Deep Learning II : unsupervised tasks with Auto-encoders

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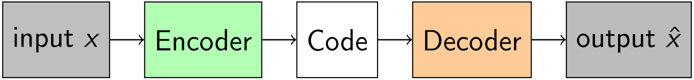
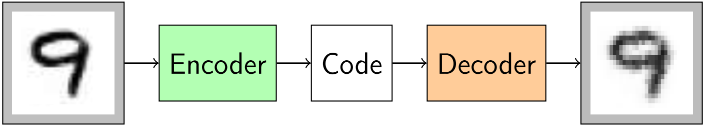
Agenda

General architecture of an Autoencoder



General architecture of an Autoencoder



Autoencoders basics: encoder and decoder

Encoder

Produces Code or Latent Representation

$$\mathbf{h} = s(\mathbf{W}\mathbf{x} + \mathbf{b}) = f(\mathbf{x})$$

Autoencoders basics: encoder and decoder

Encoder

Produces Code or Latent Representation

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Decoder

Produces Reconstruction of the input

$$\hat{\mathbf{x}} = s(\mathbf{W}'\mathbf{h} + \mathbf{b}') = g(\mathbf{h})$$

Tied weights when $\mathbf{W}' = \mathbf{W}^T$

Autoencoders basics: loss function

Given the output $\hat{\mathbf{x}} = g(f(\mathbf{x})$
We want to minimize some reconstruction loss:

$$\mathcal{L}(\mathbf{x}, g(f(\mathbf{x})) = \hat{\mathbf{x}})$$

Cross entropy (bits or probability vectors)

$$\mathcal{L}(\mathbf{x}, \hat{\mathbf{x}}) = \mathbf{x} \log \hat{\mathbf{x}} + (1 - \mathbf{x}) \log(1 - \hat{\mathbf{x}})$$

Mean squared error (continuous values)

$$\mathcal{L}(\mathbf{x}, \hat{\mathbf{x}}) = ||\mathbf{x} - \hat{\mathbf{x}}||^2$$

Autoencoders basics: flavours

Undercomplete

- Bottleneck layer produces code $\mathbf{h}$ with less dimensions then input $\mathbf{x}$

Overcomplete

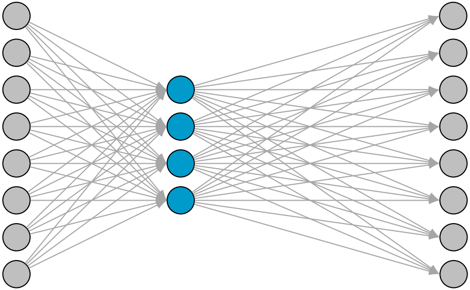
- Code $\mathbf{h}$ has more dimensions then the input $\mathbf{x}$
- Different versions e.g. sparse, denoising, contractive.

Agenda

Undercomplete

Learns a Lossy Compression of the input data.

- has a “bottleneck” layer
- can be used for Dimensionality Reduction — often compared to Principal Component Analysis (PCA)
- often code is a good representation for the training data only



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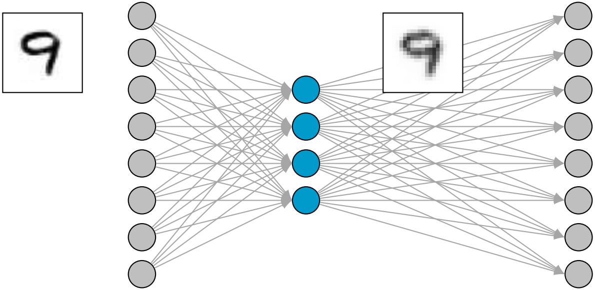

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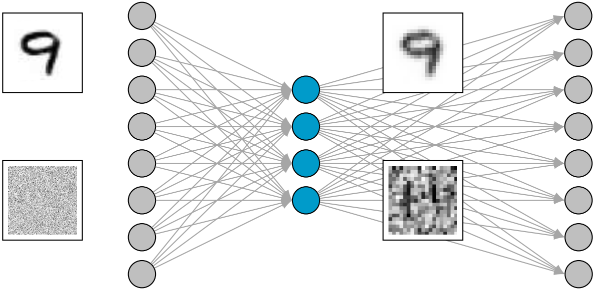
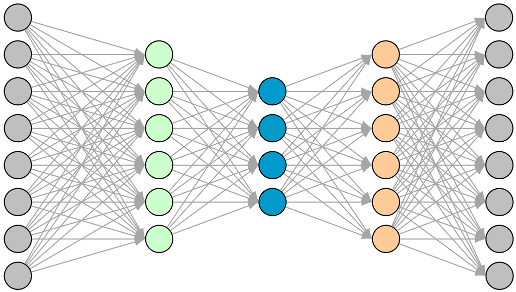


Undercomplete

Increasing the number of layers adds capacity to the AE.

