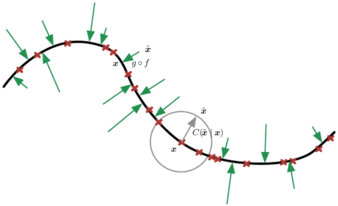
Deep Learning

Regularized Autoencoders



Learning goals

- Overcomplete AEs
- Sparse AEs
- Denoising AEs
- Contractive AEs

Overcomplete Autoencoders

OVERCOMPLETE AE – PROBLEM

Overcomplete AE (code dimension $\geq$ input dimension): even a linear AE can copy the input to the output without learning anything useful.

How can an overcomplete AE be useful?

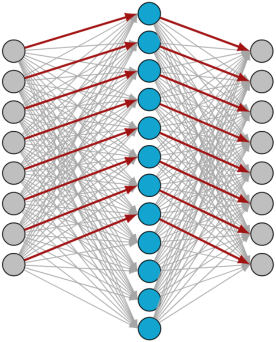


Figure: Overcomplete AE that learned to copy its inputs to the hidden layer and then to the output layer (Credits to M. Ponti).

REGULARIZED AUTOENCODER

- Goal: choose code dimension and capacity of encoder/decoder based on the problem.
- **Regularized AEs** modify the original loss function to:
  - prevent the network from trivially copying the inputs.
  - encourage additional properties.
- Examples:
  - **Sparse AE:** sparsity of the representation.
  - **Denoising AE**: robustness to noise.
  - **Contractive AE**: small derivatives of the representation w.r.t. input.

$\Rightarrow$ A regularized AE can be overcomplete and nonlinear but still learn something useful about the data distribution!

Sparse Autoencoder

SPARSE AUTOENCODER

- **Idea:** Regularization with a sparsity constraint

$$L(\mathbf{x}, dec(enc(\mathbf{x}))) + \lambda \|\boldsymbol{z}\|_1$$

- Try to keep the number of active neurons per training input low.
- Forces the model to respond to unique statistical features of the input data.

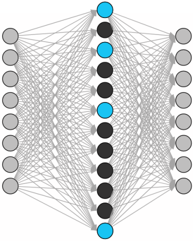


Figure: Sparse Autoencoder (Credits to M. Ponti).

Denoising Autoencoders

DENOISING AUTOENCODERS (DAE)

The denoising autoencoder (DAE) is an autoencoder that receives a corrupted data point as input and is trained to predict the original, uncorrupted data point as its output.

- Idea: representation should be robust to introduction of noise.
- Produce corrupted version $\tilde{\mathbf{x}}$ of input $\mathbf{x}$, e.g. by
  - random assignment of subset of inputs to 0.
  - adding Gaussian noise.
- Modified reconstruction loss: $L(\mathbf{x}, dec(enc(\tilde{\mathbf{x}})))$
  $\rightarrow$ denoising AEs must learn to undo this corruption.

DENOISING AUTOENCODERS (DAE)

- With the corruption process, we induce stochasticity into the DAE.
- Formally: let $C(\tilde{\mathbf{x}}|\mathbf{x})$ present the conditional distribution of corrupted samples $\tilde{\mathbf{x}}$, given a data sample $\mathbf{x}$.
- Like feedforward NNs can model a distribution over targets $p(\mathbf{y}|\mathbf{x})$, output units and loss function of an AE can be chosen such that one gets a stochastic decoder $p_{decoder}(\mathbf{x}|\mathbf{z})$.
- E.g. linear output units to parametrize the mean of Gaussian distribution for real valued $\mathbf{x}$ and negative log-likelihood loss (which is equal to MSE).
- The DAE then learns a reconstruction distribution $p_{reconstruct}(\mathbf{x}|\tilde{\mathbf{x}})$ from training pairs $(\mathbf{x}, \tilde{\mathbf{x}})$.
- (Note that the encoder could also be made stochastic, modelling $p_{encoder}(\mathbf{z}|\tilde{\mathbf{x}})$.)

