Multilingual Ontology Merging Using Cross-lingual Matching

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***Abstract*—With the growing amount of multilingual data on the Semantic Web, several ontologies (in different natural languages) have been developed to model the same domain. Creating multilingual ontologies by merging such monolingual ones is important to promote semantic interoperability among different ontologies in different natural languages. This is a step towards achieving the multilingual Semantic Web. In this paper, we propose MULON, an approach for merging monolingual ontologies in different natural languages producing a multilingual ontology. MULON approach comprises three modules; *Preparation Module*, *Merging Module*, and *Assessment Module*. We consider both classes and properties in the merging process. We present three real-world use cases describing the usability of the MULON approach in different domains. We assess the quality of the merged ontologies using a set of predefined assessment metrics. MULON has been implemented using Scala and Apache Spark under an open-source license. We have compared our cross-lingual matching results with the results from the Ontology Alignment Evaluation Initiative (OAEI 2019). MULON has achieved relatively high precision, recall, and F-measure in comparison to three state-of-the-art approaches in the matching process and significantly higher coverage without any redundancy in the merging process.**

***Index Terms*—ontology merging, cross-lingual matching, multilingual ontology, quality assessment, knowledge management**

I. Introduction

Ontologies are being widely used in various fields of science such as information retrieval, question-answering, document retrieval, and text summarization. With the rapid expansion of multilingual data on the Semantic Web, more ontologies have become available in different natural languages. According to Linked Open Vocabularies (LOV)[1], English is by far the most prominent language, i.e., the majority of ontologies in the Semantic Web are in English, however, there are many ontologies in other Indo-European languages also exist. Specifically, out of a total of 720 vocabularies found in LOV, 533 are in English, 57 in French, and 34 in German. Few ontologies in LOV are in non-Indo-European languages, i.e. nine ontologies in Chinese and seven in Arabic. Some ontologies have been designed to model already existing domains in an independent way, which leads to ontologies with overlapping and redundant information. Although the Web of Data contains information in various natural languages and internationalization is one of the design goals of OWL standard (i.e., ontologies should handle multiple languages), it still lacks efficient mechanisms to automatically exploit and reconcile such information [19], [13]. Therefore, for building a multilingual web and enhancing semantic interoperability between ontologies in different natural languages, approaches for building multilingual ontologies by merging the existing ones must be developed [13], [29]. In multilingual ontologies, resources (classes and properties) can be published in a language-independent way, associated with language-dependent (linguistic) information, which supports access across various natural languages. Merging means creating a single ontology to provide a unified view of the input ontologies by maintaining all information contained in them [26]. The creation of such ontology is a complex task and requires considerable adaptation and rigorous techniques to control various steps of the creation, especially when merging ontologies in different natural languages. Identification of mappings between multilingual input ontologies, the first step in the merging process, plays a vital role in the ontology merging process [5]. Most of the existing work in ontology merging focuses only on English ontologies [24], [26], [2], without considering other ontologies in different natural languages. To the best of our knowledge, no work has been done for creating multilingual ontologies by merging ontologies in different natural languages. However, our previous work OECM [15], a fully automated ontology enrichment approach, creates a multilingual ontology from ontologies in different natural languages. OECM enriches an ontology from another one in a different natural language. We have identified two limitations in OECM; 1) only classes from the source ontology are added to the target ontology (i.e., properties are not considered), and 2) experts are needed for creating a reference ontology to evaluate the enrichment process, which is an infeasible task for large ontologies.

In this paper, we propose MULON (MULtilingual Ontology mergiNg) approach for creating a multilingual ontology by merging two ontologies, in different natural languages. As an illustration example, first, MULON identifies cross-lingual

[1]https://lov.linkeddata.es/dataset/lov/vocabs

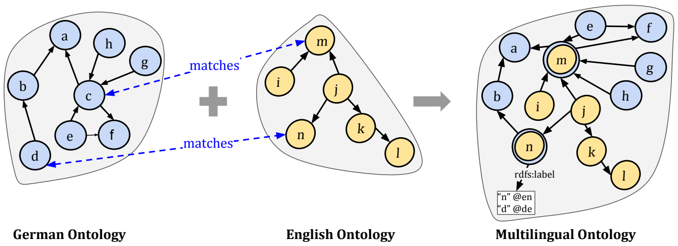

Fig. 1. An illustration of generating a multilingual ontology from merging German and English ontologies.

matches between input ontologies using cross-lingual matching techniques, then adds them to the merged multilingual ontology by adding `rdfs:label` for each language (using language-tagged strings) as shown in Figure 1. Cross-lingual matching helps to lower redundancy in the merged ontology. MULON comprises three modules: 1) *preparation module*, which extracts and processes resources of the input ontologies, 2) *merging module*, in which the match and the merge processes occur, and 3) *assessment module*, which validates and assesses the quality of the merged ontology. By providing such approach that enables researchers to easily integrate ontologies in different natural languages, MULON is an essential step in the direction of a multilingual Semantic Web. MULON is available in a public repository in GitHub[2], in which the source code is documented, describing each configurable parameter and function.

