Automatic Acquisition of a High-Precision Translation Lexicon from Parallel Chinese-English Corpora

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Abstract

This paper presents a hybrid approach to deriving a translation lexicon from unaligned parallel Chinese-English corpora. Two types of information, namely, proximity and document-external distributions of word pairs, are proposed to enhance the precision of the translation lexicon derived from statistical and dictionary-based methods. The former can identify translations of Chinese compounds, while the latter can filter out spurious word correspondences. Both methods achieve more than 94% precision.

1. Introduction

The compilation of a large translation lexicon is very costly, laborious, and time-consuming. Automation of the compilation process is therefore highly desirable. This goal has been made possible by the availability of large parallel corpora, machine-readable bilingual dictionaries, and statistical algorithms that have been proposed in recent years. In this paper, we address the problems encountered by statistics-based and dictionary-based approaches in deriving and augmenting a translation lexicon. We advocate a hybrid approach combining statistical and dictionary information to increase the recall. In addition, we suggest using proximity and document-external distributions of word pairs to enhance the precision.

2. The K-vec Algorithm

Fung and Church (1994) propose a simple algorithm to find word correspondences from unaligned parallel texts. The basic idea is that a true word pair should have similar distributions in terms of the position of its occurrence in the text. To estimate the similarity of co-occurrence, the parallel texts are split into the same number of segments (K) and the distributions of each word are represented in a 1...K binary vector. For instance, suppose the Chinese and English texts are divided into ten segments. Suppose further that the Chinese word ¤j¾Ç *daxue* occurs ten times, with the first 3 occurrences in the fourth segment and the remaining 7 occurrences in the seventh segment and that the English word *university* appears twelve times, with the first 4 occurrences in the fourth segment and the remaining 8 occurrences in the seventh segment. Using the K binary vectors, the distributions of both the Chinese and English word in question can be represented as <0,0,0,1,0,0,1,0,0,0>. Mutual information (MI) and t-score are then used to estimate the correlation of a proposed word correspondence. The mutual information and t-score of the word pair are defined in (1) and (2).

(1).

$$MI(V_c, V_e) = \log_2 \frac{P(V_c, V_e)}{P(V_c)P(V_e)}$$

$$P(V_c) = \frac{a+b}{a+b+c+d}$$

$$P(V_e) = \frac{a+c}{a+b+c+d}$$

$$(2).\quad t(V_c, V_e) = \frac{P(V_c, V_e) - P(V_c)P(V_e)}{\sqrt{\frac{P(V_c, V_e)}{K}}}$$

where V_c and V_e represent the Chinese and English word, respectively; *a* is the number of pieces of segments in which both the Chinese and the English word occur; *b* is the number of pieces of segment where only the Chinese word is found; *c* is the number of pieces of segment where only the English word is found; and *d* is the number of pieces of segment where neither the Chinese word nor the English word is found. Fung and Church suggest that K be set to the square root of the size of the corpus. MI is a measure of association between elements. It is used here to calculate how strongly two words co-occur in the same segment.

The t-score is a statistical significance test used to measure how likely something happens by chance. If the MI value of two words are high but the t-score is low, the strong association suggested by MI is probably the result of pure chance. The t-score is introduced here to filter out word pairs with low frequency which co-occur in the same segment by chance. The threshold value of MI and t-score are set to be 0 and 1.65, respectively. Only word pairs which are higher than the predetermined threshold values and are in the frequency range 3-10 are considered to be potential mutual translations.

We reimplemented the K-vec algorithm and tested it against seven articles of the *Sinorama* Chinese-English parallel corpora, which consist of bilingual articles from the *Sinorama* Magazine. Since there are no delimiters between words in Chinese, the Chinese texts were first preprocecessed by the word segmentation program at Chinese Knowledge Information Processing Group at Academia Sinica, Taiwan.

Table 1 summarizes the results of the experiments. It indicates that the performance of K-vec crucially depends on the length of the text. Although K-vec invariably performs poorly with short texts, there are also significant discrepancies between bilingual texts of similar length. Take fifth and sixth texts for example, which are of similar length but for which the results differ radically. Equally noticeable in Table 1 is the fact that longer texts do not necessarily have better performance in terms of recall or precision, as can be seen from comparisons between the second and fifth texts, as well as the sixth and seventh texts.

