

Advancements in Arabic-to-English Hierarchical Machine Translation

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Outline



- 2. Extensions
 - Shallow rules
 - IBM-style reorderings
 - Soft syntactic labels
 - Lightly-supervised training
 - Discriminative word lexicon
- 3. Experimental results NIST Arabic \rightarrow English





Review: Hierarchical Phrase-based Translation

- ► Allow for *gaps* in the phrases
- ► Formalization as a *synchronous context-free grammar*
 - \triangleright Rules of the form $X \to \langle \gamma, \alpha, \sim \rangle$, where:
 - $\circ X$ is a non-terminal
 - $\circ\,\gamma$ and α are strings of terminals and non-terminals
 - $\circ \sim$ is a one-to-one correspondence between the non-terminals of lpha and γ
- Parsing-based decoding (extension of CYK algorithm)





Review: Hierarchical Extraction Process

Basic idea:

- Extract standard phrases
- If the extracted phrases contain further sub-phrases, create "holes"
- > Assign probabilities using relative frequencies
- Main restrictions:
 - Maximum of two non-terminals per rule
 - Non-terminals must be non-adjacent in the source side
 - Rules must have at least one terminal symbol
- ► Additionally: *Initial and glue rule*

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

• Only one *generic non-terminal symbol* X plus the start symbol S





Hierarchical Rules: Example







Review: CYK Algorithm



- Parse tree of the source sentence induces a parse tree of the target sentence
- Additionally to parsing algorithm: Handle translation alternatives
- Cube pruning [Huang and Chiang, ACL 2007]



Hierarchical Phrase-based Translation System

Extensions described here have been integrated into an open source toolkit:



RWTH's open source hierarchical phrase-based translation toolkit (free for non-commercial purposes)

- Implemented in C++
- ► See [Vilar et al., WMT 2010]
- http://www.hltpr.rwth-aachen.de/jane



RWTH

$\textbf{Arabic}{\rightarrow}\textbf{English NIST Task}$

- Our baseline setup: 2.5M sentences of parallel training data
- Systems tuned towards BLEU on MT06
- Results reported on MT08 (news wire and web text) as unseen test set (45K running words)

	Arabic \rightarrow English (MT08)			
	BLEU [%]	TER [%]		
HPBT Baseline	44.3 ±1.1	50.0 ±0.9		

- Tiny numbers: 95% confidence interval
- For comparison: RWTH's standard PBT baseline system (without extensions) performs at 44.7% BLEU / 49.1% TER with the same parallel training data and LM





Extensions to Hierarchical Machine Translation

Goals:

- ► Significantly improved translation quality within large-scale Arabic→English system
- Decoding speedups without loss in translation performance

Evaluated techniques:

- Shallow rules
- IBM-style reorderings
- Soft syntactic labels
- Lightly-supervised training
- Discriminative word lexicon



Related Work

- Iglesias et al., EACL 2009] Shallow rules for efficient hierarchical phrase-based decoding
- ► [Vilar et al., WMT 2010] IBM-style reorderings for HPBT (German→English)
- ► [Stein et al., AMTA 2010] Syntactic extensions to HPBT (Chinese→English)
- [Schwenk, IWSLT 2008]
 Lightly-supervised training for phrase-based system (French→English)
- [Mauser et al., EMNLP 2009] Discriminative word lexicon model in phrase-based system



Shallow Rules



Idea:

- Modification of the grammar to constrain the search space
- ► Restriction of the depth of the hierarchical recursion to one
- No modifications to the decoder necessary

Method:

- ► Generic non-terminal *X* replaced by two distinct non-terminals *XH* and *XP*
- On all right-hand sides of hierarchical rules: XP
- Left-hand sides of lexical rules: XP
- Left-hand sides of hierarchical rules: XH
- Gaps within hierarchical phrases can thus only be filled with purely lexicalized phrases





Shallow Rules: Initial and Glue Rule

Initial rule has to be substituted with two rules

► *Glue rule* has to be substituted with two rules

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



IBM-Style Reorderings



Include additional reorderings on top of the hierarchically motivated ones

Method:

- Phrase-based IBM-style reorderings with a window length of 1
- Grammar-based implementation (replacement of initial and glue rule), with minimal modifications to the decoder
- Computation of distance-based jump cost





