Machine Transliteration

Kevin Knight*
University of Southern California

Jonathan Graehl†
University of Southern California

It is challenging to translate names and technical terms across languages with different alphabets and sound inventories. These items are commonly transliterated, i.e., replaced with approximate phonetic equivalents. For example, "computer" in English comes out as "konpyuutaa" in Japanese. Translating such items from Japanese back to English is even more challenging, and of practical interest, as transliterated items make up the bulk of text phrases not found in bilingual dictionaries. We describe and evaluate a method for performing backwards transliterations by machine. This method uses a generative model, incorporating several distinct stages in the transliteration process.

1. Introduction

One of the most frequent problems translators must deal with is translating proper names and technical terms. For language pairs like Spanish/English, this presents no great challenge: a phrase like *Antonio Gil* usually gets translated as *Antonio Gil*. However, the situation is more complicated for language pairs that employ very different alphabets and sound systems, such as Japanese/English and Arabic/English. Phonetic translation across these pairs is called **transliteration**. We will look at Japanese/English transliteration in this article.

Japanese frequently imports vocabulary from other languages, primarily (but not exclusively) from English. It has a special phonetic alphabet called **katakana**, which is used primarily (but not exclusively) to write down foreign names and loanwords. The katakana symbols are shown in Figure 1, with their Japanese pronunciations. The two symbols shown in the lower right corner (ー, ッ) are used to lengthen any Japanese vowel or consonant.

To write a word like *golfbag* in katakana, some compromises must be made. For example, Japanese has no distinct L and R sounds: the two English sounds collapse onto the same Japanese sound. A similar compromise must be struck for English H and F. Also, Japanese generally uses an alternating consonant-vowel structure, making it impossible to pronounce LFB without intervening vowels. Katakana writing is a syllabary rather than an alphabet—there is one symbol for ga (ガ), another for gi (ギ), another for gu (グ), etc. So the way to write *golfbag* in katakana is ゴルフバッグ, roughly pronounced go-ru-hu-ba-ggu. Here are a few more examples:

* USC/Information Sciences Institute, Marina del Rey, CA 90292 and USC/Computer Science Department, Los Angeles, CA 90089
† USC/Computer Science Department, Los Angeles, CA 90089

ア (a)	カ (ka)	サ (sa)	タ (ta)	ナ (na)	ハ (ha)	マ (ma)	ラ (ra)
イ (i)	キ (ki)	シ (shi)	チ (chi)	ニ (ni)	ヒ (hi)	ミ (mi)	リ (ri)
ウ (u)	ク (ku)	ス (su)	ツ (tsu)	ヌ (nu)	フ (hu)	ム (mu)	ル (ru)
エ (e)	ケ (ke)	セ (se)	テ (te)	ネ (ne)	ヘ (he)	メ (me)	レ (re)
オ (o)	コ (ko)	ソ (so)	ト (to)	ノ (no)	ホ (ho)	モ (mo)	ロ (ro)
バ (ba)	ガ (ga)	パ (pa)	ザ (za)	ダ (da)	ァ (a)	ヤ (ya)	ャ (ya)
ビ (bi)	ギ (gi)	ピ (pi)	ジ (ji)	デ (de)	ィ (i)	ヨ (yo)	ョ (yo)
ブ (bu)	グ (gu)	プ (pu)	ズ (zu)	ド (do)	ゥ (u)	ユ (yu)	ュ (yu)
ベ (be)	ゲ (ge)	ペ (pe)	ゼ (ze)	ン (n)	ェ (e)	ヴ (v)	ッ
ボ (bo)	ゴ (go)	ポ (po)	ゾ (zo)	ヂ (chi)	ォ (o)	ワ (wa)	ー

Figure 1
Katakana symbols and their Japanese pronunciations.

Angela Johnson	*New York Times*	*ice cream*
アンジラ・ジョンソン	ニューヨーク・タイムズ	アイスクリーム
(a n jira jyo n so n)	(nyu u yo o ku ta i mu zu)	(a i su ku ri i mu)

Omaha Beach	*pro soccer*	*Tonya Harding*
オマハビーチ	プロサッカー	トーニャ・ハーディング
(omahabiitchi)	(purosakkaa)	(toonya haadingu)

ramp	*lamp*	*casual fashion*	*team leader*
ランプ	ランプ	カジュアルヒァッション	チームリーダー
(ranpu)	(ranpu)	(kajyuaruhasshyon)	(chiimuriidaa)

Notice how the transliteration is more phonetic than orthographic; the letter *h* in *Johnson* does not produce any katakana. Also, a dot-separator (•) is used to separate words, but not consistently. And transliteration is clearly an information-losing operation: ranpu could come from either *lamp* or *ramp*, while aisukuriimu loses the distinction between *ice cream* and *I scream*.