Table 1. The Influence of Text Length on the Performance of K-vec

No	Chinese length	English length	proposed pairs	correct pairs	precision
1	990	1221	0	0	0.00
2	1582	1754	6	3	0.50
3	2305	2743	2	2	1.00
4	3859	4805	8	6	0.75
5	4428	5138	5	2	0.40
6	4605	5557	40	24	0.60
7	5155	6414	24	12	0.50

Since none of the bilingual articles chosen involved additions or deletions of a large segment, we suspect that the huge disparity of performance manifested in Table 1 may be attributed to differences in text structures. Quantitatively speaking, if a bilingual text is full of recurrent terms or proper names, the co-occurrence ratio of a true word pair will be high, as they do not have morphological variants, synonyms, or hyponyms which discount the similarity measures. As a result, K-vec can perform better. If, however, the lexical patterning of a bilingual text involves relatively few identical repetitions, the performance of K-vec will inevitably be poor. In other words, the cohesive devices employed in a bilingual text dictate the performance of K-vec.

K-vec is a typical example which shows the strength and limitations of statistical word alignment algorithms. In fact, all the statistical algorithms that have been proposed to extract word correspondences from unaligned parallel corpora including Kay and Röscheisen (1993), K-vec, and DK-vec (Fung and McKeown (1994, 1997)) cannot be exempt from the limitations on text length and frequency (c.f. Jones and Somers' (1995) experiments on K-vec, Somers and Ward's (1996) evaluation of DK-vec against several parallel corpora, Haruno and Yamazaki's (1996) critique of Kay and Röscheisen (1993)). Due to the shortcomings of statistical approaches, several researchers (e.g. Kumano and Hirakawa (1994), Utsuro et al. (1994), Haruno and Yamazaki (1996)) have advocated combining statistical and linguistic information. In the following section, we first explore a dictionary-based approach and show why it is necessary to integrate linguistic with statistical information.

3. Why is it Non-trivial to Use Bilingual Dictionary Lookup for Word Alignments?

Contrary to one's intuition, using bilingual dictionary lookup to find word correspondences is non-trivial. We conducted a small experiment using English-to-Chinese dictionary lookup on the basis of exact string matching. The result showed that of 212 English words our bilingual dictionary actually only found 17 translations, five of which were contextually incorrect. In other words, the precision of exact matching was only 70.59%, while the recall was as low as 5.66%.

The low recall was due to three factors. First, the bilingual dictionary we used was not comprehensive. Second, we did not use morphological processing and simply removed the most productive suffixes such as -*ed*, -*ing*, -*er*, and -*est*. Third, words might not be the smallest units for translation. Instead, translations are often done chunk by chunk, where a chunk might consist of a phrase, collocation, fixed expression, or even a sentence. Furthermore, some constructions or patterns must be regarded as translation templates that cannot be decomposed into smaller units.

Since the recall of dictionary lookup based on exact matching was too low, we experimented on using inexact (i.e. partial) matching. In a paragraph of 212 English words, English-to-Chinese dictionary lookup based on partial matching suggested 172 word correspondences, 51 of which were correct, obtaining 29.65% precision and 24.05% recall. This result showed higher recall (24.05% vs. 5.66%) but lower precision (29.65% vs. 70.59%) than exact matching. The choice of exact or inexact matching is thus a trade-off between precision and recall. The following question naturally arises. How can we filter out spurious word pairs?

4. Using Positional Information to Filter Out Unlikely Word Correspondences

Positional information plays an important role in distinguishing which word correspondence is more likely. The notion of applying positional difference information to word alignments has been used by several researchers in various forms, e.g. Dagan et al. (1993), Fung and McKeown (1994, 1997), Jones and Somers (1995). Intuitively, we would expect that the positional ratio of a word in the source text to its translation in the target text should not differ too much if there are not many omissions or additions. This intuition can be expressed in (3).

$$(3).\quad \left|\frac{x_i}{n_e}-\frac{y_i}{n_c}\right| \le k$$

The value of k is in inverse proportion to the length of the text. In our experiment with texts of 3000 - 4000 words, *k* was set to 0.02. Using the constraint in (3), we observed that about 95% of correct word correspondences were retained, while approximately 60% incorrect word correspondences were excluded. Positional difference information significantly reduced a lot of uncertainties. However, there are still a lot of spurious word correspondences that haven't been filtered out. Obviously, we need another method to clean the translation lexicon.

5. Using Proximity to Find the Translations of Chinese Compounds

It has been noticed that there is a large number of Chinese compounds whose English translations involve more than one word. This characteristic can be easily utilized to identify translations of Chinese compounds from the output of K-vec and dictionary lookup based on partial matching. Since K-vec extracts bilingual word pairs which co-occur in the same segment more often than by chance, if it associates the same Chinese word with two or more English words which are adjacent to each other, then we can reasonably infer that these English words are translations of the Chinese word. Given the fact that tables of word position indexes of the bilingual text are already constructed by K-vec, extraction of the translations of Chinese compounds is quite easy and straightforward. The second and third columns (i.e. the Chinese and English word) of Table 4 were the word pairs extracted by K-vec. Using these word pairs and word position indexes, we can extract the translations of Chinese compounds such as (¤f¸Õ*koshi* ⇔ *oral exam*) and (©ÊÄÌÂZ *xingshaorao* ⇔ *sexual harassment*). Similar approaches have also been mentioned in Fung and McKeown (1994, 1997).

