Improve Event Extraction via Self-Training with Gradient Guidance

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Abstract

Data scarcity and imbalance have been the main factors that hinder the progress of event extraction (EE). In this work, we propose a self-training with gradient guidance (STGG) framework which consists of (1) a base event extraction model which is firstly trained on existing event annotations and then applied to large-scale unlabeled corpora to predict new event mentions, and (2) a scoring model that takes in each predicted event trigger and argument as well as their path in the Abstract Meaning Representation (AMR) graph to estimate a probability score indicating the correctness of the event prediction. The new event predictions along with their correctness scores are then used as pseudo labeled examples to improve the base event extraction model while the magnitude and direction of its gradients are guided by the correctness scores. Experimental results on three benchmark datasets, including ACE05-E, ACE05-E+, and ERE, demonstrate the effectiveness of the STGG framework on event extraction task with up to 1.9 F-score improvement over the base event extraction models. Our experimental analysis further shows that STGG is a general framework as it can be applied to any base event extraction models and improve their performance by leveraging broad unlabeled data, even when the high-quality AMR graph annotations are not available.

1 Introduction

Event extraction (EE), which aims to identify and classify event triggers and arguments, has been a long challenging problem in natural language processing. Despite the large performance leap brought by advances in deep learning, recent studies (Huang and Riloff, 2012; Wang et al., 2020) have shown that the data scarcity and imbalance of existing event annotations have been the major issues that hinder the progress of EE. Figure 1 shows the distribution of argument role annotations in ACE05-E dataset\(^1\). As we can see, 10 types have less than 80 annotations. On the other hand, the creation of event annotations is extremely time consuming and complicated, e.g., it takes several linguists over one year to annotate 500 documents for ACE05.

To overcome the data scarcity and imbalance issue of EE, we propose to leverage self-training to make use of the large-scale unlabeled corpora and enrich the event annotations with examples automatically detected and labeled by the EE system. However, simply adding the high-confidence event predictions to the training set can introduce noises (Liu et al., 2021; Arazo et al., 2020; ?; Jiang et al., 2018), especially given that the current state-of-the-art performance of event argument extraction is still less than 59% F-score. To tackle this challenge, we introduce a general self-training with gradient guidance (STGG) framework, which consists an event extraction model that is firstly trained on the existing event annotations and then continuously updated on the unlabeled corpora with self-training, and a scoring model that is to evaluate the correctness of the event predictions (pseudo labels) on an unlabeled corpora. During self-training, the

\(^1\)https://www.ldc.upenn.edu/collaborations/past-projects/ace
scores from the scoring model guide the direction and magnitude of the gradient computed on the pseudo labels.

Specifically, the event extraction model of our self-training with gradient guidance framework can be based on any state-of-the-art architecture, while in this paper, we choose OneIE (Lin et al., 2020) and AMR-IE (Zhang and Ji, 2021), due to their superior performance. The scoring model leverages the Abstract Meaning Representation (AMR) (Banarescu et al., 2013) which has been proved to be able to provide rich semantic and structural signals to map AMR structures to event predictions (Huang et al., 2016, 2018; Wang et al., 2021c). The scoring model is a self-attention network that takes in a predicted event trigger, a candidate argument and its corresponding argument role, as well as their path in the AMR graph of the whole sentence. Different from Zhang and Ji (2021) which learns the AMR representation via graph encoder and ignores the semantic of the AMR relations, our score model explicitly considers both the semantics of nodes and relations as well as their interactions, and thus can better measure the correctness of the predictions of both the candidate event trigger and argument.

We take AMR 3.0\(^2\) and part of New York Times (NYT)\(^3\) 2004 as the additional unlabeled corpora to enhance the event extraction model with STGG, and evaluate the event extraction performance on three public benchmark datasets: ACE05-E\(^4\), ACE05-E\(^+\)\(^5\), and ERE-EN\(^6\). The experimental results demonstrate that: (1) self-training alone barely improves event extraction due to the noise introduced by the unlabeled examples, while the proposed self-training with gradient guidance framework leverages the confidence scores of the pseudo labels to guide the direction and magnitude of the gradients, and thus make use of such pseudo labels more efficiently and robust; (2) self-training with gradient guidance can be applied to improve most, if not all, of the event extraction models and achieves new state of the art on the three public benchmark datasets; (3) By exploring different unlabeled corpora with gold or system-based AMR parsing, self-training with gradient guidance always improves the base event extraction models, demonstrating that it’s a general framework and has very light reliance on the quality of AMR parsing.

