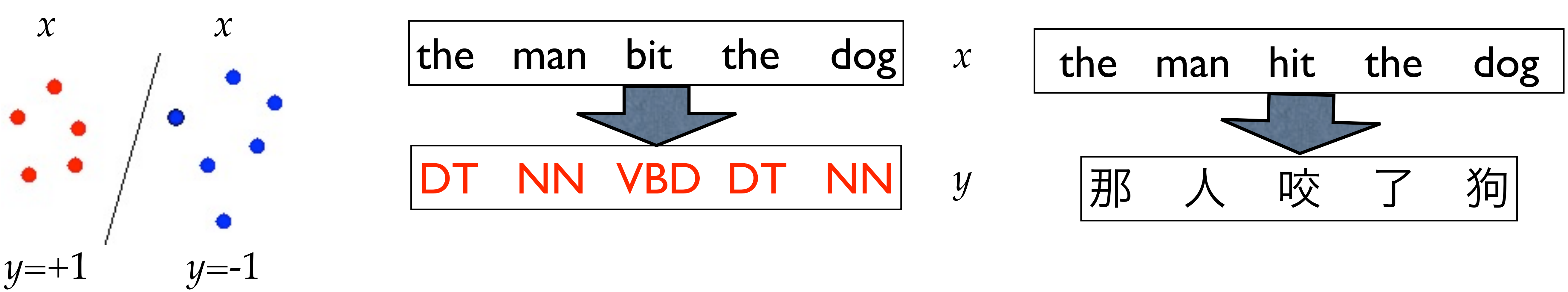
Scalable Large-Margin Structured Learning: Theory and Algorithms



Liang Huang   Kai Zhao   Lemao Liu

The City University of New York (CUNY)

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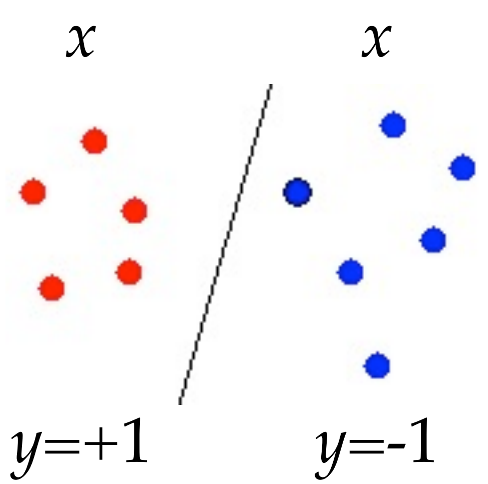
slides at: http://acl.cs.qc.edu/~lhuang/

What is Structured Prediction?



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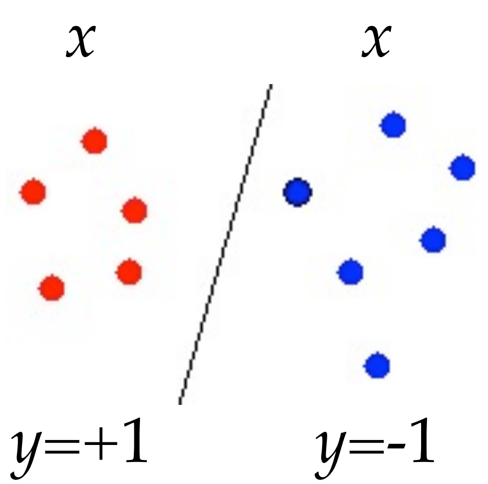

- binary classification: output is binary

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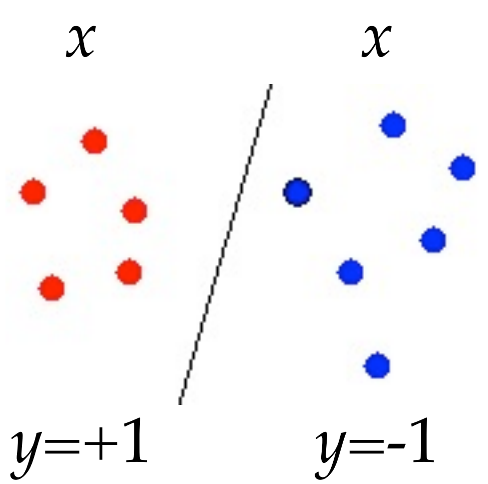

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- multiclass classification: output is a (small) number

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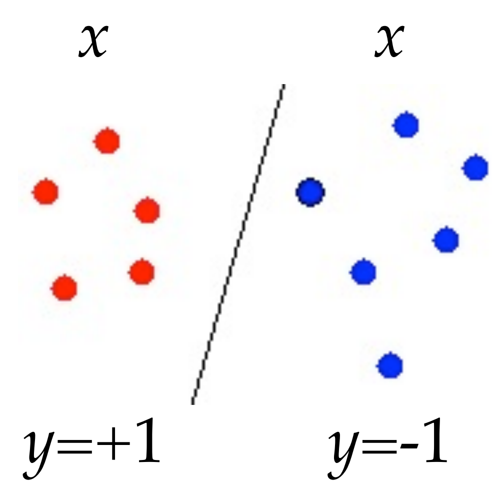

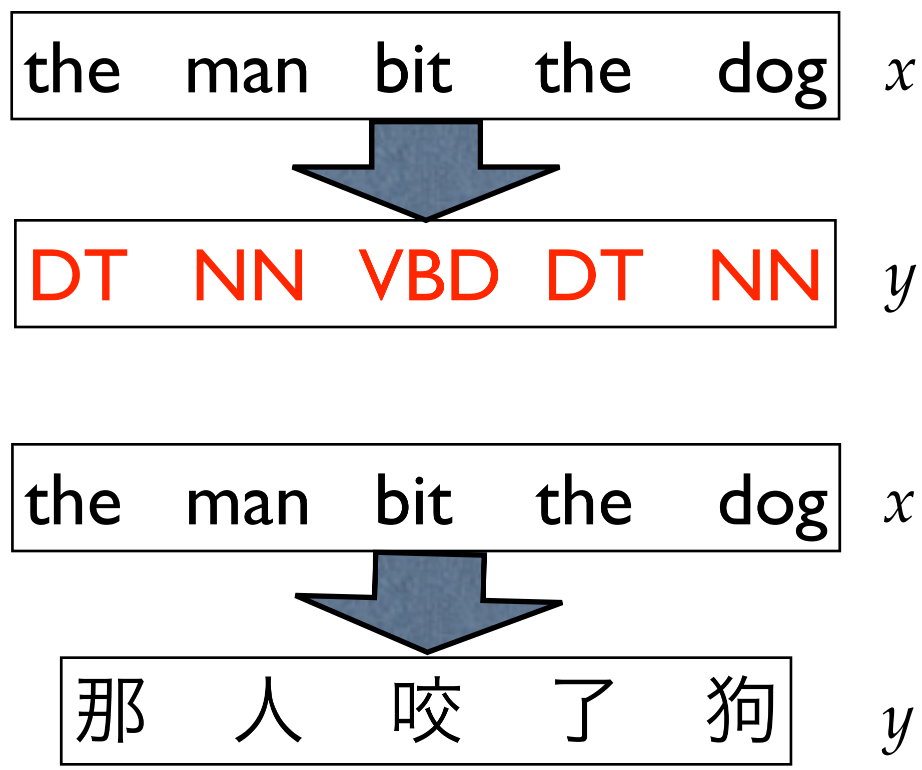

- binary classification: output is binary
- multiclass classification: output is a (small) number
- structured classification: output is a structure (seq., tree, graph)
  - part-of-speech tagging, parsing, summarization, translation

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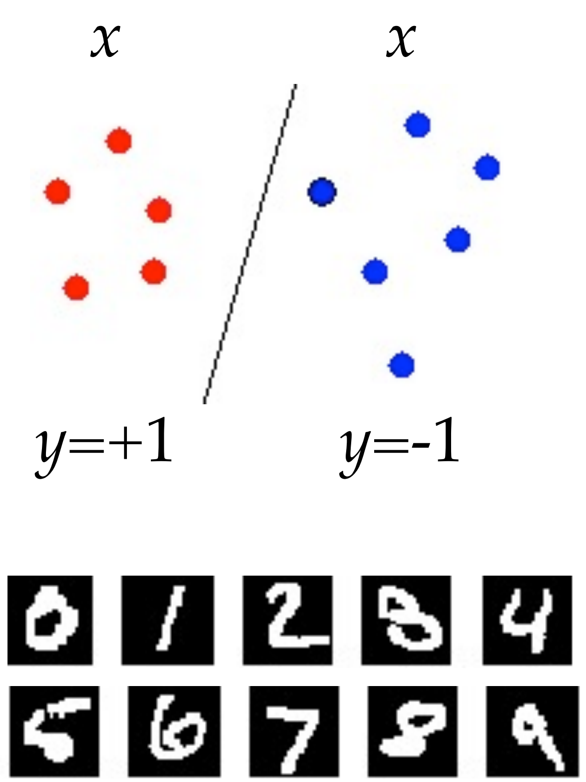

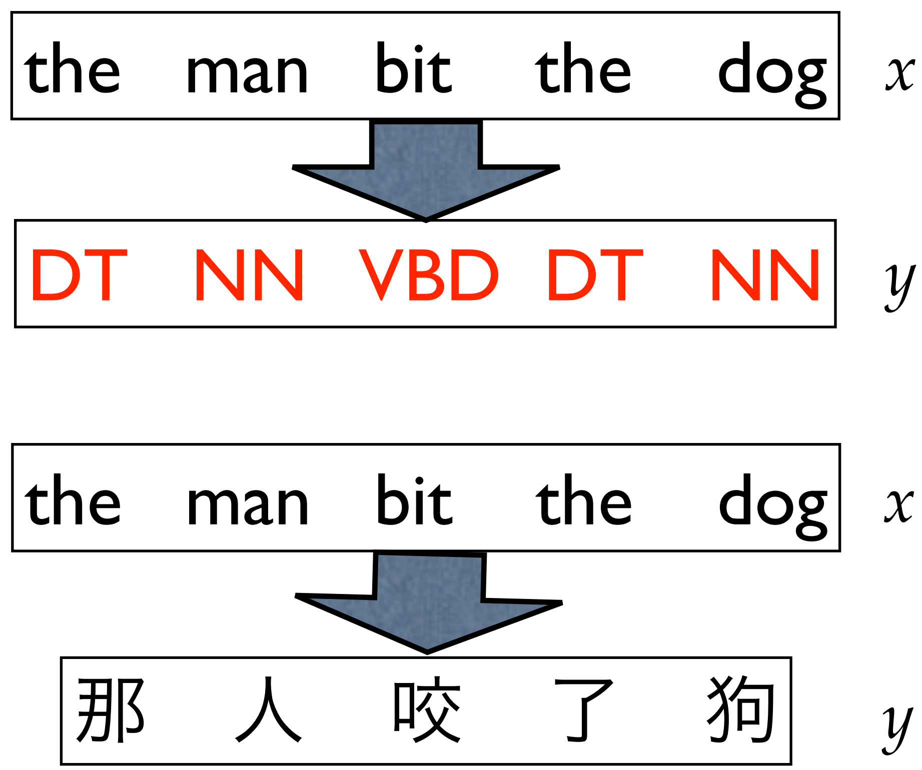

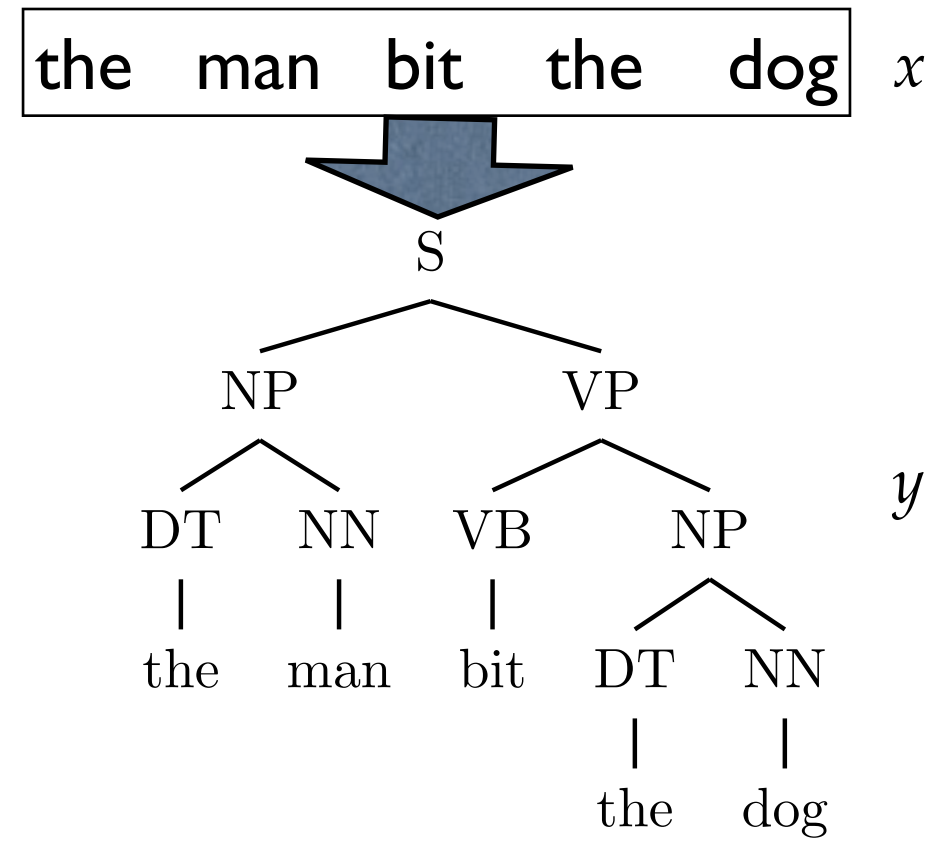

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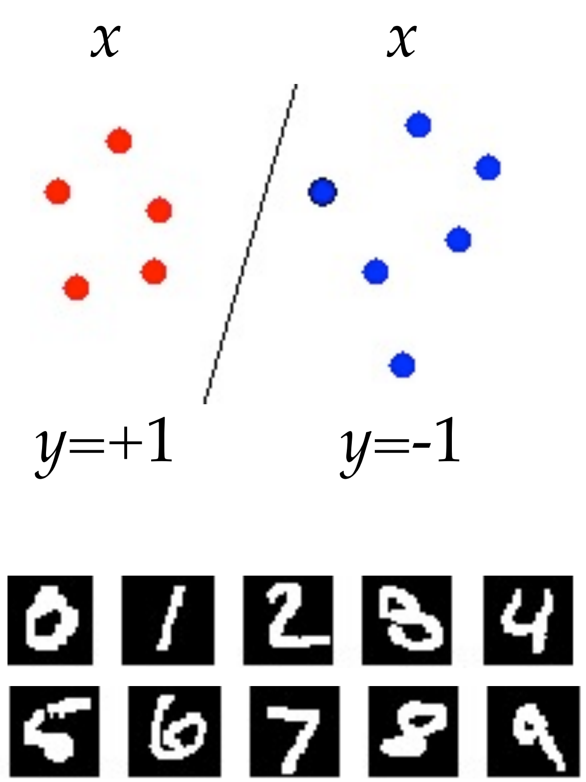

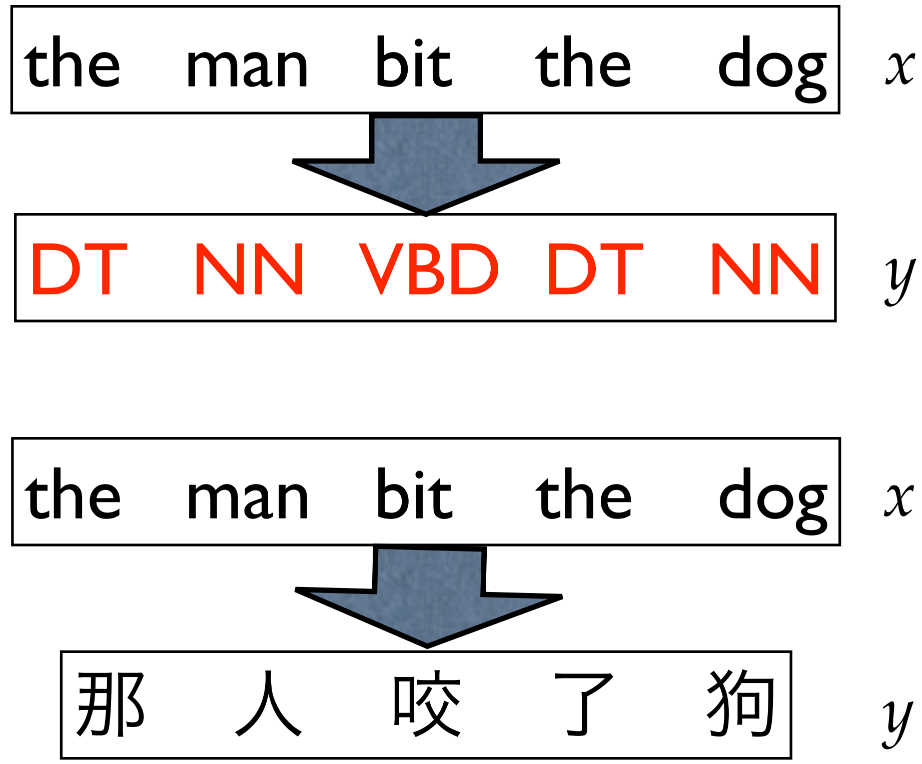

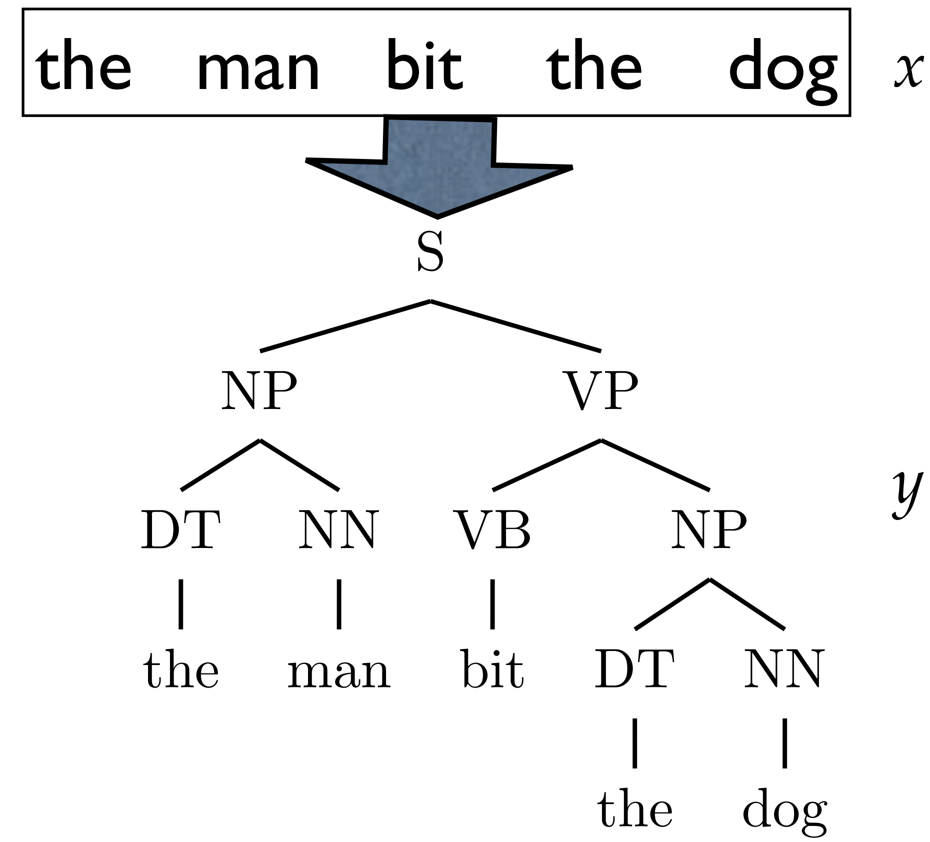

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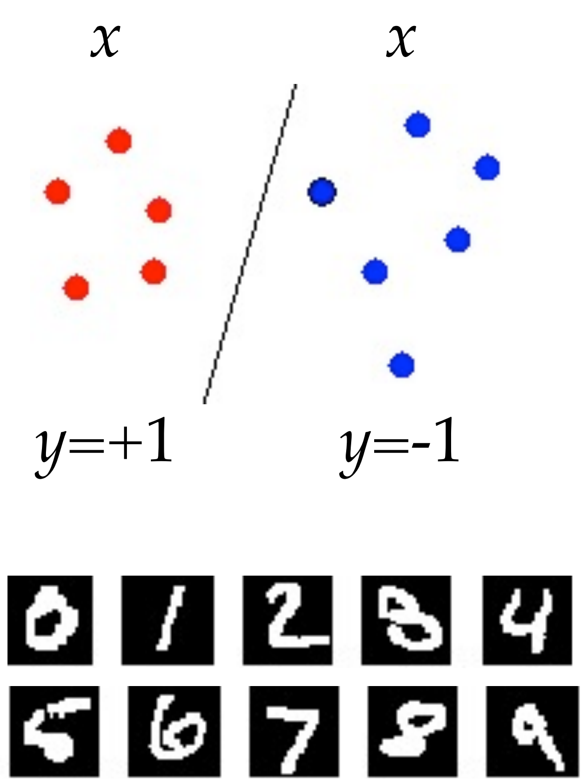

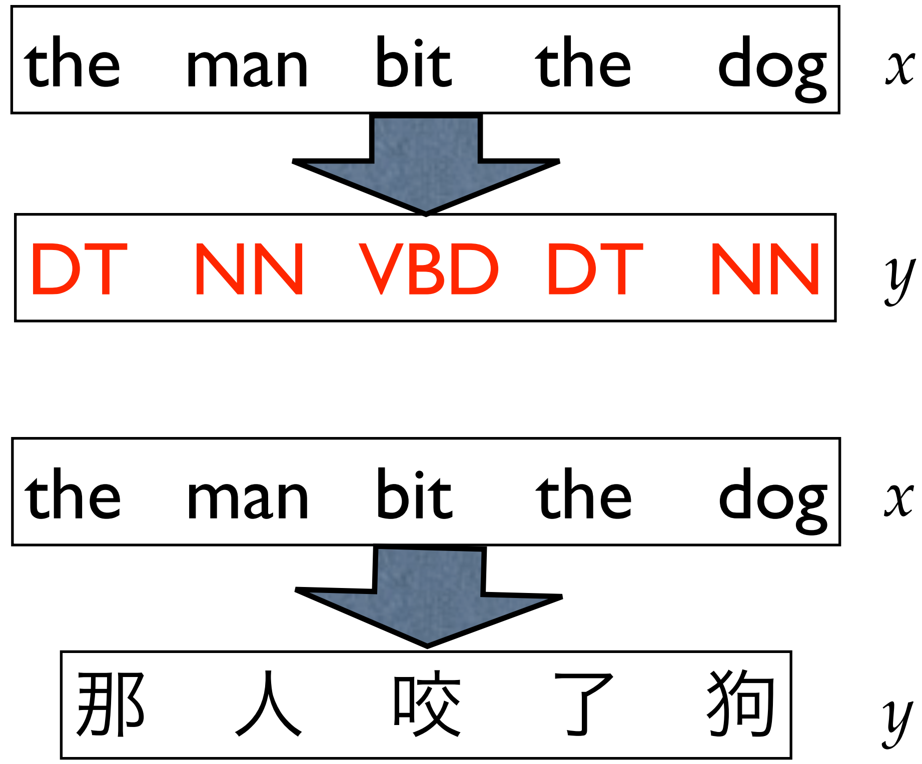

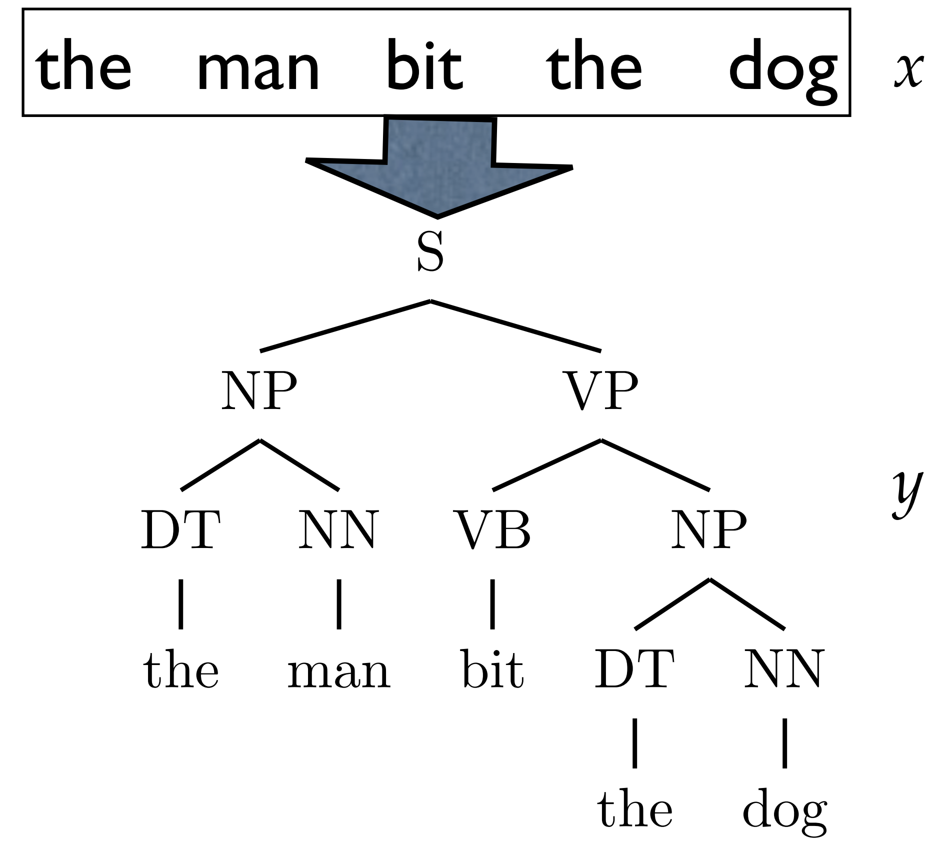

- bin
- mu

NLP is all about structured prediction!

- structured classification: output is a structure (seq., tree, graph)
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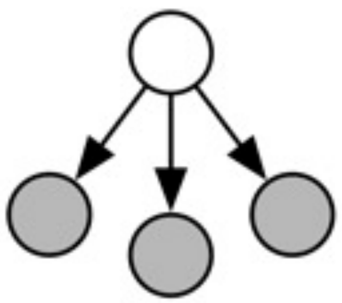
Examples of Bad Structured Prediction

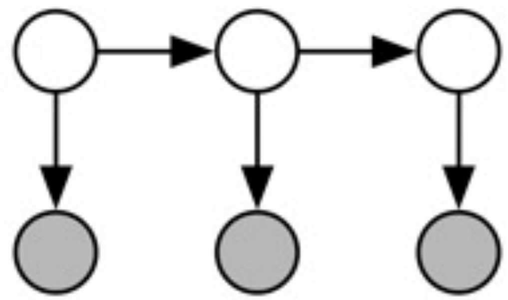
Learning: Unstructured vs. Structured

binary/multiclass



naive bayes

structured learning

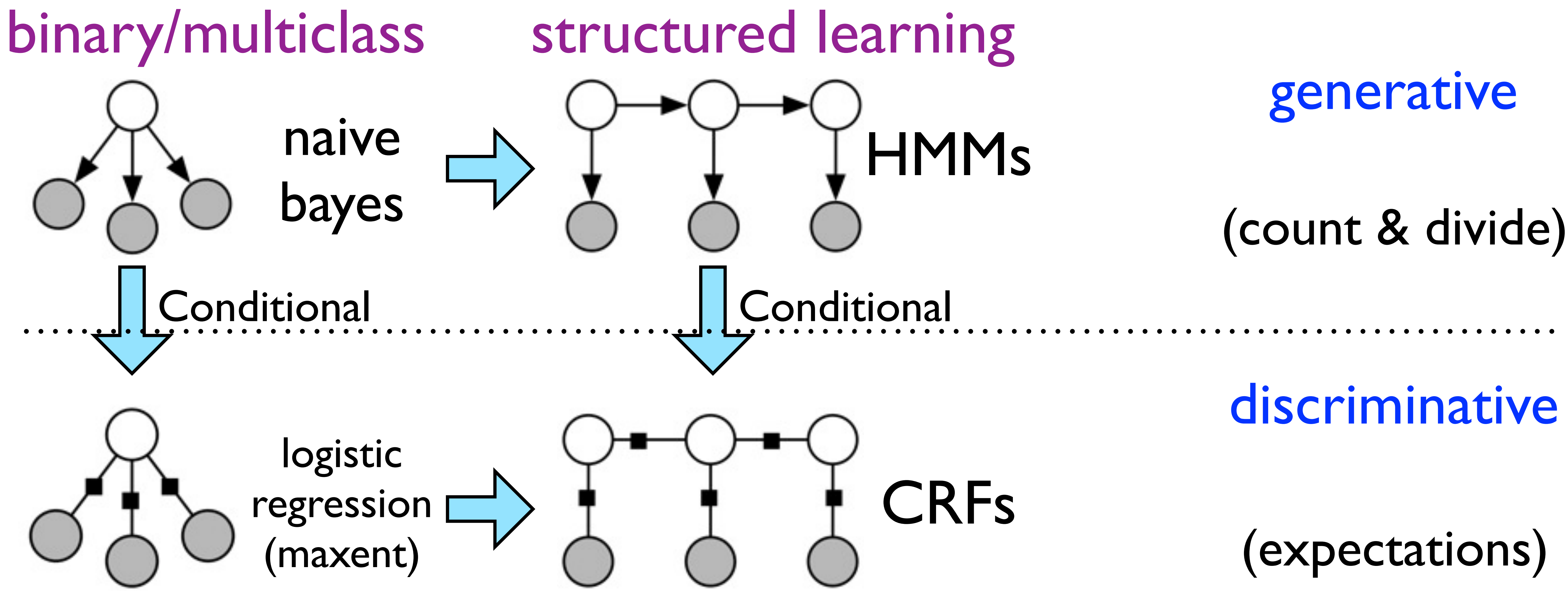


HMMs

generative

(count & divide)

Learning: Unstructured vs. Structured



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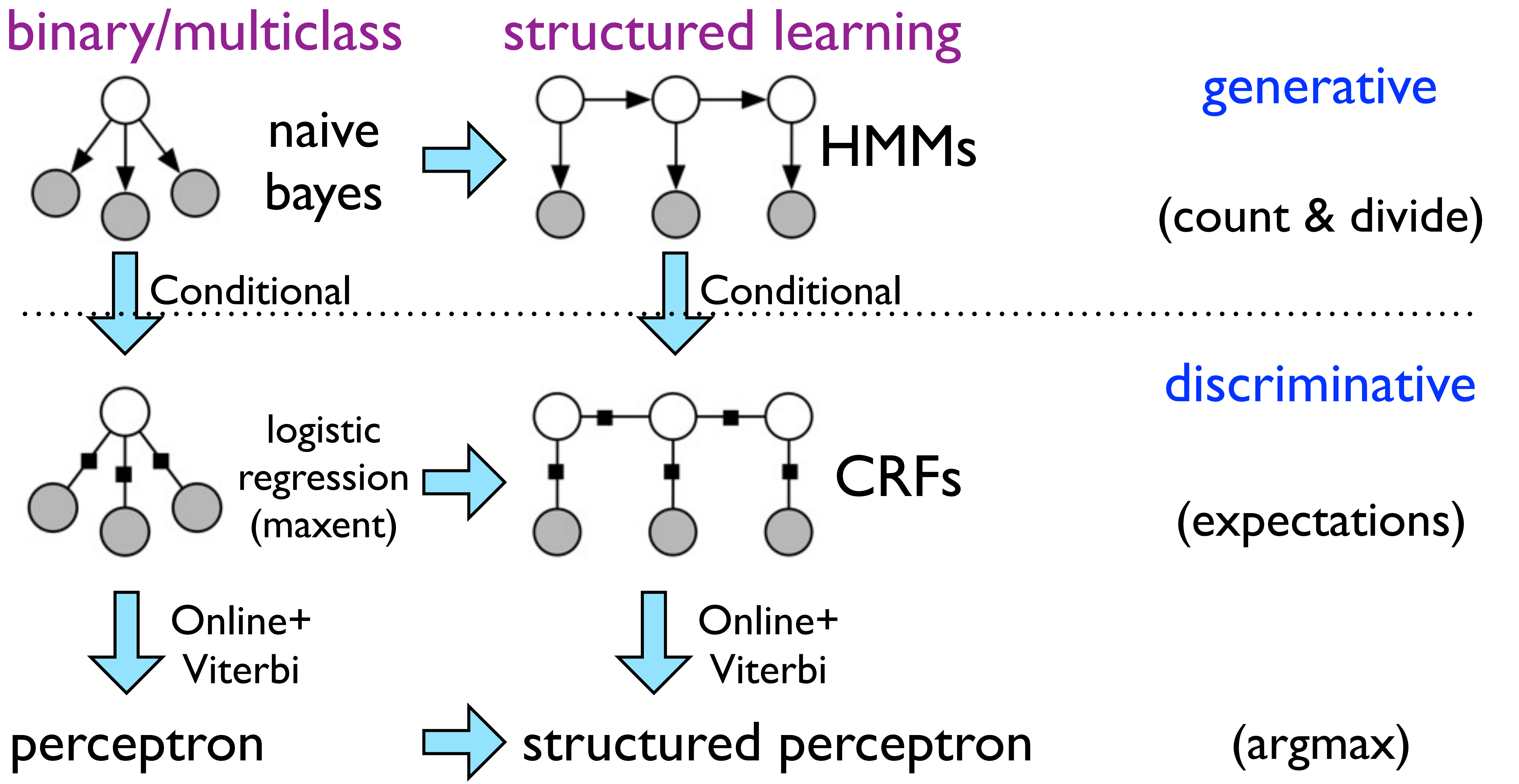

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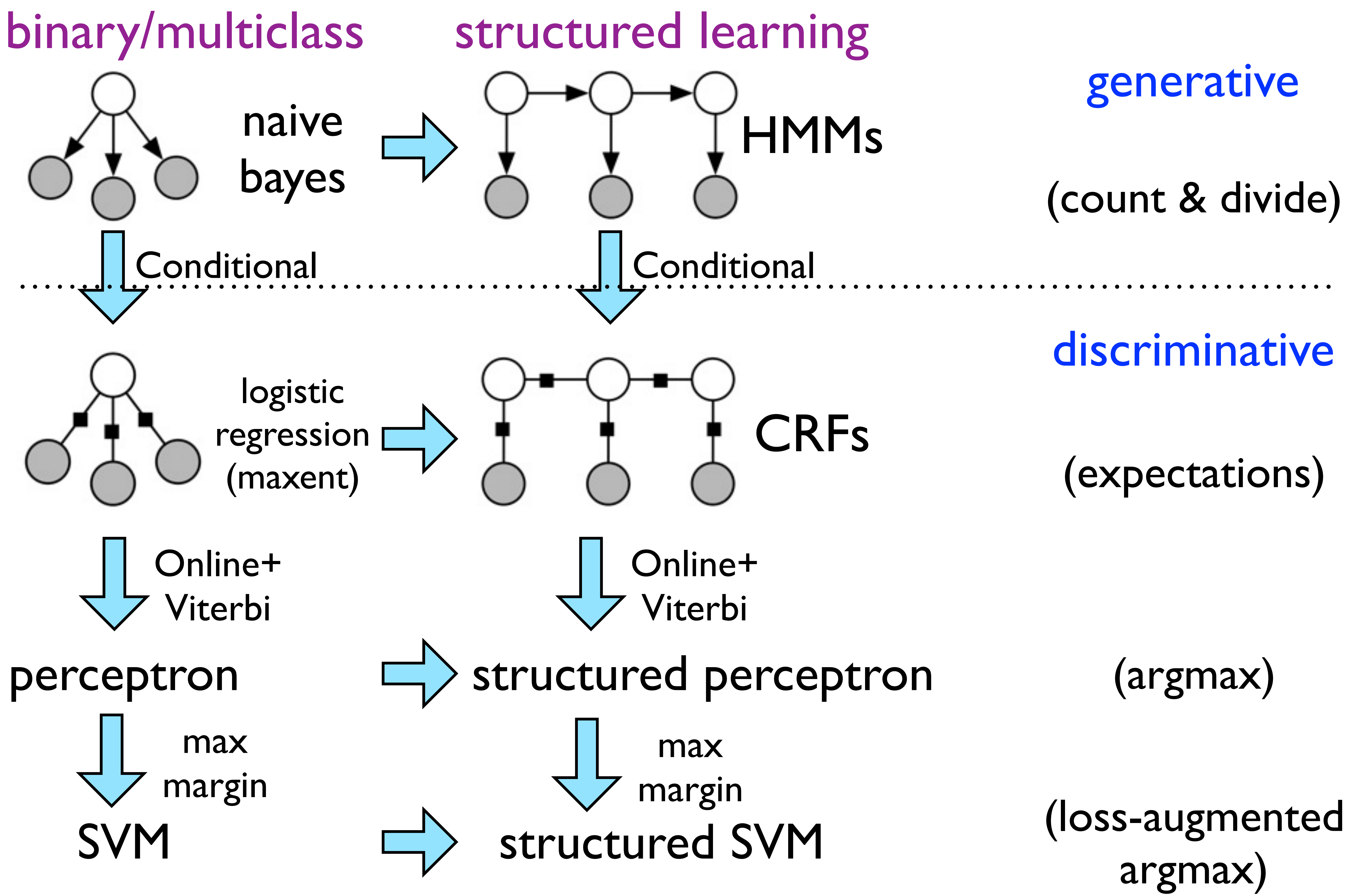

Why Perceptron (Online Learning)?

- because we want scalability on big data!
- learning time has to be linear in the number of examples
  - can make only constant number of passes over training data
  - only online learning (perceptron/MIRA) can guarantee this!
  - SVM scales between $O(n^2)$ and $O(n^3)$; CRF no guarantee
- and inference on each example must be super fast
  - another advantage of perceptron: just need argmax

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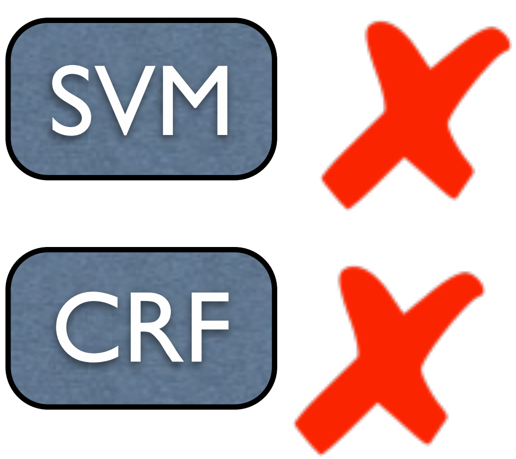
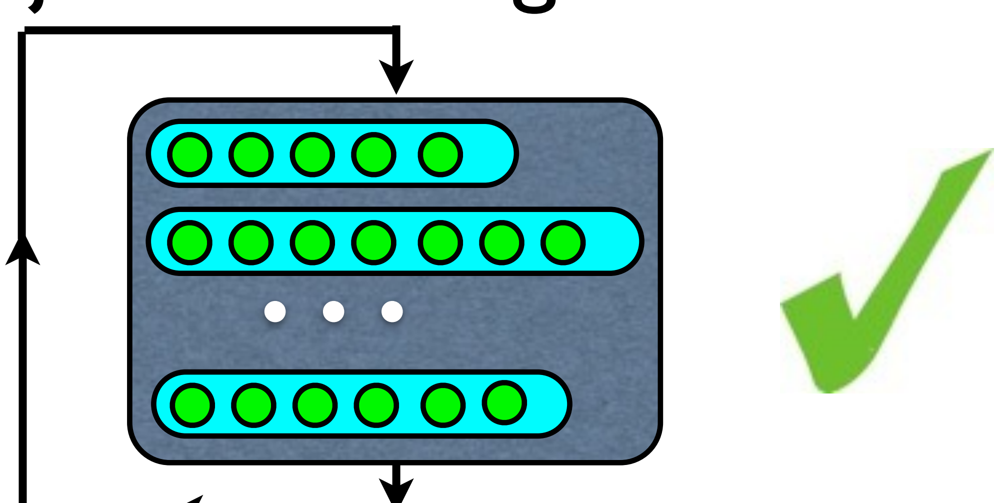
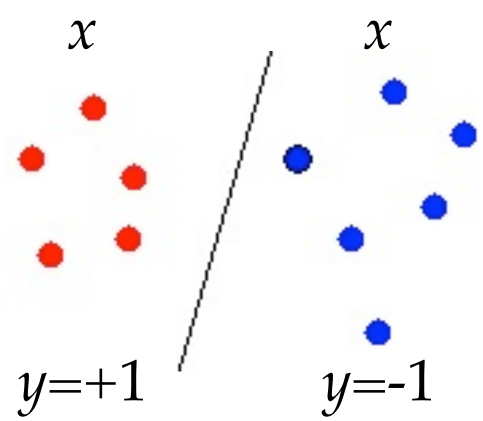


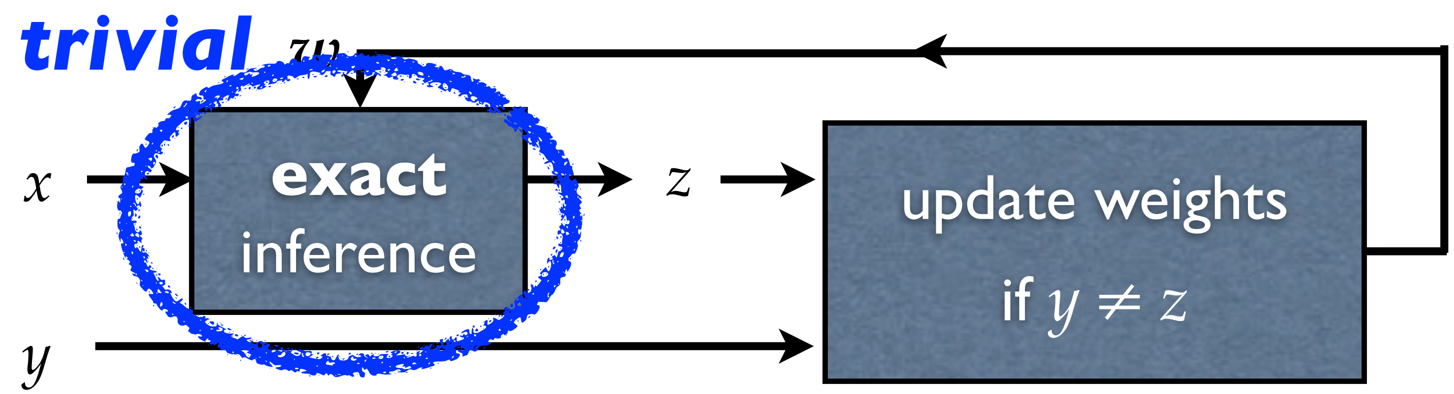


Perceptron: from binary to structured

binary perceptron
(Rosenblatt, 1959)



2 classes



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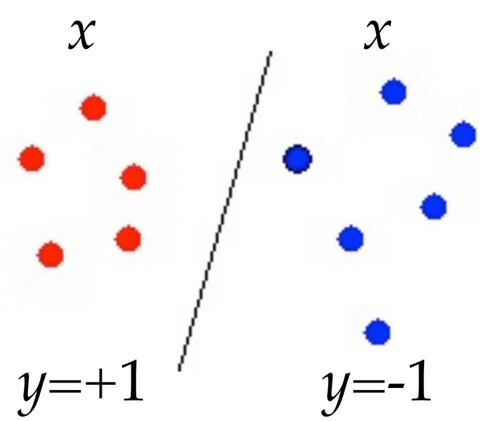

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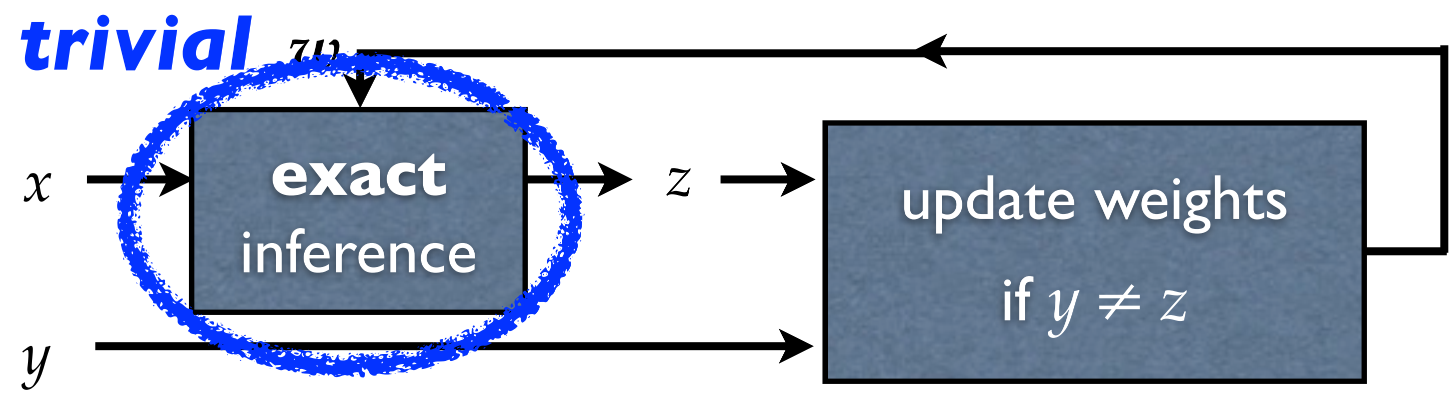
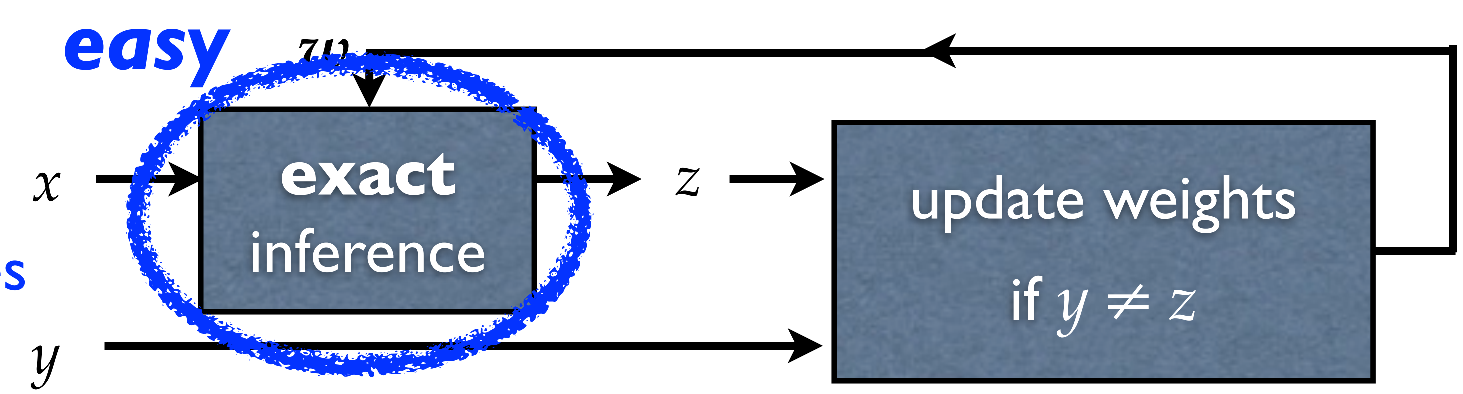


multiclass perceptron
(Freund/Schapire, 1999)

constant
# of classes



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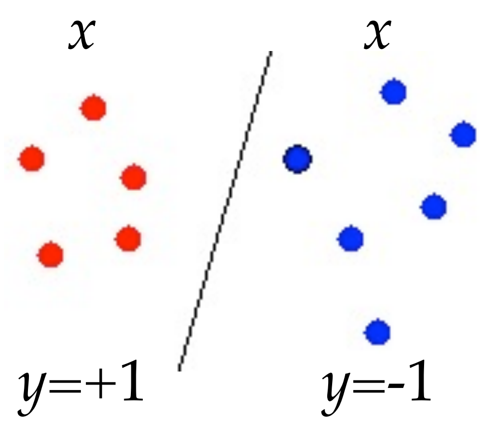
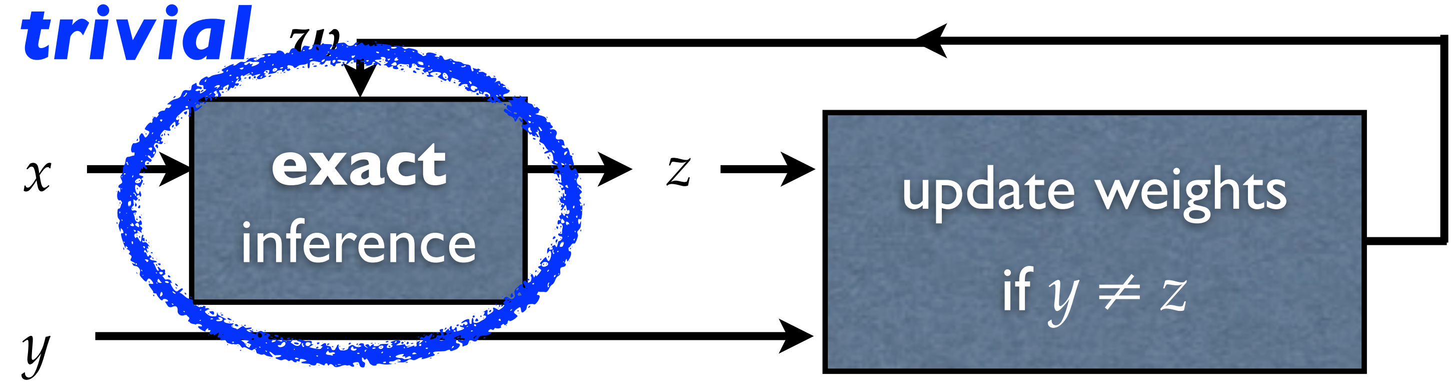


trivial

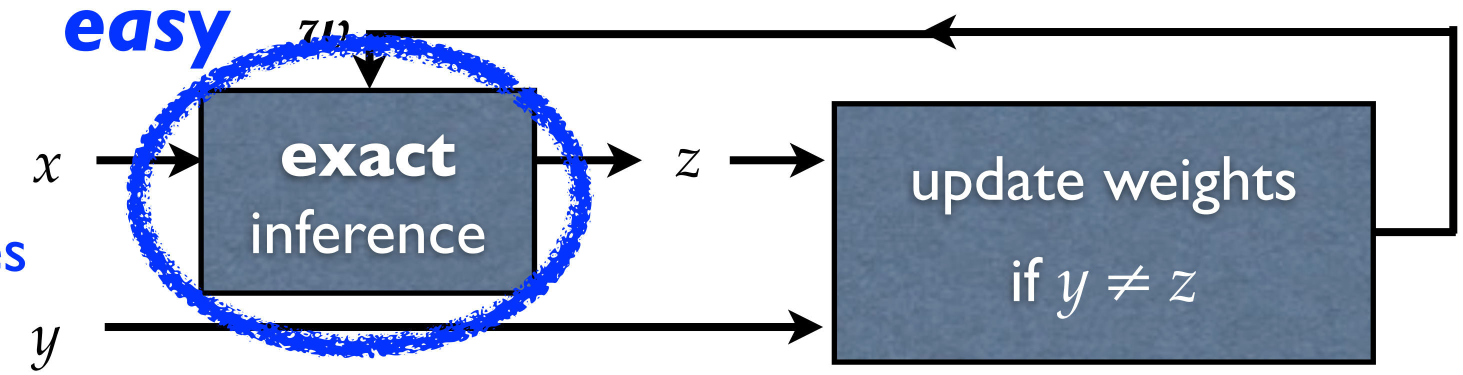
2 classes



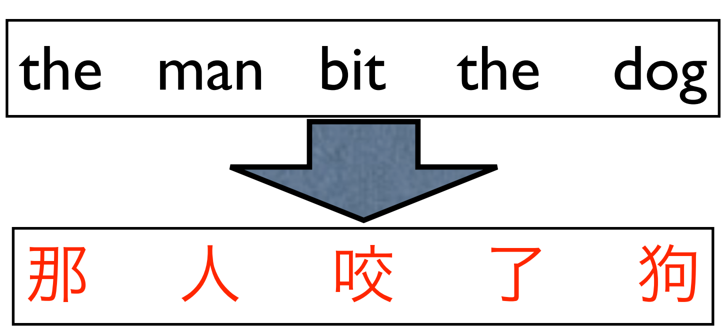
multiclass perceptron
(Freund/Schapire, 1999)

easy

constant
# of classes



structured perceptron
(Collins, 2002)

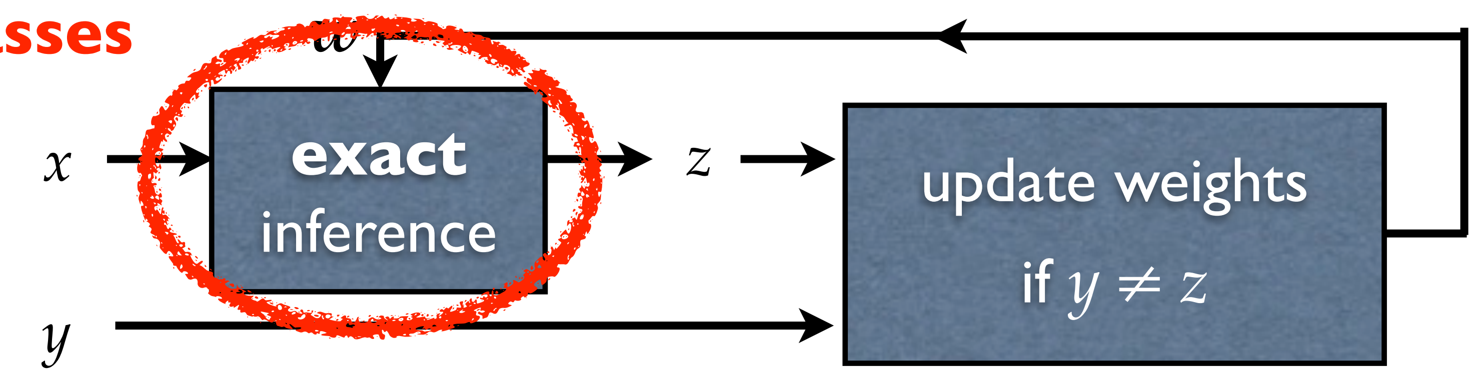


x

y

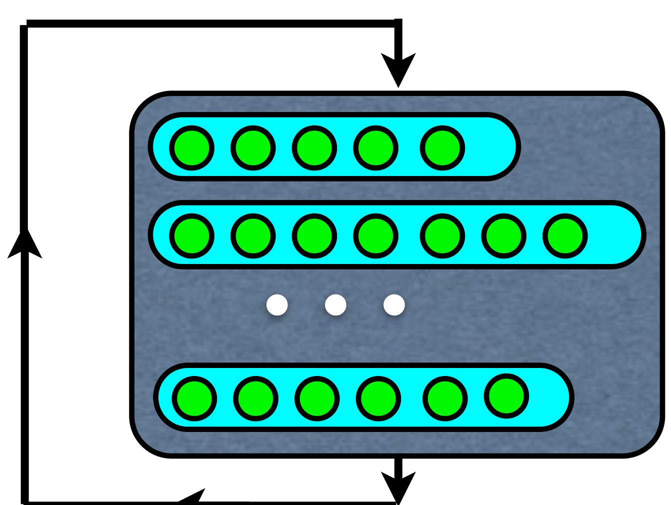
exponential
# of classes

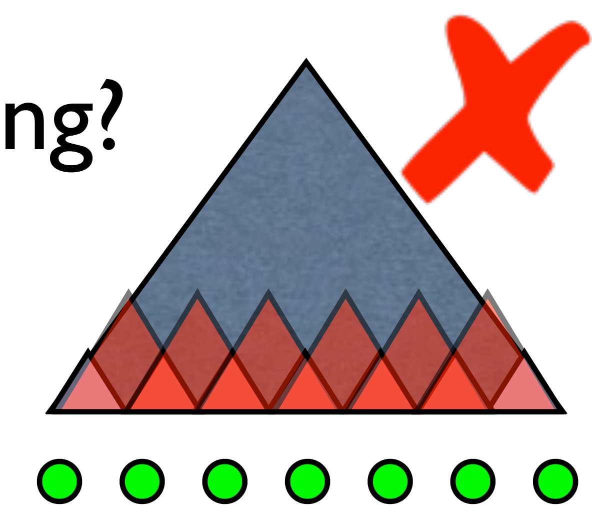
hard



Scalability Challenges

- inference (on one example) is too slow (even w/ DP)
  - can we sacrifice search exactness for faster learning?
  - would inexact search interfere with learning?
  - if so, how should we modify learning?
- even fastest inexact inference is still too slow
  - due to too many training examples
  - can we parallelize online learning?





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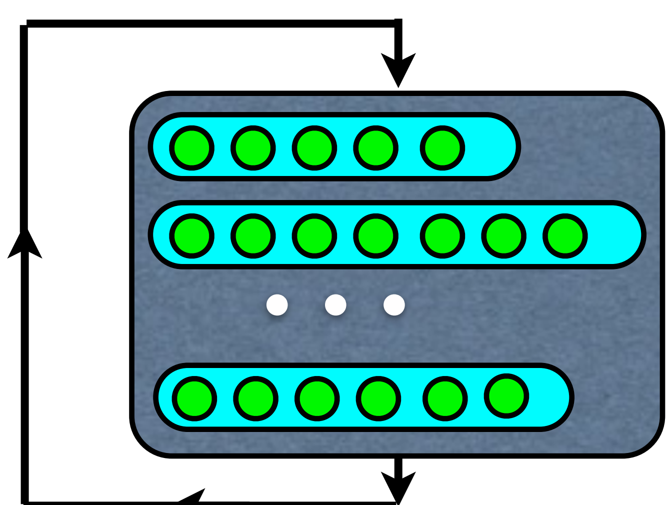

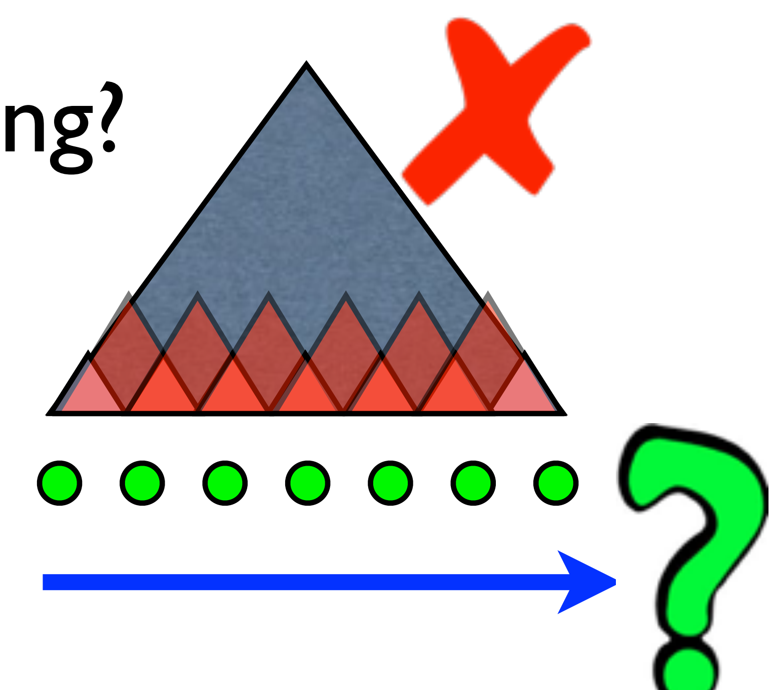

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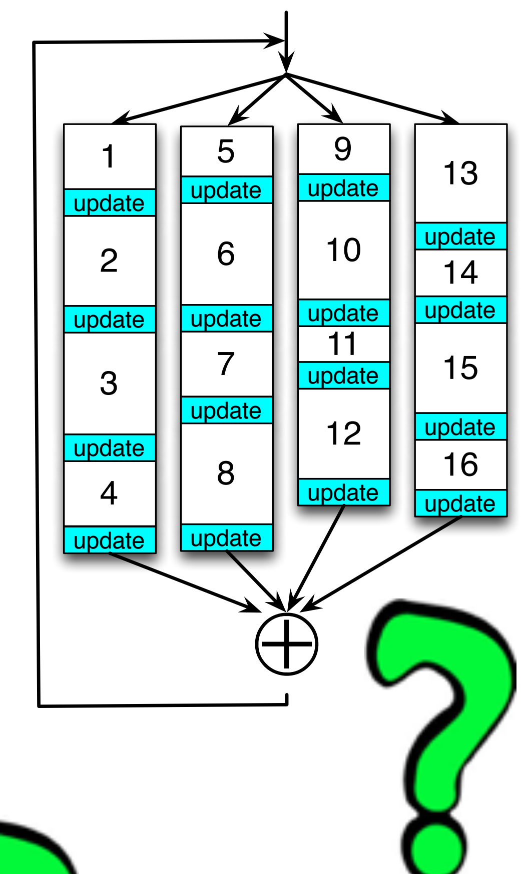
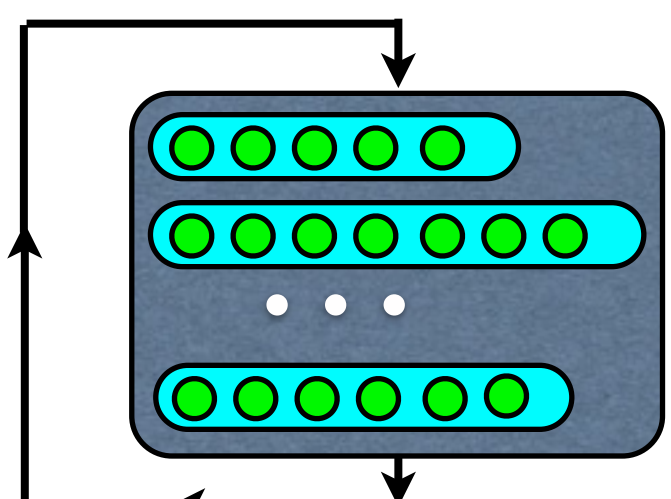
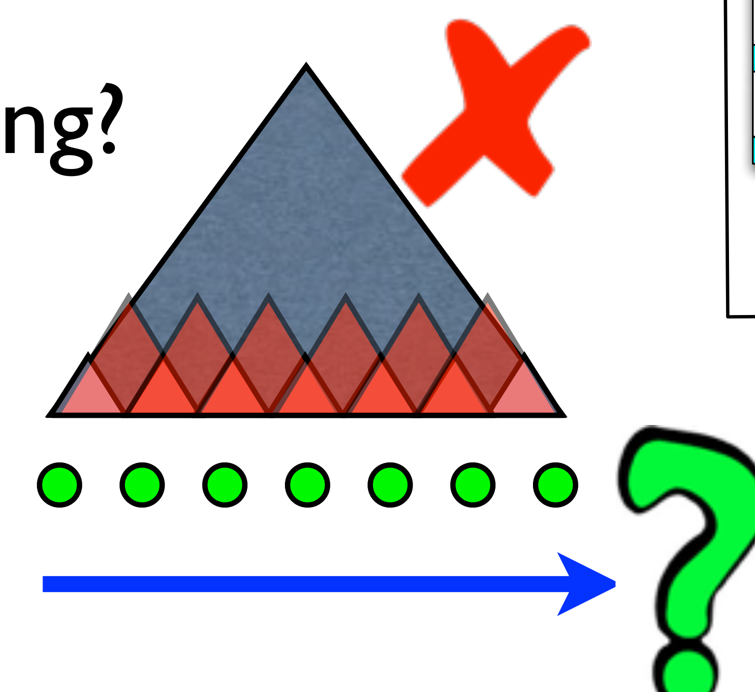




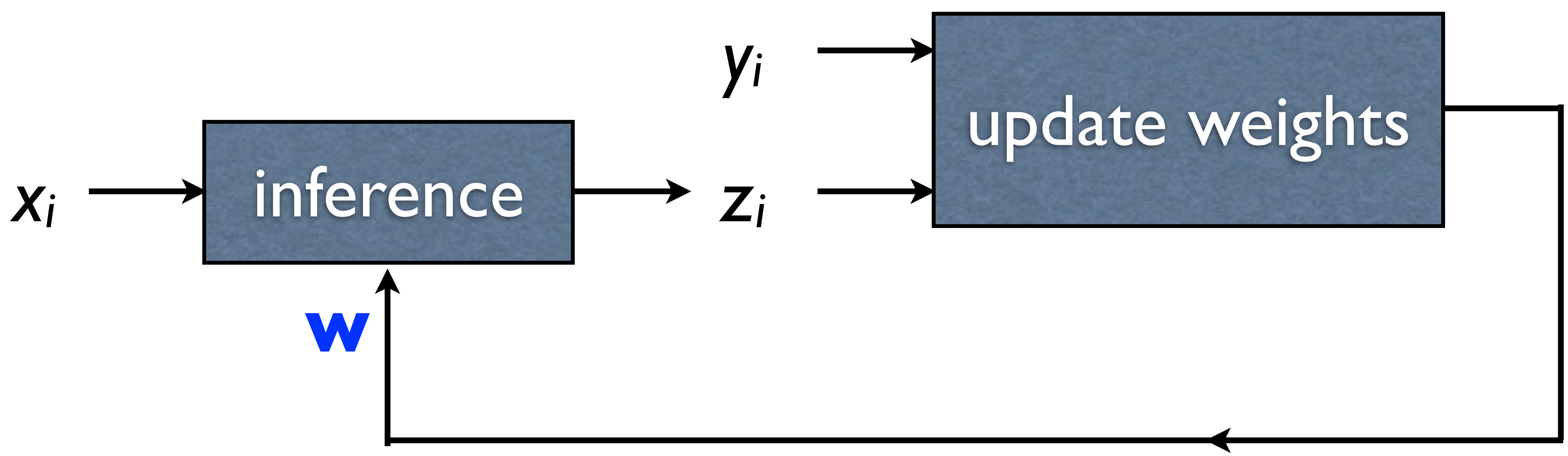


Tutorial Outline

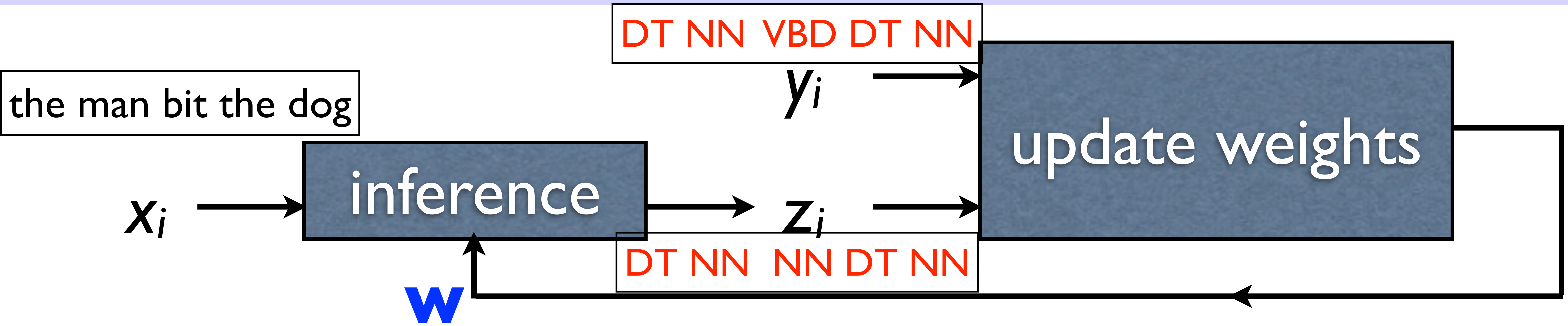
- Overview of Structured Learning
  - Challenges in Scalability
- Structured Perceptron
  - convergence proof
- Structured Perceptron with Inexact Search
- Latent-Variable Structured Perceptron
- Parallelizing Online Learning (Perceptron & MIRA)

Generic Perceptron

- perceptron is the simplest machine learning algorithm
- online-learning: one example at a time
- learning by doing
  - find the best output under the current weights
  - update weights at mistakes



Structured Perceptron



Inputs: Training set (x_i, y_i) for $i = 1 \ldots n$

Initialization: $\mathbf{W} = 0$

Define: $F(x) = \boxed{\operatorname{argmax}_{y \in \mathbf{GEN}(x)}} \mathbf{\Phi}(x, y) \cdot \mathbf{W}$

Algorithm: For $t = 1 \ldots T, i = 1 \ldots n$

$z_i = F(x_i)$

If $(z_i \neq y_i)$ $\boxed{\mathbf{W} \leftarrow \mathbf{W} + \mathbf{\Phi}(x_i, y_i) - \mathbf{\Phi}(x_i, z_i)}$

Output: Parameters $\mathbf{W}$

Example: POS Tagging

y

$\Phi(x, y)$

x

---

z

$\Phi(x, z)$

x

Example: POS Tagging

- gold-standard: DT NN VBD DT NN y
  - the man bit the dog x

$\Phi(x, y)$

- current output: DT NN NN DT NN z
  - the man bit the dog x

$\Phi(x, z)$

- assume only two feature classes
  - tag bigrams t_{i-1} t_i
  - word/tag pairs w_i

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- weights ++: (NN,VBD) (VBD, DT) (VBD $\rightarrow$ bit)

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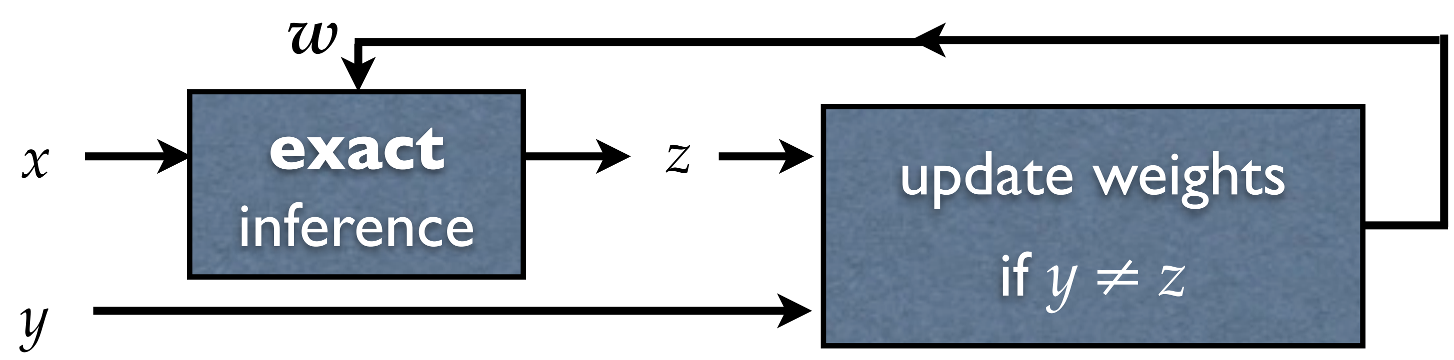
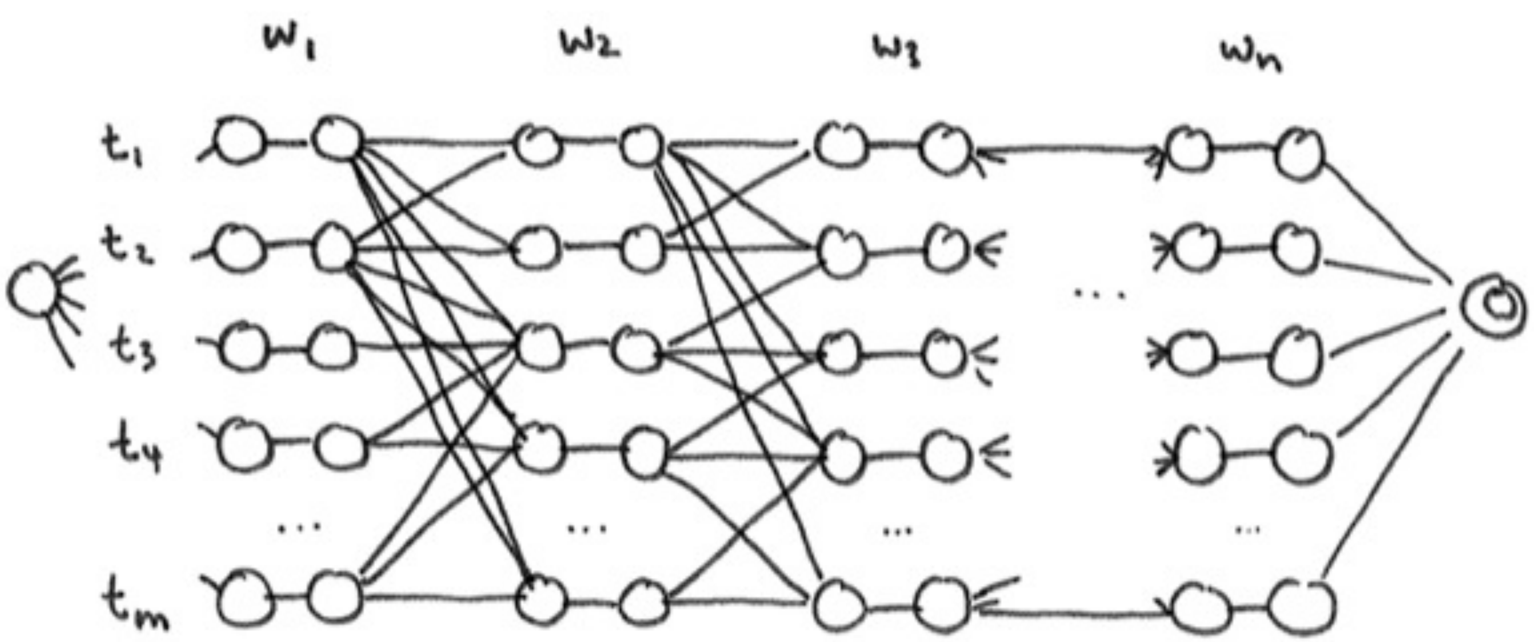
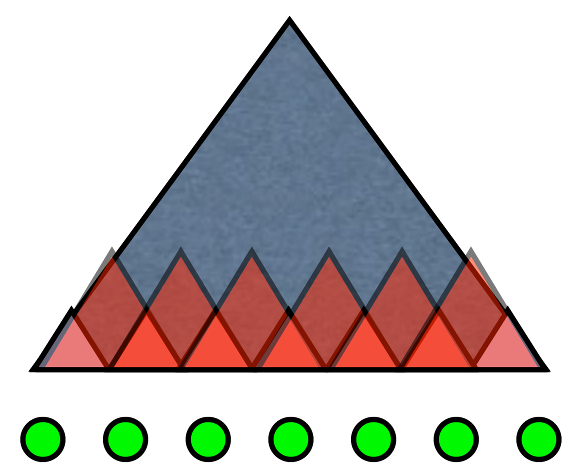
- weights −−: (NN, NN) (NN, DT) (NN $\rightarrow$ bit)

Inference: Dynamic Programming



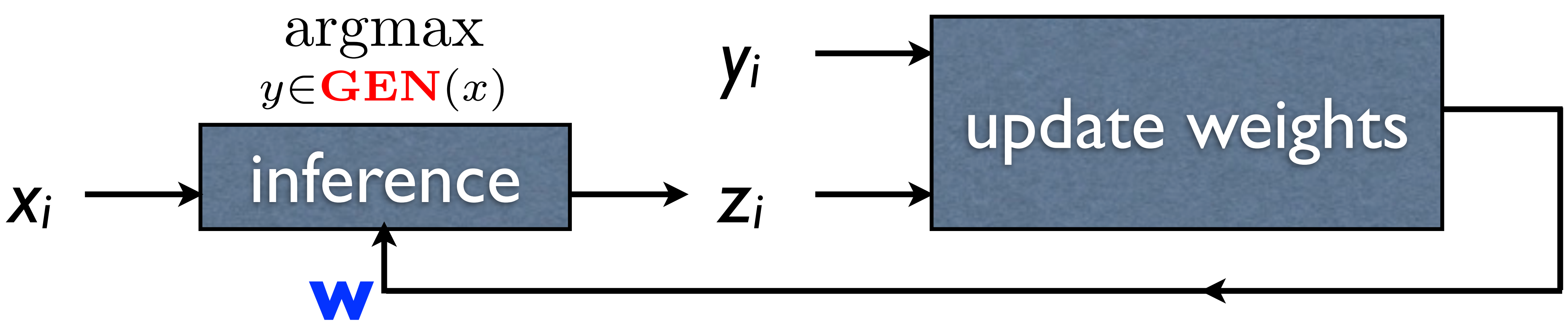


tagging: $O(nT^3)$

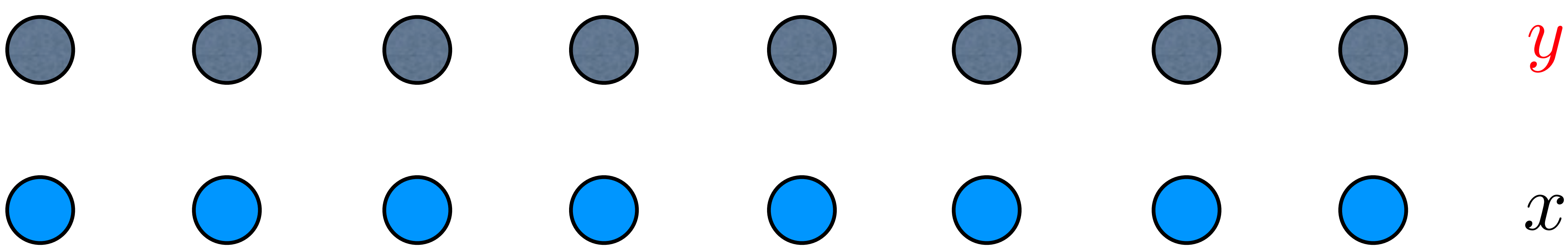


CKY parsing: $O(n^3)$

Efficiency vs. Expressiveness



- the inference (argmax) must be efficient
  - either the search space GEN(x) is small, or factored
  - features must be local to y (but can be global to x)
    - e.g. bigram tagger, but look at all input words (cf. CRFs)



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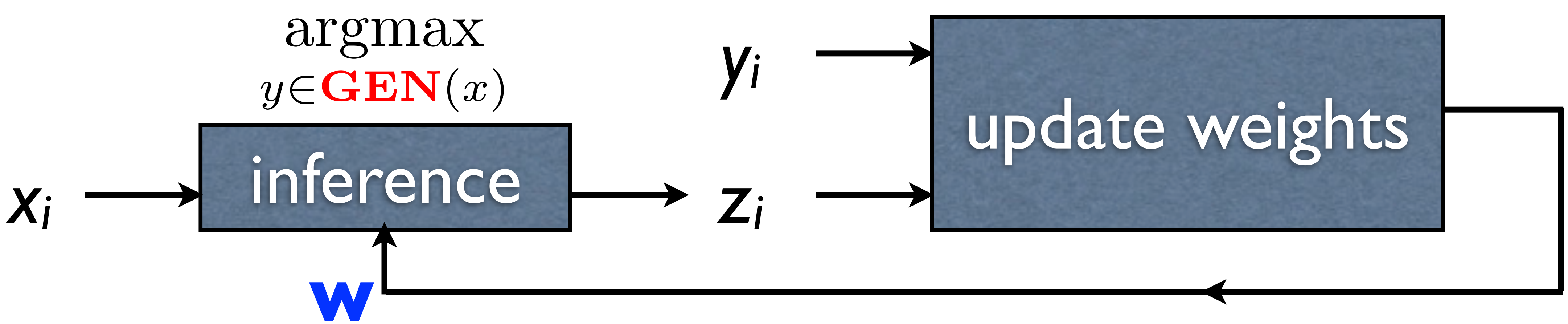

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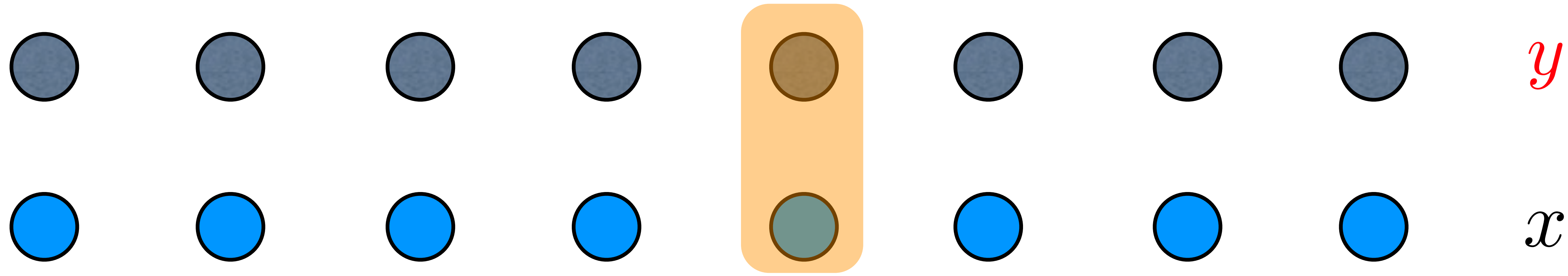

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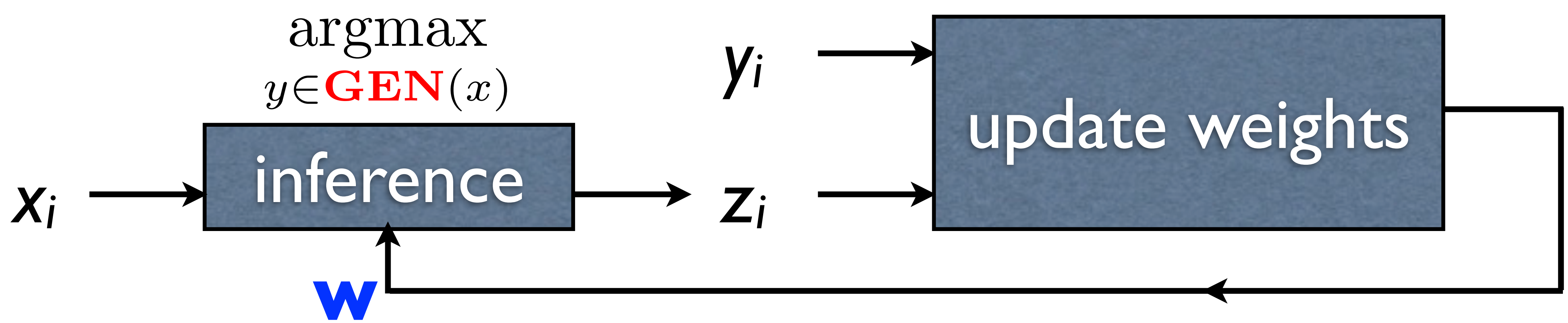

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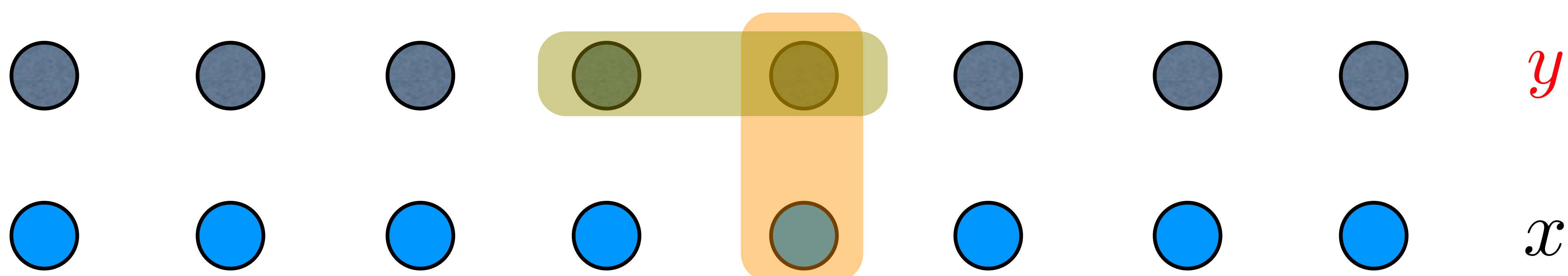

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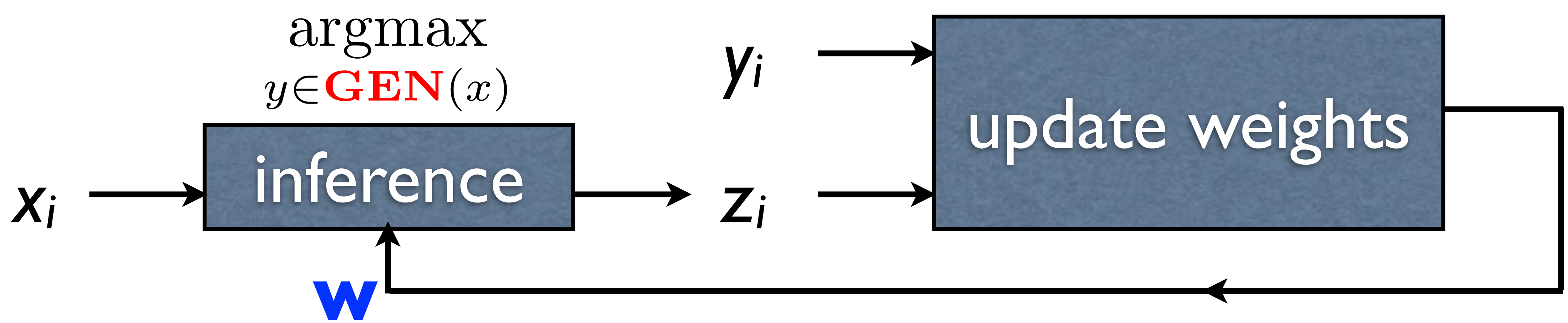

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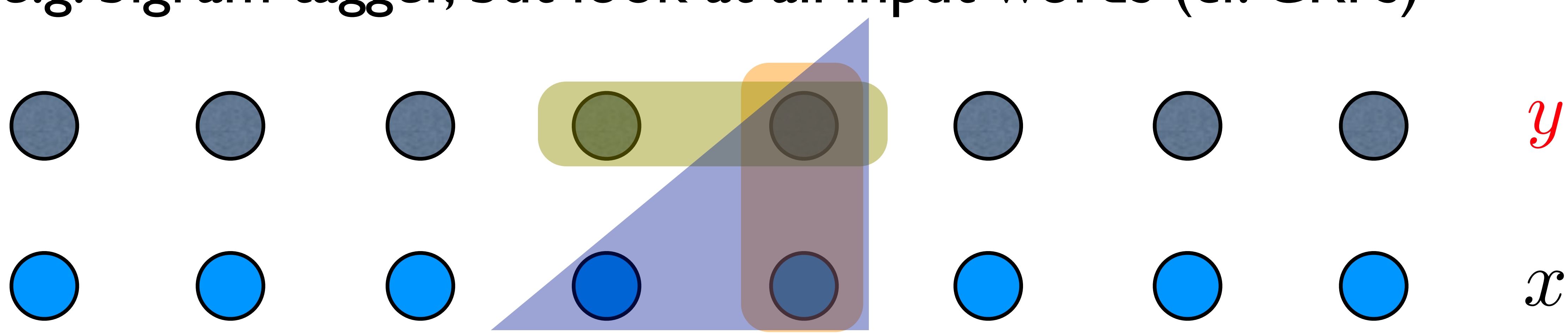
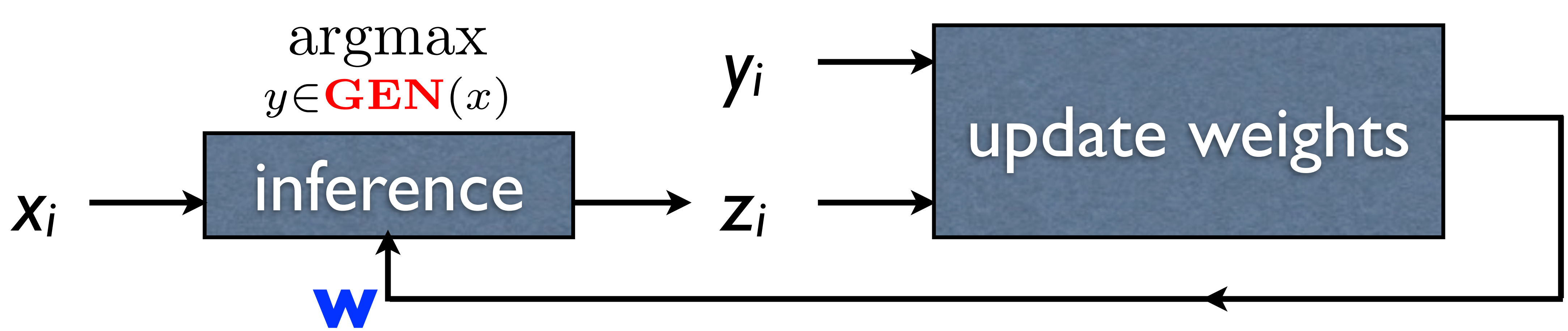
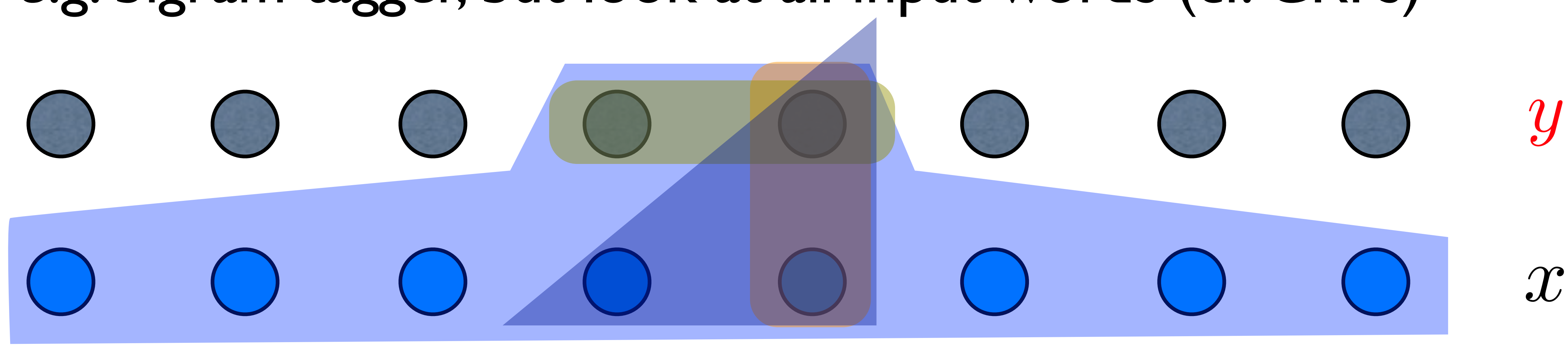


Efficiency vs. Expressiveness



- the inference (argmax) must be efficient
  - either the search space GEN(x) is small, or factored
  - features must be local to y (but can be global to x)
    - e.g. bigram tagger, but look at all input words (cf. CRFs)



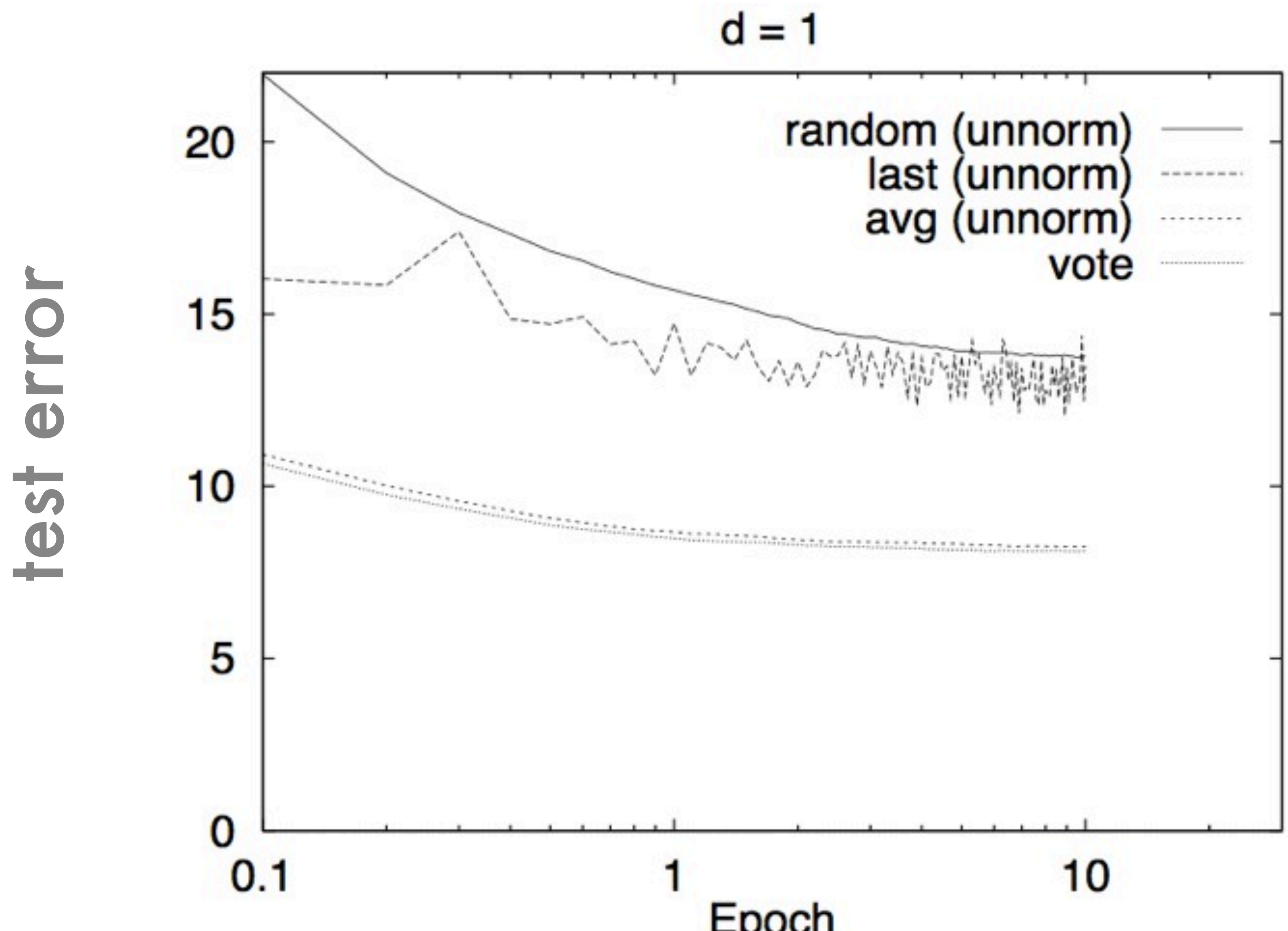
Averaged Perceptron

- much more stable and accurate results
- approximation of voted perceptron (large-margin) (Freund & Schapire, 1999)

Inputs:	Training set (x_i, y_i) for $i = 1 \ldots n$
Initialization:	$\mathbf{W}_0 = 0$
Define:	$F(x) = \mathrm{argmax}_{y \in \mathbf{GEN}(x)} \mathbf{\Phi}(x, y) \cdot \mathbf{W}$
Algorithm:	For $t = 1 \ldots T$, $i = 1 \ldots n$ $z_i = F(x_i)$ If $(z_i \neq y_i)$ $\mathbf{W}_{j+1} \leftarrow \mathbf{W}_j + \mathbf{\Phi}(x_i, y_i) - \mathbf{\Phi}(x_i, z_i)$
Output:	Parameters $\mathbf{W} = \sum_j \mathbf{W}_j$

Averaging => Large Margin

- much more stable and accurate results
- approximation of voted perceptron (large-margin) (Freund & Schapire, 1999)



Efficient Implementation of Averaging

- naive implementation (running sum) doesn't scale
- very clever trick from Daume (2006, PhD thesis)

Algorithm AVERAGEDSTRUCTUREDPERCEPTRON$(x_{1:N}, y_{1:N}, I)$

$\boldsymbol{w}_0 \leftarrow \langle 0, \ldots, 0 \rangle$
$\boldsymbol{w}_a \leftarrow \langle 0, \ldots, 0 \rangle$
$c \leftarrow 1$
for $i = 1 \ldots I$ **do**
    for $n = 1 \ldots N$ **do**
        $\hat{y}_n \leftarrow \arg\max_{y \in \mathcal{Y}} \boldsymbol{w}_0{}^\top \Phi(x_n, y_n)$
        if $y_n \neq \hat{y}_n$ **then**
            $\boldsymbol{w}_0 \leftarrow \boldsymbol{w}_0 + \Phi(x_n, y_n) - \Phi(x_n, \hat{y}_n)$
            $\boldsymbol{w}_a \leftarrow \boldsymbol{w}_a + c\Phi(x_n, y_n) - c\Phi(x_n, \hat{y}_n)$
        end if
        $c \leftarrow c + 1$
    end for
end for
return $\boldsymbol{w}_0 - \boldsymbol{w}_a / c$

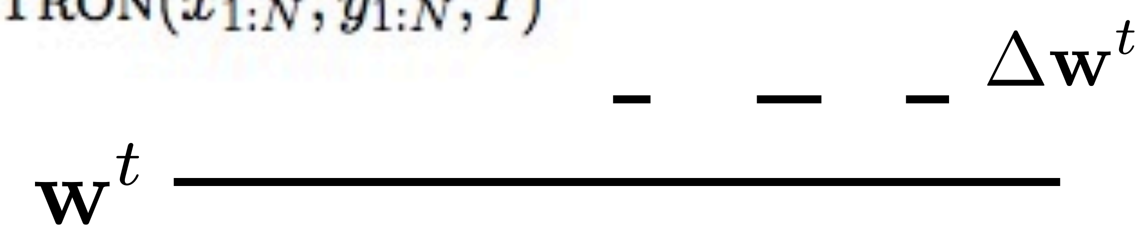


Figure 2.3: The averaged structured perceptron learning algorithm.

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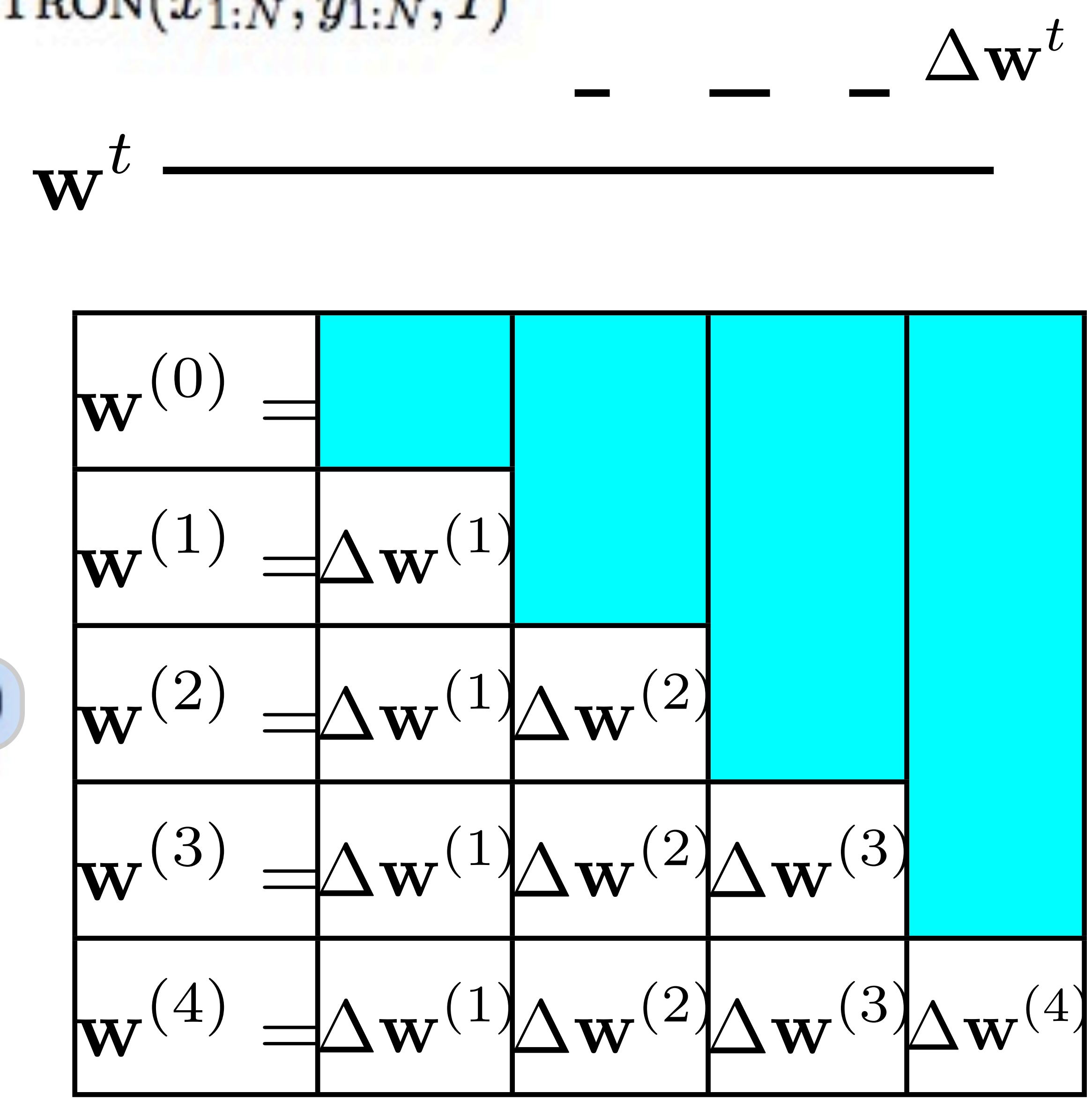

Figure 2.3: The averaged structured perceptron learning algorithm.

