Extracting Bilingual Persian Italian Lexicon from Comparable Corpora Using Different Types of Seed Dictionaries

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Bilingual dictionaries are very important in various fields of natural language processing. In recent years, research on extracting new bilingual lexicons from non-parallel (comparable) corpora have been proposed. Almost all use a small existing dictionary or other resource to make an initial list called the "seed dictionary". In this paper we discuss the use of different types of dictionaries as the initial starting list for creating a bilingual Persian-Italian lexicon from a comparable corpus.

Our experiments apply state-of-the-art techniques on three different seed dictionaries; an existing dictionary, a dictionary created with pivot-based schema, and a dictionary extracted from a small Persian-Italian parallel text. The interesting challenge of our approach is to find a way to combine different dictionaries together in order to produce a better and more accurate lexicon. In order to combine seed dictionaries, we propose two different combination models and examine the effect of our novel combination models on various comparable corpora that have differing degrees of comparability. We conclude with a proposal for a new weighting system to improve the extracted lexicon. The experimental results produced by our implementation show the efficiency of our proposed models.

1 Introduction

Bilingual lexicons are a key resource in a multilingual society. Their application can be found in a range of activities such as translation, language learning, or as a basic resource for natural language processing (NLP). The availability of translation resources varies depending on the languages pairs. Therefore, bilingual dictionaries for languages with fewer native speakers are scarce or even non-existent. There are many papers describing different methods for building bilingual dictionaries automatically. Though automatic methods often have drawbacks such as including noise in the form of erroneous translations of some words, they are still popular because the alternative – manually constructing a dictionary – is very time consuming. Automatic methods are often used to generate a first noisy dictionary that can be cleaned up and extended by manual work (Sjöbergh 2005).

A pivot language (bridge language) is useful for creating bilingual resources such as bilingual dictionaries. The Pivot-based bilingual dictionary building is based on merging two bilingual dictionaries that share a common language. For example, using the Persian-English and the English-Italian dictionaries to build a new Persian-Italian lexicon. In recent years, some approaches based on this idea have been proposed (Tanaka & Umemura 1994; Sjöbergh 2005; István & Shoichi 2009; Tsunakawa, Okazaki & Tsujii 2008; Tsunakawa, Yamamoto & Kaji 2013;
Ahn & Frampton 2006). The main problem of these methods is the amount of noise in extracted dictionaries when they have many incorrect translations.

In the last decade, some research has been proposed to acquire bilingual lexicons from non-parallel (comparable) corpora. A comparable corpus consists of sets of documents in several languages dealing with a given topic, or domain when documents have been composed independently of each other in different languages. Unlike the parallel corpora, which are clearly defined as translated text, there is a wide variation of non-parallelism in comparable texts (Ansari et al. 2014b). In comparison with parallel corpus, comparable corpora are much easier to build from commonly available documents, such as news article pairs describing the same event in different languages. Therefore, there is growing interest in acquiring bilingual lexicons from comparable corpora. These methods have been proposed to extract a lexicon from comparable corpora when a suitable lexicon does not exist or is not complete enough. These methods are based on this assumption: there is a correlation between co-occurrence patterns in different languages (Rapp 1995). For example, if the words teacher and school co-occur more often than expected by chance in an English corpus then the German translations of teacher and school, Lehrer and schule, should also co-occur more often than expected in a German corpus (Rapp 1995).

In recent years, many methods have been proposed to build bilingual dictionaries based on above correlation. Most of them share a standard strategy based on context similarity. The basis of these methods are finding the target words that have the most similar distributions with a given source word. The starting point of this strategy is a list of bilingual expressions that are used to build the context vectors of all words in both languages. This starting list, or initial dictionary, is named the seed dictionary (Fung 1995) and is usually provided by an external bilingual dictionary (Rapp 1999; Chiao & Zweigenbaum 2002; Fung & McKeown 1997; Fung & Yee 1998). Some of recent methods use small parallel corpora to create their seed list (Otero 2007) and some other use no dictionary for starting phases (Rapp & Zock 2010). Sometimes there are different types of dictionaries, with each having its own accuracy. (Ansari et al. 2014a) propose two simple methods to combine four different dictionaries (one existing dictionary and three dictionaries extracted using pivot based method) to increase the accuracy of the output. They use three languages English, Arabic and French to create their pivot based lexicons.

In this work, we use three different types of dictionaries and then combine them to create our seed dictionaries. The first dictionary is a small existing Persian-Italian dictionary. The second dictionary is extracted from a pivot-based
method. The third dictionary is created from our small parallel Persian-Italian corpus. Using these dictionaries, we propose different model combinations and a new weighting method to use on these different dictionaries. In comparison with (Ansari et al. 2014a)’s approach, we introduce some new combination schemas to improve the quality of the result seed dictionary. Moreover, parallel based extracted lexicon also is used as one of our initial seed dictionaries. Contrary to previous work, we apply our idea on various comparable corpora that have different degrees of comparability.

In Section 2, we describe works related to our approach; Section 3 describes our approach; Section 4 describes the methodology and resources used in our work; Section 5 shows the experimental results; and Section 6 is the conclusion of the paper.

2 Related works

In Section 2 we discuss approaches and implementations in three parts and show how their relation to our work. Section 2.1 describes the process of building a bilingual lexicon by using a pivot language using source-pivot and pivot-target dictionaries. In Section 2.2, the idea of using parallel corpora to extract a bilingual dictionary is discussed. In Section 2.3 methods relying on comparable corpora to build a bilingual lexicon are studied.

