False-Friend Detection and Entity Matching via Unsupervised Transliteration

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Abstract

Transliterations play an important role in multilingual entity reference resolution, because proper names increasingly travel between languages in news and social media. Previous work associated with machine translation targets transliteration only single between language pairs, focuses on specific classes of entities (such as cities and celebrities) and relies on manual curation, which limits the expression power of transliteration in multilingual environment.

By contrast, we present an unsupervised transliteration model covering 69 major languages that can generate good transliterations for arbitrary strings between any language pair. Our model yields top-(1, 20, 100) averages of (32.85%, 60.44%, 83.20%) in matching gold standard transliteration compared to results from a recently-published system of (26.71%, 50.27%, 72.79%). We also show the quality of our model in detecting true and false friends from Wikipedia high frequency lexicons. Our method indicates a strong signal of pronunciation similarity and boosts the probability of finding true friends in 68 out of 69 languages.

1 Introduction

Transliterations play an important role in multilingual entity reference resolution, because proper names increasingly travel between languages. This process tends to create a substantial number of out of vocabulary (OOV) words in the multilingual analysis of news and social media. When “Gangnam style” topped the music charts of more than 30 countries, a word imported from Korean suddenly became part of the language spoken by millions of people around the world. News events like the catastrophic failure at nuclear power plant bring words associated with new people and places (“Fukushima”) across languages into common use. These words do not reside in standard vocabulary lexicons, but are generated as needed via a process of transliteration. Detecting transliterated word pairs contributes to many language processing tasks, including entity resolution, translation, topic classification and sentiment analysis, as well as facilitates studying linguistic phenomenon like cross-language morphologic evolution. However, previous transliteration systems generally focus on a small number of language pairs. Further, they only consider morphological similarity even in translation systems, creating a problem of “false friends” of word pairs which look/sound alike but mean different things.

In this paper, we target the problem of generating transliterations between arbitrary pairs of 69 languages, and detecting borrowed words and entities across these languages. We train both transliteration models and semantic word embeddings in an unsupervised manner using large-scale corpus from Wikipedia. As an example, Figure 1 shows our transliterations of the name ‘obama into 25 non-Latin scripts. We provide both our transliteration (constructed from scratch) and lowest edit-distance match appearing in 100,000 most frequent Wikipedia lexicons for these languages. Our closest match proves to equal the gold standard for 20 out of 23 languages where it appears in the lexicon. Further, our constructed best differs from the gold standard name within at most one character substitution for 22 out of 25 languages.

Our major contributions are:

- Training Methods for Transliteration – We used Wikipedia to build a training set for transliteration, starting from the cross-language links between personal and place names in Wikipedia. We collect a dataset
Figure 1: Constructed best and detected best for word “obama” where capitalization is disabled. Constructed best is generated via cost matrices without any prior knowledge of vocabulary. Detected best is the best match in 100,000 most frequent words in Wikipedia. Last column shows the rank of gold standard reference if it appears in these 100,000 high frequency words.

with 576,403 items contributing one or more transliterations from English to other languages yielding reasonable training and testing sets to learn transliterations. But this is a very dirty training set, because many such translation pairs are not transliterations (e.g. Estados Unidos for United States). We develop unsupervised methods to distinguish true transliterations from false, and thus clean the training set.

• **Accurate Transliteration via Substring Matching** – We use an expectation maximization approach to use statistics of string alignments to train improved cost matrices via a Bayesian probability model. Our methods employ substring matching instead of single-character transition matrices, enabling the recognition of phonemes, character bigrams, and beyond.

We have trained models that permit us to construct transliterations for any string between all pairs of 69 languages. We evaluate our work against a recently-published transliteration system [Durrani et al., 2014] which has been integrated into the Moses statistical machine translation system. We compare our transliteration to Moses on the four languages it supports (Arabic, Chinese, Hindi, and Russian), outperforming it in 61 of 64 standards over the set of languages.

• **Distinguishing Translations from False Friends** – Similarly spelled or sounding words can have substantially different meanings. Such pairs that span language boundaries are called false friends, e.g. ropa in Spanish means clothes, not rope). By coupling transliteration pair analysis with semantic tests using distributed word embeddings, we can generate comprehensive lexicons of true and false friends. Our methods get very good results in tests against human annotated standards for French (F1=0.890) and Spanish (F1=0.825).

