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.

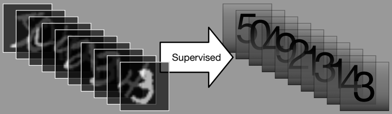

Figure: MNIST classification [1].

Figure: ImageNet examples [2].

Unsupervised Learning

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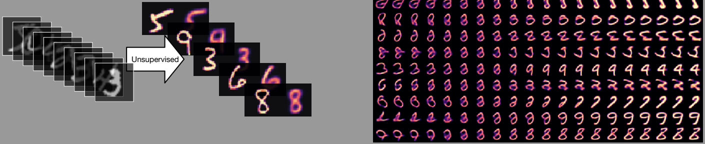

Figure: latent space learned by an auto-encoder.

Semi-supervised Learning

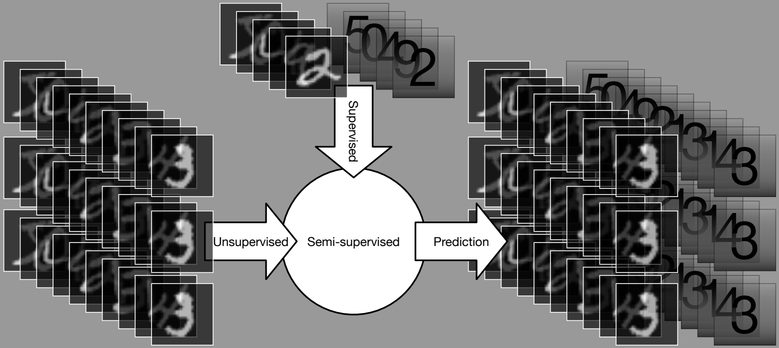

Figure: semi-supervised learning.

Starting from Scratch

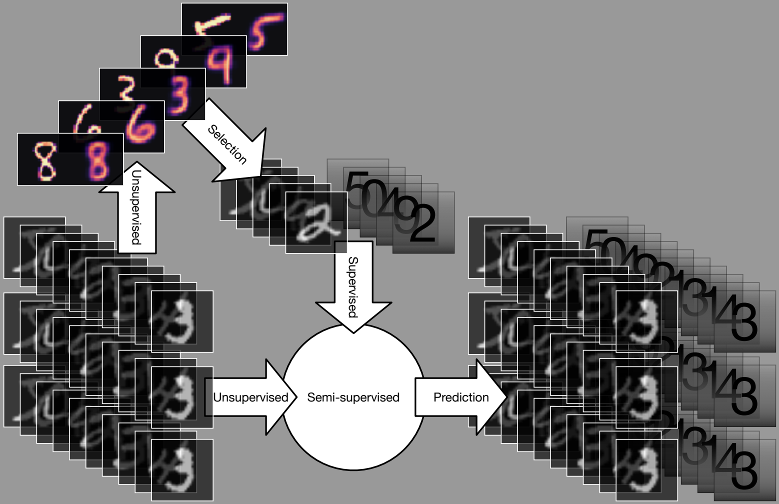

Figure: semi-supervised learning.

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

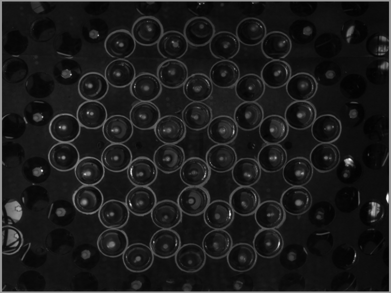


Figure: gyroscope tracking [3].

Method

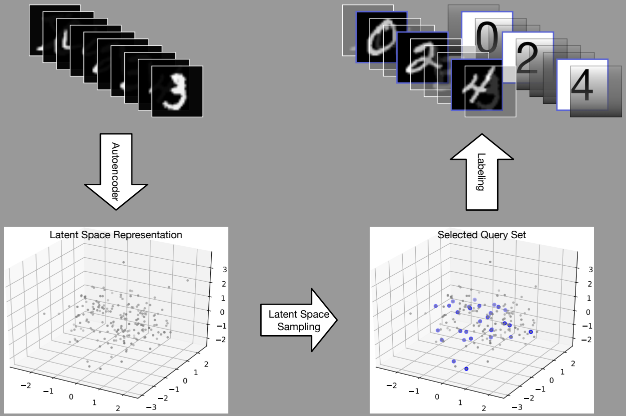
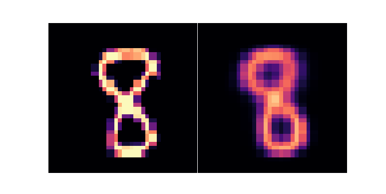


