ExtEnD: Extractive Entity Disambiguation

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Abstract
Local models for Entity Disambiguation (ED) have today become extremely powerful, in most part thanks to the advent of large pre-trained language models. However, despite their significant performance achievements, most of these approaches frame ED through classification formulations that have intrinsic limitations, both computationally and from a modeling perspective. In contrast with this trend, here we propose ExtEnd, a novel local formulation for ED where we frame this task as a text extraction problem, and present two Transformer-based architectures that implement it. Based on experiments in and out of domain, and training over two different data regimes, we find our approach surpasses all its competitors in terms of both data efficiency and raw performance. ExtEnd outperforms its alternatives by as few as 6 $F_1$ points on the more constrained of the two data regimes and, when moving to the other higher-resourced regime, sets a new state of the art on 4 out of 6 benchmarks under consideration, with average improvements of 0.7 $F_1$ points overall and 1.1 $F_1$ points out of domain. In addition, to gain better insights from our results, we also perform a fine-grained evaluation of our performances on different classes of label frequency, along with an ablation study of our architectural choices and an error analysis. We release our code and models for research purposes at https://github.com/SapienzaNLP/extend.

1 Introduction
Being able to associate entity mentions in a given text with the correct entity they refer to is a crucial task in Natural Language Processing (NLP). Formally referred to as Entity Disambiguation (ED), this task entails, given a mention $m$ occurring in a text $c_m$, identifying the correct entity $e^*$ out of a set of candidates $e_1, \ldots, e_n$, coming from a reference knowledge base (KB). First introduced by Bunescu and Paşca (2006), ED aims to identify the actors involved in human language and, as such, has shown potential in downstream applications like Question Answering (Yin et al., 2016), Information Extraction (Ji and Grishman, 2011; Guo et al., 2013), Text Generation (Puduppully et al., 2019) and Semantic Parsing (Bevilacqua et al., 2021; Procopio et al., 2021).

Since the advent of Deep Learning within the NLP community, this task has mostly been framed as a multi-label classification problem (Shahbazi et al., 2019; Broscheit, 2019), especially leveraging the bi-encoder paradigm (Humeau et al., 2020; Wu et al., 2020). However, although simple and yet powerful enough to push scores past 90% in KB Micro $F_1$ on standard benchmarks, this formulation suffers from a number of downsides. First, the actual disambiguation is only modeled through a dot product between independent mention and entity vectors, which may not capture complex mention-entity interactions. Second, from a computational perspective, entities are represented through high-dimensional vectors that are cached in a pre-computed index. Thus, classifying against a large KB has a significant memory cost that, in fact, scales linearly with respect to the number of entities. Besides this, adding a new entity also requires modifying the index itself. To address these issues, De Cao et al. (2021b) have recently proposed an auto-regressive formulation where, given mentions in their context, models are trained to generate, token-by-token, the correct entity identifiers.

While this approach has addressed the aforementioned issues effectively, it requires an auto-regressive decoding process, which has speed implications, and, what is more, does not let the model see its possible output choices, something

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that has shown significant potential in other semantic tasks (Barba et al., 2021a). In this work, we focus on these shortcomings and, inspired by this latter research trend, propose Extractive Entity Disambiguation (ExtEND), the first entity disambiguator that frames ED as a text extraction task. Given as input a context \( c_m \) in which a mention \( m \) occurs, along with a text representation for each of the possible candidates \( e_1, \ldots, e_n \), a model has to extract the span associated with the text representation of the entity that best suits \( m \). We implement this formulation through 2 architectures: i) a Transformer system (Vaswani et al., 2017; Devlin et al., 2019) that features an almost identical modeling power to that of previous works, and ii) a variant that relaxes the computational requirements of our approach when using common Transformer-based architectures. Evaluating our two systems over standard benchmarks, we find our formulation to be particularly suited to ED. In particular, when restricting training resources to the AIDA-CoNLL dataset (Hoffart et al., 2011) only, ExtEND appears to be significantly more data-efficient than its alternatives, surpassing them by more than 6 \( \text{inKB Micro F}_1 \) points on average across \( \text{in-domain} \) and \( \text{out-of-domain} \) datasets. Furthermore, when pre-training on external ED data as in De Cao et al. (2021b), our system sets a new state of the art on different benchmarks under consideration, with average improvements of 0.7 overall and 1.1 when moving out of domain. Finally, we also perform a thorough investigation of our system performances, providing insights and pinpointing the reasons behind our improvements via a fine-grained evaluation on different label-frequency classes.

