CONTAINER: Few-Shot Named Entity Recognition via Contrastive Learning

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Abstract

Named Entity Recognition (NER) in Few-Shot setting is imperative for entity tagging in low resource domains. Existing approaches only learn *class-specific* semantic features and intermediate representations from source domains. This affects generalizability to unseen target domains, resulting in suboptimal performances. To this end, we present CONTAINER, a novel contrastive learning technique that optimizes the inter-token distribution distance for Few-Shot NER. Instead of optimizing class-specific attributes, CONTAINER optimizes a generalized objective of differentiating between token categories based on their Gaussian-distributed embeddings. This effectively alleviates overfitting issues originating from training domains. Our experiments in several traditional test domains (OntoNotes, CoNLL'03, WNUT '17, GUM) and a new large scale Few-Shot NER dataset (Few-NERD) demonstrate that on average, CONTAINER outperforms previous methods by 3%-13% absolute F1 points while showing consistent performance trends, even in challenging scenarios where previous approaches could not achieve appreciable performance.

1 Introduction

Named Entity Recognition (NER) is a fundamental NLU task that recognizes mention spans in unstructured text and categorizes them into a pre-defined set of entity classes. Recent deep-learning based approaches (Huang et al., 2015; Ma and Hovy, 2016; Lample et al., 2016; Peters et al., 2018; Devlin et al., 2018) have achieved impressive performance. As these supervised NER models require large-scale human-annotated datasets, few-shot techniques that can effectively perform NER in resource constraint settings have recently garnered a lot of attention.

Few-shot learning involves learning unseen classes from very few labeled examples (Fei-Fei et al., 2006; Lake et al., 2011; Bao et al., 2020).

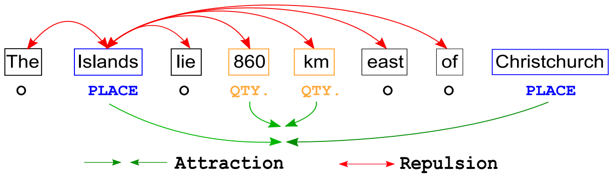

Figure 1: Contrastive learning dynamics of a token (*Islands*) with all other tokens in an example sentence from GUM (Zeldes, 2017). CONTAINER decreases the embedding distance between tokens of the same category (PLACE) while increasing the distance between different categories (QTY. and O).

Meta-learning methods such as Prototypical Networks (Snell et al., 2017) focus on *how to learn* (Vinyals et al., 2016; Bao et al., 2020) from this limited data. Fritzler et al. (2019) and Hou et al. (2020) also used Prototypical Networks for few-shot NER. Yang and Katiyar (2020), on the other hand, proposed a supervised NER model that learns class-specific features and extends the intermediate representations to unseen domains.

Few-shot NER poses some unique challenges that make it significantly more difficult than other few-shot learning tasks. First, as a sequence labeling task, NER requires label assignment according to the concordant context as well as the dependencies within the labels (Lample et al., 2016; Yang and Katiyar, 2020). Second, in NER, tokens that do not refer to any defined set of entities are labeled as `Outside` (O). Consequently, an "O" token in the training entity set may correspond to a valid target entity in test set. This challenges the notion of entity examples being clustered around a single prototype which is the key idea of Prototypical Networks. As for Nearest Neighbor based methods such as Yang and Katiyar (2020), these methods are initially "pretrained" with the objective of source class-specific supervision. As a result, the trained weights will be closely tied to the source classes and the network will project training set `O-tokens` so that they get clustered in embedding space. This will force the embeddings to drop a lot of useful features pertaining to its true target entity in the test set. Third, in few-shot setting, we do not have enough samples to select a validation set for hyperparameter tuning, which particularly affects template based methods where prompt selection is crucial for good performance (Cui et al., 2021). In fact, the absence of held-out validation set puts a lot of earlier language model based few-shot works into question whether their strategy is truly "Few-Shot" (Perez et al., 2021).

To deal with these challenges, we present a novel approach CONTAINER that uses contrastive learning to improve Few-Shot NER. As Figure 1 shows, CONTAINER decreases the distance of token embeddings of similar entities while increasing it for dissimilar ones. This explicit contrast between tokens enables CONTAINER to better capture the label dependency. Besides, since CONTAINER is trained with a generalized objective of optimizing token embedding distances, it alleviates the pitfall of `O-tokens` that the prior methods struggle with. Also, CONTAINER does not require any dataset specific prompt or hyperparameter tuning; it works well under standard settings used in prior works (Yang and Katiyar, 2020) across different domains in different evaluation settings. CONTAINER also gets some additional advantage compared to the prior methods. Unlike traditional contrastive learners (Chen et al., 2020; Khosla et al., 2020) that optimize similarity objective between point embeddings, CONTAINER optimizes distributional divergence effectively modeling Gaussian Embeddings. This helps CONTAINER extract embedding uncertainties resulting from data scarcity. Furthermore, even with an extremely small number of samples, this strategy lets us finetune the model to better capture unseen novel class distribution - a very useful attribute of our model that none of the previous SOTA models can take advantage of due to overfitting.

A nearest neighbor classification scheme during evaluation reveals that on average, CONTAINER significantly outperforms previous SOTA approaches in a wide range of tests by up to 13% absolute F1-points. In particular, we extensively test our model in both in-domain and out-of-domain experiments as proposed in Yang and Katiyar (2020) in various datasets (CoNLL '03, OntoNotes 5.0, WNUT '17, I2B2). We also test our model in a recent large dataset Few-NERD (Ding et al., 2021) where CONTAINER outperforms all other SOTA approaches setting a new benchmark result.

In summary, our contributions are as follows: (1) We propose a novel Few-Shot NER approach CONTAINER that leverages contrastive learning to infer distributional distance of their Gaussian Embeddings. (2) We effectively fine-tune the model representations to adapt to the unseen novel classes, even with a prohibitively low number of support samples. (3) We extensively test CONTAINER in a wide range of experiments using several datasets and evaluation schemes. In almost every case, our model largely outperforms present SOTAs establishing new benchmark results.

