Exploiting Discourse Analysis for Article-Wide Temporal Classification

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Outline

- Preliminaries
- Discourse Analysis
- Methodology
- Experiments
- Discussion

Temporal Classification

At least 19 people were <u>killed</u> and 114 people were <u>wounded</u> in Tuesday's southern Philippines airport blast, officials <u>said</u>, but reports said the death toll could climb to 30.

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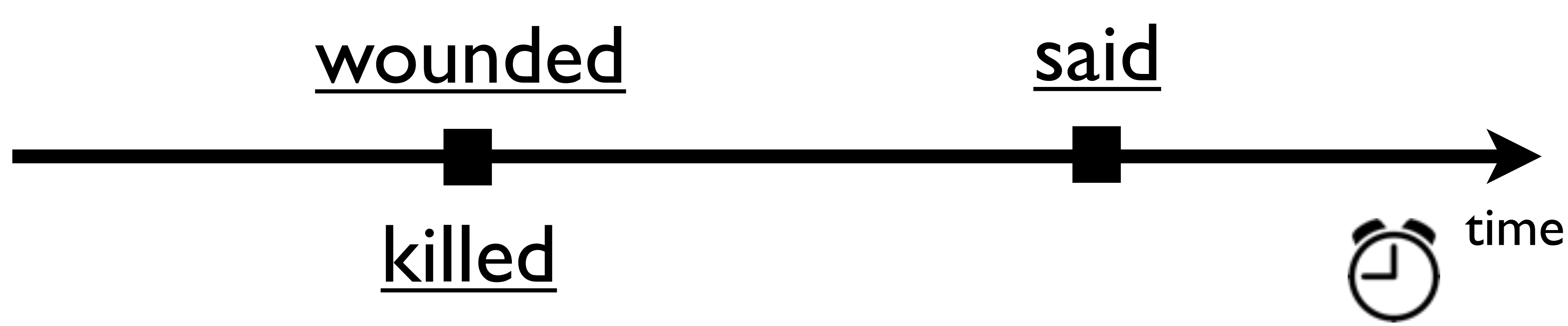

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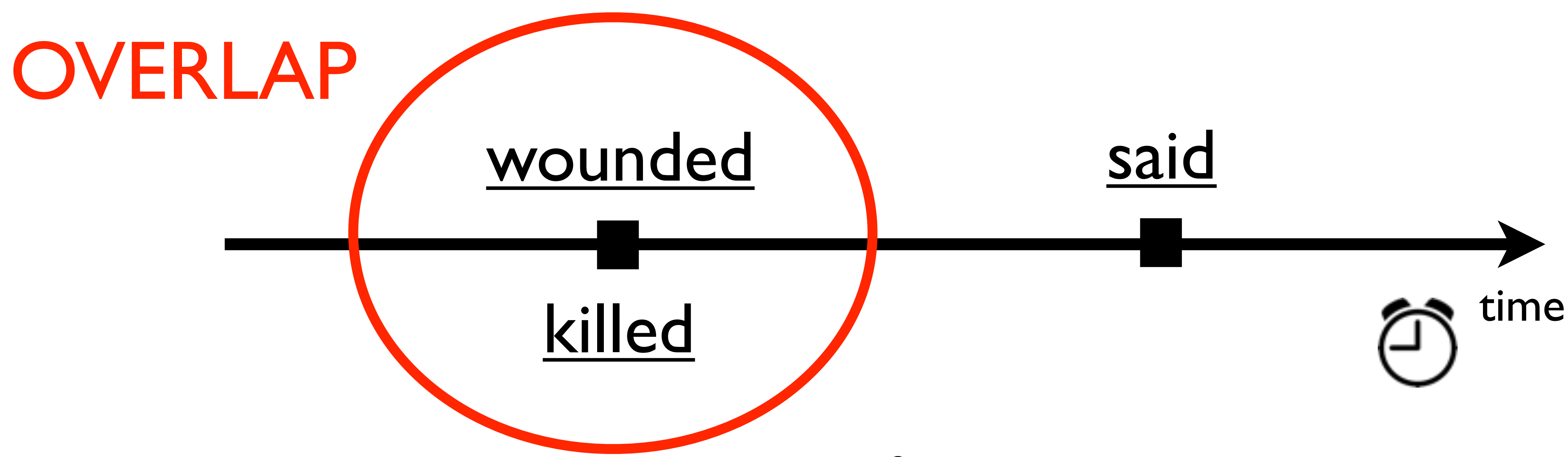

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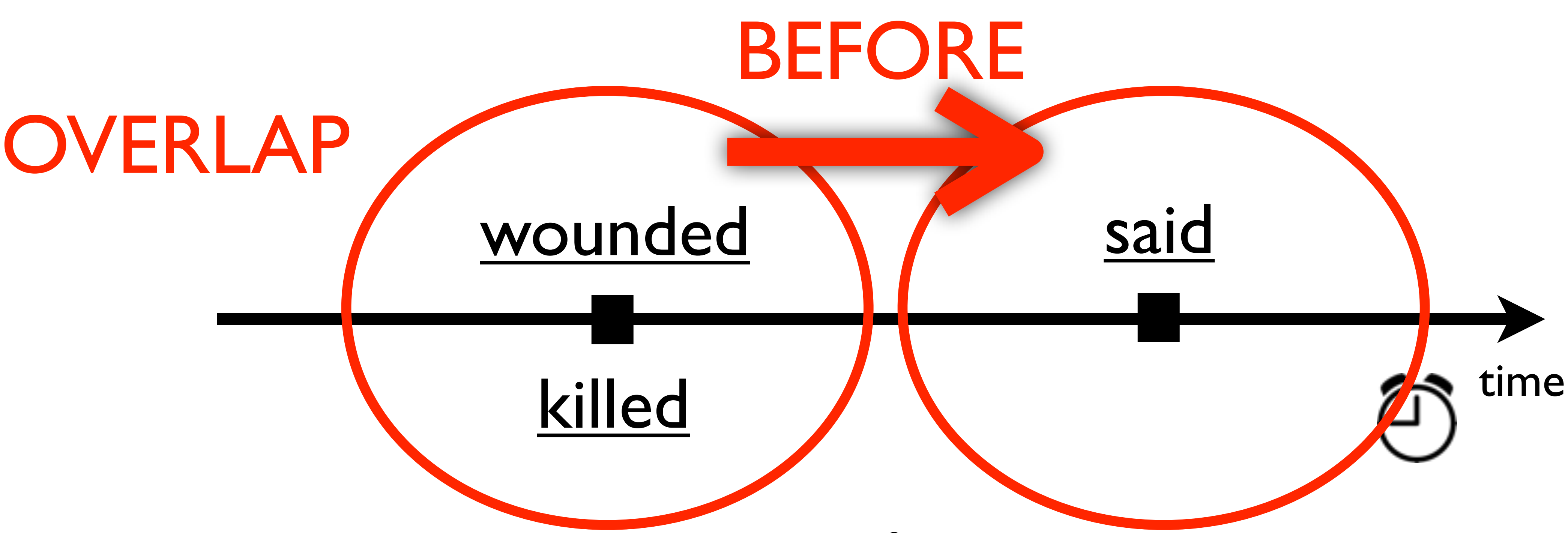

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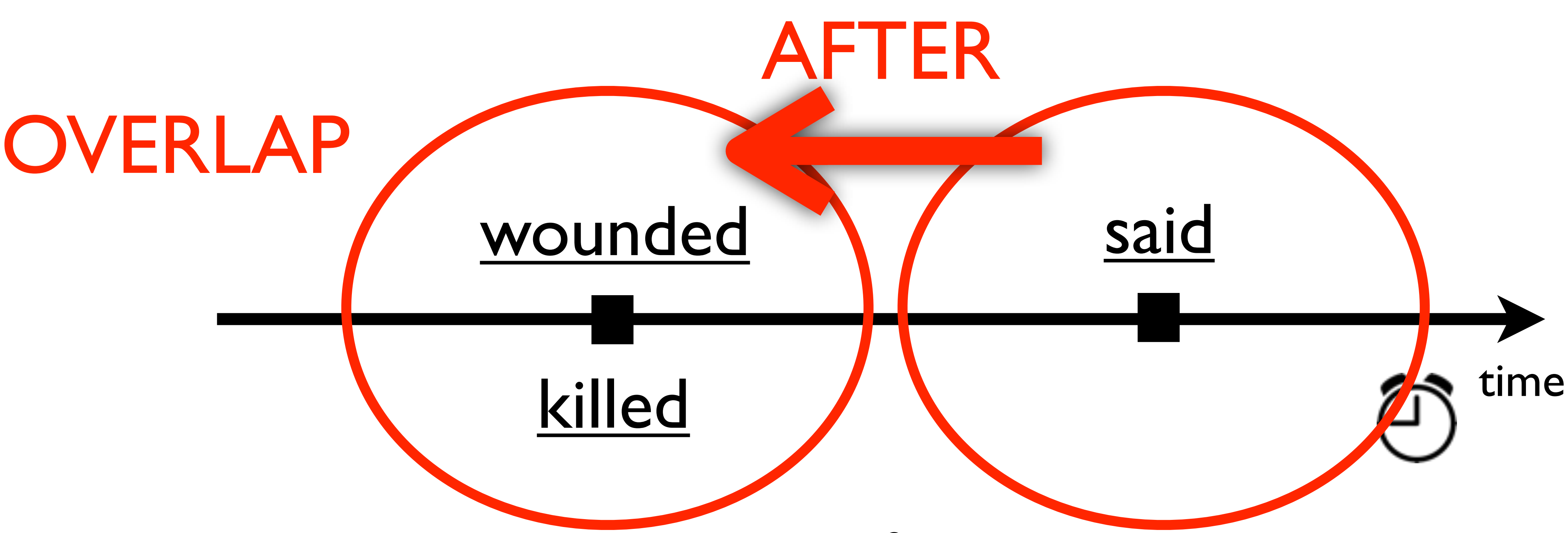

Article-Wide Event Pairs

- Decide on temporal relationship between any two events in an article
- Helps give us a more complete picture of temporal relations between event pairs

Challenge

- Distance between event pairs can potentially be significant
- Current approaches which are heavy on lexical and syntactic features are not useful

Discourse Analysis

- Tells us how sentences are composed together
- Relating sentences together gives us a better idea of temporal ordering

Discourse Analysis

- Rhetorical Structure Theory (RST)
- PDTB-styled Discourse Relations
- Topical Text Segmentation

RST

- Breaks up text into basic textual units called Elementary Discourse Units (EDU)
- Relates neighbouring EDUs via a set of typed discourse relations

