Medical Crossing: a Cross-lingual Evaluation of Clinical Entity Linking

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Abstract

Medical data annotation requires highly qualified expertise. Despite the efforts devoted to medical entity linking in different languages, available data is very sparse in terms of both data volume and languages. In this work, we establish benchmarks for cross-lingual medical entity linking using clinical reports, clinical guidelines, and medical research papers. We present a test set filtering procedure designed to analyze the “hard cases” of entity linking approaching zero-shot cross-lingual transfer learning, evaluate state-of-the-art models, and draw several interesting conclusions based on our evaluation results.

Keywords: medical entity linking, embeddings, linking evaluation, cross-lingual methods, zero-shot learning

1. Introduction

Entity linking is the task of establishing correspondences between free-form text mentions and a formalized list of concepts (Shen et al., 2014; Sevgili et al., 2020). In this work, we consider medical entity linking – the task where entity mentions are mapped against a large set of medical concept names and their concept unique identifiers (CUIs). The biomedical domain is characterized by extensive dictionaries of concepts such as the Unified Medical Language System (UMLS) (Bodenreider, 2004), Medical Subject Headings (MeSH) (Coletti and Bleich, 2001), Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT) (Spackman et al., 1997), or Medical Dictionary for Regulatory Activities (MedDRA) (Brown et al., 1999), and a high variation of mentions. Early models for biomedical entity linking commonly used classification type losses (Rios and Kavuluru, 2018; Miftahutdinov and Tutubalina, 2019; Lou et al., 2020) that work well on narrow benchmarks but often lead to significant performance degradation on other domains and structurally different texts. Modern approaches usually employ similarity between embeddings (distributed representations) of words and concepts. From classical tf-idf and word2vec embeddings (Aronson, 2001; Ghiasvand and Kate, 2014; Van Mulligen et al., 2016; Leaman and Lu, 2016; Dermouche et al., 2016), entity linking systems have evolved to leverage vector representations constructed by deep neural models that take advantage of self-attention (Vaswani et al., 2017) and a BERT-like ranking architecture (Zhu et al., 2019; Sung et al., 2020; Tutubalina et al., 2020). We especially note the Biomedical Named Encoder (BNE) (Phan et al., 2019) and BioSyn (Sung et al., 2020) – a Transformer model based on BioBERT (Lee et al., 2020).

Along with the progress of embedding techniques and neural architectures, the reported performance of state-of-the-art entity linking models has been steadily increasing over the past years. However, their evaluation in many works remains limited. Oftentimes, models are evaluated in the single-terminology setting, on the same kind of data they were trained on, and in a very narrow domain devoted to a specific type of texts and/or a specific set of diseases (e.g. oncological) simply divided into training and test parts. Moreover, standard train/test splits often contain data leaks where the same terminology and even mentions of the same kind leak from the training set into the test set, significantly improving the scores and restricting fair evaluation of transfer capabilities to other domains. Tutubalina et al. (2020) show that this effect leads to a significant positive bias in reported quality metrics and that such data leaks do exist in biomedical datasets of English scientific abstracts widely used for entity linking evaluation.

Lately, entity linking has started to shift towards the zero-shot setting, where the test set contains only novel concepts that have not been seen in the training data (Logeswaran et al., 2019; Basaldella et al., 2020; Mohan et al., 2021; Sevgili et al., 2020). This setting is harder and can be considered more “fair” since it mitigates many trivial linking cases. In this work, unlike commonly used single-terminology evaluation, where all concept names and CUIs from a target dictionary are seen during training, we consider a zero-shot setting – a sophisticated version of cross-terminology setting – a sophisticated version of zero-shot: test sets contain novel concepts from a target terminology, while another terminology is used during
training.

A recent systematic literature survey (Kersloot et al., 2020) reviews the current state of the development and evaluation of NLP algorithms for mapping medical text fragments onto ontology concepts. The authors study 77 works, and only 17 (22%) of them perform the evaluation on non-English datasets, including Italian (Combi et al., 2018), Portuguese (Duarte et al., 2018), Japanese (Usui et al., 2018), and Korean (Kang et al., 2008). Although those datasets do not always contain entity linking annotations, there is an imbalance of English/non-English data. Moreover, prior art with cross-terminology evaluation has been restricted to the single-language setting. In this work, we make another step towards the fair evaluation of medical entity linking models across languages. We unite these two directions, providing both cross-terminology and cross-lingual evaluation on real-life biomedical and clinical texts.

