Curriculum Learning

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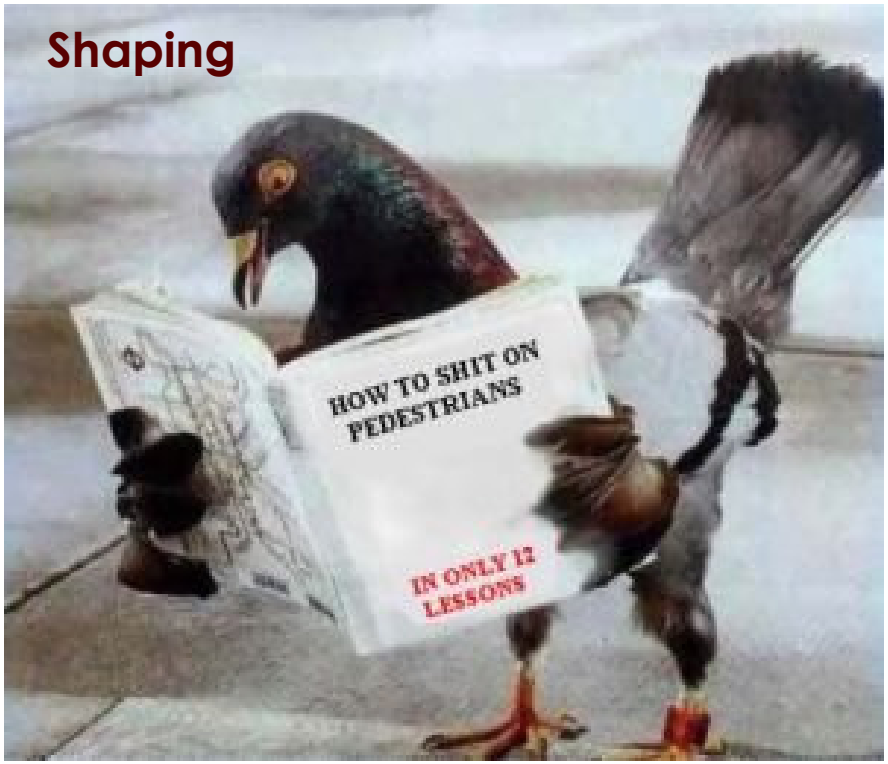
Curriculum Learning

Guided learning helps training humans and animals



Start from simpler examples / easier tasks (Piaget 1952, Skinner 1958)

The Dogma in question

It is best to learn from a training set of examples sampled from the same distribution as the test set. Really?

Question

Can machine learning algorithms benefit from a curriculum strategy?

Cognition journal:
(Elman 1993) vs (Rohde & Plaut 1999),
(Krueger & Dayan 2009)

Convex vs Non-Convex Criteria

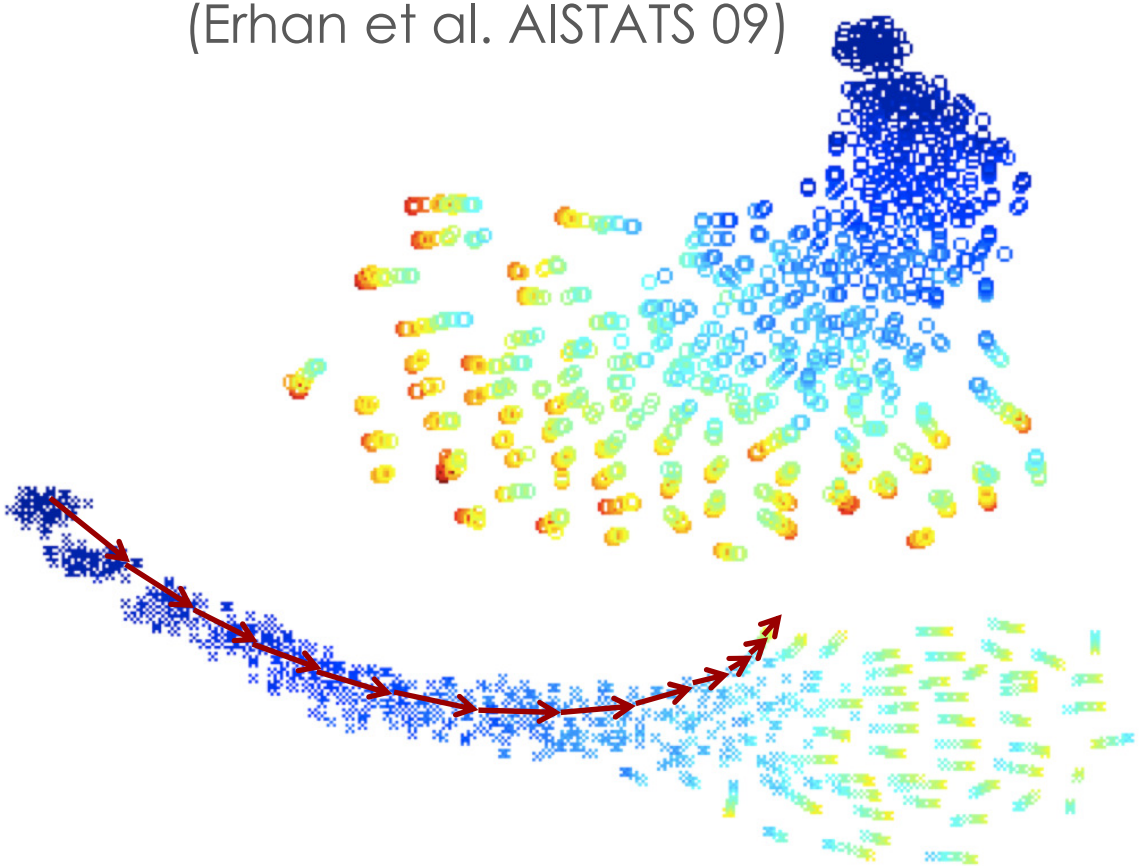
- **Convex criteria**: the order of presentation of examples should not matter to the convergence point, but could influence **convergence speed**
- **Non-convex criteria**: the order and selection of examples could yield to a **better local minimum**

