Automated Mining Of Names Using Parallel Hindi-English Corpus

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Abstract

Machine transliteration has a number of applications in a variety of natural language processing related tasks such as machine translation, information retrieval and question-answering. For automated learning of machine transliteration, a large parallel corpus of names in two scripts is required. In this paper we present a simple yet powerful method for automatic mining of Hindi-English names from a parallel corpus. An average 93% precision and 85% recall is achieved in mining of proper names. The method works even with a small corpus. We compare our results with Giza++ word alignment tool that yields 30% precision and 63% recall on the same corpora. We also demonstrate that this very method of name mining works for other Indian languages as well.

1 Introduction

Transliteration of names from one script/language to another has a number of applications in a variety of natural language processing tasks. These include machine translation, information retrieval, question-answering, multilingual directories, reservation charts, name lists etc.

Machine transliteration has been studied by a number of researchers (Knight et al., 1998; Al-Onaizan et al., 2002; Goto et al., 2003; Huang et al., 2003; Feng et al., 2004; Asif et al., 2006; Kuo et al. 2006); Knight and Graehl(1998) use a modular approach in which five probability distributions are obtained for various phases of the transliteration - generation and pronunciation of English word sequences, conversion of English sounds to Japanese and then Japanese sounds to Katakana writing. Al-Onaizan and Knight (2002) present work on transliteration from English to Arabic. It relies on an existing named entity recognition system, which identifies possible named entities in English. A predefined phoneme mapping is used to generate all possible transliterations. The validity of transliterations is examined by rating it based on web counts, and co-references by querying for the candidate transliteration on popular search engines such as Google. Huang et al. (2003) have worked on extracting Hindi-English named entity pairs through alignment of a parallel corpus. Chinese-English pairs are first extracted using a dynamic programming string matching. This Chinese-English model is then adapted to Hindi-English iteratively, by using already extracted Hindi-English named entity pairs to bootstrap the model. The precision achieved by this model is 91.8%. Feng et al. (2004) have used a maximum entropy model, in which an alignment probability for target/source named entities is defined over 4 features - translation score, transliteration score, co-occurrence score and distortion score. The extraction of each feature is involved, but the maximum entropy model over these features is straightforward. Kuo et al. (2006) uses a syllable alignment algorithm for cross-language syllable-phoneme conversion. Asif et al. (2006) have considered Bengali to English transliteration. They present a model which upon supervised training provides direct orthographical mapping. They report an accuracy of 69-89%. The success of all of these works depends upon the volume and nature of name corpora used.

In this paper, we present a simple yet powerful method for mining of Hindi-English names from a parallel text corpus. In Hindi, the words are written as they are spoken i.e. it is phonetic in nature. On the other hand, English is non-phonetic in the sense that there is a specified usage of a spelling for every word. Hindi names when written in English have a similar problem that the users have developed their own spellings for names that are commonly accepted. Though these English spellings do retain the phonetic structure of Hindi to a large extent, there are variations that cannot be easily captured through rules. In table 1 a few illustrative examples are given. It is evident that the Hindi vowel modifiers (called ‘matra’) do not have unique mappings to English vowel combinations. It is difficult to derive simple mapping rules for these. The map-
ping of semivowels ‘y’ and ‘v’ and ‘schwa’ deletions are highly contextual. However, for the consonants, the mappings are straightforward barring a few exceptions.

Our strategy for automatic mining of Hindi-English proper names from parallel corpus exploits this near-invariance in consonant mapping. We compare our results with Giza++ word alignment. In the following section, we present our design methodology followed by experimental results and conclusions.

