Entity Linking is one of the essential tasks of information extraction and natural language understanding. Entity linking mainly consists of two tasks: recognition and disambiguation of named entities. Most studies address these two tasks separately or focus only on one of them. Moreover, most of the state-of-the-art entity linking algorithms are either supervised, which have poor performance in the absence of annotated corpora or language-dependent, which are not appropriate for multi-lingual applications. In this paper, we introduce an Unsupervised Language-Independent Entity Disambiguation (ULIED), which utilizes a novel approach to disambiguate and link named entities. Evaluation of ULIED on different English entity linking datasets as well as the only available Persian dataset illustrates that ULIED in most of the cases outperforms the state-of-the-art unsupervised multi-lingual approaches.

**Keywords**  Entity Linking, Named Entity Disambiguation, Multilingual, Knowledge Base

1 Introduction

In this section, we first present a general introduction to entity linking (EL). We then introduce the knowledge bases as an essential requirement for entity linking task and then discuss the general steps of it. At the end of this section, we outline the general structure of this paper.
1.1 Entity Linking

Entity Linking (EL) is the task of linking a set of entities mentioned in a text to an external dataset. Entity linking plays an essential role in text analysis, information extraction, question answering, text understanding, and recommender systems [1]. It also allows users to know about the background knowledge of entities in the text [2]. However, there are two types of ambiguities which make this task challenging. Firstly, entities may have different names, even in a single document. For example, the name of a person can appear in the text as the first name, last name, or nickname. EL should link all of these names to a single entity in the knowledge base. Secondly, different entities may have the same name, but the entity linking system should be able to refer them to various entities from the knowledge base. Therefore, information about entities is crucial in choosing the correct entities [3, 2, 4].

With few exceptions, most of entity linking methods separately address the mention detection (also known as entity detection or named entity detection) and entity disambiguation stages [5]. Our approach also focuses on entity disambiguation. The proposed approach is an Unsupervised Language-Independent Entity Disambiguation method, dubbed as ULIED.

1.2 Knowledge Base

A knowledge base is one of the fundamental components in entity linking systems. Generally, the KB consists of a set of entities, information, semantic categories, and the relationship between entities. Knowledge bases used in EL systems should have features such as public availability, machine readability, persistent identifiers, and credibility [6]. There are currently several knowledge bases for EL systems such as DBpedia [7], YAGO [8], Freebase [9], and Probase [10]. In the case of low-resource languages, cross-lingual methods are used if there is no knowledge base with the above characteristics [11]. Fu et al. [12] showed that cross-lingual methods are heavily dependent on Wikipedia and only work well on Wikipedia texts. These methods perform poorly in non-Wikipedia texts and require outside-Wikipedia cross-lingual resources to improve their performance. This study employs FarsBase [13], which is the first multi-source KB especially designed for the Persian language and includes more than 500,000 entities with 25 million relations between them. FarsBase can provide various information such as locations, persons, and organizations.

1.3 Entity Linking Steps

Generally, the EL process includes four subtasks, which are consistent with most of both supervised and unsupervised EL systems. The first step, Mention Detection (MD), is the operation of specifying named entities in the input natural language raw text. The last three steps can be grouped as Entity Disambiguation (ED) subtask. ED is the operation of the disambiguation of a named entity using a set of candidate entities and then linking it to a knowledge base.

**Mention Detection** An MD algorithm captures the raw text and specifies the place of occurrence of named entities at the output. Most studies [14, 15, 16] in EL employed existing algorithms, provided by the other researches, for MD, and address the other three modules.

**Candidate Entity Generation** In this step, the system proposes a set of candidate entities for every entity mentions in the text provided by the previous step [4, 17]. In this regard, most studies [4, 18, 19, 20] use features such as redirect pages, disambiguation pages, and hyperlinks in Wikipedia (or other knowledge bases and resources), to make a name dictionary for each entity mention with the aim of mapping the entity mention to a set of candidate entities.

**Candidate Entity Ranking** In most cases, candidate entity generation modules, generates multiple candidate entities for a single mention. Therefore, candidate entities should be ranked by the EL system to find the most likely entity from the knowledge base [6]. The EL system can use two types of features for ranking candidates entities: Context-Independent Features and Context-Dependent Features [21]. In the literature, the term “phase entity disambiguation” [22, 23, 24] has the same meaning as candidate entity ranking. Additionally, both supervised and unsupervised methods can be used to achieve the results. Supervised ranking methods depend on the annotated training dataset, where its data annotation should be done manually. In the case of low-source languages, such a resource is not available, and alternative solutions are needed. For example, Kile et al. [25] have provided a novel domain-agnostic Human-In-The-Loop (HITL) annotation approach which uses recommenders that suggest potential concepts and adaptive candidate ranking to speed up the overall annotation process and make it less tedious for users. NERank+ proposed by Wang et al. [26] is another example of entity ranking approaches, which utilizes Topical Tripartite Graph, consisting of document, topic and entity nodes as well as a random walk algorithm to propagate prior entity and topic ranks based on the graph model.

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1 Yet Another Great Ontology
Unlinkable Mention Prediction  In cases where entity mentions do not have any relevant entities in the knowledge base, unlinkable entity mentions are separated from other entities and tagged as NIL. Different approaches are suggested by researchers to separate unlinkable entity mentions: (1) ignoring unlinkable entity mentions [2, 27, 14], (2) ignoring the low-probability candidates (NIL threshold) [28, 24] and (3) supervised machine learning techniques [4, 6, 29, 30].

