



# A Research Tool for User Preferences Elicitation with Facial Expressions

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## ABSTRACT

We present a research tool for user preference elicitation that collects both explicit user feedback and unobtrusively acquired facial expressions. The concrete implementation is a web-based user interface where the user is presented with two music excerpts. After listening to both, the user provides a pairwise score (i.e. which of the two items is preferred) for each pair of music excerpts. The novelty of the demo is the integration of the unobtrusive acquisition of facial expressions through the webcam. During the listening of the music excerpts, the system extracts features related to the facial expressions of the user several times per second. The interaction runs as a web application, which allows for a large-scale remote acquisition of emotional data. Up to now, such acquisitions were usually done in controlled environments with few subjects, hence being of little use for the recommender systems community.

## CCS CONCEPTS

• **Human-centered computing** → *Interaction devices; Empirical studies in HCI*; • **Computing methodologies** → *Machine learning*;

## KEYWORDS

pairwise scores, implicit preference elicitation, facial expressions, emotions

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## 1 INTRODUCTION

This demo addresses elicitation of user preferences. Preference elicitation deals with retrieving user feedback about items. The feedback is usually provided in the form of explicitly entered ratings of some numerical form (e.g., one to five stars) or signals of implicit preferences, such as click, preview, purchase etc. Furthermore, feedback can be acquired as a single judgment or in the form of pairwise comparison [4]. These forms of feedback reflect the opinions of users about items. However, these opinions are not based only on rational thinking but are often fast, intuitive and emotionally charged, as described by the two-systems model [3]. This model describes human decision making as an aggregation of a fast, emotional (System I) and a slow, rational, cognitive process. When the preferences are acquired explicitly, content-based recommender systems [6] exploit well the rational part, i.e. the relationship between item characteristics and expressed user preferences. Still, the relationship between the user's emotional state and the expressed preference and its impact on the performance of recommender systems is a less explored area. Research on emotions-based recommender systems have been done on a smaller scale [1, 9] as the acquisition of such data has been traditionally difficult.

In recent years, the unobtrusive acquisition of emotional user responses has become more accessible. Algorithms, that take advantage of multiple modalities, such as facial expressions, voice and physiological responses, have become robust and accurate [7]. Furthermore, a number of off-the-shelf products have become available, such as the Affectiva API<sup>1</sup>.

This demo showcases a tool for researchers in the form of a web interface, which allows preference elicitation both in the forms of (i) explicit comparison of item pairs and (ii) unobtrusively acquired affective responses of users. The added value of extracting facial features, related to emotions, from the web camera allows to pursue new research directions: (i) development of unobtrusive acquisition of user ratings from facial expressions and (ii) new multidimensional models of user preferences.

<sup>1</sup><https://developer.affectiva.com/>

## 2 TECHNICAL DESCRIPTION

The demo user interface is available at the URL <https://recsys.musielab.si/PairwiseComparisonsStudy/> while a video walkthrough is available at the URL <http://www.inf.unibz.it/~tkalcic/RecSysD emo2017Walkthrough/>. It is written in PHP using the CodeIgniter framework and using JavaScript on the client side. The information flow is shown in Fig. 1. The facial expressions are acquired through the webcam video stream. The stream is sent to the Affectiva API directly using Javascript. In this way our server is not burdened with proxying the multiple video streams. The Affectiva API returns to the web browser a JSON file containing the extracted facial features. The sampling frequency is not constant through time but in practice it fluctuates around 11 frames per second. The features are then sent from the web browser to our server and stored in a database. The database also stores the user-entered pairwise scores and other user characteristics, acquired through pre- and post-questionnaires, such as personality and the Music Sophistication Index [5].

The music excerpts are taken from the Moodo dataset [8], which consists of 200 snippets of songs, each lasting approximately 15 seconds. The songs are not widely known to the general public, which reduces the popularity bias. The selection of song pairs for comparison was done randomly, however, we used a weighting schema to simulate the short-head, long-tail effect.

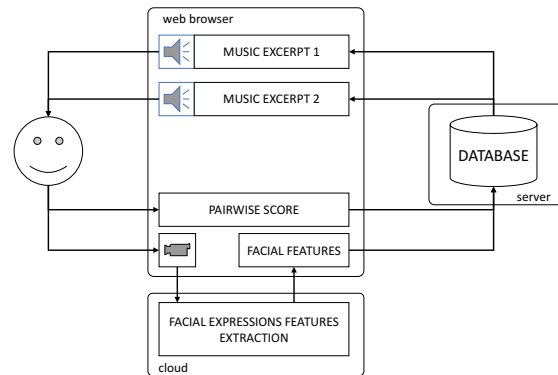
Each music comparison, which is defined by the tuple  $(user, song1, song2, score)$  contains several database entries. The pairwise score  $score$  is on the scale  $\{-2, -1, 0, 1, 2\}$ , where  $-2(2)$  means the user preferred the left-most (right-most) song and  $0$  means both songs were equal. Each entry within the same comparison contains the facial features acquired at a sampling point while the user was comparing the two items. In the study conducted up to this point, we had 27 users (10 males, median age 27 years) who completed the interaction. On average, each user compared 9.4 pairs of songs. The average comparison lasted 27.9 seconds. The average facial features sampling frequency was 11.2 times per second. Hence, for each comparison we had on average 312 database entries with facial features.

From the Affectiva API we collect a total of 47 features for each video frame. Examples of concrete features are

- **appearance:** gender, age, glasses, ethnicity
- **low-level facial features:** innerBrowRaise, browFurrow, noseWrinkle, upperLipRaise, lipCornerDepressor, eyeClosure, chinRaise, jawDrop etc.
- **emotions:** joy, sadness, disgust, contempt, anger, fear, surprise, valence, engagement

The low-level facial features and the emotions are integers on the scale  $[0, 100]$ .

Beside the pairwise music preference elicitation part, the users are asked to fill-in a pre- and post-questionnaires. In the pre-questionnaire, we inquired about the user demographics, while in the post-questionnaires we inquired about the user personality (using the TIPI questionnaire[2]) and the Music Sophistication Index (using the MSI [5] questionnaire).



**Figure 1: Demo flow: the user listens to two music snippets and then provides a pairwise score. During the listening to the music, a web camera streams the video to an API that extracts the facial features.**

## 3 IMPLICATIONS FOR RECOMMENDER SYSTEMS RESEARCH AND FUTURE WORK

The demo presented in this paper is targeted primarily at researchers, who are interested in advanced preference elicitation techniques. The data collected with this system allows to pursue new research directions, such as (i) development of unobtrusive acquisition of user ratings from facial expressions and (ii) new multidimensional models of user preferences.

An open issue is privacy. Systems, that extract sensitive information, such as emotions, should be carefully designed, but this is beyond the scope of this demo.

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