

# Enriching Social Communication Through Semantics and Sentic

**Praphul Chandra**

Hewlett Packard Labs,  
India

praphul.chandra@hp.com

**Erik Cambria**

National University of Singapore,  
Singapore

cambria@nus.edu.sg

**Alvin Pradeep**

Hewlett Packard,  
India

alvin.pradeep@hp.com

## Abstract

Online communication is one of the key value propositions of mobile devices. While a variety of instant messaging clients offer users the ability to communicate with other users in real-time, the user experience remains dominated by a basic exchange of textual content. When compared to face-to-face communication, this experience is significantly poorer. In our proposed solution, we seek to enhance the chat experience by using an intelligent adaptive user interface that exploits semantics and sentics, that is the cognitive and affective information, associated with the ongoing communication. In particular, our approach leverages sentiment analysis techniques to process communication content and context and, hence, enable the interface to be adaptive in order to offer users a richer and more immersive chat experience.

## 1 Introduction

Online communication is an extremely popular form of social interaction. Unlike face-to-face communication, online instant messaging (IM) tools are extremely limited in conveying emotions or the context associated with a communication. Users have adapted to this environment by inventing their own vocabulary, e.g., by putting actions within asterisks ('I just came from a shower \*shivering\*'), by using emoticons (☺), by addressing a particular user in a group communication (@Ravi).

Such evolving workarounds clearly indicate a latent need for a richer, more immersive user experience in social communication. We address this problem by exploiting the semantics and sentics, that is the cognitive and affective infor-

mation, associated with the ongoing communication to develop an adaptive user interface (UI) capable to change according to content and context of the online chat.

## 2 Related Work

Popular approaches to enhance and personalize computer mediated communication (CMC) include emoticons, skins, avatars, customizable status messages, etc. However, all these approaches require explicit user configuration or action: the user needs to select the emoticon, status-message or avatar, which best represents her. Furthermore, most of these enhancements are static – once selected by the user, they do not adapt themselves automatically. There is some related work on automatically updating the status of the user by analyzing various sensor data available on mobile devices (Milewski and Smith, 2000). However, most of these personalization approaches are static and do not automatically adapt.

Our approach is unique in that it is: *intelligent*, as it analyzes content and does not require explicit user configuration; *adaptive*, as the UI changes according to communication content and context; *inclusive*, as the emotions of one or more participants in the chat session are analyzed to let the UI adapt dynamically.

The underlying technique in our approach is based on sentiment analysis of natural language text. Text analysis for understanding the underlying semantics is a large and well-established field of work (Fellbaum, 1998). Sentiment analysis is also an active research field and has been applied previously for a variety of applications including customer reviews (Hu and Liu, 2004) and news content (Subasic and Huettner, 2001).

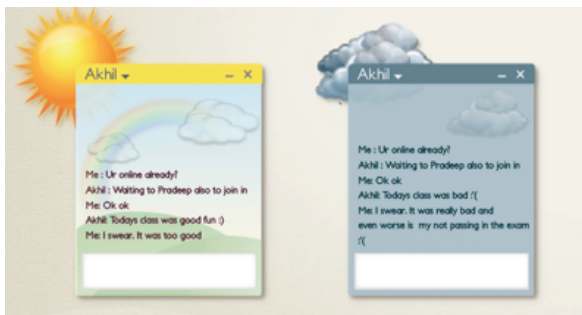
Uniquely, our approach applies sentiment analysis techniques to social communication in order to create an adaptive UI. Our module architecture can be deployed either on the cloud (if the client has low processing capabilities) or on the client (if privacy is a concern). Another advantage of our solution is that, even when the interface is used by only one participant in the communication session, it enhances the experience of that user.

### 3 The Weather Metaphor

Most IM clients offer a very basic UI for text communication. In this work we focus on extracting the semantics and sentics embedded in the text of the chat session to provide a UI, which adapts itself to the mood of the communication. For our prototype application we worked with the weather metaphor, as it is scalable and has previously been used effectively to reflect the subject's mood (Chang, 2009) or content's 'flavor' (Pampalk et al., 2002).

