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Extracting Condition-Opinion Relations in Online Reviews

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Abstract: A fundamental issue in opinion mining is to search a corpus for opinion units, each of which typically comprises the evaluation by an author for a target object from an aspect, such as "This hotel is in a good location". However, only few attempts have been made to address cases where the validity of an evaluation is restricted on a condition in the source text, such as "for traveling with small kids". In this paper, we propose a method to extract condition-opinion relations from online reviews, which enables fine-grained analysis for the utility of target objects depending the user attribute, purpose, and situation. Our method uses supervised machine learning to identify sequences of words or phrases that comprise conditions for opinions. We propose several features associated with lexical and syntactic information, and show their effectiveness experimentally.

1. Introduction

Reflecting the rapid growth in the use of opinionated texts on the Web, such as comments on news articles and customer reviews, opinion mining has been explored to facilitate utilizing opinions mainly for improving products and decision-making purposes. While in a broad sense opinion mining refers to a process to discover useful knowledge latent in a corpus of opinionated texts, fundamental issues involve modeling an unit of opinions and searching the corpus for those units, each of which typically comprises the evaluation by an author for a target object from an aspect. We take the following review sentence as an example opinionated description.

(1) I think hotel A offers a reasonable price if you take a family trip with small kids.

From the above example, existing methods [3], [4], [8], [9], [10], [17], [18], [19], [20] are intended to extract the following quintuple as an opinion unit.

Target = "hotel A", Aspect = "price", Evaluation (Polarity) = "reasonable" (positive), Holder = "I (author)", Time = N/A

Depending on the application, "Evaluation" can be any of a literal opinion word (e.g., "reasonable"), a polarity (positive/negative), or a value for multipoint scale rating.

Given those standardized units extracted from a corpus, it is easy to overview the distribution of values for each element or a combination of elements. For example, those who intend to improve the quality of hotel A may investigate representative values for "Aspect" in the units satisfying "Target=hotel A & Polarity=negative", while those who look for accommodation may collect the opinion units for one or more candidate hotels and investigate the distribution of values for "Polarity" on an aspect-by-aspect basis.

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However, in the above example (1), the evaluation for hotel A ("a reasonable price") is valid for "if you take a family trip with small kids", and it is not clear whether this evaluation is valid irrespective of the condition. For example, the price may not be reasonable for a single customer intending for business purposes. In this paper, we shall call such a condition "condition for opinion (CFO)". The existing methods for opinion mining, which do not consider if a target opinion is conditional, potentially overestimate or underestimate the utility of hotel A and consequently decrease the quality of opinion mining. We manually analyzed the first 7 000 sentences in review text on an online travel site, and found that 2 272 sentences are opinions of which 630 opinions are conditional and thus the result for an existing method includes up to 28% errors.

To alleviate the above problem, a passive solution is detecting conditional opinions, if any, and isolating them from target opinions. As a result, we can avoid potential errors as much as possible but the coverage is decreased. An active solution is identifying the span of each CFO in conditional opinions and classify them according to semantic categories, such as purpose, so that finer-grained opinion mining can be realized. For example, the distribution of positive and negative opinions can be available on a category-by-category basis.

Additionally, it is useful to identify user-restrictive or user-dependent CFOs (U-CFOs) from general CFOs so that users can selectively read opinions associated with their attributes, purposes, and situations. For example, those who travel alone for business purposes do not need to read reviews specific to "traveling with small kids". In other words, the identification for U-CFOs facilitates predicting the review helpfulness [14], [16].

Motivated by the above discussion, in this paper we propose a method to extract pairs of a condition and opinion unit from online reviews, in which a condition is either a CFO or U-CFO depending on the application. However, we leave classification of CFOs as future work.

We target several types of CFOs including conditional clauses as in example (1). The remaining types are shown below, in which the CFO and opinion word are in bold and italic faces, respectively.

(2) **My mother** *recommends* special dishes. (Opinion holder)
(3) Hotel A offers a *reasonable* price **for taking a family trip with small kids** (Target)
(4) Hotel A offers a *reasonable* price **because we take a family trip with small kids** (Reason)
(5) The room *spacious* **for the price**. (Comparative)
(6) Hotel A offers the *best* location **in center of a capital** (Superlative)

Section 2 discusses the literature related to our research. Sections 3 and 4 proposes a method for extracting condition-opinion relations and evaluates its effectiveness, respectively, followed by the conclusion in Section 5.

