Hierarchical Phrase-Based Translation with Jane 2

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Introduction



- RWTH's open source statistical machine translation toolkit (free for non-commercial purposes)
- Implemented in C++
- ► See [Vilar et al., WMT 2010]
- Version 2.1 now available at http://www.hltpr.rwth-aachen.de/jane
- Note that Jane 2 also supports standard phrase-based translation



Outline

Extensions presented here:

- ► Insertion and deletion models [Huck & Ney, NAACL 2012]
- Lexical scoring variants [Huck et al., IWSLT 2011]
- Reordering extensions [Huck et al., EAMT 2012]
 - Non-lexicalized reordering rules
 - b discriminative lexicalized reordering model
- ► Soft string-to-dependency hierarchical MT [Peter et al., IWSLT 2011]

The Jane manual describes how to use the toolkit:

http://www.hltpr.rwth-aachen.de/jane/manual.pdf





Statistical Machine Translation Architecture







Hierarchical Phrase-Based Translation



- Allow for gaps in the phrases
- Formalization as a synchronous context-free grammar
- ▶ Rules of the form $X \to \langle \alpha, \beta \rangle$, where:
 - $\triangleright X$ is a non-terminal
 - $\triangleright \alpha$ and β are strings of terminals and non-terminals
 - $\triangleright \sim$ is a one-to-one correspondence between the non-terminals of α and β
- Parsing-based decoding (extension of CYK algorithm)
- Cube pruning to handle translation alternatives





Insertion and Deletion Models

- Goal: Penalize the omission of words in the hypothesis, or unjustified inclusion of words in it
- Idea: Introduce phrase-level feature functions which count the number of inserted or deleted words

Modeling of insertions and deletions relies on standard word lexicon models

- An English word is considered inserted or deleted based on lexical probabilities with the words on the foreign language side of the phrase
- Thresholding of lexical probabilities
 - > from different types of word lexicon models
 - > with different types of thresholding methods

Insertion model scoring will be presented on the next two slides. See our paper to learn about deletion models and thresholding methods.





Insertion Modeling (Source-to-Target)

- An occurrence of a target word e is considered an insertion *iff* no source word f exists within the phrase with p(e|f) greater than or equal to τ_f
- The feature function counts the number of inserted words on the target side β with respect to the source side α

Insertion model feature function in source-to-target direction:

$$t_{s2tlns}(\alpha,\beta) = \sum_{i=1}^{I_{\beta}} \prod_{j=1}^{J_{\alpha}} \left[p(\beta_i | \alpha_j) < \tau_{\alpha_j} \right]$$
(1)

- ► J_{α} is defined as the number of terminal symbols in α
- ▶ I_{β} is defined as the number of terminal symbols in β
- ▶ α_j , $1 \le j \le J_{\alpha}$, denotes the *j*-th terminal symbol on the source side
- ▶ β_i , $1 \le i \le I_\beta$, denotes the *i*-th terminal symbol on the target side
- \blacktriangleright [·] denotes a true or false statement (1 if the condition is true, 0 otherwise)





Insertion Modeling (Target-to-Source)

- An occurrence of a source word f is considered an insertion *iff* no target word e exists within the phrase with p(f|e) greater than or equal to τ_e
- The feature function counts the number of inserted words on the source side α with respect to the target side β

Insertion model feature function in target-to-source direction:

$$t_{ t t2slns}(lpha,eta) = \sum_{j=1}^{J_lpha} \prod_{i=1}^{I_eta} \left[p(lpha_j | eta_i) < au_{eta_i}
ight]$$

- ► J_{α} is defined as the number of terminal symbols in α
- ▶ I_{β} is defined as the number of terminal symbols in β
- ▶ α_j , $1 \le j \le J_{\alpha}$, denotes the *j*-th terminal symbol on the source side
- ▶ β_i , $1 \le i \le I_\beta$, denotes the *i*-th terminal symbol on the target side
- \blacktriangleright [·] denotes a true or false statement (1 if the condition is true, 0 otherwise)



(2)

Lexical Scoring Variants

- Problem: Overestimation of phrase translation probabilities of phrase pairs for which little evidence in the training data exists
- Typical solution in state-of-the-art systems: Interpolate phrase translation scores with lexical scores

Jane 2 implements four different methods to score phrase pairs, for use either with

- a lexicon model which is extracted from word-aligned training data (RF word lexicon), or
- the IBM Model 1 lexicon

See our paper for the lexical scoring formulas, and the Jane manual for usage instructions.





