Causality Extraction based on Self-Attentive BiLSTM-CRF with Transferred Embeddings

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Abstract

Causality extraction from natural language texts is a challenging open problem in artificial intelligence. Existing methods utilize patterns, constraints, and machine learning techniques to extract causality, heavily depend on domain knowledge and require considerable human efforts and time on feature engineering. In this paper, we formulate causality extraction as a sequence labeling problem based on a novel causality tagging scheme. On this basis, we propose a neural causality extractor with BiLSTM-CRF model as the backbone, named SCIFI (Self-Attentive BiLSTM-CRF with Flair Embeddings), which can directly extract Cause and Effect, without extracting candidate causal pairs and identifying their relations separately. To tackle the problem of data insufficiency, we transfer the contextual string embeddings, also known as Flair embeddings, which trained on a large corpus into our task. Besides, to improve the performance of causality extraction, we introduce the multi-head self-attention mechanism into SCIFI to learn the dependencies between causal words. We evaluate our method on a public dataset, and experimental results demonstrate that our method achieves significant and consistent improvement as compared to other baselines.

Keywords: Causality extraction, Sequence labeling, BiLSTM-CRF, Flair

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1. Introduction

Natural language text contains much causal knowledge, as Fig. 1 shows. In recent years, causality extraction has become increasingly important for many natural language processing tasks, such as information retrieval [1, 2], event prediction [3, 4], question answering [5, 6, 7], generating future scenarios [8, 9], decision processing [10], medical text mining [11, 12, 13] and behavior prediction [14]. However, due to the ambiguity and diversity of natural language texts, causality extraction remains a hard NLP problem to solve.

Traditional methods for causality extraction can be divided into two categories: methods based on patterns [1, 11, 15, 16] (Section 5.1), and methods based on the combination of patterns and machine learning techniques [5, 17, 18, 19] (Section 5.2). The former often have poor cross-domain applicabilities, failing to balance precision and recall, and may require extensive domain knowledge to solve problems in a particular area. The latter usually requires considerable human effort and time on feature engineering, relying heavily on the manual selection of textual features. Generally, it divides causality extraction into two subtasks, candidate causal pairs extraction and relation classification (filtering non-causal pairs). The results of candidate causal pairs extraction may affect the performance of relation classification and generate cascading errors.

Ref. [20] firstly proposed a tagging scheme that makes it possible for models to extract entities and relations simultaneously. Inspired by their novel idea, we focus on causal triplet that is composed of two event entities and their relation.
For instance, the sentence in Fig. 1 contains a causal triplet: “Financial stress, Cause-Effect, divorce”. Thus, we can model the causal triplets directly, rather than break causality extraction into two subtasks. Based on the motivations, we formulate causality extraction into a sequence tagging problem and propose a causality tagging scheme (Section 2.1) to achieve the purpose of direct causality extraction. However, the tagging scheme proposed by Ref. [20] is unable to identify the overlapping relations in a sentence: it only considers the situation where an entity belongs to a triplet. To combat this problem, we design a Tag2Triplet algorithm (Section 2.2) to handle multiple causal triplets and embedded causal triplets in the same sentence. Finally, we combine the causality tagging scheme with deep learning architecture (Section 2.3) to minimize feature engineering while efficiently model causal relations in natural language text.

We notice that some researchers also proposed deep learning techniques-based methods for the causality extraction in recent years (Section 5.3). Although their works are commendable, some works [21, 22, 23, 24] are only a classification of causal relations rather than an extraction of complete causal triplets, and others [25, 26] mainly focus on the identification of the linguistic expressions for causality instead of commonsense causality extraction in this paper.

By applying our causality tagging scheme, we use the model based on BiLSTM-CRF [27] to extract causal triplets directly. However, we find that two obstacles hinder the further improvement of the performance of the deep learning model.

**Firstly**, it is difficult to train a superior deep learning model without any prior knowledge in the case of data insufficiency in existing corpus [28, 29, 30]. To alleviate this problem, we transfer Flair embeddings [31] into our task, which uses the internal states of a character language model trained on a large corpus to create word embeddings (Section 2.3.2). Experimental results show this contextual string embedding that has paved the way for a new technology trend in NLP can drastically improve the performance of causality extraction.

**Secondly**, the distance between Cause and Effect is sometimes far away
Figure 2: The second causal triplet: “[[lesions], Cause-Effect, [distally predominant and a less severe proximal weakness]]” spans almost the entire sentence.

from each other, as Fig. 2 shows. The long-range dependency in the causal triplet brings difficulty and ambiguity to the deep learning model, but a set of logical rules based on dependency trees can easily and accurately extract such triplet. To learn this kind of long-range dependency between Cause and Effect, we introduce the multi-head self-attention mechanism [32] into our model (Section 2.3.4). Unlike LSTM-based models recursively process each word, the self-attention mechanism can conduct direct connections between two arbitrary words in a sentence, and thus allows unimpeded information flow through the network [33].

The contributions of this paper can be summarized as follows:

1. We design a novel causality tagging scheme to directly extract causality in the text, which can easily transform the causality extraction into a sequence labeling task and handle multiple causal triplets and embedded causal triplets in the same sentence.

2. Based on our causality tagging scheme, we propose SCIFI (Self-Attentive BiLSTM-CRF with Flair Embeddings), a neural-based causality extractor with transferred contextual string embeddings trained on a large corpus. To the best of our knowledge, we are the first to transfer Flair embeddings into causality extraction.