Transliteration is not trivial to automate, but we will be concerned with an even more challenging problem—going from katakana back to English, i.e., **back-transliteration**. Human translators can often "sound out" a katakana phrase to guess an appropriate translation. Automating this process has great practical importance in Japanese/English machine translation. Katakana phrases are the largest source of text phrases that do not appear in bilingual dictionaries or training corpora (a.k.a. "not-found words"), but very little computational work has been done in this area. Yamron et al. (1994) briefly mention a pattern-matching approach, while Arbabi et al. (1994) discuss a hybrid neural-net/expert-system approach to (forward) transliteration.

The information-losing aspect of transliteration makes it hard to invert. Here are some problem instances, taken from actual newspaper articles:

?	?	?
アースデー	ロバート・ショーン・レナード	マスターズトーナメント
(aasudee)	(robaato shyoon renaado)	(masutaazutoonamento)

English translations appear later in this article.

Here are a few observations about back-transliteration that give an idea of the difficulty of the task:

- Back-transliteration is less forgiving than transliteration. There are many ways to write an English word like *switch* in katakana, all equally valid, but we do not have this flexibility in the reverse direction. For example, we cannot drop the *t* in *switch*, nor can we write *arture* when we mean *archer*. Forward-direction flexibility wreaks havoc with dictionary-based solutions, because no dictionary will contain all katakana variants.
- Back-transliteration is harder than **romanization**. A romanization scheme simply sets down a method for writing a foreign script in roman letters.

  For example, to romanize アンジラ, we look up each symbol in Figure 1 and substitute characters. This substitution gives us (romanized) `anjira`, but not (translated) *angela*. Romanization schemes are usually deterministic and invertible, although small ambiguities can arise. We discuss some wrinkles in Section 3.4.
- Finally, not all katakana phrases can be "sounded out" by back-transliteration. Some phrases are shorthand, e.g., ワープロ (`waapuro`) should be translated as *word processing*. Others are onomatopoetic and difficult to translate. These cases must be solved by techniques other than those described here.

The most desirable feature of an automatic back-transliterator is accuracy. If possible, our techniques should also be:

- portable to new language pairs like Arabic/English with minimal effort, possibly reusing resources.
- robust against errors introduced by optical character recognition.
- relevant to speech recognition situations in which the speaker has a heavy foreign accent.
- able to take textual (topical/syntactic) context into account, or at least be able to return a ranked list of possible English translations.

Like most problems in computational linguistics, this one requires full world knowledge for a 100% solution. Choosing between *Katarina* and *Catalina* (both good guesses for カタリナ) might even require detailed knowledge of geography and figure skating. At that level, human translators find the problem quite difficult as well, so we only aim to match or possibly exceed their performance.

2. A Modular Learning Approach

Bilingual glossaries contain many entries mapping katakana phrases onto English phrases, e.g., (*aircraft carrier* ↔ エアクラフトキャリア). It is possible to automatically analyze such pairs to gain enough knowledge to accurately map new katakana phrases that come along, and this learning approach travels well to other language pairs. A naive approach to finding direct correspondences between English letters and katakana

symbols, however, suffers from a number of problems. One can easily wind up with a system that proposes *iskrym* as a back-transliteration of `aisukuriimu`. Taking letter frequencies into account improves this to a more plausible-looking *isclim*. Moving to real words may give *is crime*: the *i* corresponds to `ai`, the *s* corresponds to `su`, etc. Unfortunately, the correct answer here is *ice cream*.

After initial experiments along these lines, we stepped back and built a generative model of the transliteration process, which goes like this:

1. An English phrase is written.
2. A translator pronounces it in English.
3. The pronunciation is modified to fit the Japanese sound inventory.
4. The sounds are converted into katakana.
5. Katakana is written.

This divides our problem into five subproblems. Fortunately, there are techniques for coordinating solutions to such subproblems, and for using generative models in the reverse direction. These techniques rely on probabilities and Bayes' theorem. Suppose we build an English phrase generator that produces word sequences according to some probability distribution P(w). And suppose we build an English pronouncer that takes a word sequence and assigns it a set of pronunciations, again probabilistically, according to some P($p|w$). Given a pronunciation p, we may want to search for the word sequence w that maximizes P($w|p$). Bayes' theorem lets us equivalently maximize $P(w) \cdot P(p|w)$, exactly the two distributions we have modeled.

