Neural Entity Linking on Technical Service Tickets

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Abstract—Entity linking, the task of mapping textual mentions to known entities, has recently been tackled using contextualized neural networks. We address the question whether these results — reported for large, high-quality datasets such as Wikipedia — transfer to practical business use cases, where labels are scarce, text is low-quality, and terminology is highly domain-specific.

Using an entity linking model based on BERT, a popular transformer network in natural language processing, we show that a neural approach outperforms and complements hand-coded heuristics, with improvements of about 20% top-1 accuracy. Also, the benefits of transfer learning on a large corpus are demonstrated, while fine-tuning proves difficult. Finally, we compare different BERT-based architectures and show that a simple sentence-wise encoding (Bi-Encoder) offers a fast yet efficient search in practice.

Index Terms—Entity Linking, Attention Models, Natural Language Processing

I. INTRODUCTION

Entity Linking refers to the challenge of matching entity mentions in text (e.g. “FAZ”) with the corresponding entity they refer to (e.g. Frankfurter Allgemeine Zeitung). The task is an essential building block to various NLP tasks such as information extraction [10] or question answering [3]. While some challenges (such as spelling errors or abbreviations) can be resolved using heuristics, more complicated cases (such as synonyms, hyponyms or coreferences) must be resolved based on mentions’ contexts. Here, recent neural models based on representation learning on large-scale text collections (typically using language modeling) have achieved impressive results and are commonly considered state-of-the-art [2] [13].

These results have mostly been reported for web-based encyclopedic text (namely, Wikipedia) and knowledge graphs (namely, Freebase). On the other hand, information extraction is increasingly applied for knowledge management in business contexts. Even in vast sectors with a rather technical focus such as mechanical engineering, service and other knowledge based activities are becoming more and more important to revenue (“service is the new marketing”). Given the rapid development of technology paired with a scarce and increasingly fluctuating workforce, experience management becomes vital: domain experts and service technicians must be enabled on the job even when inexperienced or when facing outdated technology. Frequently, documentation is scarce and reduces to hastily collected error messages, service reports, chat protocols or CRM entries. Linking this information to leverage it for a highly efficient support is a vital challenge to knowledge centered businesses. It requires the semantic indexing of unstructured text collections, from the classification of terms and phrases over the automatic extraction of facts to dialogue-based interfaces for digital assistants.

In this paper, we address the question whether the results achieved with neural models on large web-based encyclopedic text and knowledge graphs can be transferred to entity linking “in the wild” (more precisely, in a business context). We present a study in cooperation with our business partner Empolis Information Management, where automated entity linking is of vital interest to facilitate a highly efficient knowledge engineering on a diverse landscape of customer data. Particular, our study focuses on entity linking in a mechanical engineering application scenario: Entities refer to machine parts such as “Flansch”/“Luftanschluss” (flange) or error symptoms such as “Leck”/“laustritt” (leakage). About 1200 of such entities are to be linked to mentions in over 1.6 million tickets collected by service technicians in the field. This setting differs substantially from Wikipedia-based scenarios:

• Domain Change: While Wikipedia covers a breadth of topics, business contexts come with particular terminology, entities and relations. This raises the question how a domain-specific model compares to a generic one pre-trained on Wikipedia.

• Density and Quality: The German Wikipedia contains over 2 million entities, each with concise textual descriptions and manually annotated mentions (backlinks). Business domains are often less rich and come with little annotated data. Also, texts such as error diagnoses and repair descriptions — particularly when entered via mobile devices — tend to suffer from spelling errors and incorrect grammar.

• Language: Finally, business texts come in arbitrary languages (in our case, German). This raises the question whether language-specific models or generic multilingual models [2] are preferable.

