The CMU-UKA Statistical Machine Translation Systems for IWSLT 2007

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Overview

- Overview of submission systems
- Research Topics Investigated
  - **Topic-Aware Spoken Language Translation**
  - **Morphological-Decomposition for Arabic SMT**
  - Comparison of Punctuation-Recovery Approaches

Submission Systems

Submission Systems ("diversity")

- Submissions made for three language pairs
- All systems based on phrase-based SMT
- Each language-pair focused on specific research area

Language Pair	System Description	Rank (1)
Japanese → English	SMT with Punctuation Recovery / Topic-based N-best-list rescoring	1
Chinese → English	Syntax Augmented SMT	3
Arabic → English	SMT with Morphological Decomposition	7

(1) Spoken language translation task - ASR (BLEU)

Japanese Submission System

Training Corpora	IWSLT-training, IWSLT-dev1-3, Tanaka
Corpora-size	200k sentence pairs, 2M words
Phrase-Extraction	PESA **[Vogel05]**
LMs	6-gram SA-LM 4-gram interpolated n-gram LM
Reordering Window	6
Decoder	STTK (phrase-based SMT) **[Vogel03]**

- Punctuation estimated on source-side via HELM
- N-best candidates rescored: **Topic-Confidence Scores**

Chinese Submission System

Training Corpora	IWSLT-training, IWSLT-dev1-3,5
Corpora-size	67k sentence pairs
Rule-Extraction	Giza++, Pharaoh, Stanford-parser
Decoder	SAMT [www.cs.cmu.edu/~zollmann/samt]

- Identical to IWSLT 2006 submission system
  - Improved efficiency and robustness decoder
    "to handle GALE size data"
  - Slight increase in training data
- See IWSLT 2006 paper for detailed system description

Arabic Submission System

Training Corpora	IWSLT-training
Corpora-size	20k sentence pairs
Phrase-Extraction	Giza++, Pharoah
Decoder	STTK (phrase-based SMT) **[Vogel03]**

- **Morphological decomposition** performed using **[Smith05]**
- **30% of morphemes discarded** to obtain source/target ratio close to 1

Research Topics

- **Topic-aware SLT**
  - Apply utterance-level topic constraints for SLT
- **Morphological-Decomposition for Arabic SMT**
  - Decompose Arabic words into morphemes
  - Discard “un-necessary” morphemes before translation
- Comparison of Punctuation Recovery Techniques (described in paper)

Topic-aware SLT

Topic-aware SLT

- Previous work have focused on document level adaptation for translation of monologue data
  - Bi-LSA: Adaptation of Target-LM [Tam07]
  - Adaptation of IBM-1 Lexicon [Tam07]
  - Bi-TAM: Incorporate *topic* during alignment [Zhao06]
- Investigate approach, appropriate for spoken dialogue (applicable to small training corpora)
- Apply independently to each utterance

Topic-aware SLT

- Apply topic-constraints within SLT

  → **Detect topic of discourse and apply topic-constraints during translation**

- Investigate two additional feature-functions
  - **Topic-Dependent LM Score**
  - **Topic-Confidence Scores**

