Rule Filtering by Pattern for Efficient Hierarchical Translation

Gonzalo Iglesias[1] Adrià de Gispert[2]
Eduardo R. Banga[1] William Byrne[2]

[1]Department of Signal Processing and Communications
University of Vigo, Spain

[2]Department of Engineering.
University of Cambridge, U.K.

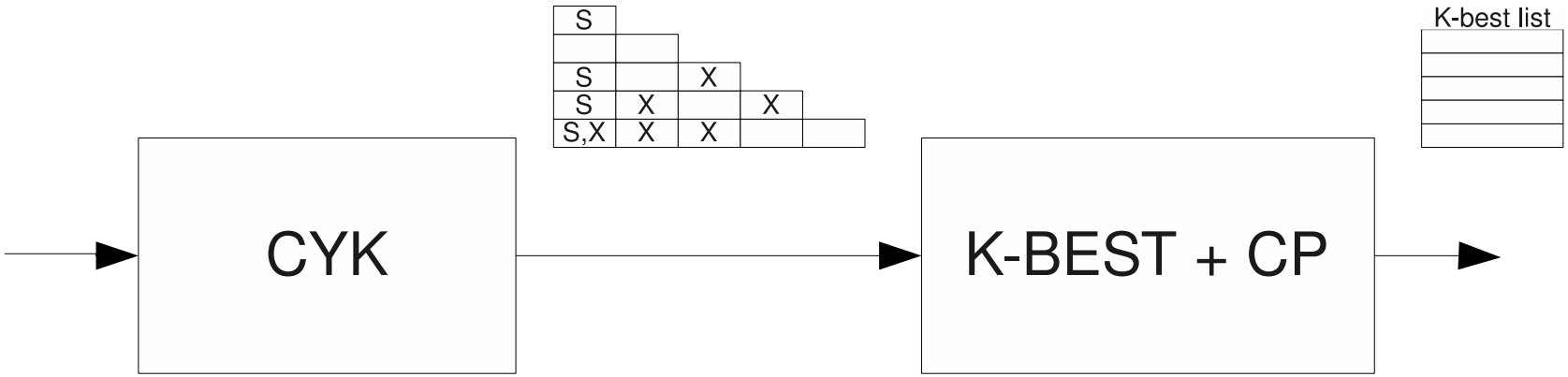
12th Conference of the EACL.
Athens, April 2009.

Outline

Outline

Hierarchical Cube Pruning

Very Brief Description!

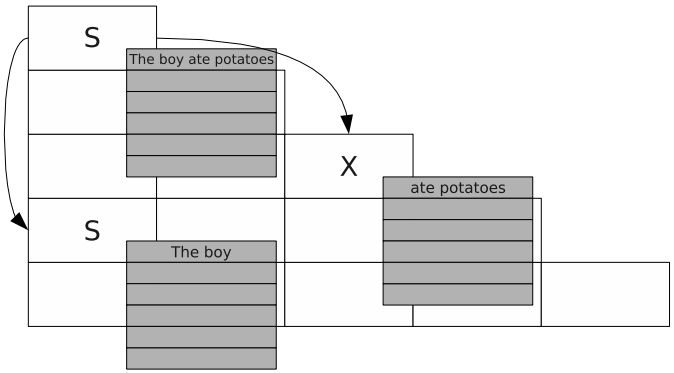


- CYK: source side, hypotheses recombination, no pruning
- k-best algorithm: uses cube pruning with LM costs to extract efficiently k-best lists
- NIST 2008 Arabic-to-English task, k-best=10000

Outline

Smart Memoization

- Key aspect of Chiang's k-best algorithm: memoization!
- Each cell reached at least once by the k-best algorithm will store a k-best list
- Only after finishing translation you can free memory (Gigs)

