EnTDA: Entity-to-Text based Data Augmentation Approach for Named Entity Recognition Tasks

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Abstract

Data augmentation techniques have been used to improve the generalization capability of models in the named entity recognition (NER) tasks. Existing augmentation methods either manipulate the words in the original text that require hand-crafted in-domain knowledge, or leverage generative models which solicit dependency order among entities. To alleviate the excessive reliance on the dependency order among entities in existing augmentation paradigms, we develop an entity-to-text instead of text-to-entity based data augmentation method named EnTDA to decouple the dependencies between entities by adding, deleting, replacing and swapping entities, and adopt these augmented data to bootstrap the generalization ability of the NER model. Furthermore, we introduce a diversity beam search to increase the diversity of the augmented data. Experiments on thirteen NER datasets across three tasks (flat NER, nested NER, and discontinuous NER) and two settings (full data NER and low resource NER) show that EnTDA could consistently outperform the baselines.

1 Introduction

Recent neural networks show decent performance when a large amount of training data is available. However, these manually labeled data are labor-intensive to obtain. Data augmentation techniques (Shorten and Khoshgoftaar, 2019) expand the training set by generating synthetic data to improve the generalization and scalability of deep neural networks, and are widely used in computer vision (Perez and Wang, 2017; Mounsaveng et al., 2021) and speech (Ko et al., 2017). However, compared with computer vision and speech, which can easily adopt hand-crafted rules (such as rotation, cropping, flipping, etc.) to modify the original data while keeping the visual information unchanged, language is more ambiguous and contextualized. Therefore, it is more difficult to apply data augmentation techniques to natural language processing (NLP) tasks.

One successful attempt for data augmentation in NLP is manipulating a few words in the original text, such as word swapping (Şahin and Steedman, 2018; Min et al., 2020) and random deletion (Kobayashi, 2018; Wei and Zou, 2019). These methods generate synthetic texts effortlessly without considering hand-crafted knowledge. More importantly, these augmentation approaches work on sentence-level tasks like classification but cannot be easily applied to fine-grained and fragile token-level tasks like Named Entity Recognition (NER).

Named Entity Recognition aims at inferring a label for each token to indicate whether it belongs to an entity and classifies entities into predefined types. Due to transformations of tokens that may change their labels, Dai and Adel (2020) augment the token-level text by randomly replacing a token with another token of the same type. However, it still inevitably introduces incoherent replacement operation techniques to natural language processing (NLP) tasks.

Table 1: Texts generated by EnTDA. We adopt four operations to obtain augmented entity set and generate texts marked with the updated entity set.

| Operation | Entity | Text |
|-----------|--------|------|
| None | EU, German, British | EU’s stance on German beef is British’s stance on beef. |
| Add | EU, German, British, Spanish | EU’s veterinary committee ruled that German beef, British lamb and Spanish sheep should be banned. |
| Delete | EU, German | EU’s German wing says it has received a warning. |
| Replace | EU, German, Spanish | EU’s veterinary committee ruled that German beef was to eat after being imported from Spanish. |
| Swap | British, EU, German | A British farmer accused the EU of failing to protect his sheep from German imports. |

Table 1: Texts generated by EnTDA. We adopt four operations to obtain augmented entity set and generate texts marked with the updated entity set.
and results in the generation of illegal texts. Ding et al. (2020) investigates data augmentation with a generation approach for text tagging tasks and identifies entities during text generation to avoid introducing additional knowledge like WordNet (Miller, 1994). However, it is limited in increasing the generalization ability for the NER models because of the difficulty to generate the texts in which entity dependency orders are not present in the training set. For example, if the NER model is only aware of the entity dependency order: EU, German and British in the training set: EU’s stance on German beef is British’s stance on beef, when there is an unseen text in the test set: A British farmer accused the EU of failing to protect his sheep from German imports, the model will fail to perceive the entities after changing order: British, EU and German.

To improve the generalization and coherence of the augmented texts for the NER models, we propose a novel entity-to-text based data augmentation approach named EnTDA. Compared with the previous attempts leveraging text-to-entity augmentation approaches, we investigate that modifying the entities in the entity list will not introduce grammatical errors and generate more combinatorial generalizable entity lists. Additionally, generated texts by the updated entity list could alleviate the reliance on the dependency order among entities. We illustrate this idea in Table 1. EnTDA decouples the dependency order among entities in two ways: 1) Modify the co-occurrence of entities in the entity list by adding, deleting, and replacing operations. 2) Modify the order of the entities in the entity list by a swapping operation. We adopt a conditional language model which has been fine-tuned on the labeled entity-to-text data to generate texts and introduce the diversity beam search strategy to increase the diversity of texts.

