Chinese Event Factuality Detection

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Abstract. There are a large number of expression forms and semantic information in natural language, which contain fake, speculative, and fuzzy statements. Identifying event factuality is vital to various natural language applications, such as information extraction and knowledge base population. Most of existing methods for Chinese event factuality detection adopt shallow lexical and syntactic features to determine the factuality of target event via end-to-end classification models. Although such methods are easy to implement, they ignore the linguistic features related to event factuality, which limits the performances on this task. On this basis, we introduce three kinds of linguistic features to represent event factuality, including factuality cue, event polarity, and tense. Then, we employ a CNN-based feature encoder to capture their latent feature representations automatically. Finally, we integrate three kinds of features with word embeddings to identify the factuality label of target event. The experimental results show that our method achieves 94.15% of accuracy, with 12.34% of improvement on the state-of-the-art. In addition, we also demonstrate and analyze the effectiveness of three linguistic features for Chinese event factuality detection.

Keywords: Event Factuality Detection, Linguistic Features, Convolutional Neural Network.

1 Introduction

Event factuality in text refers to the author's description of the degree of certainty about whether events actually occur or not in the real world [1]. There are a large number of semantic expressions and descriptions in natural language texts, such as false, speculative, vague, and so on. These information often involves the factuality of events, distinguishing them from real events is of great significance to the downstream natural language processing applications related to events, such as event detection and event relation extraction. Generally, existing studies classify events factuality into the following four categories[1]:

- Certainty(CT+): events has occurred;

[1] FactBank annotation guideline [1] to classify and define the categories of event factuality.

- Impossible(CT-): events will never happen;
- Possible(PS+): events may occur;
- MayNot(PS-): events may not occur.

Note that the event factuality studied in this paper is only rely on the attitudes and perceptions reflected from the textual expression, rather than the original factuality of the event in the real world. For example, given a sentence, “特朗普**叛国**罪名可能不会被确认(*Trump’s* ***treason*** *may not be confirmed in the end)*”, we are concerned about the description of the event itself in sentence rather than whether the event "***treason***" really happened. Thus the event “***treason***” is MayNot(PS-) in the above instance.

Existing studies on event factuality detection mainly focus on the coarse-grained level such as judging whether an event actually occurs or not, or only identifying the linguistic coverage of a cue of negation or speculation in sentence. For example, Schuetze et al. (2017) employed a CNN model to detect the unspecified event on a biomedical domain corpus [2]. Qian et al. (2015) utilized event factuality reporting structures (i.e., *someone guesses/claims/doubts*) and syntactic structures with negative words to identify whether the target event is within the scope of the reporting structure or the negative syntactic structure, so as to obtain the corresponding categories of event factuality [3]. These approaches only rely on a single linguistic feature to judge the value of event factuality which are limited. However, they ignore the other syntactic information, such as tense and the interaction of various features on the value of event factuality. In this paper, we propose an event factuality detection approach based on linguistic features, which includes 1) factuality cue, which aims to determine the degree of certainty about whether the event actually happened, such as reporting predicates (e.g., “推测” (*Speculate*), “证实”(*Confirm*)) and adverbs/adjectives expressing degree of certainty (e.g., “必须” (*must*), “可能”(*possible*)); 2) event polarity, which aims to determine about whether an event occurred or existed, such as negative cue; and 3) tense, which aims to detect the time of event took place, such as past tense, future tense.

(E1) 他证实新院的校长黄茂树现在没有正式**就职**，就遭人检举有双重国籍.
(*He has confirmed that Huang Maoshu, the president of the New College, has not yet officially* ***taken office*** *and has been accused of having dual nationality.*)

(E2) 信息部要求美国移民局执行法院判决，**释放**张宏宝以保障他的人权.
(*He Information Ministry asked the U.S.Immigration Service to enforce the court’s ruling and* ***realease*** *Zhang Hongbao to guatantee his human rights* .)