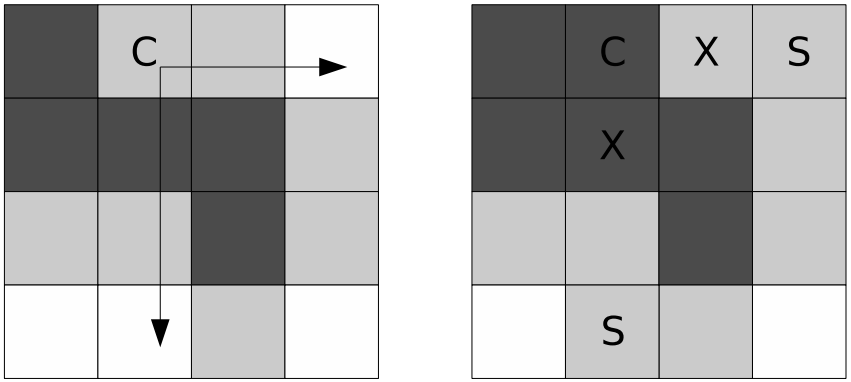


Smart Memoization

- Idea: Couldn't we delete k-best lists on the fly?
- Problem: We do not know how many times will each cell be accessed
- Solution: Traverse back-pointers twice:
  - 1st pass: count how many times each cell will be accessed (very fast)
  - 2nd pass, build translation hyps: Decrease counter for each cell. If counter=0, delete k-best list!
- typically reduces memory usage in 30%

Outline

Spreading Neighborhood Exploration I



- Cube Pruning: extracts efficiently first k-best hyps
- Original CP items X already added! Queue of candidates shrinks$\rightarrow$ Search Errors!
- Spreading neighborhood exploration adds candidates S to the queue

Hiero Search Errors I

A study in Phrase-Based Translation

- How can we assess the impact of SNE?
- We use as a reference TTM, a phrase-based SMT system implemented with Weighted Finite-State Transducers
- TTM Reordering Models: MJO, or an MJ1 (maximum phrase jump of 0 and 1, respectively)
- TTM works largely without pruning (even with big models)
- HCP can easily emulate TTM MJ0 and MJ1 models

Hiero Search Errors II

A study in Phrase-Based Translation

HIERO MJ1
$S \rightarrow \langle S\ X, S\ X \rangle$
$S \rightarrow \langle X, X \rangle$
$X \rightarrow \langle V_2 V_1, V_1 V_2 \rangle$
$X \rightarrow \langle V, V \rangle$
$V \rightarrow \langle s, t \rangle$
$s, t \in \mathbf{T}^+$

Table: Hierarchical grammars for MJ1

Hiero Search Errors III

A study in Phrase-Based Translation

	Monotone		MJ1+MET	
	BLEU	SE	BLEU	SE
TTM	44.7	-	49.1	-
HCP	44.5	342	48.4	822
HCP+SNE=20	44.7	77	48.9	360

Table: Phrase-based TTM and Hiero performance comparison on Arabic-to-English *mt02-05-tune*. SE is the number of Hiero hypotheses with search errors.

Outline

Initial Rule Sets Are Really Big

- Initial Rule Extraction: 175 M rules!
- Other approaches:
  - Lopez(2008) enforces rules with minspan of two words (115M)
  - Zollman et al.(2008) enforce mincount: (e.g. 57M mincount=3)
  - Shen et al.(2008) filter target-side rules that are not well-formed dependency trees
  - Chiang(2007) reports experiments with 5.5M
- Are all these rules needed for translation?

Rule Patterns I

- Hierarchical rules $X \rightarrow \langle \gamma, \alpha \rangle$: sequences of terminals and non-terminals (elements)
- Source Pattern and Target Pattern: replace every sequence of terminals by a single symbol 'w' ($w \in \mathbf{T}^{+}$).
- Each hierarchical rule corresponds to a unique source and target pattern which together define the *rule pattern*.