3. We introduce the multi-head self-attention mechanism into SCIFI that enables the model to capture long-range dependencies between Cause and
The current view is that [the chronic inflammation] in the distal part of the stomach caused by [Helicobacter pylori infection] results in [an increased acid production] from the non-infected upper corpus region of the stomach.

Figure 3: Two causal triplets share the same one causal event entity: “the chronic inflammation” within a sentence.

4. Extensive experimental results (Section 3) and further analysis (Section 4) show that our method achieves significant and consistent improvement as compared to other baselines. We release the code and dataset to the research community for further research.¹

2. Method

2.1. Causality Tagging Scheme

We use the “BIO” (Begin, Inside, Other) and “C, E, Emb” (Cause, Effect, Embedded Causality) signs respectively to represent the position information of the words and the semantic roles of the causal events, where Embedded Causality means that a causal event has different roles of causality in different triplets. Fig. 3 is an example of an Embedded Causality in a sentence. The example sentence contains two causal triplets: “{the chronic inflammation, Cause-Effect, an increased acid production}” and “{Helicobacter, Cause-Effect, the chronic inflammation}”, note that “the chronic inflammation” is the Cause in the first triplet and also the Effect in the second triplet.

¹https://github.com/Das-Boot/scifi
Fig. 4 shows an example of such causality sequence tagging. Based on our causality tagging scheme, we label the causal event entities: “the chronic inflammation”, “Helicobacter pylori infection” and “an increased acid production” separately with our special tags. Concretely, tag “O” represents the “Other”, which means that the corresponding word is irrelevant in any causality components. Tag “B-C” represents the “Cause Begin”, tag “I-C” represents the “Cause Inside”, tag “B-E” represents the “Effect Begin”, tag “I-E” represents the “Effect Inside”, tag “B-Emb” represents the “Embedded Causality Begin” and tag “I-Emb” represents the “Embedded Causality Inside”. Thus, the total number of tags is $N_t = 7$.

2.2. From Tag Sequence to Causal Triplets

We design a Tag2Triplet algorithm for automatically getting the final extracted triplets from the tag sequence in Fig. 4. To better illustrate this algorithm, we define two types of causality here: simple causality and complex causality.
2.2.1. The Case of Simple Causality

Simple causality can be classified into two types:

1. There is only one Cause or one Effect in the sentence, and there is no Embedded Causality, that is, \( N_C = 1 \) or \( N_E = 1 \) and \( N_{Emb} = 0 \), where \( N_C \), \( N_E \), and \( N_{Emb} \) respectively indicate the number of tags “B-C”, “B-E”, and “B-Emb” in the sentence. The example sentences in Fig. 1 and Fig. 2 are both of this type of causality.

2. There are multiple Causes and Effects in the sentence, and there is no Embedded Causality, i.e., \( N_C > 1 \), \( N_E > 1 \) and \( N_{Emb} = 0 \). In addition to this, for each causal triplet in the sentence, there must be at least one causal triplet that shares the same Cause or Effect with it. The example sentence in Fig. 5 is this type of causality.

2.2.2. The Case of Complex Causality

Complex causality has the following two types:

1. There is Embedded Causality in the sentence, that is, \( N_C > 0 \), \( N_E > 0 \) and \( N_{Emb} > 0 \). The example sentences in Fig. 3 is this type of causality.

2. There are multiple Causes and Effects in the sentence, and there is no Embedded Causality, i.e., \( N_C > 1 \), \( N_E > 1 \) and \( N_{Emb} = 0 \). In addition to this, in all the causal triplets in the sentence, there must be at least
one causal triplet that does not share the same Cause or Effect with any other triplets. The example sentence in Fig. 6 is this type of causality. Note that the distribution of causality in the sentence of Fig. 5 is different from that in Fig. 6: each causal triplet in the former is mixed together, and each causal triplet in the latter is separated.

2.2.3. Tag2Triplet Algorithm

The Tag2Triplet algorithm is described in Algorithm 1. We will elaborate on Tag2Triplet algorithm by taking the sentence $S$ and its corresponding tag sequence $S_{tag}$ as an example in Fig. 4, the intermediate result is shown in Table 1.

Firstly, we count the out-degree and in-degree for the causality and find the index of causality in the $S_{tag}$. Specifically, the out-degree of “Cause” is recorded as 1, the in-degree of “Effect” is recorded as 1, the out-degree and in-degree of “Embedded Causality” are both recorded as 1. Then, we determine whether the $S$ is simple causality or complex causality according to the number and the distribution of each causal tag: “C”, “E” and “Emb”. In $S_{tag}$, $N_{Emb} = 1$ and thus $S$ is complex causality. And then, we apply a Cartesian Product of the causal tags to obtain the candidates of the causal triplet. In Table 1, the candidate “(0, 2)” means the causal triplet “{the chronic inflammation, Cause-Effect, an increased acid production}.

