Multi-Strategy system for translation inference across dictionaries

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Abstract
This paper describes four different strategies proposed to the TIAD 2020 Shared Task for automatic translation inference across dictionaries. The proposed strategies are based on the analysis of Apertium RDF graph, taking advantage of characteristics such as translation using multiple paths, synonyms and similarities between lexical entries from different lexicons and cardinality of possible translations through the graph. The four strategies were trained and validated on the Apertium RDF EN ↔ ES dictionary, showing promising results. Finally, the strategies, applied together, obtained an F-measure of 0.43 in the task of inferring the dictionaries proposed in the shared task, ranking thus third with respect to the other new systems presented to the TIAD 2020 Shared Task. No system presented to the shared task exceeded the baseline proposed by the TIAD organizers.

Keywords: Dictionary generation, Automatic inference translation, Graph based heuristics

1. Introduction

The TIAD (Gracia and Kabashi, 2020) shared task is aimed at exploring methods and techniques that infer translations indirectly between language pairs, based on other bilingual resources.

The organizers provide Apertium RDF (Gracia et al., 2014), a set of 22 Apertium bilingual dictionaries, published as linked data on the Web. The Apertium RDF groups the bilingual dictionaries in the same graph, interconnected through the common lexical entries of the monolingual lexicons that they share.

Although the Apertium RDF graph contains multiple connections that represent translations, not all the Apertium RDF lexicons are interconnected. The challenge of the task is to automatically infer translations between English and French lexicons, French and Portuguese lexicons, and Portuguese and English lexicons, respectively, based on the existing bilingual dictionaries from Apertium RDF. Additionally, there is also possible to make use of other freely available sources of background knowledge to improve performance, as long as no direct translation among the target language pairs is applied.

The automatically inferred translation methods could reduce the costs of constructing bilingual dictionaries. Nevertheless, despite the advantages that the automatic translation inference across dictionaries might have, this task is still challenging (Gracia et al., 2019).

Translation inference across dictionaries based on current methods such as word embeddings (Donandt and Chiarcos, 2019) (Garcia et al., 2019) still obtains lower results than more traditional heuristics (Tanaka and Umemura, 1994).

Some graph traversal heuristics for this shared task have been proposed previously in (Torregrosa et al., 2019). The hypothesis of this work is that graph-based heuristics may still have potential for improving results. The aim of this work is to try to take full advantage of the potential of translation inference heuristics, based on the Apertium RDF graph, with the benefit of obtaining possibly more interpretable methods.

2. Materials and methods

The Apertium RDF (Gracia et al., 2014) is used to develop the proposed translation heuristics proposed in this paper. The Figure 1 shows the Apertium RDF graph available for the TIAD shared task. The graph contains 13 lexicons, the solid lines show the available translations, the dashed line between English (EN) and Spanish (ES) lexicons is the available translation set that is used in this work for training and validation of the translation strategies proposed in this paper. The dotted lines show the translations aimed to infer with the TIAD shared task and are used for testing the strategies.

Figure 1: Apertium RDF Graph

As explained by (Saralegi et al., 2011) inferring an A-B bilingual dictionary by merging A-P and P-B dictionaries, using P as pivot lexicon, often produce wrong translations due to polysemous pivot words. To avoid this problem, four translation heuristics or strategies are proposed here, in order to infer translations from a lexicon A to a lexicon B. These strategies are presented below.
2.1. Strategy I

A natural way to address the problem, when multiple paths are available between lexicons A and B, is to validate a translation from \( a \in A \) to \( b \in B \) if there are multiple paths from \( a \) to \( b \) across different pivot lexicons. We consider the translation \( T = a \leftrightarrow b \) as correct if:

\[
b \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(a) \cap \text{translation}_{A \leftrightarrow P' \leftrightarrow B}(a)
\]

where

\[
\text{translation}_{A \leftrightarrow P \leftrightarrow B}(a) = \\
\text{translation}_{P' \leftrightarrow B}(\text{translation}_{A \leftrightarrow P}(a))
\]

The equation 5 exploits the end-to-end lexical similarity across a path with \( P \) as pivot lexicon:

\[
(b \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(a)) \land (s(a, b) < t_1) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

The equation 6 exploits the overall lexical similarity across a path with \( P \) as pivot lexicon:

\[
(p \in \text{translation}_{A \leftrightarrow P}(a)) \land (b \in \text{translation}_{P' \leftrightarrow B}(p)) \\
\land (s(a, p) + s(p, b) < t_2) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

The equation 7 exploits the lexical similarity between translations of the same word \( a \in A \) to different lexicons:

\[
(b \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(a)) \\
\land (p' \in \text{translation}_{A \leftrightarrow P'}(a)) \\
\land (s(b, p') < t_3) \\
\Rightarrow \exists T = a \leftrightarrow b
\]

The three equations have a corresponding threshold that has been adjusted during training phase. In this work, \( t_1 \) and \( t_3 \) have been set to 0.17 and \( t_2 \) to 0.5.

