The MIT-LL/AFRL IWSLT-2008 MT System

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Outline

System Overview

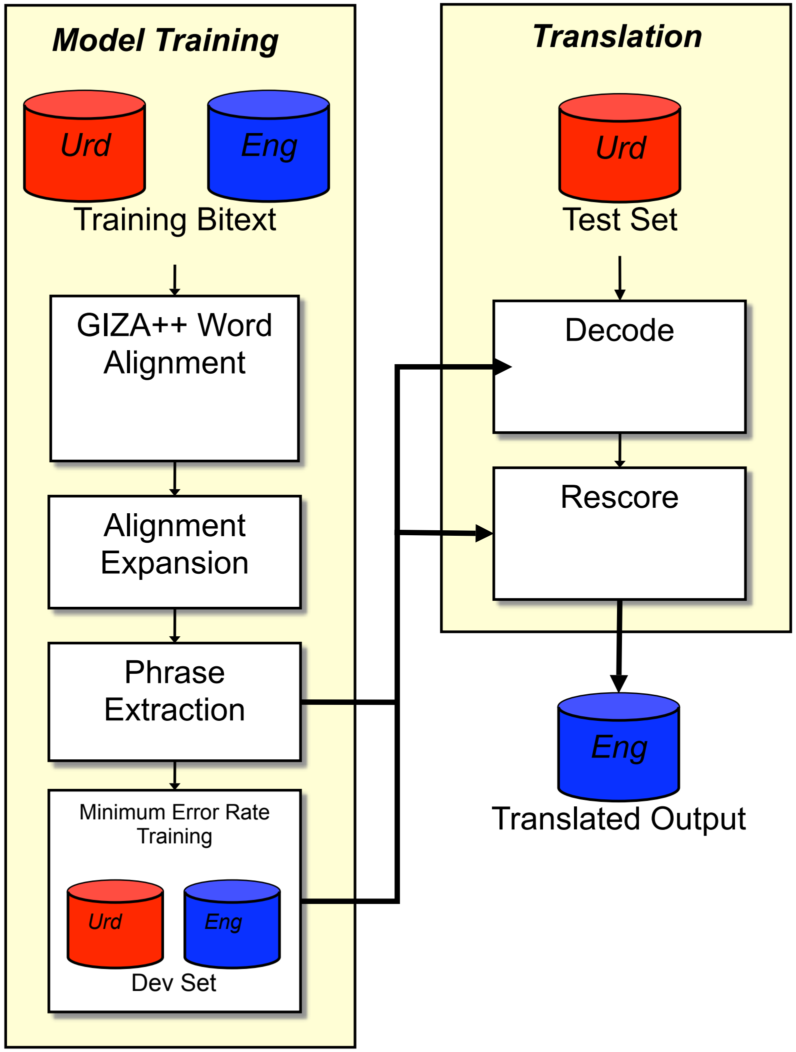
What's New in 2008?

- Segmentation Models
- System Combination
- Improved Arabic Morphological Processing
- Added Data
- Additional Improvements

Summary

Statistical Translation System

- **Standard Statistical Architecture**
- **Developed in-house to support SMT experiments**
  - **Framework for experiments with low-resource languages**
  - **Test-bed for S2S MT system**
- **Custom Components**
  - **FST-based Decoder**
  - **Segment EM Aligner/Decoder**
  - **MBR Rescoring**
  - **System Combination**
  - **Phrase Training/Minimum Error Rate Training**
- **Use Moses decoder for baseline systems**



Phrase Based FST Decoder

- Based on MIT FST toolkit: http://people.csail.mit.edu/ilh/fst/

- The target language hypothesis is the best path through the following transducer:

$$E = I \circ P \circ D \circ T \circ L$$

- where,
  - I = source language input acceptor
  - P = phrase segmentation transducer
  - D = weighted phrase swapping transducer
  - T = weighted phrase translation transducer (source phrases to target words)
  - L = weighted target language model acceptor

- Apply phrase swapping twice for long distance reordering

- OOV words are inserted during decoding as parallel links to P, D, T, and L models.

