Evaluating Effectiveness of Smartphone Typing as an Indicator of User Emotion

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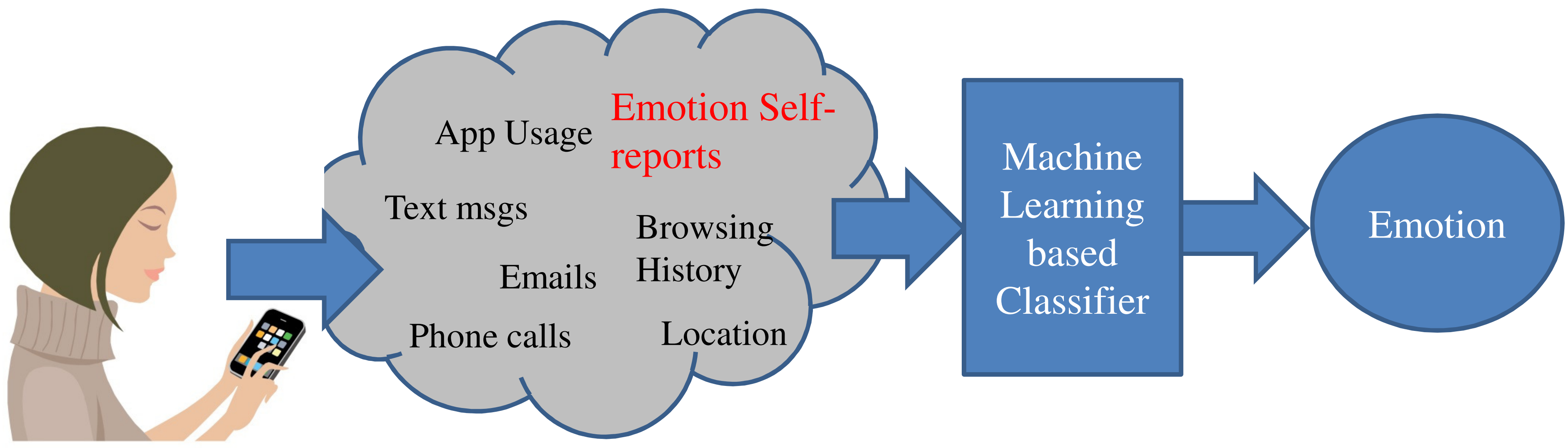
Smartphone-based Emotion Detection

- Smartphones
  - Integral part of our daily life
  - Easy to track activities, location details, call history etc.
  - Opportunity to determine emotion states
    - Moodscope [Mobisys 13], Boredom detection [UbiComp 15]



Objective

- Design light-weight, non-intrusive emotion detection application using smartphone

- *Typing activity* in smartphone
  - Non-intrusive
  - Low resource consumption
  - Prevents monitoring overhead of multiple sensors
  - Privacy preserving (if content not looked at)

- Inspired by emotion detection using keyboard dynamics
  - Epp et al. [SigChi 11]

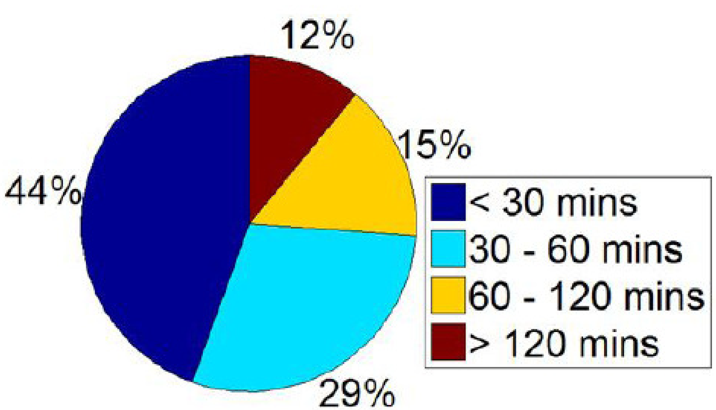
Outline

- Qualitative Study
  - Smartphone, Typing and Emotion correlation
- TapSense Architecture
  - Challenges
  - Design Principles
- User Study
- Evaluation
  - Feature Selection and Impact
  - Classification Accuracy
- Take-home Points

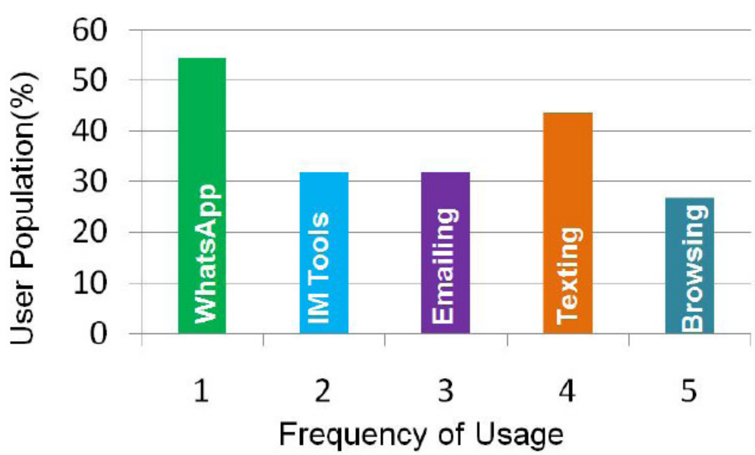
User Survey

- Goal: Qualitative insight
  - on use of typing based applications on smartphones
  - Correlation between typing and emotion

Daily Aggregate Typing durations ?