We use our approach to generate lexicons of true and false friends between English and 69 languages. We show that the lexically-closest cohort of word pairs has a higher probability of being true friends than words that are more lexically distant in 68 out of 69 languages, indicating our methods provide a good signal to identify borrowed words.

We provide a demo that can transiterate any English string to non-Latin languages [1]. Our transliteration code, corpora, weight matrices, and false-friend lexicons for all 69 languages will be made publicly available upon acceptance of this paper.

The rest of this paper is organized as follows. We review related work in Section [2] In Section [3] we describe the procedure of collecting data. Section [4] talks about our model of learning character-based transliteration cost matrices. We analyze the performance of our model in Section [5]. Section [6] discusses the application of detecting true and false friends. Finally, we conclude with discussion and ideas for future work.

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[1] https://soundaword.appspot.com/
2 Related Work

Transliteration research first associates with the field of orthographic similarity detections since sound similarities co-exist with orthographic similarities (Brew et al., 1996; Mann and Yarowsky, 2001; Dijkstra et al., 1999; Van Heuven et al., 1998; Kondrak, 2004; Chamizo Dominguez and Nerlich, 2002). This work shows reasonableness of character-based transliteration between close languages (i.e. languages sharing characters) but does not discuss on distant language pairs.

Similarly, work on cognate identification also focus on close language pairs (Simard et al., 1993; Inkpen et al., 2005; Schepens et al., 2013; Boada et al., 2013; Kolb, 2008; Kondrak and Dorr, 2004; Resnik, 2011). However, we believe multilingual transliterations contribute to even distant languages (e.g. English and Japanese) when handling OOV words and resolving ambiguities.

Further transliteration researches divide into two branches. One tries to study delicate sound changing rules of specific languages (Knight and Graehl, 1998; AbdulJaleel and Larkey, 2003; Suwanvisat and Prasitjutrakul, 1998; Gao et al., 2005; Virga and Khudanpur, 2003; Jagarlamudi and Daume III, 2012; Hong et al., 2009). Especially, an excellent ideas of using Wikipedia external links is proposed in (Kirschenbaum and Wintner, 2009; Kirschenbaum and Wintner, 2010) and achieve promising results in English-Hebrew transliteration using Moses (Koehn et al., 2007). However, all these systems are supervised and require extra linguistic background knowledge during processing. Plus, only one among this work evaluates transliteration on up to 4 languages and it is hard to generalize for multiple languages.

The other branch learns from only sequence of characters. One of the great advantages against sound based transliteration is that multilingual texts are much easier to obtain. Al-Onaizan and Knight (2002) compares phonetic based systems with spelling based systems on transliterations between English and Arabic. Pouliquen et al. (2006) makes transliteration model based on similar spelling rules in close languages. Recent work of Durrani et al. (2014) is integrated in Moses as a module, providing an unsupervised character-based transliteration training model. Matthews (2007) proposed a proper name transliteration model on several language pairs. However, we believe utilizing character-based transliteration model can provide us with even more valuable information in natural language processing tasks.

3 Data Collection and Pre-processing

Kirschenbaum and Wintner (2009) inspire us to use Wikipedia external links to build an aligned multilingual corpus. However, their work requires language-specific knowledge, for instance, discarding vowels and filtering out junk data using pre-defined consonant matching. In our task, we use the names of entities (people and places) to create a training set for transliteration. (Francis et al., 2002) state that over 40% of the brands choose to create corresponding foreign names via transliterations. By querying Freebase in categories containing 3,388,225 entries, we create a precise multilingual transliteration dictionary through Wikipedia page titles. We then perform a rough clean up procedure to (1) unify punctuation by converting hyphens, dots, comma to underscores and, (2) remove entries which do not adhere to the (first name, last name) or whole name format. Our final collection contains 576,403 English entries with multilingual mapping.

