Focusing on Context is NICE: Improving Overshadowed Entity Disambiguation

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Abstract
Entity disambiguation (ED) is the task of mapping an ambiguous entity mention to the corresponding entry in a structured knowledge base. Previous research showed that entity overshadowing is a significant challenge for existing ED models: when presented with an ambiguous entity mention, the models are much more likely to rank a more frequent yet less contextually relevant entity at the top. Here, we present NICE, an iterative approach that uses entity type information to leverage context and avoid over-relying on the frequency-based prior. Our experiments show that NICE achieves the best performance results on the overshadowed entities while still performing competitively on the frequent entities.

1 Introduction
Entity disambiguation (ED) is the task of mapping an ambiguous entity mention to the corresponding entry in a structured knowledge base. Despite ED being a well-researched task, recent work has shown that the existing methods are still far from achieving human-level performance: in particular, the case of entity overshadowing remains a big challenge. An entity e₁ overshadows e₂ if the two entities share the same surface form m, and e₁ is more common than e₂, i.e., has a higher prior probability to be linked to m (Provatorova et al., 2021). For example, when given the sentence “Michael Jordan published a paper on machine learning” and the task of linking Michael Jordan either to the basketball player (a frequent entity) or to the scientist (an overshadowed entity), a human will correctly choose the latter, while a typical model is likely to ignore the context and give the wrong yet more popular answer due to over-relying on prior probability. Figure 1 shows another example of entity overshadowing: the entity Rome (TV series) is overshadowed by Rome (city).

According to previous research, current ED systems are prone to over-relying on prior probability instead of focusing on context information, which causes them to underperform on overshadowed entities. In benchmarking experiments performed by Provatorova et al. (2021), all ED systems under evaluation appeared to have a large performance gap between Top and Shadow subsets of the ShadowLink dataset, where Top contains most frequent entities and Shadow contains their overshadowed counterparts. The results of a human evaluation experiment in the same study indicate that the challenge of entity overshadowing is unique to automated ED methods: human participants achieved equally good results at disambiguating entities sampled from Top and Shadow. These findings call for further research in the field of ED, with the goal of building a method that outperforms existing systems on overshadowed entities while still achieving competitive results on standard datasets.

Interestingly, the best results on Shadow in the benchmarking experiments were achieved by AIDA (Hoffart et al., 2011), an unsupervised collective entity disambiguation method: while still affected by overshadowing, this method appeared to be the best at capturing the context information in comparison with modern neural approaches. Specifically, AIDA relies on two main sources of context information: semantic similarity between an entity and its context and graph-based relatedness between the candidate entities of different
mentions. Our study continues this line of work, incorporating modern neural methods to measure semantic similarity and adding novel heuristics to improve candidate filtering and collective disambiguation.

We introduce NICE (NER\(^1\)-enhanced Iterative Combination of Entities), a combined entity disambiguation algorithm designed to tackle the challenge of entity overshadowing by focusing on three aspects of context-based information: entity types, entity-context similarity and entity coherence. The pipeline of NICE includes a NER-enhanced candidate filtering module designed to improve robustness on overshadowed entities (Section 2.1), a prescoring module that calculates semantic similarity between a candidate entity and a mention in context, and an unsupervised iterative disambiguation algorithm that maximizes entity coherence (Section 2.3), combining the relatedness scores between candidate entities with the scores of the semantic similarity module (Sections 2.3-2.4). To the best of our knowledge, our study is the first attempt to build an entity disambiguation method designed specifically to tackle the problem of entity overshadowing.

We perform a systematic evaluation of the NICE method, and use our experimental results to answer the following research questions:

**RQ1:** Does focusing on context information improve ED performance on overshadowed entities?

**RQ2:** Does focusing on context information instead of relying on mention-entity priors in ED allow to maintain competitive performance on more frequent entities?

**RQ3:** In what ways do the different aspects of context information contribute to ED performance on overshadowed entities?

We hope that our work will encourage further studies concerning overshadowed entities. The source code of the NICE method is provided as supplementary material and will be released publicly upon acceptance.

## 2 The NICE method

Our method is based on the assumption that the main challenge in disambiguating overshadowed entities stems from over-relying on entity commonness, and therefore switching the focus to the context (entity relatedness) can improve the performance. We consider three main ways of extracting information from the context: (1) using mention-entity similarity to predict entity types and improve candidate filtering, (2) using word embeddings enhanced with entity types to measure semantic similarity between an entity and its context, and (3) using entity-entity similarity to make sure that the entity disambiguating decisions within one document are coherent (collective disambiguation).

