NCODE:
an Open Source Bilingual N-gram SMT Toolkit

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Plan

History

- Phrase-based approach (early 2000)
  - state-of-the-art results for many MT tasks

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- Phrase-based approach (early 2000)
  - state-of-the-art results for many MT tasks
- Bilingual *n*-gram approach (an alternative to PBMT)
  - Derives from the finite-state perspective introduced by (Casacuberta and Vidal, 2003)
  - First implementation dates back to 2004 (Ph.D. at UPC)
  - Extended for the last three years (Postdoc at Limsi-CNRS)

Standard SMT mainstream

1 take a set of parallel sentences (*bitext*)
  - align each pair (**f**,**e**), word for word
  - train translation model: the "phrase" table $\{(f, e)\}$

2 take a set of monolingual texts
  - train statistical target language model

3 make sure to tune your system

4 translate $\mathbf{f} = \operatorname*{argmax}_{\mathbf{e} \in E} \{\sum_{k=1}^{K} \lambda_k F_k(\mathbf{e}, \mathbf{f})\}$

5 evaluate

6 not happy ? goto 1

Underlying formal device: finite-state SMT

- phrase-table lookup [*pt*] is finite-state
- *n*-gram models [*lm*] can be implemented as weighted FSA

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$$\mathbf{e}^* = bestpath(\pi_2(\mathbf{f} \circ pt) \circ lm)$$

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- monotonic decode of **f**:

$$\mathbf{e}^* = bestpath(\pi_2(\mathbf{f} \circ pt) \circ lm)$$

- decode with reordering:

$$\mathbf{e}^* = bestpath(\pi_2(\mathbf{perm}(\mathbf{f}) \circ pt) \circ lm)$$

$perm(\mathbf{f})$ is a word lattice (FSA) containing reordering hypotheses

Bilingual *n*-grams

- a **bilingual** *n*-gram language model as main translation model
  - Sequence of tuples (training bitexts):

we	want	translations	perfect
nous	voulons	des traductions	parfaites

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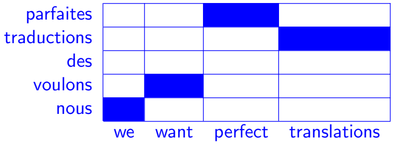
- translation context introduced via tuple **n**-grams

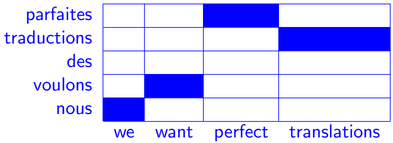
$$p((s,t)_k|(s,t)_{k-1},(s,t)_{k-2})$$

multiple back-off schemes, smoothing techniques, *etc.*

Tuples from word alignments



Tuples from word alignments



1 a **unique** segmentation of each sentence pair:

- no word in a tuple can be aligned to a word outside the tuple
- target-side words in tuples follow the original word order
- no smaller tuples can be found

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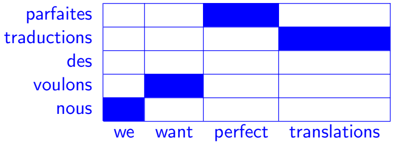

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2. source-NULLed units are not allowed (complexity issues):
   - attach the target word to the **previous**/**next** tuple

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Coupling reordering and decoding

$$\mathbf{e}^* = \mathit{bestpath}(\pi_2(\mathbf{perm}(\mathbf{f}) \circ \mathit{pt}) \circ \mathit{lm})$$

- **perm** is responsible of the NP-completeness of SMT

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Problem: Full permutations computationally too expensive (EXP search)

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POLY search, but little correlation with language

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Problem: Full permutations computationally too expensive (EXP search)

Sol1: Heuristic constraints (distance-based): IBM, ITG, *etc.*
POLY search, but little correlation with language

Sol2: Linguistically-founded rewrite rules:

- learn **reordering rules** from the bitext word alignments

  perfect translations $\rightsquigarrow$ translations perfect

- compose rules as a reordering transducer: $R = \bigcirc_i (r_i \cup Id)$
- in decoding: $perm(\mathbf{f}) = \mathbf{f} \circ R$

$perm(\mathbf{f})$ is a word lattice (FSA) with reordering hypotheses

Plan

Search structure

- Exhaustive search is *unfeasible* $\rightsquigarrow$ pruning needed!

