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Deep Extreme Learning Machines: Supervised Auto-Encoding Architecture for Classification

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Outline

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- Brief introduction to Extreme Learning Machines (ELM)
- Motivation for Deep Extreme Learning Machines (Deep ELM)
- Deep ELM Architecture
- Improving accuracy using Weight Shaping Methods
- Experiments
- Discussion and conclusion

Extreme Learning Machines

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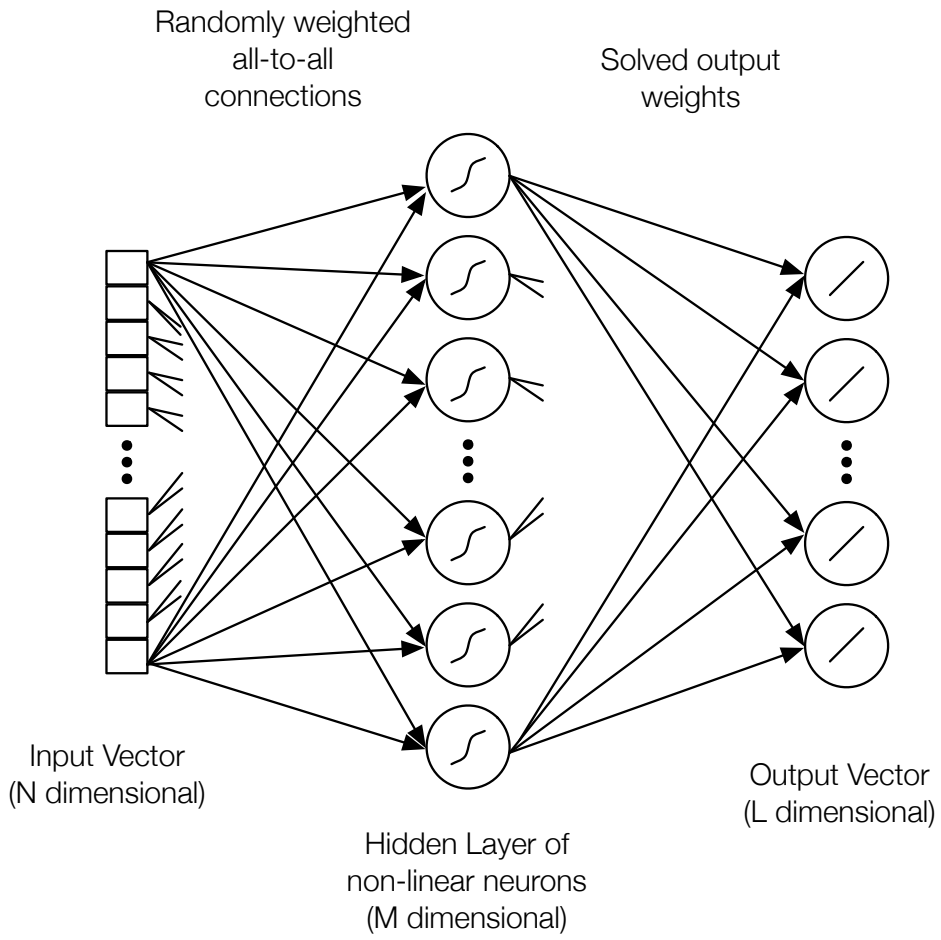
General Approach

1. Using random and fixed weights, connect an input layer to a hidden layer of sigmoidal neurons

2. Using training data, numerically solve for the output weights between the hidden and the output layers



Extreme Learning Machines

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Training an Extreme Learning Machine

Input to the hidden layer,

$$H_1 = \mathbf{W}_{P1} I$$

$$f[H_1]_i = \frac{1}{1 + \exp(-(H_1)_i)}$$

For *k* training data, we then form a matrix using the hidden layer activations,

$$\mathbf{A} \in \mathbb{R}^{M \times k}$$

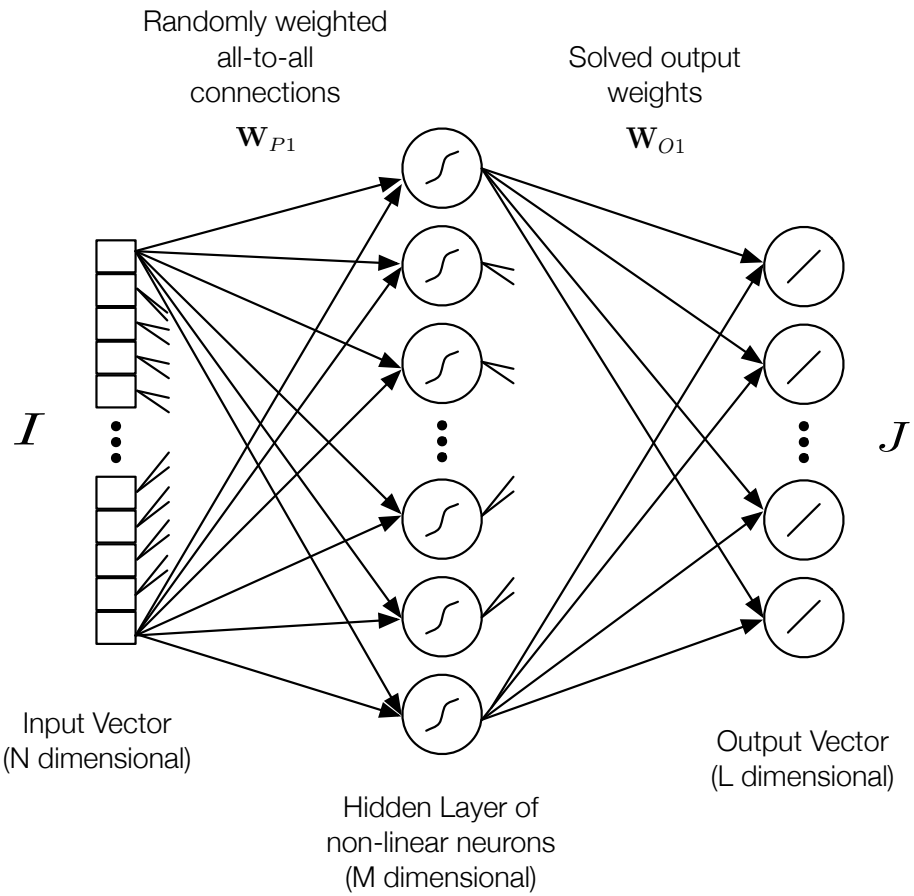
We then take the Moore-Penrose Pseudoinverse of A,

$$\mathbf{A}^{+} \in \mathbb{R}^{k \times M}$$

Now we can calculate the output weight matrix,

$$\mathbf{W}_{O1} = J\mathbf{A}^{+}$$

Where J represents the desired target output.