- Rescore N-best trans. candidates incorporating above scores

Description of Scores

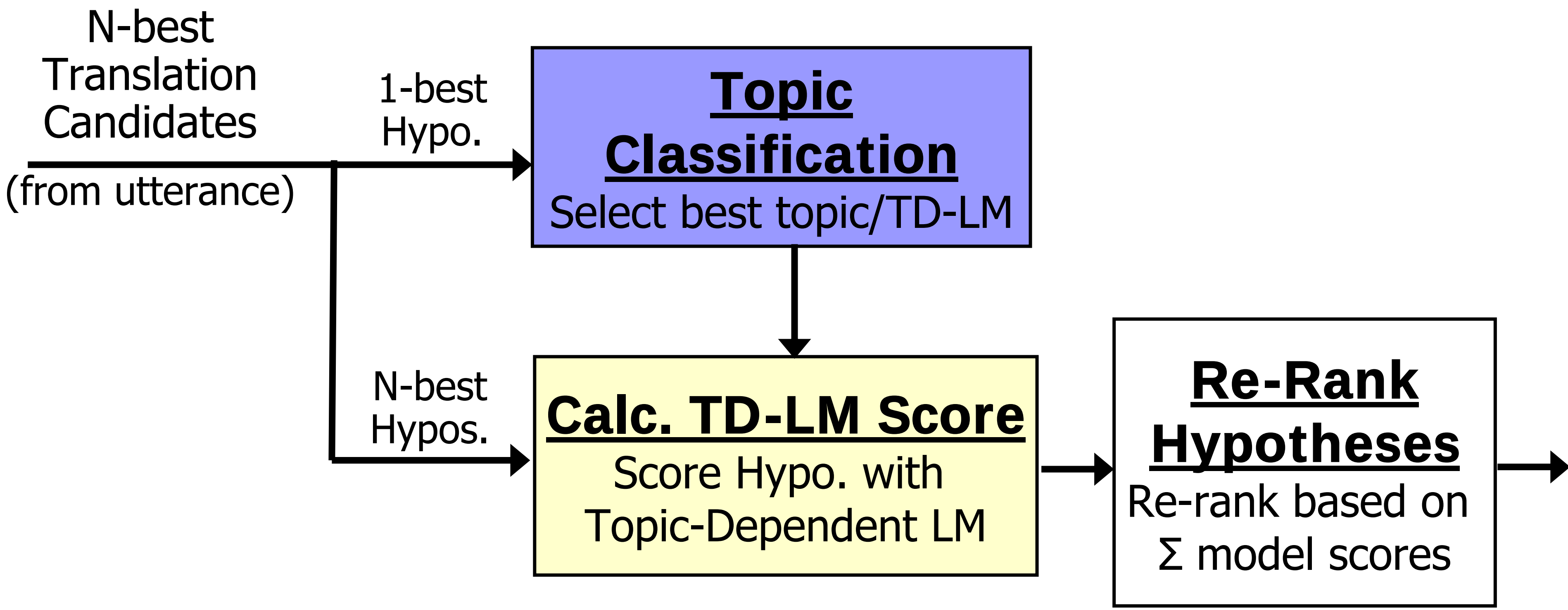
Topic-Dependent LM Score

- Topic-specific LM should better discriminate between acceptable and bad translations
- Add additional Topic-Dependent LM score

Topic Confidence Score

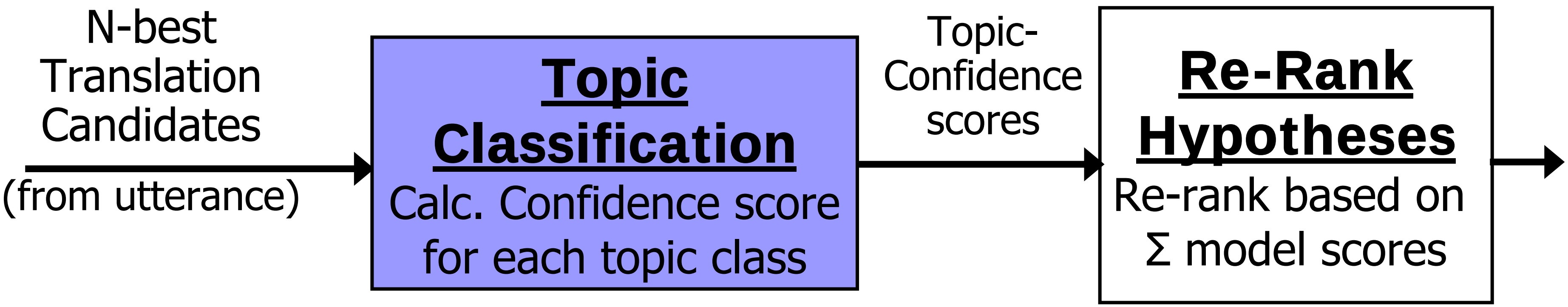
- No constraint to maintain topic consistency within translation hypothesis
- Visual inspecting identified the following:
  - "Good" translation hypotheses typically obtained high topic-confidence score (for a single topic)
  - "Bad" translations typically obtained low-confidence scores for all topics

