

# Event Extraction as Machine Reading Comprehension

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# Overview

- This paper casts the event extraction (EE) as a machine reading comprehension (MRC) task.
- This strategy has been done before for other tasks, e.g., Relation Extraction, Document-level Event Argument Extraction.
- The main contribution of this paper is how they design the questions which are decomposed into two components: (i) Question Topic, and (ii) Question Context.
- Casting EE as a MRC task enables the use of data augmentation.
- Finally, their MRC-based method achieves state-of-the-art performance on ACE2005 dataset with a significant margin.

# Casting EE as a MRC task

S1: On Sunday, a protester stabbed an officer with a paper cutter.

## 1) Event Trigger Extraction

$Q_{\text{trigger}}$ : [EVENT]  
 $A_{\text{trigger}}$ : *stabbed* (Type=Attack)

## 2) Unsupervised Question Generation

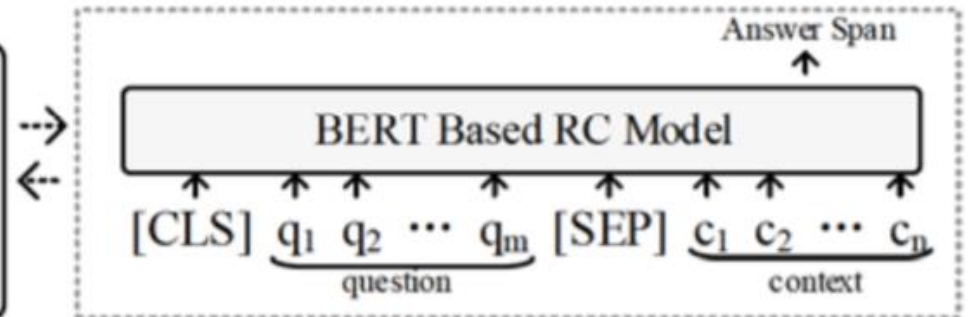
Instrument  
↓ *Template*  
 $Q_{\text{instrument}}$ : [What is the **instrument**] [that a protester use to stab an officer?]

S1  
↓ *Style Transfer*

## 3) Event Argument Extraction

$Q_{\text{instrument}}$ : What is the **instrument** that a protester use to stab an officer?  
 $A_{\text{instrument}}$ : *A paper cutter*

$Q_{\text{attacker}}$ : Who is the **attacker** that stabbed an officer?  
 $A_{\text{attacker}}$ : *A protester.*



EE Result: Stabbed (Type=Attack) | Instrument=*a paper cutter*, Attacker=*a protester*, Target=*an officer*, Time=*Sunday*

# Finding event triggers

- Finding event triggers:

[CLS] [EVENT] [SEP] Sentence [SEP]

S1: On Sunday, a protester stabbed an officer with a paper cutter.



## 1) Event Trigger Extraction

Q<sub>trigger</sub>: [EVENT]

A<sub>trigger</sub>: *stabbed* (Type=Attack)

# Finding event arguments

- Generating questions to find event arguments:

S1: On Sunday, a protester stabbed an officer with a paper cutter.

↓  
1) Event Trigger Extraction

$Q_{\text{trigger}}$ : [EVENT]  
 $A_{\text{trigger}}$ : *stabbed* (Type=Attack)



2) Unsupervised Question Generation

	Instrument	S1
	↓ <i>Template</i>	↓ <i>Style Transfer</i>
$Q_{\text{instrument}}$ :	[What is the <b>instrument</b> ]	[that a protester use to stab an officer?]

↓  
Question Topic

↓  
Question Context

# Finding event arguments

- Generating questions to find event arguments:
  - + Question topic generation:

CATEGORY	ROLE	TEMPLS.
Time-related	Time	When
Place-related	Place	Where
Person-related	Victim, Attacker, ...	Who is the ROLE
General role	Instrument, Target, ...	What is the ROLE

# Finding event arguments

- Generating questions to find event arguments:
  - + Question context generation:
    - Crawl (topic description, question) pairs from question.com



spr1nkles

## What are some of the legal issues in declaring bankruptcy?

Posted: [3+ months ago](#) by [spr1nkles](#)

Topics: [company](#), [future](#), [job](#), [bankruptcy](#), [legal](#)

Details: If I declare that I am bankrupt, how will this affect me in the future for getting jobs? building a company? etc. Also curious as to the different types of bankruptcy.  
Thanks!

# Finding event arguments

- Generating questions to find event arguments:
  - + Question context generation:
    - Crawl (topic description, question) pairs from question.com
    - Train a MT system to "translate" topic descriptions to questions.

$$P_{S \rightarrow Q}(q_s | s)$$



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- Inference: the evidence sentence  $s_x$  is formed by taking a window of text around the predicted trigger.

$$q_{s_x} = \arg \max_{q_{s_x}} P_{S \rightarrow Q}(q_{s_x} | s_x)$$

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- Create the final question:  $Q = [\text{Question topic}] + [\text{Question Context}]$

# Finding event arguments

- Finding event arguments: standard MRC model.

$$H_c^q = \text{BERT}([CLS] \text{ Question } [SEP] \text{ Sentence } [SEP])$$

- Start and end token of the argument is determined by:

$$p_{start} = \text{softmax}(H_c^q W_{start})$$

$$p_{end} = \text{softmax}(H_c^q W_{end})$$

# Data Augmentation

- Pretrain the model with SQUAD 2.0 dataset.
- Use pretrained MRC model to train it on ACE2005.

# Results: standard case

METHOD	$G_E$	$P_E$	$\Delta F1$
JointBeam (2013)	52.7	41.8	$\downarrow 10.9$
DMCNN (2015)	56.8	48.0 <sup>†</sup>	$\downarrow 8.8$
JMEE (2018b)	60.3	50.4 <sup>†</sup>	$\downarrow 9.9$
BERTEE	60.6 <sup>†</sup>	51.9 <sup>†</sup>	$\downarrow 8.7$
Joint3EE (2019)	-	52.1	-
JointTrans (2019)	-	53.3	-
RCEE	63.6	<b>59.3*</b>	$\downarrow 4.3$
RCEE <i>w/o</i> DA	62.7	58.7	$\downarrow 4.0$

Table 3: Results of argument extraction with unknown entities ( $P_E$ ).  $\Delta F1$  indicates the performance gap compared with results with known entities ( $G_E$ ).

# Results: zero-short (golden triggers)

METHOD	1%	5%	10%	20%
DMCNN	-	8.7	16.6	23.7
dbRNN	-	8.1	17.2	24.1
BERTEE	2.20	10.5	19.3	28.6
RCEE	38.8	51.3	55.7	59.4
RCEE <i>w/o</i> DA	2.00	23.8	35.2	49.2
RCEE_ER	<b>49.8</b>	<b>59.9</b>	<b>65.1</b>	<b>67.6</b>
RCEE_ER <i>w/o</i> DA	2.20	26.5	37.8	54.1

Table 4: F1 score (%) on exploring the extremely data-scarce scenarios.