

## TacoERE: Cluster-aware Compression for Event Relation Extraction

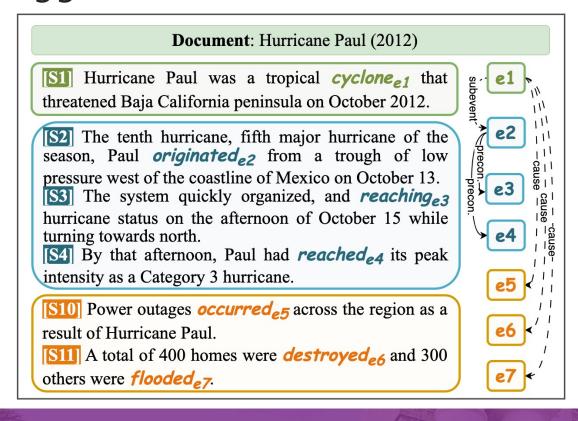
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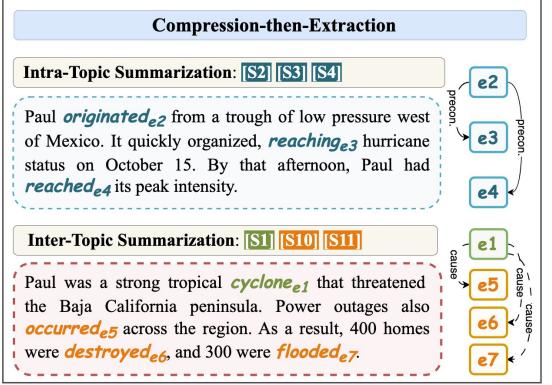
#### Outline

- Introduction
- Approach
- Experiments
- Conclusions

#### Introduction—Definition

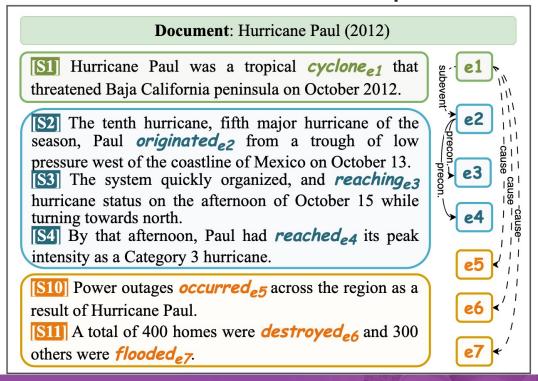
■ Event Relation Extraction (ERE) aims to predict relations, such as causal and subevent relations, between event mentions or trigger words in a document

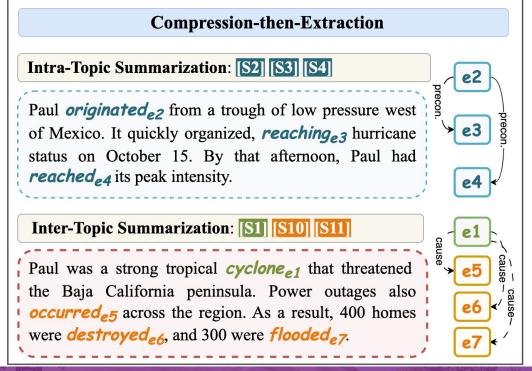




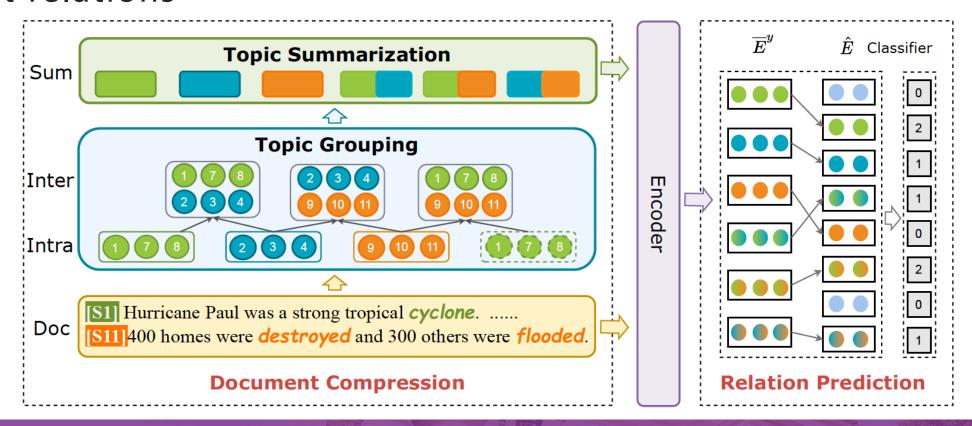
## Introduction—Challenges

- □ Long-Range Dependencies indicates events may be scattered across multiple sentences
- □ Information Redundancy refers to the existence of information non relevant for relation prediction



