

A Hybrid Approach for the Automatic Extraction of Causal Relations from Text

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Abstract This chapter presents an approach for the discovery of causal relations from open domain text in English. The approach is hybrid, indeed it joins rules based and machine learning methodologies in order to combine the advantages of both. The 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

Causality is an important element for textual inference and the automatic extraction of causal relations plays an important role 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]. Also, with the growth of textual unstructured information on web, it is a fundamental tool to provide effective insights about the data. In fact, many websites¹

¹One of the most prominent examples is <http://www.recordedfuture.com/>.

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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, in particular the English language presents some hard problems for the detection of causal relations. 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:

The most dreaded types of scars are contracture scars **from** burns.

In this case, the words (*scars* and *burns*) 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:

In the past, insulin was extracted from the pancreases of cows or pigs.

Most of the existing approaches [5, 6] to discover 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 chapter 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 cause-effect pairs from the sentence, then we use a Bayesian approach to discard the incorrect pairs.

The chapter is organized as follows. In Sect. 2 we present a concise overview of the previous works about causal relations extraction from text. In Sect. 3 we briefly introduce the dependency grammars. Section 4 describes the proposed method. Results are presented in Sect. 5. At the end we offer some discussions 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 [6] 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.

With respect to the classification of semantic relations, the SemEval challenge proposes two tasks (task 4 in 2007 [7] and task 8 in 2010 [8]). The tasks concern about the classification of pairs of words, in particular, 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 and Harabagiu [9] 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 causes and effects in sentences was proposed in [2] where a semi-automatic method to discover causal relations having the particular pattern $\langle NP\ verb NP \rangle$ was defined. The authors reported a precision of 65% on a corpus containing a set of documents related to terrorism.

A system for mining causal relations from Wikipedia is proposed in [5]. In order to select the patterns, the authors used a semi-supervised model based on the dependency relations between the words able to extract pairs of nominals in the causal relations. They reported a precision of 76% and a recall of 85%. Also in this case, 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 handcrafted rules was used for this task (with a precision of 78%). Finally, 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 Some Aspects of Dependency Grammars

Dependency grammars are used to describe the grammatical relations of a sentence [12]. In this grammars, all the words of a sentence, except a specific verb, depend on other words. The verb which doesn't depend on any word is considered the central element of the clause. All the other words are either directly or indirectly dependent on the verb. In this type of segmentation sentence each relation involves two words, one of them is called *head* and the other *dependent*. In this work we have used the Stanford typed dependencies [13], in particular the collapsed version. An example of dependency representation is the following:

$$\begin{aligned} &det(fire, The), \\ &nsubjpass(caused, fire), \\ &auxpass(caused, was), \\ &root(ROOT, cause), \\ &det(bombing, the), \\ &agent(cause, bombing). \end{aligned} \tag{1}$$

This is a dependency representation of the sentence “*The fire was caused by the bombing*” (a graphical form of the same representation is showed in Fig. 4 where a dependency link represented as an arrow pointing from the head to the dependent). The dependency structure can be seen as a tree (directed acyclic graph) having the main verb as root. In the example above, *nsubjpass(cause, fire)* indicates that *fire* is the passive subject of the verb *cause*; *auxpass(cause, was)* indicates that *was* is the auxiliary; *root(ROOT, cause)* indicates that *caused* is the root of the dependency tree; *agent(cause, bombing)* indicates that *bombing* is the complement of *caused*; *det(fire, the)* and *det(bombing, the)* represent, respectively, a connection between the words *fire* and *bombing* with their determiners. A complete list of dependency relations has been presented in [13].

4 Extraction Method

In this work, the goal is to extract from a sentence S a set of *cause-effect* pairs $\{(C_1, E_1), (C_2, E_2), \dots, (C_n, E_n)\}$ where (C_i, E_i) represents the i th cause-effect pair in S . To this end, we propose a method represented 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. Also, a Bayesian classifier is applied to filter out the pairs produced by the rules derived from ambiguous patterns.