Motivation for Deep ELM

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- Drawbacks of classical single layer ELM
  - Large hidden layer size
  - Batch training (Restricts the use of it for real-time learning applications)
  - Combined batch training and a large hidden layer is computationally expensive, even for an extreme learning machine
  - Is it feasible for hardware implementations?
- Batch training have been addressed in on-line training algorithms
- How can we reduce the hidden layer size, and keep the same performance?
  - Can we have multiple hidden layers of smaller size?
    - Which would reduce the computational resources required, and significantly reduce the training time

Deep ELM Architecture

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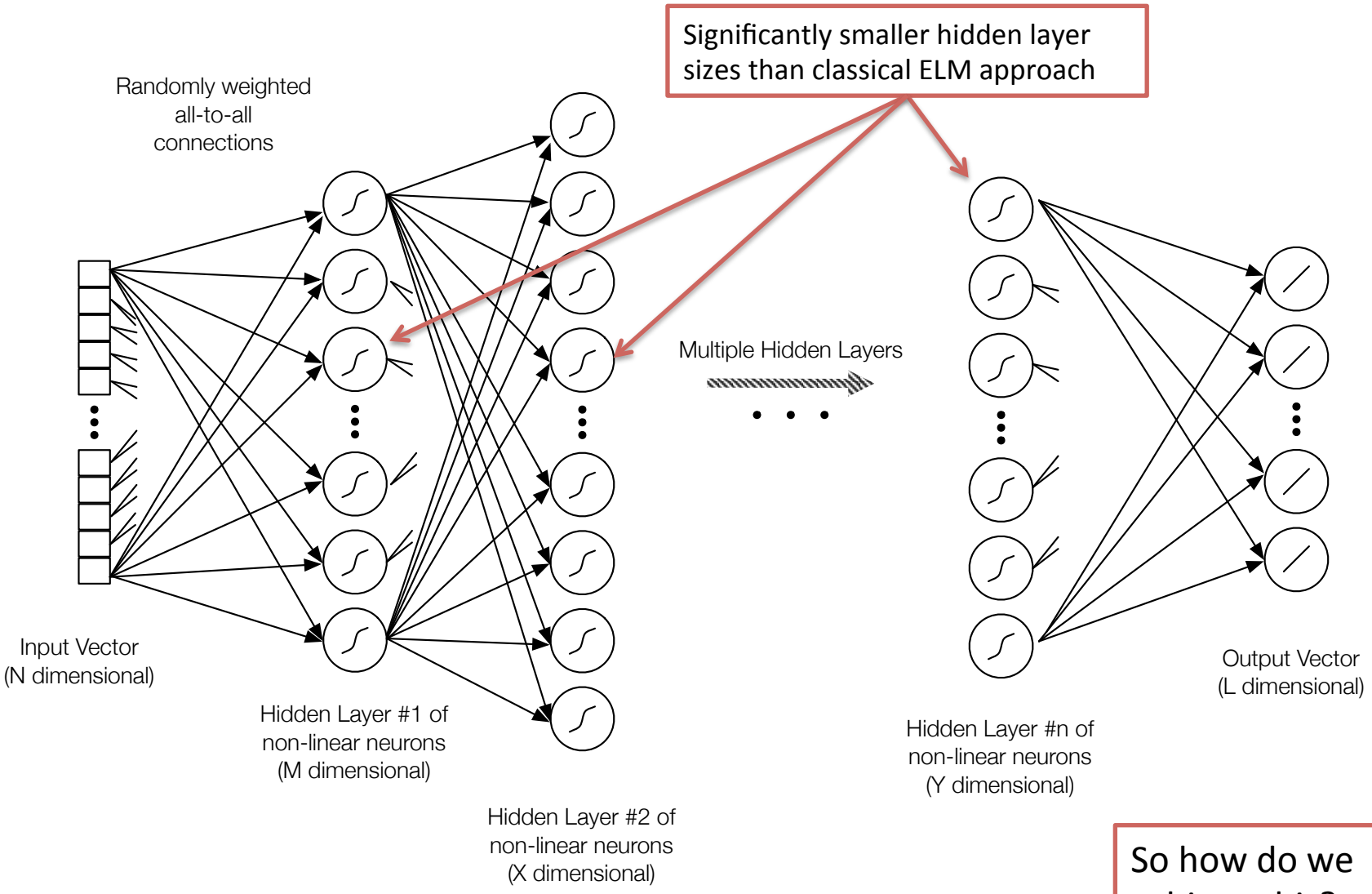

Deep ELM Architecture

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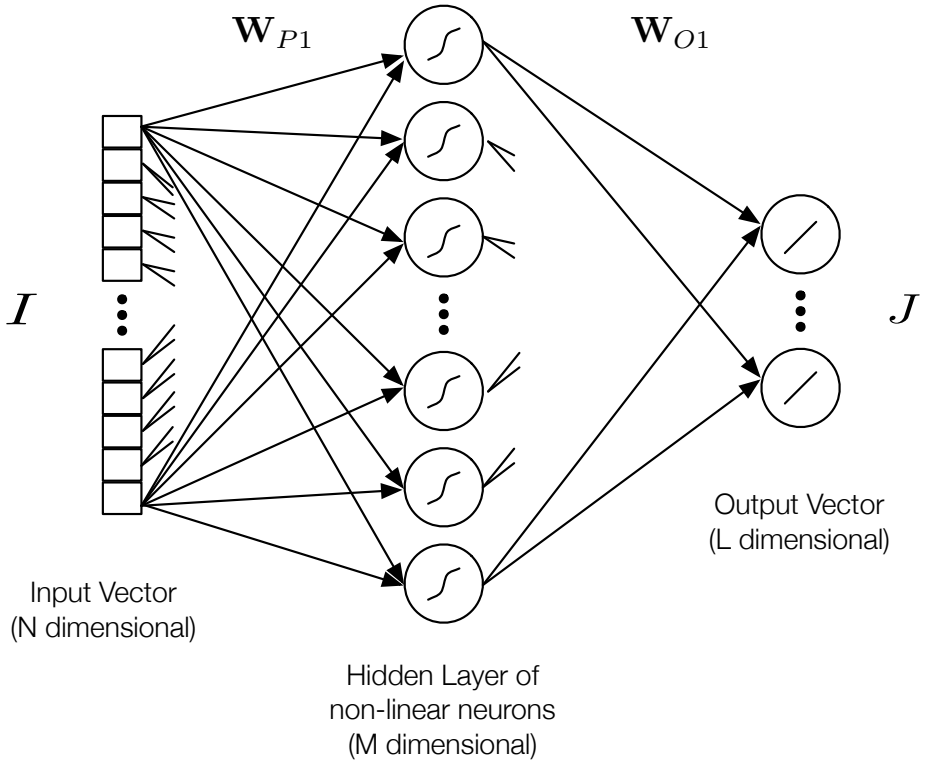

- We start by constructing a single layer ELM

$$H_1 = \mathbf{W}_{P1} I$$

$$f[H_1]_i = \frac{1}{1 + \exp(-(H_1)_i)}$$

$$\mathbf{W}_{O1} = J\mathbf{A}^{+}$$

- Here, J is the target vectors. In most ELMs, this will be a K dimensional vector, where K is equal to the number of classes in the training dataset.