The contributions of this work can be summarized in the following points:

- We propose MULON to create a multilingual ontology by merging two ontologies in different natural languages based on linguistic and structure knowledge of these ontologies,
- We consider not only classes but also properties,
- MULON adapts a set of quality metrics to automatically assess not only the merged ontology but also any ontology,
- MULON considers ontologies in Indo and non-Indo-European languages,
- We present three real-world use cases demonstrating the usability of the MULON approach and showing its impact to the Semantic Web community, and
- MULON empirically showed significantly better results when compared to three state-of-the-art approaches.

The remainder of this paper is structured as follows: we present an overview of related work in section II. An overview of the proposed approach is described in section III. In order to illustrate the usability of MULON, three use cases are presented in section IV. Experiments and evaluation results are presented in section V. Finally, we conclude with an outline of the future work in section VI.

[2]https://smartdataanalytics.github.io/MULON/

II. Related Work

A recent review of the literature on multilingual Web of Data found that in order to support Multilingual Semantic Web, techniques for building multilingual ontologies are desired [13]. Bhatt [1] proposed an unsupervised learning algorithm to automatically learn multilingual ontology from unstructured text. Florrence and Lourdusamy [10], [18] developed an approach for building multilingual ontologies by 1) collecting terms in different natural languages for a specific domain from different resources, 2) creating identical monolingual ontologies based on these terms for each natural language, and 3) mapping and merging these monolingual ontologies. Merging different ontologies in different natural languages is a good solution for building multilingual ontologies. However, all the literature has focused on merging ontologies in the same natural language [2], without considering other ontologies in different natural languages. PROMPT [24] is one of the earliest tools in ontology merging, which utilizes a semi-automated approach for ontology merging based on linguistic and structural knowledge. PROMPT lets the user choose between merging suggestions. ATOM [26] is an automatic target-driven approach to merge large taxonomies such as product catalogs or web directories. It preserves the structure of the target taxonomy as much as possible. Fahad [5] has created an algorithm to map class expressions of concepts and merge them in an automatic ontology merging process. His algorithm addresses how to combine multiple axiomatic definitions into one compact definition considering the consistency of the merged solution.

In order to merge ontologies in different natural languages, cross-lingual ontology matching is required. Cross-lingual ontology matching techniques are used for matching linguistic information across ontologies [13], [29]. Fu et al. [11], [12] proposed an approach to match English and Chinese ontologies by considering the semantics of the target ontology, the mapping intent, the operating domain, the time and resource constraints, and user feedback. In the context of OAEI 2019 campaign[3] for evaluating ontology matching technologies, AML [6], LogMap [17] and Wiktionary Matcher [25] provide high-quality alignments for the matching task. AML [6] is based on lexical and structural matching algorithms. It utilizes machine translation technologies, such as Microsoft Translator, before starting the matching process. AML uses external biomedical ontologies and WordNet[4] as sources of background knowledge. LogMap [17] implements optimized data structures for lexically and structurally indexing the input ontologies for the matching process. It is an iterative process that starts from initial mappings (almost exact lexical correspondences) till discovering new mappings. Therefore, LogMap is not able to find matching between ontologies that do not provide enough lexical information. Wiktionary Matcher [25] is an element-level, label-based matcher which uses multiple language versions of Wiktionary. Good literature

[3]http://oaei.ontologymatching.org/2019/results/multifarm/index.html
[4]https://wordnet.princeton.edu/

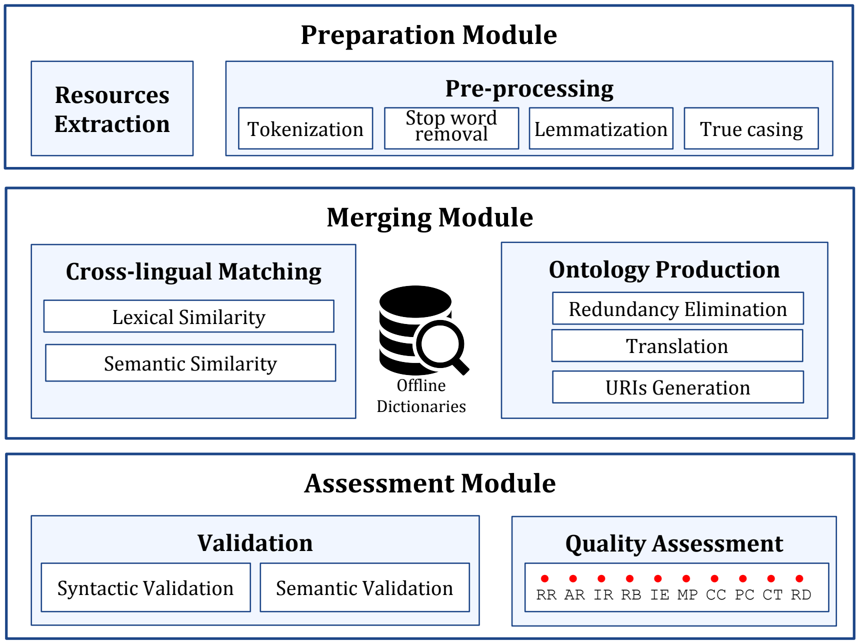

Fig. 2. MULON architecture

of the state-of-the-art approaches in cross-lingual ontology matching is provided in [29].

