Distantly-Supervised Joint Extraction with Noise-Robust Learning

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Abstract

Joint entity and relation extraction is a process that identifies entity pairs and their relations using a single model. We focus on the problem of joint extraction in distantly-labeled data, whose labels are generated by aligning entity mentions with the corresponding entity and relation tags using a knowledge base (KB). One key challenge is the presence of noisy labels arising from both incorrect entity and relation annotations, which significantly impairs the quality of supervised learning. Existing approaches, either considering only one source of noise or making decisions using external knowledge, cannot well-utilize significant information in the training data. We propose DENRL, a generalizable framework that 1) incorporates a lightweight transformer backbone into a sequence labeling scheme for joint tagging, and 2) employs a noise-robust framework that regularizes the tagging model with significant relation patterns and entity-relation dependencies, then iteratively self-adapts to instances with less noise from both sources. Surprisingly, experiments[1] on two benchmark datasets show that DENRL, using merely its own parametric distribution and simple data-driven heuristics, outperforms large language model-based baselines by a large margin with better interpretability.

1 Introduction

Joint extraction aims to detect entities along with their relations using a single model (see Figure 1), which is a critical step in automatic knowledge base construction (Yu et al., 2020). In order to cheaply acquire a large amount of labeled joint training data, distant supervision (DS) (Mintz et al., 2009) was proposed to automatically generate training data by aligning knowledge base (KB) with an unlabeled corpus. It assumes that if an entity pair has a relationship in a KB, all sentences that contain this pair express the corresponding relation.

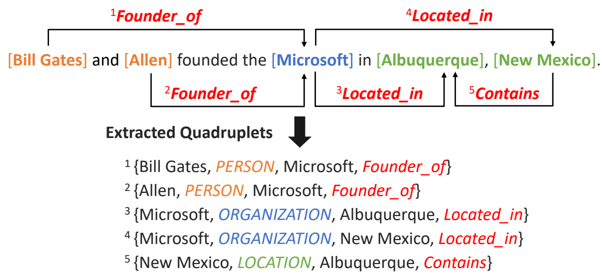

Figure 1: An example of joint extraction on a sentence with multiple relations that share the same entity, e.g., "*Microsoft*" in both the third and the forth relations.

Nevertheless, DS brings plenty of noisy labels which significantly degrade the performance of the joint extraction models. For example, given a sentence "*Bill Gates lived in Albuquerque*" and the sentence in Figure 1, DS may assign the relation type between "*Bill Gates*" and "*Albuquerque*" as *Place_lived* for both sentences. The words "*lived in*" in the first sentence is the pattern that explains the relation type, thus it is correctly labeled. While the second sentence is noisy due to the lack of corresponding relation pattern. Moreover, due to the ambiguity and limited coverage over entities in open-domain KBs, DS also generates noisy and incomplete entity labels. In some cases, DS may lead to over 30% noisy instances (Mintz et al., 2009), making it impossible to learn useful features.

Previous studies for handling such noisy labels consider either weakly-labeled entities, i.e., distantly-supervised named entity recognition (NER) (Shaalan, 2014), or noisy relation labels, i.e., distantly-supervised relation extraction (RE) (Rink and Harabagiu, 2010), where they focus on designing novel hand-crafted relation features (Yu et al., 2020), neural architectures (Chen et al., 2020), and tagging scheme (Dai et al., 2019) to improve relation extraction performance. Additionally, In-Context Learning (ICL)

[1]Our code is available at https://github.com/yul091/DENRL.

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using external knowledge of Large Language Models (LLMs) (Pang et al., 2023) is popular. However, they are resource-demanding, sensitive to prompt design, and may struggle with complex tasks.

To cheaply mitigate both noise sources, we propose **DENRL**—**D**istantly-supervised joint **E**xtraction with **N**oise-**R**obust **L**earning. DENRL assumes that 1) reliable relation labels, whose relation patterns significantly indicate the relationship between entity pairs, should be explained by a model, and 2) reliable relation labels also implicitly indicate reliable entity tags of the corresponding entity pairs. Specifically, DENRL applies *Bag-of-word Regularization* (BR) to guide a model to attend to significant relation patterns that explain correct relation labels, and *Ontology-based Logic Fusion* (OLF) that teaches underlying entity-relation dependencies with Probabilistic Soft Logic (PSL) (Bach et al., 2017). These two information sources are integrated to form a noise-robust loss, which regularizes a tagging model to learn from instances with correct entity and relation labels. Next, if a learned model clearly locates the relation patterns and understands entity-relation logic of candidate instances, they are selected for subsequent adaptive learning. We further sample negative instances that contain corresponding head or tail entities of recognized patterns in those candidates to reduce entity noise. We iteratively learn an interpretable model and select high-quality instances. These two-fold steps are mutually reinforced—a more interpretable model helps select a higher quality subset, and vice versa.

Given the superiority of unified joint extraction methods, we introduce a sequence labeling (Zheng et al., 2017) method to tag entities and their relations simultaneously as token classification. We incorporate a BERT (Devlin et al., 2019) backbone that learns rich feature representations into the tagging scheme to benefit the information propagation between relations and entities. The transformer attention mechanism builds a direct connection between words and contributes to extracting long-range relations (Li et al., 2022, 2023a). Its multi-head attention weights indicate interactions between each pair of words, which is further leveraged by self-matching to produce position-aware representations. These representations are finally used to decode different tagging results and extract all entities together with their relations.

Our contributions are summarized as follows:

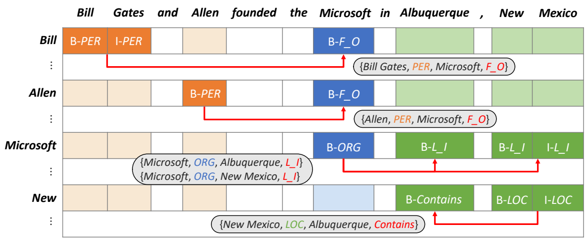


Figure 2: A example of our tagging scheme. For each head entity, we fill a T-tag sequence to represent corresponding relations. *PER*, *ORG*, *LOC* are abbreviations for entity *PERSON*, *ORGANIZATION*, *LOCATION*; *F_O*, *L_I* for relation *Founder_of*, *Located_in*.