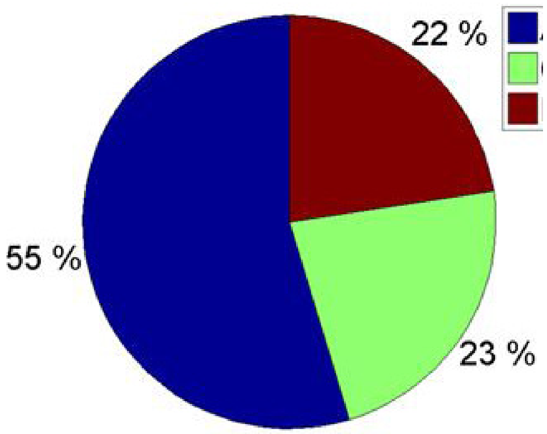
Which typing based apps ?



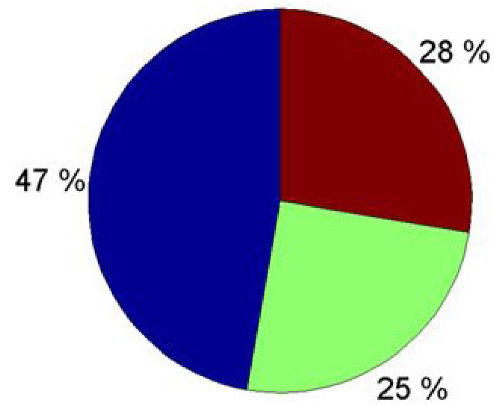
- 56% users spent more than 30 mins daily
- Most used typing based apps are messaging apps