In summary, the major challenge faced by the ontology merging research is to design an automatic and consistent multilingual ontology merging approach that produces reliable (good quality) and usable multilingual merged ontology. We found that previous work has only focused on merging monolingual ontologies. Consequently, we propose an approach for merging monolingual ontologies to generate a multilingual ontology, where each resource is presented by more than one natural language.

III. MULON Architecture

The architecture of MULON is comprised of three modules namely, preparation, merging, and assessment (cf. Figure 2). In the following subsections, we describe each of these modules in detail. The input is two ontologies (O_1 and O_2) in two different natural languages L_1 and L_2 respectively. The output is 1) a multilingual merged ontology (O_m) and 2) an assessment sheet presenting the quality of the merged ontology.

A. Preparation Module

This module is responsible for extracting resources from the input ontologies and prepare them for further steps. Preparation module has two components:

Resources Extraction. The aim of this component is to extract all resources (both classes and properties) from the two input ontologies into the resources matrix R. R is a two-dimensional matrix ($n \times 4$), where n is the number of resources. Each row in R is represented as a tuple of $\langle$`resource, type, source, language`$\rangle$, which contains the resource label, the type of the resource ('C' for class and 'P' for property), the source ontology (O_1 or O_2), and the language tag. For more illustration, consider the tuple $\langle$`BestPosterAward, C,` O_1`, en`$\rangle$, in which the resource "BestPosterAward" is a class extracted from O_1 and its language is English. The output of this component is R.

Pre-processing. To prepare extracted resources for the next modules, all resources are processed by employing a variety of natural language processing techniques, such as stop words removal, tokenization, POS-tagging (part-of-speech tagging), and lemmatization. Normalization methods and regular expressions are used to remove stop words, punctuations, symbols, and additional white spaces. Furthermore, true casing techniques are used to recognize resources with camel cases, e.g., "BestPosterAward" and "isSponsorOf" became "Best Poster Award" and "is Sponsor Of" respectively. The output of this component is the pre-processed resources matrix (R').

B. Merging Module

This module is responsible for merging the two input ontologies into a new multilingual one O_m. Generally, there are two types of ontology merging [27]: a) *Symmetric merging*; which aims to integrate all resources (classes and properties) in the input ontologies to a single ontology, i.e. preserves all input resources (which is used in this paper), and b) *Asymmetric merging*; which considers one of the input ontologies as the target ontology and merges the remaining non-redundant resources of the input ontologies into the target ontology. Merging module has two components:

Cross-lingual Matching. The aim of this component is to identify potential matches between the extracted resources. We divide the ontology resources into two sets: classes and properties. We match only resources of the same set, i.e., classes in one ontology are matched with the classes of the other one. Additionally, we identify particular threshold values in the matching process to select the top matched results. Cross-lingual matches are identified using machine translation tools and similarity measures. Machine translation tools are able to return useful translations for a very large number of resources in the cross-lingual matching task [14]. We build offline dictionaries for all resources in R using Yandex translate API[5]. Such offline dictionaries reduce extra translation overhead that is produced when translating the same resources several times. Each resource in O_1 is translated from L_1 to L_2 and similarly, each resource in O_2 is also translated (to be used in merging). In order to identify the matched resources between O_1 and O_2, we perform a pairwise lexical and semantic similarity between resources of O_1 and the translated resources of O_2 (now both are in L_1). First, Jaccard similarity [23] is used to identify the identical resources in order to save extra computations that are produced when computing semantic similarity between already identical resources. We choose Jaccard similarity because it achieved the best score in terms of precision for the ontology alignment task for the MultiFarm benchmark in [3]. Second, semantic similarity is used to compute the similarity between non-identical resources (by Jaccard). For each pair of resources, the path length is computed, based on WordNet[4], which returns the shortest path between two words in WordNet hierarchy [4]. The output of this component is a matched resources matrix (M). M is a two-dimensional matrix ($m \times 4$), where m is the number of matched resources. Each row in M is represented as a tuple of $\langle$`resource(`O_1`), resource(`O_2`), type, simScore`$\rangle$, which contains a resource from O_1, a resource from O_2, type of the resources, and the similarity score between them. For example, $\langle$`Car, سيارة, C, 1.00`$\rangle$, i.e. "Car"in English and "سيارة"in Arabic are two resources of type class, from O_1 and O_2 respectively, with similarity score of 1.00.

