

**The Johns Hopkins University 2004
Chinese-English and Arabic-English
MT Evaluation Systems**

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The Development of the Translation Template Model

- **Investigation of Weighted Finite State Transducer Frameworks for SMT**
 - Interested in WFST techniques from work in ASR
 - WFST Formulation of IBM-3 model (Knight and Al-Onaizan '98)
 - Basis for Minimum Bayes-Risk word alignments of bitexts (Kumar and Byrne '02)
- **Quest for a powerful SMT framework**
 - Alignment Template Translation Model (Och, Tillmann and Ney '99)
 - Overcomes weakness of IBM-style models by phrase translations
 - Formulation and Implementation of WFST-ATTM (Kumar and Byrne '03)
 - Basis for JHU 2003 Chinese-English system
- **Translation Template Model (Kumar and Byrne '04)**
 - Correct integration of Language and Translation Models via Source-Channel Formulation
 - Ignores word alignments within phrase-pairs
 - Allow insertions of Target (French) phrases in the generative translation process
 - Easily scaled up to large bitexts

The Development of the 2004 MT Evaluation Systems

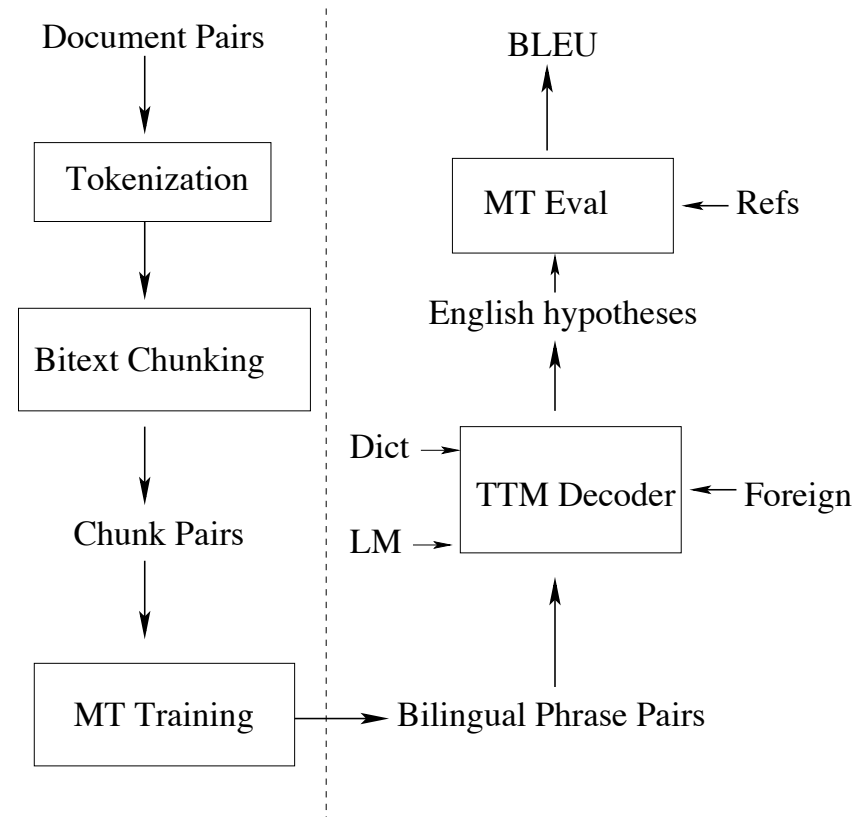
- Need to use all the available bitext for MT training
- Need better language modeling
 - More monolingual text
 - FSM implementations of arbitrary n-gram LMs (4-grams)
- Evaluation of all model components in terms of overall system BLEU
- We failed in all attempts to incorporate "linguistic knowledge" & improve BLEU
 - Morphology, Named entities, Syntax (Kumar and Byrne, HLT '04)
 - Modeling phrase movement did not help
- Multiple phrase segmentations of source sentence is essential in translation
- Eval '04 systems mainly developed by two graduate students (S. Kumar and Y. Deng)
- C-E system was developed in under a month
- A-E system was developed in under two weeks