We test the transfer capabilities of recently proposed models for medical entity linking across languages, taking care to avoid leaks from training to test parts of the datasets used. We seek to answer the following research questions:

RQ1: Do test sets of current benchmarks in English, Spanish, French, German, and Dutch lead to an overestimation of performance?

RQ2: What is the fair evaluation strategy?

RQ3: What is the potential of a model trained on a corpus in English to generalize for the zero-shot clinical entity linking in other languages?

RQ4: What types of word representations can be used for cross-lingual clinical entity linking (state-of-the-art contextual word representations, sparse representations)?

We show that filtering the test sets to avoid leaks proves to be crucial for a fair evaluation and provides new interesting and sometimes unexpected conclusions: sparse baselines consistently outperform BERT-based models, domain knowledge is very important for the quality, and fine-tuning on medical datasets can significantly improve the results, an effect that is not noticeable in common benchmarks without filtering.

2. Data

We construct a full-scale multilingual evaluation benchmark from several real-life clinical and biomedical datasets. Table 1 summarizes basic statistics of these datasets: number of concepts, number and the average length of entity mentions, percentage of mentions with numerals. Examples of dataset instances are presented in Table 2.

2.1. CodiEsp

The CodiEsp dataset was presented at Clinical Case Coding in Spanish Shared Task at the CLEF 2020 evaluation forum (Miranda-Escalada et al., 2020). It contains structured information (clinical records) with entities mapped against the ICD-10 vocabulary (CodeBooks, 2016); we use the CodiEsp Diagnosis (CodiEsp-D) subset and the dictionary provided in CodiEsp.

2.2. Cantemist

Cantemist (CANcer TExt Mining Shared Task on IberLEF 2020 (Miranda-Escalada et al., 2020a)) is a manually annotated text corpus of tumor morphology mentions in Spanish mapped to the latest Spanish version of the oncological ontology, which is a part of ICD-O (World Health Organization, 2013); we use the dictionary from (López-Úbeda et al., 2020).

2.3. MCN

MCN (Medical Concept Normalization) (Luo et al., 2019) is a large-scale manually annotated corpus in English for clinical concept normalization produced from a corpus released for the 4th i2b2/VA shared task (Uzuner et al., 2011) with a dictionary of concepts from SNOMED-CT extracted from the UMLS 2020 AA release.

2.4. Mantra

Mantra GSC (Kors et al., 2015) is a collection of biomedical text units such as drug labels and patent claims manually cross-labeled by several annotators in five different languages: English, French, German, Spanish, and Dutch. The Mantra terminology is a subset of UMLS with concepts from MeSH, SNOMED-CT, and MedDRA extracted from the UMLS 2020 AA release; we use DISO entities (UMLS semantic group “Disorders” (Bodenreider and McCray, 2003)).

2.5. Other Datasets

Other available clinical datasets do not suit our needs. The German clinical guidelines dataset (Borchert et al., 2020) does not have concept-level annotations. English, Spanish, and Portuguese texts in MultinEL (Ruas et al., 2020) are synthetic. The Portuguese clinical notes dataset (Peters et al., 2020), the Japanese dataset of patient complaints (Usui et al., 2018), the Korean clinical dataset (Kang et al., 2008), and the Italian drug reaction corpus (Combi et al., 2018) are not publicly available yet. The dataset of death certificates in Portuguese does not contain annotated entities and is not publicly available (Duarte et al., 2018).

