Investigations in Exact Inference for Hierarchical Translation

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Optimisation in hierarchical translation

Hierarchical phrase-based translation

- SCFG compactly encodes the translation equivalences
- incorporate the language model requires intersecting a wFSA
  - while this is guaranteed polynomial in time and space
  - it is **prohibitive** even for low order LMs
  - "requires" approximation [Chiang, 2007]

Proposal

Avoid performing the full intersection, but **without** losing exactness

1. start from an optimistic unigram LM
2. incorporate higher-order *n*-grams on the basis of evidence of the need to do so

Exact inference over a tractable proxy representation of the target distribution (dynamic programming)

Using a technique that is also directly applicable to **sampling**

Sampling

During **decoding**, when a single output is required, **optimisation** is a natural choice

However,

- Minimum Bayes Risk decoding is based on samples
- samples are also useful for exploring different modes of the distribution

During **learning**, **samples** are necessary for training the parameters

- however, often n-best lists are used as a proxy
  e.g. MERT, minimum risk training

[Blunsom and Osborne, 2008, Arun et al., 2009]

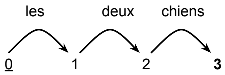
Exact optimisation and sampling with OS*

A unified view on optimisation and sampling

- A cross between Adaptive Rejection Sampling and A* optimisation
- An exact alternative to the usual approximate MCMC sampling techniques (e.g. Gibbs)

OS* [Dymetman et al., 2012]

Revisiting hierarchical SMT in 30 seconds



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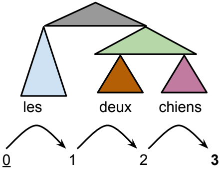

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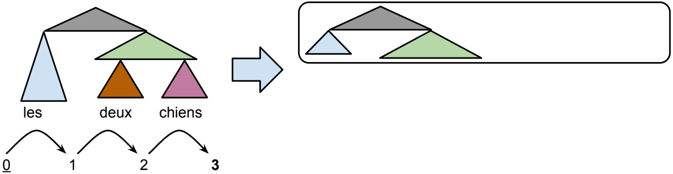

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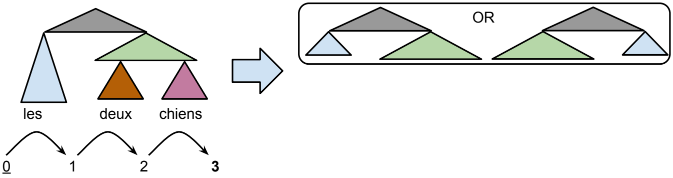

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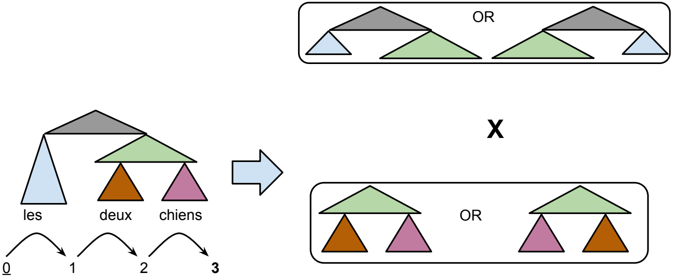

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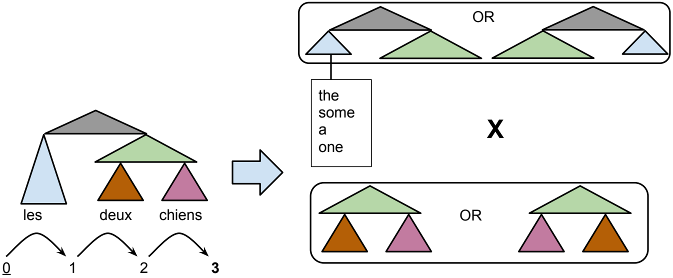

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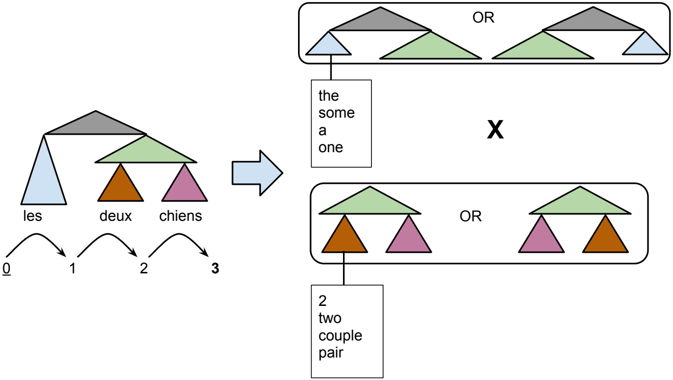

