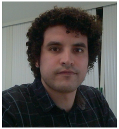
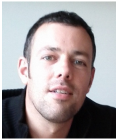
Deep multi-task learning with evolving weights

Normastic



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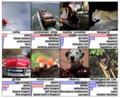
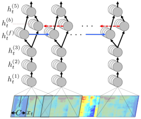
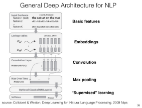
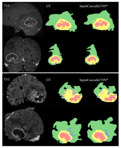
28 June, 2016

Deep learning Today
Deep learning state of the art









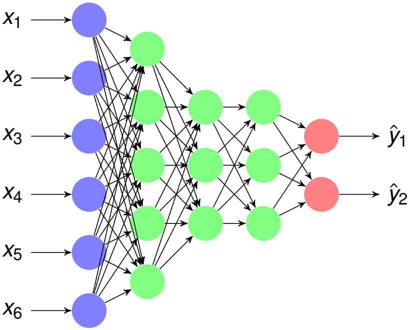
What is new today?

- Large data
- Calculation power (GPUS, clouds)

$\Rightarrow$ optimization

- Dropout
- Momentum, AdaDelta, AdaGrad, RMSProp, Adam, Adamax
- Maxout, Local response normalization, local contrast normalization, batch normalization
- RELU
- CNN, RBM, RNN

Deep neural networks (DNN)



- Feed-forward neural network
- Back-propagation error
- Training **deep** neural networks is **difficult**

  ⇒ Vanishing gradient

  ⇒ Pre-training technique [Y.Bengio et al. 06, G.E.Hinton et al. 06]

  ⇒ More parameters ⇒ Need more data

  ⇒ Use unlabeled data

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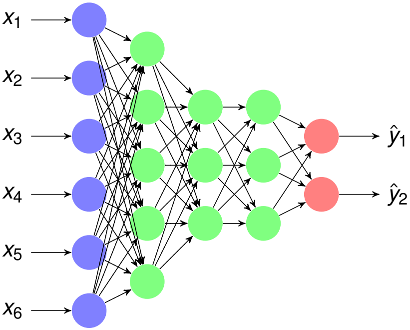

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Semi-supervised learning

General case:

$$\mathit{Data} = \{ \underbrace{\mathit{labeled\ data}\ (\mathbf{x}, \mathbf{y})}_{\text{expensive (money, time), few}}, \underbrace{\mathit{unlabeled\ data}\ (\mathbf{x}, --)}_{\text{cheap, abundant}} \}$$

E.g:

- Collect images from the internet
- Medical images

$\Rightarrow$ semi-supervised learning:

Exploit unlabeled data to improve the **generalization**

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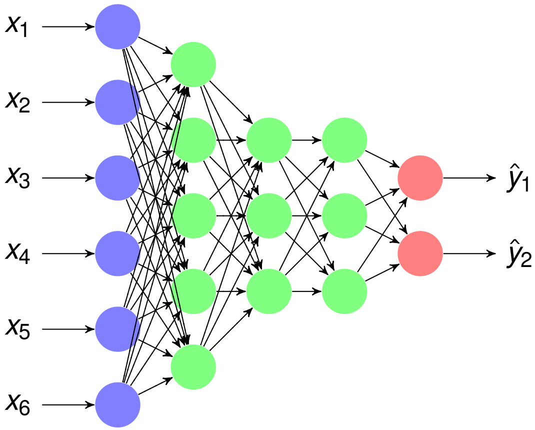
Pre-training and semi-supervised learning

The pre-training technique can exploit the unlabeled data

A **sequential** transfer learning performed in 2 steps:

1. **Unsupervised task** ($\mathbf{x}$ labeled and unlabeled data)
2. **Supervised task** (($\mathbf{x}$, $\mathbf{y}$) labeled data)

Layer-wise pre-training: auto-encoders

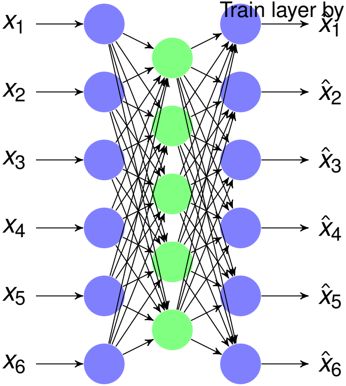


A DNN to train

Layer-wise pre-training: auto-encoders

1) Step 1: **Unsupervised layer-wise pre-training**

Train layer by layer **sequentially** using **only x** (labeled or unlabeled)