Our contributions are therefore as follows:

- We propose a new framing of ED as a text extraction task;

- We put forward two architectures that implement our formulation, whose average score across different benchmarks surpasses all previous works in both data regimes we consider;

- We perform a thorough analysis of our systems’ performances, evaluating their behavior over different label-frequency classes.

We release our code and models for research purposes at https://github.com/SapienzaNLP/extend.

2 Related Work

Entity Disambiguation (ED) is the task of identifying, given a mention in context, the most suitable entity among a set of candidates stored in a knowledge base (KB). Generally the last step in an Entity Linking system (Broscheit, 2019), coming immediately after mention detection and candidate generation, this task has been the object of a vast and diverse literature, with approaches typically clustered into two groups, depending on how they model co-occurring mentions in the same document. On the one hand, \textit{global models} strive to enforce a global coherence across the disambiguations within the same document, leveraging different techniques and heuristics to approximate this objective\(^2\) (Hoffart et al., 2011; Moro et al., 2014; Yamada et al., 2016; Ganea and Hofmann, 2017; Le and Titov, 2018; Yang et al., 2018).

On the other hand, \textit{local models} disambiguate each mention independently of the others, conditioning the entity choice only on the mention and its context. Thanks to the advent of large pre-trained language models, this group has recently witnessed a significant improvement in performances, which are nowadays on par with, or even above, those achieved by state-of-the-art global systems (Shahbazi et al., 2019). These approaches usually frame ED as a multi-label classification problem (Broscheit, 2019) and a diverse set of formulations have been proposed. Among these, the bi-encoder paradigm (Bromley et al., 1994; Humeau et al., 2020) has been particularly successful (Gillick et al., 2019; Tedeschi et al., 2021; Botha et al., 2020): here, two encoders are trained to learn vector representations in a shared space for mentions in context and entities, respectively. Classification of a given mention is then performed by retrieving the entity whose representation is closest according to some metric (e.g. cosine similarity).

Although remarkably powerful, these formulations present a number of disadvantages, such as their large memory footprint (each entity in the KB needs to be represented by a high-dimensional vector) and the fact that the actual disambiguation process is only expressed via a dot product of independently computed vectors, potentially neglecting mention-entity interactions. While a number of works (Logeswaran et al., 2019; Wu et al., 2020) attempt to address the latter issue via multi-stage

\(^2\)Approximation is necessary as the exact computation of coherence objectives is NP-hard (Le and Titov, 2018).
approaches where a cross-encoder is stacked after an initial bi-encoder\(^3\) or other retrieval functions, an interesting alternative direction that tackles both problems was recently presented by De Cao et al. (2021b): the authors frame ED as a generation problem and, leveraging an auto-regressive formulation, train a sequence-to-sequence model to generate the correct entity identifier for a given mention and its context.

Nevertheless, while this approach can model more complex interactions, some of these can only occur indirectly inside the backtracking of their beam search. Furthermore, the disambiguation involves an auto-regressive decoding that, although mitigated by later efforts (De Cao et al., 2021a), has intrinsic speed limitations. In contrast, here we propose an extractive formulation, where a model receives as input the mention, its context and the text representation of each candidate, and has to extract the span corresponding to the representation of the entity that best matches the \((\text{mention, context})\) pair. Note that this differs from the aforementioned cross-encoder formulations (Logeswaran et al., 2019; Wu et al., 2020) where, instead, each entity was encoded together with the \((\text{mention, context})\) pair, but independently from all the other entities. With our schema, complex mention-entity and entity-entity interactions can be explicitly modeled by the neural system, as all the information is provided in input.

