AffectPro: Towards Constructing Affective Profile Combining Smartphone Typing Interaction and Emotion Self-reporting Pattern

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ABSTRACT

The ubiquity of smartphones and the widespread usage of text entry by soft keyboard in different instant messaging applications (e.g., WhatsApp, FB messenger) have opened the possibilities of inferring emotions from longitudinal typing data. To build this emotion inference engine, we apply machine learning models on features extracted from user's typing patterns (not content). However, one major challenge encountered while developing the emotion inference model is the requirement of individual training data as typing patterns are often person-specific. In this paper, we investigate the possibility of combining typing pattern with emotion self-reporting to identify a group of similar users so that the training data among these users can be shared to fulfill the requirement of personalized dataset. We develop a framework *AffectPro*, which quantifies the typing interaction behavior (e.g., typing speed, error rate) and self-reporting pattern (e.g., emotion state transition probability) to construct the affective profiles of users. We evaluated AffectPro in a 6-week in-the-wild study involving 28 users, who used an Android application encompassing a custom keyboard to perform all their typing activities, and to report their instantaneous emotions. We extracted different typing signatures and self-report behavior details from the collected dataset (≈5000 typing sessions, ≈108 hours of typing data) to construct the affective profile of users. Our results demonstrate similarity across users in terms of typing signature, emotion self-reporting pattern, and a combination of both; which can be leveraged to share training data among similar users to overcome the challenges of personalized data collection.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; **Empirical studies in HCI**; *Keyboards.*

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KEYWORDS

Affective profile; Smartphone typing; Emotion self-report; Emotion detection

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1 INTRODUCTION

Smartphone typing-based emotion detection systems have shown potential for different applications such as unobtrusive mental health monitoring [6, 10, 14, 30, 33], interface design [2, 24], guided response generation [15], and auto-suggestion usage optimization [12]. The value-added services offered by these systems are often based on the inferred emotion of the user. To automatically infer emotion, these systems typically deploy a machine learning model that utilizes the typing interaction characteristics (not actual text) of the users. But typing characteristics are often personalized in nature [8]; so these models require a large amount of individual user's data for acceptable performance [11, 23]. Therefore, efficient approaches to reduce the dependencies on personalized data are needed.

Currently, researchers follow different approaches to counter these challenges. Broadly, these approaches can be divided into two categories. In the *first* approach, training data collected from individual user's typing interaction logs are often inflated (to counter data imbalance) using some oversampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) [5, 6, 10, 11]. In these approaches, new (synthetic) training instances are created based on the underlying distribution of the actual data collected from a user. Although useful, these approaches do not scale well as they rely on small amount of personal data and may fail to capture the variation in data distribution [9, 29]. In the *second* approach, auxiliary modalities (e.g., location, smartphone usage details, online social network activities) are used along with the typing interaction signatures [4, 17, 23]. However, these additional data logs might be unavailable in different scenarios [32], might not be privacy-preserving [27], and might incur significant resource cost (e.g., energy when using GPS) [3]. More recently, researchers also demonstrated that combining the emotion self-report transition

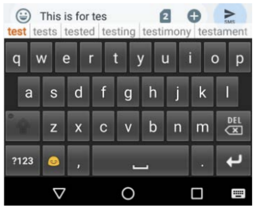


Figure 1: App keyboard

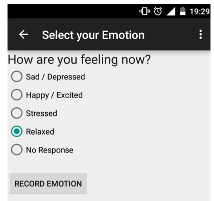


Figure 2: Self-reporting UI

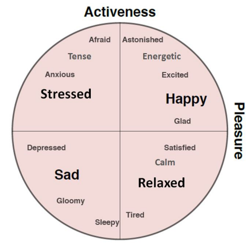


Figure 3: Circumplex model [28]

patterns of a user with the typing interaction characteristics can help inferring the emotion states accurately [11]. Such an approach is preferred over including information from other modalities as it eliminates the resource and privacy concerns. One possible, yet under-explored avenue to counter the requirement of significant amount of personal training data could be aggregating data from similar users and train the model by sharing the data among these users. However, although earlier works (e.g., [10, 11]) showed that smartphone typing can be used for emotion inference, to the best of our knowledge, no prior work investigated affective profile based data sharing among similar users to deal with the challenges of personalized data collection for smartphone typing-based emotion inference.

