NTT SMT System for IWSLT 2008

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Overview

- 2-stage translation system
  - k-best translation candidates are generated by **hierarchical phrase-based SMT**
  - The top-best candidate is chosen by a reranker based on **Ranking SVMs with large-scale sparse features**

- Evaluation on **Chinese-to-English challenge task**

Stage 1: Translation

- Hiero (Chiang, CL 2007) : in-house implementation
  - **Hierarchical phrase-based SMT**
  - CKY-based decoder
  - **Minimum Error Rate Training**
    - Decoder features are same as our IWSLT '06 system
      - Hierarchical and lexical translation probabilities
      - Insertion, deletion, and reordering penalties
      - Length penalties (words / hierarchical phrases)
      - Word 5-gram language model scores

Stage 2: Reranking

- Reorder k-best translation candidates after decoding
  - Ranking SVMs with large scale sparse features
  - Incorporate *context features*
    - Difficult to use in decoding (e.g. MIRA-based method)

Ranking SVMs (Joachims, 2002)

- Ranking samples (not classification)
  - Trained using ordered k-best candidates $e_1^*, \ldots, e_k^*$
    - Metric: **Approximated BLEU**
    - Converted to top-best vs. non-best pairwise difference pairs D
      - $D = \{ d_{ij} = e_i^* - e_j^* \mid e_i^* \in \langle \text{top-best} \rangle,\ e_j^* \in \langle \text{non-best} \rangle \}$

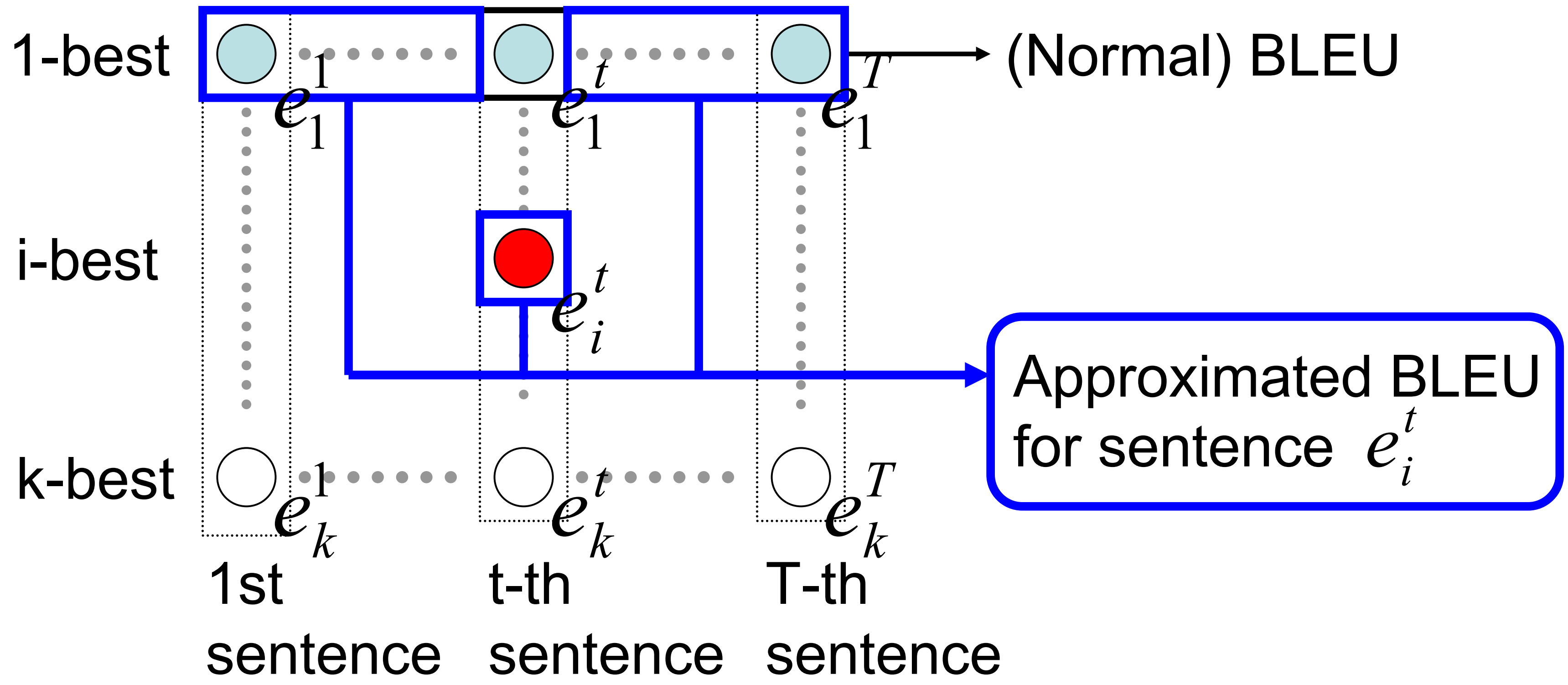
$$D' = \{ d_{ij} = e_i^* - e_j^* \mid 1 \le i < k,\ 1 < j \le k,\ i < j \}$$