2 Event Extraction

The event extraction task consists of three subtasks: event detection, argument identification and argument role classification. Given an input sentence \(W = [w_1, w_2, ..., w_N]\), event detection aims to identify the span of an event trigger \(\tau_i\) from \(W\) and assign label \(l_i^7\) to the trigger from a set of predefined event types \(L^1\). Argument identification aims to find the span of an argument \(\varepsilon_j\) in \(W\), and argument role classification further predicts the role \(a_{i,j}\) of an argument \(\varepsilon_j\) in an event \(\tau_i\) given a set of predefined argument roles \(L^a\).

2.1 Base Event Extraction Model

OneIE (Lin et al., 2020) jointly extracts entities, relations and events from each single sentence. It has four components: First, a language model encoder (Devlin et al., 2019; Liu et al., 2019) computes the contextualized word representations \(W = [w_1, w_2, ..., w_N]\) from an input sequence \(W\). Then, two local classifiers \(FFN^I\)'s with CRF layers (Lafferty et al., 2001) are trained to identify the spans of events and arguments respectively. The sequence of score vectors for all labels is \(\hat{Y} = \text{Softmax}(FFN^I(W))\). The ground-truth labels for the sequence are denoted as \(\hat{y}\). The score for the ground-truth label sequence is calculated as

\[
S(\hat{y}) = \sum_{i=1}^{N} Y_{i,\hat{y}_i} + \sum_{i=1}^{N-1} T_{\hat{y}_i,\hat{y}_{i+1}},
\]

where \(T\) is a transition matrix which consists the transition scores from \(\hat{y}_i\) to \(\hat{y}_{i+1}\). The objective is to maximize the negative log-likelihood of the ground-truth label sequence.

\[
L^I(\hat{y}) = -S(\hat{y}) + \log \sum_{y\in\hat{Y}} \exp S(y),
\]

The representations of identified event triggers and entities are computed as the averaged token representations across the identified trigger and entity spans and are fed into two local classifiers \(FFN^V\)'s to classify the event types and entity types. For simplicity, we consider both event triggers and entities as a set of nodes \(V\). The score vector for node \(v_i\) is \(y_{v_i} = \text{Softmax}(FFN^V(\frac{1}{m} \sum_{d=m}^{d+m} w_d))\) where \(d\) is the starting index of node \(v_i\) in the \(W\) and \(m\) is the span size of \(v_i\). The representation

\(^2\)https://catalog.ldc.upenn.edu/LDC2020T02.
\(^3\)https://catalog.ldc.upenn.edu/LDC2008T19.
\(^4\)Automatic Content Extraction (ACE) 2005 dataset.
\(^5\)Automatic Content Extraction (ACE) 2005 dataset.
\(^6\)Deep Exploration and Filtering of Test (DEFT) program.
\(^7\)We use bold symbols to denote vector representations.
of each event trigger is concatenated with the representation of each entity and is fed into a local classifier \(FFNE^E\) to compute the score for argument role types. The score vector for edge \(e_{ij}\) which connects node \(v_i\) and node \(v_j\) is \(y_{e_{ij}} = \text{Softmax}(\text{FFNE}(\frac{1}{\eta} \sum_{d} w_d, \frac{1}{\eta} \sum_{c} w_c)))\), where \(d\) is the starting index of \(v_i\) and \(c\) is the starting index of \(v_j\) in \(W\) and \(m\) is the span size of \(v_i\) and \(n\) is the span size of \(v_j\). The objective is to minimize the cross-entropy loss:

\[
\mathcal{L}_c^C(\hat{y}) = -\frac{1}{|V|} \sum_{v_i \in V} \hat{y}_{v_i} \log y_{v_i} - \frac{1}{|E|} \sum_{e_{ij} \in E} \hat{y}_{e_{ij}} \log y_{e_{ij}},
\]

\(\hat{y}_{v_i}\) and \(\hat{y}_{e_{ij}}\) are the ground truth label vectors for node \(v_i\) and edge \(e_{ij}\).

Finally, OneIE learns an additional global weight vector \(u\) which captures interactions across subtasks and instances. The interactions across subtasks are between entity types, event types and argument roles. For example, in an 'Attack' event, the argument with a 'LOC' entity type is unlike to have an 'Attacker' role. The interactions across instances happen between event instances. For example, the 'Defendant' in an 'Sentence' event can also be an 'Agent' in a 'Die' event. During training, the global feature \(f(G)\) is collected on the current local optimal graph \(G\) and the gold annotation \(G'\). The objective is to make sure the \(G'\) has higher global score than \(G\).

\[
\mathcal{L}_g^G(\hat{y}) = u f(G) - u f(\hat{G}),
\]

The combined objective for training the whole OneIE model is

\[
\mathcal{L}^E = \mathcal{L}^I + \mathcal{L}^C + \mathcal{L}^G
\]

3 Proposed Method

In this section, we first explain the self-training algorithm and then present self-training with gradient guidance (STGG) to alleviate the noises introduced by low-quality pseudo-labels and inject AMR knowledge into the self-training process.

