Machine Translation with Source-Predicted Target Morphology

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OVERVIEW

- Novel pipeline for translation into morphologically rich languages
- Source enriched with target morphology
- Challenges:
  - Predicting target morphology
  - Learning salient attributes
  - Integration into MT systems

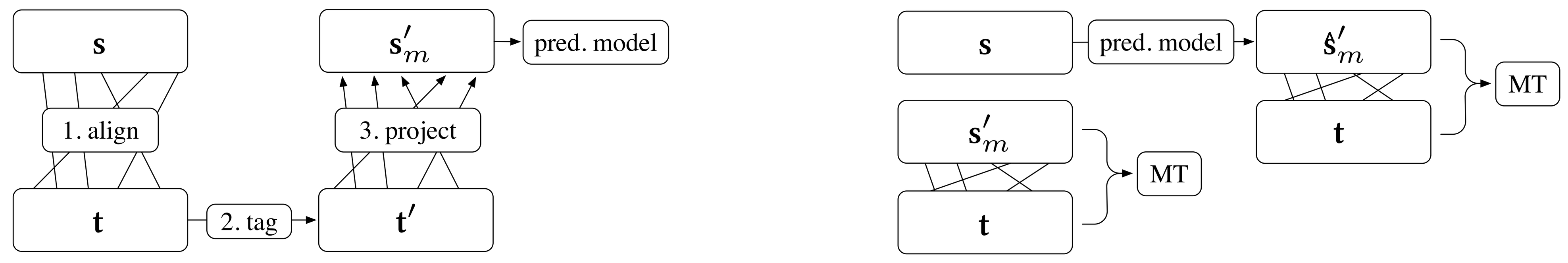
MOTIVATION

- Knowing morphological target properties helps translation
- Possible improvements both in lexical selection and reordering

MORPHOLOGICAL ATTRIBUTES

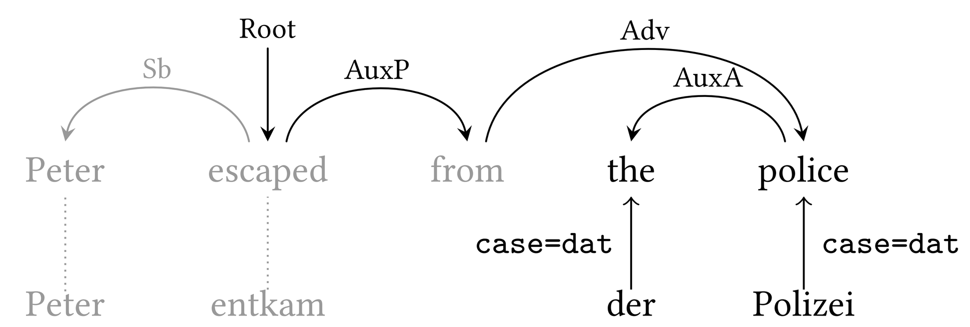
Part of speech	Manual selection	Automatic selection
noun	gender† number case	gender number case
adj	gender† number‡ case‡ declension	gender number case synpos degree
verb	number$^{\ddagger *}$ person$^{\ddagger *}$ tense* mode*	-

SYSTEM TRAINING AND TRANSLATION



(a) Morphology projection and pred. model training (b) Machine translation system training

MODELING TARGET-SIDE MORPHOLOGY

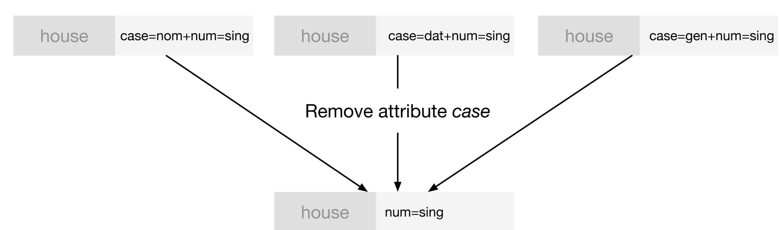


- Source-side dependency chains:
  - word order might differ significantly
  - source predicate-argument structure is informative for predicting target morph.
- $P(\mathbf{s}'_m \mid \tau, \mathbf{s})$: Source-side dependency chain model to predict morph. enriched source $\mathbf{s}'_m$.

  - Estimation: Coarse-to-fine CRF [1]
  - Decoding: root $\rightarrow$ leaves
  - Features as in morph. tagging and additionally: dependency labels, number of children, source POS and child tokens.
- Best performance:
  - 5$^{\text{th}}$ order CRF
  - Trained on 50k-100k dependency chains
  - Dep. chains from non-isomorphic trees

LEARNING SALIENT MORPHOLOGICAL ATTRIBUTES

- We want only attributes helpful for language pair (less sparsity, better predictions)
- Salient attributes: attributes that enable better lexical selection
- Learning via latent variable model (as in [2]):
  - Simple translation model (IBM model 1)
  - Merging tag occurrences $\rightarrow$ removing morph. attribute



MT INTEGRATION

- Integration as sparse features, e.g.
  `gender=fem+number=sing+case=dat X` $\rightarrow$ `-er X`
- Strategies:
  - training on Viterbi predictions
  - training on gold projections

EVALUATION

		Translation		Word order	Lexical choice
Morphological attributes	Training decor.	METEOR	BLEU	Kendall's τ	BLEU-1
No morphology	-	35.74	15.12	45.26	49.86
Manual selection	Predicted	35.85	15.19	45.43	50.01
	Projected	34.63^{A}	14.00^{A}	44.07	48.75
Autom. selection	Predicted	35.99^{AC}	15.23^{B}	45.88	50.27
	Projected	35.98^{AC}	15.22^{C}	45.89	50.27

^{A}Statistically significant against baseline at $p < 0.05$ ^{B}Statistically significant against baseline at $p < 0.06$ ^{C}Statistically significant against Manual selection at $p < 0.05$

Standard phrase-based MT setup on English-to-German.

REFERENCES

[1] Thomas Müller, Helmut Schmid, and Hinrich Schütze. Efficient higher-order CRFs for morphological tagging. In *Proceedings of EMNLP 2013*, pages 322--332, Seattle, USA, 2013.

[2] Slav Petrov, Leon Barrett, Romain Thibaux, and Dan Klein. Learning accurate, compact, and interpretable tree annotation. In *Proceedings of ACL 2006*, pages 433--440, Sydney, Australia, 2006.

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EXPERT

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