Evaluation of Knowledge Ontology Research and Rule Implementation Postprint

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Abstract

Purpose: To establish an intelligent evaluation analysis system that integrates evaluation sentence identification, sentiment orientation determination, and evaluation object extraction. Method: Research on Chinese evaluation knowledge ontology was conducted, an evaluation analysis rule base was established based on the ontology research findings, and a dictionary-rule-based intelligent evaluation analysis system CUCsas was implemented. Results: Using 50,000 Weibo posts (totaling 133,201 sentences) released by the 7th Chinese Opinion Analysis Evaluation (COAE2015) as experimental data, the system' s precision, recall, and F-score for evaluation sentence identification and sentiment orientation determination are 0.83, 0.70, and 0.76, respectively, while the results for evaluation object extraction are relatively poor. Limitations: The system currently lacks modules for discovering new evaluation words and automatically constructing domain dictionaries. Conclusion: A practical intelligent evaluation analysis system has been preliminarily established.

Full Text

Preamble

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Research on Evaluation Knowledge Ontology and Rule Implementation*

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Abstract

[**Objective**] To establish an integrated intelligent evaluation analysis system that combines evaluation sentence recognition, polarity determination, and evaluation object extraction.

[**Methods**] We conducted research on Chinese evaluation knowledge ontology and constructed an evaluation analysis rule base based on the ontology findings, implementing a dictionary- and rule-based intelligent evaluation analysis system called CUCsas.
[**Results**] Using 50,000 Weibo posts (totaling 133,201 sentences) released by the 7th Chinese Opinion Analysis Evaluation Conference (COAE2015) as experimental data, the system achieved precision, recall, and F-score of 0.83, 0.70, and 0.76 respectively for evaluation sentence recognition and polarity classification. However, evaluation object extraction performance was relatively poor.
[**Limitations**] The system currently lacks modules for discovering new evaluation terms and automatically constructing domain-specific dictionaries.
[**Conclusions**] We have preliminarily established a practical intelligent evaluation analysis system.

Keywords: Evaluation ontology; Evaluation sentence recognition; Polarity identification; Rule-based method; Evaluation object extraction
Classification Number: G350; H146

1 Literature Review

Evaluation refers to people' s subjective judgments—positive, negative, or mixed—made about things based on certain criteria. Evaluation analysis (also known as sentiment analysis) has remained a hot topic in natural language processing research in recent years, with applications in election prediction, user recommendation, public opinion monitoring, and academic reputation tracking. An evaluation sentence (ES) contains four basic elements: evaluation subject (Sub), evaluation object (Obj), evaluation factor (Fac), and evaluation context (Con), i.e., ES = {Sub, Obj, Fac, Con}. An Evaluation Analysis Intelligent System (EAIS) is a system that can automatically identify sentences with evaluative meaning from mixed texts, determine sentence polarity, and extract evaluation objects. EAIS typically comprises two fundamental modules: evaluation ontology (EOntology) and evaluation solving methods (ESM), i.e., EAIS = EOntology + ESM. EOntology belongs to linguistic knowledge ontology, referring to the linguistic knowledge required for evaluation analysis tasks, including lexical knowledge (evaluation dictionaries, negation dictionaries, degree dictionaries, transition dictionaries, etc.), syntactic knowledge (part-of-speech, NP and VP phrases, dependency relations, etc.), and semantic knowledge (semantic orientation features of evaluation words, agent and patient semantic roles, etc.). ESM includes two basic approaches: statistical and rule-based methods.

(1) Statistical Methods: Zhang et al. identified sentiment neologisms and determined their polarity by calculating Pointwise Mutual Information (PMI-IR) between candidate sentiment words and positive/negative seed word sets from large-scale corpora [**?**]. Ding et al. trained an SVM classifier using features such as sentiment words, degree adverbs, and negation words, adjusting parameters to obtain an optimal model for sentence polarity classification [**?**]. Tong et al. employed ensemble learning, using classification results from rule-based and CRF-based classifiers as features to train an SVM for microblog opinion sentence polarity determination [?]. Jiang et al. extracted 14 types of features—including words, position, sentiment words, part-of-speech, parent node position, dependency relations, nearest nouns, basic phrase types, dependency relations with sentiment words, candidate evaluation objects, feature words, keywords, sentence polarity, and opinion sentences—to train a CRF model for extracting evaluation objects from microblog opinion sentences [?].

