# Shifting Valence Helps Verify Contextual Appropriateness of Emotions

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## Abstract

This paper presents a method for estimating contextual appropriateness of speaker's emotions, supported with the analysis of Contextual Valence Shifters (CVS), which determine the semantic orientation of the valence of emotive expressions. In the proposed method a Web mining technique is used to verify the contextual appropriateness of the emotions recognized by a system for affect analysis supported with CVS. A conversational agent equipped with this system can choose an appropriate conversational procedure. The proposed method is evaluated using two conversational agents. The use of CVS has shown an improvement in the method.

## 1 Introduction

In recent years there has been a rising tendency in Artificial Intelligence research to enhance Human-Computer Interaction by implementing human factors in machines [Treur, 2007]. One of the most important human factors is expressing and understanding emotions - a vital part of human intelligence [Salovey and Mayer, 1990]. The field of AI embracing this subject, Affective Computing focuses on recognizing the emotions of users in human-computer interaction from: facial expressions or voice. However, such methods, based on behavioral approach, ignore the pragmatics and context dependence of emotions.

This led to creation of Affect Analysis - a field focused on developing natural language processing techniques for estimating the emotive aspect of text. For the Japanese language, which this paper focuses on e.g., Ptaszynski et al. [2008] tried to estimate emotive aspect of utterances with lexical representations of emotive information in speech or Shi et al. [2008] used a Web mining technique. However, obtaining information about the emotion expressed by a user does not tell us anything about whether it is appropriate or not to express that emotion in a given situation e.g., expressing joy during a funeral would be very inappropriate. Salovey and Mayer [1990] proposed a framework of human Emotional Intelligence (EI). Its first part assumes acquiring by a person the abilities to **a)** identify emotions and **b)** discriminate between appropriate and inappropriate expression of emotions. The few attempts to implement the EI Framework into machines [Picard *et al.*, 2001] eventually still do not go beyond the first basic step - recognition of emotions and none of the present methods is capable to perform contextual affect analysis.

We present a method not only specifying what type of emotion was expressed, but also determining whether the emotion is appropriate for the context it appears in. We use Shi's method for gathering emotive associations from the Web and Ptaszynski's system for affect analysis of utterances [Ptaszynski *et al.*, 2008]. One of the problems with this system was confusing the valence polarity of emotive expressions in the last step of the analysis. To solve this problem we applied the analysis of Contextual Valence Shifters.

## 2 ML-Ask

Ptaszynski's et al. [2008] ML-Ask (Emotive Elements / Emotive Expressions Analysis System) performs affect analysis of utterances in two steps: 1) Analyzing the general emotiveness of utterances; 2) Recognizing the particular emotion types. The system is based on Ptaszynski's idea of two-part analysis of realizations of emotions in language into: **Emotive elements**, indicating that emotions have been conveyed, but not detailing what specific emotions there are, e.g. interjections, mimetic expressions, or vulgarities; **Emotive expressions**, parts of speech or phrases, that in emotive sentences describe emotional states, e.g. nouns, verbs or adjectives.

The emotive element database was divided into interjections, mimetics, endearments, vulgarities and representations of non-verbal emotive elements, such as exclamation mark or ellipsis [907 items in total]. The database of emotive expressions contains Nakamura's [1993] collection [2100 items in total]. For a textual input utterance provided by the user, the system searches in order for: 1) emotive elements to determine the emotiveness; 2) emotive expressions to determine the specific types of the conveyed emotions. The system uses Nakamura's 10 type-classification of emotions said to be the most appropriate for the Japanese language: [joy], [anger], [sadness], [fear], [shame], [fondness], [dislike], [excitement], [relief] and [surprise].

However, keyword-based extraction of emotive expressions caused misinterpretations in valence polarity determination. To solve this problem, we applied an analysis of Contextual Valence Shifters.

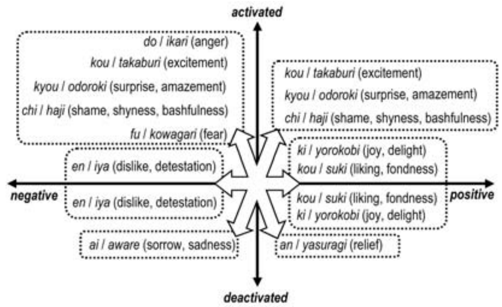


Figure 1: Nakamura's emotions on Russell's space.

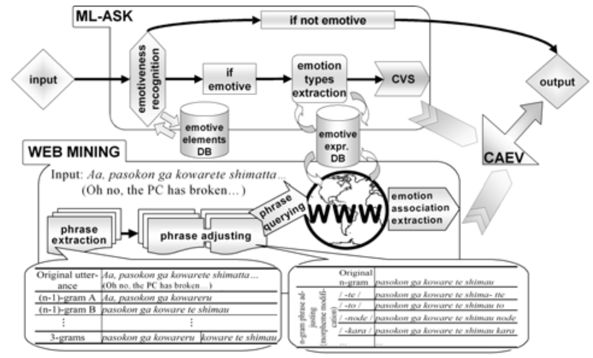


Figure 2: Flow chart of the CAEV procedure.