2. Related work

As described in Section 1, the fundamental methods for opinion mining include opinion extraction, which identifies elements for opinion units (i.e., target, aspect, evaluation, holder, and time) [3], [4], [9], [18], [19], [20], and opinion classification, which determines the non-literal evaluation of each opinion unit based on bipolar categories (i.e., positive and negative) [3], [12] or multipoint scale categories [2], [13]. We rely on these existing methods to extract opinion units from reviews. However, unlike our research, none of these methods intends to determine whether or not an opinion is conditional and to extract their condition, if any.

Narayanan et al. [15] proposed a method for sentiment analysis of conditional sentences. They intended to determine whether a conditional sentence as a whole includes an opinion about an object. However, we target both conditional and non-conditional sentences, and determine whether the input sentence includes both an opinion and its corresponding condition. To explain this difference more clearly, we divide conditional sentences into three categories and show an example sentence for each category as follows.

(1) I think hotel A offers a reasonable price if you take family trip with small kids.
(7) Hotel A would not have survived if the price was not reasonable.
(8) If you are looking for a hotel with a reasonable price, stay at hotel A.

In example (1), which is identical to the one in Section 1, the evaluation for hotel A in the main clause is conditional on the conditional clause. However, example (7) is not associated with evaluation for hotel A, whereas the opinion word "reasonable" is included. In example (8), the entire sentence states an unconditional positive evaluation about the price for hotel A.

In contrast, as described in Section 1, we focus on the case for example (1) and the case where the opinion is expressed in a non-conditional sentence, such as a paraphrase of a conditional sentence as in example (3) and the CFO is described as a reason as in example (4). Thus, our focus is different from that of Narayanan et al. [15].

Kim and Hovy [5] proposed a method to identify a reason for the evaluation in an opinion, such as "the service was terrible because the staff was rude". However, their purpose is to identify grounds that justify the evaluation and they do not distinguish U-CFO from other CFO. Thus, their purpose is different from ours.

O'Mahony and Smyth [16] proposed a method to predict the helpfulness for product reviews irrespective of the user. In other words, unlike our method, their method cannot recommend reviews based on user-related attributes. Moghaddam et al. [14] used collaborative filtering for the same task. An advantage of collaborative filtering is its applicability to item types whose content is usually difficult to analyze, such as videos. However, this advantage is overshadowed in recommending reviews, in which useful features, such as U-CFOs, can be obtained by means of opinion mining.

3. Proposed method

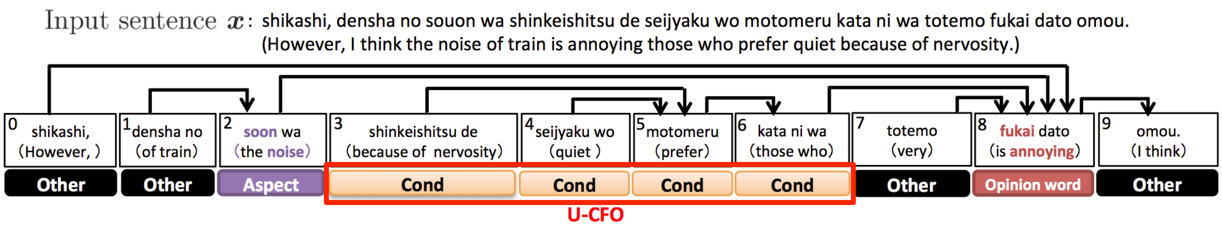
The task in this paper is to extract condition-opinion relations from reviews in Japanese. Currently, we assume that an opinion unit and its corresponding CFO are in the same sentence, and thus perform the extraction on a sentence-by-sentence basis. Given a sentence in reviews, we first search for an opinion unit, and if found, we also search for its corresponding CFO. Because in the first process we rely on an existing method for the opinion extraction, in this paper we focus only on the extraction for CFOs.

