

Using Part-Of Relations for Discovering Causality

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Information Sciences Institute

What is the Relation?



Car on Fire



Car Accident



Sequential



Car on Fire



Car Accident



Sequential



Car on Fire



Granular

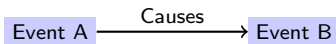


Engine Burst

Types of Causality

There are 3 types of causality:

- Sequential Causality

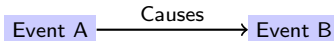


E.g. *John fell because Mary pushed him.*

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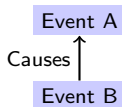
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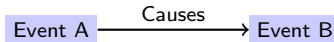


where Event B is sub-event of Event A
E.g. *John fell because his knee gave way.*

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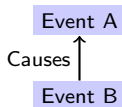
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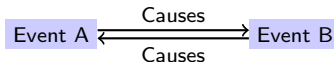
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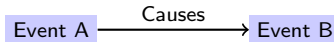


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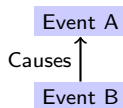
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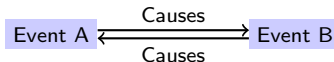
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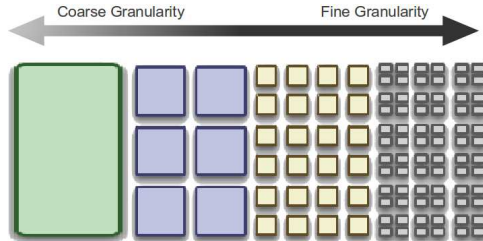
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This talk focuses on granular causality, and how identification of granularity structure in text can help infer causal relations.

What is Granularity?

Definition

Granularity: the level of detail of description of an event or object.



Domain	Domain elements in decreasing granularity			
Software	Services	Modules	Packages	Classes
Football	Season	Game	Drive	Play
Shopping	Shopping	Travel to Store	Walk	Move a foot
Cleaning	Clean a house	Clean a Room	Dust a cabinet	Dust a shelf

Real Examples of Granularity in Natural language Descriptions

How did the WTC **collapse**?

As the joists on one or two of the most heavily burned floors **gave way** and the outer box columns began to **bow outward**, the floors above them also **fell**. The floor below could not support the roughly 45,000 t of ten floors (or more) above **crashing down** on these angle clips. This started the domino effect that **caused** the building to **collapse** within ten seconds

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Motivation to Study Granular Causality

The **heart** is a muscular organ that pumps blood through the body.

Oxygen-poor blood enters the **right atrium** which is then pumped into the **right ventricle**.

The blood then moves through the pulmonary artery to the lungs, where the blood is enriched with oxygen.

The oxygen-rich blood is then carried back to the **left atrium**.

The blood is then pumped to the **left ventricle**, then the blood is pumped through the aorta and to the rest of the body.

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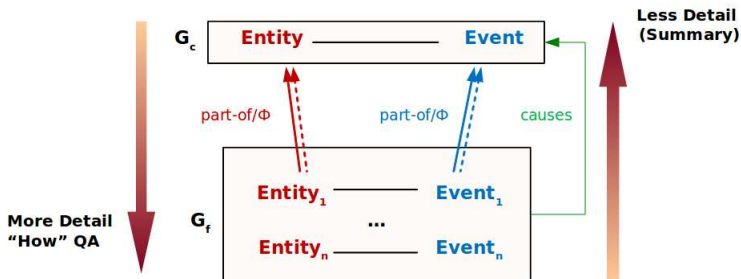
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Linking Part-of Relations to Causality

Theory of Causal Granularity in Natural Language Discourse

The following is a visual description of the theory of granularity in Natural Language Text



Real Examples of Granularity in Natural Language Descriptions

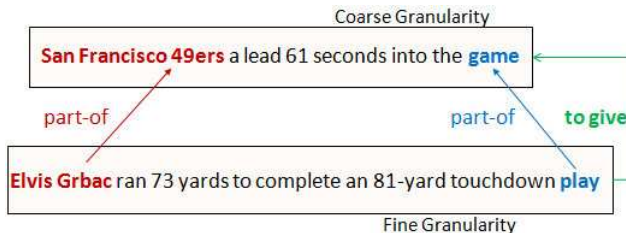
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Elvis Grbac ran 73 yards to complete an 81-yard touchdown play to give the San Francisco 49ers a lead 61 seconds into the game.

