The MITLL/AFRL TC-Star System

Experiments with Large Vocabulary Speech Translation

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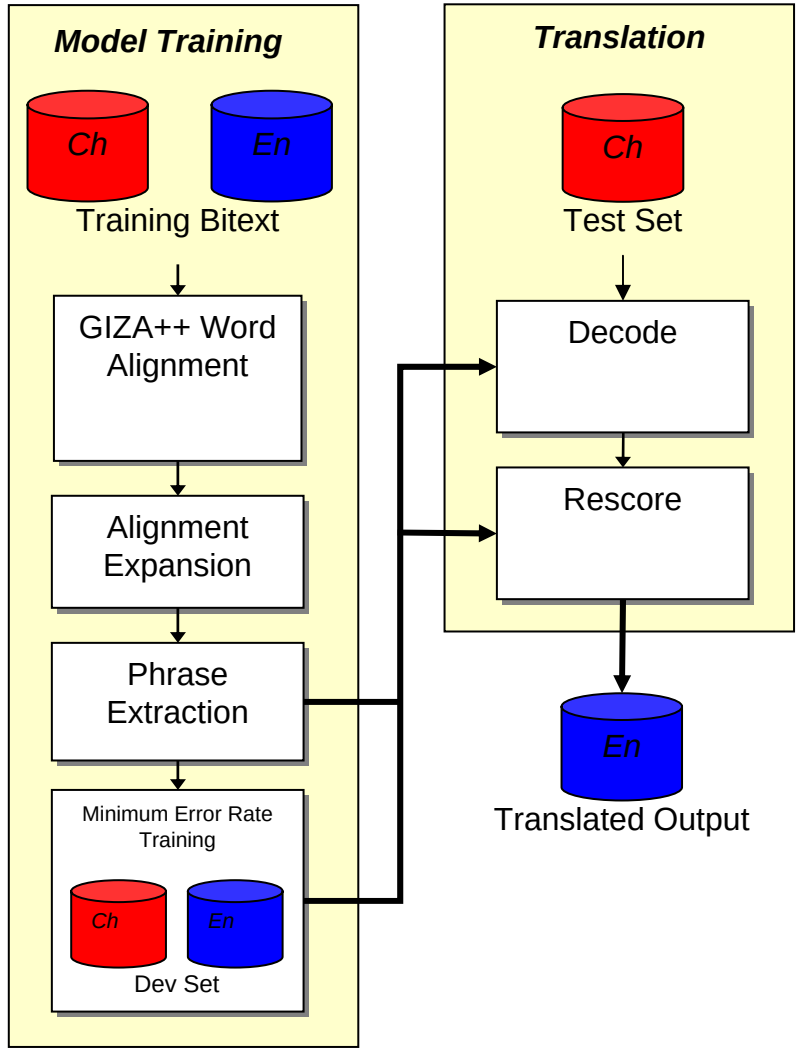
Statistical Translation System

Experimental Architecture

- **Standard Statistical Architecture**
- **Developed in-house to support SMT experiments**
  - **Framework for experiments with low-resource languages**
  - **Test-bed for S2S MT system**
- **Most components are home-grown**
  - **Phrase Training/Minimum Error Rate Training**
  - **Internal Viterbi n-best decoder and Pharaoh used.**
- **Recent work**
  - **Scaling to large vocabulary**
  - **FST Decoder**