Reordering Extensions: Motivation

In hierarchical phrase-based machine translation, reordering is modeled implicitely as part of the phrase translation model

- Typically no additional mechanism to perform reorderings that do not result from the application of hierarchical rules
- No integration of lexicalized reordering models (e.g. in the manner of phrase orientation models of standard phrase-based systems)





Example for Reordering Rules: Swap Rule

Standard initial rule and glue rule:

$$egin{aligned} S &
ightarrow \left\langle X^{\sim 0}, X^{\sim 0}
ight
angle \ S &
ightarrow \left\langle S^{\sim 0} X^{\sim 1}, S^{\sim 0} X^{\sim 1}
ight
angle \end{aligned}$$

Bring in more reordering capabilities by adding a single swap rule:

$$X
ightarrow \left\langle X^{\sim 0} X^{\sim 1}, X^{\sim 1} X^{\sim 0}
ight
angle$$

► The swap rule allows adjacent phrases to be transposed





Discriminative Reordering Model (1)

Integrate a discriminatively trained lexicalized reordering model (discrim. RO) that predicts the orientation of neighboring blocks

- Two orientation classes *left* and *right*
- Orientation probability is modeled in a maximum entropy framework
- Different feature sets possible
- Training with Generalized Iterative Scaling (GIS)





Discriminative Reordering Model (2)

- The discriminative reordering model is applied at *block boundaries*, where words which are adjacent to gaps within hierarchical phrases are defined as boundary words as well
- Example: an embedding of a lexical phrase (light) in a hierarchical phrase (dark), with orientations scored with the neighboring blocks:



The gap in the hierarchical phrase $\langle f_1 f_2 X^{\sim 0}, e_1 X^{\sim 0} e_3 \rangle$ is filled with the lexical phrase $\langle f_3, e_2 \rangle$.

RWTH

Translation Example: Baseline





Translation Example: Swap Rule and Discrim. RO







Soft String-to-Dependency Hierarchical MT

Training

- Use a parser to create dependencies on the target side of the training corpora
- Phrase extraction: Store dependency information for each phrase
- Train dependency language model

Decoding

- Assemble dependencies
- Penalize phrases with invalid dependency structures
- Penalize tree merging errors
- Apply dependency language model





Phrases with Invalid Dependency Structures

Valid fixed on head structure (left) and a counterexample (right)

Only head node allowed to have dependency outside the structure



Valid floating with children structure (left) and a counterexample (right)

► All dependencies point to one head outside the structure



Here: No restrictions on phrase inventory, but penalty during decoding



Merging Dependency Tree Fragments

Merging tree fragments without merging errors

► All dependency pointers point into the same directions as the parent dependencies



Merging tree fragments with one left and two right merging errors

- ► The dependency pointers point into other directions as the parent dependencies
- Merging errors are penalized





Dependency Language Model



$$p(e_1^I|T) = p_h(\text{submitted}) \times p_l(\text{were}|\text{submitted-as-head}) \times p_l(\text{bills}|\text{were, submitted-as-head}) \times p_r(\text{on}|\text{bills-as-head}) \times \dots$$

Three n-gram models:

- $\blacktriangleright p_h$: 1-gram model for word being head of structure
- $\blacktriangleright p_l$: n-gram model for dependency level left of head
- $\blacktriangleright p_r$: n-gram model for dependency level right of head





Some Experimental Results

NIST Chinese \rightarrow English translation task

- ► 3.0M sentences of parallel training data (77.5M Chinese / 81.0M English running words)
- ► 4-gram LM

	MT06	(Dev)	MT08	(Test)
	BLEU	TER	BLEU	TER
	[%]	[%]	[%]	[%]
Baseline (with RF word lexicons)	32.6	61.2	25.2	66.6
+ insertion model	32.9	61.4	25.7	66.2
+ deletion model	32.9	61.4	26.0	66.1
+ IBM Model 1	33.8	60.5	26.9	65.4
+ discrim. RO	33.0	61.3	25.8	66.0
+ swap rule + binary swap feature	33.2	61.3	26.2	66.1
Soft string-to-dependency	33.5	60.8	26.0	65.7
— only valid phrases	32.8	62.0	25.4	67.1
— no merging errors	32.5	61.5	25.5	66.4
+ insertion model + discrim. RO + DWL + triplets	35.0	59.5	27.8	64.4





Summary



- Efficient toolkit for phrase-based and hierarchical phrase-based translation
- Open source, free for non-commercial use
- http://www.hltpr.rwth-aachen.de/jane
- Extensions to HPBT in Jane 2:
 - ▷ Insertion and deletion models
 - Lexical scoring variants
 - Lexicalized reordering
 - Soft string-to-dependency hierarchical MT





Thank you for your attention!

Previous papers about Jane:

D. Vilar, D. Stein, M. Huck, and H. Ney. Jane: Open Source Hierarchical Translation, Extended with Reordering and Lexicon Models. In ACL 2010 Joint Fifth Workshop on Statistical Machine Translation and Metrics MATR, Uppsala, Sweden, July 2010.

D. Stein, D. Vilar, S. Peitz, M. Freitag, M. Huck, and H. Ney. A Guide to Jane, an Open Source Hierarchical Translation Toolkit. In The Prague Bulletin of Mathematical Linguistics, Prague, Czech Republic, April 2011.

D. Vilar, D. Stein, M. Huck, and H. Ney. Jane: an advanced freely available hierarchical machine translation toolkit. In Machine Translation (Online First), January 2012. http://dx.doi.org/10.1007/s10590-011-9120-y.





Thank you for your attention

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