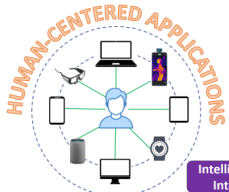# PResUP: Physiological Response based User Profiling for Opportunistic Emotion Annotation

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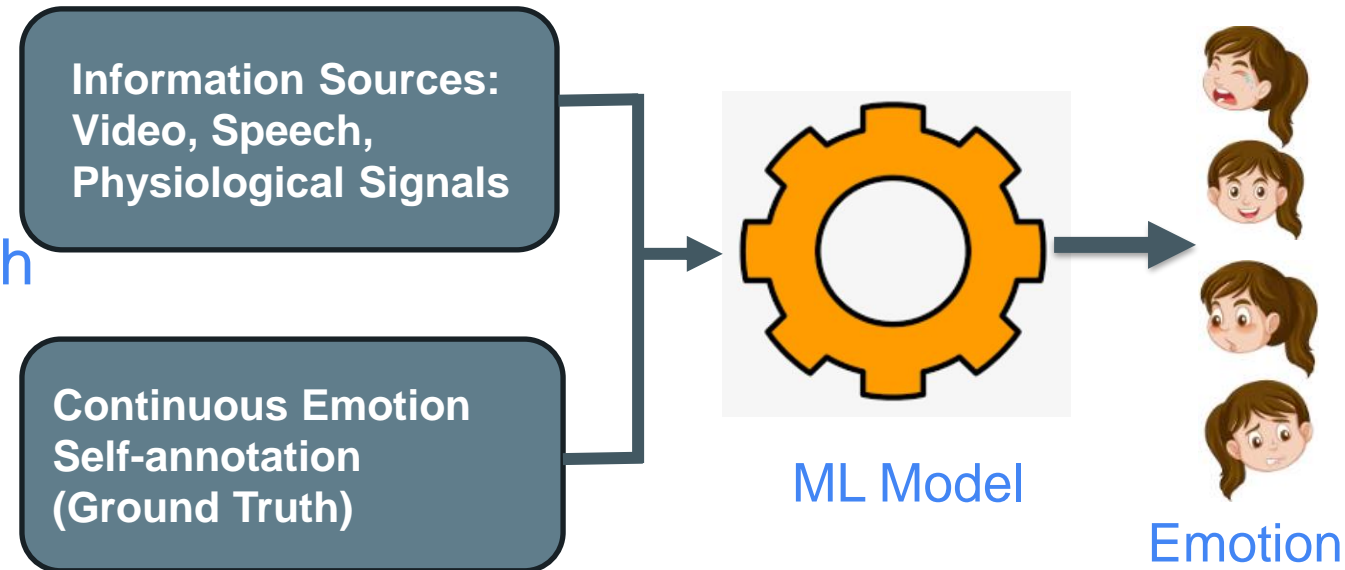
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India

UACHI'24

Motivation and Background

- Video-based applications

- Emotion Detection Using ML Models : A Multi-Modal Approach
  - Integrating Multiple Modalities
  - Emotion ground truth

Information Sources: Video, Speech, Physiological Signals

Continuous Emotion Self-annotation (Ground Truth)

ML Model

Emotion

Typical ML-based emotion detection model
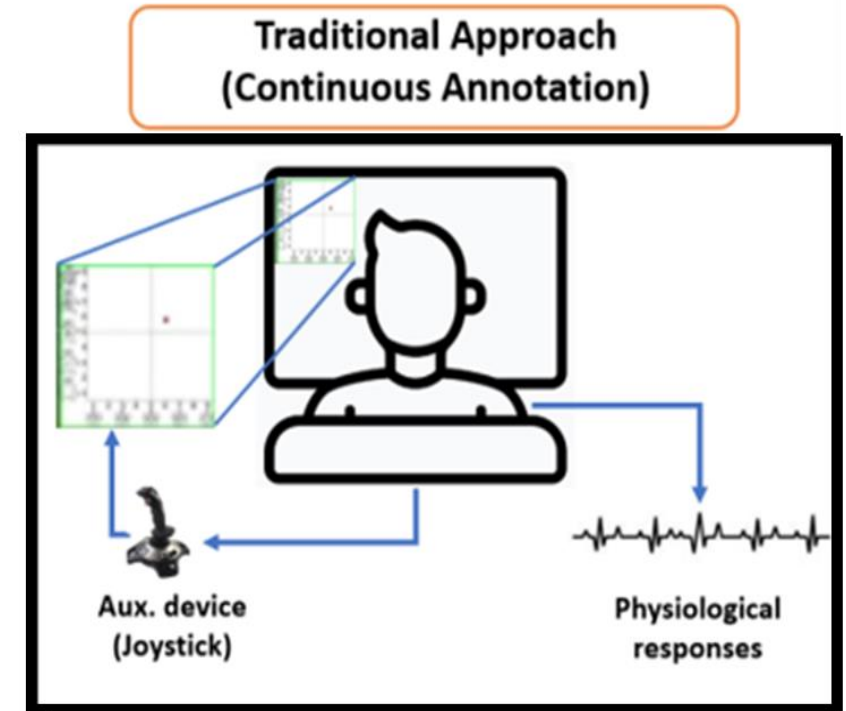
Motivation and Background

Emotion Self-Annotation

- **Post-interaction/ post stimuli**
  - Fails to capturing subtle intra-video nuances.

Motivation and Background

Emotion Self-Annotation

- **Continuous annotation**
    - Degrades viewing experience.
    - Increases cognitive load, leading to less accurate emotion labels.

Participant watching videos and annotate continuously

Research Question

Can we develop an intelligent annotation approach to address this problem ?

- Capture *opportune moments* for emotion self-report collection

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Can we develop an intelligent annotation approach to address this problem ?

- ***opportune moments***
  - are the ones when there is large variation in emotion

Research Question

Can we develop an intelligent annotation approach to address this problem ?

- ***opportune moments***
  - are the ones when there is large variation in emotion
  - ***rationale***
    - if the emotion does not change, no need to annotate
    - in a video, the emotion does not change very frequently

Research Question

Can we develop an intelligent annotation approach to address this problem ?

