Fusion meets Function: The Adaptive Selection-Generation Approach in Event Argument Extraction

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Abstract

Event Argument Extraction is a critical task of Event Extraction, focused on identifying event arguments within text. This paper presents a novel Fusion Selection-Generation-Based Approach, by combining the precision of selective methods with the semantic generation capability of generative methods to enhance argument extraction accuracy. This synergistic integration, achieved through *fusion prompt*, *element-based extraction*, and *fusion learning*, addresses the challenges of input, process, and output fusion, effectively blending the unique characteristics of both methods into a cohesive model. Comprehensive evaluations on the **RAMS** and **WikiEvents** demonstrate the model's competitive performance and efficiency.

Model Formulation

fusion prompt

... with ***participant*** about ... (original role)

... with ***participant*** **Torres** about ... (role with argument)

... with ***participant*** **<mask>** about ... (role with mask)

element-based extraction

$$p^{(\text{sel\_start})} = \text{Softmax}(\boldsymbol{h}_{r,t}^{T} \boldsymbol{V}_s \boldsymbol{H}_X) \in \mathbb{R}^L$$

$$p^{(\text{sel\_end})} = \text{Softmax}(\boldsymbol{h}_{r,t}^{T} \boldsymbol{V}_e \boldsymbol{H}_X) \in \mathbb{R}^L$$

In Selection Part, through the vector representation of roles, they encapsulate the starting and ending positions of arguments.

$$p_{a_i}^{(\text{vocab})} = \begin{cases} \boldsymbol{h}_a^{i\,T} \text{Retrieve}(w; \boldsymbol{E}_X), & w \in X \\ 0, & w \notin X \end{cases}$$

In Generation Part, through the vector representation of arguments, they generate a vocabulary-sized probability distribution.

fusion learning

$$p^{(\text{gen\_start})} = \text{Softmax}(\boldsymbol{h}_m^{T} \boldsymbol{E}_X \odot \boldsymbol{w}_s) \in \mathbb{R}^L$$

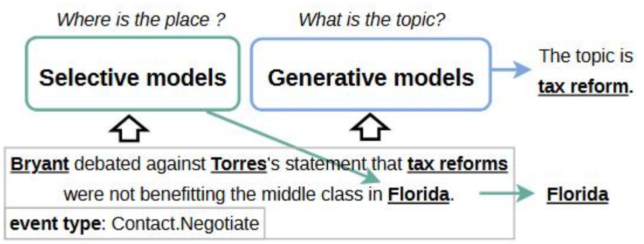
$$p^{(\text{gen\_end})} = \text{Softmax}(\boldsymbol{h}_m^{T} \boldsymbol{E}_X \odot \boldsymbol{w}_e) \in \mathbb{R}^L$$

In the Fusion Part, the vector representation of masks is combined with the selective probability distribution.

Conclusion

In conclusion, our research presents a Fusion Selection-Generation-Based Approach for Event Argument Extraction, merging selective and generative methods. Empirical evaluations on the RAMS and WikiEvents indicate improved performance and efficiency. This study contributes to the EAE field by demonstrating the practicality of integrating different approaches. In future work, we plan to design a more suitable fusion method and adapt our fusion model to other domains, thereby exploring broader applications and achieving deeper integrations in information extraction.

Difference Between Selective and Generative Methods in EAE



Selective methods identify tokens in text for answer selection, while generative methods employ natural language generation to produce exhaustive answer sequences.

Model Overview

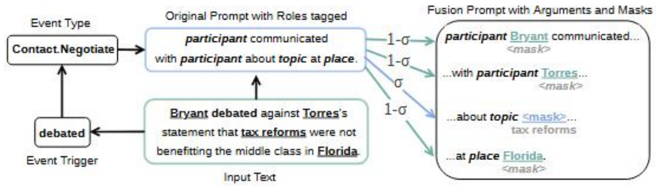
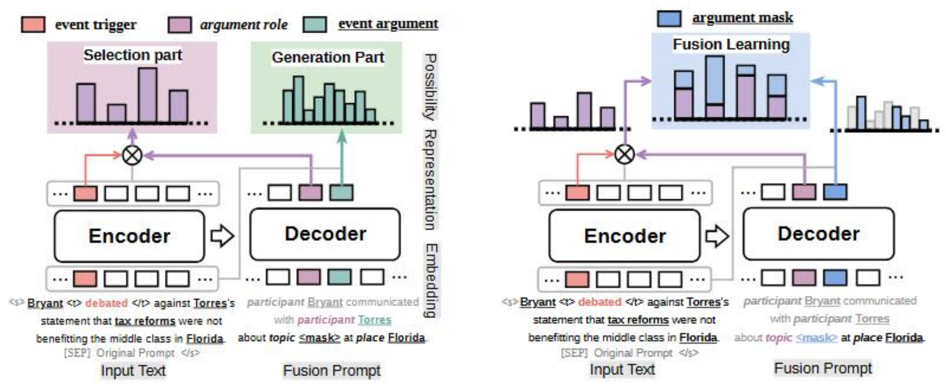


Figure 2: *Fusion Prompt*: Given an input text and its event type, the original prompt is obtained. Under the current probability σ, event arguments and masks are randomly integrated after argument roles, creating the final fused Pt.



(a) Selection and Generation Parts are trained concurrently, utilizing roles and arguments from the fusion prompt separately.

(b) Selection and Generation Parts are integrated by using *<mask>* from the fusion prompt and a dynamic masking mechanism.

Performance (%) in Event Argument Extraction

Models	RAMS Arg-I	RAMS Arg-C	WikiEvents Arg-I	WikiEvents Arg-C	WikiEvents Head-C	PLM
Selective Models						
BERT-CRF (Shi and Lin, 2019)*	-	40.3	-	32.3	43.3	BERT-base
EEQA (Du and Cardie, 2020)*	46.4	44.0	54.3	53.2	56.9	BERT-base
	48.7	46.7	56.9	54.5	59.3	BERT-large
PAIE (Ma et al., 2022)*	54.7	49.5	68.9	63.4	66.5	BART-base
	<u>56.8</u>	52.2	**70.5**	<u>65.3</u>	68.4	BART-large
Generative Models						
BART-Gen (Li et al., 2021)*	50.9	44.9	47.5	41.7	44.2	BART-base
	51.2	47.1	66.8	62.4	65.4	BART-large
Retrieval-augmented (Ren et al., 2023)*	53.3	46.3	61.4	46.1	62.5	T5-base
	54.6	48.4	69.6	63.4	68.4	T5-large
Fusion Selection-Generation-Based Models						
Fusion Generatively Biased	53.0	47.8	68.7	63.7	67.8	BART-base
	56.1	51.7	<u>70.1</u>	**65.4**	<u>68.5</u>	BART-large
Fusion Balanced	53.6	48.6	68.3	63.9	67.7	BART-base
	56.6	<u>52.5</u>	69.9	64.7	**68.8**	BART-large
Fusion Selectively Biased	53.5	48.4	68.7	63.3	67.5	BART-base
	56.9	**52.6**	69.9	64.4	68.1	BART-large