Topic-Dependent LM Scores



1. Select topic of utterance by 1-best hypo.
2. Generate additional score by applying TD-LM to each hypothesis
3. Re-rank N-best hypotheses based on log-lin. Σ model scores

Topic-Confidence Scores



1. Calculate topic confidence score [0,1] for each topic class
2. Re-rank N-best hypotheses based on log-lin. Σ model scores (features used during decoding (10) + *M* topic confidence scores)

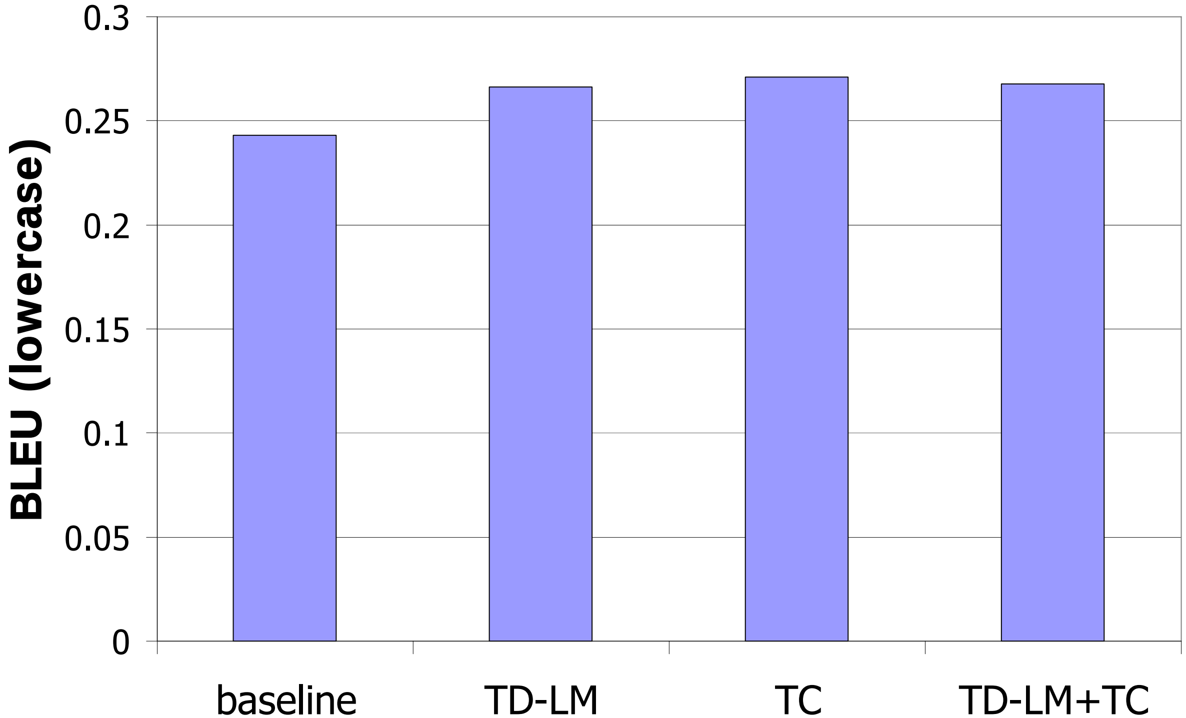
Experimental Evaluation

- **Topic Class Definition**
  - Training corpora split into eight classes
    - Hierarchical clustering, minimize global perplexity
- **Topic Models**
  - SVM classification models trained for each class
    - **Features:** word, word-pairs and 3-grams
  - TD-LMs trained for each topic class
- **Tuning / Evaluation Sets**
  - MERT Set: IWSLT06-dev.
  - Eval. Set: IWSLT06-eval, IWSLT07-eval

Effectiveness on '06 Eval. Set

- **Baseline:** JE phrase-based SMT system (described earlier)