RST

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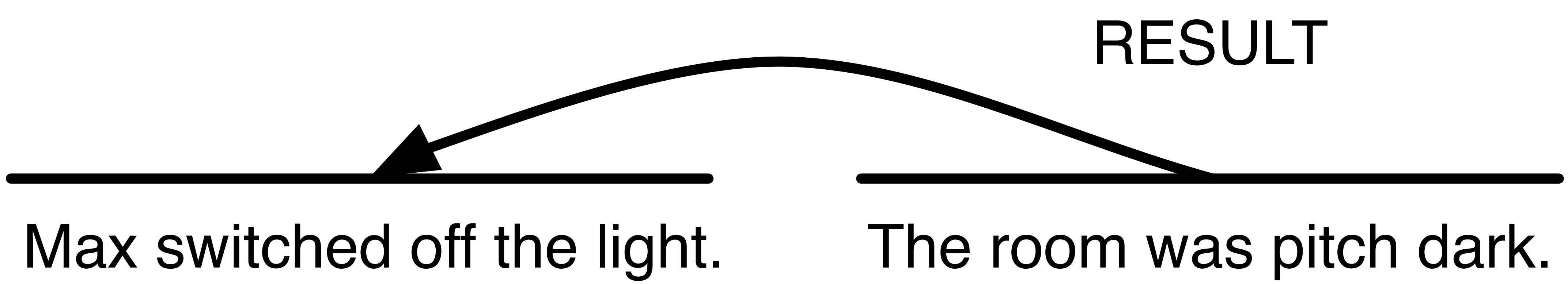

PDTB-styled Discourse Relations

- Identifies explicit and implicit relations between text
- Also relates text fragments together via a set of typed relations

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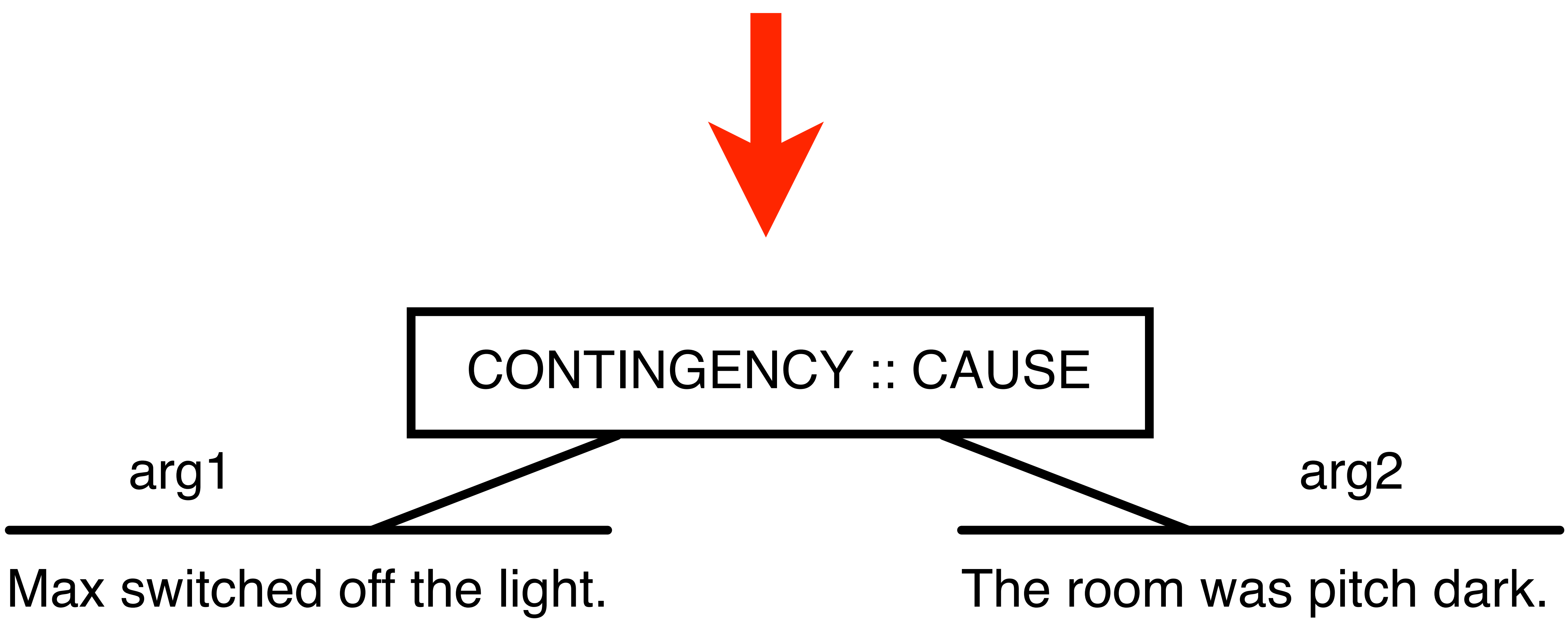

Topical Text Segmentation

- Groups neighbouring sentences about the same topic together
- Transitioning across groups of sentences represents a shift in the topic being discussed
- Coarse-grained discourse analysis

Topical Text Segmentation

The Davao Medical Centre, a regional government hospital, recorded 19 deaths with 50 wounded.

Medical evacuation workers however said the injured list was around 114, spread out at various hospitals.

A powerful bomb tore through a waiting shed at the Davao City international airport at about 5.15 pm (0915 GMT) while another explosion hit a bus terminal at the city.

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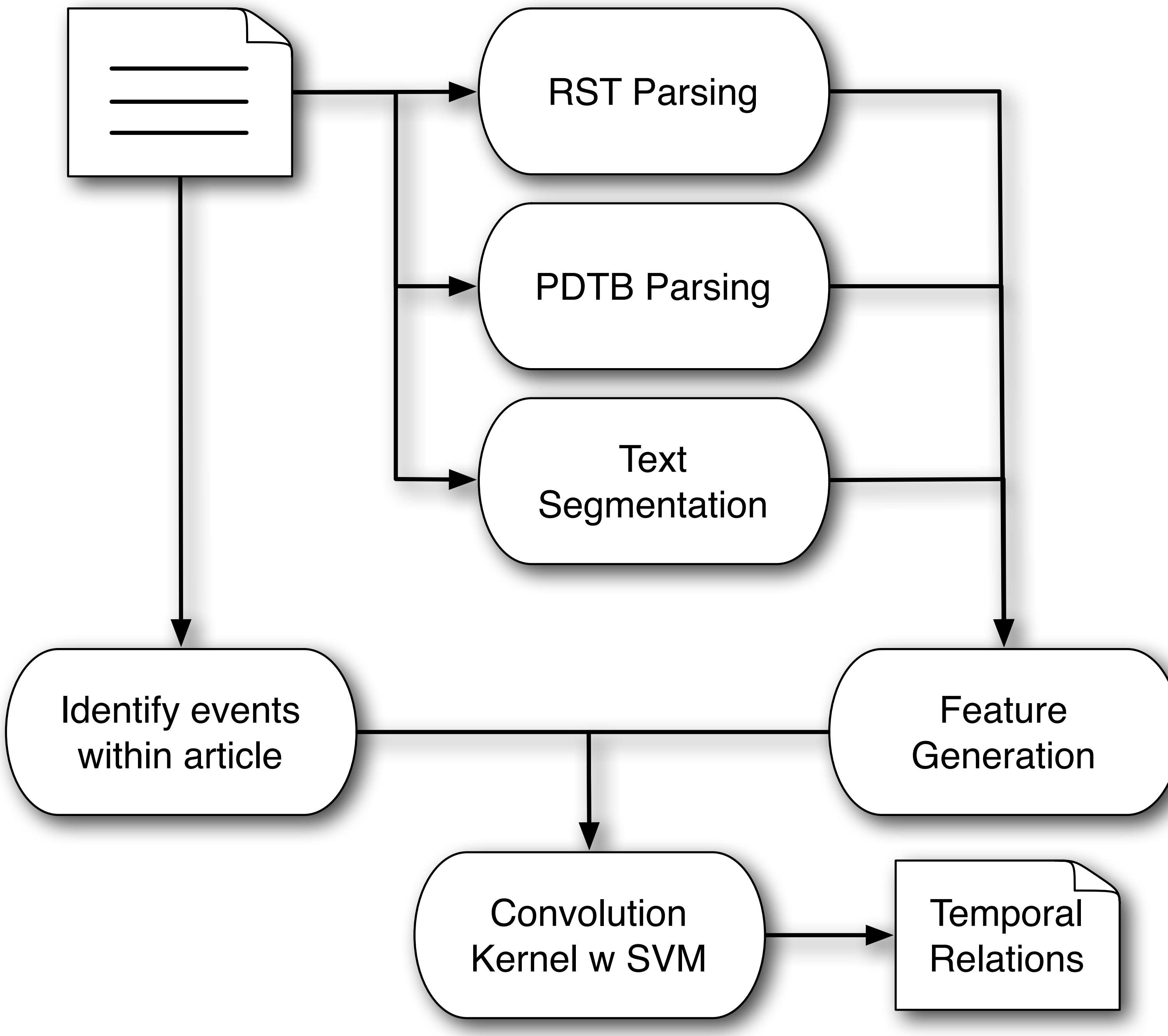

