On stochastic tree distances and their training via expectation-maximisation

Martin Emms

February 6, 2012

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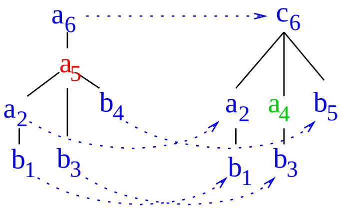

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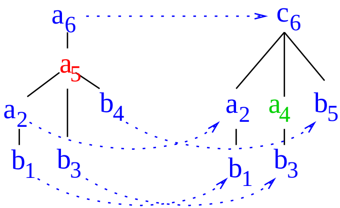

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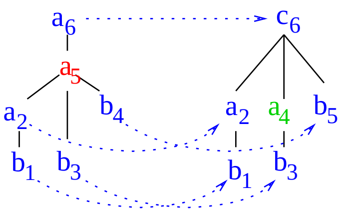

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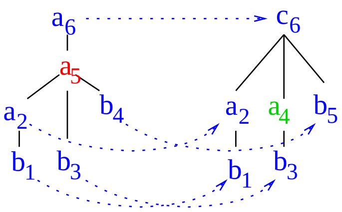

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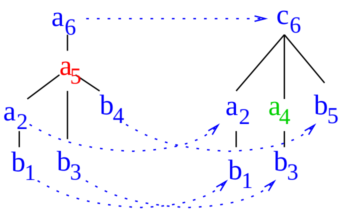

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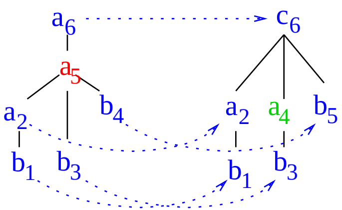

given cost table $\mathcal{C}$:

	λ	*a*	*b*	*c*
λ		•	1	•
a	1	0	•	1
b	•	•	0	•
c	•	•	•	•

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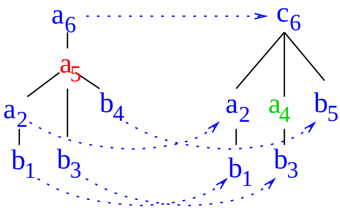

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total cost of σ is sum on non-zero costs

$\mathcal{C}[\lambda][a] + \mathcal{C}[a][\lambda] + \mathcal{C}[a][c] = 3$

this is also a least cost mapping for this table

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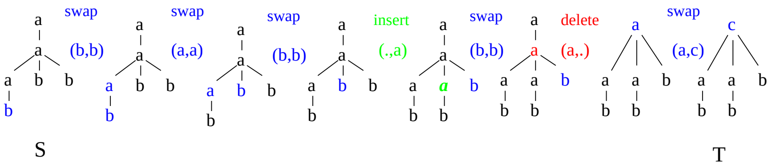

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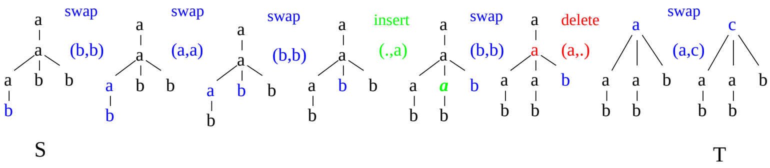

  and seek to define distance via least-cost script
- The mapping- and script-based definitions are known to be equivalent, with a script serving as a serialised representation of a mapping. (Tai 79, Kuboyama 07)

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  and represent a script with $op_1 \ldots op_n \#$, with each $op_i \in EdOp$.
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- Can think of a script as *yielding* a pair of strings (s, t). If $E(s, t)$ is all scripts which yield (s, t), they defined

  all-paths stochastic edit distance:
  the sum of the probabilities of all scripts $e \in E(s, t)$

  viterbi stochastic edit distance:
  prob. of the most probable $e \in E(s, t)$

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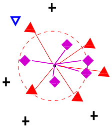

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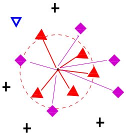

