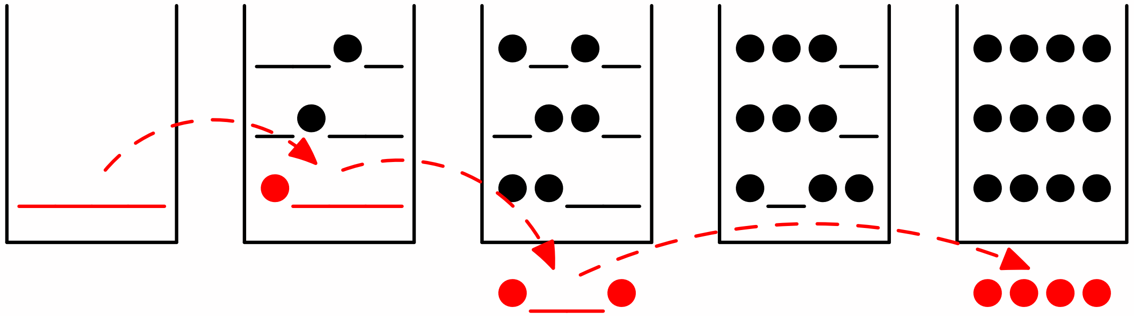
Search Aware Tuning for Machine Translation



Lemao Liu   Liang Huang

City University of New York

EMNLP 2014. Presented by Taro Watanabe.

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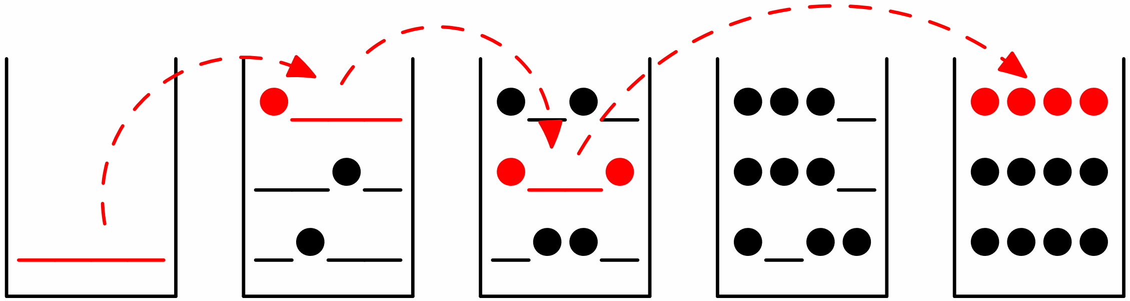

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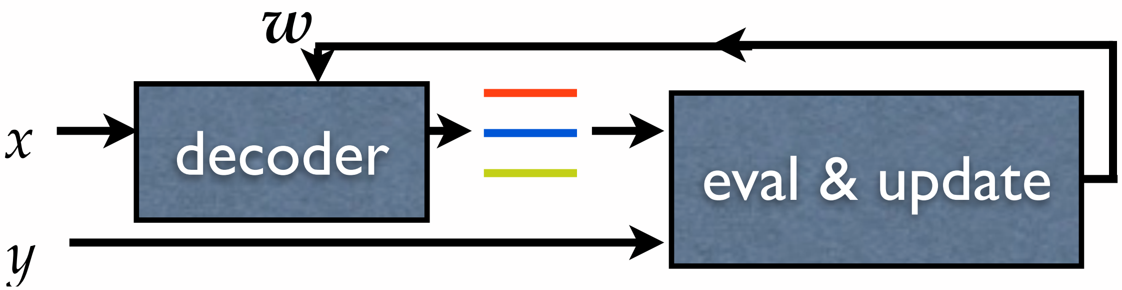
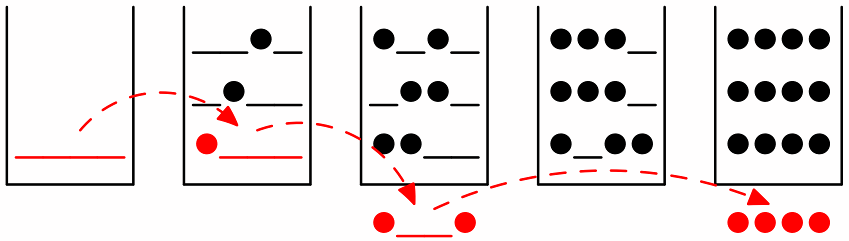
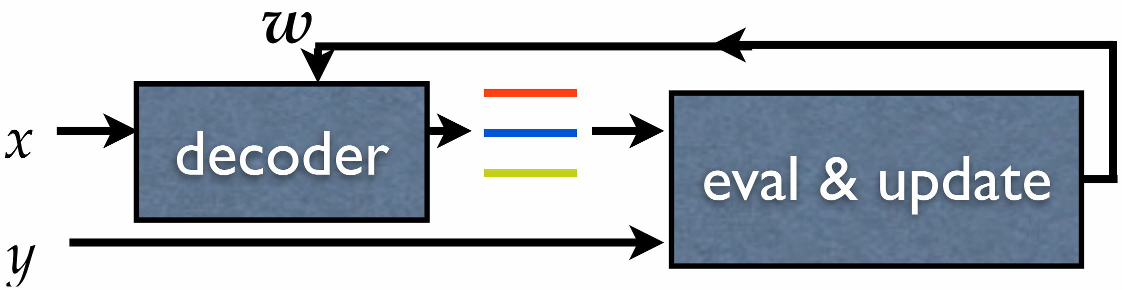
Parameter Tuning for MT





- most tuning methods view MT decoder as a black box
  - “search-agnostic” tuning (MERT, MIRA, PRO, ...)
- but actually search error is a main reason of bad quality
  - potentially good sub-translations pruned early in search
  - final *k*-best list also lacks diversity

Parameter Tuning for MT

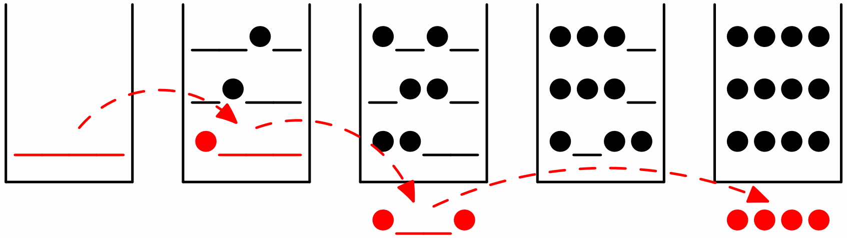

w

x

decoder

eval & update

y



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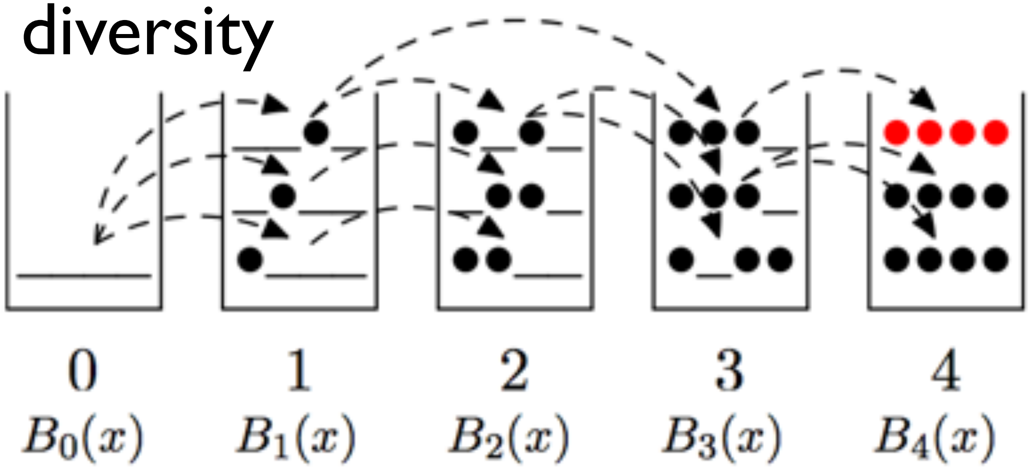

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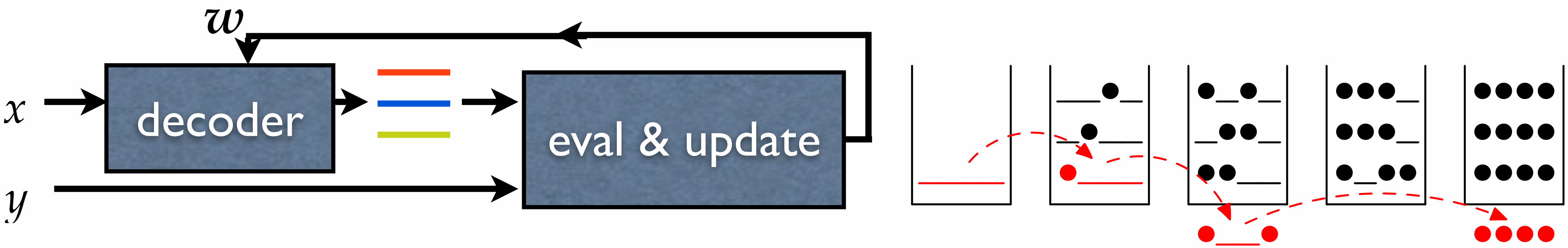