As an additional resource, we query Google translation API to get formal translations of certain English proper nouns to all 69 languages. To reduce machine translation error, we manually pick 1,373 entities without no multi-sense ambiguities from the names of people (Census, 2000), countries and capital cities (Wikipedia.org, 2014), resulting in more than 70,000 pairs of proper name transliteration from English. Table 1 shows statistics of final data size in each language. 80% of the final data will be used for training, 10% is for tuning and the remaining 10% is for testing.

| Largest Lang | Count | Smallest Lang | Count |
|--------------|-------|--------------|-------|
| French       | 183,270 | Khmer        | 1,585 |
| German       | 178,715 | Amharic      | 2,035 |
| Italian      | 132,545 | Gujarati     | 2,130 |
| Polish       | 124,870 | Maltese      | 2,415 |
| Spanish      | 107,790 | Yiddish      | 2,835 |
| Russian      | 100,085 | Kannada      | 3,100 |
| Swedish      | 91,125  | Telugu       | 3,840 |
| Dutch        | 87,870  | Swahili      | 4,620 |
| Portuguese   | 86,515  | Haitian      | 5,245 |
| Norwegian    | 74,790  | Urdu         | 6,115 |

Table 1: Languages with the largest and smallest set of translated entities, i.e. reflecting the availability of training data.
4 Training Transliteration Model

The purpose of our training is to get a quantified measurement of sound similarities between any possible character strings in arbitrary scripts. We expect to learn pairwise word segmentations and n-gram statistics of correlated string pieces between different languages.

We maintain a cost matrix in which the cost of substituting any string $s_1$ in Language$_1$ with string $s_2$ in Language$_2$ will first be initialized to $\text{len}(s_1) + \text{len}(s_2)$, including empty strings. This way each training example has a fixed cost equal to the total length of two strings. After that we start an $R$ round iteration. In each round we go through all training examples and compute the minimum-cost segmentation matching. We keep tracking of all observations of matched n-grams during this round in observation table. We then adapt Bayesian setting mentioned in Snyder and Barzilay, 2008 to update cost matrix according to probability calculated by observation table. Figure 2 illustrates the training procedure.

Data used in training example may be flawed as it might not reflect transliteration. Such training examples act as outliers during out training and we cannot find any reasonable matching even for partial string pieces. We here define “Dirtiness” to measure how many training examples are flawed in training a specific language. Table 2 shows 10 dirtiest among 69 languages. Big languages included in Table 2 (e.g. Chinese, Korean) are not problematic since we have plenty of training examples. However, we expect a bad performance on small languages like Khmer and Amharic due to lack of high quality data.

| Dirtiest Lang | Dirtiness | Cleanest Lang | Dirtiness |
|---------------|-----------|---------------|-----------|
| Hungarian     | 41.00%    | Norwegian     | 1.23%     |
| Amharic       | 36.09%    | Bulgarian     | 1.80%     |
| Vietnamese    | 32.10%    | Macedonian    | 1.83%     |
| Khmer         | 24.58%    | Latvian       | 1.99%     |
| Thai          | 24.50%    | Russian       | 2.20%     |
| Chinese       | 23.80%    | Greek         | 2.27%     |
| Korean        | 22.20%    | Armenian      | 2.41%     |
| Malay         | 20.11%    | Georgian      | 2.60%     |
| Tamil         | 18.72%    | Czech         | 2.95%     |
| Japanese      | 16.81%    | Latin         | 3.26%     |

Table 2: The 10 cleanest and dirtiest languages, defined according to the ratio of flawed examples in the training set.

Figure 3a and Fig. 3b present heatmaps generated from our cost matrix showing 1-1 matching rules between characters in these languages. The highlighted diagonals indicate strong similarity between identical Latin characters as expected, making transliteration inside the same language family meaningless. However, these matrices also reflect language differences: e.g. the Spanish “y” more often acts as an English “j” than an English “y”; and the Spanish “b” is close to English “v” while the French “b” matches only with English “b”.

5 Experimental Results

In this section we evaluate the quality of our transliteration model.

5.1 Baseline Model

We use the transliteration system described in (Durrani et al., 2014) as baseline method to compare our results. The Moses statistical machine translation system integrates their work as a module, and allows training unsupervised transliteration for OOV words.

