

Neural networks

Deep learning - example

DEEP LEARNING

Topics: pseudocode

- for $l=1$ to L
 - ▶ build unsupervised training set (with $\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x}$):

$$\mathcal{D} = \left\{ \mathbf{h}^{(l-1)}(\mathbf{x}^{(t)}) \right\}_{t=1}^T$$

- ▶ train “greedy module” (RBM, autoencoder) on \mathcal{D}
 - ▶ use hidden layer weights and biases of greedy module to initialize the deep network parameters $\mathbf{W}^{(l)}, \mathbf{b}^{(l)}$
- Initialize $\mathbf{W}^{(L+1)}, \mathbf{b}^{(L+1)}$ randomly (as usual)
- Train the whole neural network using (supervised) stochastic gradient descent (with backprop)

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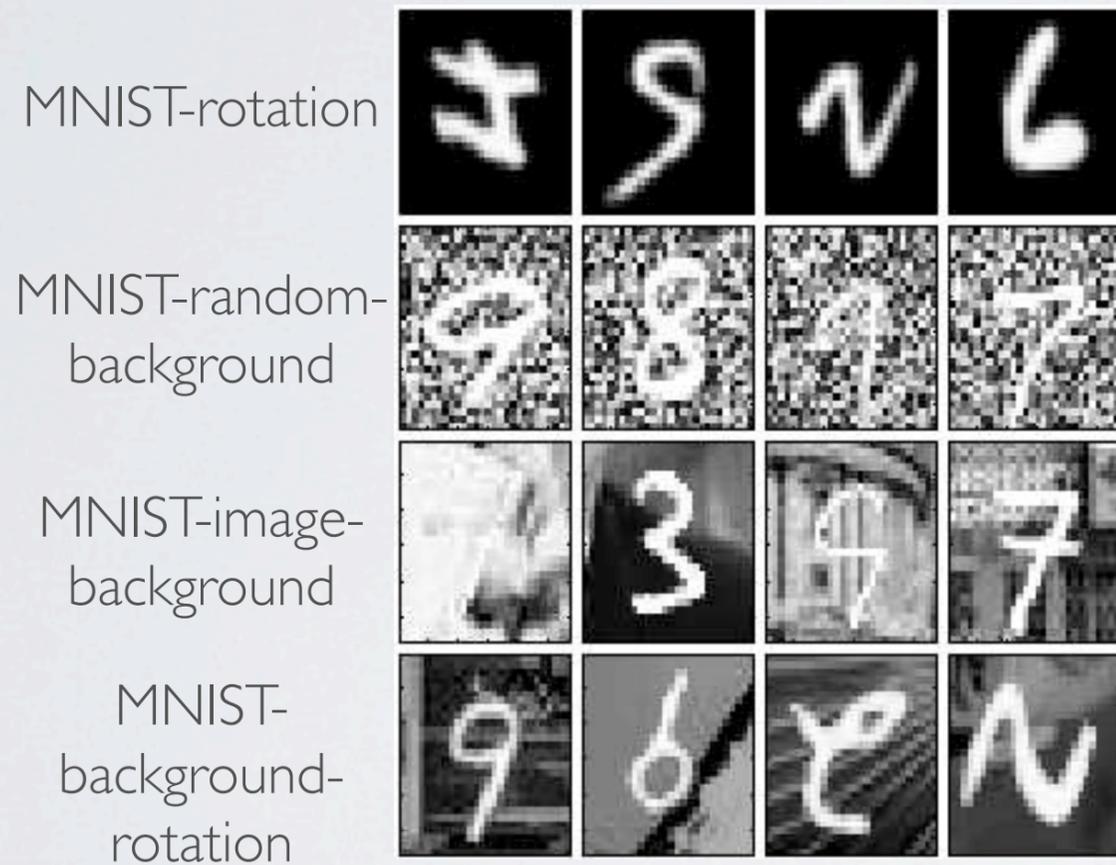
fine-tuning

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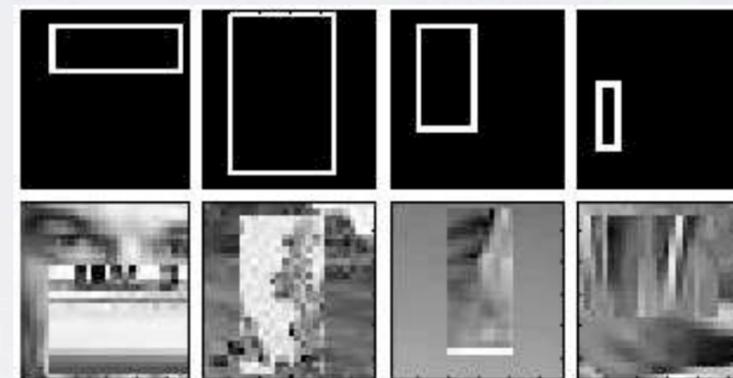
Topics: datasets

