Joint Extraction of Entities, Relations, and Events via Modeling Inter-Instance and Inter-Label Dependencies

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Abstract

Event trigger detection, entity mention recognition, event argument extraction, and relation extraction are the four important tasks in information extraction that have been performed jointly (Joint Information Extraction - JointIE) to avoid error propagation and leverage dependencies between the task instances (i.e., event triggers, entity mentions, relations, and event arguments). However, previous JointIE models often assume heuristic manually-designed dependency between the task instances and mean-field factorization for the joint distribution of instance labels, thus unable to capture optimal dependencies among instances and labels to improve representation learning and IE performance. To overcome these limitations, we propose to induce a dependency graph among task instances from data to boost representation learning. To better capture dependencies between instance labels, we propose to directly estimate their joint distribution via Conditional Random Fields. Noise Contrastive Estimation is introduced to address the maximization of the intractable joint likelihood for model training. Finally, to improve the decoding with greedy or beam search in prior work, we present Simulated Annealing to better find the globally optimal assignment for instance labels at decoding time. Experimental results show that our proposed model outperforms previous models on multiple IE tasks across 5 datasets and 2 languages.

1 Introduction

To extract structured information from unstructured text, a typical information extraction (IE) pipeline involves four major tasks: event trigger detection (ETD), event argument extraction (EAE), entity mention recognition (EMR), and relation extraction (RE). Previous work has performed such IE tasks via pipelined approaches (Li et al., 2013; Chen et al., 2015; Du and Cardie, 2020; Li et al., 2020), where a model for one task uses output predictions from other models performing other tasks. Consequently, errors from the predictions can be propagated between the models in the pipeline.

Recently, ETD, EMR, EAE, and RE have been solved jointly in a single model, i.e., Joint Information Extraction - JointIE (Wadden et al., 2019; Lin et al., 2020; Nguyen et al., 2021a; Zhang and Ji, 2021), to avoid error propagation and leverage dependency between prediction instances of the four IE tasks (i.e., event trigger, entity mention, relation, and event argument candidates in a sentence). For example, if a Person entity mention is a Victim argument for a Die event, it is likely that the same entity mention is also a Target argument for an Attack event in the same sentence. To implicitly exploit instance dependency for representation learning, Wadden et al. (2019) and Lin et al. (2020) employ a shared encoder to obtain representation vectors to classify instances of different IE tasks. Later work heuristically captures dependency between IE task instances via explicitly connecting the task instances that share an entity mention or event trigger (Nguyen et al., 2021a) or aligning the task instances that share text spans with some nodes on a semantic graph (Zhang and Ji, 2021) to aid representation learning. While natural, these manual designs for dependency between task instances might not be optimal for representation learning of JointIE.

In addition to representation learning, at the prediction level, previous work tends to factorize the joint distribution of labels for all the task instances in JointIE into the product of label distributions for each individual instance (i.e., performing local normalization), thus hindering the ability to fully exploit the interactions of instance labels across IE tasks. (Lin et al., 2020) and (Zhang and Ji, 2021) mitigate this problem by decoding instance labels with handcrafted global features while (Nguyen et al., 2021a) focuses on encoding label interactions via consistency regularization over global type dependency graphs. However, these approaches still
One house was destroyed during the strike and casualties have been removed from the area.

In this work, we propose a novel decoding algorithm for JointIE via Simulated Annealing (SA) (Kirkpatrick et al., 1983), which has been shown to be able to approximate the global optimum of a function (Kirkpatrick et al., 1983; Van Laarhoven and Aarts, 1987). Experimental results show that our proposed model for JointIE significantly outperforms previous models on multiple tasks with large margins across 5 datasets and 2 languages.

2 Problem Statement

Given an input sentence, ETD aims to predict text spans and event types for event triggers based on a predefined set of event types, e.g., “Attack” and “Transport” (Lai et al., 2020). Similarly, EMR seeks to determine text spans and entity types (e.g., “Person”, “Organization”) for entity mentions in the sentence (Nguyen et al., 2016b). Different from the
first two tasks, EAE and RE involves predictions for a pair of objects at a time. Given an event trigger and an entity mention, EAE aims to predict the argument role (e.g., “Victim”) of the entity mention for the event trigger (Veyseh et al., 2020c). An argument role can be “Not-an-argument” indicating that the entity mention is not an argument for the trigger. For RE (Veyseh et al., 2020a,b), the task focuses on the classification of relation (e.g., “Work for”) for a given pair of entity mentions. There is also a special type “No-relation” to specify no relation between two entity mentions. As such, we call the union set \( C \) of the predefined event types, entity types, argument roles, and relation types as the information types (excluding “Not-an-argument” and “No-relation”).

