Neural Networks: promises of current research

Pascal Vincent

Université de Montréal

Laboratoire d'Informatique

des Systèmes Adaptatifs

http://www.iro.umontreal.ca/~lisa

ApSTAT TECHNOLOGIES

www.apstat.com

April 2008

Current research on deep architectures

A few labs are currently researching deep neural network training:

- Geoffrey Hinton's lab at U.Toronto
- Yann LeCun's lab at NYU
- Our LISA lab at U.Montreal
- . . . many others to come! (we hope)

I will talk about my latest work
(with Hugo Larochelle, Yoshua Bengio, Pierre-Antoine Manzagol):
Extracting and Composing Robust Features with Denoising Autoencoders
$\longrightarrow$ upcoming ICML 2008

The problem

- Building good predictors on complex domains
  means learning complicated functions.
- These are best represented by multiple levels of non-linear operations
  i.e. deep architectures.
- Learning the parameters of deep architectures proved to be challenging!

Training deep architectures: attempted solutions

- **Solution 1**: initialize at random, and do gradient descent (Rumelhart et al., 1986).
  $\longrightarrow$ disappointing performance. Stuck in poor solutions.

- **Solution 2**: Deep Belief Nets (Hinton et al., 2006): initialize by stacking Restricted Boltzmann Machines, fine-tune with Up-Down.
  $\longrightarrow$ impressive performance.

  Key seems to be good unsupervised layer-by-layer initialization...

- **Solution 3**: initialize by stacking autoencoders, fine-tune with gradient descent. (Bengio et al., 2007; Ranzato et al., 2007)
  $\longrightarrow$ Simple generic procedure, no sampling required.
  Performance almost as good as Solution 2

...but not quite. Can we do better?

Training deep architectures: attempted solutions

- **Solution 1**: initialize at random, and do gradient descent (Rumelhart et al., 1986).
  $\longrightarrow$ disappointing performance. Stuck in poor solutions.

- **Solution 2**: Deep Belief Nets (Hinton et al., 2006): initialize by stacking Restricted Boltzmann Machines, fine-tune with Up-Down.
  $\longrightarrow$ impressive performance.

  Key seems to be good unsupervised layer-by-layer initialization...

- **Solution 3**: initialize by stacking autoencoders, fine-tune with gradient descent. (Bengio et al., 2007; Ranzato et al., 2007)
  $\longrightarrow$ Simple generic procedure, no sampling required.
  Performance almost as good as Solution 2

...but not quite. Can we do better?

Training deep architectures: attempted solutions

- **Solution 1**: initialize at random, and do gradient descent (Rumelhart et al., 1986).
  $\longrightarrow$ disappointing performance. Stuck in poor solutions.

- **Solution 2**: Deep Belief Nets (Hinton et al., 2006): initialize by stacking Restricted Boltzmann Machines, fine-tune with Up-Down.
  $\longrightarrow$ impressive performance.

  Key seems to be good unsupervised layer-by-layer initialization...

- **Solution 3**: initialize by stacking autoencoders, fine-tune with gradient descent. (Bengio et al., 2007; Ranzato et al., 2007)
  $\longrightarrow$ Simple generic procedure, no sampling required.
  Performance almost as good as Solution 2

...but not quite. Can we do better?

Training deep architectures: attempted solutions

- **Solution 1**: initialize at random, and do gradient descent (Rumelhart et al., 1986).
  $\longrightarrow$ disappointing performance. Stuck in poor solutions.

- **Solution 2**: Deep Belief Nets (Hinton et al., 2006): initialize by stacking Restricted Boltzmann Machines, fine-tune with Up-Down.
  $\longrightarrow$ impressive performance.

  Key seems to be good unsupervised layer-by-layer initialization...

- **Solution 3**: initialize by stacking autoencoders, fine-tune with gradient descent. (Bengio et al., 2007; Ranzato et al., 2007)
  $\longrightarrow$ Simple generic procedure, no sampling required.
  Performance almost as good as Solution 2

...but not quite. Can we do better?

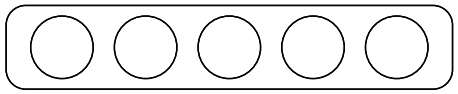
Can we do better?

Open question: what would make a good unsupervised criterion for finding good initial intermediate representations?

- Inspiration: our ability to "fill-in-the-blanks" in sensory input.
  missing pixels, small occlusions, image from sound, ...
- Good fill-in-the-blanks performance $\leftrightarrow$ distribution is well captured.
- $\longrightarrow$ old notion of associative memory (motivated Hopfield models (Hopfield, 1982))

What we propose:
unsupervised initialization by explicit fill-in-the-blanks training.

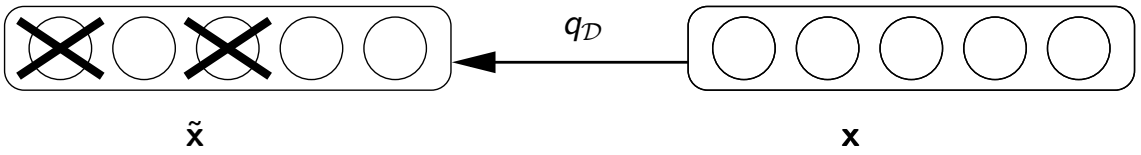
The denoising autoencoder



x

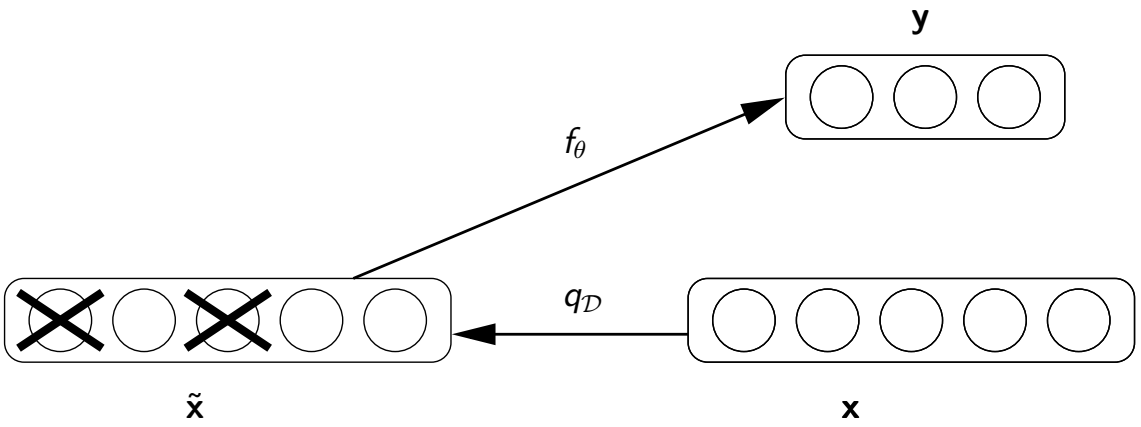
- Clean input $\mathbf{x} \in [0,1]^d$ is partially destroyed, yielding corrupted input: $\tilde{\mathbf{x}} \sim q_{\mathcal{D}}(\tilde{\mathbf{x}}|\mathbf{x})$.
- $\tilde{\mathbf{x}}$ is mapped to hidden representation $\mathbf{y} = f_\theta(\tilde{\mathbf{x}})$.
- From $\mathbf{y}$ we reconstruct a $\mathbf{z} = g_{\theta'}(\mathbf{y})$.
- Train parameters to minimize the cross-entropy "reconstruction error"

The denoising autoencoder



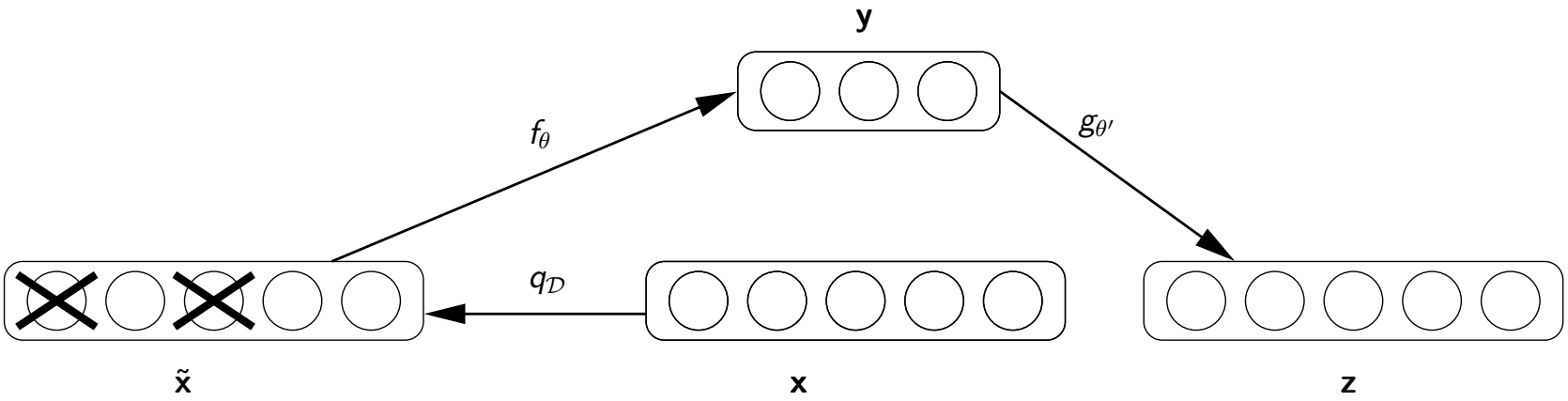
- Clean input $\mathbf{x} \in [0,1]^d$ is partially destroyed, yielding corrupted input: $\tilde{\mathbf{x}} \sim q_{\mathcal{D}}(\tilde{\mathbf{x}}|\mathbf{x})$.
- $\tilde{\mathbf{x}}$ is mapped to hidden representation $\mathbf{y} = f_\theta(\tilde{\mathbf{x}})$.
- From $\mathbf{y}$ we reconstruct a $\mathbf{z} = g_{\theta'}(\mathbf{y})$.
- Train parameters to minimize the cross-entropy "reconstruction error"

