Two Improvements to Left-to-Right Decoding for Hierarchical Phrase-based Machine Translation

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Abstract

Left-to-right (LR) decoding (Watanabe et al., 2006) is promising decoding algorithm for hierarchical phrase-based translation (Hiero) that visits input spans in arbitrary order producing the output translation in left to right order. This leads to far fewer language model calls, but while LR decoding is more efficient than CKY decoding, it is unable to capture some hierarchical phrase alignments reachable using CKY decoding and suffers from lower translation quality as a result. This paper introduces two improvements to LR decoding that make it comparable in translation quality to CKY-based Hiero.

1 Introduction

Hierarchical phrase-based translation (Hiero) (Chiang, 2007) uses a lexicalized synchronous context-free grammar (SCFG) extracted from word and phrase alignments of a bitext. Decoding for Hiero is typically done with CKY-style decoding with time complexity \(O(n^3)\) for source input with \(n\) words. Computing the language model score for each hypothesis within CKY decoding requires two histories, the left and the right edge of each span, due to the fact that the target side is built inside-out from sub-spans (Heafield et al., 2011; Heafield et al., 2013).

LR-decoding algorithms exist for phrase-based (Koehn, 2004; Galley and Manning, 2010) and syntax-based (Huang and Mi, 2010; Feng et al., 2012) models and also for hierarchical phrase-based models (Watanabe et al., 2006; Siahbani et al., 2013), which is our focus in this paper. Watanabe et al. (2006) first proposed left-to-right (LR) decoding for Hiero (LR-Hiero henceforth) which uses beam search and runs in \(O(n^2b)\) in practice where \(n\) is the length of source sentence and \(b\) is the size of beam (Huang and Mi, 2010). To simplify target generation, SCFG rules are constrained to be prefix-lexicalized on target side aka Griebach Normal Form (GNF). Throughout this paper we abuse the notation for simplicity and use the term GNF grammars for such SCFGs. This constraint drastically reduces the size of grammar for LR-Hiero in comparison to Hiero grammar (Siahbani et al., 2013). However, the original LR-Hiero decoding algorithm does not perform well in comparison to current state-of-the-art Hiero and phrase-based translation systems. Siahbani et al. (2013) propose an augmented version of LR decoding to address some limitations in the original LR-Hiero algorithm in terms of translation quality and time efficiency.

Although, LR-Hiero performs much faster than Hiero in decoding and obtains BLEU scores comparable to phrase-based translation system on some language pairs, there is still a notable gap between CKY-Hiero and LR-Hiero (Siahbani et al., 2013). We show in this paper using instructive examples that CKY-Hiero can capture some complex phrasal re-orderings that are observed in language pairs such as Chinese-English that LR-Hiero cannot (c.f. Sec.3).

We introduce two improvements to LR decoding of GNF grammars: (1) We add queue diversity to the cube pruning algorithm for LR-Hiero, and (2) We extend the LR-Hiero decoder to capture all the hierarchical phrasal alignments that are reachable in CKY-Hiero (restricted to using GNF grammars). We evaluate our modifications on three language pairs and show that LR-Hiero can reach the translation scores comparable to CKY-Hiero in two language pairs, and reduce the gap between Hiero and LR-Hiero on the third one.

2 LR Decoding with Queue Diversity

LR-Hiero uses a constrained lexicalized SCFG which we call a GNF grammar: \(X \rightarrow (\gamma, \bar{b}, \beta)\) where \(\gamma\) is a string of non-terminal and terminal symbols, \(\bar{b}\) is a string of terminal symbols and \(\beta\) is a possibly empty sequence of non-terminals. This ensures that as each rule is used in a derivation,
Algorithm 1: LR-Hiero Decoding