We envision that sharing data with similar typing interaction signatures and emotion self-reporting behavior can aid in overcoming the individual data requirement. However, such an approach requires addressing several challenges. First, individual typing interaction pattern and emotion self-report transition characteristics need to be quantified in order to measure similarity among different users. Second, these characteristics need to be quantified in a way so that they can be used as indicators of user emotion. Then the data sharing among similar users would be beneficial for emotion model construction. Finally, the process of identifying similar users should be unsupervised so that the users, based on typing interaction and emotion reporting behavior, can be identified and training data among them can be shared.

We, in this paper, propose *AffectPro*, an affective profile construction framework to identify similar users combining smartphone typing modality and emotion self-reporting characteristics. Affective profile contains a user's emotional signatures or preferences in different emotions [25, 26], similar to user profile that contains user preferences, interest, or settings [7, 16]. We construct the affective profile based on typing interaction and emotion transition pattern (from one emotion) as both of these carry signatures of user's emotion [6, 11, 13, 31]. Specifically, we extract several typing interaction characteristics (such as typing speed, typing session length, error rate) during different emotions based on a user's daily typing activities. We consider four emotions (*happy, sad, stressed, relaxed*) for this study. Similarly, we calculate the emotion transition probabilities from one to the other emotion based on a user's emotion self-reporting behavior. We concentrate on these emotions as they represent four different quadrants of the Circumplex plane and therefore having unambiguous valence-arousal representation, which makes self-reporting easier [20, 28]. Lastly, we empirically evaluate similarity in user's affective profile based on typing interaction and emotion self-reporting pattern.

For experimental evaluation of AffectPro, we conducted a 6-week in-the-wild study involving 28 participants. We developed and distributed an Android smartphone keyboard that captures a user's typing logs (one must note that the app does not collect and store any text content) and collects the emotion self-reports (*happy, sad, stressed, relaxed*), once the user completes typing in an application. We extracted four typing characteristics corresponding to every emotion and represent it as 16x1 vector. Similarly, we computed the transition probabilities among these four emotion states as a 16x1 vector. We compute the inter-user similarity for every user pairs using Pearson correlation score for typing interaction, self-report transition, and a combination of both. The combination of these two similarities as offered by *AffectPro* helps to group similar users in terms of similar typing interaction characteristics and emotion self-reporting behavior. These results demonstrate the possibility of grouping similar users based on typing interaction characteristics, and share data among them to overcome the requirement of personalized data to develop a smartphone typing based emotion detection system.

2 USER STUDY

2.1 Apparatus

We designed the keyboard app (Fig. 1) based on the Android Input Method Editor (IME) [1]. It functions similar to a QWERTY keyboard, but with the additional capability of capturing a user's typing interactions. We do not store any alphanumeric character because of privacy reasons. It also collects user's emotion self-reports based on typing interactions. The experiment apparatus developed for this study is based on earlier works by Ghosh et al., who used similar apparatus for smartphone keyboard interaction based emotion data collection [10]. Next, we discuss both the functionalities of the apparatus.

Tracing Typing Interactions: We collect typing interactions from every typing session. A *session* is defined as *the time period spent by the user at-a-stretch on a single application.* We record the timestamp of every touch event within a session and compute the interval between two consecutive touch events as the *Inter-tap duration (ITD).* For instance, we represent a session S of length $S_l (= n)$ as a sequence of timestamps $[t_1, t_2, t_3, ...t_n]$, depicting the respective touch events, with session duration $S_d = t_n - t_1$. We measure ITD as $v_i = t_{i+1} - t_i$, which reflects the typing speed of the user; higher value of ITD indicates lower typing speed. Hence, a session S may be further expressed as a sequence of ITDs, $S = [v_1, v_2, v_3, ..., v_n]$, where v_i indicates the i^{th} ITD. Additionally, we record the usage of the backspace or delete keys pressed in a session, which helps to identify the amount of typing mistakes made in a session.