In our UI, if the detected mood of the conversation is 'happy', the UI will reflect a clear sunny day. Similarly a gloomy weather reflects a melancholy tone in the conversation. Of course, this is a subjective metaphor – one that we think scales well with conversation analysis. We can think of other scalable metaphors that are relevant, e.g., colors (Havasi et al., 2010).

Our adaptive UI primarily consists of three features: the stage, the actors and the story. For any mapping these elements play a crucial role in conveying the feel and richness of the conversation mood, e.g., in the 'happy' conversation the weather 'clear sunny day' will be the stage, the actors will be lush green valley, the rainbow and the cloud which may appear or disappear as per the current conversation tone of the story. The idea is similar to a visual narrative of the mood the conversation is in; as the conversation goes on the actors may come in or go off as per the tone of the thread.



“Figure 1. Happy and Sad adaptive UI”



“Figure 2. Cry and Anger adaptive UI”

By analyzing the semantics and sentics associated with communication content (data) and context (metadata), the UI may adapt to include images of landmarks from remote-user's location (e.g., Times Square), images about concepts in the conversation (pets, education, etc.) or time of day of remote user (e.g., sunrise or dusk).

### 4 Social Communication Analysis

For the extraction of semantics and sentics, we leverage sentic computing (Cambria et al., 2010a), a multi-disciplinary approach to opinion mining and sentiment analysis that exploits both computer and social sciences to better recognize, interpret and process emotions over the Web. In sentic computing, the analysis of natural language is based on common sense reasoning tools and domain-specific ontologies.

Unlike statistical classification, which generally requires large inputs and thus cannot appraise texts with satisfactory granularity, sentic computing enables the analysis of documents not only at page- or paragraph-level but also at sentence and clause-level.

In particular, we exploit the following four modules (re-adapted for real-time analysis): a natural language processing (NLP) module, which performs a first skim of chat text, a Semantic Parser, whose aim is to extract concepts from the lemmatized text, the ConceptNet module, for the inference of semantics, and the AffectiveSpace module, for the extraction of sentics.

#### 4.1 Preprocessing Modules

The NLP module parses the textual metadata associated with media to output lemmatized text. It recognizes and interprets the affective valence indicators usually contained in text such as special punctuation (e.g., '!!!!'), complete uppercase words ('I DID NOT SAY THAT'), exclamations ('as if!'), degree adverbs, emoticons (☺) etc. This makes the NLP module suitable for short emotive texts used in chat.

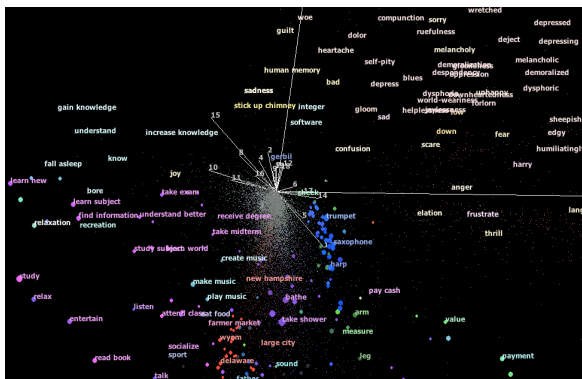


common-sense assertion relations (from ConceptNet, e.g., isA-pet) or affective features (from WordNet-Affect, e.g., hasEmotion-joy). We then apply truncated singular value decomposition (TSVD) (Wall et. al. 2003) on this large matrix.

