Larger Feature Set Approach for MT: IWSLT 2007

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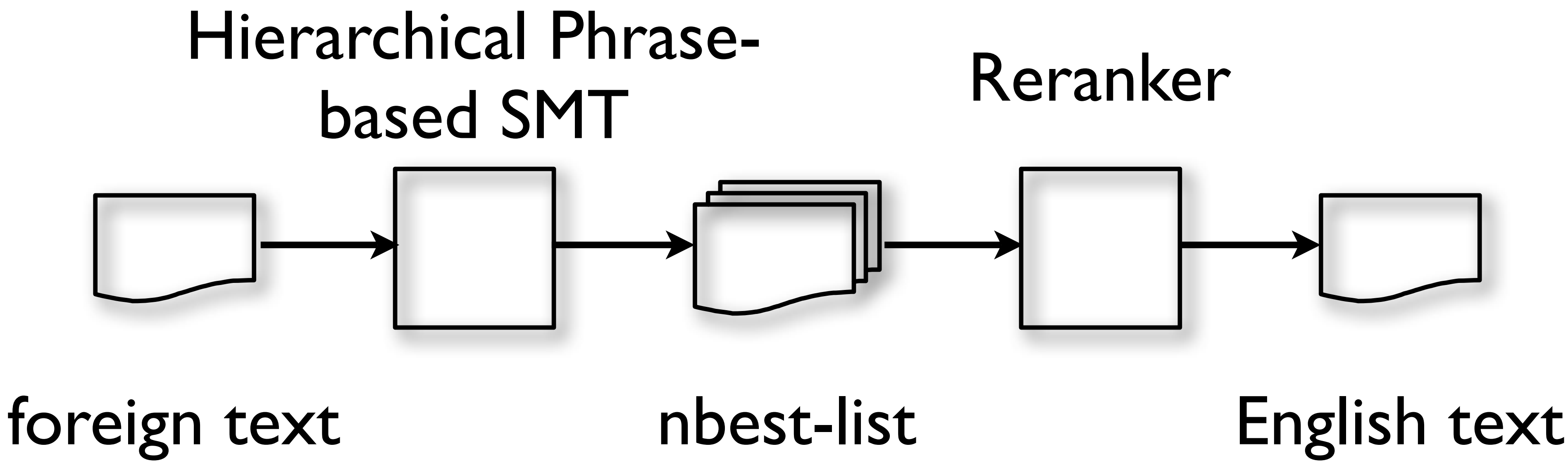
NTT SMT System



Decoder maximizes:

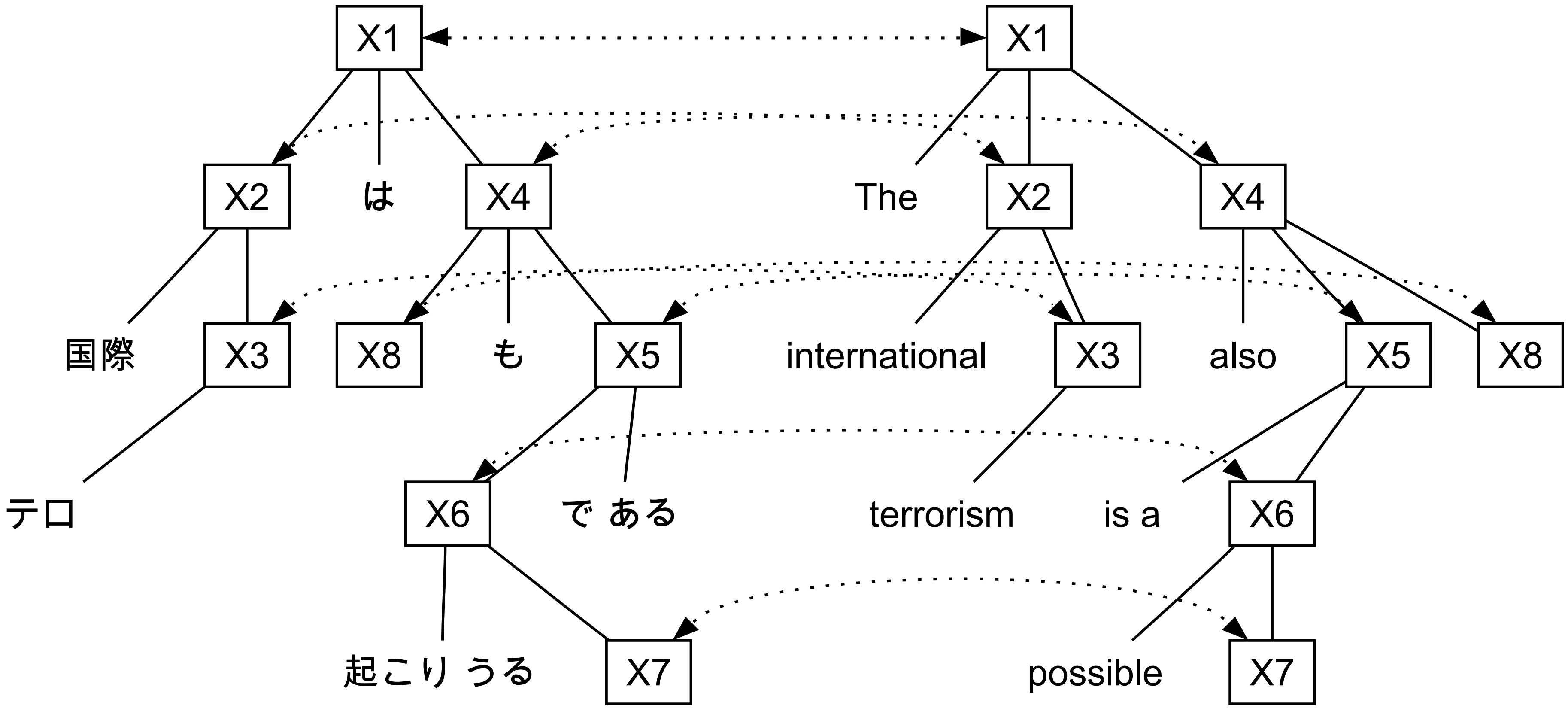
$$\hat{e} = \operatorname*{argmax}_{e} \mathbf{w}^{\top} \cdot \mathbf{h}(f, e)$$

Reranker votes:

$$\hat{e} = \operatorname*{argmax}_{e} \left\{ \mathbf{w_i}^{\top} \cdot \mathbf{h}(f, e) \right\}_{i=1}^{n}$$

Both systems employ large # of sparse features

Hierarchical SMT



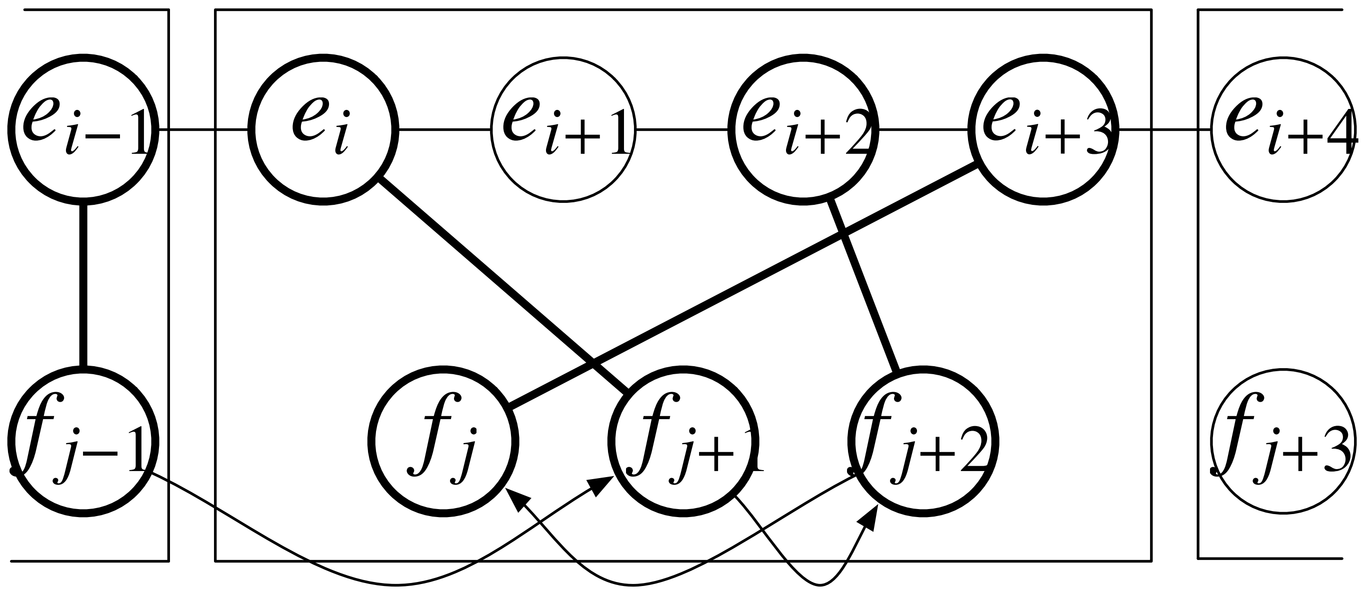
- Hierarchically embedded phrases (Chiang, 2005)
- An efficient top-down search (Watanabe et al., 2006)