Extending this notion, we settled down to build five probability distributions:

1. P(w) — generates written English word sequences.
2. P($e|w$) — pronounces English word sequences.
3. P($j|e$) — converts English sounds into Japanese sounds.
4. P($k|j$) — converts Japanese sounds to katakana writing.
5. P($o|k$) — introduces misspellings caused by optical character recognition (OCR).

Given a katakana string o observed by OCR, we want to find the English word sequence w that maximizes the sum, over all e, j, and k, of

$$\mathrm{P}(w) \cdot \mathrm{P}(e|w) \cdot \mathrm{P}(j|e) \cdot \mathrm{P}(k|j) \cdot \mathrm{P}(o|k)$$

Following Pereira and Riley (1997), we implement P(w) in a weighted finite-state acceptor (WFSA) and we implement the other distributions in weighted finite-state transducers (WFSTs). A WFSA is a state/transition diagram with weights and symbols on the transitions, making some output sequences more likely than others. A WFST is a WFSA with a pair of symbols on each transition, one input and one output. Inputs and outputs may include the empty symbol ϵ. Also following Pereira and Riley (1997), we have implemented a general composition algorithm for constructing an integrated model P($x|z$) from models P($x|y$) and P($y|z$), treating WFSAs as WFSTs with identical inputs and outputs. We use this to combine an observed katakana string with each

of the models in turn. The result is a large WFSA containing all possible English translations.

We have implemented two algorithms for extracting the best translations. The first is Dijkstra's shortest-path graph algorithm (Dijkstra 1959). The second is a recently discovered k-shortest-paths algorithm (Eppstein 1994) that makes it possible for us to identify the top k translations in efficient $O(m + n \log n + kn)$ time, where the WFSA contains n states and m arcs.

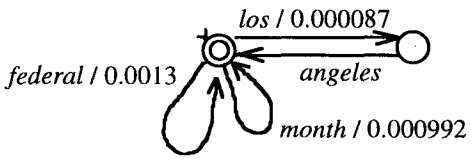
The approach is modular. We can test each engine independently and be confident that their results are combined correctly. We do no pruning, so the final WFSA contains every solution, however unlikely. The only approximation is the Viterbi one, which searches for the best path through a WFSA instead of the best sequence (i.e., the same sequence does not receive bonus points for appearing more than once).

3. Probabilistic Models

This section describes how we designed and built each of our five models. For consistency, we continue to print written English word sequences in italics (*golf ball*), English sound sequences in all capitals (G AA L F B AO L), Japanese sound sequences in lower case (g o r u h u b o o r u) and katakana sequences naturally (ゴルフボール).

3.1 Word Sequences

The first model generates scored word sequences, the idea being that *ice cream* should score higher than *ice creme*, which should score higher than *aice kreem*. We adopted a simple unigram scoring method that multiplies the scores of the known words and phrases in a sequence. Our 262,000-entry frequency list draws its words and phrases from the Wall Street Journal corpus, an on-line English name list, and an on-line gazetteer of place names.[1] A portion of the WFSA looks like this:



An ideal word sequence model would look a bit different. It would prefer exactly those strings which are actually grist for Japanese transliterators. For example, people rarely transliterate auxiliary verbs, but surnames are often transliterated. We have approximated such a model by removing high-frequency words like *has, an, are, am, were, their,* and *does,* plus unlikely words corresponding to Japanese sound bites, like *coup* and *oh.*

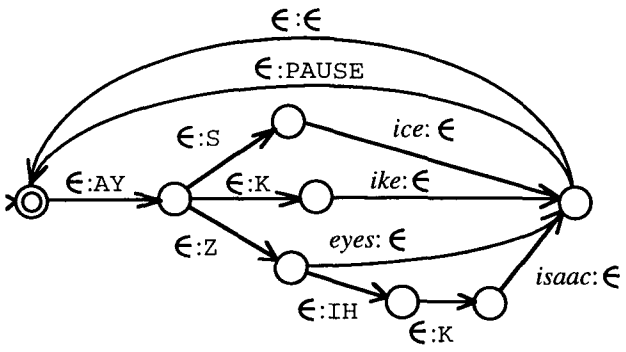
We also built a separate word sequence model containing only English first and last names. If we know (from context) that the transliterated phrase is a personal name, this model is more precise.

