Automatic extraction of cause-effect relations in Natural Language Text

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Abstract. The discovery of causal relations from text has been studied adopting various approaches based on rules or Machine Learning (ML) techniques. The approach proposed joins both rules and ML methods to combine the advantage of each one. In particular, our approach first identifies a set of plausible cause-effect pairs through a set of logical rules based on dependencies between words then it uses Bayesian inference to reduce the number of pairs produced by ambiguous patterns. The SemEval-2010 task 8 dataset challenge has been used to evaluate our model. The results demonstrate the ability of the rules for the relation extraction and the improvements made by the filtering process.

Keywords: Natural Language Processing, Information Extraction, Relations extraction, Causal relations.

1 Introduction

The extraction of causal relations from English sentences is an important step for the improvement of many Natural Language Processing applications such as question answering [1, 2], document summarization and, in particular, it enables the possibility to reason about the detected events [3, 4]. Besides, many websites[1] specialized in web intelligence provide services for the analysis of huge amounts of texts and in this scenario the extraction of causal information can be used for the creation of new insights and for the support of the predictive analysis.

The automatic extraction of causal relations is also a very difficult task because the English presents some hard problems for the detection of causal relation. Indeed, there are few explicit lexico-syntactic patterns that are in exact correspondence with a causal relation while there is a huge number of cases that can evoke a causal relation not in a uniquely way. For example, the following sentence contains a causal relation where *from* is the pattern which evokes such relation:

"Pollution ***from*** *cars is causing serious health problems for Americans."*

[1] One of the most prominent examples is http://www.recordedfuture.com/

In this case, the words (*pollution* and *cars*) connected by the cue pattern (*from*) are in a causal relation while in the following sentence the *from* pattern doesn't evoke the same type of relation:

"A man ***from*** *Oxford with leprosy was cured by the water."*

Although most of the existing approaches for discovering causal relations are centered on the extraction of a pair of words or noun phrases that are in a causal relation, they do not discriminate causes and effects.

In this paper we propose an approach based on a set of rules that uses the dependency relations between the words. It is able to extract the set of potential pairs cause-effect from the sentence, then we use a Bayesian approach to discard the incorrect pairs. In particular, we identify words that are in a causal relation within a single sentence where the relation is marked by a specific linguistic unit and the causation is explicitly represented (both arguments of the relations are present in the sentence [5]). In particular, we detect nominal words denoting an occurrence (an event, a state or an activity), or nouns denoting an entity, either as one of its readings (like *breakfast*, which can denote an entity, or like *devastation*, which can denote an event) or metonymies (like *the mall*, which can stand in for shopping).

The rest of this paper is organized as follows. In Section 2 we present a brief review of the previous works about causal relations extraction from text. Section 3 describes the proposed method. Results are presented in Section 4. At the end we offer some discussion and conclusions.

2 Related works

In this section we will briefly introduce some approaches proposed by other authors concerning the automatic extraction of causal knowledge.

In [5] a method, based on Decision Trees, for the detection of marked and explicit causations has been proposed. The authors showed that their method is able to recognize sentences that contain causal relations with a precision of 98% and a recall of 84%. However, this method is not able to detect the causes and the effects.

The task 4 of SemEval-2007 [6] and the task 8 of SemEval-2010 [7] concerned about the classification of pairs of words. In each sentence a specific pair of words is already annotated and the target of the tasks consists in classifying the pairs according to the relation evoked in the sentence. The tasks take in account seven types of relations, one of which is the causal relation. In SemEval-2010, Rink et al. [8] had the best results. They obtained an overall precision of 89% and an overall recall of 89% using a SVM classifier, for the specific class of the causal relations they obtained a precision of 89% and a recall of 89%.

An approach to identify cause and effect in sentence was proposed in [2]. In this work, a semi-automatic method to discover causal relations having the particular pattern <*NP verb NP*> was defined. They reported a precision of 65% on a corpus containing a set of documents related to terrorism.

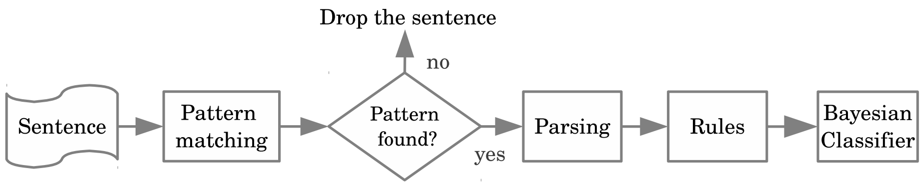

Fig. 1. Steps for the detection of causes and effects.