For example, (E1) and (E2) both include the factuality cue, the event polarity and the tense. In sentence E1, the target event “就职(*take office*)” is certainty(CT+) according to the reporting predicate “证实(*confirmed*)” which has a deterministic tendency towards the clause, However, the tense word “现在(*yet*)” and the negative cue “没有(*not*)” indicate that the factuality type of target event is CT-. Based on the above analyses, the final factuality type of target event “就职(*take office*)” is CT-. It can be seen that the event factuality is often determined by several clues in sentence, and there may be contradictions among them, which pose the challenge for the task. For example, in E2, the word related to the event “释放(*release*)” are the modal word “要求(*asked*)” (we regard modal word as the first type of feature, i.e. factuality cues)". Thus the factuality type of the target event is PS+.

In this paper, we propose a feature encoder based on Convolutional Neural Network (CNN) to automatically extract and learn the three types of linguistic features. Then we utilize the latent feature representations to fused with pre-trained word embeddings to detect event factuality. Experimental results on Chinese Event Factuality Datasets[i] show that our approach achieves 94.15% (F1), with 12.34% of improvement on the state-of-the-art system. In addition, we also demonstrate the effectiveness of the proposed three types of linguistic features in practical application scenarios.

2 Related Work

Early event factuality detection in text processing mainly focused on biomedical domain. For instance, Kilicoglu et al. (2003) employed a heuristic rule-based method on the biomedical corpus, GENIA [4], which identified the degree of certainty and polarity of events according to the association between event predicates and modal or negative words [5]. Sauri et al. (2003) constructed the FactBank corpus [1] based on the TimeML corpus [7]. They show that factuality can be characterized by the combination of the degree of certainty (*Certain/Probable/Possible*) and polarity(*Positive/ Negative),* while it classified the value of event factuality into six categories in a more fine-grained way above two dimensions. In addition, events whose factuality cannot be judged means *underspecified*. Qian et al. (2017) employed a maximum entropy classifier to identify "*underspecified*" event category in FactBank corpus, and then developed a series of heuristic rules to classify other events [3].

For event factuality detection in Chinese, Cao et al. (2016) constructed a Chinese dataset [8] based on ACE 2005 event extraction dataset [9]. They classified event factuality into 5 categories and annotated basic factors related to event factuality (i.e., reporting predicates, negative cues, sources, clauses). In addition, He et al. (2017) developed a CNN-based model to identify event factuality, where they utilized Word2Vec [10] and Chinese synonym word forest [11] to detect the similarity between words in Chinese synonym word forest and reporting predicates in sentence so as to extracted more cues related to event factuality in sentence. Finally, the linguistic rules are applied to detect event factuality with the cues which are described above [12]. These approaches are not only rely on domain knowledge, such as rule-based methods, but also failed to consider the interaction of linguistic features related to event factuality, which limited the performance and can be costly to obtain.

3 Chinese event factuality detection model

This section describes our approach for chinese event detection, which is recast as a classification task to determine the value of target event factuality in sentence. It can be categories into five below: "*Certainy", "Impossible", "Possible", "May not" and "Unspecified".* For the probability $P(e)=\max\{P_i(e|S)\}$, $1 \leq i \leq 5$, is the probability of target event *e* conditioned on sentence *S* containing the target event, which aims to select the maximum probability value of target event factuality in 5 categories.