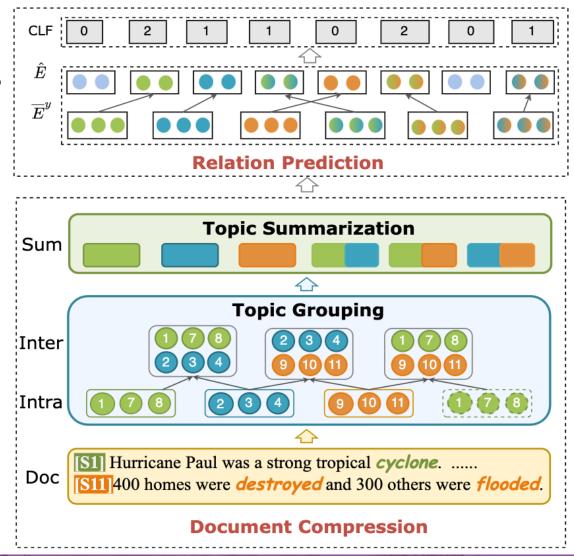


■ **TacoERE**: A cluster aware compression method for improving ERE, which explores a compression then-extraction paradigm to extract event relations



■ **TacoERE**: Implementation on small scale pre-trained language models (PLMs), such as RoBERTa

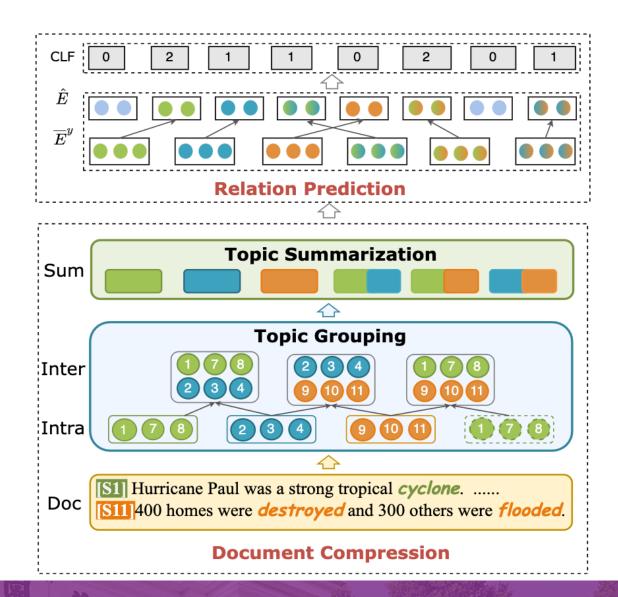
- Document Clustering
- Cluster Summarization
- Relation Prediction
- Joint Training



- **Document Clustering** aims to reduce the distance between events by splitting document into intra- and inter-clusters
  - ➤Intra-Clusters aim to enhance the relations within the same cluster

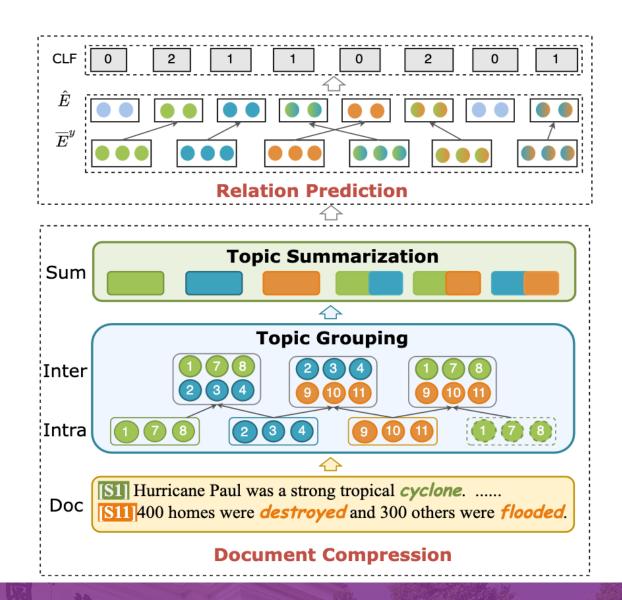
$$J = \sum_{i=1}^{k} \sum_{j=1}^{k} p_{ij} ||v_j - u_i||^2$$

➤ Inter-Clusters attempt to model the related events at arbitrary distances.