- Capture **opportune moments** for emotion self-report collection

Opportunistic annotation → reduces the cognitive workload and the number of self-annotations

User Study I

- **Experiment apparatus**
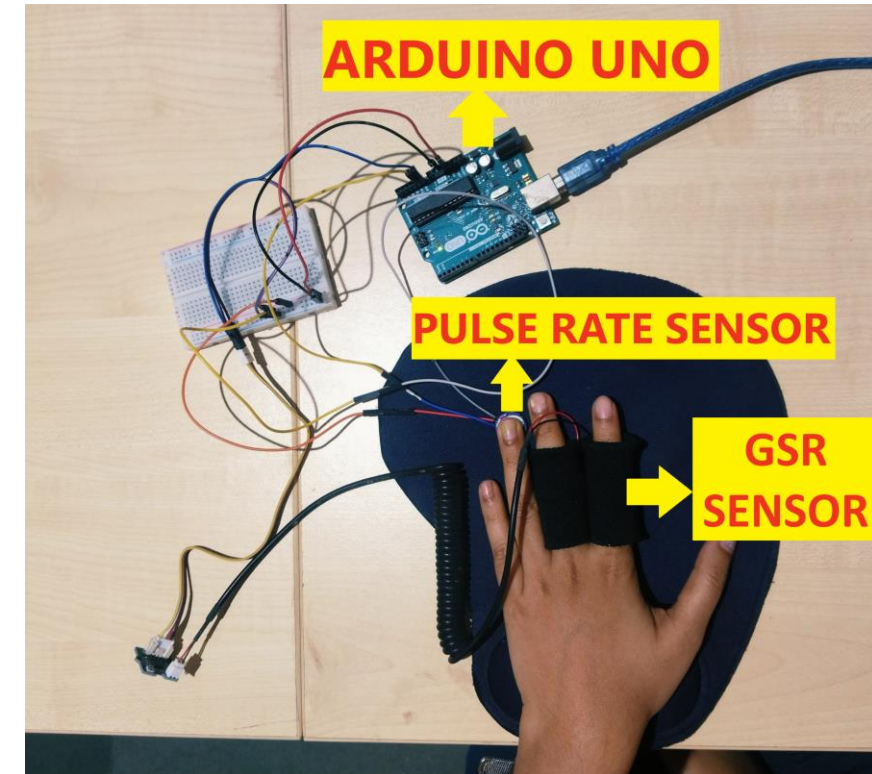 - Sensor setup
  - Annotate app

User Study I

- **Experiment apparatus**
  - Sensor setup
    - GSR sensor (GSR V1.2, Seeed Studio Grove)
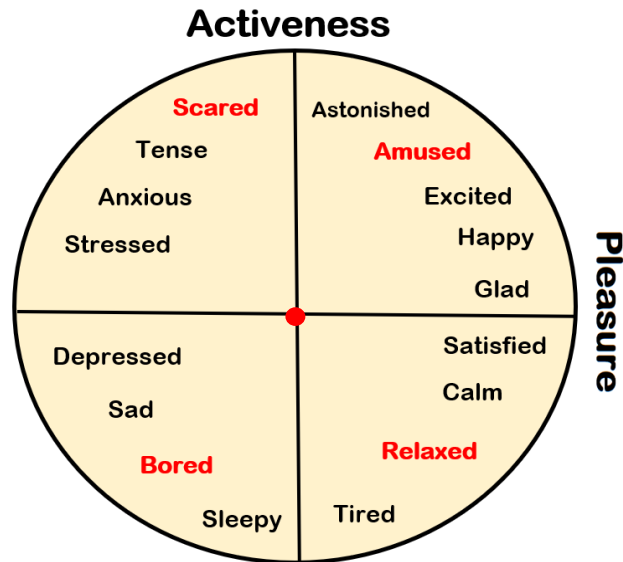   - Pulse rate sensor (HW-827, World Famous Electronics LLC)

User Study I

- **Experiment apparatus**
  - Annotate app
    - Annotate using arrow keys
    - Red dot → feedback
    - Valence, arousal → 1 to 9

Circumplex Model
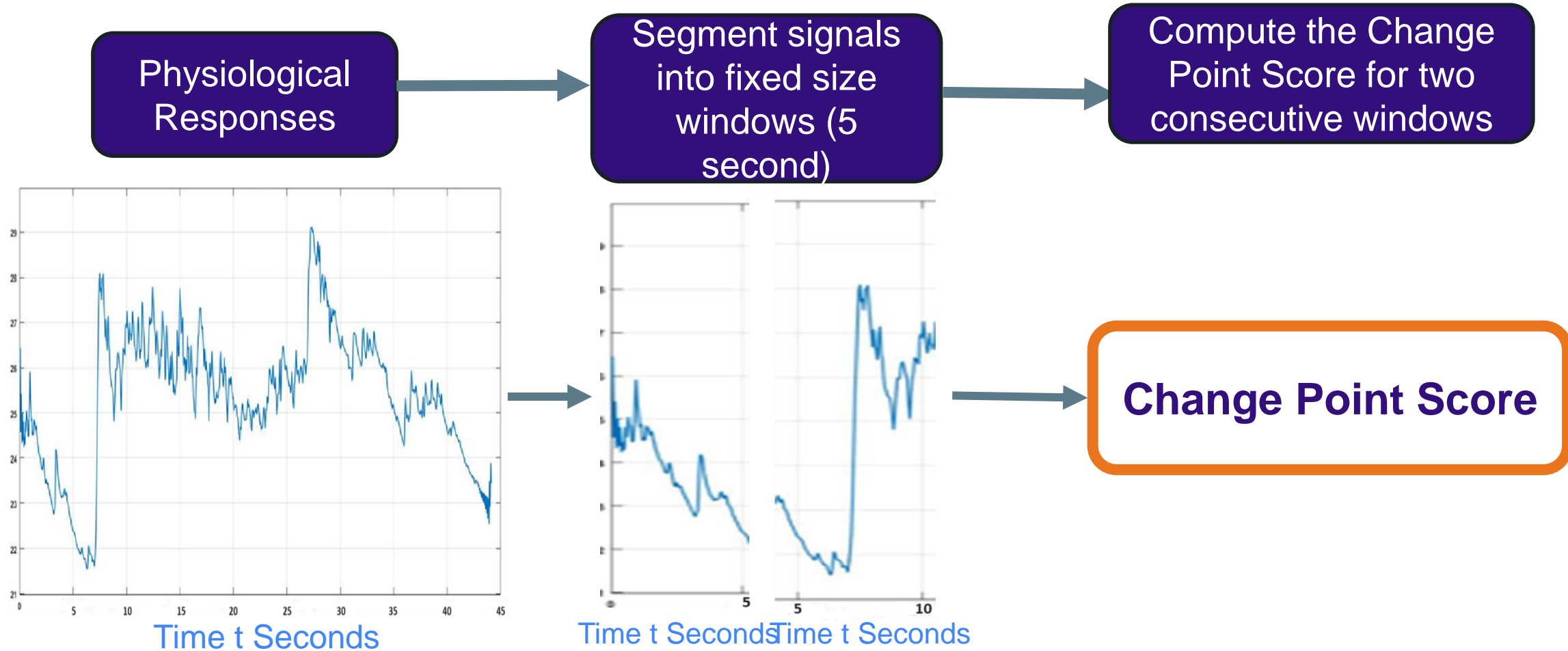
User Study I

- **Study procedure**

  - 36 participants (18M, 18F).