3.1 Self-Training

The self-training algorithm (Nigam et al., 2000; Rosenberg et al., 2005) alternates between generating pseudo labels and training the model on the union of the high-confident pseudo-labeled data and the labeled data. In the first stage of the algorithm, an event extraction model is trained on a labeled dataset \((X_L, Y_L)\) until converges. Then the fully trained event extraction model generates pseudo labels \(\hat{Y}_U\) on an unlabeled dataset \(X_U\). The pseudo-labeled instances are filtered by a confident threshold \(s^t\) and instances with probabilities higher than \(s^t\) are collected and form \((\hat{X}_U, \hat{Y}_U)\). The event extraction model is trained on \((X_L, Y_L) \cup (\hat{X}_U, \hat{Y}_U)\) and later is used to find more confident predictions. This process ends until no new confident instance can be found.

3.2 Self-Training with Gradient Guidance

As shown in Figure 2, STGG consists of two models, an event extraction model \(f^E\) and a scoring model \(f^S\). Like self-training, the event extraction model is trained on labeled event extraction dataset until it converges and then generates event predictions on the unlabeled dataset

\[
\tilde{y} = \arg \max_y f^E(y; \hat{W}), \quad \hat{W} \sim X_U,
\]

where \(\tilde{y}\) is the set of predicted events on an unlabeled sentence \(\hat{W}\).

To compute the compatibility score between an event prediction \((\tilde{\tau}_i, \tilde{a}_{i,j}, \tilde{\varepsilon}_j)\) and an AMR graph \(G^a = (V^a, E^a)\), we first need to align the event trigger \(\tilde{\tau}_i\) to \(v^a_i \in V^a\) and \(\tilde{\varepsilon}_j\) to \(v^a_j \in V^a\). Then we find the AMR path \(p_{i,j}\) connecting \(\tilde{\tau}_i\) and \(\tilde{\varepsilon}_j\) by finding the shortest path between \(v^a_i\) and \(v^a_j\) in \(G^a\). If there is no path between \(v^a_i\) and \(v^a_j\), we add a new edge to connect them and assign other as the relation. We follow (Zhang and Ji, 2021) to perform node alignment between AMR nodes, and event triggers and arguments. Specifically, if a AMR node, and an event trigger or argument have overlaps in the text \(W\), we align them. The scoring model takes the event prediction \((\tilde{\tau}_i, \tilde{a}_{i,j}, \tilde{\varepsilon}_j)\) and its corresponding AMR path \(p_{i,j}\) as input and computes a compatibility score:

\[
c_{i,j} = f^S_p((\tilde{\tau}_i, \tilde{a}_{i,j}, \tilde{\varepsilon}_j); p_{i,j}, \hat{W})
\]

where \(c_{i,j}\) can be interpreted as the probability of an event prediction given its corresponding AMR path and the score model’s parameters. Following self-training, the event predictions with pseudo labels are passed into the event extraction model and the gradient is computed as follows:

\[
g^s_{i,j} = \nabla_\theta \mathcal{L}^E (\hat{W}, (\tilde{\tau}_i, \tilde{a}_{i,j}, \tilde{\varepsilon}_j); \theta)
\]
The direction and magnitude of the gradient \( g^{\text{st}}_{i,j} \) can be incorrect due to the errors of the pseudo labels. To tackle this problem, we further use the compatibility score \( c_{i,j} \) to guide the gradient by multiplying them together. However, by definition, the compatibility scores can only be non-negative which can not change the direction of the gradients for wrong predictions, thus we further design a transformation function \( f^c \) to project the range of the compatibility score onto \([-1, 1]\). In our case it’s a simple linear mapping as \( f^c(c_{i,j}) = 2 	imes c_{i,j} - 1 \) and the gradients computed by STGG for a pseudo-labeled example \( \tilde{x} \) is formulated as:

\[
g^{\text{stgg}} = \sum_{i,j} f^c(c_{i,j})g^{\text{st}}_{i,j},
\]

To improve the efficiency of self-training, we propose to update the event extraction on every minibatch. Thus, the loss of STGG is computed as follows:

\[
\mathcal{L}^{\text{ST}} = \frac{1}{|B|} \sum_{B} \sum_{i,j} f^c(c_{i,j}),
\]

\[
\mathcal{L}^E(\tilde{x}, (\tilde{\tau}_i, \tilde{a}_{i,j}, \tilde{\varepsilon}_j); \theta),
\]

To avoid the model diverging, we add the self-supervised loss to the self-training loss and the final loss for STGG is:

\[
\mathcal{L} = \mathcal{L}^E + \alpha \mathcal{L}^{\text{ST}}
\]

where \( \alpha \) is the combination rate.