3 Model

To capture dependency among task instances for JointIE, an approach is to obtain all text spans for entity/event mention candidates along with their possible pairs to form the nodes for a dependency graph to improve representation learning. However, this approach will retain many text spans for non-entity/event mentions to introduce noise into the modeling. It will also entail a large dependency graph that can hinder the efficiency of the model. To this end, our model for JointIE first identifies text spans for entity mentions and event triggers. Afterwards, all possible pairs of event-entity and entity-entity mentions are considered to identify positive pairs for event arguments and relations respectively. The detected entity mentions, event triggers, event arguments, and relations are called task instances that should be classified to different CRF layers (Lafferty et al., 2001; Chiu and Nichols, 2016) to compute two distributions for the tag sequences of \( w \) for event triggers and event mentions. The negative log-likelihoods \( L_t \) and \( L_e \) for golden trigger and entity tag sequences are then obtained to be included in the overall training loss. At test time, the Viterbi algorithm (Forney, 1973) is employed to determine the best tag sequences for event triggers and event mentions in \( w \).

Let \( V^t \) and \( V^e \) be the sets of text spans for event triggers and entity mentions respectively in \( w \) (i.e., golden spans in the training time and predicted spans in the test time). To prepare for the next components, we compute the representations vectors \( \mathbf{z}^t_i \) and \( \mathbf{z}^e_j \) for each event trigger/instance \( t_i \in V^t \) and entity mention/instance \( e_j \in V^e \) respectively by averaging over the contextualized embeddings of the words inside the spans.

3.2 Identifying event arguments and relations

Given the detected event triggers and entity mentions, we obtain a representation vector \( \mathbf{z}^t_{ij} \) for each pair of event-entity mentions \( a_{ij} = (t_i, e_j) \) (i.e., \( t_i \in V^t \), \( e_j \in V^e \)), and a representation vector \( \mathbf{z}^e_{ij} \) for each pair of entity-entity mentions \( r_{ij} = (e_i, e_j) \) (i.e., \( e_i, e_j \in V^e \)) via:

\[
\mathbf{z}^t_{ij} = \text{FFN}_{\text{down}}(\text{concat}(\mathbf{z}^t_i, \mathbf{z}^t_j)) \quad \text{and} \quad \mathbf{z}^e_{ij} = \text{FFN}_{\text{down}}(\text{concat}(\mathbf{z}^e_i, \mathbf{z}^e_j)).
\]

Here, we use the feed-forward networks \( \text{FFN}_{\text{down}} \) and \( \text{FFN}_{\text{down}} \) to make sure that \( \mathbf{z}^t_i \), \( \mathbf{z}^e_i \), \( \mathbf{z}^t_{ij} \), and \( \mathbf{z}^e_{ij} \) have the same dimensionality. Next, the pair representation vectors \( \mathbf{z}^a_{ij} \) and \( \mathbf{z}^r_{ij} \) are sent into two different feed-forward networks followed by sigmoid activations to compute the possibilities for being positive examples for event arguments and relations of \( a_{ij} \) and \( r_{ij} \) respectively:

\[
p^a_{ij} = \sigma(\text{FFN}^a(\mathbf{z}^a_{ij})), \quad \text{and} \quad p^r_{ij} = \sigma(\text{FFN}^r(\mathbf{z}^r_{ij})).
\]

Here, \( p^a_{ij}, p^r_{ij} \in [0, 1] \) is the probability for the entity mention \( e_j \) being an actual argument for the
event trigger \( t_i \) while \( p_{ij}^t \in (0, 1) \) is the likelihood that there exists a relation of interest between the entity mentions \( e_i \) and \( e_j \). At training time, we obtain the the negative log-likelihoods \( L_{a} \) and \( L_{r} \) for the golden event argument and relation identification to be included in the overall loss function for minimization. At test time, the event-entity pair \( a_{ij} \) and entity-entity pair \( r_{ij} \) are retained as positive examples for event arguments and relations if their likelihoods \( p_{ij}^a \) and \( p_{ij}^r \) are greater than 0.5.

For convenience, let \( V^a \) and \( V^r \) be the sets of positive event-entity pairs \( a_{ij} \) (called argument instances) and entity-entity pairs \( r_{ij} \) (called relation instances) respectively. Also, let \( V = V^a \cup V^r \cup V^a \cup V^r \) be the set of all detected event, entity, argument, and relation instances. For each instance \( v_i \in V \), we will use \( \mathbf{v}_i \) for its corresponding instance representation (i.e., from \( z_i^s, z_i^j, z_i^t, \) or \( z_i^r \)).

