Four methods for Morpheme-based Machine Translation

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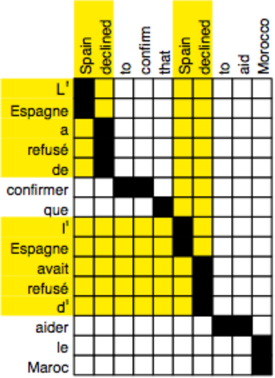
Phrase-Based Machine Translation (The Basics)

Factored models are a subtype of phrase-based translation models.

Word alignments used to extract all possible phrases (Koehn et al, 2007):



L' Espagne	Spain
L' Espagne a refusé de	Spain declined
L' Espagne a refusé de confirmer	Spain declined to confirm
a refusé de	declined
a refusé de confirmer	declined to confirm
a refusé de confirmer que	declined to confirm that
confirmer	to confirm
confirmer que	to confirm that
que	that
que l' Espagne	that Spain
que l' Espagne avait refusé d'	that Spain declined
l' Espagne	Spain
l' Espagne avait refusé d'	Spain declined
l' Espagne avait refusé d' aider	Spain declined to aid
...	...

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Phrase pairs along with their probabilities are used to score translation candidates.

Candidate translation $\bar{t}$ given $\bar{s}$ is scored using a log-linear model. $\bar{\lambda}$ are trained to minimize error on a tuning set (Och, 2003):

$$\log \Pr(\bar{t}|\bar{s}) \propto \lambda_1 \sum_{s,t \in \bar{s},\bar{t}} \log \Pr(s|t) + \lambda_2 \sum_{s,t \in \bar{s},\bar{t}} \log \Pr(t|s) + \lambda_3 \log \Pr(\bar{t})$$

Evaluation: BLEU (Papineni et al., 2002)

- Precision-based: counts candidate translation *n*-grams found in multiple reference translations.
- Higher scores are better; for some language pairs (e.g. Chinese-English) the best systems achieve $\sim 40\%$ BLEU

Challenges of Morphological Complexity for SMT

Human languages encode information in very diverse ways:

'ista+hta+isi+n+ko	suure+sa	talo+ssa	.'
sit+FREQ+COND+SG1+INTR	big+IN	house+IN	.

  'Should I sit down for a while in the big house ?'

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Four major approaches to Morphology in SMT

- Bilingual Morphology Induction using Parallel Data
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- Factored Phrase-Based Translation Models
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- In this talk: experimental results on Korean and Finnish.

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- Can be done using unsupervised methods of morphological segmentation, without reliance on expensive, rare supervised segmentation methods.
- We can successfully apply these unsupervised morpheme segmentation methods to machine translation.
- Combining segmented translation with post-processing morphology generation (morphological awareness inside the MT model as well as in post-processing) improves translation morphological fluency. (Finnish)

Unsupervised Monolingual Morphology Induction

- **Input English**: but he failed
- **Output Korean**: 그러나 실패했다
- Consider monolingual segmentation of 실패했다

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2. s(0011) 실패했 다
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- Given a sequence of character $c_1, c_2, \ldots, c_n$ find the most likely segmentation s^*
- $s^* = \text{argmax}_{k_1, k_2, \ldots, k_\ell} P(k_1)P(k_2)\ldots P(k_\ell)$

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- source language sentence e, target language sentence k
- Start with IBM Model 1: $P(\bar{k} \mid \bar{e}) = P(\bar{k})P(\bar{e} \mid \bar{k})$

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e_j : English word at position j

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- For each e_j, k_i we can learn $P(e_j \mid k_i)$ using the EM algorithm, e.g.:

$$P(\text{failed} \mid \text{실패했다}) = \frac{ec(\text{failed}, \text{실패했다})}{\sum_e ec(e, \text{실패했다})}$$

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$$P(\text{failed} \mid \text{실패}) = \frac{ec(\text{failed}, \text{실패})}{\sum_e ec(e, \text{실패})}.$$

- Once we have learned $P(e \mid k)$ using EM, we can obtain the segmentation based on the best alignment $\bar{a}^*$:

$$\bar{a}^* = \operatorname*{argmax}_a P(\bar{e}, \bar{a} \mid \bar{k})$$

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- This naive exponential time method can be replaced with a dynamic programming algorithm.
- Extension of forward-backward algorithm for HMMs applied to IBM Model 1 training.
- Like (Chung & Gildea, 2009) we also use Variational Bayes instead of EM, and use a length penalty.

