On Feature Selection in Maximum Entropy Approach to Statistical Concept-based Speech-to-Speech Translation

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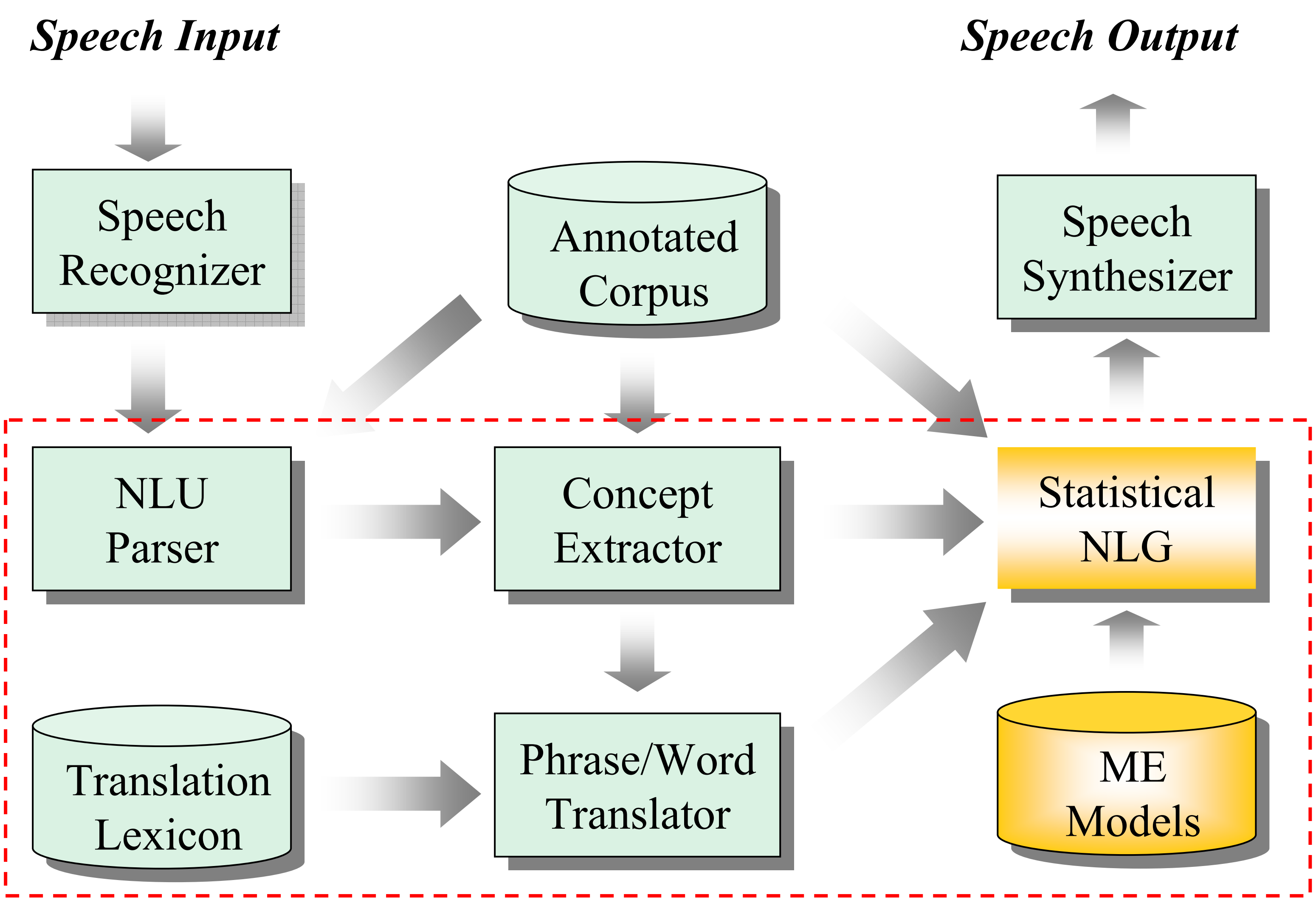
Outline

- Statistical Concept-based Speech Translation
- Natural Concept Generation (NCG)
- Feature Selection in Statistical NCG
  - Conciseness vs. Informativity of Concepts
  - Features using both Concept & Word Information
  - Multiple Feature Selection
- Experimental Results

