

# Acquire common sense knowledge between events via weakly supervised approach

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# The Relationship Between Events



Voters **go to the polls**

Voters **go to the polls** *before* Election **ceremony**



Election **ceremony**



**Rescue** residents

**Rescue** residents *after* Hurricane **struck** city



Hurricane **struck** city

# The Relationship Between Events

Typhoon Haiyan struck the eastern Philippines on Friday,

BEFORE

CAUSE

which killed thousands of people.

**Temporal Relations:** create event timelines, document summarization

**Causal Relations:** predict future events, risk analysis

## Motivation

- Extract common sense relations between events  
(*happens\_before* and *happens\_after* relations)

# Observation

- **Regular event pairs**: Event pairs that tend to show the same temporal relation despite of various contexts
- attacks *before* PEOPLE be arrested
  - Under pressure following suicide attacks, police arrested scores of activists on Monday.
  - Two men were arrested on suspicion of carrying out the Mumbai attacks.
  - Carlos was arrested in Sudan in August in connection with two bomb attacks in France in 1982.

# System Overview

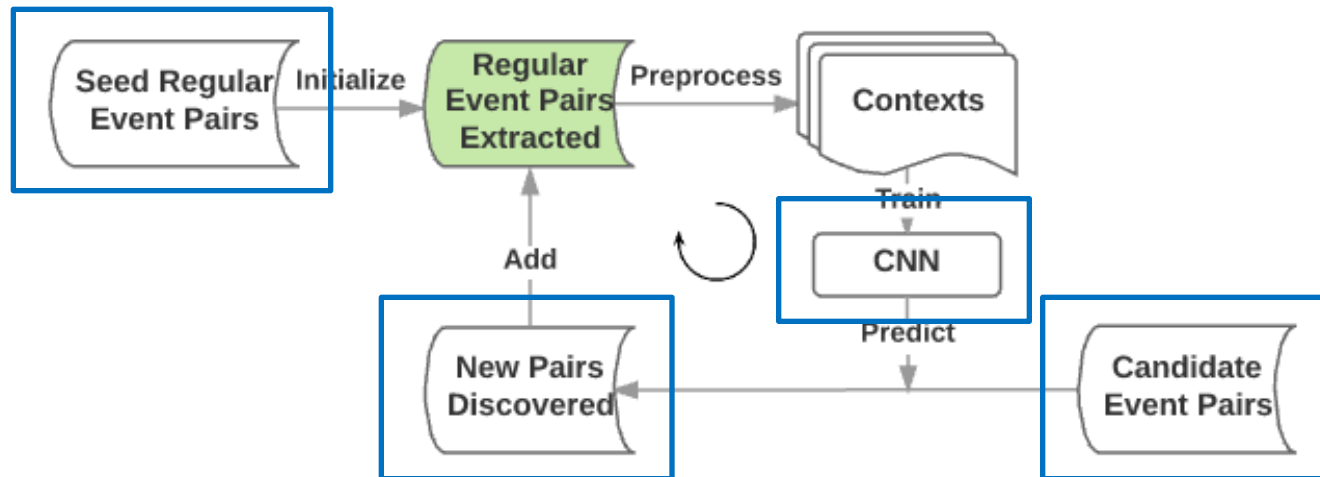


Figure: Overview of the bootstrapping system

- Data: English Gigaword ([Napoles et al., 2012](#))
  - 10 million documents from seven news outlets (e.g., New York Times, Washington Post, etc.)
  - Stanford CoreNLP tools to tokenize, POS tag, parse, etc.

# Event Representation

- Goal: Make individual events expressive and self-contained
- Verb events (use Stanford dependency relation)
  - Transitive verb: include the direct object (e.g., **win** lottery)
  - Intransitive verb: include the agent (e.g., water **evaporates**)
- Noun events (e.g., attack, election, etc.)
- Use named entity types (NER) to replace specific name
  - **visit** to Location ← **visit** to New York, **visit** to Houston



# Seed/Candidate Event Pairs

- Governor and dependent word of pattern *after* and *before*
  - He worked in a company in New York *after* graduation.
- Regular event pairs show a temporal order most of the time (80%), more than 10 times
- Prepare event pairs that are likely to have temporal relations (narrow down the search space)
- Clue: Two event phrases co-occur many times within one sentence (40278 pairs)



