet examples [2].

Unsupervised Learning

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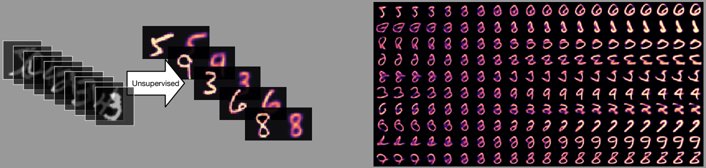


Figure: latent space learned by an auto-encoder.

Semi-supervised Learning

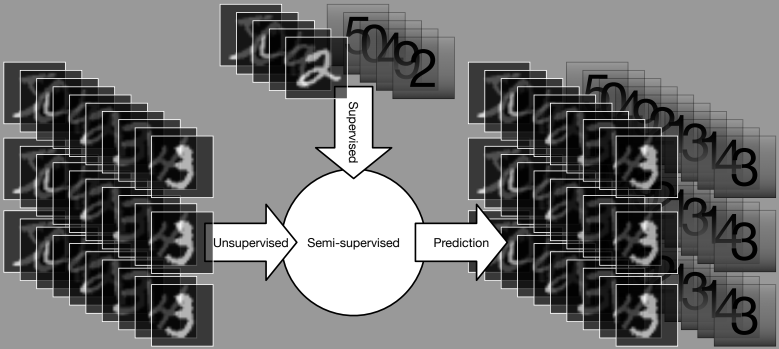
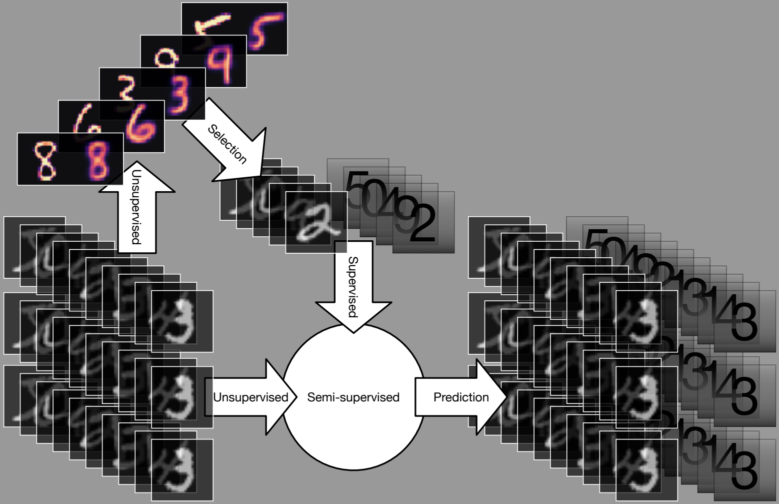


Figure: semi-supervised learning.

Starting from Scratch



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- Many domains require **starting from scratch** with absolutely no labels.
- *e.g.* scientific image analysis.

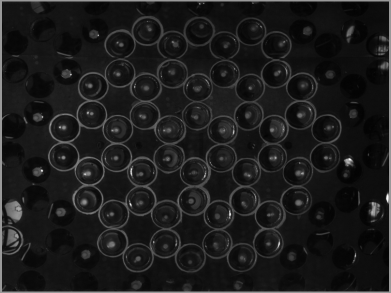

Figure: gyroscope tracking [3].

Method

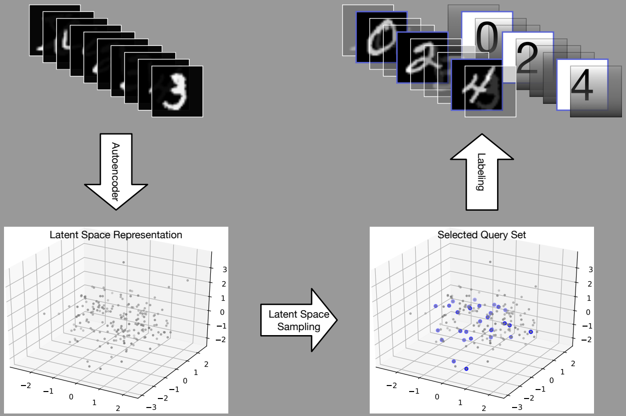

Figure: high-level overview

Method

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

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- **Explore** multiple sampling strategies:
  - Distribution based
  - Cluster based (hierarchical)
  - Performance based

Convolutional Auto-encoder

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

Sampling

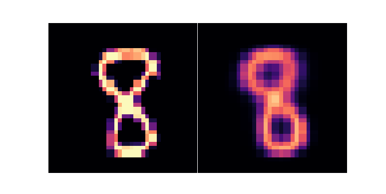
Algorithm 1 Select examples from the encoding Z according to a distribution f.