  - 8 stimuli videos in random order

  - 2-minute blue screen interleaving the videos to avoid the carry-over effect

Video id	Emotion	Valence	Arousal	Duration (in sec.)
1	amusing	med/high	med/high	185
2	amusing	med/high	med/high	173
3	boring	low	low	119
4	boring	low	low	160
5	relaxing	med/high	low	145
6	relaxing	med/high	low	147
7	scary	low	high	197
8	scary	low	high	144

Details of the stimuli videos

Dataset: Pre-processing

Physiological Responses → Segment signals into fixed size windows (5 second) → Compute the Change Point Score for two consecutive windows

Time t Seconds

Time t Seconds Time t Seconds

Change Point Score

Dataset: Descriptive Statistics
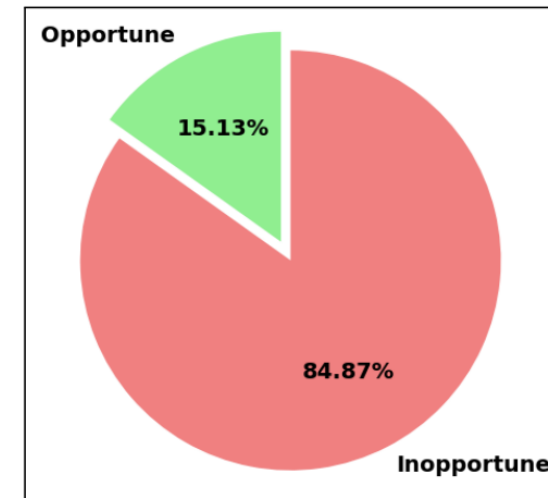
- **Dataset description**

Total number of segments	8608
Total number of opportune segments	1303
Total number of inopportune segments	7305
Average (SD) number of segments per users	239 ± 1.29
Duration of every segment	5 Second
Duration of total sensor dataset	11.96 Hr.

Final dataset details
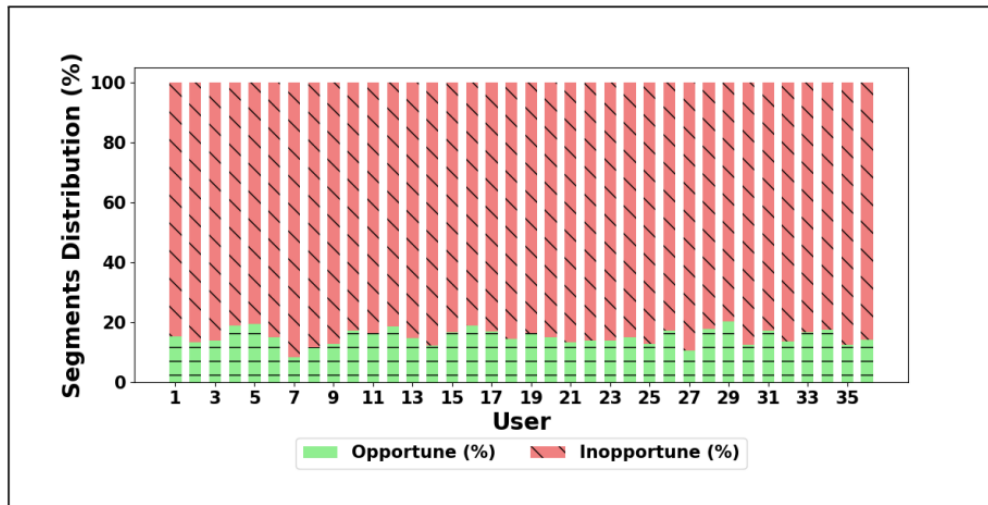
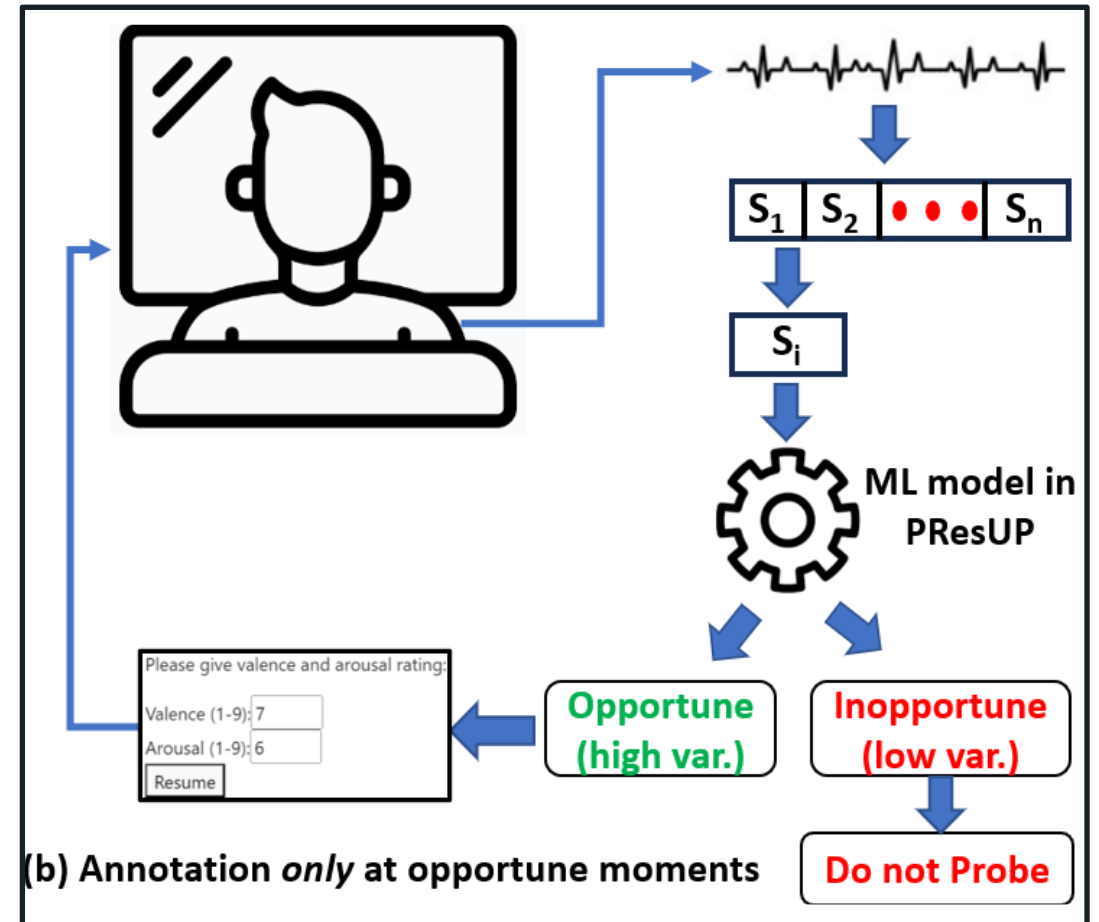

