

Scalable Variational Inference for Extracting Hierarchical Phrase-based Translation Rules*

Baskaran Sankaran
Simon Fraser University
Burnaby BC, Canada
baskaran@cs.sfu.ca

Gholamreza Haffari
Monash University
Clayton VIC, Australia
reza@monash.edu

Anoop Sarkar
Simon Fraser University
Burnaby BC, Canada
anoop@cs.sfu.ca

Abstract

We present a Variational-Bayes model for learning rules for the Hierarchical phrase-based model directly from the phrasal alignments. Our model is an alternative to heuristic rule extraction in hierarchical phrase-based translation (Chiang, 2007), which uniformly distributes the probability mass to the extracted rules locally. In contrast, in our approach the probability assigned to a rule is globally determined by its contribution towards all phrase pairs and results in a sparser rule set. We also propose a distributed framework for efficiently running inference for realistic MT corpora. Our experiments translating Korean, Arabic and Chinese into English demonstrate that they are able to exceed or retain the performance of baseline hierarchical phrase-based models.

1 Introduction

Hierarchical phrase-based translation (Hiero) as described in (Chiang, 2005; Chiang, 2007) uses a synchronous context-free grammar (SCFG) derived from heuristically extracted phrase pairs obtained by symmetrizing bidirectional many-to-many word alignments (Och and Ney, 2004). The phrase-pairs are constrained by the source-target alignments such that all the alignment links from the source (target) words are connected to the target (source) words *within* the phrase. Given a word-aligned sentence pair $\langle f_1^j, e_1^I, A \rangle$, where A indicate the alignments, the source-target sequence pair $\langle f_i^j, e_{i'}^{j'} \rangle$ can be a phrase-pair *iff* the following alignment constraint is satisfied.

$$(k, k') \in A : k \in [i, j] \Leftrightarrow k' \in [i', j']$$

Given the phrase-pairs, SCFG rules are extracted by replacing aligned sequences of words in source

*This research was partially supported by an NSERC, Canada (RGPIN: 264905) grant and a Google Faculty Award to the third author.

and target sides by co-indexed non-terminals and rewriting the replaced source-target word sequences as separate rules. Consider a rule $X \rightarrow \langle \beta, \gamma \rangle$, where β and γ are sequences of terminals and non-terminals. Now, given another rule $X \rightarrow \langle f_i^j, e_{i'}^{j'} \rangle$, such that f_i^j and $e_{i'}^{j'}$ are contained fully within β and γ as sub-phrases, the larger rule could be rewritten to create a new rule.

$$X \rightarrow \langle \beta_p X_k \beta_s, \gamma_p X_k \gamma_s \rangle \quad (1)$$

Here β_p (β_s) refers to any prefix (suffix) of β that precedes (follows) f_i^j . Note that the non-terminals are co-indexed with a unique index so that they are rewritten simultaneously.

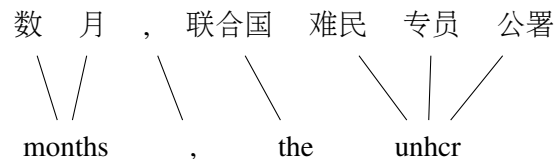


Figure 1: Chinese-English *phrase-pair* with alignments

As a concrete example, consider the word aligned Chinese-English phrase pair shown in Figure 1. Notice that the phrase 联合国 (united nations) is incorrectly aligned to English determiner *the*, even though in ideal case the entire Chinese phrase 联合国难民专员公署 should be aligned on the English side to *the unhr*. The heuristic approach extracts 32 rules, some of which are shown in Figure 2.

The distribution of the rules is unknown, as the different derivations of the sentences are not explicitly observed. Thus, Chiang (2007) follows an approach similar to that of Bod (1998) and hypothesizes a distribution over the rules. Under this each phrase-pair is assumed to have a unit count, which is uniformly distributed to all the rules extracted from this phrase-pair. The locally assigned rule counts are then aggregated across the entire set of phrase-pairs. The probability for each phrase pair

Translation rule	$P_{Heu}(e f)$	$P_{VB}(e f)$
* $X \rightarrow \langle \text{在 中 南海} \mid \text{at chong nan hai} \rangle$	0.333	0.003
* $X \rightarrow \langle \text{在 中 南海} \mid \text{at zhong nan hai} \rangle$	0.333	0.008
$X \rightarrow \langle \text{在 中 南海} \mid \text{at zhongnanhai} \rangle$	0.333	0.988

Figure 3: Rules extracted for translating the Chinese phrase 在中南海. The probabilities are shown for grammar extracted from heuristic as well our proposed method. The least preferred translations are shown with *. Our Variational-Bayes method extracts a grammar having a peaked distribution as shown.

* $X \rightarrow \langle \text{联合国} \mid \text{the} \rangle$
* $X \rightarrow \langle \text{数月, 联合国} \mid \text{months, the} \rangle$
$X \rightarrow \langle \text{数月, } X_1 \mid \text{months, } X_1 \rangle$
$X \rightarrow \langle \text{数月} \mid \text{months} \rangle$
$X \rightarrow \langle \text{联合国 难民 专员 公署} \mid \text{the unhcr} \rangle$

Figure 2: Rules extracted for the example phrase-pair in Figure 1. The rules encoding incorrect translations are marked with *.

is then estimated using relative frequency estimation.