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  - Problem: Search bias (translate first 'easiest' segments)
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Feature cost estimation problem for NCODE
(multiple n-gram LMs without accurate estimations)

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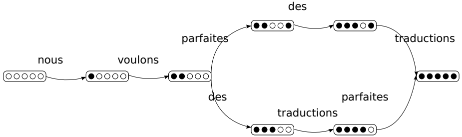
  Feature cost estimation problem for NCODE

  (multiple *n*-gram LMs without accurate estimations)
- NCODE: $[2^J]$ stacks (hyps. translating the **same** input words)
  + Highly fair comparisons
  + Problem: efficiency problem (2^J)
  + Solution: limit reordering (linguistically motivated)

Search algorithm (sketched)

- Word lattice encoding permutations (up to 2^J nodes)



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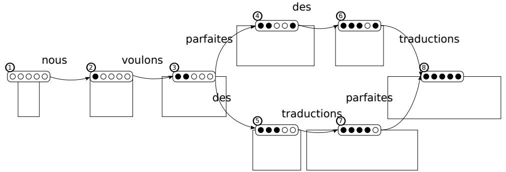

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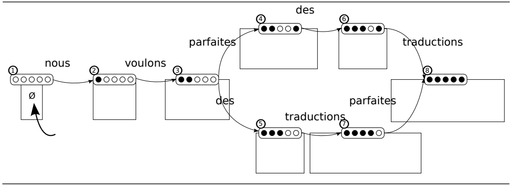

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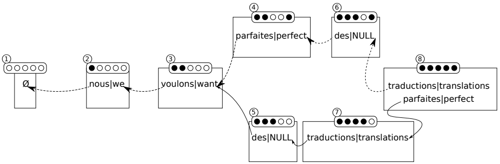

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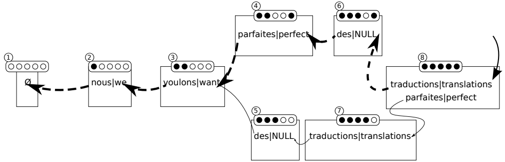

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- nodes of the input lattice are transformed into search stacks after being topologically sorted
- search starts setting the empty hypothesis in stack (0^J)
- it proceeds expanding hypotheses in the stacks following the topological sort
- Translation output through tracing back the best hypothesis of the ending stacks

Search complexity and speed ups

- Complexity: upper bound of the number of hypotheses valued for an exhaustive search:

$$2^J \times (|V_u|^{n_1-1} \times |V_t|^{n_2-1})$$

  - J is the length of the input sentence,
  - $|V_u|$ is the size of the vocabulary of translation units,
  - $|V_t|$ is the size of the target vocabulary.
  - n_1/n_2 are the order of the bilingual/target n-gram LMs,

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- Speed ups:
  - Recombination: exact (unless N-best output required)
  - i-best hypotheses within a stack (beam pruning)
  - i-best translation choices (based on uncontextualized scores)
  - prune reordering rules (reduce the size of the input lattice)
  - use several threads (when possible)

Plan

Bilingual *n*-gram approach to SMT

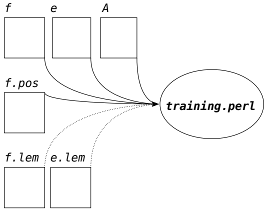
Decoding

The NCODE toolkit
- Training
- Inference
- Optimization

Comparison: NCODE vs. MOSES

Concluding remarks

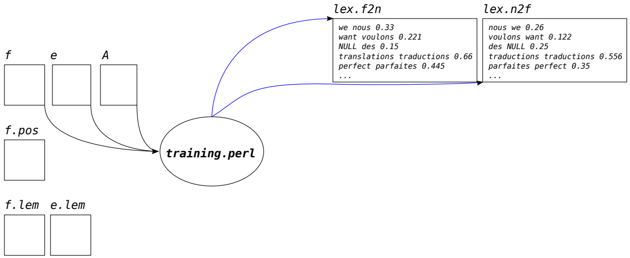
Model estimation



`training.perl [--first-step --last-step --output-dir]`

- NCODE systems are built from a training bitext (f,e) and the corresponding word alignment (A). Part-of-speeches (f.pos) are (typically) used to learn rewrite rules
- Target n-gram LMs are **not** estimated within `training.perl`
- Training is deployed over 8 steps