2.2. Strategy II

As mentioned before, the main problem of a direct translation through a pivot lexicon is polysemous words. The polysemy of pivot words implies several meanings for the same word. However, considering the available dictionaries as complete, if the cardinality of a translation through a pivot lexicon is one in both directions, then we assume that it is less likely the translation to be influenced by polysemous words in the pivot lexicon. For these situations we have considered the translation as correct, as expressed in the following equation:

\[
a \in A, b \in B \\
(\text{translation}_{A \leftrightarrow P \leftrightarrow B}(a) = \{b\}) \\
\land (\text{translation}_{B \leftrightarrow P' \leftrightarrow A}(b) = \{a\}) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

2.3. Strategy III

This strategy attempts to exploit the similarities between different lexicons. A lexical similarity measure \( s \) is defined for \( a \in A, b \in B \) as follows:

\[
s(a, b) = \frac{2 \times \text{levenshtein}(a, b)}{\text{length}(a) + \text{length}(b)}
\]  

This similarity measure is based on the levenshtein distance and the length of the compared words. Notice that for \( a = b \) then \( s(a, b) = 0 \).

Before calculating the lexical similarity between two words, the special characters, typical of each lexicon, have been replaced by the most similar characters from the English alphabet.

For the inference of translations based on lexical similarity for \( a \in A, b \in B \) we have considered three settings as follows.

The equation 5 exploits the end-to-end lexical similarity across a path with \( P \) as pivot lexicon:

\[
(b \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(a)) \land (s(a, b) < t_1) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

The equation 6 exploits the overall lexical similarity across a path with \( P \) as pivot lexicon:

\[
(p \in \text{translation}_{A \leftrightarrow P}(a)) \land (b \in \text{translation}_{P' \leftrightarrow B}(p)) \\
\land (s(a, p) + s(p, b) < t_2) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

The equation 7 exploits the lexical similarity between translations of the same word \( a \in A \) to different lexicons:

\[
(b \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(a)) \\
\land (p' \in \text{translation}_{A \leftrightarrow P'}(a)) \\
\land (s(b, p') < t_3) \\
\Rightarrow \exists T = a \leftrightarrow b
\]

2.4. Strategy IV

This strategy attempts to exploit the existence of synonymous words in a lexicon, words that might have the same translation to another lexicon. As with the previous strategy 2.3 three settings have been considered.

The first approach is shown in Figure 3 (solid lines show existing translations, dashed line shows new inferred translation).

The equivalent equation is shown below. For \( a \in A, b \in B \),

\[
\{p_k, p_l\} \in \text{translation}_{A \leftrightarrow P}(a) \\
\land \{p_k, p_l\} \in \text{translation}_{B \leftrightarrow P}(b) \\
\Rightarrow \exists T = a \leftrightarrow b
\]  

where \( p_k \) and \( p_l \) might be synonymous words in lexicon \( P \), as reported also in (Torregrosa et al., 2019).

The second approach related to synonymous words is shown in Figure 4 (solid lines show existing translations, dashed lines show new inferred translations)
The equivalent equation is shown below. For $a_i, a_j \in A, b \in B$,

\[
\begin{align*}
& (a_i \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(b)) \\
& \land (a_j \in \text{translation}_{A \leftrightarrow P \leftrightarrow B}(b)) \\
& \land (\exists a' \in A') \land (\exists a'' \in A'') \\
& \land \{a_i, a_j\} \in \text{translation}_{A' \leftrightarrow A}(a') \\
& \land \{a_i, a_j\} \in \text{translation}_{A'' \leftrightarrow A}(a'') \\
\Rightarrow & (\exists T_1 = a_i \leftrightarrow b) \land (\exists T_2 = a_j \leftrightarrow b)
\end{align*}
\]

(9)

where $a_i$ and $a_j$ are considered as synonymous words in lexicon A.

This configuration assumes a graph cycle of length $= 7$ words across 6 lexicons.

The third approach related to synonymous words is shown in Figure 4 (solid lines show existing translations, dotted line show an inferred translation in a previous step of the algorithm, dashed line shows a new inferred translation).

The equivalent equation is shown below.

The strategies have been evaluated on the available $EN \leftrightarrow ES$ Apertium dictionary and tested by TIAD organizers on $EN \leftrightarrow FR, PT \leftrightarrow EN$ and $FR \leftrightarrow PT$ dictionaries. The obtained results are shown below.