1: Input sentence: \( f = f_0 f_1 \ldots f_n \)
2: \( \mathcal{F} = \text{FutureCost}(f) \) (Precompute future cost for spans)
3: \( S_0 = \{ \} \) (Create empty initial stack)
4: \( h_0 = (s, \{0, n\}, \emptyset, \mathcal{F}(0, n)) \) (Initial hypothesis 4-tuple)
5: Add \( h_0 \) to \( S_0 \) (Push initial hyp into first Stack)
6: for \( i = 1, \ldots, n \) do
7: \( \text{cubeList} = \{ \} \) (MRL is max rule length)
8: for \( p = \max(i - \text{MRL}, 0), \ldots, i - 1 \) do
9: \( \{G\} = \text{Grouped}(S_p) \) (based on the first uncovered span)
10: for \( g \in \{G\} \) do
11: \( [u, v] = g_{span} \)
12: \( R = \text{GetSpanRules}(u, v) \) (d best hypotheses of each cube)
13: for \( R_s \in R \) do
14: \( \text{cube} = [g_{hyps}, R_s] \)
15: Add cube to cubeList
16: \( S_i = \text{Merge}(\text{cubeList}, \mathcal{F}) \) (Create stack \( S_i \) and add new hypotheses to it, see Figure 1)
17: return \( \arg \max(S_n) \)
18: \( \text{Merge}(\text{CubeList}, \mathcal{F}) \)
19: \( \text{heapQ} = \{ \} \)
20: for each \((H, R)\) in \( \text{cubeList} \) do
21: \( \text{hypList} = \text{getBestHypotheses}((H, R), \mathcal{F}, d) \) (d best hypotheses of each cube)
22: for each \( h' \) in \( \text{hypList} \) do
23: push(\( \text{heapQ}, (h', h', [H, R]) \)) (Push new hyp in queue)
24: \( \text{hypList} = \{ \} \)
25: while \( |\text{heapQ}| > 0 \) and \( |\text{hypList}| < K \) do
26: \( (h'_t, h'_g, [H, R]) = \text{pop}(\text{heapQ}) \) (pop the best hypothesis)
27: push(\( \text{heapQ}, \text{GetNeighbours}([H, R]) \)) (Push neighbours to queue)
28: Add \( h'_t \) to \( \text{hypList} \)
29: return \( \text{hypList} \)

the target string is generated from left to right. The rules are obtained from a word and phrase aligned bitext using the rule extraction algorithm in (Watanabe et al., 2006).

LR-Hiero decoding uses a top-down depth-first search, which strictly grows the hypotheses in target surface ordering. Search on the source side follows an Earley-style search (Earley, 1970), the dot jumps around on the source side of the rules based on the order of nonterminals on the target side. This search is integrated with beam search or cube pruning to find the \( k \)-best translations.

Algorithm 1 shows the pseudocode for LR-Hiero decoding with cube pruning (Chiang, 2007) (CP). LR-Hiero with CP was introduced in (Stabani et al., 2013). In this pseudocode, we have introduced the notion of queue diversity (explained below). However to understand our change we need to understand the algorithm in more detail.

Each source side non-terminal is instantiated with the legal spans given the input source string, e.g., if there is a Hiero rule \( \langle aX_1, a'X_1 \rangle \) and if \( a \) only occurs at position 3 in the input then this rule can be applied to span \([3, i]\) for all \( i, 4 < i \leq n \) for input of length \( n \) and source side \( X_1 \) is instantiated to span \([4, i]\). A worked out example of how the decoder works is shown in Figure 2. Each partial hypothesis \( h \) is a 4-tuple \((h_t, h_s, h_{cov}, h_c)\): consisting of a translation prefix \( h_t \), a (LIFO-ordered) list \( h_s \) of uncovered spans, source words coverage set \( h_{cov} \) and the hypothesis cost \( h_c \). The initial hypothesis is a null string with just a sentence-initial marker \( \langle s \rangle \) and the list \( h_s \) containing a span of the whole sentence, \([0, n]\). The hypotheses are stored in stacks \( S_0, \ldots, S_n \), where \( S_p \) contains hypotheses covering \( p \) source words just like in stack decoding for phrase-based SMT (Koehn et al., 2003).

To fill stack \( S_i \) we consider hypotheses in each stack \( S_p^2 \), which are first partitioned into a set of groups \( \{G\} \), based on their first uncovered span (line 9). Each group \( g \) is a 2-tuple \((g_{span}, g_{hyps})\), where \( g_{hyps} \) is a list of hypotheses which share the same first uncovered span \( g_{span} \). Rules matching the span \( g_{span} \) are obtained from routine GetSpanRules. Each \( g_{hyps} \) and possible \( R_s \) create a cube which is added to \( \text{cubeList} \).

The Merge routine gets the best hypotheses from all cubes (see Fig.1). Hypotheses (rows) and columns (rules) are sorted based on their scores. GetBestHypotheses((\( H, R \), \( \mathcal{F}, d \)) uses current hypothesis \( H \) and rule \( R \) to produce new hypotheses. The first best hypothesis, \( h'_t \) along with its score \( h'_t \), and corresponding cube \((H, R)\) is placed in a priority queue \( \text{heapQ} \) (triangle in Figure 1 and line 23 in Algorithm 1). Iteratively the \( K \) best
hypotheses in the queue are popped (line 26) and for each hypothesis its neighbours in the cube are added to the priority queue (line 27). Decoding finishes when stack $S_n$ has been filled.