1.1 Motivation

A major problem with this heuristic rule extraction method is the lack of *global re-weighting* of the pseudo-counts beyond their local assignments. By assigning uniform weight to the rules, Chiang (2007) assumes all the rules extracted from a given phrase-pair to be equally good. However, some rules might be better than others in terms of generalization, for capturing a syntactic phrase-pair, or being a semantically coherent unit of translation.

Due to this uniform treatment of good and poor translations, probability mass is wasted on poor translation candidates. For example the phrase-pair in Fig 1 would generate several poor translation rules (shown with * in Fig. 2). This is due to the incorrect alignment link between 联合国 and *the* (note that the word *the* is typically aligned with a large number of words due to its frequency). The heuristic extraction method simply assigns uniform count to all translations and as a result the first translation in Fig. 2 becomes the fourth best translation for this source phrase.

In Chiang (2007) the rule extraction algorithm produces a fairly flat distribution over rules. For example the different translation options of the Chinese phrase 在中南海 (*at zhongnanhai*) all

have the same $p(e|f)$ probability as shown in Figure 3. In contrast, our method produces a peaked distribution and shifts the probability mass towards *at zhongnanhai*, which is the preferred translation.

In this paper, we propose a method which distributes the probability mass among the rules (generated from a phrase-pair) based on their contribution in explaining the collection of all phrase-pairs in a global manner. This difference in estimation methods can lead to a peaked distribution of rule probabilities. Secondly we also present a distributed framework that enables rule extraction on large datasets that are typical in SMT. Our Variational-Bayes approach for rule extraction improves/ retains the translation quality for the three different language pairs. Finally, we also present a detailed analysis comparing the extracted SCFG with the heuristically extracted SCFG.

2 Model

Our model uses the notion of a *derivation*: the set of rules that fully derive an aligned phrase pair, and learns the estimates for the rules contained in the derivations through Variational inference. Setting the notations, we denote the set of derivations for a given phrase pair x as ϕ_x and the set of all rules as \mathcal{G} . Given the set of initial phrase pairs \mathcal{X} and a prior over the grammars \mathcal{G} , we formulate Hiero grammar extraction as the task of inferring a posterior distribution over Hiero grammars. Using Bayes' rule, we can express the posterior over the grammar \mathcal{G} given the set of bilingual phrases \mathcal{X} as: $P(\mathcal{G}|\mathcal{X}) \propto P(\mathcal{G})P(\mathcal{X}|\mathcal{G})$.

As mentioned earlier, our model replaces the heuristic rule extraction step in Hiero pipeline. Consequently our model assumes the existence of *initial* phrase-pairs obtained from bidirectional symmetrization of word alignments. We use the following two-step generative story to create an aligned phrase pair from the Hiero rules.

$\phi^z \sim \text{Dirichlet}(\alpha_z)$	[draw derivation type parameters]
$\theta \sim \text{Dirichlet}(\alpha_h p_0)$	[draw rule parameters]
$z_d \sim \text{Multinomial}(\phi^z)$	[decide the derivation type]
$r \mathbf{r} \in d_x \sim \text{Multinomial}(\theta)$	[generate rules deriving phrase-pair x]

Figure 4: Definition of the proposed model

1. First decide the derivation type z_d for generating the aligned phrase pair x . It can either be a terminal derivation or hierarchical derivation with one/two gaps,¹ i.e. $z_d = \{\text{TERM}, \text{HIER-A1}, \text{HIER-A2}\}$.
2. Then identify the constituent rules \mathbf{r} in the derivation to generate the phrase pair.

Under this model the probability of a particular derivation $d \in \phi_x$ for a given phrase pair x can be expressed as:

$$p(d) \propto p(z_d) \prod_{r \in d} p(r | \mathcal{G}, \theta) \quad (2)$$

where r is a rule in grammar \mathcal{G} and θ is the grammar parameter.

Figure 4 depicts the generative story of our generative model. The derivation-type z_d is sampled from a multinomial distribution parameterized by ϕ^z , where ϕ^z is distributed itself by a Dirichlet distribution with hyper-parameter α_z . The grammar rules are generated from a multinomial distribution parameterized by θ , where θ itself is distributed according to a Dirichlet distribution parameterized by a concentration parameter α_h and a base distribution p_0 . For the base distribution, we use a simple but yet informative prior based on geometric mean of the bidirectional alignment scores. This allows us to only explore the rules that would be consistent with the underlying word alignments.² Thus our setting closely resembles that of the Hiero heuristic rule extraction.

Our goal is thus to infer the joint posterior $p(\theta, \Phi | \alpha_h, p_0, \alpha_z, \mathcal{X})$, where θ are the model parameters and Φ the latent derivations over all the phrase pairs.

¹This refers to the maximum arity of a rule involved in the derivation.

²While a non-parametric prior would be better from a Bayesian perspective, we leave it for future consideration.

3 Training

For inference we resort to a variational approximation and factorize the posterior distributions over grammar parameters θ and latent derivations Φ as:

$$p(\theta, \Phi | \alpha_h, p_0, \alpha_z, \mathcal{X}) \approx q(\theta | \mathbf{u}) q(\Phi | \pi)$$

where \mathbf{u} and π are the parameters of the variational distributions.

