Cross-lingual and Cross-domain Transfer Learning for Automatic Term Extraction from Low Resource Data

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Abstract
Automatic Term Extraction (ATE) is essential to domain knowledge understanding and an important basis for further natural language processing applications. Even with persistent improvements, ATE still exhibits weak results exacerbated by small training data inherent to specialized domain corpora. Recently, transformers-based deep neural models, such as BERT, have proven to be efficient in many downstream NLP tasks. However, no systematic evaluation of ATE has been conducted so far. In this paper, we run an extensive study on fine-tuning pre-trained BERT models for ATE. We propose strategies that empirically show BERT’s effectiveness using cross-lingual and cross-domain transfer learning to extract single and multi-word terms. Experiments have been conducted on four specialized domains in three languages. The obtained results suggest that BERT can capture cross-domain and cross-lingual terminologically-marked contexts shared by terms, opening a new design-pattern for ATE.

Keywords: ATE, automatic term extraction, terminology, low resource, multilingual.

1. Introduction
Automatic Term Extraction (ATE) is essential to specialized domains knowledge understanding and can further be used as input for other NLP applications, including information retrieval, thesauri construction, machine, and computer-aided translation, etc. The aim of ATE is to identify terminological units in specific domains (Castellvi et al., 2001). For that purpose, several methods have been proposed, ranging from linguistic-based (Ananiadou, 1994; Justeson and Katz, 1995), statistical (Schäfer et al., 2015), feature-based (Conrado et al., 2013) as well as hybrid (Basili et al., 1997; Aubin and Hamon, 2006) and deep neural-based (Wang et al., 2016; Hatty and Schulte im Walde, 2018) approaches. Nonetheless, they still exhibit weak results, and manual post-filtering remains necessary to exploit current system outputs (Terryn et al., 2018). Furthermore, feature-based approaches, which, up to now, are considered among the most accurate, require labor-intensive feature engineering with no straightforward transfer learning if a new domain is addressed. The only transfer learning-based method that we are aware of deals with clinical concept detection, and still requires feature engineering (Lv et al., 2014).

Current research on ATE deals with two main problems: (1) the small size of data collections inherent to specialized domains and (2) the limited availability of annotations due to the lack of consensus about the nature of terms (Terryn et al., 2018). The former problem has been addressed in other downstream applications using data selection or data augmentation, as shown in SMT (Moore and Lewis, 2010; Axelrod et al., 2011; Gascó et al., 2012), and NMT (Parcheta et al., 2018) as well as combining specialized and general domain word embeddings as demonstrated in the clinical concept detection (El Boukkouri et al., 2019) and bilingual terminology extraction (Liu et al., 2018) tasks. Nonetheless, these techniques are often difficult to apply for ATE since they all require a reasonable amount of annotated data.

The latter problem has also been addressed in other applications using transfer learning, such as, in conversational AI (Schuster et al., 2019) and named entity recognition (Jia et al., 2019; Rahimi et al., 2019) tasks. However, transfer learning is based on mapped representations learned from one sufficient annotated source data and targeted another less-resourced data. In ATE, proper and sufficient source annotations are not available, making such transfer learning difficult even to consider. To overcome the annotation gap occurring in ATE, Judea et al. (2014) proposed an unsupervised data generation approach. However, it relies on linguistic features that need to be defined beforehand.

Over the last few years, a new family of deep neural approaches impulsed by transformers has brought forward significant improvements in many downstream applications (Vaswani et al., 2017; Devlin et al., 2018; Raffel et al., 2019). BERT, for instance, can learn bidirectional context representations from a considerable amount of general domain data that can be fine-tuned for a specific task.

These approaches remarkably capture semantic and syntactic information (Rogers et al., 2020; Reif et al., 2019), and supersede classical approaches on many NLP tasks. Based on the assumption that terms share terminologically-marked contexts (Meyer, 2001), we put greater stress on this hypothesis and propose to investigate its validity on cross-domain and cross-lingual scenarios by experiencing the usage of BERT for ATE on four specialized domains in three different languages. We believe our work provides three important contribu-

1 Data augmentation-based SMT, and NMT systems often require additional annotated bi-texts for training or improving language models. In clinical concept detection and bilingual term extraction, embedding models are used as features for deep neural approaches, such as biLSTM, but these methods also require enough annotated data to be trained on.
2. Related Work

Several approaches for ATE have been proposed so far, ranging from the early linguistic-based (Bourigault, 1992; Justeson and Katz, 1995) to the recent deep neural-based (Wang et al., 2016; Hatty and Schulte im Walde, 2018). We divide their classification into supervised versus unsupervised methods.

2.1. Unsupervised Methods

Unsupervised methods usually involve two steps: (i) the identification of term-like units and (ii) the filtering and sorting of the extracted units that may not be terms using several rules (Daille, 2017). The term-like units are often sequences of noun chunks that are selected during the identification step according to their part-of-speech and their morpho-syntactic patterns (Justeson and Katz, 1995), as well as general phrase rules involving phrase borders (Bourigault, 1992), samples of annotated texts and lists of seed terms (Jacquemin, 2001). Bourigault (1992), for instance, introduced a two steps-based method: (1) analysis: in which a set of rules of frontier marker identification (e.g., punctuation marks, verbs, pronouns, etc.) is defined and (2) parsing: in which the maximal-length noun phrases are determined, and sub-group candidates are extracted based on grammatical structure rules. Justeson and Katz (1995) used the linguistic properties of technical terminology. Terms can also be collected using the lexical expansion of seed term lists and nominal phrases that include seed terms (Jacquemin, 2001; Burgos Herera, 2014).