- Our work introduces a novel framework for distantly-supervised joint extraction. This innovation lies in identifying and addressing multi-source noise arising from both entity and relation annotations, and a unified joint tagging scheme adaptable to various backbones.
- Our method DENRL is generalizable and effective and offers a cost-effective alternative to predominant LLMs that use a much larger backbone.
- Our comprehensive experiments show that DENRL is interpretible and well-motivated.

2 Joint Extraction Architecture

We incorporate a pre-trained BERT backbone into our sequence tagging scheme to jointly extract entities and their relations (see Figure 3).

2.1 Tagging Scheme

To extract both entities (mention and type) and relations, we tag quadruplets $\{e_1, tag_1, e_2, re\}$ for each start position p and define "BIO" signs to encode positions (see Figure 2). Here, e_1 is the detected entity at p (head entity), tag_1 is the entity type of e_1, e_2 is another detected entity that has a relationship with e_1 (tail entity), and re is the predicted relation type between e_1 and e_2. For a T-token sentence, we annotate T different tag sequences according to different start positions.

For each tag sequence, if p is the start of an entity (this sequence is an instance), the entity type is labeled at p, and other entities that have relationship to the entity at p are labeled with relation types. The rest of tokens are labeled "O" (Outside), meaning they do not correspond to the head entity. In this way, each tag sequence will produce a relation quadruplet. For example, if p is 7, the head entity is

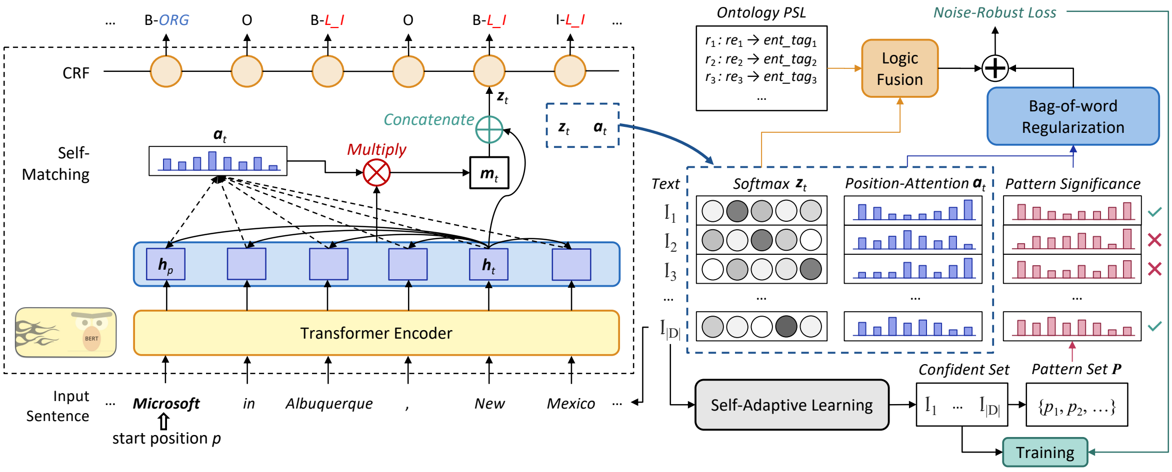


Figure 3: An overview of DENRL framework. The left part is our position-attentive joint tagging model, which receives a sentence input and different start position p to extract all entities and relations. $\boldsymbol{a}_t$ are position-attention weights and $\boldsymbol{z}_t$ are sequence scores. The right part is our noise-robust learning mechanism, which employs BR (on $\boldsymbol{a}_t$) and OLF (on $\boldsymbol{z}_t$) to guide the model to attend to significant patterns and entity-relation dependencies. Then, a fitness score u for each training instance is calculated to select and build new distributed training sets as well as confident pattern sets. These two steps are run iteratively as self-adaptive learning.

"*Microsoft*" and its tag is *ORG*. Other entities, such as "*Albuquerque*" and "*New Mexico*", are labeled as *L_I* and *L_I* indicating their (unidirectional) relations with "*Microsoft*". If p is 9, the head entity "*Albuquerque*" has no relationship with other entities, thus only the entity type *LOC* is labeled. If p is 13, all tokens are labeled as "O" because there is no entity at the head position to attend to.

We define instances that contain at least one relation as positive instances (e.g., p is 7), and those without relations as negative instances (e.g., p is 9). "BIO" (Begin, Inside, Outside) signs are used to indicate the position information of tokens in each entity for both entity and relation type annotation to extract multi-word entities. Note that we do not need the tail entity type, because every entity will be queried and we can obtain all entity types as well as their relations from the T tag sequences.

2.2 Tagging Model

Encoder with Self-Matching We follow BERT (Devlin et al., 2019) to use a multilayer transformer (Vaswani et al., 2017) that takes an input sequence $\mathcal{S} = \{w_1, ...w_T\}$ and converts it into token-level representations $\boldsymbol{h}^0 = \{\boldsymbol{h}_t\}_{t=1}^T$, where $\boldsymbol{h}_t \in \mathbb{R}^d$ is a d-dimensional vector corresponding to the t-th token in $\mathcal{S}$. The model applies L transformer layers over the hidden vectors to produce contextual representations: $\boldsymbol{h}^l = \text{TRANSFORMER}^{(l)}(\boldsymbol{h}^{l-1}), \quad l \in [1, L]$. Each layer contains a Multi-Head Self-Attention (MHSA) layer followed by a Feed-Forward Network (FFN) over the previous hidden state $\boldsymbol{h}^{l-1}$. The final representations $\boldsymbol{h}^L \in \mathbb{R}^{T\times d}$ integrate the contextual information of all previous tokens but are inadequate for decoding a T-tag sequence, since for each position p we still need to encode e_1 and its overlapping relations re with other entities e_2.