### 3.3 Scoring Model

The scoring model aims to estimate the correctness of the prediction of each candidate trigger and argument. Inspired by the coherence between the event structures and AMR graphs, we propose to leverage the AMR graph to better capture the semantic relation between the candidate trigger and argument in our scoring model.

Given an input sentence \( W \) and its corresponding AMR graph \( G^a = (V^a, E^a) \), each node \( v^a_i \in V^a \) can be mapped to a word in \( W \). Thus, we first apply a language model encoder (Devlin et al., 2019; Liu et al., 2019) to compute the contextual representations for the sequence of tokens in \( W \) and then use them to initialize the representation \( h^a_i \) of each node \( v^a_i \). For each AMR relation \( e^a_{i,j} \), we randomly initialize a vector representation \( h^a_{i,j} \) for \( e^a_{i,j} \), and use \( \mathbf{E}^{\text{rel}} \) to denote the embedding matrix of all AMR relations. Given a predicted trigger \( \tilde{\tau}_i \) and argument \( \tilde{\varepsilon}_j \), we identify their corresponding nodes \( v^a_i \) and \( v^a_j \) in \( G^a \) by node alignment following (Zhang and Ji, 2021), and utilize the Breadth First Search (BFS) to find the shortest path \( p_{i,j} \) that connects \( v^a_i \) and \( v^a_j \) in \( G^a \). Then we concatenate a virtual event type node, the path and a virtual argument role node as an overall sequence \( H^a_{i,j} = [h^a_i, h^a_j, h^a_{i+1}, \ldots, h^a_{j-1}, h^a_{j}, h^a_{j+1}], \) where both the event type representation \( h^a_i \) and argument role representation \( h^a_{i,j} \) are drew from the randomly initialized event embedding matrix \( \mathbf{E}^{\text{tri}} \) and argument role embedding matrix \( \mathbf{E}^{\text{arg}} \). We also add token type embeddings to \( H^a_{i,j} \) to help the model understand the input types which are AMR node, AMR relation, event trigger type, and argument role type.

In order to estimate the correctness of the predicted event trigger and candidate argument, we further design a self-attention layer (Vaswani et al., 2017) over \( H^a_{i,j} \) to learn a new contextual representation for each node or relation in the AMR graph.
path:

\[ H_{i,j}^{\text{final}} = \text{self-attention}(H_{i,j}^{\text{final}}) \times M, \]

where \( M \) denotes the number of attention layers.

We compute an overall vector representation from \( H_{i,j}^{\text{final}} \) as \( h_{i,j}^{\text{final}} \) based on average-pooling and feed it into a linear-layer and a Sigmoid function to compute a probability \( c_{i,j} \), indicating the correctness of the predicted event trigger and argument. We optimize the scoring model based on the binary cross-entropy objective:

\[ L^s = \text{BCE}(y_{i,j}, c_{i,j}), \]

where \( y_{i,j} \) is a binary label which indicates whether the argument role is correct \((y_{i,j} = 1)\) or not \((y_{i,j} = 0)\). During training, we have the ground-truth labels as positive training instances and we swap the labels of argument roles in positive training instances with randomly sampled incorrect labels to create negative training instances.

4 Experimental Setups

4.1 Datasets and Pre-processing

For evaluation, we consider two base event extraction models: OneIE (Lin et al., 2020) and AMR-IE (Zhang and Ji, 2021) due to their superior performance on event extraction, and demonstrate the effectiveness of our self-training with gradient guidance framework on the following three public benchmark datasets. For fair comparison, we use the same evaluation metrics as previous studies (Ji and Grishman, 2008b; Li et al., 2013a; Nguyen et al., 2016; Huang et al., 2016; Wadden et al., 2019; Lin et al., 2020; Zhang and Ji, 2021; Wang et al., 2021a).

ACE05-E The Automatic Content Extraction (ACE) 2005 dataset (ACE05-E) contains annotations for entity, relation, event trigger, argument and argument role. We follow previous data pre-processing and splits as in (Wadden et al., 2019; Lin et al., 2020). The processed dataset contains 7 entity types, 6 relation types, 33 event types, and 22 argument roles.