The MITLL/AFRL MT System

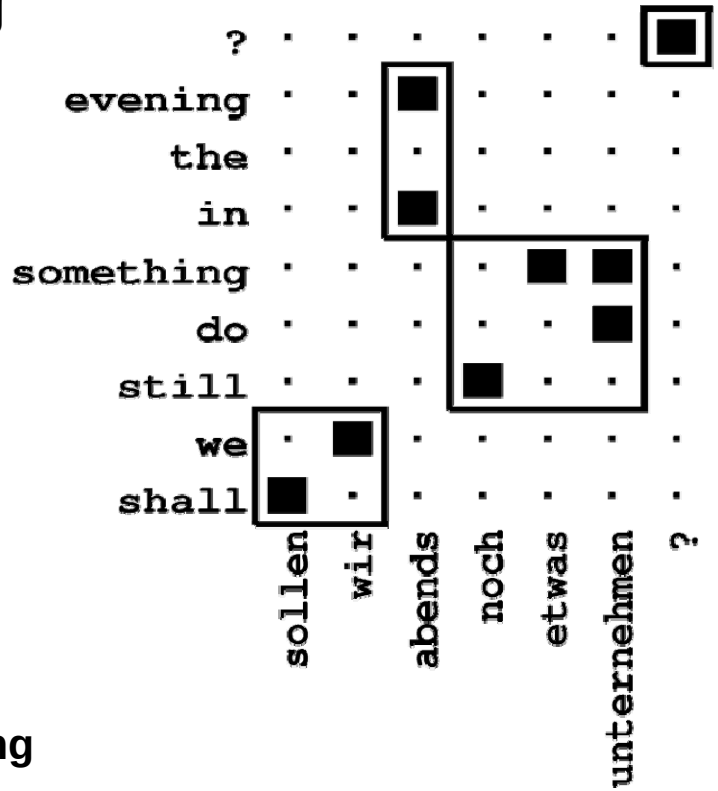
Overview

- Translation Model
- Minimum Error Rate Training
- Decoder
- Simple and Effective Truecasing
- Evaluation Results
  - Text Evaluation
  - ASR Evaluation
- Next Steps

Translation Model

Phrase Extraction

- **Basic Alignment Template Model Proposed by Och & Ney 2000**
  - **Expand word alignments interpolating between the intersection and union of bidirectional GIZA++ alignments**
  - **Extract consistent *phrase* pairs from expanded alignments**



- **Modifications**
  1. **Minor modifications result in +2 BLEU point gain**
  2. **Multiple parallel models:**
     1. **Tag-based PT**
     2. **Stemmed PT**
     3. **Can be combined in decoding/rescoring for optimization**

Translation Model

Distortion, Lexical and Language Models

- **Distortion**
  - **We used Pharaoh's simple model:**

$$P_D(e|f) = exp(-\sum_i |FinalW_{i-1} + 1 - FirstW_i|)$$

- **Lexical Weighting**
  - **Both model 4 and expanded alignment lexical translation models tried**
  - **Expanded alignments ⇨ 1.5 BLEU point gain**

- **Language Model**
  - **Trained with SRILM**
  - **Interpolated with Knesser-Ney discounting used for decoding**
  - **Bigram, 4-gram LM and 5-gram LM used during rescoring**
  - **2-8 gram LM also tried**
  - **No cleanup or normalization performed on base models**