TDLM: Topic-Dependent LMs **TC:** Topic Confidence Scores

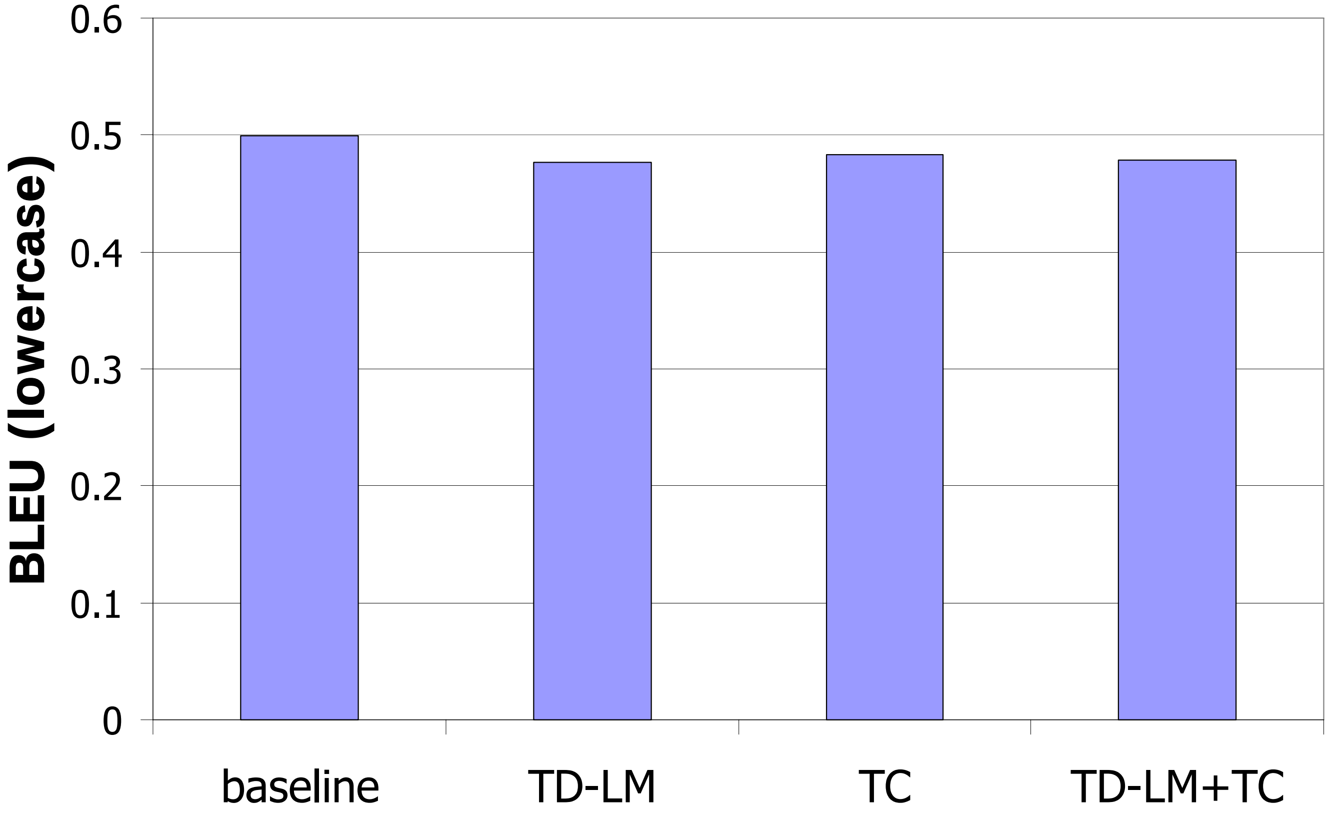


- Both TDLM and TC feature sets improve translation performance (0.0022 and 0.0027 BLEU-points respectively)

→ **Use Topic-Confidence scores in submission system**

Effectiveness on ‘07 Eval. Set

TDLM: Topic-Dependent LMs **TC:** Topic Confidence Scores



- Slight degradation in BLEU-score on 2007 Evaluation-Set (0.4990 → 0.4828)
- ‘06 Eval.-set typically contained multiple sentences per utterance

