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Performance Evaluation of Domain-Specific Sentiment Dictionary Construction Methods for Opinion Mining[1]

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Abstract

Sentiment dictionaries or lexicons are core elements for "bag-of-word" approaches of opinion mining or sentiment analysis. Rather than using general-purpose sentiment dictionaries, domain-specific sentiment lexicons can contribute to improve performance because they can reflect domain specific terms and meanings. This paper presents four domain-specific sentiment dictionary construction methods for opinion mining, and describes performance evaluation results using a practical data set. The comparison subjects of this research include SO-PMI (Semantic Orientation from Pointwise Mutual Information) and three term frequency-based methods with different term polarity measures. To evaluate the performance of four different methods, a movie review data set from a representative Internet movie community site, IMDb (Internet Movie Database) is collected using a web crawling program, and is analyzed using R programs. Based on training data set, domain specific sentiment dictionaries are constructed using four different methods, and are compared their performance of sentiment analysis. The experimental results show that domain-specific sentiment dictionaries are working better than general-purpose dictionaries except one genre, 'animation'. Also, term frequency-based approaches show better performance than SO-PMI.

***Keywords**: Sentiment Analysis, Opinion Mining, Sentiment Dictionary, Sentiment Lexicon, SO-PMI*

1. Introduction

Sentiment analysis which is also called opinion mining is an important area in text mining. The purposes of sentiment analysis is to understand how people have feeling about something – a product, a brand, a company, a celebrity, and a social issue based on published sources of information from Internet online communities, blogs, and social networking services [13]. As a subcategory of text mining, sentiment analysis approaches are in continuum whose one end is the "bag of words" approach and the other is the "natural language processing" approach. The natural language approaches try to understand actual meaning of the document and words in the document. The bag-of-words approaches which are also called "knowledge-based approaches" are relatively simple because a document is considered just as a list of words regardless linguistic

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structures [3]. Even though bag-of-words approaches have many limitations, they are popular because they are less costly and easy to use.

In the bag-of-words approaches of sentiment analysis, a sentiment dictionary or a lexicon which includes terms with their polarities such as positive or negative levels has a central role to determine the polarities of documents. To support opinion mining, there are general sentiment lexicons such as SentiWordNet[2], MPQA, and SentiNet [7, 14]. Even though general-purpose sentiment lexicons are very useful and contribute to reduce time and efforts to build sentiment dictionaries for each opinion mining project, it has limitations in reflecting domain specific meanings. For example, ‘spooky’ is a negative term in general, however, it can be a positive term in reviews in horror movies. Similarly, ‘predictable’ is usually a positive term, however, it can be used as negative meaning in movie reviews because it implies that the storytelling of the move was trite and obvious. So, domain-specific sentiment lexicons can provide better performance on sentiment analysis than general-purpose dictionaries.

Even though domain-specific sentiment lexicons are useful, manual construction is difficult and time-consuming task. In order to reduce time and efforts, supervised learning approaches can be applied to the task rather than manual construction. The ultimate goal of this research is to develop effective methods to construct domain specific lexicons using supervised learning approach. Especially, in this paper, we focus on the comparison of four different supervised learning-based lexicon construction methods including SO-PMI (Semantic Orientation from Pointwise Mutual Information) and term frequency-based approaches. The rest of the paper is organized as follows. In the next section, related works are presented, which include sentiment dictionary construction approaches and SO-PMI. In Section 3, the four lexicon construction methods are presented. In Section 4 and 5, experimental design and experiment results are described, respectively. Section 6 includes conclusion remarks.

2. Related Works

2.1. Sentiment Analysis

The term *opinion mining* which is firstly mentioned in Dave *et al.* (2003) is the “process a set of search results for a given item, generating a list of product attributes (quality, features, *etc.*) and aggregating opinions about each of them (poor, mixed, good)” [16]. Sentiment analysis refers to “the use of natural language processing, text analysis and computational linguistics to identify and extract subjective information in source materials”.[3] An essential task of sentiment analysis is determination of the *polarity* of a text for the given document. There are different approaches to detect the polarity of texts. The polarity detection can be tried in document level [15, 17] or sentence level [20, 21]. Existing sentiment analysis approaches can be categorized into three groups: knowledge-based approach, statistical approach, and hybrid approach [3]. Knowledge-based approaches or bag-of-word approaches are popular because they are accessible and easy to use. In knowledge-based approach, texts are classified based on the presence of unambiguous sentiment words such as ‘happy’, ‘afraid’, and ‘sad’. Main limitation of knowledge-based approaches is that they ignore linguistic rules in texts. Statistical approaches use machine learning algorithms such as support vector machines and deep learning with large training corpus of sentiment annotated texts [9, 15, 18]. Statistical approaches also have drawbacks. The main drawback is that they are generally semantically weak, which means they do not work well on smaller text units [3]. Hybrid approaches try to combine knowledge-based approach and statistical approach [4].