Outline

- Bitext Chunking
- Translation Template Model
- Evaluation Systems

Bitext Chunking

- Goal
 - chop up document aligned bitext into smaller chunk pairs for Translation Model training.
 - improve chunking to improve translation performance
 - coarse Models of aligning documents in terms of subsentence segments
- Desired properties
 - High efficiency, discard as little as possible
 - Chunks are subsentences
 - Start from scratch, language independent, minimal linguistic knowledge required

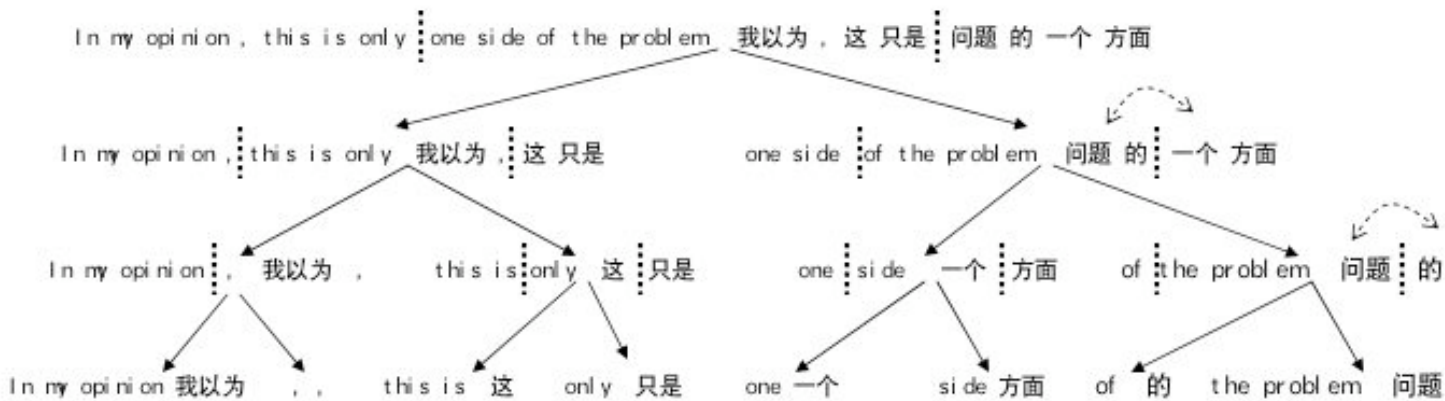


Stochastic Models of Bitext Chunking

- Coarse Models of aligning documents in terms of subsentence segments
- Define probability distribution over bitext documents and bitext chunks
- Incorporate any word translation model, e.g. IBM Model 1
- Different modeling assumptions lead to different alignment algorithms
 - Dynamic Programming (DP) [similar to Gale & Church '91]
 - Divisive Clustering (DC)

Divisive Clustering

- Modeling assumption
 - Smaller chunks are generated by binary splitting of bigger chunks
- Iteratively obtain a finer alignment by successive binary splitting
 - Reordering enables complicated linking structures between segments
- Potential splitting points
 - English, Chinese: at punctuations; Arabic : all words
- Model assigns likelihood to chunks produced
 - Simple length and likelihood based stopping rule
- Not parsing
 - strictly text string segmentation driven by word-to-word translation probs (Model 1)