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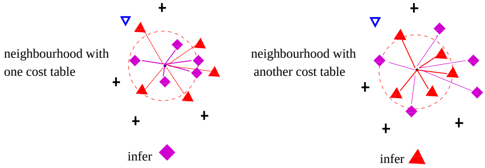

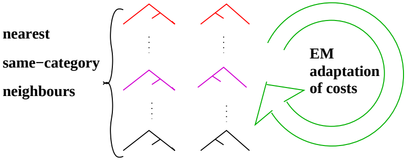

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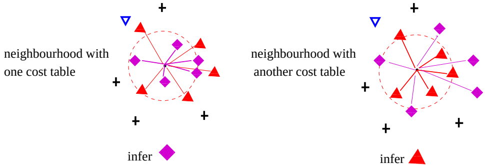

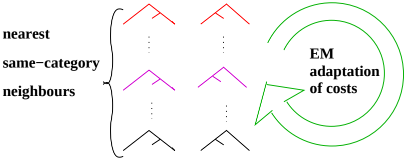

scripts between between *same-category neighbours should have distinctive probs* $\Rightarrow$ perhaps can use *Expectation-Maximisation techniques to adapt edit-probs from a corpus of same-category nearest neighbours*

Outline

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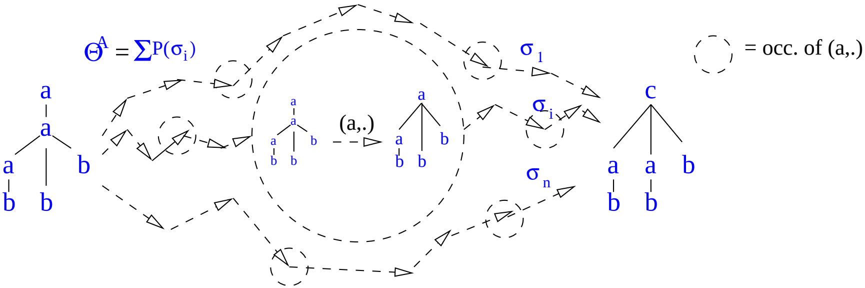

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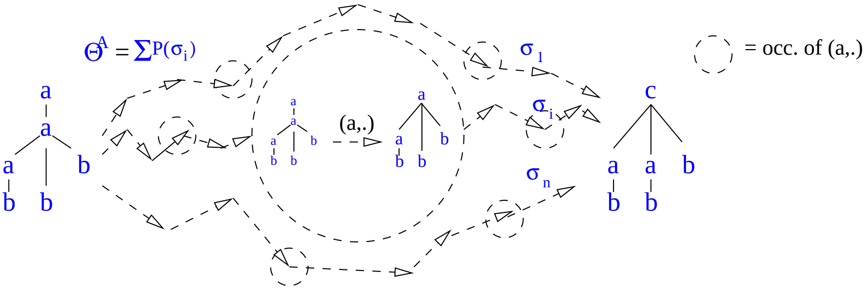

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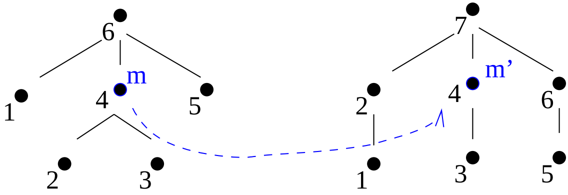

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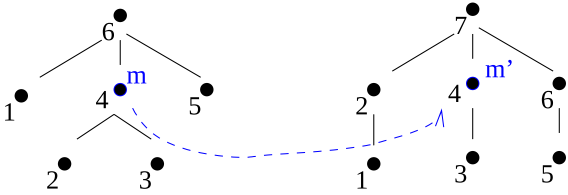