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[2] http://sentiwordnet.isti.cnr.it/
[3] http://en.wikipedia.org/wiki/Sentiment_analysis

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2.2. Sentiment Lexicon Construction

Sentiment lexicons can be constructed by different approaches. SentiWordNet is developed using semi-supervised learning approach [2, 8]. MPSA Opinion Corpus annotated news articles from a wide variety of news sources manually [7]. Kim and Kim (2014) constructed a domain-specific sentiment dictionary manually, which was used to determine the polarity of nuclear power social opinions in Twitter [11]. Jeong *et al.* (2015) used term frequency-based approach to construct sentiment dictionary based on supervised learning approach for individual stock price prediction based on sentiment analysis. Socher *et al.* (2013) applied crowdsourcing approach to create the Sentiment Treebank. An and Kim (2015) used collective intelligence approach to build a Korean sentiment lexicon.

2.3. PMI and SO-PMI

PMI (Pointwise Mutual Information) is a measure of association used in information theory and statistics [5]. It can be used as a measure to determine terms' polarity based on the assumption that two terms have similar polarity if the co-occurrence probability of two terms is high [19]. The formula to calculate PMI value of two words *w1* and *w2* is as follow.

$$PMI(w1,w2) = \log_2 \frac{p(w1,w2)}{p(w1)p(w2)} \quad (1)$$

SO-PMI (Semantic Orientation from PMI) is an application of PMI to construct sentiment dictionaries. In SO-PMI, the starting point is to define two seed sets: positive seed words and negative seed words. If we denote positive seed set as $PW=\{pw_1, pw_2, \ldots, pw_n\}$ and negative seed set as $NW=\{nw_1,nw_2, \ldots, nw_n\}$, the formula to determine the polarity of a word x is as follow [12].

$$SO-PMI(x) = \sum_{i=1}^{n} PMI(x, pw_i) - \sum_{i=1}^{n} PMI(x, nw_i) \quad (2)$$

3. Domain Specific Lexicon Building Methods

The purpose of this research is to construct domain-specific lexicons rather than using general-purpose lexicons to improve sentiment analysis performance. The proposed overall approach is shown in Figure 1.

Experimental data (in this paper, Internet movie review data) is crawled using a web crawler program. The collected data set is divided into two sets, training data set and test data set. Training data set is used to construct domain-specific lexicons, and test data set is used to compare the performance of constructed lexicons with general-purpose dictionaries.

The data preprocessing phase have three subtasks; data decomposition, filtering, and morphological analysis. In the data decomposition, the training set which includes documents (in this paper, Internet movie reviews) is divided into several domains (in the case, movie genres). In the filtering, text preprocessing tasks are performed including punctuations and stop words removing. Using morphological analysis, adjectives are extracted from documents. In this study, we use only adjectives because they have central role to express sentiment in movie reviews. Other part of documents such as verbs and adverbs, however, are also important, and they need to be included in future researches.

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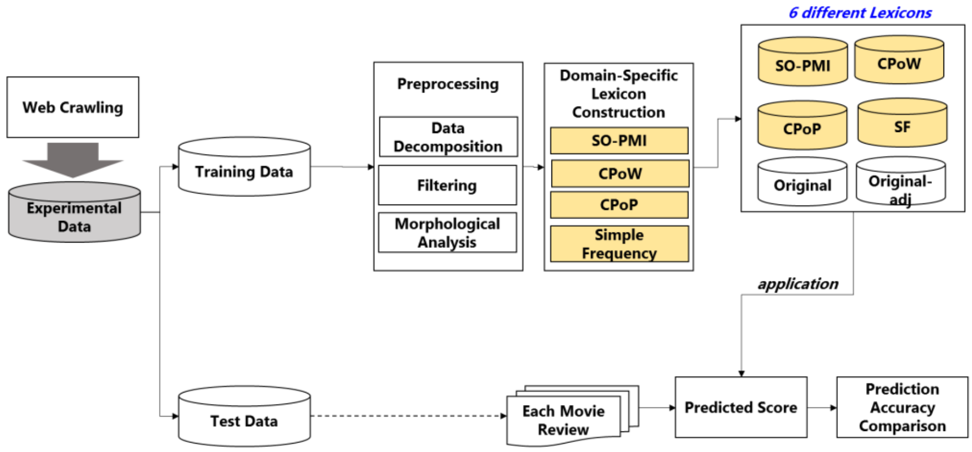

Figure 1. Domain-Specific Lexicon Construction Approach

In this research, we consider four different methods to construct domain-specific dictionaries, and compare them with two general-purpose lexicons. In fact, six lexicons are compared in this research. The brief description of six dictionaries is as follows.