(a) User-wise segment distribution

(b) Segment distribution (total)
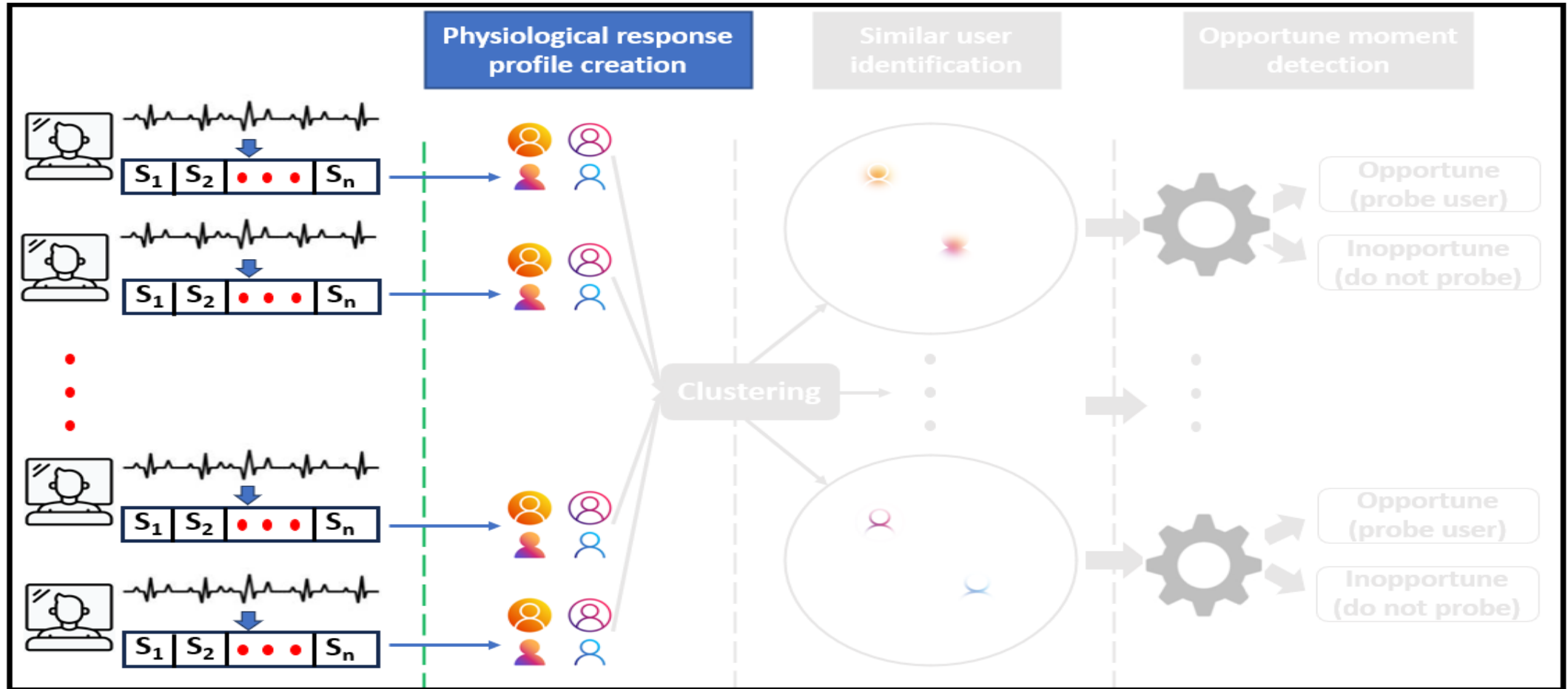
Distribution of segments

PResUP Framework

PResUP: Physiological **Res**ponse based **U**ser **P**rofiling

- Detects opportune moments

- Reduces continuous emotion self-report annotation effort by probing at these opportune moments *only*
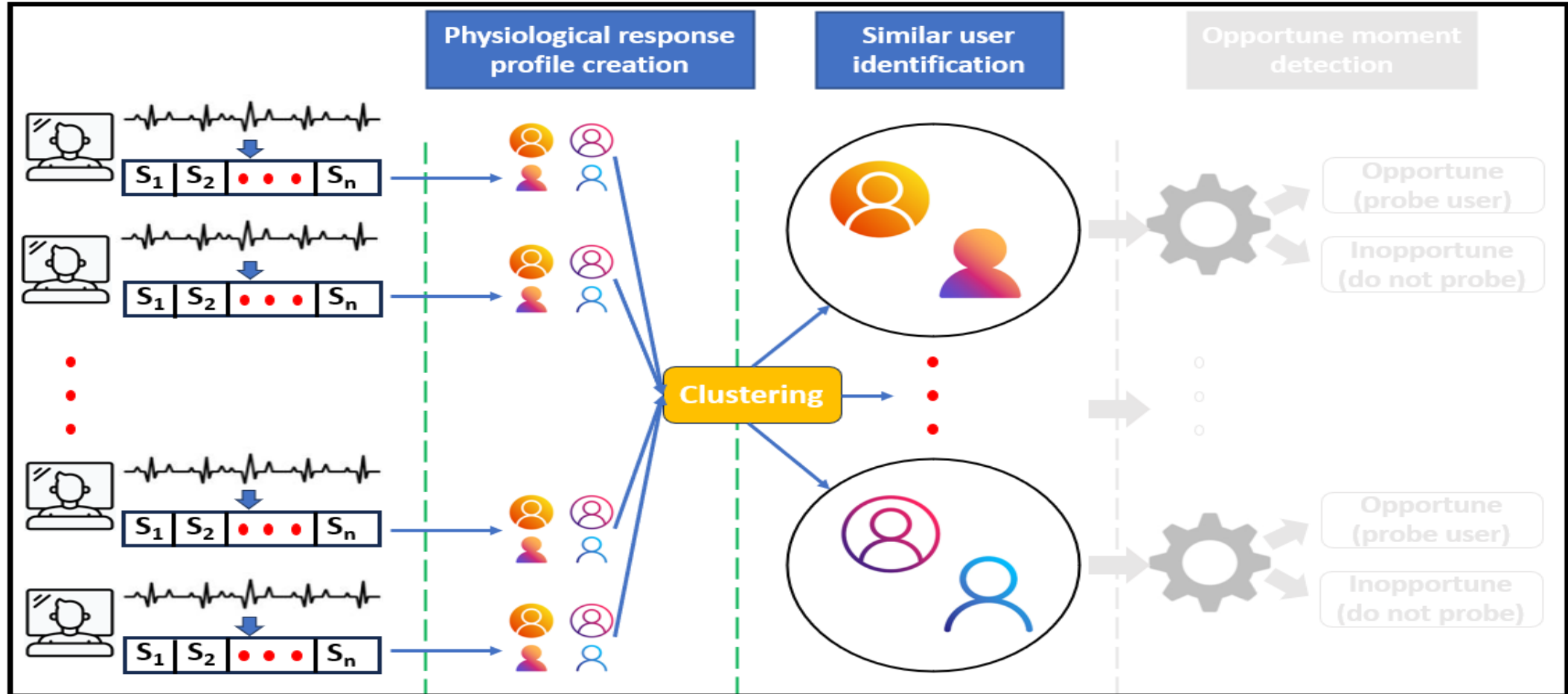