2.1 Using Pivot languages

Over the past twenty years different approaches have been proposed to build a new source-pivot lexicon using a pivot language and consequently source-pivot and pivot-target dictionaries (Tanaka & Umemura 1994; István & Shoichi 2009; Tsunakawa, Okazaki & Tsujii 2008; Tsunakawa, Yamamoto & Kaji 2013; Ahn & Frampton 2006). One of the most known and highly cited methods is the approach of Tanaka and Umemura (Tanaka & Umemura 1994) where they only use dictionaries to translate into and from a pivot language in order to generate a new dictionary. These pivot language based methods rely on the idea that the lookup of a word in an uncommon language through a third intermediated language could be done with machines. Tanaka and Umemura use bidirectional source-pivot and pivot-target dictionaries (harmonized dictionaries). Correct translation pairs are selected by means of inverse consultation. This method relies on counting the number of pivot language definitions of the source word, which identifies the target language definition (Tanaka & Umemura 1994). Sjoergh presented an-
other well-known method in this field (Sjöbergh 2005). He generated his English pivoted Swedish-Japanese dictionary where each Japanese-to-English description is compared with all Swedish-to-English descriptions. The scoring metric is based on word overlaps, weighted with inverse document frequency and consequently the best matches are selected as translation pairs. These two approaches (Tanaka & Umemura 1994; Sjöbergh 2005) are the best performing ones and are general enough to be applicable with other language pairs as well. The basis of most of other ideas and approaches proposed in recent years is based on those two described approaches (Tanaka & Umemura 1994; Sjöbergh 2005).

Compared to other implementations, our approach needs a small and reliable extracted dictionary as a part of our seed input. The usage of this extracted dictionary is discussed in Section 3.2. In our work, the (Sjöbergh 2005)'s method is used. Moreover as we needed only the top translations with the highest scores the generality of a selected method was not a factor.

2.2 Using Parallel Corpora

Another way to create a bilingual dictionary is to use parallel corpora. Using parallel corpora to find a word translation (i.e. word alignment) started with primitive methods of (Brown et al. 1990) and continued with some other word alignment approaches such as (Gale & Church 1991; 1993; Melamed 1997; Ahrenberg, Andersson & Merkel 1998; Tiedemann 1998; Och, Tillmann & Ney 1999). These approaches share a basic strategy of first having two parallel texts aligned in pair segments and second having word co-occurrences calculated based on that alignment. This approach usually reaches high score values of 90% precision with 90% recall, (Otero 2007). Many studies show that for well-formed parallel corpora high accuracy rates of up to 99% can be achieved for both sentence and word alignment. Currently almost the entire task of bilingual dictionary creation and especially the creation of a probability table for any word pairs could be done with well-known statistical machine translation software, GIZA++ (Och & Ney 2003). Using Parallel corpora as the input of the dictionary creation process is attractive in two ways. First, alignment between sentences and words is very accurate as a natural characteristic of parallel corpora and these methods do not need any other external knowledge to build a bilingual lexicon. Second, no external bilingual dictionary (seed dictionary) is required. The main problem of creating a parallel corpus lexicon is the lack of extensive language pairs, therefore reliance on just using parallel corpora to build accurate bilingual dictionaries is impossible. For the selected languages in this work, Persian and Italian, the creation of an accurate bilingual dictionary based on the existing parallel corpora
is not applicable, although using our low resource parallel corpora to create a small dictionary may be practical. This dictionary could be used as an input in other methods that would use this subordinate input to build a larger dictionary. This is used as the seed dictionary in comparable corpora based approaches as discussed in Section 3.2.

2.3 Using Comparable Corpora

There is a growing interest in the number of approaches focused on extracting word translations from comparable corpora (Fung & McKeown 1997; Fung & Yee 1998; Rapp 1999; Chiao & Zweigenbaum 2002; Déjean, Gaussier & Sadat 2002; Kaji 2005; Otero 2007; Otero & Campos 2010; Rapp & Zock 2010; Bouamor, Semmar & Zweigenbaum 2013; Irimia 2012; E. Morin & Prochasson 2013; Emmanuel & Hazem 2014). Most of these approaches share a standard strategy based on context similarity. All of them are based on an assumption that there is a correlation between co-occurrence patterns in different languages (Rapp 1995). For example, if the words “teacher” and “school” co-occur more often than expected by chance in a corpus of English, then the Italian translations of them, “insegnante” [teacher] and “scuola” [school] should also co-occur in a corpus of Italian more than expected by chance. The general strategy extracting bilingual lexicon from the comparable corpus could be described as follows:

Word target \( t \) is a candidate translation of word source \( s \) if the words with which word \( t \) co-occur within a particular window in the target corpus are translations of the words with which word \( s \) co-occurs within the same window in the source corpus.

The goal is to find the target words having most similar distributions with a given source word. The starting point of this strategy is a list of bilingual expressions that are used to build the context vectors of all words in both languages. This starting list is called the seed dictionary. The seed dictionary is usually provided by an external bilingual dictionary. (Déjean, Gaussier & Sadat 2002) uses one multilingual thesaurus as the starting list instead of using a bilingual dictionary. In (Otero 2007) the starting list is provided by bilingual correlations previously extracted from a parallel corpus. In (Rapp, Sharoff & Babych 2012), the authors extract a bilingual lexicon without using an existing starting list. Although they do not use any seed dictionary, their results are acceptable.

Another interesting issue considered in recent years is to evaluate the effect of the degree of comparability on the accuracy of extracted resources (Li & Gaussier 2010; Li, Gaussier & Aizawa 2011; Sharoff 2013). In (Li & Gaussier 2010) the authors propose a metric calculating the degree of comparability and they use an iterative construction process to improve the quality of a given comparable cor-
pus to extract a bilingual lexicon. In (Li & Gaussier 2010) a cluster-based method
is used to enhance corpus comparability based on the metric they introduced in
(Li, Gaussier & Aizawa 2011) where it was claimed that most of the vocabulary
of the initial corpus was preserved despite of their changes in corpus.

As described before, it is assumed that there is a small bilingual dictionary
available at the beginning. Most methods use an existing dictionary (Rapp 1999;
Chiao & Zweigenbaum 2002; Fung & McKeown 1997; Fung & Yee 1998) or build
one with some small parallel resources (Otero 2007). Entries in the dictionary are
used as an initial list of seed words. Texts in both source and target languages are
lemmatized and part-of-speech (POS) tagged with function words are removed.