- Datasets generated with varying number of factors of variations

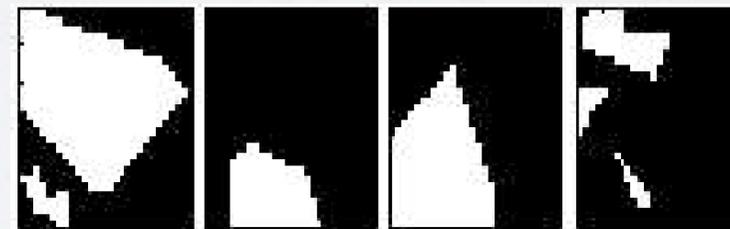
Variations on MNIST



Tall or wide?



Convex shape or not?



An Empirical Evaluation of Deep Architectures on Problems with Many Factors of Variation
 Larochelle, Erhan, Courville, Bergstra and Bengio, 2007

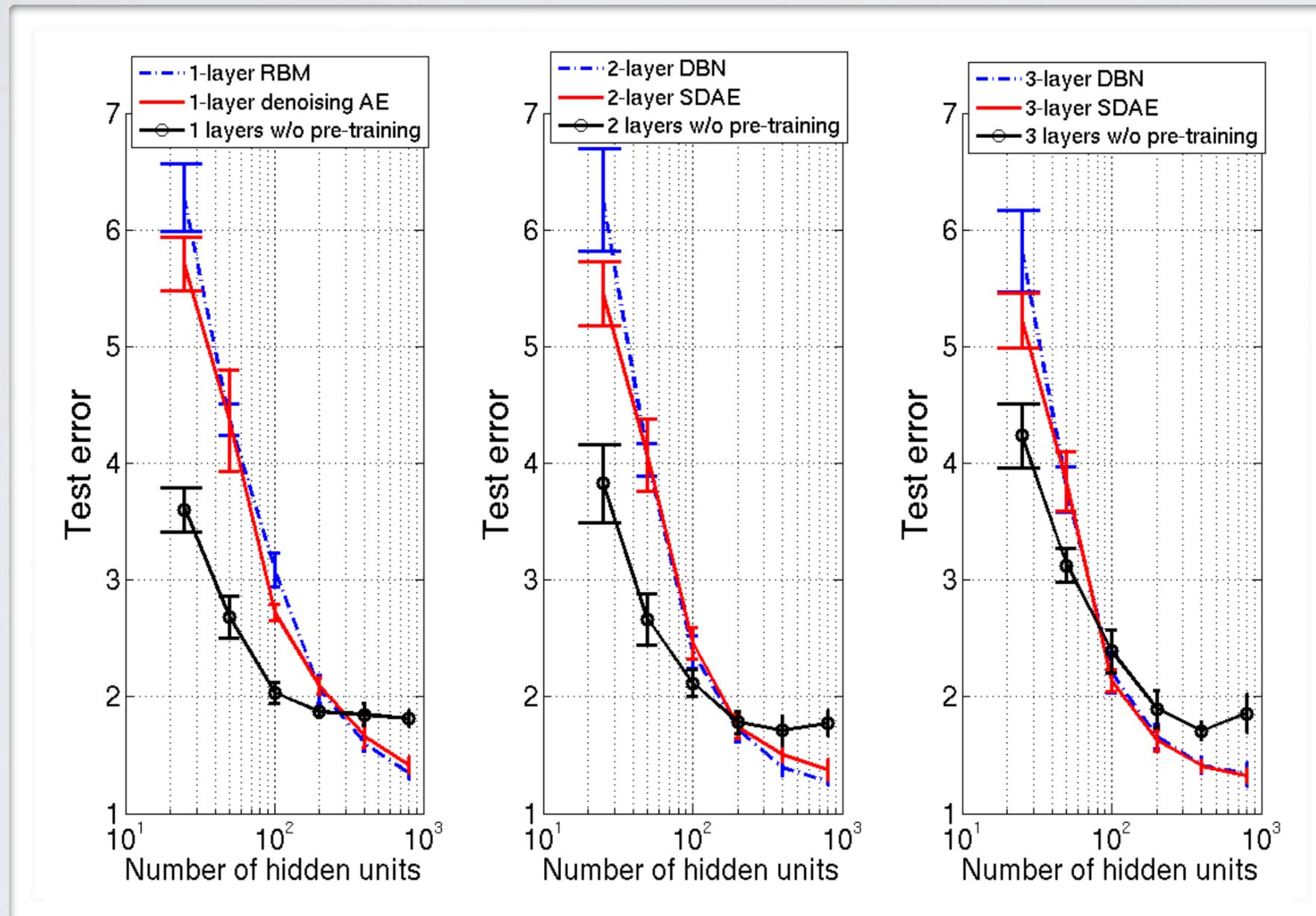
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Topics: impact of initialization

