

Text Mining for Causal Relations

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Abstract

Given a semantic relation, the automatic extraction of linguistic patterns that express that relation is a rather difficult problem. This paper presents a semi-automatic method of discovering generally applicable lexico-syntactic patterns that refer to the causal relation. The patterns are found automatically, but their validation is done semi-automatically.

Introduction

The automatic identification of semantic relations in text has become increasingly important in Information Extraction, Question Answering and Information Retrieval in the last decade. The MUC competitions have brought a significant contribution to AI, as many Information Extraction systems used new and innovative techniques to discover relevant information from texts. In order to extract the exact answer to user queries, Q&A and IR systems need to synthesize information gathered from multiple documents or to identify new relationships between facts/entities and discover new knowledge.

An important semantic relation for all these applications is the *causal relation*. Although many researchers focused their attention on this semantic relation, they used hand-coded patterns to extract causation information from text.

This paper is part of a project to automatically discover knowledge from texts. In addition to concepts, the knowledge consists of relationships that express various semantic relations between concepts (e.g., CAUSATION, INFLUENCE, PART-WHOLE, etc.). In this paper we focus only on the causal relation and show a method for automatic detection of causation patterns and a semi-automatic validation of ambiguous lexico-syntactic patterns referring to causation. In the next sections we talk about previous work on causality and describe our approach. Results are presented, and at the end we offer some discussion and conclusions.

Previous Work in Computational Linguistics

Broadly speaking, causality refers to the way of knowing if one state of affair causes another. Although the notion of

causality is very old (beginning with the Aristotle's *Metaphysics*), over the time it has been surrounded by controversy as scientists and philosophers have not agreed on the definition of causality and when two states of affairs are causally linked.

The theory of causality is very broad, and perhaps the most interesting feature of the work on causation on the last decades has been its diversity. Several theories have been developed resulting in an overwhelming number of publications. This explosion of approaches can be explained in part by the plurality of perspectives the researchers used, and by the diversity of domains to which the causation notion applies: *philosophy, statistics, linguistics, physics, economics, biology, medicine*, etc.

In Computational Linguistics, many previous studies have attempted to extract implicit inter-sentential cause-effect relations from text using knowledge-based inferences (Joskowicz, Ksiezyk and Grishman 1989), (Kaplan 1991). These studies were based on hand-coded, domain-specific knowledge bases difficult to scale up for realistic applications.

Other researchers (Garcia 1997), (Khoo et al. 2000) used linguistic patterns to identify explicitly expressed causal relations in text without any knowledge-based inference. Garcia focused in 1997 on the extraction of causal relations from French texts, using hand coded lexico-syntactic patterns. She reported a precision of 85% (Garcia 1997). Khoo et al. (Khoo et al. 2000) extracted by hand English linguistic patterns from a medical database, reporting an accuracy of about 68%.

The Approach

The algorithm for the detection of lexico-syntactic patterns that refer to causation consists of two major procedures. The first procedure discovers lexico-syntactic patterns that can express the causal relation, and the second procedure validates and ranks the ambiguous patterns acquired based on semantic constraints on nouns and verbs.

Automatic discovery of lexico-syntactic patterns referring to causation

The causal relation can be expressed in text in various ways, from explicit to implicit, and from intra to extra-sentential

patterns. One of the most frequent explicit intra-sentential pattern that can express causation is $\langle NP1 \text{ verb } NP2 \rangle$.

According to two Russian linguists (Nedjalkov and Silnickij 1973) who made multilingual causation studies, the causation verbs can be classified in the following categories:

1. **Simple causatives** - the linking verb refers only to the causal link, most of the time being synonymous with *cause*. For example,
Earthquakes generate tidal waves.
Here the verb “generate” is synonymous with “cause”.
2. **Resultative causatives** - the linking verb refers to the causal link plus a part of the resulting situation. E.g.: *kill* (cause to die), *melt*, *dry*, *break*, *drop*, etc.
3. **Instrumental causatives** - they express a part of the causing event as well as the result. E.g., *poison* (killing by poisoning), *hang*, *punch*, *clean*, etc.

In this paper we focus on explicit intra-sentential syntactic-patterns of the form $\langle NP1 \text{ verb } NP2 \rangle$, where the verb is a simple causative.