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

```
Q ← {}
while |Q| < n do
    Draw z ∼ f
    for z_i ∈ Z do                    ▷ the ith row of Z
        if d(z, z_i) < t then
            Q ← Q ∪ {i}
        end if
    end for
end while
return Q
```

Results

- Reconstructions



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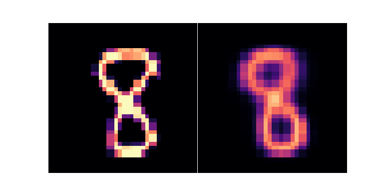
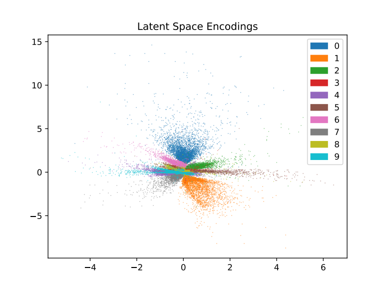
- Encodings





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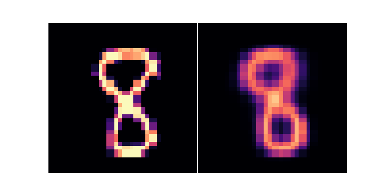

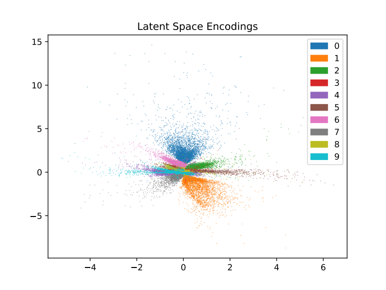

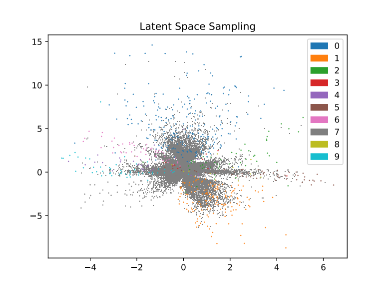

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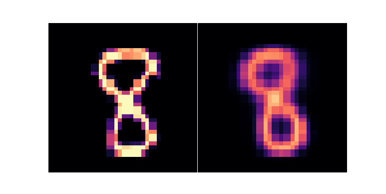
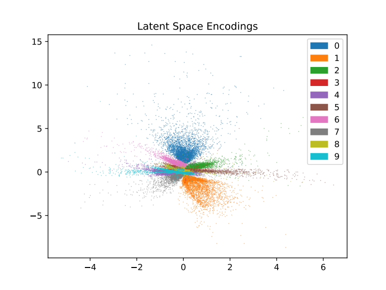
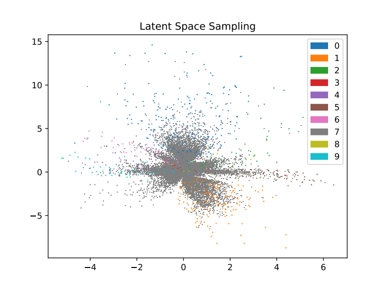
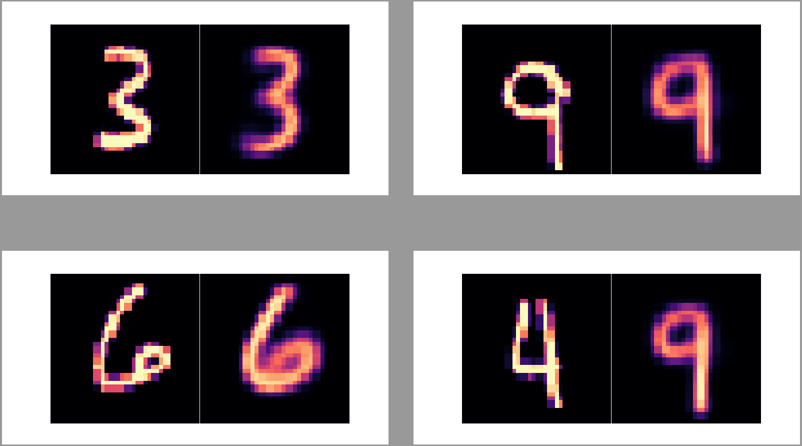






