OPTIMIZING BI-ENCODER FOR NAMED ENTITY RECOGNITION VIA CONTRASTIVE LEARNING

Anonymous authors
Paper under double-blind review

ABSTRACT

We present a bi-encoder framework for named entity recognition (NER), which applies contrastive learning to map candidate text spans and entity types into the same vector representation space. Prior work predominantly approaches NER as sequence labeling or span classification. We instead frame NER as a representation learning problem that maximizes the similarity between the vector representations of an entity mention and its type. This makes it easy to handle nested and flat NER alike, and can better leverage noisy self-supervision signals. A major challenge to this bi-encoder formulation for NER lies in separating non-entity spans from entity mentions. Instead of explicitly labeling all non-entity spans as the same class `Outside` (`O`) as in most prior methods, we introduce a novel dynamic thresholding loss, learned in conjunction with the standard contrastive loss. Experiments show that our method performs well in both supervised and distantly supervised settings, for nested and flat NER alike, establishing new state of the art across standard datasets in the general domain (e.g., ACE2004, ACE2005) and high-value verticals such as biomedicine (e.g., GENIA, NCBI, BC5CDR, JNLPBA).

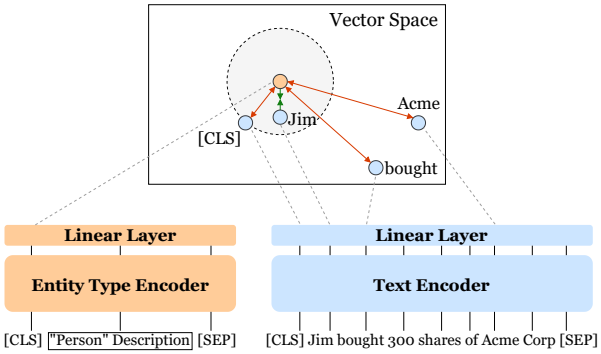
1 INTRODUCTION

Named entity recognition (NER) is the task of identifying text spans associated with named entities and classifying them into a predefined set of entity types such as person, location, etc. As a fundamental component in information extraction systems (Nadeau & Sekine, 2007), NER has been shown to be of benefit to various downstream tasks such as relation extraction (Mintz et al., 2009), coreference resolution (Chang et al., 2013), and fine-grained opinion mining (Choi et al., 2006).

Inspired by recent success in open-domain question answering (Karpukhin et al., 2020) and entity linking (Wu et al., 2020; Zhang et al., 2021a), we propose an efficient **BI**-encoder for **N**ame**D** **E**ntity **R**ecognition (**BINDER**). Our model employs two encoders to separately map text and entity types into the same vector space, and it is able to reuse the vector representations of text for different entity types (or vice versa), resulting in a faster training and inference speed. Based on the bi-encoder representations, we propose a unified contrastive learning framework for NER, which enables us to overcome the limitations of popular NER formulations (shown in Figure 1), such as difficulty in handling nested NER with sequence labeling (Chiu & Nichols, 2016; Ma & Hovy, 2016), complex learning and inference for span-based classification (Yu et al., 2020; Fu et al., 2021), and challenges in learning with noisy supervision (Straková et al., 2019; Yan et al., 2021).[1] Through contrastive learning, we encourage the representation of entity mentions to be similar with the corresponding entity type, and to be dissimilar with that of the wrong type. Existing work labels all non-entity tokens or spans as the same class `Outside` (`O`), which can introduce false negatives when the training data is partially annotated (Das et al., 2022; Aly et al., 2021). We instead introduce a novel dynamic thresholding loss in contrastive learning, which learns candidate-specific dynamic thresholds to distinguish entity spans from non-entity ones.

To the best of our knowledge, we are the first to optimize bi-encoder for NER via contrastive learning. We conduct extensive experiments to evaluate our method in both supervised and distantly

[1] Das et al. (2022) applies contrastive learning for NER in a few-shot setting. In this paper, we focus on supervised NER and distantly supervised NER.



	Nested NER	Noisy Supervision	Fast Speed
Sequence labeling	✗	✗	✓
Span-based classification	✓	✗	✗
Seq-to-seq generation	✓	✗	✗
BINDER (Ours)	✓	✓	✓

Figure 1: Left: The architecture of **BINDER**. The entity type and text encoder are isomorphic and fully decoupled Transformer models. In the vector space, the anchor point (●) represents the special token `[CLS]` from the entity type encoder. Through contrastive learning, we maximize the similarity between the anchor and the positive token (●`Jim`), and minimize the similarity between the anchor and negative tokens. The dotted gray circle (delimited by the similarity between the anchor and ●`[CLS]` from the text encoder) represents a threshold that separates entity tokens from non-entity tokens. To reduce clutter, data points that represent possible spans from the input text are not shown. Right: We compare **BINDER** with existing solutions for NER on three dimensions: 1) whether it can be applied to nested NER without special handling; 2) whether it can be trained using noisy supervision without special handling; 3) whether it has a fast training and inference speed.

supervised settings. Experiments demonstrate that our method achieves the state of the art on a wide range of NER datasets, covering both general and biomedical domains. In supervised NER, compared to the previous best results, our method obtains a 2.4%-2.9% absolute improvement in F1 on standard nested NER datasets such as ACE2004 and ACE2005, and a 1.2%-1.9% absolute improvement on standard flat NER datasets such as BC5-chem, BC5-disease, and NCBI. In distantly supervised NER, our method obtains a 1.5% absolute improvement in F1 on the BC5CDR dataset. We further study the impact of various choices of components in our method, and conduct breakdown analysis at entity type level and token level, which reveals potential growth opportunities.

2 METHOD

In this section, we present the design of **BINDER**, a novel architecture for NER tasks. As our model is built upon a bi-encoder framework, we first provide the necessary background for encoding both entity types and text using the Transformer-based (Vaswani et al., 2017) bi-encoder. Then, we discuss our ways of deriving entity type and individual mention span representations using the embedding output from the bi-encoder. Based on that, we introduce two types of contrastive learning objectives for NER using the token and span-level similarity respectively.

2.1 BI-ENCODER FOR NER

The overall architecture of **BINDER** is shown in Figure 1. Our model is built upon a bi-encoder architecture which has been mostly explored for dense retrieval (Karpukhin et al., 2020). Following the recent work, our bi-encoder also consists of two isomorphic and fully decoupled Transformer models (Vaswani et al., 2017), *i.e.* an entity type encoder and a text encoder. For NER tasks, we consider two types of inputs, entity type descriptions and text to detect named entities. At the high level, the entity type encoder produces type representations for each entity of interests (*e.g.* `person` in Figure 1) and the text encoder outputs representations for each input token in the given text where named entities are potentially mentioned (*e.g.* `Jim` in Figure 1). Then, we enumerate all span candidates based on corresponding token representations and match them with each entity type in the vector space. As shown in Figure 1, we maximize the similarity between the positive span and its corresponding entity type, and minimize the similarity of negative spans.

We first formally discuss encoding both inputs using a pretrained Transformer model, BERT (Devlin et al., 2019).[2] Specifically, we use $x_1, \ldots, x_N$ to denote an input sequence of length N. When using BERT, there is a prepended token [CLS] and an appended token [SEP] for all input sequences, *i.e.* [CLS], $x_1, \ldots, x_N$ [SEP]. Then the output is a sequence of hidden states $\mathbf{h}_{\texttt{[CLS]}}, \mathbf{h}_1, \ldots, \mathbf{h}_N, \mathbf{h}_{\texttt{[SEP]}} \in \mathbb{R}^d$ from the last BERT layer for each input token, where d is the hidden dimension. Note that as [CLS] is always in the beginning, $\mathbf{h}_0$ and $\mathbf{h}_{\texttt{[CLS]}}$ are interchangeable here. Based on this, we then discuss the way of computing entity type and text token embeddings, which are the basic building blocks for deriving our NER constrative learning objectives later.

