Extended Translation Models in Phrase-based Decoding

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Introduction

Phrase-based translation models
[Och & Tillmann^{+} 99, Zens & Och^{+} 02, Koehn & Och^{+} 03]

- **phrases extracted from alignments obtained using GIZA++ [Och & Ney 03]**
- **estimation as relative frequencies of phrase pairs**
- **drawbacks:**
  - **single-word phrases translated without any context**
  - **uncaptured dependencies beyond phrase boundaries**
  - **difficulties with long-range reorderings**

Related Work

- bilingual language models [Niehues & Herrmann^{+} 11]
  - atomic source phrases, no reordering context
- reordering model based on sequence labeling [Feng & Peter^{+} 13]
  - modeling only reorderings
- operation sequence model (OSM) [Durrani & Fraser^{+} 13]
  - n-gram model based on minimal translation units
- neural network models for extended translation context
  - rescoring [Le & Allauzen^{+} 12, Sundermeyer & Alkhouli^{+} 14]
  - decoding [Devlin & Zbib^{+} 14, Auli & Gao 14, Alkhouli & Rietig^{+} 15]
  - stand-alone models [Sutskever & Vinyals^{+} 14, Bahdanau & Cho^{+} 15]
- joint translation and reordering models [Guta & Alkhouli^{+} 15]
  - word-based and simpler reordering approach than OSM
  - count models and neural networks (NNs)

This Work

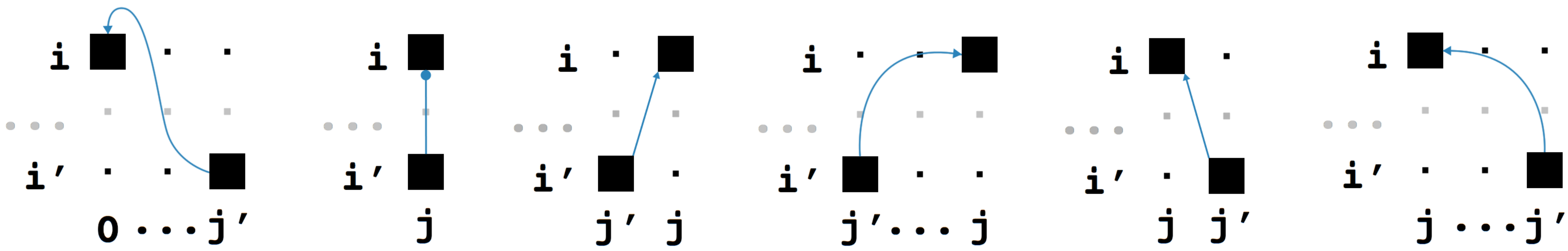
- develop two variants of extended translation models (ETM)
  - extend IBM models by a bilingual word pair and a reordering operation
  - integrated into log-linear framework of phrase-based decoding
  - explicit treatment of multiple alignments and unaligned words
- benefits:
  - lexical and reordering context for single-word phrases
  - dependencies across phrase boundaries
  - long-range source dependencies
- first step: implementation as smoothed count models
- the long-term goal:
  - application as stand-alone models in decoding
  - retraining the word alignments

Extended Translation Models

- **source sentence** $f_1^J = f_1 \dots f_j \dots f_J$
- **target sentence** $e_1^I = e_1 \dots e_i \dots e_I$
- **inverted alignment** b_1^I **with** $b_i \subseteq \{1 \dots J\}$
  - **unaligned source positions** b_0
- **empty words** f_0, e_0

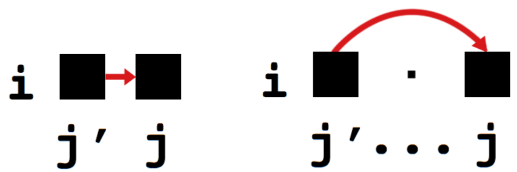
Jump Classes

- **generalizing alignments to**
  - **jump classes for source positions aligned to subsequent target positions**



insert (↓) stay (•) forward (→) jump forward (↷) backward (←) jump backward (↶)

  - **jump classes source positions aligned to the same target position**



forward (→) jump forward (↷)

Extended Inverse Translation Model (EiTM)