Perceptron vs. CRFs

- perceptron is online and Viterbi approximation of CRF
- simpler to code; faster to converge; ~same accuracy

CRFs
(Lafferty et al, 2001)

$$\sum_{(x,y)\in D} \sum_{z\in \mathbf{GEN}(x)} \frac{\exp(\mathbf{w}\cdot\Phi(x,z))}{Z(x)}$$

$$\text{for } (x,y)\in D,\ \underset{z\in\mathbf{GEN}(x)}{\mathbf{argmax}}\ \mathbf{w}\cdot\Phi(x,z)$$

structured perceptron
(Collins, 2002)

Perceptron vs. CRFs

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CRFs
(Lafferty et al, 2001)

online

$$\boxed{\sum_{(x,y)\in D}} \sum_{z\in \mathbf{GEN}(x)} \frac{\exp(\mathbf{w}\cdot\Phi(x,z))}{Z(x)}$$

stochastic gradient descent (SGD)

$$\boxed{\text{for } (x,y)\in D}, \ \mathop{\mathbf{argmax}}_{z\in \mathbf{GEN}(x)} \mathbf{w}\cdot\Phi(x,z)$$

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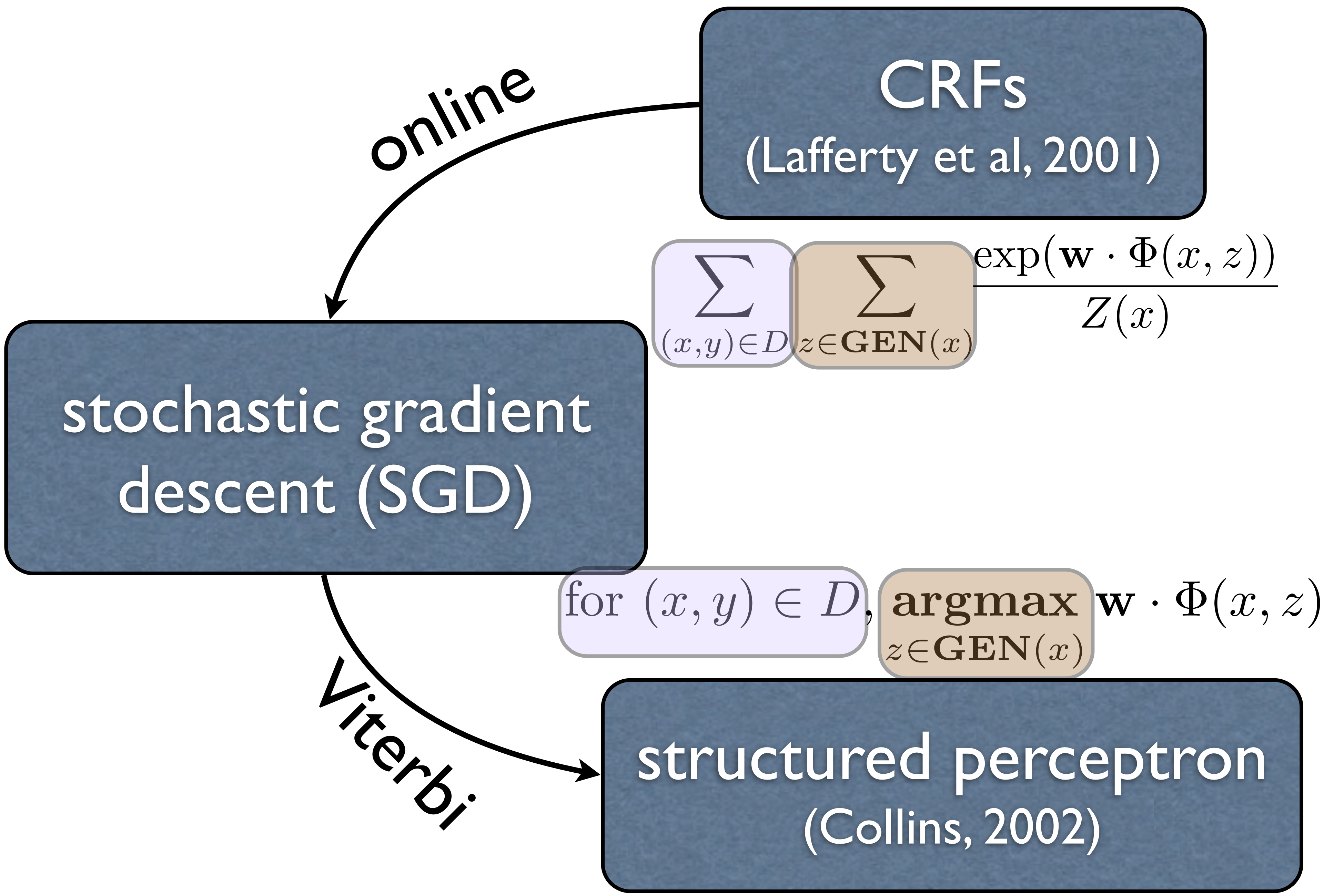

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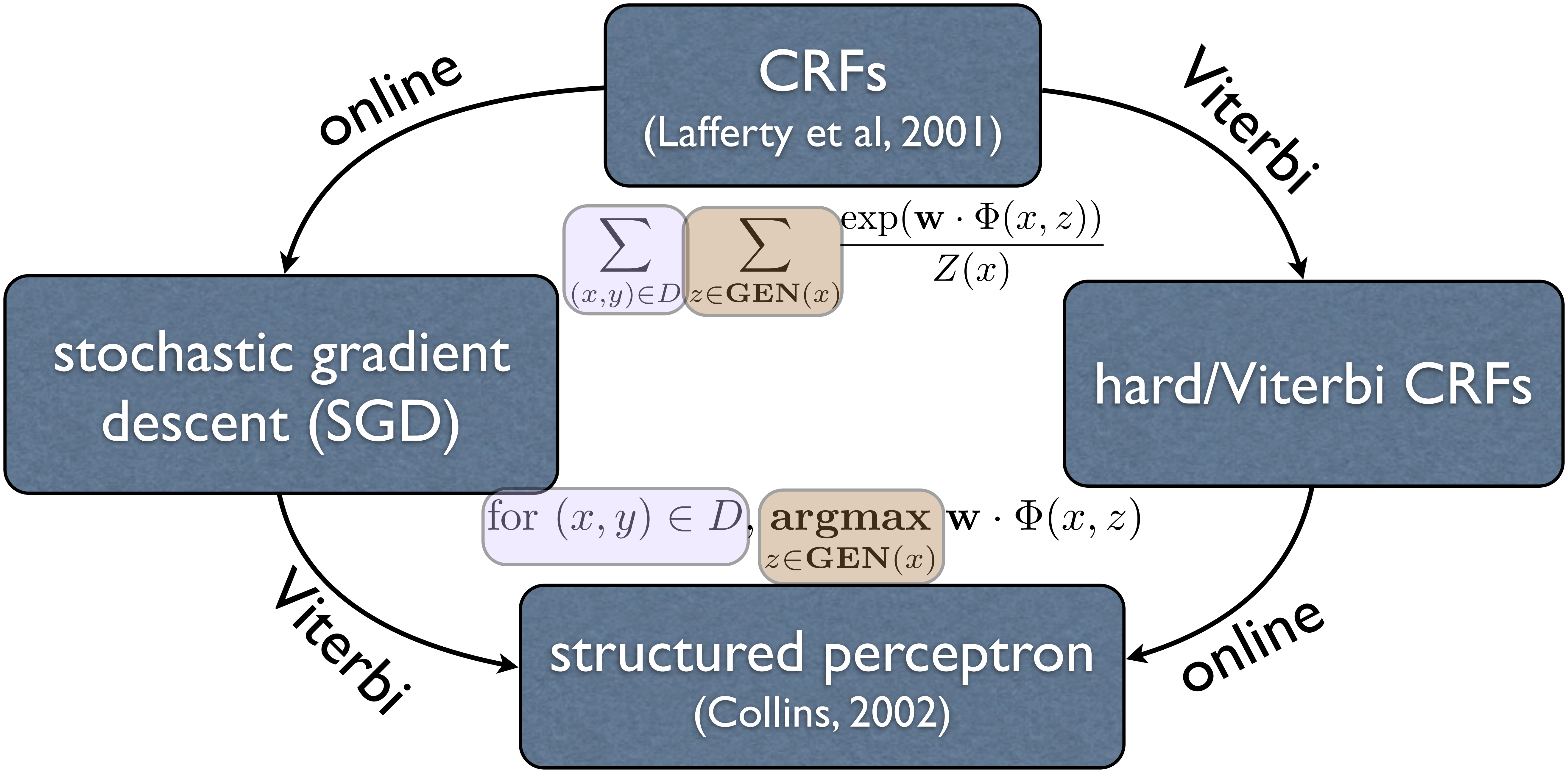
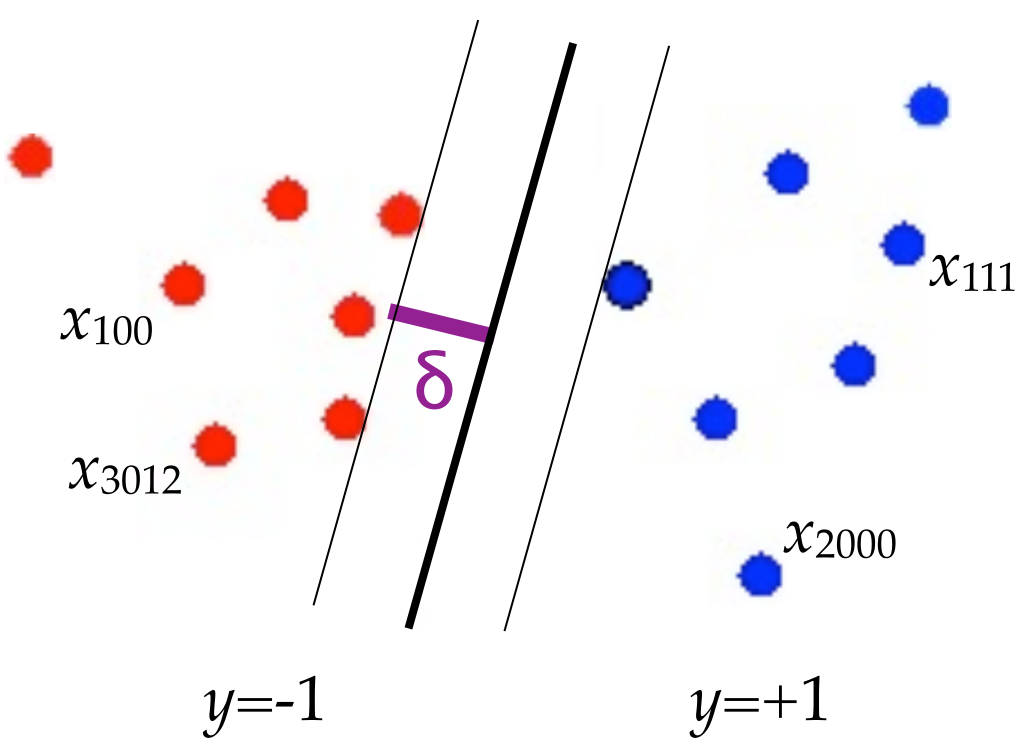
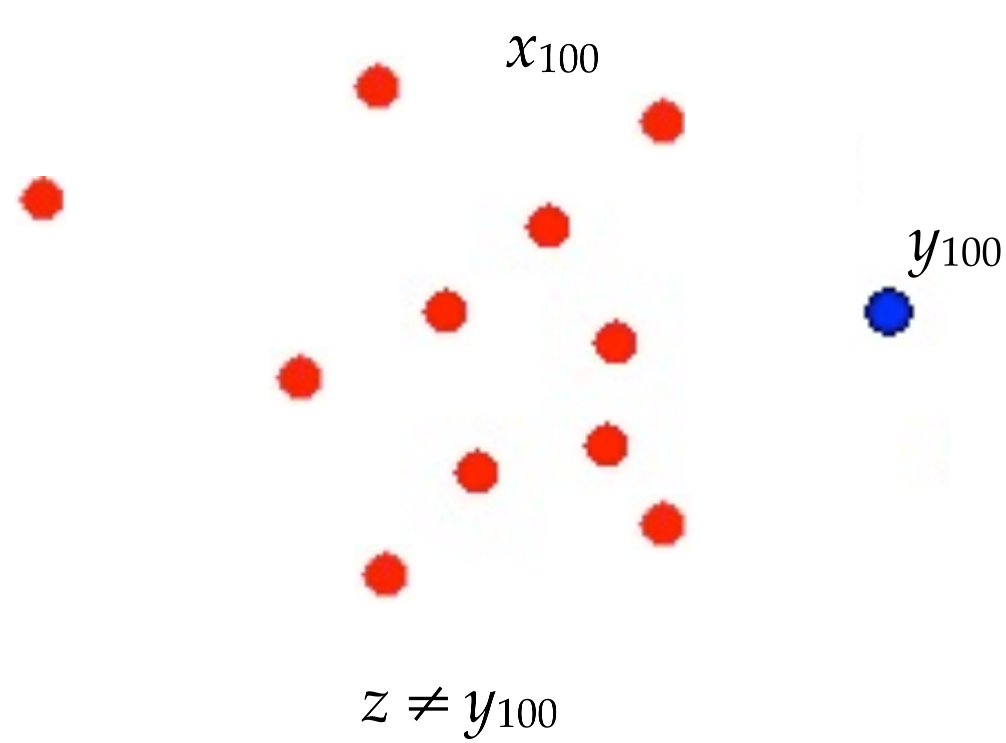


Perceptron Convergence Proof

- binary classification: converges iff. data is separable
- structured prediction: converges iff. data is separable
  - there is an oracle vector that correctly labels all examples
  - one vs the rest (correct label better than all incorrect labels)
- theorem: if separable, then **# of updates $\leq$ R^2 / δ^2** R: diameter





Novikoff => Freund & Schapire => Collins
1962 1999 2002

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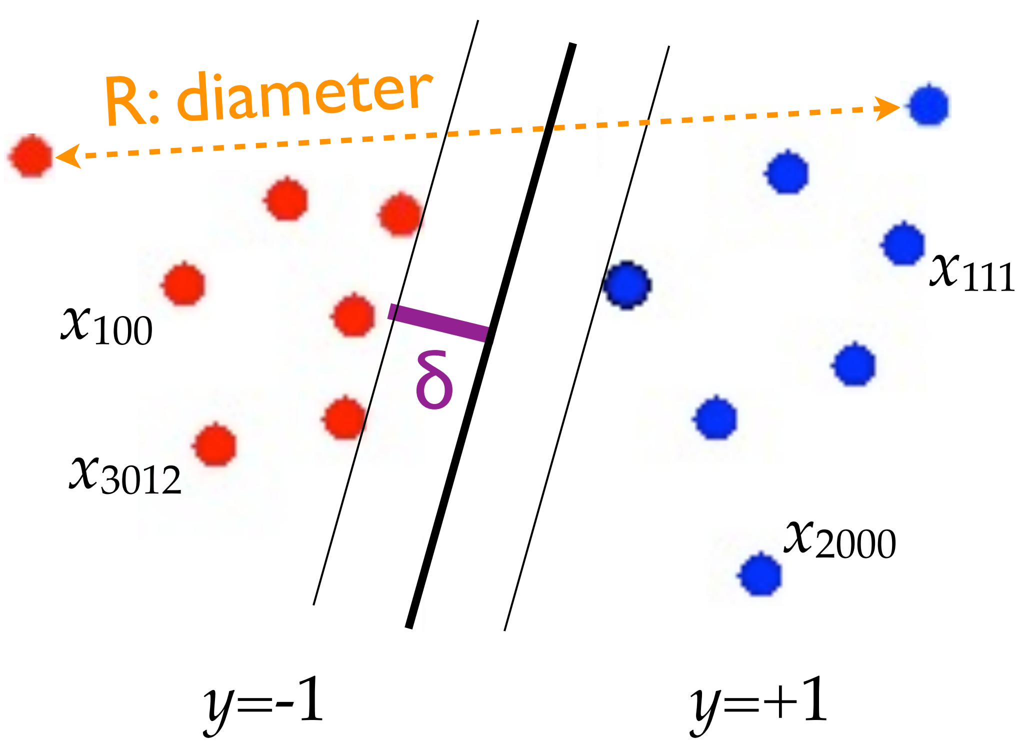

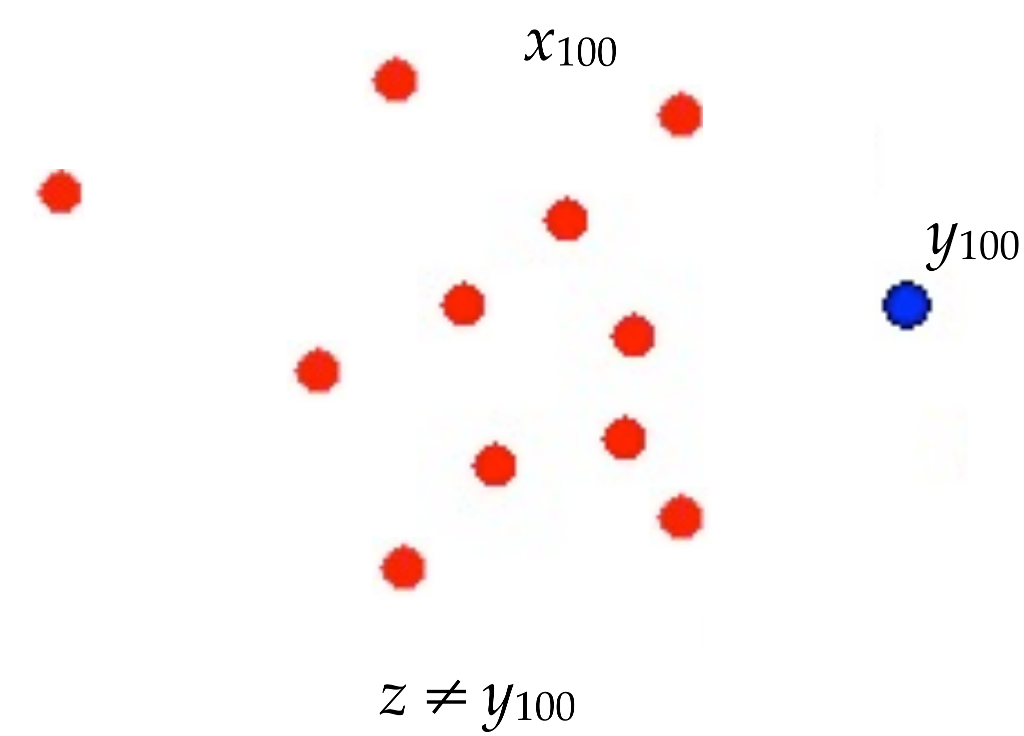

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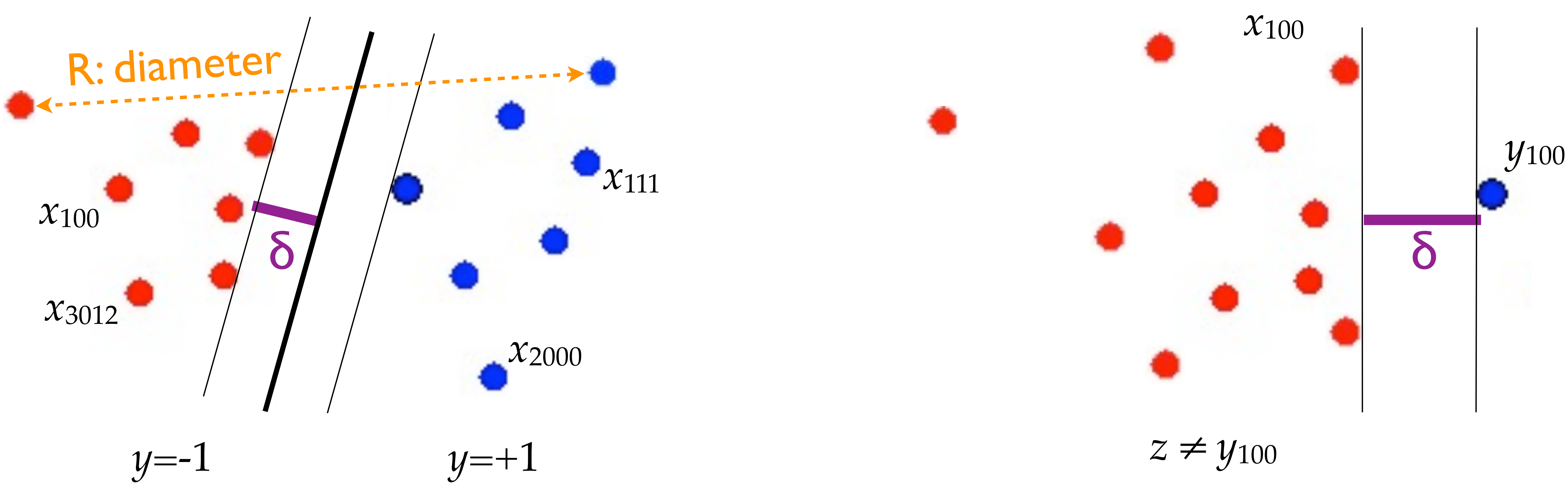

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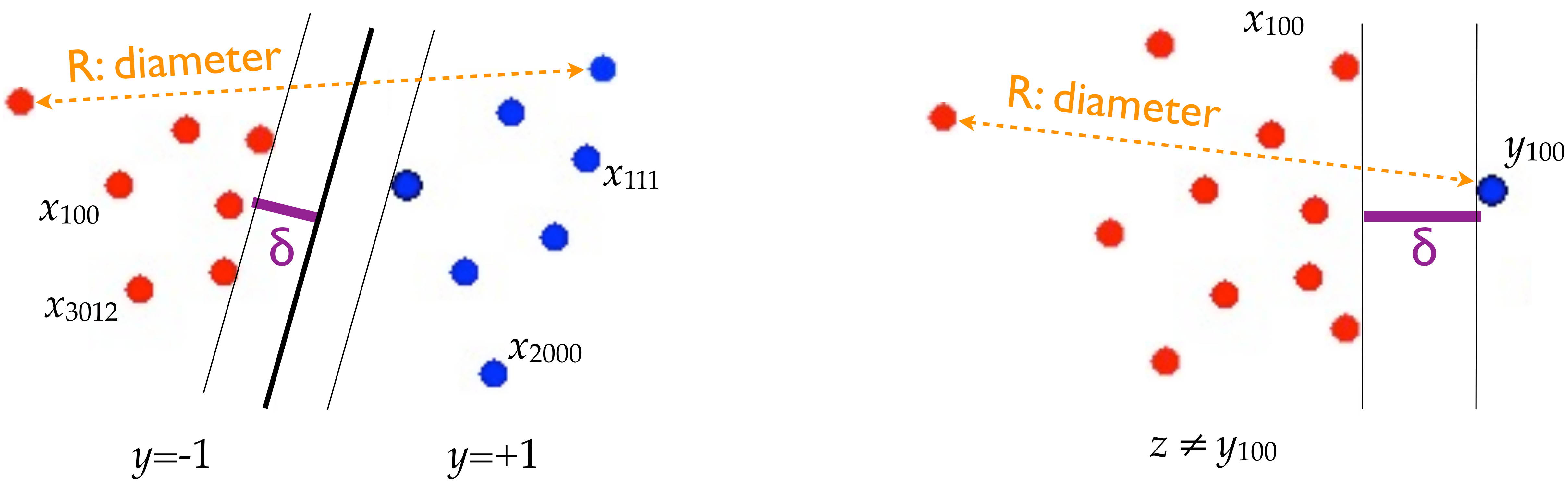
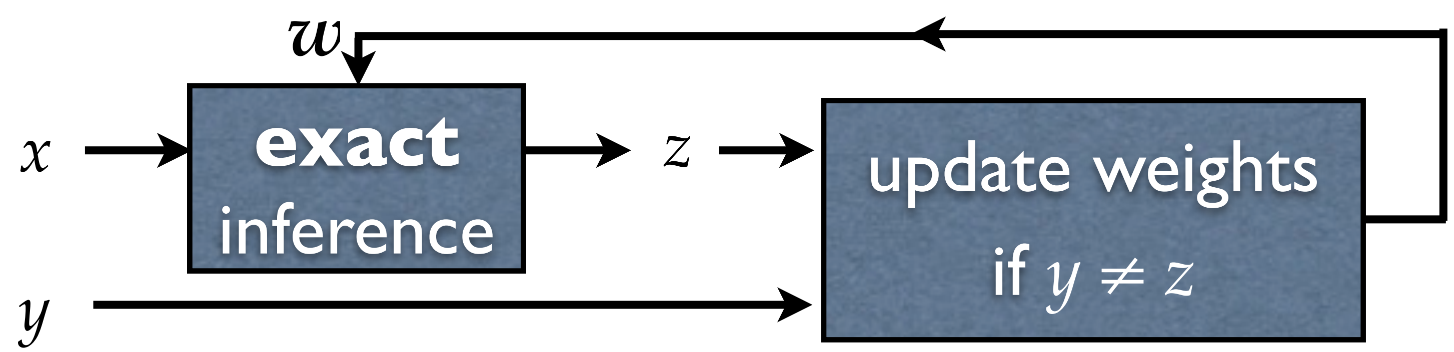
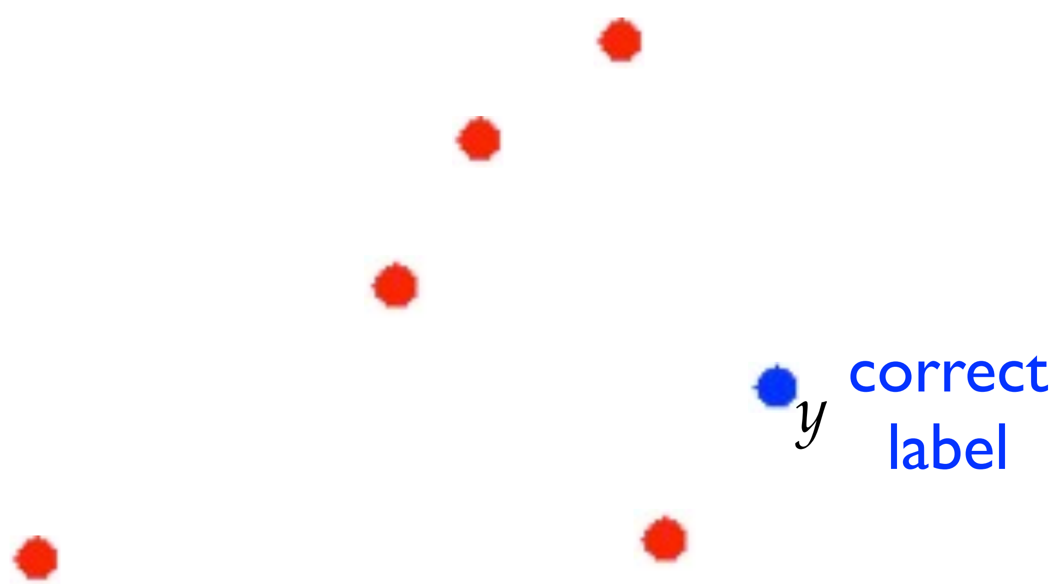


Novikoff => Freund & Schapire => Collins
1962 1999 2002

Geometry of Convergence Proof pt 1

repeat
  for each example (x, y) **in** D **do**
    $z \leftarrow \textsc{Exact}(x, \mathbf{w})$
    if $z \neq y$ **then**
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\Phi(x, y, z)$
until converged





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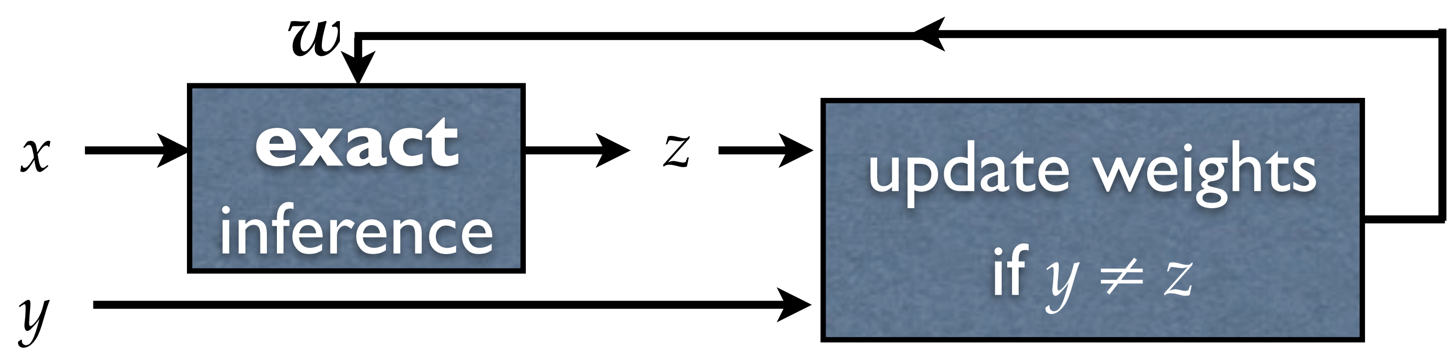

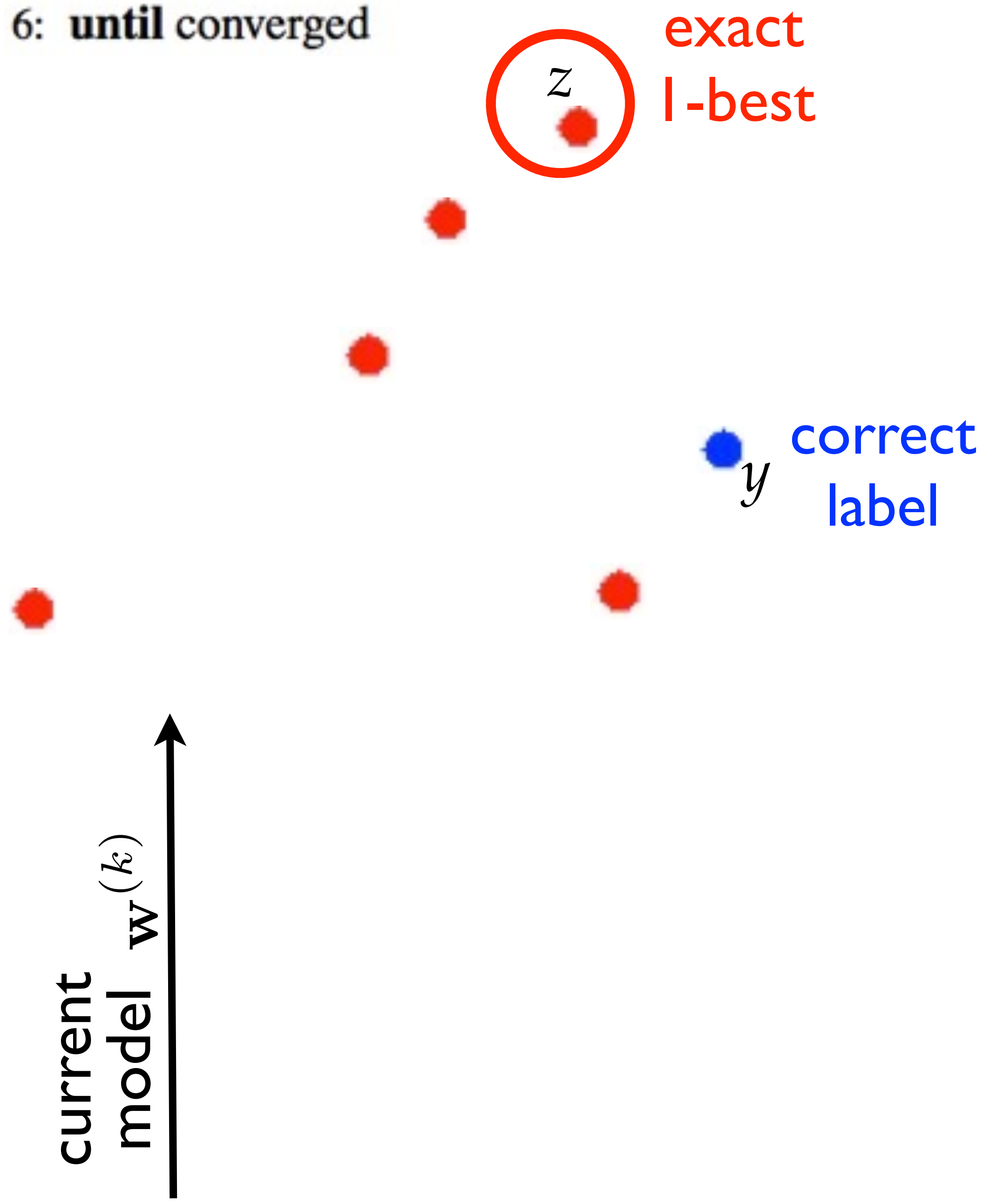

Geometry of Convergence Proof pt 1

```
repeat
    for each example (x, y) in D do
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        if z ≠ y then
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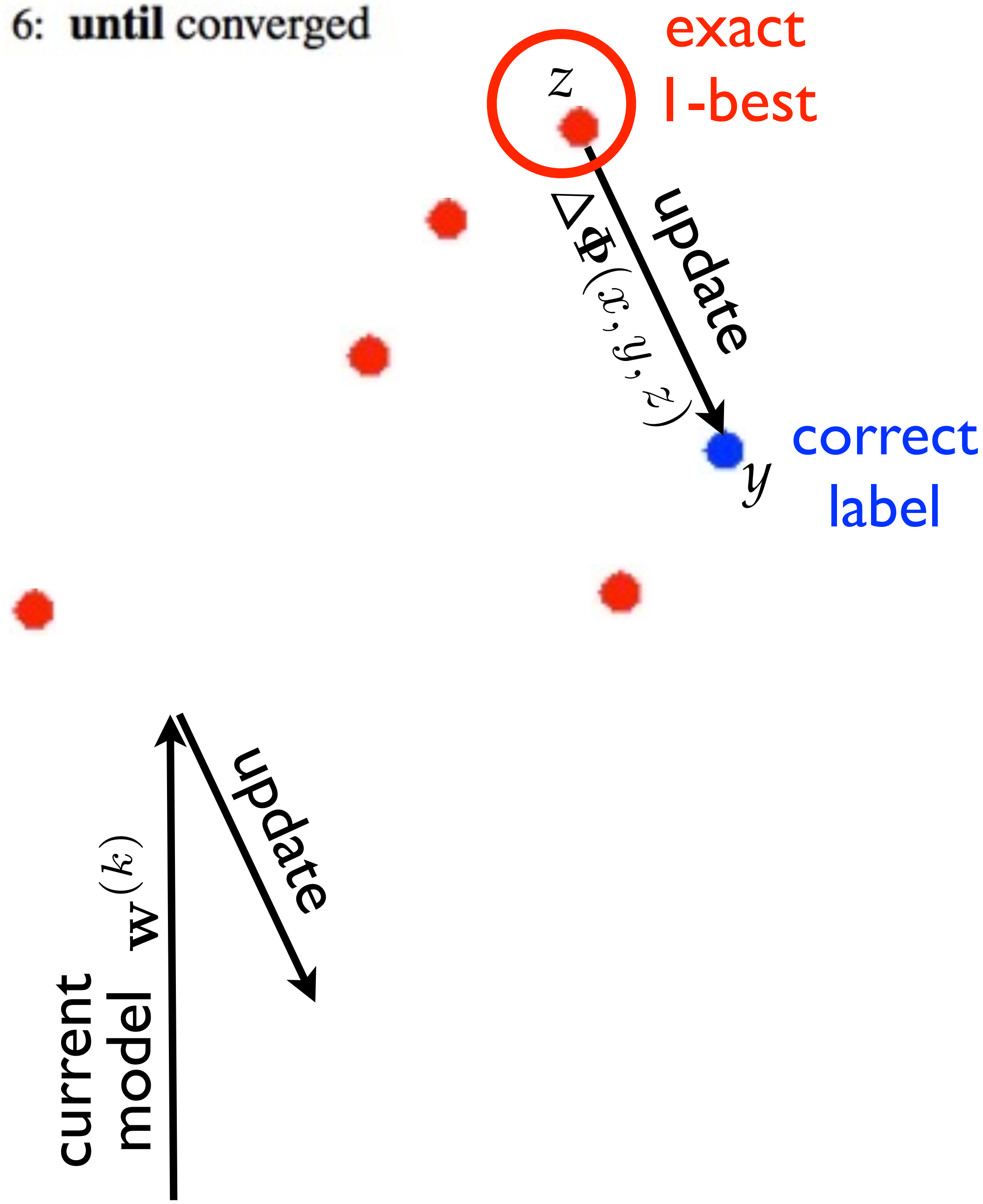
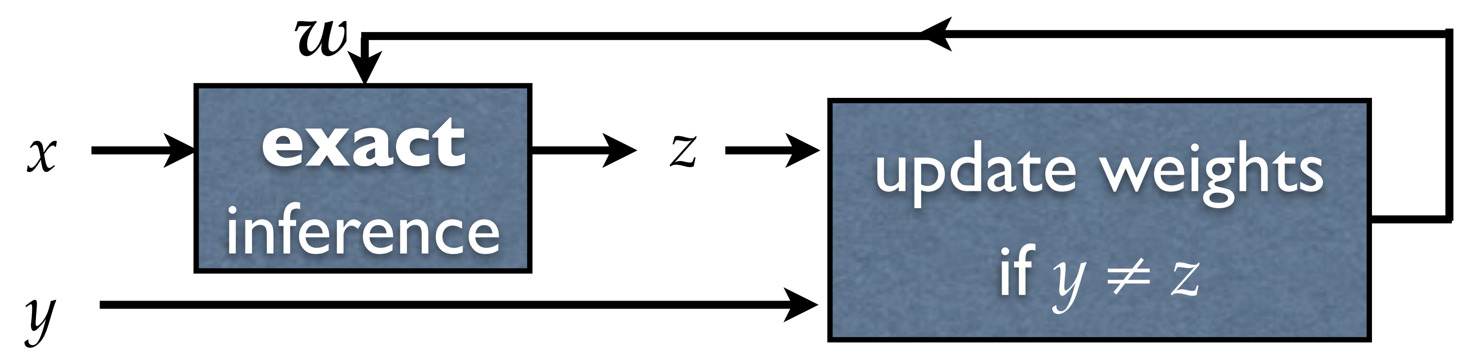
```





perceptron update:

$$\mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} + \Delta\boldsymbol{\Phi}(x, y, z)$$

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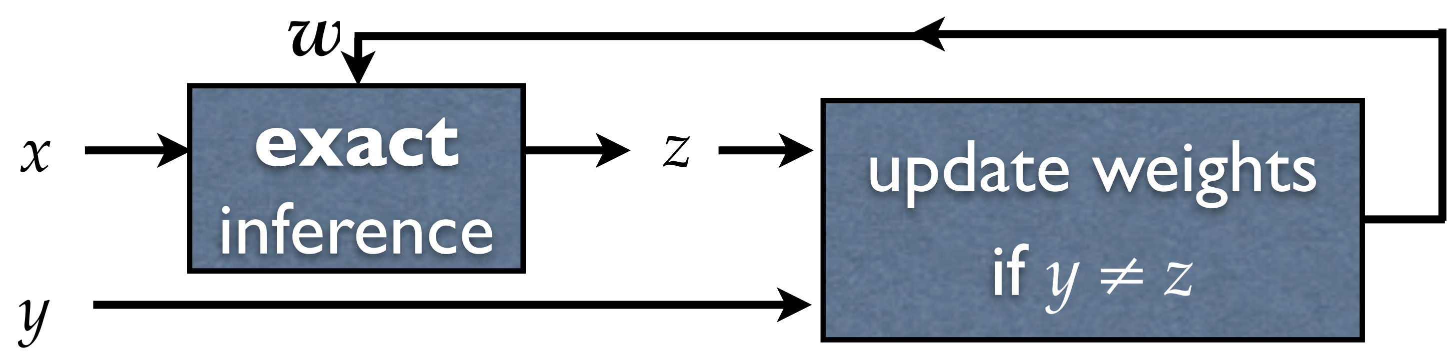

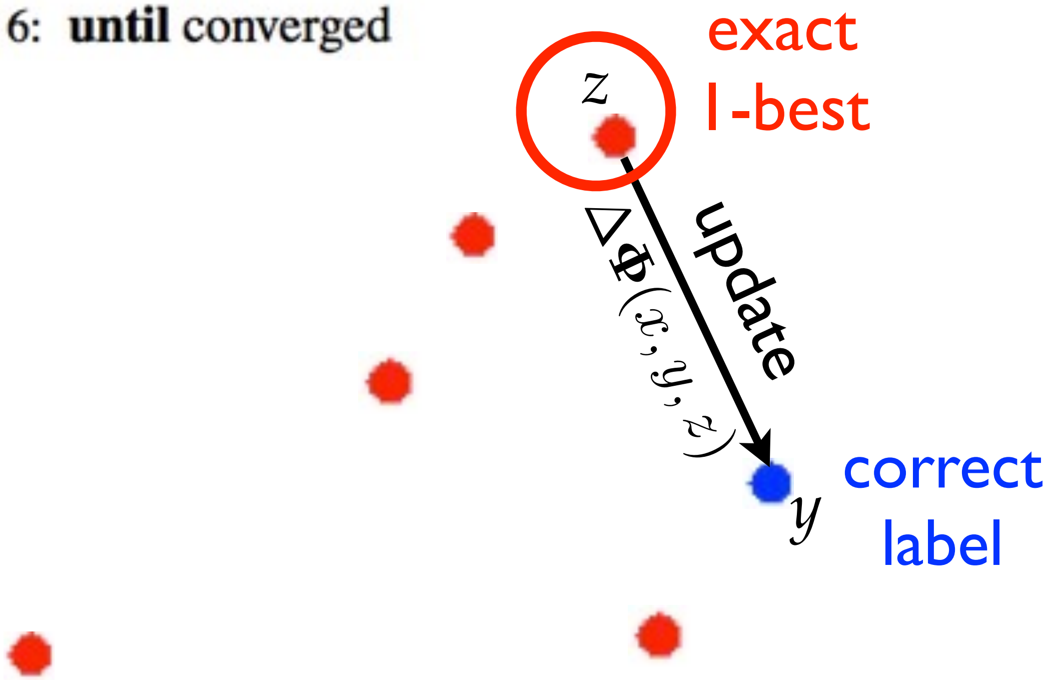

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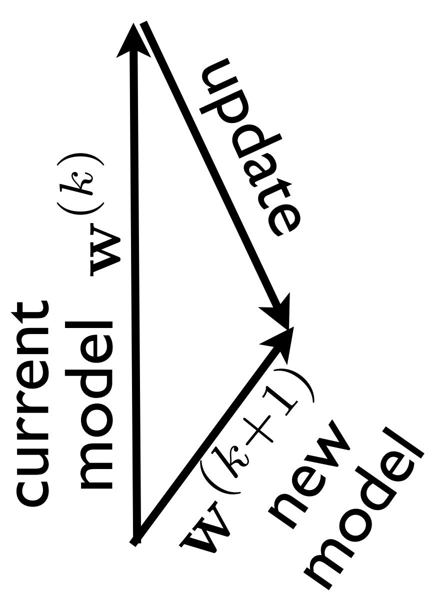

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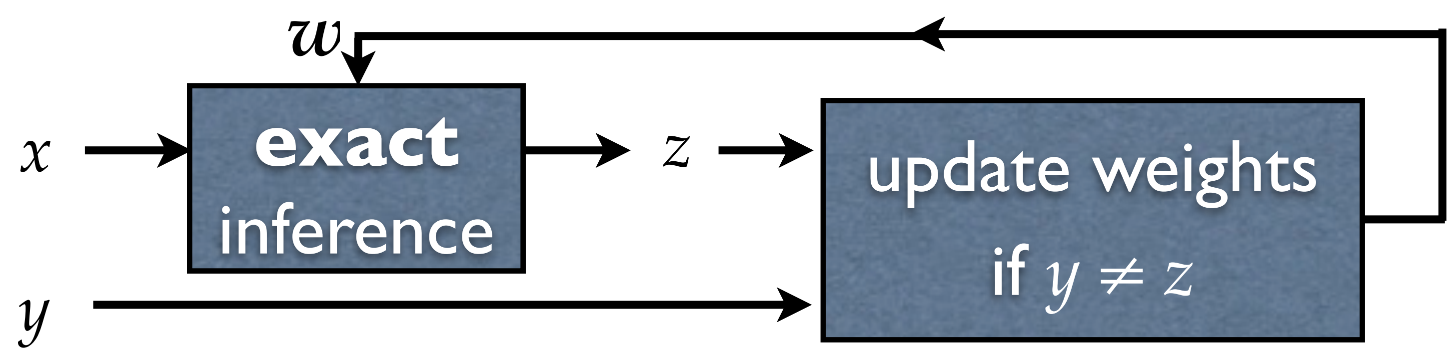

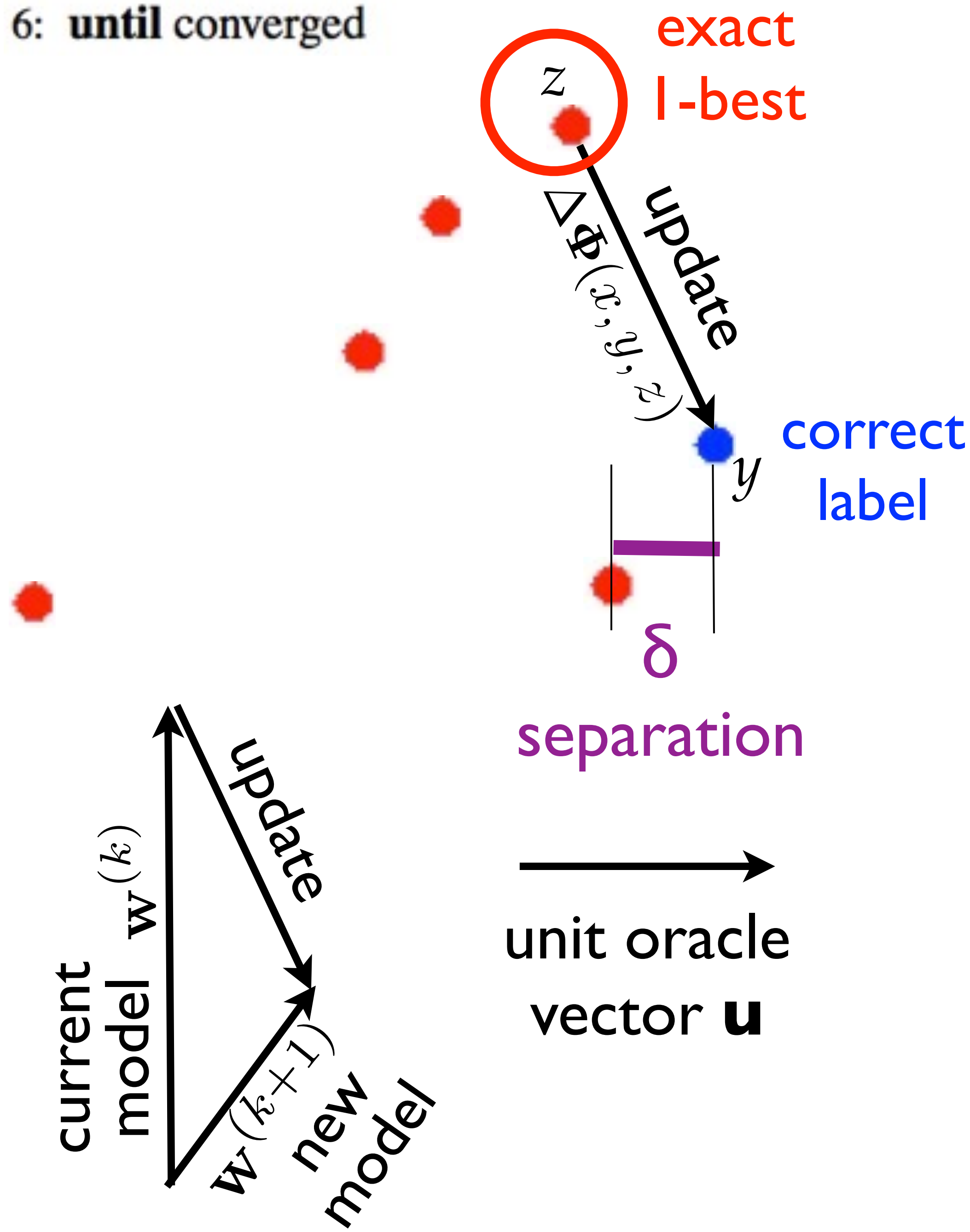

perceptron update:

$$\mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} + \Delta\mathbf{\Phi}(x, y, z)$$

$$\mathbf{u} \cdot \mathbf{w}^{(k+1)} = \mathbf{u} \cdot \mathbf{w}^{(k)} + \boxed{\mathbf{u} \cdot \Delta\mathbf{\Phi}(x, y, z) \geq \delta}$$

margin

Geometry of Convergence Proof pt 1

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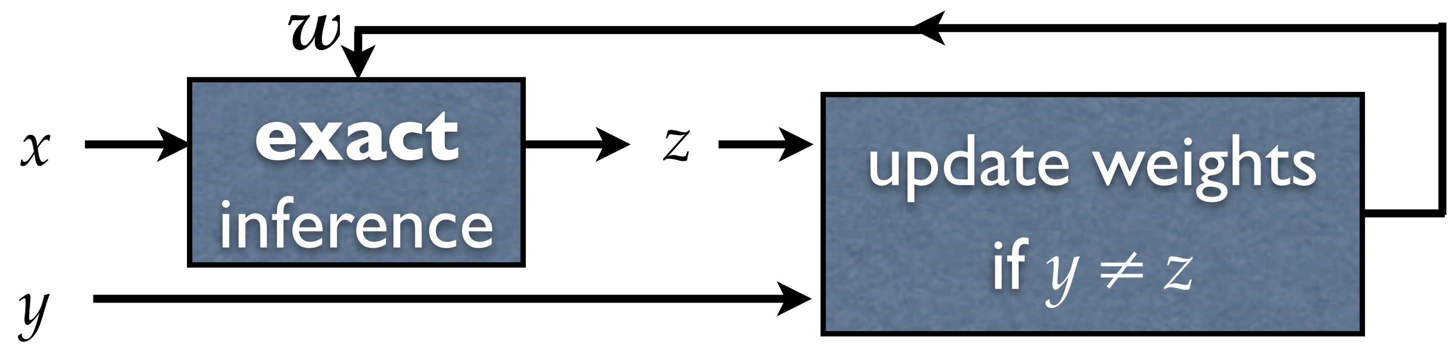

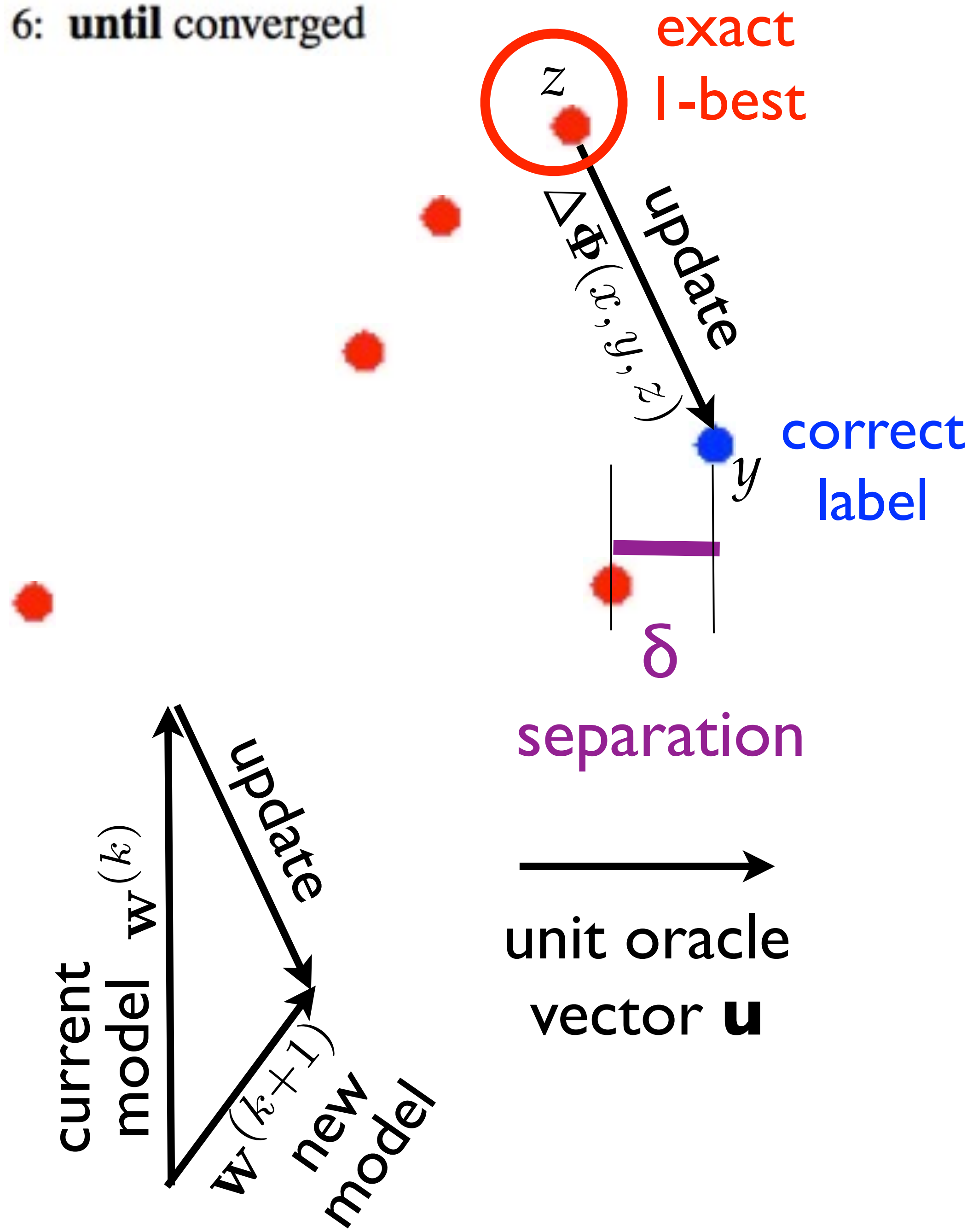

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$$\mathbf{u} \cdot \mathbf{w}^{(k+1)} \geq k\delta \qquad \text{(by induction)}$$

$$\|\mathbf{w}^{k+1}\| \geq k\delta \qquad \text{(part 1: lowerbound)}$$

Geometry of Convergence Proof pt 2

repeat
  for each example (x, y) **in** D **do**
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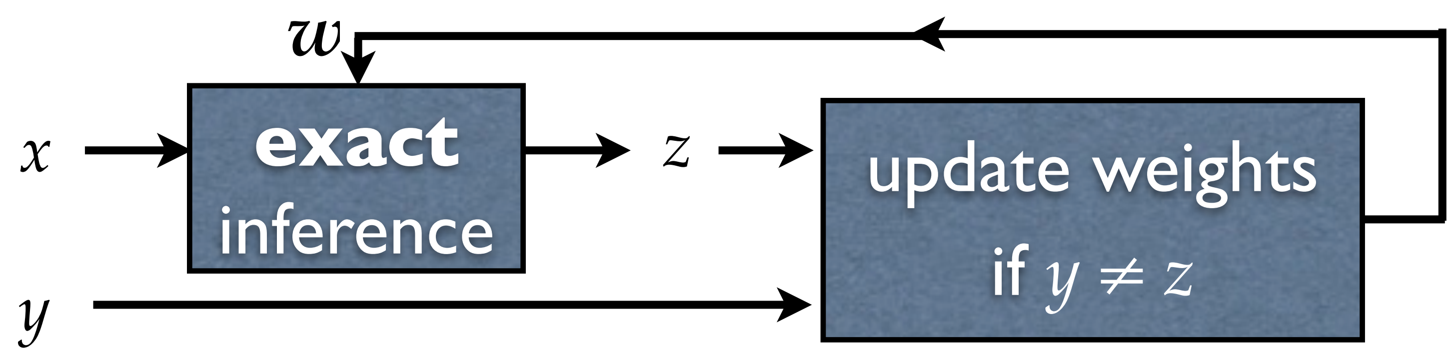

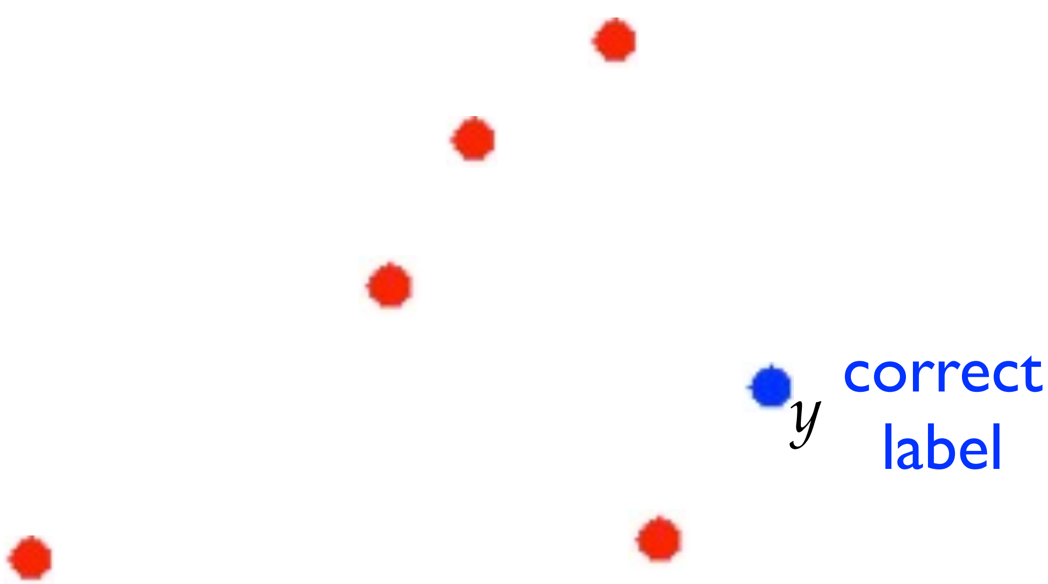

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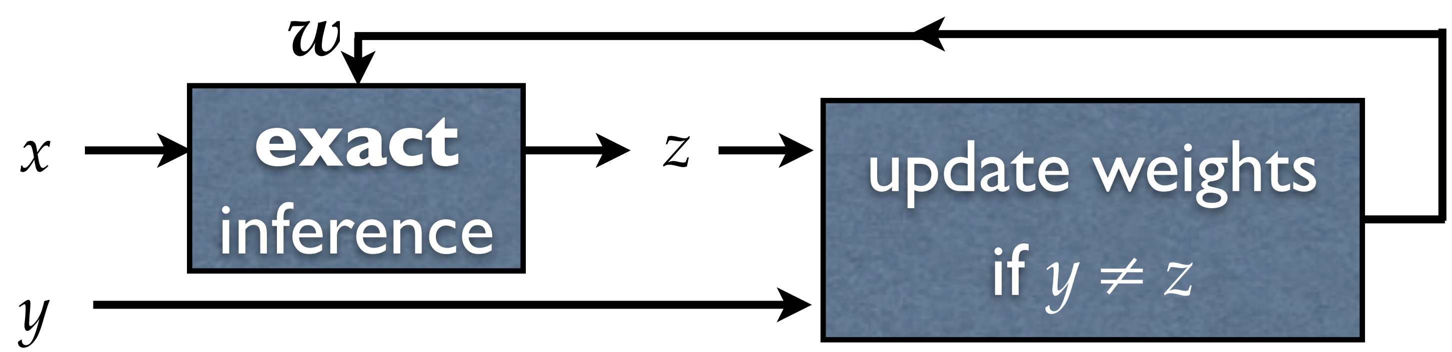

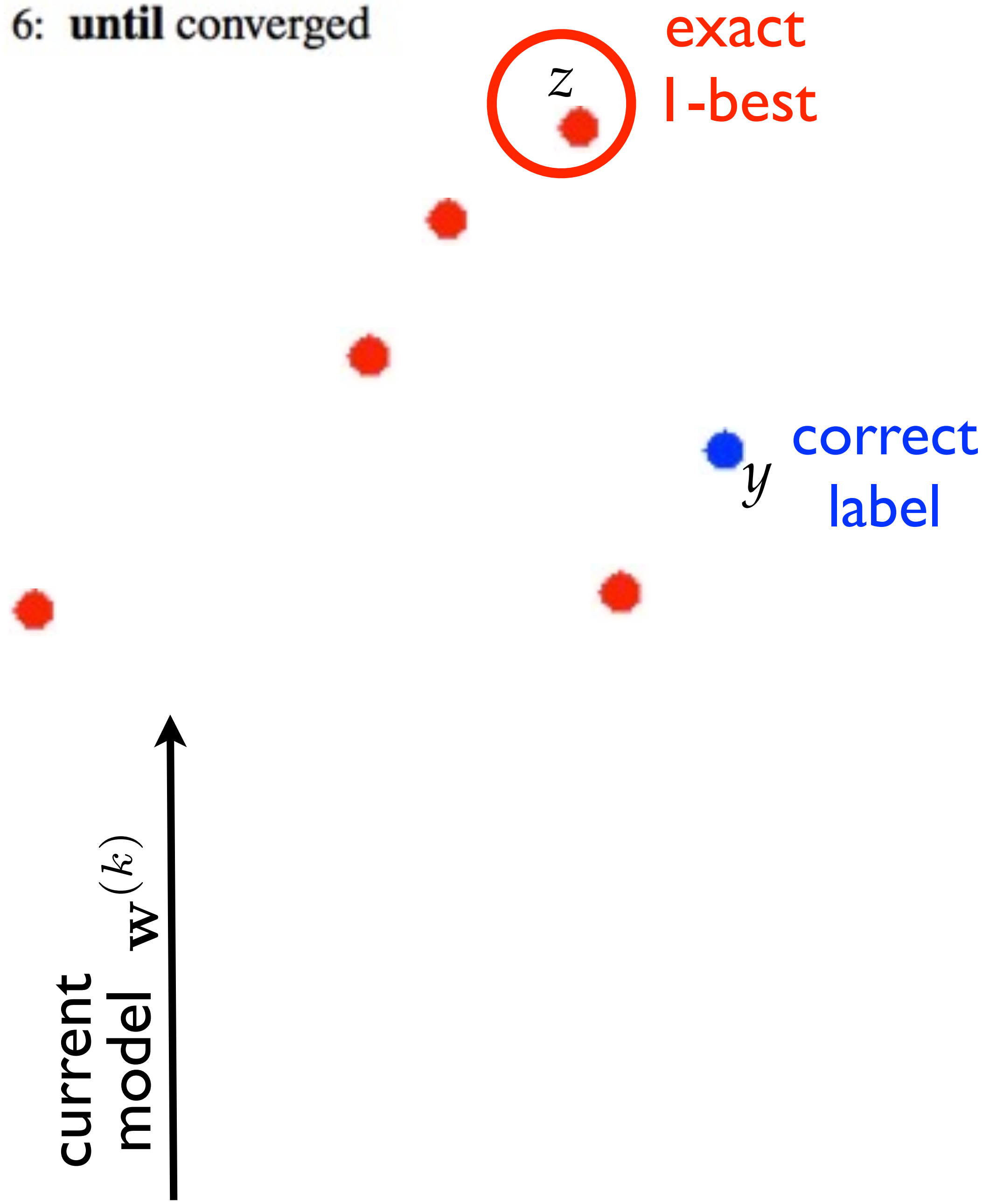

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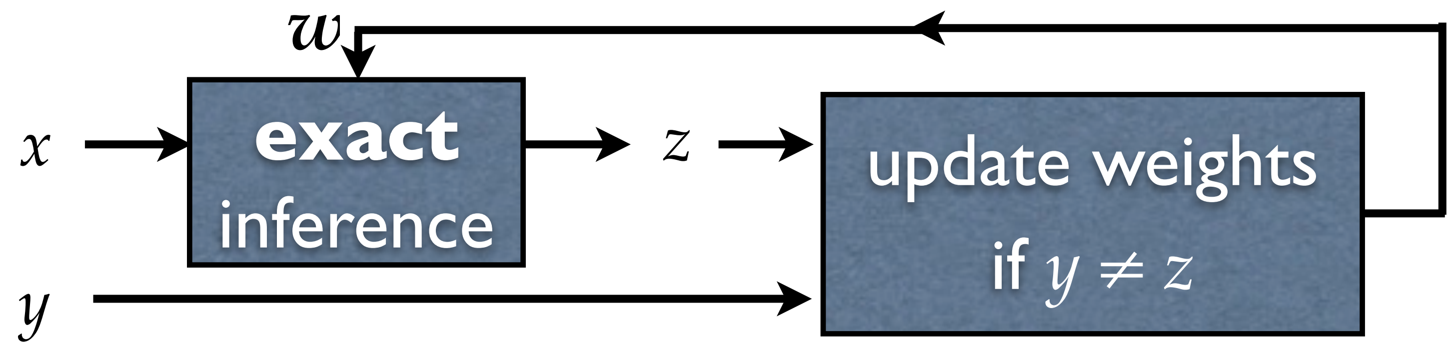

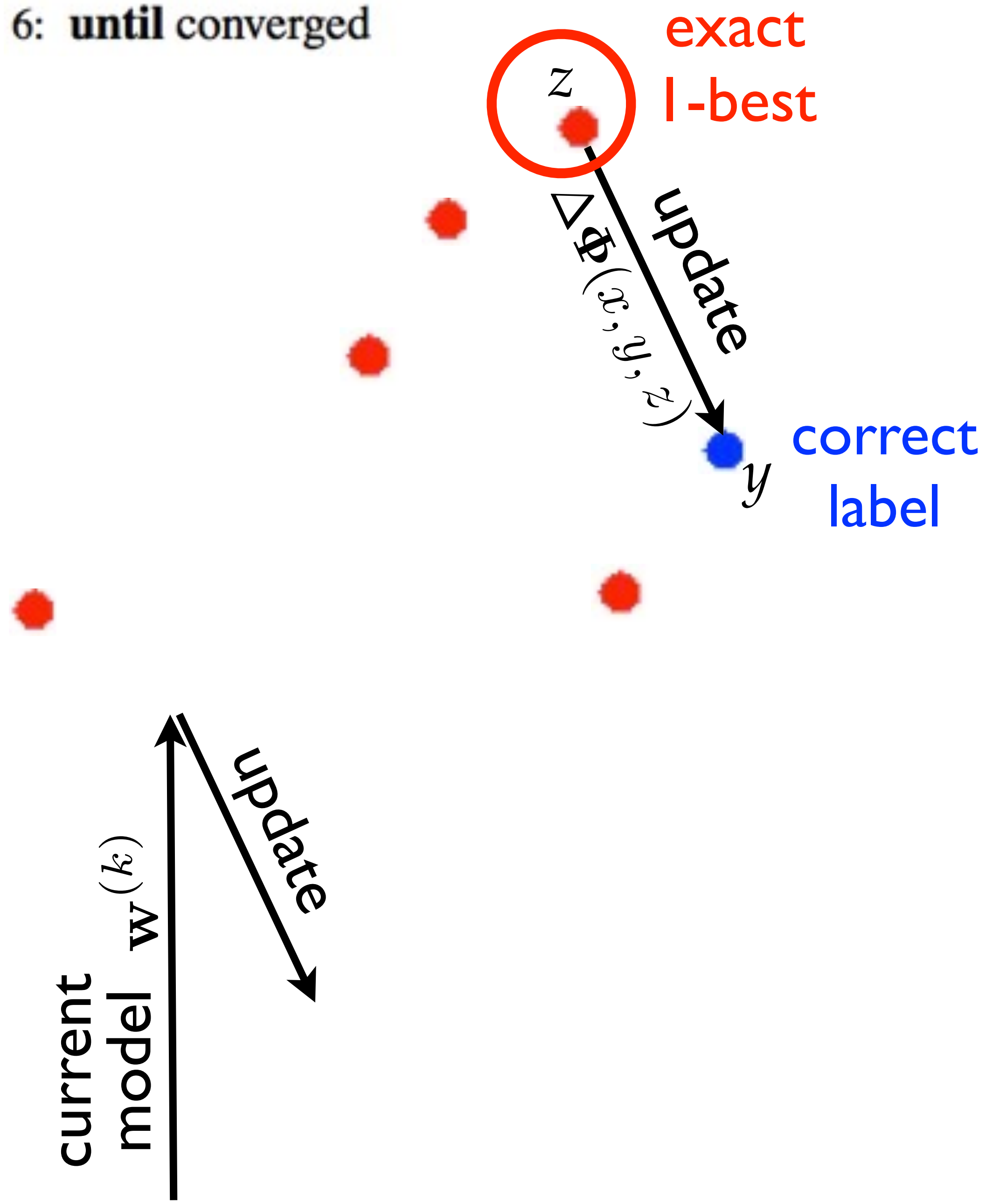

perceptron update:

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Geometry of Convergence Proof pt 2

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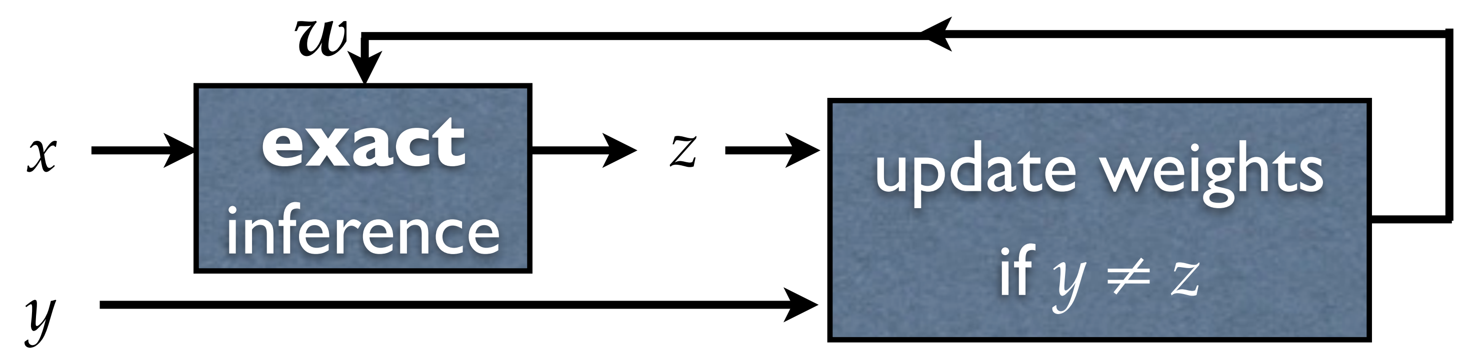

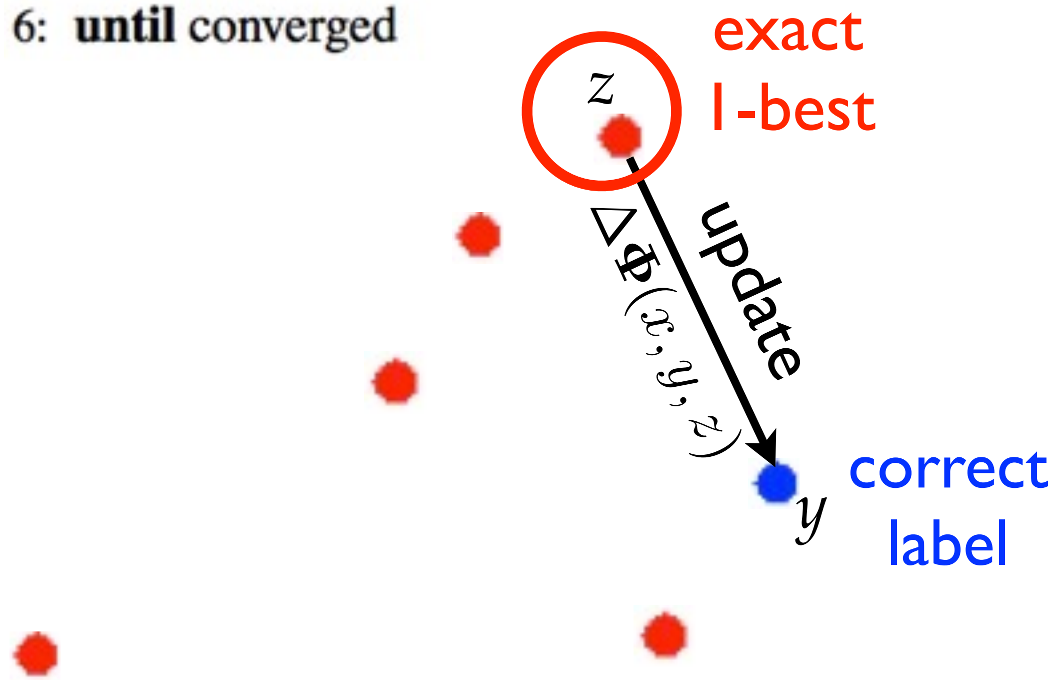

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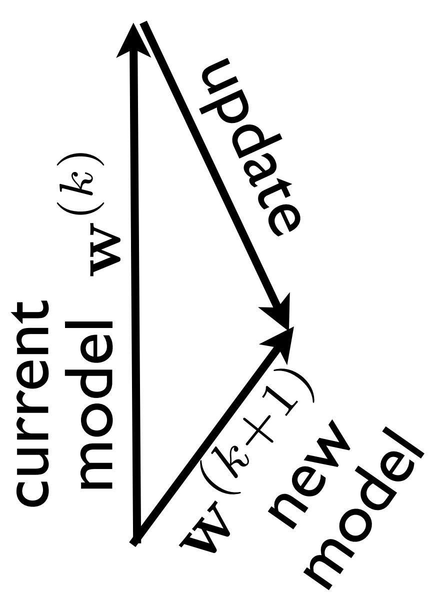

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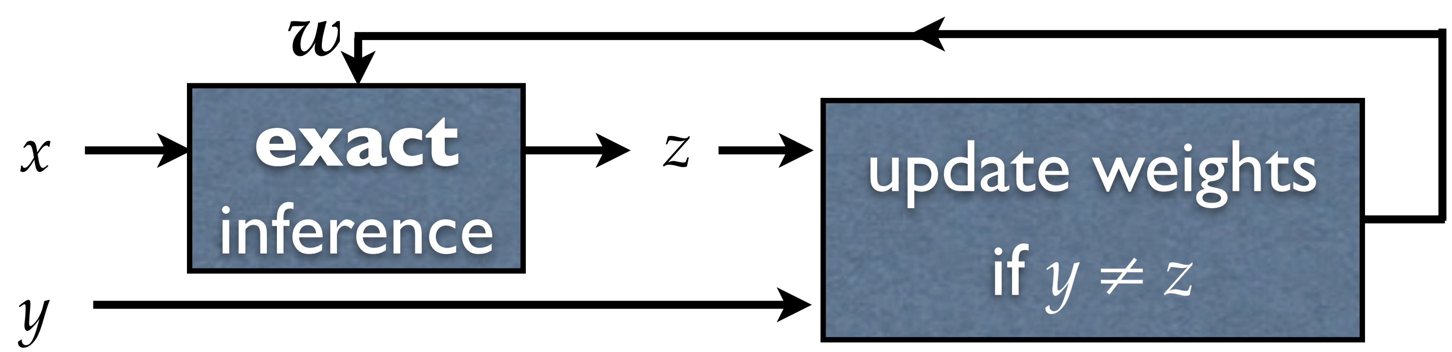

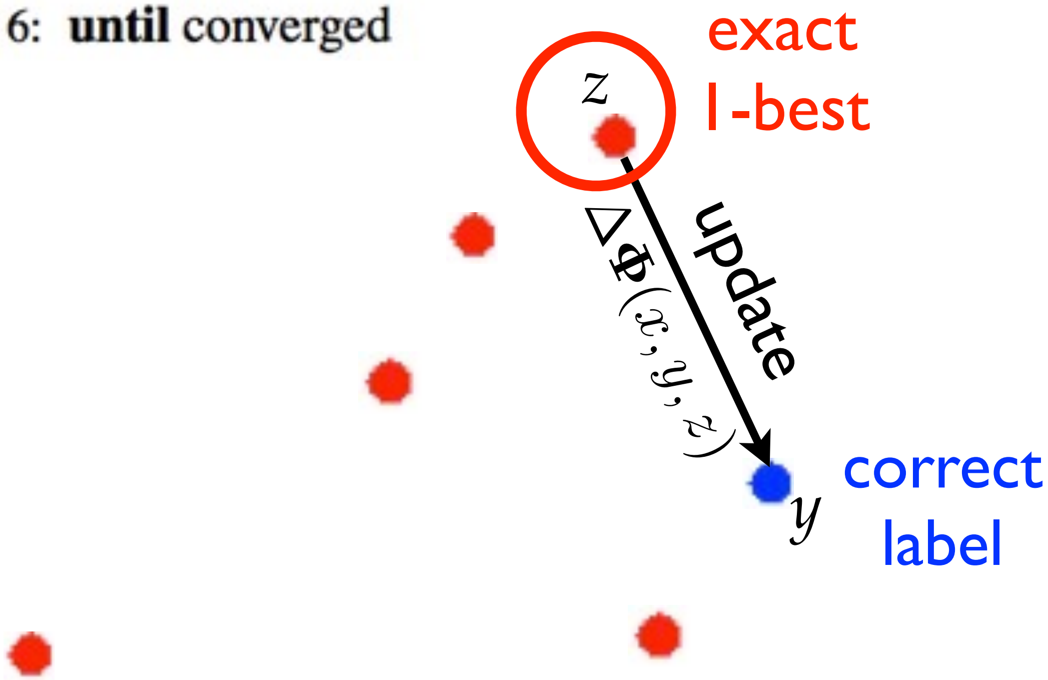

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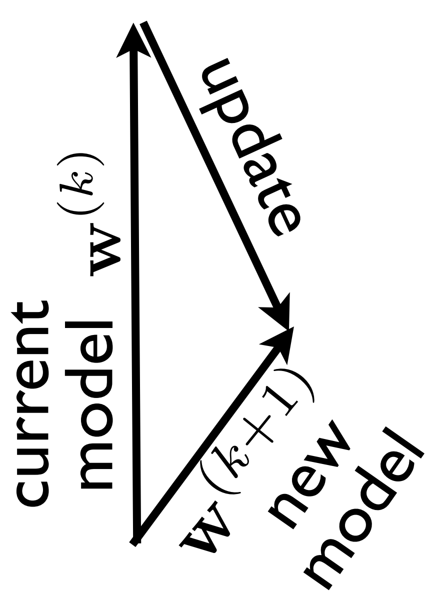
$$\|\mathbf{w}^{(k+1)}\|^2 = \|\mathbf{w}^{(k)} + \Delta\mathbf{\Phi}(x, y, z)\|^2$$



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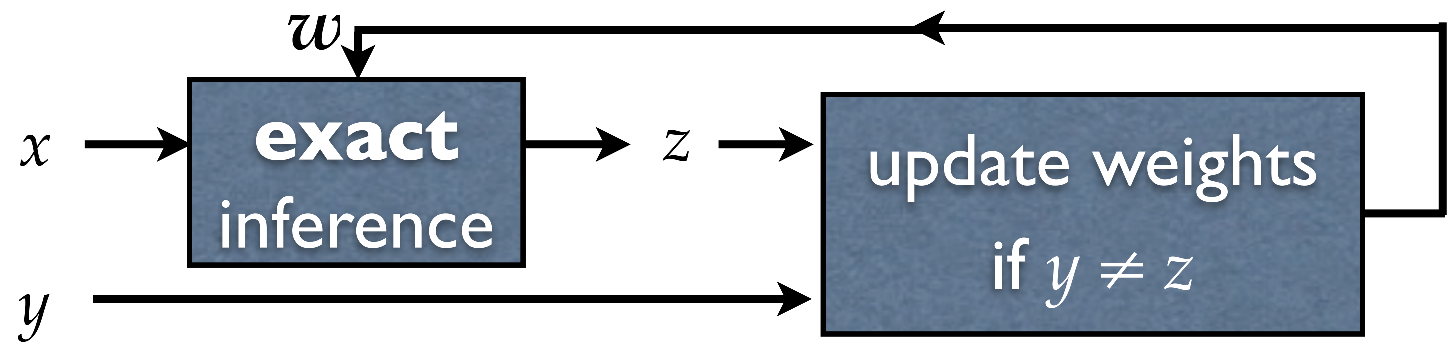

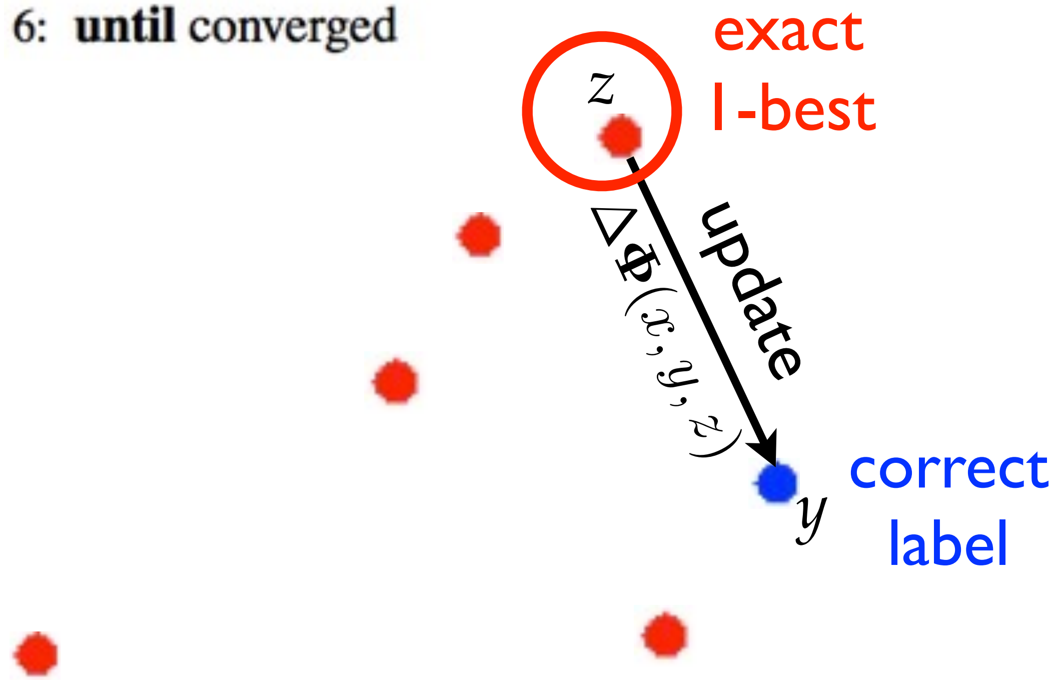

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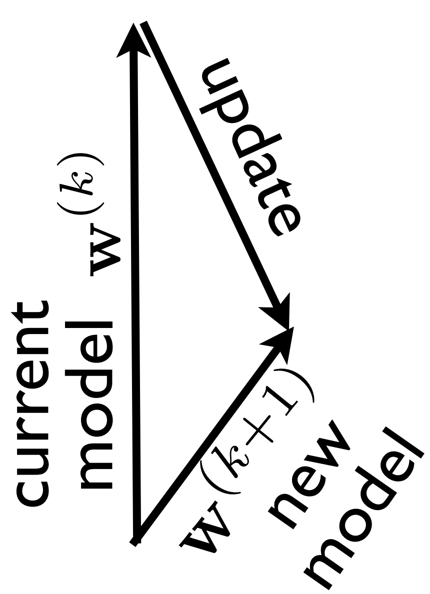
$$= \|\mathbf{w}^{(k)}\|^2 + \|\Delta\mathbf{\Phi}(x, y, z)\|^2$$