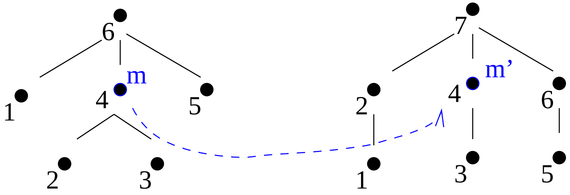
$\gamma_{(S,T)}[4][4](m,m')$, the expectation for a swap (m,m') at $(4,4)$ has the semantics

$$\begin{aligned}\gamma_{(S,T)}[4,4](m,m') &= \sum_{\sigma \in E(S,T),(m_4,m'_4)\in\sigma} \left[\frac{p(\sigma)}{\Theta^A_s(S,T)}\right] \\ &= \frac{1}{\Theta^A_s(S,T)} \times \sum_{\sigma \in E(S,T),(m_4,m'_4)\in\sigma} [p(\sigma)]\end{aligned}$$

in words,

> the sum over the conditional probabilities of any script σ containing a m_4, m'_4 substitution, given that it is a script between S and T

Efficient calculation of $\gamma_{(S,T)}[i][j](op)$?



So how to efficiently calculate:

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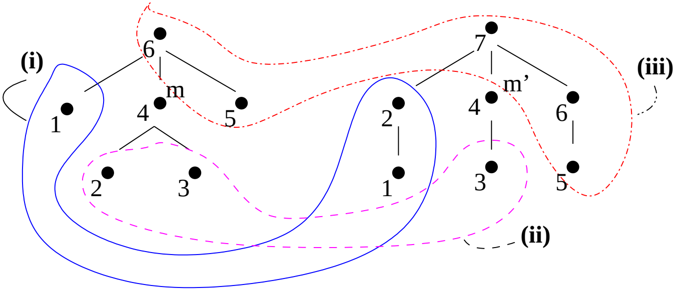

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but we can show that this is not a sound factorisation

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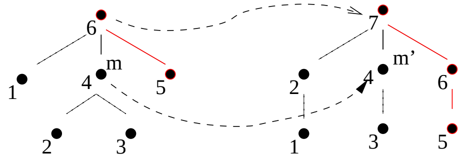

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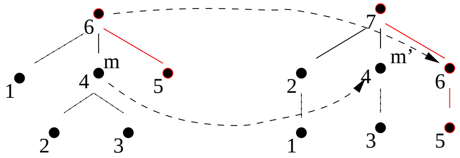

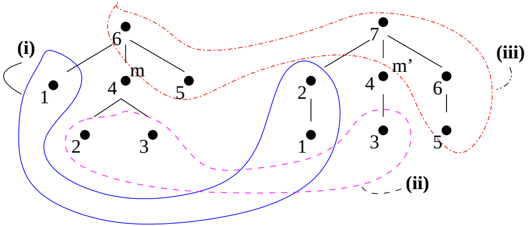

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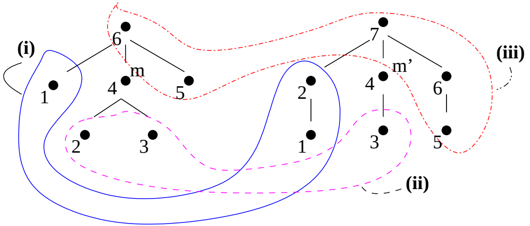

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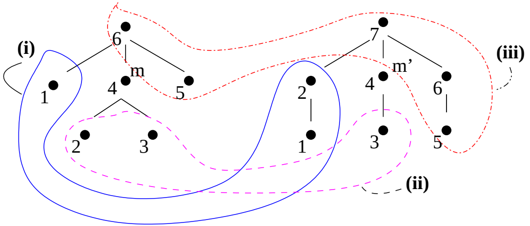

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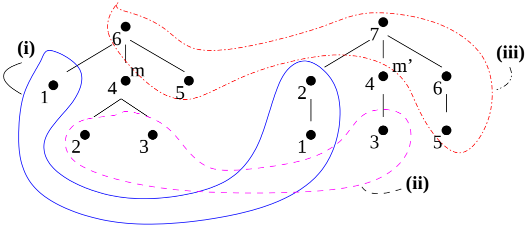

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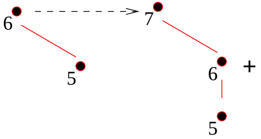