Entity Type Embeddings The goal of entity type encoder is to produce entity type embeddings that serve as anchors in the vector space for contrastive learning. In this work, we focus on a predefined set of entity types $\mathcal{E} = \{E_1, \ldots, E_K\}$, where each entity type has one or multiple natural language descriptions. The natural language description can be *formal textual definitions* based on the dataset annotation guideline or Wikipedia, and *prototypical instances* where a target type of named entities are mentioned. For simplicity, the discussion proceeds with one description per type and we use E_k to denote a sequence of tokens for the k-th entity type description. For a given entity type E_k, we use BERT as the entity type encoder ($\texttt{BERT}^E$) and add an additional linear projection to compute corresponding entity type embeddings in the following way:

$$\mathbf{h}^{E_k}_{\texttt{[CLS]}} = \texttt{BERT}^E(E_k), \tag{1}$$

$$\mathbf{e}_k = \texttt{Linear}^E(\mathbf{h}^{E_k}_{\texttt{[CLS]}}), \tag{2}$$

where Linear is a learnable linear layer and $\mathbf{e}_k \in \mathbb{R}^d$ is the vector representation for E_k.

Text Token Embeddings Instead of using [CLS] embeddings as done in the recent bi-encoder work for entity retrieval (Wu et al., 2020), we consider using text token embeddings as the basic unit for computing similarity with entity span embeddings. As there are multiple potential named entities not known as a prior in the input, naively using special markers (Wu et al., 2020) incurs huge computation overhead for NER. Similar to the entity type embeddings, we again use BERT as the text encoder ($\texttt{BERT}^T$) and simply use the final hidden states as the basic text token representations[3],

$$\mathbf{h}^T_1, \ldots, \mathbf{h}^T_N = \texttt{BERT}^T(x_1, \ldots, x_N). \tag{3}$$

2.2 Contrastive Learning for NER

Based on the entity type embeddings and text token embeddings discussed above, we then introduce two different contrastive learning objectives for NER in this part. Here, we assume a *span* (i, j) is a contiguous sequence of tokens in the input text with a start token in position i and an end token in position j. Throughout this work, we use the similarity function, $\texttt{sim}(\cdot, \cdot) = \frac{\cos(\cdot,\cdot)}{\tau}$, where τ is a scalar parameter.

As shown in Figure 1, the overall goal of NER constrastive learning is to push the entity mention span representations close to their corresponding entity type embeddings (positive) and far away from irrelevant types (negative) in vector space, *e.g.* Person closer to Jim but away from Acme. To achieve that, we propose a multi-objective formulation consisting of two objectives based on *span* and *token* embedding spaces respectively.

Span-based Objective Here, we consider the following way for deriving the vector representation for span (i, j)

$$\mathbf{s}_{i,j} = \texttt{Linear}^S(\mathbf{h}^T_i \oplus \mathbf{h}^T_j \oplus D(j-i)), \tag{4}$$

where $\mathbf{h}^T_i, \mathbf{h}^T_j$ are text token embeddings (Equation 3), $\mathbf{s}_{i,j} \in \mathbb{R}^d$, $\texttt{Linear}^S$ is a learnable linear layer, $\oplus$ indicates the vector concatenation, $D(j-i) \in \mathbb{R}^m$ is the $(j-i)$-th row from the span width embedding matrix $D \in \mathbb{R}^{L \times m}$, and L is the maximum span width considered. Based on this, the span-based infoNCE (Oord et al., 2018) can be defined as

$$\ell_{\texttt{span}} = -\log \frac{\exp(\texttt{sim}(\mathbf{s}_{i,j}, \mathbf{e}_k))}{\sum_{\mathbf{s}' \in \mathcal{S}^-_k \cup \mathbf{s}_{i,j}} \exp(\texttt{sim}(\mathbf{s}', \mathbf{e}_k))}, \tag{5}$$

[2]Although different BERT variants are considered later in experiments, they all follow the same way of encoding discussed here.

[3]Here, we leave out special tokens for simplicity.

where the span (i, j) belongs to entity type E_k, $\mathcal{S}_k^-$ is the set of negative spans that are all possible spans from the input text, excluding entity spans from E_k, and $\mathbf{e}_k$ is the entity type embedding.

Position-based Objective One limitation of the span-based objective is that it penalizes all negative spans in the same way, even if they are partially correct spans, e.g., spans that have the same start or end token with the gold entity span. Intuitively, it is more desirable to have partially correct spans than spans that have completely no overlap with the gold span. Therefore, we propose additional position-based contrastive learning objectives. Specifically, we compute two additional entity type embeddings for E_k by using additional linear layers, $e_k^{\text{B}} = \texttt{Linear}_B^E(\mathbf{h}_{\texttt{[CLS]}}^{E_k}), e_k^{\text{Q}} = \texttt{Linear}_Q^E(\mathbf{h}_{\texttt{[CLS]}}^{E_k})$, where $e_k^{\text{B}}, e_k^{\text{Q}}$ are the type embeddings for the start and end positions respectively, $\mathbf{h}_{\texttt{[CLS]}}^{E_k}$ is from the entity type encoder (Equation 1). Accordingly, we can use two addtional linear layers to compute the corresponding token embeddings for the start and end tokens respectively, $\mathbf{u}_n = \texttt{Linear}_B^T(\mathbf{h}_n^T), \mathbf{v}_n = \texttt{Linear}_Q^T(\mathbf{h}_n^T)$, where $\mathbf{h}_n^T$ is the text token embeddings (Equation 3). Using $e_{\text{B}}^k, e_{\text{Q}}^k$ as anchors, we then define two position-based objectives

$$\ell_{\text{start}} = -\log \frac{\exp(\text{sim}(\mathbf{u}_i, \mathbf{e}_k^{\text{B}}))}{\sum_{\mathbf{u}' \in \mathcal{U}_k^- \cup \mathbf{u}_i} \exp(\text{sim}(\mathbf{u}', \mathbf{e}_k^{\text{B}}))} \tag{6}$$

$$\ell_{\text{end}} = -\log \frac{\exp(\text{sim}(\mathbf{v}_j, \mathbf{e}_k^{\text{Q}}))}{\sum_{\mathbf{v}' \in \mathcal{V}_k^- \cup \mathbf{v}_j} \exp(\text{sim}(\mathbf{v}', \mathbf{e}_k^{\text{Q}}))}, \tag{7}$$

where $\mathcal{U}_k^-, \mathcal{V}_k^-$ are two sets of positions in the input text that do not belong to the start/end of any span of entity type k. Compared with Equation 5, the main difference of position-based objectives comes from the corresponding negative sets where start and end positions are independent of each other. In other words, the position-based objectives can potentially help the model to make better start and end position predictions.

Thresholding for Non-Entity Cases Although the contrastive learning objectives defined above can effectively push the positive spans close to their corresponding entity type in vector space, it might be problematic for our model at test time to decide how close a span should be before it can be predicted as positive. In other words, the model is not able to separate entity spans from non-entity spans properly. To address this issue, we use the similarity between the special token `[CLS]` and the entity type as a dynamic threshold (as shown in Figure 1). Intuitively, the representation of `[CLS]` reads the entire input text and summarizes the contextual information, which could make it a good choice to estimate the threshold to separate entity spans from non-entity spans. We compare it with several other thresholding choices in §4.

To learn thresholding, we extend the original contrastive learning objectives with extra adaptive learning objectives for non-entity cases. Specifically, for the start loss (Equation 6), the augmented start loss $\ell_{\texttt{start}}^+$ is

$$\beta \ell_{\texttt{start}} - (1-\beta) \log \frac{\exp(\text{sim}(\mathbf{u}_{\texttt{[CLS]}}, \mathbf{e}_k^{\text{B}}))}{\sum_{\mathbf{u}' \in \mathcal{U}_k^-} \exp(\text{sim}(\mathbf{u}', \mathbf{e}_k^{\text{B}}))}. \tag{8}$$

An augmented end loss $\ell_{\texttt{end}}^+$ can be defined in a similar fashion. For the span loss (Equation 5), we use the span embedding $\mathbf{s}_{0,0}$ for deriving the augmented span loss $\ell_{\texttt{span}}^+$

$$\beta \ell_{\texttt{span}} - (1-\beta) \log \frac{\exp(\text{sim}(\mathbf{s}_{0,0}, \mathbf{e}_k))}{\sum_{\mathbf{s}' \in \mathcal{S}_k^-} \exp(\text{sim}(\mathbf{s}', \mathbf{e}_k))}. \tag{9}$$

Note that we use a single scalar hyperparameter β for balancing the adaptive thresholding learning and original contrastive learning for all three cases.

