Acronym Extraction and Acronym Disambiguation Shared Tasks at the Scientific Document Understanding Workshop 2022

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Abstract

Acronyms are short forms of longer phrases that facilitate the communication, specifically in technical domain that are replete with lengthy phrases. Due to the prevalence of acronyms in various types of documents, it is useful for document understanding systems to have the capability of correctly processing acronyms in text. More specifically, a system should be capable of recognizing the acronym and their long-forms in text (i.e., acronym extraction) and also to provide the correct meaning for the acronyms in case their long-form is missing from the document (i.e., acronym disambiguation). Due to their importance, both acronym extraction (AE) and acronym disambiguation (AD) are studied in the literature. However, the prior works are limited to English and specific domains (e.g., biomedical). To address this limitations, we introduce new resources for AE and AD in multiple languages and domains. Moreover, we organized two shared tasks on multilingual and multi-domain AE and AD. This paper gives an overview of the proposed resources and the participating systems in both shared tasks.

Keywords

Acronym Extraction, Acronym Disambiguation, Multi-lingual, Scientific Document Understanding

1. Introduction

Technical documents are normally replete with domain-specific phrases that might be lengthy to repeat in every mention. As such, to facilitate communication, acronyms are heavily employed in technical writing. Concretely, an acronym is defined as a shortened form of a longer phrases and consists of few letters selected from the long phrase. Using acronyms saves space and could help the audience to more easily read the documents. However, they might also propose challenges for those that are not familiar with the meaning of the acronym. The acronyms that are not defined in a technical document prevent the efficient communication of concepts due to lack of clarity. Therefore, providing the meaning for acronyms is an important requirement for any technical document to avoid any confusion about the concepts mentioned in the document. Manual glossaries could be an option to address this limitation. However, they might not be complete and also preparing them takes considerable amount of time in case the number of acronyms in the document are huge. Thus, automatic processing of acronyms is highly demanded to facilitate writing and reading technical documents. Both AE and AD models could be used in downstream applications including information extraction [1, 2] and question answering [3, 4]. Beyond AE, other related work looked at definition extraction [5, 6, 7, 8, 9] and mathematical symbol definition [10].

An automatic acronym understanding system should be able to recognize the mentions of the acronyms and their meanings in text. This task is called Acronym Extraction (AE). For instance, in the sentence "*All input features are encoded by the Long Short-Term Memory (LSTM) network*", an acronym, i.e., "*LSTM*", and a long-form, i.e., "*Long Short-Term Memory*", are provided. An AE system should be able to recognize the acronym and the long-form in the sentence. This task is normally modeled as a sequence classification. In particular, the input sentence is sent to a sequential model (e.g., Recurrent Neural Network (RNN)) to predict the boundaries for the acronym and the long-form. Another task that an automatic acronym understanding system should be capable is acronym disambiguation (AD). In this task, the goal is to provide the correct meaning for a given acronym in a sentence or paragraph while its long-form is missing from the context. For instance, in the sentence "*The event is fully covered by CNN*", the meaning of the acronym "*CNN*" is not provided in the context, therefore, an AD system is needed to find the correct meaning. Note that an acronym might refer to multiple meanings. For instance in the above mentioned example, the acrony "*CNN*" can be expanded to "*Cable News Network*" or "*Convolution Neural Network*". To correctly select the right meaning for an ambiguous acronym, an

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AD system should employ the context of the acronym and other information regarding different meanings of an acronym.

Due to the importance of both AD and AE, in the literature, there are various models proposed for each task. However, one limitation in the existing methods is that they are trained and evaluated on specific languages and domains. In particular, the majority of the existing AD and AE resources are limited to English and biomedical or general domain. As such, the. challenges of these tasks in other languages and domains are not adequately studied. To fill this gap, we present novel acronym extraction and disambiguation datasets that covers multiple languages and domains. In particular, for acronym extraction, we collect and manually annotate documents in scientific and legal domain in languages: English, Spanish, French, Danish, Persian and Vietnamese. For acronym disambiguation task, we collect and automatically annotate documents in scientific and legal domains in languages: English, Spanish and French. We also conduct two shared tasks on the proposed dataset. In Acronym Extraction shared task, 58 teams participates and in Acronym Disambiguation shared task 44 teams participates. This paper present the details of the dataset and the overview of the submitted systems for each task.