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Part-Of Relations



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ALCOHOL

Part-Of Relations



ALCOHOL

Part-of Relations (Winston et al. 1987)

Category

Component-Integral

Member-Collection

Portion-Mass

Stuff-Object

Feature-Activity

Place-Area

Example

pedal - bike

ship - fleet

slice - pie

steel - car

pay - shop

LA - USA

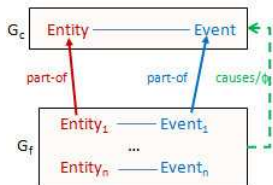
Causal Markers

Causal Connectives (Girju et al. 2002)		
Category	Type	Example
Causal Connectives	Prepositional Adverbial Clause links	<i>because of, thanks to, due to for this reason, the result that because, since, for</i>
Causation Verbs		<i>kill, melt</i>
Conditionals		<i>poison, hang If S1 then S2.</i>

Discovering Causal Relations using Part-Of relations

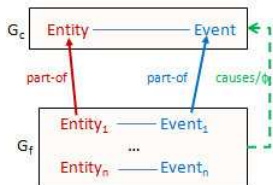
Overview of Experiments

I Causality detection using Part-Of Relations



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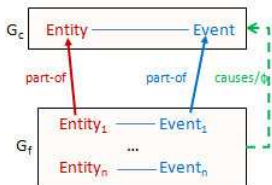


(a) Shallow Syntactic Reasoning

(b) Deep Semantic Reasoning

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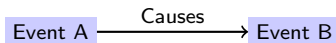
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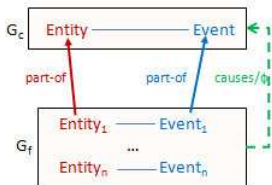
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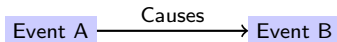
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(a) Shallow Syntactic Reasoning

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II Causal relation detection using causal markers



(i) Domain Independent Markers

(ii) Domains Dependent Markers

Experiment I(a): Shallow Syntactic Reasoning

Entities	
PART	WHOLE
Elvis Grbac	SF 49ers
William Floyd	SF 49ers

Parse Tree, POS Tags, Lexical Mapping

Events	
PART	WHOLE
play	game
touchdown	game

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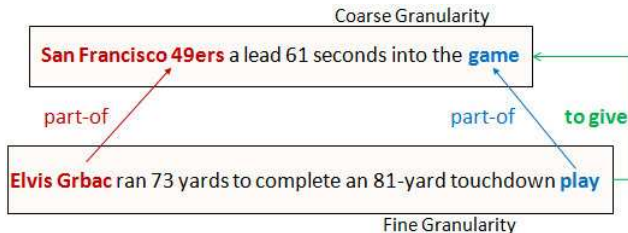
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Experiment I(b): Deep Semantic Reasoning

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ChrisKinzer-nn'(e4,x0) & kick-vb'(e6,x0,x8) & fieldgoal-nn'(e13,x8) & give-vb'(e10,x8,x9,x10) & VirginiaTech-nn'(e16,x9) & a'(e19,x10,e15) & victory-nn'(e15,x10) & over-in'(e18,x10,x15) & NorthCarolina-nn'(e20,x15)

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1	PERSON(x1) → ChrisKinzer-nn'(e1,x1)
2	TEAM(x1) → VirginiaTech-nn'(e1,x1)
3	SCORE(x1,x2) → fieldgoal-nn'(e1,x1)
Part-Whole relation between events	
4	PART-OF(x0,x3) → PERSON(x0) & TEAM(x3)
Part-Whole relation between entities	
5	PART-OF(x1,x2) → SCORE(x1,x2) & victory-nn'(e1,x2)

Experiment I(b): Deep Semantic Reasoning



Final Granularity Levels:

ChrisKinzer-nn'(e4,x0) & kick-vb'(e6,x0,x8) & fieldgoal-nn'(e13,x8)

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Experiment 2(a): Domain Independent Causal Connectives

The domain independent causal cue words were obtained from the causal QA system developed by Prager et al. (2004) for TREC QA.

Causal Marker
because
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Causal Marker
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The National Football League

was moved **because** of the
approach of Hurricane Ivan.

approach of Hurricane Ivan

causes

The National Football League was moved

Experiment 2(b): Domain dependent Causal Connectives

Causal Marker
lead to
give
cause
drive

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Gold Standard

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.