The inference is then performed in an EM-style algorithm- iteratively updating the parameters \mathbf{u} and π . We initialize $\mathbf{u}^0 := \alpha_h p_0$, which is then updated with expected rule counts in subsequent iterations. The expected count for a rule r at time-step t can be written as:

$$\mathbb{E}[r^t] = \sum_{d \in \phi_x} p(d | \pi^{t-1}, x) f_d(r) \quad (3)$$

where $p(d | \pi^{t-1}, x)$ is the probability of the derivation d for the phrase pair x and $f_d(r)$ is the frequency of the rule r in derivation d . The $p(d | \cdot)$ term in Equation 3 can then be written in terms of π as:

$$p(d | \pi^{t-1}, x) \propto p(z_d) \prod_{r \in d} \pi_r^{t-1} \quad (4)$$

The $p(d | \cdot)$ are normalized across all the derivations of a given phrase pair to yield probabilities. For each *derivation type* z_d , its expected count (at time t) is the sum of the probabilities of all the derivations of its type.

$$\mathbb{E}[z_d^t] = \sum_x \sum_{\{z_d=z_{d'} | d' \in \phi_x\}} p(d' | \pi^{t-1}, x) \quad (5)$$

We initialize the Dirichlet hyperparameters α_{z_d} using a Gamma prior ranging between 10^{-1} and 10^3 : $\alpha_{z_d} \sim \text{Gamma}(10^{-1}, 10^3)$.³

³In initial experiments we used an initial prior of $\alpha_z = [10^0, 10, 10^4]$ to compensate for the smaller probabilities for arity-2 derivation resulting from two multiplications. However, our later experiments showed it to be unnecessary and so we used an initial prior that does not prefer any particular outcome.

Algorithm 1 Variational-Bayes for Hiero Rules

Input: Set of aligned phrase-pairs \mathcal{X}
Get prior distribution $\mathbf{u} = \{u_r = \alpha_h p_0(r) | r \in \mathcal{G}\}$
Set $\mathbf{u}^0 = \mathbf{u}$
for time-step $t = 1, 2, \dots$ **do**
 for $z_d \in Z$ **do**
 $p(z_d) \leftarrow \exp\left(\psi(\alpha_{z_d}^{t-1}) - \psi(\sum_{z_d} \alpha_{z_d}^{t-1})\right)$
 end for
 for $r \in \mathcal{G}$ **do**
 $\pi_r^{t-1} \leftarrow \exp\left(\psi(u_r^{t-1}) - \psi(\sum_r u_r^{t-1})\right)$
 end for
 for $x \in \mathcal{X}$ **do**
 for $d \in \phi_x$ **do**
 Compute $p(d|\pi^{t-1}, x)$ as in (4)
 $\mathbb{E}[z_d^t] \leftarrow \mathbb{E}[z_d^t] + p(d|\pi^{t-1}, x)$
 for $r \in d$ **do**
 $\mathbb{E}[r^t] \leftarrow \mathbb{E}[r^t] + p(d|\pi^{t-1}, x) f_d(r)$
 end for
 end for
 end for
 for $z_d \in Z$ **do**
 Estimate $\alpha_{z_d}^t \leftarrow \alpha_{z_d}^0 + \mathbb{E}[z_d^t]$
 end for
 for $r \in \mathcal{G}$ **do**
 Estimate posterior \mathbf{u}^t : $u_r^t \leftarrow u_r^0 + \mathbb{E}[r^t]$
 end for
Output: Posterior distribution \mathbf{u}^t

We run inference for a fixed number of iterations⁴ and use the grammar along with their posterior counts from the last iteration for the translation table. Following (Sankaran et al., 2011), we use the shift-reduce style algorithm to efficiently encode the word aligned phrase-pair as a normalized decomposition tree (Zhang et al., 2008). The possible derivations (that are consistent with the word alignments) could then be enumerated by simply traversing every node in the decomposition tree and replacing its span by a non-terminal X .

3.1 Distributing Inference

While the above training procedure works well for smaller datasets, it does not scale well for the realistic MT datasets (which have millions of sentence pairs) due to greater memory and time requirements. To address this shortcoming, we distribute the training using a Map-Reduce style framework, where each node works on the local dataset in computing the required statistics and then communicates the statistics to a central aggregator reduce node.

Distributed inference for Expectation Maximization algorithm was studied in (Wolfe et al., 2008). They used three different topologies in

⁴In our experiments, we set the number of iterations to 10.

terms of computation time, bandwidth requirement and so on. While Map-Reduce is substantially slower than the All-pairs and Junction-tree topologies, it takes much lesser bandwidth than the other two apart from being much easier to implement. Furthermore our choice of the Variational inference naturally lends itself to distributed training.

We simply shard the set of aligned phrase pairs and parallelize the training steps for the shards across different nodes. At the end of local computation of the statistics (expected rule counts for example), we need to aggregate the statistics to get a global view, which will then be used in the next iteration/training step. We parallelize this aggregation across several nodes in one or two reduce steps as required. At the end of aggregation we communicate the updated statistics to each node on a need basis.⁵

4 Experiments

We experiment with three datasets of varying sizes. We use the University of Rochester Korean-English dataset consisting of almost 60K sentence pairs for the small data setting. For moderate and large datasets we use Arabic-English (ISI parallel corpus) and Chinese-English (Hong Kong parallel text and GALE phase-1) corpora. We use the MTC dataset having 4 references for tuning and testing for our Chinese-English experiments. The statistics of the corpora used in our experiments are summarized in Table 1.