2. Related work

Acronym Extraction and Disambiguation are well known tasks for document understanding. In the last two decades, several methods have been proposed for AE or AD [11, 12, 13, 14, 15, 16, 17, 18]. Early works employed rule-based models. More specifically, a set of linguistic rules are defined to identify the acronyms and their long-forms in text. Schwartz and Hearst [13] proposed to identify the long-forms and their acronyms based on character match. That is, an acronym is labeled as the short-form of a phrase if there are a sequence of characters in the phrase that can form the acronym. Veyseh et al. [19] extended the Schwartz's rules by by identifying the acronyms that are not accompanied by their long form. Later, feature engineering methods and deep learning have been also employed for acronym extraction [20, 21]. Acronym disambiguation have been also extensively studied in the literature. This task can be modeled as a supervised classification task [22, 23, 24, 25, 26, 27]. Also, Zero-shot models, in which the long-forms of the acronym in test set are not seen by the models, have been proposed [19].

Moreover, in addition to the shared tasks presented in this work, SDU@AAAI-21 also hosted two shared tasks on acronym identification and disambiguation. In these shared tasks, the winning solutions employed deep learning models based on BERT transformer to encode the sentence and identify and find the correct meaning of the ambiguous acronyms [28].

Despite all progress so far on AD and AE, the majority of the prior works are trained and evaluated on limited domains and languages. In particular, English and Biomedicine are the predominant language and domain for these tasks. This is a shortcoming as the challenges for AD and AE in other domains and languages are not adequately studied. To address this limitation, in this work, we propose a large scale acronym extraction and disambiguation dataset in multiple languages and domains.

3. Acronym Extraction

We collect information in two spaces of legitimate and logical records for AE explanation. For each space, archives totally different dialects are required. As such, for the legitimate space, we utilize the Joined together Countries Parallel Corpus (UNPC) [29] and the Europarl corpus [30]. The UNPC corpus contains official records in 6 dialects whereas the Europarl corpus comprises of the procedures of the European Parliament in European dialects. To suit our comment budget and differentiate the coming about dataset, we select reports from four dialects within the two corpora (i.e., English, French, and Spanish in UNPC, and Danish in Europarl) for our AE explanation. In expansion, for the scientific domain, we utilize the freely accessible papers and M.S./Ph.D. theses within the field of computer science for AE explanation. Particularly, we collect the papers distributed within the ACL collection of common dialect handling inquire about for English. Also, for typologically different languages, we crawl public computer science thesis in Persian and Vietnamese.

To annotate the data, we hire freelancers from Upwork. The workers are fluent in the target language and have experience in data annotation. For a sentence in a dialect, we as it were comment on long shapes that are within the same dialect as the sentence's. A short time later, for each dialect, we hold two candidates who pass and accomplish most elevated comes about in our planned test for AE as our official annotators. Following, the two annotators in each dialect autonomously perform AE explanation for the inspected sentences of that dialect. At long last, the two annotators will examine to resolve any difference within the comment, hence creating a last adaptation of our MACRONYM dataset [31]. The dataset statistics and agreement scores are presented in Table 1.

We conduct a shared task on Acronym Extraction at SDU@AAAI-22 workshop. In this shared task, 58 teams participated in the task. Among which, 9 teams submit their systems in the test phase. Table 2 shows the performance of the participating systems in the test phase. Among all participating teams, "*WENGSYX*" achieve the

Domain & Language		IAA	Size	# Unique Acronyms	# Unique Long-forms
Legal	English	0.824	4,000	3,688	3,037
	Spanish	0.810	6,400	4,059	4,437
	French	0.823	8,000	5,638	5,728
	Danish	0.810	3,000	907	923
Scientific	English	0.811	4,000	3,604	4,260
	Persian	0.782	1,000	641	203
	Vietnamese	0.791	800	270	61

Table 1
Statistics of Acronym Extraction dataset. IAA scores use Krippendorff's alpha with MASI distance based on initial independent annotations. Size refers to the number of annotated sentences.

