

TAC 2017

Jay DeYoung

Yee Seng Chan, Chinnu Pittapally,
Hannah Provenza

Ryan Gabbard*, Marjorie Freedman*

Distribution Statement 'A' (Approved for Public Release, Distribution Unlimited)

*now at USC ISI

The views, opinions, and/or findings expressed are those of the author(s) and should not be interpreted as representing the official views or policies of the Department of Defense or the U.S. Government.

Document Level Event Extraction

- Argument Assertions e.g. (*Contact.Meet, Place, Pittsburgh, Actual*)
 1. Logistic regression to identify (1) event –focused terms and (2) roles/arguments for events
 - Two argument classifiers: one that depends on event-focused terms, the second relies of just identifying a role in the argument context
 2. Identify a canonical string for the argument using
 - SERIF within document coreference
 - SERIF time normalization
 3. ERE-based trained classifier for distinguishing ACTUAL/GENERIC
 - Syntactic rules for identifying past/negated as OTHER
 4. Joint optimization using system confidence of 1-3
 5. World-knowledge based inference using event structure
- Within document event frame creation
 - Sieve-based system that relies on argument overlap, argument conflict, and syntactic links between arguments and event-focused terms

2017 Updates

- Incorporated additional training data
 - More Rich ERE
 - Event Nugget Training
 - BBN-developed targeted training
- Incorporated additional event types
 - Contact.Broadcast
 - Contact.Contact
 - Transaction.Transaction

Challenges with Contact.Broadcast

- Rich ERE only marks the first mention of a Contact.Broadcast, subsequent mentions are ignored
 - Unmarked RichERE text is ambiguous between
 - Negative example for Contact.Broadcast
 - 2nd, 3rd, 4th,..... positive example of a Contact.Broadcast event
- System trained exclusively with targeted training on EAL dry-run data
 - Many false alarms that seem like annotation errors
 - Contact.Broadcast annotation agreement may be low enough to interfere with measuring system performance

Targeted Training (1)

- Core challenge of EAL task is sparsity of training data
 - Many annotated documents
 - Few positive examples of events
- Develop targeted event annotation using human intuitions about event contexts
 - Ask annotator to find useful examples
 - Let annotator skip hard examples
- Annotation process
 - Annotator asked to come up with a list of likely event-related phrases
 - Nuggets OR other words likely to be associated with an event
 - Annotator searches & then marks ~10 examples per-term
 - Only marks sentences with one event mention (and may skip confusing sentences)
 - Marks all words that could be considered an event trigger
 - Marks arguments
 - Annotator asked to mark negative examples in the surrounding context (e.g. sentence N-1 does not contain a Contact.Meet event)
 - Annotator revises list to include additional event words
- Resulting annotation is
 - Dense in events
 - Likely to contain multiple syntactic contexts for arguments <-> triggers
 - For polysemous triggers, likely to contain positives and negatives

Targeted Training (2)

- 2015: Annotated ~5.8K positive & 6.4K negative sentences
 - Each sentence for a single event type
 - 4-8 hours per event type for all event types
 - Additional annotation for a few event types where we observed poor system performance
 - 2015 TAC system used only trigger annotation
 - ~12% relative improvement on *argument* score for system (BBN1 vs BBN2)
 - Arg F1: BBN2 35.5
 - Arg F1: BBN1 38.0 (*rank 1*)
- 2016: Additional annotation for new event types

	P	R	F1
No spannotator	26.3	26	26.2
Target:Trigger	26.1	26	26.1
Target:Trigger+Arg	28.1	26.2	27.1