An important recent work presented the XL-BEL cross-lingual biomedical entity linking task (Liu et al., 2021) that allowed to test domain transfer across languages. However, XL-BEL does not allow for cross-terminology transfer evaluation and basically represents WikiMed (Vashishth et al., 2020) aligned across
| Dataset          | Lang | # in full corpus | Avg. len in chars | % with numerals | Split Train | Test | Filtering Train set | Filt. | Filt.0.2 | Dictionary Filt. | Filt. | Filt.0.2 |
|-----------------|------|------------------|-------------------|-----------------|-------------|-----|---------------------|-------|----------|-----------------|-------|----------|
| CANTEMIST       | es   | 10031            | 18.73             | 6.92            | 6396        | 3635 | 998                 | 711   | 3268     | 3040            | 3447  | 3347     |
| CodiEsp-D       | es   | 10874            | 15.84             | 1.05            | 7209        | 3665 | 1386                | 1167  | 3449     | 3347            | 3449  | 3347     |
| MCN             | en   | 13609            | 12.36             | 1.54            | 6684        | 6925 | 3204                | 2819  | 3386     | 2304            | 3449  | 3347     |
| Mantra          | de   | 201              | 17.62             | 0.50            | -           | 201  | -                   | -     | 107      | 62             | -     | -        |
|                 | en   | 452              | 16.42             | 1.11            | -           | 452  | -                   | -     | 126      | 66             | -     | -        |
|                 | es   | 166              | 19.67             | 2.41            | -           | 166  | -                   | -     | 65       | 38             | -     | -        |
|                 | fr   | 222              | 17.64             | 0.45            | -           | 222  | -                   | -     | 99       | 50             | -     | -        |
|                 | nl   | 127              | 16.06             | 0.00            | -           | 127  | -                   | -     | 65       | 44             | -     | -        |

Table 1: Statistics of the datasets in English (en), Spanish (es), French (fr), German (de), and Dutch (nl).

ten different languages via Wikipedia, so the critique above fully applies to XL-BEL as well. We note an important difference between datasets such as WikiMed (Vashishth et al., 2020) and medical texts such as clinical health records or scientific abstracts. The usage of medical terms is very different between Wikipedia and other texts, so entity linking results may not transfer well. In this work, we use a disease-centric approach to data collection, with a broad collection of datasets with real medical texts.

2.6. Filtering Strategies

We present a novel test set filtering strategy to avoid train/test leaks and provide a fair and more challenging comparison in the cross-terminology setting. We construct a reference set of terms from concept names in an entity dictionary (thesaurus) and filter out from the test set all instances, in which mention surface forms match any term in the reference set (filtering by a dictionary). We also perform the evaluation in a less challenging setting suggested by Tutubalina et al. (2020) where the reference set for filtering is constructed from the entity mentions in the training dataset (filtering by a training set). For a reference set of terms/entities, we provide the following evaluation types:

- **Full**: compute metrics on the test set as provided in the dataset itself;
- **Filtered**: remove from the test set all entities that are already present in the reference set (exact match, e.g., we remove all instances of “depression” from the test set if it is already present in the reference set);
- **Filtered0.2**: remove from the test set all entities where the character-based Levenshtein distance to the nearest neighbor in the reference set is under 0.2 (e.g., we remove “depressed” if “depression” occurs in the reference set). This complicates the task even further since a model cannot rely on word similarity and have to use more sophisticated contextual features. The bigger the threshold the harder the evaluation setting.

Table 1 shows how many concepts and entity mentions remain in the test sets of each of the datasets after the corresponding filtering method is applied. Note that filtering significantly reduces the number of entity mentions in test sets across all datasets, and the difference is especially striking for training set filtering. This indicates a large number of train set leaks that we discussed in Section 1.

3. Models for Medical Entity Linking

For entity linking, we use a ranking model based on embeddings of a mention and a possible concept. Each entity mention and a concept name is passed first through a model that produces their embeddings and then through an average pooling layer that yields a fixed-sized vector. The inference task is then reduced to finding the closest concept name representation to entity mention representation in a common embedding space, where the Euclidean distance can be used as the metric. Nearest concept names are chosen as top-k concepts for entities.