Convolutional Auto-encoder



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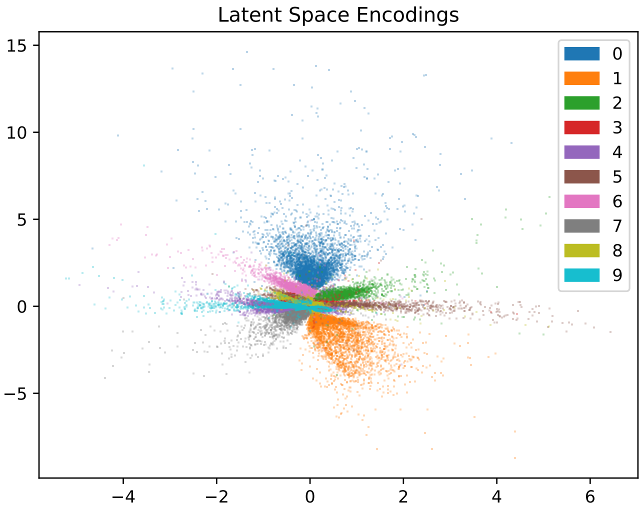
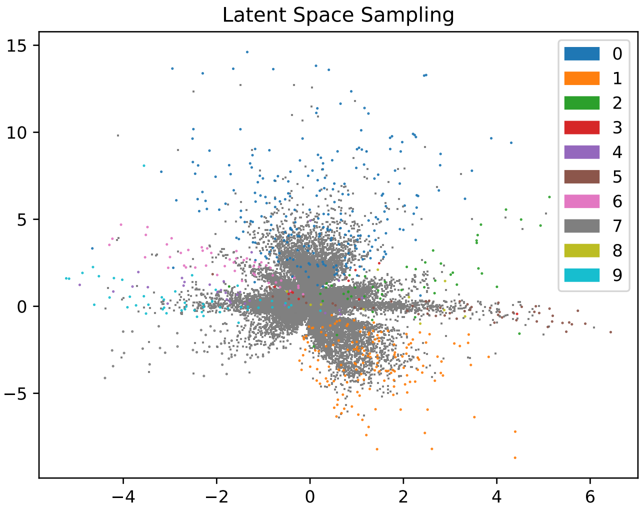


Uniform Spatial Sampling



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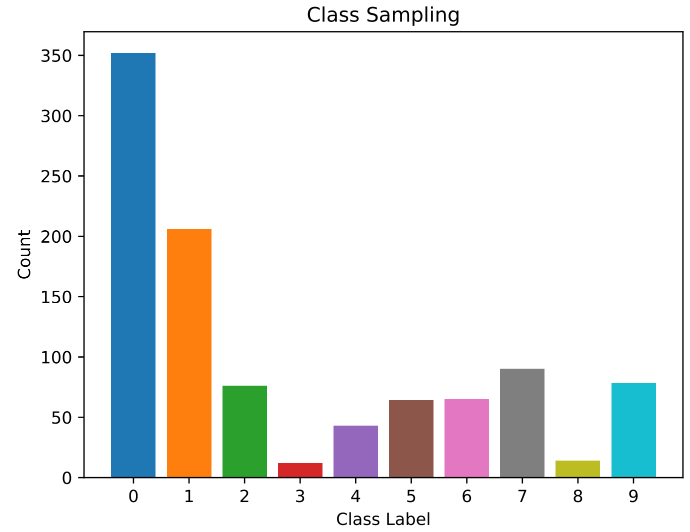

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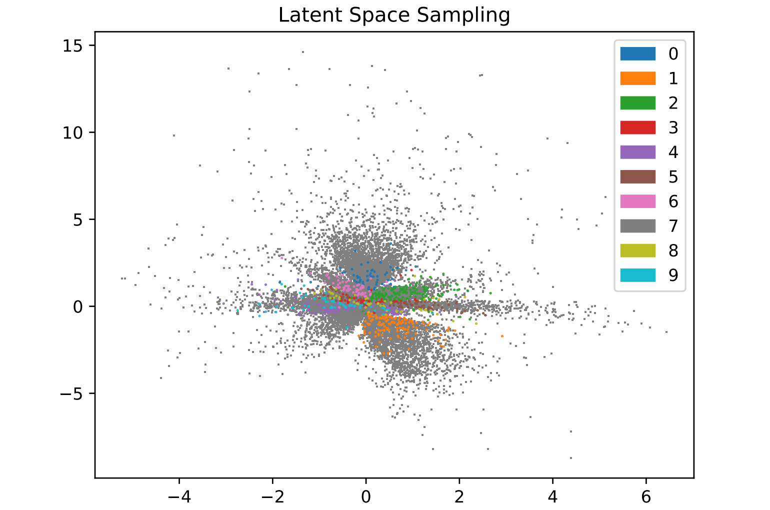

