



New feature weighting approaches for speech-act classification[☆]

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ABSTRACT

Speech-act classification is essential to generation and understanding of utterances within a natural language dialogue system since the speech-act of an utterance is closely tied to a user intention. The binary feature weighting scheme has mainly been used for speech-act classification because traditional feature weighting schemes such as *tf.idf* are not effective in speech-act classification due to the short length of utterances. This paper studies two effective feature weighting schemes using the category distributions of features: (1) the first one exploits the entropy of whole category distributions and (2) the second one the log-odds ratio of positive and negative category distributions. As a result, the proposed schemes show significant improvement on SVM and *k*-NN classifiers in our experiments.

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1. Introduction

A dialogue system is a software program that enables a user to interact with a computer using a natural language [5]. Since an essential task of the dialogue system is to understand what the user says, it must be able to determine the user's intention indicated in the user's utterance. A speech-act is a linguistic action and implies the user's intention. Therefore, the dialogue system must identify the speech-act of user's utterance. Although researchers have developed many techniques for the speech-act classification, they have mainly used the binary feature weighting scheme because it is simpler but more effective than other schemes such as *tf* (traditional term frequency), *idf* (inverse document frequency) and *tf.idf* [11,13,14]. An utterance is usually much shorter than a document, and it means that the utterance has only the small number of features. For example, as two major factors of traditional *tf.idf*, *tf* is the number of term occurrence in a document and *idf* (document frequency) is the number of documents that a term occurs in a collection. In particular, since *tf* rarely becomes more than 2 in an utterance due to the short length of the utterance, terms with more than 2 frequencies make the distribution of term weights biased and it causes the poor performance of speech-act classification.

This paper explores to find more effective feature weighting schemes for the cases of classification with the small number of features such as speech-act classification, and proposes two weighting schemes that are based on feature distributions through categories. (1) One feature weighting scheme applies the entropy concept to

estimate the feature importance using all category distributions of each feature, and (2) the other scheme utilizes the ratio of positive and negative category distributions to estimate the feature importance of each category. In the experiments, these weighting schemes achieved better performances than the binary feature weighting, *tf*, *idf* and *tf.idf* schemes.

The remainder of the paper is organized as follows. Section 2 describes the related work. Section 3 explains two proposed feature weighting schemes in detail and Section 4 is devoted to the analysis of our experimental results. The final section states the conclusions and future work.

2. Related work

Some previous studies on Korean speech-act classification have been based on rules extracted from a tagged dialogue corpus [3,8], while others have been based on statistical models learned from a tagged dialogue corpus [1,5,6,9].

The initial speech-act classification studies used rules that are extracted from a tagged dialogue corpus such as linguistic rules and dialogue grammar. Lee [8] developed a two-step speech-act classification system using linguistic rules and dialogue flow diagrams; the first step in this model classifies surface speech acts, whereas the second step classifies deep speech acts. Choi et al. [1] proposed a statistical dialogue classification model that performs both speech-act classification and discourse structure analysis using the maximum entropy model (MEM). This model automatically acquired discourse knowledge from a discourse-tagged corpus to resolve ambiguities. Lee and Seo [9] classified speech acts by a bigram hidden Markov model (HMM). Kim et al. [6] presented a speech-act classification model to utilize contextual information by adjacency pairs and a discourse stack, and Kang et al. [5] proposed to use a hierarchical structure to

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Table 1
Example dialogue annotated with speech-acts.

Speaker	Utterance	Speech-act
Clerk	안녕하세요. 서울호텔입니다. (Hello. This is Seoul Hotel.)	Introducing-oneself
User	가족이 4명인데요. (I have four people in my family.)	Inform
User	방을 하나 예약하려고요. (I want to reserve one room.)	Request
Clerk	성함이 어떻게 되세요? (What is your name?)	Ask-ref
User	내 이름은 홍길동입니다. (My name is Kildong Hong.)	Response

improve the speech-act classification. The both of these studies exploited SVM as a classifier, and they achieved better performances than other classification models. Feature weighting of their SVM classifiers is based on the binary weighting scheme because it is more effective than other feature weighting schemes.

3. Proposed feature weighting schemes for speech-act classification

Traditional feature weighting schemes of document classification are based on tf , idf and $tf.idf$ [11,13,14]. They are calculated by using the unit of a document. That is, tf is the number of occurrences of a term in a document and idf is the number of documents that a term occurs in a collection. In speech-act classification, the unit of an utterance has to be used instead of one of a document. Since the input of speech-act classification is only one utterance, its length is very short and it contains much smaller number of features than a document does. It causes a problem that tf , idf and $tf.idf$ do not work well for speech-act classification.