A system for mining causal relations from Wikipedia is proposed in [9]. The authors used a semi-supervised model in order to select lexico-syntactic patterns represented by the dependency relations between the words able to extract pair of nominals in causal relation. They reported a precision of 76% and a recall of 85%. The patterns discovered by their algorithm are not able to discriminate the causes from the effects.

In order to predict future events from news, in [10] the authors implemented a method for the extraction of causes and effects. In this case, the domain of interest was restricted to the headlines of newspaper articles and a set of hand-crafted rules was used for this task (with a precision of 78%). In [11] regarding a medical abstracts domain, separated measures of precision and recall for causes and effects are reported: a precision of 46% and a recall of 56% for the causes and a precision of 54% and a recall of 64% for the effects. In the last two works mentioned, the approaches proposed are able to discriminate between causes and effects, but they are limited to particular domains.

3 Our approach

In this work, the goal is to extract from a sentence S a set of pairs *cause-effect* $\{(C_1, E_1), (C_2, E_2), \ldots, (C_n, E_n)\}$ where (C_i,E_i) represents the ith cause-effect pair in S. To this end, we propose a method showed in Fig. 1. First, we check if the sentence contains a causal pattern. Then, if a pattern is found the sentence is parsed and a set of rules is applied. A Bayesian classifier is applied to filter out the pairs produced by the rules derived from ambiguous patterns.

3.1 Lexico-syntactic patterns

For the extraction of the pairs, we have defined a set of lexico-syntactic patterns that represent the structure of the causal relations in the sentence. In order to identify the lexico-syntactic patterns, we have inspected the structure of the sentences that contain causal relations in the train dataset provided for the task 8 of SemEval-2010.

The patterns identified are:

- *Simple causative verbs* are single verbs having the meaning of “causal action” (e.g. *generate, trigger, make* and so on).

– *Phrasal verbs* are phrases consisting of a verb followed by a particle (e.g. *result in*).
– *Nouns + preposition* are expressions composed by a noun followed by a preposition (e.g. *cause of*).
– *Passive causative verbs* are verbs in passive voice followed by the preposition *by* (e.g. *caused by*, *triggered by*, and so on).
– *Single prepositions* are prepositions that can be used to link "cause" and "effect" (e.g. *from*, *after*, and so on).

<table>
<tr><th>Pattern</th><th>Regular expression</th></tr>
<tr><td>Simple causative verbs</td><td>(.*) <cause|generate|triggers|...> (.*)</td></tr>
<tr><td>Phrasal verbs / Noun + preposition</td><td>(.*) <result|cause|lead|...> <in|of|to> (.*)</td></tr>
<tr><td>Passive causative verbs</td><td>(.*) <caused|generated|triggered|...> by (.*)</td></tr>
<tr><td>Single prepositions</td><td>(.*) <from|after|...> (.*)</td></tr>
</table>

Table 1. List of lexico-syntactic patterns and related regular expression used to detect causal sentence.

For each lexico-syntactic pattern a regular expression (see Table 1) is defined to recognize the sentences that contain such pattern, and a set of rules is defined in order to detect causes and effects.

3.2 Rules

The rules for the detection of causes and effects are based on the relations in the dependency tree of the sentence, in particular on the Stanford dependencies representation [12]. The rules are made analyzing the most frequent relations that involve the words labeled as cause or effect in the dependency tree. For example, in the case of *phrasal verb* we have observed that the cause is linked to the verb while the effect is linked to the preposition or in the case of single preposition both cause and effect are linked to the preposition. The defined rules are introduced as Horn-Clauses. The main rule that allows to detect the cause-effect relation is:

$$cause(S,P,C) \wedge effect(S,P,E) \rightarrow cRel(S,C,E). \tag{1}$$

where $causeS(S,P,C)$ means that the C is a cause in S in accordance to the pattern P while $effectS(S,P,E)$ means that E is the effect in C with respect to P.

Rules for Simple causative verbs For this pattern, generally the cause and effect are respectively the subject (rule 2) and the object (rule 3) of the verb.

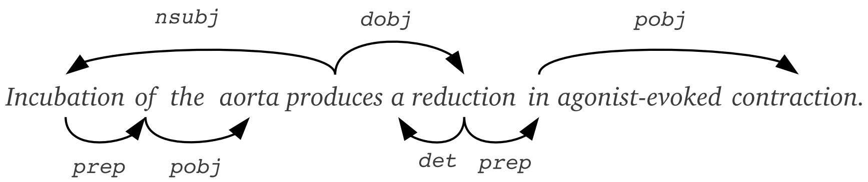

Fig. 2. Dependencies among the words of the sentence *"Incubation of the aorta produces a specific reduction in agonist-evoked contraction"*.