In the filtering step, all the collected term-like sequences are usually ranked according to termhood and unithood (Kageura and Umino, 1996) criteria, which can be measured by frequency, association measures (e.g., mutual information, log-likelihood), specificity measures (Ahmad et al., 1993), etc. Filtering can also be done by removing nested sequences (incorrect, incomplete, or expansions that are not part of the base term). This is usually done using several measures, such as the C-value (Frantzi and Ananiadou, 2000), contextual filtering under the assumption that terms are gregarious, the NC-value (Frantzi and Ananiadou, 2000) or by exploiting the fact that terms, contrary to regular noun phrases, share terminologically-marked contexts (Meyer, 2001; Condamines, 2002). In this work, we assume that terms do share strongly marked contexts that BERT is able to capture, and we push this hypothesis further to cross-domain and cross-lingual scenarios.

2.2. Supervised Methods

Prior works on ATE used different learning algorithms and feature sets (Conrado et al., 2013; Judea et al., 2014; Hatty et al., 2017). (Hatzivassiloglou V, 2001), for instance, presented an automated system for assigning protein and gene class labels to biological terms in free texts. They explored three established learning techniques: Bayesian learning (Duda and Hart, 1973), decision tree using C4.5 implementation (Quinlan, 1993), and inductive rule learning using RIPPER implementation (Cohen, 1996). Takeuchi and Collier (2005) used support vector machines to extract Bio-medical entities, while Zhang and Fang (2010) used Conditional Random Fields (CRF) and syntactic features. These methods, among others, require quite a high number of features to be set. Conrado et al. (2013), for instance, explored Naive Bayes and decision tree using 17 linguistic, statistical, and hybrid features, such as frequency, TF-IDF, POS tags, etc. They also used two additional features from corpora that belong to another domain. Finally, Hatty et al. (2017) used a random forest classifier, trained on several termhood measures, and recursively applied to the components. To overcome the lack of training data, Judea et al. (2014) proposed an unsupervised training data augmentation step prior to using a binary classifier and a CRF trained on different types of features. Even if their approach is language-independent, it has only been tested on English and still relies on linguistic features that need to be defined beforehand.

More recently, several deep neural approaches have also been applied to ATE. Wang et al. (2016) used two deep neural classifiers: a CNN that learns terms representation using multiple filters to capture sub-gram information and an LSTM that captures the meaning of a term from the sequential combination of its constituents. Amjadian et al. (2016) leveraged local and global embeddings to encapsulate the meaning of the term for the classification step, although they only work with unigram terms. Few neural-based methods regard ATE as a sequence labeling task. Han et al. (2018). In clinical concept detection, which can be seen as a sub-task of ATE, several methods have, however, been proposed (Lv et al., 2014; El Boukkouri et al., 2019). Finally, Sajatovic et al. (2019) evaluated 16 state-of-the-art methods at the corpus and document level, showing that there is no best-performing single method for corpus-level ATE.

3. BERT for ATE

We address ATE by introducing three different strategies. The first consists in using BERT as a binary classifier, while the second uses BERT as a sequence labeling model for Named Entity Recognition (NER). Finally, we propose a feature-based strategy which consists in using BERT embeddings as input features for a bidirectional LSTM (biLSTM) with a Conditional Random Fields (CRF) layer.
3.1. BERT as Binary Classifier

BERT is a supervised learning model that has been trained on the Masked Language Model (MLM) objective and Next Sentence Prediction (NSP). For NSP, the model takes as input pairs of sentences and learns to predict if the second sentence is the subsequent sentence of the first one. We similarly fine-tune our model, providing sentence/term pairs and sentence/non-term pairs instead of sentence pairs. In a similar fashion to NSP, we select 50% of the training pairs where the second sequence is a term, while the other 50% pairs consist of randomly chosen n-grams. Therefore, for each positive training pair, we randomly select within the sentence of the same pair an n-gram as non-term to keep a balanced training set. Class balancing is often a vital setup for classifiers’ efficiency. Even if some existing techniques do reduce the impact of unbalanced classes, we only deal with balanced training in this work. The intuition behind this step is that BERT will learn shared features between terms and their contexts the same way it does for subsequent pairs of sentences. Moreover, for each correct input pair, the term is present in both sequences, which we expect to be advantageous to learn more context about terms during the masked LM phase. Upon testing, all the n-grams of a sentence are used to provide sentence/term-like pairs.

3.2. BERT as NER system

We also address ATE as a named entity recognition task where each term is seen as a named entity. Therefore, we can easily adapt the pre-trained BERT for NER in order to perform ATE. This procedure can be seen as an over-simplification of the actual NER task where we consider only one named entity type (a term), whereas, in the classical task, we consider several named entities. Similarly to NER, we use the IOB scheme (I indicates that the token is inside an entity, O indicates that a token is outside the entity, and B indicates that the token begins the entity).

Since the BERT NER is already pre-trained following the IOB scheme, we chose the ORG tag for all the experiments. Hence, each term of a given sentence is assigned by B-ORG or I-ORG labels, and all non-terms are assigned by O-ORG.

3.3. Bi-LSTM for Sequence Labeling with BERT Embeddings

We finally address ATE as sequence labeling task. Bidirectional LSTM (biLSTM) are standard to the task of named entity recognition using sequence labeling. A Conditional Random Fields (CRF) layer is connected to the LSTM last output layer, enabling it to efficiently use neighboring tag information to better model the conditional probability of the output state sequence. Weights in vanilla LSTM can either be initialized with random values or with third-party word embeddings: here, BERT embeddings are used as input of our model to overcome the problem of low training data.

