Nonparametric Bayesian Machine Transliteration with Synchronous Adaptor Grammars

Yun Huang$^{1,2}$ Min Zhang$^1$ Chew Lim Tan$^2$

huangyun@comp.nus.edu.sg mzhang@i2r.a-star.edu.sg tancl@comp.nus.edu.sg

$^1$Human Language Department Institute for Infocomm Research 1 Fusionopolis Way, Singapore
$^2$Department of Computer Science National University of Singapore 13 Computing Drive, Singapore

Abstract

Machine transliteration is defined as automatic phonetic translation of names across languages. In this paper, we propose synchronous adaptor grammar, a novel nonparametric Bayesian learning approach, for machine transliteration. This model provides a general framework without heuristic or restriction to automatically learn syllable equivalents between languages. The proposed model outperforms the state-of-the-art EM-based model in the English to Chinese transliteration task.

1 Introduction

Proper names are one source of OOV words in many NLP tasks, such as machine translation and cross-lingual information retrieval. They are often translated through transliteration, i.e. translation by preserving how words sound in both languages. In general, machine transliteration is often modelled as monotonic machine translation (Rama and Gali, 2009; Finch and Sumita, 2009; Finch and Sumita, 2010), the joint source-channel models (Li et al., 2004; Yang et al., 2009), or the sequential labeling task (Reddy and Waxmonsky, 2009; Abdul Hamid and Darwish, 2010).

Syllable equivalents acquisition is a critical phase for all these models. Traditional learning approaches aim to maximize the likelihood of training data by EM algorithm. However, the EM algorithm may over-fit the training data by memorizing the whole training instances. To avoid this problem, some approaches restrict that a single character in one language could be aligned to many characters of the other, but not vice versa (Li et al., 2004; Yang et al., 2009). Heuristics are introduced to obtain many-to-many alignments by combining two directional one-to-many alignments (Rama and Gali, 2009). Compared to maximum likelihood approaches, Bayesian models provide a systemic way to encode knowledges for learning sparse and accurate structures. They have been successfully applied to many machine learning tasks (Liu and Gildea, 2009; Zhang et al., 2008; Blunsom et al., 2009).

Among these models, Adaptor Grammars (AGs) provide a framework for defining nonparametric Bayesian models based on PCFGs (Johnson et al., 2007). They introduce additional stochastic processes (named adaptors) allowing the expansion of an adapted symbol to depend on the expansion history. Since many existing models could be viewed as special kinds of PCFG, adaptor grammars give general Bayesian extension to them. AGs have been used in various NLP tasks such as topic modeling (Johnson, 2010), perspective modeling (Hardisty et al., 2010), morphology analysis and word segmentation (Johnson and Goldwater, 2009; Johnson, 2008).

In this paper, we extend AGs to Synchronous Adaptor Grammars (SAGs), and describe the inference algorithm based on the Pitman-Yor (PY) process (Pitman and Yor, 1997). We also describe how transliteration could be modelled under this formalism. It should be emphasized that the proposed method is language independent and heuristic-free. Experiments show the proposed approach outperforms the strong EM-based baseline in the English to Chinese transliteration task.
2 Synchronous Adaptor Grammars

2.1 Model

A Pitman-Yor Synchronous Adaptor Grammar (PYSAG) is a tuple $G = (G_s, N_a, a, b, \alpha)$, where $G_s = (N, T_s, T_r, \mathcal{R}, S, \Theta)$ is a Synchronous Context-Free Grammar (SCFG), $N$ is a set of non-terminal symbols, $T_s/T_r$ are source/target terminal symbols, $\mathcal{R}$ is a set of rewrite rules, $S$ is the start symbol, $\Theta$ is the distribution of rule probabilities, $N_a \subseteq N$ is the set of adapted nonterminals, $a, b \geq 0$ are vectors of discount and concentration parameters respectively both indexed by adapted nonterminals, and $\alpha$ are Dirichlet prior parameters.

**Algorithm 1 Generative Process**

1: draw $\theta_A \sim \text{Dir}(\alpha_A)$ for all $A \in N$
2: return $\text{SAMPLE}(S)$ \Comment*{Sample from root}
3: function $\text{SAMPLE}(A)$ \Comment*{For $A \in N$}
4: if $A \in N_a$ then
5: return $\text{SAMPLESAG}(A)$
6: else
7: return $\text{SAMPLESCFG}(A)$
8: function $\text{SAMPLESCFG}(A)$ \Comment*{For $A \notin N_a$}
9: draw rule $r = (\beta / \gamma) \sim \text{Multi}(\theta_A)$
10: tree $t_B \leftarrow \text{SAMPLE}(B)$ for nonterminal $B \in \beta \cup \gamma$
11: return $\text{BUILD_TREE}(t_B, t_B, \ldots)$
12: function $\text{SAMPLESAG}(A)$ \Comment*{For $A \in N_a$}
13: draw cache index $z_{n+1} \sim P(z|z_{<n},)$, where
14: if $z_{n+1} = m + 1$ then \Comment*{New entry}
15: tree $t \leftarrow \text{SAMPLESCFG}(A)$
16: $m \leftarrow m + 1; n_m = 1$ \Comment*{Update counts}
17: $\text{INSERTTOCACHE}(C_A, t)$.
18: else \Comment*{Old entry}
19: $n_k \leftarrow n_k + 1$.
20: tree $t \leftarrow \text{FINDINCACHE}(C_A, z_{n+1})$
21: return $t$