Deep Architectures

- Theoretical arguments: deep architectures can be exponentially more compact than shallow ones representing the same function
- Cognitive and neuroscience arguments
- **Many local minima**
- **Guiding the optimization** by unsupervised pre-training yields much better local minima o/w not reachable
- Good candidate for testing curriculum ideas

Deep Training Trajectories

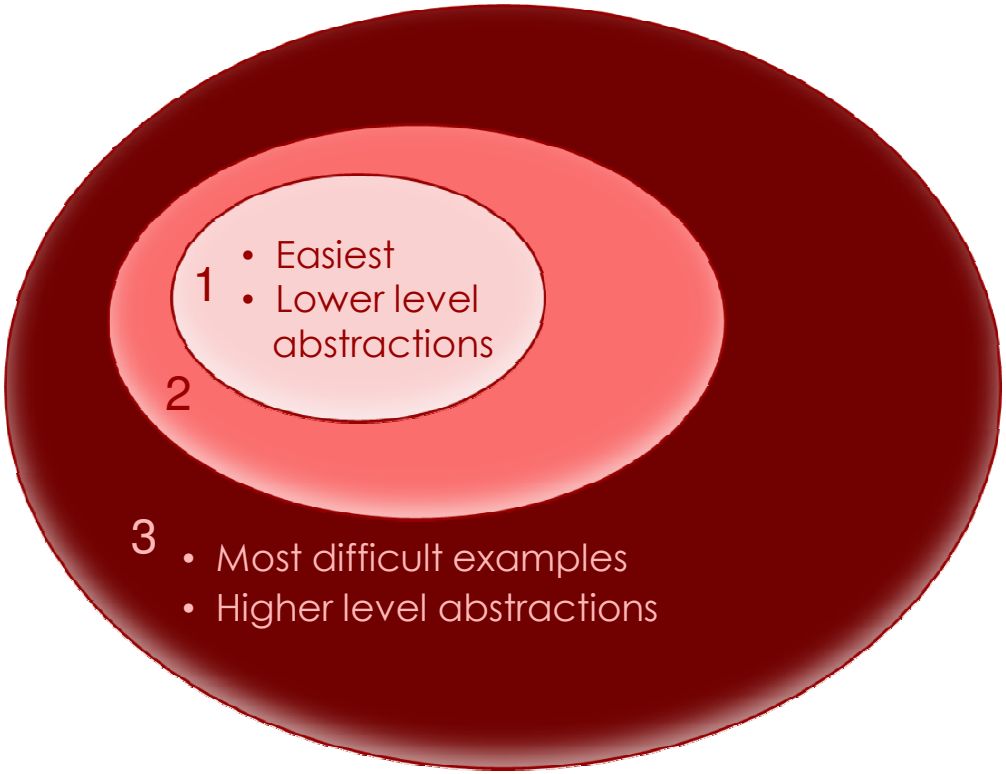
(Erhan et al. AISTATS 09)