The denoising autoencoder



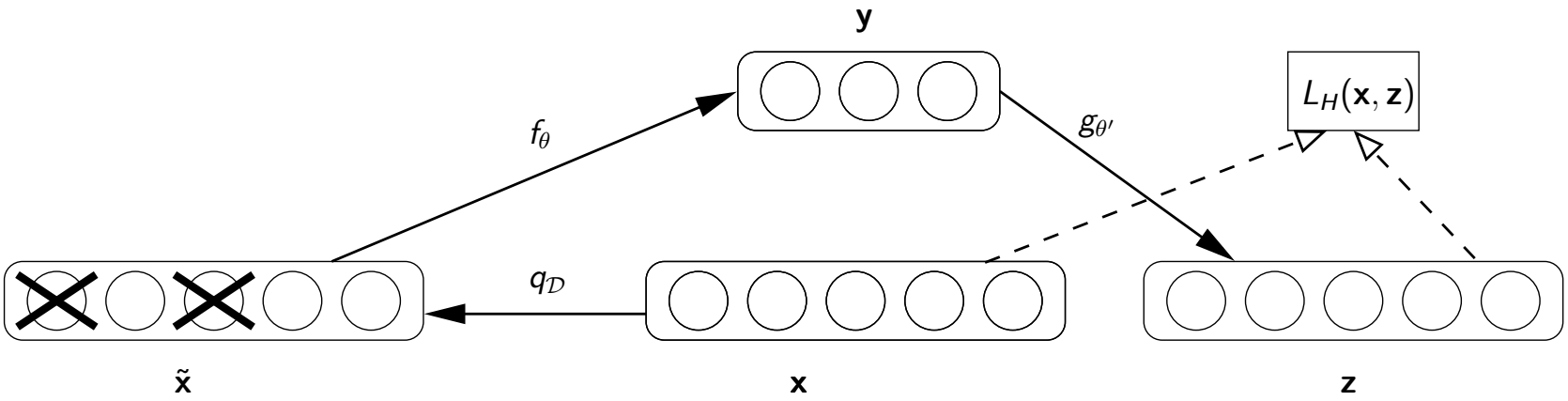
- Clean input $\mathbf{x} \in [0,1]^d$ is partially destroyed, yielding corrupted input: $\tilde{\mathbf{x}} \sim q_\mathcal{D}(\tilde{\mathbf{x}}|\mathbf{x})$.
- $\tilde{\mathbf{x}}$ is mapped to hidden representation $\mathbf{y} = f_\theta(\tilde{\mathbf{x}})$.
- From $\mathbf{y}$ we reconstruct a $\mathbf{z} = g_{\theta'}(\mathbf{y})$.
- Train parameters to minimize the cross-entropy "reconstruction error"

The denoising autoencoder



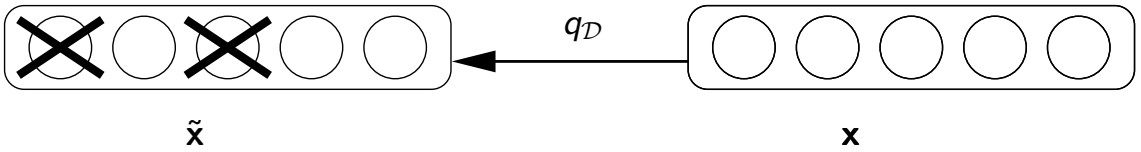
- Clean input $\mathbf{x} \in [0,1]^d$ is partially destroyed, yielding corrupted input: $\tilde{\mathbf{x}} \sim q_{\mathcal{D}}(\tilde{\mathbf{x}}|\mathbf{x})$.
- $\tilde{\mathbf{x}}$ is mapped to hidden representation $\mathbf{y} = f_\theta(\tilde{\mathbf{x}})$.
- From $\mathbf{y}$ we reconstruct a $\mathbf{z} = g_{\theta'}(\mathbf{y})$.
- Train parameters to minimize the cross-entropy "reconstruction error"

The denoising autoencoder



- Clean input $\mathbf{x} \in [0,1]^d$ is partially destroyed, yielding corrupted input: $\tilde{\mathbf{x}} \sim q_\mathcal{D}(\tilde{\mathbf{x}}|\mathbf{x})$.
- $\tilde{\mathbf{x}}$ is mapped to hidden representation $\mathbf{y} = f_\theta(\tilde{\mathbf{x}})$.
- From $\mathbf{y}$ we reconstruct a $\mathbf{z} = g_{\theta'}(\mathbf{y})$.
- Train parameters to minimize the cross-entropy "reconstruction error"

The input corruption process $q_{\mathcal{D}}(\tilde{\mathbf{x}}|\mathbf{x})$



- Choose a fixed proportion ν of components of $\mathbf{x}$ at random.
- Reset their values to 0.
- Can be viewed as replacing a component considered missing by a default value.

Other corruption processes could be considered.

Form of parameterized mappings

We use standard sigmoid network layers:

- $\mathbf{y} = f_\theta(\tilde{\mathbf{x}}) = \text{sigmoid}(\underbrace{\mathbf{W}}_{d' \times d} \tilde{\mathbf{x}} + \underbrace{\mathbf{b}}_{d' \times 1})$
- $g_{\theta'}(\mathbf{y}) = \text{sigmoid}(\underbrace{\mathbf{W}'}_{d \times d'} \mathbf{y} + \underbrace{\mathbf{b}'}_{d \times 1})$.

Denoising using autoencoders was actually introduced much earlier (LeCun, 1987; Gallinari et al., 1987), as an alternative to Hopfield networks (Hopfield, 1982).

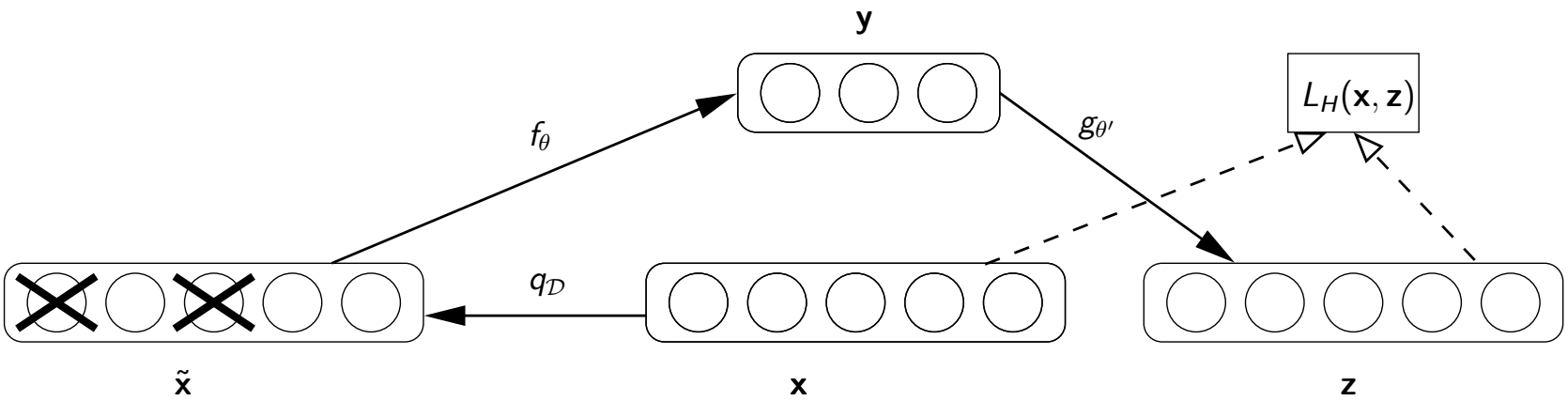
Form of parameterized mappings

We use standard sigmoid network layers:

- $\mathbf{y} = f_\theta(\tilde{\mathbf{x}}) = \text{sigmoid}(\underbrace{\mathbf{W}}_{d' \times d} \tilde{\mathbf{x}} + \underbrace{\mathbf{b}}_{d' \times 1})$
- $g_{\theta'}(\mathbf{y}) = \text{sigmoid}(\underbrace{\mathbf{W}'}_{d \times d'} \mathbf{y} + \underbrace{\mathbf{b}'}_{d \times 1})$.

