Open Source Affect Analysis System with Extensions

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Abstract: In research on human-agent interaction (HAI) it is important to perform affect analysis, or emotion recognition of user input for further implementation, such as adaptation of agent behavior to affective states of the user. Several affect analysis systems have been proposed till now. However, none of them has been released yet as open source software. We present the first open source affect analysis system, ML-Ask, and some of its extensions. The system has been developed for several years and has matured enough to be released to the public. The system can be used for basic affect analysis in HAI research for Japanese, as well as an experimental baseline for specific research in affect analysis.

1 Introduction

The research on human-agent interaction (HAI) has gained increasing interest through recent years. A large number of HAI applications has been proposed from various sub-fields, including robotics, artificial intelligence (AI) or natural language processing (NLP). Since HAI focuses on interaction between human user and artificial agent, one of the most important tasks in HAI is to properly recognize current state of the user. Depending on application, the focus could be on different states of the user, such as user engagement in conversation (e.g., with a dialog agent [1]), user intention (e.g., to buy a certain product, or chose a specific migration route [2]), user attitude (e.g., toward a specific object, or the agent itself [3]), or user emotions (e.g., to choose different conversation strategy if the user is sad or happy, etc. [4]). In many of those tasks techniques for affect analysis have proved to be effective. Affect analysis refers to recognizing user affective states (emotions, moods, attitudes, etc.). Several affect analysis systems have been proposed till now [7, 19, 9, 10, 21, 28]. However, none of them has yet been released as open source software. By this paper we wish to present the first open source system for text-based affect analysis in Japanese, ML-Ask, including some of its extensions. The system has been developed for several years and, although not ideal, has matured enough to be released to the public. The system has already proved to be useful in many tasks and can be used for basic affect analysis in various HAI research, as well as an experimental baseline for specific research in affect analysis.

The outline of this paper is as follows. In section 2 we present previous research on affect analysis. In section 3 we discuss the necessity for open-source software and describe the license under which we release our system. Section 4 describes the system with all its features. Section 5 presents the extensions with which ML-Ask proved to be compatible and which improved the system performance in the past. Sections 6 contains references to works which evaluate the system in various ways. Finally, in section 7 we conclude the paper and present some of the future plans for releasing other systems.

2 Affect Analysis

Text based Affect Analysis (AA) has been defined as a field focused on developing natural language processing techniques for estimating the emotive aspect of text [5]. For example, Elliott [6] proposed a keyword-based Affect Analysis system applying an affect lexicon (including words like "happy", or "sad") with modifiers (extremely, somewhat). Liu et al. [7] presented a model of text-based affect sensing based on OMCS (Open-Mind Common Sense), a generic common sense database, with an application to e-mail interpretation. Alm et al. [8] proposed a machine learning method for Affect Analysis of fairy tales. Aman and Szpakowicz also applied machine learning techniques to analyze emotions expressed on blogs [19].

There have also been several attempts to achieve this goal for the Japanese language. For example, Tsuchiya et al. [9] tried to estimate emotive aspect of utterances with a use of an association mechanism. On the other hand, Tokuhisa et al. [10] as well as Shi et al. [11] used a large number of examples gathered from the Web to estimate user emotions. Furthermore, Ptaszynski et al. [12] proposed a Web-based supported Affect Analysis system for Japanese text-based utterances.

Unfortunately, until now there have been no open-source affect analysis systems. Although there exist several online demos, such as "Sentiment Analysis with Python NLTK Text Classification"[1], or "EmoText"[2], all of them refer to sentiment analysis, not affect analysis. In sentiment analysis the focus is usu-

[1] http://text-processing.com/demo/sentiment/
[2] http://www.socioware.de/technology.html

ally put on determining emotion valence, or whether input (sentence, paragraph, product review) is of positive or negative valence. In affect analysis one focuses not only on the polarity of the input, but on particular emotion classes that are expressed by the input (joy, anger, fear, etc.).

