Hierarchical MT Training using Max-Violation Perceptron

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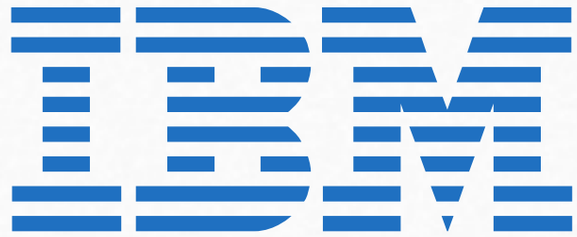

MT is hard


HERITAGE
WALK


遗产
走路


Watertable
Renaissance Baltimore Harborplace
E Pratt St
Phillips Seafood
USS Constellation
National Aquarium
Chipotle Mexican Grill
Jones Falls
Columbus Park
Miss Shirley's
S President St
Slemmer's Alley
Stiles St
Fawn St
Trinity St
Mince Alley
S Central Ave
S Eden St
Eastern A
Duker Ct
Whole Foods Market
Baltimore Marriott Waterfront
Baltimore Marriott Waterfront
Royal Sonesta Harbor Court Baltimore
Rusty Scupper Restaurant & Bar
Rash Field
Key Hwy
Key Hwy

Discriminative Training for SMT

- discriminative training is not very successful yet in MT
  - although dominant in parsing/tagging
  - can use arbitrary, overlapping, lexicalized features
- most efforts on MT training tune feature weights on the small dev set (~1k sents) not the training set!
  - as a result can only use ~10 dense features (MERT)
  - or ~10k rather impoverished features (MIRA/PRO)
- Liang et al ('06) train on the training set but not successful

MT as Structured Classification

- with latent variables (hidden derivations)
- structured perceptron => latent-variable structured perceptron

training example

那	人	咬	了	狗	x

the	man	bit	the	dog	y

(Liang et al '06)

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那	人	咬	了	狗	x

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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 '06)

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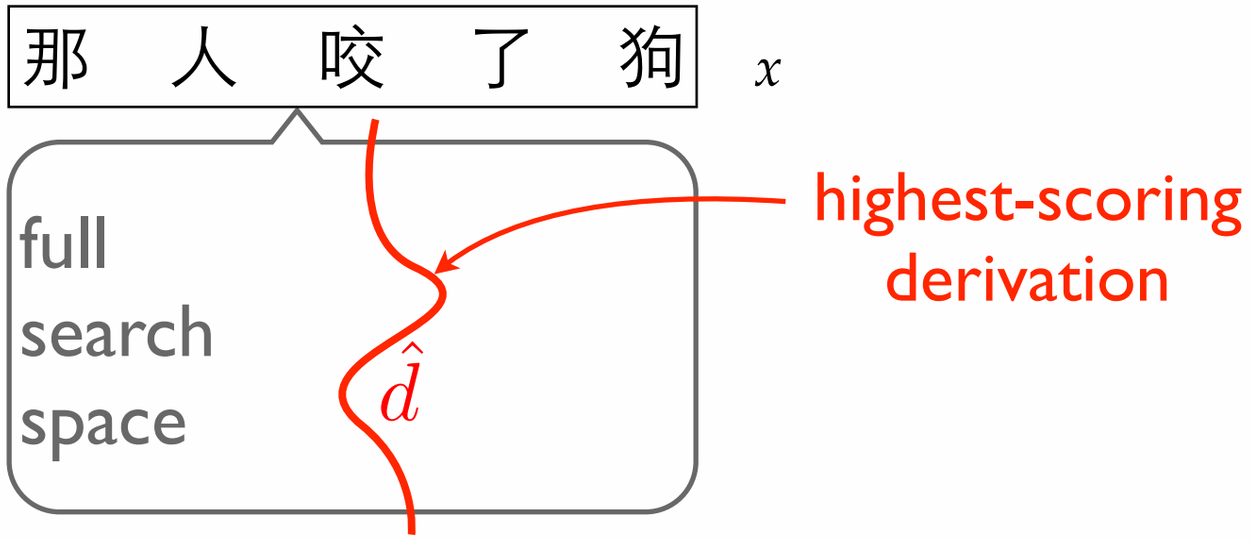

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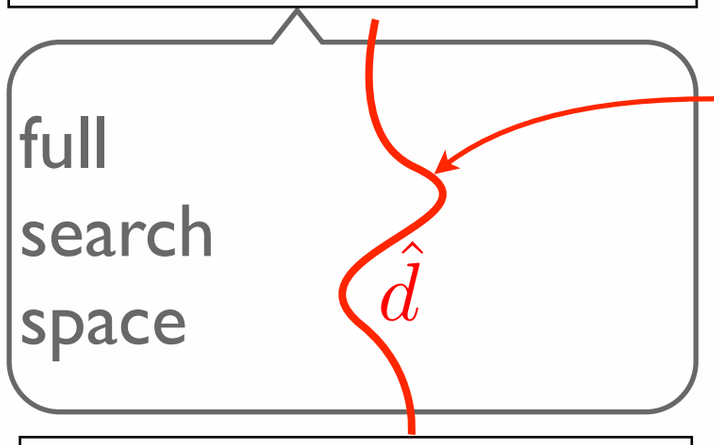

the dog bit the man z

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training example

那 人 咬 了 狗 x

the man bit the dog y $\neq$

during online learning...

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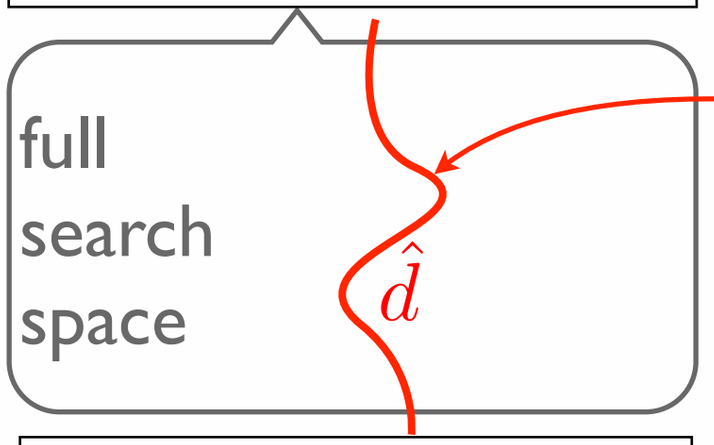

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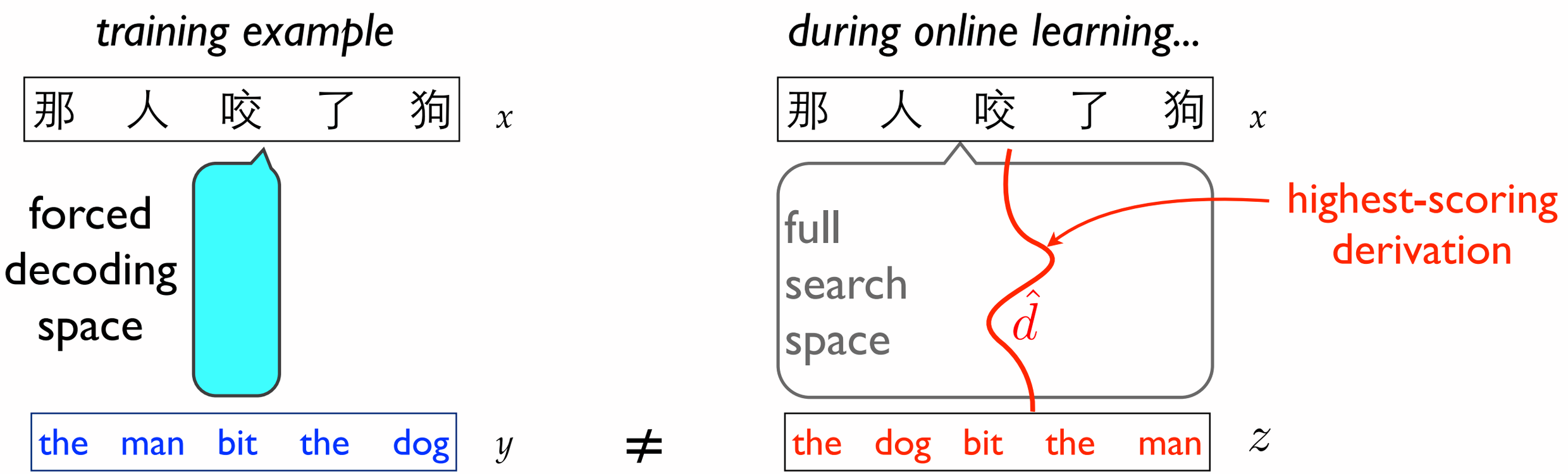

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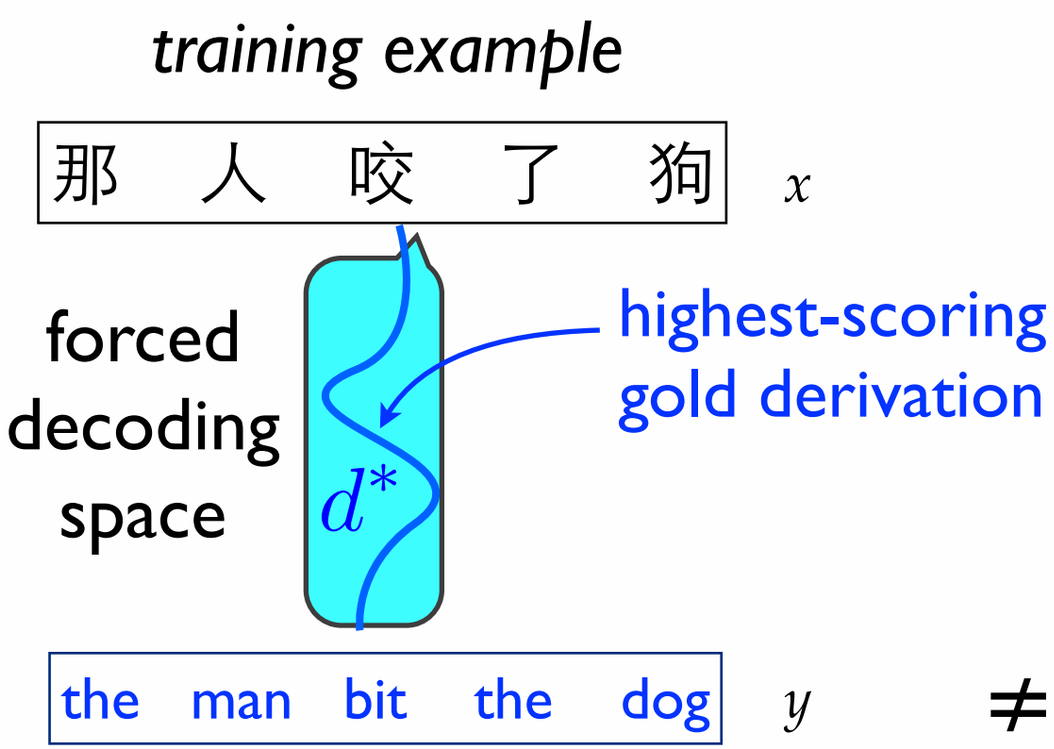

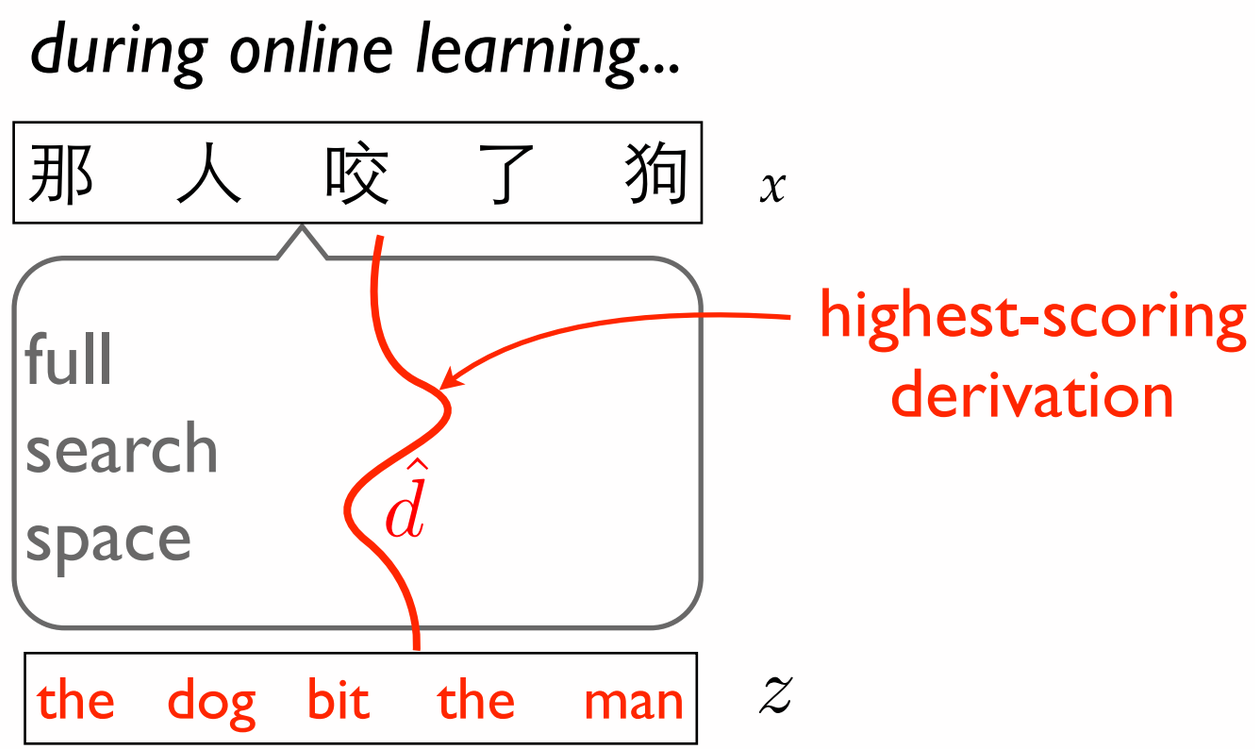

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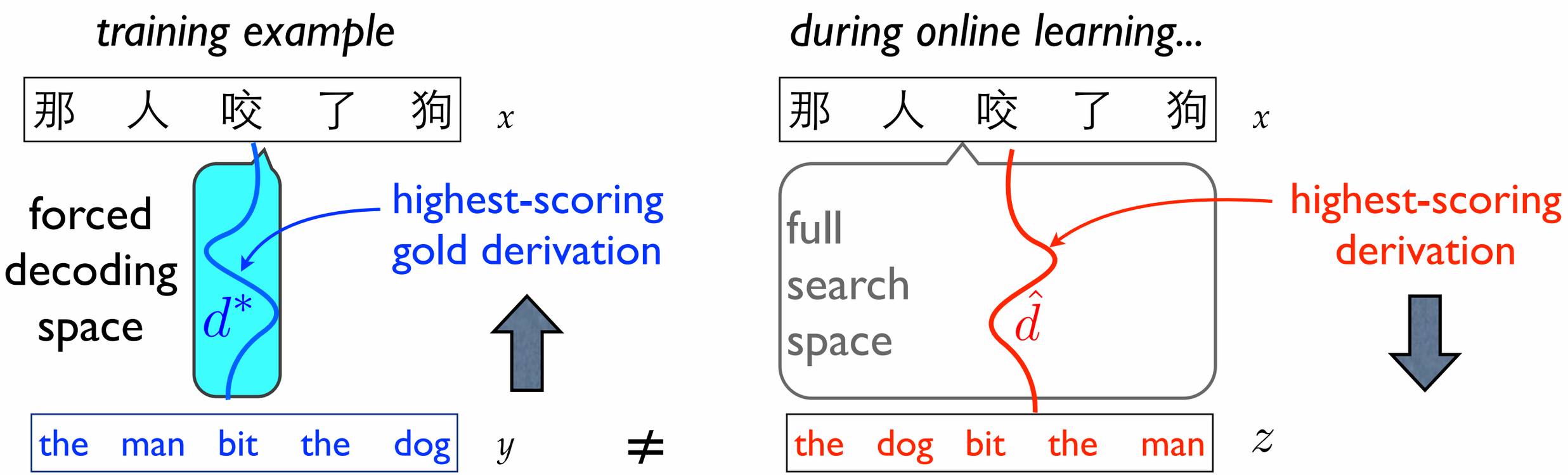

$$\mathbf{w} \leftarrow \mathbf{w} + \Phi(x, d^*) - \Phi(x, \hat{d})$$

reward correct

penalize wrong

(Liang et al '06)

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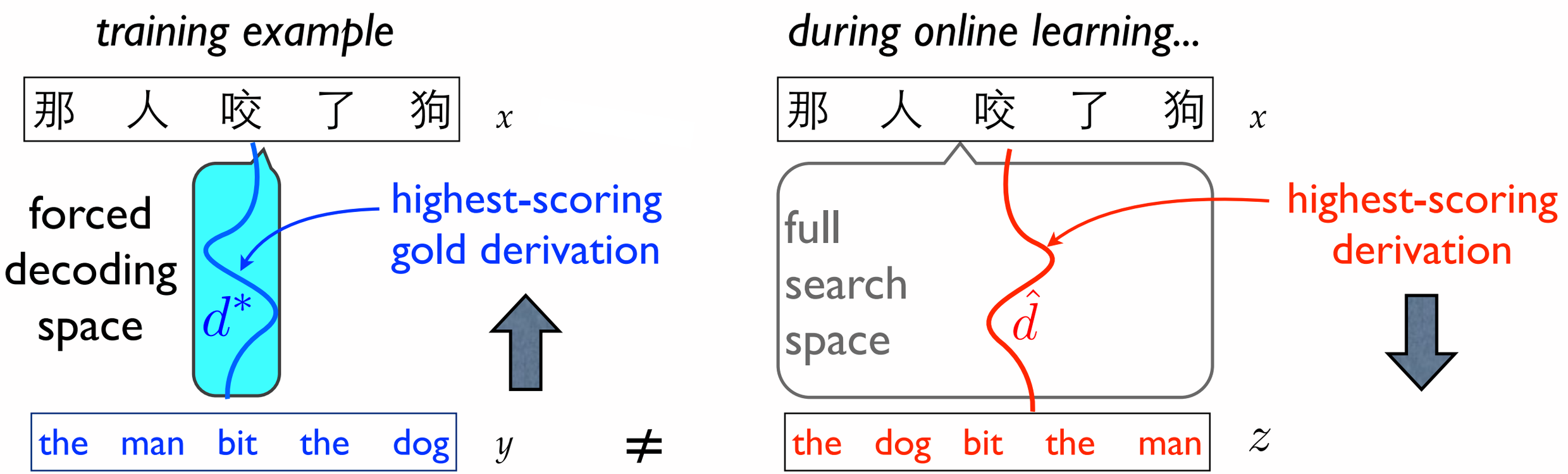