Lang.	Training Corpus	Train/ Tune/ Test
<i>Ko-En</i>	URochester data	59218/ 1118/ 1118
<i>Ar-En</i>	ISI Ar-En corpus	1.1 M/ 1982/ 987
<i>Cn-En</i>	HK + GALE ph-1	2.3 M/ 1928/ 919

Table 1: Corpus Statistics in # of sentences

We follow the standard MT practice and use GIZA++ (Och and Ney, 2003) for word aligning the parallel corpus. We then use the heuristic step that symmetrizes the bidirectional alignments (Och et al., 1999) to extract the initial phrase-pairs up to a certain length, consistent with the word alignments. Finally we employ our proposed Variational-Bayes training to learn rules for

⁵We simulate the Map-Reduce style of computation using a regular high-performance cluster using a mounted filesystem rather than a Hadoop cluster with a distributed filesystem.

Model	Ko-En	Ar-En	Cn-En
<i>Baseline</i>	7.18	37.82	28.58
<i>Variational-Bayes</i>	7.68	37.76	28.40

Table 2: BLEU scores for baseline heuristic extraction and the proposed Variational-Bayes model. Best scores are in **boldface** and statistically significant differences are *italicized*.

Hiero. As a baseline Hiero model, we use the heuristic rule extraction (Chiang, 2007) approach to extract the rules. In both cases the parameters are estimated by the relative frequency estimation.

For decoding we use our in-house hierarchical phrase-based system- Kriya⁶ (Sankaran et al., 2012b). We use the following 8 standard features for the log-linear model: translation probabilities ($p(e|f)$ and $p(f|e)$), lexical probabilities ($p_l(e|f)$ and $p_l(f|e)$), phrase and word penalties, language model and glue rule penalty.

4.1 Results

The main BLEU score results are summarized in Table 2 and the key aspects are summarized below.

- **Higher BLEU scores:** Our Bayesian model performs better than the baseline heuristic rule extractor for Korean-English. Furthermore, the improvement of 0.5 BLEU is statistically significant at p -value of 0.01.
- **Large corpora:** Our distributed inference model easily scales to the large corpora and the inference completes in less than a day for Chinese-English. It also retains BLEU scores in the same level as the baseline models for both Arabic-English and Chinese-English.

4.2 Compact Models

Some earlier research on Hiero have explored model size reduction as a means of reducing the time and space complexity of the Hiero decoder as well as for mitigating issues such as *overgeneration* (Setiawan et al., 2009). These approaches use a variety of compression strategies, *viz.* threshold pruning (Zollmann et al., 2008), pattern-based filtering (He et al., 2009; Iglesias et al., 2009) and significance pruning (Yang and Zheng, 2009).

While compact models is not the central idea of our work, we nevertheless explore the effect of

⁶<https://github.com/sfu-natlang/Kriya>

a simple threshold pruning strategy on the grammar learned from our proposed model. Table 3 shows the results for the pruned grammars, where we prune the rules having expected count below a mincount threshold. We present the results for specific mincount settings based on our experiments on the held-out tuning set for each language pair.

Model	Ko-En	Ar-En	Cn-En
Model size: <i>VB</i>	2.67	331.6	471.7
BLEU: <i>VB</i>	7.68	37.76	28.40
<i>Pruning mincount</i>	0.25	1.0	1.0
Model size: <i>pruned</i>	1.65	58.9	87.3
Reduction:	38.2%	82.2%	81.5%
BLEU: <i>pruned</i>	7.64	37.58	28.45

Table 3: Model sizes (in millions) and BLEU scores of the full VB and pruned VB grammars. Mincount implies the expected rule count threshold used for pruning the full VB grammar. Best/indistinguishable BLEU scores are shown in **boldface**.

- **Retains score with smaller grammar:** The pruned grammars retain the performance of the full grammar, even while using just 18% of the complete model.
- **Higher reduction for large dataset:** Variational inference reduces the model size over 80% for the large corpora. While this is similar to the findings of Johnson et al. (2007) and that of the pruning strategies mentioned above; the question of whether an intelligent model selection strategy can yield higher BLEU scores is still open.
- **Faster decoding:** The compact grammars naturally result in faster decoding and we observed up to 20-30% speedup in the translation including the time spent for loading the model.

Sankaran et al. (2012a) proposed a model for extracting *compact* Hiero grammar with restricted arity (at most 1 non-terminal). In contrast our model is close the classical Hiero model Chiang (2007) having an arity of two. Though our results are not directly comparable to theirs, we nevertheless find our model to yield a better model size reduction than theirs. While they claim up to 57%

reduction, we achieve over 80% for the two large data conditions and about 38% reduction for the Korean-English small data setting.

4.3 Analysis

We now compare the probability distributions of the two grammars at the level of individual rules to understand the differences between them. We considered a set of source phrases that are common in both grammars and analyzed their probability distributions over the translation options.