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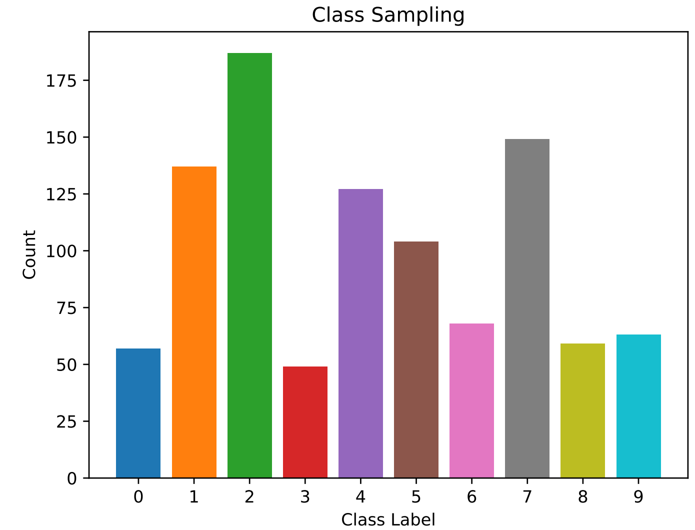
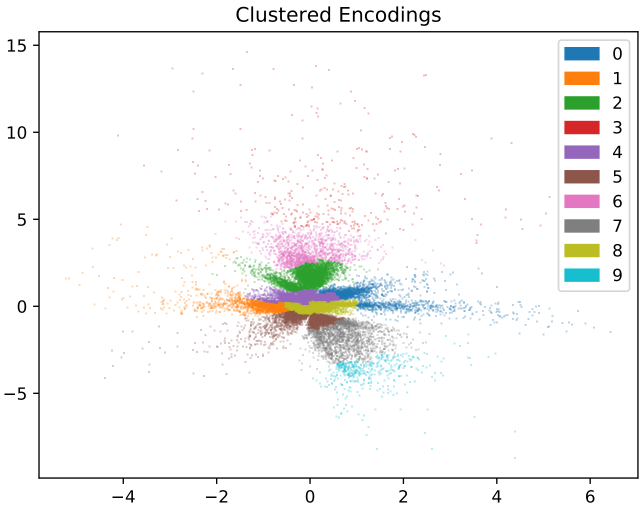
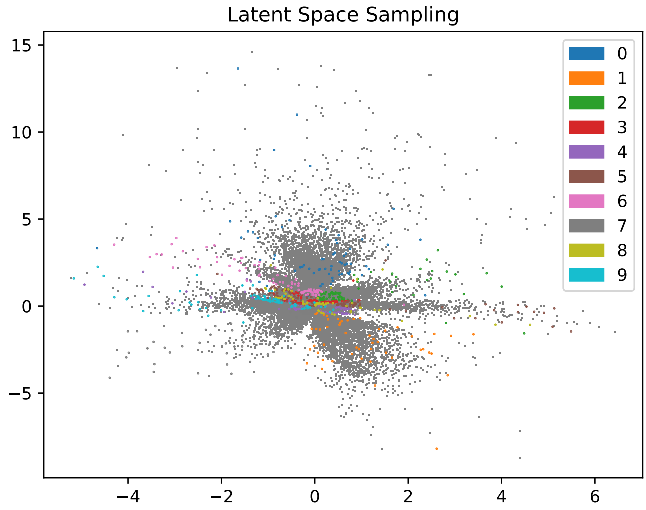
- Motivation
- Method
- Results
  - Convolutional AE
  - Variational AE
  - t-SNE Style AE
  - Variational t-SNE Style AE
  - Reconstruction Error Sampling
- Discussion
- Future Work
- References



Clustering



Cluster Sampling



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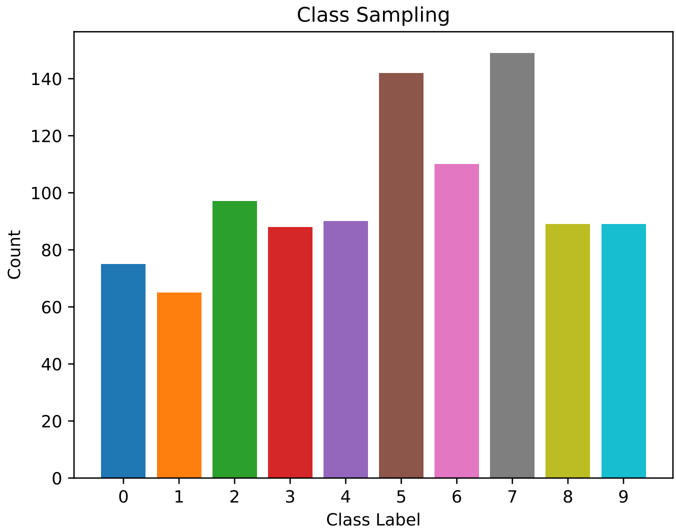

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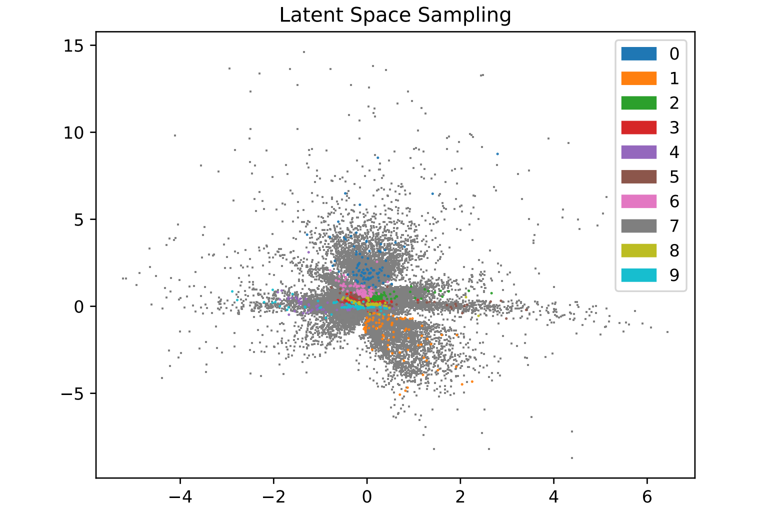

