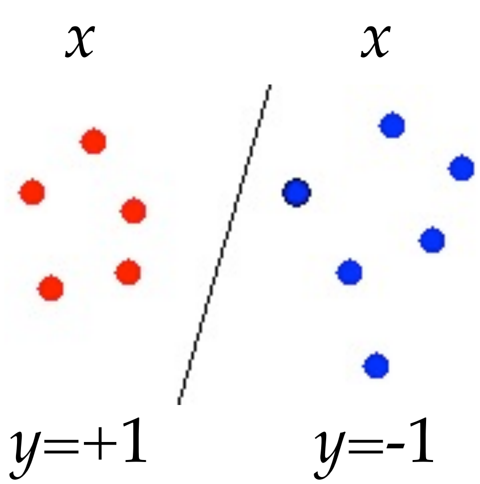
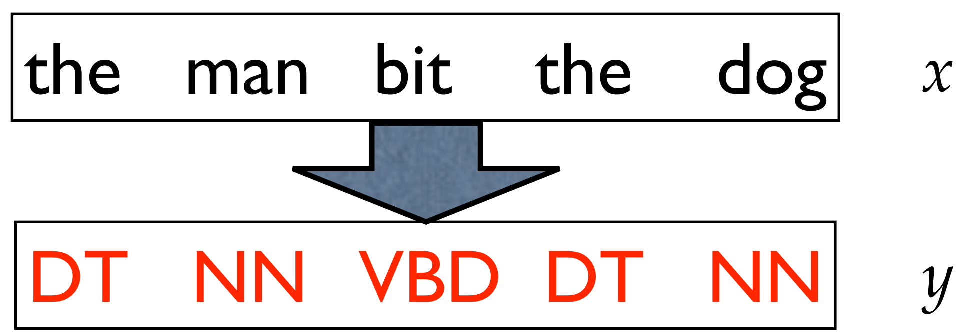
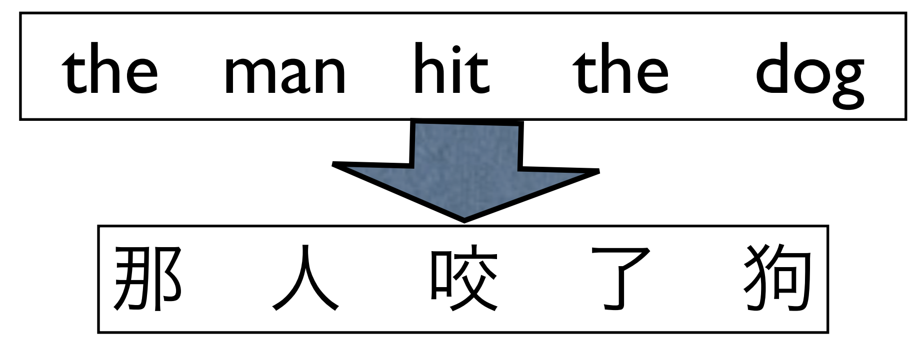
Structured Learning with Inexact Search







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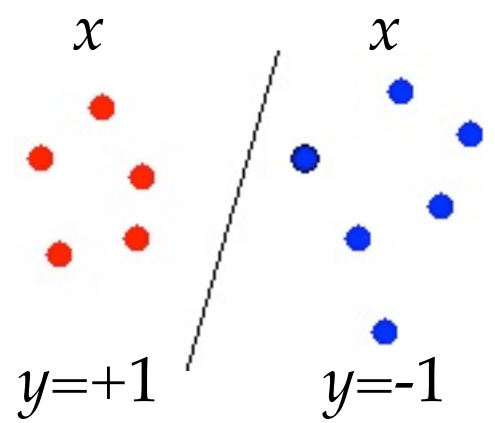
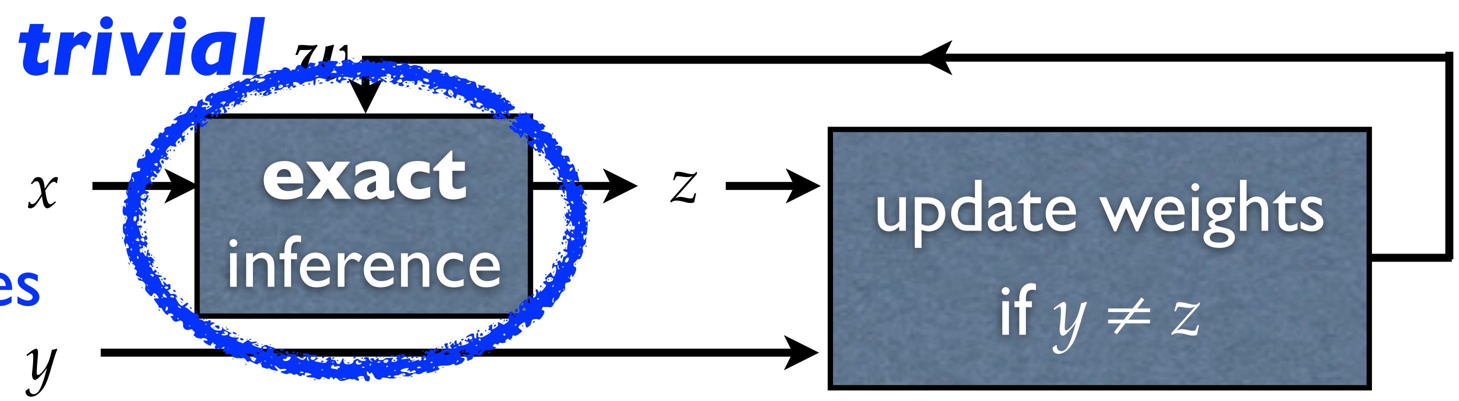
includes joint work with S. Phayong, Y. Guo, and K. Zhao

Structured Perceptron (Collins 02)

binary classification

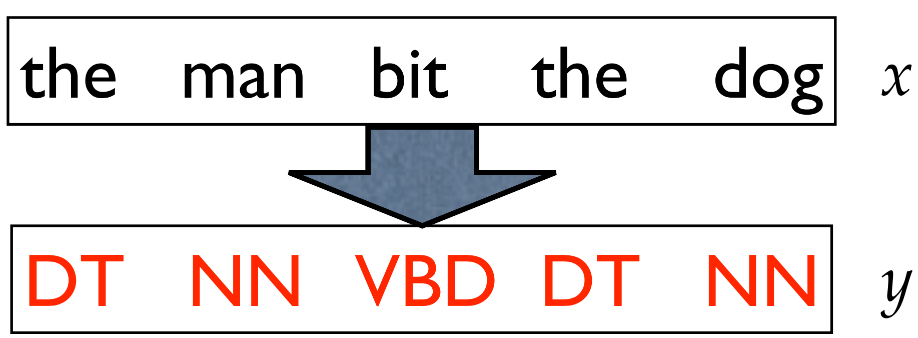


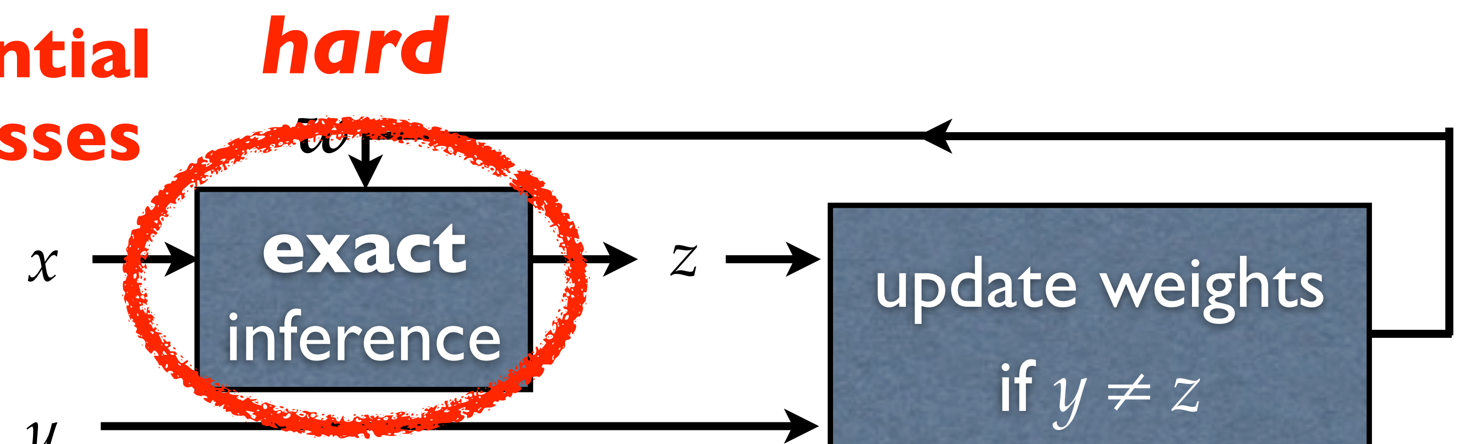
constant
# of classes



structured classification

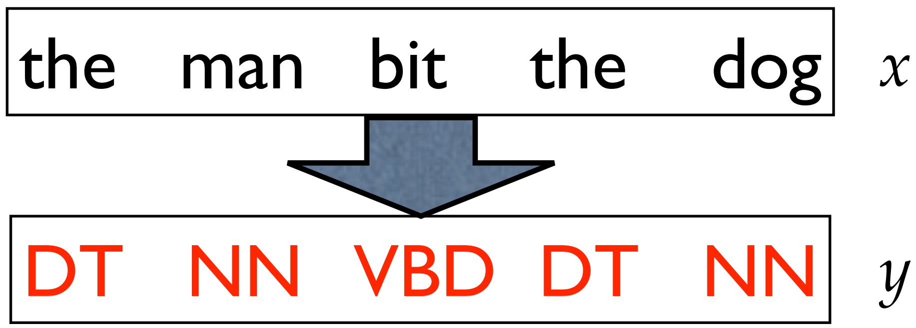
exponential
# of classes

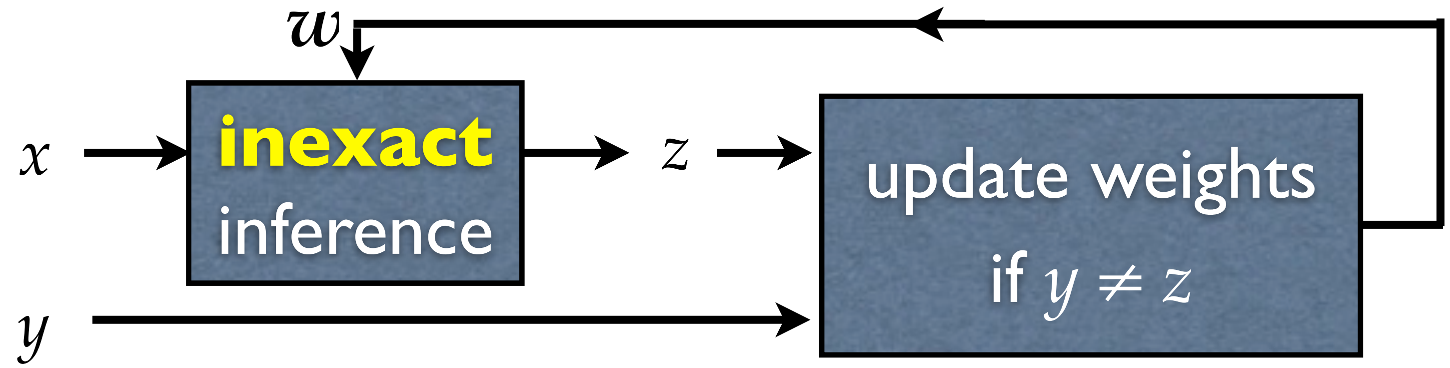


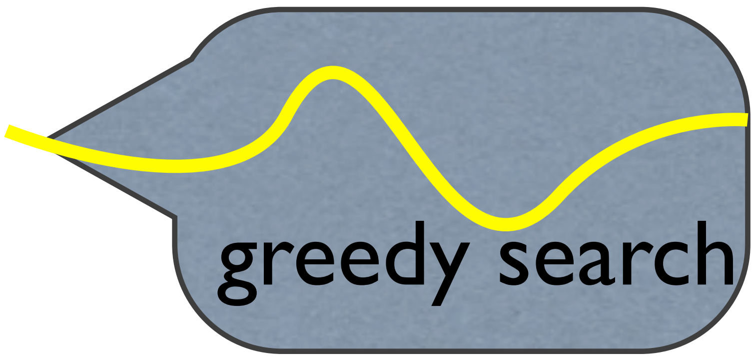


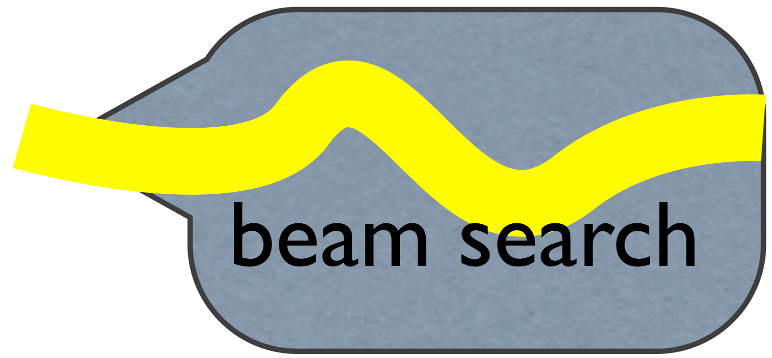
- challenge: search efficiency (exponentially many classes)
  - often use dynamic programming (DP)
  - but still too slow for repeated use, e.g. parsing is $O(n^3)$
  - and can't use non-local features in DP

Perceptron w/ Inexact Inference





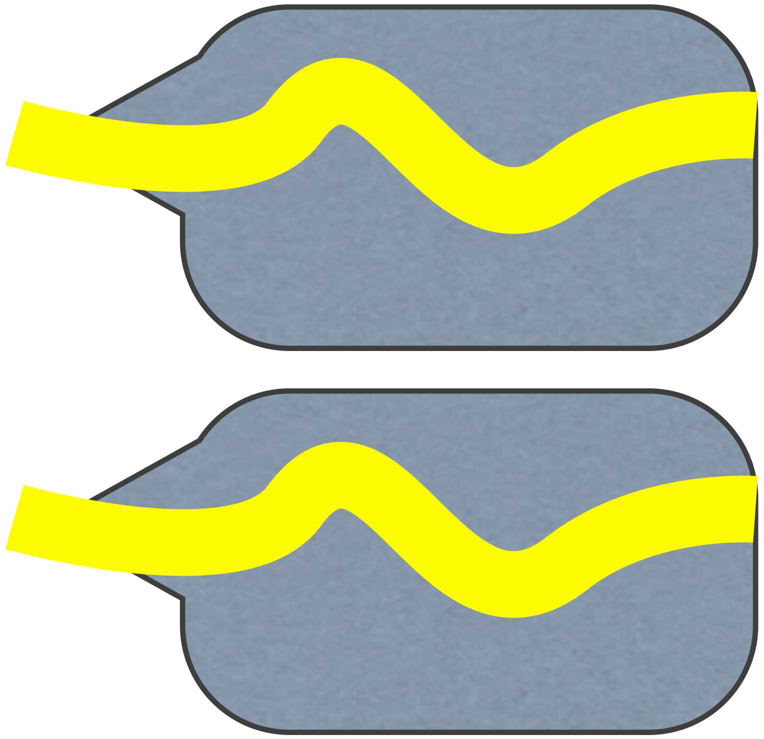


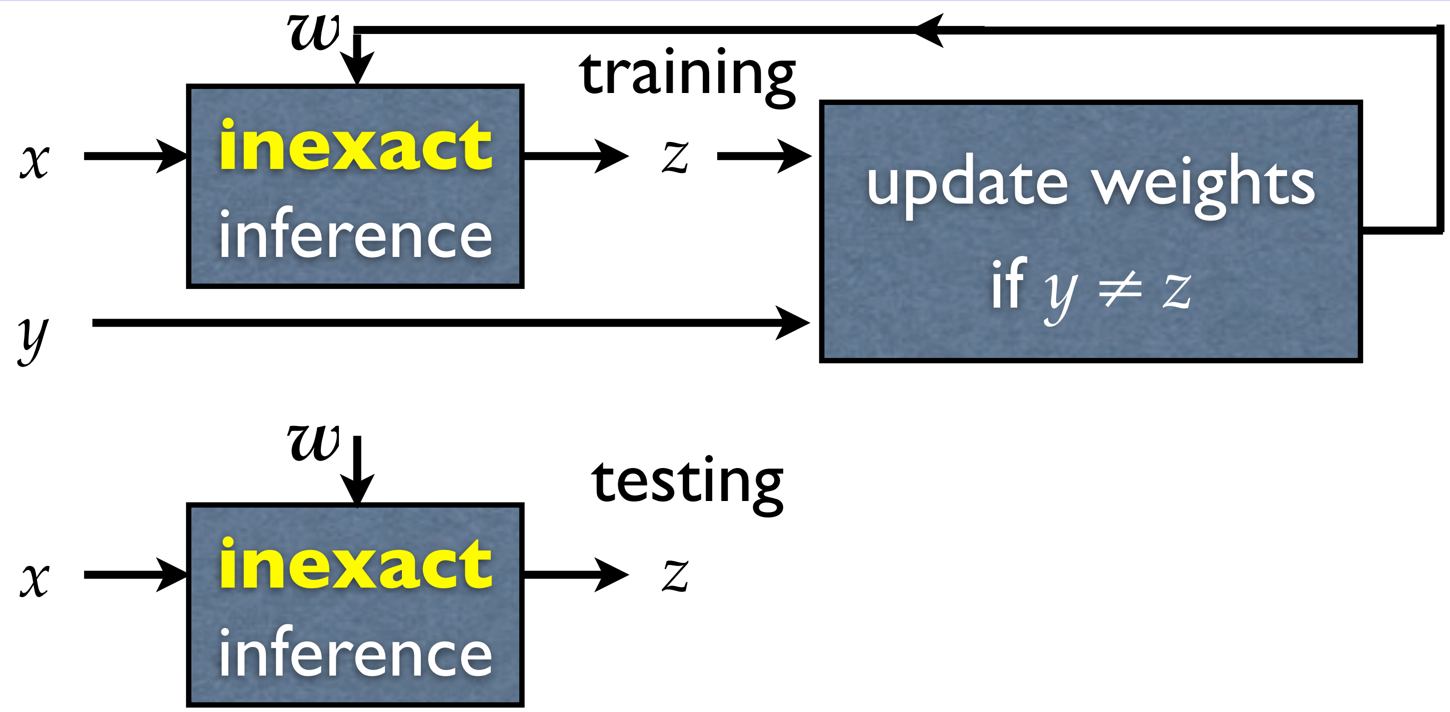


does it still work???

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

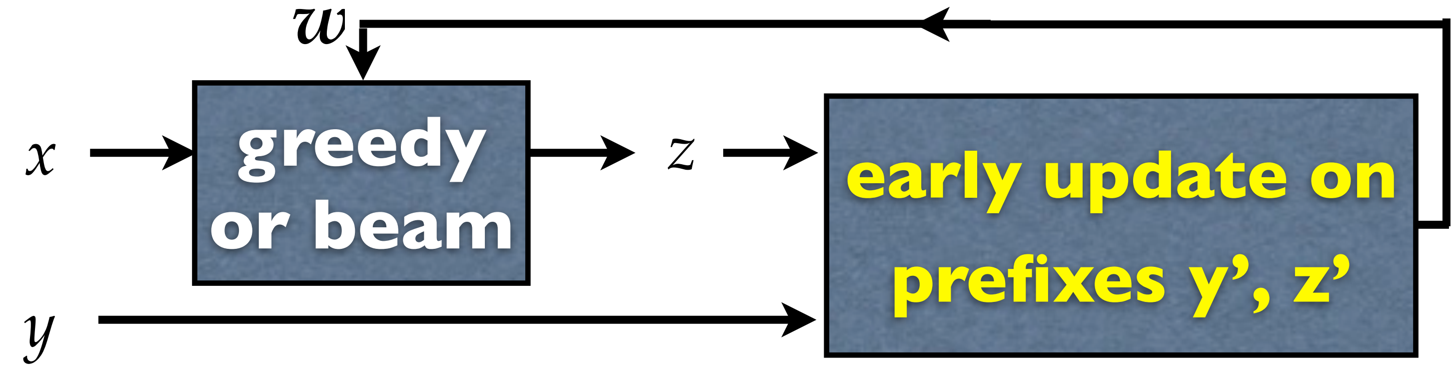
Idea: Search-Error-Robust Model





- train a "search-specific" or "search-error-robust" model
  - we assume the same "search box" in training and testing
  - model should "live with" search errors from search box
- exact search => convergence; greedy => no convergence
  - how can we make perceptron converge w/ greedy search?

