

[EMNLP2020] Event Extraction by Answering (Almost) Natural Questions

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Input:

As part of the 11-billion-dollar **sale** of USA Interactive's film and television operations to the French company and its parent company in December 2001, USA Interactive received 2.5 billion dollars in preferred shares in Vivendi Universal Entertainment.



Extracted Event:

Event type		Transaction- Transfer-Ownership
Trigger		“sale”
Args.	Buyer	“French company”, “parent company”
	Seller	“USA Interactive”
	Artifact	“operations”
	Place	-

Motivations

1.Heavily rely on entity recognition, causing the problem of error propagation.

- identify entities and their general semantic class.
- assign argument roles to each entity.

2.Inability to exploit the similarities of related argument roles across event types.

- zero-shot scenario

Contributions

1. Formulating event extraction tasks as a question answering (QA)/ machine reading comprehension (MRC) task.
2. Treating event extraction as QA overcomes the weaknesses in existing methods.
 - No entity annotation and no entity recognition; argument extraction is performed as an end-to-end task.
 - Permits the transfer of argument extraction knowledge across semantically related argument roles.
 - Rule-based question generation strategies.
3. Our framework extends to the zero-shot setting.

Input sentence:

As part of the 11-billion-dollar sale of USA Interactive's film and television operations ...

Trigger
question
template
instantiation

[CLS] the action [SEP] As part of
... sale of ... film and television
operations ...

BERT QA
model for
trigger
extraction

As part of ... **sale**
of ... film and
television
operations to the
French company
and its parent
company ...

Buyer	"French company", "parent company", <u>"USA Interactive"</u>
Seller	"USA Interactive"
Artifact	"operations"
Place	<u>"USA"</u>

Applying
dynamic
threshold to
keep only top
arguments

Buyer	"French company", "parent company", "USA Interactive"
Seller	"USA Interactive"
Artifact	"operations"
Place	"USA"

BERT QA
model for
argument
extraction

Buyer: [CLS] Who is the buying
agent in sale?
Artifact: [CLS] What was
bought in sale?
Seller: [CLS] Who is the selling
agent in sale?
Place: [CLS] Where the event
takes place in sale?

+

[SEP] <input sentence>

Argument
question
template
instantiation

Detected event:
Type: Transaction-
Transfer-
Ownership,
Triggered by: **sale**

Input sequences:

[CLS] <question> [SEP] <sentence> [SEP]

Question Generation Strategies:

- **Event trigger detection**: we experiment with a set of four
 - fixed templates – “what is the trigger”, “trigger”, “action”, “verb”.
 - the input sequence:
[CLS] action [SEP] As part of the 11-billion-dollar sale ... [SEP].

Question Generation Strategies:

- Event argument extraction:

- Template 1 (Role Name)
- Template 2 (Type + Role)--we first determine the argument role's general semantic type.
eg. <WH_word> is the <role name> ?
- Template 3 (Incorporating Annotation Guidelines)--we utilize the descriptions of each argument role provided in the ACE annotation guidelines for events.
- + “in <trigger>”--<WH_word> is the <argument> in <trigger>?

Argument	Template 1 (Role name)	Template 2 (Type + Role question)	Template 3 (Annotation guideline question)
Artifact	artifact	What is the artifact?	What is being transported?
Agent	agent	Who is the agent?	Who is responsible for the transport event?
Vehicle	vehicle	What is the vehicle?	What is the vehicle used?
Origin	origin	What is the origination?	Where the transporting originated?
Destination	destination	What is the destination?	Where the transporting is directed?

Input sentence:

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Trigger
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[CLS] the action [SEP] As part of
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As part of ... **sale**
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Seller	"USA Interactive"
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Applying
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Buyer	"French company", "parent company", "USA Interactive"
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BERT QA
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+

[SEP] <input sentence>

Argument
question
template
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Detected event:
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Triggered by: **sale**

Question Answering Models

trigger detection

$$\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N]$$

$$\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_N = \text{BERT}_{Tr}(e_1, e_2, \dots, e_N)$$

$$P_{tr} = \text{softmax}(\mathbf{E}\mathbf{W}_{tr}) \in \mathbb{R}^T \times N$$

event type

argument span extraction

$$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_M]$$

$$\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_M = \text{BERT}_{Arg}(a_1, a_2, \dots, a_M)$$

$$P_s(i) = \text{softmax}(\mathbf{a}_i \mathbf{W}_s)$$

$$P_e(i) = \text{softmax}(\mathbf{a}_i \mathbf{W}_e)$$

the start and end offsets

Inference with Dynamic Threshold for Argument Spans

Algorithm 1: Harvesting Argument Spans
Candidates

Input : $P_s(i)$, where $i \in \{1, \dots, M\}$,
 $P_e(i)$, where $i \in \{1, \dots, M\}$

Output : valid candidate spans for the argument role

```
1 for  $start \leftarrow 1$  to  $M$  do
2   for  $end \leftarrow 1$  to  $M$  do
3     if  $start$  or  $end$  not in the input sentence
4       then continue;
5     if  $end - start + 1 > MaxSpanLength$  then
6       continue;
7     if  $P_s(start) < P_s([CLS])$  or
8        $P_e(end) < P_e([CLS])$  then continue;
9     // add the valid candidate
10    span to the set
11     $score \leftarrow P_s(start) + P_e(end)$ ;
12     $no\_ans\_score \leftarrow P_s(1) + P_e(1) - score$ ;
13     $candidates.add([start, end, no\_ans\_score])$ 
14  end
15 end
```