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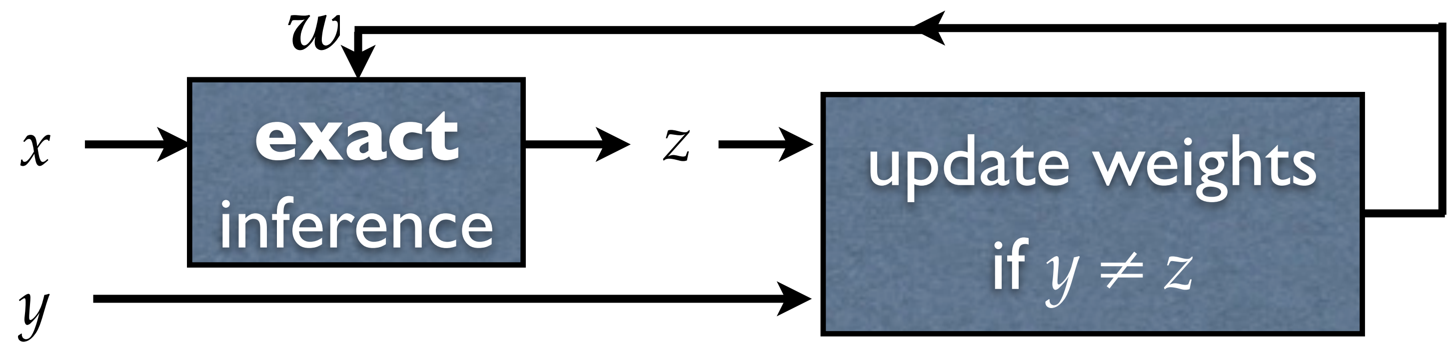
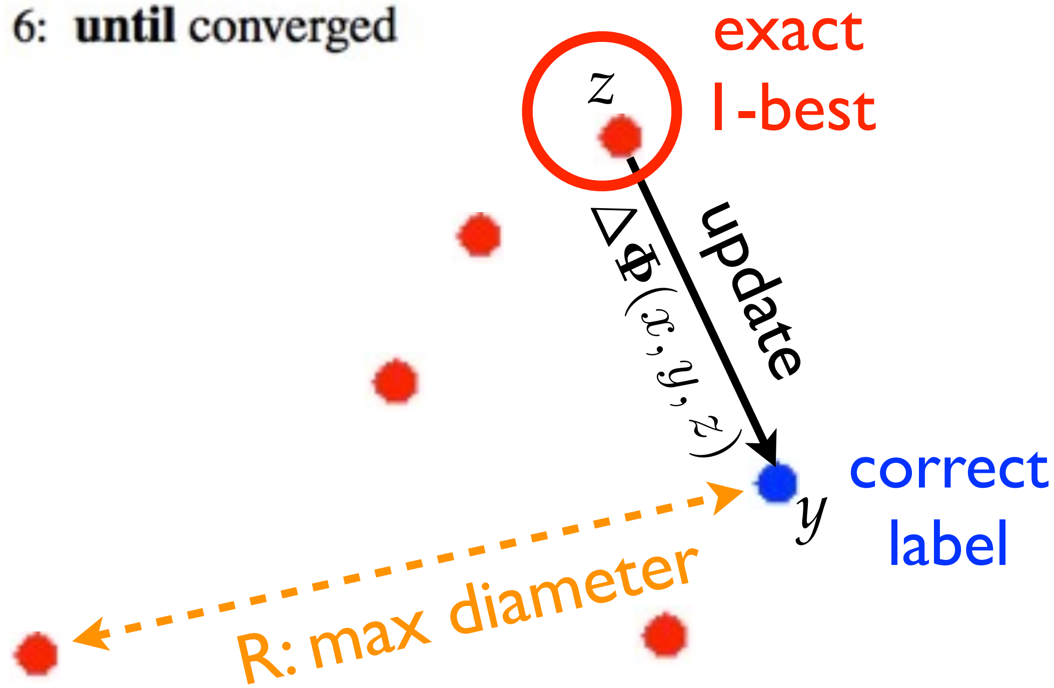
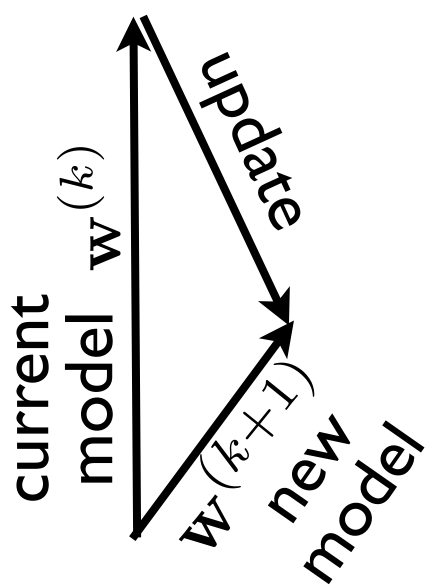
until converged
```







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diameter

Geometry of Convergence Proof pt 2

repeat
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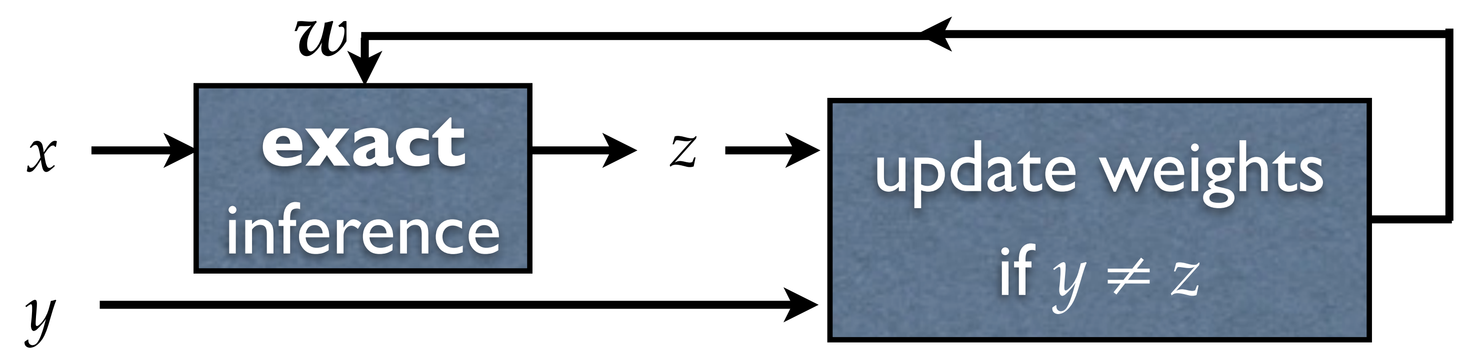

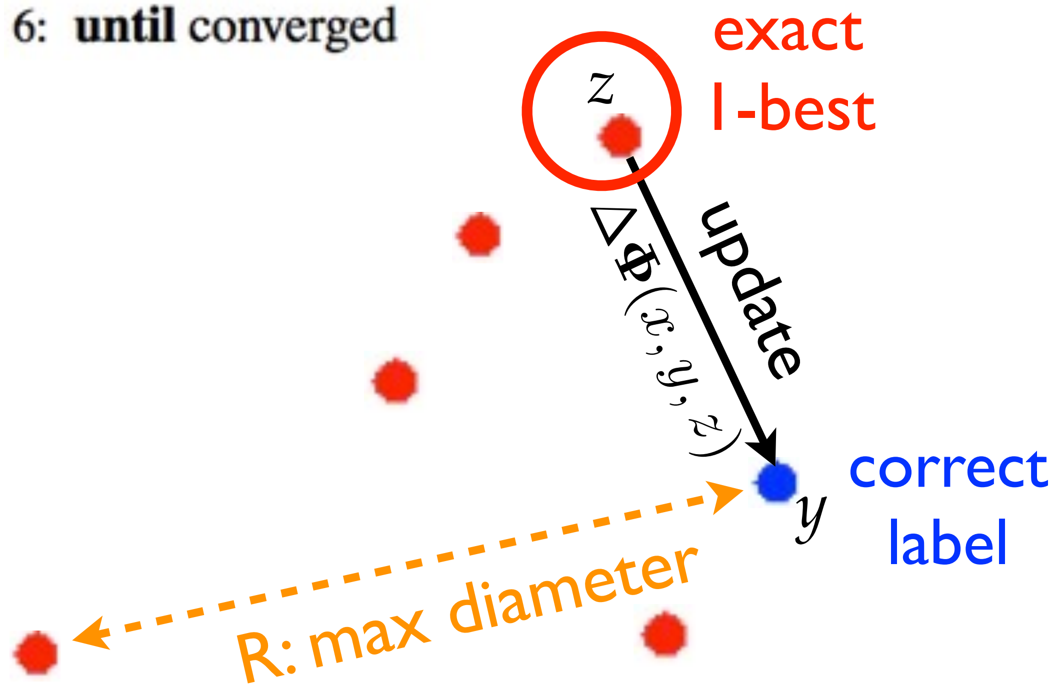

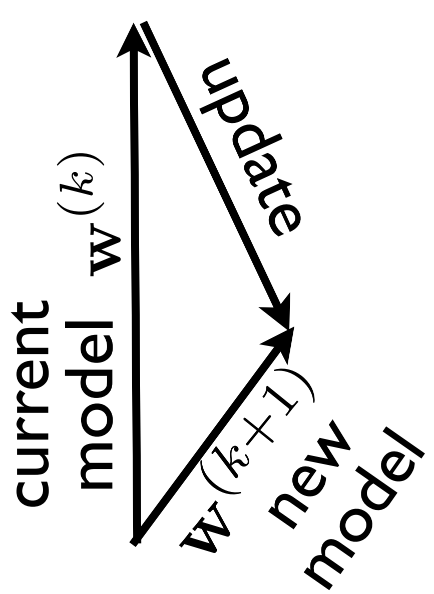

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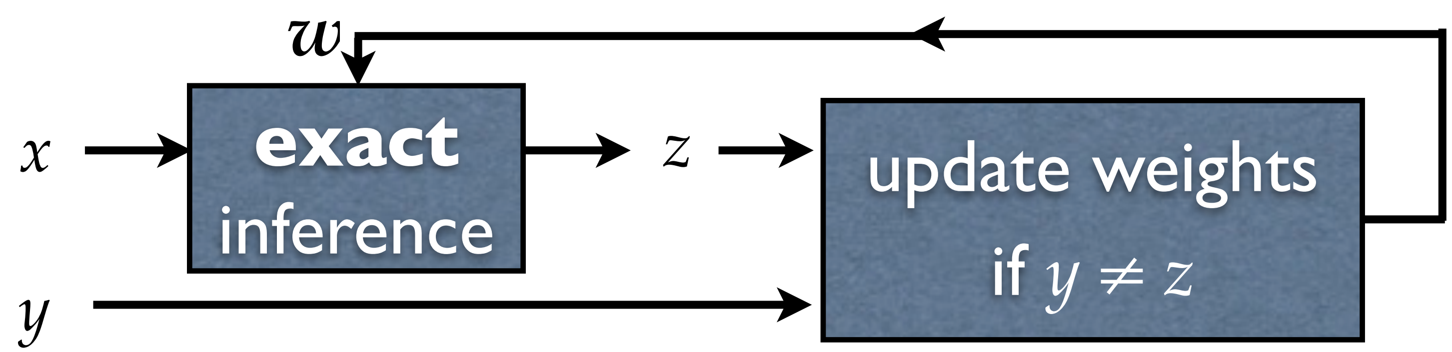
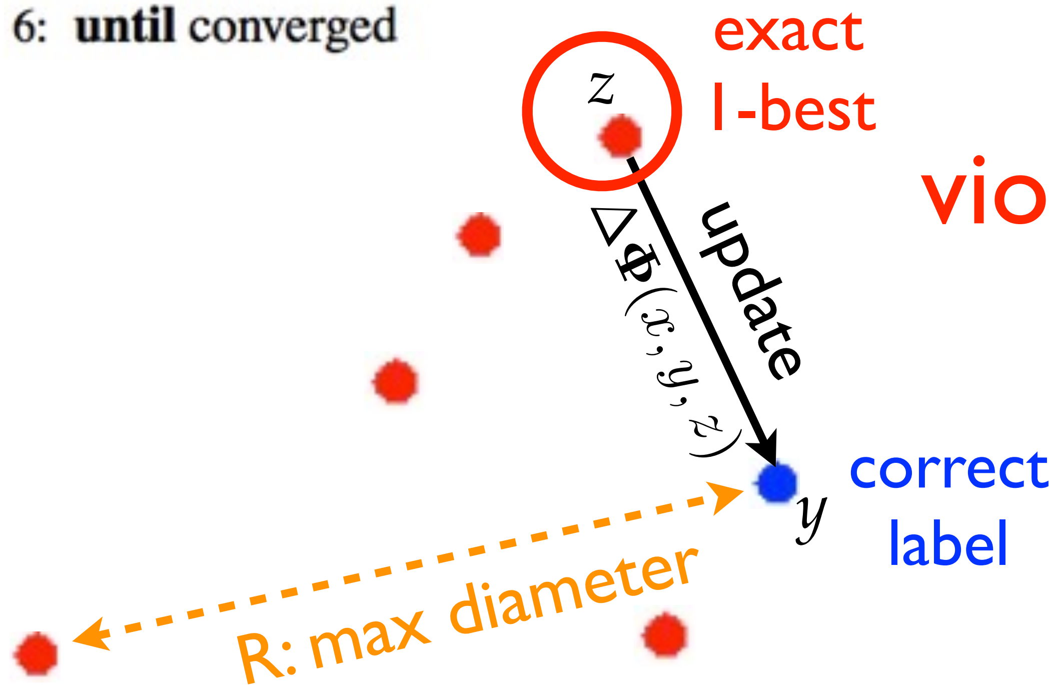
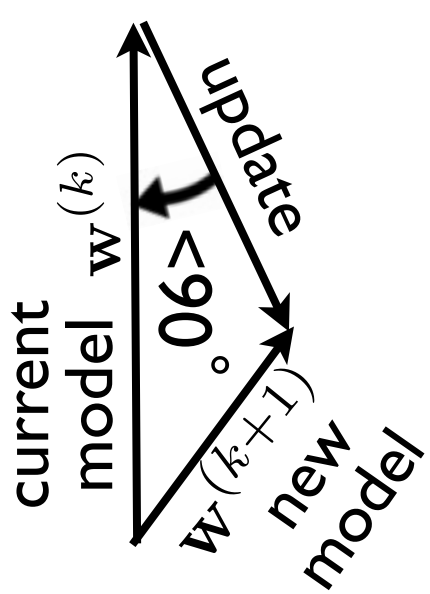




violation: incorrect label scored higher



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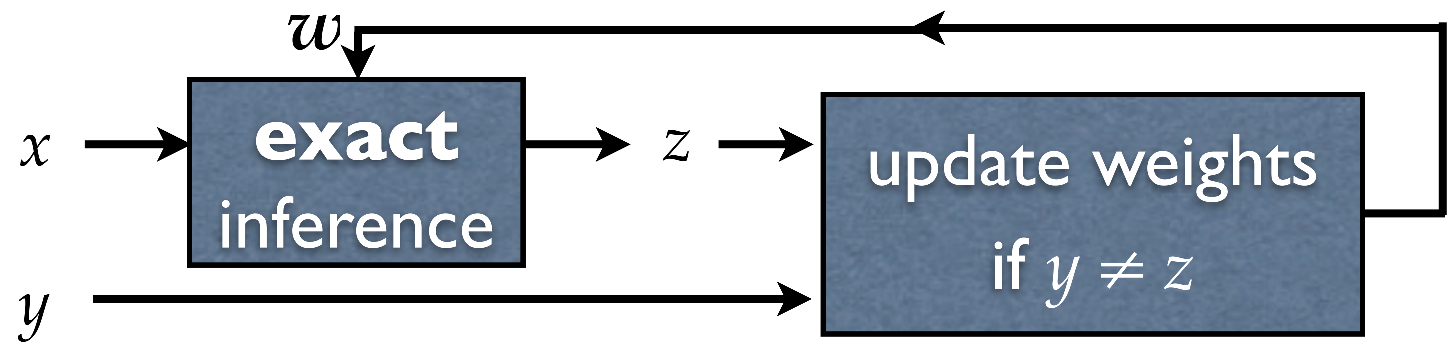

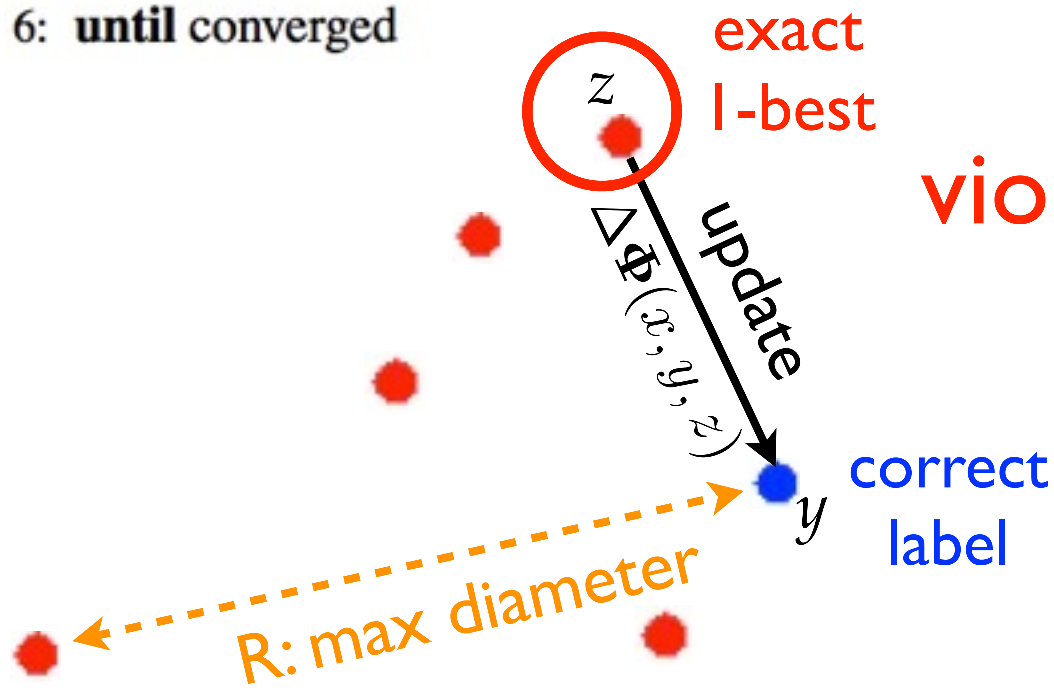

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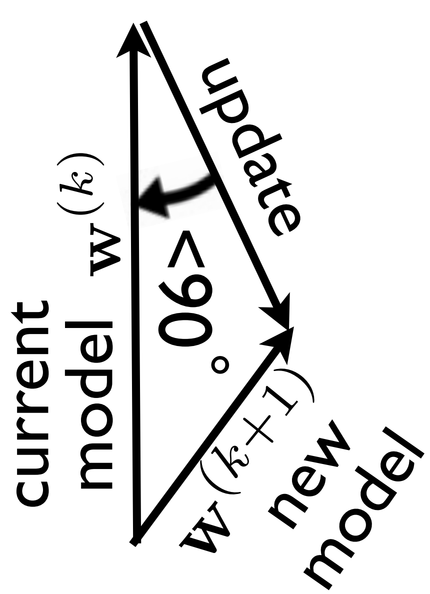

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$\|\mathbf{w}^{k+1}\| \leq \sqrt{k}R$

(part 2: upperbound)

Geometry of Convergence Proof pt 2

1: **repeat**
2: **for each** example (x, y) **in** D **do**
3: $z \leftarrow \text{EXACT}(x, \mathbf{w})$
4: **if** $z \neq y$ **then**
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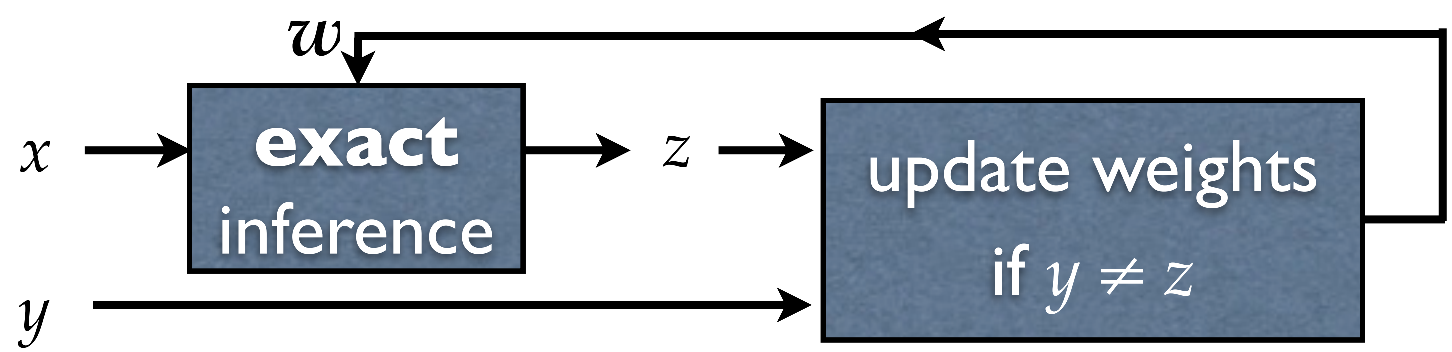
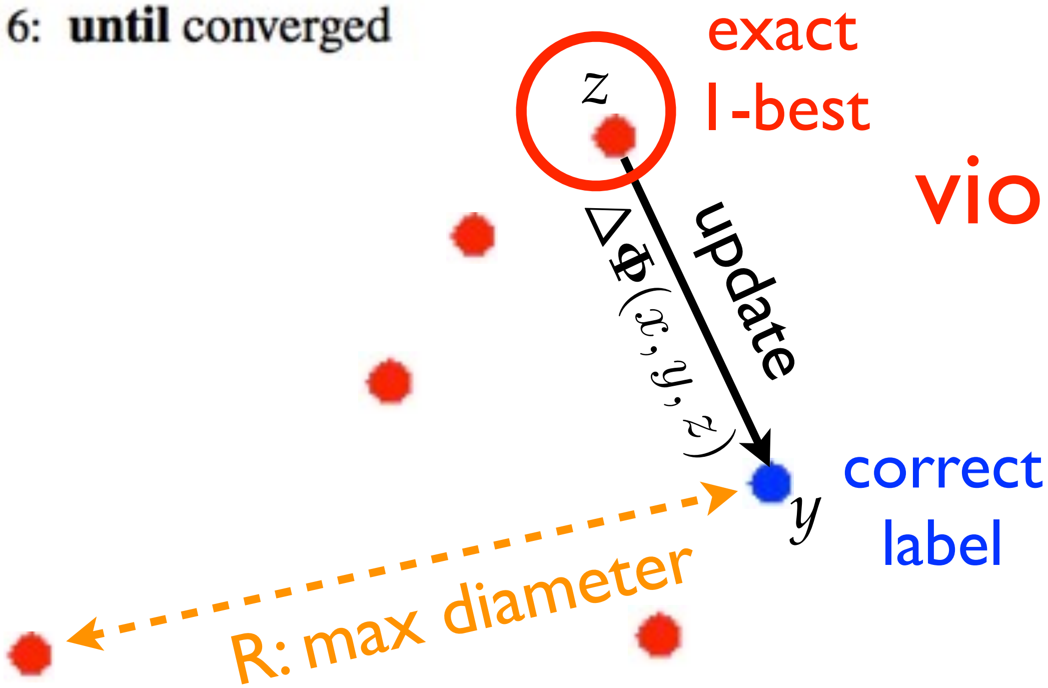
6: **until** converged





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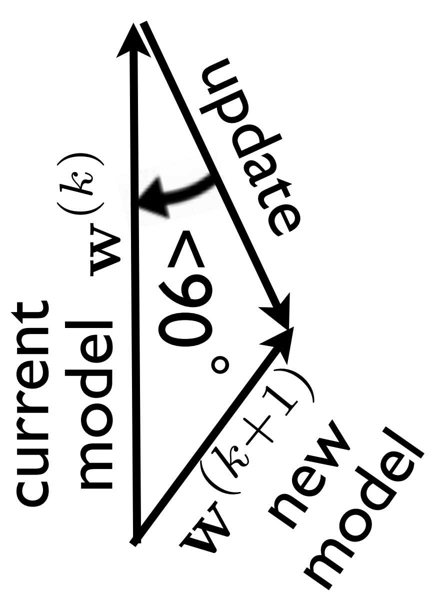

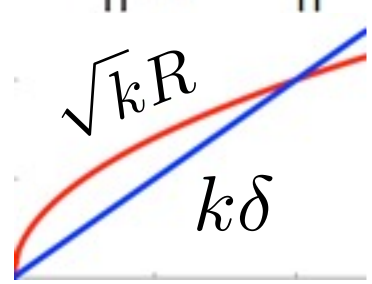

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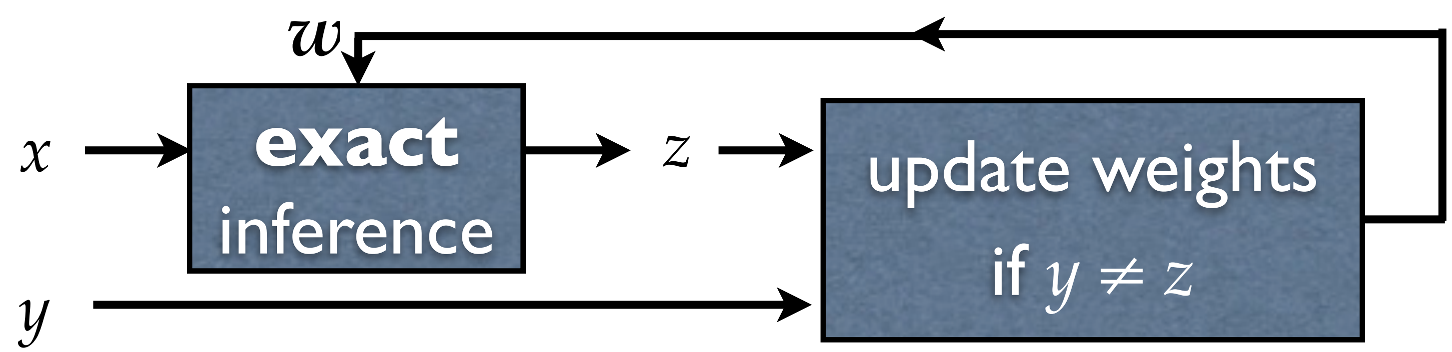

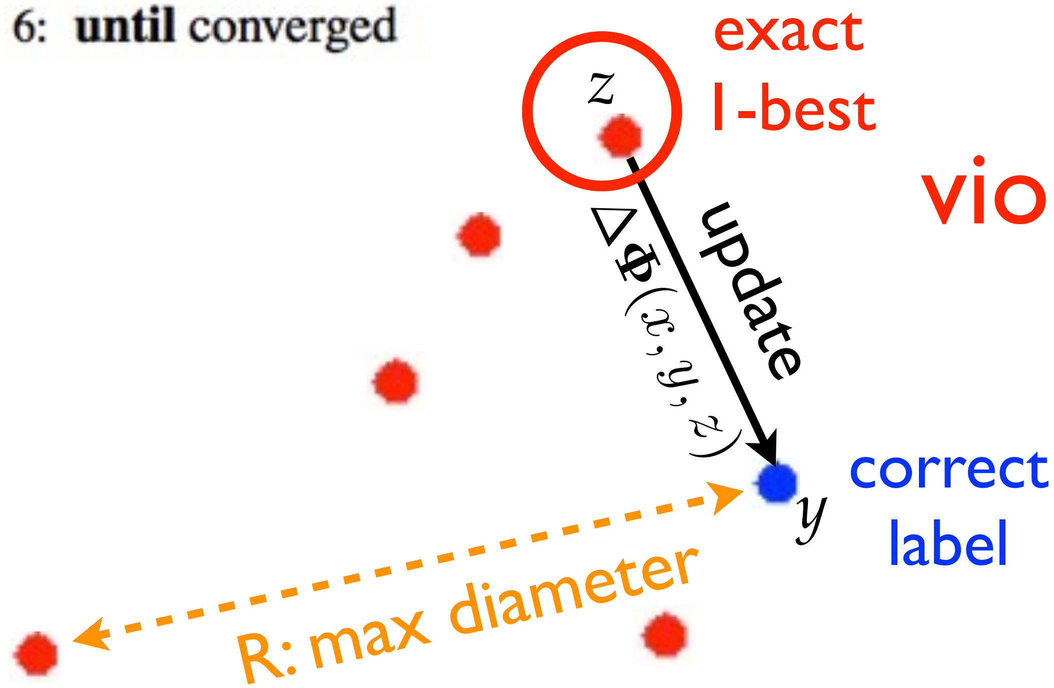

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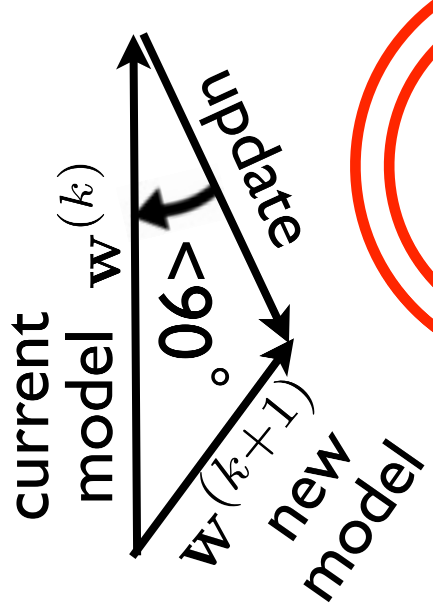

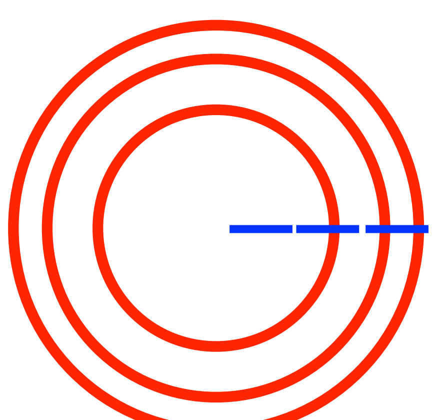

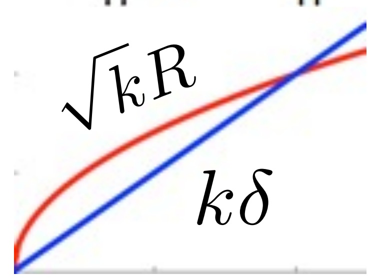

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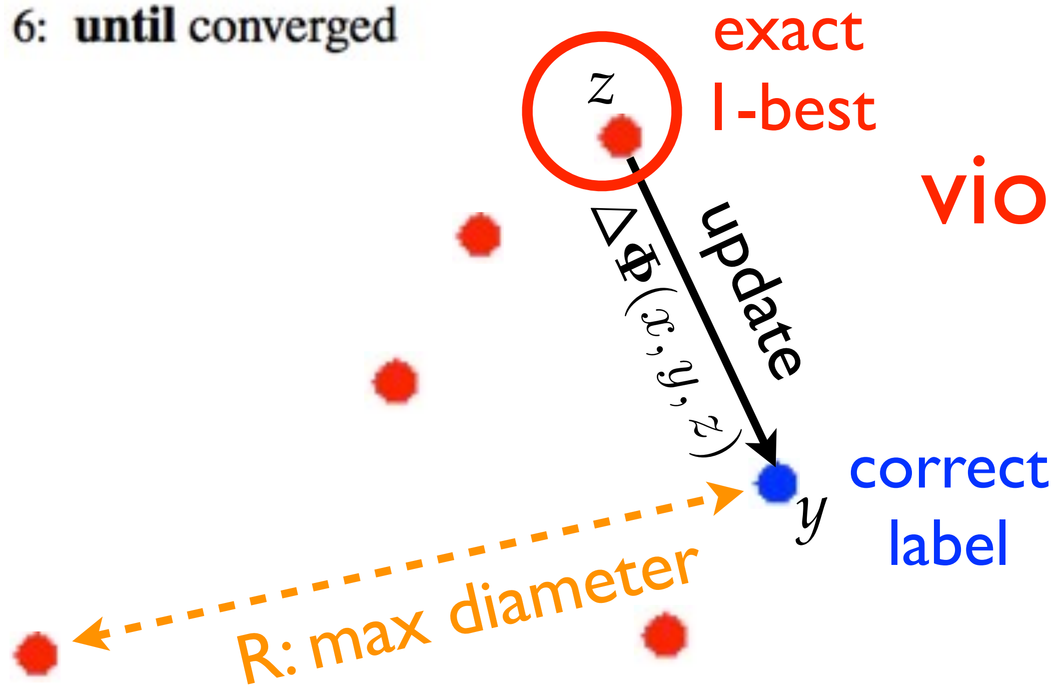
summary: the proof uses 3 facts:

1. separation (margin)
2. diameter (always finite)
3. violation (guaranteed by exact search)



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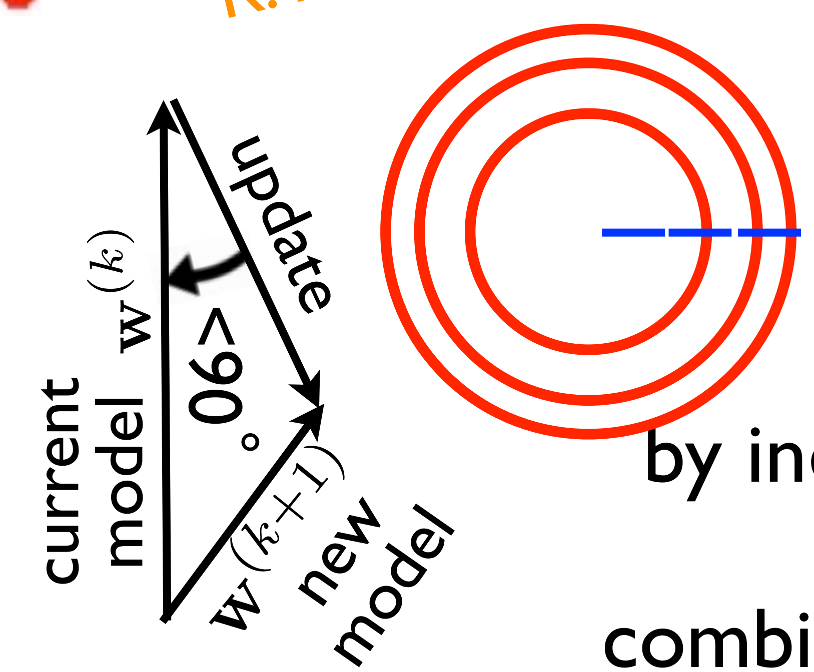

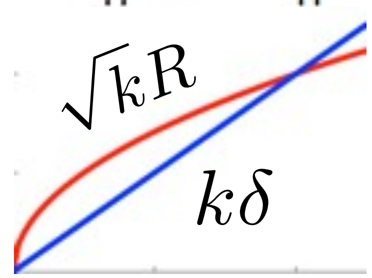

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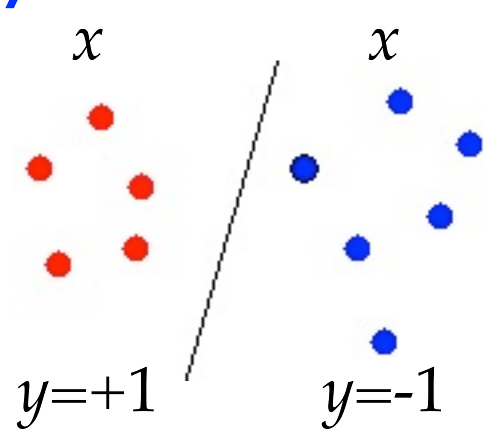
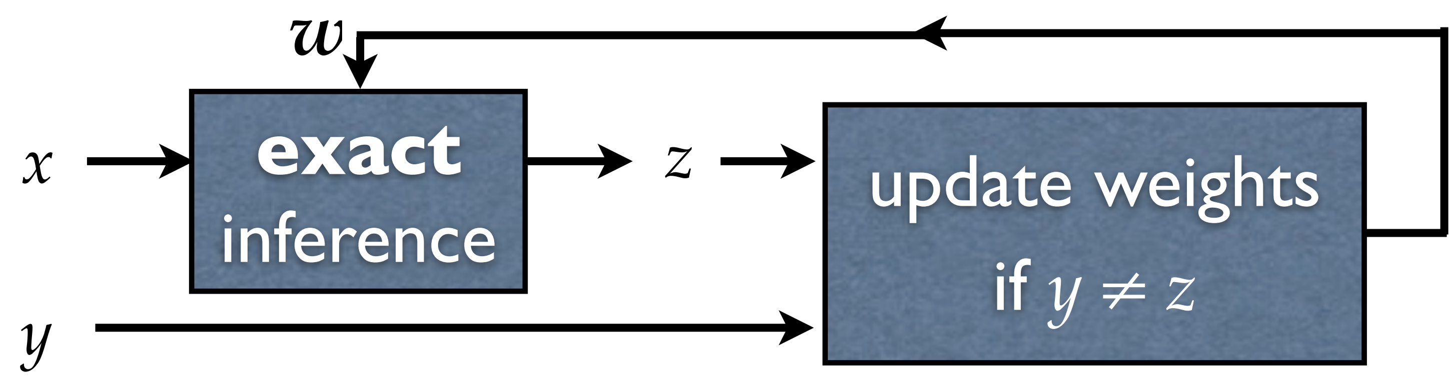
Tutorial Outline

- Overview of Structured Learning
  - Challenges in Scalability
- Structured Perceptron
  - convergence proof
- Structured Perceptron with Inexact Search
- Latent-Variable Perceptron
- Parallelizing Online Learning (Perceptron & MIRA)

Scalability Challenge 1: Inference

binary classification





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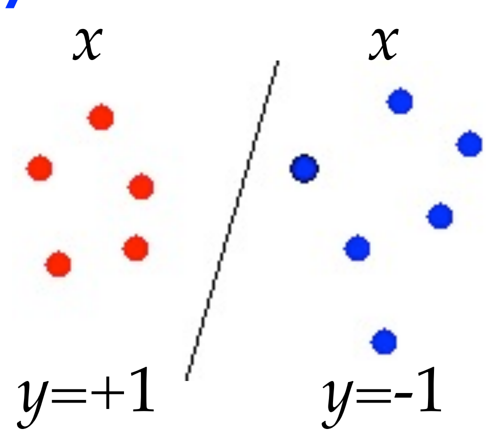
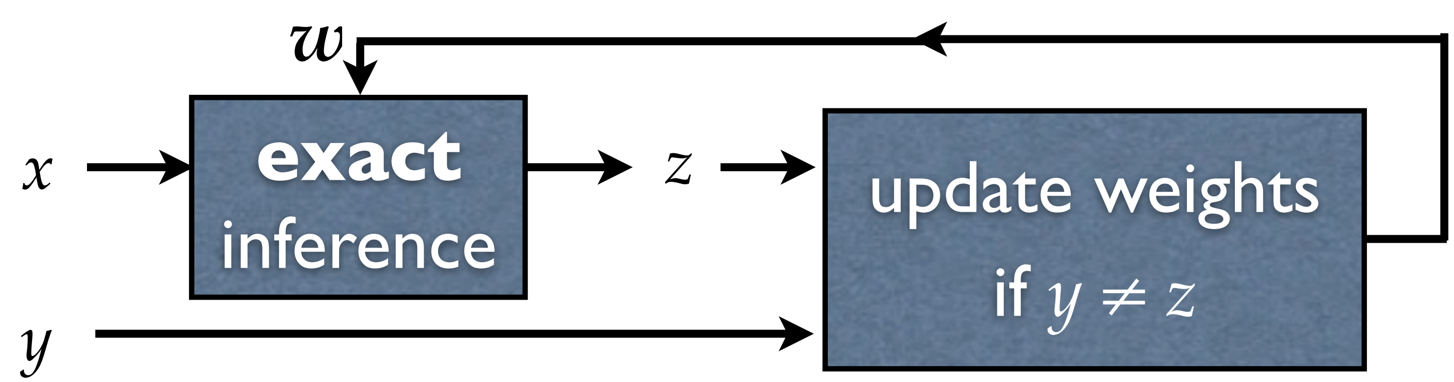
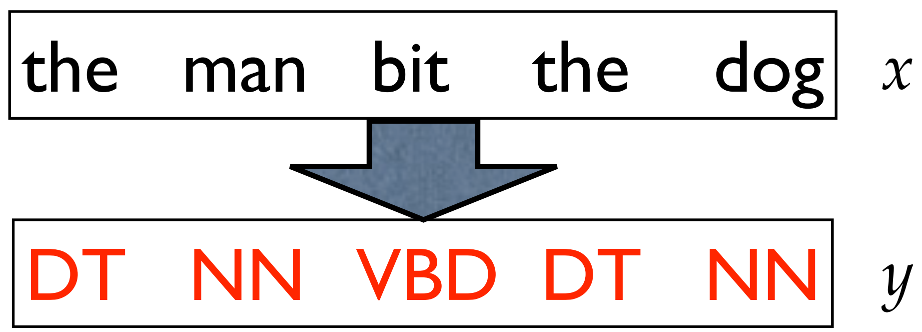




structured classification



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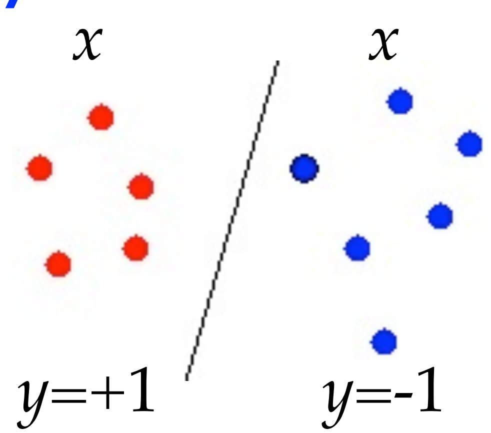

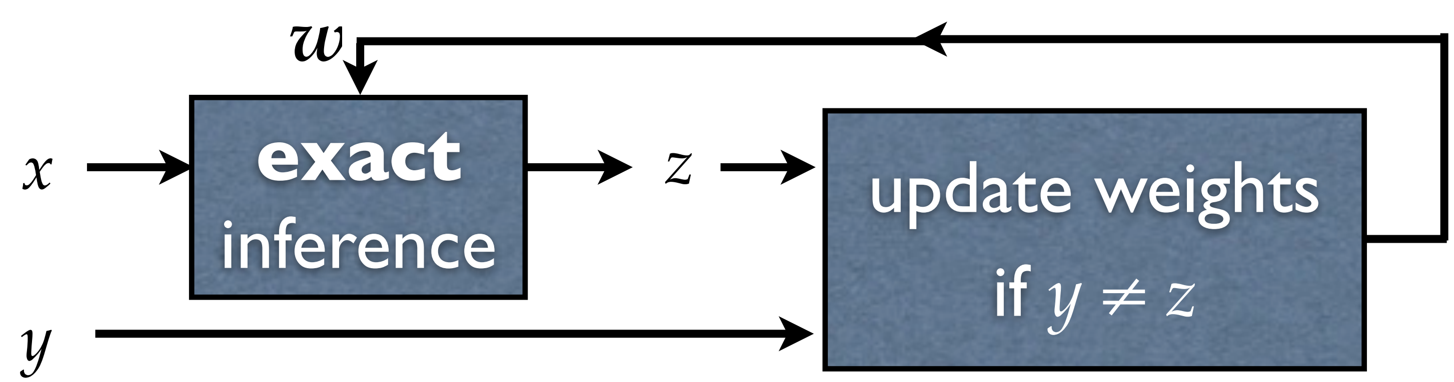

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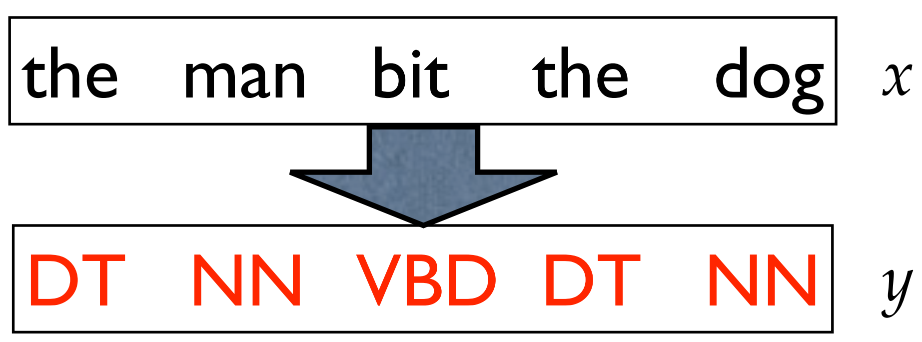

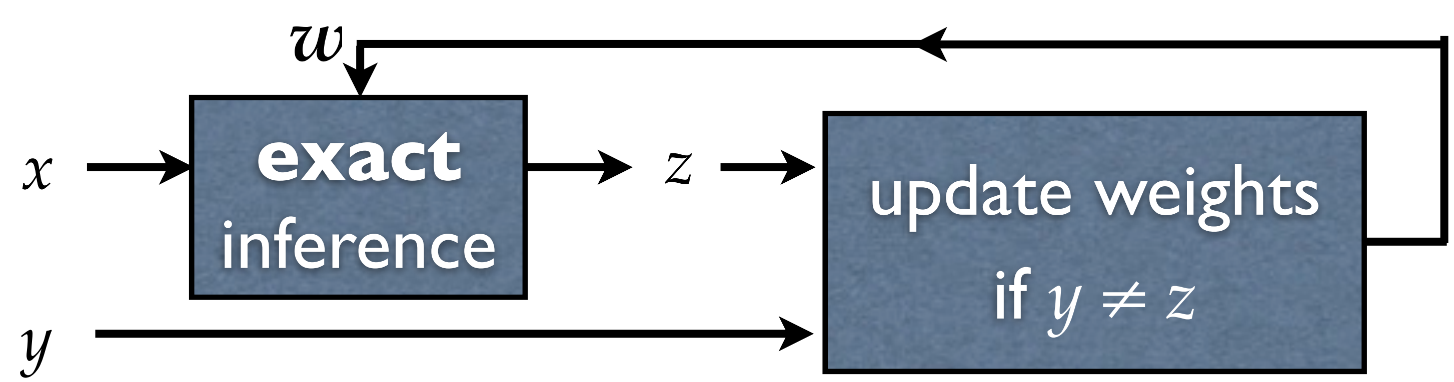

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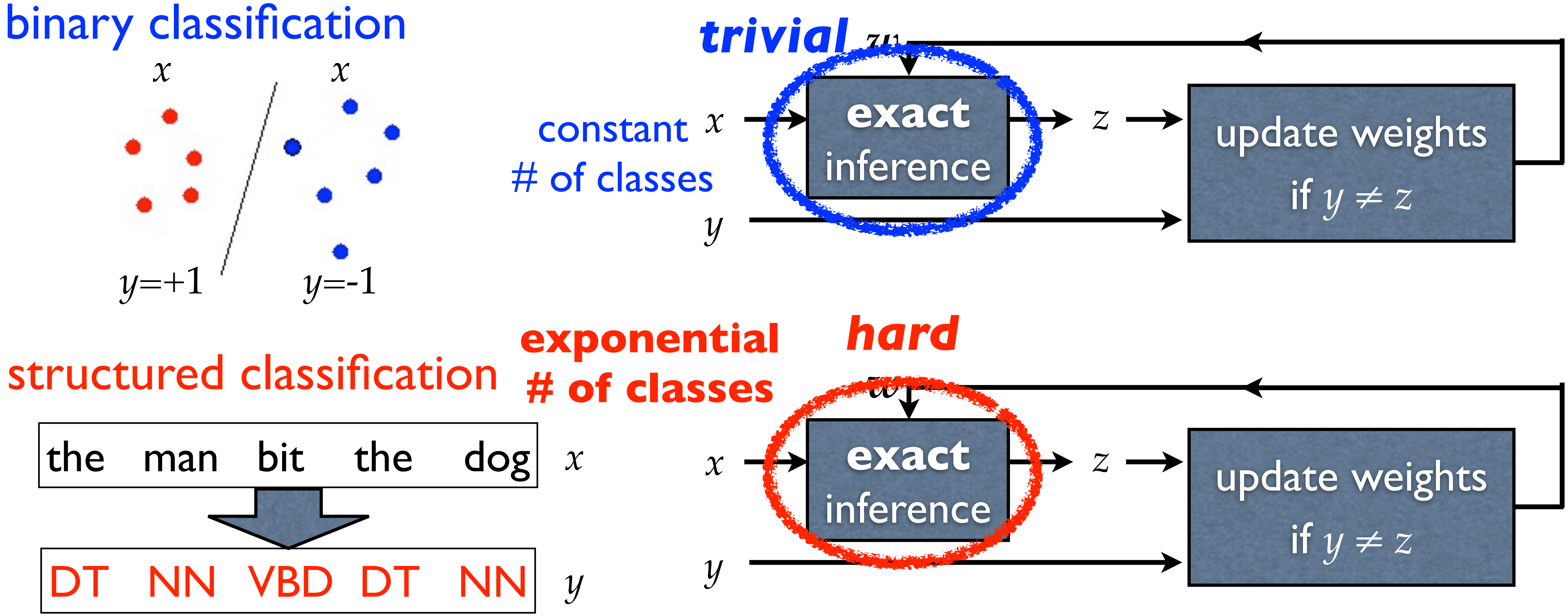
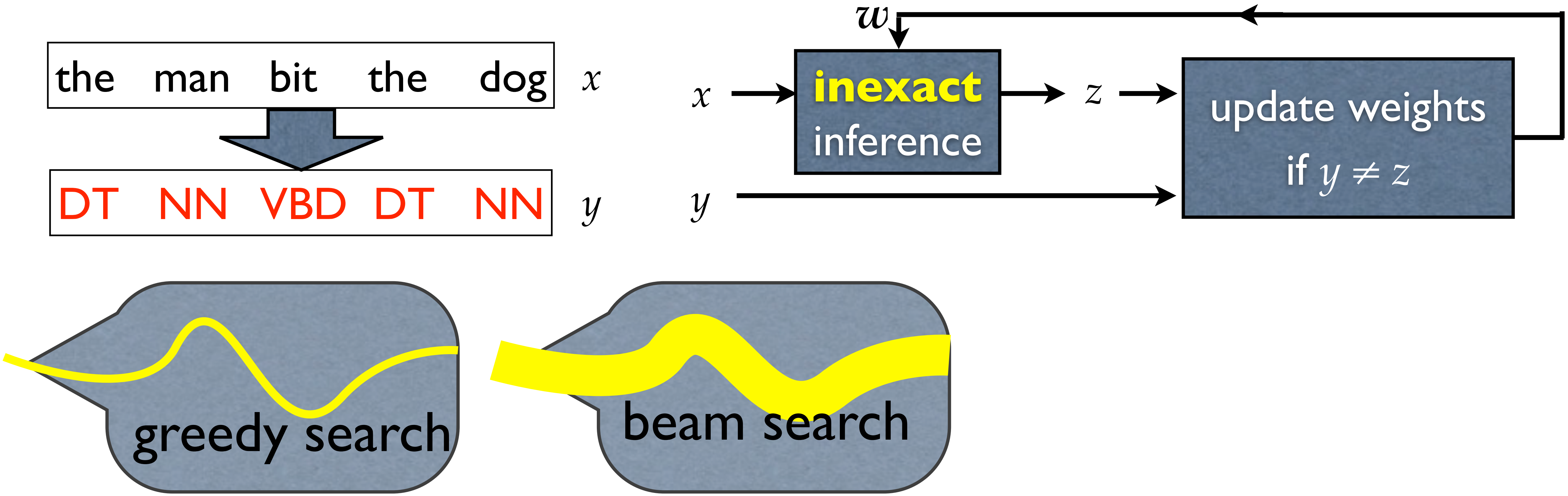


- challenge: search efficiency (exponentially many classes)
  - often use dynamic programming (DP)
  - but DP is still too slow for repeated use, e.g. parsing $O(n^3)$
  - Q: can we sacrifice search exactness for faster learning?

Perceptron w/ Inexact Inference



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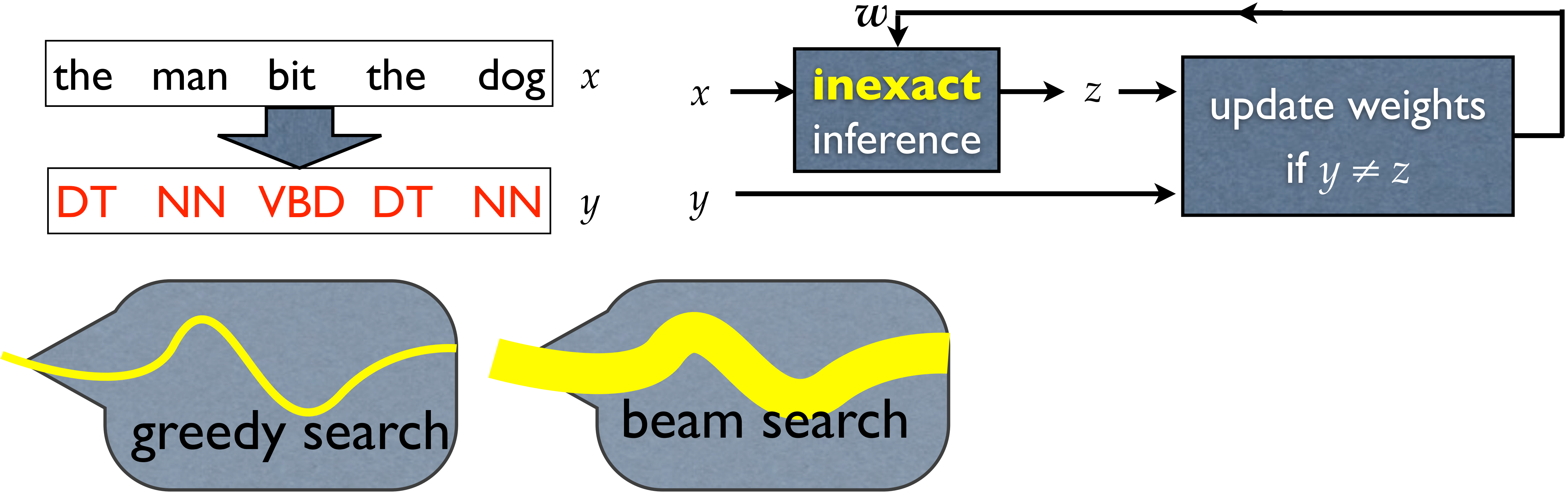

- routine use of inexact inference in NLP (e.g. beam search)

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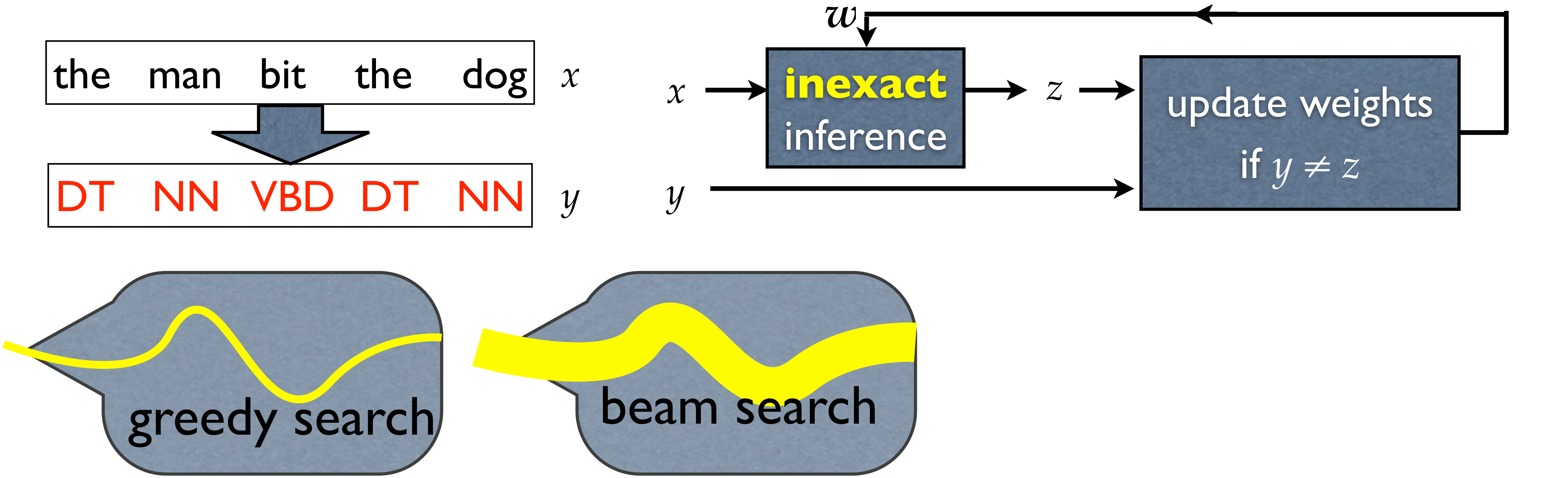

- routine use of inexact inference in NLP (e.g. beam search)
- how does structured perceptron work with inexact search?

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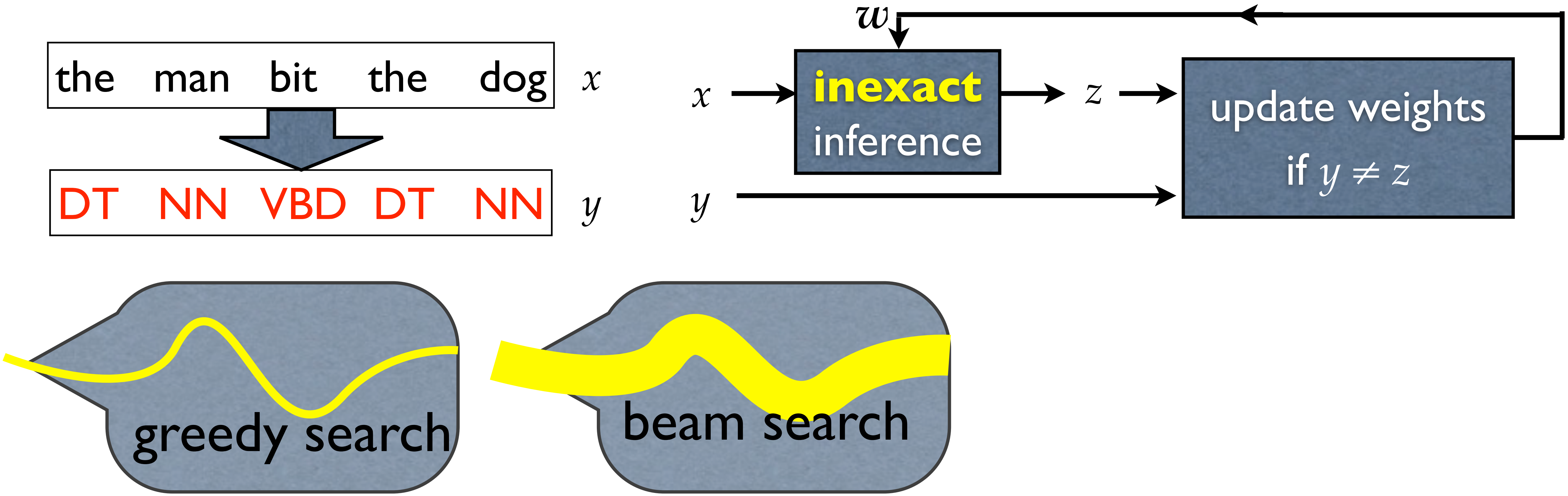

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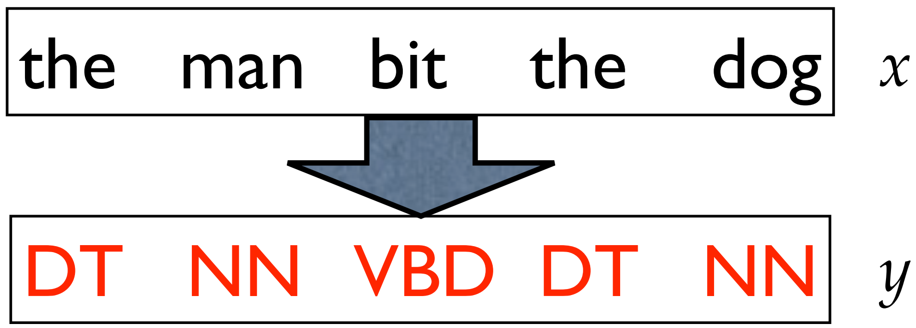

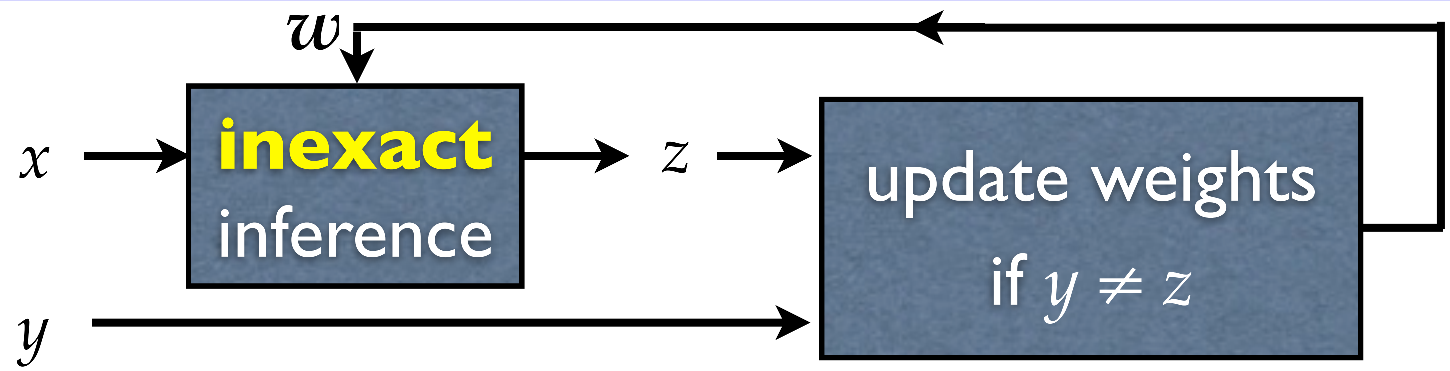

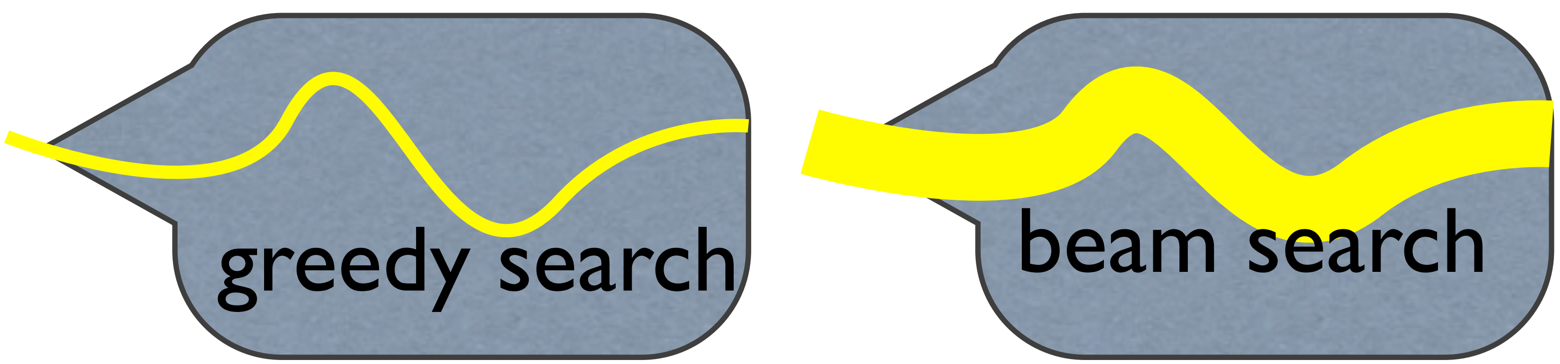

Q: does perceptron still work???

- routine use of inexact inference in NLP (e.g. beam search)
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  - would search errors break these learning properties?

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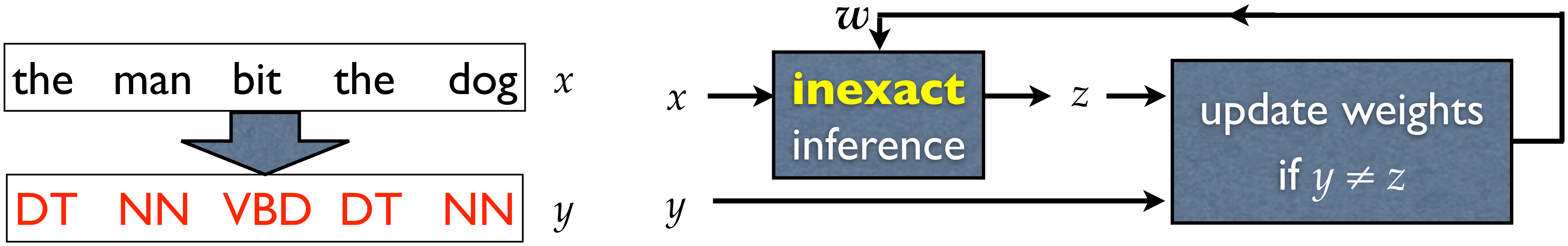

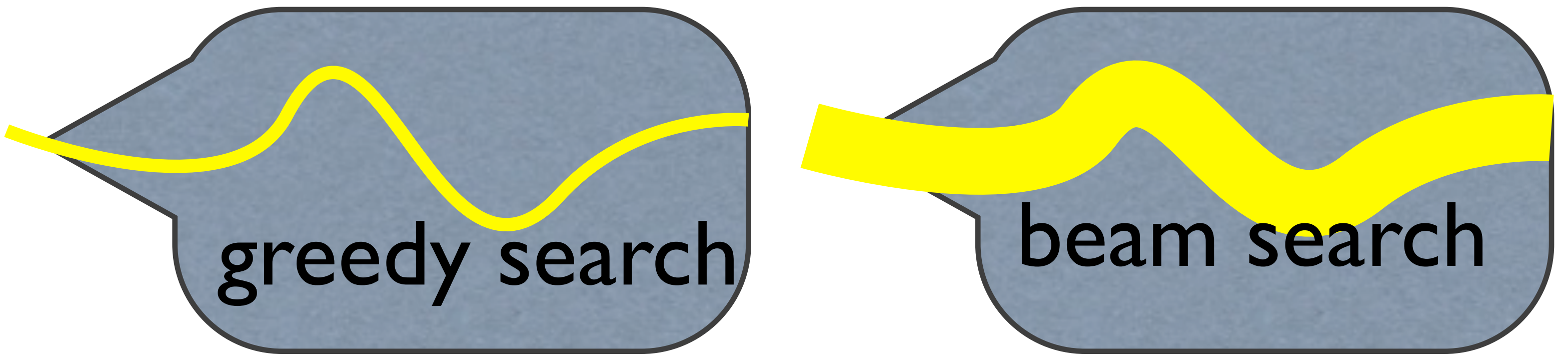

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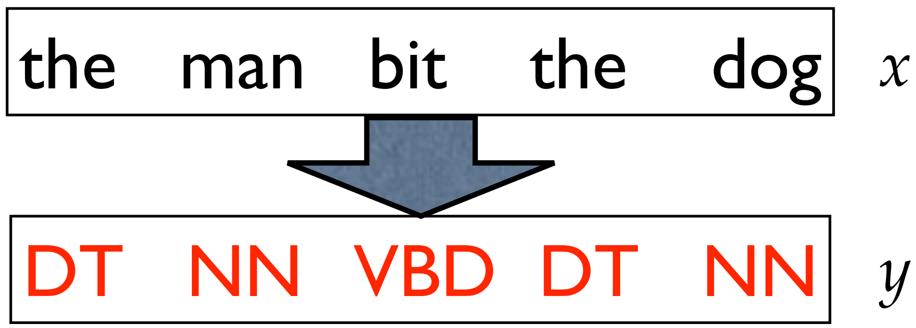
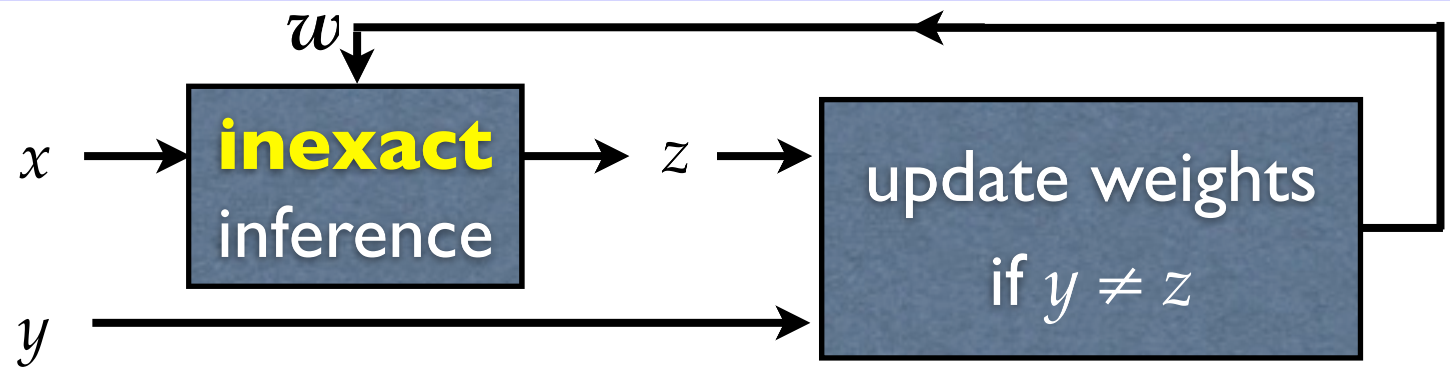
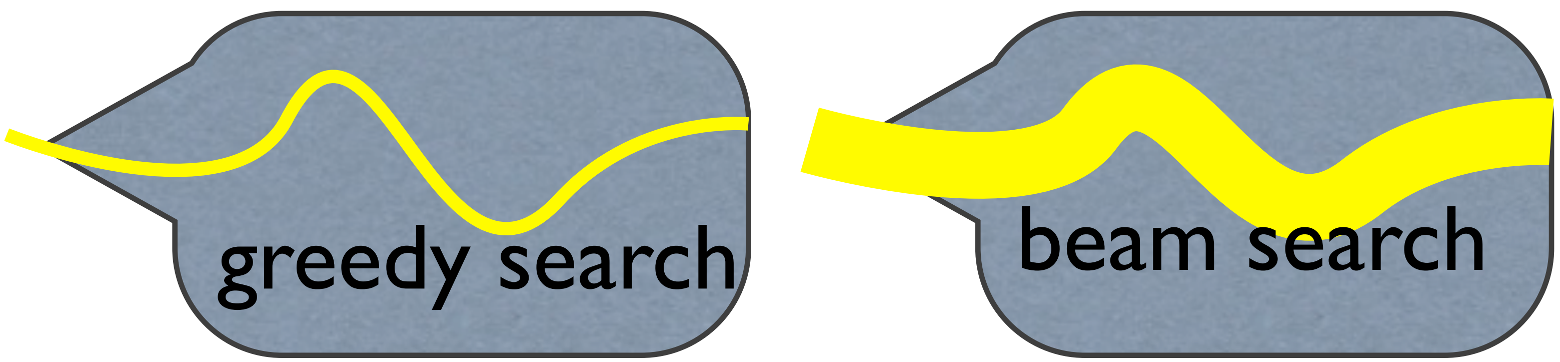
  - so far most structured learning theory assume exact search
  - would search errors break these learning properties?
  - if so how to modify learning to accommodate inexact search?

Bad News and Good News







A: it no longer works as is, but we can make it work by some magic.

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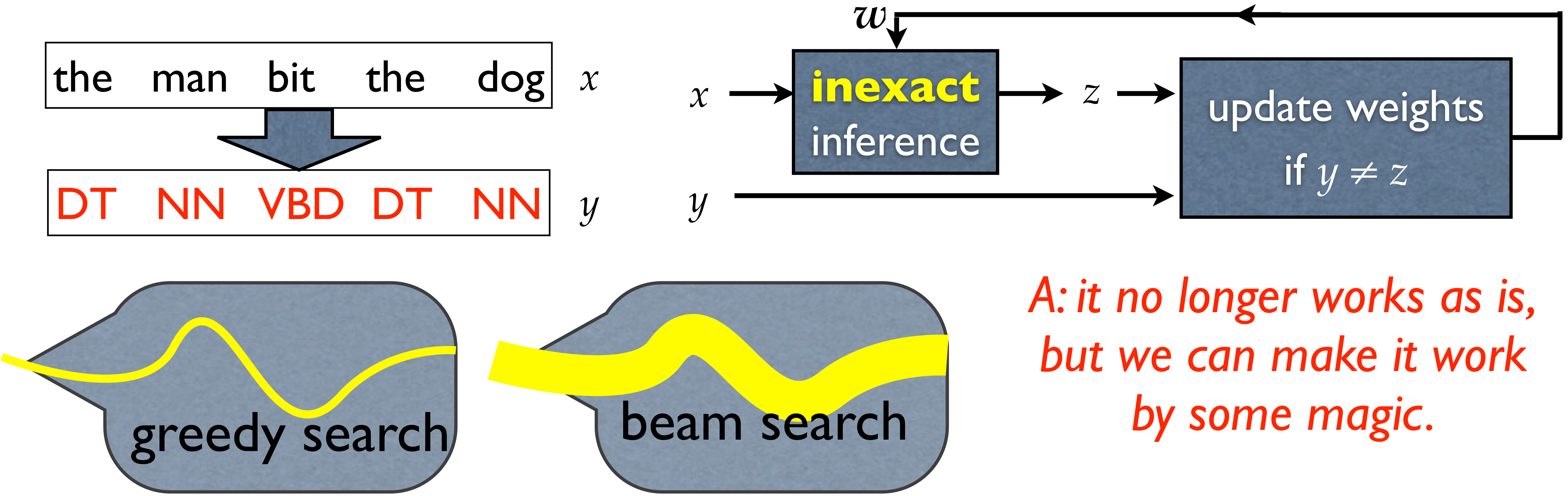

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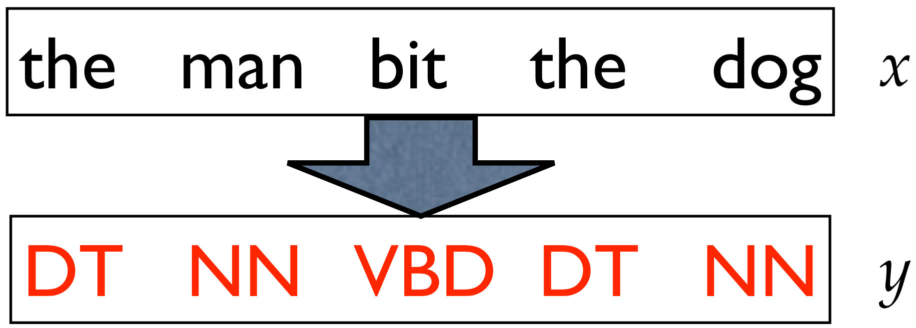

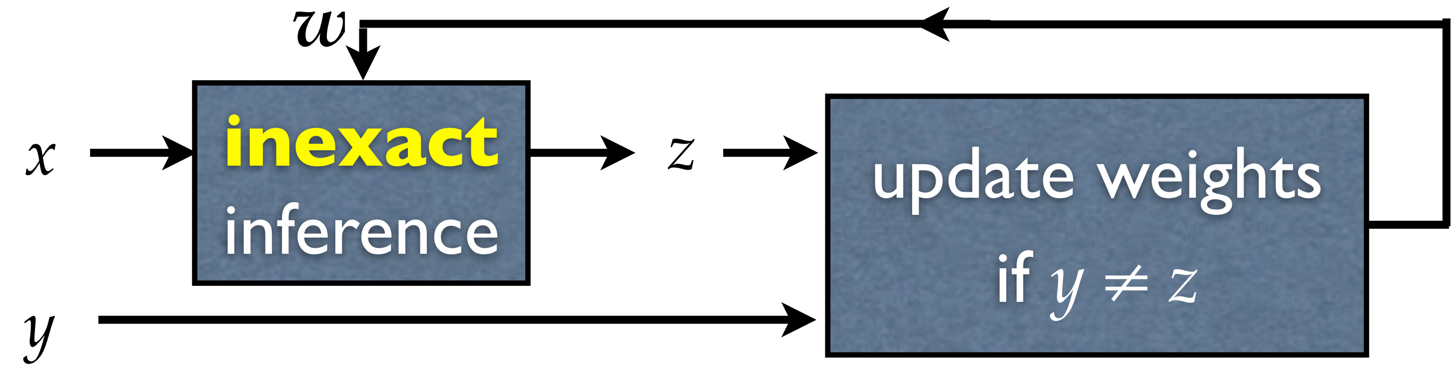

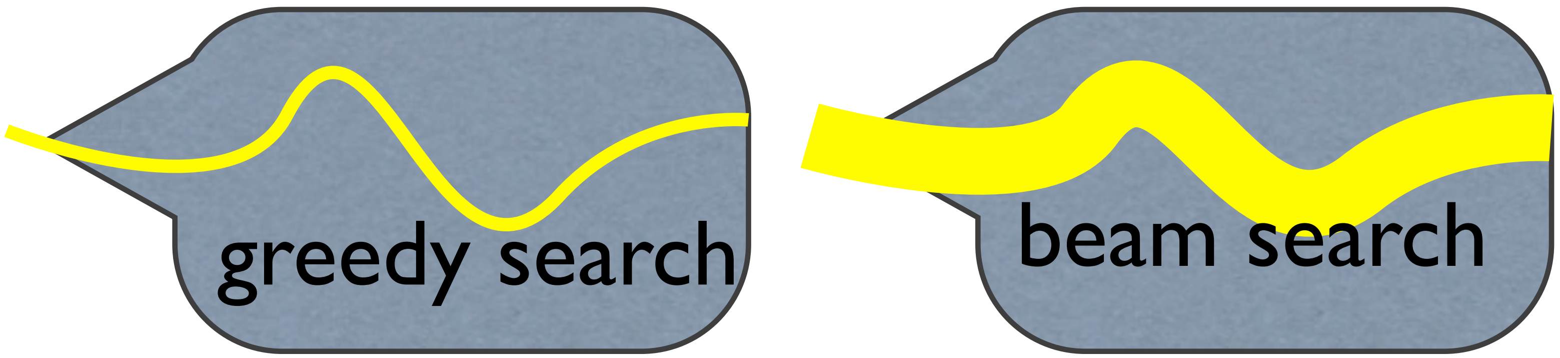

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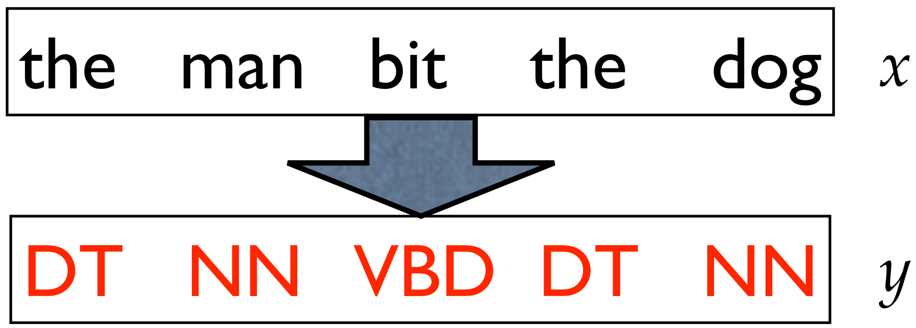
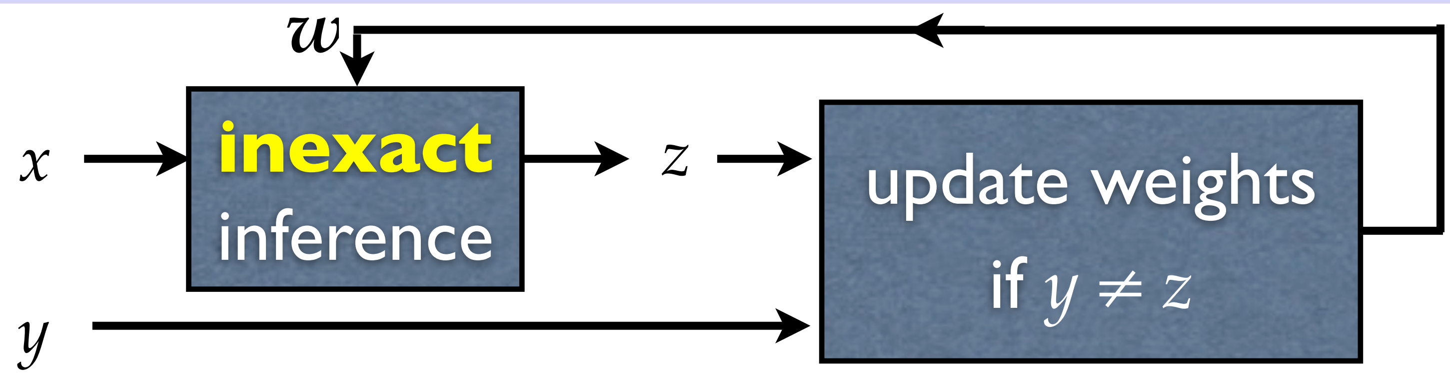
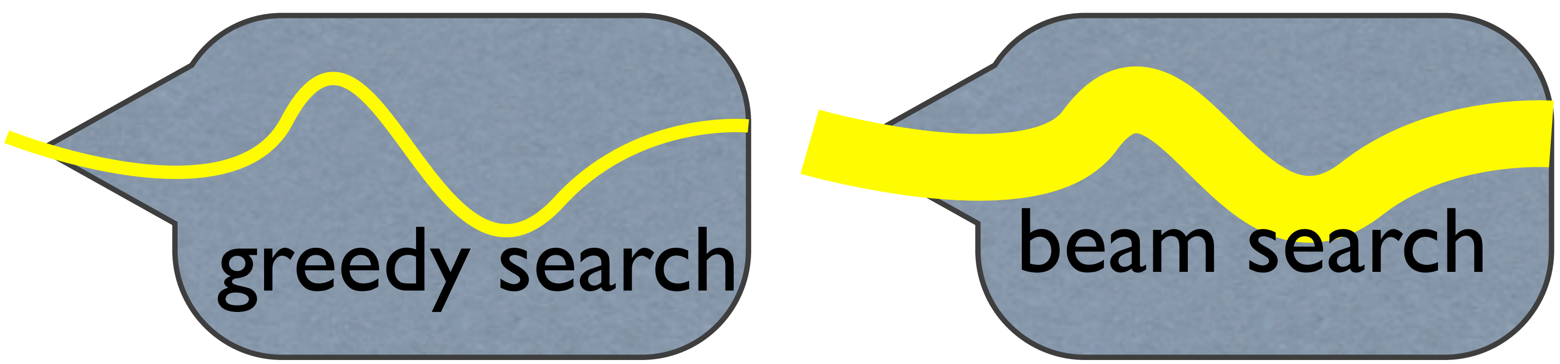
- bad news: no more guarantee of convergence
  - in practice perceptron degrades a lot due to search errors

Bad News and Good News







A: it no longer works as is,
but we can make it work
by some magic.

- bad news: no more guarantee of convergence
  - in practice perceptron degrades a lot due to search errors
- good news: new update methods guarantee convergence

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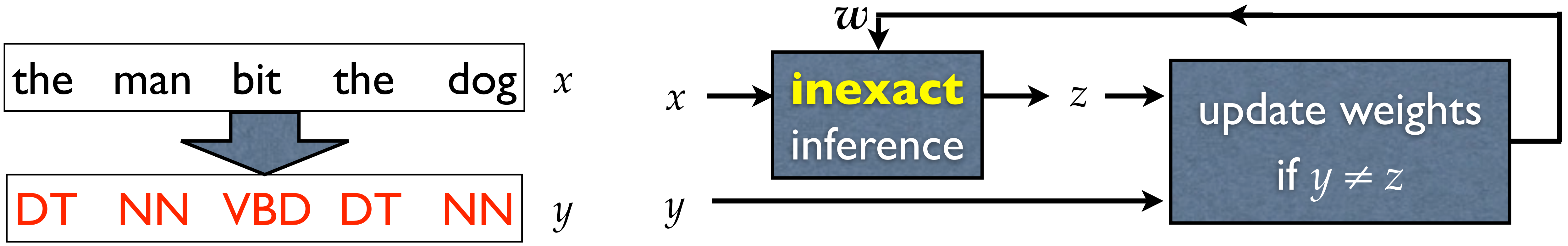

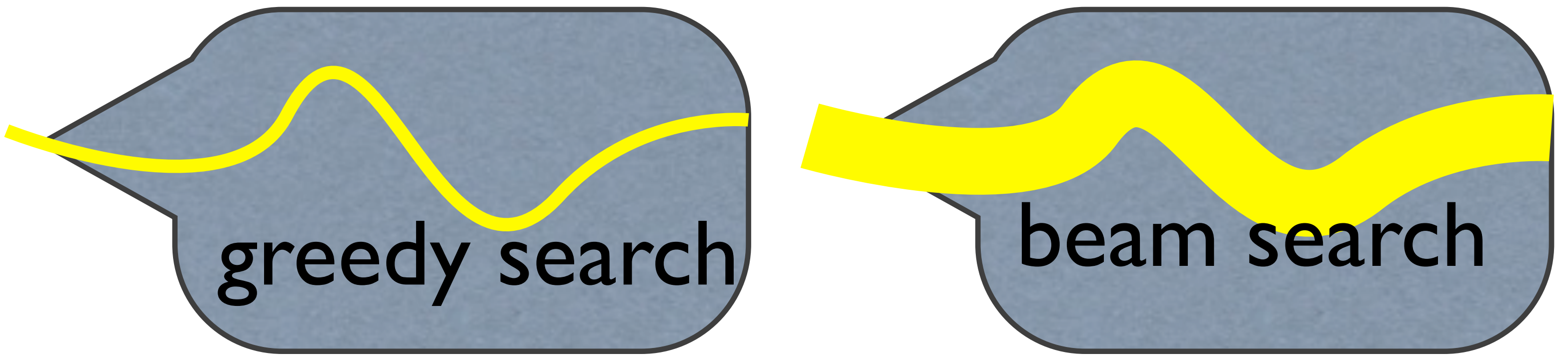

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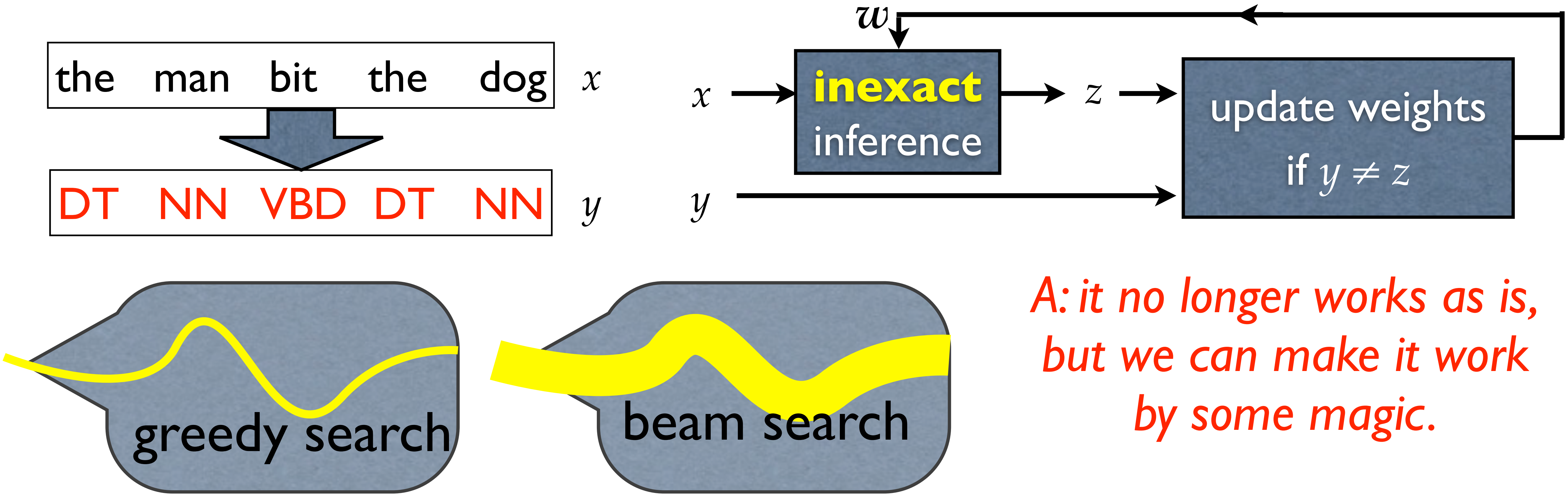

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- bad news: no more guarantee of convergence
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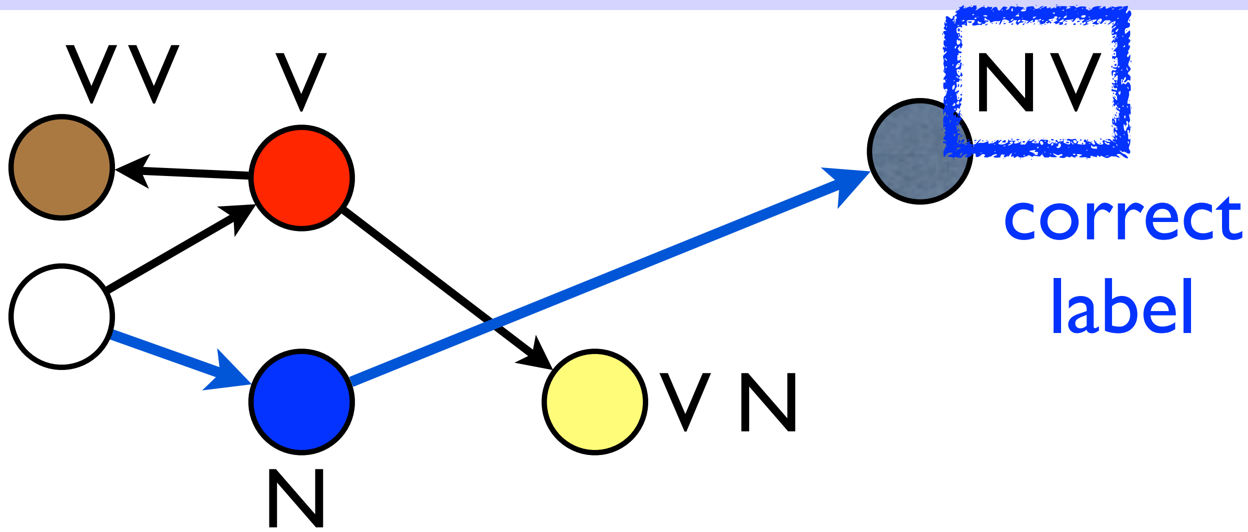
- good news: new update methods guarantee convergence
  - new perceptron variants that "live with" search errors
  - in practice they work really well w/ inexact search

Convergence with Exact Search

current model



training example

time flies

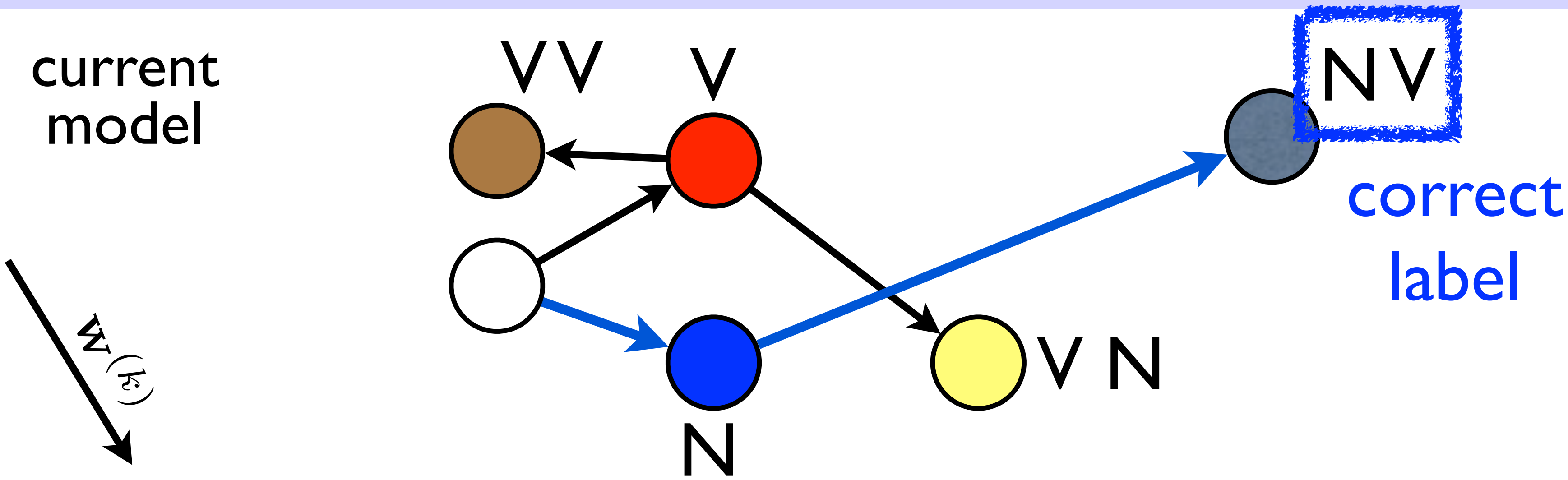
N V

output space

{N,V} x {N,V}

Convergence with Exact Search

current model



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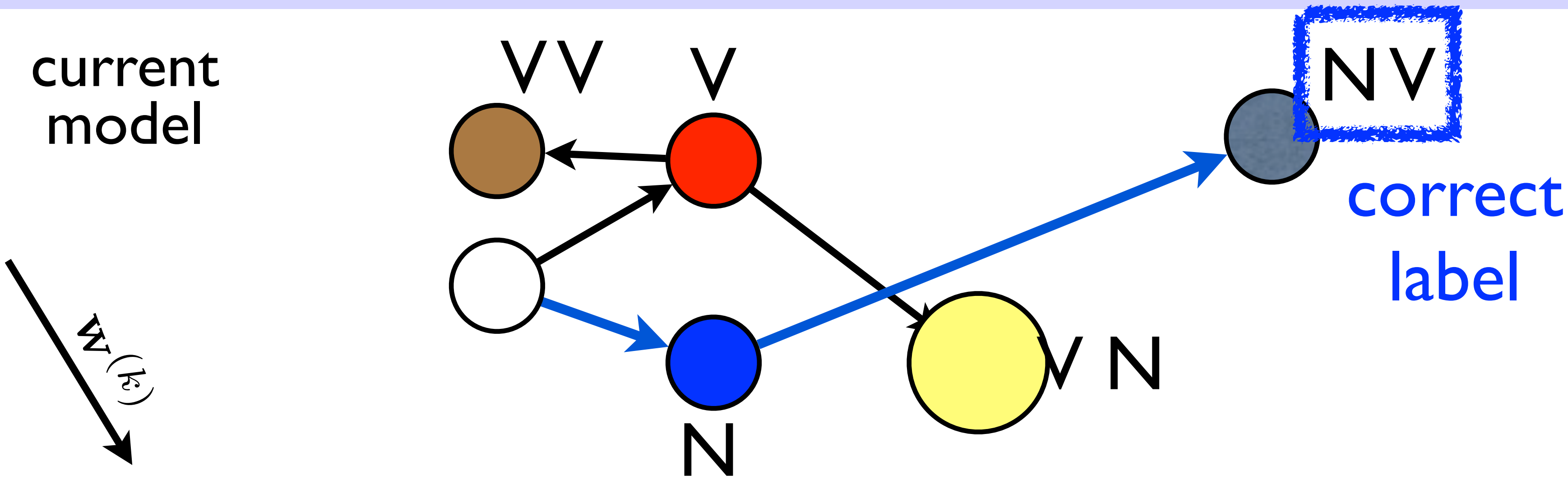

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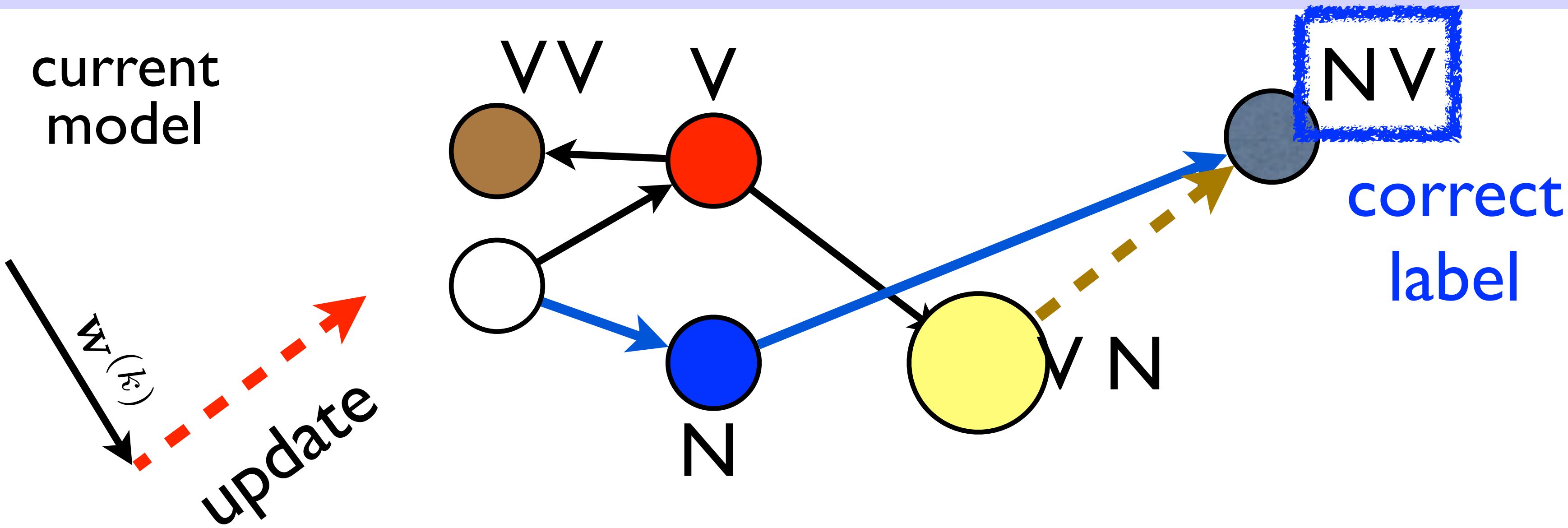

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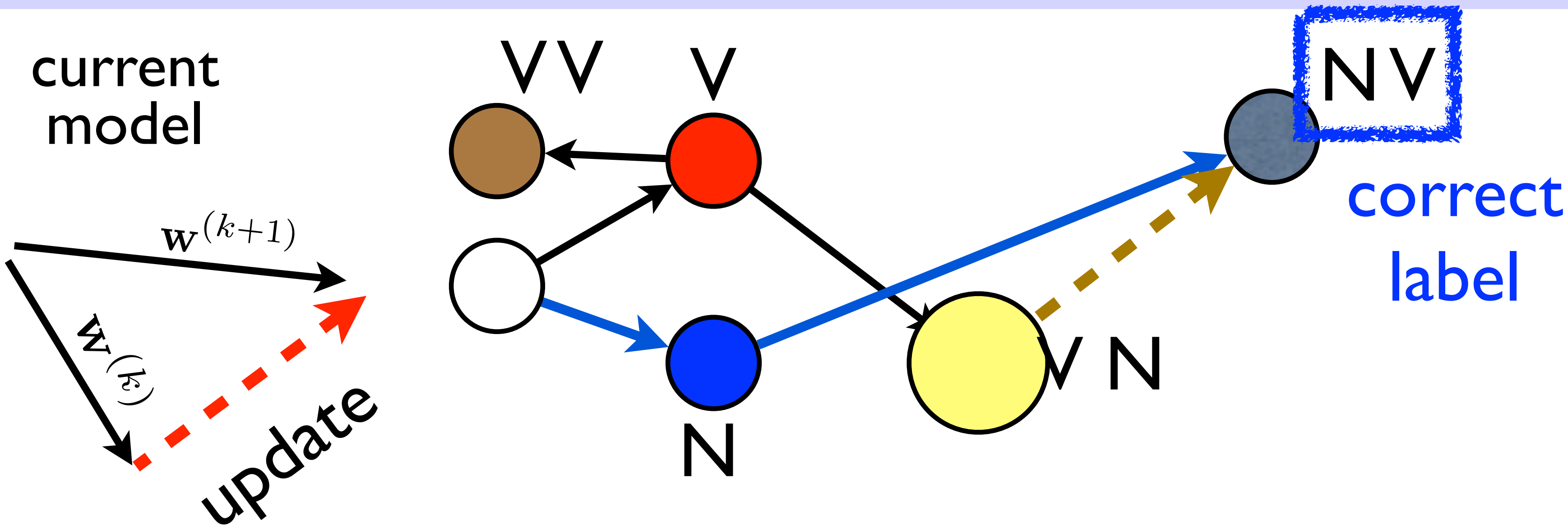

training example

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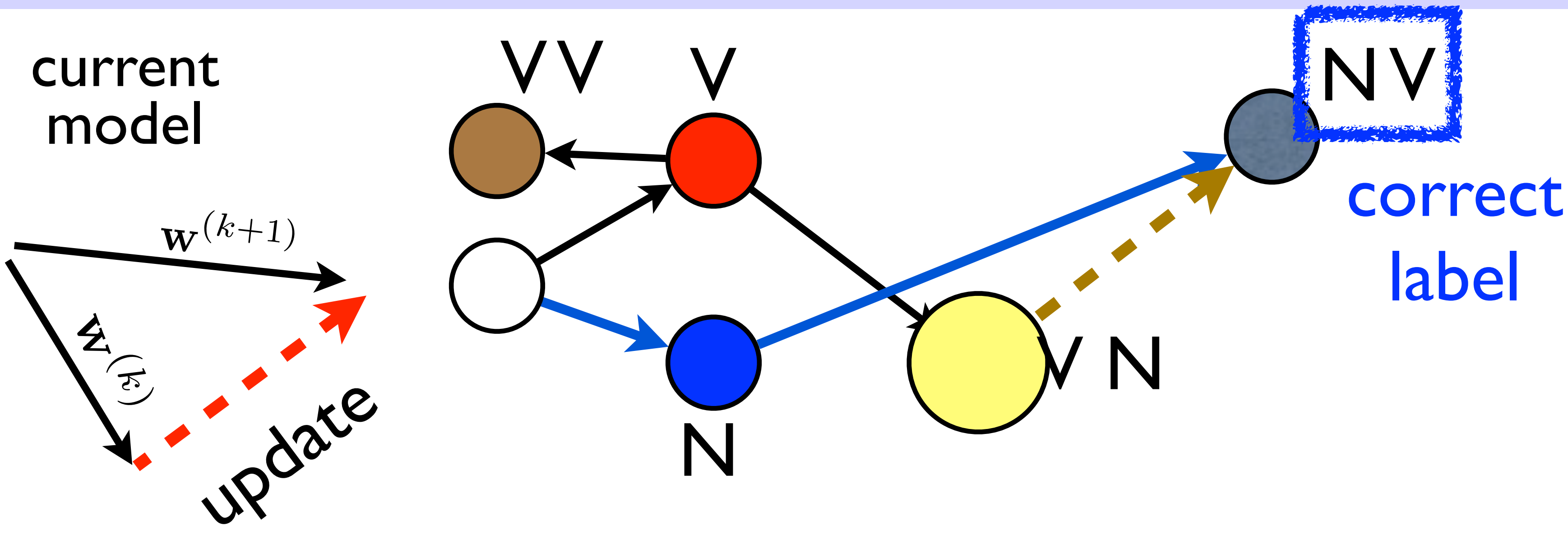

training example

time flies

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output space