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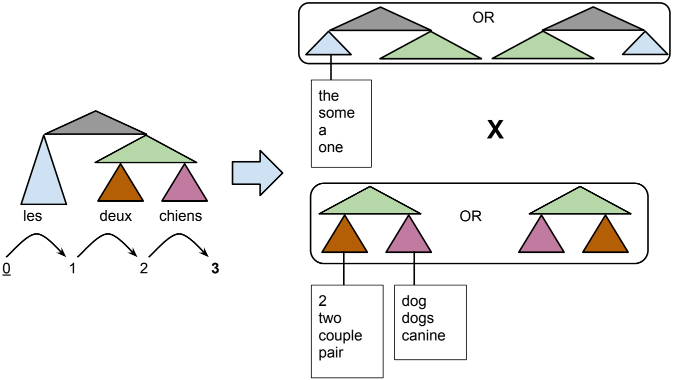

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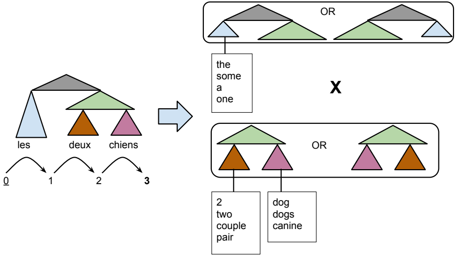
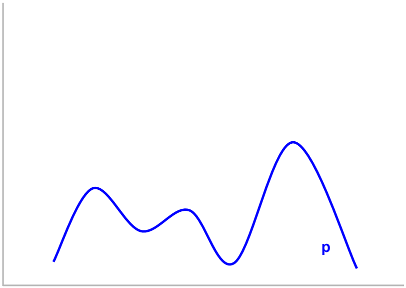


- translation hypergraph without the LM: $G(f)$
  wCFG
- language model: A
  wFSA

$G(f) \cap A$ **intractable** space of weighted translations of the input [Dyer, 2010]

- defines an unnormalised probability distribution over target derivations
- number of rules in the intersected grammar grows exponentially with the order of A

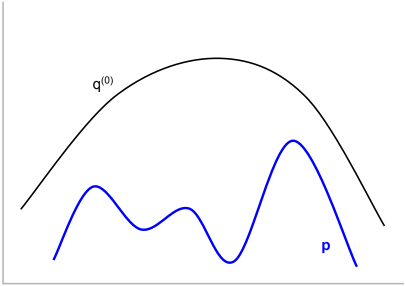
OS* for hierarchical SMT



$p = G(f) \cap A$

intractable $\rightarrow$ ~~**dynamic programming**~~

OS* for hierarchical SMT



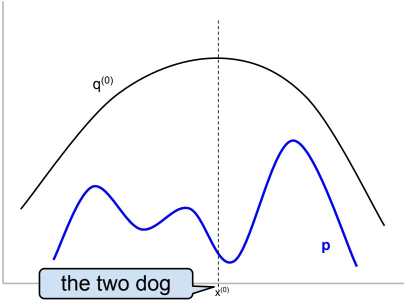
Simpler and optimistic proposal

$$q^{(0)} = G(f) \cap A^{(0)}$$

tractable $\rightarrow$ **dynamic programming**

- $A^{(0)}$ is an optimistic unigram version of the full LM
- Progress by lowering the upper-bound based on observed samples
- Efficient "Earley intersection" [Dyer, 2010]

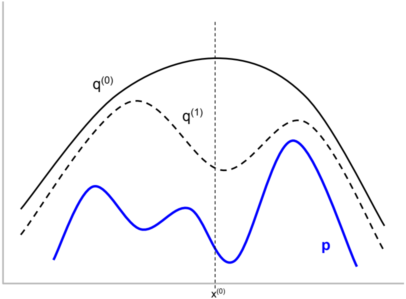
OS* for hierarchical SMT



Sample from $q^{(0)}$

- Accept sample with probability $r = p(x)/q^{(0)}(x)$
- Poor acceptance rate
- Rejected samples are used to refine the proxy