Feature Set

- 5-gram language model
- Phrase probabilities
- Lexical weights
- Insertion/deletion penalties
- # of words/phrases

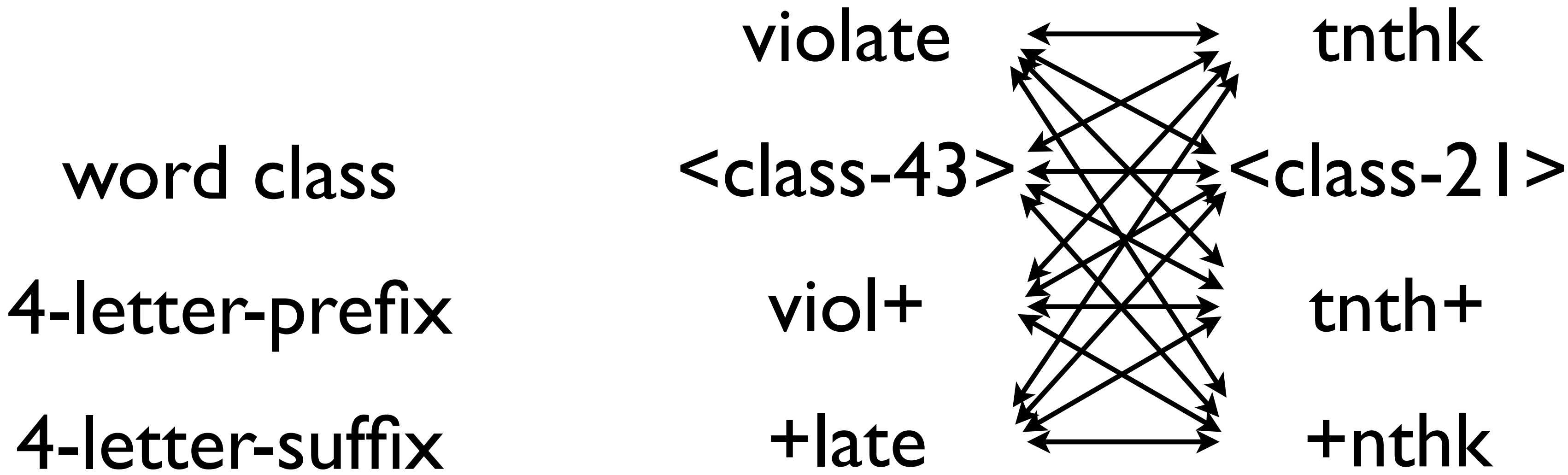
+ Sparse Features

Sparse Features



- Preserve word alignment inside hierarchical phrases
- Word-wise features (word-pair, target-bigram etc.)

Factoring



- Use of normalized tokens (POS/word class/prefix/etc.)
- Consider all possible combinations
  - POS: expanded into all possible solutions

Sparse Features

- Sparse features:
  - {1,2}-gram of word-pairs
  - target word bigram
  - Insertion/deletion features
  - Hierarchical dependency features
- Word Factoring:
  - Surface word
  - Word class
  - POS/NE
  - WordNet's synset
  - 4-letter prefix/suffix

Online Training

Training data: $\mathcal{T} = \{(f^t, \mathbf{e}^t)\}_{t=1}^{T}$
m-best oracles: $\mathcal{O} = \{\}_{t=1}^{T}$
$i = 0$

for $n = 1, \ldots, N$ **do**
  for $t = 1, \ldots, T$ **do**
    $C^t \leftarrow \text{best}_k(f^t; \mathbf{w}^i)$
    $\mathcal{O}^t \leftarrow \text{oracle}_m(\mathcal{O}^t \cup C^t; \mathbf{e}^t)$
    $\mathbf{w}^{i+1}$ = update $\mathbf{w}^i$ using C^t w.r.t. $\mathcal{O}^t$
    $i = i + 1$
  end for
end for
return $\frac{\sum_{i=1}^{NT} \mathbf{w}^i}{NT}$