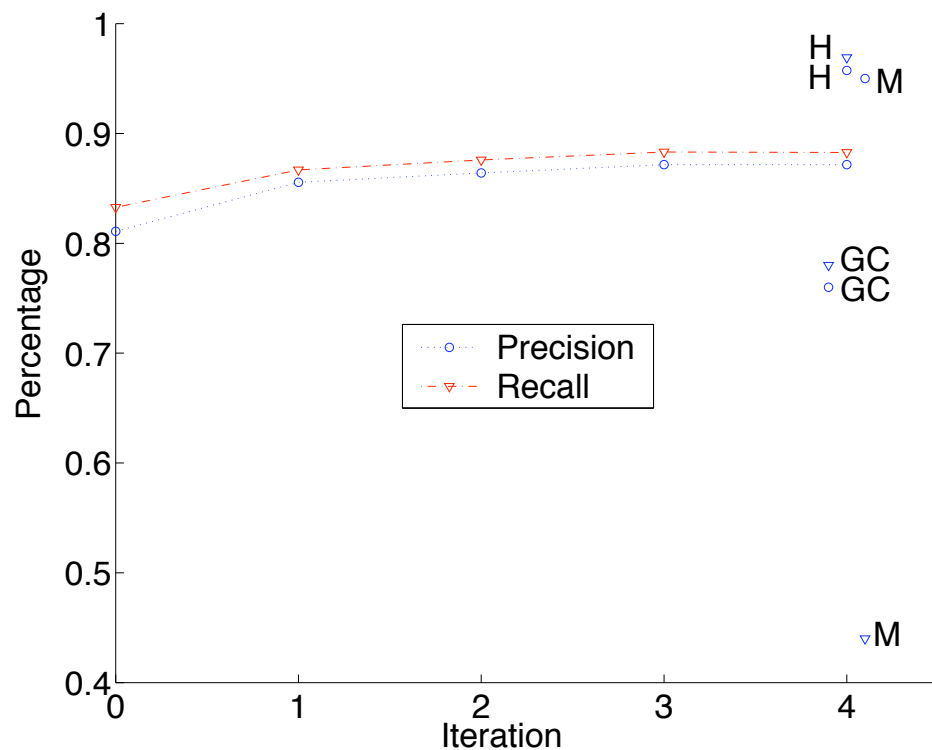


Why Divisive Clustering (DC)?

- Deriving short chunk pairs by going below sentence level
- Practical benefits
 - Shorter bitext segments can lead to quicker training of MT systems
 - Thorough exploitation of all available bitext
- DP vs. DC
 - DP: global scale, sequential links
 - DC: local optimal, swapping links
- Two level alignment procedure DP+DC
 - Initial steps DP - produce a coarse alignment by allowing big chunks
 - Refine by DC

Sentence Alignment Experiments

- If we restrict chopping points to sentence boundaries, we have a sentence aligner
- Unsupervised alignment of 122 Chinese/English documents from FBIS corpus
 - reference alignments were created manually
- Different algorithms have different operating points
- We benefit through iterative estimation of Model 1
- When Model 1 is estimated from manual sentence alignments, we get best Pre/Rec



- GC: (Gale & Church '91) aligner
- M: (Moore '02) aligner
- H: DP+DC w/ model trained from manually aligned pairs

DC Improves MT Performance

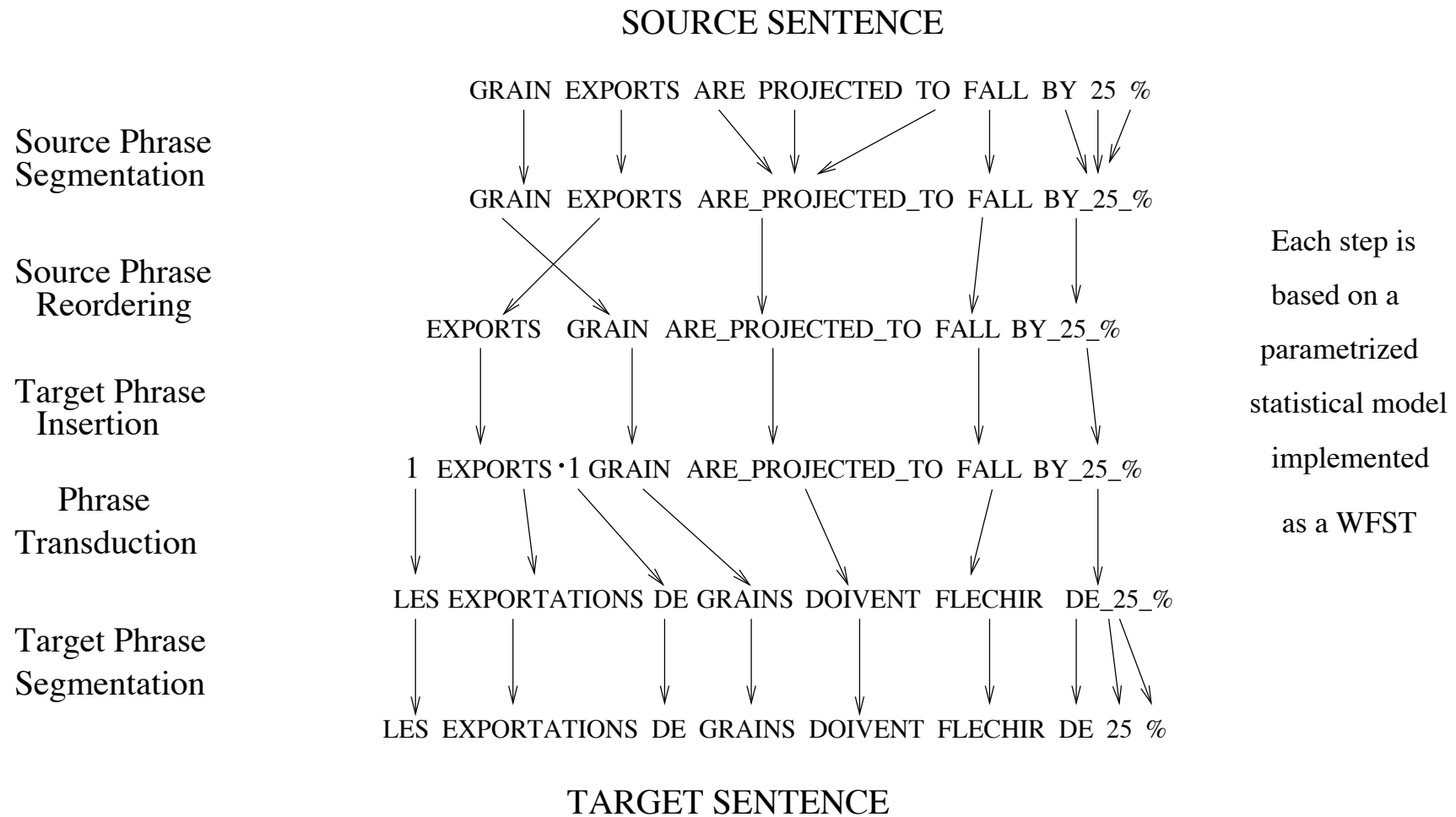
- Chinese/English bitext
 - start from scratch
 - processed by 2 iteration DP+DC procedures
- Arabic/English bitext
 - Keep existing sentence pairs (w/ <60 words) from LDC alignments
 - Apply DC to long sentence pairs
 - Percentage of usable Arabic bitext for MT training