3.1. Entity and Concept Representations

We compare the following mention/entity vector representations:

- **Tf-idf**: standard sparse tf-idf representations constructed from character-level unigrams and bigrams;
Table 2: Data samples from test sets (with fragments of original source texts where available). Each contains a mention (e.g. “sinusitis”) and a concept ID (e.g. “C0037199”). Note that identifiers come from different sets. “Names” are taken from: “valid_codes.txt” (a list of codes and names provided by the competition organizers) for Cantemist, “codiesp_codes” (a list of valid CIE10 codes provided by the CLEF2020 eHealth track organizers as a dictionary for the corresponding task) for CodiEsp, SNOMEDCT US part of UMLS for MCN and Mantra-En, the rest are taken from MedDRA in German, Spanish, French, and Dutch, respectively.

| Dataset       | Lang | Name                                | CUI   | Mention                                      |
|---------------|------|-------------------------------------|-------|----------------------------------------------|
| CANTEMIST     | es   | “Neoplasia maligna”                 | 8000/3 | malignidad                                   |
|               |      | ...malignado o de malignidad       |       | intermedia...                                |
|               |      | “Neoplasia metastásica”            | 8000/6 | metástásico                                  |
|               |      | ...compromiso metastásico, y tras  |       | presentarse.                                 |
| CodiEsp-D     | es   | “otros trastornos especificados de | M62.89 | hipertrofia del psoas                         |
|               |      | músculo”                           |       |                                              |
| MECA          | en   | “Gastritis”; “Gastric catarrh”, etc.| C0017152 | gastritis                                    |
|               |      | ...was negative for gastritis,      |       | stricture or ulcer...                        |
|               |      | “Empirical therapy (procedure)”    | C1299597 | empiric treatment                            |
| MCN           | en   | “Arthralgia”, “Gelenkschmerz”, etc. | C0003862 | arthralgien                                  |
|               |      | ...Übelkeit, Arthralgien, niedrigem |       | Blutdruck...                                 |
|               |      | “Lumbalgie”, “Unterer Rückenschmerz”, etc.| C0024031 | kreuzschmerzen                               |
|               |      | ...und mittelstarken Kreuzschmerzen |       | kommen...                                    |
| Mantra (DISO) | de   | “Inflammation pulmonaire”, “Pneumonie”, etc.| C0032285 | pneumonie                                    |
|               |      | ...incluent fièvre, anorexie (perte d’ appétit)... |
|               | en   | “Nausea” (disorder), “Feeling     | C0027497 | nausea                                       |
|               |      | queasy, etc.                        |       |                                              |
|               |      | “Arthralgia”, “Pain in joint”, etc. | C0003862 | arthralgia                                   |
|               |      | ...reactions, nausea, arthralgia,   |       | low blood pressure...                        |
|               | es   | “Enflamación pulmonar”, “Neumonia”, etc.| C0032285 | neumonia                                     |
|               |      | “...reacciones, neumonia, ...       |       |                                              |
|               | fr   | “Anoréxique”, “Anorexie”, etc.      | C0003123 | anorexie                                     |
|               |      | ...incluent fièvre, anorexie (perte d’ appétit)... |
|               | nl   | “blaasneoplasma”, “neoplasma blaas”, etc.| C0005695 | blaastumoren                                  |
|               |      | ...classificatie van blaastumoren en de behandeling... |
|               |      | “weefsel infiltratie”               | C0332448 | infiltrerende                                 |

3.2. Fine-tuning

To fine-tune SapBERT models, we use synonym marginalization and iterative candidate retrieval as suggested in a recent state-of-the-art model BioSyn (Sung et al., 2020). We compare the following versions:

- **SapBERT+target** with fine-tuning on the target train set;
- **SapBERT+mcn** with fine-tuning on the MCN English train set;
- **SapBERT+mcn-fz4** and **SapBERT+mcn-fz10** on the MCN English training set with freezing the first four and ten layers, respectively.