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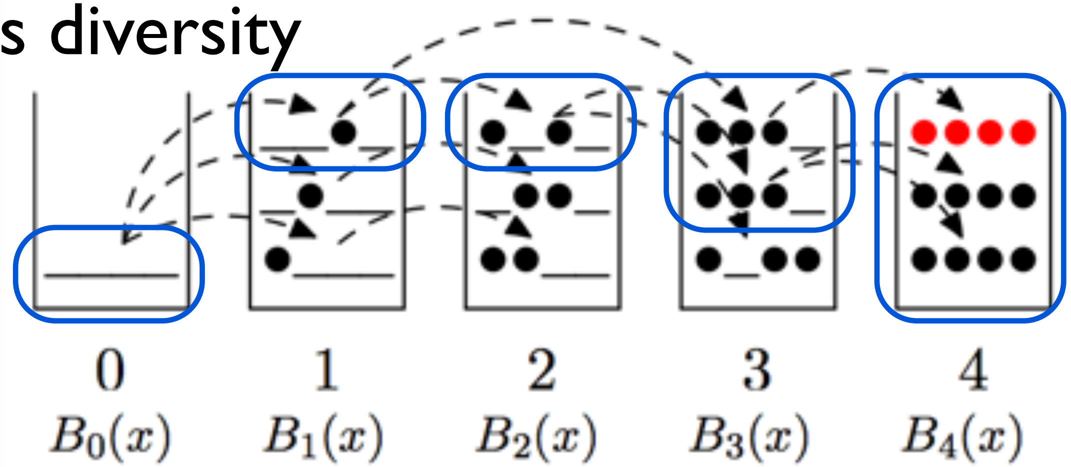
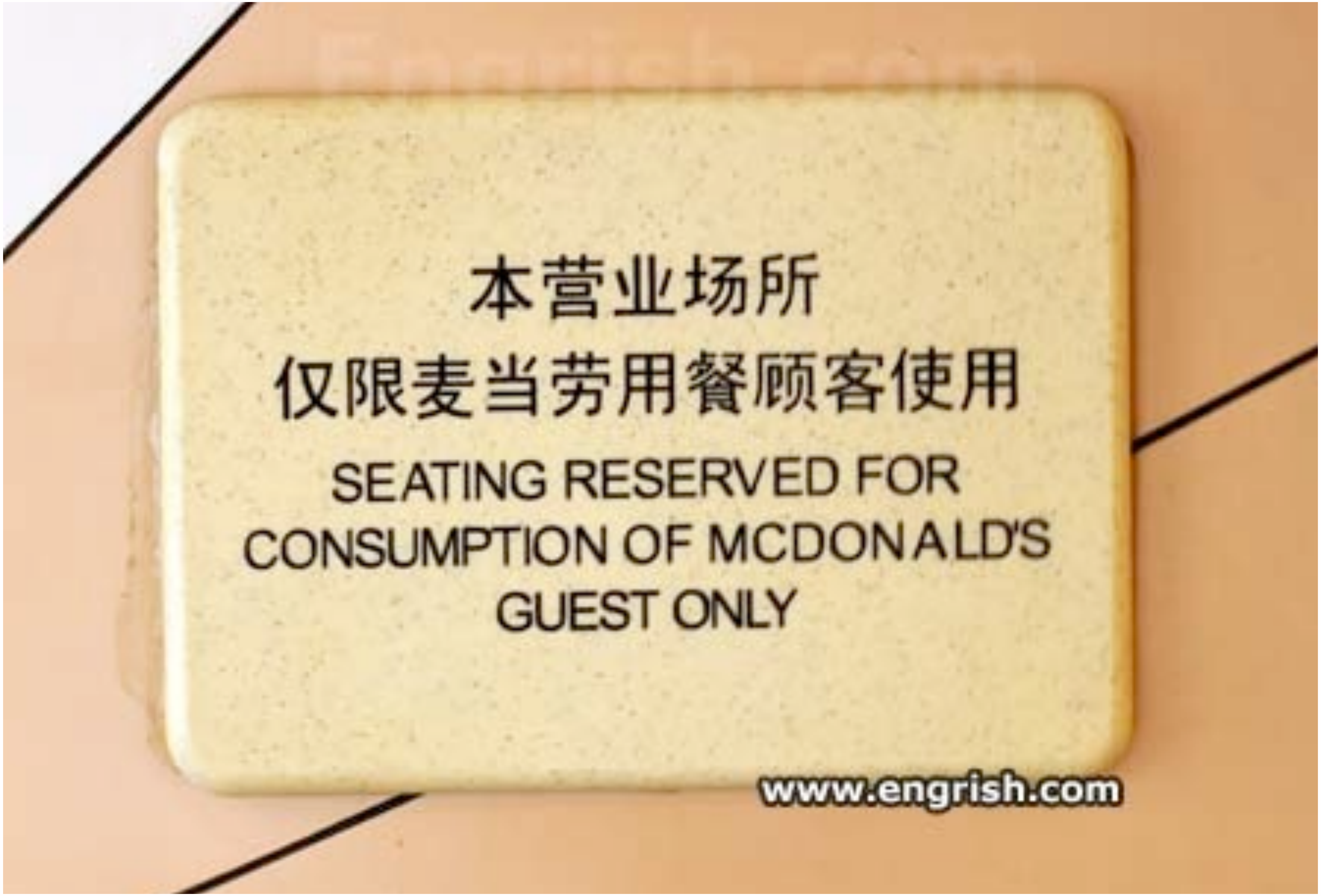
cf.: Y-chromosome Adam
Mitochondria Eva



Search Error in MT



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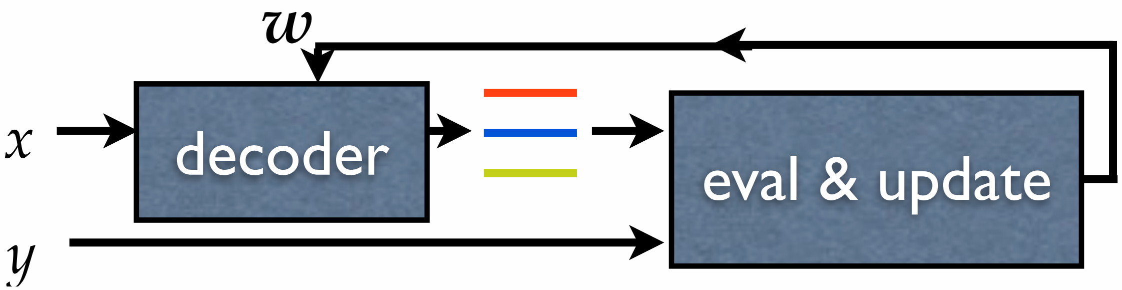
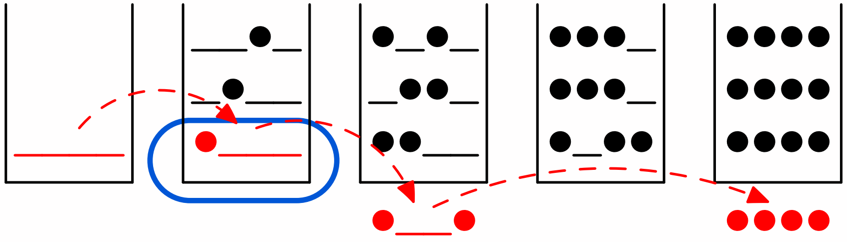
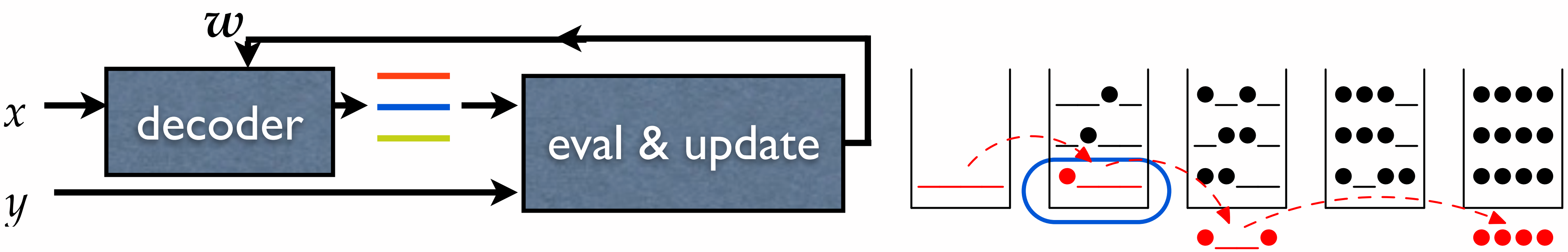
Parameter Tuning for MT





Parameter Tuning for MT



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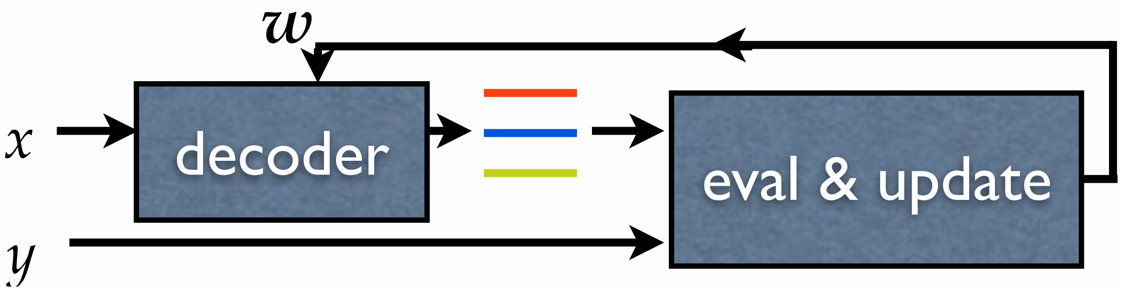