Our Contributions



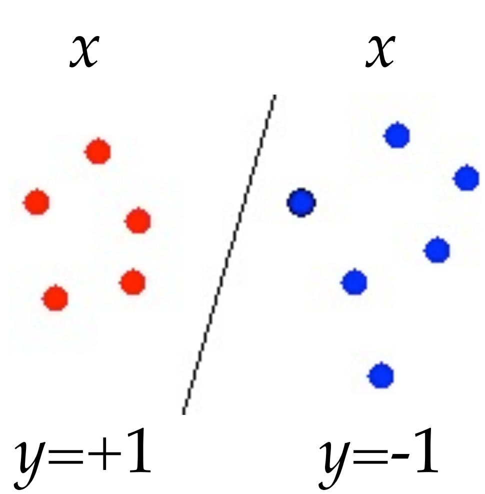
- theory: a framework for perceptron w/ inexact search
  - explains previous work (early update etc) as special cases
- practice: new update methods within the framework
  - converges faster and better than early update
  - real impact on state-of-the-art parsing and tagging
  - more advantageous when search error is severer

In this talk...

- Motivations: Structured Learning and Search Efficiency
- Structured Perceptron and Inexact Search
  - perceptron does not converge with inexact search
  - early update (Collins/Roark '04) seems to help; but why?
- New Perceptron Framework for Inexact Search
  - explains early update as a special case
  - convergence theory with *arbitrarily* inexact search
  - new update methods within this framework
- Experiments

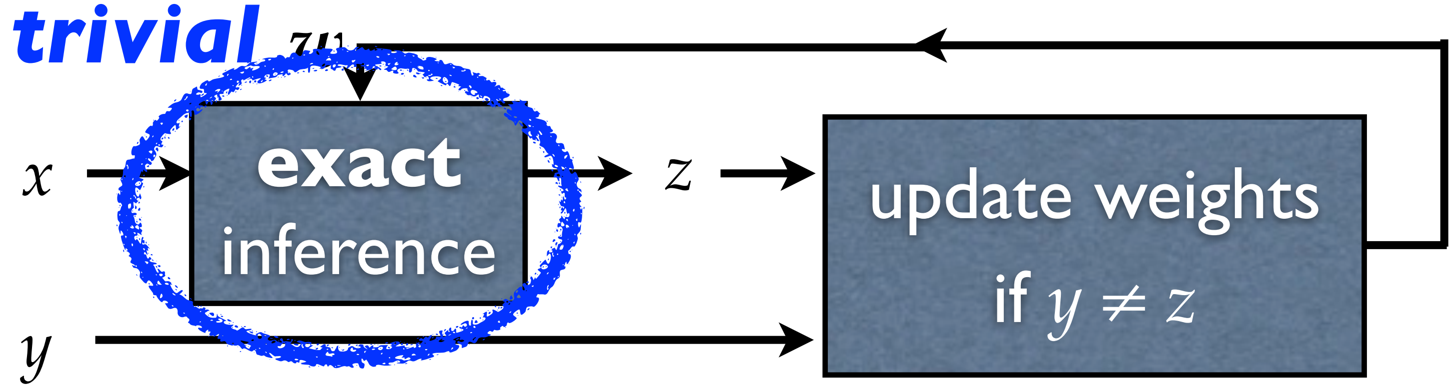
Structured Perceptron (Collins 02)

- simple generalization from binary/multiclass perceptron
- online learning: for each example (x, y) in data
  - inference: find the best output z given current weight w
  - update weights when if y ≠ z



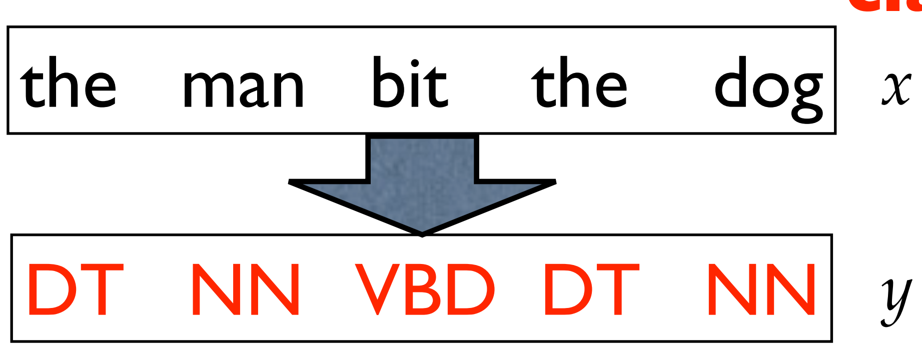
constant classes

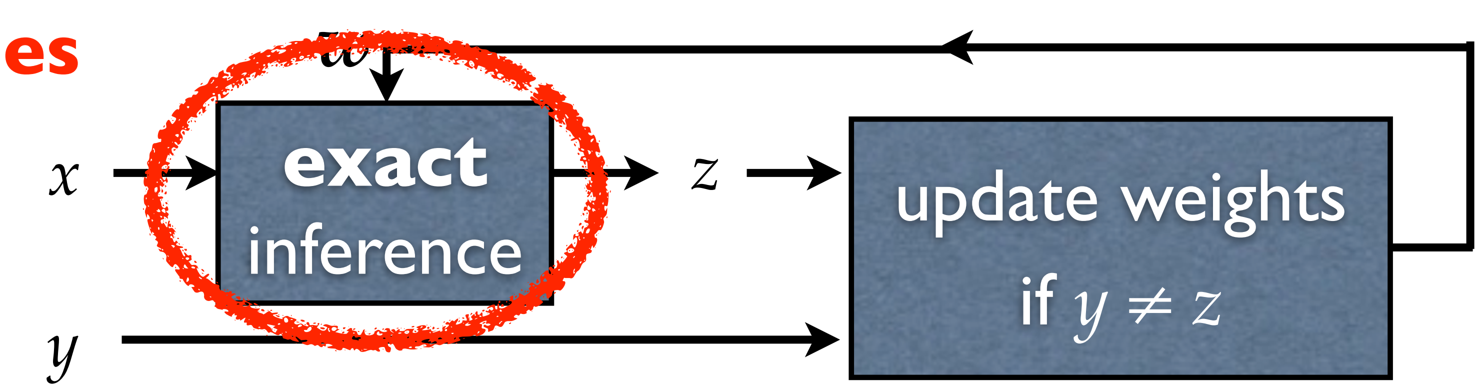
trivial



exponential classes

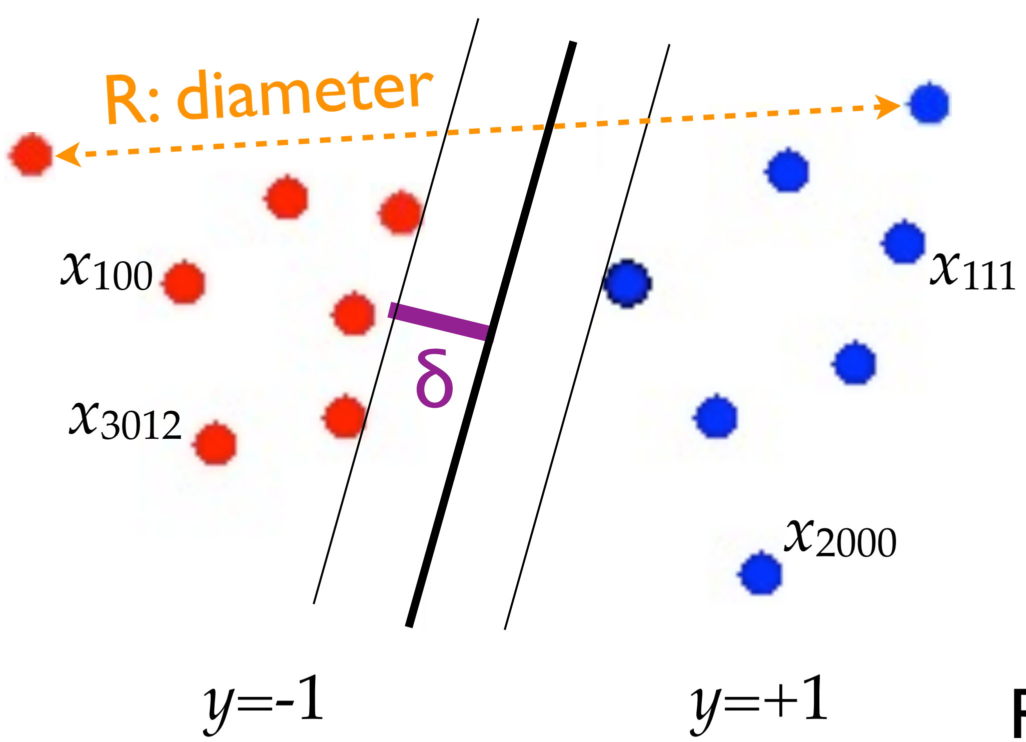
hard



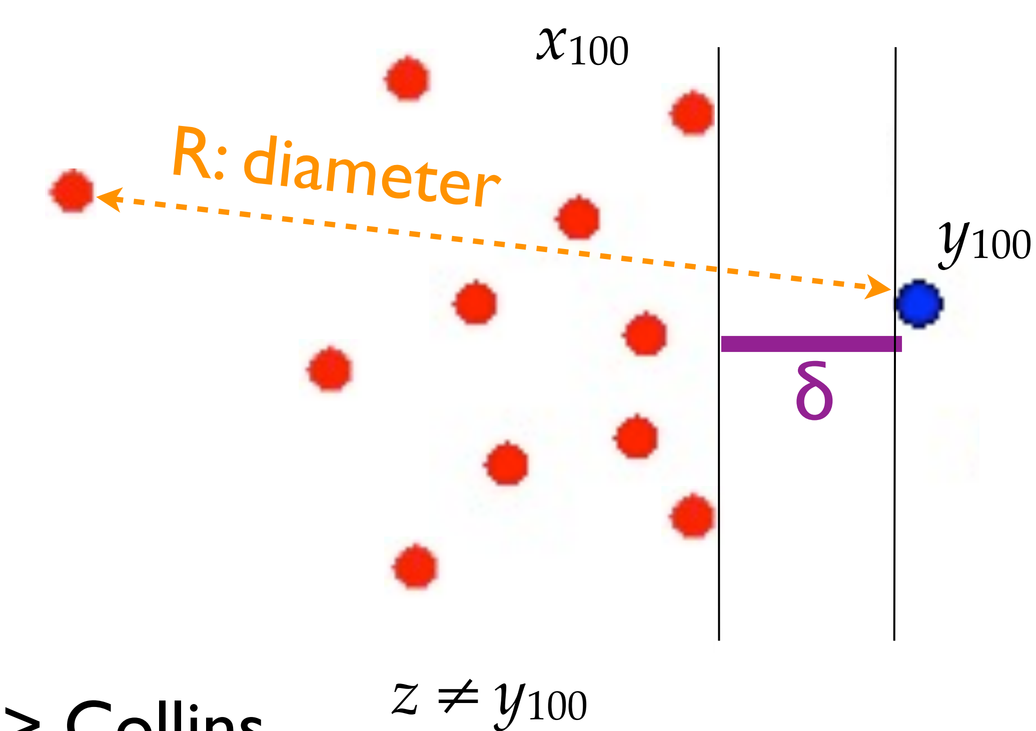


Convergence with Exact Search

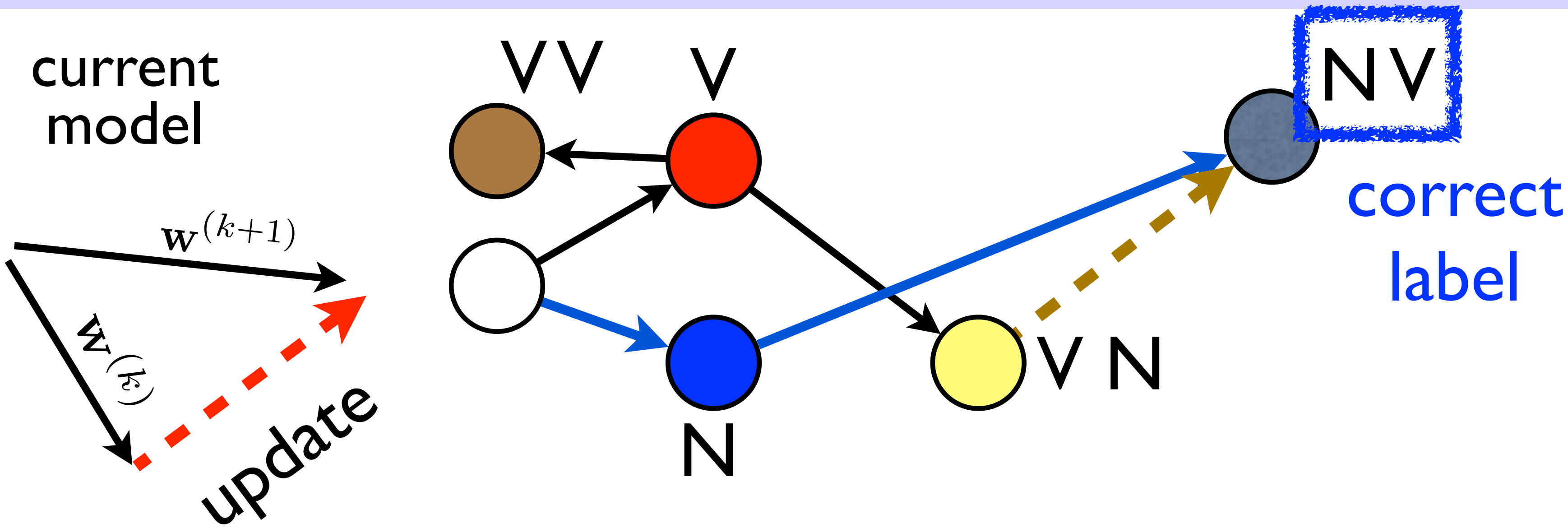
- linear classification: converges iff. data is separable
- structured: converges iff. data separable & search exact
  - there is an oracle vector that correctly labels all examples
  - one vs the rest (correct label better than all incorrect labels)
- theorem: if separable, then **# of updates ≤ R^2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



Rosenblatt => Collins
1957 2002



Convergence with Exact Search



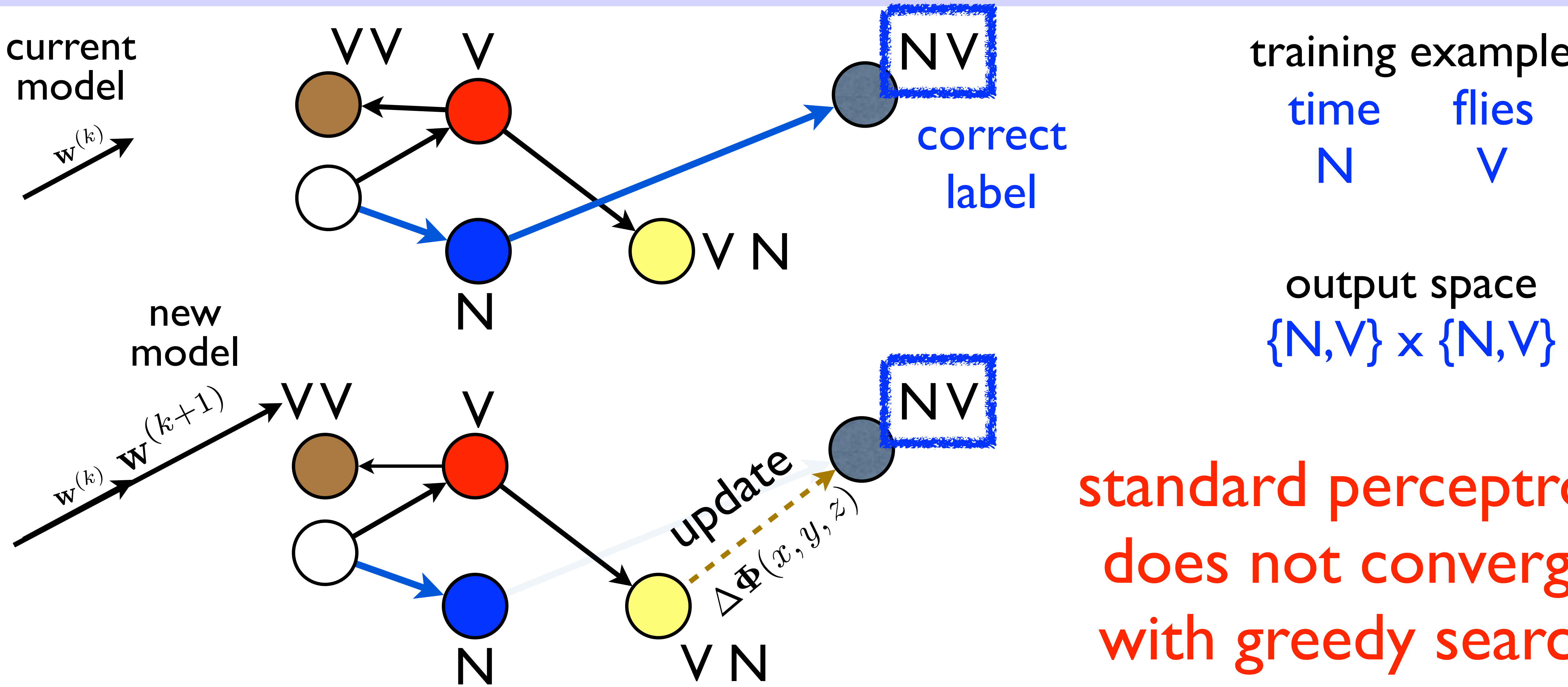
training example

time	flies
N	V

output space
{N,V} x {N,V}

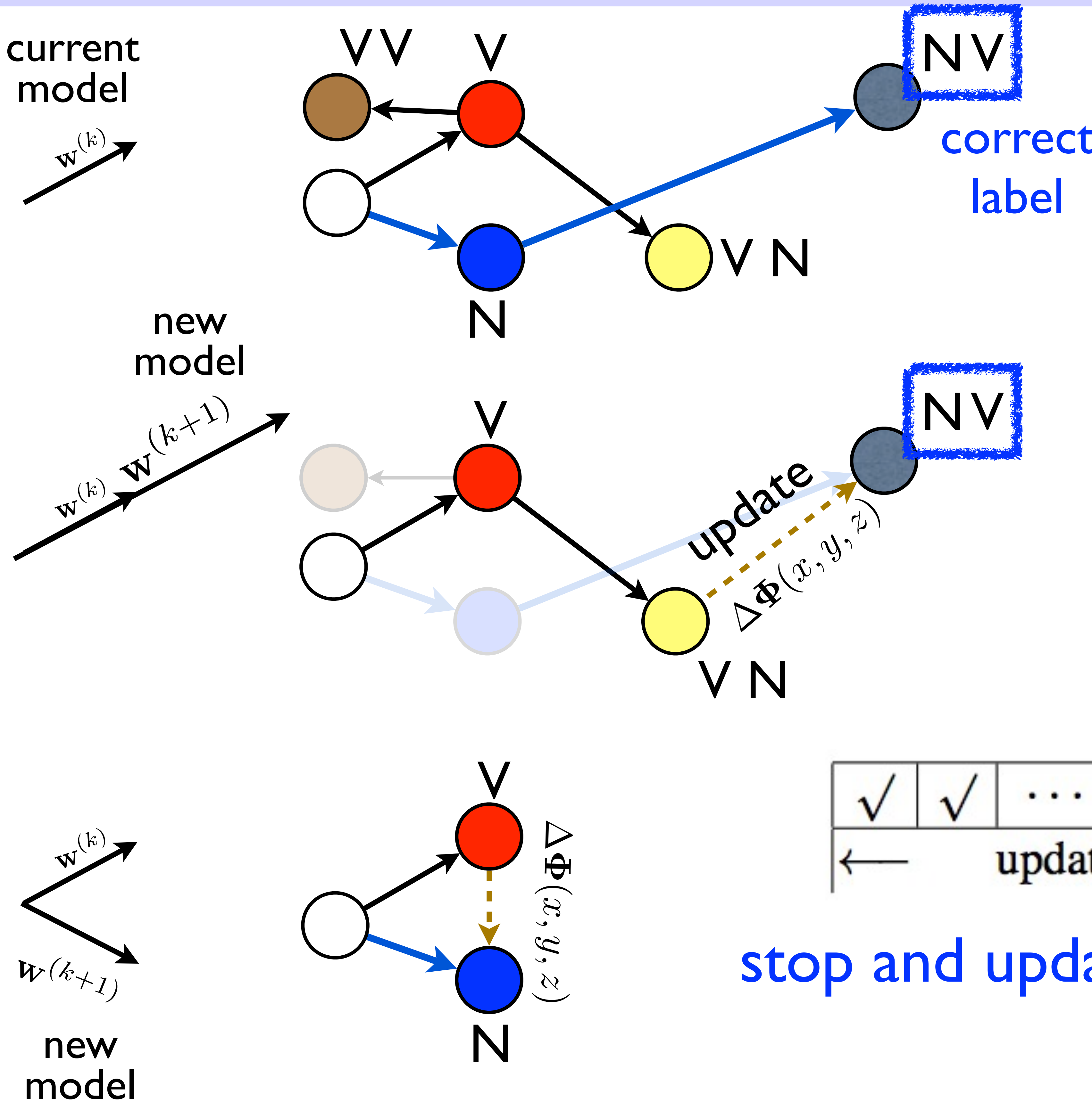
standard perceptron converges with exact search