Experiments

Dataset: ACE 2005

event trigger✓: offsets ✓ + type ✓

event argument ✓: offsets ✓ +semantic role ✓

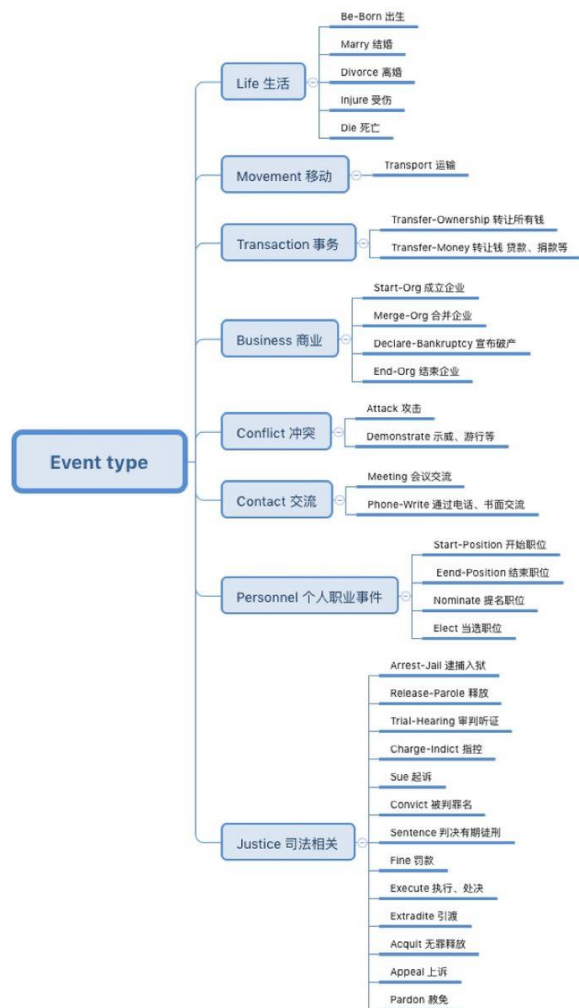


表 2-2 ACE 2005 定义的事件元素角色

Table 2-2 Event Argument Roles Defined by ACE 2005

事件类别	事件元素角色
婚嫁 (Marry)	人物 (Person), 时间 (Time), 地点 (Place)
攻击 (Attack)	攻击者 (Attacker), 目标 (Target), 时间 (Time), 地点 (Place)
受伤 (Injure)	施事者 (Agent), 受害者 (Victim), 工具 (Instrument), 时间 (Time), 地点 (Place)
出生 (Be-born)	人物 (Person), 时间 (Time), 地点 (Place)
任职 (Start-Position)	人物 (Person), 时间 (Time), 机构 (Org), 地点 (Place)
会面 (Meet)	人物 (Person), 持续时间 (Duration), 地点 (Place)
运输 (Transport)	Origin (始发地), 目的地 (Destination), 物品 (Entity)
...	...

	Trigger Identification			Trigger ID + Classification		
	P	R	F1	P	R	F1
dbRNN (Sha et al., 2018)	-	-	-	74.10	69.80	71.90
Joint3EE (Nguyen and Nguyen, 2019)	70.50	74.50	72.50	68.00	71.80	69.80
GAIL-ELMo (Zhang et al., 2019b)	76.80	71.20	73.90	74.80	69.40	72.00
DYGIE++, BERT + LSTM (Wadden et al., 2019)	-	-	-	-	-	68.90
DYGIE++, BERT FineTune (Wadden et al., 2019)	-	-	-	-	-	69.70
Our BERT FineTune	69.77	76.18	72.84	67.15	73.20	70.04
BERT_QA_Trigger (best trigger question strategy)	74.29	77.42	75.82	71.12	73.70	72.39

Table 2: Trigger detection results.

	Argument Identification			Argument ID + Classification		
	P	R	F1	P	R	F1
dbRNN (Sha et al., 2018)	-	-	57.20	-	-	50.10
Joint3EE (Nguyen and Nguyen, 2019)	-	-	-	52.10	52.10	52.10
GAIL-ELMo (Zhang et al., 2019b)	63.30	48.70	55.10	61.60	45.70	52.40
DYGIE++, BERT + LSTM (Wadden et al., 2019)	-	-	54.10	-	-	51.40
DYGIE++, BERT + LSTM ensemble (Wadden et al., 2019)	-	-	55.40	-	-	52.50
BERT_QA_Arg (annot. guideline question template)	58.02	50.69	54.11	56.87	49.83	53.12*
w/o dynamic threshold	53.39	54.69	54.03	50.81	52.78	51.77
BERT_QA_Arg (ensemble argument question template 2&3)	58.90	52.08	55.29	56.77	50.24	53.31

Table 3: Argument extraction results. * indicates statistical significance ($p < 0.05$).

	Argument ID + Classification		
	P	R	F1
Random NE	26.61	24.77	25.66
GAIL (Zhang et al., 2019b)	-	-	-
Our model			
w/ Role name	73.83	53.21	61.85
w/ Type + Role Q	77.18	55.05	64.26
w/ Annot. Guideline Q	78.52	59.63	67.79

Table 4: Evaluation on unseen argument roles.

Future work:

It would be interesting to try incorporating **broader context** (e.g., paragraph/document-level context).