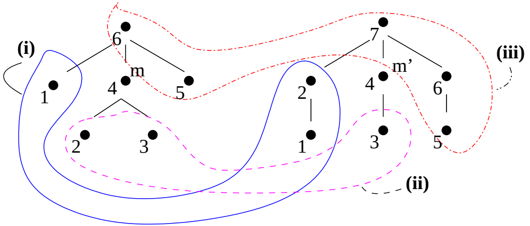

so the problem with the factorisation

$$\sum_{e_1\in E([\cdot_1],[\cdot_2(\cdot_1)])}[p(e_1)] \times \sum_{e_2\in E([\cdot_2\cdot_3],[\cdot_3])}[p(e_2)]\times p(m,m')\times \sum_{e_3\in E([\cdot_6(\cdot_5)],[\cdot_7(\cdot_6(\cdot_5))])}[p(e_3)]$$

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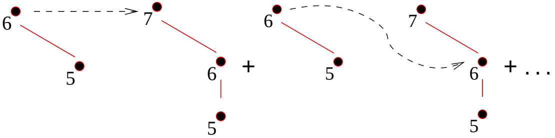

For general trees, a feasible equivalent to the brute-force EM^{bf}_{A} remains an unsolved problem.

Outline

Let *the Viterbi EM algorithm* EM^V, be iterations of pair of steps

(Exp)$_V$ *generate a virtual corpus of scripts by treating each training pair* (S, T) *as standing for the* best *edit-script* σ*, which can relate* S *to* T*, weighting it by its conditional probability* $P(\sigma)/\Theta^A_s(S, T)$*, under current costs* $\mathcal{C}$

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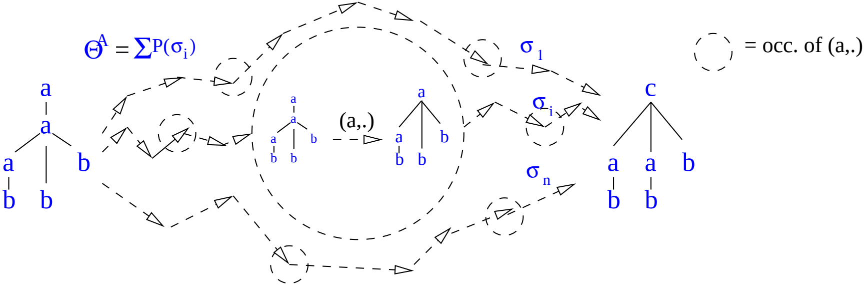
(Exp)$_V$ accumulates the $\gamma_{S,T}(op)$ for all *op*'s, for all (S, T)

Viterbi approximation EM^V (feasible)

All paths



$$\gamma_{S,T}(op) = \sum_{\sigma:S\mapsto T}\left[\frac{P(\sigma)}{\Theta_s^A(S,T)} \times freq(op \in \sigma)\right]$$

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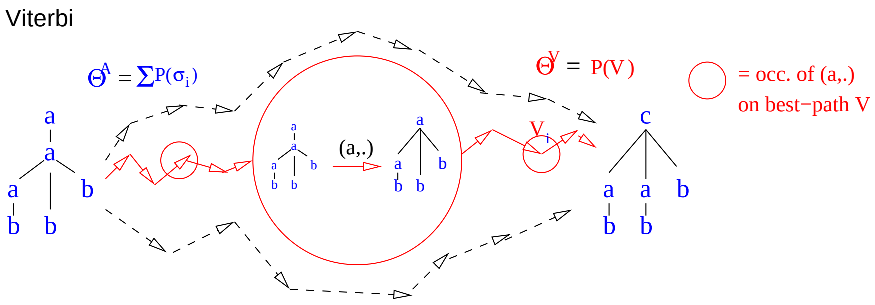

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LOC	What country is the biggest producer of tungsten ? (SBARQ (WHNP (WDT What)(NN country))(SQ (VBZ is)(NP (NP (DT the)(JJS biggest)(NN producer)) (PP (IN of)(NP (NN tungsten)))))(. ?))
HUM	What is the name of the managing director of Apricot Computer ? (WHNP (WP What))(SQ (VBZ is)(NP (NP (DT the)(NN name))(PP (IN of)(NP (NP (DT the)(JJ managing)(NN director))

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Intuitiion: in scripts between between same-category neighbours *should* have distinctive probs eg. . $P(\textit{who}/\textit{when}) << P(\textit{state}/\textit{country})$.