No Convergence w/ Greedy Search



standard perceptron does not converge with greedy search

Early update (Collins/Roark 2004) to rescue



training example

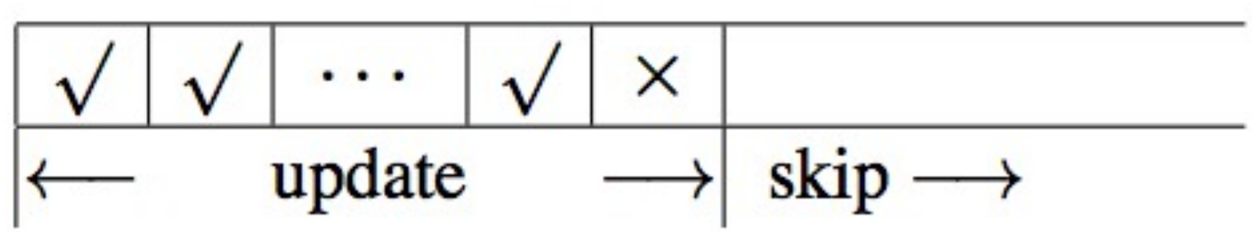
time flies

N V

output space

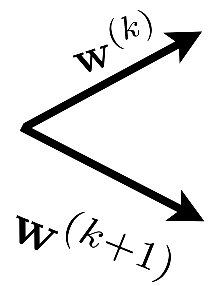
{N,V} x {N,V}

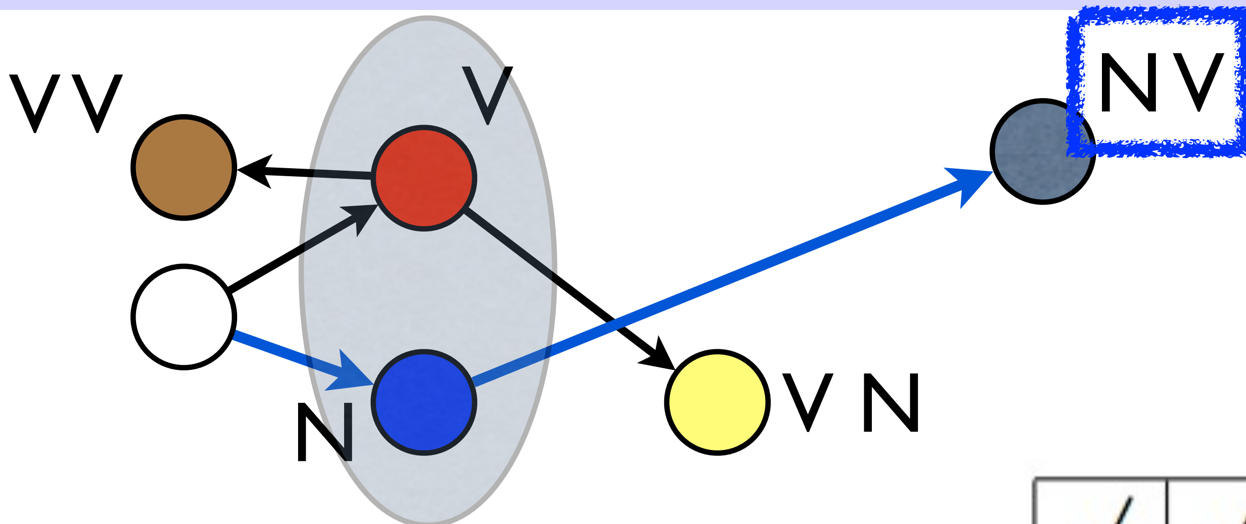
standard perceptron does not converge with greedy search

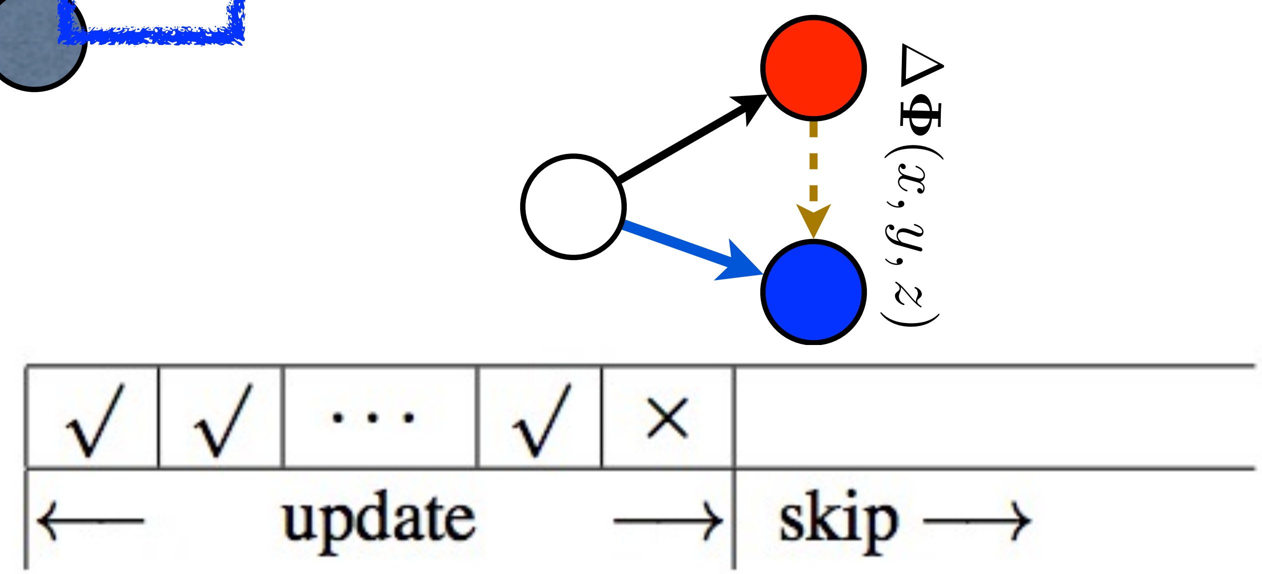


stop and update at the first mistake

Why?



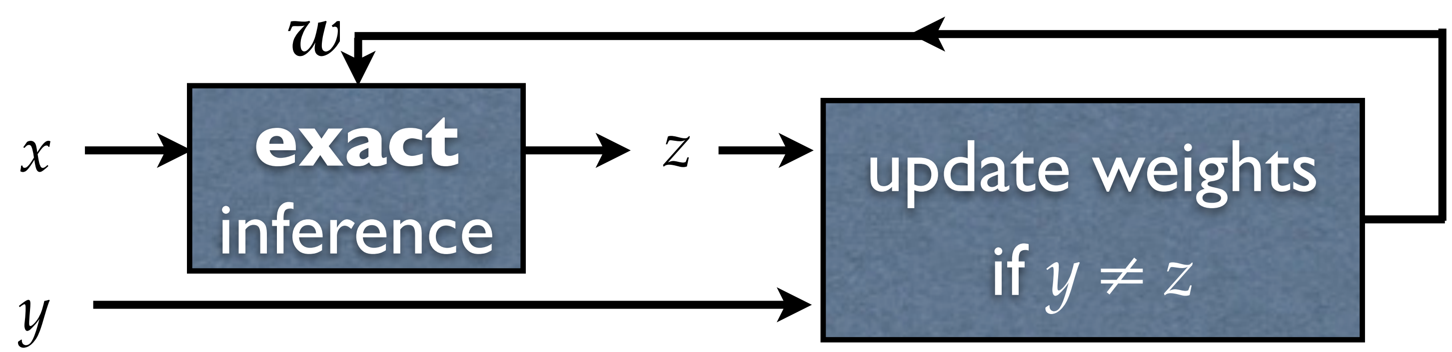


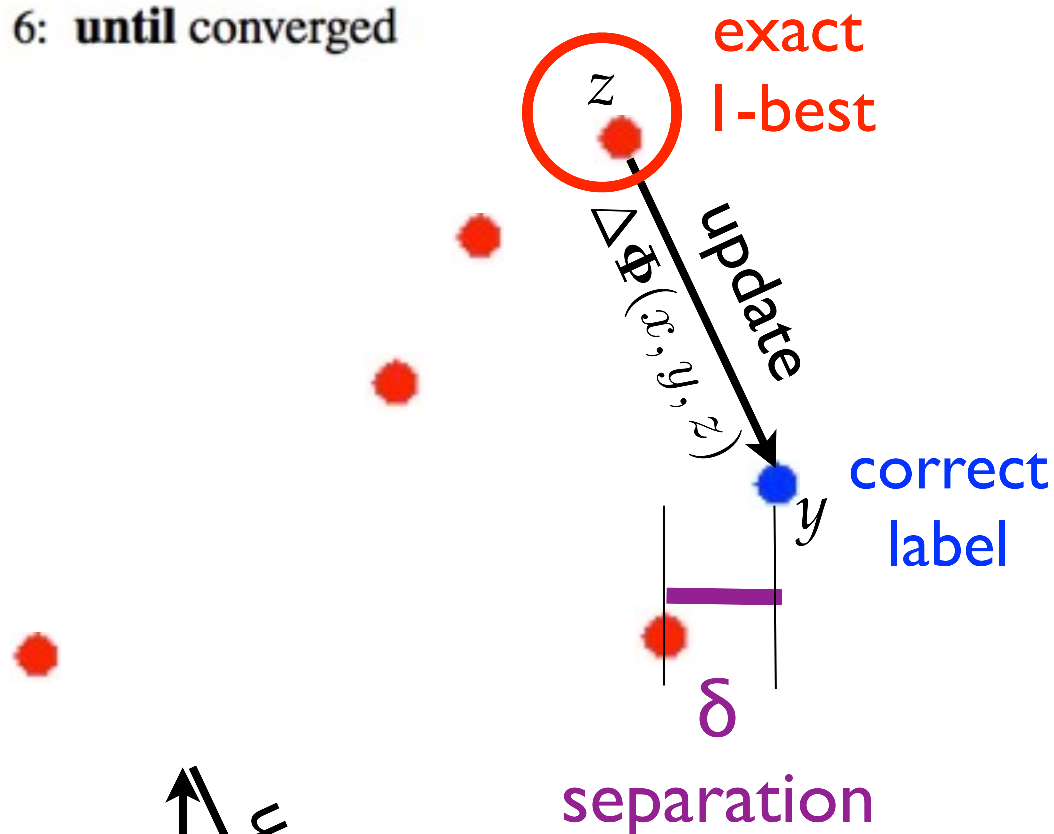


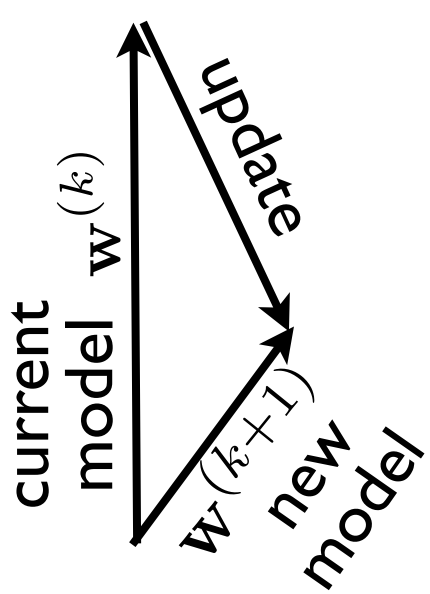
- why does inexact search break convergence property?
  - what is required for convergence? exactness?
- why does early update (Collins/Roark 04) work?
  - it works well in practice and is now a standard method
  - but there has been no theoretical justification
- we answer these Qs by inspecting the convergence proof

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**
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\mathbf{\Phi}(x, y, z)$
until converged







unit oracle
vector **u**

perceptron update:

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

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

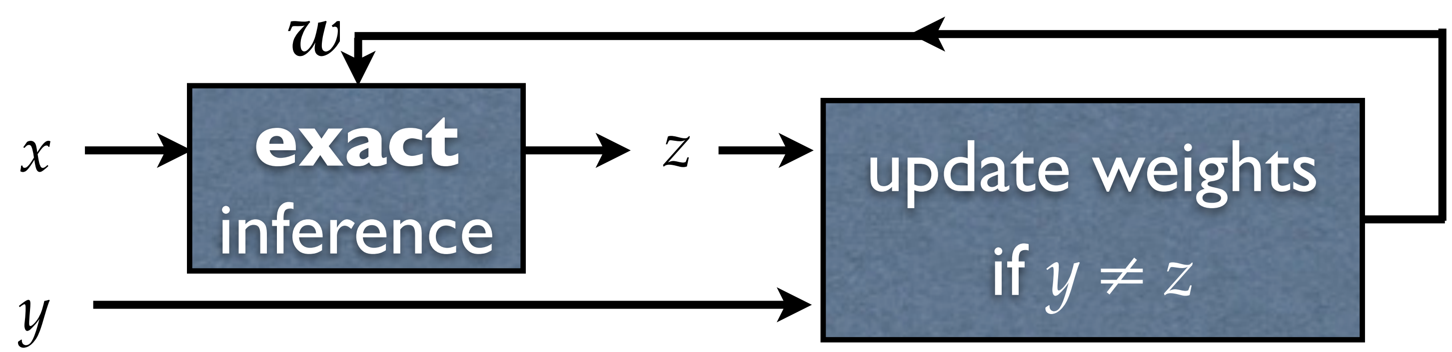
$$\mathbf{u} \cdot \mathbf{w}^{(k+1)} \geq k\delta \qquad \text{(by induction)}$$

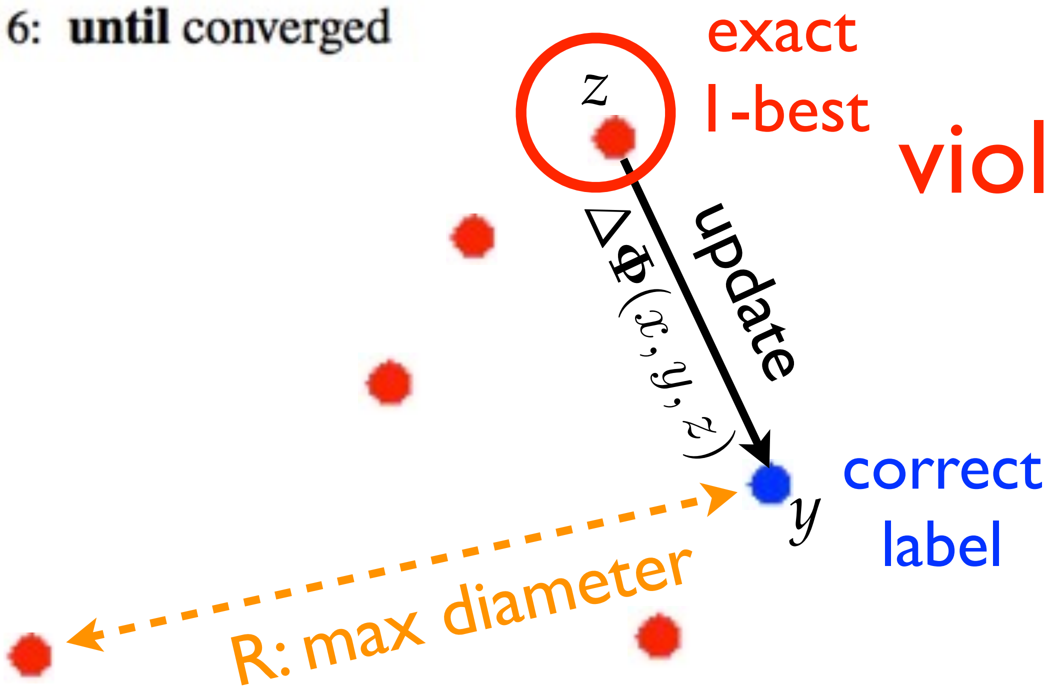
$$\|\mathbf{u}\| \|\mathbf{w}^{(k+1)}\| \geq \mathbf{u} \cdot \mathbf{w}^{(k+1)} \geq k\delta$$

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

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**
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\mathbf{\Phi}(x, y, z)$
until converged





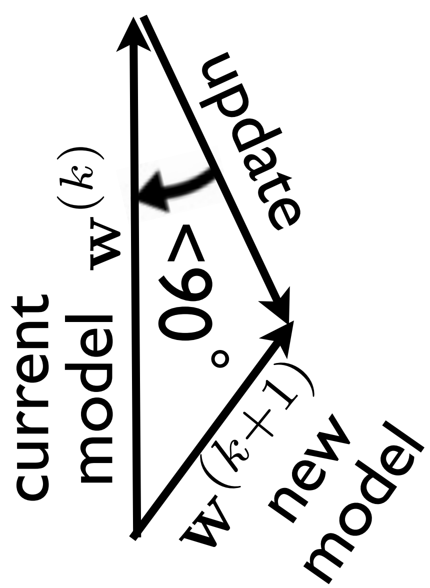
violation: incorrect label scored higher

perceptron update:

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

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

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

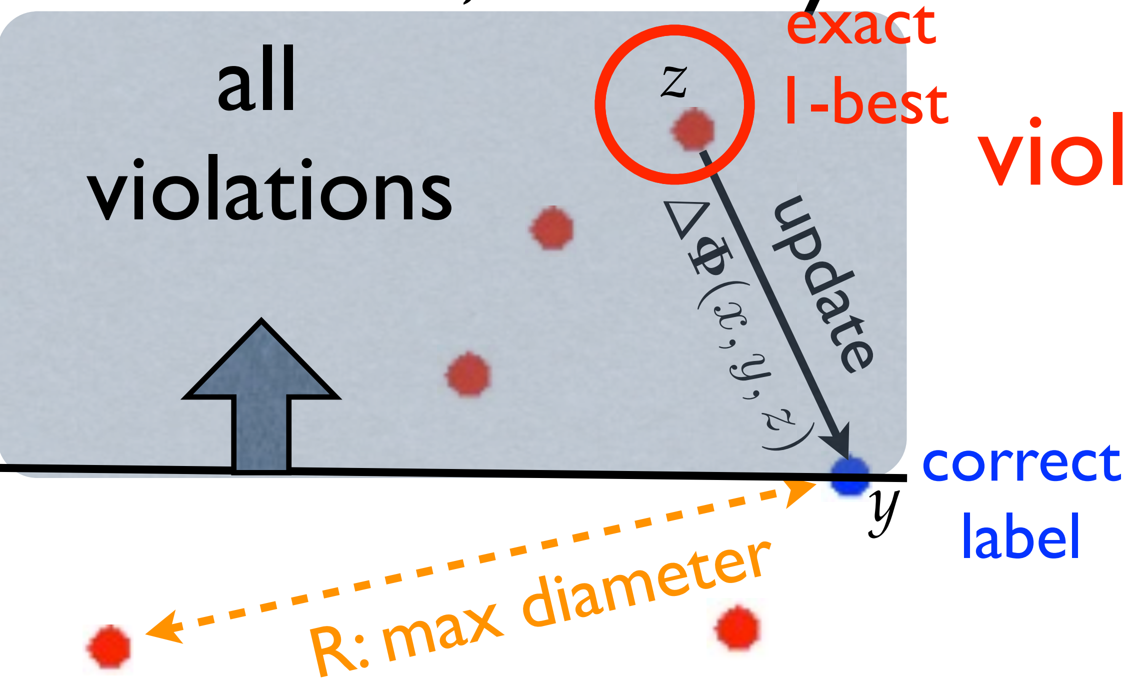


by induction: $\|\mathbf{w}^{(k+1)}\|^2 \leq kR^2$ (part 2: upperbound)

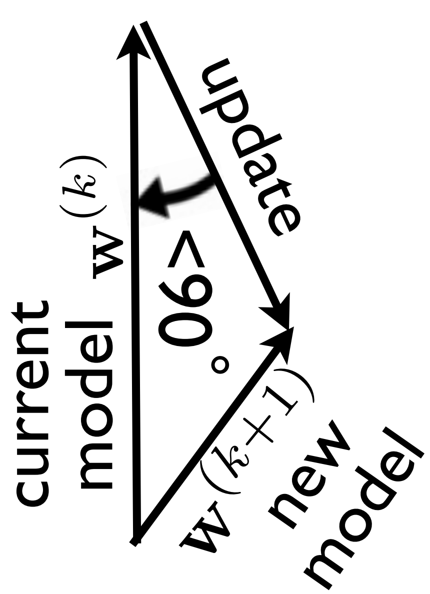
parts 1+2 => update bounds: $\boxed{k \leq R^2/\delta^2}$

Violation is All we need!