4.1 Assumptions

The extraction model has been developed under the following assumptions:

1. The relation is **marked** by a linguistic unit. A sentence contains a marked relation if there is a specific linguist unit that evokes the relation. For example the sentence “*the boy was absent because he was ill*” is marked, indeed there is the unit *because* that evoke the causal relation, while “*Be careful, its unstable*” contains a causal relation but has not a linguist unit.
2. The causation is **explicitly** represented, which means that both arguments of the relation (cause and effect) are present in the sentence. For example the sentence

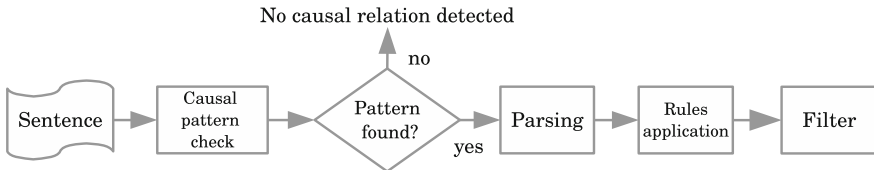


Fig. 1 Steps for the detection of causes and effects of the proposed method

“*I’m a success today because I had a friend who believed in me*” is explicit because contains both cause *I had a friend who believed in me* and the effect *I’m a success*, while the sentence “*John killed Bob*” is implicit because the effect, *the death of Bob*, is not explicitly reported.

3. The arguments of the relation are nominal words denoting:

- an occurrence of an event, a state or an activity;
- a noun as an entity or one of its readings (like *breakfast*, which can denote an entity, or like *devastation*, which can denote an event);
- a metonymy (like *the mall*, which can stand in for shopping).

The assumption 1 and 2 are the basis of the extraction rules, while the last assumption is given by the data available for the analysis.

4.2 Lexico-Syntactic Patterns

In this work, as first step, we have defined a set of lexico-syntactic patterns that represent the structure of the causal relations in the sentence. They represent causal patterns through groups of syntactic structures having common features. 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.

For this goal, we have analyzed the train dataset studying the χ^2 measure. This statistics measures the dependence between the features and a target variable and it is often used to discover which features are more relevant for statistical classification. The study proposed by Yang and Pedersen in [14] shows that χ^2 is an effective statistics for terms selection. Therefore, we decided to use χ^2 to select the most characterizing patterns associated with the causal relation. We also experimented with the Information Gain statistics and obtained similar results. Analyzing the χ^2 measure we have identified the following groups of patterns:

- *Simple causative verbs*: single verbs having the meaning of “causal action” (e.g. *generate, trigger, make* and so on).
- *Phrasal verbs*: phrases consisting of a verb followed by a particle (e.g. *result in*).
- *Noun + preposition*: expressions composed by a noun followed by a preposition (e.g. *cause of*).
- *Passive causative verbs*: verbs in passive voice followed by the preposition *by* (e.g. *caused by, triggered by*, and so on).
- *Single prepositions*: prepositions that can be used to link “cause” and “effect” (e.g. *from, after*, and so on).

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.

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

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

4.3 Rules

For the extraction of causes and effects in the sentence, the proposed approach uses a set rules based on the relations in the dependency tree of the sentence. For the definition of rules we have analyzed, in the train dataset, the most frequent relations that involve the words labeled as *cause* or *effect* in the dependency tree. This analysis was performed grouping the sentences with respect to the lexico-syntactic patterns. For example, in the case of sentences that match with *phrasal verb* pattern we have observed that the cause is associated to the verb while the effect is associated to the preposition; or in the case of sentences that match with a single preposition both cause and effect are associated to the preposition. The defined rules are formalized by Horn-Clauses. The main rule that allows to detect the cause-effect relation is:

$$cause(S, P, C) \wedge effect(S, P, E) \rightarrow cRel(S, C, E), \quad (2)$$

where $cause(S, P, C)$ means that the C is a cause in S in accordance with the pattern P while $effect(S, P, E)$ means that E is the effect in C with respect to P . So, $cRel(S, C, E)$ represents the causal relation detected in a sentence.

4.3.1 Rules for Simple Causative Verbs

For this pattern, generally the cause and the effect are respectively the subject (rule expressed in Eq. 3) and the object (rule expressed in Eq. 4) of the verb. Examples of verbs which evoke causal relations 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 complies with a pattern P , which has to be a simple causative verb (first row in Table 1), while the relation $nsubj(S, V, C)$ indicates that C is the subject of V in S , and $doj(S, V, E)$ indicates that E is the direct object of V in S . According to the given definitions, we have formulated the following rules:

$$verb(S, P, V) \wedge nsubj(S, V, C) \rightarrow cause(S, P, C), \quad (3)$$

$$verb(S, P, V) \wedge doj(S, V, E) \rightarrow effect(S, P, E). \quad (4)$$

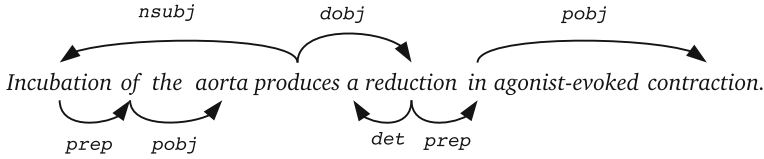


Fig. 2 Dependencies among the words of the sentence “*Incubation of the aorta produces a specific reduction in agonist-evoked contraction*”