We explore these aspects using different entity linkers based on the state-of-the-art transformer network BERT [2]. The approach is based on context matching, i.e. a match likeliness is derived from sentences containing the entity mention on the one hand and the reference entity on the other. Particu-
larly, we study different BERT-based model architectures and pre-training strategies on Wikipedia excerpts as well as the business-domain tickets mentioned above. Our findings are:

- The BERT model does offer benefits compared to a rule-based baseline using manually engineered heuristics. Particularly, combining both approaches in a simple hybrid model gives strong improvements on all domains.
- We found pre-training to be vital, and fine-tuning on the target domain’s limited data to be of little use.
- We compare two BERT-based approaches \[8\], either encoding single sentences (Bi-Encoder) or sentence pairs (Cross-Encoder, which allows attention between sentences). While the latter comes with small performance improvements, the first approach is significantly more scalable and thus preferable in practice.

II. RELATED WORK

Research on entity linking (or named entity disambiguation) \[9\] is usually conducted on Wikipedia-based datasets, where hyperlinks between wikipages serve as mentions and the link targets as entities \[13\] \[14\]. We distinguish between graph-, embedding- and attention-based approaches:

1. Graph-based: These methods aim to encode the relationships that entities form with each other as features to exploit possible interdependencies between them. A method to encode pair-wise interdependence is proposed by Milne and Witten \[14\]. Here models are trained to classify the proposed entity based on a set of statistical features including relatedness (which encodes the semantic proximity of wikipages based on their shared hyperlinks). Han et al. \[7\] extend this approach by defining a weighted graph where vertices are both entities+mentions, and perform a Page-Rank like inference.

2. Embedding-based: Embedding based approaches map entities, mentions and sometimes mention contexts to dense vector representations. Sun et al. \[17\] propose neural tensor networks \[16\] as encoders, trained to minimize the cosine distance between correct entity mention pairs. Yamada et al. \[21\] use the previously mentioned relatedness feature to learn entity embeddings jointly with context and mention embeddings to obtain a geometrical alignment. Francis-Landau et al. \[4\] train a model which learns the similarity between a mention and an entity by applying a logistic regression to a feature matrix comprised of both statistical information gathered on Wikipedia and a feature map of a CNN that received word embeddings of the mention. Nguyen et al. \[15\] follow a similar approach but use RNNs to model both local and global features of the documents containing the mentions and learn to rank candidate entities by their likelihood to be the correct one. Finally, Gupta et al. \[6\] train a joint model to produce entity embeddings from a combination of mentions, contexts and descriptions. The most likely entity is determined by using the mention-context-encoder of the joint model.

3. Attention-based: Most similar to our work are embedding-based methods that rely on the attention mechanism, where embeddings are contextualized using an attention-based architecture such as transformer networks \[2\]. Yamada and Shindo \[20\] approach the problem by fine-tuning a pre-trained transformer model \[18\]. They optimize a masked entity prediction task where the model is trained to predict an entity given an entity and a sample sentence containing the entity. Kolitsas et al. \[11\] use a bidirectional sentence encoder and combine it with the attention mechanism proposed by Ganea and Hofmann \[5\] to obtain a score for mention-entity pairs while considering a given textual context both locally (on sentence level) and globally (considering all other mentions on document level). Logeswaran et al. \[12\] and Wu et al. \[19\] study the problem of entity linking in a zero-shot scenario where the model is confronted with entities unseen in training (we also tackle this setting). Logeswaran et al. \[12\] generate entity candidates by selecting mentions via BM25 scoring and then re-rank those with different BERT-based models. Both encoders score with the dot product of their output. Wu et al. \[19\] employ BERT-based models called Bi-Encoder and Cross-Encoder for ranking. We evaluate similar architectures in our work. In contrast to this, our approach neither needs special encodings nor markers for the Bi-Encoder and can thus be used without any fine-tuning.