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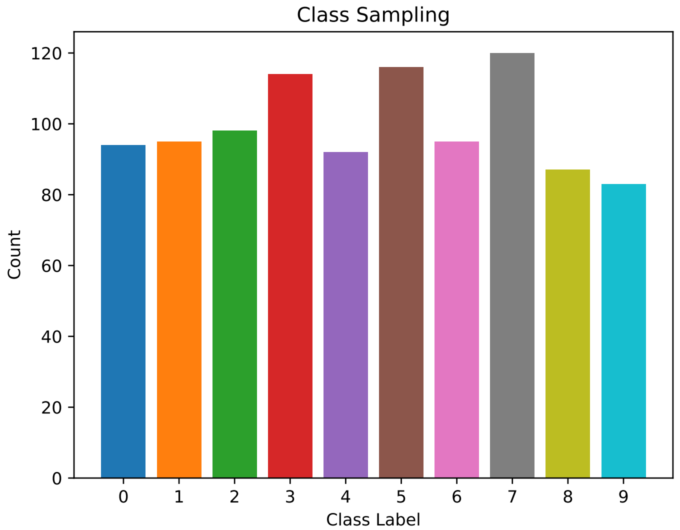
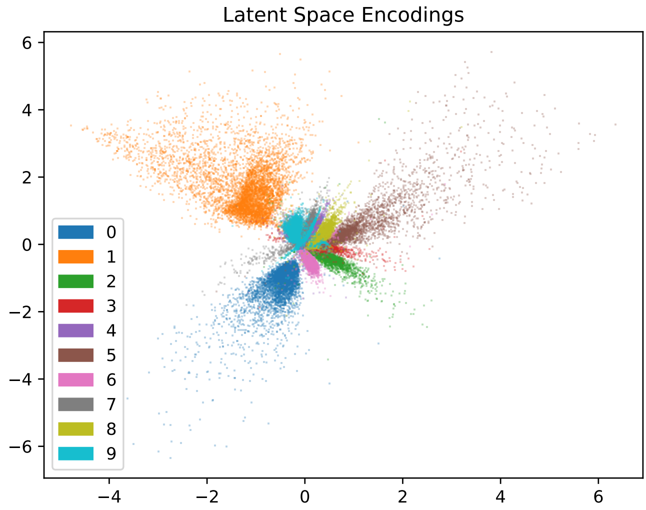


Variational Auto-encoder



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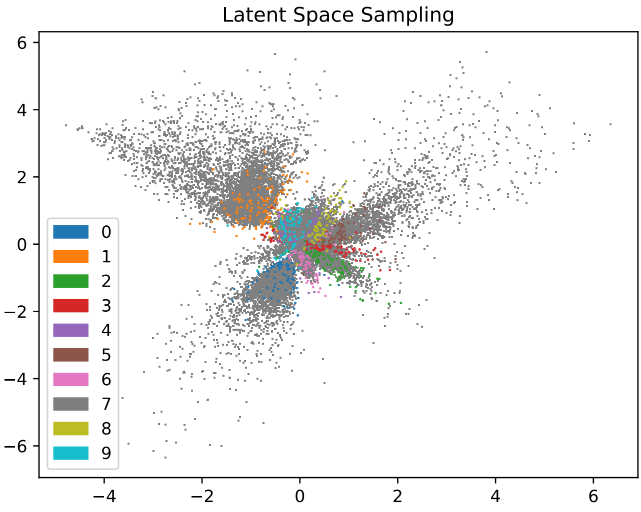

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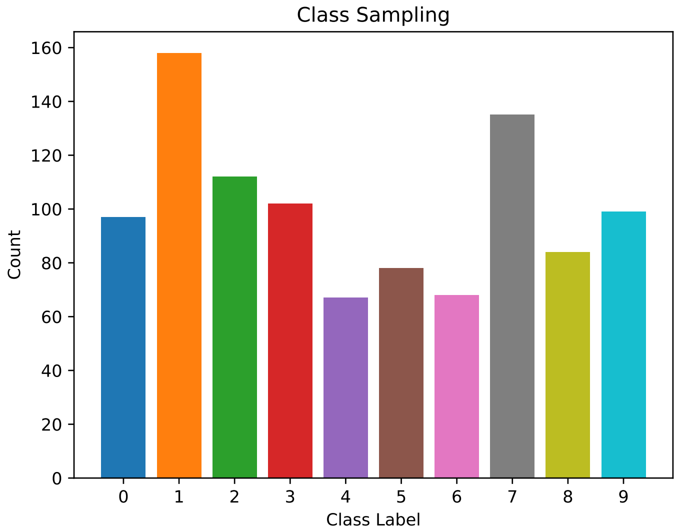
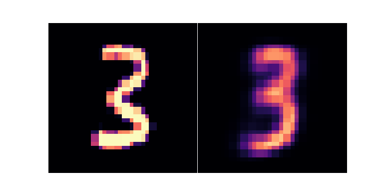
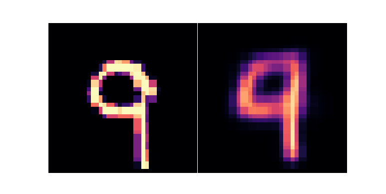
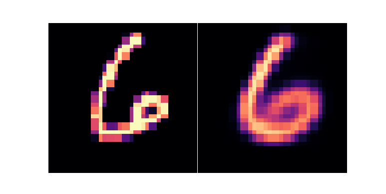
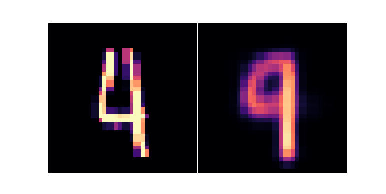