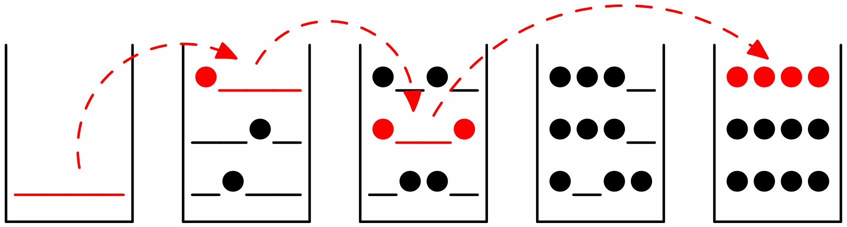

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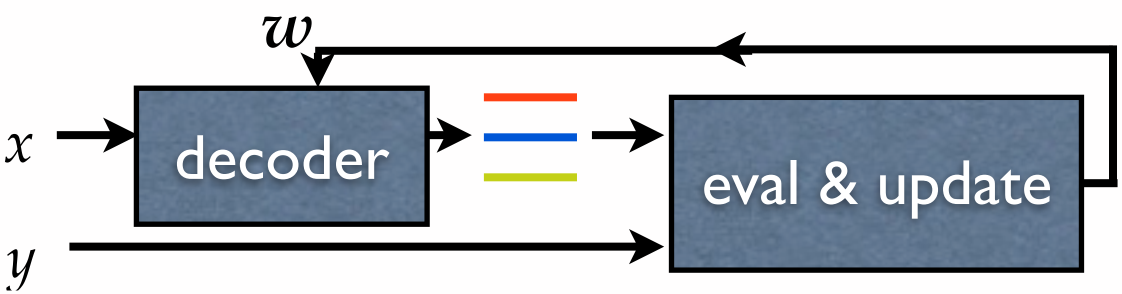

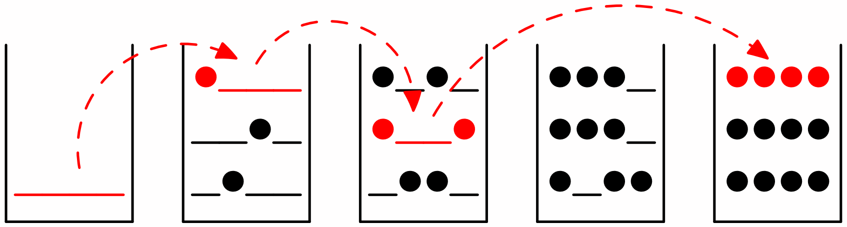

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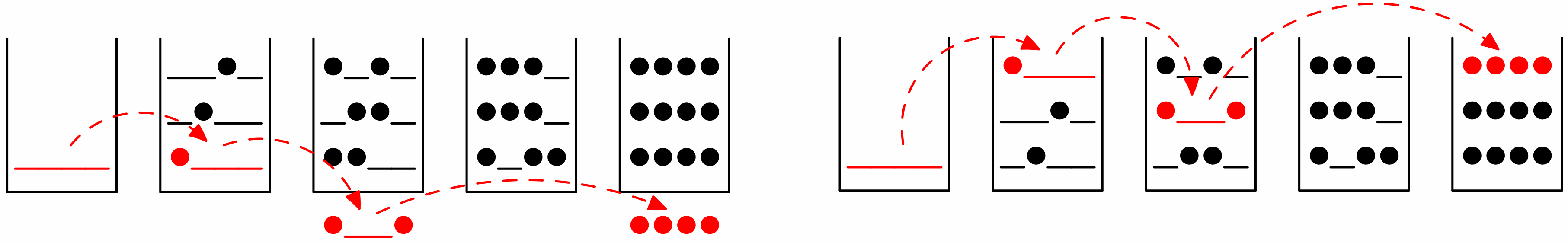
  - "search-agnostic" tuning (MERT, MIRA, PRO, ...)
- but actually search error is a main reason of bad quality
  - potentially good sub-translations pruned early in search
- Q: how to promote these promising sub-derivations?
- A: tune the ranking of non-final bins as well as final bin
  - "search-aware tuning" (SA-MERT, SA-MIRA, SA-PRO, ...)
  - Q: how to evaluate the "potential" of a sub-derivation?

Outline

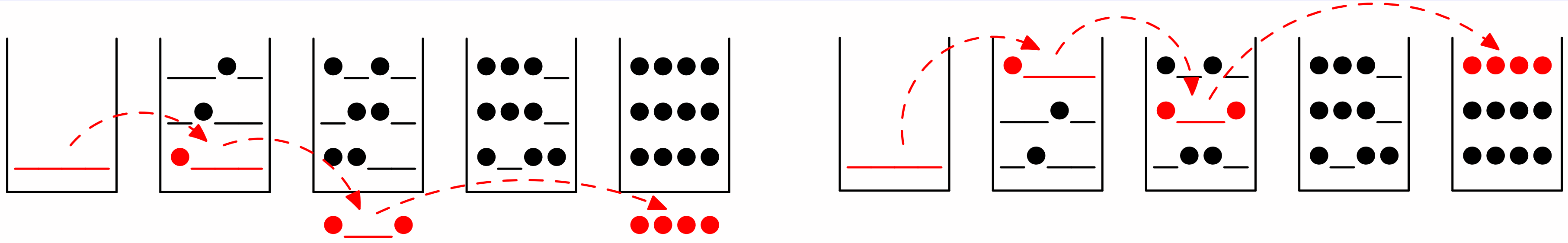
- Motivations
- Evaluating Partial Derivations
  - challenges
  - method 1: naive partial BLEU
  - method 2: novel potential BLEU
- Search-Aware MERT, MIRA, and PRO
- Experiments
  - consistent +1 BLEU improvement with dense features

Challenges in Partial Evaluation



- challenge 1: there is no "partial" references
- challenge 2: in phrase-based MT, partial translations in the same bin may cover different source words

Challenges in Partial Evaluation



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source: 我 从 上海 飞 到 北京

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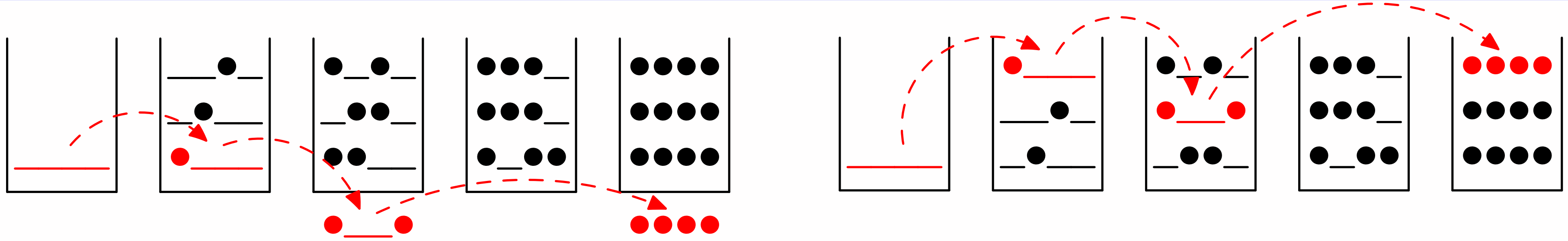
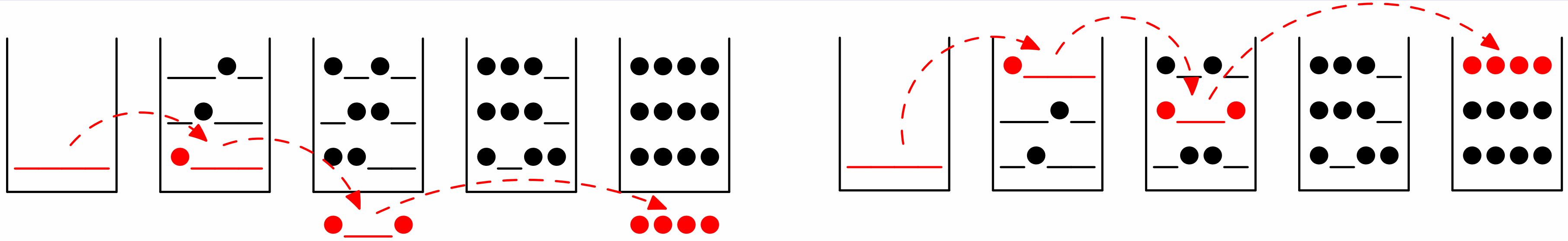