### 2.1 Candidate filtering

Adding the step of filtering candidate entities before disambiguation brings the benefits of reduced inference time and potential improvements in accuracy. To perform this step in the NICE method, we follow the work of Tedeschi et al. (2021) by using entity type information. Given an entity mention \( m \) surrounded by textual context \((\text{cont}_\text{left}, \text{cont}_\text{right})\) and a list of candidate entities \( \text{cands} = \{e_1, \ldots, e_n\} \), we use a NER classifier to predict the top-k possible entity types of \( m \). Then, we discard all candidate entities that have an entity type not matching any of these \( k \) classes:

\[
\text{cands}_{\text{filtered}} = \{e_i : \text{type}(e_i) \in \hat{T} \mid e_i \in \text{cands}\},
\]

where \( \hat{T} \) is the set of top-k predicted entity types. If the confidence score of the NER classifier is above a threshold value \( t \), only one class is used instead of \( k \). In the current setup of the NICE method, the number of top predicted classes is \( k = 3 \) and the confidence threshold value is \( t = 1 \), which means that the classifier always outputs the top-3 entity classes. Figure 2 shows an example of NER-based candidate filtering.

To obtain the entity types for the candidates, we use the Wiki2NER dictionary provided by Tedeschi et al. (2021)\(^2\). Then, instead of using the NER classifier as provided by Tedeschi et al. (2021), which has been trained only on the AIDA training set and therefore may be biased towards frequent entities as well, we introduce a refined version of it, which is more robust to overshadowing. Specifically, we filter the training set of BLINK (Wu et al., 2020)\(^3\) by discarding the entries where the ground truth answer has the highest popularity score among all candidate entities. Then, we use the 2M remaining data entries to fine-tune the classifier. The motivation behind fine-tuning the classifier rather than training it from scratch is to achieve an improvement in recognising overshadowed entities without

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\(^1\)Named Entity Recognition (Yadav and Bethard, 2018)

\(^2\)https://github.com/Babelscape/ner4el

\(^3\)BLINK is a dataset for ED consisting of 9M entries extracted from Wikipedia.
2.2 Candidate pre-scoring

To obtain relevance scores for the candidate entities before the collective disambiguation phase, NICE relies on semantic similarity between a candidate entity and its corresponding mention in context. To calculate these semantic similarity scores, we use the NER-enhanced word embeddings produced by the NER4EL model (Tedeschi et al., 2021). This model uses a dual-encoder Transformer-based architecture that, given as input a mention-candidate pair \(\langle m, c \rangle\), produces a vector representation for both \(m\) and \(c\). Then, the relatedness between the two vectors is measured as the cosine similarity score. To encode the mention, the model uses both the mention itself and its context as input. To encode the candidate entities, instead, the model uses their textual descriptions from Wikipedia.

2.3 Collective disambiguation

We follow the assumption that the entities within one document are coherent, i.e. there exists a coherence measure \(C\) such that \(C(e_1^*, ..., e_n^*) \geq C(e_1, ..., e_n)\) where \(e_1^*, ..., e_n^*\) are the correct entities for mentions \(m_1, ..., m_n\), and \(e_1, ..., e_n\) is any other selection of candidate entities for these mentions (with one candidate per mention). Then, we use the following heuristic to reduce the search space and speed up the disambiguation process: if the entities within one document are coherent, and different mentions have different degrees of ambiguity (different sizes of candidate sets), then using an iterative process that starts with the least ambiguous mention may reduce the chance of wrong disambiguation decisions (Barba et al., 2021).