Collecting Emotion Self-reports: We also collect self-reported emotions from users. Once user completes typing in an application and switches from the current application, we probe them for the emotion self-report to record one of the following emotions (*happy, sad, stressed, relaxed*) by sending a popup as shown in Fig. 2. We selected these emotions based on the Circumplex model (Fig. 3) of emotion [28], as they represent largely represented emotion from separate quadrants, which makes self-reporting easier for the user. We keep the interface simple by explicitly recording emotion and do not consider the intensity of perceived emotion; reporting the perceived emotion intensity can make self-reporting difficult. We also keep the provision of *No Response*, so that user can skip self-reporting by selecting this option. By default, when the UI is displayed, the *No Response* option is selected. To provide the emotion self-report, the user needs to select a valid emotion and record the same.

2.2 Participants and Study Procedure

We recruited 32 participants (26 male, 6 female, aged between 18 and 35 years) to participate in the study. Before the study, we obtained the Institute Review Board (IRB) approval. We installed the app on their smartphones and instructed them to use it for 6 weeks. 2 participants did not complete the mandatory 6 weeks of data collection, while 2 other participants entered less than 50 labels during 6 weeks. We thus used data from 28 users (24 male, 4 female) for our analysis. The average age of the 28 participants was 26.3 years (SD: 5.3).

We installed the app on the smartphones of the participants, instructed them to use the custom keyboard as the default keyboard, and use it for their regular typing activity. We informed the participants that once they switched from their current application after typing, they would receive a survey questionnaire as a pop-up, where they would report their current emotion state. They were further instructed that if the pop-up appeared at an inopportune moment and they wanted to skip responding, they should select the *No Response* button instead of dismissing the pop-up.

2.3 Dataset

We collected a total of $4,846$ sessions, out of which 843 (17.4%) sessions were marked as *No Response*. We eliminated the *No Response* sessions as they did not provide any information about the user's emotion. The remaining $4,003$ (82.6%) sessions consists of $\approx$ 108 hours of typing data and $1,029,039$ touch instances. The average number of sessions per user was 142.96 (std. dev 114.15), and the average session length was 214.38 characters (std. dev 107.24). Each session was tagged with different emotion labels (*happy, sad, stressed, relaxed*). Out of these sessions 16%, 7%, 23%, and 54% sessions were tagged with *happy, sad, stressed,* and *relaxed* emotion respectively. The distribution of emotions is skewed (more relaxed sessions), which can be attributed to the in-the-wild nature of the study, as encountered in earlier studies also [11, 18]. We summarize the final dataset in Table 1. We also looked at the emotion distribution for individual users. We observed that all users have reported at least 3 emotion states, and 21 out of the 28 users have reported all the four emotions during the data collection period. We present the user-wise distribution of emotion states in Fig. 4.

Total participants	28 (24 M, 4 F)
Total typing instance	1,029,039
Total typing duration	107.92 Hrs
Total *No Response* sessions	843
Total valid sessions	4003
Avg session per user	142.96 (Std dev. 114.15)
Avg session length	214.38 (Std dev. 107.24)
Total happy sessions	622 (16%)
Total sad sessions	284 (7%)
Total stressed sessions	928 (23%)
Total relaxed sessions	2169 (54%)

Table 1: Final dataset details

Figure 4: Emotion distribution of users. All but 7 (6, 7, 12, 13, 18, 21, 22) users have reported each of the four emotions.

3 AFFECTPRO: AFFECTIVE PROFILE CONSTRUCTION FRAMEWORK

We next discuss the construction of affective profile using the AffectPro framework. The affective profile of every user is composed of (a) typing interaction profile, and (b) emotion self-report transition profile. Both these characteristics carry a set of behavioral parameters for the four emotion states (*happy, sad, stressed, relaxed*). Next, we describe the process of extracting these signatures for different emotion states.

$$p_{xy} = \frac{n_{xy}}{n_x} \tag{1}$$

3.1 Typing Interaction Profile

We express the typing interaction profile in terms of the following characteristics - (a) mean session ITD, (b) session length, (c) special character (or non-alphanumeric character) usage, and (d) typing error. Prior works demonstrated that these features carry emotion

	MSI	Session length	Spl. Char percentage	Error rate
Happy (h)	s_{msi}^{h}	s_{l}^{h}	s_{spl}^{h}	s_{err}^{h}
Sad (s)	s_{msi}^{s}	s_{l}^{s}	s_{spl}^{s}	s_{err}^{s}
Stressed (t)	s_{msi}^{t}	s_{l}^{t}	s_{spl}^{t}	s_{err}^{t}
Relaxed (r)	s_{msi}^{r}	s_{l}^{r}	s_{spl}^{r}	s_{err}^{r}

