WikiUMLS: Aligning UMLS to Wikipedia via Cross-lingual Neural Ranking

Afshin Rahimi†, Timothy Bladwin†, Karin Verspoor‡
†School of ITEE, The University of Queensland
‡School of Computing and Information Systems, The University of Melbourne
a.rahimi@uq.edu.au, {tbaldwin, karin.verspoor}@unimelb.edu.au

Abstract

We present our work on aligning the Unified Medical Language System (UMLS) to Wikipedia, to facilitate manual alignment of the two resources. We propose a cross-lingual neural reranking model to match a UMLS concept with a Wikipedia page, which achieves a recall@1 of 71%, a substantial improvement of 20% over word- and char-level BM25, enabling manual alignment with minimal effort. We release our resources, including ranked Wikipedia pages for 700k UMLS concepts, and WikiUMLS, a dataset for training and evaluation of alignment models between UMLS and Wikipedia. This will provide easier access to Wikipedia for health professionals, patients, and NLP systems, including in multilingual settings.¹

1 Introduction

The Unified Medical Language System (UMLS)² is a controlled vocabulary resource, enabling standardisation of biomedical terminology and interoperability of electronic health systems across the world. UMLS has good coverage in only a handful of languages such as English, impeding its uptake in health systems in different language settings. In addition, concept definitions in UMLS are either missing or are very short (e.g. one sentence), impeding its use as a medical encyclopedia. Wikipedia, on the other hand, is a crowd-sourced encyclopedia that is a primary source of online medical knowledge by practitioners, students, and the general public (Heilman et al., 2011; Heilman and West, 2015; Shafee et al., 2017; Murray, 2019). Wikipedia hosts an increasing number of health-related articles (Matheson-Monnet and Matheson, 2017), augmented with the Wikidata knowledge-base (Vrandecic and Krötzsch, 2014). Wikipedia articles exist in 100s of languages, far exceeding the cross-lingual support in UMLS.

Our goal in this work is to align UMLS concepts to their corresponding Wikipedia pages, to expand the language support for UMLS terminology with little effort. This will have a direct impact on patients worldwide by increasing adoption of UMLS (including clinical terminology SNOMED-CT or Medical Subject Headings, MeSH) in international healthcare systems, and also facilitating medical information seeking of patients with varying linguistic backgrounds. For example, a patient whose native language is not English might receive a discharge summary in English with mentions of symptoms, diagnoses, or medications. UMLS terms often don’t match Wikipedia titles exactly, making search hard (and noisy). Aligning UMLS and Wikipedia facilitates such information seeking, makes medical information accessible in a patient’s native language, and supports the need for patient access to information in friendlier terms (Zeng et al., 2001). Wikipedia’s coverage of medical terms is not complete, yet most terms, particularly the most frequent, are covered. Ngo et al. (2019) report that 80% of SNOMED-CT terms have a corresponding Wikipedia page.

Our contributions are as follows:

- We utilise the multilingual resources in UMLS and Wikipedia in a neural ranking model to retrieve Wikipedia articles given a UMLS concept, and achieve a recall@1 of 71%, a 20% increase over a BM25 model;
- We release our new WikiUMLS dataset for training and evaluation of UMLS-to-Wikipedia alignment models;
- We release the output of our cross-lingual

¹Resources available at https://github.com/afshinrahimi/wikiumls
²https://www.nlm.nih.gov/research/umls

8 May 2020
Wikipedia page exists in more than 134 languages. Wikipedia have longer descriptions, are connected well when the two embeddings spaces are learnt on the same concept to a single concept ID (CUI). A single CUI can have several aliases in different languages from various vocabularies. A large proportion of UMLS concepts (roughly 100k) have descriptions that are unfortunately very short (mostly one sentence), and so not adequate for dissemination of knowledge. Medical entity pages in Wikipedia have longer descriptions, are connected to other entities through hyperlinks, and are enriched by the Wikidata (Vrandecic and Krötzsch, 2014) knowledge graph. Wikipedia is rich in content and multilinguality, as anyone can contribute to or revise an article. For example, the diabetes Wikipedia page exists in more than 134 languages, compared to only a dozen languages in UMLS.

There are three main approaches for aligning knowledge bases such as Wikipedia and UMLS:

**Embedding alignment:** For entities of each KB, embeddings are learned separately, and then aligned using a method such as Procrustes based on seed alignments, similar to cross-lingual word embedding learning (Mikolov et al., 2013; Faruqui and Dyer, 2014; Lample et al., 2018). These methods rely heavily on structural similarity (isometricity) of the two embedding spaces, and don’t work well when the two embeddings spaces are learnt on non-comparable corpora (Ormazabal et al., 2019). It is possible to train the two embeddings jointly, but that requires corpus interconnections that are insufficient for our problem.