    - Optimizing *classification* SVMs on D
  - Test: choose highest-scored candidate

Approximated BLEU

- BLEU : document-wise score
  - **Requires re-computation in every iteration**
  - Not suitable for independently assigning scores to k-best candidates
- Approximated BLEU (Watanabe, IWSLT 2006)
  - Sentence-wise approximation of document-wise BLEU *(not sentence-wise BLEU)*
  - **Independently calculated for each candidate**
  - Constant throughout optimization

Approximated BLEU (cont'd)



Reranker Features

- Intra-sentence features
  - Word alignments
    - Source-target word pairs aligned by IBM Model 1
    - Target-source direction was also considered
    - Alignment bigram : a(i)*a(i+1)
  - Word pairs
    - Arbitrary source-target unigram/bigram pairs within each sentence
  - Target-side skip bigrams

Reranker Features (cont'd)

- Inter-sentence feature
  - Context-dependent word pairs
    - Arbitrary pair of [target word unigram] and [source/target word unigram **in the previous sentence**]

Pegasos

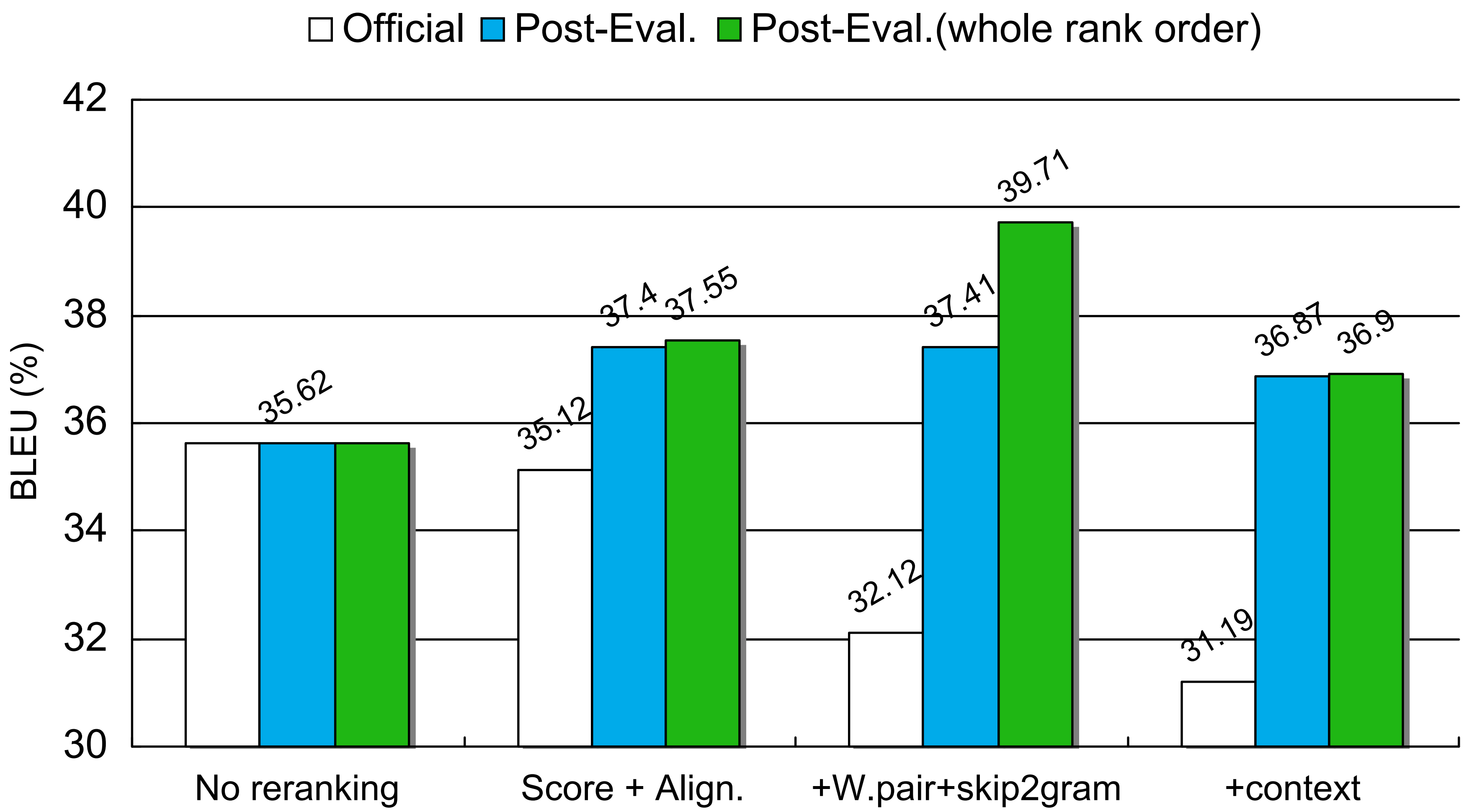
- Fast optimization algorithm for linear-kernel SVMs (Shalev-Shwartz et al., ICML 2007)
  - Use sub-gradients calculated based only on k samples in each iteration
  - Learning time does *not* depend on data size