As shown in example sentences for Section 1, each CFO can be a phrase or clause and thus their length and structure are not standardized. We model the extraction for CFO as the BIO chunking, which labels each token in a sentence as being the beginning (B), inside (I), or outside (O) of a span of interest. However, because there is no specific characteristics at the beginning of CFO in Japanese, we do not use the "B" label. We regard Japanese *bunsetsu* phrases, which consist of a content word and one or more postpositional particles, as tokens, and extract a sequence of I-phrases as a CFO. However, words and phrases in an opinion unit, such as aspects and opinion words, are always classified into O-phrases. For the enhanced readability, we use terms "cond" and "other" instead of "I" and "O", respectively.

Given an input sequence of *bunsetsu* phrases, $\boldsymbol{x} = x_1 \dots x_n$, in principle our task is to predict a sequence of labels, $\boldsymbol{y} = y_1 \dots y_n$, where $y_i \in \{Cond, Other, Target, Aspect, Opinion\ word\}$. However, because an opinion unit in an input sentence has been identified in advance, in practice the task is a binary classification with respect to $y_i \in \{Cond, Other\}$. We use Conditional Random Fields (CRF) [7] to train a classifier for categorizing each *bunsetsu* phrase into "cond" or "other". We use a combination of unigram and bigram models and calculated the conditional probability $p(\boldsymbol{y}|\boldsymbol{x})$ for linear-chain CRF by Equation (1).

$$p(\boldsymbol{y}|\boldsymbol{x}) = \frac{1}{Z_{\boldsymbol{x}}} \exp\Big(\sum_{i,k} \lambda_k \cdot f_k(y_i, \boldsymbol{x}) + \sum_{i,k} \mu_k \cdot g_k(y_{i-1}, y_i, \boldsymbol{x})\Big) \quad (1)$$

Here, $Z_{\boldsymbol{x}}$ denotes a normalization factor, and f_k and g_k denote feature functions for unigram and bigram models, respectively. While in the unigram model y_i depends on either $x_{i-1,v}$ or $x_{i,v}$, in the bigram model y_i depends on either a combination of $x_{i,v}$ and y_{i-1} or that of $x_{i-1,v}$ and y_{i-1}. Here, $x_{i,v}$ denotes a feature value



F1	1	2	aspect	3	3	2	1	1	opinion word	-1
F2	8	7	aspect	5	4	1	2	1	opinion word	-1
F3	1	0	aspect	1	1	1	1	1	opinion word	1
F4	2	1	aspect	-1	-1	-1	-1	-1	opinion word	-1
F5	7	5	aspect	2	1	1	1	0	opinion word	0
F6	0	0	aspect	0	0	0	0	0	opinion word	0
F7	nothing	nothing	aspect	nothing	nothing	nothing	ni wa	nothing	opinion word	nothing
F8	nothing	nothing	aspect	nothing	nothing	nothing	topic	nothing	opinion word	nothing
F9	nothing	nothing	aspect	ni wa	ni wa	ni wa	ni wa	nothing	opinion word	nothing
F10	nothing	nothing	aspect	topic	topic	topic	topic	nothing	opinion word	nothing
F11	nothing	densha	aspect	shinkeishitsu	nothing	nothing	kata	nothing	opinion word	nothing
F12	0	1	aspect	1	0	0	1	0	opinion word	0
F13	conjunction	noun	aspect	noun	noun	verb	noun	adverb	opinion word	verb

Fig. 1 Example of Japanese sentence and the feature value for each constituent *bunsetsu* phrase.

for x_i. Feature functions are produced for any possible patterns of the values for the valuables used ($x_{i,v}$, y_{i-1}, and y_i in f_k), and take 1 if the corresponding pattern is true or otherwise 0. We use the following four patterns for feature functions.

- P1: unigram $x_{i,v}$
- P2: unigram $x_{i-1,v}$
- P3: bigram y_{i-1} $x_{i,v}$
- P4: bigram y_{i-1} $x_{i-1,v}$

Figure 1 depicts an example input sentence and information related to its constituent *bunsetsu* phrases. In the upper part of Figure 1, a rectangle and an arrow denote a phrase and a syntactic dependency between two phrases, respectively, and in each phrase we show Japanese words based on the Hepburn system and their English translations in parentheses.

As in Figure 1, CFO has the following characteristics, on which we model it based.