(1) Entire original lexicon (denoted as 'Original' in Figure 1): the whole set of terms in original sentiment dictionary in the 'sentR' package in R[4]
(2) Adjectives in original lexicon (denoted as 'Original-adj' in Figure 1): a subset of original sentiment dictionary in the 'sentR' package, which includes only adjectives
(3) SO-PMI lexicon: a domain-specific dictionary constructed based on SO-PMI method
(4) CPoP lexicon: a domain-specific dictionary constructed using term frequency-based approach which is based on CPoP similarity measure
(5) CPoW lexicon: a domain-specific dictionary constructed using term frequency-based approach which is based on CPoW similarity measure
(6) Simple Frequency lexicon (dented as 'SF' in Figure 1): a domain-specific dictionary constructed using term frequency-based approach which is based on Simple Frequency similarity measure

In the case of a general-purpose lexicon (in here, 'Original' or 'Original-adj'), it have a set of terms and their polarities ('Strong Positive', "Weak Positive", "Weak Negative", and "Strong Negative"). In the case of four domain-specific lexicons (in this case, SO-PMI lexicon, CPoP lexicon, CPoW lexicon, and Simple Frequency lexicon), they have several sets of terms and their polarities, and each set is corresponding to a domain (refer Figure 2).

Using six different dictionaries, sentiment scores of documents (in this case, 10-scale star ratings which are given by reviewers) are predicted using Naïve Bayesian classifier in 'sentR' package. The performance measure to compare six dictionaries is MAE (Mean Absolute Error). The formula is as follows.

$$MAE = \frac{\sum_{i=1}^{N} |\,Actual(i) - Predicted(i)\,|}{N} \tag{3}$$

In the above formula, *Actual*(*i*) is actual rating of review *i* and *Predicted*(*i*) is predicted rating using a specific dictionary of review *i*.

[4] https://github.com/mananshah99/sentR

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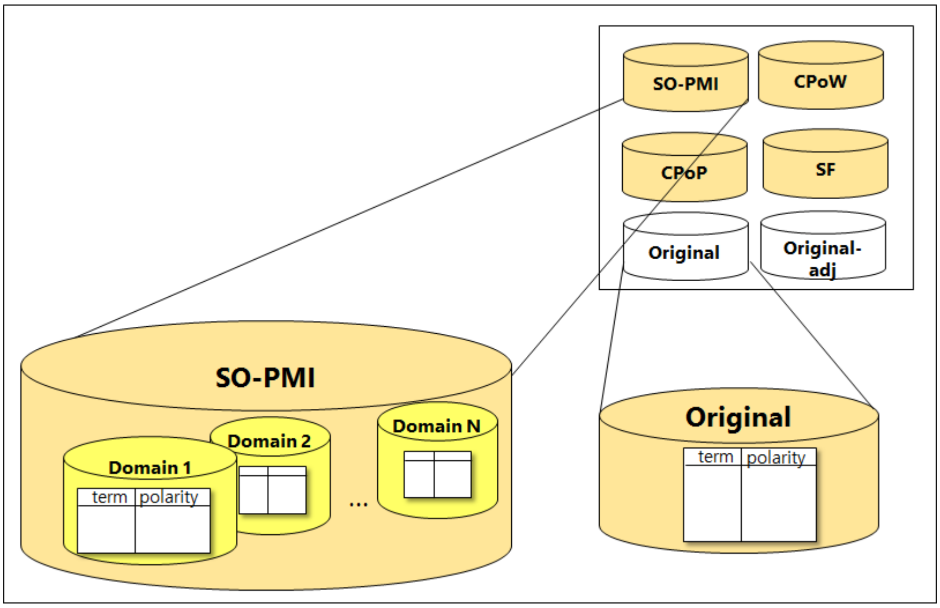

