The TALP Ngram-based SMT System for IWSLT 2007

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Translation Model

The best translation hypothesis $\mathbf{T}$, for a given source sentence $\mathbf{S}$, is that which maximizes a log-linear combination of feature functions:

$$\hat{\mathbf{T}} = \arg\max_{\mathbf{T}} \sum_m \lambda_m h_m(\mathbf{T}, \mathbf{S})$$

- Translation Model:
  N-gram language model of bilingual units (tuples)

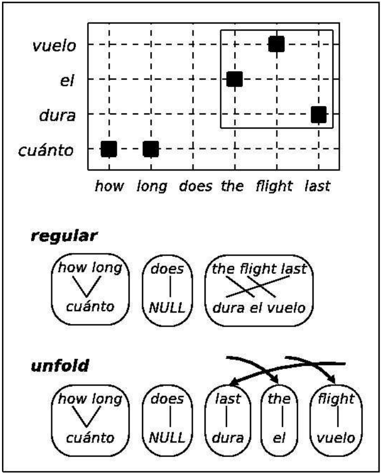
$$p(\mathbf{T}, \mathbf{S}) \approx \prod_n p((t,s)_n | (t,s)_{n-N+1}, \ldots, (t,s)_{n-1})$$

Tuple extraction

Tuples are extracted from word alignment

- A unique and monotonic segmentation of each sentence is produced.
- No word in a tuple is aligned to words outside of it
- No smaller tuples can be extracted without violating the previous constraints

Tuple extraction example



Unfolding produces a different bilingual n-gram model with reordered source words.

Additional feature functions

Additional feature functions:

- Target language model
- POS target language model
- Word bonus model, giving a bonus proportional to the number of target words.
- Source-to-target and target-to-source lexicon models, which compute a lexical weight for each tuple, using IBM model 1 translation probabilities

Alignment Minimum Translation-Error Training

Our Method

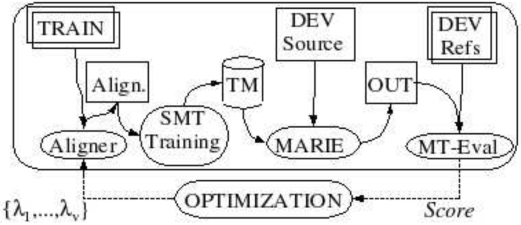
Tuning alignment parameters directly in a Minimum translation Error Training scheme: use automated translation metrics as minimization criterion.

Alignment optimization parameters chosen for GIZA++:

- Smoothing factors for models HMM, IBM3 and IBM4
- The probability for the empty word
- Deficient distorsion for the empty word

Procedure

- Optimal coefficients were estimated with the following procedure:



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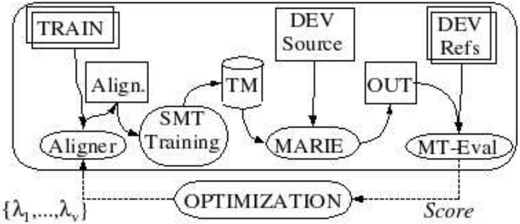


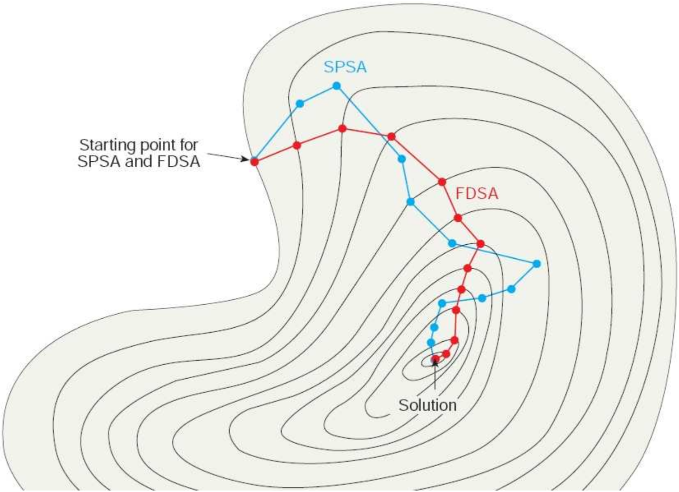
- SMT system with TM model (bilingual language model)

Simultaneous Perturbation Stochastic Approximation

- The SPSA method [J. Spall, 1992] is based on a gradient approximation which requires only two evaluations of the objective function, regardless of the dimension of the optimisation problem.
- SPSA procedure is in the general recursive stochastic approximation form:

$$\hat{\lambda}_{k+1} = \hat{\lambda}_k - \mathbf{a}_k \hat{\mathbf{g}}_k(\hat{\lambda}_k)$$

$\hat{\mathbf{g}}_k(\hat{\lambda}_k)$: estimate of the gradient $\mathbf{g}(\lambda) \equiv \partial E / \partial \lambda$ at iterate k



The simultaneous approximation causes deviations of the search path.
These deviations are averaged out in reaching a solution.