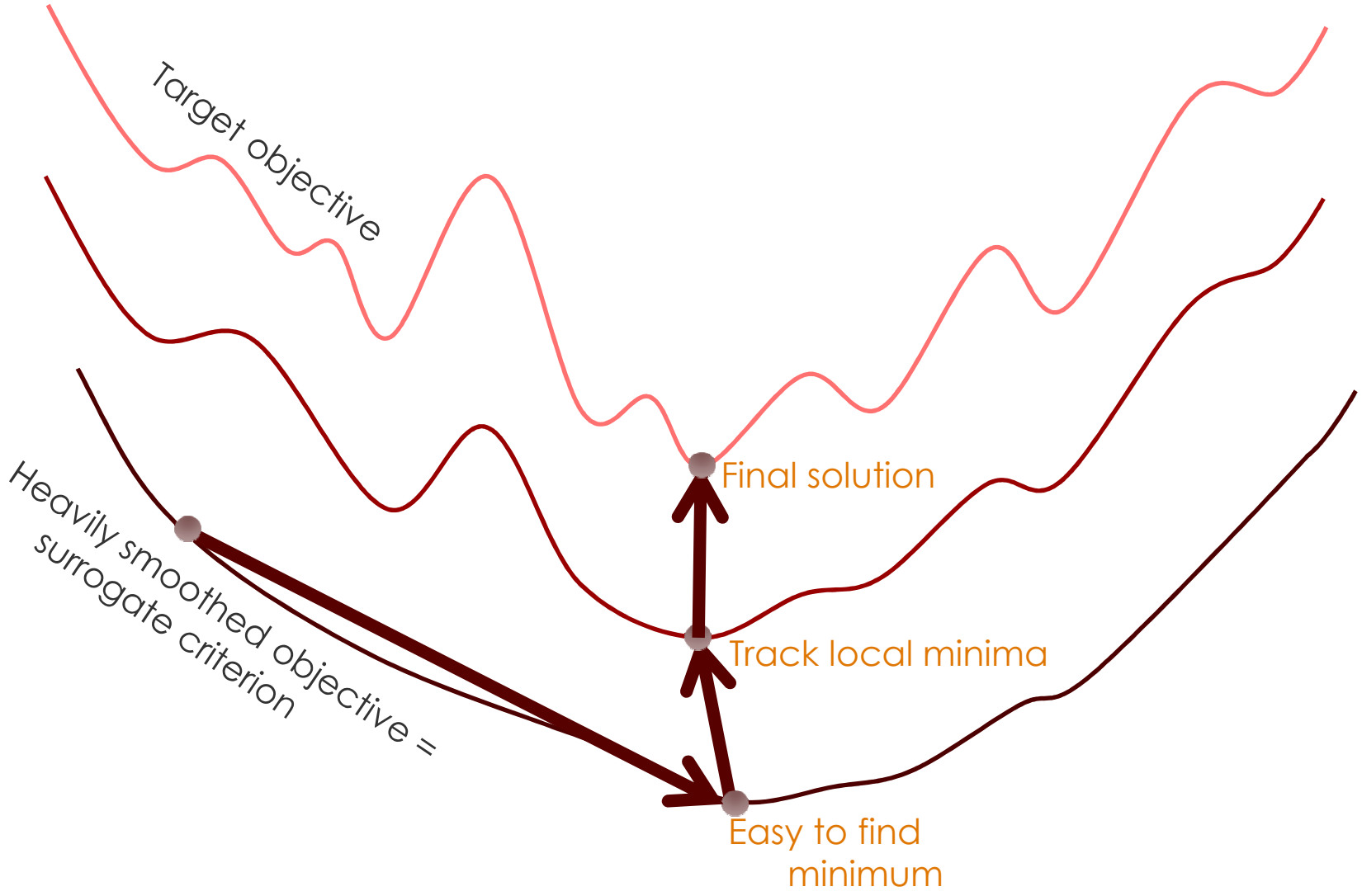
Random initialization

Unsupervised guidance

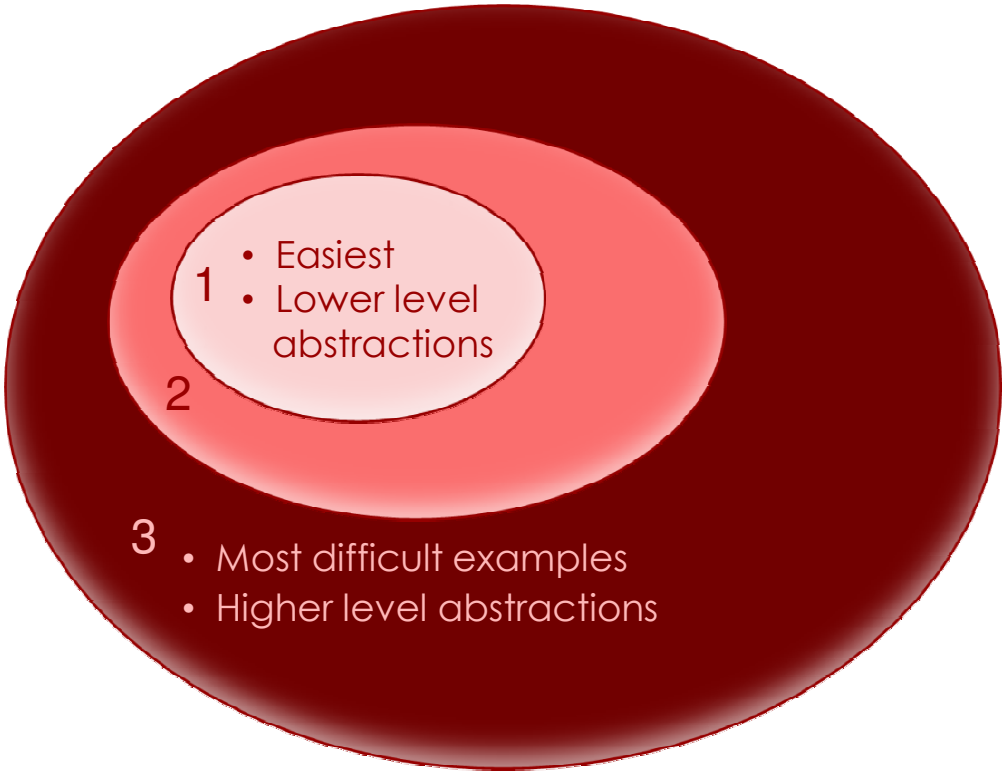
Starting from Easy Examples



