# We have no feelings, we have emoticons ;-)

Sarah Leon Rojas
Fraunhofer FIT
Schloss Birlinghoven
sarah.leon.rojas@fit.fraunhofer.de

Uwe Kirschenmann
Fraunhofer FIT
Schloss Birlinghoven
uwe.kirschenmann@fit.fraunhofer.de

Martin Wolpers
Fraunhofer FIT
Schloss Birlinghoven
martin.wolpers@fit.fraunhofer.de

***Abstract*—Positive emotions have been proven to be a key factor for successful learning. In modern personalized learning environments informal learning takes a prominent role and with this the use of computer-mediated communication. Communication-data, like for example chat-logs, can be harvested for sentiments. Most sentiment-analyses operate processing verbal information. But chat-messages also contain low key nonverbal communication: Emoticons are used to compensate the missing visual information and transmit emotions.**

**In this paper we want to introduce a method to perform a sentiment analysis on text-based chat-logs, disregarding all verbal information and using only emoticons to detect positive sentiments. We implemented and tested this method for the instant messenger Skype. Our first results show emoticons do indeed represent a strong indicator for detecting positivity within chat communication.**

***Index Terms*—component; formatting; style; styling;**

## I. Introduction

Emotions have been proven to have a great impact on work- and learning processes. They can influence affective experiences such as attitude, motivation, creativity and problem solving skills [1]. Also they can widen the attention scope of students and serve as an enhancing factor for memory processes [2][3].

Of course emotions during learning are not always helpful. Negative emotions can impede learning processes and distract the learner from the matter at hand[3]. But negative emotions do not necessarily affect the performance negatively, they can also manifest themselves as part of the problem solving process[1]. Additionally positive sentiment can act as a buffer against negative emotions, lessening their influence on the results[1].

Social relationships are a part of the learning process in collaborative environments [4] [5]. Knowledge acquired during collaborative learning is constructed actively with the aid of communication processes [6]. Personalized Learning Environments (PLEs) let the learner assemble a learning environment adjusted to his own needs [7]. In these informal settings, interpersonal communication takes a prominent role for learning and a positive relationship is one of the key factors to set up a successful learning situation as well as create the necessary willingness [8].

In order to measure the positive sentiment of the chat relationship between two peers, we analyzed their emoticon use during chat sessions. For this purpose we extracted emoticon-related key values from chat logs and combined them in order to estimate the positivity value for this relationship.

To illustrate the use of an emoticon-based sentiment analysis let's consider the following scenario: Gustav and Christa study computer science and are working together on a small project for one of their courses. They mostly work on separate locations and communicate using the Skype-widget integrated into their PLE. By analyzing their emoticon-use extracted from the chat-logs the positivity of their relationship can be estimated. This way they can monitor the quality of their relationship while working together. Apart from themselves the course-supervisor also can access the analysis results, which in this case are pseudonymized to mask the real identity of the students. At the end of the project the team of Gustav and Christa shows high positivity values for their relationship. Their work results also are excellent. A different team, Simone and Nina, while also reaching a high positivity has presented quite poor work results. In this case the combination of the indicator with the final work results, can lead to the conclusion, that the positivity of their communication was achieved primarily due to private chat during the work sessions.

### A. *Sentiment analysis*

Sentiment-analysis combines the methods of computational linguistics and text-mining in order to detect the predominant sentiment in a fragment of written text [9]. Most work in the area of sentiment analysis is based on the processing of verbal information. To this end, words are classified according to their emotional value [10]. In our approach, we decided to abstain from the processing of verbal information. This is due to two reasons: The processing of verbal data is known to often generate a big amount of processing time. Furthermore an analysis of verbal information implies a bigger intrusion upon the privacy of the analyzed user than the analysis of only emoticons. The goal was to evaluate to which extent a relationship could be predicted relying only on nonverbal information to determine the predominant sentiment of the interpersonal communication of the peers.

### B. *Emoticon analysis*

In the past CMC has often been characterized as bare of all nonverbal expressions. Text-based mediums like chat may not provide a visual channel, but the absence of visual cues can be compensated to a certain extent. For this purpose emoticons are often used [11][12][13]. Emoticons are small images or conjunctions of diacritical symbols, which represent moods, facial expressions and activities which can be considered non-verbal substitutes for communicating emotions and feelings in a text-based environment[11][12][14].