### 3.3 Inducing Instance Dependency

Given the detected event, entity, argument, and relation instances in \( V \), it remains to predict the information types in \( C \) for the instances to solve JointIE. While it is possible to directly employ the instance representations \( \mathbf{v}_i \) for label prediction, our goal is to exploit instance dependency in IE to enhance the representation vector for one instance with the information from other instances to facilitate type prediction. In particular, using the instances \( v_i \) in \( V \) as the nodes in a dependency graph \( G \), we aim to enrich instance representations by feeding them into a GCN model. As such, instead of assuming a heuristically manually-designed dependency graph among the instances as in previous work (Zhang and Ji, 2021; Nguyen et al., 2021a), we propose to automatically learn the dependency graph \( G \) for the instances in \( V \). To this end, our dependency graph \( G \) is a fully connected graph among the nodes in \( V \) where a weight \( \alpha_{ij} \in (0, 1) \) is learned for each edge to quantify the dependency between the instances \( v_i \) and \( v_j \) in \( V \). In this work, we present two sources of information that can be used for determining the dependency between the task instances: (i) semantic and (ii) syntactic information.

#### Semantic Information: The semantic-based weight \( \alpha_{ij}^{sem} \) for the edge between \( v_i \) and \( v_j \) quantifies their relatedness/dependency based on semantic information, i.e., via the representation vectors \( \mathbf{v}_i \) and \( \mathbf{v}_j \): \( \alpha_{ij}^{sem} = FFN^{sem}(\text{concat}(\mathbf{v}_i, \mathbf{v}_j)) \). Here, \( FFN^{sem} \) is a feed-forward network with the sigmoid function in the end.

#### Syntactic Information: The syntax-based weight \( \alpha_{ij}^{syn} \) for the edge between \( v_i \) and \( v_j \) is computed in a similar way as \( \alpha_{ij}^{sem} \). In particular, for each word \( w_k \in \mathbf{w} \), we retrieve the dependency relation \( d_k \) between \( w_k \) and its governor in the dependency tree of \( \mathbf{w} \), which is generated by the TranKit’s dependency parser (Nguyen et al., 2021b). We then obtain the embedding \( \mathbf{m}_k \) of \( d_k \) by looking up the learnable dependency embedding matrix \( \mathbf{M} \). Afterwards, the syntax-based representation vector \( \mathbf{u}_i \) for the instance \( v_i \in V \) is computed via: \( u_i = \max\text{-pool}_{w_k \in \text{SPAN}(\mathbf{v}_i)}(\mathbf{m}_k) \). Here, \( \text{SPAN}(\mathbf{v}_i) \) involves the words in the corresponding text span of \( v_i \) in \( \mathbf{w} \) if \( v_i \) is an event trigger or entity mention instance. Otherwise, \( \text{SPAN}(\mathbf{v}_i) \) contains the words inside the text spans of the involving event triggers and entity mentions in the pair for \( v_i \). As such, we compute the syntax-based dependency weight \( \alpha_{ij}^{syn} \) for \( v_i \) and \( v_j \) via: \( \alpha_{ij}^{syn} = FFN^{syn}(\text{concat}(\mathbf{u}_i, \mathbf{u}_j)) \) where \( FFN^{syn} \) is also a feed-forward network with the sigmoid function in the end. Finally, we combine the semantic- and syntax-based weights to obtain the overall dependency weight \( \alpha_{ij} \) for \( v_i \) and \( v_j \) in \( V \): \( \alpha_{ij} = (\alpha_{ij}^{sem} + \alpha_{ij}^{syn})/2 \).

### 3.4 Enhancing Representations with GCNs

To enhance the representation vectors for the instances \( v_i \in V \), a GCN model with \( K \) layers is applied over the induced dependency graph \( G \) to compute richer representations for the instances:

\[
h_k^i = \text{ReLU} \left( \frac{\sum_{v_j \in V} \alpha_{ij}W^k_{ij}h_{k-1}^j + b^k}{\sum_{v_j \in V} \alpha_{ij}} \right), 1 \leq k \leq K \tag{1}
\]

Here, \( h_k^i \) is the representation for the instance \( v_i \) at the \( k \)-th layer of the GCN (\( h_0^i \cong \mathbf{v}_i \)), and \( W^k, b^k \) are trainable weight and bias for the layer.

In this way, representation information from all the other instances \( v_j \ (j \neq i) \) will be incorporated into the enhanced representation vector for \( v_i \) according to their learned dependency weights. Finally, the last layer’s representation \( h_K^i \cong \mathbf{h}_i \) (we omit \( K \) for simplicity) is used to compute the score vector \( \mathbf{s}_i \in \mathbb{R}^{|C|} \) for \( v_i \), where \( s_i[c] \) measure the possibility for \( v_i \) to have the \( c \)-th label in the label set \( C \): \( s_i = FFN^{score}(\mathbf{h}_i) \) (\( FFN^{score} \) is a scoring feed-forward network). The score vectors \( \mathbf{s}_i \) will later be used for modeling the joint distribution of the labels for all the instances in \( V \).