### Table 1: Number of unique tokens and documents per corpus

| Domain        | # Tokens | # Documents | # Term lists |
|---------------|----------|-------------|--------------|
| corruption    | en       | 468,711     | 1174         |
|               | fr       | 475,244     | 1217         |
|               | nl       | 470,242     | 1295         |
| dressage      | en       | 102,654     | 1575         |
|               | fr       | 109,572     | 1183         |
|               | nl       | 103,851     | 1546         |
| wind energy   | en       | 314,618     | 1534         |
|               | fr       | 314,681     | 968          |
|               | nl       | 308,742     | 1245         |
| heart failure | en       | 45,788      | 2585         |
|               | fr       | 46,751      | 2423         |
|               | nl       | 47,888      | 2257         |

Table 1: Number of unique tokens and documents per corpus for English (en), French (fr) and Dutch (nl) as well as the size of the evaluation term lists.

4. Data Sets

Up to now, cross-lingual and cross-domain transfer methods for ATE have been hindered by the lack of multilingual data sets annotated according to the same guidelines. However, the recently released data set from the first TermEval shared task (Rigouts Terryn et al., 2020) offers an appropriate annotation methodology that falls within both multilingual and multi-domain scenarios. Therefore, in our experiments and evaluation, we use the TermEval data sets, which consist of four specialized domains: corruption, dressage, wind energy, and heart failure in three languages: English (en), French (fr), and Dutch (nl). Table 1 depicts the number of documents and tokens for each corpus as well as the test lists size.

5. Experiments and Results

We follow the evaluation procedure defined in the TermEval shared task (Rigouts Terryn et al., 2020) which consists in using three domains (corruption, wind energy, and dressage) for training and validation and the heart failure domain for testing. We first report the results on the development sets used for cross-validation and fine-tuning, and then the obtained results on the heart failure test set. For each experiment, reported results are the mean average of 10 runs.

5.1. Pre-trained Models

As pre-trained models can behave differently according to the addressed tasks (Liu et al., 2019), we evaluate several BERT models that we have fine-tuned on
the specialized corpora. The tested models for English were: bert-base-cased (BERT) (Devlin et al., 2018), bert-base-multilingual-cased (BERT-multi), and roberta-base (RoBERTa) (Liu et al., 2019). For French, we used Camembert (Martin et al., 2019) and bert-base-multilingual-cased (BERT-multi). Finally, for Dutch, we only considered bert-base-multilingual-cased.


table 2: ATE scores (%) in terms of Precision (P), Recall (R) and F1-score (F1). For each validation corpus, the two remaining ones were used for fine-tuning. We contrast 3 usages of BERT: as a binary classifier, BERT-NER and BERT embeddings used with a biLSTM-CRF. We also contrast BERT’s multi-lingual version as well as RoBERTa for English and Camembert for French.

|               | Corp | Equi | Wind |
|---------------|------|------|------|
|               | P    | R    | F1   | P    | R    | F1   | P    | R    | F1   |
| BERT          | 29.46 | 49.45 | 36.79 | 30.76 | 71.61 | 42.94 | 21.87 | 74.03 | 34.94 |
| BERT-multi    | 25.47 | 58.21 | 35.25 | 27.87 | 71.94 | 40.15 | 22.92 | 74.51 | 34.94 |
| RoBERTa       | 26.85 | 62.53 | 37.33 | 29.17 | 75.59 | 42.03 | 20.93 | 77.08 | 32.91 |
| BERT (NER)    | 52.92 | 22.46 | 31.48 | 54.45 | 22.46 | 31.48 | 43.21 | 22.46 | 31.48 |
| BERT-multi (NER) | 39.09 | 11.59 | 17.89 | 42.38 | 20.20 | 27.45 | 32.63 | 20.20 | 27.45 |
| RoBERTa (NER) | 31.91 | 22.46 | 31.48 | 49.39 | 28.44 | 36.11 | 49.39 | 28.44 | 36.11 |
| BERT-biLSTM-CRF | 22.61 | 18.98 | 20.63 | 20.65 | 16.03 | 18.05 | 20.65 | 16.03 | 18.05 |
|               | P    | R    | F1   | P    | R    | F1   | P    | R    | F1   |
| BERT-multi    | 27.53 | 53.03 | 35.91 | 21.17 | 60.77 | 31.35 | 13.82 | 68.99 | 22.97 |
| Camembert     | 29.73 | 62.61 | 40.25 | 24.38 | 65.89 | 35.53 | 15.63 | 68.99 | 22.97 |
| BERT (NER)    | 39.17 | 11.59 | 17.89 | 42.38 | 20.20 | 27.45 | 32.63 | 20.20 | 27.45 |
| Camembert (NER) | 42.61 | 12.33 | 19.13 | 48.01 | 23.33 | 31.40 | 24.48 | 24.28 | 24.48 |
| BERT-biLSTM-CRF | 18.78 | 16.21 | 17.40 | 18.53 | 19.08 | 17.96 | 17.20 | 20.72 | 18.79 |
|               | P    | R    | F1   | P    | R    | F1   | P    | R    | F1   |
| BERT-multi    | 23.70 | 68.59 | 35.21 | 30.39 | 63.85 | 41.10 | 15.85 | 66.55 | 25.52 |
| BERT (NER)    | 40.93 | 15.68 | 22.67 | 65.25 | 32.79 | 43.65 | 37.41 | 38.31 | 37.85 |
| BERT-biLSTM-CRF | 20.51 | 21.75 | 21.11 | 21.17 | 18.90 | 19.97 | 21.70 | 15.28 | 17.93 |

Table 2: ATE scores (%) in terms of Precision (P), Recall (R) and F1-score (F1). For each validation corpus, the two remaining ones were used for fine-tuning. We contrast 3 usages of BERT: as a binary classifier, BERT-NER and BERT embeddings used with a biLSTM-CRF. We also contrast BERT’s multi-lingual version as well as RoBERTa for English and Camembert for French.