3.2 Words to English Sounds

The next WFST converts English word sequences into English sound sequences. We use the English phoneme inventory from the on-line CMU Pronunciation Dictio-

1 Available from the ACL Data Collection Initiative.

nary, minus the stress marks.[2] This gives a total of 40 sounds, including 14 vowel sounds (e.g., AA, AE, UW), 25 consonant sounds (e.g., K, HH, R), plus one special symbol (PAUSE). The dictionary has pronunciations for 110,000 words, and we organized a tree-based WFST from it:



Note that we insert an optional PAUSE between word pronunciations.

We originally thought to build a general letter-to-sound WFST (Divay and Vitale 1997), on the theory that while wrong (overgeneralized) pronunciations might occasionally be generated, Japanese transliterators also mispronounce words. However, our letter-to-sound WFST did not match the performance of Japanese transliterators, and it turns out that mispronunciations are modeled adequately in the next stage of the cascade.

3.3 English Sounds to Japanese Sounds

Next, we map English sound sequences onto Japanese sound sequences. This is an inherently information-losing process, as English R and L sounds collapse onto Japanese r, the 14 English vowel sounds collapse onto the 5 Japanese vowel sounds, etc. We face two immediate problems:

1. What is the target Japanese sound inventory?
2. How can we build a WFST to perform the sequence mapping?

An obvious target inventory is the Japanese syllabary itself, written down in katakana (e.g., ニ) or a roman equivalent (e.g., ni). With this approach, the English sound K corresponds to one of カ (ka), キ (ki), ク (ku), ケ (ke), or コ (ko), depending on its context. Unfortunately, because katakana is a syllabary, we would be unable to express an obvious and useful generalization, namely that English K usually corresponds to Japanese k, independent of context. Moreover, the correspondence of Japanese katakana writing to Japanese sound sequences is not perfectly one-to-one (see Section 3.4), so an independent sound inventory is well-motivated in any case. Our Japanese sound inventory includes 39 symbols: 5 vowel sounds, 33 consonant sounds (including doubled consonants like kk), and one special symbol (pause). An English sound sequence like (P R OW PAUSE S AA K ER) might map onto a Japanese sound sequence like (p u r o pause s a kk a a). Note that long Japanese vowel sounds

2 The CMU Pronunciation Dictionary can be found on-line at http://www.speech.cs.cmu.edu/cgi-bin/cmudict.

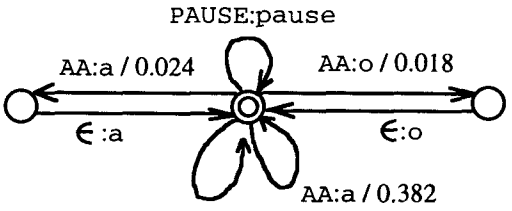
are written with two symbols (a a) instead of just one (aa). This scheme is attractive because Japanese sequences are almost always longer than English sequences.

Our WFST is learned automatically from 8,000 pairs of English/Japanese sound sequences, e.g., ((S AA K ER) ↔ (s a kk a a)). We were able to produce these pairs by manipulating a small English-katakana glossary. For each glossary entry, we converted English words into English sounds using the model described in the previous section, and we converted katakana words into Japanese sounds using the model we describe in the next section. We then applied the estimation-maximization (EM) algorithm (Baum 1972; Dempster, Laird, and Rubin 1977) to generate symbol-mapping probabilities, shown in Figure 2. Our EM training goes like this:

1. For each English/Japanese sequence pair, compute all possible **alignments** between their elements. In our case, an alignment is a drawing that connects each English sound with one or more Japanese sounds, such that all Japanese sounds are covered and no lines cross. For example, there are two ways to align the pair ((L OW) <-> (r o o)):

   In this case, the alignment on the left is intuitively preferable. The algorithm learns such preferences.
2. For each pair, assign an equal weight to each of its alignments, such that those weights sum to 1. In the case above, each alignment gets a weight of 0.5.
3. For each of the 40 English sounds, count up instances of its different mappings, as observed in all alignments of all pairs. Each alignment contributes counts in proportion to its own weight.
4. For each of the 40 English sounds, normalize the scores of the Japanese sequences it maps to, so that the scores sum to 1. These are the symbol-mapping probabilities shown in Figure 2.
5. Recompute the alignment scores. Each alignment is scored with the product of the scores of the symbol mappings it contains. Figure 3 shows sample alignments found automatically through EM training.
6. Normalize the alignment scores. Scores for each pair's alignments should sum to 1.
7. Repeat 3–6 until the symbol-mapping probabilities converge.