Training Finally, we consider a multi-task contrastive formulation by combing three augmented contrastive learning discussed above, leading to our overall training objective

$$\mathcal{L} = \alpha \ell_{\texttt{start}}^+ + \gamma \ell_{\texttt{end}}^+ + \lambda \ell_{\texttt{joint}}^+, \tag{10}$$

where α, γ, λ are all scalar hyperparameters.

Inference Strategy During inference, we enumerate all possible spans that are less than the length of L and compute three similarity scores based on the start/end/span cases for each entity type. We consider two prediction strategies, *joint position-span* and *span-only* predictions. In the joint position-span case, for entity type E_k, we prune out spans (i, j) that have either start or end similar scores lower than the learned threshold, *i.e.* $\text{sim}(\mathbf{u}_i, \mathbf{e}_k^{\text{B}}) < \text{sim}(\mathbf{u}_{\texttt{[CLS]}}, \mathbf{e}_k^{\text{B}})$ or $\text{sim}(\mathbf{v}_j, \mathbf{e}_k^{\text{Q}}) < \text{sim}(\mathbf{v}_{\texttt{[CLS]}}, \mathbf{e}_k^{\text{Q}})$. Then, only those spans with span similarity scores higher than the span threshold are predicted as positive ones *i.e.* $\text{sim}(\mathbf{s}_{i,j}, \mathbf{e}_k) > \text{sim}(\mathbf{s}_{0,0}, \mathbf{e}_k)$. For the span-only strategy, we just rely on the span similarity score and keep all qualified spans as final predictions. As shown later in our experiments (§4), we find the span-only inference is more effective, because the joint inference is more likely to be affected by annotation artifacts. The full inference algorithm is summarized in Appendix A.1.

3 EXPERIMENTS

We evaluate our method in both supervised and distantly supervised settings. The implementation details of our method are described in Appendix A.2

Evaluation Metrics We follow the standard evaluation protocol and use micro F1: a predicted entity span is considered correct if its span boundaries and the predicted entity type are both correct.

Datasets In the *supervised setting*, we evaluate our method on both nested and flat NER. For nested NER, we consider ACE2004[4], ACE2005[5], and GENIA (Kim et al., 2003). ACE2004 and ACE2005 are collected from general domains (e.g., news and web). We follow Luan et al. (2018) to split ACE2004 into 5 folds, and ACE2005 into train, development and test sets. GENIA is from the biomedical domain. We use its v3.0.2 corpus[6] and follow Finkel & Manning (2009) and Lu & Roth (2015) to split it into 80%/10%/10% train/dev/test splits. For flat NER, we consider five biomedical NER datasets from the BLURB benchmark[7]: BC5-chem/disease (Li et al., 2016), NCBI (Doğan et al., 2014), BC2GM (Smith et al., 2008), and JNLPBA (Collier & Kim, 2004). Preprocessing and splits follow Gu et al. (2021). Appendix A.3 reports the dataset statistics.

In the *distantly supervised setting*, we consider BC5CDR (Li et al., 2016). It consists of 1,500 articles annotated with 15,935 chemical and 12,852 disease mentions. We use the standard train, development, and test splits. In the train and development sets, we discard all human annotations and only keep the unlabeled articles. Their distant labels are generated using exact string matching against a dictionary released by Shang et al. (2018).[8] On the training set, the distant labels have high precision (97.99% for chemicals, and 98.34% for diseases), but low recall (63.14% for chemicals, and 46.73% for diseases).

Supervised NER Results Table 1 presents the comparison of our method with all previous methods evaluated on three nested NER datasets, ACE2004, ACE2005, and GENIA. We report precision, recall, and F1. As is shown, our method achieves very strong performance on all three datasets. On ACE2004 and ACE2005, it outperforms all previous methods with 89.7% and 90.0% F1. Particularly, in comparison with the previous best method (Tan et al., 2021), our method significantly improves F1 by the absolute points of +2.4% and +2.9% respectively. On GENIA, our method advances the previous state of the art (Yu et al., 2020) by +0.3% F1. Note that the previous methods are built on top of different encoders, e.g., LSTM, BERT-large, BART-large, and T5-base. We also report our method using a BERT-base encoder, which even outperforms the previous methods that use a larger encoder of BERT-large (Tan et al., 2021) or BART-large (Yan et al., 2021). Overall, our method has substantial gains over the previous methods. We conduct more detailed analysis in §4.

Table 2 compares our method with all previous submissions on the BLURB benchmark. We only report F1 due to unavailability of precision and recall of these submissions. The major difference among these submissions are encoders. A direct comparison can be made between our method

[4] catalog.ldc.upenn.edu/LDC2005T09
[5] catalog.ldc.upenn.edu/LDC2006T06
[6] geniaproject.org/genia-corpus
[7] aka.ms/blurb
[8] github.com/shangjingbo1226/AutoNER

and Gu et al. (2021) which formulates NER as a sequential labeling task and fine-tunes a standard LSTM+CRF classifier on top of the pretrained transformer encoder. While both using PubMedBERT as the encoder, our method significantly outperforms Gu et al. (2021) across the board. Compared to the previous best submissions (Kanakarajan et al., 2021; Yasunaga et al., 2022), our method also show substantial gains on BC5-chem (+1.2%), BC5-disease (+1.9%), and NCBI (1.5%).

Table 1: Test scores on three nested NER datasets. **Bold-and-underline**, **bold-only** and underline-only indicate the best, the second best, and the third best respectively. The different encoders are used: L = LSTM, Bl = BERT-large, BioB = BioBERT, BioBl = BioBERT-large, BAl = BART-large, T5b = T5-base, Bb = BERT-base. † Original scores of Li et al. (2020) are not reproducible. Like Yan et al. (2021), we report the rerun of their released code.

	Encoder	ACE2004			ACE2005			GENIA		
		P	R	F1	P	R	F1	P	R	F1
Lu & Roth (2015)	-	70.0	56.9	62.8	66.3	59.2	62.5	74.2	66.7	70.3
Katiyar & Cardie (2018)	L	73.6	71.8	72.7	70.6	70.4	70.5	77.7	71.8	74.6
Shibuya & Hovy (2020)	Bl	83.7	81.9	82.8	83.0	82.4	82.7	78.1	76.5	77.3
Wang et al. (2020)	Bl/BioB	86.1	86.5	86.3	84.0	85.4	84.7	79.5	78.9	79.2
Li et al. (2020)†	Bl/BioB	85.8	85.8	85.8	85.0	84.1	84.6	81.2	76.4	78.7
Yu et al. (2020)	Bl/BioB	87.3	86.0	86.7	85.2	85.6	85.4	81.8	79.3	**80.5**
Tan et al. (2021)	Bl/BioB	88.5	86.1	87.3	87.5	86.6	87.1	82.3	78.7	80.4
Yan et al. (2021)	BAl	87.3	86.4	86.8	83.2	86.4	84.7	78.6	79.3	78.9
Zhang et al. (2022)	T5b	86.5	84.5	85.4	83.3	86.6	84.9	81.0	77.2	79.1
Wan et al. (2022)	Bb	86.7	85.9	86.3	84.4	85.9	85.1	77.9	80.7	79.3
BINDER (Ours)	Bb/BioB	88.3	89.1	**88.7**	89.1	89.8	**89.5**	81.5	79.6	**80.5**
	Bl/BioBl	89.7	89.7	**89.7**	89.6	90.5	**90.0**	83.4	78.3	**80.8**

Table 2: Test F1 scores on five flat NER datasets from the BLURB benchmark (aka.ms/blurb). Bold and underline indicate the best and the second best respectively. All encoders use their base version.

