Using Part-Of Relations for Discovering Causality

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Abstract

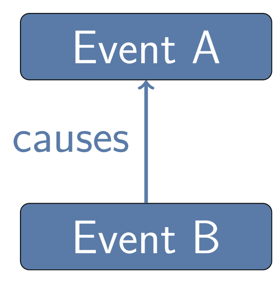
This paper introduces the theory of granularity and describes different approaches to identify granularity in natural language. As causality is often granular in nature (Mazlack 2004), we use granularity relations to discover and infer the presence of causal relations in text. We compare this with causal relations identified using just causal markers. We achieve a precision of 0.91 and a recall of 0.79 using granularity for causal relation detection, as compared to a precision of 0.79 and a recall of 0.44 using pure causal markers for causality detection.

Causality

- Sequential Causality

E.g. *John fell because Mary pushed him.*

- Granular Causality



where Event B is sub-event of Event A

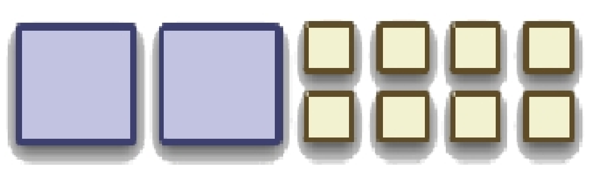
E.g. *John fell because his knee gave way.*

- Continuous Causality (Forbus 1986)

E.g. *increase in the heat of the water is causing its temperature to increase*

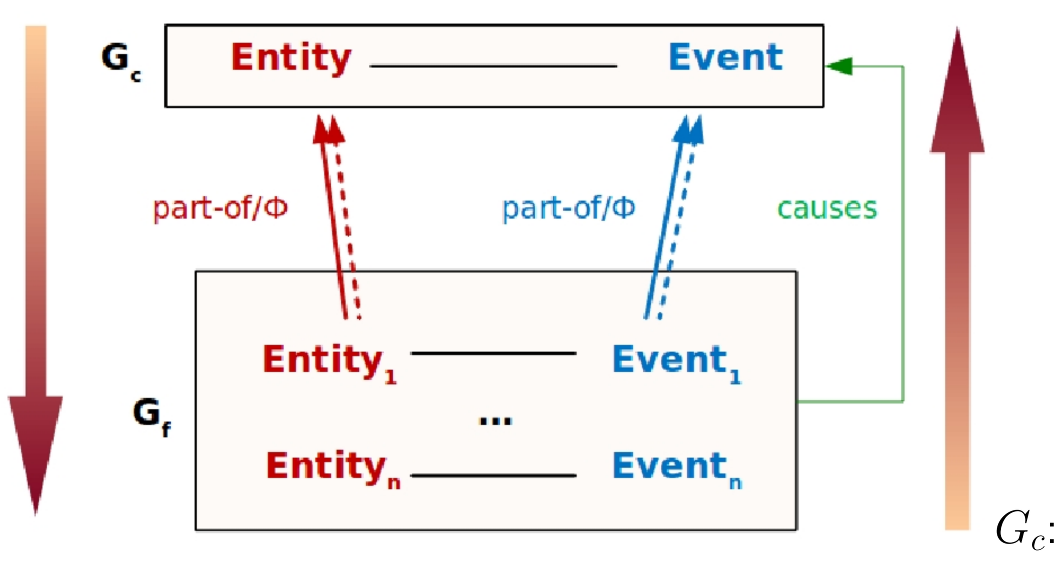
Granularity

We use the phenomenon of granularity on a regular basis in our everyday life. For planning and scheduling of important tasks, we often divide or split our tasks into smaller pieces, till each task is easily manageable. For instance, the day-to-day activity of shopping for groceries involves some finer grained events such as *driving to the grocery store*, *carrying a list*, *picking out required items* and *paying the cashier*. Each of these events in turn involve some finer level events. For instance, *driving to the grocery store* involves sub-events like *opening the car door*, *starting the engine*, *planning the route* and *driving to the destination*. In this sense, granularity decomposition is script or plan decomposition.



Clean a house — Clean a Room

Theory of Causal Granularity



G_c: Coarse granularity information
G_f : Fine granularity information

Relevant categories of Part-of Relations (Winston et al. 1987) and Causal Relations (Girju et al. 2002) as they occur in natural language discourse.