Figure: high-level overview

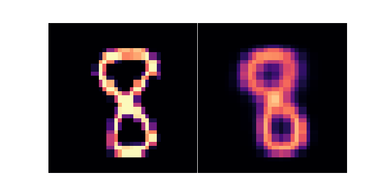
Results

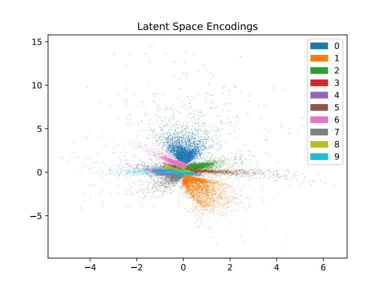
- Reconstructions



Results

- Reconstructions
- Encodings





Results

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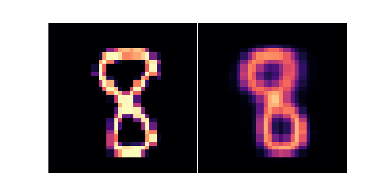

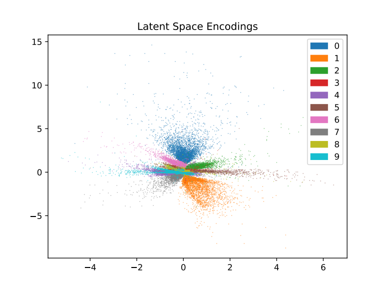

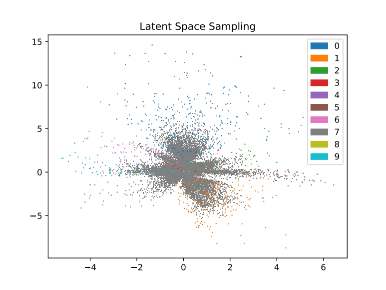

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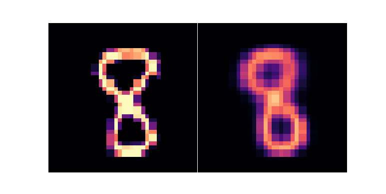
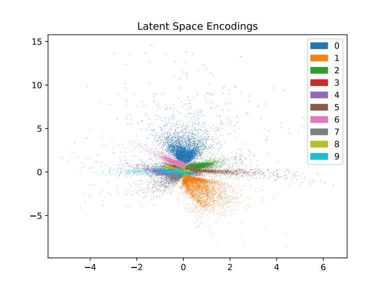
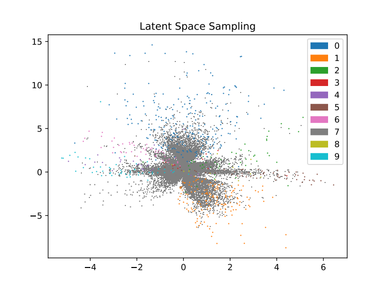
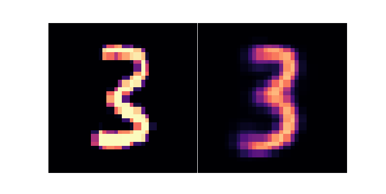
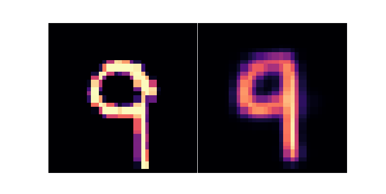