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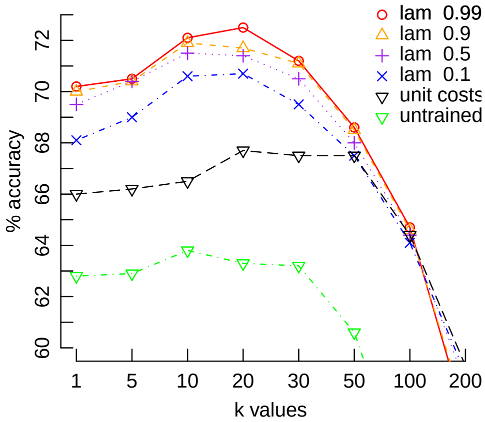
  stochastic tree distance with trained costs
  training by EM^V on same-category neighbours from the Example set

Experimental outcome (brief)



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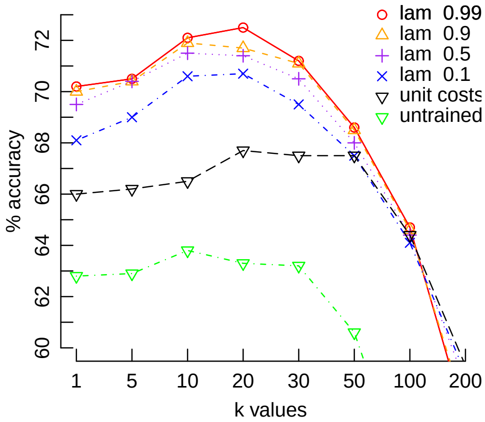

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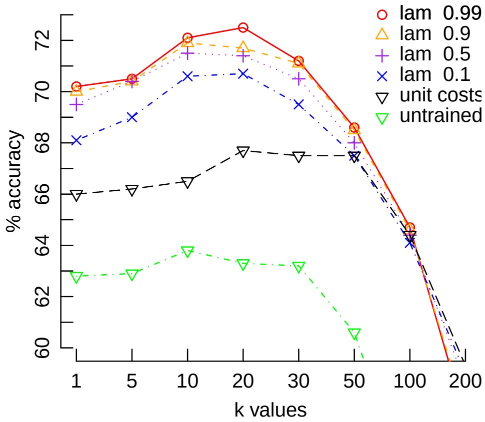

Experimental outcome (brief)

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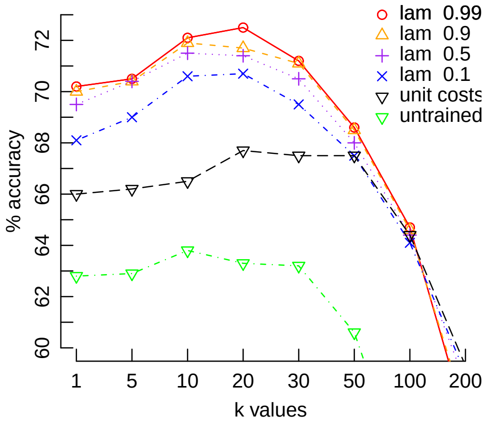
- best EM^V-adapted costs
  ○, max. 72.5%
  about 5% better than unit-costs
  (▽, max. 67.7%)



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examples for $d = 3, 10, 100$, and 1000 are:

3	λ	a	b
λ	3.7	3.7	3.7
a	3.7	2.115	3.7
b	3.7	3.7	2.115

10	λ	a	b
λ	4.755	4.755	4.755
a	4.755	1.433	4.755
b	4.755	4.755	1.433

100	λ	a	b
λ	7.693	7.693	7.693
a	7.693	1.05	7.693
b	7.693	7.693	1.05

1000	λ	a	b
λ	10.97	10.97	10.97
a	10.97	1.005	10.97
b	10.97	10.97	1.005

NOTE: diagonal entries are not insignificant

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$$2^{-C^{\Delta}{}_{\lambda}[x][y]} = \lambda(2^{-C^{\Delta}[x][y]}) + (1-\lambda)(2^{-C^{\Delta}{}_{u}(d)[x][y]})$$