2 Task Formulation

Given a sequence of n tokens $\{x_1, x_2, \ldots x_n\}$, NER aims to assign each token x_i to its corresponding tag label y_i.

Few-shot Setting For Few-shot NER, a model is trained in a source domain with a tag-set $\{C^s_{(i)}\}$ and tested in a data-scarce target domain with a tag-set $\{C^d_{(j)}\}$ where i, j are index of different tags. Since $\{C^s_{(i)}\} \cap \{C^d_{(j)}\} = \emptyset$, it is very challenging for models to generalize to unseen test tags. In an *N-way K-shot* setting, there are N tags in the target domain $|\{C^d_{(j)}\}| = N$, and each tag is associated with a support set with K examples.

Tagging Scheme For fair comparison of CONTAINER against previous SOTA models, we follow an IO tagging scheme where `I-type` represents that all of the tokens are inside an entity, and `O-type` denotes all the other tokens (Yang and Katiyar, 2020; Ding et al., 2021).

Evaluation Scheme To compare with SOTA models in Few-NERD (Ding et al., 2021), we adopt *episode evaluation*: a model is assessed by calculating the micro-F1 score over multiple test episodes, each consisting of a *K-shot* support set and a *K-shot* unlabeled query (test) set to make predictions.

While Few-NERD is explicitly designed for episode evaluation, traditional NER datasets (e.g., OntoNotes, CoNLL'03, WNUT '17, GUM) have their distinctive tag-set distributions. Thus, sampling test episodes from the actual test data perturbs the true distribution that may not represent the actual performance. Consequently, Yang and Katiyar (2020) proposed to sample multiple support sets from the original development set for prediction in

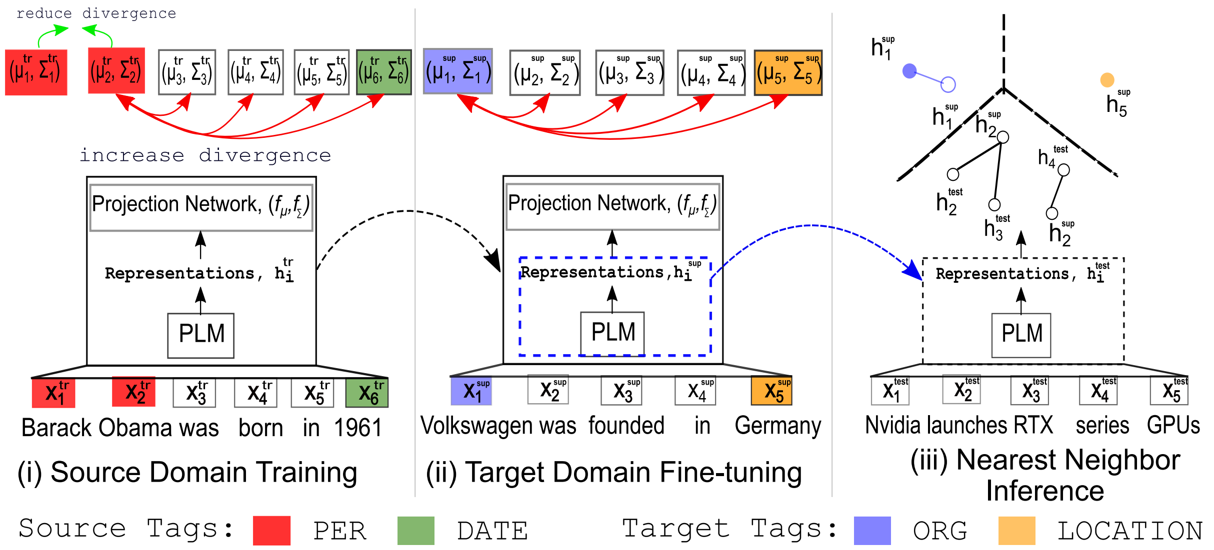

Figure 2: Illustration of our proposed CONTAINER framework based on Contrastive Learning over Gaussian Embedddings: (i) Training in source domains using training NER labels PER and DATE, (ii) Fine-tuning to target domains using target NER labels ORG and LOCATION, (iii) Assigning labels to test samples via Nearest Neighbor support set labels.

the original test set. Performance over multiple support sets are averaged to report final performance. We also use this evaluation strategy for these traditional NER datasets.

3 Method

CONTAINER utilizes contrastive learning to optimize distributional divergence between different token entity representations. Instead of focusing on label specific attributes, this contradistinction explicitly trains the model to distinguish between different categories of tokens which results in better generalization. Furthermore, modeling embedding distribution instead of traditional point representation effectively lets CONTAINER capture the embedding uncertainties originating from sample scarcity in target domain. Finally, this contrastive learning technique lets us carefully finetune our model even with an extremely small number of samples without overfitting which is imperative for domain adaptation.

As demonstrated in Figure 2, we first **train** our model in source domains. Next, we **finetune** model representations using few-sample support sets to adapt it to target domains. The training and finetuning of CONTAINER is illustrated in Algorithm 1. Finally, we use an **instance level nearest neighbor classifier** for inference in test sets.