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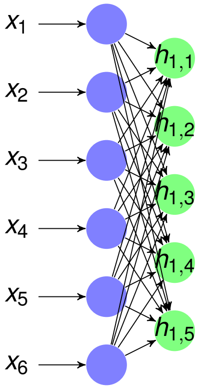

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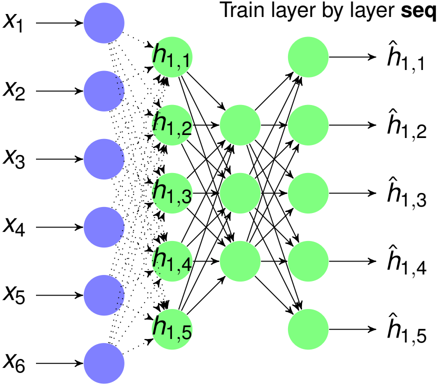

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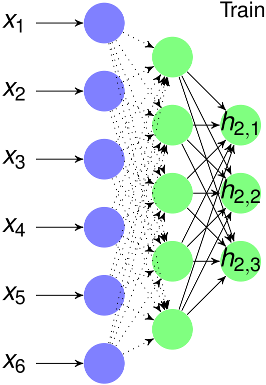

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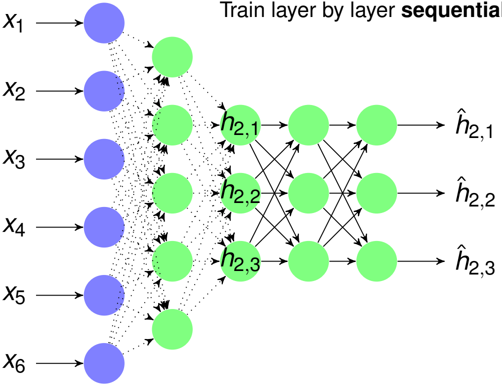

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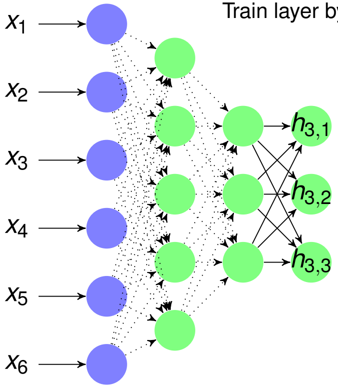

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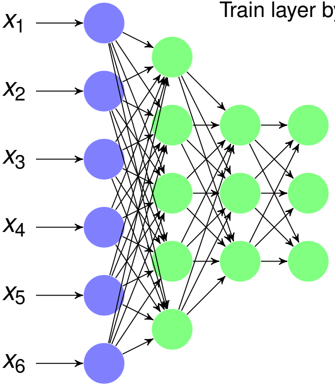


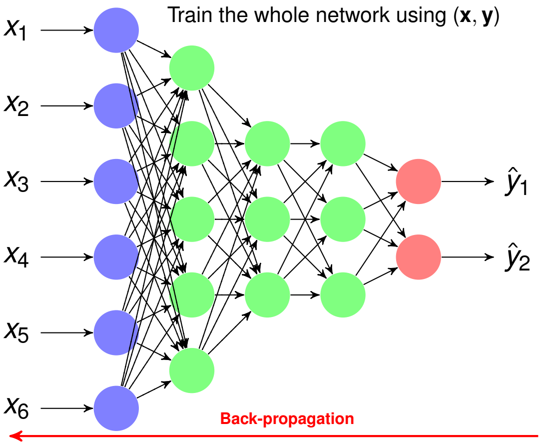
At each layer:

⇒ What hyper-parameters to use? When to stop training?

⇒ How to make sure that the pre-training improves the supervised task?

Layer-wise pre-training: auto-encoders

2) Step 2: **Supervised training**



Pre-training technique: Pros and cons

Pros

- Improve generalization
- Can exploit unlabeled data
- Provide better initialization than random
- Train deep networks

  $\Rightarrow$ Circumvent the vanishing gradient problem

Cons

- Add more hyper-parameters
- No good stopping criterion during pre-training phase

  Good criterion for the unsupervised task

  But

  May not be good for the supervised task

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Proposed solution

Why is it difficult in practice?

$\Rightarrow$ **Sequential** transfer learning

Possible solution:

$\Rightarrow$ **Parallel** transfer learning

Why in parallel?

- Interaction between tasks
- Reduce the number of hyper-parameters to tune
- Provide **one stopping criterion**

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Parallel transfer learning: Tasks combination

$$\text{Train cost} = \textbf{supervised task} + \underbrace{\textbf{unsupervised task}}_{\text{reconstruction}}$$

l labeled samples, u unlabeled samples, $\mathbf{w}_{sh}$: shared parameters.