OS* for hierarchical SMT



Obtain a better proxy by intersecting with a small "refinement" automaton $A^{(1)}$

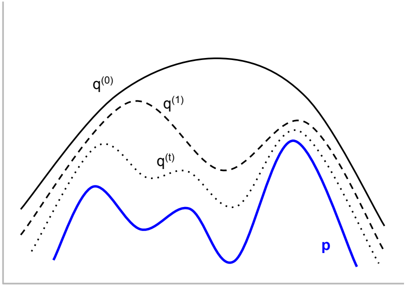
$$q^{(1)} = q^{(0)} \cap A^{(1)}$$

- $A^{(1)}$ accounts for a more precise context

$$\mathrm{w(two)w(dog)} \rightarrow \mathrm{w(two)w(dog|two)}$$

- $q^{(1)}$ is only slightly more complex than $q^{(0)}$ thus dynamic programming remains feasible
- leads to a better acceptance rate

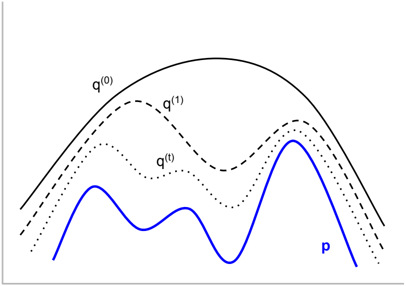
OS* for hierarchical SMT



Repeat the process (sample + refine) until:

- Sampling: a pre-defined acceptance rate is reached

OS* for hierarchical SMT



Repeat the process (sample + refine) until:

- Sampling: a pre-defined acceptance rate is reached
- Optimisation: maximum from $q^{(t)}$ is sufficiently close to p

An upper-bound on the LM distribution

Maximise away the history of an *n*-gram [Carter et al., 2012]

$$w_1(a) \equiv \max_h p_{lm}(a|h)$$

$$w_2(a|a_{-1}) \equiv \max_h p_{lm}(a|h, a_{-1})$$

$$w_3(a|a_{-2}\, a_{-1}) \equiv \max_h p_{lm}(a|h, a_{-2}\, a_{-1})$$

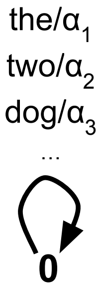
...

Pre-computed

Initial proposal

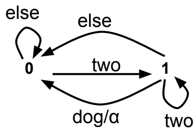
The initial proposal $q^{(0)}$ incorporates only unigrams

- $A^{(0)}$ is a very simple automaton
- $q^{(0)} = G(f) \cap A^{(0)}$ has the same size of $G(f)$



Incremental updates

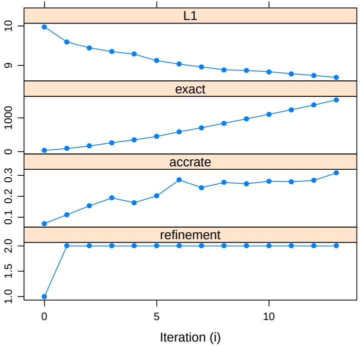
Down-weight occurrences of **dog** *in the context of* **two**



where $\alpha = \frac{w_2(\text{dog}|\text{two})}{w_1(\text{dog})}$

Affects derivations yielding strings that contain occurrences of "two dog"
Each such occurrence is now scaled by α

Illustration (sampling)

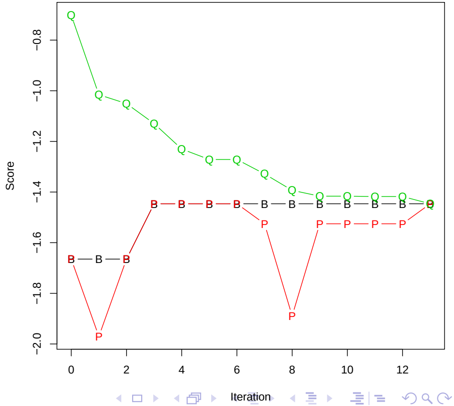


Due to refinements

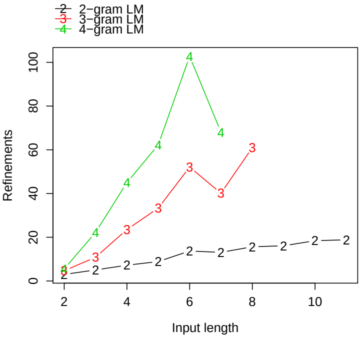
- better acceptance rate

Illustration (optimisation)