Deep ELM Architecture

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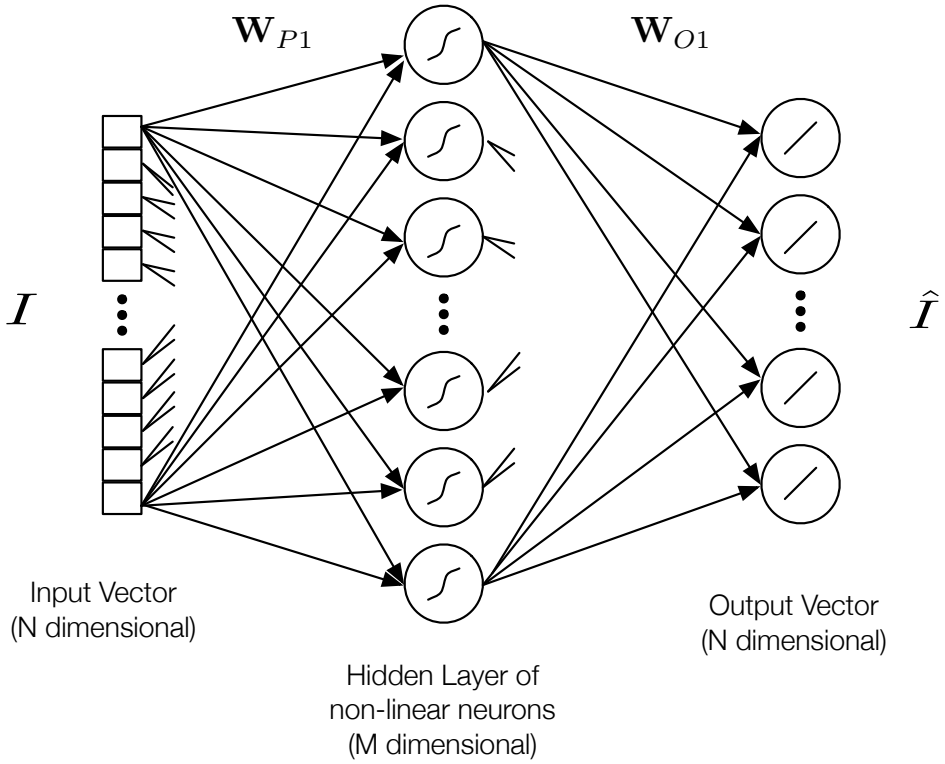

- Instead of performing classification at the output layer, we train the output weight matrix such that the target outputs are auto-encoded versions of the inputs

$$H_1 = \mathbf{W}_{P1} I$$

$$f[H_1]_i = \frac{1}{1 + \exp(-(H_1)_i)}$$

$$\mathbf{W}_{O1} = \hat{I}\mathbf{A}^{+}$$

Note our target has now changed

Deep ELM Architecture

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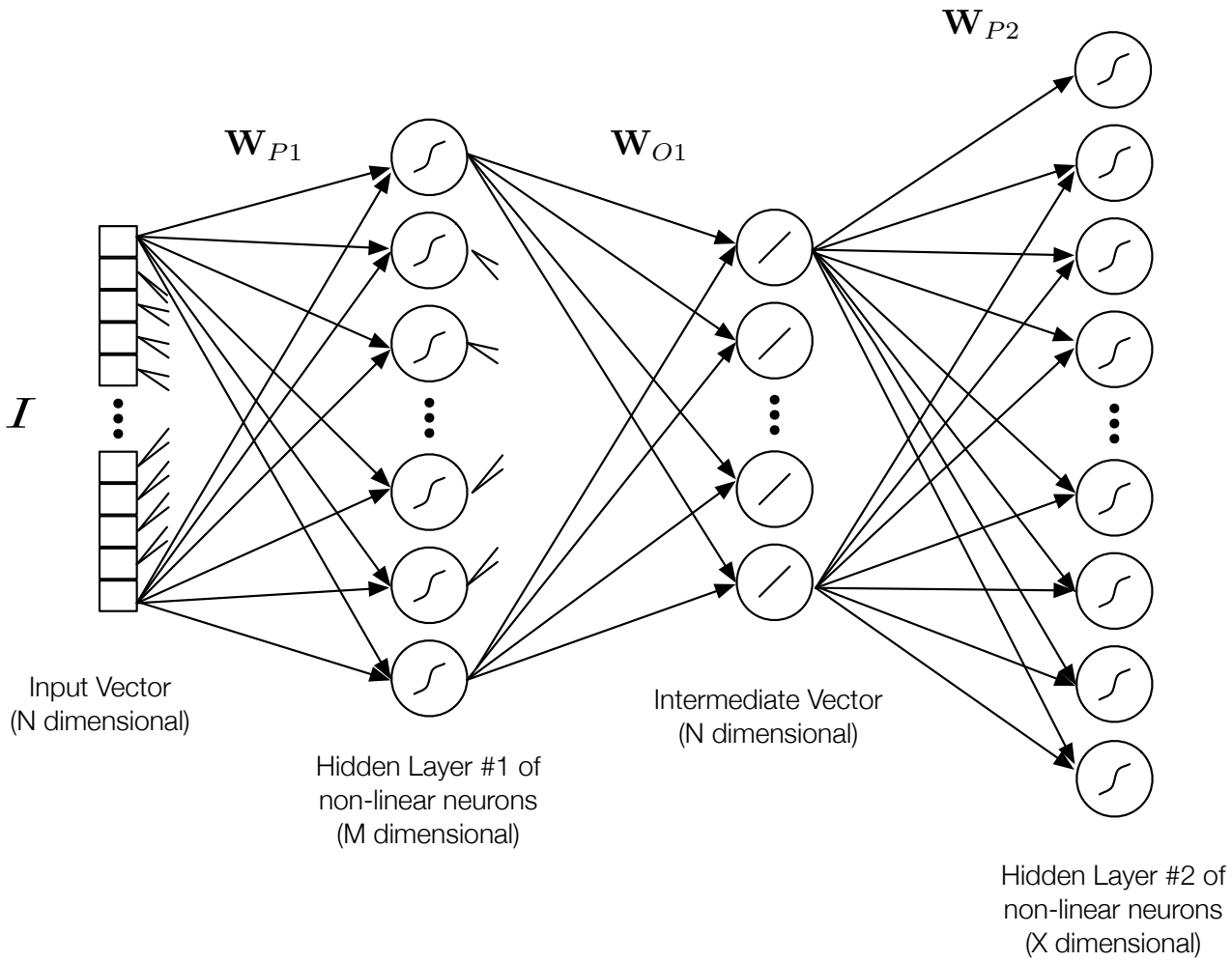