Overview of IBM MASTOR System



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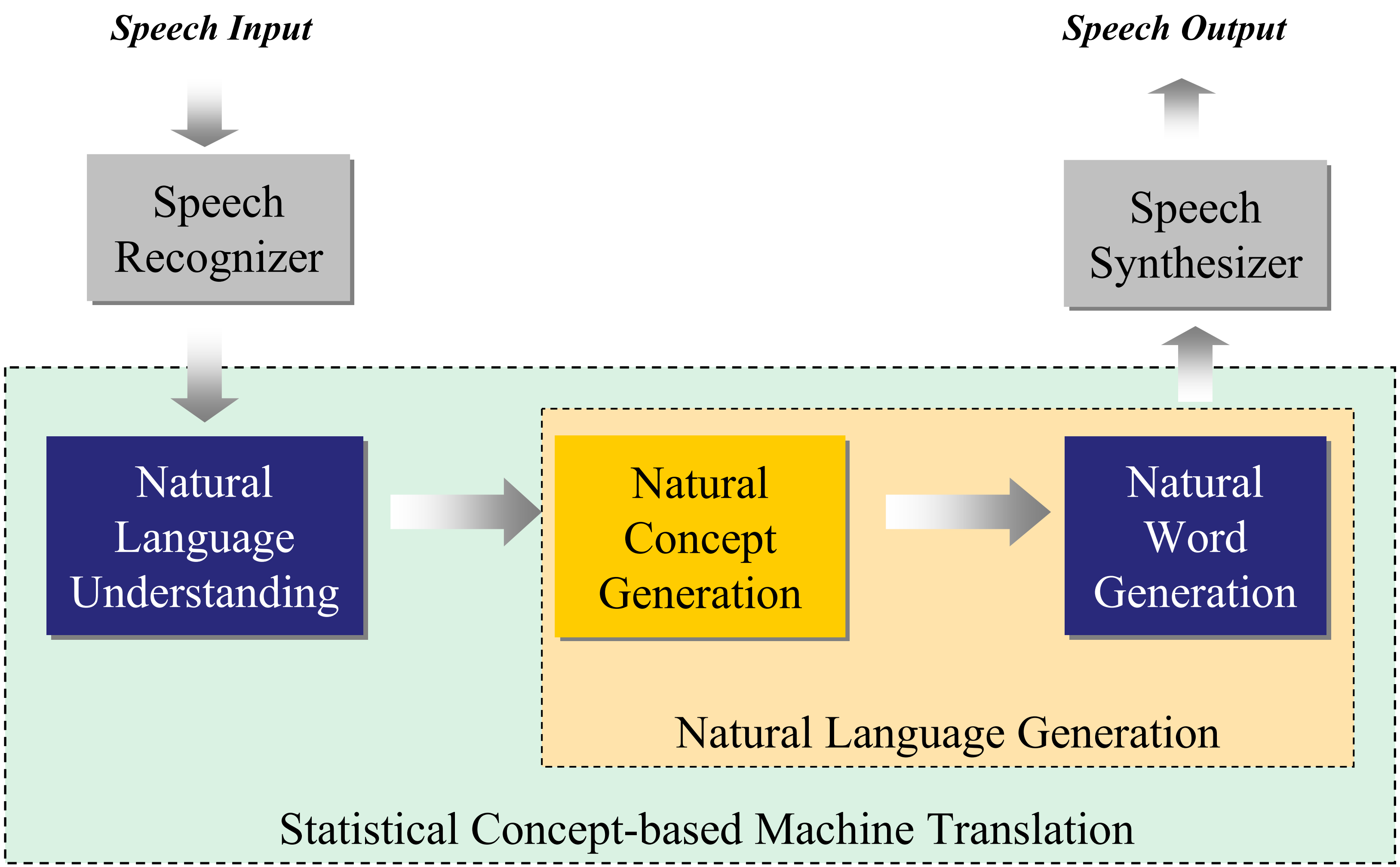
Spoken Language Translation via Concepts