4. Experiments

4.1. Experimental Setup

For monolingual evaluation, we leverage the train / test splits provided with each corpus. As shown in Table 1, only CANTEMIST, CodiEsp, and MCN have a train/test split in our study: Mantra subsets are too small for fine-tuning. For cross-lingual evaluation, we train models on the MCN English train set with a source dictionary and evaluate on the test sets of each other corpora (i.e., the target). Specifically, ranking models retrieve the nearest concept name in a target dictionary for a given mention representation at the inference time. We note that cross-lingual evaluation pro-
| Dataset       | Model         | Full Acc@1 | Full Acc@5 | Filtered Acc@1 | Filtered Acc@5 | Filtered₂ Acc@1 | Filtered₂ Acc@5 |
|--------------|---------------|------------|------------|----------------|----------------|----------------|----------------|
| CodiEsp      | TF-idf        | 20.55%     | 39.24%     | 14.21%         | 25.76%         | 13.62%         | 24.51%         |
|              | BERT          | 10.45%     | 15.58%     | 6.49%          | 9.88%          | 6.51%          | 9.68%          |
|              | BETO          | 9.47%      | 15.09%     | 5.92%          | 10.03%         | 5.83%          | 10.03%         |
|              | BioBERT-esp   | 10.07%     | 14.38%     | 6.78%          | 11.98%         | 7.11%          | 12.34%         |
|              | SapBERT       | 47.83%     | 63.66%     | 32.61%         | 46.10%         | 31.62%         | 45.33%         |
|              | SapBERT+target| 67.18%     | 76.23%     | 47.62%         | 61.26%         | 45.42%         | 58.33%         |
|              | SapBERT+mcn   | 48.27%     | 64.07%     | 33.48%         | 47.40%         | 32.56%         | 45.76%         |
|              | SapBERT+mcn-fz4| 49.14% | 64.31% | 33.26% | 47.76% | 31.62% | 45.67% |
| MCN          | TF-idf        | 59.00%     | 65.91%     | 52.12%         | 62.77%         | 51.15%         | 61.58%         |
|              | BERT          | 48.61%     | 52.16%     | 36.64%         | 41.29%         | 36.64%         | 41.15%         |
|              | SapBERT       | 66.28%     | 74.55%     | 62.84%         | 71.99%         | 59.95%         | 69.03%         |
|              | SapBERT+target| 69.36%     | 80.90%     | 66.94%         | 74.42%         | 63.64%         | 73.79%         |
| CANTEMIST    | TF-idf        | 27.02%     | 47.92%     | 20.24%         | 31.76%         | 20.25%         | 32.07%         |
|              | BERT          | 25.50%     | 34.69%     | 8.72%          | 13.43%         | 8.72%          | 13.50%         |
|              | BETO          | 13.43%     | 19.17%     | 9.82%          | 14.13%         | 10.13%         | 14.77%         |
|              | BioBERT-esp   | 15.24%     | 23.41%     | 11.72%         | 18.94%         | 11.81%         | 19.13%         |
|              | SapBERT       | 25.47%     | 36.73%     | 28.06%         | 36.47%         | 28.41%         | 36.99%         |
|              | SapBERT+target| 29.06%     | 43.76%     | 35.31%         | 48.54%         | 35.68%         | 48.51%         |
|              | SapBERT+mcn   | 61.29%     | 67.02%     | 29.06%         | 39.98%         | 29.54%         | 40.51%         |
|              | SapBERT+mcn-fz4| 61.60% | 66.63% | 29.66% | 39.28% | 30.10% | 40.23% |
|              | SapBERT+mcn-fz10| 57.47% | 65.45% | 28.06% | 37.27% | 28.55% | 37.41% |

Table 3: Results of the evaluation with filtering by a training set.

The implementation of the core SapBERT is based on the publicly available repository [Sung et al., 2020](https://github.com/cambridgeltl/sapbert). The modifications are taken from the public BioSyn repository [Conneau et al., 2019](https://github.com/dmis-lab/BioSyn). We fine-tune various SapBERT models (Liu et al., 2021b) starting from the pre-trained checkpoint [SapBERT-UMLS-2020AB-all-lang-from-XLMR](https://github.com/dmis-lab/BioSyn) and the following pre-trained models available in the Hugging Face (Wolf et al., 2020) repository:

- BERT-multilingual ([Devlin et al., 2019](https://github.com/insilicomedicine/Fair-Evaluation-BERT)): bert-base-multilingual-cased;
- BETO ([Cainete et al., 2020](https://github.com/insilicomedicine/Fair-Evaluation-BERT)): dcccuchile/bert-base-spanish-wwm-uncased;
- BioBERT-esp ([Villena, 2021](https://github.com/dmis-lab/BioSyn)): fvillena/bio-bert-base-spanish-wwm-uncased.