We then build a WFST directly from the symbol-mapping probabilities:



Our WFST has 99 states and 283 arcs.

e	j	P(j|e)
AA	o	0.566
	a	0.382
	a a	0.024
	o o	0.018
AE	a	0.942
	y a	0.046
AH	a	0.486
	o	0.169
	e	0.134
	i	0.111
	u	0.076
AO	o	0.671
	o o	0.257
	a	0.047
AW	a u	0.830
	a w	0.095
	o o	0.027
	a o	0.020
	a	0.014
AY	a i	0.864
	i	0.073
	a	0.018
	a i y	0.018
B	b	0.802
	b u	0.185
CH	ch y	0.277
	ch	0.240
	tch i	0.199
	ch i	0.159
	tch	0.038
	ch y u	0.021
	tch y	0.020
D	d	0.535
	d o	0.329
	dd o	0.053
	j	0.032
DH	z	0.670
	z u	0.125
	j	0.125
	a z	0.080
EH	e	0.901
	a	0.069
ER	a a	0.719
	a	0.081
	a r	0.063
	e r	0.042
	o r	0.029

e	j	P(j|e)
EY	e e	0.641
	a	0.122
	e	0.114
	e i	0.080
	a i	0.014
F	h	0.623
	h u	0.331
	hh	0.019
	a h u	0.010
G	g	0.598
	g u	0.304
	gg u	0.059
	gg	0.010
HH	h	0.959
	w	0.014
IH	i	0.908
	e	0.071
IY	i i	0.573
	i	0.317
	e	0.074
	e e	0.016
JH	j	0.329
	j y	0.328
	j i	0.129
	jj i	0.066
	e j i	0.057
	z	0.032
	g	0.018
	jj	0.012
	e	0.012
K	k	0.528
	k u	0.238
	kk u	0.150
	kk	0.043
	k i	0.015
	k y	0.012
L	r	0.621
	r u	0.362
M	m	0.653
	m u	0.207
	n	0.123
	n m	0.011
N	n	0.978
NG	n g u	0.743
	n	0.220
	n g	0.023

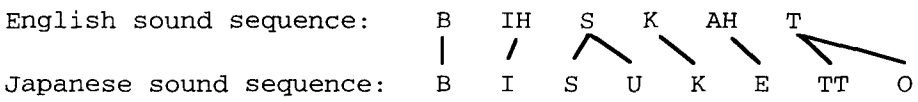
e	j	P(j|e)
OW	o	0.516
	o o	0.456
	o u	0.011
OY	o i	0.828
	o o i	0.057
	i	0.029
	o i y	0.029
	o	0.027
	o o y	0.014
	o o	0.014
P	p	0.649
	p u	0.218
	pp u	0.085
	pp	0.045
PAUSE	pause	1.000
R	r	0.661
	a	0.170
	o	0.076
	r u	0.042
	u r	0.016
	a r	0.012
S	s u	0.539
	s	0.269
	sh	0.109
	u	0.028
	ss	0.014
SH	sh y	0.475
	sh	0.175
	ssh y u	0.166
	ssh y	0.088
	sh i	0.029
	ssh	0.027
	sh y u	0.015
T	t	0.463
	t o	0.305
	tt o	0.103
	ch	0.043
	tt	0.021
	ts	0.020
	ts u	0.011
TH	s u	0.418
	s	0.303
	sh	0.130
	ch	0.038
	t	0.029

e	j	P(j|e)
UH	u	0.794
	u u	0.098
	dd	0.034
	a	0.030
	o	0.026
UW	u u	0.550
	u	0.302
	y u u	0.109
	y u	0.021
V	b	0.810
	b u	0.150
	w	0.015
W	w	0.693
	u	0.194
	o	0.039
	i	0.027
	a	0.015
	e	0.012
Y	y	0.652
	i	0.220
	y u	0.050
	u	0.048
	b	0.016
Z	z	0.296
	z u	0.283
	j	0.107
	s u	0.103
	u	0.073
	a	0.036
	o	0.018
	s	0.015
	n	0.013
	i	0.011
	sh	0.011
ZH	j y	0.324
	sh i	0.270
	j i	0.173
	j	0.135
	a j y u	0.027
	sh y	0.027
	s	0.027
	a j i	0.016

Figure 2
English sounds (in capitals) with probabilistic mappings to Japanese sound sequences (in lower case), as learned by estimation-maximization. Only mappings with conditional probabilities greater than 1% are shown, so the figures may not sum to 1.

