AutoTriggER: Named Entity Recognition with Auxiliary Trigger Extraction

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Abstract

Deep neural models for low-resource named entity recognition (NER) have shown impressive results by leveraging distant supervision or other meta-level information (e.g., explanation). However, the costs of acquiring such additional information are generally prohibitive, especially in domains where existing resources (e.g., databases to be used for distant supervision) may not exist. In this paper, we present a novel two-stage framework (AUTOTriggER) to improve NER performance by automatically generating and leveraging “entity triggers” which are essentially human-readable clues in the text that can help guide the model to make better decisions. Thus, the framework is able to both create and leverage auxiliary supervision by itself. Through experiments on three well-studied NER datasets, we show that our automatically extracted triggers are well-matched to human triggers, and AUTOTriggER improves performance over a RoBERTa-CRF architecture by nearly 0.5 F1 points on average and much more in a low resource setting.\textsuperscript{1}

1 Introduction

Named Entity Recognition (NER) serves as a key building block in information extraction systems. Recent advances in deep neural models for NER have yielded state-of-the-art performance when sufficient human annotations are available (Lample et al., 2016; Liu et al., 2018; Peters et al., 2017; Ma and Hovy, 2016). However, such success cannot easily transfer to practitioners developing NER systems in specific domains (e.g., biomedical papers, financial reports, legal documents), where domain-expert annotations are expensive and slow to obtain.

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\textsuperscript{1}Code and data have been uploaded and will be published: https://github.com/INK-USC/AutoTriggER

Recent attempts addressing label scarcity have explored various types of human-curated resources as auxiliary supervision, such as entity dictionaries (Peng et al., 2019; Shang et al., 2018; Yang et al., 2018; Liu et al., 2019a), labeling rules (Safranchik et al., 2020; Jiang et al., 2020), and labeling explanations (Hancock et al., 2018; Wang et al., 2020; Ye et al., 2020; Lin et al., 2020; Lee et al., 2020).

In particular, prior works on label-efficient learning for classification (e.g., relation extraction) (Hancock et al., 2018; Wang et al., 2020; Zhou et al., 2020) and question answering (Ye et al., 2020) with explanations show that human provided explanations as auxiliary supervision signals are more cost-effective than collecting label-only annotations for larger number of instances. For the NER task, Lin et al. (2020) introduced the concept of an entity trigger, an effective way to represent explanations for the labeling decisions. An entity trigger is defined as a group of words in a sentence that helps to explain why humans would assign a type to an
entity in a sentence, and it serves as an effective proxy of rationale, as shown in Figure 1 (a) vs. (b).

Prior works primarily use a limited number of crowd-sourced triggers for improving data (label) efficiency of model training. While such human-curated auxiliary supervision are of high quality, the crowd-sourcing procedure can be very expensive and time-consuming. This largely limits the scale and domains of the collected entity triggers. In addition, trigger-aware NER models (e.g., Trigger Matching Networks (Lin et al., 2020)) are built on conventional sequence tagging architectures, e.g., BLSTM-CRFs (Lample et al., 2016), while recent NER models are incorporating pre-trained language models as contextualized embedding, which can be highly beneficial for low-resource languages. In this paper, we propose a novel two-stage NER framework, named AUTO_TRIGGER, that automatically generates and exploits entity triggers as explainable inductive bias to enhance NER models with little human effort (see Figure 1 (c)).

The first stage of our framework (Sec. 3.2) aims to automatically extract entity triggers using a saliency map technique based on input perturbations. Here, we propose to exploit the syntactic features of sentences for assigning importance scores to a group of input tokens such that we can extract useful entity triggers as auxiliary supervision. Specifically, for a given sentence and a target entity in it, we first extract phrases from its constituency parsing tree (Joshi et al., 2018) to form a collection of trigger candidates. Then, we score each trigger candidate by testing its ability to predict the target entity in a variety of sampled contexts. The rationale here is the intuition that a better trigger should be robust and help recognize the target entity in many different context. Here, we compare the system’s ability to identify the target entity in versions of the sentence with and without the candidate trigger; if a trigger is indeed a meaningful clue, then removing it should cause a noticeable drop in score.