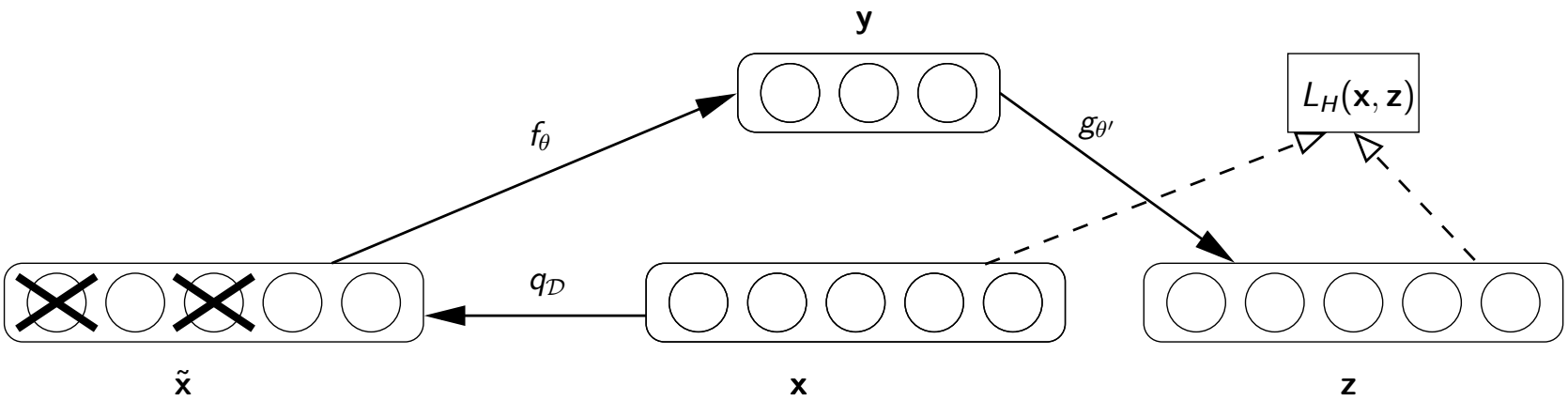
Denoising using autoencoders was actually introduced much earlier (LeCun, 1987; Gallinari et al., 1987), as an alternative to Hopfield networks (Hopfield, 1982).

Learning deep networks
Layer-wise initialization



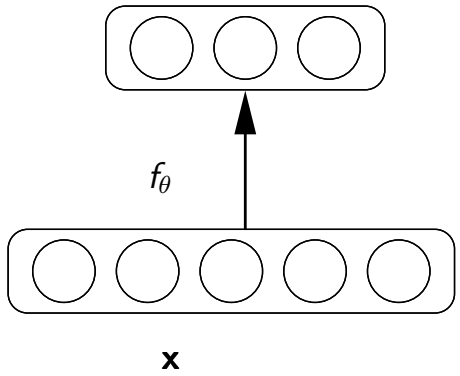
1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

Learning deep networks
Layer-wise initialization

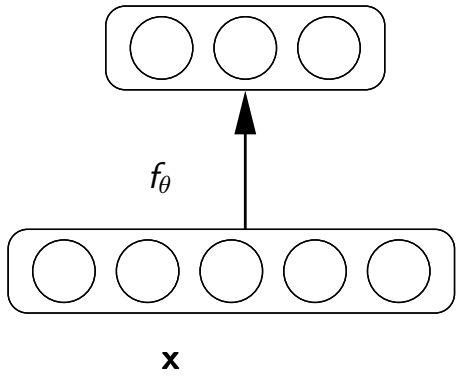


1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

Learning deep networks
Layer-wise initialization

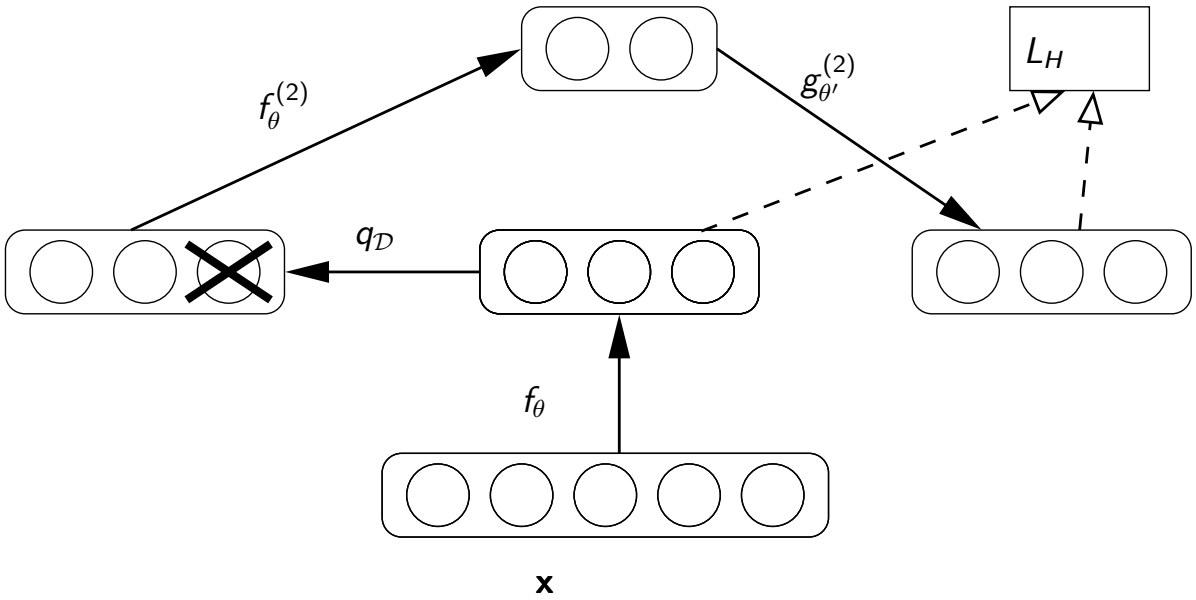


1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.



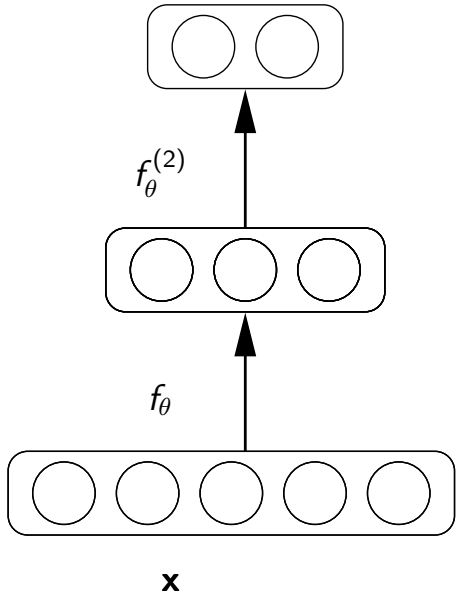
1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

Learning deep networks
Layer-wise initialization



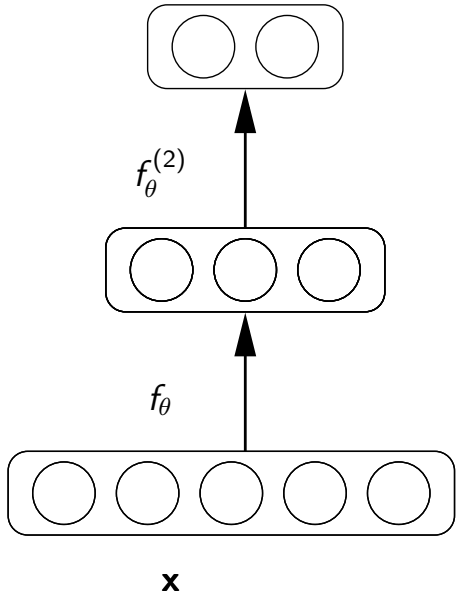
1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

Learning deep networks
Layer-wise initialization



1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

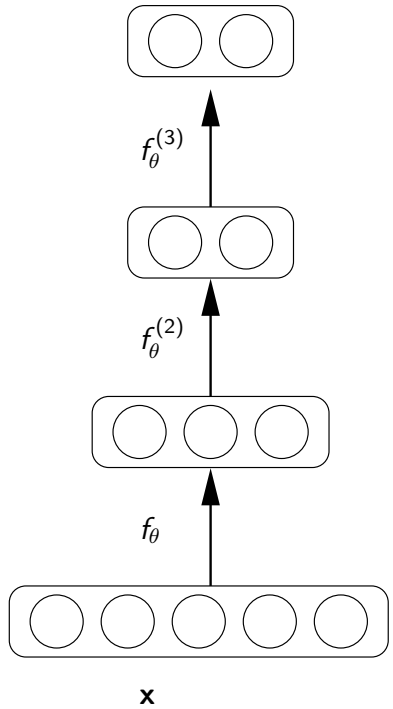
Learning deep networks
Layer-wise initialization



1. Learn first mapping f_θ by training as a denoising autoencoder.
2. Remove scaffolding. Use f_θ directly on input yielding higher level representation.
3. Learn next level mapping $f_\theta^{(2)}$ by training denoising autoencoder on current level representation.
4. Iterate to initialize subsequent layers.