| | total English words(M) | Sent. Aligned Bitext | Sent. Aligned Bitext + DC |
|------------------------------------|------------------------|----------------------|---------------------------|
| News | 3.59 | 67% | 98% |
| UN | 131 | 74% | 98% |
| BLEU with chunks from News: eval02 | | 33.0 | 33.9 |
| eval03 | | 35.4 | 36.1 |

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Generative Translation Process Underlying the TTM



Investigative Experiments

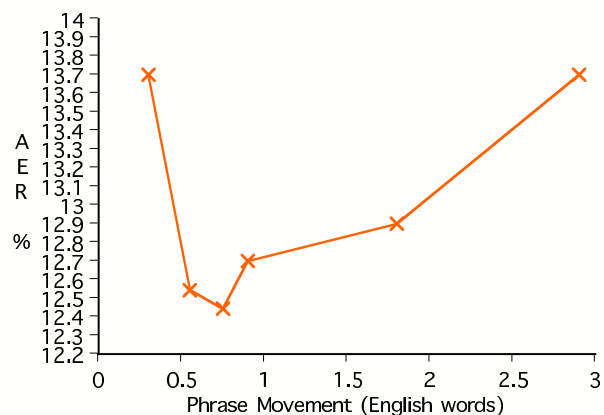
Goal: Identify contribution of each TTM component to the overall alignment and translation performance

- Effect of Phrase-level movement on Word Alignment
- Effect of Coverage of the Test Set (by the Phrase-Pair Inventory) on Translation
- For more experiments, see CLSP Research Note 48 (Kumar and Byrne '04)

Given the TTM, does allowing phrase-level movement help word alignment ?