Bidirectional Segmentation

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실패+ +했다

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- To segment the English text, we need bilingual data, but at test time we only have English input!
- **Solution**: get monolingual probabilities from the bilingual model:

$$P(e) = \sum_{k} \underbrace{P(k \mid e)}_{\text{Korean input with English output}} P(k)$$

English-Korean Experiments

- Datasets (sizes shown refer to the English side):
  1. For the morph segmenter: KAIST corpus, 590,000 words & 60,000 sentence pairs
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Model	BLEU Score
Baseline	3.13
Monolingual(3)	3.25
Monolingual(5)	3.29
Monolingual(10)	3.20
Single-direction Bilingual	3.36
Bidirectional Bilingual (without VB)	3.22
Bidirectional Bilingual (with VB)	**3.46**

Table: BLEU Scores for English-Korean. Boldface indicates a result significantly better than the baseline.

Example Segmentations

English	there is no way that software can upgrade itself just by changing the hardware .
Korean	하드웨어를 바꾼다고 소프트웨어가 저절로 업그레이드될 리 없다 .

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English-Finnish Experiments

Dataset: the European parliamentary proceedings corpus Europarl (1.2 million sentence parallel corpus), filtered for sentence length 40; 2,000 sentence dev and test sets

SMT system: We use the open-source phrase-based MT system Moses, (`http://statmt.org/moses`), with default settings

Evaluation: BLEU (Papineni et al., 2002)

- In our experiments, we only have one reference translation.

Why Finnish?

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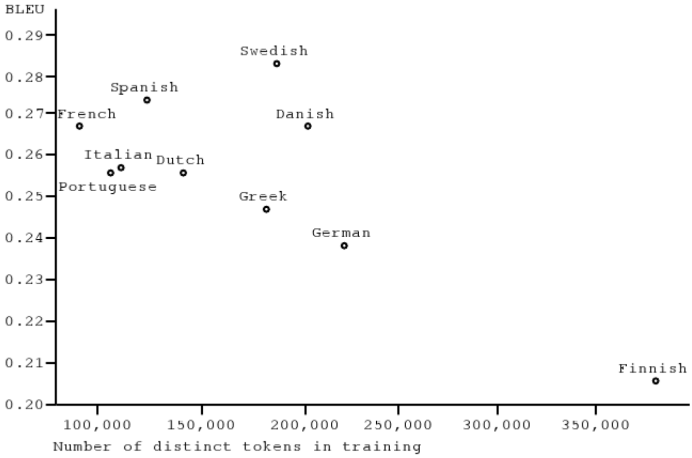

Figure: Translation scores (into English) v.s. No. of training tokens in the European Parliament corpus (Koehn, 2005)

Factored Models

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In factored models,

- Words represented as (more general) factors, e.g., 'daughters|daughter|NN|PL'
- phrase translation probabilities are decomposed over the available factors for the words in the phrase.
- probabilistic generative model

Using Factored Models for Finnish

Words and Part-of-Speech (POS) tags for the source side factors,
Words, stems, and unsupervised morph segments for target factors:

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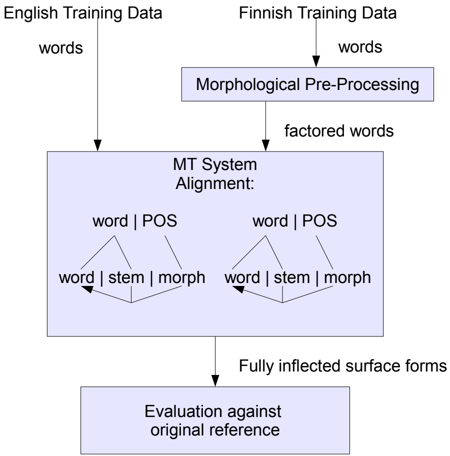
4. generate most likely surface form from stem and suffix
   tyttär|et $\rightarrow$ tyttäret

Model Comparison: Factored Translation



Better Unsupervised Monolingual Segmentation

⇒ Morfessor segmentation model (Creutz and Lagus, 2005):

(1) Input sentence: monet meistä haluavat kansallisten jäsenvaltioiden muodostamaa liittovaltiota .

(2) Segmented output: monet me+ +istä haluavat kansallisten jäsen+ +valtioiden muodo+ +sta+ +ma+ +a liittovaltiota .

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We varied this model over granularity and coverage parameters to get the best segmentation for our MT system.