### 3.5 Computing Joint Distribution of Labels

Let \( Y \) be the set of labels \( y_i \) for the instances \( v_i \in V \). To infer the labels for the instances in \( V \), we
need to estimate the joint distribution \( P(Y|w, V) \). In previous work (Wadden et al., 2019; Lin et al., 2020; Nguyen et al., 2021a; Zhang and Ji, 2021), JointIE methods mostly focus on learning representations for the task instances to compute a label distribution for each instance \( v_i \) for prediction: \( P(y_i|w, V) := \text{softmax}(s_i) \). This practice essentially implies the following factorization for \( P(Y|w, V) \): \( P(Y|w, V) = \prod_{v_i \in V} P(y_i|w, V) \). As a result, this factorization assumes the independence of the instance labels, thus unable to fully capture beneficial label dependency for IE tasks.

To address this issue, we directly estimate the joint distribution \( P(Y|w, V) \) so that the dependency between instance labels can be facilitated to improve prediction performance. To this end, we formulate the joint distribution \( P(Y|w, V) \) with Conditional Random Fields (Lafferty et al., 2001):

\[
P(Y|w, V) = \frac{1}{Z(V)} \prod_{(v_i, v_j)} \psi_{ij}(y_i, y_j, V) \tag{2}
\]

where \( \psi_{ij}(y_i, y_j, V) \) is a positive potential function defined on the edge \((v_i, v_j)\) of the dependency graph \(G\), and \(Z(V) = \sum_{Y' \in C_V} \prod_{(v_i, v_j)} \psi_{ij}(y'_i, y'_j, V)\) is the normalization term to make sure that \( P(Y|w, V) \) is a valid probability distribution \((C_V\) is the set of all possible label assignments \(Y\) for the instances in \(V\)). Considering the instance information, the instance dependency, and the label dependency, we propose the potential function as:

\[
\psi_{ij}(y_i, y_j, V) := \exp(s_i[y_i] + s_j[y_j] + \alpha_{ij}\pi_{y_i \rightarrow y_j}) \tag{3}
\]

where \( s_i[y_i] \) is the local score for instance \( v_i \) being assigned with the label \( y_i \), \( \alpha_{ij} \) is the induced dependency weight for the edge \((v_i, v_j)\) in \(G\), and \( \pi_{y_i \rightarrow y_j} \) is a learnable transition score indicating the dependency between the labels \( y_i \) and \( y_j \). With this formulation, we can derive the joint distribution \( P(Y|w, V) \):

\[
P(Y|w, V) = \frac{\exp(s(Y))}{\sum_{Y' \in C_V} \exp(s(Y'))} \tag{4}
\]

where:

\[
s(Y) = \gamma \sum_{v_i \in V} s_i[y_i] + \sum_{(v_i, v_j)} \alpha_{ij}\pi_{y_i \rightarrow y_j} \tag{5}
\]

is the global score for the label assignment/configuration \( Y \) of the instances. \( \gamma \) is a hyperparameter to balance the local and transition scores.

To train the model, we need to maximize the joint likelihood in Equation (4) for the golden label configuration \( Y^\star \). However, this requires the computation of the normalization term \( \sum_{Y' \in C_V} \exp(s(Y')) \), which is intractable. To overcome this issue, we employ Noise Contrastive Estimation (NCE) (Gutmann and Hyvärinen, 2012; Mikolov et al., 2013). NCE converts the maximization problem into the nonlinear logistic regression that discriminates between the golden label configurations and the noise label configurations. In particular, the maximization of \( P(Y^\star|w, V) \) is done with NCE via minimizing the contrastive loss:

\[
L_{NC} = -\log \sigma(s(Y^\star)) - \sum_{n=1}^{N_{noi}} \mathbb{E}_{Y_n \sim P_{noi}} \left[ \log \sigma(-s(Y_n')) \right] \tag{6}
\]

where \( \sigma \) is the sigmoid function and \( N_{noi} \) is the number of noise configurations \( Y_n' \) drawn from \( P_{noi} \), assumed to be a uniform distribution. Intuitively, the minimization of \( L_{NC} \) increases the global score \( s(Y^\star) \) for the true label configuration \( Y^\star \) while decreasing the global scores \( s(Y') \) for the noise label configurations \( Y' \) to appropriately train the model. To the end, the overall loss function to train our model is: \( L = L_t + L_e + L_a + L_r + L_{NC} \).