Related Papers

1. Mulkar-Mehta R, Welty C, Hobbs JR, Hovy E. Using Part-Of Relations for Discovering Causality. FLAIRS. 2011.(to appear)
2. Mulkar-Mehta R, Hobbs JR, Hovy E. Granularity in Natural Language Discourse. International Conference on Computational Semantics, Oxford, UK. 2011:360–364.
3. Mulkar-Mehta R, Hobbs JR, Hovy E. Applications and Discovery of Granularity Structures in Natural Language Discourse. AAAI Spring Symposium, Stanford, CA. 2011

Experimental Details

The objective was to compare the performance of causality relation detection using only granularity features as opposed to using pure causal connectives/indicators. The entity part-of relations were extracted from *http://databasefootball.com* and the event part-of relations were manually developed from ∼100 sentences. We performed the experiments by implementing the following four systems:

GRANULAR CAUSALITY

1(a): Using Part-Of Relations (Surface Level)

Syntactic Parser, **Part-Of Relation List**
e.g. *William Ali Floyd is part of San Francisco 49ers*

1(b): Using Part-Of Relations (Deep Semantic Reasoning)

Syntactic Parser, **Part-Of Relation Axioms**, Abduction Engine (Mini-TACITUS)
1 PERSON(x1) → ChrisKinzer-nn'(e1,x1)
2 TEAM(x1) → VirginiaTech-nn'(e1,x1)
4 PART-OF(x0,x3) → PERSON(x0) & TEAM(x3)

SEQUENTIAL CAUSALITY

2(a): Using Causal Markers (Domain Independent)

Causal Markers from the causal QA system developed by Prager et al. (2004) which were used in for TREC QA
e.g. *because, cause*

2(b): Using Causal Markers (Domain Dependent)

football domain specific **Causal Markers** extracted by studying 10 articles (∼100 sentences)
e.g. *gave, lead to, set up*

Related Information

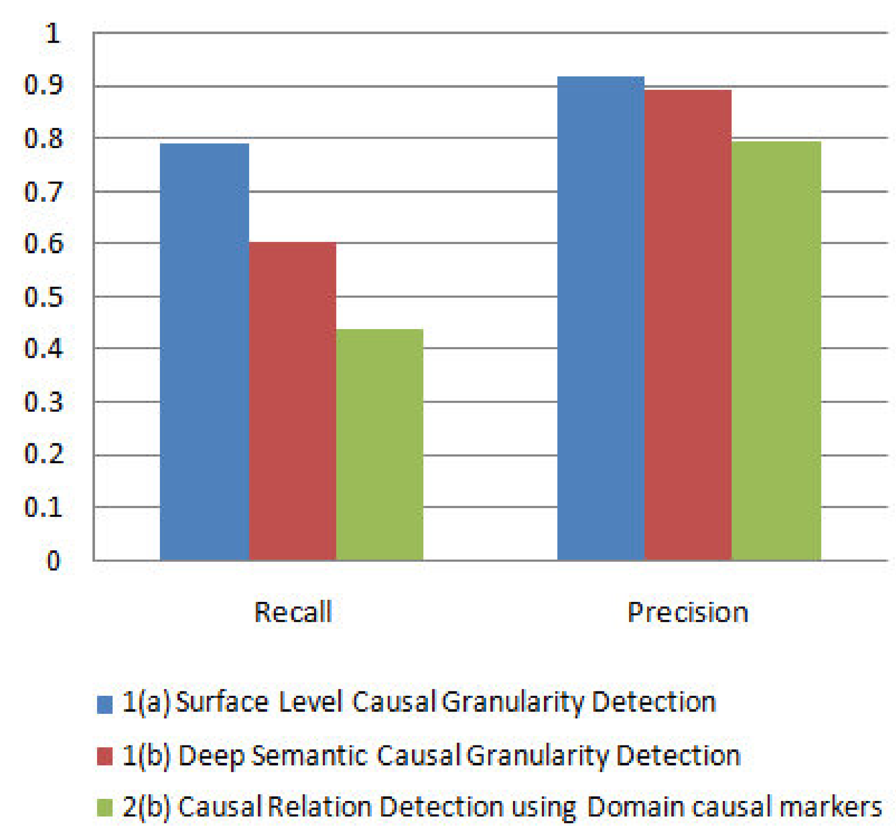
A gold standard was created on the union of all the sentences that were marked to have a positive causality by any of the above systems.
Annotators: 2 annotators.
Guidelines:

- Does the sentence contain a causal relation?
- Mark the causal cue words in the sentence

Kappa Agreement (Cohen 1960): 0.86

In order to simplify the downstream process, we manually converted all the proper names into their canonical form. As a result, we are not currently able to scale this to a larger corpus. i.e. *San Francisco,49ers* were converted to *San Francisco 49ers*

Results



Analysis of Mini-TACITUS

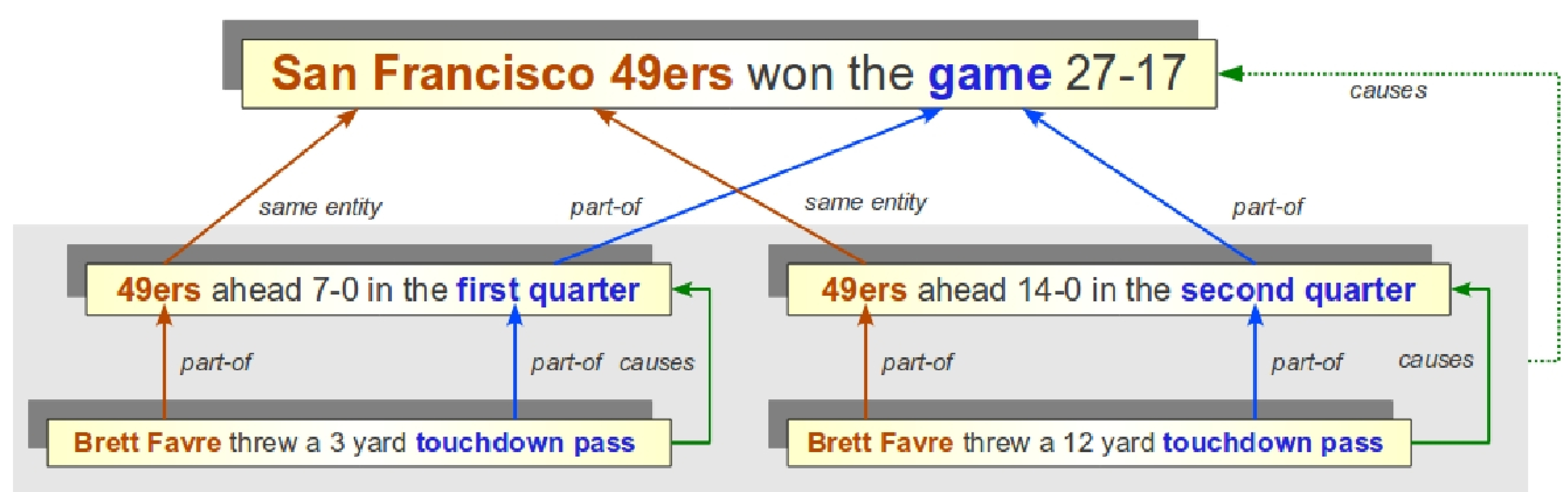
It was unexpected that the deep semantic reasoning system 1(b) would be outperformed by the surface level system 1(a). One of the major problems we faced with Mini-TACITUS was that the system did not allow backchaining on the same proposition more than once. This created issues in cases where a sentence contained mentions of a team and multiple players in the team. Another issue with Mini-TACITUS was that it did not support loopy axioms. This meant that one could not write axioms such as $a \rightarrow b$ and $b \rightarrow a$ in the same axiom set.

Example Causal Markers

Derek Loville added a 19-yard touchdown catch and a one-yard touchdown run in the second quarter ***as*** *the San Francisco 49ers rolled to a 31-7 half-time edge*

The Miami Dolphins went ahead 21-6 at halftime ***behind*** *three touchdown throws by Dan Marino, who found Keith Jackson twice.*

Example Applications: How QA and Summarization



Conclusion

In this paper we describe a theory of granularity as it occurs in natural language text. We use this theory for identification of sentences containing causal relations. We compare this with a system that identifies causal relations using causal markers only. Our granularity based system outperforms the causal markers based system in precision as well as recall. This provides strong evidence that causality is not always sequential in nature and can often have a granular structure, which is a theory that has been largely overlooked.