Ontology Production. The aim of this component is to eliminate redundancy that might occur in the merged ontology. Therefore, the input ontologies have been merged based on linguistic and structural knowledge. First, we select matched resources, from M, with specific thresholds θ (for classes) and α (for properties) in order to get matched classes C_{match} and matched properties P_{match} respectively. Then, for each pair of matched resources (r_1,r_2), where $r_1 \in resource(O_1)$ and $r_2 \in resource(O_2)$, we merge these matched resources by representing them as r_m associated with the two labels of r_1 and r_2 with the corresponding language tags. For instance, consider the match $\langle$`hatWichtigesDatum, hasImportantDates, P, 1.00`$\rangle$, these two properties are merged and associated with English and German labels as $\langle$`hasImportantDates, rdfs:label, "has important dates"@en`$\rangle$ and $\langle$`hasImportantDates, rdfs:label, "hat wichtiges datum"@de`$\rangle$. For non-matched resources, we translate them, using the offline dictionaries, to the other language. Similarly, a new label with the other language tag is created. For instance, the non-matched resource "InvitedSpeakers" is translated to "EingeladeneReferenten" and associated with English and German labels as in the previous example. At this step, we have a multilingual ontology containing all information in both input ontologies.

C. Assessment Module

This module is responsible for validating and assessing the quality of the merged ontology.

Validation. The aim of this component is to validate the merged ontology, which is a crucial step to detect inconsistencies and syntax errors, which might be introduced during the merging process [7]. There are two types of validation: syntactic and semantic validation. In the syntactic validation, we validate O_m to conform with the W3C RDF standards using the online RDF validation service[6] which detects syntax errors, such as missing tags. For semantic validation, we have used FaCT++[7] reasoner for detecting inconsistencies in O_m.

Quality Assessment. The aim of this component is to assess the quality of the merged ontology. Evaluating the quality of the merged ontology strongly depends on the quality of the input ontologies. We assess the quality of the two input ontologies and the resulting merged ontology by adapting and reformulating the metrics defined in [28], [21], [27].

- *Relationship richness (RR)* [28]: refers to the diversity of relations and their position in the ontology. The more relations the ontology has (except `rdfs:subClassOf` relation), the richer it is. The quality score function $f_{RR}: O \rightarrow \mathbb{R}$ for an input ontology O is defined as follows:

$$f_{RR}(O) = \frac{|P_{obj}|}{|P_{subClassOf}| + |P_{obj}|} \tag{1}$$

  where P_{obj} represents the relationships (i.e. object properties) and $P_{subClassOf}$ represents the `rdfs:subClassOf` relations in O.
- *Attribute Richness (AR)* [28]: refers to how much knowledge about classes is in the schema. The more attributes are defined, the more knowledge the ontology provides. The quality score function f_{AR} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:

$$f_{AR}(O) = \frac{|P_{attr}|}{|C|} \tag{2}$$

  where C represents the ontology classes and P_{attr} represents the attributes (i.e., data properties) for all classes.
- *Inheritance Richness (IR)* [28]: refers to how well knowledge is distributed across different levels in the ontology. The more `rdfs:subClassOf` relations, the wider range of general knowledge the ontology provides. The quality score function f_{IR} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:

$$f_{IR}(O) = \frac{|P_{subClassOf}|}{|C|} \tag{3}$$

[5]https://tech.yandex.com/translate/

[6]https://www.w3.org/RDF/Validator/

[7]https://github.com/ethz-asl/libfactplusplus

- *Readability (RB)* [28]: refers to the existence of human-readable descriptions (HRD) in the ontology, such as comments, labels, or descriptions. The more HRD exists, the more readable the ontology is. The quality score function f_{RB} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:
$$f_{RB}(O) = \frac{|HRD|}{|R|} \tag{4}$$
where $HRD \in \{label, comment, description\}$ and R represents the ontology resources.
- *Isolated Elements (IE)* [21]: refers to classes and properties which are defined but not connected to the rest of the ontology, i.e. not used. The quality score function f_{IE} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:
$$f_{IE}(O) = \frac{|R_{isolated}|}{|R|} \tag{5}$$
where $R_{isolated}$ represents resources which are defined but not used in O.
- *Missing Domain or Range in Properties (MP)* [21]: refers to missing information about properties. The less of missing information about properties, the more the ontology is complete. The quality score function f_{MP} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:
$$f_{MP}(O) = \frac{|P_{incomplete}|}{|P|} \tag{6}$$
where $P_{incomplete}$ represents properties which do not have domain or range.
- *Redundancy (RD)* [27]: refers to how many redundant resources exist. Resources which are syntactically (e.g. "isMemberOf" and "is_member_of") or semantically (e.g. "Chair" and "Chairman") close are considered as redundant resources. The quality score function f_{RD} :O$\rightarrow \mathbb{R}$ for an input ontology O is defined as follows:
$$f_{RD}(O) = \frac{|R_r|}{|R|} \tag{7}$$
where R_r represents the redundant resources in O.

All the previous metrics can be used to assess the quality of any ontology. The following metrics are adapted in order to assess the quality of the merged ontology by comparing it with the input ontologies.