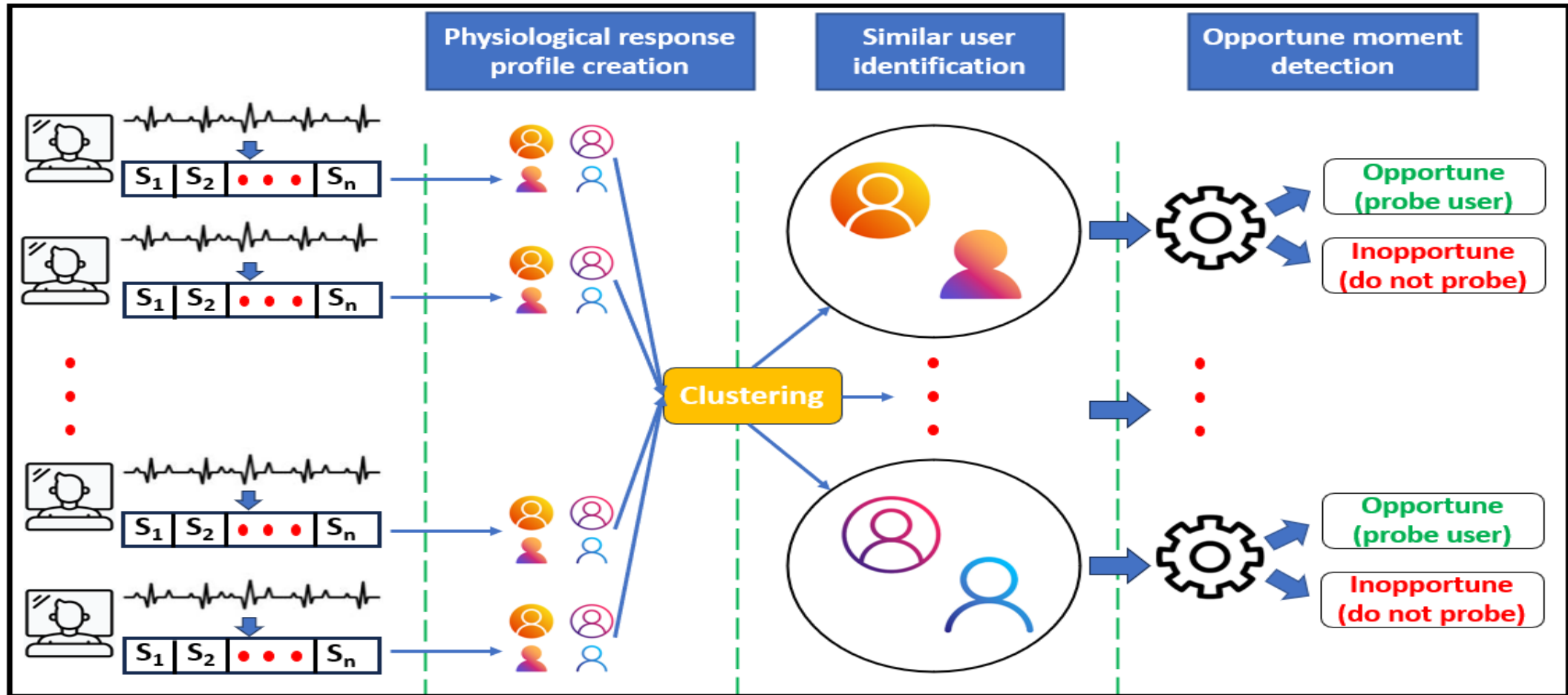(b) Annotation *only* at opportune moments

PResUP Framework

Response profile (4-tuple): $\langle mu_{opp}, sig_{opp}, mu_{inopp}, sig_{inopp} \rangle$

PResUP Framework

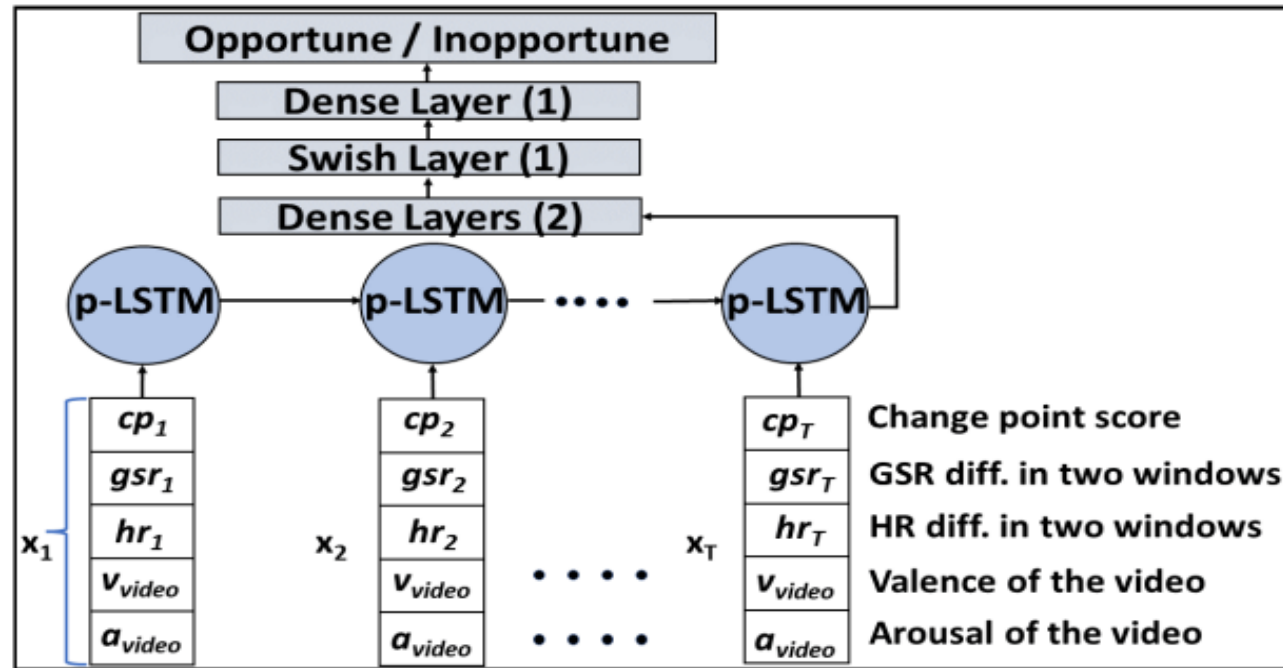We found 2 clusters provide optimal silhouette score.