Emoticons can transport different types of information. Studies have shown, that emoticons representing an abstract depiction of a human face are perceived in the same manner as the corresponding facial expression. A smiling emoticon activates the same brain areas as the image of a person smiling and can therefore be considered as a representation of that emotion [15]. Other emoticons can represent actions (dancing, jumping, singing) or objects (sun, heart, rain). They can even represent a specific mood not associated with a particular facial expression (tired, bored, creative)[16][17].

The motives behind emoticon use are diverse. They can be used to strengthen the emotional content of a verbal message as well as contradict it with the purpose of expression irony or sarcasm. Not all emoticons strengthen a verbal message with the same intensity. A positive emoticon can increase the positivity of a positive message more than a negative emoticon can increase the negativity of a negative message [18]. Positive emoticons are also used to soften otherwise harsh or rude verbal messages [13]. However, they do not have the strength to turn around the valence of the verbal message [19] Generally it can be established, that positive emoticons convey positivity more than negative emoticons convey negativity. Negative emoticons are often used in a light context or as part of a joke and are therefore not associated with negative feelings. In consequence a negative context does not lead to an increased number of negative emoticons but to an overall decrease of emoticon-use. On the other hand a lack of emoticons is not necessarily caused by a negative context, but could also occur in a neutral conversation with a higher emotional distance between the partners [13].

In F2F communication emotions are mimicked when feeling sympathy for the partner [20]. Derks showed that a similar behavior is also observable in CMC, where emoticons can be mimicked, when expressing sympathy for the chat partner [13].

The remainder of this paper is organized as follows: In section II-A we will expand on the technical details and architecture of our prototype followed by a description of our analysis algorithm in section II-B. Subsequently in section III we will present our experimental setup. We will conclude with our evaluation (section IV) and the interpretation of the results in section IV-A.

## II. ARCHITECTURE

We implemented our concept for the instant messenger (IM) Skype[1] using the Skype4Java API-Wrapper[2] to access the chat-history. A real-time analysis was not implemented, but would be applicable to the concept as well. The application consists of two modules: extraction and analysis as shown in figure 1. The extraction module extracts and formats the data from the chat-log and stores it to a central database. The extraction module contains an anonymization module which masks all analyzed users to prevent the storage of personal data. The analysis module operates exclusively on the database with the exception of finding logged on Skype users. An analysis can only be performed while being logged on to Skype this way it can be made sure a user can only access and analyze his own communication data. Of course the integration into a PLE would require a more fine-grained handling of access-rights, considering a course supervisor will have to have access to all analysis results for his students.

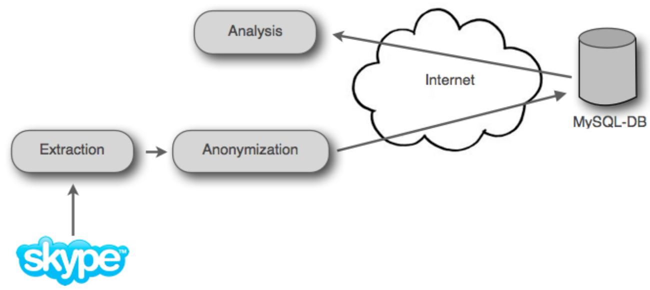


Fig. 1. Architecture of the chat-tracker.

### A. Extraction module

Prior to the actual analysis the data is extracted from the Skype chat-logs and stored in a central database. The extracted data includes all chat-messages with their respective date, sender and receivers. For the extraction and storage of the contacts[3] it was of importance to protect the privacy of the analyzed contacts, while at the same time being able to identify them in order to perform the analysis. Here we opted for assigning each extracted contact a pseudonym paired with an unique ID for identification. This ID was obtained creating a hash value based on the Skype-ID [4] using the SHA-1 hash-algorithm[5]. The pseudonyms were generated automatically using a compilation of the 100 most common German names (male and female) and surnames. Since verbal information is not relevant for the later analysis, the content of the chat-messages was discarded after the detection of emoticons.