The rest of this paper is organized as follows. Section 2 presents an overview study of EL, especially with a view to entity disambiguation and language independent and unsupervised approaches. In this section, we will also introduce the only available entity disambiguation dataset for the Persian language, and we will review multilingual entity linking datasets as well as entity disambiguation datasets for the English language. Section 4 describes the proposed approach for unsupervised, language-independent entity disambiguation. Experimental results and the comparison of obtained results with the baseline methods on English and Persian datasets are discussed in section 5. The last section concludes this research and expresses our future work.

2 Related Work

Supervised approaches need adequate resources and are not suitable for low-resource languages. There are a limited number of EL system which are focused on multilingual strategies. This manuscript targets multilingual unsupervised entity disambiguation as the best approach for entity linking in low-resources languages. In this section, we first describe the related literature in unsupervised EL and multilingual EL and then introduce some popular existing datasets for entity disambiguation.

2.1 Unsupervised Entity Disambiguation

There are various algorithms proposed to perform unsupervised EL. Here we review notable studies in this field.

Some researchers [19, 22, 18, 20] used Vector Space Model (VSM) [31] based methods for unsupervised candidate ranking. In this method, the first step is calculating the similarity between the vector representations of the entity mention and the candidate entity. The system links the candidate entity with the highest similarity to the entity mention. These methods are different in the calculation of vector similarity and vector representation [4]. Methods have also been proposed that use a combination of different SVM methods as an ensemble. For example, Alokaili and Menai proposed an ensemble learning using SVM [32], which produces competitive performance levels compared to well-known entity annotation systems and ensemble models on different benchmark corpora.

Cucerzan [22] used entity mentions and Wikipedia articles of the candidate entities to build vectors. To this end, the system will choose a candidate that maximizes vector similarity and have the same category as an entity mention. This system got 91.4% accuracy on a news dataset.

Chen et al. [19] built the entity mention and candidate entities vectors based on the Bag of Words model by using the context of their article to capture word co-occurrence information and computed the similarity between them by TF-IDF similarity. They reported 71.2% accuracy on the TAC-KBP2010 dataset.

Han and Zhao [18] used two types of similarity measures: the Wikipedia Semantic Knowledge-Based Similarity alongside Bag of Words based similarity. For generating vectors in the first similarity, the method detects Wikipedia concepts in candidate entities and context of the mentioned entity. It then computes the vector similarity of the entity mention and candidate entities using a weighted average of semantic relations between articles of Wikipedia concepts and the context of the mentioned entity. After that, these two types of similarity are merged, and the final similarity vector of the candidate entities is reported, and finally, the entity that maximizes this merged similarity is chosen. Their system achieves 76.7% accuracy on the TAC-KBP2009 dataset.

Xu et al. [20] applied a linking approach for medical texts and exploited name similarity, entity popularity, category consistency, context similarity, and the semantic correlation between the entity mention and candidate entities, and ranked candidate entities by combining these features. They called their ranking measure, Confidence Score. On average, their Confidence Score got about 82% precision on their medical dataset.

Zhang et al. [33] proposed an unsupervised bilingual entity linker inspired by Han et al. [2] and Yamada et al. [24] researches. As we discussed before, they utilized a pre-built dictionary for the candidate generation, and after that, they used probabilistic generative methods to disambiguate the entities. Their system achieves 91.2% precision on the CoNLL dataset.

Pan et al. [34] used Abstract Meaning Representation (AMR) [35] to select high-quality sets of entities for their similarity measure. They claimed that their representation using AMR could capture some contextual properties.
which are very critical and helpful for disambiguating entities without using training data. Next, for comparing the
context of the entities, they used an unsupervised graph to get final results and reported 92.12% precision on a dataset
annotated from news and discussion forum posts.

Xie et al. [36] proposed the graph-ranking collective Chinese entity linking (GRCEEL) algorithm, which utilizes both
the structured relationship between entities in the local knowledge base and the additional background information
offered by external knowledge sources. To measure similarity, they used improved weighted word2vec and improved
PageRank methods. They reported the effectiveness of GRCEEL in Chinese entity linking task and demonstrated the
superiority of their method over state-of-the-art methods in Chinese.

2.2 Multi-Lingual Entity Linking

Some studies target multilingual entity linking. Babelfy [37] is one of the most distinguished studies on unsupervised
multilingual EL and Word Sense Disambiguation (WSD). Moro et al. used a unified graph-based approach to EL and
WSD based on a loose identification of candidate meanings coupled with the densest subgraph heuristic, which selects
high-coherence semantic interpretations.

Hoffart et al. proposed the AIDA [16] system which provides an integrated NED method using popularity, similarity,
and graph-based coherence, and includes robustness tests for self-adaptive behavior. Later, they extended their
approach [38] presenting a novel notion of semantic relatedness between two entities represented as sets of weighted
(multi-word) keyphrases, with consideration of partially overlapping phrases. This measure improves the quality of
prior link-based models and also eliminates the need for (usually Wikipedia-centric) explicit interlinkage between
entities.

Usbeck et al. [39] present AGDISTIS, a knowledge-base-agnostic approach for named entity disambiguation. Their
approach combines the Hypertext-Induced Topic Search (HITS) algorithm with label expansion strategies and string
similarity measures. They extended their AGDISTIS to a multilingual approach named MAG [40].