Network		MNIST-small	MNIST-rotation
Type	Depth	classif. test error	classif. test error
Deep net	1	4.14 % \pm 0.17	15.22 % \pm 0.31
	2	4.03 % \pm 0.17	10.63 % \pm 0.27
	3	4.24 % \pm 0.18	11.98 % \pm 0.28
	4	4.47 % \pm 0.18	11.73 % \pm 0.29
Deep net + autoencoder	1	3.87 % \pm 0.17	11.43% \pm 0.28
	2	3.38 % \pm 0.16	9.88 % \pm 0.26
	3	3.37 % \pm 0.16	9.22 % \pm 0.25
	4	3.39 % \pm 0.16	9.20 % \pm 0.25
Deep net + RBM	1	3.17 % \pm 0.15	10.47 % \pm 0.27
	2	2.74 % \pm 0.14	9.54 % \pm 0.26
	3	2.71 % \pm 0.14	8.80 % \pm 0.25
	4	2.72 % \pm 0.14	8.83 % \pm 0.24

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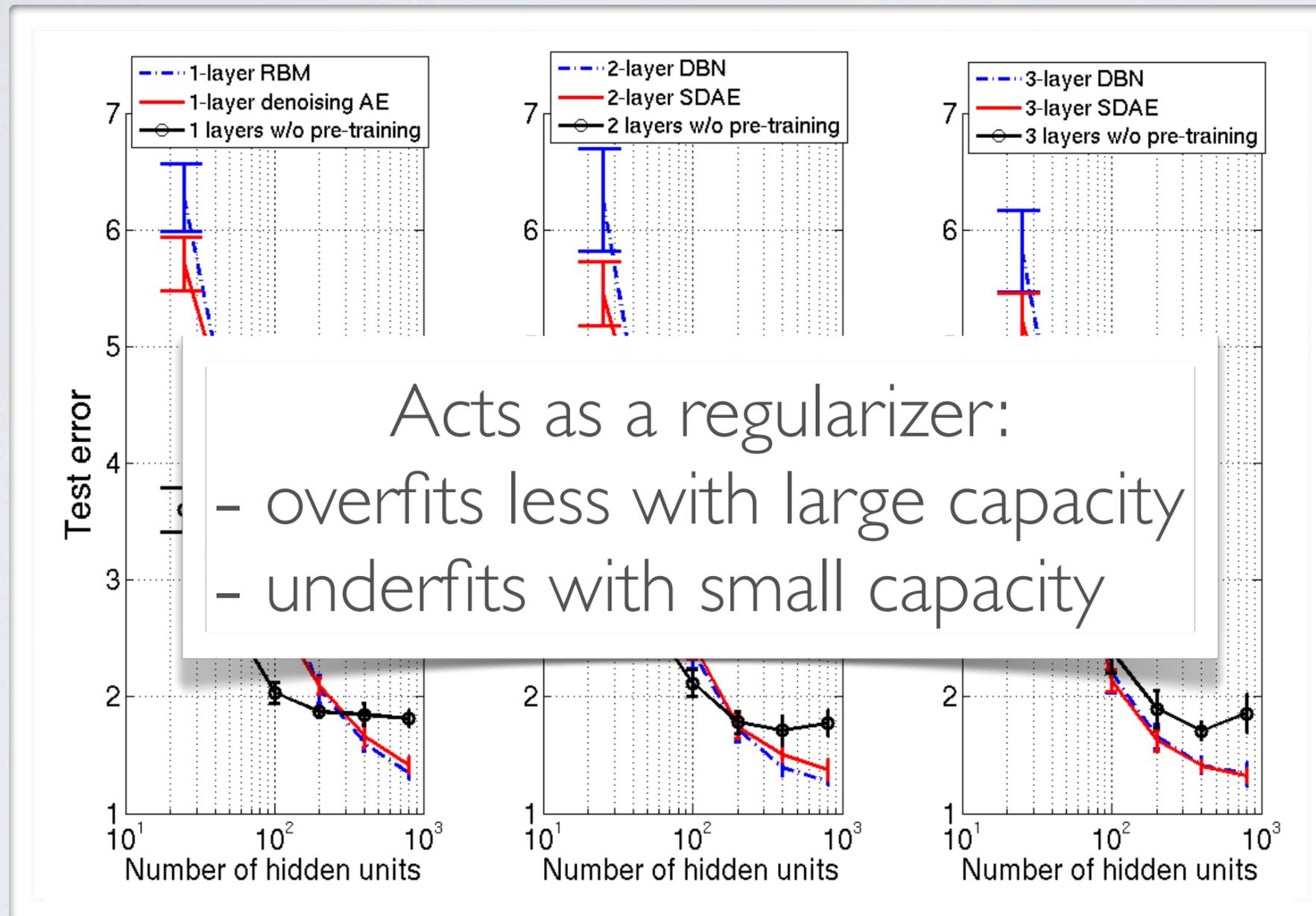
Topics: impact of initialization