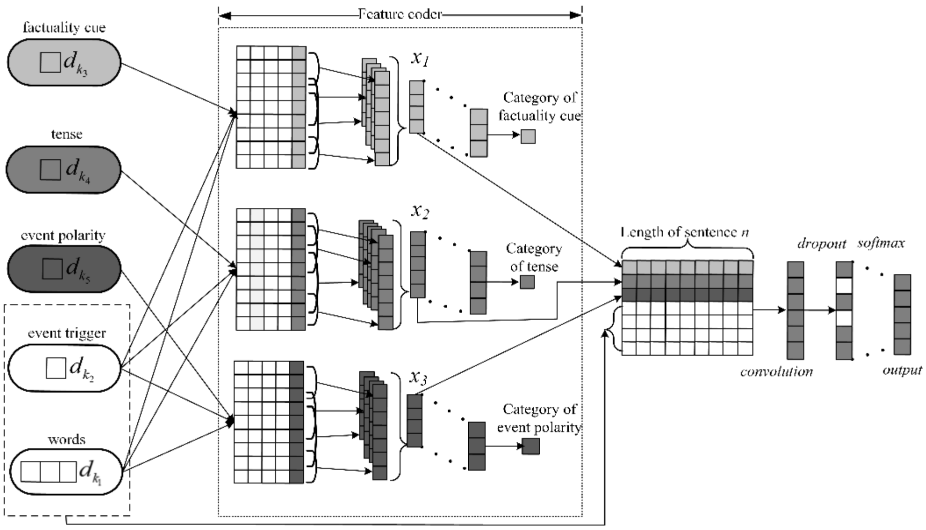

Fig. 1. Architecture of Chinese Event Factuality Detection Model

Figure 1 shows the framework of our model based on CNN, which consists of the two parts: 1) feature encoding layer, which aims to extract three types of linguistic features(factuality cue, event polarity, tense) in sentence and encode them as feature vectors on CNN-based encoder; 2) chinese event factuality classification model, which aims to utilize three types of linguistic features vectors to fused with pre-trained word vectors and event trigger vectors that fed into CNN model to obtain event factuality.

3.1 Feature encoding Layer

3.1.1 Factuality Cue

In this paper, factuality cues are defined as a special type of vocabulary that reveal the degree of certainty whether the event actually occurs, including the reporting predicate (i.e., "*speculate*", "*confirm*"), the adverb or adjective expressing degree of certainty(i.e., "*must*", "*possibility*"). Factuality cues are categorized into three categories according to their attributes, such as “报道(*report*)” and “证明(*prove*)” as definite, “估计(*estimate*)” and “怀疑(*doubt*)” as possible, “打听(*inquiry*)” and “咨询(*consult*)” as uncertain. Factuality cues are represented by vector matrix C_E. In addition, in order to capture the semantic information of event trigger in sentence, we utilize a sentence to segmentation(given sentence *S* with length *N*, $S=(w_1,w_2,\ldots,w_i,\ldots,w_n)$, where w_i denotes the i_{th} word in sentence *S*), the event trigger labels matrix T_E, which is represented as follows: 1) A token is labeled as “Trigger” if w_i is the event trigger in sentence; 2) A token is labeled as “NTrigger” if w_i is not the event trigger in sentence. The reminder of this section is organized as follows:

1) Embedding layer

As the input of our model, it is consist of three matrix as follows: 1) word embedding matrix $M_E \in \mathbb{R}^{d_{k1} \times |v_n|}$, where d_{k1} is the dimension of each word in sentence and V_n is the number of words in sentence; 2) event trigger labels matrix $T_E \in \mathbb{R}^{d_{k2} \times |v_{k2}|}$, where d_{k2} is the dimension of event trigger labels, V_{k2}={Trigger,NTrigger}, and indicate a set of event trigger labels; 3) $C_E \in \mathbb{R}^{d_{k3} \times |v_{k3}|}$, the factuality cue matrix, where d_{k3} is the dimension of factuality cue and V_{k3} is a set of factuality cues in sentence.

2) Convolutional layer

In this paper, we employ CNN-based model to classify factuality cues. Given a sentence *S* with the length *N*, the dimension is transferred into $d_{w1} = d_{k1} + d_{k2} + d_{k3}$ according to embedding table. We utilize $X_{cue} \in \mathbb{R}^{d_{w1} \times |v_n|}$ as the input, while we consider a fixed size window W_1 to capture its local features in the current layer. Here, the window size is set as *l* to capture a new feature.

After fed into the convolutional layer, the input matrix X_{cue} is processed with a convolutional operation:

$$c_i = tanh(W_1 \cdot X_{cue} + b_1) \quad (1)$$

where $b_1 \in \mathbb{R}^{|v_n|}$ is the bias term, *tanh* is nonlinear activation function. These new features are consists of a new feature matrix:

$$c_{cue} = [c_1, c_2, \dots, c_{n-l+1}] \quad (2)$$

3) Maxpooling layer

To extract the most active convolutional features from c_{cue}, we consider to select the max value ($\hat{c} = \max\{c_{cue}\}$), which is taken as input to maxpooling layer. This operation can effectively reduce the number of features of input matrix and filter out the features with weak representativeness [13].