Team	Language-Domain	P	R	F1
	English-Legal	0.87	0.90	0.88
	Spanish-Legal	0.90	0.91	**0.91**
	French-Legal	0.93	0.92	0.92
WENGSYX	Danish-Legal	0.95	0.98	**0.96**
	Persian-Scientific	0.76	0.82	**0.79**
[32]	Vietnamese-Scientific	0.85	0.82	**0.84**
[33]	English-Scientific	0.85	0.87	0.86
	English-Legal	0.84	0.89	0.87
	Spanish-Legal	0.90	0.91	0.90
	French-Legal	0.81	0.80	0.81
fazlfrs	Danish-Legal	0.78	0.84	0.81
	Persian-Scientific	0.92	0.43	0.59
[35]	Vietnamese-Scientific	0.37	0.36	0.36
	English-Scientific	0.80	0.86	0.83
	English-Legal	0.88	0.91	0.90
	Spanish-Legal	0.90	0.90	0.90
	French-Legal	0.92	0.93	0.93
LiSiheng	Danish-Legal	0.95	0.95	0.95
	Persian-Scientific	0.69	0.53	0.60
[36]	Vietnamese-Scientific	0.96	0.62	0.76
	English-Scientific	0.89	0.89	0.89
	English-Legal	0.87	0.91	0.89
	Spanish-Legal	0.90	0.90	0.90
nithishkannen	French-Legal	0.94	0.95	**0.94**
	Danish-Legal	0.95	0.97	0.96
[34]	Vietnamese-Scientific	0.83	0.84	0.83
	English-Scientific	0.83	0.88	0.86
	English-Legal	0.78	0.81	0.80
	Spanish-Legal	0.87	0.90	0.88
	French-Legal	0.77	0.76	0.77
uyaseen	Danish-Legal	0.89	0.90	0.89
	Persian-Scientific	0.58	0.54	0.56
[37]	Vietnamese-Scientific	0.48	0.67	0.56
	English-Scientific	0.75	0.74	0.74
	English-Legal	0.75	0.69	0.72
	Spanish-Legal	0.65	0.65	0.65
	French-Legal	0.68	0.59	0.63
dipteshkanojia	Danish-Legal	0.78	0.70	0.74
	Persian-Scientific	0.64	0.51	0.57
[38]	Vietnamese-Scientific	0.64	0.66	0.65
	English-Scientific	0.77	0.69	0.73
	English-Legal	0.90	0.42	0.57
	Spanish-Legal	0.92	0.49	0.64
guneetsk99	French-Legal	0.89	0.35	0.50
	Danish-Legal	0.90	0.45	0.60
	English-Scientific	0.90	0.48	0.62
TC_AI_Lab	Danish-Legal	0.09	0.06	0.07
shihanmax	English-Legal	0.90	0.92	**0.91**
	English-Scientific	0.89	0.92	**0.90**

Table 2
Performance of the participating teams in test phase of acronym extraction task, in terms of precision, recall and F1. The highest F1 score for each Language-Domain is in bold-face.

highest score on four language-domain pairs (Spanish and Danish in legal and Persian and Vietnamese in scientific domains). This model [32, 33] employs an adversarial training strategy. In particular, two methods are employed for extracting the acronym and long-forms: (1) Sequence labeling, the task is modeled as sequence classification in BIO format. To this end, a BILSTM+CRF model is employed. (2) Spand Detection: In this method the acronyms and long-forms spans are directly predicted by the transformer-based model. "*shihanmax*" achieve best performance on English test set for both scientific and legal domain, and "*nithishkannen*" has the highest score on French legal domain. This model [34] employs character-level BERT model to address the out-of-vocabulary issues which is restricting for acronym extraction.

From Table 2, is is evident that the performance of the models in scientific domain is lower than their performance on legal domain. This performance drop indicates the challenges in the scientific domain. Also, the lower performance of the models in non-English languages, specifically Persian and Vietnamese, reveal the challenging nature of AE in non-English languages.