- □ Cluster Summarization aims to simplify and highlight important text content of clusters
- Relation Prediction aims to predict the relations based on the text content from cluster summarization

$$\mathcal{L}_{rp} = -\sum_{i \neq j} \sum_{\mathcal{R}} \{r_{ij} log P_{ij} + (1 - r_{ij}) log (1 - P_{ij})\}$$

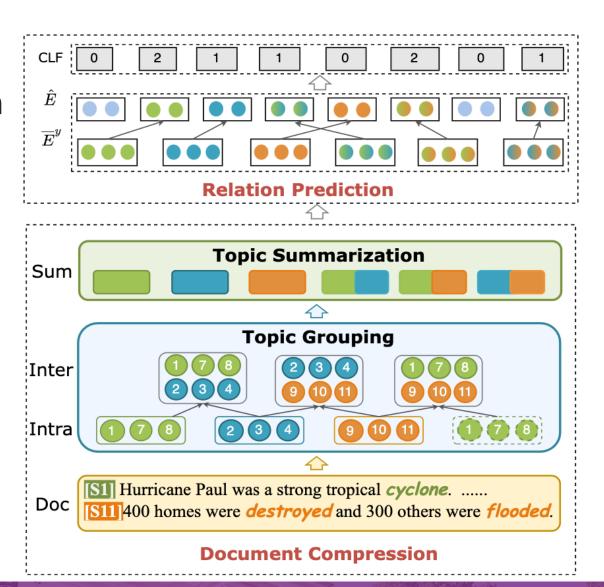


□ **Joint Training** aims to jointly optimize the cluster summarization and relation prediction

$$\mathcal{R}(C) = \alpha \mathcal{R}^{per}(C) + \beta \mathcal{R}^{ec}(C)$$

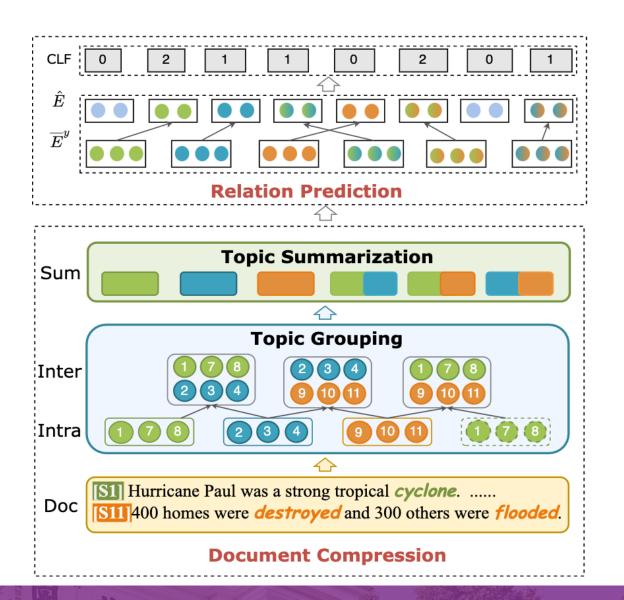
$$\mathcal{L}_{sum} = -\mathbb{E}_{C' \sim P(C'|e_i, e_j, D)}[\mathcal{R}(C')]$$

$$\nabla \mathcal{L}_{sum} = -(\mathcal{R}(C) - \theta) \nabla log P(C|e_i, e_j, D)$$



□ **TacoERE**: Implementation on large language models (LLMs), such as ChatGPT and GPT-4

- Document Clustering
- Cluster Summarization
- Relation Prediction



- Datasets
  - > MAVEN-ERE
  - > HiEve
  - EventStoryLine

Datasets	Documents	Evens	Temporal	Causal	Subevent
MAVEN-ERE	4,480	112,276	1,216,217	57,992	15,841
HiEve	100	2,734	-	-	3,648
EventStoryLine	258	4,732	8,111	4,584	-