Specifically we use the Q-Q plot to study the behaviour of two probability distributions as explained below considering the Chinese phrase 联合国 (*united nations*) as a representative example. The Q-Q plot in Figure 5 plots the $p(e|f)$ probabilities (sorted for the baseline grammar) for different translations of the source phrase. The translations from the baseline grammar are then paired off with the points in the sorted VB curve and the corresponding probabilities are plotted in the same order as the baseline translations. The following conclusions can be drawn from this plot:

- **Penalize poor translations:** Among the low-probability translations, majority of the translations in the VB-grammar have probability less than the corresponding baseline translations. This has the desired property of potentially shifting the probability mass away from poor translations.
- **Reward good translations:** VB-grammar rewards some translations that were deemed to be poor by the heuristic method, by assigning a slightly higher probability than the heuristic grammar. A manual inspection showed that the rules with higher probabilities were objectively better translation rules. For example Table 4 contrasts the probabilities assigned by the two methods for the first four translation options in Fig. 5.
- **Uniform probability is not informative:** The heuristic extraction method tends to assign an uniform probability for groups of translations and this is evident in the flat segments of the baseline curve and is especially dominant in the low probability region. In contrast, the VB-grammar is more peaked (in Fig. 5 the probabilities are sorted for the VB grammar).

Translations	Heu $p(e f)$	VB $p(e f)$
alert the united nations	4.28e-04	3.46e-04
during	4.28e-04	3.20e-04
<i>for un</i>	4.28e-04	<i>5.02e-04</i>
human	4.28e-04	3.20e-04

Table 4: Probabilities assigned by the two methods for the first four translations in Fig. 5. The better translation among four and the higher probability assigned by our model are *italicized*.

We also observe similar trend for several source phrases in both Arabic-English and Chinese-English corpora.

At the macro level, we compare the sizes of the different types of rules in the heuristic and the Variational-Bayes grammar. The baseline grammar extract slightly more rules with arity-1 than the grammar extracted by our model (see Figure 6). Our model extracts rules used in a *derivation* of a phrase-pair, only if *all* its constituent rules are consistent with the Hiero rule constraints (such as restriction on the total number of terminals and non-terminals in the rule). However the heuristic method extracts all the consistent rules and does *not* consider the derivations. While this is a more stricter constraint, the VB model extracts slightly more (about 170K) arity-2 rules as we allow the unaligned words to be attached to different levels of hierarchical rules during the construction of the decomposition tree. This extracts translation rules that are beyond the purview of the heuristic method, since the Viterbi alignments cannot capture them.

We earlier examined the effect of pruning the VB grammar in Section 4.2 and noted that the grammar could be substantially reduced for different language pairs without sacrificing translation quality. In this context, we compare the effects of pruning the heuristic and VB grammars in Figure 6 for Chinese-English. For the same mincount threshold of 1 as the best performing VB setting, the BLEU score of the heuristic grammar drops by over 1 point. However this setting prunes over 99% of the arity-1 and arity-2 rules even while it retains all the terminal rules. This is primarily because of the way the heuristic method estimates rule counts by uniformly distributing the weight among all the rules. The terminal rules are sufficient for coverage but does not capture long distance movements; and the lack of arity-1 and arity-2 rules further restrict the reordering ability of the model. We have to substantially lower the

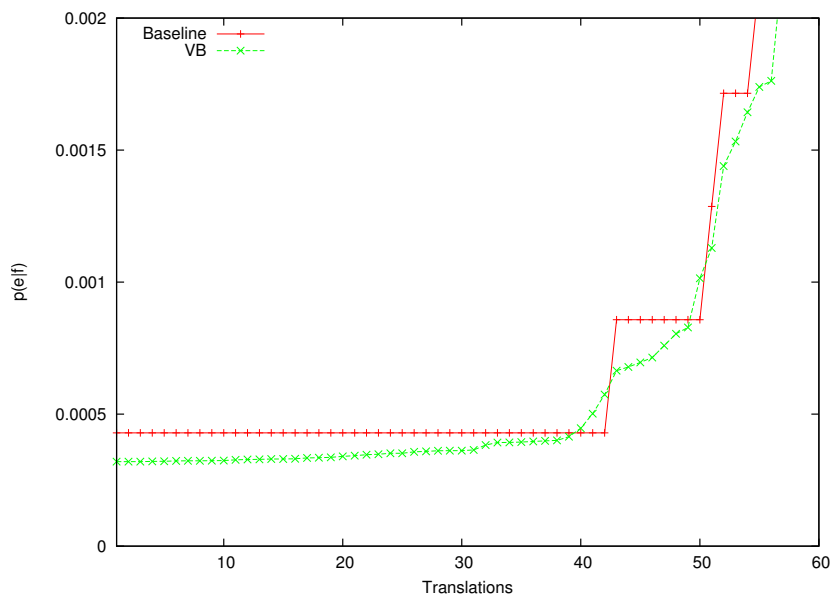


Figure 5: Q-Q plot comparing the $p(e|f)$ distributions of the baseline and VB-grammars for the Chinese phrase 联合国 (*united nations*). The points on the two curves represent distinct target translations (the numbers on the x -axis indicate the indices) and the points are sorted according to VB translation probabilities against the paired-off translation probabilities from the baseline grammar. The y -axis is clipped to highlight the variations in the low-probability range.

mincount threshold to 0.05, in order to get performance comparable to the pruned VB grammar setting. Interestingly, this uses about 7M more rules (13M more arity-1 rules, but 6M fewer arity-2 rules) than VB-Pr (1.0), but its BLEU score is marginally lower than the latter. This could be ascribed to the missing arity-2 rules, which could be crucial for certain long-distance reordering.