- Encoder and Decoder layers can also be convolutional layers



In principle with a sufficiently large capacity it may map every input to a single neuron on bottleneck layer.

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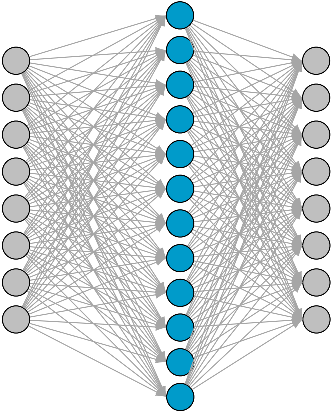
Overcomplete AEs

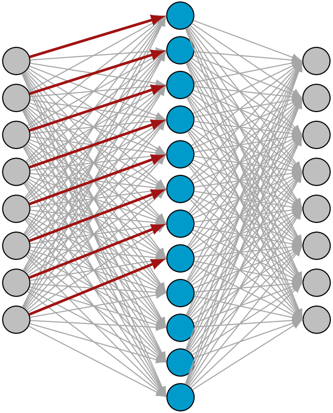
High-dimensional intermediate layer



Overcomplete AEs

High-dimensional intermediate layer

- a naive implementation would allow a copy so that $\mathbf{x} = \hat{\mathbf{x}}$



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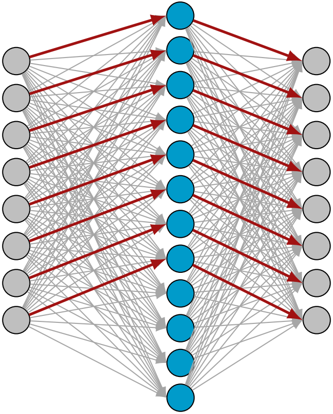


Overcomplete regularized AEs

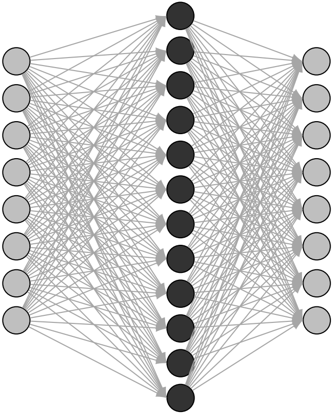
Regularization with sparsity constraint

$$\mathcal{L}(x, g(f(x))) + \Omega(f(x))$$
$$\mathcal{L}(x, g(f(x))) + \lambda \sum_i |h_i|,$$

- loss function tries to keep a low number of activation neurons per training input

Overcomplete regularized AEs

Regularization with sparsity constraint



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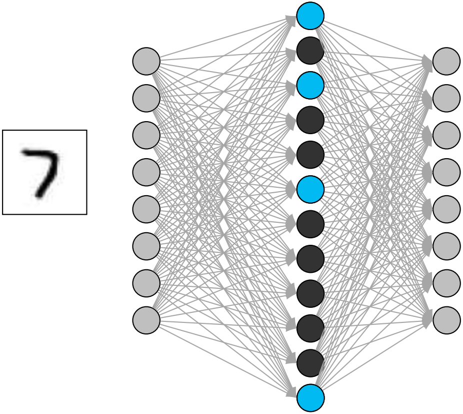

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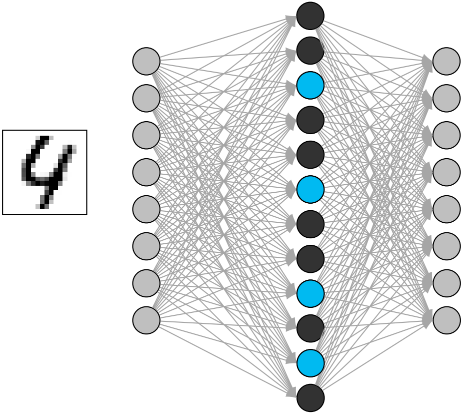


Denoising AEs (DAEs)

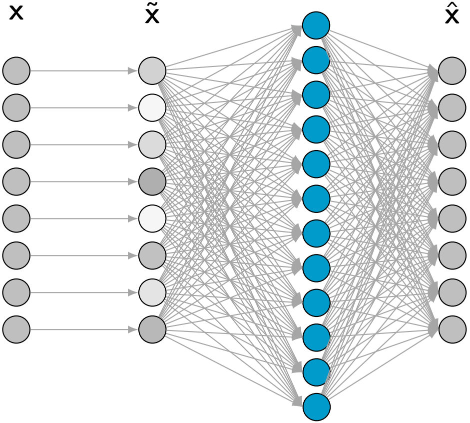
Regularization achieved by adding noise to $\mathbf{x}$

- the loss is computed using the noiseless input $\mathbf{x}$
- AE has to reconstruct $\mathbf{x}$ using a noisy input $\tilde{\mathbf{x}}$, so representation must be robust to noise
- this prevents the overcomplete AE to simply copy the data