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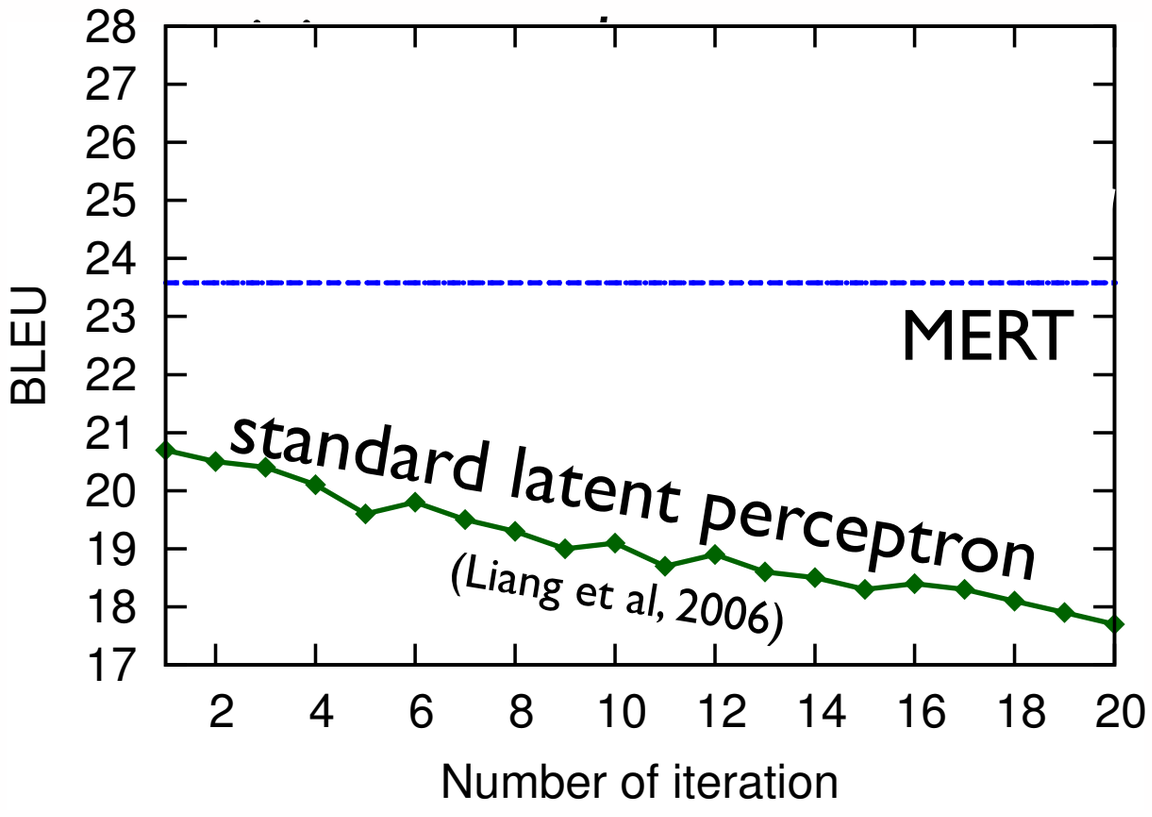

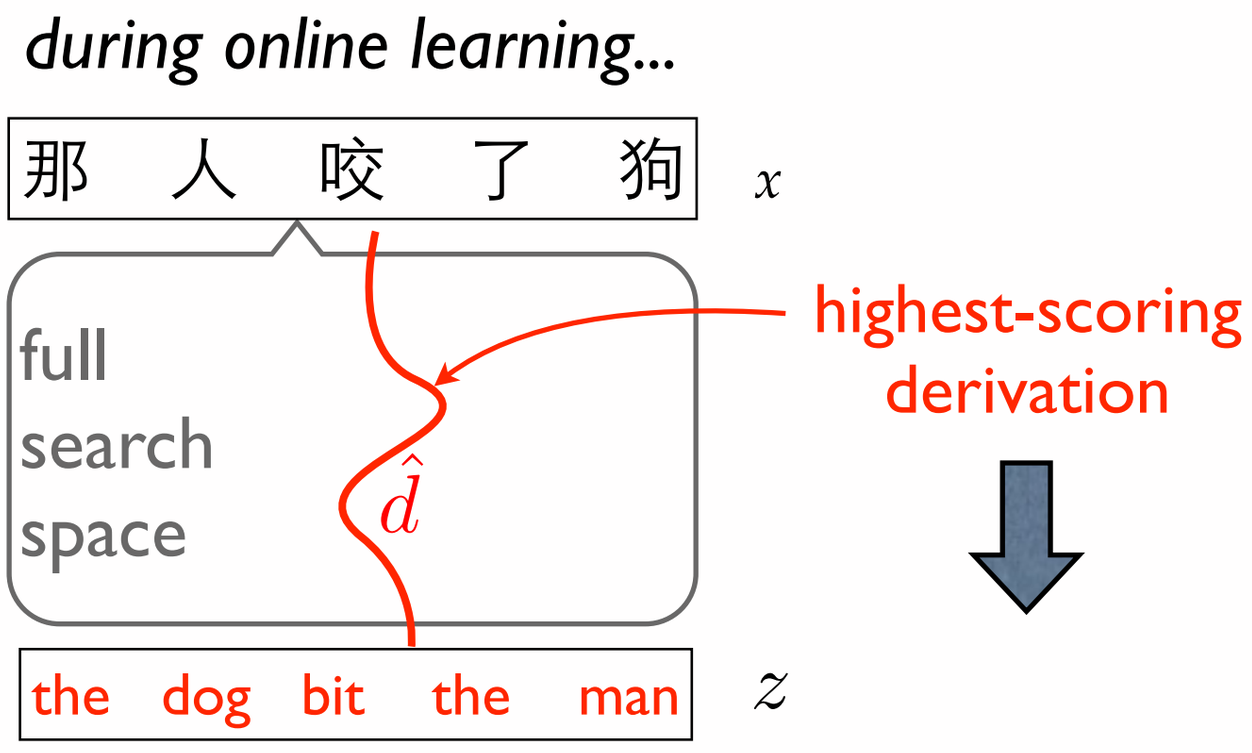

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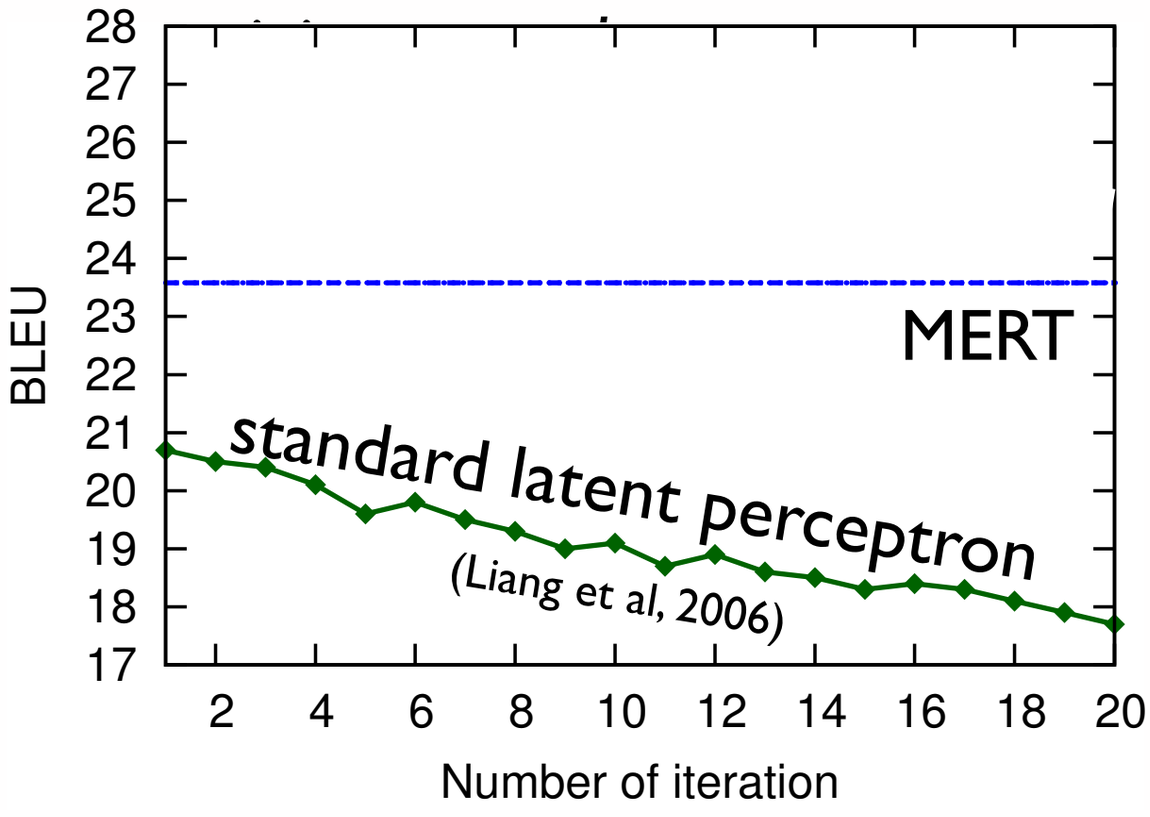

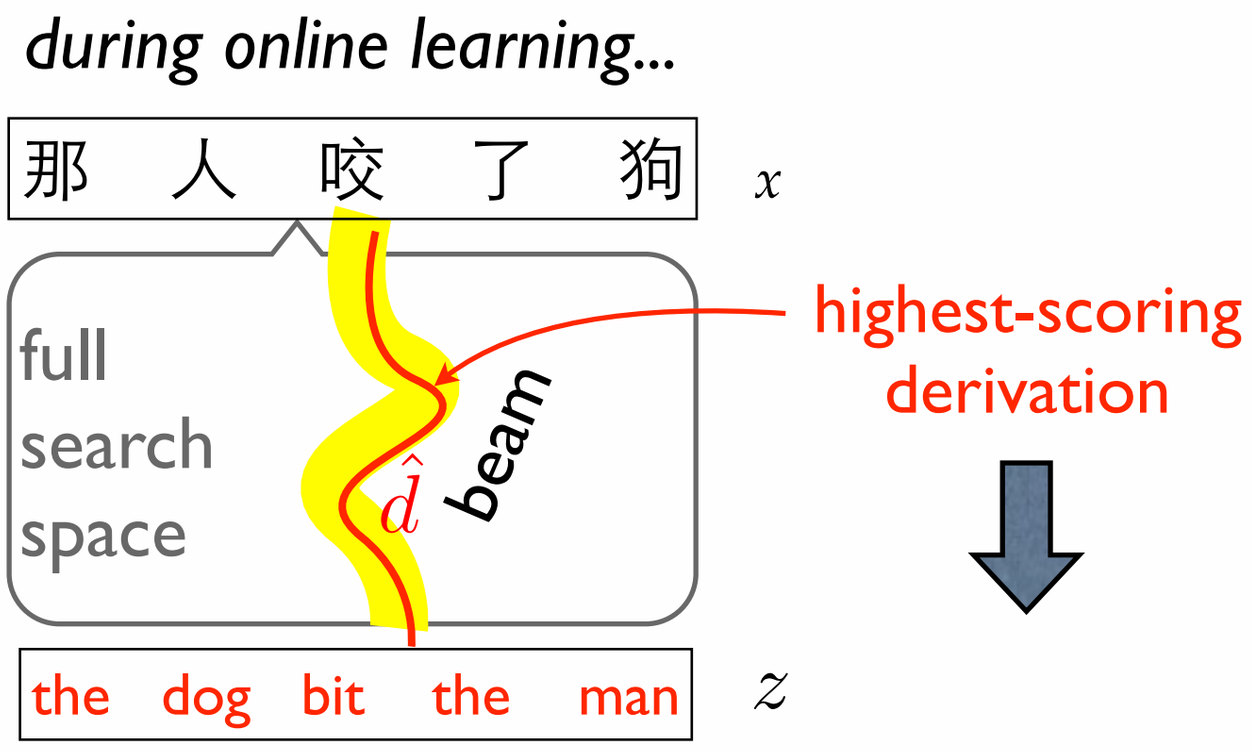

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(Yu et al 2013)

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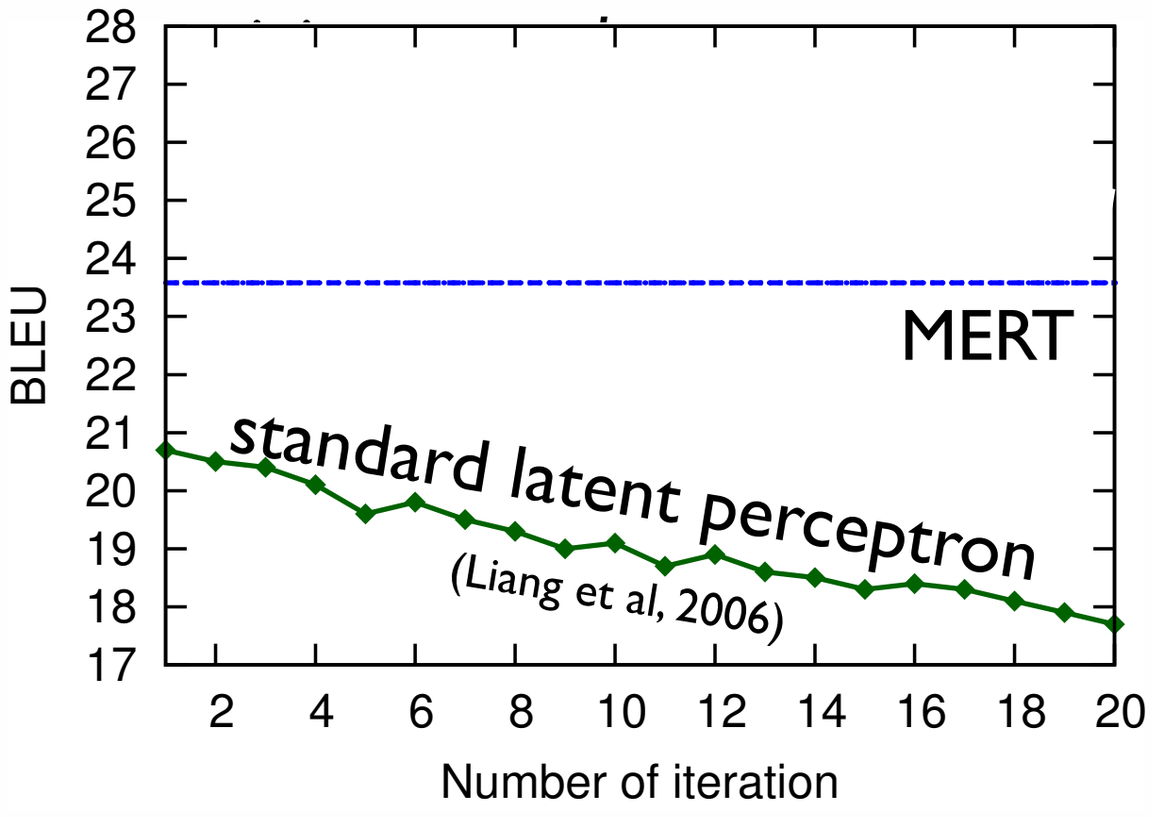

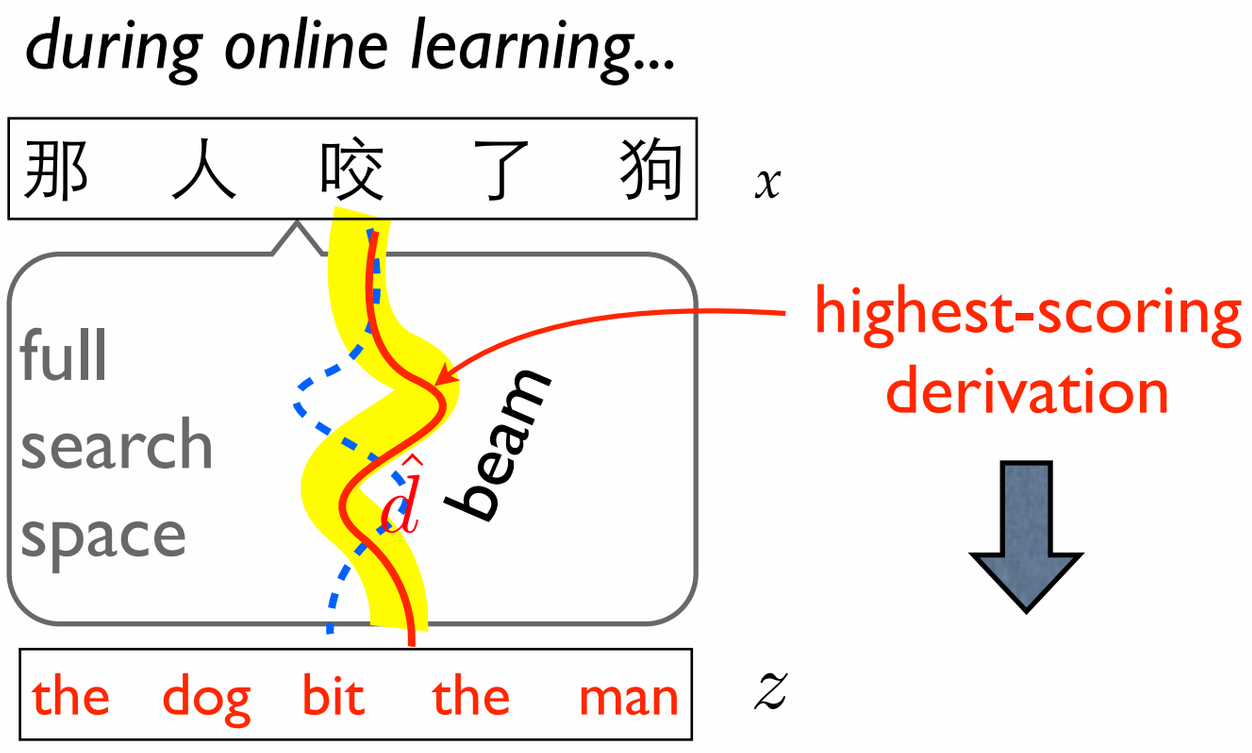

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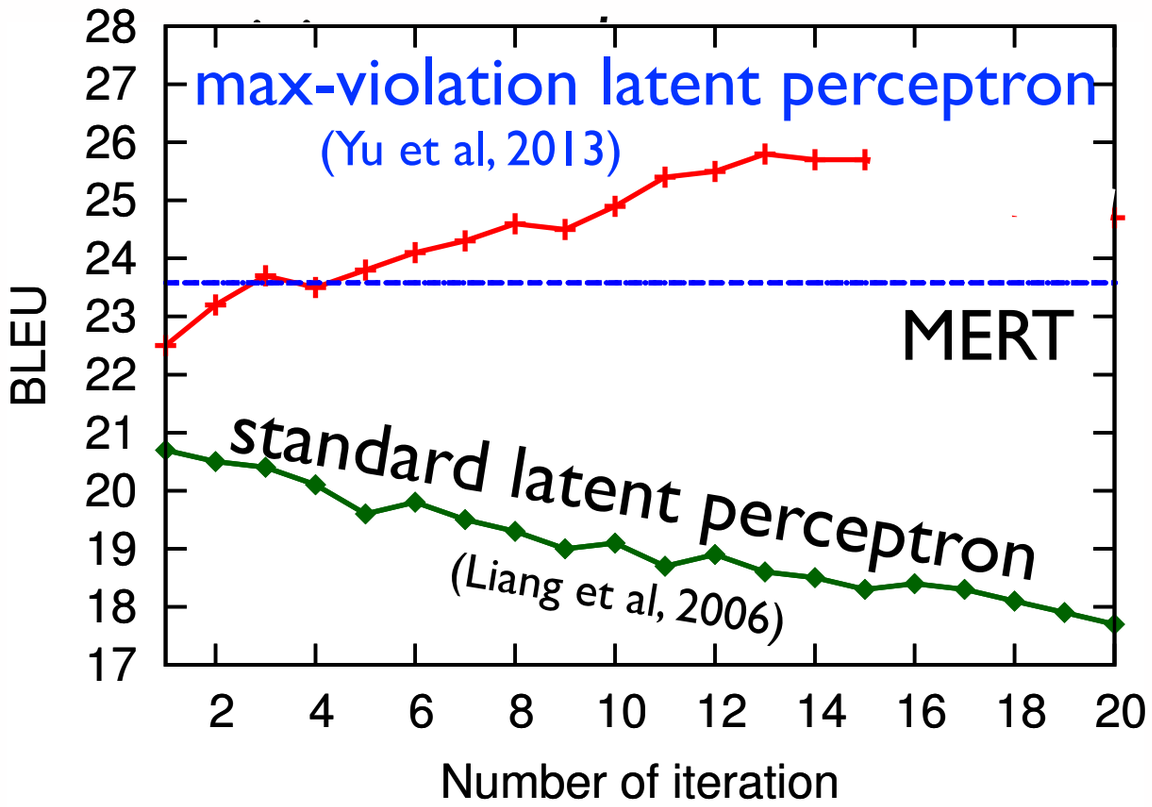