Glancing over other related tasks in the area of semantics, arguably closest to our work is ESC (Barba et al., 2021a), where the authors propose a new framing of Word Sense Disambiguation (WSD) as an extractive sense comprehension task. Yet, differently from their work, we propose here a new framing for ED, i.e. focus on entity descriptions rather than word sense definitions, present a baseline system that implements it and devise an additional architecture that deals with the computational challenges that arise from such implementation.

3 Model

We now introduce ExtEND, our proposed approach for ED. We first present the formulation we adopt (Section 3.1) and, then, describe the two architectures that implement it (Section 3.2).

3.1 Formulation

Inspired by recent trends in other semantic tasks (Barba et al., 2021a), we formulate Entity Disambiguation as a text extraction problem: given a query \(x_q\) and a context \(x_c\), a model has to learn to extract the text span of \(x_c\) that best answers \(x_q\). Formally, let \(m\) be a mention occurring in a context \(c_m\) and denote by \(\text{Cnd}(m) = \{\text{cnd}_1, \ldots, \text{cnd}_n\}\) the set of \(n\) text representations associated with each candidate of \(m\). Then, we formulate ED as follows: we treat the tuple \((m, c_m)\) and the concatenation of \(\text{cnd}_1, \ldots, \text{cnd}_n\) as the query \(x_q\) and the context \(x_c\), respectively, and train a model to extract the text span from \(x_c\) associated with the correct \(\text{cnd}^* \in \text{Cnd}(m)\); the overall process is illustrated in Figure 1. This formulation helps to better model the input provided, with the possible
candidates of \( m \) included in the contextualization process, while also disposing of large output vocabularies as in De Cao et al. (2021b) and, yet, not resorting to auto-regressive decoding strategies.

3.2 Architectures

To implement our formulation, we consider two Transformer-based architectures. For both of these, the input is composed of the concatenation of the query \( x_q \) and the context \( x_c \), subword-tokenized and separated by a \([SEP]\) special symbol. Since \( x_q \) is a tuple in our formulation, whereas Transformer models only support text sequences as input, we convert \( x_q \) into a string \( \hat{x}_q \) by taking only \( c_m \) and surrounding the text span where \( m \) occurs with the special tokens \(<t>\) and \(</t>\). Additionally, to better separate entity candidate representations and ease their full span identification, we add a trailing special symbol \(</ec>\) to each of them; henceforth, we denote this resulting modified context by \( \hat{x}_c \).

As our first architecture, we use two independent classification heads on top of BART (Lewis et al., 2020) computing, respectively, for each word \( w \) in \( \hat{x}_c \), whether \( w \) is the start or end of the correct entity representation \( cnd^* \). We train the model with a cross-entropy criterion over the start and end of \( cnd^* \). At inference time, we select the entity candidate representation \( cnd \in Cnd(m) \) whose joint probability over the 2 heads is highest.