DENOISING AUTOENCODERS (DAE)

The general structure of a DAE as a computational graph:

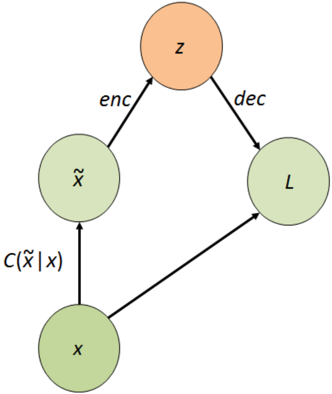


Figure: Denoising autoencoder: “making the learned representation robust to partial corruption of the input pattern.”

DENOISING AUTOENCODERS (DAE)

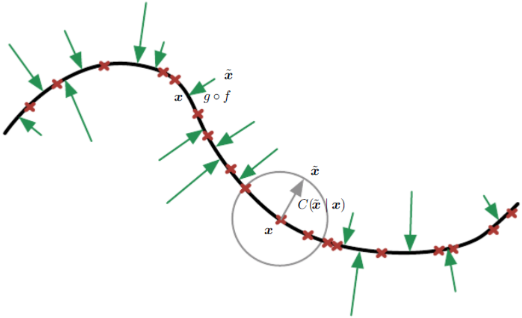


Figure: Denoising autoencoders - “manifold perspective” (Ian Goodfellow et al. (2016))

A DAE is trained to map a corrupted data point $\tilde{\mathbf{x}}$ back to the original data point $\mathbf{x}$.

DENOISING AUTOENCODERS (DAE)

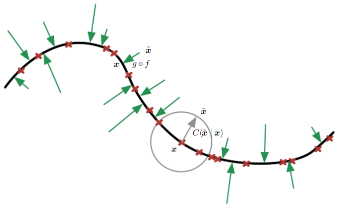


Figure: Denoising autoencoders - “manifold perspective” (Ian Goodfellow et al. (2016))

- The corruption process $C(\tilde{\mathbf{x}}|\mathbf{x})$ is displayed by the gray circle of equiprobable corruptions
- Training a DAE by minimizing $||dec(enc(\tilde{\mathbf{x}})) - \mathbf{x}||^2$ corresponds to minimizing $\mathbb{E}_{\mathbf{x},\tilde{\mathbf{x}} \sim p_{data}(\mathbf{x})C(\tilde{\mathbf{x}}|\mathbf{x})}[-\log p_{decoder}(\mathbf{x}|f(\tilde{\mathbf{x}}))]$.

DENOISING AUTOENCODERS (DAE)

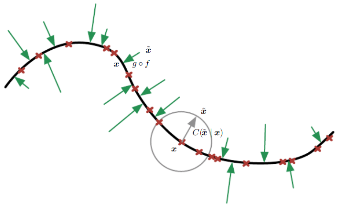


Figure: Denoising autoencoders - "manifold perspective" (Ian Goodfellow et al. (2016))

- The vector $dec(enc(\tilde{\mathbf{x}})) - \tilde{\mathbf{x}}$ points approximately towards the nearest point in the data manifold, since $dec(enc(\tilde{\mathbf{x}}))$ estimates the center of mass of clean points $\mathbf{x}$ which could have given rise to $\tilde{\mathbf{x}}$.
- Thus, the DAE learns a vector field $dec(enc(\tilde{\mathbf{x}})) - \mathbf{x}$ indicated by the green arrows.

DENOISING AUTOENCODERS (DAE)

An example of a vector field learned by a DAE.

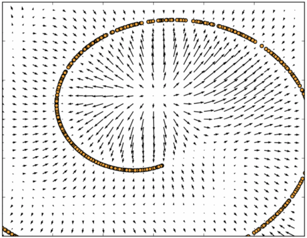


Figure: source: Ian Goodfellow et al. (2016)

EXPERIMENT: ENCODE MNIST WITH A DAE

- We will now corrupt the MNIST data with Gaussian noise and then try to denoise it as good as possible.