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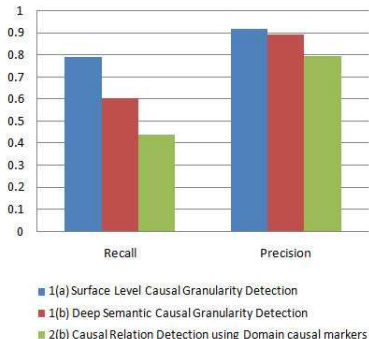
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Guidelines:

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

Kappa Agreement (Cohen 1960): 0.86.

Results



Prepositions are inherently ambiguous in nature:

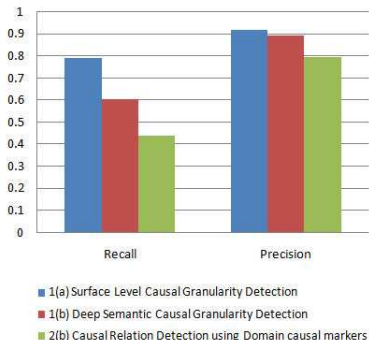
*Derek Loville added a 19-yard touchdown catch and a one-yard touchdown run in the second quarter **as** the San Francisco 49ers rolled to a 31-7 half-time edge*

Here causality is represented by the word “as”.

The Miami Dolphins went ahead 21-6 at halftime behind three touchdown throws by Dan Marino, who found Keith Jackson twice and gave seldom-used Mike Williams his first touchdown in four seasons with the Miami Dolphins

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Data Collection

Part of Relations

- Part-of Relations for Entities: team-player relations from <http://databasefootball.com>
 - *William Ali Floyd is part of San Francisco 49ers*
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Corpus

- Corpus: 31 articles of LDC - *New York Times Annotated corpus* (LDC2008T19A) that describes football games.
- Sentences: 544 sentences

Conclusions and Future Work

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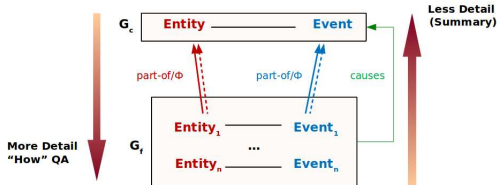
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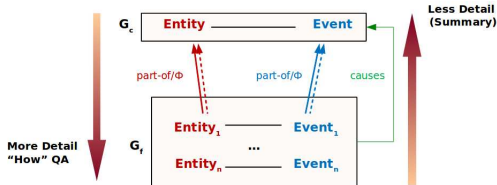
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- **Achieved better accuracy than using causal markers**

Future Work



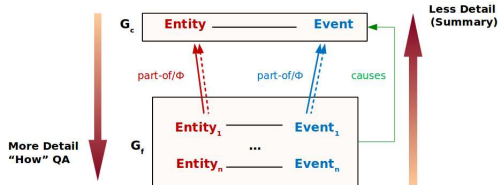
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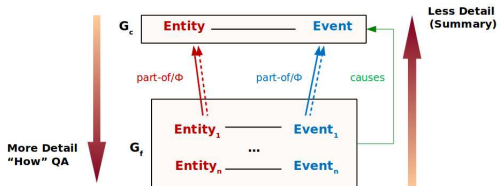
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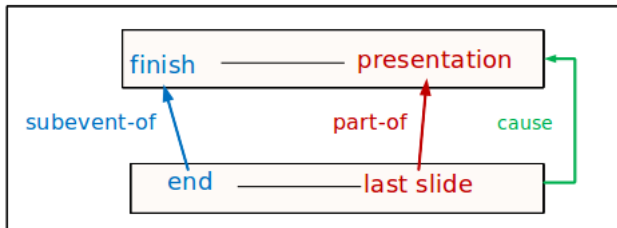


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- Using Causal Granularity structures for answering “How” style questions
- Using Causal Granularity structures for summarization
- Differentiating between Granularity and Causal Granularity

Relevant Papers

1. Mulkar-Mehta R, Gordon AS, Hobbs JR, Hovy E. Causal Markers across Domains and Genres of Discourse. The Sixth International Conference on Knowledge Capture, 2011
2. Mulkar-Mehta R, Welty C, Hobbs JR, Hovy E. Using Part-Of Relations for Discovering Causality. The 24th International Florida Artificial Intelligence Research Society Conference, 2011
3. Mulkar-Mehta R, Hobbs JR, Hovy E. Granularity in Natural Language Discourse. International Conference on Computational Semantics, Oxford, UK. 2011:360–364.
4. Mulkar-Mehta R, Hobbs JR, Hovy E. Applications and Discovery of Granularity Structures in Natural Language Discourse. AAAI Spring Symposium, Stanford, CA. 2011

Thank you!



Questions?