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



violation: incorrect label scored higher

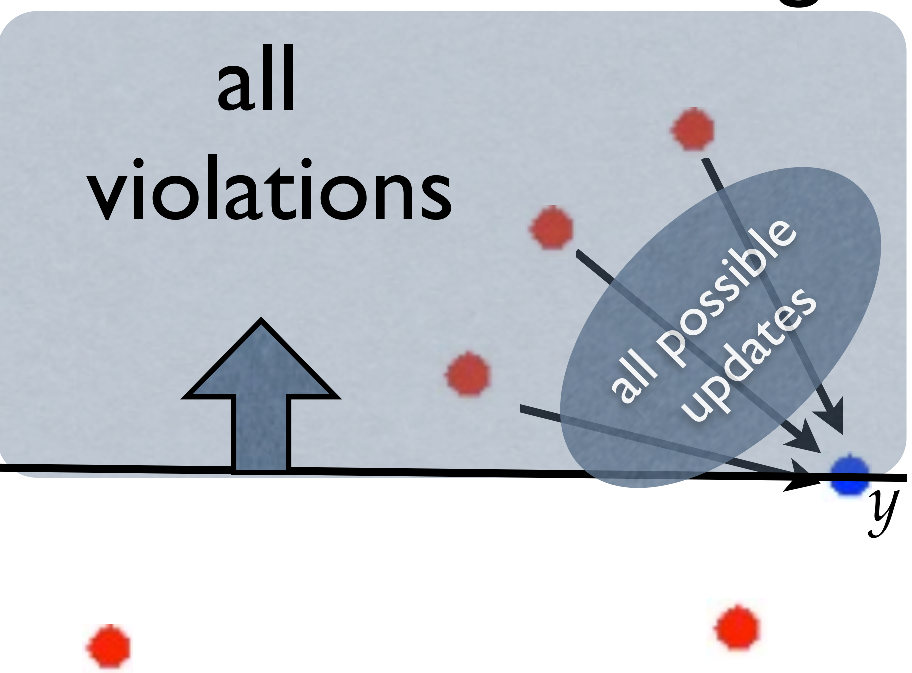


the proof only uses 3 facts:

1. separation (margin)
2. diameter (always finite)
3. violation (but no need for exact)

Violation-Fixing Perceptron

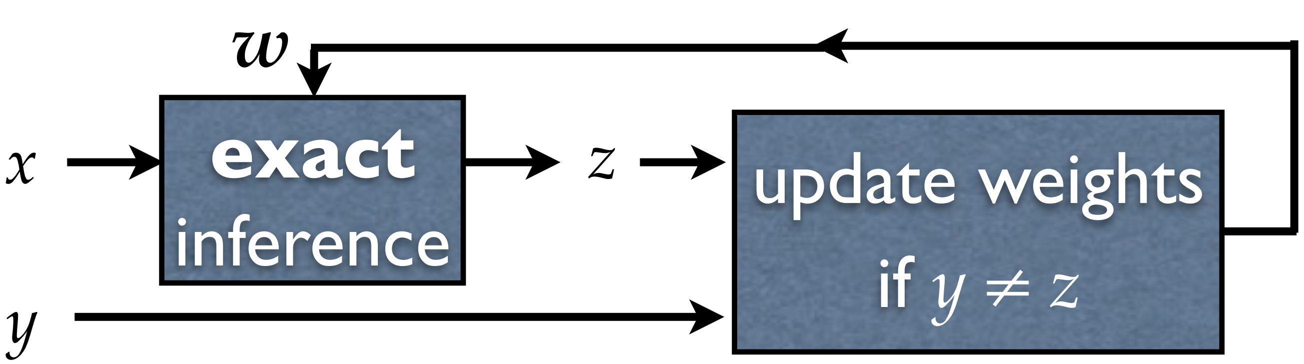
- if we guarantee violation, we don't care about exactness!
  - violation is good b/c we can at least fix a mistake



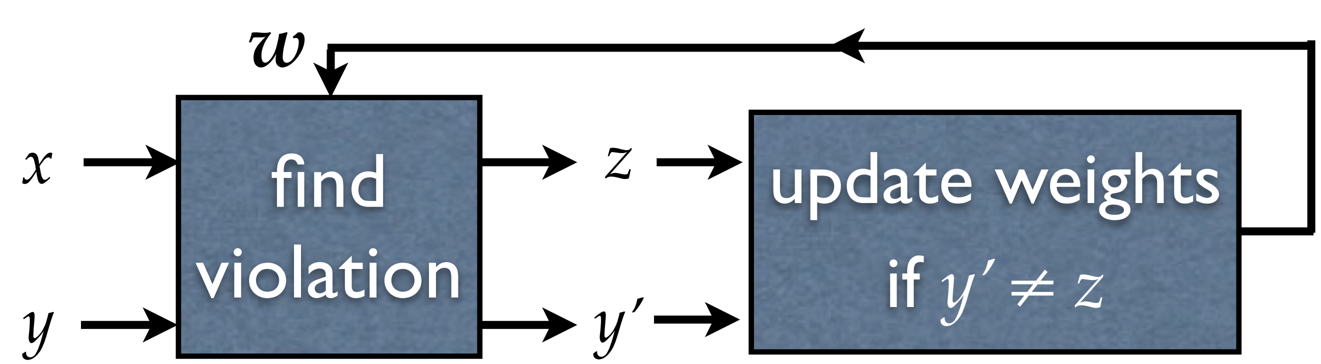
same mistake bound as before!

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
      $\mathbf{w} \leftarrow \mathbf{w} + \Delta\mathbf{\Phi}(x, y', z)$
until converged

standard perceptron

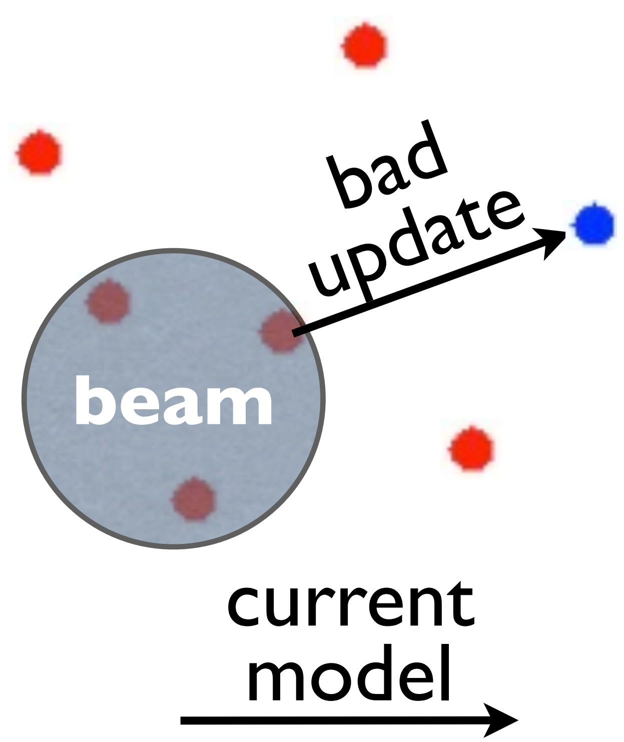


violation-fixing perceptron

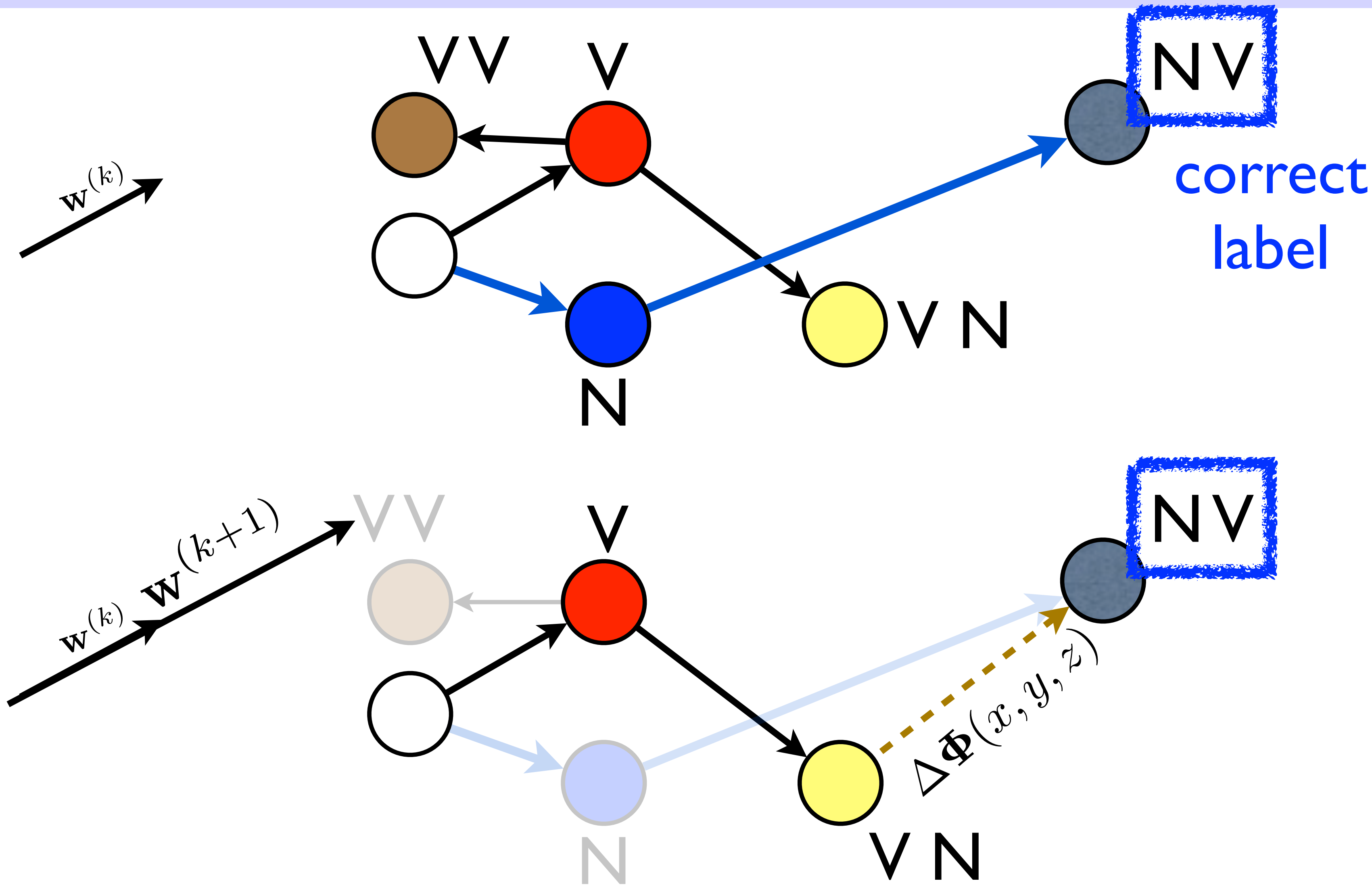


What if can't guarantee violation

- this is why perceptron doesn't work well w/ inexact search
  - because not every update is guaranteed to be a violation
  - thus the proof breaks; no convergence guarantee
- example: beam or greedy search
  - the model might prefer the correct label (if exact search)
  - but the search prunes it away
  - such a non-violation update is "bad" because it doesn't fix any mistake
  - the new model still misguides the search



Standard Update: No Guarantee



training example

time flies

N V

output space

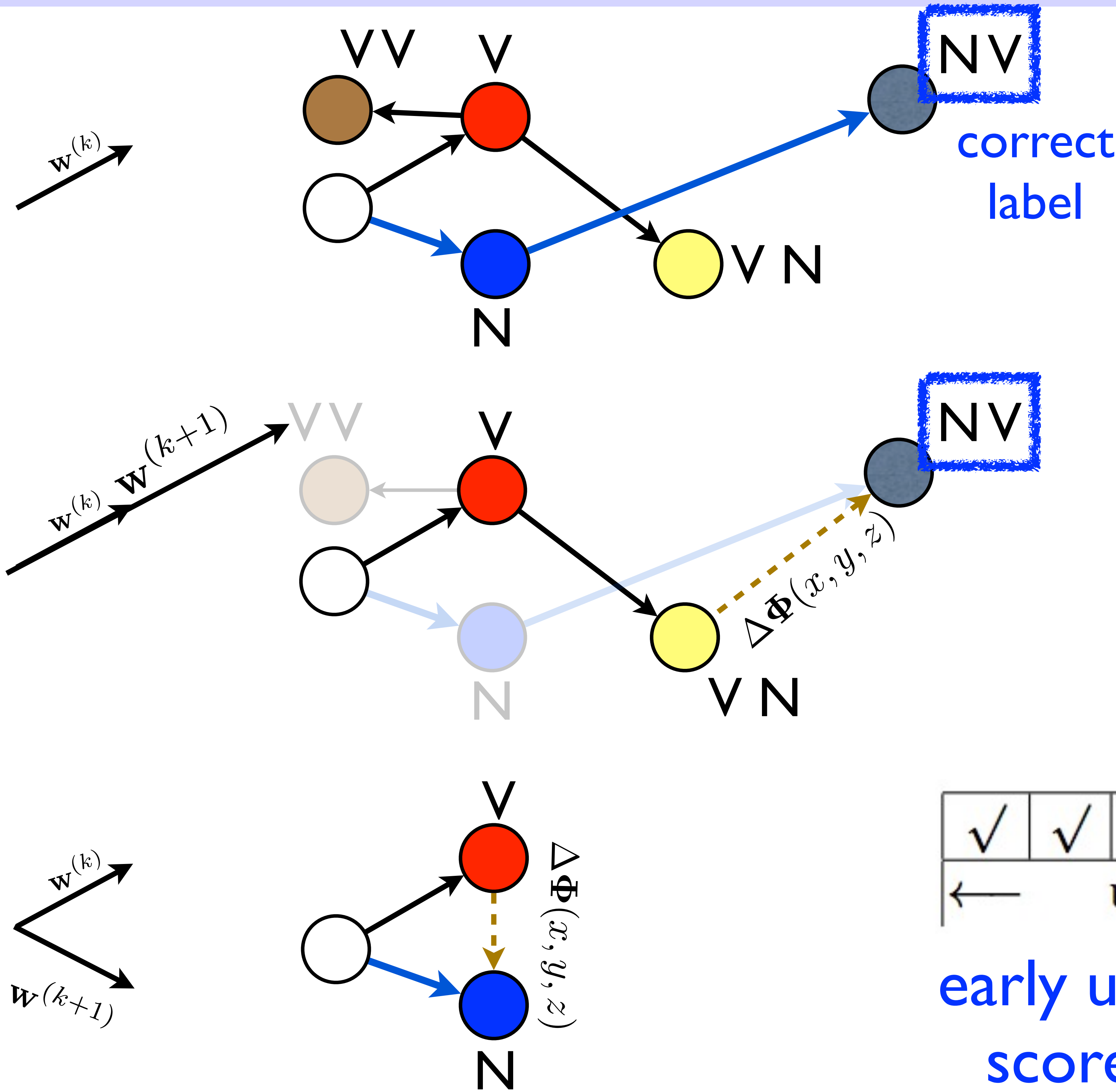
{N,V} x {N,V}

standard update doesn't converge b/c it doesn't guarantee violation

correct label scores higher.

non-violation: bad update!

Early Update: Guarantees Violation



training example

time	flies
N	V

output space

{N,V} x {N,V}

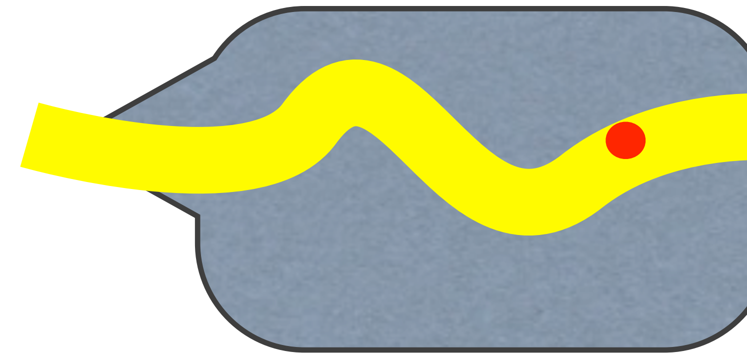
standard update doesn't converge b/c it doesn't guarantee violation

√	√	···	√	×	
⟵	update			⟶	skip ⟶

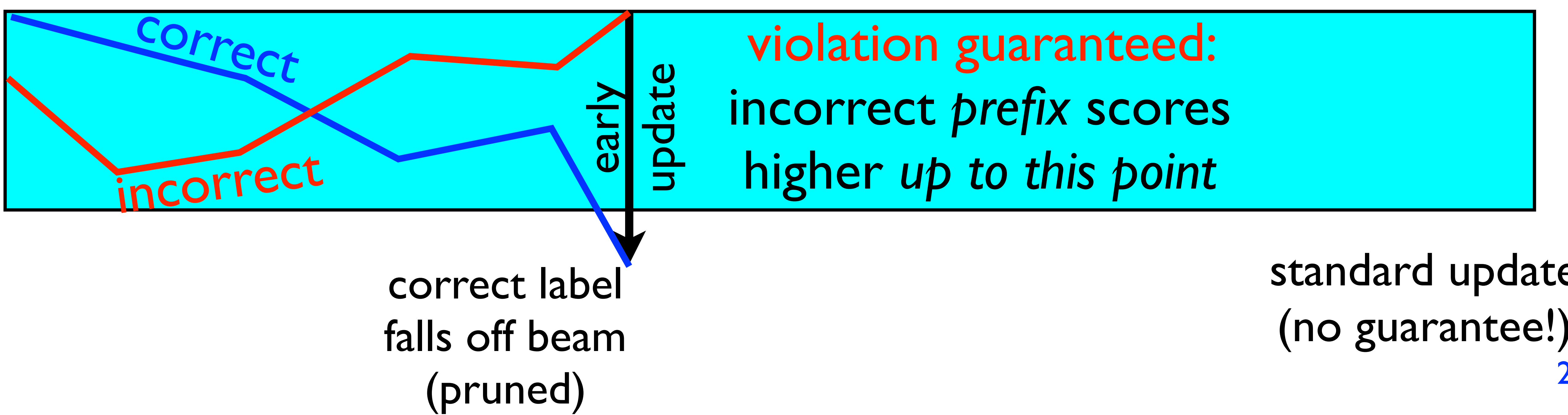
early update: incorrect prefix scores higher: a violation!

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...

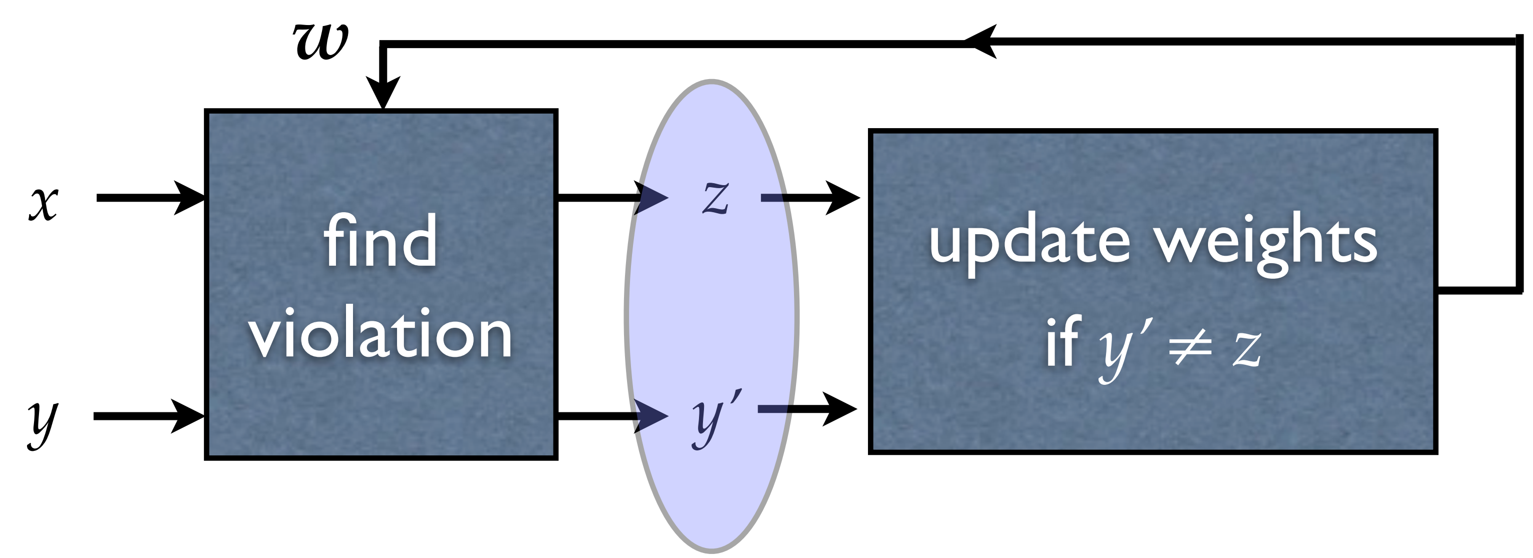


- early update -- when correct label first falls off the beam
  - up to this point the incorrect prefix should score higher
- standard update (full update) -- no guarantee!