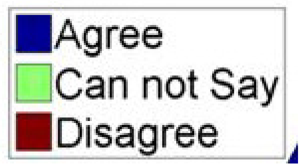
User Survey: Typing Cues for Emotion

App Usage

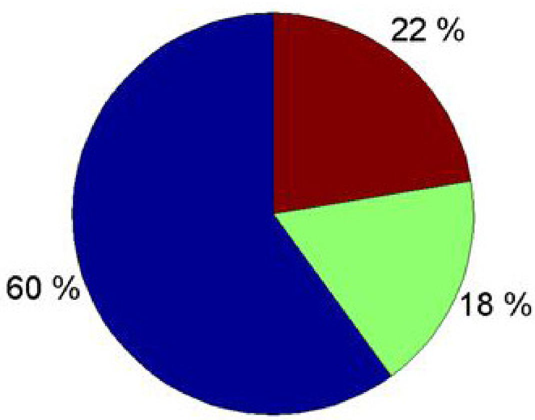


Typing Mistake

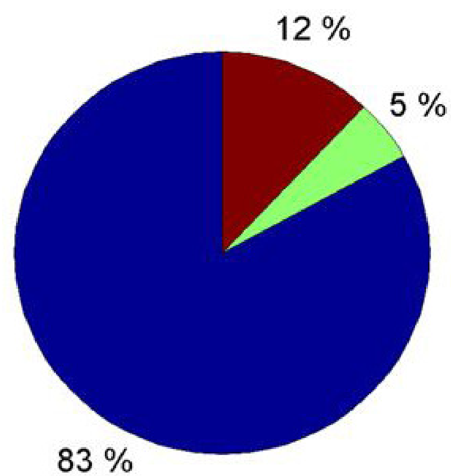




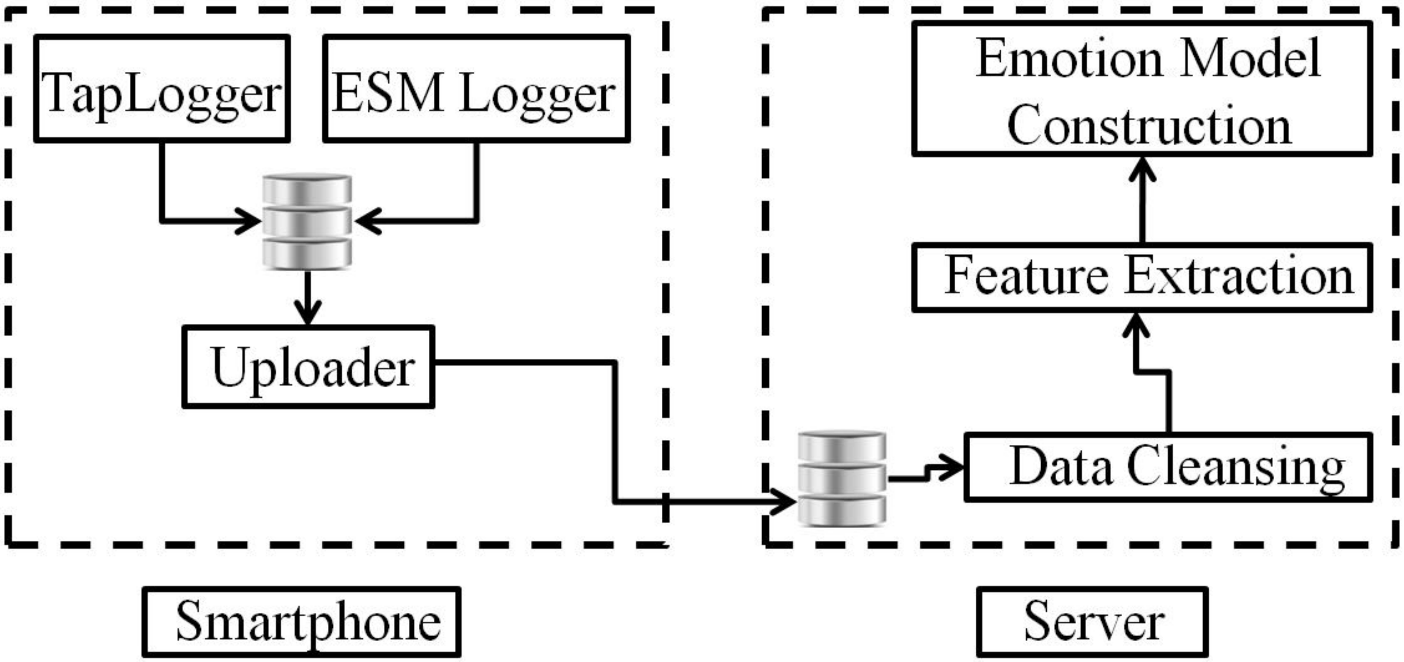
Typing Speed



Special characters



TapSense Architecture



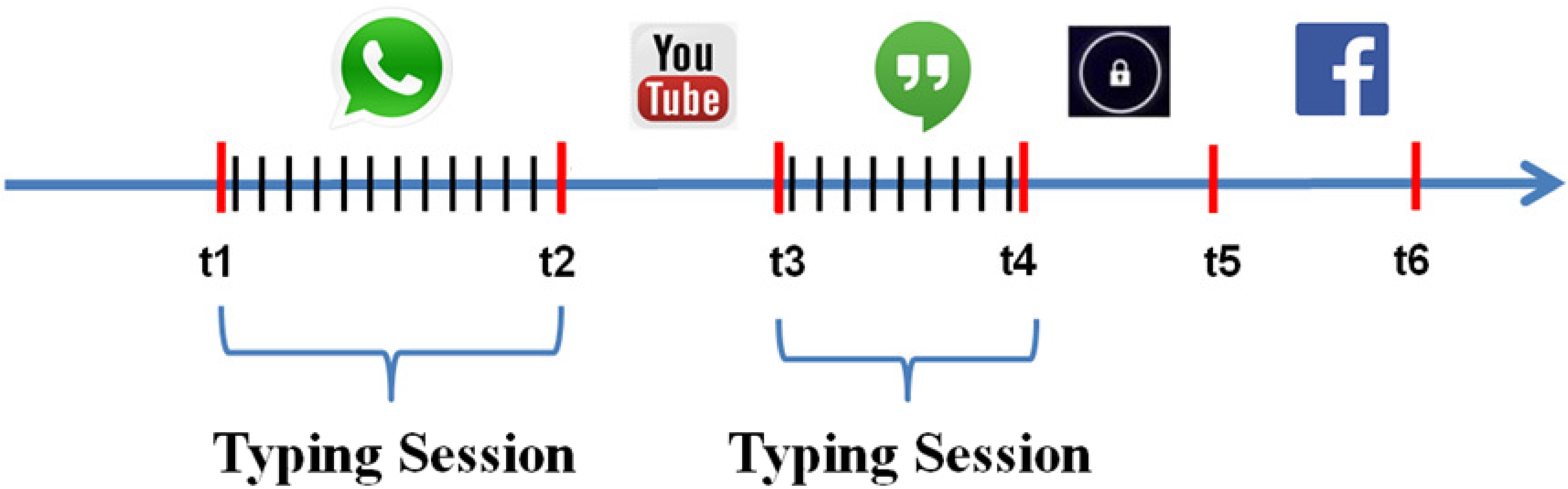
- *TapLogger*
  - Traces typing activity
- *ESMLogger*
  - Collects emotion self-reports
- *Feature Extraction*
  - Identify features
- *Model Construction*
  - Personalized, RF based