Continuation Methods



Curriculum Learning as Continuation

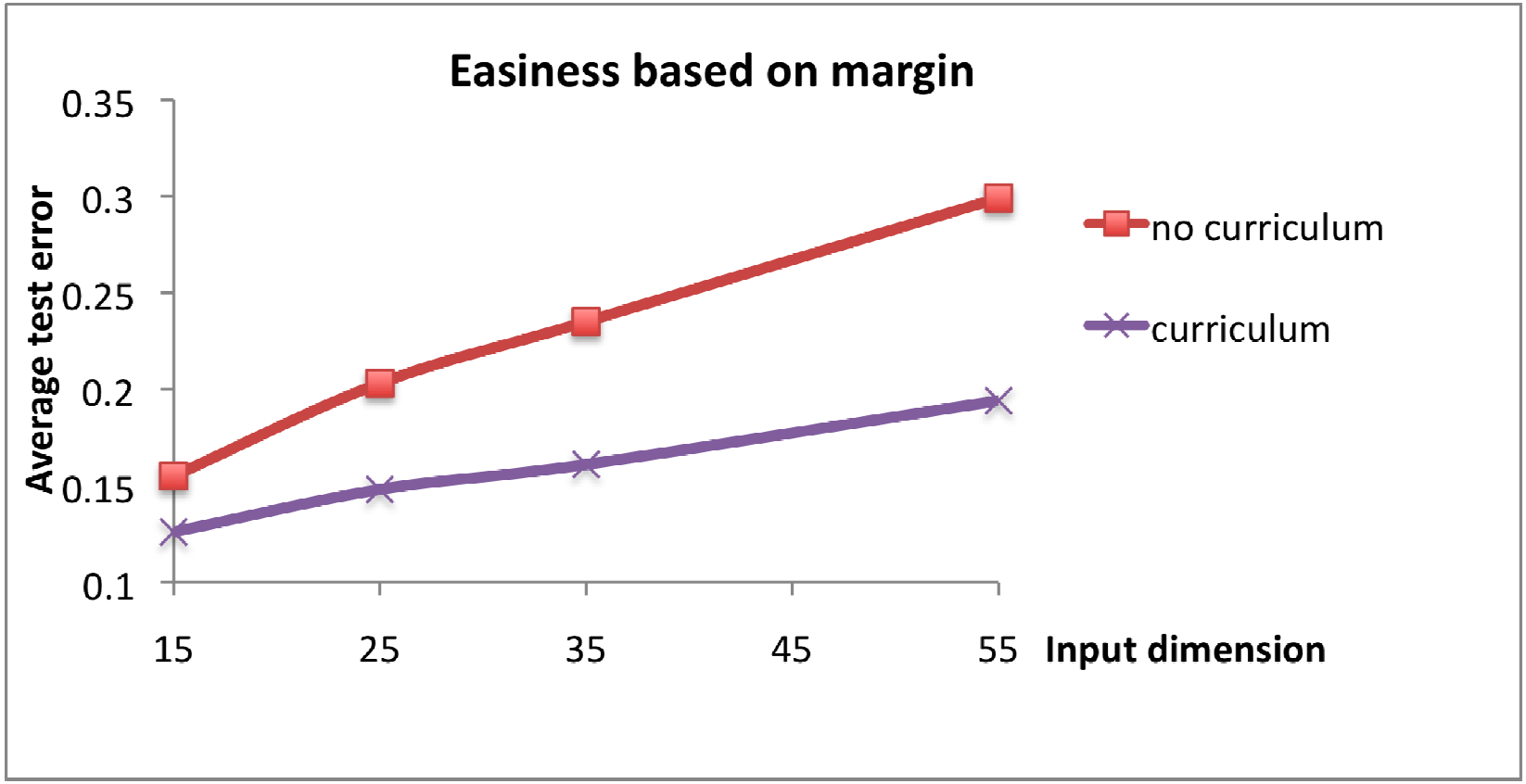


- Sequence of training distributions
- Initially peaking on easier / simpler ones