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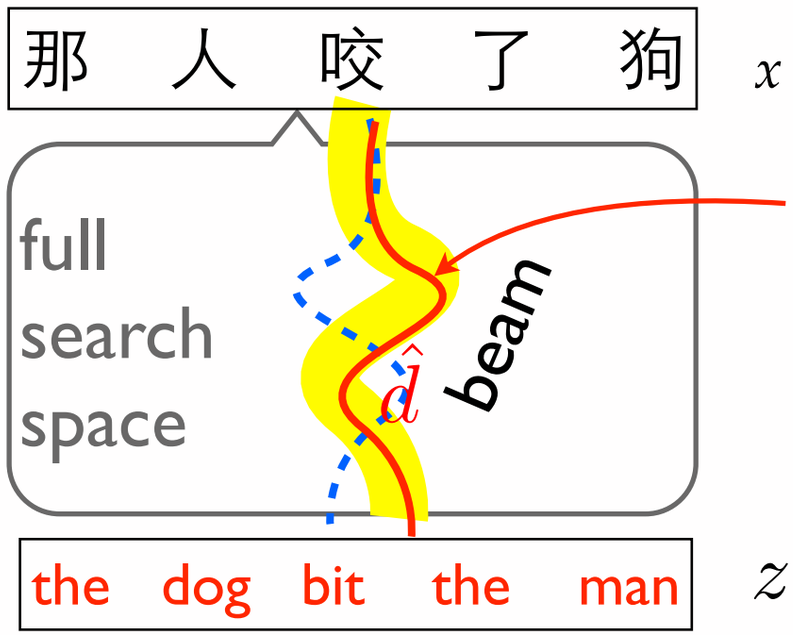

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- Phrase-based translation suffers from distortion limit
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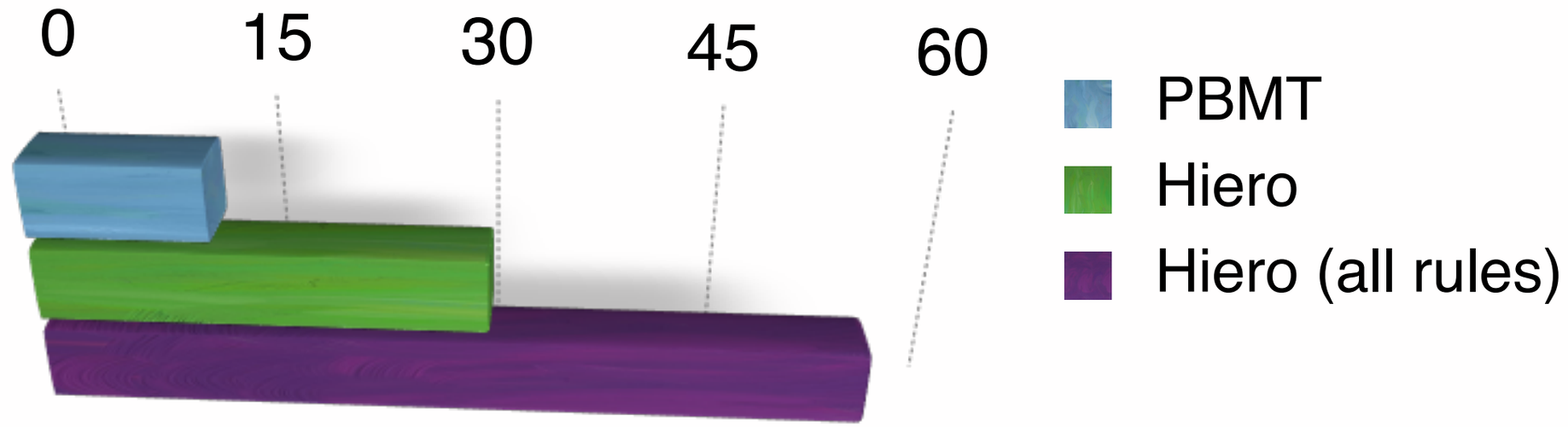
  - translation quality is often slightly worse than hierarchical models



reachability % (in # of words) on FBIS

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  - potentially more sentences to train
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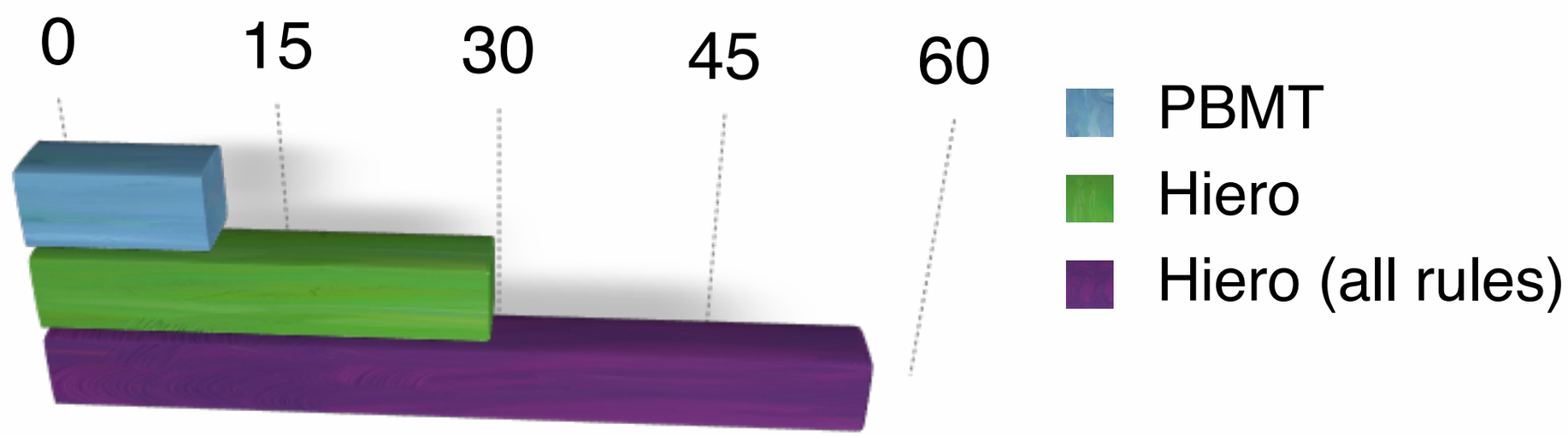

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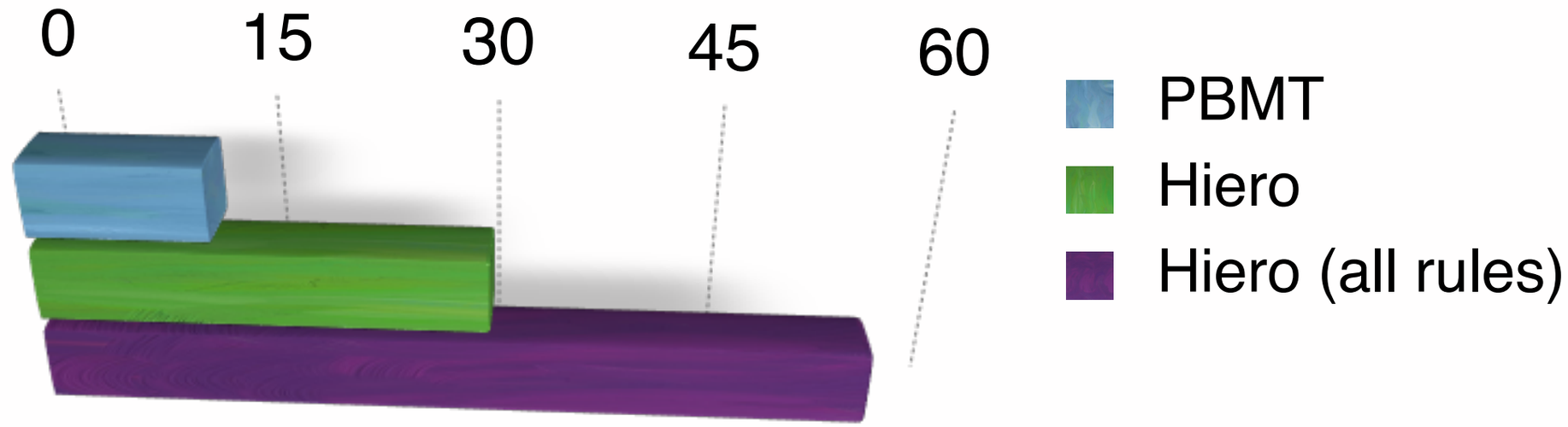
- Challenge: generalize max-violation latent perceptron to hypergraphs?



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A Hiero Example

source

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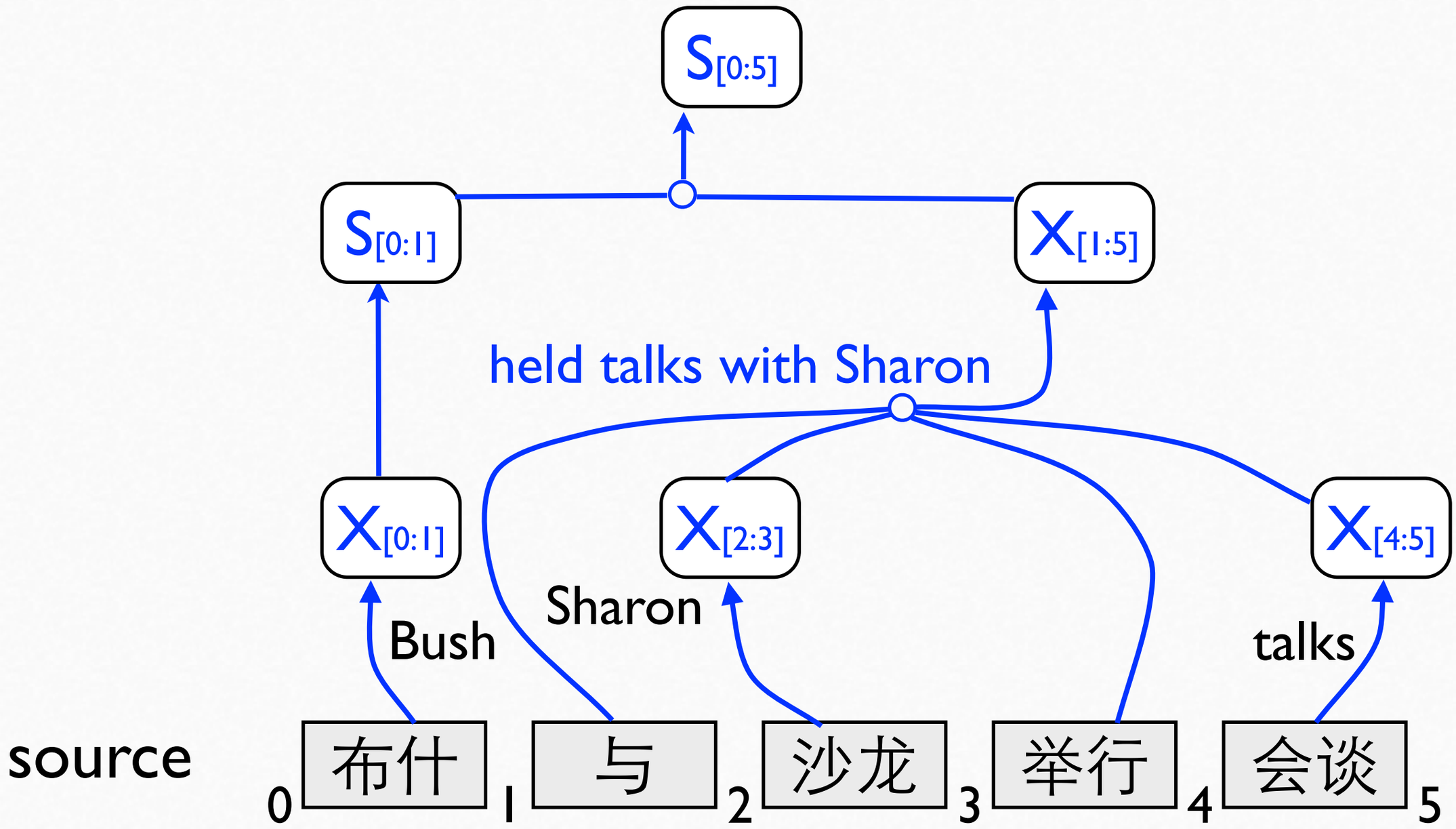

Reference Bush held talks with Sharon

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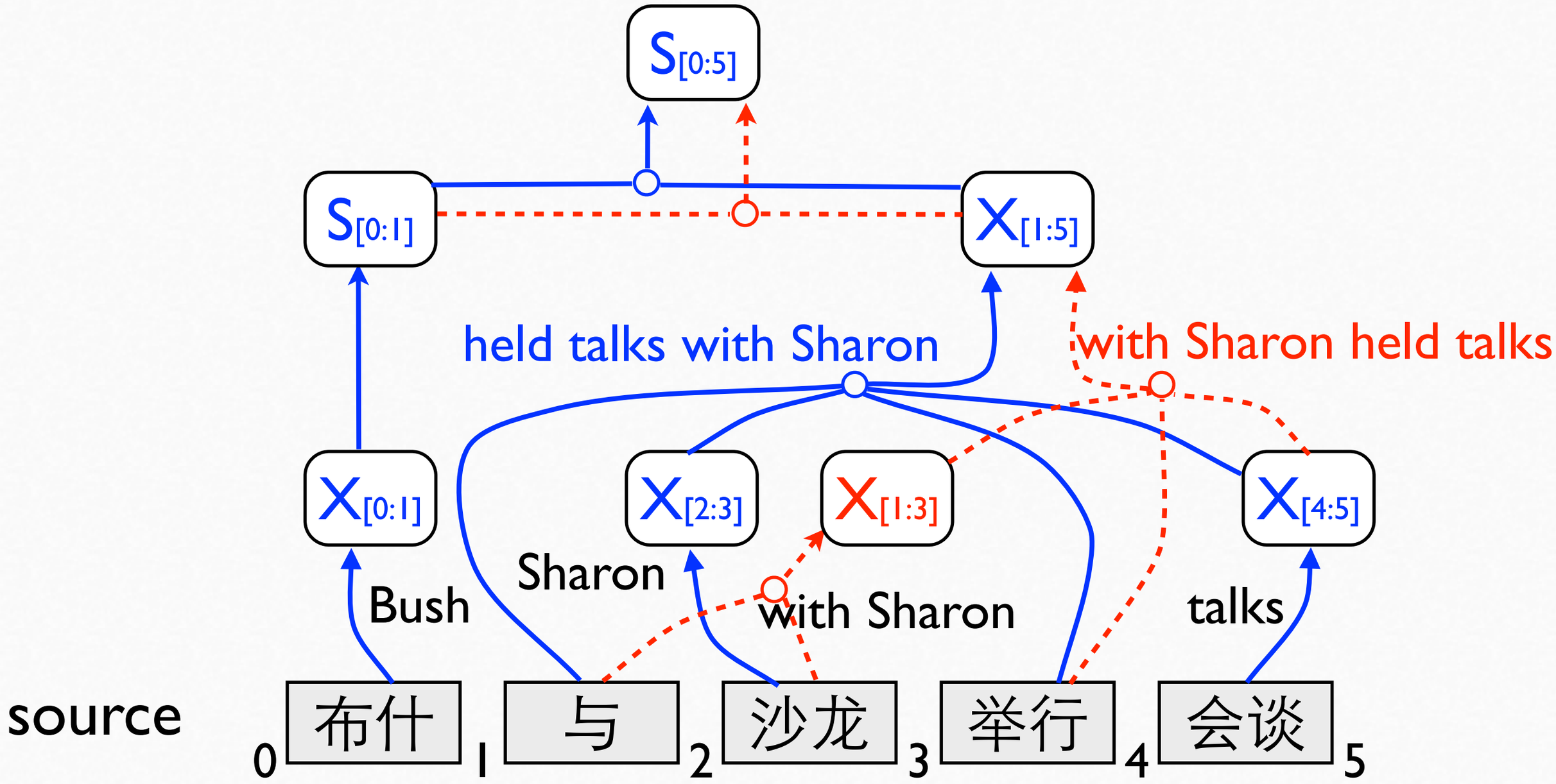

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Viterbi Bush with Sharon held talks