# Temporal Relation Classifier

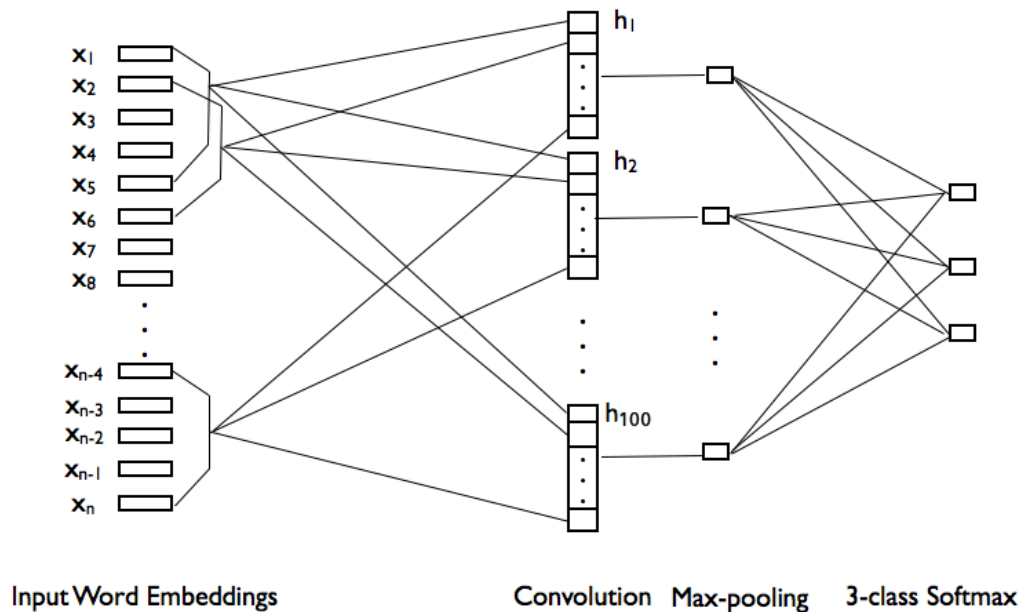
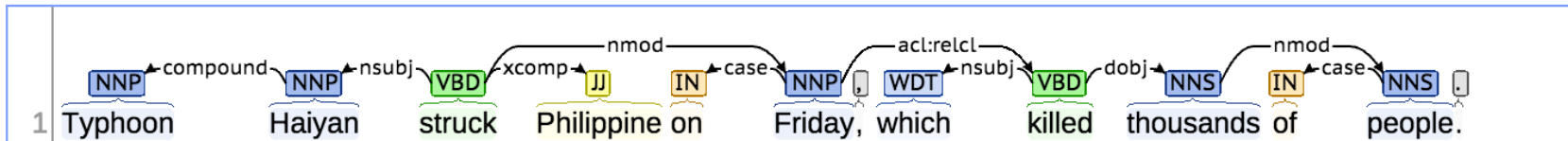


Figure: Temporal Relation Classifier

- CNN has been shown successful in sentiment analysis, sequence labeling, etc.
- Capture compositional meaning
- Pre-trained 300-dimension word2vec ([Mikolov et al., 2013](#))
- 3 classes - **after**, **before**, **other** (no relation)



# Sentence Contexts



## 1. Local window in the sentence

- 5 words before the first event
- All words in between
- 5 words after the second event

## 2. Dependency path in the sentence

- Consider dependency tree as an undirected graph
- Extract the sequence of words connecting two events in the graph

# Discover New Pairs

- Regular event pairs tend to show a particular temporal relation despite various contexts
- Selection criteria
  - Candidate event pairs are selected if 60% of context were labeled as *after* or *before* by CNN
  - Absolute difference between *after* and *before* labels  $> 40\%$
- Stop criteria
  - New pairs discovered is less than 100



# Experiments

|              |   |
|--------------|---|
| Common Sense | PERSON <b>worked</b> ← <b>graduation</b><br><b>career</b> → <b>announced</b> retirement<br><b>wash hands</b> → <b>eating</b><br>PERSON <b>returned</b> ← <b>visit</b>   |
| Politics     | government be <b>formed</b> ← <b>elections</b><br><b>fled</b> mainland ← <b>losing</b> war<br><b>imposed</b> sanctions ← <b>invasion</b> of LOCATION<br>LOCATION <b>split</b> ← <b>war</b>                        |
| Business     | <b>reached</b> agreement ← <b>negotiations</b><br><b>hosted</b> banquet ← <b>meeting</b><br><b>trading</b> → stock <b>closed</b>  |
| Health       | <b>cause</b> of death ← <b>cancer</b><br>PERSON be <b>hospitalized</b> ← <b>suffering</b> stroke<br>PERSON <b>died</b> ← <b>admitted</b> to hospital  |
| Sports       | <b>games</b> → <b>ended</b> season<br>PERSON be <b>sidelined</b> ← <b>undergoing</b> surgery<br>PERSON be <b>suspended</b> ← <b>testing</b> for cocaine<br>PERSON <b>returned</b> ← <b>recovering</b> from injury |
| Crime        | <b>shooting</b> → PERSON be <b>arrested</b><br><b>spending</b> in jail → PERSON be <b>released</b><br>PERSON be <b>arrested</b> ← <b>bombings</b><br>driver <b>fled</b> ← <b>accident</b>                         |

Table: Regular event pairs extracted

# Experiments

| Systems                                  | 0 (Seeds) | 1    | 2   | 3   | 4   | 5  | Total |
|--|-----------|------|-----|-----|-----|----|-------|
| Basic System                             | 1057      | 213  | 102 | 48  | –   | –  | 1420  |
| + Arg Generalization                     | 2110      | 638  | 323 | 81  | –   | –  | 3152  |
| + Dependency Path Contexts (Full System) | 2110      | 1230 | 555 | 288 | 156 | 62 | 4401  |

Table: Number of New Pairs Generated after Each Bootstrapping Iteration

| Systems                    | Seed Pairs | New Pairs |
|----------------------------|------------|-----------|
| Basic System               | 0.73       | 0.55      |
| + Arg Generalization       | 0.71       | 0.63      |
| + Dependency Path Contexts |            | 0.67      |

Table: Accuracy of 100 Randomly Selected Event Pairs