TapSense: Design Challenges

- How to collect Typing data ?
  - Granularity of typing data collection

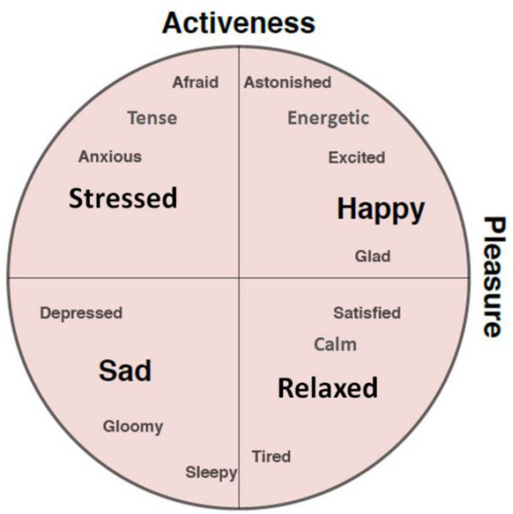
- Collect Self-reports from users
  - Apply Experience Sampling Method (ESM)
  - Must maintain a balance between “how many probes” and “timeliness” of the probe
  - How accurate are the self-reports ?

Typing Session Identification

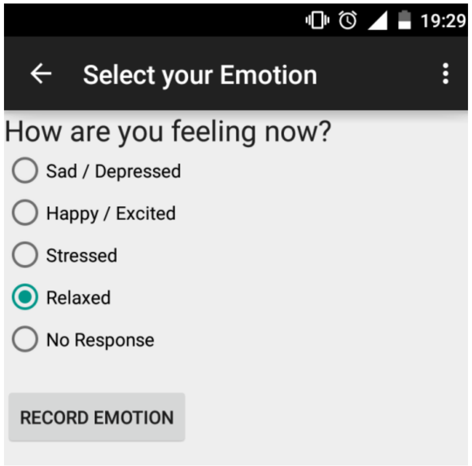


- Typing details are extracted session-wise
- Typing session
  - Tap events within an app without app switch