	Encoder	BC5-chem	BC5-disease	NCBI	BC2GM	JNLPBA
Lee et al. (2019)	BioBERT	92.9	84.7	89.1	83.8	78.6
Gu et al. (2021)	PubMedBERT	93.3	85.6	87.8	84.5	79.1
Kanakarajan et al. (2021)	BioELECTRA	93.6	85.8	89.4	84.7	80.2
Yasunaga et al. (2022)	LinkBERT	93.8	86.1	88.2	**84.9**	79.0
BINDER (Ours)	PubMedBERT	**95.0**	**88.0**	**90.9**	84.6	**80.3**

Distantly Supervised NER Results Table 3 compares test scores of our method and previous methods on BC5CDR. It presents a clear advantage of our method over all previous methods in the distantly supervised setting. The F1 score is advanced by +1.5% over the previous best method (Zhou et al., 2022), which adapts positive and unlabeled (PU) learning to obtain a high recall yet at the loss of precision. In contrast, our method maintains a reasonable recall (comparable to Shang et al., 2018; Peng et al., 2019) and substantially improves the precision. Note that besides the dictionary used to generate distant supervisions, Zhou et al. (2022); Shang et al. (2018) require an additional high-quality dictionary to estimate the noisiness of non-entity spans. Our method does not have such a requirement. For reference, Table 2 also includes the supervised state of the art. Our method in the supervised setting achieves 91.9% F1, outperforming the previous state of the art Wang et al. (2021) by 1.0%. Comparing both settings, we observe that

Table 3: Test scores on BC5CDR. All baselines scores in the distantly supervised setting are quoted from Zhou et al. (2022).

	BC5CDR		
	P	R	F1
Distantly Supervised			
Dict/KB Matching	86.4	51.2	64.3
AutoNER (Shang et al., 2018)	82.6	77.5	80.0
BNPU (Peng et al., 2019)	48.1	77.1	59.2
BERT-ES (Liang et al., 2020)	80.4	67.9	73.7
Conf-MPU (Zhou et al., 2022)	76.6	83.8	80.1
BINDER (Ours)	87.6	76.3	**81.6**
Fully Supervised			
Nooralahzadeh et al. (2019)	92.1	87.9	89.9
Wang et al. (2021)	-	-	90.9
BINDER (Ours)	92.6	91.2	**91.9**

the distantly supervised state of the art still has an over-10-point gap with the supervised one, indicating a potential to further reduce the false negative noise.

4 ANALYSIS

Here we conduct extensive analyses of our method. For efficiency, all analysis in this section is done based on the uncased BERT-base encoder.

Ablation Study We compare several variants of our method and report their test scores on ACE2005 in Table 4. We observe performance degradation in all these variants. *Shared linear layers* uses the same linear layer for span and token embeddings, and the same linear layer for entity type embeddings, in the hope of projecting them into the same vector space and sharing their semantics. It leads to a slightly better precision but a drop of recall. Similar changes are observed in *Joint position-span inference*, which adopts a more stringent strategy to prune out spans – only keep spans whose start, end, and span scores are all above the thresholds. *No position-based objectives* only optimizes the span-based objective, which penalizes partially corrected spans in the same way as other spans, resulting in a marginal improvement of recall but a significant loss of precision.

Choices of Entity Type Descriptions Table 5 compares different choices of entity type descriptions. Our final model uses annotation guidelines, which outperforms other choices: (1) *Atomic labels* considers each entity type as an atomic label. Instead of learning an entity type encoder, we directly learn an embedding vector for each entity type. (2) *Keywords* uses a keyword for each entity type as the input to the entity type encoder, e.g., "person" for `PER`. (3) *Prototypical instances* for each minibatch during training dynamically samples from the training data a prototypical instance for each entity type and uses it as input to the entity type encoder. Unlike annotation guidelines, we add special markers to indicate the start and end of an entity span and use the hidden states of the start marker as entity type embeddings. At test time, we increase the number of prototypical instances to three for each entity type. Larger number of prototypical instances may improve the performance. Prototypical instances may also lead to a better performance in few-shot or zero-shot settings. We leave them to future exploration.

Table 4: Test scores of our method and its variants on ACE2005.

	ACE2005		
	P	R	F1
Our full model	89.1	89.8	89.5
Shared linear layers	89.3	89.3	89.3
Joint position-span inference	89.4	89.2	89.3
No position-based objectives	88.7	89.9	89.3

Table 5: Test scores on ACE2005 with different entity type descriptions.

	ACE2005		
	P	R	F1
Atomic labels	88.9	89.6	89.2
Keywords	88.7	89.8	89.2
Prototypical instances	88.7	90.1	89.4
Annotation guidelines	89.1	89.8	89.5

Thresholding Strategies Our method uses dynamic similarity thresholds to distinguish entity spans from non-entity spans. We compare the impact of dynamic thresholds in our method with two straightforward variants: (1) *Learned global thresholds* replaces dynamic thresholds with global thresholds, one for each entity type. Specifically, we consider the global similarity thresholds as scalar parameters (initialized as 0). During training, we replace the similarity function outputs $\mathrm{sim}(\mathbf{u}_{\texttt{[CLS]}}, \mathbf{e}^{\mathrm{B}}_k)$ in Equation 8 and $\mathrm{sim}(\mathbf{s}_{0,0}, \mathbf{e}_k)$ in Equation 9 with the corresponding global thresholds. At test times, the global thresholds are used to separate entity spans from non-entity spans. (2) *Global thresholds tuned on dev* introduces global thresholds after the training is done and tune them on the development set. During training, instead of Equation 10, we optimize a simplified loss without thresholding, $\alpha\ell_{\texttt{start}} + \gamma\ell_{\texttt{end}} + \lambda\ell_{\texttt{joint}}$. Table 6 compares their test scores on the ACE2005 dataset. Dynamic thresholds have the best scores overall. Learned global thresholds performs better than global thresholds tuned on the development set, indicating the necessity of learning thresholds during training. Note that the global thresholds tuned on dev still outperforms all the previous methods in Table 1, showing a clear advantage of our bi-encoder framework. In Appendix A.4, We further visualize and discuss the distribution of similarity scores between text spans and entity types based on different thresholding strategies.

Time Efficiency Table 7 compares the training and inference speed of our method against several prominent methods. To ensure fair comparisons, all speed numbers are recorded based on the same machine using their released code with the same batch size and the same maximum sequence length. MRC-NER (Li et al., 2020) formulates NER as a machine reading comprehension problem and employs a cross-attention encoder. Comparing with it, our bi-encoder framework has 17x and 8x speed on training and inference respectively. Biaffine-NER (Yu et al., 2020) formulates NER as a dependency parsing problem and applies a biaffine classifier to classify the typed arc between an entity span start and end. Comparing with it, our framework does not need a biaffine layer and is 1.7x and 2.4x faster at training and inference. Without the need of conditional random fields (CRFs), our framework is even faster than the widely used BERT-CRF framework. A drawback of BERT-CRF is that it cannot be applied to nested NER. Here we test it on a flat NER dataset CoNLL2003 (Tjong Kim Sang & De Meulder, 2003). All other frameworks are tested on ACE2005.

Table 6: Test scores of our method using different thresholding strategies on ACE2005.

	ACE2005		
	P	R	F1
Dynamic thresholds	89.1	89.8	89.5
Learned global thresholds	88.2	89.0	88.6
Global thresholds tuned on dev	86.3	88.7	87.5

Table 7: Training and inference speed.

	Speed (w/s)	
	Training	Inference
MRC-NER (Li et al., 2020)	147	1,110
Biaffine-NER (Yu et al., 2020)	1,548	3,634
BERT-CRF (pytorch_neural_crf)	2,273	8,596
BINDER (Ours)	**2,571**	**8,886**

Table 8: Test F1 score breakdowns on ACE2005 and GENIA. Columns compare F1 scores on different entity types. Rows compare F1 scores based on the entire entity span, or only the start or end of entity span. S-F1 denotes the strict F1 requiring the exact boundary match. L-F1 denotes the loose F1 allowing partial overlaps. The color signifies substantially better F1 scores than the corresponding entity span strict F1 scores.