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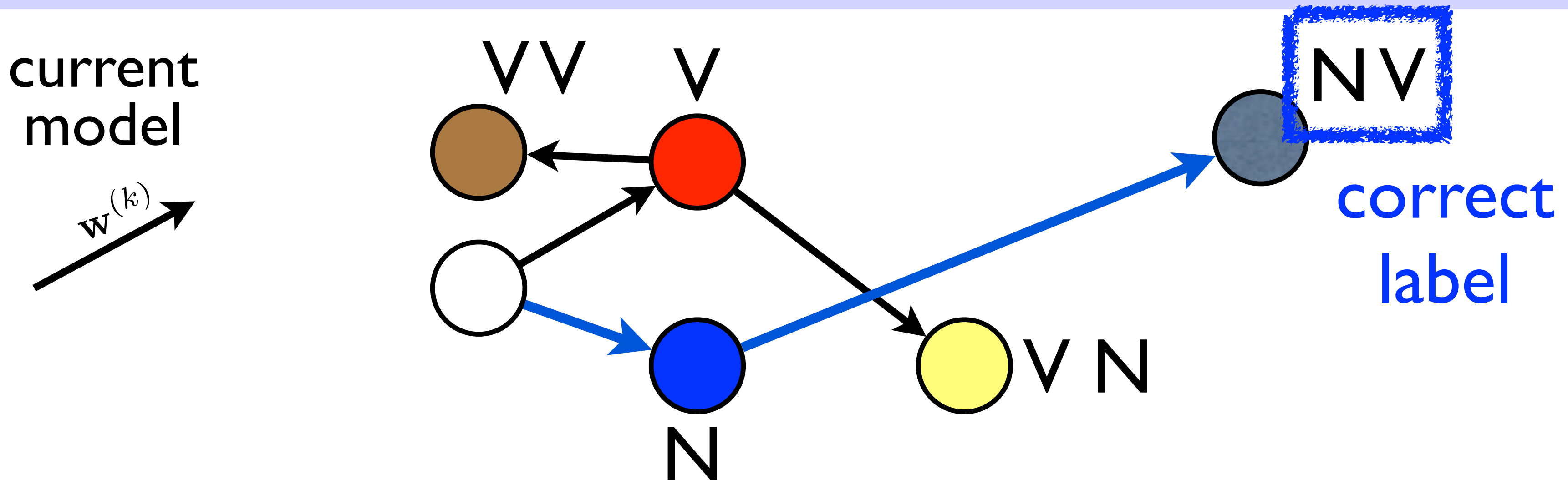
structured perceptron converges with exact search

No Convergence w/ Greedy Search



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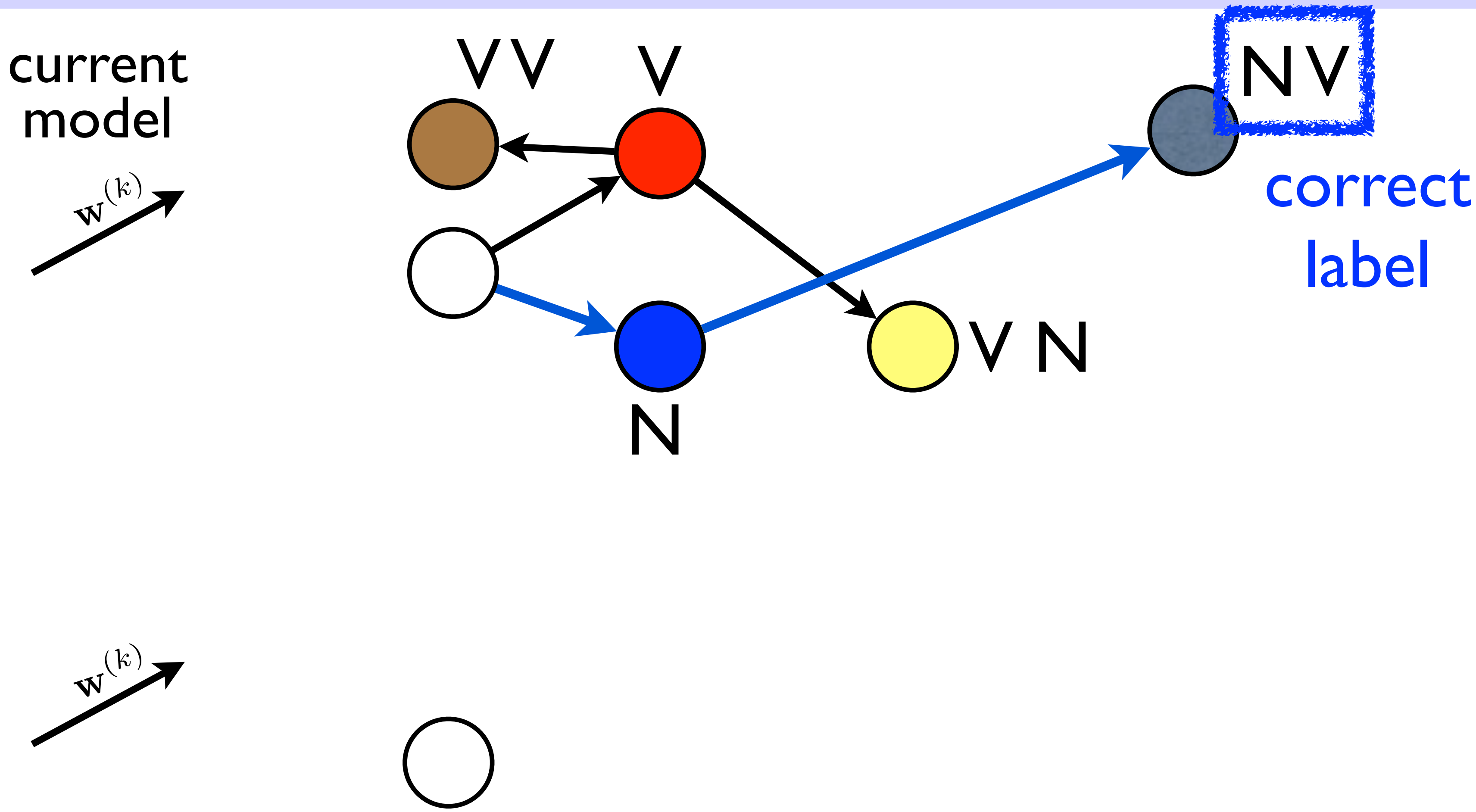

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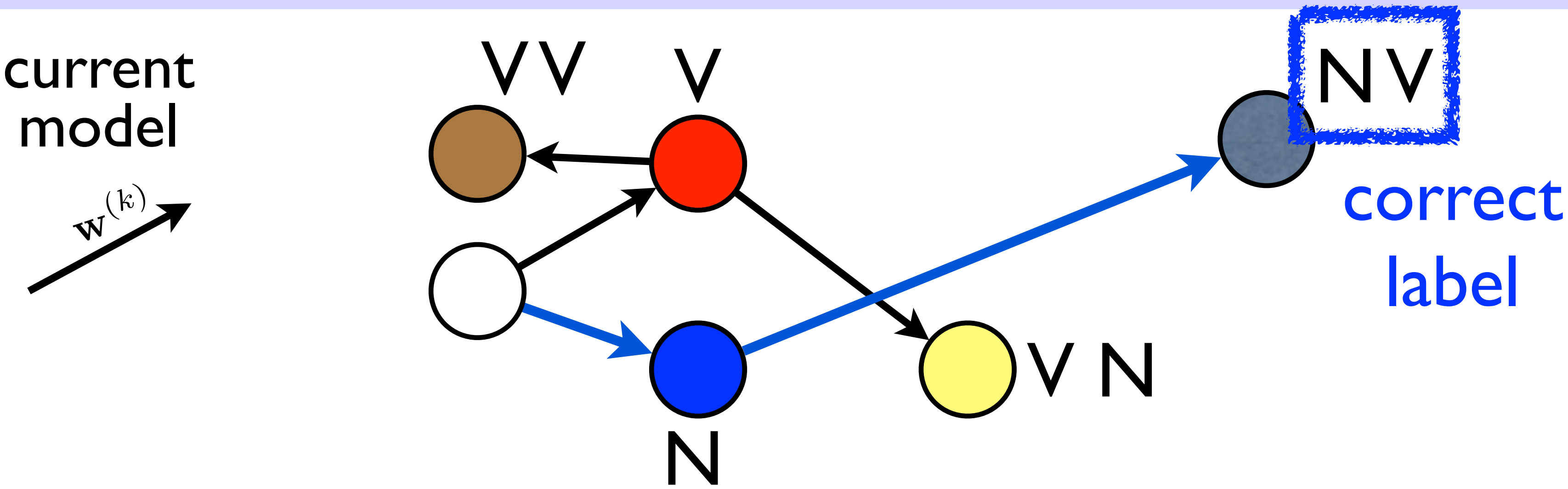

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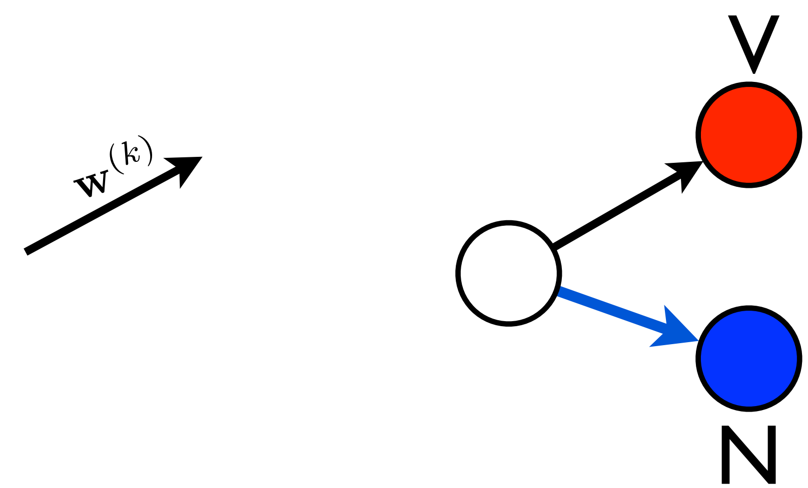

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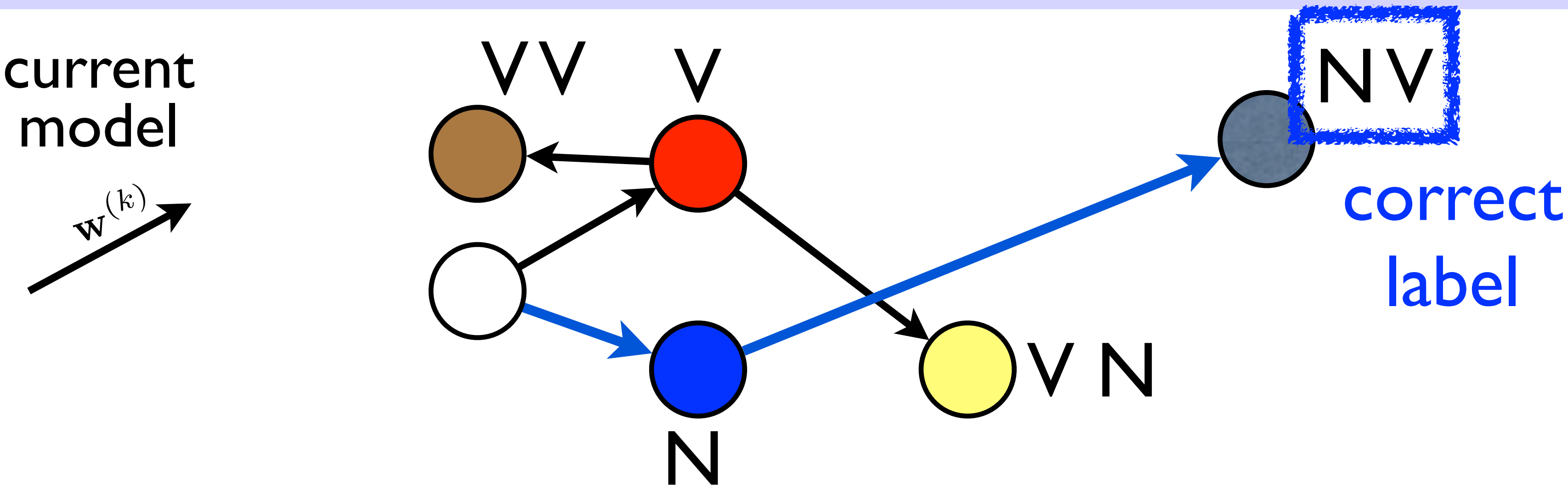

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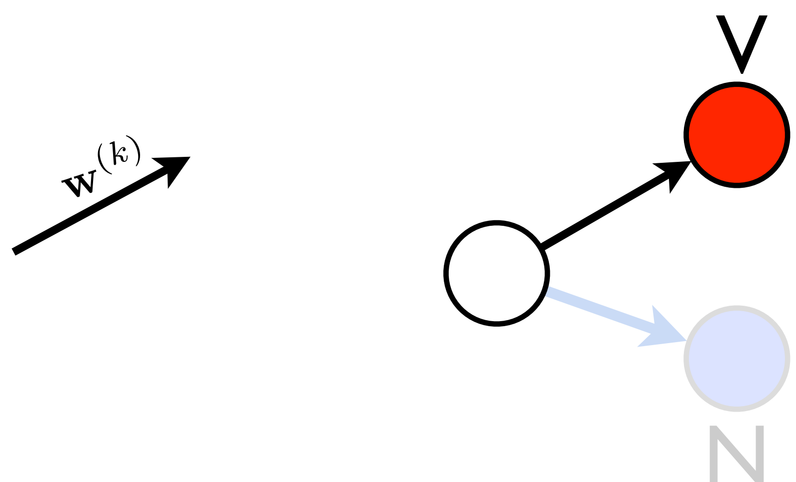

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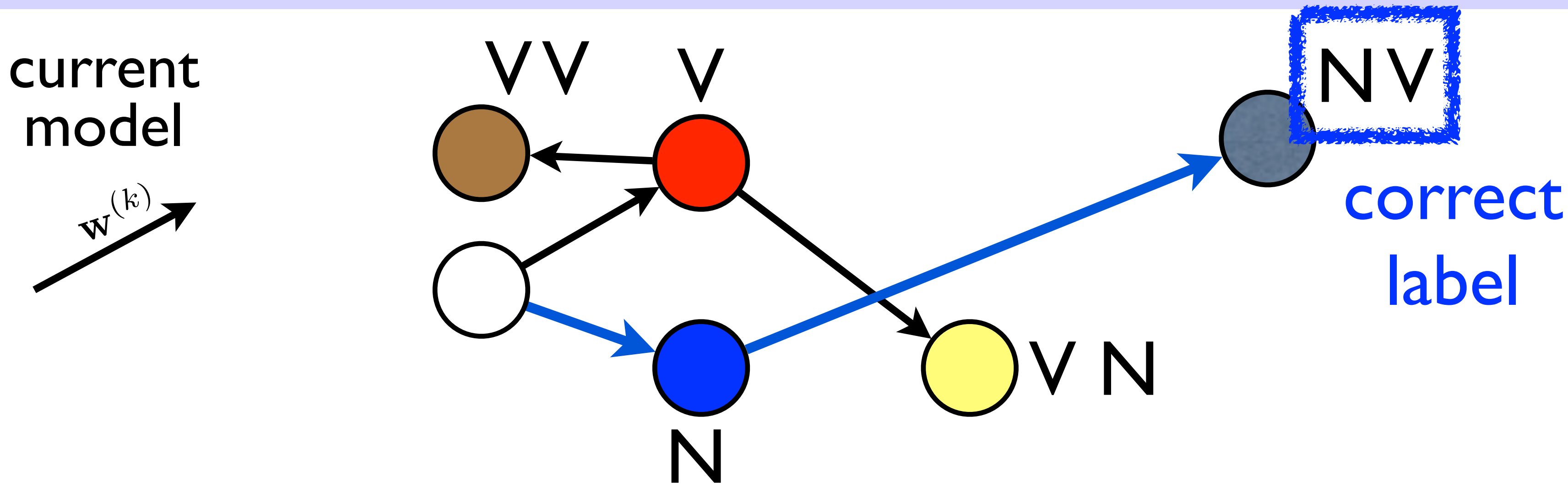

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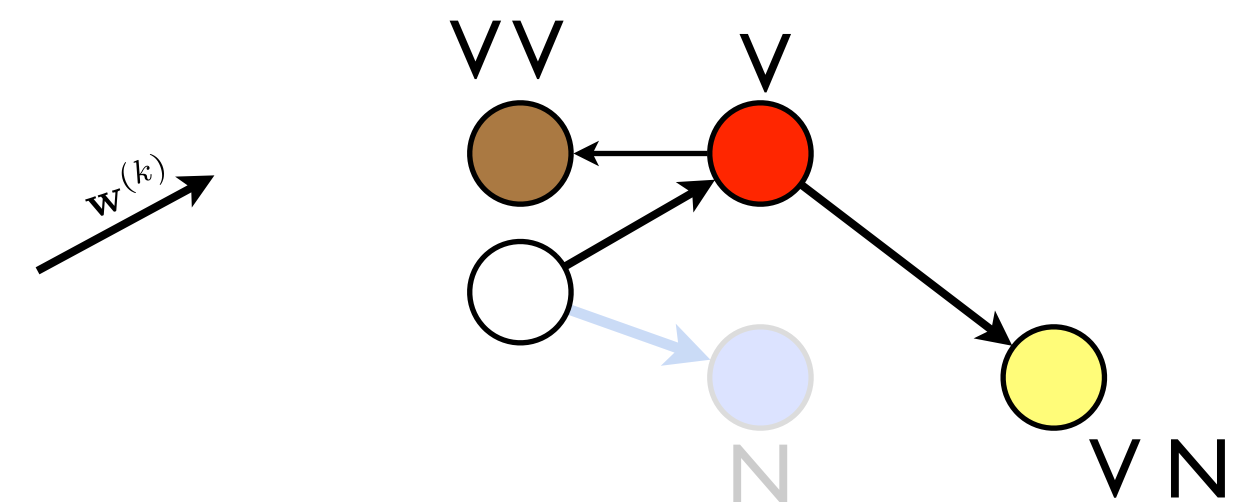

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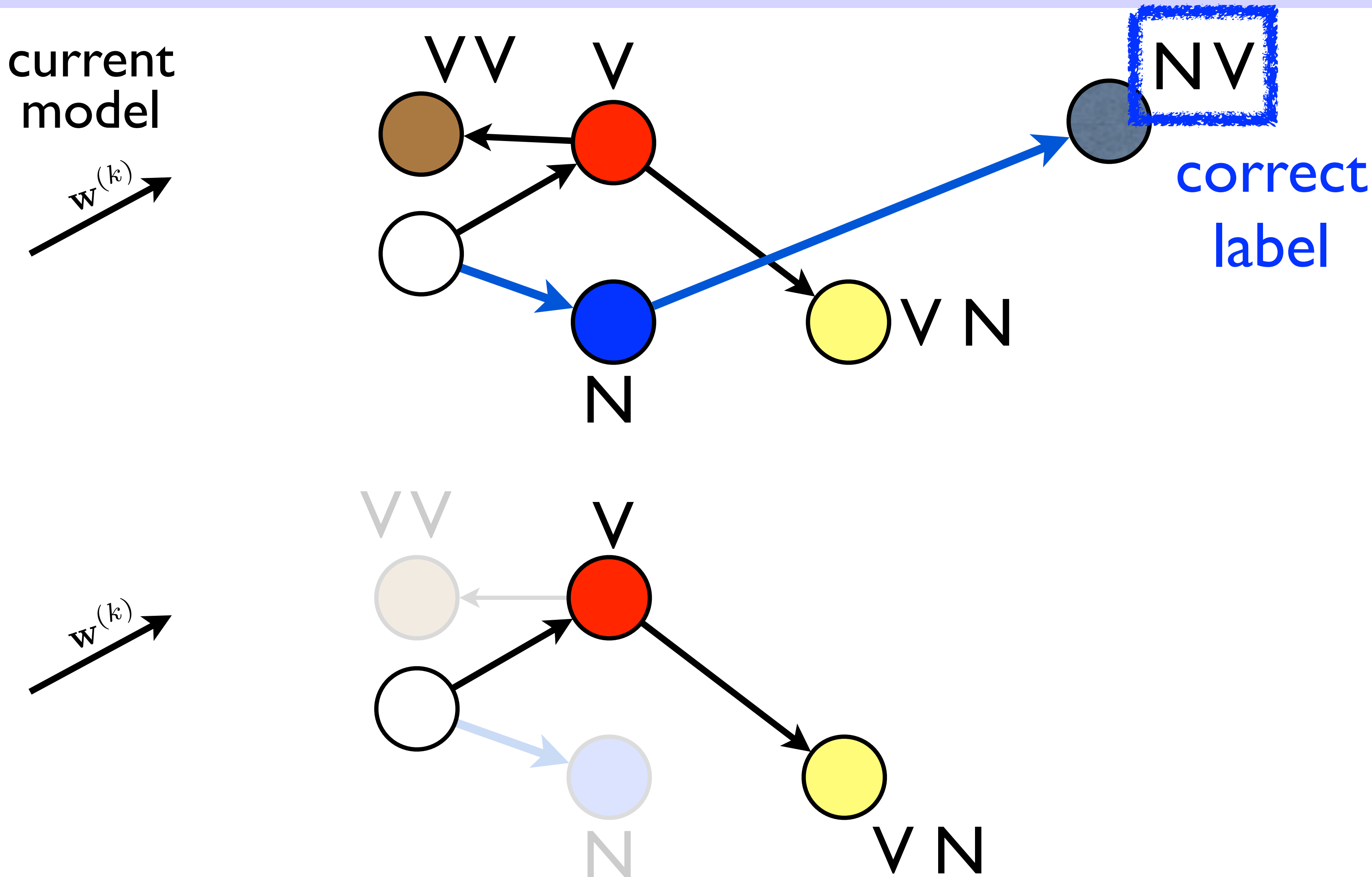

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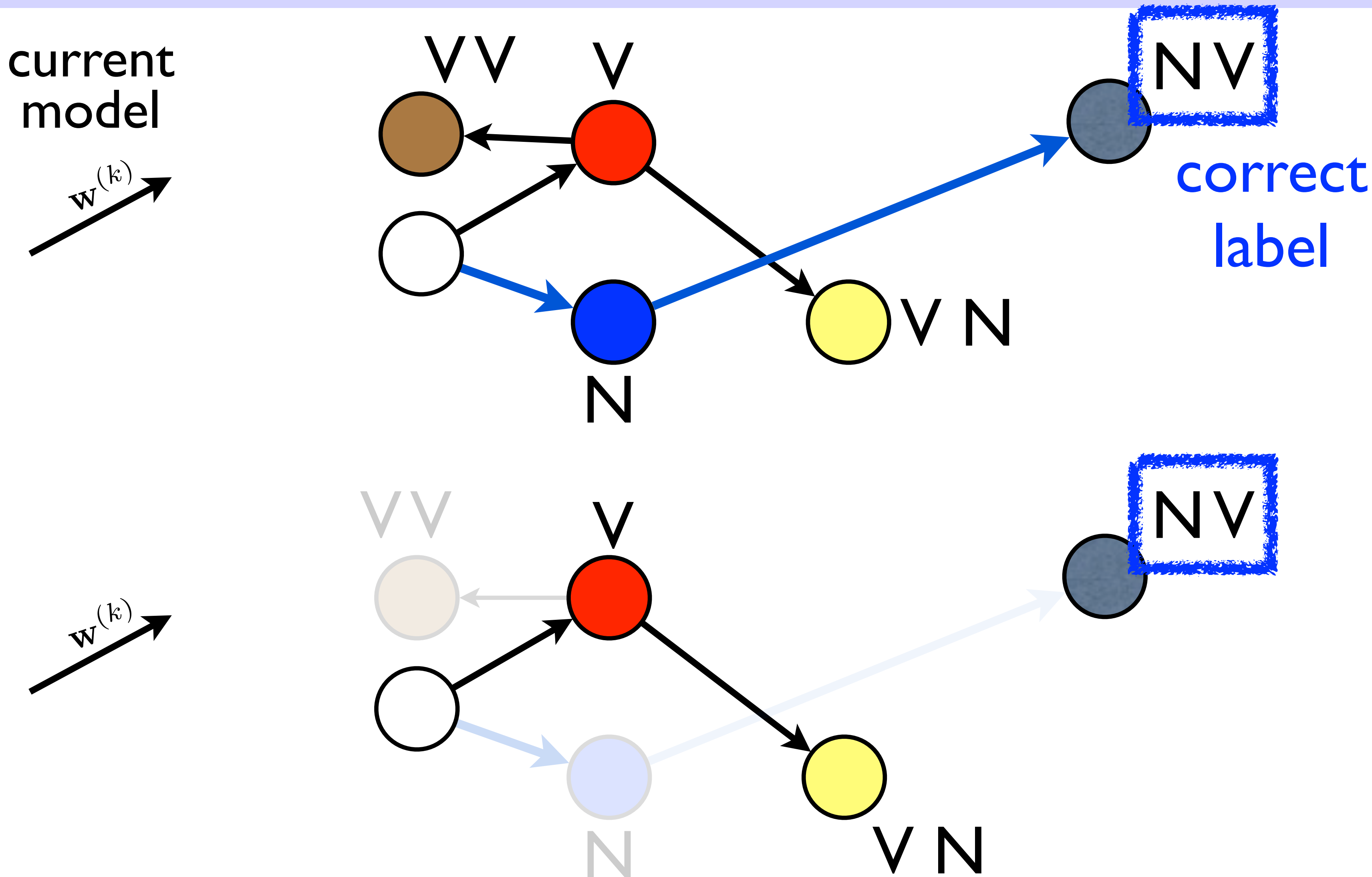

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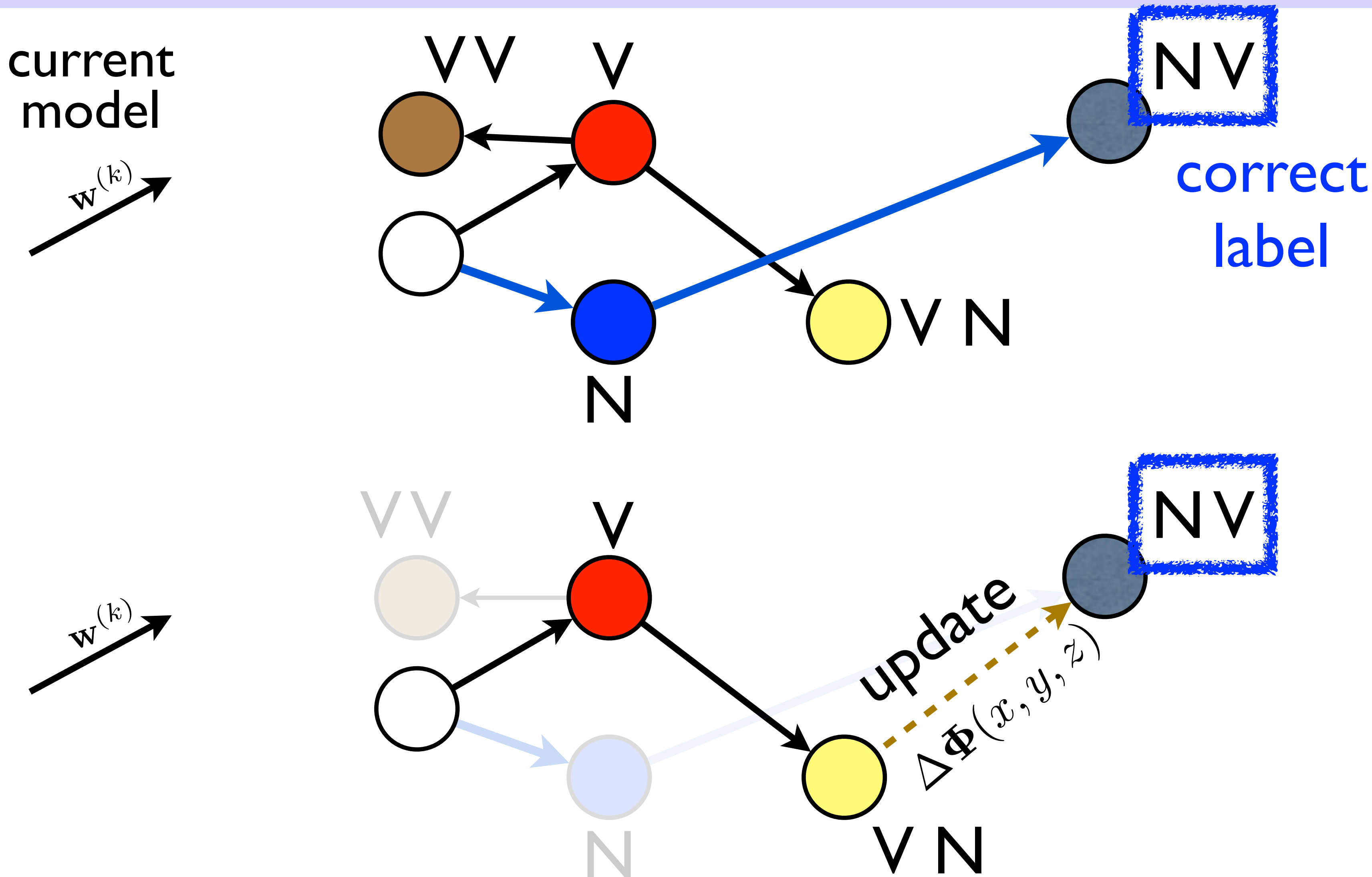

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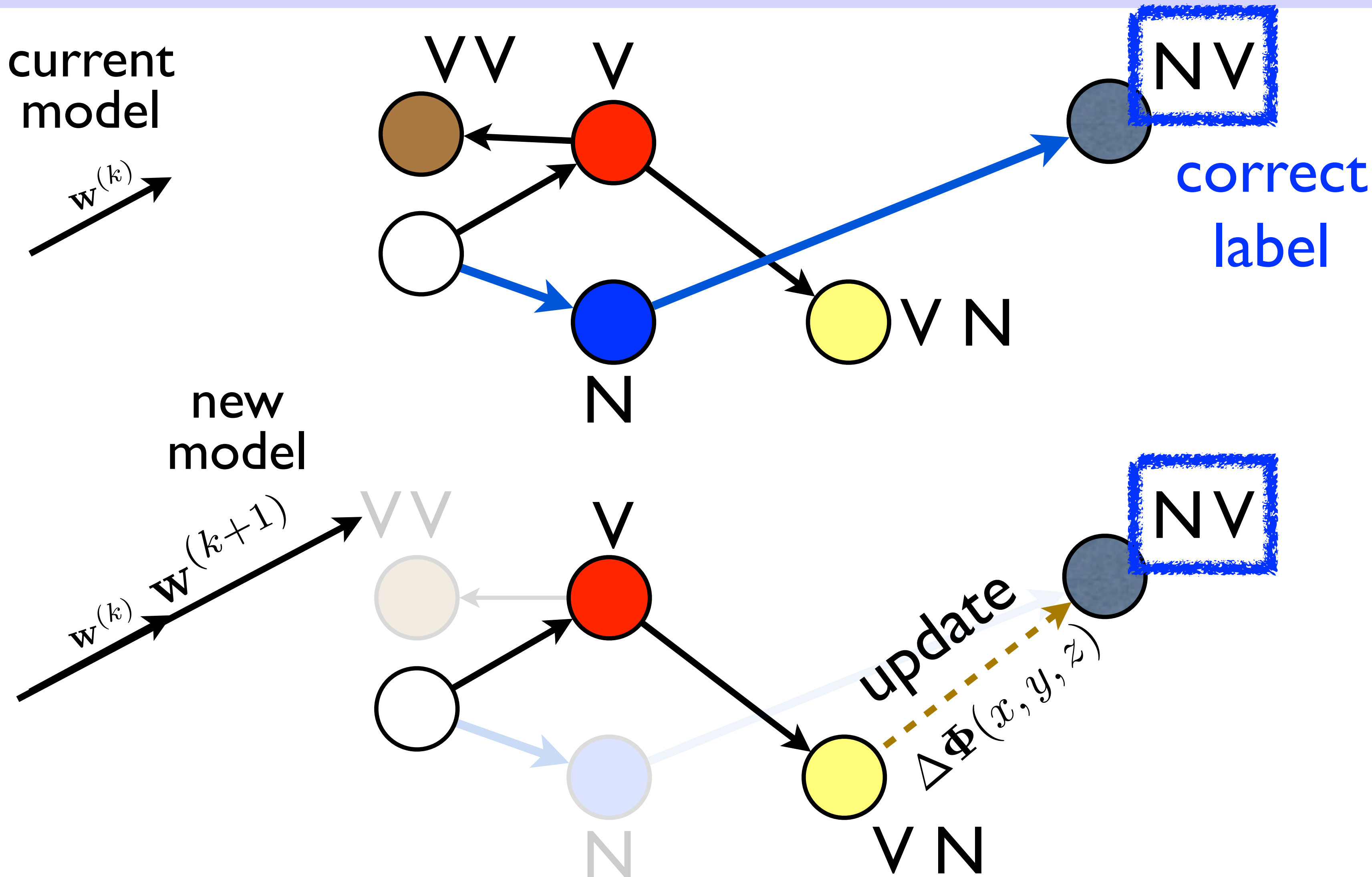

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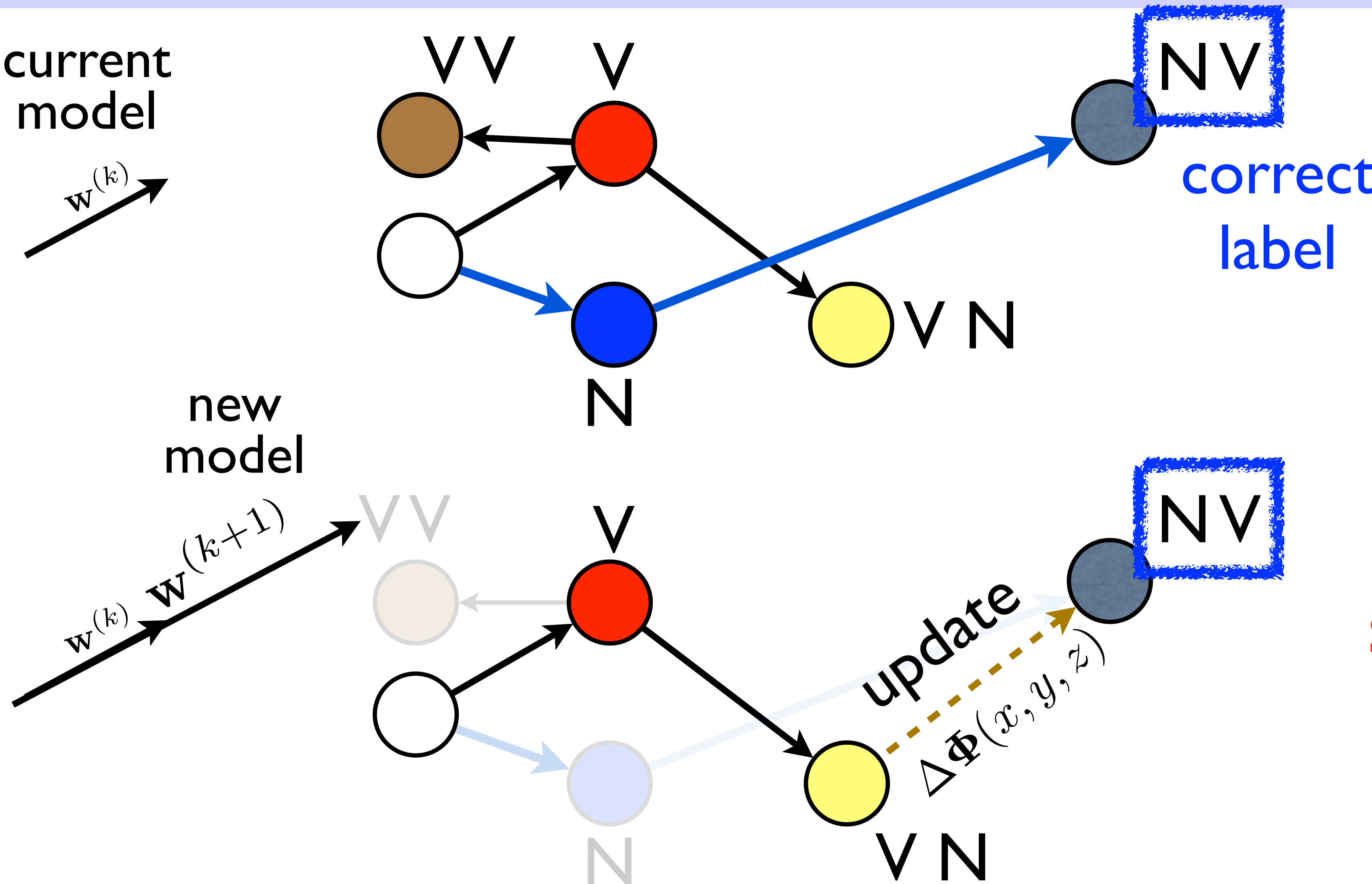

training example

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structured perceptron does not converge with greedy search

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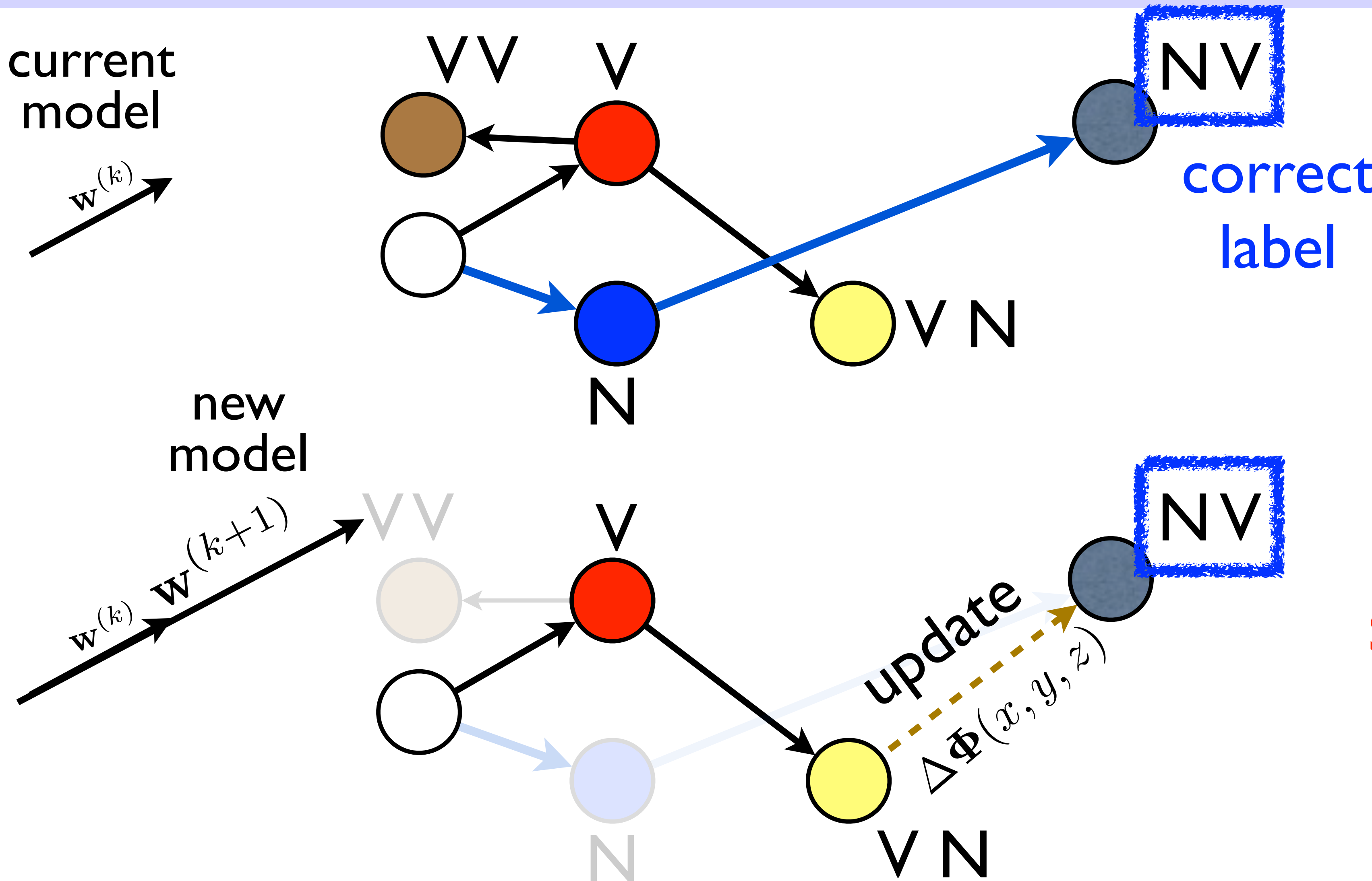

training example
time flies
N V

output space
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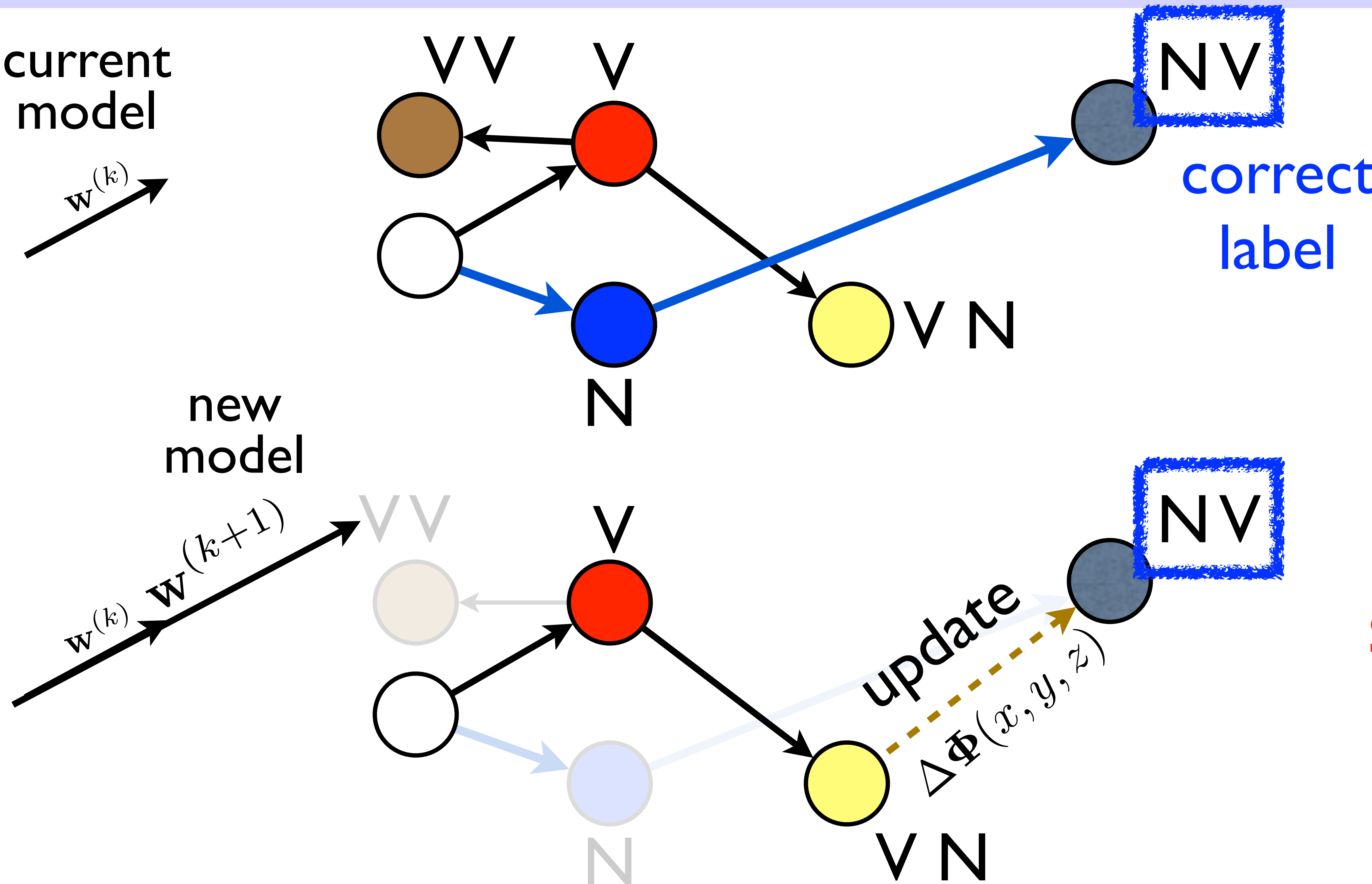
structured perceptron
does not converge
with greedy search

Which part of the convergence proof no longer holds?

No Convergence w/ Greedy Search



training example

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structured perceptron does not converge with greedy search

Which part of the convergence proof no longer holds?

the proof only uses 3 facts:

1. separation (margin)
2. diameter (always finite)
3. violation (guaranteed by exact search)

Geometry of Convergence Proof pt 2

repeat
  for each example (x, y) **in** D **do**
    $z \leftarrow \textsc{Exact}(x, \mathbf{w})$
    if $z \neq y$ **then**
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\mathbf{\Phi}(x, y, z)$
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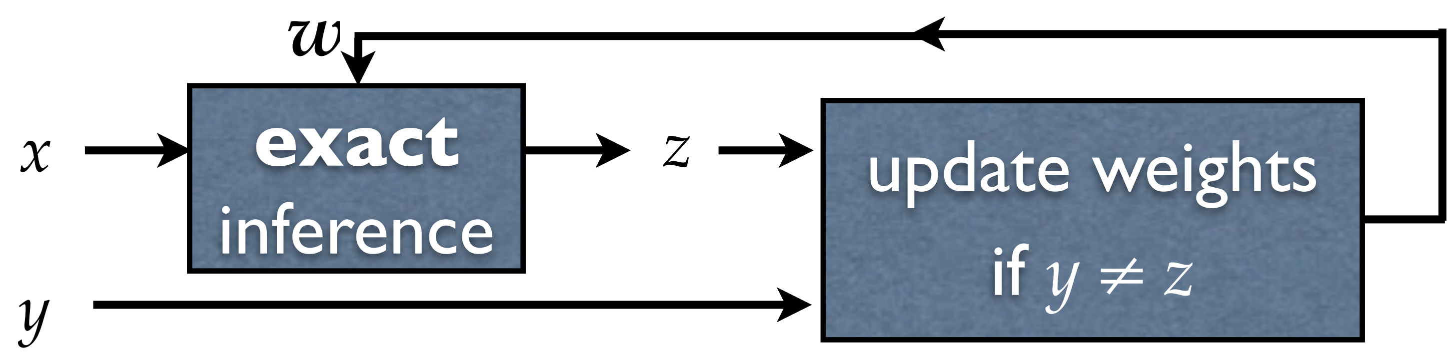
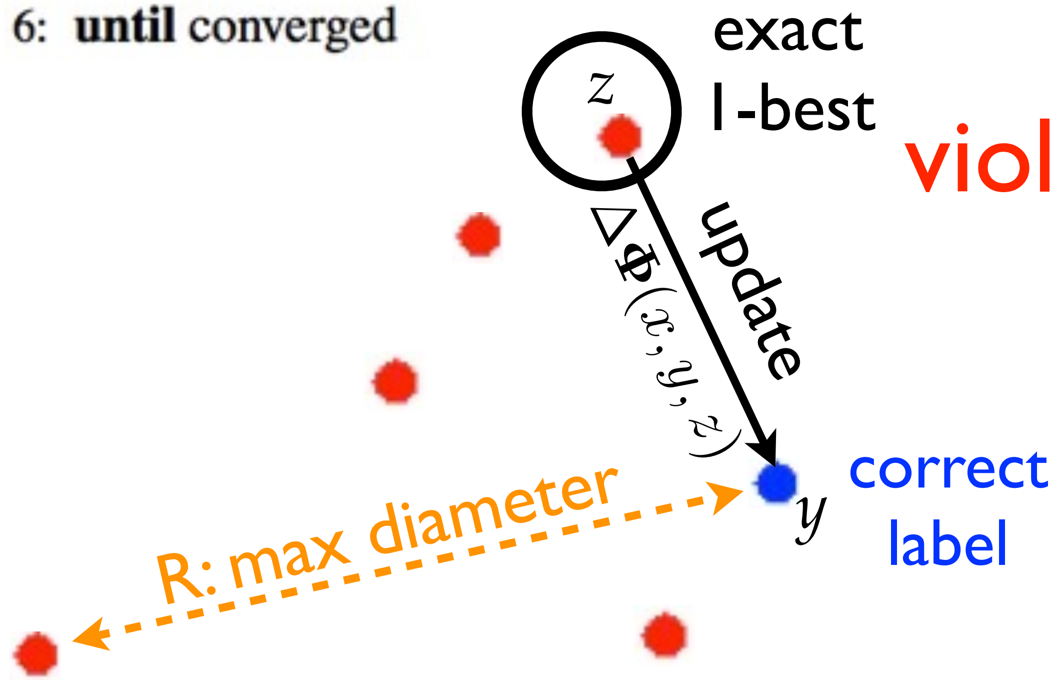




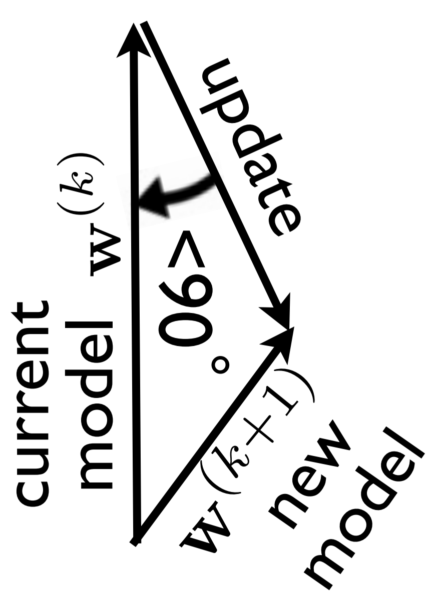
violation: incorrect label scored higher

perceptron update:

$$\mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} + \Delta\mathbf{\Phi}(x, y, z)$$

$$\|\mathbf{w}^{(k+1)}\|^2 = \|\mathbf{w}^{(k)} + \Delta\mathbf{\Phi}(x, y, z)\|^2$$

$$= \|\mathbf{w}^{(k)}\|^2 + \underbrace{\|\Delta\mathbf{\Phi}(x, y, z)\|^2}_{\leq R^2 \text{ diameter}} + 2\,\underbrace{\mathbf{w}^{(k)} \cdot \Delta\mathbf{\Phi}(x, y, z)}_{\leq 0 \text{ violation}}$$



Geometry of Convergence Proof pt 2

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repeat
    for each example (x, y) in D do
        z ← EXACT(x, w)
        if z ≠ y then
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until converged
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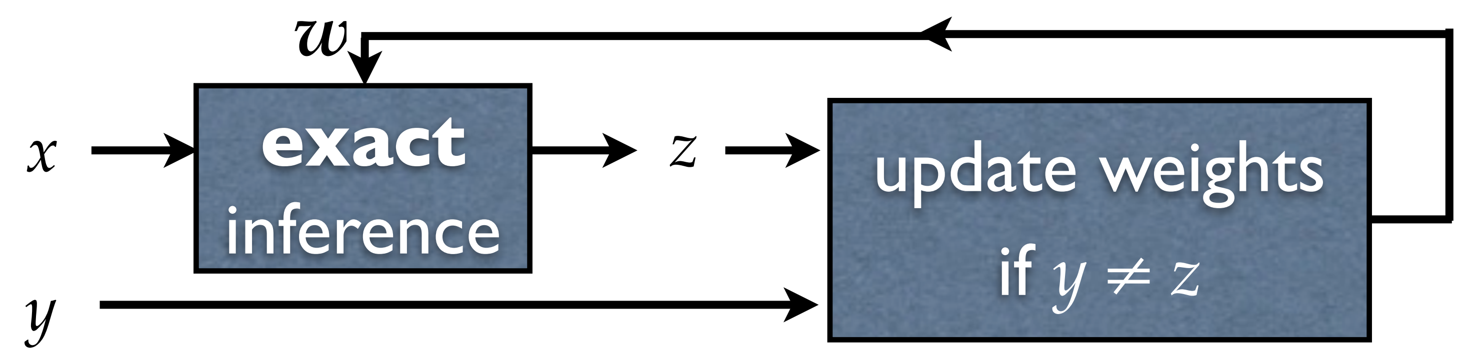

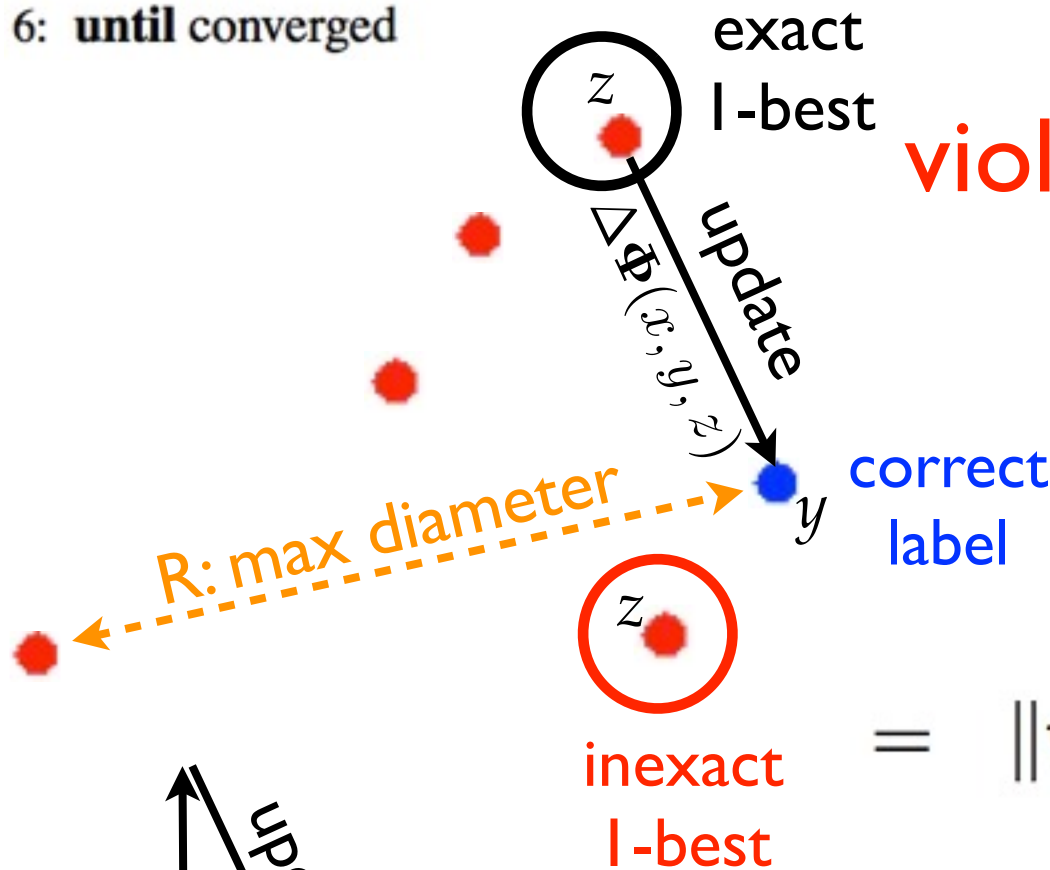

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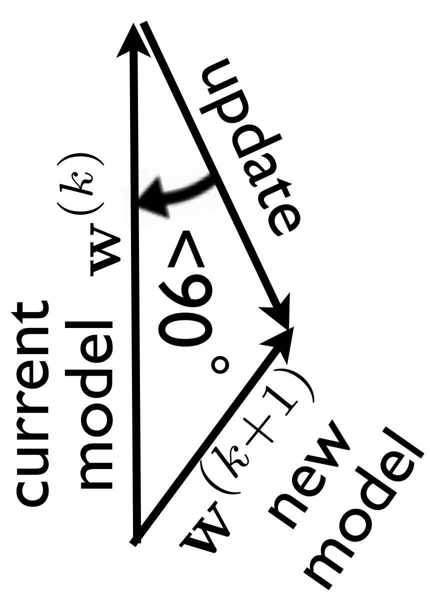

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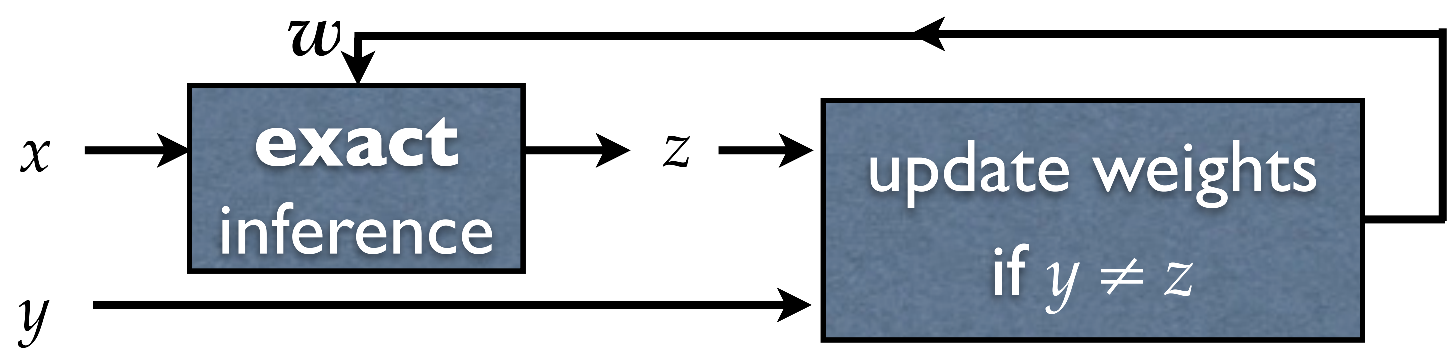

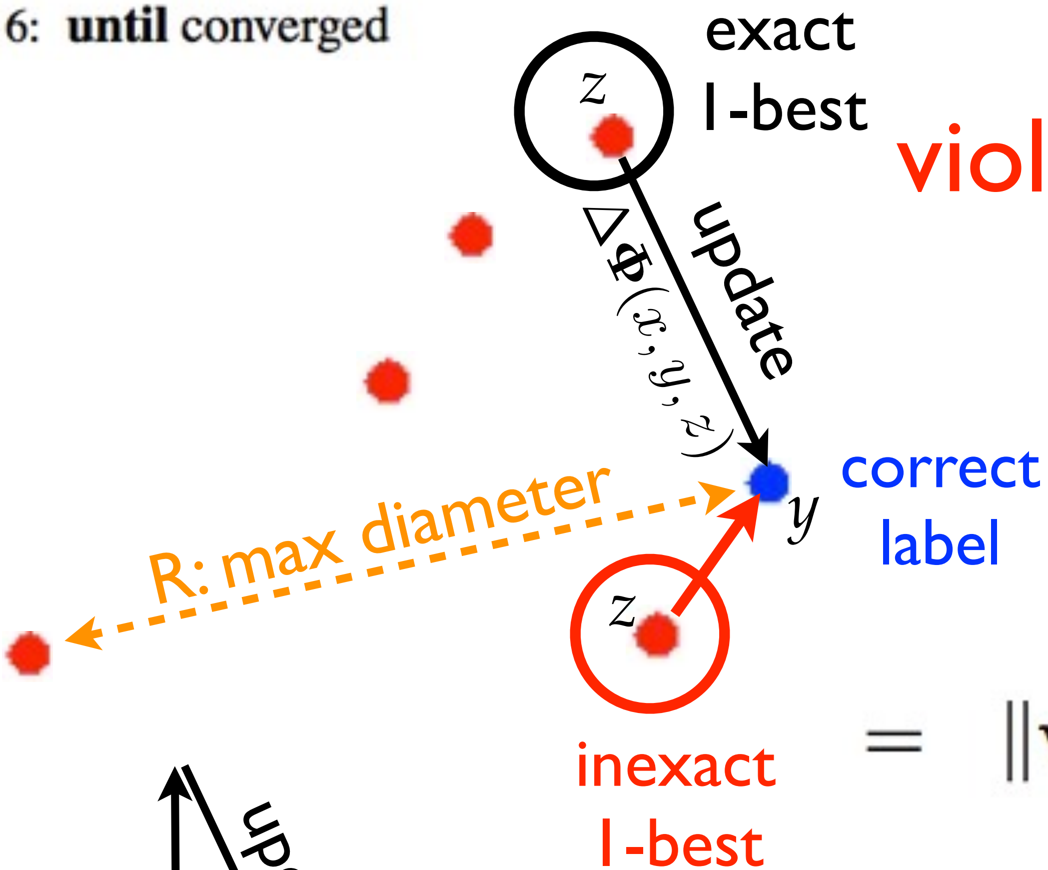

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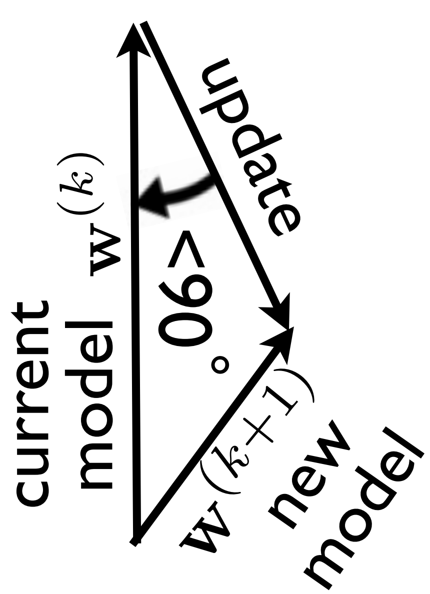

Geometry of Convergence Proof pt 2

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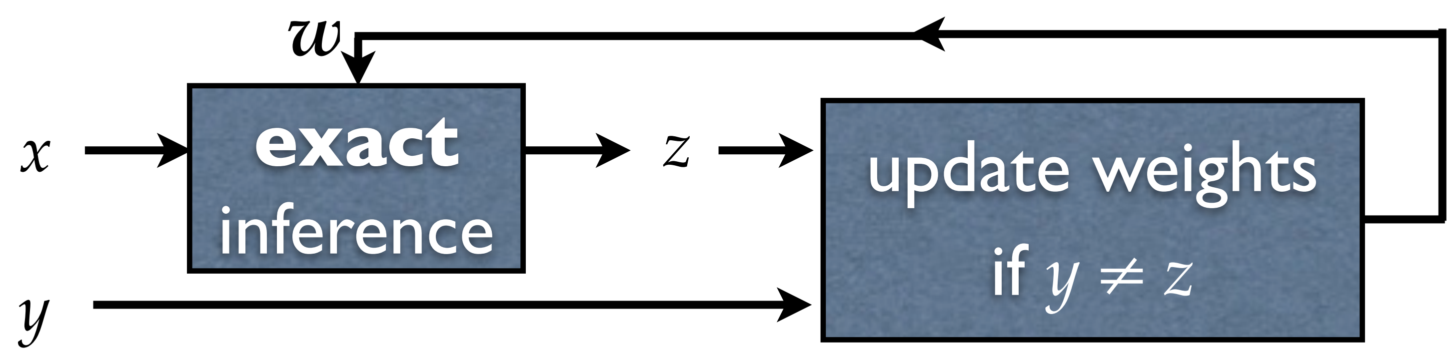

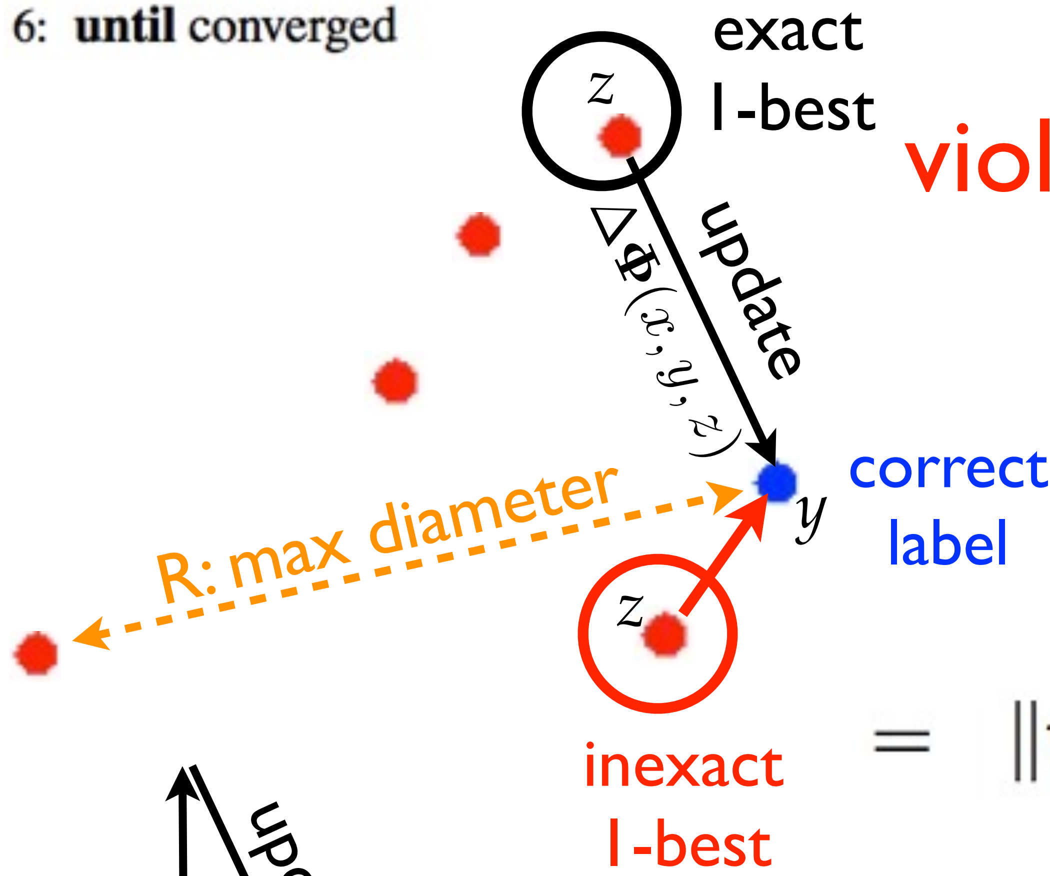

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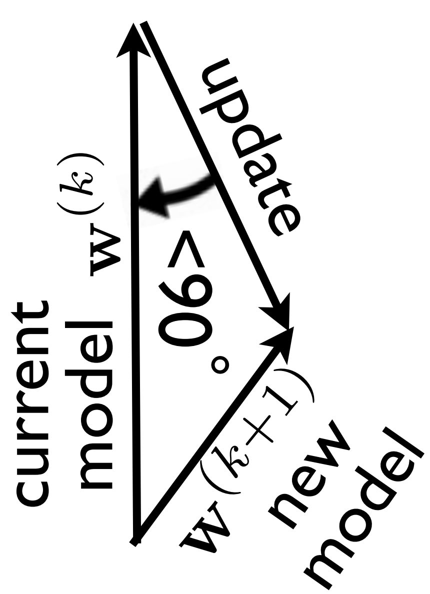

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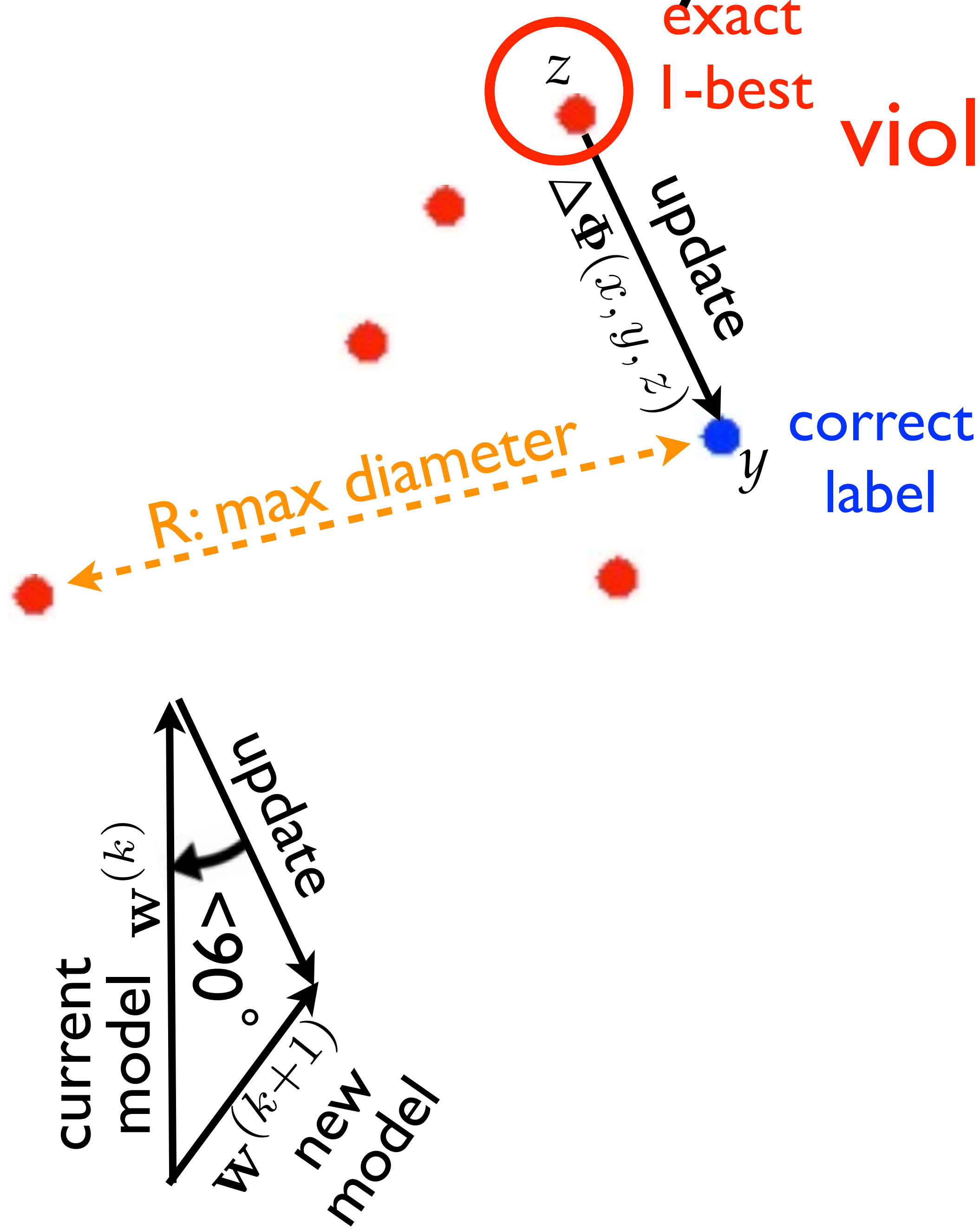
inexact search doesn't guarantee violation!

Observation: Violation is all we need!

- exact search is **not** really required by the proof
  - rather, it is only used to ensure violation!



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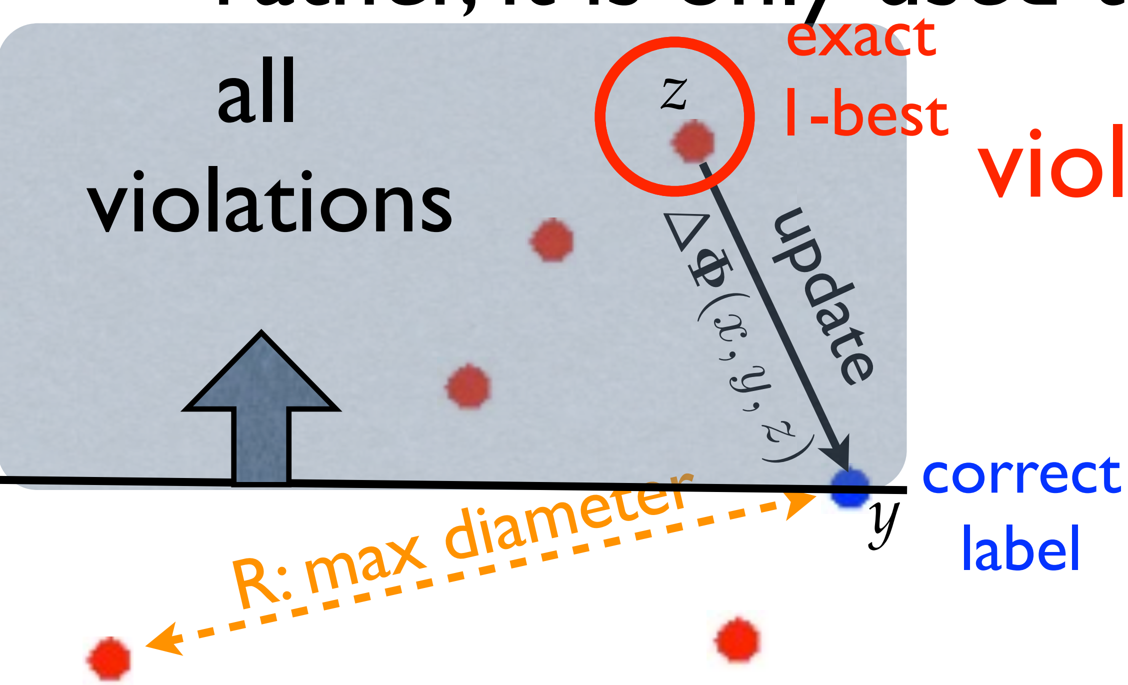

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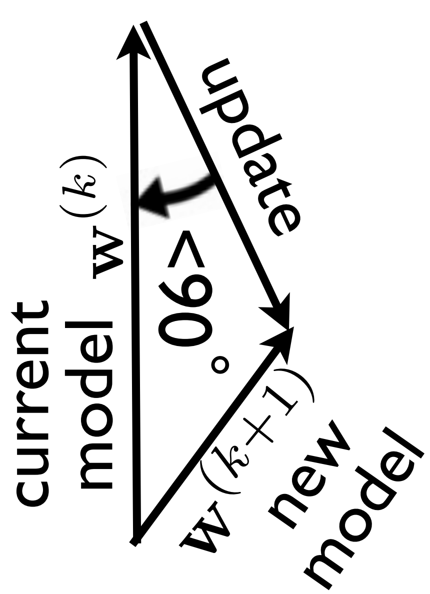

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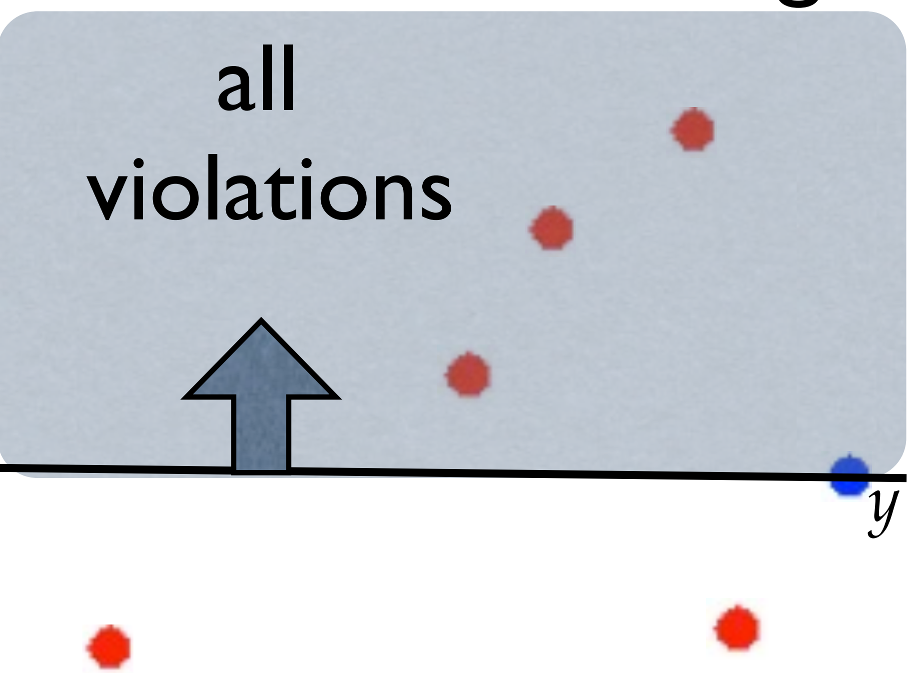
Violation-Fixing Perceptron

- if we guarantee violation, we don't care about exactness!
  - violation is good b/c we can at least fix a mistake



same mistake bound as before!

repeat
  for each example (x, y) **in** D **do**
    $(x, y', z) = \textsc{FindViolation}(x, y, \mathbf{w})$
    if $z \neq y$ **then** $\triangleright$ (x, y', z) is a viol
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\Phi(x, y', z)$
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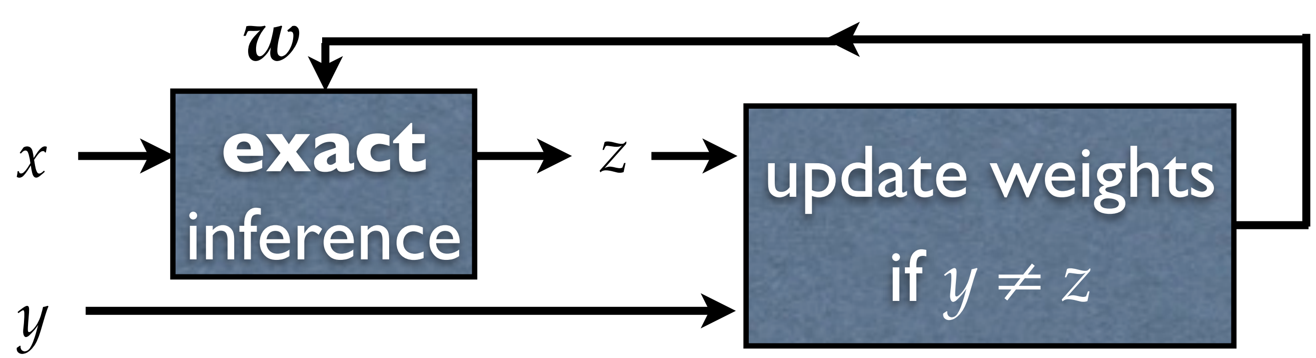
standard perceptron



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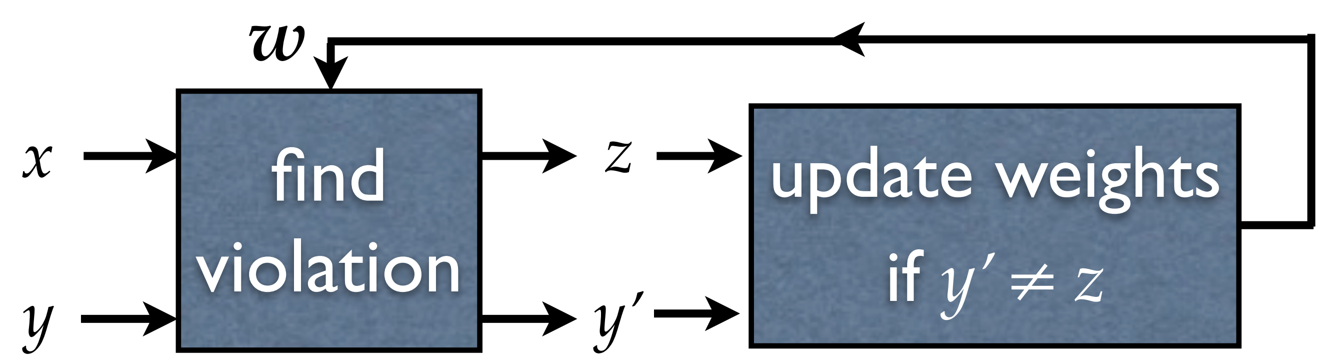

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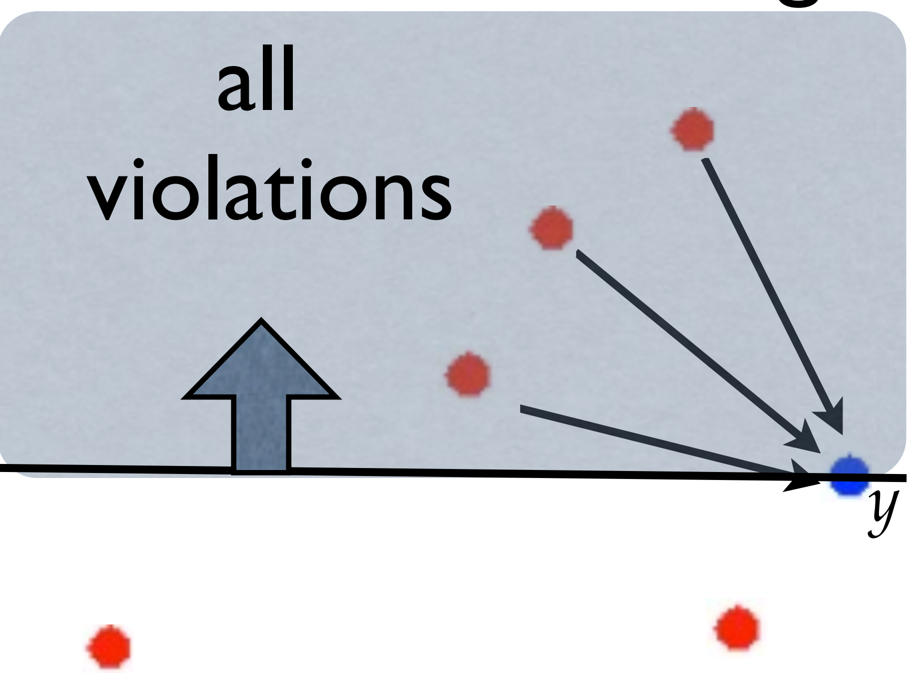

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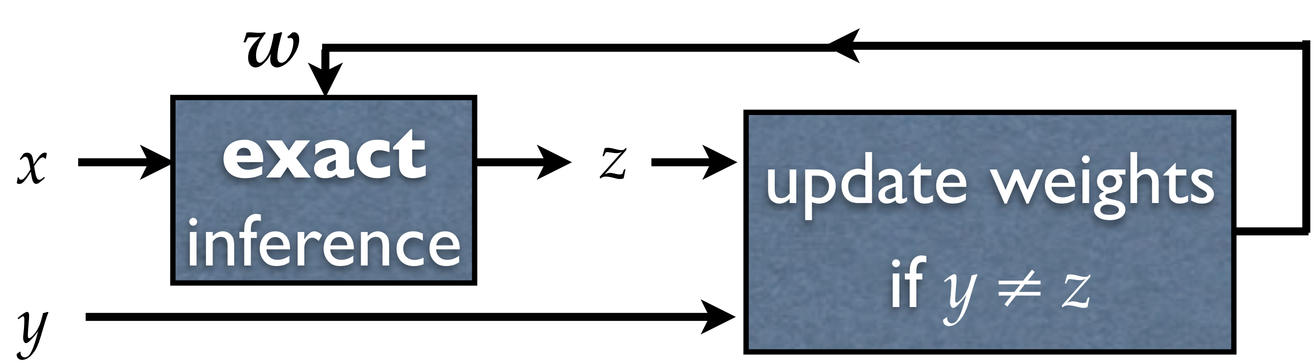
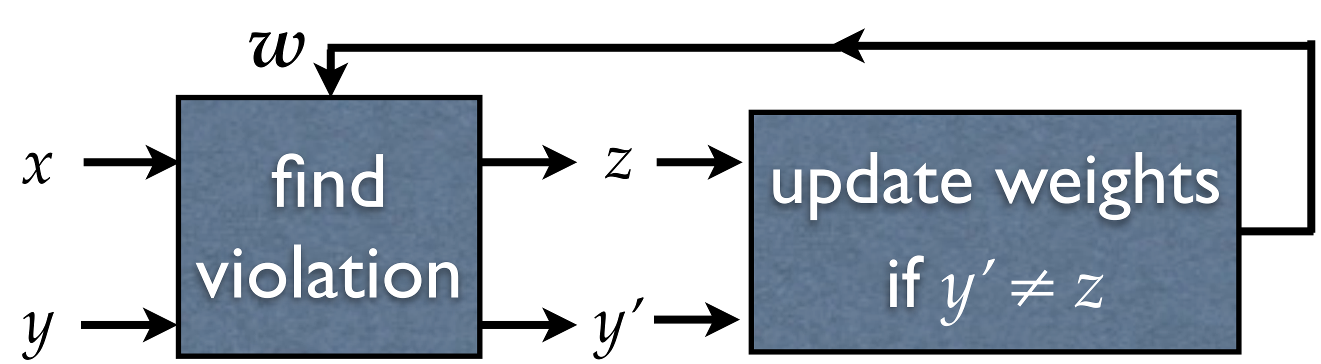


violation-fixing perceptron



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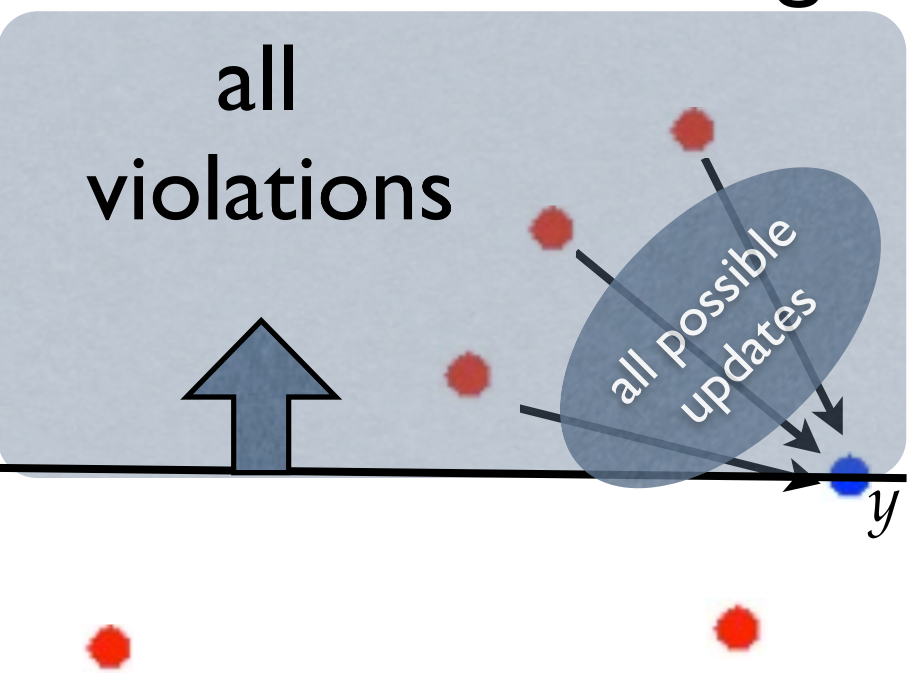

same mistake bound as before!

repeat
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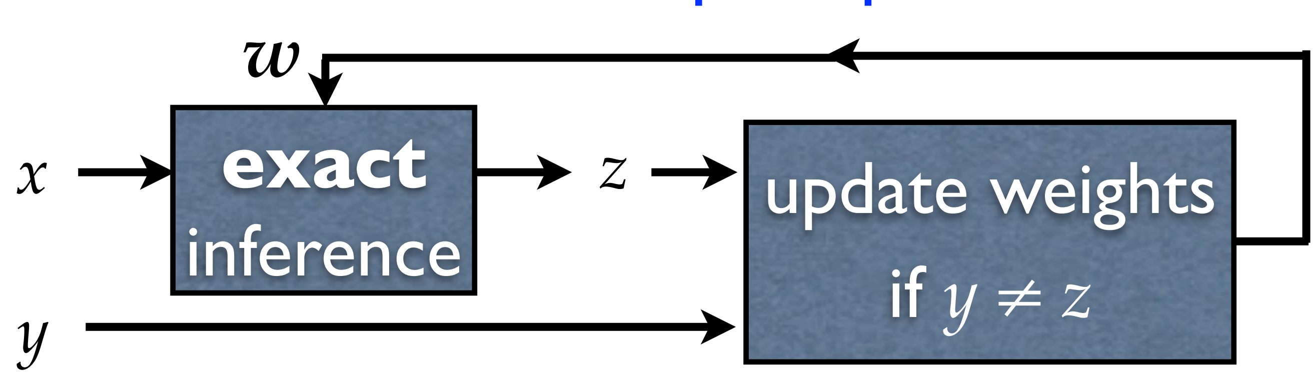

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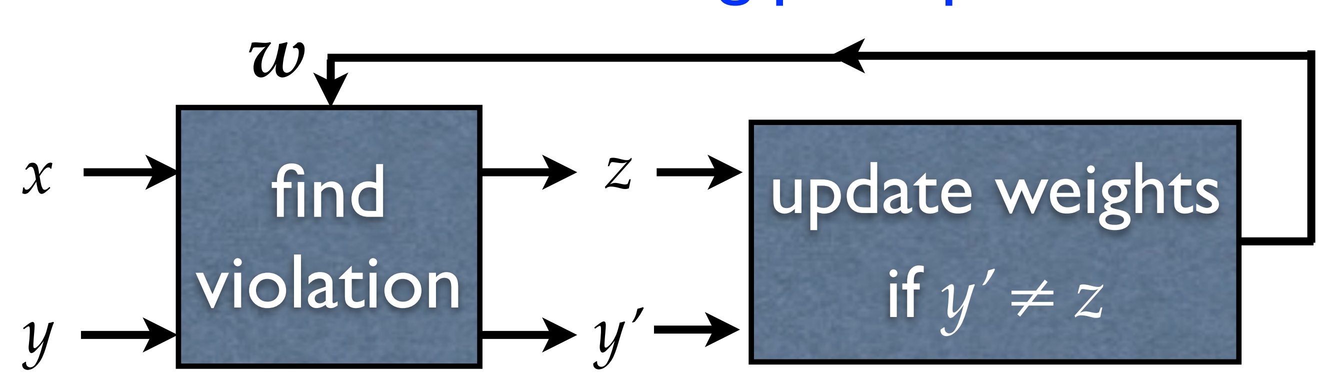
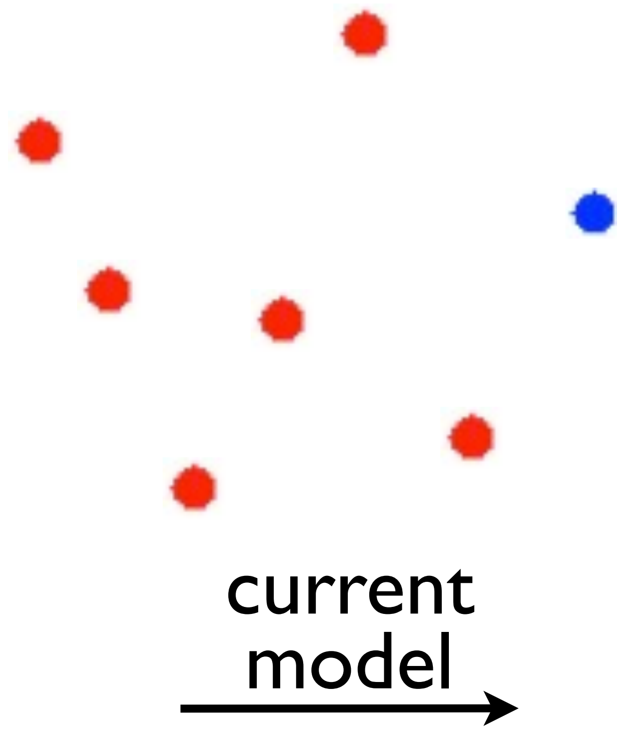


What if can't guarantee violation



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- this is why perceptron doesn't work well w/ inexact search
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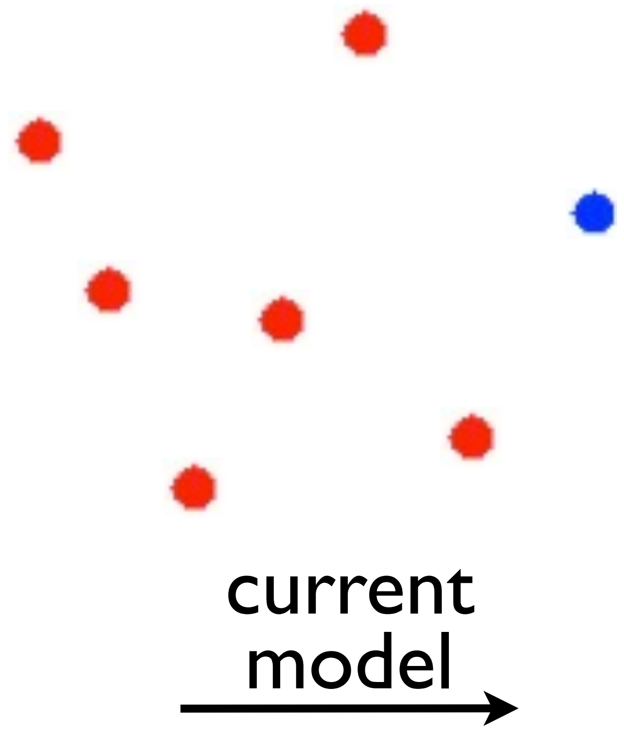

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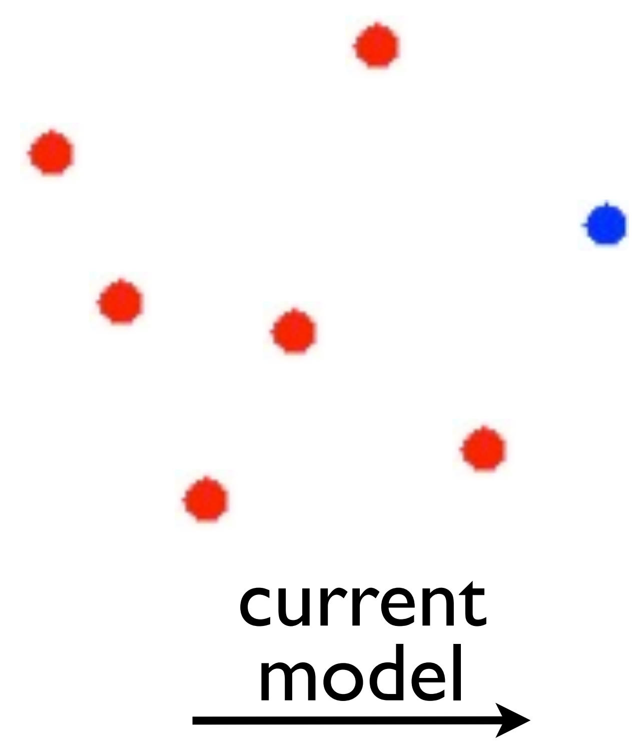
  - the new model still misguides the search



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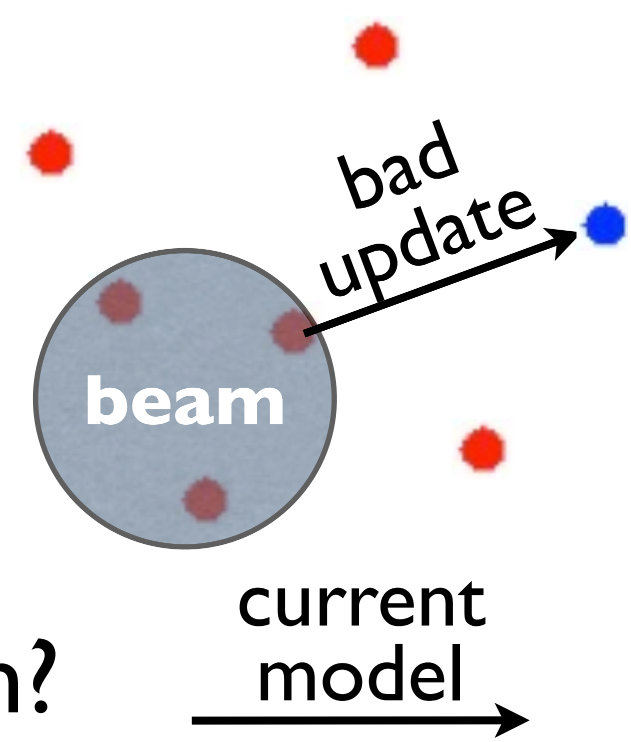
- Q: how can we always guarantee violation?



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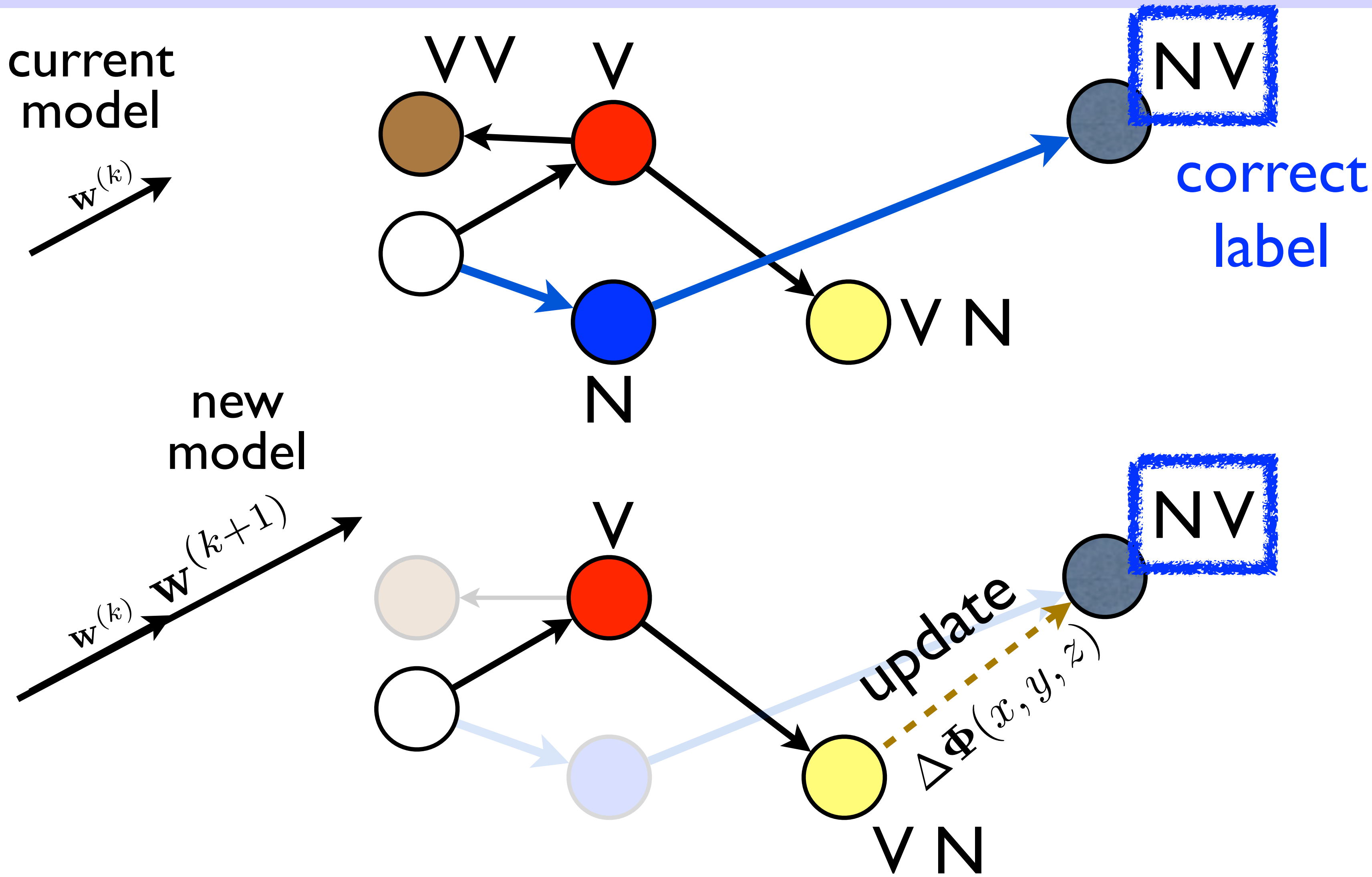


training example

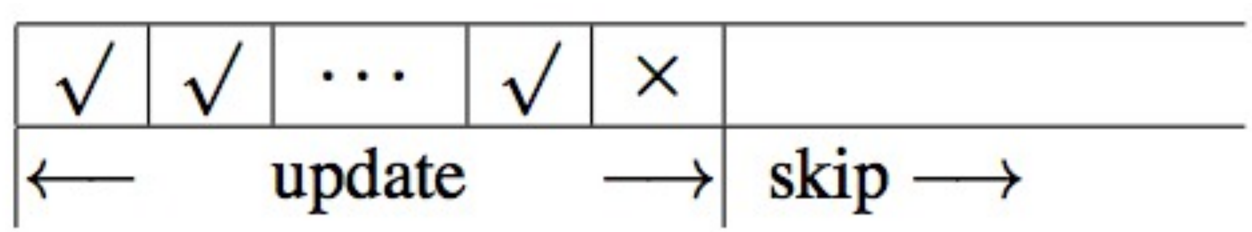
time flies

N V

output space

{N,V} x {N,V}

standard perceptron does not converge with greedy search



stop and update at the first mistake

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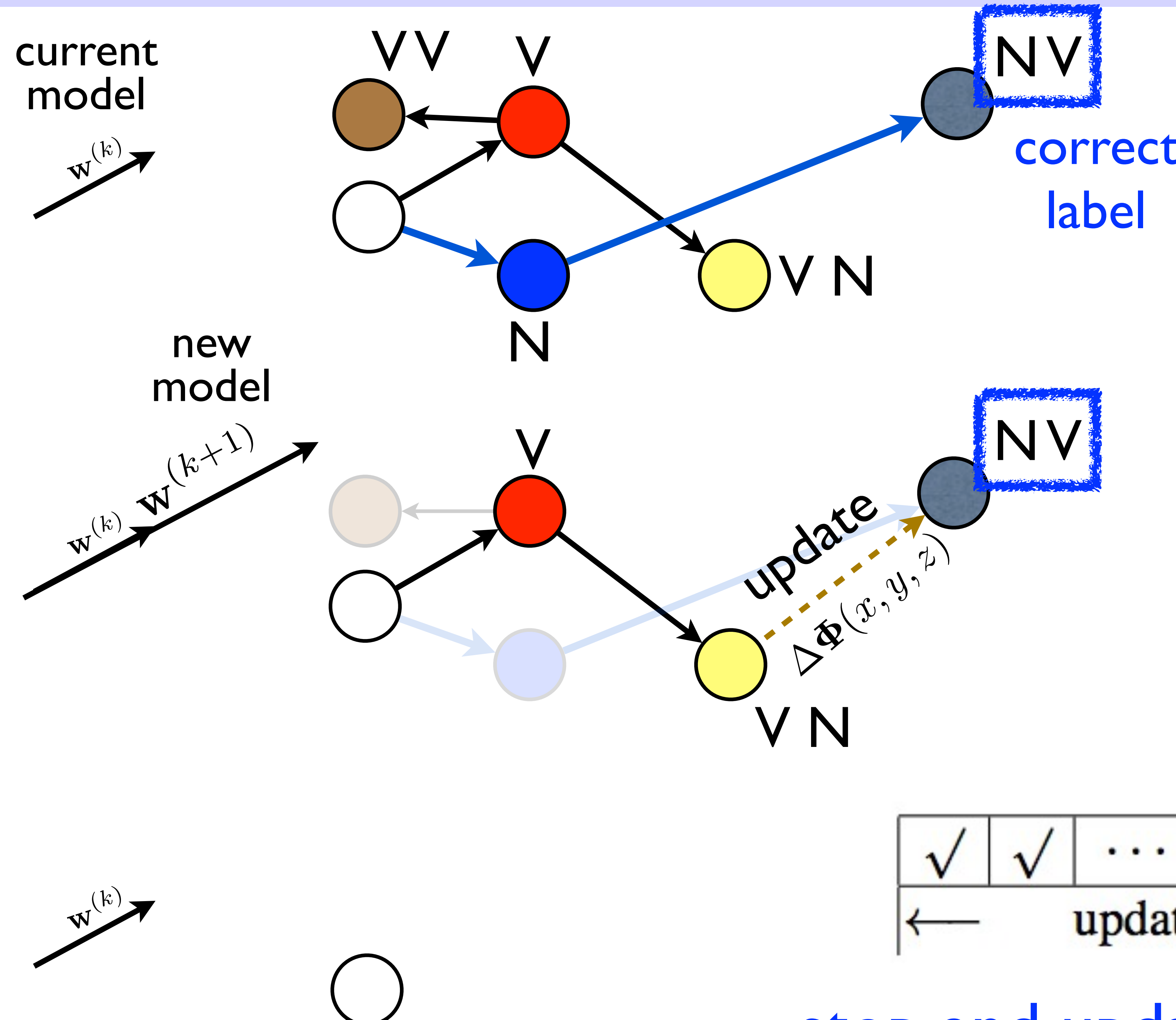

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$\surd$	$\surd$	$\cdots$	$\surd$	$\times$	
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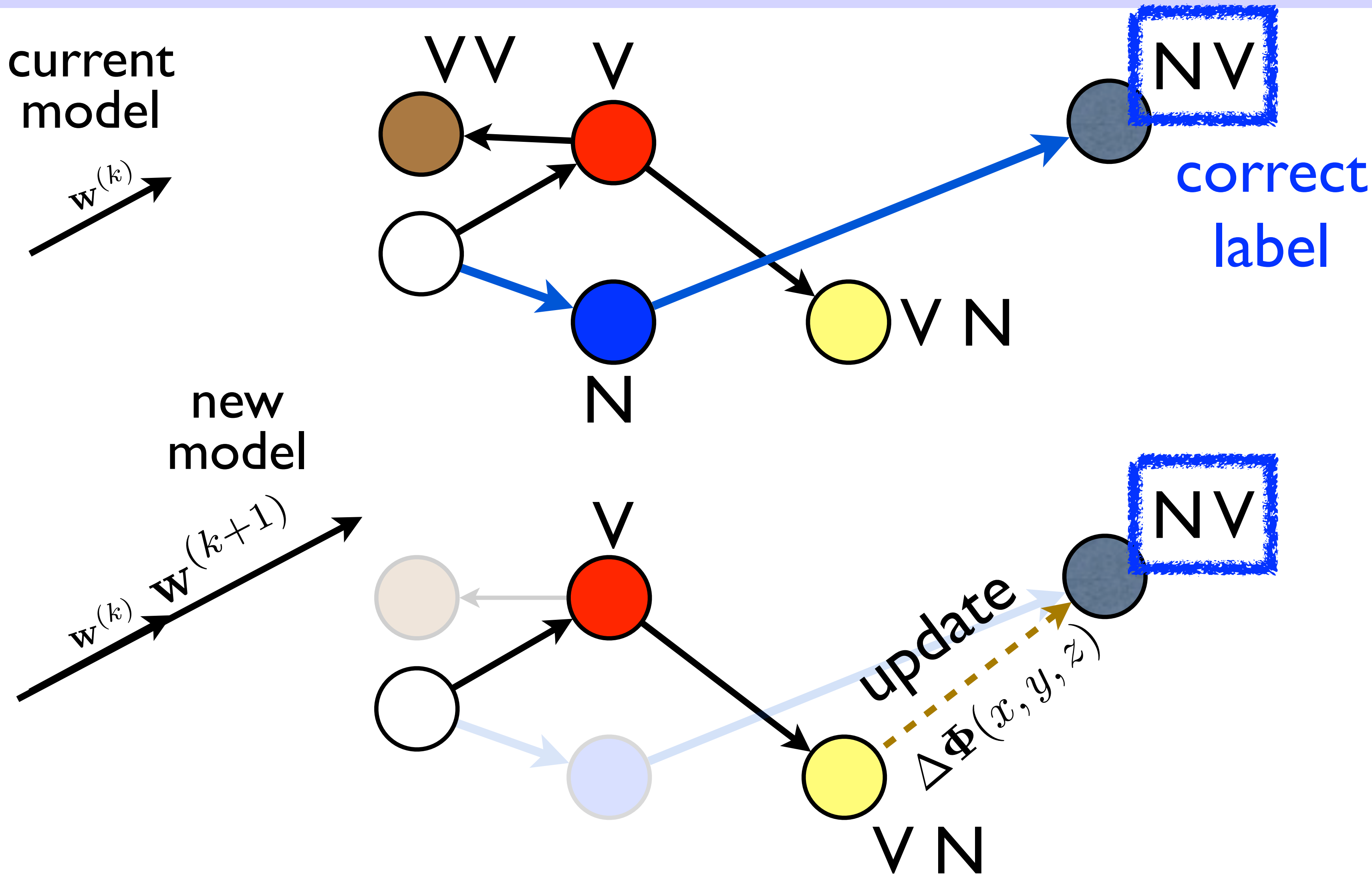

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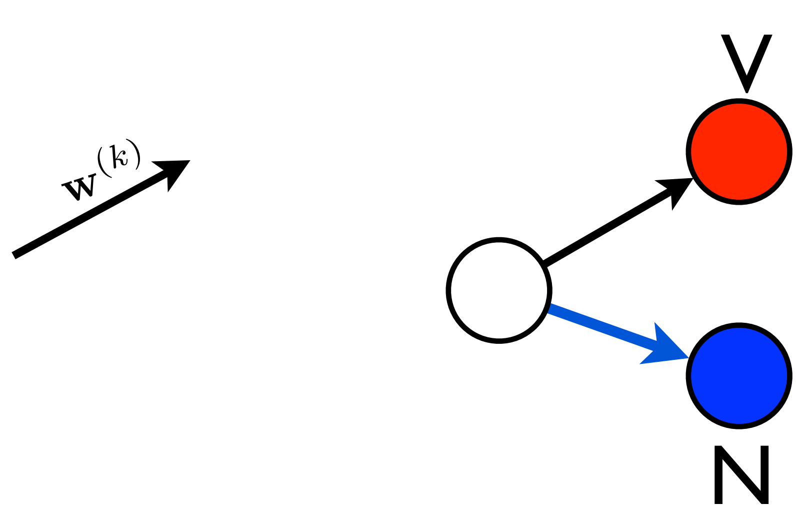

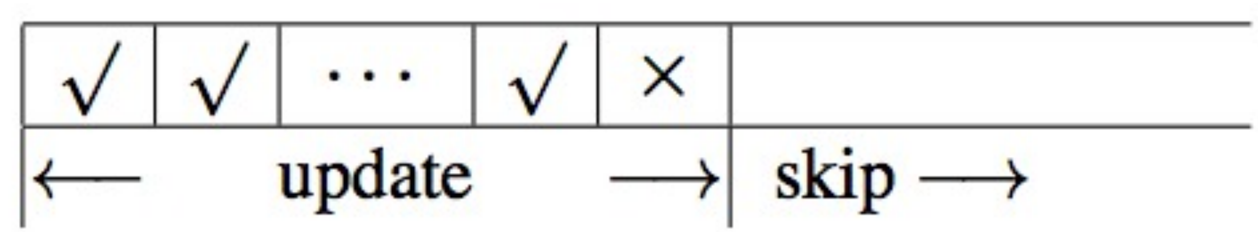

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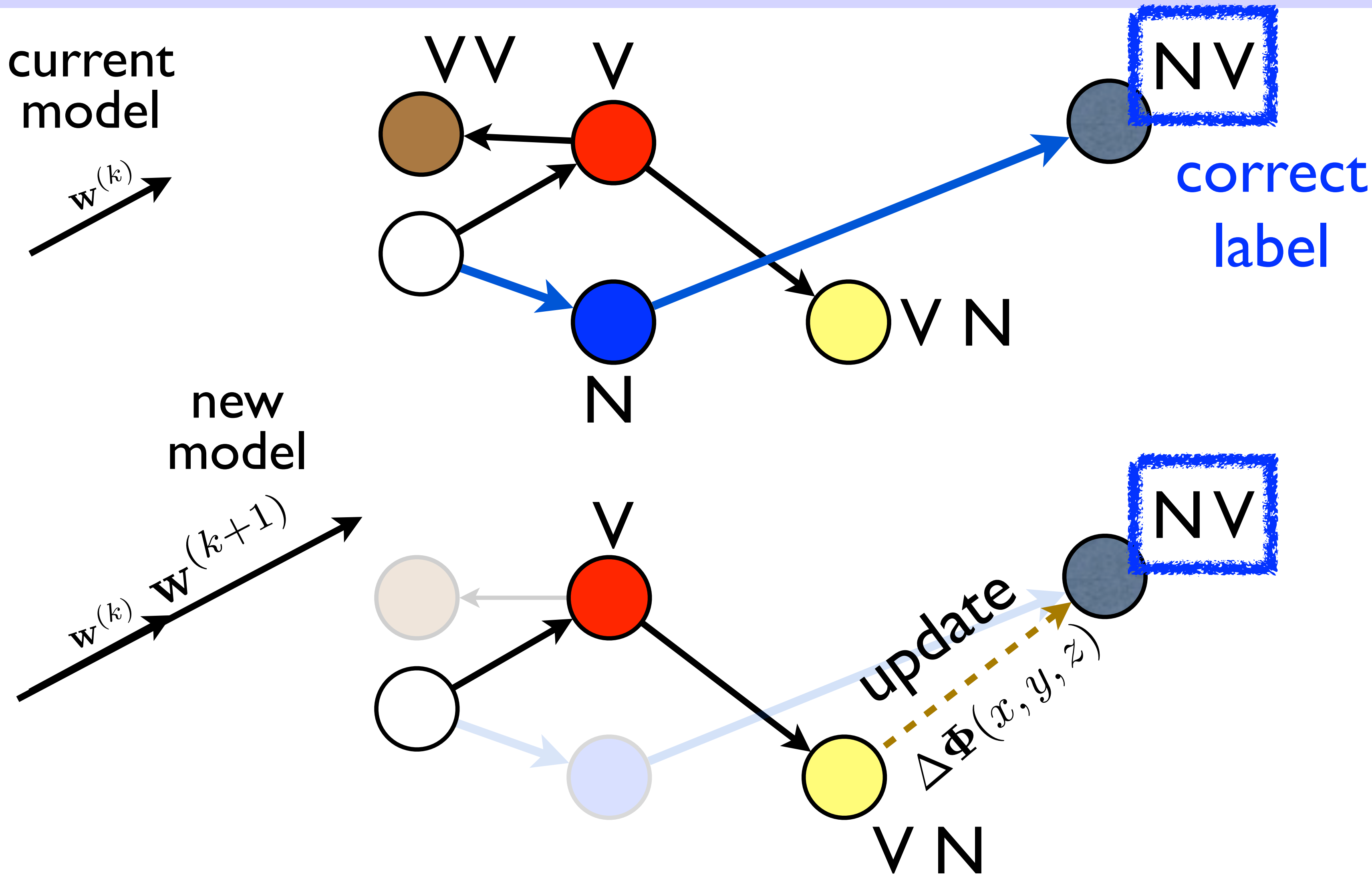