Rosales et al. [41] introduce VoxEL as a benchmark dataset for multilingual Entity Linking including German, English,
Spanish, French and Italian languages based on 15 news articles from VoxEurop, a multilingual newsletter, totaling 94
sentences. The study compares 15 multilingual entity linkers with General Entity Annotation Benchmark Framework
(GERBIL) [42], KIM [43], TagME [44], SDA [45], ualberta [46], HITS [47], THD [48], DBpedia Spotlight [49, 50],
Wang-Tang [51], AGDISTIS [39], Babelfy [47], FREME [52], WikiME [53], FEL [54], FOX [55] and MAG [40] and
checks the availability of entity recognition, having a demo, having an API and availability of source codes for each
system.

DBpedia Spotlight proposed by Mendes et al. [49] is a system for automatically annotating text documents with
DBpedia URIs. Their algorithm uses the same four-step approach and VSM and TF-IDF similarity measure, which is
described earlier.

3 Datasets

In this section, we present a review of some popular entity disambiguation datasets, for the English language, which
is used in the evaluation of this research and the only published dataset for the Persian language.

3.1 ACE2004

In the 2004 Automatically Content Extracting (ACE) technology evaluation, the ACE 2004 Multilingual Training
Corpus contains all English, Arabic, and Chinese education data. This collection includes various types of data
annotated for organizations and connections, and a Linguistic Information Consortium has been formed with the help
of the ACE Program with the additional support of the DARPA TIDES program.

3.2 AIDA/CoNLL

This dataset contains assignments of entities to the mentions of named entities annotated for the original CoNLL 2003
text recognition task [16]. This dataset consists of proper noun annotations for 1393 Reuters newswire articles.
All these proper nouns are hand-annotated with corresponding entities in YAGO2. Two experts disambiguated each
mention, and in case of conflict, another expert resolved the conflict.
3.3 AQUAINT

AQUAINT Corpus [56], Linguistic Data Consortium (LDC) catalog number LDC-2002T31 and ISBN 1-58563-240-6 consists of English-language newswire text data from three sources: the Xinhua News Service (People’s Republic of China), the New York Times News Service, and the Associated Press Worldstream News Service. It was prepared for the AQUAINT Project by the LDC and will be used by the National Institute of Standards and Technology (NIST) in official benchmark evaluations.

3.4 DBpediaSpotlight

DBpedia Spotlight [49] is a system where text documents with DBpedia URIs are automatically annotated. DBpedia Spotlight enables users to configure annotations to their specific needs utilizing DBpedia Ontology and quality measures such as prominence, topical relevance, contextual ambiguity, and confidence in disambiguation.

3.5 KORE50

The goal of KORE50 [38] is to stress testing EL systems using highly ambiguous mentions using hand-crafted sentences via difficult disambiguation tasks. KORE is a new notion of entity relatedness, based on the overlap of two sets of keyphrases, e.g., partial matches of 2 sentences.

3.6 KORE 50-DYWC

An excess of different evaluation data sets relies on either Wikipedia or DBpedia. Noullet et al. [57] have recently extended KORE50, to not only accommodate EL tasks for DBpedia, but also for YAGO, Wikidata, and Crunchbase.

3.7 IITB

IITB [58] was established in 2009 and had the highest corporate entity/document density. It is a list of ground truths (called "IITB") using an annotation system based on a browser. Manual annotation documents were gathered from the links to popular websites belonging to a handful of domains that included sports, culture, science and technology, and education. The annotations can be found in the public domain.

3.8 N3-Reuters-128

N3 Reuters-128 [59] includes 128 news articles sampled randomly from the Reuters-21578 news articles and manually annotated by domain experts.

3.9 N3-RSS-500

N3 RSS-500 [59] consists of 1,457 RSS feeds scraped from a list containing all major newspapers around the world and a wide range of topics. Domain experts manually annotated the corpus. The RSS list was compiled using a 76-hour crawl, leading to a corpus of approximately 11.7 million sentences. By render selecting 1% of the contained words, a subset of this corpus was generated.

3.10 ERD2014

The ERD2014 [60] dataset is constructed for the 2014 Entity Recognition and Disambiguation Challenge (ERD’14), which took place from March to June 2014 and was summarized in a dedicated workshop at SIGIR 2014. The ERD challenge’s main goal was to promote research in recognition and disambiguation of entities in unstructured text. For the short-text track, the dataset was built by sampling 500 queries from a commercial search engine’s query log to form a development set and 500 queries for the test set. The average query length was four words per query. For the long-text track, the dataset was built by sampling 100 web pages for the development and 100 web pages for the test set. Also, all HTML tags from the web pages were stripped, and various heuristics were applied to extract the main content from each document. Particularly, boilerplate content from header and side panes were removed. Among all documents, 50% were sampled from general web pages; the remaining 50% were news articles from msn.com.
3.11 MSNBC

Silviu Cucerzan launched MSNBC dataset [22] in 2007. The data set contains unique SF media reports and a distinctive lexicalization.

3.12 ParsEL-Social

To evaluate ULIED and competing methods in Persian, we used ParsEL-Social Dataset [61], which is introduced in the conference version of this paper. ParsEL-Social is constructed from social media contents derived from 10 Telegram channels in 10 different categories: sport, economics, gaming, general news, IT news, travel, art, academic, entertainment, and health. To create this dataset, firstly, entity mentions are automatically identified in raw text, and a list of candidates is created based on redirect and disambiguation links of that entity mention in Wikipedia. Then the text with identified entity mentions and candidate lists is given to a Persian linguistics expert. The expert either selects one of the candidates for each entity. In some cases, a mention must be linked to an entity. However, the right entity is not found in the candidates due to an error in the automatic candidate generation algorithm. The expert may add it to the candidate list and selects it as the right link. It should be noted that the automatic candidate generator only appears as an expert helper.