Minimum Error Rate Training

- **Log-linear Model Combination**

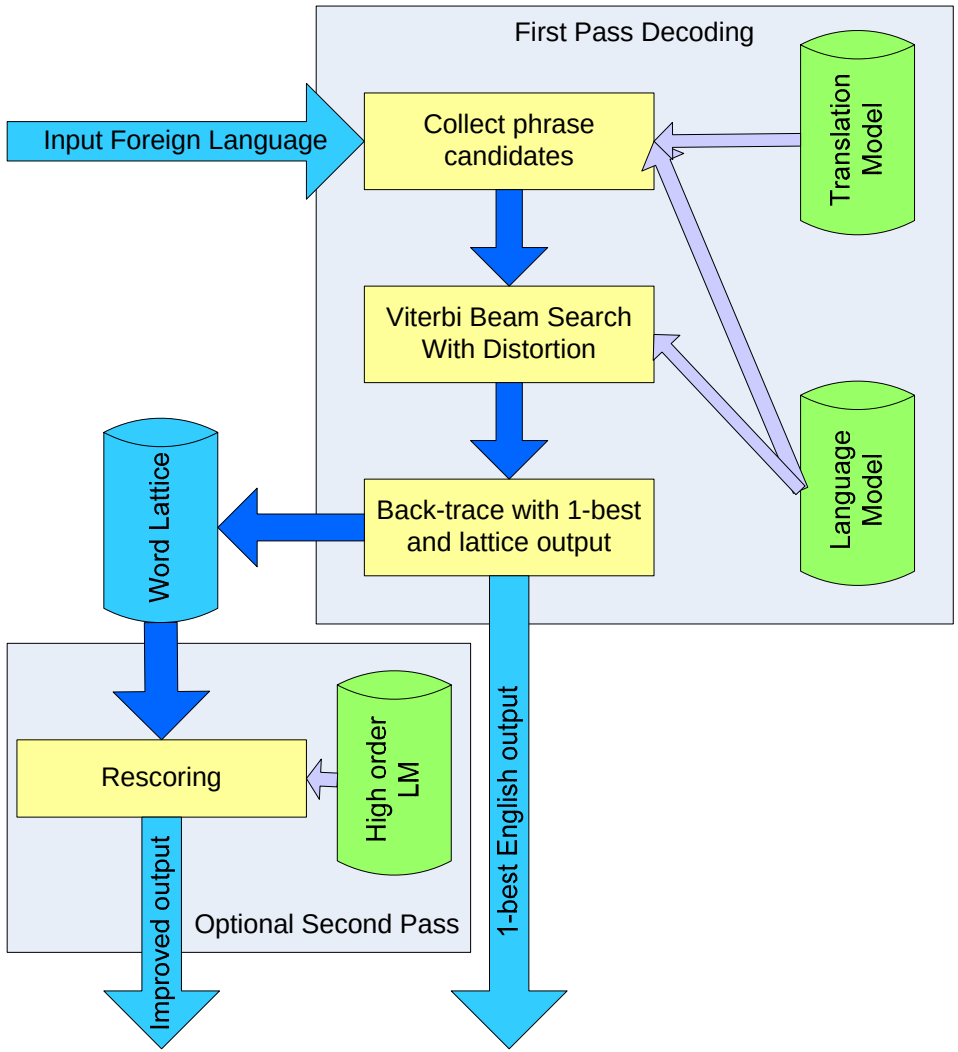
$$\hat{P}(e|f) = \frac{\sum_M \lambda_M h_M(e,f)}{\sum_{e'} exp(\sum_M \lambda_M h_M(e',f))}$$

- **Additional Language models applied during rescoring**
- **N-best lists of 2k used**
  - **Minor gain with 8k n-best**
- **15-20% relative improvement over hand optimized parameters**
- **Insignificant differences from beam-width relaxation**

Model Weight Parameters	
1	*P(f|e)* – Forward Translation Model
2	*P(e|f)* – Backward Translation Model
3	*LexW(f|e)* – Forward Lexical Weight
4	*LexW(e|f)* – Backward Lexical Weight
5	*PPen* – Constant, per-phrase Penalty
6	*WPen* – Constant, per-word Penalty
7	*Dist* – Distortion Model
8	Bi-LM – Bigram Language Model
9	*Tri-LM* – Trigram Language Model
10	*4-LM* – Four-gram Language Model
11	5-LM – Five-gram Language Model
12	*ClassLM* – Nine-gram class-based LM
13	*WordPost – Word Posterior*

Decoder Development

- **A phrase-based Viterbi beam search decoder has been implemented**
- **Decoder can account for word movement between source and target languages (*distortion*)**
  - **With distortion, search complexity approaches $O(2^n)$**
- **Decoding speed:**
  - **Monotone search (without distortion) can exceed 500 words per second**
  - **With distortion, search slows to 10 words per second but can be improved with limits on distortion**
- **Decoder can produce word lattice output for optional second pass rescoring with higher order language models**



TrueCasing

Problem

- **Reduced vocabulary size of lower cased training data often results in better models**
- **However, lower cased output has reduced readability and may affect other down stream processing such as named entity detection**
- **TrueCasing is the process of reintroducing case information to the translated output**
- **Example:**
  - **the it department at intel is hiring cs majors.**
  - **The IT department at Intel is hiring CS majors.**

TrueCasing
Design (cont)

- **Problem can be solved by searching through all possible capitalizations seen in the training set and choosing the most probable result**

$$\hat{W} = \arg\max_{W_i} P_{lm}(W_i) \prod_{w \in W_i} P_m(w_{uc}|w_{lc})$$

  - **P_{lm} is the case-sensitive language model probability of candidate word sequence W_i**
  - **P_m is the unigram probability of each possible case mapping given a lower cased input word**

