Employing Multi-cues to Identify Event Factuality

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- We introduce the combination of negative, speculative, time and adverb cues ar-riving event to event factuality identification, which can effectively filter the noise comparing with the event sentence.
- Our model can identify event factuality from raw texts, which does not rely on annotated information, and is beneficial for application in industry.
- The training time of our model is just one-fifth of the Bert benchmark.

Model

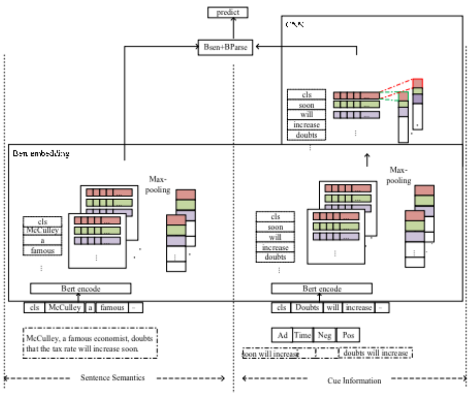

Fig. 1. The architecture of our Bert_CNN model for EFI

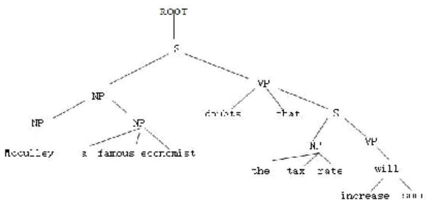

Fig. 2. dependency syntactic structure diagram

Experiments

Table 1. Performance comparison between our BERT_CNN and the Baselines

	CT+			CT-			PS+			overall	
	P	R	F1	P	R	F1	P	R	F1	Micro-F1	Macro-F1
Qian	86.57	88.95	87.73	73.89	74.92	74.20	72.78	65.65	68.88	81.98	76.94
Bert_Sen	87.58	88.96	88.27	75.07	77.51	76.27	78.22	63.08	69.84	83.30	78.36
Bert_CNN	89.23	92.86	91.01	84.43	76.42	80.23	79.12	77.42	78.26	87.08	83.24

Table 2. Performance comparison on different simplified models

	CT+			CT-			PS+			overall	
	P	R	F1	P	R	F1	P	R	F1	Micro-F1	Macro-F1
Bert_CNN	89.23	92.86	91.01	84.43	76.42	80.23	79.12	77.42	78.26	87.08	83.24
Bert_Sen	87.58	88.96	88.27	75.07	77.51	76.27	78.22	63.08	69.84	83.30	78.36
Sen_Pos	88.48	89.88	89.17	74.86	72.63	73.73	79.25	75.27	77.21	84.38	80.06
Sen_Time_AD	88.55	88.55	88.55	73.40	74.80	74.09	78.37	79.21	78.79	84.18	80.48
Sen_Neg	88.08	91.45	89.70	85.80	76.69	80.86	74.82	73.48	74.14	85.71	81.64
Sen_Neg_Pos	88.42	92.53	90.43	86.25	74.80	80.12	75.45	74.91	75.18	86.23	82.04

Table1 shows performance comparison between BERT_CNN and the baselines. Qian used BiLSTM and the attention mechanism to extract sentence features and the adversarial training through the whole process to add more semantic information. Bert_Sen used Bert to encode sentence and did not use any additional information.

Table 2 shows the detail performance comparison on different input features, where Sen, Pos, Neg and Time_AD refer to the event sentence, the path from speculative cue to event, the path from negative cue to event, and the path from time and ad-verb cue to event, respectively.

Conclusion

This paper proposes an event factuality identification model to identify event factu-ality from raw texts. It first extracts basic factors related with factuality, and then utilizes a BERT-based Convolutional Neural Network (Bert_CNN) with the integra-tion of speculative cues, negative cues, time words and adverb cues which can make up for the inability of BERT to learn long-distance syntactic knowledge and pay more attention to the important words in the sentence. In the future work, we will focus on how to increase the information in the adjacent sentence to enrich the se-mantic features of the event sentence and how to use the syntactic tree structure to learn the information.

Examples

- (S1) McCulley, a famous economist, doubts that the tax rate will *increase* soon.(PS+)
- (S2) The report added that, because they did not understand Gondola's *driving skills*, they can't change directions between the moored boats.(CT-)
- (S3) It is reported that another Israeli driver was *killed* in a shooting in the Gaza Strip on the 13th.(CT+)