A fixed window size is chosen and it is determined how often a pair of words
occurs within that text window. These windows are called the “fixed size win-
dow” which does not take into account word orders within a window. R. Rapp
observed that word order of content words is often similar between languages,
even between unrelated languages such as English and Chinese (Rapp 1996). In
approaches considering word order, for each lemma there is a context vector
whose dimensions are the same as the starting dictionary but in different win-
dow positions with regard to that lemma. For instance, if the window size is
2, the first context vector of lemma A, where each entry belongs to a unique
seed word, shows the number of co-occurrences two positions to the left of A
for that seed word. Three other vectors should also be computed, counting co-
occurrents between A and the seed words appearing one position to the left
of A and the same for two right hand positions following lemma A. Finally, all
four vectors of length n are combined (where n is the size of the seed lexicon)
into a single vector of length 4n. This method takes into consideration the word
orders to define contexts. In this paper the efficiency of considering the word
order schema is evaluated.

Simple context frequency and some additional weights such as inverse docu-
ment frequency can be considered in bilingual lexicon construction approaches
(Chiao & Zweigenbaum 2002). Well-known and widely used weighting for these
approaches is log-likelihood (Rapp 1999). In this paper both frequencies, simple
context and log-likelihood are evaluated and compared. In computation of the
log-likelihood ratio, the simplified formula from Dunning and Rapp (Dunning
1993) is used:

\[
\text{loglike}(A, B) = \sum_{i,j \in 1,2} K_{ij} \times \log \frac{K_{ij} \times N}{C_i \times R_j}
\]  
(1.1)

Therefore:
$$\text{loglike}(A, B) = K_{11} \log \frac{K_{11} \times N}{C_1 \times R_1} + K_{12} \log \frac{K_{12} \times N}{C_1 \times R_2} +$$

$$K_{21} \log \frac{K_{21} \times N}{C_2 \times R_1} + K_{22} \log \frac{K_{22} \times N}{C_2 \times R_2}$$  \hspace{1cm} (1.2)

Where:

$$C_1 = K_{11} + K_{12}$$  \hspace{1cm} (1.3)

$$C_2 = K_{21} + K_{22}$$  \hspace{1cm} (1.4)

$$R_1 = K_{11} + K_{21}$$  \hspace{1cm} (1.5)

$$R_2 = K_{12} + K_{22}$$  \hspace{1cm} (1.6)

$$N = C_1 + C_2 + R_1 + R_2$$  \hspace{1cm} (1.7)

With parameters $K_{ij}$ expressed in terms of corpus frequencies:

- $K_{11}$ = frequency of common occurrence of word $A$ and word $B$
- $K_{12}$ = corpus frequency of word $A$ - $K_{11}$
- $K_{21}$ = corpus frequency of word $B$ - $K_{11}$
- $K_{22}$ = size of corpus (no. of tokens) - corpus frequency of word $A$ - corpus frequency of word $B$

All numbers have been normalized in our experiments.

For any word in a source language, the most similar word in a target language should be found. First, using a seed dictionary all known words in the co-occurrence vector are translated to the target language. Then, With consideration of the result vector, a similarity computation is performed to all vectors in the co-occurrence matrix of the target language. Finally, for each primary vector in the source language matrix, the similarity values are computed and the target words are ranked according to these values. It is expected that the best translation will be ranked first in the sorted list (Rapp 1999). Different similarity scores have been used in the variants of the classical approach (Rapp 1999). In (Laroche & Langlais 2010) the authors presented some experiments for different parameters like context, association measure, similarity measure, and seed lexicon. Some of the famous similarity metrics are included in the Appendix of this
We decided to use diceMin similarity score in our work which has been used previously in (Curran & Moens 2002; Plas & Bouma 2005; Otero 2007). The diceMin score is the similarity of two vectors, X and Y is computed using below similarity measure.

\[
diceMin(X, Y) = \frac{2 \cdot \sum_{i=1}^{n} \min(X_i, Y_i)}{\sum_{i=1}^{n} X_i + \sum_{i=1}^{n} Y_i}
\]  

(1.8)

3 Our Approach

Our experiments to build a Persian-Italian lexicon are based on the comparable corpora window approach discussed in Section 2.3. An interesting challenge in our work is to combine different dictionaries with varying accuracies and use all of them as the seed dictionary for comparable corpora based lexicon generation. We address this problem using different strategies: First, combining dictionaries with some simple priority rules, and then, using all translations together with and without considering the differences in their weights. In Section 3.1, our method to collect and create seed dictionaries and consequently, our implementation to use them independently are explained. In Section 3.2, we describe the usage of comparable corpora to build a new Persian-Italian lexicon. Sections 3.3 and 3.4, our approaches for combining three different dictionaries are explained. Section 3.5 described our proposed weighting method.

3.1 Building Seed Dictionaries

We have used three different dictionaries and their combinations as the seed dictionaries. The first dictionary is a small Persian-Italian dictionary, the second dictionary is created based on the pivot-based method presented in (Sjöbergh 2005), which contains top entries with highest score, and third dictionary is built using two little parallel Persian-Italian corpora. When there is more than one translation for an entry in the primary dictionary, we should select one translation. Most standard approaches select the first translation in existing dictionary or the candidate with the highest score in the extracted (created) dictionary. However, in (Irimia 2012), several definitions for one word based on their scores could be selected in the seed dictionary generation step. Like other standard methods, we selected the first translation among all the candidates. In the following three subsections, our three dictionaries and the process of creating them are discussed.
3.1.1 The Existing Dictionary – DicEx

We used a small Persian-Italian dictionary as the existing dictionary named DicEx. For each entry, only the first translation are selected to create lemmas. While DicEx is a manually created dictionary, it is the most accurate dictionary in our experiments, and its size is the smallest in comparison with the other dictionaries.

3.1.2 The Dictionary created by a Pivot based method – DicPi

We used the method introduced in (Sjöbergh 2005) as the baseline for the Pivot based dictionary creation. Translations with the highest scores are selected in this phase while removing the low scoring results. A Persian-English dictionary and an English-Italian dictionary are considered as inputs. All stop-words and all non-alphabet characters are removed from English portion of these two dictionaries. Then the inverse document frequency, $idf$, is calculated for the remaining English words as follows:

$$
idf(w) = \log \left( \frac{|Pr| + |It|}{Pr_w + It_w} \right)$$ (1.9)

Where $w$ is the word we calculate the weight for, $|Pr|$ is the total number of dictionary entries in the Persian-English dictionary, $|It|$ total number of dictionary entries in the English-Italian dictionary, $Pr_w$ is the number of descriptions in the Persian-English dictionary where the word $w$ occurs, and $It_w$ is this number for English-Italian.