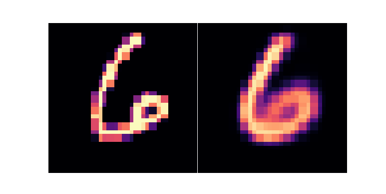


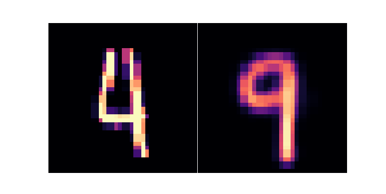


Convolutional Auto-encoder









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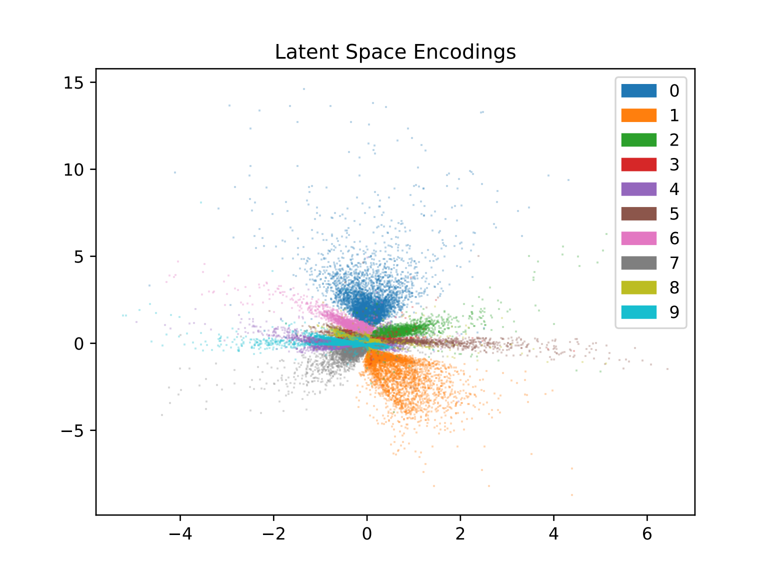
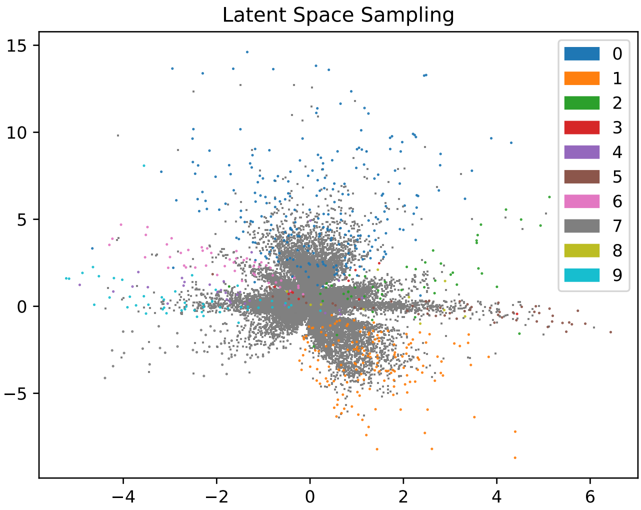


Uniform Spatial Sampling



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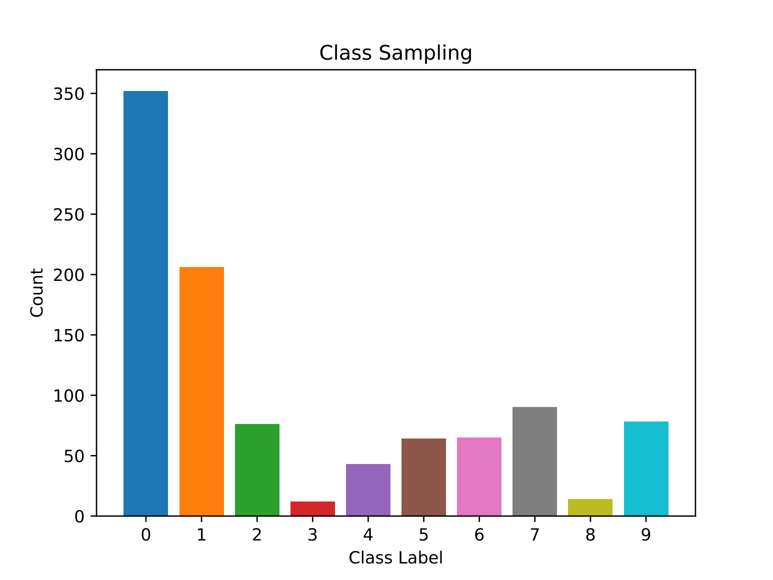
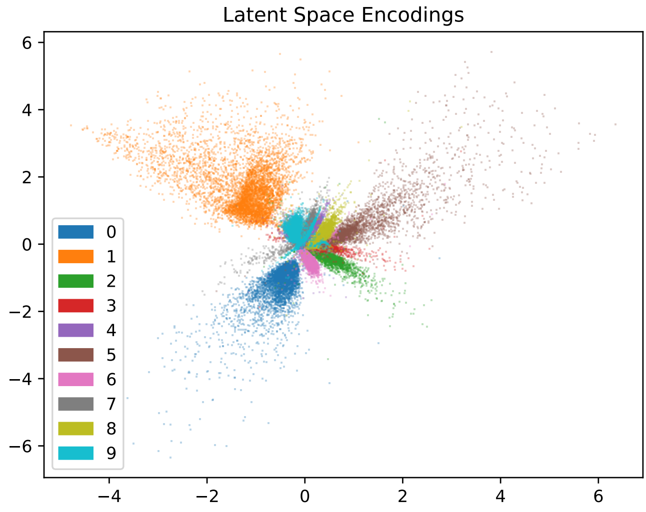
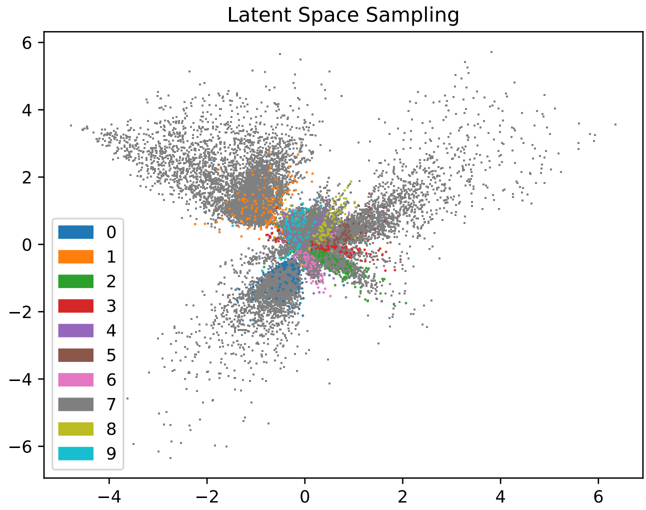