Large Margin Constraints

$$\hat{\mathbf{w}}^{i+1} = \operatorname*{argmin}_{\mathbf{w}^{i+1}} \frac{1}{2}\|\mathbf{w}^{i+1} - \mathbf{w}^{i}\|^2 + C \sum_{\hat{e},e'} \xi(\hat{e}, e')$$

subject to

$$s^{i+1}(f^t, \hat{e}) - s^{i+1}(f^t, e') + \xi(\hat{e}, e') \geq L(\hat{e}, e'; \mathbf{e}^t)$$

$$\xi(\hat{e}, e') \geq 0$$

$$\forall \hat{e} \in \mathcal{O}^t, \forall e' \in \mathcal{C}^t$$

- Constrained by m-oracle + k-best.
- “C” to control the amount of updates.

Reranker

Reranking

Perceptron Training

Training data: $\mathcal{T} = \{(f^t, C^t, \mathbf{e}^t)\}_{t=1}^{T}$

```
for n = 1, ..., N do
    w^n = w^{n-1}
    for t = 1, ..., T do
        R = rerank(C^t; w^n)
        for i = 1, ..., |R| do
            for j = i + 1, ..., |R| do
                if L(R_j, R_i; e^t) > 0 then
                    w^n = update w^n using R_i and R_j
                end if
            end for
        end for
    end for
end for
return {w^n}_{n=1}^N
```

Decoding (Voting)

k-best translation list: (f, C)

Weight vectors: $\{\mathbf{w}^n\}_{n=1}^{N}$

Votes: $\mathcal{V} = \mathbf{0}$

```
for n = 1, ..., N do
    î = argmax_i {w^n}^T · h(f, C_i)
    V_î = V_î + 1
end for
return C_î where î = argmax_i V_i
```

Parameter Update

$$\mathbf{w}^n = \mathbf{w}^n + L(\mathcal{R}_j, \mathcal{R}_i; \mathbf{e}^t) \cdot \Big(\mathbf{h}(f^t, \mathcal{R}_j) - \mathbf{h}(f^t, \mathcal{R}_i)\Big)$$

Objectives

- Document-BLEU or sentence-BLEU?

$$\mathrm{BLEU}(E;\mathbf{E}) = \exp\left(\frac{1}{N}\sum_{n=1}^{N}\log p_n(E,\mathbf{E})\right)\cdot \mathrm{BP}(E,\mathbf{E})$$

- Our method: compute the difference from an oracle BLEU (Watanabe et al., 2006)

$$\mathrm{BLEU}(\{\hat{e}^1, ..., \hat{e}^{t-1}, e', \hat{e}^{t+1}, ..., \hat{e}^T\};\mathbf{E})$$

- Loss by an approximated BLEU ≈ doument-wise loss.

Task Setting

Preprocessing

- Removed bitexts matching regexp: [0-9]
- English: MaxEnt/Brill POS tagger
- Arabic: Isolate Arabic scripts/punctuations
- Italian: Treetagger
- Japanese/Chinese: HMM-based POS/NE tagger
- Casing preserved for English
- Punctuation removed for source side

Bitexts

	ar-en	it-en	ja-en	zh-en
sentences	833K	854K	1.0M	3.3M
words	25M	24M	8.6M	57M
vocabulary	132K	67K	254K	961K
source	LDC	EuroParl	NiCT	LDC

- Data comes from various sources (LDC or public domain)
- We used devset 4,5,5b for tuning, since they had ASR data.

Task Adaptation

Source side 3-gram perplexity

	ar-en	it-en	ja-en	zh-en
dev 4,5,5b	561.96	277.24	51.29	188.49
test	214.99	271.39	13.45	73.18

- Sample bitexts for phrase-table extraction (Ittycheriah and Roukos, 2007)
- For each source sentence in test(dev) set:
  - Extract bitexts from the universe of training data.
  - Similarity measured by ngram precision.