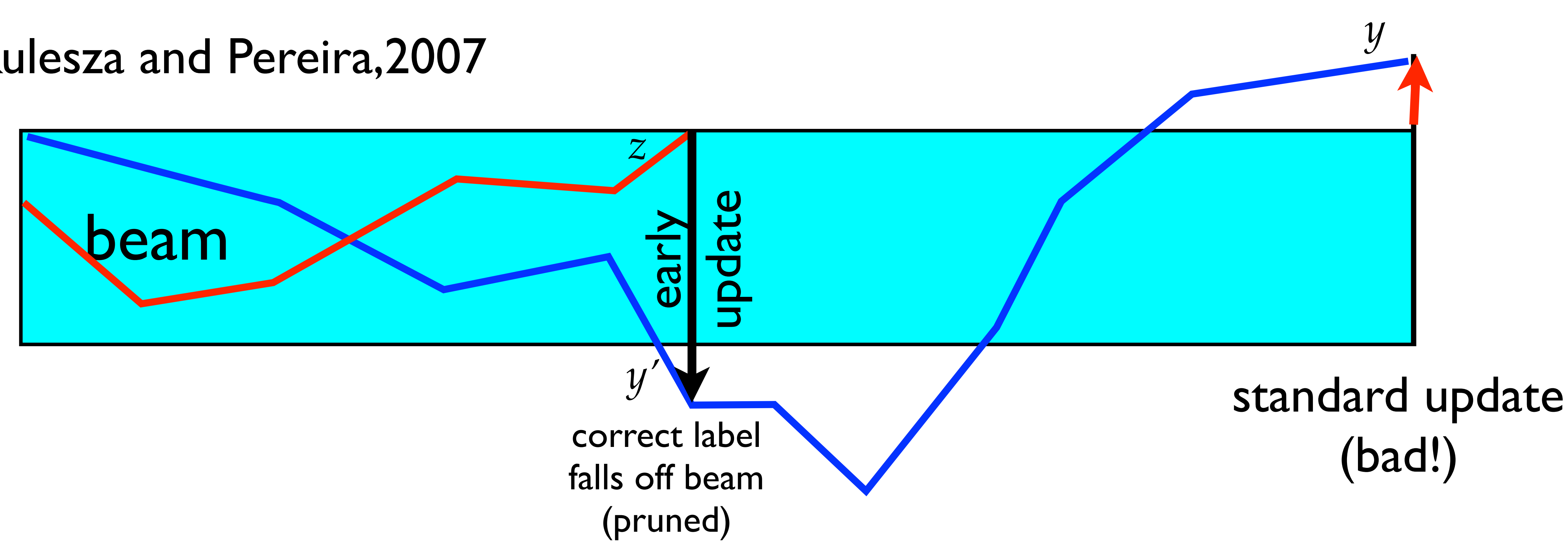
Early Update as Violation-Fixing

also new definition of
"beam separability":
a correct prefix should
score higher than
any incorrect prefix
of the same length
(maybe too strong)

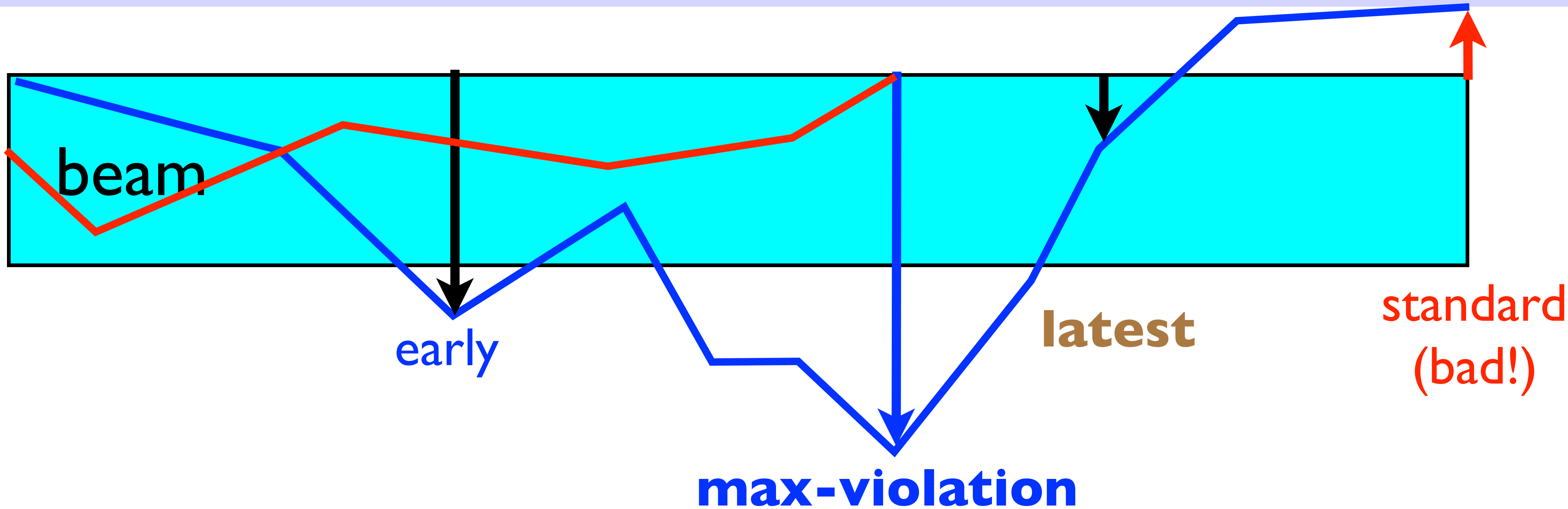


prefix violations

cf. Kulesza and Pereira,2007



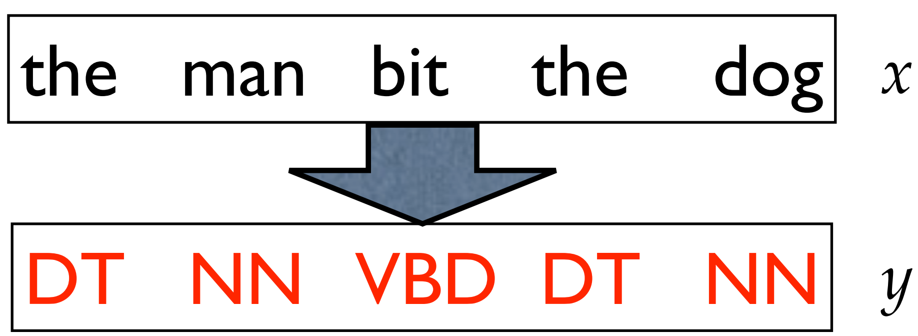
New Update Methods: max-violation, ...



- we now established a theory for early update (Collins/Roark)
- but it learns too slowly due to partial updates
- max-violation: use the prefix where violation is maximum
  - "worst-mistake" in the search space
- all these update methods are violation-fixing perceptrons

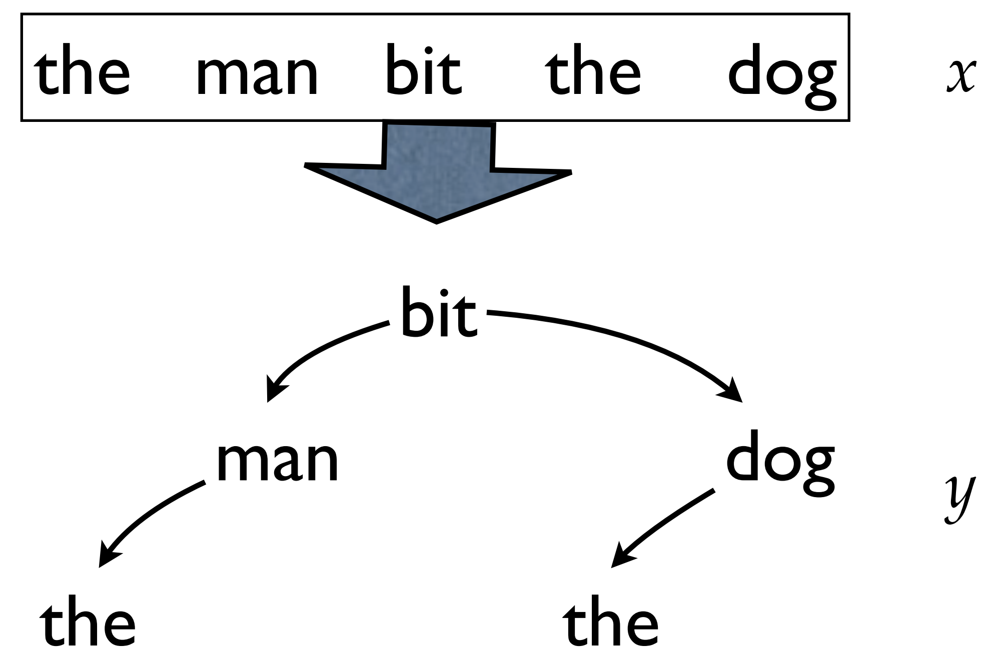
Experiments

trigram part-of-speech tagging



local features only,
exact search tractable
(proof of concept)

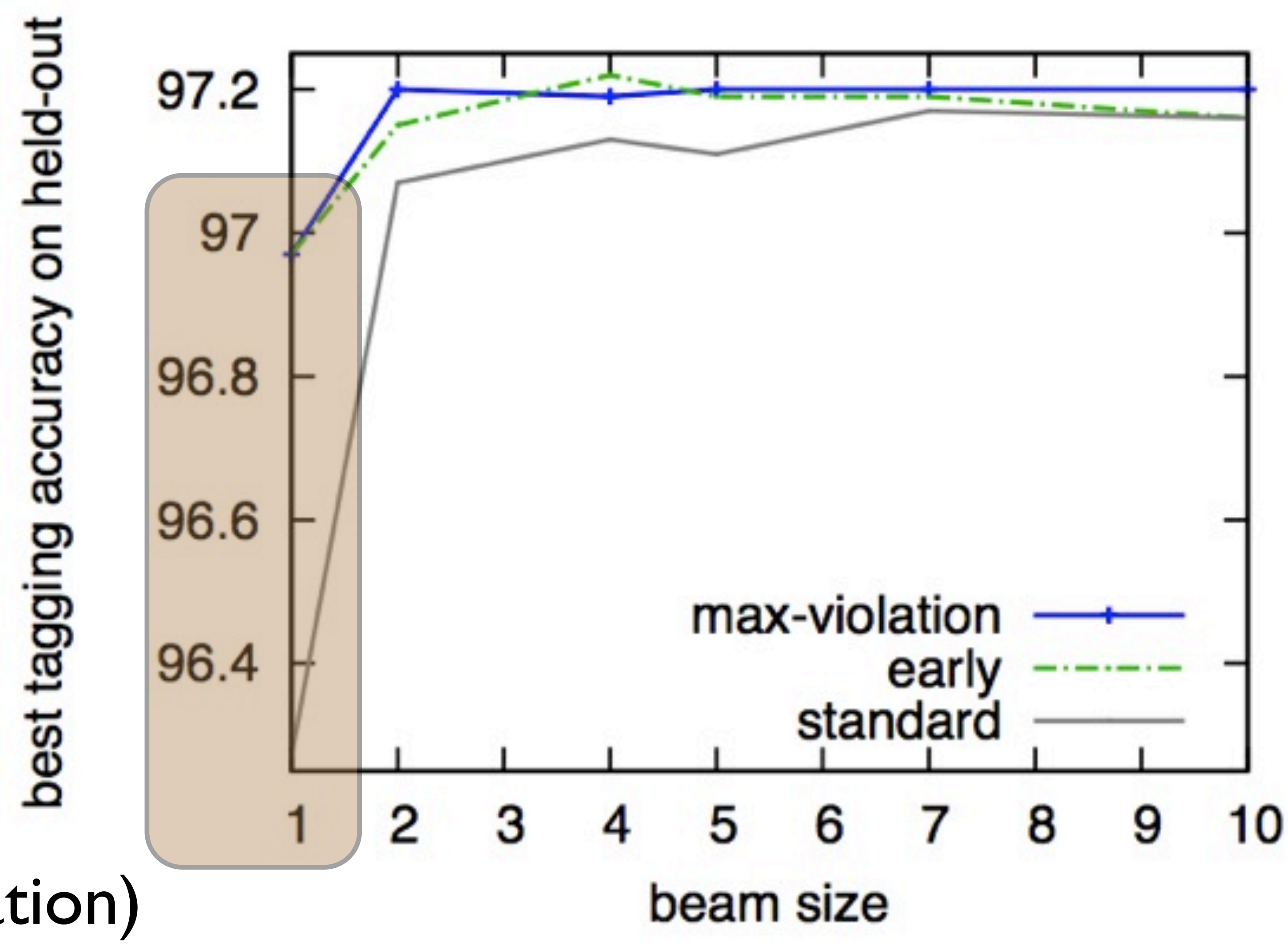
incremental dependency parsing



non-local features,
exact search intractable
(real impact)

1) Trigram Part of Speech Tagging

- standard update performs terribly with greedy search (b=1)
  - because search error is severe at b=1: half updates are bad!
  - no real difference beyond b=2: search error becomes rare

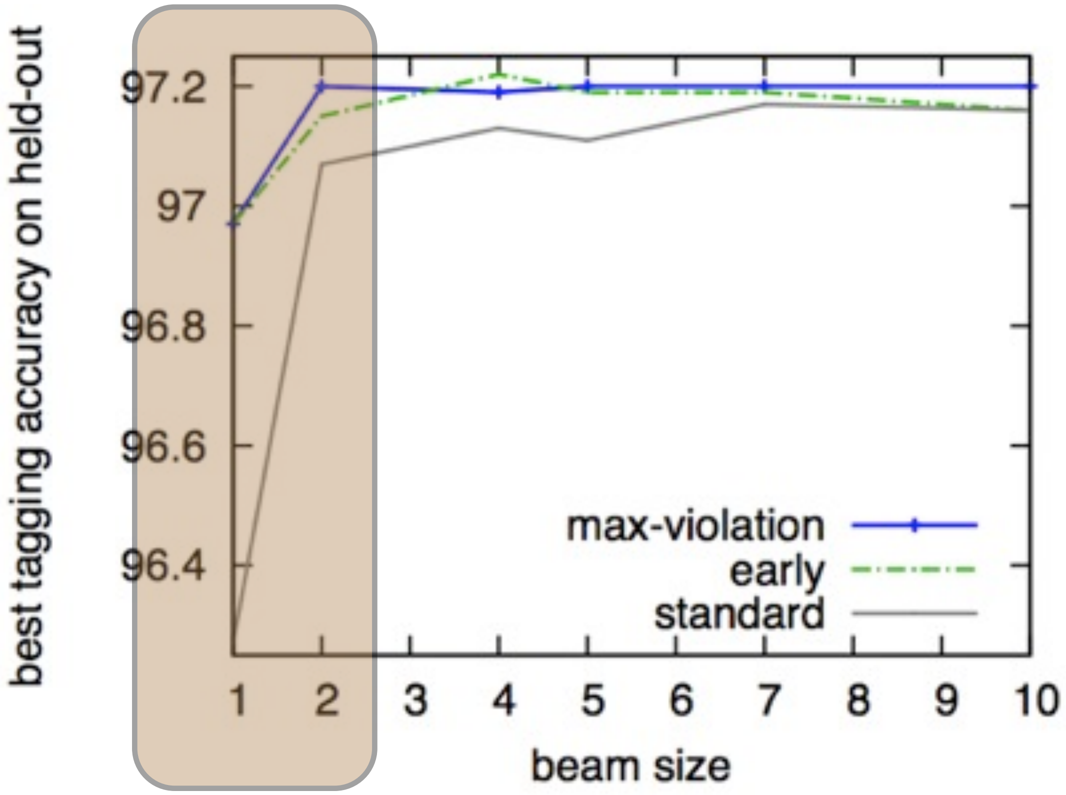


% of bad (non-violation) standard updates

53% 10% 1.5% 0.5%

Max-Violation Reduces Training Time

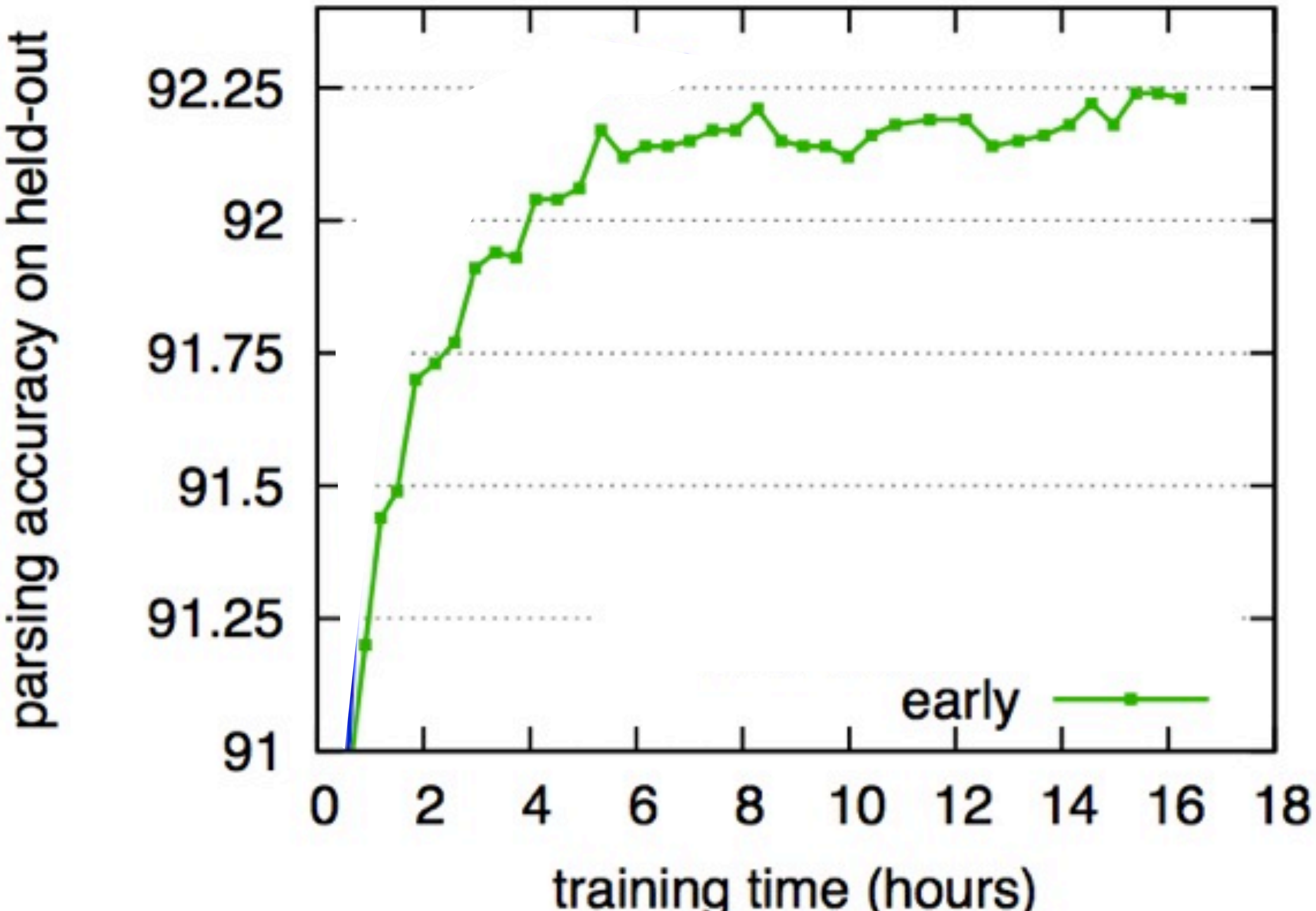
- max-violation peaks at b=2, greatly reduced training time
- early update achieves the highest dev/test accuracy
    - comparable to best published accuracy (Shen et al '07)
- future work: add non-local features to tagging



	beam	*iter*	*time*	*test*
standard	-	6	162m	97.28
early	4	6	37m	97.27
max-violation	2	3	26m	97.27
Shen et al (2007)				97.33