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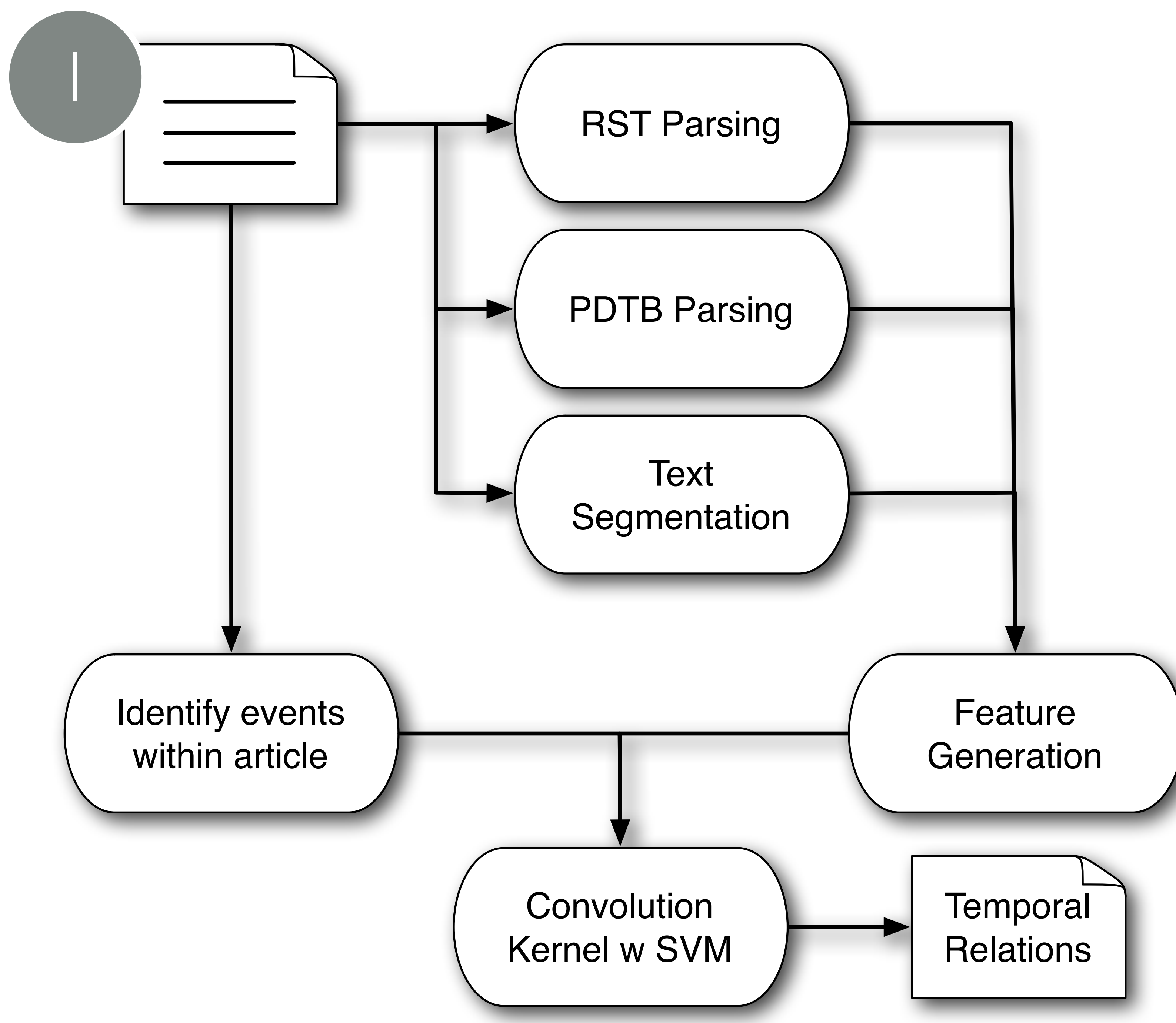

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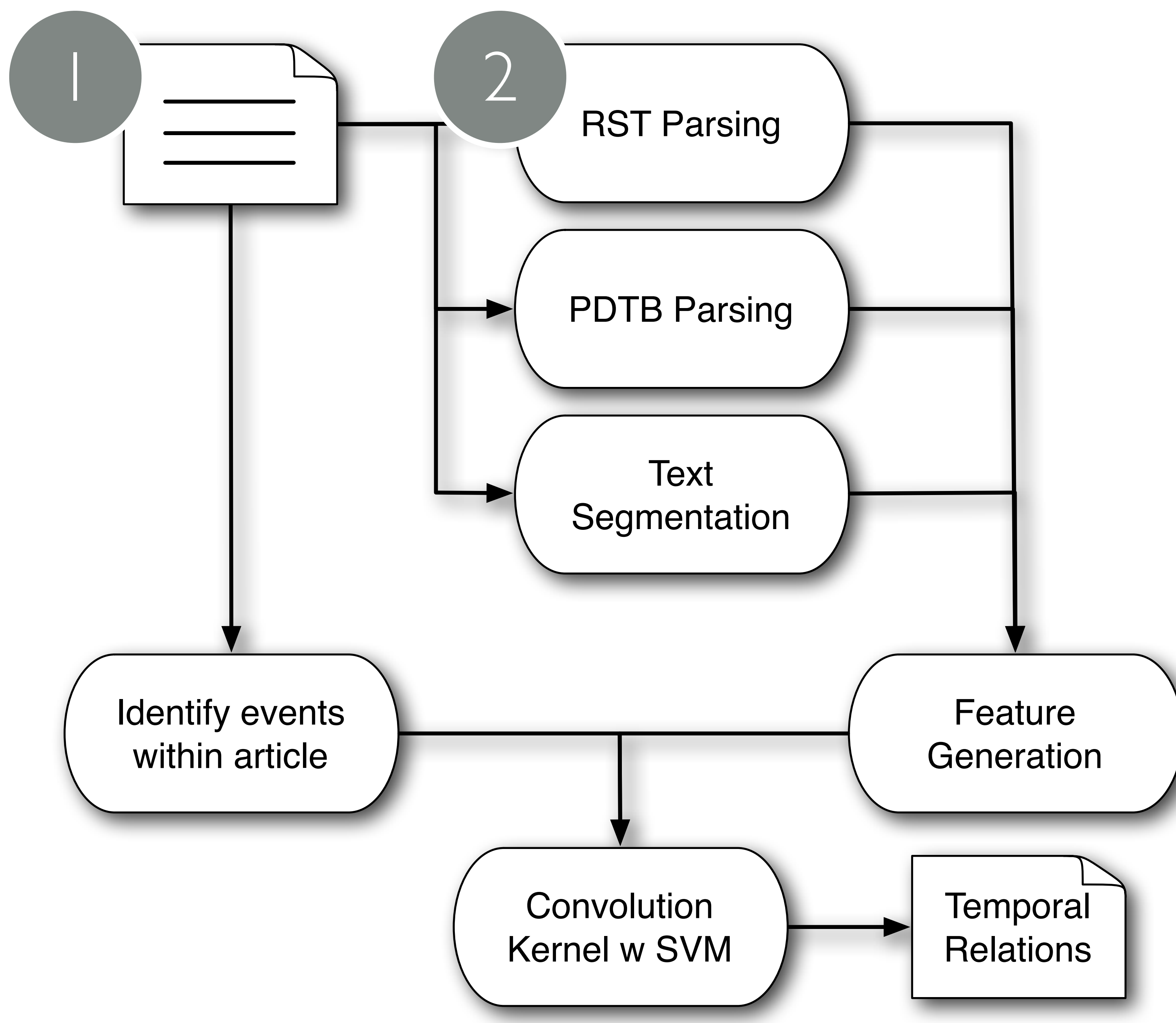

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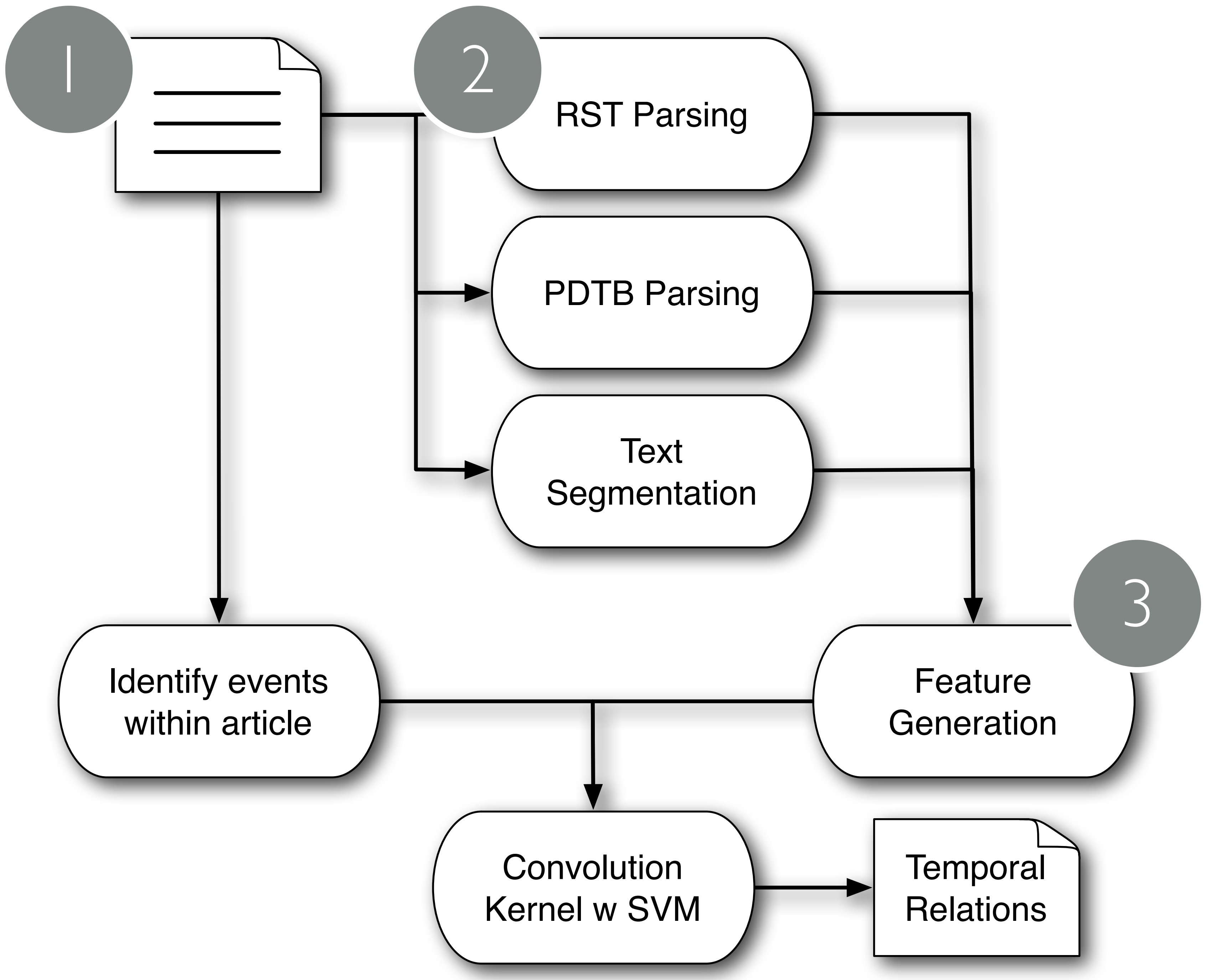