- challenge 1: there is no “partial” references
- challenge 2: in phrase-based MT, partial translations in the same bin may cover different source words

source:	我	从	上海	飞	到	北京
gloss:	I	from	Shanghai	fly	to	Beijing

Challenges in Partial Evaluation



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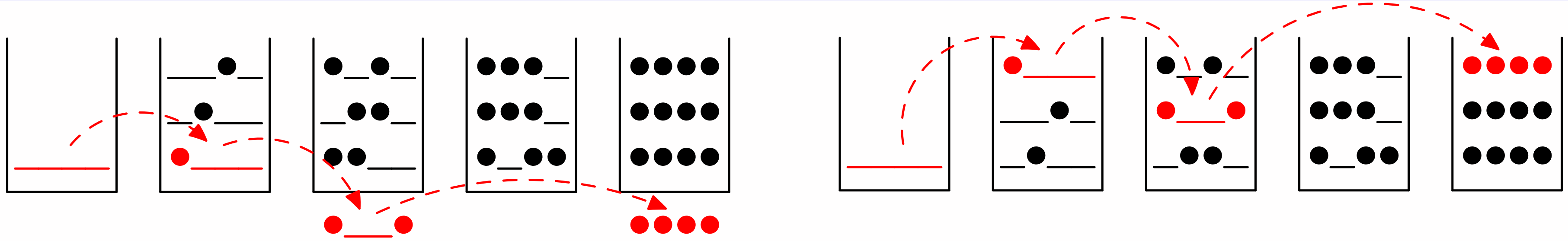
source: 我 从 上海 飞 到 北京

gloss: I from Shanghai fly to Beijing

reference: I flew from Shanghai to Beijing

Challenges in Partial Evaluation



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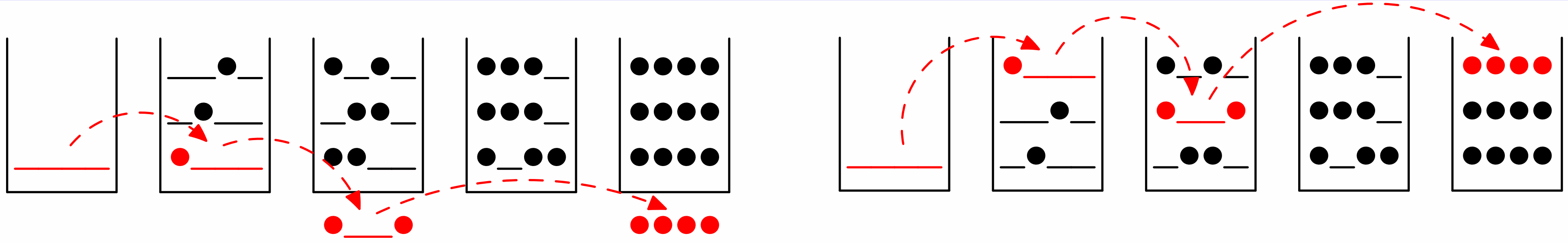
Challenges in Partial Evaluation



- challenge 1: there is no "partial" references
- challenge 2: in phrase-based MT, partial translations in the same bin may cover different source words

source: 我 从 上海 飞 到 北京

gloss: I from Shanghai fly to Beijing

reference: I flew from Shanghai to Beijing

partial 1: I from
partial 2: I fly

Method 1: Naive Partial BLEU

- naive solution: just evaluate against the full reference
  - but using a prorated reference length
    - proportional to number of source words translated so far
  - inspired by oracle extraction (Li & Khudanpur 10; Chiang 12)
- problem: favoring those translating "easier" words first

source: 我 从 上海 飞 到 北京

gloss: I from Shanghai fly to Beijing

reference: I flew from Shanghai to Beijing

partial 1: I from unigram=2

partial 2: I fly unigram=1

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source: 我 从 上海 飞 到 北京

gloss: I from Shanghai fly to Beijing

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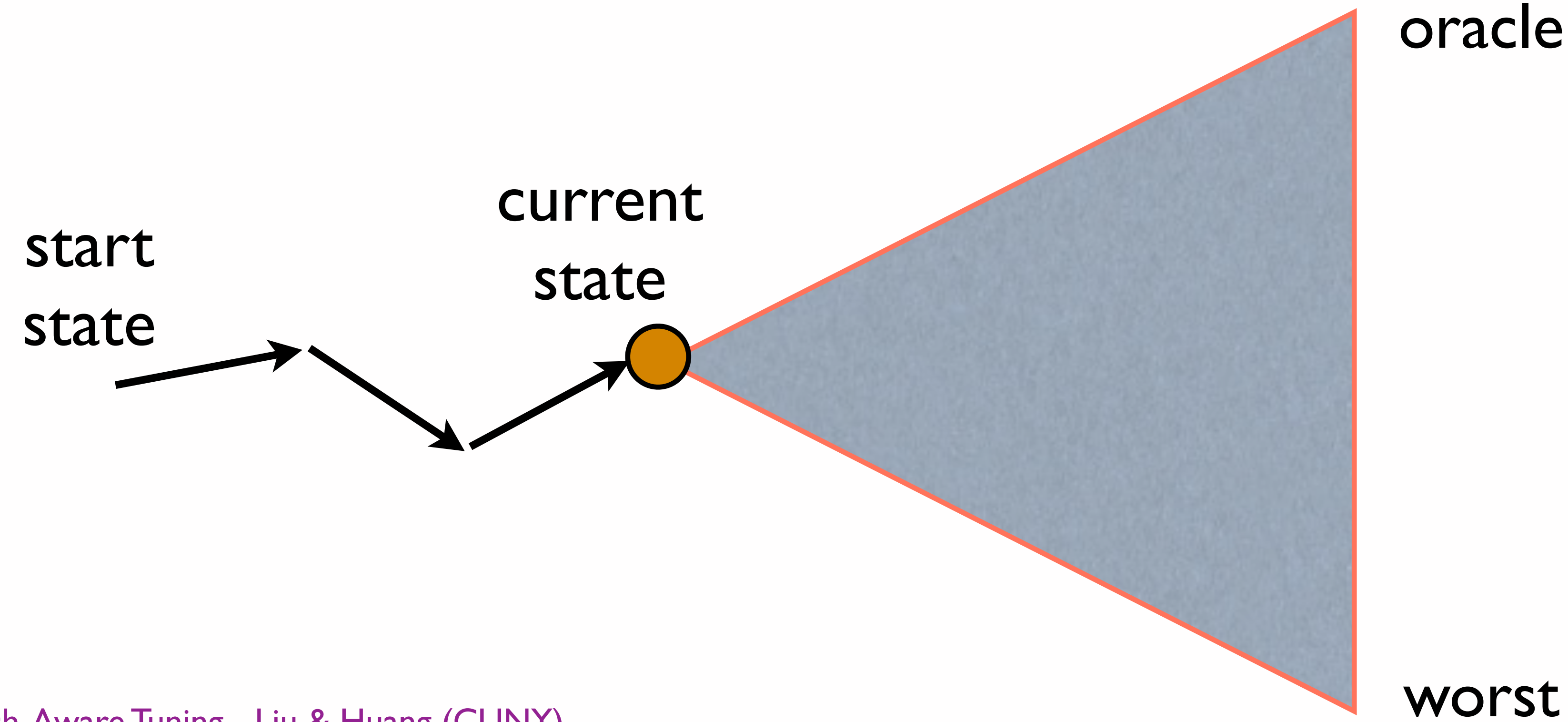
partial 1: I from unigram=2 ✔

partial 2: I fly unigram=1

Evaluating the "Potential"

- better not evaluate partial translation as is, but its *potential*
- do we want the oracle (best) or average potential?
  - oracle is too hard to compute, and maybe not that useful
  - want the "most likely" potential given the current model



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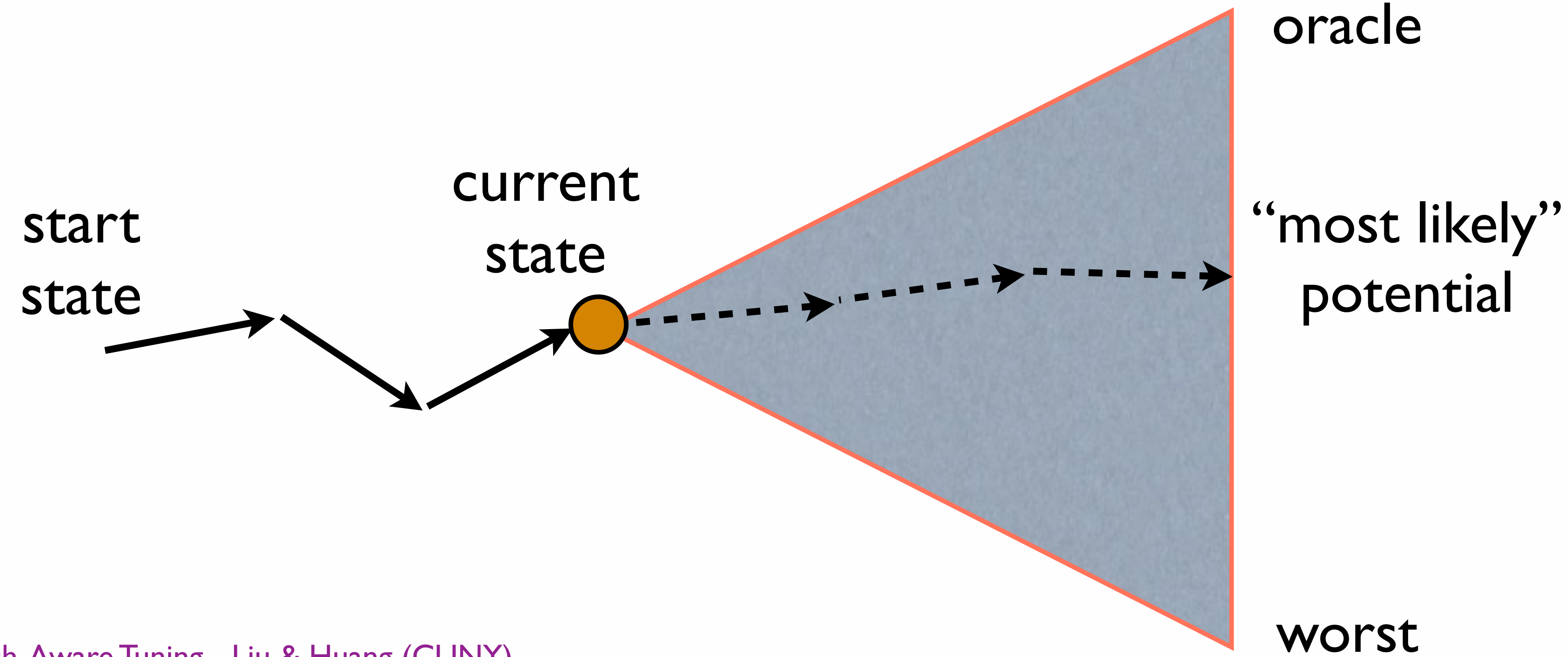