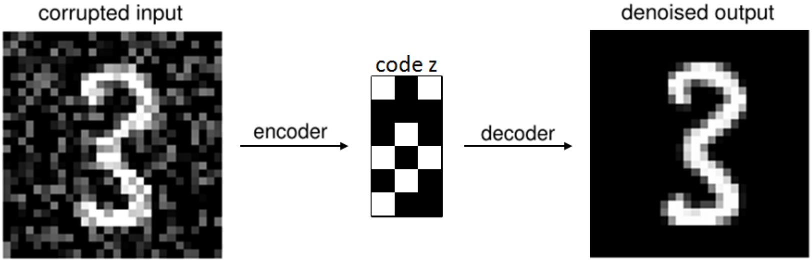


Figure: Flow chart of our autoencoder: denoise the corrupted input.

EXPERIMENT: ENCODE MNIST WITH A DAE

- To corrupt the input, we randomly add or subtract values from a uniform distribution to each of the image entries.

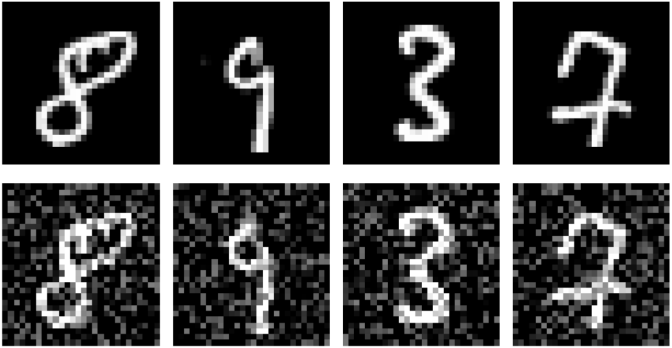


Figure: Top row: original data, bottom row: corrupted mnist data.

EXPERIMENT: ENCODE MNIST WITH A DAE

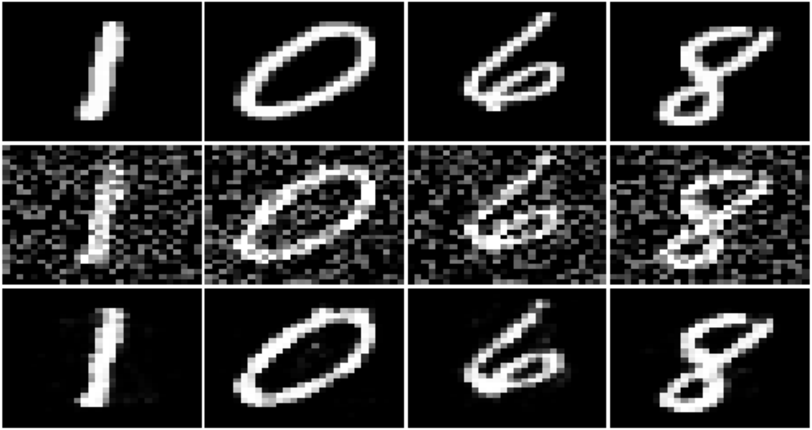


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 1568$ (overcomplete).

EXPERIMENT: ENCODE MNIST WITH A DAE

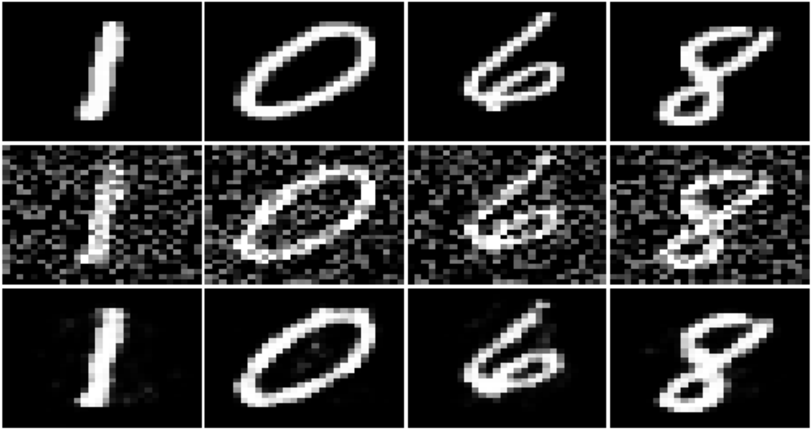


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 784$ ($= dim(\mathbf{x})$).