- *Class Coverage (CC)* [27]: refers to how many classes in the input ontologies (C_1+C_2) are preserved in the merged ontology (C_m) excluding matched classes (C_{match}). The more preserved classes exist, the more coverage the ontology provides. The quality score function f_{CC} :O$\rightarrow \mathbb{R}$ for the merged ontology O is defined as follows:
$$f_{CC}(O) = \frac{|C_m|}{|C_1| + |C_2| - |C_{match}|} \tag{8}$$
- *Property Coverage (PC)* [27]: refers to how many properties in the input ontologies are preserved in the merged ontology excluding matched properties P_{match}. The more preserved properties exist, the more coverage the ontology provides. The quality score function f_{PC} :O$\rightarrow \mathbb{R}$ for the merged ontology O is defined as follows:
$$f_{PC}(O) = \frac{|P_m|}{|P_1| + |P_2| - |P_{match}|} \tag{9}$$
where P_m, P_1, P_2 are properties of merged and two input ontologies respectively. P_{match} are the matched properties between the two input ontologies.
- *Compactness (CT)* [27]: refers to how much the size of the merged ontology compared to the combination of the two input ontologies. The smaller the size of merged ontology, the more the ontology is compacted, e.g. if some resources are removed in order to avoid redundant resources in the merged ontology. The quality score function f_{CT} :O$\rightarrow \mathbb{R}$ for the merged ontology O is defined as follows:
$$f_{CT}(O) = \frac{|R_m|}{|R_1| + |R_2|} \tag{10}$$
where R_m, R_1, R_2 are resources of merged and two input ontologies respectively.

At the end of this module, MULON provides the user with the resulting merged ontology O_m in addition to the assessment sheet which has the quality assessment results for the input and merged ontology.

IV. Impact and Use Cases

The main goal of MULON is to develop a generic approach which can merge monolingual ontologies into a multilingual ontology, offering algorithms for cross-lingual ontology matching, and automatically assess the quality of not only the merged ontology but, in principle, any ontology.

Impact on the Semantic Web Community. Ontologies occupy a key role in capturing space knowledge and providing a standard understanding of knowledge across different domains and different natural languages. Considering that ontologies often have overlapping and redundant information, MULON can be applied in numerous applications to effectively merge such ontologies. To validate this, we investigate use case implementations in several domains and projects below.

Fiscal Data. OpenBudgets[8] has build a platform to upload, visualize, and analyze fiscal data coming from different countries in different natural languages. Fiscal datasets are heterogeneous in nature, since they are published by various administrations. One of the major challenges faced in OpenBudgets, is to link concepts in different languages in order to analyze fiscal data [22]. OpenBudgets is currently investigating MULON for cross-lingual vocabulary matching. The vocabulary matching can allow automated cross-regional budget comparisons which was not easily possible before.

Food. AutoChef [16] is a framework for culinary arts. It takes input from well-rated recipes of different cuisines and invents new recipes by recombining the instructions, spices, and ingredients. AutoChef aims to extend their framework by

[8]http://openbudgets.eu/

TABLE I
STATISTICS OF ALL INPUT AND MERGED ONTOLOGIES.

	Ontology Name	Classes	Object Properties	Data Properties
Input	SEO	106	66	23
	$Ekaw$	74	33	0
	$Edas$	104	30	20
	$Conference$	60	46	18
	$ConfOf$	38	13	23
	Cmt	36	49	10
	$Iasted$	140	38	3
	$Sigkdd$	49	17	11
Merging Pairs	$Conference_{de} \times SEO_{en}$	156	103	40
	$Conference_{de} \times Ekaw_{en}$	121	78	18
	$ConfOf_{ar} \times Edas_{en}$	132	41	38
	$Cmt_{ar} \times Ekaw_{en}$	99	78	10
	$Iasted_{fr} \times Edas_{en}$	233	67	23
	$Sigkddfr \times Ekaw_{en}$	118	51	11

considering different kinds of recipes from different countries, i.e., in different natural languages. Therefore, at present, AutoChef is investigating MULON for merging recipe-ontologies into a multilingual ontology which can assist in the discovery of new ingredient relationships and deliver new recipes.

Scholarly Communication. Scientific events play a key role in publishing scholarly data on the Web. They are considered as the focal point for establishing scientific relations between scholarly objects in the scholarly communication domain. Scholarly events are organized by people from different countries, therefore event's related information, such as a call for papers and events topics, is published, in some cases, in different natural languages, particularly for local events [8]. To facilitate the management of such data, a multilingual integration approach is desired. MULON has successfully merged the Scientific Events Ontology[9] (SEO_{en}) [9], in English, which describes the scientific events, and the Conference ontology ($Conference_{de}$), in German, which exists in the MultiFarm dataset (see section V). Statistics for these ontologies and the merged ontology are presented in Table I. MULON was able to find nine matched classes and four matched properties between the two ontologies and remove duplicated resources in the merged ontology. The merged ontology was consistent and free of syntax errors. The merging process was free of redundancy and achieved significantly high results in terms of coverage and compactness. The produced merged ontology and the assessment sheet are available at the GitHub[2] repository.