The same principle can be easily applied to the output of dictionary lookup based on partial matching. If the translations of two or three consecutive English words partially match different characters of the same Chinese word in the text then they are more likely to be correct word pairs, as the probability of the translations of two consecutive English words coincidentally partially matching different characters of a Chinese word is very low. This method takes advantage of the linguistic characteristics of Chinese compounds, which usually consist of two or three Chinese characters each representing the abbreviation of the original multi-character words. For example, the Chinese translations for the word *oral* and *exam* are ¤fªº *ko de* and ¦Ò¸Õ *kaoshi*, respectively. Given that *oral* and *exam* are adjacent and that their Chinese translations match the first and second character of the word¤f¸Õ *koshi* in the Chinese text, they are most probably translations of ¤f¸Õif the positional difference between *oral exam* and ¤f¸Õhappens to be small. Let us illustrate this method with concrete examples. Table 2 shows the information required to extract translations of Chinese compounds using this method.

Table 2. Extracted Translations of Chinese Compounds Based on Proximity 1

WI	English	WI	Chinese	MC
49	deep	26	根深蒂固	深
50	roots	26	根深蒂固	根
157	academic	112	學術界	學術
158	world	112	學術界	界
310	sexual	223	性騷擾	性
311	harassment	223	性騷擾	騷擾
501	eldest	387	長子	長
502	son	387	長子	子
1353	teaching	987	教材	教
1354	materials	987	教材	材
1886	oral	1412	口試	口
1887	exam	1412	口試	試
2443	research	1889	研究室	研究
2444	room	1889	研究室	室
3789	accept	3031	受辱	受
3790	insult	3031	受辱	辱

Based on Table 2, the equivalence between the following pairs can be identified and extracted *deep roots* ⇔ ®Ú²`¸¦©T*genshengdigu*, *academic world* ⇔ ¾Ç³N¬É*xuesujie*, *eldest son* ⇔ ªø¤l*zhangzi*, *teaching materials* ⇔ ±Ð§÷ *jiaocai*, *oral exam* ⇔ ¤f¸Õ*koshi*, *research room* ⇔ ¬ã¨s«Ç*yanjiushi*, *accept insult* ⇔

¨ü°d*shouru*. This simple method can achieve more than 96% precision in extracting translations of Chinese compounds.

6. Using Co-occurrences of Word Pairs in Individual Document to Filter Out Spurious Word Correspondences

Given that the precision of statistics-based and dictionary-based approaches is not satisfactory, is there any method of improving it? Melamed (1995) introduces a novel and sophisticated method to clean incorrect word correspondences induced by statistical word alignment algorithms that assign symmetrical association scores such as likelihood ratios.

Instead of adopting document-internal distributional properties and the sophisticated statistical model proposed by Melamed, we tried to use some simple methods to improve the precision of translation lexicon derived from K-vec and dictionary lookup. We used the distributional information of the words in the individual documents that made up the corpus as a criterion of deciding which word pair was more likely to be correct. For instance, if *a* and *b* are an English-Chinese word pair, then there should be a significant correlation between the documents in which they appear.

To calculate the co-occurrences of a word pair in the whole corpus, each Chinese text was assigned the same index as its English translation. Two indexes, Chinese Word-Document index and English Word-Document index, were then constructed which recorded the document indexes of all the Chinese and English words occurring in the 58 Chinese and English documents in our corpus, respectively. The Jaccard Coefficient in (4) can be used as a measure to calculate the similarity of the distributions of a proposed English-Chinese word pair,

$$(4).\quad \mathrm{Jaccard}(x,y) = \frac{c}{n_x + n_y - c}$$

The Jaccard Coefficient, however, is unreliable for high frequency words which appear in many documents. In information retrieval, it has been established that the importance of a term is inversely proportional to the total number of documents in which it occurs (cf. Salton and McGill (1983)). In other words, the more documents a word occurs in, the less likely it is to be a keyword of the document. This measure, known as Inverse Document Frequency (IDF), is as follows.

$$(5)\ \log_2 \frac{n}{DOCFREQ_k} + 1$$

We first used the output of dictionary lookup using partial matching and set the threshold of the Jaccard Coefficient to 0.5 and IDF to 2. After the filtering, we obtained a bilingual translation lexicon of 94% precision. Table 3 shows some of the results. The value of 0.5 of the Jaccard Coefficient was chosen in view of the fact that there are many morphological alternations of a given English word. The recall was about 43% for those word pairs that could be found by partial matching and 10.37% for the translations of all the English words in the text.