### 3. Results and discussion

The validation results of the different translation inference strategies can be seen in Table 1. Proper nouns were not considered for training and validation tasks.

As may be noticed in Table 1, individually, the best strategy for the $EN \leftrightarrow ES$ translations case, considering its F-measure, is strategy II. However, the lexical similarity, the basis of strategy III, is close to strategy II and largely overlaps its correct translations. In the case of Strategy I, it seems important the correct selection of the paths to use, that is, the lexical pivots. Different combinations of two lexical pivots may obtain high degrees of precision (see results for strategy I’), depending on the pivot lexicons used. The path $EN \leftrightarrow EO \leftrightarrow ES$ proven lower precision for both strategies I and IV.

The combination of strategies II, III, IV, without considering Strategy I, also produces competitive results.
Table 1: Validation results of $EN \leftrightarrow ES$ translations

| Strategy         | Precision | Recall | F measure |
|------------------|-----------|--------|-----------|
| I                | 0.87      | 0.39   | 0.54      |
| $I'$             | 0.94      | 0.29   | 0.44      |
| II               | 0.85      | 0.48   | 0.62      |
| III              | 0.88      | 0.46   | 0.60      |
| $IV'$            | 0.81      | 0.15   | 0.25      |
| $I + II$         | 0.83      | 0.63   | 0.72      |
| $I + II + III$   | 0.81      | 0.66   | 0.73      |
| $I + II + III + IV'$ | 0.80   | 0.67   | 0.73      |
| $II + III$       | 0.83      | 0.59   | 0.69      |
| $II + III + IV'$ | 0.81      | 0.65   | 0.72      |

Table 2: TIAD shared task - average systems results

| System                  | P    | R    | F    |
|-------------------------|------|------|------|
| Baseline-OTIC           | 0.70 | 0.47 | 0.56 |
| Ciclos-OTIC             | 0.64 | 0.47 | 0.54 |
| NUIG                    | 0.77 | 0.35 | 0.49 |
| Multi-StategyI-II+III+IV | 0.61 | 0.33 | 0.43 |
| Multi-StategyI-II+III    | 0.62 | 0.33 | 0.43 |
| CL-embeddings           | 0.62 | 0.32 | 0.42 |
| Multi-StategyI-II       | 0.65 | 0.30 | 0.40 |
| ACOLIbaseline           | 0.60 | 0.28 | 0.38 |
| Baseline-Word2Vec       | 0.30 | 0.37 | 0.33 |
| Multi-StategyI          | 0.63 | 0.22 | 0.32 |
| ACOLIwordnet            | 0.61 | 0.16 | 0.25 |

Table 3: Systems results for $EN \rightarrow FR$

| System                  | P    | R    | F    |
|-------------------------|------|------|------|
| Ciclos-OTIC             | 0.57 | 0.44 | 0.50 |
| Baseline-OTIC           | 0.64 | 0.38 | 0.48 |
| NUIG                    | 0.68 | 0.31 | 0.43 |
| CL-embeddings           | 0.52 | 0.35 | 0.42 |
| Multi-StategyI-II+III+IV | 0.52 | 0.34 | 0.41 |
| Multi-StategyI-II+III    | 0.52 | 0.34 | 0.41 |
| Multi-StategyI-II       | 0.53 | 0.31 | 0.39 |
| Multi-StategyI          | 0.53 | 0.28 | 0.37 |
| ACOLIbaseline           | 0.48 | 0.24 | 0.32 |
| Baseline-Word2Vec       | 0.23 | 0.39 | 0.29 |
| ACOLIwordnet            | 0.54 | 0.13 | 0.21 |

Table 4: Systems results for $PT \rightarrow EN$

| System                  | P    | R    | F    |
|-------------------------|------|------|------|
| Ciclos-OTIC             | 0.65 | 0.43 | 0.53 |
| Baseline-OTIC           | 0.71 | 0.40 | 0.51 |
| Multi-StategyI-II+III+IV | 0.74 | 0.32 | 0.45 |
| Multi-StategyI-II+III    | 0.76 | 0.31 | 0.44 |
| CL-embeddings           | 0.80 | 0.28 | 0.41 |
| Multi-StategyI-II       | 0.8  | 0.27 | 0.4  |
| ACOLIbaseline           | 0.66 | 0.26 | 0.38 |
| Baseline-Word2Vec       | 0.37 | 0.33 | 0.35 |
| Multi-StategyI          | 0.74 | 0.17 | 0.28 |
| ACOLIwordnet            | 0.67 | 0.16 | 0.25 |
| NUIG                    | -    | -    | -    |

