Events, Relationships, and Script Learning

Presenter: Ed Morris

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Events, Relationships, and Script Learning Summary

Problem: Lack of automated methods that reliably recognize *actors*, *activities*, and *objects* comprising an *event* or *sequences of events* (i.e., *scripts*) within textual data sources

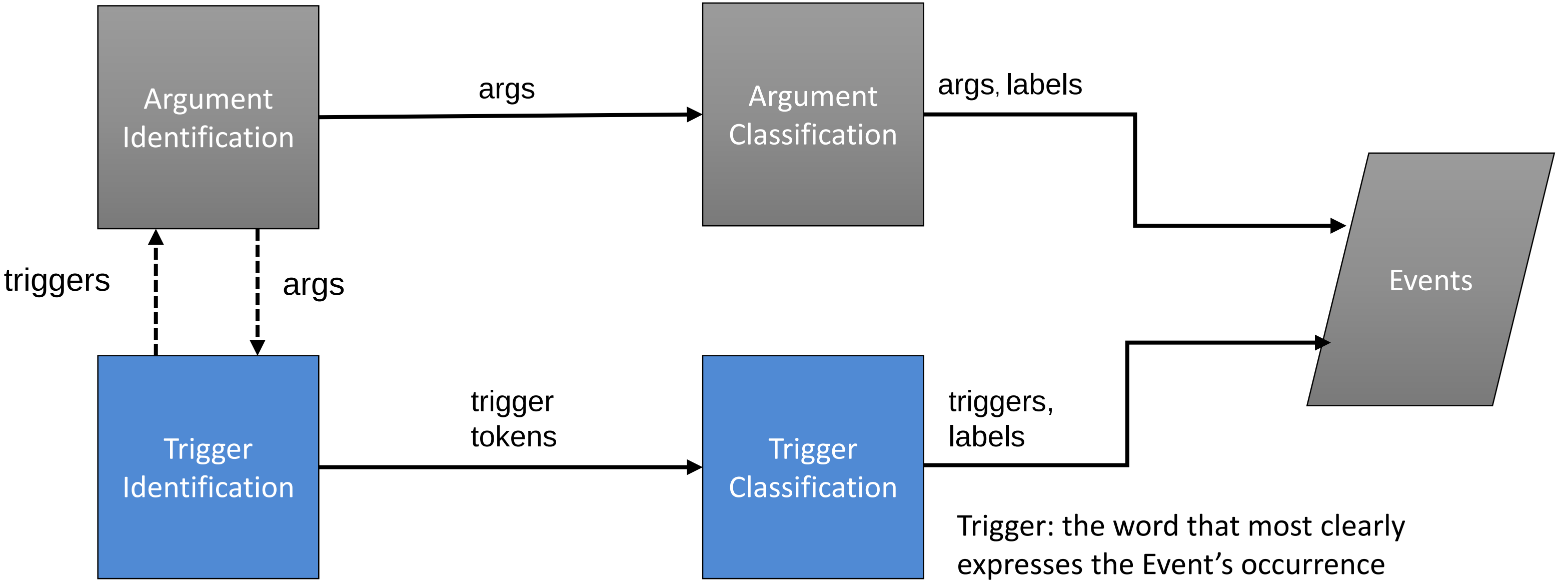
FY17 Activities

1. Extract events from unstructured text sentences
2. DTRA BMIP and Cornerstone Support
   - BMIP: provides access to biological material information for situational awareness
   - Cornerstone: automated ID of dangerous biological material holdings worldwide
3. Extract structured summaries from document text
   - Use multiple clues within a document to improve accuracy
   - Complete pre-defined event templates
4. Extract events from social media (tweets) (Dr. Alan Ritter, OSU)
   - Use minimally supervised approaches for training NLP algorithms
   - Use redundancy (multiple tweets) to improve accuracy

Demonstration available at: http://kb1.cse.ohio-state.edu:8123/events/shooting

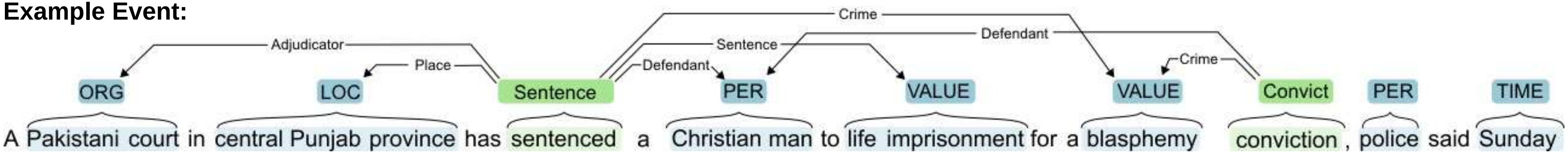
Unstructured Text – Sentence Level Event Extraction Process