- Allows for direct decoding on pruned ASR lattices

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Segmentation Models

Introduction

- **Scoring the Phrase-based Models**

$$P(\mathbf{E}|\mathbf{F}) \propto P(\mathbf{E})P(\mathbf{F}|\mathbf{E})$$

$$\approx P(\mathbf{E}) \max_{(\mathbf{f},\mathbf{e})_1^k \in seg(\mathbf{F},\mathbf{E})} p((\mathbf{f},\mathbf{e})_1^k) * \prod_{i=1}^{k} p(\mathbf{f_i}|\mathbf{e_i})$$

Segmentation Models

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Normally uniform or phrase penalty: $p((\mathbf{f},\mathbf{e})_1^k) \approx e^{-\rho k}$

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- **constant phrase penalty (bonus)**

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Segment EM Models

Framework

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$$p(\mathbf{f_i}|F) \approx p(\mathbf{f_i}|\lambda) \approx \frac{E_{\mathcal{F}}(\mathbf{f_i}|\lambda)}{N_{\mathcal{F}}(\mathbf{f_i})}$$

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Expected number of f_i from forced alignment

Number of possible occurrences of f_i

Segment EM Models

Training Procedure

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1. Train standard phrase-based model

Segment EM Models

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1. **Train standard phrase-based model**
2. **Augment phrase model probabilities with initial segmentation probabilities**

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5. Reestimate segmentation probabilities using equations (M-step)
6. MER training to optimize model exponents (λs)
7. Repeat 2-6

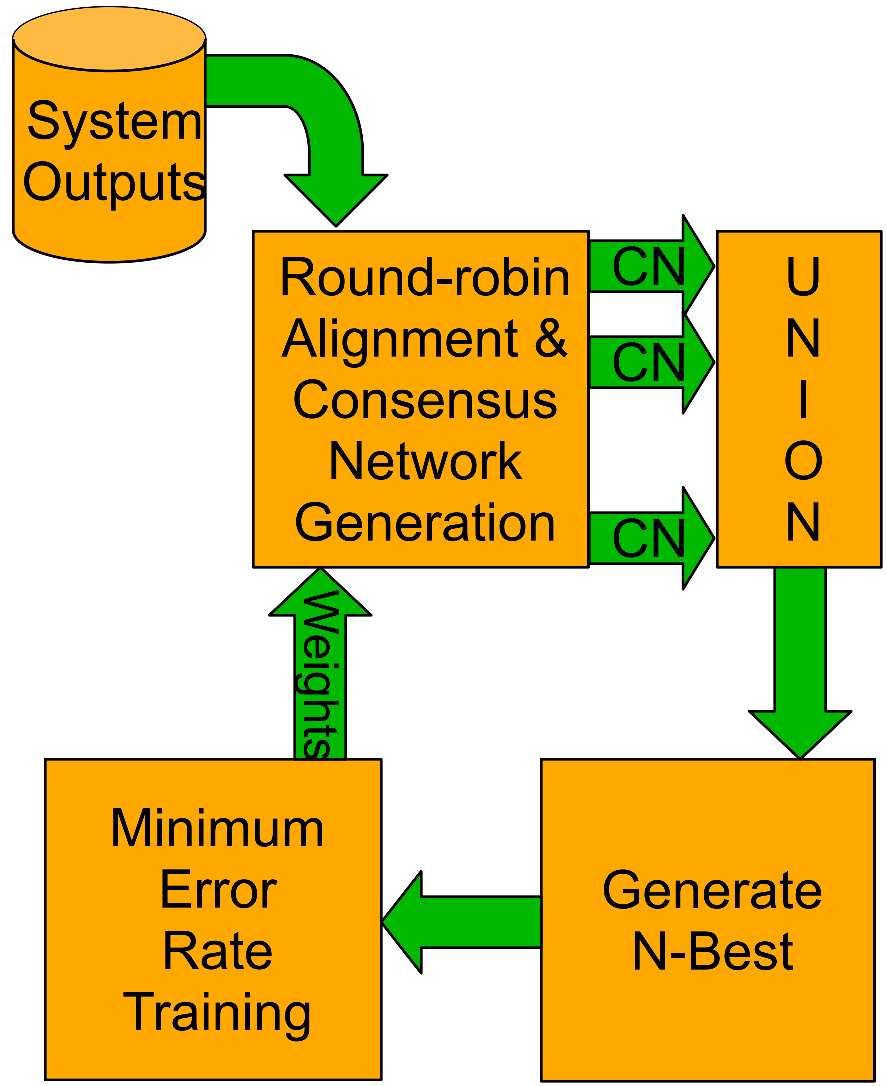
Chinese Experiments

System	dev7	dev3
Baseline (no rescoring)	39.6	52.9
+ phrase segmentation models	40.3	53.6
Baseline (with rescoring)	42.1	53.8
+ phrase segmentation models (iter=3)	42.8	54.1

- Segmentation Models improve overall on dev experiments
  - Even with one iteration of training only
- Multiple iterations + rescoring (post-eval) showed improvements
  - Submitted results had no rescoring, one iter only

System Combination

- Generate consensus networks using round-robin TER alignment, where each system gets to be the skeleton alignment
- Take union of all consensus networks and apply a language model
- Weight optimization via Nelder-Meade simplex on a development set using n-best lists
  - Individual system weights, language model, word penalty, system priors
- Final combination on unseen data using optimized weights