t-SNE Style Auto-encoder









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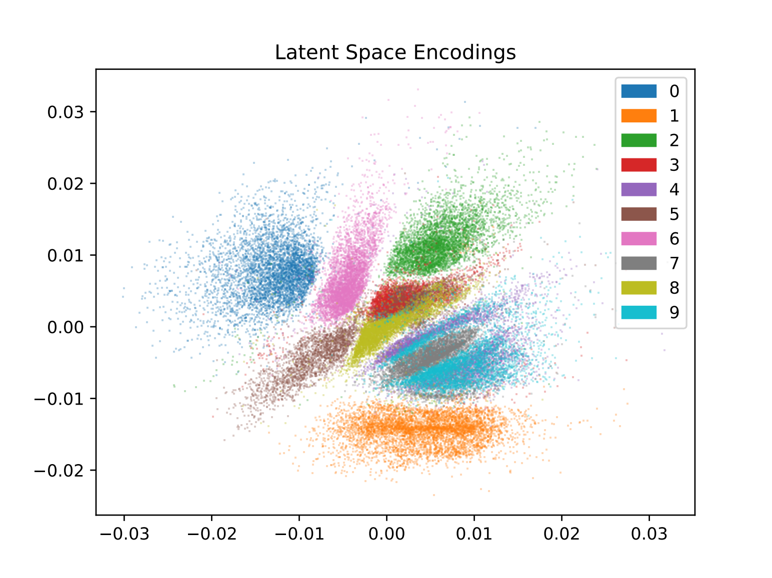

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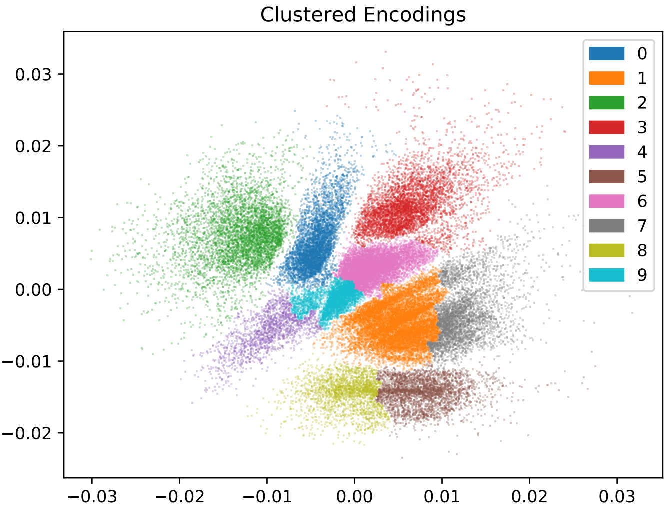
Clustered Encodings
0
1
2
3
4
5
6
7
8
9
0.03
0.02
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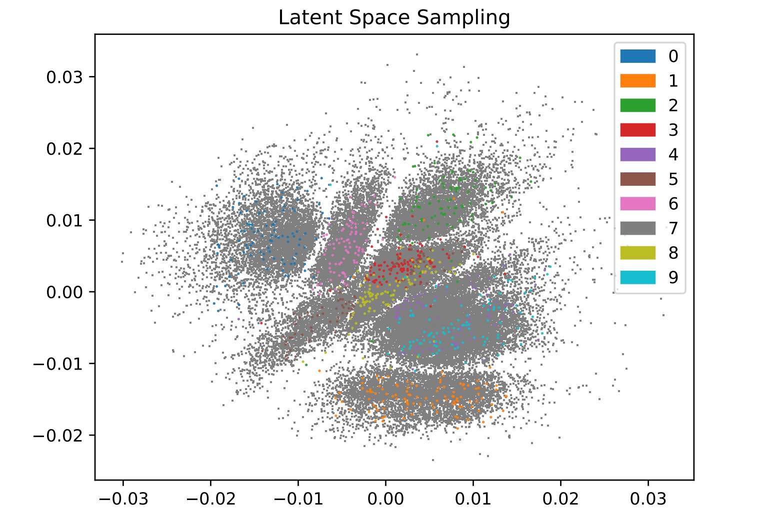
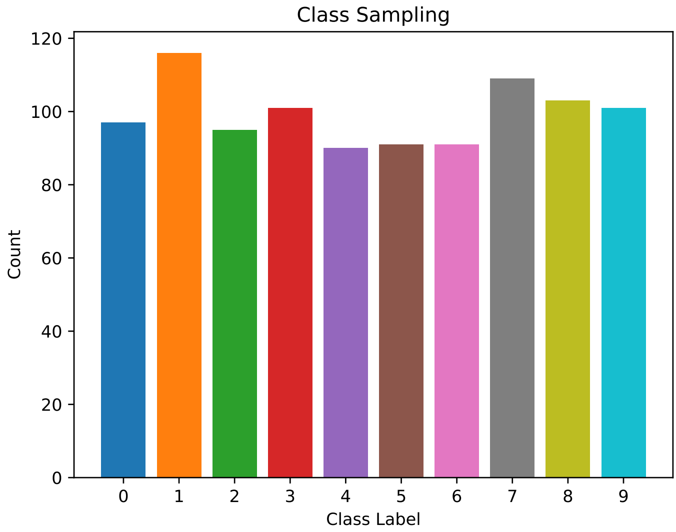
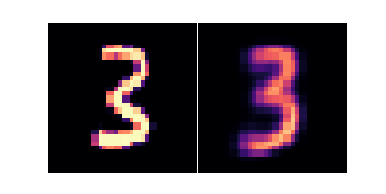
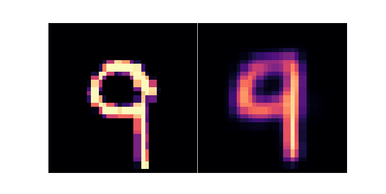