\[\textbf{Algorithm 1: Simulated Annealing Search}\]

\begin{algorithmic}[1]
\State Input: \( Y_0 \) where \( y_{i,0} = \text{argmax}_{c \in C} s_i[c] \).
\State \( Y_{cur} \leftarrow Y_0; n \leftarrow 1 \);
\While {\( n \le N_{iter} \)}
\State \( t \leftarrow T/n ;\)
\If {\( t < \epsilon \)}
\State return \( Y_{cur} \);
\Else \( Y_{new} = \text{random successors}(Y_{cur});\)
\State \( \delta_n = s(Y_{new}) - s(Y_{cur});\)
\If {\( \delta_n > 0 \)}
\State \( Y_{cur} \leftarrow Y_{new};\)
\Else \( Y_{cur} \leftarrow Y_{new} + p = \exp(\delta_n);\)
\EndIf
\State \( n \leftarrow n + 1;\)
\EndIf
\EndWhile
\State return \( Y_{cur} \).
\end{algorithmic}

### 3.6 Joint Decoding via Simulated Annealing

At inference time, we need to search for the configuration \( \hat{Y} \) that has the highest global score \( s(\hat{Y}) \) in \( C_V \): \( \hat{Y} = \text{argmax}_{Y' \in C_V} s(Y') \). A brute-force search for \( \hat{Y} \) cannot be done as the search space \( C_V \) is exponentially large \((|C_V| = |C|^{|V|})\). Previous work has made several attempts to deal with this issue. (Wadden et al., 2019) and (Nguyen et al., 2021a) simply perform greedy decoding for each
instance label independently, thus unable to exploit the label dependency. (Lin et al., 2020) and (Zhang and Ji, 2021) resort to beam search that step by step constructs a complete decoding assignment $Y$ for the instances in $V$ by expanding an initially empty assignment. Each step corresponds to an instance in $V$ where only top candidate labels for the instance are considered for assignment expansion and only top partial assignments produced so far are kept for the next step. Unfortunately, the selection of top candidate labels for expansion at each step is based only on the local scores $s_i$, which might discard the candidates that can eventually provide greater global scores. To overcome this issue, we propose to apply Simulated Annealing (SA) (Kirkpatrick et al., 1983) to search for the optimal assignment $\hat{Y}$ for $V$. SA is a probabilistic algorithm that is able to approximately find the global optimum of a function (Kirkpatrick et al., 1983; Van Laarhoven and Aarts, 1987). Algorithm 1 presents our implementation for SA to find $\hat{Y}$.

$$\hat{Y}_{cur} = \hat{Y}_0 = \{\hat{y}_{i,0}\},$$

which contains the greedily predicted labels for each instance: $\hat{y}_{i,0} = \arg\max_{c \in \mathcal{C}} s_i[c]$. The algorithm then runs over $N_{iter}$ iterations to improve the global score $s(\hat{Y}_{cur})$ for the current label configuration $\hat{Y}_{cur}$. This is done via updating the current configuration to a successor configuration $\hat{Y}_{new}$ that gives a higher global score (i.e., $\delta_n > 0$). A successor configuration is obtained via the function $random\_successor()$ by randomly changing some label $\hat{y}_i \in \hat{Y}_{cur}$. Different from beam search decoding with partial assignments, each searching step in SA examines a complete label assignment for the instances in $V$ to provide complete information to measure the global scores/quality of the assignments. Importantly, SA sometimes allows the current configuration to transition to a successor configuration with a lower global score (i.e., $\hat{\delta}_n \leq 0$) with an acceptance probability of $p = \exp(\frac{\delta_n}{T})$. Here, $t$ is the temperature of the algorithm, gradually decreased via $t \leftarrow T/n$ ($T$ is a hyper-parameter). This exploration property enables SA to escape from local optimum configurations, thus increasing the chance to find the globally optimal configuration $\hat{Y}$.

### 4 Experiments

**Datasets:** Following previous work (Wadden et al., 2019; Lin et al., 2020; Zhang and Ji, 2021; Nguyen et al., 2021a; Lu et al., 2021; Hsu et al., 2021), we conduct experiments on 5 different datasets created by the 2005 Automatic Content Extraction (ACE05) (Walker et al., 2006) and Entity Relation Event (ERE) (Song et al., 2015) programs. The three ACE05 datasets feature ACE05-R, ACE05-E, and ACE-E+, all in English, involving 33 event types, 7 entity types, 6 relation types, and 22 argument roles. The two ERE datasets are ERE-EN (English portion) and ERE-ES (Spanish portion), introducing 38 event types, 7 entity types, 5 relation types, and 20 argument roles. We use the same data processing and train/dev/test splits as the prior work for a fair comparison. Detailed statistics for the datasets are shown in Table 1.