Furthermore, the entity-to-text procedure can be naturally viewed as an inverse text-to-entity NER task. Therefore, we can label the augmented texts according to the entities input by EnTDA, which allows our EnTDA model to generalize to all NER subtasks (flat NER, nested NER, and discontinuous NER). Overall, the main contributions of this work are as follows:

- We introduce the diversity beam search strategy for EnTDA to increase the diversity of the augmented data.
- We show that EnTDA outperforms strong data augmentation baselines across three NER subtasks (flat NER, nested NER, and discontinuous NER).

2 Related Work
2.1 NER Subtasks
Named Entity Recognition is a pivotal task in information extraction which aims at locating and classifying named entities from texts into the predefined types such as PERSON and LOCATION, etc (Chiu and Nichols, 2016; Xu et al., 2017; Yu et al., 2020). In addition to flat NER subtasks (Sang and De Meulder, 2003), Kim et al. (2003) proposed nested NER subtasks in the molecular biology domain. For example, in the text: Alpha B2 proteins bound the PEBP2 site, the entity PEBP2 could belong to the type PROTEIN and PEBP2 site belongs to DNA.

Furthermore, some entities recognized in the text could be discontinuous (Mowery et al., 2013, 2014; Karimi et al., 2015). For example, in the text: I experienced severe pain in my left shoulder and neck, the entities pain in shoulder and pain in neck contain non-adjacent mentions. Some previous works proposed the unified frameworks which are capable of handling both three NER subtasks (Li et al., 2020; Yan et al., 2021; Li et al., 2021). However, there is no unified data augmentation method designed for all three NER subtasks due to the complexity of entity overlap. In this work, we try to bridge this gap and propose the first generative augmentation approach EnTDA that can generalize to all NER subtasks (flat NER, nested NER, and discontinuous NER).

2.2 Data Augmentation for NLP and NER
2.2.1 Replacement Augmentation
Various replacement augmentations for NLP tasks such as word replacement (Zhang et al., 2015; Cai
1. EU bans German beef from British market.
2. A British farmer accused the EU of failing to protect his sheep from imports.

Dai and Adel (2020) proposes a replacement augmentation method to decide whether the selected token should be replaced by a binomial distribution, and if so, then the token will be replaced by another token with the same label. Furthermore, the similar approaches could be extended from token-level to mention-level. However, these methods still inevitably introduce incoherent replacement due to the ill-considered in-domain expansion. In this work, we try to introduce the entity-to-text based augmentation approach to improve the coherence of the augmented texts.

2.2.2 Generative Augmentation

Classic generative augmentations for NLP tasks such as back translation, which could be used to train a question answering model (Yu et al., 2018) or transfer texts from a high-resource language to a low-resource language (Xia et al., 2019). Hou et al. (2018) introduces a sequence-to-sequence model to generate diversely augmented data, which could improve the dialogue language understanding task. Anaby-Tavor et al. (2020); Kumar et al. (2020) adopt language model which is conditioned on sentence-level tags to modify original data for classification tasks exclusively. To utilize generative augmentation on more fine-grained and fragile token-level NER subtasks, Ding et al. (2020) treats the NER labeling task as a text tagging task and requires generative models to annotate entities during generation. Zhou et al. (2022) builds the pre-trained masked language models on corrupted training sentences and focuses on entity replacement. However, these methods excessively rely on the dependency order among entities. In this work, we decouple the dependencies between entities to bootstrap the generalization ability of the NER model.

3 Proposed Method

The proposed entity-to-text based data augmentation approach EnTDA consists of three modules: Entity List Augmentation, Entity-to-Text Generation, and Text-to-Entity Data Exploitation. As illustrated in Figure 1, the Entity List Augmentation takes entities as the input, and leverages four operations: add, delete, replace and swap to decouple the dependencies between entities in the original entity lists. The augmented entity lists are further utilized to guide the Entity-to-Text model to generate texts with diversity beam search. Finally, these generated texts will be selected and marked by the input entities of EnTDA. Texts marked with entities could be treated as the input to the Text-to-Entity (NER) model.