<table>
<thead>
<tr>
<th>Hindi word in Devanagari</th>
<th>Hindi word in IITK-Roman (Appendix-A)</th>
<th>Corresponding commonly used English (Roman) transliteration</th>
<th>Unacceptable English (Roman) transliterations</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>हरीश</td>
<td>harISa</td>
<td>Harish</td>
<td>Hareesh / Hariesh / Hareish</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. ‘schwa’ deletion</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>iii. consonant cluster mapping</td>
<td></td>
</tr>
<tr>
<td>संजीव</td>
<td>saMjIva</td>
<td>Sanjeev or Sanjiv</td>
<td>Sanjiv / Sanjeev / Sanjiv</td>
<td>i. variation in long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. ‘schwa’ deletion</td>
<td></td>
</tr>
<tr>
<td>पालगुणी</td>
<td>PALgunI</td>
<td>Phalguni</td>
<td>Falguni</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. consonant mapping</td>
<td></td>
</tr>
<tr>
<td>मूना</td>
<td>mUnA</td>
<td>Moona</td>
<td>Muna / Muuna / Moonaa</td>
<td>preferred long vowel mapping</td>
</tr>
<tr>
<td>सूरज</td>
<td>sUraja</td>
<td>Suraj</td>
<td>Sooraj / Suraj / Suraz / Surag</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. ‘schwa’ deletion</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>iii. consonant mapping</td>
<td></td>
</tr>
<tr>
<td>सोमनाथ</td>
<td>somanAWa</td>
<td>Somenath or Somnath</td>
<td>Somanath / Somanaath</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. ‘schwa’ deletion</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>iii. peculiar vowel mapping to ‘e’</td>
<td></td>
</tr>
<tr>
<td>सक्सेना</td>
<td>saksenA</td>
<td>Saxena</td>
<td>Saksena</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. preferred consonant mapping</td>
<td></td>
</tr>
<tr>
<td>दीक्षित</td>
<td>xIkSiwa</td>
<td>Dixit or Dikshit</td>
<td>Deexit / Dikchhit etc.</td>
<td>i. long vowel mapping</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ii. ‘schwa’ deletion</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>iii. preferred consonant mapping</td>
<td></td>
</tr>
<tr>
<td>मोदी</td>
<td>moxl</td>
<td>Modi</td>
<td>Modee / Modi / Mody etc.</td>
<td>preferred long vowel mapping</td>
</tr>
<tr>
<td>सोनिया</td>
<td>soniyA</td>
<td>Sonia</td>
<td>Soniya</td>
<td>preferred semivowel mapping</td>
</tr>
<tr>
<td>रामदेव देव</td>
<td>rAmaxeva xeva</td>
<td>Ramdeo</td>
<td>Ramdev / Ramadev / Ramadeo / Dev</td>
<td>preferred semivowel mapping</td>
</tr>
</tbody>
</table>

Table 1: An Illustration of Hindi to English Name Transliteration Variations

2 Hindi-English Name Corpus Creation

We use an aligned parallel Hindi-English text corpus for creation of Hindi-English name corpus. The size of the corpus is immaterial and it could be as small as a few lines. The sentence alignment also need not be perfect as long as the aligned set of sentences contain the translated sentences. Our methodology is even capable of capturing to some extent mapping between old city names with new city names such as Bombay and Mumbai. Figure 1 depicts the process of name mining diagrammatically.

The Hindi text written in Devanagari is first converted to IITK-Roman form (appendix-A). IITK-Roman has become a de-facto standard used by a large number of researchers in India. The conversion to IITK-Roman form is straightforward and is a direct representation of UTF-8 or ISSCII-8 coding schemes without any
loss of constituent information in terms of phonemes or constituent symbols. The usage of IITK-Roman form is more for entry and programming convenience.

Figure 1: Schematic flow diagram of the name mining process

As outlined earlier, in order to simplify the learning process, the trivial consonant (C) and consonant cluster (C') mappings are provided separately in the form of rules. The main consonant mappings from IITK-Roman to English are shown in figure 2.

Figure 2: IITK-Roman to English consonant mapping

i. For each aligned line, collect all the words in the English sentence that have first letter in upper case. These are potential English proper names excepting the first word that may or may not be a proper name.

ii. For each word, apply consonant cluster mapping from English to Hindi (using the mapping as given in figure 2 in reverse fashion). In absence of a defined mapping, the consonant is ignored. This yields one or more plausible Hindi names as there are one to many reverse mappings. The following three mappings are very rare and so are ignored for efficiency: f→n; F→n; H→h. Further, the semivowel ‘y’ is not treated as a consonant if it is the last character of the word. It is treated as a consonant if it is preceded or followed by a vowel.

iii. Collapse each of the above word into being part of the plausible Hindi name by deleting all vowels in it.

iv. Each collapsed plausible Hindi name, as derived in the preceding step, is string-matched with the Hindi words in the corresponding aligned Hindi line. The process of matching looks for maximal ordered string match omitting the Hindi vowels.

