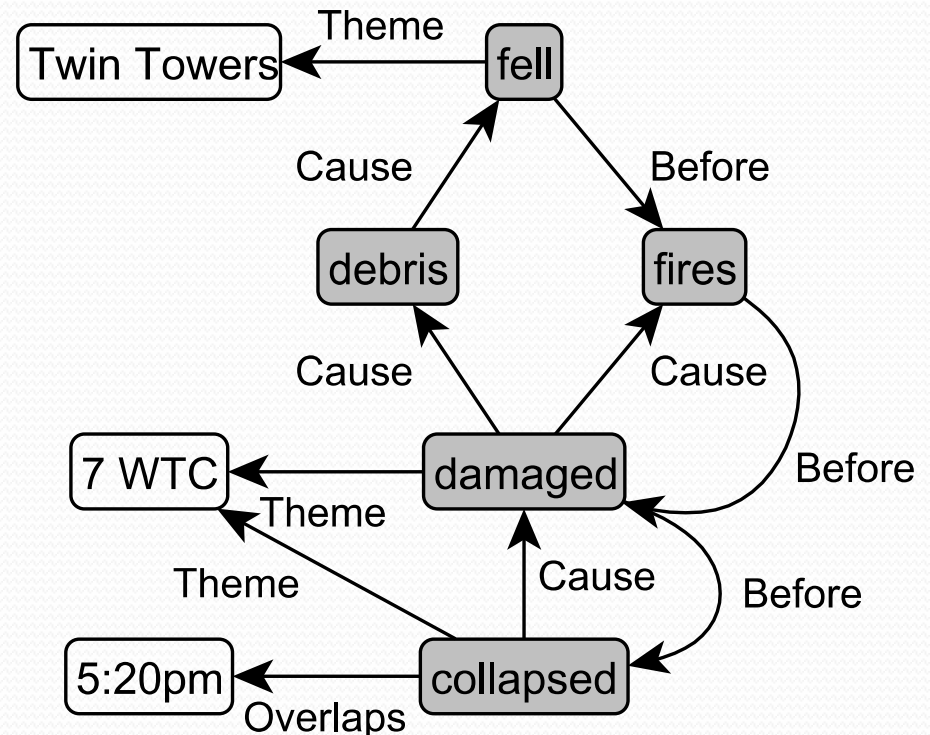


Building a Corpus of Temporal-Causal Structure

Steven Bethard, William Corvey,
Sara Klingenstein, James H. Martin
University of Colorado