V. EVALUATION

The aim of this evaluation is to measure the quality of the cross-lingual matching process in addition to the quality of the merged ontology. We use ontologies in MultiFarm[10], a benchmark designed for evaluating cross-lingual ontology matching systems. MultiFarm consists of seven ontologies (*Cmt*, *Conference*, *ConfOf*, *Iasted*, *Sigkdd*, *Edas*, and *Ekaw*) originally coming from the Conference benchmark of OAEI, translations of the first five ontologies (i.e., *Edas* and *Ekaw* are available in English only) into nine languages (Chinese, Czech, Dutch, French, German, Portuguese, Russian, Spanish and Arabic), and the corresponding cross-lingual alignments between them.

Experimental Setup. All modules of MULON have been implemented using Scala and Apache Spark[11] (available under Apache License 2.0) which is a distributed processing engine for large-scale data. SANSA-RDF library[12] [20] with Apache Jena framework[13] are used to parse and manipulate the input ontologies (as RDF triples) in a distributed manner. We used Apache Spark and SANSA-RDF library because we want to extend this work to merge large-scale ontologies efficiently (see section VI). In order to process the resource labels, the Stanford CoreNLP[14] is used. All experiments are carried out on Ubuntu 16.04 LTS operating system with an Intel Corei7-4600U CPU @ 2.10GHz x 4 CPU and 10 GB of memory. Our evaluation has two tasks: 1) comparing MULON matching results with three state-of-the-art approaches, and 2) evaluating the merged ontology.

Comparison with the state-of-the-art. We identified three state-of-the-art approaches (AML [6], LogMap [17], and Wikitionary Matcher [25]) to be included in our evaluation. The other related works, neither published their codes, nor evaluation data [12], [11]. In order to compare our results with the state-of-the-art, we use the five ontologies *Cmt*, *Conference*, *ConfOf*, *Iasted*, and *Sigkdd* in German, Arabic, and French, in addition to the two ontologies *Edas* and *Ekaw* in English as mentioned in the results of OAEI 2019[3]. We chose Arabic as a non-Indo European language to show the promising potential of MULON across different languages. *Edas* and *Ekaw* are available in English only because they are used for blind evaluation in OAEI. In order to translate such ontologies into German, Arabic, and French, experts will be needed for each language to validate such translations which makes this task is difficult to achieve. As we didn't participate in OAEI, we found that there is no need to translate them in order to avoid translation errors. Therefore, we consider all different ontology pairs in different languages where *Edas* or *Ekaw* are in English. Inspired by the information retrieval community, the quality of the matching process can be measured through precision, recall, and F-measure metrics. We use the gold standard alignments between each pair of ontologies which exist in the dataset in order to compute precision, recall, and F-measure. Precision is the fraction of the retrieved matched resources that are relevant, while recall is the fraction of relevant matched resources retrieved by MULON. The F-measure is the harmonic mean of precision and recall. Formally, precision is defined as $TP/(TP + FP)$ and recall is defined as $TP/(TP + FN)$, where TP (true positive) is the matching results which are retrieved by MULON and exist in the gold standard, FP (false positive) is the matching results which are retrieved by MULON and do

[9]https://w3id.org/seo
[10]https://www.irit.fr/recherches/MELODI/multifarm/
[11]https://spark.apache.org/
[12]https://github.com/SANSA-Stack/SANSA-RDF
[13]https://jena.apache.org/
[14]https://stanfordnlp.github.io/CoreNLP/

TABLE II
STATE-OF-THE-ART COMPARISON RESULTS. MULON* DESCRIBES RESULTS WITH ADJUSTED PRECISION AND F-MEASURE. RED ENTRIES ARE THE TOP SCORES FOR EACH METRIC PER ROW.