We did not segment the communication into individual conversational units. De facto, Skype groups chat-messages between two peers into *chats* but this is done on neither a temporal nor a semantic basis. A segmentation based on temporal gaps between messages to detect the start and end

[1] `http://www.skype.com`

[2] `http://es.sourceforge.jp/projects/skype/`

[3] In Skype frequent chat-partners (contacts) can be be added to a *contact list*. It is however not necessary to add a person to the contact list to chat with them. Nonetheless in the following we will refer to all chat-partners as contacts

[4] The Skype-ID is the username and at the sam time login-id in Skype. It frequently contains parts or the entire real name

[5] `http://csrc.nist.gov/groups/ST/toolkit/secure_hashing.html`

TABLE I
LEGEND

| | |
|---|---|
| AP | number of positive emoticons |
| AN | number of negative emoticons |
| ANt | neutral emoticons |
| AM | number of messages containing emoticon mimickry |
| WC | word count |
| MC | message count |

TABLE II
POSITIVITY VALUES

| | |
|---|---|
| 0 | No emoticons used |
| 1 | Not positive |
| 2 | Slightly positive |
| 3 | Normal positivity |
| 4 | Positive |
| 5 | Very positive |

of a new conversation is also unreliable given the semi-synchronous nature of IM-chat: One of the peers may initiate a conversation while his partner is not online or away from his computer. At his return the partner can answer the question thus continuing a conversation started a few hours ago. If the initiator now is offline another temporal gap would originate without the actual conversation ending. A dependable method to segment the chat communication from the chat logs would be the detection of conversational units based on the topics being discussed. But this solution would include the analysis of verbal information we were trying to avoid in our approach. In conclusion we opted for analyzing the whole chat history between two peers as one conversation.

### B. Analysis module

Currently an analysis can only be performed by the logged-in user. On reason behind this is the protection of the users privacy. The analysis module identifies the user and gets his already extracted and formatted chat data from the central database. Based on the theory presented in section I-B three indicators are calculated which later are going to determine the positivity of the chat communication between two peers. The positivity of chat communication in our concept is defined as the amount of positive sentiment transmitted by the emoticons in a chat conversation. The legend for all formulas in this section can be found in table I.

*1) Emoticon-rates:* To use the mere emoticon count of a conversation would lead to people with a greater amount of chat communication obtaining higher positivity values since they are bound to have a higher emoticon count. Contacts with less communication would automatically be classified as less positive. To avoid this, we calculated the rate of emoticons per word (*GEQ*) using the number of emoticons (positive, negative and neutral) based on the theory that in a positive context the overall emoticon count increases (see section I-B).

$$GEQ = \frac{AP+AN+ANt}{WC}$$

We also mentioned in section I-B that positive emoticons on one hand convey more positivity than other emoticons. On the other hand they are also always used in a positive context or with positive intentions. Based on this we assume that positive emoticons constitute a stronger indicator for positivity and therefore should be considered separately. The second indicator represents the rate of the positive emoticons per word (*PEQ*).

$$PEQ = \frac{AP}{WC}$$

*2) Emoticon-mimicry-rate:* The third indicator is the emoticon mimicry rate (*EMQ*) and is calculated per message. To detect emoticon mimicry it is determined if chat partners reacts to an emoticon with another one with the same emotional value. For this we classified emoticons in initiative and reactive. We define an initiative emoticon as being sent autonomously at the beginning of a conversation, after a quantity of messages without emoticons or after a longer pause. If an initiative emoticon is detected the following *three* messages of the peer are examined for an emoticon of the same emotional value. An occurrence is classified as a reactive emotion. The number of three messages was chosen to balance the offset in turn-taking addressed in section I-B.

$$EMQ = \frac{AM}{MC}$$

*3) Positivity rating:* Each *active* contact in Skype[6], obtained a positivity rating (*PR*) based on the three indicators described in the previous section. The positivity rating was aimed to represent the amount of positive sentiment inherent to the chat relationship of two peers. It was calculated considering the entire chat history of the peers. Contacts with whom there never had been any chat communication were considered *inactive* and excluded from the analysis. The *PR* results as the dot product of the vector *K* containing the three previously described indicators (GEQ, PEQ and EMQ) and the weight vector *G*. The function of the weight vector is to scale the indicators according to their influence. The weights were chosen in regarding that (a) a high amount of emoticons indicates a positive conversation and (b) positive emoticons convey more positivity than negative oder neutral emoticons (see section I-B). The *EMQ* received the lowest weight (0.2) due to the fact of being a more experimental measure than the *GEQ* amd *PEQ*.

