# NLPR Machine Translation System for IWSLT 2006

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# Outline

1. Overview of NLPR MT System
2. Adaptations to the Baseline System
3. Experiments
4. Future work

# 1. Overview of NLPR MT System

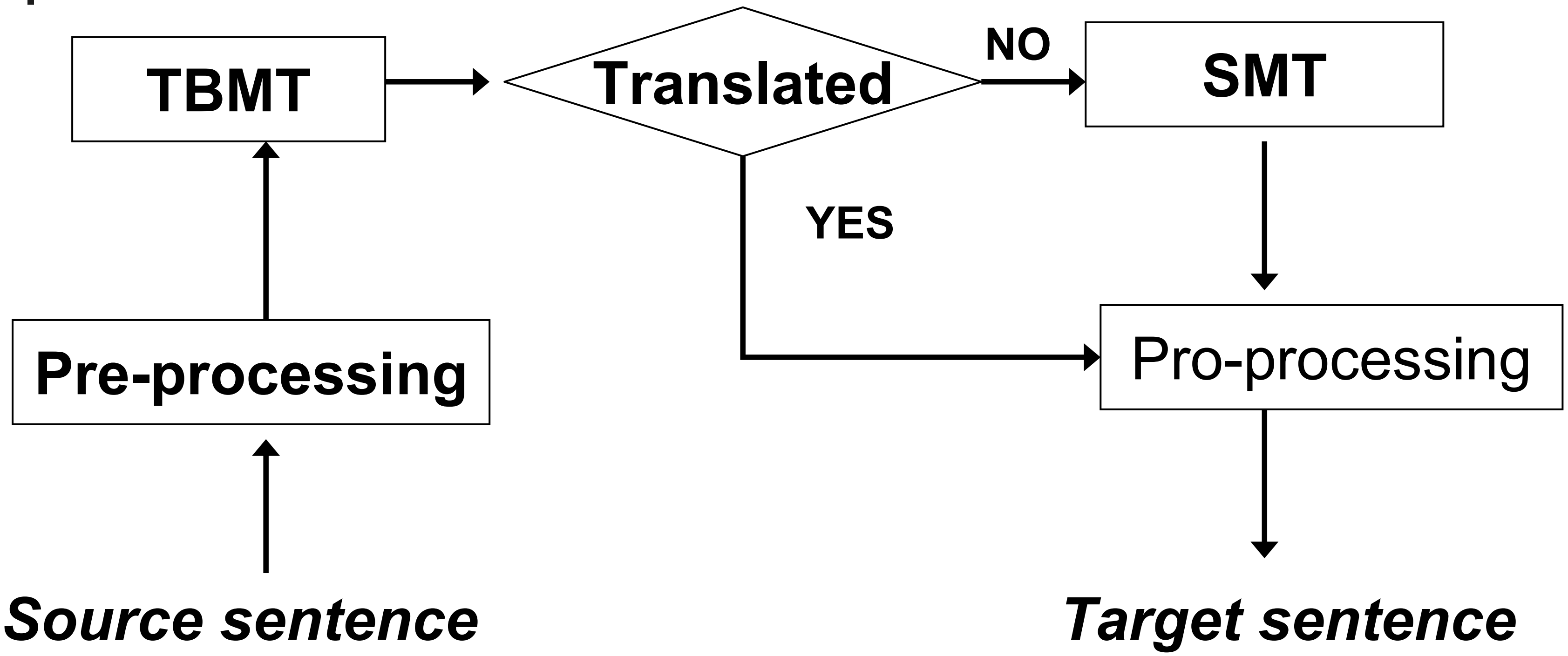
# 1.1 NLPR MT System

- Chinese-to-English
- A hybrid approach
  - Template based machine translation
  - Phrase based machine translation
- Some improvements
  - Restore punctuation information
  - Number pre-processing

# 1.1 NLPR MT System

- Motivations
  - How many complete correct translations from TBMT engine even the BLEU score is very low? And how many complete correct translations from the phrase-based MT engine even the BLEU score is higher than that of TBMT engine?

# 1.1 NLPR MT System



System architecture

$C_1 C_2 \cdots C_n \Rightarrow T$

# 1.2 Template-based MT

- Template format:

$$C_1 C_2 \cdots C_n \Rightarrow T$$

• ***$C_i$* *(n≥i≥1)*** is a component which expresses a condition that the input utterance has to meet.

***T*** is the output result corresponding to the input.

It means if an input utterance of source language meets the conditions $C_1$ $C_2$ … $C_n$, the input will be translated into the target language expression *T*.