- 65 hierarchical rule patterns

Rule Patterns II

- Example:
  Pattern $\langle wX_1 \ , \ wX_1w \rangle$:
  $\langle w+ \ qAl \ X_1 \ , \ the \ X_1 said \rangle$
  Pattern $\langle wX_1w \ , \ wX_1 \rangle$:
  $\langle fy \ X_1 kAnwn \ Al>wl \ , \ on \ december \ X_1 \rangle$
  Pattern $\langle wX_1wX_2 \ , \ wX_1wX_2w \rangle$:
  $\langle Hl \ X_1 lAzmp \ X_2 \ , \ a \ X_1 solution \ to \ the \ X_2 crisis \rangle$
- Rules can be classed by their number of non-terminals, N_{nt}, and their number of elements, N_e(source side).
- There are 5 possible classes:
  $N_{nt}.N_e = 1.2, 1.3, 2.3, 2.4, 2.5$.

Rule Patterns III

Class $N_{nt}.N_e$	Rule Pattern $\langle$source , target$\rangle$	Types
1.2	$\langle wX_1 , wX_1 \rangle$	1185028
	$\langle wX_1 , wX_1w \rangle$	153130
	$\langle wX_1 , X_1w \rangle$	97889
1.3	$\langle wX_1w , wX_1w \rangle$	32903522
	$\langle wX_1w , wX_1 \rangle$	989540
2.3	$\langle X_1wX_2 , X_1wX_2 \rangle$	1554656
	$\langle X_2wX_1 , X_1wX_2 \rangle$	39163
2.4	$\langle X_1wX_2w , X_1wX_2w \rangle$	26053969
	$\langle wX_1wX_2 , wX_1wX_2w \rangle$	2534510
	$\langle wX_2wX_1 , wX_1wX_2 \rangle$	349176
2.5	$\langle wX_1wX_2w , wX_1X_2w \rangle$	3149516
	$\langle wX_1wX_2w , X_1wX_2w \rangle$	2330797
	$\langle wX_2wX_1w , wX_1wX_2w \rangle$	275810

Towards a more Workable Rule Set I

- Greedy approach to building a rule set:
- Rules belonging to a pattern are added to the rule set guided by the improvements relative to Hiero Monotone
- Certain patterns seem not to contribute to any improvement.
  - No improvement when adding $\langle X_1 w, X_1 w \rangle$ (1.2M)
  - Adding $\langle w X_1, X_1 w \rangle$ (0.01M), provides substantial gains.
  - Situation is analogous two non-terminals (N_{nt}=2).

Towards a more Workable Rule Set II

	Excluded Rules	Types
a	$\langle X_1 w, X_1 w \rangle$, $\langle w X_1, w X_1 \rangle$	2332604
b	$\langle X_1 w X_2, * \rangle$	2121594
c	$\langle X_1 w X_2 w, X_1 w X_2 w \rangle$, $\langle w X_1 w X_2, w X_1 w X_2 \rangle$	52955792
d	$\langle w X_1 w X_2 w, * \rangle$	69437146
e	$N_{nt}.N_e$= 1.3 w mincount=5	32394578
f	$N_{nt}.N_e$= 2.3 w mincount=5	166969
g	$N_{nt}.N_e$= 2.4 w mincount=10	11465410
h	$N_{nt}.N_e$= 2.5 w mincount=5	688804

Table: Rules excluded from the initial rule set. 171M filtered out, 3.5 hierarchical rules, 4.2 including phrase-based rules

Outline

Hiero Full versus Hiero Shallow I

HIERO	HIERO SHALLOW
$X \rightarrow \langle \gamma, \alpha \rangle$ $\gamma, \alpha \in (\{X\} \cup \mathbf{T})^+$	$X \rightarrow \langle \gamma_s, \alpha_s \rangle$ $X \rightarrow \langle V, V \rangle$ $V \rightarrow \langle s, t \rangle$ $s, t \in \mathbf{T}^+; \gamma_s, \alpha_s \in (\{V\} \cup \mathbf{T})^+$

Table: Hierarchical grammars, Shallow versus Full

Hiero Full versus Hiero Shallow II

mt02-05-	*-tune*		*-test*
System	**Time**	**BLEU**	**BLEU**
HIERO	14.0	52.1	51.5
HIERO - shallow	2.0	52.1	51.4

Table: Translation performance and time (in seconds per word) for full vs. shallow Hiero. Arabic-to-English task, kbest=10000, SNE=20

Outline

Filtering by Number of Translations I

- $\forall\gamma \notin \mathbf{T}^{+}$ filter $X \rightarrow \langle\gamma,\alpha\rangle$ with the following criteria:
  - Keep the **NT** most frequent α, i.e. each γ is allowed to have at most **NT** rules.
  - Keep the **NRT** most frequent α with monotonic non-terminals and the **NRT** most frequent α with reordered non-terminals.
  - Keep the most frequent α until their aggregated number of counts reaches a certain percentage **CP** of the total counts of $X \rightarrow \langle\gamma,*\rangle$.