- Gradually give more weight to more difficult ones until reach target distribution

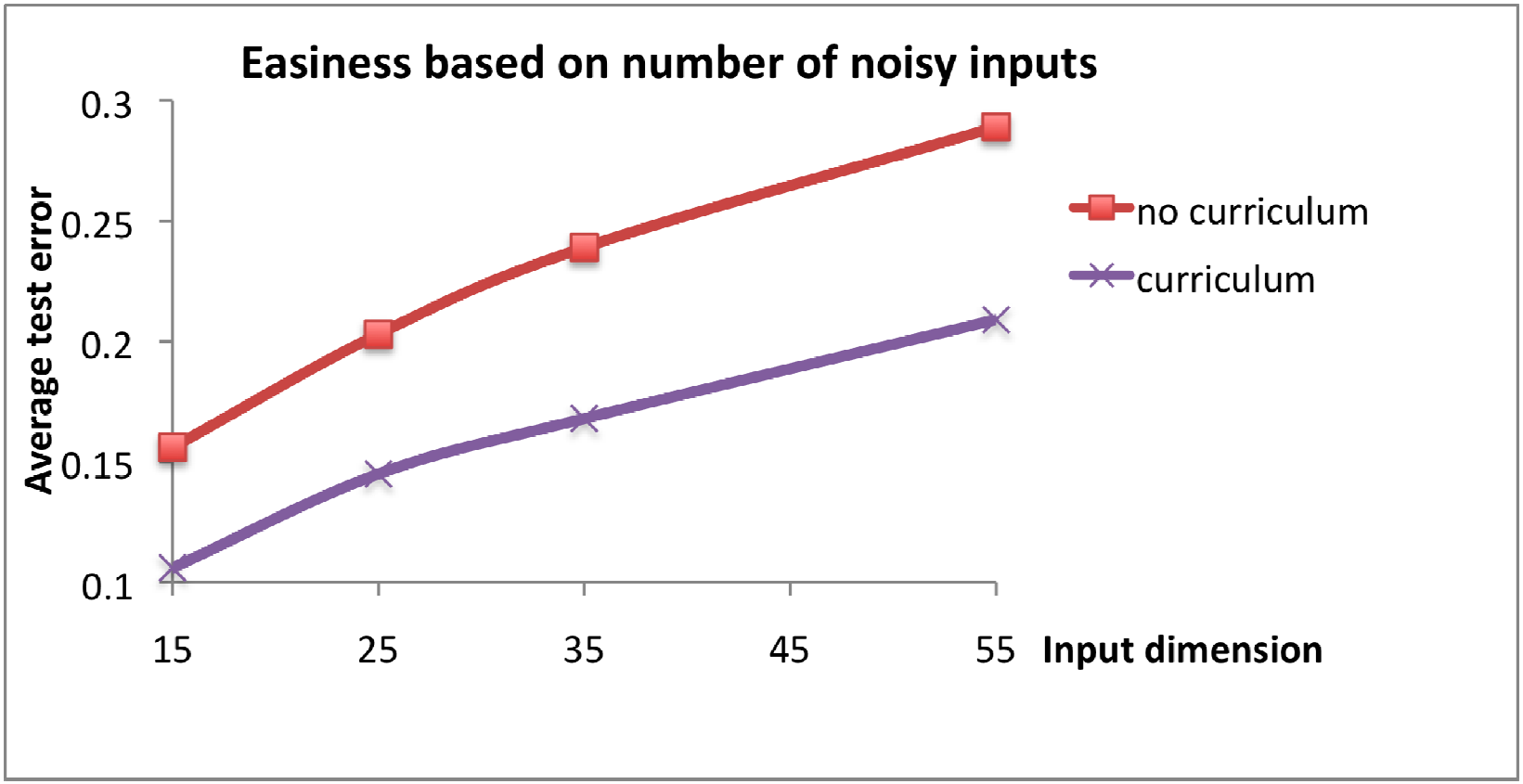
How to order examples?