Examples of verbs which evoke causal relation are *cause, create, make, generate, trigger, produce, emit* and so on. We indicate with $verb(S, P, V)$ that the verb V of the sentence S belongs to pattern P of simple causative verb (row 1 in Table 1), while the relation $nsubj(S, V, C)$ is true if C is the subject of V and $dobj(S, V, E)$ is true if E is the direct object of V. The rules defined are:

$$verb(S, P, V) \wedge nsubj(S, V, C) \rightarrow cause(S, P, C), \tag{2}$$

$$verb(S, P, V) \wedge dobj(S, V, E) \rightarrow effect(S, P, E). \tag{3}$$

If we consider, for example, the dependency tree of the sentence *"Incubation of the aorta produces a specific reduction in agonist-evoked contraction"* (showed in Fig. 2), applying the rules 2 and 3, we have that *Incubation* is the cause and *reduction* is the effect.

Rules for Phrasal verbs / Noun + preposition For this pattern, the cause is linked to the verb (or noun) while the effect is linked to the preposition. We indicate with $prep\_verb(S, P, V)$ that the verb or the noun V of the sentence S belongs to the pattern P of phrasal verbs (row 2 in Table 1). While, $prep(S, E, Pr)$ is true when Pr is a propositional modifier of V. The rule defined for the detection of the causes is:

$$prep\_verb(S, P, V) \wedge nsubj(S, V, C) \rightarrow cause(S, C) \tag{4}$$

while, the detection of the effect depends on the preposition. Then, we have defined the following rule:

$$\begin{aligned} &prep\_verb(S, P, V) \wedge preposition\_of(S, V, Pr) \wedge \\ &\wedge\, prep(S, E, Pr) \rightarrow effect(S, P, E). \end{aligned} \tag{5}$$

A particular case is the causal relation introduced by the expression **"due to"**. For this pattern, with respect to previous rules, the relations are inverted. So, the cause is linked to the preposition and the effect to the verb. The rules are:

$$\begin{aligned} &prep\_verb(S, P, due) \wedge prep(S, due, to) \wedge pobj(S, to, C) \rightarrow cause(S, P, C), \\ &prep\_verb(S, P, due) \wedge nsubj(S, due, E) \rightarrow effect(S, P, E). \end{aligned} \tag{6}$$

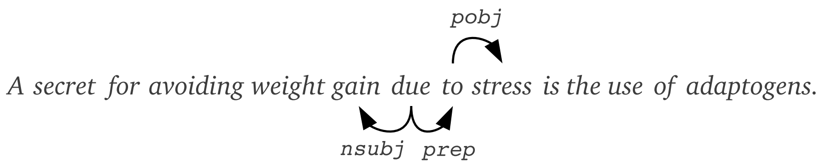

Fig. 3. Dependencies among the words of the sentence *"A secret for avoiding weight gain due to stress is the use of adaptogens"*.

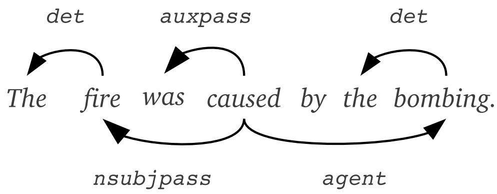

Fig. 4. Dependencies among the words of the sentence *"The fire was caused by the bombing"*.

where $pobj(S, Pr, C)$ is true when C is the object of a preposition Pr.

In this case, applying the rules on the dependency tree of the sentence *"A secret for avoiding weight gain due to stress is the use of adaptogens"* (showed in Fig. 3), we are able to correctly detect *stress* as cause and *gain* as effect.

Rules for Passive causative verbs In this pattern the cause is the word that has an *agent* relation with the verb. In fact, as reported in [12], the *agent* is the complement of a passive verb which is introduced by the preposition *by* and does the action, while the effect is the passive subject of the verb. We indicate with $passive(S, P, V)$ that the verb V of the sentence S belongs to the pattern P of passive causative verbs (row 3 in Table 1).

The rules defined are:

$$\begin{aligned} &passive(S, P, V) \wedge agent(S, V, C) \rightarrow cause(S, P, C), \\ &passive(S, P, V) \wedge nsubjpass(S, V, E) \rightarrow effect(S, P, E) \end{aligned} \tag{7}$$

where $agent(S, V, C)$ is true when C is the complement of a passive verb V and $nsubjpass(S, V, E)$ is true when E is the subject of V.