5.2. Dev Set Experiments

5.2.1. Domain Transfer Learning Evaluation

The domain transfer learning procedure consists of fine-tuning BERT on a given domain and testing on another domain. Having three validation data sets (corruption (Corp), dressage (Equi), and wind energy (Wind)), and several BERT models, we subdivided the domain transfer evaluation into two experiments: 1) fixing the training data sets while varying BERT models and 2) fixing the models while varying the training data sets.

Table 2 reports the obtained results when varying BERT models using BERT as a binary classifier, BERT as NER, and BERT with biLSTM-CRF. The contrasted models are BERT and its multilingual version (BERT-multi), as well as RoBERTa for English and Camembert for French. For each specialized test set, we fine-tuned on the combination of the remaining data sets, which consists of providing BERT with both domains as one single data set. If this procedure may seem counter-intuitive, we expect that BERT can capture correlations between terms across domains by assuming that they have terminologically-marked contexts.

Overall, better results were obtained in terms of the F1 score when using BERT as a binary classifier. However, BERT (NER) showed competitive results and was sometimes better for Dutch and always better in terms of precision (P). When comparing BERT models used for binary classification, we see that the results are more contrasted for English and that no single model performs the best in each domain. For French, it is clear that Camembert is the best performing model in terms of the F1 score. When it comes to BERT (NER), we observe in some cases a considerable drop in the results for BERT-multi (NER) and Roberta (NER) for the Corp domain. This drop could be linked to the lower number of named entities in the Corp data set compared to the other corpora. Conversely, BERT-multi (NER) outperformed BERT-multi for Dutch on Equi and Wind test sets. Finally, we observe that BERT-biLSTM-CRF obtained way lower results, suggesting that using BERT embeddings as features for a biLSTM-CRF is less effective than using BERT as a classifier. This is not surprising as we already know that biLSTM models often require a massive amount of training data, which is definitely not the case in our data sets.

Based on the previous experiment’s best performing models, we report in Table 3 the obtained results by varying the training data sets. Training on the English Wind corpus and testing on Corp, for instance, shows better results (+2.64% with RoBERTa) than combining Wind with Equi. On the contrary, better results are
Table 3: Domain transfer results (F1%) of ATE on the English and French data sets (for the sake of clarity, Dutch results are put in the supplementary material).

|                | Test corpus | Training corpus |
|----------------|-------------|-----------------|
|                | Corp        | Equi Wind Equi+Wind |
|                | en en+fr+nl | en en+fr+nl     |
| RobBERTa       | 36.16       | 39.97 37.33     |
| BERT (NER)     | 15.97       | 22.18 31.48     |
| BERT-biLSTM-CRF| 20.54       | 19.01 20.63     |
| Equi Corp      | Wind        | Corp + Wind     |
| RobBERTa       | 42.07       | 44.99 42.03     |
| BERT (NER)     | 38.55       | 41.74 40.81     |
| BERT-biLSTM-CRF| 17.65       | 19.51 18.04     |
| Wind Corp      | Equi        | Corp + Equi    |
| RobBERTa       | 36.16       | 33.77 32.91     |
| BERT (NER)     | 30.58       | 26.89 28.39     |
| BERT-biLSTM-CRF| 19.99       | 20.64 22.11     |

Table 4: Language transfer learning results (F1%) on the validation sets. All the experiments were based on bert-base-multilingual model (BERT-multi).

The language transfer experiment, shown in Table 4 questions the usefulness of adding other languages for fine-tuning. Hence, given the English corruption test set for instance (annotated as corp (en)), we fine-tune the multilingual BERT model (BERT-multi) on each of the two remaining data sets separately (equi or wind) as well as their combination (noted as All), which simultaneously represent cross-lingual and cross-domain evaluation. As can be seen, adding other languages often increases the results, and when it is not the case, the F1 score difference remains very low. Improvements are more noticeable for the Dutch test sets, where we obtained an F1 score of 41.56% versus F1 of 37.52% without the use of multiple languages when compared to a fine-tuning using the Corp data set only. Nonetheless, we notice that, in some cases, adding more languages decreases the performance, as it can be noticed when testing on Wind (en) and fine-tuning on Corp. Indeed, the F1 score dropped from 34.04% to 32.89% when adding French and Dutch languages to English (en+fr+nl). Finally, some improvements can also be observed when using both cross-lingual and cross-domain combination.