Post-evaluation

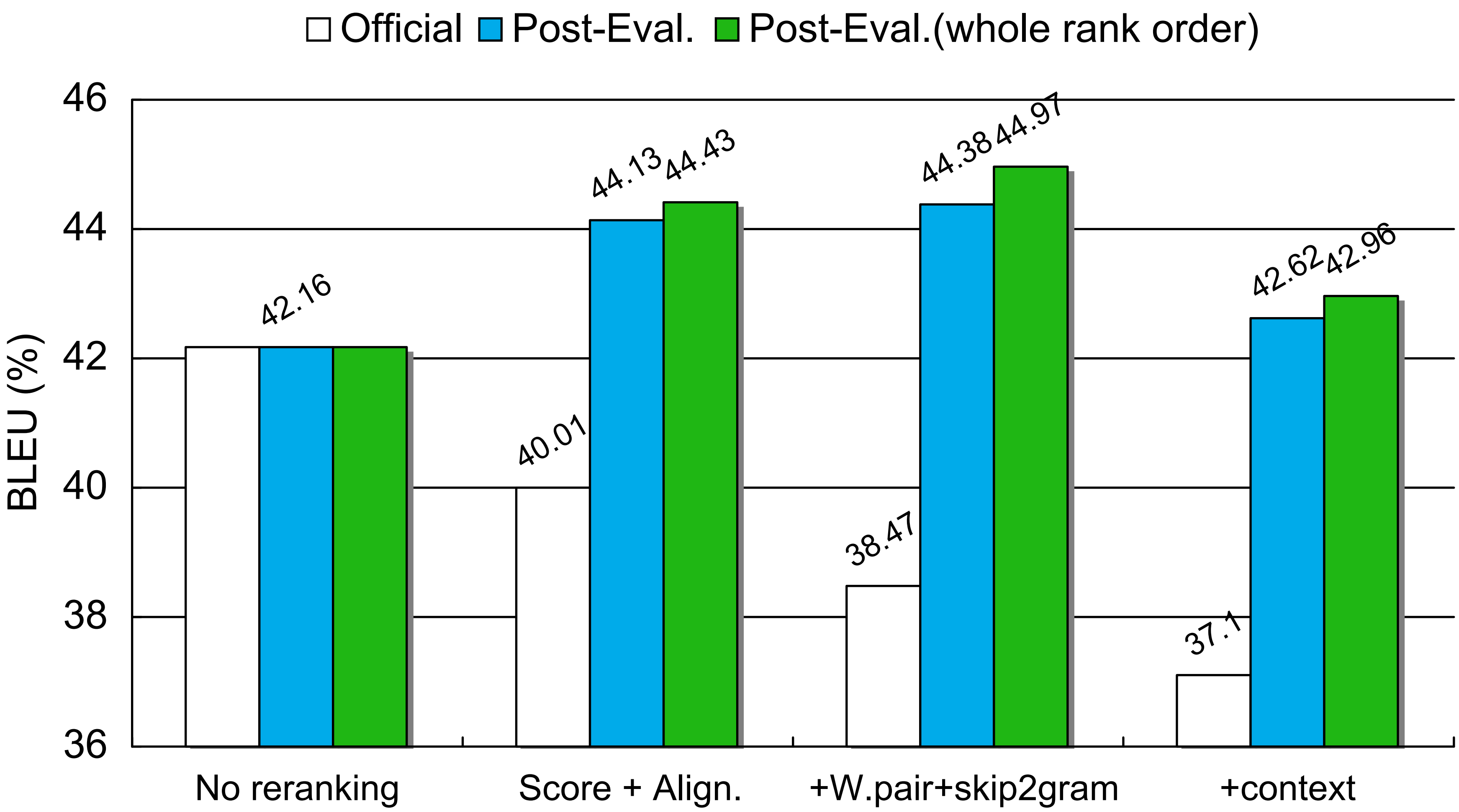
- Optimize SVM soft-margin parameter
  - 2-/3-fold cross validation on devset.CT_CE (246 sentences)
  - We didn’t optimize it in the official evaluation!!