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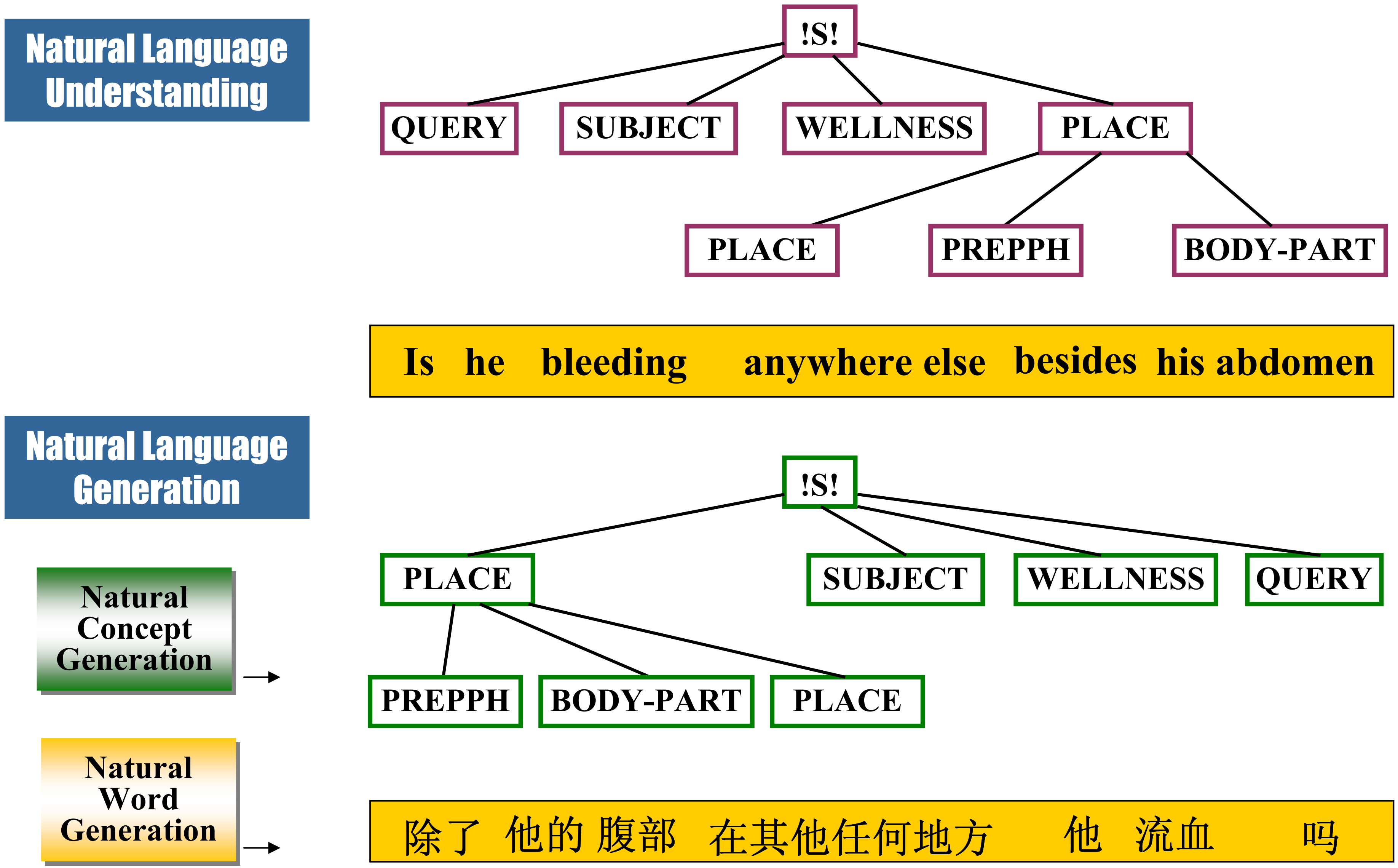

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Concept-based Speech Translation

Concepts

- **Language-independent** representation of intended meanings
- Parsed from source language
- Organized in a **language-dependent** tree-structure
- Comparable to interlingua

Merits

- More flexible meaning preservation
- Wider sentence coverage
- Easier portability between different domains

Challenges

- Design and selection of concepts
- **Generation of concepts**

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Natural Concept Generation (NCG)

Purpose

- Correct set of concepts in target language
- Appropriate order of concepts in target language