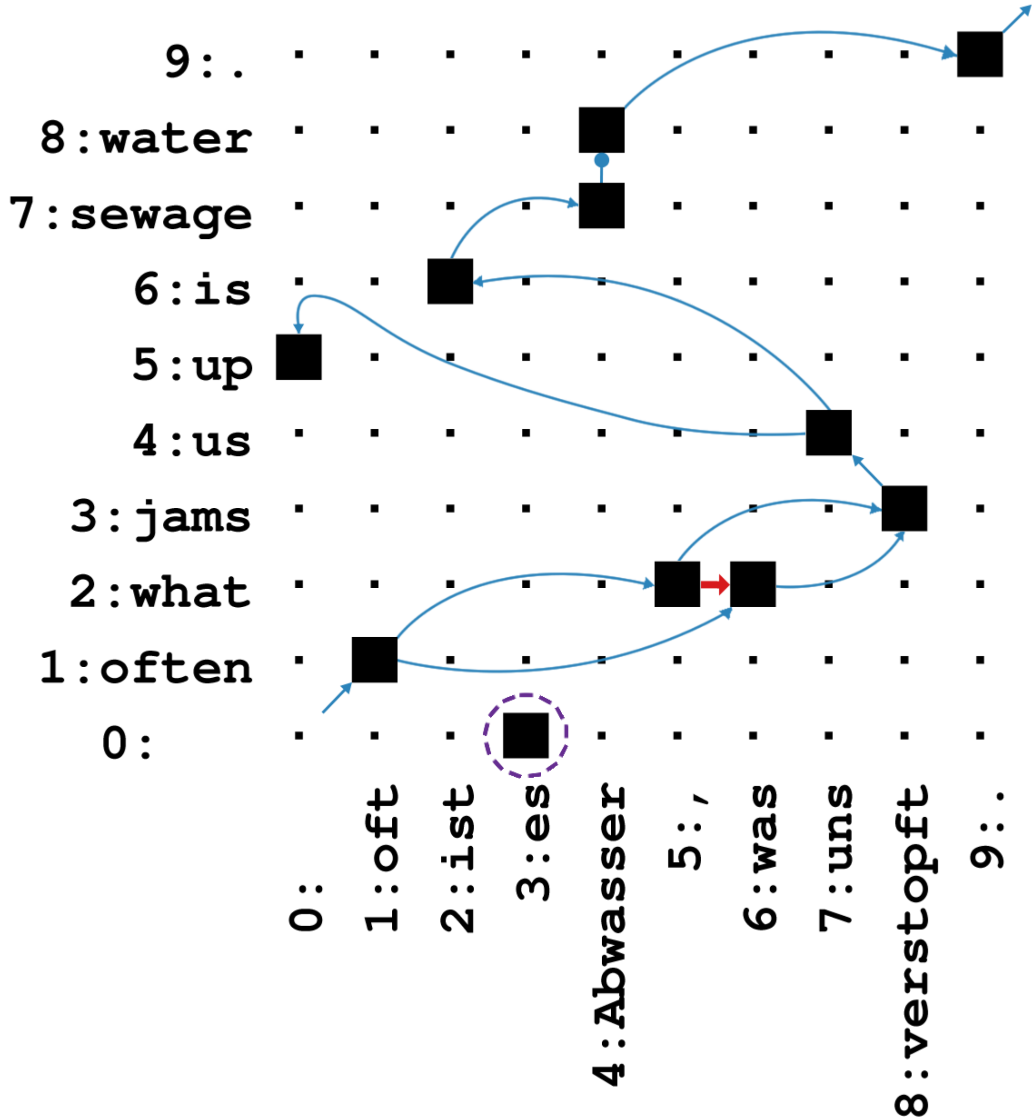
- **EiTM models the inverse probability $p(f_1^J|e_1^I)$**

$$p(f_1^J|e_1^I) = \max_{b_1^I} \left\{ \prod_{i=1}^{I} \left(\underbrace{p(f_{b_i}|e_{i'}, e_i, f_{b_{i'}}, b_{i'}, b_i)}_{\text{lexicon model}} \cdot \underbrace{p(b_i|e_{i'}, e_i, f_{b_{i'}}, b_{i'})}_{\text{alignment model}} \right) \cdot \underbrace{p(f_{b_0}|e_0)}_{\text{deletion model}} \right\}$$

- **current source words f_{b_i} and target word e_i**
- **previous source words $f_{b_{i'}}$ and target word $e_{i'}$**

- **generalize aligments $b_{i'}, b_i$ to jump classes**
- **multiple source predecessors j' in $b_{i'}$ or b_i**
  - **average probabilities over all j'**

