Appendix-Leveraging Common Sense Knowledge and LLMs for Joint Event Extraction and Relation Classification

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A Appendix

A.1 Examples of Semantically Precise Event Relations

To better contextualise the research described in this paper, we provide some definitions and examples for the four semantically precise event relations as found in textual excerpt from our data sources. The definitions come from the FARO ontology[1].

Prevent It connects an event with its cause of not happening. E.g. *The government's swift action to impose a lockdown* ***prevents*** *the rapid spread of COVID-19 among the population.*

$$\textbf{lockdown} \xrightarrow{\textbf{prevents}} \textbf{spread of COVID-19}$$

Enable Connect a condition with the event it is contributing to realise as an enabling factor. E.g. *The presence of abundant natural gas reserves* ***enables*** *the country to boost its economic growth by exporting energy.*

$$\textbf{natural gas reserves} \xrightarrow{\textbf{enables}} \textbf{economic growth}$$

Cause or **Direct Cause** It connects an event with its cause of not happening. E.g. *The significant increase in global temperatures* ***causes*** *more frequent and severe weather events.*

$$\textbf{increase in global temperatures} \xrightarrow{\textbf{causes}} \textbf{severe weather events}$$

[1] https://purl.org/faro/

Intend Connects an Event with the effect it is intended to cause (independently if the result is achieved or not). *The company's strategic investment in renewable energy* ***aims*** *to reduce its carbon footprint.*

$$\textbf{investment} \xrightarrow{\textbf{intends}} \textbf{reduce carbon footprint}$$

A.2 Prompt for Generating More Common Sense Knowledge Using LLMs

We provide below the prompt used for the relation *prevent*:

Request → "I am seeking data augmentation for sentences containing two events with a preventative relationship between them."

Def$_{\textbf{Relation}}$ → "Each sentence consists of two events, where one event prevents the other from happening."

Def$_{\textbf{Event1}}$ → "Event1: the event that prevents the next event from happening, to be enclosed between <ARG0> and </ARG0>."

Def$_{\textbf{Event2}}$ → "Event2: the event that is prevented by the first event, to be enclosed between <ARG1> and </ARG1>."

Example → <ARG0> Limiting exposure to sun, heat, or UV radiation during summer months</ARG0> prevents <ARG1> sunburns or skin cancer</ARG1>.

A.3 Event Relation Extraction from Text

The flowing figures 1, 2, 3 represents the architectures of BERT for sequence classification used for relation classification, ALBERT for event extraction and REBEL for joint relation classifications and event extraction respectively.

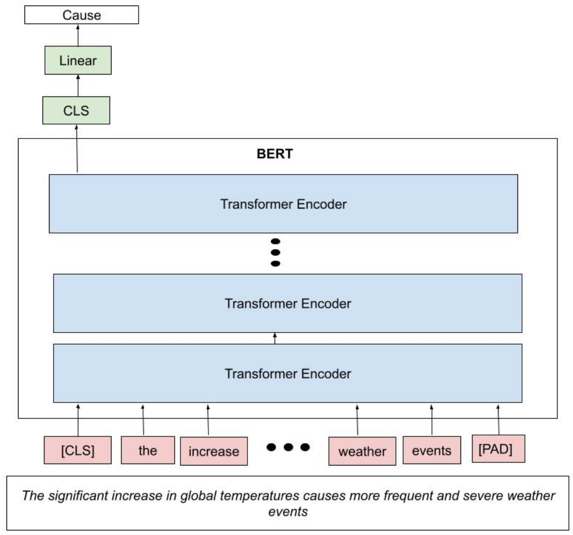

Fig. 1. BERT for Relation Classification

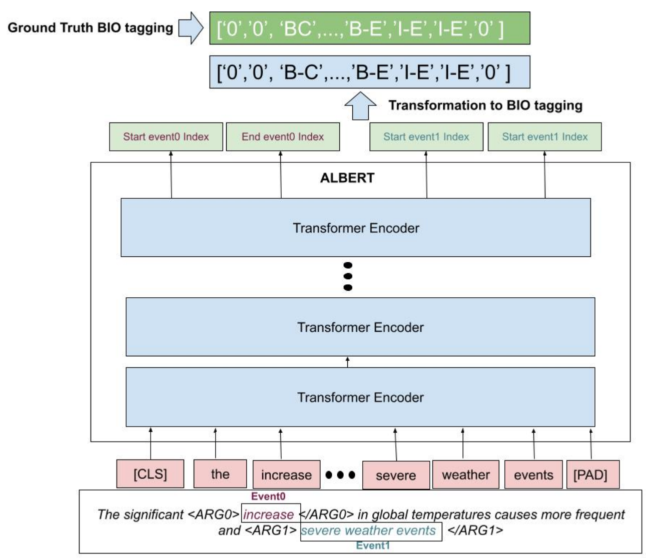

Fig. 2. ALBERT for Event Extraction

A.4 Large Language Models as Relation Classifiers and Event Extractors

The prompt was formatted as in the following panel:

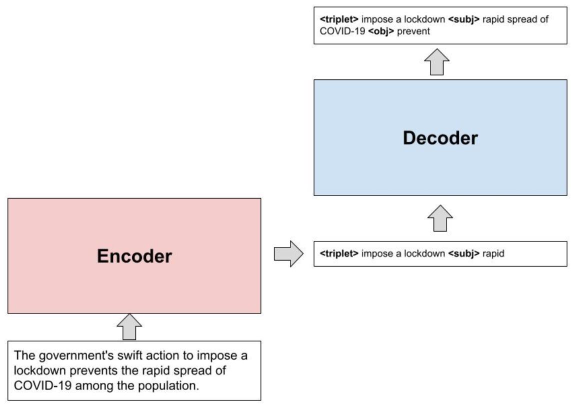

Fig. 3. REBEL for Joint Relation Classification and Event Extraction

Prompt Template

*Extract the subject, object, and relation from the following sentences. The sentence has one of the following relations: **cause**, **enable**, **prevent**, or **intend**.*

Definitions:

- ***Cause**: Connect an event with its effect.*
- ***Intend**: Connects an event with the effect it is intended to cause (independently if the result is achieved or not).*
- ***Enable**: Connect a condition with the event it is contributing to realize as an enabling factor.*
- ***Prevent**: Connect a Relata entity with the event for which it is the cause of not happening.*

Examples:

`{examples}`

***Instruction:** Extract the Subject, Object, and relation for the following sentence:*
***Sentence:** "{input_sentence}"*

***Output Format:** Subject: <subject>, Object: <object>, Relation: <relation>*

***Note:** Please respect the format of the output.*

A.5 Event Extraction

Table 1 shows the comparison between BIO tagging for ground truth and prediction sequences.

Word	BIO Tagging Ground Truth	BIO Tagging Prediction
The	O	O
recent	O	O
earthquake	B-C	B-C
in	O	O
Hiroshima	O	O
has	O	O
resulted	O	O
in	O	O
a	O	O
staggering	B-E	O
number	I-E	O
of	I-E	O
deaths	I-E	B-E

Table 1. Comparison of BIO Tagging between Ground Truth and Prediction. B, I and O refers to *Begin*, *Inside* and *Outside*, while C and E are the two events, for simplicity *Cause* and *Effect*