We define *self-matching* (Tan et al., 2018) that calculates position-attention $\boldsymbol{a}_t$ between tokens at start position p as well as each target position t:

$$\begin{aligned} \boldsymbol{a}_t &= \text{softmax}(\{a_j^t\}_{j=1}^T) \\ s.t. \quad a_j^t &= \boldsymbol{w}^\top(\boldsymbol{h}_p^L + \boldsymbol{h}_t^L + \boldsymbol{h}_j^L), \end{aligned} \tag{1}$$

where $\boldsymbol{w} \in \mathbb{R}^d$ is a parameter to be learned, $\boldsymbol{h}_p$, $\boldsymbol{h}_t$, $\boldsymbol{h}_j \in \mathbb{R}^d$ are hidden states at position p, t, j, respectively. a_j^t is the score computed by comparing $\boldsymbol{h}_p$ and $\boldsymbol{h}_t$ with each hidden state $\boldsymbol{h}_j$. $\boldsymbol{a}_t \in \mathbb{R}^T$ is the softmax attention produced by normalizing a_j^t. The start hidden state $\boldsymbol{h}_p$ serves as comparing with the sentence representations to encode position information, and $\boldsymbol{h}_t$ matches the sentence representations against itself to collect context information. The position-aware representation $\boldsymbol{m}_t \in \mathbb{R}^{T\times d}$ is an attention-weighted sentence vector:

$$\boldsymbol{m}_t = \boldsymbol{a}_t^\top \boldsymbol{h}^L. \tag{2}$$

We concatenate $\boldsymbol{h}_t$ and $\boldsymbol{m}_t$ to generate position-aware and context-aware representations $\{\boldsymbol{x}_t\}_{t=1}^T$:

$$\boldsymbol{x}_t = [\boldsymbol{h}_t; \boldsymbol{m}_t]. \tag{3}$$

For each start position, self-matching produces different sentence representations and thus can model different tag sequences of a sentence.

CRF Decoder CRF (Lafferty et al., 2001) considers the correlations between labels in neighborhoods and jointly decodes the best chain of labels, which benefits sequence labeling models. For each position-aware representation $\boldsymbol{x}_t$, the input sequence scores $\boldsymbol{Z} = \{\boldsymbol{z}_t\}_{t=1}^{T}$ is generated by:

$$\boldsymbol{z}_t = \boldsymbol{W}^x \boldsymbol{x}_t, \tag{4}$$

where $\boldsymbol{z}_t \in \mathbb{R}^V$ is tag score of the t-th token, V is the number of distinct tags, and z_t^j is the score of the j-th tag at position t.

For a sequence of labels $\boldsymbol{y} = \{y_1, ..., y_T\}$, the decoding score $score(\boldsymbol{Z}, \boldsymbol{y})$ is the sum of transition score from tag y_t to tag y_{t+1}, plus the input score $z_t^{y_t}$ for each token position t. The conditional probability $p(\boldsymbol{y}|\boldsymbol{Z})$ is the softmax of $score(\boldsymbol{Z}, \boldsymbol{y})$ over all possible label sequences $\boldsymbol{y}'$ for $\boldsymbol{Z}$. We maximize the log-likelihood of correct tag sequences during training:

$$\mathcal{L}_c = \sum\nolimits_i \log p(\boldsymbol{y}|\boldsymbol{Z}). \tag{5}$$

Decoding searches for the tag sequence $\boldsymbol{y}^*$ that maximizes the decoding score. The best tag sequence $\boldsymbol{y}^*$ is computed using the Viterbi algorithm.

3 Noise-Robust Learning

To reduce the impact of noisy labels on tagging performance, we introduce *Bow Regularization* (BR) to attend to confident relation patterns for reducing relation noise and *Ontology-based Logic Fusion* (OLF) to increase entity-relation coherence for reducing entity noise. Finally, we employ *Self-Adaptive Learning* (SAL) to iteratively train on instances that can be explained by the model.

3.1 Bag-of-word Regularization (BR)

Originally proposed as a pattern-attentive loss, attention regularization (Jia et al., 2019) has been shown effective for reducing relation noise, yet it only considers attention over a single relation pattern and neglects models' position-awareness, thus cannot identify overlapping relations. We formulate target attention distribution by introducing BoW frequency as an oracle to learn informative relations. For an input sentence $\mathcal{S}$, an entity pair (e_1, e_2) in $\mathcal{S}$, a relation label re, and a relation pattern p that explains the relation re of e_1 and e_2, we define BoW frequency (i.e., pattern significance) as the corresponding guidance score $\boldsymbol{a}^p$ conditional on pattern p. Take the relation *Contains* as an example, its BoW is a set of tokens that appear in a corresponding pattern set {*"capital of", "section in", "areas of", ...*}. The motivation is to guide the model to explore new high-quality patterns p, e.g., "*section of*", "*areas in*", etc. The guidance $\boldsymbol{a}^{\mathcal{I}}$ for an instance $\mathcal{I}$ is the average of $\boldsymbol{a}^p$ regarding all patterns m corresponding to each relation type re:

$$\begin{aligned} \boldsymbol{a}^p &= \text{softmax}(\{\text{BoW}_t\}_{t=1}^{T}), \\ \boldsymbol{a}^{\mathcal{I}} &= \text{AvgPooling}\left(\boldsymbol{a}^{p_1}, \cdots, \boldsymbol{a}^{p_{|R_{\mathcal{I}}|}}\right), \end{aligned} \tag{6}$$

where BoW_t represents the BoW frequency of w_t under relation re if w_t belongs to corresponding relation pattern words or 1 if it belongs to entity words, e.g., $f($*"of"*$|$*Contains*$) = 2$. $|R_{\mathcal{I}}|$ is the number of distinct relation types in instance $\mathcal{I}$.

We expect a joint tagger to approximate its position-attention $\boldsymbol{a}^{\mathcal{S}}$ to $\boldsymbol{a}^{\mathcal{I}}$, where $\boldsymbol{a}^{\mathcal{S}} =$ AvgPooling $(\boldsymbol{a}_1, \ldots, \boldsymbol{a}_T)$ is the average pooling of model's position-attention $\boldsymbol{a}_t$ defined in Equation (1) for each position j in $\mathcal{S}$. We compute the mean squared error (MSE) as the objective:

$$\mathcal{L}_{BR} = \text{MSE}(\boldsymbol{a}^{\mathcal{I}}, \boldsymbol{a}^{\mathcal{S}}) = \sum (\boldsymbol{a}^{\mathcal{I}} - \boldsymbol{a}^{\mathcal{S}})^2. \tag{7}$$

3.2 Ontology-Based Logic Fusion (OLF)

Probabilistic Soft Logic (PSL) (Bach et al., 2017) uses soft truth values for predicates in an interval between $[0, 1]$, which represents our token classification probability $p(y_t|w_t)$ as a convex optimization problem. Inspired by Wang and Pan (2020); Kirsch et al. (2020) that considers relation logic as rules for inference, we adapt PSL to entity-relation dependency rules according to data ontology using human annotation (see details in Table 8 and Table 9), e.g., relation type *Founder_of* should entail (head) entity type *PERSON*. Training instances that violate any of these rules are penalized to enhance comprehension of entity-relation coherence. Suppose BR guides a model to recognize confident relations, OLF further helps explore instances with reliable entity labels, especially when no relations exist in them.