5.3. Test Set Experiments

5.3.1. Baselines

In contrast to our proposed approaches, we implemented a feature-based baseline that exploits eXtreme Gradient Boosting (XGBoost) \cite{Chen2016}. We also implemented a Vanilla-biLSTM-
| Baselines | P    | R    | F1   |
|-----------|------|------|------|
| Features (en) | 39.44 | 29.28 | 33.61 |
| Features (enfrnl) | 14.96 | 39.20 | 21.65 |
| Vanilla-biLSTM-CRF | 6.84  | 10.16 | 8.17  |

| Team results |
|-------------|
| TALN-LS2N | 34.78 | 70.87 | 46.66 |
| RACAI | 42.40 | 40.27 | 41.31 |
| NYU | 43.46 | 23.64 | 30.62 |
| e-Termino | 34.43 | 14.20 | 20.10 |
| NLPLab | 21.45 | 15.59 | 18.06 |

| Proposed |
|-----------|
| BERT (en) | 36.31 | 72.15 | **48.21** |
| BERT (NER) | **57.22** | 27.74 | 37.37 |
| BERT-biLSTM-CRF | 24.17 | 38.32 | 29.54 |
| BERT-multi (en) | 33.67 | 71.79 | 45.77 |
| BERT-multi (enfrnl) | 33.01 | 72.67 | 45.37 |

| Baselines | P    | R    | F1   |
|-----------|------|------|------|
| Features (fr) | 48.90 | 53.47 | 50.92 |
| Features (enfrnl) | 18.71 | 40.75 | 25.64 |
| Vanilla-biLSTM-CRF | 4.52  | 11.79 | 6.53  |

| Team results |
|-------------|
| TALN-LS2N | 45.17 | 51.55 | 48.15 |
| e-Termino | 36.33 | 13.50 | 19.68 |
| NLPLab | 16.07 | 11.18 | 13.19 |

| Proposed |
|-----------|
| CamemBert | 40.11 | 70.51 | **51.09** |
| CamemBert (NER) | **57.51** | 25.75 | 35.57 |
| BERT-biLSTM-CRF | 21.13 | 32.48 | 25.60 |
| Bert-multi (fr) | 36.13 | 68.11 | 47.18 |
| BERT-multi (enfrnl) | 33.16 | 69.61 | 44.91 |

| Baselines | P    | R    | F1   |
|-----------|------|------|------|
| Features (nl) | 32.29 | 36.07 | 34.07 |
| Features (enfrnl) | 16.45 | 49.83 | 24.73 |
| Vanilla-biLSTM-CRF | 6.27  | 9.34  | 7.50  |

| Team results |
|-------------|
| NLPLab | 18.9 | 18.6 | 18.7 |
| e-Termino | 29.0 | 9.6 | 14.4 |

| Proposed |
|-----------|
| BERT-multi | 32.86 | **75.47** | 45.73 |
| BERT (NER) | **63.75** | 42.53 | 51.02 |
| BERT-biLSTM-CRF | 22.65 | 34.62 | 27.38 |

Table 5: Our methods results on the heart failure test set (%) contrasted with the baselines and results of the participating teams on the shared task CRF to contrast with our BERT-biLSTM-CRF. The results are reported in Table 5 alongside the results of

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5.3.2. Results

Table 5 shows the obtained results on the heart failure test set. We first report the results for our cross-domain feature-based approach, noted Features (en) for English and its cross-lingual version, noted Features (enfrnl) for all languages as well as our Vanilla-biLSTM-CRF baseline. We also list the official results of the shared task for all the participating teams. Finally, we report the results of our proposed approaches using BERT, BERT (NER), as well as BERT-biLSTM-CRF.

Overall, our achieved results on the test sets follow the observed results obtained on the development sets. Indeed, BERT for English, CamemBERT for French, and BERT-multi for Dutch obtained the best F1 scores, while BERT (NER) obtained the best precision. Our methods outperformed the baselines as well as the participating teams with a large margin for Dutch. Using cross-lingual transfer learning did not improve the results compared to BERT-multi (en) and BERT-multi (enfrnl). It also noticeably weakened the results for French. This can also be observed for the Features (enfrnl) baseline, where the results drop significantly. Finally, even if the BERT-BiLSTM-CRF is behind the classifier based-BERT model, it shows, however, noticeably better results than the Vanilla-biLSTM CRF, which highlights the substantial contribution of BERT embeddings as input features for the biLSTM for this task.

6. Analysis and Discussion

Table 6 represents the proportion of heart failure term types for BERT for different domain transfer configurations. Regardless of the training sets, we see that specific and common terms are the most captured elements. However, the overall scores and the high percentage of false positives indicate that there is still a big room for improvement. It should also be remarked that the named entities or out-of-domain terms categories are less represented in the training sets; making them harder to spot upon testing. The models’ training was

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It should be noted that this work focuses on BERT-based strategies, and these baselines were implemented solely for comparison’s sake.

Not all the teams submitted outputs for all languages.

See Table 5 in the supplementary material for details.
Table 6: Percentage of each term type in the true positives for BERT output list on the English heart failure test set with respect to transfer learning on different domains. The information about the other models can be found in the supplementary material.

|                  | English (BERT) | French (Camembert) | Dutch (BERT-multi) |
|------------------|----------------|-------------------|--------------------|
|                  | P   | R   | F1  | P   | R   | F1  | P   | R   | F1  |
| No filtering     | 34.75 | 71.23 | 46.71 | 40.71 | 68.81 | 51.15 | 63.76 | 42.55 | 51.04 |
| Patterns         | 34.88 | 70.11 | 46.58 | 40.83 | 67.94 | 51.01 | 64.59 | 42.24 | 51.08 |
| Specificity      | 53.74 | 54.64 | 54.18 | 57.65 | 48.30 | 52.57 | 66.21 | 21.78 | 32.04 |
| C-Value          | 48.08 | 61.02 | 53.78 | 55.10 | 58.78 | 56.88 | 83.58 | 39.90 | 54.01 |

Table 7: Results after filtering down our best models output lists using different filters, improving the results. For the pattern filtering, all terms that fit nominal patterns are kept. For the C-Value and the Specificity, we only keep the first half of the ordered filtered list.