## 3 Contextual Valence Shifters in ML-Ask

The idea of Contextual Valence Shifters (CVS) was proposed by Polanyi and Zaenen [2004]. They distinguish 2 kinds of CVS: negations (changing the valence polarity of semantic orientation of an evaluative word) and intensifiers (intensifying the semantic orientation). Examples of CVS negations in Japanese are: *amari -nai* (not quite-), *-to wa ienai* (cannot say it is-), or *-te wa ikenai* (cannot+[verb]-). Intensifiers are: *sugoku-* (-a lot) or *kiwamete-* (extremely).

When a CVS structure is discovered, ML-Ask changes the valence polarity of the detected emotion. To specify the emotion types afterwards, we applied the 2-dimensional model of affect [Russell, 1980] which assumes that all emotions can be described in 2 dimensions: valence polarity (positive/negative) and activation (activated/deactivated). Nakamura's emotion types were mapped on the 2-dimensional model of affect and their affiliation to one of the spaces determined. The appropriate emotion after valence shifting is determined as the one with valence polarity and activation parameters different to the contrasted emotion (see Figure 1).

## 4 Web Mining Technique

As a verifier of appropriateness of the speaker's emotions recognized by ML-Ask we apply Shi's Web mining technique for extracting emotive associations from the Web [Shi *et al.*, 2008]. This technique performs common-sense reasoning about what emotions are the most natural to appear in a context of the utterance or which emotions should be associated with it. Emotions expressed, which are unnatural for the context are perceived as inappropriate. The technique is made up of three stages: **a)** extracting from an utterance n-gram phrases (of the length from one whole utterance to trigrams); **b)** modification of phrases ending with adjectives and verbs by the use of causality morphemes; and **c)** extraction of emotion associations from the Web using the prepared n-gram phrases as query inputs in Google search engine and cross-referencing them with the emotive expressions database.

## 5 Appropriateness Verification Procedure

The two described above systems are combined as follows. When ML-Ask discovers an emotive utterance and successfully specifies an emotion type, the Web mining technique verifies whether the expressed emotion type is appropriate for the context. The emotions commonsensically associating with the context of the utterance are extracted from the Web and the emotions discovered by ML-Ask in user's utterance are compared to the Web mining procedure results. If the two match, the emotions expressed by the user are determined as appropriate. In such situations, a conversational agent equipped with this method can choose an appropriate dialogue strategy (2 examples below).

**Positive-appropriate emotion:**
*User:* I'm so happy I passed the exam!
`ML-Ask:joy; Web mining:joy, excitement`
*Agent:* Yeah! That's great! `[sympathy]`
**Negative-appropriate emotion:**
*User:* I hate him for making a fool of me in front of everyone.
`ML-Ask:dislike; Web mining:anger, dislike`
*Agent:* You have a reason to be angry. `[empathy]`

However, if the verification procedure indicates that the expressed emotion is inappropriate for the context, the agent could undertake different measures e.g., helping the user to manage their emotions (2 examples below).

**Positive-inappropriate emotion:**
*User:* I'd be happy if he was hit by a car!
`ML-Ask:joy; Web mining:fear, sadness`
*Agent:* Is that what you really feel? `[counselling]`
**Negative-inappropriate emotion:**
*User:* I won the prize, but I feel so bored.
`ML-Ask:dislike, depression; Web mining:excitement, joy`
*Agent:* You should be happy! `[consolation]`

The flow chart of this Contextual Appropriateness of Emotions Verification (CAEV) procedure is presented in Figure 2.

## 6 Evaluation

In the evaluation experiment we used two conversational agents: 1) **Modalin**, a non-task oriented keyword-based conversational agent, which uses modality to enhance Web-based propositions for dialogue [Higuchi *et al.*, 2008]; 2) **Pundalin**, also a non-task oriented conversational agent, but equipped with Dybala's Pun generating system [Dybala *et al.*, 2009] to enhance interaction with a user.

13 users performed a ten turn conversation with both agents. All conversations were analyzed by ML-Ask (both without and with CVS). 6 of 26 conversations contained no specified emotional states and were excluded from the further

Table 1: 3 examples of the results of emotion appropriateness verification procedure (CAEV) with a separate display of the examples showing the improvement of the procedure after applying CVS.

| Part of conversation in Japanese (English translation) | ML-Ask output | Web Mining | CAEV |
|---|---|---|---|
| **USER**: *Konpyuuta wa omoshiroi desu ne.* (Computers are so interesting!) | **positive** [joy] | **positive** [joy] | **appro-priate** |
| **SYSTEM**: *Sore wa oishii desu ka.* (Is it tasty?) [about instant noodles] | × | × | × |
| **USER**: *Oishii kedo, ore wa akita kana.* (Its tasty, but I've grown tired of it.) | **negative** [dislike] | **negative** [dislike] | **appro-priate** |

| Part of conversation in Japanese (English translation) | ML-Ask baseline | with CVS | Web Mining | CAEV |
|---|---|---|---|---|
| **SYSTEM**: *Sore wa omoshiroi tte* (Its so interesting!) [about conversation] | × | × | × | × |
| **USER**: *Sore hodo omoshiroku mo nakatta yo.* (It wasn't that interesting.) | positive [joy] | **negative** [dislike] | **negative** [fear], [sad] | **appro-priate** |

evaluation. For the rest, the Web mining procedure determined whether the emotions expressed by the user were contextually appropriate. After that every conversation set was evaluated by 10 other people regarding what was the valence and the specific emotion types conveyed in conversations, and whether they were contextually appropriate.