#### □ Performance on small scale pre-trained language models

Methods	Р	R	F1		
MAN	/EN-ERI	<u> </u>			
BERT	31.6	28.2	29.9		
RoBERTa	33.8	29.5	31.5		
Hierarchical	31.8	29.2	30.6		
SIEF	33.6	30.8	32.3		
TacoERE (PLMs)	34.8	32.4	34.1		
EventStoryLine					
BERT	30.3	9.4	12.8		
RoBERTa	31.1	10.7	14.4		
Hierarchical	30.1	10.2	13.1		
SIEF	32.4	11.3	14.8		
SCS-EERE	32.7	10.9	15.1		
TacoERE (PLMs)	32.9	12.3	16.4		

Results of	f Caucal	Relations

Methods	Р	R	F1			
MAVEN-ERE						
BERT	27.5	24.7	26.8			
RoBERTa	29.8	25.6	27.5			
Hierarchical	28.4	25.4	27.1			
SIEF	30.2	26.4	28.7			
TacoERE (PLMs)	31.8	28.9	30.6			
HiEve						
BERT	19.8	15.2	16.3			
RoBERTa	20.2	16.1	17.8			
Hierarchical	21.4	17.3	16.7			
SIEF	21.8	17.4	18.6			
SCS-EERE	20.6	19.7	19.2			
TacoERE (PLMs)	22.6	19.5	20.8			

Results of Sub-Event Relations

□ Performance on large language models (LLMs)

Methods	Text-Davinci-003		ChatGPT			GPT-4			
	P	R	F1	P	R	F1	P	R	F1
Document	13.8	6.2	8.5	21.7	32.2	25.9	27.1	41.5	32.8
Sentence Pair	21.9	7.1	10.7	24.3	31.2	27.3	33.4	38.6	35.7
Topic Grouping TacoERE (LLMs)	17.3	8.1	10.9	24.6	32.9	28.2	31.9	47.1	38.1
	<b>30.2</b>	<b>8.9</b>	<b>13.8</b>	<b>31.3</b>	<b>45.6</b>	<b>37.1</b>	<b>38.9</b>	<b>45.5</b>	<b>41.9</b>

Table 5: Model performance of causal relation on different LLMs. Results are obtained under 2-shot setting.

#### □ Case Study

**Document:** [S1] The Harrow and Wealdstone rail crash was a three-train <Event> collision </Event> at Harrow and Wealdstone station in Wealdstone, Middlesex during the morning rush hour of 8 October 1952; 112 were killed and 340 injured; it remains the worst peacetime rail crash in the UK.

S2 An overnight express train from Perth crashed at speed into the rear of a local passenger train standing at a platform at the station.

[S3] The wreckage blocked adjacent lines and was struck within seconds by a `` double-headed " express train travelling north at.

[S4] The Ministry of Transport report on the crash found that the driver of the Perth train had passed a caution signal and two danger signals before colliding with the local train.

S6 The accident <Event> accelerated </Event> the introduction of Automatic Warning System by the time the report on the accident had been published, British Railways had agreed to a five-year plan to install the system to give drivers an in-cab audible and visual warning of being about to pass a distant signal at caution. Text-Davinci-003: ChatGPT: GPT-4:

**Ground Truth: PRECONDITION** 

Text-Davinci-003: 🛭 ChatGPT: 🔃 GPT-4: 🔀 Sentence Pair: [S1], [S6] **Topic Grouping:** [S1], [S2], [S3], [S6] Text-Davinci-003: 🔀 ChatGPT: 🔀 GPT-4: 🗸

**TacoERE** (LLMs): The Harrow and Wealdstone rail crash, a devastating <Event> collision </Event> involving three trains, occurred at Harrow and Wealdstone station. The crash resulted in the loss of 112 lives and injuries to 340 individuals, making it the worst peacetime rail crash in the UK. The accident prompted the <Event> accelerated </Event> introduction of the Automatic Warning System, ensuring caution when approaching distant signals.

Text-Davinci-003: ChatGPT: GPT-4:

#### Conclusions

- We propose a novel cluster-aware compression method for event relation extraction, namely, TacoERE, which explores a compression-then-extraction paradigm to extract relations.
- We utilize document clustering to split the document into intraand inter-clusters to allow the modeling of dependencies without any reliance on event distance.
- Experimental results show that our proposed TacoERE outperforms existing methods, especially on LLMs, with improvements by 11.2% and 9.1% on ChatGPT and GPT-4 respectively.





# Thanks for your listening!