Particularly, we define *Logic Distance* based on a model's softmax scores over the head entity given its predicted relation type to measure how severely it violates logic rules. For a training instance, we define an *atom* l as each tag and the *interpretation*

Algorithm 1 Logic Distance Calculation $\mathcal{D}$

Input: Softmax $p(y|e_i)$, Prediction $\hat{y}_i$, $i \in \{1, 2\}$, PSL rules $\mathcal{R}$ w.r.t. ontology;

Output: Distance d;

Initialize $d \leftarrow 1$; Satisfied $\leftarrow$ False;
for each $r : l_{re} \rightarrow l_{ent} \in \mathcal{R} \wedge \hat{y}_2 == l_{re}$ **do**
    $\overline{y}_1 \leftarrow l_{ent}$;
    $d' \leftarrow \max\{p(\hat{y}_2|e_2) - p(\overline{y}_1|e_1), 0\}$;
    $d \leftarrow \min\{d', d\}$;
    Satisfied $\leftarrow$ True;
if Satisfied $==$ False **then**
    $d \leftarrow 0$.

$I(l)$ as the soft truth value for the atom. For each rule r : RELATION $\rightarrow$ ENTITY, the distance to satisfaction $d_r(I)$ under the interpretation I is:

$$d_r(I) = \max\{0, I(l_{re}) - I(l_{ent})\}. \tag{8}$$

PSL determines a rule r as satisfied when the truth value of $I(l_{re}) - I(l_{ent}) \geq 0$. For each instance $\mathcal{I}$, we set l_{ent} as (head) entity type and l_{re} as relation type. This equation indicates that the smaller $I(l_{ent})$ is, the larger the penalty it has. We compute the distance to satisfaction for each rule r and use the smallest one as a penalty because at least one rule needs to be satisfied.

We learn a distance function $\mathcal{D}(\cdot, \cdot)$ that minimizes all possible PSL rule grounding results, as described in Algorithm 1. $\mathcal{D}(\cdot, \cdot)$ should return 0 if at least one PSL rule is satisfied. The prediction probability $p(y|e_1)$ over head entity e_1 is regarded as the interpretation $I(l_{ent})$ of ground atom l_{ent}, so as $p(y|e_2)$ over tail entity e_2 for $I(l_{re})$ of l_{re}. If no rules are satisfied, the distance is set as 0. We formulate the distance to satisfaction as a regularization term to penalize inconsistent predictions:

$$\mathcal{L}_{OLF} = \sum \mathcal{D}(\mathcal{R}; \{(p(y|e_i), \hat{y}_i)\}), \tag{9}$$

where $p(y|e_i)$ is the softmax probability of $\boldsymbol{z}_{t_i}$ in Equation (4) for position t_i of e_i in $\mathcal{S}$, and $\mathcal{L}_{OLF}$ is the sum of $\mathcal{D}(\cdot, \cdot)$ over all entity-relation pairs (e_1, e_2) in instance $\mathcal{I}$. We finalize a noise-robust loss function by summing up (5), (7) and (9):

$$\mathcal{L} = \mathcal{L}_c + \alpha\mathcal{L}_{BR} + \beta\mathcal{L}_{OLF}, \tag{10}$$

where α, β are two balancing hyper-parameters.

3.3 Self-Adaptive Learning (SAL)

Self-adaptive learning (Jia et al., 2019) aims to iteratively select high-quality instances with informative relation patterns p and entity tags. In each training epoch, more precisely labeled instances are chosen to guide a model to attend to informative evidence for joint extraction. For instance selection, more versatile patterns are required to select clean labels and to discover more confident relation patterns. According to the attention mechanism and entity-relation logic, a trained tagger can tell the importance of each word for identifying the entity pair along with their relationship, and predict reasonable entity-relation label pairs. For instance $\mathcal{I}$, if 1) the model's attention weights do not match the target attention that explains the relation types in $\mathcal{I}$, or 2) its confidence distribution over entity and relation tags violates the logic dependencies, this instance is likely a false alarm. We add up both BR and OLF loss for an instance $\mathcal{I}$ to measure its *fitness* $u(\mathcal{I})$, i.e., how likely it is correctly labeled:

$$u = \sigma[\text{MSE}(\boldsymbol{a}^{\mathcal{I}}, \boldsymbol{a}^{\mathcal{S}}) + \mathcal{D}(\mathcal{R}; \mathcal{I})], \tag{11}$$

where σ is the sigmoid function that bounds u in the range $[0, 1]$. The lower u is, the more confident an instance $\mathcal{I}$ is. We compute fitness scores for all training instances and select those whose score is smaller than a predefined threshold τ.

Because trustable relation labels also indicate trustable entity tags, we further consider *Entity Selection* (ES), i.e., selecting negative instances containing either the head or tail entity corresponding to each relation pattern in the selected positive candidates. Specifically, we consider relation pattern p as the text between two entities in an instance. We build an initial trustable pattern set $\mathcal{P}$ by counting all patterns up and selecting the top 10% frequent patterns for each relation type. Next, we redistribute the training dataset $\mathbf{D}$ based on $\mathcal{P}$, where all positive instances that match patterns in $\mathcal{P}$ as well as negative instances that contain the head entity or tail entity of these patterns are retained to train the model for a few epochs. Finally, we select more reliable instances according to fitness scores over $\mathbf{D}$, from which we extract new trustable patterns to enrich $\mathcal{P}$. These new confident instances are learned in the subsequent iteration. We repeat the above procedure until the validation F1 converges.