Next, we check whether the out-degree and in-degree of each combination of candidates is consistent with the original out-degree and in-degree of $S_{tag}$, and check whether the combination matching the rules according to the coordinating conjunction in the $S$, such as: if there is a coordinating conjunction “and” between adjacent Causes in the same clause, then the two Causes will form their respective causal triplets with the same Effect, as in the “Bacteria” and “comedonal debris” in Fig. 5. Finally, we select the combination with the shortest distance from the combinations who passed the checks as the extracted causal triplets. Since only one combination “(0, 2), (1, 0)” passed all the checks, we directly output it as the final result.
**Algorithm 1: Tag2Triplet**

| Line | Description |
|------|-------------|
| 1 | input: A tag sequence $S_{tag}$ corresponding to sentence $S$ |
| 2 | output: The causal triplets in sentence $S$ |
| 3 | 1. Count the out-degree and in-degree for the causality in the $S_{tag}$; |
| 4 | 2. Find the index of causality $idx$ in the $S_{tag}$; |
| 5 | 3. if Causality in $S$ ∈ Simple Causality then |
| 6 | 4. candidate ← CartesianProduct($idx$); |
| 7 | 5. if CheckConjunction(candidate, $idx$, $S$) is true then |
| 8 | 6. causal triplets ← candidate; |
| 9 | 7. end |
| 10 | 8. end |
| 11 | 9. if Causality in $S$ ∈ Complex Causality then |
| 12 | 10. candidates ← CartesianProduct($idx$); |
| 13 | 11. for $i ← \text{Max}(\text{Sum(out-degree)}, \text{Sum(in-degree)})$ to $\text{Len}(\text{candidates})$ do |
| 14 | 12. flag ← 0; |
| 15 | 13. records ← [ ]; |
| 16 | 14. for $j ∈ \text{Combination}(\text{candidates}, i)$ do |
| 17 | 15. if CheckDegree($j$, out-degree, in-degree) is true and |
| 18 | 16. CheckConjunction($j$, $idx$, $S$) is true then |
| 19 | 17. distance ← SumDistance($j$, $idx$); |
| 20 | 18. AppendToRecord($j$, distance); |
| 21 | 19. flag ← 1; |
| 22 | 20. end |
| 23 | 21. if flag ≠ 0 then |
| 24 | 22. break; |
| 25 | 23. end |
| 26 | 24. end |
| 27 | 25. causal triplets ← Min(records, key=records[-1]); |
| 28 | 26. end |
Table 1: The intermediate result of running Tag2Triplet when we input the sentence $S$ and its corresponding tag sequence $S_{tag}$, and we highlight the correct combination of candidates in bold.

| $S$ | ... [the chronic inflammation]$_0$ ... [Helicobacter pylori infection]$_1$ ... [an increased acid production]$_2$ ... |
|-----|---------------------------------------------------------------|
| $S_{tag}$ | [B-Emb I-Emb I-Emb]$_0$ [B-C I-C I-C ]$_1$ [B-E I-E I-E I-E]$_2$ |
| Index | $[5, 6, 7]_0$ $[17, 18, 19]_1$ $[22, 23, 24, 25]_2$ |
| Out-degree | 1 1 0 |
| In-degree | 1 0 1 |
| Candidates | (0, 2) (1, 0) (1, 2) |
| Combinations | (0, 2), (1, 0) (0, 2), (1, 2) (1, 0), (1, 2) |
| Out-degree | (1, 1, 0) (1, 1, 0) (1, 0, 0) |
| In-degree | (1, 0, 1) (0, 0, 1) (1, 0, 1) |

2.3. SCIFI

Fig. 7 gives the main structure of our model SCIFI for causality sequence labeling. We will take the input sentence $S = \{x_t\}_{t=1}^n$ and its corresponding label sequence $y = \{y_i\}_{i=1}^n$ as an example introduce each component of SCIFI from bottom to top as following, where $n$ is the length of the $S$.

2.3.1. CNN for Character Representations

To capture task-specific subword features, we take the same convolutional neural network [34] (CNN) architecture as [35], using one layer CNN structure followed by a max-over-time pooling operation [36] to learn character-level representations. The process is depicted on the left side of Fig. 7.

Formally, denoting the embedding of character $r^t_i$ as $e^r(r^t_i)$, the character representation $c_t$ for word $x_t$ can be given by:

$$c_t = \max_{1 \leq i \leq \text{len}(x_t)} \left(W^T[e^r(r^t_{i-k+1}), ..., e^r(r^t_{i+k-1})] + b\right), \quad (1)$$

where $W$ is the weight matrix, $b$ denotes the bias vector, and $k = 3$ is the kernel size.
2.3.2. Transferring Contextualized Representations Learned from Large Corpus

In recent years, deep learning has ushered in incredible advances in natural language processing (NLP) tasks due to its powerful representation learning ability. However, in the case of data insufficiency of the existing corpus, the data-hungry nature of deep learning limits the performance of our neural-based model in causality extraction. The recent development of contextualized language representation models [37, 38, 31] trained on a large corpus shed light on the possibility of transfer learning.

In this paper, we use transfer learning to alleviate the problem of data insufficiency. Specifically, we propose to transfer the Flair embeddings [31], which derived from a character-level language model (CharLM) trained on a 1-billion word benchmark corpus [39] to our task. This CharLM consists of a forward language model (fLM) and a backward language model (bLM). Following Ref. [31], we extract the output hidden state $h_{\text{end}+1}$ from the fLM after the last character $r_{\text{end}}$ of the word $x_t$. Similarly, we obtain the output hidden state $h_{\text{start}-1}$ from
the bLM before the first character $r_{start}^t$ of the word $x_t$. Then, both output hidden states are concatenated to form the final embedding $f_t^{CharLM}$ of the word $x_t$ as follow:

$$f_t^{CharLM} = [h_{end+1}^t, h_{start-1}^t]$$ (2)

Finally, we concatenate transferred Flair embeddings $f_t$ and the character representations $c_t$ with the word embeddings $e_t$ and feed them into a BiLSTM layer.