III. APPROACH

We assume a set of entities \(E = \{e_1, e_2, \ldots, e_m\}\) to be given (such as New York Times). Entity linking is targeted at mapping a textual entity mention (such as “Times”) to the correct entity. Each mention comes with a context sentence (such as “The Times reported the Dow Jones to drop by 1%”). The entity linker is trained on a different set of entities \(E'\) with \(E' \cap E = \emptyset\) (i.e., we tackle an open-world setting where entity linking is applied to novel entities unseen when learning). For all entities \(e \in E \cup E'\), we assume a set of reference sentences \(S(e)\) to be given, each containing a mention of the entity.

We evaluate three entity linking models: a heuristic one, a BERT-based one, and a hybrid method combining the other two. Those strategies are outlined in the following.

A. Heuristic Linking

A simple way of matching a mention (such as “FAZ”) to an entity (such as Frankfurter Allgemeine Zeitung) is to simplify both strings and then perform a string comparison. Our first approach follows this strategy and applies a set of symbolic transformations (or heuristics) \(f\) on the given mention \(m_i\) and entity name \(e_j\) to find matches of the form \(f(m_i) \approx f(e_j)\). Thereby, we compare \(f(m_i)\) and \(f(e_j)\) with the Damerau Levenshtein distance \(d^L(f(m_i), f(e_j))\). We adopted several heuristics commonly used in name matching tasks, and picked the following combination \(f_1, \ldots, f_7\) which worked best on our Wikipedia-based datasets:

1) Remove Punctuation: removes non-alphanumeric characters such as ,!#,(),[], or .
2) Corporate Forms: removes corporate suffixes, e.g. HolidayCheck Group AG \(\rightarrow\) HolidayCheck.
3) Lowercasing, for example IBM \(\rightarrow\) ibm
4) Stemming, for example working \(\rightarrow\) work
entity with the closest reference sentence compared to the
mention’s context is returned. We investigate two approaches
employing BERT as an encoder, referred to as Bi-Encoder
and Cross-Encoder in reminiscence to Humeau et al. [8].
Both approaches (illustrated in Figure 1) fine-tune BERT on
the entity linking task by aligning mentions referring to the
same entity.

Bi-Encoder: Let $s = (t_1, \ldots, t_m, \ldots, t_{m+k}, \ldots, t_n)$
be a sentence in which the (word-piece) token subsequence
$t_m, \ldots, t_{m+k}$ refers to the entity mention. BERT transforms
$s$ to an embedding sequence $b_1, \ldots, b_n$ of 768-dimensional
vectors (excluding the obligatory CLS and SEP tokens). We
define the mention’s representation as the average over its
tokens’ BERT embeddings:

$$v(s) = \frac{1}{k+1} \cdot (b_m + \cdots + b_{m+k})$$  (1)

In training, we sample pairs $(s, s')$ of sentences either
describing the same entity (positive samples) or not (negative
samples). These sentences are then transformed by the model
and their cosine distance $d(s, s') := 1 - \cos(v(s), v(s'))$ is
computed. The (BERT) model’s weights are updated using
SGD with a contrastive max-margin loss:

$$L^{(mm)}(s, s', y) := y \cdot d(s, s')^2 + (1-y) \max(\gamma - d(s, s'), 0)^2$$  (2)

where the label $y \in \{0,1\}$ denotes whether a sentence pair
is positive (1) or negative (0), and $\gamma$ is the margin.

For inference, the sentence containing the mention to be
linked is matched against each entity $e$’s set of reference
sentences $S(e)$. The entity with the most similar BERT mention
embedding is returned:

$$e^*(s) := \arg \min_{e \in E} \min_{s' \in S(e)} d(s, s').$$  (3)

A scalable search over all entities is realized using
approximate nearest neighbor search with annoy[3].

Cross-Encoder In the second approach the sentence pairs
are not successively but simultaneously passed to the model.
This enables attention between the sentences, which has been
proven beneficial in other tasks [8]. To do so, special markers
are introduced before/after the beginning/end of a mention.
Furthermore, the input sentences $s, s'$ are separated by a
dedicated separator token (see Figure [1]).