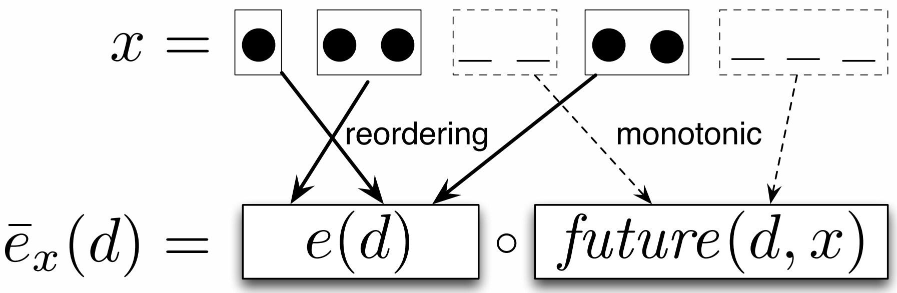
Method 2: Potential BLEU

- the “most likely potential” BLEU of a derivation
- extend partial derivation to cover uncovered words
    - using best monotonic translation for uncovered portions
    - inspired by “future cost” in phrase-based decoding
        - (inadmissible) A* heuristic computed by DP (Koehn, 2004)

source: 我 从 上海 飞 到 北京

gloss: I from Shanghai fly to Beijing

reference: I flew from Shanghai to Beijing



partial 1: I from

partial 2: I fly

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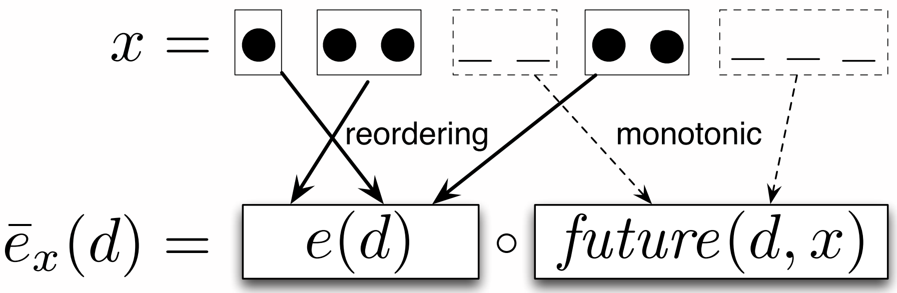

$$\bar{e}_x(d) = \boxed{e(d)} \circ \boxed{future(d, x)}$$

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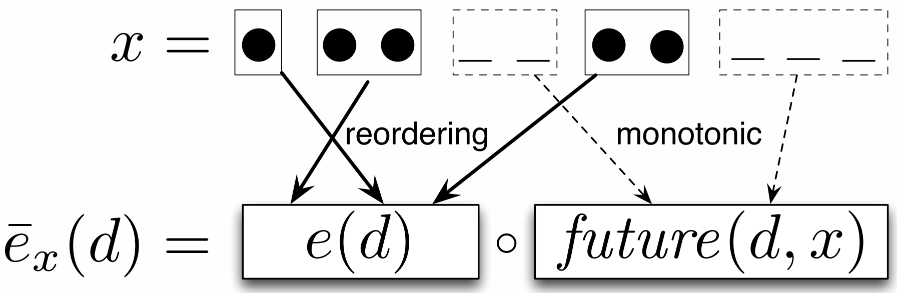

partial 1: I from Shanghai fly to Beijing

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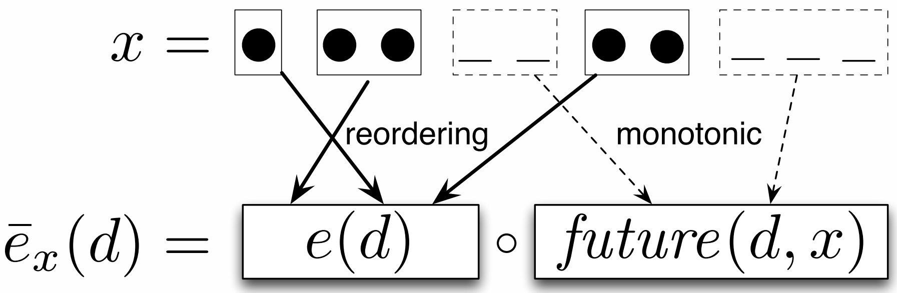

partial 1: I from Shanghai fly to Beijing

partial 2: I fly from Shanghai to Beijing

unigram=5, bi=2

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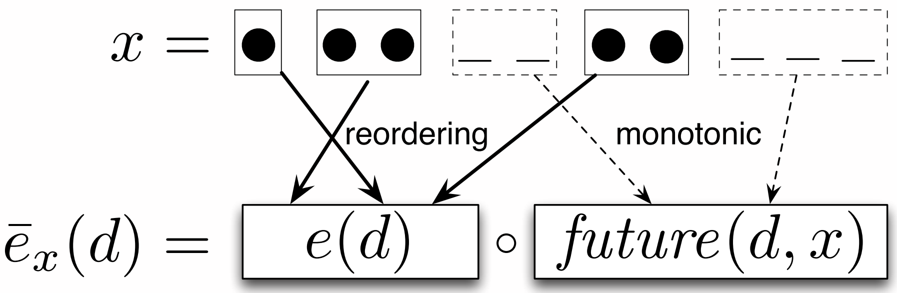

partial 1: I from \boxed{Shanghai fly to Beijing} unigram=5, bi=2

partial 2: I fly \boxed{from Shanghai to Beijing} unigram=5, bi=3, tri=2, 4gram=1

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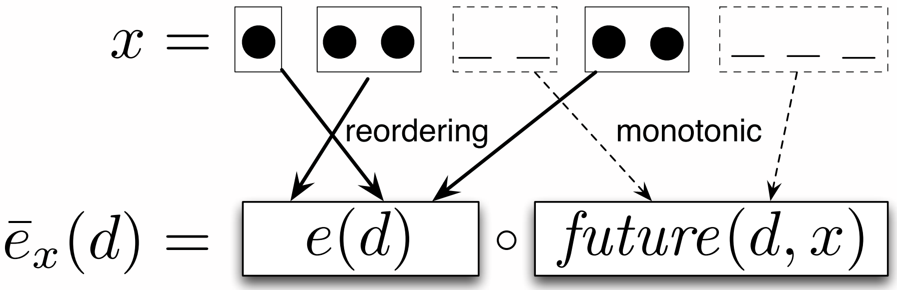