3.1 NER Task Formulation

Considering that EnTDA has sufficient augmentation ability on flat NER, nested NER and discontinuous NER, we first formulate the general NER task framework as follows. Given an input text $X = [x_1, x_2, \ldots, x_n]$ of length $n$ and the entity type set $T$, the output is an entity list $E = [e_1, e_2, \ldots, e_m, \ldots, e_l]$ of $l$ entities, where $e_m = [s_{m1}, d_{m1}, \ldots, s_{mj}, d_{mj}, t_{mj}]$. The $s, d$ are the start and end indexes of a space in the text $X$. The $j$ indicates that the entity consists of $j$ spans. The $t_m$ is an entity type in the entity type set $T$. For example, the discontinuous entity stomach...
EU bans German beef from British market. A British farmer accused the EU of failing to protect his sheep from stomach discomfort and pain. The cancer patient has constant stomach discomfort.

3.2 Entity List Augmentation

Entity List Augmentation aims to introduce a knowledge expansion and bootstrap the generalization ability of the augmented data via decoupling the dependencies among entities in two ways:

1) Modify the co-occurrence of entities in the entity list by adding, deleting, and replacing operations.

2) Modify the order of entities in the entity list by the swapping operation.

Now, we give the details of four operations on the original entity list \( E = [e_1, e_2, \ldots, e_m, \ldots, e_l] \) as follows:

i. **Add.** We first randomly select one entity \( e_m \) from the entity list \( E \). Then we search for other entities in the training set and add \( e'_m \) with the same entity type as \( e_m \) to the original entity list as \( E = [e_1, e_2, \ldots, e_{m-1}, e_m, e'_m, \ldots, e_l] \), which could be considered as a knowledge expansion.

ii. **Delete.** We randomly select one entity \( e_m \) from the original entity list \( E \) and delete it as \( E = [e_1, e_2, \ldots, e_{m-1}, e_{m+1}, \ldots, e_l] \).

iii. **Replace.** We first randomly select one entity \( e_m \) from the original entity list \( E \). Similar to i, then we search a knowledge expansion \( e'_m \) to replace \( e_m \) as \( E = [e_1, e_2, \ldots, e_{m-1}, e_m, e'_m, \ldots, e_l] \).

iv. **Swap.** Unlike modifying the co-occurrence of entities in the entity list, we randomly select two entities \( e_m, e'_m \) in the original entity list \( E \) and swap their positions as \( E = [e_1, e_2, \ldots, e'_m, \ldots, e_m, \ldots, e_l] \).

3.3 Entity-to-Text Generation

After we obtain the augmented entity lists using the Entity List Augmentation, Entity-to-Text Generation is proposed to generate the text for each entity list, which is further utilized to construct the augmented NER dataset in the later steps.

Compared to traditional generation models that rely on greedy decoding (Chickering, 2002) and choosing the highest-probability logit at every generation step, we further adopt a diversity beam search decoding strategy to increase the diversity of generated texts. More specifically, we first inject the entity types into the augmented entity list \( E = [[t_1], e_1, [t_1], \ldots, [t_m], e_m, [t_m], \ldots, [t_l], e_l, [/t_l]] \) as the input sequence, which should provide sufficient type guidance for the generation model, then we adopt T5 (Raffel et al., 2020) as the generation model. We first fine-tune T5 on the original entity-to-text data and then adopt T5 (\( \theta \)) to estimate the conditional probability distribution over all tokens in the dictionary \( \mathcal{V} \) at time step \( t \) as:

\[
\theta(y_t) = \log \Pr(y_t | y_{t-1}, \ldots, y_1, E). \tag{1}
\]

where \( y_t \) is the \( t \)th output token \( y \) in texts. We simplify the sum of log-probabilities (Eq. 1) of all previous tokens decoded \( \Theta(y_{[t]} \) as:

\[
\Theta(y_{[t]} = \sum_{\tau \in [t]} \theta(y_{\tau}), \tag{2}
\]

where \( y_{[t]} \) is the token list consisting of \( [y_1, y_2, \ldots, y_t] \). Therefore, our decoding problem is transformed into the task of finding the text that could maximize \( \Theta(y) \). The classical approximate decoding method is the beam search (Wiseman and Rush, 2016), which stores top beam width \( B \) candidate tokens at time step \( t \). Specifically, beam search selects the \( B \) most likely tokens from the set:

\[
y_t = Y_{t-1} \times \mathcal{V}, \tag{3}
\]

where \( Y_{t-1} = \{y_1, [t-1], \ldots, y_B, [t-1]\} \) and \( \mathcal{V} \) is the dictionary. However, traditional beam search keeps a small proportion of candidates in the search space and generates the texts with minor perturbations (Huang, 2008), which impedes the diversity of generated texts. Inspired by Vijayakumar et al. (2016), we introduce an objective to increase the dissimilarities between candidate texts and modify