5.2 Test Results

We first compare both systems trained on our Wikipedia dataset. We focus on the performance of phrase table, i.e. measurement of sound similarities between string pieces since our dataset does not contain corpus context. We generate the 100-best transliterations for entries in testing set on four languages of different language families: Chinese, Arabic, Hindi and Russian.

We repeated this test using third party datasets to check consistency of training models.

We cleaned data and retained only name mapping to feed the model, since our model does not rely on context and target a generalized method for multiple languages. Note Moses provides several language-specific optimization methods, including weights optimizing (e.g. Mert) and Language Model Smoothing (e.g. Kneser-Ney) that

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We use the following parameters when configuring Moses: maximum phrase length=3, language model N-gram order=3, language model smoothing & interpolation=Automatically Disabled, Interpolate; alignment heuristic= grow-diag-final; reordering=Mono-

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*We use the following parameters when configuring Moses: maximum phrase length=3, language model N-gram order=3, language model smoothing & interpolation=Automatically Disabled, Interpolate; alignment heuristic= grow-diag-final; reordering=Monotone; and maximum distortion length=0. The weights for the models are: translation model (0.2, 0.2, 0.2, 0.2, 0.2), language model (0.5), and distortion Model (0.0), with word penalty=1.

*Chinese: Chinese - English Name Entity List sv1.0(LDC2005T34). Arabic: Combination of 10001 Arabic Names(LDC2005G02) and Indian multi-parallel corpus made available for IWSLT-13. Hindi: (Post et al., 2012), and Russian: WMT-13 data (Bojar et al., 2014).
Figure 2: Illustration of the training procedure. Each round we compute minimum-cost-matching and record matched string pieces for all training examples and update costs matrix through a Bayesian model.

Figure 3: Probability/cost matrix for single character pairs between English and a) French and b) Spanish. The bright diagonal shows that we discover common equivalence for most Latin characters.

might improve performance (Durrani et al., 2014). However, given our goal of unsupervised transliteration, we did not attempt to employ these in our experiments.

Figure 3 shows the statistics. Our system generally outperforms Moses, winning on 61 of 64 comparisons over the eight languages and metrics. The absolute closest transliteration (top-1) result only matches the translation target in roughly 1/3 of the test examples, indicating that there are typically a large number of transliterations of similar edit cost. Indeed, the absolute performance score substantially increases with top-20 and top-100 results, showing the need to reduce ambiguity through context matching. Our high scores under Levenshtein 1 metric show that we generate reasonable transliteration for a large fraction of strings, retaining good lexical consistency with
Table 3: Comparison of performances on Wikipedia and third party (TP) datasets. Top-k measures the percentage of correct transliterations in the top k candidates. Levenshtein 1 measures the percentage of the highest ranked transliteration that is no more than 1 substitution away from the reference transliteration, given that we consider insertion / deletion to be a special kind of substitution.

6 True and False Friends Detection

Although our transliteration model is accurate at detecting lexical similarity across languages, words that look alike or sound alike do not necessarily mean the same thing. **False friends** are word pairs across languages that look the same, but mean something different. For example, the Spanish word *ropa* means clothes, not rope.

Such false friends are the bane of students learning foreign languages. For our transliteration tests to identify true language borrowings, we must also establish that the words have similar semantics. To perform such a test, we relied on the Polyglot distributed word embeddings presented in (Al-Rfou et al., 2013). The $L_2$ norm between two word representations captures its semantic distance.

However, the Polyglot embeddings do not reside in same geometric space of latent dimensions for different languages. Thus instead of directly computing the distance between representations across languages, we check how many pairs of known translations lie within the 300 words closest words in each language in case we are lack of direct translation evidences. This process is illustrated in Figure 4.