i	Rules	Optimum
0	311	<s> one last observation . </s>
1	454	<s> **one** last observation . </s>
2	628	<s> one **last** observation . </s>
3	839	<s> one final **observation** . </s>
4	1212	<s> one **final observation** . </s>
		...
12	3000	<s> **a final** observation . </s>
13	3128	<s> one final observation . </s>



Optimisation

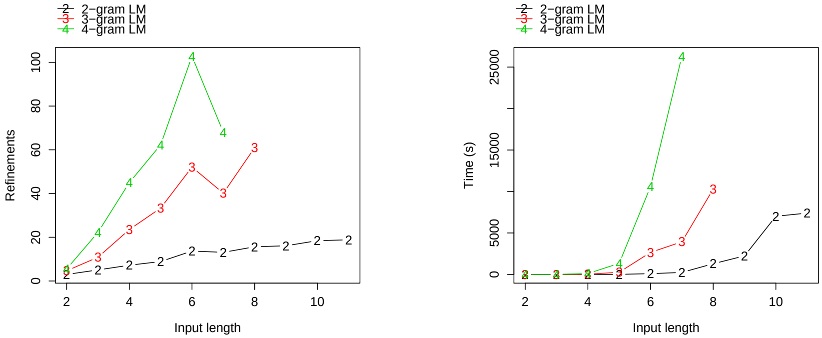


Length	ctxt	count	$\frac{\vert R_f \vert}{\vert R_0 \vert}$
4	1	20.3	74.6 ± 53.9
	2	19.2	
	3	5.4	
5	1	21.9	145.4 ± 162.6
	2	32.9	
	3	7.5	
6	1	**34.7/75**	535.8 ± 480.0
	2	**54.9/2000**	
	3	**13.2**	

4-gram LM

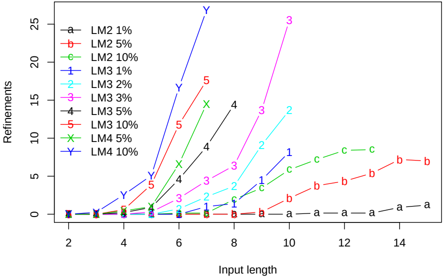
- Needs to account for very few contexts

Optimisation



- Needs to account for very few contexts

Sampling

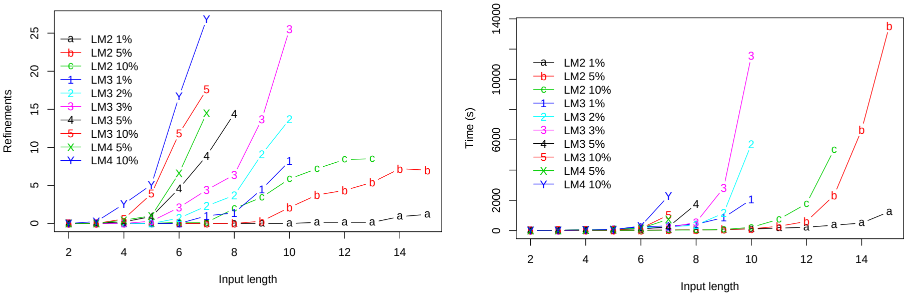


Input	ctxt	count	$\frac{\lvert R_f \rvert}{\lvert R_0 \rvert}$
5	1	1.0	1.9 ± 1.0
6	1	6.3	17.6 ± 13.6
	2	0.3	
7	1	**12.9/90**	93.8 ± 68.9
	2	**1.5/3000**	
	3	**0.1**	

4-gram LM

- Needs to account for very few contexts (mostly lower-order)

Sampling



- Needs to account for very few contexts (mostly lower-order)

Summary

Contributions

- common framework for optimisation and sampling
- exactness
- anytime guarantees: acceptance rate / distance to optimum
- explore only a sub-space of the possible *n*-grams

Challenge: control the time $\rightarrow$ complexity of the intersection

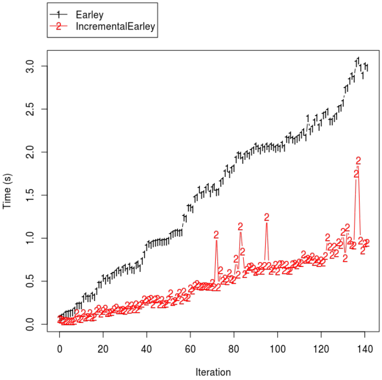
Thanks!