In order to catch the most frequently used lexico-syntactic patterns referring to causation, we used a modified version of the Hearst’s procedure (Hearst 1998), as described below:

Procedure 1. Discovery of lexico-syntactic patterns:

1. Pick a semantic relation R (e.g., CAUSATION)
2. Pick a pair of noun phrases C_i, C_j among which R holds.
In order to get as many causation patterns as possible, we repeated step 2 for a list of noun phrases extracted from WordNet 1.7. WordNet (Miller 1995) contains 17 semantic relations: IS-A, reverse IS-A, MERONYMY/HOLONYMY, ENTAIL, CAUSE-TO, ATTRIBUTE, PERTAINYMY, ANTONYMY, SYNSET (SYNONYMY), etc. The CAUSE-TO relation is a transitive relation between verb synsets. For example, in WordNet the second sense of the verb *develop* is *causes to grow*. Given the fact that almost all these verbs have nominalizations, it is easy to find noun concepts among which the WordNet causal relations hold. Although WordNet contains numerous causal relationships between nouns that are always true, they are not directly mentioned. One way to determine such relationships is to look for all patterns $\langle NP1 \text{ cause.vb } NP2 \rangle$ that occur between a noun entry and another noun in the corresponding gloss definition. One such example is the causal relationship between $\{bonyness\}$ and $\{starvation\}$.
The gloss of $\{bonyness \text{ (}\#1/1\text{)}\}$ is (*extreme leanness (usually caused by starvation or disease)*).
WordNet 1.7 contains 429 such relations linking nouns from different domains, the most frequent being medicine (about 58.28%).
3. Extract lexico-syntactic patterns that link the two selected noun phrases by searching a collection of texts.
For each pair of causation nouns determined above, search the Internet or any other collection of documents. Retain only the sentences containing the pair. From these sentences, determine automatically all the patterns $\langle NP1$

verb/verb_expression $NP2 \rangle$, where $NP1 - NP2$ is the pair considered.

The result is a list of verbs/verbal expressions that refer to causation. Some of these verbs are always referring to causation, but most of them are ambiguous, in the sense that they express a causation relation only in a particular context and only between specific pairs of nouns. For example, $\langle NP1 \text{ causes } NP2 \rangle$ refers always to causation, but this is not true for $\langle NP1 \text{ produces } NP2 \rangle$. In most cases, the verb *produce* has the sense of *manufacture*, but in some particular contexts it refers to causation.

In her procedure, Hirst selects the patterns by hand and applies them to text without making any semantic filtering on the relationships obtained. In this approach, the acquisition of linguistic patterns is done automatically, as the pattern is predefined ($NP1 \text{ verb } NP2$). As is described in the next subsection, the relationships are disambiguated and ranked and only those referring to causation are retained.

Validation of causation patterns and ranking of causation relationships

Because the exact disambiguation of the verb sense is often very difficult, we try to validate the lexico-syntactic patterns using a coarse-grain approach. The approach consists of detecting the constraints necessary and sufficient on nouns and verb for the pattern $\langle NP1 \text{ verb } NP2 \rangle$ such that the lexico-syntactic pattern indicates a causal relationship.

Semantic constraints on nouns $NP1$ and $NP2$

The basic idea we employ here is that only some categories of noun phrases can be associated with a causation link. According to the philosophy researcher Jaegwon Kim (Kim 1993), any discussion of causation implies an ontological framework of entities among which causal relations are to hold, and also “an accompanying logical and semantical framework in which these entities can be talked about”. He argues that the entities that represent either causes or effects are often *events*, but also *conditions*, *states*, *phenomena*, *processes*, and sometimes even *facts*, and that coherent causal talk is possible only within a coherent ontological framework of such states of affairs.

In a relationship of the form $\langle NP1 \text{ verb } NP2 \rangle$, the nouns $NP1$ (*cause_noun*) and $NP2$ (*effect_noun*), can express explicit or implicit states of affairs. The following four situations can occur:

1. *cause_noun* and *effect_noun* are explicit states of affairs.
e.g: *Earthquakes cause tidal waves.*
2. *effect_noun* expresses an explicit state of affair, and *cause_noun* an implicit one.
e.g: *John caused the disturbance.*
3. *cause_noun* shows an explicit state of affair, and *effect_noun* an implicit one.
e.g: Sometimes *rain* can cause you *bad days*.
4. *cause_noun* and *effect_noun* are implicit states of affairs.
e.g: *John* caused her really *bad days*.

Examples 2 and 4 denote a causal relationship as the verb *caused* indicates, but the relation is not explicit. John cannot cause directly a psychological state (e.g., the *disturbance*), but the action John undertook caused it. In this paper we focus only on the situations 1 and 2, as they are the most frequently used in texts.