4 Proposed Approach

In this section, we describe the architecture of our unsupervised language independent entity disambiguation system (ULIED) and propose our new approach in which entity mentions of input text are disambiguated and linked to Wikipedia. We first look at the architecture as a general system and then describe each of its modules separately.

4.1 Unsupervised Language-Independent Entity Disambiguation System (ULIED) Architecture

The ULIED system implemented in a pipeline architecture. It is assumed that the input text only specifies the entity mentions, and the system at the output should disambiguate these entity mentions and link them to Wikipedia. To this end, a list of candidates is first generated in the Candidate Generation module for each entity mention. Four candidate entity weighting modules are used in the ED component; two context-dependent modules and two context-independent modules. Figure 1 shows a block diagram of the architecture and data flow of ULIED.

In this architecture, in the Candidate Generation module, candidates are generated for all entity mentions of the text using Wikipedia redirects and disambiguation pages. The output of this module is a set of entity mentions and several candidates for each entity mention.

Entity Disambiguation Component consists of five modules; four are grouped as Candidate Entity Weightening subsystem and one named Top-weight Entity Selection and Linking Module. We utilize both of the context-dependent and context-independent features in the ranking step. Context-dependent features rely on the context where entity mention appears, but context-independent features are independent of context and rely on entity mention and candidate entities[4]. These modules are described below.

4.1.1 Infobox type similarity Module

In this module, we examine whether the type of candidate can match the entity’s context by the type of candidate entity derived from Wikipedia’s Infobox and the context surrounding the original entity.

Some entities have a very generic name that may cause a high level of ambiguity. For instance, جبل سالگی ("At the age of 40") is an Iranian movie while it can be part of a general sentence, e.g., "Vahid died at the age of 40". Such names are widespread in artworks (e.g., movies or books) and a limited number of the other specialized classes. To improve the disambiguation process, we will look for more evidence in the context using a hand-made reference list if the candidate entity belongs to individual classes. Considering the above example, "At the age of 40", the surrounding context containing phrases such as a director, artist, channel, cinema, ticket, and movie is required. Otherwise, the algorithm multiplies the candidate’s real rate by a predefined constant number between 0 and 1 based on each case.

4.1.2 Shallow Textual Similarity Module

In this module, using the surface properties of the text of the document that contains a given entity mention and corresponding Wikipedia page of its candidates, we perform a vector similarity to determine the degree of similarity between each candidate and its corresponding entity mention.
4.1.3 Level 1 and Level 2 Link-Graph Module

Previous research has shown that internal links between Wikipedia pages can be a useful feature for examining and measuring the semantic relevance of concepts [62]. The main idea behind the Link-Graph modules is that candidates with more Wikipedia internal links to other candidates are more likely to be suitable candidates for disambiguation.

In the following, we will explain this method in more detail. Given the candidate list \( CL \) including all candidates of all mentions in the context, for each candidate \( c_i \in CL \), we create a list \( LLC^1_i \) including all candidates which are linked in the corresponding Wikipedia article for \( c_i \) and their frequencies in the article, \( (\text{link}_{ij}, \text{count}_{ij}) \). For example, the Wikipedia article of “Saadi” contains ten links to “Shiraz” article, four links to “Persian”, 12 links to “Poet”, and so on. The list \( LLC^1_{Saadi} \) will be:

\[
[(\text{Shiraz}, 10), (\text{Persian}, 4), (\text{Poet}, 12), ...].
\]

In the next step, we assign a weight to each \( c_i \) of \( CL \):

\[
w_{c_i} = \sum_{(\text{link}_{ij}, \text{count}_{ij}) \in LLC^1_i} \text{count}_{ij} \times e_{ij}
\]

and \( e_{ij} \) is

\[
e_{ij} = \begin{cases} 
1 & \text{if } \text{link}_{ij} \in CL \\
0 & \text{otherwise} 
\end{cases}
\]

In the last step, for each mention, we choose the entity with the highest weight for the mention.

The Level 1 Link-Graph Module only counts the number of links per candidate and accordingly assigns a weight to each candidate. The Level 2 Link-Graph Module is not limited to first-level links. Instead, we create a \( LLC^2 \) list which equals to \( LLC^1 \) of the entity + \( LLC^1 \) of entities which are linked to each of them. In the previous example about “Saadi”, we add all of the links of “Shiraz”, “Persian” and “Poet” article to \( LLC^2 \) of Saadi.

To accelerate this phase, we have created a cache \( LLC \) for all of the articles in Wikipedia dump, and the system can fetch the list for each member of list \( CL \) instantly from the cache.

Suppose the following text as the input: “Saadi was born in the city of Shiraz.”
**Level-1 graph formation:** Suppose “Saadi” has three candidate entities: A1, A2, and A3, and the “city” can also refer to two entities: B1 and B2. “Shiraz” also has four ambiguities: C1, C2, C3, and C4. The rest of the words have no candidate entity. In this example, a graph is formed that has the following nodes:

A1, A2, A3, B1, B2, C1, C2, C3, C4

If the Wikipedia page of a node has _n_ internal links to another node’s Wikipedia page, an edge of value _n_ is created between the two nodes.