- The right order is not known
- 3 series of experiments:
  1. Toy experiments with simple order
     - Larger margin first
     - Less noisy inputs first
  2. Simpler shapes first, more varied ones later
  3. Smaller vocabulary first

Larger Margin First: Faster Convergence



Cleaner First: Faster Convergence



Shape Recognition

First: easier, basic shapes

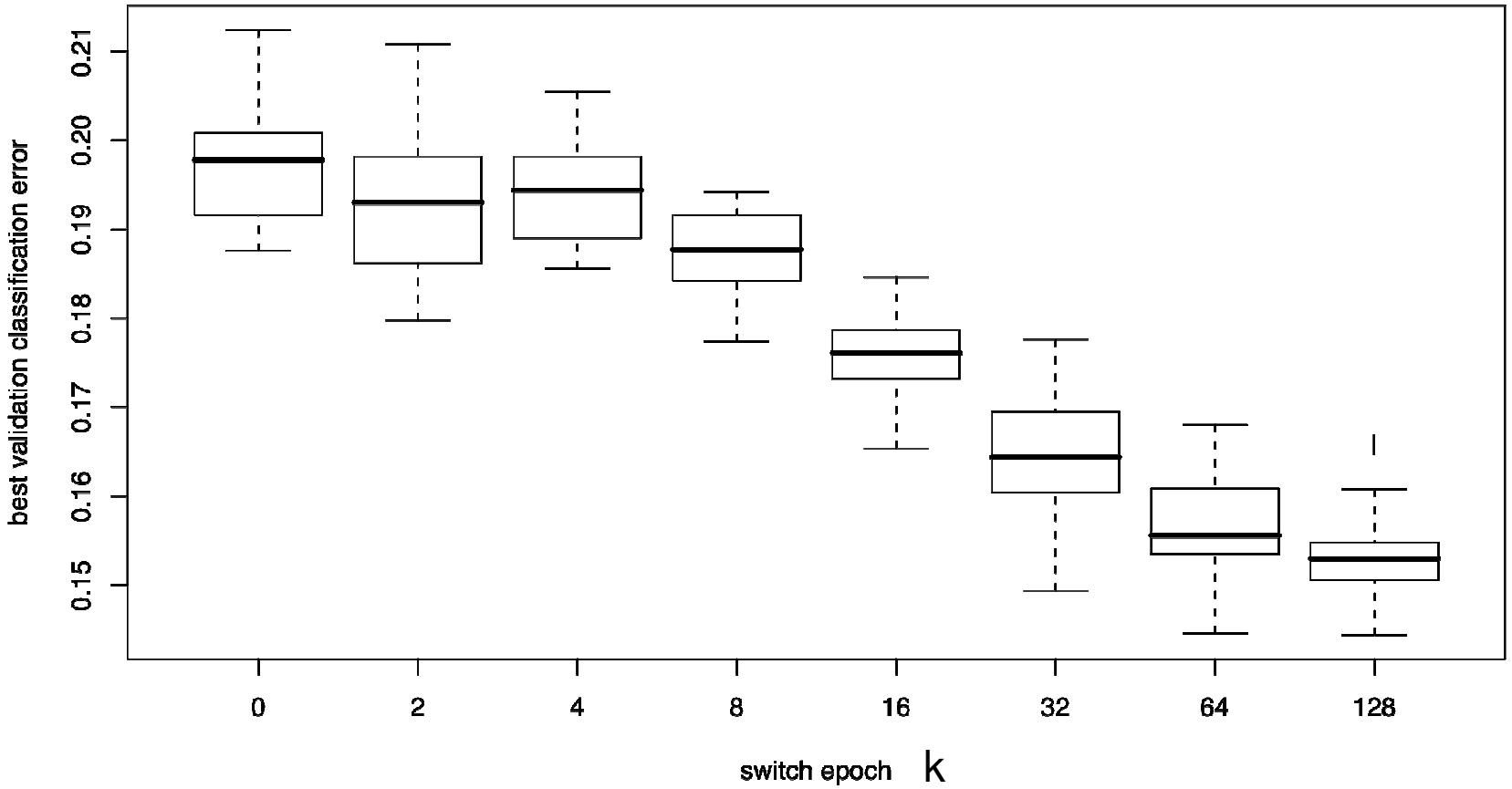
Second = target: more varied geometric shapes