- Task: French-English Hansards (Train: 48K pairs, Test: 500 sents)
- Generate an N-best list of reordered phrase sequences under TTM
- By varying Phrase Exclusion Probability (PEP), we can search over reorderings of the English phrase sequence to find optimal Alignment Error Rate (AER)
- Allows us to plot Phrase movement versus AER under the TTM (over the N-best list)

With a fixed number of reorderings (N=400),
vary PEP



- At optimum AER, phrases move less than 1 word on average

With PEP fixed at optimal value, vary # of reorderings

| # of reords. | AER (%) | Avg. Movement |
|--------------|---------|---------------|
| None | 12.8 | 0.0 |
| 1 | 12.8 | 0.2 |
| 200 | 12.5 | 0.7 |
| 1000 | 12.5 | 0.8 |

- Conclusion: Given current model, allowing phrases to move doesn't help AER
- Based on this, we construct our system to disallow phrase-level movement, allow only word-level movement within phrase-pairs

Coverage of the Test Set by the Phrase-Pair Inventory (PPI)

- Task: French-English Hansards (Train: 48K sent. pairs, Test: 500 sents)
- Train IBM-4 models on all bitext (48K sentence pairs) and obtain word alignments
- Collect Phrase Pair Inventories over 4 subsets of these word alignments (Och '02)
 - Alignment quality over these variable size inventories is held constant
- Coverage = % of phrases in the test set that exist in the PPI

| # of sentence-pairs (K) | Test-Set Coverage (%) | BLEU (%) |
|-------------------------|-----------------------|----------|
| 5 | 20.79 | 19.6 |
| 12 | 26.75 | 20.8 |
| 24 | 31.35 | 21.5 |
| 48 | 36.02 | 22.3 |

- A higher coverage of the test set by PPI improves translation performance

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Text Processing and Bitexts

Text Processing

- Chinese Text segmented into words using LDC segmenter
- Arabic Text processing pipeline
 - Modified Buckwalter analyzer (D. Smith)
 - Post Processing to separate conjunctions, prepositions, AI- and pronouns
 - AI- and w- deletion (maybe wrong decision!)
- English Text processed using a simple tokenizer

Bitext for Translation Model Training

| | Chinese-English | Arabic-English | |
|----------------------|-----------------|----------------|---------------|
| | | Primary | Late Contrast |
| # of sent. pairs (K) | - | 68.0 | - |
| # of chunk pairs (M) | 7.6 | N/A | 5.1 |
| # of words (M) | 175.7/207.4 | 2.0/2.1 | 123.0/132.5 |

English Language Models

| Source | Xin | AFP | PD | FBIS | UN | AR-news | Total |
|----------|-------|-------|------|------|-------|---------|-------|
| C-E | | | | | | | |
| Small 3g | 4.3 | - | 16.2 | - | - | - | 20.5 |
| Big 3g | 155.7 | 200.8 | 16.2 | 10.5 | - | - | 373.3 |
| Big 4g | 155.7 | 200.8 | 16.2 | 10.5 | - | - | 373.3 |
| A-E | | | | | | | |
| Small 3g | 63.1 | 200.8 | - | - | - | 2.1 | 266.0 |
| Big 3g | 83.0 | 210.0 | - | - | 131.0 | 3.6 | 428.0 |
| Big 4g | 83.0 | 210.0 | - | - | 131.0 | 3.6 | 428.0 |

- Baseline Language Models : Fixed linear interpolation weights
- Document-Specific 4-gram Language Models (W. Kim and P. Virga)
- For each test document
 - Decode using static LM to obtain 1-best hypothesis
 - Use 1-best hyp to query English text collection & retrieve 10k docs (\approx 3Mwords)
 - Interpolate 3-gram (doc. specific) with Big 4-gram
 - Compute interpolation weights to maximize likelihood of 1-best hypothesis

Translation Model Training

- Partition bitext and IBM-4 train models on each partition
- Merge word alignments & collect translation templates (phrase-pairs)

Chinese-English (Decode with Small3g)

| Bitext Partition | Contribution by Source: En words (M) | | | | | BLEU (%) | | |
|---------------------|--------------------------------------|--------|------|------|-------|----------|--------|--------|
| | FBIS | HKNews | XHTS | UN | Total | eval01 | eval02 | eval03 |
| 1 | 10.5 | 16.3 | - | 26.7 | 53.5 | 25.1 | 25.5 | 24.1 |
| 2 | 10.5 | - | - | 85.0 | 95.5 | 25.8 | 25.9 | 25.0 |
| 3 | 10.5 | 16.3 | 43.0 | 25.8 | 95.6 | 28.0 | 25.8 | 24.9 |
| 1+2+3 | | | | | | 28.1 | 26.6 | 25.5 |

(XHTS = Xinhua, Hansards, Treebank, Sinorama)