Questions/comments?

Incremental intersection

Reuse chart items compatible with the new automaton

Motivating example



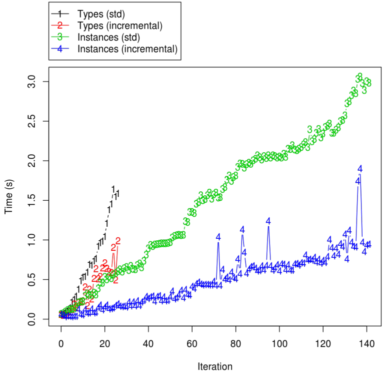
- about a third of the time

Making refinements more local

Distinguish instances of terminals

Motivating example: 47 types [506 instances]

#refinements	#instances	context
2	11	,
5	15	@-@
2	7	central
7	15	centre
1	12	heart
6	57	**in**
5	5	secret
1	8	secretive
4	7	secretly
16	108	**the**
8	41	middle
2	3	midst
5	27	of
1	1	<s>



1-word context:

- types: 314 (62%) instances are affected
- instances: 65 (7%) instances are affected

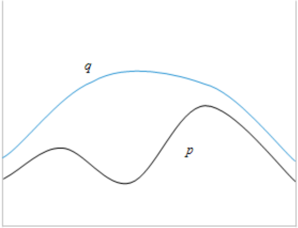
OS*

Exact **O**ptimisation an **S**ampling with Connections to A* (OS*) [Dymetman et al., 2012]

- Coarse-to-fine strategy
- Tractable form of adaptive rejection sampling

OS* (sampling)

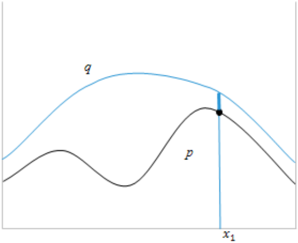
We upper-bound the target distribution p by a simpler proposal q and proceed in a adaptive rejection sampling fashion



- we can optimise/sample from q directly

OS* (sampling)

In sampling, we sample from q



- x_1 is accepted with probability $r = p(x_1)/q(x_1)$

OS* (sampling)

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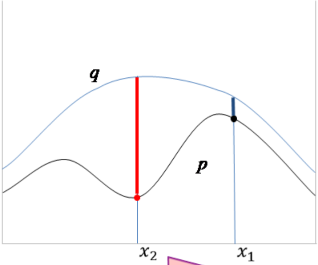
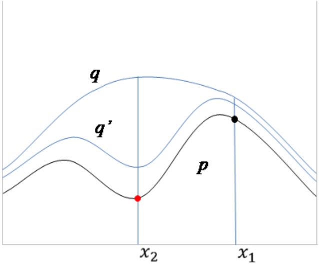


Evidence that we are being too optimistic!
However, not everywhere, rather at around $x = x_2$

- x_1 is accepted with probability $r = p(x_1)/q(x_1)$
- x_2 is rejected

OS* (sampling)

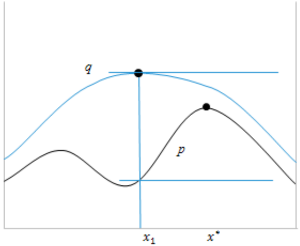
Rejected samples are used to motivate an increase in the complexity of q



- accounts for some underspecified context
- brings the proxy closer to the target
- increases the rate of acceptance

OS* (optimisation)

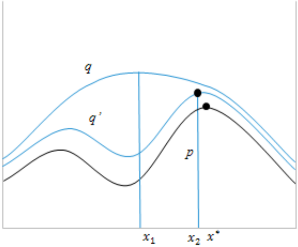
In optimisation, we find the maximum of q



- x_1 is rejected due to low ratio $r = p(x_1)/q(x_1)$

OS* (optimisation)

Rejected maxima are used to motivate an increase in the complexity of q



- accounts for some underspecified context
- brings q's maximum closer to the true maximum