Model estimation



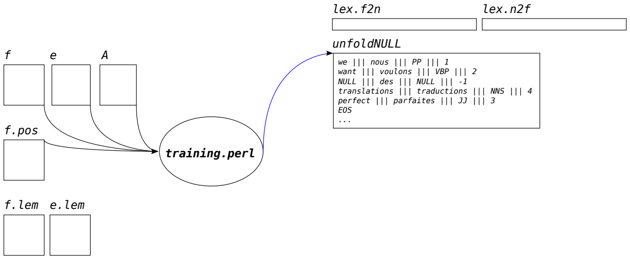
Step 0: lexicon distribution

- Distributions computed based on counts using word alignments:

$$P_{lex}(e,f) = \frac{count(f,e)}{\sum_{f'} count(f',e)} \quad ; \quad P_{lex}(f,e) = \frac{count(f,e)}{\sum_{e'} count(f,e')}$$

- **NULL** tokens are considered (to allow tuples with **NULL** target side)

Model estimation

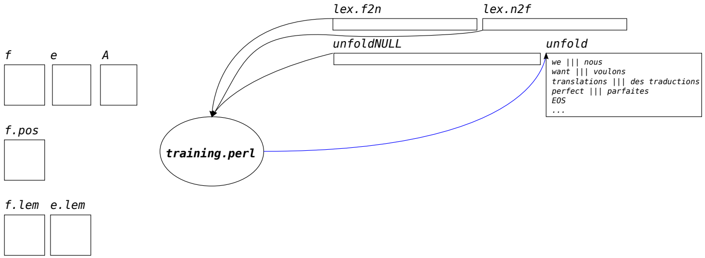


Step 1: tuple extraction

- Unfold technique previously outlined:

Minimal segmentation of source/target training sentences, following alignments and allowing source distortion

Model estimation

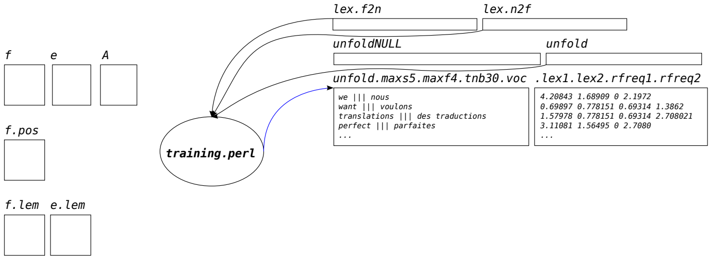


Step 2: tuple refinement (src-NULLed units)

- Source-NULLed words ($NULL|||des$) are attached to the previous or the next unit, after evaluating the likelihood of both alternatives using the unit lexicon distribution $P_{lw}(e, f)$ (next slide):

$$max \begin{cases} P_{lw}(want|||voulons\ \mathbf{des}) \times P_{lw}(translations|||traductions) & '\mathit{attachment : previous}' \\ \quad or & \\ P_{lw}(want|||voulons) \times P_{lw}(translations|||\mathbf{des}\ traductions) & '\mathit{attachment : next}' \end{cases}$$

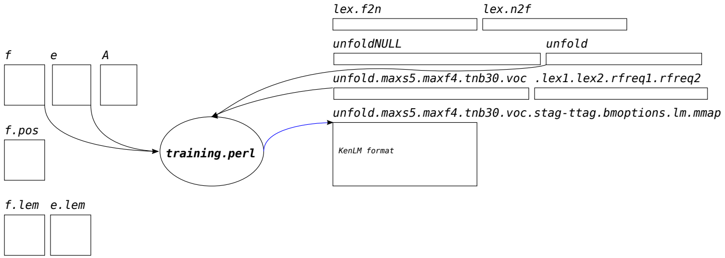
Model estimation



Step 3: tuple pruning & uncontextualized distributions [--max-tuple-length --max-tuple-fert --tuple-nbest]