We utilize *m* filters of three different window sizes h_1, h_2, h_3 with convolutional operation to obtain various new feature matrices, and then the maxpooling layer is applied to select the max value from each new feature matrix. Finally, they are concatenated into the matrix X_1:

$$X_1 = [\hat{c}_{cue1}, \hat{c}_{cue2}, \hat{c}_{cue3}, \dots, \hat{c}_{cuem}]^T \quad (3)$$

4) Sofxmax layer

X_1 is fed into the softmax layer:

$$o = softmax(W_2 \cdot X_1 + b_2) \quad (4)$$

where $W_2 \in \mathbb{R}^{d_{n2} \times n_m}$ is the parameter matrix, and $b_2 \in \mathbb{R}^{n_2}$ is the bias term. The dimension of *o* is n_2=3, which is the probability of three types of factuality cues, we select the maximum probability as factuality cue category *Vcue*.

3.1.2 Tense

Tense is the time when an event occurs. event factuality will be different because of the different tenses, such as “他已经**去**了美国*(he has **gone** to America*)”and “他将前往美国(*he will **go** to America*)”, The factuality cues of “*gone*” and “*go*” both are certainty, but the tense of “*gone*” is past and “*go*” is future, which makes the event factuality of “*gone*” to be CT+ and “*go*” to be PS+. Thus, tense is of significance to identify the event factuality in NLP tasks. Tense usually appear in the form of tense words(i.e., “现在(*now*)”, “将(*will*)”) or adverbs(i.e., “要求(*demand*)” denote the tense as future, “已经(*already*)” denote the tense as past). Tense will be classified into four categories: “过去(past)”, “现在(now)”, “将来(future)” and “未指明(unspecified)”.

The maxtrices M_E, T_E and S_E (the tense words matrix where $S_E \in \mathbb{R}^{d_{k4} \times |v_{k4}|}$, d_{k4} is the dimension of tense words, and V_{k4} is a set of tense words in sentence) are concanated into a matrix $X_{ten} \in \mathbb{R}^{d_{w2} \times |v_n|}$, where $d_{w2} = d_{k1} + d_{k2} + d_{k4}$. Similary, Matrix X_{ten} is encoded according to the factuality cue encoding method. Finally, we obtain the tense category V_{ten}.

3.1.3 Event Polarity

Event polarity describes whether the event itself occurs or exists, such as “他现在还没有去美国（*He hasn't* ***gone*** *to America yet*）”, and the negative cue “没有(*hasn't*)” reverses the target event polarity (CT+ → CT-). And it plays an important role in identifying the negative events (CT-, PS-). We classify event polarity into three categories: positive, negative and unspecified.

In this paper, the negative cues vocabulary are extracted on CNeSp Corpus[1], we utilize the sentence *S* to match with the vocabulary, and then vectorized them to a matrix P_E, where $P_E \in \mathbb{R}^{d_{k5} \times |v_{k5}|}$, d_{k5} is the dimension of negative cues in sentence, and V_{k5} is a set of negative cues in sentence.

The maxtrices M_E, T_E and P_E are concanated into a matrix $X_{pol} \in \mathbb{R}^{d_{w3} \times |v_n|}$, where $d_{w3} = d_{k1} + d_{k2} + d_{k5}$. Similary, Matrix X_{pol} is encoded according to the factuality cue encoding method and we obtain the event polarity category V_{pol}

3.2 Chinese event factuality detection Model

Currently, CNN have been proven effective in extracting sentence-level features [14]. For example, Kim et al. (2014) utilized a CNN-based model to extract sentence-level features for sentence classification [15].

Event factuality will produces different values at the interaction of the three types of linguistic features. Thus, three types of linguistic feature vectors X_1, X_2 and X_3 obtained by feature encoding layer are concatenated into X_{fea}, where $X_{fea} = X_1 + X_2 + X_3$. And then we utilized X_{fea} to fused with M_E and T_E to obtain the matrix X_4, where $X_4 = X_{fea} + M_E + T_E$ and $X_4 \in \mathbb{R}^{d_w \times |v_n|}$.