We have also built models that allow individual English sounds to be "swallowed" (i.e., produce zero Japanese sounds). However, these models are expensive to compute (many more alignments) and lead to a vast number of hypotheses during WFST composition. Furthermore, in disallowing "swallowing," we were able to automatically remove hundreds of potentially harmful pairs from our training set, e.g., `((B AA R B ER SH AA P)` ↔ `(b a a b a a))`. Because no alignments are possible, such pairs are skipped by the learning algorithm; cases like these must be solved by dictionary

biscuit



divider

filter

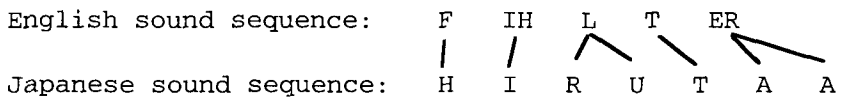


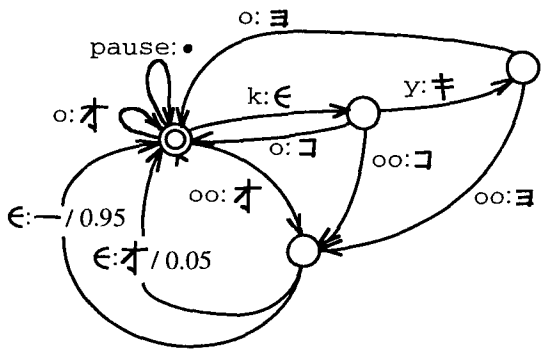
Figure 3
Alignments between English and Japanese sound sequences, as determined by EM training. Best alignments are shown for the English words *biscuit*, *divider*, and *filter*.

lookup anyway. Only two pairs failed to align when we wished they had—both involved turning English `Y UW` into Japanese `u`, as in `((Y UW K AH L EY L IY)` ↔ `(u k u r e r e))`.

Note also that our model translates each English sound without regard to context. We have also built context-based models, using decision trees recoded as WFSTs. For example, at the end of a word, English `T` is likely to come out as `(t o)` rather than `(t)`. However, context-based models proved unnecessary for back-transliteration. They are more useful for English-to-Japanese forward transliteration.

3.4 Japanese Sounds to Katakana

To map Japanese sound sequences like (`m o o t a a`) onto katakana sequences like (モータア), we manually constructed two WFSTs. Composed together, they yield an integrated WFST with 53 states and 303 arcs, producing a katakana inventory containing 81 symbols, including the dot-separator (•). The first WFST simply merges long Japanese vowel sounds into new symbols `aa`, `ii`, `uu`, `ee`, and `oo`. The second WFST maps Japanese sounds onto katakana symbols. The basic idea is to consume a whole syllable worth of sounds before producing any katakana. For example:



This fragment shows one kind of spelling variation in Japanese: long vowel sounds (oo) are usually written with a long vowel mark (オー) but are sometimes written with repeated katakana (オオ). We combined corpus analysis with guidelines from a Japanese textbook (Jorden and Chaplin 1976) to turn up many spelling variations and unusual katakana symbols:

- the sound sequence (j i) is usually written ジ, but occasionally ヂ.
- (g u a) is usually グア, but occasionally グァ.
- (w o o) is variously ウオー, ウォー, or with a special old-style katakana for wo.
- (y e) may be エ, イエ, or イェ.
- (w i) is either ウイ or ウィ.
- (n y e) is a rare sound sequence, but is written ニェ when it occurs.
- (t y u) is rarer than (ch y u), but is written テュ when it occurs.

and so on.

Spelling variation is clearest in cases where an English word like *switch* shows up transliterated variously (スィッチ, スイッチ, スウィッチ) in different dictionaries. Treating these variations as an equivalence class enables us to learn general sound mappings even if our bilingual glossary adheres to a single narrow spelling convention. We do not, however, generate all katakana sequences with this model; for example, we do not output strings that begin with a subscripted vowel katakana. So this model also serves to filter out some ill-formed katakana sequences, possibly proposed by optical character recognition.