3.1 Model

Figure 2 shows the key components of our model. To generate contextualized representation of sentence tokens, CONTAINER incorporates a pretrained language model encoder PLM. For proper comparison against existing approaches, we use BERT (Devlin et al., 2018) as our PLM encoder. Thus given a sequence of n tokens $[x_1, x_2, \ldots, x_n]$, we take the final hidden layer output of the PLM as the intermediate representations $\boldsymbol{h}_i \in \mathbb{R}^{l'}$.

$$[\boldsymbol{h}_1, \boldsymbol{h}_2, \ldots, \boldsymbol{h}_n] = \mathtt{PLM}([x_1, x_2, \ldots, x_n]) \quad (1)$$

These intermediate representations are then channeled through simple projection layer for generating the embedding. Unlike SimCLR (Chen et al., 2020) that uses projected point embedding for contrastive learning, we assume that token embeddings follow Gaussian distributions. Specifically, we employ projection network f_μ and f_Σ for producing Gaussian distribution parameters:

$$\boldsymbol{\mu}_i = f_\mu(\boldsymbol{h}_i), \;\; \boldsymbol{\Sigma}_i = \mathrm{ELU}\left(f_\Sigma(\boldsymbol{h}_i)\right) + (1+\epsilon) \quad (2)$$

where $\boldsymbol{\mu}_i \in \mathbb{R}^l, \boldsymbol{\Sigma}_i \in \mathbb{R}^{l \times l}$ represents mean and diagonal covariance of the Gaussian Embedding respectively; f_μ and f_Σ are implemented as ReLU followed by single layer networks; ELU for exponential linear unit; and $\epsilon \approx e^{-14}$ for numerical stability.

3.2 Training in Source Domain

For calculating the contrastive loss, we consider the KL-divergence between all valid token pairs in the sampled batch. Two tokens x_p and x_q are considered as positive examples if they have the same label $y_p = y_q$. Given their Gaussian Embeddings $\mathcal{N}(\boldsymbol{\mu}_p, \boldsymbol{\Sigma}_p)$ and $\mathcal{N}(\boldsymbol{\mu}_q, \boldsymbol{\Sigma}_q)$, we can calculate their KL-divergence as following:

$$\begin{aligned} D_{\text{KL}}[\mathcal{N}_q||\mathcal{N}_p] &= D_{\text{KL}}[\mathcal{N}(\boldsymbol{\mu}_q, \boldsymbol{\Sigma}_q)||\mathcal{N}(\boldsymbol{\mu}_p, \boldsymbol{\Sigma}_p)] \\ &= \frac{1}{2}\Bigg(\text{Tr}(\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\Sigma}_q) - l + \log\frac{|\boldsymbol{\Sigma}_p|}{|\boldsymbol{\Sigma}_q|} \\ &\quad + (\boldsymbol{\mu}_p - \boldsymbol{\mu}_q)^T\boldsymbol{\Sigma}_p^{-1}(\boldsymbol{\mu}_p - \boldsymbol{\mu}_q)\Bigg) \end{aligned} \tag{3}$$

Both directions of the KL-divergence are calculated since it is not symmetric.

$$d(p,q) = \frac{1}{2}\left(D_{\text{KL}}[\mathcal{N}_q||\mathcal{N}_p] + D_{\text{KL}}[\mathcal{N}_p||\mathcal{N}_q]\right) \tag{4}$$

We first train our model in resource rich source domain having training data $\mathcal{X}_{\text{tr}}$. At each training step, we randomly sample a batch of sequences (without replacement) $\mathcal{X} \in \mathcal{X}_{\text{tr}}$ from the training set having batch size of b. For each $(x_i, y_i) \in \mathcal{X}$, we obtain its Gaussian Embedding $\mathcal{N}(\mu_i, \Sigma_i)$ by channeling the corresponding token sequence through the model (Algorithm 1: Line 3-6).

We find in-batch positive samples $\mathcal{X}_p$ for sample p and subsequently calculate the Gaussian embedding loss of x_p with respect to that of all other valid tokens in the batch:

$$\mathcal{X}_p = \{(x_q, y_q) \in \mathcal{X} \mid y_p = y_q, p \neq q\} \tag{5}$$

$$\ell(p) = -\log \frac{\sum\limits_{(x_q,y_q)\in\mathcal{X}_p} \exp(-d(p,q))/|\mathcal{X}_p|}{\sum\limits_{(x_q,y_q)\in\mathcal{X}, p\neq q} \exp(-d(p,q))} \tag{6}$$

In this way we can calculate the distributional divergence of all the token pairs in the batch (Algorithm 1: Line 7-10). We do not scale the contrastive loss by any normalization factor as proposed by Chen et al. (2020) since we did not find it to be beneficial for optimization.

3.3 Finetuning to Target Domain using Support Set

After training in source domains, we finetune our model using a small number of support samples for unseen classes in the target domains. We follow a similar procedure as in training stage. When multiple few-shot samples (e.g., 5-shot) are available for the target classes, the model can effectively adapt to the new domain by optimizing KL-divergence of Gaussian Embeddings as in Eq. 4.

Algorithm 1 Training and Finetuning of CONTAINER

Require: Training data $\mathcal{X}_{tr}$, Support Data $\mathcal{X}_{sup}$, Train loss function d_{tr}, Finetune loss function d_{ft} , f_μ, f_Σ, `PLM`

1: *// training in source domain*
2: **for** sampled (w/o replacement) minibatch $\mathcal{X} \in \mathcal{X}_{tr}$ **do**
3:   **for all** $i \equiv (x_i, y_i) \in \mathcal{X}$ **do**
4:     $\boldsymbol{\mu}_i = f_\mu(\texttt{PLM}(x_i))$ *//[Eq. 1]*
5:     $\boldsymbol{\Sigma}_i = ELU(f_\Sigma(\texttt{PLM}(x_i))) + (1+\epsilon)$ *//[Eq. 2]*
6:   **end for**
7:   **for** all $i \equiv (x_i, y_i) \in \mathcal{X}$ **do**
8:     Calculate $\ell(i)$ as in Eq. 5 and 6
9:   **end for**
10:   $\mathcal{L}_{tr} = \frac{1}{|\mathcal{X}|}\sum\limits_{i\in\mathcal{X}} \ell(i)$
11:   update f_μ, f_Σ, `PLM` by backpropagation to reduce $\mathcal{L}_{tr}$
12: **end for**
13: *// finetuning to target domain*
14: $\mathcal{L}_{prev} = \infty$
15: $\mathcal{L}_{ft} = \mathcal{L}_{prev} - 1$ *//Stable Initialization*
16: **while** $\mathcal{L}_{ft} < \mathcal{L}_{prev}$ **do**
17:   $\mathcal{L}_{prev} = \mathcal{L}_{ft}$
18:   **for all** $i \equiv (x_i, y_i) \in \mathcal{X}_{sup}$ **do**
19:     Calculate $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ using Eq. 1, 2 *//Line 4,5*
20:   **end for**
21:   **for** all $i \equiv (x_i, y_i) \in \mathcal{X}_{sup}$ **do**
22:     Calculate $\ell(i)$ as in Eq. 5 and 6
23:   **end for**
24:   $\mathcal{L}_{ft} = \frac{1}{|\mathcal{X}_{sup}|}\sum\limits_{i\in\mathcal{X}_{sup}} \ell(i)$
25:   update f_μ, f_Σ, `PLM` by backpropagation to reduce $\mathcal{L}_{ft}$
26: **end while**
27: **return** `PLM` and discard f_μ, f_Σ