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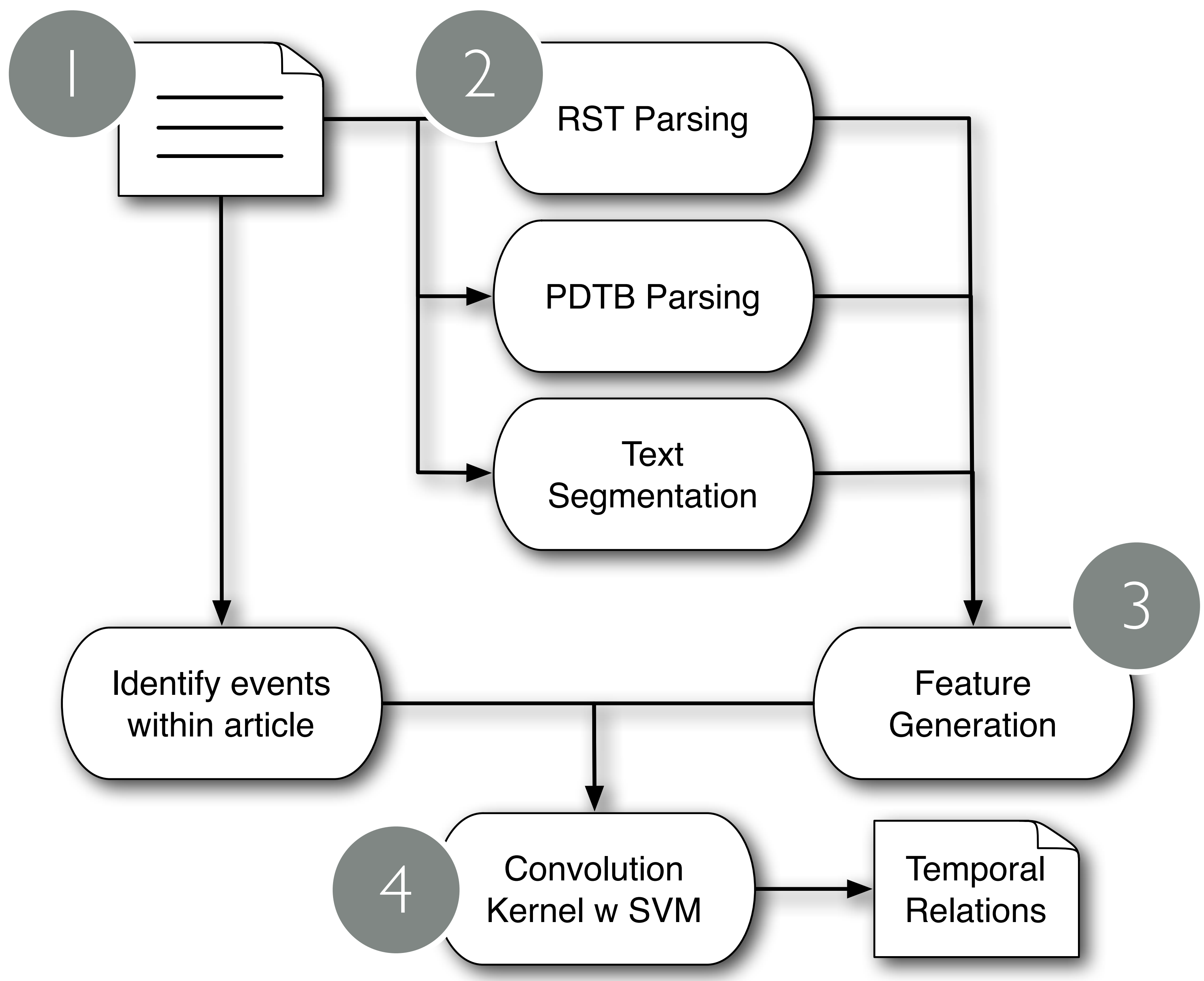

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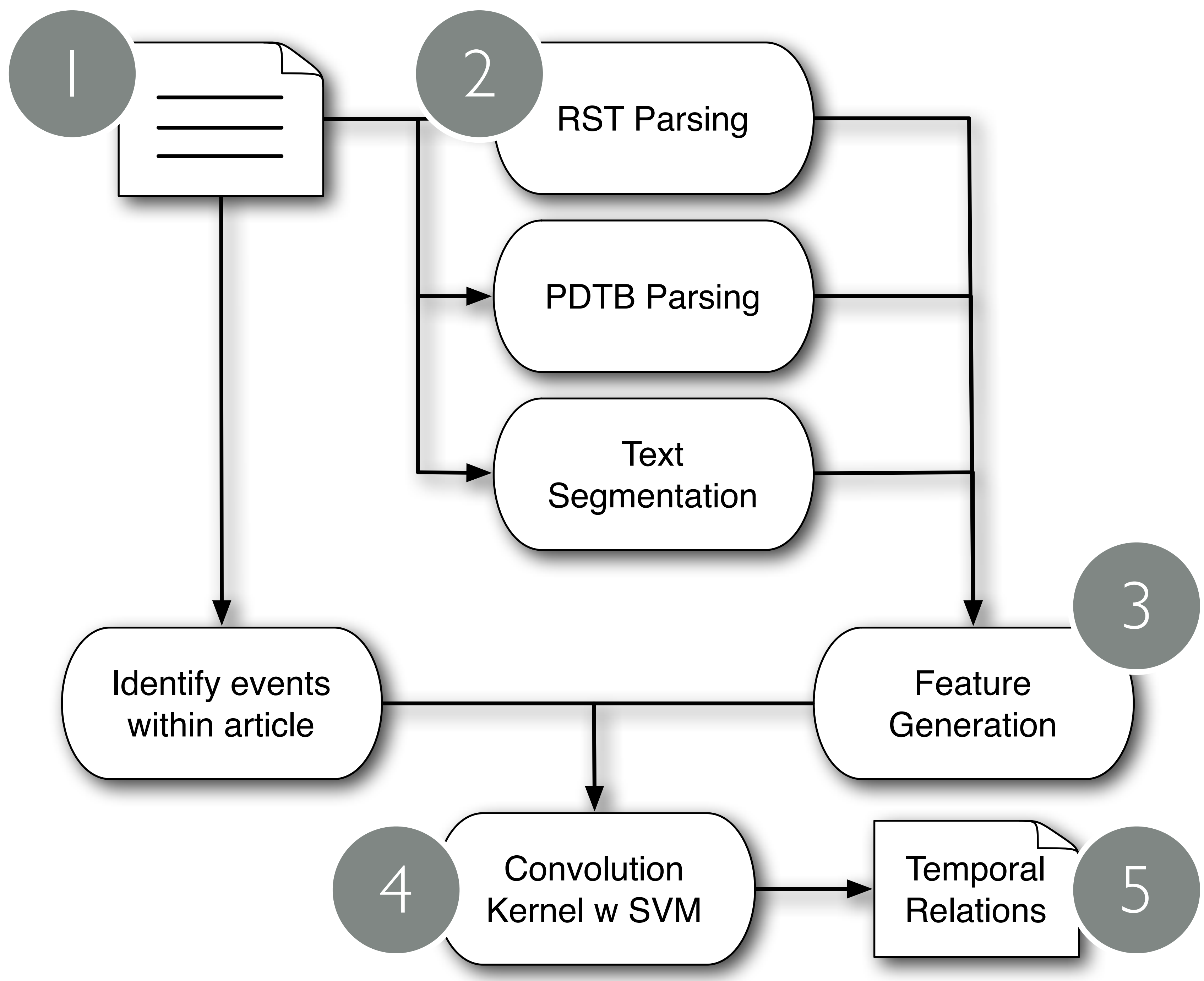
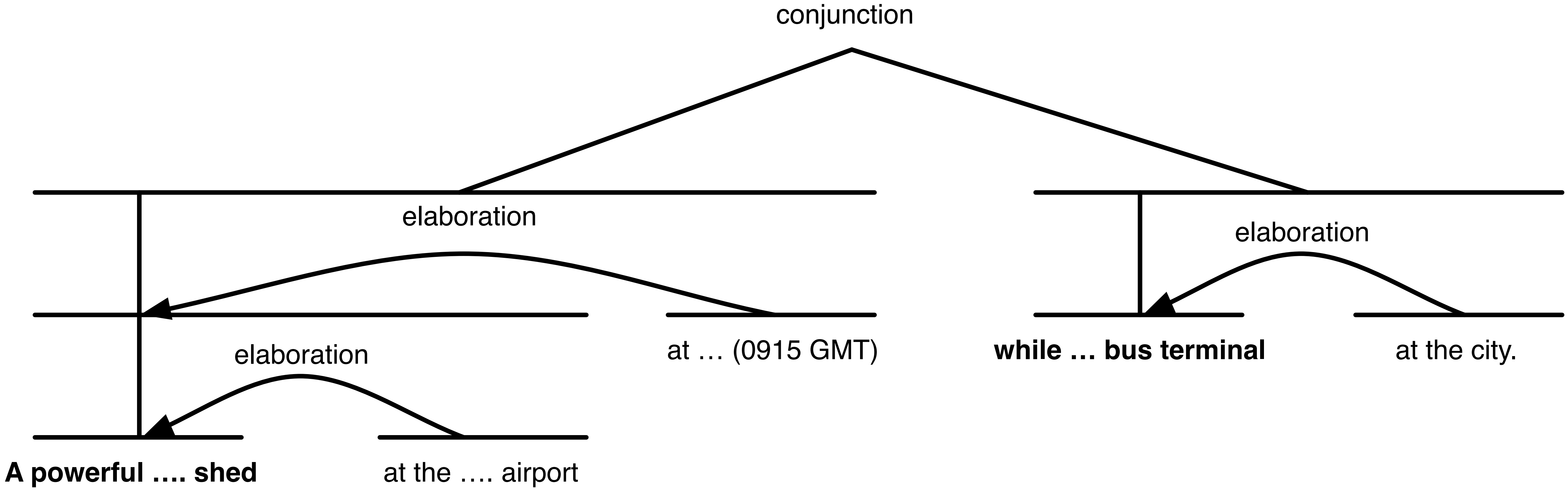


RST - Feature



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while … bus terminal
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at the city.
A powerful …. shed
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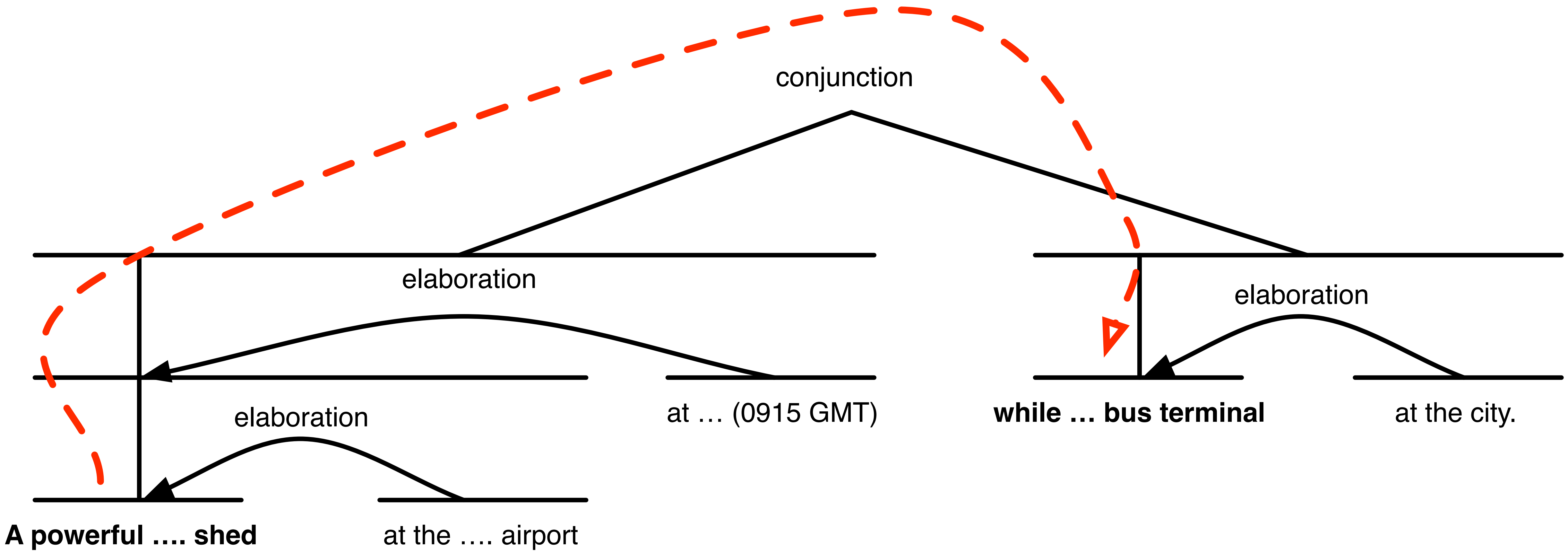