	ACE2005								GENIA					
	PER	GPE	ORG	FAC	LOC	VEH	WEA	ALL	Prot.	DNA	CellT.	CellL.	RNA	ALL
S-F1$_{span}$	93.4	91.2	79.7	81.0	78.7	84.8	82.1	89.5	82.9	77.6	74.5	76.3	87.9	80.5
S-F1$_{start}$	93.9	91.2	80.7	81.0	79.0	84.8	82.1	89.9	86.1	80.9	74.5	80.2	88.7	83.2
S-F1$_{end}$	93.9	91.2	81.9	83.1	79.0	86.8	82.1	90.3	87.6	82.6	83.7	82.8	91.0	85.8
L-F1$_{span}$	94.4	91.4	83.0	83.1	79.4	87.2	82.1	90.8	91.6	87.4	84.8	87.2	91.7	89.9

Performance Breakdown Table 8 shows the test F1 scores on each entity type of ACE2005 and GENIA. We report four types of F1 scores: S-F1$_{span}$ is the strict F1 based on the exact match of *entity spans*; S-F1$_{start}$ is the strict F1 based on the exact match of *entity start words*; S-F1$_{end}$ is the strict F1 based on the exact match of *entity end words*; L-F1$_{span}$ is the loose F1 allowing the *partial* match of entity spans. We notice that S-F1$_{end}$ is often substantially better than S-F1$_{span}$ and S-F1$_{start}$. To explain this difference, we go through these partially corrected predictions and summarize the common errors in Table 9. The most common one is the inclusion or exclusion of modifiers. This could be due to annotation disagreement: in ACE2005, sometimes generic spans are preferred (e.g., "tomcats" vs. "f-14 tomcats"), while in some cases specific spans are preferred (e.g., "cruise ship" vs. "ship"). This issue is more common in the biomedical dataset GENIA, e.g., "human GR" is considered as wrong while "human lymphocytes" are correct, which explains the higher scores of S-F1$_{end}$ than

Table 9: Examples of common errors among the partially corrected predictions. Red indicates error spans. Blue indicates missing spans. The number after each span mean the span frequency in the training data.

Error Type	Ent. Type	Predicted ↔ Gold
Modifier Error	VEH	f-14 tomcats (0) ↔ tomcats (0)
	FAC	federal court (0) ↔ court (0)
	VEH	ship (29) ↔ cruise ship (1)
	CellL.	unstimulated T cells (0) ↔ T cells (553)
	Prot.	human GR (0) ↔ GR (88)
	CellT.	lymphocytes (117) ↔ human lymphocytes (18)
	DNA	E6 motif (0) ↔ synthetic E6 motif (0)
Missing Genitive	PER	attendant (3) ↔ attendant's (0)
Annotation Error	PER	Dr. Germ (0) ↔ Dr (1) / Germ (0)
	Prot.	Ag amino acid sequence (0) ↔ Ag (1) / amino acid sequence (6)
	CellL.	EBV-transformed human B cell line SKW6.4 (0) ↔ EBV-transformed human B cell line (0) / SKW6.4 (1)
	DNA	second-site LTR revertants (0) ↔ second-site LTR (0)

S-F1$_{\text{start}}$. Missing genitives for person names are another common errors in ACE2005. We also discover some annotation errors, where names of a single person, protein, or cell line are sometimes broken into two less meaningful spans, e.g., "Dr. Germ" is annotated as two person mentions "Dr" and "Germ", and "EBV-transformed human B cell line SKW6.4" is annotated as two separate cell lines "EBV-transformed human B cell line" and "SKW6.4".

5 Related Work

Supervised NER Early techniques for NER are based on hidden markov models (e.g., Zhou & Su, 2002) and conditional random fields (CRFs) (e.g., McDonald & Pereira 2005). However, due to the inability to handle nested named entities, techniques such as cascaded CRFs (Alex et al., 2007), adpated constituency parsing (Finkel & Manning, 2009), and hypergraphs (Lu & Roth, 2015) are developed for nested NER. More recently, with the advance in deep learning, a myriad of new techniques have been used in supervised NER. Depending on the way they formulate the task, these techniques can be categorized as NER as sequence labeling (Chiu & Nichols, 2016; Ma & Hovy, 2016; Katiyar & Cardie, 2018); NER as parsing (Lample et al., 2016; Yu et al., 2020); NER as span classification (Sohrab & Miwa, 2018; Xia et al., 2019; Ouchi et al., 2020; Fu et al., 2021); NER as a sequence-to-sequence problem (Straková et al., 2019; Yan et al., 2021); and NER as machine reading comprehension (Li et al., 2020; Mengge et al., 2020). Unlike previous work, we formulate NER as a contrastive learning problem. The span-based design of our bi-encoder and contrastive loss provides us with the flexibility to handle both nested and flat NER.

Distantly Supervised NER Distant supervision from external knowledge bases in conjunction with unlabeled text is generated by string matching (Giannakopoulos et al., 2017) or heuristic rules (Ren et al., 2015; Fries et al., 2017). Due to the limited coverage of external knowledge bases, distant supervision often has a high false negative rate. To alleviate this issue, Shang et al. (2018) design a new tagging scheme with an `unknown` tag specifically for false negatives; Mayhew et al. (2019) iteratively detect false negatives and downweigh them in training; Peng et al. (2019); Zhou et al. (2022) address overfitting to false negatives using Positive and Unlabeled (PU) learning; Zhang et al. (2021b) identify dictionary biases via a structural causal model, and de-bias them using causal interventions. Liu et al. (2021) introduce a calibrated confidence estimation method and integrate it into a self-training framework. Without replying on sophisticated de-noising designs, our bi-encoder framework can be directly used in distant supervision. Experiments in §3 show the robustness of our contrastive learning algorithm to the noise in distantly supervised NER.

Bi-Encoder The use of bi-encoder dates back to Bromley et al. (1993) for signature verification and Chopra et al. (2005) for face verification. These works and their descendants (e.g., Yih et al., 2011; Hu et al., 2014) refer to the architecture as *siamese networks* since two similar inputs are encoded separately by two copies of the same network (all parameters are shared). Wsabie (Weston et al., 2010) and StarSpace (Wu et al., 2018) subsequently employ bi-encoder to learn embeddings for different data types. Using deep pretrained transformers as encoders, Humeau et al. (2019) compare three different architectures, bi-encoder, poly-encoder, and cross-encoder. The bi-encoder architecture afterwards has been use in various tasks, e.g., information retrieval (Huang et al., 2013; Gillick et al., 2018), open-domain question answering (Karpukhin et al., 2020), and entity linking (Gillick et al., 2019; Wu et al., 2020; Zhang et al., 2021a). To our best knowledge, there is no previous work learning bi-encoder for NER.

6 Conclusions

We present a bi-encoder framework for NER using contrastive learning, which separately maps text and entity types into the same vector space. To separate entity spans from non-entity ones, we introduce a novel contrastive loss to jointly learn span identification and entity classification. Experiments in both supervised and distantly supervised settings show the effectiveness and robustness of our method. We conduct extensive analysis to explain the success of our method and reveal growth opportunities. Future directions include further improving low-performing types and applications in self-supervised zero-shot settings.

REFERENCES

Beatrice Alex, Barry Haddow, and Claire Grover. Recognising nested named entities in biomedical text. In *Biological, translational, and clinical language processing*, pp. 65–72, Prague, Czech Republic, June 2007. Association for Computational Linguistics. URL https://aclanthology.org/W07-1009.

Rami Aly, Andreas Vlachos, and Ryan McDonald. Leveraging type descriptions for zero-shot named entity recognition and classification. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 1516–1528, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.120. URL https://aclanthology.org/2021.acl-long.120.

Jane Bromley, Isabelle Guyon, Yann LeCun, Eduard Säckinger, and Roopak Shah. Signature verification using a" siamese" time delay neural network. *Advances in neural information processing systems*, 6, 1993.