ACE05-E+ To show the effectiveness of STGG on multi-token event triggers, we perform experiments on ACE05-E+ introduced in (Lin et al., 2020). ACE05-E+ adds back the order of relation arguments, pronouns, and multi-token triggers. It also skips the line before the \texttt{text} tag. ACE05-E+ contains the same number of labels as ACE05-E.

ERE-EN To understand if STGG can work when the performance of the event extraction model is fairly low, we also conduct event extraction on ERE-EN (Entities, Relations and Events) (Song et al., 2015). ERE-EN contains 7 entity types, 5 relation types, 38 event types, and 20 argument roles. The detailed statistics of ACE05-E, ACE05-E+, and ERE-EN are shown in Appendix A.

To show the generalizability of our STGG framework and the impact of AMR parsing to the scoring model, we explore two unlabeled corpora for self-training: AMR 3.0 (Knight et al., 2021) which contains 55,635 sentences while each sentence is associated with a manually annotated AMR graph. During self-training, we only consider the sentences that contain predicted event triggers and arguments based on the base event extraction models. In addition, following (Huang et al., 2016; Zhang and Ji, 2021), we also group the original set of AMR relations into 19 categories as some relations are irrelevant to event extraction. The details are shown in Appendix B. New York Times Annotated Corpus (NYT) is organized by over 1.8 millions articles which were published between 1987 to 2007. We randomly sample 55,635 sentences from articles published in 2004. Because NYT dataset does not have AMR annotations, we run an AMR parser (Astudillo et al., 2020) pretrained on AMR 3.0 to generate system AMR parsing.

4.2 Training Details

Base OneIE We follow the same training process as (Lin et al., 2020) to train the OneIE model, but we use RoBERTa (Liu et al., 2019) instead of BERT (Devlin et al., 2019) as the language model encoder as it shows significantly better performance on event extraction than BERT-based OneIE. We use BertAdam as the optimizer and train the model for 60 epochs with 1e-5 as learning rate and weight decay for the language encoder and 1e-3 as learning rate and weight decay for other parameters. The batch size is set to 16. We keep all other hyperparameters exactly the same as (Lin et al., 2020). For each dataset we train 5 OneIE models and remove the best and worst models based on their performance on the validation set and report the performance based on the average of the rest 3 models for each dataset.

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8To show the effect of unlabeled dataset vs labeled dataset, we sample the same number of unlabeled sentence as AMR 3.0.
**Base AMR-IE** We follow the same training process as (Zhang and Ji, 2021) to train the AMR-IE model. We use BertAdam as the optimizer and train the model for 60 epochs with 1e-5 as learning rate and weight decay for the language encoder and 1e-3 as learning rate and weight decay for other parameters. The batch size is set to 16. We keep all other hyperparameters exactly the same as (Zhang and Ji, 2021).

**Scoring Model** We use BertAdam as the optimizer and train the score model for 80 epochs with 1e-5 as learning rate and weight decay for the language encoder and 1e-4 as learning rate and weight decay for other parameters. The batch size is set to 10. The scoring model contains two self-attention layers. Because of the distinct distributions of the various event extraction models, we train a dedicated scoring model for each event extraction model.

**Further-Training, Self-Training, and Self-Training with Gradient Guidance** To better show the effectiveness of STGG, we also compare it with several other training strategies based on OneIE, including: Further-Training and Self-Training. For all three training strategies we use SGD as optimizer and continue to train the converged base OneIE model for 10 epochs with batch size 10 and with 1e-4 as lr and 1e-5 as weight decay for all other parameters except the CRF layers and global features which are frozen. For self-training, we select 0.9 as the confident threshold based on the model’s performance. For STGG, we select 0.6 as the confidence threshold for scoring model. We search the score thresholds for both self-training and STGG in range of 0.5-0.9.

### 5 Results and Discussion

**5.1 Evaluation of Scoring Model**

We evaluate the performance of the scoring model by measuring how well it distinguishes the correct and incorrect argument role predictions from an event extraction model. Specifically, we compute event predictions by running a fully trained event extraction model on the validation and test sets of the three benchmark datasets. Based on the gold event annotations, we create a gold binary label (correct or incorrect) for each argument role prediction to indicate its correctness. For each event prediction, we pass it along with the corresponding AMR graph of the source sentence into the scoring model. If the correctness predicted by the scoring model agrees with the gold correctness label, we treat it as a true prediction for scoring model, otherwise, a false prediction.