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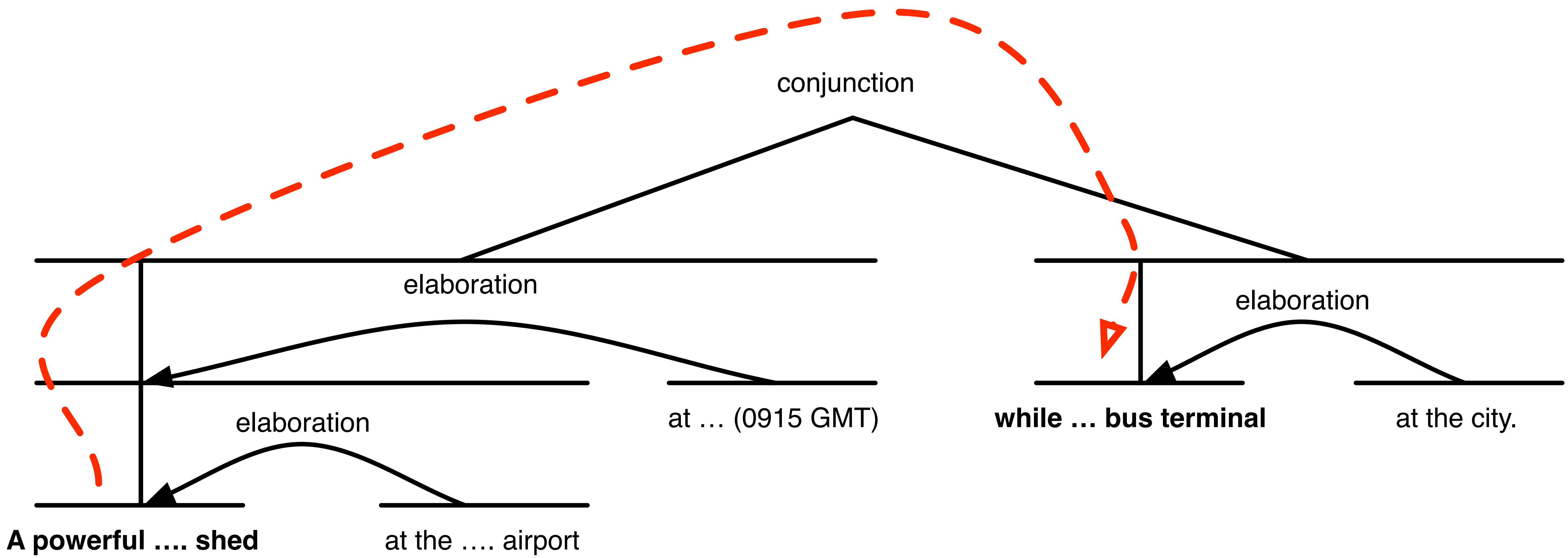

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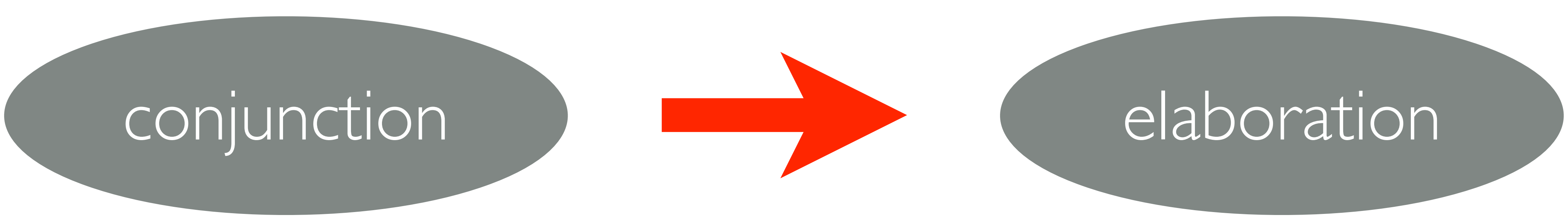

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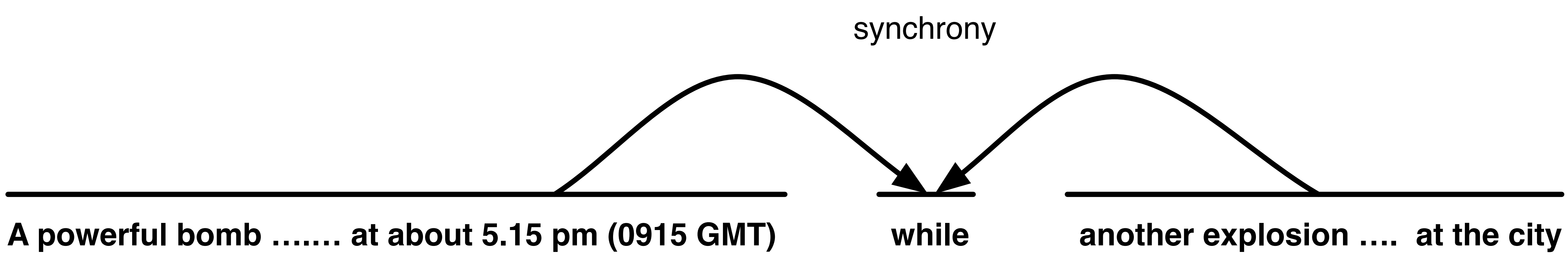

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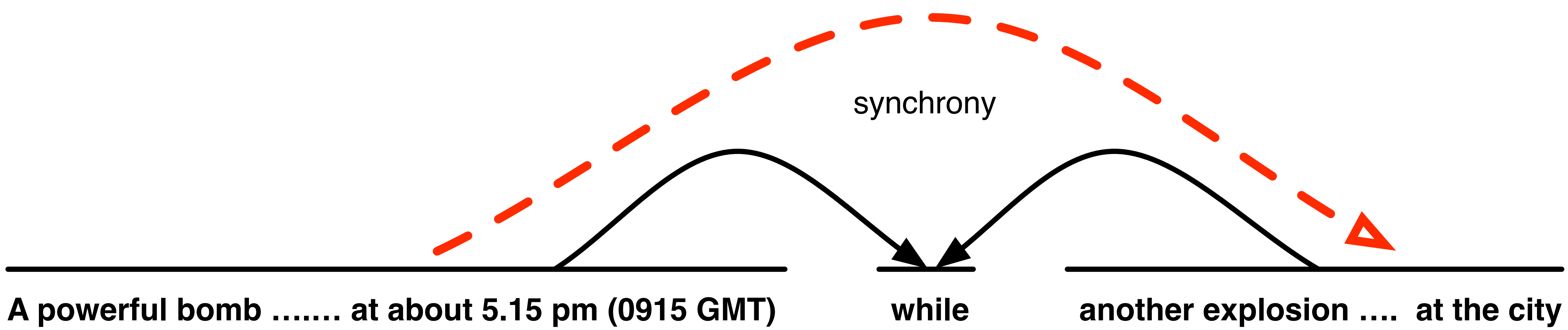

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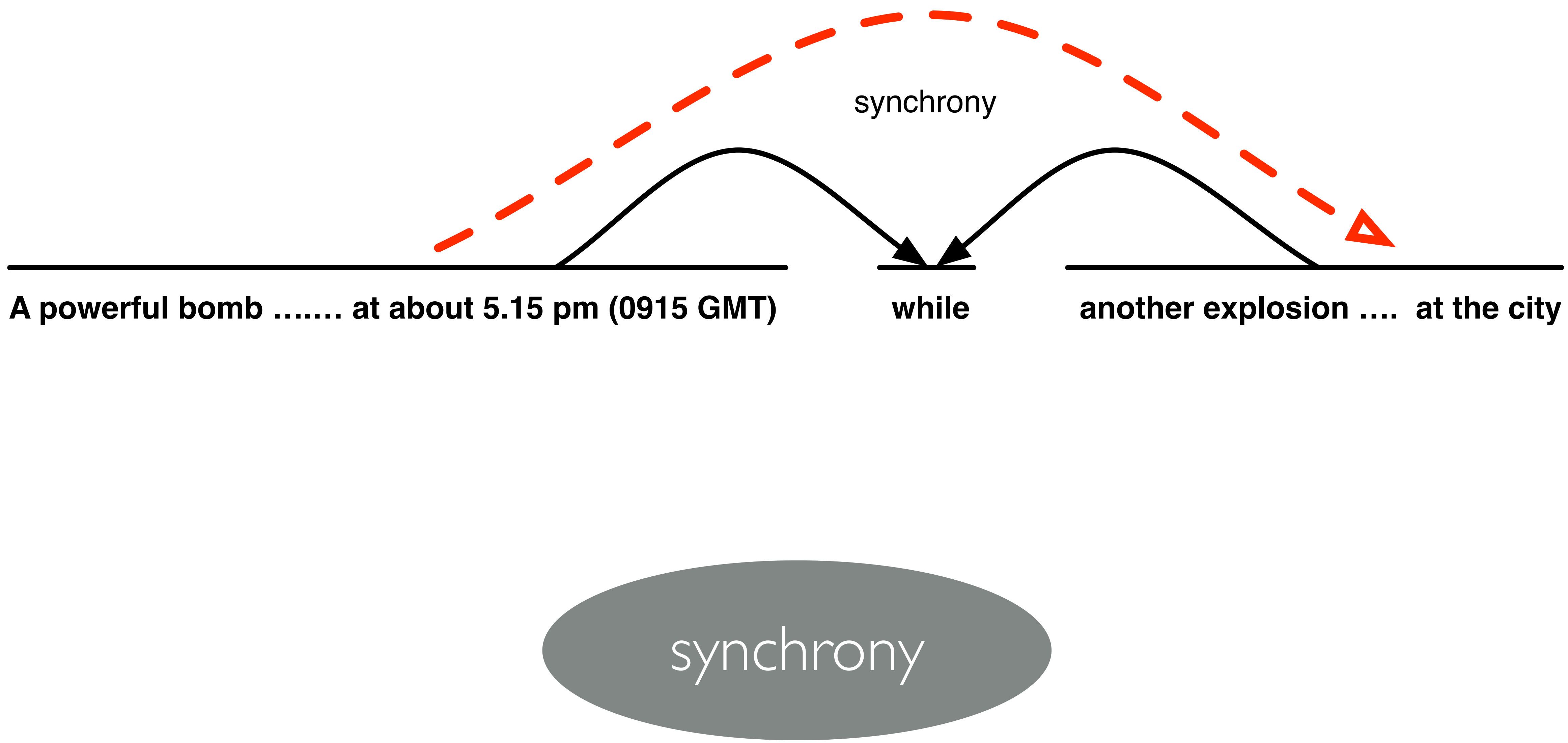