Figure 2. General-Purpose Lexicon vs. Domain-Specific Lexicon

4. Experimental Design

4.1. Experiment Data Set

Experiment data set in this research is movie reviews in six genres; 'Action'. 'Animation', 'Comedy', 'Drama', 'Horror', and 'SciFic' in IMDb (Internet Movie Database)[5]. Reviews on 'Action' genre are the largest set and those of 'Animation' are the smallest set among six genres. Training data set includes reviews of top-5 and bottom-5 movie per genre, which has 47,196 reviews. Test data set which is for performance comparison of six different dictionaries contains reviews of top-100 movies per genre between September 2012 and June 2014. The number of reviews in test data set is 42,083. The detail numbers of training and test data set are shown in Table 1.

4.2. Four Different Term Polarity Determination Measures

In this paper, we compare four different methods to construct sentiment dictionaries: SO-PMI, CPoP (Conditional Probability of Polarity), CPoW (Conditional Probability of Word), and SF (Simple Frequency).

Table 1. The Number of Reviews in Training and Test Data Set

	Test data	Training data
Action	13,894	15,724
Animation	2,870	4,109
Comedy	9,126	3,618
Drama	9,318	7,549
Horror	2,449	7,600
Sci-fi	4,426	8,597
All Movies	42,083	47,197

[5] http://www.imdb.com/

4.2.1. SO-PMI

The formula to determine word polarities based on SO-PMI was introduced in Formula (2). To use SO-PMI for sentiment dictionary construction, it is necessary to generate two seed sets: positive seed words and negative seed words. The steps to generate two seed sets in this research are as follows. Before determining terms' polarities, we determine reviews' polarities based star rating on reviews. That is, like Figure 3, a reviewer evaluates the movie with 10-scale scores with a textual review on a movie in IMDb. Figure 4 shows the distribution of star ratings in the experiment data set. We classify reviews with 8, 9, and 10 star rating as positive, 1, 2, 3 star rating as negative, and others as neutral. From each group, we extract frequently used adjectives and sort them by descending order. We define positive-negative ratio of term *x* as follows.

$$PositiveNegativeRatio(x) = \frac{N_{x \cap pos}}{N_{x \cap neg}} \tag{4}$$

In the above formula, $N_{x \cap pos}$ and $N_{x \cap neg}$ are the numbers of positive reviews and negative reviews including term *x*, respectively. The term whose positive-negative ratio is higher than 3 is considered as a potential candidate for positive seed words, that whose inverse of positive-negative ratio is higher than 3 is considered as a potential candidate for negative seed words. Among those candidates, top-10 highest frequency terms are selected as final positive and negative seed words, respectively.