# 1.2 Template based MT

- The template is expressed by
  - (1) Keywords
  - (2) POS or POS with Semantic Features

    Such as N, V, N(nso), QP, ……
  - (3) * Variable

    It means any word or phrase may appear at the * position or nothing appears.
  - (4) Logical expression of candidate components

(See *Proc. ICSLP'2000*)

# 1.3 Phrase-based SMT model

- The log-linear model

$$p(e\,|\,c) = p_T(c\,|\,e)^{\lambda_t} \times p_L(e)^{\lambda_l} \times p_D(e,c)^{\lambda_d}$$

$P_T(c\,|\,e)$is the translation model

$P_L(e)$is the target language model

$P_D(e,c)$is the distortion model and

$$P_D(e,c) = \lambda\,|\,a_i - b_{i-1} - 1\,|$$

# 1.3 Phrase-based SMT model

- **Phrase extraction**
  - Refined model from bi-directional word-based alignment (Och 2002, Koehn *et al*.,2003 )
- **Phrase translation probability**

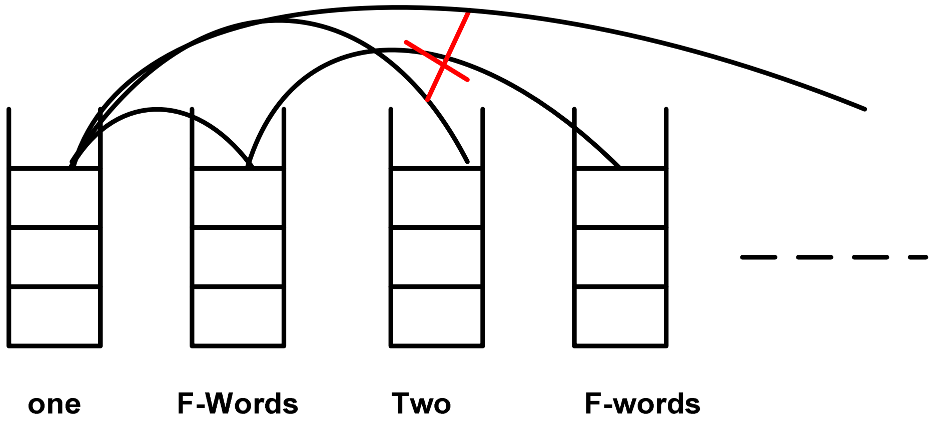
$$P_T(\overline{f}_k \mid \overline{e}_k) = \lambda_1 P_{lex}(\overline{f}_k \mid \overline{e}_k) + \lambda_2 P_{lex}(\overline{e}_k \mid \overline{f}_k) + \lambda_3 P_{freq}(\overline{f}_k \mid \overline{e}_k) + \lambda_4 P_{lex}(\overline{e}_k \mid \overline{f}_k)$$

$P_{lex}$ is the lexical probability based on IBM model-4

$P_{freq}$ is the probability based on phrase frequency.

# 1.4 Beam-Search Decoding

- **The basic algorithm is Beam-Search, same as Pharaoh. (Och & Ney, 2002; Zens *et al*, 2002)**
- **Improvement of integrating F-zerowords bins:** the hypotheses are stored in different stacks; bin label: number of Chinese words covered; insert the Functional Words( of , the, for…..) bins.



# 1.4 Beam-Search Decoding

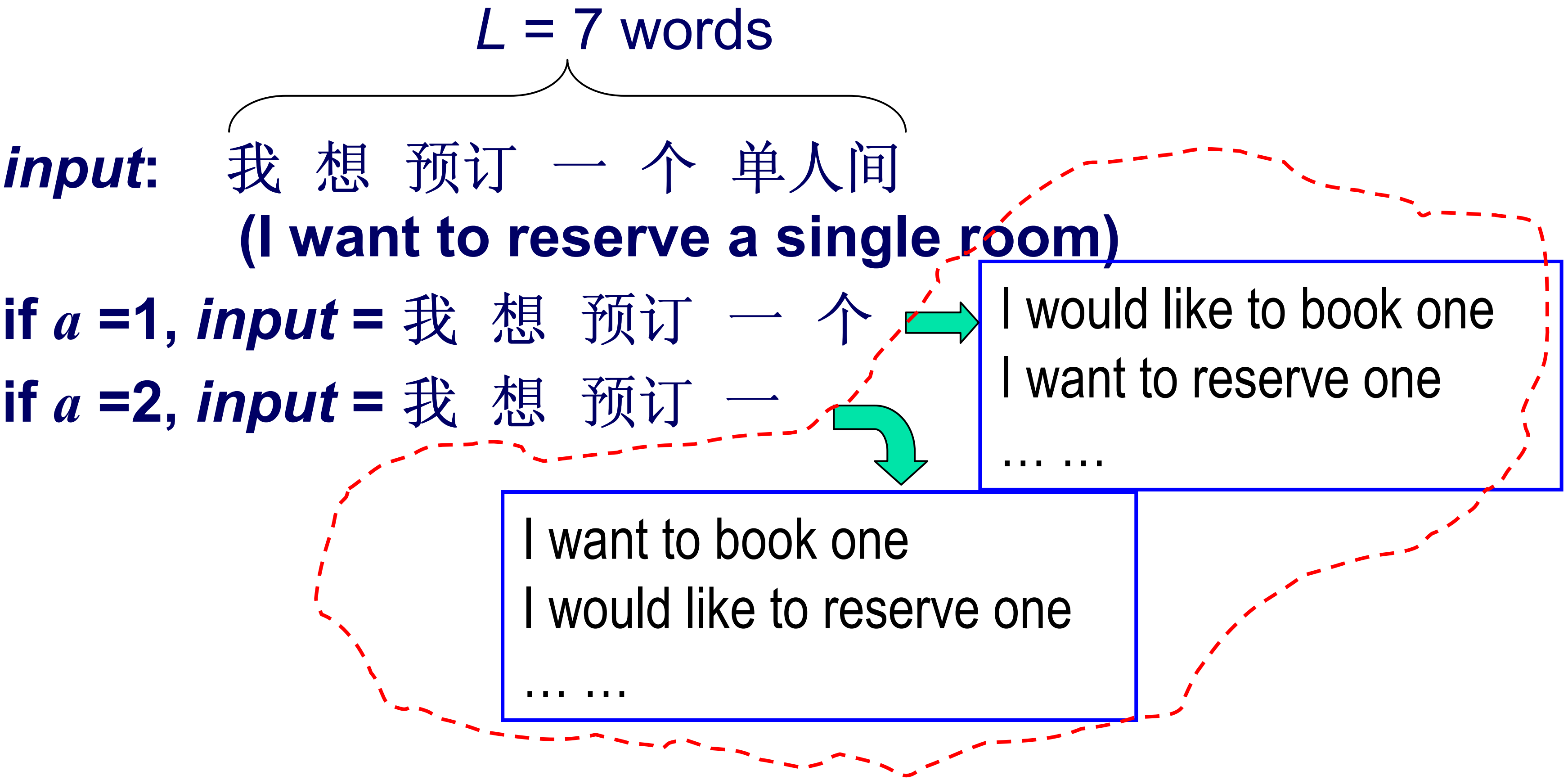
- ***Considering there are some auxiliary words and mood words in the Chinese sentence, and these words sometimes don’t have the corresponding words in the English sentence. So, the system does not require the all words in the Chinese sentence to be translated.***