The second stage (Sec. 3.3) focuses on how to use our triggers as structured priors to reinforce the model to focus on useful contextual clues in making the prediction. We propose Trigger Interpolation Network (TIN), a novel architecture that effectively uses trigger-labeled NER data to train a model. Here, we employ two separate masking passes when learning our model’s embeddings, one masking the entity words (forcing the model to rely more on the triggers) and one masking the triggers (forcing the model to rely more on the entity words). We then interpolate the embeddings of both entity-masked and trigger-masked sentences as the input to learn a mixed sentence representation as the input to standard sequence labeling. In this manner, the TIN can effectively learn to focus on useful contextual clues to infer entity boundaries and types with the powerful contextualized embeddings from pre-trained language models such as BERT (Devlin et al., 2019).

Extensive experimental results on several domains show that AUTO_TRIGGER framework consistently outperforms baseline methods by 0.5 F1 points on average in fully supervised setting. Our work shows the strong performance especially in low-resource setting for technical domains where expert annotations are limited due to the high cost. In the low-resource setting ranging from extreme to moderate, assuming a task that needs to be annotated from scratch, our model gains more than 3-4 F1 score on average.

2 Background and Formulation

We consider the problem of automatically extracting cue phrases as entity triggers (Lin et al., 2020) and using them to improve NER models. In this section, we introduce basic concepts about named entity recognition, entity triggers and trigger-labeled datasets. We then formally introduce our goal — creating trigger-labeled NER datasets without human annotation and then developing a learning framework that uses them to improve NER models.

Named Entity Recognition. We let \( x = [x^{(1)}, x^{(2)}, \ldots, x^{(n)}] \) denote the sentence consisting of a sequence of \( n \) words and \( y = [y^{(1)}, y^{(2)}, \ldots, y^{(n)}] \) denote the NER-tag sequence. The task is to predict the entity tag \( y^{(i)} \in Y \) for each word \( x^{(i)} \), where \( Y \) is a pre-defined set of tags such as \{B-PER, I-PER, ..., O\}. We let \( D_L \) denote the labeled dataset consisting of the set of instances \( \{(x_i, y_i)\} \), where \( x_i \) is the \( i \)-th input sentence and \( y_i \) is its output tag sequence.

Entity Trigger. Lin et al. (2020) introduce the concept of “entity trigger,” a novel form of explanatory annotation for NER, which is defined as a group of words that can help explain the recognition process of an entity in the sentence. For example, in Figure 2, “had ... dinner at” and “where the food” are two distinct triggers associated with the RESTAURANT entity “Sunnongdan.” These
Danny had a fantastic dinner at Sunnongdan last week

where the food is delicious.

Figure 2: Example of entity trigger. Entity trigger \( t_i \) is a cue phrase toward the entity \( e \) in the sentence, which is represented by a set of corresponding word indices. Both entity triggers \( \{t_1,t_2\} \) are associated to the same entity \( e \) (“Sunnongdan”) typed as restaurant.

explanatory cue phrases enable NER models to interpret a particular prediction and help them to generalize in a low-resource learning setting. Formally, given a particular NER example \((x,y)\), we have \( T \) denoting the set of entity triggers for that example. Each trigger \( t_i \in T \) is associated with an entity \( e \) and a set of word indices \( \{w_i\} \). That is, \( t = \{\{w_1, w_2, \ldots \} \rightarrow e\} \) represents an entity trigger, e.g., \( t_1 = \{2, 5, 6\} \rightarrow e \) in Figure 2. A trigger-labeled NER dataset, \( D_T = \{(x_1, y_1, T(x_1, y_1))\} \), consists of examples in a labeled NER dataset \( D_L \) with their associated entity triggers.