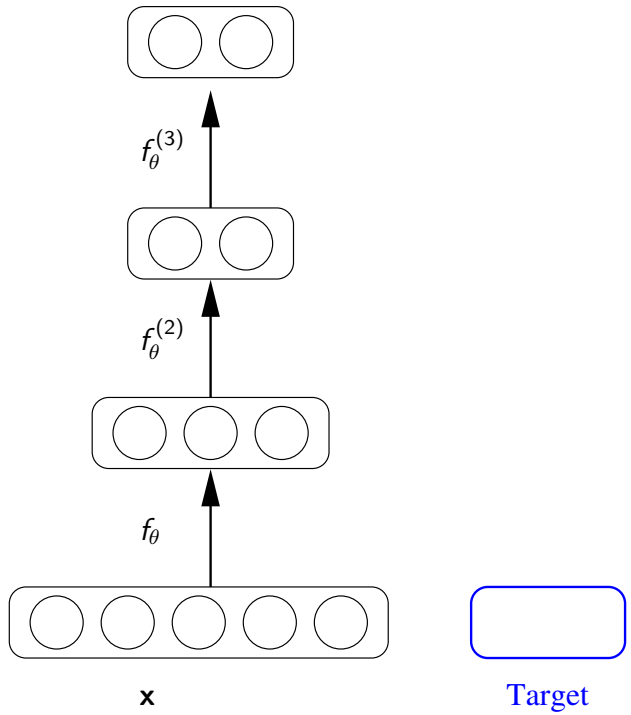
Learning deep networks
Supervised fine-tuning

- Initial deep mapping was learnt in an unsupervised way.
- $\longrightarrow$ initialization for a supervised task.
- Output layer gets added.
- Global fine tuning by gradient descent on supervised criterion.



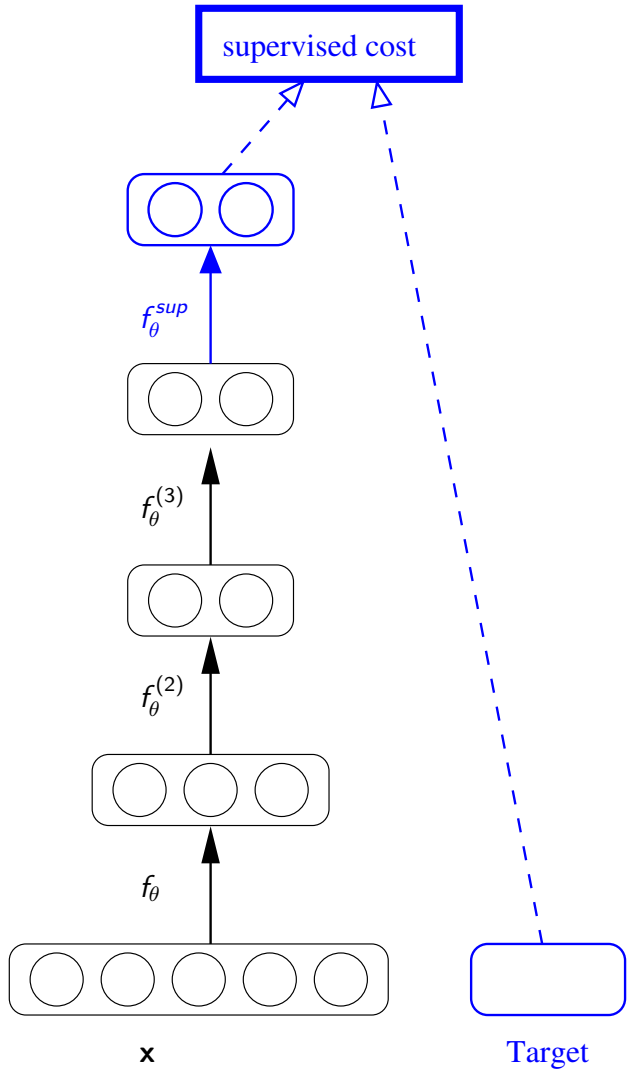
Learning deep networks
Supervised fine-tuning

- Initial deep mapping was learnt in an unsupervised way.
- $\longrightarrow$ initialization for a supervised task.
- Output layer gets added.
- Global fine tuning by gradient descent on supervised criterion.

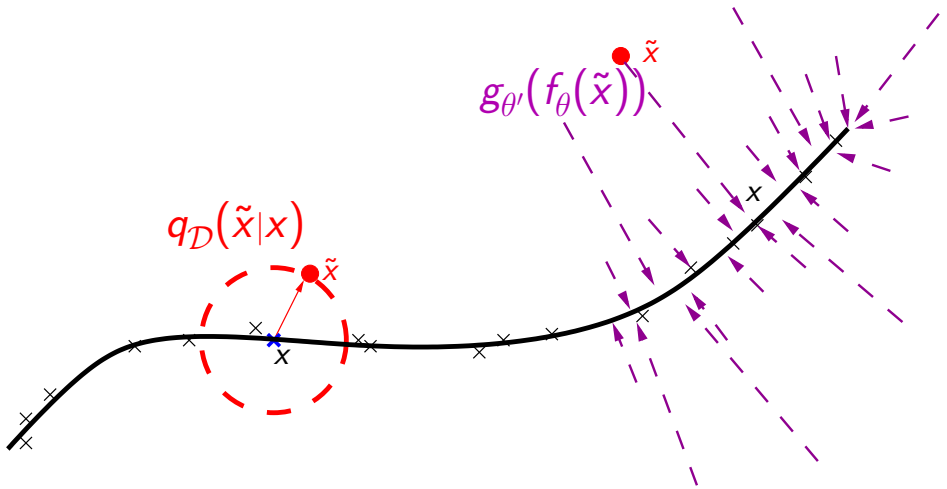


Learning deep networks
Supervised fine-tuning

- Initial deep mapping was learnt in an unsupervised way.
- $\longrightarrow$ initialization for a supervised task.
- Output layer gets added.
- Global fine tuning by gradient descent on supervised criterion.



Perspectives on denoising autoencoders
Manifold learning perspective



Denoising autoencoder can be seen as a way to learn a manifold:

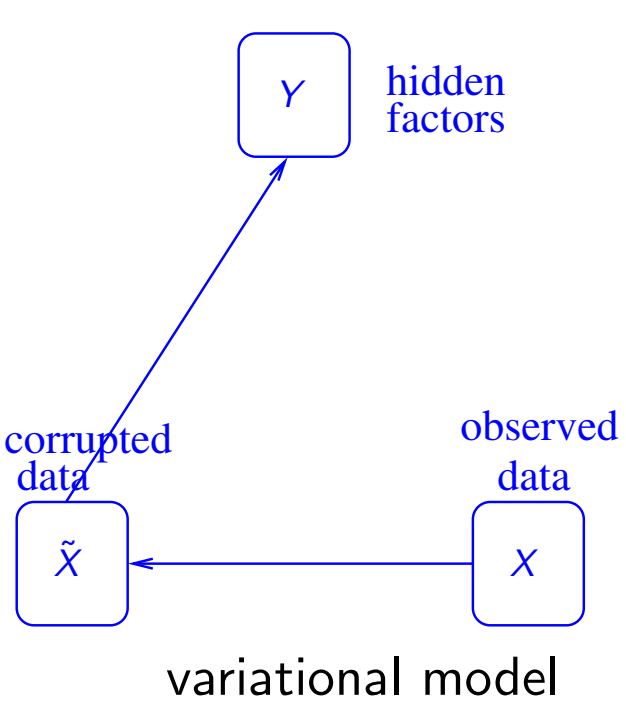
- Suppose training data ($\times$) concentrate near a low-dimensional manifold.
- Corrupted examples ($\bullet$) are obtained by applying corruption process $q_{\mathcal{D}}(\widetilde{X}|X)$ and will lie farther from the manifold.
- The model learns with $p(X|\widetilde{X})$ to "project them back" onto the manifold.
- Intermediate representation Y can be interpreted as a coordinate system for points on the manifold.

Perspectives on denoising autoencoders

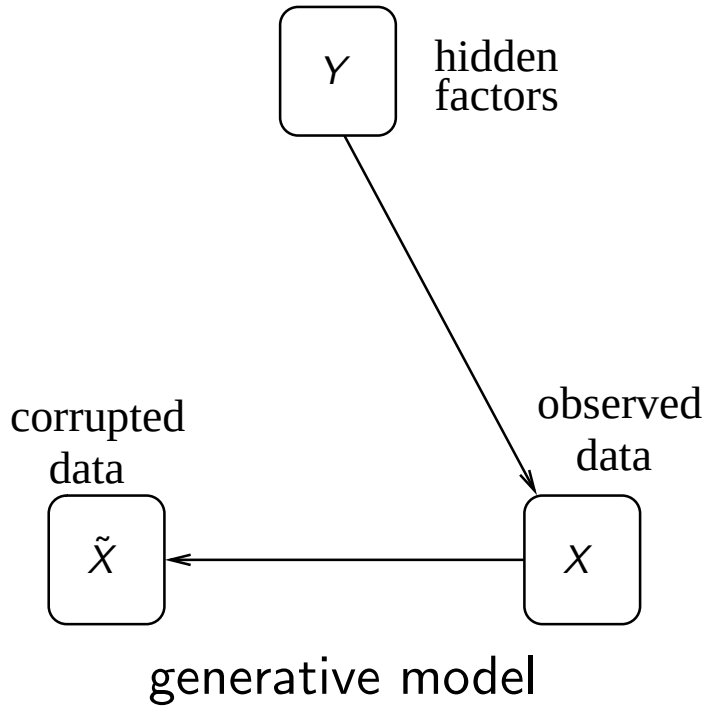
Information theoretic perspective

- Consider $X \sim q(X)$, q unknown. $\widetilde{X} \sim q_{\mathcal{D}}(\widetilde{X}|X)$. $Y = f_\theta(\widetilde{X})$.
- It can be shown that minimizing the expected reconstruction error amounts to maximizing a lower bound on mutual information $\mathbf{I}(X; Y)$.
- Denoising autoencoder training can thus be justified by the objective that hidden representation Y captures as much information as possible about X *even as* Y *is a function of corrupted input.*