By contrast, for the 1-shot case, it turns out challenging for models to adapt to the target class distribution. If the model has no prior knowledge about target classes (either from direct training or indirectly from source domain training where the target class entities are marked as `O-type`), a single example might not be sufficient to deduce the variance of the target class distribution. Thus, for 1-shot scenario, we optimize $d'(p,q) = ||\boldsymbol{\mu}_p - \boldsymbol{\mu}_q||_2^2$, the squared Euclidean distance between mean of the embedding distributions, essentially treating them as point embeddings. When the model has direct or indirect prior knowledge about the target classes involved, we still optimize the KL-divergence of the distributions similar to the 5-shot scenario. In Appendix Table 8, we demonstrate that optimizing with squared Euclidean distance gives us slightly better performance in 1-shot scenario. Nevertheless, in all cases with 5-shot support set, optimizing the KL-divergence between the Gaussian Embeddings gives us the best result.

Early Stopping Finetuning a model with a small support set runs the risk of overfitting. Thus an effective early stopping scheme needs to be maintained in the finetuning stage. Unfortunately, without access to a held-out validation set due to data scarcity in the target domain, we cannot keep tabs on the saturation point where we need to stop finetuning. To alleviate this, we rely on the calculated contrastive loss as our early stopping criteria. We continue finetuning our model until the loss starts to increase. (Algorithm 1: Line 16-17, 24).

3.4 Instance Level Nearest Neighbor Inference

After training and finetuning CONTAINER, we extract the pretrained language model encoder PLM for inference. Similar to SimCLR (Chen et al., 2020), we found that representations before the projection layers actually contain more information than the final output representation which contributes to better performance, so f_μ and f_Σ projection heads are not used for inference. We thus calculate the representations of the test data from PLM and find nearest neighbor support set representation for inference (Wang et al., 2019; Yang and Katiyar, 2020).

The PLM representations $\boldsymbol{h}_j^{\text{sup}}$ of each of the support token $(x_j^{\text{sup}}, y_j^{\text{sup}}) \in \mathcal{X}_{\text{sup}}$ can be calculated as in Eq. 1. Similarly for test data $\mathcal{X}_{\text{test}}$, we get the PLM representations $\boldsymbol{h}_i^{\text{test}}$ where $x_i^{\text{test}} \in \mathcal{X}_{\text{test}}$. Here we assign x_i^{test} the same label as the support token that is nearest in the PLM representation space:

$$y_i^{\text{test}} = \underset{y_k^{\text{sup}} \text{ where } (x_k^{\text{sup}}, y_k^{\text{sup}}) \in \mathcal{X}_{\text{sup}}}{\arg\min} ||\boldsymbol{h}_i^{\text{test}} - \boldsymbol{h}_k^{\text{sup}}||_2^2 \quad (7)$$

Viterbi Decoding Most previous works (Hou et al., 2020; Yang and Katiyar, 2020; Ding et al., 2021) noticed a performance improvement by using CRFs (Lafferty et al., 2001). Thus we also employ Viterbi decoding in the inference stage with an abstract transition distribution as in StructShot (Yang and Katiyar, 2020). For the **transition probabilities**, the transition between three abstract tags O, I, and I-other is estimated by counting their occurrences in the training set. Then for the target domain tag-set, these transition probabilities are evenly distributed into corresponding target distributions. The **emission probabilities** are calculated from Nearest Neighbor Inference stage.

Comparing domain transfer results (Table 2) against other tasks (Table 1, 4, 5) we find that, interestingly, if there is no significant domain shift involved in the test data, contrastive learning allows CONTAINER to automatically extract label dependencies, obviating the requirement of extra Viterbi decoding stage.

4 Experiment Setups

Dataset	Domain	# Classes	# Sentences
OntoNotes	General	18	76K
I2B2'14	Medical	23	140K
CoNLL'03	News	4	20K
WNUT'17	Social	6	5K
GUM	Mixed	11	3.5K
FEW-NERD	Wikipedia	66	188K

Table 3: Summary Statistics of Datasets

Datasets For evaluating the Few-Shot NER capabilities, we use datasets across different domains: General (OntoNotes 5.0 (Weischedel et al., 2013)), Medical (I2B2 (Stubbs and Uzuner, 2015)), News (CoNLL'03 (Sang and De Meulder, 2003)), Social (WNUT'17 (Derczynski et al., 2017)). We also test on GUM (Zeldes, 2017) that represents a wide variety of texts: interviews, news articles, instrumental texts, and travel guides. The miscellany of domains makes it an extremely challenging dataset to work on. Ding et al. (2021) argue that the distribution of these datasets may not be suitable for proper representation of Few-Shot capability. Thus, they proposed a new large-scale dataset Few-NERD that contains 66 fine-grained entities across 8 coarse-grained entities, significantly richer than previous datasets (4-18 entities). A summary of these datasets is given in Table 3.

Baselines We compare the performance of CONTAINER with state-of-the-art Few-Shot NER models on different datasets across several settings. We first measure the model performance in traditional NER datasets in tag-set extension and domain transfer tasks as proposed in Yang and Katiyar (2020). We then evaluate our model in Few-NERD (Ding et al., 2021) dataset that is explicitly designed for Few-Shot NER and compare it against the Few-NERD leaderboard baselines. Similar to Ding et al. (2021), we take Prototypical Network based ProtoBERT (Snell et al., 2017; Fritzler et al., 2019; Hou et al., 2020), nearest neighbor based NNShot, and additional Viterbi decoding based Structshot (Yang and Katiyar, 2020) as the main SOTA baselines.