The language model (LM) score violates the hypotheses generation assumption of CP and can cause search errors. In Figure 1, the topmost and leftmost entry of the right cube has a score worse than many hypotheses in the left cube due to the LM score. This means the right cube has hypotheses that are ignored. This type of search error hurts LR-Hiero more than CKY-Hiero, due to the fact that hypotheses scores in LR-Hiero rely on a future cost, while CKY-Hiero uses the inside score for each hypothesis. To solve this issue for LR-Hiero we introduce the notion of queue diversity which is the parameter $d$ in $GetBestHypotheses((H, R), F, d)$. This parameter guarantees that each cube will produce at least $d$ candidate hypotheses for the priority queue. $d=1$ in standard cube pruning for LR-Hiero (Siahbani et al., 2013). We apply the idea of diversity at queue level, before generating $K$ best hypothesis, such that the $GetBestHypotheses$ routine generates $d$ best hypotheses from each cube and all these hypotheses are pushed to the priority queue (line 22-23). We fill each stack differently from CKY-Hiero and so queue diversity is different from lazy cube pruning (Pust and Knight, 2009) or cube growing (Huang and Chiang, 2007; Vilar and Ney, 2009; Xu and Koehn, 2012).

3 Capturing Missing Alignments

Figure 3(a) and Figure 3(b) show two examples of a common problem in LR-Hiero decoding. The decoder steps for Figure 3(b) are shown in Figure 2. The problem occurs in Step 5 of Figure 2 where rule #5 is matched to span $[7, 15]$. During decoding LR-Hiero maintains a stack (last-in-first-out) of yet-to-be-covered spans and tries to translate the first uncovered span (span $[7, 15]$ in Step 5). LR-Hiero should match rule #5 to span $[7, 15]$, therefore $X_2$ is forced to match span $[12, 15]$ which leads to the translation of span $[7, 9]$ (corresponding to $X_1$) being reordered around it.

![Figure 2: The process of translating the Chinese sentence in Figure 3(b) in LR-Hiero. Left side shows the rules used in the derivation (G indicates glue rules as defined in (Watanabe et al., 2006)). The hypotheses column shows the translation prefix and the ordered list of yet-to-be-covered spans.](image)

![Figure 3: Two Chinese-English sentence pairs from devset data in experiments. (a) Correct rule cannot be matched to $[6, 18]$, and the ordered list of yet-to-be-covered spans. (b) LR-Hiero detects a wrong span for Figure 3(b) in LR-Hiero. Left side shows the rules used in the derivation and the ordered list of yet-to-be-covered spans and tries to translate the first uncovered span (span $[7, 15]$ in Step 5). LR-Hiero should match rule #5 to span $[7, 15]$, therefore $X_2$ is forced to match span $[12, 15]$ which leads to the translation of span $[7, 9]$ (corresponding to $X_1$) being reordered around it.](image)
causing the incorrect translation in Step 9. If we use the same set of rules for translation in Hi-
ero (CKY-based decoder), the decoder is able to
generate the correct translation for span \([7, 14]\) (it
works bottom-up and generate best translation for
each source span). Then it combines translation of
\([7, 14]\) with translation of spans \([0, 7]\) and \([14, 15]\)
using glue rules (monotonic combination).

In Figure 3(a) monotonic translations after span
\([6, 9]\) are out of reach of the LR-Hiero decoder
which has to use the non-terminals to support the
reordering within span \([6, 9]\). In this example
the first few phrases are translated monotonically,
then for span \([6, 18]\) we have to apply rule
\(\text{wending} \ X_1 \ \text{wending is now in stable} \ X_1\) to
obtain the correct translation. But this rule cannot
be matched to span \([6, 18]\) and the decoder fails
to generate the correct translation. While CKY-
Hiero can apply this rule to span \([6, 9]\), generate
correct translation for this span and monotonically
combine it with translation of other spans \(([0, 6],
[9, 18])\).

In both these cases, CKY-Hiero has no difficulty
in reaching the target sentence with the same
GNF rules. The fact that we have to process spans
as they appear in the stack in LR-Hiero means
that we cannot combine arbitrary adjacent spans
to deal with such cases. So purely bottom-up decoders
such as CKY-Hiero can capture the alignments in Figure 3 but LR-Hiero cannot.