(a) CFO tends to syntactically modify an opinion word while does not for aspect
(b) CFO includes a clue expression in the tail phrase
(c) CFO has phrases whose head is skewed to specific part of speech

Also, only U-CFO has the following characteristics, on which we model it based.

(d) For opinion holder as in example (2), U-CFO tends to appear in beginning of sentence
(e) U-CFO includes an expression associated with factors of user restriction defined in Section 1

We propose thirteen features to model CFO and U-CFO. In lower part of Figure 1, for each phrase we show the values of the thirteen features F1–F13 proposed below. These features are used for any of above five characteristics. F1–F5, F7–F10 and F13 are associated with characteristic (a), (b) and (c), respectively. Also, F6 and F11–F12 are related with characteristic (d) and (e), respectively.

F1: Dependency distance to opinion word

CFO, which affects the evaluation in that opinion, usually syntactically modifies the opinion word. Thus, there should be a pass of dependencies between a cond-phrase and the opinion word, and a phrase that leads to the opinion word via a smaller number of dependency arrows is more likely to be a cond-phrase. We use the dependency distance (i.e., the number of dependencies) between a phrase in question and the opinion word as the value for feature F1. The value for a phrase is -1 if there is no pass between that phrase and the opinion word. We use "CaboCha" [6] for dependency analysis purposes.

F2: Phrase distance to opinion word

F1 is not robust against errors of the dependency analysis. To alleviate this problem, we approximate the dependency distance by a phrase distance. In practice, we use the difference between the phrase IDs between a phrase in question and the opinion word as the value for feature F2. If the opinion word consists of more than one phrase, we take the minimum difference. Because in Japanese a modifier is usually followed by its modifying object, a phrase with a negative value for feature F2 is usually an other-phrase. For example, in Figure 1 the last phrase, which cannot be a modifier for the opinion word, is an other-phrase.

F3: Dependency pass to aspect

Because a CFO rarely modifies an aspect other than the opinion word, for the value of feature F3 we take 0 if there is a pass of dependencies between a phrase in question and an aspect or otherwise 1.

F4: Phrase distance to aspect

As with F1, F3 is not robust against errors of the dependency analysis. We estimate the value of F4 by a phrase distance between a phrase including aspect and a phrase in question.

F5: Difference between values for features F2 and F1

CFO usually consists of a sequence of cond-phrases, in which each phrase modifies the next phrase, as in Figure 1. Thus, there is a tendency that as the values of F1 and F2 for a phrase becomes smaller, that phrase is more likely to be a cond-phrase. In Figure 1, #4–#7 take smaller values while the feature values for other-phrase #1 and #2 take 7, 5 respectively, which are bigger values.

F6: Beginning of sentence

The subject of an opinion sentence is often its CFO because the evaluation is valid only from a perspective of that person. For example, in "my daughter was pleased with cartoons in the room" the positive evaluation is restricted by the daughter's perspective. Thus, the value of F6 takes 1 for the first phrase in a sentence, excluding a conjunction, or otherwise 0.

F7: Clue expressions

Because a CFO often ends with one or more specific particles and auxiliary verbs, we use the existence (1/0) of those clue expressions in a phrase as the value for feature F7. We use words registered in a dictionary of Japanese functional expressions "Tsutsuji" [11] as the clue expressions. Table 1 shows the examples of entries for Tsutsuji. Each entry is represented as hierarchy structure with nine abstraction levels. We firstly collect words in the nineteen categories appropriate for our purpose using "Meaning categories" and "Surface forms". And then we group "Head word" and its corresponding surface forms as same expressions by using L1 and L9 in Table 1. For ID 1 and ID 3 in Table 1, "to sure ba" and "nde' are grouped into "to suru to" and "node", respectively. As a result, we collected 94 groups consisting of 388 words such as "ba (if)" and "ni (for)".

F8: Semantic categories for clue expressions

There is a possibility that F7 may not work well for specific expressions because of low frequency in corpus. To alleviate this problem, we abstract F7 according to the semantic category of Tsutsuji. In Table 1, "to suru to" and "ba" have the same feature values "resultative condition". If a clue expression belongs to a number of semantic categories as shown in "ni" of Table 1, the feature value is a set of these categories.