Factored Models: Results and Analysis

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Baseline	14.39
Factored	13.98

Table: Factored Model BLEU Scores

Factored model analysis:

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- Generates candidate translation phrase pairs on the fly;
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- Productive morphology limited to phrase pairs
- No long-distance dependencies between morphemes

Segmented Translation: The Goal

- Segment and translate target morphology with lexical equivalents in source, while generalizing over morphological information that we can't translate.
- By treating segmented forms the same as stems, allow productive combination of morphs and stems across phrase boundaries

Example:

(7) ‘ista+ $\boxed{\text{hta}}$ + $\boxed{\text{isi}}$ + $\boxed{\text{n}}$ + $\boxed{\text{ko}}$ talo+ $\boxed{\text{ssa}}$.’
sit+ $\boxed{\text{FREQ}}$ + $\boxed{\text{COND}}$ + $\boxed{\text{SG1}}$ + $\boxed{\text{INTER}}$ house+ $\boxed{\text{IN}}$.
‘ $\boxed{\text{Should}}$ $\boxed{\text{I}}$ sit down $\boxed{\text{for a while}}$ $\boxed{\text{in}}$ the house $\boxed{\text{?}}$ ’

Conditional, interrogative, and case markers all have lexical reflexes in the English parallel sentence.

Segmented Translation: The Approach

Segment corpus before training translation model, treating morphs like words. (Oflazer and El-Kahlout, 2007; Virpioja et al., 2007)

Supervised or unsupervised means of segmentation:

- 'toimivaltaan'
  - Supervised: Omorfi (Pirinen and Listenmaa, 2007)
    toimia|VERB/ACT/INF/SG/ABL/POSS
    toimiv+ +altaan
  - Unsupervised (Morfessor)
    toimi+ +valtaa+ +n

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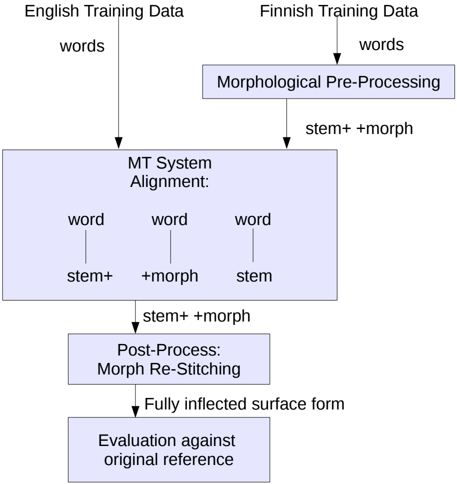
The MT system trained on the segmented model ('Unsup') generates a phrase table with $\sim$ 17% of phrases bounded by a productive word-internal morph ('Hanging Morph').

	Unsup
Total	64,106,047
Morph	30,837,615
Hanging Morph	10,906,406

Model Comparison: Segmented Translation



Segmented Translation: Experiments

- Frequently seen complex words may be left unsegmented, but the segmentation model remembers their hierarchical substructure
- Because common (complex) words have their own entries in the segmentation lexicon, Morfessor tends to undersegment
- To make it segment more aggressively, we devised a longest-suffix-substring-match heuristic ('L-match') to do additional word splitting, e.g.,

regular segmentation: '**euroopan**'
substring matching: unsegmented '**euroopan**' matches suffix '**-an**'
$\Rightarrow$ additionally split segmentation: '**euroop+ +an**'

Segmented Translation: Results (1)

Segmentation	BLEU Score
Baseline	14.39
Factored	13.98
Sup	14.58
Luong et al (2010)	14.82
Unsup	**14.94**
Unsup L-match	**15.09**

- Boldface indicates a result significantly better than the baseline.
- We also outperform other systems on WER and TER.

Segmented Translation: Results (2)

Segmentation	*m*-BLEU Score	
Baseline	14.84	
Sup	18.41	
Unsup	16.07	
Unsup L-match	20.74	
Luong at al (2010)	**55.64**	

- *m*-**BLEU**: output was evaluated in segmented form before morph re-stitching against a segmented version of the baseline *and* reference.

Segmented Translation: Results (2)

Segmentation	*m*-BLEU Score	No Unigram
Baseline	14.84	9.89
Sup	18.41	13.49
Unsup	16.07	10.46
Unsup L-match	20.74	**15.89**
Luong at al (2010)	**55.64**	-

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- *m*-**BLEU**: output was evaluated in segmented form before morph re-stitching against a segmented version of the baseline *and* reference.
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- 39.75% percent improvement over baseline *m*-BLEU compared to Luong et al (2010) with 0.6% percent improvement.