Denoising AEs (DAEs)

Regularization achieved by adding noise to $\mathbf{x}$

- DAEs aim to learn a good internal representation as a side effect of learning to denoise the input



Denoising AEs (DAEs)

Noise processes

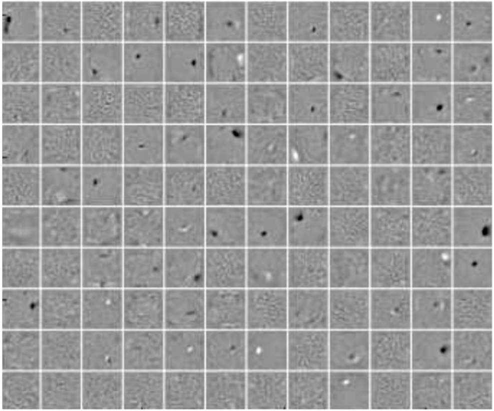
- Additive Gaussian Noise with $\mu = 0$, and some σ;
- Set a percentage of the input data to zero with some probability *p*.

Interpretation

- Learns to project data around some manifold to the distribution of the original (noiseless) data
- If some input is to far from the original distribution, it produces a high reconstruction error

Denoising AEs (DAEs): example

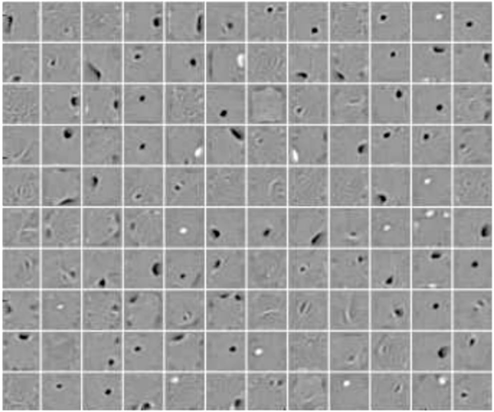
Using MNIST dataset, without noise



Vincent, Pascal, et al. "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion." Journal of Machine Learning Research, 2010: 3371-3408.

Denoising AEs (DAEs): example

Using MNIST dataset, zero input variable with 25% probability



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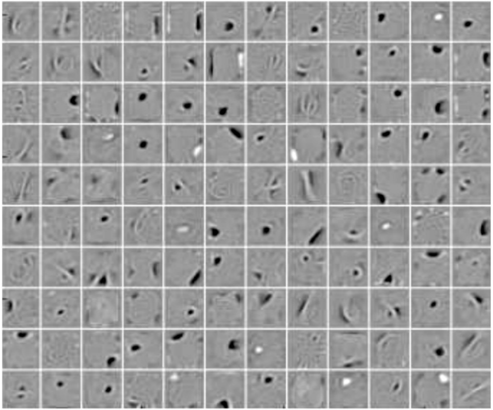
Denoising AEs (DAEs): example

Using MNIST dataset, zero input variable with 50% probability



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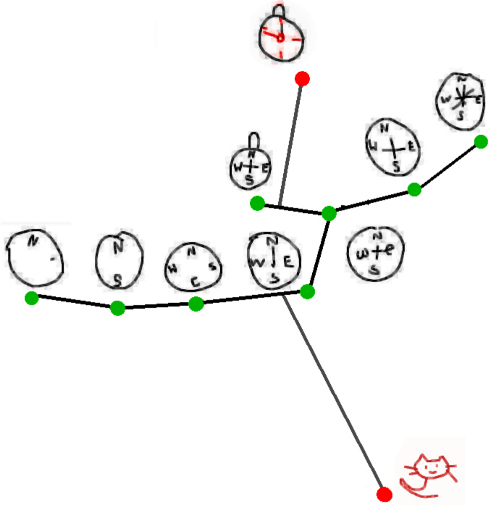
A sketch manifold illustration



Concluding remarks

- AEs can be a good choice with unsupervised data;
- Deep autoencoders can be useful to many applications, via manifold learning;
- The potential for manifold learning can be used for instance on Generative tasks (Generative and Variational Autoencoders).
- Those can also be plugged in supervised architectures.

References

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- **Ponti, M.; Ribeiro, L.; Nazare, T.; Bui, T.; Collomosse, J. Everything you wanted to know about Deep Learning for Computer Vision but were afraid to ask. In: SIBGRAPI – Conference on Graphics, Patterns and Images, 2017.** `http://sibgrapi.sid.inpe.br/rep/sid.inpe.br/sibgrapi/2017/09.05.22.09`
- Vincent, Pascal, et al. "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion." Journal of Machine Learning Research, 2010: 3371-3408.
- Goodfellow, I., Bengio, Y., and Courville, A. Deep learning. MIT press, 2016.