3 Open-Source Software

Open-source software (OSS) refers to computer software (a system, a program, a script, a library or set of libraries, etc.), which has been released by the creator of the software (copyright holder) as freely available to the public and licensed with a specific open-source license. The source code of the software can be used without any fees or restrictions, including modifications by end-users. The copyright holder allows end-users to perform research, studies, and further changes to the software, while the copyrights are retained by the software creator. Open-source software has contributed greatly to the development of software in general, while allowing saving significant amounts of money [13]. The most representative examples of OSS include GNU/Linux operating system distributions or Mozilla Firefox internet browser.

There are several different kinds of licenses under which software can be released. The most popular are GNU General Public License (GPL), MIT License, or BSD License. Although they differ slightly when it comes to the contents, most of the licenses are compatible with each other. Our system is released under the New BSD License. We decided to apply this type of license and not the comparable GNU GPL or the MIT License for the following reason. The GPL enforces the child-software/products to be also compatible with the GNU GPL. This becomes an obstacle when GPL licensed software is used in a larger system together with non-free software. In research projects, especially HAI-related it is often the case that different modules are used within one project (e.g., open-source scripts as well as closed-source commercial visualization software, or humanoid robots available on the market, etc.). The MIT License allows this, however, contrary to somewhat strict GNU GPL, MIT License allows the third party to use the software in any way even re-sell the system without any notice to the copyright holders. We wish to make our system widely available, even together with commercial applications. However, we could not allow commercialization of the system without prior consent. Therefore we chose the type of license which is balanced between the two. The New BSD License is equally permissive as the MIT License, however, it forces contacting the copyright holders when the system is used for commercial purposes.

4 Open Source Affect Analysis System

ML-Ask[3], or *e**M**otive e**L**ement and Expression **A**nalysis **s**ystem* is a keyword-based language-dependent system for automatic affect annotation on utterances in Japanese constructed by Ptaszynski et al. [21, 12]. It uses a two-step procedure:

1. Specifying whether an utterance is emotive, and
2. Recognizing the particular emotion types in utterances described as emotive.

ML-Ask is based on the idea of two-part classification of realizations of emotions in language into:
1) *Emotive elements* or *emotemes*, which indicate that a sentence is emotive, but do not detail what specific emotions have been expressed. For example, interjections such as "whoa!" or "Oh!" indicate that the speaker (producer of the utterance) have conveyed some emotions. However, it is not possible, basing only on the analysis of those words, to estimate precisely what kind of emotion the speaker conveyed. Ptaszynski et al. include in emotemes such groups as interjections, mimetic expressions, vulgar language and emotive markers. The examples in Japanese are respectively: *sugee* (great! - interjection), *wakuwaku* (heart pounding - mimetic), *-yagaru* (syntactic morpheme used in verb vulgarization) and '!', or '??' (sentence markers indicating emotiveness). Ptaszynski et al. collected and hand-crafted a database of 907 emotemes. A set of features similar to what is defined by Ptaszynski et al. as emotemes has been also applied in other research on discrimination between emotive (emotional/subjective) and non-emotive (neutral/objective) sentences [14, 16, 19].
2) *Emotive expressions* are words or phrases that directly describe emotional states, but could be used to both express one's emotions and describe the emotion without emotional engagement. This group could be realized by such words as *aijou* (love - noun), *kanashimu* (feel sad, grieve - verb), *ureshii* (happy - adjective), or phrases such as: *mushizu ga hashiru* (to give one the creeps [of hate]) or *ashi ga chi ni tsukanai* (walk on air [of happiness]). Examples from affect lexicon used in ML-Ask are represented in Table 1.

Contextual Valence Shifters To improve the system performance we also implemented Contextual Valence Shifters (CVS). The idea of CVS was first proposed by Polanyi and Zaenen [17]. They distinguished two kinds of CVS: negations and intensifiers. The group of negations contains words and phrases like "not", "never", and "not quite", which change the valence polarity of the semantic orientation of an evaluative word they are attached to. The group of intensifiers contains words like "very", "very much", and "deeply", which intensify the semantic orientation of

[3]All system files related to ML-Ask released as open-source can be found under the following link: http://arakilab.media.eng.hokudai.ac.jp/~ptaszynski/repository/mlask.htm

Table 1: Examples from affect lexicon used in ML-Ask (N=noun, V=verb, Phr=phrase, Id=idiom, Adj=adjective, Adv=adverb).