![Beam Search Decoding](image-url)
1. EU bans German beef from British market.
2. A British farmer accused the EU of failing to protect his sheep from ... Beam Search Decoding

Three NER subtasks:
- Flat: stomach discomfort [5,6,DISORDER]
- Nested: cancer, cancer patient [1,1,DISORDER] [1,2,PERSON]
- Discontinuous: stomach pain [5,5,8,8,DISORDER]

Figure 3: Details of marking the texts with the augmented entity lists for three NER subtasks.

The traditional greedy decoding chooses the highest-probability logit at every generation step and results in British farmer. Compared to the diversity beam search decoding method, the beam search decoding method maintains a small proportion of candidates in the search space without the introduction of a penalty text of beam width \([1, 2, ..., B]\) which punishes bottom ranked tokens among candidates and thus generates tokens from diverse previous tokens. For a better understanding, we give an example about the generated text with beam search decoding and diversity beam search decoding in Figure 2.

The Eq. 2 as diversity beam search decoding:

\[
\hat{\Theta}(y_t) = \sum_{\tau \in \Theta} (\theta(y_{\tau}) - \gamma k_\tau),
\]

where \(\gamma\) is a hyperparameter and represents the punishment degree. \(k_\tau\) denotes the ranking of the current tokens among candidates. In practice, it’s a penalty text of beam width: \([1, 2, ..., B]\) which punishes bottom ranked tokens among candidates and thus generates tokens from diverse previous tokens. For a better understanding, we give an example about the generated text with beam search decoding and diversity beam search decoding in Figure 2.



4 Experiments and Analyses

We conduct extensive experiments on thirteen NER datasets across three tasks (flat NER, nested NER, and discontinuous NER) and two settings (full data NER and low resource NER) to show the effectiveness of EnTDA on NER, and give a detailed analysis to show its advantages.

4.1 Backbone Models

We adopt three representative backbone models to solve all three NER subtasks:
1) The unified MRC framework (Li et al., 2020) transforms the extracting entity with type problem into extracting answer spans about the question, which could handle the nested NER task by answering more independent questions about different entity types.
2) The unified Span framework (Li et al., 2021) traverses over all possible token spans in the text to recognize entity mentions, then handle nested and discontinuous NER tasks by performing relation classification to judge whether a given pair of entity mentions to being overlapping or succession.
3) The unified Seq2Seq framework (Yan et al.,
Table 2: Dataset statistics. “#” denotes the amount. “Nes.” and “Dis.” denote nested and discontinuous entities respectively.

| Dataset Type | Dataset      | All   | Train | Dev   | Test  | Avg. Len | All   | Nes. | Dis. | Avg. Len |
|--------------|--------------|-------|-------|-------|-------|----------|-------|------|------|----------|
| Flat NER     | CoNLL2003    | 20,744| 17,291| –     | 3,453 | 14.38    | 35,089| –    | –    | 1.45     |
|              | OntoNotes    | 76,714| 59,924| 8,528 | 8,262 | 18.11    | 104,151| –    | –    | 1.83     |
|              | Politics     | 1,392 | 200   | 541   | 651   | 50.15    | 22,854| –    | –    | 1.35     |
|              | Nature Science | 1,193 | 200   | 450   | 543   | 46.50    | 14,671| –    | –    | 1.72     |
|              | Music        | 936   | 100   | 380   | 456   | 48.40    | 15,441| –    | –    | 1.37     |
|              | Literature   | 916   | 100   | 400   | 416   | 45.86    | 11,391| –    | –    | 1.47     |
|              | AI           | 881   | 100   | 350   | 431   | 39.57    | 8,260 | –    | –    | 1.55     |
| Nested NER   | ACE2004      | 8,512 | 6,802 | 813   | 897   | 20.12    | 27,604| 12,626| –    | 2.50     |
|              | ACE2005      | 9,697 | 7,606 | 1,002 | 1,89  | 17.77    | 30,711| 12,404| –    | 2.28     |
|              | Genia        | 18,546| 15,023| 1,669 | 1,854 | 25.41    | 56,015| 10,263| –    | 1.97     |
| Discontinuous NER | CADEC | 7,597 | 5,340 | 1,097 | 1,160 | 16.18    | 6,316| 920  | 670  | 2.72     |
|              | ShAre13      | 18,767| 8,508 | 1,250 | 9,009 | 14.86    | 11,148| 663  | 1,088| 1.82     |
|              | ShAre14      | 34,614| 17,404| 1,360 | 1,850 | 15.06    | 19,070| 1,058| 1,656| 1.74     |