Table 5: Systems results for $FR \rightarrow PT$

| System                  | P    | R    | F    |
|-------------------------|------|------|------|
| Baseline-OTIC           | 0.74 | 0.54 | 0.62 |
| Ciclos-OTIC             | 0.67 | 0.55 | 0.6  |
| NUIG                    | 0.84 | 0.40 | 0.54 |
| Multi-StategyI-II+III+IV | 0.58 | 0.34 | 0.43 |
| Multi-StategyI-II+III    | 0.59 | 0.34 | 0.43 |
| CL-embeddings           | 0.55 | 0.34 | 0.42 |
| Multi-StategyI-II       | 0.62 | 0.31 | 0.41 |
| ACOLIbaseline           | 0.63 | 0.27 | 0.38 |
| Multi-StategyI          | 0.61 | 0.21 | 0.31 |
| Baseline-Word2Vec       | 0.27 | 0.34 | 0.30 |
| ACOLIwordnet            | 0.62 | 0.15 | 0.24 |

3.2. Test of TIAD inferred translations

Several systems have been presented to TIAD 2020 shared task. The average results of those systems can be seen in Table 2 (in bold letters the strategies proposed in this paper).

As it can be seen, the four strategies proposed in this paper, applied together, obtain a medium result, ranking third with respect to the other new systems presented to the shared task and below the Baseline-OTIC of the task. (results ordered by F-measure - F columns in Table 2). It should be noted that the OTIC method proposed as baseline by the TIAD organizers continues to be the method with the best results, despite being a traditional method (Tanaka and Umemura, 1994) that only use the Apertium RDF graph.

Perhaps, having used other dictionaries for training, either as an alternative or in addition to the EN ↔ ES dictionary, that might prove that using the Apertium RDF graph. The results for the three dictionaries that we have inferred with the strategies presented in this work can be seen in Table 3 for $EN \leftrightarrow ES$ translations, in Table 4 for $PT \rightarrow EN$ translations and in Table 5 for $FR \rightarrow PT$ translations, respectively.

As may be observed, the precision of this proposal is superior to the Baseline-OTIC only in the case of the dictionary $EN \rightarrow PT$. This may be due to the fact that the strategies developed here have been trained on the $EN \leftrightarrow ES$ dictionary and the Portuguese lexicon might have more similarities to the Spanish lexicon and the pivot lexicons used. Perhaps, having used other dictionaries for training, either as an alternative or in addition to the $EN \leftrightarrow ES$ dictionary, could have improved the results of the approach used in this work. The worst precision of this strategy is obtained for the $EN \rightarrow FR$ dictionary, that might prove that using EO lexicon as pivot was not a correct approach.
pending on the dictionary to be inferred. This was also observed during the training and validation phases. This strategy is highly dependent on the pivot lexicons used (see results in Table 1). Those good results for Strategy I in the validation phase, as concerns the precision, have been a mirage. This may be because some of the pivot lexicons used for the shared task might be related to each other and might share polysemous cases.

Strategy II has better precision than Strategy I in the shared task and it seems a good strategy to maintain in a future work.

Regarding Strategy III, lexical similarity could be useful to improve results in dictionary inference. It improves de F-measure results in the three inferred dictionaries for the shared task, with respect to Strategy I+II. It could be a good method to improve results of other approaches. This method still has room for improvement, using, for example, other similarity measures and optimization techniques to set the thresholds of the method.

Strategy IV, based on the use of synonyms, has proven to be a valid strategy, although it improves the final results very little, at least when used in conjunction with Strategy I. In the validation phase, Strategy IV, used in conjunction with strategies II and III, has shown more significant improvements in the results with respect to the Strategy I+II configuration. Nevertheless, the second setting of Strategy IV (see Figure 4) might have similar drawbacks as Strategy I. It would have been interesting to test a Multi-Strategy I+II+III+IV in the TIAD shared task, as the results in the validation phase were promising.

4. Conclusion

In this paper four strategy for translation inference across dictionaries have been proposed. The strategies are based on translation using multiple paths, the use of synonyms and similarities between lexical entries from different lexicons and cardinality of possible translations through the graph. The strategies have been trained and validated on the Apertium RDF graph using the dictionary $EN \leftrightarrow ES$, showing promising results. The four proposed strategies, applied together, obtained an F-measure of 0.43 in the task of inferring the proposed dictionaries for the TIAD 2020 Shared Task, thus ranking third with respect to the new systems presented to the shared task. Among the four strategies, the strategy based on lexical similarity stands out. It is a strategy that could enhance other systems and that still has room for improvement.

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6. Bibliographical References

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