Table 3. Different Measures to Estimate the Co-occurrences of Word Pairs in Individual Documents Based on the Results of Dictionary Lookup

Chinese	English	*Jaccard*	*C/N*	*E/N*	IDF_C	IDF_E
傳統	traditional	0.708	0.809	0.85	2.465	2.536
中國	Chinese	0.673	0.968	0.688	1.857	1.366
根深蒂固	roots	0.153	1.000	0.153	5.857	3.157

In addition to the Jaccard Coefficient and IDF for Chinese and English words, we used two other ratios *C/N* and *E/N* to measure the distributional information, in which *N* is the number of common documents in which both the proposed English and Chinese pair occur and *c* and *e* are the number of documents in which the Chinese and English word occurs. The information in the C*/N* and E*/N* columns provides further clues about the co-occurrence of a proposed word correspondence. It can be used to make inferences about cases where a word in the source text corresponds to more than one word in the target text. For instance, in Table 3, it shows that the word *roots* occurs in all the English corresponding documents where the word ®Ú²`¸¦©T*genshengdigu* occurs. But of all the documents in which the word *root* occurs only 15.3% of the Chinese corresponding documents can find the occurrences of ®Ú²`¸¦©T. This suggests that the English word *root* might be part of the translation of the Chinese word ®Ú²`¸¦©T.

Although the method introduced above produced a high precision lexicon, the recall was still low. This was partly because it could not adequately handle cases where a word in the source text corresponded to more than one word in the target text. This included cases where a Chinese word corresponded to an

English lemma with several word forms (i.e. inflections) or cases where a Chinese compound or idiom corresponded to more than two English words. The first situation could be improved by lemmatisation, while the second situation could be improved by using proximity as discussed in the preceding section.

An alternative method to calculate the co-occurrences of word pairs in individual documents is to merge all the bilingual texts into one `super' bilingual text and then use K-vec again to estimate the co-occurrence of a word pair by regarding each document as a segment based on the output of the original K-vec or dictionary lookup. Table 4 shows the result of this method based on the word pairs extracted via the original K-vec.

Table 4. Using Co-occurrences of Word Pairs in the Whole Corpus to Clean the Output of the Original K-vec Algorithm

Chinese	English	MI	t-score	Jaccard	$Ratio_C$	$Ratio_E$	IDF_C	IDF_E
+ 媒體	media	1.60	2.68	0.84	0.88	0.94	2.68	2.77
+ 教育	education	1.34	2.35	0.68	0.78	0.83	2.61	2.68
+ 呂	Lu	2.20	2.07	0.58	0.87	0.63	3.85	3.39
% 不再	longer	1.14	1.97	0.54	0.76	0.65	2.77	2.53
+ 權威	authority	2.31	1.95	0.54	0.85	0.60	4.05	3.53
+ 劉	Liu	1.57	1.87	0.47	0.61	0.66	3.15	3.27
+ 社會	society	0.62	1.85	0.75	0.87	0.84	1.85	1.81
+ 張	Chang	0.54	1.43	0.56	0.67	0.77	1.90	2.10
% 性騷擾	harassment	4.85	1.36	1.00	1.00	1.00	5.85	5.85
% 性騷擾	sexual	4.27	1.34	0.66	1.00	0.66	5.85	5.27
+ 導師	advisor	4.27	1.34	0.66	0.66	1.00	5.27	5.85
+ 言論	speech	2.12	1.33	0.30	0.60	0.37	4.53	3.85
亦	friend	1.05	1.26	0.30	0.50	0.42	3.27	3.05
權	equal	2.53	1.17	0.28	0.50	0.40	4.85	4.53
華	Kao	1.53	1.13	0.21	0.25	0.60	3.27	4.53
+ 中國	Chinese	0.31	1.10	0.67	0.96	0.68	1.85	1.36
便	increasingly	0.68	1.00	0.23	0.25	0.77	2.05	3.68
# 虹	Hsiaohung	5.85	0.98	1.00	1.00	1.00	6.85	6.85
% 校務	affairs	1.68	0.97	0.11	1.00	0.11	5.85	2.68
% 口試	oral	4.85	0.96	0.50	1.00	0.50	6.85	5.85
# 芬	Tehfen	4.85	0.96	0.50	0.50	1.00	5.85	6.85
+ 友	friend	1.46	0.90	0.13	0.66	0.14	5.27	3.05