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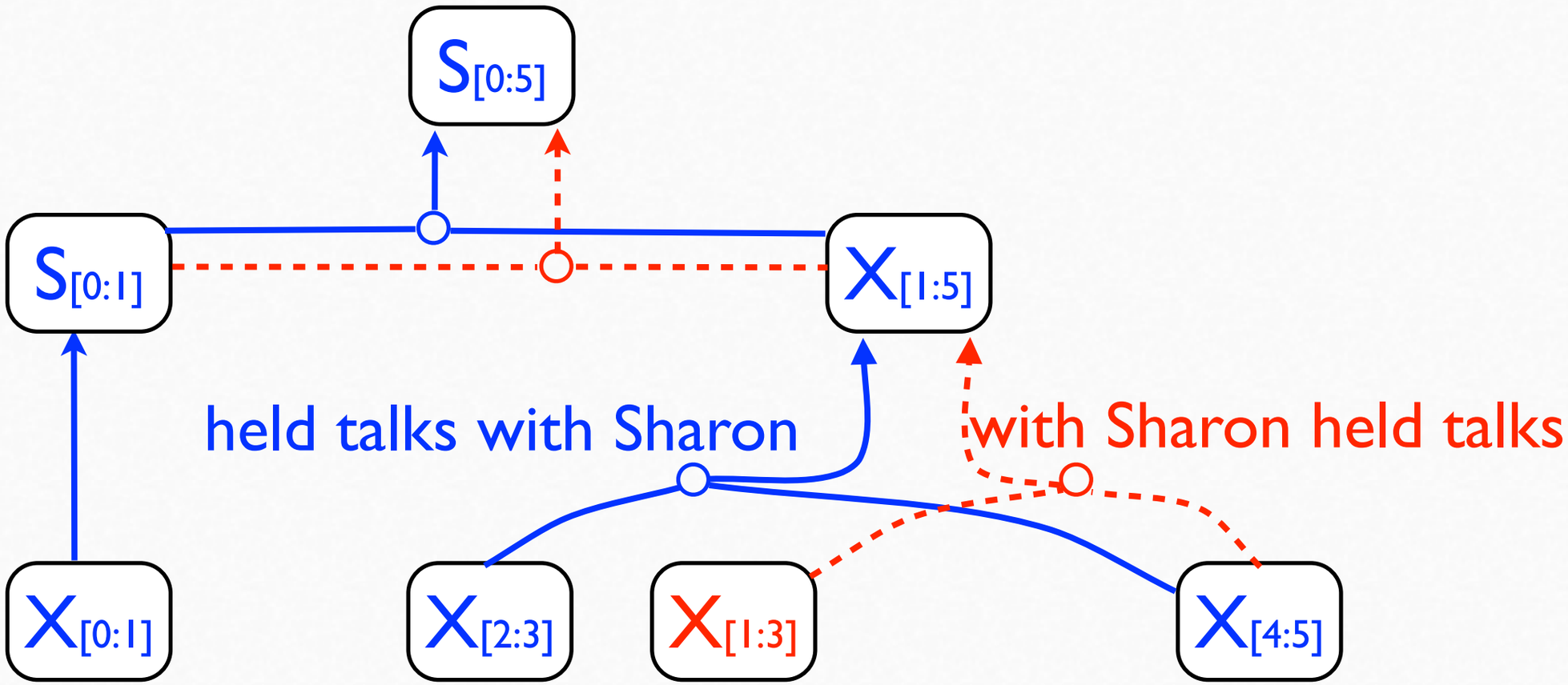
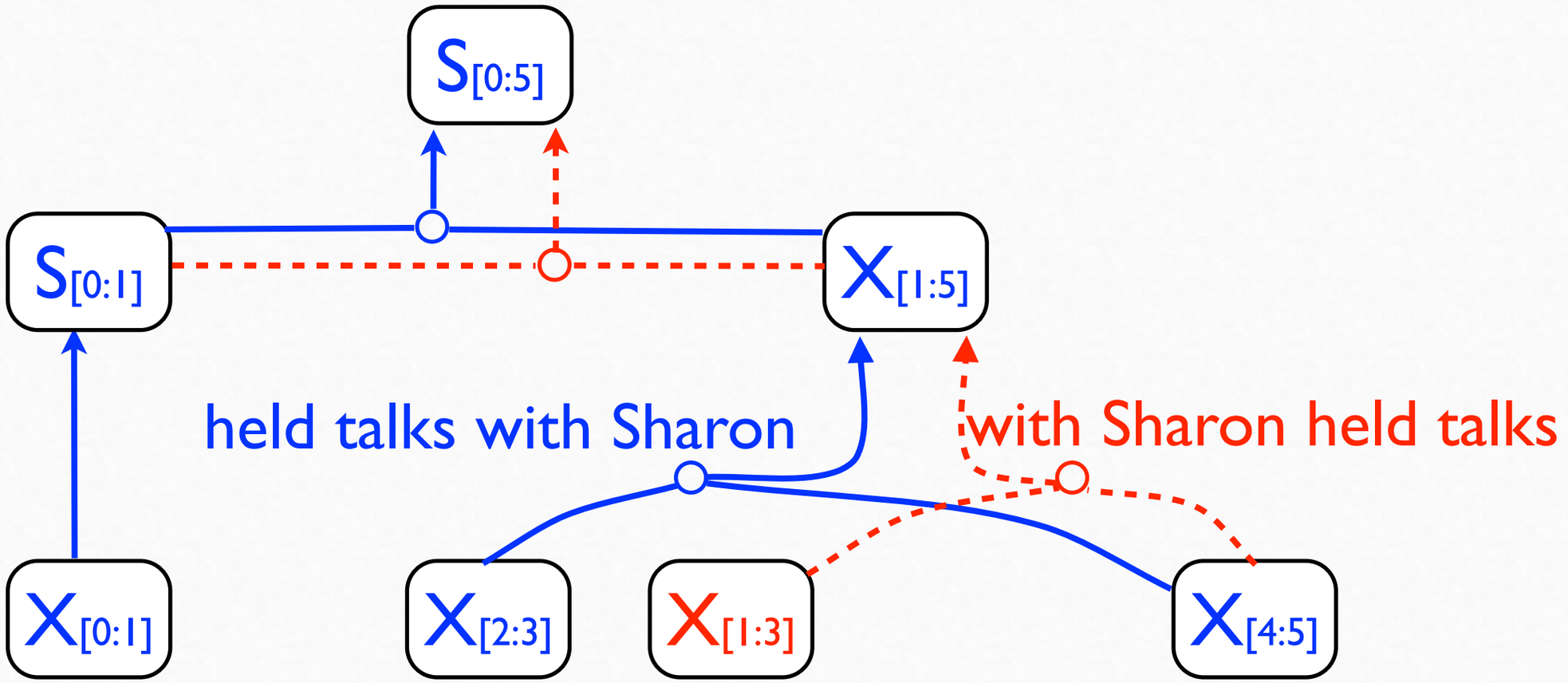


Search Error: Reference Got Pruned



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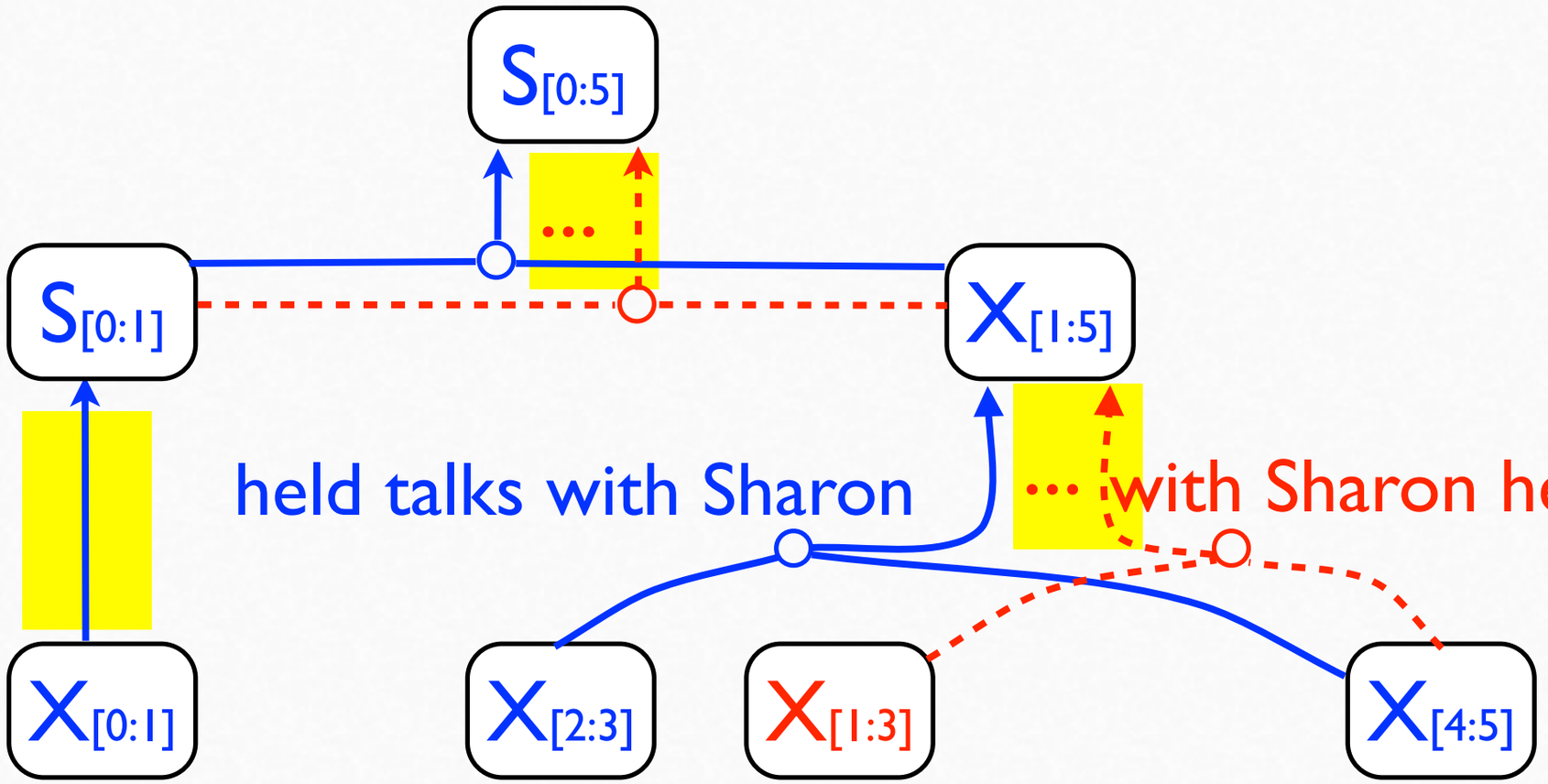

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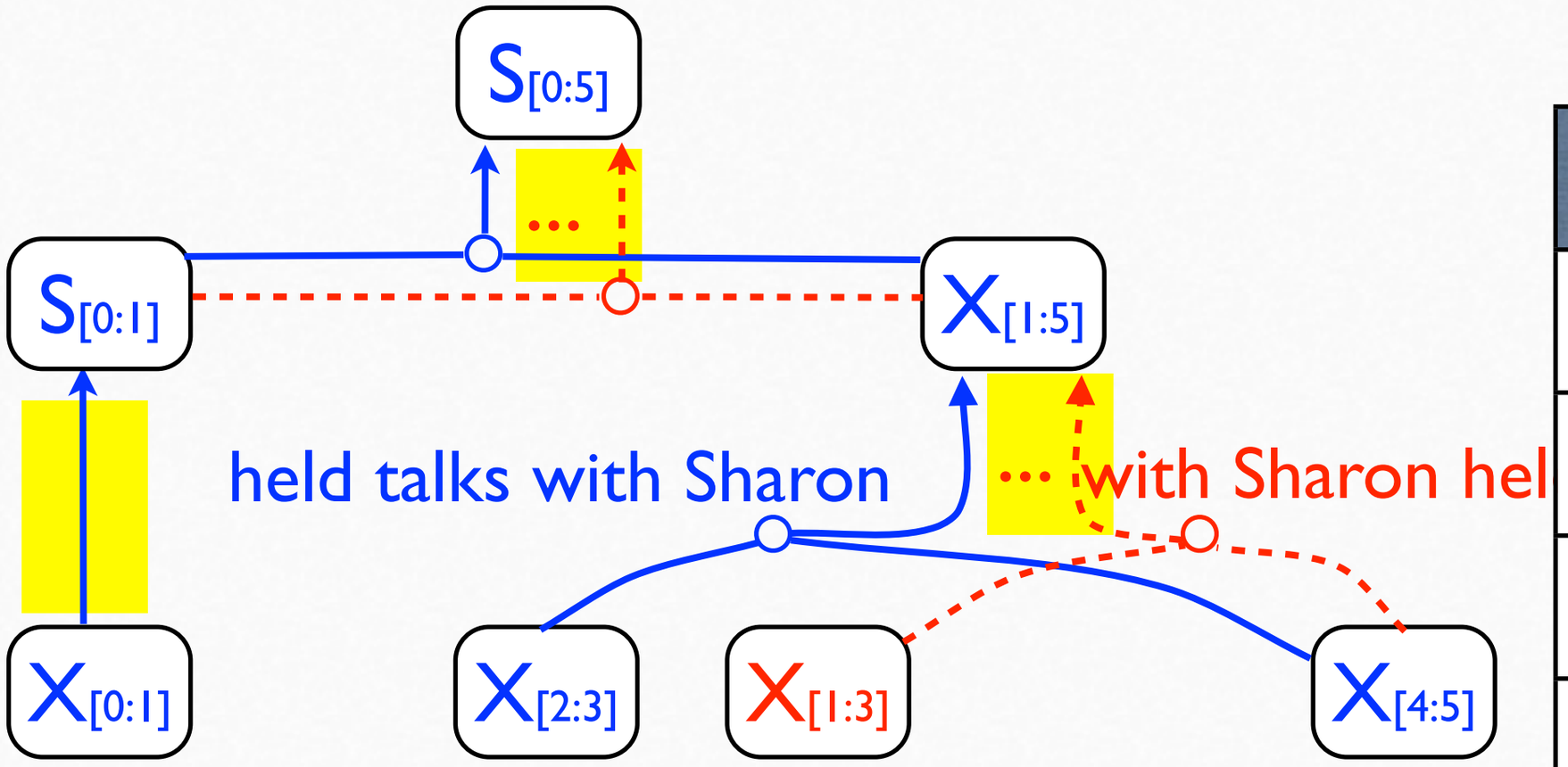

beam at $X_{[1:5]}$

candidate	score
X_1 held X_2	0.88
X_1 holds X_2	0.86
...	...
held X_2 with X_1	0.25
...	...

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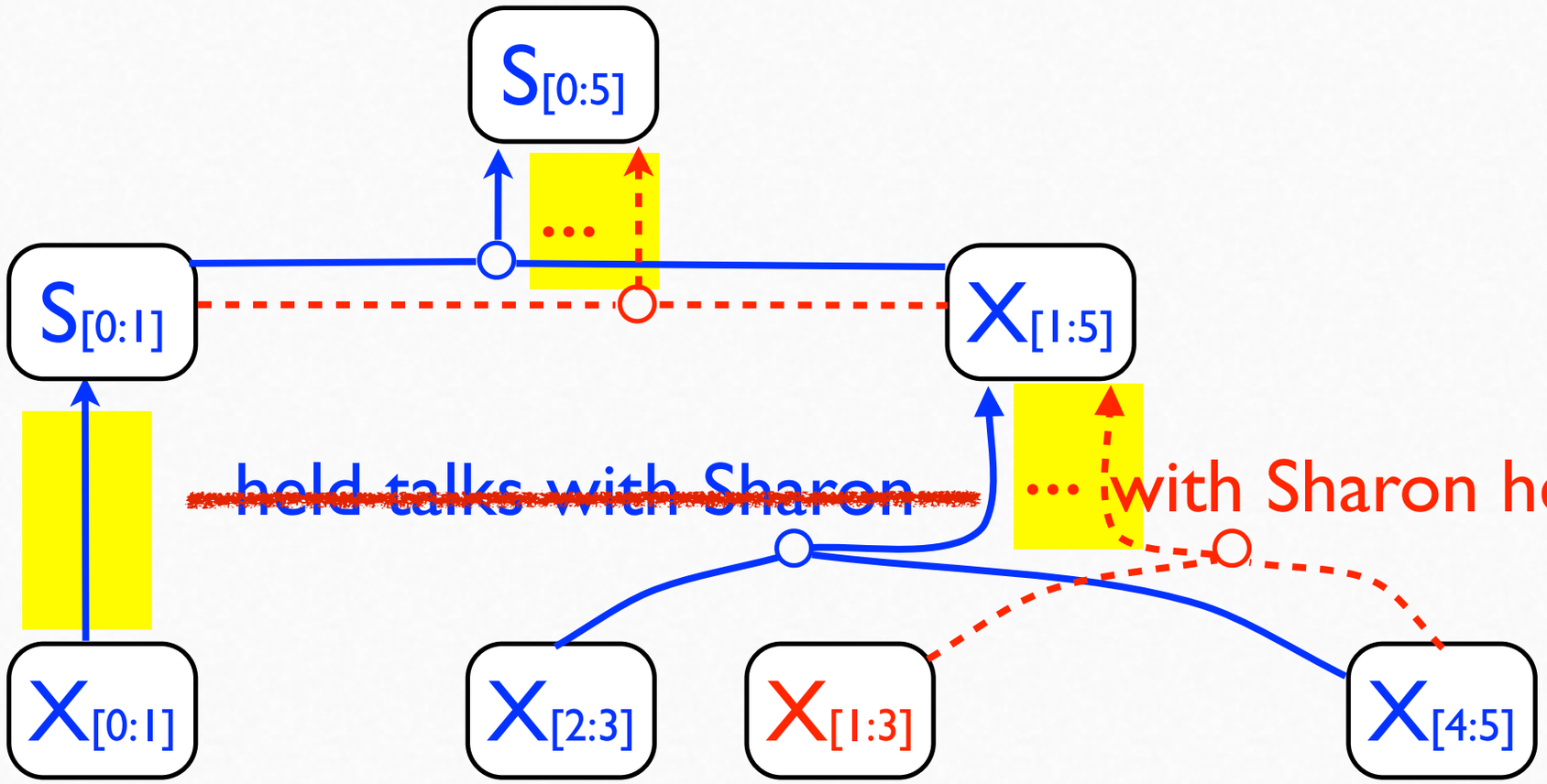

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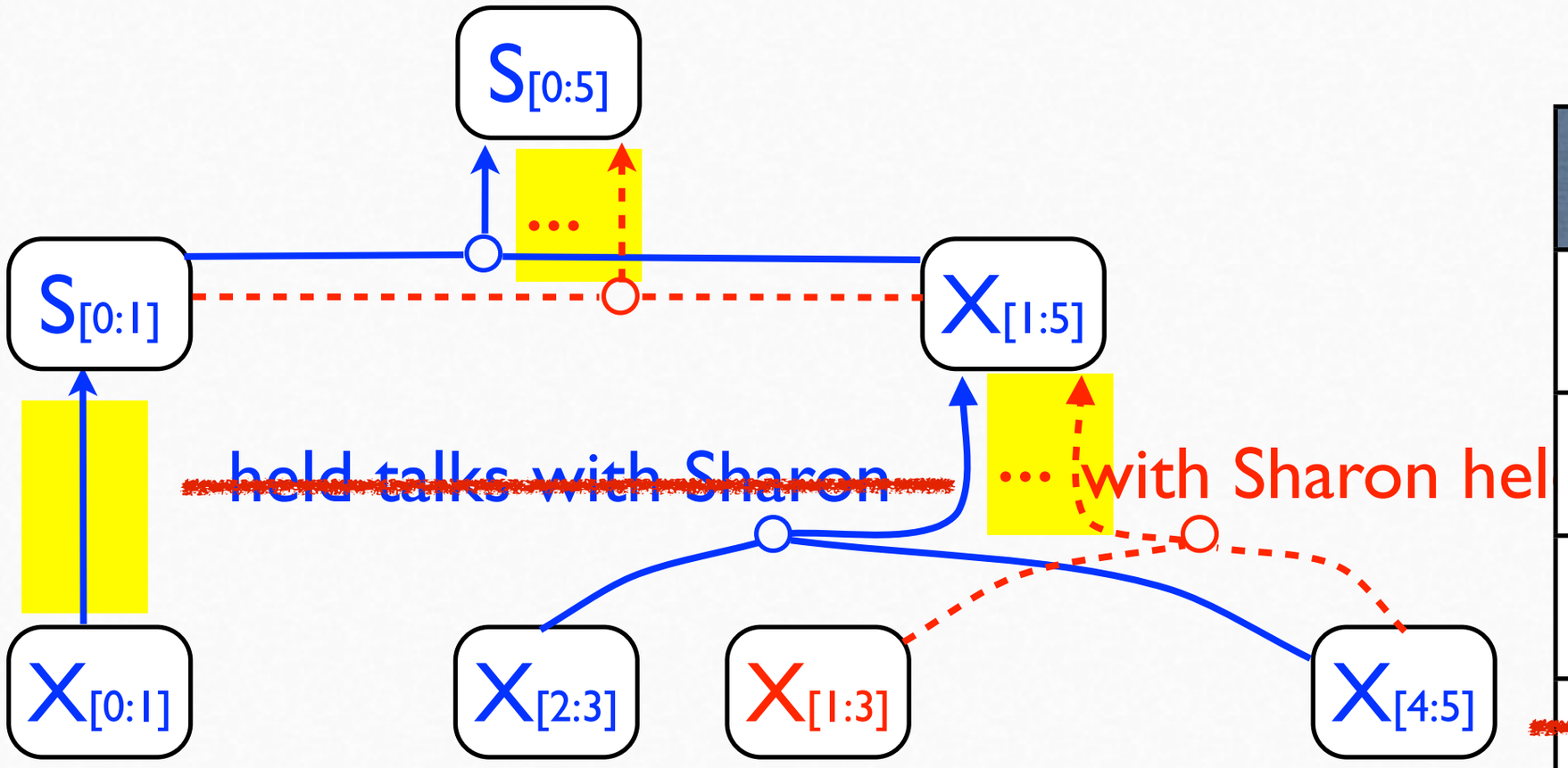

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- We call it a **Violation** iff. score(viterbi) - score(reference) > 0