Shape Recognition Experiment

- 3-hidden layers deep net known to involve local minima (unsupervised pre-training finds much better solutions)
- 10 000 training / 5 000 validation / 5 000 test examples

- Procedure:
  1. Train for k epochs on the easier shapes
  2. Switch to target training set (more variations)

Shape Recognition Results



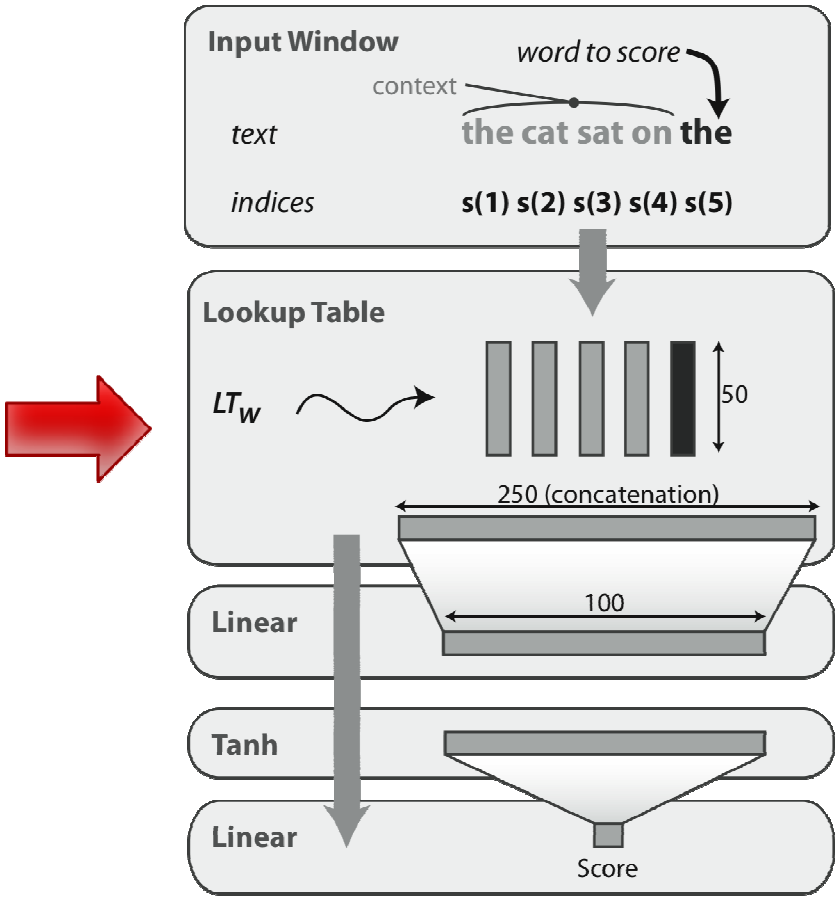
Language Modeling Experiment

- Objective: compute the score of the next word given the previous ones (ranking criterion)