Filtering by Number of Translations II

mt02-05-	*-tune*			*-test*
Filter	**Time**	**Rules**	**BLEU**	**BLEU**
baseline	2.0	4.20	52.1	51.4
NT=10	0.8	3.25	52.0	51.3
NT=15	0.8	3.43	52.0	51.3
NT=20	0.8	3.56	**52.1**	**51.4**
NRT=10	0.9	3.29	52.0	51.3
NRT=15	1.0	3.48	52.0	51.4
NRT=20	1.0	3.59	**52.1**	**51.4**
CP=50	0.7	2.56	51.4	50.9
CP=90	1.0	3.60	52.0	51.3

Table: Impact of general rule filters on translation (IBM BLEU), time (in seconds per word) and number of rules (in millions).

Outline

Revisiting Pattern Filtering Strategies I

- As many decisions were based on the initial greedy approach, we revisit our strategy
- Different (class) mincount filterings.
- Rule pattern filterings: Reintroduce different monotone patterns

Revisiting Pattern Filtering Strategies II

mt02-05-		*-tune*			*-test*
$\mathbf{N_{nt}.N_e}$	Filter	**Time**	**Rules**	**BLEU**	**BLEU**
baseline **NRT**=20		1.0	3.59	52.1	51.4
2.3	+monotone	1.1	4.08	51.5	51.1
2.4	+monotone	2.0	11.52	51.6	51.0
2.5	+monotone	1.8	6.66	51.7	51.2

- Reintroducing monotonic rules degrades performance, substantial increase of n of rules.

Revisiting Pattern Filtering Strategies III

mt02-05-		*-tune*			*-test*
$\mathbf{N_{nt}.N_e}$	Filter	**Time**	**Rules**	**BLEU**	**BLEU**
baseline **NRT**=20		1.0	3.59	52.1	51.4
1.3	mincount=3	1.0	5.61	52.1	51.3
2.3	mincount=1	1.2	3.70	52.1	51.4
2.4	mincount=5	1.8	4.62	52.0	51.3
2.4	mincount=15	1.0	3.37	52.0	51.4
2.5	mincount=1	1.1	4.27	52.2	**51.5**
1.2	mincount=5	1.0	3.51	51.8	51.3
1.2	mincount=10	1.0	3.50	51.7	51.2

Outline

Large Language Models and Evaluation I

- Rescoring steps:
  - *Large-LM rescoring* of 10000-best list with 5-gram language models,
  - *Minimum Bayes Risk (MBR)*. Rescore 1000-best hyps

	mt06-nist-nw	*mt06-nist-ng*	*mt08*
HCP+MET	48.4 / 43.6	35.3 / 53.2	42.5 / 48.6
+rescoring	49.4 / 42.9	36.6 / 53.5	43.4 / 48.1

Table: Arabic-to-English translation results (lower-cased IBM BLEU / TER)

- Mixed case NIST BLEU for *mt08* is 42.5

Summary

- Smart memoization and spreading neighborhood exploration reduce memory consumption and Hiero search errors.
- For Arabic-to-English, Shallow hierarchical decoding is as good as fully hierarchical decoding (and much faster!)
- Filtering Rules by Translations further increases speed with no cost in scores
- For hierarchical rules grouped in classes and patterns:
  - Certain patterns are of much greater value in translation than others
  - Separate minimum count filtering should be applied

Thank you!

For further reading, check out NAACL2009 paper:
"Hierarchical Phrase-Based Translation with Weighted Finite State Transducers"