This study explores new feature weighting schemes with category distributions to improve biased information from the short length of utterances; here, category means speech-act. The new schemes are expected to elevate the speech-act classification because they exploit the probabilistic distribution on a category that is larger than an utterance. Two different schemes are proposed in this study. One is based on entropy of probabilistic distributions of each feature on category and the other is on the distribution difference from a positive category to negative categories.

3.1. Examples of dialogue annotated with speech-acts and features extracted from an utterance

Table 1 shows an example dialogue between a clerk and a user in a hotel booking domain.

In general, speech-act analysis has exploited multiple knowledge sources in the form of lexical, syntactic, prosodic and contextual information [12]. These sources have typically been modeled using various stochastic models. Many previous studies on speech-act classification have applied syntactic patterns as intra-utterance features. Although a syntactic pattern can represent the syntactic and semantic features of utterances, previous studies have found that syntactic patterns from a conventional syntactic parser are incomplete owing to errors in the syntactic analysis and are dependent on time-consuming tasks and manually generated knowledge [9, 15]. To overcome this problem, a lexical feature extraction method is developed to use only the analysis results from a morphological analyzer so that our method becomes more robust to errors propagated from basic language analysis. A morphological analyzer generally creates fewer errors than a syntactic analyzer because the output of the morphological analyzer becomes the input of the syntactic one. We assume that content words and Part-Of-Speech (POS) tag sequences in an utterance can provide very effective information for detecting the speech act of that

Table 2
Example of lexical features.

Input utterance	내 이름은 홍길동입니다. (My name is Gildong Hong.)
Morphological analysis (morpheme/POS tag ^a)	나/np 의/j 이름/ncn 은/j 홍길동/nq 이/jcp 버니다/ef .s. (My/np name/ncn is/jcp Gildong Hong/nq .s.)
Content words features	나/np 이름/ncn 홍길동/nq .s. (My/np name/ncn Gildong Hong/nq .s.)
POS-bigram features	np-j j-ncn ncn-j j-nq nq-jcp jcp-ef ef-s.

^a The Korean POS tags in this example are as follows:

Noun: *np* (pronoun), *ncn* (common noun), *nq* (proper noun).

Particle: *j* (case particle), *jcp* (predicative case particle).

Ending: *ef* (final ending).

Symbol: *s.* (sentence closer).

utterance. Based on this assumption, we extract informative features for speech-act analysis using only a morphological analyzer. Lexical features include content words annotated with POS tags and POS bigrams of all words in an utterance (see Table 2). Content words generally have noun, verb, adjective, adverb and symbol (punctuation/exclamation/question marks) POS tags. For example, the lexical features of the example utterance in Table 2 consist of four content words and seven POS bigrams. These features represent the linguistic function and meaning of an utterance. This lexical-based classification has demonstrated better and more robust performance than syntactic-based classification for speech-act analysis, because morphological analysis results have fewer errors than a syntactic parser in most cases [5,6]. Therefore, we also employed the same lexical features in this study.

Table 2 shows an example of lexical feature extraction using a morphological analyzer.

Eventually, the final feature set is composed of these lexical features and the speech-act of the previous utterance.

3.2. Estimation of feature probabilistic distribution for categories

The expected likelihood estimator [10,11] is used for the estimates of the probability of a feature in positive and negative categories as follows:

$$P(f_i|c_j) = \frac{N(f_i, c_j) + 0.5}{\sum_{t=1}^{|V|} N(f_t, c_j) + 0.5 \times |V|}, \quad (1)$$

$$P(f_i|\bar{c}_j) = \frac{N(f_i, \bar{c}_j) + 0.5}{\sum_{t=1}^{|V|} N(f_t, \bar{c}_j) + 0.5 \times |V|}, \quad (2)$$

where $N(f_i, c_j)$ is the count of the number of times that feature f_i occurs in category, c_j , $|V|$ is a vocabulary size and \bar{c}_j is the negative categories of a positive category, c_j . Herein, 0.5 is a smoothing factor and it can be viewed as a linear interpolation between the maximum likelihood estimation and a uniform prior. This guarantees no zero probabilities yet retains the relative likelihoods for the frequently occurring values. In multiclass classification, a single text classifier is generally trained per a category to distinguish that category (positive category) from all other categories (negative categories). This strategy is called one-versus-all or one-versus-rest [2].