喜 Joy	かたじけない *katajikenai* [Adj] grateful; 喜ばしい *yorokobashii* [Adj] delightful; 相好を崩す *soukou wo kuzusu* [Phr] be all smiles; 歓天喜地 *kantenkichi* [Id] extreme pleasure or satisfaction; わくわく *waku-waku* [Adv] be excited (with); 満足感 *manzoku-kan* [N] a feeling of satisfaction;
好 Fondness	恋い焦がれる *koikogareru* [V] be deeply in love, yearn; 気に入る *ki ni iru* [V] like something/somebody; 可愛がる *kawaigaru* [V] love, pet; 片思い *kata-omoi* [N] unrequited love; 大好き *dai-suki* [Adj] be very fond of; 愛欲 *aiyoku* [N] sexual desire, lust;
安 Relief	肩の荷が下りる *kata no ni ga oriru* [Phr] to have a weight removed from one's mind; 落ち着く *ochitsuku* [V] to calm down; らくらく *rakuraku* [Adv] very easily, effortlessly; ほっとする *hotto suru* [V] feel relieved; 一安心 *hitoanshin* [V] have peace of mind for a while
哀 Gloom	顔を曇らせる *kao wo kumoraseru* [Phr] cloud one's face; じいんと来る *jiin-to kuru* [Phr] be very touching; 一人ぼっち *hitoribocchi* [N] loneliness; 泣き叫ぶ *nakisakebu* [V] howl; 痛ましい *itamashii* [Adj] sad, pitiful; 思いやり *omoiyari* [N] sympathy, empathy;
厭 Dislike	むしゃくしゃ *musha-kusha* [Adv] irritated; 気に食わない *ki ni kuwanai* [Phr] be dissatisfied with; 虫酸が走る *mushizu ga hashiru* [Phr] be disgusted; 小憎らしい *konikurashii* [Adj] irritating; 陰気くさい *inki-kusai* [Adj] gloomy; やるせない *yarusenai* [Adj] downhearted;
怒 Anger	風向きが悪い *kazamuki ga warui* [Phr] be in bad mood; 食って掛かる *kuttekakaru* [V] fly at somebody; 怒り出す *okoridasu* [V] get into rage; ぷんぷん *punpun* [Adv] angrily, in huff; 息巻く *ikimaku* [V] storm at somebody; 不愉快 *fuyukai* [Adj] unpleasant;
怖 Fear	肝を冷やす *kimo wo hiyasu* [Phr] be frightened; 恐ろしい *osoroshii* [Adj] frightening, terrifying; おびえる *obieru* [V] be scared; 鳥肌 *torihada* [N] gooseflesh; 恐怖 *kyoufu* [N] fear; 不安 *fuan* [N] anxiety; 心配 *shinpai* [N] concern, anxiety;
恥 Shame	恥ずかしがる *hazukashigaru* [V] feel shy; 恥ずかしい *hazukashii* [Adj] disgraceful, shameful; はにかみ *hanikami* [N] bashfulness; 恥をかく *haji wo kaku* [V] be embarrassed; 赤面 *sekimen* [N] blush of shame; 恥 *haji* [N] shame; 俯く *utsumuku* [V] cast one's eyes down of shame;
昂 Excitement	飛び上がる *tobiagaru* [V] spring to one's feet; 気が急く *ki ga seku* [Phr] to feel impatient; 隔靴掻痒 *kakkasouyou* [Phr] scratching through the sole of one's shoe; 感情的 *kanjouteki* [Adj] emotional, in hightened emotion; 興奮 *koufun* [N] excitement;
驚 Surprize	きょとんとする *kyotontosuru* [V] with a look of amazement; ショッキング *shokkingu* [Adj] shocking; 思いかけない *omoikakenai* [Adj] unexpected; びっくり仰天する *bikkurigyouten suru* [V] be absolutely astonished; びっくり *bikkuri* [N] surprize;

an evaluative word. ML-Ask fully incorporates the negation type of CVS with a 108 syntactic negation structures. Examples of CVS negations in Japanese are structures such as: *amari -nai* (not quite-), *-to wa ienai* (cannot say it is-), or *-te wa ikenai* (cannot [verb]-). In this paper we also compared the performance of ML-Ask with and without CVS improvement (baseline), within evaluation of the procedure for verification of emotion appropriateness. As for intensifiers, although ML-Ask does not include them as a separate database, most Japanese intensifiers are included in the emoteme data-base. The system also calculates emotive value, or emotional intensity of a sentence, on the basis of the number of emotemes in the sentence.

