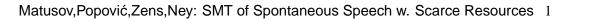


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Statistical Machine Translation of Spontaneous Speech with Scarce Resources

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Content

- 1. overview: data sparseness problem
- 2. overview: statistical machine translation
- 3. acquiring additional training data
- 4. morphological information for word alignments
 - lexicon smoothing
 - hierarchical lexicon counts
- 5. part-of-speech information for reordering
- 6. experimental results
- 7. summary and outlook



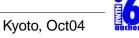
Overview: Translation with Scarce Resources

- language pair specific data sparseness
- lack of bilingual sentence-aligned data in a specific domain (e.g. spontaneous utterances)
- limited coverage of the vocabulary (e.g. highly inflected languages)
- insufficient data to learn non-monotonous translations



Related work

- S. Nießen and H. Ney. 2001. Morpho-syntactic analysis for Reordering in Statistical Machine Translation. In Proc. MT Summit VIII, pages 247–252, Santiago de Compostela, Galicia, Spain, September.
- S. Nießen and H. Ney. Toward hierarchical models for statistical machine translation of inflected languages. In *Data-Driven Machine Translation Workshop*, pages 47–54, Toulouse, France, July.
- F. J. Och and H. Ney. 2003. A systematic comparison of various statistical alignment models. *Computational Linguistics*, 29(1):19–51, March.
- D. Sündermann and H. Ney. 2003. Synther a new m-gram POS tagger. In *Proc. NLP-KE-2003, International Conference on Natural Language Processing and Knowledge Engineering*, pages 628–633, Beijing, China, October.
- R. Zens and E. Matusov and H. Ney. 2004. Improved Word Alignment Using a Symmetric Lexicon Model. In *Proc. COLING04*, pages 36–42, Geneva, Switzer-land, August.
- Y. Al-Onaizan, U. Germann, U. Hermjakob, K. Knight, P. Koehn, D. Marcu, and K. Yamada. 2002. Translating with Scarce Bilingual Resources. *Machine Translation* 17, pp. 1–17.





Overview: Statistical Machine Translation

- source string $f_1^J = f_1...f_j...f_J$ to be translated into a target string $e_1^I = e_1...e_i...e_I$.
- classical source-channel approach:

$$egin{aligned} \hat{e}_1^I &= rgmax \ e_1^I & \left\{ Pr(e_1^I|f_1^J)
ight\} \ &= rgmax \ e_1^I & \left\{ Pr(e_1^I) \cdot Pr(f_1^J|e_1^I)
ight\} \ &e_1^I \end{aligned}$$

- $Pr(e_1^I)$: language model
- $Pr(f_1^J|e_1^I)$: translation model
- word alignment is introduced as a hidden variable:

$$Pr(f_1^J|e_1^I) \,=\, \sum_A Pr(f_1^J,A|e_1^I)$$

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Statistical word alignments

- alignment A is a mapping from source sentence positions to target sentence positions $a_1...a_J$, $a_j \in \{0, ..., I\}$.
- alignment may contain connections $a_j = 0$ with the 'empty' word e_0
- commonly used translation models: IBM-1 to IBM-5, HMM.
- ullet all of the models include single-word based lexicon parameters p(f|e)
- model parameters are trained iteratively with the EM algorithm
- usually: restricted alignments (many-to-one mappings only), alignment combination heuristics
- recent suggestions: symmetrized lexicon models, symmetric alignments (Zens, Matusov, Ney: CoLing 2004)



Translation

- primary model: alignment templates
 - pairs of source and target phrases and the alignment within the phrases
 - extracted from word alignments
 - automatically trained word classes are used instead of words for better generalization
- \bullet search: direct modeling of the posterior probability $Pr(e_1^I|f_1^J)$ using a loglinear model
- easy integration of additional models/feature functions
 - word translation model
 - a word trigram and a class-based five-gram language model
 - word penalty, alignment template penalty, ...
- minimum error training of model scaling factors





Acquiring Additional Training Data

- include additional bilingual training data from other sources
- select domain-relevant data only
- relevance measure: *n*-gram coverage
- compute the set C of n-grams occuring in the source part of the initial (small) training corpus
- count the occurrence of the n-grams from C in the additional sentences
- coverage score: geometric mean of n-gram precisions (n = 1, 2, 3, ..., 4)
- add only sentences with high coverage score