4.1 Tag-set Extension Setting

A common use-case of Few-Shot NER is that new entity types may appear in the existing text-domain. Thus (Yang and Katiyar, 2020) proposed to evaluate tag-set extension capability in OntoNotes

Model	1-shot				5-shot			
	Group A	Group B	Group C	Avg.	Group A	Group B	Group C	Avg.
Proto	19.3 ± 3.9	22.7 ± 8.9	18.9 ± 7.9	20.3	30.5 ± 3.5	38.7 ± 5.6	41.1 ± 3.3	36.7
NNShot	28.5 ± 9.2	27.3 ± 12.3	21.4 ± 9.7	25.7	44.0 ± 2.1	51.6 ± 5.9	47.6 ± 2.8	47.7
StructShot	30.5 ± 12.3	28.8 ± 11.2	20.8 ± 9.9	26.7	47.5 ± 4.0	53.0 ± 7.9	48.7 ± 2.7	49.8
CONTaiNER	**32.2 ± 5.3**	**30.9 ± 11.6**	**32.9 ± 12.7**	**32.0**	**51.2 ± 5.9**	**55.9 ± 6.2**	**61.5 ± 2.7**	**56.2**
+ Viterbi	**32.4 ± 5.1**	**30.9 ± 11.6**	**33.0 ± 12.8**	**32.1**	**51.2 ± 6.0**	**56.0 ± 6.2**	**61.5 ± 2.7**	**56.2**

Table 1: F1 scores in Tag Set Extension on OntoNotes. Group A, B, C are three disjoint sets of entity types. Results vary slightly from Yang and Katiyar (2020) as they used different support set (publicly unavailable) than ours.

Model	1-shot					5-shot				
	I2B2	CoNLL	WNUT	GUM	Avg.	I2B2	CoNLL	WNUT	GUM	Avg.
Proto	13.4 ± 3.0	49.9 ± 8.6	17.4 ± 4.9	17.8 ± 3.5	24.6	17.9 ± 1.8	61.3 ± 9.1	22.8 ± 4.5	19.5 ± 3.4	30.4
NNShot	15.3 ± 1.6	61.2 ± 10.4	22.7 ± 7.4	10.5 ± 2.9	27.4	22.0 ± 1.5	74.1 ± 2.3	27.3 ± 5.4	15.9 ± 1.8	34.8
StructShot	21.4 ± 3.8	**62.4 ± 10.5**	24.2 ± 8.0	7.8 ± 2.1	29.0	30.3 ± 2.1	74.8 ± 2.4	30.4 ± 6.5	13.3 ± 1.3	37.2
CONTaiNER	16.4 ± 1.7	57.8 ± 10.7	24.2 ± 2.9	17.9 ± 1.8	29.1	24.1 ± 1.9	72.8 ± 2.0	27.7 ± 2.2	24.4 ± 2.2	37.3
+ Viterbi	**21.5 ± 1.7**	61.2 ± 10.7	**27.5 ± 1.9**	**18.5 ± 4.9**	**32.2**	**36.7 ± 2.1**	**75.8 ± 2.7**	**32.5 ± 3.8**	**25.2 ± 2.7**	**42.6**

Table 2: F1 scores in Domain Extension with OntoNotes as the source domain. Results vary slightly compared to Yang and Katiyar (2020) since they used different support set samples.

(Weischedel et al., 2013). The 18 existing entity classes are split into 3 groups: A, B, and C, each having six classes. Models are tested in each few sample support group being trained in the remaining two groups. During training, test group entities are replaced with O-tag. Since source and destination domains are the same, the training phase will induce some indirect information about unseen target entities. Consequently, during finetuning of CONTaiNER, we optimize the KL-divergence between output embeddings as in Eq. 4.

We use the same entity class splits as used by Yang and Katiyar (2020) and used `bert-base-cased` as the backbone encoder for all models. Since they could not share the sampled support set for licensing reasons, for a proper comparison, we sampled five sets of support samples for each group and averaged the results, as done by the authors. We show these results in Table 1.

4.2 Domain Transfer Setting

In this experiment, a model trained on a source domain is deployed to a previously unseen novel text-domain. Here we take OntoNotes (General) as our source text domain, and evaluate the Few-Shot performance in I2B2 (Medical), CoNLL (News), WNUT (Social) domains as in (Yang and Katiyar, 2020). Additionally, we also evaluate the performance in GUM (Zeldes, 2017) dataset due to its challenging nature. We show these results in Table 2. While all the other domains have almost no intersection with OntoNotes, the target entities in CoNLL are fully contained within OntoNotes entities, making it comparable to supervised learning.

4.3 Few-NERD Setting

Model	5-way		10-way		Avg.
	1∼2 shot	5∼10 shot	1∼2 shot	5∼10 shot	
StructShot	35.92	38.83	25.38	26.39	31.63
ProtoBERT	23.45	41.93	19.76	34.61	29.94
NNShot	31.01	35.74	21.88	27.67	29.08
CONTaiNER	**40.43**	**53.70**	**33.84**	**47.49**	**43.87**
+ Viterbi	**40.40**	**53.71**	**33.82**	**47.51**	**43.86**

Table 4: F1 scores in FEW-NERD (INTRA).

Model	5-way		10-way		Avg.
	1∼2 shot	5∼10 shot	1∼2 shot	5∼10 shot	
StructShot	**57.33**	57.16	**49.46**	49.39	53.34
ProtoBERT	44.44	58.80	39.09	53.97	49.08
NNShot	54.29	50.56	46.98	50.00	50.46
CONTaiNER	55.95	**61.83**	48.35	**57.12**	**55.81**
+ Viterbi	56.1	**61.90**	48.36	**57.13**	**55.87**

Table 5: F1 scores in FEW-NERD (INTER).