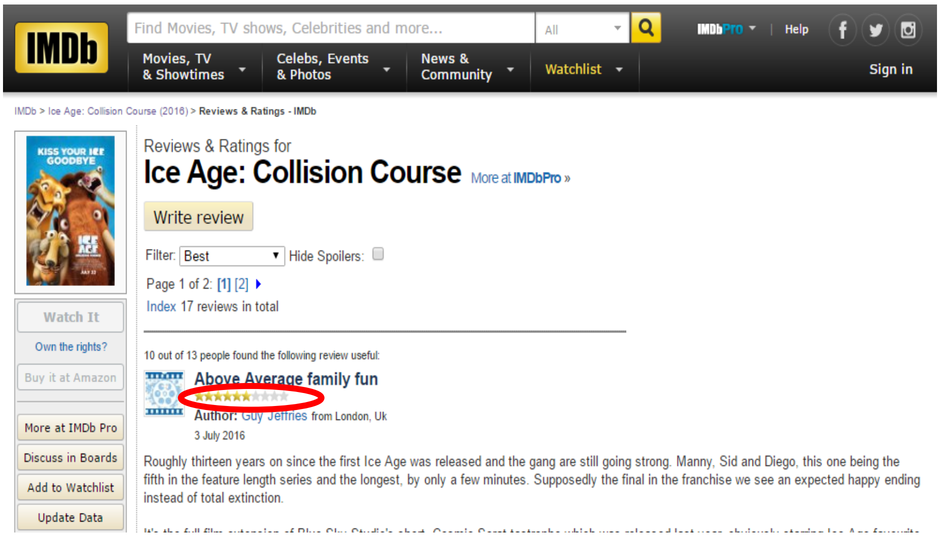

Figure 3. Sample Movie Review in IMDb

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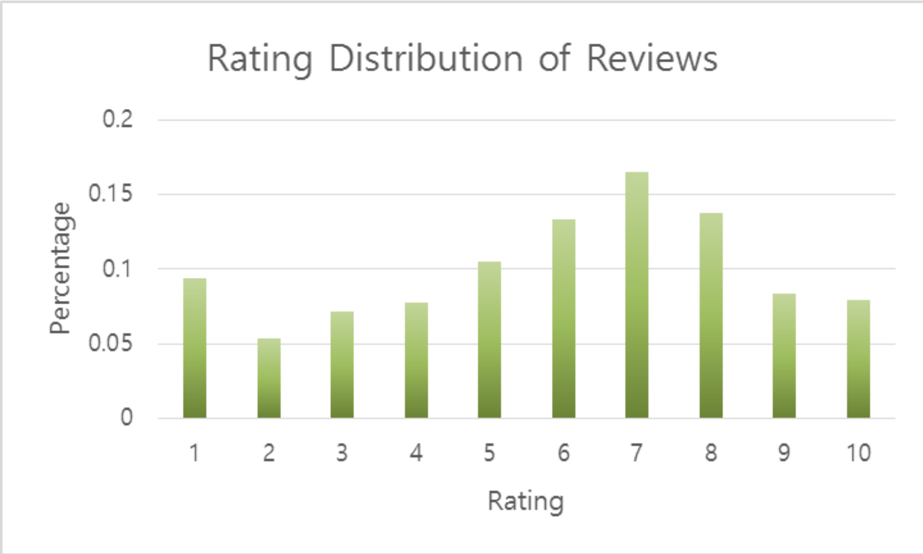

Figure 4. Distribution of Star Ratings of Movie Reviews

After selecting positive and negative seed words, we can calculate polarity scores of terms in training set using Naïve Bayesian classifier in 'sentR' package. Based on polarity scores, terms are divided into five categories: Strong Positive, Weak Positive, Neutral, Week Negative, and Strong Negative.

The classification results and polarity scores are used to predict sentiment scores of reviews in test data set.

4.2.2. CPoP

The first polarity measure based on term frequency-based approach is *CPoP*. The polarity of a term *x* is calculated using the following formula.

$$CPoP(x) = \frac{N_{pos \cap x}}{N_{pos}} - \frac{N_{neg \cap x}}{N_{neg}} \quad (5)$$

In the above formula, N_{pos} and N_{neg} are the numbers of positive and negative reviews, respectively. And $N_{x \cap pos}$ and $N_{x \cap neg}$ are already explained in formula (4). If term *x* is included more in positive reviews and less in negative reviews, *CPoP*(*x*) is higher than that of terms which are included more in negative reviews.

After calculating polarities of terms in training set, the steps to classify terms into five categories and to use to predict sentiment scores of reviews in test data set are the same with the case of SO-PMI.

4.2.3. CPoW

The second polarity measure based on term frequency-based approach is *CPoW*. The polarity of a term *x* is determined using the following formula.

$$CPoW(x) = \frac{N_{pos \cap x} - N_{neg \cap x}}{N_x} \quad (6)$$

In the formula N_x is the number of reviews including term x in training data set. And the next steps after calculating polarities of terms in training set are the same as *CPoP* case.

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Table 2. The Numbers of Polarity Terms for Each Genre

	Strong Positive	Weak Positive	Neutral	Weak Negative	Strong Negative
236 words	**Action**				
SO-PMI	58	57	78	21	22
CPoP	58	57	78	21	22
CPoW	48	47	87	27	27
Simple Freq.	48	47	87	27	27
258 words	**Animation**				
SO-PMI	63	62	85	24	24
CPoP	52	51	85	35	35
CPoW	77	77	77	13	14
Simple Freq.	77	77	77	13	14
213 words	**Comedy**				
SO-PMI	38	38	71	33	33
CPoP	39	39	71	32	32
CPoW	47	47	77	21	21
Simple Freq.	47	47	77	21	21
196 words	**Drama**				
SO-PMI	38	37	65	28	28
CPoP	35	34	65	31	31
CPoW	51	51	64	15	15
Simple Freq.	51	51	64	15	15
255 words	**Horror**				
SO-PMI	54	54	91	28	28
CPoP	55	55	91	27	27
CPoW	32	32	120	35	36
Simple Freq.	32	32	120	35	36
259 words	**Sci-fi**				
SO-PMI	57	56	86	30	30
CPoP	55	55	86	31	32
CPoW	57	57	89	28	28
Simple Freq.	57	57	89	28	28
225 words	**Movie all**				
SO-PMI	49	49	75	26	26
CPoP	48	48	75	27	27
CPoW	50	50	80	22	23
Simple Freq.	50	50	80	22	23

4.2.4. Simple Frequency

The last polarity measure based on term frequency-based approach is *SF* (*Simple Frequency*). The polarity of a term *x* is calculated using the following formula.