Russell's 2-dimensional Model of Affect Finally, the last distinguishable feature of ML-Ask is implementation of Russell's two dimensional affect space [18]. It assumes that all emotions can be represented in two dimensions: the emotion's valence or polarity (positive/negative) and activation (activated/deactivated). An example of negative-activated emotion could be "anger"; a positive-deactivated emotion is, e.g., "relief". The mapping of Nakamura's emotion types on Russell's two dimensions proposed by Ptaszynski et al. [21] was proved reliable in several research [21, 22, 27]. The mapping is represented in Figure 1. An example of ML-Ask output is represented in Figure 2.

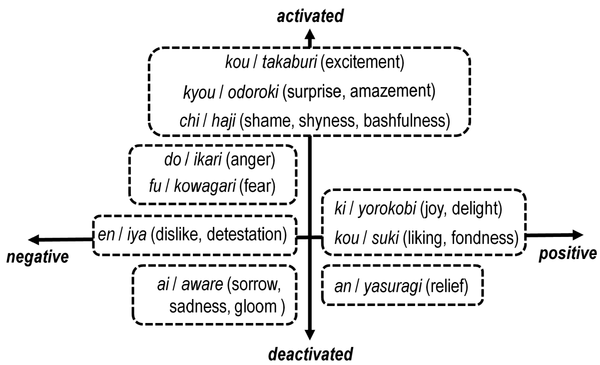

Figure 1: Mapping of Nakamura's classification of emotions on Russell's 2D space.

ML-Ask-simple We also compiled a simpler version of ML-Ask, not using emotemes, only the emotive expression lexicon with CVS and Russell's emotion space (this version is called further **ML-Ask-simple**). ML-Ask was originally designed to analyze mostly conversation-like contents. In the first step of ML-Ask analysis the system specifies if a sentence is emotive or non-emotive. Analysis of particular emotion types is performed only on emotive sentences. A

Sentence:	なぜかﾚﾃﾞｨｰｶﾞｶﾞを見ると恐怖感じる(;´艸`)
Transliteration:	*Nazeka Lady Gaga wo miru to kyoufu kanjiru* (;´艸`)
Grammar:	Somehow Lady Gaga OBJ see COND fear feel EMOTICON
Translation:	Somehow Lady Gaga frightens me (;´艸`)

ML-Ask output:

```
なぜかﾚﾃﾞｨｰｶﾞｶﾞを見ると恐怖感じる(;´艸`)
sentence: emotive
emotemes: EMOTICON:(;´艸`)
emotions:(1),FEAR:恐怖
2D: NEGATIVE, ACTIVE
```

Figure 2: Output example for ML-Ask.

sentence is emotive if it contains at least one *emoteme*, or a marker of emotive context. Emotemes are typical in conversations (in particular spontaneous conversations). Generally perceived narratives (blogs, fairytales, etc., often used in evaluation of affect analysis systems) contain at least two main types of sentences:

1. **descriptive sentences** for introduction of the main storyline, and
2. **dialogs** between characters of the narrative.

ML-Ask can be expected to deal with the second type of sentence. However, since emotemes rarely appear in descriptive sentences, the system would not precede to the recognition of particular emotion types for such sentences. Therefore, to allow ML-Ask deal with descriptive sentences as well we compiled a version of the system which excludes emotemes from the analysis and focuses primarily on analysis of emotion types. However, we retained the analysis of CVS and Russell's emotion space. Since in this version of the system we simplified the analysis, we called it **ML-Ask-simple**.