As the final part of the analysis, we also present the 100 high probability lexical phrases extracted by both rule extraction methods for the Arabic-English corpus in Figure 7. As seen, the heuristic grammar assigns high probability to the rules translating proper nouns and short phrases, whereas the VB method assigns high probability to more generic translations.

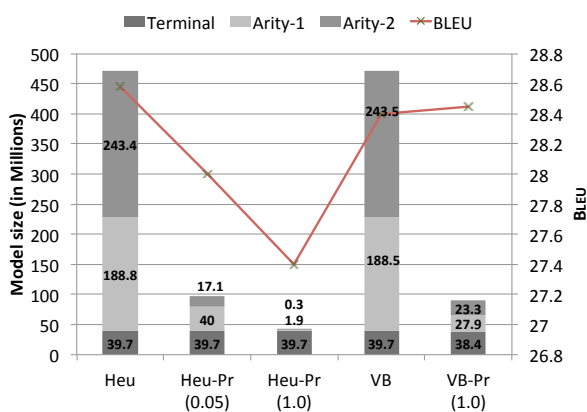


Figure 6: Cn-En: Model sizes and BLEU for different grammars. The pruned models are identified by the suffix 'Pr', whose mincount is shown in the brackets. The y -axis on the left marks the model sizes and that on the right denotes BLEU. The numbers in the stacked bars denote the # of rules (in millions) for the corresponding rule type.

5 Related Research

Most of the research on learning Hiero SCFG rules has been focussed on inducing phrasal alignments between source and target using Bayesian models (Blunsom et al., 2008; Blunsom et al., 2009; Levenberg et al., 2012; Cohn and Haffari, 2013). Broadly speaking, these generative approaches learn a posterior over parallel tree structures on the sentence pairs. While these methods extract hierarchical rules, they do not conform to Hiero-style rules. Consequently the hierarchical rules are used *only* for learning an alignment model and cannot be used directly in the Hiero decoder. Instead, these approaches employ the standard Hiero heuristics to extract rules to be used by the decoder from the alignments predicted by their model. In this sense, these are similar to Bayesian models for learning alignments using stochastic Inversion transduction grammars (ITG) (Wu, 1997) or linear

Phrases from Heuristic Grammar

مليون سهم/ million shares هوجو/ hugo مؤشر الاسهم " ب " :/: b share index فيما يلي العناوين الرئيسية في/ in major news items واندونيسيا ولاوس/ indonesia , laos , yuan ايجور/ igor مؤشر الاسهم " ب " / b share index توني/ tony جاك استرو/ jack straw ، وفقا لما ذكره بنك/ . national according to the bank of masood khan/ مسعود خان/ manmohan singh خان جمالي/ khan jamali الامن القومي/ jose hui الصين (china (hong kong) (هونغ كونغ)/ danie nanjing نانجينغ/ celta/ نانجينغ/ security سلتا/ security هونغ كونغ/ china (hong kong) (هونغ كونغ)/ athletico/ موى كيباكي/ mwai kibaki (hong kong) (هونغ كونغ)/ pradesh فلاديبير/ vladimir للتايل/ a tael/ دانيال/ daniel كارلو/ carlo سهم . / نهاية الخبر/ .// shares الاستقرار الاجتماعي/ social stability جون هوارد/ john howard وكيموديا واندونيسيا ولاوس/ indonesia , laos , cambodia (هونغ كونغ/ hong kong) الرئيس هو جين/ hu/ nato/ ناتو/ toledo تشانغ تشون/ changchun الرئيسة تشاندريكا/ chandrika اوداردو دوهالدي/ eduardo duhalde هرفيه دوهالدي/ herve de/ ramirez/ راميريز/ everton/ افرتون/ dos santos جلافكوس/ glafcos ياشوانت/ yashwant. حوسيه/ jose جونتشيرو/ junichiro يوريكو كاواجوتشي/ yoriko kawaguchi براديش/ pradesh/ nato/ ناتو/ toledo تشانغ تشون/ changchun الرئيس التزاني/ tanzanian president/ man/ مانه/ man/ nabil ابو/ nabil ابو/ lake victoria بحيرة فيكتوريا/ lake victoria yen/ يات/ state warren/ وارن/ syndrome/ kong/ 31 مارس/ 31 march سيسي/ sese/ kufuor قيمة التداول :/: turnover اسعار بورصة طوكيو/ tokyo stock price / سارس/ sars yellow نظيره الفلسطيني/ his palestinian counterpart/ 50/50 : جوزيه/ jose الخارجية العراقي/ iraqi foreign/ lithuania وليتوانيا/ lithuania عبدالله جول/ abdullah كبار المتعاملين في الذهب في هونغ/ gold dealers in hong/ international humanitarian/ yen/ احد كبار المتعاملين في الذهب في هونغ/ one of the major gold dealers in hong/ fidel ساو تومي/ saو tome/ racing اتلتيكو/ atletico بالصفة الغربية/ west bank ين (/) yen تشاو شينغ/ zhaoxing سيلفا/ silva/ فيردر/ werder فرناندو/ fernando امريكي (/) dollars الصيني الزائر/ visiting chinese/ 1 0 الخارجية الامريكية نيكلاس/ nicholas في عام 1996 ./: in بغداد --/ baghdad الرئيس موسيني/ president museveni/ president فلاديمير/ vladimir the major المتعاملين/ hong/ زوران/ zoran يانغ لي/ yang liwei ين الي/ yen تو/ to