(2) Rule-Based Methods: Wang et al. used a pattern-based bootstrapping method to extract sentiment neologisms from microblog corpora. For example, the pattern "veryparticle" was used to select high-confidence patterns for matching corpora to obtain new terms [?]. Hou et al. studied the polarity of evaluation phrases [?], while Zhou et al. researched Chinese comparative sentence identification and comparative element extraction based on semantic classification [?].

2.2 Research Content: Linguistic Features and Their Combinatorial Relations

The basic form of rules is a "condition → action" pair, where "condition" refers to linguistic features and their combinatorial relations. Compared with theoretical linguistics, computational linguistics focuses more on describing linguistic phenomena than explaining them. It requires accurate characterization of the objective state of the linguistic problem under study without subjective explanations of why such states occur. Therefore, computational linguistics rarely considers external factors such as social, cultural, or psychological aspects as theoretical linguistics does. However, this does not mean computational linguistic research is simpler than theoretical linguistics. Theoretical research emphasizes speculation, allowing multiple explanations for the same problem with open-ended, non-unique answers. Computational linguistics emphasizes practice—self-consistency alone is insufficient; only solutions that withstand large-scale real-world corpus testing are considered valid, with typically only one optimal answer: the solution adopted by the best-performing system. Some language engineering tasks (e.g., machine translation, human-computer dialogue) are so complex that providing accurate and comprehensive descriptions of the linguistic problems is challenging, often resulting in lengthy research cycles that span generations.

(1) Features for Distinguishing Evaluation Sentences from Non-Evaluation Sentences

Evaluation sentences contain four basic elements: evaluation subject, evaluation object, evaluation factor, and evaluation context. Among these, the evaluation factor is essential, while the other three are optional. Evaluation factors are further divided into context-independent and context-dependent types. The former express evaluative meaning independently of context, while the latter only express evaluative meaning in specific contextual environments [?]. The semantic types of evaluation factors are shown in Table 2 .

However, sentences containing evaluation factors are not necessarily evaluation sentences. For example: 1. "No matter what you do, as long as you bravely take the first step, there' s a fifty percent chance of success." 2. "Strive hard for future happiness!" 3. "This is the birthday gift I gave you, do you like it?"

Words like "brave," "happiness," "success," "strive," and "like" are all evaluation factors, but they do not express evaluative meaning in these examples because they are governed by hypothetical conjunctions ("as long as"), purpose prepositions ("for"), and interrogative structures ("…?"). We refer to such words and constructions that cancel the evaluative meaning of evaluation factors within their scope as evaluation cancellation factors (Xjc), summarized in Table 3 .

Therefore, a sentence containing an evaluation factor that is not governed by an evaluation cancellation factor constitutes a sufficient condition for identifying an evaluation sentence: Fac + !Xjc => ED.

(2) Features for Extracting Evaluation Objects

Semantic orientation refers to the direction in which words in a sentence semantically govern or modify each other [**?**]. The semantic orientation target of an evaluation factor is precisely the evaluation object to be extracted. Extracting evaluation objects requires comprehensive consideration of the evaluation factor' s semantic orientation features and the sentence' s syntactic structure to determine the syntactic position of the evaluation object relative to the evaluation factor, then extract the component at that position (represented by part-of-speech or part-of-speech combinations). While specific sentences in language are infinite, the number of words as basic sentence-building units is relatively limited, as are words' grammatical categories (parts-of-speech) and semantic categories. The combinatorial patterns of parts-of-speech and word meanings (syntactic structures, semantic structures) are not arbitrary but follow certain regularities. Therefore, we can use three basic linguistic features—word form, part-of-speech, and word meaning—to describe the elements of evaluation (Sub, Obj, Fac, Con) and their combinatorial relations (including Fac-Obj semantic orientation relations). The semantic features relevant to determining evaluation object positions mainly fall into four categories [**?**], as shown in Table 4 .

These four semantic features are subdivisions of evaluation factors based on semantic orientation direction. Their function is to distinguish cases where the same syntactic structure has two different potential semantic structures (same form, different meaning). For example: 4a. "The child' s father admires the child' s mother."
4b. "The child' s father deceives the child' s mother."
5a. "The child' s father is dissatisfied with the child' s mother."
5b. "The child' s father has feelings for the child' s mother."
6a. "The child' s father is the child' s mother' s idol."
6b. "The child' s father is thanks to the child' s mother."