### 6.1 Results and Discussion

We assumed that the results are correct when at least 4 participants of 10 per 1 set agree with the system. This is a fair ratio when we consider that it means that at least four people of ten provided exactly the same results as the system, which is a difficult thing to achieve in emotion research. The survey provided many positive results. In most cases affect analysis results were confirmed by humans, which proves the system is implementational in practice. ML-Ask supported with the CVS procedure acquired 85% of accuracy in recognition of particular emotion types (10% of improvement to the same method without CVS) and 90.0% of accuracy in emotion valence recognition (15% of improvement). Applying CVS analysis procedure improved also the performance of the contextual appropriateness verification procedure on the level of emotion types from 45.0% to 50.0% and valence from 50% to 55%. Some of the successful examples as well as the ones showing the improvement after applying CVS are shown in Table 1.

Since one of the agents was using humorous responses we also checked whether the jokes influenced the human-computer interaction. 67% of the emotions expressed in the conversations with Pundalin were positive whereas for Modalin 75% of the emotions were negative, which confirms that users tend to be positively influenced by the use of jokes in conversational agents [Dybala *et al.*, 2009].

## 7 Conclusions and Future Work

The paper presents one of the means to enhance a novel method performing and automated reasoning about whether the emotions expressed in a conversation are appropriate for the context. The system uses affect analysis to determine emotions conveyed by the speaker and a Web-based method performing approximate reasoning about which emotions should-, or are thought as natural (or commonsensical) to associate with the contents of the utterance. We enhanced the emotion types extraction in the baseline affect analysis system with Contextual Valence Shifters, which determine the semantic orientation of the valence of emotive expressions. We also applied a two-dimensional model of affect to determine which types of emotions are most probable to appear instead of the contrasted ones. Our system can provide a conversational agent with hints about what communication strategy would be the most desirable at a certain moment.

We are planning to use the system to gather a large ontology of actions/events with emotions associating with them divided according to their appropriateness. This task should be helpful in improving the newly created Japanese WordNet by supplementing it with Japanese version of WordNet Affect.

We were able to show that computing contextual appropriateness of emotions is a feasible task. Although the system's components (ML-Ask, Web mining) need improvement, it defines a new set of goals for Affective Computing. Contextual Affect Analysis including proper valence shifting is the next step towards practical implementation of Emotional Intelligence Framework in machines.

## Acknowledgments

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## References

[Dybala *et al.*, 2009] Pawel Dybala, Michal Ptaszynski, Rafal Rzepka and Kenji Araki. Humoroids - Talking Agents That Induce Positive Emotions with Humor, In *Proceedings of AAMAS'09*, 2009. (in print)

[Higuchi *et al.*, 2008] Shinsuke Higuchi, Rafal Rzepka and Kenji Araki. A Casual Conversation System Using Modality and Word Associations Retrieved from the Web. In *Proceedings of the EMNLP 2008*, pages 382-390, 2008.

[Nakamura, 1993] Akira Nakamura. *Kanjo hyogen jiten* [Dictionary of Emotive Expressions] (in Japanese), Tokyodo, 1993.

[Picard *et al.*, 2001] R. W. Picard, E. Vyzas, J. Healey. Toward Machine Emotional Intelligence: Analysis of Affective Physiological State, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 10, pp. 1175-1191. 2001.

[Polanyi and Zaenen, 2004] L. Polanyi and A. Zaenen. Contextual Valence Shifters, *AAAI Spring Symposium on Exploring Attitude and Affect in Text: Theories and Applications*, 2004.

[Ptaszynski *et al.*, 2008] Michal Ptaszynski, Pawel Dybala, Rafal Rzepka and Kenji Araki. Effective Analysis of Emotiveness in Utterances Based on Features of Lexical and Non-Lexical Layers of Speech. In *Proceedings of NLP2008*, pages 171-174. 2008.

[Russell, 1980] James A. Russell. A circumplex model of affect. *J. of Personality and Social Psychology*, 39(6):1161-1178. 1980.

[Shi *et al.*, 2008] Wenhan Shi, Rafal Rzepka and Kenji Araki. Emotive Information Discovery from User Textual Input Using Causal Associations from the Internet. *FIT-08*,pp.267-268,2008.

[Salovey and Mayer, 1990] Peter Salovey and John D. Mayer. Emotional intelligence, *Imagination, Cognition, and Personality*, 9:185-211, 1990.

[Treur, 2007] Jan Treur. On Human Aspects in Ambient Intelligence. In *Proceedings of The First International Workshop on Human Aspects in Ambient Intelligence*, pages 5-10, 2007.