- Compute the pseudoinverse of the second hidden layer, which we denote as $\mathbf{B}^{+}$

$$H_2 = \mathbf{W}_{P2}\hat{I} \qquad f[H_2]_i = \frac{1}{1+\exp(-(H_2)_i)}$$

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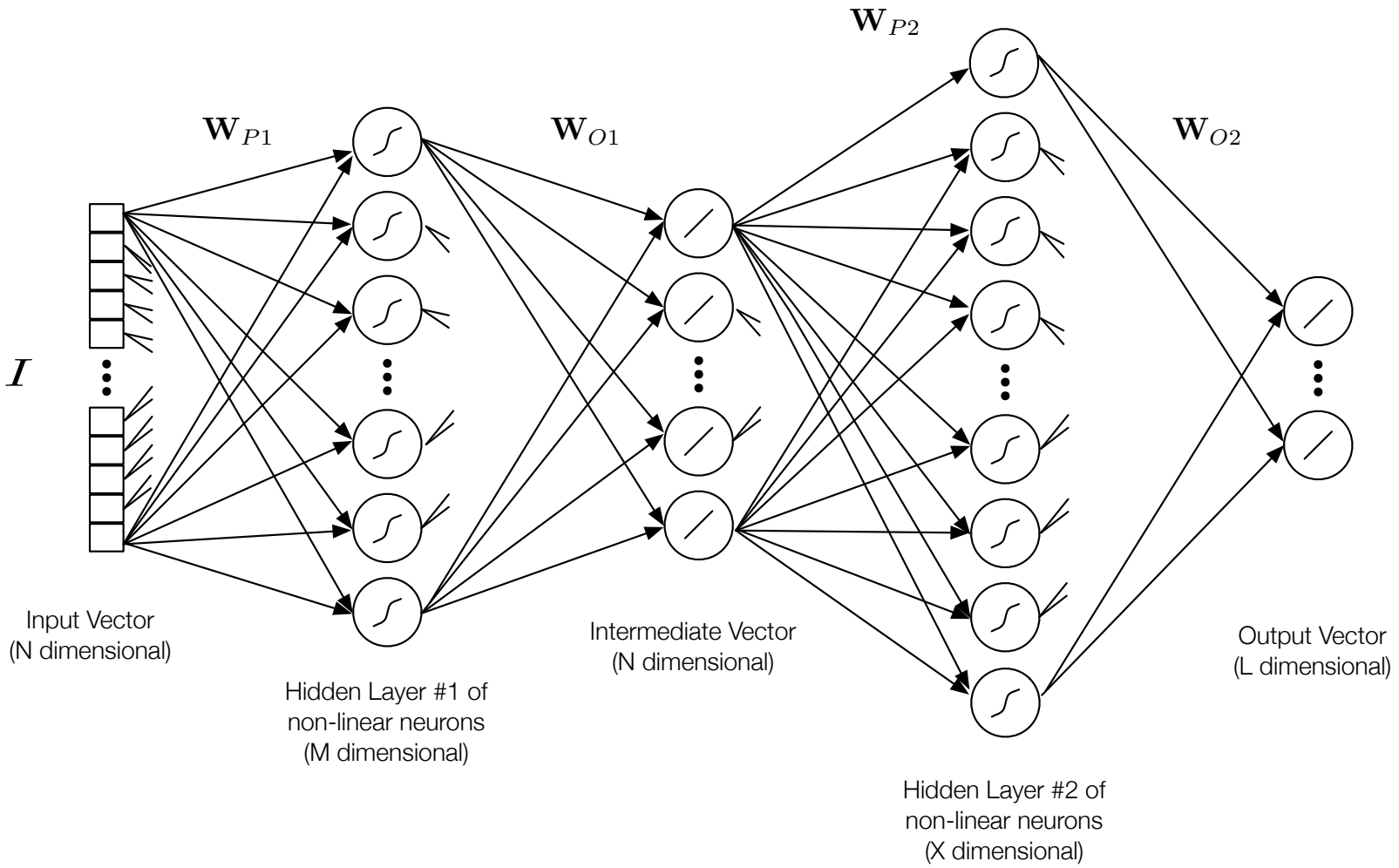

$$\mathbf{W}_{O2} = J\mathbf{B}^{+}$$

Deep ELM Architecture

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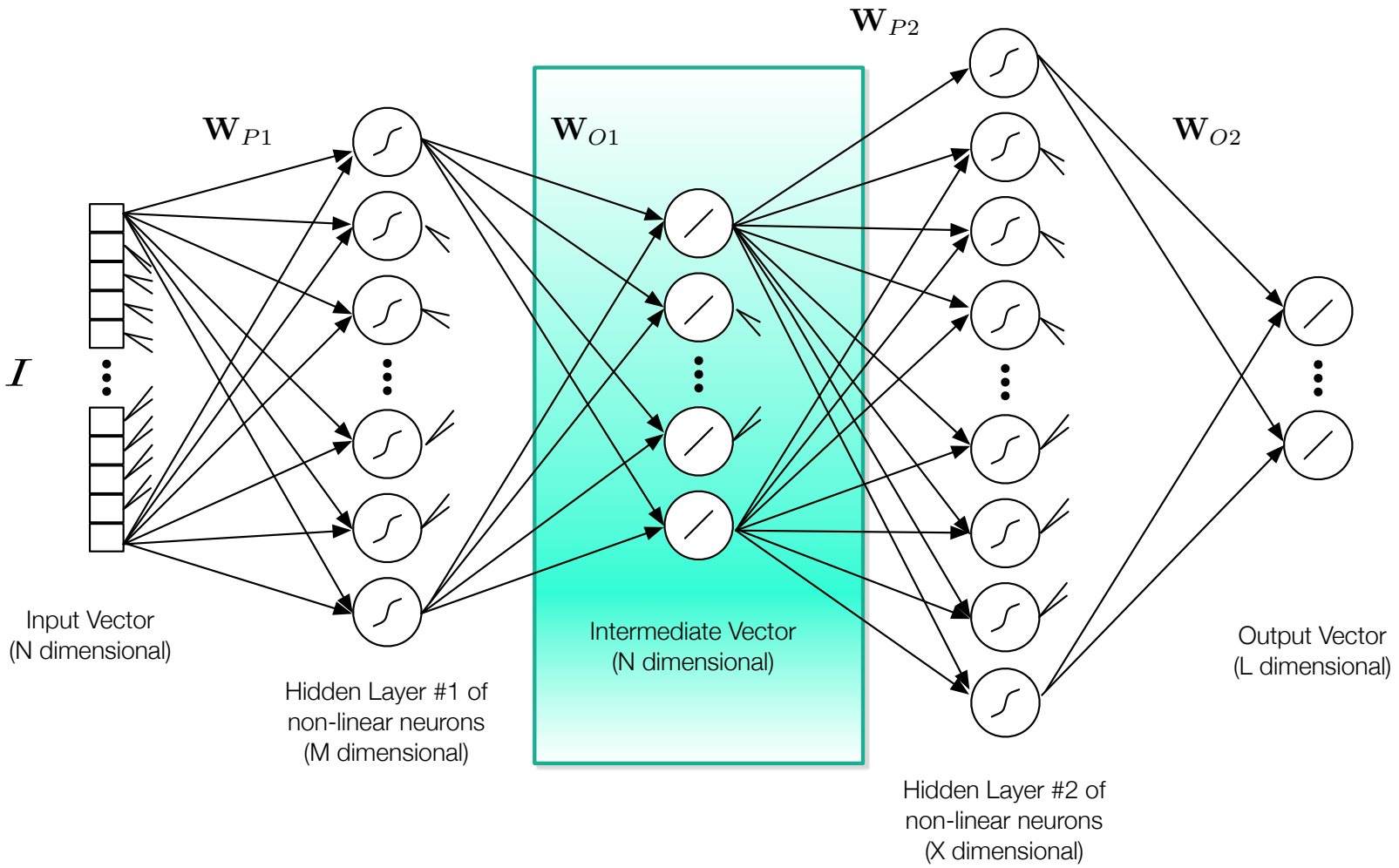