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- **No Unigram**: *m*-BLEU scores without unigrams.
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- *m*-BLEU is not correlated with human judgements.

Unsupervised Segmented Translation: Analysis (1)

(8) a. Input: '..summarises and makes visible **the fundamental rights which the public are entitled to**'

b. Reference: 'kansalaisten/GEN **perusoikeudet/ACC**

(9) a. Regular Unsup: 'perusoikeuksia/PAR ja näkyvyyttä/PAR , johon/ILL kansalaisilla/ADE on **oikeus/NOM**'

b. Back-translation: '**the fundamental rights and visibility, which the citizens have the right**'

(10) a. Unsup L-match: 'perusoikeudet/ACC, jotka kansalaiset/ACC ovat **oikeutettuja/PAR**'

b. Back-translation: '**basic rights that citizens are entitled to**'

Segmentation model remembers substructure of frequent complex words, but does not pass it on to the translation model.
Extra-split segmentation model propagates substructure awareness forward to the translation model,
⇒ more frequent correct case-marking in system output.

Unsupervised Segmented Translation: Analysis (2)

Benefits and drawbacks of segmented translation:

- Model benefits from morphology it can translate, but not morphology without lexical reflexes (e.g., agreement);
- Only able to utilize a coarse-grained segmentation; finer-grained segmentation causes overfitting.
- Model is unaware of the relationship between stems and morphs, and is unable to distinguish between them.

CRFs for Post-Processing Morphology Generation

- In this model, translation is performed on stemmed words, then morphology is predicted on MT output, using a Conditional Random Field (CRF).

Word Stem	$s_{t-n}, .., s_t, .., s_{t+n} (n = 4)$
Morph Prediction	y_{t-2}, y_{t-1}, y_t

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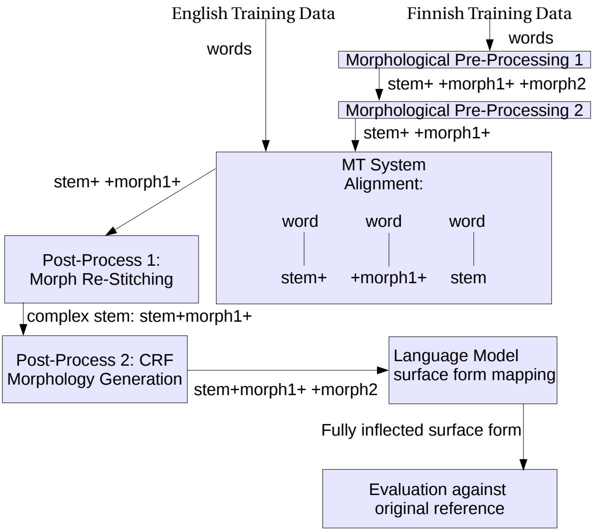
- We preprocess the data in two steps to keep one layer of morphology in the translation model and another for post-processing to capture lexical equivalents as well as target-side morphological dependencies.

Model Comparison: Segmented Translation with Post-Processing Morphology Generation



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  - Unsupervised model: suffixes with vowels collapsed into equivalence classes for vowel harmony, e.g.,
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    vaihee**ssa** $\rightarrow$ vaihee+ +**ssA**

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    vaihee**ssa** → vaihee+ +**ssA**
- Language model recovers fully inflected surface forms from ambiguous stem+morphology pairs, e.g.,
  'alus+PAR/PL': candidate surface forms 'aluksia' 'aluksiaan', 'aluksiamme';
  language model selects appropriate surface form in the sentence context.