We thus propose ICE (for "Iteratively Combining Entities"), a collective disambiguation algorithm based on the iterative disambiguation process described in Algorithm 1. The input of the algorithm is a set of entity mentions within one document, where every mention is matched with a pre-scored list of candidate entities. The first step of the disambiguation process consists of selecting a seed mention: the least ambiguous entity mention, i.e., one that has the lowest number of candidates. The seed mention is disambiguated without using entity relatedness information, relying on the input scores instead. Then, an iterative process begins: on every step of the algorithm the least ambiguous entity mention is selected and removed from the set of unprocessed mentions. This mention is disambiguated based on coherence: for every candidate entity, the algorithm calculates an aggregated relatedness score between the entity and the set of already disambiguated entities, and chooses the candidate that maximises this score. The algorithm is terminated when the set of unprocessed entity mentions is empty. Note that the relatedness score in Algorithm 1 can be calculated and aggregated in different ways. In the setup used in the NICE method, we calculate the score of each candidate as a weighted average between the entity coherence score and the original input score:

\[
\text{score}_{\text{final}} = \alpha \text{score}_{\text{coherence}} + (1-\alpha) \text{score}_{\text{input}}.
\]

The process of choosing the parameter values is...
The best aggregation method according to our experiment with: confidence threshold \( t \) of the candidate filtering model, weight \( \alpha \) of the ICE coherence score, the relatedness measure used in collective disambiguation and the relatedness aggregation method. To find the best combination of the parameters, we sampled a development set from the training data of ShadowLink and used grid search. The development set contains 100 Top and 100 Shadow entities: the two classes are represented equally because a system cannot distinguish between Top and Shadow on the inference step. For the confidence threshold value \( t \), we considered the values from 0.5 to 0.9 with the step 0.1. For the ICE score weight \( \alpha \), the search space consisted of the values between 0 and 1 with the step 0.1.

To find the most suitable entity relatedness measure, we experimented with the seven measures available in the WAT relatedness API \(^4\) (Piccinno and Ferragina, 2014), which retrieves relatedness scores by Wikipedia IDs of the corresponding entity pages. The measures available in the API are the following: PMI (Pointwise Mutual Information), Milne-Witten, LM (language model), Word2Vec, Jaccard, Barabasi-Albert, and conditional probability.

\(^4\)https://sobigdata.d4science.org/web/tagme/wat-api

For aggregation of the relatedness scores in Algorithm 1, we considered three setups: max, min and avg. The max setup is a greedy approach, where the score of a candidate entity is calculated as its maximum pairwise relatedness to the already disambiguated entities. It relies on the assumption that a relevant entity does not necessarily need to be close to all other entities in the document: it is enough to have a high pairwise relatedness with just one other entity. The opposite setup is min: it follows a strict assumption that all entities within one document must be coherent, and calculates the aggregated score as the minimum pairwise relatedness to the already disambiguated entities. Finally, the avg setup calculates the score as a mean pairwise relatedness between a candidate and the disambiguated entities. Figure 3 shows the scores achieved on the development set by using the combinations of the seven relatedness measures and three aggregation setups. One point on the figure represents the score achieved with one combination of the four parameters of NICE. The best relatedness measure turned out to be Milne-Witten Milne and Witten (2008):

\[
MW(e_1, e_2) = \log \frac{\max(|L_{e_1} \cap L_{e_2}|)}{|L_{e_1}| |L_{e_2}|},
\]

where \( L_{e_i} \) is the set of Wikipedia pages that link to the page of entity \( e_i \), and \( W \) is the entire Wikipedia. The best aggregation method according to our experiments is taking the maximum value of relatedness:

\[
s(e_i) = \max\{MW(e_i, e_j) | e_j \in S_{ans}\},
\]
Figure 4 demonstrates a heatmap of F-scores achieved on the ShadowLink development set with different combinations of candidate filtering threshold values and relatedness score weights while using the Milne-Witten relatedness measure and the max aggregation method. The value -1 of the filtering confidence threshold indicates not using the filter at all. From the figure it can be seen that the best combination of the two remaining parameters is the confidence value of 1 (which means always predicting top-3 entity classes) and the weight 0.7 assigned to the relatedness score, which corresponds to the weight 0.3 of the semantic similarity score. Thus, the final score of each candidate entity is calculated as:

\[
s(e_i) = 0.7 \max\{MW(e_i, \hat{e}_j)|\hat{e}_j \in S_{\text{ans}}\} + 0.3s_{\text{input}}(e_i).\]

2.5 Implementation details

Our contribution is focused on the task of entity disambiguation, where the mention boundaries and the candidate entities are given. We note that different methods of mention detection and candidate generation can be combined with the NICE disambiguation module to perform end-to-end entity linking. To perform collective disambiguation on ShadowLink, where only one entity span per entry is available, we used TagMe API \(^5\) (Ferragina and Scaiella, 2010) for mention detection and REL\(^6\) (van Hulst et al., 2020) for candidate generation.