- In case no match is found, it is ignored.
- In case of multiple matches, minimal word length distance is taken as the criterion for selection.
• In order to avoid false matching, length must be greater than 1 and at least 30% of characters must match.
• Further, a constraint that the first character of the mapped words must both be either a consonant or both be a vowel, is imposed.

v. In case two or more matches have same maximal length match, then the maximal match with the plausible un-collapsed (i.e. including the intervening vowels with their mapping using figure 3) Hindi name is matched and the ordered maximal length match is selected. Usually such a situation is encountered when two or more similar names are encountered in the aligned lines. An example of this would be say the two names ‘Hindi’ and ‘Hindu’ occur in the same sentence. These will get matched to the same degree by step (iv) above. The way to resolve this is to also take intervening vowels into account. The IITK Roman vowel mapping to English used here is given in figure 3. It may be noted that only one vowel mapping out of the many possibilities, has been taken. This is the most frequent mapping and is taken as the baseline vowel mapping.

vi. The final stage is that of filtering and smoothening.
• For every English name, the corresponding Hindi name mapping(s) with their frequency of occurrence is recorded for the entire corpus.
• In case of multiple mappings, each mapping is examined. The suffix that represent the post-position markers such as ne (ने), ka(का), ko (को), ki(की), ke(के), se(se से), men(meM में), par(para पर), vala (vA-ला वाला) etc. in Hindi are stemmed. Further, other morphological co-joiners (‘sandhi’) for other Indian scripts are also stemmed.
• After stemming, the frequency is recomputed.
• The mapping with the highest frequency is selected.

Although these post-position markers in Hindi are separate words and are usually written with a preceding blank, many a time it is not properly observed and appears as a suffix.

Given below is an illustrative example:
English sentence: It goes daily from Delhi to Mumbai, Bangalore, Varanasi and Lucknow.
Aligned Hindi Sentence: 
यह रोजाना दिल्ली से मुंबई, बेंगलुरू, वाराणसी और लखनऊ जाती है।
(Converted to IITK-Roman)
yaha rojA nA xillI se mumbaI, bEMgaluru, vArANasI Ora lAKanaU jAwI hE.
Probable English Proper Nouns: It Delhi Mumbai Bangalore Varanasi Lucknow
Plausible Hindi Names after reverse consonant substitutions: {it iw} {delhi xelhi} {mmb} {bnglr bMglr} {vrns vrNs vrMs} {lkvn lkNv lkmv} Hypothesized Hindi Names after matching:
Delhi→ xillI दिल्ली;
Mumbai→mumbaI मुंबई;
Bangalore→bEMgaluru बेंगलुरू;
Varanasi→vArANasI वाराणसी;
Lucknow→lAKanaU लखनऊ.

In the above example, the first word ‘It’ does not get matched to any of the Hindi words because of the constraint that the matching length has to be greater than 1 and a minimum of 30% of length must match.

It is interesting to note the method outlined captures even those names that differ in their forms or spelling such as Delhi & दिल्ली (xillI), Bangalore & बेंगलुरू (bEMgaluru) and Lucknow & लखनऊ (lAKanaU) based on maximal match. For transliteration, these have to made table driven.

Given below is an illustration of step (v) of the procedure:
English sentence: Mr. Handa speaks Hindi and he is a Hindu.
Aligned Hindi Sentence: 
श्री हांडा हिंदी बोलते हैं और वह एक हिंदू है।
(Converted to IITK-Roman)
SrI hAMdA hinxI bolawe hEM Ora vaha eka hin-xU hEM.
Probable English Proper Nouns:

Mr Handa Hindi Hindu.

Plausible Hindi Names after reverse consonant substitutions:

{mr mq} {haNda handa haMda haNx haNxa haMxa} {hiNdii hindi hiMdi hiNxii hiMi} {hiNdii hindi hiMdu hiNxu hiMxu}

Collapsed plausible corresponding Hindi Names:

{mr mq} {hNd hnd hMd hNx hnx hMx} {hNd hnd hMd hNx hnx hMx}

Hypothesized Hindi Names after matching:

Handa → hAMdA हांडा; hinxI इहृदय; hinxU इहृदू

Hindi → hAMdA हांडा; hinxI इहृदय; hinxU इहृदू;

Hindu → hAMdA हांडा; hinxI इहृदय; hinxU इहृदू;