$$PR = \vec{K} \cdot \vec{G} \qquad \vec{G} = \begin{pmatrix} 0.5 \\ 0.3 \\ 0.2 \end{pmatrix}, \vec{K} = \begin{pmatrix} PEQ \\ GEQ \\ EMQ \end{pmatrix}$$

The *PR* was first calculated for all active contacts and then normalized to a range from 1 to 5 as shown in table II The value 0 was reserved for communication with absolutely no emoticons.

*4) Problems:*

- **No emoticon use:** Communication without any emoticons is automatically classified as not positive. This may not be always the case. When communicating with

[6]A contact with whom there has been communication via Skype chat is considered an *active contact*

contacts with an higher emotional distance, emoticons are often suppressed out of respect [13]. But this does not necessarily mean that this relationship is not positive. With the current algorithm, however, it is not possible to distinguish between a neutral and an non-positive conversation.

- **Two-dimensional relationships:** An emoticon-ratio considered high given the chat behavior of the current user, may not be the same for the corresponding peer. In order to make a statement about both peers a complete analysis about their chat behavior and emoticon-use would be necessary. For this reason the calculated positivity refers only to the relationship from users point of view.
- **False emoticon mimicry:** If an initiative emoticon is detected, every response is considered a reaction. Since no verbal analysis is performed it is not possible to detect topic changes. If an emoticon was sent initiatively in reaction to a topic change *after* an initiative it would wrongly classified as reactive.
- **False emotions:** Emoticons can be easily reproduced, even in absence of the represented sentiment [13]. Given the case of someone pretending a false emotion using emoticons, the connection would still be rated as positive.
- **Emoticon weights:** Given the lack of time to perform a larger study concerning the emotional intensity of all used emoticons, we did not employ different weights. All emoticons received the weight of 1.

## III. Experimental setup

We tested the implementation of our concept in a small test group (N=6) with the goal of performing a first validation of our approach. The test subjects were between 30 and 40 years old and worked in a research group at Fraunhofer FIT. All used Skype on a regularly basis and the majority (83,3%) were mutual contacts in Skype. The test was performed at the work computers of the test subjects. All test-subjects, as well as their analyzed contacts, received a pseudonym in order to protect their privacy. While the prototype performed the analysis in the background, the test subjects answered a questionnaire concerning their chat behavior. In the questionnaire the test subjects were asked to choose their top ten contacts from the contactlist[7]; the first ranking according the sympathy and the second according to the perceived quality of the chat relationship.

## IV. Evaluation

We evaluated the test results by comparing the answers from the questionnaire to the values calculated by the prototype. First we compared the top ten contacts (ordered by the calculated positivity rating *PR*) to the sympathy and the quality ranking established by the test subjects (described in section III). To compare the rankings rank matches were considered, but the focus was on the intersection of the calculated and the test subject's values. Also we observed if the program tended to rank contacts higher or lower than the test ranking.

[7]The contactlists of the test-subjects contained between 20 and 100 contacts

TABLE III
Testers sympathy ranking and calculated values

| | $Mean(\bar{x})$ | Median ($\hat{x}$) |
|---|---|---|
| Matches | 48,33% | 50% |
| Rank matches | 3,33% | 0% |
| Rank-discrepances higher | 56,53% | 60% |
| Rank discrepance lower | 40,14% | 40% |
| Not analysed | 15% | 10% |

We expected the chat quality ranking to have a higher concordance with the calculated results. The test subjects had to define the term chat quality according to their own perception. Here we anticipated them to employ a simple heuristic for estimating the chat-quality. Such a heuristic may, among others, include measurable indicators like the amount of the communication and be therefore comparable to the values considered in the calculation. In the case of a high self-assessment degree of the test subject when estimating communication values, we expected a higher concordance between the chat quality ranking and the calculated positivity. The self-assessment degree of the test subjects could be determined by comparing the self-assessed communication values from the first part of the questionnaire with the measured values.