In the above example, “Saadi” has two candidates. Suppose the Wikipedia page of candidate A1 is linked to the “Shiraz” Wikipedia page (C2), and candidate A2 is not linked to this page. Considering that the city of Shiraz (C2) is one of the candidates for the word “Shiraz” in the text and has appeared in the graph, the score of the first candidate, “Saadi” (A1), will be higher than the second candidate (A2).

**Level-2 graph formation:** In the previous example, suppose that Saadi’s (A1) candidate is linked to the other four entities D1, D2, D3, and D4. In the second level graph, these entities are also added to the graph. The adding operation will be done for all other level-1 nodes (A2, A3, B1, B2, C1, C2, C3, C4). The level-2 graph will always be more crowded, but the criterion for forming edges is the same as the previous graph: the internal Wikipedia link between the entities’ pages.

A1, A2, A3, B1, B2, C1, C2, C3, C4, D1, D2, D3, D4, …. (links of all other candidates)

Suppose the previous example with some differences. “Saadi” has two candidates A1 and A2. Suppose that neither candidate A1 nor candidate A2 has a link to the Shiraz Wikipedia page (C2). However, A1 is linked to another Wikipedia page D2, and D2 is linked to C2. A2 has no any connection to C2, even with one node in between. In this example, C2 exists in the level-2 graph, and the score of the first candidate A1 will be higher than the second candidate A2.

4.1.4 Top-weight Entity Selection and Linking Module

In this module, we first multiply all the weights of the candidates obtained from the previous four modules, and then we sort all the candidates according to the final number of these results, and we consider the highest weighted candidate as the selected candidate. The link is to the Wikipedia page for this candidate. As such, the entity has been disambiguated. Finally, the system links the candidate entity with the highest score to the entity mention. Other entities will be added to the entity mention’s “ambiguity-list” to persist the rejected candidates for possible future applications such as error checking. After candidate generation and ranking, the NIL threshold method is used for unlinkable mention prediction. In this method, if the score of the top-ranked candidate entity is lower than the predefined threshold, the entity mention will be tagged as NIL, and the system will add all of the candidate entities to the ambiguity-list.

5 Experimental Results and Evaluation

We implemented our proposed method, ULIED, on the Persian and English languages using existing datasets and compared the evaluation results with other state-of-the-art multilingual unsupervised methods, Babelfy, and DBpedia Spotlight. We then analyze these results and evaluations.

We evaluate ULIED on ParsEL-Social dataset, and the results are reported in Figure 2.

To evaluate ULIED on the English language, we use ten different datasets that are widely used in entity linking evaluations, which are introduced in Section 3.

To evaluate the system, we input the documents of each dataset with the spanning of each mentions within the text in the NIF standard format. Giving the position of each mentions in the text, ULIED selects some candidate Wikipedia articles for the mention and performs the ED phase and links the mention to an entity. If there is no candidate entity for the mention, or confidence value of all entities is under a threshold value, ULIED does not link the mention to any entity.

Rosales et al. [41] reports the results of some state-of-the-art unsupervised language-independent EL systems on their multilingual dataset and report the superiority of Babelfy and DBpedia Spotlight on the other systems.

Figure 2 depicts the results of ULIED with DBpedia Spotlight and Babelfy based on micro F1-measure. The results show ULIED outperforms Babelfy in 5 datasets. Spotlight records the best performance only in the DBpediaSpotlight dataset. Therefore the performance of ULIED in the English language is comparable with other multilingual approaches and outperforms them in the Persian language.
Moreover, it is notable that the size of Wikipedia articles in the Persian language is almost 500,000 (i.e., One-twentieth of English), and consequently the number of candidates for each mention, in the Persian, is very smaller in comparison to mentions in the English language. This fact causes ULIED F-score to be meaningfully more than its F-score in the English datasets.

To evaluate ULIED on the Persian language, we use Babelfy as the Baseline, which works based on BabelNet 3. In the first step, We run Babelfy on our dataset by public APIs of Babelfy. Babelfy returns all of the BabelNet synsets for each token in the text. Each synset is linked to some sources, including Wikipedia articles. FarsBase knowledge base is constructed from Persian Wikipedia and uses Wikipedia articles to construct its entities. Therefore, although we only get Persian Wikipedia sources for each BabelNet synset and convert it to its corresponding entity in the FarsBase. Babelfy (despite its multilingual nature) is not expected to perform comparably with ULIED, in Persian, because (in English) Babelfy utilizes additional lexical data sources such as WordNet whereas, in Persian, neither of Babelfy and ULIED have access to additional lexical resources or knowledge resources to Wikipedia. Indeed, it is the reason for the high difference of ULIED F-score compared to Babelfy, in the Persian language. Babelfy API does not return entity candidates in the results; Thus, comparing the reported recall rate with the ParsEL is not rational, and predictably the recall of our baseline method is lower than ULIED. It should be noted that it was not possible to compare ULIED with DBpedia-SpotLight. DBpedia-SpotLight covers specific languages for entity disambiguation, and Persian is not one of those languages.

Figure 2: Evaluation of entity disambiguation results using the proposed method ULIED on 10 different datasets and comparison with DBpedia-SpotLight and Babelfy as baseline algorithms. Results are reported according to the F1 measure.

9
6 Conclusion and Future Trends

In this paper, we presented an approach for UnSupervised, Language-Independent Entity Disambiguation, dubbed as ULIED. ULIED utilizes only the link-graph of Wikipedia pages (for each language) and the raw text of their corresponding articles.