Instead of averaging token embeddings as in Equation (1),
we define the mention pair’s representation $v^{(s,s')} := b_{CLS}$
to be BERT’s embedding of the classifier token. From this, we
infer the probability that the two mentions in their respective
context refer to the same entity:

$$P(s, s') := \sigma(W \cdot v^{(s,s')} + b),$$  (4)

5) Stopword removal, e.g. Procter and Gamble → Procter
Gamble

6) Sorting tokens alphanumerically, e.g. reeves keanu →
keanu reeves.

7) Abbreviations All token n-grams are abbreviated to
their initials, after decomposing words into their comp-
ounds\footnote{1https://github.com/dtuggener/CharSplit}
e.g. allgemeiner wirtschaftsdienst → awd.

For inference, a yet unlinked mention $m$ and entity $e$
are transformed by applying each heuristic to the outcome of its
predecessor. We then define the distance between $e$ and $m$
as the minimum Levenshtein distance over the sequence of
heuristics:

$$d(m, e) := \min_{t=0, \ldots, 7} d^L \left( f_t \circ \cdots \circ f_1 (m),
\quad f_t \circ \cdots \circ f_1 (e) \right)$$

Finally, the heuristic linker returns the entity $e$ with
minimum distance $d(m, e)$ to mention $m$. A scalable search over
all entities is achieved by indexing with SymSpell\footnote{2https://github.com/wolfgarbe/SymSpell}.

B. Contextual Linking

While the heuristic linker is based on a string comparison
of mention and entity name, our second method includes
mentions’ context sentences. The approach matches mentions
in query sentences with mentions of known entities in
reference sentences. All mentions are mapped to dense,
documentized vectors (embeddings). For inference, the

Fig. 1. Model Overview: On top is the Bi-Encoder (a) model where a BERT
is fine-tuned in a Siamese fashion to reduce the distance of the pooled mention
embbeddings. Below is the Cross-Encoder (b) version where two sentences are
fed into BERT simultaneously. Here, the mentions are wrapped by special
BEG and END tokens. The CLS embedding is regressed to a scalar to learn the
the likelihood of the two mentions expressing the same entity.

\begin{itemize}
  \item \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \hspace{1cm} \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \hspace{1cm} \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \hspace{1cm} \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \hspace{1cm} \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \hspace{1cm} \textbf{CLS} \hspace{1cm} \textbf{BEG} \hspace{1cm} \textbf{SEP} \\
  b_1 \hspace{0.5cm} \ldots \hspace{0.5cm} b_n \hspace{0.5cm} b_{m-1} \hspace{0.5cm} b_m \hspace{0.5cm} b_{m+1} \hspace{0.5cm} b_{m+2} \\
  b'_1 \hspace{0.5cm} \ldots \hspace{0.5cm} b'_n \hspace{0.5cm} b'_{m-1} \hspace{0.5cm} b'_m \hspace{0.5cm} b'_{m+1} \hspace{0.5cm} b'_{m+2} \\
  v \hspace{0.5cm} + \hspace{0.5cm} b \hspace{0.5cm} \rightarrow \hspace{0.5cm} \sigma
\end{itemize}
where $W \in \mathbb{R}^{d \times 1}$ reduces the BERT CLS representation to a scalar and $\sigma$ denotes the sigmoid activation function. As a training objective, we use a binary cross entropy loss:

$$L_{CE}(s, s', y) := -(y \cdot \log(P(s, s')) + (1-y) \cdot \log(1 - P(s, s')))$$

Note that — since both sentences are passed simultaneously through BERT — this model does not allow to precompute embeddings in an index structure but requires a sequential pairwise comparison of the input sentence with all reference samples.

C. Hybrid Linking

It is reasonable to assume that heuristic matching offers a reliable solution for simple cases such as abbreviations or spelling errors, while the BERT-based linker can disambiguate more complicated cases based on context. Therefore, we combine both using a simple strategy: We first apply the heuristic linkers. If this returns none or multiple suitable entities with the same distance, the BERT-based linker is applied instead.