→ Maintains topic-consistency between sentences (mismatch with ‘07 Eval. set)

Morphological-Decomposition for Arabic SMT

Morphological-Decomposition for Arabic SMT

- Traditional word-alignment models assume similar number of source/target tokens
- For diverse language-pairs significant mismatch
  - Highly agglomerative language (Arabic)
  - Non-agglomerative language (English)

- Decompose Arabic words into prefix/stem/suffix morphemes
  → Also improve translation coverage
  - Able to translate unseen Arabic words at Morpheme-level

Morphological-Decomposition for Arabic SMT

- Prefix / stem / suffix of an Arabic word often corresponds to individual English word

Prefix:	conjunction:	*wa* → and
	article:	*Al* → the
	preposition:	*li* → to/for
Suffix:	Pronoun:	*hm* → their/them

- Some specific morphemes are redundant in A→E trans.

  → **can be discarded during translation**

Suffix:	Gender:	*f* → female singular
	Case marker, number, voice, etc..	

Proposed Approach

- Previous works [Habash06] used manually defined rules to remove inflectional features before translation

- Data driven approach to discard non-informative morphemes

1. Perform full morphological decomposition on Arabic-side
2. Align training corpora: Arabic morpheme-level / English word-level
3. Discard morphemes with zero-fertility > θ_{th}

   Morphemes not aligned to any English word → high zero-fertility

   Morphemes typically aligned to a English word → low zero-fertility

Experimental Evaluation

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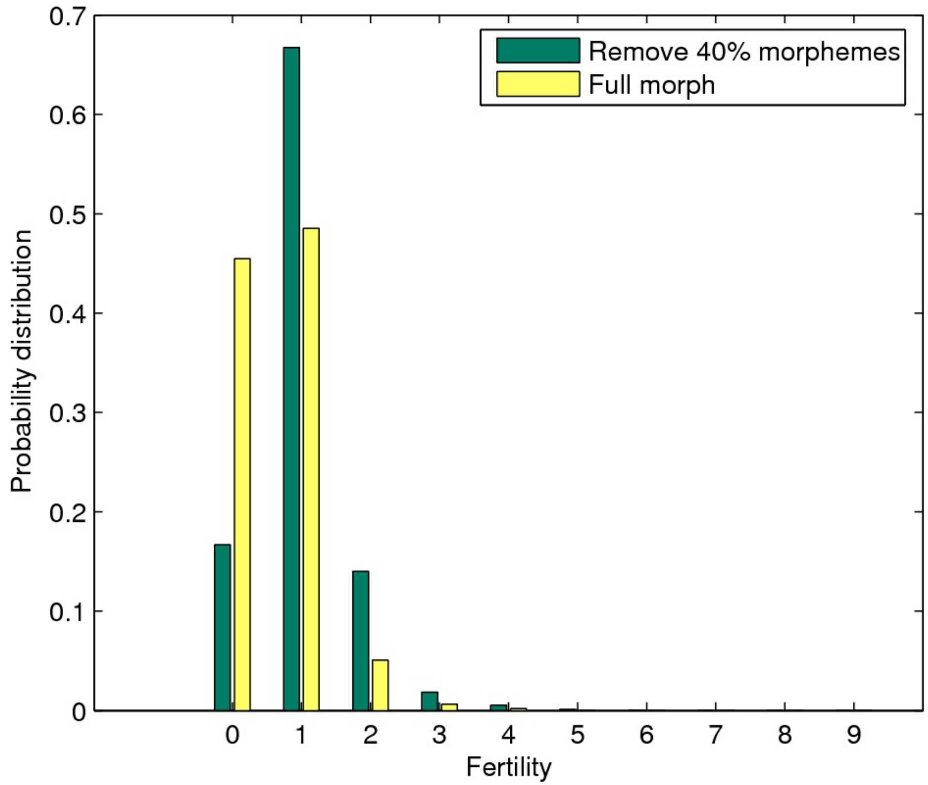
Morpheme Removal (fertility)