Ontology Pairs	AML			LogMap			Wiktionary			MULON			MULON*	
	P	R	F	P	R	F	P	R	F	P	R	F	P	F
$Cmt_{de} \times Edas_{en}$	1.00	0.31	0.47	0.80	0.31	0.44	0.83	0.38	0.53	0.64	0.58	0.61	0.88	0.70
$Cmt_{de} \times Ekaw_{en}$	0.80	0.36	0.50	1.00	0.36	0.53	0.75	0.27	0.40	1.00	0.45	0.63	1.00	0.63
$ConfOf_{de} \times Edas_{en}$	0.93	0.68	0.79	0.86	0.63	0.73	0.82	0.47	0.60	0.81	0.68	0.74	1.00	0.81
$ConfOf_{de} \times Ekaw_{en}$	0.92	0.60	0.73	0.93	0.65	0.76	0.80	0.40	0.53	0.92	0.58	0.71	1.00	0.73
$Conference_{de} \times Edas_{en}$	0.86	0.35	0.50	0.71	0.29	0.42	0.71	0.29	0.42	0.69	0.56	0.62	1.00	0.72
$Conference_{de} \times Ekaw_{en}$	0.56	0.20	0.29	0.71	0.20	0.31	0.83	0.20	0.32	0.85	0.44	0.58	1.00	0.61
$Iasted_{de} \times Edas_{en}$	0.38	0.16	0.22	0.43	0.16	0.23	0.67	0.21	0.32	0.86	0.32	0.46	1.00	0.48
$Iasted_{de} \times Ekaw_{en}$	0.83	0.50	0.63	0.75	0.60	0.67	0.60	0.30	0.40	1.00	0.60	0.75	1.00	0.75
$Sigkdd_{de} \times Edas_{en}$	0.75	0.40	0.52	0.63	0.33	0.43	0.67	0.27	0.38	0.67	0.40	0.50	0.86	0.55
$Sigkdd_{de} \times Ekaw_{en}$	1.00	0.45	0.63	1.00	0.45	0.63	0.83	0.45	0.59	1.00	0.55	0.71	1.00	0.71
$Cmt_{ar} \times Edas_{en}$	1.00	0.38	0.56	0.60	0.23	0.33	1.00	0.00	0.00	0.67	0.67	0.67	0.89	0.76
$Cmt_{ar} \times Ekaw_{en}$	1.00	0.27	0.43	1.00	0.27	0.43	1.00	0.00	0.00	1.00	0.45	0.63	1.00	0.63
$ConfOf_{ar} \times Edas_{en}$	0.86	0.32	0.46	0.86	0.32	0.46	1.00	0.11	0.19	0.73	0.58	0.65	1.00	0.73
$ConfOf_{ar} \times Ekaw_{en}$	1.00	0.60	0.75	1.00	0.60	0.75	1.00	0.10	0.18	0.91	0.56	0.69	1.00	0.71
$Conference_{ar} \times Edas_{en}$	0.71	0.29	0.42	0.40	0.12	0.18	1.00	0.00	0.00	0.62	0.50	0.55	0.89	0.64
$Conference_{ar} \times Ekaw_{en}$	0.60	0.24	0.34	0.40	0.08	0.13	1.00	0.00	0.00	0.78	0.28	0.41	1.00	0.44
$Iasted_{ar} \times Edas_{en}$	0.60	0.32	0.41	0.43	0.16	0.23	1.00	0.05	0.10	0.86	0.32	0.46	1.00	0.48
$Iasted_{ar} \times Ekaw_{en}$	0.57	0.40	0.47	1.00	0.30	0.46	1.00	0.10	0.18	1.00	0.57	0.73	1.00	0.73
$Sigkdd_{ar} \times Edas_{en}$	1.00	0.47	0.64	0.71	0.33	0.45	1.00	0.07	0.13	0.67	0.40	0.50	0.86	0.55
$Sigkdd_{ar} \times Ekaw_{en}$	1.00	0.27	0.43	1.00	0.27	0.43	1.00	0.09	0.17	1.00	0.36	0.53	1.00	0.53
$Cmt_{fr} \times Edas_{en}$	1.00	0.62	0.76	n/a	n/a	n/a	0.60	0.46	0.52	0.88	0.54	0.67	1.00	0.70
$Cmt_{fr} \times Ekaw_{en}$	1.00	0.27	0.43	0.80	0.36	0.50	0.67	0.36	0.47	0.80	0.36	0.50	1.00	0.53
$ConfOf_{fr} \times Edas_{en}$	0.90	0.47	0.62	0.73	0.42	0.53	0.73	0.42	0.53	0.58	0.58	0.58	1.00	0.73
$ConfOf_{fr} \times Ekaw_{en}$	1.00	0.70	0.82	1.00	0.60	0.75	0.67	0.30	0.41	0.91	0.50	0.65	1.00	0.67
$Conference_{fr} \times Edas_{en}$	0.57	0.24	0.33	0.43	0.18	0.25	0.57	0.24	0.33	0.64	0.44	0.52	0.88	0.58
$Conference_{fr} \times Ekaw_{en}$	0.55	0.24	0.33	0.50	0.20	0.29	0.50	0.16	0.24	0.73	0.32	0.44	1.00	0.48
$Iasted_{fr} \times Edas_{en}$	0.67	0.32	0.43	0.50	0.26	0.34	0.42	0.26	0.32	0.64	0.37	0.47	1.00	0.54
$Iasted_{fr} \times Ekaw_{en}$	0.67	0.40	0.50	0.63	0.50	0.56	0.63	0.50	0.56	0.57	0.40	0.47	1.00	0.57
$Sigkdd_{fr} \times Edas_{en}$	0.80	0.53	0.64	0.71	0.33	0.45	0.60	0.40	0.48	1.00	0.50	0.67	1.00	0.67
$Sigkdd_{fr} \times Ekaw_{en}$	1.00	0.55	0.71	1.00	0.36	0.53	0.86	0.55	0.67	1.00	0.45	0.63	1.00	0.63