To make sure the quality ranking of the testers was accurate we additionally checked the self assertion of the testers by comparing the answer they gave concerning the amount of conversation and emoticons with the analysis partner.

### A. Results

When comparing the tester and program rankings, as anticipated, we encountered a higher concordance with the quality ranking (as shown in tables IV and III). The exact rank was seldom matched, neither with the quality ($\bar{x} = 10.71\%, \hat{x} = 7.14\%$) nor the sympathy ranking ($\bar{x} = 3.33\%, \hat{x} = 0\%$). In comparison with the sympathy ranking the calculated rank was predominantly higher than the one given by the test subjects ($\bar{x} = 56.53\%, \hat{x} = 60\%$). Contrarily the rank was predominantly lower for the quality ranking ($\bar{x} = 58.57\%, \hat{x} = 60\%$). There were also some cases of contacts appearing in a testers ranking which were not analyzed by the program due to a lack of conversational data. Here the number of not analyzed contacts was higher for the sympathy ranking.

Also it resulted to be very difficult for the testers to sort their top contacts in an ordered list. All test subjects needed a long timespan to establish their rankings, which in all cases had been corrected several times. They said they experienced difficulties putting their contacts in a fixed ranking and that some contacts they would have liked to have the same rank. This led us to the conclusion, that a relative classification of the contacts positivity might be easier to process for test subjects and users in general.

The discrepancies with the sympathy ranking could have been partly caused by the fact that some contacts were very close friends in real life but they did seldom chat with them via Skype. Others said, that they did communicate via Skype, but tended to call. Another reason for the discrepancies, in both quality and sympathy ranking could be incomplete chat-logs. Some test subjects stated, that they used Skype on several computers and due to local storage of Skype chat logs not all communication data could be extracted.

TABLE IV
TESTERS CHAT QUALITY RANKING AND CALCULATED VALUES

| | $Mean(\bar{x})$ | Median ($\hat{x}$) |
|---|---|---|
| Matches | 55% | 60% |
| Rank matches | 10,71% | 7,14% |
| Rank-discrepances higher | 29,28% | 30,95% |
| Rank discrepance lower | 60% | 58,57% |
| Not analysed | 1,67% | 0% |

## V. CONCLUSION

We developed, implemented and tested a method to perform a sentiment analysis on text-based chat using only the emoticons exchanged between the peers. The underlying concept was based on the assumption that emoticons represent the nonverbal communication in text-based chat and convey the emotions of the communication partners. We tried to determine the amount of positive sentiment conveyed by emoticons to estimate the positivity of a chat conversation.

Determining the positivity within chat-communication can be of great value for analyzing collaboration processes in a learning environment. Positive emotions can boost productivity and motivation and therefore lead to a successful learning experience. In many learning environments informal chat is used as a communication channel, providing the necessary data to perform such an analysis.

Although it might be, in some cases, difficult to determine whether a detected positivity is related to private or work-related talk, in combination with work results, this indicator could be quite valuable. Also positivity caused by private chat can indicate a positive and successful learning relationship. If the results of a learning process are negative, then a high positivity can hint to an excess of private chat leading to distraction from work.

We tested our prototype by comparing the calculated positivity values for chat contacts to the self-assessed values of the test-subjects. Our results show, that while it might not be possible to estimate the actual sympathy between chat contacts in all cases, an emoticon analysis can be a good indicator for the perceived quality of the chat relationship. To confirm and stabilize these preliminary results, further testing with a larger test group would be necessary.

A possible expansion of our concept is the introduction of different emotional intensities for Skype emoticons based on a larger study. We also plan on improving the precision of the emoticon analysis by combining it with an analysis of further nonverbal cues contained in chat communication like for example the frequency of communication or the number of messages and calls per time unit. Also a combination with an analysis of verbal information will be taken into consideration.

All in all the presented implementation is a first throw in the direction of analyzing the emotional content of relationships that could lead to a better learning experience.

## REFERENCES


[1] J. A. A. Abe, "Positive emotions, emotional intelligence, and successful experiential learning," *Personality and Individual Differences*, vol. 51, no. 7, pp. 817–822, Nov. 2011.