Approaches

- Statistical model-based generation
  - Trained on Maximum-Entropy models

Challenges

- Design of generation procedure
  - Generation of concept sequences
  - Transformation of semantic parse tree
- **Selection of features**

Statistical NCG on Sequence Level

English	QUERY	PRON	POSSESS	WEAPON
Chinese	PRON	POSSESS	WEAPON	QUERY

Statistical NCG on Sequence Level

Source ***C***	C_1	C_2	…	C_M
Target ***S***	S_1	S_2	…	S_n	S_{n+1}

$$p\left(s \middle| c_m, s_n, s_{n-1}\right) = \frac{\prod_k \alpha_k^{\,g\left(\vec{f}_k, s, c_m, s_n, s_{n-1}\right)}}{\sum_{s \in V} \prod_k \alpha_k^{\,g\left(\vec{f}_k, s, c_m, s_n, s_{n-1}\right)}}$$

α_k : probability weight corresponding to feature $\vec{f}_k$

$\vec{f}_k$: feature of concepts

g : binary test function

$$g\left(\vec{f}_k, s, c_m, s_n, s_{n-1}\right) = \begin{cases} 1 & if\ \vec{f}_k = \left(s, c_m, s_n, s_{n-1}\right) \\ 0 & otherwise \end{cases}$$

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Statistical NCG on Sequence Level (Cont.)

Source *C*	C_1	C_2	…		C_M
Target *S*	S_1	S_2	…	S_{n+1} …	S_N

Select the concept candidate with highest probability:

Generation

$$s_{n+1} = \arg\max_{s \in V} \left\{ \prod_{m=1}^{M} p\left(s \middle| c_m, s_n, s_{n-1}\right) \right\}$$

$$s_0 = s_{-1} = \text{START}$$

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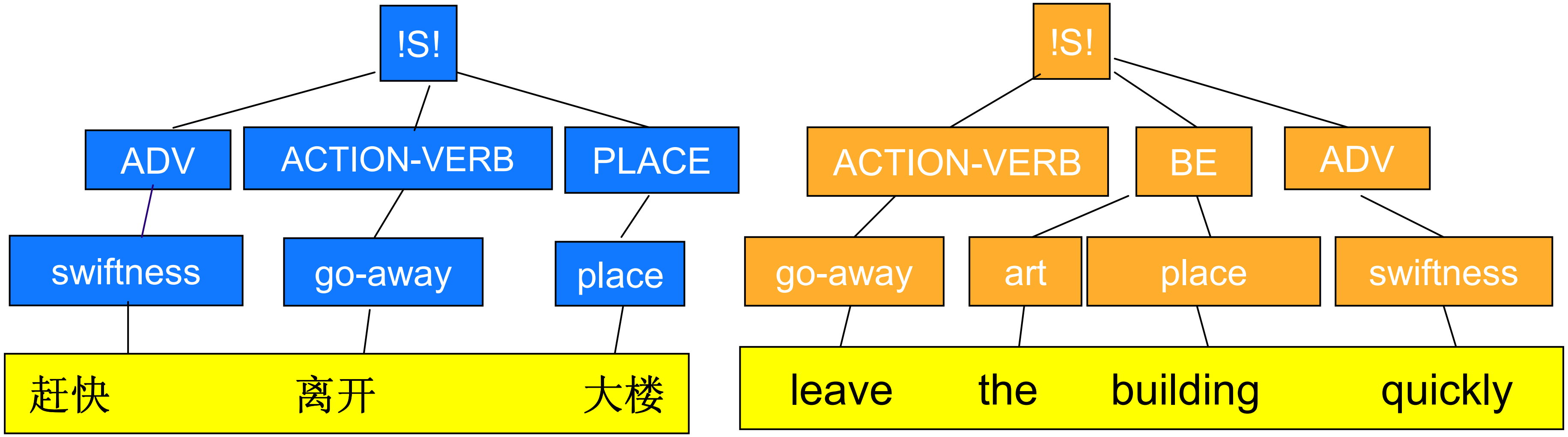
Model Training by Maximizing Entropy

$$p\left(s \middle| c_m, s_n, s_{n-1}\right) = \frac{\prod_k \alpha_k^{g\left(\vec{f}_k, s, c_m, s_n, s_{n-1}\right)}}{\sum_{s \in V} \prod_k \alpha_k^{g\left(\vec{f}_k, s, c_m, s_n, s_{n-1}\right)}}$$

$$\alpha_k = \arg\max_{\alpha} \sum_{l=1}^{L} \sum_{s \in q_l} \sum_{m} \log\left[p\left(s \middle| c_m, s_n, s_{n-1}\right)\right]$$