![Figure 4: Illustration of word embedding test. In case no direct evidences of semantic similarity between “Cat” and “Gato” are found, we check number of translations that links nearest neighbors of “Cat” and “Gato” . Since ( “Dog”, “Monkey”, “Duck”) matches perfectly with (“Perro”, “Mono”, “Pato”), we can judge that (“Cat”, “Gato”) has close semantic meanings. (“Car”, “Gato”) will definitely fail this test.](image-url)
6.1 Evaluation against Human Annotation

For two languages (French and Spanish) we found published lists of true and false friends with English. We did an evaluation of our results against these human-annotated gold standards, in particular 1756 French-English cognates and 541 false friends suggested in (Inkpen et al., 2005) as well as 1345 of Spanish-English cognates\(^2\) plus 217 false friends\(^3\). Our performance is shown in the table below:

| Language | TP | EP | B | N |
|----------|----|----|---|---|
| French   | 0.86 | 0.82 | 89.2% | 82.3% |
| Spanish  | 0.87 | 0.81 | 89.5% | 82.3% |

Table 4: Statistics of True and False Friends between English and all 69 languages. TP denotes Google translation pairs which are not close in our word embeddings. EP denotes close embedding test performed poorly. Red or Green languages. By contrast, the yellow languages are those where the embedding test performed poorly.

6.2 Cross-Language Scan

Embodied by these results, we performed a search for lexically/semantically similar words between English and all 69 of our transliterated languages. The results appear in Table 4. For each language, we report the number of false friends we identify (column N). The other three columns reflect different notions of true friends: single-word translations according to Google (TP), near neighbors in embedding test (EP), and those which survive both of these semantic tests (B).

Without a language-specific analysis of each of the classes, it is difficult to determine which of these reflect language borrowings most accurately. The quality of the word embeddings vary substantially by language, as does the quality of Google’s translation support. Our preferred measure of quality is the ratio of word pairs which survive both tests (B) over all that having Google translations (B+TP). The 33 languages colored red and green all have a ratio of greater than 0.5, indicating the highest quality embeddings. The red languages denote the five with the best embeddings, with the poorest five (in yellow) reflect languages with excessively small training data (Amharic and Khmer). Our methods have a particularly difficult time with Vietnamese, which bases a misleading similarity to Latin languages at the character level.

6.3 Cross-Language Validation

Figure 5 provides a deeper assessment of our cross-language scan. For each language, we identified which words in its 100,000 word vocabulary were lexically very similar (edit distance ≤ 2, which is decided by initial value of substitution) to a word in the English vocabulary. We then con-
Figure 5: (left) Fraction of gold standard translations within very close edit distance pairs ($d < 2$) versus the next closest 10,000 pairs. (right) Same fractions after retaining only the 50% of pairs which are closest by embedding distance. For 68 of 69 languages, the lexically closer pairs are more likely to be translations (left). Further, eliminating pairs failing the embedding test shifts all languages to the upper right, showing that the embedding test accurately captures semantic similarity (right).

considered the next closest 10,000 word pairs, which should also be enriched in real transliterations (by contrast, only 0.01% random word pairs have a translation link) – but less enriched than the initial cohort. Indeed, Figure 5 (left) shows this to be true for 68 of 69 languages, denoted by points in the upper left triangle.

To establish that our embedding test accurately eliminates false friends, we pruned the lower half of each cohort according to the embedding test, i.e. retained only those words whose distance in embedding space was below the median value. Figure 5 (right) shows that this action dramatically shifts each language up and to the right. With the exception of three outlier languages (Vietnamese, Latin, and Maltese), well over 50% of our closest cohort are now true friends (translations). For somewhat more than half of the languages, the lexicographically second cohort is now rich in true friends to the 50% level.

7 Conclusion

In this paper, we have developed transliteration models that accurately identify borrowed out of vocabulary (OOV) words, for 69 different languages. We have evaluated our transliterations against published gold standards when available and against intrinsic measures when such standards are not available. Further, we demonstrated that adding word embeddings to provide a semantic test enables us to distinguish true borrowings from false friends.

There are several directions to improve the future quality of our transliteration model:

- **Phonetic Information** – Our models improve with additional training data, particularly for resource-poor languages. An exciting way to increase this volume would be aligning speech translations as represented in a phonetic dictionary or sound system (e.g. IPA) as suggested in (Jagarlamudi and Daume III, 2012).

- **Multiple transliteration** – Though English Wikipedia has the richest resources in the world, it is not guaranteed that English is the source language of borrowed names. Currently we employ a star network of transliteration pairs centered through English. A richer graph with other important languages (e.g. Russian and Chinese) would improve performance.