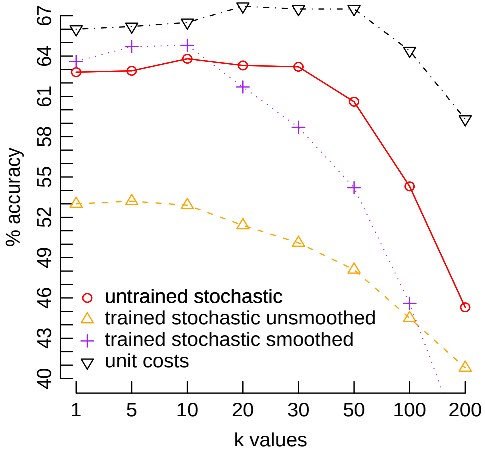
with $0 \leq \lambda \leq 1$

$\lambda = 1$ gives all the weight to the derived table

$\lambda = 0$ gives all the weight to the initial table

Outline

Experiment One



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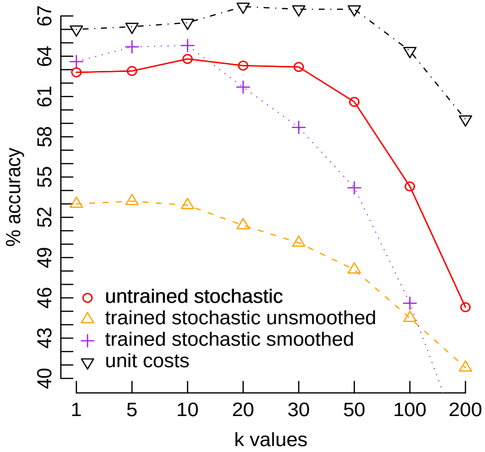
- unit-costs (▽, max. 67.7%) exceeds non-adapted $C^{\Delta}{}_u(3)$ costs (○, max. 63.8%)



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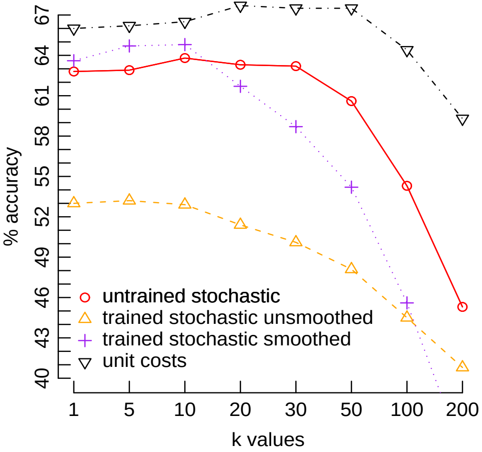

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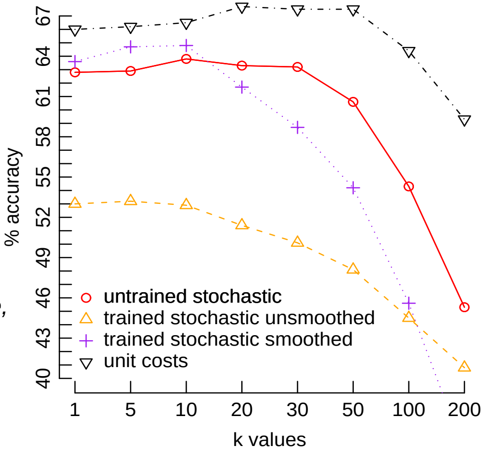