4 Experiments

4.1 Datasets and Evaluation

We evaluate the performance of DENRL on two public datasets: (1) **NYT** (Riedel et al., 2010). We use the human-annotated test dataset (Jia et al.,

Method	NYT			Wiki-KBP		
	Prec.	Rec.	F1	Prec.	Rec.	F1
LSTM-CRF (Zheng et al., 2017)	66.73	35.02	45.93	40.14	35.27	37.55
PA-LSTM-CRF (Dai et al., 2019)	37.90	**76.25**	50.63	35.82	45.06	39.91
OneIE (Lin et al., 2020)	52.33	64.40	57.74	36.25	46.51	40.74
PURE (Zhong and Chen, 2021)	53.11	65.84	58.79	38.20	44.89	41.28
CoType (Ren et al., 2017)	51.17	55.92	53.44	35.68	46.39	40.34
CNN+RL (Feng et al., 2018)	40.72	58.39	47.98	36.20	44.57	39.95
PCNN+RL (Qin et al., 2018)	46.84	53.15	49.80	37.75	42.36	39.92
ARNOR (Jia et al., 2019)	59.64	60.78	60.20	39.37	47.13	42.90
FAN (Hao et al., 2021)	58.22	64.16	61.05	38.81	47.14	42.57
SENT (Ma et al., 2021)	63.88	62.12	62.99	41.37	46.72	43.88
Llama-ICL (Pang et al., 2023)	61.81	58.79	60.26	40.52	45.60	42.91
GPT-4-ICL (Pang et al., 2023)	63.04	57.69	60.25	44.14	41.92	43.00
DENRL (triplet)	**69.37**$_{\pm 0.68}$	67.01$_{\pm 0.70}$	**68.17**$_{\pm 0.69}$	**42.49**$_{\pm 0.31}$	**50.78**$_{\pm 0.25}$	**46.27**$_{\pm 0.28}$
DENRL	69.24$_{\pm 0.61}$	66.23$_{\pm 0.44}$	67.70$_{\pm 0.52}$	41.96$_{\pm 0.34}$	50.21$_{\pm 0.26}$	45.72$_{\pm 0.30}$

Table 1: Evaluation results on NYT and Wiki-KBP datasets. Baselines include normal RE methods (the 1st part), DS RE methods (the 2nd part), and ICL method (the 3rd part). We ran the model 5 times to get the average results.

2019) including 1,024 sentences with 3,280 instances and 3,880 quadruplets. The training data is automatically generated by DS (aligning entity pairs from Freebase with handcrafted rules), including 235k sentences with 692k instances and 353k quadruplets. (2) **Wiki-KBP** (Ling and Weld, 2012). Its test set is manually annotated in 2013 KBP slot filling assessment results (Ellis et al., 2013) containing 289 sentences with 919 instances and 1092 quadruplets. The training data is generated by DS (Liu et al., 2017) including 75k sentences with 145k instances and 115k quadruplets.

We evaluate the extracted quadruplets for each sentence in terms of Precision (Prec.), Recall (Rec.), and F1. A quadruplet $\{e_1, tag_1, e_2, re\}$ is marked correct if the relation type re, two entities e_1, e_2, and head entity type tag_1 are all matched. Note that negative quadruplets with "None" relation are also considered for evaluating prediction accuracy. We build a validation set by randomly sampling 10% sentences from the test set.

4.2 Baselines

We compare DENRL with the following baselines:
LSTM-CRF (Zheng et al., 2017) that converts joint extraction to a sequence labeling problem based on a novel tagging scheme.
PA-LSTM-CRF (Dai et al., 2019), which uses sequence tagging to jointly extract entities and overlapping relations.
OneIE (Lin et al., 2020), a table-filling approach that uses an RNN table encoder to learn sequence features for NER and a pre-trained BERT sequence encoder to learn table features for RE.
PURE (Zhong and Chen, 2021), a pipeline approach that uses a pre-trained BERT entity model to first recognize entities and then employs a relation model to detect underlying relations.
CoType (Ren et al., 2017), a feature-based method that handles noisy labels based on multi-instance learning, assuming at least one mention is correct.
CNN+RL (Feng et al., 2018) that trains an instance selector and a CNN classifier using reinforcement learning.
PCNN+RL (Qin et al., 2018), a baseline whose RL method used to detect and remove noise instances is independent of the training of RE systems.
ARNOR (Jia et al., 2019) which uses attention regularization and bootstrap learning to reduce noise for DS RE.
FAN (Hao et al., 2021), an adversarial method including a BERT encoder to reduce noise for DS RE.
SENT (Ma et al., 2021), a negative training method that selects complementary labels and re-labels noisy instances with BERT for DS RE.
Llama-ICL (Pang et al., 2023), we follow the basic prompt with two demonstration examples using Llama, each as a pair of input text and extracted triplets.
GPT-4-ICL (Pang et al., 2023), the same setting as Llama-ICL but with GPT-4 as the backbone.

4.3 Implementation Details

For DENRL and baselines using pre-trained BERT, we use the pre-trained *bert-large-cased* from Hugging Face. For baselines using LSTM, we apply a single layer with a hidden size of 256. We also ex-

Component	Prec.	Rec.	F1
BERT+FC	44.17	72.76	54.97
BERT+CRF	44.98	**74.79**	56.18
+IDR	**73.18**	48.60	58.41
+BR	69.33	54.02	60.72
+OLF	70.89	52.14	60.09
+BR+OLF	71.35	56.29	62.93
+BR+SAL	70.62	62.84	66.50
+OLF+SAL	70.81	59.76	64.82
+BR+OLF+SAL (DENRL)	69.37	67.01	**68.17**

Table 2: Ablation study of components in DENRL. BERT+FC and BERT+CRF are two backbone models. IDR denotes initial data redistributing using the initial pattern set. BR and OLF are only for the first loop.

Method	Prec.	Rec.	F1
w/o ES	67.39	**67.04**	67.21
DENRL	**69.37**	67.01	**68.17**

Table 3: Comparison of Precision, Recall, and F1 after using Entity Selection (ES) during SAL.

tend DENRL to two other backbones: T5 and GPT-2, and demonstrate the generalizability of DENRL in Appendix C. For Llama-ICL, we use Llama-2-7B (Touvron et al., 2023). The prompt configuration and training setup for both Llama-2 and GPT-4 are detailed in Appendix A.