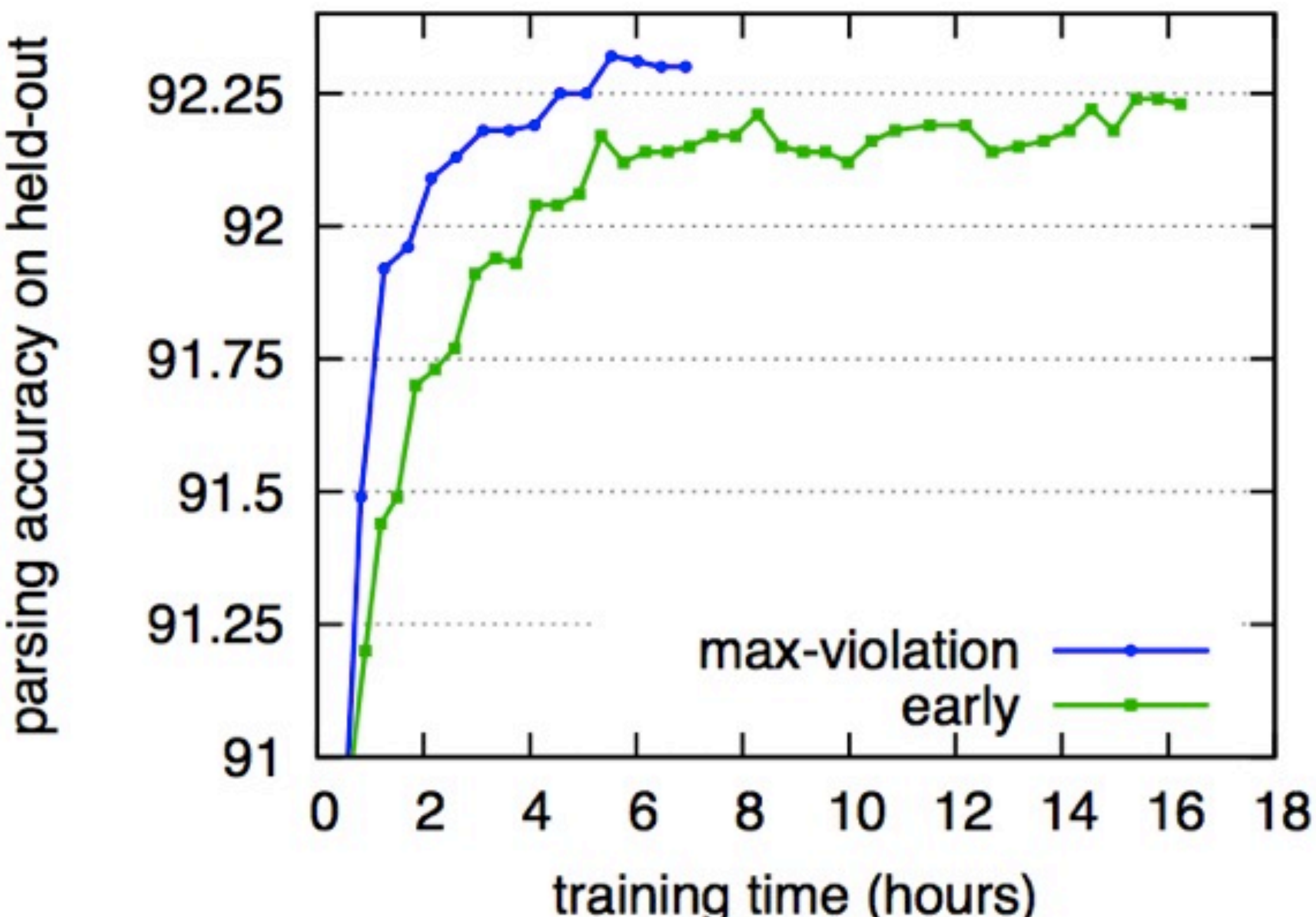
2) Incremental Dependency Parsing

- DP incremental dependency parser (Huang and Sagae 2010)
- non-local history-based features rule out exact DP
  - we use beam search, and search error is severe
  - baseline: early update. extremely slow: 38 iterations



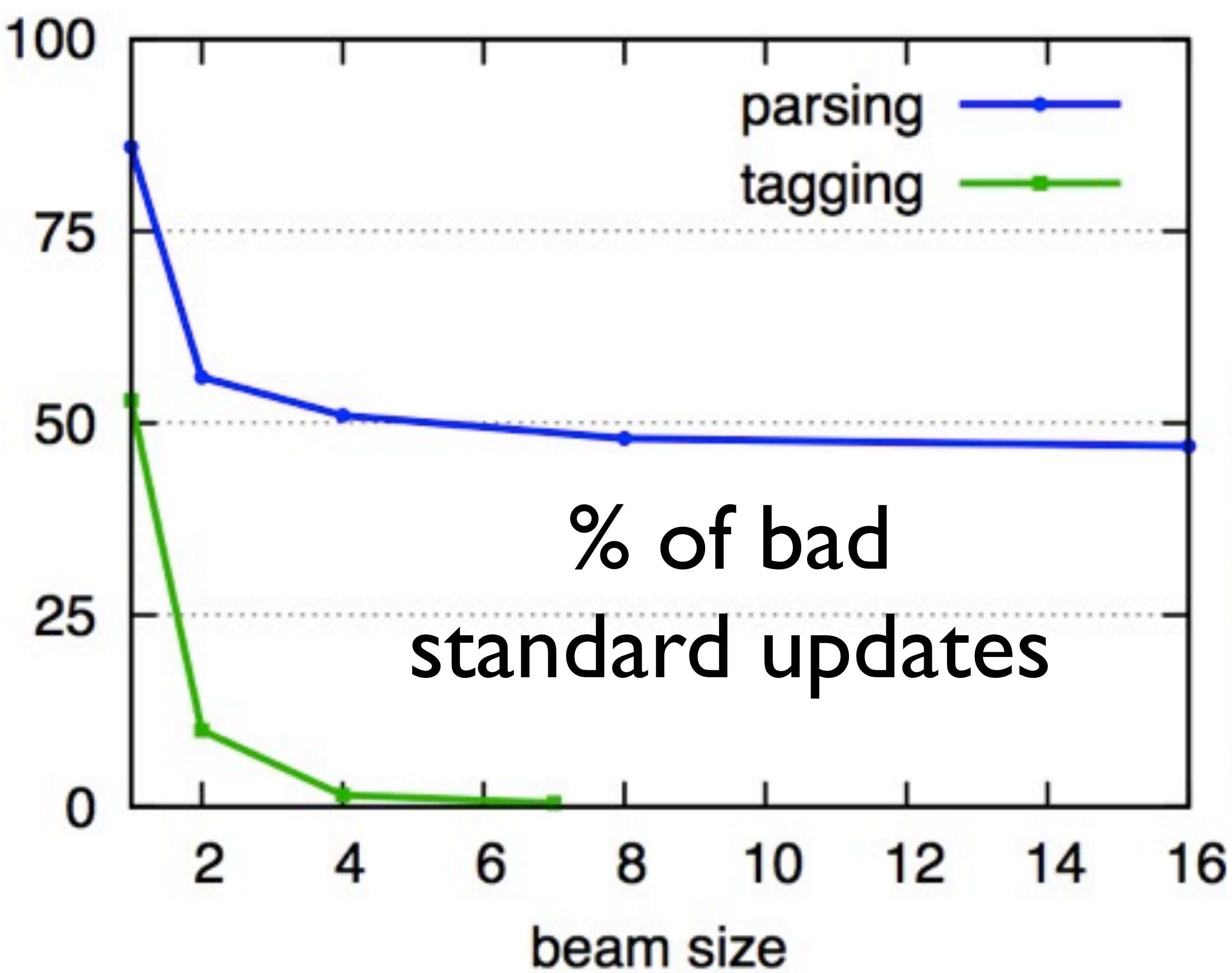
Max-violation converges much faster

- early update: 38 iterations, 15.4 hours (92.24)
- max-violation: 10 iterations, 4.6 hours (92.25)
  12 iterations, 5.5 hours (92.32)

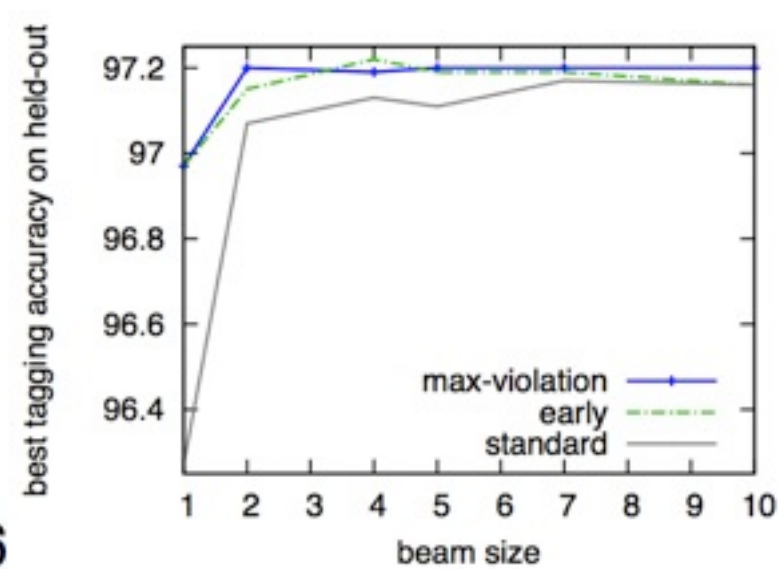


Comparison b/w tagging & parsing

- search error is much more severe in parsing than in tagging
- standard update is OK in tagging except greedy search (b=1)
- but performs horribly in parsing even at large beam (b=8)
  - because ~50% of standard updates are bad (non-violation)!



take-home message:
our methods are more helpful
for harder search problems!



	test
standard	**79.1**
early	92.1
max-violation	92.2

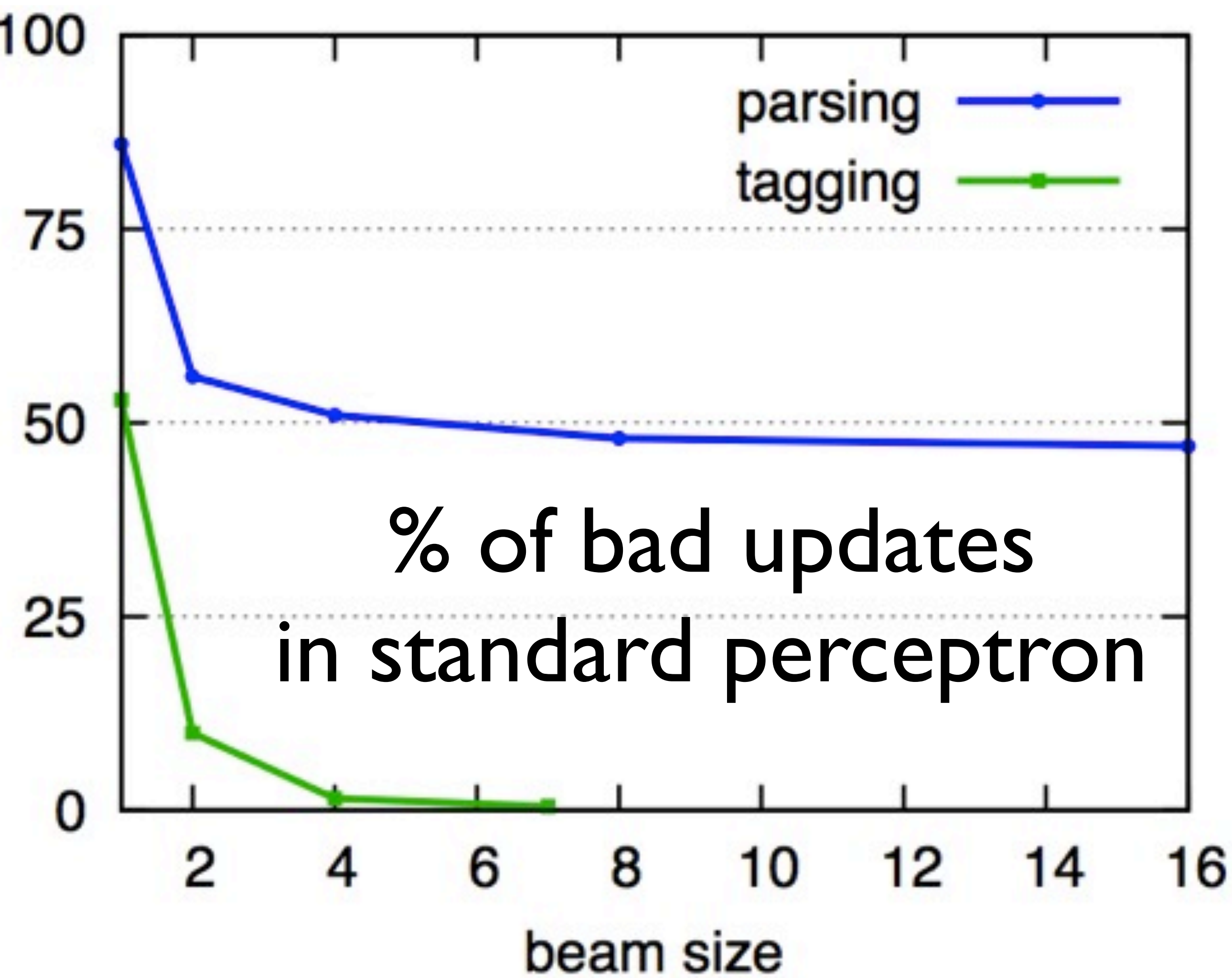
Related Work and Discussions

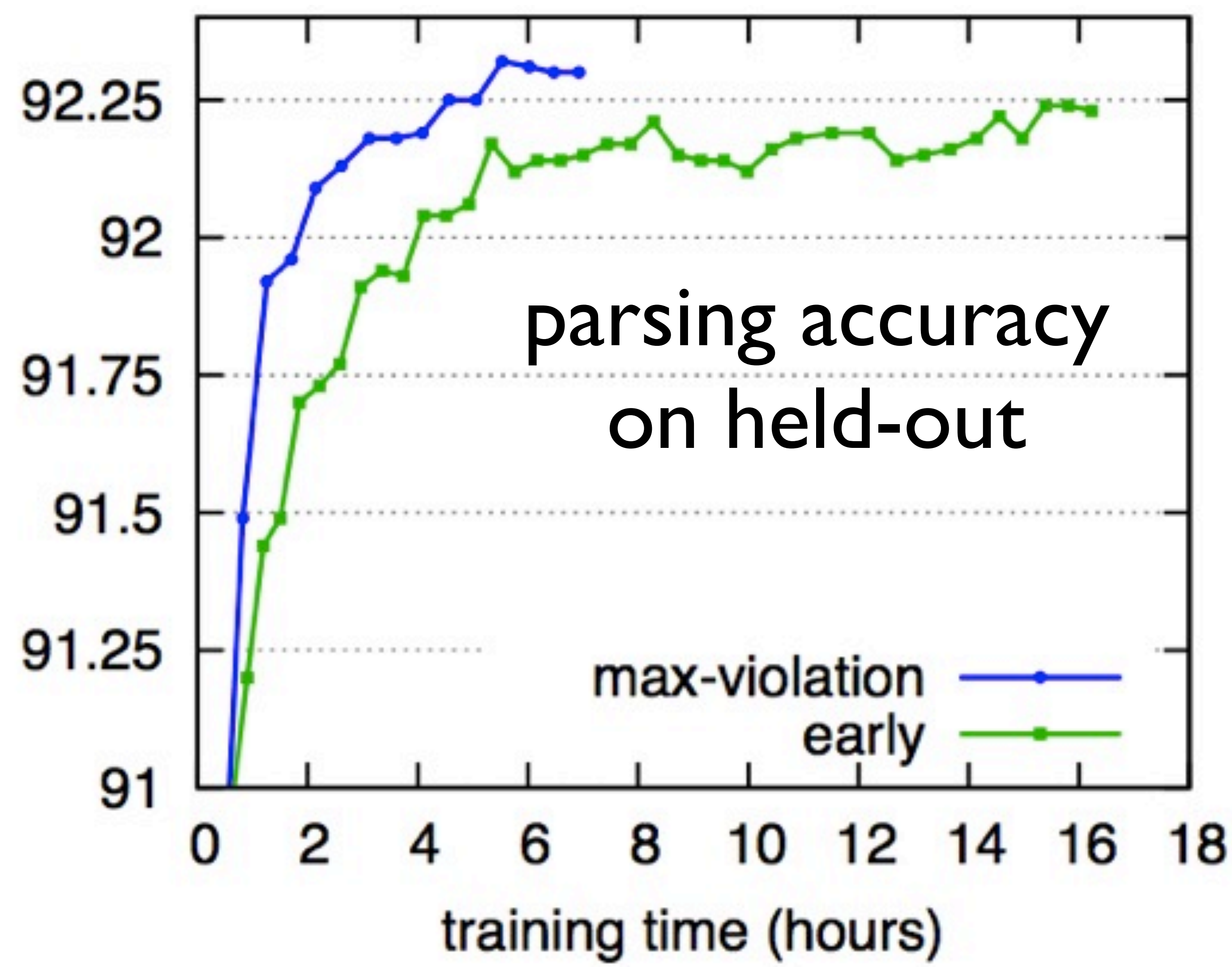
- our "violation-fixing" framework include as special cases
  - early-update (Collins and Roark, 2004)
  - a variant of LaSO (Daume and Marcu, 2005)
  - not sure about Searn (Daume et al, 2009)
- "beam-separability" or "greedy-separability" related to:
  - "algorithmic-separability" of (Kulesza and Pereira, 2007)
  - 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

- Structured Learning with Inexact Search is Important
- Two contributions from this work:
  - theory: a general violation-fixing perceptron framework
    - convergence for inexact search under new defs of *separability*
    - subsumes previous work (early update & LaSO) as special cases
  - practice: new update methods within this framework
    - "max-violation" learns faster and better than early update
      - dramatically reducing training time by 3-5 folds
      - improves over state-of-the-art tagging and parsing systems
    - our methods are more helpful to harder search problems! :)

Thank you!