Kai-Wei Chang, Rajhans Samdani, and Dan Roth. A constrained latent variable model for coreference resolution. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pp. 601–612, Seattle, Washington, USA, October 2013. Association for Computational Linguistics. URL https://aclanthology.org/D13-1057.

Jason P.C. Chiu and Eric Nichols. Named entity recognition with bidirectional LSTM-CNNs. *Transactions of the Association for Computational Linguistics*, 4:357–370, 2016. doi: 10.1162/tacl_a_00104. URL https://aclanthology.org/Q16-1026.

Yejin Choi, Eric Breck, and Claire Cardie. Joint extraction of entities and relations for opinion recognition. In *Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing*, pp. 431–439, Sydney, Australia, July 2006. Association for Computational Linguistics. URL https://aclanthology.org/W06-1651.

Sumit Chopra, Raia Hadsell, and Yann LeCun. Learning a similarity metric discriminatively, with application to face verification. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 1, pp. 539–546. IEEE, 2005.

Nigel Collier and Jin-Dong Kim. Introduction to the bio-entity recognition task at JNLPBA. In *Proceedings of the International Joint Workshop on Natural Language Processing in Biomedicine and its Applications (NLPBA/BioNLP)*, pp. 73–78, Geneva, Switzerland, August 28th and 29th 2004. COLING. URL https://aclanthology.org/W04-1213.

Sarkar Snigdha Sarathi Das, Arzoo Katiyar, Rebecca Passonneau, and Rui Zhang. CONTaiNER: Few-shot named entity recognition via contrastive learning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 6338–6353, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.439. URL https://aclanthology.org/2022.acl-long.439.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1423. URL https://aclanthology.org/N19-1423.

Rezarta Islamaj Doğan, Robert Leaman, and Zhiyong Lu. Special report: Ncbi disease corpus: A resource for disease name recognition and concept normalization. *J. of Biomedical Informatics*, 47:1–10, feb 2014. ISSN 1532-0464.

Jenny Rose Finkel and Christopher D. Manning. Nested named entity recognition. In *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing*, pp. 141–150, Singapore, August 2009. Association for Computational Linguistics. URL https://aclanthology.org/D09-1015.

Jason Fries, Sen Wu, Alex Ratner, and Christopher Ré. Swellshark: A generative model for biomedical named entity recognition without labeled data. *arXiv preprint arXiv:1704.06360*, 2017.

Jinlan Fu, Xuanjing Huang, and Pengfei Liu. SpanNER: Named entity re-/recognition as span prediction. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 7183–7195, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.558. URL https://aclanthology.org/2021.acl-long.558.

Athanasios Giannakopoulos, Claudiu Musat, Andreea Hossmann, and Michael Baeriswyl. Unsupervised aspect term extraction with B-LSTM & CRF using automatically labelled datasets. In *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pp. 180–188, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/W17-5224. URL https://aclanthology.org/W17-5224.

Daniel Gillick, Alessandro Presta, and Gaurav Singh Tomar. End-to-end retrieval in continuous space. *arXiv preprint arXiv:1811.08008*, 2018.

Daniel Gillick, Sayali Kulkarni, Larry Lansing, Alessandro Presta, Jason Baldridge, Eugene Ie, and Diego Garcia-Olano. Learning dense representations for entity retrieval. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pp. 528–537, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/K19-1049. URL https://aclanthology.org/K19-1049.

Yu Gu, Robert Tinn, Hao Cheng, Michael Lucas, Naoto Usuyama, Xiaodong Liu, Tristan Naumann, Jianfeng Gao, and Hoifung Poon. Domain-specific language model pretraining for biomedical natural language processing. *ACM Transactions on Computing for Healthcare (HEALTH)*, 3(1): 1–23, 2021.

Baotian Hu, Zhengdong Lu, Hang Li, and Qingcai Chen. Convolutional neural network architectures for matching natural language sentences. *Advances in neural information processing systems*, 27, 2014.

Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck. Learning deep structured semantic models for web search using clickthrough data. In *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management*, CIKM '13, pp. 2333–2338, New York, NY, USA, 2013. Association for Computing Machinery. ISBN 9781450322638. doi: 10.1145/2505515.2505665. URL https://doi.org/10.1145/2505515.2505665.

Samuel Humeau, Kurt Shuster, Marie-Anne Lachaux, and Jason Weston. Poly-encoders: Architectures and pre-training strategies for fast and accurate multi-sentence scoring. In *International Conference on Learning Representations*, 2019.

Kamal raj Kanakarajan, Bhuvana Kundumani, and Malaikannan Sankarasubbu. BioELECTRA:pretrained biomedical text encoder using discriminators. In *Proceedings of the 20th Workshop on Biomedical Language Processing*, pp. 143–154, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.bionlp-1.16. URL https://aclanthology.org/2021.bionlp-1.16.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. Dense passage retrieval for open-domain question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6769–6781, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.550. URL https://aclanthology.org/2020.emnlp-main.550.

Arzoo Katiyar and Claire Cardie. Nested named entity recognition revisited. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pp. 861–871, New Orleans,

Louisiana, June 2018. Association for Computational Linguistics. doi: 10.18653/v1/N18-1079. URL https://aclanthology.org/N18-1079.

J-D Kim, Tomoko Ohta, Yuka Tateisi, and Jun'ichi Tsujii. Genia corpus—a semantically annotated corpus for bio-textmining. *Bioinformatics*, 19(suppl_1):i180–i182, 2003.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. Neural architectures for named entity recognition. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 260–270, San Diego, California, June 2016. Association for Computational Linguistics. doi: 10.18653/v1/N16-1030. URL https://aclanthology.org/N16-1030.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, 36(4):1234–1240, 09 2019. ISSN 1367-4803. doi: 10.1093/bioinformatics/btz682. URL https://doi.org/10.1093/bioinformatics/btz682.

Jiao Li, Yueping Sun, Robin J Johnson, Daniela Sciaky, Chih-Hsuan Wei, Robert Leaman, Allan Peter Davis, Carolyn J Mattingly, Thomas C Wiegers, and Zhiyong Lu. Biocreative v cdr task corpus: a resource for chemical disease relation extraction. *Database*, 2016, 2016.

Xiaoya Li, Jingrong Feng, Yuxian Meng, Qinghong Han, Fei Wu, and Jiwei Li. A unified MRC framework for named entity recognition. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 5849–5859, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.519. URL https://aclanthology.org/2020.acl-main.519.

Chen Liang, Yue Yu, Haoming Jiang, Siawpeng Er, Ruijia Wang, Tuo Zhao, and Chao Zhang. Bond: Bert-assisted open-domain named entity recognition with distant supervision. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '20, pp. 1054–1064, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450379984. doi: 10.1145/3394486.3403149. URL https://doi.org/10.1145/3394486.3403149.

Kun Liu, Yao Fu, Chuanqi Tan, Mosha Chen, Ningyu Zhang, Songfang Huang, and Sheng Gao. Noisy-labeled NER with confidence estimation. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 3437–3445, Online, June 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.naacl-main.269. URL https://aclanthology.org/2021.naacl-main.269.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.

Wei Lu and Dan Roth. Joint mention extraction and classification with mention hypergraphs. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 857–867, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1102. URL https://aclanthology.org/D15-1102.

Yi Luan, Luheng He, Mari Ostendorf, and Hannaneh Hajishirzi. Multi-task identification of entities, relations, and coreference for scientific knowledge graph construction. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 3219–3232, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1360. URL https://aclanthology.org/D18-1360.

Xuezhe Ma and Eduard Hovy. End-to-end sequence labeling via bi-directional LSTM-CNNs-CRF. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1064–1074, Berlin, Germany, August 2016. Association for Computational Linguistics. doi: 10.18653/v1/P16-1101. URL https://aclanthology.org/P16-1101.

Stephen Mayhew, Snigdha Chaturvedi, Chen-Tse Tsai, and Dan Roth. Named entity recognition with partially annotated training data. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pp. 645–655, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/K19-1060. URL https://aclanthology.org/K19-1060.

