

# Exploring Smartphone Keyboard Interactions for Experience Sampling Method driven Probe Generation

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# Background

- **Smartphone Keyboard Interaction based Emotion Detection**
  - Mental state tracking <sup>[1,2]</sup>
  - Guided response generation <sup>[3]</sup>
  - Adaptive interface design <sup>[4,5]</sup>
- **At the core of such value-added services**
  - Supervised ML model for emotion inference
    - It requires emotion self-reports (ground truth)
- **Manual Self-report Collection → Experience Sampling Method (ESM)**
  - Time-consuming, fatigue-inducing

Intelligent probing strategies to **probe at opportune moments** for emotion self-report collection are essential.

# Research Question

- **Typing activities in smartphone contains two facets**
  - *Timing* – relates to time-domain characteristics
  - *Rhythm* – relates to frequency-domain characteristics

Can we leverage these **time and frequency domain characteristics** for intelligent probing?

# Keyboard Interaction based Probing

- **Identify typing sessions**

- Track typing sessions from user's smartphone interactions

- **Extract typing characteristics from these sessions**

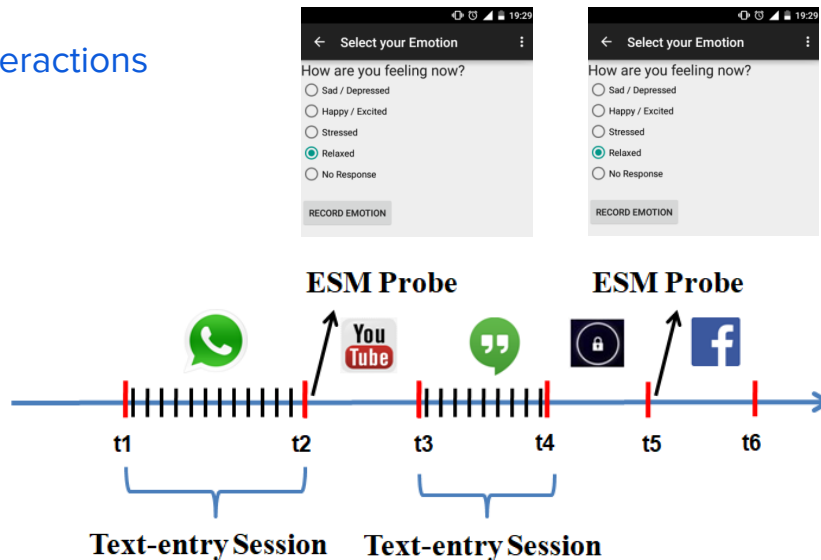
- Based on typing patterns, not actual text

- **Label the sessions (probing moments)**

- By collecting self-reports after sessions

- **Develop ML models**

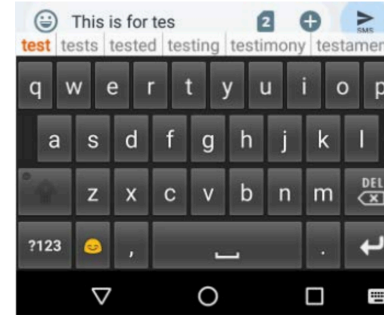
- Correlating typing characteristics and session labels (opportune / inopportune)



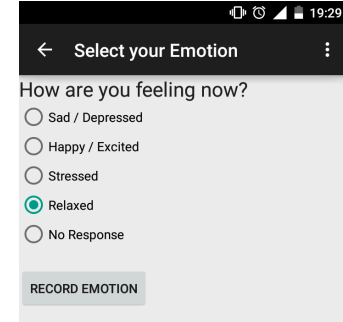
# Field Study & Dataset

## ● Experiment Apparatus

- Android application
  - Tracing keyboard interaction
  - Collect self-reports
    - Emotion labels → Opportune
    - No Response → Inopportune



App Keyboard



Self-report UI

## ● Study details

- 3-week in-the-wild study
- Number of participants – 22 (18 m, 4 f)

## ● Dataset

- 3463 sessions (83% opportune, 17% inopportune)