The generative process is described in Algorithm 1. First, rule probabilities are sampled for each non-terminal $A \in N$ (line 1) according to the Dirichlet distribution. Synchronous trees are generated in the top-down fashion from the starting symbol $S$ (line 2). For nonterminals that are not adapted, the grammar expands it just as the original synchronous grammar (function SAMPLESCFG). For each adapted nonterminal $A \in N_a$, the grammar maintains a cache $C_A$ to store previously generated subtrees under $A$. Let $z_i$ be the subtree index in $C_A$, denoting the synchronous subtree generated at the $i$th expansion of $A$. At some particular time when $n$ subtrees rooted at $A$ have been generated, assuming there have been $m$ different type of synchronous subtrees in the cache, each of which has been generated for $n_1, \ldots, n_m$ times respectively. Then the grammar either generates the $(n+1)$th synchronous subtree just as PSCFG (line 15) or choose an existing subtree (line 20).

Integrating out the adaptors, the joint probability of a particular sequence of indexes $z$ with cached counts $(n_1, \ldots, n_m)$ under PY process is

$$PY(z|a, b) = \frac{\prod_{k=1}^{n_1} (a(k-1) + b) \prod_{j=1}^{n_k} (j - a)}{\prod_{i=0}^{n-1} (i + b)}$$

(1)

Equation 1 demonstrates “rich get richer” dynamics, i.e. previous sampled subtrees would more likely be sampled again in following procedures. This is suitable for many learning tasks since they prefer sparse solutions to avoid the over-fitting problems.

Given synchronous tree set $T$, the joint probability under the PYSAG is

$$P(T|\alpha, a, b) = \prod_{A \in N} \frac{B(\alpha_A + f_A)}{B(\alpha_A)} PY(z(T)|a, b)$$

(2)

where $f_A$ is the vector containing the number of times that rules $r \in \mathcal{R}_A$ are used in the $T$, and $B$ is the Beta function.

2.2 Inference for PYSAGs

Directly drawing samples from Equation 2 is intractable, so we extend the component-wise Metropolis-Hastings algorithm (Johnson et al., 2007) to the synchronous case. In detail, we draw sample $T_i'$ from some proposal distribution $Q(T_i|y_i, T_{-i})$, then accept the new sampled synchronous tree with probability

$$A(T_i, T_i') = \min \left\{ 1, \frac{P(T_i'|\alpha, a, b)Q(T_i|y_i, T_{-i})}{P(T_i|\alpha, a, b)Q(T_i'|y_i, T_{-i})} \right\}.$$

(3)

\(^1\)Obviously, $n = \sum_{k=1}^{m} n_k$.
\(^2\) $T_{-i}$ means the set of sampled trees except the $i$th one.
In theory, $Q$ could be any distribution if it never assigns zero probability. For efficiency reason, we choose the probabilistic SCFG as the proposal distribution. We pre-parse the training instances before inference and save structure of synchronous parsing forests. During the inference, we only change rule probabilities in parsing forests without changing the structures. The probability of rule $r \in \mathcal{R}_A$ in $Q$ is calculated using relative frequency $\theta_r = \frac{[f_r]_{-1}}{\sum_{r' \in \mathcal{R}_A} [f_{r'}]_{-1}}$, where $\mathcal{R}_A$ is the set of rules rooted at $A$, $[f_r]_{-1}$ is the number of times that rule $r$ is used in tree set $T_{-1}$. We use the sampling algorithm described in (Blunsom and Osborne, 2008) to draw a synchronous tree from the parsing forest according to the proposal $Q$. Following (Johnson and Goldwater, 2009), we put uninformative Beta(1,1) prior on $a$ and a “vague” Gamma(10, 0.1) prior on $b$ to model the uncertainty of hyperparameters.