Morphological Information for Word Alignments

- common statistical lexicon models are based on full form words only
- lexicon coverage is low, especially when training with scarce data
- a big problem for highly inflected languages like German
- smooth the lexicon model with a backing-off lexicon based on word base forms
- perform smoothing after each iteration of the EM algorithm
- smoothing technique: absolute discounting with interpolation:

$$p(f|e) = rac{\max\left\{N(f,e) - d,0
ight\}}{N(e)} + lpha(e) \cdot eta(f|\overline{e})$$

- \overline{e} is the base form (generalization) of e.
- backing-off distribution: $\beta(f|\overline{e}) = rac{N(f,\overline{e})}{\sum\limits_{f'} N(f',\overline{e})}$





Hierarchical Lexicon Counts

- for each German word, determine the base form and sequence of morpho-syntactic tags
 - e.g. gehe#gehen-V-IND-PRES#gehen
- collect three types of counts in the E-step of the EM algorithm:
 - regular full form counts N(f,e)
 - base form+tag counts $N(ilde{f},e)$
 - base form counts $N(\overline{f},e)$
- in each iteration, combine these counts to hierarchical counts:

$$N_{hier}(f,e)\,=\,N(f,e)+N(ilde{f},e)+N(\overline{f},e)$$

• M-step: obtain new estimation of the lexicon probability:

$$p(f|e) \,= \, rac{N_{hier}(f,e)}{\sum\limits_{f'} N_{hier}(f',e)}$$



Monotonization of Translation Process

- some language pairs have significantly different word order
- with limited training data, word alignments and phrase structures are estimated poorly
- differences in word order can be reduced by re-ordering of the source sentences (in training and in testing)
- re-ordering rules: using part-of-speech information and knowledge about target sentence structure
- POS tags obtained by using a statistical POS tagger
- POS information is less context-dependent than a syntactic tree structure and thus can be relied upon even when tagging spontaneous utterances
- monotonization of alignments will result in more robust phrase extraction (e.g. non-contiguous phrases can be extracted)



Reordering Rules - 1

• verb prefixes:

Ich fahre um 9 Uhr vom Bahnhof ab

> Ich fahre ab um 9 Uhr vom Bahnhof

• compound verbs:

Ich kann Ihnen noch heute meine Nummer geben

- > Ich kann geben Ihnen noch heute meine Nummer
- verb position in subordinate clauses:
 - ... weil ich erst dann Ihnen meine Nummer geben kann
 - > ... weil ich kann geben erst dann Ihnen meine Nummer



Reordering Rules - 2

• translation improvements:

oh, then I will call there, if you the telephone number give.
> oh, then I will call there if you give me the telephone number.

I would like a winter vacation in Val-di-Fiemme plan for 2 people.

- > I would like to plan a winter vacation in Val-di-Fiemme
- > for 2 people.

I can from my vacation place easy reach, right?
> can I reach from my vacation place easily, right?

and can you say a hotel in case that could not possible for me?

- > and can you tell me a hotel in case that apartment
- > is not possible?



Experimental results

- improvements in word alignment quality
- translation results
- Verbmobil and Nespole! German-English tasks





Evaluation Methodology

- word alignment quality: Alignment Error Rate (AER)
 - compare produced alignment connections A with reference alignment connections
 - Sure (S) and Possible (P) reference alignment connections exist, $S\subseteq P$
 - recall error: sure alignment is not found;
 precision error: a found alignment is not even possible

 $\begin{aligned} \text{recall} &= \frac{|A \cap S|}{|S|} & \text{precision} &= \frac{|A \cap P|}{|A|} \\ \text{AER}(S,P;A) &= 1 - \frac{|A \cap S| + |A \cap P|}{|A| + |S|} \end{aligned}$

- translation results: automatic evaluation
 - Word Error Rate (WER)
 - Position-Independent Word Error Rate (PER)
 - BLEU score



Verbmobil Alignment Training Corpus Statistics

- Verbmobil German-English task, spontaneous speech
- domain: appointment scheduling, travel planning, hotel reservation