The City University of New York

my parser with max-violation update is available at:
http://acl.cs.qc.edu/~lhuang/#software

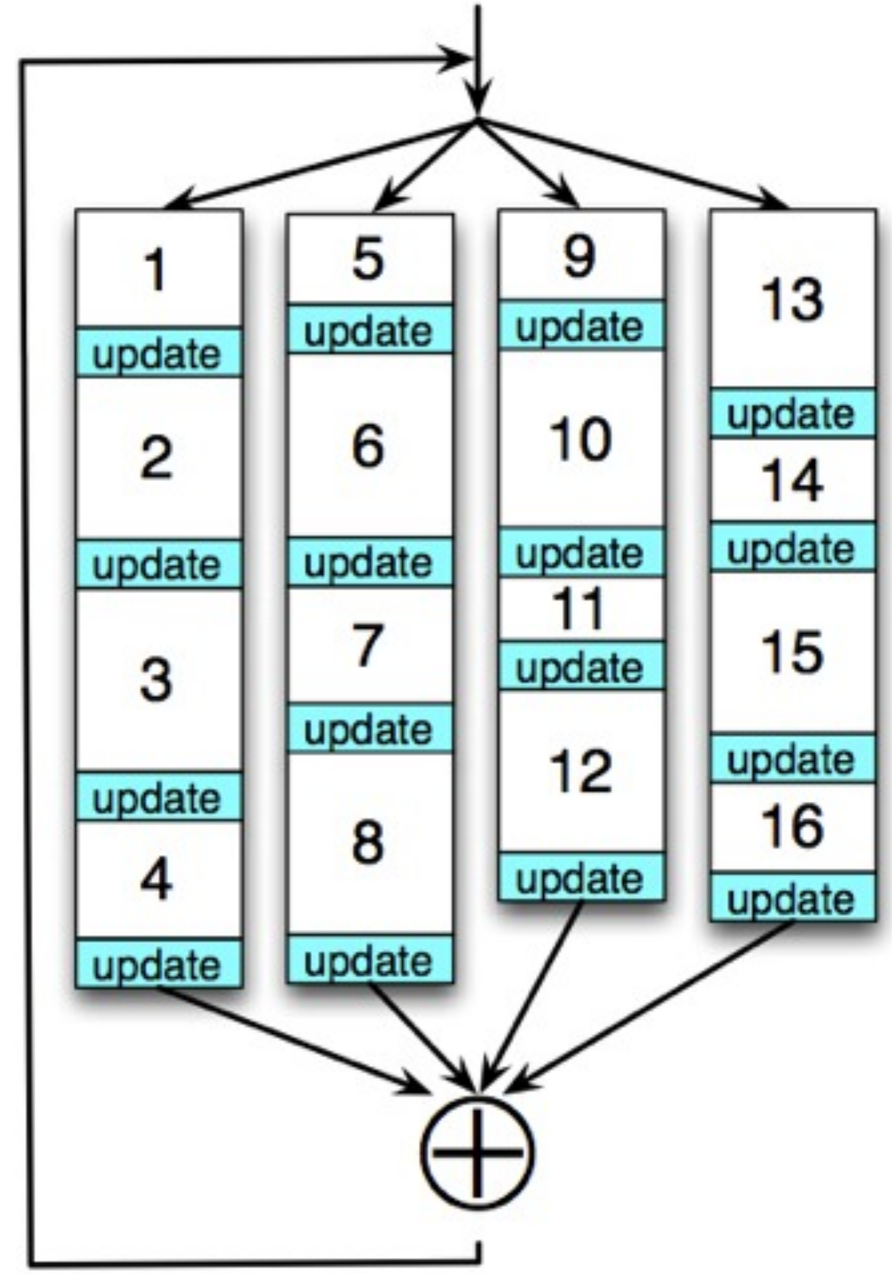
liang.huang.sh@gmail.com

Bonus Track: Parallelizing Online Learning

(K. Zhao and L. Huang, NAACL 2013)

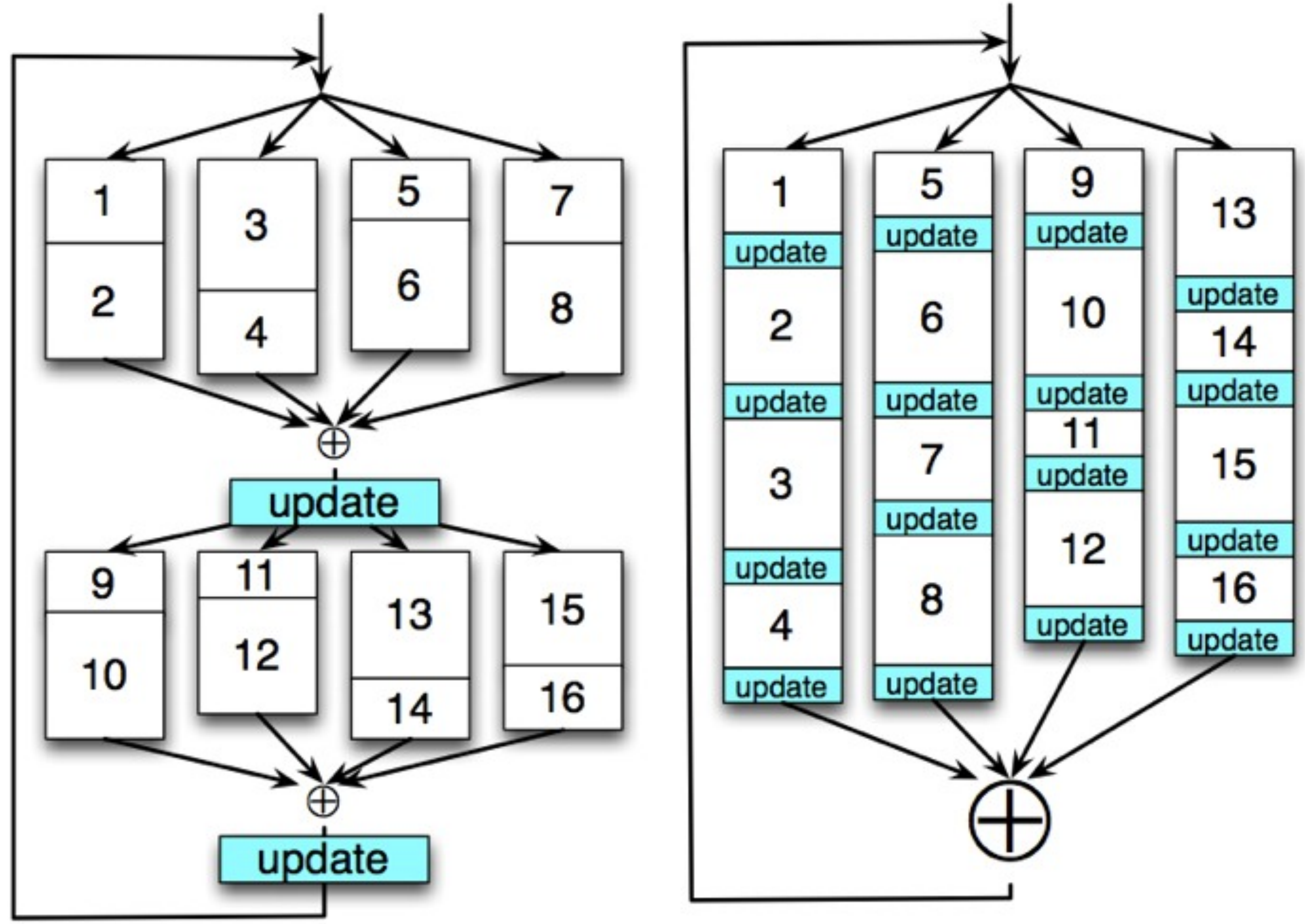
Perceptron still too slow

- even if we use very fast inexact search because
  - there is too much training data, and
  - has to go over the whole data many times to converge
- can we parallelize online learning?
  - harder than parallelizing batch learning (e.g. CRF)
  - losing dependency b/w examples
  - McDonald et al (2010): ~3-4x faster



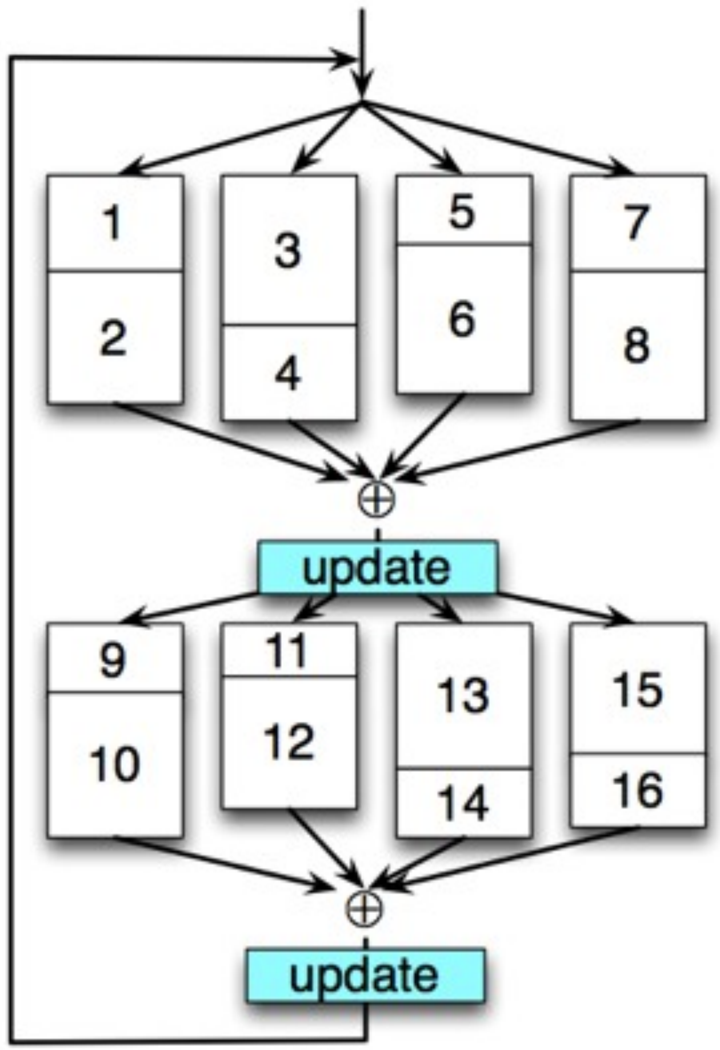
Minibatch Parallelization

- parallelize in each minibach
- do aggregate update after each minibatch
- becomes batch if minibatch size is the whole set



Minibach helps in serial also

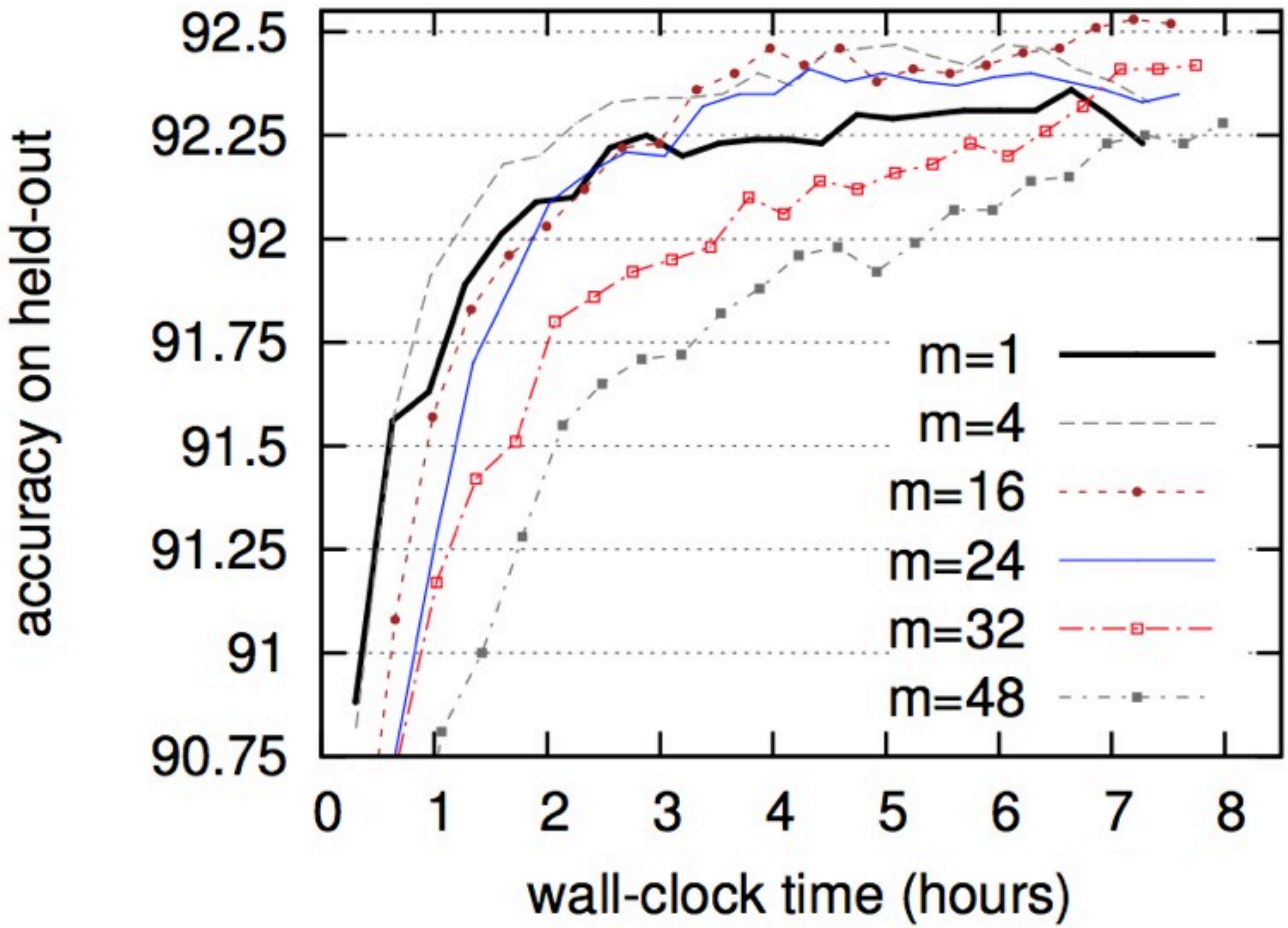
- minibatch perceptron
  - use average of updates within minibatch
  - “averaging effect” (cf. McDonal et al 2010)
  - easy to prove convergence (still R^2/δ^2)
- minibatch MIRA
  - optimization over more constraints
  - MIRA: online approximation of SVM
  - minibatch MIRA: better approximation
    - approaches SVM at maximum batch size
    - middle-ground b/w MIRA and SVM



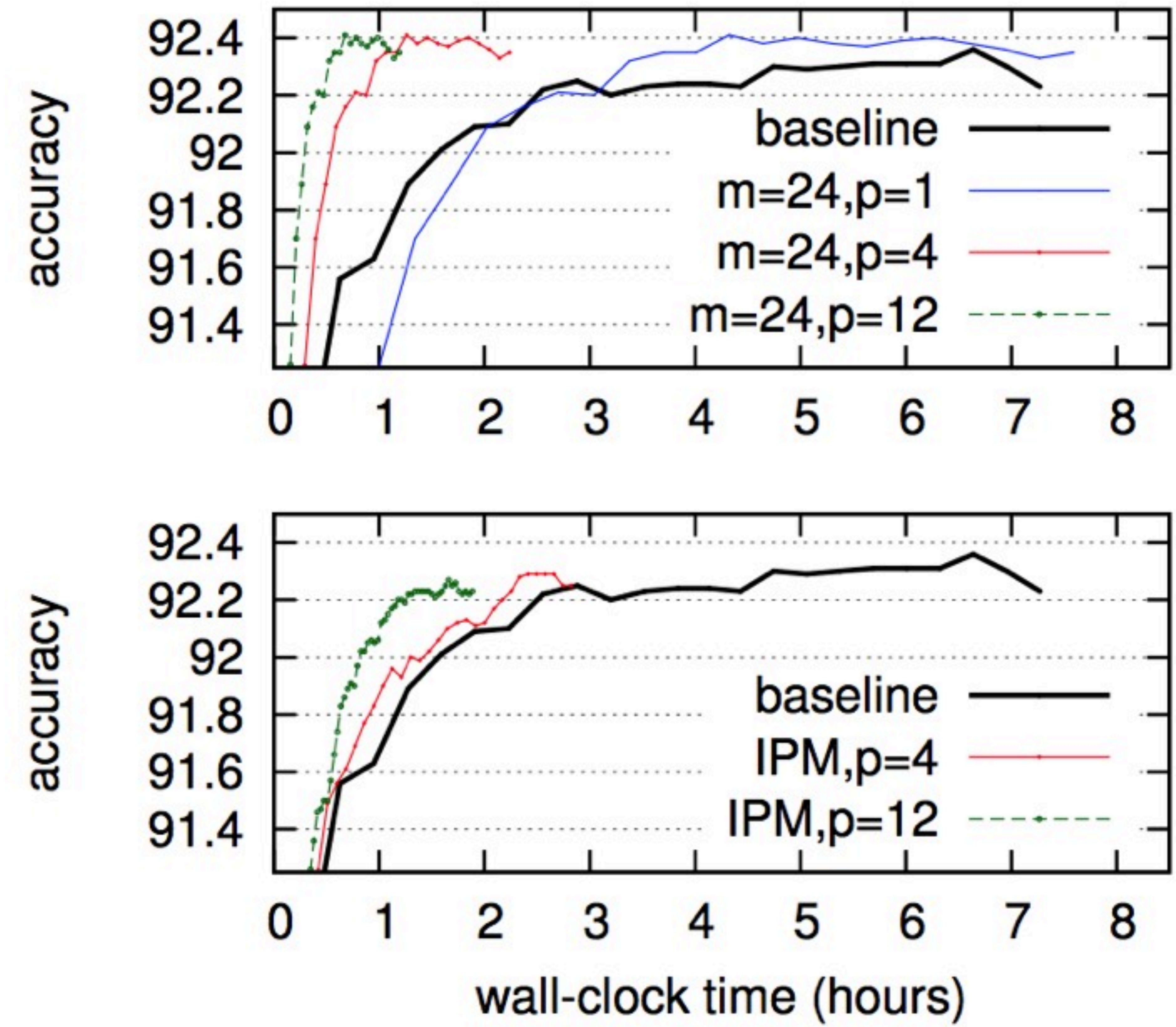
4x constrains
in each update

Parsing - MIRA - serial minibach

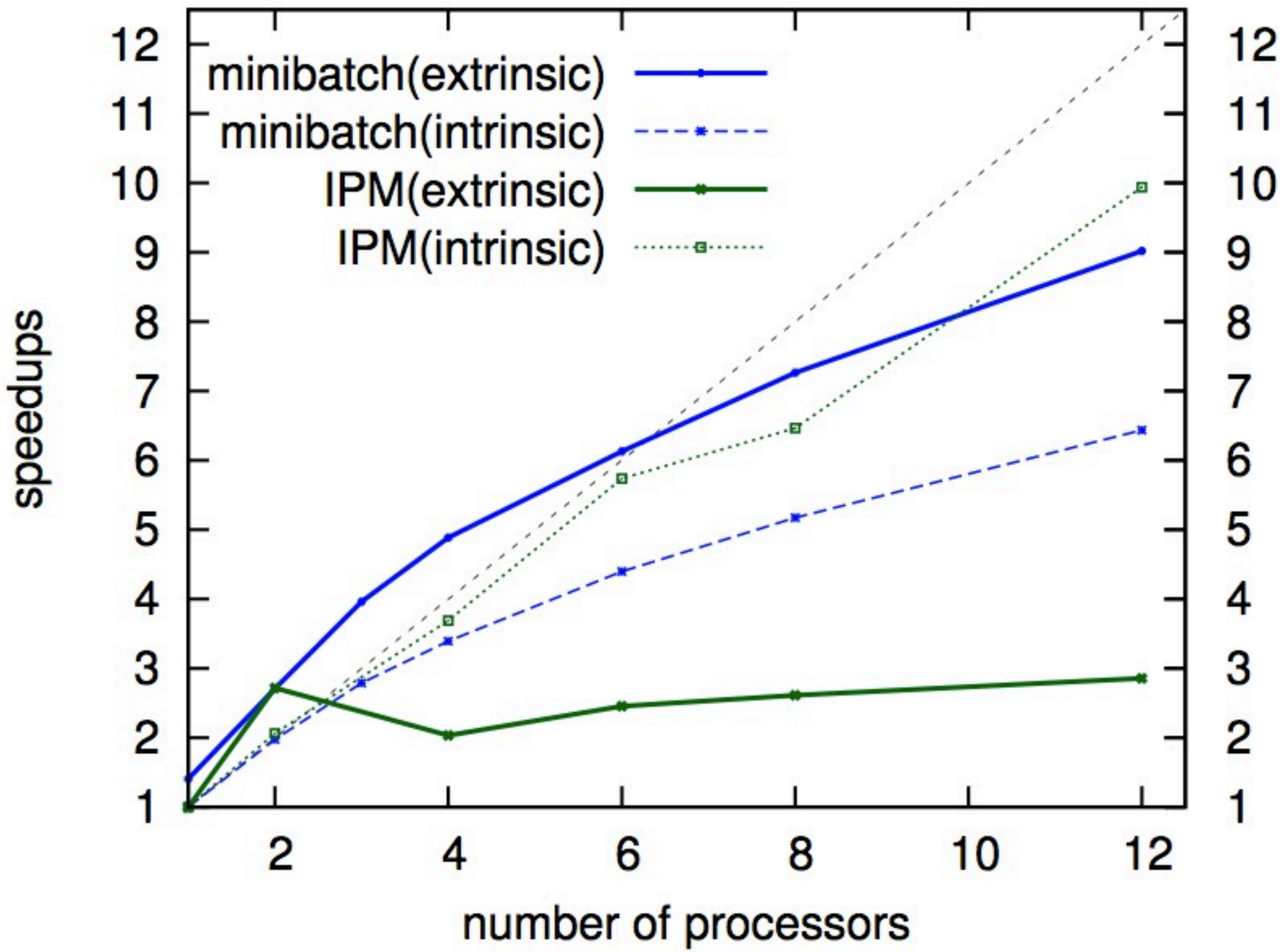
- on incremental dependency parser w/ max-violation