Optimization schemes

Concept	Procedure	Optimized parameters
Dev translated in each iteration	*Alignment Minimum Translation-Error Training*	*Align. smoothing factors*

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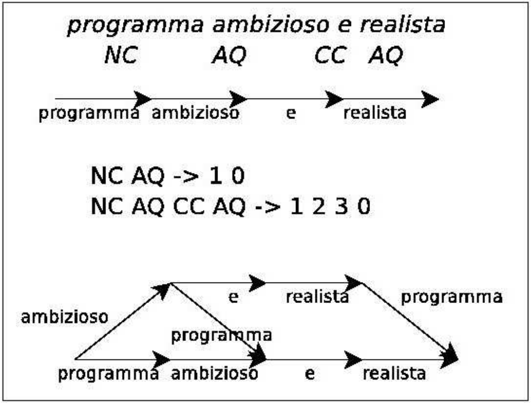
Dev translated in each iteration	*Alignment Minimum Translation-Error Training*	*Align. smoothing factors*
Nbest-list produced by the decoder	*(Double-loop) Minimum Error Training*	*Translation feature functions*

Reordering patterns

Use a set of rewrite rules for Part-Of-Speech sequences to extend the monotonic search graph with reordering hypotheses



Neural Network Language Model

The basic idea of the neural network LM is to project the word indexes onto a continuous space and to use a probability estimator operating on this space.

- The resulting probability functions are smooth functions of the word representation $\longrightarrow$ better generalization to unknown n-grams can be expected.
- A neural network $\longrightarrow$ simultaneously learns the projection of the words onto the continuous space and estimates the n-gram probabilities.

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- A neural network → simultaneously learns the projection of the words onto the continuous space and estimates the *n*-gram probabilities.

The LM posterior probabilities are "interpolated" for any possible context of length *n*-1 instead of backing-off to shorter contexts.

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- **English**
  $\rightarrow$ Part-Of-Speech tagging *TnT* tagger.
  $\rightarrow$ For alignment purpose only (of the ZhEn system), the Snowball stemmer.

Experimental Settings

- Alignment parameters
  - running 5, 5, 3 and 3 iterations of models 1, HMM, 3 and 4,
  - using English stems and 50 classes,
  - taking the union of source-target and target-source alignments.
- Decoding parameters
  - the beam search was set to 50,
  - no reordering limit in search (all paths present in the input reordering graph are considered).
- Rescoring
  - incorporation of the NNLM into the SMT system was done using 1000-best lists.

Internal Experiments Summary

	dev (dev4)	test (dev5)		
	$\frac{1}{2}$(BLEU+METEOR)	BLEU	NIST	METEOR
Chinese→English				
baseline	0.340	0.186	5.84	0.487
giza++ MET	0.349	0.190	5.97	0.490
giza++ MET+NNLM	0.350	0.205	6.06	0.496

Table: *Internal translation results for IWSLT 2007 Chinese-English task. MET refers to alignment tuning with Minimum (translation) Error Training. NNLM refers to rescoring a translation N-best list with a continuous space target language model.*

Participation in the IWSLT 2007 Evaluation

	UPC	Best	Rank
AE ASR Primary	0.4445	0.4445	1/11
AE Clean Primary	0.4804	0.4923	3/11
CE Clean Primary	0.2991	0.4077	11/15
CE Clean Primary + NNLM	0.2920	0.4077	-

Table: *Official translation results (BLEU scores) for IWSLT 2007 Chinese-English and Arabic-English tasks. Next to our system's score, we indicated the Best system's score. For the primary runs, we also indicated the rank of our system among all primary runs.*

1. TALP Ngram-based Translation System
2. Alignment Minimum Translation-Error Training
3. Simultaneous Perturbation Stochastic Approximation method
4. Word ordering strategies
5. Neural Network Language Model
6. Experiments
7. **Conclusions and Further Work**

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1. The optimization of alignment parameters allows to improve translation when using the Alignment Minimum Translation-Error Training.
2. The NNLM obtained an improvement of 1.5 Bleu in the internal set.
3. Our system was ranked 1st in the Arabic-English task. It was not very competitive in the Chinese-English task.

Thanks

Grazie a tutti

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