ULIED is compared to Babelfy and DBpedia-Spotlight as the state-of-the-art of unsupervised and language-independent entity disambiguation methods. For the English datasets, ULIED F-score is almost similar to (and in some cases better than) Babelfy and almost always better than Spotlight. However, in the Persian dataset, it meaningfully outperforms the Babelfy F-score. This expected superiority is because (in English) Babelfy utilizes additional data resources (e.g., WordNet), and its performance comes down, for the cases in which such additional lexical and knowledge resources are absent or are not accessible.

ULIED is suggested for the applications in which training data is not available or costly to produce as an unsupervised method. However, ULIED is not suggested to the problems for which large enough annotated entity linking corpora are available, for which the supervised methods are the best solution.

As the future work of this study, we plan to improve the proposed method to be an end-to-end approach, by focusing on the mention detection sub-task of entity linking.

Additionally, using phrase embedding can also improve the proposed method, especially for the context similarity detection phase. As another future work, the strategy of weight aggregation is expected to be upgraded. Moreover, the proposed method is expected to be evaluated in other languages, especially in the multilingual entity linking datasets.

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References

[1] Weiqian Yan and Kanchan Khurad. Entity linking with people entity on wikipedia. CoRR, abs/1705.01042, 2017.
[2] Xianpei Han, Le Sun, and Jun Zhao. Collective entity linking in web text: a graph-based method. In Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, pages 765–774. ACM, 2011.
[3] Octavian-Eugen Ganea, Marina Ganea, Aurelien Lucchi, Carsten Eickhoff, and Thomas Hofmann. Probabilistic bag-of-hyperlinks model for entity linking. In Proceedings of the 25th International Conference on World Wide Web, pages 927–938. International World Wide Web Conferences Steering Committee, 2016.
[4] Wei Shen, Jianyong Wang, and Jiawei Han. Entity linking with a knowledge base: Issues, techniques, and solutions. IEEE Transactions on Knowledge and Data Engineering, 27(2):443–460, 2014.
[5] Nikolaos Kolitsas, Octavian-Eugen Ganea, and Thomas Hofmann. End-to-end neural entity linking. In Proceedings of the 22nd Conference on Computational Natural Language Learning, pages 519–529. Association for Computational Linguistics, 2018.
[6] Pavel Taufer. Named entity recognition and linking. Master’s thesis, Univerzita Karlova, Matematicko-fyzikální fakulta, 2017.
[7] Sören Auer, Christian Bizer, Georgi Kobilarov, Jens Lehmann, Richard Cyganiak, and Zachary Ives. Dbpedia: A nucleus for a web of open data. In The Semantic Web, 6th International Semantic Web Conference, 2nd Asian Semantic Web Conference, ISWC 2007 + ASWC 2007, volume 4825 of Lecture Notes in Computer Science, pages 722–735. Springer, 2007.
[8] Fabian M Suchanek, Gjergji Kasneci, and Gerhard Weikum. Yago: a core of semantic knowledge. In Proceedings of the 16th international conference on World Wide Web, pages 697–706. ACM, 2007.
[9] Kurt Bollacker, Colin Evans, Praveen Paritosh, Tim Sturge, and Jamie Taylor. Freebase: a collaboratively created graph database for structuring human knowledge. In Proceedings of the 2008 ACM SIGMOD international conference on Management of data, pages 1247–1250. ACM, 2008.

4http://farsbase.net/ParsEL.html
[10] Wentao Wu, Hongsong Li, Haixun Wang, and Kenny Q Zhu. Probase: A probabilistic taxonomy for text understanding. In Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data, pages 481–492. ACM, 2012.

[11] Shuyan Zhou, Shruti Rijhwani, John Wieting, Jaime Carbonell, and Graham Neubig. Improving candidate generation for low-resource cross-lingual entity linking. Transactions of the Association for Computational Linguistics, 8:109–124, 2020.

[12] Xingyu Fu, Weijia Shi, Zian Zhao, Xiaodong Yu, and Dan Roth. Design challenges for low-resource cross-lingual entity linking. CoRR, abs/2005.00692, 2020.

[13] Majid Asgari, Ali Hadian, and Behrouz Minaei-Bidgoli. Farsbase: The persian knowledge graph. Semantic Web, pages 1169–1196, 2019.

[14] Maria Pershina, Yifan He, and Ralph Grishman. Personalized page rank for named entity disambiguation. In Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 238–243. The Association for Computational Linguistics, 2015.

[15] Chenwei Ran, Wei Shen, and Jianyong Wang. An attention factor graph model for tweet entity linking. In Proceedings of the 2018 World Wide Web Conference, pages 1135–1144. International World Wide Web Conferences Steering Committee, 2018.

[16] Johannes Hoffart, Mohamed Amir Yosef, Ilaria Bordino, Hagen Fürstenau, Manfred Pinkal, Marc Spaniol, Bilyana Taneva, Stefan Thater, and Gerhard Weikum. Robust disambiguation of named entities in text. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, pages 782–792. Association for Computational Linguistics, 2011.

[17] Gongqing Wu, Ying He, and Xuegang Hu. Entity linking: an issue to extract corresponding entity with knowledge base. IEEE Access, 6:6220–6231, 2018.

[18] Xianpei Han and Jun Zhao. Nlpr_kbp in tac 2009 kbp track: A two-stage method to entity linking. In TAC, page 8. Citeseer, 2009.