3 Experimental Setup

In this section, we describe the datasets we use to evaluate our methods (Section 3.1) and the baseline systems we compare with (Section 3.2).

3.1 Datasets

As the NICE method is designed specifically for improving disambiguation of overshadowed entities, the main dataset for evaluating its performance is ShadowLink (Provatorova et al., 2021). ShadowLink contains ambiguous entities with short textual context gathered from the Web: it includes the Top subset which contains popular entities, and the Shadow subset which contains overshadowed entities, where every Shadow entry is matched with one Top entry by a shared entity surface form. To make sure that the main challenge is entity disambiguation and not candidate generation, we excluded all entries for which the candidate generation module of REL failed to retrieve the correct entity. The remaining dataset contains 491 Shadow and 614 Top entries.

Note that, by design, ShadowLink contains ground truth information for only one entity mention per entry. As our method relies on collective disambiguation, we extract all different entity mentions from every entry and use them in the inference – however, the evaluation is only performed on the “target mention” that has a ground truth label assigned to it. To test the collective disambiguation approach for multiple mentions within one document, as well as to make sure that our method performs competitively on standard data, we also evaluate NICE on the test subset of the AIDA-YAGO-CoNLL dataset (Hoffart et al., 2011), the largest manually annotated ED evaluation set which consists of 388 news articles.

3.2 Baselines

We compare the NICE method with five popular ED models available in the GERBIL evaluation framework (Röder et al., 2018): AIDA (Hoffart et al., 2011), DBpedia Spotlight (Mendes et al., 2011), AGDISTIS/MAG (Usbeck et al., 2014), Babelfy (Moro et al., 2014) and WAT (Piccinno and Ferragina, 2014), as well as three novel models not yet available in GERBIL: REL (van Hulst et al., 2020) and REL (van Hulst et al., 2020) for candidate generation.

\(^5\)https://sobigdata.d4science.org/web/tagme/tagme-help

\(^6\)https://github.com/informagi/REL
et al., 2020), GENRE (De Cao et al., 2020), and NER4EL (Tedeschi et al., 2021).

The newest of the systems under evaluation is NER4EL, a neural model that uses the information about entity types to make ED decisions based on semantic similarity between a candidate entity and its context. As NER4EL turns out to achieve high results on Shadow, we include it as the semantic similarity module in the combined NICE method. Combining NER4EL with the ICE algorithm allows to extract more information from the context than by using each of the two methods alone, as NER4EL does not include entity relatedness information and ICE does not include semantic similarity.

4 Results and discussion

The results of our experiments are presented in Table 1. Note that the term "filtered" in the dataset description refers to filtering out the entries where the correct candidate entity was not retrieved by our candidate generation model, and not to the NER-based candidate filtering. We use the experimental data to answer the research questions introduced in Section 1.

**RQ1:** Does focusing on context information improve ED performance on overshadowed entities?

From the evaluation results in Table 1 it can be seen that NICE outperforms all baseline systems on the Shadow subset by a large margin. Moreover, all variations of our method considered in the experiments achieve top results on Shadow, which shows that all ways of leveraging context information considered in our study lead to performance improvements on overshadowed entities.

**RQ2:** Does focusing on context information instead of relying on mention-entity priors in ED allow to maintain competitive performance on more frequent entities?

Our experimental data shows that NICE outperforms all baselines on the Top subset of ShadowLink, where every entry contains the most frequent entity from the corresponding entity space. This demonstrates that placing more impact on context information does not automatically decrease the performance on more frequent entities: the contrary, it appears to be beneficial in the setup of using the short textual context of ShadowLink.

The results on the AIDA dataset, however, are considerably lower compared to several of the base-lines. There are different factors contributing to this performance drop. Firstly, it appears that the original NER classifier used for candidate filtering in NER4EL works much better on the AIDA dataset than our classifier, which has been trained to focus on overshadowed entities. Secondly, the input structure differed between the two dataset types: for Top and Shadow we extracted auxiliary mention spans from the context to perform collective disambiguation (as the ShadowLink dataset only contains one ground truth entity mention per entry), and for AIDA we only used the mention spans provided in the dataset. In the case of AIDA, all the labelled mentions satisfy the strict definition of a named entity, while for ShadowLink the auxiliary mentions were noun phrases extracted using the TagMe API, which considers all Wikipedia anchors as entities. For example, in the sentence "Michael Jordan published a paper", paper is not a named entity but a common concept that can be linked to Wikipedia and used for collective disambiguation. Interestingly, a similar idea is used by Babelfy (Moro et al., 2014), which disambiguates named entities and common concepts simultaneously using graph information, achieving the second-highest score both on Top and Shadow datasets. This indicates that considering all linkable mentions within a short textual context is beneficial for disambiguating overshadowed entities.