2021) formulates three NER subtasks as an entity span text generation task without the special design of the tagging schema to enumerate spans.

These three backbone models are leveraged to solve the general NER task framework illustrated in Section 3.1 and demonstrate the effectiveness of EnTDA.

4.2 Datasets

To demonstrate that our proposed data augmentation approach could be used in various NER subtasks and backbone models, we follow Li et al. (2020); Yan et al. (2021); Li et al. (2021) and adopt the same datasets (split) as follows:

1) Flat NER Datasets: We adopt the CoNLL-2003 (Sang and De Meulder, 2003) and OntoNotes (Pradhan et al., 2013) datasets. For OntoNotes, we evaluate in the English corpus with the same setting as Yan et al. (2021).

2) Nested NER Datasets: We adopt the ACE 2004 (Doddington et al., 2004), ACE 2005 (Christopher Walker and Maeda., 2005) and GENIA (Kim et al., 2003) datasets. Following Yan et al. (2021), we split the ACE 2004/ACE 2005 into train/dev/test sets by 80%/10%/10% and GENIA into 81%/9%/10% respectively.

3) Discontinuous NER Datasets We adopt the CADEC (Karimi et al., 2015), ShAre13 (Mowery et al., 2013) and ShAre14 (Mowery et al., 2014) datasets from biomedical domain. Following Yan et al. (2021), we split the CADEC into train/dev/test sets by 70%/15%/15% and use 10% training set as the development set for ShAre13/ShAre14.

In Table 2, we show the detailed statistics of the datasets. We further give details on entity types for datasets in the Appendix B.

4.3 Baseline Augmentation Methods

Unlike sentence-level classification tasks, NER is a fine-grained token-level task, so we adopt six token-level data augmentation baselines, which are designed for various NER subtasks.

1) Label-wise token replacement (Dai and Adel, 2020) utilizes a binomial distribution to decide whether each token should be replaced, and then replaces the chosen token with another token that has the same entity type.

2) Synonym replacement (Dai and Adel, 2020) replaces the chosen token with the synonym retrieved from WordNet.

3) Mention replacement (Dai and Adel, 2020) replaces the chosen entity with another entity, which has the same entity type.

4) Shuffle within segments (Dai and Adel, 2020) splits the sentences into segments based on whether they come from the same entity type, and uses a binomial distribution to decide whether to shuffle tokens within the same segment.

5) DAGA (Ding et al., 2020) treats the NER labeling task as a text tagging task and annotates entities with generative models during generation.

6) MELM (Zhou et al., 2022) generates augmented data with diverse entities, which is built upon pre-trained masked language models. MELM is further finetuned on corrupted training sentences with only entity tokens being randomly masked to focus on entity replacement.

Finally, we present another two models: 1)
Table 3: F1 results of various NER tasks. For all three backbone models and six baseline augmentation approaches, we rerun their open source code and adopt the given parameters. We **bold** and *underline* the best results for all augmentation approaches and baseline augmentation approaches respectively.

EnTDA (None), which does not adopt any entity list operations, only uses generative models with the diversity beam search to augment texts. 2) **EnTDA (All)**, which adopts four entity list operations simultaneously to generate augmented texts.

### 4.4 Experiment Settings

For **EnTDA**, we fine-tune the T5-base (Raffel et al., 2020) with the initial parameters on the entity-to-text data of the training set and utilize the default tokenizer with max-length as 512 to preprocess the data. We use AdamW (Loshchilov and Hutter, 2018) with $5e−5$ learning rate to optimize the cross entropy loss. The batch size is set to 5 and the number of training epoch is set to 3. During diversity beam search decoding, we set $\gamma$ as 10 and beam width $B$ as 3, which means that each entity set will generate three texts.