Given this approach the system selects automatically the causation classes with the following procedure:

STEP 1. Semantic constraints on NP1

For each noun occupying the EFFECT position in the causation pairs detected in step 1 of Procedure 1, select as causation class the most general subsumer in WordNet for that given sense. For example, the most general subsumer of the word *excitement* (#1/4) in WordNet is *psychological feature*. In WordNet, all the EFFECT nouns in the causation pairs represent entities that express explicit states of affairs.

At the end of this step, the system detected the following causation classes: *human action*, *phenomenon*, *state*, *psychological feature*, and *event*. Our assumption is that these classes represent causation categories, and anything else that is not in this list refers to noncausation.

STEP 2. Semantic constraints on NP2

We noticed from the corpus created in Procedure 1 that metonymy occurs with high frequency in causal relationships, but mostly on the CAUSE position, and quite rarely on the EFFECT position.

This observation is also supported by the large number of classes obtained for the NP2 nouns on the *cause* position with the procedure describe above. This shows that the CAUSE nouns can be represented by almost any noun. Thus, we use here only a soft constraint which would help validate the relationships in some special cases explained later in section 4:

soft constraint on CAUSE: the noun should have as subsumer the concept *causal agent* in WordNet. For example, the second most general subsumer of the word *drug* in WordNet is *causal agent*.

Semantic constraints on verbs

We ranked the verbs/verb expressions extracted in step 3 of Procedure 1 based on their ambiguity and frequency levels in WordNet. In WordNet, verbs are represented in *synsets*, which are lists of synonyms for that verb, and each verb can have multiple senses. For a given verb, in WordNet 1.7 the senses are ranked based on the number of times each sense occurs in the semantically tagged corpus used by the WordNet lexicographers. Based on the observation on WordNet of the extracted verbs, we considered the following categories of constraints along with their thresholds:

1. low ambiguity: - if the number of senses for the verb considered ≤ 7
2. high ambiguity: if the number of senses for the verb considered > 7
3. low frequency: - if (the frequency for that particular sense $<$ the sum of the frequency of all other senses) or (the frequency for that particular sense < 30)

4. high frequency: if (the frequency for that particular sense \geq the sum of the frequency of all other senses) or (the frequency for that particular sense ≥ 30)

Table 1 shows a part of the verbs extracted with Procedure 1 ranked according with the constraints defined above.

For example, the verb *make* is ranked at the end because it is highly ambiguous (there are 49 senses in WordNet 1.7 for this verb) and occurs with high frequency (79 occurrences in WordNet tagged corpus). Thus, the sentence “*Greenspan makes a recession*” is highly ambiguous as it can be interpreted in two ways: either (1) as a causal relation if *recession* has the sense #1/4 (*the state of the economy declines*), or (2) as noncausative relation if *recession* has the sense #2/4 (*a small concavity*).

The Algorithm

The algorithm for the validation and ranking of the causal relationships is an iterative procedure in which a step is followed if the condition in the previous step was not satisfied. In this algorithm we consider as NP1 and NP2 only the head noun of the noun phrases extracted, as it occurs in WordNet (e.g. for the noun phrase “giant tidal wave”, *tidal wave* is automatically selected).

Procedure 2.

Step 1.

If the EFFECT and CAUSE head nouns are monosemous and they belong to one of the causation classes, or are polisemous and all their senses belong to the causation classes, then classify the relationship as causation of rank 1.

For example, “*Hitler’s invasion of Poland provoked the Second World War*”.

Here, both *invasion* and *Second World War* have all their senses in causation classes, so even if the verb *provoke* is ambiguous, the relationship is detected as causation.

Step 2.

If the EFFECT head noun is monosemous and it belongs to one of the causation classes, or is polisemous and all its senses belong to the causation classes, then classify the relationship as causation of rank 2.

For example, “In 1958, it was *Bleustein-Blanchet* who sparked a controversy when he opened Le Drugstore, the American-inspired combination pharmacy, all-hours restaurant and gift store that now has branches at both ends of the avenue”. Here, the causal relation is obvious as *controversy* is monosemous and its sense has the semantic class *human action*.

Step 3.

If the EFFECT is represented by an enumeration of noun phrases and the head noun of at least one of them has all the senses in one of the causation classes, than the others also refer to causation in that context. Classify the relationship as causation of rank 3.