For few-shot setting, Ding et al. (2021) proposed two different settings: **Few-NERD (INTRA)** and **Few-NERD (INTER)**. In Few-NERD (INTRA) train, dev, and test sets are divided according to coarse-grained types. As a result, fine-grained entity types belonging to `People, Art, Product, MISC` coarse-grained types are put in the train set, `Event, Building` in dev set, and `ORG, LOC` in test set. So, there is no overlap between train, dev, test set classes in terms of coarse-grained types. On the other hand, in Few-NERD (INTER) coarse-grained types are shared, although all the fine-grained types are mutually disjoint. Because of the restrictions of sharing coarse-grained types, Few-NERD (INTRA) is more challenging. Since few-shot performance of any model relies on the sampled support set, the authors also released train, dev, test split for both **Few-NERD (INTRA)** and **Few-NERD (INTER)**. We evaluate our model performance using these provided dataset splits and compare the performance in the Few-NERD leaderboard. All models use `bert-base-uncased` as the backbone encoder. As shown in Table 4 and Table 5, CONTAINER establishes new benchmark results in the leaderboard in both of these tests.

5 Results and Analysis

We prudently analyze different components of our model and justify the design choices in CONTAINER. We also examine the results discussed in the previous section that gives some intuitions about few-shot NER in general.

5.1 Overall Results

Table 1-5 demonstrates that overall, in every scenario CONTAINER convincingly outperforms all other baseline approaches. This improvement is particularly noticeable in challenging scenarios, where all other baseline approaches perform poorly. For example, FEW-NERD (intra) (Table 4) is a challenging scenario where the coarse grained entity types corresponding to train and test sets do not overlap. Here, other baseline approaches face a substantial performance hit, whereas CONTAINER still performs well. In tag-set extension (Table 1), we see a similar performance trend - CONTAINER performs consistently well across the board. Likewise, in domain transfer to a very challenging unseen text domain like GUM (Zeldes, 2017), baseline models performs miserably; yet CONTAINER manages to perform consistently outperforming SOTA models by a significant margin.

Analyzing the results more closely, we notice that the improvement margin of CONTAINER is more prominent in 5-shot cases. Evidently, CONTAINER is able to make better use of multiple few-shot samples thanks to distribution modeling via contrastive Gaussian Embedding optimization. In this context, note that StructShot actually got marginally higher F1-score in 1-shot CoNLL domain adaptation and 1$\sim$2 shot FEW-NERD (INTER) cases. In CoNLL, the target classes are subsets of training classes, so supervised learning

	Point Embedding	Gaussian Embedding
1-shot	6.37	32.17
5-shot	25.47	51.20

Table 6: F1 scores comparison in OntoNotes Group A. Gaussian Embedding surpasses point embedding based optimization in all cases.

	W/O Finetuning	W/ Finetuning
1-shot	31.76	32.90
5-shot	56.99	61.48

Table 7: Comparison of F1-Scores with and without support set finetuning of CONTAINER

based feature extractors are expected to get an advantage in prediction. On the other hand, Ding et al. (2021) carefully tuned the hyperparameters for baselines like StructShot for best performance. We could also improve performance in a similar manner, however for uniformity of model across different few-shot settings, we use the same model architecture in every test. Nevertheless, CONTAINER shows comparable performance even in these cases while significantly outperforming in every other test.

5.2 Training Objective

Traditional contrastive learners usually optimize cosine similarity of point embeddings (Chen et al., 2020). While this has proven to work well in image data, in more challenging NLU tasks like Few Shot NER, we find it to give subpar performance. We see an example scenario in Table 6, where we show the performance comparison of tag-set extension in Group A of OntoNotes. Basically, modeling class distribution via Gaussian Distribution allows us to capture the uncertainties in Few-Shot embedding, which is useful in this data scarce environment. This is one of the novel features of CONTAINER that sets it apart from competition.

5.3 Effect of Model Fine-tuning

Being a contrastive learner, CONTAINER can take advantage of extremely small support set to refine its representations through fine-tuning. To closely examine the effects of fine-tuning, we conduct a case study with OntoNotes tag-extension task using `PERSON, DATE, MONEY, LOC, FAC, PRODUCT` target entities.

From Table 7, we see that finetuning indeed improves few-shot performance. Besides, the effect of finetuning is even more marked in 5-shot case indicating that CONTAINER finetuning can make the best use of few-samples available in target domain.

5.4 Modeling Label Dependencies

Analyzing the results, we observe that domain transfer (Table 2) sees some good gains in performance from using Viterbi decoding. In contrast, tag-set extension (Table 1) and FEW-NERD (Table 4,5) gets almost no improvement from Viterbi decoding. This indicates an interesting property of CONTAINER. During domain transfer the text domains have no overlap in train and test set. So, an extra Viterbi decoding actually provides additional information regarding the label dependencies. On the other hand, the train and target text domain have substantial overlap in both tagset extension and FEW-NERD. Thus CONTAINER can indirectly learn the label dependencies through in-batch contrastive learning. Consequently, unless there is a marked shift in the target text domain, we can achieve the best performance even without employing additional Viterbi decoding.

6 Related Works

Meta Learning The idea of Few-shot learning was popularized in computer vision through Matching Networks (Vinyals et al., 2016). Subsequently, Prototypical Network (Snell et al., 2017) was proposed where class prototypical representations were learned. Test samples are labelled according to the nearest prototype. Later this technique was proven successful in other domains as well. Wang et al. (2019), on the other hand found simple feature transformations to be quite effective in few shot image recognition These metric learning based approaches have also been deployed in different NLP tasks (Geng et al., 2019; Bao et al., 2020; Han et al., 2018; Fritzler et al., 2019).