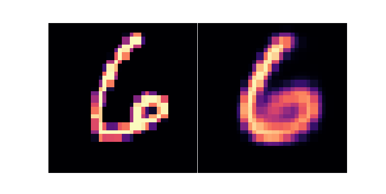
Clustered Normal Spatial Sampling

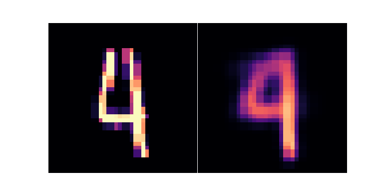


Variational t-SNE Style Auto-encoder









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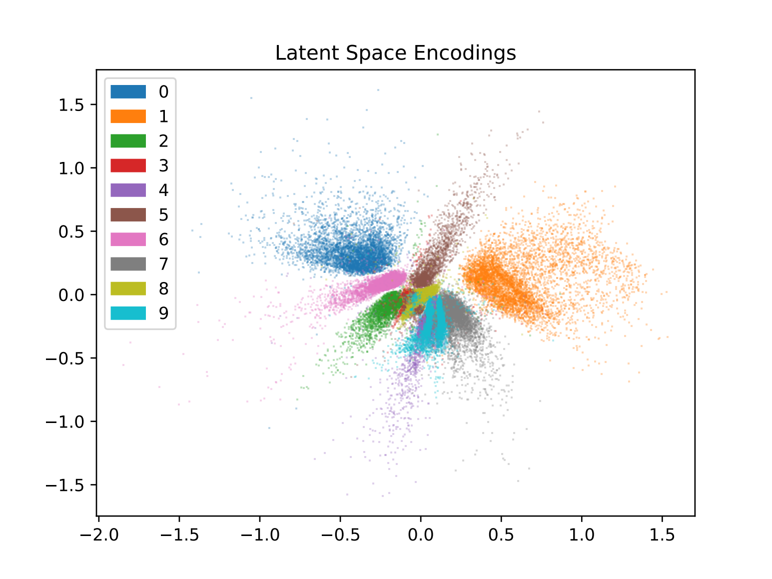

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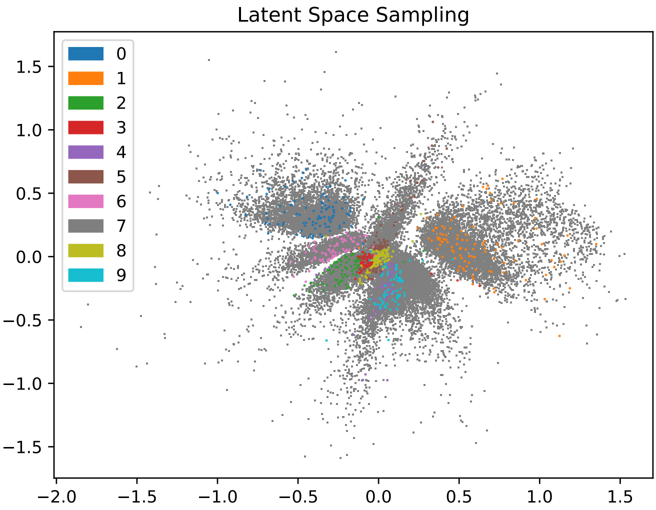