OS* (convergence)

In sampling

- longer contexts are incorporate till a pre-defined acceptance rate is achieved

OS* (convergence)

In sampling

- longer contexts are incorporate till a pre-defined acceptance rate is achieved

In optimisation

- contexts are incorporated while $q(x)$ differs sufficiently from $p(x)$ for $x = \text{argmax}_x q(x)$
  i.e.
  $$r(x) = p(x)/q(x) < \epsilon$$

Chart item combination

In $G' \equiv G(f) \cap A$

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- rules have same length, structure and terminals of those in $G(f)$

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- rules have same length, structure and terminals of those in $G(f)$
- but nonterminals are indexed versions of those in $G(f)$ [Bar-Hillel et al., 1961]
  e.g. (i, N, j) where
  - i and j are states in A
  - N is a nonterminal in the original grammar

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  e.g. (i, N, j) where
  - i and j are states in A
  - N is a nonterminal in the original grammar
- number of states in A grows exponentially with the order of the LM

Related work

- Rush and Collins [2011] address exact decoding in HPB-SMT using Dual Decomposition

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- Rush and Collins [2011] address exact decoding in HPB-SMT using Dual Decomposition
- Blunsom and Osborne [2008] address probabilistic inference (at both decoding and training)
  they sample derivations from a cube pruned space
- Arun et al. [2009] introduce a Gibbs sampler for PB-SMT
  MBR training/decoding and approximate "max-translation"

OS* for hierarchical SMT

Produce a sequence of "proposal" grammars which all upper-bound p

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$A^{(0)}$ is an optimistic unigram version of the full LM

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$A^{(t)}$ is a small automaton that refines $q^{(t-1)}$ relative to some k-gram context not yet made explicit

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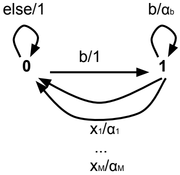
$A^{(0)}$ is an optimistic unigram version of the full LM
$A^{(t)}$ is a small automaton that refines $q^{(t-1)}$ relative to some k-gram context not yet made explicit
Note that for some large M

$$\bigcap_{t=0}^{M} A^{(t)} = A$$

Refining automata

Substring searching construction [Cormen et al., 2001]
Makes a specific **context** explicit

- lower all possible continuations of the history
  e.g. "**b** a", "**b** c", "**b** d"



- note that this does not increase the computational cost of the intersection

Algorithm

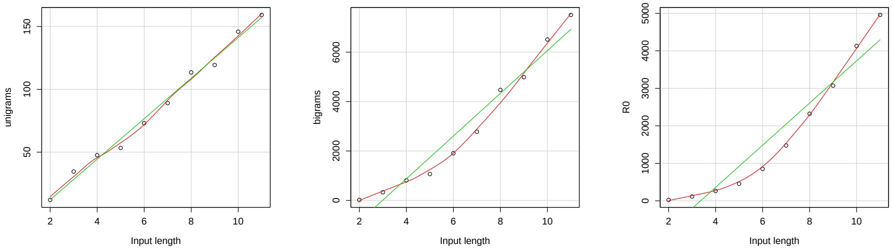
Algorithm 1 OS* for Hierarchical Translation: Optimisation (left) and Sampling (right).

$t \leftarrow 0$
$q^{(0)} \leftarrow G(f) \cap A^{(0)}$
while not an x has been accepted **do**
    Find maximum x in $q^{(t)}$
    $r \leftarrow p(x)/q^{(t)}(x)$
    Accept-or-Reject x according to r
    if Rejected(x) **then**
        define $A^{(t+1)}$ based on x and $q^{(t)}$
        $q^{(t+1)} \leftarrow q^{(t)} \cap A^{(t+1)}$
        $t \leftarrow t+1$
return x