3.5 Katakana to OCR

Perhaps uncharitably, we can view optical character recognition (OCR) as a device that garbles perfectly good katakana sequences. Typical confusions made by our commercial OCR system include ボ for ポ, チ for ナ, ア for ァ, and 7 for ブ. To generate pre-OCR text, we collected 19,500 characters worth of katakana words, stored them in a file, and printed them out. To generate post-OCR text, we OCR'd the printouts. We then ran the EM algorithm to determine symbol-mapping ("garbling") probabilities. Here is part of that table:

k	o	$P(o\|k)$
ビ	ビ	0.492
	ビ	0.434
	ヒ	0.042
	7	0.011
ビ	ビ	1.000
ハ	ハ	0.964
	ノ、	0.036

This model outputs a superset of the 81 katakana symbols, including spurious quote marks, alphabetic symbols, and the numeral 7.[3]

4. A Sample Back-transliteration

We can now use the models to do a sample back-transliteration. We start with a katakana phrase as observed by OCR. We then serially compose it with the models, in reverse order. Each intermediate stage is a WFSA that encodes many possibilities. The final stage contains all back-transliterations suggested by the models, and we finally extract the best one.

We start with the `masutaazutoonamento` problem from Section 1. Our OCR observes:

マスクーズトーチメント

This string has two recognition errors: ク (`ku`) for タ (`ta`), and チ (`chi`) for ナ (`na`). We turn the string into a chained 12-state/11-arc WFSA and compose it with the P($k|o$) model. This yields a fatter 12-state/15-arc WFSA, which accepts the correct spelling at a lower probability. Next comes the P($j|k$) model, which produces a 28-state/31-arc WFSA whose highest-scoring sequence is:

`m a s u t a a z u t o o ch i m e n t o`

Next comes P($e|j$), yielding a 62-state/241-arc WFSA whose best sequence is:

`M AE S T AE AE DH UH T AO AO CH IH M EH N T AO`

Next to last comes P($w|e$), which results in a 2982-state/4601-arc WFSA whose best sequence (out of roughly three hundred million) is:

masters tone am ent awe

This English string is closest phonetically to the Japanese, but we are willing to trade phonetic proximity for more sensical English; we rescore this WFSA by composing it with P(w) and extract the best translation:

masters tournament

Other Section 1 examples (`aasudee` and `robaato shyoon renaado`) are translated correctly as *earth day* and *robert sean leonard*.

We may also be interested in the k best translations. In fact, after any composition, we can inspect several high-scoring sequences using the algorithm of Eppstein (1994). Given the following katakana input phrase:

アンジラホーラステルナイト

3 A more thorough OCR model would train on a wide variety of fonts and photocopy distortions. In practice, such degradations can easily overwhelm even the better OCR systems.

(pronounced anjirahoorasuterunaito), the top five English sound sequences are

	P(k|e)
AE N JH IH R AE HH AO AO R AE S T EH R UH N AE IH T AO	0.00753
AE N JH IH R AE HH AO AO R AE S T EH R UH N AY T AO	0.00742
AE N JH IH L AE HH AO AO R AE S T EH R UH N AE IH T AO	0.00735
AE N JH IH R AE HH AO AO R AE S T EH L UH N AE IH T AO	0.00735
AE N JH IH R AE HH AO AO L AE S T EH R UH N AE IH T AO	0.00735

Notice that different R and L combinations are visible in this list. The top five final translations are:

	P(w) * P(k|w)
angela forrestal knight	3.6e-20
angela forrester knight	8.5e-21
angela forest el knight	2.7e-21
angela forester knight	2.5e-21
angela forest air knight	1.7e-21

Inspecting the *k*-best list is useful for diagnosing problems with the models. If the right answer appears low in the list, then some numbers are probably off somewhere. If the right answer does not appear at all, then one of the models may be missing a word or suffer from some kind of brittleness. A *k*-best list can also be used as input to a later context-based disambiguator, or as an aid to a human translator.

5. Experiments

We have performed two large-scale experiments, one using a full-language P(*w*) model, and one using a personal name language model.