Contrastive Learning Early progress was made by contrasting positive against negative samples (Hadsell et al., 2006; Dosovitskiy et al., 2014; Wu et al., 2018). Chen et al. (2020) proposed SimCLR by refining the idea of contrastive learning by utilizing modern image augmentation to learn robust sets of features. Khosla et al. (2020) leveraged this to boost supervised learning performance as well. In-batch negative sampling has also been explored for learning representation (Doersch and Zisserman, 2017; Ye et al., 2019). Storing instance class representation vectors is another popular direction (Wu et al., 2018; Zhuang et al., 2019).

Few-Shot NER Established few-shot learning approaches have also been applied in NER. Fritzler et al. (2019) leveraged prototypical network (Snell et al., 2017) for few shot NER. Inspired by the potency of simple feature extractors and nearest neighbor inference (Wang et al., 2019; Wiseman and Stratos, 2019) in few-Shot learning, Yang and Katiyar (2020) used supervised learner based feature extractors. Pairing it with abstract transition tag Viterbi decoding, they achieved current SOTA result in Few-Shot NER tasks. The role of data augmentation in low-resource NER has also been explored (Ding et al., 2020). Huang et al. (2020) proposed noisy supervised pre-training for Few-Shot NER. However, this method requires access to a large scale noisy NER dataset such as WiNER (Ghaddar and Langlais, 2017) for the supervised pretraining. Acknowledging the shortcomings and evaluation scheme disparity in Few-Shot NER, Ding et al. (2021) proposed a large scale dataset specifically designed for this task. Wang et al. (2021b) explored model distillation for Few-Shot NER which requires access to a large unlabelled dataset for good performance. Recently, prompt based techniques have also surfaced in this domain (Cui et al., 2021; Ma et al., 2021; Chen et al., 2021; Wang et al., 2021a). However, the performance of these methods rely heavily on the chosen prompt. As denoted by Cui et al. (2021), the performance delta can be massive (upto 19% absolute F1 points) depending on the prompt. Thus, in the absence of a large validation set, their applicability becomes limited in true few-shot learning (Perez et al., 2021).

7 Conclusion

In this work, we propose a contrastive learning based framework CONTAINER that models Gaussian embedding and optimizes inter token distribution distance. This generalized objective helps us model a class agnostic feature extractor that avoids the pitfalls of prior Few-Shot NER methods. Additionally, CONTAINER can take advantage of few-sample support data to adapt the model representations to new tag domains. Extensive evaluations in multiple few-shot NER datasets reveal that, CONTAINER performs consistently even in challenging scenarios outperforming prior SOTAs. While we investigate the efficacy of distribution optimization based contrastive learning in Few-Shot NER, it will be of particular interest to investigate its potency in other domains as well.

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A Implementation Details

For all of our experiments. we chose the same hyperparameters as in Yang and Katiyar (2020). Across all our tests, we kept Gaussian Embedding dimension fixed to $l = 128$. In order to guarantee proper comparison against prior competitive approaches, we use the same backbone encoder for all methods in same tests, i.e. `bert-base-cased` was used for all methods in Tag-Set Extension and Domain Transfer tasks while `bert-base-uncased` was used for Few-NERD following the respective evaluation strategies. Finally, to observe the effect of Viterbi decoding on CONTAINER output, we set the re-normalizing temperature τ to 0.1. We will also release the full source code of CONTAINER upon publication. All the model trainings were conducted using an RTX A6000 GPU.

B Fine-tuning Objective

During finetuning, if a model does not have any prior knowledge about the target classes, directly or indirectly, a 1-shot example may not give sufficient information about the target class distribution (i.e. the variance of the distribution). Consequently during finetuning, for 1-shot adaptation to new classes, optimizing euclidean distance of the mean embedding gives better performance. Nevertheless, for 5-shot cases, KL-divergence of the Gaussian Embedding always gives better performance indicating that it takes better advantage of multiple samples. We show this behavior in the best result of domain transfer task with WNUT in Table 8. Since this domain transfer task gives no prior information about target embeddings during training, optimizing KL-divergence in 1-shot fineutuning actually hurts performance a bit compared to euclidean fine-tuning. However, in 5-shot, KL-finetuning again gives superior performance as it can now adapt better to the novel target class distributions.

C NER Prediction Examples

Table 9 demonstrates some predictions with CONTAINER and StructShot using `PERSON, DATE, MONEY, LOC, FAC, PRODUCT` as target few-shot entities while being trained on all other entity types in OntoNotes dataset.

	KL-Gaussian	Euclidean-mean
1-shot	18.78	27.48
5-shot	32.50	31.12

Table 8: F1 scores comparison in Domain Transfer Task with WNUT with different finetune objectives. While optimizing the KL-divergence of the Gaussian Embedding gives superior result in 5-shot, optimizing Euclidean distance of the mean embeddings actually achieve better result in 1-shot.