### 4.5 Results and Analyses

Table 3 shows the average F1 results on three runs. All backbone NER models gain F1 performance improvements from the augmented data when compared with the models that only use original training data, demonstrating the effectiveness of data augmentation approaches in the various NER subtasks. Surprisingly, **EnTDA (None)** outperforms the baseline methods by 0.26% F1 performance among the backbone models, which shows that the generative models using a diversity beam search have sufficient capacity to generate high-quality texts.
Tackling Real Low Resource NER Tasks

We adopt real low resource NER datasets (Liu...}

Table 4: F1 results of various NER tasks under low resource scenarios. The **bold** and underline the best results for all augmentation approaches and baseline augmentation approaches respectively.

| Method/Datasets | CoNLL2003 | ACE2005 | CADEC |
|-----------------|-----------|---------|-------|
| Unified MRC Framework | 82.03 | 77.70 | – |
| +Label-wise token rep. | 82.40 | 77.70 | – |
| +Synonym replacement | 82.88 | 78.06 | – |
| +Mention replacement | 83.33 | 78.32 | – |
| +Shuffle within segments | 82.51 | 78.15 | – |
| +DAGA | 83.93 | – | – |
| +EnTDA (None) | 84.71 | 79.08 | – |
| +EnTDA (Delete) | 85.85 | 79.93 | – |
| +EnTDA (Add) | 85.94 | 79.92 | – |
| +EnTDA (Replace) | 85.30 | 80.01 | – |
| +EnTDA (Swap) | 85.66 | 79.70 | – |
| +EnTDA (All) | **86.23** | **80.22** | – |

| Method/Datasets | Politics | Natural Science | Music | Literature | AI |
|-----------------|----------|-----------------|-------|------------|----|
| Seq2Seq Framework | 70.11 | 70.72 | 72.90 | 63.69 | 56.77 |
| +Label-wise token rep. | 70.45 | 70.91 | 73.48 | 63.97 | 57.04 |
| +Synonym replacement | 70.43 | 71.04 | 73.84 | 63.92 | 57.34 |
| +Mention replacement | 70.47 | 71.07 | 73.54 | 64.02 | 57.42 |
| +Shuffle within segments | 70.39 | 70.94 | 73.50 | 63.88 | 57.26 |
| +DAGA (None) | 71.06 | 71.51 | 77.46 | 64.21 | 57.83 |
| +EnTDA (None) | 71.78 | 72.66 | 74.62 | 65.87 | 59.20 |
| +EnTDA (Delete) | 72.60 | 72.05 | 75.87 | 67.18 | 61.58 |
| +EnTDA (Add) | 72.81 | 72.55 | 76.20 | 67.22 | 61.97 |
| +EnTDA (Replace) | 72.94 | 72.46 | 76.12 | 67.57 | 61.89 |
| +EnTDA (Swap) | 72.47 | 71.89 | 75.58 | 67.06 | 61.37 |
| +EnTDA (All) | **72.98** | **72.47** | **76.55** | **68.84** | **62.31** |

Table 5: F1 results of real low resource NER tasks. We **bold** and underline the best results for all augmentation approaches and baseline augmentation approaches respectively.

Handling Low Resource NER Scenarios

We further introduce an extreme yet practical scenario: only limited labeled data is available. This low resource NER scenario demonstrates that our EnTDA approach bootstraps the generalization ability of the NER model and is a quite appealing approach for data-oriented applications in the real-world. In practice, we randomly choose 10% training data from CoNLL2003/ACE2005/CADEC to represent the three NER subtasks. Note that the fine-tuning of T5-large and our four operations on the entity list are also done on 10% training data.

From Table 4, compared to training directly on the 10% training set, leveraging the augmented data achieves the performance improvement in F1. We also observe that EnTDA approach obtains the most competitive F1 performance improvement when compared with baseline data augmentation approaches. More specifically, EnTDA (All) achieve an average 2.97% F1 boost among three backbone models, which means EnTDA obtains more performance gains under the low resource scenario than in the full data scenario. Especially for the most challenging discontinuous dataset CADEC, EnTDA (All) obtains the largest F1 performance gain of 3.87%, further indicating the importance of decoupling the dependencies among entities for the complicated discontinuous NER task. Surprisingly, on 10% CoNLL2003, EnTDA (All) has only a 2.96% decrease in F1 performance compared to using the full training data in the unified Seq2Seq framework, but EnTDA (All) saves 10x the annotated data, which fully shows that adopting EnTDA is quite appealing for real-world applications.
et al., 2021) from Wikipedia which contains politics, natural science, music, literature and artificial intelligence domains with only 100 or 200 labeled texts in the training set. EnTDA and baseline data augmentation approaches still augment the training set by 3x.