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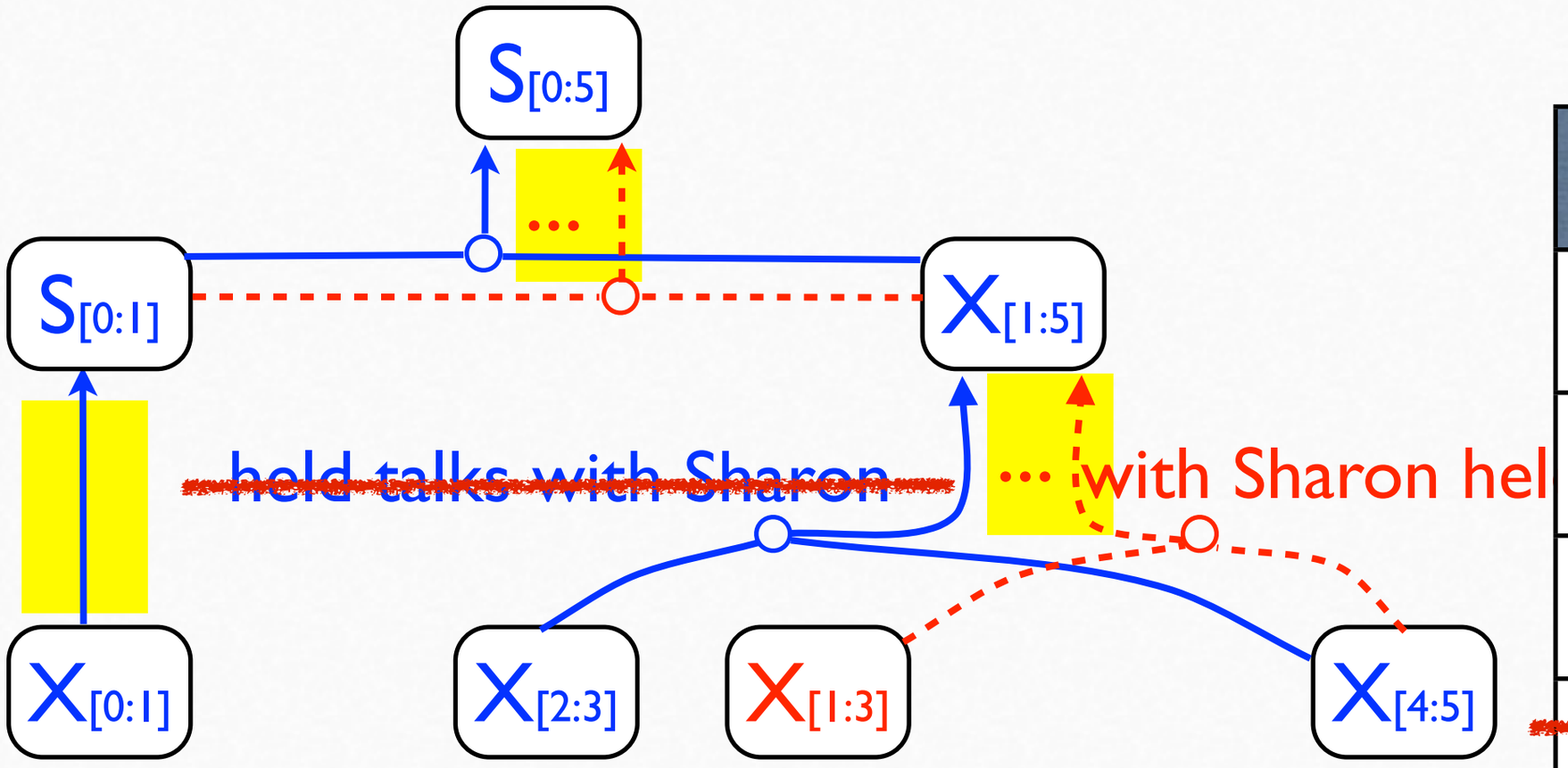

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= amount of violation

Fixing Search Error: Max-Violation

- standard perceptron does not guarantee violation
  - w/ pruning, the correct derivation might score higher at the ends
  - called "invalid" update b/c it doesn't fix the search error
- max-violation: update at where the violation is maximum
  - "worst-mistake" in the search
  - learns more and faster
- "violation-fixing perceptron" (Huang et al 2012)

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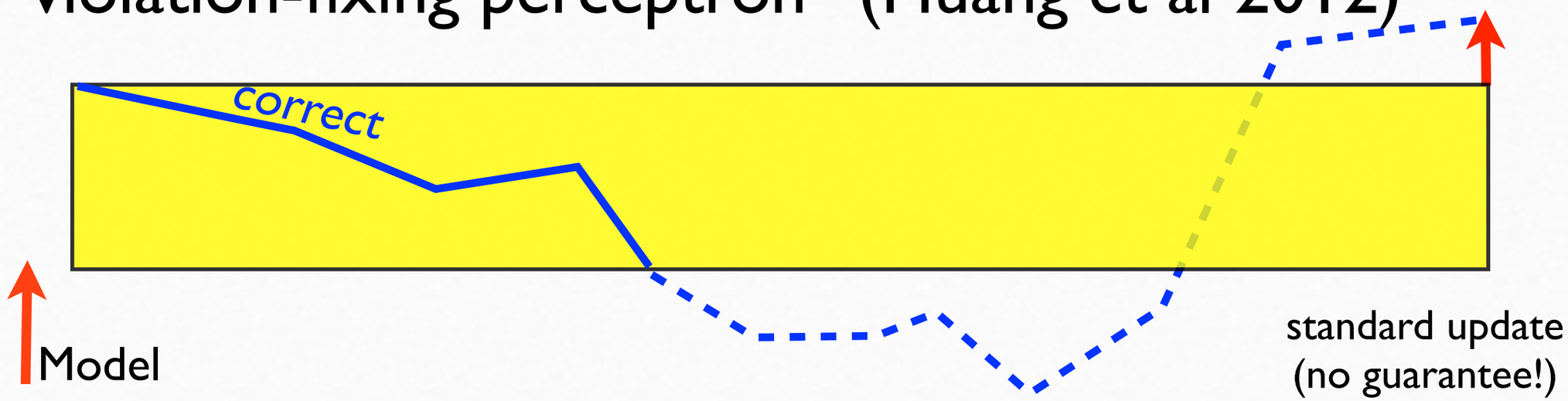

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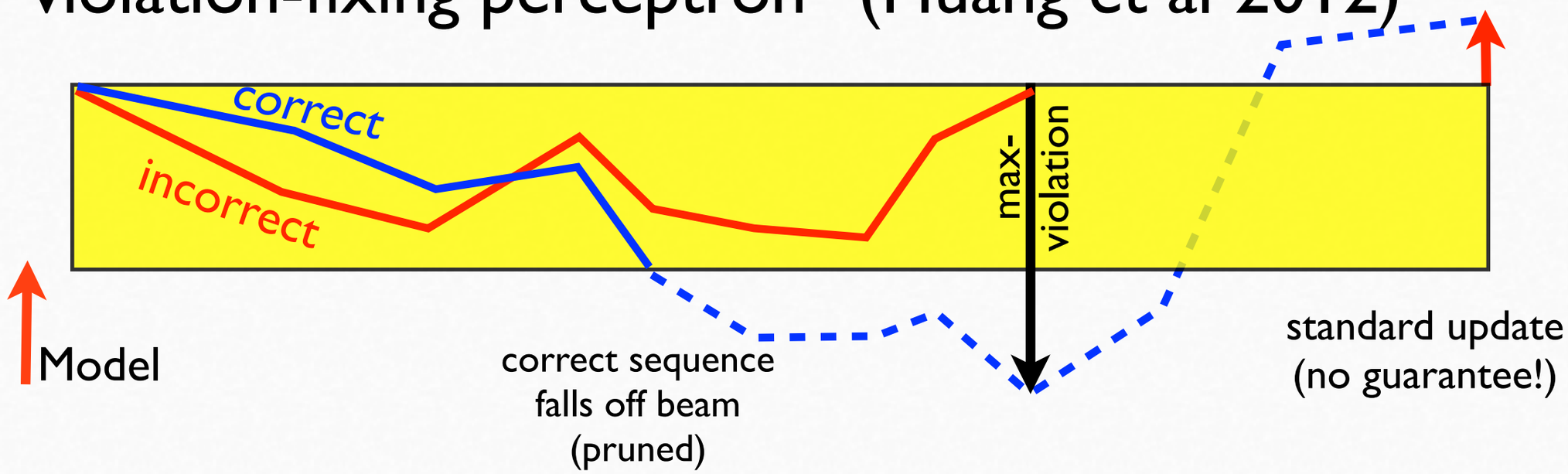
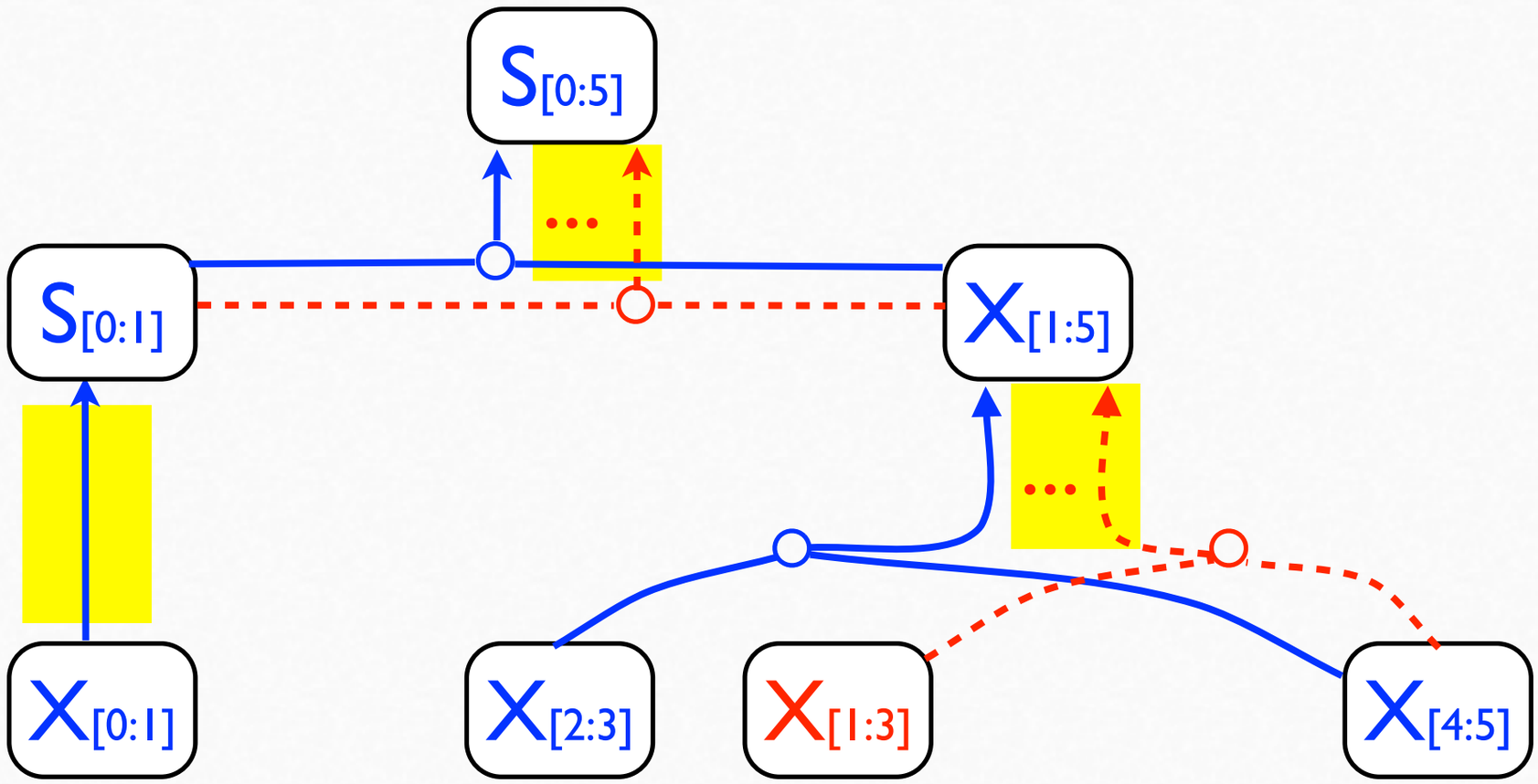


Max-Violation over Hypergraphs



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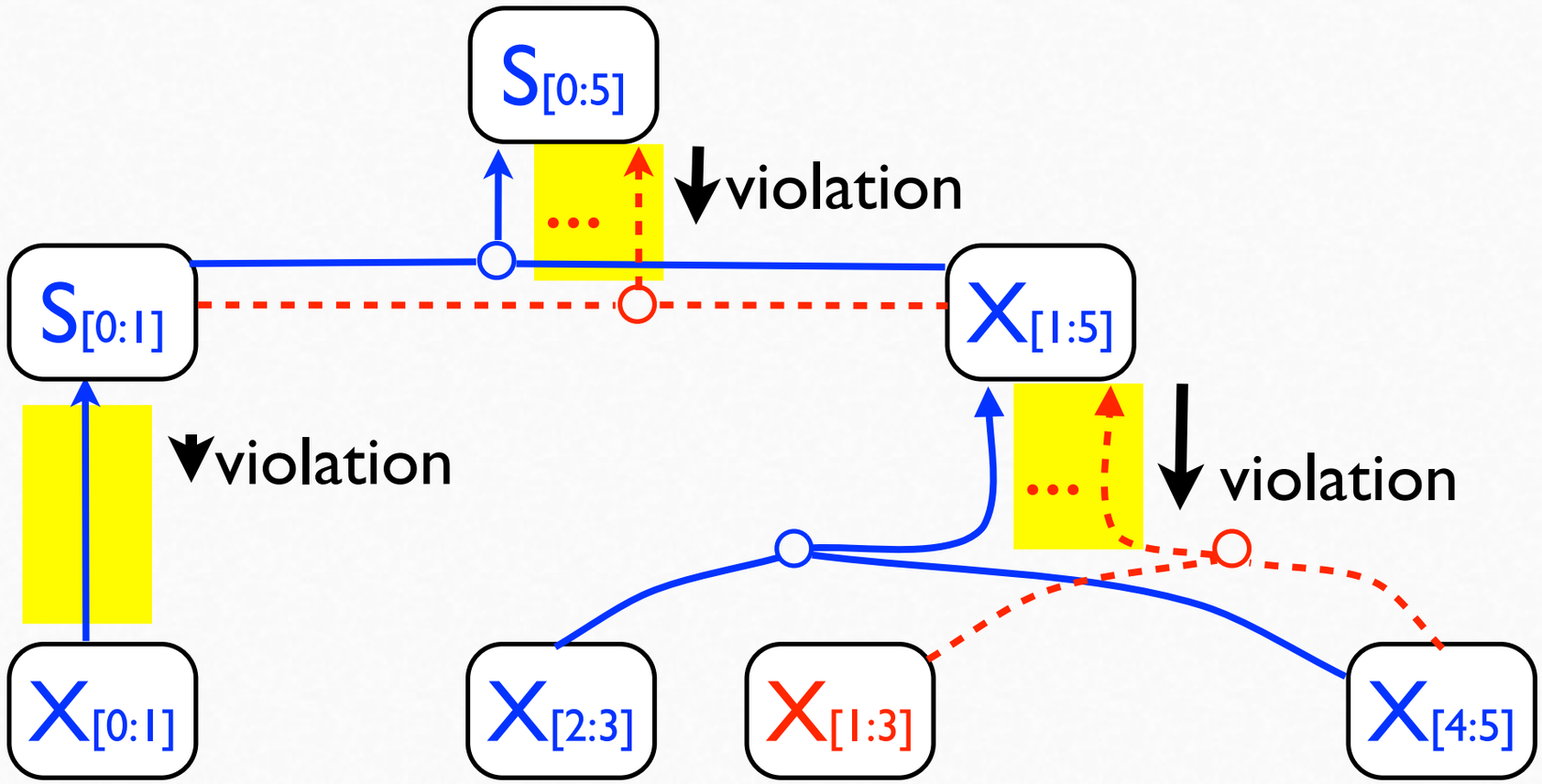

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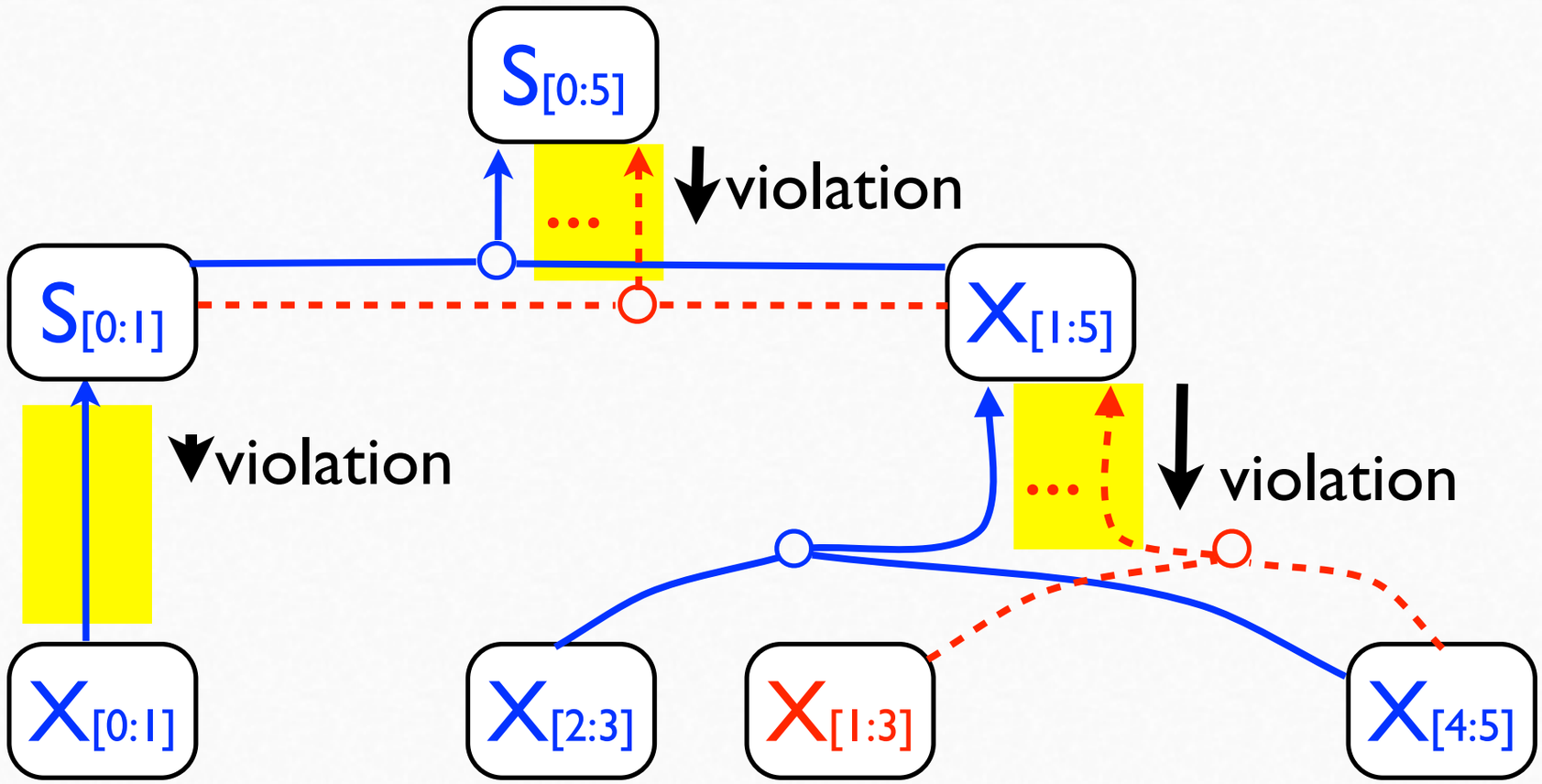