Reconstruction (auto-encoder) task:

$$\mathcal{J}_r(\mathcal{D}; \mathbf{w}' = \{\mathbf{w}_{sh}, \mathbf{w}_r\}) = \sum_{i=1}^{l+u} \mathcal{C}_r(\mathcal{R}(\mathbf{x}_i; \mathbf{w}'), \mathbf{x}_i) \ .$$

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Weighted tasks combination

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Problem

How to **fix** λ_s, λ_r?

Intuition

At the end of the training, only $\mathcal{J}_s$ should matters

Tasks combination with evolving weights (our contribution)

$$\mathcal{J}(\mathcal{D}; \{\mathbf{w}_{sh}, \mathbf{w}_s, \mathbf{w}_r\}) = \lambda_s(t) \cdot \mathcal{J}_s(\mathcal{D}; \{\mathbf{w}_{sh}, \mathbf{w}_s\}) + \lambda_r(t) \cdot \mathcal{J}_r(\mathcal{D}; \{\mathbf{w}_{sh}, \mathbf{w}_r\}) \ .$$

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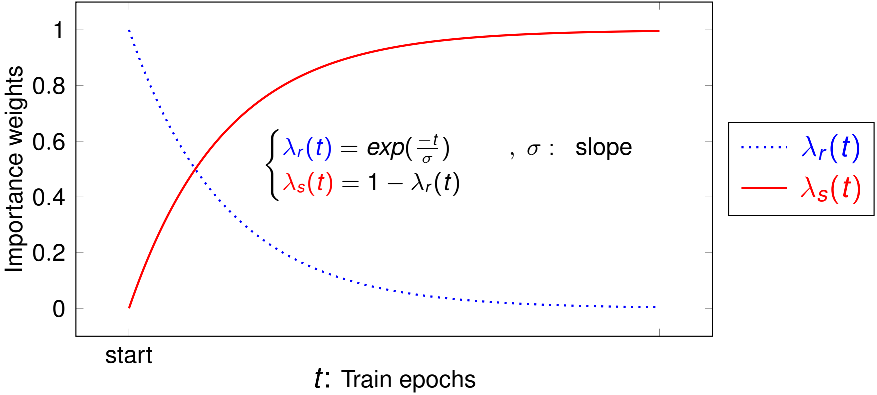
Exponential schedule



$$\begin{cases} \lambda_r(t) = exp(\frac{-t}{\sigma}) \\ \lambda_s(t) = 1 - \lambda_r(t) \end{cases}, \quad \sigma: \text{ slope}$$

Tasks combination with evolving weights: Optimization

Tasks combination with evolving weights (our contribution)

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Algorithm 1 Training our model for one epoch

1: $\mathcal{D}$ is the *shuffled* training set. B a mini-batch.
2: **for** B in $\mathcal{D}$ **do**
3: Make a gradient step toward $\mathcal{J}_r$ using B (update $\mathbf{w}'$)
4: $B_s \Leftarrow$ labeled examples of B,
5: Make a gradient step toward $\mathcal{J}_s$ using B_s (update $\mathbf{w}$)
6: **end for**

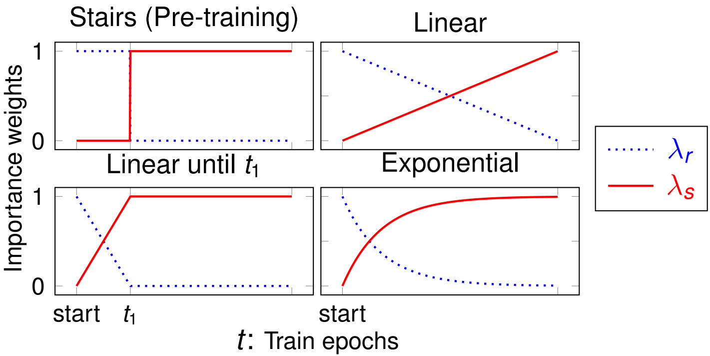
[R.Caruana 97, J.Weston 08, R.Collobert 08, Z.Zhang 15]

Experimental protocol

Objective: Compare Training DNN using different approaches:

- No pre-training (base-line)
- With pre-training (Stairs schedule)
- Parallel transfer learning (proposed approach)