Training with post-processing morphology prediction

original training data:
koskevaa mietintöä käsitellään

Training with post-processing morphology prediction

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segmentation:
koske+ +va+ +a mietintö+ +ä käsi+ +te+ +llä+ +ä+ +n

Training with post-processing morphology prediction

original training data:
koskevaa mietintöä käsitellään
segmentation:
koske+ +va+ +a mietintö+ +ä käsi+ +te+ +llä+ +ä+ +n
(train bigram language model on complex stems with suffix)
map final suffix to abstract tag-set (e.g. mapping $A = \{ a, ä \}$):
koskeva+ +A mietintö+ +A käsitelllää+ +n

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(train CRF model to predict the final suffix from full segmentation)
peeling of final suffix:
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(train bigram language model on complex stems with suffix)
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(train CRF model to predict the final suffix from full segmentation)
peeling of final suffix:
koske+ +va+ mietintö+ käsi+ +te+ +llä+ +ä+
(train SMT model on this transformation of training data)

Decoding with post-processing morphology prediction

decoder output:
koske+ +va+ mietintö+ käsi+ +te+ +llä+ +ä+

Decoding with post-processing morphology prediction

decoder output:
koske+ +va+ mietintö+ käsi+ +te+ +llä+ +ä+
decoder output stitched up:
koskeva+ mietintö+ käsitellää+

Decoding with post-processing morphology prediction

decoder output:
koske+ +va+ mietintö+ käsi+ +te+ +llä+ +ä+
decoder output stitched up:
koskeva+ mietintö+ käsitellää+
CRF model prediction:
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Decoding with post-processing morphology prediction

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CRF model prediction:
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language model disambiguation:
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final stitching:
koskevaa mietintöä käsitellään
(the output is then compared to the reference translation)

Supervised Morphology Generation: Results

Intrinsic evaluation on reference translation:

- 77.18% accuracy predicting the morphology tag sequences.
- comparable to a similar task performed using log-linear models on Russian and Arabic (Minkov, Toutanova, and Suzuki, 2007), languages with simpler morphological systems than Finnish

Extrinsic evaluation after the application of the language model to restore surface form:

Model	BLEU Score
Baseline	14.39
Factored	13.98
Unsup L-match	**15.09**
CRF-Sup	10.09

Table: Supervised Prediction Model BLEU Scores

Unsupervised Morphology Generation: Results

Intrinsic evaluation on the reference translation:

Model	All	Predictions Only
CRF-Unsup	95.61	77.57

Table: Model Accuracy

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Table: Model Accuracy

Extrinsic evaluation on MT system output:

Model	BLEU Score
Baseline	14.39
Factored	13.98
Unsup L-match	**15.09**
CRF-Sup	10.09
CRF-Unsup	**14.55**

Table: Unsupervised Prediction Model BLEU Scores

Unsupervised Morphology Generation: Further Results and Morphological Fluency Analysis (1)

Translation fluency evaluation on the sub-word level:

Construction	Baseline		Unsup L-match		CRF-LM	
	P	R	P	R	P	R
Noun Marking	51.74	78.48	53.11	**83.63**	**54.99**	80.21
Trans Obj	32.35	27.50	33.47	29.64	**35.83**	**30.71**
Noun-Adj Agr	72.75	67.16	69.62	**71.00**	**73.29**	62.58
Subj-Verb Agr	56.61	40.67	55.90	**48.17**	**57.79**	40.17
Postpositions	43.31	29.89	39.31	**36.96**	**47.16**	31.52
Possession	66.67	**70.00**	75.68	**70.00**	**78.79**	60.00

Table: Model Accuracy: Morphological Constructions.

Unsupervised Morphology Generation: Further Results and Morphological Fluency Analysis (2)

Example: postposition ‘kanssa’ requires genitive preceding noun.

Input: ‘with the basque nationalists’:

Reference: ‘baskimaan kansallismielist**en** kanssa’
basque-SG/NOM+land-SG/GEN,ACC
nationalists-PL/**GEN** with-POST

Baseline: ∗‘baskimaan kansallismielis**et** kanssa’
basque-SG/NOM-+land-SG/GEN,ACC
kansallismielinen-PL/**NOM,ACC**-nationalists POST-with

CRF: ‘kansallismielisten baski**en** kanssa’
nationalists-PL/GEN basques-PL/**GEN** with-POST

CRF’s grammatically correct translation scored as incorrect under BLEU because doesn’t match reference.

Conclusion and Future Work

In this work:

- Bilingual unsupervised morpheme segmentation shows promise for Korean MT $\boxed{3.13 \rightarrow 3.46}$
- Morphologically segmented MT model outperforms word-based model for Finnish MT $\boxed{14.39 \rightarrow 15.09}$
- Linguistic analysis of CRF post-processing model output shows improved translation fluency across different morphological constructions

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In future work:

- Evaluation metrics for incorporating subword information (modified character-level BLEU?)
- Totally integrated model encompassing morphological segmentation, MT system training, and morphology generation

Thank you

감사+ +합니다

Thank you (?)

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