To show the impact of AMR structure to the scoring model, we develop a baseline approach that estimates the correctness of an event prediction by considering only the contextual representations of the event trigger and argument, which is essentially an ablation of our scoring model where the AMR path is omitted. As shown in Table 1, the performance of our scoring model significantly outperforms the one without considering the AMR path, demonstrating its effectiveness in characterizing the semantic relationship between the event trigger and argument.

|          | ACE05-E | ACE05-E+ | ERE-EN |
|----------|---------|----------|--------|
| w/o AMR  | 87.4    | 85.9     | 87.8   | 86.9   | 82.6  | 83.3  |
| w/ AMR   | 88.7    | 88.4     | 88.8   | 88.9   | 84.5  | 84.4  |

Table 1: The F-score of the scoring models on various datasets. w/o AMR is the baseline scoring model without using AMR path. w/ AMR is the scoring model we proposed.

![Figure 3: Performance of various methods on the ACE-E argument roles with less than 80 training instances. The blue bars show the number of labeled instance and the orange bars show the number of pseudo-labeled instance found by STGGAMR.](image-url)
Table 2: Test F1 score on event extraction, event trigger identification and classification, and argument role identification and classification.

|                | ACE05-E | ACE05-E+ | ERE-EN |
|----------------|---------|----------|--------|
|                | Ent | Tri-I | Tri-C | Arg-I | Arg-C | Ent | Tri-I | Tri-C | Arg-I | Arg-C | Ent | Tri-I | Tri-C | Arg-I | Arg-C |
| DyGIE          | 89.7 | 69.7  | 53.0  | 48.8  | -     | 67.3 | -    | 42.7  | -     | -     | -    | -     | -     | -     |
| BERTQA_Arg     | -    | 75.8  | 72.4  | 55.3  | 53.3  | -    | 70.6 | -     | 48.3  | -     | 57.0 | -     | 39.2  | -     |
| Text2Event     | -    | 71.9  | -     | 53.8  | -     | 71.8 | -    | 54.4  | -     | 59.4  | -    | -     | 48.3  | -     |
| FourIE         | 91.3 | 78.3  | 75.4  | 60.7  | 58.0  | 91.1 | 76.7 | 73.3  | 59.5  | 57.5  | 87.4 | 69.3  | 57.9  | 52.2  |
| AMR-IE         | 92.1 | 78.1  | 75.0  | 60.9  | 58.6  | -    | -    | -     | -     | 87.9 | 68.0 | 61.4  | 46.4  | 45.0  |
| Query_Extract  | -    | -     | -     | 89.3  | -     | -    | -    | 55.1  | -     | 60.4  | -    | -     | 50.4  | -     |

**Base OneIE**

|                | Ent | Tri-I | Tri-C | Arg-I | Arg-C |
|----------------|-----|-------|-------|-------|-------|
| +further-training | 91.8 | 77.8  | 74.4  | 60.4  | 58.2  |
| +self-training   | 91.9 | 78.0  | 74.5  | 60.8  | 58.7  |
| +STGGw/o_AMR    | 91.8 | 77.8  | 74.4  | 60.4  | 58.2  |
| +STF_AMR        | 91.7 | 78.2  | 74.8  | 62.4  | 60.1  |

**Base AMR-IE**

|                | Ent | Tri-I | Tri-C | Arg-I | Arg-C |
|----------------|-----|-------|-------|-------|-------|
| +STGG_AMR      | 92.2 | 78.0  | 74.5  | 60.0  | 57.9  |
| +STF_AMR       | 92.0 | 77.7  | 74.4  | 60.4  | 58.7  |

5.2 Evaluation of Self-Training with Gradient Guidance

We further evaluate the effectiveness of our self-training with gradient guidance framework to event extraction on the three benchmark datasets based on two base event extraction models: OneIE (Lin et al., 2020) and AMR-IE (Zhang and Ji, 2021). To show the impact of scoring model to the self-training process, we also show the performance of STGG based on the baseline scoring model (w/o AMR), which is referred as STGGw/o_AMR. For clarity, in the rest of the section we refer our proposed self-training with gradient guidance as STGG_AMR.

As shown in Table 2, both STGG_AMR and STGGw/o_AMR improve the performance of the event extraction models while self-training alone barely works. We argue that the scoring models in STGG_AMR and STGGw/o_AMR works as regularizers to prevent diverging of the event extraction model and the dynamic between gradient and guidance alleviates the effect of event predictions that both model are not confident and focus more on valid predictions. In addition, by considering AMR structure, STGG_AMR significantly outperforms all other methods, yielding the new state of the art for two benchmark datasets. Note that the argument classification (Arg-C) performance of OneIE based methods are not comparable to Query_Extract on ERE-EN because in ERE-EN one event trigger can trigger multiple events and Query_Extract can handle multi-label classification problem but the base event model OneIE cannot.