**Baselines:** We compare our method, called GraphIE, with the following baselines for JointIE:

- **Generative baselines:** Text2event (Lu et al., 2021) and DEGREE (Hsu et al., 2021). The generative baselines perform ETD and EAE via formulating the tasks as text generation. The models receive an input sentence and generate an output text containing text spans and labels for event triggers and event arguments, structured in a way that a post-processing step can be used to extract ETD and EAE predictions for the models.
- **Classification baselines:** OneIE (Lin et al., 2020), AMRIE (Zhang and Ji, 2021), and FourIE (Nguyen et al., 2021a). The classification baselines represent the instances for ETD, EMR, EAE, and RE via a shared encoder and perform classification for the instances based on task-specific label distributions. AMRIE and FourIE employ a heuristic dependency graph among task instances to improve representation learning. Dependency between instance labels is exploited in OneIE and AMRIE via a beam search decoding with manually-designed

| Datasets   | Split | #sents | #ents | #rels | #events |
|------------|-------|--------|-------|-------|---------|
| ACE05-R    | Train  | 10,051 | 26,473 | 4,788 | -       |
|            | Dev    | 2,424  | 6,362  | 1,131 | -       |
|            | Test   | 2,050  | 5,470  | 1,131 | -       |
| ACE05-E    | Dev    | 9,203  | 29,006 | 4,968 | 4,202   |
|            | Test   | 832    | 3,017  | 636   | 405     |
| ACE05-E+   | Dev    | 19,240 | 47,525 | 7,152 | 4,419   |
|            | Test   | 766    | 3,673  | 802   | 424     |
| ERE-EN     | Train  | 14,219 | 38,804 | 5,045 | 6,419   |
|            | Dev    | 1,627  | 3,320  | 424   | 352     |
|            | Test   | 1,129  | 2,291  | 477   | 339     |
| ERE-ES     | Dev    | 1,987  | 11,539 | 1,098 | 3,772   |
|            | Test   | 556    | 886    | 120   | 210     |
|            | Train  | 1,987  | 11,539 | 1,098 | 3,772   |

Table 1: Data statistics. #sents, #ent, #rels, and #events indicate the number of sentences, entity mentions, relations, and events respectively.
Table 2: Model performance on the test data of 5 datasets. “Ent”, “Rel”, “Trg”, and “Arg” are the F1 scores for identification and classification of entity mentions, event triggers, relations, and event arguments respectively. * indicates results that are not reported in the original papers but produced by our official code. Underlined numbers designate the tasks where GraphIE is significantly better (p < 0.01) than the baselines.

global features, and in FourIE via global type dependency regularization. FourIE and AMRIE are the current state-of-the-art models for JointIE.

Hyper-parameters: Prior work for JointIE employs two different versions of pre-trained language models (PLM), i.e., BERT (Devlin et al., 2019; Lin et al., 2020; Nguyen et al., 2021a) and RoBERTa (Liu et al., 2019; Zhang and Ji, 2021), which might cause incompilable compression. To this end, we explore both BERT and RoBERTa to obtain the word representations \( x \) for GraphIE for a fair comparison. For the Spanish ERE-ES dataset, following prior work (Lin et al., 2020; Nguyen et al., 2021a), we utilize the multilingual versions of BERT and RoBERTa. For each PLM, we fine-tune the hyper-parameter for GraphIE on the development data.

In particular, the best values for the hyper-parameters of the proposed model are reported as follows. We employ the learning rate of \( 1e^{-5} \) for the models with the BERT-based PLM (i.e., using bert-large-cased and bert-multilingual-cased) and the learning rate of \( 5e^{-6} \) for the RoBERTa-based PLM (i.e., using roberta-large and xlm-roberta-large). For other hyper-parameters, our tuning process results in the same values for BERT-based and RoBERT-based models: Adam (Kingma and Ba, 2014) for the optimizer, batch size of 10, 100 for the size of the dependency relation embeddings, 400 for the size of the hidden vector for the feed-forward networks, 200 for the hidden vector size in the GCN model, 2 for the number of layers for the feed-forward networks and GCN model, \( \gamma = 1 \) for the trade-off hyper-parameter for the global score, \( N_{\text{noi}} = 5 \) for the number of noise examples for the contrastive loss (we re-sample the noise examples every epoch), \( T = 5 \) for the initial temperature, \( N_{\text{iter}} = 50 \) for the number of iterations of Simulated Annealing (SA), and \( \epsilon = 0.1 \) for the temperature threshold for the SA decoding.