Phrases from Variational-Bayes Grammar

21 يونيو/ 21 june الشيخ علي/ sheikh ali 100 طن/ 100 tons البيت الابيض سكوت مكليلان/ scott mclellan من 77/77 from دومنيك دو/ dominique de جيانغسو/ jiangsu المعلومات الالكترونية/ electronic information donald دونالد/ donald افريقيا 1/1 africa سانجا فرنسا/ french tourists الابحاث الاقتصادية/ economic research جنوب افريقيا بعد/ south africa after الحدودي مع مصر/ egypt/ border المخاوف المشروعة/ legitimate concerns هونغ كونغ (احد/) , hong kong العام 1961/1961 150 مليون شخص/ 150 million people في مدينة القدس/ in jerusalem الاسرائيلي موشيه كاتساف/ moshe katsav ضغط دولي/ international pressure جبل الي/ generation to/ جيانغ تسه من كرئيس/ jiang zemin as chairman دورية الشرطة/ police patrol الاليس/ 86 alaves 33/33 في الغابون/ in gabon/ وسط تقارير/ amid reports/ بين برلين/ between berlin/ الخارجية الامريكية نيكلاس/ 7 nicholas iran supports dialogue with israel/ الحوار مع اسرائيل/ russia 5/5 روسيا north of basra/ شمال البصرة/ bulgaria 2/2 بلغاريا 7 15 8/8 15 الارجنطين ويران/ iran/ ملايين جنيه/ million pounds حتى الان من هذا/ so far this/ peter struck/ peter ان صرح/ said عناصر مع هذه/ members of the/ الاسرائيلي زيف/ zeev الافواج الفوري/ immediate release of/ اعلن متحدث باسم قوات التحالف/ coalition spokesman said/ with rwanda/ توافق بدون/ accept without/ اطباء فلسطينيون/ palestinian doctors/ اوروبية كثيرة/ many european / / هارتس/ ha 'aretz والسودان وسوازيلاند/ , swaziland , sudan السبت مما/ saturday اكد شهود/ 1 witnesses 1.4 مليار يوان (/) billion yuan او بدونها/ or without مظفر اباد/ muzaffarabad مني مليار/ 200 billion على بعد حوالي/ kilometres الفحص والموافقة/ examination and approval/ on all fronts المصالحة والديمقراطية/ reconciliation and democracy موافقته المدينة/ agreed in principle/ سياسة الشمس المشروعة/ sunshine policy اللبناني فارس/ fares ليبيري علي/ liberians to/ radar لانتظار/ warning radar on the level/ الرئيس ديديه/ didier لكن جيزيب/ peres جوزيب بيكه الذي/ josep pique , whose لانتخابات جزئية/ partial elections اجمالي 63/63 مزدحمة بالركاب/ crowded جوف هون/ geoff hoon الى 96/96 يعط تفاصيل/ give details العقيبات المتبقية/ remaining obstacles والخيرات في/ in/ and experience في/ apache امن الدولة في/ s state security تعاون سعودي/ saudi/ maariib , demanding mutual cooperation التركي احمد/ ahmet كان سابقا/ previously يقود الا/ only lead/ مستوى لها/ level كان موسى/ moussa مأرب مطالبين/ demanding mutual الارووي والصين/ eu and china/ من حيفا/ haifa/ مساجد ومستشفيات/ mosques and hospitals غير الغذائية/ non-food الدعم المتبادل/ mutual support - نيويورك :/: new york مصر لاجراء/ egypt for انه يتحدث باسم/ be speaking for/ اندرو سميث/ andrew smith تدخل دولية/ international intervention

Figure 7: 100 high probability Arabic-English lexical rules extracted by the two methods.

ITG (Saers et al., 2010). In addition, most of these works except for Levenberg et al. (2012) use small datasets with fewer than 100K sentence pairs.

More recently Sankaran et al. (2012a) proposed a Bayesian model employing Variational inference for directly extracting Hiero grammar from aligned phrase pairs. While our work is similar to theirs, there are notable differences as well. Firstly their model extracts a simpler arity-1 grammar, where the source and target sides can have at most 1 non-terminal. In contrast the grammar extracted by our model fully conforms to Hiero-style rules and hence can potentially capture larger reordering (than the unary grammar). Secondly, their inference does not scale for the larger datasets and consequently they train only on a subset of initial phrase-pairs thresholded by some high frequency. We further distribute the inference under a simple MapReduce style framework, which allows us to scale to large datasets.

A different line of work focuses on reducing the size of Hiero models, and we discussed these pa-

pers in Section 4.2. While this is not the central aspect of our work, we showed that simple pruning of the grammar (extracted by our model) could reduce the size by more than 80% without sacrificing translation quality.