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$$SF(x) = \frac{N_{pos\cap x} \quad N_{neg\cap x}}{N_{pos\cap x} + N_{neg\cap x}} \tag{7}$$

The next steps are the same as the *CPoP* case.

5. Experiment Results

The numbers of polarity words for each genre are summarized in Table 2. The numbers of polarity terms per genre are from 196 to 259. The MAEs of six dictionaries are shown in Table 3. The results of pairwise t-test with 'Original-adj' are also included in Table 3. The numbers within parentheses are p-values of pairwise t-test. Table 3 shows that domain-specific lexicons show better performance than general-purpose lexicon except 'Animation' genre. Term-frequency approaches including CPoP, CPoW and SF show better performance than SO-PMI in all genres even though the differences are minor. Among term-frequency approaches, CPoP is the best performing method because it is the best in three genres among six genres, and the best in the overall movie review set.

The reasons why domain-specific dictionaries do not work well in 'Animation' genre can be explained from the characteristics of 'Animation' genre. A difference of 'Animation' genre from other five categories is that it has the smallest review set among six categories. Another inference is possible based on the distributions of 10-scale star ratings. In the case of 'Animation' genre, the distribution of 10-scale start ratings is quite different from other categories. The ratings on 'Animation' genre are relatively higher than those of other genre, which means that there are more positive reviews than negative reviews. Two characteristics of 'Animation' genre can be potential keys to resolve low performance of domain-specific lexicons in the genre.

Table 3. MAEs of Six Dictionaries

Genre	Original Adj.	SO-PMI	CPoP	CPoW	Simple Frequency	Original
Action	2.26 -	2.19*** (<0.001)	2.17*** (<0.001)	2.17*** (<0.001)	2.17*** (<0.001)	2.30* (0.013)
Animation	2.22 -	2.21 (0.443)	2.15* (0.045)	2.14* (0.033)	2.15 (0.05)	2.12** (0.056)
Comedy	2.42 -	2.41 (0.296)	2.36** (0.006)	2.37** (0.010)	2.36** (0.004)	2.43 (0.343)
Drama	2.50 -	2.42*** (<0.001)	2.37*** (<0.001)	2.33*** (<0.001)	2.32*** (<0.001)	2.37*** (<0.001)
Horror	2.42 -	2.33* (0.027)	2.24*** (<0.001)	2.35 (0.051)	2.34* (0.039)	2.51** (0.010)
Sci-Fic	2.60 -	2.49*** (<0.001)	2.47*** (<0.001)	2.45*** (<0.001)	2.47*** (<0.001)	2.56 (0.117)
All Movies	2.43 -	2.36*** (<0.001)	2.33*** (<0.001)	2.35*** (<0.001)	2.34*** (<0.001)	2.40** (0.002)

Note. : $^{***}p<0.001$, $^{**}:p<0.01$, : $^{*}p<0.05$
Note. Shaded cells mean the best performing dictionaries in the genre

6. Conclusion Remarks

This research tests the performance of four different domain-specific lexicon construction methods using supervised learning approach. SO-PMI and other three term frequency-based measures are compared using a movie review data set with six genres.

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The experimental results show that domain-specific lexicons using supervised learning approach provide better performance than general purpose lexicons. Especially term frequency-based measures are recommendable than SO-PMI in terms of simplicity and stability.

There are still many further research issues which need to be resolve in order to construct domain-specific sentiment dictionaries more effectively. First, in the experiment, a general-purpose lexicon shows the better performance in ‘Animation’ genre comparing to domain-specific lexicons. It is necessary to explain the reason and needs to propose to improve the performance of domain-specific lexicons in ‘Animation’ genre. Even though term frequency-based approaches provide better performance than SO-PMI, however, the experiment results are not enough to conclude that term frequency-based approaches are better than SO-PMI. Since the performance of SO-PMI depends highly on the initial positive and negative seed term sets, there are potentials to improve the performance of SO-PMI with different ways to select seed term sets. Also, in the study, we only consider adjectives as terms in domain-specific lexicons. In the future research, we need to extend lexicons to include other text components such as verbs and adverbs.

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