$$\mathbf{W}_{h_{12}} = \mathbf{W}_{O1} \times \mathbf{W}_{P2}$$

Deep ELM Architecture

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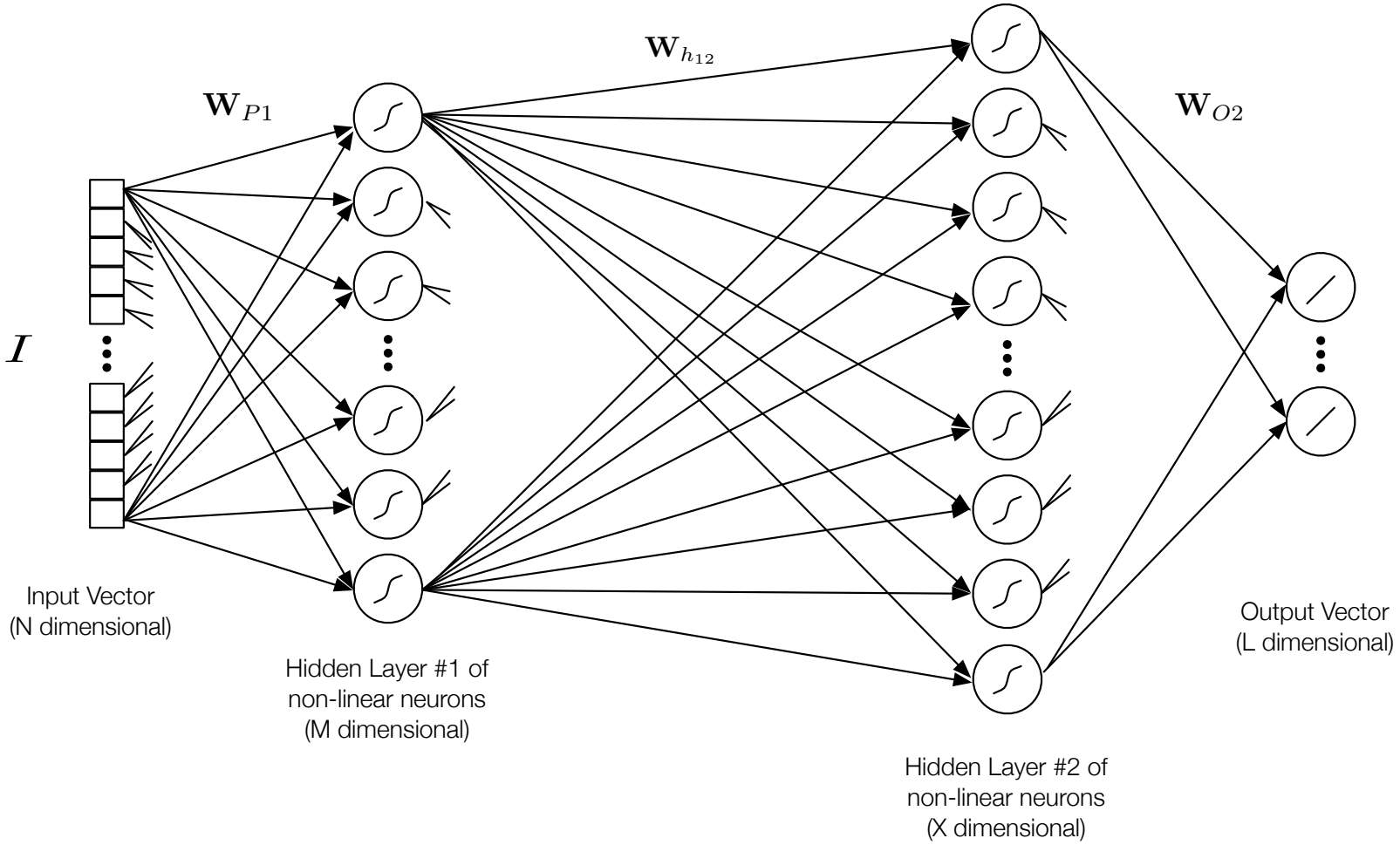