- Tuples filtered following several constraints (length, fertility, n-best translation choices per source segment)
- Conditional probability (x2): $P_{rf}(e,f) = \frac{count(f,e)}{\sum_{f'} count(f',e)}$; $P_{rf}(f,e) = \frac{count(f,e)}{\sum_{e'} count(f,e')}$
- Lexicon weights (x2):
  $P_{lw}(e,f) = \frac{1}{(J+1)^I} \prod_{i=1}^{I} \sum_{j=0}^{J} P_{lex}(e,f)$; $P_{lw}(f,e) = \frac{1}{(I+1)^J} \prod_{j=1}^{J} \sum_{i=0}^{I} P_{lex}(f,e)$

Model estimation



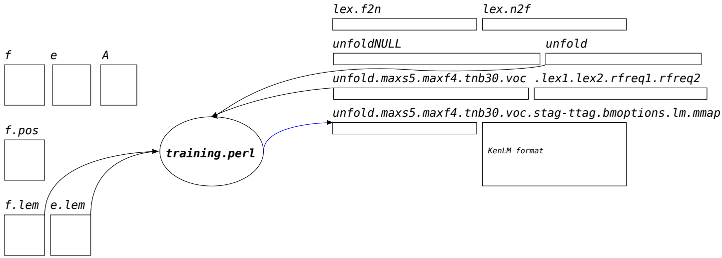
Step 4: bilingual n-gram lm [--train-src-bm --train-trg-bm --options-bm --name-src-bm --name-trg-bm]

- Standard *n*-gram LM (units built from words):

$$p(f_1^J, e_1^I) = \prod_{k=1}^{K} p((f,e)_k | (f,e)_{k-1}, \ldots, (f,e)_{k-n+1})$$

- Options passed to SRILM, Ex: –options-bm -order_3_-unk_-gt3min_1_-kndiscount_-interpolate

Model estimation



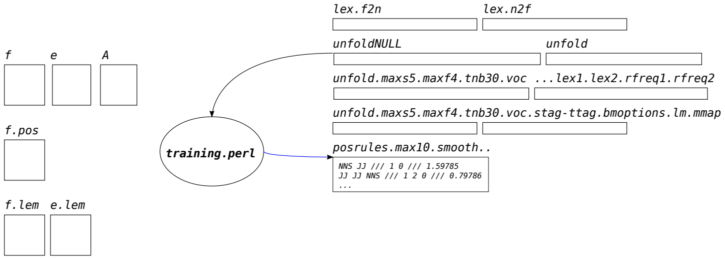
Step 4: bilingual n-gram lm [--train-src-bm --train-trg-bm --options-bm --name-src-bm --name-trg-bm]

- Bilingual units built from: POS-tags, lemmas, *etc.*, or any src/trg combination. Ex:

$$(f, e)^{wrd} : \ 'translations|||traductions'$$
$$(f, e)^{lem} : \ 'translation|||traduction'$$
$$(f, e)^{pos} : \ 'NNS|||Noun'$$
$$(f, e)^{lem:pos} : \ 'translation|||Noun'$$

- Each unit (--train-src --train-trg) is assign to **one** token (--train-src-bm --train-trg-bm)

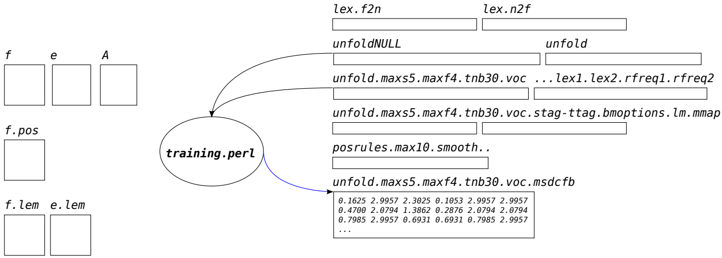
Model estimation



Step 5: rewrite rules (POS-based) [`--max-rule-length --max-rule-cost`]

- Rewrite rules are automatically learned from the bitext word alignments
- POS tags are used to gain generalization power
- Rules are filtered according to: $P(f \rightsquigarrow f^r) = \frac{count(f, f^r)}{\sum_{f' \in perm(f)} count(f, f')}$