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 Eqs. 3 and 4, we have that *Incubation* is the cause and *reduction* is the effect.

4.3.2 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 complies to the pattern P , which has to be a phrasal verb (second row in Table 1). While, $prep(S, E, Pr)$ indicates that Pr is a propositional modifier of V in S . According to the given definitions, we have formulated the following rules:

$$prep_verb(S, P, V) \wedge nsubj(S, V, C) \rightarrow cause(S, P, C), \quad (5)$$

$$prep_verb(S, P, V) \wedge preposition_of(S, V, Pr) \wedge prep(S, E, Pr) \rightarrow effect(S, P, E). \quad (6)$$

In the particular case where the causal relation is introduced by the expression “**due to**” we have that, with respect to other expressions that are complied to this pattern, the terms of the relations are *inverted*. So, the cause is linked to the preposition and the effect to the verb. The rules are:

$$\begin{aligned} prep_verb(S, P, due) \wedge prep(S, due, to) \wedge pobj(S, to, C) &\rightarrow cause(S, P, C), \\ prep_verb(S, P, due) \wedge nsubj(S, due, E) &\rightarrow effect(S, P, E), \end{aligned} \quad (7)$$

where $pobj(S, Pr, C)$ indicates that C is the object of the preposition Pr in S . In this case, applying the rules Eq. 7 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.

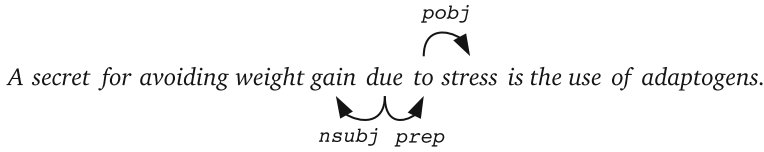


Fig. 3 Dependencies among the words of the sentence “A secret for avoiding weight gain due to stress is the use of adaptogens”

4.3.3 Rules for Passive Causative Verbs

In this pattern, the cause is the word of the sentence that has an *agent* relation with the verb. In fact, as reported in [15], 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 complies with the pattern P , which has to be a passive causative verb (third row in Table 1). According to the given definitions, we have formulated the following rules:

$$\begin{aligned} passive(S, P, V) \wedge agent(S, V, C) &\rightarrow cause(S, P, C), \\ passive(S, P, V) \wedge nsubjpass(S, V, E) &\rightarrow effect(S, P, E), \end{aligned} \quad (8)$$

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

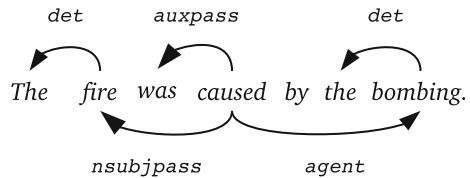
In this case, applying the rules on the dependency tree of the sentence “The fire was caused by the bombing.” (showed in Fig. 4), we are able to correctly detect *bombing* as cause and *fire* as effect.

4.3.4 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.

We use $preposition(S, P, Pr)$ to indicate that the preposition Pr of the sentence S complies with the pattern P , which has to be a single preposition (forth row in Table 1). In this case, we have formulated the following rules:

Fig. 4 Dependencies among the words of the sentence “The fire was caused by the bombing”



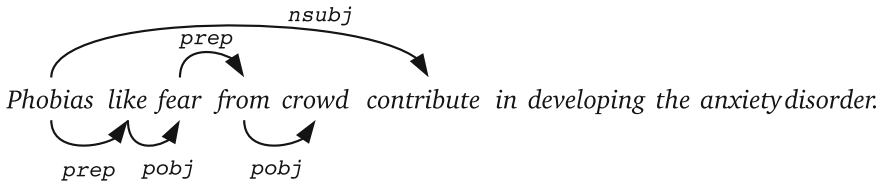


Fig. 5 Dependencies among the words of the sentence “*Phobias like fear from crowd contribute in developing the anxiety disorder*”

$$\begin{aligned} \text{preposition}(S, P, Pr) \wedge \text{pobj}(S, Pr, C) &\rightarrow \text{cause}(S, P, C), \\ \text{preposition}(S, P, Pr) \wedge \text{prep}(S, E, Pr) &\rightarrow \text{effect}(S, P, E). \end{aligned} \quad (9)$$