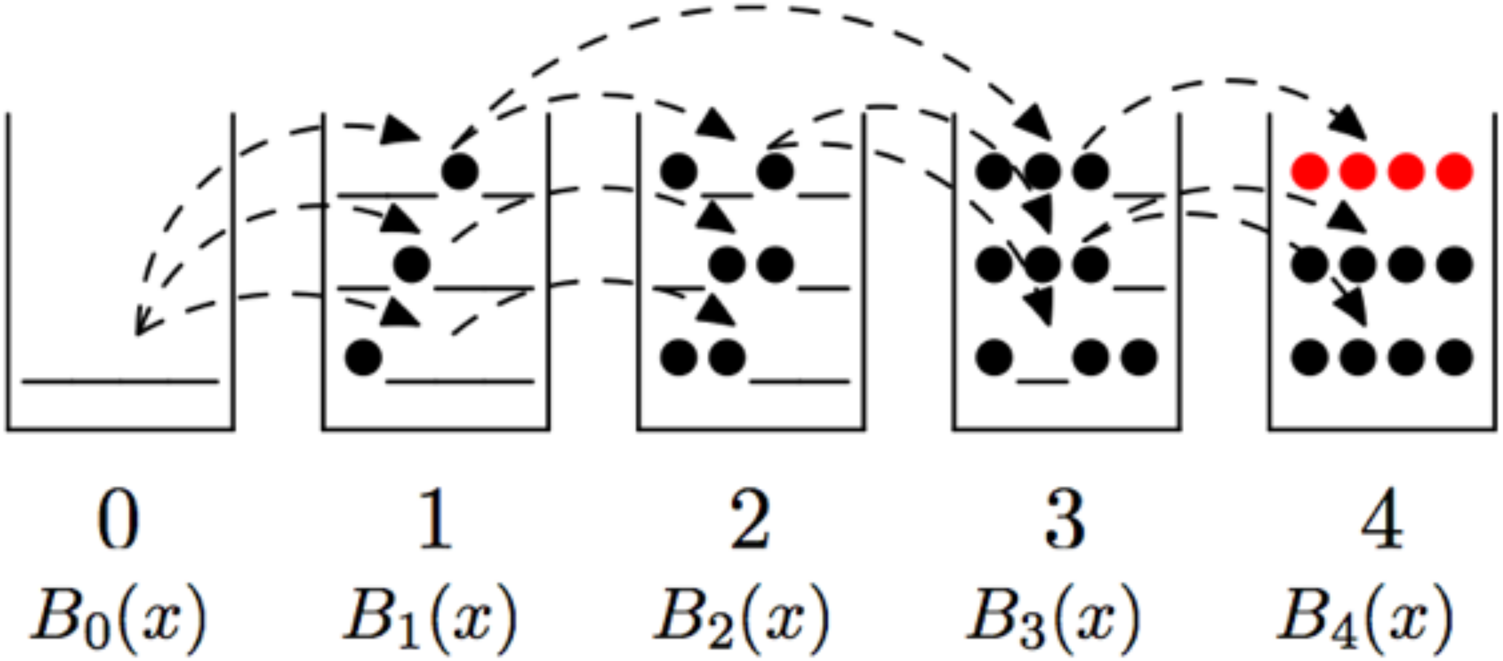
$x =$ ● ●● _ _ ●● _ _ _

$\bar{e}_x(d) = e(d) \circ future(d, x)$

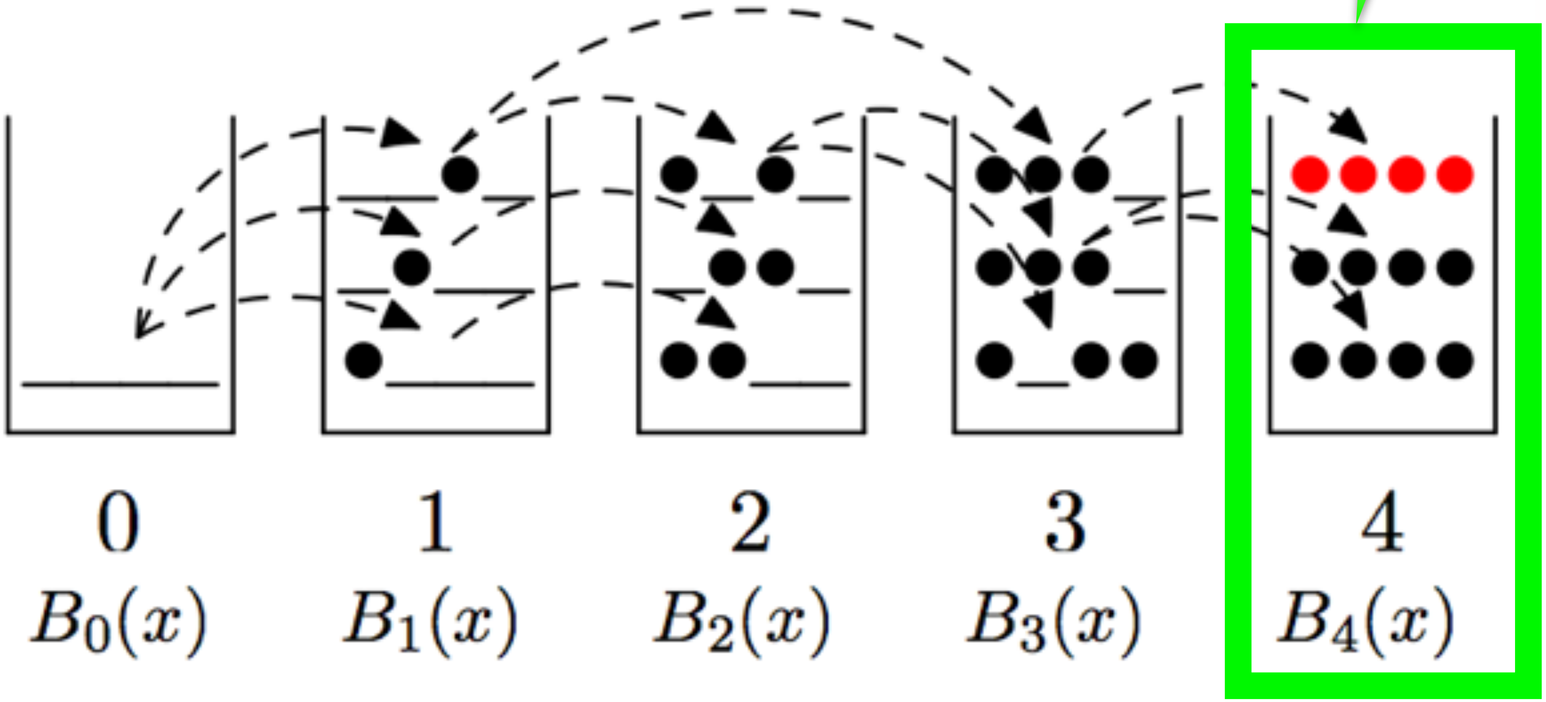
partial 1: I from | Shanghai fly to Beijing | unigram=5, bi=2