To learn the parameters of the network, we supervise the labels which are adopted from CNN-based model with the gold labels in the training set, and utilize the following training objection function:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m} logP(e_i|s_i, \theta) + \frac{\lambda}{2}\|\theta\|^2 \tag{5}$$

where θ={W_1,W_2,b_1,b_2} is the set of parameters, λ is the regularization coefficient, p(e_i | s_i, θ) is the confidence score of the golden label e_i of the training instance s_i , *m* is the

[1] http://nlp.suda.edu.cn/corpus/CNeSp

number of the training instances. To train the CNN-based model, the Adam algorithm is applied to convergence.

4 Experimentation

4.1 Settings

We evaluate our model on Chinese event factuality datasets [9], which annotated 4,852 instances with factuality cue, event polarity, and tense of event. The dataset only considers five types of event factuality, including CT+, CT-, PS+, PS-, and U. We divide the dataset into training set, development set, and test set, according to the proportion of 65%, 15%, 20%. Table 1 shows the statistics of five types of event factuality. We can see that the number of CT+ is far more than that of CT-, PS- and U. The main reason is that this dataset mainly comes from news texts, thus the certain information is more common.

Table 1. The statistics of Chinese cvent factuality dataset.

	CT+	CT-	PS+	PS-	U
Training	2,392	69	568	40	28
Dev	597	17	141	9	7
Test	810	20	156	14	48

For the hyper-parameters, we adopt windows size in the set {3,4,5} to generate feature maps, and utilize 100 feature maps for each window size in this set. We set the learning rate as 0.001, the dropout as 0.5, the mini-batch size as 50. The word embeddings are initialized by Word2Vec[1] with 300 dimensions from Mikolov et al. (2013). Finally, Adam algorithm is applied to optimize our model. The performance is measured by Precision (P), Recall (R), F1-score (F1).

4.2 Experimental Results

To verify the effectiveness of the proposed three linguistic features, we add each feature into the Baseline, respectively, which are described as follows:

- Baseline: A CNN-based system, which contains only word embeddings and the target event embedding with the dimension 100 initialized randomly.
- Baseline+Cue: Baseline system adds the factuality cue embedding with the dimension 100 initialized randomly.
- Baseline+Polarity: Baseline system adds the event polarity embedding with the dimension 200 initialized randomly.
- Baseline+Tense: Baseline system adds the tense embedding with the dimension 100 initialized randomly.
- ALL-Features: Baseline system adds the above three kind of embeddings.

[1] `https://github.com/Embedding/Chinese-Word-Vectors`

Table 2. Effects of three types of linguistic features

system	Marco-Ave			Micro-Ave		
	P(%)	R(%)	F(%)	P(%)	R(%)	F(%)
Baseline	46.14	33.48	38.81	81.33	81.33	81.33
Baseline+Cue	67.54	46.68	55.02	84.02	84.02	84.02
Baseline+Polarity	75.98	71.38	73.61	82.28	82.28	82.28
Baseline+Tense	68.44	49.66	57.56	91.64	91.64	91.64
ALL-Features	**87.86**	**81.64**	**84.64**	**94.15**	**94.15**	**94.15**

Table 2 lists the performances of three types of linguistic features on Chinese event factuality detection. The results show that when adding all of the three types of features, our proposed model achieves the best performance, which significantly better than Baseline (Micro-Ave[1]: 94.15% vs 81.33%, Macro-Ave: 84.64% vs 38.81%). It demonstrates the effectiveness of these features on Chinese event factuality detection. Besides, the results show the different effectiveness among features: 1) the Baseline+Polarity system achieves better performances than the others in Macro-Ave. It might be due to the better ability of Baseline+Polarity models in identifying the negative events (CT- and PS-), with fewer instances by adding the event polarity features; 2) The performance of Baseline+Tense is higher than the others on Micro-Ave. It is mainly attributed to that tense features play an important role in identifying the possible type of events. For example, two sentences are given as follows:

(E3) 他们扯下了旗帜，并**逮捕**了向他们投掷石头的人.