Figure 5: Typing interaction profile

To / From	Happy (h)	Sad (s)	Stressed (t)	Relaxed (r)
Happy (h)	p_{hh}	p_{hs}	p_{ht}	p_{hr}
Sad (s)	p_{sh}	p_{ss}	p_{st}	p_{sr}
Stressed (t)	p_{th}	p_{ts}	p_{tt}	p_{tr}
Relaxed (r)	p_{rh}	p_{rs}	p_{rt}	p_{rr}

Figure 6: Emotion self-report transition profile

signatures [6, 10, 11]. We compute these values for every emotion state and include them in the typing interaction profile. In specific, for every emotion state, we compute the mean session ITD (S_{msi}), mean session length (S_l), mean special character percentage (S_{spl}), and mean error rate (S_{err}). Empirically, for an emotion x, mean session ITD, mean session length, mean special character percentage, and mean error rate are denoted as s^x_{msi}, s^x_l, s^x_{spl}, and s^x_{err} respectively, where $x \in$ {happy, sad, stressed, relaxed}. These values are computed for every user and organized in a 4×4 matrix (Fig. 5). This matrix captures the typing interaction profile of a user.

3.2 Emotion Self-report Transition Profile

We quantify the emotion state-transition profile based on the emotion self-report transition behavior, i.e. how the transition form one emotion self-report to another takes place. In specific, we consider the transition probability from one emotion to another, as this helps to determine next emotion based on the current one following a Markov Chain property [31]. Precisely, we quantify the emotion state transition of every user as the probability of switching from the current self-reported emotion, to the any of the four emotions, in the next self-report. However, for simplicity, while computing these probability values, we did not consider the elapsed time between two emotion self-reports, which may improve the profile construction. We organize these probabilities in a 4×4 matrix, as shown in Fig. 6, and define it as the state-transition matrix (P). We denote the state transition probability from state x to state y using p_{xy}, where $x, y \in \{happy, sad, stressed, relaxed\}$. We compute the transition probability p_{xy} as the ratio of the total number of transitions made from emotion x to y (n_{xy}) and the total number of transitions made from emotion x to any state (n_x) (see Eq. 1). The state-transition matrix is calculated for every user and considered as the emotion self-report transition profile.

4 EVALUATION

In this section, we evaluate the effectiveness of AffectPro to find similar users in terms of typing interaction, emotion transition, and a combination of these. To measure the similarity, we used Pearson Correlation Coefficient as its value ranges from -1 to +1 and a higher positive value indicates stronger correlation and vice versa [19]. We also present the efficacy of different profile parameters in emotion inference.

4.1 Typing Interaction Profile Similarity

Once we construct the typing interaction profile of every user (as shown in Fig. 5), we express it as a 16×1 vector and compute the Pearson correlation coefficient for every pair of users. We show the user pair-wise typing interaction profile similarity in Fig. 7a using a heatmap. Each cell in the heatmap denotes the correlation score for two users. We observe that there are many groups (or clusters) of users (e.g., {1, 2, 4, 5, 6, 7, 9}, {25, 26, 27, 28}) having high similarity (lighter shade in a cell indicates high similarity) value in terms of typing interaction parameters. Overall, we obtain an average Pearson correlation score of 0.79 (SD: 0.15) across all user pairs. This findings demonstrate that there are a group of users with similar typing interaction profile.