4.4 Overall Results

As shown in Table 1, DENRL (triplet) denotes ignoring head entity type tag_1 when computing correctness, because all baselines only extract triplets $\{e_1, e_2, re\}$. The results of triplet and quadruplet have little difference, indicating that DENRL predicts precise entity types. DENRL significantly outperforms all baselines in precision and F1 metrics. Specifically, it achieves roughly 5∼20% F1 improvement on NYT (3∼6% on Wiki-KBP) over the other denoising methods—CoType, CNN+RL, ARNOR, FAN, SENT. Compared to LSTM-CRF which also trains on selected subsets, DENRL achieves 31% recall improvements on NYT (15% on Wiki-KBP) with still better precision, suggesting that we explore more diverse entity and relation patterns. Compared to the sequence tagging approach PA-LSTM-CRF, DENRL achieves improvements of 32% in precision and over 18% F1 improvement. DENRL also outperforms baselines using pre-trained transformers (OneIE, PURE, FAN, SENT) or LLMs (Llama-2-ICL, GPT-4-ICL), showing our noise-robust learning effectively reduces the impact of mislabeled instances on joint extraction performance.

4.5 Ablation Study

We investigate the effectiveness of several components of DENRL on NYT dataset, as shown in Table 2. Before noise reduction, we first evaluate the impact of CRF layer by substituting it with an FC layer. We found it improves the final performance by over 1% F1. We then build an initial redistributed dataset (via IDR), which helps the joint model earn over 2% improvement in F1 and a sharp 28% precision increase compared to BERT+CRF. This suggests the original DS dataset contains plenty of noise, thus a simple filtering method would effectively improve the performance.

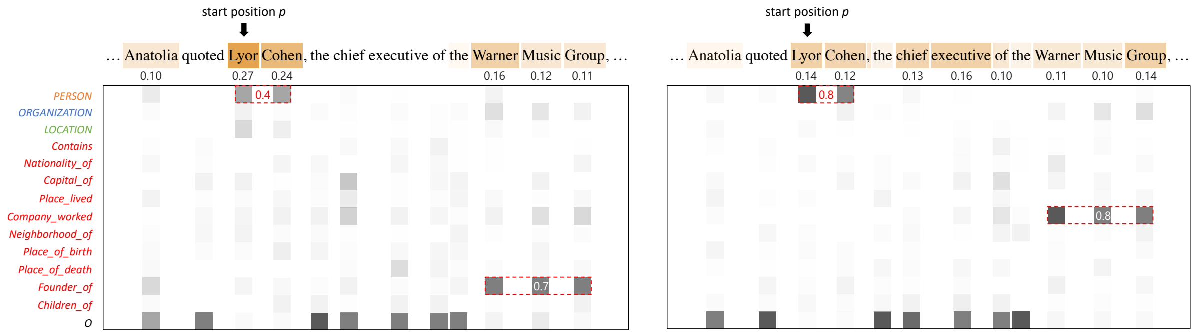
However, this initial data induces poor recall performance, which means a large proportion of true positives with long-tail patterns are mistakenly regarded as false negatives. Assuming that some relation patterns in the training data are too rare to guide the model to learn to attend them, we employ BR to training and achieve 5% recall increases with a slight decline in precision, inducing another 2% F1 improvement. This shows the effect of guiding the model to understand important feature words for identifying relations.

After we introduce OLF to training, both precision and recall improve by about 2%, leading to another 2% F1 improvement, proving that logic rules guide a model to learn the entity-relation dependencies and further reduce entity labeling noise.

After we obtain an initial model trained by BR and OLF, we continue SAL where DENRL collects more confident long-tail patterns to mitigate false negatives and finally achieves 5% F1 improvement. We observe that BR better facilitates SAL than OLF regarding the recall increase, as BoW helps explore more high-quality relation instances and reduces false negatives. Additionally, BR+OLF outperforms both BR and OLF. This proves our assumption that significant relation patterns and entity-relation dependencies can reinforce each other during training, i.e., understanding significant relation patterns facilitates the predictions of correct entity-relation dependencies, and vice versa.

4.6 Interpretability Study

To understand the effect of attention and logic guidance, we select some instances from the test set and visualize their attention weights, as well as the model's softmax probability distribution over all la-



(a) BERT+CRF

(b) DENRL

Figure 4: Attention heat maps (top) and softmax probability heat maps (bottom). In this case, e_1: Lyor Cohen, e_2: Warner Music Group, and re: *Company_worked*. BERT+CRF misclassifies the relation as *Founder_of*, because it only attends to entities. DENRL can locate relation indicators and make correct predictions.

bels. As shown in Figure 4, BERT+CRF, which is trained on original noisy data without BR or OLF, only focuses on entity pairs and makes wrong predictions. Its logic distance for r : *Founder_of* $\rightarrow$ *PERSON* is $d_r(I) = \max\{0, 0.7 - 0.4\} = 0.3$. While DENRL precisely captures important words and correctly predicts the relation. The logic distance for r : *Company_worked* $\rightarrow$ *PERSON* is $d_r(I) = \max\{0, 0.8 - 0.8\} = 0 < 0.3$, suggesting the effect of OLF.

Suppose the start position is at "Lyor", for a target position at "Warner", the model should pay more attention to (1) the pattern words "chief executive of" to determine their correct relation type *Company_worked*, and (2) the entity words "Lyor Cohen" to determine the correct head entity type. This is exactly how attention guidance is built in BR. During BR, for the relation *Company_worked*, its pattern set contains corresponding patterns, e.g., {*'CEO at', 'manager in', 'chief executive of', ...*} and the BoW will count tokens and their frequencies, e.g., {*'chief': 8, 'manager': 14, 'at': 7, 'of': 16,* }. Consequently, the guidance scores for the words "chief", "executive", and "of" become large (after softmax computation) as they appear in the BoW with high frequencies. Also, the head entity tokens "Lyor", and "Cohen" will be given a score of 1. In this way, both "Lyor Cohen" and "chief executive of" will be assigned a high guidance score, and we want the model's attention to approximate such guidance distribution (by minimizing their discrepancy) so that it can better identify correct relations.