Our goal. Prior works mainly focus on creating \( D_T \) via manual annotation. Although trigger-labeled human annotations are cost-effective than entity-only annotations, they are still expensive and need domain experts for specialized domains. Therefore, in this work, we focus on how to automatically create such a trigger-labeled dataset \( D_T \) from \( D_L \) without manual effort, and then we propose a more label-efficient learning framework to use such \( D_T \) to improve NER models.

3 Approach

This section introduces the concepts in AUTO\(T\)RIGGER, and provides details of the framework design. We first present an overview of our AUTO\(T\)RIGGER framework (Sec. 3.1) and then discuss each of its components in detail (Sec. 3.2-3.3).

3.1 Framework Overview

\( \text{AUTO}T\text{RIGGER} \) is a two-stage architecture that begins with an automatic trigger extraction stage followed by a trigger interpolation network (TIN). It automatically extracts and scores entity trigger phrases in the first stage (Sec. 3.2) and uses them in the later stage to learn the NER model (Sec. 3.3). Prior work (Lin et al., 2020) on incorporating such entity triggers focused on encoding human-provided entity triggers. In contrast, \( \text{AUTO}T\text{RIGGER} \) automatically generates triggers and directly uses them for learning (Figure 3). Note that once we train the NER model, it is able to tag an entity token sequence without trigger extraction. Thus we do not have the additional complexity for trigger extraction at inference time.

3.2 Automatic Trigger Extraction

Automatic trigger extraction is the first stage of our \( \text{AUTO}T\text{RIGGER} \) framework. To extract triggers, here we adopt the sampling and occlusion (SOC) algorithm (Jin et al., 2020), which is a saliency map technique for model interpretation. Previous works on such input analysis techniques primarily focus on modeling the relative importance of each input token based on its 1) attention intensity (Li et al., 2016b), 2) gradients (Ribeiro et al., 2016) or 3) the changes of the output by excluding it from the input (Koh and Liang, 2017). These methods can indeed produce useful explanations for sentence classification tasks such as sentiment analysis, however, they are not well-aligned to our desired entity triggers — a group of input tokens that often poses structural constraints to a target entity.
In contrast, SOC aims to compute context-independent phrase-level importance for sequence classification tasks such as sentiment analysis and relation extraction (Jin et al., 2020). We reformulate and apply this technique for a sequence tagging task and retrieve important phrases as entity triggers. Given an input instance of the labeled corpus \((x_i, y_i) \in D_L\), we consider four primary steps to generate entity triggers: 1) phrase candidate \(P\), 2) entity token classifier \(M_t\), 3) phrase scoring, and 4) phrase selection.

**Phrase Candidate.** Given a training sentence, we construct a constituency parse tree and consider the set of phrase nodes \(P\) from the tree as auto trigger candidates. Figure 4 shows auto trigger candidates generated from constituency parsing of a sentence. The target entity mention “Cary Moon” is not included as a candidate. Note that the original SOC computes the word-level scores and extends to phrases by agglomerative clustering. Since clustering creates a large number of combinations of words to construct phrases, output phrases can be incomplete and noisy. By limiting the search space to a set of complete phrases, we could avoid such noisy triggers. Mathematically, given an input instance \((x_i, y_i) \in D_L\) and a target entity \(e \in x_i\), we generate a set of phrase candidate \(P = \{p_i\}\) where \(p_i = (w_s, w_e)\) and \(w_s, w_e\) is denoting the start and end index of the phrase span \(p_i\). To generate \(P\), we parse the input sentence \(x_i\) using constituency parsing and collect \(p_i\) corresponding to phrase nodes of the constituency-based parse tree. To avoid considering target entity as part of an entity trigger, we discard a set of entity-overlapped phrases \(\{p_j|e \in p_j\}\).