4.2 Emotion Self-report Transition Profile Similarity

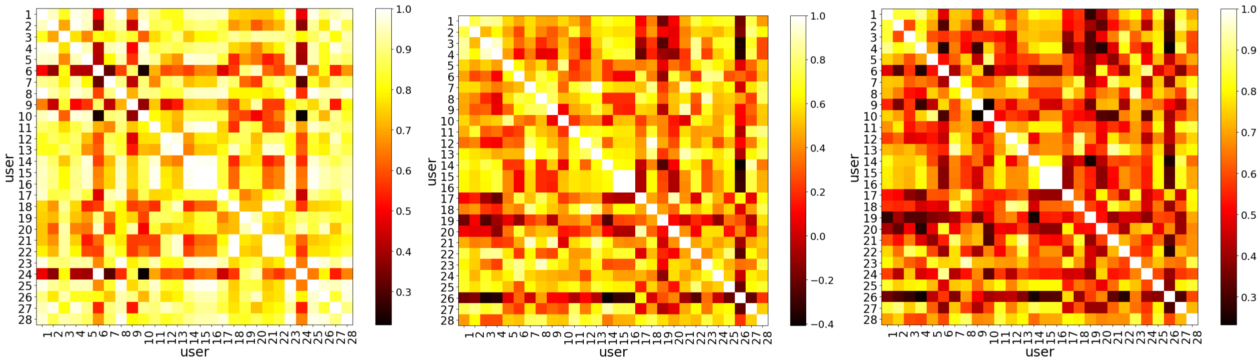
We also investigate the inter-user similarity in terms of emotion self-report transition profile. In this case also, first, we express the emotion-transition profile matrix to a 16×1 vector and then compute the user pair-wise similarity using the Pearson Correlation coefficient. We show the similarity values using a heatmap in Fig. 7b. This reveals that for a group of users (e.g, {1, 2, 3, 4}, {14, 15, 16, 17}) the emotion transition profiles are alike (lighter shade implies more similar) and we obtain an average Pearson correlation score of 0.43 (SD: 0.27). In this case, we obtain a relatively low similarity score (in comparison to typing interaction similarity). This may be attributed to the fact that we did not consider the frequency distribution of emotions for every user while constructing the profile. Combining the frequency distribution of emotions along with the emotion state transition probability may help to identify similar users more accurately.

4.3 Combined Profile Similarity

We aimed to merge these two profile aspects (typing interaction, and emotion self-report transition) into a single profile so that it becomes easier to find out the group of users both in terms of similar typing interaction profile and emotion self-report transition profile. We combine these two profile similarities for every pair of users in the following way,

$$comb_{sim} = \alpha.kb_{sim} + (1 - \alpha).st_{sim} \quad (2)$$

where, $kb_{sim}, st_{sim}, comb_{sim}$ denote typing interaction similarity, emotion self-report state transition similarity, and the combined similarity for a given user pair, and α ($0 \le \alpha \le 1$) denotes the weighing factor between two types of similarities. In our experiments, we set the value of α to 0.5 to assign equal weights to both the similarity values. We compute the user pair-wise combined similarity using Eq. 2, and plot the values as a heatmap in Fig. 7c. In this case also, we observe many cluster of users with similar affective profile (combined in terms of typing interaction and emotion transition

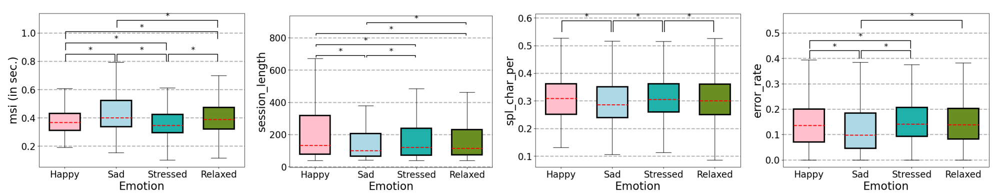


(a) Typing interaction similarity

(b) Emotion-transition similarity

(c) Combined similarity

Figure 7: Heatmaps showing user profile similarity in terms of typing interaction, emotion state transition, and a combination of both of these modalities (equal weight). In each of the cases, we observe a number of similar users. Each cell in the hetmaps depicts the Pearson correlation value for two users. The similarity increases as the shade goes from darker to lighter.



(a) MSI variation

(b) Session length

(c) Spl. char usage

(d) Error rate

Figure 8: Comparison of different typing interaction features across different emotions reveals that each of the features varies significantly across emotions using Kruskal-Wallis test. * denotes pair-wise significance ($p < 0.05$) using the posthoc Mann-Whitney test.

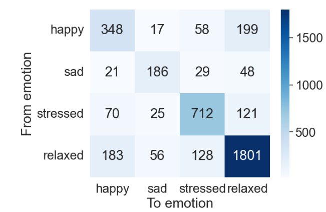


Figure 9: Computation of the emotion state transition matrix reveals that from every emotion, the same emotion is reported (as the next emotion) most number of times.

behavior). We obtain an average Pearson correlation score of 0.62 (SD: 0.16).