# Methodology

- **Session Representation**

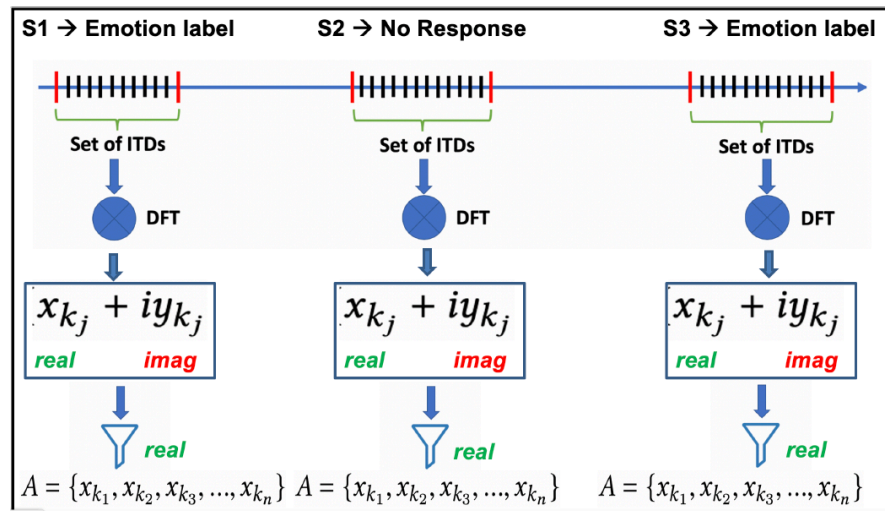
- A set of ITDs → elapsed time between two consecutive typing events

- **Time-domain characteristics**

- Session length
- Session duration
- Session speed
- Error rate

- **Frequency-domain characteristics (after DFT)**

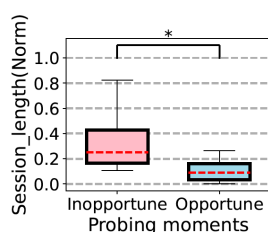
- No of peaks
- Peak\_amp1
- Peak\_amp2
- Peak\_amp3



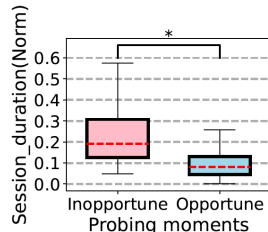
# Data Analysis

## Time-domain characteristics

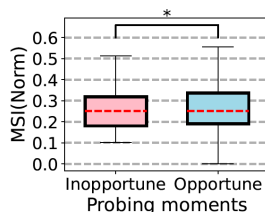
- Vary significantly ( $p < 0.001$ ) between two types of probing moments



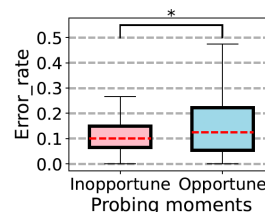
(a) Session length



(b) Session duration



(c) Session speed

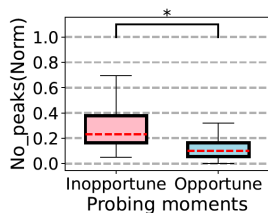


(d) Error rate

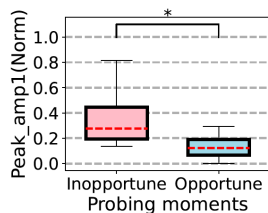
- Not normal distribution
- Unpaired Mann-Whitney Test

## Frequency-domain characteristics

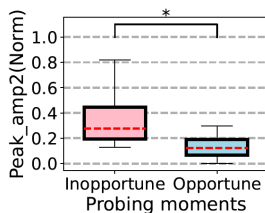
- Vary significantly ( $p < 0.001$ ) between two types of probing moments