Kevin Pitstick



Trigger: the word that most clearly expresses the Event’s occurrence

Example Event:


Crime
Defendant
Adjudicator
Sentence
Place
Defendant
Crime
ORG
LOC
Sentence
PER
VALUE
VALUE
Convict
PER
TIME
A Pakistani court in central Punjab province has sentenced a Christian man to life imprisonment for a blasphemy conviction, police said Sunday

Unstructured Text: Trigger Identification

Joint Event and Entity Model*

Train linear chain Conditional Random Field (CRF) models to identify candidate triggers and entities

- Features – word, part-of-speech tag, context words, word type, gazetteer-based, pre-trained word embedding

Uses a joint inference approach to find globally-optimal assignments for all trigger, argument, and entity variables

Results	P	R	F1
Reported	77.6	65.4	71.0
Replicated	61.4	71.0	65.9

Significant false positives and negatives

Precision: $\frac{\text{true positives}}{\text{true positives + false positives}}$

Recall: $\frac{\text{true positives}}{\text{true positives + false negatives}}$

F1: weighted average of P and R

Differences between reported, replicated results could be due to slightly different models, or different dev, test datasets. We used replicated numbers to ensure consistency.

**Described in "Joint Extraction of Events and Entities within a Document Context" (Yang & Mitchell, 2016)*

Unstructured Text: Trigger Identification
Bi-directional LSTM + CRF

Concatenate character embeddings with pre-trained word embeddings to get vectors representing each word

Run a bi-LSTM over the sequence of word vectors to obtain the two hidden states

Use a CRF to find the sequence with the highest probability

Results	P	R	F1
JointEventEntity	61.4	71.0	65.9
Bi-LSTM + CRF	66.7	66.0	**66.4**

Significant false positives and negatives

Bottom line: Neither technique performs accurate trigger identification

Unstructured Text: Trigger Classification
Support Vector Machine (SVM)

Train SVMs to label triggers as belonging to one of 33 subtypes (e.g. attack, sentence, convict, etc.)

Results	P	R	F1
JointEventEntity (reported)	75.1	63.3	68.7
JointEventEntity (replicated)	61.5	71.2	66.0
SVM	81.6	54.5	65.3

Relatively few false positives

Many false negatives

However, with perfect trigger identification, F1 for trigger classification is 80.0.

Bottom line: If we can find a better way to identify triggers, classification works fairly well

Redirected Effort: Support for DTRA BMIP and Cornerstone
Javier Vazquez-Trejo

Biological Materials Information Program: BMIP is a dynamic compendium of information concerning potentially dangerous biological material holdings worldwide and their security status

(U) Indonesian Research Institute for Veterinary Science (IRCVS)

BMIP Current Approach

- Manual, time consuming data entry (1 week/facility)

Cornerstone Objective

- Automate ingest of data

Cornerstone Approach

- Mine PubMed by facility, collecting pathogen, equipment, personnel data.
- Incorporate analytic algorithms from U.S. and allies

SEI Role:

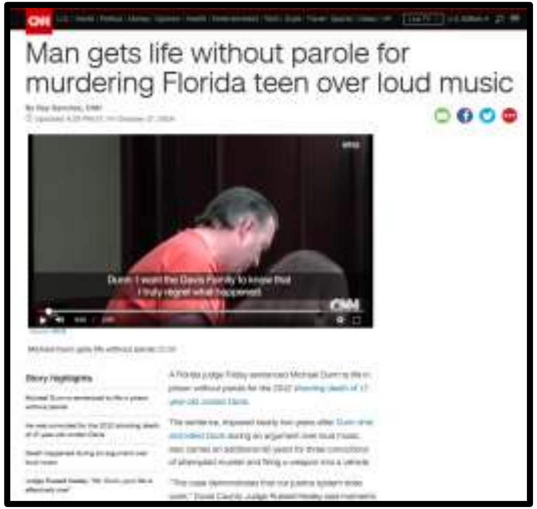
- Prototype NLP algorithms to extract information from abstract/body of PubMed articles
- Strategy to monitor the performance and behavior of Cornerstone algorithms (separately funded)