**Entity Token Classifier.** The second component is entity token classifier \(M_t\), which is a neural network for modeling the scoring module. Given an input sentence \(x_i = [x_i^{(1)}, x_i^{(2)}, \ldots, x_i^{(n)}]\), \(M_t\) classifies each token \(x_i^{(j)}\) to the named entity tag \(y_i^{(j)} \in Y\) where \(Y\) is a predefined set of named entity tags such as B-PER, I-PER and O. After training \(M_t\) with labeled corpus \(D_L\), we can derive the prediction score function \(s\) of the target entity \(e\) in the input sentence \(x_i \in D_L\). Let the conditional probability \(P(y|x)\) denote the output of \(M_t\). Then, the prediction score function \(s\) of the target entity \(e\) is computed as the average conditional probability over tokens of the target entity \(e\) as follows:

\[
s(x, e) = \frac{1}{|e|} \sum_{x^{(j)} \in e} P(y^{(j)}|x^{(j)}) \tag{1}
\]

**Phrase Scoring.** We use the phrase candidate \(P\) and prediction score function \(s\) of the \(M_t\) to measure the importance score of each phrase \(p\) towards target entity \(e\) by sampling and occlusion (SOC) algorithm. SOC is composed of two core methods: (1) input occlusion, (2) context sampling.

**Input occlusion** (Li et al., 2016b) computes the importance of \(p\) specific to the entity \(e\) in the input \(x\) by measuring the prediction difference caused by replacing the phrase \(p\) with padding tokens \(0_p\):

\[
\phi(p, x, e) = s(x, e) - s(x_{-p}, e; 0_p) \tag{2}
\]

For example, in Figure 4, “the next mayor” is replaced by pad tokens to compute its importance towards the entity “Cary Moon”. However, the importance score \(\phi(p, x, e)\) from equation 2 has a drawback that the \(p\) is dependent on context words around \(p\). It may neglect the fact that the importance score of \(p\) can vary depending on which context words are around \(p\).

To eliminate the dependence, context sampling samples the context words around the phrase \(p\) and computes the average prediction differences over the samples. Specifically, it samples the context...
words $\hat{x}_δ$ from a trained language model $p(\hat{x}_δ|x_{-δ})$ and obtains a set of context word replacements $S$. For each replacement $\hat{x}_δ \in S$, we measure the prediction difference caused by replacing the phrase $p$ with padding tokens. We take the average of these prediction differences to be the context-independent score $\phi(p,x,e)$ of the phrase $p$, as expressed in equation 3:

$$\frac{1}{|S|} \sum_{\hat{x}_δ \in S} [s(x_{-δ}, e; \hat{x}_δ) - s(x_{-(δp)}, e; \hat{x}_δ; o_p)]$$

(3)

In Figure. 4, context words “won’t be” and “of Seattle” around the phrase “the next mayor” are replaced into “will be” and “of LA” which are sampled from the language model. Then, the classifier computes the prediction difference between the sampled sentences with and without the phrase.

**Phrase Selection.** After obtaining the importance score $\phi(p,x,e)$ for all phrase candidates $P = \{p_1\}$, we pick the top $k$ candidate phrases with the highest importance score as the entity triggers, where $k$ is a hyperparameter. Specifically, for each input instance $(x_1, y_1) \in D_L$, we pick the top $k$ candidate phrases as entity triggers $T(x_1, y_1)$ to create a form $\{(x_1, y_1, T(x_1, y_1))\}$.

### 3.3 Trigger Interpolation Network (TIN)

The second stage of AUTO_TRIGGER is the trigger interpolation network (TIN), which we define as a neural network in Figure 5: Overview of the Trigger Interpolation Network (TIN). Given an input sentence we create an Entity-masked sentence and a Trigger-masked Sentence. Then we interpolate token level representations $h_i$ and $h'_i$ to create new hidden state representation, $\tilde{h}_i$. Interpolated hidden representations are fed to a CRF.