In the next step, all the English descriptions in the first dictionary must be matched to all descriptions in the second. Matches are scored by word overlaps that are weighed by predefined inverse document frequencies. A word is only counted once regardless of the number of occurrences in a same description. Based on Sjoergh’s method, (Sjöbergh 2005) scores are calculated as shown in Equation 1.10:

$$score = \frac{2 \cdot \sum_{w \in Pr \cap It} idf(w)}{\sum_{w \in Pr} idf(w) + \sum_{w \in It} idf(w)}$$ (1.10)

Where $Pr$ is the text in the translation part of Persian-English lexicon and $It$ is the translation text in the Italian-English Dictionary. When all scores are calculated, candidates with the highest score will be selected to build our new Persian-Italian dictionary. In contrast to the Sjoergh’s implementation where
the main focus is creating a dictionary with very large coverage, our goal is creating a small dictionary with more accuracy for use as a seed dictionary in the main system. Therefore, we select the top 40,000 translations from all translations and named it $\text{DicPi}$.

3.1.3 The Dictionary extracted from Parallel corpora – $\text{DicPa}$

In this paper we used our low parallel Persian-Italian resources (e.g. movie subtitles) to create a small dictionary by selecting the top translations with the highest probabilities. This parallel corpus based dictionary, named $\text{DicPa}$, is used as the seed dictionary which is subsequently combined with other main dictionaries in the following phases. It is created from a general domain translation table automatically extracted with Giza++ (Och & Ney 2003). When a word has more than one translation, only the highest probability translation is selected and others with lower probability are removed. Finally, we select the top entry words from word based translation table.

3.2 Using seed dictionaries to extract lexicon from Comparable Corpora

Our window-based approach is presented in this section. Some mathematics and theoretical points of our approach were discussed in Section 2.3. Given that there are large differences between Persian and Italian words in syntax and grammar, the window-based approach is preferred. The baseline of the method implemented in our study is an adaptation of (Rapp 1999). Based on our proposed idea, the seed dictionary could be an existing dictionary, an automatically created dictionary, or a combination of them.

There are two types of input: the seed dictionary, and the bilingual comparable corpus. Weighting vectors must be created based on corpora and lexicons. Before creation of matrices for both Persian and Italian languages, the stop words of corpora are deleted and it should be lemmatized. Two co-occurrence matrix sets are computed for the Persian and Italian corpora: one set for simple approach and another for ordered base approach. In order to check the effect of word orders in our experiments, we needed two matrices for our two corpora. These matrices have $r$ rows where $r$ is the number of unique words occurred in the corpus. If the size of our lexicon is $n$ and the selected size for windows is $k$, for simple method which does not consider word orders, the matrices (for both Persian and Italian corpora) have $n$ columns where every column corresponds to a type word in the base lexicon. Each field $(i,j)$, shows that how many times word $j$ is occurred
with distance of $k$ words, from word $i$ in the corresponding corpus. The size of this matrix is equal to $r \times n$.

In the order-based method, matrices must save the position of each word with pivot word in addition to saving the frequency in one window. We create it by dividing each field of the former matrix to $2n$ fields where each field shows a different position before or after pivot word where each new matrix is itself a $r \times n \times k$ matrix when the field $(i, j, k)$ shows the number of times word $j$ has occurred in position indexed $k$ from word $i$.

Previous approaches show the need for replacing the co-occurrence frequency in the matrix by measures that are able to eliminate word-frequency effects and consequently to favor significant word pairs. Therefore we use the log-likelihood ratio (i.e. Formula 1 (Dunning 1993)) in our approach described in Section 2.3. To see its effect, we also carried out our tests without this metric by using the simple frequency matrix.

In order to calculate the similarity scores, we should transfer our matrices from the source language to target language. The rows with all zero values are pruned from Persian matrix. All remaining rows are considered as the potential translations. For each row, all columns are translated by using the seed lexicon; i.e. the source vectors are transferred to target vectors. Then, the similarity score for all possible translations are calculated. A possible translation is a row in the transferred matrix which corresponds to a row in the target matrix. Therefore the value of similarity scores should be calculated and sorted between any row in the transferred matrix and all the rows in the target matrix. In this experiment we use $d_{iceMin}$ similarity score described in Section 2.3 as the preferred score. In Section 3.5 of this paper, a new similarity score, $newd_{iceMin}$ is proposed by the authors to weight dictionaries when different seed dictionaries are combined together.

In order to build a new lexicon, for each word (i.e. row) in the source vector, the best matches in the target vector could be considered as the translation. Therefore, for each entry, we select word corresponding to target vectors where the similarity score is more than the rest.

### 3.3 Using simple combination

In this section, the process of creating the bigger seed dictionary by using a simple combination rule is discussed. The accuracy of the existed dictionary, $DicEx$ is highest among others and the accuracy of $DicPi$ is higher than the dictionary created from parallel corpus (i.e. $DicPa$). Based on the accuracy of dictionaries, a priority order is defined to create the final seed dictionary:
DicEx > DicPi > DicPa

Our simple combination rule is:
Suppose that the priority of Dic\textsubscript{i} is more than the priority of Dic\textsubscript{j}; if a word \(w\) is in both Dic\textsubscript{i} and Dic\textsubscript{j}, its translation is selected from Dic\textsubscript{i} (i.e. the dictionary with higher priority).

By applying the above priority rule, a new Persian-Italian dictionary with more than 65,000 unique entries is created. We name this newly created dictionary DicCoSi. Apparently, all the words in DicEx are included in DicCoSi. The experimental results show an improvement in extracted lexicon when this new dictionary DicCoSi is used as the main system’s seed dictionary in comparison with using our three simple dictionaries individually.