Emotion Self-report Collection



Emotion circumplex model

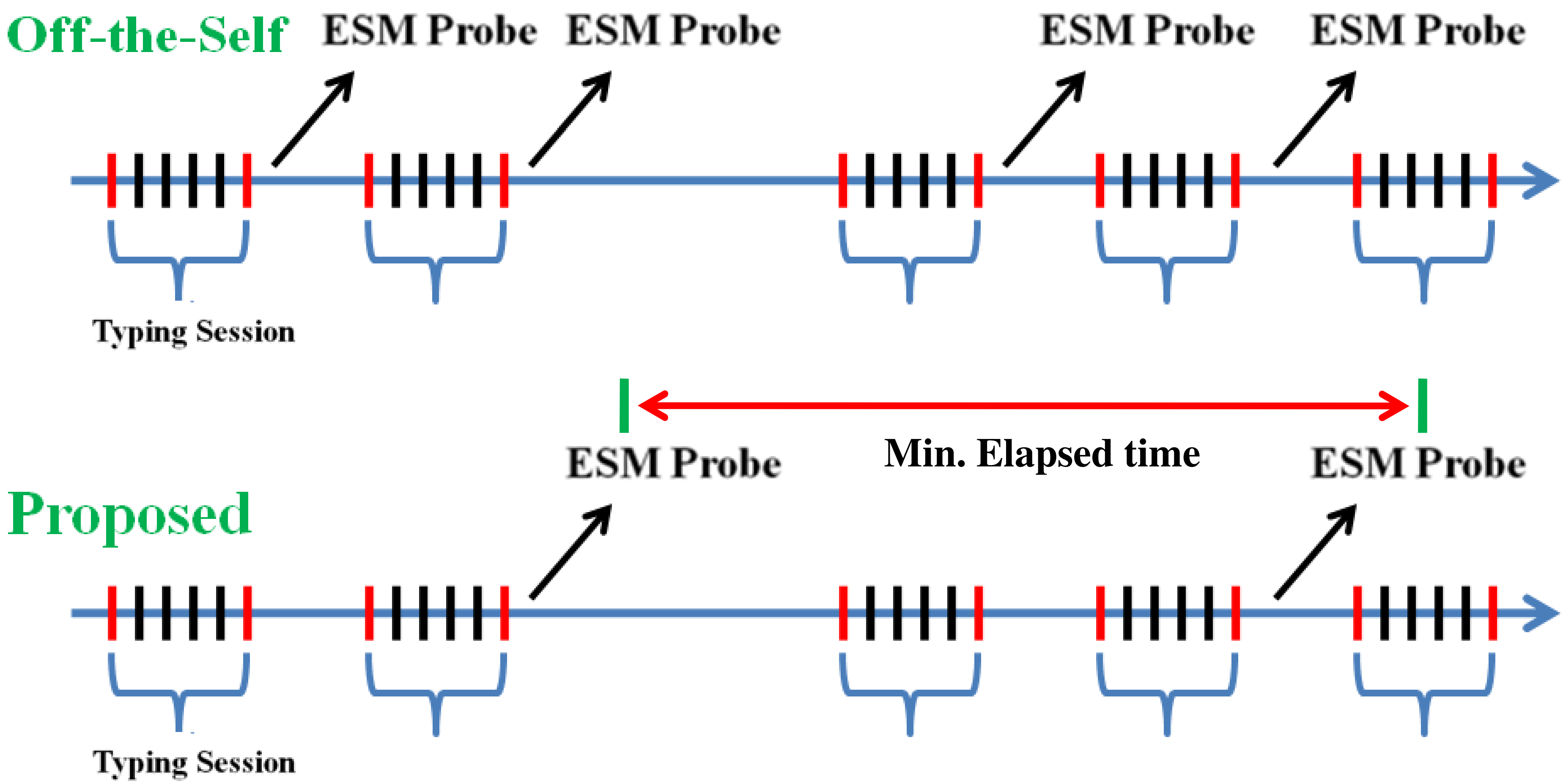


Emotion collection UI

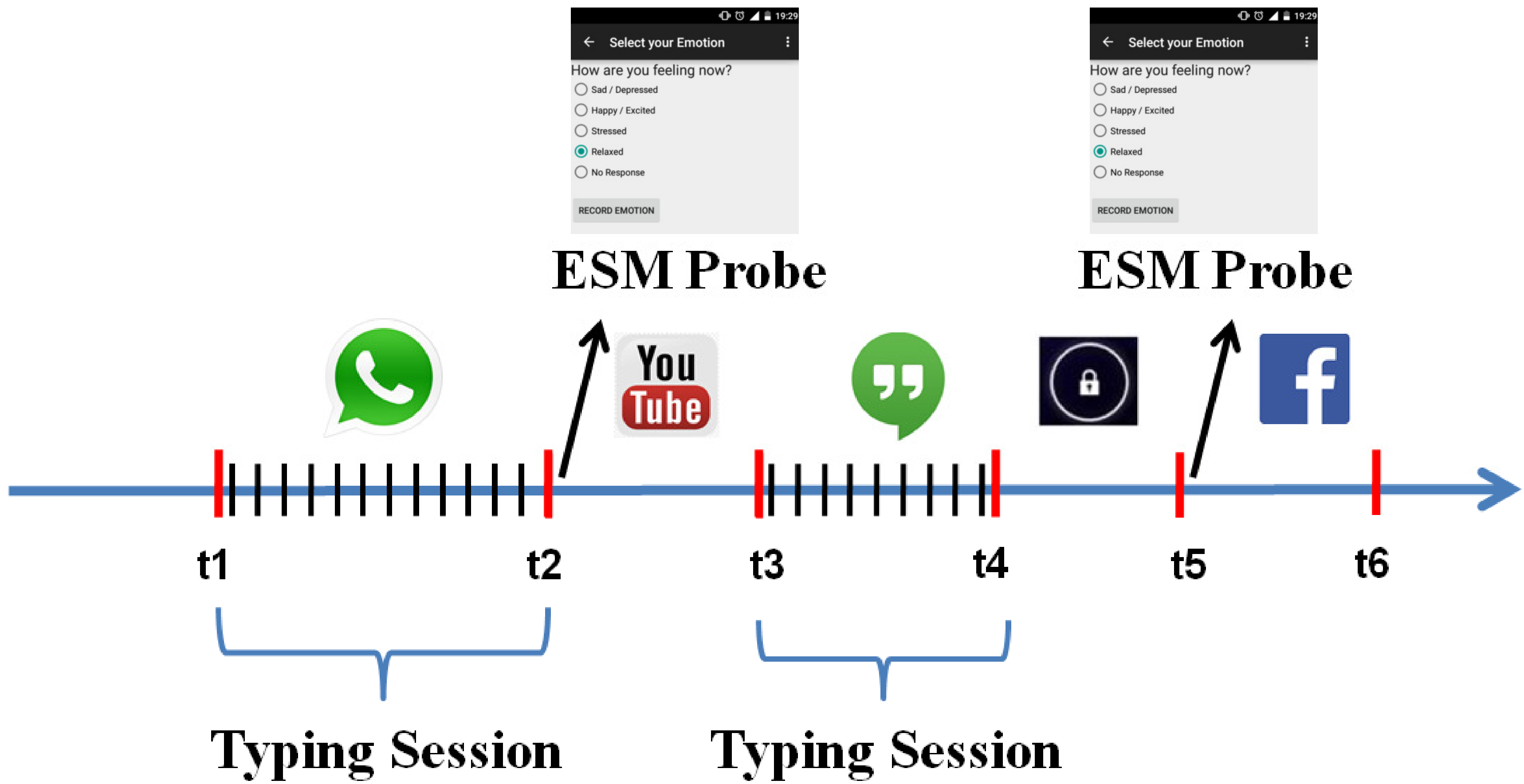
- Self-report collection
  - Report among 4 emotion state
    - Relaxed, Happy, Stressed, Sad
  - Dominant emotion from each quadrant
  - Emotion recording can be skipped by selecting *No Response*