Among the three proposed BERT-based approaches, the binary classification system obtained the best results. Varying the data sets revealed the effectiveness of cross-domain BERT fine-tuning and lent support the assumption that terms share cross-domain marked-contexts captured by BERT. This finding opens a new interesting line of research for ATE since the lack of training data can be reduced by using other specialized domains. Nonetheless, the results also revealed that using several training data sets does not necessarily guarantee better performance. We still have an unanswered question: how to choose the most appropriate training data sets? Regardless of the empirical improvements, it is worth highlighting the simplicity of our strategies, since neither feature engineering nor pattern design is needed. Besides that, observing BERT outputs underlined the presence of some inappropriate or ungrammatical term-like candidates. Post-filtering techniques proved to be remarkably helpful for improving the results.

7. Conclusion

In this paper, we proposed the first systematic study of BERT models for the ATE task on four low resource specialized domains in three languages. We experimented with BERT as a binary classifier, and as a named entity recognition system, as well as a biLSTM-CRF trained on BERT features. The obtained empirical results indicate that BERT is able to transfer learning across do-

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10See Table 5 in the supplementary material for details.
mains and languages, opening a new promising direction for ATE.

8. Bibliographical References

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9. Appendix

Additional information is presented in this supplementary material. We first present models settings and the detailed statistics of the evaluation term lists of each domain and for each language. Then, we present additional BERT models evaluations through figures and extended tables.

9.1. Settings

9.1.1. BERT Settings

For the fine-tuning phase of BERT, we used the simple-transformers\footnote{https://github.com/ThilinaRajapakse/simpletransformers} library and its default parameters setting. For BERT as a binary classifier, we used only 1 epoch for fine-tuning, while for BERT as NER task, we used 4 epochs. Nonetheless, no significant impact on the results has been observed when using more epochs.

9.1.2. BiLSTM-CRF Hyperparameters

As for our BiLSTM-CRF, we choose 150 hidden units for the BiLSTM, and 100 in the ReLU activated hidden layer, depending on the validation set performance. In a similar fashion to others who used word embeddings like GloVe\footnote{Pennington et al., 2014} or fastText\footnote{Bojanowski et al., 2017} as their input, we use the last layer of pre-trained bert-base-cased (EN), CamemBERT (FR) and bert-base-multilingual-cased-dutch (NL) as BERT embeddings. The model was built using Keras and trained with a batch size of 64, for 10 epochs.

9.1.3. Infrastructure and Average Runtime

Our models are trained using a GeForce RTX 2080 GPU, for about 6 minutes per run for BERT, 4 minutes for BERT (NER) and 20 minutes for the BiLSTM-CRF.

| Domain      | # ST | # CT | # NE | # OOD | Total |
|-------------|------|------|------|-------|-------|
| corruption  | en   | 278  | 644  | 248   | 1174  |
|             | fr   | 300  | 678  | 236   | 1217  |
|             | nl   | 310  | 731  | 249   | 1295  |
| dressage    | en   | 780  | 309  | 421   | 1575  |
|             | fr   | 705  | 238  | 221   | 1183  |
|             | nl   | 1026 | 333  | 153   | 1546  |
| wind energy | en   | 781  | 296  | 444   | 1534  |
|             | fr   | 444  | 308  | 195   | 968   |
|             | nl   | 577  | 342  | 305   | 1245  |
| heart failure| en  | 1885 | 320  | 228   | 2585  |
|             | fr  | 1714 | 505  | 147   | 2423  |
|             | nl  | 1561 | 450  | 182   | 2257  |

Table 8: Number of unique terms per corpus in three languages. Numbers are given for each type of terms: ST for Specific Terms, CT for Common Terms, NE for Named Entities, and OOD for Out of Domain terms. Total covers all the terms.

9.2. Results

In this section, we provide extensive and more comprehensive tables and experiments that we were unable to add to the main paper due to a lack of space. In Table 9, we show ATE scores for each validation corpus. In addition to the BERT models presented in the paper, we also contrast our results with extra models. Tables 10 and 11 show cross-domain and cross-lingual results in more details, on the validation sets as well as on the test set. Table 12 shows for each term type in the output list, its proportion in the gold standard, and corpus used for training for the heart failure English test set. These precise percentages can be found in Table 12. We can see that even if a term type is sometimes less represented in the training corpus, BERT (base and multi) often do a good job retrieving it. Figure 2 suggests that transfer learning for ATE is domain sensitive and that a careful choice of training data sets is undoubtedly needed for better performance since more training data does not always rhyme with better performances.
Figure 1: Proportion (%) of each term type in the output list, the gold standard, and corpus used for training for the heart failure English test set. The proportion of out-of-domain terms in the training corpus is so small, it often looks like there are none. These precise percentages can be found in Table 12.
Figure 2: Illustration of BERT, BERT-multi and BERT (NER) models outputs, with regards to term types for the heart failure test sets and for all combinations of the training sets.
|                | Corp |          |          | Equi |          |          | Wind |          |          |
|----------------|------|----------|----------|------|----------|----------|------|----------|----------|
|                | P    | R        | F1       | P    | R        | F1       | P    | R        | F1       |
| BERT           | 29.46| 49.45    | 36.79    | 30.76| 71.61    | 42.94    | 21.87| 74.03    | 33.73    |
| distilbert-base-cased | 29.07| 51.4     | 37.08    | 31.09| 72.15    | 43.42    | 22.32| 73.06    | 34.16    |
| BERT-multi     | 25.47| 58.21    | 35.25    | 27.87| 71.94    | 40.15    | 22.92| 74.51    | 34.94    |
| distilbert-base-multi-cased | 24.54| 59.29    | 34.68    | 27.46| 72.15    | 39.76    | 22.56| 74.16    | 34.56    |
| bert-large-cased | 28.21| 52.53    | 36.42    | 31.11| 70.5     | 43.02    | 21.86| 74.87    | 33.63    |
| RoBERTa        | 26.85| 62.53    | 37.33    | 29.17| 75.59    | 42.03    | 20.93| 77.08    | 32.91    |
| BERT (NER)     | 52.92| 22.46    | 31.48    | 54.45| 32.63    | 40.81    | 35.48| 23.66    | 28.39    |
| BERT-multi (NER) | 34.09| 11.51    | 17.21    | 13.41| 14.67    | 14.01    | 11.14| 18.58    | 13.93    |
| RoBERTa (NER)  | 31.91| 10.22    | 15.48    | 49.39| 28.44    | 36.11    | 32.48| 23.08    | 26.98    |
| distilroberta-base | 26.79| 55.5     | 35.89    | 27.29| 73.52    | 39.77    | 19.99| 75.12    | 31.56    |
| BERT-biLSTM-CRF | 22.61| 18.98    | 20.63    | 20.65| 16.03    | 18.05    | 21.04| 23.31    | 22.11    |

