End-to-end Event Factuality Identification via Hybrid Neural Networks

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introduce

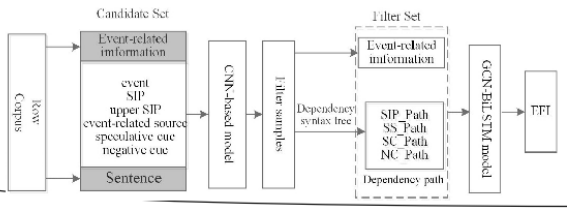
- Event factuality identification (EFI) is a task to judge the factuality of events in texts.
- Previous research on EFI relied on annotated information, which cannot be applied to real world applications directly, and most studies only considered the default source AUTHOR.

examples

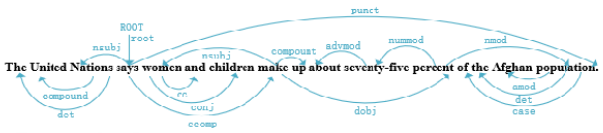
event	Source	Factuality
Strike	Author	PS+
rains	Author	Uu
stay	Author	PS+
indicated	Author	CT+
sold	Author He	Uu PS+
service	Author He	Uu PS+

1. *Northbridge is a cool, calculating and clever criminal who could **strike** again.*
2. *If it **rains** tomorrow, I may **stay** at home.*
3. *He **indicated** that some assets might be **sold** off to **service** the debt.*

Overall Framework

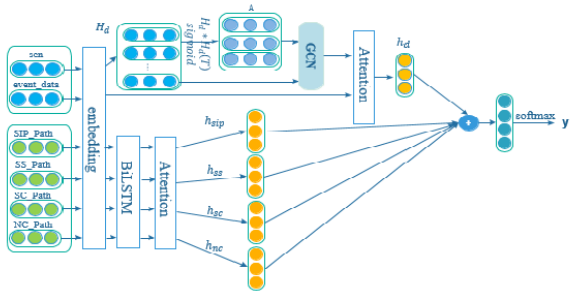


information



- ***Event: make, the current event.***
- ***SIP: 1, whether the current event introduces a predicate to the source.***
- ***Upper SIP: says, upper sip introduces the relevant source of the current event***
- ***Event related sources: Nations, event related source is introduced by the upper SIP.***
- ***Speculative cue: 0, speculative cue that affect the factuality of the current event.***
- ***Negative cue: 0, negative cue that affect the factuality of the current event.***
- ***Sen: The United Nations says women and children make up about seventy-five percent of the Afghan population, the sentence where the current event is.***
- ***SIP_Path: says ccomp make, the dependency path of upper SIP to the current event.***
- ***SS_Path: says nsubj Nations, the dependency path of upper SIP to the event related sources.***
- ***SC_Path: null, the dependency path of speculative cue to the current event.***
- ***NC_Path: null, the dependency path of negative cue to the current event.***

Model



- **Training Objectives**
  - $\square = -\sum_i \square_i \log(\square(\square_i))$

result

	CT+	Uu	CT-	PR+	PS+	Micro-F1	Macro-F1
BiLSTM + Att	44.41	41.48	20.79	21.66	18.86	40.27	29.44
CNN + Hybrid_NN_1	46.86	42.53	30.64	28.26	27.38	44.44	35.14
CNN + CNN	58.73	53.89	23.20	18.62	17.44	54.86	34.37
CNN + BiLSTM	61.14	55.82	29.18	22.43	18.09	57.23	37.33
CNN + BiLSTM_Att	62.11	56.70	31.49	23.59	18.43	58.13	38.47
CNN + GCN_BiLSTM	63.50	59.09	35.53	25.33	26.71	59.97	42.03

	CT+	Uu	CT-	PR+	PS+	Micro-F1	Macro-F1
BaseInput (w/o f)	42.20	39.43	8.80	7.49	4.79	38.09	20.54
Dep (w/o f)	35.17	29.64	22.93	16.50	21.83	32.02	25.22
BaseInput+Dep (w/o f)	44.41	41.48	20.79	21.66	18.86	40.27	29.44
BaseInput (w/ f)	54.07	49.49	7.70	3.77	3.68	50.29	23.74
Dep (w/ f)	45.97	38.37	32.08	22.41	22.54	42.50	32.27
BaseInput+Dep (w/ f)	62.11	56.70	31.49	23.59	18.43	58.13	38.47

- *w/ f: using the CNN-based filter; w/o f: not using the CNN-based filter*
- *BaseInput means that the input is event related in-formation and event sentence, and Dep means that the input is dependent path SIP_Path, SS_Path, SC_Psath, NC_Path*

- ***This result shows that our CNN-based filtering model can effectively filter out the pseudo samples to improve the performance rapidly .***
- ***This result indicates that the use of GCN-based network to obtain semantic features is more effective in obtaining word-to-word connections.***
- ***The result shows that the combination of Dep and BaseInput (i.e., BaseInput+Dep) can further improve the performance and this indicates these two types are complementary.***

Conclusion

- We propose an end-to-end model for event factuality identification, which identifies event factuality from raw texts without using annotated information.
- We introduce the event-related information, sentence and dependency paths to represent event factuality from different aspects and propose a hybrid model based on GCN and BiLSTM to learn semantic and syntactic features better