Figure 3 shows the performance of various methods for each argument role based on ACE05-E. The blue bars show the original number of labels and the orange bars show the pseudo labeled examples generated by STGG_AMR. The pseudo labels can significantly augment the original ACE05-E training dataset, especially for argument role types with low resources. Thus, by utilizing the pseudo labels, STGG_AMR can effectively address the data scarcity problem in event extraction datasets. We argue that STGG_AMR utilize pseudo label more efficiently, because unlike self-training, not only can it leverage the positive-confident pseudo labels, but the negative pseudo labels.

5.3 Why Self-Training Doesn’t Work

As shown in Figure 3, due to the data scarcity and imbalance, the base event extraction model (i.e., OneIE) performs poorly on many argument roles (lower than 40% F-score). Thus, the event predictions on unlabeled corpora can be very noisy and inaccurate. The model further accumulates errors and diverges when it’s iteratively trained on such noisy pseudo labeled examples during self-training. This problem is referred as confirmation bias (Tarvainen and Valpola, 2017; Arazo et al., 2020; Pham et al., 2020). In addition, we also notice that with self-training, the event extraction model becomes overconfident about its predictions. We check the averaged probability of all the predictions on the unlabeled dataset which is 0.933. In such case, it is clear that the predicted probability can not faithfully reflect the correctness of the predictions, which is referred as calibration error cite (Guo et al., 2017; Niculescu-Mizil and Caruana, 2005). Thus, the self-training process which relies on the confidence of the predictions, can be highly biased and...
diverge far from the starting point. As shown in Table 2, self-training on ACE05-E has the exact same performance as the original OneIE model, since it can not achieve better performance on the validation set.

5.4 Effect of Confidence Threshold

We claim that STGG can utilize both confident and unconfident pseudo labels. To verify this claim, we conduct experiments based on STGG\(_{W/O\_AMR}\) and STGG\(_{AMR}\) where the probability predicted by the scoring model works as a threshold to filter out unconfident pseudo labels.\(^9\) Specifically, the data filtering process is as follows: if the probability predicted by the scoring model is higher than a threshold \(s^{\text{st}}\) (indicating a confident positive prediction), or lower than \(1 - s^{\text{st}}\) (indicating a confident negative prediction), we add the pseudo labeled example to the original training set. Figure 4 shows that STGG\(_{AMR}\) can delay the performance drop of the training process until the confidence threshold is set as 0.6 which is much lower than STGG\(_{W/O\_AMR}\). On ERE-EN, with a confidence threshold lower than 0.9, STGG\(_{AMR}\) performs much better than STGG\(_{W/O\_AMR}\). However, when confidence threshold reaches 0.9 STGG\(_{W/O\_AMR}\) becomes slightly better. We argue that on ERE-EN dataset, the AMR knowledge is less helpful as shown in Table 2.

5.5 Impact of AMR Parsing

AMR annotations are very expensive and hard to obtain. To show the potential of STGG\(_{AMR}\) in the scenarios where gold AMR parsing is not available, we conduct experiments based on system labeled AMR. We randomly select 55,635 sentences from NYT 2004, which has the same size as AMR 3.0 and is about the same news domain as ACE05-E. Following previous data filtering process, we ran the base event extraction model on the unlabeled dataset and select 11,638 instances for model trained on ACE05-E and ACE05-E\(^+\), and 19,653 instances for model trained on ERE-EN. As shown in 3, with system labeled AMR, STGG\(_{AMR}\) also improves the performance of base event extraction models.

|             | Ent | Tri-I | Tri-C | Arg-I | Arg-C |
|-------------|-----|-------|-------|-------|-------|
| ACE-E       | 91.8| 78.1  | 74.6  | 61.5  | 59.2  |
| ACE-E+      | 91.8| 77.5  | 74.1  | 59.8  | 58.2  |
| ERE-EN      | 87.6| 69.7  | 61.6  | 47.8  | 46.0  |

Table 3: STGG performance with system labeled AMR.

6 Related Work

Most prior studies have been focusing on learning supervised models (Ji and Grishman, 2008a; McClosky et al., 2011; Li et al., 2013b; Chen et al., 2015; Nguyen et al., 2016; Wadden et al., 2019; Du and Cardie, 2020; Lin et al., 2020; Zhang and Ji, 2021; Wang et al., 2021a,c; Nguyen et al., 2021) based on manually annotated event mentions. However, the performance of event extraction has been barely improved in recent years, and one of the main reasons lies in the data scarcity and imbalance of the existing event annotations. Several self-training and semi-supervised studies have been proposed to automatically enrich the event annotations. Huang and Riloff (2012) uses extraction patterns based on nouns that, by definition, play a specific role in an event, to automatically label more data. (Li et al., 2014) proposes various event inference mechanisms to reveal additional missing event mentions. (Liao and Grishman, 2010, 2011; Ferguson et al., 2018) propose techniques to select more relevant and informative corpus for self-training. All these studies cannot handle the noise introduced by the automatically labeled data properly. Comparing with them, our STGG framework leverages a scoring model to estimate the...