Model estimation

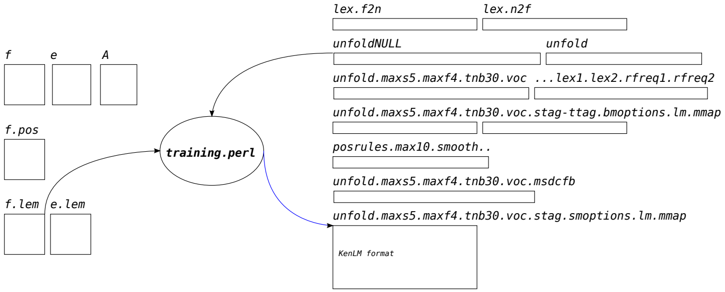


Step 6: lexicalized reordering

- **Four** orientation types: (m)onotone order; (s)wap with previous tuple; (f)orward jump; (b)ackward jump. And **two** aggregated types: (d)iscontinuous: (b) and (f); and (c)ontinuous: (m) and (s)
- Smoothed maximum likelihood estimator, $\sigma = 1/\sum_o count(o, f, e)$:

$$P(orientation|f, e) = \frac{(\sigma/4)+count(orientation,f,e)}{\sigma+\sum_o count(o,f,e)}$$

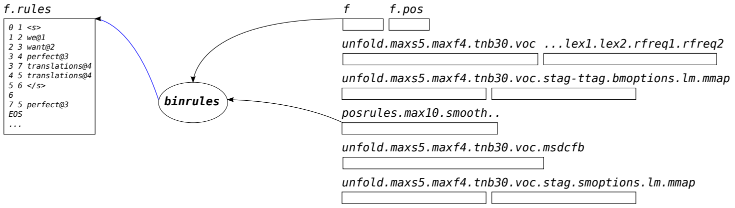
Model estimation



Step 7: source (unfolded) n-gram lm [`--train-src-unf --options-sm --name-src-unf`]

- *n*-gram LM estimated over reordered training source words (lemmas, POS, *etc.*)
- Reordering introduced in the tuple extraction process. Ex: 'we want translations perfect'
- Options passed to SRILM, Ex: –options-sm -order_5_-unk_-kndiscount_-interpolate

Inference



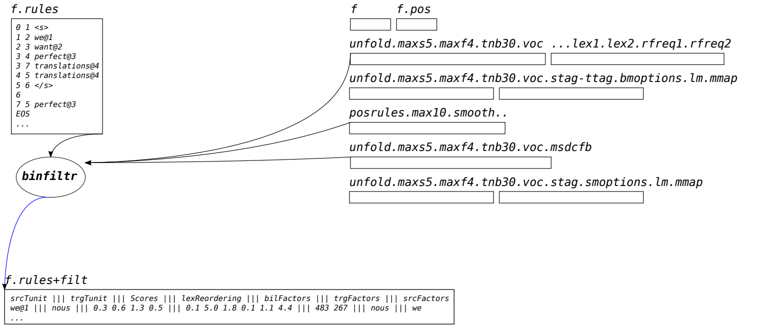
binrules `[-wrd s -tag s -rrules s -maxr i -maxc f]`

- Rules extracted from reorderings introduced in the tuple extraction

  translations perfect ⇝ perfect translations

- Referred to source-side tokens (words, POS, *etc.*): NNS JJ ⇝ JJ NNS
- Filter rules (discard noisy alignments) maxr=10 (size) maxc=4 (cost, -logP)

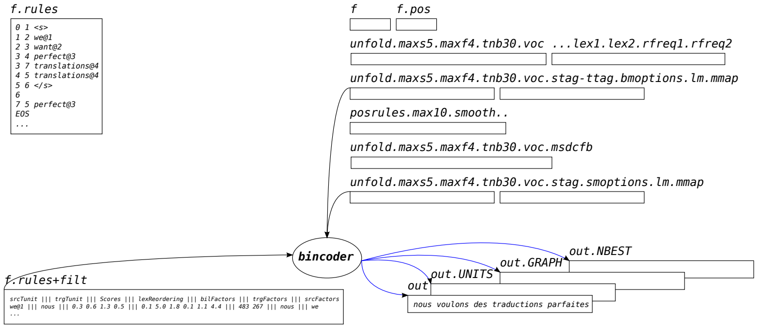
Inference



binfiltr `[-tunits s -scores s -lexrm s -bilfactor s -srcfactor s -trgfactor s -maxs i]`

- Collect useful information for given test sentences
- Filter tuples (discard noisy alignments) maxs=6 (size)
- Bilingual/source/target factors used with bilingual/source/target *n*-gram LMs
- Multiple LM's referred to multiple factors can be used
- Sentence-based LM's also available