Variational Auto-encoder



Normal Spatial Sampling



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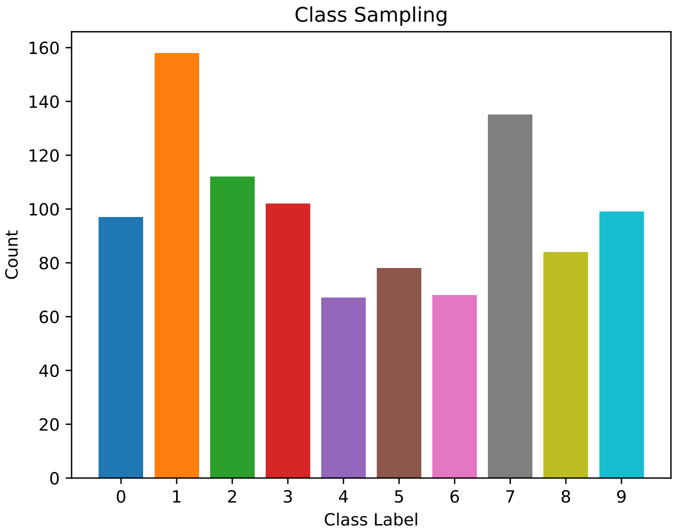
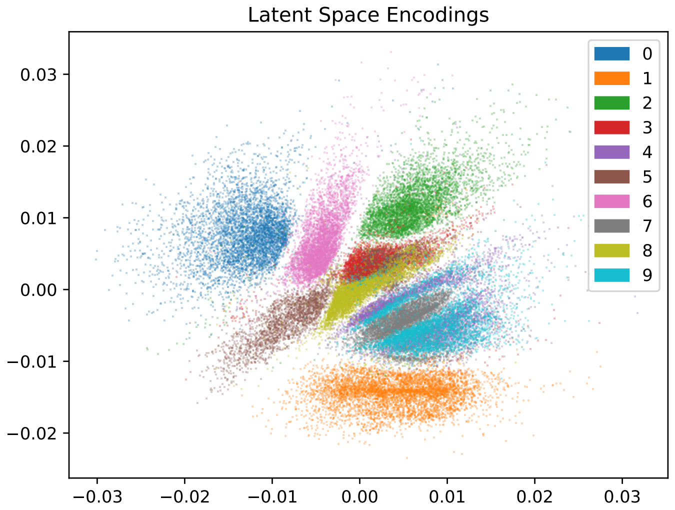
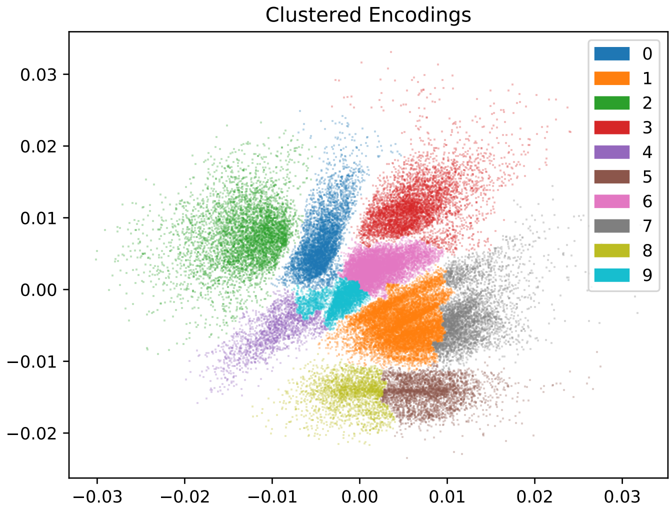