In these paired examples, the grammatical structures are identical, but the evaluation objects (double-underlined content) appear in different syntactic positions.

Distinguishing them based solely on word form and part-of-speech features is impossible. The difference in evaluation object position distribution results from different semantic orientation features of the evaluation factors (single-underlined content). Only by introducing the semantic features in Table 4 can we accurately determine the position distribution of evaluation objects in such "same form, different meaning" constructions.

For non- "same form, different meaning" constructions, determining evaluation object positions mainly relies on feature words (word form features) and syntactic structures (part-of-speech combination features). We summarize the relevant word form and part-of-speech combination features for determining evaluation object positions in Table 5 .

Evaluation sentences are divided into two basic categories—comparative and non-comparative—because the former requires extracting composite evaluation objects: <comparison subject, comparison point> and <comparison benchmark, comparison point>, while the latter extracts simple evaluation objects: <evaluation object, attribute>. They also differ in polarity determination. For example, in differential comparative sentences, the polarity of <comparison subject, comparison point> equals the evaluation factor' s polarity, while the polarity of <comparison benchmark, comparison point> equals the evaluation factor' s polarity multiplied by (-1). The polarity of {evaluation object, attribute} equals the evaluation factor' s polarity [**?**]. Additionally, Table 5 shows that determining evaluation object positions in comparative sentences mainly relies on feature words (word form features), while non-comparative sentences rely mainly on syntactic structures (part-of-speech combination features).

(3) Features for Polarity Determination (Positive, Negative, Mixed)
Polarity determination primarily uses three types of features: evaluation factors, negation words (negative adverbs and negative verbs), and transition words, as shown in Table 6 .

If an evaluation factor in a sentence is not governed by negation words, the object' s polarity equals the factor' s polarity: positive factors yield positive objects, negative factors yield negative objects. For example: 7. "This car' s performance is very good."
8. "This car' s performance is very poor."

If an evaluation factor is governed by negation words, the object' s polarity equals the factor' s polarity multiplied by (-1): positive factors yield negative objects, negative factors yield positive objects. For example: 9. "This car' s performance is not good."
10. "This car' s performance is not poor."

When two evaluation factors with opposite polarity semantically orient toward the same evaluation object (often connected by transition words), the object' s polarity is mixed. For example: 11. "This car' s performance is very good, but its appearance is very ugly."

2.3 Research Methods: Formalization and Experimentation

The research goal of theoretical linguistics is logically rigorous articles written in natural language, primarily using introspection methods. The research goal of computational linguistics is practical systems written in programming languages, requiring machine-readable formal languages and continuous experimentation during research, with methods and conclusions revised based on experimental feedback. Table 7 presents the formal symbol set for evaluation knowledge ontology that we manually defined.

These formal symbols and their corresponding specific words are stored statically in dictionaries. Dictionary entry examples: [admire v], [admire po], [admire hzv], [Santana nq], [engine na].

Using the formal symbols from Table 7, combined with logical operators (OR "|", AND "&", NOT "!") and operational symbols (rule item separator "+", wildcard "* ", position marker" Nm" , assignment operator ":" , etc.), we describe the linguistic features and their combinatorial relations from Section 2 to form the rule base module (problem-solving algorithm ESM) of the evaluation analysis system. The evaluation analysis rule base includes three sub-libraries: sentiment assignment rule base, sentiment computation rule base, and evaluation object extraction and polarity determination rule base, as shown in Table 8 .

The basic form of rules is a condition → action pair, where the left side represents conditions and the right side represents operations executed when conditions are met. The example rules in Table 8 have the following meanings:

- `*/mopo + */pxn = #2:0.75`
  Meaning: When a positive noun (e.g., "youth," "sunshine," "rationality") is modified by a positive degree adverb (e.g., "very," "extremely," "especially"), assign it a sentiment value of 0.75.
- `*/xjc + #[*/!w] + */po|ne = #3:0`
  Meaning: When an evaluation factor is governed by an evaluation cancellation factor (e.g., "wish," "if," "suppose"), cancel its evaluative meaning.
- `*/mone + */po|ne = -N2`
  Meaning: When an evaluation factor is governed by a negation word (e.g., "not," "no," "not at all"), reverse its polarity.
- `*/po + #[*/!nq] + */zzc + #[*/!(w|nq)] + */ne = [N1 + N5]:2`
  Meaning: When one positive and one negative evaluation factor semantically orient toward the same evaluation object, determine the object' s polarity as mixed.
- `*/nq + #[*/!vl] + */na + #[*/!w|nq|na] + */qzv = N1[bs] N3[ba] bs:N5`
  Meaning: When a product name is followed by a product attribute name, which is followed by an evaluation factor that is a semantically forward-pointing verb, extract the product name and attribute name

as the evaluation object and object attribute, and assign the evaluation factor' s sentiment value to the evaluation object.