2.3.3. BiLSTM

Long Short-Term Memory (LSTM) \(^40\) is a particular Recurrent Neural Networks (RNN) that overcomes the vanishing and exploding gradient problems \(^41\) of traditional RNN models. Through the specially designed gate structure of LSTM, the model can selectively save the context information. The basic unit of LSTM architecture is a memory block, which includes a memory cell (denoted as $C$) and three adaptive multiplication gates (i.e., an input gate $i$, a forget gate $f$ and an output gate $o$). Formally, the computation operations to update an LSTM unit at time $t$ are:

$$i_t = \sigma(W_i [e_t, c_t, f_t^{CharLM}] + U_i h_{t-1} + b_i), \quad (3)$$
$$f_t = \sigma(W_f [e_t, c_t, f_t^{CharLM}] + U_f h_{t-1} + b_f), \quad (4)$$
$$o_t = \sigma(W_o [e_t, c_t, f_t^{CharLM}] + U_o h_{t-1} + b_o), \quad (5)$$
$$\tilde{C}_t = \tanh(W_C [e_t, c_t, f_t^{CharLM}] + U_C h_{t-1} + b_C), \quad (6)$$
$$C_t = i_t \odot \tilde{C}_t + f_t \odot C_{t-1}, \quad (7)$$
$$h_t = o_t \odot \tanh(C_t), \quad (8)$$

where $[e_t, c_t, f_t^{CharLM}]$ and $h_t$ represent input vector and hidden state at time $t$, respectively. $\sigma$ is the element-wise sigmoid function, $\odot$ is the element-wise product. $W_i, W_f, W_o, W_C$ are the weight matrices for input vector, $U_i, U_f,$
Figure 8: The architecture of the Multi-Head Attention.

$U_o$, $U_C$ are the weight matrices for the hidden state, and $b_i$, $b_f$, $b_o$, $b_C$ denote the bias vectors.

However, LSTM only considers the information from the past, ignoring the future information. To efficiently use contextual information, we can use Bidirectional LSTM (BiLSTM). BiLSTM use a forward LSTM and a backward LSTM respectively for each sequence to obtain two separate hidden states: $\overrightarrow{h_t}$, $\overleftarrow{h_t}$, and then the final output at time $t$ is formed by concatenating these two hidden states:

$$ h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \quad (9) $$

Therefore, the final output of the BiLSTM layer for the input sentence $S$ can be represented by $H = \{h_t\}_{t=1}^n$, where $H \in \mathbb{R}^{n \times d}$ and $d$ is the layer size of BiLSTM layer.

### 2.3.4. Multi-Head Self-Attention

The self-attention is a particular case of attention mechanism, which only requires a single sequence to compute its representation, has been successfully applied to many NLP tasks and shows its superiority in capturing long-range dependency. In SCIFI, we adopt the multi-head self-attention (MHSA) proposed by Ref. to learn the dependencies of causalities in the given sentences. Fig. 8 depicts the architecture of the multi-head attention mechanism.
Specifically, given $H$ as the output of the BiLSTM layer, the multi-head attention mechanism first projects the matrix $H$ $h$ times with different learned linear projections to matrices: $HW^Q_i$, $HW^K_i$ and $HW^V_i$. Where $h$ is the number of heads, parameter matrices $W^Q_i \in \mathbb{R}^{d \times d_v}$, $W^K_i \in \mathbb{R}^{d \times d_v}$ and $W^V_i \in \mathbb{R}^{d \times d_v}$ are projections for the head $i$. Then the attention function is performed in parallel, yielding $n \times d_v$-dimensional output values. Finally, all the matrices produced by parallel heads are concatenated, resulting in the final values $M$ whose dimension is $n \times (hd_v)$, where both $h$ and $d_v$ are hyper-parameters of the self-attention layer. The formulations can be shown as follows:

$$M = \text{MultiHead}(H, H, H) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) \quad (10)$$

where $\text{head}_i = \text{Attention}(HW^Q_i, HW^K_i, HW^V_i)$ \quad (11)

Here, the attention function is the “Scaled Dot-Product Attention”, which computes the attention scores as follows:

$$\text{Attention}(HW^Q_i, HW^K_i, HW^V_i) = \text{softmax}(\frac{(HW^Q_i)(HW^K_i)^T}{\sqrt{d}})V \quad (12)$$

To fully integrate the information, we put $H$ and attention matrix $M$ together into a CRF layer, which will decode this information and get the best label sequence.

### 2.3.5. CRF

Conditional Random Field (CRF) can obtain a globally optimal chain of labels for a given sequence considering the correlations between adjacent tags. In a sequence labeling task, there are usually strong dependencies between the output labels. So instead of only using RNN to model tagging decisions separately, we adopt BiLSTM-CRF as the backbone of SCIFl to jointly decode labels for the whole sentence.

We use $\tilde{H} \in \mathbb{R}^{n \times k}$ as the matrix of scores output by BiLSTM and the attention layer, where $k$ is the number of distinct tags and $\tilde{H}_{ij}$ represents the
score of the $j^{th}$ label of $i^{th}$ word within a sentence. For the sentence $S = \{x_i\}_{i=1}^n$ along with a path of tags $y = \{y_i\}_{i=1}^n$, CRF gives a real-valued score as follows:

$$score(S, y) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=1}^{n} \tilde{H}_{i, y_i},$$  \hspace{1cm} (13)

where $A$ is the transition matrix, and $A_{i, j}$ denotes the score of a transition from the tag $i$ to tag $j$. $y_0$ and $y_n$ are the special tags at the beginning and the end of a sentence, so $A$ is a square matrix of size $k + 2$. Therefore, the probability for the label sequence $y$ given a sentence $S$ is:

$$p(y | S) = \frac{e^{score(S, y)}}{\sum_{\tilde{y} \in Y_S} e^{score(S, \tilde{y})}},$$ \hspace{1cm} (14)