- **Longer-Range Dependencies** As we target transliteration, our model should utilize longer range dependencies. Observe that a silent e at the end of English words changes the pronunciation of vowels earlier in the word, so the “li” is different in “lit” and “like”. Under context the Moses system with optimization exploits such phenomena, but we believe with we can learn such pronunciation features from the text itself.
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References

[AbdulJaleel and Larkey2003] Nasreen AbdulJaleel and Leah S Larkey. 2003. Statistical transliteration for english-arabic cross language information retrieval. In Proceedings of the twelfth international conference on Information and knowledge management, pages 139–146. ACM.

[Al-Onaizan and Knight2002] Yaser Al-Onaizan and Kevin Knight. 2002. Machine transliteration of names in arabic text. In Proceedings of the ACL-02 workshop on Computational approaches to semitic languages, pages 1–13. Association for Computational Linguistics.

[Al-Rfou et al.2013] Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2013. Polyglot: Distributed word representations for multilingual nlp. arXiv preprint arXiv:1307.1662.

[Boada et al.2013] Roger Boada, Rosa Sanchez-Casas, Jose M Gavilan, Jose E Garcia-Albea, and Natasha Tokowicz. 2013. Effect of multiple translations and cognate status on translation recognition performance of balanced bilinguals. Bilingualism: Language and Cognition, 16(01):183–197.

[Bojar et al.2014] Ondrej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, et al. 2014. Findings of the 2014 workshop on statistical machine translation. In Proceedings of the Ninth Workshop on Statistical Machine Translation, pages 12–58. Association for Computational Linguistics Baltimore, MD, USA.

[Brew et al.1996] Chris Brew, David McKelvie, et al. 1996. Word-pair extraction for lexicography. In Proceedings of the second international conference on new methods in language processing, pages 45–55. Citeseer.

[Census2000] Govenment Census. 2000. Genealogy data: Frequently occurring surnames from census 2000.

[Cettolo et al.2012] Mauro Cettolo, Christian Girardi, and Marcello Federico. 2012. Wit3: Web inventory of transcribed and translated talks. In Proceedings of the 16th Conference of the European Association for Machine Translation (EAMT), pages 261–268.

[Chamizo Dominguez and Nerlich2002] Pedro J Chamizo Dominguez and Brigitte Nerlich. 2002. False friends: their origin and semantics in some selected languages. Journal of Pragmatics, 34(12):1833–1849.

[Dijkstra et al.1999] Ton Dijkstra, Jonathan Grainger, and Walter JB Van Heuven. 1999. Recognition of cognates and interlingual homographs: The neglected role of phonology. Journal of Memory and Language, 41(4):496–518.
[Durrani et al.2014] Nadir Durrani, Hieu Hoang, Philipp Koehn, and Hassan Sajjad. 2014. Integrating an unsupervised transliteration model into statistical machine translation. *EACL* 2014, page 148.

[Francis et al.2002] June NP Francis, Janet PY Lam, and Ian Walls. 2002. The impact of linguistic differences on international brand name standardization: A comparison of english and chinese brand names of fortune-500 companies. *Journal of International Marketing*, 10(1):98–116.

[Gao et al.2005] Wei Gao, Kam-Fai Wong, and Wai Lam. 2005. Phoneme-based transliteration of foreign names for oov problem. In *Natural Language Processing–IJCNLP 2004*, pages 110–119. Springer.

[Inkpen et al.2005] Diana Inkpen, Oana Frunza, and Grzegorz Kondrak. 2005. Automatic identification of cognates and false friends in french and english. In *Proceedings of the International Conference Recent Advances in Natural Language Processing*, pages 251–257.

[Jagarlamudi and Daumé III2012] Jagadeesh Jagarlamudi and Hal Daumé III. 2012. Regularized interlingual projections: evaluation on multilingual transliteration. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, pages 12–23. Association for Computational Linguistics.

[Kirschenbaum and Wintner2009] Amit Kirschenbaum and Shuly Wintner. 2009. Lightly supervised transliteration for machine translation. In *Proceedings of the 12th Conference of the European Chapter of the ACL (EACL 2009)*, pages 433–441. Association for Computational Linguistics, March.