**RQ3:** In what ways do the different aspects of context information contribute to ED performance on overshadowed entities?

NICE uses three aspects of context information: entity types, semantic similarity between a candidate entity and its mention in context, and graph-based relatedness between candidate entities. To estimate the impact of these aspects, we turn to the experimental data of two kinds: the evaluation results presented in Table 1 and the results achieved on the development set with different combinations of component weights, shown in Figure 4.

From Table 1 it can be seen that using entity types is beneficial both for candidate filtering and for enhancing the semantic similarity module: NER4EL achieves considerably high results on Shadow when used alone and demonstrates a further improvement when combined with the robust candidate filter. Figure 4 shows that the highest scores are achieved when the weight of graph-based entity coherence score is relatively high, with the best combination being $0.3 \cdot \text{score}_{\text{NER4EL}} +$.
| Method                          | Shadow filtered | Top filtered | AIDA test |
|--------------------------------|-----------------|--------------|-----------|
| AIDA (Hoffart et al., 2011)   | 45.4            | 65.0         | 81.8      |
| DBpedia Spotlight (Mendes et al., 2011) | 16.2          | 37.9         | 49.3      |
| Babelfy (Moro et al., 2014)   | 52.9            | 66.1         | 68.2      |
| WAT (Piccinno and Ferragina, 2014) | 32.9          | 59.5         | 60.7      |
| AGDISTIS/MAG (Usbeck et al., 2014) | 12.8          | 22.8         | 59.4      |
| REL (van Hulst et al., 2020)  | 31.5            | 70.5         | 83.3      |
| GENRE (De Cao et al., 2020)   | 33.8            | 54.2         | 93.3      |
| NER4EL (Tedeschi et al., 2021) | 44.3            | 62.4         | 92.5      |
| NER4EL + no candidate filtering | 43.3            | 67.3         | 86.3      |
| NER4EL + robust candidate filter | 45.7            | 68.1         | 85.3      |
| ICE + no candidate filtering | 56.9            | 74.9         | 72.1      |
| ICE + robust candidate filter | 59.9            | 76.1         | 71.9      |
| NICE                           | 58.3            | 77.2         | 80.4      |

Table 1: Benchmark evaluation results in terms of micro-$F_1$. In the top part of the table, we report the results of the baseline systems we compare with. In the bottom and middle parts, we report the scores obtained by the NICE method and its intermediate versions, respectively. We mark in bold the best scores and underline the second best.

Moreover, the best results on the Shadow test set are achieved when using the ICE coherence score alone (middle part of Table 1). Thus, all aspects of context information are beneficial for disambiguating overshadowed entities, with the entity coherence being the most important component.

5 Related work

The task of entity linking in its modern sense has been first introduced in 2007 by Milne and Witten (2008). Since then, multiple evaluation datasets have been proposed, and numerous methods have been developed to improve the results. The first methods of entity disambiguation focused explicitly on two components: entity commonness, which shows how likely a particular entity is to be linked to a given mention regardless of the context, and entity relatedness, which shows how relevant an entity is to a given context (Mihalcea and Csomai, 2007). Three most prominent methods that used this approach are AIDA (Hoffart et al., 2011), TagMe (Ferragina and Scaiella, 2010) and WAT (Piccinno and Ferragina, 2014). AIDA (Hoffart et al., 2011) uses a graph-based collective disambiguation algorithm enhanced with robustness tests, building weighted edges between mentions and candidate entities as well between different candidate entities, and removing an edge on every iteration to maximise the minimum weighted degree of the graph. TagMe (Ferragina and Scaiella, 2010), instead, uses the relatedness measure defined by Milne and Witten (2008) weighted with the commonness of a sense together with the keyphraseness measure defined by Mihalcea and Csomai (2007) to exploit the context around the target word. Finally, WAT (Piccinno and Ferragina, 2014) is a redesigned system of TagMe and includes graph-based algorithm for ranking entities in entity graph based on entity relatedness, and vote-based algorithm for local disambiguation. Another approach to entity disambiguation presented in the same year as WAT is Babelfy (Moro et al., 2014), a method that combines entity linking with word sense disambiguation, using an algorithm based on random walks on the BabelNet multilingual graph to disambiguate all linkable mentions together with senses of words occurring in the text.