We now maximize the log-likelihood of the correct tag sequence:

$$\log (p(y | S)) = score(S, y) - \log \left( \sum_{\tilde{y} \in Y_S} e^{score(S, \tilde{y})} \right),$$ \hspace{1cm} (15)

where $Y_S$ represents all possible tag sequences for an input sentence $S$. From the formulation above, we can get a valid output sequence. When decoding, the sequence with the maximum score is output by:

$$y^* = \arg \max_{\tilde{y} \in Y_S} score(S, \tilde{y})$$ \hspace{1cm} (16)

3. Experiments

3.1. Experimental Settings

3.1.1. Dataset

In the experiment, we evaluate on a corpus obtained by extending the annotations of the SemEval 2010 task 8 dataset \[28\]. In the original dataset, only one causal triplet in each sentence has been annotated. We extend the annotation with the causal triplets not considered by the SemEval annotators, for example, we annotate all of the causal triplets in the sentence of Fig. 2 (more examples are shown in Fig. 3, Fig. 5 and Fig. 6). Specifically, the corpus is composed of
Table 2: Statistics of different types of causal tags for the dataset

| Tag Type | Training Set | Test Set |
|----------|--------------|----------|
| B-C      | 1308         | 236      |
| I-C      | 1421         | 229      |
| B-E      | 1268         | 238      |
| I-E      | 1230         | 230      |
| B-Emb    | 55           | 9        |
| I-Emb    | 55           | 16       |
| **Sum**  | **5337**     | **958**  |

5236 sentences, of which 1270 sentences contain at least a causal triplet. The training set consists of 4450 sentences, contains 1570 causal triplets. There are 804 sentences in the test set, including 296 causal triplets. Table 2 shows the statistics of six types of causal tags for the dataset.

3.1.2. Evaluation

We use standard precision (P), recall (R) and F1-score (F) as evaluation metrics, which can be calculated by the following formula:

$$P = \frac{\text{#correct extracted causal triplets}}{\text{#extracted causal triplets}}, \quad (17)$$

$$R = \frac{\text{#correct extracted causal triplets}}{\text{#total causal triplets in D}}, \quad (18)$$

$$F = \frac{2 \cdot P \cdot R}{P + R}, \quad (19)$$

where $D$ is the set of all the sentences in the dataset and a predicted causal triplet is regarded as correct if and only if it precisely matches a labeled causal triplet. In experiments, we create a validation set by randomly sampling 10% data from the training set and perform the grid search to find the optimal hyperparameters. To obtain comparable and reproducible F1-scores, we follow the advice of Ref. [45] and conduct each experiment 10 times and then report the average results and their standard deviation as Table 3 shows.
3.1.3. Hyperparameters

The model is implemented by using Keras\(^2\) version 2.2.4. The 300-D word embeddings pre-trained by Ref. \(^{16}\) are employed and kept fixed during the training process. Character embeddings are randomly initialized from a uniform distribution ranging in \([-\sqrt{\frac{3}{\text{dim}}}, +\sqrt{\frac{3}{\text{dim}}}]\), where we set \(\text{dim} = 30\). We use the flair framework\(^3\) to compute the Flair embeddings. The hidden size of LSTM is set to be 100. The parameters \(h\) (the number of heads) and \(d_v\) (the size of each head) of the multi-head self-attention mechanism are set to 3 and 8 respectively. We use the variational dropout\(^{17}\) with a dropout rate of 0.5 to regularize our network. To deal with the exploding gradient problem, We apply gradient normalization\(^{48}\) with threshold 1.0 into the SCIFI. The optimization method of the training process is Nadam with the learning rate of 0.0075, and we apply a learning rate annealing method in the case that if the training loss does not fall for more than 5 epochs, this method will halve the learning rate. We let the mini-batch size be 16 and select the optimal model among all 200 epochs with the highest validation F1-score.

3.1.4. Baselines

For the comprehensive comparison, we compare our method against several classical causality extraction methods, which can be divided into two categories: the pipeline methods and the sequence tagging models based on our causality tagging scheme. The pipelined methods that we use as our baselines are:

- **Rules+Bayesian**: Ref. \(^{17}\) did pattern matching to extract candidate cause-effect pairs based on a set of rules, then used a Bayesian classifier and Laplace smoothing to filter non-causal pairs.

- **CausalNet**: Ref. \(^{19}\) proposed Causal Strength (CS) to measure causal strength between any two pieces of short texts, integrating necessity causality with sufficiency causality. For comparison, We added the same cause-
effect extraction module as Ref. [17] to their method. We then calculate the CS score of the candidate causal pair and compare with the threshold \( \tau \) (\( \tau \) is a tunable hyper-parameter). If \( CS(c,e) > \tau \), we conclude that \( (c,e) \) is in causal relation, otherwise \( (c,e) \) is the erroneously extracted pair.

The sequence tagging structure used in this paper is divided into the CNN-based models and the BiLSTM-based models. For the CNN-based models [49], the baselines are as follows:

- **IDCNN-Softmax**: This model uses deep iterated dilated CNN (IDCNN) architecture to aggregate context from the entire text, which has better capacity than traditional CNN and faster computation speed than LSTM, and then maps the output of IDCNN to predict each label independently through a Softmax classifier.