IV. Experiments

For our experiments we investigate the advantages of contextual linking approaches over heuristic approaches as well as the combination of both methods. We further investigate the importance of the language in which a neural model is trained on, and how well these methods can be applied to synonym detection, a practical knowledge engineering use case.

A. Data

We evaluate our entity linking methods using two structured, high-quality Wikipedia-based datasets as well as the business domain dataset, which contains a significant amount of colloquialism and spelling errors.

Wikipedia – Mixed+Gerte: We crawled two different datasets (Gerte and Mixed) from the German Wikipedia using the internal hyperlink structure that links words or phrases between articles. For our approach, each article is considered an entity and referred to by multiple mentions in different contexts. The Mixed dataset contains diverse entities, while — as a topical partner’s ticket corpus. For our contextual linking approach, we use the tickets in which the synonyms appear as context information.

An overview of the size of all datasets is given in Table I. The training split is used to fine-tune the neural models, the validation split for tuning hyperparameters and the testing split for evaluation. All three splits contain disjoint sets of entities, i.e. we test on different entities than validating/training on. Furthermore, the sentences are divided into reference and query sentences (50/50% for Wikipedia, 30/70% for Empolis).

B. Hyperparameters

We evaluate the contextual linking approach using different BERT models: We start with a pre-trained, multilingual off-the-shelf BERT model\(^1\) (orig). Later experiments include variations which have been fine-tuned on the entity linking task using the losses in Equation\(^2\) and\(^5\). Finally, we also test a domain-specific BERT created by fine-tuning a pre-trained German BERT model\(^3\) on the Empolis data using the standard masked language modelling loss.

C. Heuristic vs Contextual Linking

We compare the top-1 accuracy of the heuristic linking approach with the BERT-based Bi-Encoder in Table II. Additionally, we evaluate how well the combination of the heuristic linking approach with the Bi-Encoder (Hybrid) performs. For the Bi-Encoder approaches, results using the original multilingual BERT model as well as a fine-tuned version are reported.

The results show that the combination of heuristic linking with contextual information (Hybrid) leads to the best performance. This improvement is most significant on the Empolis target domain where we observe improvements of the linking accuracy of up to 20% relative to the heuristic baseline. Here, we found the models to best complement each other (heuristic linking covers simple cases reliably, BERT-based linking more complicated synonyms). A few entity linking examples using our hybrid approach are detailed in Table III.

\(^{1}\)https://github.com/google-research/bert

\(^{2}\)https://deepset.ai/german-bert

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### Table I

**Dataset Statistics (Number of Entities and Sentences)**

| Dataset  | Train #Ent. | Train #Sent. | Test #Ent. | Test #Sent. | Validation #Ent. | Validation #Sent. |
|----------|-------------|--------------|------------|-------------|------------------|-------------------|
| Mixed    | 8331        | 107082       | 1027       | 12853       | 1031             | 13560             |
| Gerte    | 5717        | 65101        | 698        | 7680        | 3231             | 35823             |
| Empolis  | 401         | 13587        | 200        | 6601        | 201              | 6281              |

### Table II

**Comparing Different Linking Approaches on Two Wikipedia Excerpts (Gerte, Mixed) and the Partner’s Business Data (Empolis). A Combination of Heuristic and BERT-based Approaches (Hybrid) Offers the Highest Accuracy.**

| Classifier | Top1 Accuracy [%] | Gerte | Mixed | Empolis |
|------------|-------------------|-------|-------|---------|
| Heuristic  | 77.87             | 83.98 | 51.16 |
| BERT-Bi (orig) | 93.30             | 95.93 | 40.06 |
| BERT-Bi (fine-tuned) | 93.32             | 97.25 | 35.11 |
| Hybrid (orig)      | 94.72             | 97.52 | 71.40 |
| Hybrid (fine-tuned) | 93.40             | 97.84 | 69.76 |
D. Bi-Encoder vs Cross-Encoder

Next, we address the question which BERT-based architecture is more suitable. Table [IV] compares Bi-Encoder and Cross-Encoder. Both approaches are evaluated individually as well as in combination with the heuristic linking approach (Hybrid). Note that — due to the introduction of additional markers — the Cross-Encoder can only be evaluated using a fine-tuned BERT model.