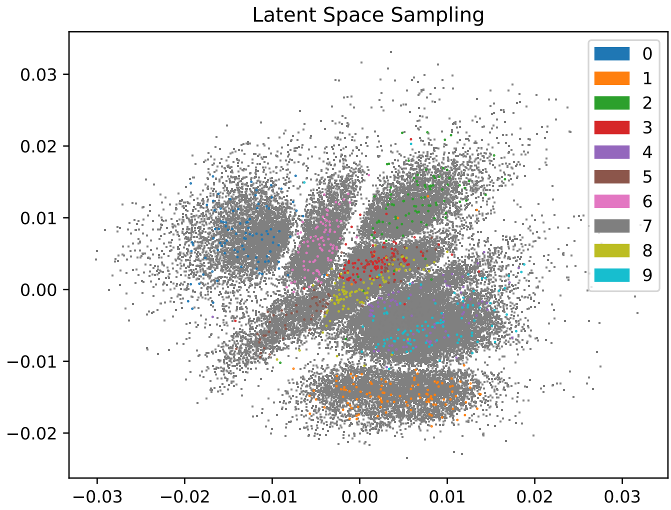
t-SNE Style Auto-encoder



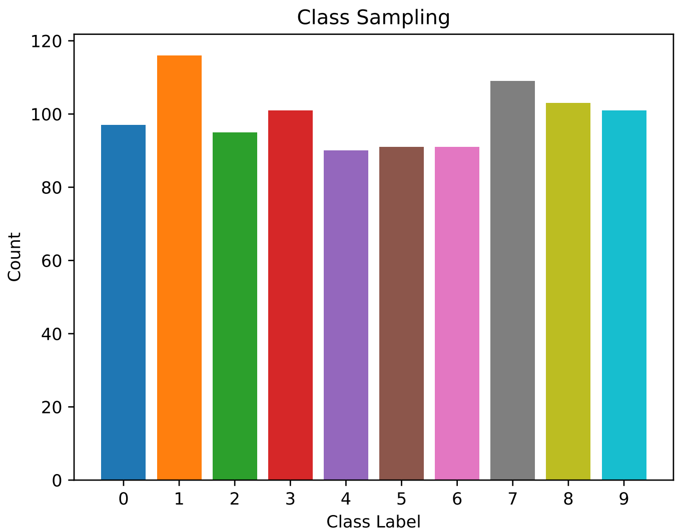
Clustering


Clustered Encodings
0
1
2
3
4
5
6
7
8
9
0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
−0.02
−0.01
0.00
0.01
0.02
0.03

Normal Sampling inside Clusters



Clustered Normal Spatial Sampling



Discussion

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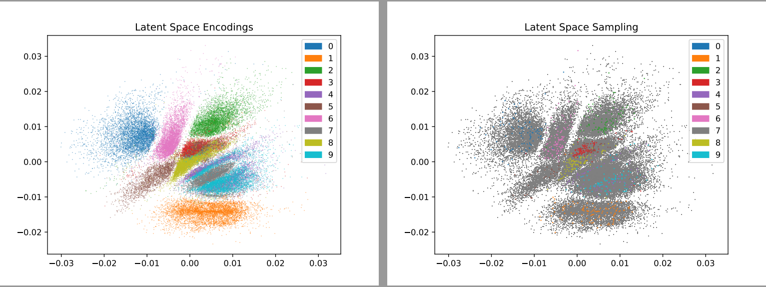

Figure: Visualizing points which are difficult to learn.

Future Work

- Transfer learning **without overfitting**.

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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.

References I

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