$Q = \{q_l, 1 \le l \le L\}$: total set of concept sequences

Structural Concept Sequence Generation



Traverse the semantic parse tree in a bottom-up left-to-right breath-first mode

For each un-processed concept unit on a parse tree, generate an optimal concept unit in target language via the procedure

Repeat until all units in the parse tree in the source language are processed

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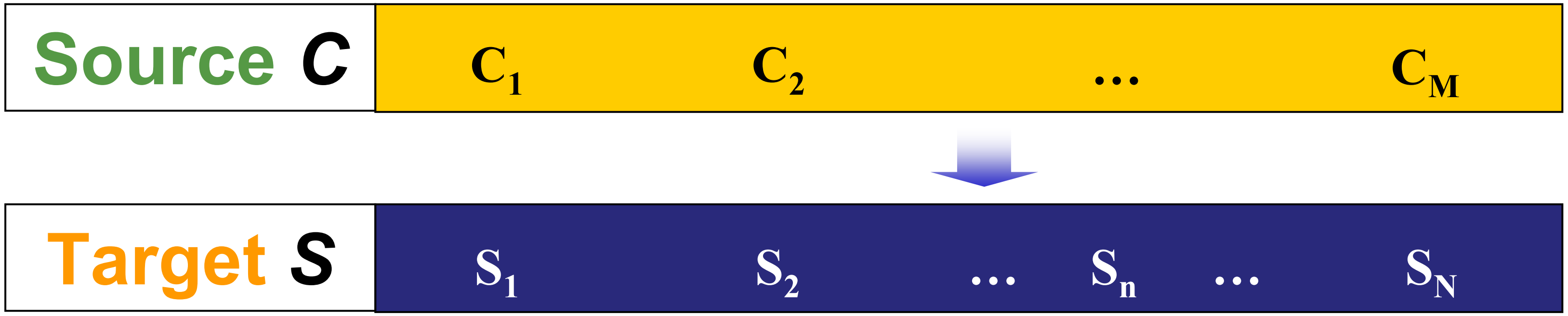
Feature Selection in Maximum-Entropy-based Statistical NCG



Baseline Features

$$\vec{f}_k^{(4)} = \left(s_{+1}^k, c^k, s_0^k, s_{-1}^k\right)$$

Augmented Features on Parallel Corpora

$$\vec{f}_k^{(5)} = \left(s_{+1}^k, c_0^k, c_{+1}^k, s_0^k, s_{-1}^k\right)$$

- new features derived from both source language and target language
- Trained on **parallel tree-bank**
- Strengthen the link between source language and target language

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Conciseness vs. Informativity of Concepts