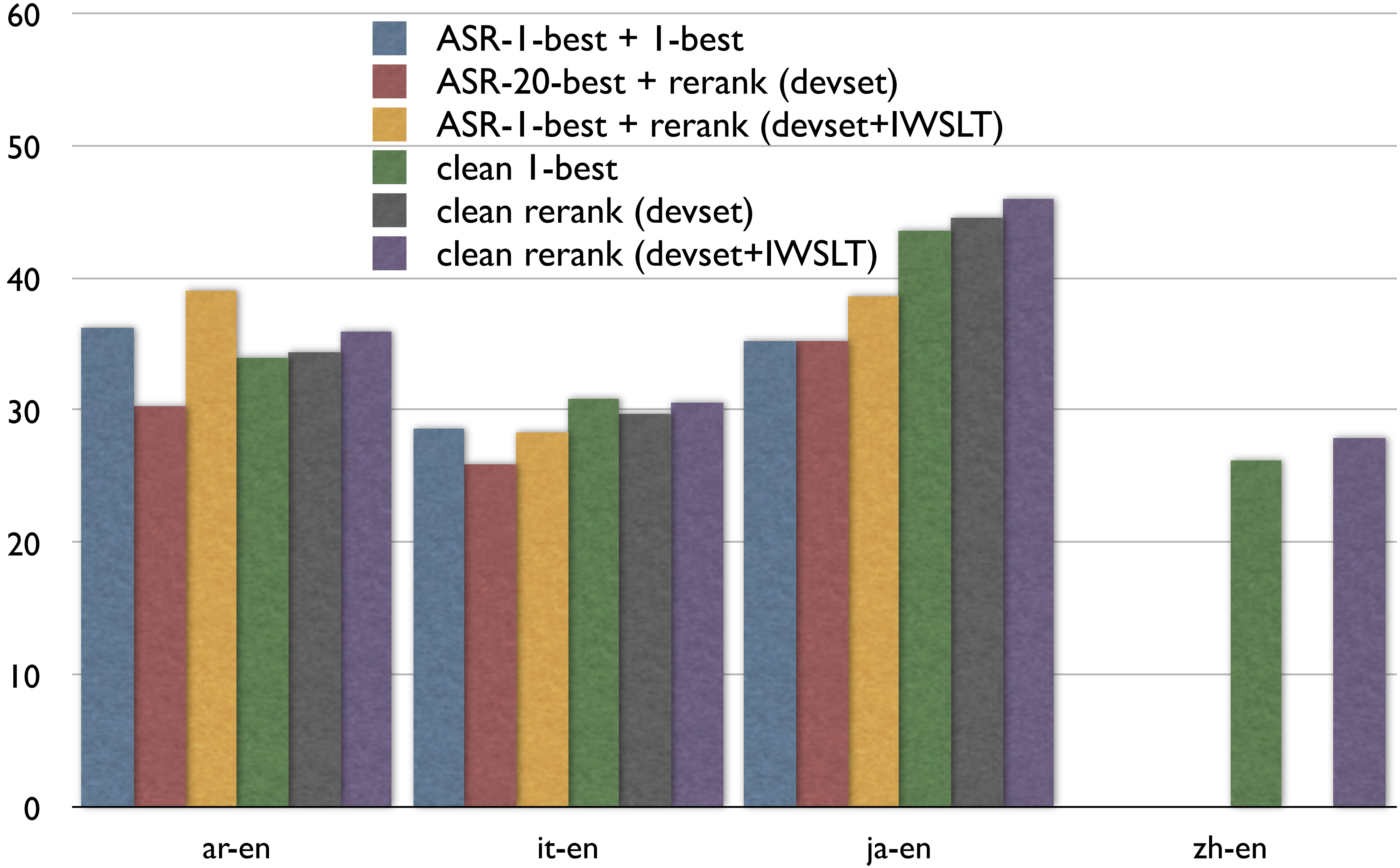
ASR Translation

- 1-best ASR translation
- 20-best ASR translation
  - Translate all the 20-bests and select the best one by our reranker.
  - Various word/sentence-wise confidence measures integrated as features.

Parameter Estimation

- Decoder:
  - Estimated on devset 4, 5, 5b.
  - 200-300 iteratins
- Reranker:
  - 1,000-best list
  - Estimated on devset 4, 5, 5b and IWSLT's 20,000 sentences.