5 Extensions of ML-Ask

5.1 CAO

CAO[4] is a system for estimation of emotions conveyed through emoticons[5] developed by Ptaszynski et al. [27]. Emoticons are sets of symbols widely used to convey emotions in text-based online communication, such as blogs. CAO, or *emotiCon Analysis and decOding of affective information system* extracts an emoticon from an input (a sentence) and determines specific emotion types expressed by it using a three-step procedure. Firstly, it matches the input to a predetermined emoticon database containing over ten thousand unique emoticons. The emoticons, which could not be estimated using only the database are automatically divided into semantic areas, such as representations of "mouth" or "eyes". The areas are automatically annotated according to their co-occurrence in database. The annotation is firstly based on eye-mouth-eye triplet. If no triplet was found, all semantic areas are estimated separately and summarized. This provides information about potential groups of expressed emotions giving the system coverage of over 3 million possibilities. The performance of CAO was evaluated as very high [27] (exceeding 97%) which proved CAO as a reliable tool for analysis of Japanese emoticons. In the annotation process CAO was used as a supporting procedure in ML-Ask to improve the performance of affect annotation and add detailed information about emoticons appearing in the text.

[4]All publicly released files related to CAO can be found under the following link: http://arakilab.media.eng.hokudai.ac.jp/~ptaszynski/repository/cao.htm

[5]In particular Japanese emoticons called *kaomoji*.

5.2 Web-mining Method for Emotional Information Retrieval

Shi et al. [11] developed a technique for extracting emotive associations from the Web. It takes a sentence as an input and in the Internet searches for emotion types associating with the sentence contents. This could be interpreted as online common sense reasoning about what emotions are the most common to appear within a certain context. The technique is composed of four steps: a) extraction of input phrase; b) modification of the phrase with causality morphemes; c) searching for the modified phrase in the Internet and matching to the predetermined emotion lexicon; d) extraction of emotion associations and ranking creation. In the first step, an utterance is analyzed morphologically by a part-of-speech (POS) tagger, phrases for further processing are composed using the separated parts of speech. The phrases ending with a verb or an adjective are modified grammatically by the addition of causality morphemes (Shi et al. distinguished five most frequently used morphemes stigmatized emotively in the Japanese language: *-te, -to, -node, -kara, -tara,* which correspond to causality markers, like "because", "since", etc. in English). Finally, the modified phrases are queried in the Internet with 100 snippets for one modified phrase. This way a maximum of 500 snippets for each queried phrase is extracted from the Web and cross-referenced with the emotive expression lexicon. The higher hit-rate an expression had in the Web, the stronger was the emotive association between the original phrase and the emotion type.

6 Evaluations and Applications of ML-Ask

6.1 Evaluations

ML-Ask, including its extensions, has been evaluated a number of times on different datasets. In first evaluations Ptaszynski et al. [12, 20, 21] focused on evaluating the system on separate sentences. For example, in [20] there were 90 sentences (45 emotive and 45 non-emotive) annotated by authors of the sentences (first-person standpoint annotations). On this dataset ML-Ask achieved 83% of balanced F-score for determining whether a sentence is emotive, 63% of

Table 2: References describing evaluations and applications of ML-Ask.

Evaluations	**ML-Ask**	**Web-mining**	**CAO**	**ML-Ask+ Web-mining**	**ML-Ask+ CAO**
Separate Sentences	[12, 20, 21]	[11]	[27, 28, 33]	[12, 20, 21]	[30, 33]
BBS	[21]	–	–	–	–
Conversations	[3, 23, 24, 25] [26, 34]	[23, 25, 26, 34]	[34]	[3, 23, 25] [26, 34]	[34]
Blogs	[25, 30, 33, 34]	[25, 33, 34]	[27, 28, 33]	[25, 34]	[33]
Fairytales	[32]	–	–	–	–
Applications					
Dialog agent:					
· Analysis of user input	[1, 3, 4, 15] [23, 24, 25, 26] [34]	[23, 24, 25] [26, 34]	[34]	[23, 24, 25] [26, 34]	[34]
· Decision making support	[1, 4]	–	–	–	–
· Automatic evaluation	[3]	–	–	–	–
Verification of emotion appropriateness	[23, 24, 25, 26] [34]	[23, 24, 25, 26] [34]	[34]	[23, 24, 25] [26, 34]	[34] [34]
Corpus annotation	[33]	–	[33]	–	[33]
Emotion object database construction	[31]	[31]	[31]	[31]	[31]
Retrieval of moral consequences of actions	–	[35]	–	–	–