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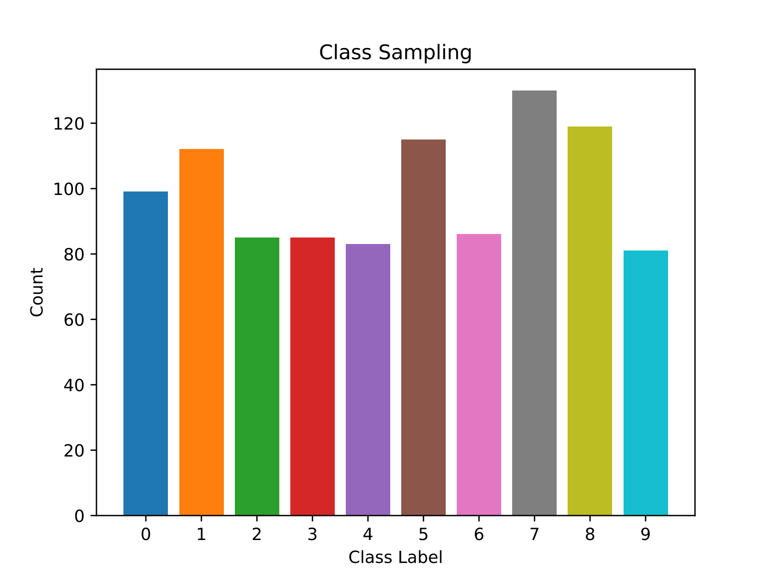
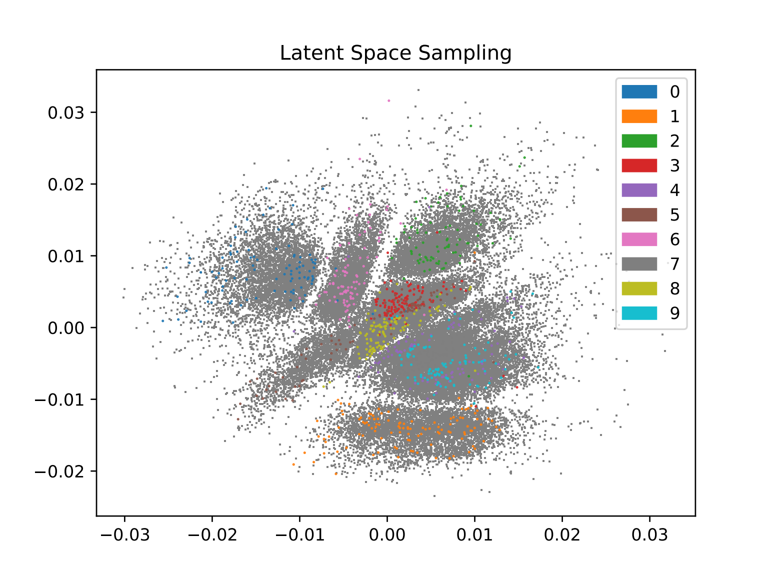


Reconstruction Error Sampling



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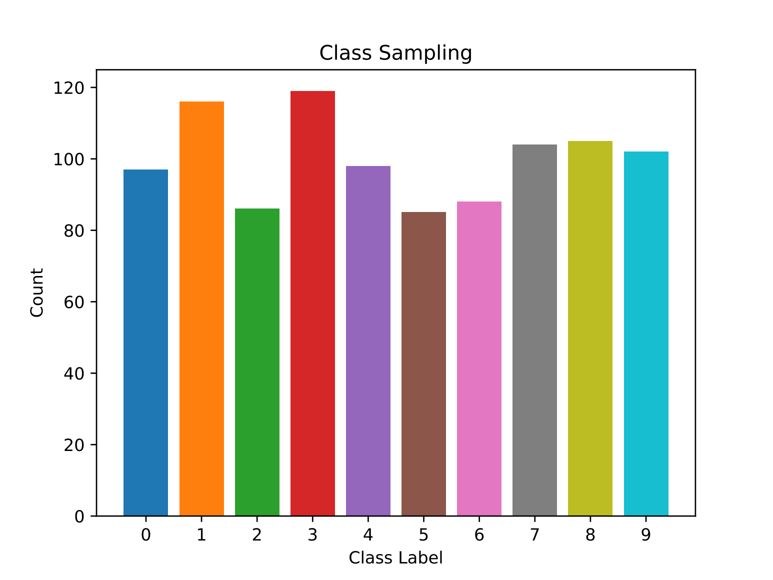

Discussion

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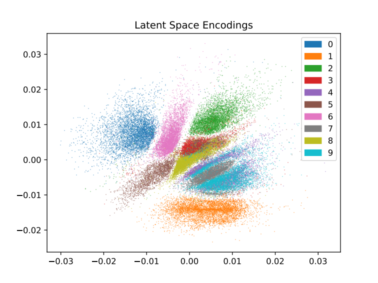

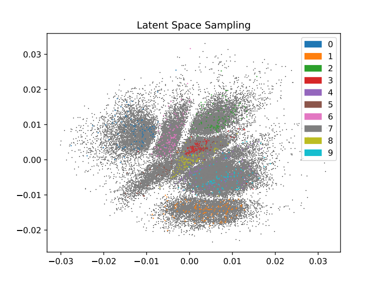

Figure: Visualizing points which are difficult to learn.

Future Work

- Transfer learning **without overfitting**.

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References I

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