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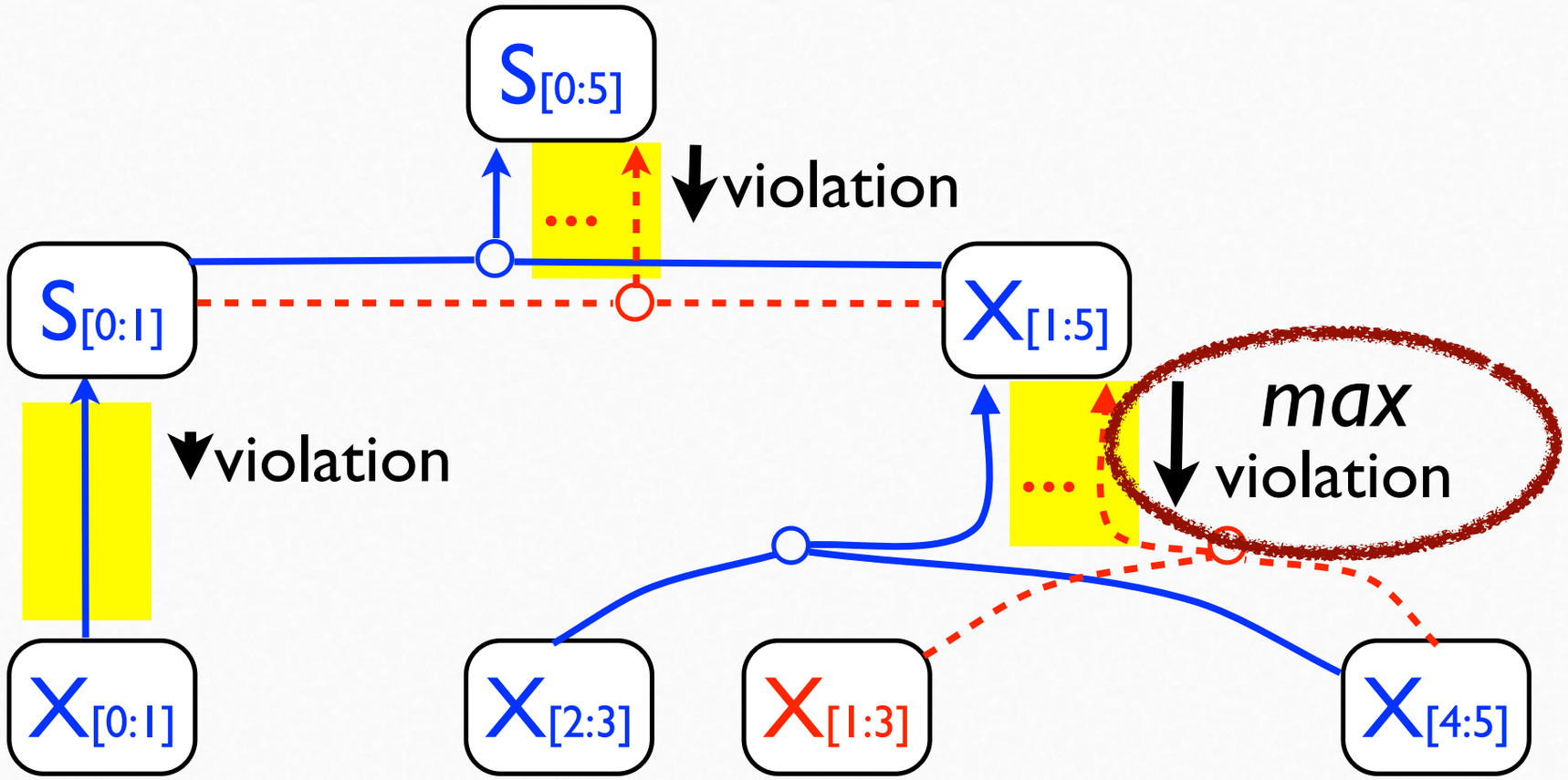

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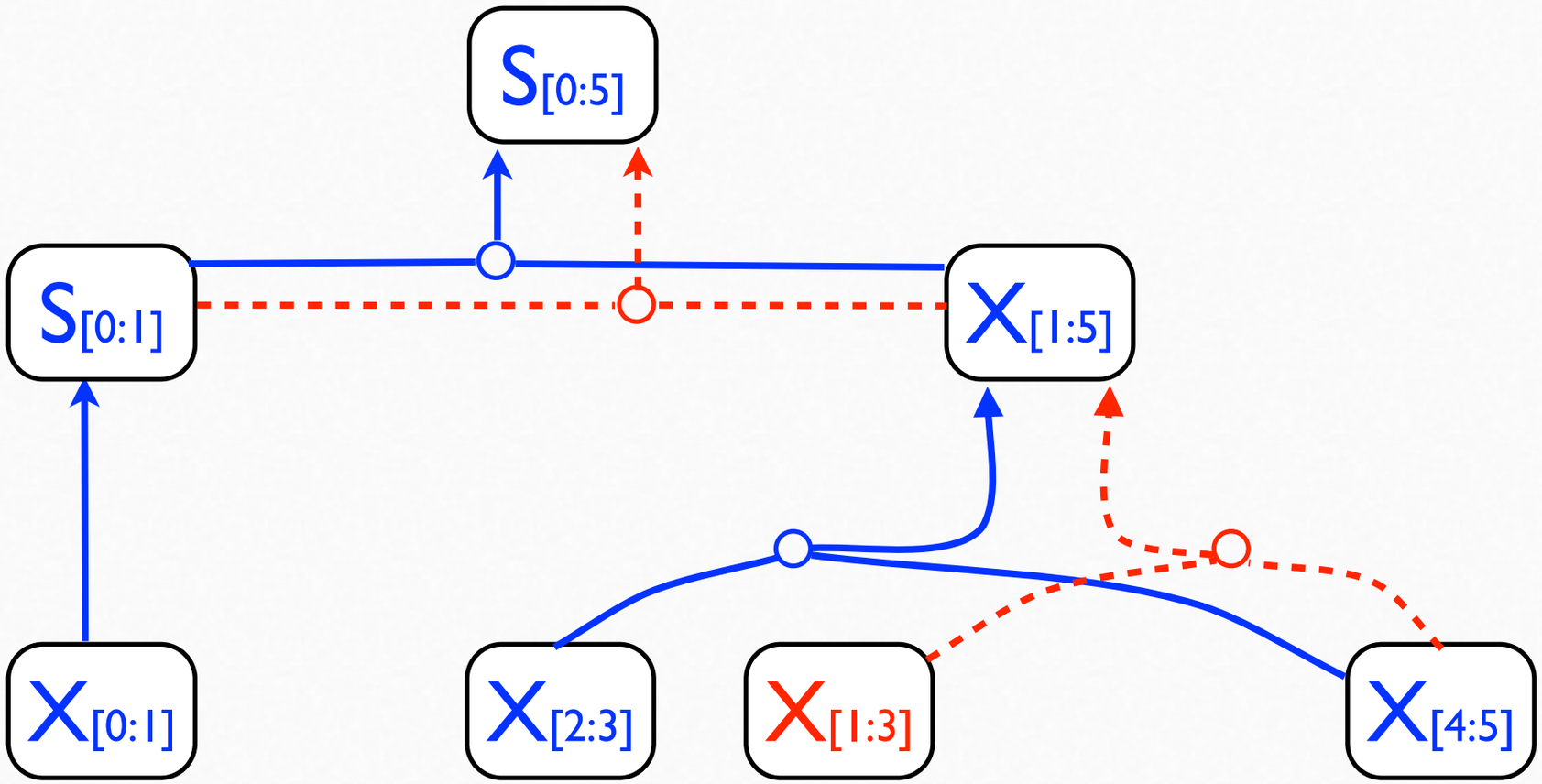
Max-Violation over Hypergraphs w/ Latent Var.



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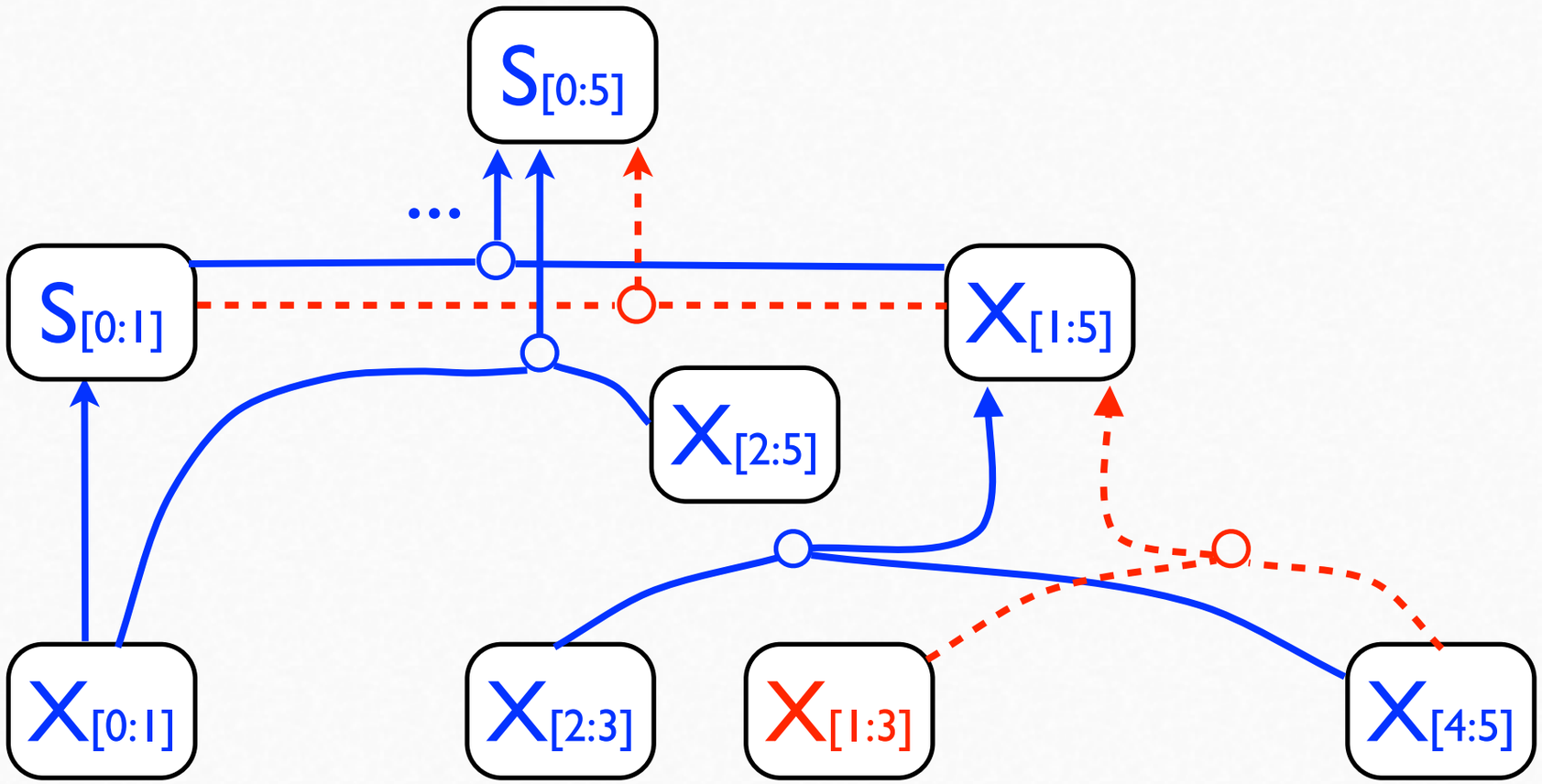
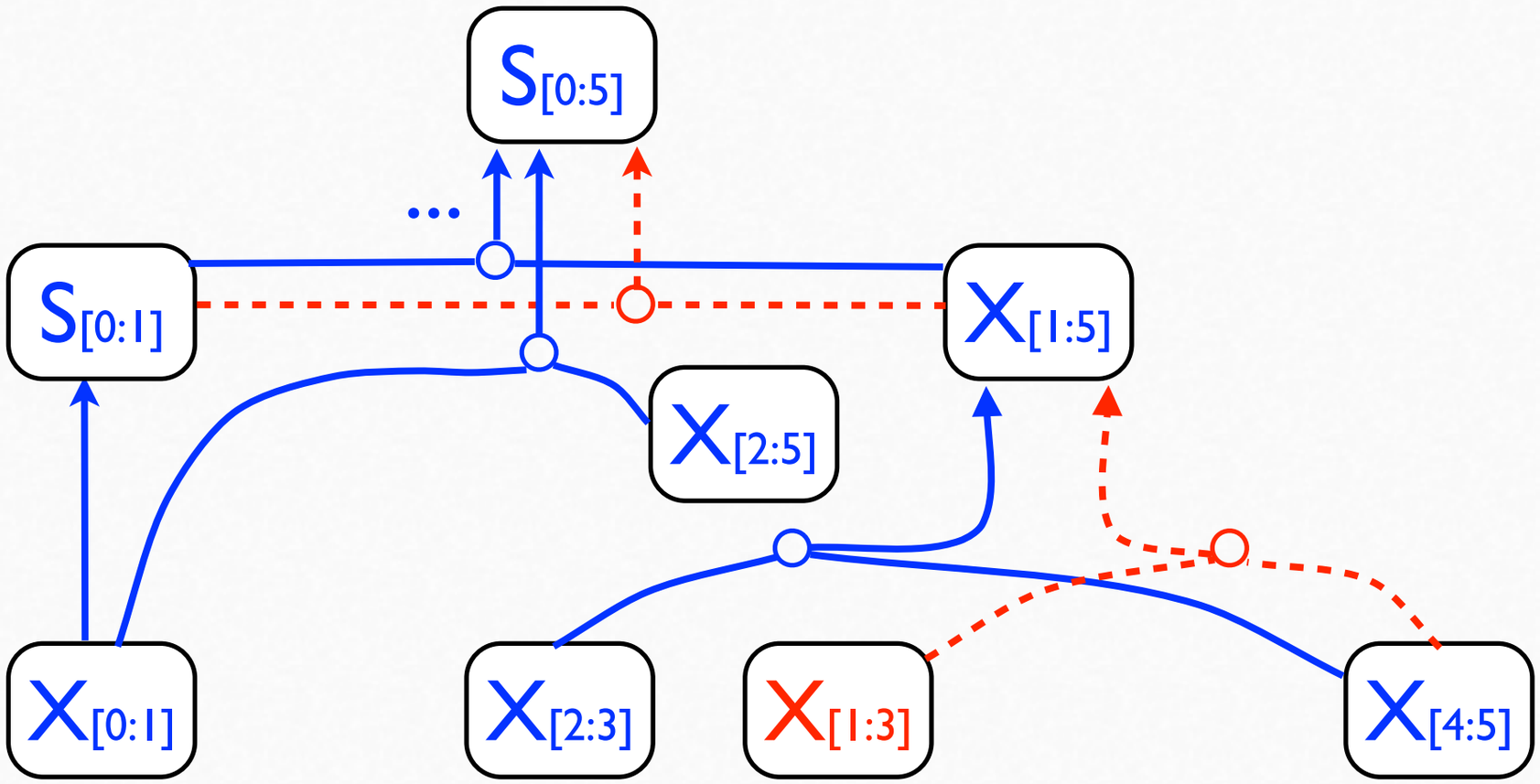
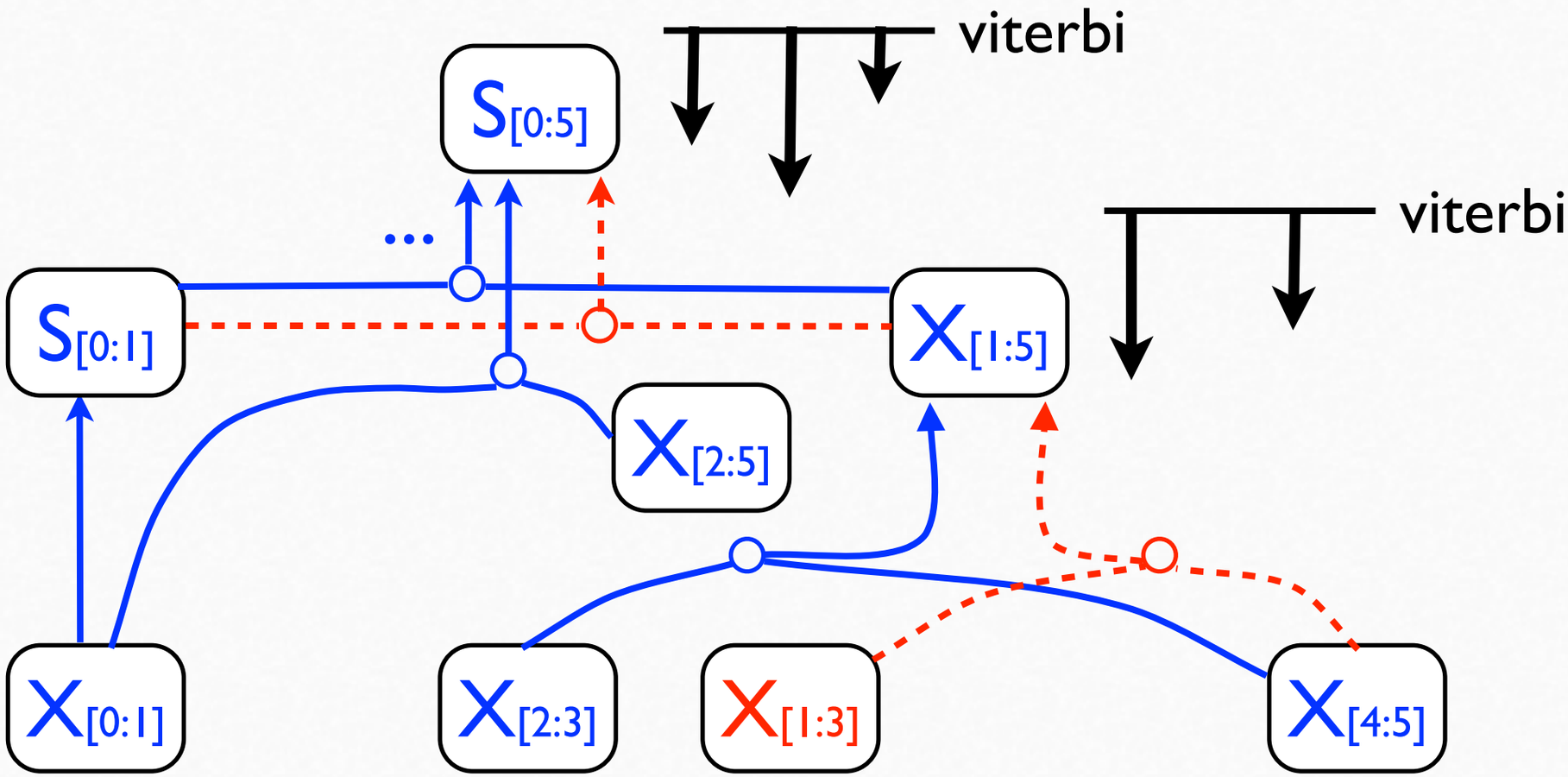


Max-Violation over Hypergraphs w/ Latent Var.



- multiple reference derivations at one node
  - at one node, pick the best reference
  - globally choose max-violated best reference

Max-Violation over Hypergraphs w/ Latent Var.