		German	English	
Train	Sentences	34K		
	Words	329 625	343 076	
	Vocabulary	5 936	3 505	
	Singletons	2 600	1 305	
Dictionary	Entries	4 4 0 4		
Alignment	Sentences	354		
test corpus	Words	3 2 3 3	3 1 0 9	





Results Verbmobil Task: smoothed lexicon

	German→English		English→German		rman	
	Pre.[%]	Rec.[%]	AER [%]	Pre.[%]	Rec.[%]	AER [%]
34k Base	93.5	95.3	5.7	91.4	88.7	9.9
smooth	94.8	94.8	5.2	93.4	88.2	9.1
8k Base	92.5	95.4	6.2	88.7	88.3	11.5
smooth	93.2	94.9	6.0	89.9	87.8	11.1

- SMT system trained either on 34K or on 8K bilingual sentence pairs
- Method works better with larger training corpora (distribution of base forms can be better estimated)



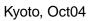


Results Verbmobil Task: hierarchical lexicon counts

AER [%] corpus size = 0.5k				
Training	Model	G ightarrow E	E ightarrow G	combined
$1^4 H^5$	hmm	18.8	24.0	16.9
	+hier	16.9	21.5	14.8
$1^4 H^5 3^3 4^3$	ibm4	16.9	21.5	16.2
	+hier	15.8	20.7	14.9
$1^4 H^5 3^3 4^3 6^5$	model6	16.7	21.1	15.9
	+hier	15.6	20.9	14.8

AER [%] corpus size = 34k				
Training	Model	$G \rightarrow E$	E ightarrow G	combined
$1^4 H^5$	hmm	8.9	14.9	7.9
	+hier	8.4	13.7	7.3
$1^4 H^5 3^3 4^3$	ibm4	6.3	10.9	6.0
	+hier	6.1	10.8	5.7
$1^4 H^5 3^3 4^3 6^5$	model6	5.7	9.9	5.5
	+hier	5.5	9.7	5.0

- method is effective for small and large training corpora
- improvements are more significant for simpler alignment models





Nespole! corpus statistics

- translation experiments on the Nespole! corpus of manually transcribed telephone inquiries (kindly provided by IRST)
- domain: travel information, hotel reservation
- training corpus extended with relevant in-domain data automatically selected from larger corpora
- *n*-gram coverage scores were used to select additional data

	German	English		
Sentence pairs	3046			
Running words	14437	14743		
Vocabulary	1452	1118		
Singletons	734	472		
Extension through <i>n</i> -gram coverage				
Sentence pairs	15835			
Running words	201907	207515		
Vocabulary	17361	12367		
Singletons	10423	4583		







Translation results Nespole! Task

- compound splitting of German nouns performed in training and in testing
- test corpora statistics:

	Development	Test
Sentence pairs	300	106
Running words	1437	933
OOV-Rate	0.84 %	0.96 %

• results:

	WER [%]	PER [%]	BLEU
Baseline	60.7	47.4	0.212
+ in-domain corpus	56.1	45.2	0.238
+ sentence reordering (German)	53.7	45.5	0.270

• most improvements are in translation fluency





Translation Results Verbmobil Task

- training performed using the 8K training corpus to intensify the data sparseness problem
- test corpora statistics:

	Development	Test
Sentence pairs	276	251
Running words	3159	2628
OOV-Rate	3.3 %	4.0 %

• translation results:

	WER [%]	PER [%]	BLEU
Baseline	56.3	38.2	0.241
+ reordering (German)	52.3	37.9	0.261



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Conclusions

Translation of speech with limited amount of training data:

- a consistent way of selecting additional in-domain data from foreign sources
- two effective methods for inclusion of morpho-syntactic information in word alignment training to improve vocabulary coverage
 - morpho-syntactic information helped to improve alignment quality
- utilization of part-of-speech information to monotonize the translation process
 - significant improvements in translation fluency achieved on two tasks with highly spontaneous utterances



Outlook

- goal: integrate the POS-based reordering in the search process
- perform experiments on automatically transcribed speech
- use syntax and morphology to reduce the Out-Of-Vocabulary rates