**Knowledge Graph alignment:** Similar to embedding-based approaches, these methods learn embeddings of the entities, but utilise the relationships between entities in the KG, rather than distributional semantics, for alignment. Many methods have been proposed to learn such embeddings, e.g. TransE (Bordes et al., 2013) learns the embeddings of entities h and t with relation r in triplet \((h, r, t)\) such that \(h + r \approx t\). The embeddings are trained separately, and then aligned using a seed alignment dictionary (Chen et al., 2017), or adversarial learning (Qu et al., 2019). Similar to embedding-based approaches, it is possible to train the embeddings jointly if interconnections between the two KGs are strong (Trisedya et al., 2019; Li et al., 2019). We leave this approach to future work.

**String and semantic matching:** These methods are based on similarity between the entity names or their descriptions. Each entity in KB1 is used as a query against all the entities in KB2. Entities are represented by representations such as bag of words or bag of character n-grams, and compared against all the entities using a similarity measure such as cosine similarity. The individual features are often weighted using TF-IDF, BM25, or their variants. Neural reranking models, trained to rerank documents retrieved by an IR-based method, have proven to be very effective in practice (Guo et al., 2016; Rao et al., 2019). Particularly when query and candidate documents are represented by an encoder such as BERT (Devlin et al., 2019), pre-trained on massive amounts of text data, neural rerankers perform substantially better (Nogueira and Cho, 2019; Akkalyoncu Yilmaz et al., 2019).

### 3 Method

Given a UMLS concept \(c_i\) represented by query \(q_i = \{t_1^i, \ldots, t_N^i\}\), where \(t_n^i\) is an alias term for \(c_i\) in UMLS, our goal is to use English Wikipedia as a document collection \(D = \{d_1, \ldots, d_{|D|}\}\), and retrieve page \(d_j\) that matches concept \(c_i\). Each page is represented by its title, text, and multilingual aliases.\(^3\) We follow a two-stage retrieval procedure: (1) candidate generation, where an IR method (e.g. BM25) is used to retrieve related documents; and (2) reranking of the top \(k\) candidates via a learn-to-rank method (Liu, 2009).

#### 3.1 Candidate Generation

We index Wikipedia collection \(D\) using Lucene, and build query \(q_i\) from UMLS to retrieve the top \(k=64\) relevant pages. We use a Boolean disjunction between all alias terms in UMLS, and search in the title, text, and multilingual aliases fields in \(D\). BM25 relies on exact term matches, and small variations can result in a mismatch. As a result, we also experimented with a character \(n\)-gram method (TFIDF\(_{\text{char}}\)) successfully used in Murty et al. (2018) for candidate generation in medical entity linking. We build a bag of character \(n\)-grams (\(n \in [1, 5]\)) weighted by TF-IDF within term boundaries, and use cosine similarity between \(q_i\).

\(^3\)We only use Wikipedia text for candidate generation, and ignore it for neural reranking.
and each \( d \in D \) (excluding page text) to generate the top \( k=64 \) candidates.

### 3.2 Reranking

We formulate the reranking task as a passage pair binary classification (Nogueira and Cho, 2019), where the first passage is \( q_i \) for concept \( c_i \) from UMLS, and the second passage is the set of Wikipedia alias names for each of top \( k=64 \) documents ranked by candidate generation. The goal is to predict if a pair is a match or not, by minimising the following objective:

\[
L(q_i, \text{cand}_i) = -\log(f(q_i, d^+)) \\
- \sum_{d^- \in \text{cand}_i} \log(1 - f(q_i, d^-))
\]

where \((q_i, d^+)\) is the matching UMLS-Wiki pair, and \(\text{cand}_i^-\) is the set of remaining negative candidates generated by BM25. Function \(f\) is the passage pair encoder, for which we use BERT’s <cls> token encoding (Devlin et al., 2019). We also experiment with BioBERT (Lee et al., 2019) because it is pre-trained on medical literature, which is a better domain fit for our task.