EXPERIMENT: ENCODE MNIST WITH A DAE

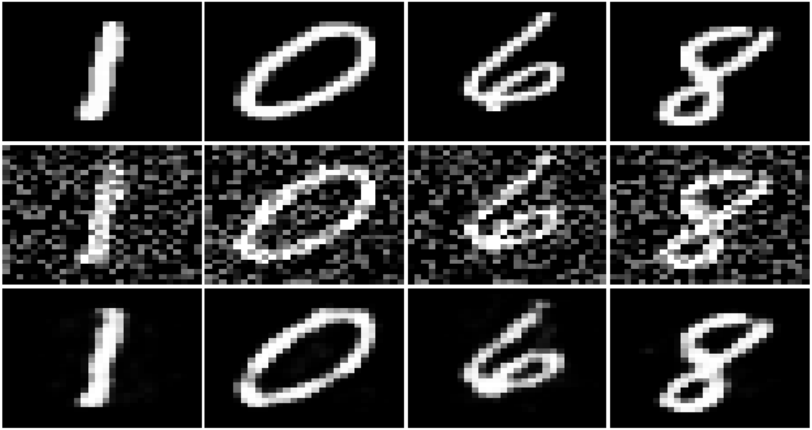


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 256$.

EXPERIMENT: ENCODE MNIST WITH A DAE

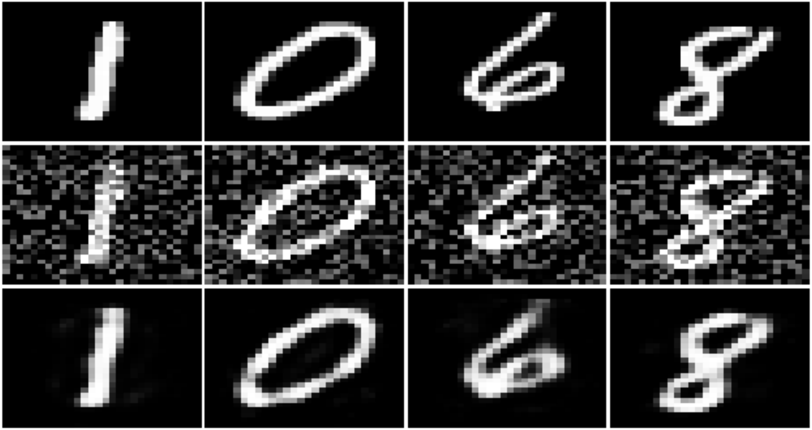


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 64$.

EXPERIMENT: ENCODE MNIST WITH A DAE

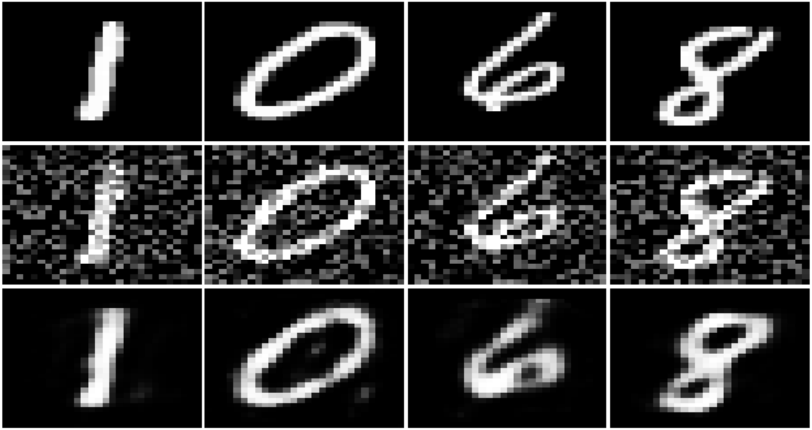


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 32$.