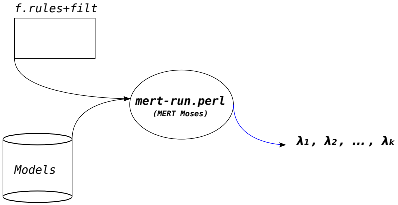
Inference



bincoder (weights) (files) (search settings)

- Model weights
- Files: (input) language models, filtered input (output) 1-best target word/translation unit hypotheses, Search graph, *N*-best hypotheses (OPENFST)
- Search settings: beam size, translation choices, input (OOV) words strategy, threads, *etc.*

Optimization (MERT)



`mert-run.perl`

- A wrapper for the MERT software made available in the MOSES toolkit (... soon also ZMERT)

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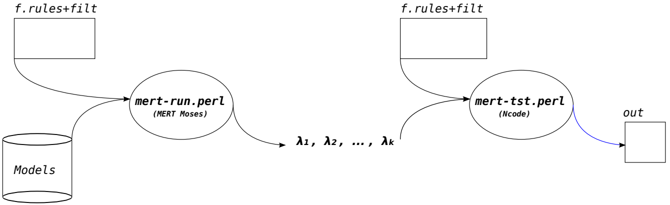

mert-tst.perl

- Translates a given input file using the optimized model weights

Plan

Experimental framework

- French-to-German (2) tasks:

  news : News Commentary corpus (6^{th} Workshop on SMT, WMT11)

  full : Additional data (up to 4 million sentence pairs)
- **Tune**: newstest2010, **Test**: newstest2009, newstest2011
- Same alignment (GIZA++), target LM (SRILM)
- NCODE employs TREETAGGER POS tags (rewrite rules)
- **default** MOSES settings: 14 features
- **default** NCODE settings: 14 + 2 features:
  - Bilingual *n*-gram over tuples built from words
  - Bilingual *n*-gram over tuples built from POS tags

Performance results

BLEU : Translation accuracy

#units : Number of phrases/tuples (millions) after training (limited to 6 tokens)

Memory : Memory (Mb) used by each decoder

Speed : Decoding speed (Words/second) (single-threaded translations)

System	*Task*	*BLEU* *newstest2009*	*BLEU* *newstest2011*	*#units*	*Memory*	*Speed*
NCODE	*news*	13.89	13.83	0.5	7.7	54.4
	full	15.09	15.26	7.5	9	33.9
MOSES	*news*	13.70	13.51	7.5	7.9	23.1
	full	14.66	14.51	141	16	14.7

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- Slightly higher accuracy results for NCODE (within the confidence margin)
- NCODE outperforms MOSES in data efficiency:
  - smaller set of tuples than phrases (full: 20 times smaller)
  - lower memory needs for NCODE (full: $\sim$ half than MOSES)

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- **BLEU** : Translation accuracy
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- **Memory** : Memory (Mb) used by each decoder
- **Speed** : Decoding speed (Words/second) (single-threaded translations)

System	*Task*	*BLEU* *newstest2009*	*BLEU* *newstest2011*	*#units*	*Memory*	*Speed*
NCODE	*news*	13.89	13.83	0.5	7.7	54.4
	full	15.09	15.26	7.5	9	33.9
MOSES	*news*	13.70	13.51	7.5	7.9	23.1
	full	14.66	14.51	141	16	14.7

- Slightly higher accuracy results for NCODE (within the confidence margin)
- NCODE outperforms MOSES in data efficiency:
  - smaller set of tuples than phrases (full: 20 times smaller)
  - lower memory needs for NCODE (full: $\sim$ half than MOSES)
- Nearly twice faster (search pruning settings are **not** tested)

Plan

Concluding remarks

- Developed to run on LINUX systems
- Written in PERL and C++
- Prerequisites
  - to compile: KENLM and OPENFST libraries
  - to run: SRILM and the MERT implementation in MOSES

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- Factored src/trg/bil *n*-gram LM's
- Under development:
  - Client/server architecture
  - Optimization by ZMERT
  - Sentence-based bonus models

Thanks

NCODE is freely available at `http://ncode.limsi.fr/`
(`http://www.limsi.fr/Individu/jmcrego/bincoder/`)

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