3.4 Using independent word combination

In our simple priority based combination which is described in Section 3.3, there is an important issue that should be discussed. Given two words, where the first one appears in all three dictionaries and the second one just appears in one dictionary. In our simple approach, there is no difference between these words. Therefore, a new advanced combination method is proposed. Our advanced combination method is based on the assumption that one word in two different dictionaries should be considered independently as two different words. For example if a word appears in both dictionaries Dic\textsubscript{1} and Dic\textsubscript{2}, it may have two independent columns in our vector matrix (i.e. it has two different weights in the transferred vectors). Therefore, the new dictionary named DicCoIn is created where its size is equal to the sum of our three dictionary’s sizes. In this new dictionary if the word \(x\) occurs in two dictionaries, there are two different entries for it named \(x_i\) and \(x_j\) where \(i\) and \(j\) are the indicator of corresponding dictionaries.

3.5 New weighting method

There is another problem in our proposed advanced combination. Even though some dictionaries are more accurate than others, there is no difference in dealing with initial seed dictionaries. In order to ease this problem, a new weighting model for similarity scores is introduced. This new metric relies on two following aspects:

(1) We could change the effect of each seed dictionary in order to suppose higher weights for more accurate dictionary. These weights could be tuned manually.
(2) If a word appears in two dictionaries, then it is not necessary to count it twice as a double-count would produce an unfair skew. We could consider its weight a little bit more than a normal occurrence weight and then to divide it between different dictionaries.

If there are $k$ different dictionaries in our proposed independent word based combination, to calculate the similarity scores between bilingual lemmas we could use the proposed equation 1.11:

$$newdicedMin(X, Y) = \frac{2 \cdot \sum_{j=1}^{k} \sum_{X_i \in Dic_j} min(X_i, Y_i) \cdot w_j}{\sum_{i=1}^{n} X_i + \sum_{i=1}^{n} Y_i} \quad (1.11)$$

Where $n$ is the size of new combined dictionary and $w_j$ is the weight of dictionary $j$. In our experiments, the size of $k$ is equal to three. This is apparent that if $w_j = 1$ for $j = 1, 2$ and $3$, then the method is the same as previous approach described in Section 3.4. The new weighting method is based on this assumption that the dictionary with higher accuracy should affect the extracted lexicon more. In our experiments, two different sets of $w_j$ are studied and the results are evaluated in Section 5.3.

4 Preparing The Inputs

As stated prior, two primary inputs are needed to perform comparable corpora based lexicon generation: seed dictionary and comparable corpus/corpora. The procedures to prepare these needed data are described in sections 4.1 and 4.2, To evaluate the result, a test dataset is needed. The evaluation of the test is performed by two people.

The first evaluator is one of the authors, who is a native Persian speaker and fluent in Italian and the second one is a Persian native who teaches the Italian language. If both of the evaluators agree on a translation word, it is accepted as a true translation, otherwise the translation is considered false. We selected 400 Persian objective test words from Nabid Persian-English dictionary \(^1\). Since it is not appropriate to apply our approach for words that are already in the base lexicons, we removed all entries belonging to the 400 test words. The frequencies of all the selected words in our corpora (general corpus and specific domain corpus) were greater than 100.

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\(^1\) Nabid Dictionary, written by Hani Kaabi, Iran, 2002
4.1 Seed Dictionaries

Three different seed dictionaries are used in our experiments. The first was a small preexisting Persian-Italian dictionary named DicEx. Another usage of this dictionary was to extract Persian-Italian parallel sentences from comparable corpora.

The second dictionary, DicPi, is a dictionary extracted by the pivot-based approach proposed in (Sjöbergh 2005). To extract DicPi, two Persian-English and English-Italian dictionaries are needed. The Persian-English dictionary we used was the Nabid dictionary. It contains about 100,000 Persian index words. For the English-Italian dictionary, we used a personal dictionary created by the University of Pisa for their internal experiments\(^2\). This simple dictionary contains about 130,000 words. From the English portion of selected dictionaries, we removed the few stop words and all the characters that were not letters and then, the method described in Section 3.2 was applied to our data and a new dictionary was created. Although in the classic method (Sjöbergh 2005), having a large coverage is very important; but in our experiment we needed a smaller and more accurate extracted dictionary. Therefore, the top 40,000 words from all translation are extracted and inserted into the dictionary DicPi. We checked 200 randomly translated words and 84% of them are acceptably translated. This accuracy is near, but slightly less than the best results in the famous pivot based approaches described in Section 2.2.

The parallel corpus based lexicon, DicPa was a word-to-word sub-part of a translation table, extracted with Giza++. Our parallel corpus contains about 29,000 sentences in both the Persian and Italian languages. These corpora are gathered from the Opus\(^3\) database and WikiRetriever\(^4\). When more than one definition was found for a word, the first one is selected and the others are discarded. Finally, the top 40,000 entries of the translation table with a high probability are selected as the new dictionary. Table 1 shows some characteristics of three dictionaries.

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\(^2\) English-Italian words collected for projects DeSR Parser and Tanl Linguistic Pipeline, Prof. Giusseppe Attardi, Dipartimento di Informatica Università di Pisa

\(^3\) OPUS, the open parallel corpus: http://opus.lingfil.uu.se/

\(^4\) Wikiretriever is a C++ crawler to retrieve very accurate parallel sentences from two different languages of Wikipedia website and has written to retrieve limited amount of parallel sentences by using dates, numbers and famous words. The accurate of this retriever for English and Persian, which has been evaluated before, is about 98%, so is ideal for our purpose.
Table 1: Dictionaries used in Experiments

| Dictionary Name | Entries | Mutual words with DicEx |
|-----------------|---------|------------------------|
| DicEx           | 13,309  | N/A                    |
| DicPi           | 40,000  | 6,954                  |
| DicPa           | 40,000  | 4,220                  |

4.2 Comparable Corpora

In our experiments, three different types of comparable corpora are gathered: The first one is a small corpus of Wikipedia\(^5\) articles in Persian and Italian extracted by WikiRetriever’s preliminary phase\(^6\). In order to skip those articles which are famous and well described in one of our languages (e.g. an article about an Italian village) we selected those article pairs where the difference between their sizes is not more than 50%. After applying this criterion, 6,500 articles are selected in both languages: about 150,000 sentences for Persian and 176,000 sentences in Italian. Both groups of sentences were tokenized and lemmatized. The result corpus is called WikiCorpus in our studies. This corpus is the most comparable corpus among our corpora (The comparability degree is more than the rest).