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\(^9\)We don’t use the probability from the event extraction model due to the calibration error and (Niculescu-Mizil and Caruana, 2005) suggests that models usually compute calibrated probabilities on binary-classification tasks.
correctness of each pseudo labeled example, which further guides the gradients learning of the event extraction model, thus it can efficiently mitigate the impact of the noisy pseudo labeled examples.

Self-training has been studied for many years (Yarowsky, 1995; Riloff and Wiebe, 2003; Rosenberg et al., 2005) and widely adopted in many NLP tasks including speech recognition (Kahn et al., 2020; Park et al., 2020), parsing (McClosky et al., 2006; McClosky and Charniak, 2008), and pre-training (Du et al., 2021). Self-Training suffers from inaccurate pseudo labels (Arazo et al., 2020, 2019; Hu et al., 2021a) especially when the teacher model is trained on insufficient and unbalanced datasets. To address this problem, (Pham et al., 2020; Wang et al., 2021b; Hu et al., 2021a) propose to utilize the performance of the student model on the held out labeled data as a Meta Learning objective to update the teacher model or improve the pseudo-label generation process. (Hu et al., 2021b) leverage the cosine distance between gradients computed on labeled data and pseudo-labeled data as feedback to guide the self-training process. (Mehta et al., 2018) propose to inject span constraints from constituency parsing during self-training of semantic role labeling.

7 Conclusion

We propose a self-training with gradient guidance (STGG) framework to overcome the data scarcity and imbalance issues of the event extract task. The STGG framework consists of a base event extraction model which is pre-trained on existing event annotations and then extracts new event mentions from large-scale unlabeled corpora, and a scoring model that estimates a correctness score for each event prediction. The base event extraction model is further self-trained on the pseudo event mentions predicted from the unlabeled corpora while utilizes the correctness score to guide the magnitude and direction of the gradients learned from these pseudo examples. We conduct experiments on three public benchmark datasets, including ACE05-E, ACE05-E+, and ERE, and prove that STGG is effective and general as it can improve any base event extraction models with up to 1.9 F-score gain. STGG can also make use of broad unlabeled corpora even without high-quality AMR annotations to improve event extraction models.

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## A The Statistics of Datasets

|                | ACE05-E | ACE05-E+ | ERE-EN |
|----------------|---------|----------|--------|
|                | Train   | Dev      | Test   | Train   | Dev      | Test   | Train   | Dev      | Test   |
| Num Sent       | 17,172  | 923      | 833    | 19,240  | 902      | 768    | 14,738  | 676      | 1,083  |
| Num Events     | 4,202   | 430      | 413    | 4,419   | 468      | 424    | 6,208   | 528      | 551    |
| Num entities   | 26,006  | 2,451    | 3,017  | 47,525  | 3,422    | 3,673  | 6,208   | 528      | 551    |

Table 4: The statistics of the three benchmarks used in our paper.

## B Groups of AMR Relations

| AMR Relations | Group Label |
|---------------|-------------|
| ARG0          | ARG0        |
| ARG1          | ARG1        |
| ARG2          | ARG2        |
| ARG3          | ARG3        |
| ARG4          | ARG4        |
| Destination   | destination |
| Source         | source      |
| Instrument     | instrument  |
| Beneficiary    | beneficiary |
| Prep roles     | role starts with prep |
| Op roles       | role start with op |
| Entity role    | wiki, name  |
| Arg-X role     | ARG5, ARG6, ARG7, ARG8, ARG9 |
| Place role     | location, path, direction |
| Medium role    | manner, poss, medium, topic |
| Modifier role  | domain, mod, example |
| Part-whole role| part, consist, subevent, subset |
| Time role      | calendar, century, day, dayperiod, decade, era, month, quarter, season, timezone, weekday, year, year2, time |
| Others         | purpose, li, quant, polarity, condition, extent, degree, snt1, snt2, ARG5, snt3, concession, ord, unit, mode, value, frequency, polite, age, accompanier, snt4, snt10, snt5, snt6, snt7, snt8, snt9, snt11, scale, conj-as-if, rel |

Table 5: The 19 groups of the AMR relations used in our paper.