$$\mathbf{W}_{h_{12}} = \mathbf{W}_{O1} \times \mathbf{W}_{P2}$$

Adding supervision to the network

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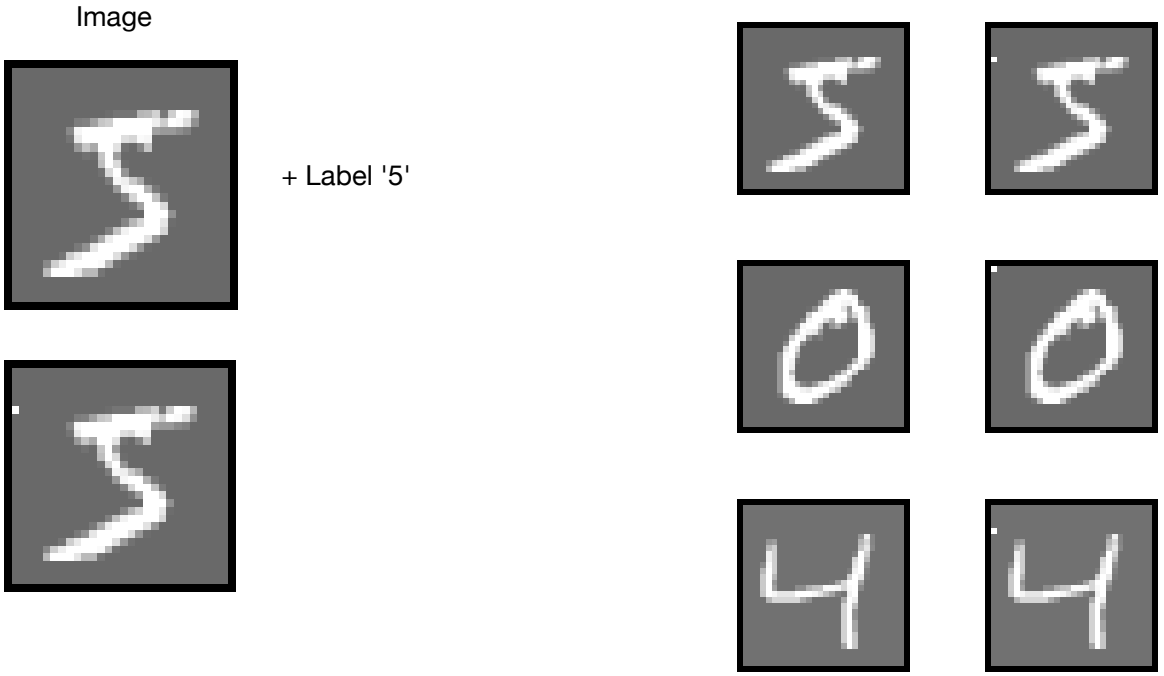
- If we do this purely using the training images (without labels), the advantages become unclear. So what can we do?
- Supervised Auto-Encoding
- We add training labels combined with training images to create a single training dataset.



Weight Shaping Methods

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- In standard ELM approach, the input weights are initialised randomly. For example between -0.5 and +0.5
- Methods
  - Computed Input Weights for ELM (CIW-ELM)[1]
  - Receptive Fields (RF-ELM)[2]
  - Combined CIW and RF ELM

[1]. J. Tapson, P. de Chazal, and A. van Schaik, "Explicit computation of input weights in Extreme Learning Machines," Proceedings of ELM2014, Accepted, vol. arXiv:1406.2889, 2014.

[2]. M. D. McDonnell, M. D. Tissera, A. van Schaik, and J. Tapson, "Do we need deep networks? Pushing the envelope with Extreme Learning Machines," Submitted, 2014.

Experiments

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- Image Classification
  - MNIST (10 Classes)
    - 60,000 Training and 10,000 Test Images
    - 28 x 28 Greyscale
  - CIFAR-10 (10 Classes)
    - 50,000 Training and 10,000 Test Images
    - 32 x 32 RGB, treated as one image in our experiments, 32 x 32 x 3
  - SVHN (Google Street View House Numbers)
    - 73,257 Training images used
    - 32 x 32 RGB, converted to greyscale in our experiments, 32 x 32

Results - MNIST

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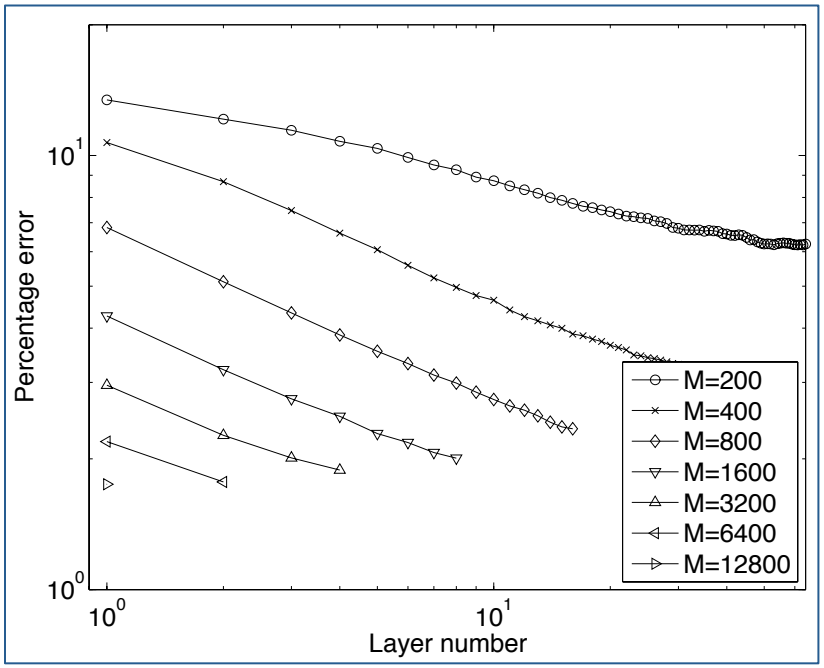
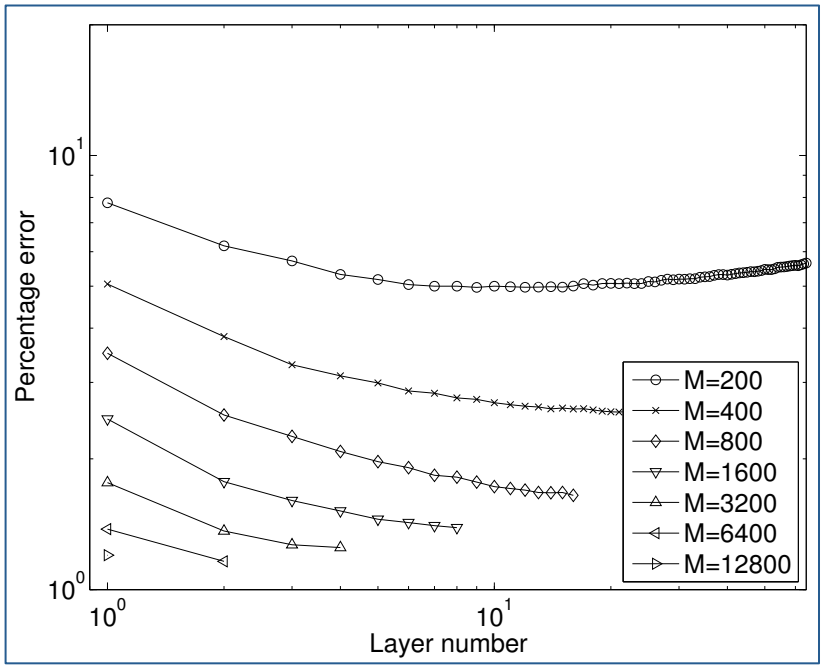
Classification error rates on MNIST for increasing number of hidden layers



Random Input Weights
(Gaussian)



Shaped Input Weights
(CIW and RF Combined)

[1]. All data was calculated as the average over 10 repeats for each condition.

