Disentangling Variational Autoencoders for Image Classification

Motivation

Goal: Improve classification performance using unlabelled data

- There is a wealth of unlabelled data; labelled data is scarce • **Unsupervised learning** can learn a representation of the domain
- **Disentangled representations** contain statistically independent generative factors of the data
 - Improves representation quality and prevents latent co-adaptation
- **Supervised learning** benefits from knowledge of the underlying factors

Problem Statement

Unsupervised Learning:

- **Input:** Unlabelled image data
- **Output:** Reconstructed images
- **Evaluation:** Disentanglement

Supervised Learning:

- **Input:** Labelled image data
- **Output:** Classification label of image
- **Evaluation:** Test classification error



Dataset

MNIST Handwritten Digits [1]

- 55,000 training images
- 10,000 test images
- 10 classes



Conclusions and Future Work

- **Conclusion:** Disentangling VAE [3] improves classification performance over standard VAE and vanilla baseline when labelled data is scarce
- **Future work:** 1) Use synthetic MNIST with more continuous data (e.g. continuous) rotations) so the DVAE can better learn the generative manifolds, and 2) use a semi-supervised learning objective on top of unsupervised pre-training.

References

[1] Y. LeCun and C. Cortes. The mnist database of handwritten digits, 1998.

- [2] D. P. Kingma and M. Welling. Auto-encoding variational bayes. *arXiv preprint arXiv: 1312.6114, 2013*.
- [3] I. Higgins et al. Early visual concept learning with unsupervised deep learning, 2016.

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