Emotion Self-report Collection

- Self-report collection
  - *Survey fatigue* to be kept low

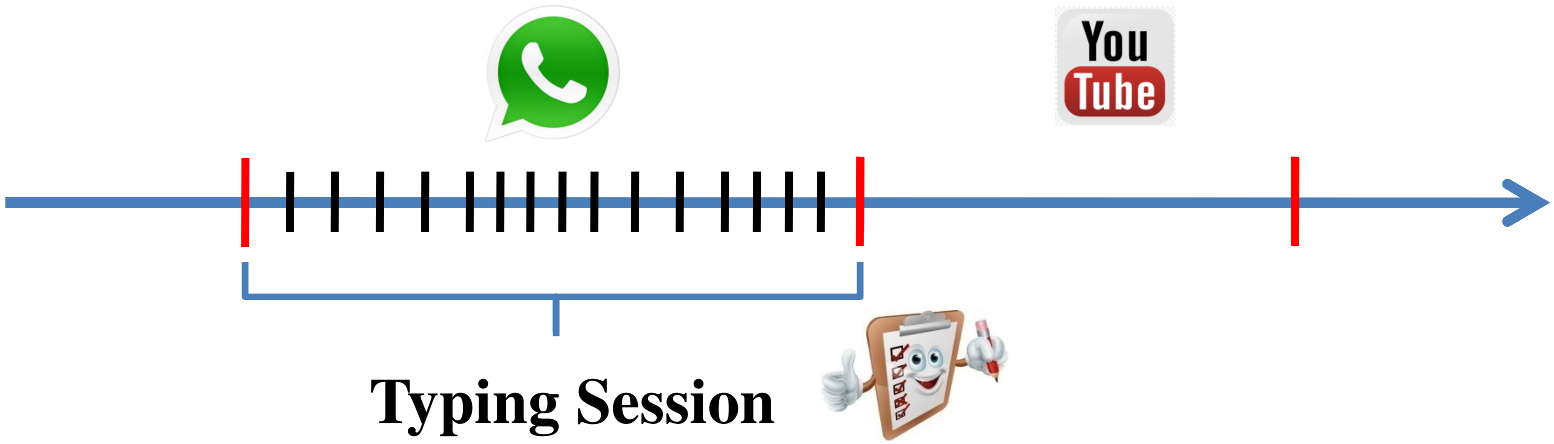


Attach Self-reports to Typing Session



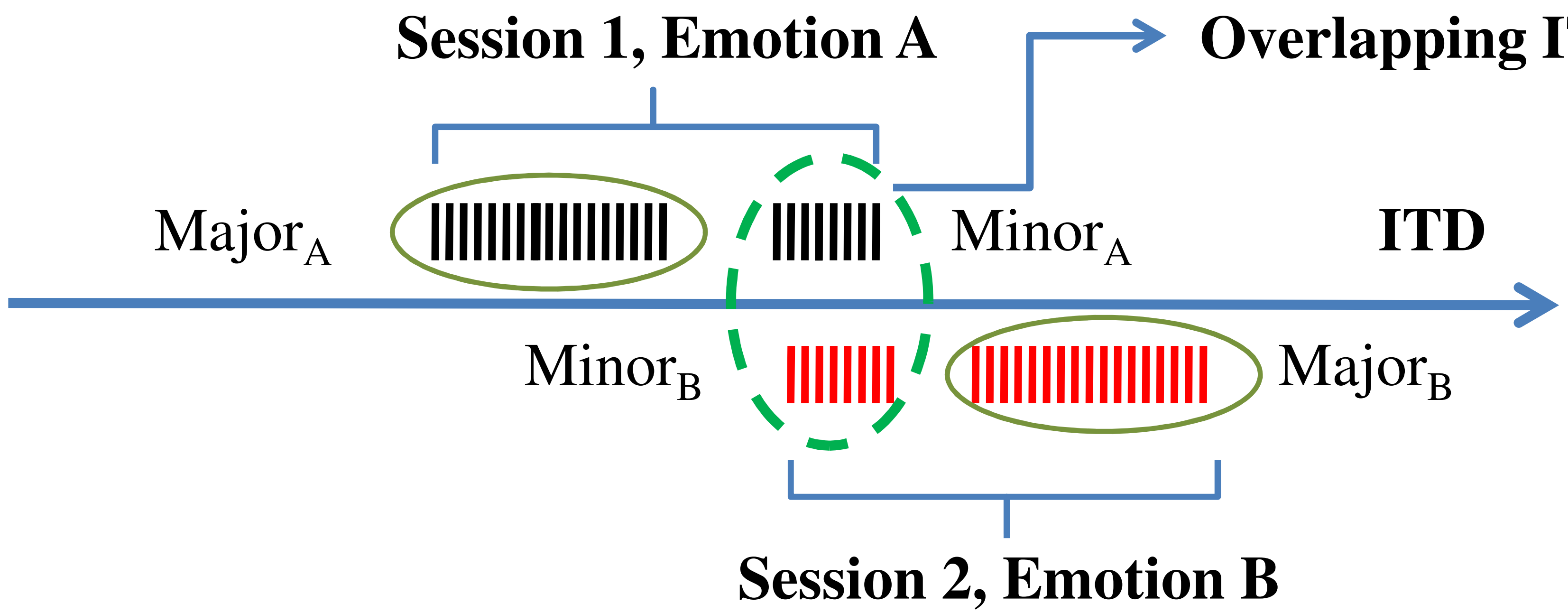
Collected self-report is tagged to the previous typing session