3.3. Entropy of probabilistic distributions

The first proposed feature weighting scheme is based on the Entropy value of Category Probabilities (ECP) for each feature. Since entropy is a measure of uncertainty in a feature for a collection, features with a high entropy value are regarded as bad features for speech-act classification. Therefore, the new feature weighting scheme is developed by following an idf form. That is, the weight of a feature

is calculated by dividing the maximum entropy value, which is on a uniform distribution, by an entropy value calculated on category probability distributions.

$$\text{ECP}(f_i) = \frac{\text{MaxEntropy}}{-\sum_{j=1}^{|C|} P(c_j|f_i) \log P(c_j|f_i)}, \quad (3)$$

$$\begin{aligned} \text{MaxEntropy} &= -\sum_{j=1}^{|C|} P_{\text{uniform}}(c_j) \log P_{\text{uniform}}(c_j) \\ &= -\sum_{j=1}^{|C|} \frac{1}{|C|} \log \frac{1}{|C|} = \log |C|, \end{aligned} \quad (4)$$

where $|C|$ is the number of categories, $P(c_j|f_i) = P(f_i|c_j)P(c_j)/\sum_{t=1}^{|C|} P(f_i|c_t)P(c_t) \approx P(f_i|c_j)/\sum_{t=1}^{|C|} P(f_i|c_t)$ by assuming that $P(c_j)$ is a uniform distribution and $P_{\text{uniform}}(c_j) = 1/|C|$ is a category probability on a uniform distribution.

Since this scheme is based on category distributions, it can make better unbiased feature weighting than *idf*, which is based on document (*utterance*) distribution.

3.4. Log-odds ratio of positive and negative categories

The second feature weighting scheme uses the log-odds ratio (LOR) of probability of positive category (Eq. (1)) and one of negative categories (Eq. (2)). This scheme provides us a method to utilize a discriminating power between positive category and negative categories. Although supervised-learning based speech-act classification is learned from labeled training data with category information, the previous feature weighting schemes, including *binary*, *tf*, *idf* and *tf.idf*, do not use any category information. Thus, we believe that it is more effective to distinguish positive examples from negative examples on this proposed scheme by the following equation.

$$\text{LOR}(f_i, c_j) = \log \left(\frac{P(f_i|c_j)}{P(f_i|\bar{c}_j)} + \alpha \right), \quad (5)$$

where α is a constant value of the base of this logarithmic operation, e , because it makes a logarithmic value a non-negative one; the non-negative weight has commonly been used for text classification as well as speech-act classification, and speech-act classification with non-negative weights achieved better performance than one with real value weights in our experiments.

A new representation method for a test utterance is required in this scheme because a test utterance does not have any assigned category, c_j . That is, the weight of a feature can be calculated by Eq. (5) just when its positive category, c_j , and negative categories, \bar{c}_j , are fixed. Thus a test utterance is first represented as $|C|$ different vectors by assuming that the test utterance has one category, c_j , of $|C|$ categories, and then it has to be represented as one representative vector using those $|C|$ represented vectors. Eventually, the weight of a feature is chosen by the maximum value among $|C|$ feature weights of the $|C|$ vectors.

$$\text{TW}(f_i) = \max_{c_j} \text{LOR}(f_i, c_j), \quad (6)$$

where $\text{TW}(f_i)$ denotes the final feature weight of test utterances.

4. Experiments

4.1. Data sets and evaluation measures

Two different dialogue corpora¹ were used for evaluating the proposed feature weighting schemes to various dialogue environments. Both of these corpora are trained and tested separately. The first one (RES) is collected from real fields including hotel, airline and tour reservations. This corpus consists of 528 dialogues (19.5 utterances per a dialogue and 16 speech acts) and 10,281 utterances (training

data (8349) and test data (1932)) [1,5,9]. Each utterance in the dialogues was manually annotated with a speaker and a speech act. The second corpus (SM-11) is collected from various domains of schedule management and consists of different speech-acts from the first corpus. This corpus is composed of 954 dialogues (22.3 utterances per a dialogue and 11 speech acts) and 21,310 utterances (training data (17,054) and test data (4256)). In addition, a new version of corpus is created from the second data (SM-11) because it has three very rare categories. After they are removed from SM-11, the new corpus is named SM-8 in the experiments.