However, framing ED as we propose here implies that the length of the input to the model scales linearly with the number of output choices \( m \). Taking into account that the attention mechanism of Transformer architectures has quadratic complexity and that several pre-trained models actually support inputs only up to a fixed maximum length,\(^4\) this might pose significant computational limitations depending on the dataset and knowledge base under consideration. To cope with these technical challenges, we consider a second system, similar to the previous one but for two main differences. First, we change the underlying Transformer model, replacing BART with a pre-trained Longformer model (Beltagy et al., 2020), a Transformer architecture with an attention mechanism that is linear with respect to the input length and that can handle longer sequences. This linear complexity is achieved by essentially applying a sliding attention window over each token but for a few pre-selected ones (e.g. \([CLS]\)), which instead feature a symmetric global attention: they attend upon and are attended by all the other tokens in the input sequence. This global mechanism is intended to be task-specific and enables the model to learn representations potentially close to those standard fully-attentive Transformers would learn, while still maintaining the overall attention complexity linear with respect to the input size. Therefore, as our second modification, we adapt this global pattern to our setting, activating it on the \([CLS]\) special token and on the first token of each \( cnd_i \in Cnd(m) \); this allows to better mimic the original quadratic mechanism where different entity candidate representations can also attend upon each other. Furthermore, differently from Beltagy et al. (2020), we disable the global attention mechanism on the tokens in the query \( \hat{x}_q \). In Section 5, we report and discuss the impact of these modifications. We illustrate the proposed architecture in Figure 2.

4 Entity Disambiguation Evaluation

We now assess the effectiveness of ExtEND on Entity Disambiguation. We first introduce the experimental setup we consider (Section 4.1). Then, we present the results achieved by ExtEND both in terms of raw performances (Section 4.2) and via a breakdown of its behavior on different classes of label frequency (Section 4.3). For ease of readability, we focus here only on the Longformer-based architecture, which we consider as our main model. We defer the comparison with the BART-based system to Section 5.

4.1 Experimental Setup

Data To evaluate ExtEND on Entity Disambiguation, we reproduce the same setting used by De Cao et al. (2021b). Specifically, we adopt their same candidate sets, which were originally proposed by Le and Titov (2018).\(^5\) use Wikipedia titles (e.g. *Metropolis* (comics)) as the text representation for entities and perform training, along with *in-domain* evaluation, on the AIDA-CoNLL dataset (Hoffart et al., 2011, AIDA); similarly, we use their cleaned version of MSNBC, AQUAINT, ACE2004, WNED-CWEB (CWEB) and WNED-WIKI (WIKI) (Guo and Barbosa, 2018; Evgeniy et al., 2013) for *out-of-domain* evaluation.

\(^4\)For instance, the implementation of BART available in HuggingFace Transformers (Wolf et al., 2020) supports inputs only up to 1024 subwords.

\(^5\)These candidate sets were generated relying upon count statistics from Wikipedia, a large Web corpus and the YAGO dictionary.
While we use this AIDA-only training scenario, which we refer to as AIDA, to test the data efficiency of EXTEND, most ED systems actually make use of additional data and information originating from Wikipedia at training time. We denote this additional training scenario where Wikipedia is part of the training resources as Wikipedia+AIDA. Specifically, as our system is a supervised neural classifier, we follow De Cao et al. (2021b) and utilize BLINK data (Wu et al., 2020) for ED pre-training in this setting. A brief description of each dataset follows:

i) **AIDA**: one of the largest manually annotated corpora for Entity Linking and Disambiguation. It contains 388 articles from the Reuters Corpus with 27,724 labeled mentions. The training set contains 18,448 instances, while the validation and test sets feature 4791 and 4485 samples, respectively.

ii) **MSNBC**: a small news corpus with 20 articles from MSNBC on 10 different topics. It contains 656 annotated instances.

iii) **AQUAINT**: a news corpus composed of 50 documents with news coming from the Xinhua News Service, the New York Times and the Associated Press. It contains 727 annotated instances.

iv) **ACE2004**: a manually annotated subset of the ACE co-reference data set (Doddington et al., 2004). It contains 257 annotated instances.

v) **CWWEB**: a dataset automatically extracted from the ClueWeb corpus by Guo and Barbosa (2018) containing English Websites, consisting of 11,154 annotated instances.

vi) **WIKI**: an automatically extracted corpus comprised of Wikipedia pages released by Evgeniy et al. (2013), with 6821 annotated instances.

vii) **BLINK**: a dataset made up of 9 million (document, entity, mention) triples automatically extracted from Wikipedia.