We further check the performance of DENRL on negative test cases that do not contain relations from NYT dataset. After selecting confident candidates in each epoch, we further choose additional trustable negative instances that contain either the head or tail entity corresponding to each relation pattern in the selected positive candidates during bootstrap. We compare the results between methods with and without entity selection, as shown in Table 3. The improved performance with ES demonstrates that a trustable relation pattern also indicates reliable entity labels, and partially explains the overall superiority of DENRL.

Method	NYT	Wiki-KBP
BERT+CRF	0.78	0.70
T5+CRF	0.89	0.82
GPT-2+CRF	0.94	0.88
LSTM-CRF	**0.27**	**0.21**
PA-LSTM-CRF	0.35	0.33
OneIE	0.32	0.28
PURE	0.85	0.79
ARNOR	0.43	0.39
FAN	<u>1.62</u>	<u>1.59</u>
SENT	1.43	1.36
DENRL	1.39	1.07

Table 4: Comparison of training efficiency (GPU hours) between baselines and SAL training of DENRL with different backbones. **Bold** and <u>underline</u> denote most efficient and time-consuming methods.

4.7 Efficiency Analysis

While DENRL considers the position-attentive loss calculated through traversing transformer logits on different start positions, it does not significantly inflate the training overhead. For a sentence of n tokens, the time-intensive self-attention operations (squared complexity) are executed just once per sentence. The resultant hidden outputs are used to perform self-matching and CRF decoding regarding each start token, which also has an $O(n^2)$

complexity but with few extra trainable parameters introduced. This layered approach ensures a manageable overall computational overhead. Table 4 shows the average GPU hours per training epoch for each method. We observe that DS methods consume more time compared to their normal counterpart, e.g., ARNOR takes up to $\times 1.6$ the overhead of LSTM-CRF. DENRL, though consumes more time compared to BERT+CRF, is more efficient than other DS methods using PLMs.

5 Related Work

Joint extraction. Entities and relations extraction is important to construct a KB. Traditional methods treat this problem as two separate tasks, i.e., NER and RE. Joint extraction detects entities and their relations using a single model which effectively integrates the information of entities and relations, and therefore achieves better results in both subtasks (Zheng et al., 2017). Among them, unified methods tag entities and relations simultaneously, e.g., Zheng et al. (2017) propose a novel tagging scheme that converts joint extraction to a sequence labeling problem; Dai et al. (2019) introduce query position and sequential tagging to extract overlapping relations. These methods avoid producing redundant information compared to the parameter-sharing neural models (Gupta et al., 2016) and require no hand-crafted features that are used in the structured systems (Yu et al., 2020; Ren et al., 2017).

LLMs in open-domain IE. LLMs have shown significant promise in the field of open-domain Information Extraction (IE). Recent surveys (Xu et al., 2023) have highlighted the diverse prompts, paradigms, backbones, and datasets employed in this domain. These studies reveal that LLMs, through their ability to understand and generate human-like text, can effectively extract structured information from unstructured data sources across various domains (Pang et al., 2023). The adaptation of LLMs to different IE tasks, including NER, RE, and event extraction, demonstrates their versatility and effectiveness. Moreover, the integration of LLMs with prompt-based learning paradigms has further enhanced their performance by leveraging the contextual knowledge embedded within these models.

Distantly supervision. Previous studies on distantly-supervised NER rely on simple tricks such as early stopping (Liang et al., 2020) and multi-type entity labeling (Shang et al., 2018; Meng et al., 2021). For distantly-supervised RE, existing methods include multi-instance learning (Lin et al., 2016) that models noise problem on a bag of instances, reinforcement learning (RL) (Nooralahzadeh et al., 2019; Hu et al., 2021), adversarial (Chen et al., 2021; Hao et al., 2021) or probabilistic learning (Liu et al., 2022; Li et al., 2023b) that selects trustable instances, and pattern-based methods (Ratner et al., 2016; Shang et al., 2022) that directly model the DS labeling process to find noise patterns, e.g., Feng et al. (2018) propose a pattern extractor based on RL and use extracted patterns as features for RE.

Probabilistic soft logic. In recent years, PSL rules have been applied to machine learning topics, including model interpretability (Hu et al., 2016), probability reasoning (Dellert, 2020), sentiment analysis (Gridach, 2020), and temporal relation extraction (Zhou et al., 2021). We are the first to model entity-relation dependencies by designing ontology-based PSL.

6 Conclusions

We propose DENRL, a noise-robust learning framework for distantly-supervised joint extraction, which consists of a transformer backbone, a new loss function and a self-adaptive learning step. Specifically, we use Bag-of-word regularization and logic fusion to learn important relation patterns and entity-relation dependencies. The regularized model is able to select trustable instances and build a versatile relation pattern set. A self-adaptive learning procedure then iteratively improves the model and dynamically maintains trustable pattern set to reduce both entity and relation noise. In the future, we aim to explore more complex patterns when configuring pattern sets. We will also evaluate our framework on other tasks such as event extraction and open information extraction.

Limitations

We incorporate a BERT backbone into a sequence tagging scheme for distantly-supervised joint extraction. While our current framework is built upon BERT due to computation resource constraints, it's designed with flexibility in mind. It can be easily adapted to other transformers such as GPT-2, T5, and even LLMs like Llama2, as the only difference is the computation of the transformer's final representations, which is the very first step before our architecture designs. Though achieving state-of-the-art performance compared to other DS methods, DENRL can be computation costly due to the position-attentive loss computed on multiple start positions. We further conduct an efficiency analysis in Section 4.7, demonstrating a relatively small training overhead of DENRL compared to other DS methods using PLMs.

Moreover, we focus on relations within a sentence and regard words between an entity pair as relation patterns. In our future work, we aim to consider relations beyond the sentence boundary for DS joint extraction to better adapt to real-world information extraction scenarios.

Furthermore, although our OLF is a one-time effort and can benefit future training, it is still handcrafted based on ontology, and we aim to design a probabilistic method such as model uncertainty to quantify more comprehensive underlying relation-entity dependencies in the future.

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Method	ACE05			SciERC		
	Prec.	**Rec.**	**F1**	**Prec.**	**Rec.**	**F1**
Llama-ICL	63.57	68.80	66.08	42.71	47.89	45.15
DENRL	69.41	73.03	71.17	49.36	51.52	50.42

Table 5: Performance comparison of LLM-ICL and DENRL on ACE05 and SciERC datasets.