The input to the final CRF tagger is $\hat{x}_e \in \{T(x,e)\}$. The output of the CRF is a probability distribution over the class.

Here, the encoder $F(\cdot; \theta)$ for both $x_e$ and $x_{-t}$ is sharing the weights. Then we use $\hat{h}$ as the input to the final CRF tagger. When inferring tags on unlabeled sentences which have no entity triggers, we expect the trained $F(\cdot; \theta)$ is enforced to find the entity and trigger information from the input $x \in D_u$ and infuse both for generating enriched-information output. We then use it as an input to the final CRF tagger to get predictions.

### 4 Experimental Setup

In this section we describe datasets along with the baseline methods followed by experimental details.

#### 4.1 Datasets

We consider three NER datasets as target tasks. We consider two datasets for a bio-medical domain: BC5CDR (Li et al., 2016a), JNLPBA (Collier and
which is a robustly improved BERT.

To show the effectiveness of entity triggers, we apply the following models on $D_T$: (1) TMN (Lin et al., 2020) first adopts the structured self-attention layer (Lin et al., 2017) above the bidirectional LSTM, which uses GloVE for embeddings, to encode the sentence and entity trigger into vector representation respectively. Then, it jointly learns trigger representations and a soft matching module with self-attention such that can generalize to unseen sentences easily for tagging named entities. (2) BERT-TIN is trigger interpolation network where the transformer encoder $F(\cdot; \theta)$ is BERT. (3) RoBERTa-TIN is also trigger interpolation network where $F(\cdot; \theta)$ is RoBERTa.

### 4.3 Implementation Details

We implement all the baselines using PyTorch (Paszke et al., 2019) and HuggingFace (Wolf et al., 2020). We set the batch size and learning rate to 10 and 0.01 for BLSTM encoder models (i.e., BLSTM+CRF, TMN, BERT+BLSTM+CRF) while we set 30 and 2e-5 for all other transformer models (i.e., BERT+CRF, RoBERTa+CRF, BERT-TIN, RoBERTa-TIN). For TIN, we set the interpolation $\lambda$ to 0.5. For automatic trigger extraction stage, we set the batch size and learning rate to 16 and 1e-4 for training the entity token classifier model. To run context sampling in the SOC algorithm, we use a LSTM language model which is pre-trained on the training data. TIN takes 2X longer than baseline models on the training data since it needs to extract triggers using SOC algorithm. Note that for experiments in extreme low resource setting (Sec. 5.2), we set the batch size to 4 for both training TIN and entity token classifier due to the extremely limited training data.

### 5 Results and Performance Analysis

We first compare the overall performance of all baseline models and our proposed framework. Here, we test all models by varying the amount of training data from 20% to 100% to show the impact of train data size. We then discuss the effectiveness of our framework in an extremely low resource setting, assuming a task that needs to be annotated from scratch. Next, we provide a comparison of auto-triggers with human-triggers, and further show that auto-triggers can be more useful when a human judge provides binary feedback on their utility. For the ablation study, we investigate how the different variants of creating a set of trigger candidates, sensitivity of interpolation

| Dataset | Original $D_L$ | Crowd-sourced trigger $D_{HT}$ |
|---------|----------------|-------------------------------|
| CONLL 2003 | 23,495 | 5,134 | 10,938 |
| BC5CDR | 9,383 | 1,991 | 3,770 |
| JNLPBA | 46,745 | - | - |

Table 1: Train data statistics.
We hypothesize that our models will have larger performance gains in extreme low-resource settings, because of their ability to leverage additional information from auto-triggers which enables them to reap more benefits from given training data. To investigate this we observe the performance of our models and baselines under the extreme low-resource setting. Even though our best model, RoBERTa-TIN, was on par with the baseline, RoBERTa+CRF, in the CoNLL03 dataset in the previous setting, it achieves large performance gain in extremely low-resource setting. Specifically, we observe over 50% relative gain compared to the baseline for 50 training sentences. For the BC5CDR dataset we observe persistent performance gain.