[19] Zheng Chen, Suzanne Tamang, Adam Lee, Xiang Li, Wen-Pin Lin, Matthew G Snover, Javier Artiles, Marissa Passantino, and Heng Ji. Cuny-blender tac-kbp2010 entity linking and slot filling system description. In Proceedings of the Third Text Analysis Conference, page 16. NIST, 2010.

[20] Jing Xu, Liang Gan, Mian Cheng, and Quanyuan Wu. Unsupervised medical entity recognition and linking in chinese online medical text. Journal of healthcare engineering, 2018:2548537, 2018.

[21] Hongda Shen, David Francois Huynh, Grace Chung, Chen Zhou, Yanlai Huang, and Guanghua Li. Ranking search results based on entity metrics, November 19 2015. US Patent App. 14/651,332.

[22] Silviu Cucerzan. Large-scale named entity disambiguation based on wikipedia data. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), pages 708–716. ACL, 2007.

[23] Mark Dredze, Paul McNamee, Delip Rao, Adam Gerber, and Tim Finin. Entity disambiguation for knowledge base population. In Proceedings of the 23rd International Conference on Computational Linguistics, pages 277–285. Association for Computational Linguistics, 2010.

[24] Ikuya Yamada, Hiroyuki Shindo, Hideaki Takeda, and Yoshiyasu Takefuji. Joint learning of the embedding of words and entities for named entity disambiguation. In Proceedings of the 20th SIGNLL Conference on Computational Natural Language Learning, pages 250–259. ACL, 2016.

[25] Jan-Christoph Klie, Richard Eckart de Castilho, and Iryna Gurevych. From zero to hero: Human-in-the-loop entity linking in low resource domains. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6982–6993. Association for Computational Linguistics, 2020.

[26] Chengyu Wang, Guomin Zhou, Xiaofeng He, and Aoying Zhou. Nerank+: a graph-based approach for entity ranking in document collections. Frontiers of Computer Science, 12(3):504–517, 2018.

[27] Xianpei Han and Le Sun. An entity-topic model for entity linking. In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 105–115. Association for Computational Linguistics, 2012.

[28] Wei Shen, Jianyong Wang, Ping Luo, and Min Wang. Linden: linking named entities with knowledge base via semantic knowledge. In Proceedings of the 21st international conference on World Wide Web, pages 449–458. ACM, 2012.

[29] Wei Zhang, Chew Lim Tan, Yan Chuan Sim, and Jian Su. Nus-i2r: Learning a combined system for entity linking. In Text Analysis Conference 2010 TAC 2010, page 5. NIST, 2010.
[30] Wei Zhang, Yan Chuan Sim, Jian Su, and Chew Lim Tan. Entity linking with effective acronym expansion, instance selection and topic modeling. In Proceedings of the Twenty-Second international joint conference on Artificial Intelligence-Volume Three, pages 1909–1914. AAAI Press, 2011.

[31] Gerard Salton, Anita Wong, and Chung-Shu Yang. A vector space model for automatic indexing. Communications of the ACM, 18(11):613–620, 1975.

[32] Amal Alokaili and Mohamed El Bachir Menai. Svm ensembles for named entity disambiguation. Computing, 102(4):1051–1076, 2020.

[33] Jing Zhang, Yixin Cao, Lei Hou, Juanzi Li, and Hai-Tao Zheng. Xlink: An unsupervised bilingual entity linking system. In Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data - 16th China National Conference, CCL 2017, - and - 5th International Symposium, NLP-NABD 2017, pages 172–183. Springer, 2017.

[34] Xiaoman Pan, Taylor Cassidy, Ulf Hermjakob, Heng Ji, and Kevin Knight. Unsupervised entity linking with abstract meaning representation. In Proceedings of the 2015 conference of the north american chapter of the association for computational linguistics: Human language technologies, pages 1130–1139. The Association for Computational Linguistics, 2015.

[35] Laura Banarescu, Claire Bonial, Shu Cai, Madalina Georgescu, Kira Griffitt, Ulf Hermjakob, Kevin Knight, Philipp Koehn, Martha Palmer, and Nathan Schneider. Abstract meaning representation for sembanking. In Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse, pages 178–186. The Association for Computer Linguistics, 2013.

[36] Tao Xie, Bin Wu, Bingjing Jia, and Bai Wang. Graph-ranking collective chinese entity linking algorithm. Frontiers of Computer Science, 14(2):291–303, 2020.

[37] Andrea Moro, Alessandro Raganato, and Roberto Naviglio. Entity linking meets word sense disambiguation: a unified approach. Transactions of the Association for Computational Linguistics, 2:231–244, 2014.

[38] Johannes Hoffart, Stephan Seufert, Dat Ba Nguyen, Martin Theobald, and Gerhard Weikum. Kore: keyphrase overlap relatedness for entity disambiguation. In Proceedings of the 21st ACM international conference on Information and knowledge management, pages 545–554. ACM, 2012.

[39] Ricardo Usbeck, Axel-Cyrille Ngonga Ngomo, Michael Röder, Daniel Gerber, Sandro Ataide Coelho, Sören Auer, and Andreas Both. Agdistis-graph-based disambiguation of named entities using linked data. In Proceedings of the 13th International Semantic Web Conference-Part I, pages 457–471. Springer, 2014.

[40] Diego Moussallem, Ricardo Usbeck, Michael Röder, and Axel-Cyrille Ngonga Ngomo. Mag: A multilingual, knowledge-base agnostic and deterministic entity linking approach. In Proceedings of the Knowledge Capture Conference, pages 9:1–9:8. ACM, 2017.