Why Does Unsupervised Pre-training Help Deep Learning?
 Erhan, Bengio, Courville, Manzagol, Vincent and Bengio, 2011

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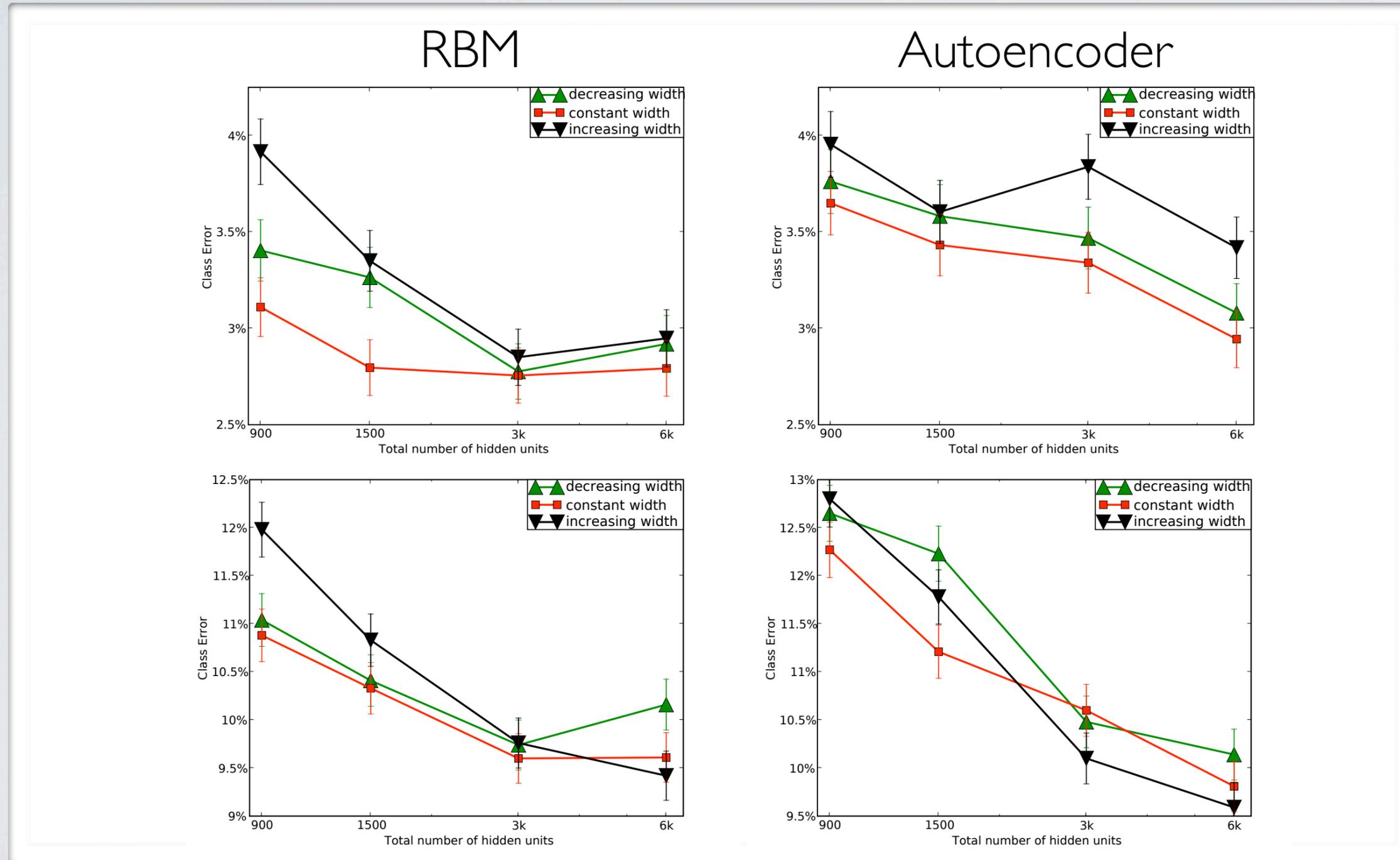
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Topics: choice of hidden layer size



DEEP LEARNING

Topics: performance on different datasets

Stacked
Autoencoders

Stacked
RBMS

Stacked
Denoising Autoencoders

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

Extracting and Composing Robust Features with Denoising Autoencoders,
Vincent, Larochelle, Bengio and Manzagol, 2008.