The system selects the candidate sentences generated after ($L$－$a$) Chinese words have been translated.

Where, $L$ is the length of the input Chinese sentence; $a$ is an integer.

# 1.4 Beam-Search Decoding

**For example**:



*L* = 7 words

***input*:** 我 想 预订 一 个 单人间

**(I want to reserve a single room)**

**if $a$ =1, *input* =** 我 想 预订 一 个

**if $a$ =2, *input* =** 我 想 预订 一

I would like to book one
I want to reserve one
… …

I want to book one
I would like to reserve one
… …

# 2. Adaptations to the Baseline System

# 2.1 Restore Punctuations

- Restore punctuations
  - Using the *hidden n-gram* in the SRILM toolkit
  - In the pre-processing
    - to use the punctuation information in training data
  - In the post-processing
    - to restore the more punctuation information

## 2.2 Number pre-processing

- Considering the different characteristics of numerical expressions in the Chinese and English, we build the number pre-processing module based on rules that are summarized from the selected corpus covered with all domains (about 5,000 sentence pairs)
  - Numeral translation
  - Temporal translation

# 3. Experiments

# 3.1 Results of Improvements

- Training data: 40K sentences
- Test data:  devset4_IWSLT06 (correct,489)

| | BLEU | NIST |
|---|---|---|
| SMT (with punc in training set) | 0.1486 | 5.4866 |
| SMT+Deletion punctuation | 0.1195 | 5.3029 |
| SMT+Punctuation (test set) | 0.1700 | 5.7994 |
| SMT+Punctuation+TBMT | 0.2238 | 6.1305 |

## 3.1 Results of Improvements

- 55 (in 489) sentences translated by TBMT
- An example:

Chinese sentence:

“我 喜欢 红色 或者 黑色 都 可以 。”

**TBMT result:**

“I would like either red or black . ”

**SMT result:**

“I'd like a red , black be all right . ”

# 3.2 Results of Test Set

| | | BLEU | NIST |
|---|---|---|---|
| Read speech | SMT | 0.0972 | 3.5557 |
| | SMT+TBMT(33) | 0.1037 | 3.6384 |
| Spontaneous speech | SMT | 0.1001 | 3.4869 |
| | SMT+TBMT(29) | 0.1070 | 3.5755 |
| Correct results | SMT | 0.1167 | 3.9288 |
| | SMT+TBMT(48) | 0.1284 | 4.0658 |

The red number is the number of sentences translated by TBMT.

# 3.2 Results of Test Set

- The errors in ASR results
- Lack of punctuation information
- Only use the 1-Best of ASR results
- Set the parameters by hand

# 3.3 The Recent Experiments

Training the parameters of SMT by Minimum Error Rate criterion.

| | BLEU | NIST |
|---|---|---|
| Manual | 0.1167 | 3.9288 |
| MER training | 0.1252 | 4.1439 |

SMT results of correct test data

# 4. The Future Work

- Collecting some ASR results
- Dealing with the noisy words in ASR results
- Approaches to word alignment and phrase extraction for SLT
- Try to use the phrasal structural information in TM

*Thanks*

谢谢!