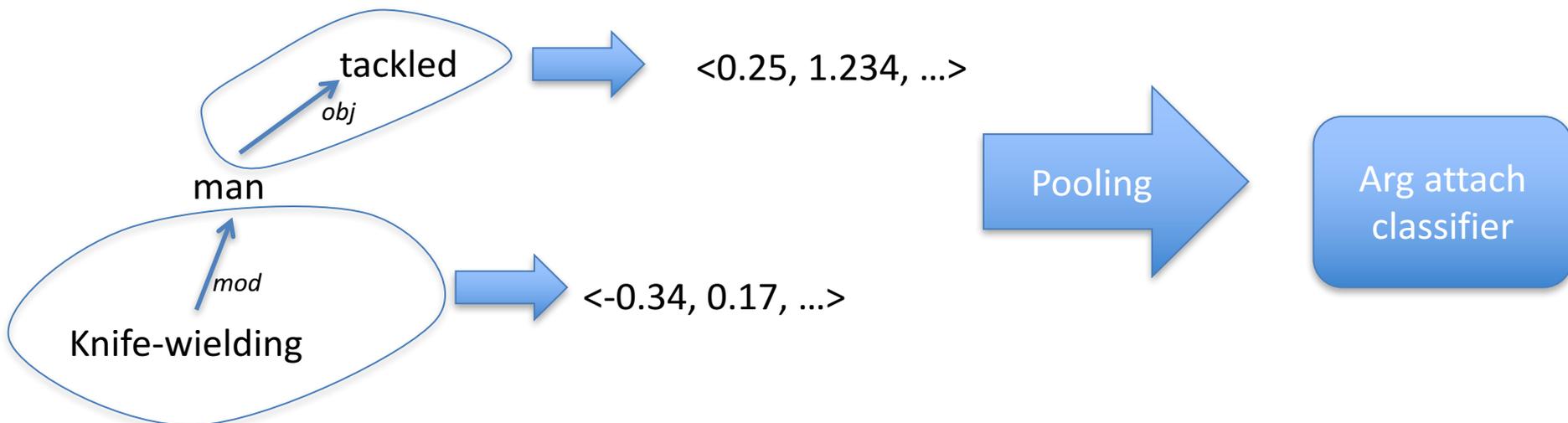
2016 Dry Run Data: All Event Types

Context Embeddings (2015)

- Event arguments can often be distant from event triggers
- But often the argument context is informative
 - *The **knife-wielding** man was tackled by a bystander, but only after three people were severely injured in the attack.*
 - *Acme Inc.'s **creditors** were disappointed by Friday's bankruptcy filing.*
- We would like to learn informative argument contexts which never appear in our supervised training data based on those which do

Context Embeddings: AA (2015)

- We trained dense vector representations of the normalized dependency trees contexts of words on Gigaword(s) using a variant of the skip-gram model due to (Levy & Goldberg, '14)
- We include this representation in our AA model



Context Embeddings: AA (2015)

- Internal development tests on KBP-2014 EA newswire eval corpus (English)
 - Embeddings improve on 2014's best system (BBN1), scored using 2014 EA scorer
- 2015's BBN1 used context embeddings, 2015's BBN3 did not
 - ~10% relative improvement from context embeddings
- Context embeddings used in all languages in 2017

CROSS DOC EVENT FRAME COREFERENCE

Cross Document Event Coreference

- Task: Identify coreferent event frames across corpus

Event-1

MEET GID: M1	Role	Fillers
	ENTITY	<ul style="list-style-type: none"> EU heads of government Ahmet Davutoglu
	LOCATION	Brussels
	DATE	11-29-2015

MEET GID: M1	Role	Fillers
	ENTITY	<ul style="list-style-type: none"> Turkey 28 EU member states the presidents of European Council...
	LOCATION	Brussels
	DATE	11-29-2015

Event-2

MEET GID: M2	Role	Fillers
	ENTITY	<ul style="list-style-type: none"> Mehment Simsek EU
	LOCATION	Brussels
	DATE	12-14-2015

MEET GID: M2	Role	Fillers
	DATE	12-14-2015

- System can (and probably needs to) use
 - Information that is available in the event frames
 - Information directly derived from the document
 - Information provided by other automatic processes
 - Cross-document entity coreference (EDL)
 - Event nuggets and their context
 - Discovered topics
 - ...

Challenges

- Imperfect automatic event-frame detection
 - Top performing 2015 system:
 - Precision: 36.8
 - Recall: 39.2
 - Linking F1: 23.3

MEET	Role	Fillers
	ENTITY	<ul style="list-style-type: none"> • Turkey • 28 EU member states • the presidents of European Council... <p><i>protesters</i></p>
	LOCATION	<p>Brussels</p> <p><i>Istanbul</i></p>
	DATE	11-29-2015

- Event-frames represent a snapshot of what goes into a knowledge-base, not all of the information necessary for coreference decision
 - Marjorie Freedman and Jason Duncan both attended 3 distinct meetings 09-29-2016
- Event nuggets do not provide same discrimination as entity names
 - Nuggets for the 09-29-2016 meetings would be: *attend* or *telecon*
- Currently, no frame-level exhaustive training data
 - Small number of assessments from pilot
 - Even when training data exists, it is likely to be small in quantity

BBN Approach: Overview

- Pipeline of decisions
 - Find arguments (*previous section*)
 - Link arguments into per-document event frames (*previous section*)
 - Cluster event-frames across the corpus using event-type (and role) specific intuitions

BBN Approach: Argument Specific Intuitions

- Define per-role equivalence
 - TIME: Year, month, and day (if available) relying on SERIF's Timex normalization
 - PLACE: Containment of GeoNames' Admin districts
 - AGENT/ENTITY/etc.:
 - For named entities, AWAKE cross-document coreference
 - Ignore non-named entities (e.g. *7 soldiers, the crowd*)
- Event Frame Coreference heuristics include
 - Specific roles that must be matched (e.g. TIME or PLACE)
 - Minimum number of arguments that must be matched (e.g. at least three arguments)
 - Maximum number of
 - Documents in which an event can be mentioned
 - Distinct arguments in an event

Thanks!