The second corpus is the international sport related news gathered from different Persian and Italian news agencies. We used the ISNA\(^7\) and the FARS \(^8\) for the Persian part, and the news agency CORRIERE DELLA SERA\(^9\) and the Gazzetta dello Sport\(^10\) for the Italian part. The numbers of selected articles are about 12,000 and about 15,000 from Persian and Italian resources, respectively. This corpus named SportCorpus, has more noise in comparison with Wikipedia created corpus but while international sport news are very similar in different agencies, the comparability degree is not too small. We combined SportCorpus and WikiCorpus and used them together in our experimental results. We call this new combined corpus SpecCorpus (Specific domain based corpus).

The third corpus is based on international news gathered from different Per-

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\(^5\) Wikipedia, The Free Encyclopedia website: http://www.wikipedia.org
\(^6\) In primary phase, Wikiretriever find articles which are about same issue to send it for next processes
\(^7\) ISNA, Iranian students News Agency, International News part, Persian, http://isna.ir/fa/service/World
\(^8\) Fars News Agency, International News part, Persian, http://www.farsnews.com/news/v.php?srv=6
\(^9\) CORRIERE DELLA SERA, International news, Italian, http://www.repubblica.it/
\(^10\) La Gazzetta dello Sport, Italian, http://www.gazzetta.it/
1 Extracting Bilingual Persian Italian Lexicon from Comparable Corpora Using Different Types of Seed Dictionaries

Persian and Italian news agencies. The difference between this corpus and SpeCorpus is that the former was gathered from sport related news and this one is gathered from general subjects. This is our biggest corpus but obviously has a very low comparability degree in comparison with SpeCorpus. The number of articles in the Persian version was about 108,000 and for the Italian version was about 140,000 articles. We used ISNA and FARS news agencies for Persian version and CORRIERE DELLA SERA as the Italian resource. We named this corpus GenCorpus. By using GenCorpus we could analyze the effect of using a very general corpus in comparison with specific domain based corpus and we can see how the comparability degree of input corpus could affect the extracted lexicon.

5 Experimental Results

As discussed in Section 3.2, In order to see the effect of using order based windows, we considered both simple window and the word order based method, separately. The results show that taking ordering into account is not very effective to extract Persian-Italian lexicons (i.e. only in a small number of cases, it has a slightly positive effect). The authors think the reason is the vast difference between the structures of Persian and Italian languages. However in our experiments we applied both schemas. Based on (Irimia 2012)’s conclusion all window sizes where set to 5. In our approach, we have calculated both simple frequency and the log-likelihood ratio. Despite our expectation, in a few cases using simple co-occurrence has a more accurate result in comparison to using log-likelihood ratio. While this difference is very small, at most demonstrated figures in this paper, simple frequency ratio is not considered and only log-likelihood ratio is shown.

All experiments described in this paper were applied on two types of comparable corpora: (1) the combination of WikiCorpus and SportsCorpus which we named SpeCorpus. (2) GenCorpus as a big, general, and less comparable corpus. The characteristics of these corpora were discussed in Section 4.2.

Finally, experiments are executed in order to evaluate our proposed combination models. In the first sub-section, we use the three previously mentioned dictionaries as the individual seed lexicon. Then we used our two different proposed strategies to combine dictionaries and consequently the effect of the combinations are studied. Finally in Section 5.3, the new weighting model and its effect with different weight sets is evaluated.

In our experiments and for each test, two different result sets are calculated. The Top-1 measure is the number of times when the test word’s acceptable trans-
lation is ranked first, divided by the number of test words. The Top-10 measure is equal to the number of times a correct translation for a word appears in the top 10 translations in the result lexicon, divided by the number of test words. The evaluation process is performed manually by two evaluators. As described in Section 4, one translation is assumed to be true if both evaluators agree.

5.1 Using independent dictionaries

In first phase of our experiments, all three previously mentioned dictionaries are used individually as the seed lexicon. These are the preexisting dictionary (DicEx), the pivot base extracted dictionary (DicPi) and the parallel corpus based dictionary (DicPa). Figures 1 and 2 summarize the evaluation results using these three seed dictionaries with and without using word order. The goal of this experiment is to see the effect of using different comparable corpora.

Figure 1 shows the results of using SpeCorpus, a corpus with higher comparability degree and Figure 2 demonstrates the results of using GenCorpus, the bigger corpus with lower comparability degree. A comparison between these two corpora and effects of using them individually is illustrated in Figure 3. The goal of this classification is to determine the effect of using comparable corpora with a higher comparability degree. Figure 3 shows that using corpus with higher comparability degree increases the accuracy in both Top-1 and Top-10 results significantly. As it is expected, this difference for Top-1 results is more than the Top-10 measure. However, it should be understood that our test words were selected from those words having a frequency more than our threshold. When SpeCorpus is much smaller than GenCorpus, this may increase the chance of finding a better translation using it. For the rest of the experiments in this paper, SpeCorpus is used as comparable corpus and GenCorpus is ignored.