Ryan McDonald and Fernando Pereira. Identifying gene and protein mentions in text using conditional random fields. *BMC bioinformatics*, 6(1):1–7, 2005.

Xue Mengge, Bowen Yu, Zhenyu Zhang, Tingwen Liu, Yue Zhang, and Bin Wang. Coarse-to-Fine Pre-training for Named Entity Recognition. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6345–6354, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.514. URL https://aclanthology.org/2020.emnlp-main.514.

Mike Mintz, Steven Bills, Rion Snow, and Daniel Jurafsky. Distant supervision for relation extraction without labeled data. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP*, pp. 1003–1011, Suntec, Singapore, August 2009. Association for Computational Linguistics. URL https://aclanthology.org/P09-1113.

David Nadeau and Satoshi Sekine. A survey of named entity recognition and classification. *Lingvisticae Investigationes*, 30(1):3–26, 2007.

Farhad Nooralahzadeh, Jan Tore Lønning, and Lilja Øvrelid. Reinforcement-based denoising of distantly supervised NER with partial annotation. In *Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019)*, pp. 225–233, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-6125. URL https://aclanthology.org/D19-6125.

Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

Hiroki Ouchi, Jun Suzuki, Sosuke Kobayashi, Sho Yokoi, Tatsuki Kuribayashi, Ryuto Konno, and Kentaro Inui. Instance-based learning of span representations: A case study through named entity recognition. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 6452–6459, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.575. URL https://aclanthology.org/2020.acl-main.575.

Minlong Peng, Xiaoyu Xing, Qi Zhang, Jinlan Fu, and Xuanjing Huang. Distantly supervised named entity recognition using positive-unlabeled learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 2409–2419, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1231. URL https://aclanthology.org/P19-1231.

Xiang Ren, Ahmed El-Kishky, Chi Wang, Fangbo Tao, Clare R Voss, and Jiawei Han. Clustype: Effective entity recognition and typing by relation phrase-based clustering. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 995–1004. ACM, 2015.

Jingbo Shang, Liyuan Liu, Xiaotao Gu, Xiang Ren, Teng Ren, and Jiawei Han. Learning named entity tagger using domain-specific dictionary. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 2054–2064, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1230. URL https://aclanthology.org/D18-1230.

Takashi Shibuya and Eduard Hovy. Nested Named Entity Recognition via Second-best Sequence Learning and Decoding. *Transactions of the Association for Computational Linguistics*, 8:605–620, 09 2020. ISSN 2307-387X. doi: 10.1162/tacl_a_00334. URL https://doi.org/10.1162/tacl_a_00334.

Larry Smith, Lorraine K Tanabe, Cheng-Ju Kuo, I Chung, Chun-Nan Hsu, Yu-Shi Lin, Roman Klinger, Christoph M Friedrich, Kuzman Ganchev, Manabu Torii, et al. Overview of biocreative ii gene mention recognition. *Genome biology*, 9(2):1–19, 2008.

Mohammad Golam Sohrab and Makoto Miwa. Deep exhaustive model for nested named entity recognition. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 2843–2849, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1309. URL https://aclanthology.org/D18-1309.

Jana Straková, Milan Straka, and Jan Hajic. Neural architectures for nested NER through linearization. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 5326–5331, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1527. URL https://aclanthology.org/P19-1527.

Zeqi Tan, Yongliang Shen, Shuai Zhang, Weiming Lu, and Yueting Zhuang. A sequence-to-set network for nested named entity recognition. In *Proceedings of the 30th International Joint Conference on Artificial Intelligence, IJCAI-21*, 2021. URL https://arxiv.org/abs/2105.08901.

Erik F. Tjong Kim Sang and Fien De Meulder. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. In *Proceedings of the Seventh Conference on Natural Language Learning at HLT-NAACL 2003*, pp. 142–147, 2003. URL https://aclanthology.org/W03-0419.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proc. Advances in Neural Information Processing Systems (NeurIPS)*, volume 30, 2017. URL https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.

Juncheng Wan, Dongyu Ru, Weinan Zhang, and Yong Yu. Nested named entity recognition with span-level graphs. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 892–903, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.63. URL https://aclanthology.org/2022.acl-long.63.

Jue Wang, Lidan Shou, Ke Chen, and Gang Chen. Pyramid: A layered model for nested named entity recognition. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 5918–5928, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.525. URL https://aclanthology.org/2020.acl-main.525.

Xinyu Wang, Yong Jiang, Nguyen Bach, Tao Wang, Zhongqiang Huang, Fei Huang, and Kewei Tu. Improving named entity recognition by external context retrieving and cooperative learning. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 1800–1812, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.142. URL https://aclanthology.org/2021.acl-long.142.

Jason Weston, Samy Bengio, and Nicolas Usunier. Large scale image annotation: learning to rank with joint word-image embeddings. *Machine learning*, 81(1):21–35, 2010.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 38–45, Online, October 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-demos.6. URL https://aclanthology.org/2020.emnlp-demos.6.

Ledell Wu, Adam Fisch, Sumit Chopra, Keith Adams, Antoine Bordes, and Jason Weston. Starspace: Embed all the things! In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

Ledell Wu, Fabio Petroni, Martin Josifoski, Sebastian Riedel, and Luke Zettlemoyer. Scalable zero-shot entity linking with dense entity retrieval. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 6397–6407, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.519. URL https://aclanthology.org/2020.emnlp-main.519.

Congying Xia, Chenwei Zhang, Tao Yang, Yaliang Li, Nan Du, Xian Wu, Wei Fan, Fenglong Ma, and Philip Yu. Multi-grained named entity recognition. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 1430–1440, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1138. URL https://aclanthology.org/P19-1138.

Hang Yan, Tao Gui, Junqi Dai, Qipeng Guo, Zheng Zhang, and Xipeng Qiu. A unified generative framework for various NER subtasks. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 5808–5822, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.451. URL https://aclanthology.org/2021.acl-long.451.

Michihiro Yasunaga, Jure Leskovec, and Percy Liang. LinkBERT: Pretraining language models with document links. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 8003–8016, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.551. URL https://aclanthology.org/2022.acl-long.551.

Wen-tau Yih, Kristina Toutanova, John C. Platt, and Christopher Meek. Learning discriminative projections for text similarity measures. In *Proceedings of the Fifteenth Conference on Computational Natural Language Learning*, pp. 247–256, Portland, Oregon, USA, June 2011. Association for Computational Linguistics. URL https://aclanthology.org/W11-0329.

Juntao Yu, Bernd Bohnet, and Massimo Poesio. Named entity recognition as dependency parsing. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 6470–6476, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.577. URL https://aclanthology.org/2020.acl-main.577.

Sheng Zhang, Hao Cheng, Shikhar Vashishth, Cliff Wong, Jinfeng Xiao, Xiaodong Liu, Tristan Naumann, Jianfeng Gao, and Hoifung Poon. Knowledge-rich self-supervised entity linking. *arXiv preprint arXiv:2112.07887*, 2021a.

Shuai Zhang, Yongliang Shen, Zeqi Tan, Yiquan Wu, and Weiming Lu. De-bias for generative extraction in unified NER task. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 808–818, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.59. URL https://aclanthology.org/2022.acl-long.59.

Wenkai Zhang, Hongyu Lin, Xianpei Han, and Le Sun. De-biasing distantly supervised named entity recognition via causal intervention. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 4803–4813, Online, August 2021b. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.371. URL https://aclanthology.org/2021.acl-long.371.

GuoDong Zhou and Jian Su. Named entity recognition using an HMM-based chunk tagger. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pp. 473–480, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073163. URL https://aclanthology.org/P02-1060.

Kang Zhou, Yuepei Li, and Qi Li. Distantly supervised named entity recognition via confidence-based multi-class positive and unlabeled learning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 7198–7211, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.498. URL `https://aclanthology.org/2022.acl-long.498`.