5.3 Human-in-the-loop Trigger Extraction

**Human-curated vs. Auto Triggers.** We compare the performance of our model variants trained with automatically extracted triggers (auto) and human-provided (crowd-sourced) triggers (human). We use $D_{HT}$ as the source of human triggers and use the same dataset to extract auto triggers with SOC algorithm. We then sample 25%, 50%, and 75% of the instances from both to construct 5%, 10%, 15% percent of our experimentation dataset (since $D_{HT}$ is a 20% random sample from $D_L$). One big difference between human and auto is whether the triggers are contiguous token

| Method / Percentage | BC5CDR | JNLPBA | CoNLL03 |
|---------------------|--------|--------|---------|
|                      | 20%    | 40%    | 60%    | 80%    | 100%  | 20%    | 40%    | 60%    | 80%    | 100%  | 20%    | 40%    | 60%    | 80%    | 100%  |
| BLSTM+CRF           |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| BERT+BLSTM+CRF      |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| BERT+CRF            |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| RoBERTa+CRF         |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| RoBERTa+CRF         |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| TMN                 |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| BERT-TIN            |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |
| RoBERTa-TIN         |        |        |        |        |       |        |        |        |        |       |        |        |        |        |       |

Table 3: Classification Report (F1-score) of BERT-CRF and BERT-TIN on 100% CoNLL03.

5.2 Performance under Low-resource Setting

We hypothesize that our models will have larger performance gains in extreme low-resource settings, because of their ability to leverage additional information from auto-triggers which enables them to reap more benefits from given training data. To investigate this we observe the performance of our models and baselines starting with only 50-200 sentences to train them. Figure 6 shows the performance of our models and baselines under the extreme low-resource setting. Even though our best model, RoBERTa-TIN, was on par with the baseline, RoBERTa+CRF, in the CoNLL03 dataset in the previous setting, it achieves large performance gain in extremely low-resource setting. Specifically, we observe over 50% relative gain compared to the baseline for 50 training sentences. For the BC5CDR dataset we observe persistent performance gain.

![Performance Comparison (F1-score) on CoNLL03 and BC5CDR by different numbers of train data (50, 100, 150, 200) which are small.](image)

(a) CoNLL03

(b) BC5CDR

Human-curated vs. Auto Triggers. We compare the performance of our model variants trained with automatically extracted triggers (auto) and human-provided (crowd-sourced) triggers (human). We use $D_{HT}$ as the source of human triggers and use the same dataset to extract auto triggers with SOC algorithm. We then sample 25%, 50%, and 75% of the instances from both to construct 5%, 10%, 15% percent of our experimentation dataset (since $D_{HT}$ is a 20% random sample from $D_L$). One big difference between human and auto is whether the triggers are contiguous token.
rebels after they were attacked by Iranian troops deep inside Iraq last month.

The Spanish Farm Minister Loyola de Palacio had earlier accused Fischer of causing unjustified alarm through "dangerous generalisation." An einzel farm minister Loyola de Palacio had earlier accused Fischer of causing unjustified alarm through dangerous generalisation.

Table 4: Performance comparison (F1-score) of entity+trigger baselines on BC5CDR and CoNLL03 with human and auto triggers.

| BC5CDR | TMN | BERT-TIN | RoBERTa-TIN |
|--------|-----|---------|-------------|
| Percentage / Model | human | auto | human | auto | human | auto |
| 5% | 26.96 | 24.70 | 66.20 | 56.50 | 75.79 | 76.92 |
| 10% | 46.24 | 43.54 | 71.25 | 71.84 | 80.92 | 81.63 |
| 15% | 51.29 | 50.44 | 73.88 | 74.11 | 83.54 | 83.87 |
| 20% | 56.28 | 54.91 | 75.97 | 76.58 | 83.88 | 84.17 |

| CoNLL03 | TMN | BERT-TIN | RoBERTa-TIN |
|--------|-----|---------|-------------|
| Percentage / Model | human | auto | human | auto |
| 5% | 56.39 | 57.95 | 78.17 | 78.56 | 84.72 | 85.71 |
| 10% | 61.89 | 66.58 | 81.67 | 82.19 | 87.80 | 88.12 |
| 15% | 67.48 | 69.4 | 83.67 | 85.13 | 88.40 | 89.12 |
| 20% | 71.11 | 74.43 | 84.88 | 85.58 | 89.62 | 90.21 |