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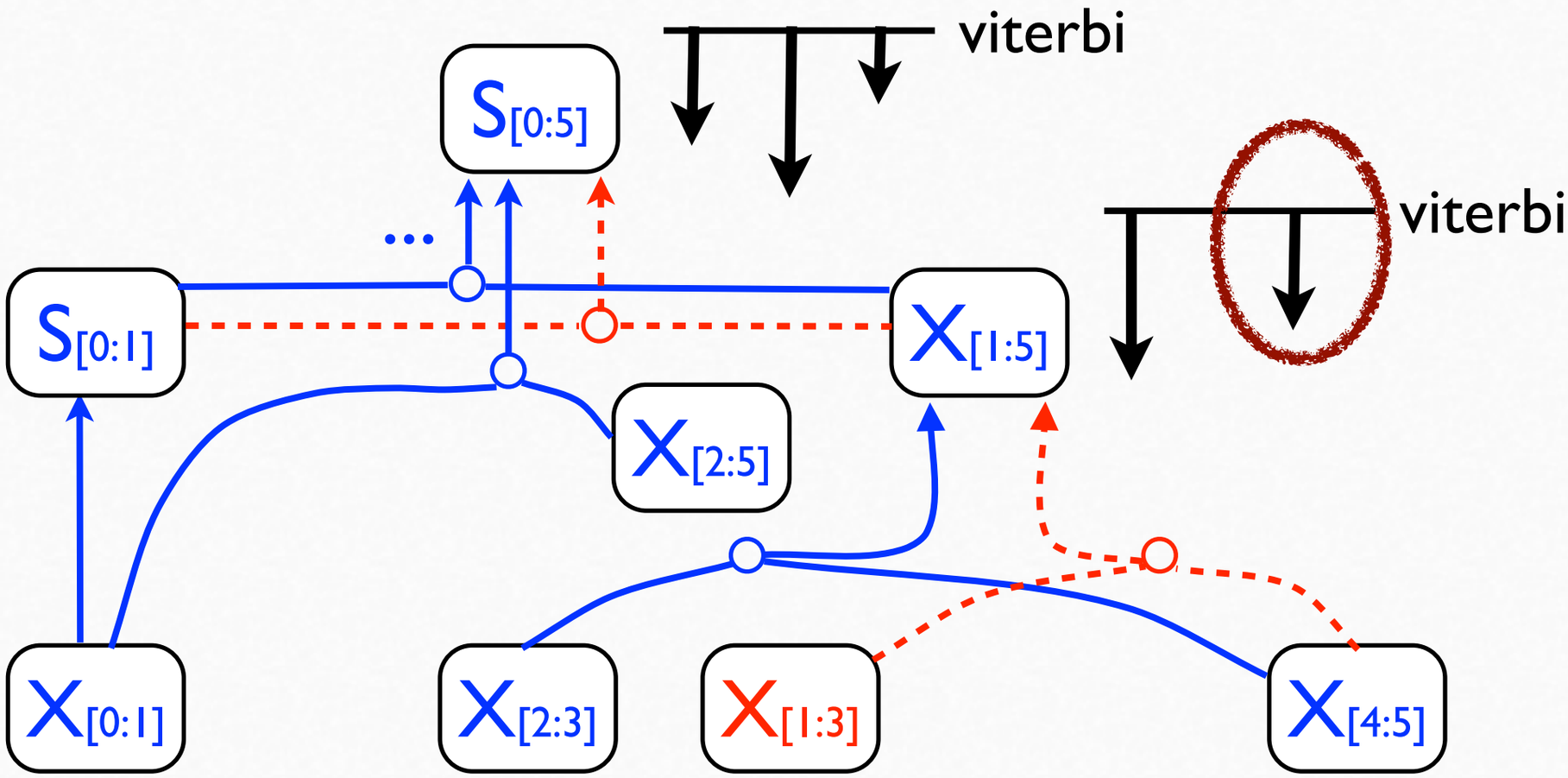
Max-Violation over Hypergraphs w/ Latent Var.



- multiple reference derivations at one node
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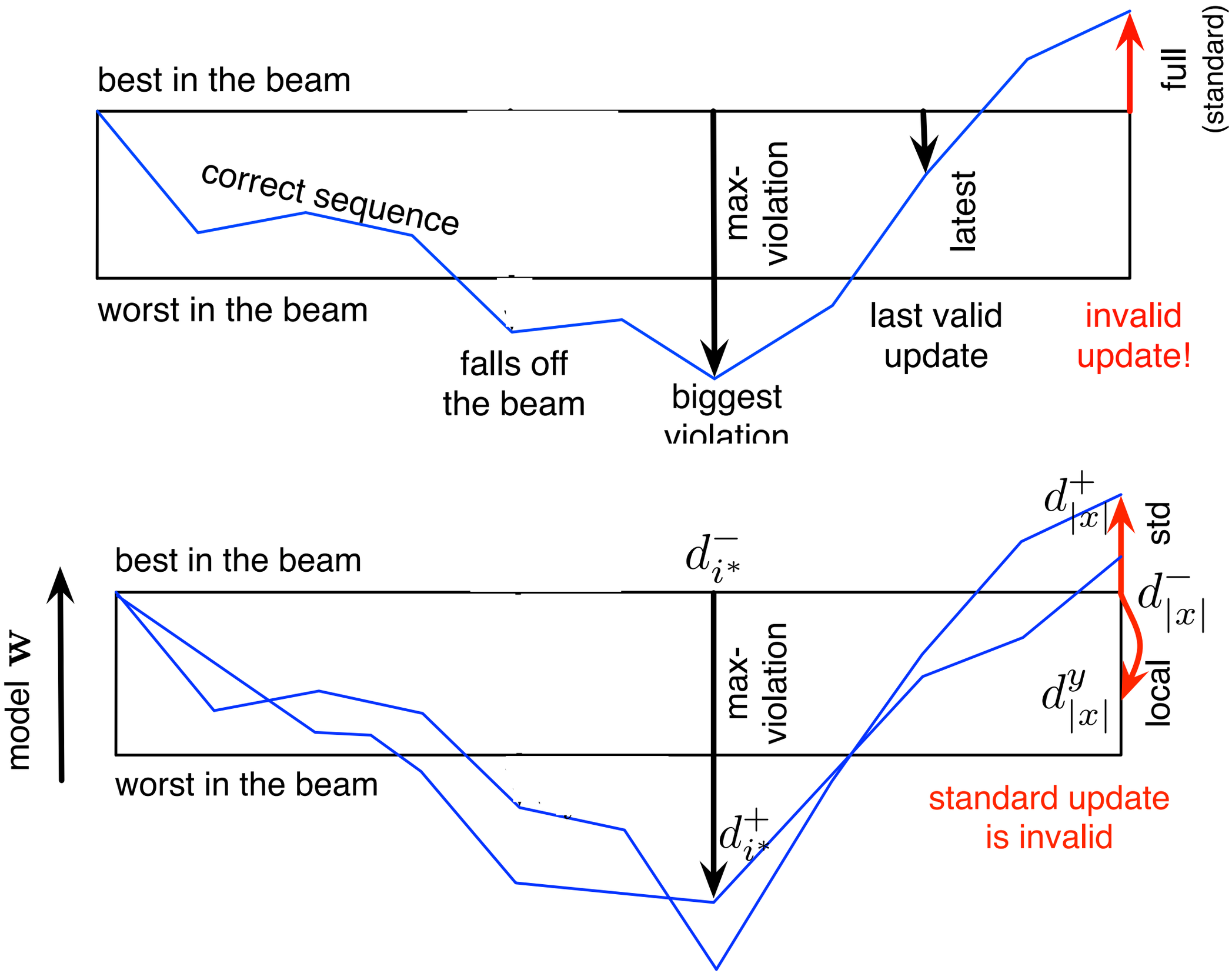
Latent-Variable Max-Violation Perceptron



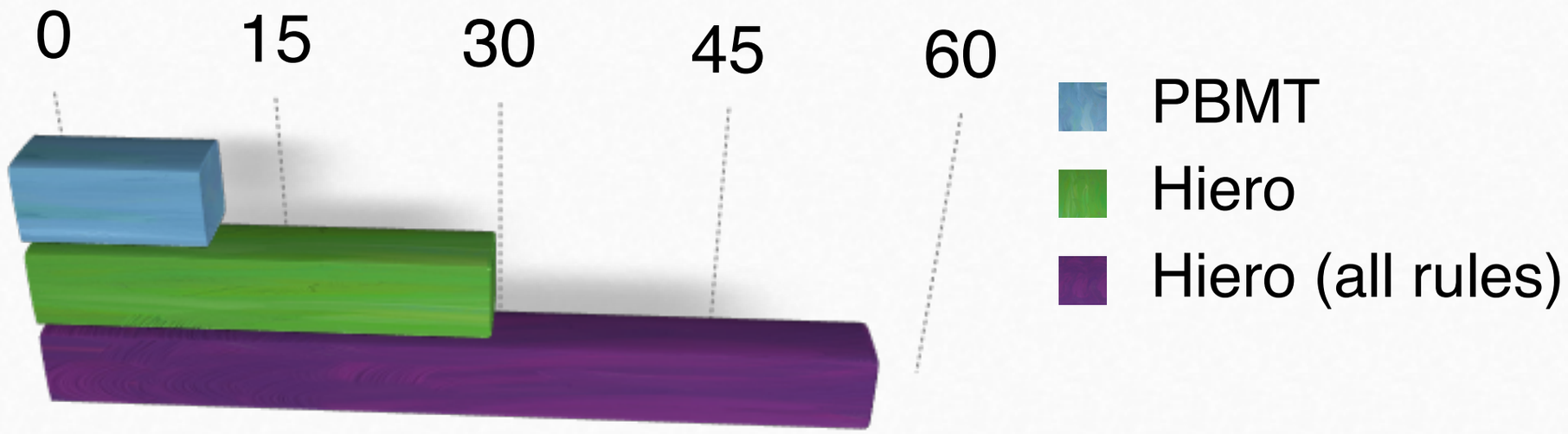
Experiments Setting

train	dev	test
IWSLT09 30k short sentences	IWSLT04 16 references	IWSLT05 16 references
FBIS 240k sentences	NIST06 4 references	NIST08 4 references

- 18 dense features from cdec
- budgeted sparse features based on Word-Edge features
  - atomic features: C/E boundary words; C boundary characters
  - complex features
    - combination of atomic features within limited budget
- we remove all 1-count rules in rule extraction
- trigram LM trained from target side

Experiments

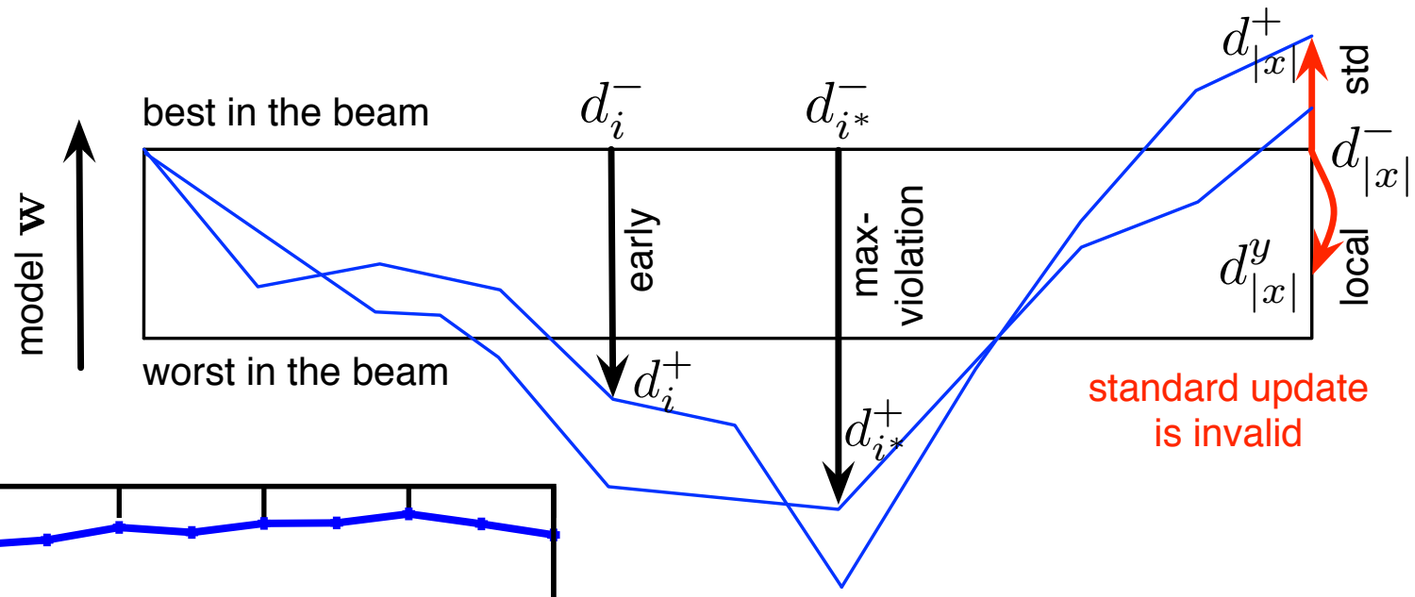
- Reachability on FBIS

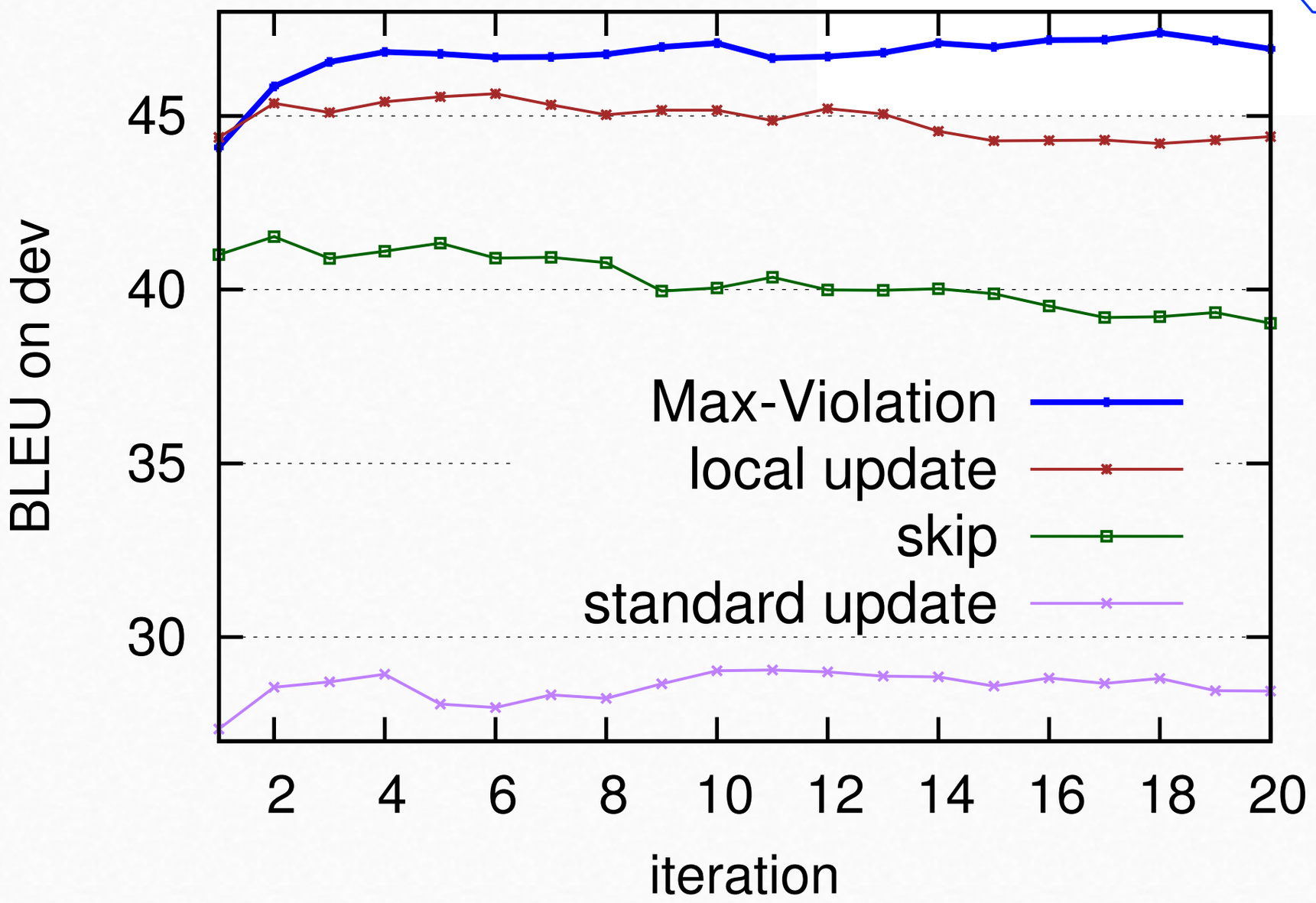


% reachability (in # of words)

Experiments

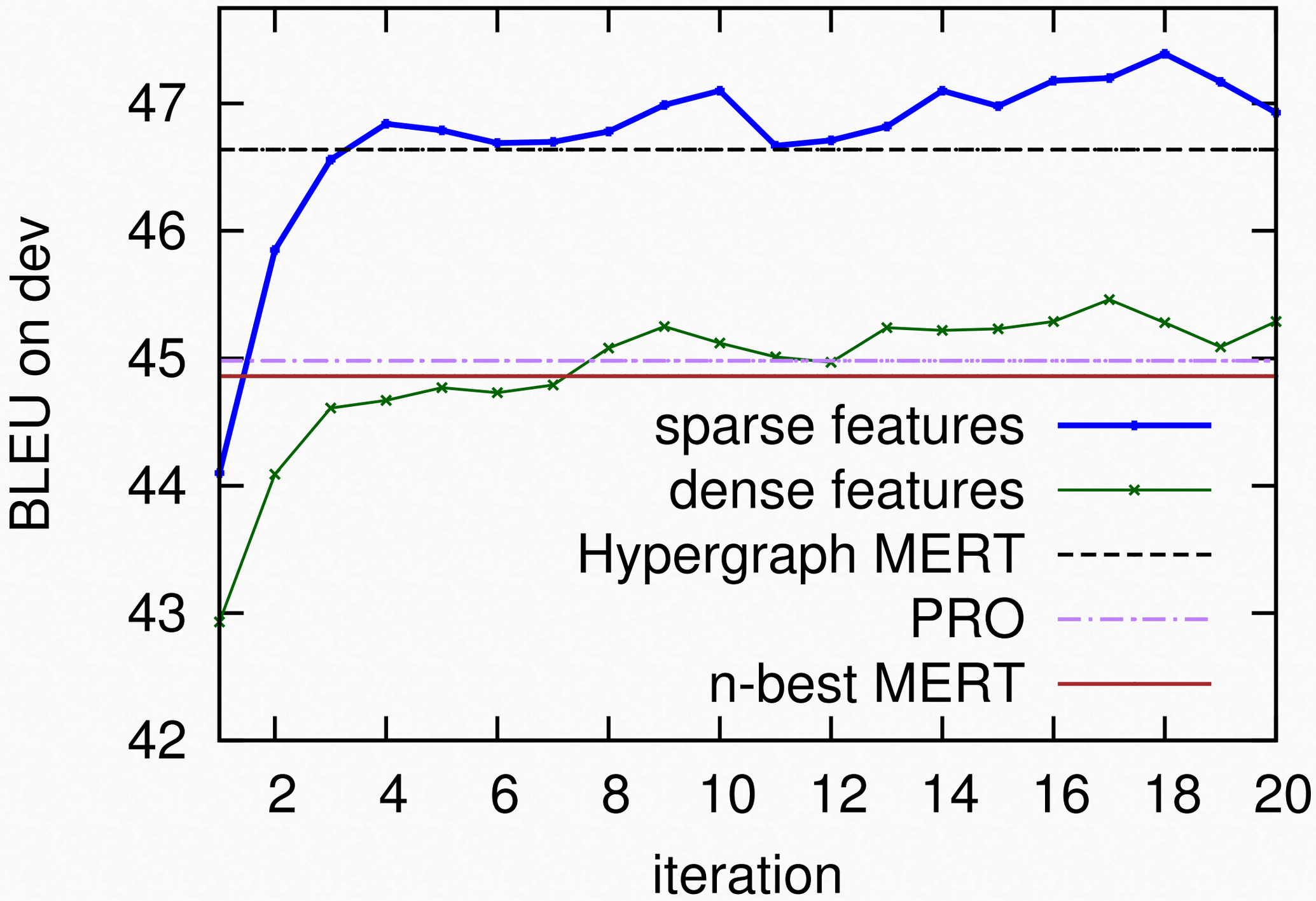
- Comparison of various update methods (IWSLT)





