Causal Relation Extraction

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Abstract

This paper presents a supervised method for the detection and extraction of Causal Relations from open domain text. First we give a brief outline of the definition of *causation* and how it relates to other Semantic Relations, as well as a characterization of their encoding. In this work, we only consider marked and explicit causations. Our approach first identifies the syntactic patterns that may encode a causation, then we use Machine Learning techniques to decide whether or not a pattern instance encodes a causation. We focus on the most productive pattern, a verb phrase followed by a relator and a clause, and its reverse version, a relator followed by a clause and a verb phrase. As relators we consider the words as, after, because and since. We present a set of lexical, syntactic and semantic features for the classification task, their rationale and some examples. The results obtained are discussed and the errors analyzed.

1. Introduction

The automatic detection and extraction of *Semantic Relations* is a crucial step to improve the performance of several Natural Language Processing applications. For example, a Question Answering system will identify (1b) as the answer to (1a) only if it detects the causation encoded in (1b).

1. (a) Why do babies cry?

   (b) Hunger is the most common cause of crying in a young baby.

This work is focused on the detection and extraction of *Causal Relations* from open domain text. A discussion of what can be considered a causation and a formal definition can be found in (Hobbs, 2005). Broadly speaking, causation is a relation between two events: *cause* and *effect*. Cause is the *producer* of the effect, and effect the *result* of the cause.

The rest of the paper is organized as follows. Section 2. provides insights on causation. Section 3. briefly describes previous approaches to extract causal knowledge. Section 4. presents the method proposed and the results obtained. Section 5. draws some conclusions and defines future lines of research.

2. Causal Relations

Causal relations have been studied in several fields. (White, 1990) provides an overview of theories within the fields of Philosophy and Psychology. In Cognitive Linguistics, one of the most important theories is *Force Dynamics* (Talmy, 2000).

2.1. Causal Relations and other Semantic Relations

Researchers have proposed different sets of Semantic Relations, ranging from a few to dozens. In this section, we relate CAUSATION to other relations.

The closest semantic relation to CAUSATION is INFLUENCE. The distinction is a matter of degree: an INFLUENCE holds between $event_1$ and $event_2$ if $event_1$ affects the *manner* or *intensity* of $event_2$, but does not affect the *occurrence* (e.g. *"Targeting skin cancer relatives improves screening."*).

CONDITION, CONSEQUENCE and REASON are subtypes of CAUSATION[1]. CONDITION holds if the cause is hypothetical (e.g. *"If he were handsome, he would be married."*). CONSEQUENCE holds if the effect is indirect or unintended (e.g. *"His resignation caused regret among all classes."*). REASON holds if it is a causation of decision, belief, feeling or acting (e.g. *"I went because I though it would be interesting."*).

A clear overlap exists between CAUSAL and TEMPORAL relations. By definition, the cause should always occur *before* the effect, i.e., if $event_1$ causes $event_2$, $event_1$ should occur before than $event_2$.

2.2. Encoding of Causation

From the point of view of *detecting* Causal Relations, the following distinctions may be useful:

- **Marked or unmarked**: a causation is *marked* if there is a specific linguistic unit that signals the relation; *unmarked* otherwise. *"I bought it because I read a good review"* is marked; *"Be careful. It's unstable"* isn't.
- **Ambiguity**: if the mark signals always a causation, it is *unambiguous* (e.g. "because"). If it signals sometimes a causation, it is *ambiguous* (e.g. "since").
- **Explicit or implicit**: a causation is *explicit* if both arguments are present; *implicit* if one or both are missing. *"She was thrown out of the hotel after she had run naked through its halls."* is explicit; *"John killed Bob."* is implicit, since the effect, *Bob's death*, is not explictily stated.

We focus on *marked* and *explicit* causations.

3. Previous Work

Several attempts have been made in order to extract causal knowledge from text. The older approaches used hand-coded and domain-specific knowledge bases (Kaplan and Berry-Rogghe, 1991).

[1] In this work we consider all of them as CAUSATION.

no.	Pattern	Productivity	Example
1	[VP *rel* C], [*rel* C, VP]	63.75 %	*We didn't go* because *it was raining.*
2	[NP *VP* NP]	13.75 %	*The speech* sparked *a controversy.*
3	[VP *rel* NP], [*rel* NP, VP]	8.12 %	*He died of cancer.*
4	other	14.38 %	*The lighting caused the workers to fall.*

Table 1: Syntactic patterns expressing causation, their productivity and examples.

relator	Example	
	encoding causation	**not encoding causation**
after	*Marty stood with his mouth hanging open foolishly after it had happened.*	*The executions took place a few hours after the radio announced their conviction.*
as	*There was no debate as the Senate passed the bill on to the House.*	*It has a fixed time, as collectors well know.*
because	*He had to leave early because he was feeling bad.*	—
since	*He had to depend on himself, since he was miles away from others.*	*It was the first time any of us had laughed since the morning began.*

Table 2: Examples of instances encoding and not encoding causation.