[Kirschenbaum and Wintner2010] Amit Kirschenbaum and Shuly Wintner. 2010. A general method for creating a bilingual transliteration dictionary. In *Proceedings of the Seventh conference on International Language Resources and Evaluation (LREC’10)*, pages 273–276. European Language Resources Association (ELRA), May.

[Knight and Graehl1998] Kevin Knight and Jonathan Graehl. 1998. Machine transliteration. *Computational Linguistics*, 24(4):599–612.

[Koehn et al.2007] Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, et al. 2007. Moses: Open source toolkit for statistical machine translation. In *Proceedings of the 45th annual meeting of the ACL on interactive poster and demonstration sessions*, pages 177–180. Association for Computational Linguistics.

[Kolb2008] Peter Kolb. 2008. Disco: A multilingual database of distributionally similar words. *Proceedings of KONVENS-2008, Berlin.*

[Kondrak and Dorr2004] Grzegorz Kondrak and Bonnie Dorr. 2004. Identification of confusable drug names: A new approach and evaluation methodology. In *Proceedings of the 20th international conference on Computational Linguistics*, page 952. Association for Computational Linguistics.

[Kondrak2004] Grzegorz Kondrak. 2004. Combining evidence in cognate identification. In *Advances in Artificial Intelligence*, pages 44–59. Springer.

[Mann and Yarowsky2001] Gideon S Mann and David Yarowsky. 2001. Multipath translation lexicon induction via bridge languages. In *Proceedings of the second meeting of the North American Chapter of the Association for Computational Linguistics on Language technologies*, pages 1–8. Association for Computational Linguistics.

[Matthews2007] David Matthews. 2007. Machine transliteration of proper names. *Master’s Thesis, University of Edinburgh, Edinburgh, United Kingdom.*

[Post et al.2012] Matt Post, Chris Callison-Burch, and Miles Osborne. 2012. Constructing parallel corpora for six indian languages via crowdsourcing. In *Proceedings of the Seventh Workshop on Statistical Machine Translation*, pages 401–409. Association for Computational Linguistics.

[Pouliquen et al.2006] Bruno Pouliquen, Ralf Steinberger, Camelia Ignat, Irina Temnikova, Anna Widerger, Wajdi Zaghouani, and Jan Zizka. 2006. Multilingual person name recognition and transliteration. *arXiv preprint cs/0609051*.

[Resnik2011] Philip Resnik. 2011. Semantic similarity in a taxonomy: An information-based measure and its application to problems of ambiguity in natural language. *arXiv preprint arXiv:1105.5444*.

[Schepens et al.2013] Job Schepens, Ton Dijkstra, Franc Grootjen, and Walter JB van Heuven. 2013. Cross-language distributions of high frequency and phonetically similar cognates. *PloS one*, 8(5):e63006.

[Simard et al.1993] Michel Simard, George F Foster, and Pierre Isabelle. 1993. Using cognates to align sentences in bilingual corpora. In *Proceedings of the 1993 conference of the Centre for Advanced Studies on Collaborative research: distributed computing–Volume 2*, pages 1071–1082. IBM Press.
[Snyder and Barzilay2008] Benjamin Snyder and Regina Barzilay. 2008. Unsupervised multilingual learning for morphological segmentation. In ACL, pages 737–745. Citeseer.

[Suwanvisat and Prasitjutrakul1998] Prayut Suwanvisat and Somboon Prasitjutrakul. 1998. Thai-english cross-language transliterated word retrieval using soundex technique. In Proceedings of the National Computer Science and Engineering Conference, Bangkok, Thailand.

[Van Heuven et al.1998] Walter JB Van Heuven, Ton Dijkstra, and Jonathan Grainger. 1998. Orthographic neighborhood effects in bilingual word recognition. Journal of Memory and Language, 39(3):458–483.

[Virga and Khudanpur2003] Paola Virga and Sanjeev Khudanpur. 2003. Transliteration of proper names in cross-lingual information retrieval. In Proceedings of the ACL 2003 workshop on Multilingual and mixed-language named entity recognition-Volume 15, pages 57–64. Association for Computational Linguistics.

[Wikipedia.org2014] Wikipedia.org. 2014. List of national capitals in alphabetical order, Jan.