Another option shown in Figures 1 and 2, is the effect of considering word orders in lemma vectors. As we expected, this could increase the efficiency slightly. However, as discussed prior, and because of the vast differences between the structure of Italian and Persian languages, this improvement is very small and could be negligible as a conclusion. According to results, and our expectation, the DicEx has better outcome despite its small size compared with the other dictionaries. A reason is the high accuracy of DicEx as it is a handmade dictionary. We could consider it a 100% accurate dictionary. The experimental results show that DicPi has a slightly better efficiency in comparison with parallel corpora based dictionary DicPa. The authors conclude that the reason is the limitation of our parallel Persian-Italian corpus used to create translation table. Therefore we have selected some unimportant words that are not translation decisive. If
with and without considering word orders. Before this experiment we expected that using log-likelihood and word ordering together has the best efficiency but based on the results, when the seed dictionary is $\text{DicEx}$ or $\text{DicPa}$, simple frequency schema has a slightly better accuracy in comparison with the log-likelihood ratio even though this superiority is very narrow and could be neglected. For $\text{DicPi}$ both schemas have almost the same outcome (i.e. in one test case using log-likelihood has better result and in other one using the simple frequency). In the legend of Figure 4, SF and LL means using simple frequency and log-likelihood respectively. In general and with considering the noise effects, this hypothesis could be supported that based on our data sets, none of these schemas has a better efficiency in comparison with other.

### 5.2 Using composite dictionaries

In this section, we evaluate our ideas of combining different dictionaries together. As described before, two different types of combination are used in our experiments. The simple combination creates a dictionary using a simple priority rule and the advanced combination for all dictionaries considering all translations of any word. Table 2 shows the results of these studies. According to this table, the best results for Top-1 measure belong to the simple combination model when all dictionaries are combined together. The best Top-10 results belong to the advanced combination model combining all dictionaries. In advanced combination, all words in all dictionaries are selected in the lexicon generation phase, and this generally gives us the better Top-10 results. An important issue for our advanced combination is that all translations in different dictionaries have the same weight and this may decrease the effect of $\text{DicEx}$. Although it is our most accurate dictionary, it is also the smallest one. This problem is tackled in next section by using our weighting lemma.
Figure 1: Results of using independent dictionaries with and without considering word orders. All results are based on log-likelihood measurement using SpeCorpus (in-domain corpus)

Figure 2: Results of using independent dictionaries with and without considering word orders. All results are based on log-likelihood measurement using GenCorpus (general corpus)

5.3 Using new weighting

In this section, we describe the proposed weighting method to use different dictionaries together. The goal of introducing this metric is to "tune" the impact of a
1 Extracting Bilingual Persian Italian Lexicon from Comparable Corpora Using Different Types of Seed Dictionaries

Figure 3: Effect of using different corpora in with different comparability degree

Table 2: The effect of different dictionaries in combination with different methods on SpeCorpus for advanced combination

| Dictionary Name | Top-1 | Top-1 | Top-10 | Top-10 |
|-----------------|------|------|-------|-------|
|                 | Simple | Advanced | Simple | Advanced |
| DicEx + DicPi   | 50.00 | 49.50 | 75.00 | 75.50 |
| DicEx + DicPa   | 48.75 | 48.00 | 74.00 | 74.75 |
| DicPi + DicPa   | 42.50 | 43.00 | 66.75 | 67.50 |
| All Dictionaries$^a$ | 50.25 | 49.75 | 75.25 | 76.75 |

$^a$ Named DicCoSi for simple combination and DicCoIn for advanced combination.

dictionary considering its accuracy and correctness. Two different heuristics are considered to adjust weights in this part. The first one is to tune weights based on dictionaries accuracy. The accuracies could be collected from Top-10 scores calculated in phase 5.1 (results in the second column of Table 2) . In the first set, the weights for DicEx, DicPi and DicPa are 0.7, 0.64 and 0.59, respectively.

In our second heuristic set, the weights are calculated based on both accuracy and the dictionary size. This weight set is constructed based on the assumption that the bigger dictionary should have a lower effect on the final result. We used the following formula to calculate the weights.

$$w_i = accuracy_i \cdot \frac{MaxSize}{size_i}$$

(1.12)
Therefore, based on the second heuristic, Formula 1.12 and with considering the results in our study the weights are:

\[ W_{\text{DicEx}} = 2.10, \ W_{\text{DicPi}} = 0.64 \] and \[ W_{\text{DicPa}} = 0.59. \]

The results of these experiments based on different weighting sets are shown in Table 3. \( W_i = 1 \) presents the classic approach without using the proposed weighting system.

Table 3: The effect of new weighting schema on accuracy of extracted dictionary (In all tests, the combination of three dictionaries is used and the comparable corpus is SpeCorpus)

| Weight  | Top-1 | Top-10 |
|---------|-------|--------|
| \(W_i=1^a\) | 50.25 | 76.75 |
| Weight 1 | 52.50 | 78.25 |
| Weight 2 | 53.75 | **81.25** |

\(^a\) Same as the previous results (without any priority)

Table 3 shows that when we consider the accuracy of dictionaries, the extracted lexicon has a better accuracy in comparison with the advanced combination. The best efficiency belongs to second weighting set where we consider both accuracy and size together when the weight of most accurate dictionary, DicEx is much higher than the rest.

Finally, Figure 5 shows a brief illustration to see the effect of our combination methods in comparison with classic approaches when they used just the existing dictionary, DicEx (the most accurate independent dictionary in our study) as the seed dictionary. In all results, log-likelihood ratio with considering word ordering issue are used to extract bilingual lexicons from SpeCorpus, our corpus with high comparability degree. In legends of this figure, AC means advanced combination model.

6 Conclusion

In the last decade, some methods have been proposed to extract bilingual lexicons from comparable corpora. In order to create a Persian-Italian lexicon, we decided to implement a comparable corpora-based lexicon generation method. This type
of methods usually need a small dictionary as their starting seed dictionary. In our study, three different seed lexicons (and combinations) are used consisting of one preexisting dictionary and two extracted dictionaries. The first extracted dictionary is based on parallel-corpora dictionary creation methods and the second one is extracted by pivot language models. While for a seed dictionary a small dictionary is needed, we just selected the top translations from these created dictionaries. In the first part of our study, the effects of using these dictionaries on...
different types of comparable corpora are evaluated.

A new and interesting challenge was introduced in our work combining different dictionaries creating the seed dictionary. We used two different strategies: First, composing dictionaries with some priority rules; second, using all dictionaries together considering similar words in two dictionaries as a different word. Both of these strategies were studied and based on our experimental results these novel dictionary combinations could improve the efficiency of the results. The proposed advanced dictionary combination is almost as accurate as our simple combination. Furthermore, in all experiments the effect of comparability degree of initial comparable corpus is studied using different types of comparable corpora. The results show that a higher degree of comparability in input corpus, has a more accurate lexicon despite the fact that the less comparable corpus is larger in comparison with the higher comparable corpus; although using a specific corpus may decrease the generality of extracted lexicon.