partial 2: I fly | from Shanghai to Beijing | unigram=5, bi=3, tri=2, 4gram=1 ✔

Towards Search-Aware Tuning

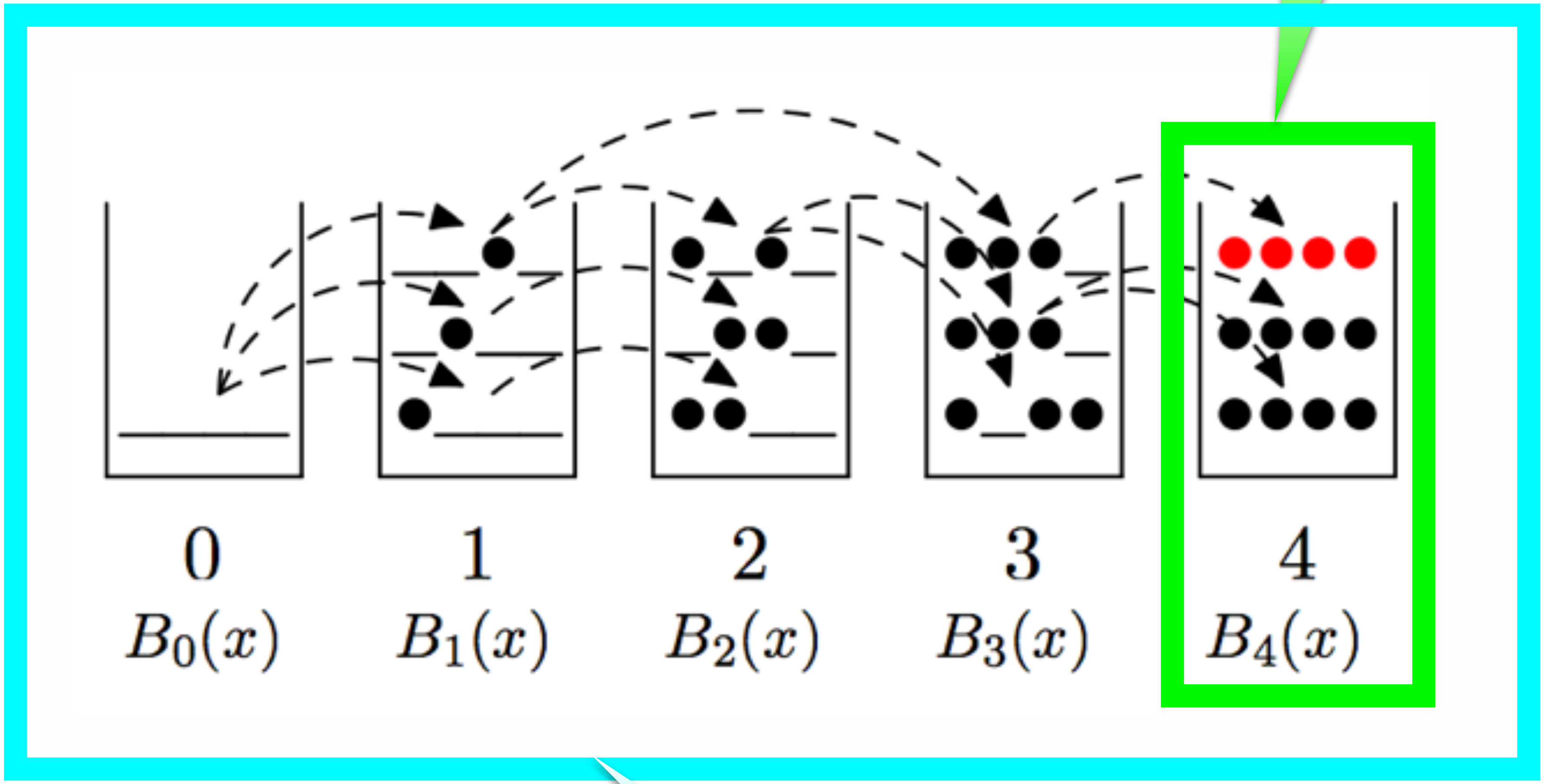


Towards Search-Aware Tuning



Traditional tuning
MERT/MIRA/PRO

Towards Search-Aware Tuning

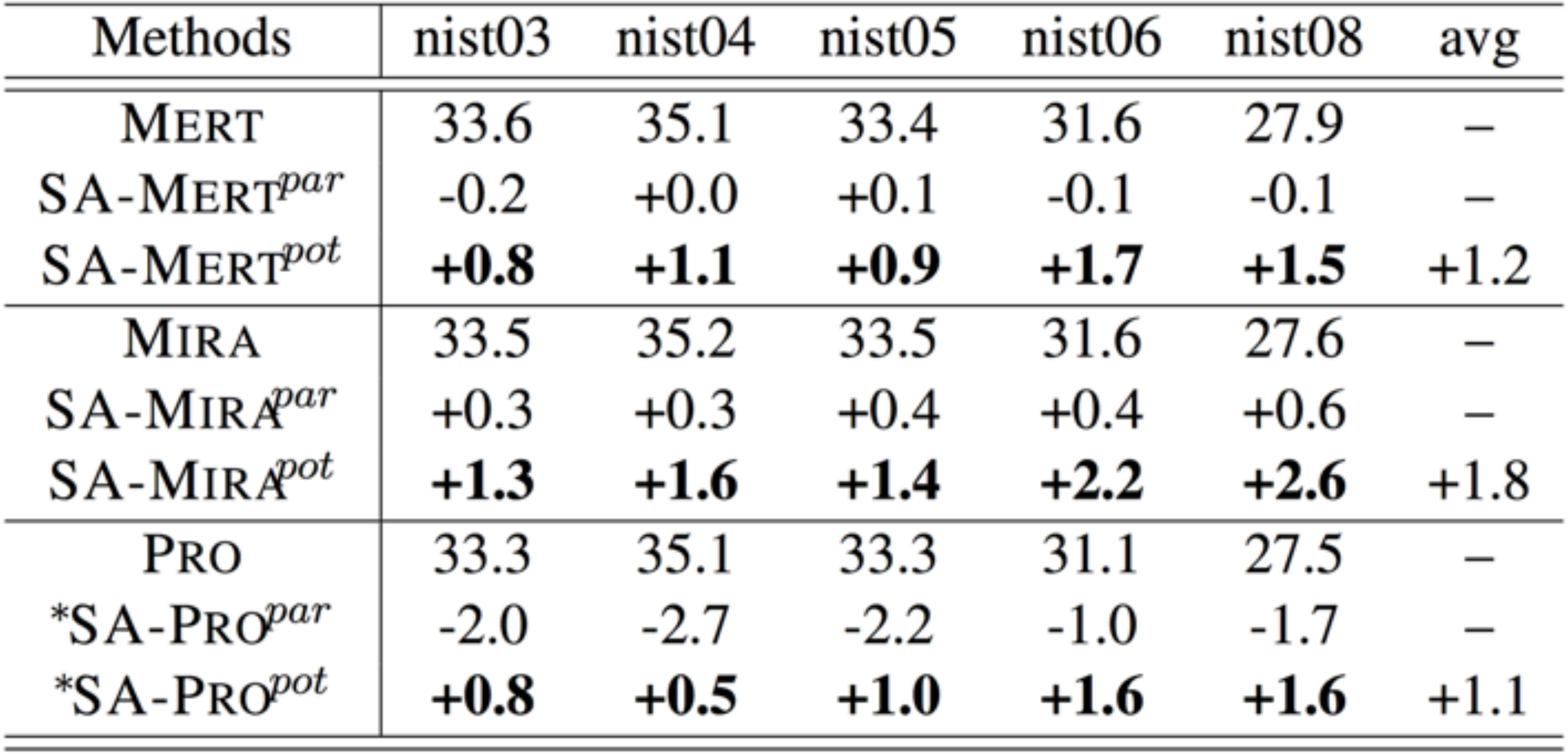


Traditional tuning
MERT/MIRA/PRO

Search-aware tuning

Experiments: Ch-to-En

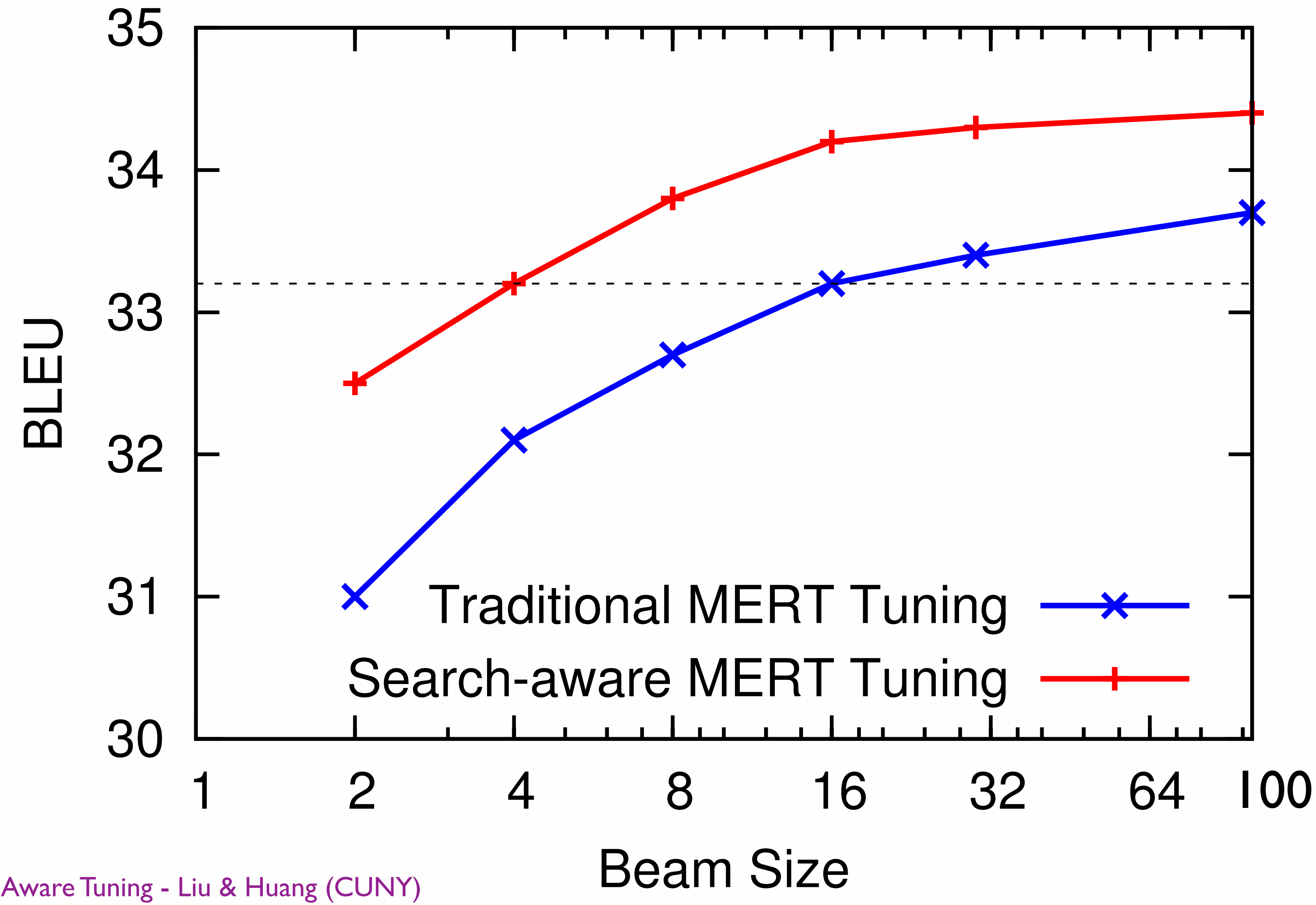
- on phrase-based decoder (Huang & Chiang 07; Yu et al 13)
  - partial BLEU not helpful, but potential BLEU very helpful
  - all experiments use only dense features



Methods	nist03	nist04	nist05	nist06	nist08	avg
MERT	33.6	35.1	33.4	31.6	27.9	–
SA-MERT^{par}	-0.2	+0.0	+0.1	-0.1	-0.1	–
SA-MERT^{pot}	**+0.8**	**+1.1**	**+0.9**	**+1.7**	**+1.5**	+1.2
MIRA	33.5	35.2	33.5	31.6	27.6	–
SA-MIRA^{par}	+0.3	+0.3	+0.4	+0.4	+0.6	–
SA-MIRA^{pot}	**+1.3**	**+1.6**	**+1.4**	**+2.2**	**+2.6**	+1.8
PRO	33.3	35.1	33.3	31.1	27.5	–
*SA-PRO^{par}	-2.0	-2.7	-2.2	-1.0	-1.7	–
*SA-PRO^{pot}	**+0.8**	**+0.5**	**+1.0**	**+1.6**	**+1.6**	+1.1