The results of our evaluation suggest several important and interesting conclusions. First, Tables 3 and 4 show a significant difference between evaluation strategies: on full test sets, there is virtually no difference between SapBERT variations, but on filtered datasets, fine-tuning on MCN or the target dataset brings a significant increase in accuracy. For weaker baselines, the filtering effect can be drastic. For example, note how the BERT-based model in Table 4 dropped from 48% top-1 accuracy to 12.5% and 6.2% on the MCN dataset after dictionary-based filtering. This indicates that the most successful matches...
| Dataset         | Model               | Full  | Filtered | Filtered  |
|-----------------|---------------------|-------|----------|-----------|
|                 |                     | Acc@1 | Acc@5    | Acc@1    | Acc@5    |
| CodEsp          | Tf-idf              | 20.55%| 39.24%   | 15.63%   | 35.49%   |
|                 | BERT                | 10.45%| 15.58%   | 4.90%    | 10.35%   |
|                 | SapBERT             | 47.83%| 63.66%   | 44.62%   | 61.44%   |
|                 | SapBERT+mcn         | 48.27%| 64.07%   | 45.09%   | 61.87%   |
|                 | SapBERT+mcn-fz4     | 48.32%| 63.68%   | 45.14%   | 61.47%   |
|                 | SapBERT+mcn-fz10    | 49.14%| 64.31%   | 46.01%   | 62.13%   |
|                 |                     |       |          | 38.54%   | 50.95%   |
| Diagnostico     | Tf-idf              | 59.00%| 65.91%   | 33.82%   | 45.87%   |
|                 | BERT                | 48.61%| 52.16%   | 12.55%   | 19.46%   |
|                 | SapBERT             | 62.86%| 74.55%   | 47.50%   | 59.08%   |
|                 | SapBERT+target      | 69.36%| 80.90%   | 54.99%   | 67.13%   |
|                 |                     |       |          | 46.14%   | 58.16%   |
|                 |                     |       |          | 26.54%   | 39.64%   |
| MCN             | Tf-idf              | 27.02%| 47.92%   | 18.85%   | 42.07%   |
|                 | BERT                | 25.50%| 34.69%   | 17.17%   | 27.36%   |
|                 | SapBERT             | 57.47%| 65.45%   | 52.72%   | 61.57%   |
|                 | SapBERT+mcn         | 58.06%| 65.52%   | 57.31%   | 62.88%   |
|                 | SapBERT+mcn-fz4     | 58.06%| 65.52%   | 57.31%   | 62.88%   |
|                 | SapBERT+mcn-fz10    | 57.47%| 65.45%   | 52.72%   | 61.57%   |
|                 |                     |       |          | 46.14%   | 58.16%   |
|                 |                     |       |          | 26.54%   | 39.64%   |
| CANTEMIST       | Tf-idf              | 73.63%| 79.10%   | 50.47%   | 60.75%   |
|                 | BERT                | 59.20%| 63.68%   | 23.36%   | 31.78%   |
|                 | SapBERT             | 87.56%| 95.52%   | 76.64%   | 91.59%   |
|                 | SapBERT+target      | 88.06%| 92.04%   | 51.59%   | 73.02%   |
|                 |                     |       |          | 43.94%   | 62.12%   |
| Mantra          | Tf-idf              | 71.69%| 80.72%   | 45.45%   | 62.34%   |
| (German)        | BERT                | 62.65%| 69.28%   | 25.97%   | 38.96%   |
|                 | SapBERT             | 82.43%| 93.24%   | 62.63%   | 84.85%   |
|                 | SapBERT+target      | 83.33%| 95.50%   | 72.73%   | 84.42%   |
|                 |                     |       |          | 75.32%   | 87.01%   |
|                 |                     |       |          | 75.32%   | 87.01%   |
| Mantra          | Tf-idf              | 71.69%| 80.72%   | 45.45%   | 62.34%   |
| (English)       | BERT                | 62.65%| 69.28%   | 25.97%   | 38.96%   |
|                 | SapBERT             | 82.43%| 93.24%   | 62.63%   | 84.85%   |
|                 | SapBERT+target      | 83.33%| 95.50%   | 72.73%   | 84.42%   |
|                 |                     |       |          | 75.32%   | 87.01%   |
| Mantra          | Tf-idf              | 71.69%| 80.72%   | 45.45%   | 62.34%   |
| (Spanish)       | BERT                | 62.65%| 69.28%   | 25.97%   | 38.96%   |
|                 | SapBERT             | 82.43%| 93.24%   | 62.63%   | 84.85%   |
|                 | SapBERT+target      | 83.33%| 95.50%   | 72.73%   | 84.42%   |
|                 |                     |       |          | 75.32%   | 87.01%   |
| Mantra          | Tf-idf              | 71.69%| 80.72%   | 45.45%   | 62.34%   |
| (French)        | BERT                | 62.65%| 69.28%   | 25.97%   | 38.96%   |
|                 | SapBERT             | 82.43%| 93.24%   | 62.63%   | 84.85%   |
|                 | SapBERT+target      | 83.33%| 95.50%   | 72.73%   | 84.42%   |
|                 |                     |       |          | 75.32%   | 87.01%   |
| Mantra          | Tf-idf              | 71.69%| 80.72%   | 45.45%   | 62.34%   |
| (Dutch)         | BERT                | 62.65%| 69.28%   | 25.97%   | 38.96%   |
|                 | SapBERT             | 82.43%| 93.24%   | 62.63%   | 84.85%   |
|                 | SapBERT+target      | 83.33%| 95.50%   | 72.73%   | 84.42%   |
|                 |                     |       |          | 75.32%   | 87.01%   |

