Context-Dependent Alignment Models

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Context Dependent Translation in Alignment

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Target Words	e_1	e_2	...	e_I
Source Words	f_1	f_2	...	f_J
Source Context	c_1	c_2	...	c_J

$$P(e_1^I, a_1^I | f_1^J, c_1^J) \approx \prod_{i=1}^{I} T(e_i | f_{a_i}, c_{a_i})$$

- **Basic models rely on context-independent word-to-word translation -- Models 1, 2, ..., HMMs and variants**
- **Not easy to introduce translation dependency on context**
  - **need to control model size and computational complexity**
- **New: Context clustering via decision trees**
  - **Each source word gets its own tree (many, many trees...)**
  - **Questions are asked about the source word contexts**
  - **Clustering is performed during iterative EM training**
  - **EM auxiliary function is used as the clustering purity function**
    - **identical to HTK acoustic clustering**

Context-dependent alignment models for statistical machine translation.
NAACL-HLT, 2009 J. Brunning, A. de Gispert, and W. Byrne.

Context-dependent alignment models: Clustering by Part of Speech tags

- **POS taggers were run on both sides of the parallel texts**
- **Created question sets for POS contexts**
  - **questions covered 5-word contexts**
  - **Grew four sets of trees: two for Ar/Zh->En and two for En->Ar/Zh**

Most frequent root node questions for Ar-En

English Question	Count	Arabic Questions	Count
Is_Next_Preposition	1523	Is_Prev_Preposition	1110
Is_Prev_Determiner	1444	Is_Next_Preposition	993
Is_Prev_Preposition	1209	Is_Prev_Noun	981
Is_Prev_Adjective	864	Is_Prev_Coordinating_Conj	627

- **26% and 40% of Arabic and English words have CD translations**
- **Question combinations get fairly complex further down the tree**

CD models improve both alignment and translation quality

- CD Model 1: Large reductions in Alignment Error Rate
- CD HMMs: Improvements in alignment and in BLEU

BLEU scores on development training and test sets

	Ar - En		Zh - En	
Alignment	mt02-05test	MT08-nw	test-nw	MT08-nw
CI-HMM	49.4	46.3	28.5	26.9
CD-HMM	49.7	46.9	29.0	27.7

- Using decision trees for context dependent translation models scales well to larger data sets:
  - Parallelized implementation using MTTK alignment tools
  - Good gains on the full AGILE training sets (0.5 -- 1.0 BLEU)