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:

$$\text{preposition}(S, P, Pr) \wedge \text{prep}(S, V, Pr) \wedge \text{nsubj}(S, V, C) \rightarrow \text{effect}(S, P, C). \quad (10)$$

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 Eqs. 9 and 10, we have that *crow* is the cause and *fear* is the effect.

4.3.5 Rules for Multiple Causes and Effects

The rules presented above allow to detect a cause and an effect for each pattern that matches 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:

$$\text{cause}(S, P, C1) \wedge \text{conj}(S, C1, C2) \rightarrow \text{cause}(S, P, C2). \quad (11)$$

A similar rule is defined to propagate through conjunctions the effect:

$$\text{effect}(S, P, E1) \wedge \text{conj}(S, E1, E2) \rightarrow \text{effect}(S, P, E2), \quad (12)$$

where $\text{conj}(S, C1, C2)$ indicates that $C1$ 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 applying these rules we detect all the causes.

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

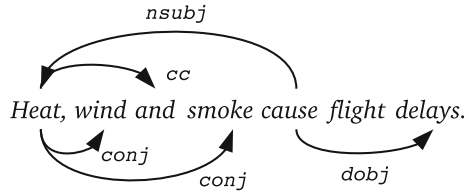
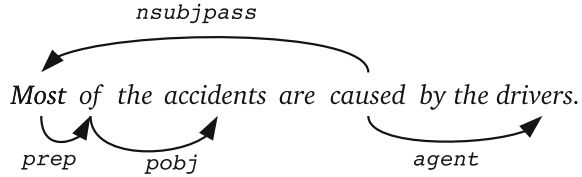


Fig. 7 Dependencies among the words of the sentence “Most of the accidents are caused by the drivers”



4.3.6 Rules for Partitives

During our test, we have observed that the rules presented below extract erroneous causes or effects when they are involved in the partitive of a sentence. The partitive denote a grammatical construction used to indicate that only a part of a whole is referred to. It usually has the form $[DP \text{ Det.} + \text{of} + [DP \text{ Det.} + NP]]$, the first determiner is a quantifier word that quantifies over a subset or part of the embedded determiner phrase (DP), which either denotes a set or a whole respectively. The second determiner is usually an article, a demonstrative, a possessive determiner, or a quantifier. For example *most of the students*, *some of the children*, *a slice of cake* and so on. In this cases the rules detect as cause or effect the quantifier, for example if we take in account the sentence showed in Fig. 7, applying the rules in Eq. 8, we extract as effect the word *Most*, while the correct word *accidents*. To overcome this problem, we have defined the following rules:

$$\begin{aligned}
 & \text{cause}(S, P, C) \wedge \text{quantifier}(C) \wedge \\
 & \quad \text{prep}(S, C, \text{of}) \wedge \text{pobj}(S, \text{of}, X) \rightarrow \text{cause}(S, P, X), \\
 & \text{effect}(S, P, E) \wedge \text{quantifier}(E) \wedge \\
 & \quad \text{prep}(S, E, \text{of}) \wedge \text{pobj}(S, \text{of}, X) \rightarrow \text{effect}(S, P, X).
 \end{aligned} \tag{13}$$

These rules are applied after the other rules introduced above. So, in the case where the cause (or the effect) identified is a quantifier, the partitive structure mentioned above is inspected to identify the object of the preposition *of*. Indeed, applying the rules in Eq. 13 after the ones in Eq. 8, we are able to correctly extract the effect from the sentence in Fig. 7.