- Denoising autoencoder training can be shown to be equivalent to maximizing a variational bound on the likelihood of a generative model for the corrupted data.



variational model



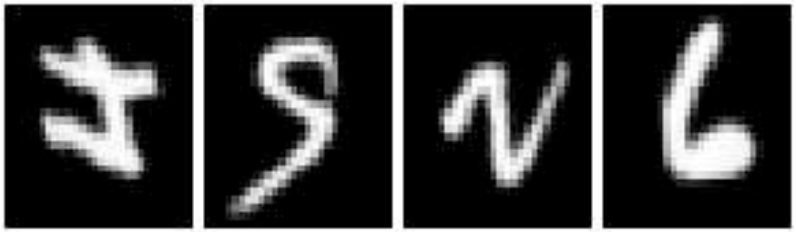
generative model

Benchmark problems
Overview

- We used a benchmark of challenging classification problems (Larochelle et al., 2007) available at `http://www.iro.umontreal.ca/~lisa/icml2007`
- 8 classification problems on 28×28 grayscale pixel images ($d = 784$).
- First 5 are harder variations on the MNIST digit classification problem. Last 3 are challenging binary classification tasks.
- All problems have separate training, validation and test sets (test set size: 50 000).

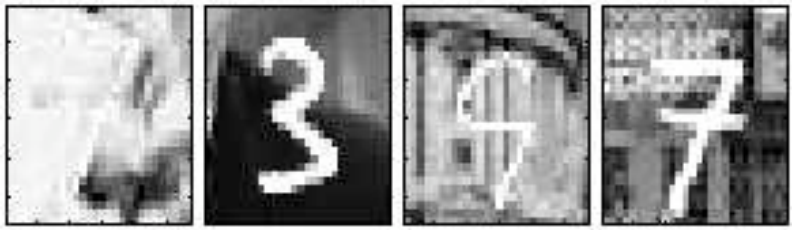
Benchmark problems
Variations on MNIST digit classification

basic: subset of original MNIST digits: 10 000 training samples, 2 000 validation samples, 50 000 test samples.

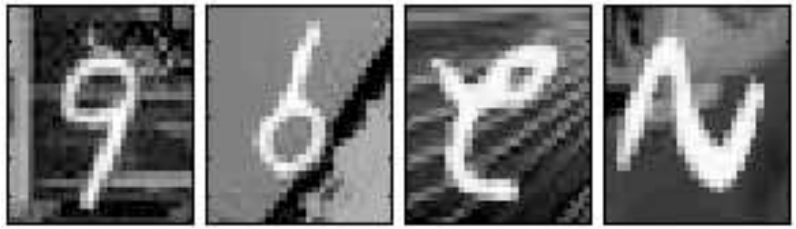


rot: applied random rotation (angle between 0 and 2π radians)

bg-rand: background made of random pixels (value in $0 \ldots 255$)



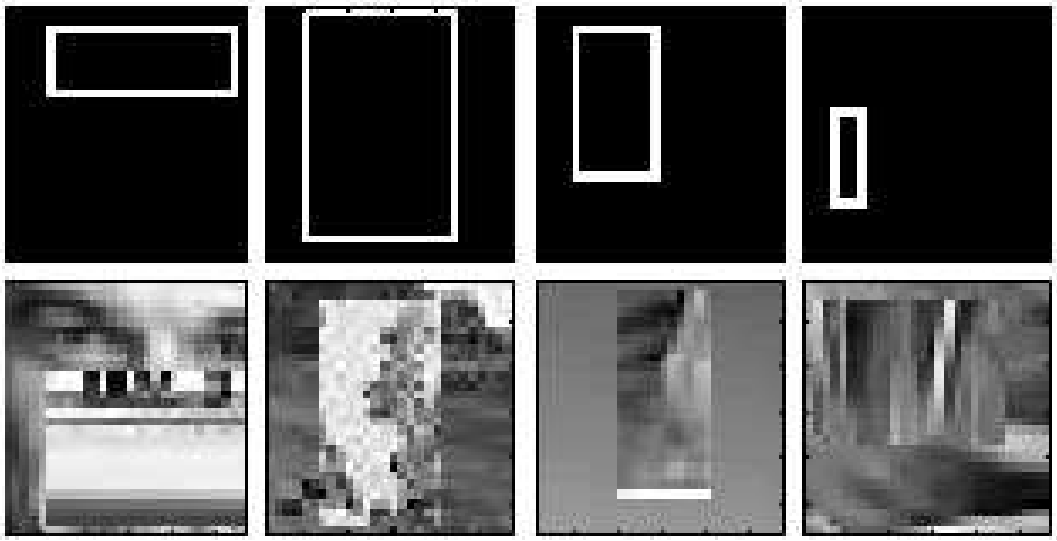
bg-img: background is random patch from one of 20 images



rot-bg-img: combination of rotation and background image

Benchmark problems
Shape discrimination

- **rect:** discriminate between tall and wide rectangles on black background.



- **rect-img**: borderless rectangle filled with random image patch. Background is a different image patch.

- **convex:** discriminate between convex and non-convex shapes.

Experiments

We compared the following algorithms on the benchmark problems:

- **SVM**$_{rbf}$: suport Vector Machines with Gaussian Kernel.
- **DBN-3**: Deep Belief Nets with 3 hidden layers (stacked Restricted Boltzmann Machines trained with contrastive divergence).
- **SAA-3**: Stacked Autoassociators with 3 hidden layers (no denoising).
- **SdA-3**: Stacked Denoising Autoassociators with 3 hidden layers.

Hyper-parameters for all algorithms were tuned based on classificaiton performance on validation set. (In particular hidden-layer sizes, and ν for **SdA-3**).

Performance comparison
Results

Dataset	SVM_{rbf}	DBN-3	SAA-3	SdA-3 (ν)
basic	$3.03_{\pm 0.15}$	$3.11_{\pm 0.15}$	$3.46_{\pm 0.16}$	$2.80_{\pm 0.14}$ (10%)
rot	$11.11_{\pm 0.28}$	$10.30_{\pm 0.27}$	$10.30_{\pm 0.27}$	$10.29_{\pm 0.27}$ (10%)
bg-rand	$14.58_{\pm 0.31}$	$6.73_{\pm 0.22}$	$11.28_{\pm 0.28}$	$10.38_{\pm 0.27}$ (40%)
bg-img	$22.61_{\pm 0.37}$	$16.31_{\pm 0.32}$	$23.00_{\pm 0.37}$	$16.68_{\pm 0.33}$ (25%)
rot-bg-img	$55.18_{\pm 0.44}$	$47.39_{\pm 0.44}$	$51.93_{\pm 0.44}$	$44.49_{\pm 0.44}$ (25%)
rect	$2.15_{\pm 0.13}$	$2.60_{\pm 0.14}$	$2.41_{\pm 0.13}$	$1.99_{\pm 0.12}$ (10%)
rect-img	$24.04_{\pm 0.37}$	$22.50_{\pm 0.37}$	$24.05_{\pm 0.37}$	$21.59_{\pm 0.36}$ (25%)
convex	$19.13_{\pm 0.34}$	$18.63_{\pm 0.34}$	$18.41_{\pm 0.34}$	$19.06_{\pm 0.34}$ (10%)

Performance comparison
Results

Dataset	SVM_{rbf}	DBN-3	SAA-3	SdA-3 (ν)
basic	$3.03_{\pm 0.15}$	$3.11_{\pm 0.15}$	$3.46_{\pm 0.16}$	$2.80_{\pm 0.14}$ (10%)
rot	$11.11_{\pm 0.28}$	$10.30_{\pm 0.27}$	$10.30_{\pm 0.27}$	$10.29_{\pm 0.27}$ (10%)
bg-rand	$14.58_{\pm 0.31}$	$6.73_{\pm 0.22}$	$11.28_{\pm 0.28}$	$10.38_{\pm 0.27}$ (40%)
bg-img	$22.61_{\pm 0.37}$	$16.31_{\pm 0.32}$	$23.00_{\pm 0.37}$	$16.68_{\pm 0.33}$ (25%)
rot-bg-img	$55.18_{\pm 0.44}$	$47.39_{\pm 0.44}$	$51.93_{\pm 0.44}$	$44.49_{\pm 0.44}$ (25%)
rect	$2.15_{\pm 0.13}$	$2.60_{\pm 0.14}$	$2.41_{\pm 0.13}$	$1.99_{\pm 0.12}$ (10%)
rect-img	$24.04_{\pm 0.37}$	$22.50_{\pm 0.37}$	$24.05_{\pm 0.37}$	$21.59_{\pm 0.36}$ (25%)
convex	$19.13_{\pm 0.34}$	$18.63_{\pm 0.34}$	$18.41_{\pm 0.34}$	$19.06_{\pm 0.34}$ (10%)