unanimity score for determining emotive value and 45% of balanced F-score for detecting particular emotion types. In [12] Ptaszynski et al. added annotations of third-party annotators and performed additional evaluation from the third-person standpoint. The evaluation showed that ML-Ask achieves better performance when supported by Web-mining procedure for extracting emotive associations from the Internet. This evaluation also showed that people are not ideal in determining emotions of other people. Additionally, in [21] Ptaszynski et al. performed an annotation of a Japanese BBS forum *2channel*. The dataset consisted of 1,840 sentences. The evaluation showed that there were two (out of ten) dominant emotion types ("dislike" and "excitement") which were often expressed by sophisticated emoticons, which the system could not analyze. Without these two emotion types the system extracted other emotive tokens similarly to human annotators (90% of agreements).

After the above initial evaluations Ptaszynski et al. continued evaluation of ML-Ask on different datasets. The system was most often evaluated on conversations, both between humans [1] and between human users and conversational agents [4, 3, 15, 23, 26]. In [1] Dybala et al. showed that ML-Ask presents comparable answers to human annotators when annotating conversations between people of different age and status (in particular young students vs. middle-aged businessmen). In other evaluations Ptaszynski et al. showed that the system performs comparably to humans when annotating human-agent dialogs. This was evaluated using only ML-Ask [3, 4], and ML-Ask confronted with the Web-mining procedure [23, 26]. Recently Ptaszynski et al. added also emoticon analysis system CAO to this evaluation [34].

Apart from the above evaluations, ML-Ask was also evaluated on blog contents. Firstly, in [25], using *Yahoo! blogs* (blogs.yahoo.co.jp) instead of the whole Web contents showed increased performance of the Web-mining procedure. Secondly, ML-Ask (alone and supported with CAO) was evaluated on YACIS, a corpus of blogs extracted from *Ameba blogs* (ameblo.jp). Finally, ML-Ask-simple was also recently evaluated using fairytales [32]. The evaluation showed performance of about 61% of accuracy, which shows that the system performs better on conversation-like contents, rather than on contents containing descriptive sentences. References to all evaluations of ML-Ask are represented in Table 2.

6.2 Applications

ML-Ask has been applied to different tasks. Most commonly, the system was used to analyze user input in human-agent interaction [1, 3, 4, 15, 23, 24, 25, 26]. In particular, the analysis of user input was utilized in decision making support about which conversation strategy to choose (normal conversation or joke) [1], and in an automatic evaluation method for dialog agents [3]. ML-Ask supported with CAO was also applied in annotation of a large scale corpus (YACIS - Ameba blog corpus containing 5.6 bil. words), and together with the Web-mining procedure in creation of a robust emotion object database [31]. The Web-mining procedure alone was also used recently in a novel task of extracting moral consequences of actions [35].

7 Conclusions and Future Work

The need for open source affect analysis software is growing, especially within the area of HAI, where complex multi-module systems are constructed with the use of smaller sub-systems. Although a number of affect analysis systems has been proposed till now, none of them has been released to the public. In this paper we presented ML-Ask, the first open source system for affect analysis of Japanese utterances. The system has been developed for several years and has matured enough to be released as open source. Although ML-Ask is not ideal, it provides basic affect analysis functionalities. It also incorporates additional post processing, such as Contextual Valence Shifters (processing of grammatical forms of negation), and mapping of emotion classes on 2-dimensional model of emotions (valence and activation). A number of different evaluations showed that ML-Ask can be positively utilized together with other systems used as extensions to the baseline system.

ML-Ask is released under the New BSD License, which allows usage without any restrictions for scientific purposes. Commercial use is also allowed, as long as an agreement with copyright holders is obtained.

In the near future we also plan releasing other systems, such as CAO, system for analysis of emoticons, or a Web-mining technique for extraction of emotional associations from the Web.

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