

Extracting Explicit and Implicit Causal Relations from Sparse, Domain-Specific Texts

Ashwin Ittoo and Gosse Bouma

University of Groningen, 9747 AE
Groningen, The Netherlands
{r.a.ittoo,g.bouma}@rug.nl

Abstract. Various supervised algorithms for mining causal relations from large corpora exist. These algorithms have focused on relations explicitly expressed with causal verbs, e.g. “to cause”. However, the challenges of extracting causal relations from domain-specific texts have been overlooked. Domain-specific texts are rife with causal relations that are implicitly expressed using verbal and non-verbal patterns, e.g. “reduce”, “drop in”, “due to”. Also, readily-available resources to support supervised algorithms are inexistent in most domains. To address these challenges, we present a novel approach for causal relation extraction. Our approach is minimally-supervised, alleviating the need for annotated data. Also, it identifies both explicit and implicit causal relations. Evaluation results revealed that our technique achieves state-of-the-art performance in extracting causal relations from domain-specific, sparse texts. The results also indicate that many of the domain-specific relations were unclassifiable in existing taxonomies of causality.

Keywords: Relation exaction, Causal relations, Information extraction.

1 Introduction

Causal relations, between causes and effects, are a complex phenomenon, pervading all aspects of life. Causal relations are fundamental in many disciplines, including philosophy, psychology and linguistics. In Natural Language Processing (NLP), algorithms have been developed for discovering causal relations from large general-purpose [2,4,7,8,14] and bio-medical corpora [9]. These algorithms rely extensively on hand-coded knowledge (e.g. annotated corpora), and only extract explicit causal relations. Explicit relations are realized by explicit causal patterns, predominantly assumed to be causal verbs [4,7,14]. Causal verbs (e.g. “induce”) are synonymous with the verb “to cause”. They establish a causal link between a distinct causal-agent (e.g. “rain”), and a distinct effect (e.g. “floods”), as in “rain causes floods”.

The discovery of causal relations from texts in other domains (e.g. business/corporate) has been largely overlooked despite numerous application opportunities. In Product Development/Customer Service, for instance, causal relations encode valuable operational knowledge that can be exploited for improving product quality. For example, in “broken cable resulted in voltage loss”, the causal relation between

the cause “broken cable” and the effect “voltage loss”, established by the pattern “*resulted in*”, helps engineers during product diagnosis. Similarly, in “*new analog processor causes system shutdown*”, the causal relation between “new analog processor” and “system shutdown”, realized by the pattern “*causes*”, provides business organizations with insights on customer dissatisfaction.

However, extracting causal relations from domain-specific texts poses numerous challenges to extant algorithms. A major difficulty in many domains is the absence of knowledge resources (e.g. annotated data), upon which traditional algorithms rely. In addition, current techniques are unable to detect implicit causal relations, which are rife in the English language. Implicit relations are realized by implicit causal patterns. These patterns do not have any (explicit) causal connotation. But they subtly bias the reader into associating certain events in the texts with causal-agents or effects [10]. Thus, implicit patterns have a causal valence, even though they are not synonymous with “*to cause*”. We consider 3 main types of implicit causal relations. Relations of the first type, *T1*, are realized by resultative and instrumentative verbal patterns. These verbs, for e.g. “*increase*”, “*reduce*”, “*kill*”, inherently specify (part of) the resulting situation, as in “*the temperature increased*”. The second type of implicit causal relations, *T2*, involves patterns that make the causal-agents inseparable from the resulting situations [10]. Such patterns include “*mar (by)*”, “*plague(by)*”. For example, in “*white spots mar the x-ray image*”, the causal-agent “white spots” is an integral component of the result “marred x-ray image”. The last type of implicit causal relations, *T3*, involves non-verbal patterns, for e.g. the preposition “*due to*”, as in “*replaced camera due to horizontal calibration problem*”. Besides the difficulties posed by implicit patterns, existing algorithms are also unable to disambiguate ambiguous causal relations that involve polysemous patterns (e.g. “*result in*”, “*lead to*”). These patterns express causality only in restricted contexts. For e.g., the pattern “*lead to*” establishes a causal relation in “*smoking leads to cancer*”, but not in “*path leads to garden*”.

To address these challenges, we develop and present a framework for automatically extracting high quality causal relations from domain-specific, sparse corpora. We implemented our methodology in a prototype as part of the DataFusion initiative¹, which aims at enhancing product quality and customer satisfaction using information extracted from corporate texts. The crux of our approach lies in acquiring a set of explicit and implicit causal patterns from Wikipedia, which we exploit as a knowledge-base. We then use these patterns to extract causal relations from domain-specific documents. Our strategy of applying the knowledge acquired from Wikipedia to specialized documents is based on domain-adaptation [3]. It circumvents the data sparsity issues posed by the domain-specific, corporate documents.

Our contributions are as follows. We present a minimally-supervised algorithm that extracts causal relations without relying on hand-coded knowledge. Also, our algorithm accurately disambiguates polysemous causal patterns, and discovers both explicit and implicit causal relations. In addition, we represent the extracted causal patterns as sophisticated syntactic structures, which overcome the shortcomings of traditional pattern representations based on surface-strings.

¹ DataFusion is a collaboration between academia and industry, sponsored by the Dutch Ministry of Economic Affairs.