Delimiting Morphosyntactic Search Space with Source-Side Reordering Models



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Introduction

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Motivation

- Current MT models work well if languages are structurally similar
- ► Difficulties with morphologically rich languages:
 - freer word order
 - more productive morphological processes
 - agreement over long distances



Motivation



"Germans like to buy holiday homes in Florida"

- Deutsche kaufen sich meistens in Florida eine Ferienwohnung
- Deutsche kaufen sich in Florida meistens eine Fehenwohnung
- In Florida kaufen sich meistens Deutsche eine Ferienwohnung
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- Meistens kaufen sich Deutsche in Florida eine Ferienwohnung

From: Frankurter Allgemeine Zeitung (August 31, 2015)



Motivation

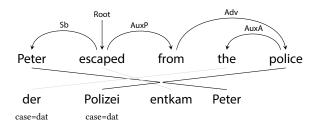


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- ► Source dependency trees are good fit for preordering:
 - Lerner and Petrov (2013) present two classifier-based dep. tree preordering models
 - Jehl et al. (2014) and de Gispert et al. (2015) preorder dep. trees via branch-and-bound search

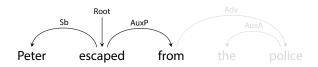


- ► Lerner and Petrov (2013) preorder trees starting at the root
- ► Order all children (model 1) or left and right children (model 2)



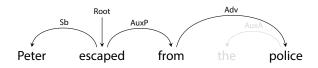


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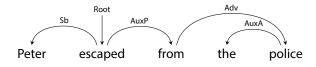


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Generating the space of potential word order choices

- Both Lerner and Petrov (2013) and Jehl et al. (2014) make only single-best predictions
- ► We want:
 - ALL REASONABLE predictions instead of SINGLE BEST
 - More flexible model



Multiple predictions:

- ► Bad: Mistakes in order decisions propagate
- \rightarrow Extract *n*-best decisions from the model to pass to subsequent model



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$



Model over possible orders of source words:

$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$

► Preordered s



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- ▶ Preordered s
- ► Source dep. tree



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$

- ▶ Preordered s
- ► Source dep. tree
- ► Heads of all families



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_{T}(\pi_{h} \mid \mathbf{s}, h, \tau)$$

- ▶ Preordered s
- ► Source dep. tree
- ► Heads of all families -
- Local permutation



$$\begin{aligned} P(\mathbf{s}' \mid \mathbf{s}, \tau) &= \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau) \\ P_T(\pi \mid \mathbf{s}, h, \tau) &= P(\psi \mid \mathbf{s}, h, \tau) \quad P_L(\pi_L \mid \mathbf{s}, h, \tau) \quad P_R(\pi_R \mid \mathbf{s}, h, \tau) \end{aligned}$$



Model over possible orders of source words:

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► Pivot decision —



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$

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- ► Pivot decision
- ► Left order decision



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$

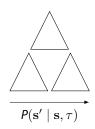
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- ► Pivot decision
- ► Left order decision
- Right order decision -



$$P(\mathbf{s}' \mid \mathbf{s}, \tau) = \prod_{h \in \tau} P_T(\pi_h \mid \mathbf{s}, h, \tau)$$

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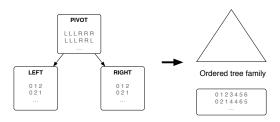
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$$P_{R}(\pi_{R} \mid \mathbf{s}, h, \tau)$$



Preordering alogrithm

- ▶ Produce k_P best pivot decisions for all the children in the family
- ▶ For every of the k_P pivot decisions:
 - Produce k₁ best left order decisions
 - Produce k_R best right order decisions





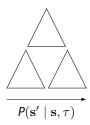
Making the model more flexible:

- ▶ Bad: Order decisions are local to tree families
- ► Khalilov and Sima'an (2012) show even weak LM helps with shortcomings



Decoding:

- ► Non-local features ruin our day...
- ► Cube pruning to the rescue (Chiang, 2007)!