F9: Dependency pass to phrase including clue expression

As described in F7 above, the last phrase in a CFO often includes one or more clue expressions. In addition, a CFO often consists of more than one phrase. Given these, a phrase that modifies a phrase containing a clue expression is also likely to be a cond-phrase. We use the existence (1/0) of a pass of dependencies between a phrase in question and a phrase containing a clue expression.

F10: Dependency pass to phrase including clue expression

As with F8, we abstract F9 based on the semantic categories of Tsutsuji and employ these categories as feature F10.

F11: User-restrictive expressions

We use expressions specific for U-CFO as feature value to model characteristic (e). For example, "business" and "sightseeing" can be frequently included in U-CFO for purpose. We try to make a dictionary of user-restrictive expressions by the following unsupervised method using plan title information, which means meta-data assigned to each review.

(1) Regular expression "(| hito | mono | kata) ni (| wa | mo) osusume" is applied to each plan title. This one corresponds to the expression "recommend this hotel to those who" in English. And then, our method extracts the sentences which matched the regular expression.
(2) Morphological analysis and division by bunsetsu-phrase are performed and then our method extracts a phrase between rearmost symbol and "ni" of the regular expression.
(3) For each bunsetsu-phrase, consecutive independent words are registered into the dictionary.

Table 1 Example of entries for Tsutsuji

	Abstraction levels			
Entry ID	L1: Head word	L2: Meaning categories	...	L9: Surface forms
1	to suru to	resultative condition	...	to sure ba
2	ba		...	ba
3	node	reason	...	nde
4	ni	purpose	...	ni
5		target	...	

For example, given the sentence "[kinen plan] tabako no kemuri ga nigatena kata ni osusume ([No smoking plan] recommend to those who dislike cigarette smoke)" derived from the regular expression, our method registers four expressions "tabako (cigarette)", "kemuri (smoke)", "nigatena (dislike)" and "kata (those who)" into the dictionary. As a result, we collected 382 expressions associated with U-CFO.

F12: Existence of user-restrictive expressions

Because F11 uses surface form, there is a possibility that the feature may not work well for specific expressions due to low frequency in corpus. To alleviate this problem, we use the existence of user-restrictive expression as feature 12.

F13: Part of speech for head

The likelihood that a phrase in question is a cond-phrases partially depends on the part of speech for the head in that phrase. For example, in Figure 1, phrase #7, whose head is an adverb to emphasize the negative evaluation, is an other-phrase. In contrast, a phrase whose head is a noun or verb tends to be a cond-phrase.

4. Experiments

To evaluate the effectiveness of our method, we used the Rakuten Travel data*1, which consists of 348 564 reviews for hotels in Japanese. From this data set, we selected 580 reviews and manually identified elements for opinion units. As a result, 3 155 sentences remained, which comprise our corpus. Because our focus is the extraction of CFOs, we used the manually identified opinion elements as output of an automatic method for opinion extraction.

Given the above corpus, two annotators independently identified one or more CFOs for each opinion unit. For both tasks, the Kappa value for the inter-annotator agreement was 0.87, indicating strong agreement. We show the details of corpus in Table 2. Using this corpus, we performed 10-fold cross-validation and compared different methods from different perspectives.

We used "detection" and "identification", which denote different criteria for the correctness of methods under evaluation. While in the detection each method was requested to only detect whether or not a test sentence includes CFO, in the identification each method was also requested to identify the span of each

*1 http://www.nii.ac.jp/cscenter/idr/rakuten/rakuten.html

CFO. Also, we used different evaluation measures, namely precision (P), recall (R), F-measure (F) and accuracy (A).

Rule-based method and SVM-based method are used as comparative methods. Rule-based method first identifies a *bunsetsu* phrase whose dependency distance to the opinion word is 1 and including clue expression (see Section 3), and also identifies all phrases from which there is a dependency path to the above phrase as a CFO. For example, in Figure 1 because phrase #6 includes clue expression, the method extracts a sequence of phrases #3–#6 as a CFO. These rules are based on features F1, F7 and F9. For U-CFO extraction task, other rule is applied to a sequences of extracted cond-phrases. The rule is that if extracted CFO includes one or more user-restrictive expressions, the method regards the CFO as U-CFO, or otherwise other-phrase. SVM used the thirteen features F1–F13 described in Section 3. We used LIBSVM [1] to train a classifier. Our method trained CRF classifier using thirteen features and four patterns for feature functions. We used CRF++[*2] to construct classifier for each phrase and regularized the parameters using L2-norm.