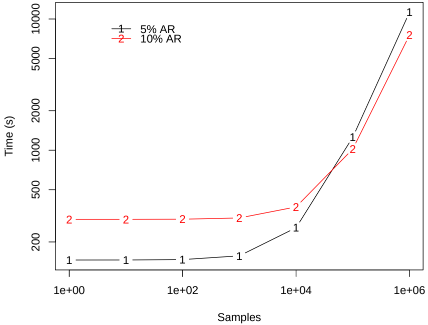
$t \leftarrow 0, AR \leftarrow 0$
$q^{(0)} \leftarrow G(f) \cap A^{(0)}$
while not $AR > threshold$ **do**
    Sample $x \sim q^{(t)}$
    $r \leftarrow p(x)/q^{(t)}(x)$
    Accept-or-Reject x according to r
    if Rejected(x) **then**
        define $A^{(t+1)}$ based on x and $q^{(t)}$
        $q^{(t+1)} \leftarrow q^{(t)} \cap A^{(t+1)}$
        $t \leftarrow t+1$
return already accepted x's along with $q^{(t)}$

Experiment

Small scale experiment: short sentences
Properties of G

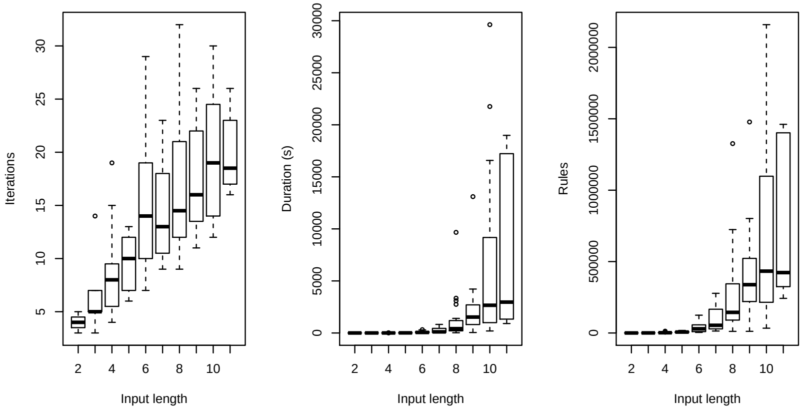


Sampling performance: 4-gram LM

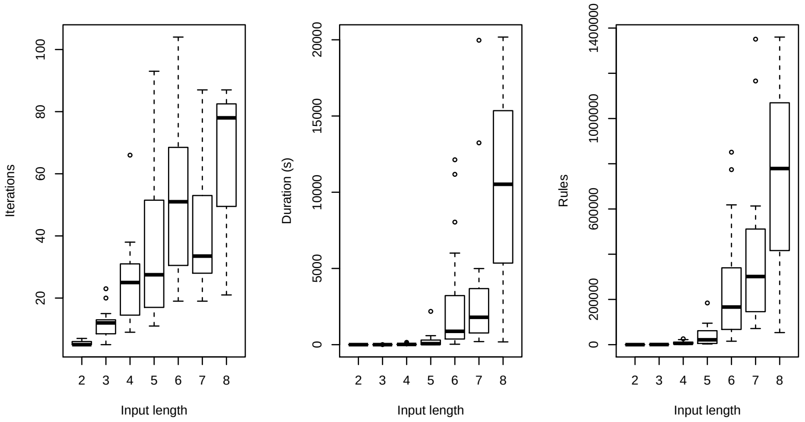


- 20 sentences of length 6
- time to draw 1M samples
- including the time to produce the sampler

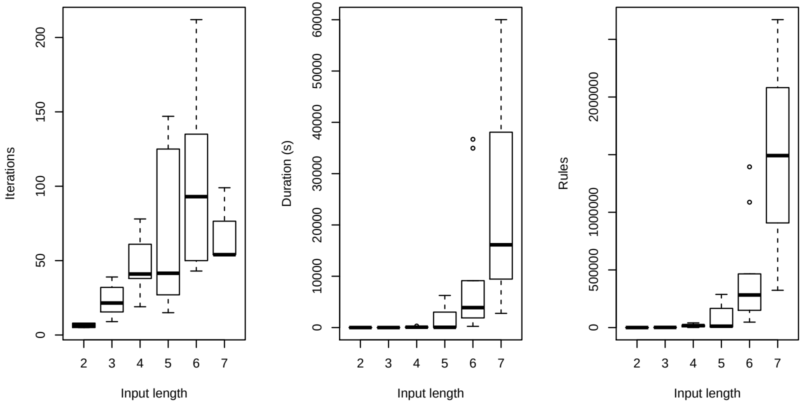
Optimisation (closer look): 2-gram LM



Optimisation (closer look): 3-gram LM



Optimisation (closer look): 4-gram LM



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