Feature Identification: Typing Speed



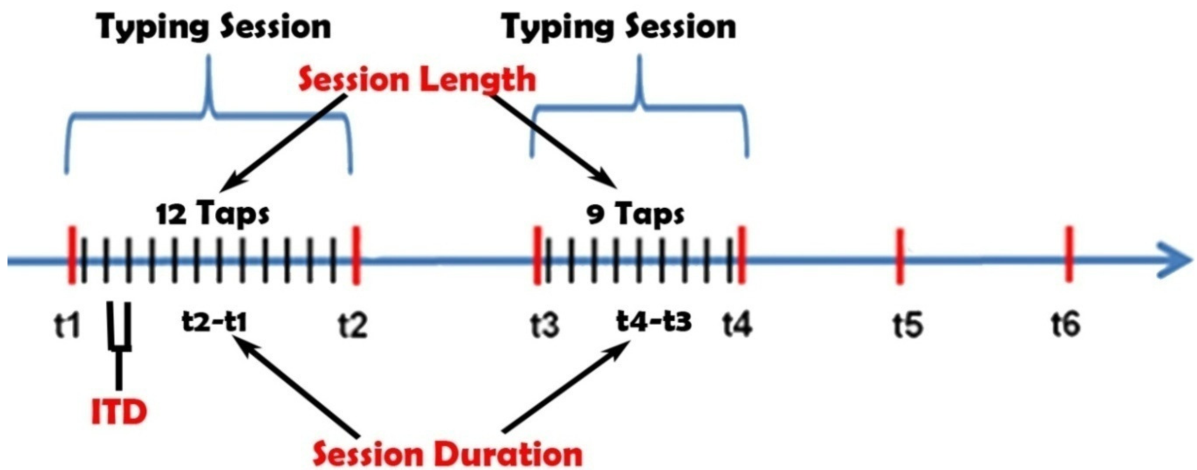
- Inter-Tap Distance (ITD)
  - Elapsed time between entering two character is *ITD*
- ***Mean Session ITD***
  - Compute mean of all *ITD*s in a session, which is known as *Mean Session ITD*
  - Representation of typing speed

Refined Mean Session ITD (*RMSI*)



- *Mean Session ITD (MSI)*
  – Overlapping ITDs, not distinguishable enough
- *Refined Mean Session ITD (RMSI)*
  – Identify major cluster using K-means
  – Compute mean of ITDs present in that cluster

Keystroke Features



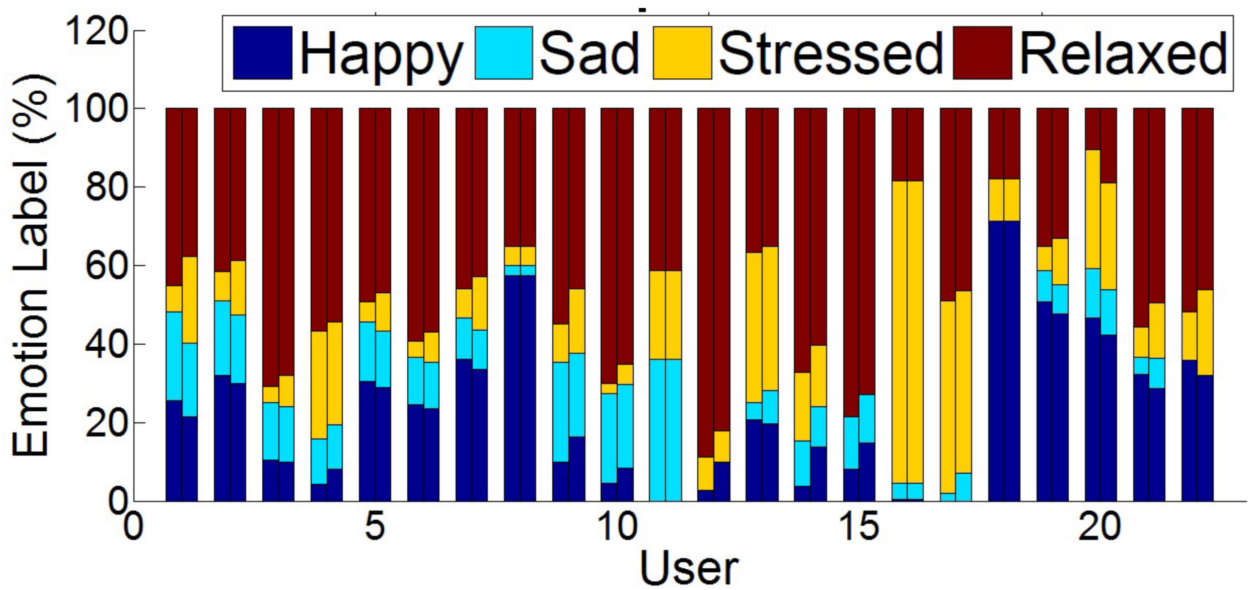
- *Session Length*
- *Session Duration*
- *Percentage of Backspaces in a Session*
  - Typing mistakes while in a given emotion
- *Percentage of Special Characters in a Session*
  - To trace usage of special chars in an emotion state