From Table 5, we are delighted to observe EnTDA could quickly learn from the extremely limited entity-to-text data and bring 3.45% F1 performance gains over various domains. Compared with baseline augmentation methods, EnTDA generates more diverse data and undoubtedly gains greater advantages.

**Ablation Study and Pre-trained Model Size Analysis**

Our augmentation approach is mainly composed of two modules: Entity List Augmentation and Entity-to-Text Generation. In Table 5, we remove the entity list augmentation module (EnTDA(None)), or change the diversity beam search to the traditional beam search (EnTDA(All) w/o Diver.). We can conclude that entity list augmentation and diversity beam search modules bring an average F1 improvement of 1.78% and 0.73% on the five real low resource datasets. Using the entity list augmentation module can give a richer entity combination, which brings more improvement.

For a fair comparison, we additionally explore the effect of the size of the pre-trained language models (PLMs) employed by the augmentation approaches on the results. MELM adopts the RoBERTa-base (125M) (Liu et al., 2019) as the PLM, and correspondingly, we use T5-Small (60M), T5-Base (220M), and T5-Large (770M) as the PLMs, respectively. From Table 5, EnTDA (All) w. T5 Large has the best performance without a doubt due to its stronger PLM. Although EnTDA (All) w. T5 Small uses half the amount of PLM parameters compared to MELM (60M vs. 125M), it still achieves an average F1 improvement of 0.85% on the five datasets, which fully demonstrates the effectiveness of our proposed augmentation approach.

**Various Augmentation Multiples Performance**

We further vary the multiples of augmented data from 2x to 10x the training set to study the influence of data augmentation approaches for the NER backbone models under low resource scenarios. We choose different low resource datasets and three representative augmentation approaches (Mention replacement, MELM, and EnTDA (All)), then represent the results in Figure 4.

We could observe that the unified Seq2Seq framework has more performance gains with ever-increasing augmented data. EnTDA (All) consistently achieves better F1 performance, with a clear margin, compared to baseline augmentation approaches under various augmentation multiples. Especially for Music, EnTDA (All) brings an incredible 4.01% improvement in F1 performance with only 300 augmented data.

**Entity Addition and Replacement Strategy**

EnTDA add and replace the entity in the training set that has the same entity type. This strategy can provide the knowledge expansion during the gen-

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Table 6: Perplexity of the augmented data with various augmentation approaches. Lower perplexity is better.

| Datasets   | γ  | 1  | 5  | 10 | 25 | 50 | 100 |
|------------|----|----|----|----|----|----|-----|
| CoNLL2003  | 93.01 | 93.26 | **93.51** | 93.44 | 93.28 | 93.16 |
| ACE2005    | 85.46 | 86.41 | 86.39 | 86.30 | 88.06 | 85.77 |
| CADEC      | 70.88 | 71.34 | **71.70** | 71.64 | 71.42 | 70.99 |

Table 7: F1 results under different γ using the unified Seq2Seq framework and EnTDA (All).

| Method/Datasets | CoNLL2003 | CADEC | AI |
|-----------------|-----------|-------|----|
| Label-wise token replacement | 8.12 | 8.87 | 7.52 |
| Synonym replacement | 7.44 | 7.88 | 7.01 |
| Mention replacement | 7.07 | 7.42 | 6.54 |
| Shuffle within segments | 10.24 | 12.32 | 9.65 |
| DAGA | 5.46 | 6.23 | 5.07 |
| EnTDA (None) | 4.98 | 5.77 | 4.92 |
| EnTDA (Delete) | 4.65 | **5.05** | 4.51 |
| EnTDA (Add) | 4.79 | 5.14 | 4.34 |
| EnTDA (Replace) | 4.66 | 5.22 | 4.29 |
| EnTDA (Swap) | 4.72 | 5.38 | 4.34 |
| EnTDA (All) | 4.74 | 5.19 | **4.28** |
EnTDA (Delete)

Entity: unsupervised learning, principal component analysis

Operation: EnTDA (Delete)

Text: In the field of unsupervised learning, principal component analysis is used to model the learning process.