[41] Henry Rosales-Méndez, Aidan Hogan, and Barbara Poblete. Voxel: A benchmark dataset for multilingual entity linking. In Proceedings of the 17th International Semantic Web Conference, pages 170–186. Springer, 2018.

[42] Ricardo Usbeck, Michael Röder, Axel-Cyrille Ngonga Ngomo, Ciro Baron, Andreas Both, Martin Brümmer, Diego Ceccarelli, Marco Cornolti, Didier Cherix, Bernd Eickmann, et al. Gerbil: general entity annotator benchmarking framework. In Proceedings of the 24th international conference on World Wide Web, pages 1133–1143. International World Wide Web Conferences Steering Committee, 2015.

[43] Borislav Popov, Atanas Kiryakov, Damyan Ognyanoff, Dimitar Manov, and Angel Kiriiev. KIM - a semantic platform for information extraction and retrieval. Natural language engineering, 10(3-4):375–392, 2004.

[44] Paolo Ferragina and Ugo Scaiella. Tagme: on-the-fly annotation of short text fragments (by wikipedia entities). In Proceedings of the 19th ACM international conference on Information and knowledge management, pages 1625–1628. ACM, 2010.

[45] Eric Charton, Michel Gagnon, and Benoit Ozell. Automatic semantic web annotation of named entities. In Advances in Artificial Intelligence - 24th Canadian Conference on Artificial Intelligence, pages 74–85. Springer, 2011.

[46] Zhaochen Guo, Ying Xu, Filipe de Sá Mesquita, Denilson Barbosa, and Grzegorz Kondrak. ualberta at tac-kbp 2012: English and cross-lingual entity linking. In Proceedings of the Fifth Text Analysis Conference, TAC. NIST, 2012.

[47] Angela Fahmi, Thierry Göckel, and Michael Strube. Hits’ monolingual and cross-lingual entity linking system at tac 2012: A joint approach. In Proceedings of the Fifth Text Analysis Conference, TAC. NIST, 2012.
[49] Pablo N Mendes, Max Jakob, Andrés García-Silva, and Christian Bizer. Dbpedia spotlight: shedding light on the web of documents. In *Proceedings of the 7th international conference on semantic systems*, pages 1–8. ACM, 2011.

[50] Joachim Daiber, Max Jakob, Chris Hokamp, and Pablo N Mendes. Improving efficiency and accuracy in multilingual entity extraction. In *Proceedings of the 9th International Conference on Semantic Systems*, pages 121–124. ACM, 2013.

[51] Zhichun Wang, Juanzi Li, and Jie Tang. Boosting cross-lingual knowledge linking via concept annotation. In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence*, pages 2733–2739. IJCAI/AAAI, 2013.

[52] Felix Sasaki, Milan Dojchinovski, and Jan Nehring. Chainable and extendable knowledge integration web services. In *Knowledge Graphs and Language Technology - ISWC 2016 International Workshops: KEKI and NLP&DBpedia*, volume 10579 of *Lecture Notes in Computer Science*, pages 89–101. Springer, 2016.

[53] Chen-Tse Tsai and Dan Roth. Cross-lingual wikification using multilingual embeddings. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 589–598. The Association for Computational Linguistics, 2016.

[54] Aasish Pappu, Roi Blanco, Yashar Mehdad, Amanda Stent, and Kapi Thadani. Lightweight multilingual entity extraction and linking. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pages 365–374. ACM, 2017.

[55] René Speck and Axel-Cyrille Ngonga Ngomo. Ensemble learning of named entity recognition algorithms using multilayer perceptron for the multilingual web of data. In *Proceedings of the Knowledge Capture Conference*, page 26. ACM, 2017.

[56] Dick Crouch, Roser Sauri, and Abraham Fowler. Aquaint pilot knowledge-based evaluation: Annotation guidelines, 2005.

[57] Kristian Noullet, Rico Mix, and Michael Färber. Kore 50dywc: An evaluation data set for entity linking based on dbpedia, yago, wikidata, and crunchbase. In *Proceedings of The 12th Language Resources and Evaluation Conference*, pages 2389–2395. European Language Resources Association, 2020.

[58] Sayali Kulkarni, Amit Singh, Ganesh Ramakrishnan, and Soumen Chakrabarti. Collective annotation of wikipedia entities in web text. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 457–466. ACM, 2009.

[59] Michael Röder, Ricardo Usbeck, Sebastian Hellmann, Daniel Gerber, and Andreas Both. N3—a collection of datasets for named entity recognition and disambiguation in the nlp interchange format. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation, LREC 2014*, pages 3529–3533. European Language Resources Association (ELRA), 2014.

[60] David Carmel, Ming-Wei Chang, Evgeniy Gabrilovich, Bo-June Paul Hsu, and Kuansan Wang. Erd’14: entity recognition and disambiguation challenge. In *ACM SIGIR Forum*, volume 48, pages 63–77. ACM, 2014.

[61] Farzaneh Fakhrian, Majid Asgari-Bdihendi, and Behrouz Minaei-Bidgoli. An unsupervised end-to-end language-independent entity linking method and its evaluation on parsel as the first persian entity linking corpus. Manuscript submitted for publication, 2020.

[62] Xinhua Zhu, Qingsong Guo, Bo Zhang, and Fei Li. An efficient approach for measuring semantic relatedness using wikipedia bidirectional links. *Applied Intelligence*, 49(10):3708–3730, 2019.