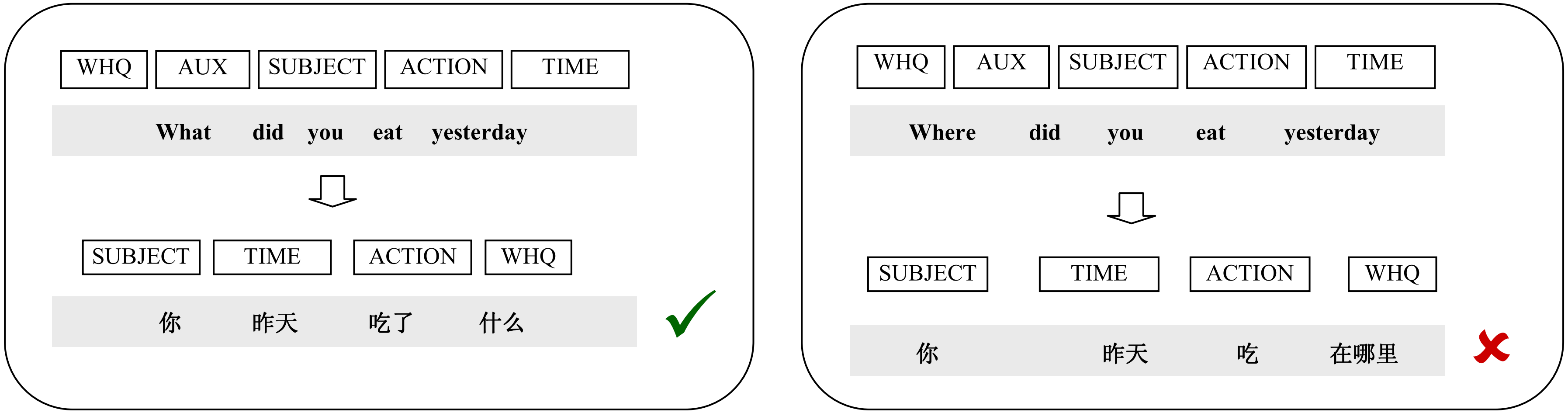
Conciseness

- Define minimum number of distinct concepts
- Reduce labor-extensive, time-consuming annotation process
- **Improve NLU parsing**

Informativity

- Define concepts as informative as possible
- Concept generation largely relies on the sufficient information provided by each concept
- **Improve NCG**

Examples of NCG with too Concise Concepts



- Two input English sentences with **SAME** set and order of concepts generate two **DIFFERENT** concept sequences
- The concept WHQ is **too concise** that it is **not informative enough** to discriminate the different generation behavior between (WHQ, what) and (WHQ, where)
- Features of $\vec{f}_k^{(4)} = \left(s_{+1}^k, c^k, s_0^k, s_{-1}^k\right)$ and $\vec{f}_k^{(5)} = \left(s_{+1}^k, c_0^k, c_{+1}^k, s_0^k, s_{-1}^k\right)$ not helpful

Using both Concept & Word Information

Concept information only

WHQ	AUX	SUBJECT	ACTION	TIME
What	did	you	eat	yesterday

SUBJECT	TIME	ACTION	WHQ
你	昨天	吃了	什么

✓

WHQ	AUX	SUBJECT	ACTION	TIME
Where	did	you	eat	yesterday

SUBJECT	TIME	ACTION	WHQ
你	昨天	吃	在哪里

✗

Concept & Word information

WHQ-what	AUX	SUBJECT	ACTION	TIME
What	did	you	eat	yesterday

SUBJECT	TIME	ACTION	WHQ-what
你	昨天	吃了	什么

✓

WHQ-where	AUX	SUBJECT	ACTION	TIME
Where	did	you	eat	yesterday

SUBJECT	TIME	WHQ-where	ACTION
你	昨天	在哪里	吃的

✓

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Features using both Concept & Word Information

Concept Sequence: $C = \{c_1, c_1, \cdots, c_M\}$

Word Sequence: $W = \{\overline{w}_1, \overline{w}_2, \cdots, \overline{w}_M\}$

$$p\left(s \middle| c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right) = \frac{\prod_k \alpha_k^{g\left(\vec{f}_k^{(7)}, s, c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right)}}{\sum_{s \in V} \prod_k \alpha_k^{g\left(\vec{f}_k^{(7)}, s, c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right)}}$$

$$\alpha_k = \arg\max_{\alpha} \sum_{l=1}^{L} \sum_{s \in q_l} \sum_{m=1}^{M-1} \log\left[p\left(s \middle| c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right)\right]$$

Optimized on parallel treebank: $QQ = \{u_l, v_l \mid 1 \le l \le L\}$

Multiple Feature Selection

Problem

- Sparser data because of higher dimensional features

Strategy

- Additional sets of features in ME-based concept generation
- Multiple sets of features represent context information in both the source and the target language at different levels

Example

Feature A: $\vec{f}_k^{(5)} = \left(s_{+1}^k, c_0^k, c_{+1}^k, s_0^k, s_{-1}^k\right)$