As evaluation measures, precision, recall and F_1 -score are used in the experimental environment. F_1 -score is given in Eq. (7) and is the harmonic mean of the precision (Eq. (8)) and the recall (Eq. (9)).

$$F_1\text{-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (7)$$

$$\text{precision} = \frac{\text{no. of true positive speech} - \text{acts}}{\text{no. of test outcome positive speech} - \text{acts}} \quad (8)$$

$$\text{recall} = \frac{\text{no. of true positive speech} - \text{acts}}{\text{no. of condition positive speech} - \text{acts by gold standard}} \quad (9)$$

The SVM and k -NN classifiers were selected in our experiments because they are the state-of-the-art classifiers in text classification [4,7,14]. The conventional *binary*, *tf*, *idf* and *tf.idf* schemes were employed in the experiments for comparing with the proposed schemes. In the speech-act classification, term frequency (tf_{ij}) can be redefined as the number of occurrences of a feature (f_i) in an utterance (u_j) and document frequency (df_j) is also as the number of utterances in the collection that f_i occurs in. Therefore, each feature weighting scheme is calculated by the following Eqs. (10)–(13).

$$\text{binary}_{ij} = \begin{cases} 1 & \text{if } tf_{ij} \geq 1 \\ 0 & \text{if } tf_{ij} = 0 \end{cases}, \quad (10)$$

$$tf_{ij} = \begin{cases} tf_{ij} & \text{if } tf_{ij} \geq 1 \\ 0 & \text{if } tf_{ij} = 0 \end{cases}, \quad (11)$$

$$idf_{ij} = \begin{cases} \log \left(\frac{N}{df_j} \right) & \text{if } tf_{ij} \geq 1 \\ 0 & \text{if } tf_{ij} = 0 \end{cases}, \quad (12)$$

$$tf.idf_{ij} = \begin{cases} tf_{ij} \cdot \log \left(\frac{N}{df_j} \right) & \text{if } tf_{ij} \geq 1 \\ 0 & \text{if } tf_{ij} = 0 \end{cases}, \quad (13)$$

where N denotes the number of total utterances in the collection in Eqs. (12) and (13).

4.2. Comparison of conventional binary, tf, idf and tf.idf schemes

First of all, the traditional feature weighting schemes such as *binary*, *tf*, *idf* and *tf.idf* are compared in Table 3. The *binary* weighting scheme shows the best performances in all three types of data sets and both of classifiers.

4.3. Comparison of the proposed schemes, ECP, LOR and the binary scheme

Overall, ECP showed better performances than the binary scheme on all of the data sets and both of the classifiers, but LOR achieved a little lower performance than the binary scheme on SVM as shown in Table 4. We think it is caused by characteristics of the classifiers and weighting schemes. Whereas SVM tries to find a decision surface using the support vectors near the decision surface, k -NN does k nearest examples in the whole vector space. LOR has a larger range

¹ <http://islab.donga.ac.kr/KorSpeechActTestSets.htm>.

Table 3
Performance comparison of conventional schemes.

		SVM		k-NN	
		Micro-avg F1	Macro-avg F1	Micro-avg F1	Macro-avg F1
RES	Binary	85.72	75.84	79.82	71.41
	tf	85.3	75.6	78.01	69.15
	idf	85.41	75.77	77.34	69.46
	tf.idf	84.63	74.88	77.13	70.59
SM-8	Binary	94.31	88.94	90.8	85.17
	tf	94.17	88.48	90.52	84.77
	idf	94.09	88.34	89.42	84.46
	tf.idf	94.09	88.54	89.42	84.33
SM-11	Binary	94.1	73.27	90.34	61.42
	tf	94.00	73.00	90.01	60.9
	idf	94.08	73.24	89.38	61.29
	tf.idf	93.96	73.16	89.26	61.16

A boldface and italic numeral denotes the highest performance value.

Table 4
Performance comparison of the proposed schemes (ECP and LOR) and the binary scheme.

		SVM		k-NN	
		Micro-avg F1	Macro-avg F1	Micro-avg F1	Macro-avg F1
RES	Binary	85.72	75.84	79.82	71.41
	ECP	86.39	78.06	80.18	71.65
	LOR	85.15	76.71	82.3	74.49
SM-8	Binary	94.31	88.94	90.8	85.17
	ECP	94.78	89.43	91.63	86.14
	LOR	93.18	88.31	91.93	87.12
SM-11	Binary	94.1	73.27	90.34	61.42
	ECP	94.67	73.79	91.33	71.16
	LOR	93.04	72.78	91.7	71.99

A boldface and italic numeral denotes the highest performance value.

of feature weight values than ECP does, because LOR exploits the log-odds ratio of positive and negative categories and ECP does all the category distributions. Moreover, LOR requires a new representation method for a test utterance, Eq. (6). It makes that LOR is more sensitive to noise features than ECP.