Document Level Macro-Event Extraction Process

Andrew Hsi, Daegun Won, Petar Stojanov, Dr. Jaime Carbonell

Use multiple clues within a document to improve accuracy of extraction

Complete pre-defined templates



Man gets life without parole for murdering Florida teen over loud music

Dunn: I want the Davis Family to know that I truly regret what happened

Story highlights

Michael Dunn is sentenced to life in prison without parole

He was convicted for the 2012 shooting death of 17-year-old Jordan Davis

Death happened during an argument over loud music

Judge Russell Healey: "Mr. Dunn, your life is effectively over"

A Florida judge Friday sentenced Michael Dunn to life in prison without parole for the 2012 shooting death of 17-year-old Jordan Davis.

The sentence, imposed nearly two years after Dunn shot and killed Davis during an argument over loud music, also carries an additional 90 years for three convictions of attempted murder and firing a weapon into a vehicle.

"The case demonstrates that our justice system does work," Duval County Judge Russell Healey said moments

ATTACK Macro-Event	
Perpetrator	Michael Dunn
Victim – Dead	Jordan Davis
Victim – Injured	None
Time	November 23, 2012
Location	Jacksonville

ARREST Macro-Event	
Arrestee	Michael Dunn
Time	(Unknown)
Location	(Unknown)

TRIAL Macro-Event	
Defendant	Michael Dunn
Crime	Murder
Verdict	Guilty
Sentence	Prison
Time	Friday
Location	Florida

Document Level Macro-Event Extraction Algorithms

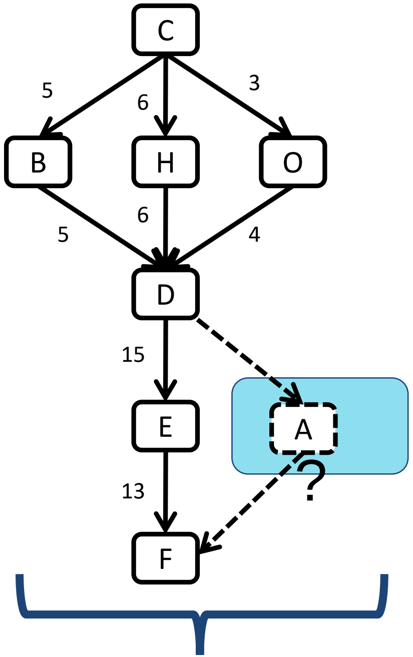
Novel ML-based algorithms for solving this problem

1. A structured prediction model based on Learning to Search
   - Reframes structured prediction as reinforcement learning problem with rewards for correct answers based on current state
   - Goal is to maximize the rewards for the system
   - Advantage: the entire document is considered without prohibitive expensive
2. A deep neural network based on machine comprehension with no reliance on target domain training data
   - Allows efficient retargeting to different domains

Preliminary results on the *attack* and *elections* domains show significantly improved performance against baseline methods

Currently gathering annotated data via Mechanical Turk

Document Level Macro-Event Extraction
Future Work: Relating Events to Scripts (CMU)



Better representation of the world

- Finer-grain event representation (actor, location, etc.)
- Probability distributions over the possible arguments

More robust script manipulation

- Better script addition (avoiding adding rare instances, etc.)
- Splitting / pruning existing scripts

Use of macro-event knowledge for inferring *constraints*

ATTACK Macro-Event	
Perpetrator	Michael Dunn
Victim – Dead	Jordan Davis
Victim – Injured	None
Time	November 23, 2012
Location	Jacksonville

TRIAL Macro-Event	
Defendant	Michael Dunn
Crime	Murder
Verdict	Guilty
Sentence	Prison
Time	Friday
Location	Florida

Scripts are stereotypical sequences of related events

Conclusion

Summary

- *Problem:* Lack of automated methods that reliably recognize *actors*, *activities*, and *objects* comprising an *event* or *sequences of events* (i.e., *scripts*) within textual data sources
- *FY17 Goal:* Develop event recognition strategies for sentences, documents, and social media
- *Results:*
  - Slight (but insufficient) improvement for event extraction from sentences, redirection of effort to support DTRA BMIP/Cornerstone
  - Good preliminary results for macro-event extraction from documents
  - Prototype for event extraction from social media

Future Work

- SEI Support for DTRA BMIP/Cornerstone
- CMU dissertation proposal for macro-event extraction from documents
- CMU pursuing development of scripts from macro-events

Contact Information

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