|                | P    | R        | F1       | P    | R        | F1       | P    | R        | F1       |
| French         |      |          |          |      |          |          |      |          |          |
| BERT-multi     | 27.53| 53.03    | 35.91    | 21.17| 60.77    | 31.35    | 13.82| 68.99    | 22.97    |
| distilbert-base-multi-cased | 25.11| 56.06    | 34.62    | 19.53| 62.47    | 29.75    | 13.21| 67.9     | 22.09    |
| CamemBERT      | 29.73| 62.61    | 40.25    | 24.38| 65.89    | 35.53    | 15.63| 72.51    | 25.71    |
| BERT-multi (NER) | 39.17| 11.59    | 17.89    | 42.83| 20.20    | 27.45    | 23.22| 25.93    | 24.5     |
| CamemBERT (NER) | 42.61| 12.33    | 19.13    | 48.01| 23.33    | 31.40    | 24.09| 24.48    | 24.28    |
| BERT-biLSTM-CRF | 18.78| 16.21    | 17.40    | 18.53| 19.08    | 19.76    | 17.20| 20.72    | 18.79    |

|                | P    | R        | F1       | P    | R        | F1       | P    | R        | F1       |
| Dutch          |      |          |          |      |          |          |      |          |          |
| BERT-multi     | 23.70| 68.59    | 35.21    | 30.39| 63.85    | 41.10    | 15.85| 66.55    | 25.52    |
| distilbert-base-multi-cased | 21.69| 69.82    | 33.09    | 28.32| 64.99    | 39.39    | 15.61| 65.54    | 25.19    |
| BERT-multi (NER) | 40.93| 15.68    | 22.67    | 65.25| 32.79    | 43.65    | 37.41| 38.31    | 37.85    |
| BERT-biLSTM-CRF | 20.51| 21.75    | 21.11    | 21.17| 18.90    | 19.97    | 21.70| 15.28    | 17.93    |

Table 9: ATE scores (%) in terms of Precision (P), Recall (R) and F1-score (F1). For each validation corpus, the two remaining ones were used for fine-tuning. We contrast 3 usages of BERT: as a binary classifier, BERT-NER and BERT embeddings used with a biLSTM-CRF. We also contrast BERT’s multi-lingual version as well as RoBERTa for English and Camembert for French (This table is similar to Table 2 of the main paper with extra models such distilbert and Roberta-large).
|        | English          |                    |                |                |
|--------|------------------|-------------------|----------------|----------------|
|        | Test             | Train             | Equi           | Wind           |
| Corp   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   | 35.33            | **38.01**         | 36.79          |                |
| BERT-multi | 35.09          | **35.56**         | 35.25          |                |
| RoBERTa | 36.16           | **39.97**         | 37.33          |                |
| BERT (NER) | 15.97           | 22.18             | **31.48**      |                |
| BERT-biLSTM-CRF | 20.54       | 19.01             | **20.63**      |                |

| Equi   |                  | Wind              | Equi + Wind    |
| BERT   | 39.93            | **44.21**         | 42.94          |
| BERT-multi | 38.93           | **40.54**         | 40.15          |
| RoBERTa | 42.07           | **44.99**         | 42.03          |
| BERT (NER) | 38.55           | 41.74             | 40.81          |
| BERT-biLSTM-CRF | 17.65       | 19.51             | 18.04          |

| Wind   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   | 33.45            | 33.34             | **33.73**      |                |
| BERT-multi | 34.04           | **35.59**         | 34.94          |                |
| RoBERTa | **36.16**       | 33.77             | 32.91          |                |
| BERT (NER) | **30.58**       | 26.89             | 28.39          |                |
| BERT-biLSTM-CRF | 19.99       | 20.64             | **22.11**      |                |

|        | French           |                    |                |                |
|        | Test             | Train             | Equi           | Wind           |
| Corp   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | 34.84          | 35.71             | **35.91**      |                |
| CamemBERT | 34.87           | 39.07             | **40.25**      |                |
| CamemBERT (NER) | 18.71           | **19.99**         | 19.13          |                |
| BERT-biLSTM-CRF | **18.04**   | 16.66             | 17.40          |                |

| Equi   |                  | Wind              | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | 27.64          | **32.88**         | 31.35          |                |
| CamemBERT | 32.73           | 32.22             | **35.53**      |                |
| CamemBERT (NER) | **34.09**      | 31.62             | 31.4           |                |
| BERT-biLSTM-CRF | 18.96          | 19.21             | **19.76**      |                |