User Study

- Study duration – 3 Weeks (in-the-wild)
- Total number of participants – 30
  – University students
  – 24 males, 6 females, aged between (24 – 33) years
- Installed *TapSense* in participant mobile phones

- Final participants – 22 (20 male, 2 female)
  – Had to exclude 8 participants
    - 3 participants left in between
    - 5 participants recorded less than 40 labels

User Study: Emotion Distribution



Emotion	Distribution
Happy	19%
Sad	9%
Stressed	23%
Relaxed	49%

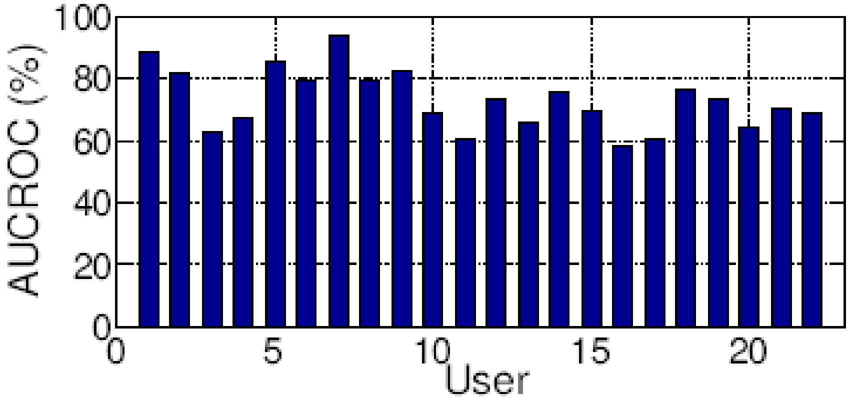
- Relaxed is the most dominant state reported
- Used SMOTE to overcome sample imbalance
  - If an emotion label is absent, then do nothing
  - If an emotion label is low, then raise it to match the next higher sample count

Evaluation

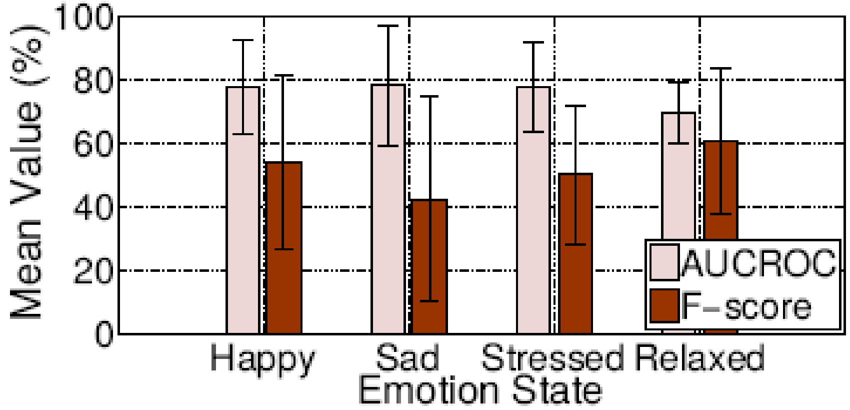
- Personalized model for individual emotion prediction
  - Logistic Regression, SVM, **Random Forests**
- Used 10 fold cross-validation

- Classification accuracy measured using
  - AUCROC
    - Weighted average of AUCROC in predicting each emotion category, where weight is the proportion of the samples
  - F-score
- Importance of each feature
  - Information gain per feature

Classification Accuracy



(a) User-wise AUCROC



(b) State-wise AUCROC, F-score

- Average AUCROC of 73% (std: 9%)
- Prediction accuracy for all states > 60%

Feature Analysis

Feature	Rank	Avg. IG
RMSI	1	0.461
MSI	2	0.422
Number of backspace	3	0.368
Number of special character	4	0.202
Session text length	5	0.199
Session duration	6	0.197

- RMSI and MSI are the most important features
  - Typing rhythm or speed
- Use of backspace → more deletions related to emotion state
- Special characters or emoticons indicate certain states

Limitations

- Importance of short typing sessions
  - Typing sessions were on average 8 mins
  - Longer typing sessions ➔ there can be multiple emotion switches ➔ how to capture without probing more frequently ?
- Alternative ESM design
  - More balanced data collection ➔ reduce sampling for cases where multiple labels collected already
    - Predict expected label and decide to drop/collect
- Gender Bias in user study group
- Adding features, like swype, auto-completion

Take-home Points

- Light-weight, non-intrusive emotion detection system using only typing features is feasible

- Average accuracy (AUCROC) of 73% in a 3-week study involving 22 participants

Project Site:
http://cse.iitkgp.ac.in/~surjya.ghosh/projects.html

BACKUP

Typing based Emotion Detection Application

- Challenges
  - Extract Typing session
  - Collect Self-reports
    - Manual → *survey fatigue*
    - Psycho-physical sensor based → *intrusive setup*
  - Personalized training for every user