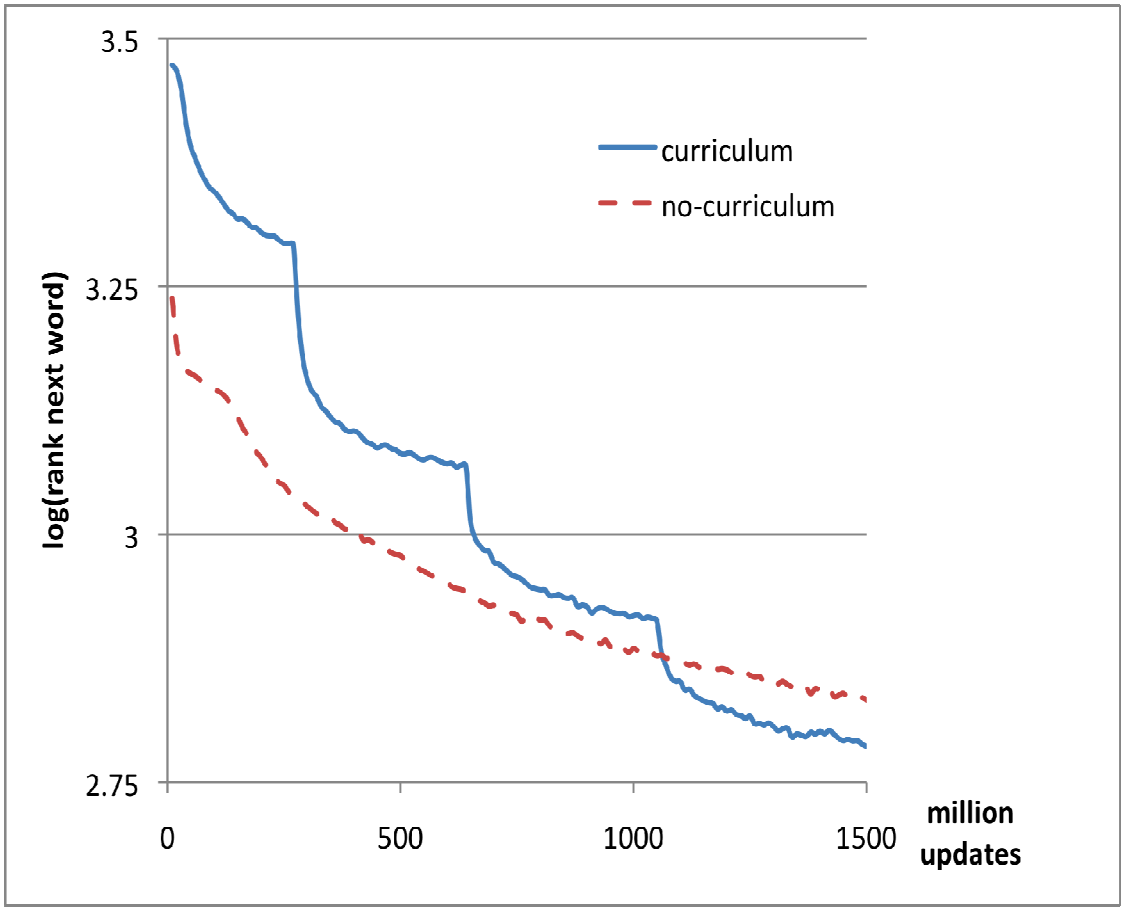
- Architecture of the deep neural network

  (Bengio et al. 2001,

  Collobert & Weston 2008)



Language Modeling Results



- Gradually increase the vocabulary size (dips)
- Train on Wikipedia with sentences containing only words in vocabulary

Conclusion

Yes, machine learning algorithms can benefit from a curriculum strategy.

Why?

- **Faster convergence to a minimum**
- Wasting less time with noisy or harder to predict examples
- **Convergence to better local minima**

Curriculum = particular continuation method

- Finds better local minima of a non-convex training criterion
- Like a regularizer, with main effect on test set

Perspectives

- How could we define better curriculum strategies?
- We should try to understand general principles that make some curricula work better than others
- Emphasizing harder examples and riding on the frontier

THANK YOU!

- Questions?
- Comments?

Training Criterion: Ranking Words

$$C_s = \sum_{w \in D} \frac{1}{|D|} C_{s,w} = \sum_{w \in D} \frac{1}{|D|} \max\left(0,\ 1 - f(s) + f(s^w)\right)$$

with

S	a word sequence
C_s	score of the next word given the previous one
w	a word of the vocabulary
D	the considered word vocabulary

Curriculum = Continuation Method?

- Examples z from $P(z)$ are weighted by $0 \leq W_\lambda(z) \leq 1$
- Sequence of distributions $Q_\lambda(z) \propto W_\lambda(z) P(z)$ called a curriculum if:
  - the entropy of these distributions increases (larger domain)

$$H(Q_\lambda) < H(Q_{\lambda+\varepsilon}) \quad \forall \varepsilon > 0$$

  - $W_\lambda(z)$ monotonically increasing in λ:

$$W_{\lambda+\varepsilon}(z) \geq W_\lambda(z) \quad \forall z, \forall \varepsilon > 0$$