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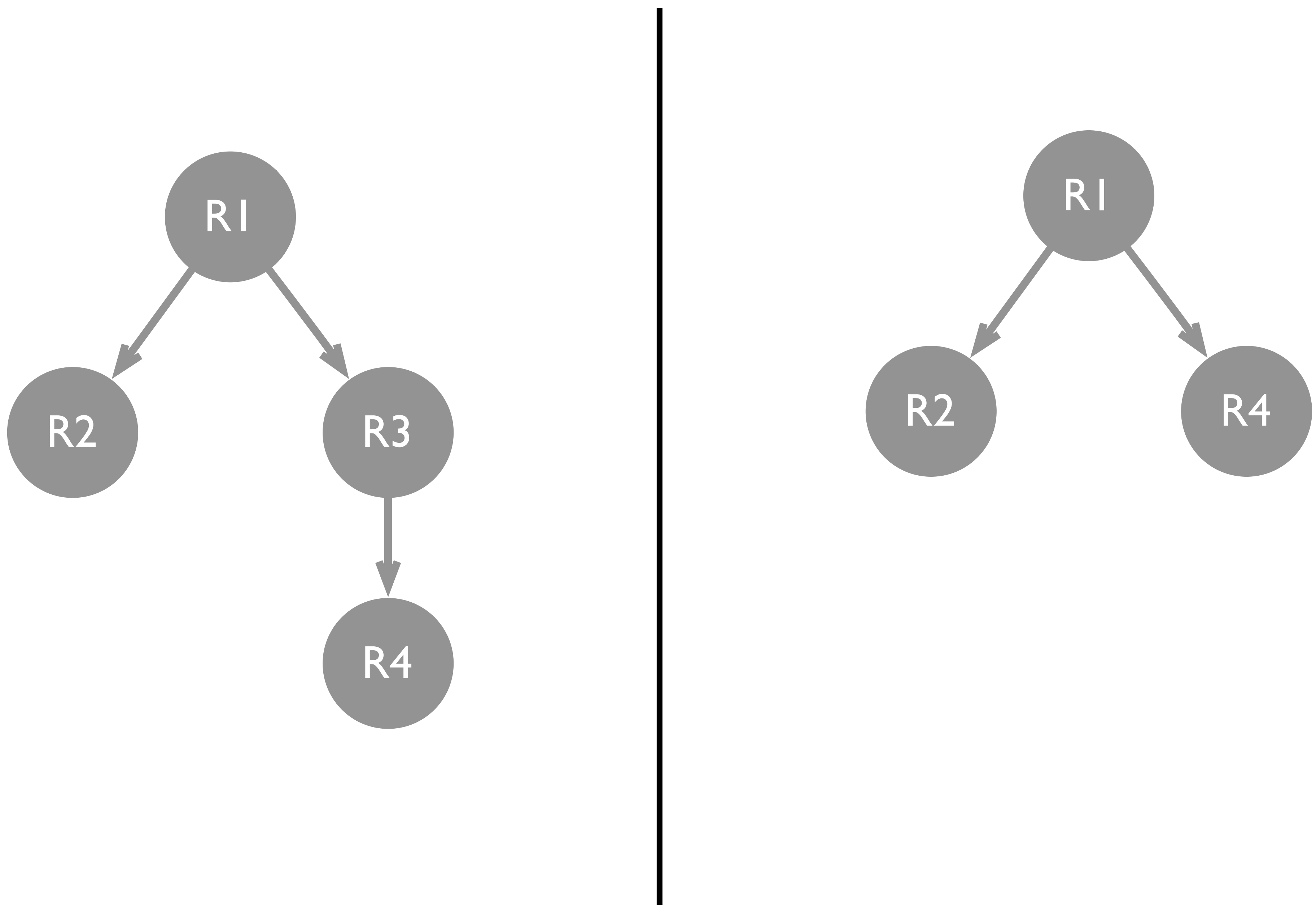
SVM + Tree Kernels

- Proposed discourse features are structural
- Tree kernels with SVM can help us capture structural similarity easily
- Does away with difficult feature engineering to vectorise discourse structures

Measuring Similarity with Tree Kernels



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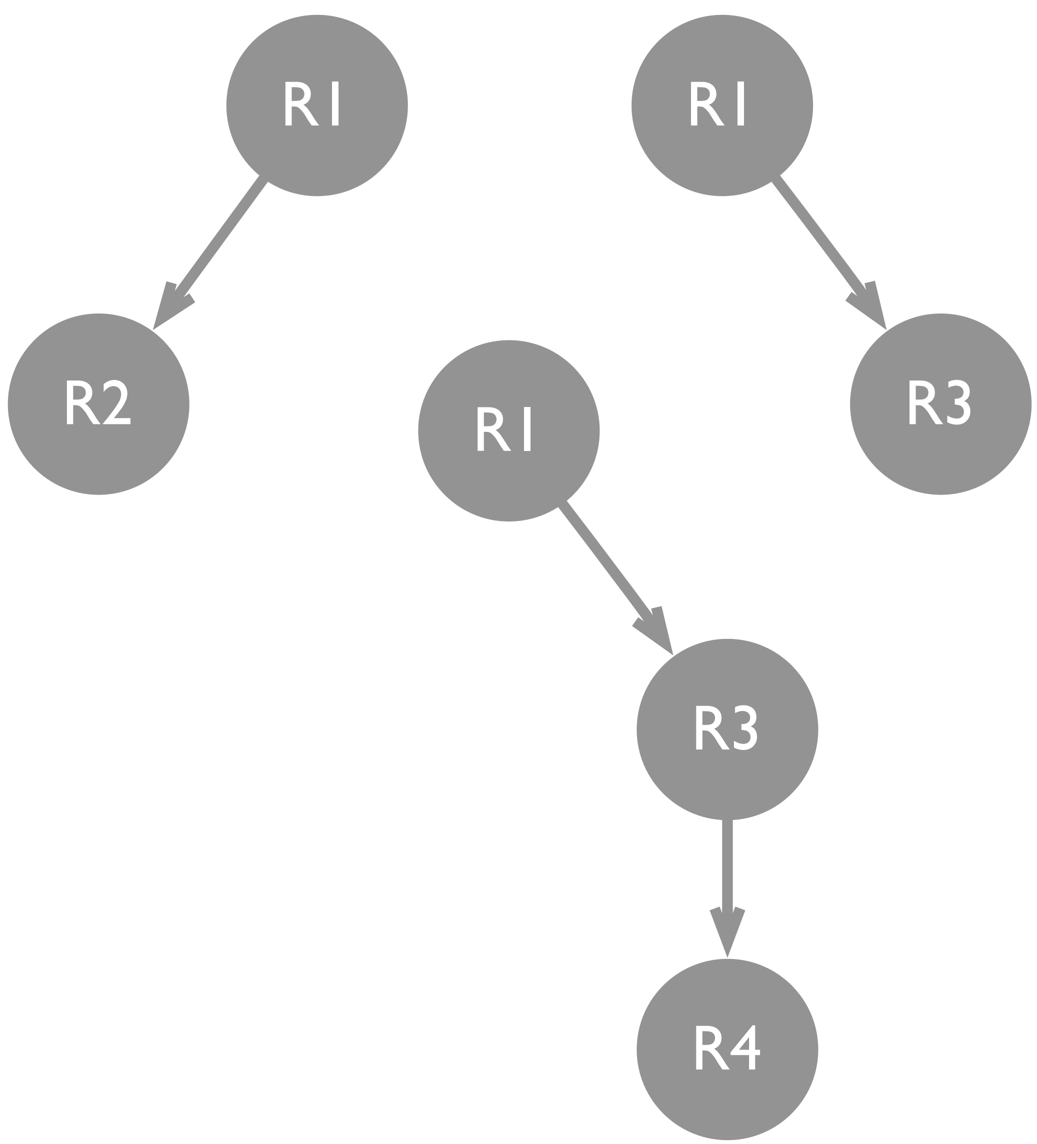