Now since these are equiprobable multiple matches, step (v) will get invoked. For each matching target word, the vowel mapping of figure 3 is applied. This yields the following:

hAMdA हांडा → hAMdA हांडा;

hinxI इहृदय → hinxI इहृदय;

hinxU इहृदू → hinxU इहृदू;

Now the English source word is matched and minimal distance word is selected. This finally yields the desired result as follows:

Handa → hAMdA हांडा;

Hindi → hinxI इहृदय;

Hindu → hinxU इहृदू;

Given below is an illustration of step (vi) of the procedure:

Suppose in the entire corpus the city name ‘Agra’ yields the following matches:

i. Agra → AgarA आगरा; count=20;

ii. Agra → Agare आगरे; count=12;

iii. Agra → AgarASe आगरासे; count=5;

iv. Agra → AgarAmeM आगरामेम; count=4;

v. Agra → AgarAka आगराका; count=2;

Now the process of smoothening will convert AgarAse आगरासे to AgarA आगरा by deleting post-position suffix ‘se’; AgarAmeM आगरामेम to AgarA आगरा by deleting post-position suffix ‘meM’; and AgarAka आगराका to AgarA आगरा by deleting post-position suffix ‘kA’.

This will yield the final table as follows:

<table>
<thead>
<tr>
<th></th>
<th>File1</th>
<th>Giza++</th>
<th>File2</th>
<th>Giza++</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name-mapping</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total no. of words</td>
<td>2439</td>
<td>2439</td>
<td>4909</td>
<td>4909</td>
</tr>
<tr>
<td>Total no. of Names(N)</td>
<td>192</td>
<td>192</td>
<td>343</td>
<td>343</td>
</tr>
<tr>
<td>Correct mapping (TP)</td>
<td>155</td>
<td>57</td>
<td>262</td>
<td>74</td>
</tr>
<tr>
<td>Incorrect mapping (FP)</td>
<td>13</td>
<td>117</td>
<td>35</td>
<td>200</td>
</tr>
<tr>
<td>Not-captured (FN)</td>
<td>24</td>
<td>18</td>
<td>46</td>
<td>69</td>
</tr>
<tr>
<td>Accuracy (TP/N)</td>
<td>0.8073</td>
<td>0.2969</td>
<td>0.7638</td>
<td>0.2157</td>
</tr>
<tr>
<td>Precision (TP/(TP+FP))</td>
<td>0.9226</td>
<td>0.3276</td>
<td>0.9495</td>
<td>0.2701</td>
</tr>
<tr>
<td>Recall (TP/(TP+FN))</td>
<td>0.8659</td>
<td>0.7600</td>
<td>0.8506</td>
<td>0.5175</td>
</tr>
<tr>
<td>F-measure (2PR/(P+R))</td>
<td>0.8934</td>
<td>0.4578</td>
<td>0.8968</td>
<td>0.3549</td>
</tr>
</tbody>
</table>

Table 2. Result for name mining and word-alignment algorithms.
Our experimentation reveals that our name mining methodology yields a precision of 92 to 95% and a recall of 85 to 86% resulting in F-measure of 0.89. On the other hand, the Giza++ word alignment tool yields a precision of 27 to 33% and a recall of 52 to 76% resulting in F-measure of 0.35 to 0.46. The results are a clear demonstration of effectiveness our approach of mining proper names from the parallel Hindi-English corpora. Most of the errors using our approach have been found to be due to short names, words not properly delineated in the target text, morphological changes in the target text, the first word in English not being a proper noun or different forms of names that are used denoting the same place. It should be noted that our approach works even for a corpus of a few lines as it is primarily a rule-based method.

The method as outlined above is equally applicable to other Indian languages. In order to demonstrate this, we conducted a limited experiment with Punjabi and Bengali languages. A corpus of about 200 sentences was taken. The same program as was used for Hindi with no change in the mapping tables was used for the experimentation. The results obtained were remarkable and a performance of about 90% and 70% of correct mining of proper names for Punjabi and Bengali respectively is yielded. The poorer performance in case of Bengali is primarily due to morphological changes that take place in the proper names based on their role in the sentence. Unlike in Hindi where the post-positions are written separately or simply suffixed, for most of the other Indian languages, these post-position markers are co-joined (‘Sandhi’) with the preceding word leading to a morphological change. This is less frequent in Punjabi. Further, Bengali has no consonant for ‘va’ and this is mapped to ‘ba’.