- **IDCNN-CRF**: It uses CRF-classifier to maximize the label probability of the complete sentence based on IDCNN. Compared to Softmax classifier, CRF-classifier is more appropriate to the tasks with strong output label dependency.

The baselines for the BiLSTM-based models are listed as follows:

- **BiLSTM-Softmax** [50]: The model consists of two parts, a BiLSTM encoder, and a Softmax classifier.

- **BiLSTM-CRF** [27]: A classic and popular choice for sequence labeling tasks, which consists of a BiLSTM-encoder and a CRF classifier.

- **CLSTM-BiLSTM-CRF** [51]: A hierarchical BiLSTM-CRF model that uses character-based representations to implicitly capture morphological features (e.g., prefixes and suffixes) through a character LSTM encoder (CLSTM) and then concatenates the character embeddings and pre-trained word embeddings as the input of BiLSTM-CRF.
• **CCNN-BiLSTM-CRF** [35]: A similar hierarchical BiLSTM-CRF model uses a character CNN encoder (CCNN) instead of a CLSTM to learn the character-level embeddings.

To further analyze the performance of Flair embeddings transferred into our task, we respectively combine the ELMo [37] and BERT [38], two powerful contextualized word representations into our task-specific BiLSTM-CRF architecture as the experimental baselines:

• **ELMo-BiLSTM-CRF** [37]: An extension of BiLSTM-CRF in which they concatenate pre-trained static word embeddings with the ELMo (Embeddings from Language Models) representations and take them as the input of BiLSTM-CRF.

• **BERT-BiLSTM-CRF** [38]: A similar extension in which they add pre-trained word embeddings and the BERT (Bidirectional Encoder Representations from Transformers) representations and take them as the input of BiLSTM-CRF.

• **Flair-BiLSTM-CRF** [31]: The model is used as a strong baseline in our work, in which they concatenate pre-trained word embeddings with the Flair embeddings and feed it into the BiLSTM-CRF model. Note that the models using Flair embeddings have achieved the current state-of-the-art results in a range of sequence labeling tasks such as Named Entity Recognition, Chunking and Part-of-Speech Tagging [31, 52].

• **Flair+CLSTM-BiLSTM-CRF** [31]: A simple extension in which they add task-trained character representations learned from a CLSTM to Flair-BiLSTM-CRF.

### 3.2. Experimental Results

The performance of different models on the causality extraction shown in Table 3. It shows that SCIFI outperforms all other models with a precision of 0.8457, a recall rate of 0.8639 and an F1-score of 0.8546 in the test set. It
Table 3: Comparison in precision (P), recall (R), and F1-score (F) on the test set with baselines. The first part is the pipeline methods (from row 1 to row 2). The second part (row 3 to row 4) is the CNN-based sequence tagging methods. The third part (row 5 to row 8) is the BiLSTM-based sequence tagging methods, and the fourth part (row 9 to row 12) is the sequence tagging methods using contextualized word embeddings. Our model SCIFI is shown in the final part (the last row).

| Model               | P     | R     | F     |
|---------------------|-------|-------|-------|
| CausalNet           | 0.6211| 0.5372| 0.5761|
| Rules-Bayesian      | 0.6042| 0.5878| 0.5959|
| IDCNN-Softmax       | 0.6102±0.0228 | 0.6081±0.0184 | 0.6090±0.0184 |
| IDCNN-CRF           | 0.7309±0.0134 | 0.6916±0.0213 | 0.7105±0.0145 |
| BiLSTM-Softmax      | 0.7703±0.0269 | 0.7912±0.0199 | 0.7805±0.0221 |
| CLSTM-BiLSTM-CRF    | 0.7891±0.0158 | 0.8240±0.0105 | 0.8061±0.0105 |
| BiLSTM-CRF          | 0.7889±0.0214 | 0.8301±0.0171 | 0.8088±0.0162 |
| CCNN-BiLSTM-CRF     | 0.7968±0.0178 | 0.8361±0.0130 | 0.8159±0.0142 |
| BERT-BiLSTM-CRF     | 0.8234±0.0185 | 0.8466±0.0068 | 0.8347±0.0099 |
| ELMo-BiLSTM-CRF     | 0.8271±0.0193 | 0.8483±0.0122 | 0.8375±0.0137 |
| Flair+CLSTM-BiLSTM-CRF | 0.8331±0.0163 | 0.8530±0.0198 | 0.8429±0.0173 |
| Flair-BiLSTM-CRF    | 0.8321±0.0226 | 0.8571±0.0172 | 0.8442±0.0154 |
| **SCIFI**           | **0.8457±0.0173** | **0.8639±0.0162** | **0.8546±0.0148** |

Our model SCIFI demonstrates the effectiveness of our proposed method. Furthermore, Table 3 also shows that the sequence tagging models based on our causality tagging scheme are better than pipeline methods.

By comparing the performance of the sequence tagging models on the test set, we can see the BiLSTM-based models is better than the CNN-based models. The reason for the superior performance of BiLSTM-based models may be that the LSTM layer can more efficiently capture the global word context information and learn semantic representations of causality. Besides, we also find that the CCNN yields the better result than CLSTM (0.8159 versus 0.8061) under the BiLSTM-CRF architecture, it seems that combining word-based BiLSTM with character-based CNN produces better results for causality extraction.

Moreover, it also shows that the performance of the model has been drastically improved after feeding contextualized word representations into the BiLSTM-
CRF architecture. In particular, the Flair-BiLSTM-CRF achieves the highest improvement of 4.38% over the BiLSTM-CRF compared with the BERT and ELMo (increases of 3.20% and 3.55%, respectively), which verifies the effectiveness of the contextualized character-level word embedding in causality extraction. The reason may be that Flair model words fundamentally as sequences of characters, and thus can better handle rare words as well as model subword structures such as prefixes and endings than the BERT and ELMo.

