Learning Contextual Information and Task Alignment for Emotion Cause Extraction in Conversation

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Problems & Ideas

- Problems of Existing Methods:
  - Treat Causal Span Extraction and Causal Emotion Entailment as independent tasks, ignoring their inherent consistency.
  - Overlook coreference coherence and positional relations in conversations, leading to fragmented causal spans.
- Ideas: A unified framework that jointly models contextual coreference, position-aware semantics, and cross-task alignment for precise emotion cause extraction.

Target Utterance: U4

Target Emotion: Satisfied

Conversation:

U0: Today's work was really tough. I'm feeling exhausted and could really use something sweet to lift my spirits. Would you like to join me for some dessert?

U1: Of course, I've been craving dessert for a long time! A little treat sounds perfect after a long day.

U2: I've heard that the dessert shop near the school is very popular. Their mango mille-feuille is supposed to be amazing. I think it will cheer me up.

U3: This is really delicious, isn't it?

U4: Yes, this is the best dessert I've had this month! It's exactly what I needed to end the day on a high note.

In the example, distinct colors are used to visually distinguish coreference clusters within the conversation. The causal spans of target non-neutral utterances are clearly marked. By applying coreference resolution, the semantic connections between utterances are enhanced, which helps to more accurately identify the emotional cause of the target sentence.

Main Contributions

- Contributions:
  - Integrate coreference information to intricately correlate the internal semantics within conversations, fostering a deeper understanding of the interconnectedness.
  - Propose a dual-level position relation mechanism to bolster the accuracy of cause span detection.
  - Devise a framework that harmoniously integrates auxiliary task predictions with cross-task alignment, bolstering stability and robustness.

Table 2 RECCON-DD results based on span-level metrics.

Model	Neg.F1	Pos.F1	Macro F1
RoBERTa-base	85.85	58.17	75.45
SpanBert	**86.02**	60.00	75.71
Two Step	83.12	58.90	72.13
MuTEC(cse)	73.89	66.92	62.90
MuTEC(e2e)	75.41	64.11	63.24
Ours	77.56	**74.97**	**76.13**

Table 3 HECE results based on span-level metrics.

Model	Pos.P	Pos.R	Pos.F1
Bert+GRU	44.33	15.16	22.60
Bert+CRF	22.70	**61.54**	33.16
SpanBert+GRU	**47.68**	8.78	14.83
SpanBert+CRF	34.90	30.06	32.30
JUW	40.67	30.97	35.16
Ours	37.30	39.36	**38.30**

Our method achieves state-of-the-art (SOTA) performance on both the RECCON-DD and HECE datasets, demonstrating superior effectiveness in emotion cause extraction tasks.