In this case, applying the rules on the dependency tree of the sentence *"The fire was caused by the bombing."* (showed in Fig. 4), we are able to correctly detect *bombing* as cause and *fire* as effect.

Rules for Single prepositions For this pattern, the cause and effect are linked, in the dependence tree, to the preposition that evokes the causal relation.

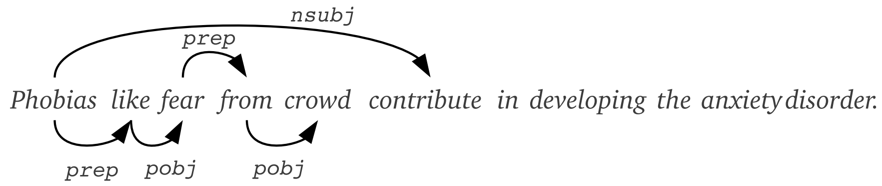

Fig. 5. Dependencies among the words of the sentence *"Phobias like fear from crowd contribute in developing the anxiety disorder"*.

We use $preposition(S, P, Pr)$ to indicate that the preposition Pr of the sentence S belongs to the pattern P of single preposition (row 4 in Table 1). In this case, the rules defined are:

$$\begin{aligned} &preposition(S, P, Pr) \wedge pobj(S, Pr, C) \rightarrow cause(S, P, C), \\ &preposition(S, P, Pr) \wedge prep(S, E, Pr) \rightarrow effect(S, P, E). \end{aligned} \tag{8}$$

In many cases the effects have a direct link with the verb that precedes *from* or *after*. In order to handle those situations we defined the following rule:

$$preposition(S, P, Pr) \wedge prep(S, V, Pr) \wedge nsubj(S, V, C) \rightarrow effect(S, P, C). \tag{9}$$

If we consider, for example, the dependency tree of the sentence *"Phobias like fear from crowd contribute in developing the anxiety disorder"* (showed in Fig. 5), applying the rules 8 and 9, we have that *crow* is the cause and *fear* is the effect.

3.3 Rules for multiple causes and effects

The rules presented above allow to detect a cause and an effect for each pattern that match in a sentence. If there are two or more causes for an effect, we want to detect them all. For example, in the sentence

"*Heat, wind and smoke cause flight delays.*"

the *and* relation indicates that the *delays* (effect) is caused by *Heat*, *wind* and *smoke*, so we have three causes. To deal with these situations we have defined rules that propagate the causal relation along the conjunct dependencies:

$$cause(S, P, C1) \wedge conj(S, C1, C2) \rightarrow cause(S, P, C2). \tag{10}$$

The same rule is defined to propagate through conjunctions the effect:

$$effect(S, P, E1) \wedge conj(S, E1, E2) \rightarrow effect(S, P, E2) \tag{11}$$

where $conj(S, C1, C2)$ is true when $C1$ and $C2$ are connected by a coordinating conjunction (*and*, *or*).

The Fig. 6 shows the dependency tree of sentence *"Heat, wind and smoke cause flight delays"* and we can see that that applying the and rule we detect all causes.

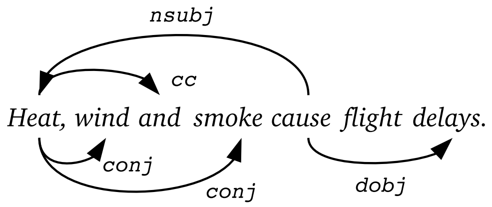

Fig. 6. Dependencies among the words of the sentence *"Heat, wind and smoke cause flight delays"*.

3.4 Pairs filtering

The patterns and the rules defined above, due to their empirical nature, are not able to produce exact results. Hence, there are some pairs (C, E) that are not in causal relation. In order to remove the erroneous pairs detected we used a binary classifier to discriminate *causal* and *non-causal* pairs. This problem is a subtask of the task 8 of the SemEval-2010 where only the causal relation have been considered. To implement the classifier we have chosen to use the Bayesian classification method. Considering the (hypothetical causal) pair $r \equiv cRel(C, E)$, the Bayes' rule becomes:

$$P(c_i|r) = \frac{P(r|c_i)P(c_i)}{P(r)}, \tag{12}$$

with $i = 1, 2$ where c_1 is *causal* and c_2 is *non-causal*. The following features have been associated to the relation r:

- *Lexical features*. The words between C and E.
- *Semantic features*. All the hyponyms and the synonyms of each sense of C and E reported in WordNet [13].
- *Dependency features*. The direct dependencies of C and E in the dependency parse tree.