3 Machine Transliteration

3.1 Grammars

For machine transliteration, we use the following syllable grammar to learn syllable mappings:

$$
\begin{align*}
\text{Name} & \rightarrow \langle \text{Syl} / \text{Syl} \rangle^+ \\
\text{Syl} & \rightarrow \langle \text{NECs} / \text{NECs} \rangle \\
\text{Syl} & \rightarrow \langle \text{NECs} \text{ SECs} / \text{NECs SECs} \rangle \\
\text{NECs} & \rightarrow \langle \text{NEC} \rangle^+ \\
\text{SECs} & \rightarrow \langle \text{SEC} \rangle^+ \\
\text{TECs} & \rightarrow \langle \text{TEC} \rangle^+ \\
\text{NECs} & \rightarrow \langle \text{Syl} / \text{TEC} \rangle \\
\text{SEC} & \rightarrow \langle \varepsilon / t_i \rangle \\
\text{TEC} & \rightarrow \langle s_i / \varepsilon \rangle
\end{align*}
$$

where the adapted nonterminal Syl is designed to capture the syllable equivalents between two languages, and the nonterminal NEC, SEC and TEC capture the character pairs with no empty character, empty source and empty target respectively. Note that this grammar restricts the leftmost characters on both sides must be aligned one-by-one. Since our goal is to learn the syllable equivalents, we are not interested in the subtree tree inside the syllables.

![Figure 1: An example of parse tree.](image)

The selection of the target characters does not only depend on the syllable itself but also depend on the context. For example, the following three transliteration pairs are found in the training set:

$$
\begin{align*}
\text{a a b y e} & / \text{奥} [\text{ao}] \text{ 比} [\text{bi}] \\
\text{a a g a a r d} & / \text{埃} [\text{ai}] \text{ 格} [\text{ge}] \text{ 德} [\text{de}] \\
\text{a a l t o} & / \text{阿} [\text{a}l] \text{尔} [\text{er}] \text{托} [\text{tuo}]
\end{align*}
$$

in which the same English syllable (a a) are transliterated to (奥[ao]), (埃[ai]) and (阿[a]l) respectively, depending on the following syllables. To model these context dependencies, we propose the hierarchical SAG. The two-layer word grammar is obtained by adding following rules:

$$
\begin{align*}
\text{Name} & \rightarrow \langle \text{Word} / \text{Word} \rangle^+ \\
\text{Word} & \rightarrow \langle \text{Syl} / \text{Syl} \rangle^+
\end{align*}
$$

Furthermore, we might add a new adapted nonterminal Col to learn the word collocations. The following rules are in the collocation grammar:

$$
\begin{align*}
\text{Name} & \rightarrow \langle \text{Col} / \text{Col} \rangle^+ \\
\text{Col} & \rightarrow \langle \text{Word} / \text{Word} \rangle^+ \\
\text{Word} & \rightarrow \langle \text{Syl} / \text{Syl} \rangle^+
\end{align*}
$$

Figure 1 gives one synchronous parsing trees under the collocation grammar of the example $\langle \text{m a x} / \text{麦} [\text{mai}] \text{ 克} [\text{ke}] \text{ 斯} [\text{si}] \rangle$. 

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3We implement the CKY-like bottom up parsing algorithm described in (Wu, 1997). The complexity is $O(|s|^3|t|^3)$.

4Following (Johnson, 2008), the adapted nonterminal are underlined. Similarly, we also use rule in the regular expression style $X \rightarrow \langle A / A \rangle^+$ to denote the following three rules:

$$
\begin{align*}
X & \rightarrow \langle \text{As} / \text{As} \rangle \\
\text{As} & \rightarrow \langle A / A \rangle \\
\text{As} & \rightarrow \langle A \text{ As} / A \text{ As} \rangle
\end{align*}
$$


3.2 Translation Model

Following (Li et al., 2004), we use n-gram translation model to estimate the joint distribution $P(s, t) = \prod_{k=1}^{K} P(p_k|p_{k-1})$, where $p_k$ is the $k^{th}$ syllable pair of the string pair $(s / t)$.

The first step is to construct joint segmentation lattice for each training instance. We first generate a merged grammar $G'$ using collected subtrees under adapted nonterminals, then use synchronous parsing to obtain probabilities in the segmentation lattice. Specifically, we “flatten” the collected subtrees under $\text{Sy1}$, i.e. removing internal nodes, to build new synchronous rules. For example, we could get two rules from the tree in Figure 1:

\[
\text{Sy1} \rightarrow (m \ a / \text{麦}) \\
\text{Sy1} \rightarrow (x / \text{克斯})
\]

If multiple subtrees are flattened to the same synchronous rule, we sum up the counts of these subtrees. For rules with non-adapted nonterminal as their parents, we assign the probability as the same of the sampled rule probability, i.e. let $\theta'_r = \theta_r$. For the adapted nonterminal $\text{Sy1}$, there are two kinds of rules: (1) the rules in original probabilistic SCFG, and (2) the rules flatten from subtrees. We assign the rule probability as

\[
\theta'_r = \begin{cases} 
\frac{m a + b}{n + b} \cdot \theta_r & \text{if } r \text{ is original SCFG rule} \\
\frac{n - a}{n + b} & \text{if } r \text{ is flatten from subtree}
\end{cases}
\]

where $a$ and $b$ are the parameters associated with $\text{Sy1}$, $m$ is the number of types of different rules flatten from subtrees, $n_r$ is the count rule $r$, and $n$ is the total number of flatten rules. One may verify that the rule probabilities are well normalized. Based on this merged grammar $G'$, we parse the training string pairs, then encode the parsed forest into the lattice. Figure 2 show a lattice example for the string pair $(\text{a a l t o} / \text{阿[a]尔[er]托[tuo]})$. The transition probabilities in the lattice are the “inside” probabilities of corresponding $\text{Sy1}$ node in the parsing forest.