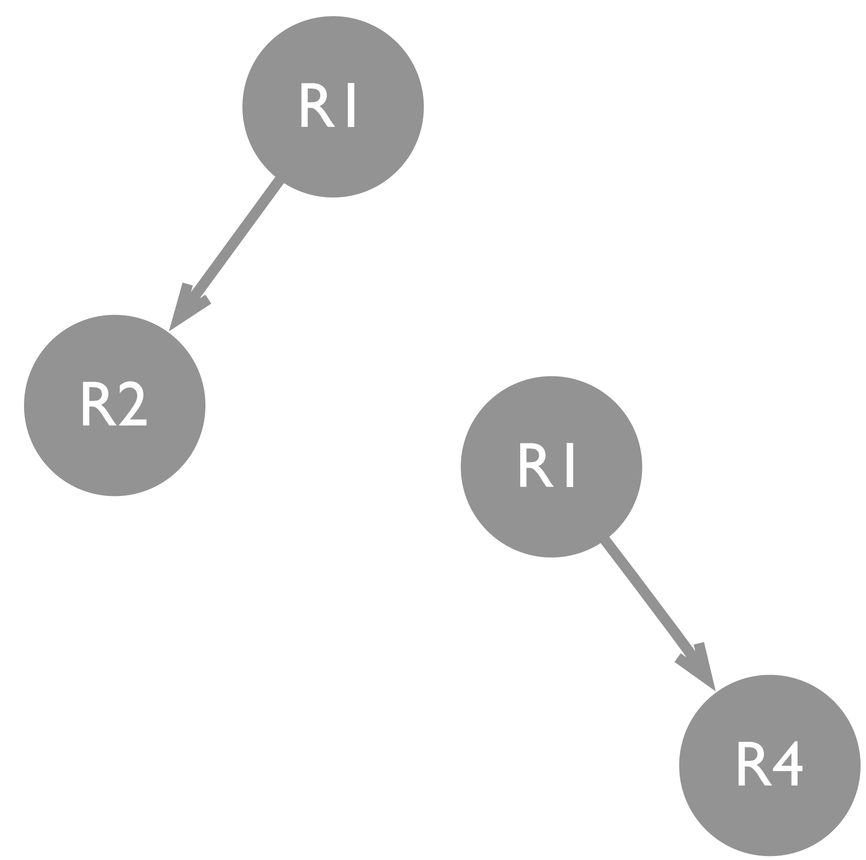

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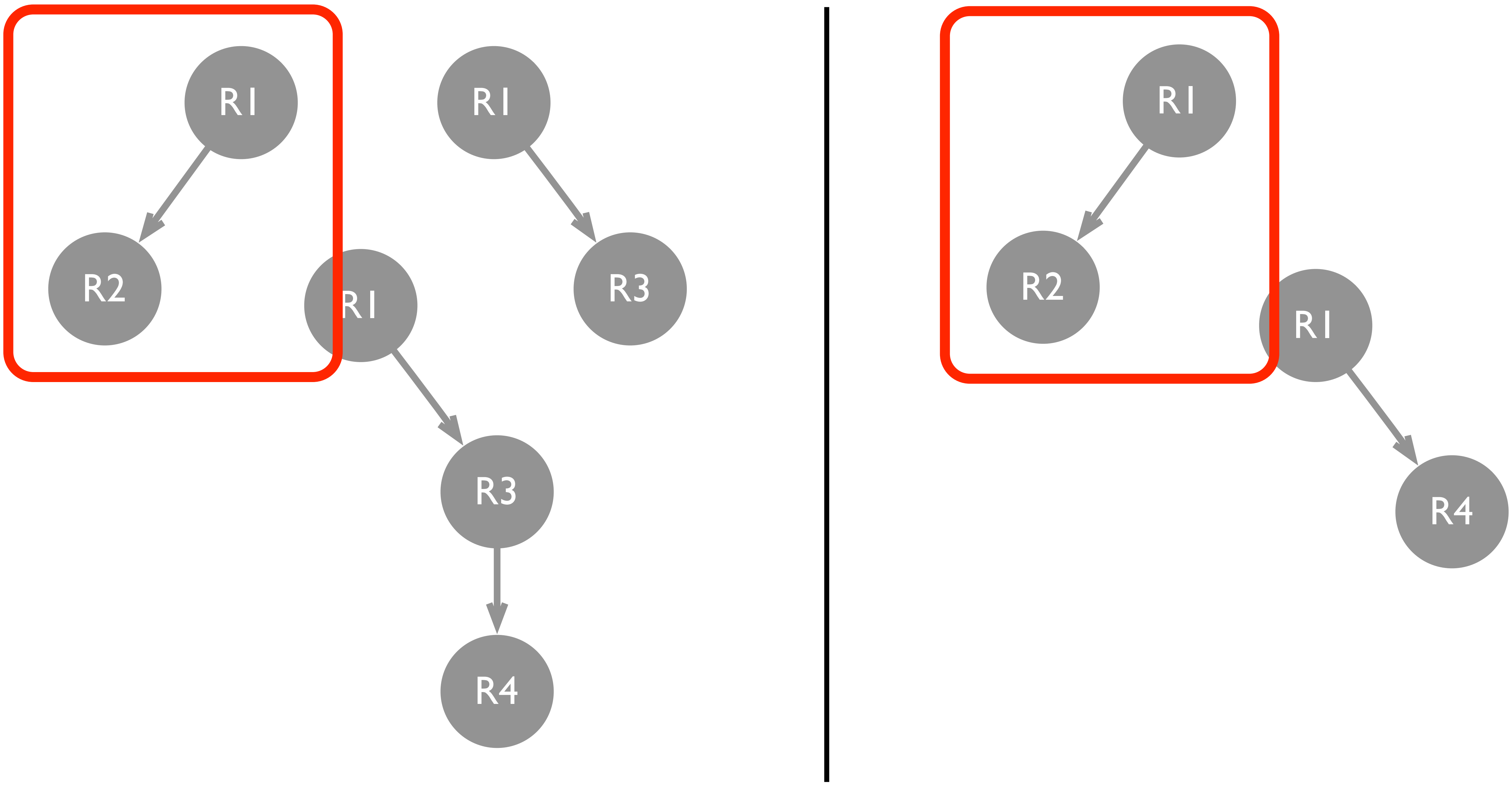

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Data Set

- Subset of 20 news articles from ACE 2005 corpus
- Annotated with 375 event pairs
- Applied temporal transitivity rules to obtain 7994 event pairs

Temporal Transitivity

- Max <u>opened</u> the door.
- He <u>went</u> into the room.
- He <u>placed</u> the book on the table.

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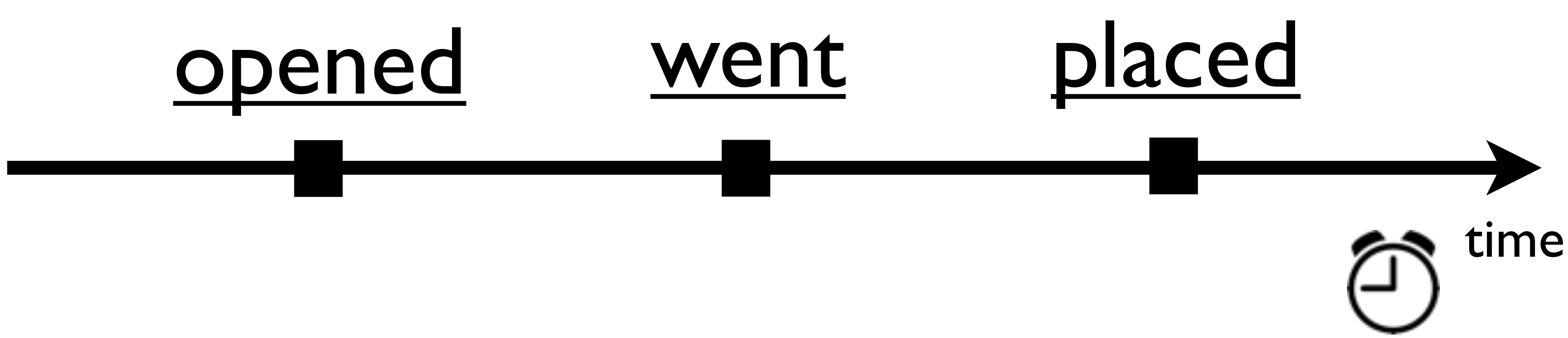

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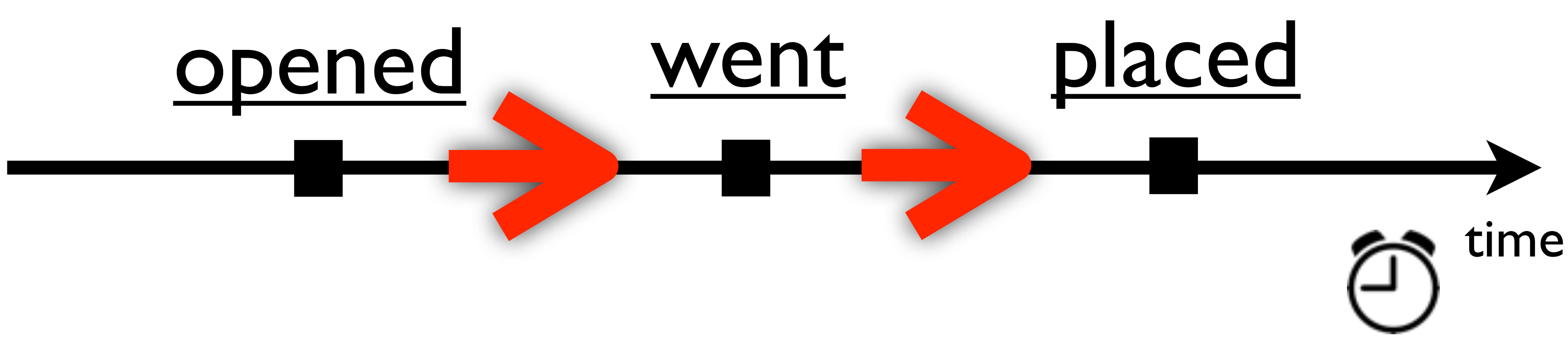