- **Can be easily implemented using the SRILM toolkit**

TrueCased Output

Results

BLEU scores with lower and mixed case references

Input \ Reference	Lower case	Mixed Case
Lower Case	54.45	40.65
Mixed Case		52.51

- **Used 5-gram LM and case mapping probabilities based on relative frequencies from training data**
- **Upper bound on performance is 45.04 when scoring against lower cased reference**
- **TrueCasing the MT output increases the BLEU score by more than 10 points when scored against the mixed case reference**

Text Evaluation Results

What Worked

Parameters Varied	
Minimum Error Rate Training	Additional Language Models (4-gram and 5-gram)
Truecasing	Word Posteriors

Configurations	BLEU
Base: UTF-8, no MER, trigram LM	*46.03*
+ Additional LMs	47.00
+ Additional LMs + MER + Default Tuning	54.07
+ Additional LMs + Word Posteriors + MER	54.23
+ Additional LMs + MER + Best Tuning	**54.45**
+ True-cased	52.51

Text Evaluation Results (Cont')

What Didn't Worked

Parameters Varied	
Stemmed LMs	Other LMs (bigram, 6-8 gram, skip LMs)
Class-based LMs	

Configurations	BLEU
Best Combination + MER	***54.45***
+ Other LMs + MER	54.20
+ Class LMs + MER	54.00
+ Stemmed LMs + MER	54.09
+ Skipped LMs + MER	53.85

ASR Transcription Results

- **ASR**
  - **Baseline Verbatim Results w/LIMSI ASR (9.8% WER): 45.10**
  - **Scored N-best using confusion net posteriors**
    - **Renormalized posterior mass to 1.0, ASR weight = 3.0**
  - **Compared 1-best vs. N-best**
    - ***Using Nbest ⇨ 2-4% relative improvement***
  - **Used system optimized with verbatim transcription and cleaned LMs**
  - **N-best and confusion network (FST-based) decoders were used**

N-best	Decoder Used	BLEU
1	Viterbi	40.33
1	FST	39.40
50 from conf-net	Viterbi	41.37
Full conf-net	FST	39.94

Continuing Experiments

Tag-based Translation Models

- **Motivation**
  - **Word-to-word translation cases generate poor output**
  - **Need “templates” in back-off conditions**
  - **Example:**

	Source	MT	Reference
Test Example	`el día 9 hemos celebrado igualmente`	`the | day | 9 we | held | equally`	`on the 9 we likewise celebrated`
Test Tag	**DA NC Z VAI VMP RB**	**DT NN CD PRP VBZ RB**	**IN DT CD PRP RB VBZ**

Can we learn this generalization of the example?

Continuing Experiments
Tag-based Translation Models II

- **Proposed method**
  - **Tag-based TMs decoded in parallel with text TMs**
  - **Related to Factored Translation Model Approach**
  - **Models combined in log-linear way (MER optimization)**

- **Status**
  - **Retagged train, dev and test data. Optimized tag models independent of text models.**
  - **Training on Openlab data tagged yields good patterns**

	MT	Reference
Text Translation	`The day 9 we held equally`	`on the 9 we likewise celebrated`
Text Tags	DT NN CD PRP VBZ RB	IN DT CD PRP RB VBZ
Tag Translation Result	IN DT CD PRP RB VBZ	

Summary

- The MIT/AFRL MT system is capable of state-of-the-art performance on a Spanish-English task in both ASR and manual transcription conditions
- Many in-house components were built, but we also rely on the existence of freely available components such as GIZA++ and SRILM to accelerate development
- Further research into error mitigation techniques for speech to speech machine translation is needed

Next Steps

- **ASR Lattice rescoring and joint optimization**
  - **Further FST Decoder engineering needed**
- **Decoder development and evaluation**
- **Further optimization to large vocabulary tasks**
  - **LM normalization**
  - **Specialized entity/number translation modules**
- **Hybrid Interlingual efforts with MIT/CSAIL**