System Combination Results

Chinese-to-English

CRR Input

System	dev3	eval
CE-contrast4	53.75	36.91
CE-contrast1	52.92	*37.78*
CE-contrast3	52.76	35.35
CE-contrast2	52.45	36.51
Combined		*37.92*

ASR Input

System	Input	dev3	eval
CE-contrast4	Conf. Net	45.80	*31.93*
CE-contrast3	1-Best	41.70	31.13
CE-contrast2	1-Best	41.65	31.41
CE-contrast7	Lattice	39.70	30.66
CE-contrast6	Lattice	38.84	31.02
Combined			*35.38*

- Used dev3 to train system combination weights
- CRR input condition
  - +0.14 BLEU → combination weights prefer CE-contrast4 which outperforms CE-contrast1 on dev3 but not on eval
- ASR input condition
  - +3.45 BLEU → significant gain by combining systems with varying input sources (1-Best vs. lattice vs. confusion network)

System Combination Results

Arabic-to-English

CRR Input

System	dev5	eval
AE-contrast4	27.95	*55.07*
AE-contrast3	27.91	54.91
AE-contrast1	26.03	50.81
AE-contrast2	28.25	51.79
Combined		56.51

ASR Input

System	Input	dev5	eval
AE-contrast4	Conf. Net	25.69	45.31
AE-contrast3	1-Best	25.34	*45.63*
AE-contrast1	Lattice	24.53	44.49
AE-contrast2	1-Best	23.44	44.35
Combined			*48.92*

- Used dev5 to train system combination weights (different ASR systems?)
- CRR input condition
  - +1.44 BLEU → decent gain despite change in system ranking between dev5 & eval sets
- ASR input condition
  - +3.29 BLEU → significant gain by combining systems with varying input sources (1-Best vs. lattice vs. confusion network)

Arabic Preprocessing

Preprocessing Method	Dev6
Baseline (No normalization or AP5)	**42.06**
Remove all diacritics except tanween, no AP5	**49.40**
Remove all diacritics, no AP5	**50.39**
Remove all diacritics, apply AP5	**53.55**

- Diacritics removed:
  - **Short vowels**
  - **Sukuun:** Marks absence of sort vowel
  - **Shadda:** Marks consonant gemination (i.e., doubling)
  - **Tanween:** Case markers for indefinite forms & other uses
  - **Tatweel:** Stretches letters in Arabic typography (not a true diacritic)
- AP5 segments the following from stems:
  - **Prefixes:** al-, bi-, fa-, ka-, li-, wa-
  - **Suffixes:** Attached pronouns

Additional Parallel and Monolingual Data

Chinese ↔ English Tasks

- **Additional parallel data (out of domain) improves system**
  - *Added ISI Chinese-English parallel corpus to training*
- **Additional English data also helps:** *Added Gigaword LMs*
- **ISI data not used for evaluation systems**

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	Configurations	Language Models			Eval Set	
		Decode	Rescore	Class	MAP	MBR
Chinese to English	Baseline System	*4g,5g*		*7g*	**53.32**	**53.50**
	+ ISI ||-corpus	*4g*	*4g ISI*	*7g*	**55.30**	**54.28**
	+ English Gigaword	*4g*	*6g GIGA*	*7g*	**54.60**	**54.10**

	Configurations	Language Models			Eval Set	
		Decode	Rescore	Class	MAP	MBR
English to Chinese	Baseline System	*4g,5g*		*7g*	**29.75**	**29.88**
	+ ISI ||-corpus	*4g*	*5g ISI*	*7g*	**30.76**	**31.60**

Other Improvements

- **Minimum Bayes Risk Rescoring**
  - Results mixed: Improve E->C task (eval), C->E (dev only)
- **Added Phrases from Berkeley Aligner**
  - Consistent +0.5 point gain
- **Additional Lexicon Data (C->E) from CEDICT**
  - 0.5-1.0 improvement depending on DEV set
- **Improved Confusion Network decoding**
  - Language model/acoustic model optimization separated
  - Better word splitting from LIG [Besacier 07]
  - Improvement: ~0.5-1.0 points
- **Lexical Approximation [Mermer 07]: +0.5 points**

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- **Segment-EM Model**
  - Preliminary results show modest improvement
- **Improved System Combination**
  - Results from ASR are especially promising for both Arabic and Chinese
- **Better morphology for Arabic**
  - Significant improvements from AP5 diacritic norm, and Lexical Approximation
  - More normalizations could further improve phrase estimation
- **Make better use of out-of-domain data**
  - Some improvements this year from ISI arabic data and GIGAWORD