Arabic-English (Decode with Small3g)

| Bitext Partition | Contribution by Source: En words (M) | | | BLEU (%) | |
|---------------------|--------------------------------------|------|-------|----------|--------|
| | UN | News | Total | eval02 | eval03 |
| 1 | 65.0 | 3.5 | 68.5 | 35.0 | 37.4 |
| 2 | 64.0 | 3.5 | 67.5 | 35.7 | 37.6 |
| 1+2 | | | | 35.8 | 37.8 |

Performance of Evaluation Stages

| System # | | Decoding Method | BLEU% | | | | | | |
|----------|----------------|-----------------|-----------------|------|------|---------|----------------|-------------------|-------------------|
| | | | Chinese-English | | | | Arabic-English | | |
| | | | e01 | e02 | e03 | e04 (c) | e02 | e03 | e04 (c) |
| 1 | JHU-UMD '03 | - | - | 16.0 | 17.0 | - | - | - | - |
| 2 | AE-Primary '04 | - | - | - | - | - | 38.0 | 30.6 ^S | |
| 3 | Small3g | | 28.1 | 26.6 | 25.5 | - | 35.8 | 37.8 | - |
| 4 | Big3g | | 28.7 | 27.7 | 27.1 | 26.5 | 38.1 | 40.1 | - |
| 5 | Big4g | Nbest from 4 | 29.6 | 28.2 | 27.3 | 27.5 | - | - | - |
| 6 | | Lattice from 4 | 29.7 | 28.5 | 27.4 | 27.6 | 39.4 | 42.1 | 36.1 ^S |
| 7 | MBR | Nbest from 5 | 29.7 | 28.4 | 27.7 | 27.5 | - | - | - |
| 8 | | Nbest from 6 | 30.0 | 28.8 | 27.6 | 27.8 | 39.6 | 42.2 | 36.5 ^S |

- Eval04 results are case-sensitive BLEU
 - Truecasing was performed using WS '03 capitalizer trained on in-domain English text
- A-E submitted systems: Primary (2), Very Late Contrast (6 and 8)
- System 6 (A-E) includes improvements from tuning word insertion penalty

Diagnostics: Development of Chinese-English Submitted Systems

All systems are MBR-BLEU rescoring over N-best lists generated by different LMs

| System Name | LM | BLEU (%) | | | |
|------------------|----------------------|----------|--------|--------|----------------|
| | | eval01 | eval02 | eval03 | eval04 (Cased) |
| JHU-TTM | Big4g | 29.6 | 28.2 | 27.3 | 27.5 |
| | MBR | 29.7 | 28.3 | 27.7 | 27.4 |
| | MBR (posteval) | 29.7 | 28.4 | 27.7 | 27.5 |
| JHU-TTM-DSL2 | Doc-specific-Dyn 4g | 29.8 | 28.9 | 27.6 | 27.5 |
| | MBR | 29.6 | 28.9 | 27.8 | 27.7 |
| JHU-TTM-DSL1 | Doc-specific-Stat 4g | 29.8 | 29.0 | 27.8 | 27.7 |
| JHU-TTM-DSL1+MBR | MBR | - | - | 27.8 | 27.1 |
| | MBR (posteval) | 29.9 | 28.9 | 27.9 | 27.8 |

- Gains from Doc-specific LMs and MBR-BLEU rescoring are not additive!
 - Doc-specific LMs assign higher likelihood to MAP hypothesis
- Subsequent to evals, we found that performance of Doc.Specific LMs can also be achieved by Lattice Rescoring with a static 4gram LM followed by MBR rescoring on the new N-best list (See Page 20, system 9)

Conclusions

- A statistical MT system based on Bitext Chunking and TTM
 - Evaluation system benefitted from a careful study of contribution of each model component to overall performance
 - Bitext chunking allows use of almost all available bitext for model training
 - Large gains relative to JHU 2003 eval system (11% BLEU absolute on eval03)
 - Respectable performance in Chinese-English and Arabic-English MT (Very Late Contrast)
 - Similar Architectures for C-E and A-E systems
 - Primary C-E system developed in 1 month
 - Very Late Contrast A-E system developed in 10 days
- WFST Architecture supports Lattice/N-best List generation and rescoring
 - Gains from 4-gram LM rescoring and MBR-BLEU rescoring

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