EEVR: A Dataset of Paired Physiological Signals and Textual Descriptions for Joint Emotion Representation Learning

Pragya Singh, Ritvik Budhiraja, Ankush Gupta, Anshul Goswami,
Mohan Kumar, Pushpendra Singh

Mélange Lab

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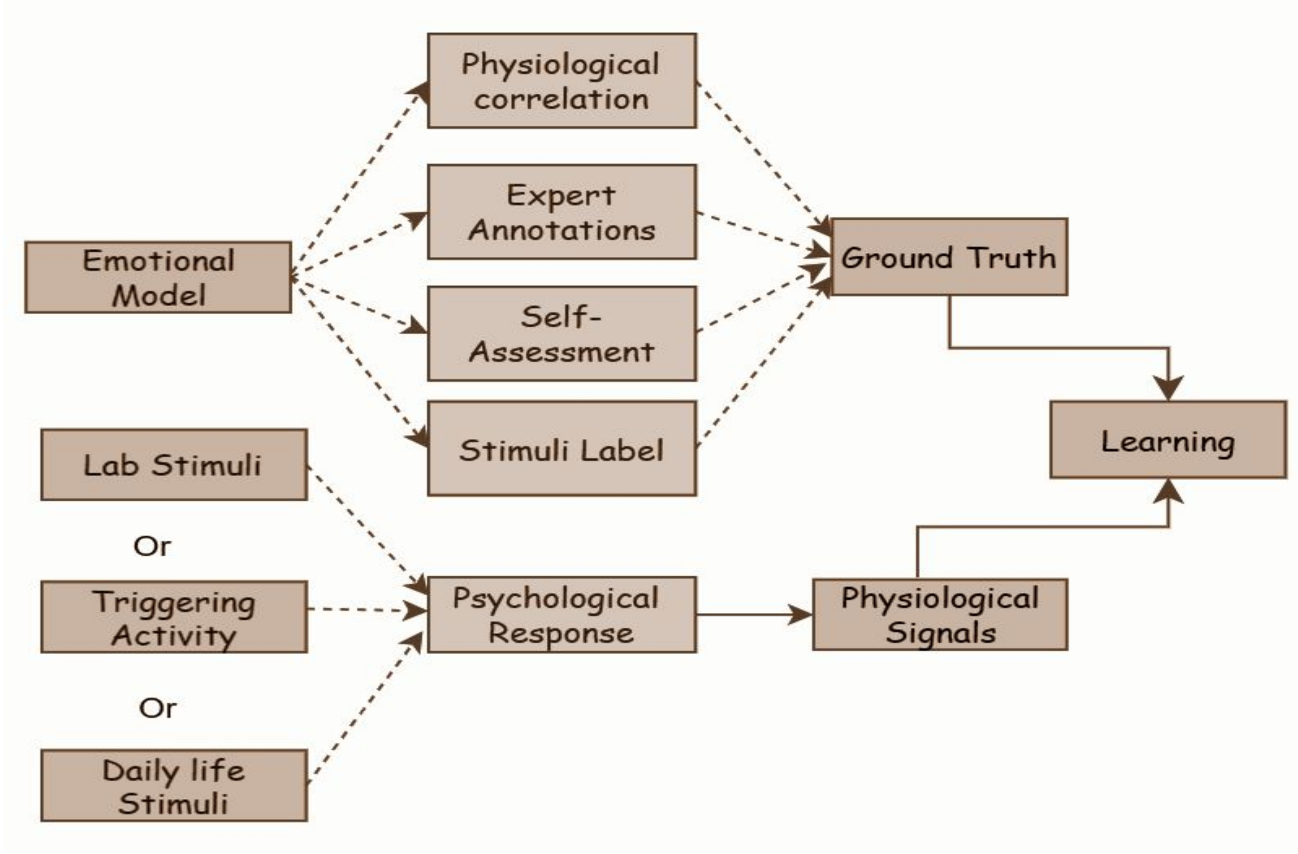
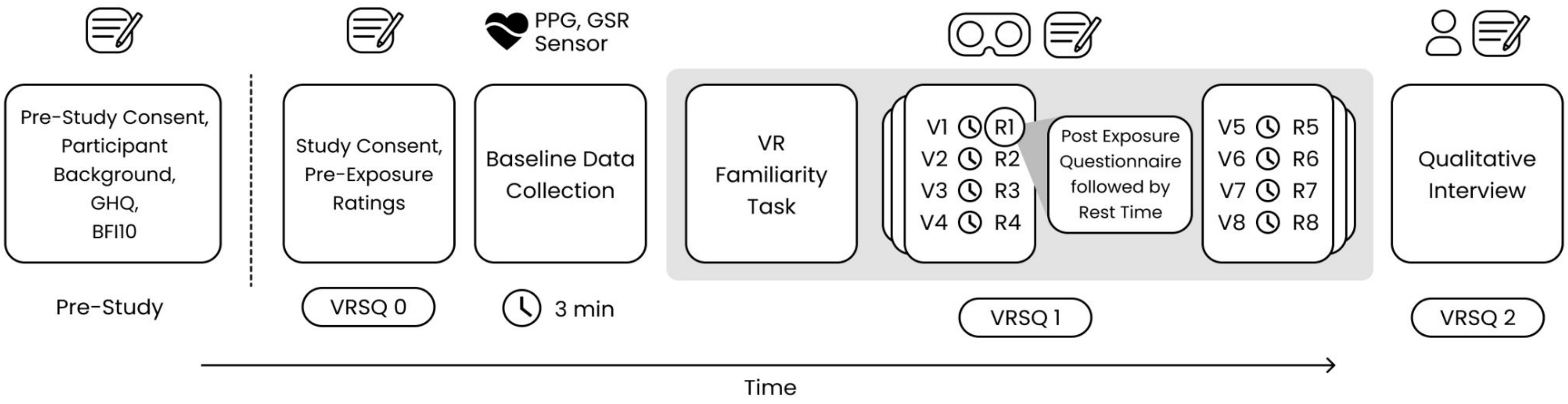
Motivation