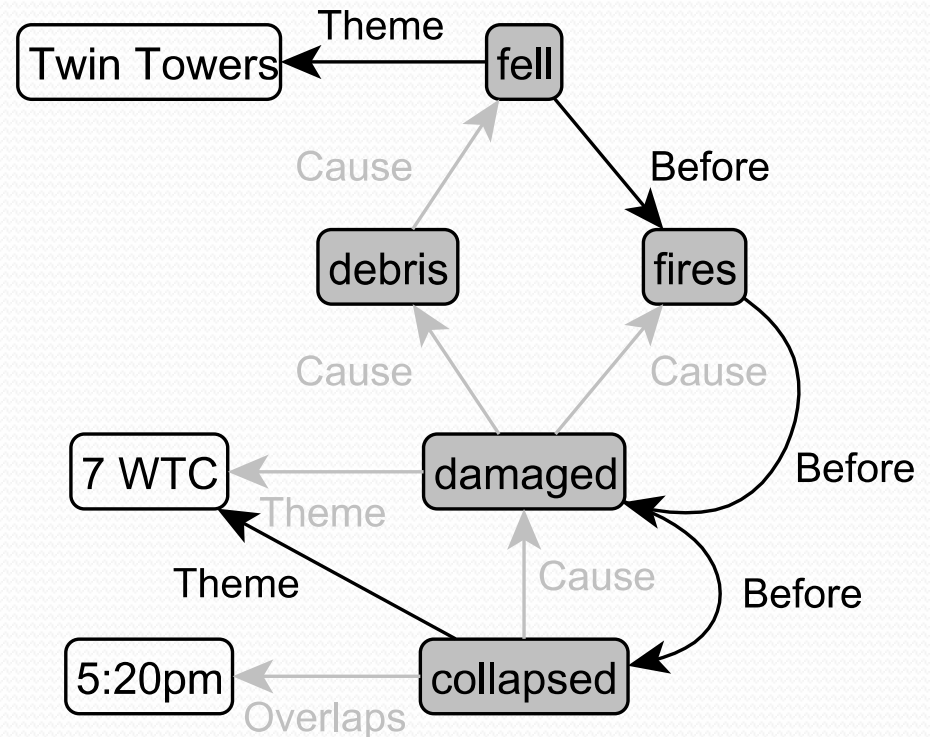
Semantic structures in text

- 7 WTC collapsed at 5:20p.m., after being heavily damaged by debris from the Twin Towers when they fell and from subsequent fires.



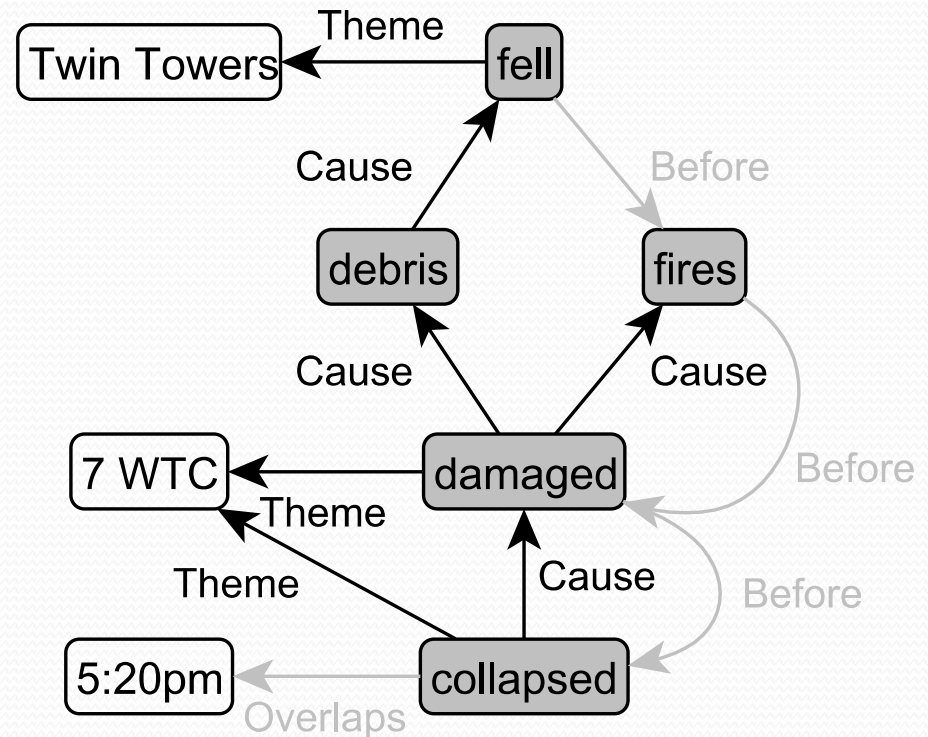
Answering temporal questions

- Which collapsed first, the Twin Towers or 7 WTC?



Answering causal questions

- What caused the 7 WTC collapse?



Temporal-causal structure

- Motivation
- Annotation
 - Temporal guidelines
 - Causal guidelines
- Corpus analysis
- Machine learning
 - Training models
 - Error analysis
- Conclusions

Annotation: corpus

- Conjoined verbal events
 - E.g. *Fuel tanks had **leaked** and **contaminated** the soil.*
- Why conjoined events?
 - Frequently expresses both temporal and causal
 - 10% of all adjacent verbal events in the TimeBank
- Corpus
 - WSJ Treebank (0416 – 0971)
 - Events identified automatically