Finally, a new weighting method has been proposed to increase the efficiency of our dictionary combination. This new weighting method uses the assumption that the effect of a more accurate seed dictionary should has a better result in comparison with others; experimental result show that using a more accurate weighting system causes the extracted lexicon to be more accurate.

7 Acknowledgment

The authors gratefully acknowledge the contribution and help of Dr. Fatemeh Alimardani, Dr. Daniele Sartiano, Vahid Pooya, Amir Onsori, S. M. H. Mirsadeghi, and Dr. M. N. Makhffif to this work.

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Extracting Bilingual Persian Italian Lexicon from Comparable Corpora Using Different Types of Seed Dictionaries

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Appendix

Different similarity scores have been used in the variants of the classical approach of extracting bilingual lexicon from comparable corpora; (Rapp 1999) used city-block as their preferred similarity vector. The cosine similarity is used by (Fung & McKeown 1997; Fung & Yee 1998; Chiao & Zweigenbaum 2002; San Vicente X Saralegui 2008) and the lin similarity metric is used by (Lin 1998). The other well-known similarity metrics are dice and jaccard (Chiao & Zweigen-
In both dice and jaccard metrics, the association values of two lemmas with the same context are joined using their product. There are two different forms of jaccard and dice; the jaccardMin metric (Grefenstette 1994; Kaji & Aizono 1996) and diceMin (Curran & Moens 2002; Plas & Bouma 2005; Otero 2007). Only the smallest association weight is considered for both of these lemmas. The jaccard and the dice are very similar based on results gathered in (Otero 2008) which authors discuss the efficiency of several similarity metrics combined with simple occurrences and log likelihood weighting schemes. In (Laroche & Langlais 2010) the authors presented some experiments for different parameters like context, association measure, similarity measure, and seed lexicon. In recent works, the similarity of two vectors, X and Y is computed using one of these similarity measures:

\[
cityblock(X, Y) = \sum_{i=1}^{n} |X_i - Y_i|
\]

\[
cosine(X, Y) = \frac{\sum_{i=1}^{n} (X_i Y_i)}{\sqrt{\sum_{i=1}^{n} X_i^2} \sqrt{\sum_{i=1}^{n} Y_i^2}}
\]

\[
diceMin(X, Y) = \frac{2 \sum_{i=1}^{n} \min[X_i, Y_i]}{\sum_{i=1}^{n} X_i + \sum_{i=1}^{n} Y_i}
\]

\[
diceProd(X, Y) = \frac{2 \sum_{i=1}^{n} (X_i Y_i)}{\sum_{i=1}^{n} X_i^2 + \sum_{i=1}^{n} Y_i^2}
\]

\[
jaccardMin(X, Y) = \frac{\sum_{i=1}^{n} \min[X_i, Y_i]}{\sum_{i=1}^{n} \max[X_i, Y_i]}
\]

\[
jaccardProd(X, Y) = \frac{\sum_{i=1}^{n} (X_i Y_i)}{\sum_{i=1}^{n} X_i^2 + \sum_{i=1}^{n} Y_i^2 - \sum_{i=1}^{n} (X_i Y_i)}
\]

\[
lin(X, Y) = \frac{\sum_{X_i Y_i \neq 0} (X_i + Y_i)}{\sum_{i=1}^{n} X_i + \sum_{i=1}^{n} Y_i}
\]
Name index

Ahn, Kisuh, 2, 4
Ahrenberg, Lars, 5
Aizawa, Akiko, 6, 7
Aizono, Toshiko, 28
Andersson, Mikael, 5
Ansari, Ebrahim, 3, 4
Babych, Bogdan, 6
Bouamor, Dhouha, 6
Bouma, Gosse, 9, 28
Brown, Peter F., 5
Campos, José Ramón Pichel, 6
Chiao, Yun-Chuang, 3, 6, 7, 27
Church, Kenneth W., 5
Curran, James R., 9, 28
Dunning, Ted, 7, 12
Déjean, Hervé, 6
E. Morin, B. Daille, 6
Emmanuel, Morin, 6
Frampton, Matthew, 2, 4
Fung, Pascale, 3, 6, 7, 27
Gale, William A., 5
Gaussier, Eric, 6, 7
Gaussier, Éric, 6
Grefenstette, Gregory, 28
Hazem, Amir, 6
Irimia, Elena, 6, 9, 17
István, Varga, 2, 4
Kaji, Hiroyuki, 2, 4, 6, 28
Langlais, Philippe, 8, 28
Laroche, Audrey, 8, 28
Li, Bo, 6, 7
Lin, Dekang, 27
McKeown, Kathleen, 3, 6, 7, 27
Melamed, I. Dan, 5
Merkel, Magnus, 5
Moens, Marc, 9, 28
Ney, Hermann, 5, 11
Och, Franz Josef, 5, 11
Okazaki, Naoaki, 2, 4
Otero, Pablo Gamallo, 3, 5–7, 9, 28
Plas, Lonneke van der, 9, 28
Prochasson, E., 6
Rapp, Reinhard, 3, 6–8, 11, 27
Sadat, Fatia, 6
San Vicente X Saralegui, A Gurrutxaga, 27
Semmar, Nasredine, 6
Sharoff, Serge, 6
Shoichi, Yokoyama, 2, 4
Sjöbergh, Jonas, 2, 5, 9, 10, 15
Tanaka, Kumiko, 2, 4, 5
Name index

Tiedemann, Jörg, 5
Tillmann, Christoph, 5
Tsujii, Jun’ichi, 2, 4
Tsunakawa, Takashi, 2, 4

Umemura, Kyoji, 2, 4, 5

Yamamoto, Yosuke, 2, 4
Yee, Lo Yuen, 3, 6, 7, 27

Zock, Michael, 3, 6
Zweigenbaum, Pierre, 3, 6, 7, 27