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 \cite{1,2}
  - Guided response generation \cite{3}
  - Adaptive interface design \cite{4,5}

- 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 \rightarrow 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

- **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

- **Frequency-domain characteristics**
  - Vary significantly ($p<0.001$) between two types of probing moments

- Not normal distribution
- Unpaired Mann-Whitney Test
Opportune Probing Moment Prediction

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

**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


Thank You!!

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https://surjiya-ghosh.github.io/