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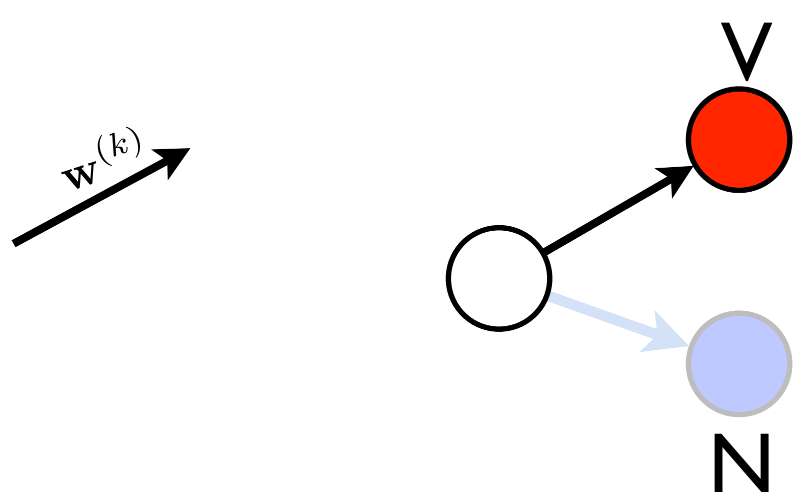

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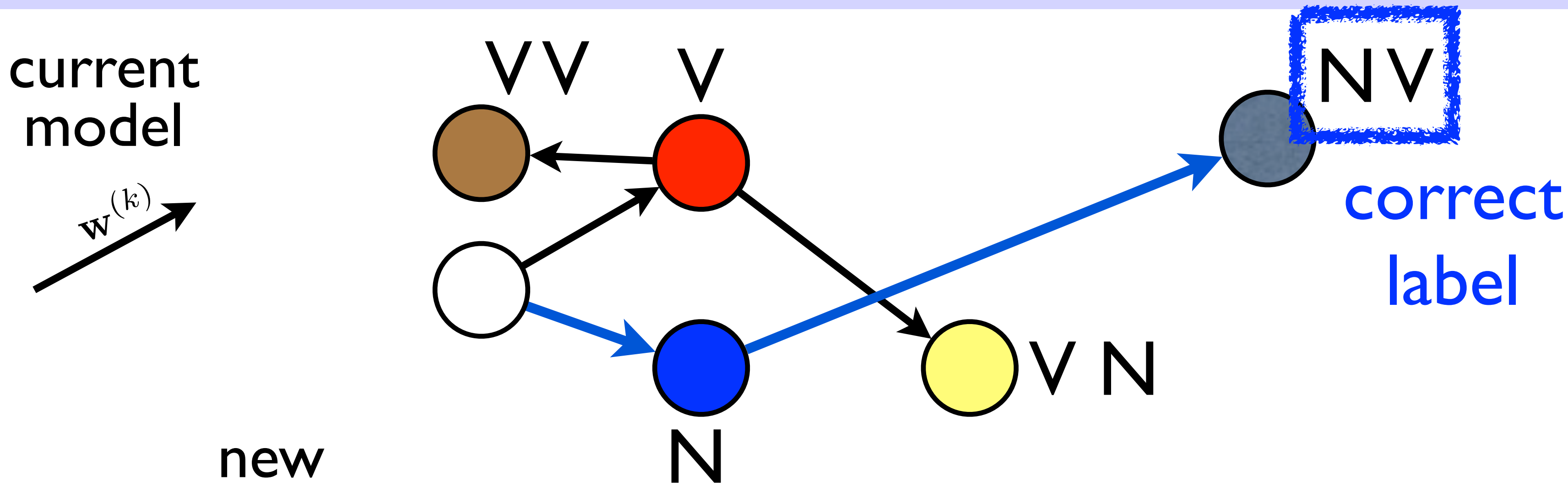

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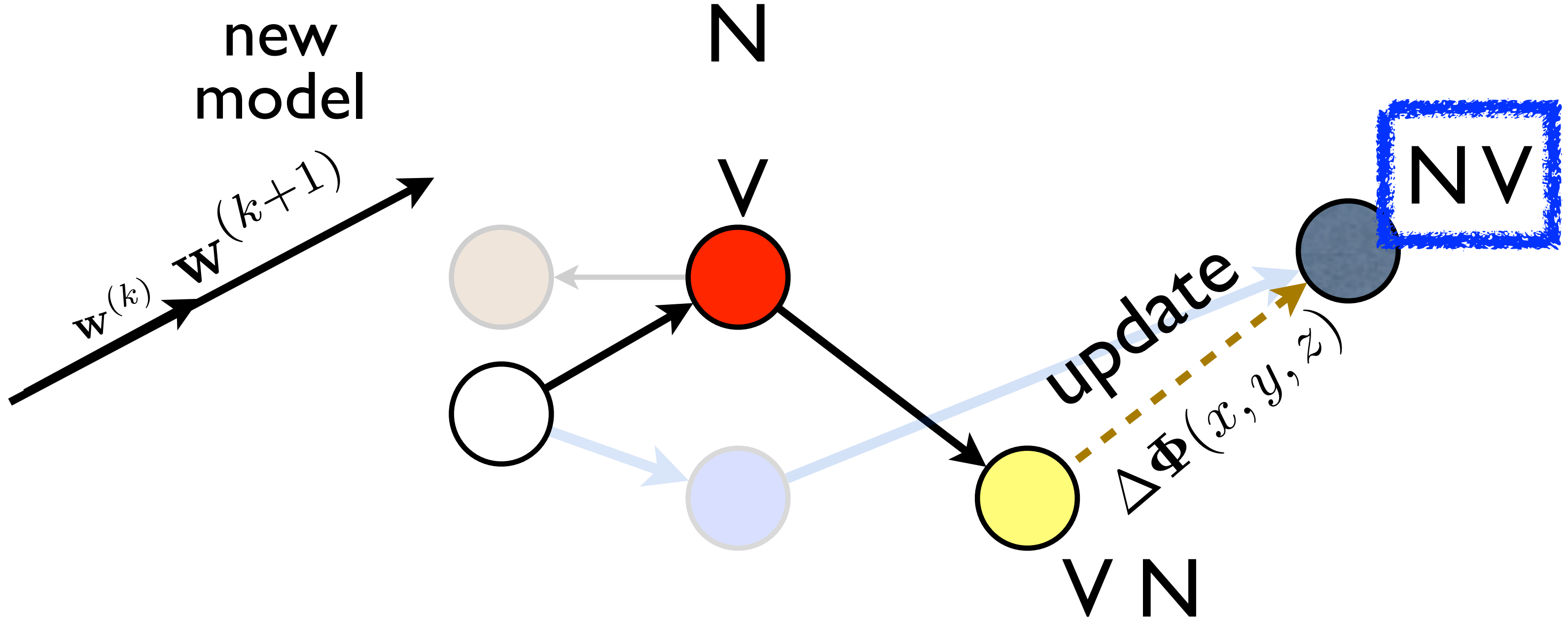

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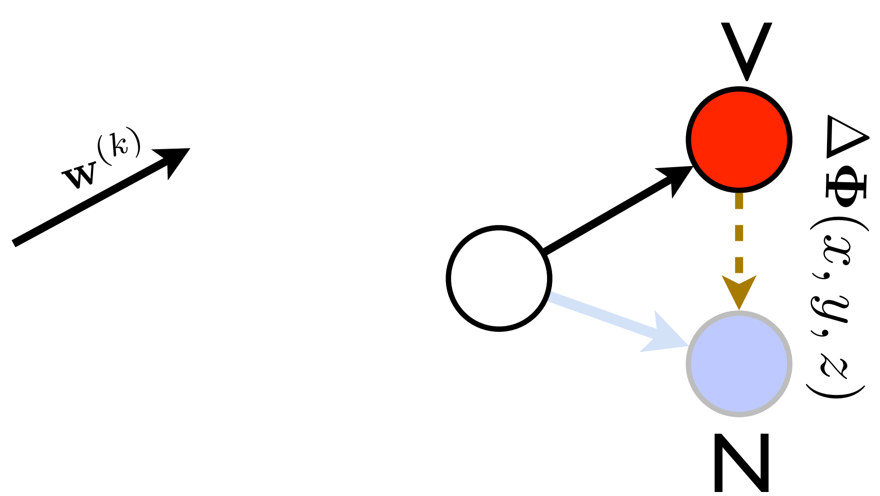

√	√	···	√	×	
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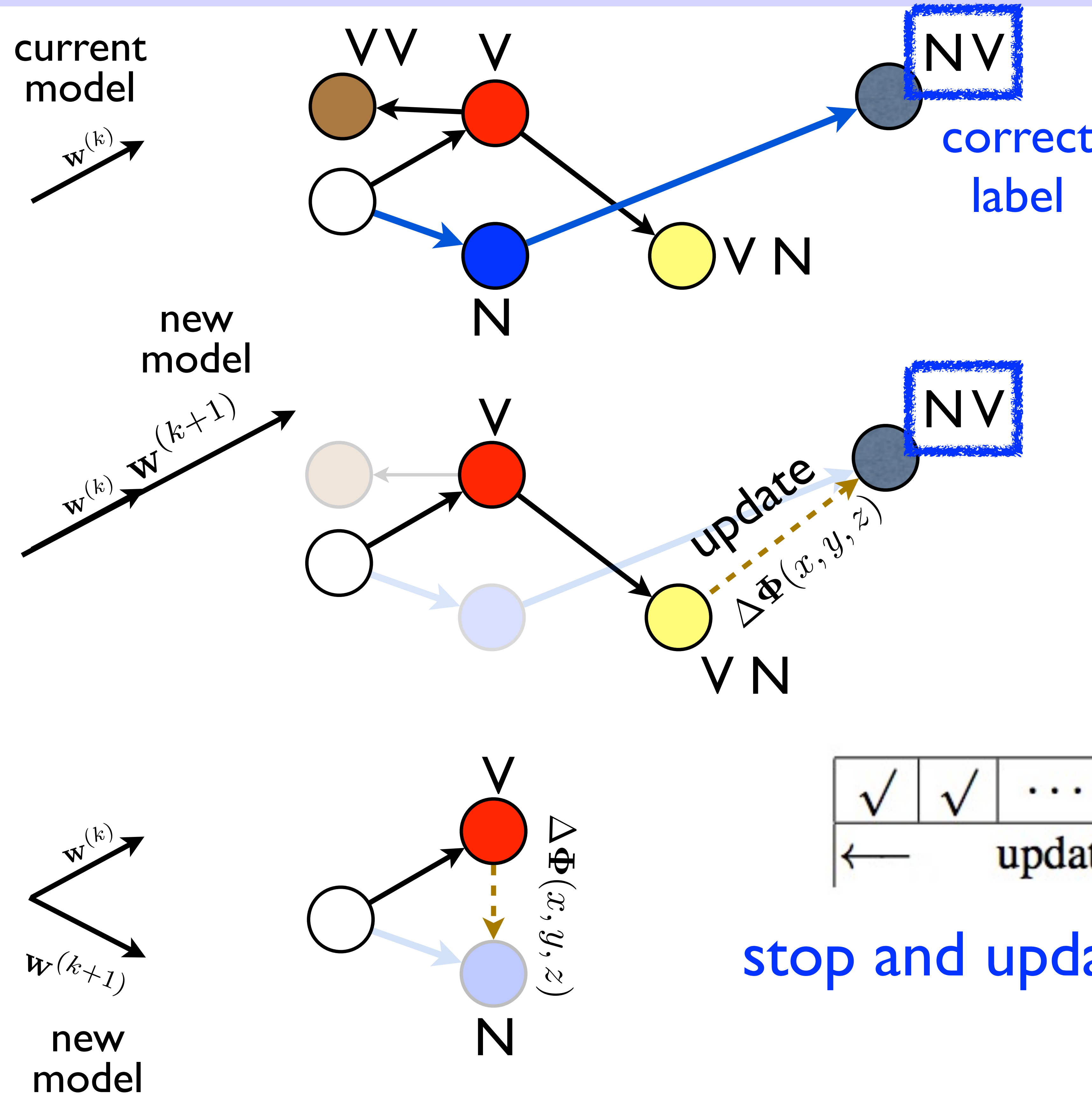

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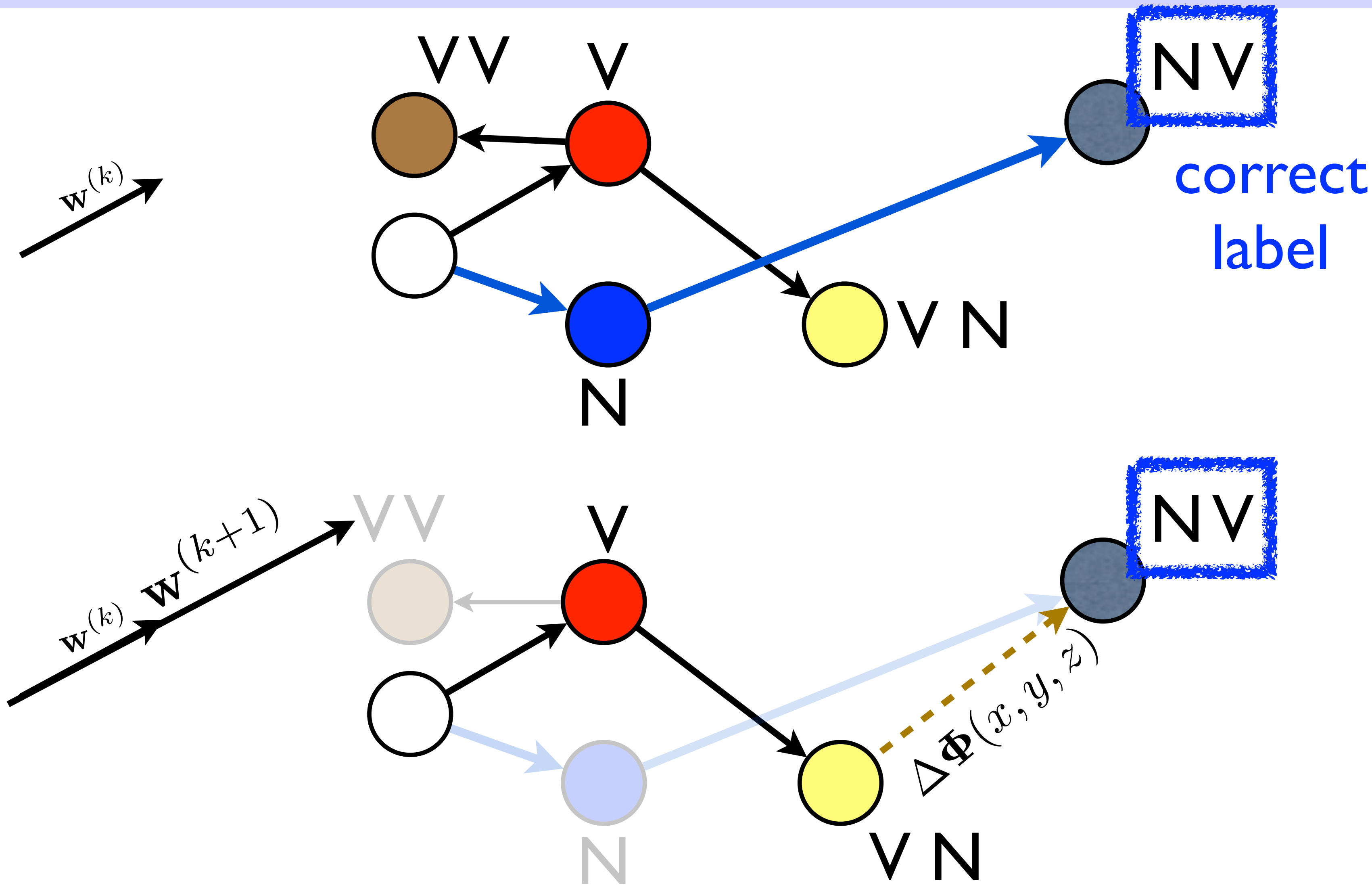

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√	√	···	√	×	
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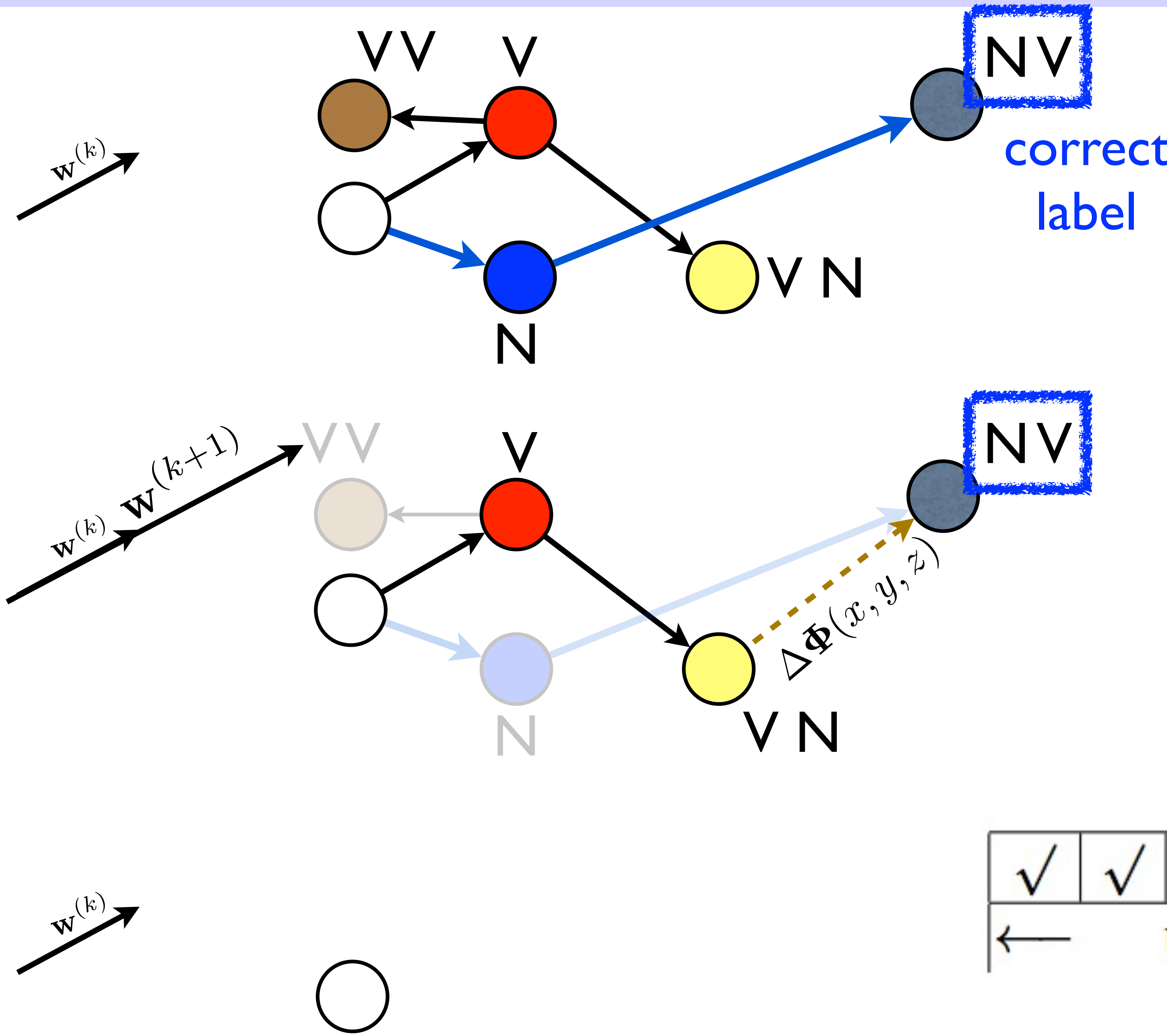

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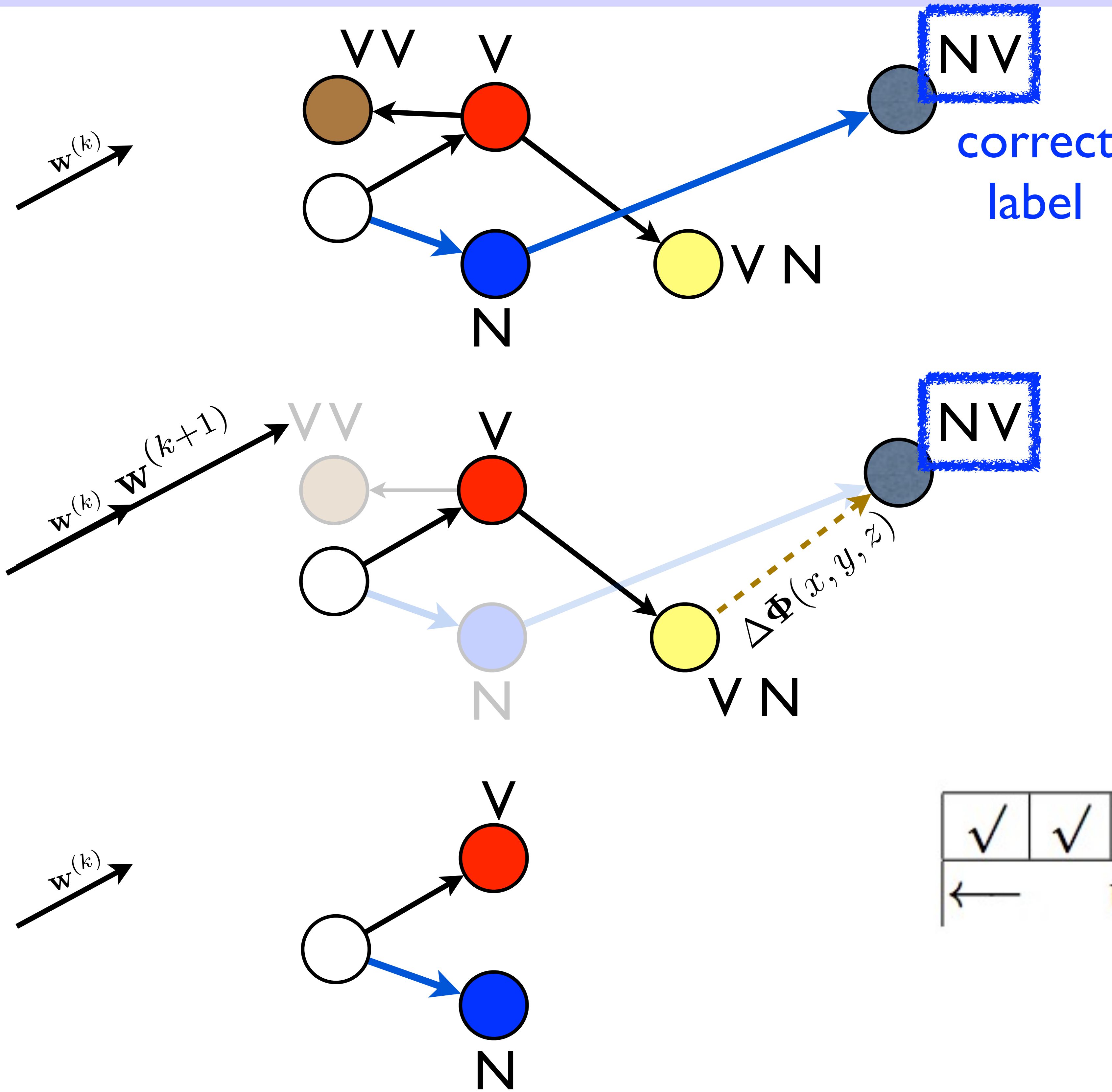

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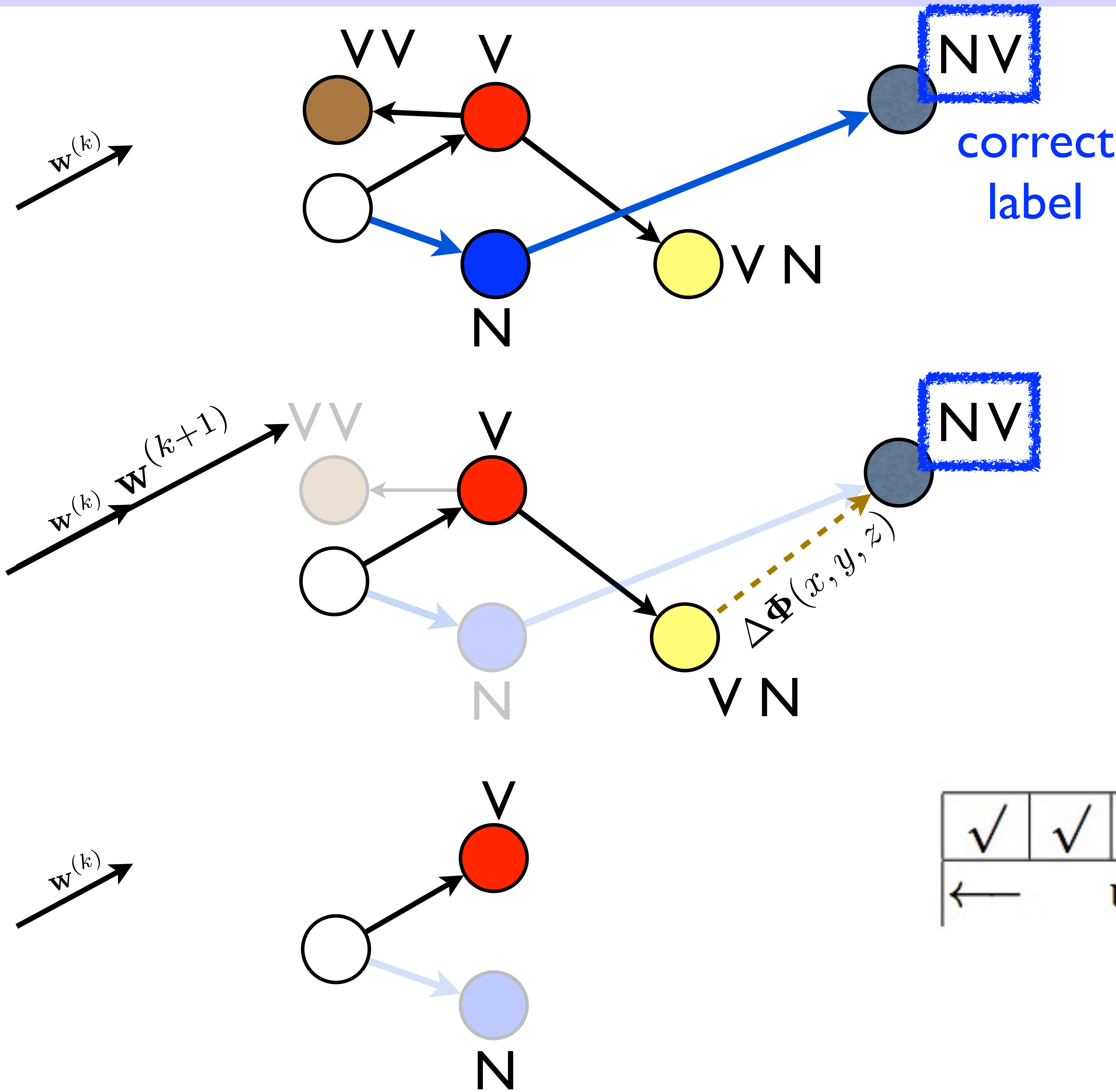

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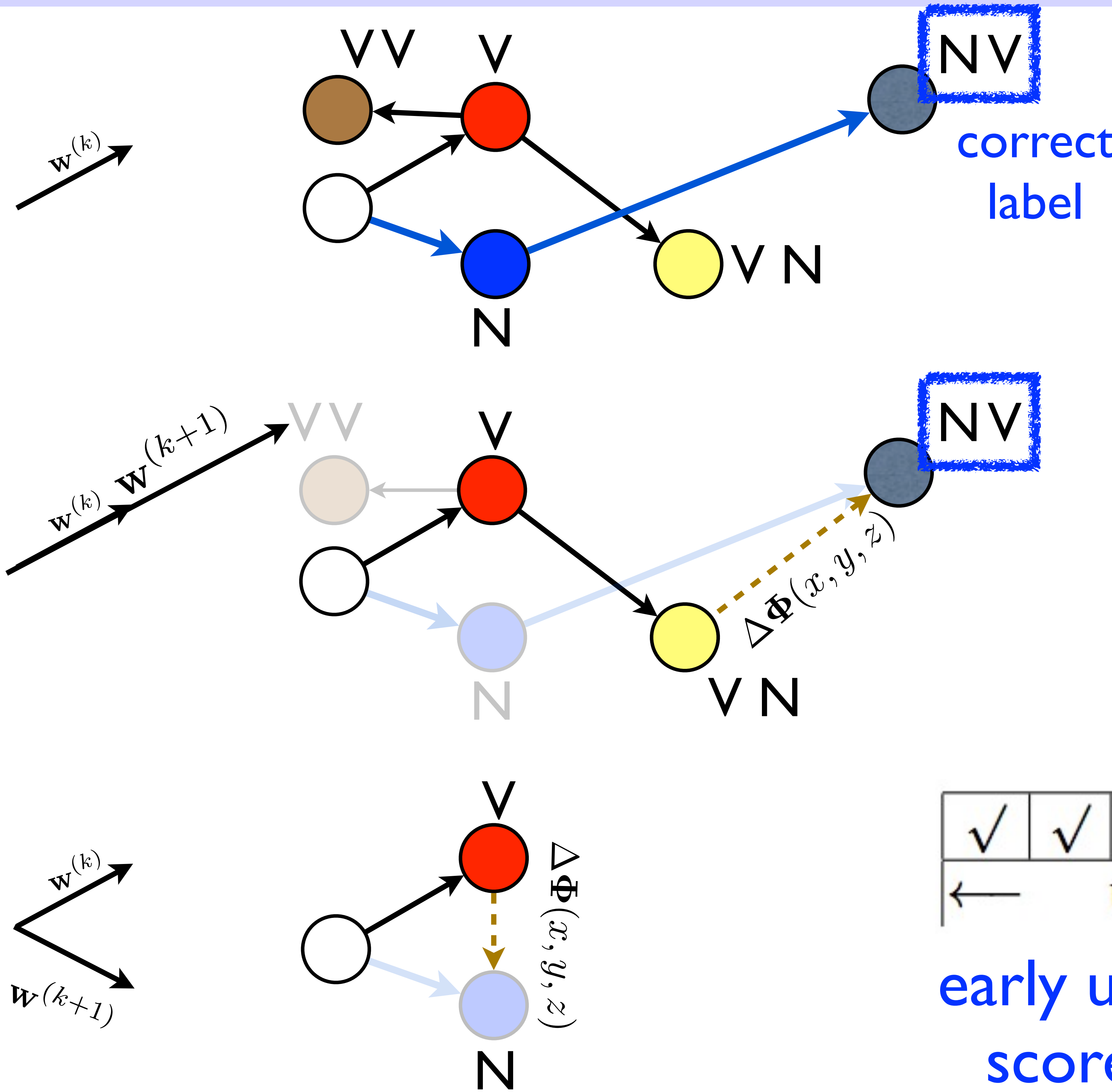

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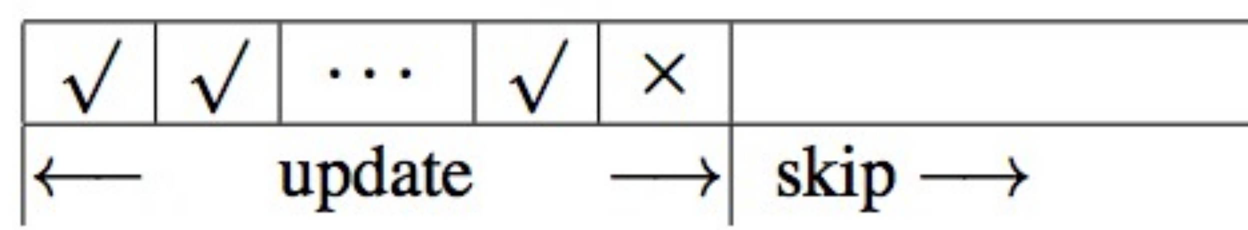
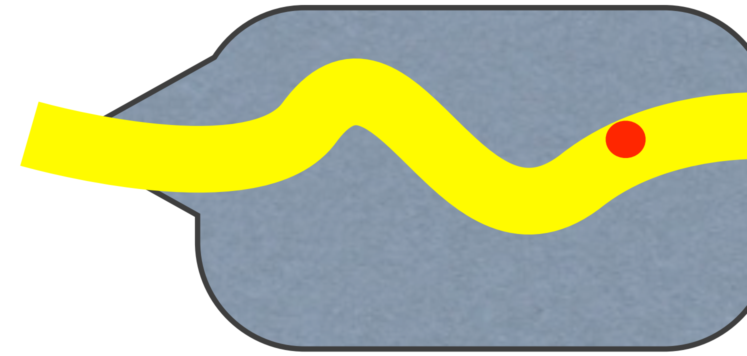


early update: incorrect prefix scores higher: a violation!

Early Update: from Greedy to Beam

- beam search is a generalization of greedy (where b=1)
  - at each stage we keep top b hypothesis
  - widely used: tagging, parsing, translation...



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standard update
(no guarantee!)

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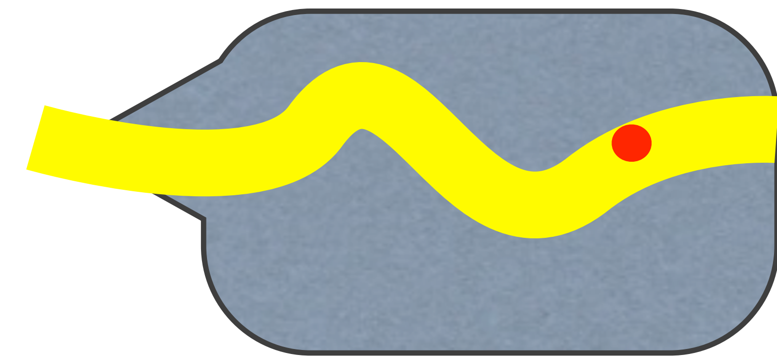

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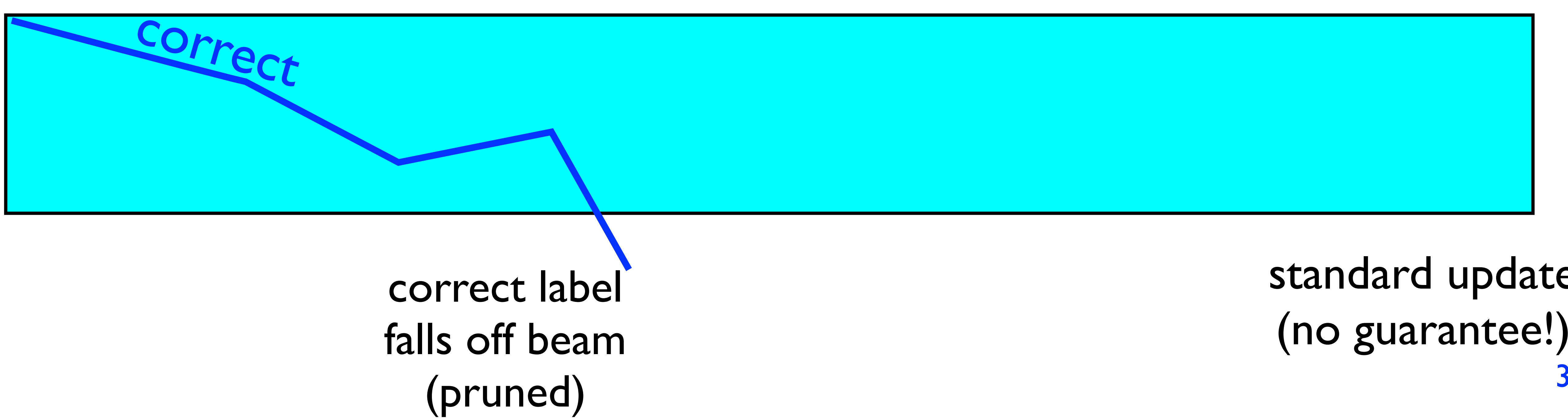

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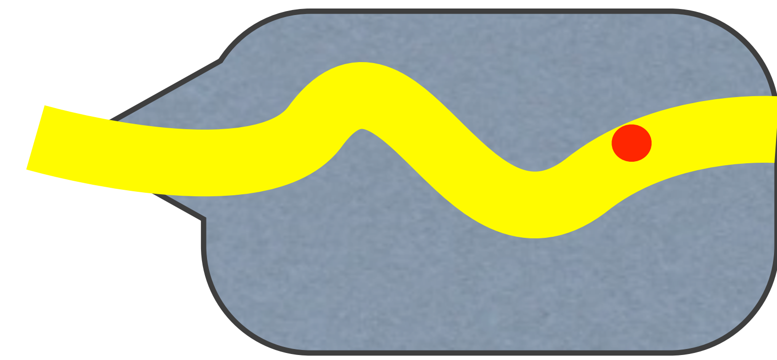

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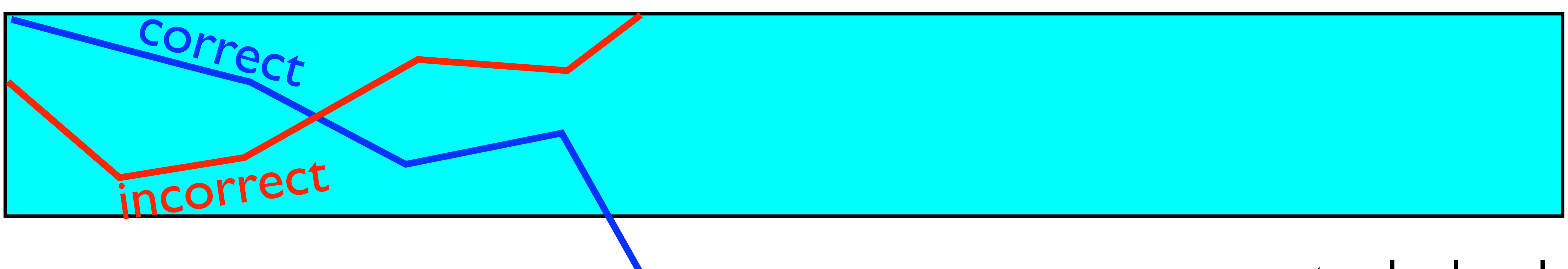

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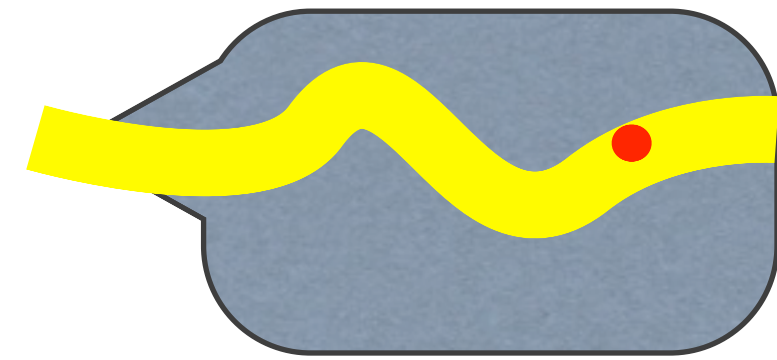

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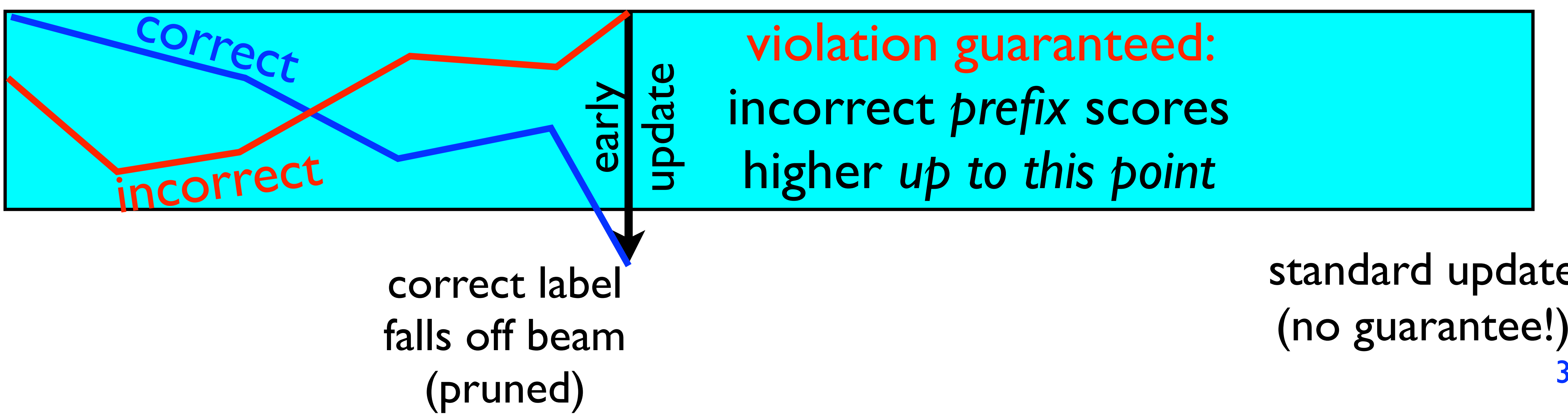

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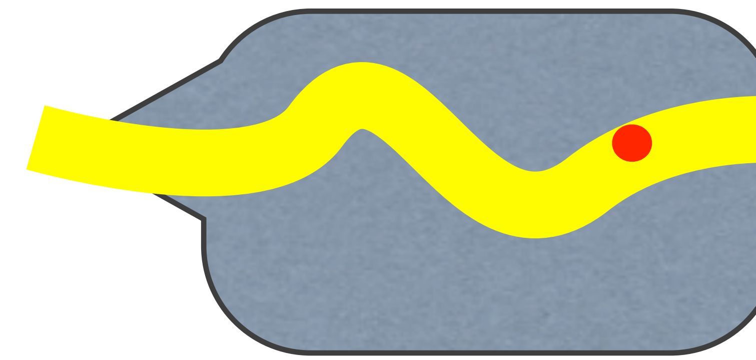

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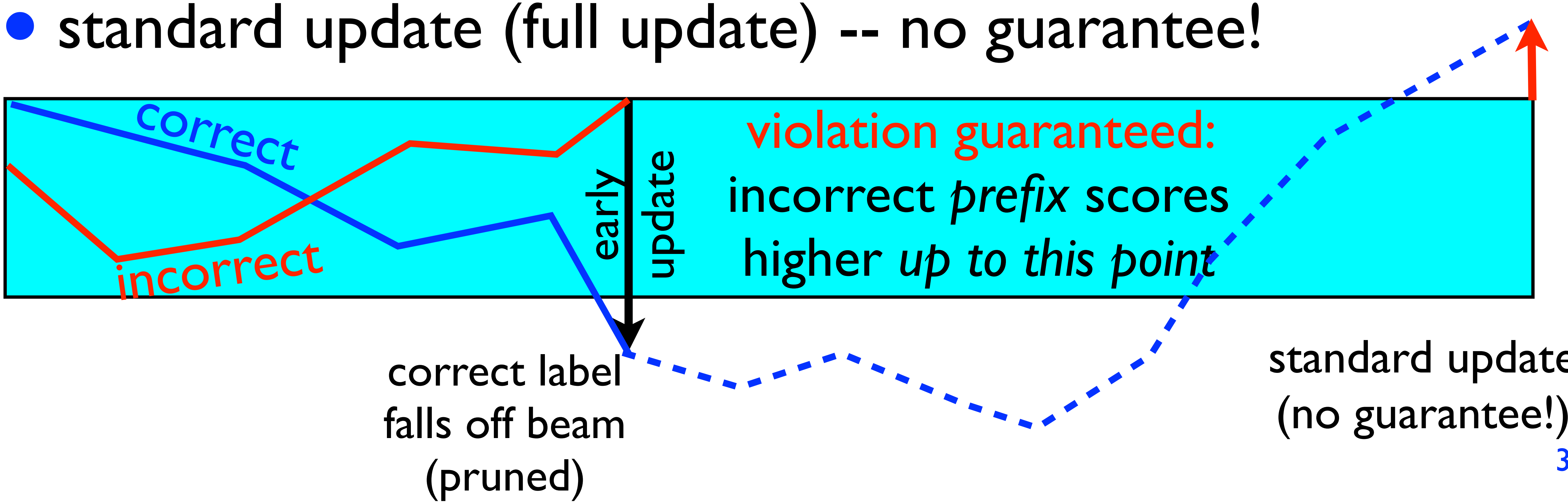
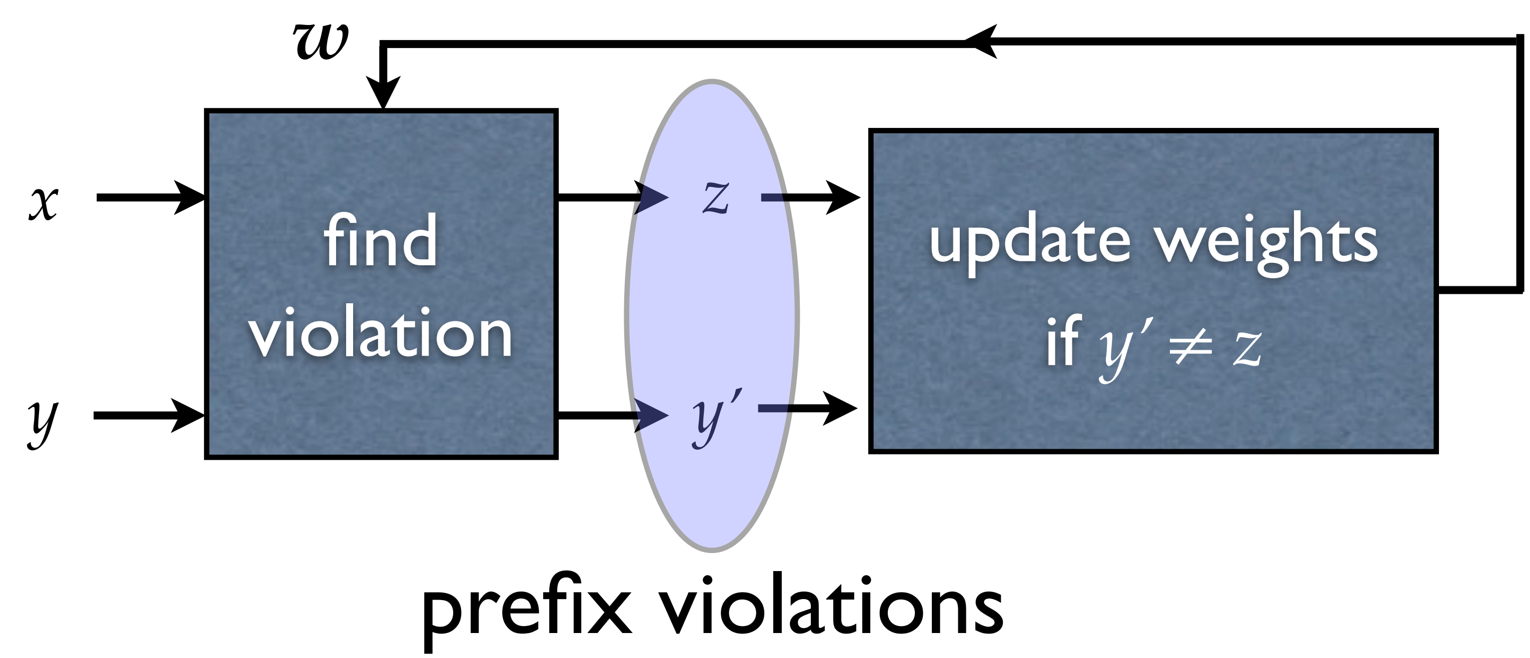
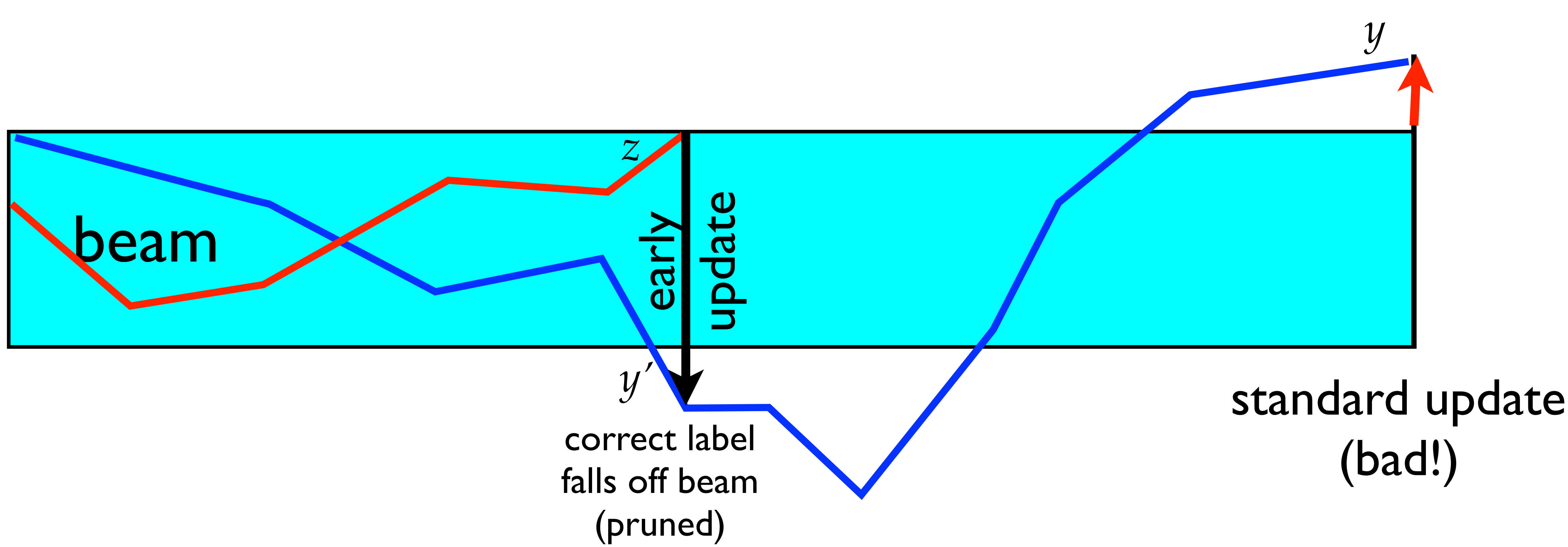


Early Update as Violation-Fixing

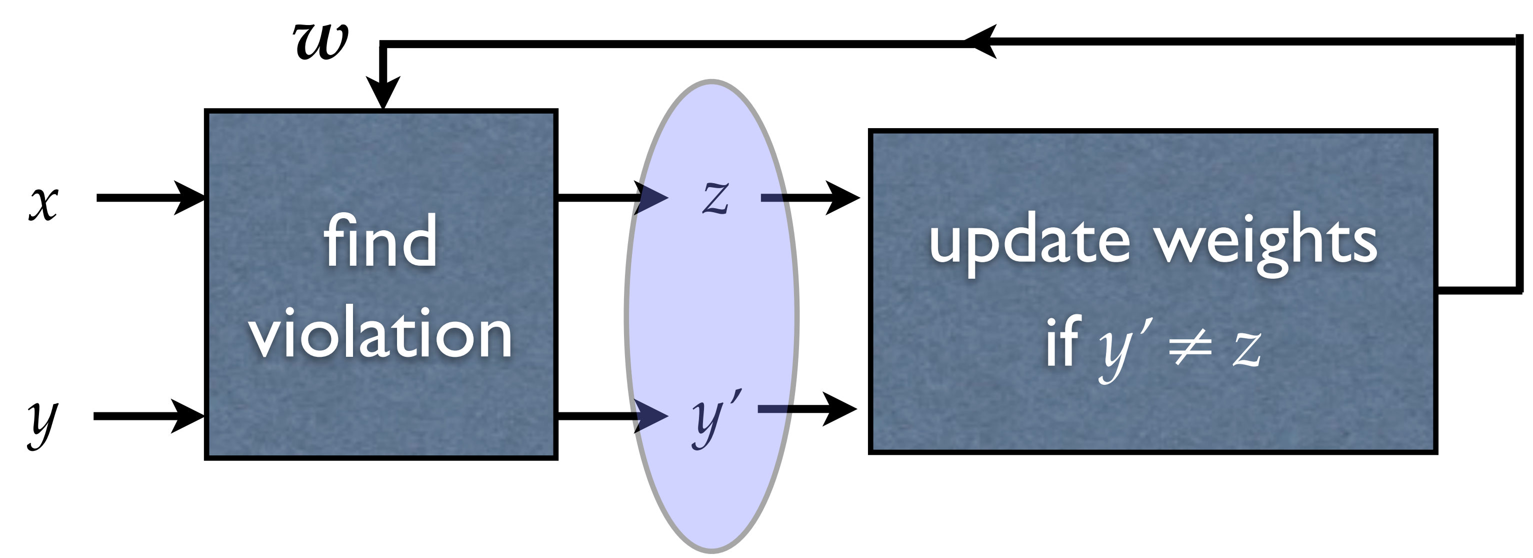




Early Update as Violation-Fixing

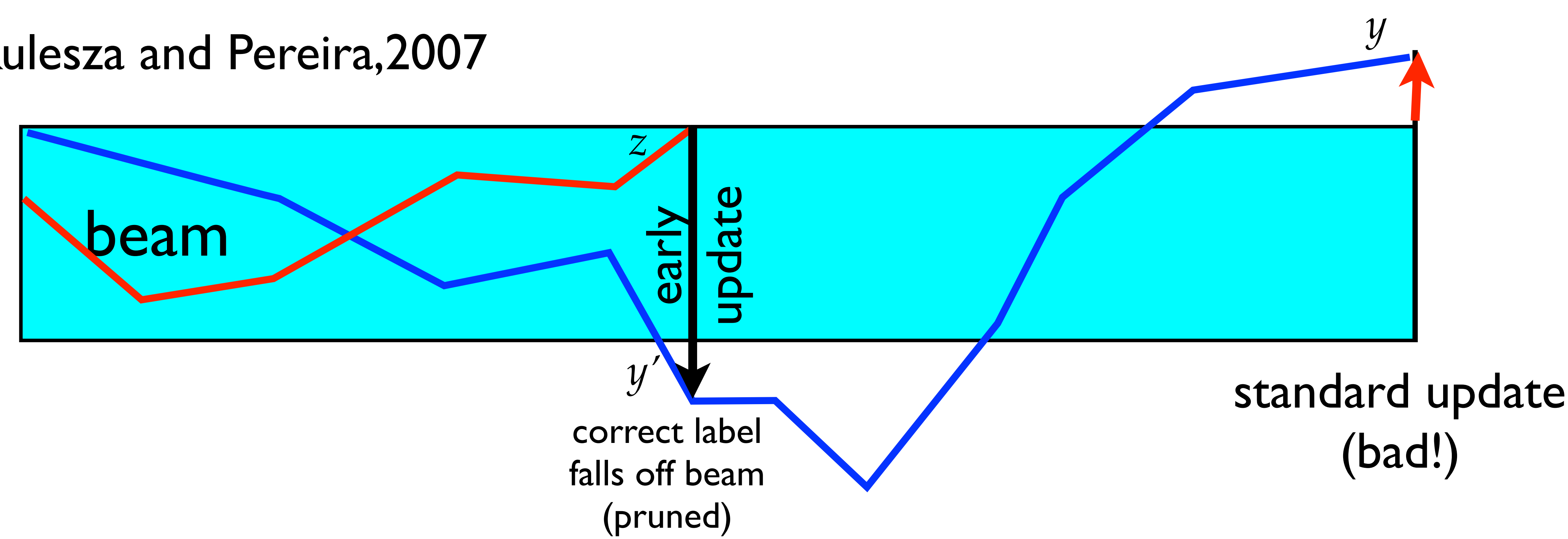
also new definition of
"beam separability":

a correct prefix should
score higher than
any incorrect prefix
of the same length
(maybe too strong)

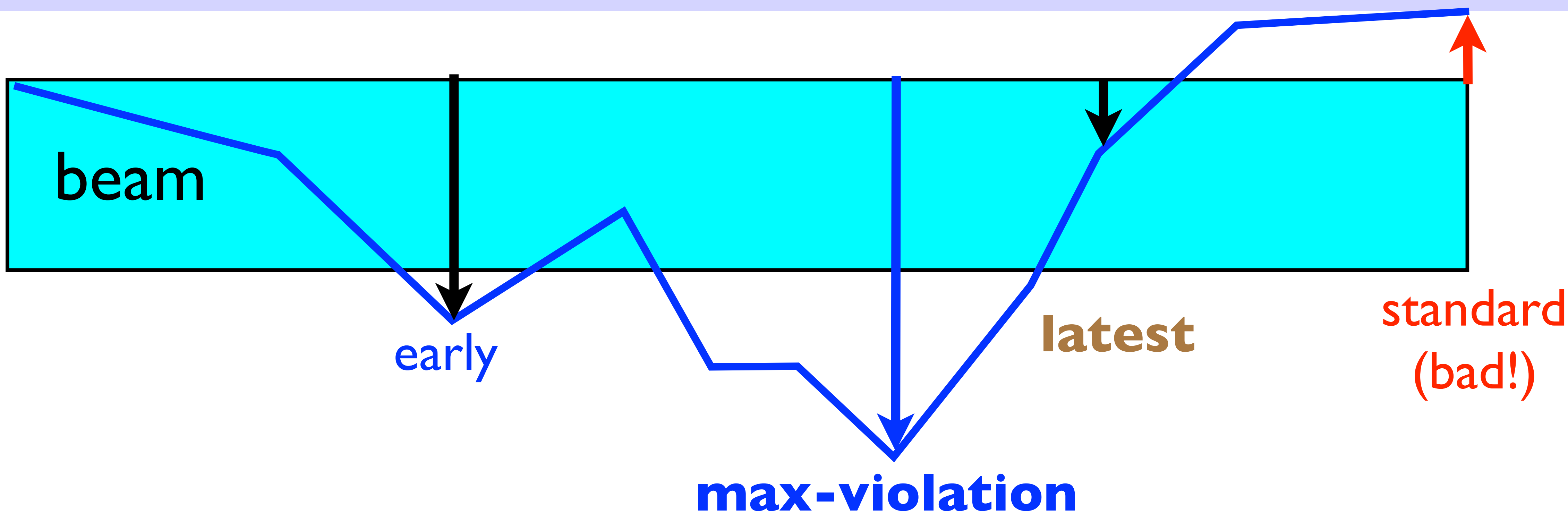


prefix violations

cf. Kulesza and Pereira,2007



Solution 2: Max-Violation (Huang et al 2012)



- we now established a theory for early update (Collins/Roark)
- but it learns too slowly due to partial updates
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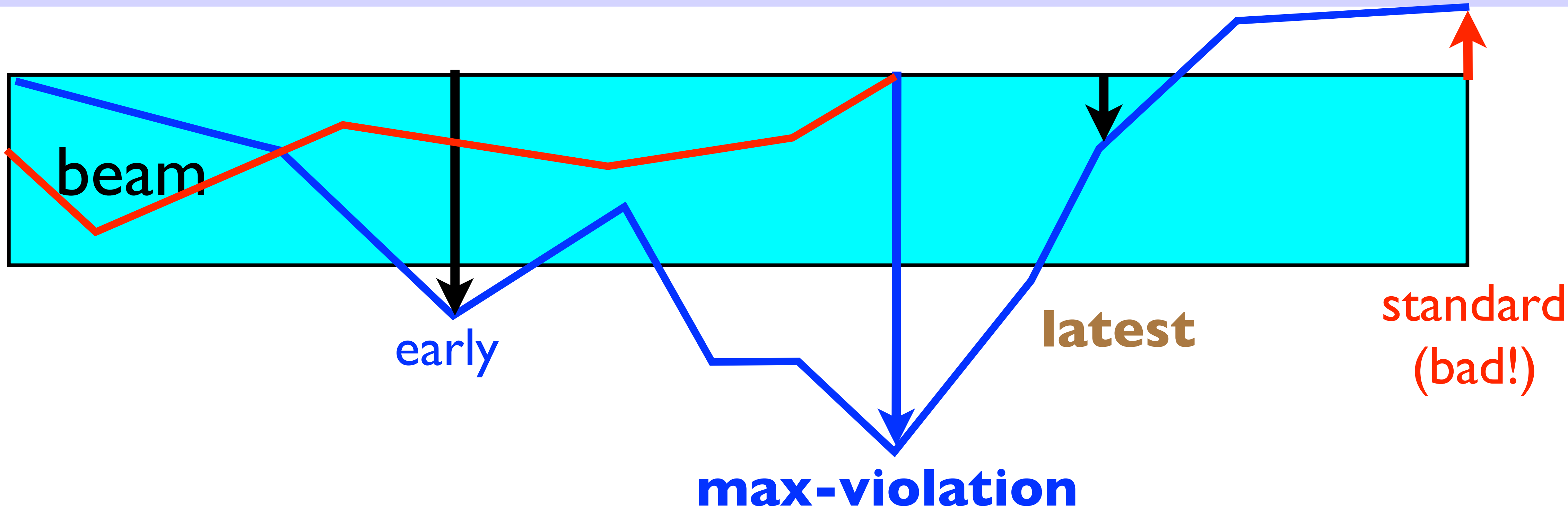

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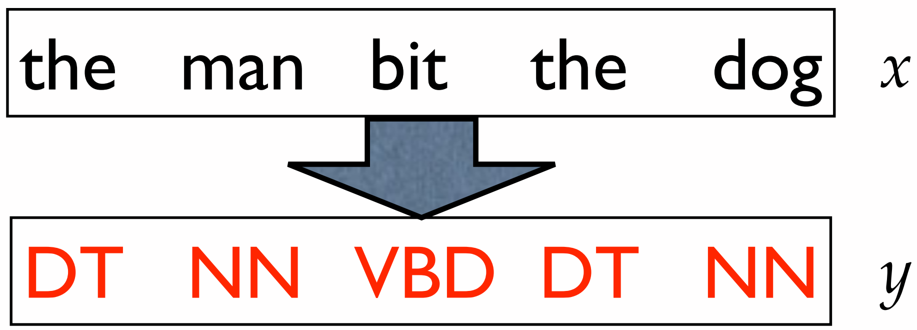
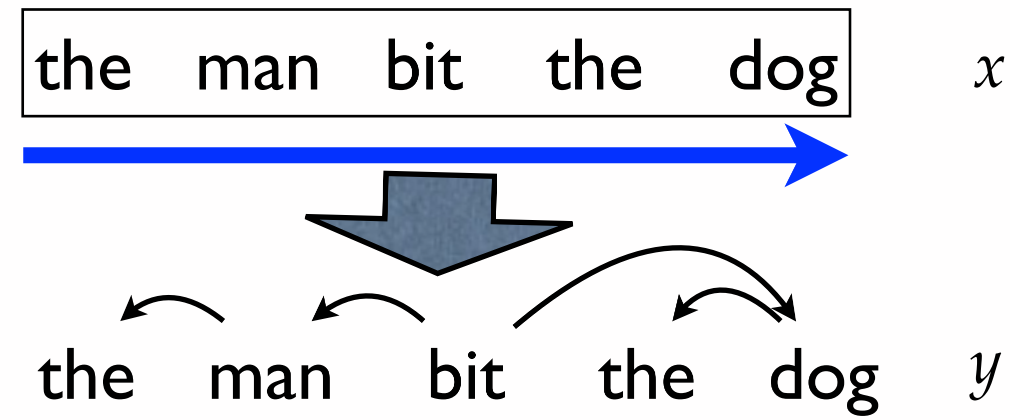
Four Experiments

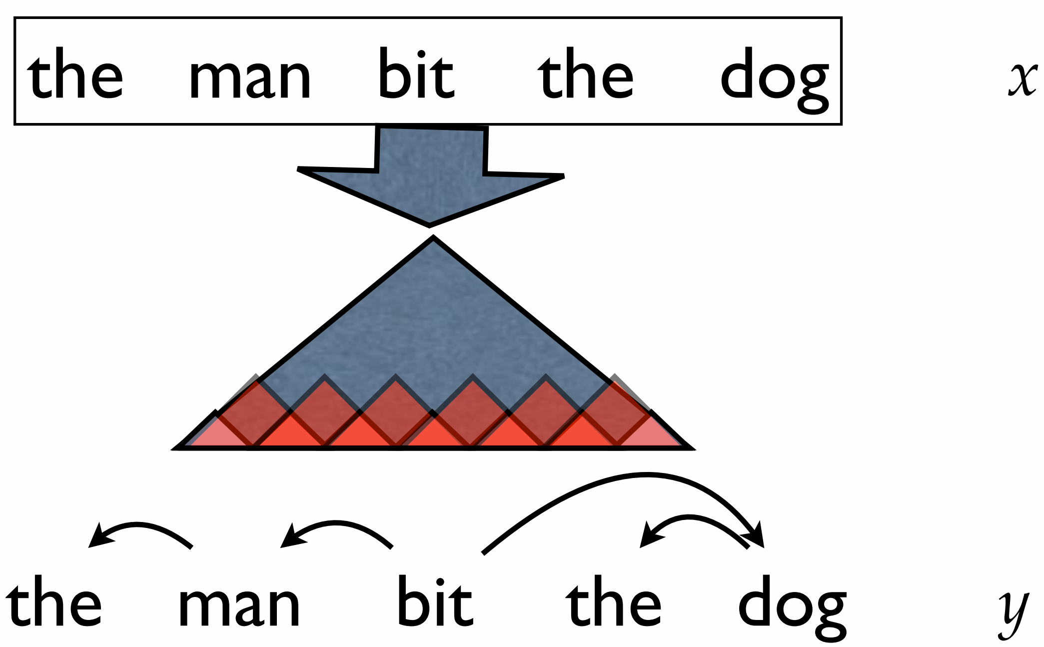
part-of-speech tagging



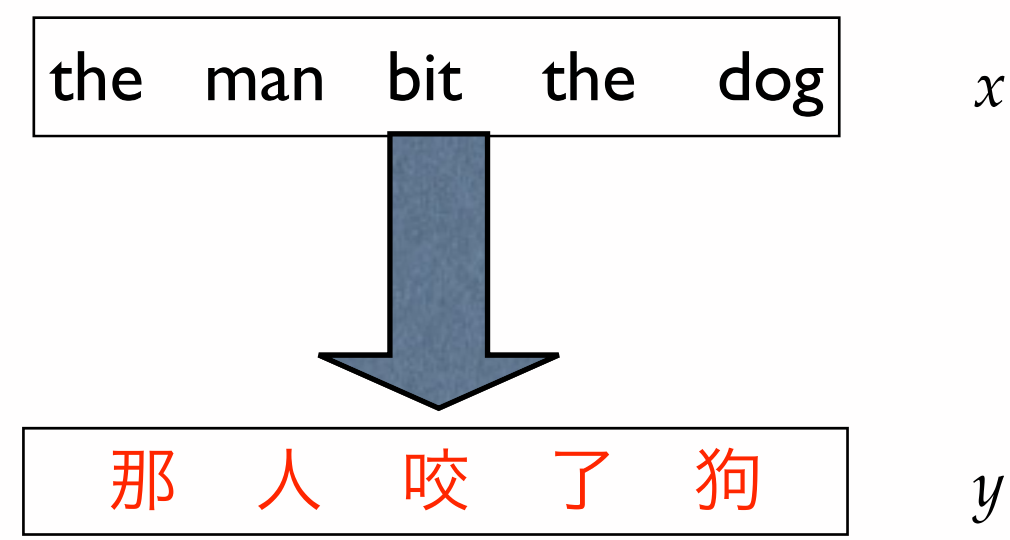
incremental parsing



bottom-up parsing w/ cube pruning

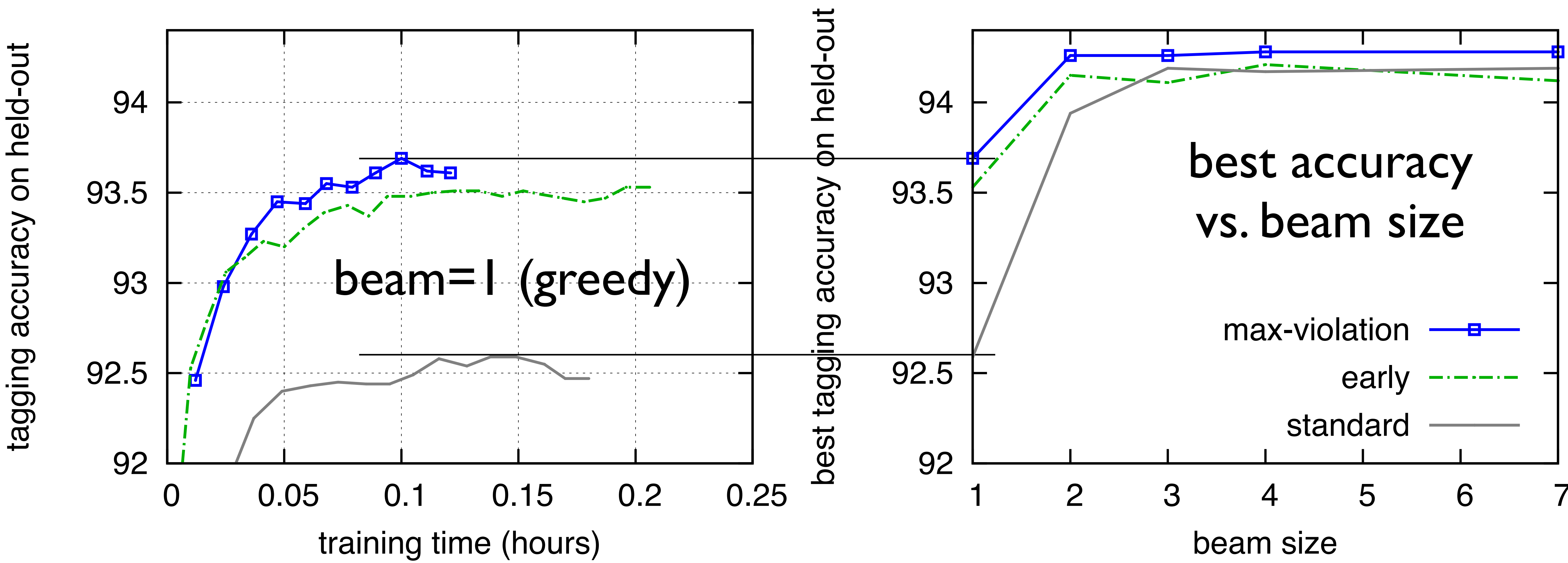


machine translation



Max-Violation > Early >> Standard

- exp 1 on part-of-speech tagging w/ beam search (on CTB5)
- early and max-violation >> standard update at smallest beams
  - this advantage shrinks as beam size increases
  - max-violation converges faster than early (and slightly better)



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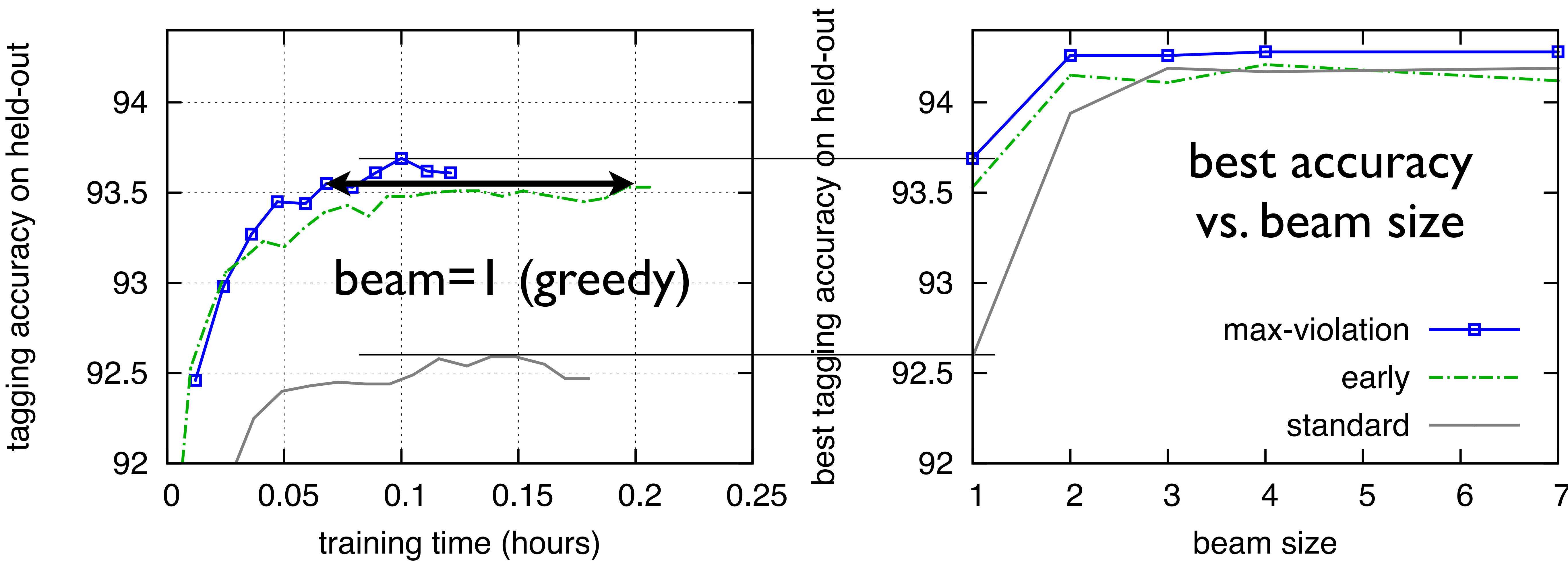

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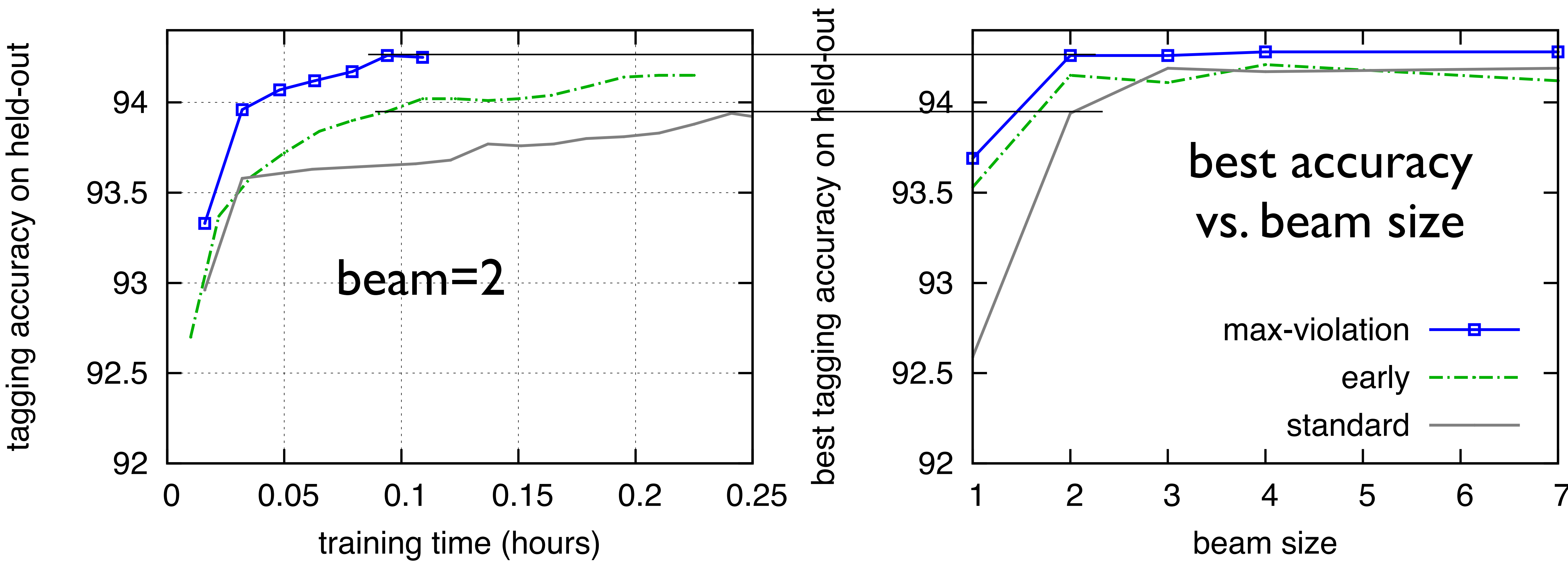

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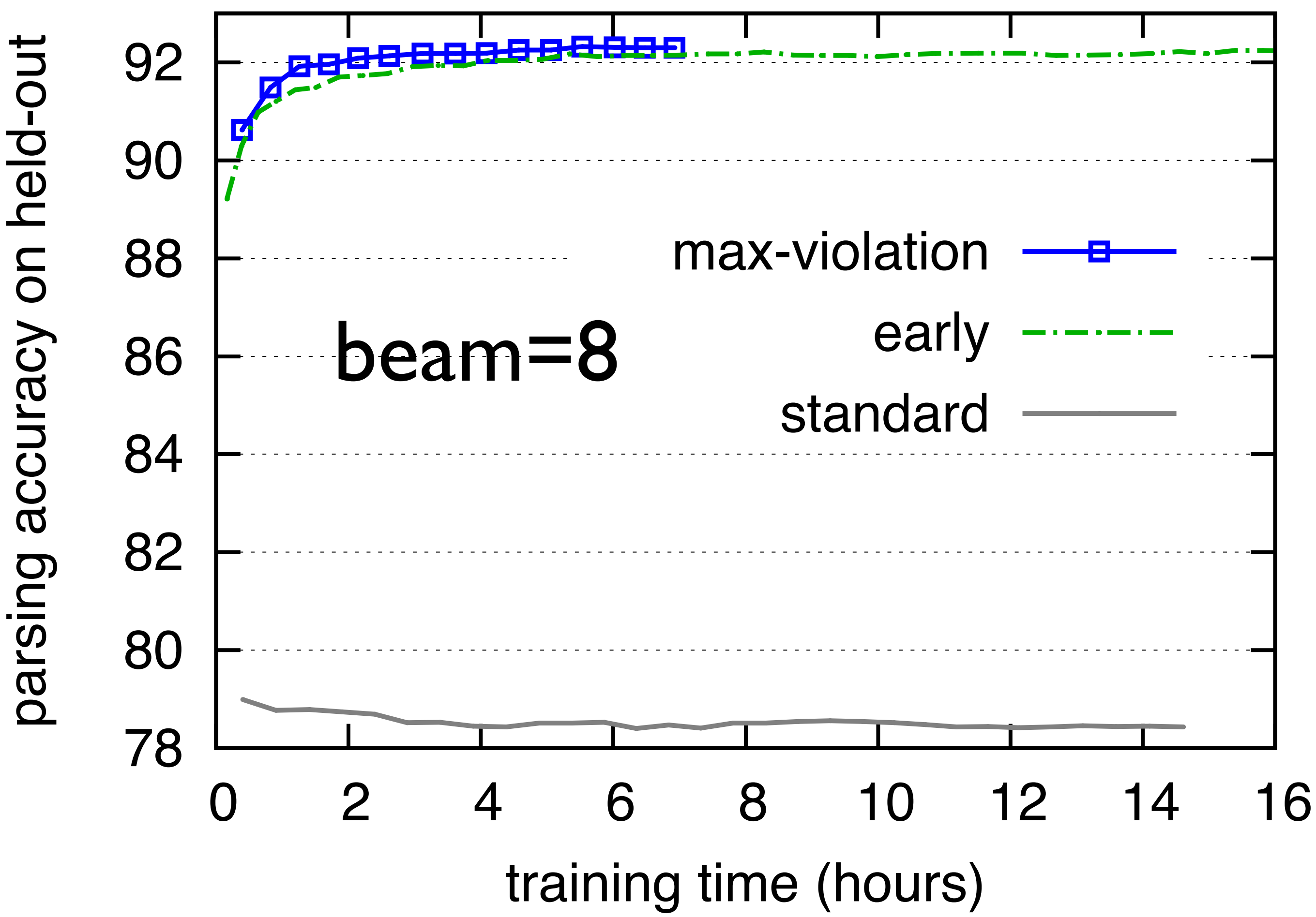
- exp 2 on my incremental dependency parser (Huang & Sagae 10)
- standard update is horrible due to search errors
- early update: 38 iterations, 15.4 hours (92.24)
- max-violation: 10 iterations, 4.6 hours (92.25)



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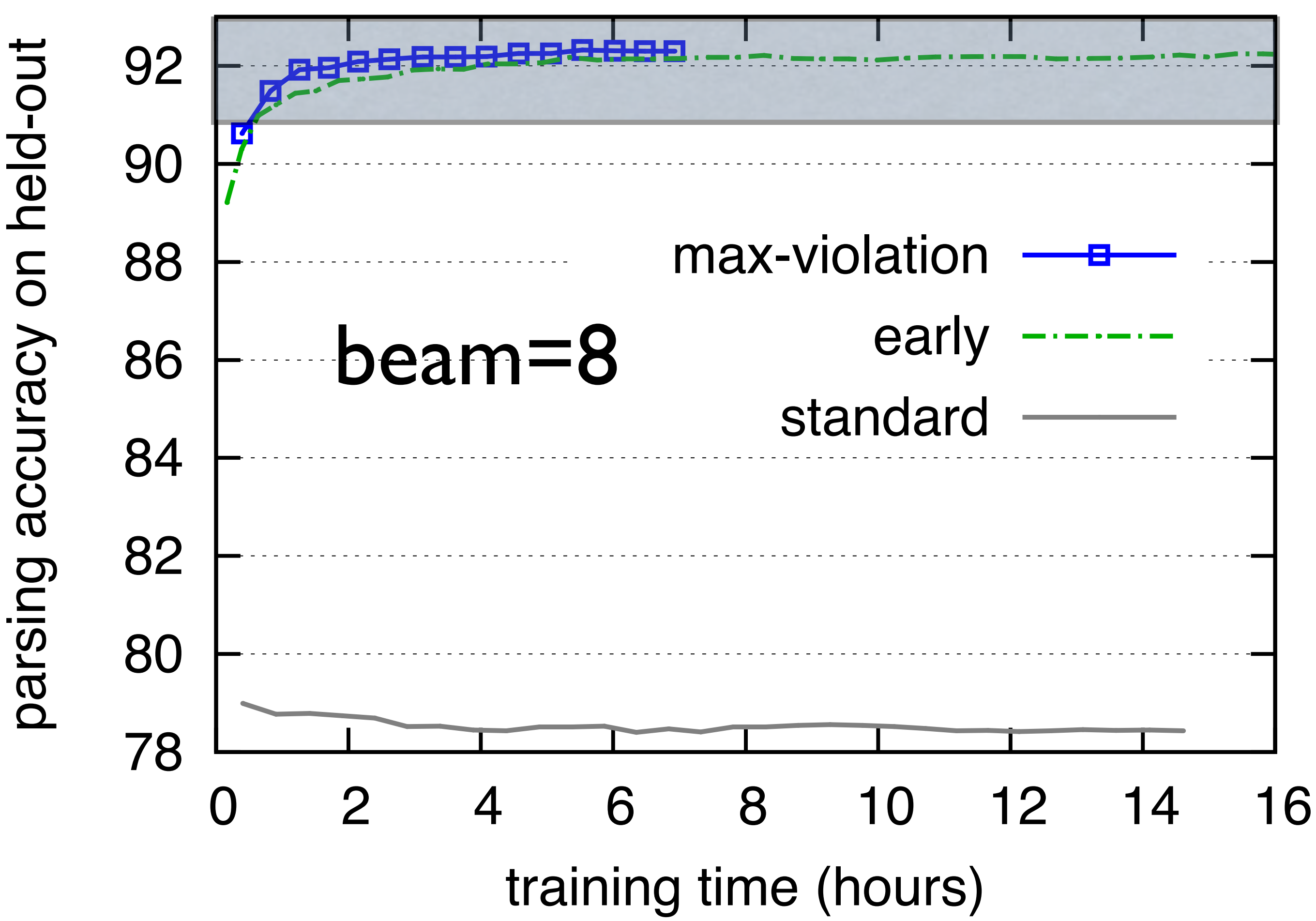

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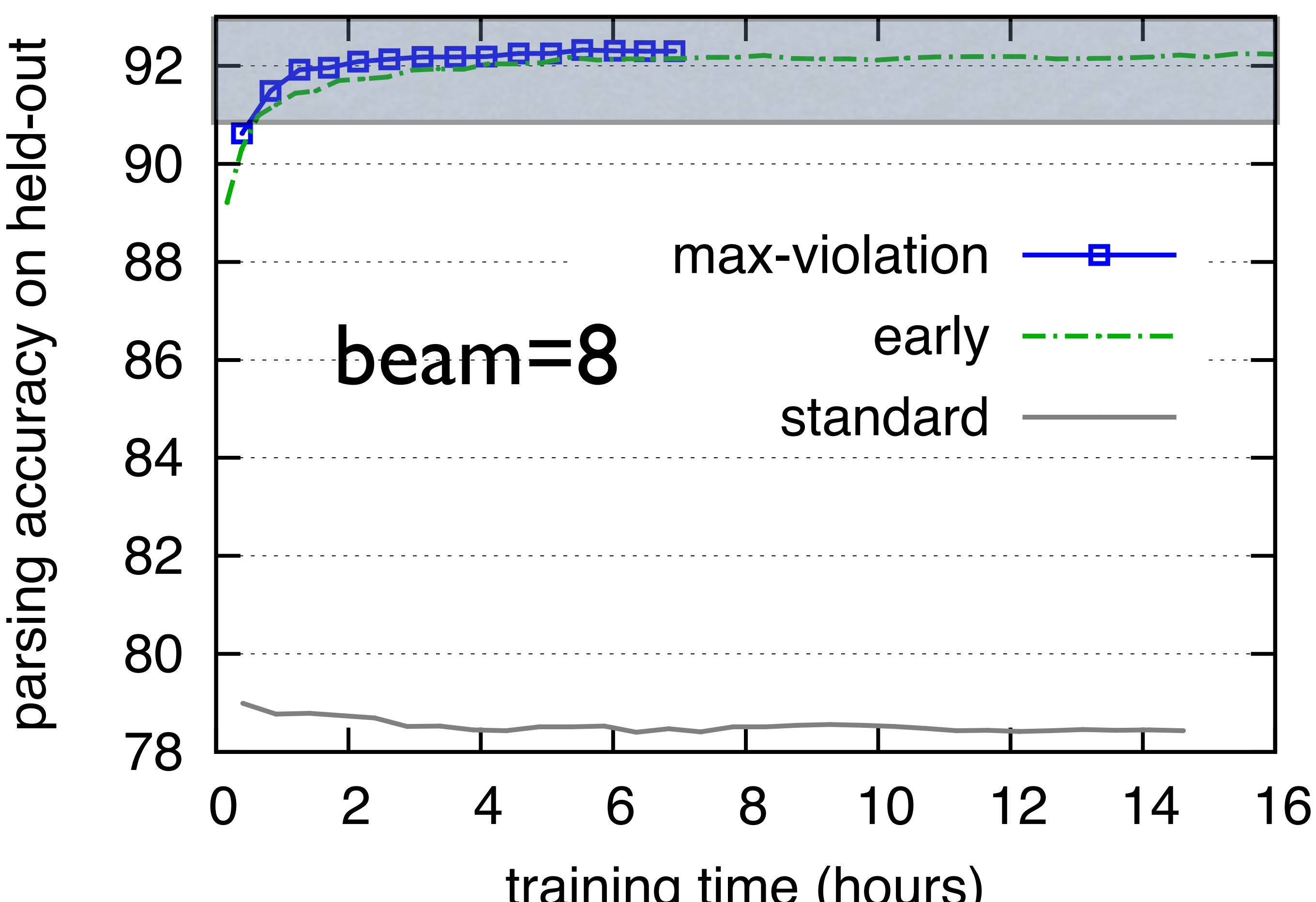
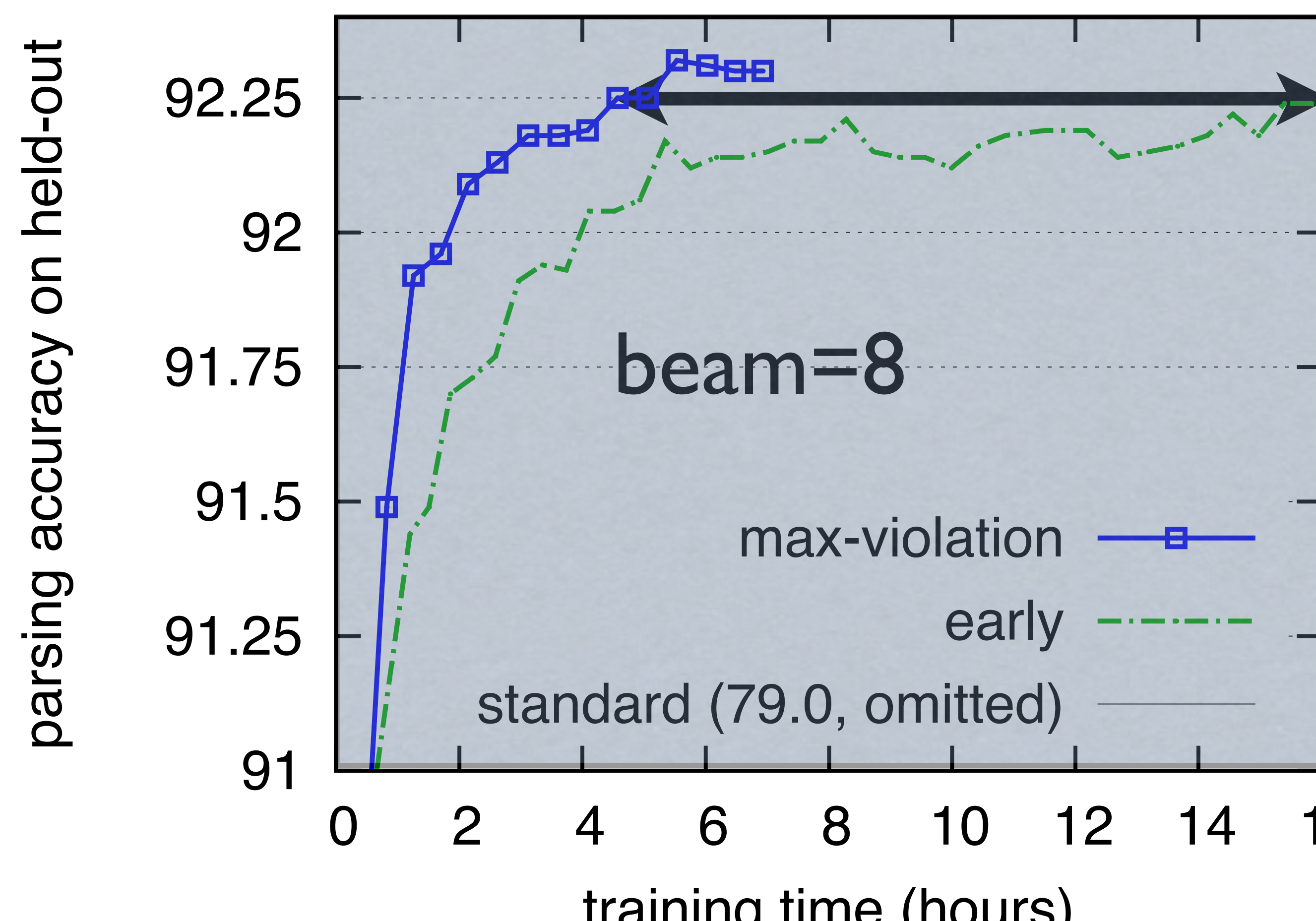
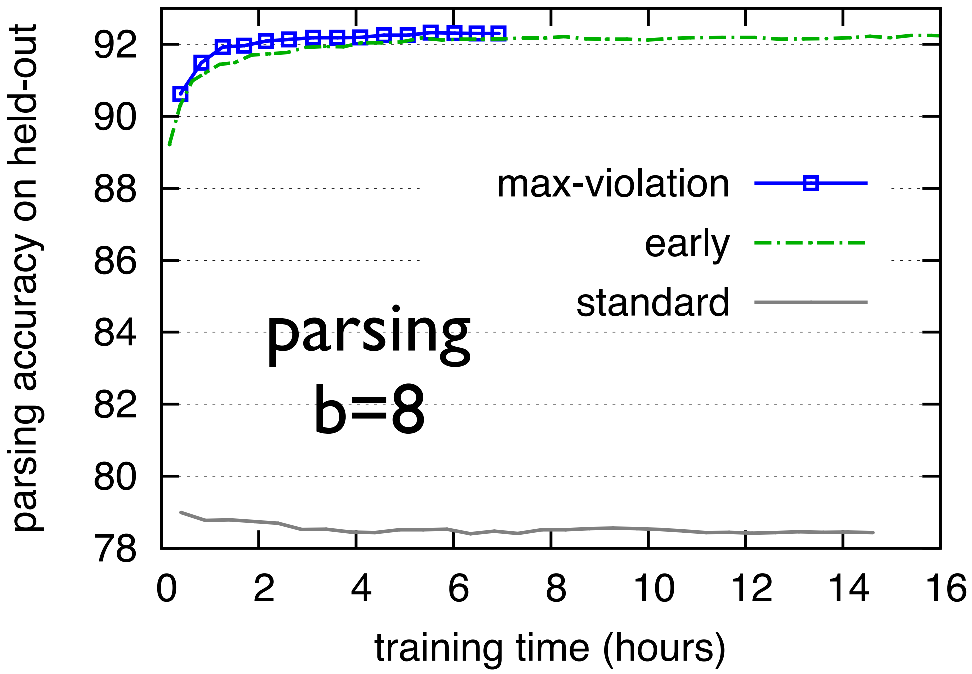


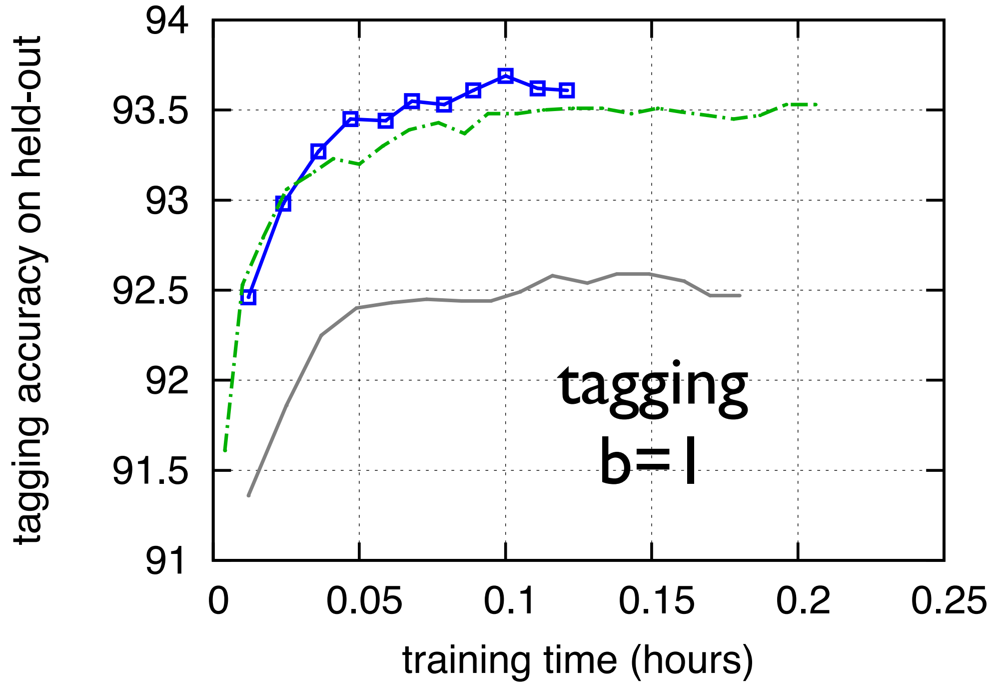


max-violation is 3.3x faster than early update

Why standard update so bad for parsing

- standard update works horribly with severe search error
    - due to large number of *invalid* updates (non-violation)





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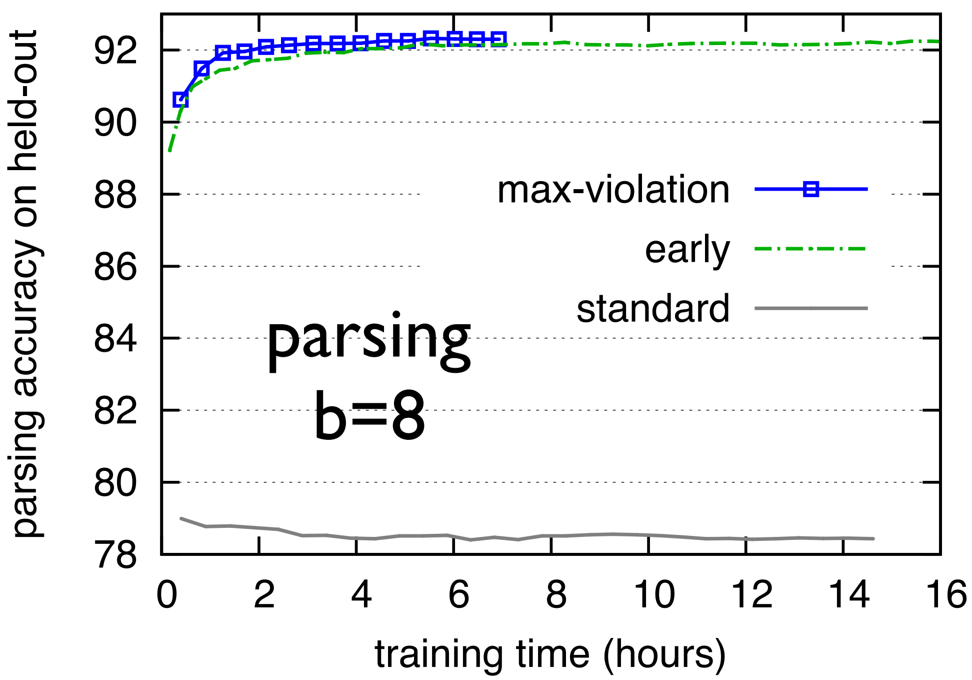

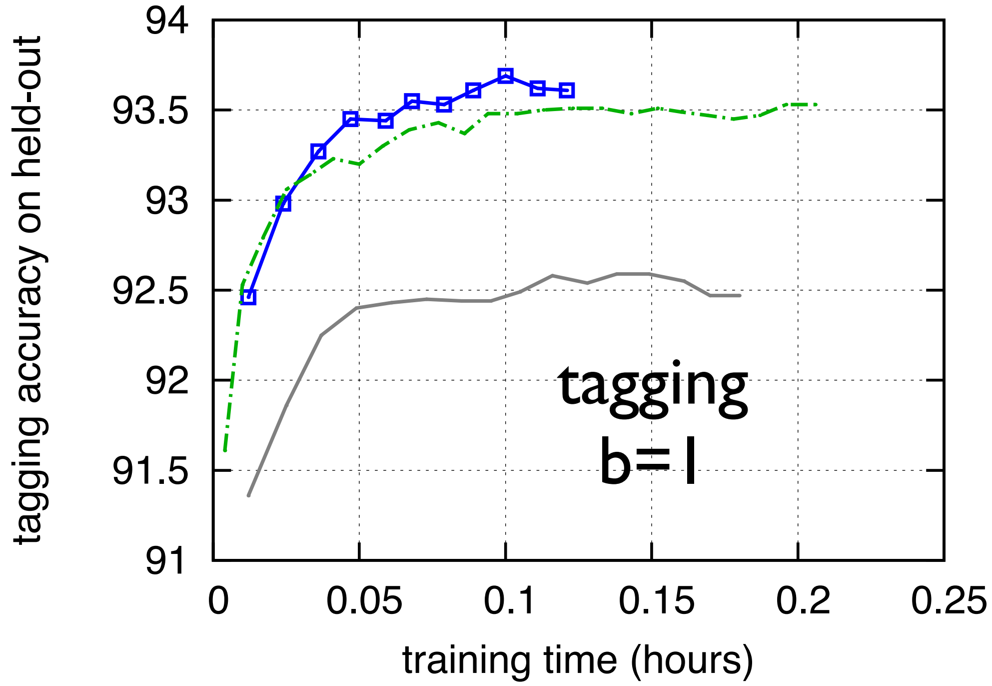

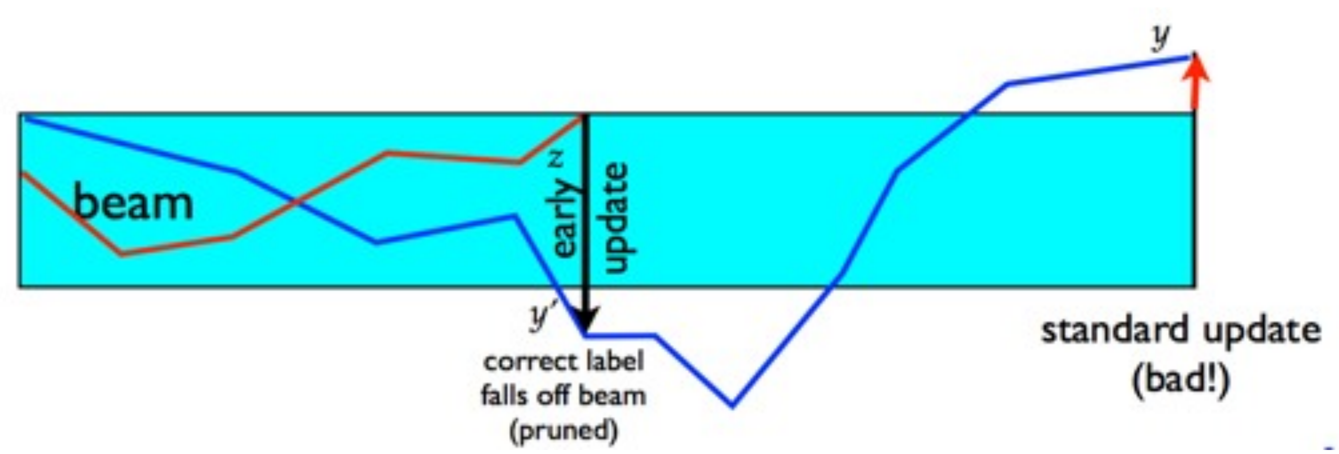

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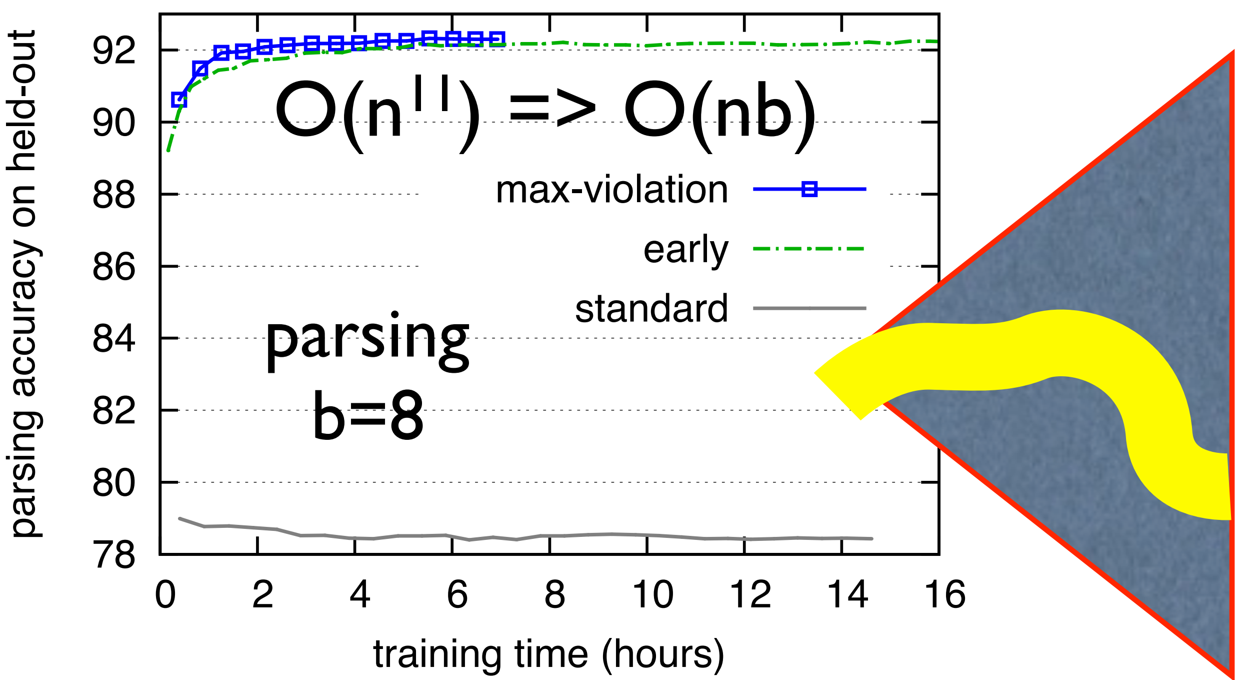
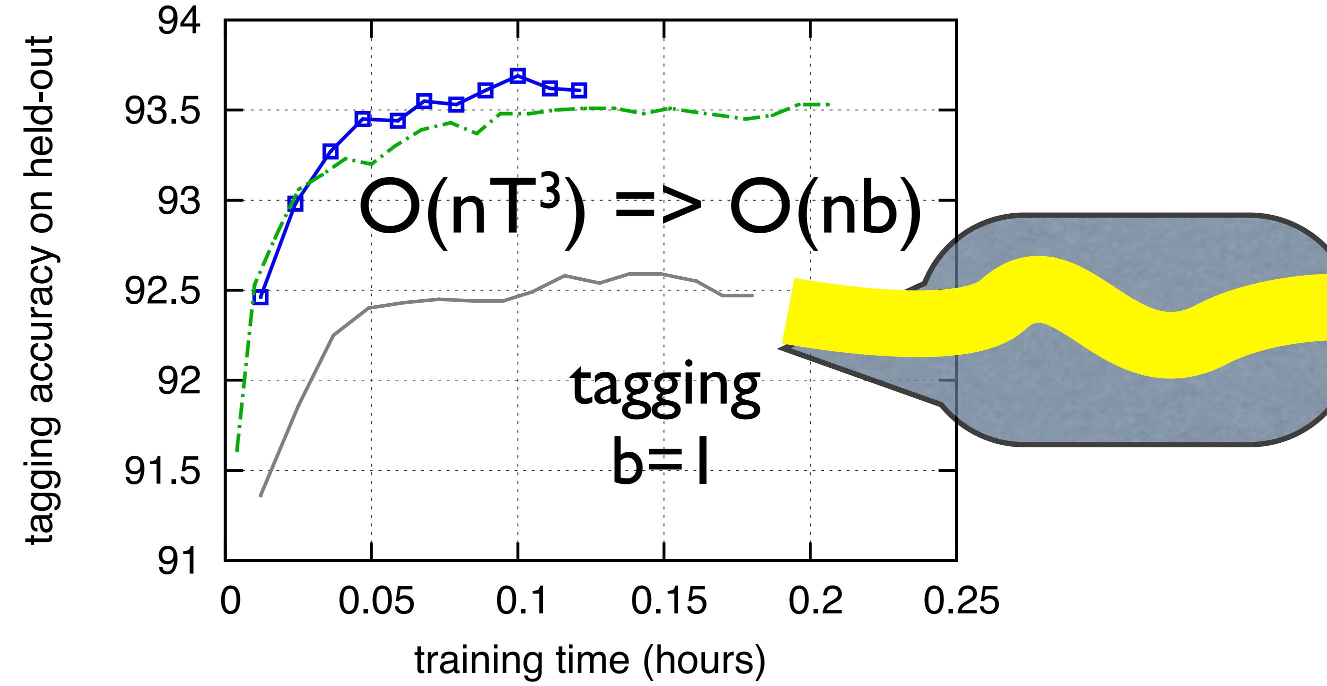
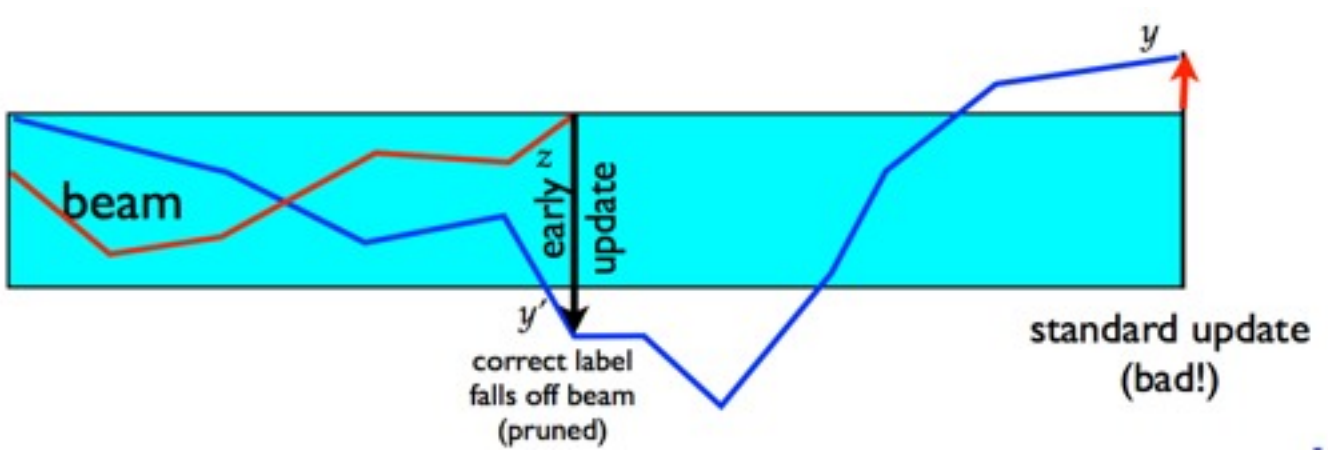
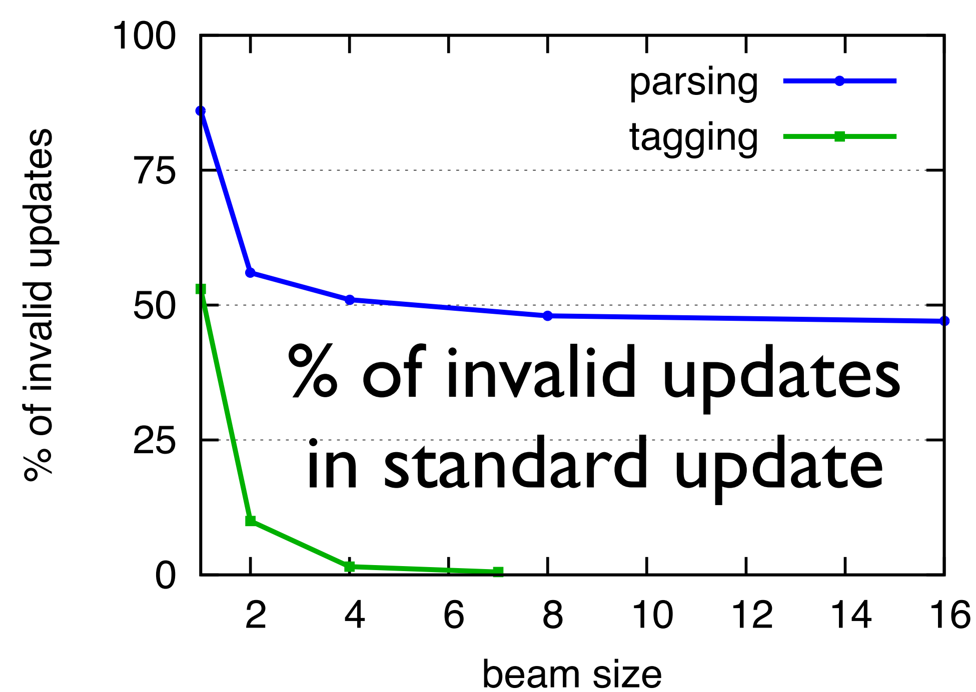
- standard update works horribly with severe search error
  - due to large number of *invalid* updates (non-violation)









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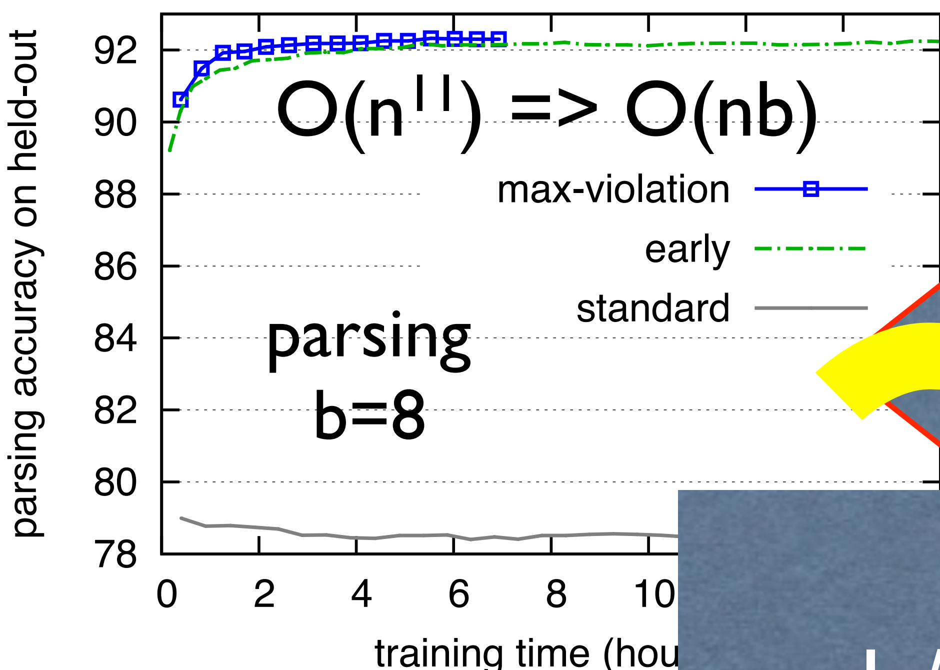
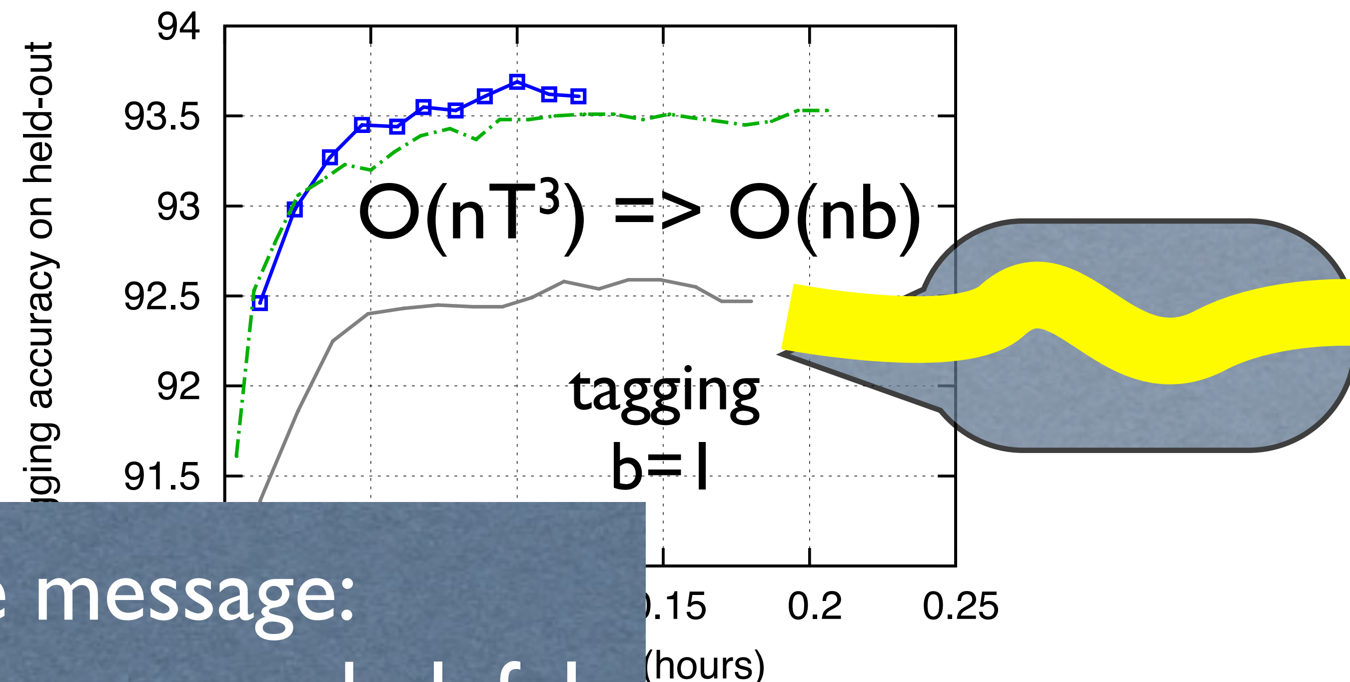
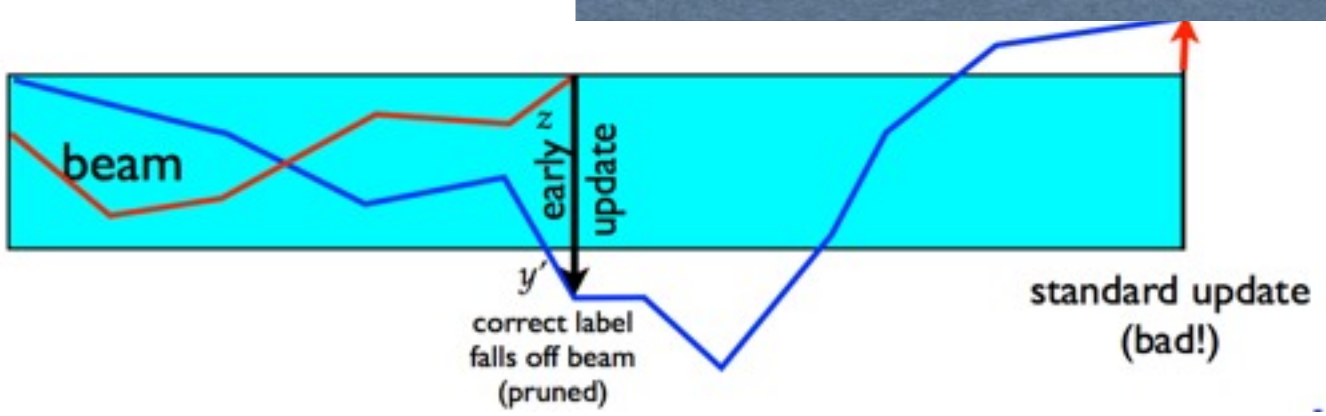
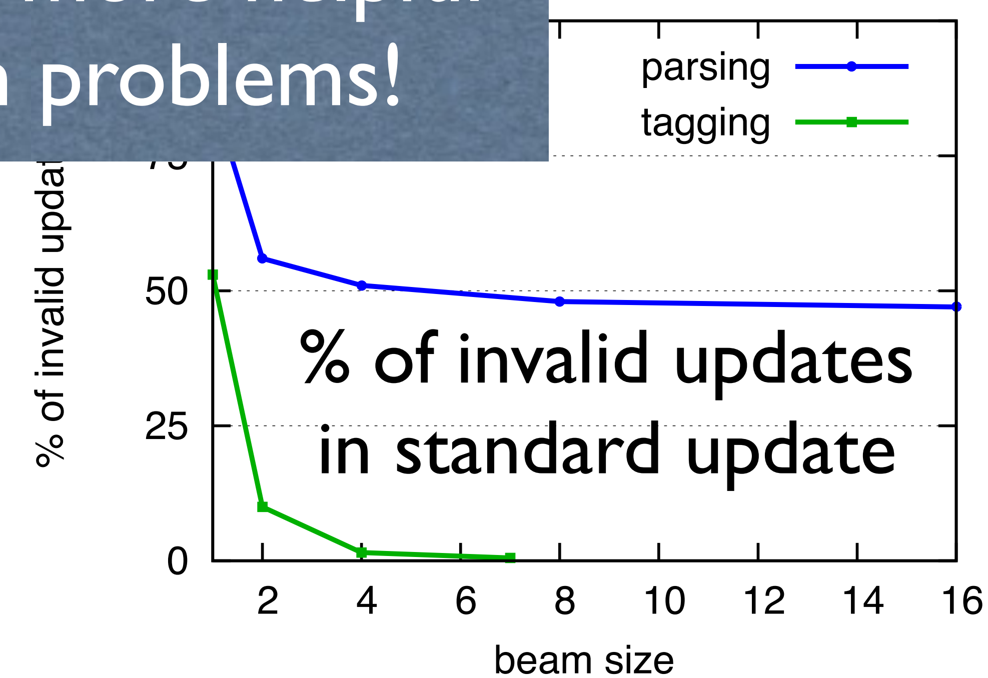




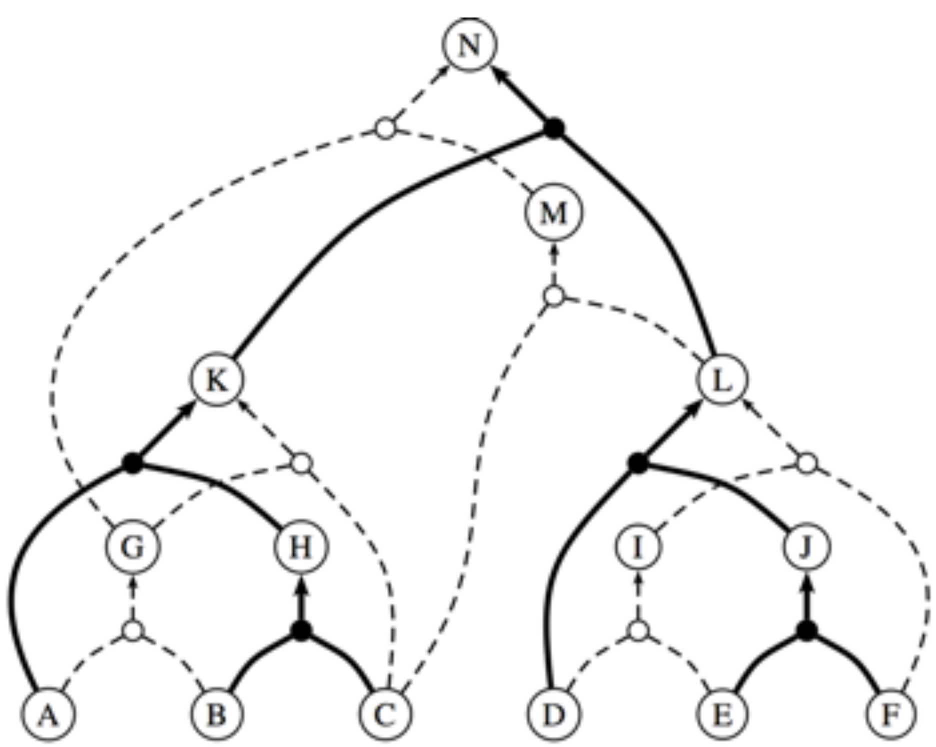
take-home message:
early/max-violation more helpful
for harder search problems!

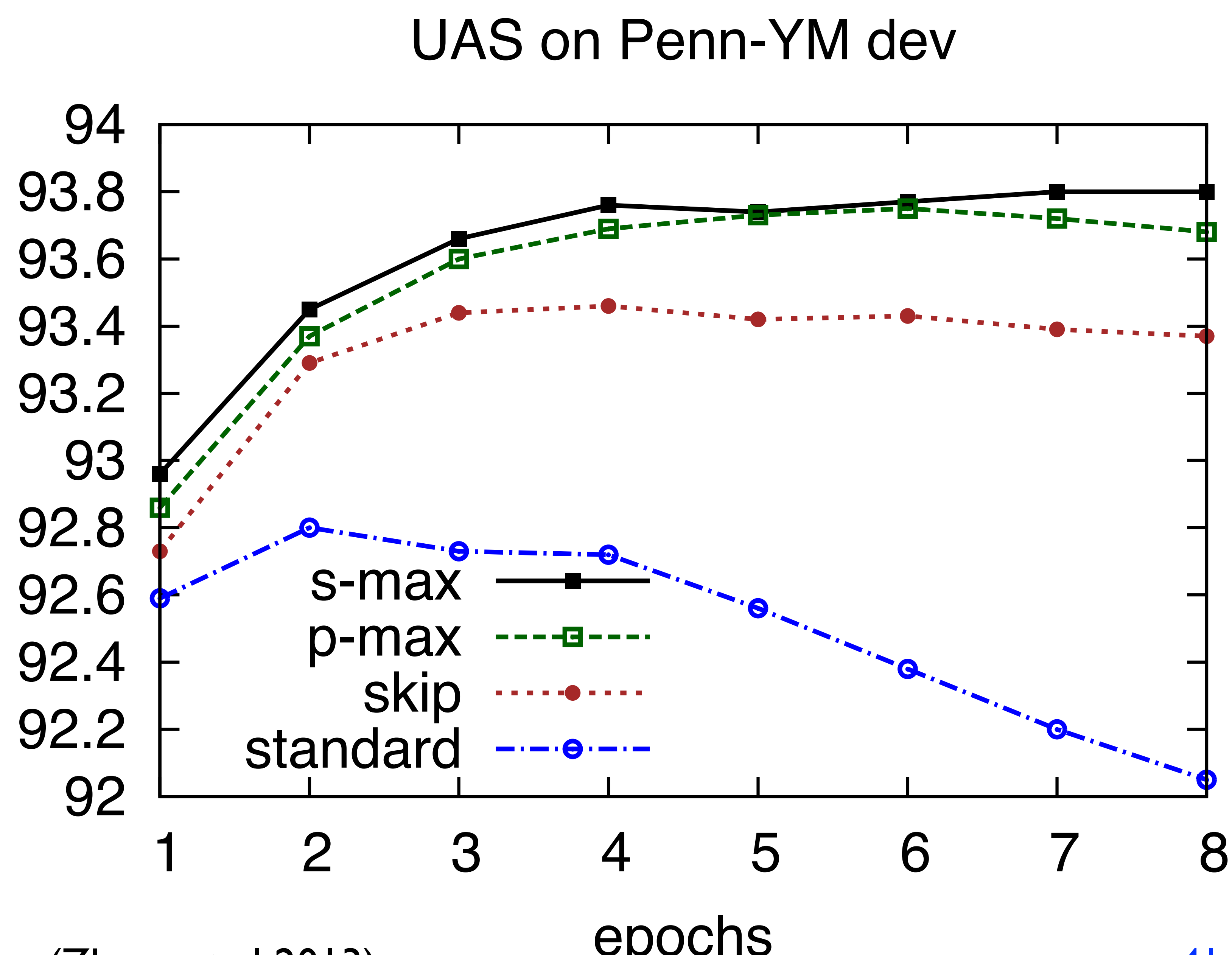




Exp 3: Bottom-up Parsing

- CKY parsing with cube pruning for higher-order features
- we extended our framework from graphs to hypergraphs





(Zhang et al 2013)

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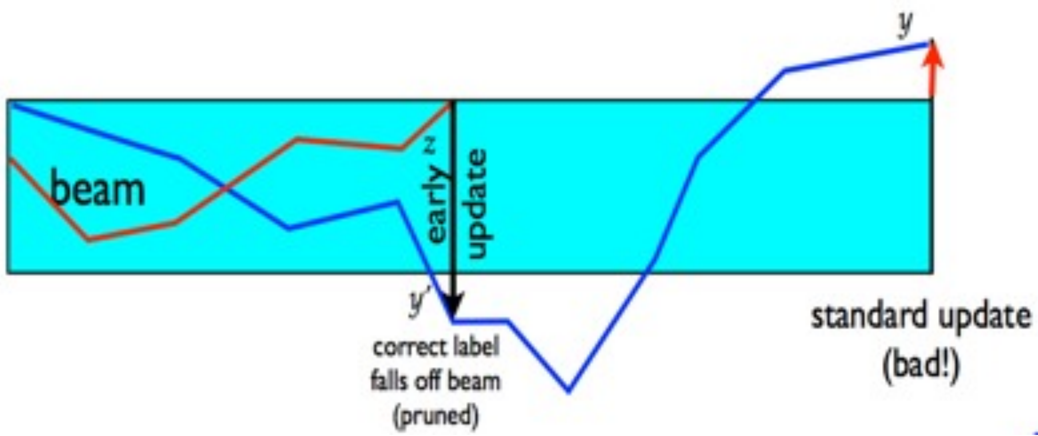
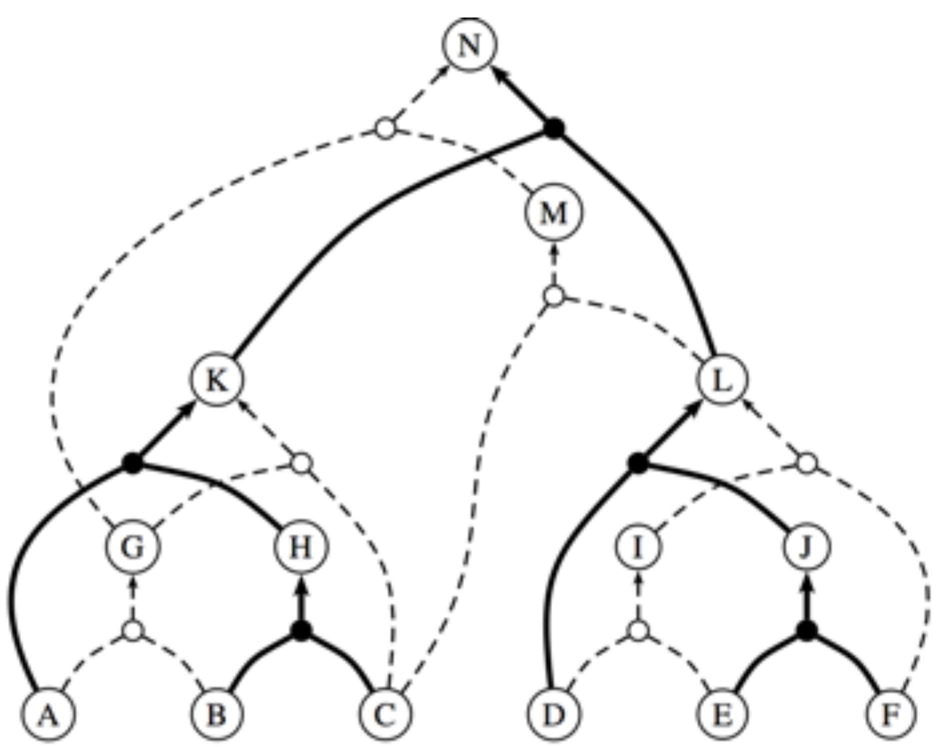
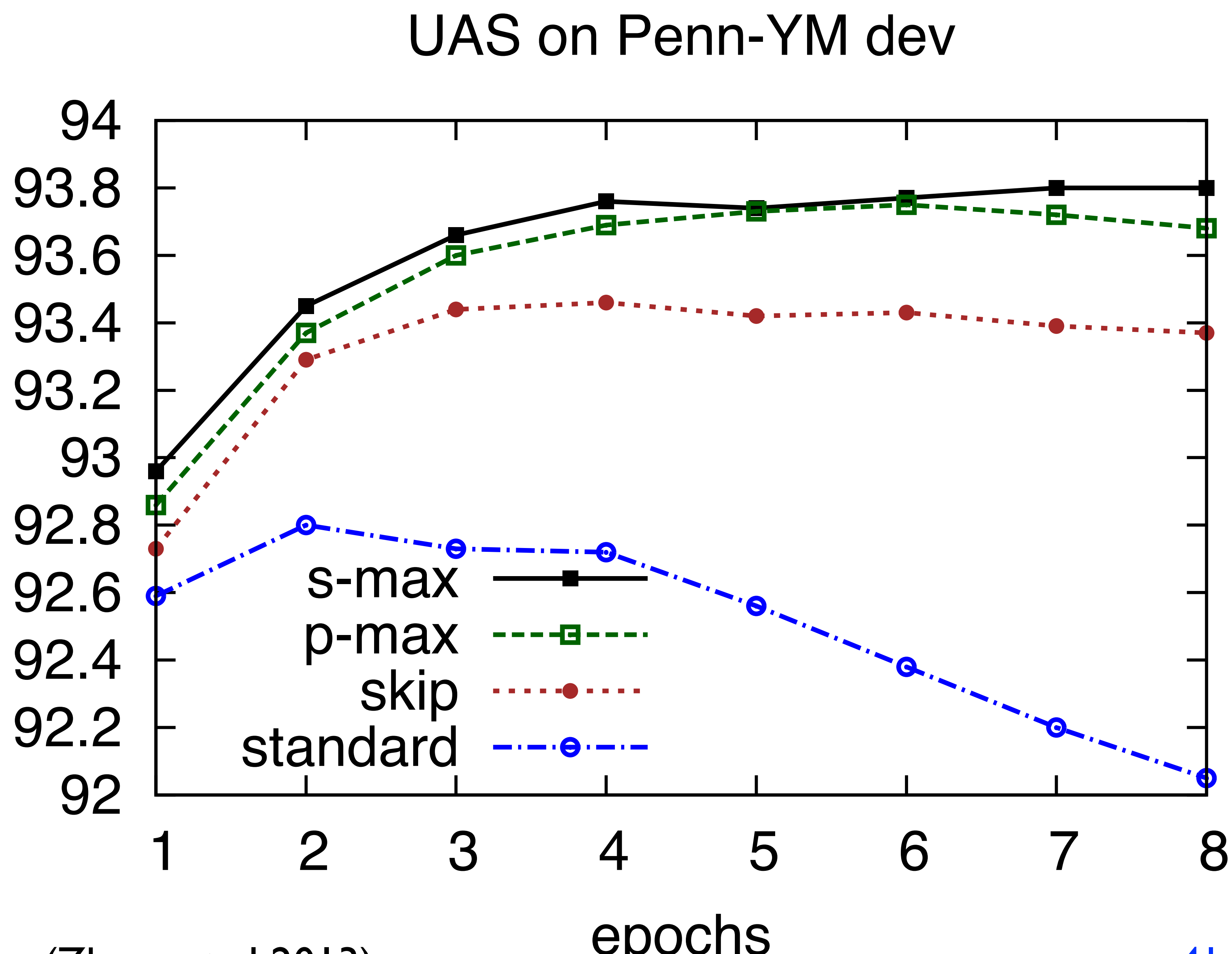


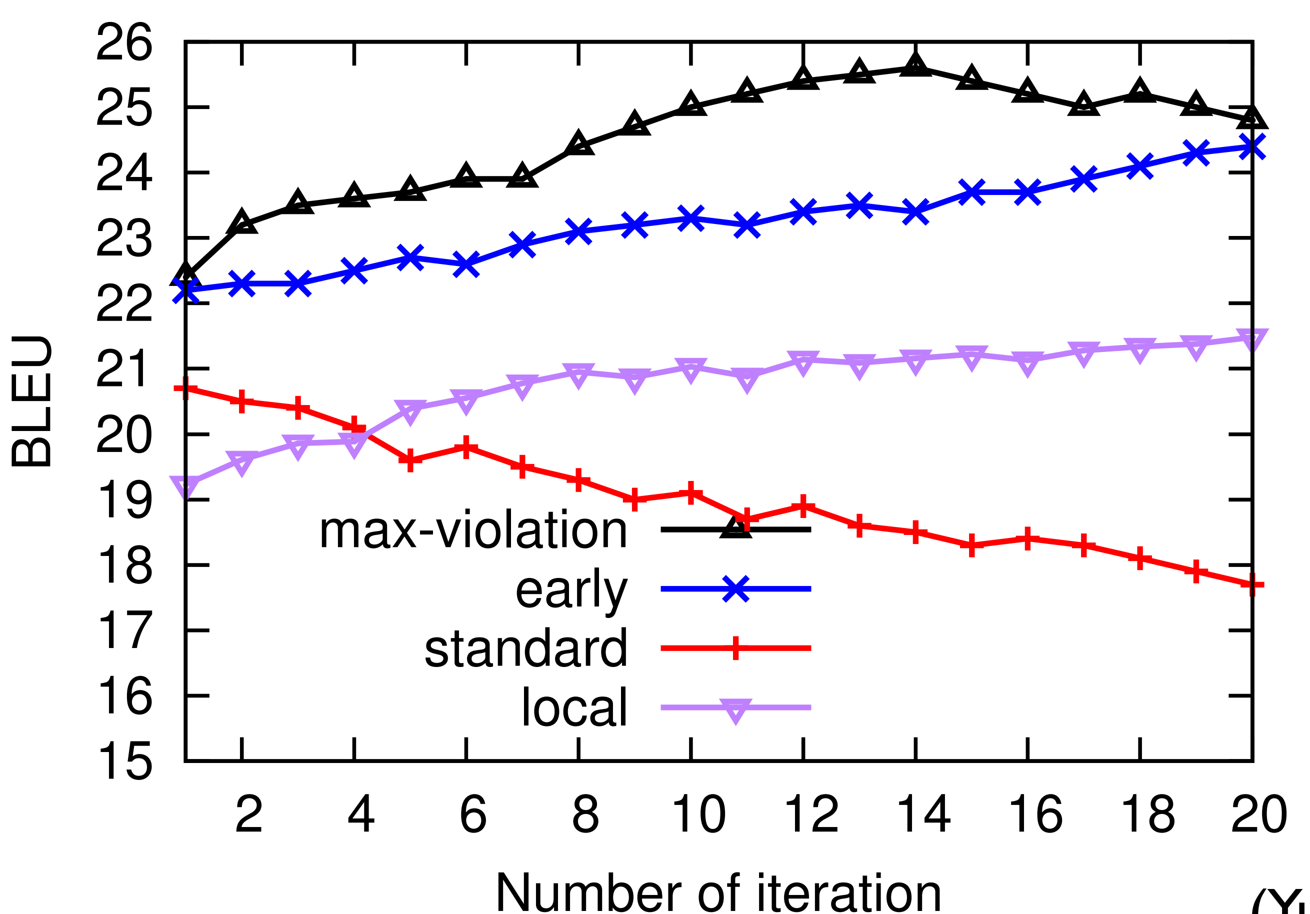




(Zhang et al 2013)

Exp 4: Machine Translation

- standard perceptron works poorly for machine translation
  - b/c invalid update ratio is very high (search quality is low)
- max-violation converges faster than early update
- first truly successful effort in large-scale training for translation



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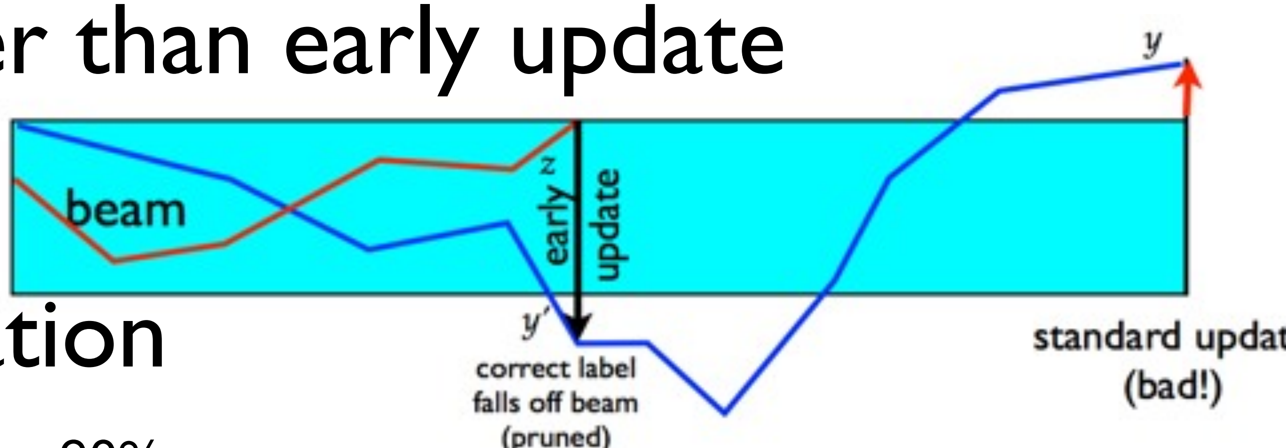

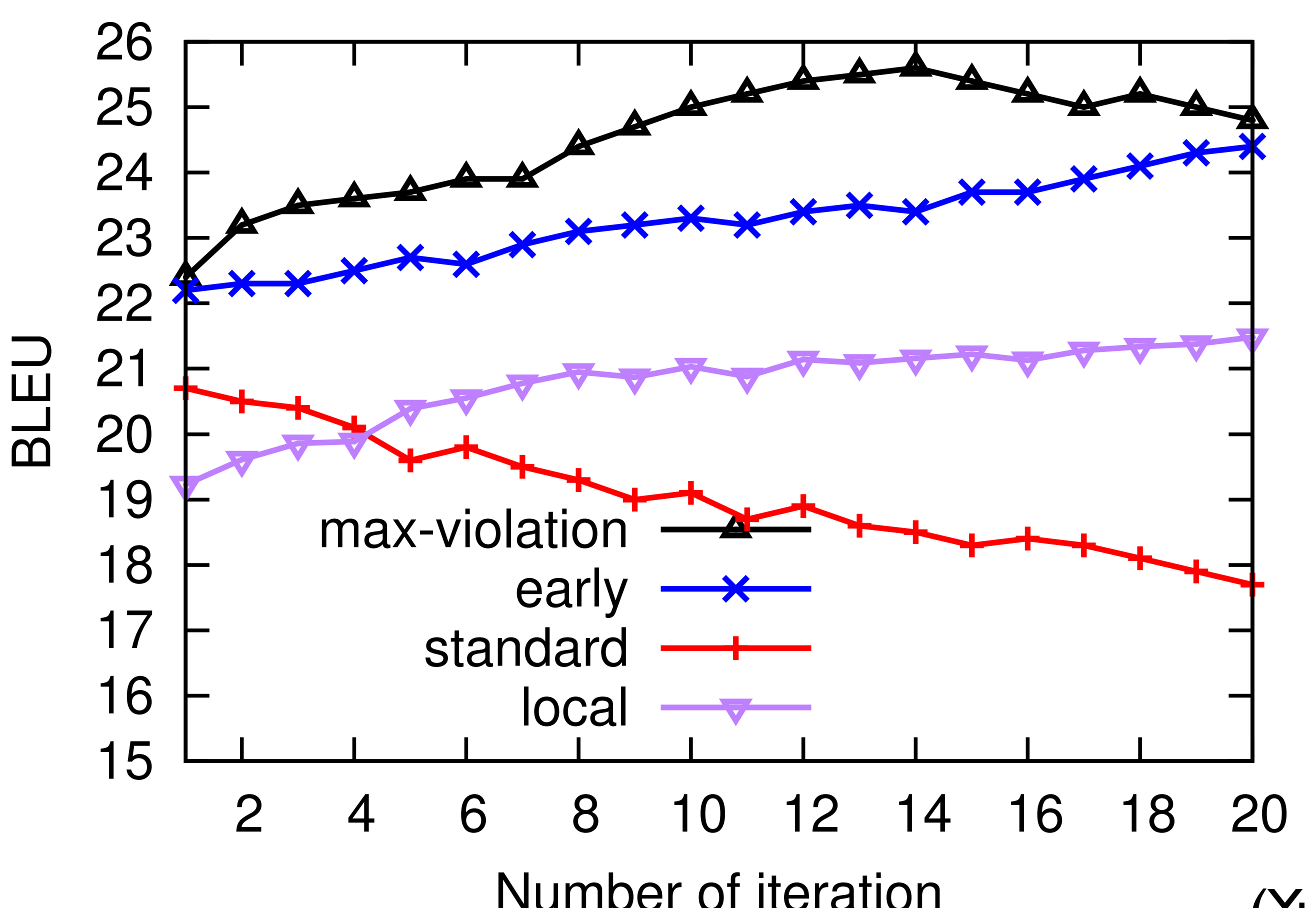

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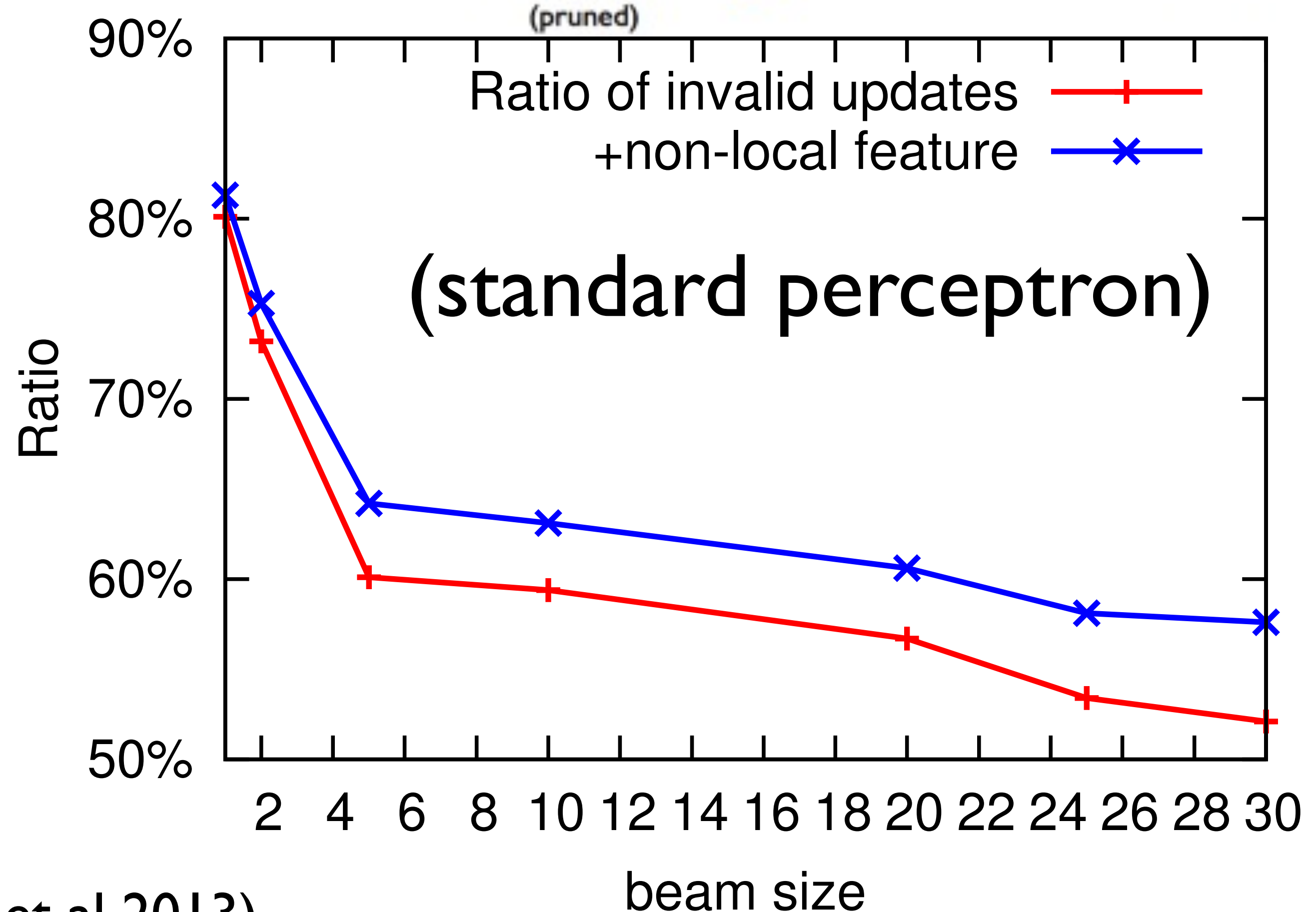
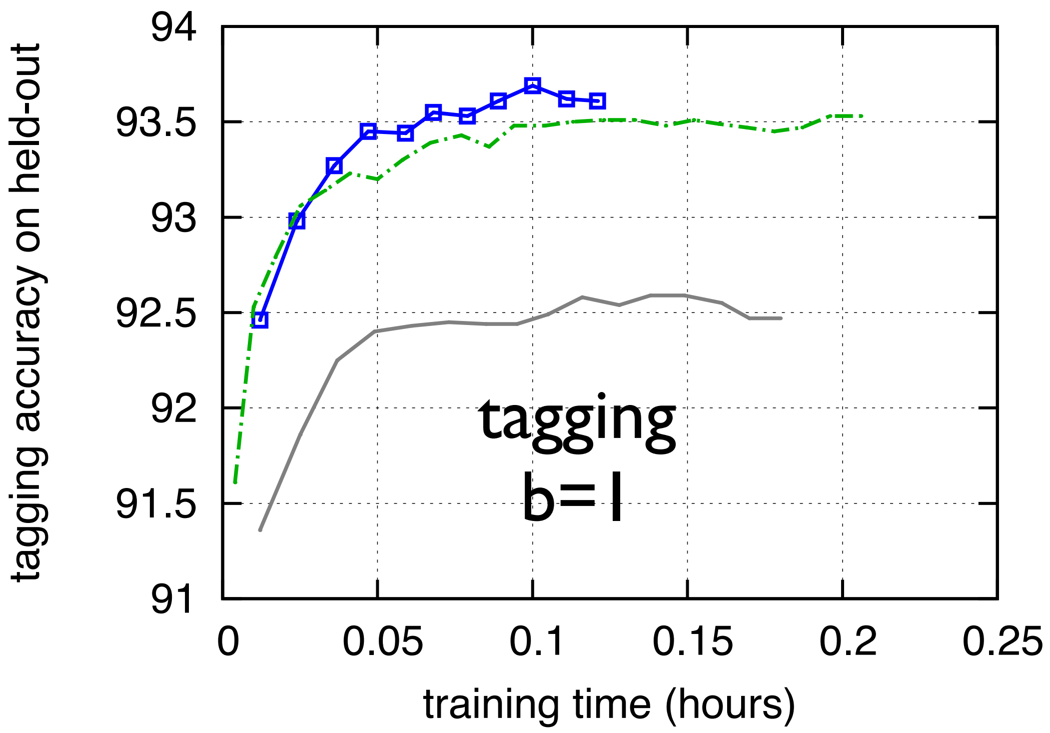
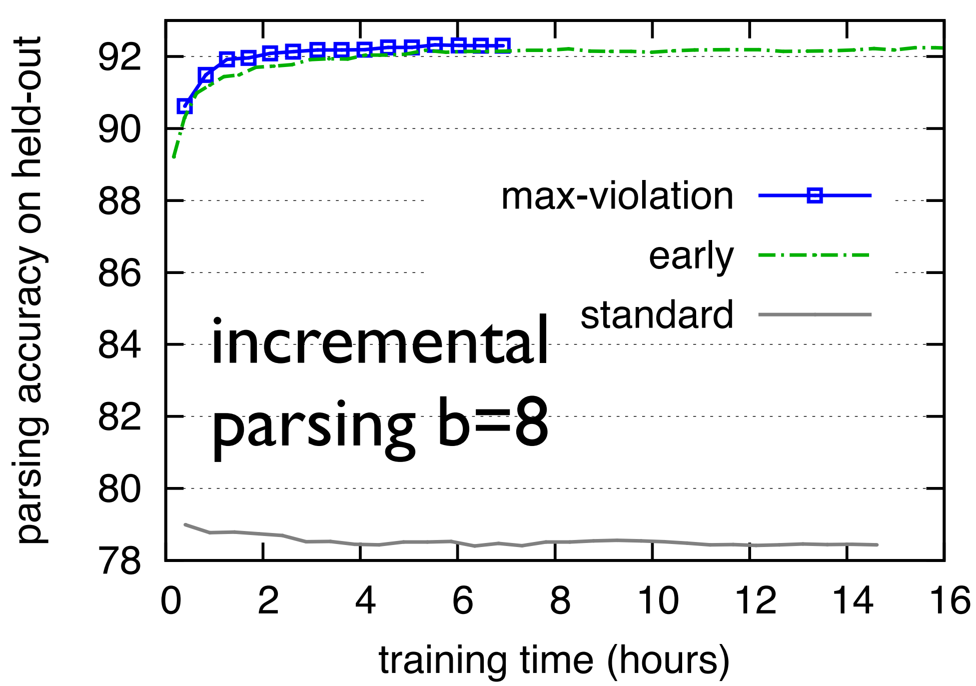
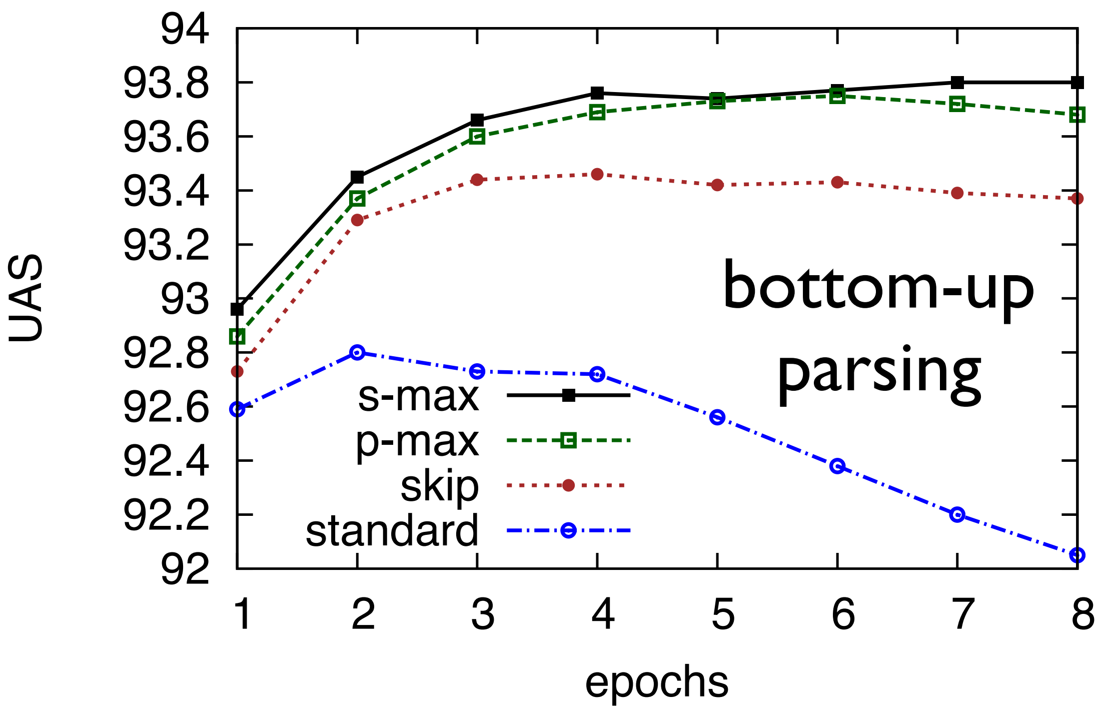


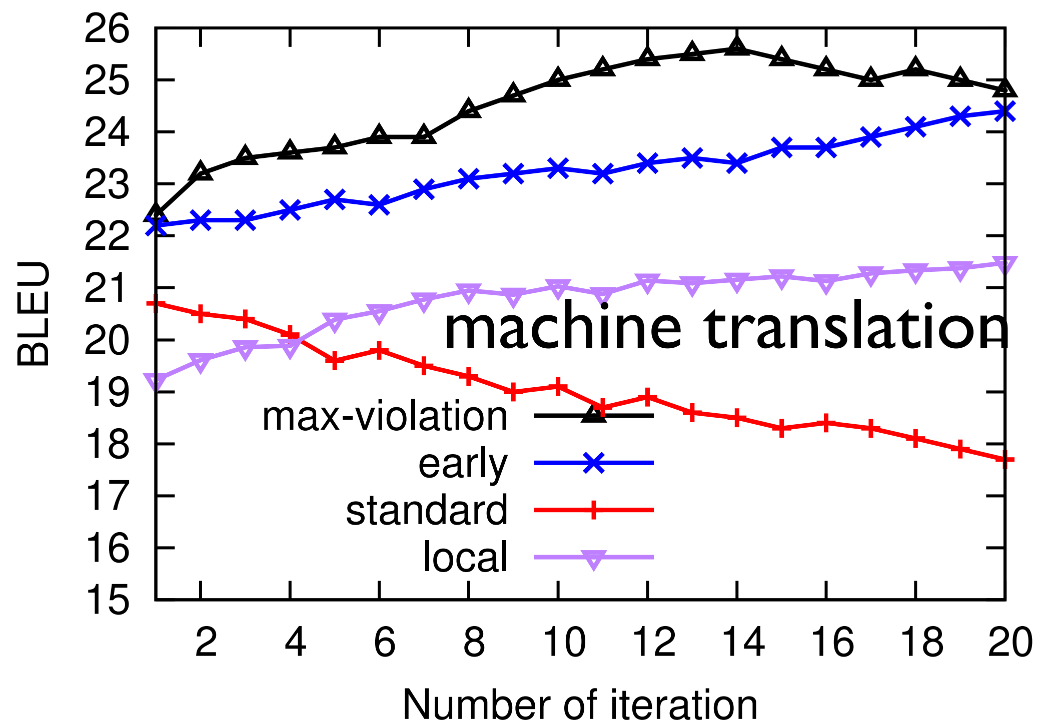
Comparison of Four Exps

- the harder your search, the more advantageous









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  - but these conditions are too strong to hold in practice
- under-generating (beam) vs. over-generating (LP-relax.)
  - Kulesza & Pereira and Martins et al (2011): LP-relaxation
  - Finley and Joachims (2008): both under and over for SVM

Conclusions So Far