It should be noted that rules in the evaluation object extraction and polarity determination rule base are not arranged arbitrarily but follow a logical order. The basic principle is: comparative sentence rules take precedence over non-comparative sentence rules, special construction rules over general construction rules, and complex sentence rules over simple sentence rules. This arrangement aims to simulate human information processing. For example:

"The freedom and comfort claimed in Jeep' s advertisements are completely absent in handling, passenger space, etc."
(Incorrect extraction: [Jeep 1]; Correct extraction: [Jeep handling, passenger space -1])

When the rule base scans the product name "Jeep" and evaluation factor "freedom and comfort," it does not immediately extract "Jeep" as the evaluation object. Instead, it continues scanning backward to check for product attribute names and negation words governing the evaluation factor. If it finds "completely absent," it multiplies the evaluation factor' s sentiment value by (-1) and extracts both the product name "Jeep" as the evaluation object and the attribute names "handling, passenger space" as object attributes. Only if no such elements are found will it confirm the initial judgment. Thus, the rule base matches corpora according to maximum matching and deterministic analysis principles, improving evaluation element extraction accuracy to some extent. Finally, the dictionaries and evaluation analysis rule base were implemented in C# as the intelligent evaluation analysis system CUCsas.

4 Experimental Results and Analysis

CUCsas participated in the 7th Chinese Opinion Analysis Evaluation Conference (COAE2015) hosted by the Chinese Information Processing Society of China and China Computer Federation. Using the 50,000 Weibo posts (133,201 sentences) released by the conference as experimental data, the dictionary- and rule-based evaluation analysis system CUCsas achieved the results shown in Table 9 .

The experimental (evaluation) results indicate that CUCsas performed well on evaluation sentence recognition and polarity classification tasks, particularly in precision, reaching 83% and approaching the best result [?]. Recall was somewhat lower at around 70%. This demonstrates that the six semantic features selected for evaluation sentence recognition and polarity classification—context-dependent evaluation factors, context-independent evaluation factors, evaluation cancellation factors, degree adverbs, negation words, and transition words—are appropriate and effective. The sentiment assignment rule base and sentiment computation rule base provide basically accurate descriptions of feature combinatorial relations (rule conditions) and their results (rule actions). Evaluation cancellation factors, degree adverbs, negation words, and transition words are relatively small, closed sets, while evaluation factors constitute a large, open set. In self-media platforms like Weibo, language use is highly dynamic, with emerging evaluation factors constantly appearing and many colloquial expressions (e.g., "scam," "can' t afford to be hurt," "really fucking awkward"). The system' s recall was directly affected by the absence of these neologisms in the evaluation dictionary, suggesting a need for future research on automatic discovery of out-of-vocabulary evaluation factors.

Evaluation object extraction is the most challenging task in evaluation analysis. The best performance in this evaluation [?] achieved an F-score of only 0.15, while CUCsas performed even worse, with very low precision and recall. This is partly due to the task' s difficulty: the evaluation required correct extraction of product names, product attribute names, and polarity simultaneously, which is extremely challenging without domain dictionary support. It also reflects imperfections in the evaluation object extraction rule base. Future work will strengthen research on automatic domain dictionary construction technology and revise the current rule base to address errors and uncovered cases.

This paper proposes a knowledge ontology and rule base construction method for evaluation analysis (sentiment analysis). From a computational linguistics perspective, we first studied the linguistic knowledge ontology required for evaluation analysis tasks (evaluation sentence recognition, evaluation object extraction, polarity determination). Based on the ontology findings, we constructed an evaluation analysis rule base and implemented it as the dictionary- and rule-based intelligent evaluation analysis system CUCsas. Experimental results demonstrate the method' s good accuracy.

Future research will include: exploring automatic discovery mechanisms for out-of-vocabulary evaluation factors to further improve system recall for evaluation sentence recognition; strengthening research on automatic domain dictionary construction technology; and revising and improving the existing rule base to further enhance system performance in evaluation object extraction.

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