Preordering model:

► Standard log-linear model (Och and Ney, 2002):

$$\hat{\mathbf{s}}' = \arg\max_{\mathbf{s}'} \sum_{i} \lambda_{i} \log \phi_{i}(\mathbf{s}')$$

- ► Where to get the weights?
 - PRO: tuning as ranking (Hopkins and May, 2011)
 - Scoring functions:
 - 1. Kendall's τ coefficient
 - Simulate word level MT system, score by BLEU



Local features:

- ▶ Lexicalized preordering model $P(\mathbf{s}' \mid \mathbf{s}, \tau)$ from before
- ▶ Unlexicalized preordering model $P_W(\pi \mid h, cs)$ as less sparse backoff

Non-local features:

- ightharpoonup ngram language models over s'
 - words
 - part-of-speech tags
 - word classes



Applicability of this model

► General model is applicable to any *n*-best preordering model over source trees

► Example:

- Preordering model:
 Pairwise neural network-based model
 (de Gispert et al., 2015)
- Parsing algorithm:
 k-best ITG-based CKY parsing
 (similar to Tromble and Eisner (2009)).



Ordered tree family

0 1 2 3 4 5 6 0 2 1 4 4 6 5 ...



Intrinsic: Do non-local features help?

- ► Intrinsic evaluation of preordering quality
- Language pair English-to-German

Model	Kendall's tau	BLEU ($\hat{\mathbf{s}}' o \mathbf{s}'$)	
First-best —LM	92.16	68.1	
First-best +LM (cube)	92.27	68.7	



Translation: Quality of potential word order choices

- ► Translation experiments with the space of word order choices
- ► Experiments with top 10 preordering outputs of this model

	Distortion	BLEU	MTR	TER
Baseline	7	15.20	35.43	66.62
Best out of k ($k = 10$)		17.26	37.97	62.64



Discussion

Preordering with non-local features

- ► Integration of LM helps improve preordering quality
 - Slight Kendall τ improvement
 - BLEU preorder score shows benefits mostly in small local windows

Quality of the space of potential word order choices

- ► Experiments show significant potential improvement contained in the space
- With arbitrary n or lattice, space is small enough to be handled by subseq. models



Conclusion

- Source preordering has big limitations but has proven very successful
- ► We are interested in source-side adaptation models more suitable for morph. rich languages
- ► As first step:
 - Introduced preordering model that can delimit space instead of first-best predictions
 - Made the model more flexible with arbitrary non-local features and cube pruning



Thank You!

Any questions?



References

- Chiang, D. (2007). Hierarchical phrase-based translation. *Computational Linguistics*, 33(2):201–228.
- de Gispert, A., Iglesias, G., and Byrne, W. (2015). Fast and accurate preordering for SMT using neural networks. In *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics Human Language Technologies (NAACL HLT 2015)*.
- Hopkins, M. and May, J. (2011). Tuning as ranking. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 1352–1362, Edinburgh, Scotland, UK. Association for Computational Linguistics.
- Jehl, L., de Gispert, A., Hopkins, M., and Byrne, B. (2014). Source-side preordering for translation using logistic regression and depth-first branch-and-bound search. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 239–248, Gothenburg, Sweden. Association for Computational Linguistics.
- Khalilov, M. and Sima'an, K. (2012). Statistical translation after source reordering: Oracles, context-aware models, and empirical analysis. *Natural Language Engineering*, 18:491–519.
- Lerner, U. and Petrov, S. (2013). Source-side classifier preordering for machine translation. In *Proceedings* of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 513–523, Seattle, Washington, USA. Association for Computational Linguistics.
- Och, F. J. and Ney, H. (2002). Discriminative training and maximum entropy models for statistical machine translation. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ACL '02, pages 295–302, Stroudsburg, PA, USA. Association for Computational Linguistics.



References (cont.)

Tromble, R. and Eisner, J. (2009). Learning linear ordering problems for better translation. In *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing*, pages 1007–1016, Singapore. Association for Computational Linguistics.