We extend the LR-Hiero decoder to handle such
cases by making the GNF grammar more expressive.
Rules are partitioned to three types based on
the right boundary in the source and target side.
The rhs after the \(\Rightarrow\) shows the new rules we create
within the decoder using a new non-terminal \(X_r\)
to match the right boundary.

\[
\begin{align*}
(a) & \quad \langle \gamma \bar{a}, \bar{b}\beta \rangle \Rightarrow \langle \gamma \bar{a} X_r, \bar{b}\beta X_r \rangle \\
(b) & \quad \langle \gamma X_n, \bar{b}\beta X_m \rangle \Rightarrow \langle \gamma X_n X_r, \bar{b}\beta X_m X_r \rangle \\
(c) & \quad \langle \gamma X_n, \bar{b}\beta X_r \rangle \Rightarrow \langle \gamma X_n X_r, \bar{b}\beta X_m X_r \rangle
\end{align*}
\]

where \(\gamma\) is a string of terminals and non-terminals,
\(\bar{a}\) and \(\bar{b}\) are terminal sequences of source and tar-
target respectively, \(\beta\) is a possibly empty sequence
of non-terminals and \(X_n\) and \(X_m\) are different
non-terminals distinct from \(X_r\).\(^3\) The extra non-
terminal \(X_r\) lets us add a new yet-to-be-covered
span to the bottom of the stack at each rule application
which lets us match any two adjacent spans just as in CKY-Hiero. This captures the missing
alignments that could not be previously captured in
the LR-Hiero decoder.\(^4\)

In Table 4 we translated devset sentences using
forced decoding to show that our modifications to
LR-Hiero in this section improves the alignment
coverage when compared to CKY-Hiero.

### 4 Experiments

We evaluate our modifications to LR-Hiero de-
coder on three language pairs (Table 1): German-
English (De-En), Czech-English (Cs-En) and
Chinese-English (Zh-En).

\(^3\)In rule type (c) \(X_n\) will be in \(\beta\) and \(X_m\) will be in \(\gamma\).

\(^4\)For the sake of simplicity, in rule type (b) we can merge
\(X_n\) and \(X_r\) as they are in the same order on both source and
target side.
We use a 5-gram LM trained on the Gigaword corpus and use KenLM (Heafield, 2011). We tune weights by minimizing BLEU loss on the dev set through MERT (Och, 2003) and report BLEU scores on the test set. Pop limit for Hiero and LR-Hiero+CP is 500 and beam size LR-Hiero is 500. Other extraction and decoder settings such as maximum phrase length, etc. were identical across settings. To make the results comparable we use the same feature set for all baselines, Hiero as well (including new features proposed by (Siahbani et al., 2013)).

We use 3 baselines: (i) our implementation of (Watanabe et al., 2006): LR-Hiero with beam search (LR-Hiero) and (ii) LR-Hiero with cube pruning (Siahbani et al., 2013): (LR-Hiero+CP); and (iii) Kriya, an open-source implementation of Hiero in Python, which performs comparably to other open-source Hiero systems (Sankaran et al., 2012).

Table 3 shows model sizes for LR-Hiero (GNF) and Hiero (SCFG). Typical Hiero rule extraction excludes phrase-pairs with unaligned words on boundaries (loose phrases). We use similar rule extraction as Hiero, except that exclude non-GNF rules and include loose phrase-pairs as terminal rules.

Table 3: Model sizes (millions of rules).

| Model    | Cs-En | De-En | Zh-En |
|----------|-------|-------|-------|
| Hiero    | 1,961.6 | 858.5 | 471.9 |
| LR-Hiero | 266.5  | 116.0 | 100.9 |

Table 4: No. of sentence covered in forced decoding of a sample of sentences from the devset. We improve the coverage by 31% for Chinese-English and more than 20% for the other two language pairs.

| Model          | Cs-En | De-En | Zh-En |
|----------------|-------|-------|-------|
| Hiero          | 318   | 351   | 187   |
| LR-Hiero       | 278   | 300   | 132   |
| LR-Hiero+(abc) | 338   | 361   | 174   |

Comparing Table 2a with Figure 2b we can see that overall our modifications to LR-Hiero decoder significantly improves the BLEU scores compared to previous LR decoders for Hiero. We obtain comparable results to CKY-Hiero for Cs-En and De-En and remarkably improve results on Zh-En, while at the same time making 2 to 3 times less LM calls on Cs-En and De-En compared to CKY-Hiero.

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We report results on Cs-En and De-En in (Siahbani et al., 2013). Row 4 is the same translation system as row 3 (LR-Hiero+CP). We achieve better results than our previous work (Siahbani et al., 2013) (row 4 vs. row 3) due to bug corrections and adding loose phrases as terminal rules.

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