Table 8: The augmented texts for AI domain. We show six approaches to generate texts marked with the corresponding entity list.

Coherence and Diversity Analysis

Compared with baseline augmentation approaches, EnTDA conditionally generates texts with the diversity beam search decoding, which provides more coherent and diverse texts. We analyze the coherence through perplexity based on a large Transformer language model: GPT-2 (Radford et al., 2019) and diversity through some cases in Table 8. From Table 6, EnTDA obtains the lowest perplexity. Although DAGA and MELM are also based on generative models, the texts are not natural enough since the generation processes are not based on the entity lists.

Hyperparameter Analysis

We study the hyperparameter γ in the diversity beam search, which represents the degree of probability penalty in the decoding process and determines the diversity of sentences. Modifying γ allows us to control the diversity of the texts. We vary the γ from 1 to 100 and represent the F1 results using the unified Seq2Seq framework and EnTDA (All) in Table 7. With no more than 1% F1 fluctuating results among three datasets, EnTDA appears robust to the choice of γ.

Case Study

We show eight approaches to obtain augmented data for the AI domain in Table 8. Compared with baseline augmentation methods, EnTDA introduces a knowledge expansion and conditionally generates texts based on the diversity beam search, which provides more coherent and diverse texts. For example, The Mention Replacement approach replaces the entities unsupervised learning with heterodyning, which ignores the semantics of the context and makes an ungrammatical replacement, resulting in incoherent and unreasonable texts. For the DAGA approach, it simply stacks three entities: unsupervised learning, principal component analysis, cluster analysis in the text, which could not provide knowledge expansions to the NER models.

5 Conclusion

In this paper, we propose an entity-to-text based data augmentation approach EnTDA for NER tasks. Different from conventional data augmentation approaches which are limited to increasing the generalization and coherence of the augmented data, our approach encourages an in-domain knowledge expansion and bootstraps the generalization ability of the augmented data via decoupling the dependencies among entities. We find our augmentation paradigm provides diverse and generalizable signals to the NER models. Experiments on thirteen public datasets and two settings show the effectiveness of EnTDA over competitive baselines.
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A Limitations

We discuss the limitations of our method from two perspectives. First, our method is based on pre-trained language models, so compared to rule-based data augmentation methods (synonym replacement, shuffle within segments, etc.), our method requires higher time complexity. Second, our data augmentation method based on the pre-trained language models. Of course, the generalization ability of the pre-trained language models are limited by the pre-trained corpus. Therefore, it is a future research direction to continue to improve the generalization ability of the data augmentation approaches.

B Dataset Statistics

We give details on entity types for thirteen datasets in Table 9.

Table 9: Detailed statistics on entity types for thirteen NER datasets.

| Datasets   | Entity Types                                                                 |
|------------|-----------------------------------------------------------------------------|
| CoNLL2003  | location, organization, person, miscellaneous                               |
| OntoNotes  | person, norp, facility, organization, gpe,                                  |
|            | location, product, event, work of art, law, language date, time, percent,   |
|            | money, quantity, ordinal, cardinal                                          |
| ACE2004    | gpe, organization, person, facility, vehicle, location, wea                |
| ACE2005    | gpe, organization, person, facility, vehicle, location, wea                |
| Genia      | protein, cell_type, cell_line, RNA, DNA,                                   |
| CADEC      | aie                                                                          |
| ShARe13    | disorder                                                                     |
| ShARe14    | disorder                                                                     |
| Politics   | politician, person, organization, political party, event, election, country, |
|            | location, miscellaneous                                                     |
| Natural    | scientist, person, university, organization, country,                       |
| Science    | enzyme, protein, chemical compound, chemical element, event, astronomical  |
|            | object, academic journal, award, location, discipline, theory, miscellaneous|
| Music      | music genre, song, band, album, musical artist, musical instrument, award, |
|            | event, country, location, organization, person, miscellaneous               |
| Literature | writer, award, poem, event, magazine, person, location, book, organization, |
|            | country, miscellaneous                                                      |
| AI         | field, task, product, algorithm, researcher, metrics, university country,   |
|            | person, organization, location, miscellaneous                              |