With the advantage of deep learning methods in NLP, new approaches have been proposed to improve the performance of ED. van Hulst et al. (2020) introduced REL, a modular system that combines several of these approaches: candidate generation with mention-entity priors proposed by Ganea and Hofmann (2017), entity disambiguation with mention-wise normalisation first introduced by Le and Titov (2018), and entity-context similarity computed with Wikipedia2Vec embeddings by Yamada et al. (2016). While achieving top performance on standard benchmarks, REL appears to suffer from over-relying on its prior predictions, which leads to a considerable performance drop on overshadowed
entities. De Cao et al. (2020), instead, proposed a novel autoregressive approach to entity linking that, given a mention in context, generates the title of the corresponding Wikipedia page.

While learning from large amounts of data allows the modern neural ED methods to achieve high performance on most of the evaluation datasets, it also puts them at risk of overfitting to the most frequently seen entities and overlooking the important edge cases. Ilievski et al. (2018) showed that entities with low frequency and high ambiguity appear to be underrepresented in standard ED evaluation datasets, despite such entities being especially challenging to disambiguate. Provatorova et al. (2021) continued this line of work, introducing the concept of entity overshadowing and releasing ShadowLink, the first dataset designed specifically to study this phenomenon. Both studies conclude that the problem of entity disambiguation is still far from solved, and call for ED systems to consider more complex cases instead of only optimising for the standard evaluation frameworks. Provatorova et al. (2021) mentioned specifically that relying more on context information and less on priors appears to be the key to achieving better performance on overshadowed entities.

Tedeschi et al. (2021) proposed NER4EL, a neural ED method that leverages the context by using information about entity types on four levels: candidate filtering, entity representation, negative sampling during training, and entity decoding. This allows NER4EL to perform on par with De Cao et al. (2020) despite only training on a small fraction of data used by GENRE. While not aiming specifically to improve performance on overshadowed entities, NER4EL achieves high results on the ShadowLink dataset in our study. One limitation of the method is its lack of a collective entity disambiguation method: every mention within a document is disambiguated separately, using only its textual context. By combining NER4EL with the ICE collective disambiguation algorithm introduced in this paper, we manage to achieve top results on overshadowed entities.

6 Conclusion

We introduced NICE, an overshadowing-aware entity disambiguation method that consists of three main components: a candidate filtering module designed for improved performance on overshadowed entities, a collective disambiguation module that uses an unsupervised iterative algorithm to capture entity coherence, and a module that measures semantic similarity between an entity and its context using NER-enhanced word embeddings. Our experimental results show that NICE achieves substantial improvements on overshadowed entities compared to the baseline methods, while still performing competitively in a standard entity disambiguation setting. This demonstrates that encompassing explicit contextual features, such as entity types and entity coherence, improves ED performance on overshadowed entities.

Future work directions include using different annotation methods for extracting linkable concepts (not necessarily named entities) from the textual context, as well as experimenting with longer textual contexts on the extended version of ShadowLink and other ED datasets.

7 Limitations

While the NICE method demonstrates top performance on overshadowed entities, its current implementation includes several limitations. Firstly, the method relies on an external web API to calculate entity relatedness, which requires the user to register and obtain an access token. Secondly, due to computational limitations our method only considers 15 candidates for calculating semantic similarity scores. Adding more candidates may lead to performance improvements. Thirdly, while the ICE algorithm attempts to minimise the runtime by processing the least ambiguous entities first, there could be a possible edge case where all the input mentions have the same high number of candidates. In this case, the time complexity will be $O(kN^2)$, where $k$ is the number of candidates and $N$ is the number of mentions, which slows down the disambiguation process, especially when using a web API for calculating relatedness. Lastly, while NICE outperforms half of the baselines on the AIDA dataset, it achieves considerably lower scores than the two newest models, GENRE and NER4EL. We assume that the main reason behind it is not using all linkable noun phrases from the textual context and only relying on the mention spans provided in the input, contrary to the setup used on ShadowLink. Further research is needed to test this assumption and experiment with extracting additional mentions from the AIDA dataset.

7 https://sobigdata.d4science.org/web/tagme/tagme-help
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