[2] E. R. Um, J. L. Plass, and H. S. Song, "The Effect of Positive Emotions on Multimedia Learning," in *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2007*. New York University, Jun. 2007, pp. 4176–4185.

[3] P. Wolfe, "The role of meaning and emotion in learning," *New Directions for Adult and Continuing Education*, vol. 2006, no. 110, pp. 35–41, 2006.

[4] C. Fowler and J. Mayes, "Learning relationships from theory to design," *Association for Learning Technology Journal*, vol. 7, no. 3, pp. 6–16, 1999.

[5] A. Soller, B. Goodman, F. Linton, and R. Gaimari, "Promoting effective peer interaction in an intelligent collaborative learning system," in *Proceeding ITS '98 Proceedings of the 4th International Conference on Intelligent Tutoring Systems*, London, Jan. 1998, pp. 186–195.

[6] H. Cho, G. Gay, B. Davidson, and A. Ingraffea, "Social networks, communication styles, and learning performance in a CSCL community," *Computers & Education*, vol. 49, no. 2, pp. 309–329, Jan. 2007.

[7] U. Kirschenmann, M. Scheffel, M. Friedrich, K. Niemann, and M. Wolpers, "Demands of modern PLEs and the ROLE approach," in *Sustaining Tel: from Innovation to Learning and Practice*. Springer-Verlag New York Inc, Oct. 2010.

[8] T. Götz, A. Zirngibl, R. Pekrun, and N. Hall, "Emotions, learning and achievement from an educational-psychological perspective," in *Learning Emotions: The Influence of Affective Factors on Classroom Learning*. Peter Lang Pub Inc, Dec. 2003, pp. 9–28.

[9] D. Das and S. Bandyopadhyay, "Discerning Emotions of Bloggers based on Topics," in *Proceedings of the 22nd Conference on Computational Linguistics and Speech Processing*, Sep. 2010, pp. 350–363.

[10] A. Esuli and F. Sebastiani, "SENTIWORDNET: A high-coverage lexical resource for opinion mining," in *Proceedings of LREC 2006*, 2006, pp. 417–422.

[11] N. Döring, *Sozialpsychologie des Internet*, ser. Die Bedeutung des Internet für Kommunikationsprozesse, Identitäten, soziale Beziehungen und Gruppen. Hogrefe, 2003, vol. 2.

[12] M. Beisswenger, *Chat-Kommunikation*, 1st ed. Ibidem Verlag, 2001, vol. 1.

[13] D. Derks, "Exploring the missing wink: emoticons in cyberspace," Ph.D. dissertation, Open Universiteit Nederland, 2007.

[14] L. Rezabek and J. Cochenour, "Visual cues in computer-mediated communication: Supplementing text with emoticons," *Journal of Visual Literacy*, vol. 18, no. 2, pp. 201–215, 1998.

[15] M. Yuasa, K. Saito, and N. Mukawa, "Emoticons convey emotions without cognition of faces: an fMRI study," *CHI'06 extended abstracts on Human factors in computing systems*, pp. 1565–1570, 2006.

[16] L. Ruan, "Meaningful Signs—Emoticons," *Theory and Practice in Language Studies*, vol. 1, no. 1, pp. 91–94, 2011.

[17] F. Radulovic and N. Milikic, "Smiley Ontology," in *1st International Workshop On Social Networks Interoperability SNI 2009 In conjuction with The 4th Asian Semantic Web Conference (2009)*, 2009, pp. 1–4.

[18] (2002) The Impact of Emoticons on Affect Interpretation in Instant Messaging. [Online]. Available: http:amysmile.comdocemoticon_paper.pdf

[19] T. Ted Luor, L.-L. Wu, H.-P. Lu, and Y.-H. Tao, "The effect of emoticons in simplex and complex task-oriented communication: An empirical study of instant messaging," *Computers in Human Behavior*, vol. 26, no. 5, pp. 889–895, Sep. 2010.

[20] L. Scissors, A. Gill, K. Geraghty, and D. Gergle, "In CMC we trust: the role of similarity," in *Proceedings of the 27th international conference on Human factors in computing systems*, 2009, pp. 527–536.