Table 5 lists the performances of all categories in each data set. Significant tests were conducted between binary and the proposed schemes by Macro t -test [16]. As a result, all the improvements on

Table 6
Performance comparison of the proposed model and other models on the first data set, RES.

Classification model	Classifier	Micro-avg F1
Choi's model	MEM	83.57
Lee's model	HMM with decision tree	81.5
Kang's model	SVM	84.52
Proposed model	SVM	86.39

three data sets and two classifiers are statistically significant, $p < 0.05$. Especially, the differences of the k -NN classifier on RES and SM-11 are statistically significant, $p < 0.01$. This t -test is based on one-tailed paired t -test.

4.4. Comparison of the proposed scheme and other previous models in the first corpus, RES

The proposed scheme is compared with other previous speech-act classification results that used the same test data set, RES: Choi's model [1], Lee's model [9] and Kang's model [5]. We do not think that it can be a completely fair comparison between our proposed model and other models. Although our model uses just an improved term weighting scheme, other studies does additional information such as results from decision tree and a hierarchical structure of speech-act. Nevertheless, the proposed model achieved the best performance among them. Table 6 lists the results from each speech-act model.

5. Conclusions and future work

This paper has presented two effective feature weighting schemes for speech-act classification. One used the entropy of probability distributions of all categories, and the other the log-odds ratio of positive and negative categories. The proposed scheme achieved higher performance than traditional feature weighting schemes and other previous models. The performance differences in the experiments were all statistically significant on t -test. We here attempted to apply a category distribution instead of an utterance distribution into speech-act classification. When classification objects have small number of features, such as speech-act classification, the proposed scheme using the category distribution outperforms other term weighting schemes.

Table 5
 F_1 scores for each category in three data sets.

Speech-act	RES				Speech-act	SM-8				SM-11			
	SVM		k-NN			SVM		k-NN		SVM		k-NN	
	Binary	EW	Binary	LR		Binary	EW	Binary	LR	Binary	EW	Binary	LR
Ask-if	83.83	89.1	76.38	79.79	Ask-if	82.07	83.33	73.87	81.81	78.26	79.62	70.9	77.98
Ask-ref	90	91.61	84.45	89.96	Ask-ref	93.44	94.36	89.62	91.68	93.44	94.33	88.96	91.57
Ask-confirm	94.54	95.18	91.35	88.09	Ask-confirm					0	0	0	0
Offer	0	20	26.66	30.76	Confirm					100	100	0	100
Suggest	63.49	66.66	50.00	60.00	Request	91.82	92.8	87.1	87.81	91.81	92.92	87.2	87.91
Request	73.75	74.53	65.55	70.93	Accept	75.9	75.9	75.82	76.77	75.9	75.9	75.11	77.35
Accept	57.5	59.52	52.72	50.54	Response	96.68	96.96	93.49	94.28	96.59	96.89	93.22	94.12
Reject	76.19	76.19	64.7	68.57	Inform	75.81	76.43	67.94	71.33	74.66	76.31	67.97	70.06
Response	91.9	91.65	86.18	88.26	Expressive	98.4	98.53	96.58	96.85	98.13	98.53	95.83	96.59
Acknowledge	83.68	84.5	77.69	82.35	Opening					0	0	0	0
Inform	75.1	75.42	68.15	68.42	Greeting	97.41	97.15	96.9	96.45	97.16	97.16	96.4	96.33
Expressive	78.76	79.63	76.19	77.44									
Promise	74.74	74.22	70.45	79.54									
Closing	72.72	73.75	61.01	67.17									
Opening	98.38	98.38	97.6	94.94									
Introduce-oneself	98.93	98.58	93.43	95.07									
Macro-avg F1	75.84	78.06	71.41	74.49		88.94	89.43	85.17	87.12	73.27	73.79	61.42	71.99

A boldface and italic numeral denotes the macro-averaging F1 score.

In future, we will make an effort to obtain the improvement of LOR on SVM. We plan to develop some new representation methods for test data for LOR.

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