Hierarchical Phrase-based Translation with Weighted Finite State Transducers

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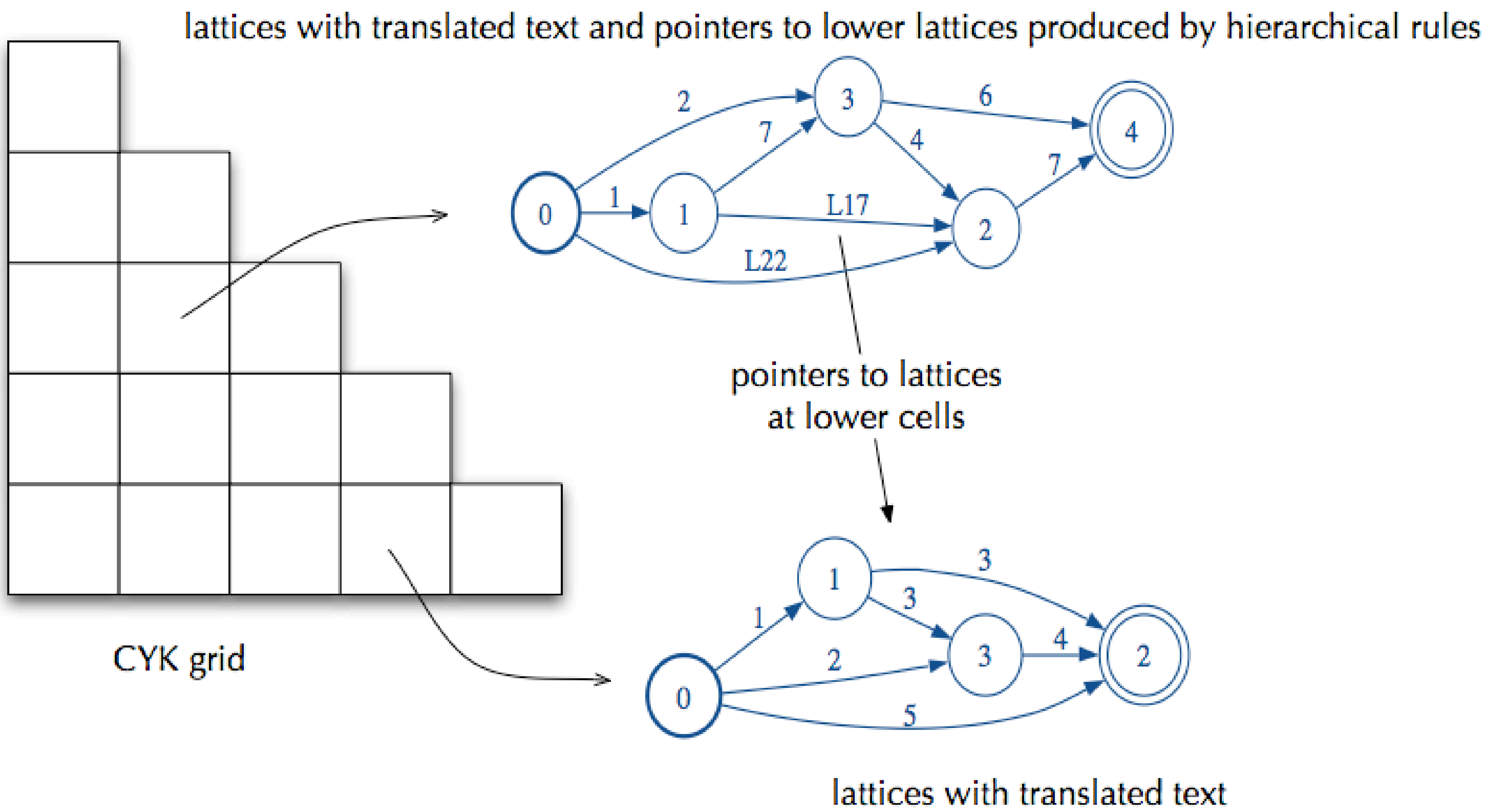
HiFST: WFST implementation of Hiero

- **WFST formulation of Hiero-style translation**
  - Alternative implementation to Cube Pruning (CPH)
  - Unioning/concatenating/pruning/etc. is done with standard WFST ops
  - Based on Google OpenFST toolkit
- **Key idea: work with lattices containing many hypotheses and avoid working with individual translation hypotheses**
  - vastly larger hypothesis spaces
- **Source language sentence is parsed using source-side of the Hiero translation rules**
  - CYK grid is built up and applicable rules are kept in each cell
- **A translation lattice is built for every cell, based on its rules**
  - lattice arcs have translated text or pointers to other lattices
  - these intermediate lattices can be minimized, determinized, etc.
  - lattice pointers are only expanded when translation is complete or if intermediate pruning is required
    - fast, and controls memory usage

Hierarchical phrase-based translation with weighted finite state transducers.
G. Iglesias, A. de Gispert, E. R. Banga, and W. Byrne. NAACL-HLT, 2009.

Delayed Translation



Translation improves with denser search spaces

- **More efficient search:**
  - **48% reduction in search errors for ZH->EN translation**
  - **AR->EN translation runs without pruning**
- **Direct generation of translation lattices**
- **Richer search space improves subsequent rescoring**
  - **HiFST is comparable to CPH in first pass [(a) vs (c)]**
  - **HiFST produces richer/better hypotheses for rescoring**
    - **increased gains from 5Gram LM + Minimum Bayes Risk rescoring [(b) vs (d)]**

		ZH->EN		AR->EN	
	Decoder	test-nw	NIST MT08	mt02-05-test	NIST MT08
		BLEU / TER		BLEU / TER	
(a)	CPH	32.2 / 59.9	27.2 / 60.2	51.5 / 42.2	42.5 / 48.6
(b)	CPH +5G+MBR	32.7 / 59.4	28.1 / 59.3	52.6 / 41.4	43.4 / 48.1
(c)	HiFST	32.2 / 60.0	27.1 / 60.5	51.6 / 42.1	42.4 / 48.7
(d)	HiFST+5G+MBR	33.4 / 58.5	28.9 / 58.9	53.3 / 40.9	44.0 / 48.0