Figure 2 shows the relations between regularization parameter and F-measure for identification. The legends "Rule", "SVM" and "CRF" denote a rule-based method, SVM-based method, our method, respectively. "Rule" has constant values because the method include no regularization parameter. CRF hardly changed over the parameter values while "SVM" significantly varied depending on its values. Also, "CRF" outperformed "Rule" regardless of any parameter values. Table 3 shows the results for optimal regularization parameter. Looking at Table 3, one can see that "CRF" outperformed the comparative methods in terms of F-measure and accuracy for detection and identification. We used the two-tailed paired t-test for statistical testing and found that the differences of each comparative method and "CRF" in F-measure and accuracy were statistically significant at the 1% level, irrespective of whether the detection or identification for both tasks.

Figure 3 shows the effectiveness of proposed features for identification. The horizontal axis "w/o X" denotes a method without feature X . The vertical axis denotes a ratio of our method to each method. For example, if a method without feature X takes less than 1 for value of vertical axis, the feature X is effective for extracting CFOs. Looking at Fig. 3, one can see that our complete method outperformed any variation of our method in terms of F-measure. Thus, we conclude that each of our thirteen features was independently effective for extracting CFO and U-CFO in review sentences and that when used together the improvement was even greater. The same tendency was a true for detection.

For identification of U-CFO extraction task, we analyze errors by side effect of feature X that "CRF" failed a extraction of U-CFO while a method w/o feature X did. The total number of errors is 253 including duplicate errors. As space is limited, we have concentrated on the representative errors resulting from each characteristic and paid scant attention to remaining errors. Outputs are described by each example and double underline and single underline denote false positive and false negative, respectively. Also, slash symbol denotes bunsetsu-phrase delimiter.

*2 http://crfpp.googlecode.com/svn/trunk/doc/index.html

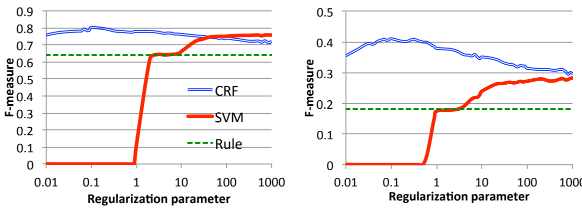
Table 2 Details of our corpus

(a)Sentence unit

		CFO extraction	U-CFO extraction
Opinion sentence	w/ CFO	799	526
	w/o CFO	1257	1530
Non opinion sentence		1 099	
#.total		3 155	

(b)Phrase unit

		CFO extraction	U-CFO extraction
#.cond-phrase		2 250	1 312
#.other-phrase		16 585	17 523
Opinion unit	#.opinion word	3 764	
	#.aspect	3 406	
	#.target	132	
#.total		26 137	



(a) CFO extraction (b) U-CFO extraction

Fig. 2 Relations between regularization parameter and F-measure

Characteristic (a): 114 errors

Output: "sutaffu no (Staff) / kata no (The people of) / taio mo (supports) / subarashiku, (have great) / chikaku ni wa (near the hotel,) / Minamigaoka bokujyo mo (Minamigaoka stock farm) / ari (because there is) / ro ken nitotte wa (for a senior dog.) / chodo (the hotel was reasonable) / yoi (the hotel was reasnable) / rokeshon desu. (location)" (The people of staff have great supports and because there is Minamigaoka stock farm near the hotel, the hotel was reasonable location for a senior dog.)

As mentioned in Section 3, CFO tends to modify an opinion word. However, because "ro ken nitotte wa" did not modify the opinion word "chodo yoi (reasonable)" due to an error of dependency analysis, this error occurred.

Characteristic (b): 68 errors

Output: "kojin teki ni wa (Personally speaking,) / kobutsu no (which is my favorite food) / chizu ga (the cheese,) / sushurui at ta no ga (because there were several kinds of cheese.) / ureshikat ta desu ne. (I was pleased with)" (Personally speaking, I was pleased with the cheese, which is my favorite food because there were several kinds of cheese.)