After building the segmentation lattice, we train 3-order language model from the lattice using the SRILM\(^5\). In decoding, given a new source string, we use the Viterbi algorithm with beam search (Li et al., 2004) to find the best transliteration candidate.

4 Experiments

4.1 Data and Settings

We conduct experiments on the English-Chinese data in the ACL Named Entities Workshop (NEWS 2009)\(^6\). Table 1 gives some statistics of the data. For evaluation, we report the word accuracy and mean F-score metrics defined in (Li et al., 2009).

| # Entry | Train | Dev | Test |
|---------|-------|-----|------|
| # En Char | 31,961 | 2,896 | 2,896 |
| # Ch Char | 218,073 | 19,755 | 19,864 |
| # Ch Type | 101,205 | 9,160 | 9,246 |
| # Type | 370 | 275 | 283 |

Table 1: Transliteration data statistics

In the inference step, we first run sampler through the whole training corpus for 10 iterations, then collect adapted subtree statistics for every 10 iteration, finally stop after 20 collections. After each iteration, we resample each of hyperparameters from the posterior distribution of hyperparameters using a slice sampler (Neal, 2003).

4.2 Results

We implement the joint source-channel model (Li et al., 2004) as the baseline system, in which the orthographic syllable alignment is automatically derived by the Expectation-Maximization (EM) algorithm. Since EM tends to memorize the training instance as a whole, Li et al. (2004) restrict that the Chinese side in the syllable equivalents must be single character. Our proposed methods are Bayesian extension of the EM-based baseline. Since synchronous adaptor grammars could learn accurate and compact transliteration units, we do not need the restriction any more.

\(^5\)http://www.speech.sri.com/projects/srilm/

\(^6\)http://www.acl-ijcnlp-2009.org/workshops/NEWS2009/
| Grammar | Dev (%) | Test (%) |
|---------|---------|----------|
| Baseline | 67.8/86.9 | 66.6/85.7 |
| Syl     | 66.6/87.0 | 66.6/86.6 |
| Word    | 67.1/87.2 | 67.0/86.7 |
| Col     | 67.2/87.1 | 66.9/86.7 |

Table 2: Transliteration results, in the format of word accuracy / mean F-score. “Syl”, “Word” and “Col” denote the syllable, word and collocation grammar respectively.

Table 2 presents the results of all experiments. From this table, we draw following conclusions:

1. The best results of our model are 67.1%/87.2% on development set and corresponding 67.0%/86.7% on test set, achieved by word grammars. The results on test set outperform the EM-based baseline system on both word accuracy and mean F-score.
2. Comparing grammars of different layers, we find that the word grammars perform consistently better than the syllable grammars. These support the assumption that the context information are helpful to identify syllable equivalents. However, the collocation grammars do not further improve performance. We guess the reason is that the instances in transliteration are very short, so two-layer grammars are good enough while the collocations become very sparse, which results in unreliable probability estimation.

### 4.3 Discussion

Table 3 shows some examples of learnt syllable mappings with highest counts in the final sampled tree. We can see that the PYSAGs could find good syllable mappings from the raw name pairs without any heuristics or restriction. In this point of view, the proposed method is language independent.

Specifically, we are interested in the English token “x”, which is the only one that has two corresponding Chinese characters (“克里斯[ke si]”). Table 3 demonstrates that nearly all these correct mappings are discovered by SAG. Note that these kinds of mapping can not be learnt if we restrict the Chinese side to be only one character (the heuristic used in (Li et al., 2004)). We will conduct experiments on other language pairs in the future.

### 5 Conclusion

This paper proposed synchronous adaptor grammars, a nonparametric Bayesian model, for machine transliteration. Based on the sampling, the PYSAG could automatically discover syllable equivalents without any heuristics or restriction. In this point of view, the proposed model is language independent. Then the joint source-channel model is used to training and decoding. Experimental results on the English-Chinese transliteration task show that the proposed method outperforms the strong EM-based baseline system. We also compare grammars in different layers and find that the two-layer grammars are most suitable for the transliteration tasks. We plan to carry out more transliteration experiments on other language pairs in the future.

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