| Wind   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | **24.12**       | 23.37             | 22.97          |                |
| CamemBERT | **26.78**       | 24.57             | 25.71          |                |
| CamemBERT (NER) | **30.35**      | 22.54             | 24.28          |                |
| BERT-biLSTM-CRF | 18.40          | 17.97             | **18.79**      |                |

|        | Dutch            |                    |                |                |
|        | Test             | Train             | Equi           | Wind           |
| Corp   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | 29.91          | **35.52**         | 35.21          |                |
| BERT (NER) | **32.42**       | 27.62             | 22.67          |                |
| BERT-biLSTM-CRF | 19.09          | 20.22             | **21.11**      |                |

| Equi   |                  | Wind              | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | 37.52          | **41.42**         | 41.1           |                |
| BERT (NER) | **46.36**       | 41.51             | 43.65          |                |
| BERT-biLSTM-CRF | 19.14          | **21.20**         | 19.97          |                |

| Wind   |                  | Equi              | Wind           | Equi + Wind    |
| BERT   |                  |                    |                |                |
| BERT multi | **26.11**       | 24.8              | 25.52          |                |
| BERT (NER) | **36.74**       | 35.86             | **37.85**      |                |
| BERT-biLSTM-CRF | 16.29          | **19.83**         | 17.93          |                |

Table 10: Domain transfer results (F1%) of ATE on the English, French and Dutch data sets (This table is the extension of Table 3 of the main paper)
|        | English          |          |          |          |          |          |          |
|--------|------------------|----------|----------|----------|----------|----------|----------|
| Test   | hf               | Train    |          |          |          |          |          |
|        | Corp             | Equi     | Wind     | corp+equi| corp+Wind| equi+Wind| All      |
| BERT   | 43.25            | 45.10    | 46.21    | 45.40    | 45.35    | 48.21    | 46.42    |
| BERT-multi (en) | 40.62 | 43.39    | 43.70    | 43.39    | 42.91    | 45.22    | 45.77    |
| BERT-multi (enfrnl) | 40.92 | 43.81    | 44.71    | 43.62    | 44.11    | 46.29    | 45.37    |
| RoBERTa| 41.75            | 44.87    | 44.6     | 44.15    | 43.58    | 44.71    | 43.35    |
| BERT-biLSTM-CRF | 24.28 | 26.57    | 28.27    | 25.22    | 26.92    | 29.93    | 29.26    |

Table 11: Heart failure test results (F1%) using cross-domain and cross-lingual (enfrnl) training. Equi+Wind means that we fine-tuned BERT on the combination of equitation and wind energy data sets. BERT-multi (enfrnl) means that the training was conducted using three languages.

|        | Domains          |          |          |          |          |          |
|--------|------------------|----------|----------|----------|----------|----------|
|        | Occ. in Training Set | Corp | Equi | Wind | Corp+Equi | Corp+Wind | Equi+Wind | Corp+Equi+Wind |
| Specific Terms | 7.11 | 94.39 | 41.50 | 84.04 | 30.30 | 82.86 | 75.65 |
| Common Terms   | 52.00 | 4.73 | 46.95 | 10.34 | 48.59 | 13.93 | 17.56 |
| Named Entities | 40.85 | 0.82 | 11.40 | 5.56 | 20.98 | 3.12 | 6.71 |
| OOD Terms      | 0.02 | 0.04 | 0.14 | 0.04 | 0.10 | 0.06 | 0.06 |
| BERT           | 81.67 | 76.47 | 82.58 | 76.36 | 82.04 | 77.48 | 73.44 |
| Specific Terms | 81.19 | 71.15 | 69.27 | 73.98 | 80.56 | 65.83 | 74.60 |
| Common Terms   | 59.73 | 53.09 | 63.71 | 61.06 | 58.84 | 58.40 | 57.96 |
| Named Entities | 68.15 | 42.03 | 71.33 | 63.05 | 64.96 | 42.03 | 33.75 |
| OOD Terms      | 27.93 | 31.01 | 25.33 | 25.65 | 32.12 | 28.67 | 29.47 |
| BERT-NER       | 81.67 | 76.47 | 82.58 | 76.36 | 82.04 | 77.48 | 73.44 |
| Specific Terms | 81.19 | 71.15 | 69.27 | 73.98 | 80.56 | 65.83 | 74.60 |
| Common Terms   | 59.73 | 53.09 | 63.71 | 61.06 | 58.84 | 58.40 | 57.96 |
| Named Entities | 68.15 | 42.03 | 71.33 | 63.05 | 64.96 | 42.03 | 33.75 |
| OOD Terms      | 27.93 | 31.01 | 25.33 | 25.65 | 32.12 | 28.67 | 29.47 |
| BERT-multi     | 79.60 | 79.39 | 73.92 | 78.81 | 79.81 | 76.84 | 79.76 |
| Specific Terms | 73.66 | 73.04 | 74.29 | 73.66 | 73.04 | 66.77 | 68.65 |
| Common Terms   | 61.94 | 59.29 | 53.53 | 60.61 | 56.63 | 50.31 | 61.06 |
| Named Entities | 64.96 | 59.23 | 38.21 | 44.58 | 61.78 | 50.31 | 52.22 |

Table 12: Percentage of each term type in the true positives list for BERT, BERT-NER and BERT-multi outputs on the English heart failure test set in respect to transfer learning on different domains. The top part of the table shows (in %) how well each type is represented in the training data.