Performance comparison

Results

Dataset	**SVM$_{rbf}$**	**DBN-3**	**SAA-3**	**SdA-3 (ν)**
basic	$3.03_{\pm 0.15}$	$3.11_{\pm 0.15}$	$3.46_{\pm 0.16}$	$2.80_{\pm 0.14}$ (10%)
rot	$11.11_{\pm 0.28}$	$10.30_{\pm 0.27}$	$10.30_{\pm 0.27}$	$10.29_{\pm 0.27}$ (10%)
bg-rand	$14.58_{\pm 0.31}$	$6.73_{\pm 0.22}$	$11.28_{\pm 0.28}$	$10.38_{\pm 0.27}$ (40%)
bg-img	$22.61_{\pm 0.37}$	$16.31_{\pm 0.32}$	$23.00_{\pm 0.37}$	$16.68_{\pm 0.33}$ (25%)
rot-bg-img	$55.18_{\pm 0.44}$	$47.39_{\pm 0.44}$	$51.93_{\pm 0.44}$	$44.49_{\pm 0.44}$ (25%)
rect	$2.15_{\pm 0.13}$	$2.60_{\pm 0.14}$	$2.41_{\pm 0.13}$	$1.99_{\pm 0.12}$ (10%)
rect-img	$24.04_{\pm 0.37}$	$22.50_{\pm 0.37}$	$24.05_{\pm 0.37}$	$21.59_{\pm 0.36}$ (25%)
convex	$19.13_{\pm 0.34}$	$18.63_{\pm 0.34}$	$18.41_{\pm 0.34}$	$19.06_{\pm 0.34}$ (10%)

Performance comparison

Results

Dataset	SVM_{rbf}	DBN-3	SAA-3	SdA-3 (ν)
basic	$3.03_{\pm 0.15}$	$3.11_{\pm 0.15}$	$3.46_{\pm 0.16}$	$2.80_{\pm 0.14}$ (10%)
rot	$11.11_{\pm 0.28}$	$10.30_{\pm 0.27}$	$10.30_{\pm 0.27}$	$10.29_{\pm 0.27}$ (10%)
bg-rand	$14.58_{\pm 0.31}$	$6.73_{\pm 0.22}$	$11.28_{\pm 0.28}$	$10.38_{\pm 0.27}$ (40%)
bg-img	$22.61_{\pm 0.37}$	$16.31_{\pm 0.32}$	$23.00_{\pm 0.37}$	$16.68_{\pm 0.33}$ (25%)
rot-bg-img	$55.18_{\pm 0.44}$	$47.39_{\pm 0.44}$	$51.93_{\pm 0.44}$	$44.49_{\pm 0.44}$ (25%)
rect	$2.15_{\pm 0.13}$	$2.60_{\pm 0.14}$	$2.41_{\pm 0.13}$	$1.99_{\pm 0.12}$ (10%)
rect-img	$24.04_{\pm 0.37}$	$22.50_{\pm 0.37}$	$24.05_{\pm 0.37}$	$21.59_{\pm 0.36}$ (25%)
convex	$19.13_{\pm 0.34}$	$18.63_{\pm 0.34}$	$18.41_{\pm 0.34}$	$19.06_{\pm 0.34}$ (10%)

Performance comparison

Results

Dataset	SVM_{rbf}	DBN-3	SAA-3	SdA-3 (ν)
basic	3.03$\pm$0.15	3.11$\pm$0.15	3.46$\pm$0.16	2.80$\pm$0.14 (10%)
rot	11.11$\pm$0.28	10.30$\pm$0.27	10.30$\pm$0.27	10.29$\pm$0.27 (10%)
bg-rand	14.58$\pm$0.31	6.73$\pm$0.22	11.28$\pm$0.28	10.38$\pm$0.27 (40%)
bg-img	22.61$\pm$0.37	16.31$\pm$0.32	23.00$\pm$0.37	16.68$\pm$0.33 (25%)
rot-bg-img	55.18$\pm$0.44	47.39$\pm$0.44	51.93$\pm$0.44	44.49$\pm$0.44 (25%)
rect	2.15$\pm$0.13	2.60$\pm$0.14	2.41$\pm$0.13	1.99$\pm$0.12 (10%)
rect-img	24.04$\pm$0.37	22.50$\pm$0.37	24.05$\pm$0.37	21.59$\pm$0.36 (25%)
convex	19.13$\pm$0.34	18.63$\pm$0.34	18.41$\pm$0.34	19.06$\pm$0.34 (10%)

Performance comparison

Results

Dataset	SVM_{rbf}	DBN-3	SAA-3	SdA-3 (ν)
basic	$3.03_{\pm 0.15}$	$3.11_{\pm 0.15}$	$3.46_{\pm 0.16}$	$2.80_{\pm 0.14}$ (10%)
rot	$11.11_{\pm 0.28}$	$10.30_{\pm 0.27}$	$10.30_{\pm 0.27}$	$10.29_{\pm 0.27}$ (10%)
bg-rand	$14.58_{\pm 0.31}$	$6.73_{\pm 0.22}$	$11.28_{\pm 0.28}$	$10.38_{\pm 0.27}$ (40%)
bg-img	$22.61_{\pm 0.37}$	$16.31_{\pm 0.32}$	$23.00_{\pm 0.37}$	$16.68_{\pm 0.33}$ (25%)
rot-bg-img	$55.18_{\pm 0.44}$	$47.39_{\pm 0.44}$	$51.93_{\pm 0.44}$	$44.49_{\pm 0.44}$ (25%)
rect	$2.15_{\pm 0.13}$	$2.60_{\pm 0.14}$	$2.41_{\pm 0.13}$	$1.99_{\pm 0.12}$ (10%)
rect-img	$24.04_{\pm 0.37}$	$22.50_{\pm 0.37}$	$24.05_{\pm 0.37}$	$21.59_{\pm 0.36}$ (25%)
convex	$19.13_{\pm 0.34}$	$18.63_{\pm 0.34}$	$18.41_{\pm 0.34}$	$19.06_{\pm 0.34}$ (10%)

Performance comparison

Results

Dataset	SVM$_{rbf}$	DBN-3	SAA-3	SdA-3 (ν)
basic	3.03$\pm$0.15	3.11$\pm$0.15	3.46$\pm$0.16	2.80$\pm$0.14 (10%)
rot	11.11$\pm$0.28	10.30$\pm$0.27	10.30$\pm$0.27	10.29$\pm$0.27 (10%)
bg-rand	14.58$\pm$0.31	6.73$\pm$0.22	11.28$\pm$0.28	10.38$\pm$0.27 (40%)
bg-img	22.61$\pm$0.37	16.31$\pm$0.32	23.00$\pm$0.37	16.68$\pm$0.33 (25%)
rot-bg-img	55.18$\pm$0.44	47.39$\pm$0.44	51.93$\pm$0.44	44.49$\pm$0.44 (25%)
rect	2.15$\pm$0.13	2.60$\pm$0.14	2.41$\pm$0.13	1.99$\pm$0.12 (10%)
rect-img	24.04$\pm$0.37	22.50$\pm$0.37	24.05$\pm$0.37	21.59$\pm$0.36 (25%)
convex	19.13$\pm$0.34	18.63$\pm$0.34	18.41$\pm$0.34	19.06$\pm$0.34 (10%)

Performance comparison
Analysis of the results

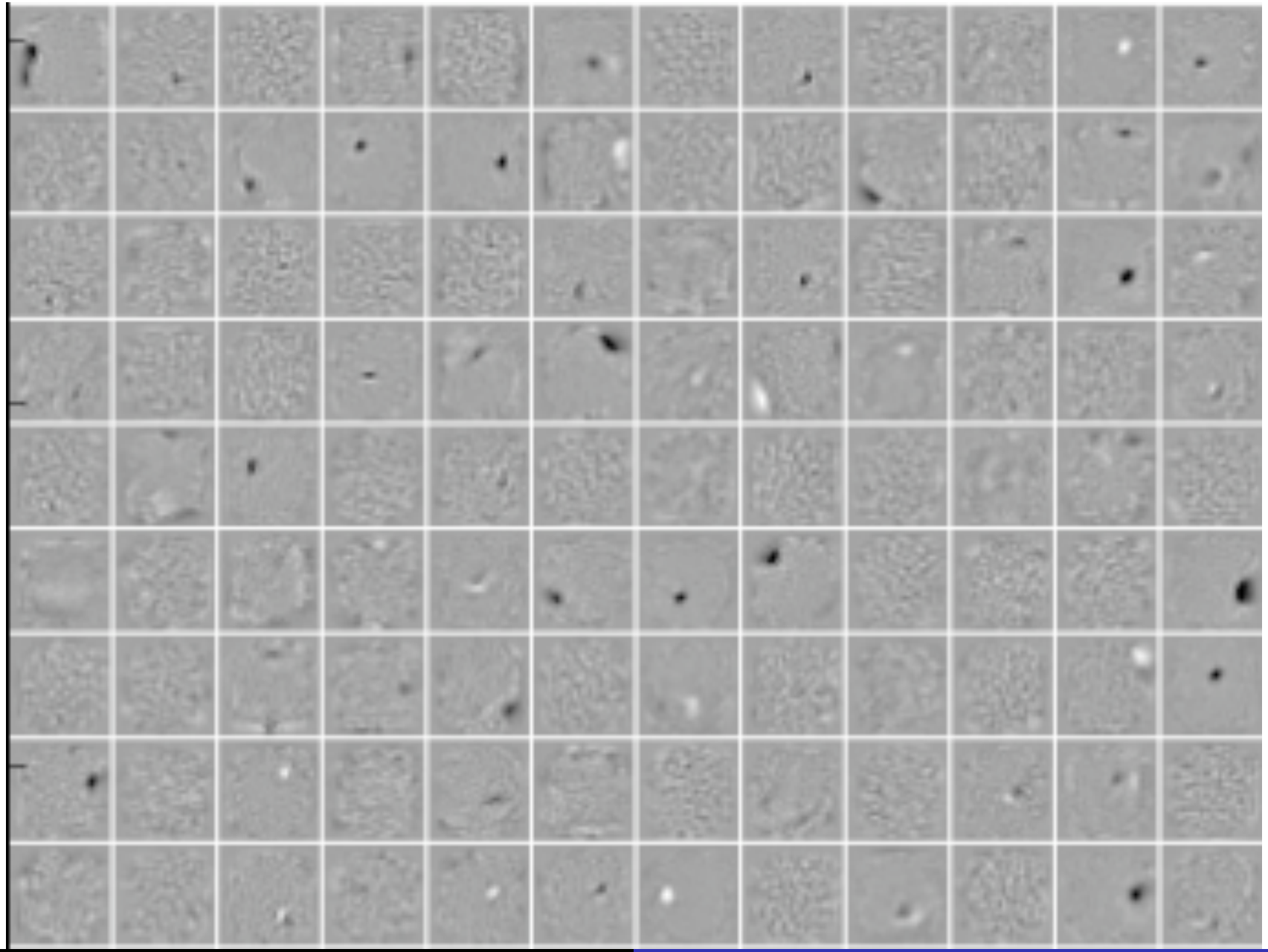
- Pretraining as denoising autoencoders appears to be a very effective initialization technique.
- **SdA-3** outperformed **SVMs** on all tasks, the difference being statistically significan on 6 of the 8 problems.
- Compared to Deep Belief Nets, **SdA-3** was significantly superior in 4 of the problems, while being significantly worse in only 1 case.
- More striking is the large gain from using noise (**SdA-3**) compared to the noise free case **SAA-3**.
- Note that best results on most MNIST tasks were obtained with first hidden layer size of 2000, i.e. with over-complete representations (since $d = 784$).