The major shortcoming of BERT and BioBERT is that they don’t encode multilingual aliases effectively, particularly if the scripts are different. As shown in Table 1, aliases of every concept in UMLS, and Wikipedia are on average in 1.4 and 11.2 different languages. This multilingual data can be utilised for triangulation of the matching pair. For example, GERD is a term used in UMLS for Gastroesophageal reflux disease, and is also a given name in many Germanic languages. If it is used for retrieval, many Wikipedia pages related to people with that name will also rank high. However, if alias names of GERD in other languages (e.g. Japanese) are used in the query and documents, the disambiguation becomes easier. To encode multilingual alias concept names we require a model that embeds tokens of different languages into the same embedding space. To this end, we also experiment with multilingual BERT (BERTmulti).

### 3.3 Data

WikiUMLS is a UMLS to Wikipedia aligned dataset we create in this work. It consists of about 17.8k UMLS concepts that are manually linked to their matching Wikipedia page by Wikipedia content contributors. All the UMLS concepts in WikiUMLS are from Medical Subject Headings vocabulary (MeSH) (Lipscomb, 2000). A WikiUMLS record is a tuple of (UMLS CUI, UMLS concept alias set, Wikipedia page title, Wikipedia concept alias set). We use a UMLS concept’s alias set as query, and compare it with every Wikipedia page’s alias set to retrieve the matching Wikipedia page. The Wikipedia aliases, and their links to UMLS are taken from their corresponding record in Wikidata, a collaborative knowledge-base that is tightly connected to Wikipedia. An entity in Wikidata has multilingual aliases, and is linked to both a Wikipedia page, and possibly a UMLS concept.

We split the matching pairs into roughly 10k, 2k, and 5.8k for training, validation, and test set, respectively. There are about 3 million remaining UMLS concepts from various vocabularies that are not aligned to Wikipedia, which we hope to align in this work. Statistics of UMLS, Wikipedia, and the WikiUMLS aligned dataset are shown in Table 1.

### 3.4 Evaluation Methodology

We use the aliases of a concept in UMLS as query, and the aliases for entities in Wikipedia as document collection. A document is relevant to a query if the pair are manually aligned in WikiUMLS (a matching UMLS-Wikipedia pair). We evaluate the models by measuring recall at different positions of their ranking (recall@\(k\)). In this paper, recall and accuracy are equivalent because we assume each UMLS concept has a unique matching Wikipedia page. Because our proposed retrieval method has two stages (candidate generation followed by neural reranking), we use normalised recall (N. recall@\(k\)) to evaluate the neural reranking

| Dataset     | #concepts | #aliases | #langs |
|-------------|-----------|----------|--------|
| UMLS        | 3.7m      | 2.9      | 1.4    |
| Wikipedia   | 8.0m      | 13.0     | 11.8   |
| WikiUMLS    | 17.8k     | 32.0     | 9.6    |

Table 1: The total number, average number of alias names, and supported languages per concept in UMLS, Wikipedia and WikiUMLS.

---

4For the purposes of this work, we focus on the 24 languages currently supported in UMLS: en, es, it, nl, fr, pt, de, cs, ru, zh, ja, hu, tr, ko, no, et, sv, pl, fi, el, lv, da, eu, he.

5A sample Wikidata record: [https://wikidata.org/wiki/Q12206](https://wikidata.org/wiki/Q12206).

---
the candidate generator doesn’t retrieve a relevant document.

4 Results

The performance of the candidate generation methods for word- (BM25) and character-level (TFIDF_char) retrieval, and also the reranking methods (BERT, BioBERT, and BERT_multi) are shown in Figure 1. In all top k positions, BM25 outperforms TFIDF_char, which is surprising given that TFIDF_char was reported to achieve strong performance for entity linking in Murty et al. (2018).

As shown in Table 2, BM25 is able to retrieve the correct Wikipedia page at k=64 with 85% accuracy (compared to 75% for TFIDF_char), an upper-bound for the performance of the reranking models.

For the reranking models, BioBERT performs only slightly better than BERT (68% vs. 67% recall@1), which is surprising given that it has been pretrained on large amounts of medical literature. BERT_multi performs better than both BERT and BioBERT, achieving a recall@1 of 72%, given the cross-lingual nature of the task. Compared to classic vector space approaches (e.g. BM25), BERT_multi shows an improvement of 22%, and 10% for recall@1 and recall@10, respectively. We also report normalised recall at k=1 and k=4, by excluding the test instances for which BM25 doesn’t retrieve the gold candidate. Here, BERT_multi achieves normalised recall at k=1 and k=4 of 84% and 95%, respectively. This indicates that BERT_multi is highly successful at ranking in the case that the correct document is retrieved.