(*They have torn down the flag and* ***arrested*** *people who threw stones at them.*)

(E4) 他总统将于本月底**前往**平壤访朝.

(*The president will* ***go*** *to Pyongyang at the end of this month for visit.*)

The tense of the target event in E3 is past and in E4 is future. Thus, the event factuality is CT+ in E3 and PS+ in E4. Both of them are completely determined by tense.

4.3 Comparison with the state-of-the-art

Table 3 compares our model with the state-of-the-art system. He et al. (2017) developed a CNN-based model to identify event factuality, where they utilized Word2Vec [10] and Chinese synonym word forest [11] to detect the similarity between words in Chinese synonym word forest and reporting predicates in sentence so as to extracted more cues related to event factuality in sentence. Finally, the linguistic rules are applied to detect event factuality with the cues which are described above [12].

Compared to He's model, our model improves the F1 of Macro-Ave and Micro-Ave by 22.82% and 12.34%, respectively. All the improvements are due to the three types of linguistic features that enhance the model's understanding of different events factualities through semantic relations. Our model can effectively identify uncertain events (PS+, PS-, U) (+31.84% for PS+, +48.80% for PS-, +44.86% for U). It can contribute

[1] In this paper, five types of event factuality are positive samples, so the value of P, R, F1 are equal when calculated on Micro-Ave.

to the outstanding result of our model mining uncertain semantic information. In addition, our model have lower performance than He's on CT-, due to heuristic linguistic rules which are designed to identify the negative events, such as when an odd number of negative cues appear in sentence. The event polarity of the target event is judged to be negative and vice versa, the model mine deeper negative semantic information.

Table 3. Comparison with the state-of-the-art system

	He[11] (2017)			ALL-Features (ours)		
	P(%)	R(%)	F(%)	P(%)	R(%)	F(%)
CT+	87.38	90.37	89.00	**95.20**	**97.94**	**96.55**
CT-	**65.73**	**81.88**	**72.83**	60.00	75.00	66.67
PS+	62.11	51.70	56.24	**94.12**	**82.76**	**88.08**
PS-	56.24	33.33	41.20	**90.00**	**90.00**	**90.00**
U	58.67	23.78	32.24	**100**	**62.50**	**76.92**
Macro-Ave	70.52	59.14	61.82	**87.86**	**81.64**	**84.64**
Micro-Ave	81.81	81.81	81.81	**94.15**	**94.15**	**94.15**

4.4 Chinese Event Factuality Detection

In this paper, the factuality cue, event polarity and tense all depend on the annotated samples just described as subsection 3.2 and 3.3, therefore, this subsection employ our model on raw texts.

Table 4. Performances of Chinese event factuality detection systems on raw text

system	Macro-Ave			Micro-Ave		
	P(%)	R(%)	F(%)	P(%)	R(%)	F(%)
Auto+Cue	51.80	36.79	43.03	80.18	80.18	80.18
Auto+Polarity	57.60	32.28	41.37	81.50	81.50	81.50
Auto+Tense	54.35	34.60	42.28	80.79	80.79	80.79
Auto+All-Features	68.38	39.76	50.55	82.42	82.42	82.42
Mannual ALL-Features	**87.86**	**81.64**	**84.64**	**94.15**	**94.15**	**94.15**

Table 4 compares the performances of detecting event factuality with automatically identifying three types of linguistic features, respectively (line 1-3) and automatically identifying three types of linguistic features as the same time (line 4). Finally, we identitify event factuality with annotating three types of linguistic features (line 5). Among the models (line 1-4), the F1 scores of Macro-Ave are far below the F1 scores of Micro-Ave. The performance gaps among these models are due to three features have data imbalance in its own classification, such as the proportion of past tense and present tense is 78.63% and 1.46% respectively. It is challenging to identifying feature classes with fewer instances.

5 Conclusion

We presented a Chinese event factuality detection method, which introduced factuality cue, event polarity and tense to describe event factuality and then employed CNN feature enconder to extract these linguistic features respectively. Finally, we identify the event factuality based on CNN model. In addition, we will optimize the model to solve the problems mentioned in subsection 4.4 and it is the direction of future work.

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