% 口試	exam	3.27	0.89	0.16	1.00	0.16	6.85	4.27
使用	conference	1.05	0.89	0.17	0.21	0.50	3.05	4.27
女性	male	1.27	0.82	0.16	0.25	0.33	3.85	4.27
叫	Hsiaohung	2.39	0.81	0.09	0.09	1.00	3.39	6.85
芬	Ho	2.27	0.79	0.14	0.50	0.16	5.85	4.27
叫	name	0.45	0.71	0.22	0.63	0.25	3.39	2.10
# 德	Tehfen	1.68	0.68	0.05	0.05	1.00	2.68	6.85
辯論	private	1.53	0.65	0.09	0.50	0.10	5.85	3.53
民主	ethical	1.46	0.63	0.11	0.14	0.33	4.05	5.27
權益	conference	1.27	0.58	0.11	0.25	0.16	4.85	4.27
賀	each	0.49	0.58	0.09	1.00	0.09	4.85	1.50
+ 事實	fact	0.18	0.49	0.37	0.72	0.43	2.39	1.64
+ 平	equal	0.95	0.48	0.10	0.16	0.20	4.27	4.53
性騷擾	another	0.53	0.43	0.05	1.00	0.05	5.85	1.53
芬	each	0.49	0.41	0.04	1.00	0.04	5.85	1.50
解嚴	recent	0.68	0.37	0.05	0.50	0.05	5.85	2.68
# 小	Hsiaohung	0.53	0.31	0.02	0.02	1.00	1.53	6.85
根本	may	0.08	0.23	0.35	0.69	0.42	2.33	1.61
德	Ho	0.10	0.09	0.09	0.11	0.33	2.68	4.27
不再	authority	0.03	0.03	0.12	0.17	0.30	2.77	3.53
也	with	0.00	0.00	0.94	1.00	0.94	1.07	1.00
你	attack	-0.04	-0.06	0.11	0.13	0.50	1.95	3.85
威權	generation	-0.12	-0.08	0.04	0.33	0.04	5.27	2.46
德	each	-0.21	-0.51	0.22	0.61	0.26	2.68	1.50

\+ Fully correct Pair   % The English gloss is part of the Chinese gloss.
\# The Chinese gloss is part of the English gloss.

From Table 4, we can see that MI and t-score are more convenient and reliable than the Jaccard Coefficient, as the latter must be used in conjunction with IDF to filter out frequently occurring words. By setting the threshold of MI and t-score to 0 and 1.6, we extracted 7 word pairs, all of which were correct, achieving 100% accuracy. However, the method left out 16 correct word pairs, obtaining a low recall of 0.3. Apparently, high precision was acquired at the cost of low recall. It is therefore more sensible to use this method to find anchor points. An interesting observation is that of all the 7 correct word pairs it identified, only one of them involved collocations or compounds. The pair (¤£¦A*buzai* ⇔ *longer*) is actually part of the translation (¤£¦A*buzai* ⇔ *no longer*).

In the previous section, it has been shown that translations of Chinese compounds can be easily and accurately extracted using proximity condition. The proximity condition and the co-occurrences of word pairs in each document in the whole corpus therefore complement each other in extracting more anchor points.

7. Conclusion

In this paper, we have shown the limitations of both statistics-based and dictionary-based approaches to deriving a translationlexicon. We have demonstrated the necessity of combining statistical and dictionary information and the usefulness of proximity and co-occurrence information of word pairs in individual documents in deriving a high precision translation lexicon. Although the recall of our method is still low, its high precision can be used to find anchor points for deriving more word correspondences. We are currently implementing an iterative algorithm in the spirit of Kay and Röscheisen to improve the recall of the translation lexicon. In the first iteration, the algorithm treats each individual document as a segment to calculate the co-occurrences of word pairs in the whole corpus. Word pairs which meet the proximity condition before the cleaning algorithm or anchor points then become boundaries of segments for the next iteration. As the number of segments in each document increases, many word pairs incorrectly filtered out by the cleaning algorithm in the first few iterations can be expected to be recovered later.

Acknowledgement

The author wishes to express his gratitude to the *Sinorama* Magazine for permission to use the Sinorama Chinese-English corpus, and to Prof. Harold Somers, Dr. Tony McEnery, Mr. John McNaught, Prof. Chu-Ren Huang, Prof. Keh-Jiann Chen, Prof. Lee-Feng. Chien, and anonymous PACLIC reviewers for their helpful comments on an earlier draft of this paper.

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