Results - MNIST

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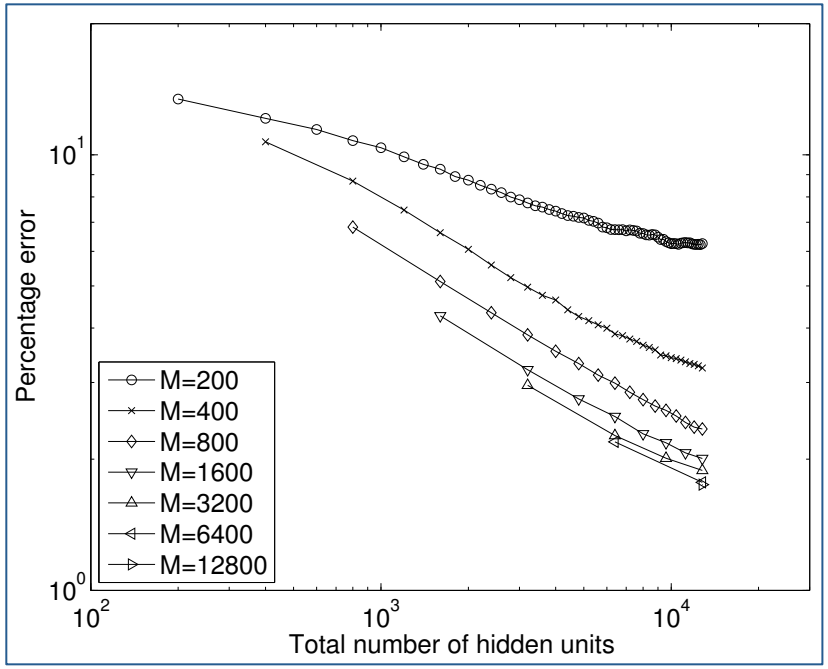
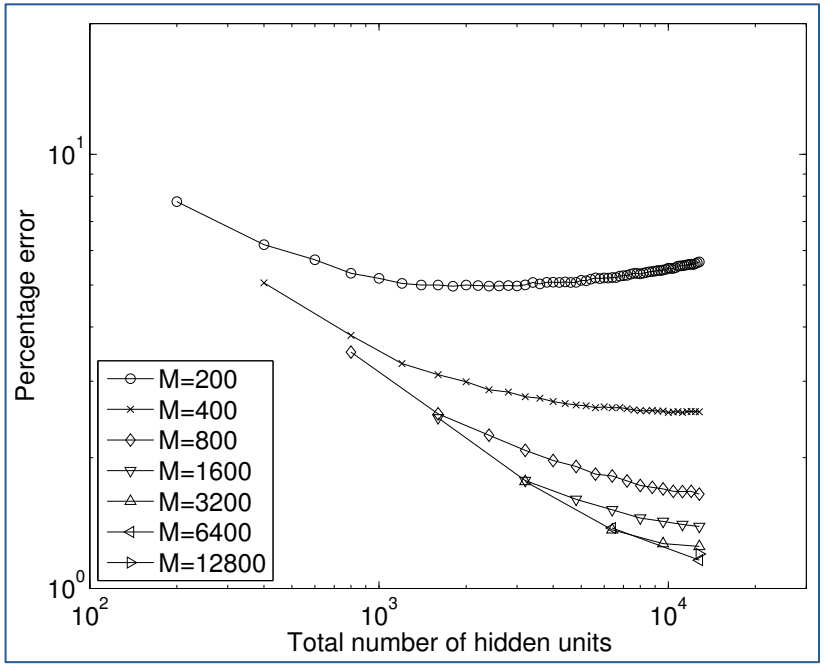
Classification error rates on MNIST for increasing total number of hidden units



Random Input Weights
(Gaussian)



Shaped Input Weights
(CIW and RF Combined)

[1]. All data was calculated as the average over 10 repeats for each condition.

Results - MNIST

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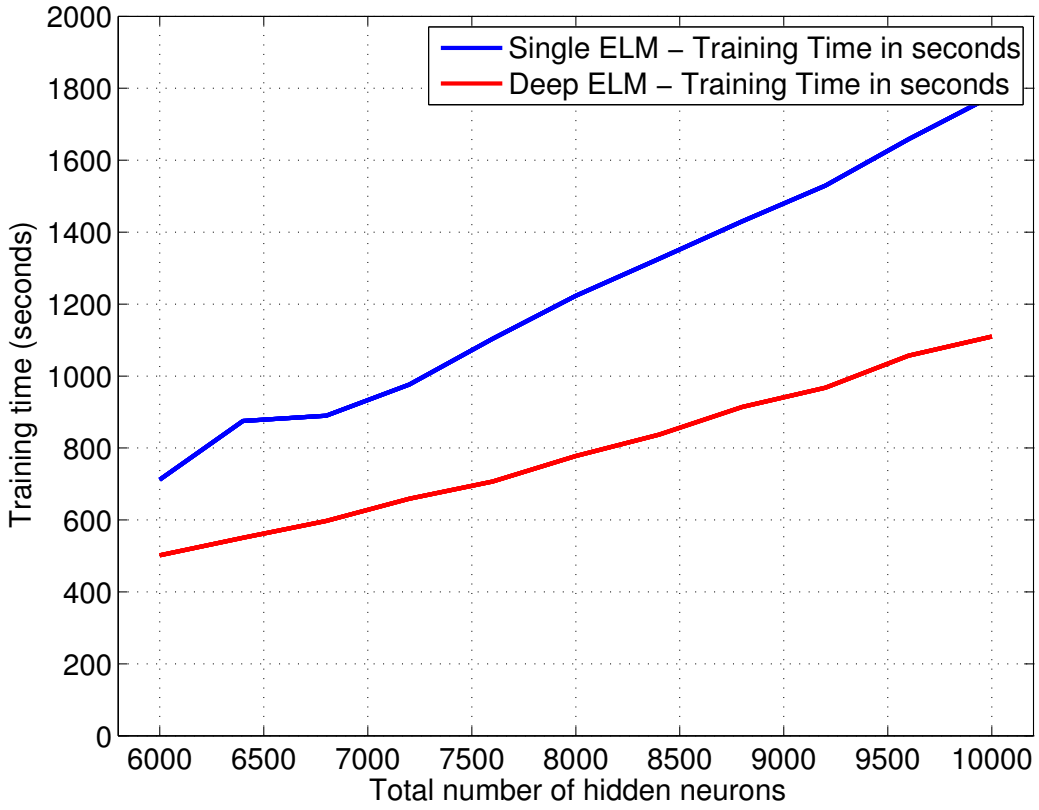
Training time on MNIST as the total number of hidden units increased