(Khoo et al., 2000) focused on the medical domain; (Garcia, 1997) developed a system based on Force Dynamics. (Girju and Moldovan, 2002) defined a set of semantic constraints to rank possible causations.
Newer approaches use Machine Learning (ML) techniques (Girju, 2003; Chang and Choi, 2006). Those systems are more robust and yield higher performance, with F-measures around 0.8.

4. The Method

Our method for the detection and extraction of causations is based on the use of syntactic patterns that may encode causation. We then redefine the problem as a classification between two classes: encoding or not encoding causation ($cause$ or $\neg cause$).

4.1. Syntactic patterns that encode causation

We manually classified 1270 sentences from the TREC5 corpus into encoding or not encoding causation; 170 intrasentencial causations were found. The sentences encoding causation were manually clustered into the syntactic patterns shown in table 1. *rel* stands for relator, which can be either a preposition or conjunction.
The manual clustering allowed us to realize that the four most common relators encoding causation are *after*, *as*, *because* and *since*. Because pattern 1 comprises more than half of the causations found, we focused only on pattern 1 and these four relators. From now on, *instance* means an instance of pattern 1 signaled by one of relators considered. Note that an instance not always encodes a causation. Some examples can be found in table 2.

4.2. Pattern Matching

We performed our experiments using the semantically annotated SemCor 2.1 corpus. 1068 instances were found.

Relator	Occurrences encoding causation	Causations signaled
after	15.35 %	6.85 %
as	11.21 %	7.34 %
because	98.43 %	73.39 %
since	49.61 %	12.52 %

Table 3: Statistics of the causations found.

They were manually classified[2] into $cause$ and $\neg cause$; 517 causation were detected[3]. Table 3 shows statistics of the instances depending on the relator.
All the instances considered encode the *cause* in the VP contained in C (VP_C) and the *effect* in the first VP, e.g., *"He, too,* $[$*was subjected*$]_{VP}$ *to anonymous calls* $[$*after*$]_{rel}$ $[$*he* $[$*scheduled*$]_{VP_C}$ *the election*$]_C$*".* The extraction of *cause* and *effect* is done at the same time than the pattern matching.

4.3. Feature Selection

The features considered in our experiments are depicted in table 4. The set came up during the manual classification. It was a slow task, but it allowed us to get a better understanding of the nature of causation. By semantic class we mean the most common subsumer in WordNet 2.1. A verb sense is *potencially causal* if its gloss or any of its subsumers' glosses contains the words *cause to* or *change*.
Out of all the features considered, only the following are useful for discriminating between $cause$ and $\neg cause$: *relator*, *relator left and right modifiers*, *semantic class cause verb*, *cause verb is potentially causal*, *cause verb is past*

[2]Only one annotator fulfill the task, so we cannot report inter-annotator agreement.
[3]This means the baseline for the classification task is 0.516.

Feature	Rationale	Examples
Relator	A relator can encode a causation always or sometimes	- $[cause]$ *"Leadership is lacking in our society* ***because*** *it has no legitimate place to develop."* - $[\neg cause]$ *"We had met two years* ***after*** *she had arrived."* - $[cause]$ *"Marty stood for several moments with his mouth hanging open foolishly* ***after*** *it had happened."*
Relator left and right Modifiers	causations can hardly be signaled by a *relator* modified by some POS tags	- *adverb + after* almost always signals a temporal relation, not a causation: *"This was* ***long after*** *Morse had left the house."* - *as + preposition* can hardly signal a causation: *". . . he felt he was noting it,* ***as if*** *it were . . . "*
Semantic Class Cause Verb	only certain verb senses can express a cause	- if the relator is *after* and the cause verb semantic class is *be-v-3*, then it is a temporal relation, not a causation: *"We heard him yelling after he was out of sight."*
Cause Verb is Potentially Causal	if a verb sense is potencially causal, then is more likely to express a cause	- *ring-v-1* is subsumed by *sound-v-2*, which gloss is "*cause to sound*"
Semantic Class Effect Verb	only certain verbs can express an effect	- If the relator is *after* and the effect verb semantic class is *express-v-2*, then is not a causation: *"My name's Gisele", the blonde said after she ordered a Scotch".*
Effect Verb is Potentially Causal	if a verb sense is potencially causal, then is more likely to express an effect	- *walk-v-3* is subsumed by *travel-v-1*, which gloss is "change location"
Verb Tense Cause and Effect Verb	depending on the relator, some verb tenses are not likely to express causation	- If the relator is *as* or *after*, the cause verb is present and it is not a copula, then is not a causation: $[\neg cause]$: *"Henrietta was discovering,* as *the born writer does, not merely . . . "*; $[\neg cause]$: *"To play the guitar* as *he aspires will devour his . . . "* - If the relator is *as* and the effect verb is conditional, then is not a causation: *"She wouldn't go* as *Maude suggested."* - If the effect verb is progressive, then is not a causation: *"The burden of his secret* was pressing *down on him,* as *it was on them."* - If the effect verb es passive, then it is more likely to express a causation: *". . . and then Richard* was shocked as*, all at once, flames shot out from the sharp features of . . . "*

Table 4: Features considered for the Machine Learning approach.

and *effect verb is perfective*. Note that the semantic features for the effect verb aren't in this set.
We added a new feature, *lexical clue*, which allows as to discard some missmatches. *lexical clue* is true if between the relator and VP$_C$ there is a ',', 'and' (e.g., *"He went as a tourist* and *ended up living there."*) or another relator (e.g., *"City planners do not always use this boundary* as *effectively* as *they might"*).