Comparison with Baselines: We compare the proposed model GraphIE with the baselines on test data of the 5 datasets in Table 2. As can be seen, the generative baselines perform worse than the classification models on most of the settings. This might be due the implicit modeling of the label distributions and the assumption of a decoding order for task instances that limit the interactions of instance labels. Comparing OneIE, FourIE and AMRIE, it is clear that the exploitation of instance and label dependency in the training phase in FourIE can lead to better performance for JointIE than using such dependency in the decoding phase as done by OneIE and AMRIE over most tasks and PLMs. Most importantly, the proposed GraphIE significantly outperforms all the baselines across a majority of settings for tasks, datasets and PLMs, thus demonstrating the benefits of induced dependency graph, joint label distribution estimation, and simulated annealing for decoding in our method.

Table 3: Performance (F1) on the ACE05-E+ development data.

Ablation Study: To understand the contributions of each proposed component to GraphIE, we conduct ablation experiments where we remove each component from the full model and evaluate the performance of the remaining models.

The first three ablated models in Table 3 are “- induced dep”, “-semantic dep”, and “- syntactic dep”, formed by excluding the dependency weight induction of \( \alpha_{ij} \) (i.e., setting \( \alpha_{ij} = 1 \)),
the semantic-based dependency $\alpha_{ij}^{\text{sem}}$, and the
syntactic-based dependency $\alpha_{ij}^{\text{syn}}$ (respectively)
from the model computation. In each case, the performance of $\text{GraphIE}$
decreases significantly; the removal of both semantic- and syntactic-based
dependency in "- induced dep" leads to the largest performance drop. This shows that the semantic
and syntactic weighting captures complementary
information for instance dependency induction that is useful for our model. The next ablated model
"- induced dep + heuristic dep" is obtained by replac-
ing the induced dependency graph represented by $\alpha_{ij}$
with the heuristic dependency graph for in-
stances from the best baseline $\text{FourIE}$. The decrease
in the performance of this model suggests that the
induced dependency graph is better than the heuris-
tic graph for JointIE. The final ablated model "-\n$\text{GCN}$" in Table 3 eliminates the GCN component
from our full model. The result shows that GCN is
beneficial to exploit the induced dependency graph
to improve representation learning.

| Model (all use Roberta) | ACE05-E+ |
|-------------------------|-----------|
|                         | Ent | Rel | Trg | Arg |
| $\text{GraphIE}$        | 89.3| 67.2| 72.6| 66.3|
| - joint distribution    | 89.3| 65.5| 70.9| 64.5|
| - SA + greedy           | 89.2| 65.9| 71.2| 65.2|
| - SA + beam             | 89.5| 66.0| 71.5| 65.4|
| - SA + hill climbing    | 89.5| 66.6| 71.7| 65.3|
| $\text{OneIE}$          | 88.7| 64.2| 69.5| 63.2|
| - beam + SA             | 88.1| 63.9| 69.4| 62.7|
| $\text{AMRIE}$          | 89.4| 65.4| 71.2| 64.4|
| - beam + SA             | 88.8| 65.1| 70.5| 64.1|

Table 4: Performance (F1) on the ACE05-E+ development data.

In Table 4, we first eliminate the computation of the joint label distribution $P(Y|w, V)$ from $\text{GraphIE}$. As such, the "- joint distribution" model employs the local label distributions $P(y_i|w, V)$ to train models and infer labels (with greedy decoding). Due to the significantly worse performance of "- joint distribution", it is clear that directly estimating the joint label distribution is helpful for JointIE. To evaluate the benefit of the proposed SA, we replace it with other decoding algorithms for $\text{GraphIE}$, including greedy search, beam search and hill climbing. The beam search is implemented with our global score function $s(Y)$ and follows those in (Lin et al., 2020; Zhang and Ji, 2021) while hill climbing is implemented by removing the configuration exploration in lines 11-12 of Algorithm 1. As reported in Table 4, SA performs much better than other decoding algorithms for $\text{GraphIE}$, thus demonstrating SA’s ability to find globally optimal labels. In addition, we also attempt to replace the beam search decoding in $\text{OneIE}$ and $\text{AMRIE}$ with SA, which indeed leads to worse performance for such models as shown in the last four rows of Table 4. We attribute this to the learning of the global scores for configurations in $\text{OneIE}$ and $\text{AMRIE}$ that involves a limited set of predefined global features. Such features do not exist for many possible assignments $Y$ for $V$, thus causing poor global score computation and hindering the configuration ranking critically required by SA.

| Label pair                                      | Transition score |
|------------------------------------------------|------------------|
| (Event:Transport, Argument:Place)              | 10.02            |
| (Event:Transport, Relation:Physical)            | 4.33             |
| (Relation:Org-All, Relation:Part-Whole)         | 3.58             |
| (Event:Execute, Event:Sentence)                 | 2.58             |
| (Event:Die, Event:Be-Born)                      | 2.34             |
| (Event:Attack, Argument:Origin)                 | -87.17           |
| (Relation:Per-Soc, Entity:Facility)             | -93.93           |
| (Transport, Attacker)                           | -99.91           |

Table 5: Transition scores for some label pairs learned by our model on ACE05-E+.