For each of these resources, we use the preprocessed datasets, along with the mention candidate sets, made available by De Cao et al. (2021b) in the authors’ official repository.  

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6[https://lemurproject.org/clueweb12](https://lemurproject.org/clueweb12)  
7Which are all freely available for research purposes.  
8[https://github.com/facebookresearch/](https://github.com/facebookresearch/)
Evaluation  Following common practice in ED literature, results over the evaluation datasets are expressed in terms of \textit{inKB Micro} $F_1$. Furthermore, to better highlight the performance on the \textit{out-of-domain} datasets, we report both the average score over those and AIDA (Avg) and over those alone (Avg\textsubscript{OOD}), that is, when the result on AIDA is excluded from the average.

Comparison Systems  In order to contextualize \textsc{ExtEnd} performances within the current landscape of Entity Disambiguation, we evaluate our approach against recent state-of-the-art systems in the literature. Specifically, we consider:

- Global Models: Ganea and Hofmann (2017); Guo and Barbosa (2018); Yang et al. (2018, 2019); Le and Titov (2019); Fang et al. (2019); De Cao et al. (2021b);
- Local Models: Shahbazi et al. (2019) and Tedeschi et al. (2021);
- The auto-regressive approach proposed by De Cao et al. (2021b).

\textsc{ExtEnd} Setup  As previously mentioned, we use the Longformer model (Beltagy et al., 2020) as our reference architecture and retrieve the pre-trained weights, for both its \textit{base} and \textit{large} variants, from the HuggingFace Transformers library (Wolf et al., 2020); we refer to these variants as \textsc{ExtEnd\textsubscript{Base}} (139M parameters) and \textsc{ExtEnd\textsubscript{Large}} (435M parameters). Following standard practice, we use the last encoder output for the representation of each token and a simple linear layer on top of it to compute the start and end tokens probability distributions. We use a 64-token attention window and fine-tune the whole architecture using the Rectified Adam (Liu et al., 2020) optimizer with $10^{-5}$ learning rate for at most 100,000 steps. We use 8 steps of gradient accumulation and batches made of a maximum of 1024 tokens. We evaluate the model on the validation dataset every 2000 steps, enforcing a patience of 15 evaluation rounds. We train every model for a single run on a GeForce RTX 3090 graphic card with 24 gigabytes of VRAM. Due to computational constraints, we do not perform any hyperparameter tuning, except for the attention window where we try [32, 64, 128], and select the other hyperparameters following previous literature. We implement our work in PyTorch (Paszke et al., 2019), using \textit{classy}\footnote{https://github.com/sunglasses-ai/classy} as the underlying framework.

4.2 Results  We report in Table 1 (top) the \textit{inKB Micro} $F_1$ score \textsc{ExtEnd} and its comparison systems attain on the evaluation datasets in the Wikipedia+AIDA setting.

Arguably the most interesting finding we report is the improvement \textsc{ExtEnd} achieves over its comparison systems. \textsc{ExtEnd\textsubscript{Large}} + BLINK, that is, \textsc{ExtEnd\textsubscript{Large}} pre-trained on BLINK\footnote{We note that, due to computational and hardware constraints, we were unable to match the training configuration} and Wikipedia + AIDA.
then fine-tuned on AIDA, sets a new state of the art on 4 out of 6 datasets, with the only exceptions being in-domain AIDA and CWEB, where we fall short compared to the global model of Yang et al. (2018). On the Avg score, ExtEND pushes performances up by 0.7 points, and this improvement becomes even more marked when considering $\text{Avg}_{\text{OOD}} (+1.1)$. These results suggest that our approach is indeed well-suited for ED and, furthermore, is particularly effective when scaling out of domain.