5 Conclusions

We proposed passage pair ranking models based on pretrained contextual encodings for aligning UMLs and Wikipedia, to help bridge between health information systems, and empower consumers with understanding of their health condition. We developed a dataset, WikiUMLS, for training and testing alignment models between the two knowledge-bases, and proposed neural reranking models that substantially outperform BM25.

We showed that the use of multilingual aliases in BERT_multi substantially improves recall@1 compared to BioBERT (72 vs. 68).

The use of subword information such as BPE (Sennrich et al., 2016) as used in XLM (Conneau and Lample, 2019) might improve performance, which we leave for future work. Utilising the relationships between concepts in UMLS and Wikipedia (through Wikidata) to align the two knowledge graphs is an interesting future direction.

We also intend to release a large Wikipedia-based Entity Linking (EL) dataset by using the top-ranked Wikipedia pages for UMLS queries, to be used in state-of-the-art EL models such as zeshel (Logeswaran et al., 2019).

References

Zeynep Akkalyoncu Yilmaz, Wei Yang, Haotian Zhang, and Jimmy Lin. 2019. Cross-domain modeling of sentence-level evidence for document retrieval. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3488–3494, Hong Kong, China.

Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhnenko. 2013. Translating embeddings for modeling multi-relational data. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 26, pages 2787–2795.

Muhao Chen, Yingtao Tian, Mohan Yang, and Carlo Zaniolo. 2017. Multilingual knowledge graph embeddings for cross-lingual knowledge alignment. In
| Method       | recall@64 | recall@4 | recall@1 | N. recall@4 | N. recall@1 |
|--------------|-----------|----------|----------|-------------|-------------|
| BM25         | 85        | 73       | 59       | —           | —           |
| TFIDF_char   | 79        | 67       | 56       | —           | —           |
| BERT<sub>en</sub> | 85   | 79       | 67       | 92          | 78          |
| BioBERT      | 85        | 80       | 68       | 94          | 79          |
| BERT<sub>multi</sub> | 85 | 81       | 72       | 95          | 84          |

Table 2: Performance of the vector space models (BM25, TFIDF<sub>char</sub>), and neural ranking models (BERT<sub>en</sub>, BioBERT, BERT<sub>multi</sub>) over Wikipedia page retrieval given a UMLS concept. The normalised recall (N. recall<sub>@k</sub>) is calculated by excluding queries for which the candidate generator (BM25) didn’t retrieve the relevant document.
Duy Hoa Ngo, Donna Truran, Madonna Kemp, Michael Lawley, and Alejandro Metke-Jimenez. 2019. Can wikipedia be used to derive an open clinical terminology? In Digital Health: Changing the Way Healthcare is Conceptualised and Delivered: Selected Papers from the 27th Australian National Health Informatics Conference (HIC 2019), volume 266, page 136. IOS Press.

Rodrigo Nogueira and Kyunghyun Cho. 2019. Passage re-ranking with BERT. CoRR, abs/1901.04085.

Aitor Ormazabal, Mikel Artetxe, Gorka Labaka, Aitor Soroa, and Eneko Agirre. 2019. Analyzing the limitations of cross-lingual word embedding mappings. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4990–4995, Florence, Italy.

Meng Qu, Jian Tang, and Yoshua Bengio. 2019. Weakly-supervised knowledge graph alignment with adversarial learning. CoRR, abs/1907.03179.

Jinfeng Rao, Linqing Liu, Yi Tay, Wei Yang, Peng Shi, and Jimmy Lin. 2019. Bridging the gap between relevance matching and semantic matching for short text similarity modeling. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5369–5380, Hong Kong, China.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Thomas Shafee, Gwinyai Masukume, Lisa Kipersztok, Diptanshu Das, Mikael Häggström, and James Heilman. 2017. Evolution of wikipedia’s medical content: past, present and future. Journal of Epidemiology & Community Health, 71(11):1122–1129.

Bayu Distiawan Trisedya, Jianzhong Qi, and Rui Zhang. 2019. Entity alignment between knowledge graphs using attribute embeddings. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019, pages 297–304.

Denny Vrandecic and Markus Krötzsch. 2014. Wikidata: a free collaborative knowledgebase. Commun. ACM, 57(10):78–85.

Qing Zeng, Sandra Kogan, Nachman Ash, and Robert A. Greeneres. 2001. Patient and clinician vocabulary: How different are they? In MEDINFO 2001 - Proceedings of the 10th World Congress on Medical Informatics, September 2-5, 2001, London, UK, pages 399–403.