Table 4: Results of the evaluation with filtering by a dictionary.

of these models come from training set leaks and very simple cases of entity linking (surface forms). A fair comparison requires filtering procedures such as the ones we suggest in this paper.

Another result is that fine-tuning on additional medical data is generally beneficial; e.g., we have found that SapBERT fine-tuned on English clinical notes outperforms basic SapBERT consistently across all datasets in our study. However, a separate experimental evaluation is required to find the best parameters for this process: which layers to freeze during fine-tuning, how many epochs of training to conduct, etc. Interestingly, fine-tuning SapBERT improves results only after one epoch (we show these in the tables), and then the quality begins to drop, probably signifying overfitting. We also note that fine-tuning on the target dataset instead of English MCN as expected helps to substantially improve the quality.

Finally, the weaker baselines also provide new insights. The sparse \textit{tf-idf} baseline consistently outper-
forms BERT-based ranking. Many recent works forgo sparse baselines entirely, but our results suggest that it may be premature. Both multilingual and Spanish BERT consistently perform much worse than all competitors, showing that biomedical domain knowledge is crucial for solving this task.

5. Conclusion

We have presented the first cross-lingual benchmark for clinical entity linking in English, Spanish, French, German, and Dutch. We perform an extensive evaluation of BERT-based models with state-of-the-art biomedical representations in two setups: with official train/test splits and with filtered test sets. Our filtering strategy keeps only entity mentions, which are dissimilar to entries from the reference set. As the reference set, we adopt a training set or a target entity dictionary. Our evaluation shows the great divergence in performance between official and proposed test sets for all languages and models, answering positively to the RQ1 and supporting the claim that fair evaluation requires the proposed dataset filtering (the answer to the RQ2). Our experiments with SapBERT show that cross-lingual training on the English MCN corpus substantially helps to improve the performance on clinical datasets in other languages, which answers the RQ3. Finally, answering the RQ4, we note that general-purpose models without domain knowledge and fine-tuning are almost useless for the considered task, falling behind even the simplistic tf-idf baseline. Our fair evaluation shows that clinical entity linking requires pretraining at least on the related biomedical corpora. The constructed benchmark for cross-lingual clinical entity linking is available at https://github.com/AIRI-Institute/medical_crossing. Our study opens up new venues for further work. First, we plan to extend this evaluation to more languages, more corpora, and other types of entities (not only diseases but, e.g., medical procedures or drugs). Second, SapBERT receives a significant boost in the performance by using synonymous relations, but in fact, the concepts form a tree-like hierarchy, and taking it into account may improve the results further. Third, since our method of evaluation moves towards zero-shot territory, we plan to apply other recently developed approaches in zero-shot learning to the entity linking problem.

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