Feature B: $\vec{f}_k^{(7)} = \left(s_{+1}^k, c_0^k, c_{+1}^k, \overline{w}_0^k, \overline{w}_{+1}^k, s_0^k, s_{-1}^k\right)$

$$\alpha_k = \arg\max_{\alpha} \sum_{l=1}^{L} \sum_{s \in q_l} \sum_{m=1}^{M-1} \left\{ \log \frac{\prod_k \alpha_k^{g_k\left(\vec{f}_k^{(5)}, s, c_m, c_{m+1}, s_n, s_{n-1}\right)}}{\sum_{s \in V} \prod_k \alpha_k^{g_k\left(\vec{f}_k^{(5)}, s, c_m, c_{m+1}, s_n, s_{n-1}\right)}} + \log \frac{\prod_k \alpha_k^{g_k\left(\vec{f}_k^{(7)}, s, c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right)}}{\sum_{s \in V} \prod_k \alpha_k^{g_k\left(\vec{f}_k^{(7)}, s, c_m, c_{m+1}, \overline{w}_m, \overline{w}_{m+1}, s_n, s_{n-1}\right)}} \right\}$$

Experimental Setup

MT Method	statistical interlingua-based speech translation
Language Pair	English – Chinese (Mandarin)
Domain	medical and force protection
Corpora	10,000 annotated parallel sentences
Vocabulary size	3000
Size of Concept Set	68

Experiments on ME-based Statistical NCG

Description

- Evaluate on primary concept sequences that represents the top-layer concepts in a semantic parser tree
- Concept sequences containing only one concept are removed as they are easy to generate
- Specific set of parallel concept sequences that contain the same set of concepts in both languages
- 5600 concept sequences are selected, 80% for training and 20% for testing
- Random partitioning of training and test set for 100 times
- Average error rates were recorded
- Worst-case test: sequences appear in the training corpus are not allowed to appear in the test corpus
- Normal-case test: sequences appear in the training corpus may appear in the test corpus

ME-NCG Experiments with Forward Models

NCG Methods	Training set (SER / CER)	Test set (SER / CER)
Baseline NCG with basic feature $\vec{f}_k^{(4)}$	14.0% / 8.8%	28.0% / 18.9%
+ feature on parallel corpora $\vec{f}_k^{(5)}$	6.2% / 3.5%	21.7% / 14.1%
+ concept-word features $\vec{f}_k^{(7)}$	0.7% / 0.4%	20.2% / 13.1%
+ multiple feature selection $\left(\vec{f}_k^{(5)} + \vec{f}_k^{(7)}\right)\vec{f}_k^{(4)}$	**0.7% / 0.4%**	**17.4% / 11.4%**

- A concept sequence is considered to have an error during measurement of sequence error rate if one or more errors occur in this sequence
- Concept error rate, on the other hand, evaluates concept errors in concept sequences such as substitution, deletion and insertion

ME-NCG Experiments with Forward-Backward Models

NCG Methods	Training set (SER / CER)	Test set (SER / CER)
Baseline NCG with basic feature $\vec{f}_k^{(4)}$	9.1% / 5.5%	24.4% / 16.4%
+ feature on parallel corpora $\vec{f}_k^{(5)}$	5.7% / 3.2%	17.8% / 11.6%
+ concept-word features $\vec{f}_k^{(7)}$	0.5% / 0.3%	17.7% / 11.5%
+ multiple feature selection $\left(\vec{f}_k^{(5)} + \vec{f}_k^{(7)}\right)\vec{f}_k^{(4)}$	**0.5% / 0.3%**	**15.8% / 10.4%**

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Experiment on Statistical Interlingua-based S2S

Translation Methods	$\vec{f}_k^{(4)}$	$\vec{f}_k^{(5)}$	$\left(\vec{f}_k^{(5)} + \vec{f}_k^{(7)}\right)$
Text-to-Text	0.536	0.578	**0.605**
Speech-to-Text	0.437	0.469	**0.489**

Bleu metric (proposed by Kishore et. al.) measures MT performance by evaluating n-gram accuracy with a brevity penalty

$$Bleu = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

$$BP = \begin{cases} 1 & if\ c > r \\ e^{(1-r/c)} & if\ c \le r \end{cases}$$

p_n : n-gram precision rate w_n : n-gram weight BP : Brevity penalty

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Summary

- Attack the problems of feature selection during maximum-entropy-based model training and concept generation
- New concept-word features proposed that exploit both information at both concept level and word level
- Multiple feature selection algorithm combines different features in maximum-entropy models to alleviate data-sparseness-caused over-training problem
- Significant improvements are achieved in both concept sequence generation test and speech translation experiments