Annotation: temporal scheme

- Labels: BEFORE/AFTER/NO-REL
- Guidelines
 - Separate events from tense and aspect, e.g.
 - *The funding mechanism, which has **received** congressional approval and is **expected** to be signed by President Bush...*
 - Possible worlds analysis, e.g.
 - *Persons who examine the materials may **make** notes and no one will **check** to determine what notes a person has taken.*
 - (See paper for full list)

Annotation: causal scheme

- Labels: CAUSAL/NO-REL
- Guidelines: paraphrase that best maintains meaning
 - CAUSAL:
 - *and as a result, and as a consequence, and enabled by that*
 - NO-REL:
 - *and independently, and for similar reasons*
- E.g. *Fuel tanks had **leaked** and **contaminated** the soil.*

Annotation: interface

wsj_0430 - Mozilla Firefox

File Edit View History Bookmarks Tools Help

Profile Logout

leaked	BEFORE	contaminated
leaked	AFTER	contaminated
leaked	NO-REL	contaminated

Skip this annotation

At stake was an \$ 80,000 settlement involving who should pay what share of cleanup costs at the site of a former gas station , where underground fuel tanks had **leaked** and **contaminated** the soil .

Corpus: overview

Event pairs	1000
Documents	556
BEFORE	313
AFTER	16
NO-REL (temporal)	671
CAUSAL	271
NO-REL (causal)	729

Task	Agree	Kappa	F
Temporal	81.2	0.715	71.9
Causal	77.8	0.556	66.5

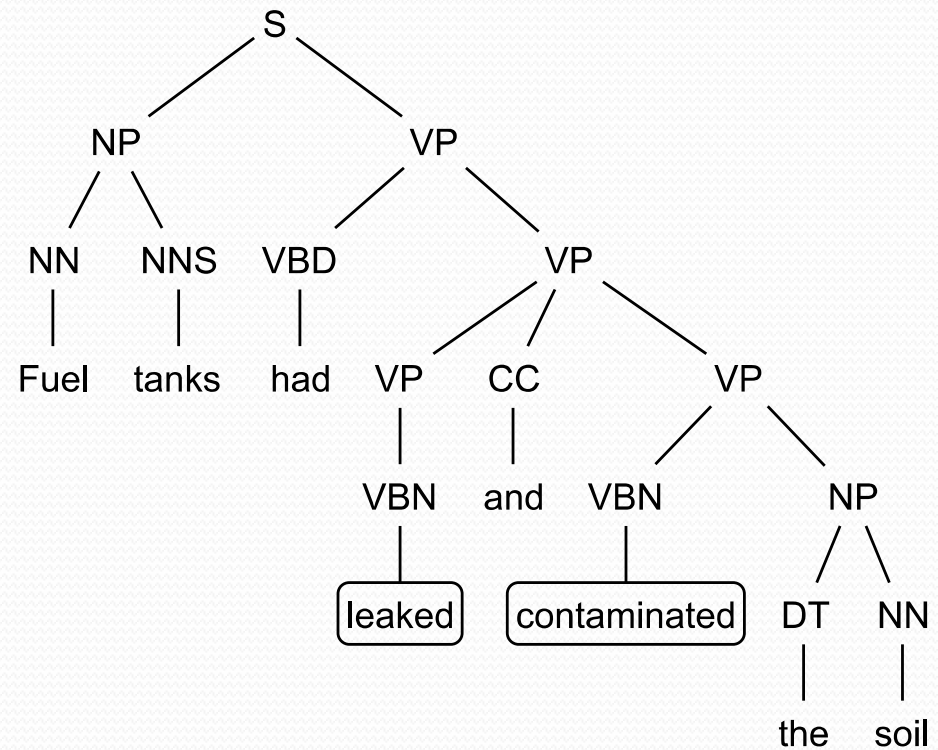
- BEFORE/CAUSAL:
“We **recognized** the problem and **took** care of it.”
- AFTER:
The Colombian minister was said to have referred to a letter that he **said** President Bush sent to Colombian President Virgilio Barco , and in which President Bush **said** it was possible to overcome obstacles to a new agreement.