not exist in the gold standard, and FN (false negative) is the matching results which exist in the gold standard and MULON could not retrieve them. Table II shows a comparison between MULON's results for matching 30 pair of ontologies against three state-of-the-art systems. Surprisingly, we found new alignments for 22 pair of ontologies which were missing in the gold standard, e.g., the German and English properties "ist Mitglied von" and "is a member of". MULON* represents results when considering the new alignments. It provides the matching results with the adjusted precision and F-measure. Therefore, MULON* presents results that are not false positive in practice. MULON outperforms most of the other systems in terms of precision, recall, and F-measure when not considering the new alignments as false positive. For instance, when matching $Conference_{de} \times Ekaw_{en}$, MULON outperforms Wikitionary Matcher, the highest precision, recall and F-measure among the others in matching German and English ontologies, by 17%, 22% and 29% in terms of precision, recall, and F-measure respectively. When matching $ConfOf_{ar} \times Edas_{en}$, MULON outperform AML and LogMap, the highest recall and F-measure among the others in matching Arabic and English ontologies, by 26% and 27% in terms of recall and F-measure respectively. When matching $Iasted_{fr} \times Edas_{en}$, MULON outperform AML, the highest precision, recall, and F-measure among the others in matching French and English ontologies, by 33%, 5%, and 11% in terms of precision, recall, and F-measure respectively.

Evaluating the merged ontology. In order to evaluate the merged ontology, we choose randomly five pairs of ontologies ($Conference_{de} \times Ekaw_{en}$, $ConfOf_{ar} \times Edas_{en}$, Cmt$_{ar}$ $\times$ $Ekaw_{en}$, Iasted$_{fr}$ $\times$ $Edas_{en}$, and Sigkdd$_{fr}$ $\times$ $Ekaw_{en}$) from Table II. We validate and assess the quality of the merging process using the assessment metrics described in subsection III-C. We found that all merged ontologies are consistent and free of syntax errors. Table III shows the assessment results for each output ontology. MULON achieves the highest relationship richness (RR) of 40% for merging $Cmt_{ar} \times Ekaw_{en}$. In terms of inheritance richness (IR), MULON achieves the highest results of 141% for merging $Iasted_{fr} \times Edas_{en}$ where number of `rdfs:subClassOf` relation in the merged ontology (328) is greater than number of classes (233) (see Table I). In terms of readability, MULON achieves significantly high results because it adds HRD (two `rdfs:label` for each resource) to the merged ontology. MULON achieves a full class coverage of 100% for the merging pair of ontologies $Conference_{de} \times Ekaw_{en}$, $Cmt_{ar} \times Ekaw_{en}$, $Iasted_{fr} \times Edas_{en}$, and $Sigkdd_{fr} \times Ekaw_{en}$, and 99% for $ConfOf_{ar} \times Edas_{en}$. In addition, MULON achieves the highest property coverage of 99% for $Conference_{de} \times Ekaw_{en}$ and $Iasted_{fr} \times Edas_{en}$. Some values for class coverage (CC) and property coverage (PC) are less than 100% due to the redundant resources that exist in the input ontologies. For instance, MULON found four redundant properties in $Conference_{de}$. Cross-lingual matching in MULON helps to remove redundant resources, therefore, the merged ontologies contain no redundant resources. MULON compacts ontologies by an average of 5.2%.

TABLE III

QUALITY ASSESSMENT RESULTS FOR THE MERGED ONTOLOGIES. BOLD ENTRIES ARE THE TOP SCORES.

Merging Ontology Pairs	RR	AR	IR	RB	IE	MP	RD	CC	PC	CT
$Conference_{de} \times Ekaw_{en}$	0.37	0.65	1.09	2.01	**0.05**	0.07	0.00	**1.00**	**0.99**	0.94
$ConfOf_{ar} \times Edas_{en}$	0.23	0.31	1.05	**2.06**	0.01	0.00	0.00	0.99	0.98	0.92
$Cmt_{ar} \times Ekaw_{en}$	**0.40**	**0.79**	1.17	2.02	0.02	0.08	0.00	**1.00**	0.96	0.95
$Iasted_{fr} \times Edas_{en}$	0.17	0.29	**1.41**	2.03	0.02	0.00	0.00	**1.00**	**0.99**	0.96
$Sigkdd_{fr} \times Ekaw_{en}$	0.28	0.43	1.12	1.99	0.04	**0.11**	0.00	**1.00**	0.98	**0.97**

VI. CONCLUSION AND FUTURE WORK

We present MULON, an approach for creating multilingual ontologies. The strength of our contribution lies in building such ontologies by merging ontologies in different natural languages using cross-lingual matching techniques. We show the usability of MULON by presenting three use cases in various domains; fiscal data, food, and scholarly communication. Indo and non-Indo-European languages ontologies are used in the merging process in order to illustrate the robustness of MULON. The results of the cross-lingual matching process are found promising compared to three state-of-the-art approaches. MULON not only produces multilingual ontologies but also automatically assesses their quality using a set of adapted quality metrics. This assessment emphasizes the validity of MULON. In conclusion, MULON established the first step towards a multilingual Semantic Web. In the future, we intend to further; 1) explore relationships between classes in the merged ontology that might occur after the merging process, e.g., a class exists in one ontology might be a subclass of another one in the other ontology, 2) resolve inconsistency that may exist in the merged ontology, 3) consider multiple labels for a resource, 4) consider individuals in the merging process, and 5) develop scalable approaches that can efficiently merge large-scale ontologies.

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