For each pair r we have extracted a set of features F and for each feature $f \in F$ we have estimated $P(f|c_i)$ by counting the number of causal relations having the feature f, then dividing by the total number of times that f appears. We have used Laplace smoothing applying an additive constant α to allow the assignment of non-zero probabilities for features which do not occur in the train data:

$$P(f|c_i) = \frac{\#(c_i, f) + \alpha}{\#f + \alpha|F|}. \tag{13}$$

Assuming that the features are independent from each other we computed

$$P(r|c_i) = \prod_{f \in F} P(f|c_i). \tag{14}$$

Class	Precision	Recall	F-score
causal	91%	94%	92%
non-causal	98%	97%	98%

Table 2. Results of the classifier for the discrimination of causal pairs on the train set of the SemEval-2010 task 8 using 10-fold cross validation ($\alpha = 1$).

According to the Bayesian classification rule, the relation is classified as *causal* if

$$P(c_1|r) \geq P(c_2|r) \tag{15}$$

and as *non-causal* otherwise.

In order to test the classification framework we used 10-fold cross validation on the train set of the SemEval-2010 dataset. The results are summarized in Table using precision, recall and f-score, they are slightly better to the best ones obtained at the SemEval-2010 challenge, the improvement can be explained by the fact that we consider only the causal relation.

4 Evaluation

We have evaluated our method on a test corpus made extending the annotations of the SemEval-2010 (Task 8) test set. In the original dataset in each sentence only one causal pair has been annotated. We have extended the annotation with the causal pairs not considered by the SemEval annotators. In the cases where an effect is caused by a combination of events or a cause produces a combination of events, pair cause-effect is annotated separately. Our corpus is composed by 600 sentences, 300 of them contain at least a causal relation and the other 300 without causal relations.

The dependency trees have been computed using the Stanford Statistical Parser [14] and the rules for the detection of cause-effect pairs have been implemented in XSB Prolog [15].

The performances have been measured globally and per sentence. The metrics used are *precision*, *recall* and *F-score* in both contexts. Let us define *precision* and *recall* in the global context as

$$P_{global} = \frac{\#\text{correct retrieved pairs}}{\#\text{retrieved pairs}}, \tag{16}$$

$$R_{global} = \frac{\#\text{correct retrieved pairs}}{\#\text{total pairs in } D}, \tag{17}$$

where D is the set of all the sentences in the dataset. The *precision* and *recall* to measure the performances *per sentence* are defined as

$$P_{sentence} = \frac{1}{|M|} \sum_{s \in M} \frac{\#\text{correct retrieved pairs in } s}{\#\text{retrieved pairs in } s}, \tag{18}$$

	Precision	Recall	F-score	α
Global	49%	66%	56%	*no filter*
Per sentence	56%	67%	61%	
Global	55%	65%	59%	0
Per sentence	59%	66%	62%	
Global	**71%**	**58%**	**63%**	0.2
Per sentence	**72%**	**57%**	**64%**	
Global	70%	54%	61%	0.5
Per sentence	70%	53%	60%	
Global	70%	56%	63%	0.7
Per sentence	71%	56%	62%	
Global	71%	54%	62%	1
Per sentence	72%	54%	61%	

Table 3. Results obtained during the tests.

$$R_{sentence} = \frac{1}{|D|} \sum_{s \in D} \frac{\#\text{correct retrieved pairs in } s}{\#\text{total pairs in } s}, \tag{19}$$

where M is the set of the sentences where the rules found at least a causal pair. In both cases the F-score is defined as

$$F = 2\frac{P \cdot R}{P + R}.$$

The *per sentence* metrics measure the ability of the system to extract all the causal pairs contained in a given sentence while the *global* metrics measure the ability of the system to extract all the causal pairs contained in the entire corpus.

The results of the evaluation are summarized in Table 3. We can see that the precision of the rules stand-alone is around 50% and the recall is around 60%. While, the application of the filter, in the best case, increases the precision of 20% but with a slight lowering of the recall. We can also observe that the best performances of the filter are obtained with Laplace smoothing setting $\alpha = 0.2$. For highest values of α we obtained the same precision, but a significant lowering of the recall.

5 Conclusion & Future Work

In this work we have presented a method for the detection and the extraction of cause-effect pairs in English sentences that contain explicit causal relations. In particular, we have used an hybrid approach which combines rules, for the extraction of all possible causes and effects, and a Bayesian classifier to filter the erroneous solutions.

The presented method have been evaluated on an extended version of the dataset used for the task of the SemEval-2010 challenge. The results achieved by our approach are encouraging, especially if we consider that the dataset contains data extracted from various domains.

In future work we will refine the rules presented and experiment other filtering techniques. Also, we will extend this system in order to handle also implicit causal relations.

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