4. Acronym Disambiguation

In addition to AE, an acronym understanding system should be able to find the correct meaning of the acronyms that are not accompanied with their long-form. To evaluate the performance of the systems for this task, we automatically construct a dataset for acronym disambiguation task. More specifically, given the annotations for the AE dataset, for every acronym in a document that is expanded to a long-form, we employed its provided long-form as the label for any other mention of the acronym in the given document (i.e., one meaning per discourse assumption). Using this approach, we construct a dataset on English (legal and scientific domain), French - Legal and Spanish - Legal. The statistics of the dataset are presented in Table 4. In this shared task, "*WENGSYX*" achieve the highest score on all languages and domains. In this model [39, 40] a multi-choice approach is employed for acronym disambiguation. In particular, the input sentence containing the ambiguous acronym along with all possible expansions are provided to the model via different channels. Each expansion is scorees separately. Finally a unified model is employed to select the expansion with the highest score. From Table 4, it is evident that models obtain higher score on English Scientific compared to other splits (i.e., legal test sets). This

Team	Language-Domain	P	R	F1
WENGSYX [39, 40]	English-Legal	0.94	0.87	**0.90**
	French-Legal	0.89	0.79	**0.84**
	Spanish-Legal	0.91	0.85	**0.88**
	English-Scientific	0.97	0.94	**0.96**
csyantins	English-Legal	0.82	0.80	0.81
	French-Legal	0.85	0.73	0.78
	Spanish-Legal	0.88	0.79	0.83
	English-Scientific	0.95	0.90	0.93
ghsong [41]	English-Legal	0.86	0.77	0.81
	French-Legal	0.81	0.72	0.76
	Spanish-Legal	0.86	0.77	0.81
	English-Scientific	0.88	0.82	0.85
TianHongZXY [42]	English-Legal	0.79	0.64	0.70
	French-Legal	0.76	0.70	0.73
	Spanish-Legal	0.83	0.80	0.81
	English-Scientific	0.81	0.77	0.79
TTaki	English-Legal	0.78	0.57	0.66
	French-Legal	0.73	0.64	0.68
	Spanish-Legal	0.76	0.66	0.70
	English-Scientific	0.81	0.69	0.75
mozhiwen	English-Legal	0.75	0.61	0.67
	French-Legal	0.72	0.63	0.67
	Spanish-Legal	0.86	0.80	0.83
	English-Scientific	0.79	0.69	0.74
Decalogue [43]	English-Scientific	0.71	0.60	0.65
sherlock314159 [44]	English-Legal	0.70	0.59	0.64
kumudlakara	English-Legal	0.74	0.45	0.56
	Spanish-Legal	0.62	0.35	0.45
	English-Legal	0.73	0.56	0.63
AbhayShukla	English-Legal	0.78	0.47	0.58
	French-Legal	0.70	0.49	0.57
	Spanish-Legal	0.77	0.54	0.64
	English-Scientific	0.73	0.52	0.61
kyspid	English-Legal	0.98	0.04	0.07
	English-Scientific	0.86	0.26	0.40

Table 3
Performance of the participating teams in test phase of the acronym disambigaution task, in terms of precision, recall and F1. The highest F1 score for each language-domain is in bold-face.

Language & Domain	Train	Dev	Test
English - Legal	2949	385	383
English - Scientific	7532	894	574
French - Legal	7851	909	813
Spanish - Legal	6267	818	862

Table 4
Statistics of acronym disambiguation dataset

higher performance indicates that in scientific domain, the acronyms are less ambiguous than the legal domain.

Using the prepared dataset, we conduct a shared task on acronym disambiguation at SDU@AAAI-22 workshop. In this shared task, 44 teams participated. Among which, 11 teams submitted their system in the test phase. Table 3 shows the performance of the participating teams in the test phase.

5. Conclusion

In this work, we presented two new acronym understanding resources in multiple languages and domains. In particular, we presented manually annotated acronym extraction dataset in two domains of scientific and legal documents and in six languages of English, Spanish, French, Danish, Persian, and Vietnamese. Moreover, we presented a novel automatically annotated dataset for acronym disambiguation in scientific and legal domain and in English, Spanish, and French. Using the proposed dataset, we conduct two shared tasks on acronym extraction and disambiguation. For each task, 9 and 11 teams participates in different domains and language. The performance of the winning systems, especially in non-English languages and legal domain, indicates the necessity of further research on this task.

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