6 Conclusion

This paper introduced a novel Bayesian model for learning Hiero SCFG translation rules which is an alternative to the commonly used heuristic rule extraction approach. For inference, we use Variational-EM along with a Map-Reduce style framework for distributing the training process. This allowed us to efficiently train the model for very large corpora. We provided quantitative results and also a detailed qualitative analysis to demonstrate the superiority of the model trained by our approach. In future work, we would like to extend our model for inference directly on full sentence pairs as has been applied for the syntax-based model (Galley et al., 2006).

References

- Phil Blunsom, Trevor Cohn, and Miles Osborne. 2008. Bayesian synchronous grammar induction. In Proceedings of the Neural Information Processing Systems.
- Phil Blunsom, Trevor Cohn, Chris Dyer, and Miles Osborne. 2009. A gibbs sampler for phrasal synchronous grammar induction. In Proceedings of the Annual meeting of Association of Computational Linguistics.
- Rens Bod. 1998. *Beyond Grammar: An Experience-Based Theory of Language*. CSLI Publications, Stanford.
- David Chiang. 2005. A hierarchical phrase-based model for statistical machine translation. In Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics, pages 263–270. Association for Computational Linguistics.
- David Chiang. 2007. Hierarchical phrase-based translation. *Computational Linguistics*, 33.
- Trevor Cohn and Gholamreza Haffari. 2013. An infinite hierarchical bayesian model of phrasal translation. In Proceedings of the Annual Meeting of Association for Computational Linguistics.
- Michel Galley, Jonathan Graehl, Kevin Knight, Daniel Marcu, Steve DeNeefe, Wei Wang, and Ignacio Thayer. 2006. Scalable inference and training of context-rich syntactic translation models. In Proceedings of the 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics. Association for Computational Linguistics.
- Zhongjun He, Yao Meng, and Hao Yu. 2009. Discarding monotone composed rule for hierarchical phrase-based statistical machine translation. In Proceedings of the 3rd International Universal Communication Symposium.
- Gonzalo Iglesias, Adrià de Gispert, Eduardo R. Banga, and William Byrne. 2009. Rule filtering by pattern for efficient hierarchical translation. In Proceedings of the European Association for Computational Linguistics.
- Howard Johnson, Joel Martin, George Foster, and Roland Kuhn. 2007. Improving translation quality by discarding most of the phrasetable. In Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning.
- Abby Levenberg, Chris Dyer, and Phil Blunsom. 2012. A bayesian model for learning scfgs with discontinuous rules. In Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 223–232, Jeju Island, Korea. Association for Computational Linguistics.
- Franz Josef Och and Hermann Ney. 2003. A systematic comparison of various statistical alignment models. *Computational Linguistics*, 29(1):19–51.
- Franz Josef Och and Hermann Ney. 2004. The alignment template approach to statistical machine translation. *Computational Linguistics*, 30:417–449.
- F. J. Och, C. Tillmann, and H. Ney. 1999. Improved alignment models for statistical machine translation. In Proc. of the Joint SIGDAT Conf. on Empirical Methods in Natural Language Processing and Very Large Corpora, pages 20–28, University of Maryland, College Park, MD, USA.
- Markus Saers, Joakim Nivre, and Dekai Wu. 2010. Word alignment with stochastic bracketing linear inversion transduction grammar. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics.
- Baskaran Sankaran, Gholamreza Haffari, and Anoop Sarkar. 2011. Bayesian extraction of minimal scfg rules for hierarchical phrase-based translation. In Proceedings of the Sixth Workshop on SMT.
- Baskaran Sankaran, Gholamreza Haffari, and Anoop Sarkar. 2012a. Compact rule extraction for hierarchical phrase-based translation. In The 10th biennial conference of the Association for Machine Translation in the Americas (AMTA), San Diego, CA. Association for Computational Linguistics.
- Baskaran Sankaran, Majid Razmara, and Anoop Sarkar. 2012b. *Kriya* – an end-to-end hierarchical phrase-based mt system. The Prague Bulletin of Mathematical Linguistics (PBML), 97(97):83–98.
- Hendra Setiawan, Min-Yen Kan, Haizhou Li, and Philip Resnik. 2009. Topological ordering of function words in hierarchical phrase-based translation. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP, pages 324–332. Association for Computational Linguistics.
- Jason Wolfe, Aria Haghighi, and Dan Klein. 2008. Fully distributed EM for very large datasets. In Proceedings of the 25th international conference on Machine learning. ACM.
- Dekai Wu. 1997. Stochastic inversion transduction grammars and bilingual parsing of parallel corpora. *Computational Linguistics*, 23(3):377–403.
- Mei Yang and Jing Zheng. 2009. Toward smaller, faster, and better hierarchical phrase-based smt. In Proceedings of the ACL-IJCNLP.
- Hao Zhang, Daniel Gildea, and David Chiang. 2008. Extracting synchronous grammar rules from word-level alignments in linear time. In Proceedings of the COLING.
- Andreas Zollmann, Ashish Venugopal, Franz Och, and Jay Ponte. 2008. A systematic comparison of phrase-based, hierarchical and syntax-augmented statistical mt. In Proceedings of the COLING.