- structured perceptron is simple, scalable, and powerful
  - (almost) same convergence proof from multiclass perceptron
- but it doesn't work very well with inexact search
- solution: violation-fixing perceptron framework
  - convergence under new defs of *separability*
  - learn to "live with" search errors
  - in particular, "max-violation" works great
    - converges fast, and results in high accuracy
  - they are more helpful to harder search problems!

Tutorial Outline

- Overview of Structured Learning
  - Challenges in Scalability
- Structured Perceptron
  - convergence proof
- Structured Perceptron with Inexact Search

- Latent-Variable Perceptron
- Parallelizing Online Learning (Perceptron & MIRA)

Learning with Latent Variables

- aka "weakly-supervised" or "partially-observed" learning
- learning from "natural annotations"; more scalable
- examples: translation, transliteration, semantic parsing...

布什 与 沙龙 会谈 x

latent
derivation

Bush talked with Sharon y

parallel text

(Liang et al 2006;
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What is the largest state?

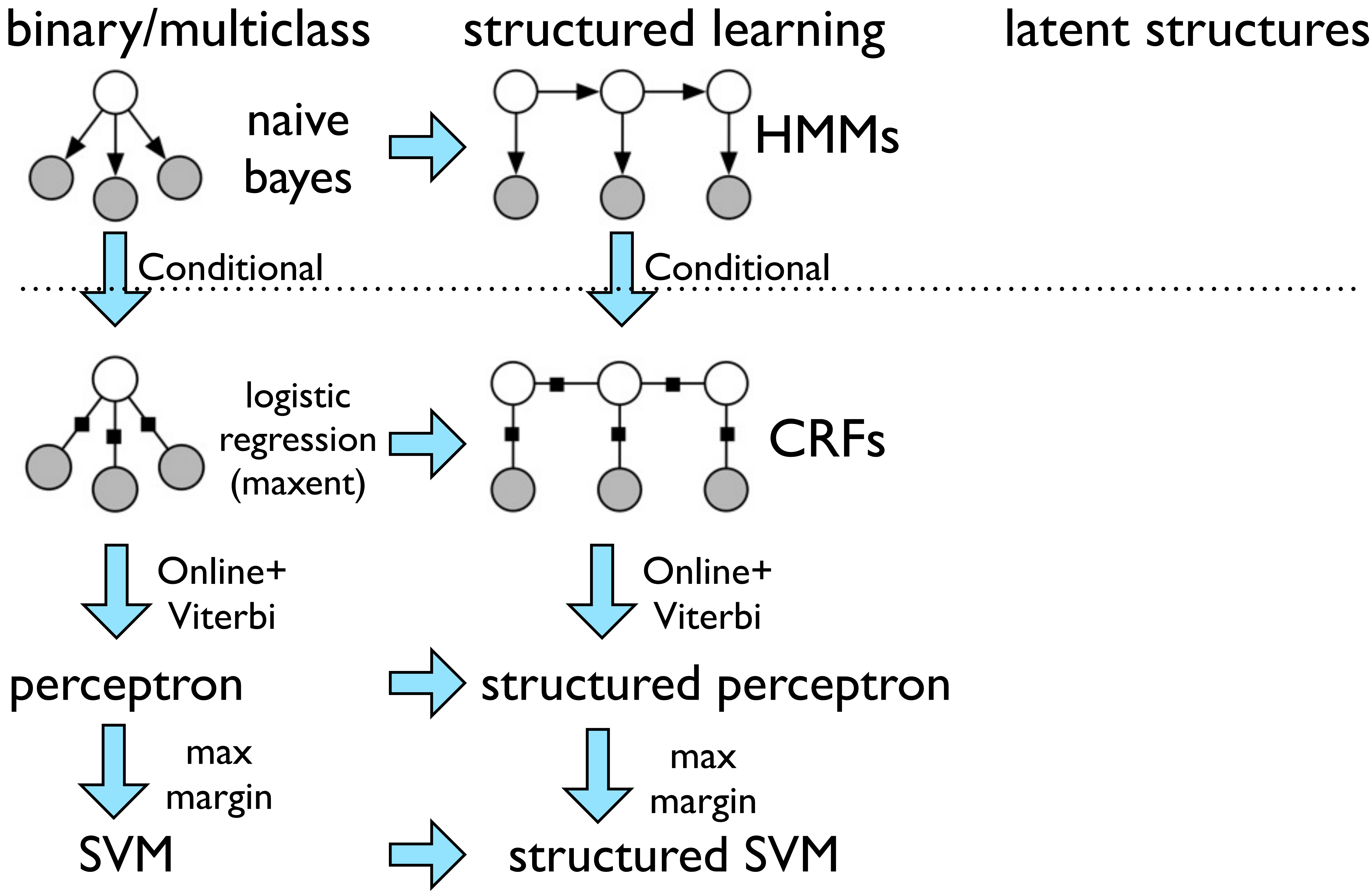
argmax(state, size)

Alaska

QA pairs

(Clark et al 2010;
Liang et al 2013;
Kwiatkowski et al 2013)

Learning Latent Structures



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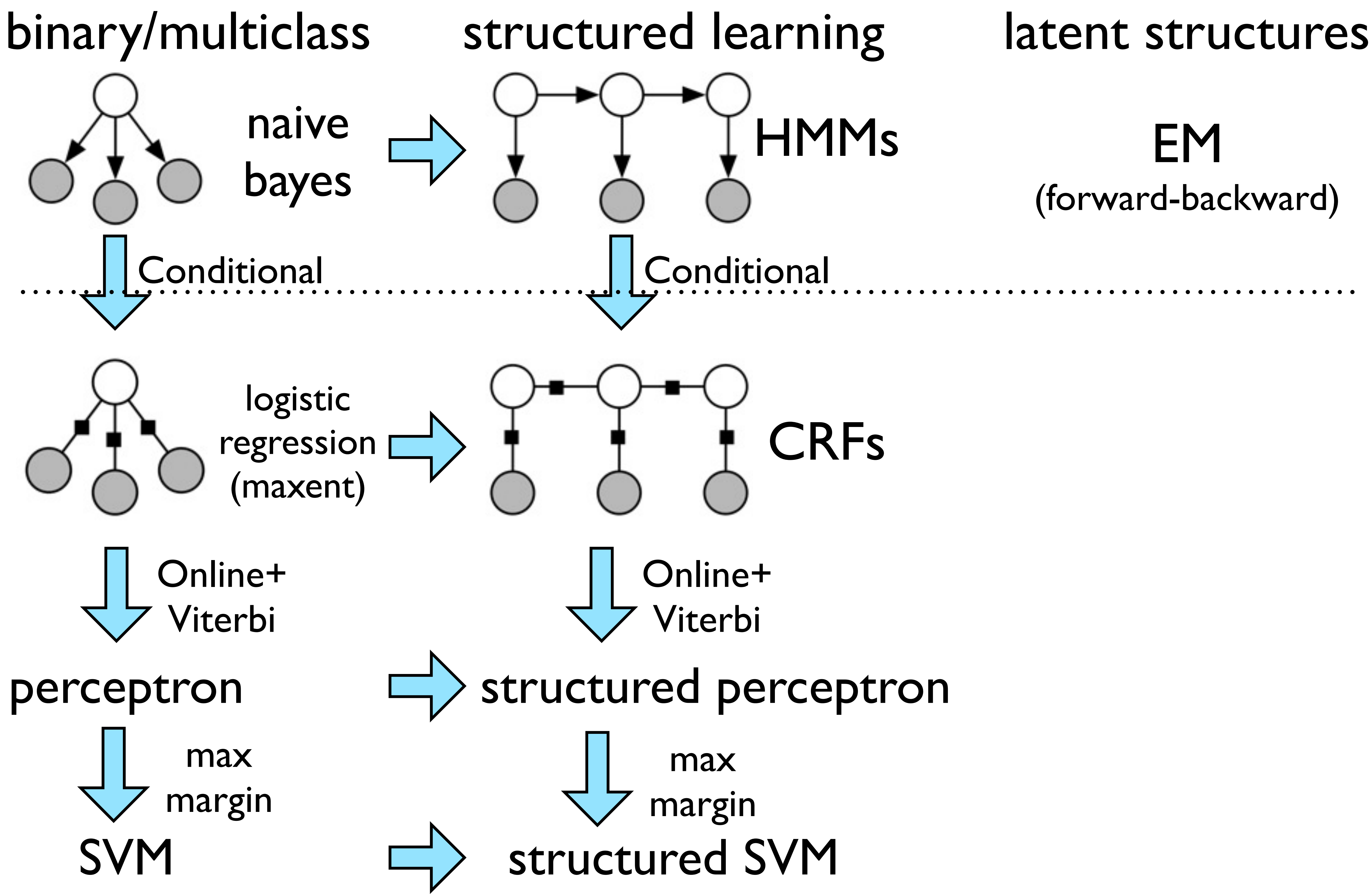

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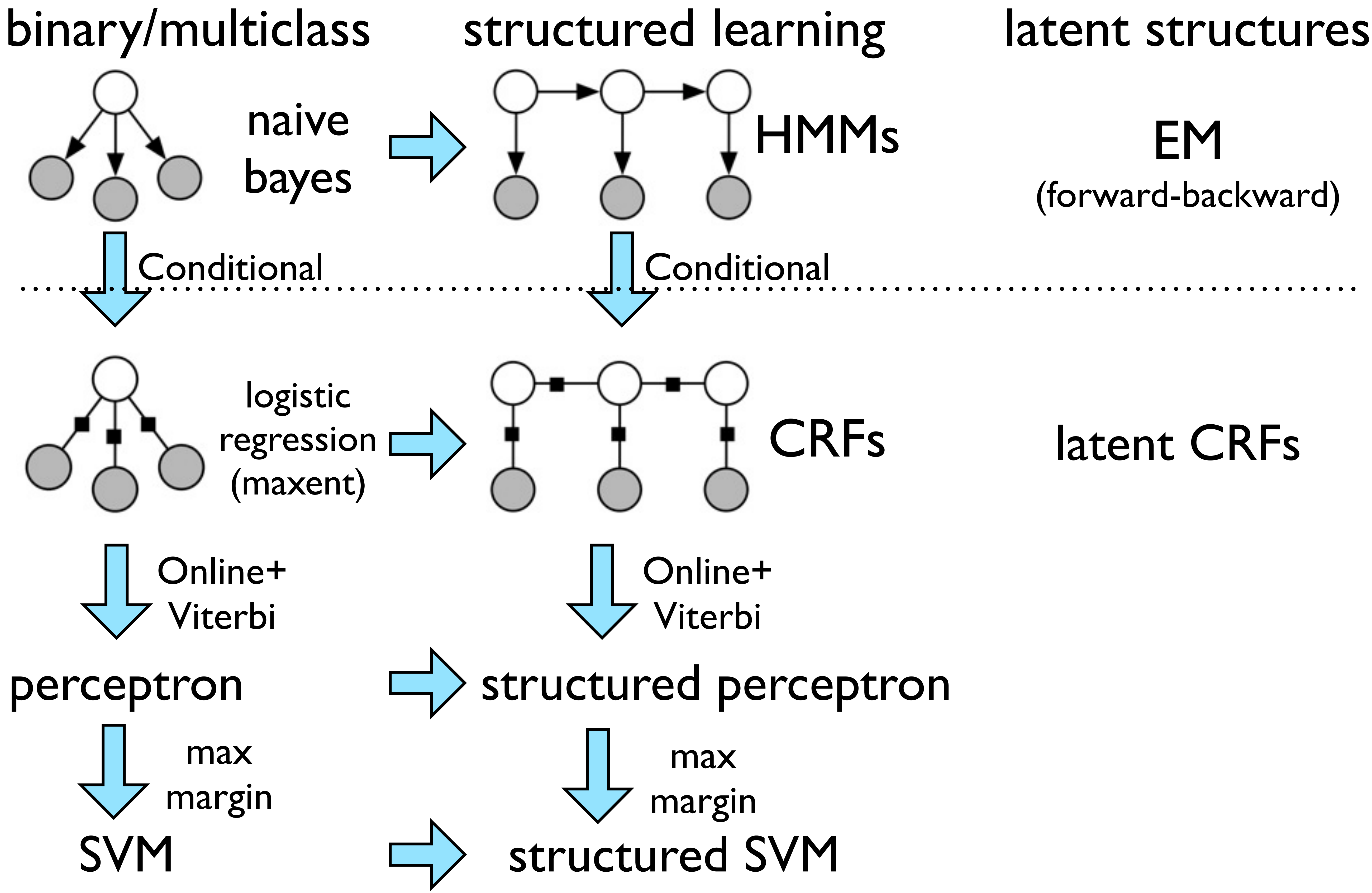
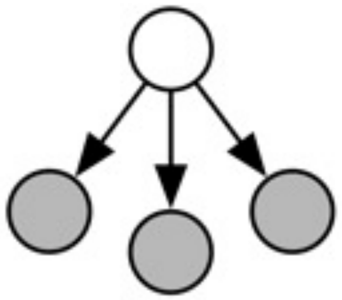
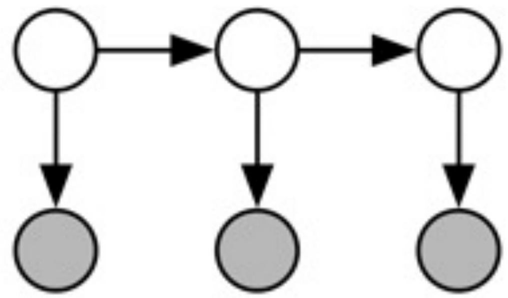


Learning Latent Structures

binary/multiclass | structured learning | latent structures



naive bayes ⇒

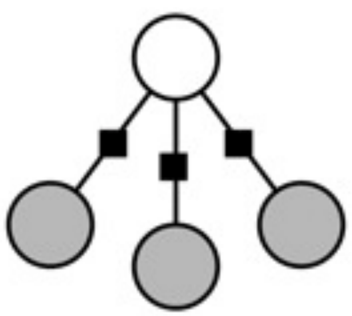


HMMs

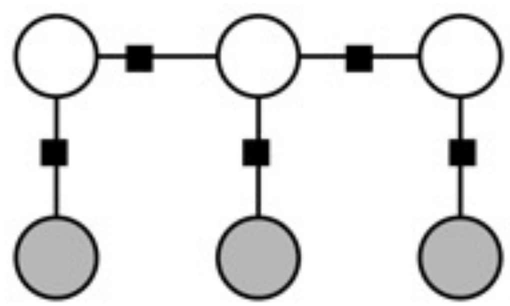
EM
(forward-backward)

Conditional

Conditional



logistic regression (maxent) ⇒



CRFs

latent CRFs

Online+ Viterbi

Online+ Viterbi

perceptron ⇒ structured perceptron

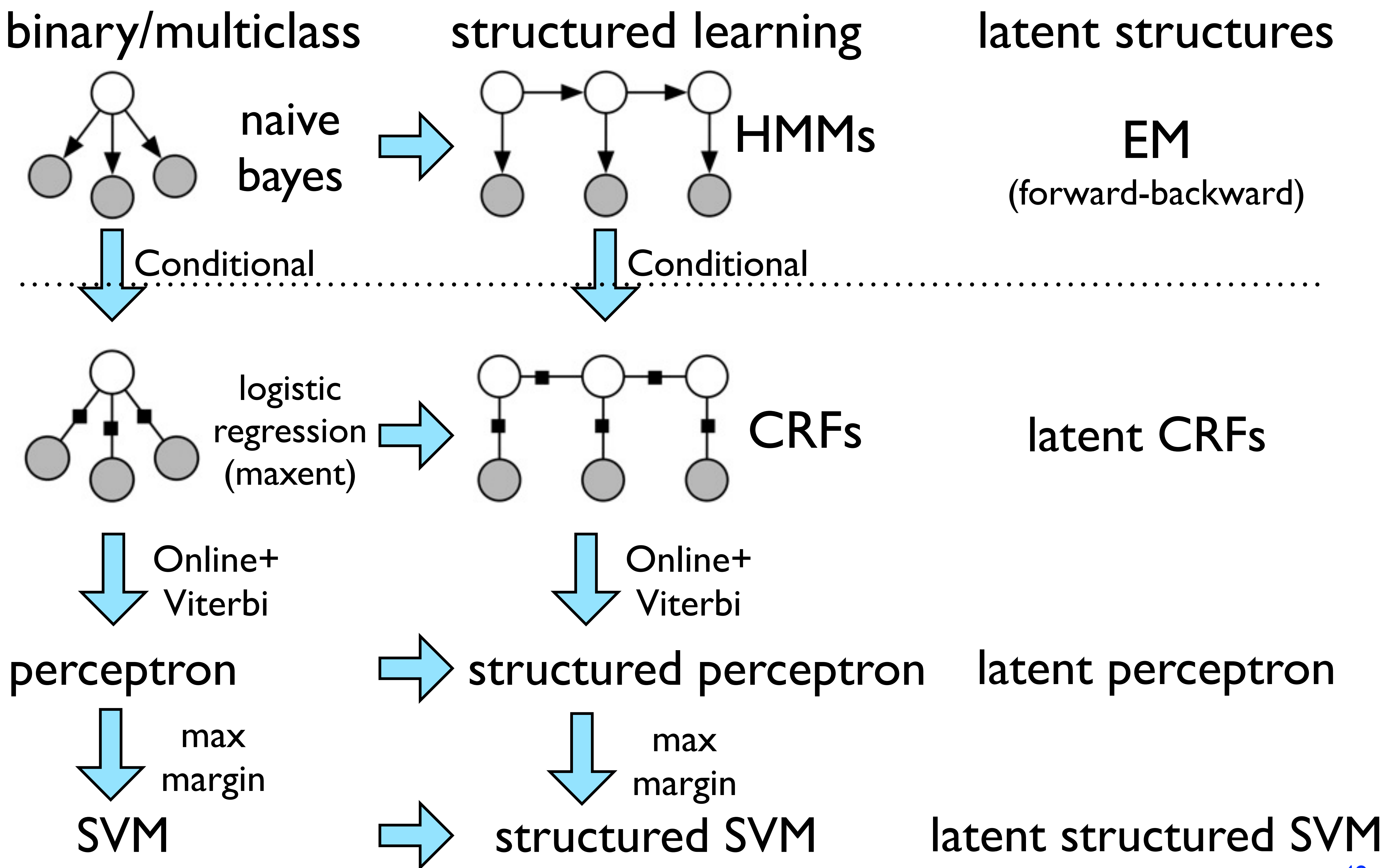
latent perceptron

max margin

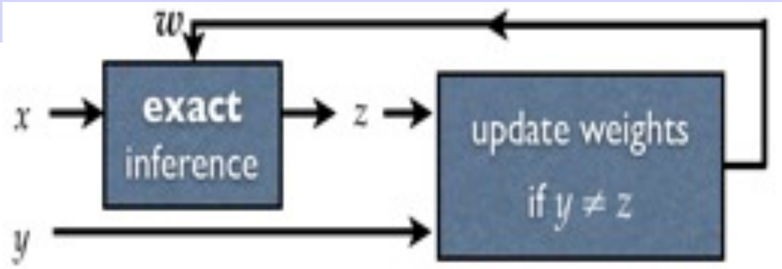
max margin

SVM ⇒ structured SVM

Learning Latent Structures



Latent Structured Perceptron



- no explicit positive signal
  - hallucinate the "correct" derivation by current weights

training example

那	人	咬	了	狗	x

the	man	bit	the	dog	y

(Liang et al 2006;
Yu et al 2013)

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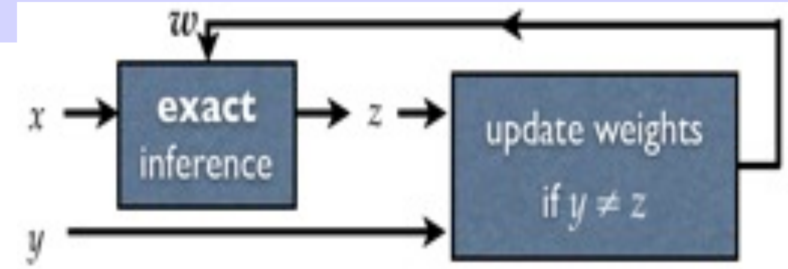

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during online learning...

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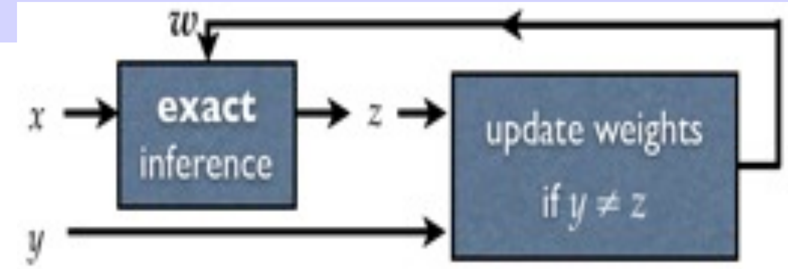

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during online learning...

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x

full
search
space

(Liang et al 2006;
Yu et al 2013)

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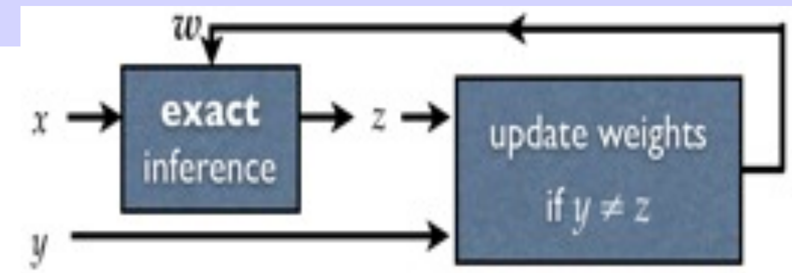

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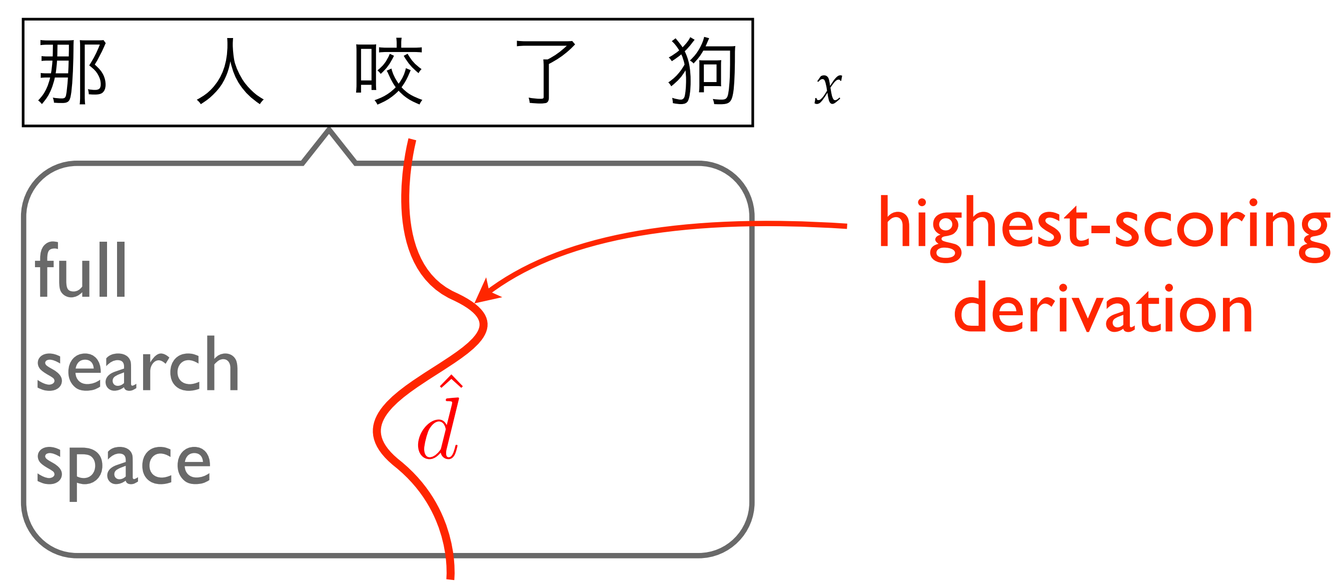

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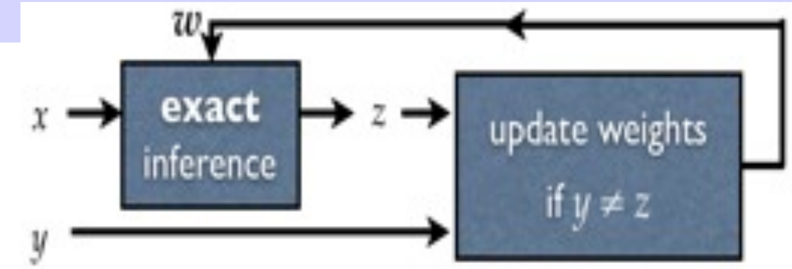

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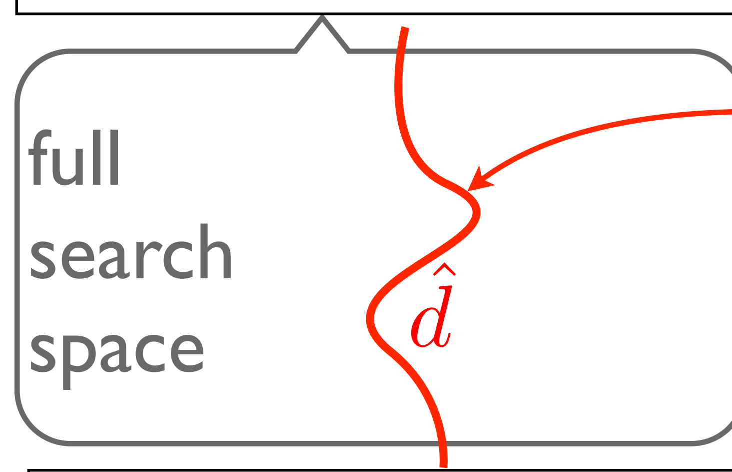

highest-scoring derivation

the	dog	bit	the	man

z

(Liang et al 2006;
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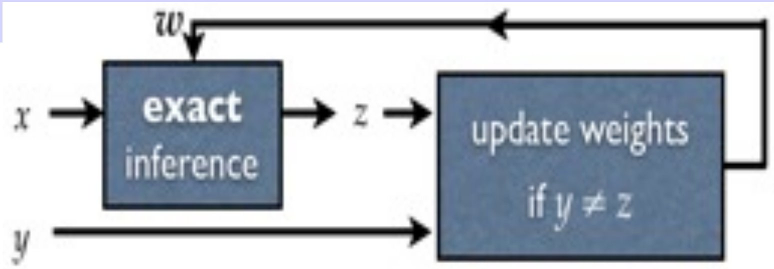
Latent Structured Perceptron



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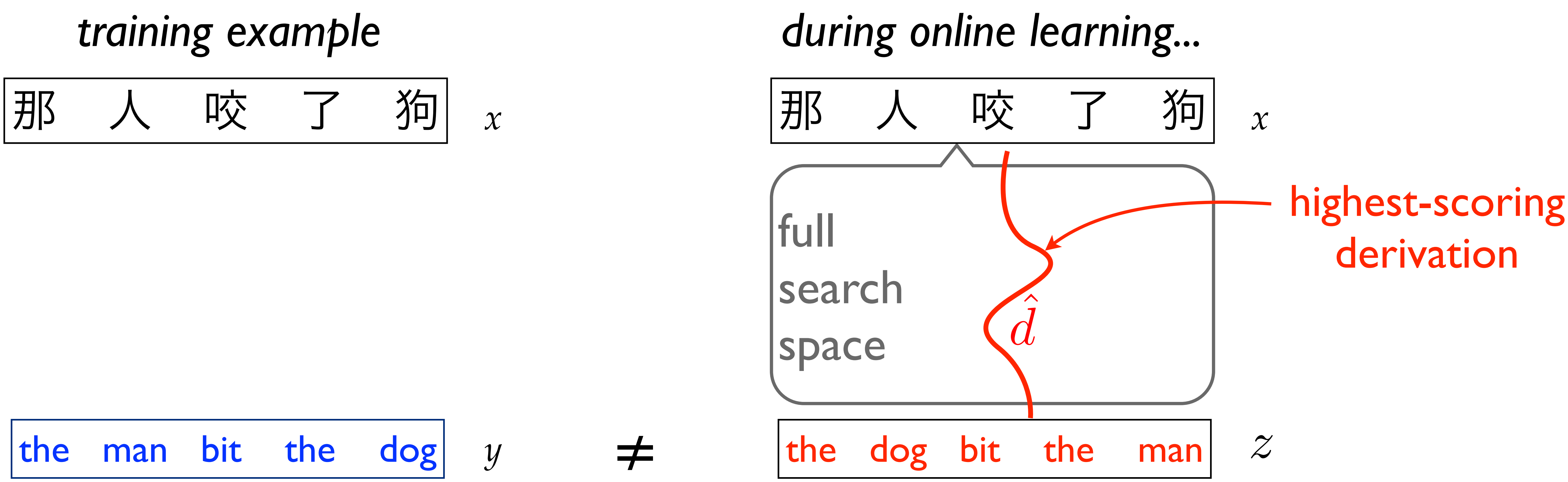

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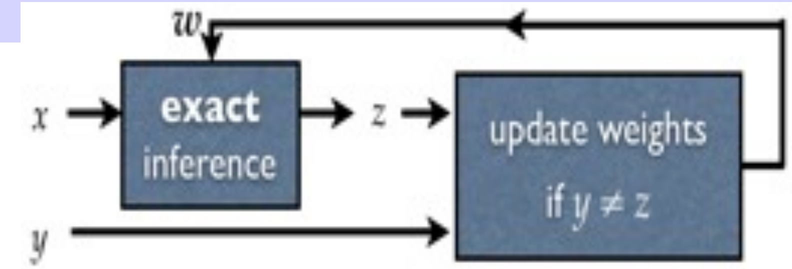

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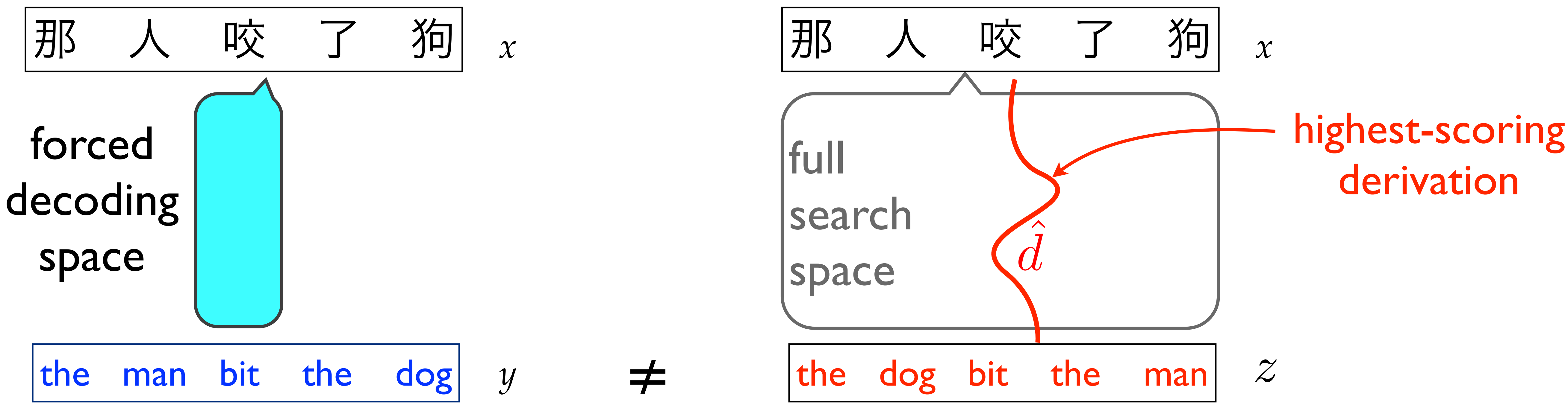
training example *during online learning...*



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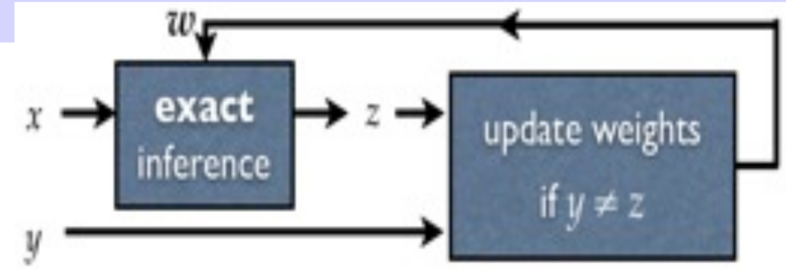

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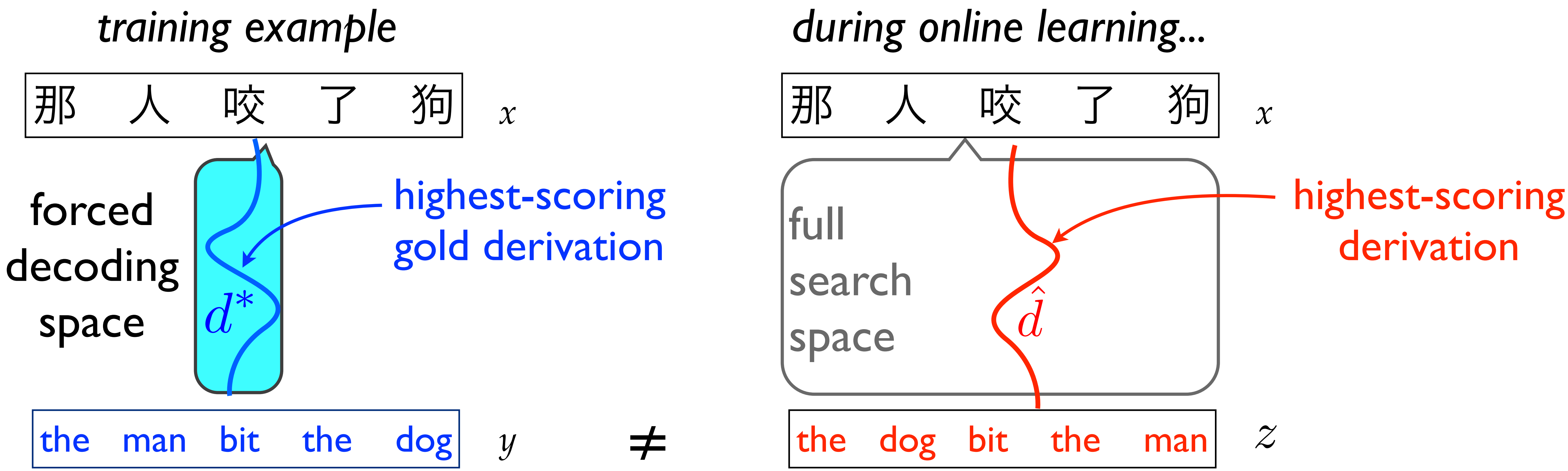

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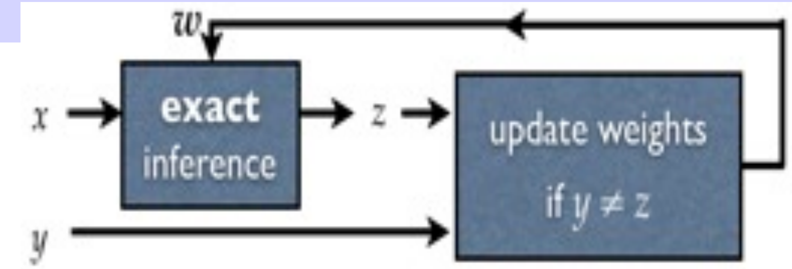

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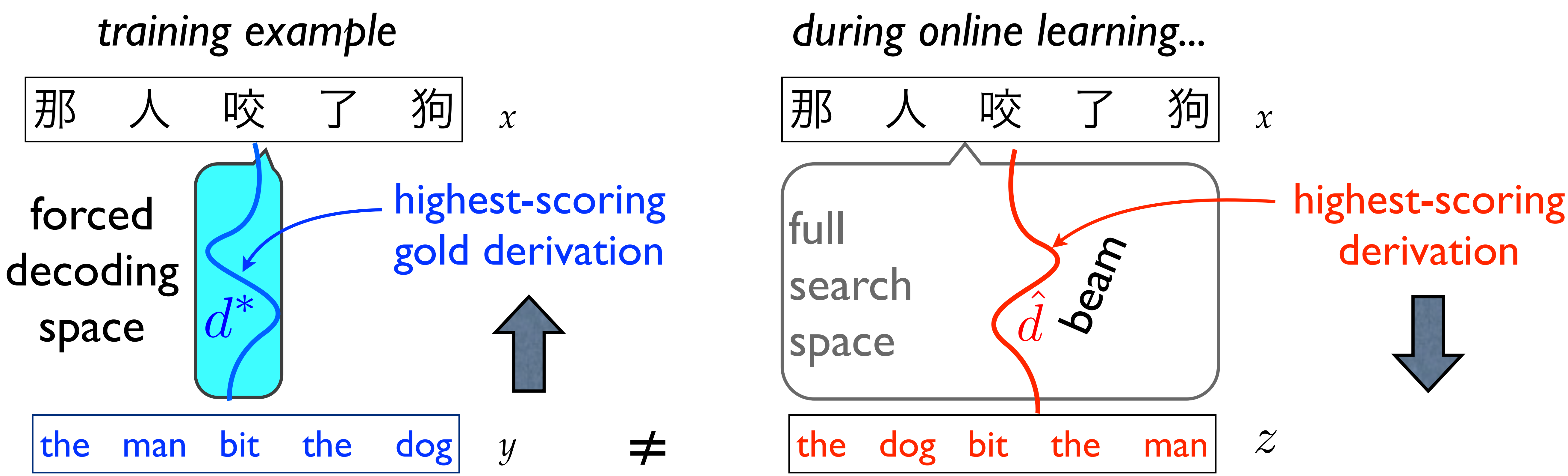

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(x, d^*) - \Phi(x, \hat{d})$$

reward correct

penalize wrong

(Liang et al 2006; Yu et al 2013)

Unconstrained Search

- example: beam search phrase-based decoding

Bushi yu Shalong juxing le huitan → *???*

Unconstrained Search

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●_____ Bush

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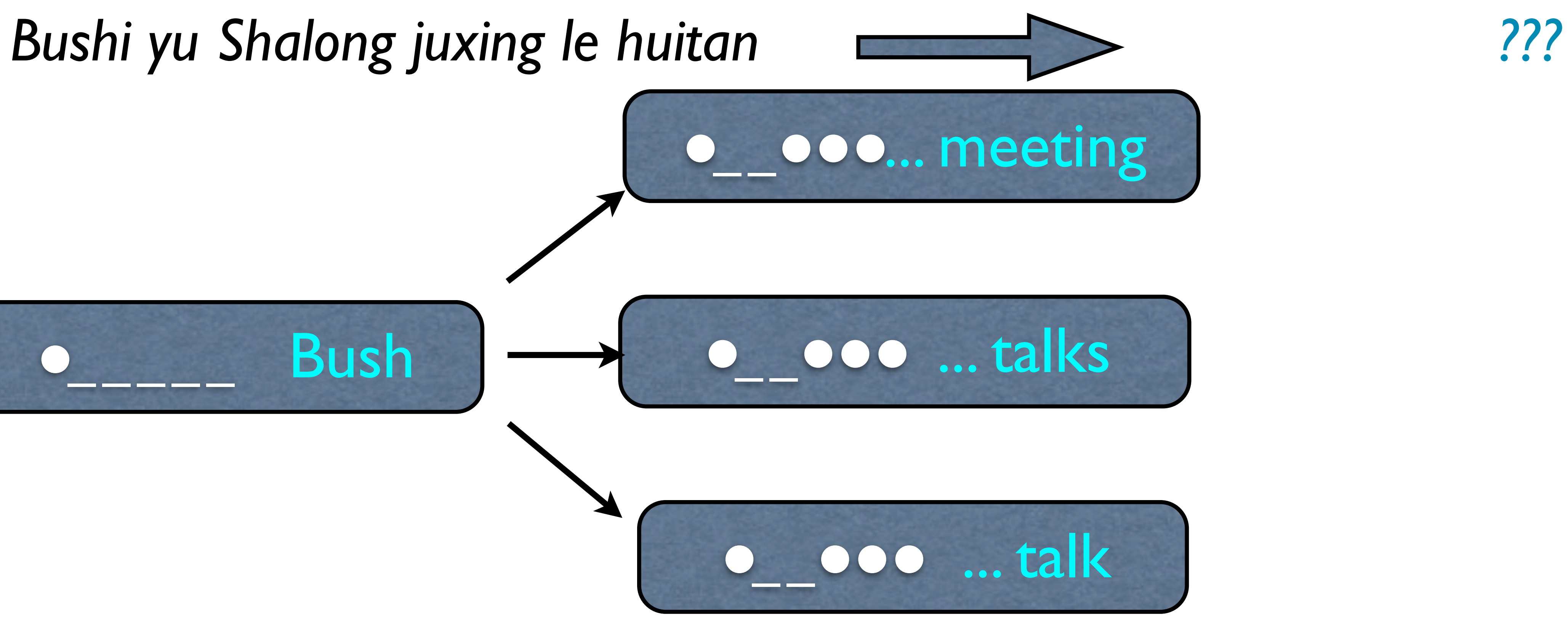

Unconstrained Search

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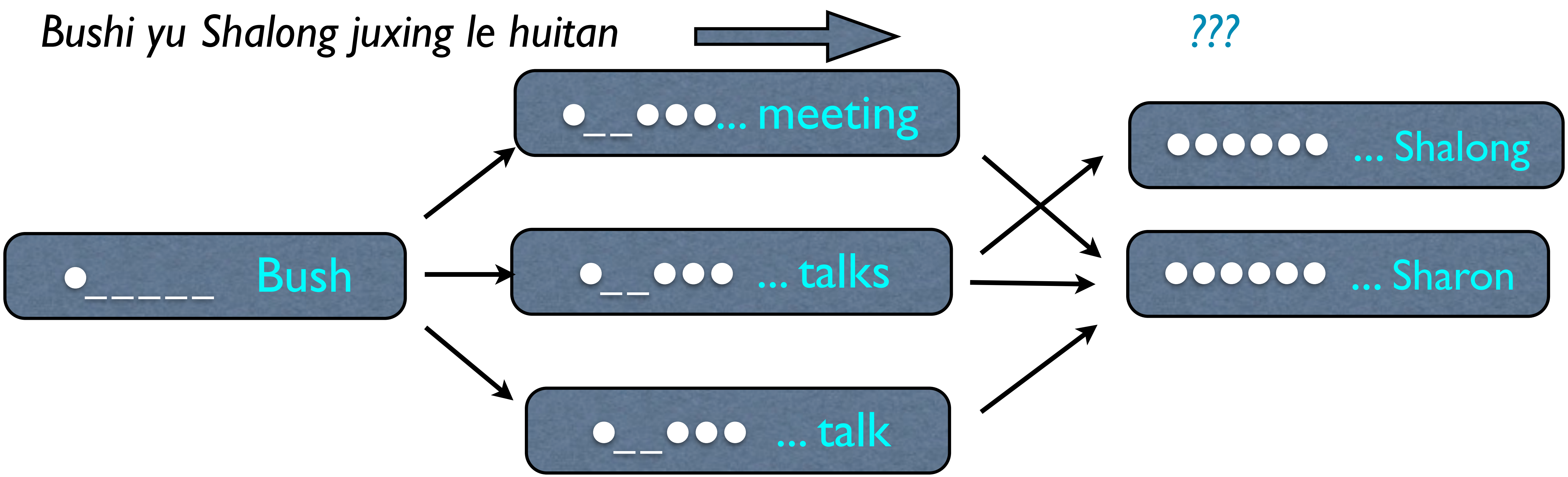

Unconstrained Search

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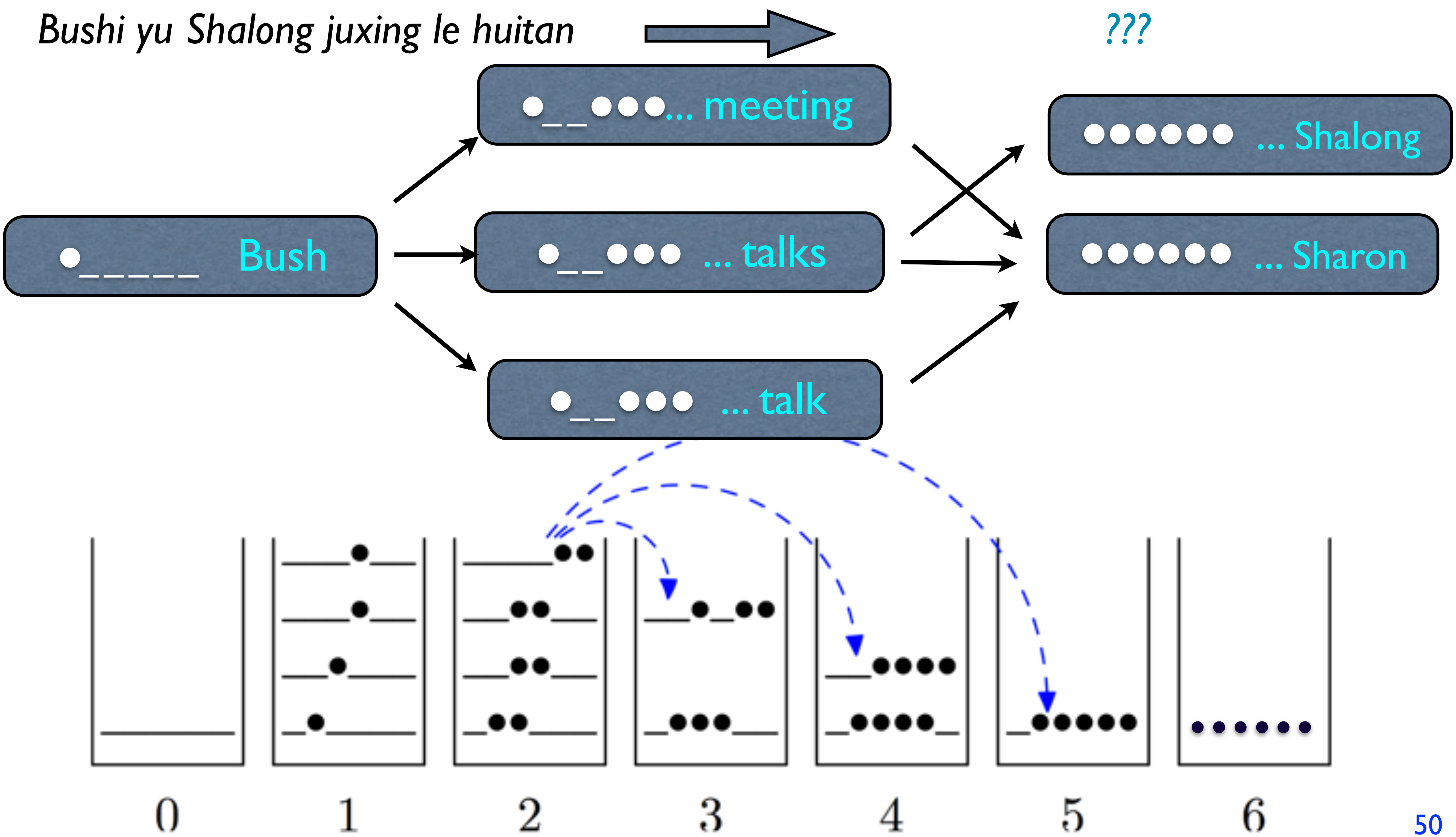
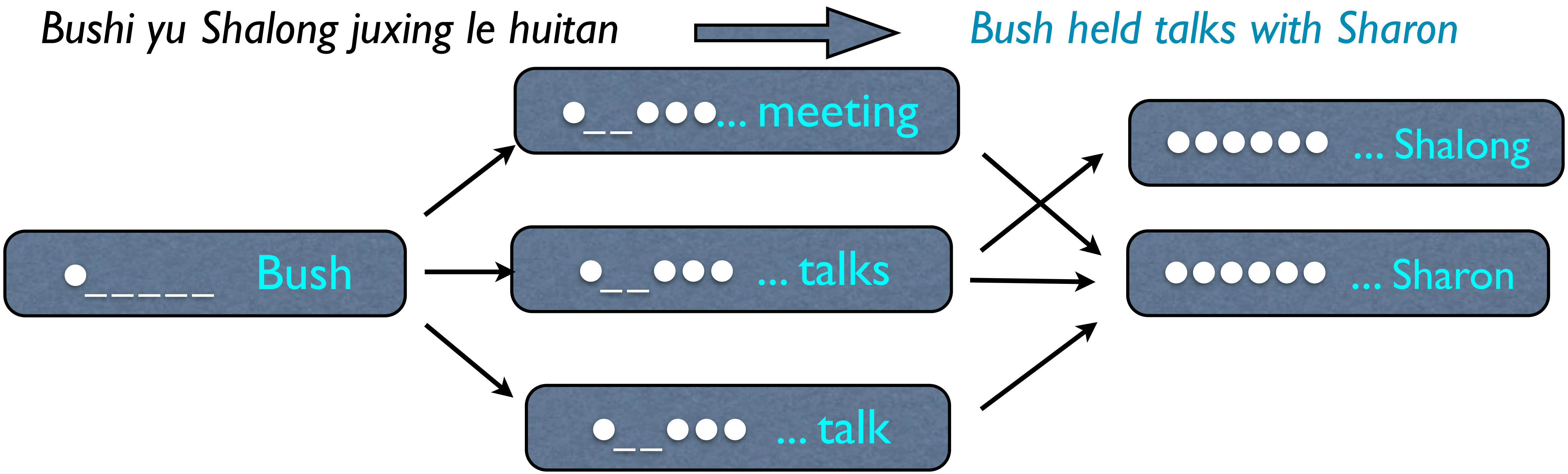


Constrained Search

- forced decoding: must produce the exact reference translation



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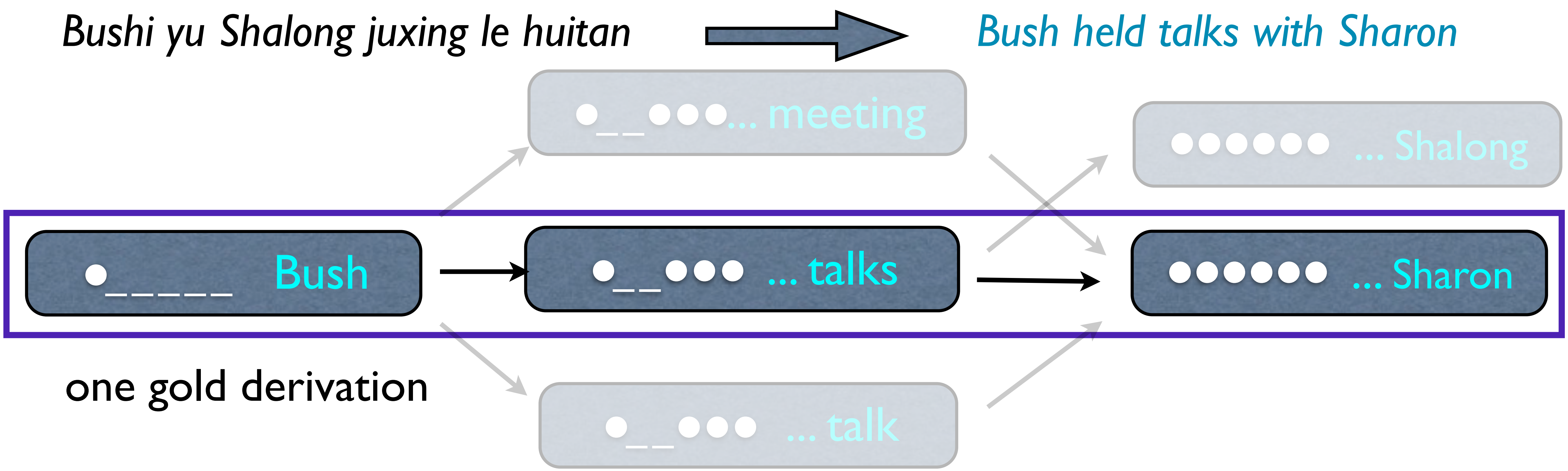

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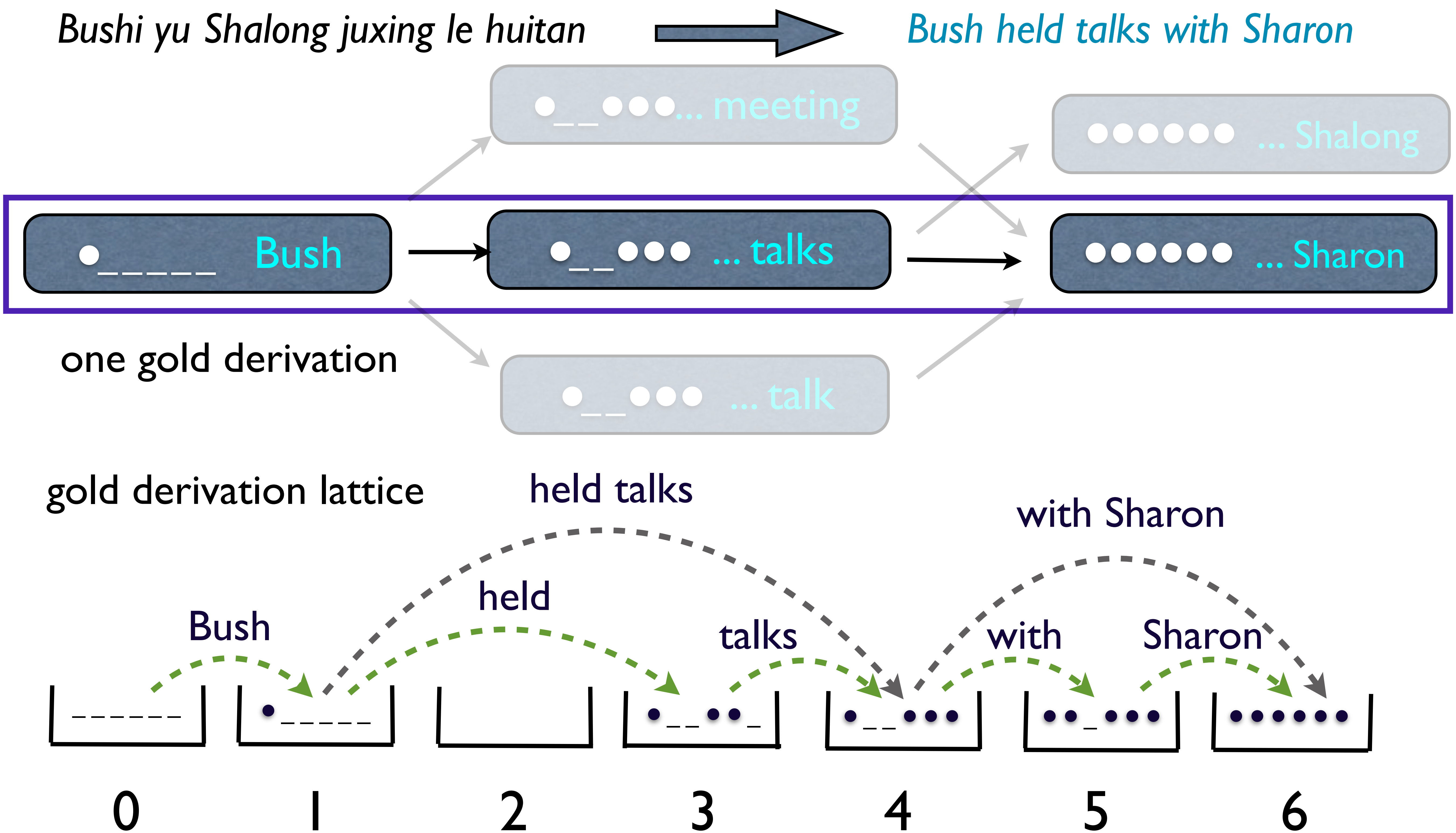
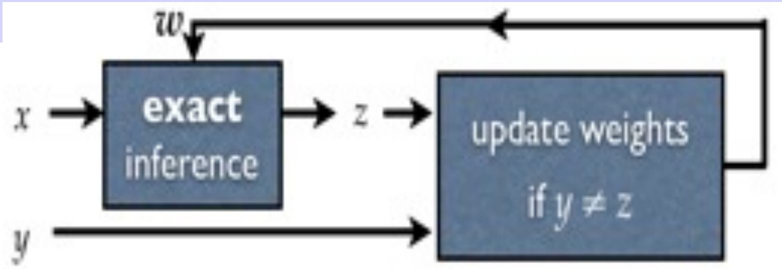


Search Errors in Decoding



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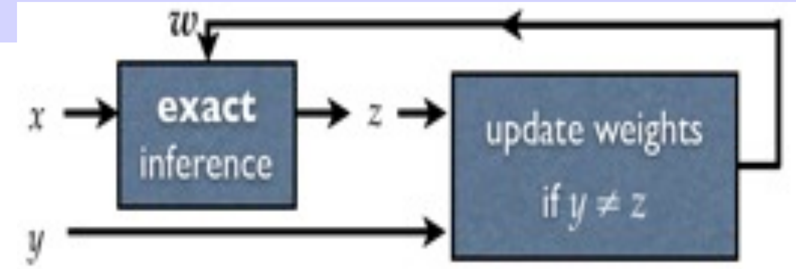

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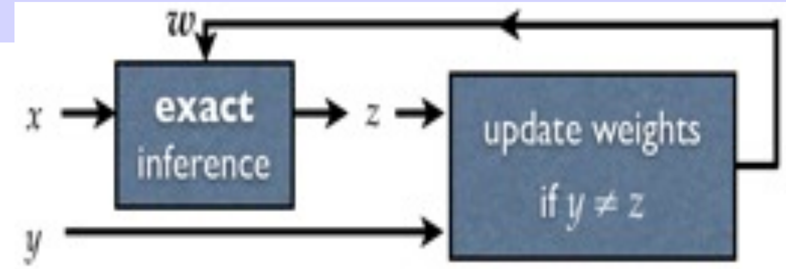
during online learning...

那	人	咬	了	狗	x

(Liang et al 2006;
Yu et al 2013)

Search Errors in Decoding



- no explicit positive signal
  - hallucinate the "correct" derivation by current weights

training example

那	人	咬	了	狗

x

the	man	bit	the	dog

y

during online learning...

那	人	咬	了	狗

x

full
search
space

(Liang et al 2006;
Yu et al 2013)

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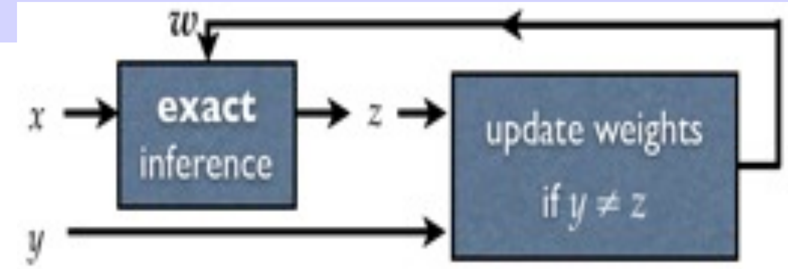

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during online learning...

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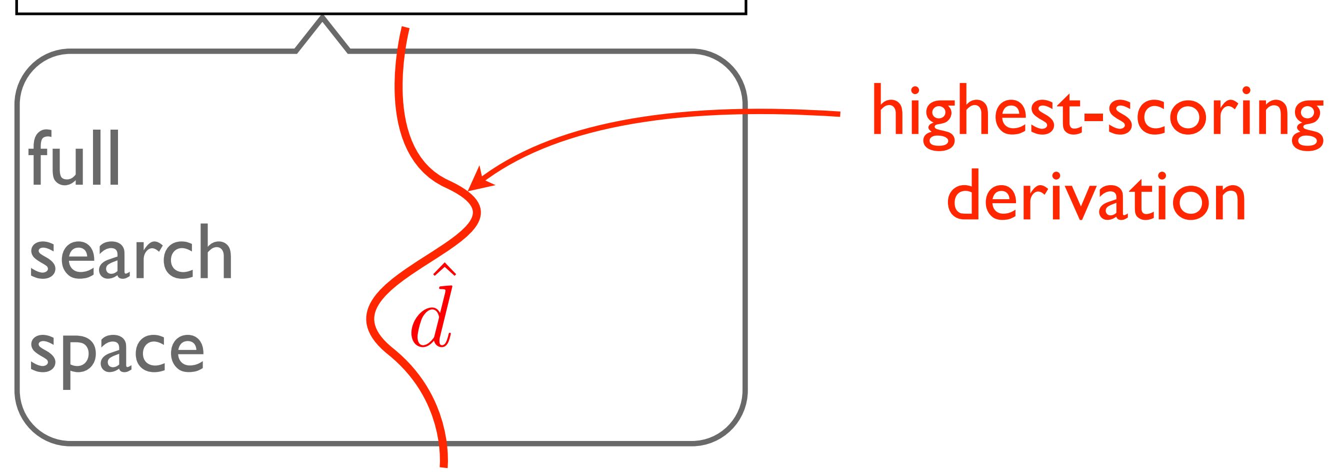

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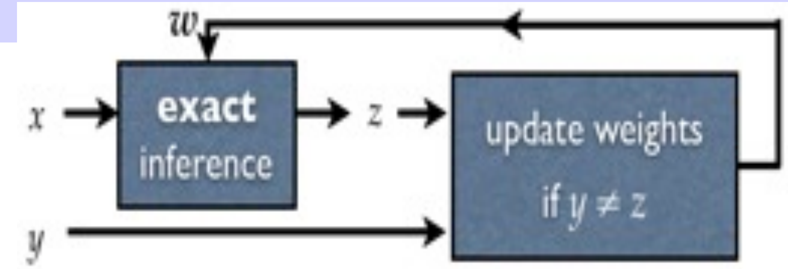

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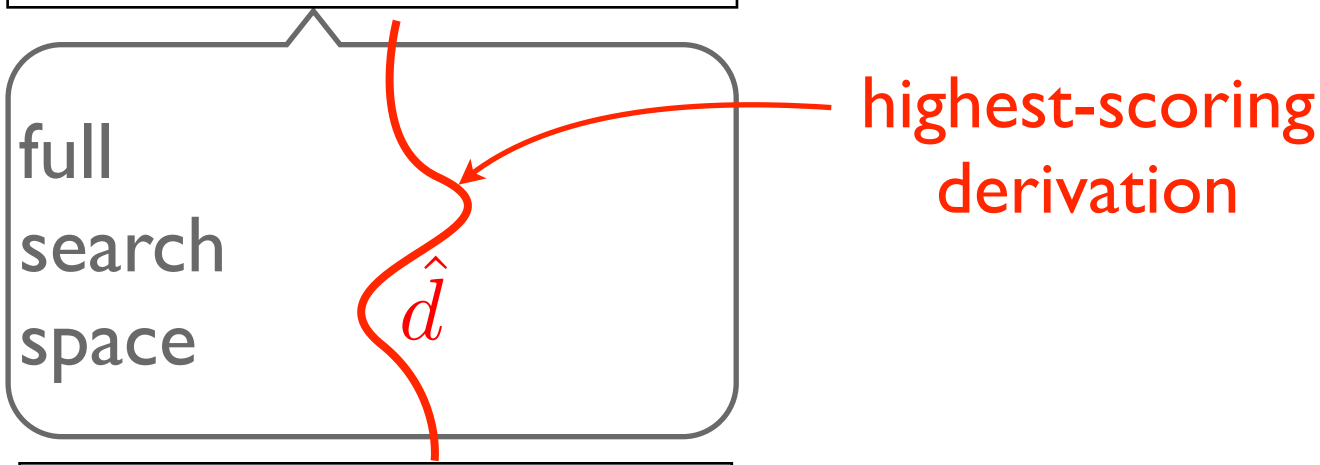
training example

那 人 咬 了 狗 x

the man bit the dog y

during online learning...

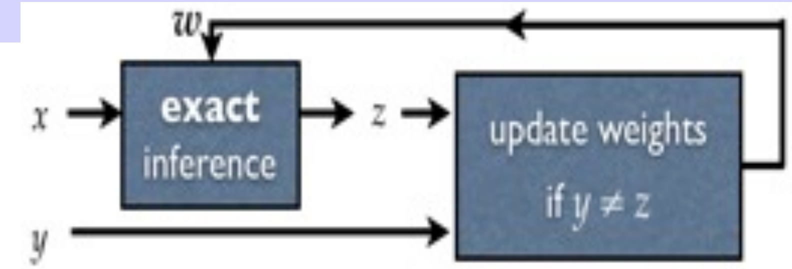
那 人 咬 了 狗 x



the dog bit the man z

(Liang et al 2006;
Yu et al 2013)

Search Errors in Decoding



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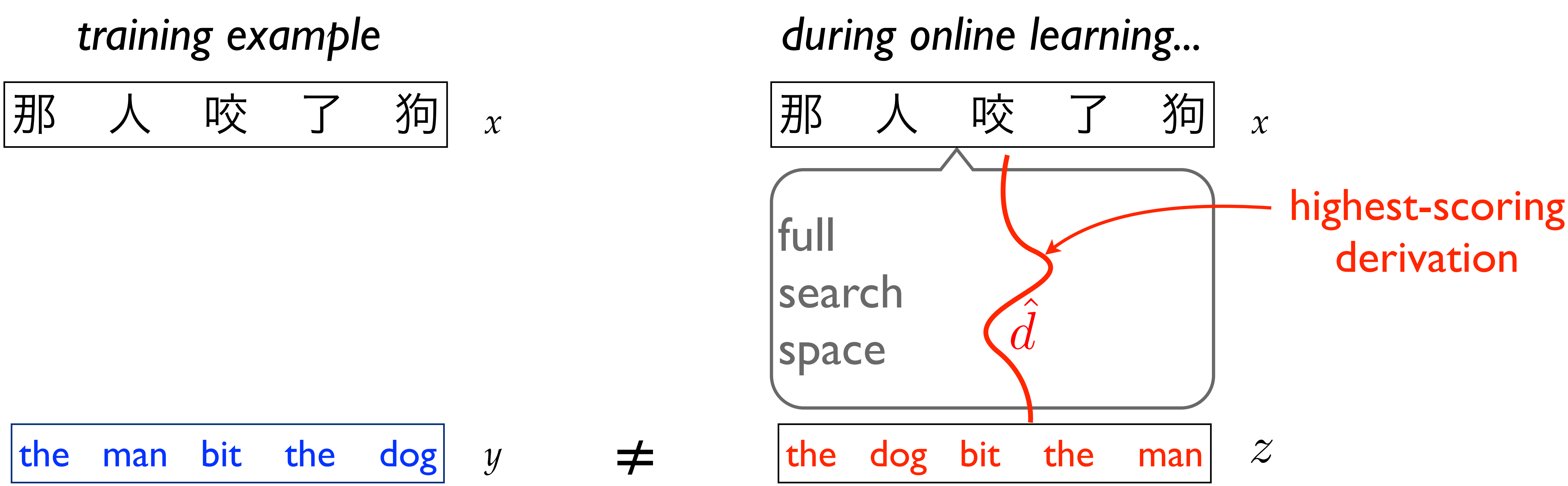

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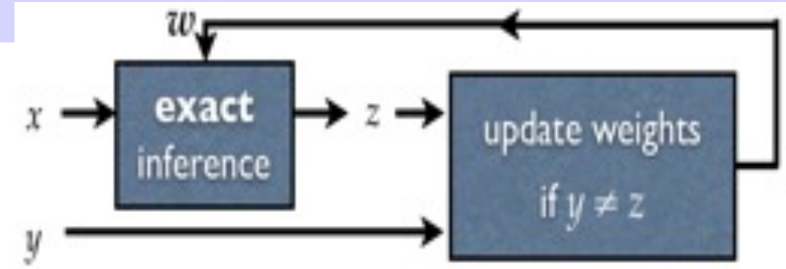

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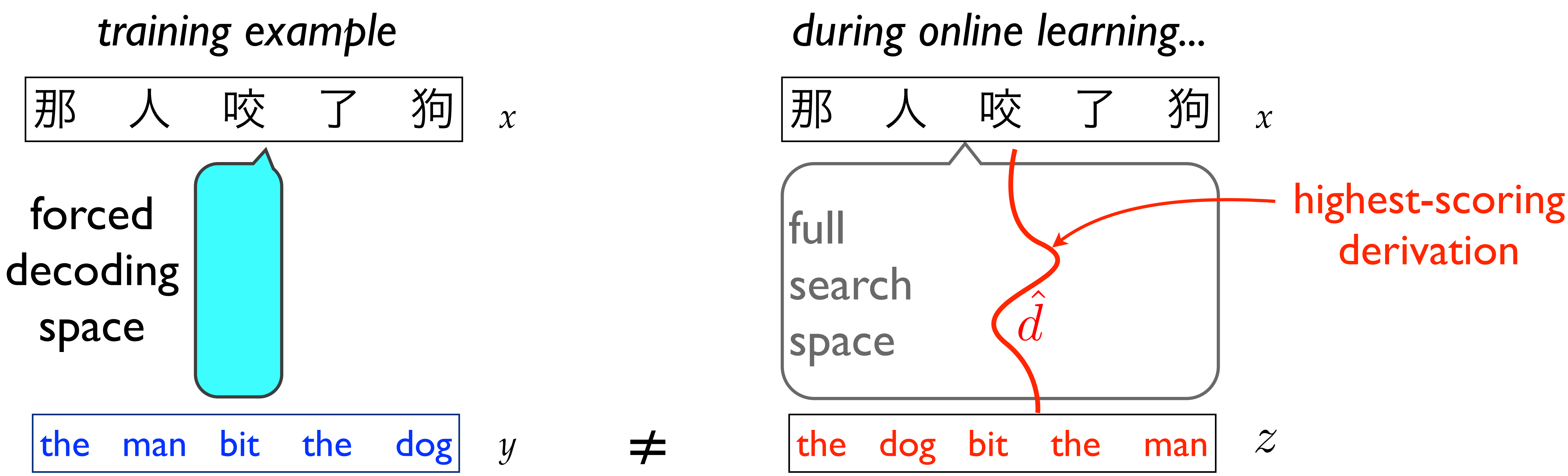

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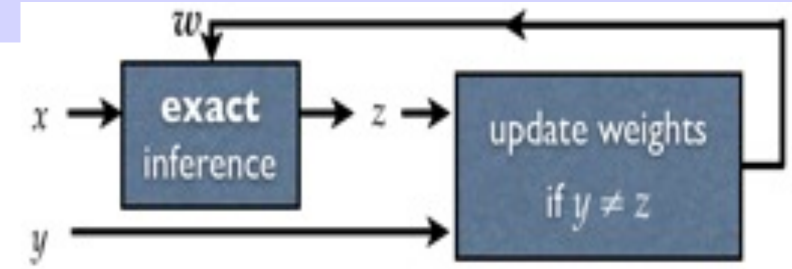

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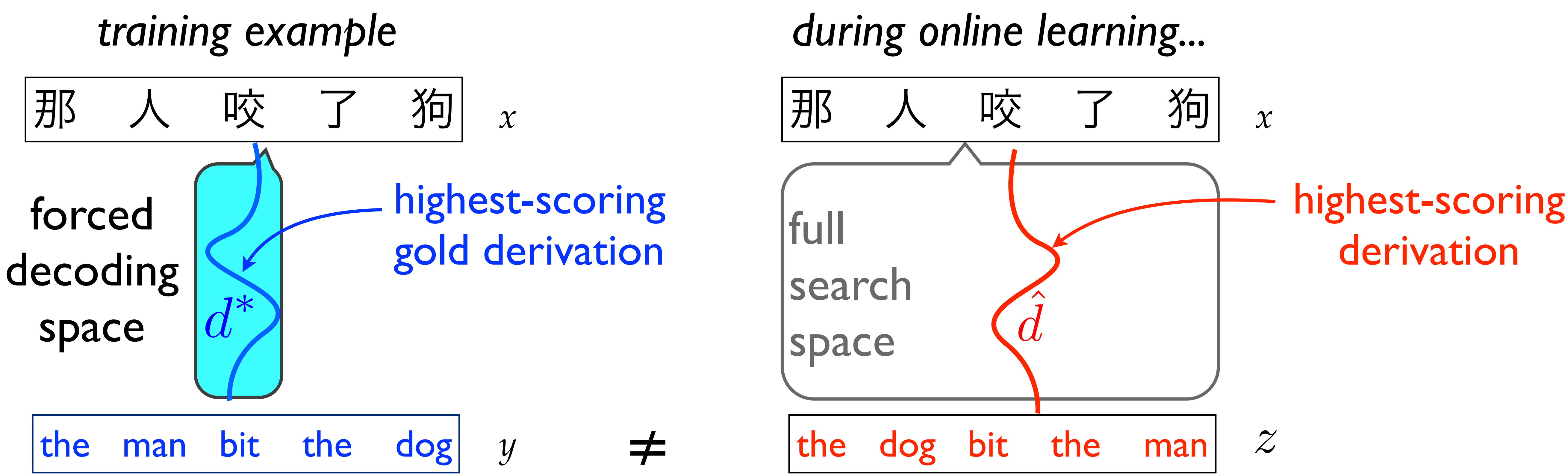

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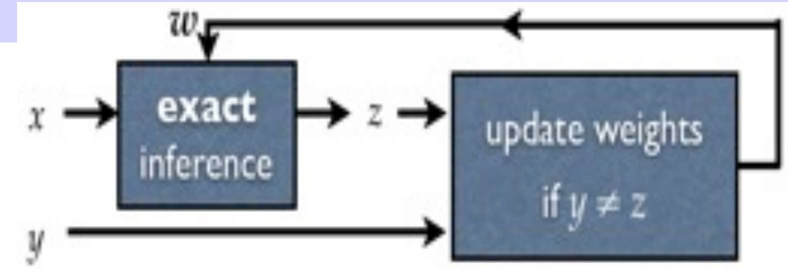

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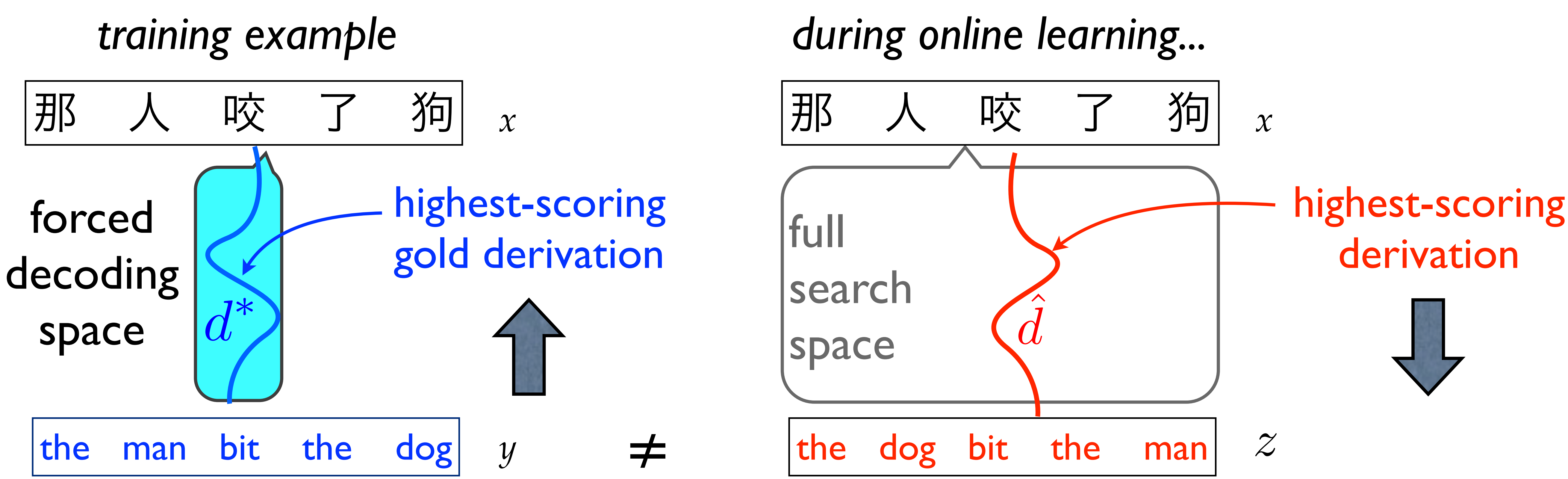


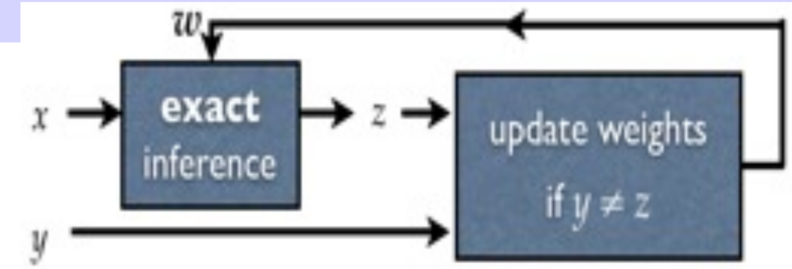
$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(x, d^*) - \Phi(x, \hat{d})$$

reward correct