EXPERIMENT: ENCODE MNIST WITH A DAE

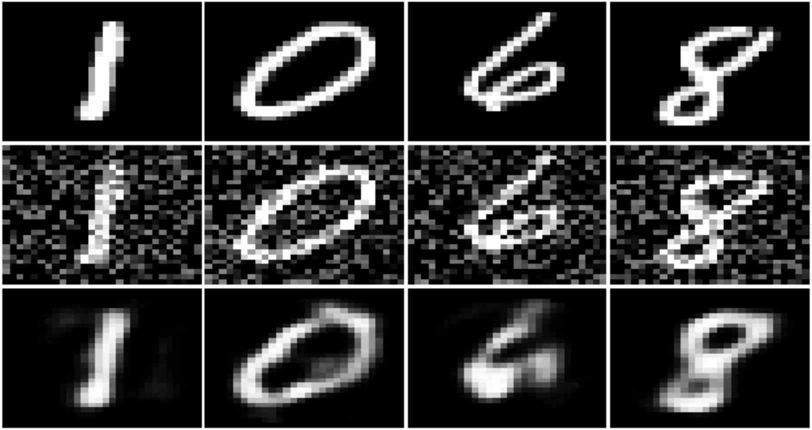


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 16$.

EXPERIMENT: ENCODE MNIST WITH A DAE

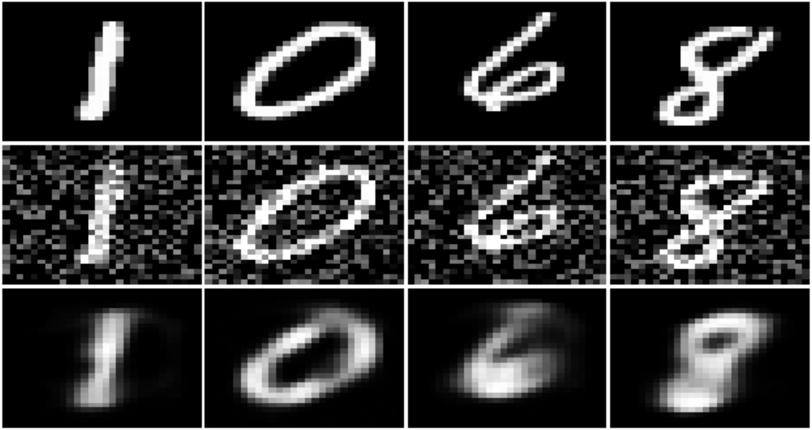


Figure: The top row shows the original digits, the intermediate one the corrupted and the bottom row the denoised/reconstructed digits (prediction).

- $dim(\boldsymbol{z}) = 8$.

Contractive Autoencoder

CONTRACTIVE AUTOENCODER

- Goal: For very similar inputs, the learned encoding should also be very similar.
- We can train our model in order for this to be the case by requiring that the **derivative of the hidden layer activations are small** with respect to the input.
- In other words: The encoded state $enc(\mathbf{x})$ should not change much for small changes in the input.
- Add explicit regularization term to the reconstruction loss:

$$L(\mathbf{x}, dec(enc(\mathbf{x}))) + \lambda \| \frac{\partial enc(\mathbf{x})}{\partial \mathbf{x}} \|_F^2$$

DAE VS. CAE

DAE	**CAE**
the *decoder* function is trained to resist infinitesimal perturbations of the input.	the *encoder* function is trained to resist infinitesimal perturbations of the input.

- Both the denoising and contractive autoencoders perform well.
- Advantage of denoising autoencoder: simpler to implement
  - requires adding one or two lines of code to regular AE.
  - no need to compute Jacobian of hidden layer.
- Advantage of contractive autoencoder: gradient is deterministic
  - can use second order optimizers (conjugate gradient, LBFGS, etc.).
  - might be more stable than the denoising autoencoder, which uses a sampled gradient.

REFERENCES

Ian Goodfellow, Yoshua Bengio and Aaron Courville (2016)
Deep Learning
http://www.deeplearningbook.org/

Everything you wanted to know about Deep Learning for Computer Vision but were afraid to ask (2017)
SIBGRAPI Tutorials 2017