Corpus: analysis

- 975 of 1000 event pairs were unique
- 75% of conjoined events had the same pos (tense)
- 32% of CAUSAL relations had no underlying BEFORE
 - Two views of the same event
 - *Abbie **lies** back and **leaves** the frame empty.*
 - Two states, but one starts earlier
 - *Japanese local governments are **expected** to invest heavily in computer systems over the next few years, and many companies **expect** that field to provide substantial revenue.*

Machine learning

- Pair-wise classifications
 - BEFORE/AFTER/NO-REL
 - CAUSAL/NO-REL
- Features
 - Words: *leaked contaminated*
 - Lemmas: *leak contaminate*
 - Pos tags: *VBN VBN*
 - Least common ancestor: *VP*
 - Path: *VBN>VP>VP<VP<VBN*
 - Preceding, intervening and following words



Machine learning: results

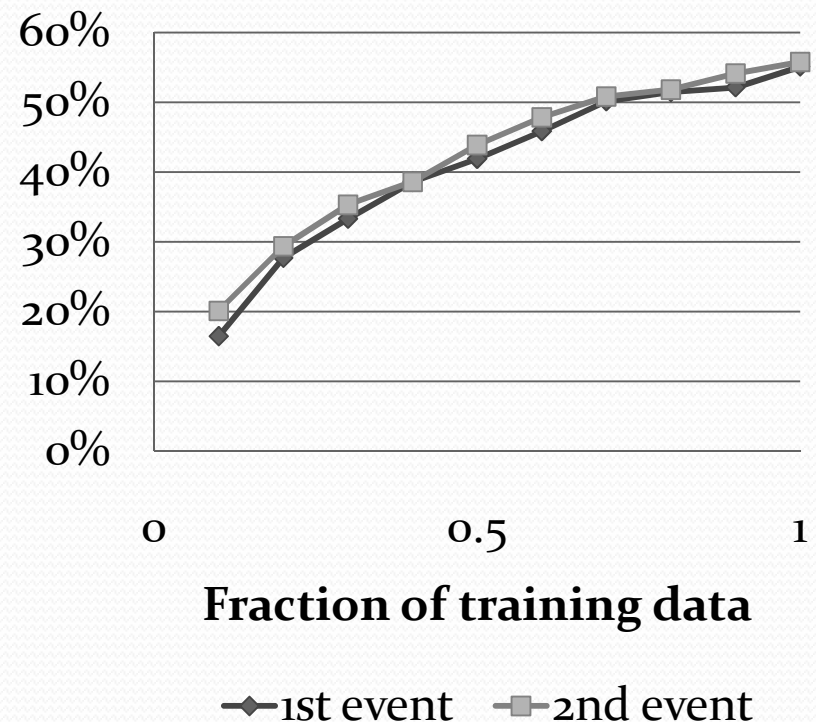
Temporal relations	
Model	F
All NO-REL	0.0
All BEFORE	41.6
Memorize pair	0.0
Memorize 1 st	28.8
Memorize 2 nd	32.9
Memorize pos pair	13.9
SVM	43.4

Causal relations	
Model	F
All NO-REL	0.0
All CAUSAL	34.8
Memorize pair	0.0
Memorize 1 st	24.5
Memorize 2 nd	19.5
Memorize pos pair	8.1
SVM	37.4

Machine learning: analysis

- SVM outperforms all baselines
 - But surface and syntactic features are not enough
- 50% of errors require world knowledge, e.g.
 - *Some of the funds will be used to **demolish** unstable buildings and **clear** sites for future construction.*
- More data will help →

Events in test data seen during training



Summary

- Annotation
 - 1000 conjoined verbal event pairs
 - Parallel temporal and causal relations
- Corpus
 - 97.5% unique event pairs
 - 32% of CAUSAL relations w/o BEFORE
- Machine learning
 - SVM – 43.4F on temporals, 37.4 F on causals
 - Lexical and syntactic features are not enough
 - Exposure to more words will help



Questions?