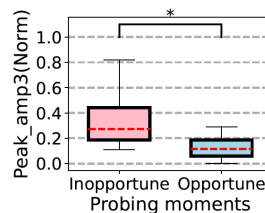
(a) Total no. of peaks



(b) First peak amp



(c) Second peak amp

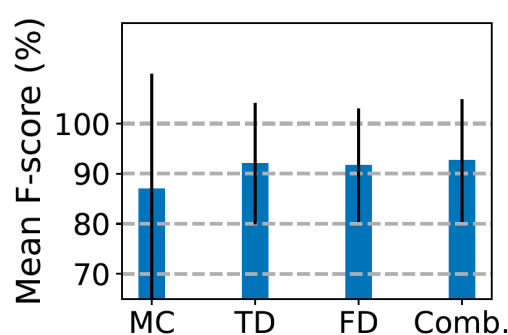


(d) Third peak amp

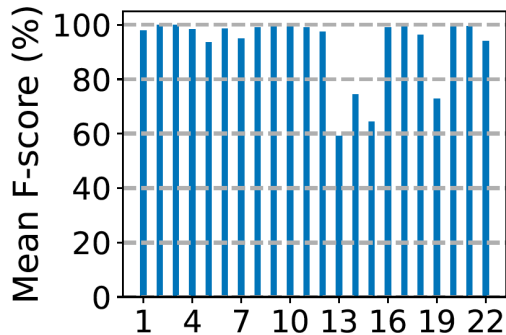
# Opportune Probing Moment Prediction

## ● Model Performance

- MC → Majority class
- TD → Only time-domain
- FD → Only freq-domain
- Comb → TD + FD



(a) Model-wise F-score



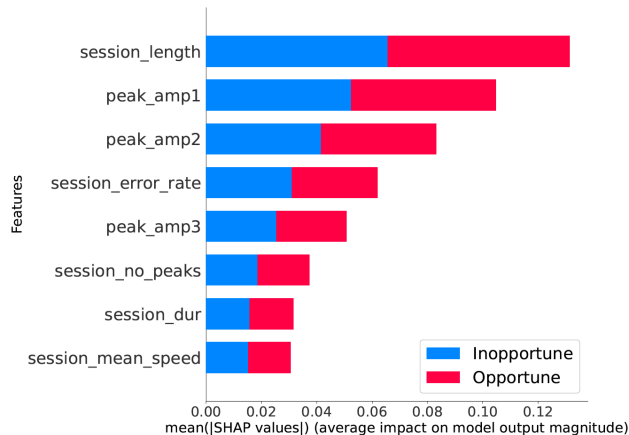
(b) User-wise F-score

## ● Model Performance

- Combined model outperforms others
- Avg F-score: 93% (std. dev 12%)

## ● Explainability Analysis

- Top time-domain feature: session length
- Top frequency-domain feature: peak\_amp1





# Conclusion

- **Smartphone keyboard interaction pattern**
  - Contains both time-domain and frequency-domain signatures
    - vary significantly between opportune and inopportune probing moments
- **Machine learning based model to determine opportune probing moments for self-report collection**
  - Combining both time-domain and frequency-domain signatures
    - Proposed model obtains an average F-score of 93% (std dev 12%)

# References

- [1] Matteo Ciman and KatarzynaWac. 2016. Individuals' stress assessment using human-smartphone interaction analysis. *IEEE Transactions on Affective Computing* 9, 1 (2016), 51–65.
- [2] Surjya Ghosh, Niloy Ganguly, Bivas Mitra, and Pradipta De. 2017. Evaluating effectiveness of smartphone typing as an indicator of user emotion. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 146–151.
- [3] Chieh-Yang Huang, Tristan Labetoulle, Ting-Hao Kenneth Huang, Yi-Pei Chen, Hung-Chen Chen, Vallari Srivastava, and Lun-Wei Ku. 2017. Moodswipe: A soft keyboard that suggests messages based on user-specified emotions. *arXiv preprint arXiv:1707.07191* (2017).
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- [5] Fariba Noori and Mohammad Kazemifard. 2016. AUBUE: An Adaptive User-Interface Based on Users' Emotions. *Journal of Computing and Security* 3, 2 (2016), 127–145.

# Thank You!!



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