PResUP Framework

We created cluster-specific (p-LSTM) models for opportune moment detection.

PResUP Framework

The parameterized Elliott activation functions: $f(x) = \dfrac{px}{1 + |x|}$

p-LSTM architecture used in PResUP

Evaluation: Model Performance

|	Probing rate↓	TPR (%)↑	FPR (%)↓	LR+↑
TBS	29.89 (0.00)	100.00 (0.00)	100.00 (0.00)	1.00
RPS	17.93 (0.01)	60.28 (0.01)	59.98 (0.01)	1.00
RePS	28.79 (0.01)	99.39 (0.02)	95.77 (0.01)	1.04
PPS	21.59 (3.46)	71.53 (0.23)	9.96 (0.04)	7.18
FBS	5.60 (4.58)	53.23 (0.03)	9.53 (0.17)	5.59
APS	7.18 (5.32)	65.27 (0.24)	15.88 (0.16)	4.11
GBPS	6.68 (4.96)	66.84 (0.24)	14.32 (0.14)	4.67
GPS	7.79 (3.11)	76.21 (0.18)	19.72 (0.11)	3.86
RNNPS	6.08 (3.25)	61.16 (0.38)	14.08 (0.12)	4.34
GRUPS	7.65 (3.60)	67.50 (0.36)	18.83 (0.09)	3.58
CNNPS	6.13 (1.75)	68.80 (0.19)	13.13 (0.08)	5.24
PResUP	**5.48 (1.73)**	**80.07 (0.16)**	**9.30 (0.05)**	**8.61**

- Probing rate → the average number of probes issued per video for every user

- LR+ = (TPR)/(FPR)

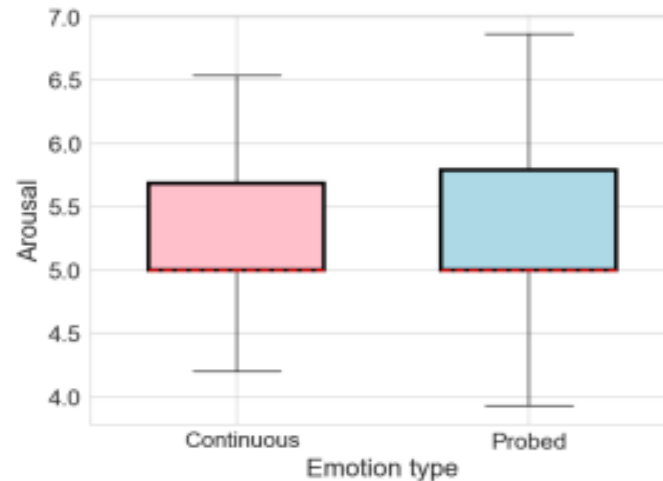PResUP has the least probing rate and highest LR+.