penalize wrong

(Liang et al 2006; Yu et al 2013)

Search Errors in Decoding



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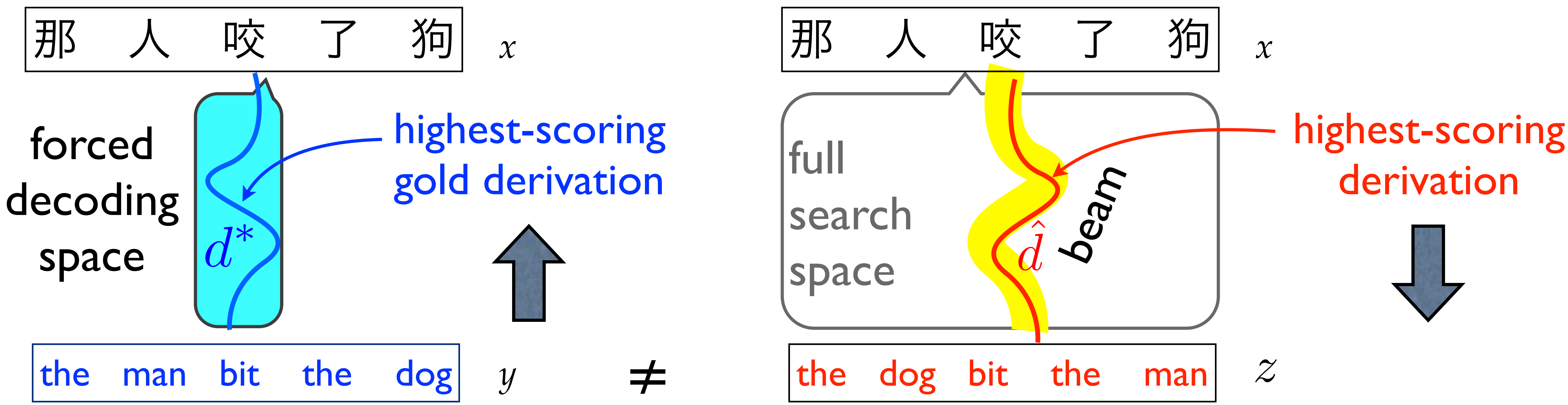
training example *during online learning...*



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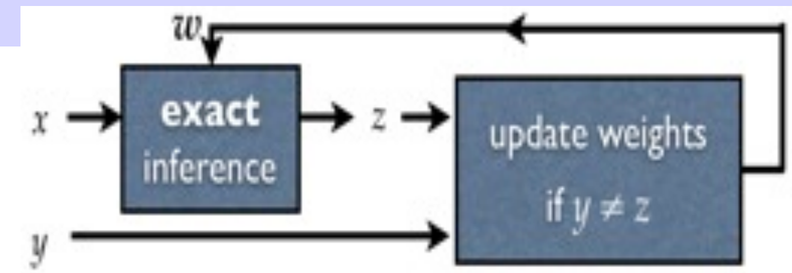

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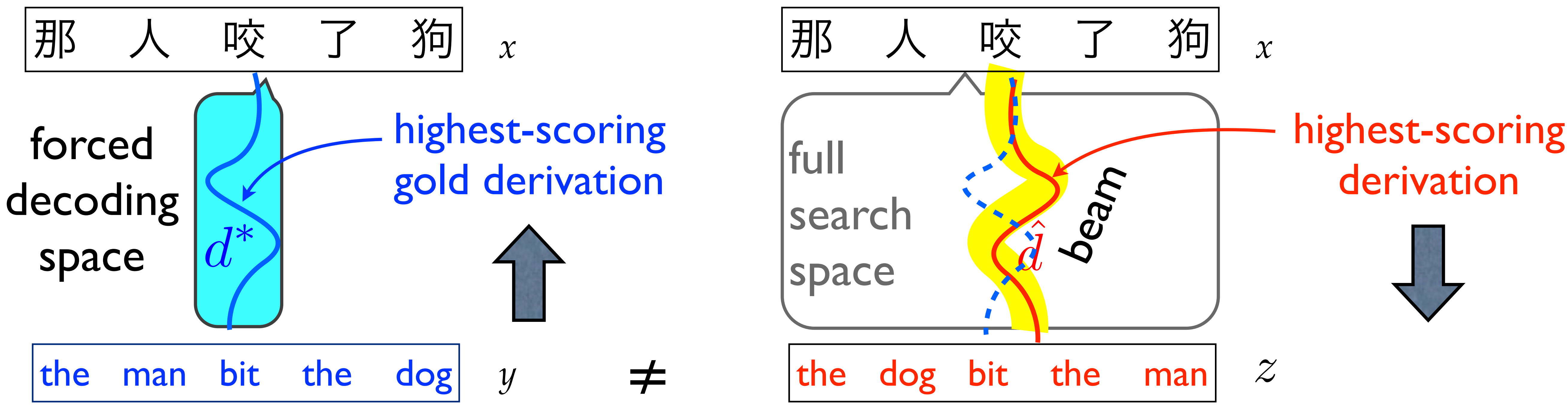

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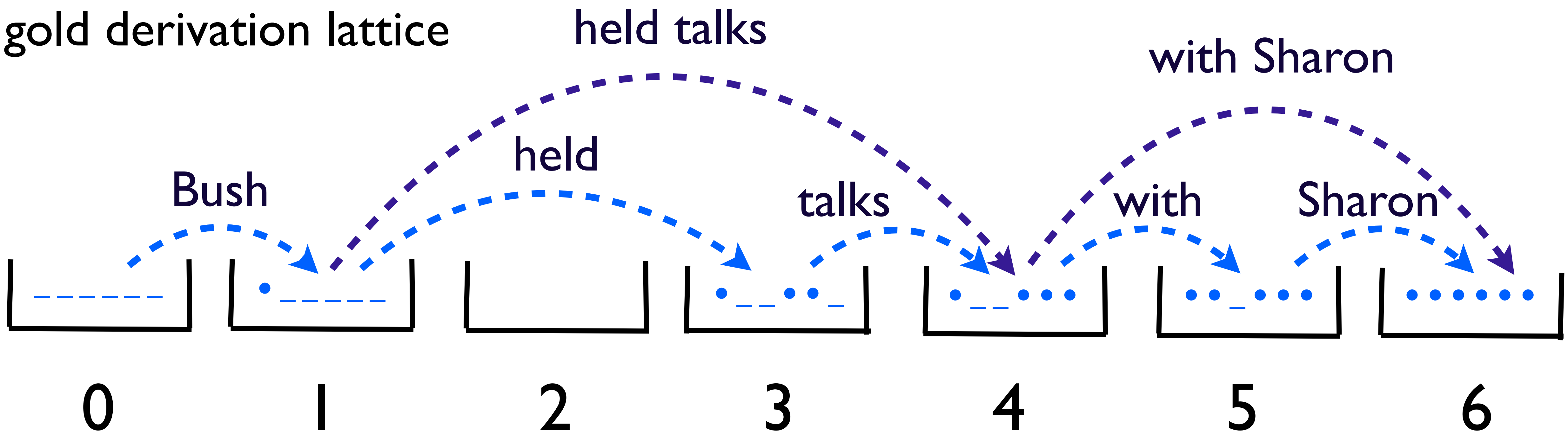
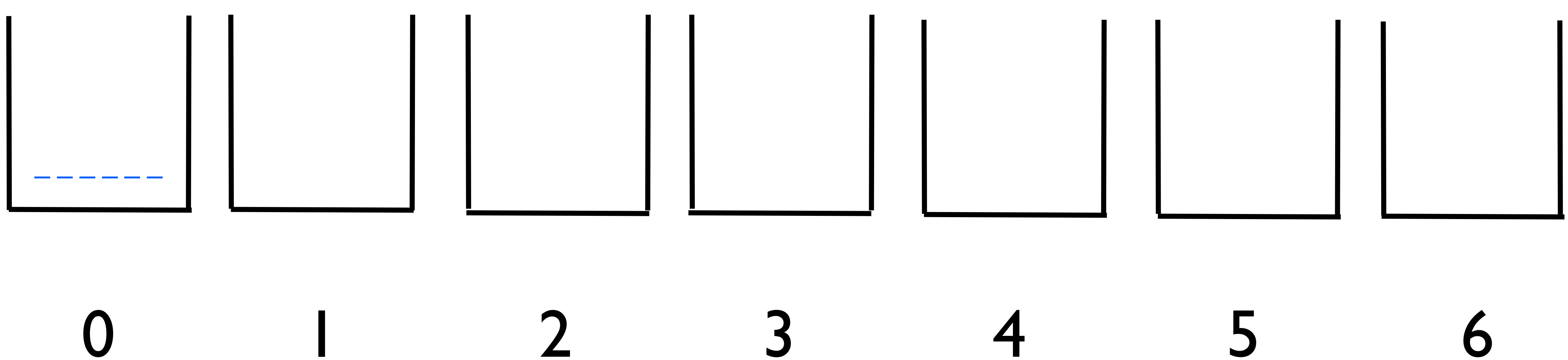
Search Error: Gold Derivations Pruned

gold derivation lattice



real decoding beam search



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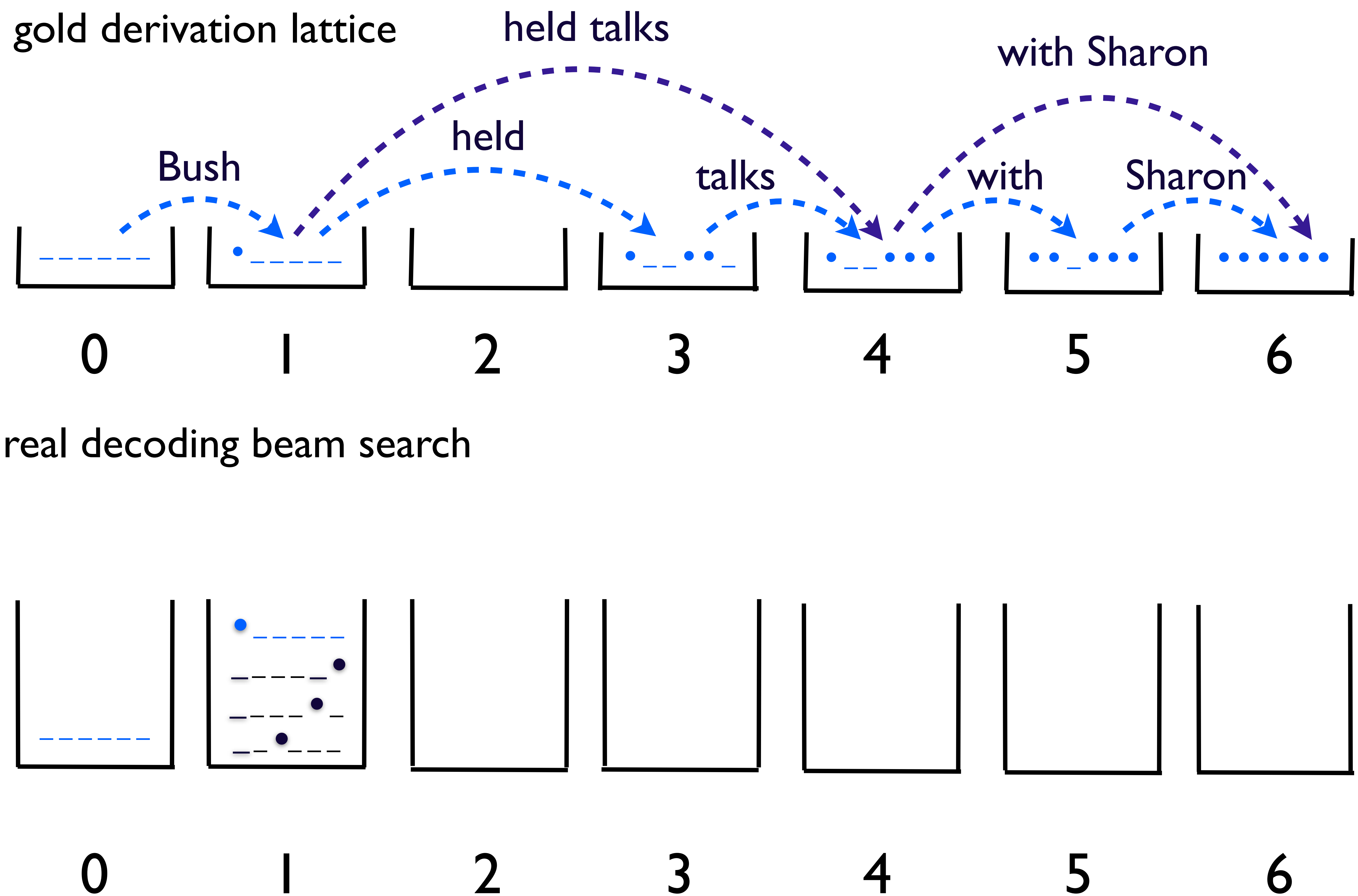

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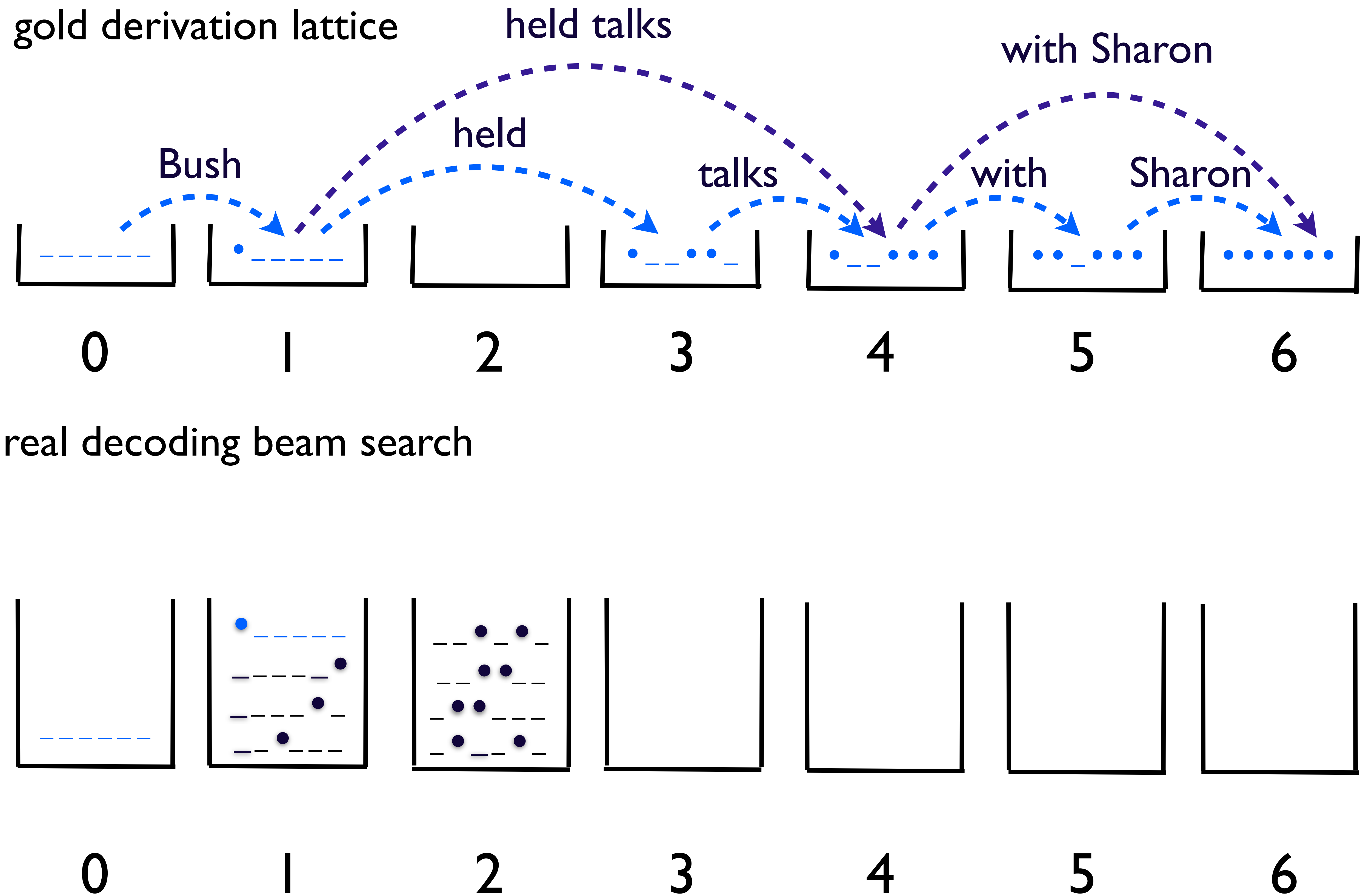

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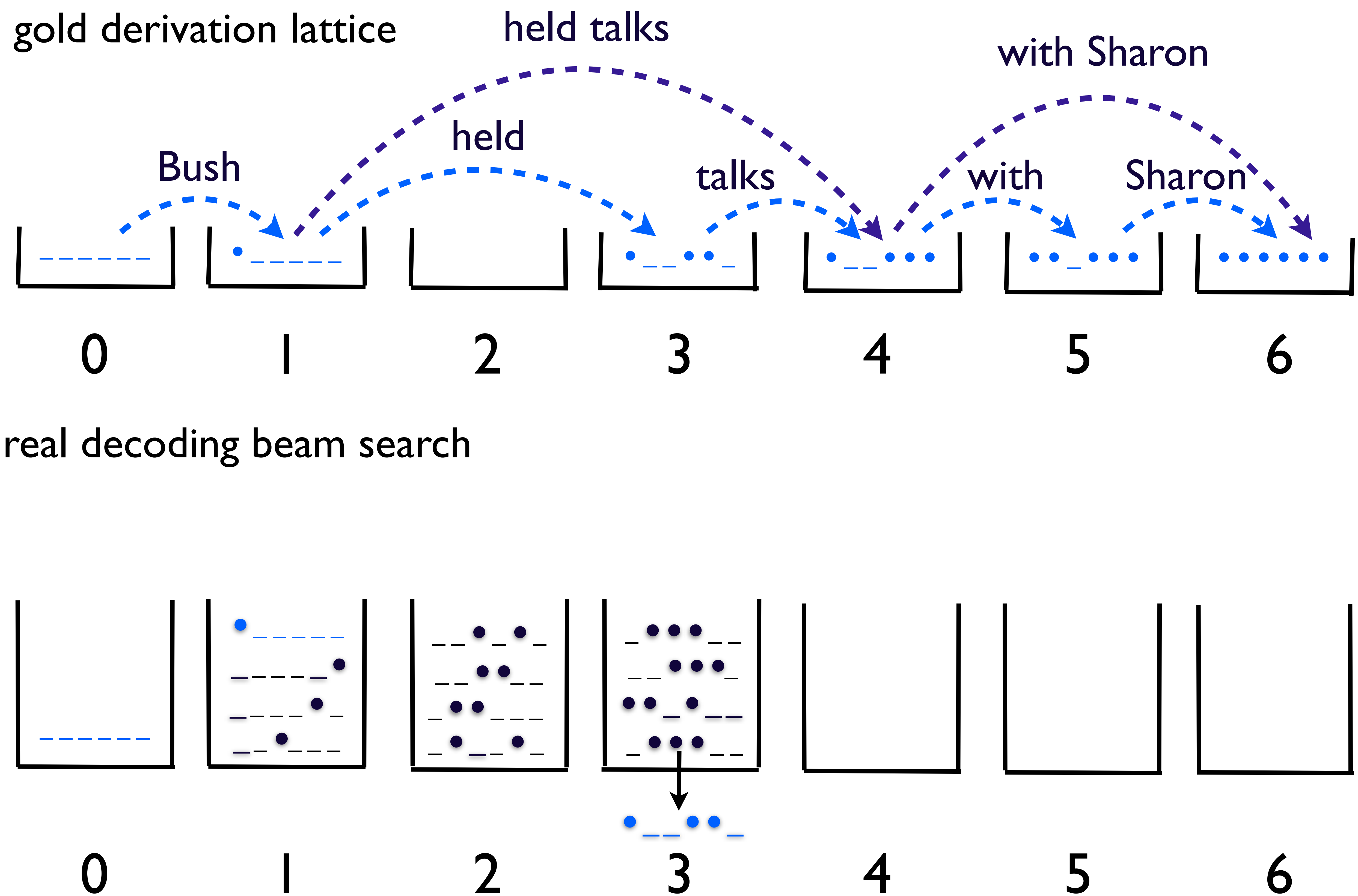

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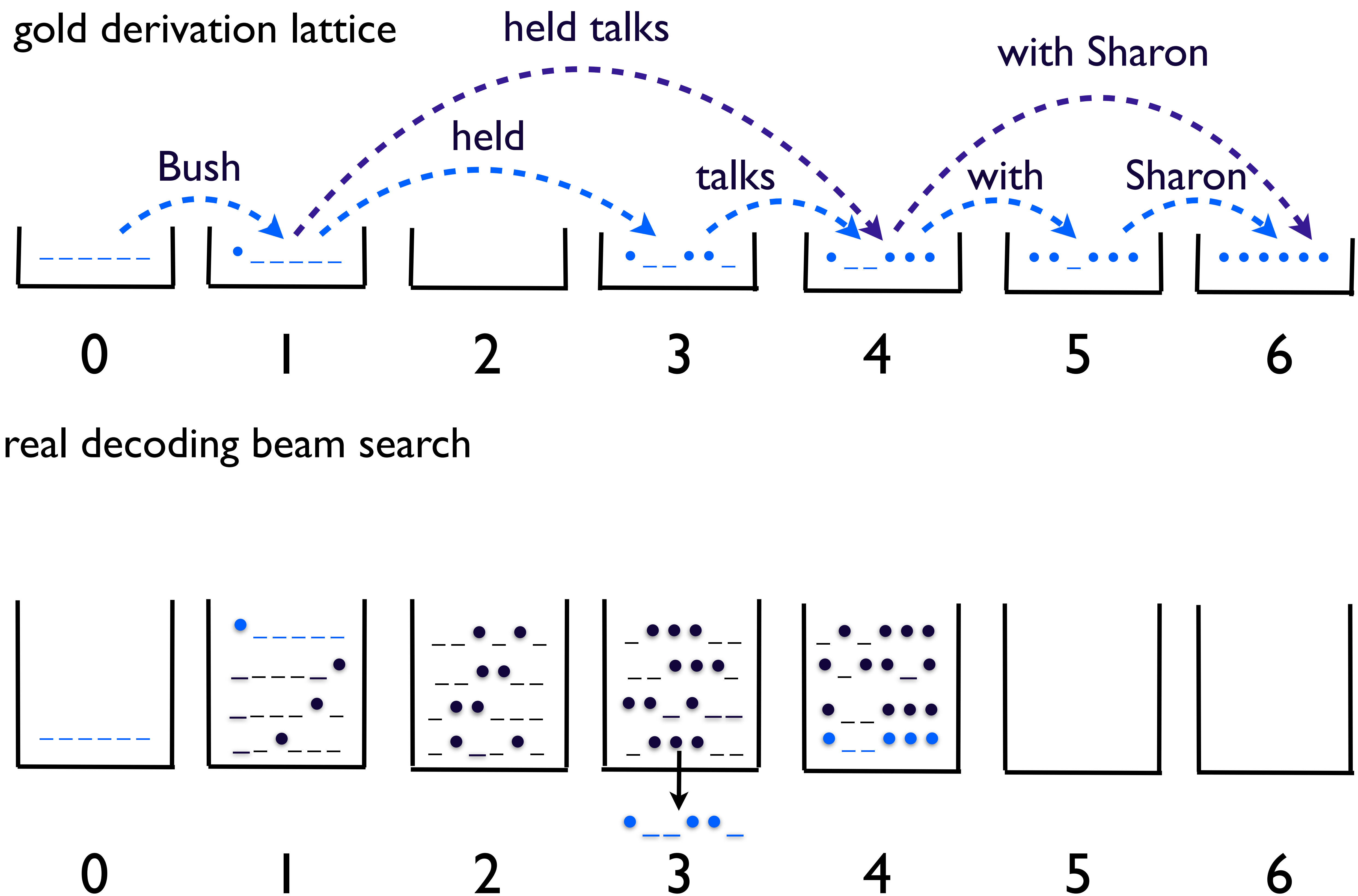

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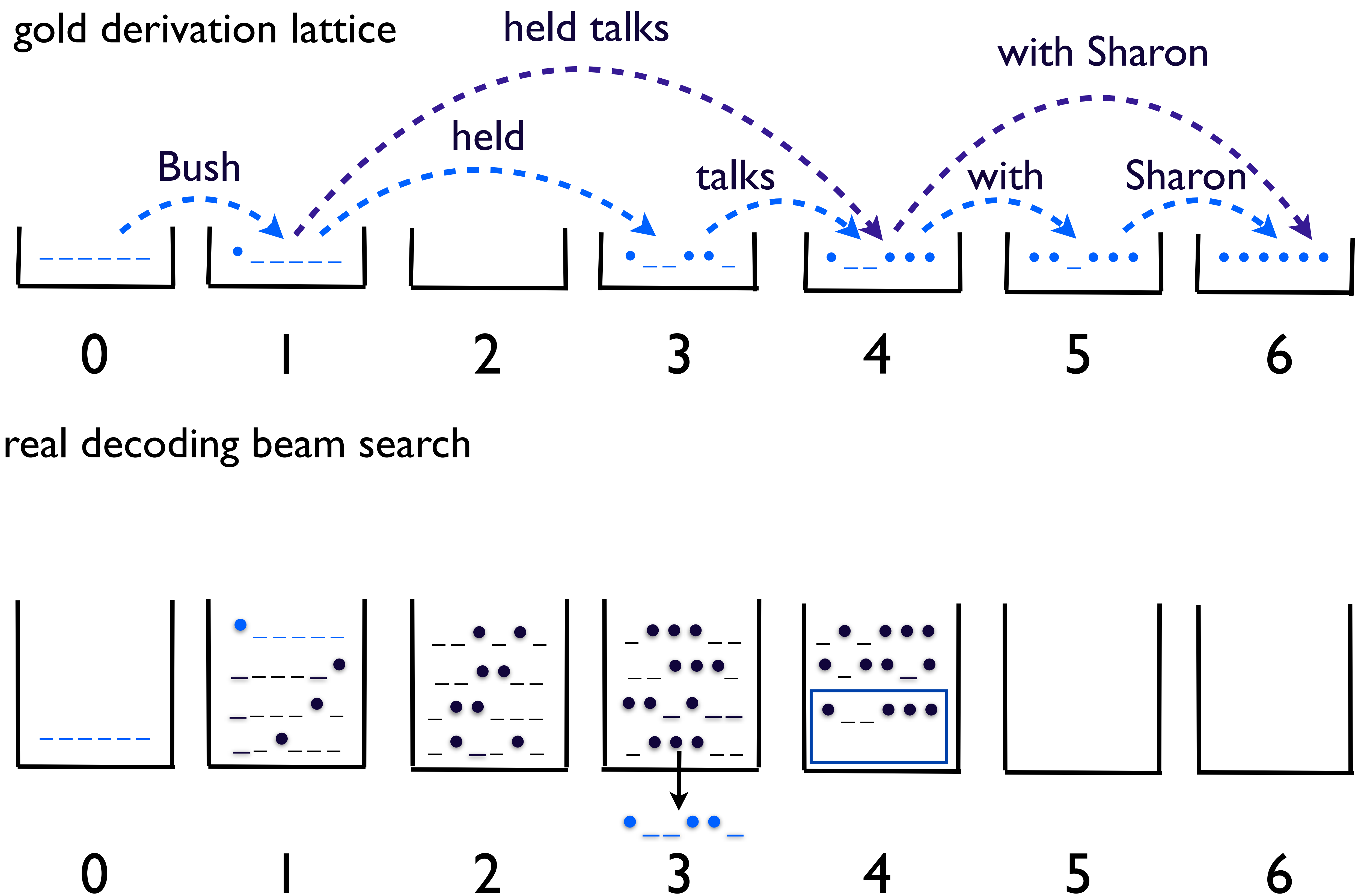

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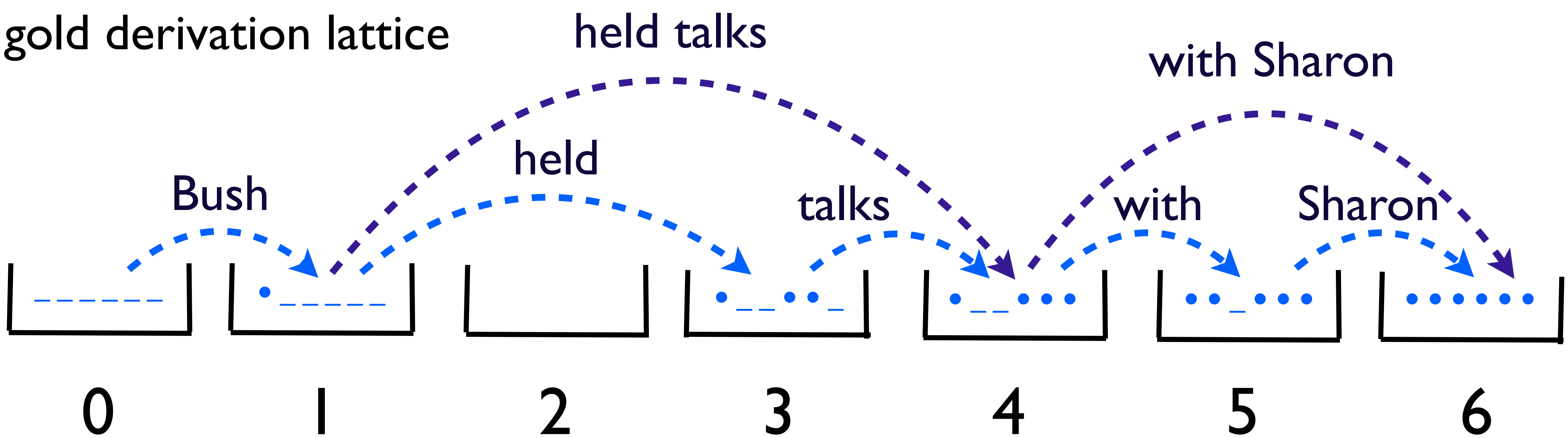
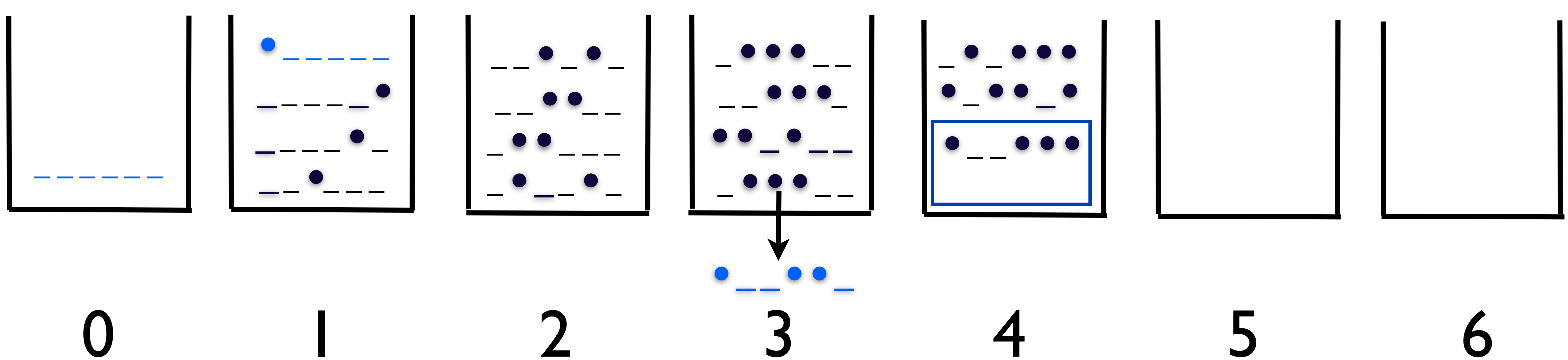
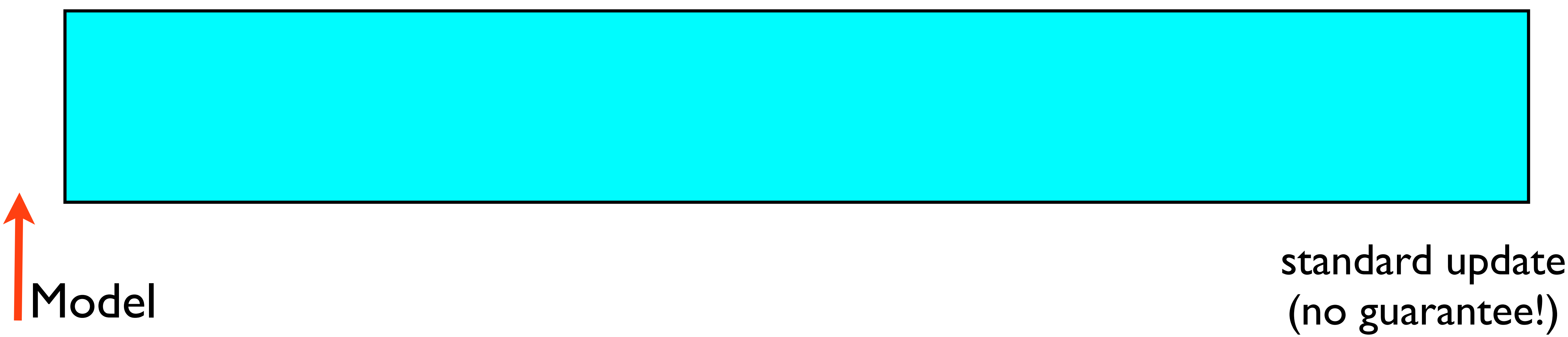


real decoding beam search

should address search errors here!



Fixing Search Error 1: Early Update



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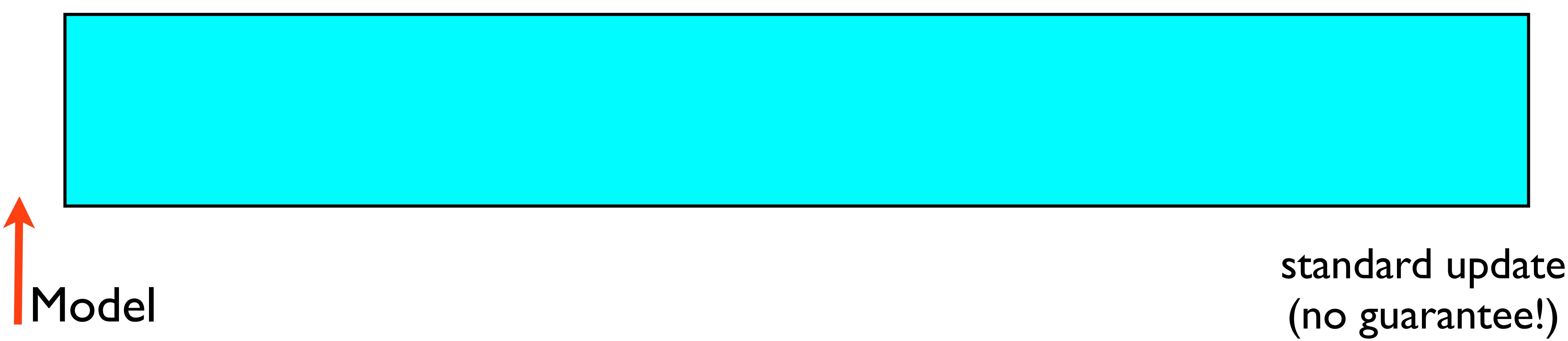
  - that's a "violation" we want to fix; proof in (Huang et al 2012)



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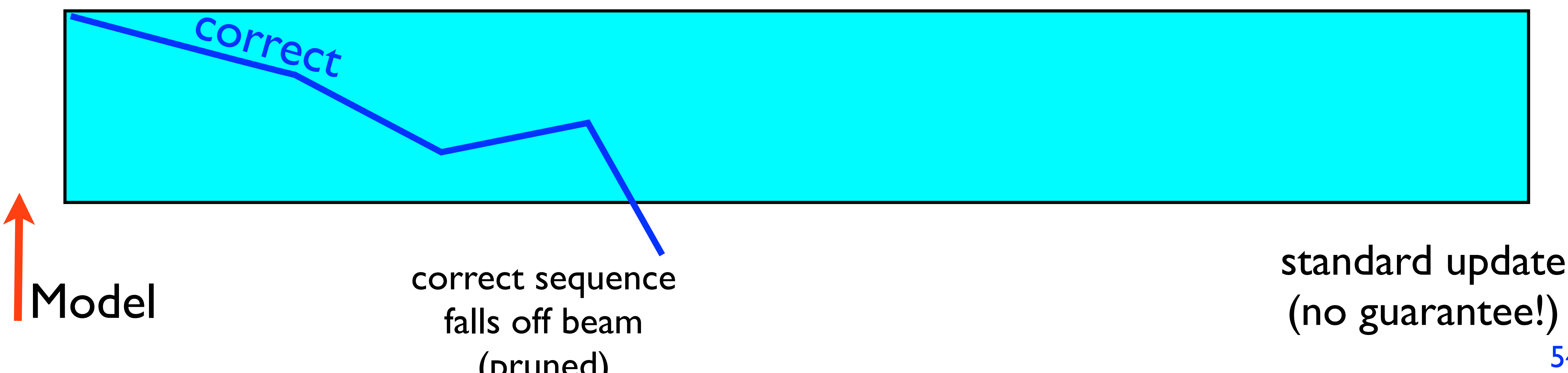

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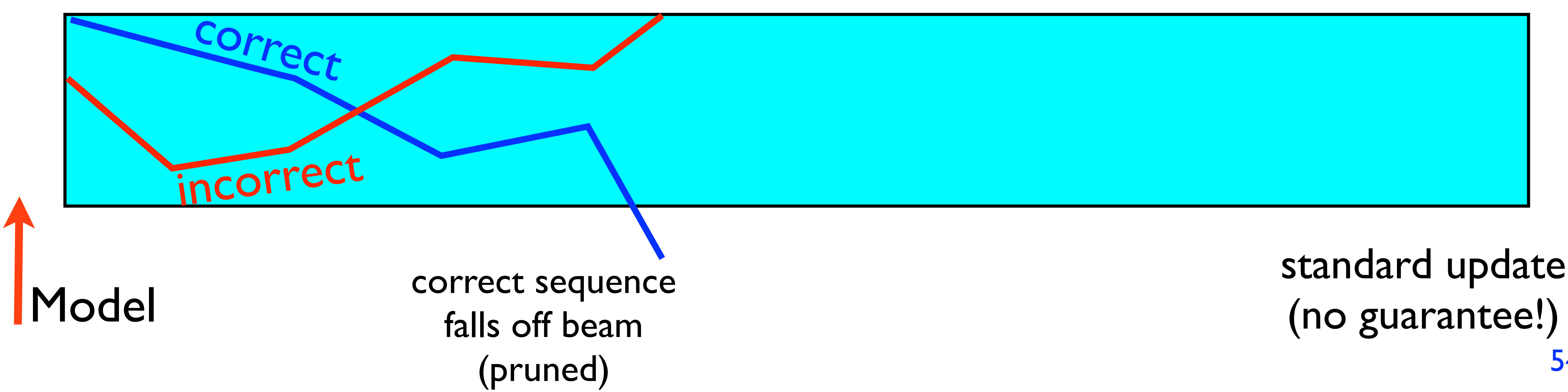

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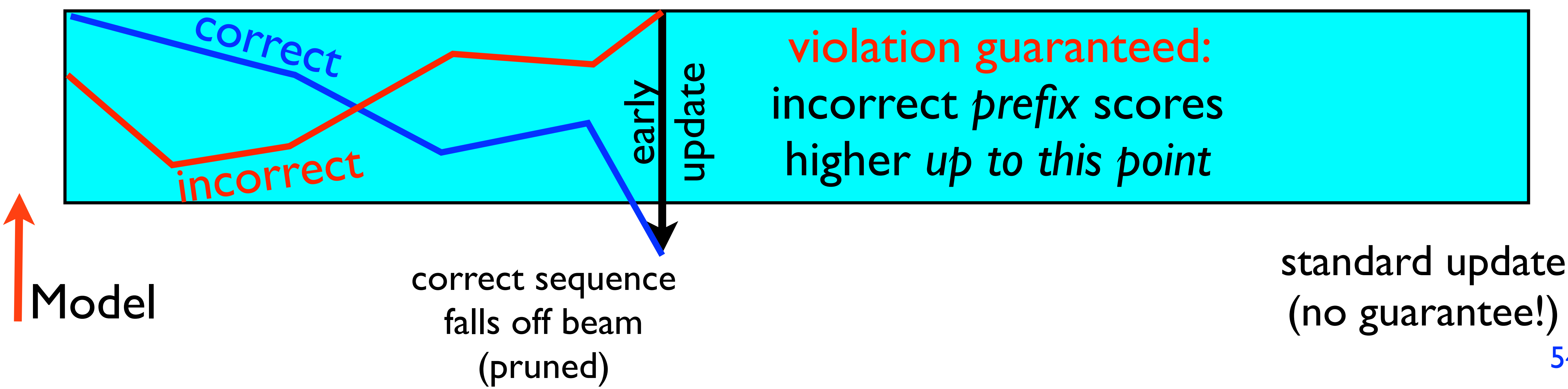

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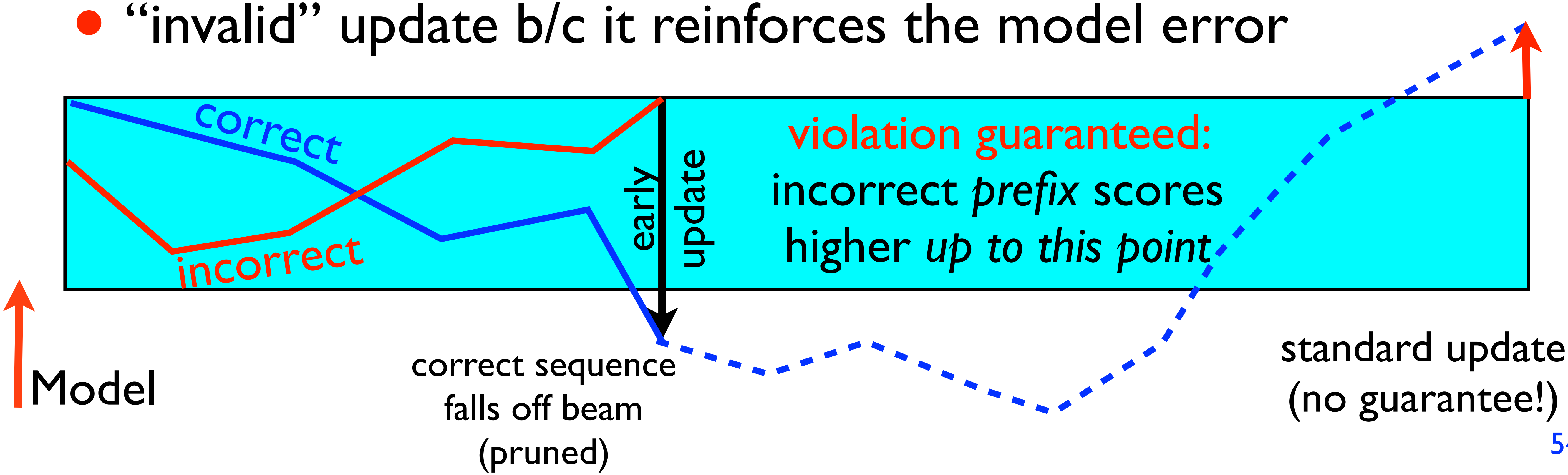
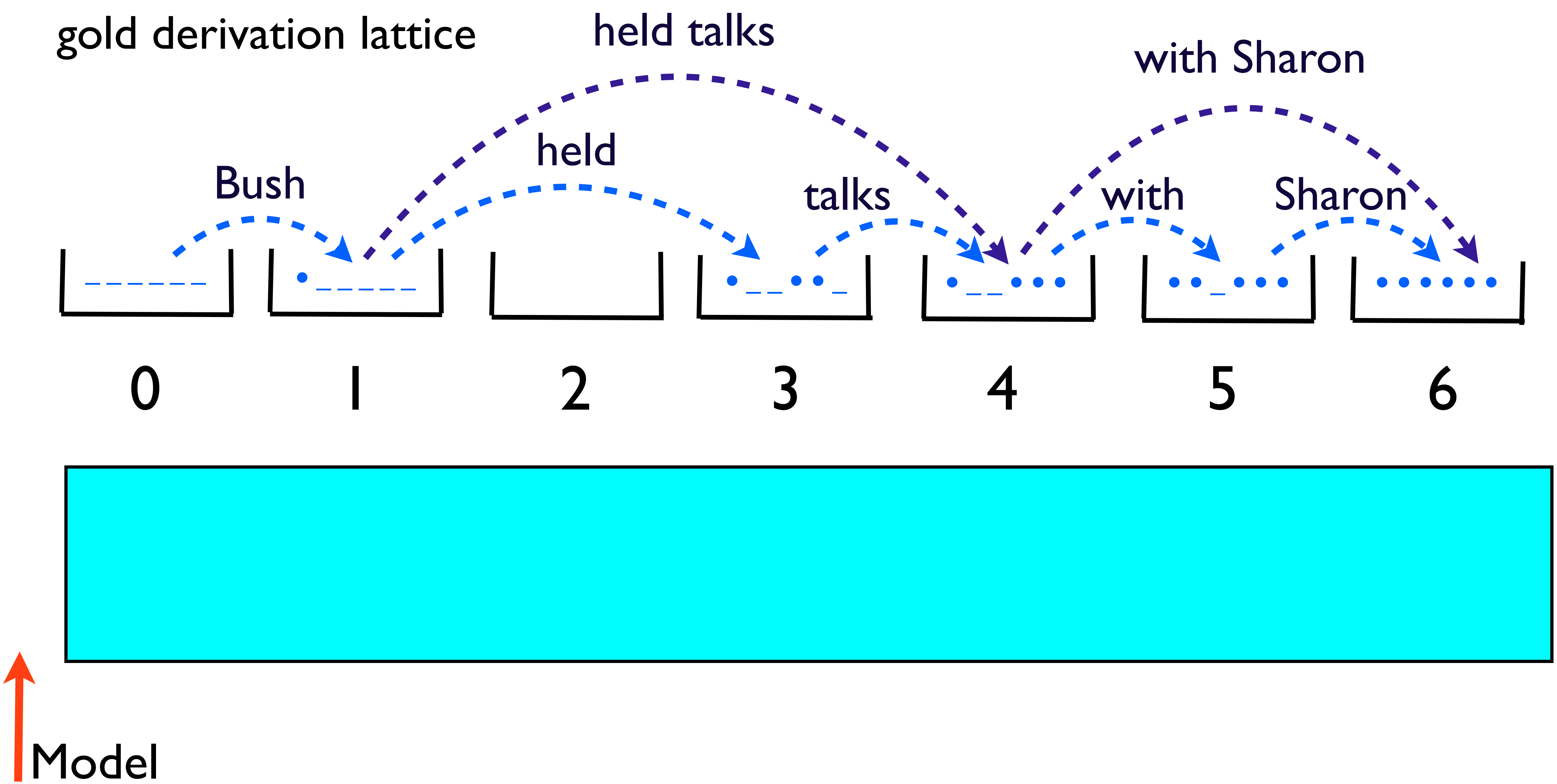
- early update (Collins/Roark'04) when the correct falls off beam
  - up to this point the incorrect prefix should score higher
  - that's a "violation" we want to fix; proof in (Huang et al 2012)
- standard perceptron does not guarantee violation
  - the correct sequence (pruned) might score higher at the end!
  - "invalid" update b/c it reinforces the model error



Early Update w/ Latent Variable

- the gold-standard derivations are ***not*** annotated
  - we treat any reference-producing derivation as good



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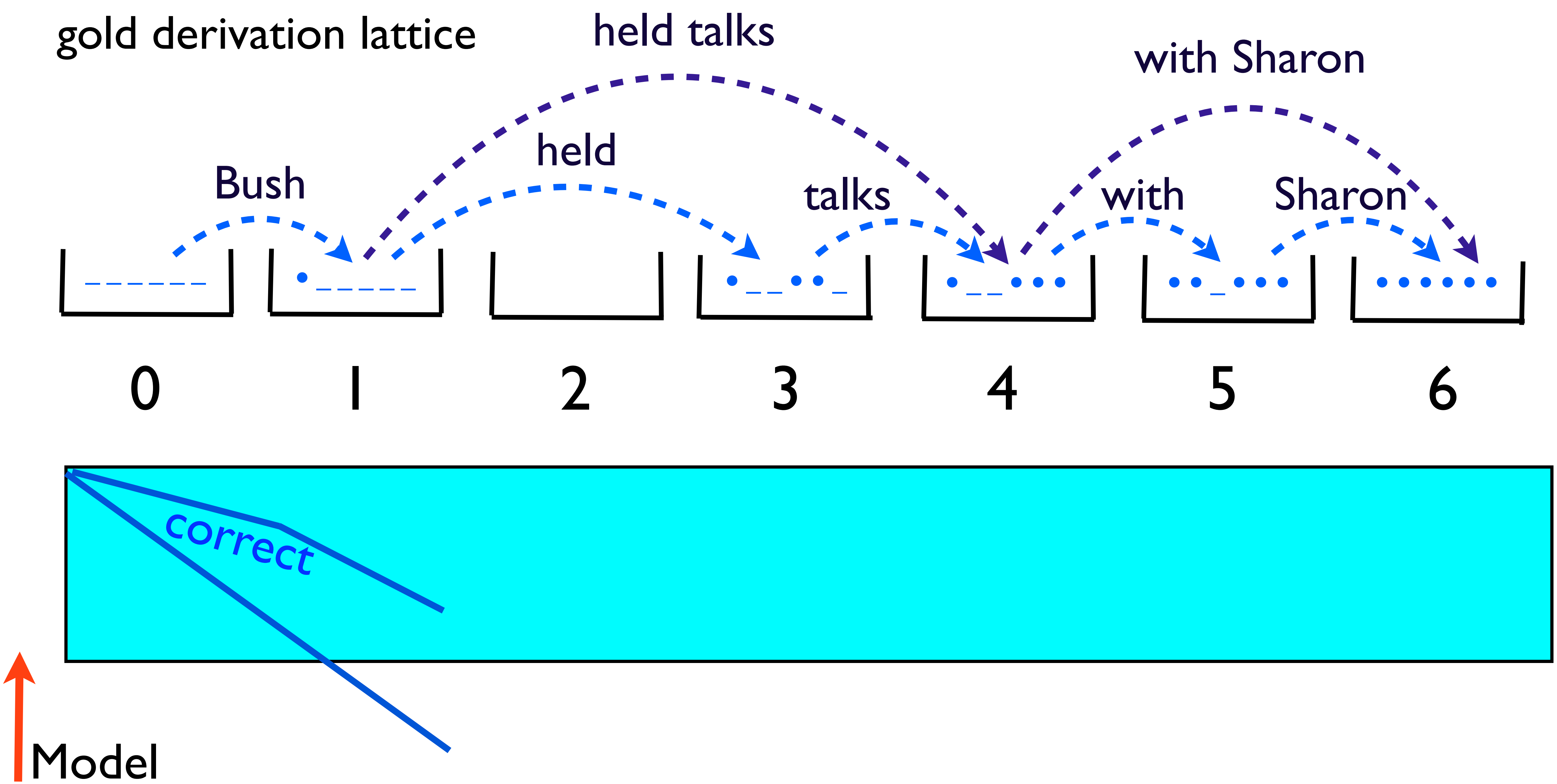

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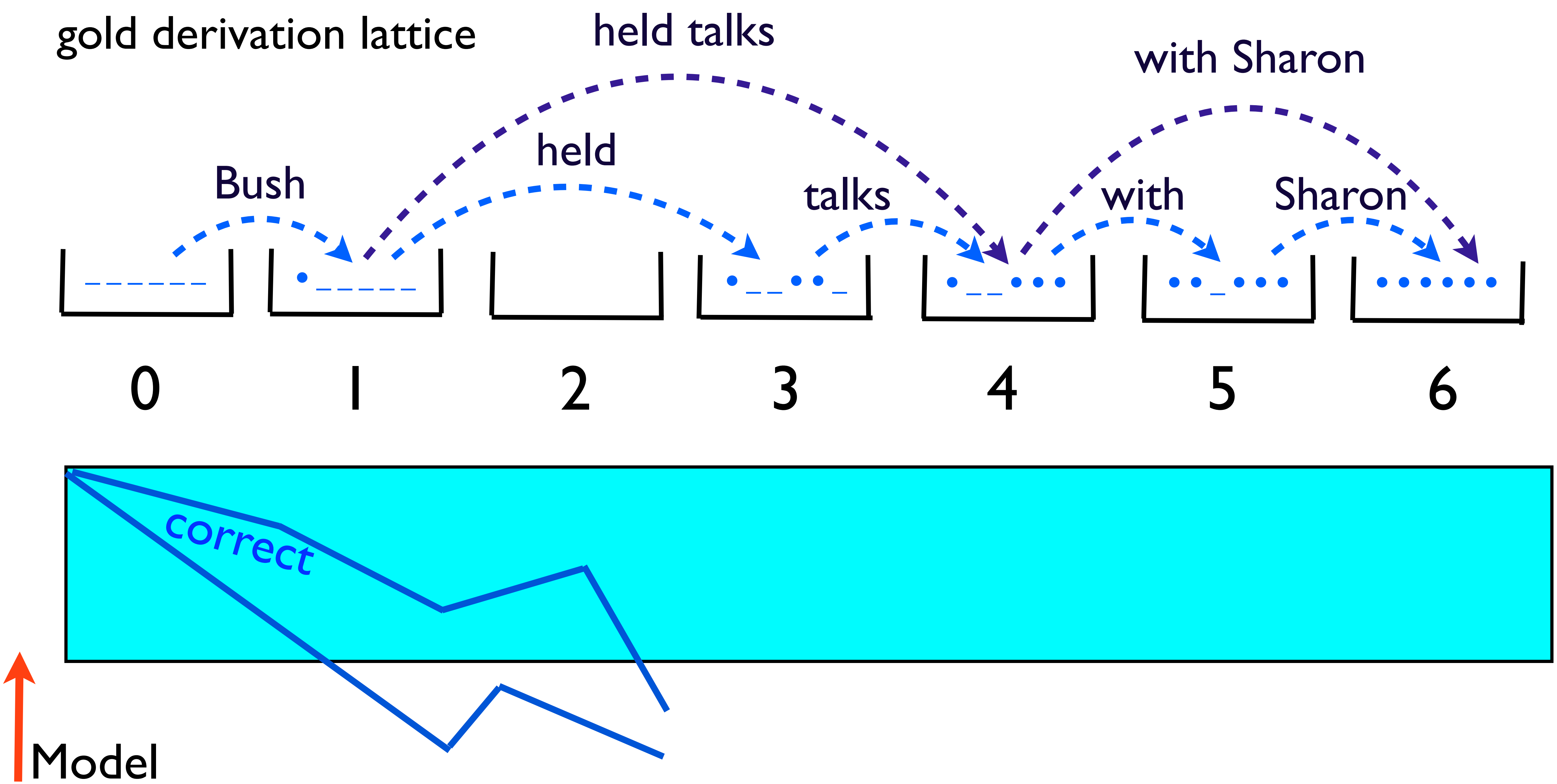

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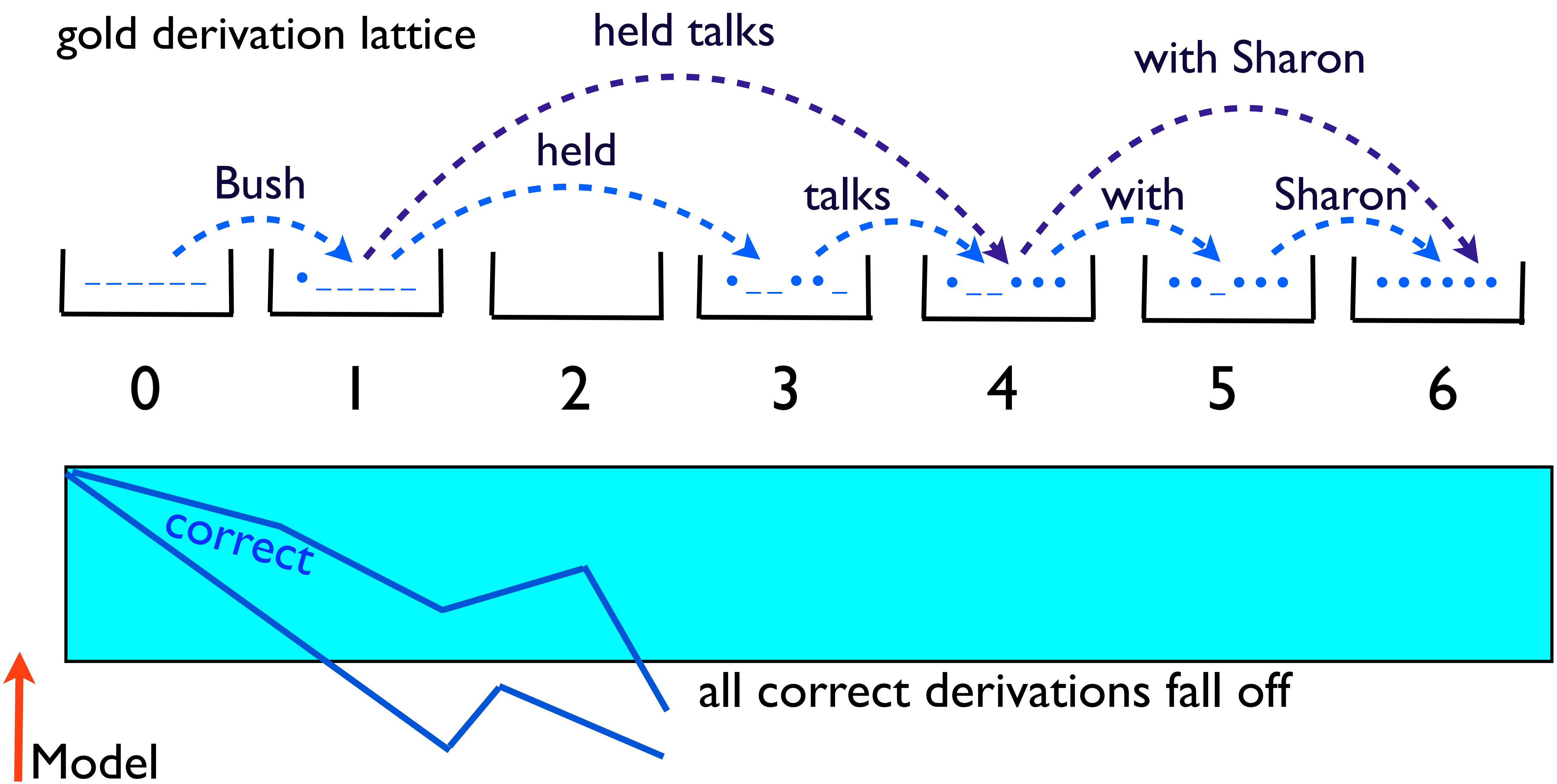

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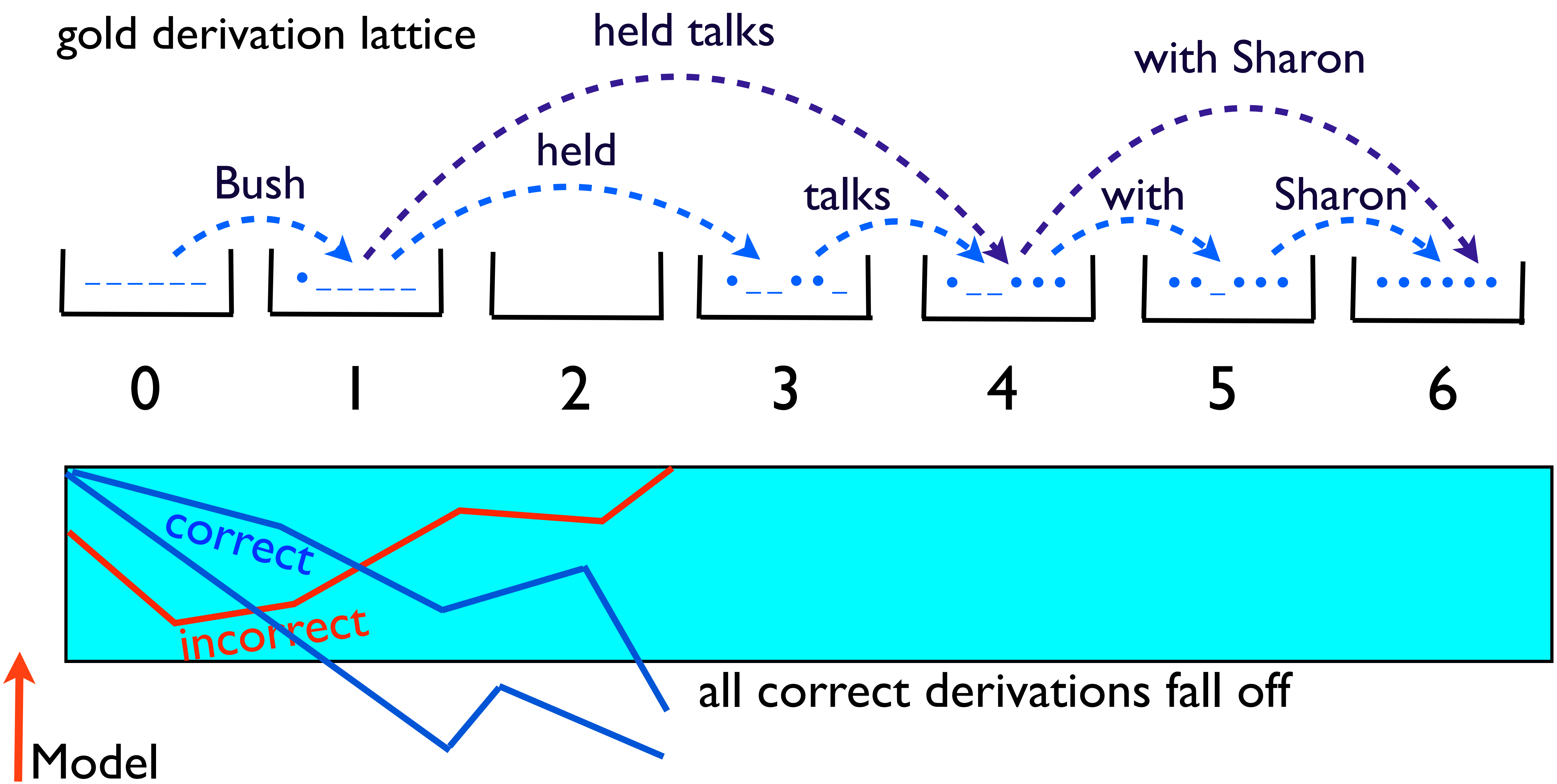

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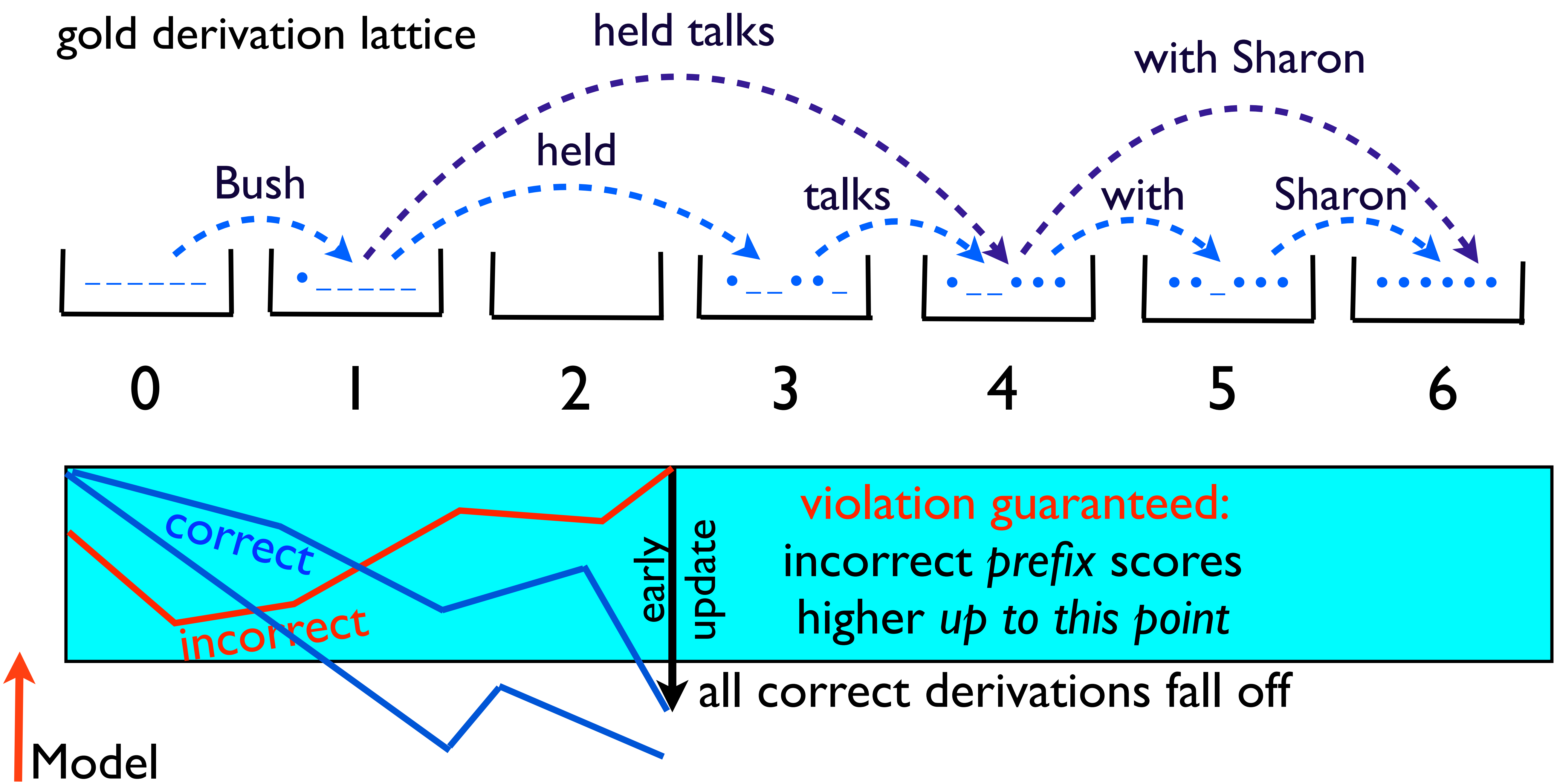

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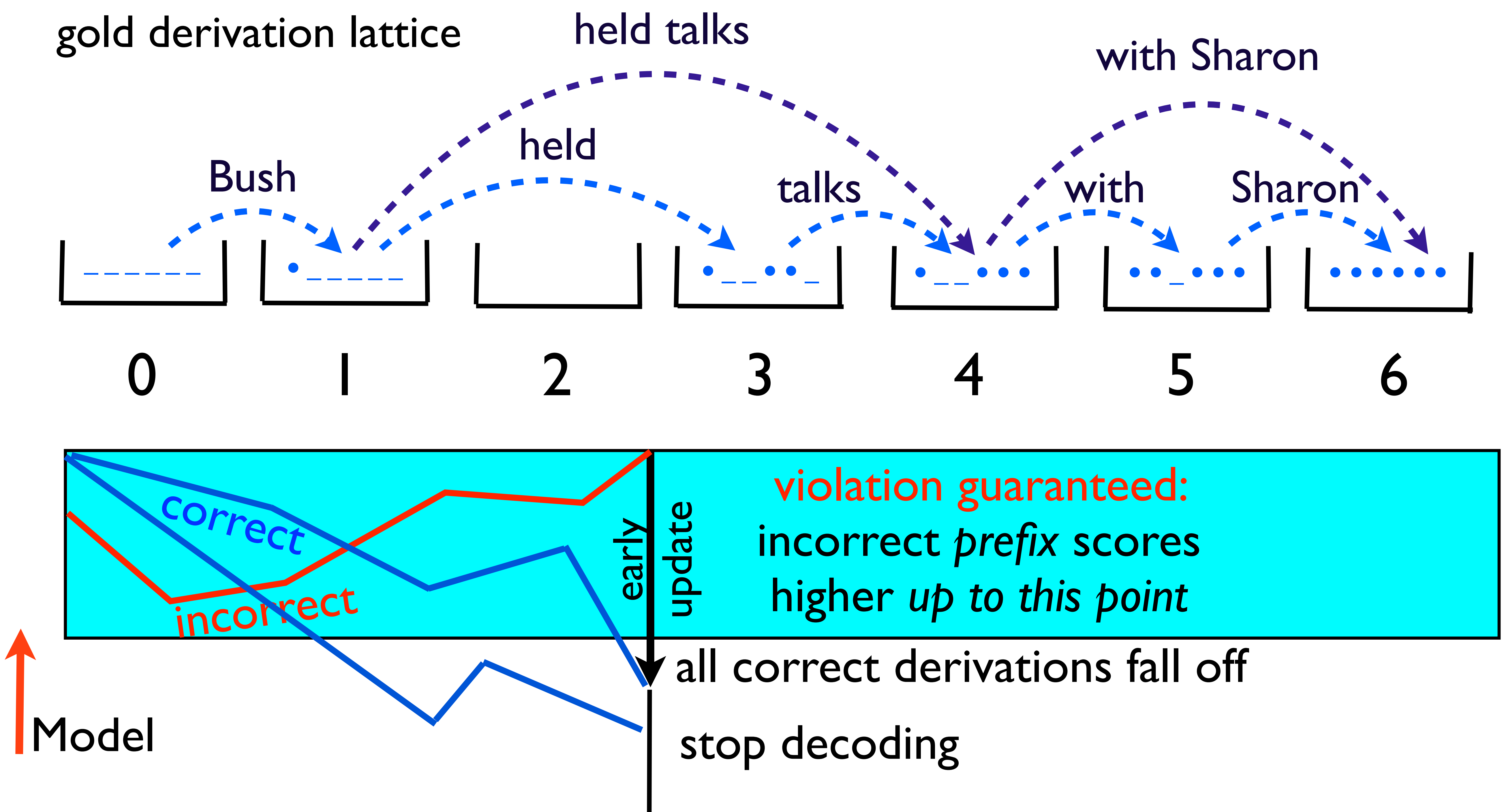
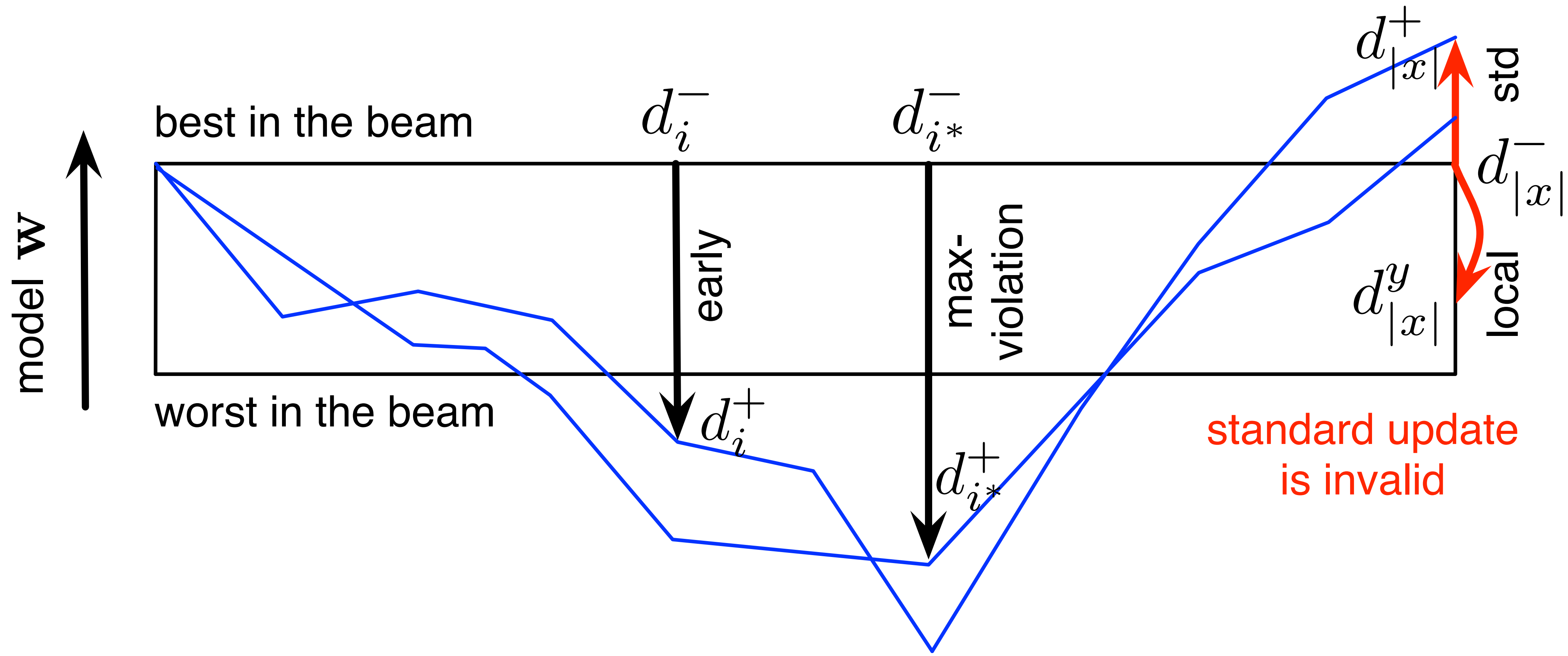
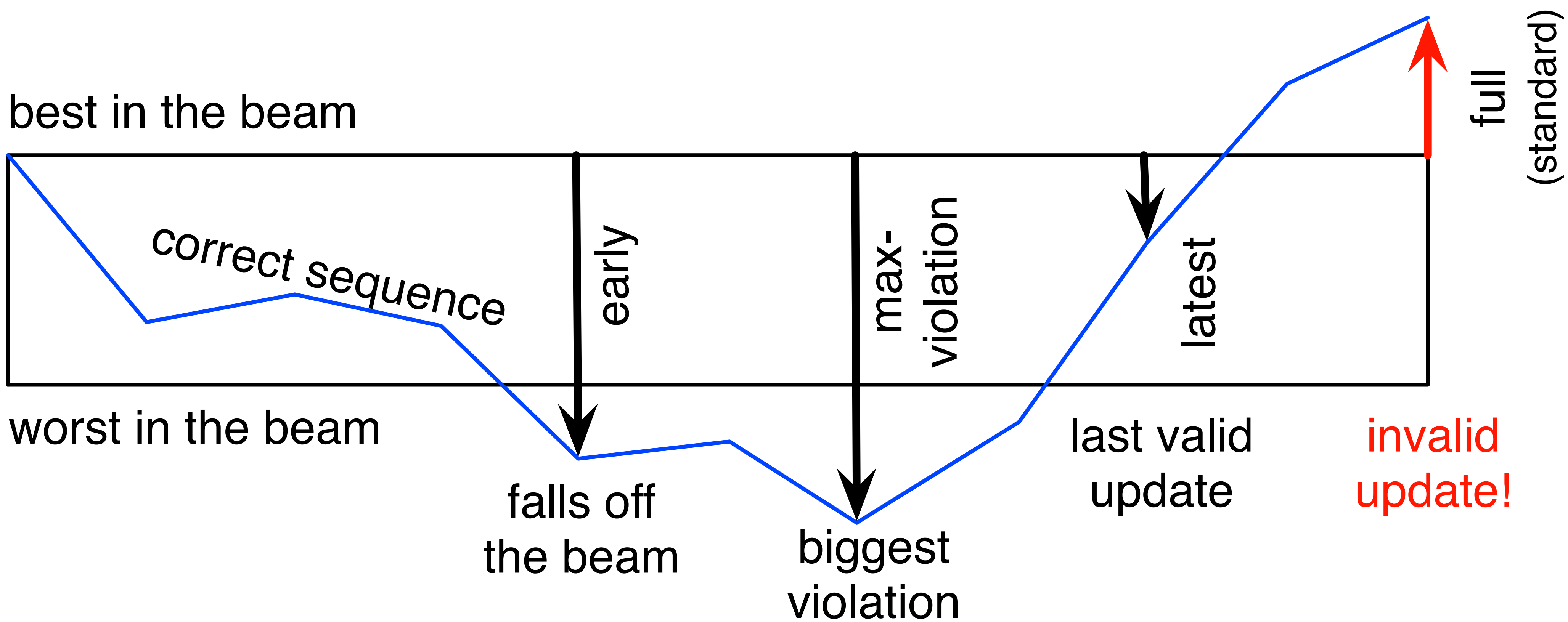


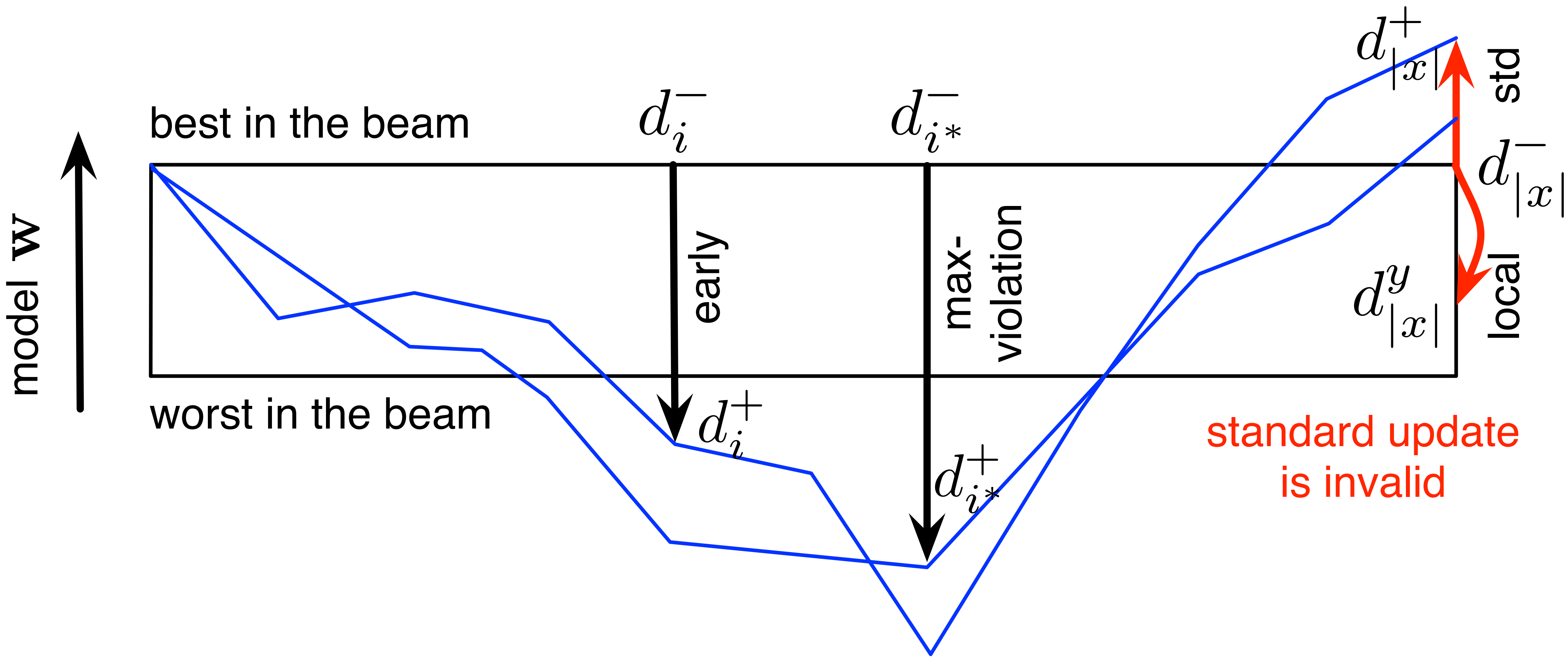
Fixing Search Error 2: Max-Violation



- early update works but learns slowly due to partial updates
- max-violation: use the prefix where violation is maximum
  - "worst-mistake" in the search space
  - now extended to handle latent-variable

Latent-Variable Perceptron





Roadmap of Techniques

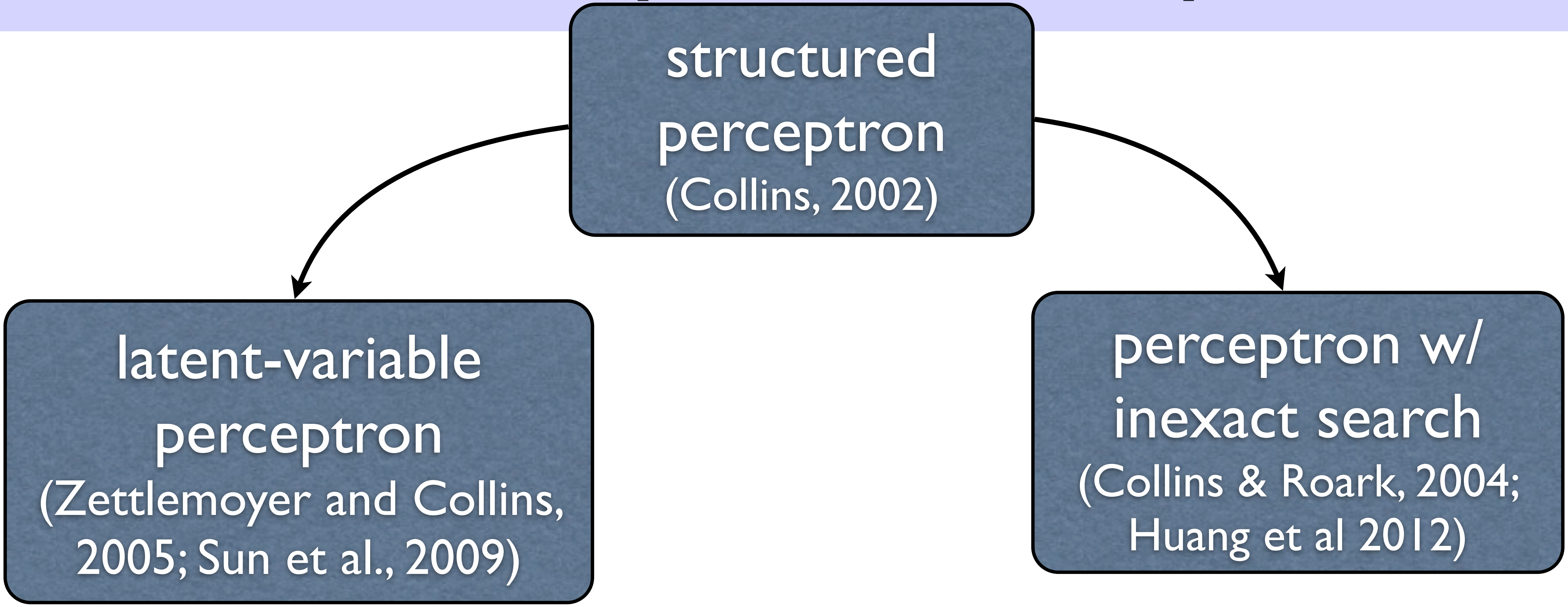
structured
perceptron
(Collins, 2002)

Roadmap of Techniques

structured perceptron
(Collins, 2002)

latent-variable perceptron
(Zettlemoyer and Collins, 2005; Sun et al., 2009)

Roadmap of Techniques



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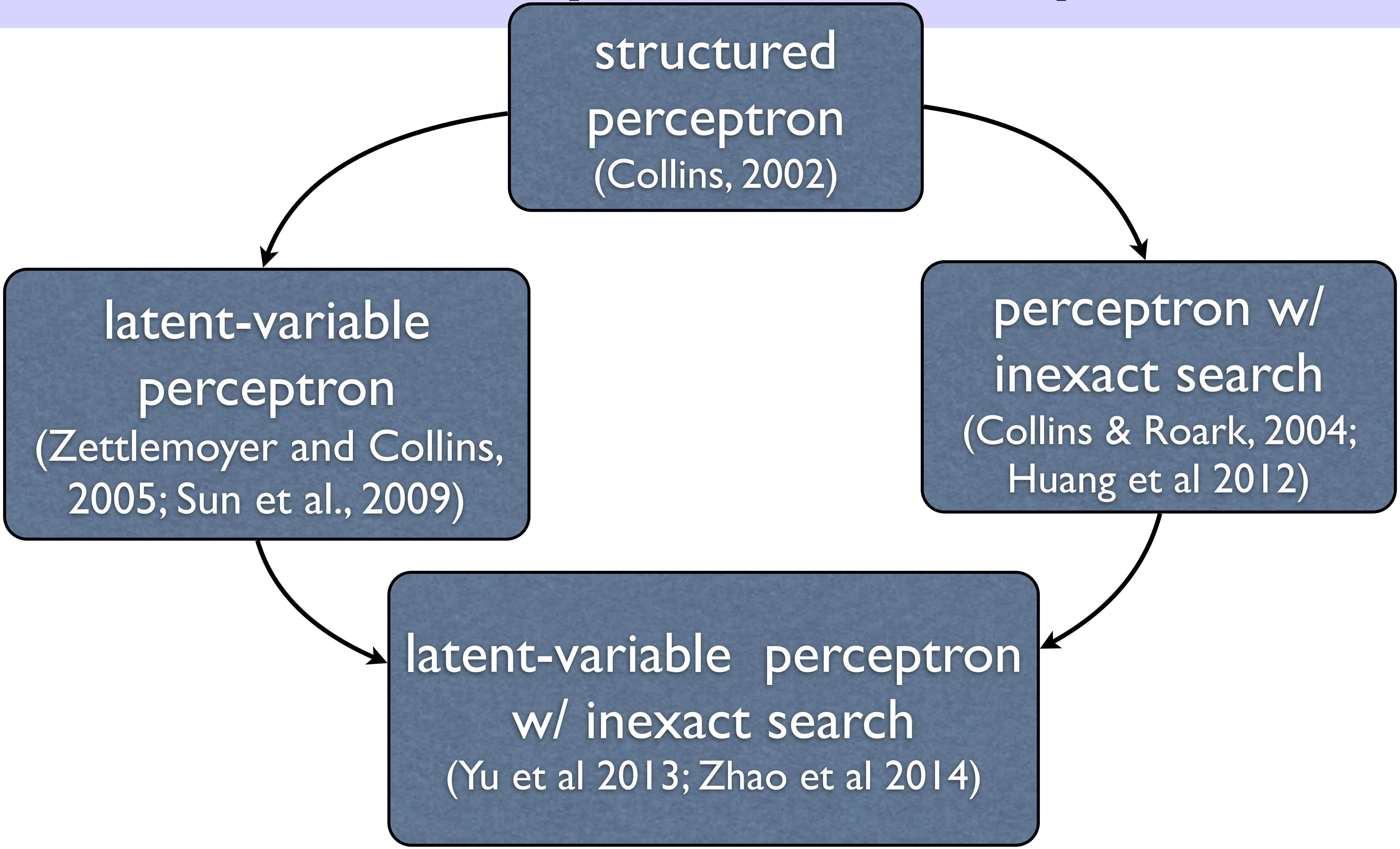

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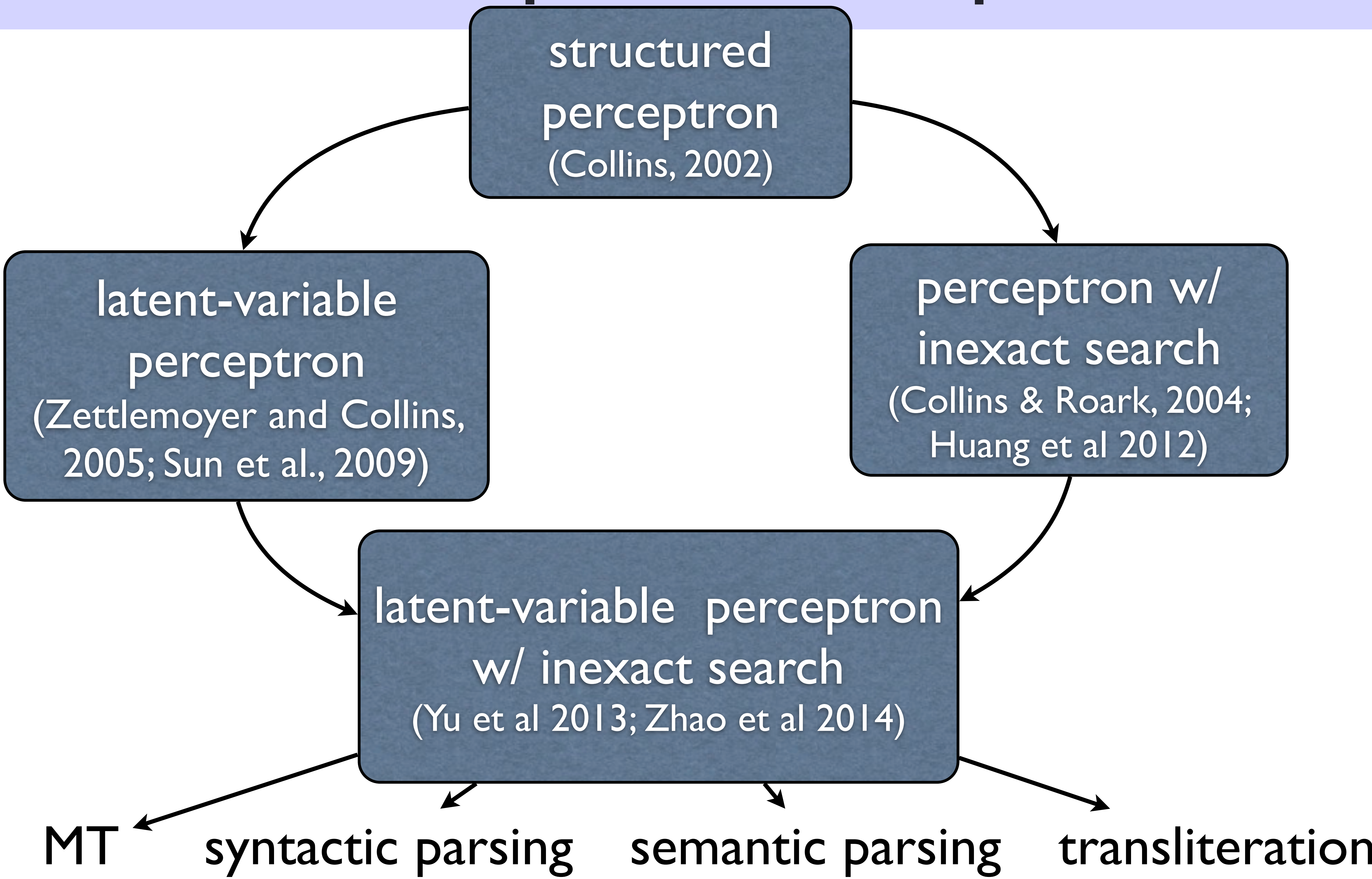
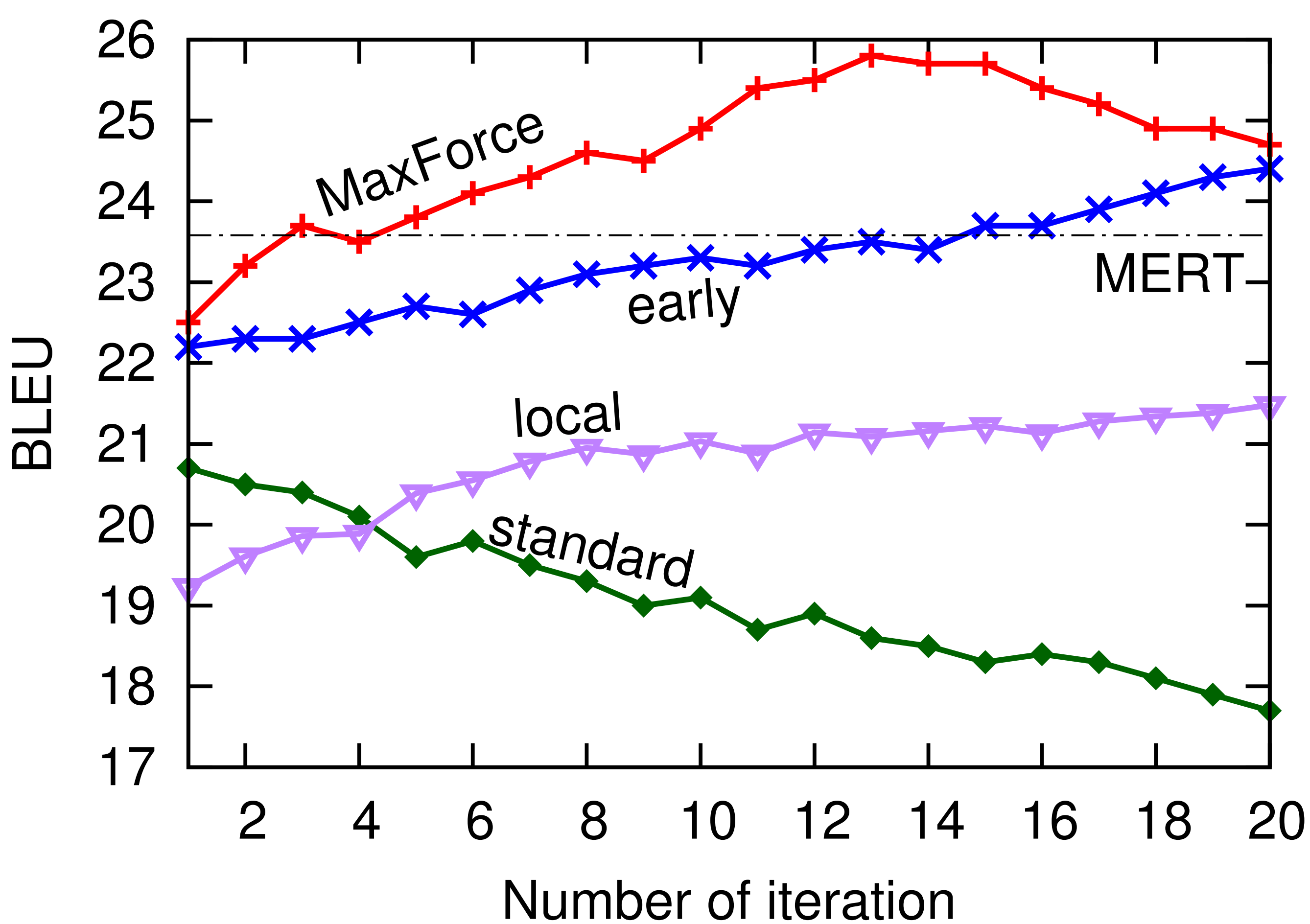


Experiments: Discriminative Training for MT

- standard update (Liang et al's "bold") works poorly
  - b/c invalid update ratio is very high (search quality is low)
- max-violation converges faster than early update



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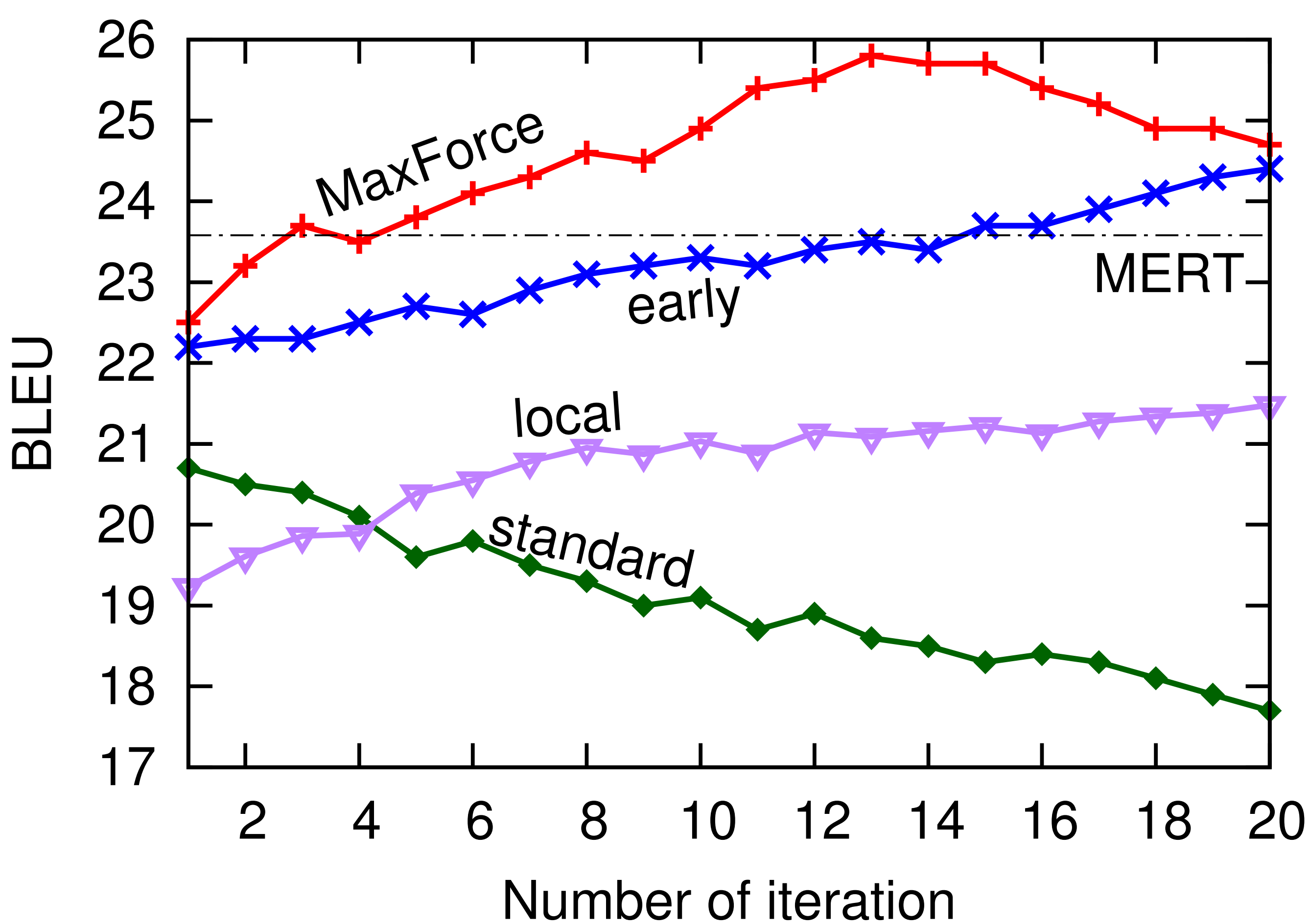
std ~ "bold"; local ~ "local"



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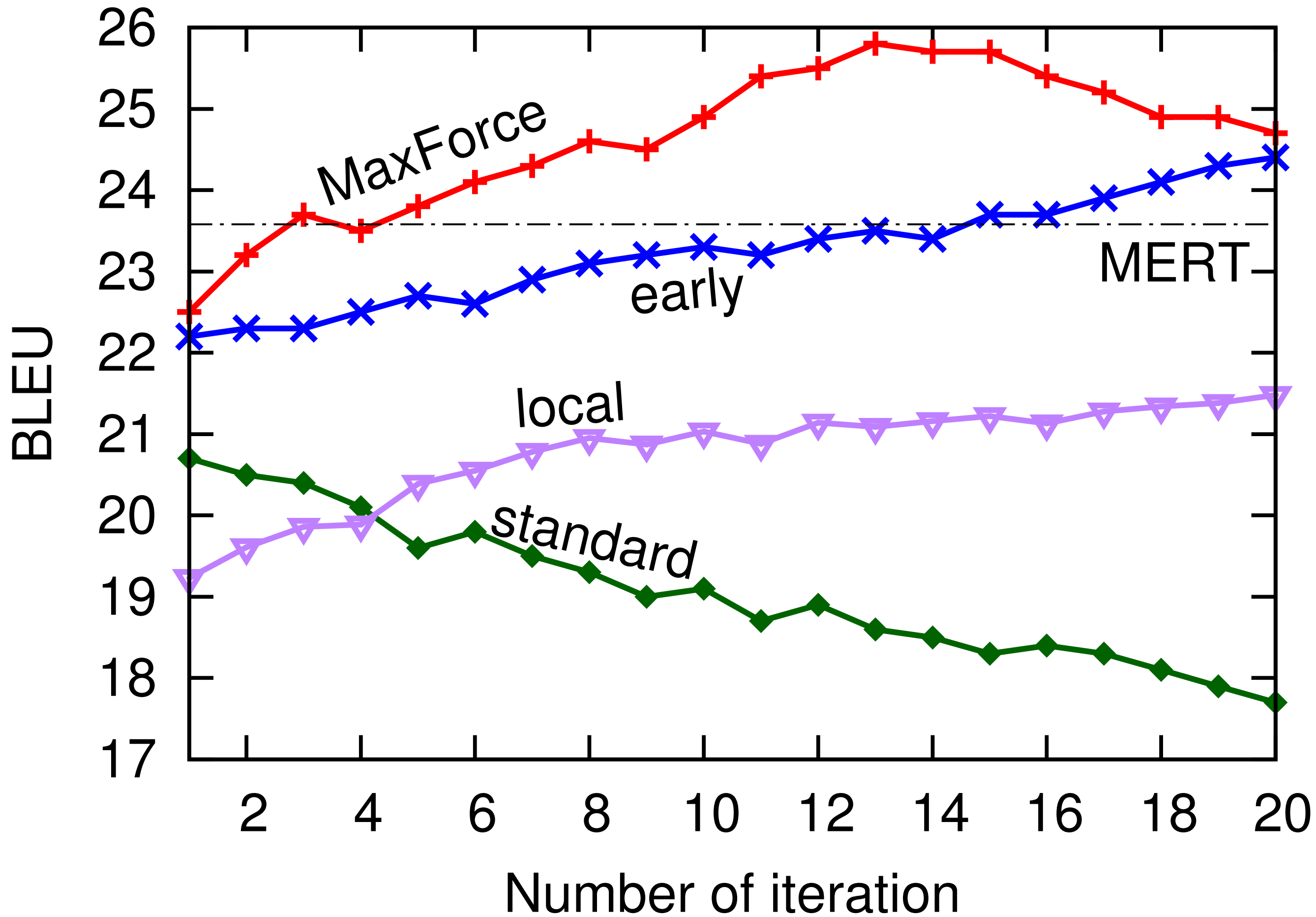

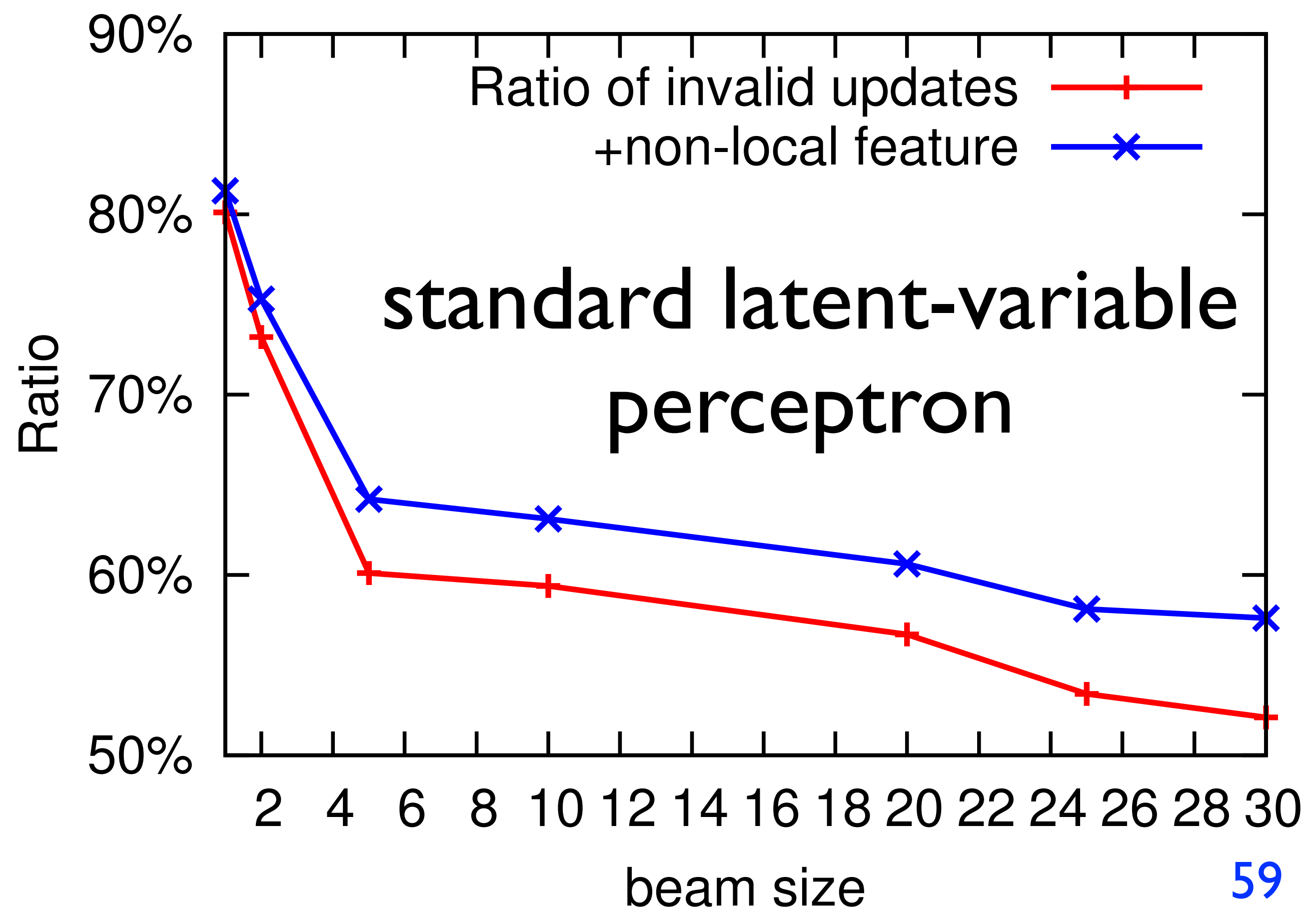

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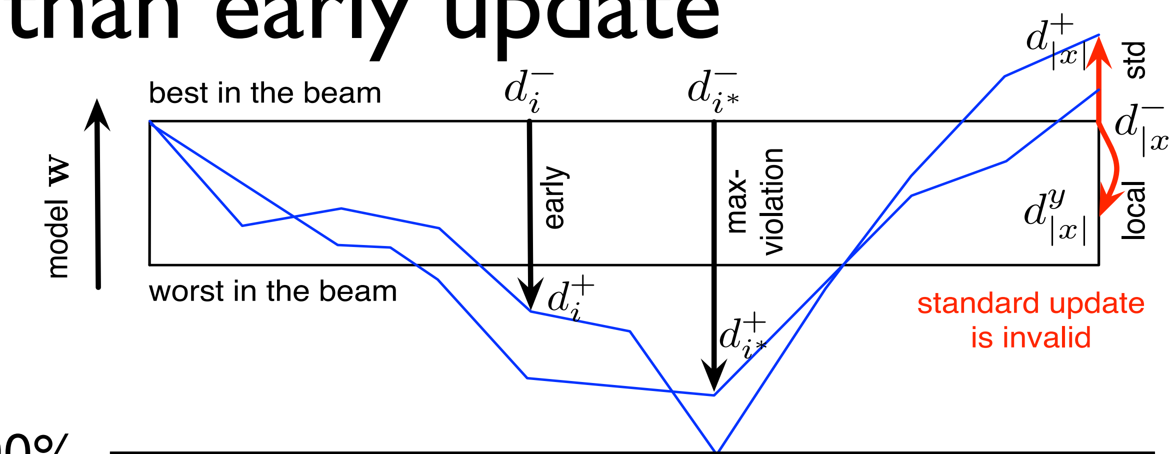

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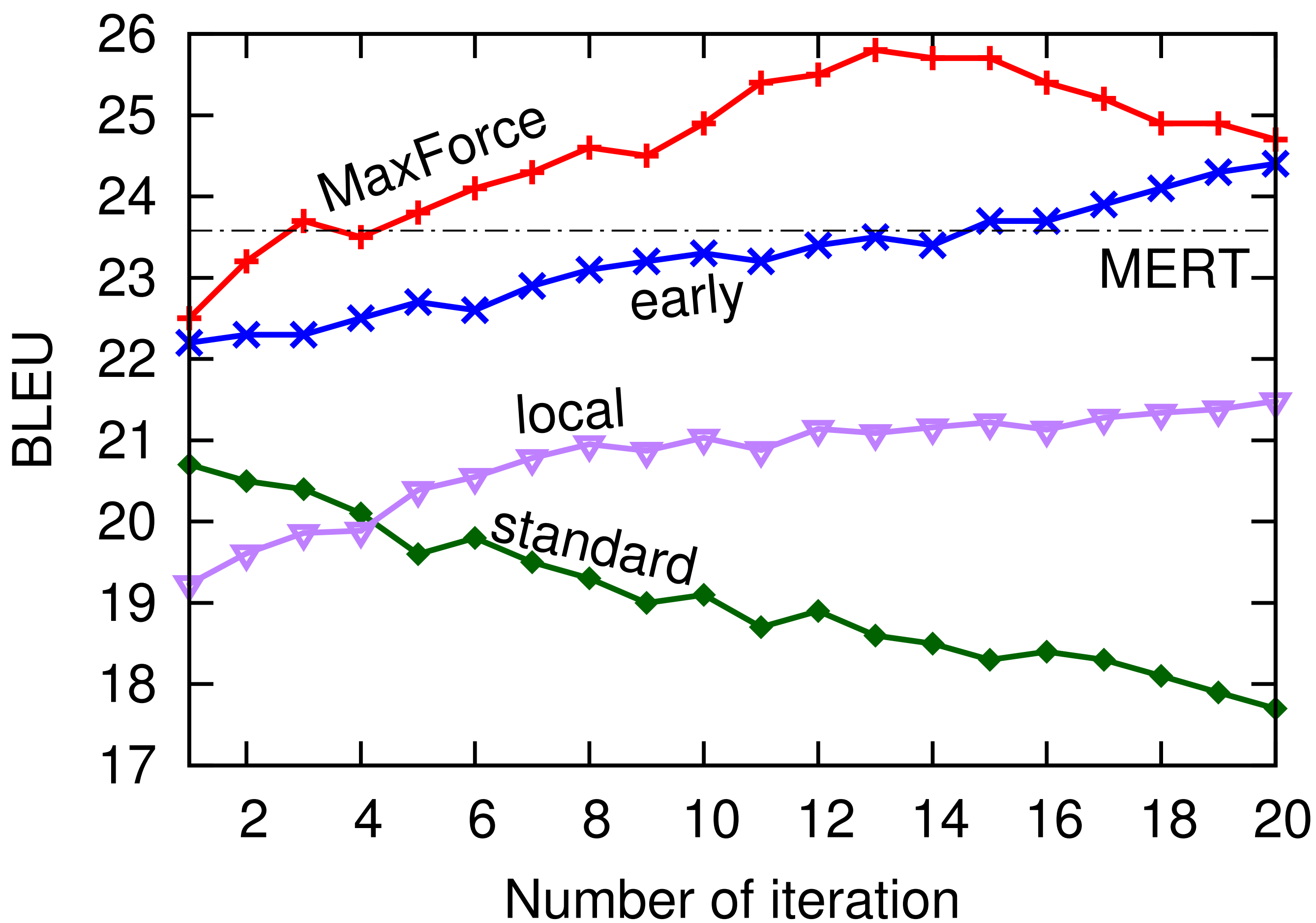
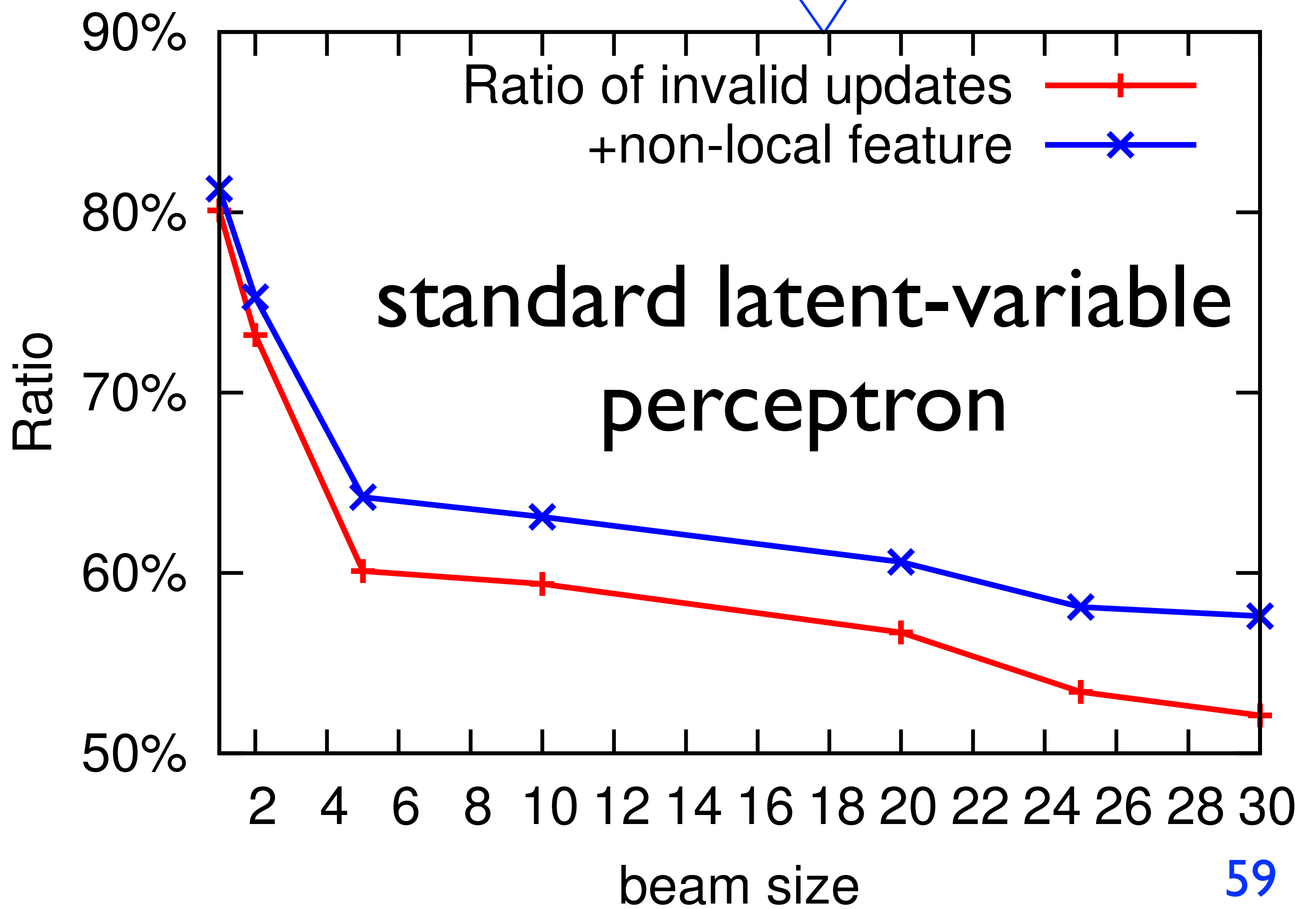
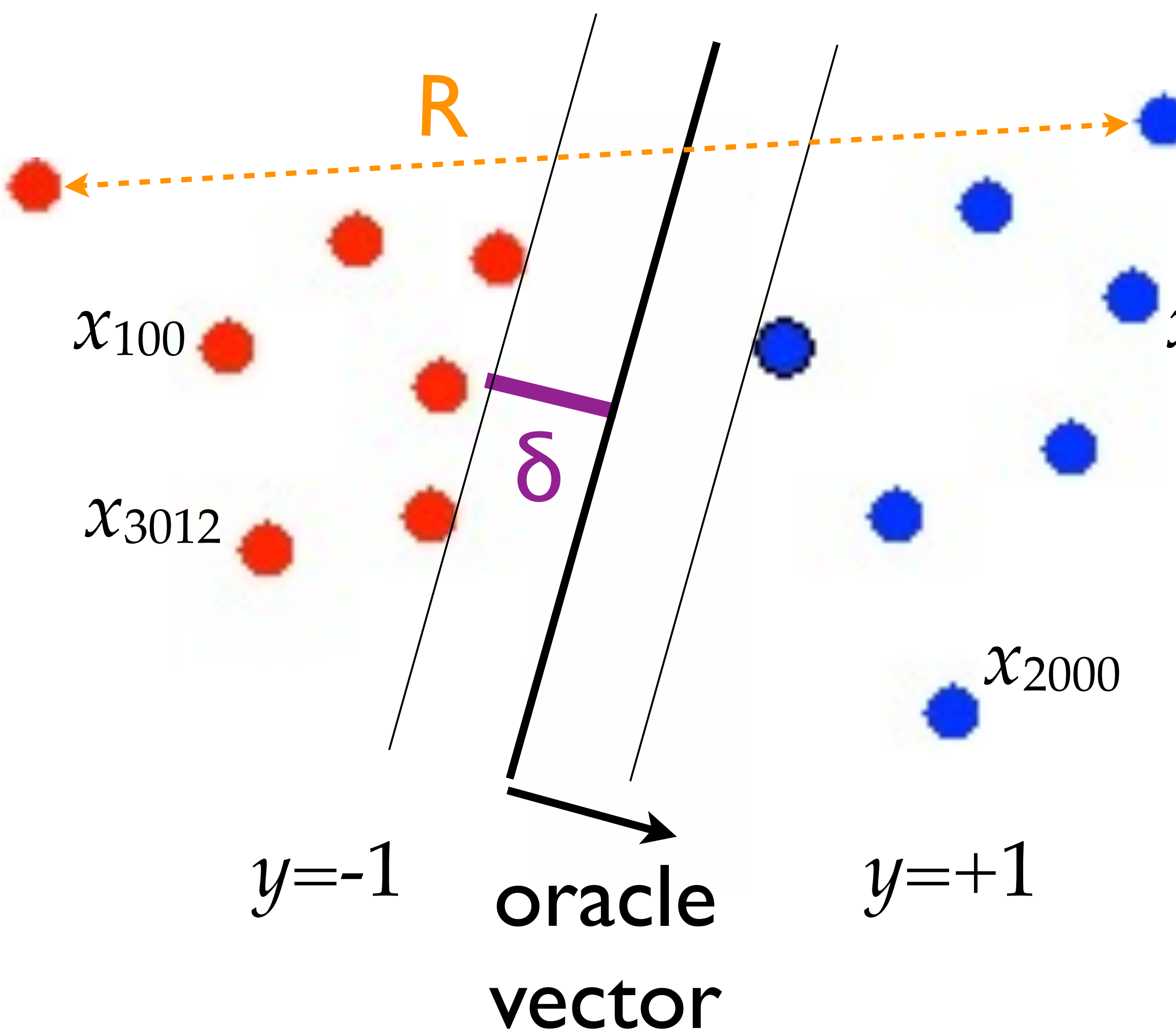




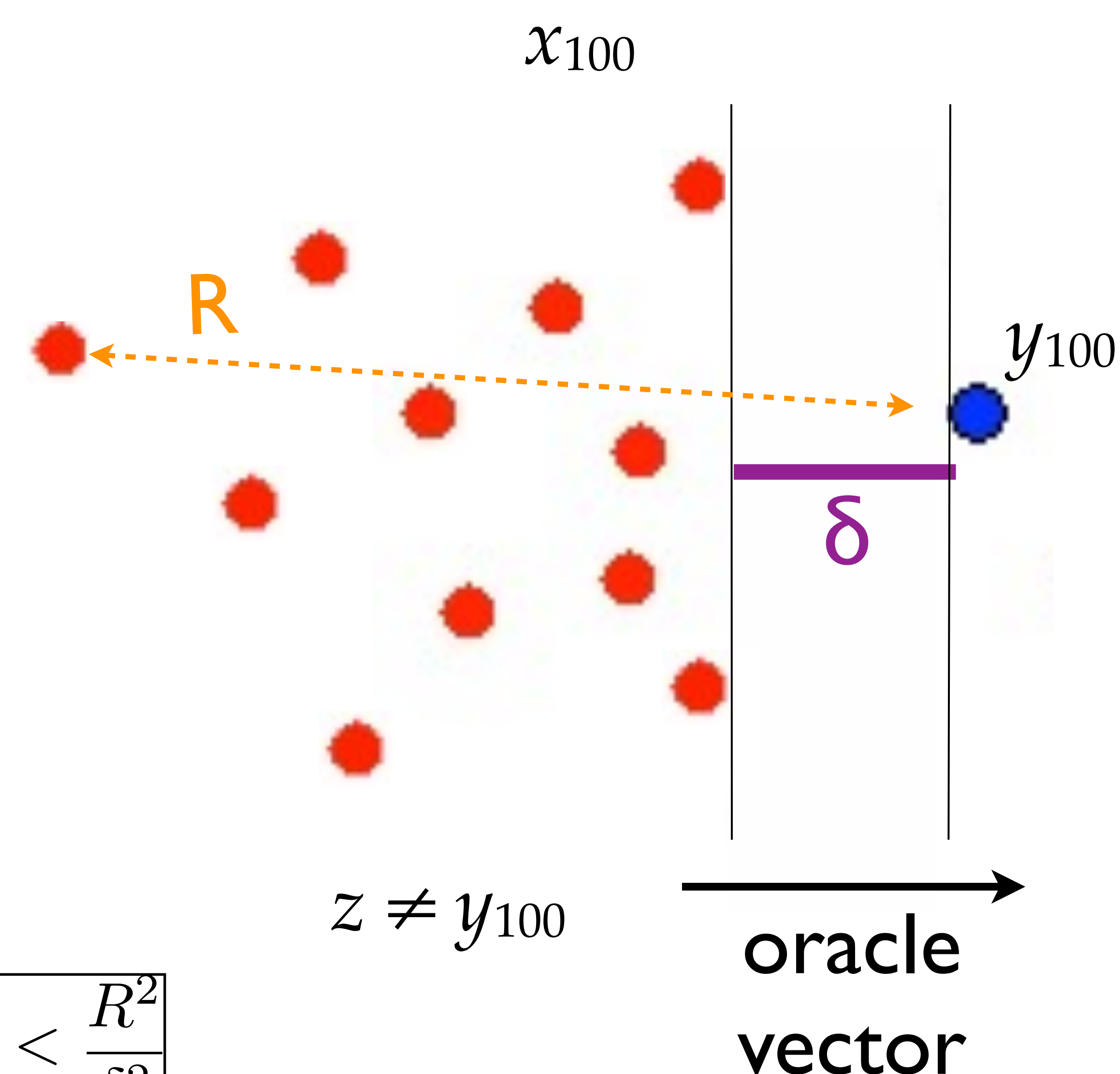
Open Problems in Theory

- latent-variable structured perceptron:
  - does it converge? under what conditions?
- latent-variable structured perceptron with inexact search
  - does it converge? under what conditions?



(Novikoff, 1962)

$$\boxed{\#\text{updates} \leq \frac{R^2}{\delta^2}}$$



(Collins, 2002)

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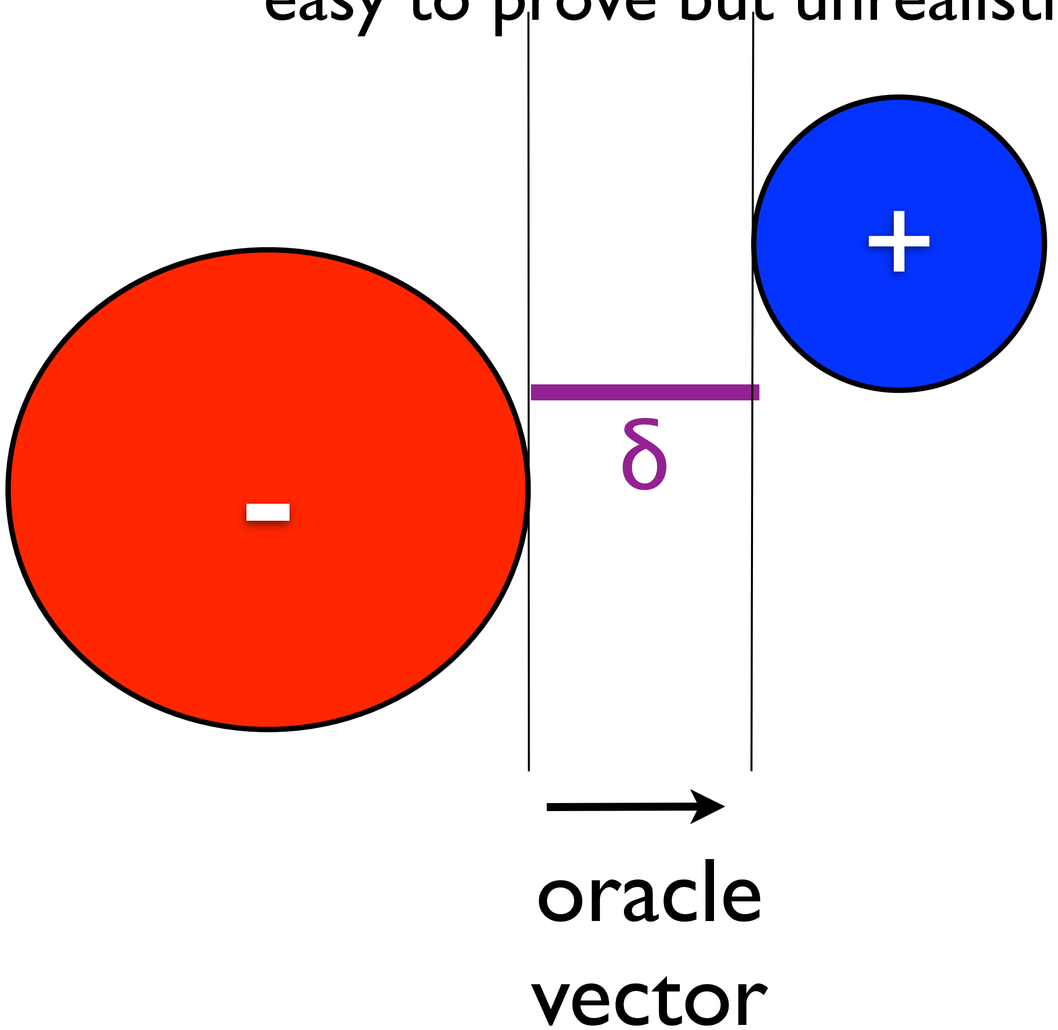
easy to prove but unrealistic



(Sun et al, 2009)

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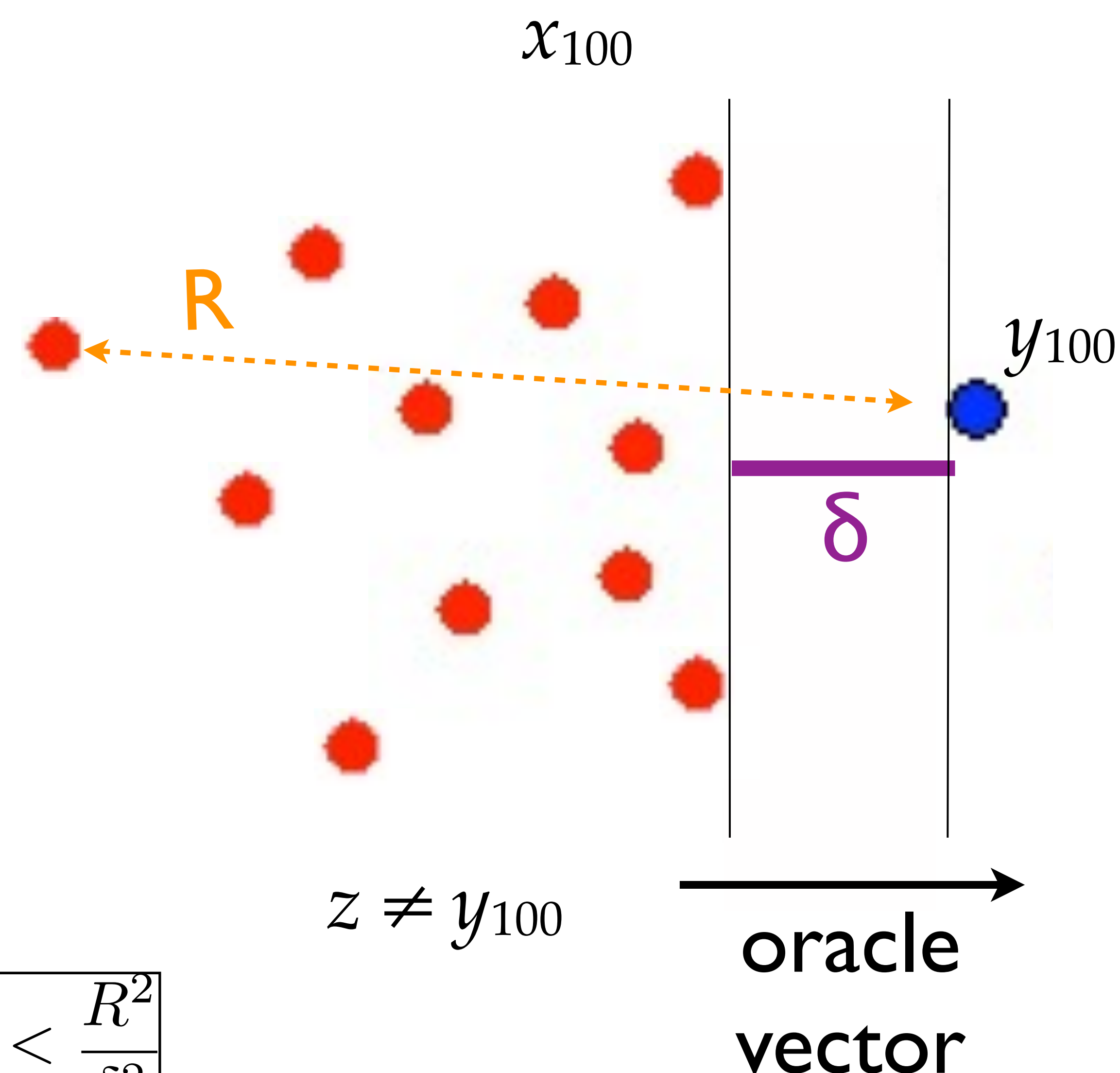

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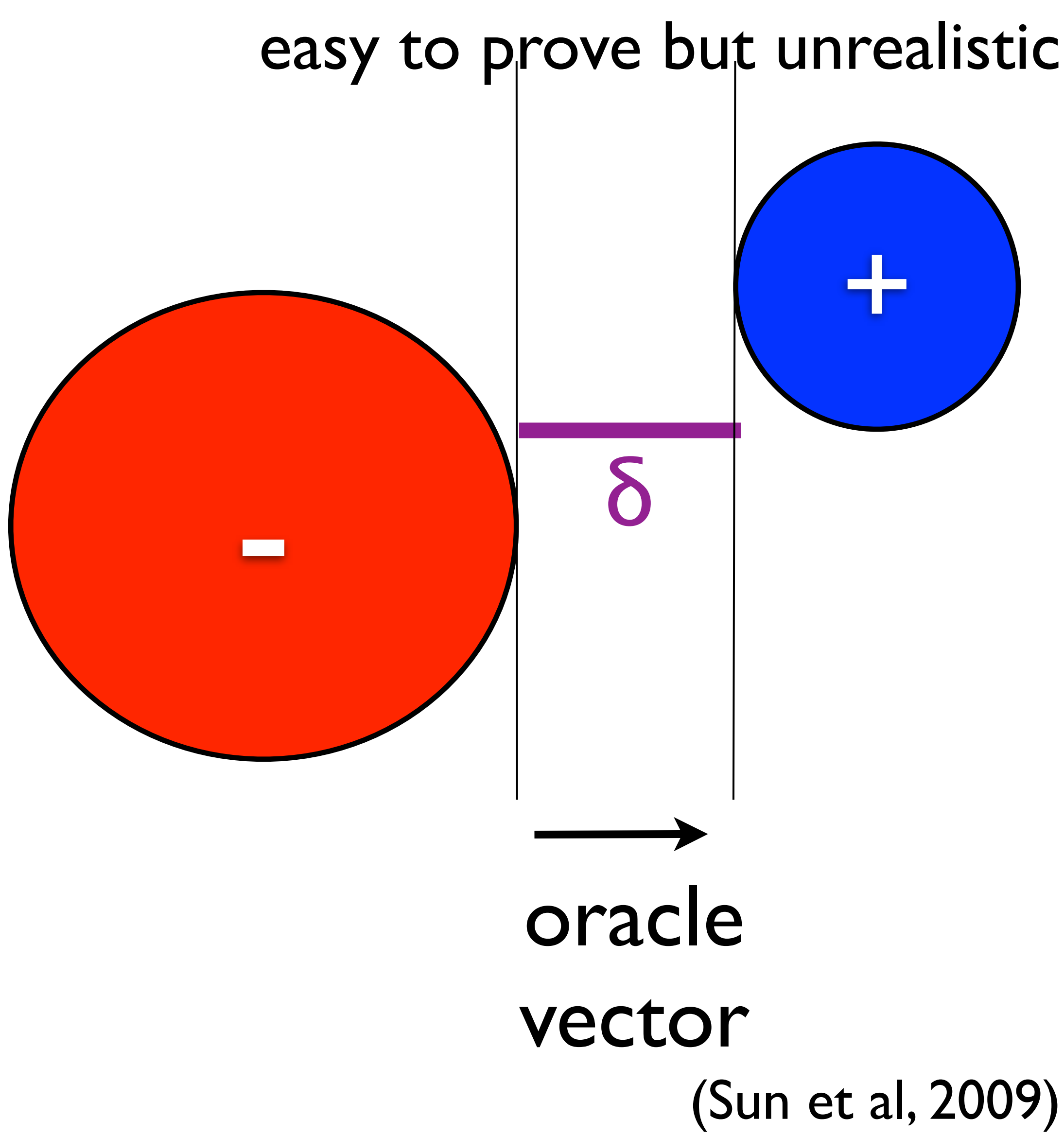
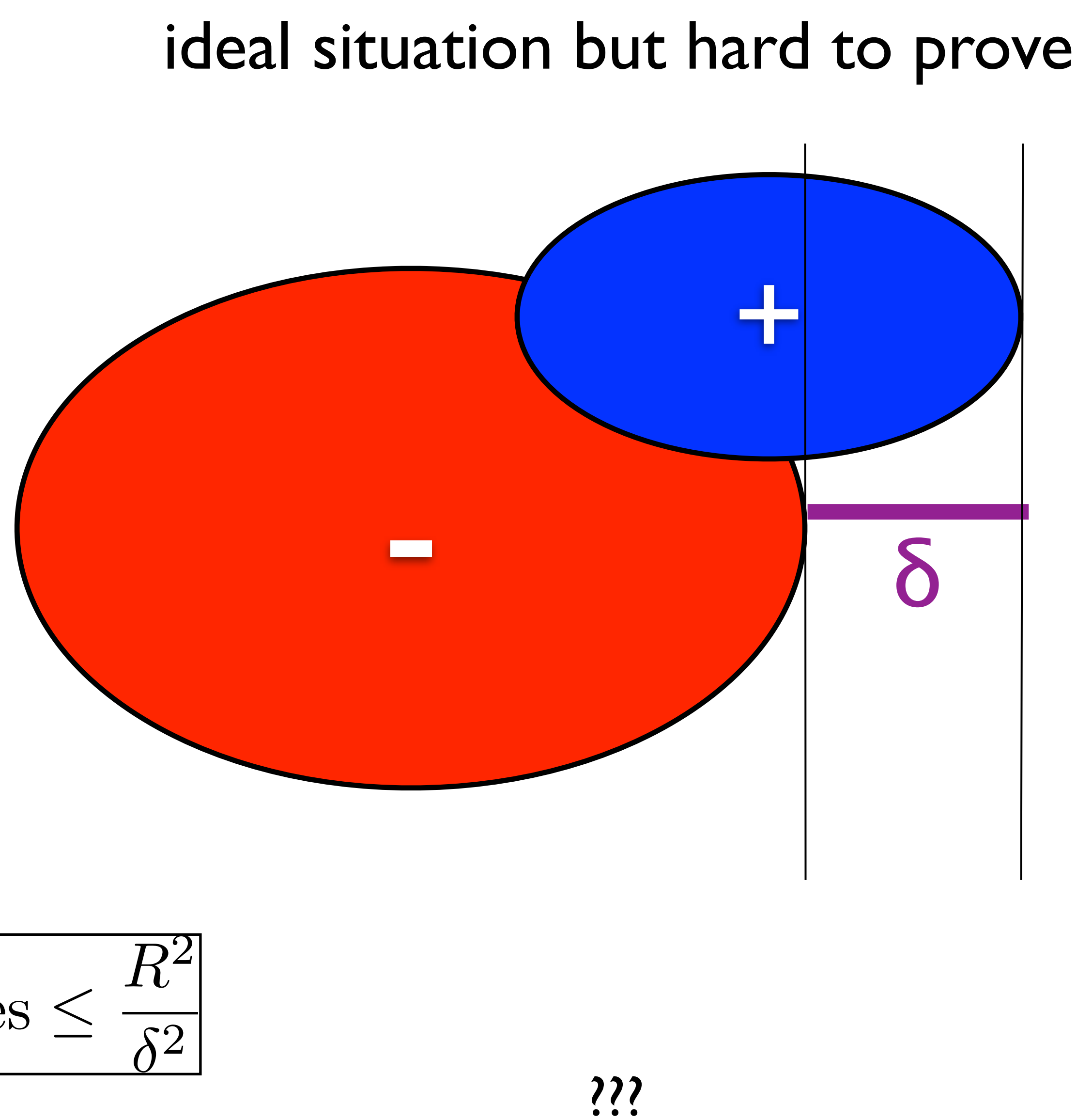


$$\boxed{\#\text{updates} \leq \frac{R^2}{\delta^2}}$$

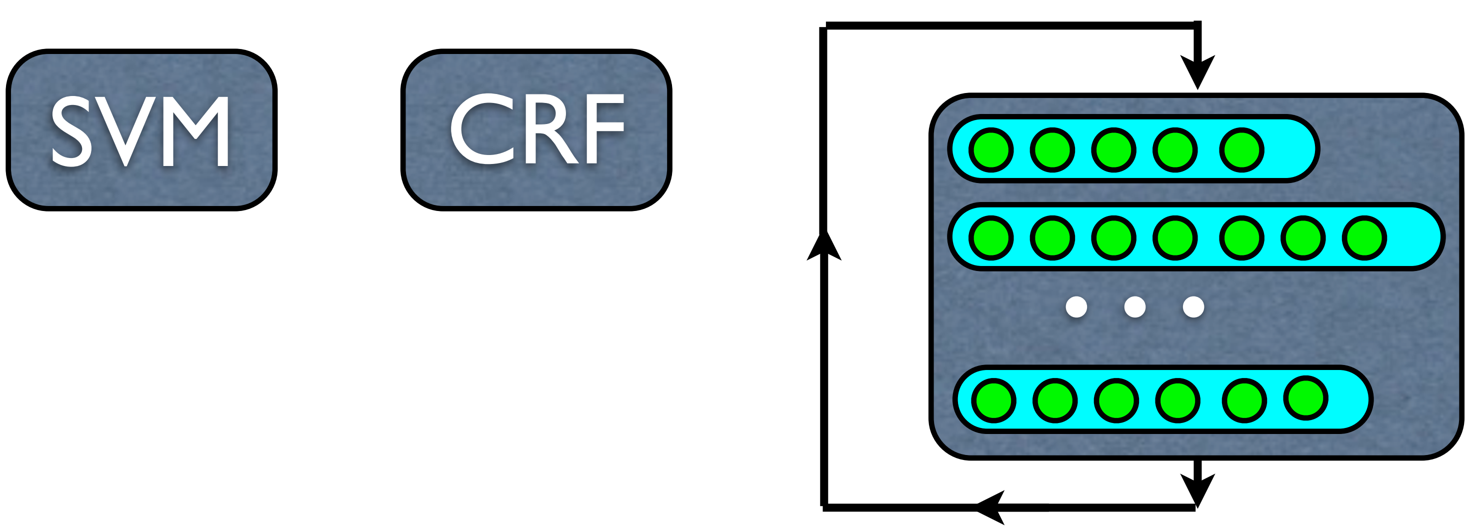


Tutorial Outline

- Overview of Structured Learning
  - Challenges in Scalability
- Structured Perceptron
  - convergence proof
- Structured Perceptron with Inexact Search
- Latent-Variable Perceptron
- Parallelizing Online Learning (Perceptron & MIRA)

Online Learning from Big Data

- online learning has linear-time guarantee
  - contrast: popular methods such as SVM/CRF are superlinear
  - but online learning can still be too slow if data is too big
    - even with the fastest inexact search (e.g. greedy)
- how to parallelize online learning for big data?



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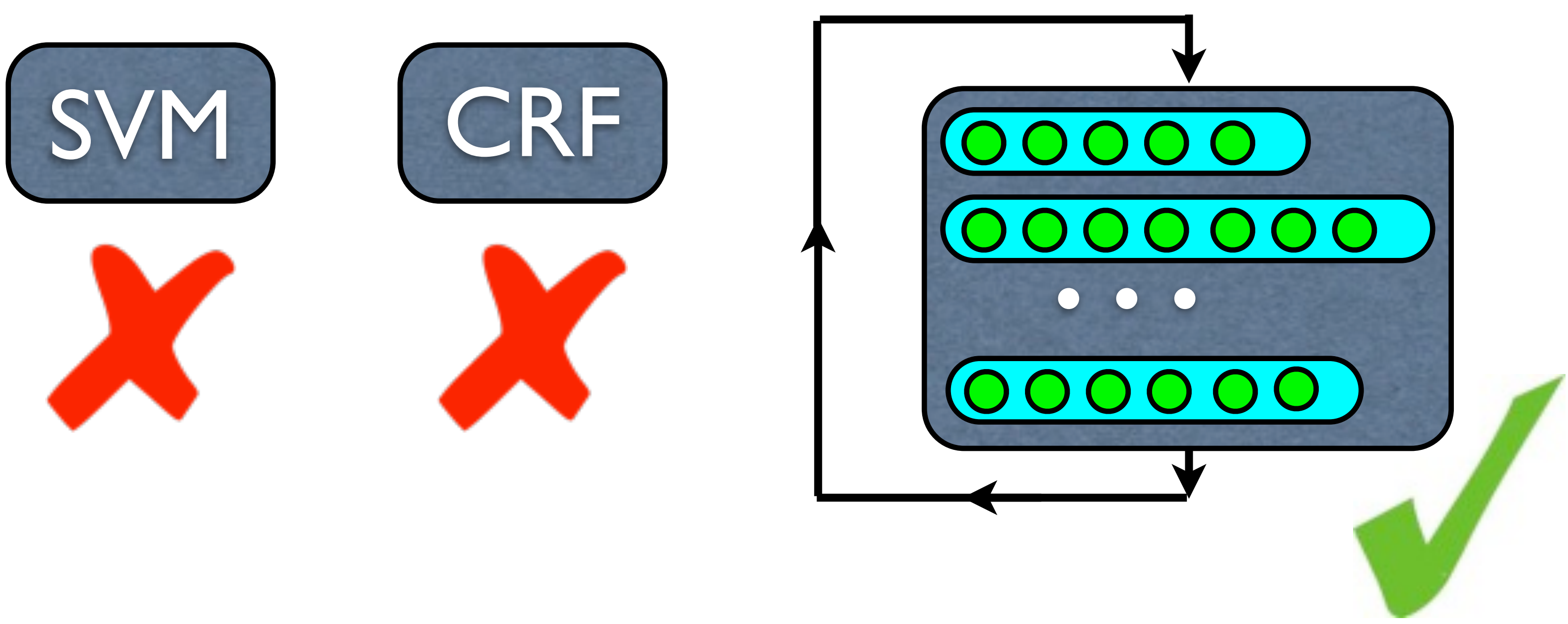

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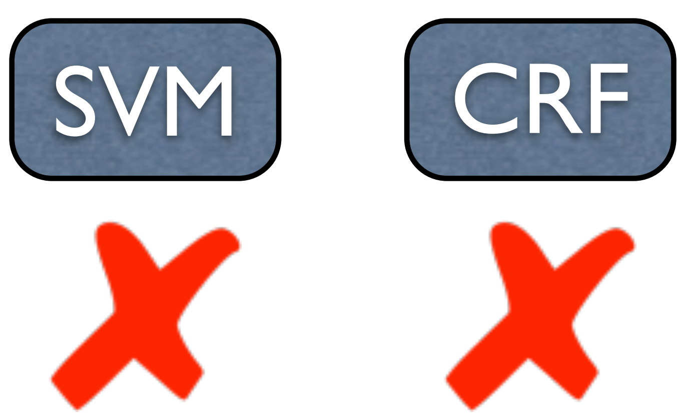
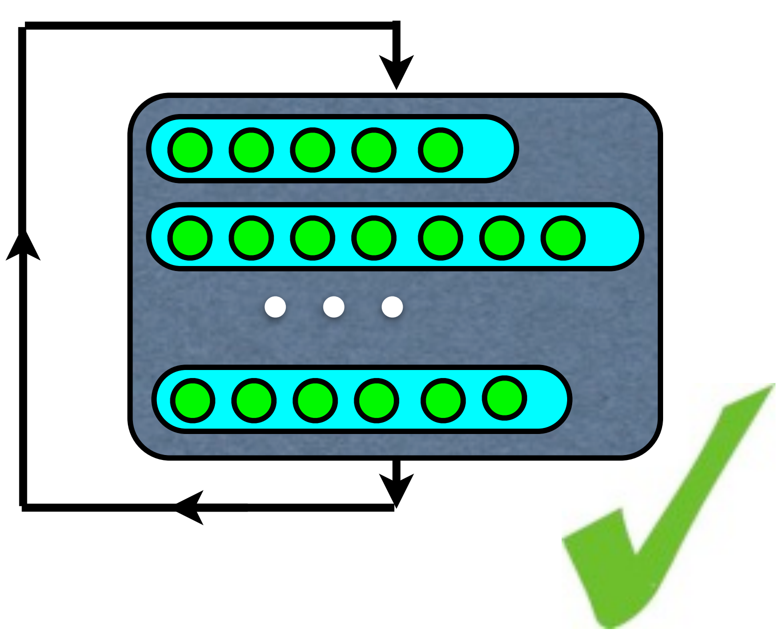
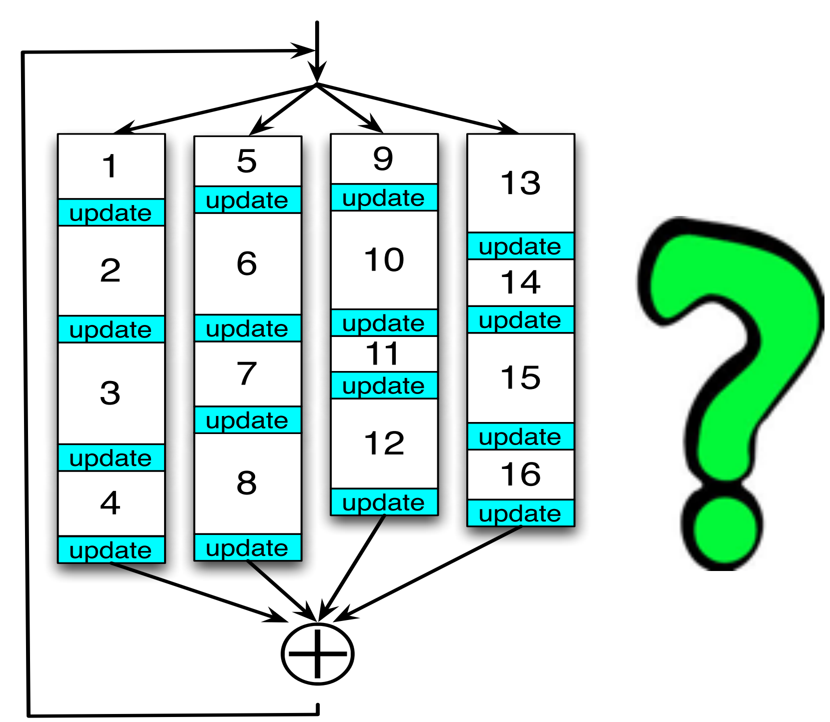
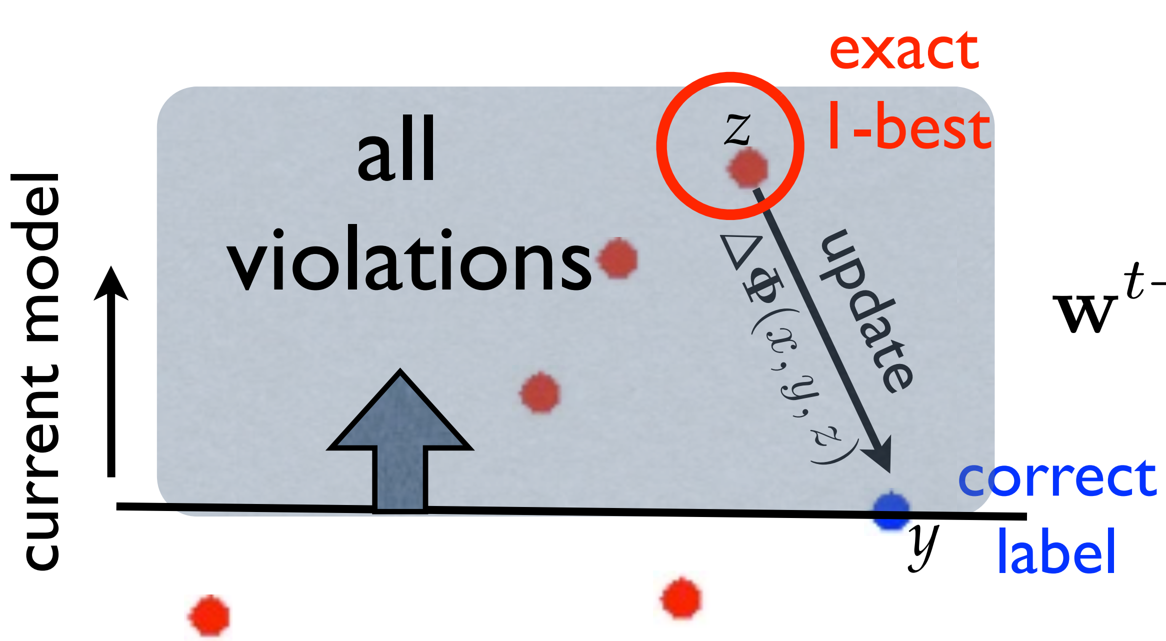






Aside: Perceptron => MIRA

- perceptron is simple but...
  - only "aims to" fixes one mistake (violation) on each example
  - but structured prediction may have many violations
  - may under- or over-correct on a violation
- MIRA (margin infused relaxation algorithm)
  - 1-best MIRA: corrects one violation "just enough" (Crammer 03)
  - *k*-best MIRA: corrects *k* violations at one time (McDonald et al 05)



$$Z = \underset{z \in \mathbf{GEN}(x)}{k\text{-best}} \ \mathbf{w}^t \cdot \mathbf{\Phi}(x, z)$$

$$\mathbf{w}^{t+1} = \underset{\mathbf{w}' : \forall z \in Z, \mathbf{w}' \cdot \Delta\mathbf{\Phi}(x,y,z) \geq \ell(y,z)}{\mathbf{argmin}} \|\mathbf{w}' - \mathbf{w}^t\|^2$$