Gold	CONTAINER	StructShot
BMEC general director Dr. Johnsee Lee$_{PER}$ says that the ITRI 's four-year$_{DATE}$ R&D program in biochip applications and technology is now in its second year$_{DATE}$.	BMEC general director Dr. Johnsee Lee$_{PER}$ says that the ITRI 's four-year$_{DATE}$ R&D program in biochip applications and technology is now in its second year$_{DATE}$.	BMEC general director Dr. Johnsee Lee$_{PER}$ says that the ITRI 's four-year$_{DATE}$ R&D program in biochip applications and technology is now in its second year.
DR. Chip Bio-technology was set up in September 1998$_{DATE}$.	DR. Chip Bio-technology was set up in September 1998$_{DATE}$.	DR. Chip Bio-technology$_{PRODUCT}$ was set up in September 1998.
Wang Shin - hwan$_{PER}$ notes that traditional bacterial and viral cultures take seven to ten days to prepare , and even with the newer molecular biology testing techniques it takes three days$_{DATE}$ to get a result .	Wang Shin$_{PER}$ - hwan notes that traditional bacterial and viral cultures take seven to ten days$_{DATE}$ to prepare , and even with the newer molecular biology testing techniques it takes three days$_{DATE}$ to get a result .	Wang Shin - hwan notes that traditional bacterial and viral cultures take seven to ten days$_{DATE}$ to prepare , and even with the newer molecular biology testing techniques it takes three days$_{DATE}$ to get a result .
Research program director Pan Chao - chi$_{PER}$ states that at present they are actively developing a " fever chip " with a wide range of applications .	Research program director Pan$_{PER}$ Chao - chi states that at present$_{DATE}$ they are actively developing a " fever chip " with a wide range of applications .	Research program director Pan$_{PER}$ Chao - chi states that at present they are actively developing a " fever chip " with a wide range of applications .
Pan explains that in clinical practice , the causes of fever are difficult to quickly diagnose .	Pan$_{PER}$ explains that in clinical practice , the causes of fever are difficult to quickly diagnose .	Pan explains that in clinical practice , the causes of fever are difficult to quickly diagnose .
Jerry Huang$_{PER}$, executive vice president of U - Vision Biotech , reveals that U - Vision , which was set up in September 1999$_{DATE}$, has signed a contract with the US company Zen - Bio to jointly develop human adipocyte cDNA microarray chips .	Jerry Huang$_{PER}$, executive vice president of U - Vision Biotech , reveals that U - Vision , which was set up in September 1999$_{DATE}$, has signed a contract with the US company Zen - Bio to jointly develop human adipocyte cDNA microarray chips .	Jerry Huang , executive vice president of U - Vision Biotech , reveals that U - Vision , which was set up in September 1999 , has signed a contract with the US company Zen - Bio to jointly develop human adipocyte cDNA microarray chips.
Huang$_{PER}$ states that research in recent years$_{DATE}$ has revealed that adipocytes -LR fat cells -RR are active regulators of the energy balance in the body , and play an important role in disorders such as obesity , diabetes , osteoporosis and cardiovascular disease .	Huang$_{PER}$ states that research in recent years$_{DATE}$ has revealed that adipocytes -LR fat cells -RR are active regulators of the energy balance in the body , and play an important role in disorders such as obesity , diabetes , osteoporosis and cardiovascular disease .	Huang states that research in recent years has revealed that adipocytes -LR fat cells -RR are active regulators of the energy balance in the body , and play an important role in disorders such as obesity , diabetes , osteoporosis and cardiovascular disease .
Maybe a 30 year old$_{DATE}$ man & a 15 year old$_{DATE}$ boy doesn't qualify .	Maybe a 30 year old man & a 15 year old boy doesn't qualify .	Maybe a 30 year old$_{DATE}$ man & a 15 year old$_{DATE}$ boy doesn't qualify .
After Tom DeLay$_{PER}$ was zapped, Charles Colson$_{PER}$ became DeLay$_{PER}$'s personal guru.	After Tom DeLay$_{PER}$ was zapped, Charles Colson$_{PER}$ became DeLay's personal guru.	After Tom DeLay was zapped, Charles Colson$_{PER}$ became DeLay's personal guru.
She does not sit still or lay still for you to change her Pampers$_{PRODUCT}$.	She does not sit still or lay still for you to change her Pampers$_{PRODUCT}$.	She does not sit still or lay still for you to change her Pampers$_{PRODUCT}$.
Russian and Norwegian divers searched the fourth compartment of the wrecked submarine Kursk$_{PRODUCT}$, Sunday$_{DATE}$, but they found too much damage to proceed with the task of recovering bodies .	Russian and Norwegian divers searched the fourth compartment of the wrecked submarine Kursk$_{PRODUCT}$, Sunday$_{DATE}$, but they found too much damage to proceed with the task of recovering bodies .	Russian and Norwegian divers searched the fourth compartment of the wrecked submarine Kursk, Sunday$_{DATE}$, but they found too much damage to proceed with the task of recovering bodies .
Zinni$_{PER}$ testifying after the attack on the "USS Cole"$_{PRODUCT}$ – Aden never had a specific terrorist threat .	Zinni$_{PER}$ testifying after the attack on the "USS Cole"$_{PRODUCT}$ – Aden never had a specific terrorist threat .	Zinni testifying after the attack on the "USS Cole"$_{PRODUCT}$ – Aden never had a specific terrorist threat .
Today , the enterovirus chip is in the testing phase , and DR. Chip is collaborating with Taipei Veterans General Hospital to obtain samples with which to establish the accuracy of the chip .	Today$_{DATE}$, the enterovirus chip is in the testing phase, and DR. Chip$_{PRODUCT}$ is collaborating with Taipei Veterans General Hospital$_{FAC}$ to obtain samples with which to establish the accuracy of the chip .	Today$_{DATE}$, the enterovirus chip is in the testing phase, and DR. Chip$_{PRODUCT}$ is collaborating with Taipei Veterans General Hospital to obtain samples with which to establish the accuracy of the chip .

And I think perhaps no one more surprised than some of the people running those firms on Wall Street$_{FAC}$.	I think perhaps no one more surprised than some of the people running those firms on Wall Street$_{FAC}$.	I think perhaps no one more surprised than some of the people running those firms on Wall Street.
We're all getting , this news in from the speech that the Homeland Security Secretary Tom Ridge$_{PER}$ is expected to be delivering at the international press club around 1:00 Eastern at the top of the hour .	We're all getting , this news in from the speech that the Homeland Security Secretary Tom Ridge$_{PER}$ is expected to be delivering at the international press club around 1:00 Eastern at the top of the hour .	We're all getting , this news in from the speech that the Homeland Security Secretary Tom Ridge$_{PER}$ is expected to be delivering at the international press club$_{FAC}$ around 1:00 Eastern at the top of the hour .
Yesterday$_{DATE}$ American pilots mechanics approved their share \$ 1.8 billion$_{MONEY}$ in labor concession .	Yesterday$_{DATE}$ American pilots mechanics approved their share \$ 1.8 billion$_{MONEY}$ in labor concession .	Yesterday American pilots mechanics approved their share $ 1.8 billion in labor concession .

Table 9: NER Prediction Examples from OntoNotes with PERSON, DATE, MONEY, LOC, FAC,PRODUCT as target few-shot entities