Figure 7: Top 2 highlighted auto and human triggers corresponding to the underlined entity.

Figure 8: Performance Comparison (F1-score) by annotators’ labeling time cost.

Figure 9: Additional F1 score after training the model with different data volumes.

Human-in-the-loop Trigger Refinement. We conduct a small-scale experiment of trigger refinement by human annotators. For all our previous experiments, we use the top two auto triggers, which limits our capacity to make the best use of them. In this experiment, given a training set with labeled entities, we extract five auto triggers (Sec. 3.2), show them to a human in a minimal interface, and ask for relevance judgments (relevant/non-relevant). We judged relevance of the automatically extracted triggers for entities in 50, 100, 150, and 200 sentences.

Figure 9 shows that we get an additional performance boost with more than 50 training sentences, when human-refined auto triggers are used in training. This small scale annotation shows promise for blending human expertise with auto triggers.

Label Efficiency. We conduct experiments to demonstrate the label efficiency of our model. We found that the time for labeling on instance plus providing entity triggers takes 1.5X more time than just simply providing a label. Given this observation, we compare the performance between TIN models with human and auto by holding annotation time constant. We present the study in Figure 8. Each marker on the x-axis of the plots indicate a certain annotation time, which is represented by approximate time. We see that our model not only is more time and label efficient compared to both entity baselines and entity+trigger baselines with human triggers, but it also outperforms.
Figure 9: Performance Comparison (F1-score) on BC5CDR by different numbers of train data (50, 100, 150, 200) with auto and human-refined auto triggers.

5.4 Performance Analysis

Trigger Candidate Variants. In Sec 3.2, we first constructed a set of phrase candidates \( P \) for which the importance score is computed. To show the efficacy of constituency parsing for constructing trigger candidates, we conduct an ablation study on different variants of it. For the construction, we compare three variants: (1) \( RS \) is random selection. It randomly chooses \( n \) contiguous tokens to be grouped as a phrase for \( k \) times. Consequently, \( P \) is composed of \( k \) random spans. (2) \( DP \) is dependency parsing. Here, to generate \( P \), we first parse the input sentence using dependency parsing. Then, we traverse from the position of entity mention in the input sentence using depth-first-traversal and get a list of tokens visited for each hop up to 2-hops. Finally, for each hop, we convert the list of tokens to a list of phrases by merging the tokens that are contiguous into a single phrase. (3) \( CP \) is constituency parsing, which is our current method (see Sec. 3.2). We expect each variant to provide different syntactic signals to our framework. Figure 10 shows the model’s performance with triggers that have been selected from different sets of phrase candidates. As we can see, constituency parsing yields consistently better performance by providing better quality of syntactic signals than others.

Sensitivity Analysis of interpolation hyperparameter (\( \lambda \)). In Sec 3.3, we linearly interpolated two different sources of knowledge by weight \( \lambda = 0.5 \). To show how the weight \( \lambda \) affects the performance, we conduct an ablation study on different \( \lambda \) distribution. As we can see from Figure 11, the framework achieves the highest performance when \( \lambda \) is set to 0.5. It supports that the model achieves the best when we interpolate the entity and trigger knowledge in equal.