Evaluation: Annotation Quality

Continuous: Original valence (and arousal) present in continuous annotation
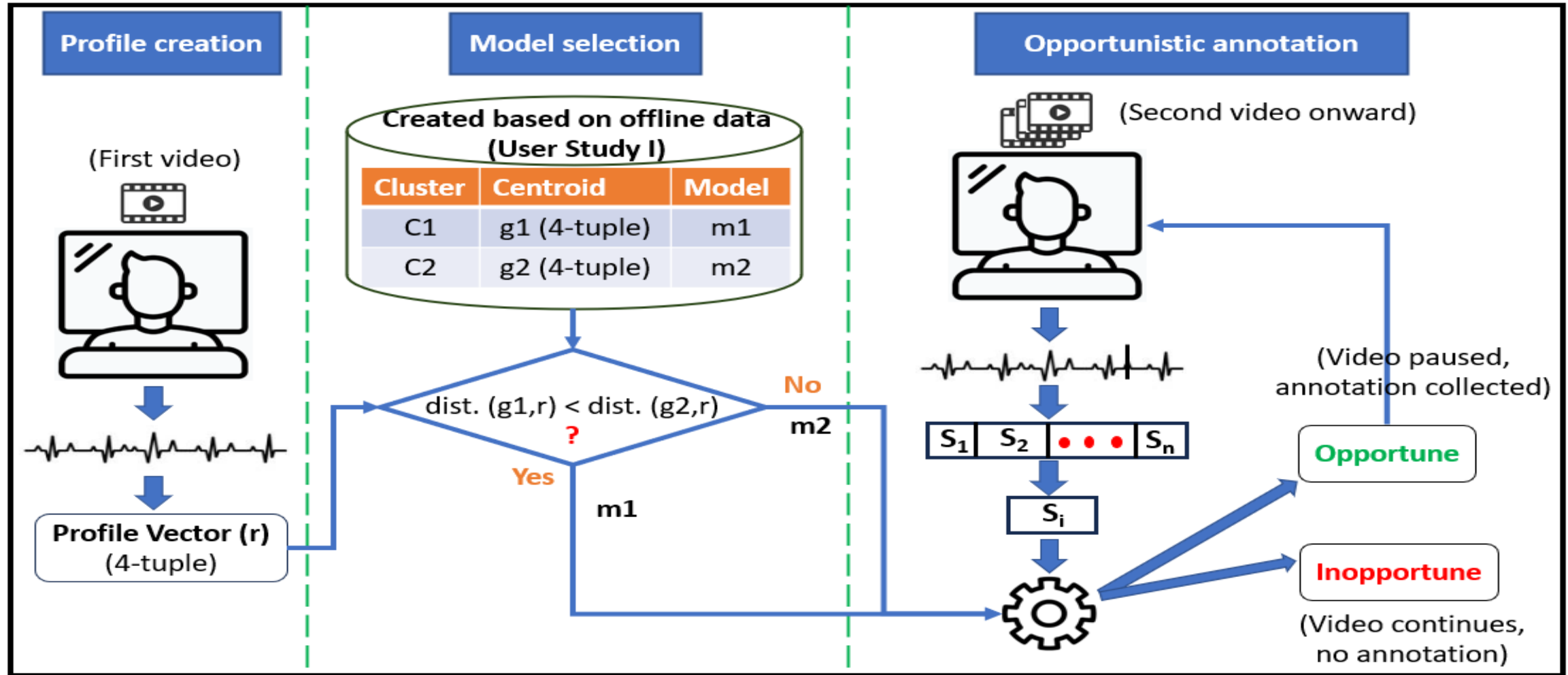Probed: Sampled valence (and arousal) using PResUP
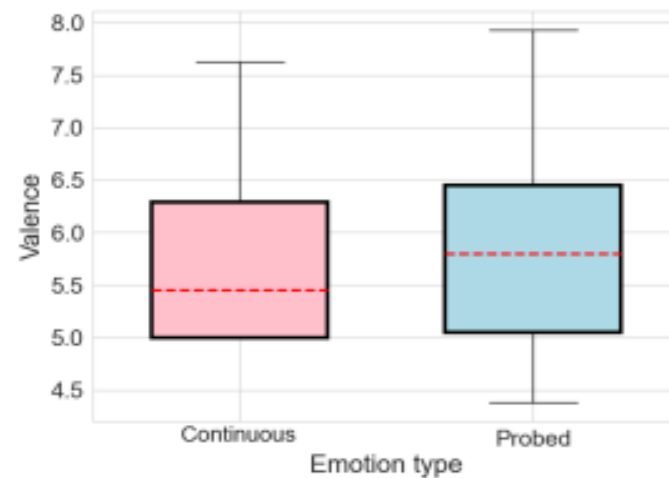
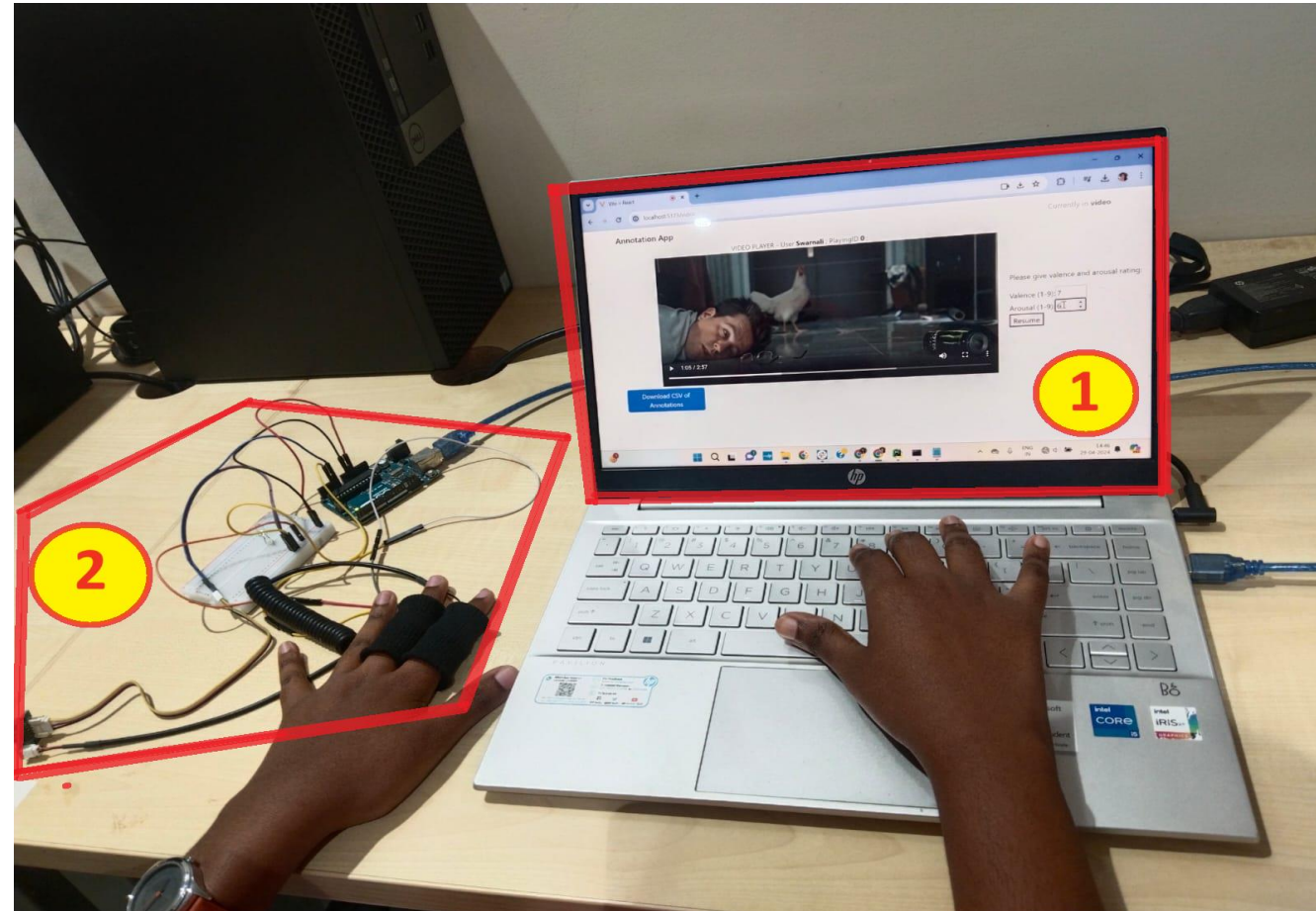(a) Comparison of valence scores   (b) Comparison of arousal scores

No significant difference between ground truth continuous annotations and probed values using PResUP