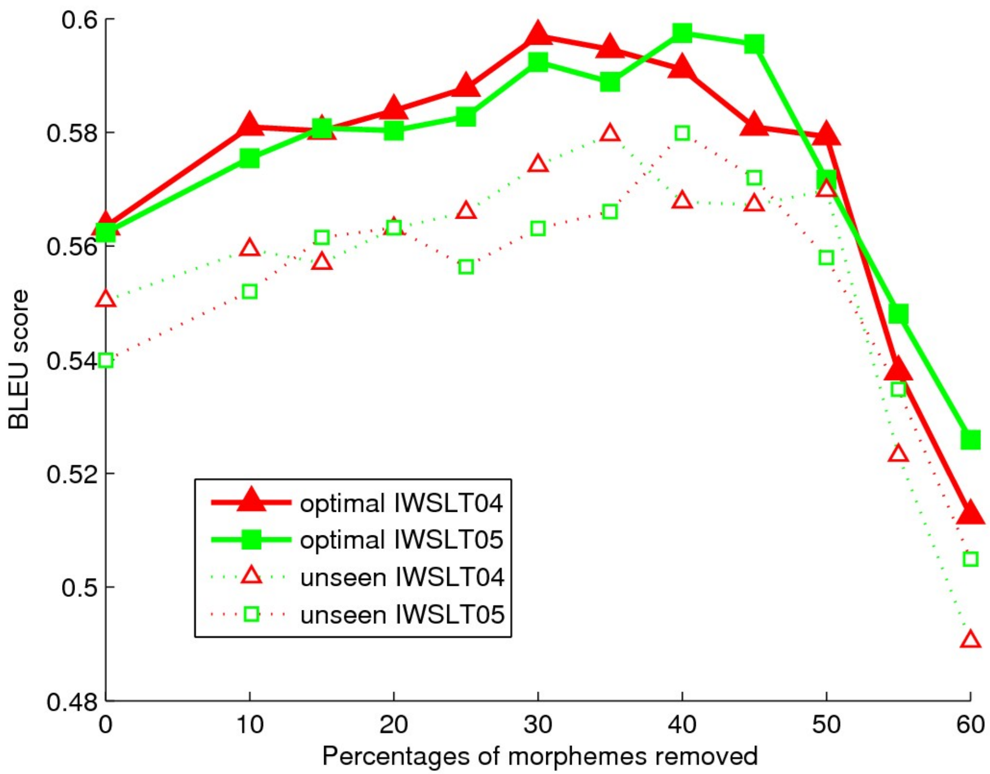
- From 158k Arabic wrds obtain 294k morph. (190k English wrds)
- Manually set θ_{th} to discard 40% of morphemes



- Discarding morphemes with high zero-fertility normalizes source/target ratio
- Shifts fertility peak > 1.0

Morpheme Removal (Trans. Quality)

- Manually set θ_{th} to discard ?% of morphemes



- Discarding 30-40% of morphemes obtains highest BLEU score
- Improved BLEU 0.5573 → 0.5631 (IWSLT05 held-out eval.-set)

Conclusions

Conclusions

- Developed evaluation systems for 3 language-pairs
  - Each language-pair focused on specific research topic
- **Punctuation Recovery**
  - Best performance obtained with source-side HELM estimation
- **Topic-aware SLT**
  - Significant improvement in performance obtained for multi-sentence utterances (IWSLT 2006 evaluation set)
  - Topic-Classification Scores more effective than TD-LM
- Morphological-Decomposition for Arabic SMT
  - Improved BLEU by applying morphological decomposition and discarding 30% morphemes with highest zero-fertility

Thank you

Other Slides

Punctuation Recovery for SLT

Punctuation Recovery for SLT

	Precision	Recall	F-score
	97.8%	96.8%	97.3%
	82.1%	44.2%	57.5%
	96.4%	95.9%	96.2%
	71.8%	43.6%	54.3%
	100%	63.9%	77.9%

Topic-aware SLT