Analyzing the filters learnt by denoising autoencoders

- To view the effect of noise, we look at filters learnt by the first layer on **mnist basic** for different destruction levels ν.
- Each filter corresponds to the weights linking input $\mathbf{x}$ and one of the first hidden layer units.
- Filters at the same position in the image for different destruction levels are related only by the fact that the autoencoders were started from the same random initialization point.

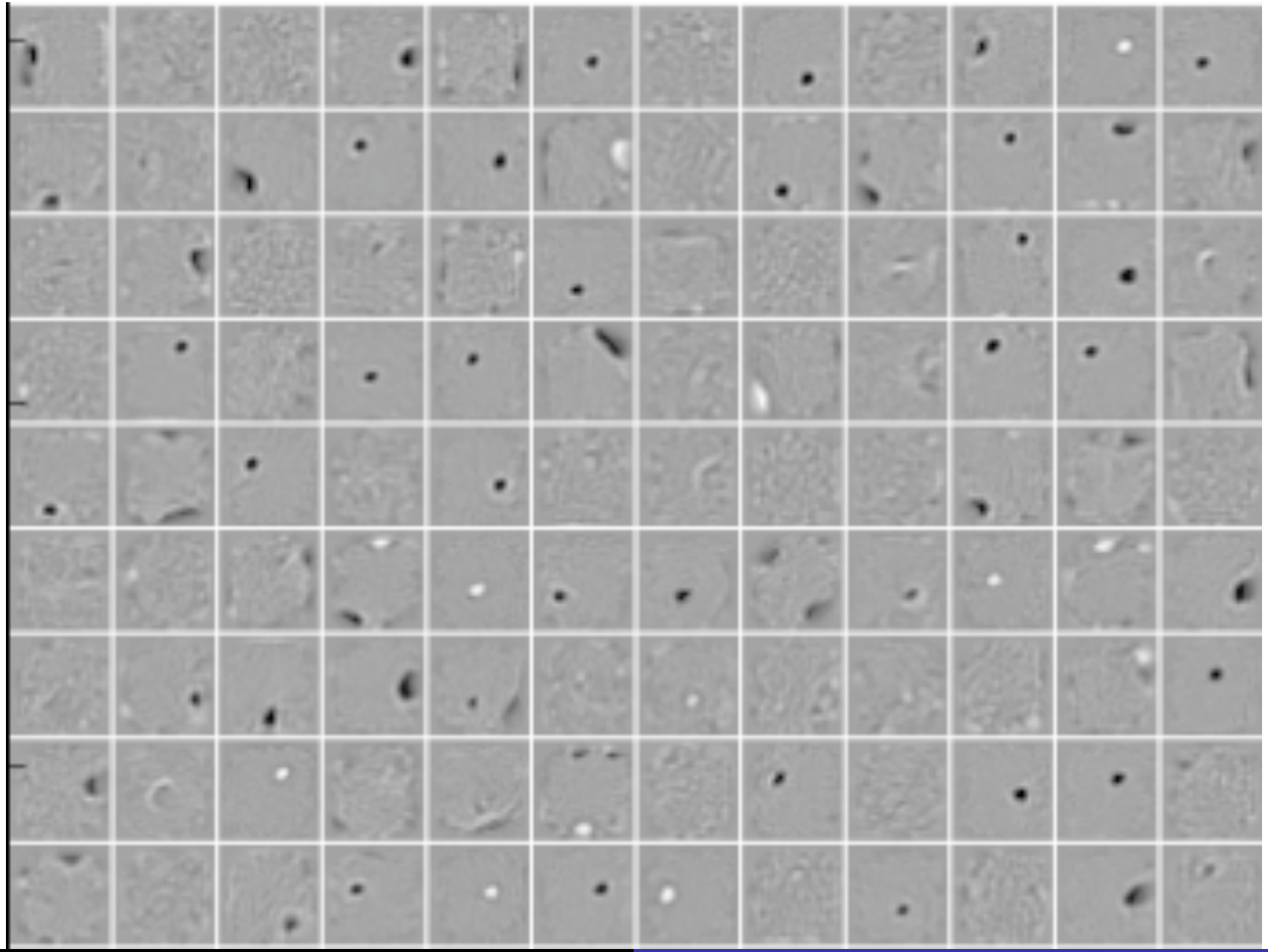
Learnt filters

0 % destroyed



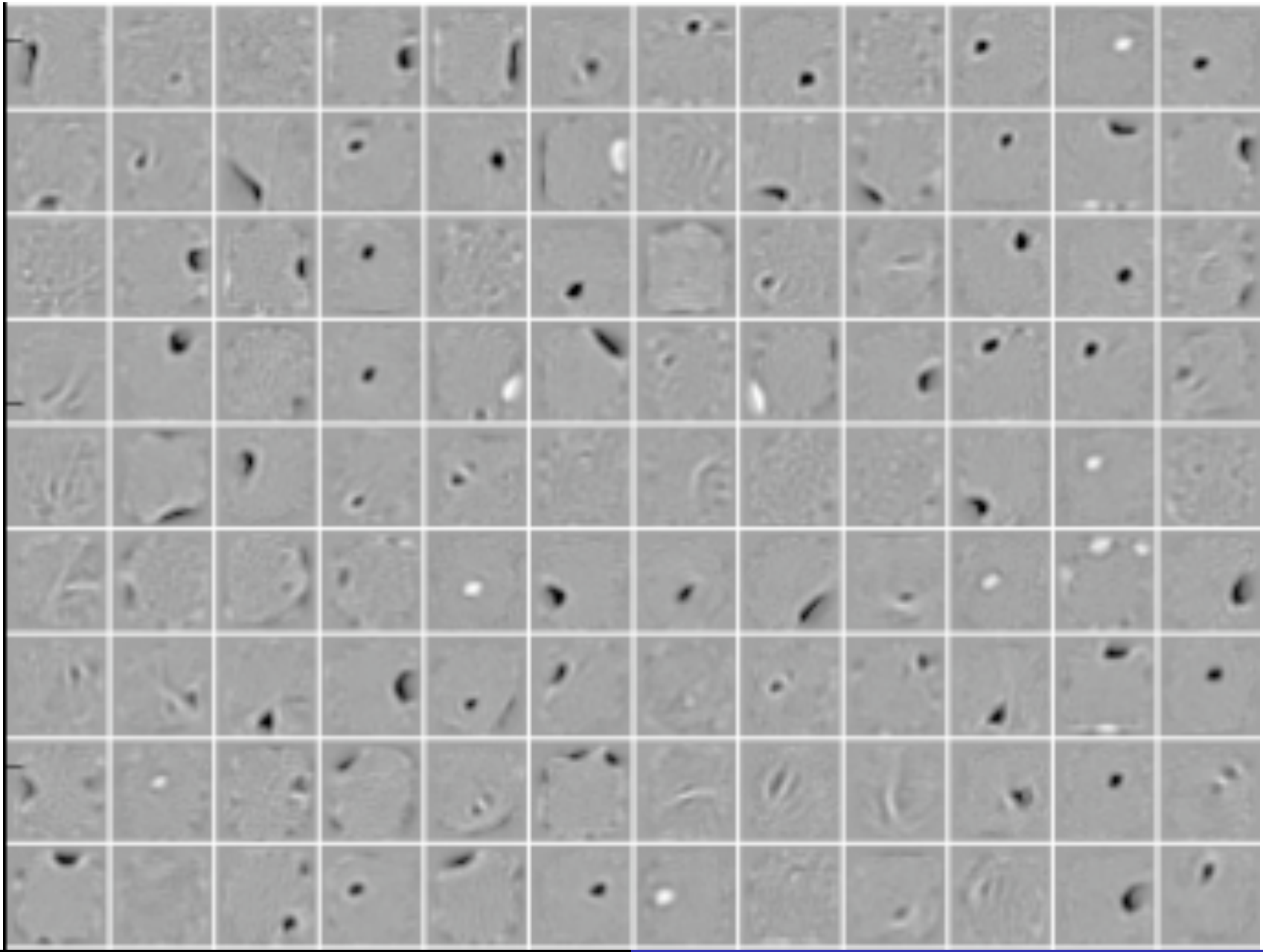
Learnt filters

10 % destroyed



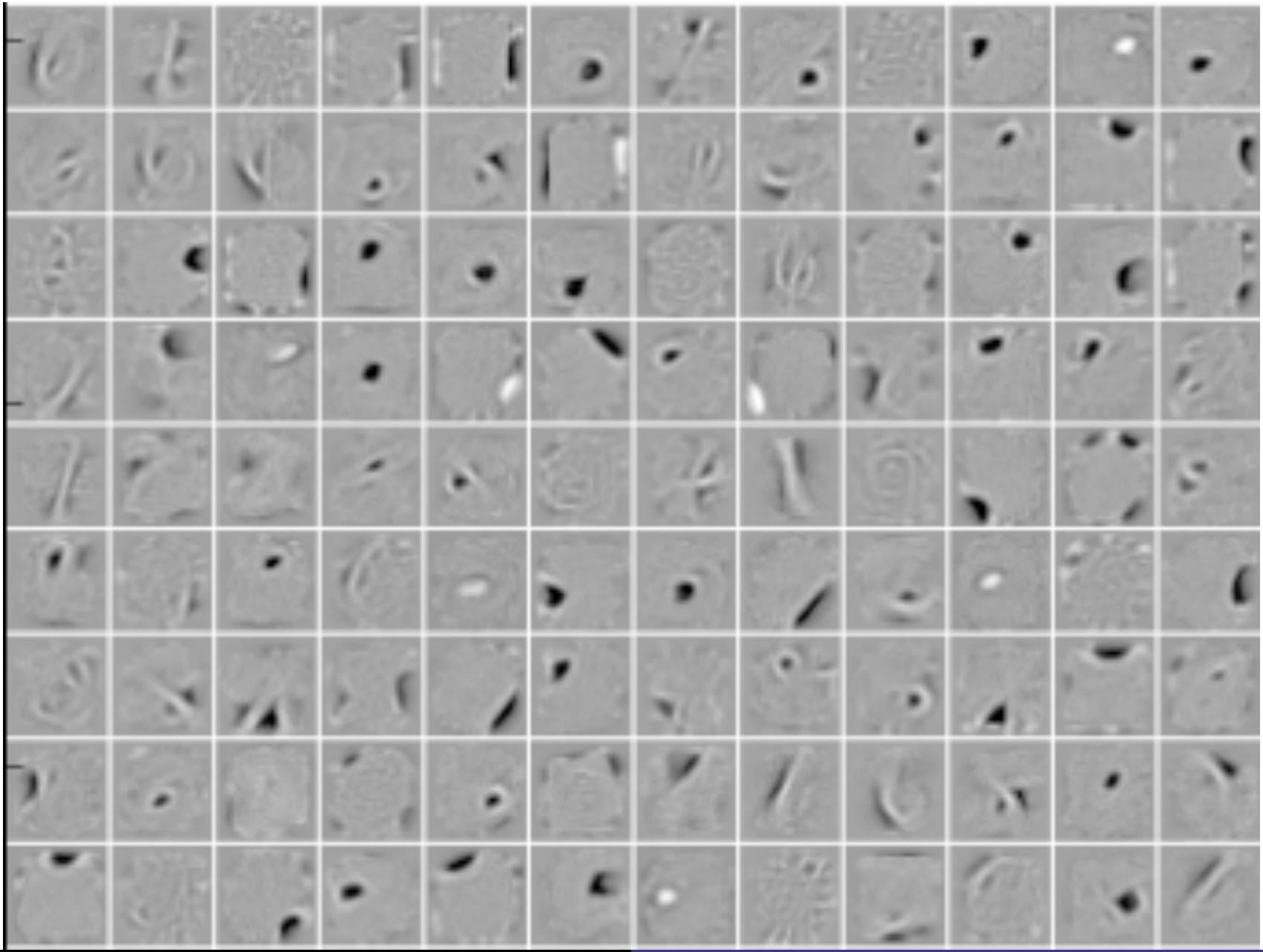
Learnt filters

25 % destroyed



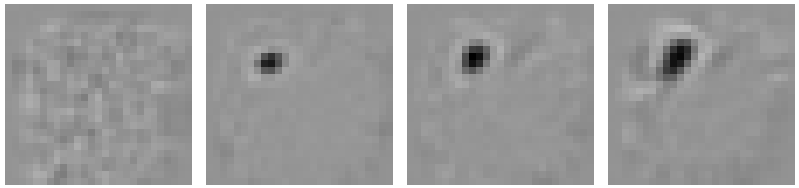
Learnt filters

50 % destroyed

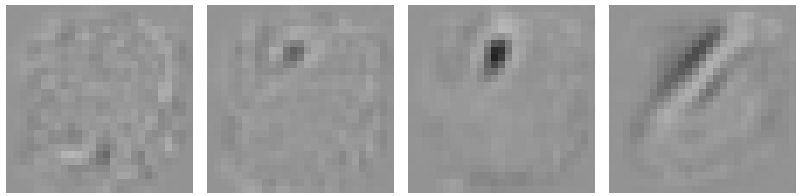


Learnt filters
Qualitative analysis

- with no noise, many filters appear similarly uninteresting (undistinctive almost uniform grey patches).
- as we increase the noise level, denoising training forces the filters to differentiate more, and capture more distinctive features.
- higher noise levels tend to induce less local filters (as we expected).
- one can distinguish different kinds of filters, from local blob detectors, to stroke detectors, and some full character detectors at the higher noise levels.



Neuron A (0%, 10%, 20%, 50% destruction)



Neuron B (0%, 10%, 20%, 50% destruction)

Conclusion and future work

- Unsupervised initialization of layers with an explicit denoising criterion appears to help capture interesting structure in the input distribution.
- This leads to intermediate representations much better suited for subsequent learning tasks such as supervised classification.
- Resulting algorithm for learning deep networks is simple and improves on state-of-the-art on benchmark problems.
- Future work will investigate the effect of different types of corruption process.

THANK YOU!

Performance comparison