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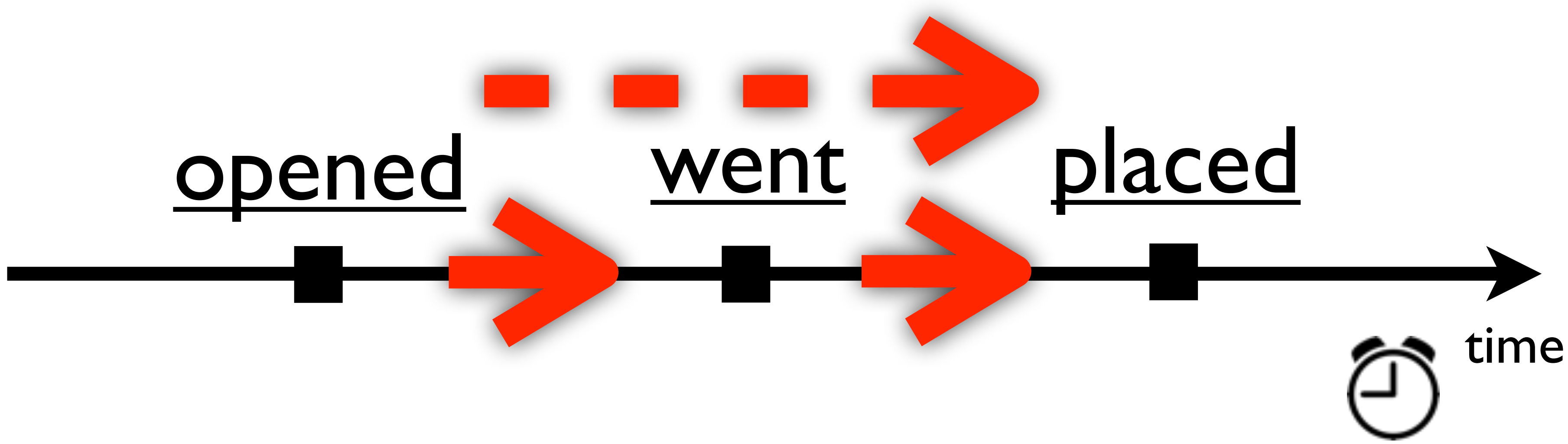
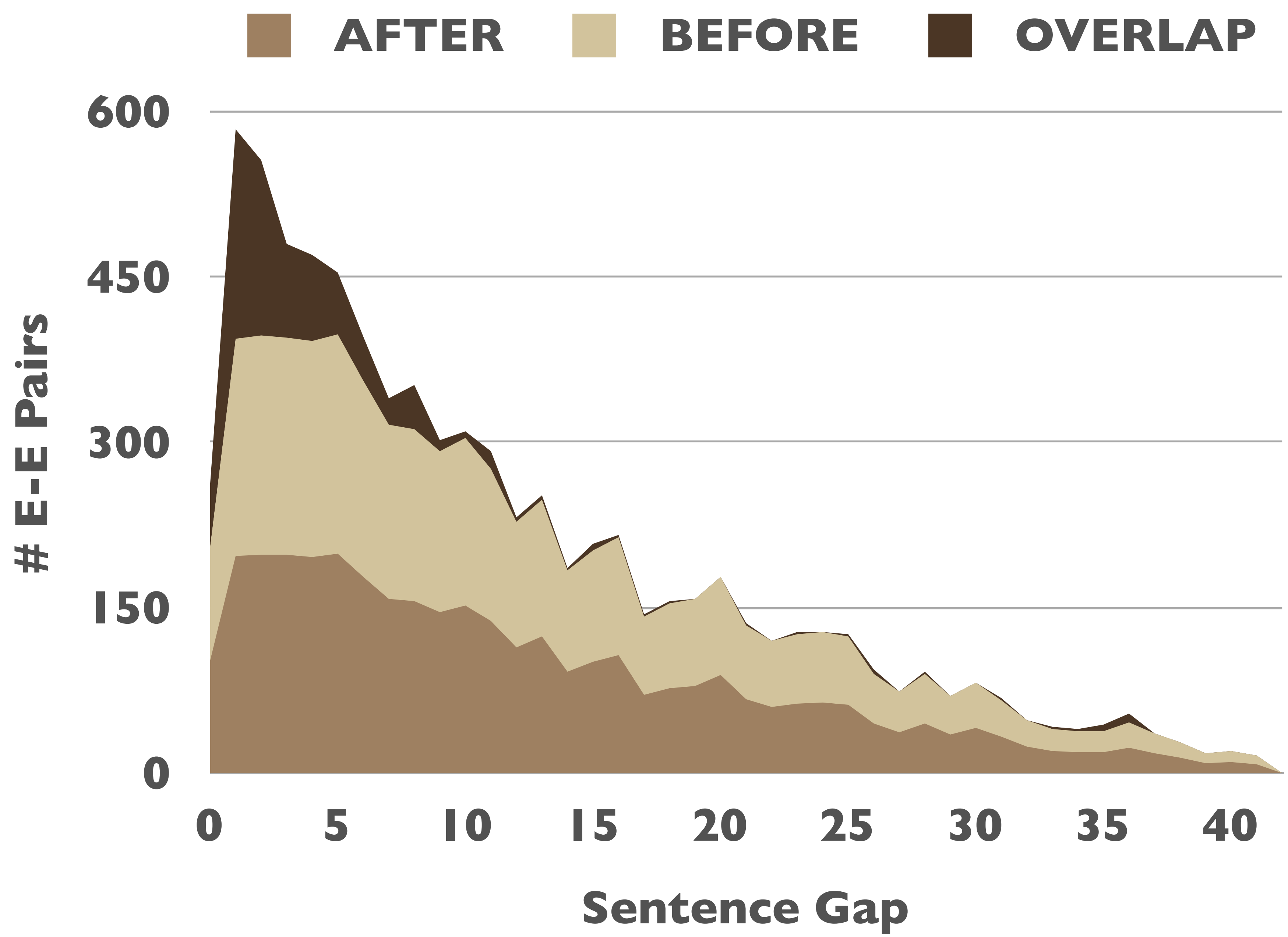


Data Set Breakdown

Class	Proportion
OVERLAP	10%
BEFORE	45%
AFTER	45%

Sentence Gap and Temporal Class



Results

	System	P	R	F_1
1	Do2012	43.86	52.65	47.46
2	Base	59.55	38.14	46.50
3	Base + RST + PDTB + TS	71.89	41.99	53.01
4	Base + RST + PDTB + TS + CR	75.23	43.58	55.19
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Useful Temporal Relations

- (Temporal ..
- (Temporal (Elaboration ...
- (Elaboration (Background ...

RST "Before" Relation

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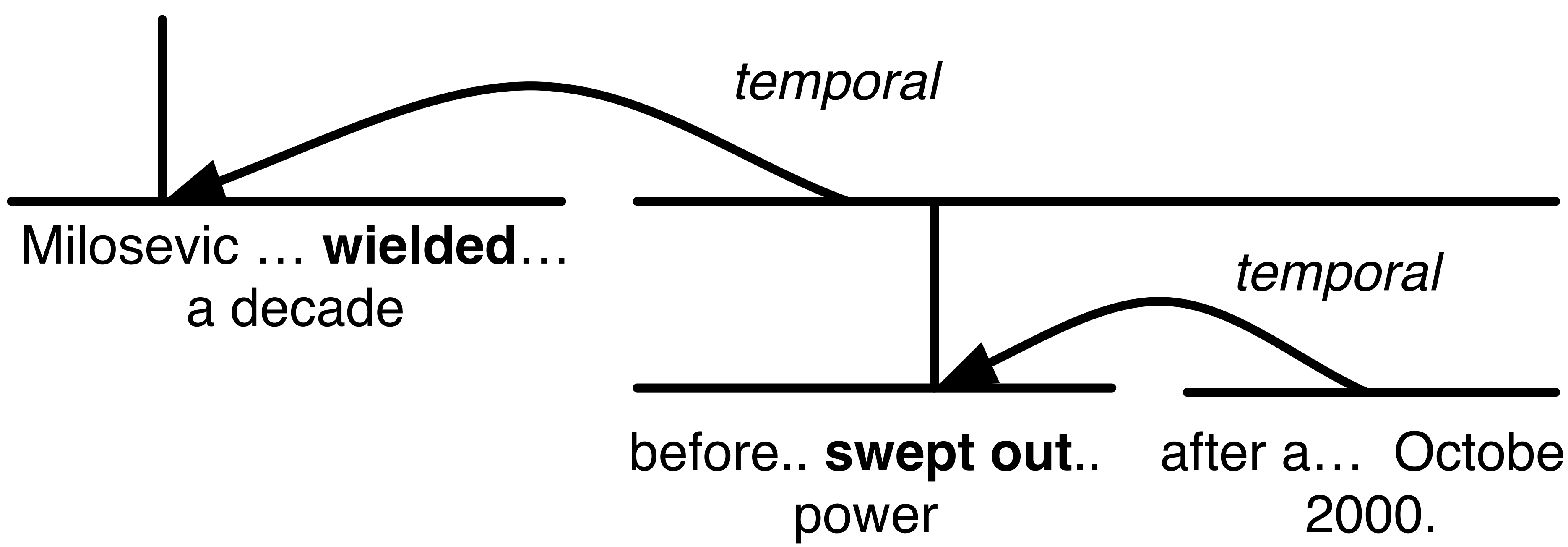

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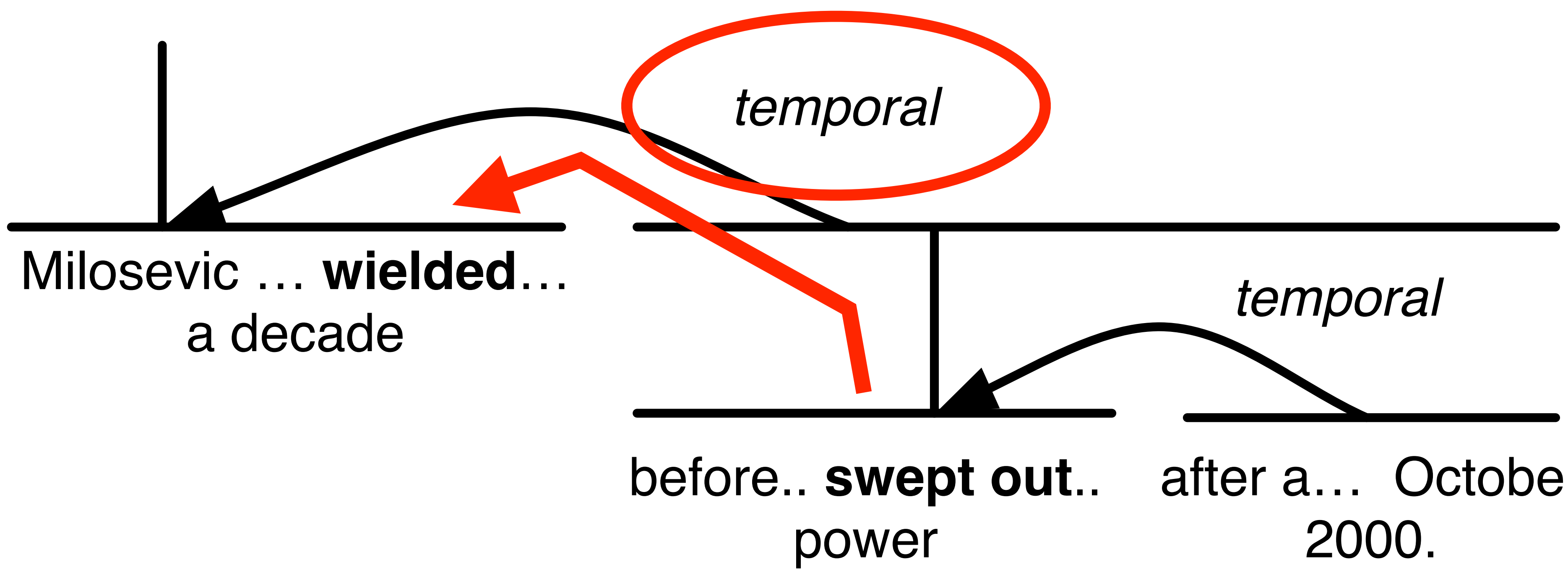

Confusion Matrix

		Predicted			
		O	B	A	N
Actual	O	14.7%	14.1%	12.8%	58.5%
	B	0.5%	57.9%	15.5%	26.0%
	A	0.5%	15.7%	57.3%	26.5%

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Doing Better

- Investigate how to exploit other aspects of discourse analysis
- Integrate features with joint-inference approaches for better overall results

Conclusion

- Discourse analysis is important for temporal classification
- Rich structural information can be robustly captured with tree kernels
- Improvements to automatic discourse parsing results will help