Comparison w/ McDonald et al 2010

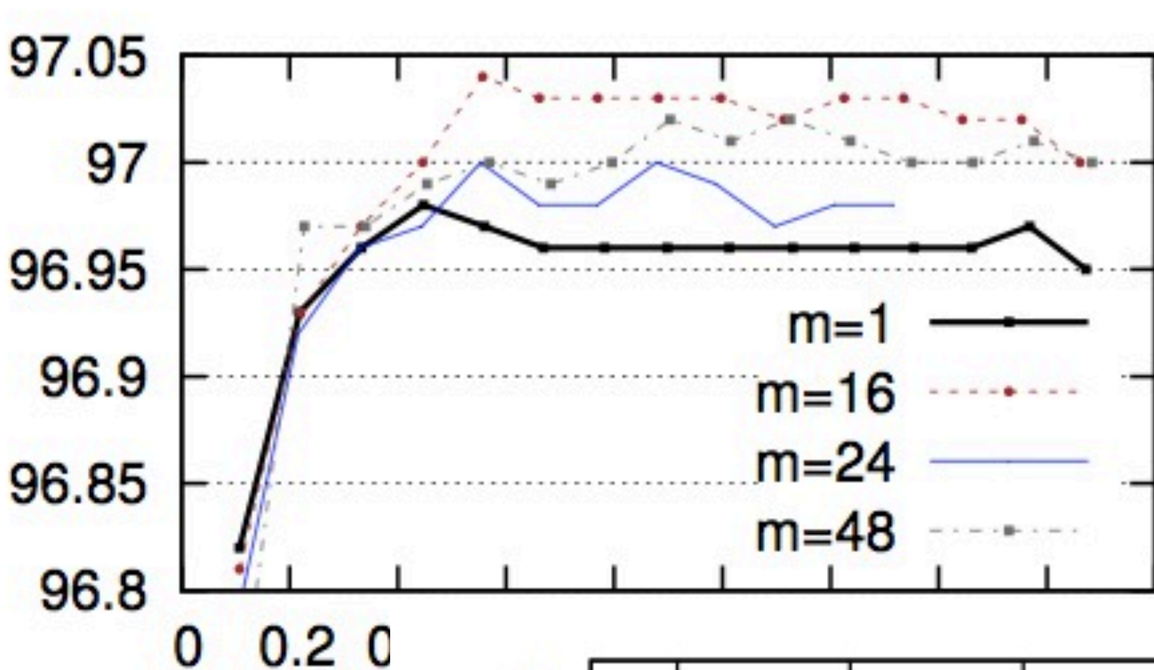


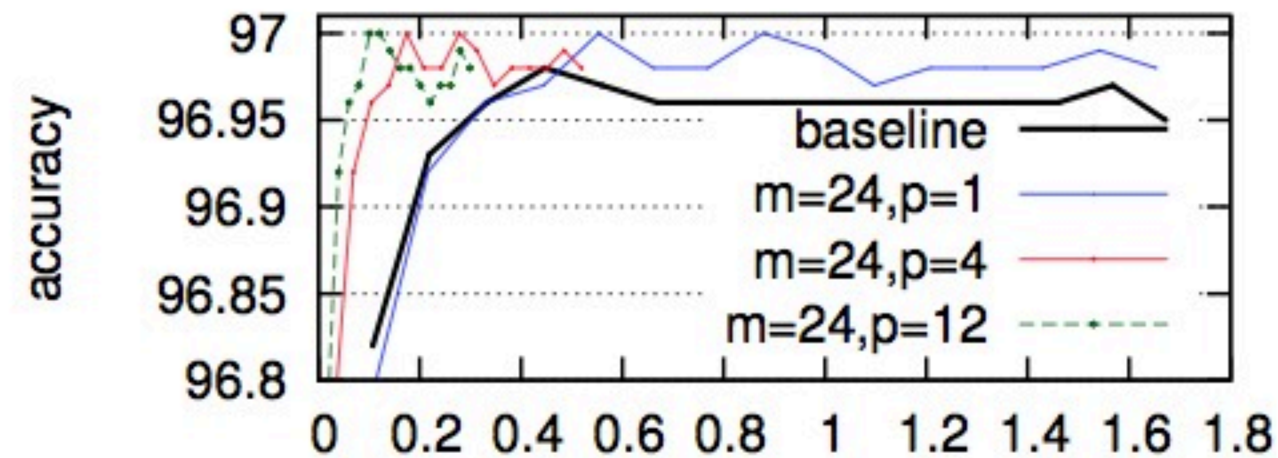
Intrinsic and Extrinsic Speedups

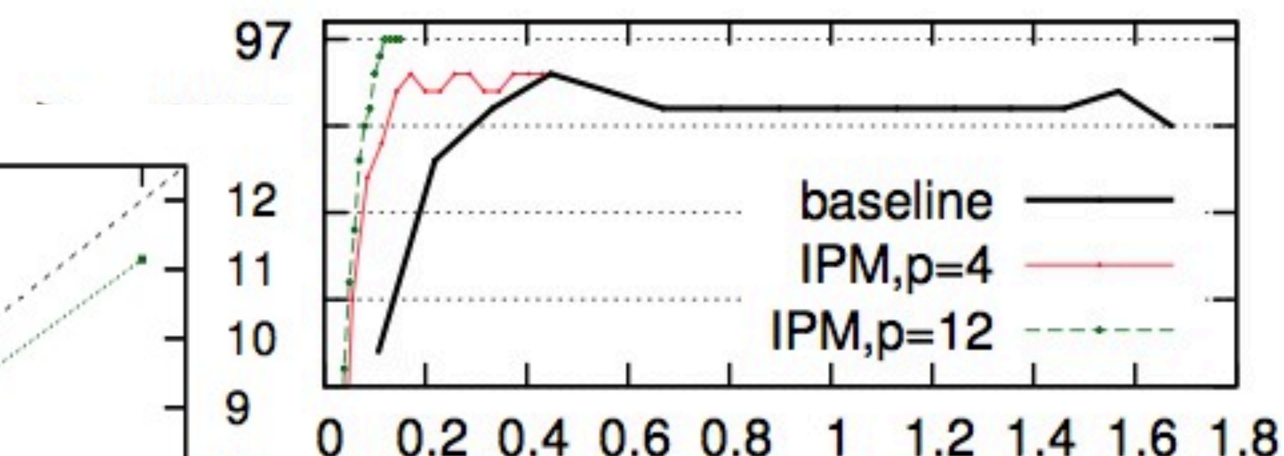


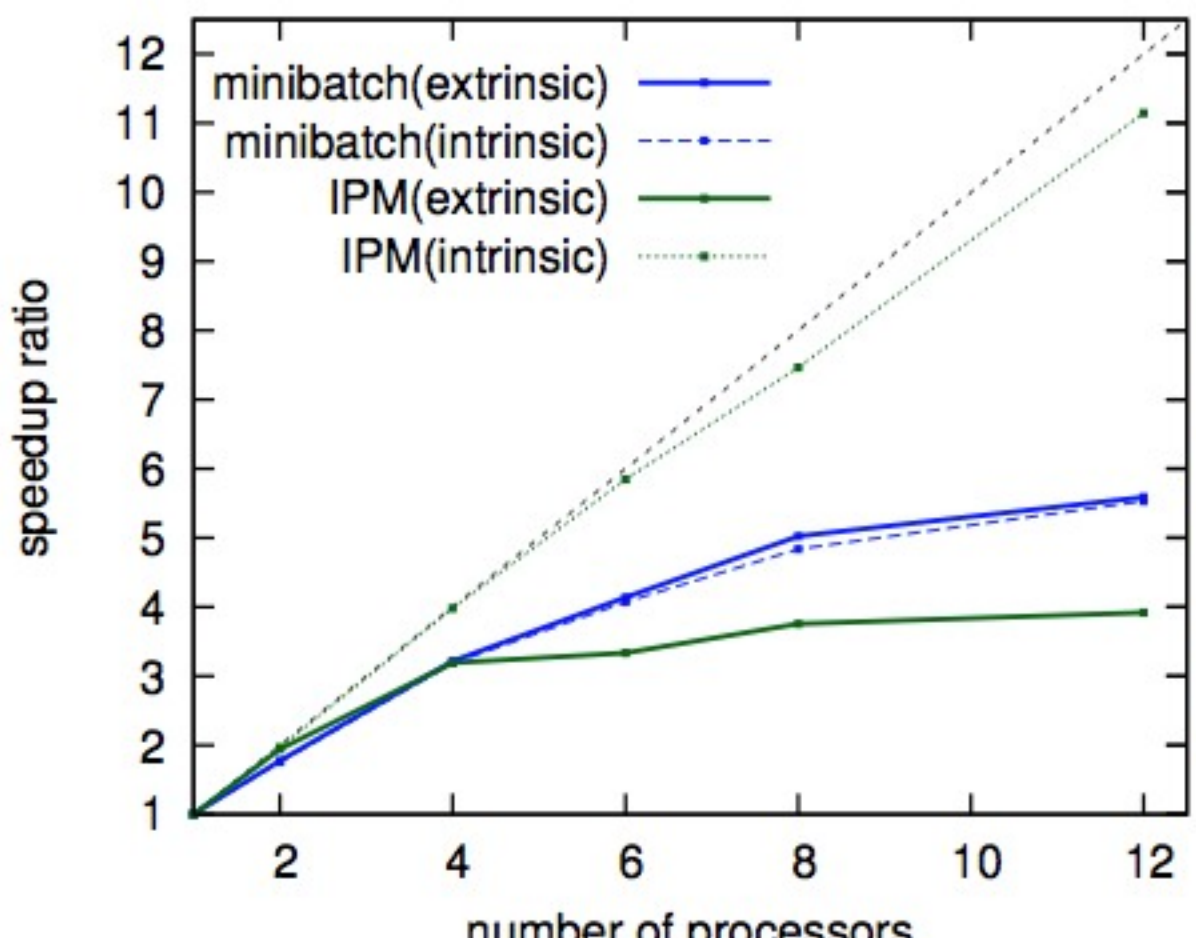
Tagging - Perceptron

- standard update with exact search

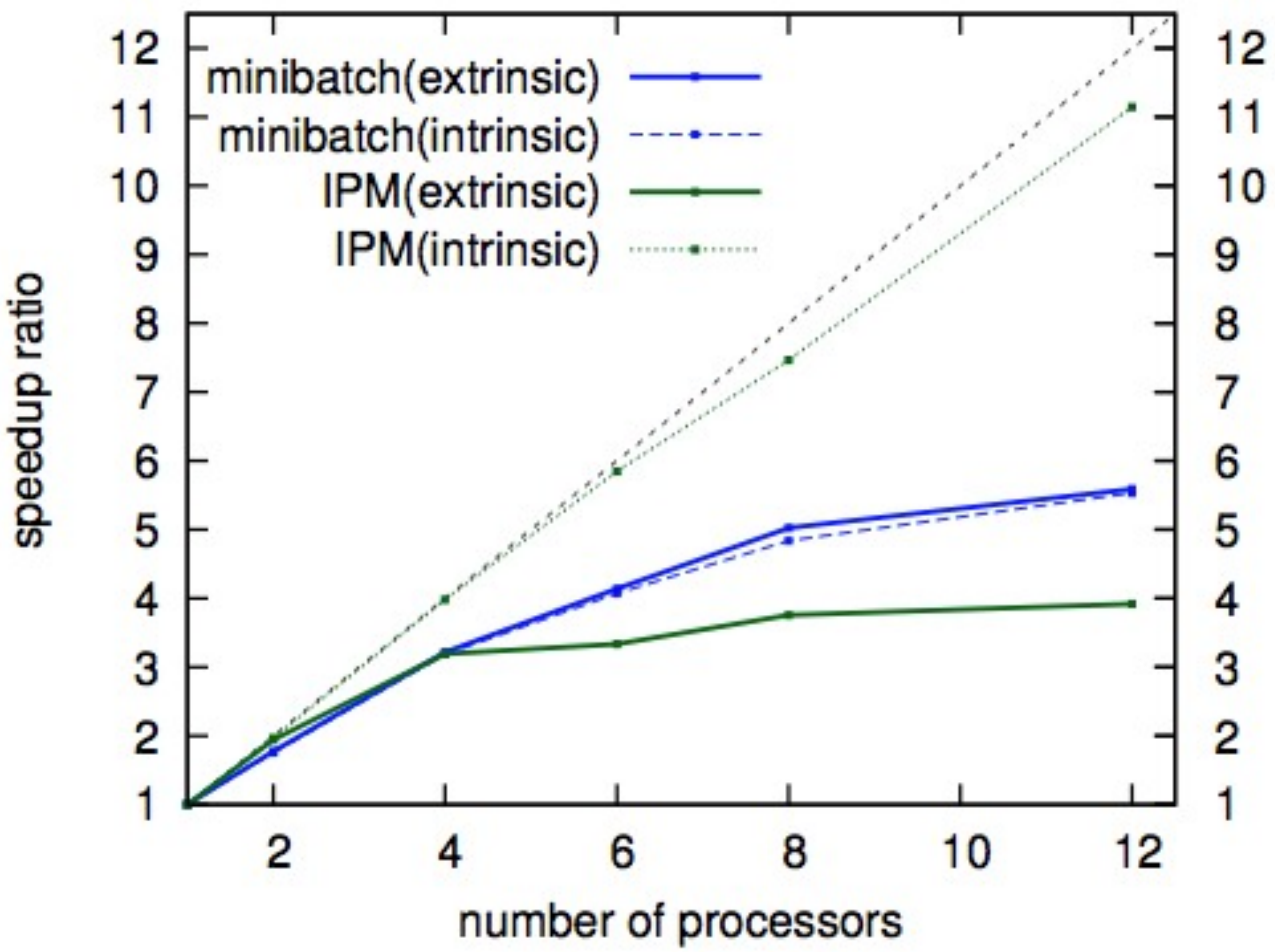


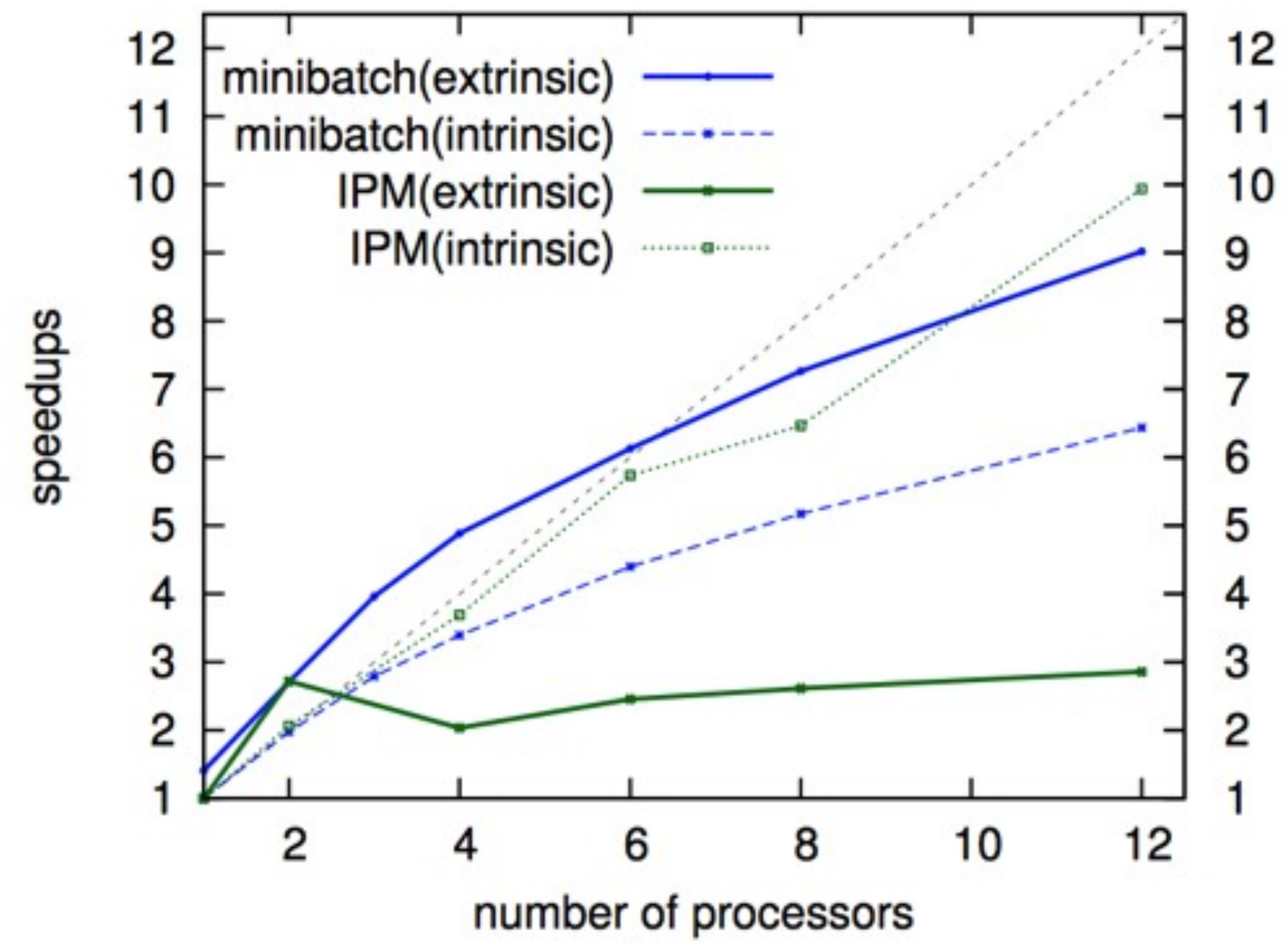


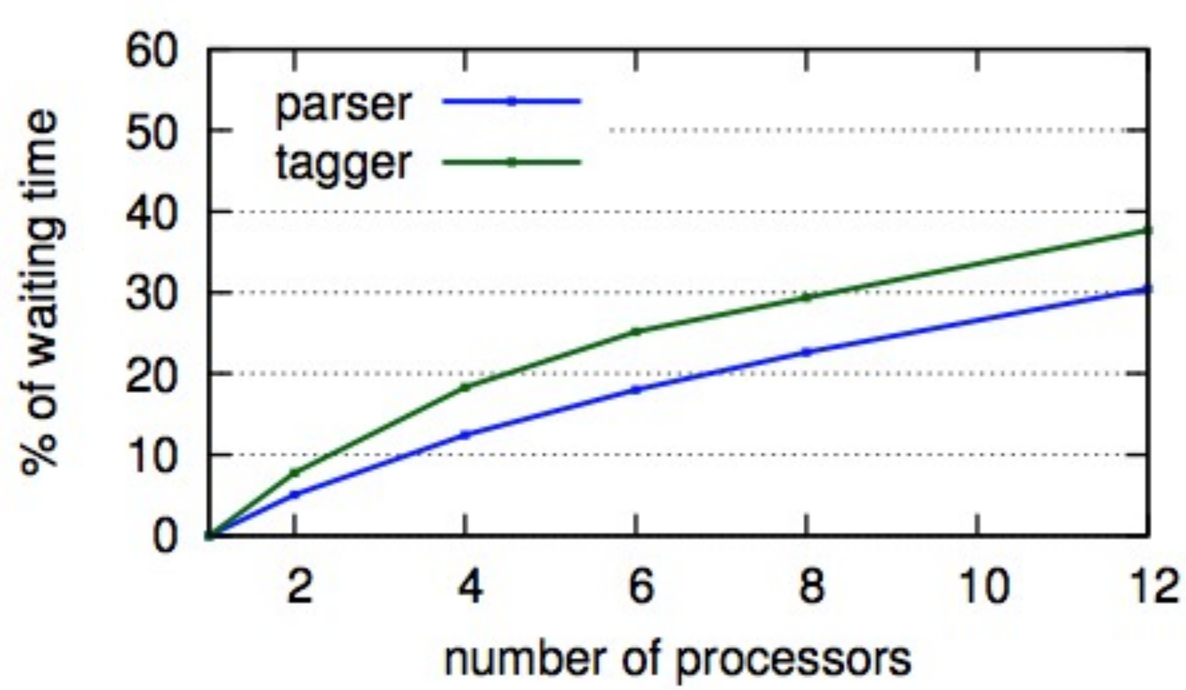




Tagging vs. Parsing







Conclusions

- Two Methods for Scaling Up Structured Learning
  - New variant of perceptron that allows fast inexact search
    - theory: a general violation-fixing perceptron framework
    - practice: new update methods within this framework
      - "max-violation" learns faster and better than early update
      - our methods are more helpful to harder search problems! :)
  - Minibatch parallelization offers significant speedups
    - much faster than previous parallelization (McDonald et al 2010)
    - even helpful in serial setting (MIRA with more constraints)