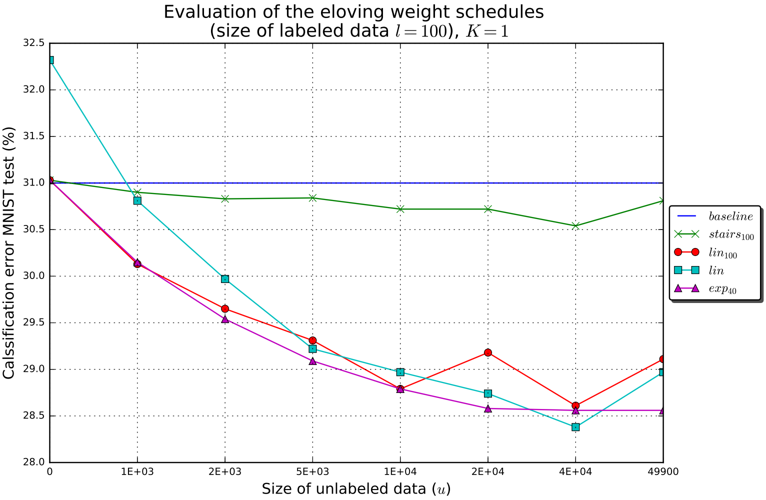
Studied evolving weights schedules:



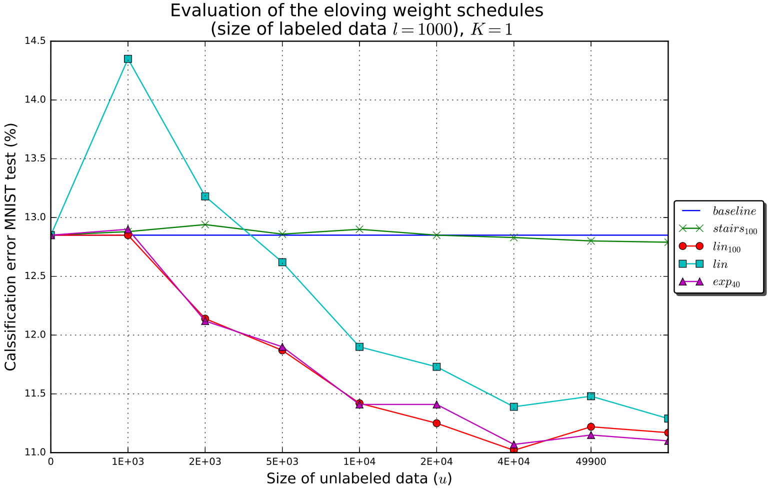
Experimental protocol

- **Task**: Classification (MNIST)
- **Number of hidden layers** K: 1, 2, 3, 4.
- **Optimization**:
  - **Epochs**: 5000
  - **Batch size**: 600
  - **Options**: **No** regularization, **No** adaptive learning rate
- **Hyper-parameters of the evolving schedules**:
  - t_1: 100
  - σ: 40

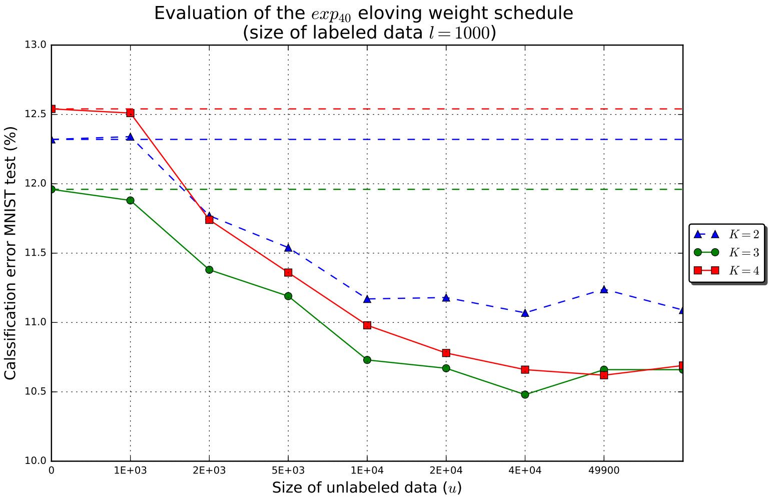
Shallow networks: $(K = 1,\ l = 1E2)$



Shallow networks: $(K = 1,\ l = 1E3)$



Deep networks: exponential schedule ($l = 1E3$)



Conclusion

- An alternative method to the pre-training.

  Parallel transfer learning with evolving weights
- Improve generalization easily.
- Reduce the number of hyper-parameters ($t_1, \ \sigma$)

Perspectives

- Evolve the importance weight according to the train/validation error.
- Explore other evolving schedules (toward automatic schedule)
- Optimization
- **Extension to structured output problems**

$$\begin{aligned}\text{Train cost} &= \textbf{supervised task} \\ &+ \textbf{Input unsupervised task} \\ &+ \textbf{Output unsupervised task}\end{aligned}$$

Questions

Thank you for your attention,

Questions?