- Use the whole rank order in training R-SVMs
  - The whole rank order did not increase BLEU in our development phase

Results (ASR 1-best input)



Results (Clean input)



Results : Summary

- Reranking with *optimized soft-margin parameters* achieved good BLEU results
- Alignment-independent features were effective
- Context features were *not* effective

Discussion

- Reranker chose **adequate** candidates
  - Word alignment features captured *lexical correspondence*
- Reranker chose **fluent** candidates
  - (Skip-)Bigram features captured *target-side natural word order*
  - Bigram pair features captured *source-target co-occurrence* of bigrams
- Reranker failed to utilize context information
  - Context features turned out to capture many *general word co-occurrence*

Distinctive Word Alignment Features

ST: ?-<EOS> / 吗
ST: 可以 / can
ST: tell-me / 请问
ST: i-would / 我-想
ST: would-like / 想
ST: you-have / 有
ST: <BOS>-i / 我

TS: 吗-<EOS> / <$.$>
TS: ? / 吗
TS: 吗-<EOS> / ?
TS: 我-想 / i*like
TS: 在-哪里 / where
TS: 最近-的 / nearest^the

Distinctive Bigram Features

Bigram: ?-<EOS>
Bigram: .-<EOS>
Bigram: me-the
BigramPair: <BOS>-我 / <BOS>-i
BigramPair: <BOS>-我 / would-like
BigramPair: 吗-<EOS> / <BOS>-can
BigramPair :吗-<EOS> / ?-<EOS>
BigramPair: 多少-钱 / how-much
BigramPair: 多少-钱 / ?-<EOS>
BigramPair: <BOS>-能 / <BOS>-can
BigramPair: 给-我 / give-me
SkipBigram: would-*-to
SkipBigram: <BOS>-*-would
SkipBigram: <BOS>-*-can
SkipBigram: do-*-have
SkipBigram: tell-*-the

Distinctive Context Features

TargetContext: for -> ?
TargetContext: is -> ?
TargetContext: a -> you
TargetContext: i -> you
TargetContext: . -> is
TargetContext: ? -> can
TargetContext: please -> ?
TargetContext: , -> can
SourceContext: 的 -> ?
SourceContext: 一 -> me
SourceContext: 吗 -> me
SourceContext: 我 -> .

Conclusion

- NTT's 2-stage SMT system
  - Hierarchical phrase-based SMT decoder
  - SVM-based reranker with sparse features
  - Achieved **39.71%(ASR), 44.97%(clean) BLEU** in Chinese-to-English challenge task
  - Reranker effectively utilized both monolingual and bilingual sparse features
  - Current context-dependent features are not effective