4.4 Emotion Detection Effectiveness of Profile Parameters

While previous results demonstrate that there is similarity among some users in terms of different typing interaction features and emotion self-report behaviour, in this section, we investigate the effectiveness of these features for emotion inference. In specific, we investigate the role of typing interaction features (typing speed, session length, special character usage, and error rate), and previous emotion to detect the current emotion of a user in a typing session.

Effectiveness of Typing Interaction Features on Emotion Detection: We investigate the variation in typing interaction features (one at a time) across emotion states. There are four emotions (*happy, sad, stressed, relaxed*). We grouped the MSI values according to these emotions and compare them using Kruskal Wallis test [21] (Fig. 8a). The Kruskal Wallis test revealed a significant effect of emotion on typing speed (MSI) ($\chi^2(3) = 112.43, p < 0.05$). A post-hoc test using Mann-Whitney tests with Bonferroni correction showed the significant differences ($p < 0.05$) between every pair of emotions [22]. We repeat the same steps for session length and note the findings in Fig. 8b. In this case, the Kruskal Wallis test revealed a significant effect of emotion on session length ($\chi^2(3) = 19.61, p < 0.05$). A post-hoc test using Mann-Whitney tests with Bonferroni correction showed the significant differences between following emotion pairs, *happy-sad*, *happy-stressed*, *happy-relaxed*, *sad-stressed*, and *sad-relaxed*. In the same way, we carried out the Kruskal Wallis test to identify the effect of emotions on special character usage (Fig. 8c) and error rate (Fig. 8d), which revealed a significant effect with the following test statistics ($\{\chi^2(3) = 10.04, p < 0.05\}$, $\{\chi^2(3) = 33.64, p < 0.05\}$) for special character usage and error rate respectively. A post-hoc test using Mann-Whitney tests with Bonferroni correction showed the significant differences between following emotion pairs, *happy-sad*, *sad-stressed*, and *stressed-relaxed* for special character usage, while for error rate the following emotion pairs are found to have a significant difference, *happy-sad*, *happy-stressed*, *sad-stressed*, and *sad-relaxed*. In summary, all of these typing interaction features vary significantly across emotions, and therefore may be used to developed machine learning model for emotion inference.

Effectiveness of Emotion Transitions on Emotion Detection: As we consider emotion transition probabilities to construct the emotion self-report profile and identify similar users, it is imperative to investigate the suitability of these transition patterns on emotion inference. We investigate this by constructing a emotion state transition matrix (as shown in Fig. 9), which shows the number of times an emotion state has been recorded from every possible emotion (*happy, sad, stressed, relaxed*). We observe a heavy diagonal, which demonstrates from every emotion the same emotion has been reported most frequently. This observation may help to determine future emotion based on the current one.

5 CONCLUSION AND FUTURE WORKS

The major implication of the AffectPro framework is that it can identify a group of similar users based on affective profile constructed using typing interaction parameters and emotion transition characteristics, i.e. in a sufficiently large group of users, there are a number of users with similar typing pattern. Moreover, these signatures are found to influence user emotion, therefore, offers possibility to share data among similar users to counter the issue of personalized dataset. At the same time to improve the profile quality and identify similar users it is required - (a) to include more relevant typing characteristics and emotion self-reporting characteristics that correlate well with emotion, (b) to assign suitable weight to each of the modalities, (c) to develop an unsupervised approach to identify the group of similar users and (d) to observe minimal amount of typing data to identify the similar users; that we aim to address in our future work. We also aim to perform large-scale studies with diverse user profile to evaluate the efficiency of the framework.

In summary, AffectPro demonstrates that by quantifying smartphone keyboard interaction and emotion transition patterns, affective profile of a user can be constructed. We evaluate the framework in a 6-week in-the-wild study constructing typing profile (using features like typing speed, typing error), emotion transition profile (using emotion transition probabilities from four emotions *happy, sad, stressed, relaxed*) of 28 participants. The initial findings demonstrate that many users have identical typing interaction profile and emotion transition profile, both of which can be combined to share data among similar users to reduce the dependency on personalized dataset.

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