PResUP: Deployment
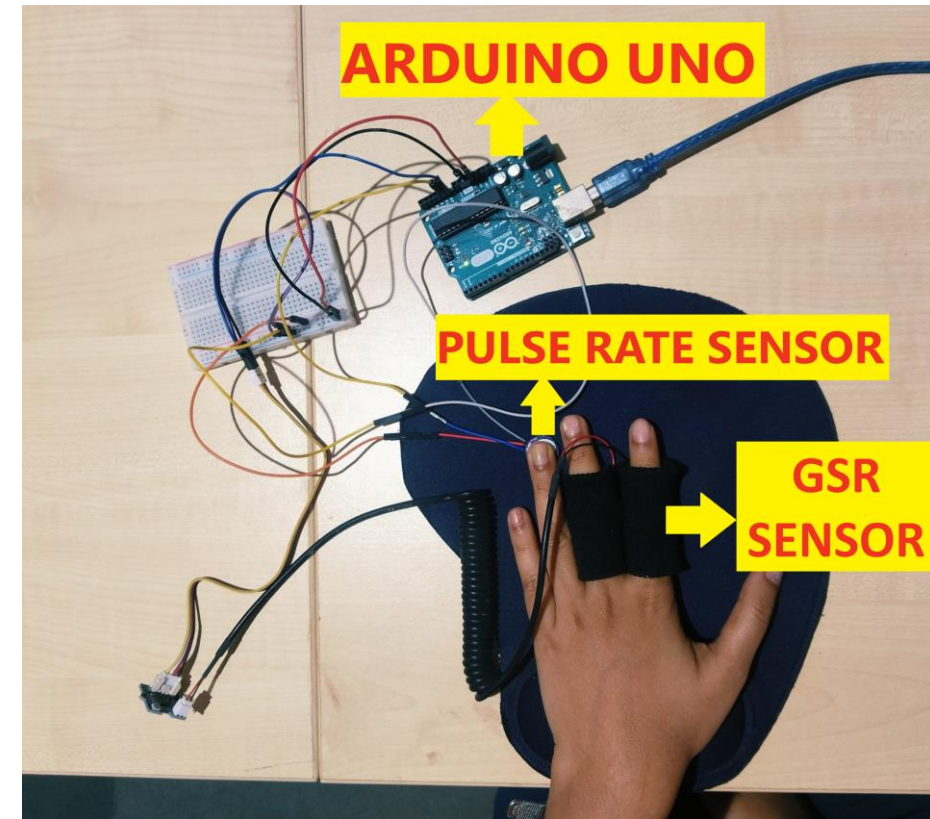
User Study II

- **Experiment Apparatus**
  - Sensor setup
  - Annotate app

User Study II

- **Experiment apparatus**
  - Sensor setup (same as earlier)
    - Galvanic skin response sensor (GSR V1.2)
    - Pulse rate sensor (HW-827)

User Study II

- **Experiment apparatus**
  - Annotate app (minor change)

    - No continuous annotation
    - Stops video and probes only when the moment is opportune

User Study II

- **Study procedure**

  - 18 participants (13M, 5F)
    - Different from user study I participants.

  - Each subject watched the 8 videos

  - First video → physiological response profile creation

  - Available segments for probing: 3912
   - 703 → (predicted as) opportune

Evaluation: Post-deployment

	Probing rate↓	TPR (%)↑	FPR (%)↓	LR+↑
TBS	34.42 (0.00)	100 (0.00)	100 (0.00)	1.00
RPS	23.99 (0.01)	69.79 (0.01)	69.6 (0.01)	1.00
RePS	30.38 (0.10)	98.82 (0.01)	96.25 (0.00)	1.03
PPS	12.16 (1.62)	78.8 (0.18)	9.49 (0.03)	8.30
FBS	5.81 (2.57)	61.62 (0.15)	9.21 (0.02)	6.69
APS	7.77 (5.21)	71.23 (0.20)	12.11 (0.12)	5.88
GBPS	7.65 (4.94)	73.82 (0.20)	11.3 (0.11)	6.53
GPS	8.22 (4.02)	64.77 (0.41)	17.54 (0.18)	3.69
RNNPS	8.09 (3.94)	54.9 (0.36)	21.29 (0.10)	2.58
GRUPS	7.36 (3.77)	51.16 (0.39)	19.7 (0.09)	2.60
CNNPS	9.59 (1.98)	34.82 (0.18)	31.13 (0.06)	1.12
PResUP	**5.79 (2.54)**	**82.26 (0.09)**	**9.01 (0.06)**	**9.13**

- Probing rate → the average number of probes issued per video for every user

- LR+ = (TPR)/(FPR)

PResUP has the least probing rate and highest LR+.

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Post-study User Survey
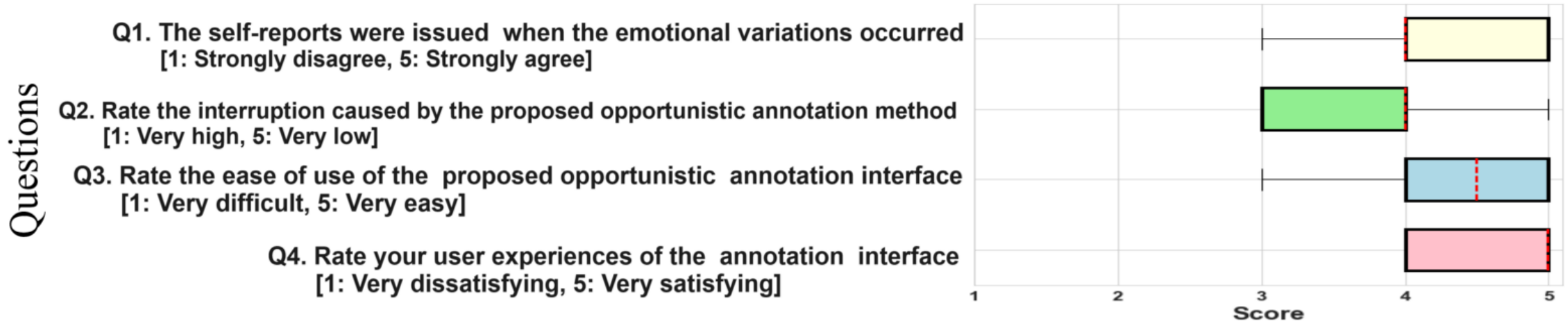
Boxplot showing the scores as obtained from the survey participants for the four survey questions in the questionnaire. Higher values for each of the four questions are desired.
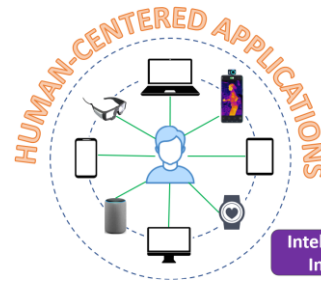
Conclusion and Future Works

- Opportunistic annotation appears to be a feasible alternative of continuous annotation
  - reduces annotation effort
  - does not deteriorate the viewing experience

- Future works
  - Deploying PResUP on mobile platforms Applicability
  - Enhance user experience further

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Thank you!!