Dataset	SVM_{rbf}	SVM_{poly}	DBN-1	DBN-3	SAA-3	SdA-3 (ν)
basic	3.03±0.15	3.69±0.17	3.94±0.17	3.11±0.15	3.46±0.16	2.80±0.14 (10%)
rot	11.11±0.28	15.42±0.32	14.69±0.31	10.30±0.27	10.30±0.27	10.29±0.27 (10%)
bg-rand	14.58±0.31	16.62±0.33	9.80±0.26	6.73±0.22	11.28±0.28	10.38±0.27 (40%)
bg-img	22.61±0.37	24.01±0.37	16.15±0.32	16.31±0.32	23.00±0.37	16.68±0.33 (25%)
rot-bg-img	55.18±0.44	56.41±0.43	52.21±0.44	47.39±0.44	51.93±0.44	44.49±0.44 (25%)
rect	2.15±0.13	2.15±0.13	4.71±0.19	2.60±0.14	2.41±0.13	1.99±0.12 (10%)
rect-img	24.04±0.37	24.05±0.37	23.69±0.37	22.50±0.37	24.05±0.37	21.59±0.36 (25%)
convex	19.13±0.34	19.82±0.35	19.92±0.35	18.63±0.34	18.41±0.34	19.06±0.34 (10%)

red when confidence intervals overlap.

References

Bengio, Y., Lamblin, P., Popovici, D., & Larochelle, H. (2007). Greedy layer-wise training of deep networks. *Advances in Neural Information Processing Systems 19 (NIPS'06)* (pp. 153–160). MIT Press.

Gallinari, P., LeCun, Y., Thiria, S., & Fogelman-Soulie, F. (1987). Memoires associatives distribuees. *Proceedings of COGNITIVA 87*. Paris, La Villette.

Hinton, G. E., Osindero, S., & Teh, Y. (2006). A fast learning algorithm for deep belief nets. *Neural Computation*, *18*, 1527–1554.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences, USA*, *79*.

Larochelle, H., Erhan, D., Courville, A., Bergstra, J., & Bengio, Y. (2007). An empirical evaluation of deep architectures on problems with many factors of variation. *Proceedings of the Twenty-fourth International Conference on Machine Learning (ICML'07)* (pp. 473–480). Corvallis, OR: ACM.

LeCun, Y. (1987). *Modèles connexionistes de l'apprentissage*. Doctoral dissertation, Université de Paris VI.

Ranzato, M., Poultney, C., Chopra, S., & LeCun, Y. (2007). Efficient learning of sparse representations with an energy-based model. *Advances in Neural Information Processing Systems 19 (NIPS'06)* (pp. 1137–1144). MIT Press.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, *323*, 533–536.