EiTM Example



Extended Direct Translation Model (EdTM)

- further aim: model $p(e_1^I|f_1^J)$ as well
- first approach by using the EiTM:
  - swap source and target corpora
  - invert also the alignment
- drawback:
  - source words not translated in monotone order
  - source word preceding a phrase might have not been translated yet
  - its last aligned predecessor and corresponding aligned target words generally unknown
- dependencies beyond phrase boundaries cannot be captured
- develop the EdTM
  - swap source and target corpora, but keep b_1^I
  - incorporate dependencies beyond phrase boundaries

Extended Direct Translation Model (EdTM)

- EdTM models the direct probability $p(e_1^I|f_1^J)$

$$p(e_1^I|f_1^J) = \max_{b_1^I} \left\{ \prod_{i=1}^{I} \left(\underbrace{p(e_i|f_{b_{i'}}, f_{b_i}, e_{i'}, b_{i'}, b_i)}_{\text{lexicon model}} \cdot \underbrace{p(b_i|f_{b_{i'}}, f_{b_i}, e_{i'}, b_{i'})}_{\text{alignment model}} \right) \cdot \underbrace{p(e_0|f_{b_0})}_{\text{deletion model}} \right\}$$

- differences to EiTM
  - lexicon model: swapped e_i and f_{b_i}
  - alignment model: dependence on f_{b_i} (instead of e_i)
  - deletion model: swapped e_0 and f_{b_0}

Count Models and Smoothing

How to train the derived EdTM and EiTM models?

- **estimate Viterbi alignment using GIZA++ [Och & Ney 03]**
- **compute relative frequencies**
- **apply interpolated Kneser-Ney smoothing [Chen & Goodman 98]**

Integration into Phrase-based Decoding

- phrase-based decoder Jane 2 [Wuebker & Huck^{+} 12]
- log-linear model combination [Och & Ney 04]
  - tuning with minimum error rate training (MERT) [Och 03]

- annotation of phrase-table entries with word alignments
- extended translation models integrated as up to 4 additional features:
  - EdTM and EiTM
  - Source→Target and Target→Source
- search state extension:
  - store the source position aligned to the last translated target word

- context beyond phrase boundaries only in Source→Target direction

Experimental Setups

	IWSLT German	IWSLT English	IWSLT English	IWSLT French	BOLT Chinese	BOLT English	BOLT Arabic	BOLT English
Sentences								
full data	4.32M		26.05M		4.08M		0.92M	
indomain	138K		185K		67.8K		0.92M	
Run. Words	108M	109M	698M	810M	78M	86M	14M	16M
Vocabulary	836K	792K	2119K	2139K	384K	817K	285K	203K

- phrase-based systems
  - phrasal and lexical models (both directions)
  - word and phrase penalties
  - distortion model
  - 4- / 5-gram language model (LM)
  - 7-gram word class LM [Wuebker & Peitz^{+} 13]
  - hierarchical reordering model (HRM) [Galley & Manning 08]

Results: IWSLT 2014 German→English

	test2010	
	BLEU [%]	TER [%]
phrase-based system + HRM	**30.7**	**49.3**
+ EiTM (Source↔Target)	**31.4**	**48.3**
+ EdTM (Source↔Target)	**31.6**	**48.1**
+ EiTM (Source→Target) + EdTM (Source→Target)	**31.6**	**48.2**
+ EiTM (Source↔Target) + EdTM (Source↔Target)	**31.8**	**48.2**

Results: Comparison to OSM

- all results measured in BLEU [%]

	IWSLT		BOLT	
	De→En	En→Fr	Zh→En	Ar→En
phrase-based system + HRM	30.7	33.1	17.0	24.0
+ ETM	31.8	33.9	17.5	24.4
+ 7-gram OSM	31.8	34.5	17.6	24.1

Conclusion

- integration of extended translation models into phrase-based decoding
  - lexical and reordering context beyond phrase boundaries
  - multiple and empty alignments
  - relative frequencies with interpolated Kneser-Ney smoothing
- improving phrase-based systems including HRM
  - by up to 1.1% BLEU and TER
  - by 0.7% BLEU on average for four large-scale tasks
- competitive to a 7-gram OSM
  - 0.1% BLEU less improvement on average on top of phrase-based systems including the HRM
- long-term goals:
  - retraining the alignments: joint optimization
  - stand-alone decoding without phrases

Thank you for your attention

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