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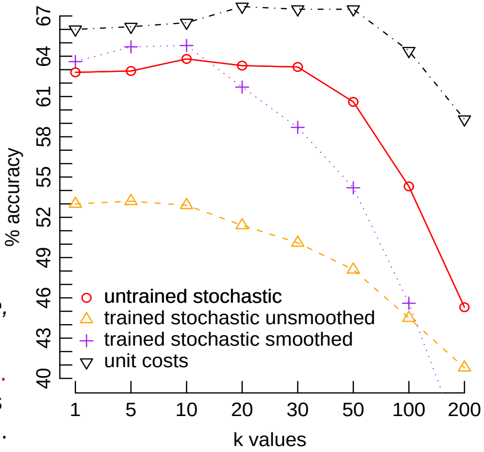
- EM^{V}-adapted costs on training set gives 95% accuracy: $\Rightarrow EM^{V}$ makes training pairs *too probable, and over-fits*.
- *smoothing* adapted costs (+,max. 64.8%) improves over initial costs (○) but is still below unit costs (▽).



Despite poor performace of the EM^V-adapted costs, some of the adapted costs seem intuitive. Here is a sample from top 1% of adapted swap costs, which are plausibly discounted relative to others:

8.50	?	.	12.31	The	the
8.93	NNP	NN	12.65	you	I
9.47	VBD	VBZ	13.60	can	do
9.51	NNS	NN	13.83	many	much
9.78	a	the	13.92	city	state
11.03	was	is	13.93	city	country
11.03	’s	is			

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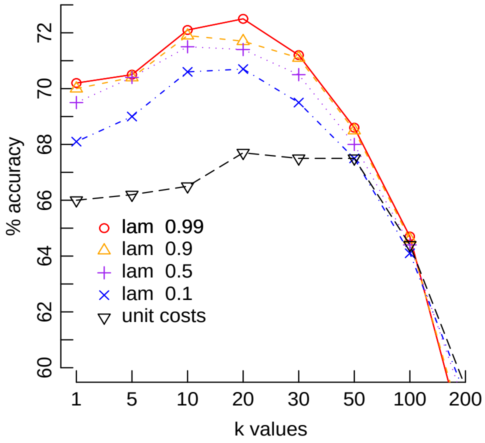
- Bilenko et al 2003 does essentially this in work on stochastic string distance

Experiment Two



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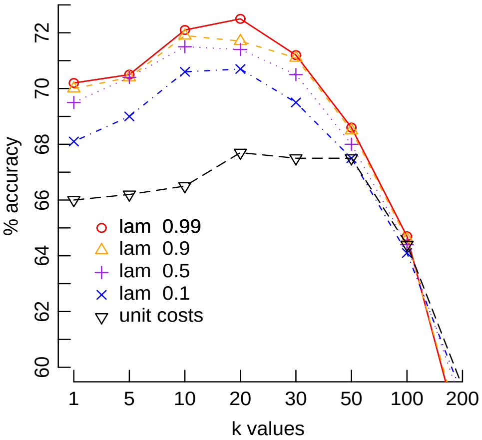

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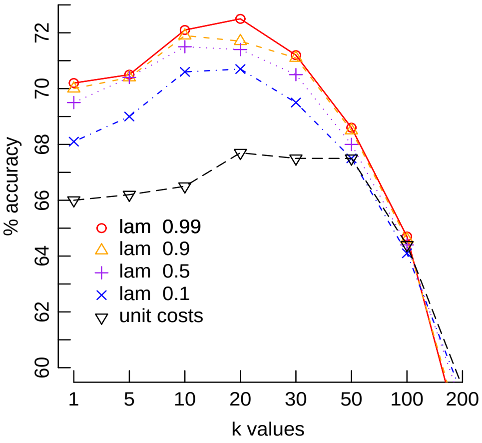
- the best result being 72.5% ($k = 20$, $\lambda = 0.99$), as compared to 67.5% for unit-costs ($k = 20$)



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- evidence to show that Viterbi EM cost-adaptation can increase the performance of a tree-distance based classifier, and improve it to above that attained in the unit-cost setting,
- experiments on further data-sets is required: one possibility is the NLP-related tasks of question-answering, where the need is to assess pairs of sentences for their likelihood to be a question-answer pairs. A training set of such pairs could also serve as potential input to the cost adaptation algorithm.