Analysis: To further understand the advantages of $\text{GraphIE}$ over baseline models, we manually analyze the instances on the ACE05-E+ development data where $\text{GraphIE}$ can make correct predictions, but the best baseline model $\text{FourIE}$ fails. Figure 2 presents some instances along with their edges and weights in the dependency graphs. The most important insight from our analysis is that $\text{GraphIE}$ is able to connect an instance (e.g., blew) with other supporting instances (e.g., suicide) in the dependency graph to provide vital information to facilitate correct prediction. Such supporting instances do not share any event trigger or entity mention with the current instance that cannot establish links in $\text{FourIE}$ and lead to failure predictions.

Finally, Table 5 shows the transition scores $\pi_{y_{i+1}|y_{i}}$ learned by $\text{GraphIE}$ for some label pairs in ACE05-E+. The table show that our model is able to learn high scores for correlated label pairs (e.g., the $\text{Execute}$ and $\text{Sentence}$ event types) and very low scores for uncorrelated label pairs (e.g., an argument for a $\text{Transport}$ event cannot play the role $\text{Attacker}$).

5 Related Work

Capturing dependency between IE tasks has been a main focus of previous work on Joint IE. Early work employed feature engineering methods (Roth and Yih, 2004; Yu and Lam, 2010; Li et al., 2013;
In the January attack, two Palestinian suicide bombers blew themselves up in central Tel Aviv, killing 23 other people.

**Explanation:** “blew” is correctly predicted by GraphIE as a “Die” event trigger while FourIE incorrectly predicted it as an “Attack” event trigger.

We pretty much know that Marinello, while on the board, has arranged to get future money from the USCF.

**Explanation:** The relation between “Marinello” and “USCF” is correctly predicted by GraphIE as a “ORG-AFF” relation while FourIE incorrectly predicted it as a “GEN-AFF” relation.

A second rocket landed in farmlands and the other hit a house inside the refugee camp, ...

**Explanation:** “other” is correctly predicted by GraphIE as an “Instrument” for the event trigger “hit” while FourIE incorrectly predicted it as an “Attacker” for the event trigger “hit”.

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**Figure 2:** Instances along with their dependency subgraphs in ACE05-E+. Supporting instances are underlined.

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Later work applied deep learning via shared parameters to facilitate joint modeling for IE, however, for only two or three tasks (Nguyen et al., 2016a; Zheng et al., 2017; Bekoulis et al., 2018; Luan et al., 2019; Zhang et al., 2019; Nguyen and Nguyen, 2019). Recently, the four IE tasks have been solved jointly (Wadden et al., 2019; Lin et al., 2020; Zhang and Ji, 2021; Paolini et al., 2021; Lu et al., 2021; Nguyen et al., 2021). However, such recent works only employ heuristics to manually design dependency graphs for instances. Mean-field factorization of the joint label distribution for JointIE instances is dominant in prior work.

Our work is also related to prior work that uses CRFs (Lafferty et al., 2001; Chiu and Nichols, 2016) to estimate joint distribution of instance labels. Sequence labeling is a typical problem that has been solved by CRFs, including part of speech tagging and named entity recognition (Lafferty et al., 2001; Ekbol et al., 2007; Shishlka et al., 2008; Sobhana et al., 2010; Zia et al., 2016; Chiu and Nichols, 2016; Xu et al., 2017). However, these prior work only employ CRFs for simple graph structures (i.e., linear chains). A few prior work has considered CRFs for more complicated graph structures (Sun et al., 2017; Gao et al., 2019; Qu et al., 2019; Yuan and Ji, 2020); however, none of such works has applied CRFs for JointIE as we do.

6 Conclusion

We propose a novel model for jointly solving four IE tasks (EMR, ETD, EAE, and RE). Our proposed model learns a dependency graph among the instances of the tasks via a novel edge weighting mechanism. We also estimate the joint distribution among instance labels to fully enable interactions between instance labels for improved performance. The experimental results show that our model achieves best performance for multiple JointIE tasks across 5 datasets and 2 languages. In the future, we plan to extend our method to cover more IE tasks such as event coreference resolution.

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