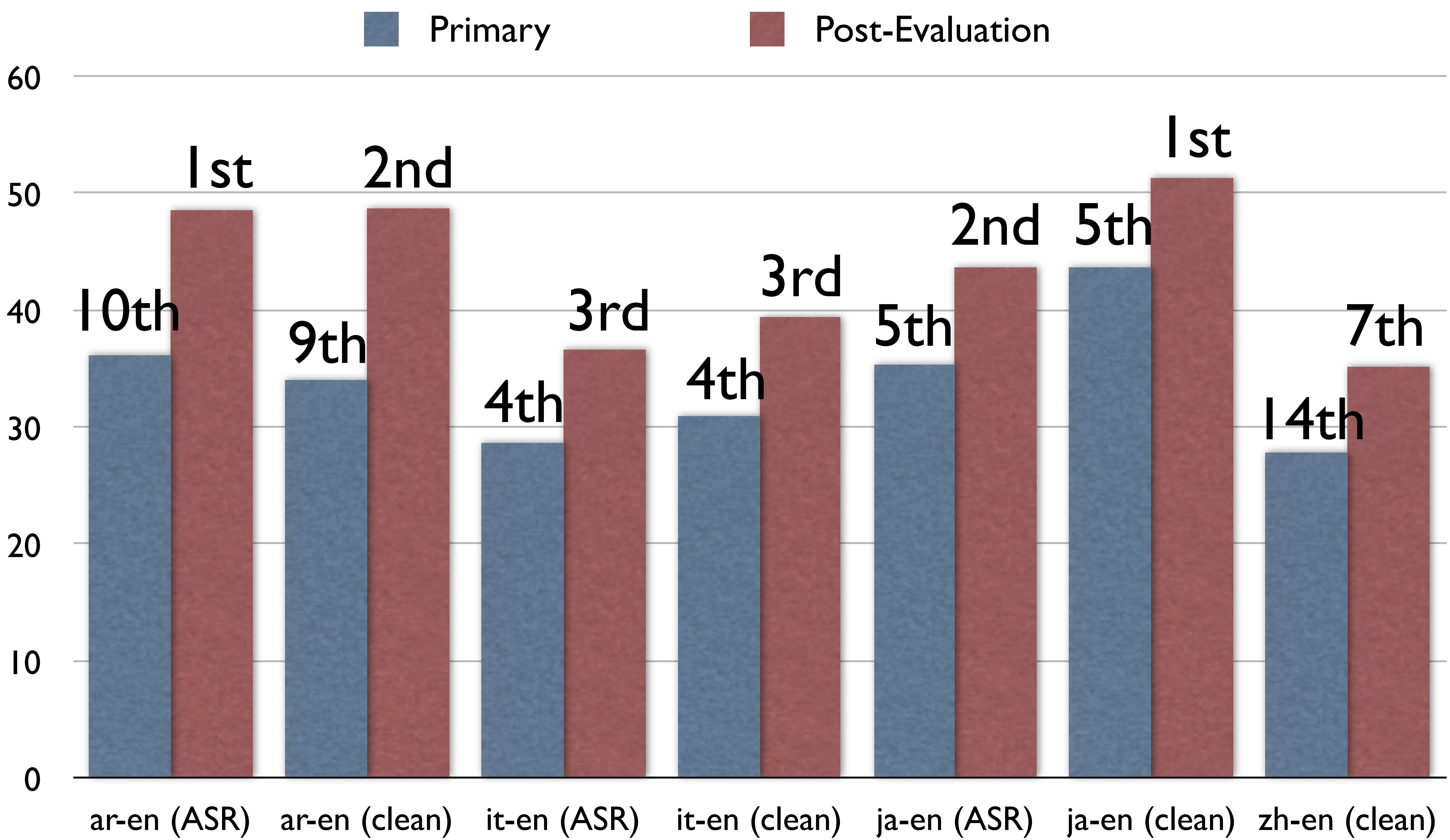
Results (BLEU)



Post Evaluation

- Use IWSLT data only.....
- Held-out set to terminate iterations
- Arabic/Japanese/Chinese are close to IWSLT data.
  - Estimated on devset 1 and 2, held-out devset 3.
- Italian data is totally different:
  - Extract phrases from devset 5b, too
  - Estimation on devset 4 and 5, held-out devset 5b

Results (BLEU)



Conclusion

- NTT SMT System:
  - Large # of features are integrated both in decoder/reranker
  - Careful devset selection
  - Careful tuning
  - Larger data helps for reranking
- Future Work:
  - More rich features, more experiments.