4. Analysis and Discussion

4.1. Ablation Analysis

To investigate the effect of the different components in SCIFI (Flair+CCNN-BiLSTM-MHSA-CRF), we also report the results of ablation experiments in Table 4. All parts positively contribute to the performance of the SCIFI model. Specifically, we find that the transferred Flair embeddings provide the most significant improvement. This validates our assumption that the lack of data containing causal triplets in the existing corpus will affect the performance of a neural-based model in causality extraction. With the help of the transferred contextualized representations, we can not only learn more semantic and syntactic information from the text but also capture word meaning in context to address the polysemous and context-dependent nature of words. Besides, we also find the multi-head self-attention (MHSA) mechanism can further boost
Figure 9: Comparison of the ratio of predicted single Cause/Effect for the three sets of models. RS-E w/o MHSA and RS-E w/ MHSA denote the ratio of predicted single Effect for the models without and with MHSA mechanism, respectively. Similarly, RS-C w/o MHSA and RS-C w/ MHSA denote the ratio of predicted single Cause for the models without and with MHSA mechanism, respectively.

the performance, especially when there are no Flair embeddings, and the reason will be discussed in Section 4.2. Finally, we find that the task-specific character features can also influence the performance of the model by a slight increase, when comparing the models with and without the character representations learned from a CCNN.

4.2. Analysis of Multi-Head Self-Attention

Different from other sequence tagging models, SCIFI uses multi-head self-attention mechanism to learn the dependencies between Cause and Effect. To further analyse the effect of the MHSA, we compute and visualize the ratio of predicted single Cause (RS-C) and single Effect (RS-E) for the three sets of models:

- BiLSTM-CRF and BiLSTM-MHSA-CRF;
- Flair-BiLSTM-CRF and Flair-BiLSTM-MHSA-CRF;
• Flair+CCNN-BiLSTM-CRF and SCIFI (Flair+CCNN-BiLSTM-MHSA-CRF)

The single Cause/Effect refer to those who cannot find their correct corresponding Effect/Cause.

As shown in Fig. 9, we find that the RS-E w/ MHSA and RS-C w/ MHSA are lower than the RS-E w/o MHSA and RS-C w/o MHSA, which indicates that the MHSA mechanism plays a crucial role in efficiently enhancing the association between Cause and Effect when compared to other models without MHSA mechanism. Besides, from Fig. 9 we can also see that SCIFI gets the lowest ratio of predicted single Cause and Effect than other models, which once again verifies the effectiveness of our proposed method.

4.3. Case Study

In Table 5, we list two representative examples to show the advantages and disadvantages of our proposed model. For each case, we show the input sentence and causal triplets contained in the sentence in the first and second row. The remaining rows show the extracted causal triplets of different models.

Sentence 1 is the case of Simple Causality (see Section 2.2.1), in which five causal triplets are waiting for models to extract. We observed that neither the SCIFI model nor the other two baseline models could obtain all causal triplets correctly. It seems to be difficult for the models to learn the “superficial or underground water” is a complete semantic unit and the phrase “as well as” may play a key role in connecting two causal components. The reason may be that the sequence tagging models based on our causality tagging scheme require a little more training data to learn these kinds of causality expression patterns.

Sentence 2 is the case of Complex Causality (see Section 2.2.2) in which there is Embedded Causality and therefore brings difficulty and ambiguity to the causality learning of the model. In this example, only the SCIFI can capture all the dependencies between Cause and Effect and thus precisely extract all three causal triplets when compared with other models.
Table 5: Results of causality extraction, where “C” is short for “Cause”, “E” is short for “Effect”. We italicize correct results and highlight the wrong ones in bold.

| Sentence 1 | True Triplets | SCIFI | Flair-BiLSTM-CRF | BiLSTM-CRF |
|------------|---------------|-------|-----------------|------------|
|            | [{mudslides}, C-E, [The damages]}, | [{mudslides}, C-E, [The damages]}, | [{mudslides}, C-E, [The damages]}, | [{mudslides}, C-E, [The damages]}, |
|            | [{tremors}, C-E, [The damages]}, | [{tremors}, C-E, [The damages]}, | [{tremors}, C-E, [The damages]}, | [{tremors}, C-E, [The damages]}, |
|            | [{subidence}, C-E, [The damages]}, | [{subidence}, C-E, [The damages]}, | [{subidence}, C-E, [The damages]}, | [{subidence}, C-E, [The damages}], |
|            | [{superficial or underground water}, C-E, [The damages]}, | [{superficial or underground water}, C-E, [The damages}}, | [{superficial or underground water}, C-E, [The damages]}, | None |
|            | [{swelling clay soils}, C-E, [The damages}] | None, | None, | None |

| Sentence 2 | True Triplets | SCIFI | Flair-BiLSTM-CRF | BiLSTM-CRF |
|------------|---------------|-------|-----------------|------------|
|            | [{an infection}, C-E, [inflammation]}, | [{an infection}, C-E, [inflammation]}, | [{an infection}, C-E, [inflammation]}, | [{an infection}, C-E, [inflammation]}, |
|            | [{an infection}, C-E, [ulceration]}, | [{an infection}, C-E, [ulceration]}, | [{an infection}, C-E, [ulceration]}, | [{an infection}, C-E, [ulceration]}, |
|            | [{the bacterium Helicobacter pylori}, C-E, [an infection]}, | [{the bacterium Helicobacter pylori}, C-E, [an infection}}, | [{the bacterium Helicobacter pylori}, C-E, [an infection]}, | None |
|            | [{the bacterium Helicobacter pylori}, C-E, [an infection}] | None, | None, | None |