Additionally, we also evaluate ExtEND on the AIDA-only training setting and compare against De Cao et al. (2021b) and Tedeschi et al. (2021), the only systems available in this setting. As shown in Table 1 (bottom), ExtEND behaves better, with both ExtEND$_{\text{Base}}$ and ExtEND$_{\text{Large}}$ achieving higher Avg scores. In particular, ExtEND$_{\text{Base}}$, which features only 149M parameters, fares better (by almost 5 points) than De Cao et al. (2021b), whose model parameters amount to 406M (2.7×). Moreover, the Avg$_{\text{OOD}}$ results, which are also higher, further confirm our previous hypothesis as regards the benefits of our approach in out-of-domain scalability. Paired together, these results highlight the higher data efficiency that our formulation achieves, in comparison to its alternatives.

### 4.3 Fine-grained Results

Inspired by standard practices in the evaluation of Word Sense Disambiguation systems (Blevins and Zettlemoyer, 2020; Barba et al., 2021a), we perform a fine-grained analysis where we break down the performances of our model into different classes of label frequency. To this end, we partition both the AIDA test set and the concatenation of all the out-of-domain datasets in three different subsets: i) MFC, containing all the instances in the test set where the target mention is associated with its most frequent candidate in the training corpus (i.e. the AIDA training split); ii) LFC, containing all the instances in the test set annotated with a least frequent candidate of the target mention that appeared at least once in the training corpus; iii) Unseen, containing all the instances in the test set whose mention was never seen in the training corpus.

We then evaluate all the systems of the AIDA setting, except for De Cao et al. (2021b) for which the original model is unavailable, on these six test sets. To put the results in perspective, we introduce a simple baseline (PEM-MFC) that consists in always predicting the most frequent candidate for each mention, taking mention-candidate frequencies from Le and Titov (2018).

As we can see from Table 2, PEM-MFC is a rather strong baseline, confirming the skewness of the distribution with which each mention is annotated with one of its possible candidates towards the most frequent ones. Indeed, the gap between the performances of all the models on the MFC split and the LFC split is rather large, with a difference of almost 50 points in the out-of-domain setting. While future works should investigate the performances on these splits more in depth, here we can see that ExtEND$_{\text{Base}}$ and especially ExtEND$_{\text{Large}}$ outperform their competitors in the LFC and Unseen splits, in both the in-domain and out-of-domain settings. This highlights the strong generalization capabilities of our proposed approach, which is able to better handle rare or unseen instances at the cost of only 1 point in $F_1$ score on the MFC of the in-domain setting.

### 5 Model Ablation

While the above-mentioned experiments showed our approach to be rather effective, we only focused on the Longformer-based architecture, to which we resorted owing to the computational challenges we mentioned in Section 3.2. We now investigate this model choice, evaluating first how the BART-based system fares. Then, we ablone the attention pattern we propose for the Longformer and, finally, discuss the trade-off between our two proposed architectures.

#### BART

Strictly speaking, the results we reported in the previous Section are not exactly conclusive as to whether or not our formulation is beneficial. Indeed, while it is true that we use a new formulation,
we also rely upon a Transformer model that none of our comparison systems considered. Therefore, to better pinpoint the origin of the improvements, we train our BART-based architecture in the AIDA setting; we refer to this model as BART. Note that the underlying Transformer is identical to that of De Cao et al. (2021b), except for the final classification heads.11 As shown in Table 3, BART with our extractive formulation attains significantly better performances. This finding suggests that the overall improvement does indeed originate from our extractive formulation. Furthermore, as the two systems are entirely identical except for the framing adopted, this finding further underlines the data efficiency of our approach.

Longformer Ablations We now compare our chosen global attention strategy with two standard alternatives. First, we consider the schema originally proposed by Beltagy et al. (2020) for question-answering tasks, where all the tokens in the input query (i.e. the text containing the mention) have a global attention (Longformerquery). Then, we compare against an EXTEND variant where the only token with global attention enabled is the start of sequence token (i.e. [CLS]). Table 3 shows how the three systems behave, reporting both their in-domain and out-of-domain scores, along with the average percentage of tokens in the input sequence with global attention enabled (GA%). From these results, we can see that i) our approach fares the best and that ii) LongformerCLS achieves performances almost in the same ballpark, making it a viable option for more computationally limited scenarios.