4.4. Machine Learning algorithm

Class	Precision	Recall	F-Measure
$cause$	0.969	0.839	0.899
$\neg cause$	0.865	0.975	0.917

Table 5: Results obtained during training.

The 1068 instances were divided into training (75%) and test (25%). As a learning algorithm, we used an implementation of Bagging with C4.5 decision trees (Witten and Frank, 2005). Table 5 and 6 show the results obtained with the training and test instances respectively. The F-measures

Class	Precision	Recall	F-Measure
$cause$	0.955	0.842	0.895
$\neg cause$	0.869	0.964	0.914

Table 6: Results obtained during testing.

obtained during training are very close to the ones obtained during test, meaning that the model was able to *generalize* the training examples.
Analyzing table 3 we can easily conclude that most of the causations are encoded by the relators *because* and *since*. The model learned is only able to classify correctly the causations signaled by these two relators. When the relator is *because*, it always classifies the instance as $cause$; when it is *as* or *after*, as $\neg cause$; when it is *since* the model decides between the two classes based on the values of the features. The results obtained when the relator is *since* are shown in table 7. Again, the results are good.
The results obtained are difficult to compare with other works, since we focus on a different pattern. (Girju, 2003; Chang and Choi, 2006) obtained a F-measure of 0.80 and

Class	Precision	Recall	F-Measure
$cause$	0.957	0.846	0.898
$\neg cause$	0.878	0.966	0.920

Table 7: Results obtained with the examples signaled by *since* during testing

Class	Precision	Recall	F-Measure
$cause$	0.541	0.713	0.615
$\neg cause$	0.628	0.445	0.521

Table 8: Restults obtained using only the semantic features.

0.81 respectively.

4.5. Error Analysis

Most of the error is due to the inability to dicriminate between $cause$ and $\neg cause$ when the causation is signaled by *as* or *after*. More training data and another set of features may improve the results.

We can find examples in the training corpus belonging to different classes and with exactly the same values for the features, e.g., sentence (1) and sentence (2) have the same values for all the features except for the *semantic* ones.

1. $[cause]$*They [arrested]*$_{VP}$ *him [after]*$_{rel}$ *[he [assaulted]*$_{VP_C}$ *them]*$_C$.
2. $[\neg cause]$*He [left]*$_{VP}$ *[after]*$_{rel}$ *[she [had]*$_{VP_C}$ *left]*$_C$.

A common way to solve the problem would be to paraphrase sentence (2). However, if we change the relator for *because*, the sentence encodes a causation: *"He left because she had left"*. Paraphrasing does not seem to be a possible solution.

One of the best rules learned states that when the relator is *since* and the effect verb is perfective tense, it doesn't encode a causation. However, the rule does not always work, e.g., $[cause]$: *"Less than half the sum [has been spent]*$_{VP_C}$*, [since]*$_{rel}$ *[the board [pinched]*$_{VP_C}$ *pennies during that negotiation]*$_C$*."*

Examining the trees learned we can conclude that most of the possible *semantic classes* are not covered. The semantic features are only useful when the rest are not enough to discriminate, and when this occurs the number of instances left to classify is low, so most of the possible *semantic classes* are not covered. We believe more data may improve the results. The results obtained when only using the semantic features (semantic classes cause and effect verb, cause and effect verb are potencially causal) are the shown in table 8.

5. Conclusions and Further Work

We have proposed a system for the detection of marked and explicit causations between a verb phrase and a subordinate clause which yields a high performance. The system is relatively simple and is able to detect causations from open domain text. So far research has focused on causations expressed with noun phrases, e.g. "*The [incident]*$_{NP_1}$ *provoked [widespread protest]*$_{NP_2}$'.

A key element to really see the potential of the method would be to integrate it with a system that extracts other *semantic relations*. We could experiment with inference rules that combine CAUSATION and other semantic relations. For example, if $event_1$ causes $event_2$ and $event_3$ is subsumed by $event_1$, then $event_3$ causes $event_2$; if $event_1$ causes $event_2$ and $event_2$ entails $event_3$, then $event_1$ causes $event_3$. Another possible inference rule would express the transivity property of causations.

To address implicit causations another system is needed. We hypothesize that working with verbs that encode part of the effect (e.g. kill, melt, drop, anger) may help.

Another possible extension would be to deal with causal chains, e.g. (1), and intricate causal relations, e.g. (2). A causal chain can be defined as a *sequence of events that lead up to some final effect.*

1. Artworks become art when they transcend the simple facts of their existence, and they can do that only when they blend with the viewer.
2. It is lined primarily by industrial developments because the constant traffic do not make it an attractive neighborhood.

6. References

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