This year’s Nobel Laureates in Physiology or Medicine made the remarkable and unexpected discovery that [inflammation] in the stomach as well as [ulceration] of the stomach or duodenum is the result of [an infection] of the stomach caused by [the bacterium Helicobacter pylori].
5. Related Works

In this section, we will briefly introduce causality extraction techniques proposed by other researchers, which fall into three categories: 1) approaches that employ pattern matching only; 2) techniques based on the combination of patterns and machine learning, and 3) methods based on deep learning techniques.

5.1. Methods based on patterns

Pattern-based methods extract causality through pattern matching using semantic features, lexicon-syntactic features, and self-constructed constraints. For example, Ref. [1] extracted causal knowledge from the Wall Street Journal using linguistic clues and pattern matching. In the domain of the medical abstract, Ref. [11] used graphical patterns to extract causal knowledge from a medical database. Ref. [15] extracted causal relations using the syntactic pattern “NP1 causal-verb NP2” with causative verbs and then employed semantic constraints to classify candidates as causal or non-causal. Ref. [16] proposed a causal pair extraction method based on part-of-speech, syntactic analysis, and causality templates. In their work, causality templates were first extracted using causal sentences on Wikipedia, and then they used these templates to extract causal relations in other sentences.

These methods that rely solely on rules for pattern matching often have poor cross-domain applicability and may require extensive domain knowledge in solving problems in a particular area, as well as formulating rules that consume significant amounts of time and effort.

5.2. Methods based on the combination of patterns and machine learning

Methods based on the combination of patterns and machine learning techniques mainly treat this task in a pipeline manner. They firstly extract candidate phrases (or entities, events) pairs that may have causal relation according to templates or some clue words, and then classify the candidate causal pairs according to some statistical features or semantic features and grammatical features to filter non-causal pairs. Such as Ref. [5] used constraints based on
causality trigger words to extract causal relations in English texts and used the C4.5 decision tree to perform classification. Ref. [17] used predefined templates to extract candidate causal pairs and then used Bayesian classifier and Laplace smoothing to filter non-causal pairs. Ref. [18] proposed a new feature called causal connectives by computing the similarity of the syntactic dependency structure of sentences. They run a partial parser to extract candidate noun phrases first and then classified the candidate causal pairs using the Restricted Hidden Naive Bayes learning algorithm in combination with other features, but their method is not able to discriminate the Causes from the Effects. Ref. [19] extracted cause-effect terms from large-scale web text corpora using causal cues and then used a new statistical metric based Point-wise Mutual Information (PMI) to measure causal strength between any two pieces of short texts.

Above methods divide causality extraction into two sub-tasks, candidate causal pairs extraction and relation classification (filtering non-causal pairs). The results of candidate causal pairs extraction may affect the performance of relation classification and generate cascading errors. These methods often require considerable human effort and time on feature engineering, relying heavily on the manual selection of textual features and the hand-selected features are relatively too simple to capture the in-depth semantic information of the context.

5.3. Methods based on deep learning techniques

Due to the powerful representation learning capabilities of deep neural networks that could effectively capture implicit and ambiguous causal relations, the adoption of deep learning techniques for causality extraction has become a popular choice for researchers in recent years. Ref. [21] used CNN to classify causal relations in the text. Ref. [22] used Multi-Column CNN with the background knowledge extracted from noisy texts to classify such commonsense causalities as “smoke cigarettes” → “die or lung cancer”. Similarly, Ref. [23] proposed a Knowledge-oriented CNN that incorporates prior knowledge from lexical knowledge bases for causal relation classification. Ref. [23] proposed an LSTM-based
model only fed with word embeddings for the task of causality classification. In addition to classifying causality from a commonsense reasoning standpoint, Ref. [25] and Ref. [26] also identified the linguistic expressions of causality in the text from a linguistic point of view through deep LSTM-based models.

The main differences between our proposed method and the above methods based on deep learning techniques can be summarized as follows:

- Our method aims to automatic extract such commonsense causal triplets as c in the text (Fig. 1), not to only classify causal relations or to identify the linguistic expressions of causality.

- Our method can easily handle multiple causal triplets and Embedded Causality in the same sentence (Section 2.1 and Section 2.2) without having to divide the sentences into sub-sentences that contain only one instance of causality and thus generate cascading errors as in Ref. [25].

6. Conclusion

In this paper, we formulate causality extraction as a sequence tagging problem and deliver a self-attentive BiLSTM-CRF-based solution for the causality extraction. In particular, we propose SCIFI to extract causality in natural language text based on our causality tagging scheme. To alleviate the problem of data insufficiency, we transfer the Flair embeddings trained from large corpus into our task. Besides, we introduce the multi-head self-attention mechanism to learn the dependencies between Cause and Effect. Experimental results demonstrate the effectiveness of our proposed method. However, the performance of SCIFI is still limited to some extent by the insufficiency of high-quality annotated data (Section 4.3).

In future work, we will try to solve this problem in the following direction:

1. Developing annotated datasets from multiple sources based on existing dataset and our causality tagging scheme.
2. Combining our method with distant supervision and reinforcement learning to achieve better performance without having to build a high-quality annotated corpus for causality extraction.

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