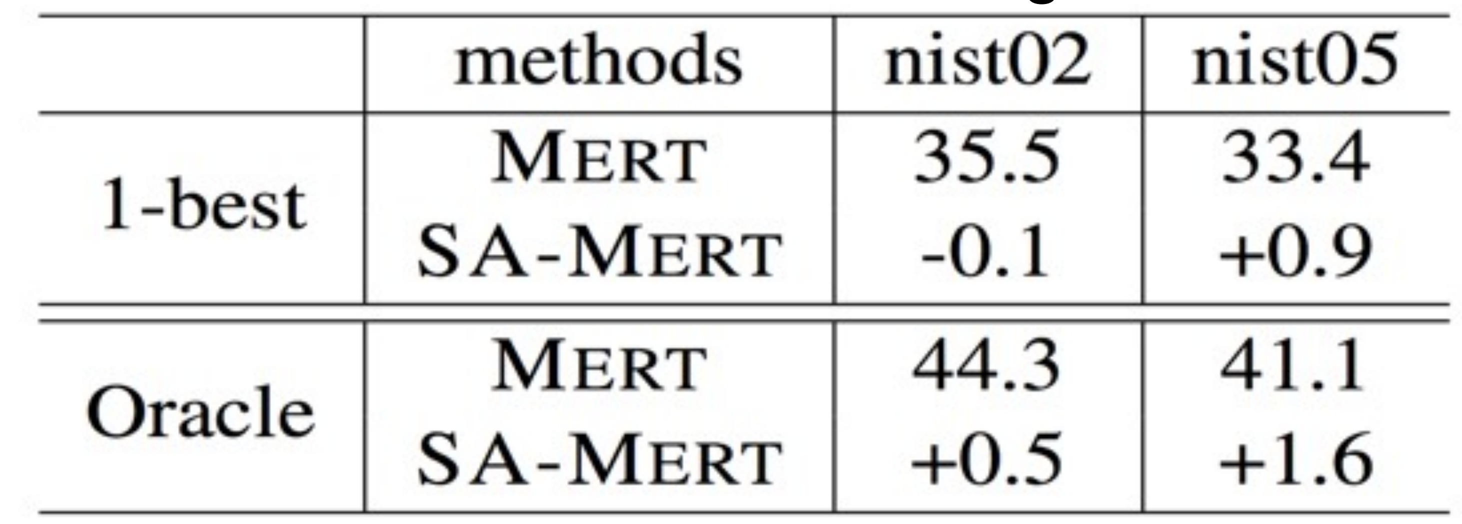
Beam Size

- helps more in smaller beam sizes

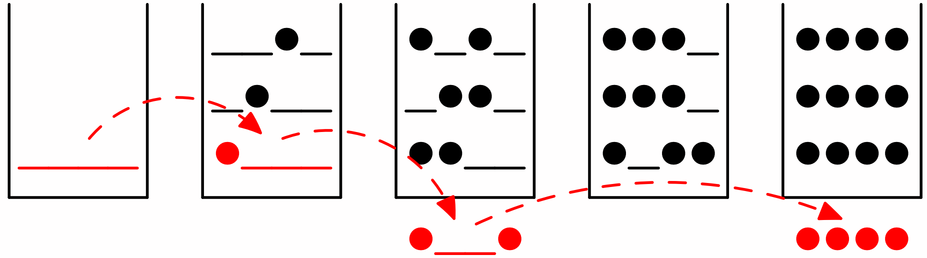


Oracle Improvement

- search-aware tuning improves *k*-best oracle in final bin
  - quality of *k*-best list improves more than 1-best
  - more improvement on test than tuning

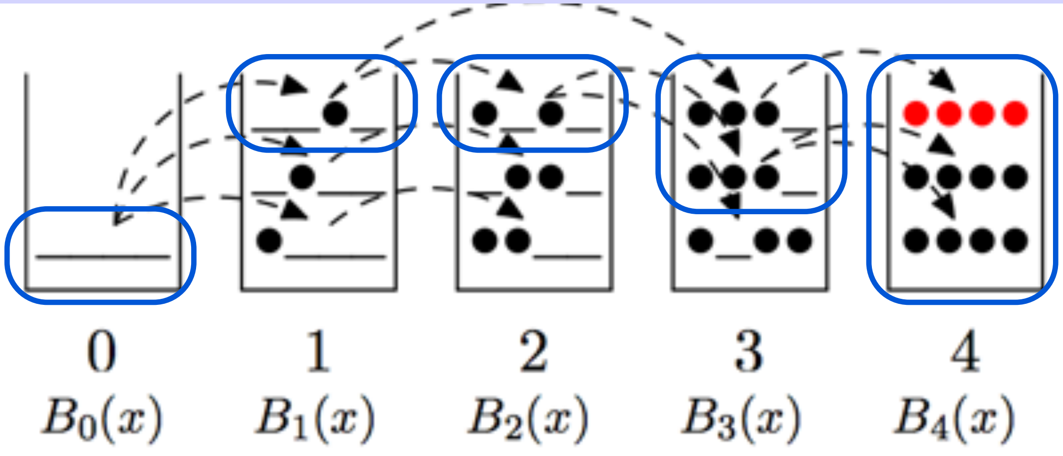


		tuning	test
	methods	nist02	nist05
1-best	MERT	35.5	33.4
	SA-MERT	-0.1	+0.9
Oracle	MERT	44.3	41.1
	SA-MERT	+0.5	+1.6



More Diversity in the Final Bin

cf.: Y-chromosome Adam
Mitochondria Eva



- search-aware tuning does promote diversity
  - even though we do *not* include diversity in the objectives
  - adapt n-gram diversity metric (Gimpel et al 2013) with modifications

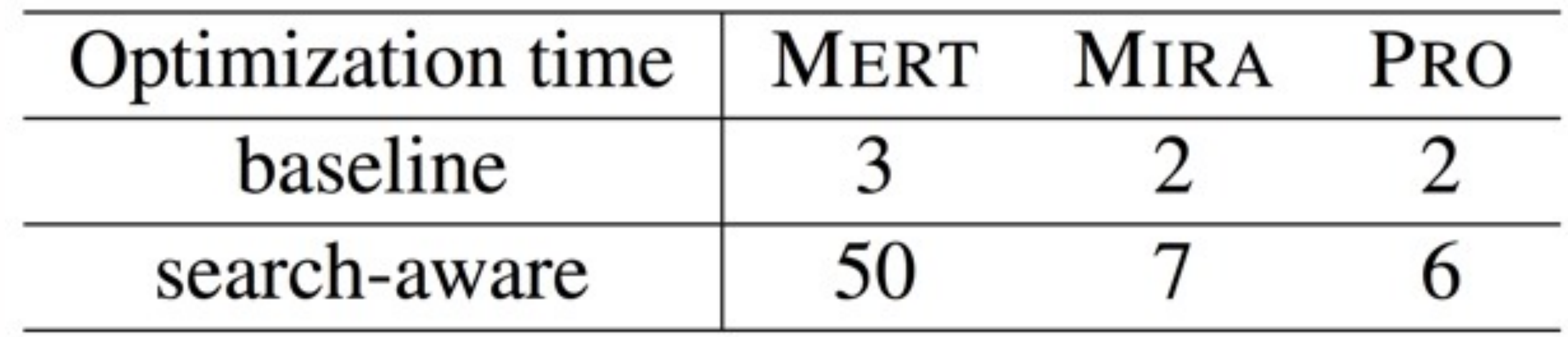
$$d(y, y') = -\sum_{i=1}^{|y|-q} \sum_{j=1}^{|y'|-q} [\![y_{i:i+q} = y'_{j:j+q}]\!]$$

$$d'(y, y') = 1 - \frac{2 \times d(y, y')}{d(y, y) + d(y', y')}$$

Diversity	nist02	nist05
MERT	0.216	0.204
SA-MERT	0.227	0.213

Drawback: Slow Optimization

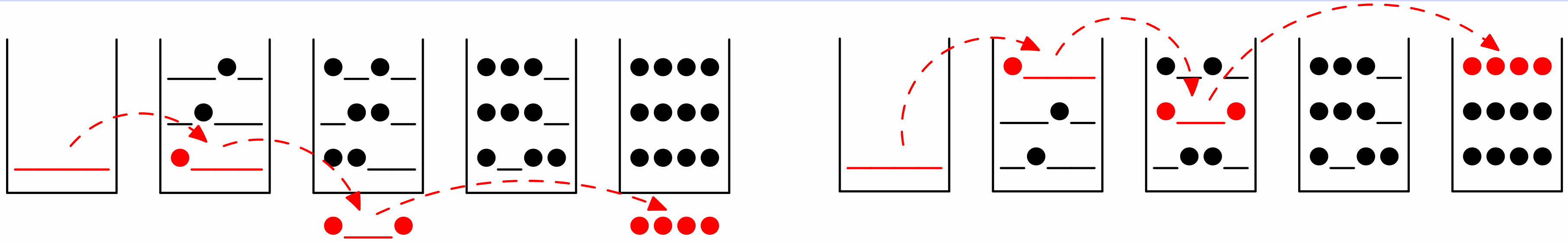
- search-aware tuning does slow down optimization
- but decoding is the bottle-neck in tuning
  - though parallelizable
- overall slowdown is not significant for MIRA/PRO



Optimization time	MERT	MIRA	PRO
baseline	3	2	2
search-aware	50	7	6

decoding time: 20 min. on single CPU

Conclusions



- search error is a major reason for bad translation
  - search-agnostic tuning does not address this problem
- our search-aware tuning promotes promising translations
- potential BLEU is a good evaluator for sub-translations
  - also works for TER and other metrics
- very simple framework; applies to MERT/MIRA/PRO...
  - first consistent ~1 BLEU point improvement with dense features
  - only drawback: slower optimization