While the Bi-Encoder offers a highly scalable search via index structures, the Cross-Encoder requires pairs of samples to be processed by the BERT model. Correspondingly, the time needed to determine an entity is proportional to the amount of reference samples in a dataset. This increases the processing time rapidly. Therefore, we conduct the experiment only on a reduced number of randomly sampled queries of about 700, 1000 and 200 mentions for the Gerte, Mixed and Empolis dataset respectively.

Comparing the Bi- and Cross-Encoder, we can see that while the Cross-Encoder does perform better on all datasets, the practical performance increase for the Hybrid-Model is limited (1–4%). In contrast, the Bi-Encoder is considerably faster by a factor of 1500 (Gerte), 3500 (Mixed) and 100 (Empolis) — Comparing a single query sentence against all 6601 reference sentences takes around 23 seconds with the Cross-Encoder. These results highlight the effectiveness of the Bi-Encoder in practical settings.

E. Domain vs Multilingual BERT

Next, we tackle the issue of switching from the large, generic Wikipedia domain to the specific business use case. We compare the performance of the pre-trained multilingual BERT model with a domain-specific BERT model (German BPE tokens, pre-trained on the domain using language modeling). We further evaluate the performance of both models after fine-tuning them on the entity linking task. Similar to the previous experiment the evaluation has been performed using a reduced number of samples.

F. Synonym Discovery on Empolis

Finally, we evaluate the utility of the Bi-Encoder in a practical use case: The detection of synonyms for domain concepts (such as “laustritt” and “Leck”) is key to understanding unstructured domain specific text, e.g. to identify descriptions of a reoccurring problems. In practice, synonyms are acquired by experts during the knowledge engineering process, which requires domain expertise and is extremely time-consuming. Therefore, it is of practical interest to suggest synonyms automatically.

Given test entities on the Empolis dataset, we apply our model (using the Hybrid Bi-Encoder) to identify synonyms in the Empolis corpus and return a ranked list of suggestions. Especially, we evaluate how well our model can identify new synonyms which have been missed by human experts. In order to determine synonyms of a query entity, we use a PoS-Tagger to detect nouns and link each noun to an entity using its context sentence. If the resulting entity is identical to the query entity, the noun is stored as potential synonym with its respective distance.

We collected synonym suggestions for 20 query entities and labeled their correctness manually into three categories (matches, non-matches, maybe-matches). Results are detailed in Figure [IV]. We observe that our system is definitely helpful in a practical knowledge engineering setting, suggesting at least one correct synonym (blue) in 13 of 20 cases and achieving an average precision of 35%. Additionally to the known synonyms acquired by experts, the Bi-Encoder is able to identify 1.4 new correct synonyms per entity on average.
Fig. 2. New synonyms suggested by the Hybrid model on the Empolis data.

V. DISCUSSION

In this paper, we have studied the application of state-of-the-art deep language models for entity linking in a business context. We show that an ensemble of symbolic transformations and a neural approach using BERT achieves impressive results — both on Wikipedia excerpts and a very noisy real-world dataset from an industry partner. It can be highlighted that our Bi-Encoder approach, which offers the opportunity to cache a set of pre-computed reference samples, is performing comparably to an expensive Cross-Encoder approach. This enables a resource-efficient production use-case. While a straightforward fine-tuning to the target domain fails so far, developing effective strategies of fine-tuning to limited noisy domains will be our main focus in the future.

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