Geometry of 1-best & *k*-best MIRA

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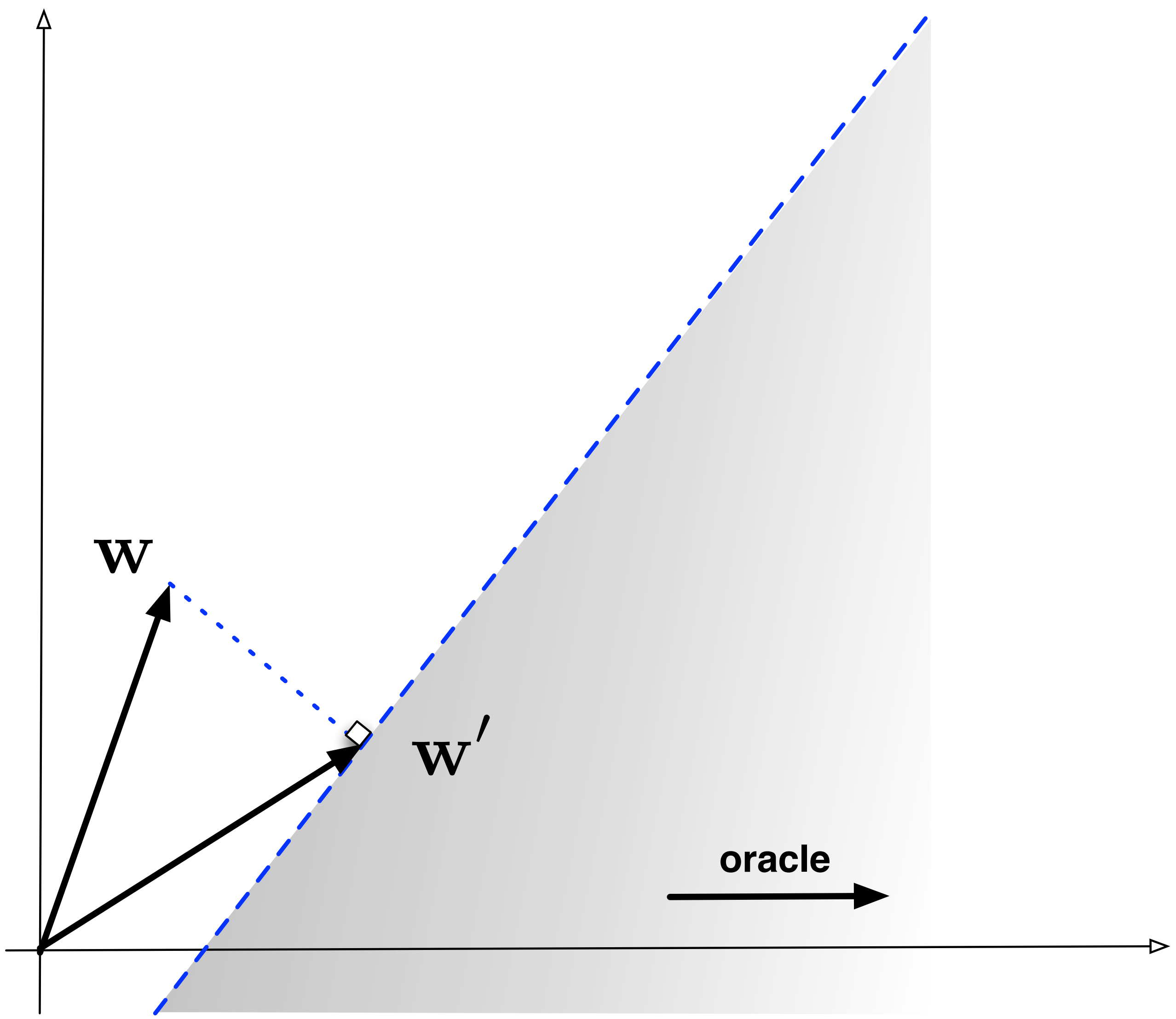
1-best MIRA

single constraint

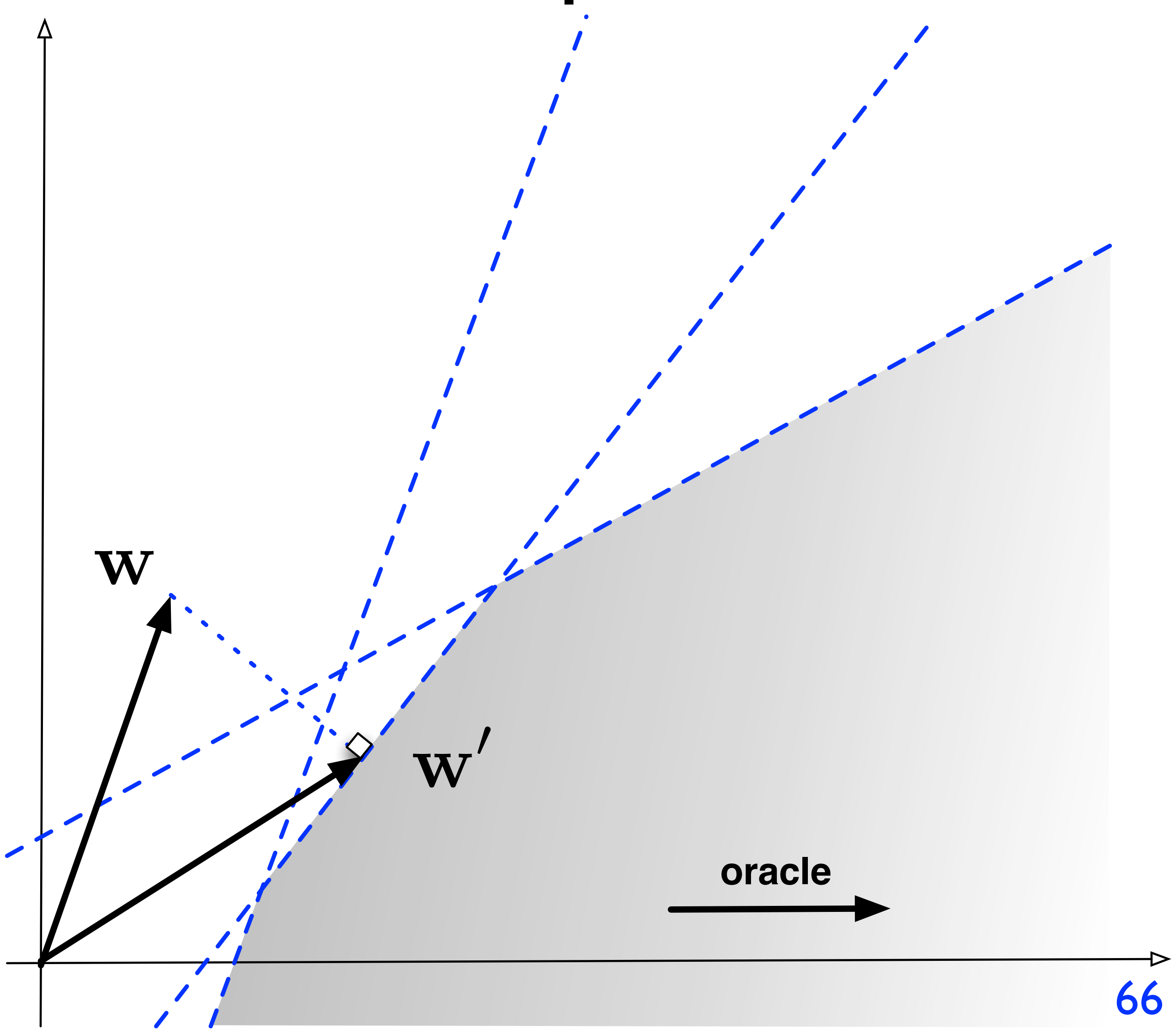
=> analytic solution



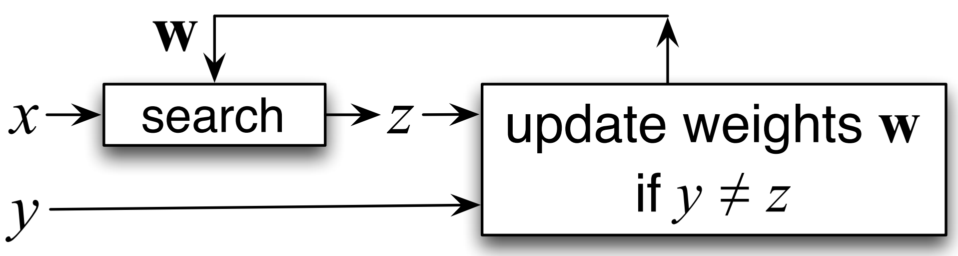
k-best MIRA

up to *k* constraints

=> convex optimization



Can We Parallelize Online Learning?



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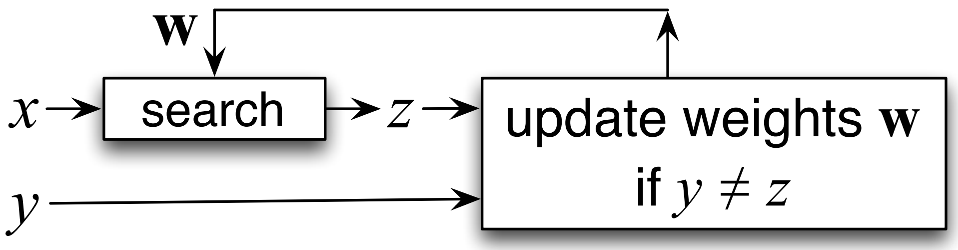
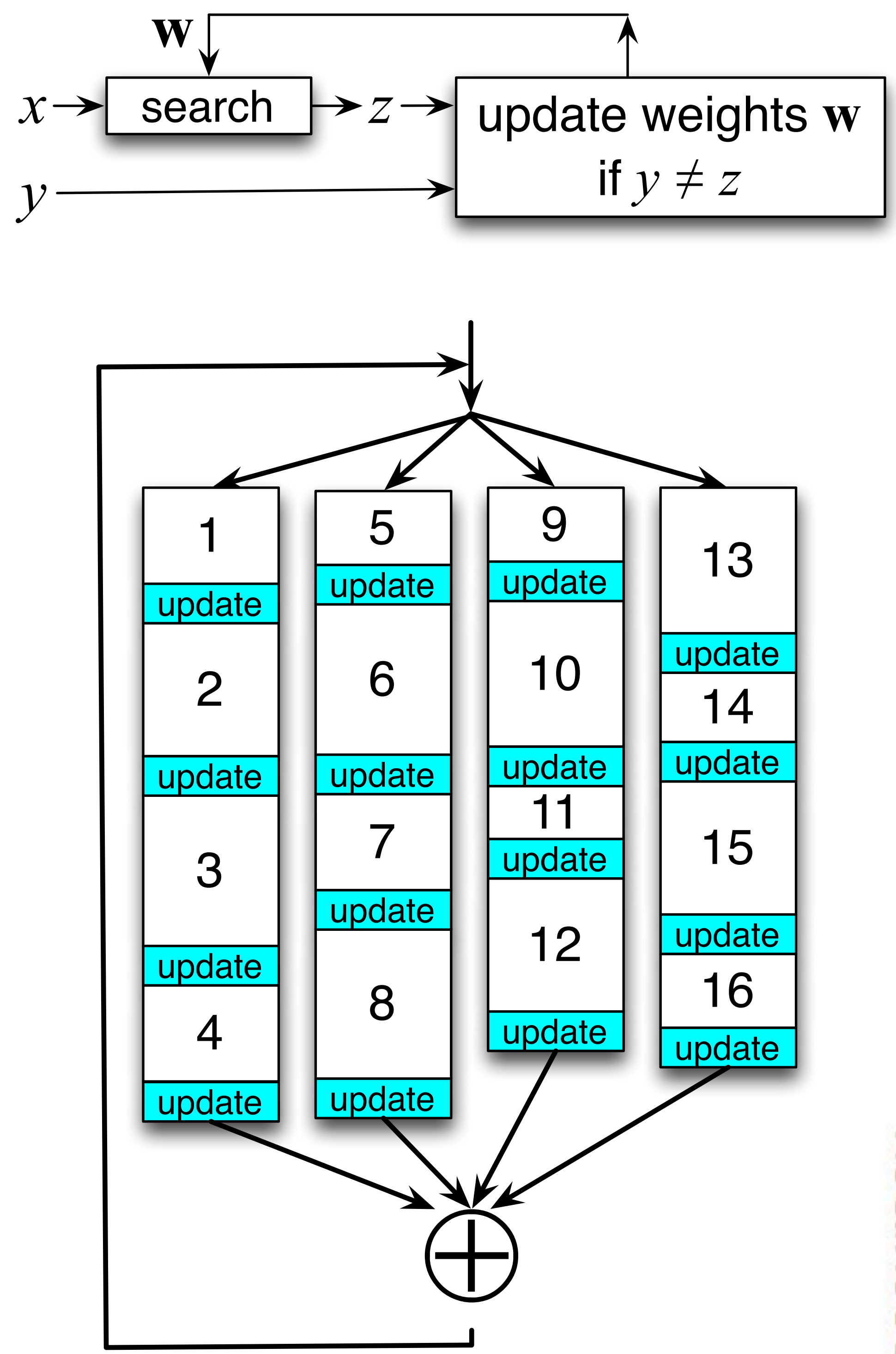


- can we parallelize online learning?
  - harder than parallelizing batch (CRF)
  - losing dependency b/w examples
  - each iteration faster, but accuracy lower

Method 1: Iterative Parameter Mixing



Iterative Parameter Mixing (IPM)
(McDonald et al 2010)

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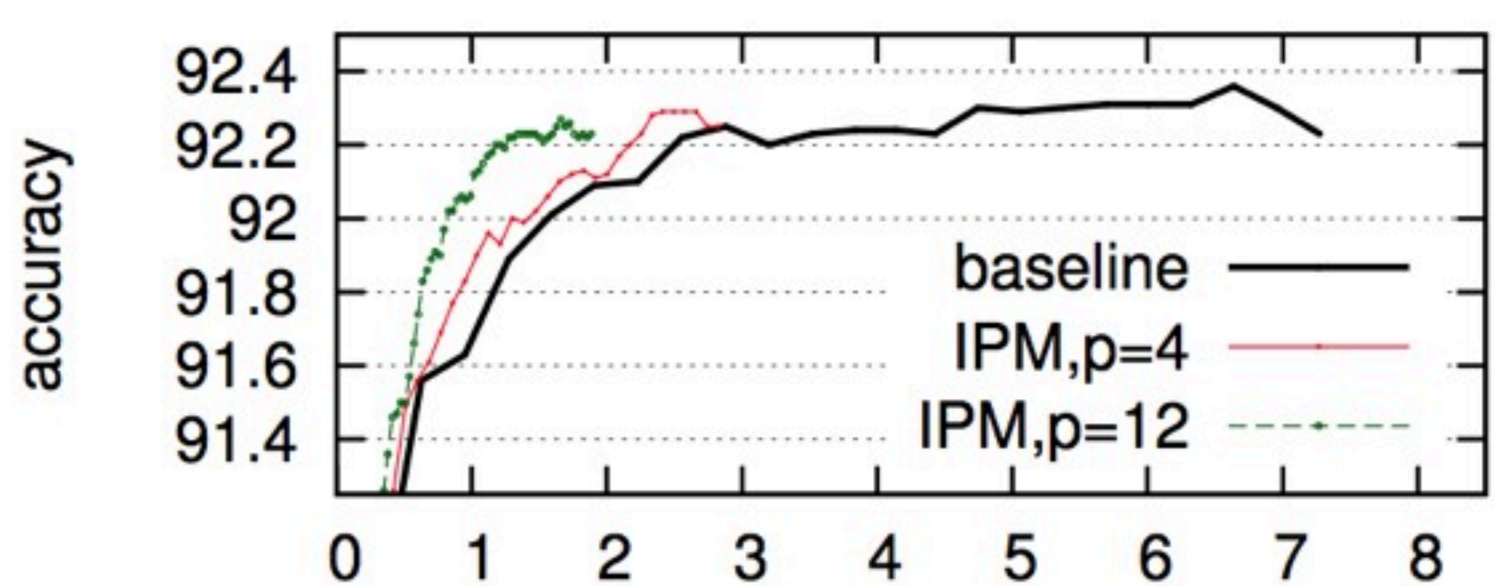

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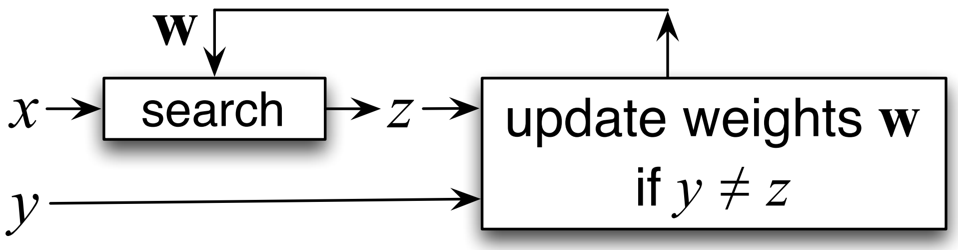

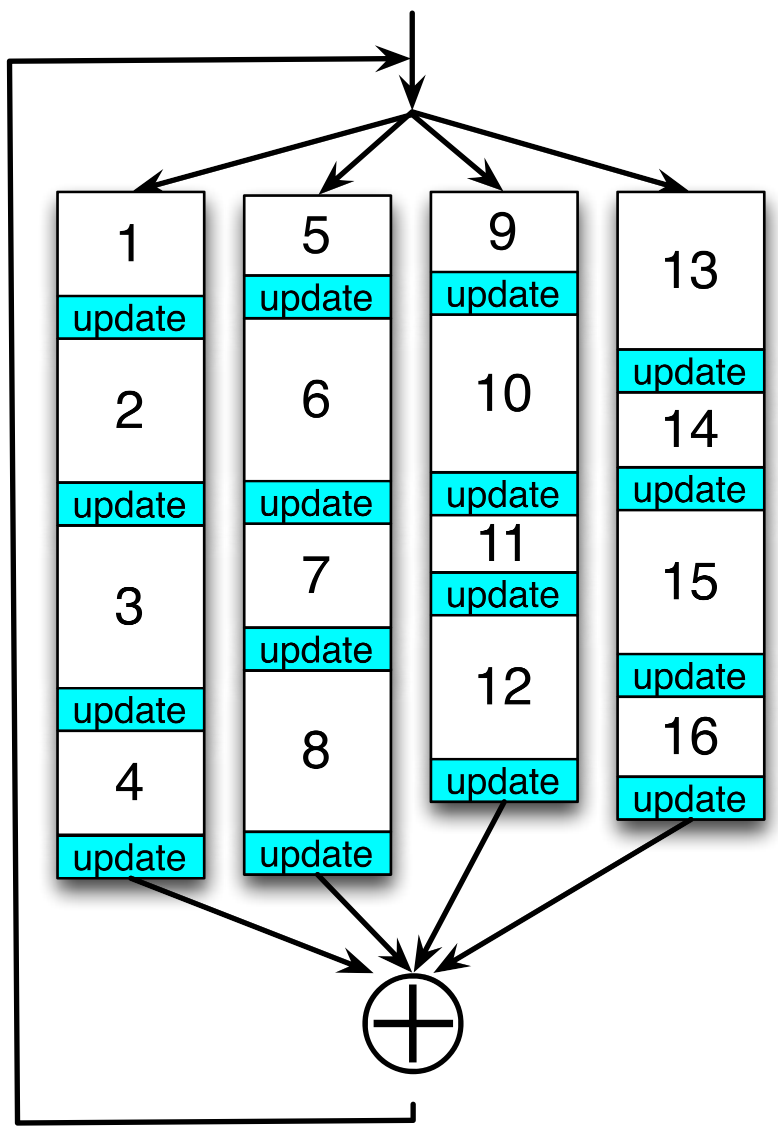

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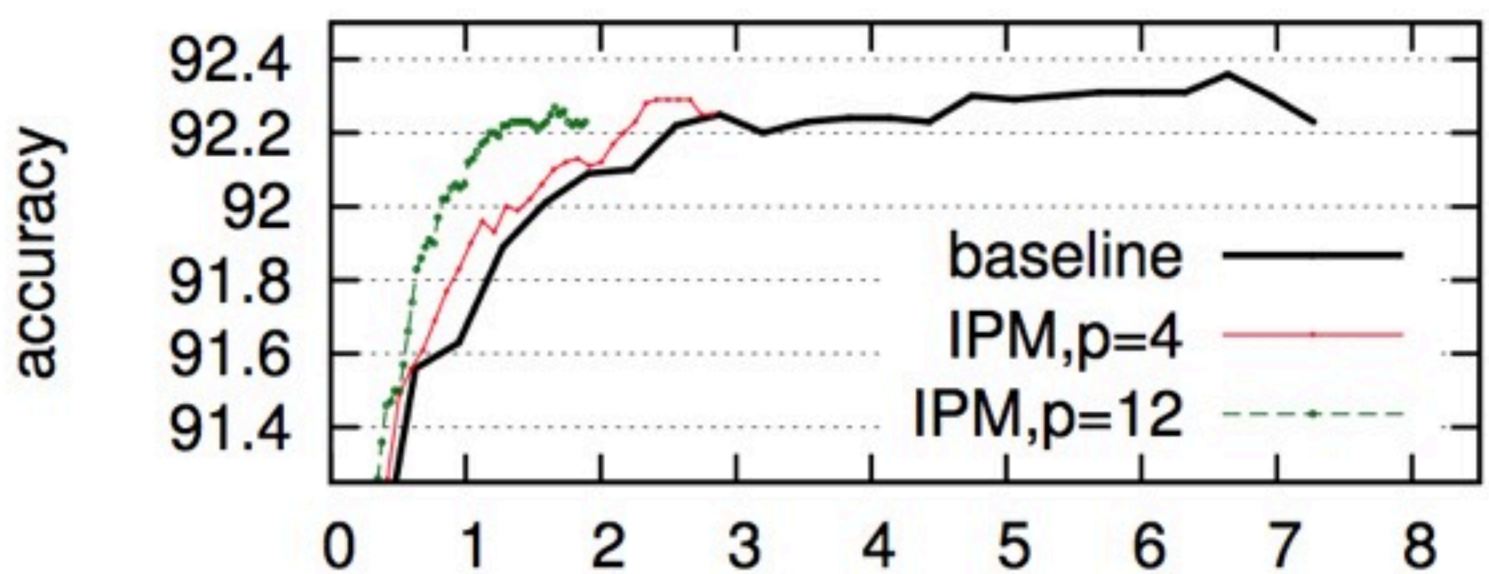
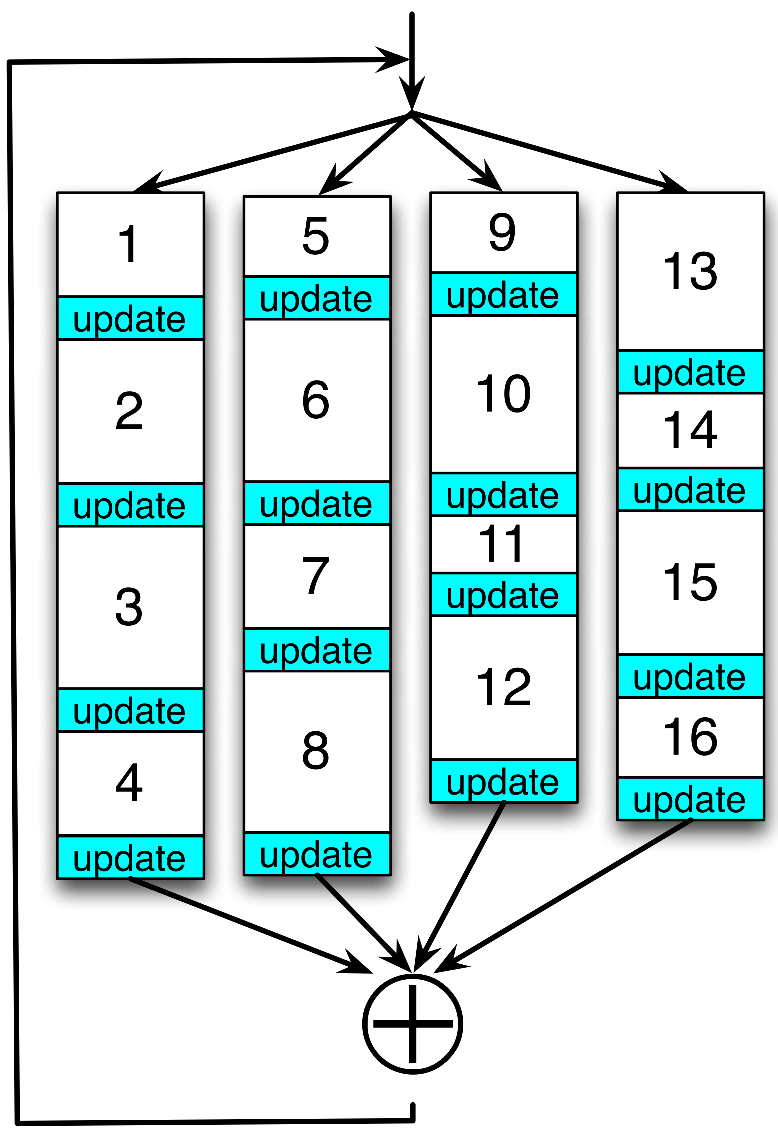
- can we do (a lot) better?



Method 2: Minibatch Parallelization

- decode a minibatch in parallel, update in serial



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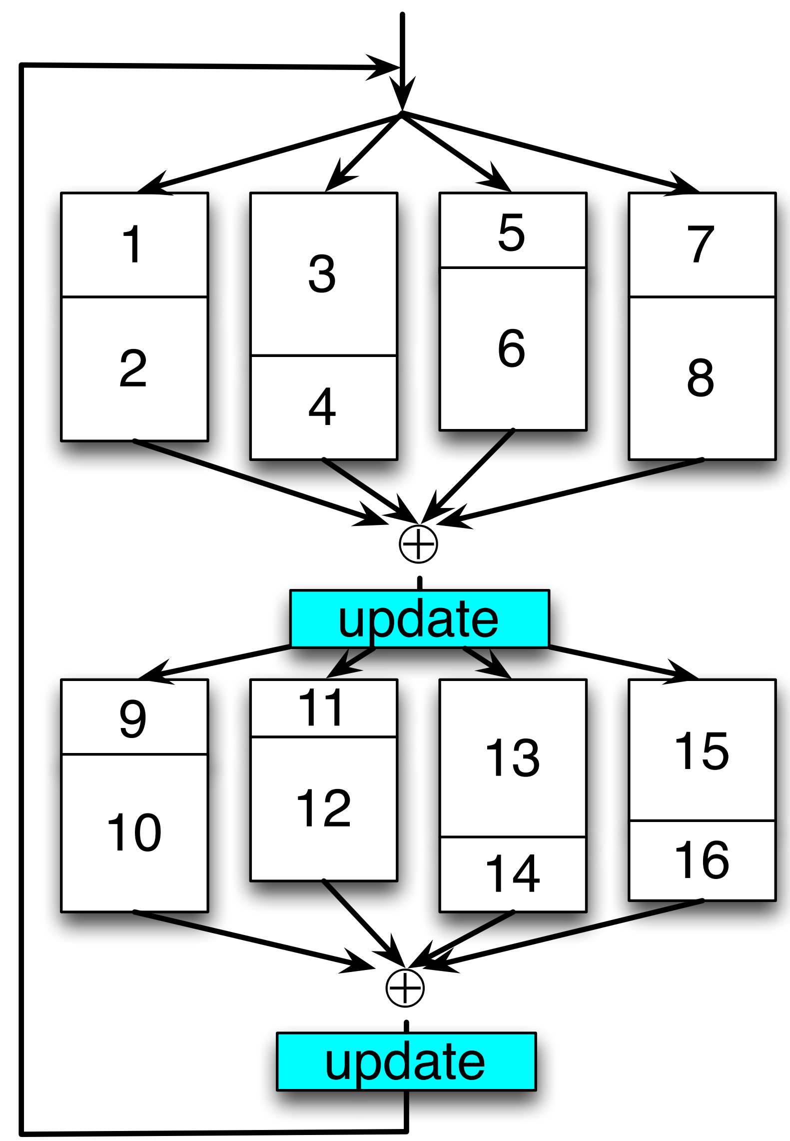

minibatch
(Zhao and Huang, 2012)

Why Minibatch?

- minibatch also helps in serial mode!
- perceptron: use average updates within minibatch
  - "averaging effect" (cf. McDonald et al 2010)
  - easy to prove convergence (still R^2/δ^2)

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lower bound

$$\mathbf{u}\cdot\mathbf{w}^{(k+1)} = \mathbf{u}\cdot\mathbf{w}^{(k)} + \boxed{\frac{1}{a}\sum_i \mathbf{u}\cdot\Delta\mathbf{\Phi}(x, y, z) \geq \delta \quad \text{margin}}$$

$$\mathbf{u}\cdot\mathbf{w}^{(k+1)} \geq k\delta$$

$$\|\mathbf{w}^{(k+1)}\| \geq k\delta$$ (by induction)

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$$\|\mathbf{w}^{(k+1)}\| \geq k\delta$$

(by induction)

upper bound

$$\|\mathbf{w}^{(k+1)}\|^2 = \|\mathbf{w}^{(k)}\|^2 + \boxed{\underbrace{\|\frac{1}{a}\sum_i \Delta\mathbf{\Phi}(x, y, z)\|^2}_{\leq R^2 \quad \text{Jensen's}}} + \boxed{\underbrace{\frac{2}{a}\mathbf{w}^{(k)} \cdot \sum_i \Delta\mathbf{\Phi}(x, y, z)}_{\leq 0 \quad \text{violation}}}$$

$$\|\mathbf{w}^{(k+1)}\|^2 \leq kR^2$$

(by induction)

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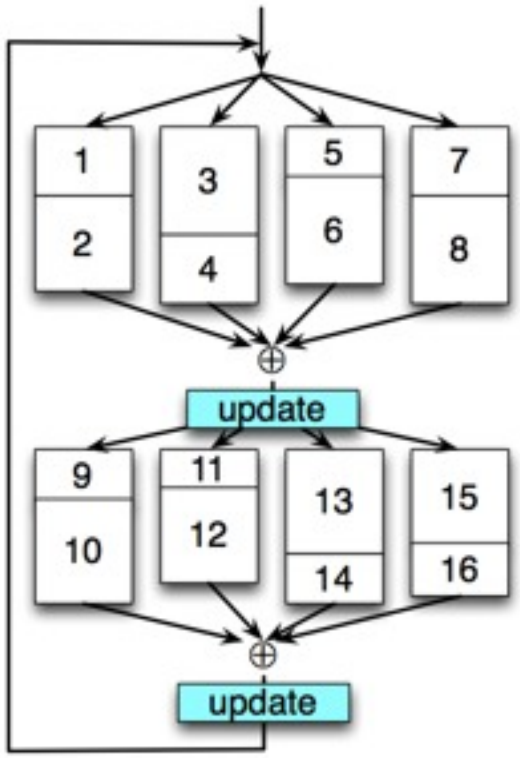

8x constrains in each update

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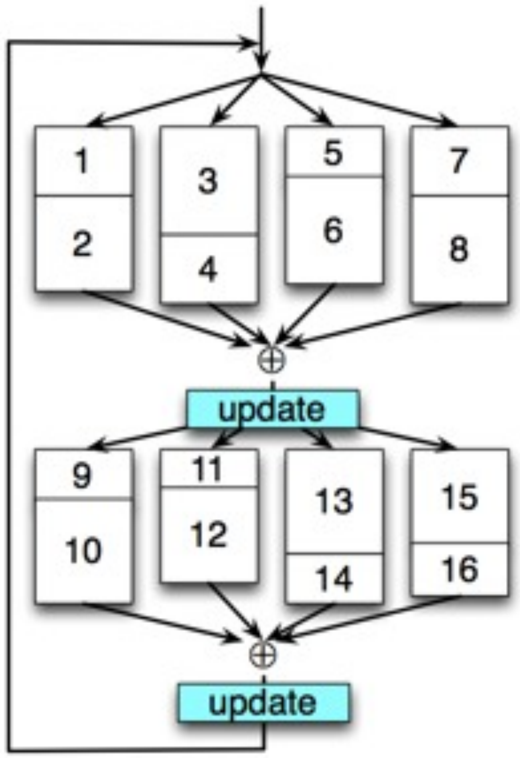
  - "averaging effect" (cf. McDonald et al 2010)
  - easy to prove convergence (still R^2/δ^2)
- MIRA: optimization over more constraints
  - MIRA is an online approximation of SVM
  - minibatch MIRA: better approximation of SVM
    - approaches SVM at maximum batch size



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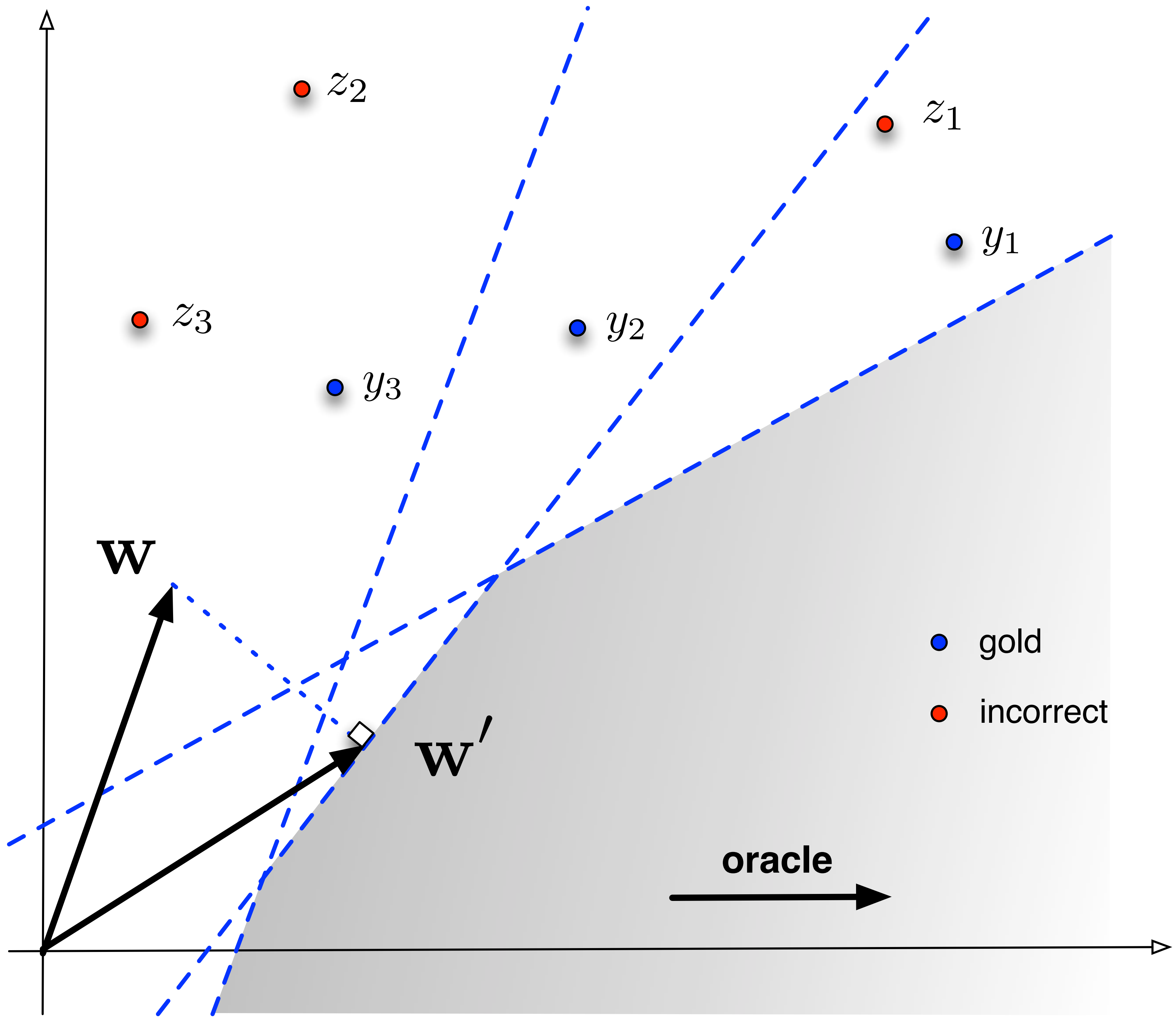
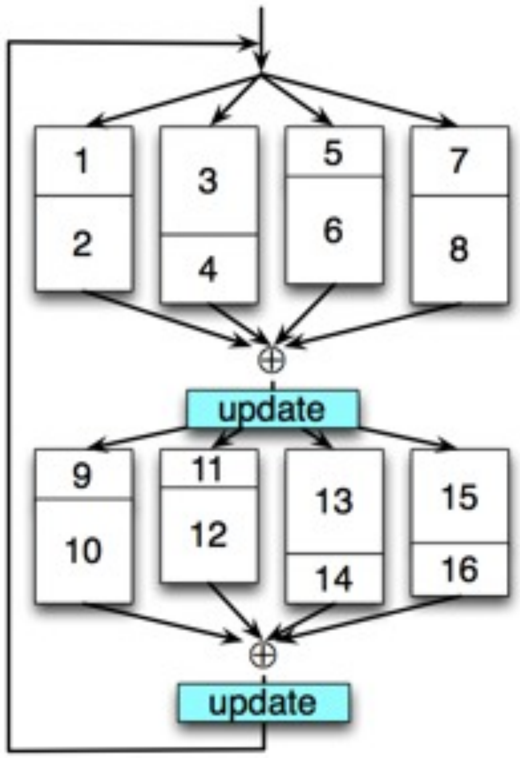
$$\forall (x, y, z) \in V$$

Geometry of Minibatch MIRA





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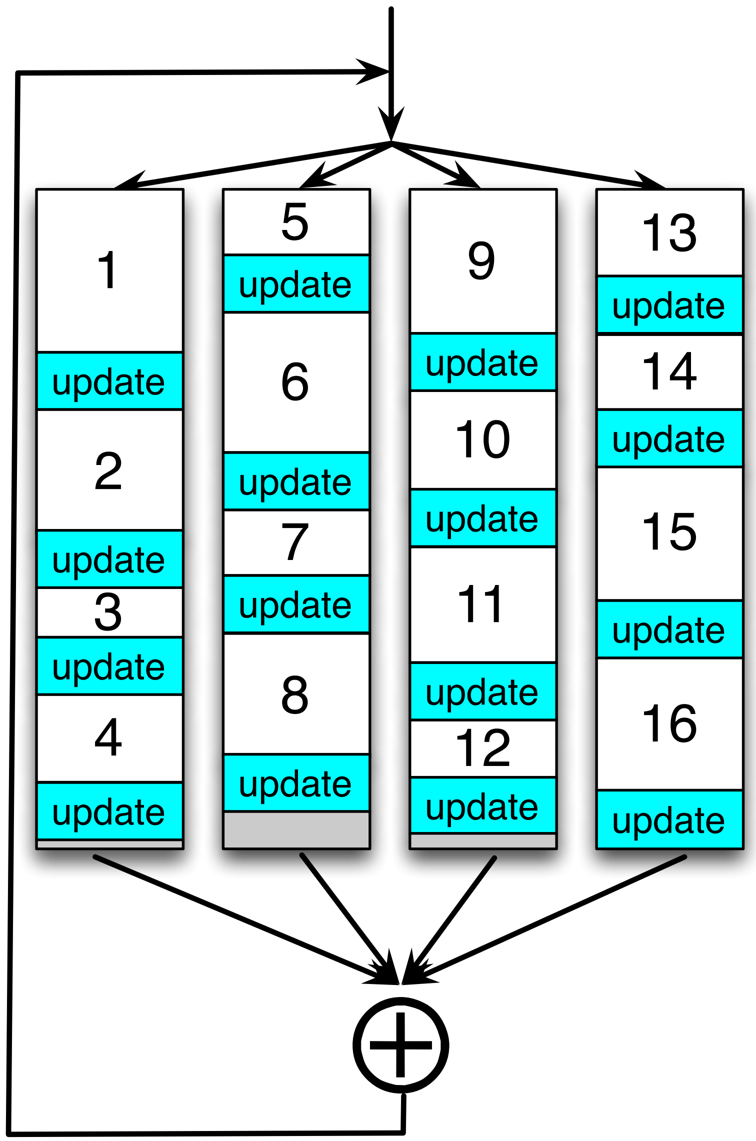
Load Balancing

- rearrange each minibatch to minimize wasted time



iterative parameter mixing
McDonald et al 2010

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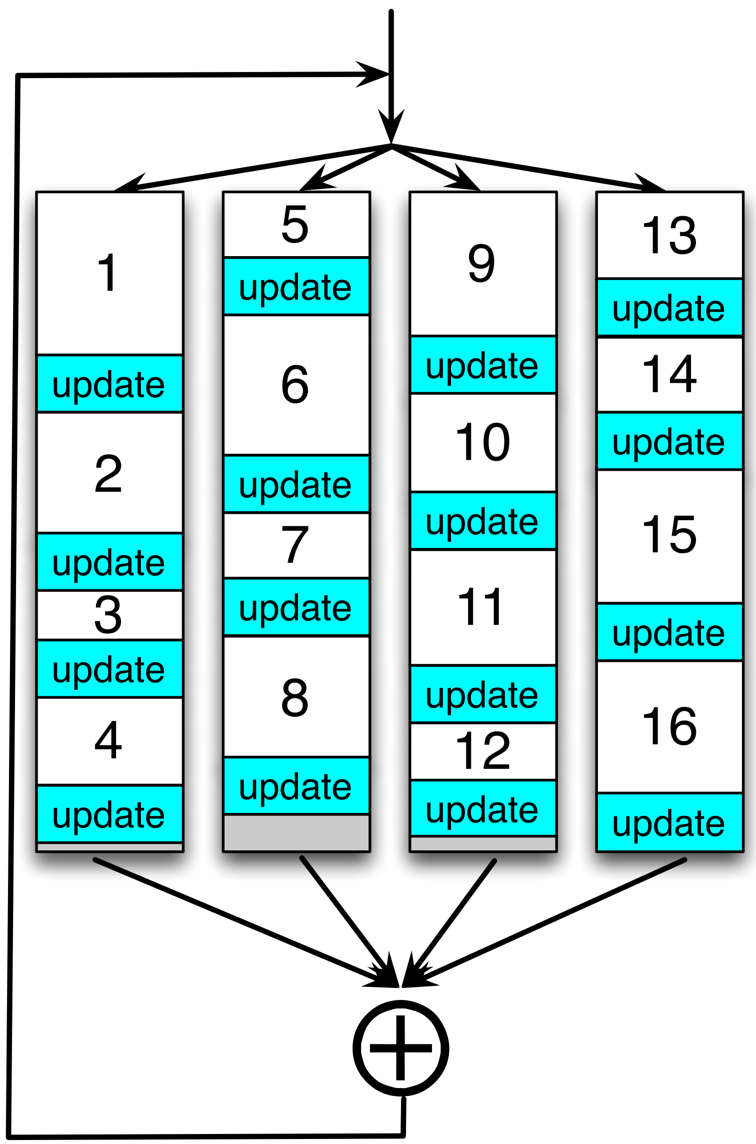

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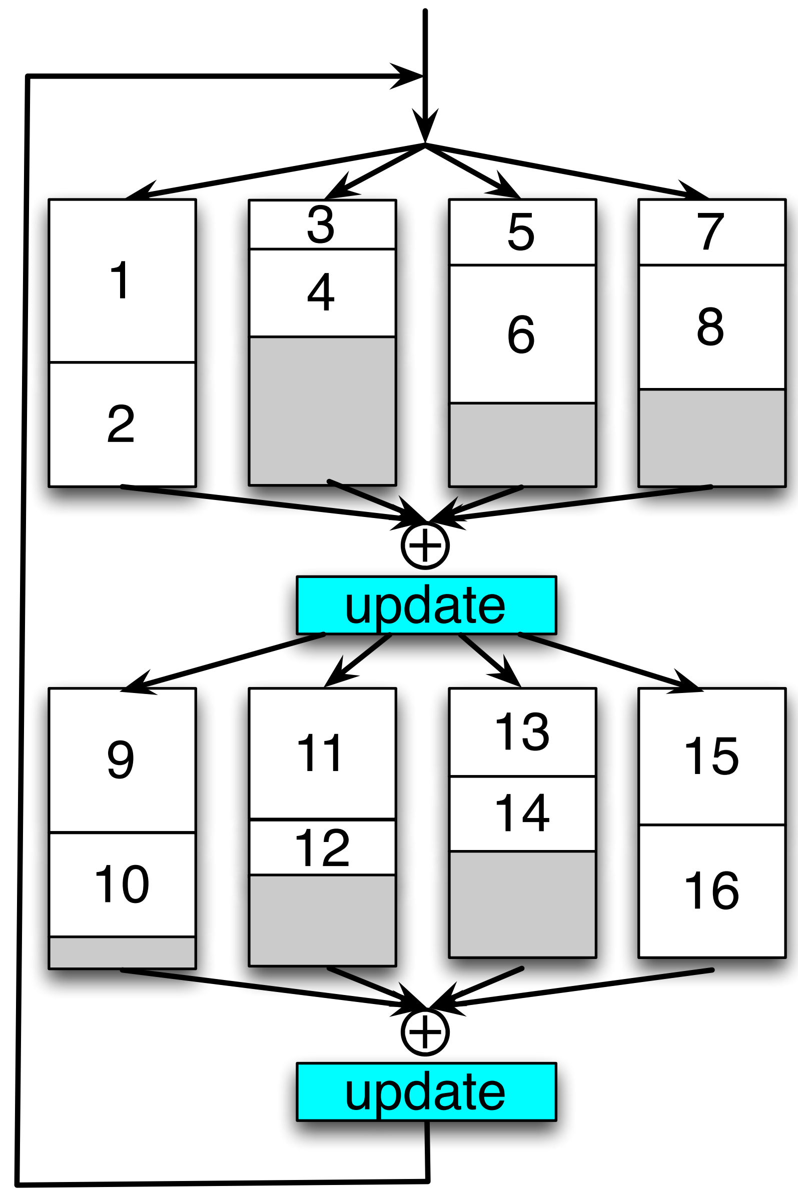

minibatch

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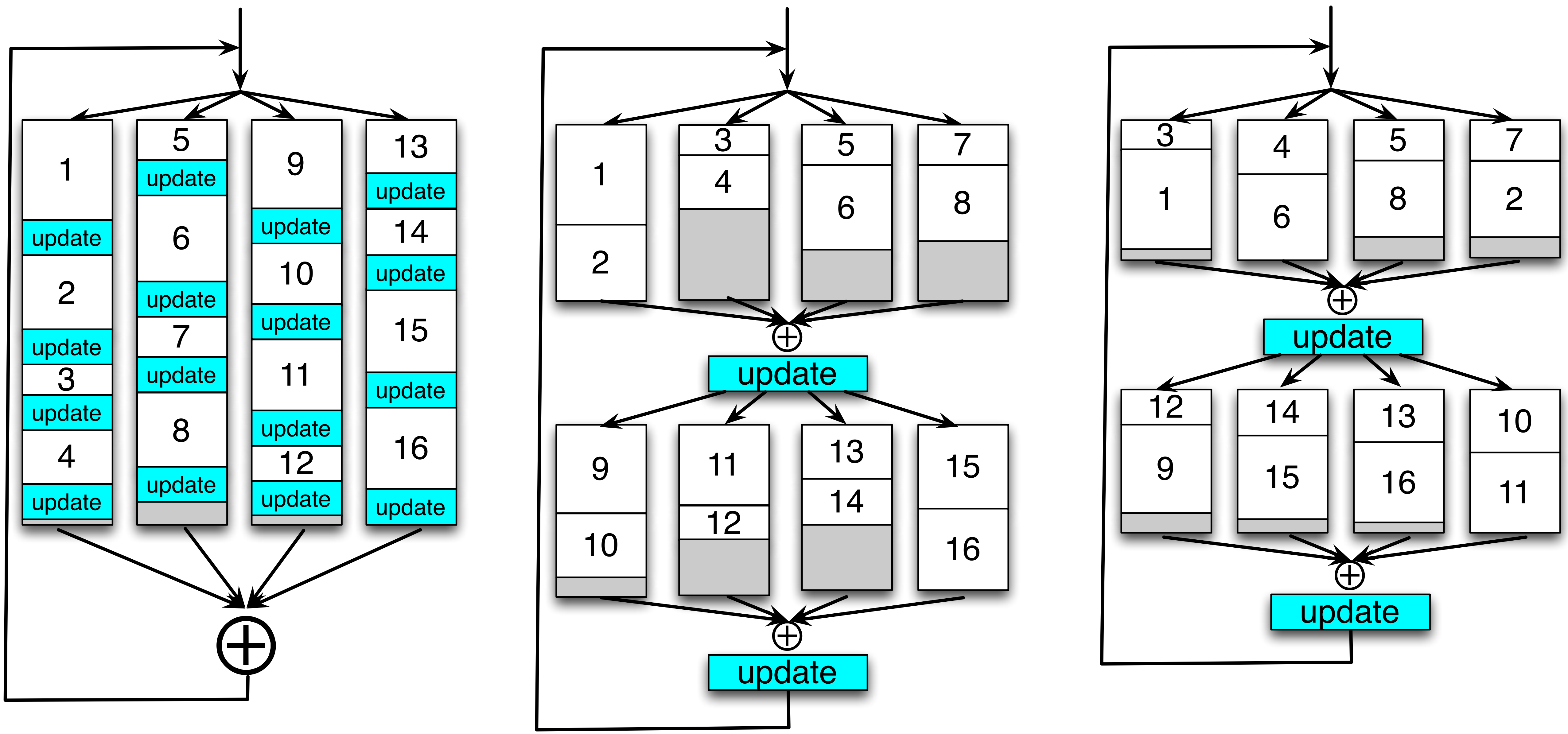
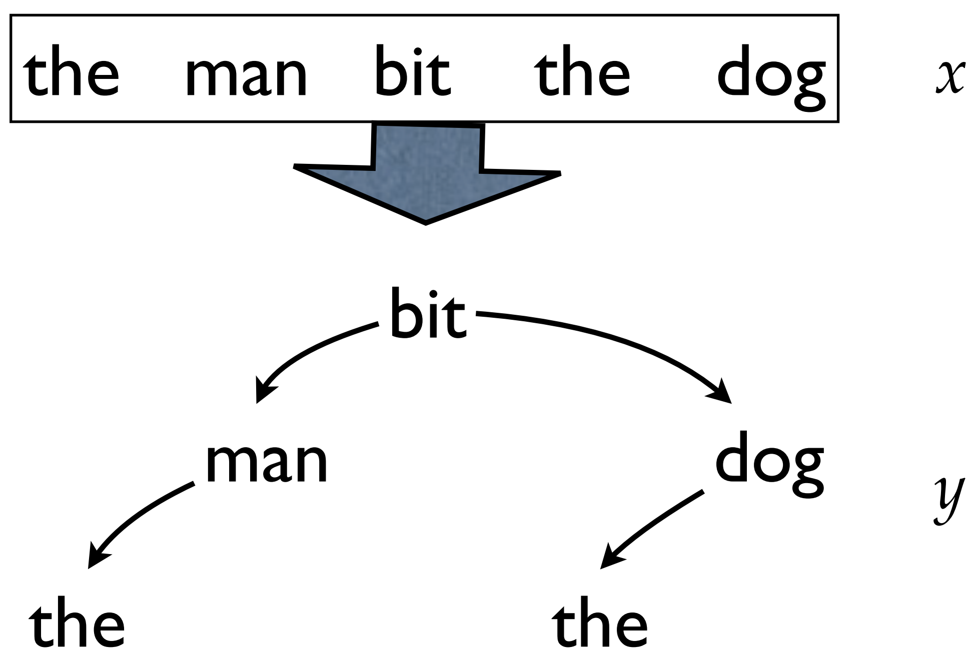


iterative parameter mixing
McDonald et al 2010

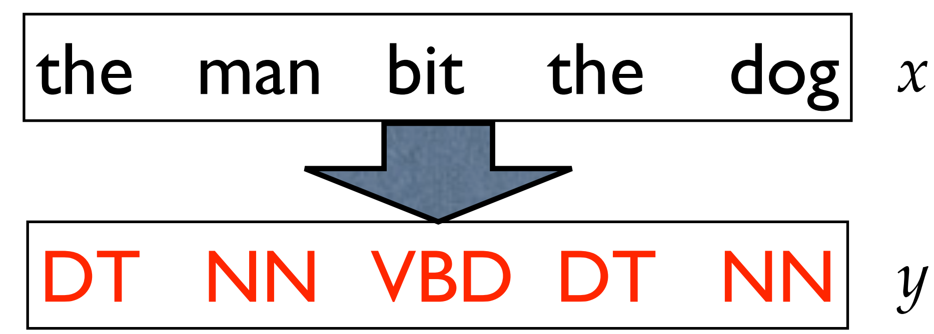
minibatch

load balanced minibatch

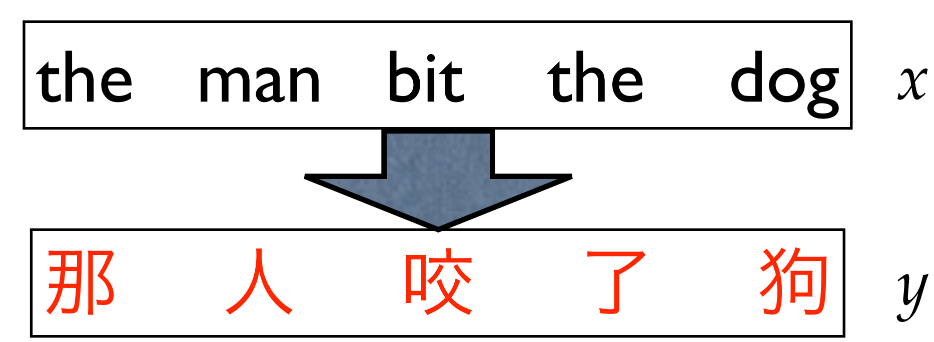
Experiments



incremental parsing



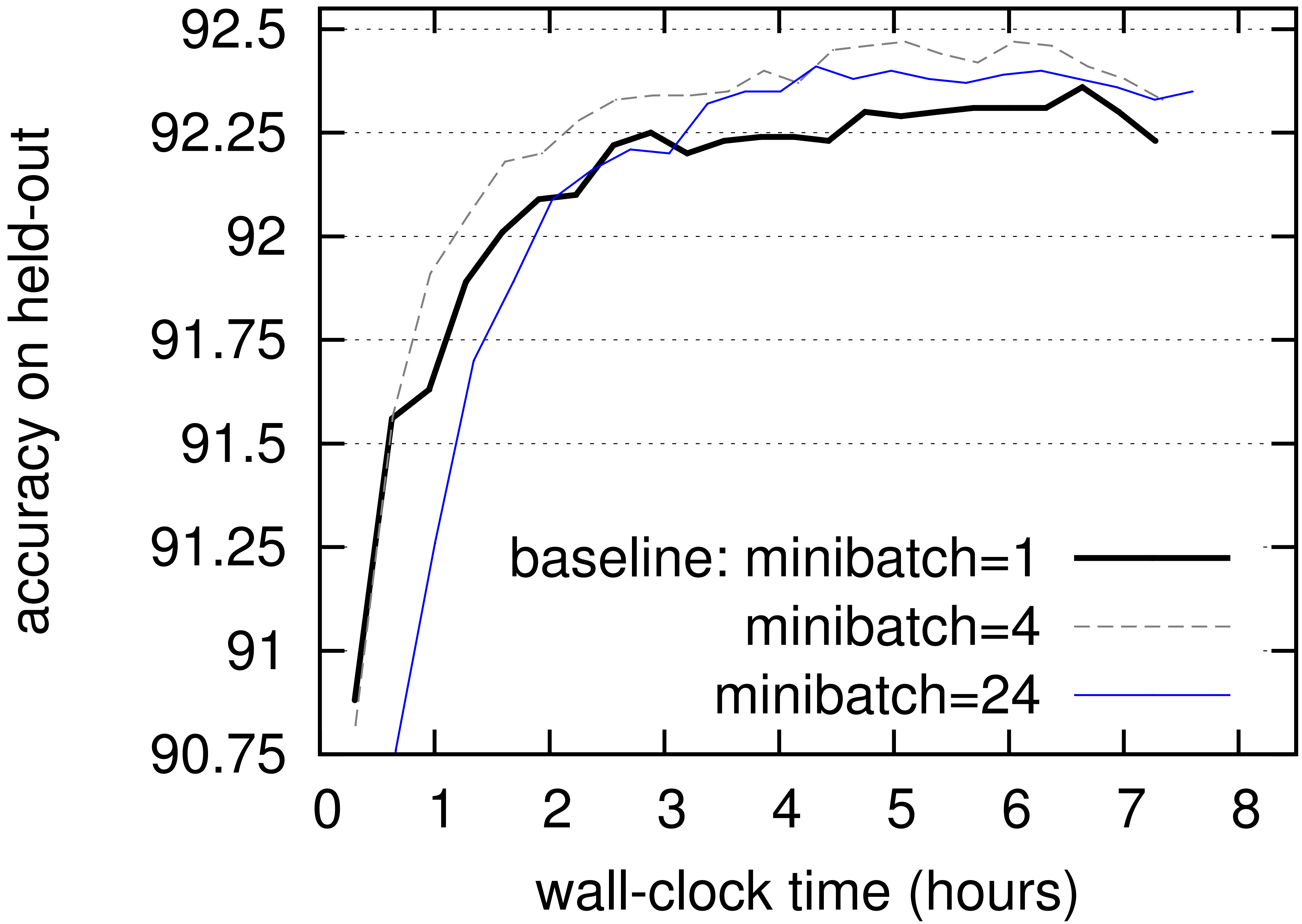
part-of-speech tagging



phrase-based translation

Experiment 1: Parsing with MIRA

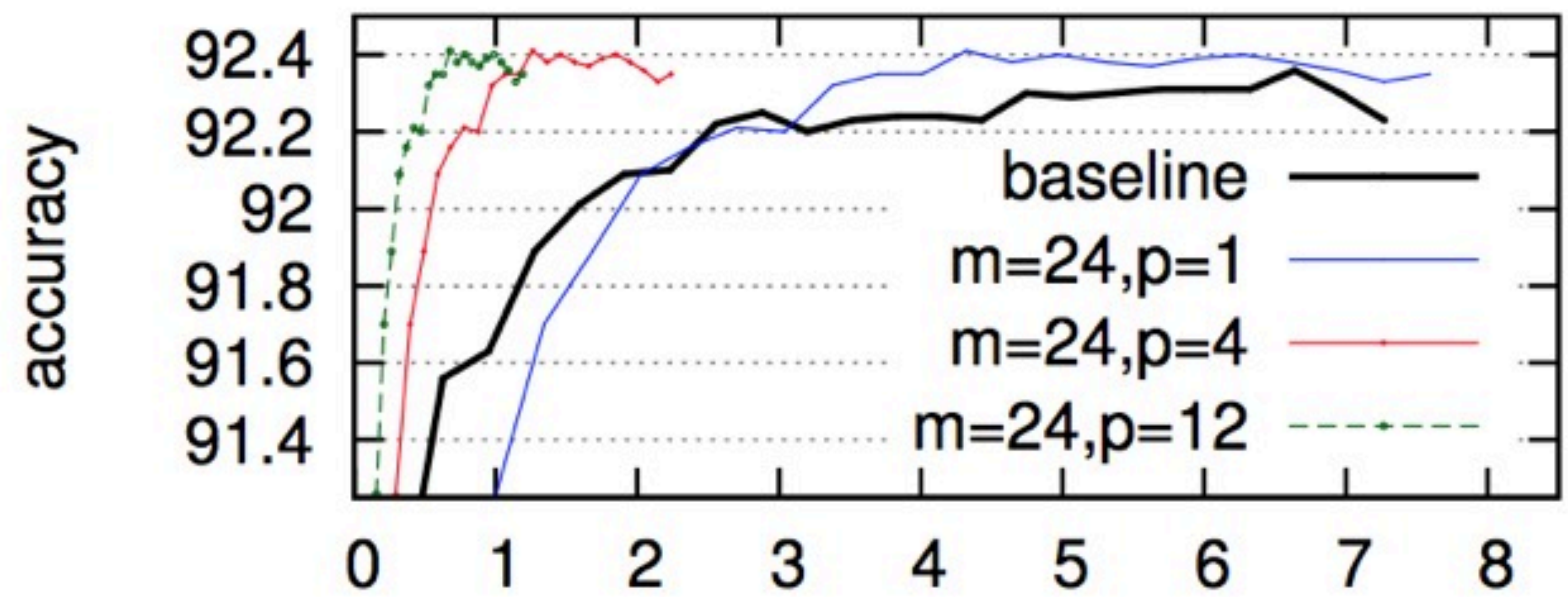
- beam search incremental parsing (Huang et al 2012) with MIRA
- minibatch learns better even in the serial setting (1 CPU)



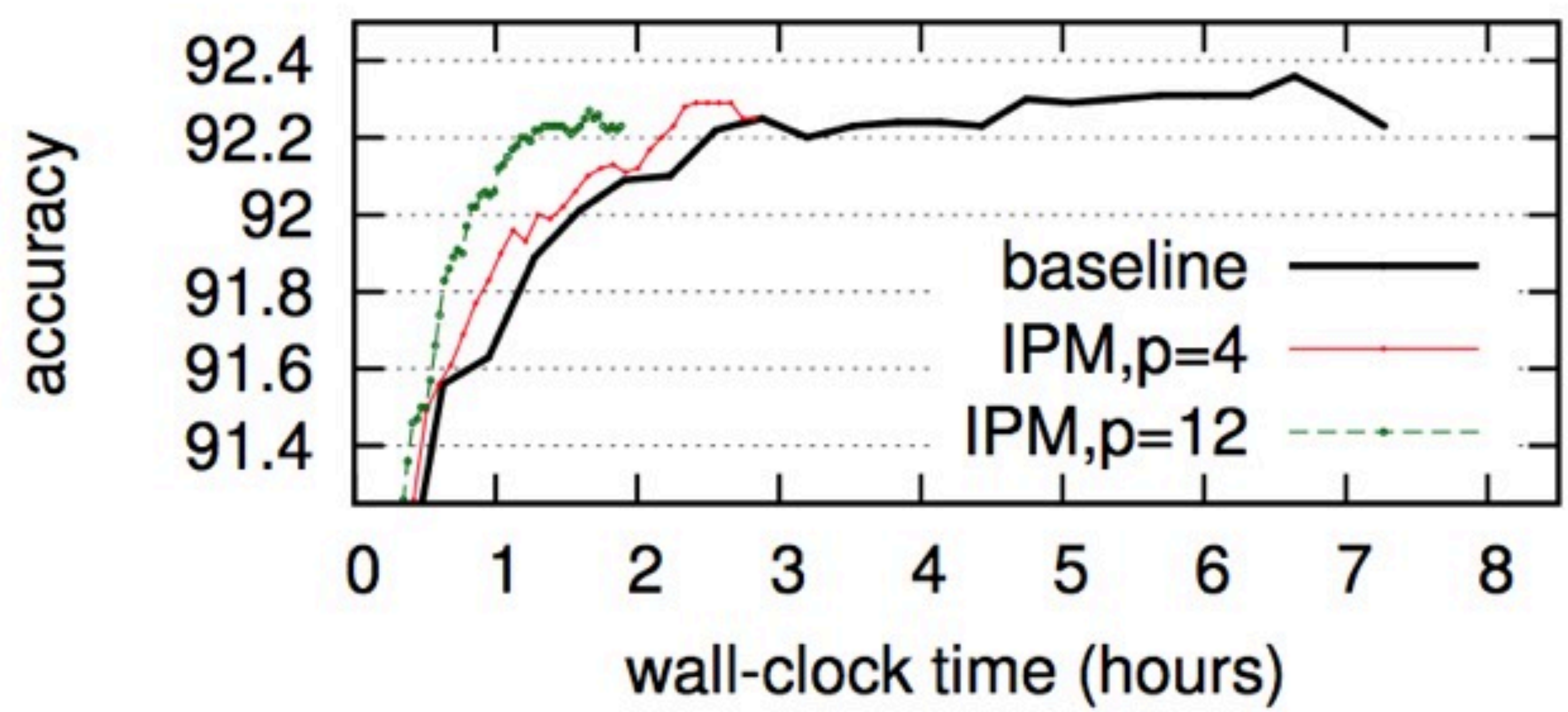
Parallelized Minibatch Faster than IPM

- minibatch is much faster than iterative parameter mixing

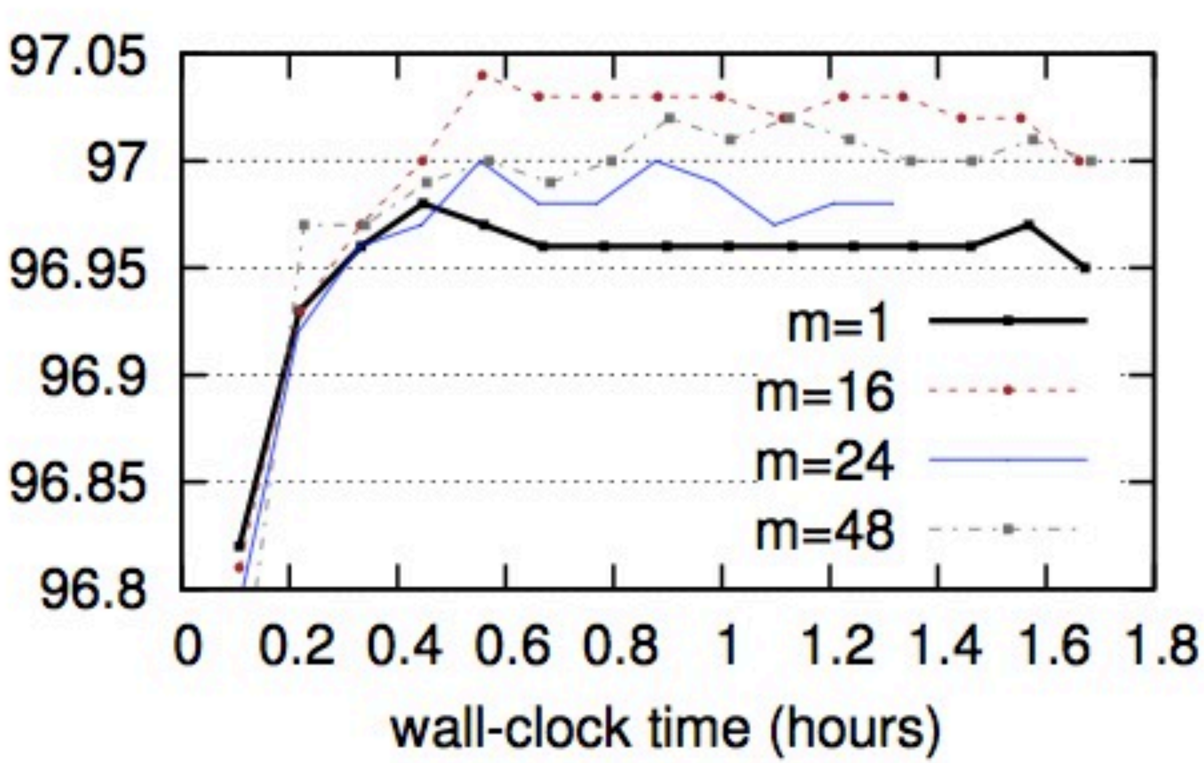
minibatch:
9x on 12 cores

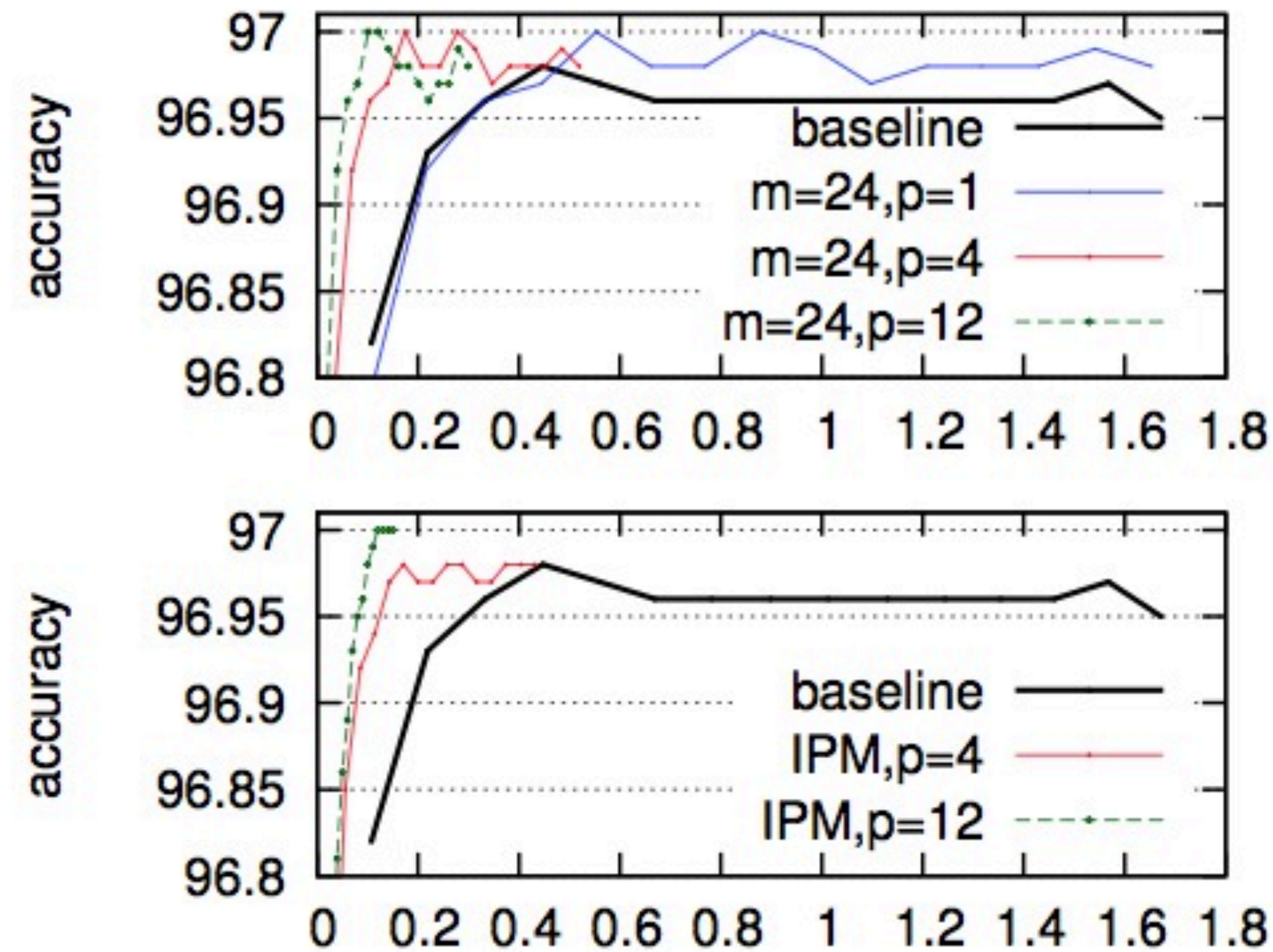


McDonald et al:
3x on 12 cores



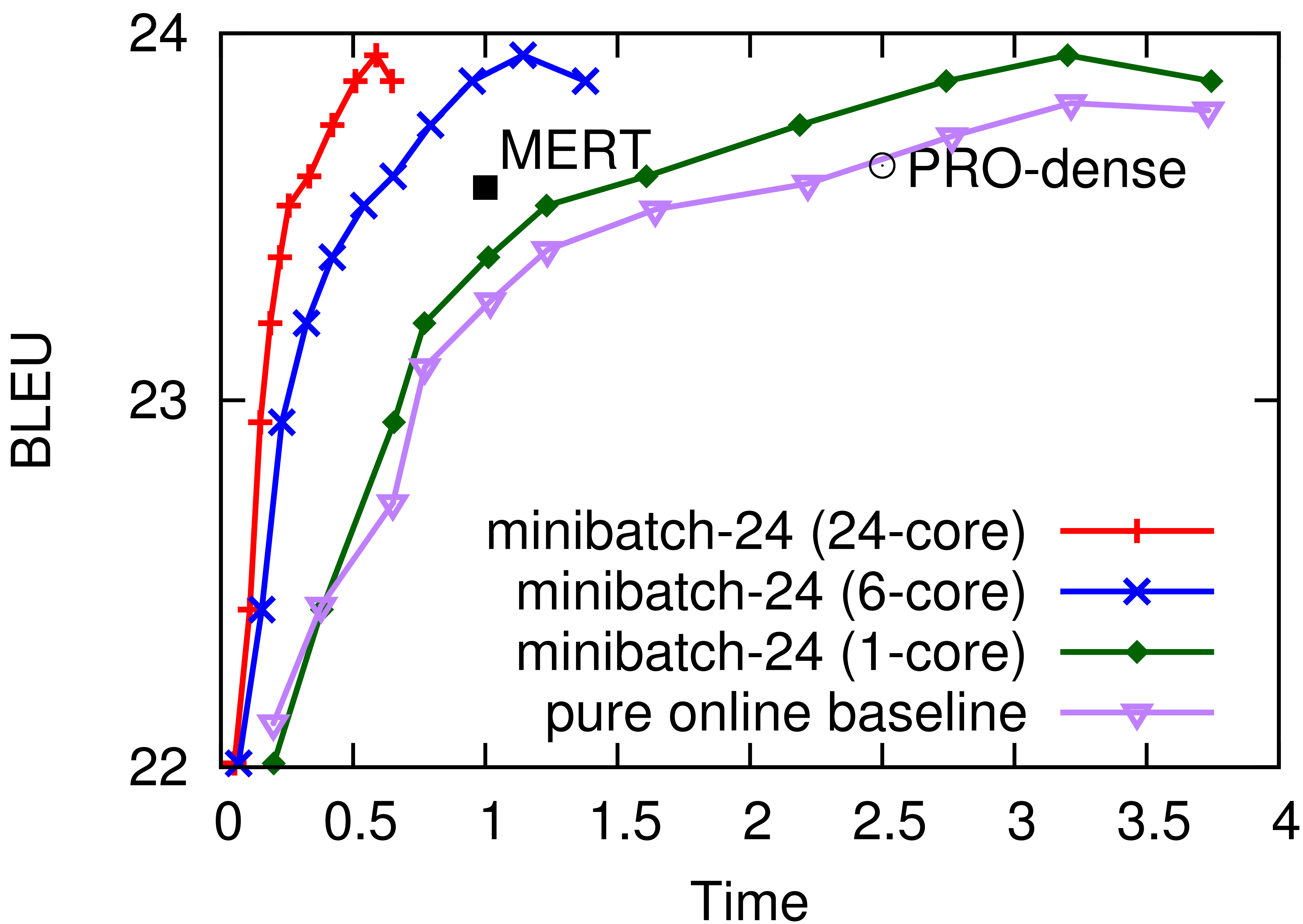
Experiment 2: Tagging (Perceptron)





Experiment 3: Machine Translation

- minibatch leads to 7x speedup on 24 cores



Roadmap of Techniques

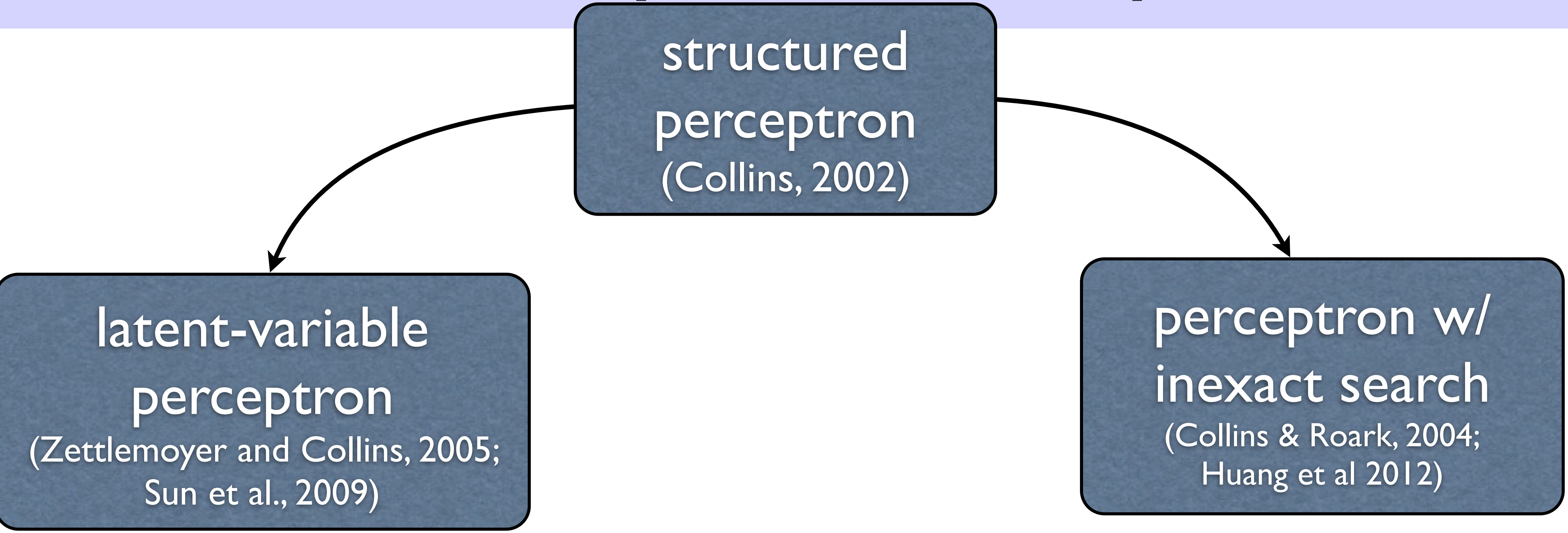
structured
perceptron
(Collins, 2002)

Roadmap of Techniques

structured perceptron
(Collins, 2002)

latent-variable perceptron
(Zettlemoyer and Collins, 2005; Sun et al., 2009)

Roadmap of Techniques



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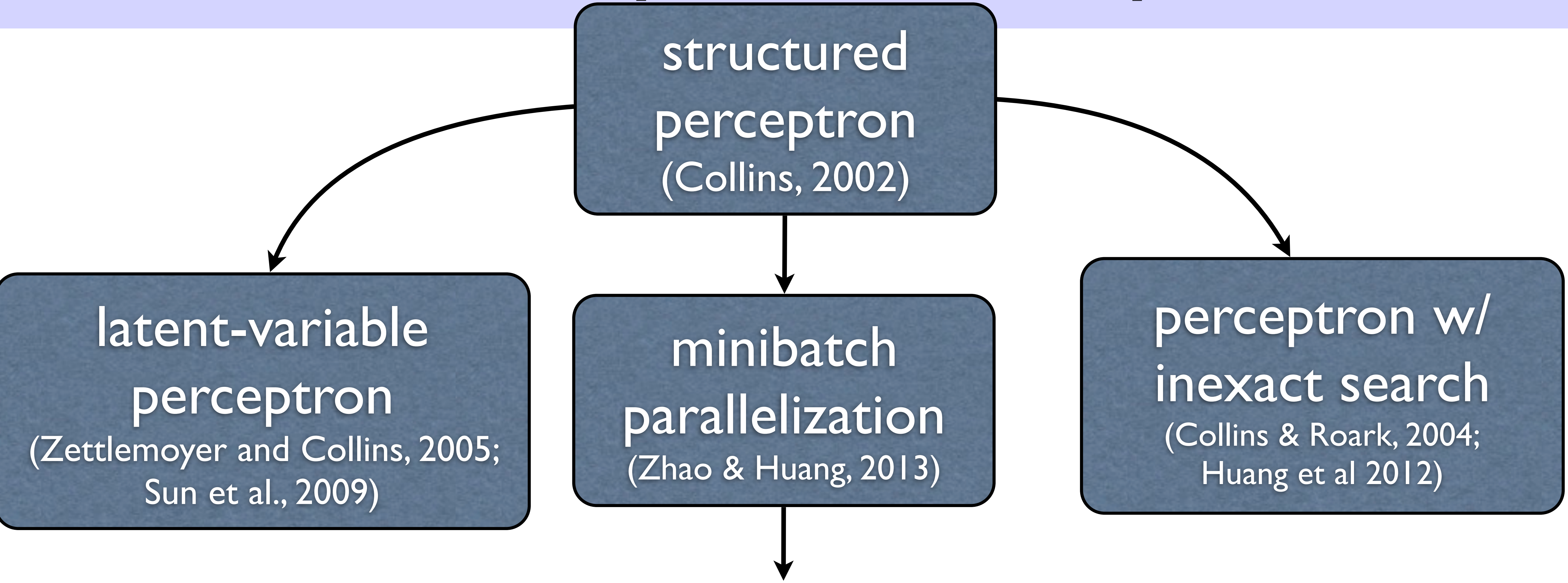

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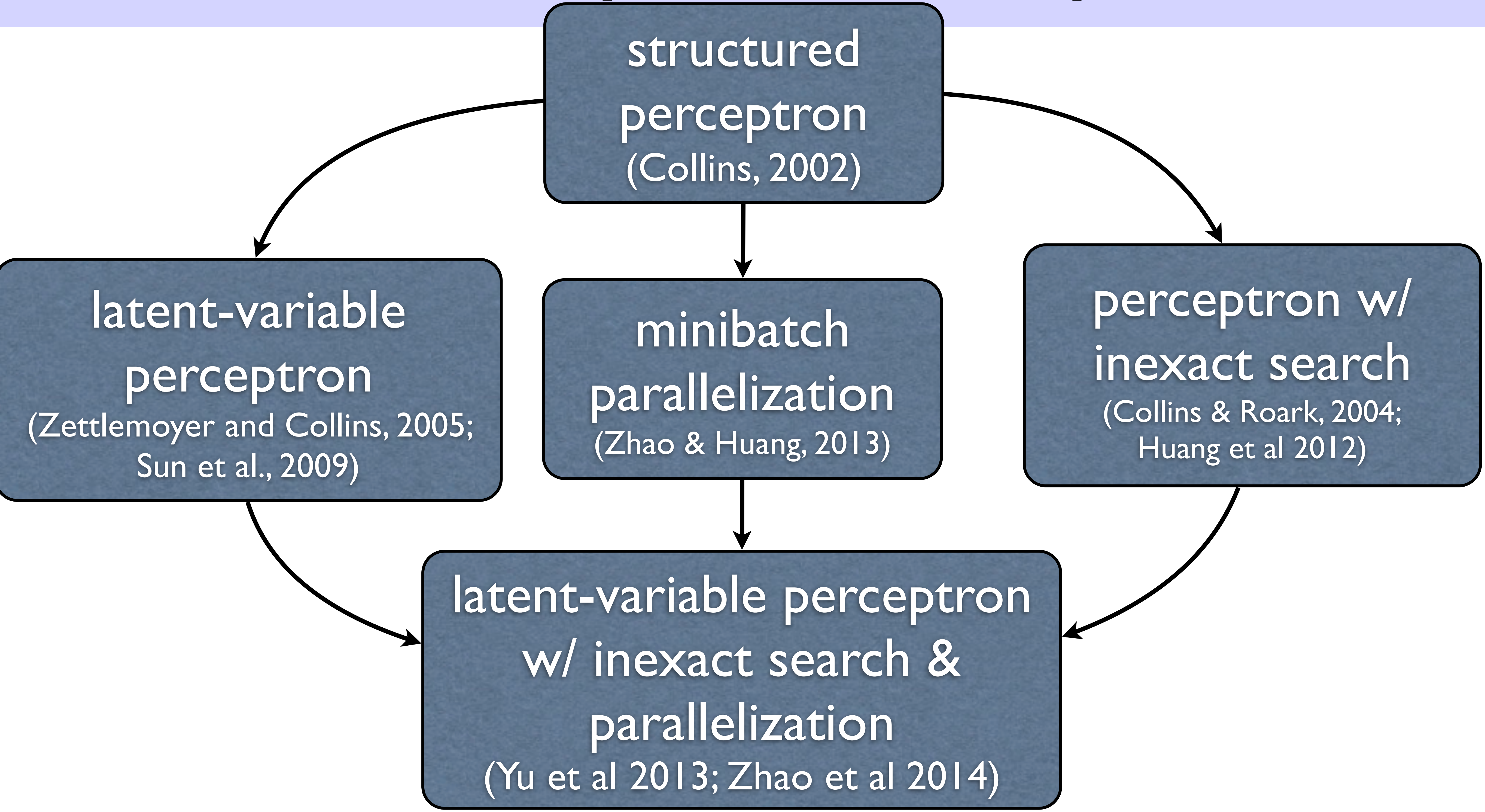

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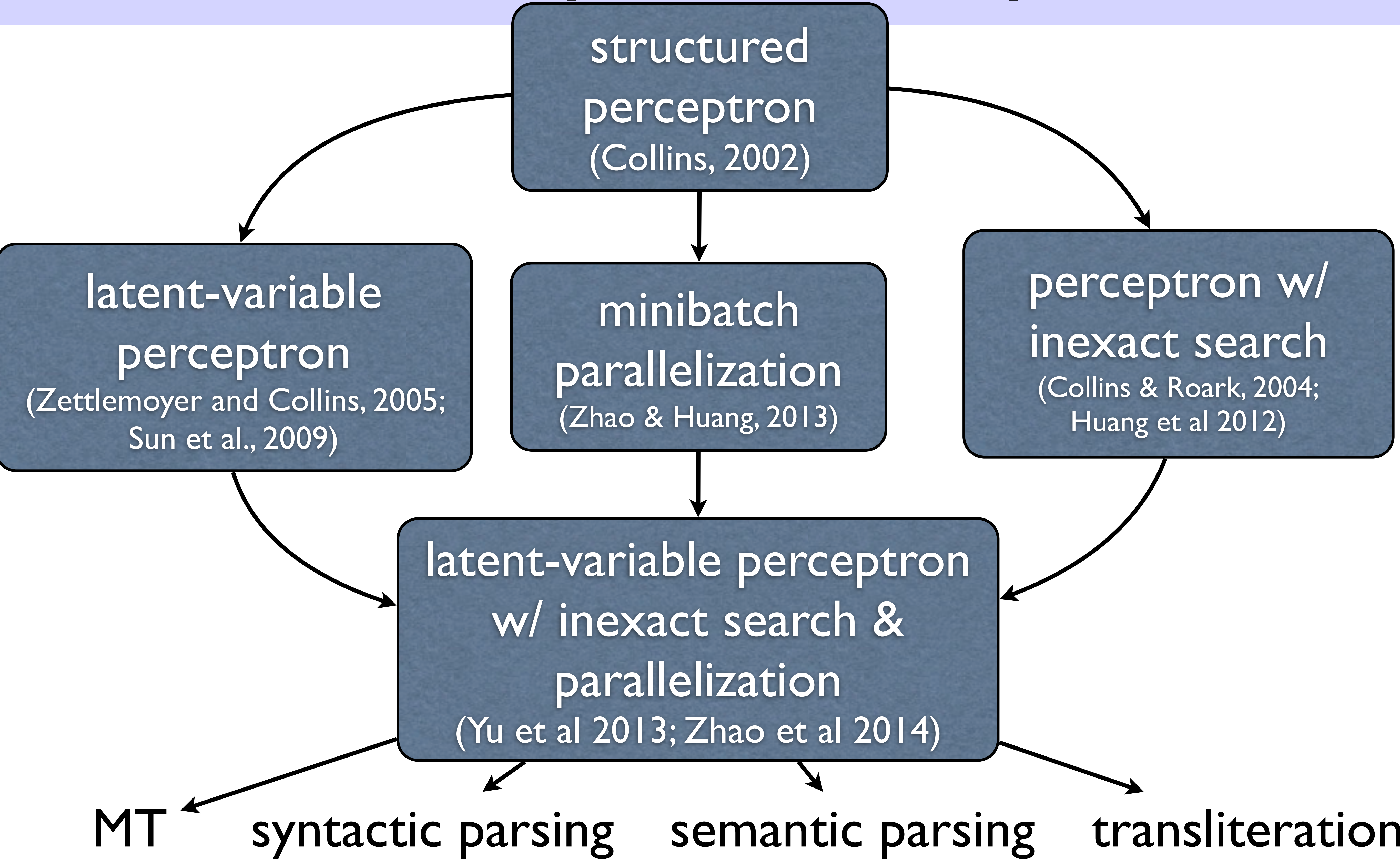

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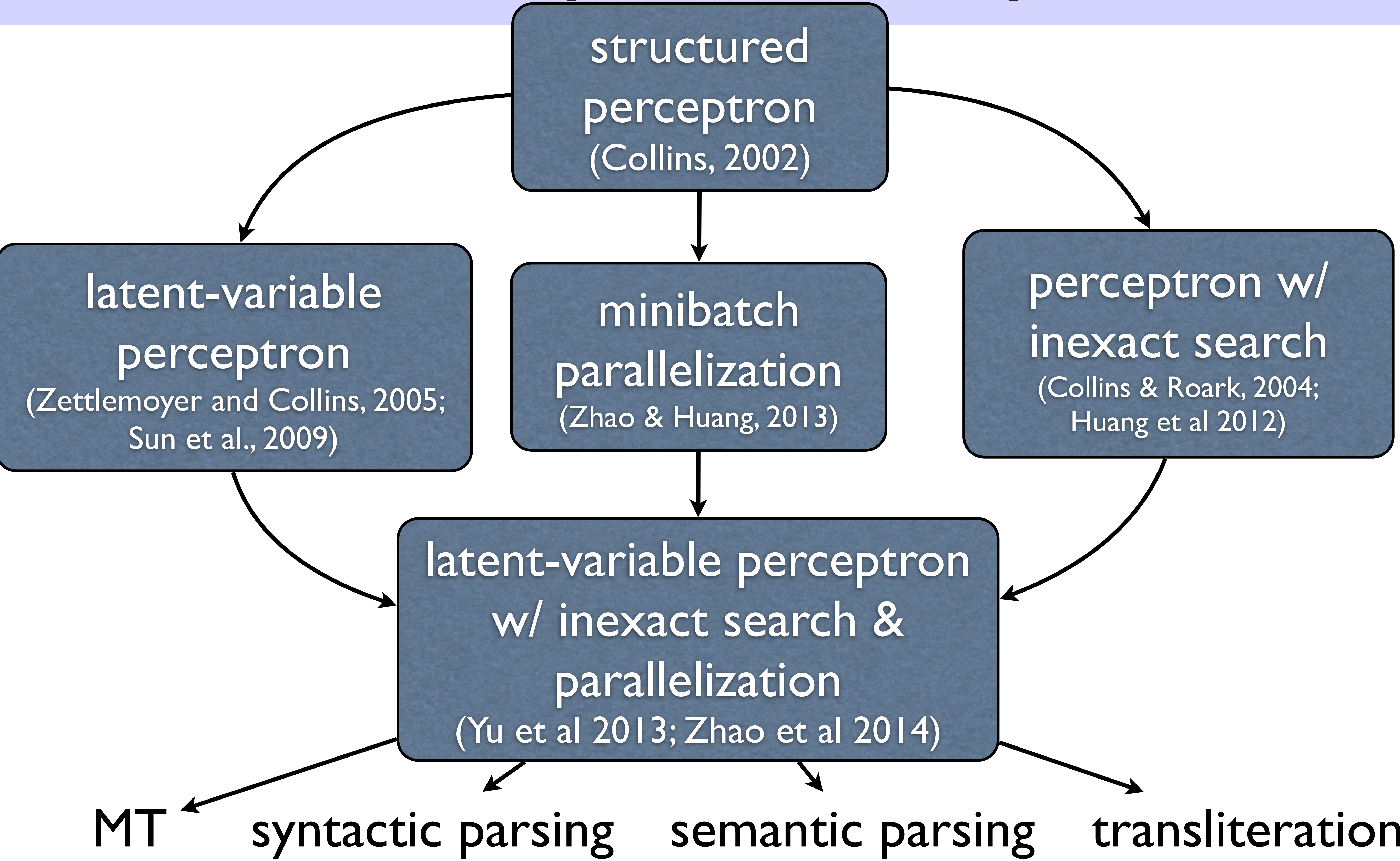

(Zhao et al 2014)

Final Conclusions

- online structured learning is simple and powerful
- search efficiency is the key challenge
- search errors do interfere with learning
  - but we can use violation-fixing perceptron w/ inexact search
- we can extend perceptron to learn latent structures
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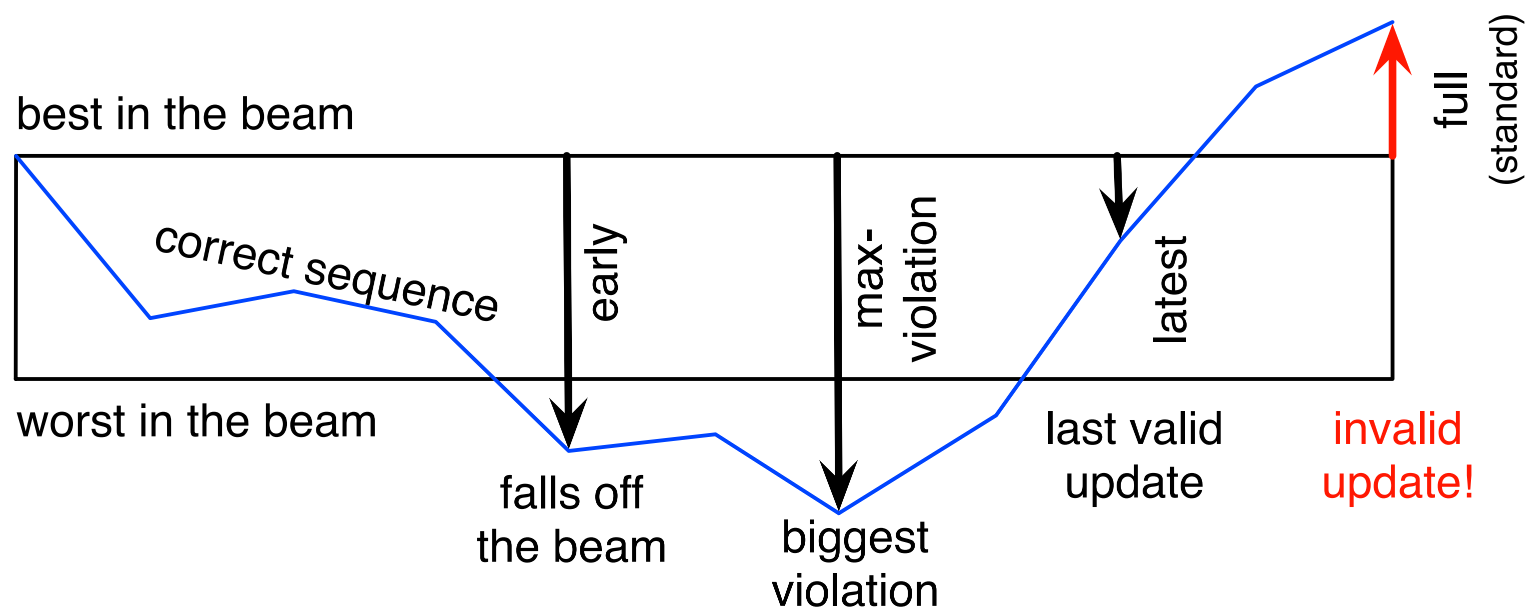

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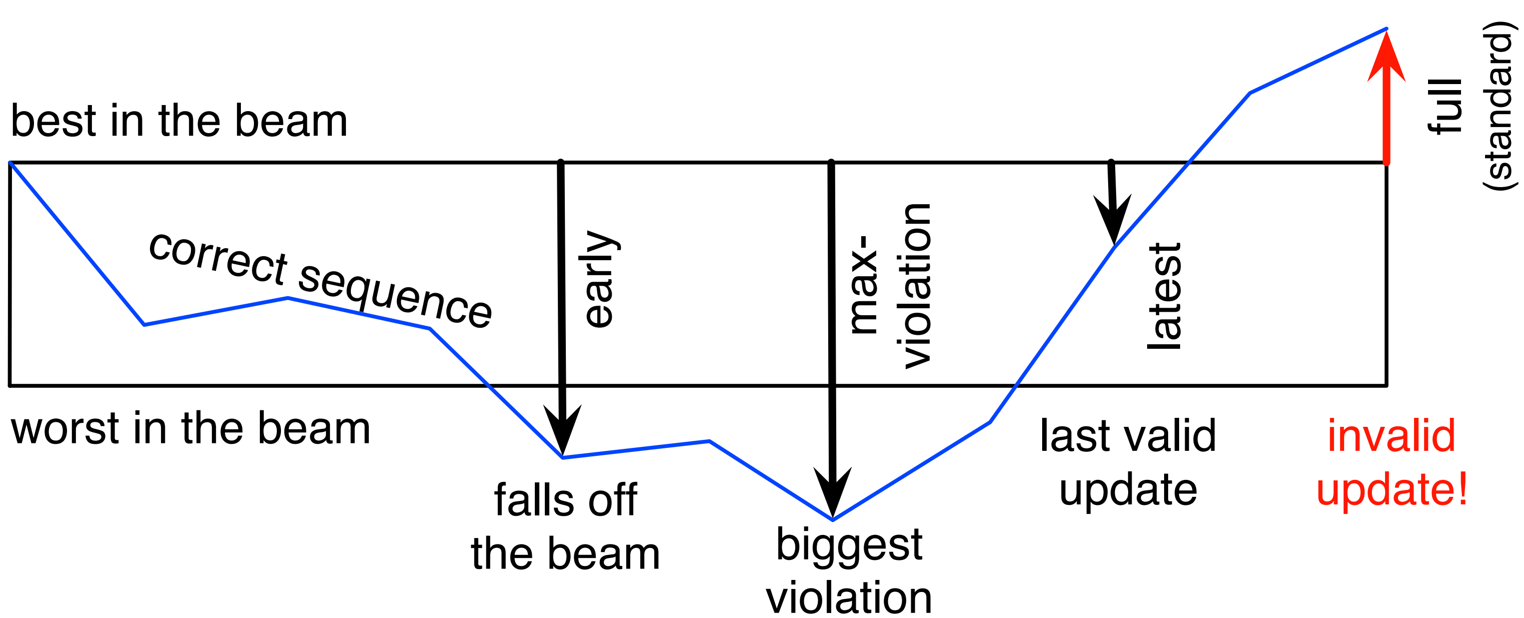

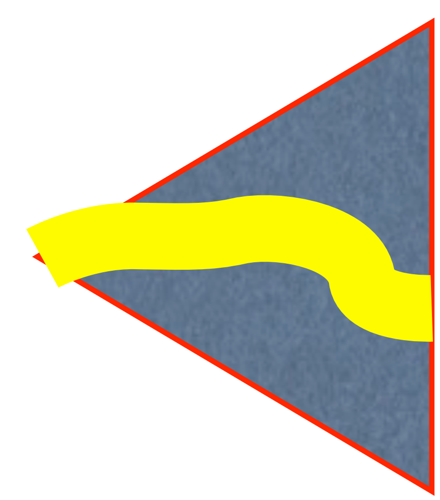

Annotated References (1)

- Binary Perceptron
  - original: Rosenblatt, 1959
  - convergence proof: Novikoff, 1962
- Multiclass Perceptron (and voted/average perceptron)
  - Freund and Schapire, 1999
- Structured Perceptron (and inexact search extensions)
  - original: Collins, 2002 (also contains generalization bounds; proofs mostly verbatim from Freund/Schapire, 1999)
  - early-update: Collins and Roark, 2004 (but no justification)
  - max-violation: Huang et al, 2012 (also defines violation-fixing perceptron framework, where early/max-violation are instances)
  - hypergraph inexact search: Zhang et al, 2013 (CKY-style parsing)

Annotated References (2)

- Latent Variable Perceptron (and inexact search extensions)
  - semantic parsing: Zettlemoyer and Collins, 2005
  - machine translation: Liang et al, 2006
  - separability condition: Sun et al, 2009
  - inexact search: Yu et al, 2013
  - hiero w/ inexact search: Zhao et al, 2014
- MIRA
  - 1-best MIRA: Crammer and Singer, 2003
  - *k*-best MIRA: McDonald et al, 2005

Annotated References (3)

- Parallelizing Online Learning
  - iterative parameter mixing: McDonald et al, 2010
  - minibatch: Zhao and Huang, 2013
- Other References
  - CRF: Lafferty et al, 2001
  - M^3N (structured SVM): Taskar et al, 2003
  - LaSO: Daumé and Marcu, 2005
  - averaging trick: Daumé, 2006, Ph.D. thesis