A Implementation Details

A.1 Prompt for ICL

For the two ICL-based baselines (Pang et al., 2023), we apply the following prompt template:

- **Instruction** (depends on datasets): "Please solve the relation extraction task. Given a context, extract all the relation triplets (head entity, relationship, tail entity), where the relationship belongs to [relation ontology]./n"
- **Demonstrations** (examples): "[context 1] → [extracted triplets list 1]; [context 2] → [extracted triplets list 2] .../n"
- **Prefix**: "Context:/n"

We create the prompt using the template: [Instruction] + [Demonstrations] + [Prefix] + [Input context] to the Llama-2 for ICL and compare the quality of extracted triplets.

A.2 Training Setup

We tune hyperparameters on the validation set via grid search. Specifically in regularization training, we find optimal parameters α and β as 1 and 0.5 for our considered datasets. We implement DENRL and all baselines in PyTorch, using the AdamW (Loshchilov and Hutter, 2019) optimizer with a learning rate of 5e-4, a dropout rate of 0.2, and a batch size of 8. For instance selection, an empirical fitness threshold is set to 0.5 with the best validation F1. We take a maximum of 5 new patterns in a loop for each relation type. In the SAL stage, we run 5 epochs in the first loop, and 1 epoch in every rest loop until the validation performance converges. We conduct experiments and record overhead on the NVIDIA A6000 Ada server.

B Study on normal IE datasets

We also evaluate DENRL and Llama-ICL in two popular IE datasets—ACE (Walker and et al., 2006) and SciERC (Luan et al., 2018). As shown in Table 5, we observe that DENRL still achieves a significant (over 5%) improvement in F1 over Llama-ICL, suggesting the generalizability and robustness of our methodology across diverse datasets. We will enrich the evaluation in our final version with the new results.

T5-base	BERT-large	GPT2-medium	Llama2-7B
220M	334M	355M	7B

Table 6: Number of parameters of different backbones.

Method	Prec.	Rec.	F1
T5+CRF	44.73	**75.31**	56.12
GPT-2+CRF	45.11	75.19	56.40
BERT+CRF	44.98	74.79	56.18
DENRL w/ T5	69.05	67.28	68.15
DENRL w/ GPT-2	**70.72**	66.49	**68.60**
DENRL	69.37	67.01	68.17

Table 7: Comparison of results on the NYT dataset using different backbones for both normal RE and DS RE settings.

C Generalizability across Backbones

To demonstrate the generalizability of our noise reduction approach, we extend DENRL to additional two transformer backbones: T5 (Raffel et al., 2020) and GPT-2 (Radford et al., 2019). Table 6 illustrates the concrete PLMs and their number of parameters for a rather fair comparison. As shown in Table 7, we can see DENRL with different backbones all achieve around 68% F1 score on the NYT dataset, significantly outperforming existing methods. This consistent superiority highlights that the efficacy of our method is agnostic to the backbone selection.

D OLF Rules

We create the OLF rules based on human annotation, as in this work we focus on open-domain IE scenarios and it is straightforward to identify such logic dependencies (apparently, this method can be substituted by querying LLM for domain-specific scenarios if human expertise is not available). Table 8 and Table 9 summarize our OLF rules for the NYT and Wiki-KBP datasets, respectively. Our OLF can be easily built given the target dataset. It is a one-time effort and can be reused for subsequent fine-tuning.

E Case Study

To show that BR explores versatile patterns to enrich pattern set $\mathcal{P}$, we summarize both high-frequency patterns obtained by IDR and meaning-

RELATION	(Head) ENTITY
/people/person/nationality	PERSON
/people/deceased_person/place_of_death	PERSON
/location/country/capital	LOCATION
/location/location/contains	LOCATION
/people/person/children	PERSON
/people/person/place_of_birth	PERSON
/people/person/place_lived	PERSON
/location/administrative_division/country	LOCATION
/location/country/administrative_divisions	LOCATION
/business/person/company	PERSON
/location/neighborhood/neighborhood_of	LOCATION
/business/company/place_founded	ORGANIZATION
/business/company/founders	ORGANIZATION
/sports/sports_team/location	ORGANIZATION
/sports/sports_team_location/teams	LOCATION
/business/company_shareholder/major_shareholder_of	PERSON
/business/company/major_shareholders	ORGANIZATION
/people/person/ethnicity	PERSON
/people/ethnicity/people	LOCATION
/business/company/advisors	ORGANIZATION
/people/person/religion	PERSON
/people/ethnicity/geographic_distribution	LOCATION
/people/person/profession	PERSON
/business/company/industry	ORGANIZATION

Table 8: Logic rules r : RELATION $\rightarrow$ ENTITY based on the NYT ontology.

RELATION	(Head) ENTITY
per:country_of_birth	PERSON
per:countries_of_residence	PERSON
per:country_of_death	PERSON
per:children	PERSON
per:parents	PERSON
per:religion	PERSON
per:employee_or_member_of	PERSON
org:founded_by	ORGANIZATION
org:parents	ORGANIZATION
org:shareholders	ORGANIZATION
org:subsidiaries	ORGANIZATION
org:member_of	ORGANIZATION

Table 9: Logic rules r : RELATION $\rightarrow$ ENTITY based on the Wiki-KBP ontology.

RELATION: *Contains* (left: u, right: pattern)	
0.749	e_2, *section of* e_1
0.692	e_2, *the capital of* e_1
...	...
0.548	e_2, *district of* e_1
0.554	e_2 *and other areas of* e_1
0.539	e_2 *and elsewhere in the* e_1
RELATION: *Company_worked* (left: u, right: pattern)	
0.667	e_1, *the chief executive of* e_1
0.673	e_2 *attorney general,* e_1
...	...
0.595	e_1, *the president of the* e_2
0.513	e_1, *an economist at the* e_2
0.526	e_1, *the chairman and chief executive of* e_2

Table 10: Pattern examples including high-frequency and top long-tail patterns (right) and corresponding average fitness scores (left).

ful long-tail patterns discovered during SAL, and statistic their average fitness (see Table 10). Some long-tail patterns are not similar syntactically but still have over 0.5 average fitness scores, meaning the model learns useful semantic correlations between related feature words.