So some consonant mapping changes are required to yield better results for another Indian language but the methodology remains the same. Here are some example mappings:

**Bengali:**

i. Sam Sand Dunes is one of the best nature’s gift to the human beings.

   sEma sEzda diUnasa manuYKa xe laI prakira-wl xe saraba SreSata wohaPZiAz viYcoz iYka hE.

   ਸੈਮ ਸੇਜ਼ਡਾ ਦੀ ਉਨਾਸਾ ਮਨੁੱਖ ਲਈ ਪ੍ਰਕਿਰੰਡ ਵਿੱਚ ਅਲੈਪਾ ਓਹਾ ਪ੍ਰੀਤੀ ਆਂ ਤੋਂ ਇਕ ਹੈ।

   Names extracted:
   Sam → sEma ਸੈਮ;
   Sand → sEzda ਸੇਜ਼ਡ;
   Dunes → diUnasa ਦੀ ਉਨਾਸ;
   Bikaner → bIkAnera ਬੀਕਾਨਾਰ;
   Rajasthan → rAjasaWAna ਰਾਜਸਥਾਨ

**Punjabi:**

i. Sam Sand Dunes is one of the best nature's gift to the human beings.

   sEma sEzda diUnasa manuYKa xe laI prakira-wl xe saraba SreSata wohaPZiAz viYcoz iYka hE.

   ਸੈਮ ਸੇਜ਼ਡਾ ਦੀ ਉਨਾਸਾ ਮਨੁੱਖ ਲਈ ਪ੍ਰਕਿਰੰਡ ਵਿੱਚ ਅਲੈਪਾ ਓਹਾ ਪ੍ਰੀਤੀ ਆਂ ਤੋਂ ਇਕ ਹੈ।

   Names extracted:
   Sam → sEma ਸੈਮ;
   Sand → sEzda ਸੇਜ਼ਡ;
   Dunes → diUnasa ਦੀ ਉਨਾਸ;
   Bikaner → bIkAnera ਬੀਕਾਨਾਰ;
   Rajasthan → rAjasaWAna ਰਾਜਸਥਾਨ

**Conclusions**

In this paper, we have presented a simple yet powerful method for mining of Hindi-English proper name corpus with a success of mining being 93% precision. In contrast, GIZA+ word alignment tool on same sized corpus yielded 29% precision. The proposed method works even for a single line text. Moreover, there is no strict requirement of sentence alignment as it works equally well for one to many and many to many sentence alignment as long as the target group of sentences contain the corresponding translation.
Thus it works under noisy environments where sentence boundaries are not correctly identified. Our approach also yields a table of similar old city names with new city names that is very frequently encountered in Indian context.

The methodology outlined in this paper for automatic mining of proper names are equally applicable to all Indian languages as all Indian scripts are phonetic in nature in the same way as Devanagari (used for Hindi). We have also demonstrated that this very method of name mining without making any changes in the program or the mapping table as used for Hindi, works for other Indian languages. Our limited experimentation for Punjabi and Bengali and have yielded performance of 90% and 70% respectively of correct mining of proper names.

There are several other advantages of our approach. Since the proper name mining is captured with a high accuracy over a rough or noisy aligned corpus, it is possible to use these as anchors (the same way as numerals) for improvement of the alignment results. These anchors will also be useful in word alignment programs for speedy convergence. Accurate word alignment is crucial to the success of any statistical machine translation system. Another byproduct of our approach is that it also yields the table of old city names with new city names. In India, a large number of city names that were used during British time, have undergone a change and most of these changes are phonetic variations of the old names.

Acknowledgements
Author is thankful to Saleem Siddiqui and Abhay Singh for experimentation and testing.

References

Appendix-A: IITK-Roman code for Hindi (Devanagari)

<table>
<thead>
<tr>
<th>अ आ इ ई उ ऊ ए ऐ ओ औ</th>
<th>A A E E O O</th>
</tr>
</thead>
<tbody>
<tr>
<td>क ख ग घ ङ च छ ज झ ञ</td>
<td>K G J J F</td>
</tr>
<tr>
<td>ट ठ ड ढ ण त थ द ध</td>
<td>T T D D N</td>
</tr>
<tr>
<td>प फ ब भ म य र ल व स</td>
<td>P P B B m y</td>
</tr>
</tbody>
</table>

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