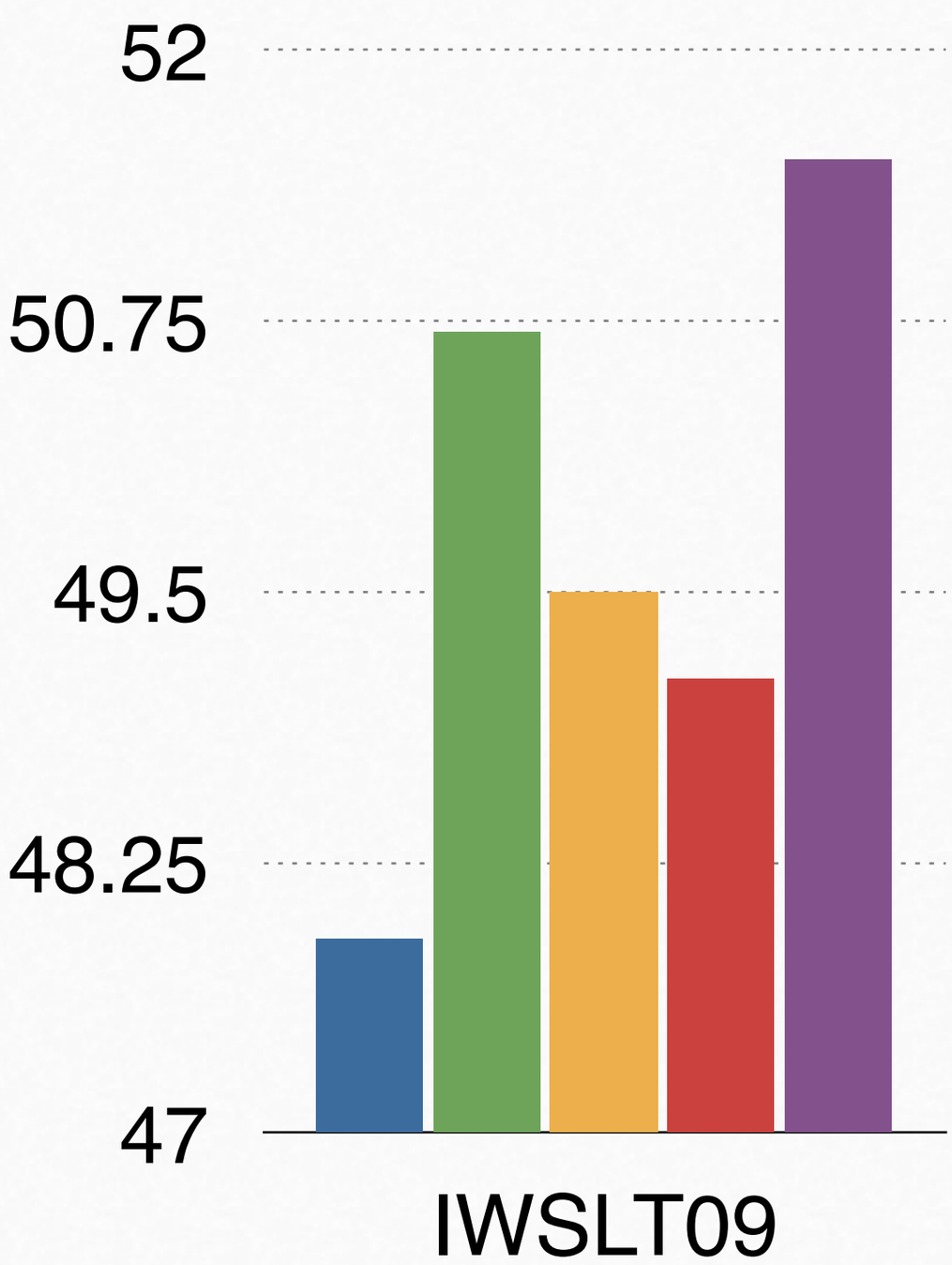
Experiments

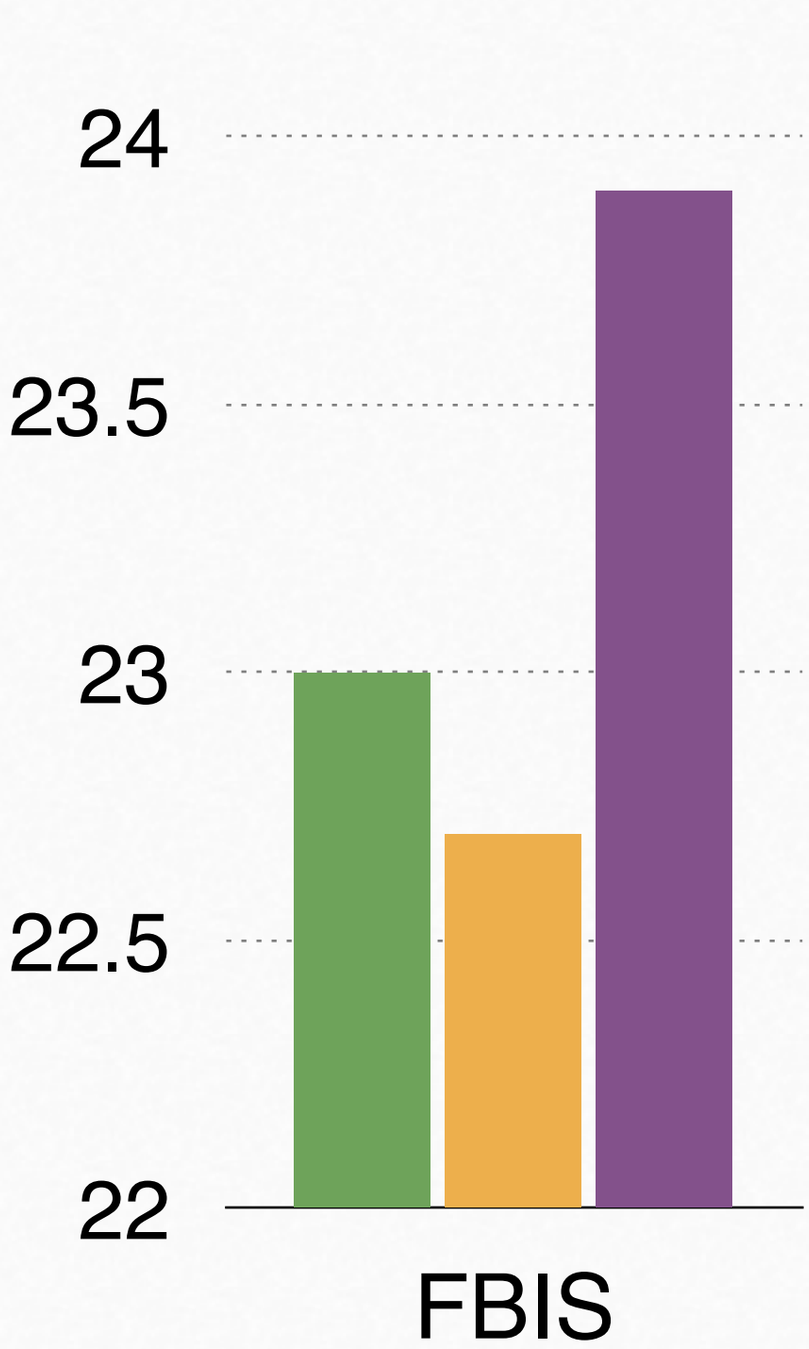
- Contribution of Sparse Features (on IWSLT09)

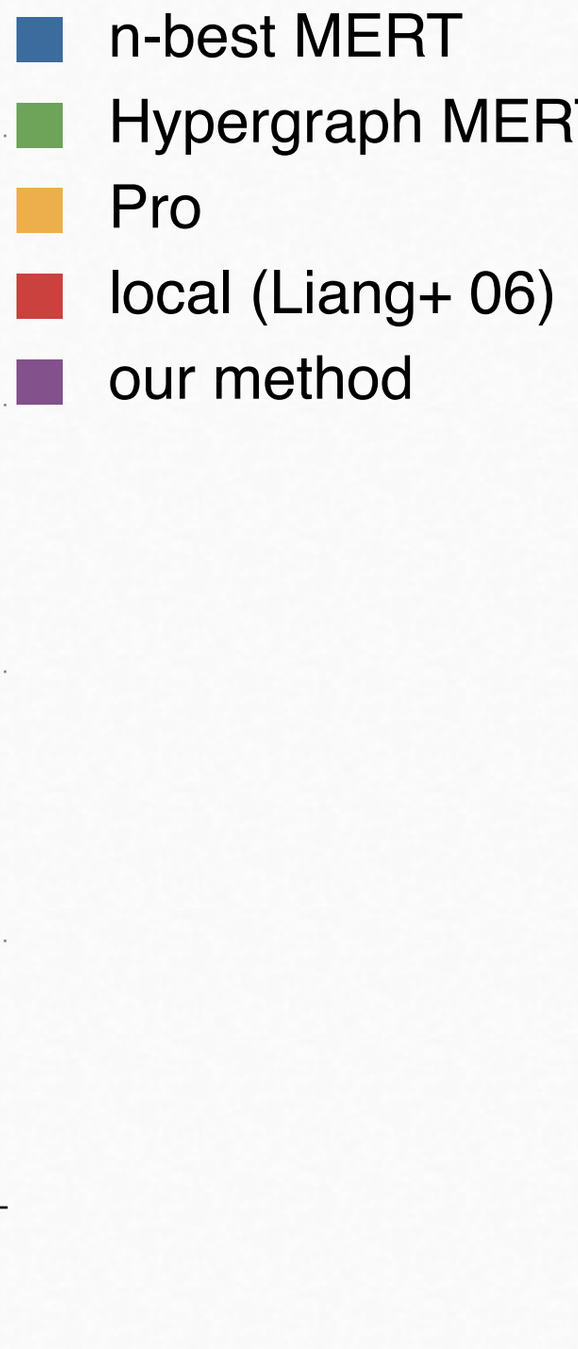


Experiments

- BLEU scores on IWSLT09 (16 refs) and FBIS (4 refs)

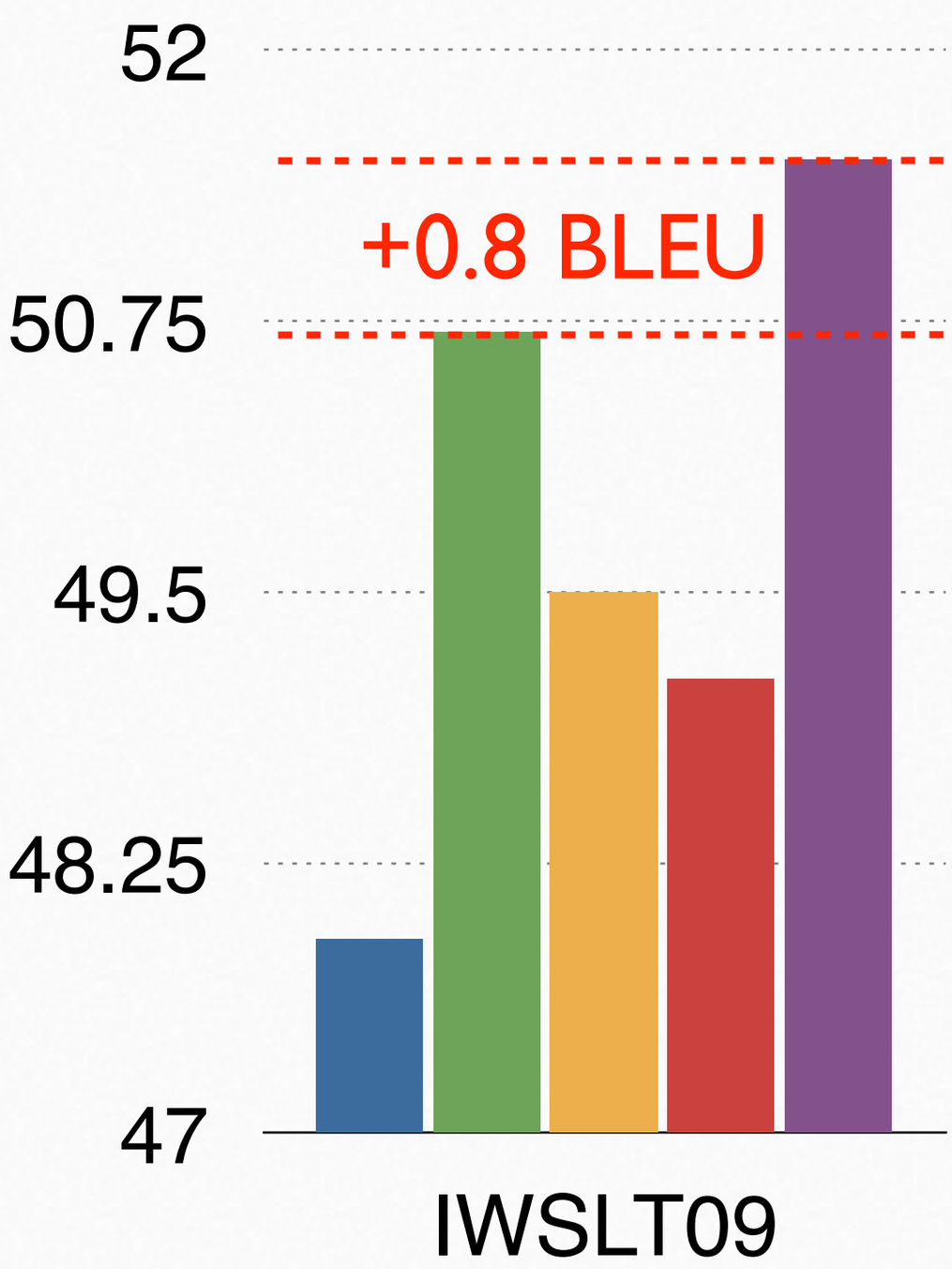


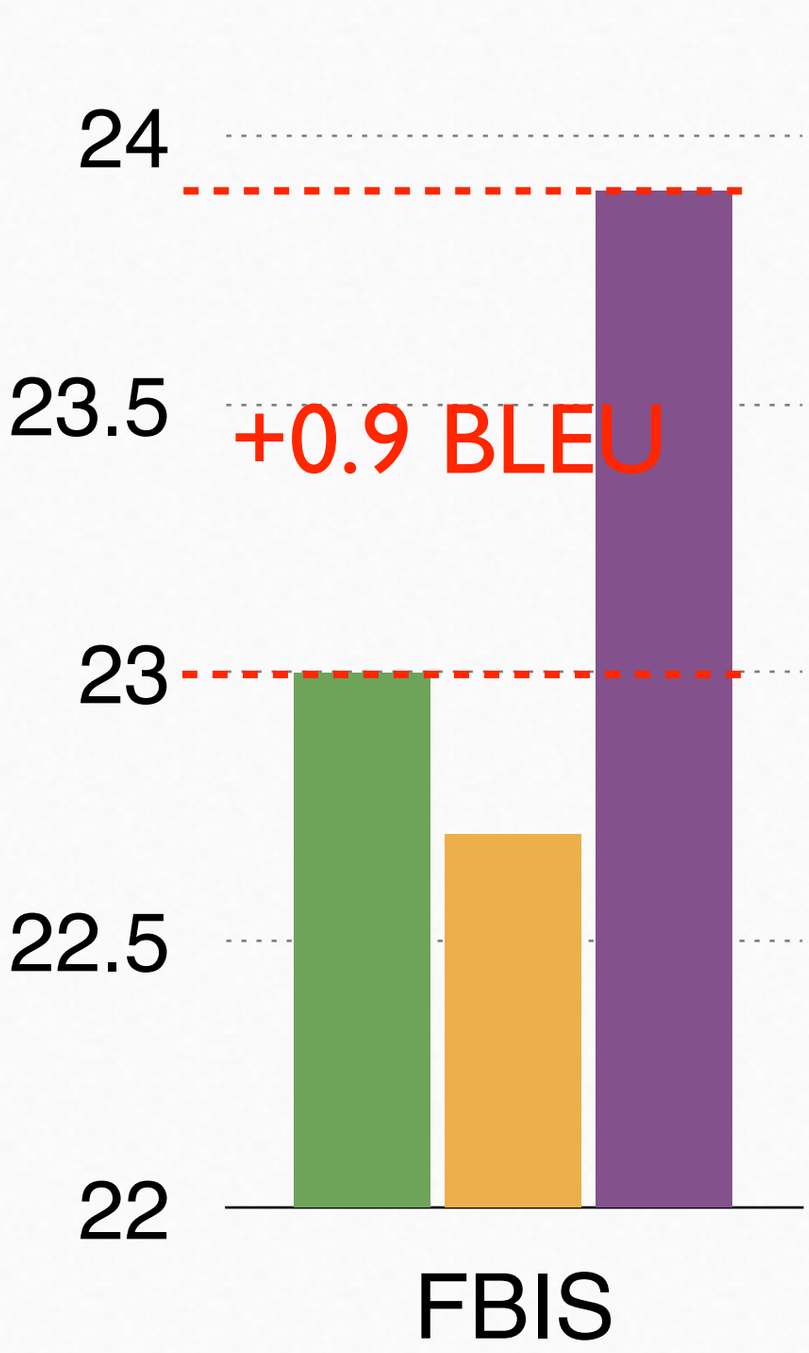


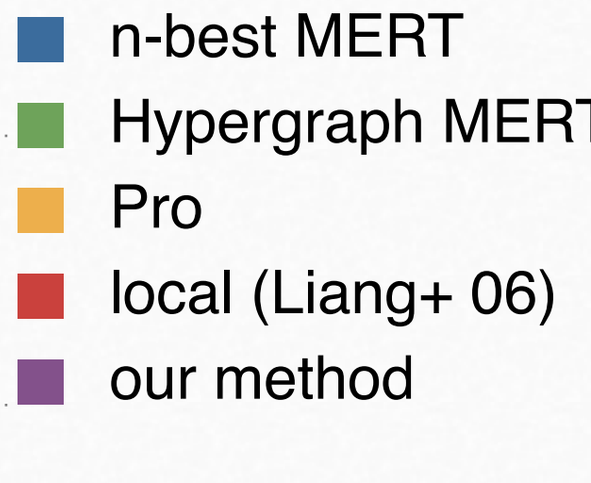


Experiments

- BLEU scores on IWSLT09 (16 refs) and FBIS (4 refs)







Conclusion

- A **latent-variable violation-fixing perceptron** framework for general structured prediction problems with **inexact search** over **hypergraphs**
- Compared with PBMT, it can use **more** training sentences.
- Compared with MERT/PRO, it is **simpler** in theory and practice, and achieves **better** translations