In the first experiment, we extracted 1,449 unique katakana phrases from a corpus of 100 short news articles. Of these, 222 were missing from an on-line 100,000-entry bilingual dictionary. We back-transliterated these 222 phrases. Many of the translations are perfect: *technical program, sex scandal, omaha beach, new york times, ramon diaz.* Others are close: *tanya harding, nickel simpson, danger washington, world cap.* Some miss the mark: *nancy care again, plus occur, patriot miss real.*[4] While it is difficult to judge overall accuracy—some of the phrases are onomatopoetic, and others are simply too hard even for good human translators—it is easier to identify system weaknesses, and most of these lie in the P(*w*) model. For example, *nancy kerrigan* should be preferred over *nancy care again.*

In a second experiment, we took (non-OCR) katakana versions of the names of 100 U.S. politicians, e.g.: ジョン・ブロー (jyon.buroo), アルホンス・ダマット (aruhonsu.damatto), and マイク・デワイン (maiku.dewain). We back-transliterated these by machine and asked four human subjects to do the same. These subjects were native English speakers and news-aware; we gave them brief instructions. The results were as in Table 1.

There is room for improvement on both sides. Being English speakers, the human subjects were good at English name spelling and U.S. politics, but not at Japanese phonetics. A native Japanese speaker might be expert at the latter but not the former. People who are expert in all of these areas, however, are rare.

4 Correct translations are *tonya harding, nicole simpson, denzel washington, world cup, nancy kerrigan, pro soccer,* and *patriot missile.*

Table 1
Accuracy of back-transliteration by human subjects and machine.

	Human	Machine
correct (e.g., *spencer abraham / spencer abraham*)	27%	64%
phonetically equivalent, but misspelled (e.g., *richard brian / richard bryan*)	7%	12%
incorrect (e.g., *olin hatch / orren hatch*)	66%	24%

On the automatic side, many errors can be corrected. A first-name/last-name model would rank *richard bryan* more highly than *richard brian*. A bigram model would prefer *orren hatch* over *olin hatch*. Other errors are due to unigram training problems, or more rarely, incorrect or brittle phonetic models. For example, *Long* occurs much more often than *Ron* in newspaper text, and our word selection does not exclude phrases like *Long Island*. So we get *long wyden* instead of *ron wyden*. One way to fix these problems is by manually changing unigram probabilities. Reducing P(*long*) by a factor of ten solves the problem while maintaining a high score for P(*long* | rongu).

Despite these problems, the machine's performance is impressive. When word separators (•) are removed from the katakana phrases, rendering the task exceedingly difficult for people, the machine's performance is unchanged. In other words, it offers the same top-scoring translations whether or not the separators are present; however, their presence significantly cuts down on the number of alternatives considered, improving efficiency. When we use OCR, 7% of katakana tokens are misrecognized, affecting 50% of test strings, but translation accuracy only drops from 64% to 52%.

6. Discussion

In a 1947 memorandum, Weaver (1955) wrote:

> One naturally wonders if the problem of translation could conceivably be treated as a problem of cryptography. When I look at an article in Russian, I say: "'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode." (p. 18)

Whether this is a useful perspective for machine translation is debatable (Brown et al. 1993; Knoblock 1996)—however, it is a dead-on description of transliteration. Most katakana phrases really *are* English, ready to be decoded.

We have presented a method for automatic back-transliteration which, while far from perfect, is highly competitive. It also achieves the objectives outlined in Section 1. It ports easily to new language pairs; the P(w) and P($e|w$) models are entirely reusable, while other models are learned automatically. It is robust against OCR noise, in a rare example of high-level language processing being useful (necessary, even) in improving low-level OCR.

There are several directions for improving accuracy. The biggest problem is that raw English frequency counts are not the best indication of whether a word is a possible source for transliteration. Alternative data collection methods must be considered.

We may also consider changes to the model sequence itself. As we have presented it, our hypothetical human transliterator produces Japanese sounds from English sounds only, without regard for the original English spelling. This means that English homonyms will produce exactly the same katakana strings. In reality, though, transliterators will sometimes key off spelling, so that *tonya* and *tanya* produce `toonya` and `taanya`. It might pay to carry along some spelling information in the English pronunciation lattices.

Sentential context should be useful for determining correct translations. It is often clear from a Japanese sentence whether a katakana phrase is a person, an institution, or a place. In many cases it is possible to narrow things further—given the phrase "such-and-such, Arizona," we can restrict our P(w) model to include only those cities and towns in Arizona.

It is also interesting to consider transliteration for other languages. In Arabic, for example, it is more difficult to identify candidates for transliteration because there is no distinct, explicit alphabet that marks them. Furthermore, Arabic is usually written without vowels, so we must generate vowel sounds from scratch in order to produce correct English.

Finally, it may be possible to embed phonetic-shift models inside speech recognizers, to explicitly adjust for heavy foreign accents.

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