Number of Triggers. In Sec. 3.2, we pick the top \( k \) candidate phrases with the highest importance score as the entity triggers after obtaining the importance score for all phrase candidates. For our main experiment, we use top 2 candidate phrases (see Table 2). To show how the number of triggers affects the performance, we conduct an ablation study on model performance by different \( k \). As we can see from Figure 12, the framework achieves the highest performance when we use top 2 phrase candidates as triggers.
Related Work

NER with Additional Supervision

Previous and recent research has shown that encoding syntactic information into NER models compensate for the lack of labeled data (Tian et al., 2020). The improvement is consistent across word embedding based encoding (e.g. biLSTM) as well as unsupervised language model based encoding (e.g. BioBERT) of the given text. Typically, the external information that is encoded include POS labels, syntactic constituents, and dependency relations (Nie et al., 2020; Tian et al., 2020). The general mechanism to include linguistic information into NER model is to represent them using word vectors and then concatenate those representations with the original text representation. This approach fails to identify the importance of different types of syntactic information. Recently, Tian et al. (2020) and Nie et al. (2020) both showed that key-value memory network (KVMN) (Miller et al., 2016) are effective in capturing importance of linguistic information arising from different sources. KVMN has been shown to be effective in leveraging extra information, such as knowledge base entities, to improve question answering tasks. Before applying KVMN, contextual information about a token is encoded as the key and syntactic information are encoded as values. Finally, weights over the values are computed using the keys to obtain a representation of the values and concatenate it with the context features. Our approach uses token level features extracted by an explanation generation model, but later train to be able to pick-up those explanations directly from the text at inference time.

Limited Training Data for NER

The simplest way to approach the problem of limited data for NER is to use dictionary based weak supervision. An entity dictionary is used to retrieves unlabeled sentences from a corpus and weakly label them to create additional noisy data. This approach suffers from low recall as the training data covers a limited number of entities. The models tend to bias towards the surface form of the entities it has observed in the dictionary. There has also been approaches to retrieve sentences from a large corpus that are similar to sentences in the low-resource corpus to enrich it. These self-training approaches have been shown to be effective both in extremely limited data (Foley et al., 2018; Sarwar et al., 2018) as well as limited data scenario (Du et al., 2021).

Learning from Explanations

Recent works on Explainable AI are primarily focused on debugging the black box models by probing internal representations (Adi et al., 2017; Conneau et al., 2018), testing model behavior using challenge sets (McCoy et al., 2019; Gardner et al., 2020; Ribeiro et al., 2020), or analyzing an impact of input examples by input perturbations or influence function (Ribeiro et al., 2016; Koh and Liang, 2017). However, for an explanation of the model to be effective, it must provide not only the reasons for the model’s prediction but also suggestions for corresponding actions in order to achieve an objective. Efforts to cope with this issue by incorporating human explanations into the model are called Explanation-based learning (DeJong and Mooney, 2004). These works are aiming to exploit generalized explanations for drawing inferences from unlabeled data while maintaining model transparency. Most prior works on explanation-based learning are mainly focused on facilitating logical rules as an explanation. They use such rules to create weak supervision (Ratner et al., 2017) and regularize posterior (Hu et al., 2016, 2017). Another form of explanations can be specific words in the sentence which aligns to our work. Notable work in this line asks annotators to highlight important words, then learn a generative model over parameters given these rationales (Zaidan and Eisner, 2008).

Conclusion

In this paper, we proposed a novel two-stage framework to generate and leverage explanations for named entity recognition. It automatically extracts essentially human-readable clues in the text, which is called entity triggers, by sampling and occlusion algorithm and leverage these triggers with trigger interpolation network. We show that our framework, named AUTO_TRIGGER, successfully generates entity triggers and effectively leverages them to improve the overall performance, especially in the low-resource setting for technical domains where domain-expert annotations are very limited due to the high cost. Extensive experiments on three public datasets prove the effectiveness of our framework. We believe that this work opens up future works that can be extended to semi-supervised learning or distant supervised learning which can effectively use automatically extracted triggers to weakly label the unlabeled corpus.
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