Deep ELM Vs Single Layer ELM

Results – CIFAR 10

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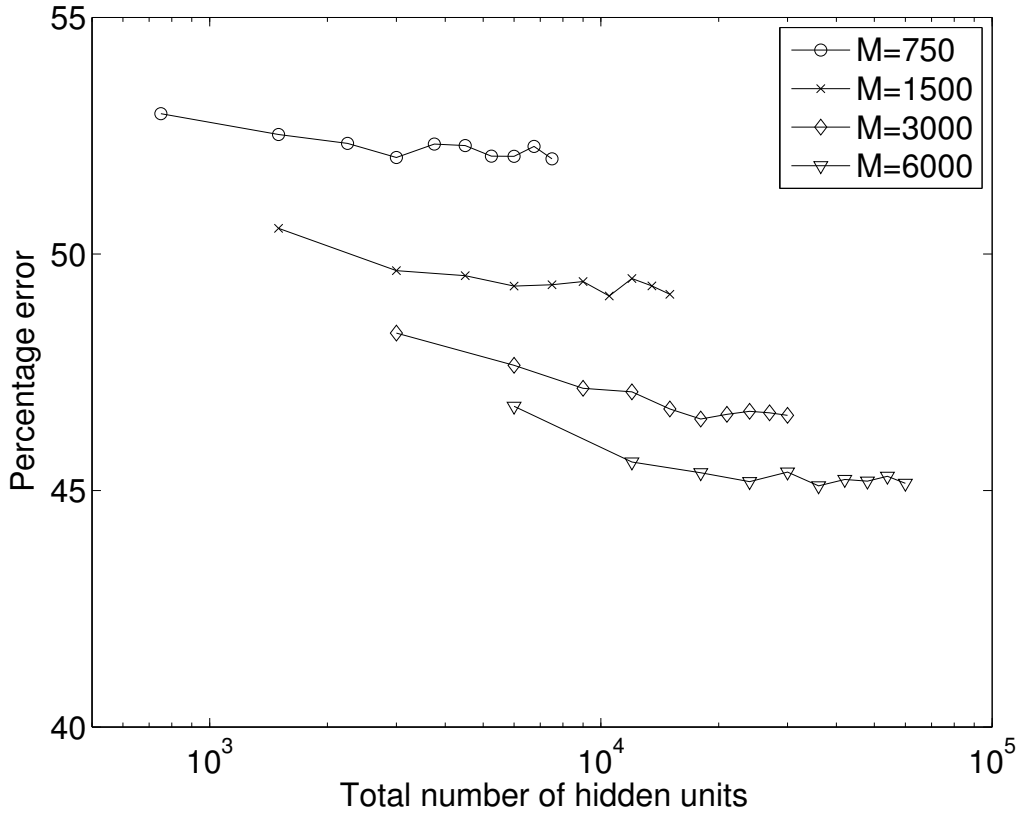
Classification error rates on CIFAR-10 for increasing total number of hidden units



Results – SVHN

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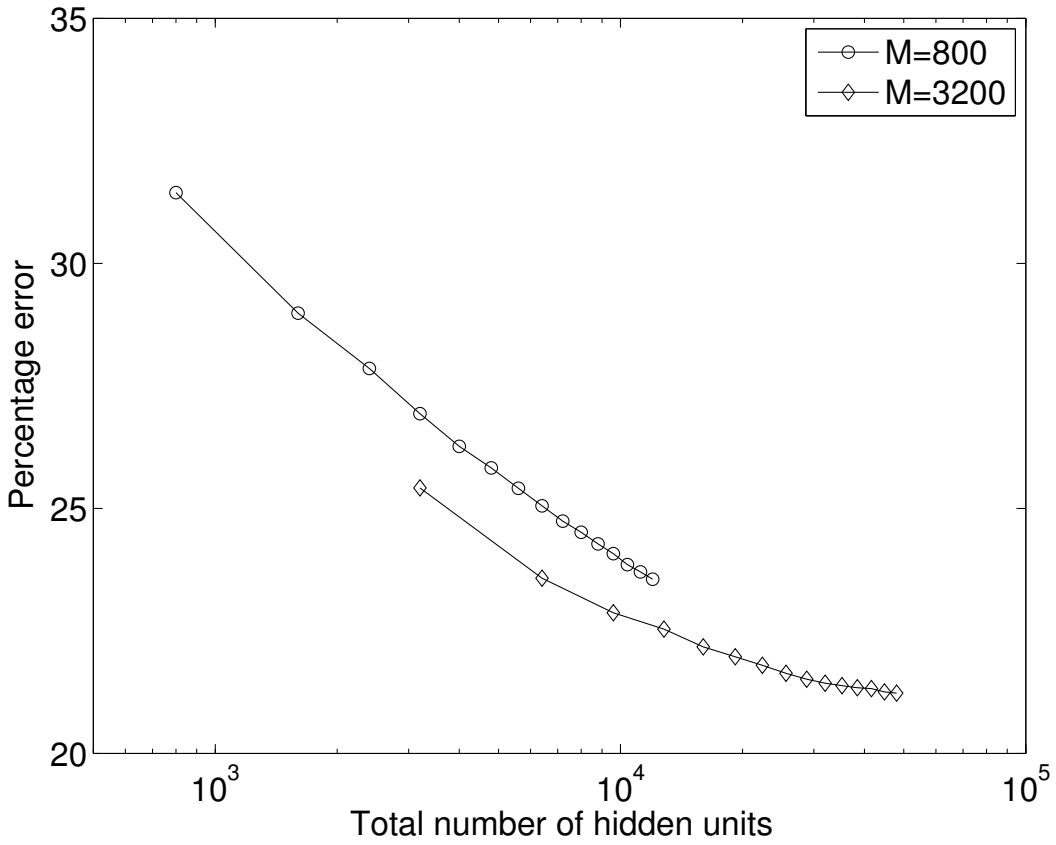
Classification error rates on SVHN dataset for increasing total number of hidden units



Discussion

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- We have presented a method for synthesising deep neural networks using Extreme Learning Machines (ELMs) as a stack of supervised autoencoders.
- Using standard multi-class image classification benchmark tasks, we show that the classification error rate can progressively improve with inclusion of additional layers.
- Very good performance on MNIST in very short time
  - 98% accuracy in less than 2 minutes
  - 99% accuracy in less than 10 minutes
- The method can potentially be applied in a resource-constrained hardware implementation to advantages in terms of significantly reduced network training time and memory usage.

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Questions?

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Thank you!

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