Clue expression "ni wa" was a expression specific for U-CFO. Thus, because such expression is included in the phrase, this error was brought about.

Characteristic (c): 35 errors

Output: "heya mo (the room) / yukkuri (good) / yasumu ni wa (for taking a rest) / manzokuna (satisfied) / hirosa de (Because has largeness) / yokat ta desu. (it was good.)" (Because the room has satisfied largeness for taking a good rest, it was good.)

The error is brought about because the phrase "yukkuri", whose part of speech is an adverb, tend to be an other-phrase.

Characteristic (d): 7 errors

Output: "kabe nado no (the wall and so on.) / soji wo (the cleaning) / shi te (do) / itadakeru to (it if) / arigatai kamo. (I would appreciate)" (I would appreciate it if you clean the wall

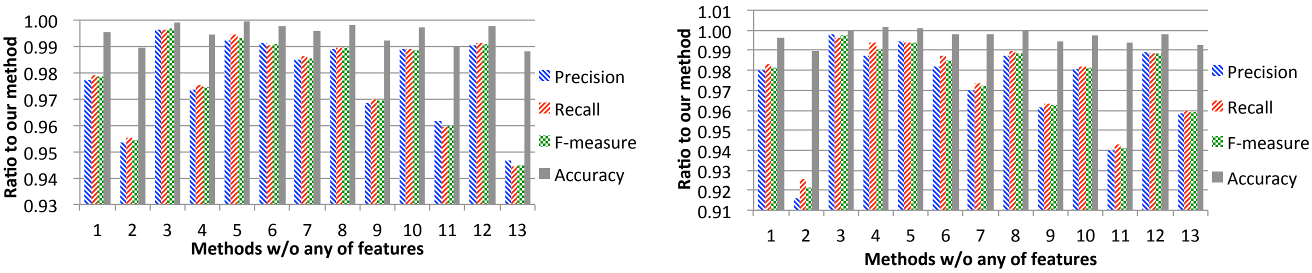
Table 3 Results of different methods for optimal regularization parameter.

(a) CFO Extraction

	Detection				Identification			
	P	R	F	A	P	R	F	A
Rule	.560	.751	.640	.789	.302	.331	.310	.702
SVM	.786	.736	.758	.881	.435	.442	.433	..823
CRF	.800	.807	.802	.901	.570	.567	.565	.876

(b) U-CFO Extraction

	Detection				Identification			
	P	R	F	A	P	R	F	A
Rule	.493	.464	.477	.831	.184	.183	.181	.794
SVM	.522	.787	.627	.845	.281	.289	.282	.787
CRF	.689	.674	.679	.894	.419	.410	.411	.866



(a)CFO extraction (b)U-CFO extraction

Fig. 3 Effectiveness of proposed features for identification

and so on.) Beginning of sentence is not always subject of an opinion sentence. We need to a method to distinguish whether or not beginning of phrase is a subject.

Characteristic (e): 29 errors

Output: "shutcho no (business) / sai ni (for) / riyo shi mashi ta ga, (I used this hotel, but) / dorinku ya (such as drink and) / amenithi no (amenity.) / sabisu ga (services) / subarashii to (this hotel have great) / omoi mashi ta. (I thought)" (I used this hotel for business, but I thought this hotel have great services such as drink and amenity.)

The initial phrase includes user-restrictive expression "shutcho", which positively works for U-CFO. Thus, because the expression is included in the phrase, the error was brought about.

5. Conclusion

Although a number of methods have been proposed to search an opinionated corpus for opinion units, only few attempts have so far been made at addressing cases where the validity of an evaluation is restricted on a condition in the source text. We proposed a method to identify such conditions from sentences including opinion units. Our method performs sequence labeling to determine whether each phrase is a constituent of CFOs. We proposed thirteen features associated with lexical and syntactic information for Japanese, and show their effectiveness using reviews for hotels. The contribution of this paper is introducing the notion of CFOs, which is language-independent, proposing a method to extract condition-opinion relations from opinionated corpora, and giving an insight into its potential applications in opinion mining.

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