For example, in the sentence “*Fed will induce a recession and unemployment*” the effect *unemployment* is monosemous and belongs to the causation class *state*. Thus, the

Low ambiguity High frequency	Low ambiguity Low frequency	High ambiguity Low frequency	High ambiguity High frequency
induce	stir up	create	start
give rise (to)	entail	launch	make
produce	contribute to	develop	begin
generate	set up	bring	rise
effect	trigger off		
bring about	commence		
provoke	set off		
arouse	set in motion		
elicit	bring on		
lead (to)	conduce to		
trigger	educe		
derive (from)	originate in		
associate (with)	lead off		
relate (to)	spark		
link (to)	spark off		
stem (from)	evoke		
originate	link up		
bring forth	implicate (in)		
lead up	activate		
trigger off	actuate		
bring on	kindle		
result (from)	fire up		
	stimulate		
	call forth		
	unleash		
	effectuate		
	kick up		
	give birth (to)		
	call down		
	put forward		

Table 1: Ambiguous causation verbs ranked based on ambiguity and frequency. The ambiguity increases from the left most column to the right.

effect noun *recession* is disambiguated and its interpretation as sense #2 *niche, corner* is eliminated.

Step 4.

If the noun phrase representing the EFFECT is ambiguous (at least one of its senses does not belong to a causation class) and the CAUSE respects the soft constraint defined in the previous section, then classify the relationship as causation of rank 4.

For example, in the sentence “*The drugs induce the growth of muscle tones*”, the head noun *growth* has two senses (#4/7 and #7/7) that are in two noncausation classes (e.g., {*group, grouping*}, and respectively {*entity*}). In this case, the noun *drugs* disambiguates the relationship as it is monosemous and has *causal agent* as one of its hypernyms.

Step 5.

At this point, the remaining nouns representing the CAUSE and EFFECT are ambiguous and the only possibility of disambiguation comes from the restrictions imposed on the verbs.

For example, in the sentence “*The issue gives rise to a big concern*”, both the CAUSE and EFFECT are ambiguous. The noun *issue* can be “*an important question that is in dis-*

pute and must be settled” (psychological feature, cf. WordNet), or “*one of a series published periodically*” (entity, cf. WordNet). The noun *concern* can refer to *an anxious feeling* (psychological feature, cf. WordNet), or *commercial or industrial enterprise* (group, grouping). In this case the relationship is considered causation only because the verb *give rise* is one of the less ambiguous and highly frequent verbs considered.

For all the remaining relationships, classify them based on the verbs’ ranking shown in Figure 1.

Results

In this section we show the results obtained by the validation and ranking algorithm. For this experiment we used the TREC-9 (TREC-9 2000) collection of texts which contains 3GB of news articles from *Wall Street Journal*, *Financial Times*, *Financial Report*, etc. Using the causation verbs obtained in step 3 of Procedure 1, the system formed queries and searched the TREC collection. This way, for each verb there were selected 50 sentences that contained it. The new corpus thus formed (3,000 sentences) was part-of-speech tagged and parsed. For each head of the noun phrases in the CAUSE and EFFECT positions, the system determined automatically the most general subsumer for each sense. The al-

gorithm presented in section 4 was implemented and the system gave as output 1,321 causal relationships <NP1 verb NP2>, ranked by generality.

The results were validated by comparison with human annotation. We asked two subjects, other than the authors, to rank a list of 300 relationships from which only 230 were referring to causation, as detected by our algorithm. Out of the 300 relationships the subjects selected as causal relationships only 151 on average (Table 2). In what concerns the rating of the causal relationships, it differed from one subject to another with about 36%, and from the system's output by 48%.

The accuracy obtained by our system in comparison with the average of two human annotations was 65.6%.

	System	Human annotator 1	Human annotator 2
Rank 1	37		
Rank 2	73		
Rank 3	28		
Rank 4	92		
Total	230	162 (70.43%)	140 (60.87%)

Table 2: Comparison with human annotation and accuracy obtained for the 230 causal relationships (the percentages in parentheses represent the accuracy obtained by the system reported to the human annotator).

Discussion and Conclusions

The approach presented in this paper for the detection and validation of causation patterns is a novel one. Even if the method is semi-automatic, it brings considerable improvement in time and user work compared with other previous attempts (Garcia 1997), (Khoo et al. 2000). Khoo et al. obtained a better accuracy, but they restricted their text corpus to a medical database and did not handle the ambiguity problem.

Our method discovers automatically generally applicable lexico-syntactic patterns referring to causation and disambiguates the causal relationships obtained from the patterns application on text.

We intend to extend the analysis to other *causation* patterns and devise a general algorithm for the detection and especially for the validation of causation patterns. We also consider to test the method for other semantic relations like PART-OF and INFLUENCE.

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