BART and Longformer Finally, we compare our two architectures. As we can see from Table 3, BART performs better in the in-domain dataset, whereas the Longformer outperforms it in the out-of-domain setting. Nevertheless, neither of these differences is very significant and, thus, this result confirms our initial hypothesis that using our second architecture is a valid approximation of the standard quadratic attention strategy for the extractive Entity Disambiguation task.

Table 3: Results (mKB Micro F1) of the ablation study for the in-domain and out-of-domain settings along with the percentage of global tokens (GA%). We mark in Bold the best scores.

| Model                  | In-domain | Out-of-domain | GA% |
|------------------------|-----------|---------------|-----|
| De Cao et al. (2021b)  | 88.6      | 78.2          | 100.0 |
| EXTEND                 | 90.0      | **84.9**      | 21.1 |
| Longformerquery        | 89.2      | 84.1          | 43.3 |
| LongformerCLS          | 88.8      | 84.3          | 0.8  |
| BART                   | **90.4**  | 84.5          | 100.0 |

Table 6: Error Analysis
To further investigate the generalization capabilities of EXTEND, we performed a black-box testing (Ribeiro et al., 2020) of our system leveraging the available test sets. Apart from the problem of label frequencies (e.g. unseen entities), we discovered two additional main classes of errors, namely i) insufficient context, and ii) titles alone might not be enough.

Insufficient Context Since the average number of candidates for each mention is roughly 50, the probability of having multiple valid candidates given the input context is far from negligible. For instance, let us consider the following example: “In the last game Ronaldo scored two goals despite coming from a bad injury.”. In this sentence, the mention Ronaldo can refer both to Cristiano Ronaldo, the Portuguese player, and to Ronaldo de Lima, the Brazilian player. While this particular problem holds for several instances in the test sets, the performance drop is, in fact, mitigated by the labels skewness towards the most frequent candidates. Indeed, the model appears always to predict the most frequent candidate for this kind of instance, therefore being right in the majority of cases.

Titles might not be enough For both comparability and performance purposes, the text representation we use for a given entity in this work is simply its Wikipedia title. While article titles in Wikipedia are rather informative, in several circumstances they do not contain enough information to make them sufficiently distinguishable from other candidates. For example, several pages describing “Persons” are entitled just with their respective names and surnames. This kind of identifier is especially ineffective if the mentions taken into consideration were not present in the training dataset, or were rare or unseen during the underlying Transformer pre-
training. To this end, we strongly believe that future research might benefit from focusing on enriching entities’ identifiers by adding a small description of the articles (summary) or at least some keyword representing the domain the entity belongs to.

7 Conclusion

In this work we presented EXTEND, a novel local formulation for ED that frames this task as a text extraction problem: given as input a string containing a marked mention in context and the text representation of each entity in its candidate set, a model has to extract the span corresponding to the text representation of the correct entity. Together with this formulation, we also presented two Transformer models that implement it and, by evaluating them across several experiments, we found our approach to be particularly suited to ED. First, it is extremely data efficient, surpassing its alternatives by more than 6 $F_1$ points when considering an AIDA-only training setting. Second, pre-training on BLINK data enables the model to set a new state of the art on 4 out of 6 benchmarks under consideration and yield average improvements of 0.7 $F_1$ points overall and 1.1 $F_1$ points when focusing only on out-of-domain evaluation datasets.

As future work, we plan to relax the requirements towards the candidate set and explore adapting this local formulation to a global one, so as to enforce coherence across predictions. For instance, we believe integrating the feedback loop strategy we proposed in Barba et al. (2021b) would be an interesting direction to pursue.

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