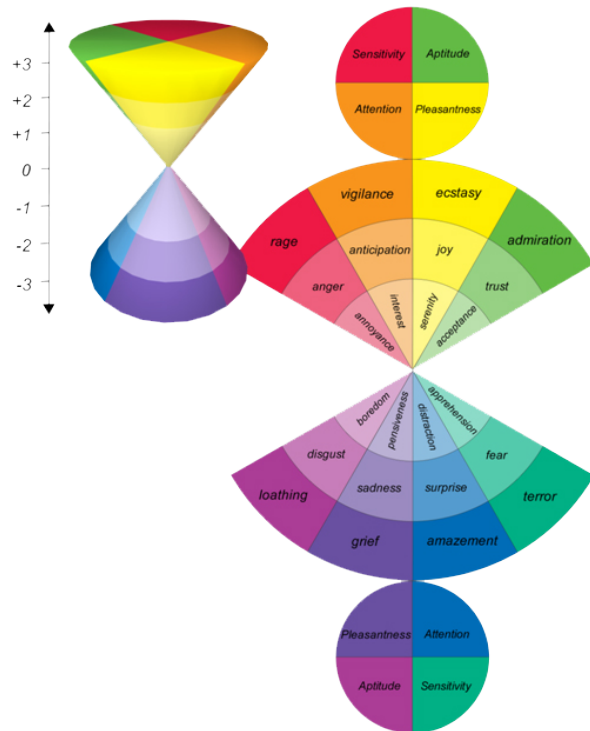
The resulting matrix has the form  $A_k = U_k S_k V_k^T$  and is a low-rank approximation of A, the original data. This approximation is based on minimizing the Frobenius norm of the difference between A and  $A_k$  under the constraint  $\text{rank}(A) = k$ . Thus,  $A_k$  is the best approximation of A in the Frobenius norm sense when  $\sigma_i = s_i$  ( $i = 1, 2, \dots, k$ ) and the corresponding singular vectors are the same as those of A. If we choose to discard all but the first-k principal components, common sense concepts and emotions are represented by vectors of k coordinates: these coordinates can be seen as describing concepts in terms of eigenmoods that form the axes of AffectiveSpace, that is, the basis  $e_0, \dots, e_{k-1}$  of the vector space. By selecting the top-k eigenvalues, we are in effect, clustering the concepts.

The clustering of this multi-dimensional space, with respect to emotion-categories can therefore help us derive sentics in the chat text. In particular, we use the Hourglass of Emotions (Cambria et al., 2010c) to infer the affective valence of the retrieved concepts according to the relative position they occupy in the multi-dimensional vector space.

In the hourglass model, emotions are classified into four concomitant but independent dimensions in order to understand the Pleasantness, Attention, Sensitivity and Aptitude. Each of these dimensions is characterized by six levels of activation, called sentic levels, which determine the intensity of the expressed/perceived emotion as a float between [-3, 3]. Thus, we specify the affective information as a four dimensional sentic vector, that can potentially express any human emotion in terms of Pleasantness, Attention, Sensitivity and Aptitude.



“Figure 4. A sketch of AffectiveSpace”



“Figure 5. The Hourglass of Emotions”

Thus, by exploiting the information sharing property of TSVD, concepts with the same affective valence are likely to have similar features, that is, concepts conveying the same emotion tend to fall near each other in AffectiveSpace, e.g., we can find concepts such as ‘beautiful day’, ‘birthday party’, ‘laugh’ and ‘make person happy’ very close in direction in the vector space, while concepts like ‘sick’, ‘feel guilty’, ‘be laid off’ and ‘shed tear’ are found in a completely different direction (nearly opposite with respect to the center of the space).

## 5 Discussion and Future Work

Popular approaches to enhance CMC include emoticons, skins, avatars, customizable status messages, etc. Sharing photos or combining video streams with text is also supported in popular IM clients. However, our approach of adaptive UI for chat is a novel concept. Text analysis for understanding the underlying semantics is a large and well-established field of work as well as sentiment analysis is an active research field.

Uniquely, our approach applies sentic computing techniques to social communication in order to create an adaptive UI. Our module architecture can be deployed either on the cloud (if the client has low processing capabilities) or on the client (if privacy is a concern). In the next future, we also plan to explore other metaphors of adaptive UIs, both sentic and semantic based.

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