IBM-Style Reorderings: Initial and Glue Rule

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

▶ *M* non-terminal represents a block that will be translated in a monotonic way

- ▶ *B* is a "back jump"
- Keep them separate for more flexibility (e.g. restriction of jump width)





Soft Syntactic Labels: Principle

- Use labels from syntactic parse trees to replace the generic non-terminals in the translation process
- Target side of the training data is parsed (here: Berkeley Parser [Petrov et al. 2006])
- Resulting syntax trees are used in the rule extraction process





Soft Syntactic Labels: Model

Computation of two additional models for the log-linear combination

- 1. *Tree well-formedness probability model* p_{syntax} for the parse tree construced by the decoder
- 2. Penalty for non-matching non-terminals
- Same phrase pairs, but syntax is stored as additional information in the rules
- ▶ Before: set of non-terminals $\mathcal{NT} = \{S, X\}$
- Now extended by a set of non-terminals in the additional model $\mathcal{H} = \{NP, PP, NN, DT \ldots\}$





Soft Syntactic Labels: Decoding



▶ $p(h_0|d_1)$ is a computed distribution over all labels $h_0 \in \mathcal{H}$ for sub-derivation d_1

ightarrow p(h|r) is the distribution computed in the rule extraction for rule r



RWTH

Lightly-Supervised Training

Idea:

- Automatically translate monolingual source language corpora
- Create word alignments on resulting bitexts
- ► Use as unsupervised parallel training data

Method:

- Cross-system and cross-paradigm variant of lightly-supervised training
 - > Automatic translations of parts of the Arabic LDC Gigaword corpus
 - Created with a standard phrase-based system and kindly provided by Holger Schwenk, LIUM, Le Mans
 - Selection of 4.7M sentence pairs
 - > Used as additional training material for RWTH's HPBT system
- Lexical phrases extracted from unsupervised data, hierarchical phrases from more reliable human-generated parallel data only
- Number of non-hierarchical phrases increased by roughly 30%





Discriminative Word Lexicon (DWL)

Discriminative, log-linear lexicon model: $p(e|f_1^J)$

- Predict the words contained in the translation from the words given in the source sentence
- 2-class classification problem: target word included / not included in translation
- Features: words in the source sentence
- Captures context beyond phrase boundaries and n-gram language model history

Training:

- Improved RProp+ [Igel & Hüsken 2003], L2-regularization
- Easy to parallelize: one target word per core
- But many parameters: weights for all source word / target word combinations
- Full model trained, threshold pruning applied afterwards to discard features with low values (separate for each class)





DWL Training NIST Arabic \rightarrow **English**

- DWL model trained on a high-quality subset of 0.3M sentence pairs
- RProp+: 100 iterations per target word
- Pruned with threshold 0.1
- On average 80 features per target word (unpruned: 122592)





Experimental Results NIST Arabic — English

	Arabic \rightarrow English (MT08)				
	deep		shallow		
	BLEU [%]	TER [%]	BLEU [%]	TER [%]	
HPBT Baseline	44.3 ±1.1	50.0 ±0.9	44.4 ±1.1	49.4 ±0.9	
+ Unsup	45.0 +0.7	49.4 -0.6	45.2 +0.8	49.2 -0.2	
+ Unsup + DWL	45.7 +1.4	48.7 -1.3	45.8 +1.4	<i>48.2</i> -1.2	
+ Unsup + Syntactic Labels	45.2 +0.9	49.3 -0.7	45.0 +0.6	49.0 - 0.4	
+ Unsup + Reorderings	45.3 +1.0	49.1 -0.9	45.3 +0.9	48.9 - 0.5	
+ Unsup + DWL + Syntactic Labels	<i>46.0</i> +1.7	<i>48.2</i> -1.8	45.8 +1.4	<i>48.3</i> -1.1	
+ Unsup + DWL + Reorderings	45.7 +1.4	48.7 -1.3	45.9 +1.5	48.2 -1.2	

► The 95% confidence interval is given for the baseline systems

Highlighted results are significantly better than the baseline





> Significant improvements in Arabic \rightarrow English HPBT due to

- > lightly-supervised training
- > a discriminative word lexicon
- Decoding speedups (factor 5-10) without loss in translation quality with shallow rules
- Soft syntactic labels and additional IBM-style reorderings have little to no impact





Thank you for your attention

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