4.4 Pairs Filtering

Due to their empirical nature, the patterns and the rules defined above are not able to produce exact results. Hence, some pairs that are not in causal relation can be extracted. 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 has been considered. To implement the classifier we have chosen to use the Bayesian classification method. Considering the (hypothetical causal) pair $r \equiv cRel(S, C, E)$, the Bayes' rule becomes:

$$P(c_i|r) = \frac{P(r|c_i)P(c_i)}{P(r)}, \quad (14)$$

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 [16].
- *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:

$$P(f|c_i) = \frac{\#(c_i, f) + \alpha}{\#f + \alpha|F|}. \quad (15)$$

Assuming that the features are independent from each other we computed

$$P(r|c_i) = \prod_{f \in F} P(f|c_i). \quad (16)$$

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

$$P(c_1|r) \geq P(c_2|r) \quad (17)$$

and as *non-causal* otherwise.

The classifier discussed in this section has been tested with 10-folds cross validation on the train set of the SemEval-2010 dataset in order to select a value for

the parameter α . Then, the classifier has been tested on the testset. We were able to achieve a precision of 91% and a recall of 88%, which slightly improve the results achieved during the SemEval challenge (87% precision, 87% recall).

5 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 [17] and the rules for the detection of cause-effect pairs have been implemented in XSB Prolog [18].

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

$$P_{global} = \frac{\text{\#correct retrieved pairs}}{\text{\#retrieved pairs}}, \quad (18)$$

$$R_{global} = \frac{\text{\#correct retrieved pairs}}{\text{\#total pairs in } D}, \quad (19)$$

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

$$P_{sentence} = \frac{1}{|M|} \sum_{s \in M} \frac{\text{\#correct retrieved pairs in } s}{\text{\#retrieved pairs in } s}, \quad (20)$$

$$R_{sentence} = \frac{1}{|D|} \sum_{s \in D} \frac{\text{\#correct retrieved pairs in } s}{\text{\#total pairs in } s}, \quad (21)$$

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

$$F = 2 \frac{P \cdot R}{P + R}. \quad (22)$$

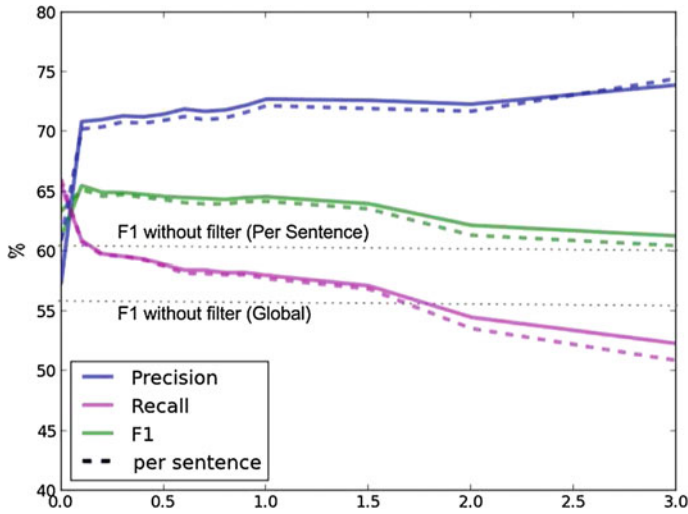


Fig. 8 Results obtained during the tests

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.

In order to evaluate the proposed model we computed the metrics described above, first, using only the rules, and then, combining the rules and the pair filter with different values of the parameter α .

The results of the evaluation are summarized in Fig. 8. We can see that the global F-score of the rules stand-alone is around 55% and the per sentence F-score is around 60% (see dotted lines Fig. 8). While, we can see that the application of the filter always increases the F-score. The best performances of the system are obtained with Laplace smoothing setting $\alpha = 0.2$. For higher values of α we are able to achieve a higher precision, but we also have a significant lowering of the recall.

6 Conclusion and Future Work

We have presented an approach for the detection and the extraction of cause-effect pairs in English sentences. With respect to the other works presented in Sect. 2, the task addressed in this chapter is more detailed because our approach focuses on the extraction of all the cause-effect pairs in a causal sentences.

The proposed method combines rules, for the extraction of all possible causes and effects, and a Bayesian classifier to filter the erroneous solutions. Such approach works on sentences that contain explicit and marked causal relation.

The evaluation of the proposed method has been done on an extended version of the testset used for the task 8 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.

Also, we believe that the rules applied by the model can be easily adapted for other information extraction tasks and that they provide interesting insights on how explicit causal relation are expressed under the point of view of the grammatical dependencies.

In the future, we plan to refine the rules presented and experiment other filtering techniques. In order to evaluate the approach we also plan to extend the dataset developed in this work. Also, we will extend this system in order to handle implicit causal relations and casual relation don't marked by an explicit lexical unit.

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