A Appendix

A.1 Inference for **Binder**

As we can see in Algorithm 1, the difference between joint position-span and span-only strategies is whether line 9 is used. Also, for flat NER datasets, we further carry out a post-processing step to remove overlapping predictions (line 19 in Algorithm 1). Here, the post-processing (`removeOverlap`) is carried out in a greedy fashion where higher scored span predictions with earlier start and end positions are preferred.

Algorithm 1: Inference for **Binder**.

Input: $\mathcal{S} = \{(i,j) | i,j = 1,\ldots,N, 0 \leq j-i \leq L\}$ the set of spans , $\mathcal{E} = \{E_1,\ldots,E_K\}$ the set of entity types, `joint` for whether using joint position-span inference, and `flat` for whether the inference is for flat NER.

$M = \{\}$;
for $E_k \in \mathcal{E}$ **do**
  4 compute start/end/span threshold scores $b_{null}, e_{null}, s_{null}$.
  6 **for** $(i,j) \in \mathcal{S}$ **do**
    compute start/end/span similarity scores b, e, s.
    9 **if** *`joint` is true and* $b < b_{null}$ *or* $e < e_{null}$ **then**
      Continue;
    end
    13 **if** $s > s_{null}$ **then**
      $M = M \bigcup \{(i,j,E_k)\}$;
    end
  end
end
19 **if** *flat is true* **then**
  return `removeOverlap`(M);
end
return M;
Function `removeOverlap`$(\hat{D})$**:**
  $\hat{M} = \{\}$;
  sort $\hat{D}$ by the similarity score in descending order and break the tie by ascending in start and end positions;
  for (i,j,E_k) *in* $\hat{D}$ **do**
    if *span* (i,j) *has no overlap in* $\hat{M}$ **then**
      $\hat{M} = \hat{M} \cup \{(i,j,E_k)\}$;
    end
  end
  return $\hat{M}$;

A.2 Implementation Details

We implement our models based on the HuggingFace Transformers library (Wolf et al., 2020). The base encoders are initialized using PubMedBERT-base-uncased (Gu et al., 2021) or BioBERT (Lee et al., 2019) for biomedical NER datasets, and BERT-base-uncased or BERT-large-uncased (Devlin et al., 2019) for NER datasets in the general domains. The linear layer output size is 128; the width embedding size is 128; the initial temperatures are 0.07. We train our models with the AdamW opti-

mizer (Loshchilov & Hutter, 2017) of a linear scheduler and dropout of 0.1. The entity start/end/span contrastive loss weights are set to $\alpha = 0.2, \gamma = 0.2, \lambda = 0.6$, and the same loss weights are chosen for thresholding contrastive learning. The contrastive losses for thresholding and entity are weighted equally in the final loss. For all experiments, we ignore sentence boundaries, and tokenize and split text into sequences with a stride of 16. For base encoders, we train our models for 20 epochs with a learning rate of 3e-5 and a batch size of 8 sequences with the maximum token length of 128. For large encoders, we train our models for 40 epochs with a learning rate of 3e-5 and a batch size of 16 sequences with the maximum token length of 256. The maximum token length for entity spans is set to 30. We use early stop with a patience of 10 in the distantly supervised setting. Validation is done at every 50 steps of training, and we adopt the models that have the best performance on the development set. We report the median score of multiple runs.

A.3 Statistics of Datasets

Table 10: The statistics of supervised NER datasets.

Dataset	$\lvert\mathcal{E}\rvert$	# Annotations		
		Train	Dev	Test
ACE2004	7	22,735 (5-fold)		
ACE2005	7	26,473	6,338	5,476
GENIA	5	46,142	4,367	5,506
BC5-chem	1	5,203	5,347	5,385
BC5-disease	1	4,182	4,244	4,424
NCBI	1	5,134	787	960
BC2GM	1	15,197	3,061	6,325
JNLPBA	1	46,750	4,551	8,662

A.4 Distributions of Similarity Scores

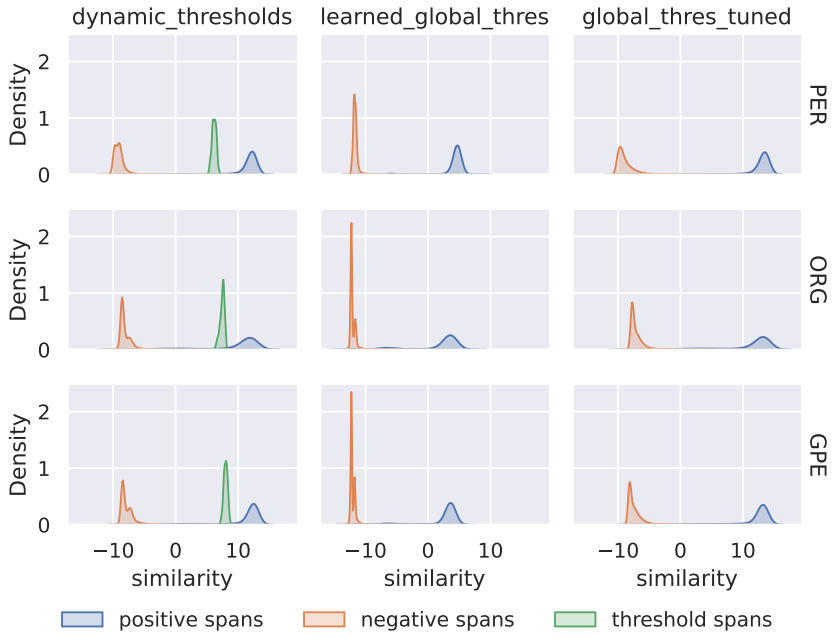


Figure 2: The kernel density estimation of similarity scores between different text spans (entity, non-entity, and threshold spans) and entity types (PER, ORG, GPE) on ACE2005 based on different thresholding strategies.

Figure 2 visualizes the distributions of similarity scores between different text spans and entity types based on different thresholding strategies. Consistent with the scores in Table 6, the majority of entity spans and non-entity spans are separable regardless of the thresholding strategy. This is

true even when no thresholds are used during training and instead we tune global thresholds on dev. We zoom in the distributions in Figure 3 and observe that the learned global thresholds tend to make the similarities less separable between entity spans and non-entity spans.

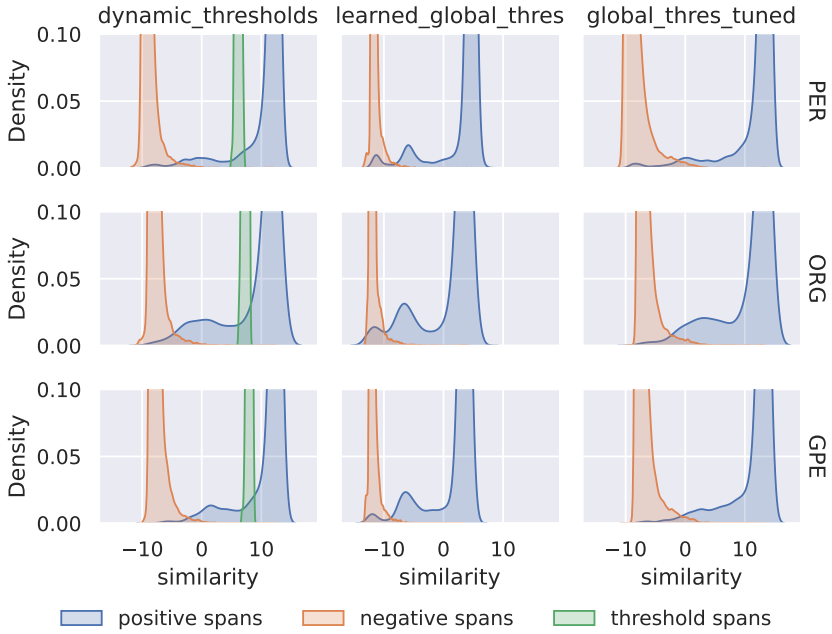


Figure 3: Zoom-in of the kernel density estimation of similarity scores in Figure 2, with the y-axis density limited to (0, 0.1).