- **Emotion Recognition** using wearables have huge potential for mental health monitoring.
- Presently, **objective scales,** stimulus-label, or self-report questionnaires are used for emotion annotation.
- These methods often **fail** to capture **mixed emotions**, **absence** of emotions, or **brief emotional** responses within the stimulus and thus lead to poor emotion representation learning.

Physiological Emotion Data Collection



Methods



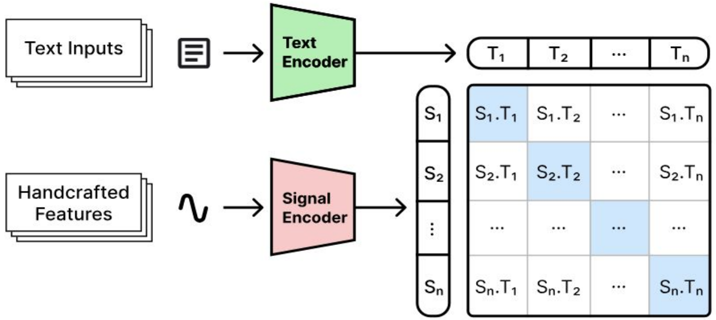
Data Curation

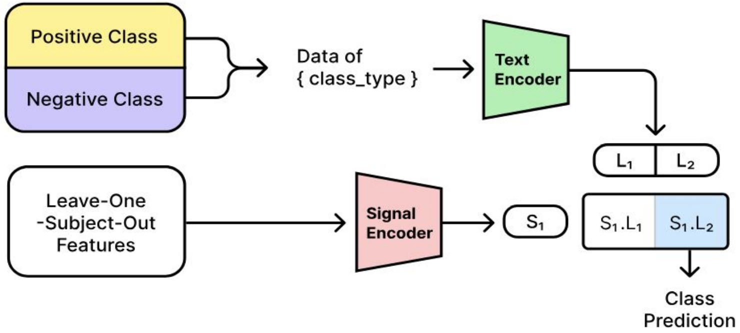
We manually extracted **textual description** data from audio recordings of semi-structured interviews for each **participant-video** pair of physiological data.

Baseline without Text-supervision

Modality	Models	Stimulus-label Accuracy	Stimulus-label F1 Score	Valence Accuracy	Valence F1 Score	Arousal Accuracy	Arousal F1 Score
EDA	**Logistic Regression**	86.78 ± 0	0.82 ± 0	61.56 ± 0	0.71 ± 0	47.41 ± 0	0.36 ± 0
	Decision Tree	85.09 ± 0.17	0.83 ± 0	58.46 ± 1.06	0.64 ± 0.01	54.05 ± 1.12	0.35 ± 0.02
	Random Forest	**90.79 ± 0.46**	**0.89 ± 0.01**	60.26 ± 1.81	0.66 ± 0.01	57.23 ± 1.19	0.28 ± 0.04
	LDA	87.69 ± 0	0.85 ± 0	**61.86 ± 0**	**0.69 ± 0**	48.97 ± 0	0.37 ± 0
	XGBoost	90.69 ± 0.52	0.89 ± 0.01	59.76 ± 0.52	0.66 ± 0.01	56.61 ± 0.34	0.37 ± 0.01
	SVM	85.29 ± 0	0.81 ± 0	59.16 ± 0	0.71 ± 0	51.66 ± 0	**0.44 ± 0**
	MLP	87.39 ± 0	0.85 ± 0	61.86 ± 0	0.68 ± 0	**57.27 ± 0**	0.39 ± 0
PPG	**Logistic Regression**	81.08 ± 0	0.77 ± 0	61.26 ± 0	0.70 ± 0	**56.29 ± 0**	**0.42 ± 0**
	Decision Tree	68.87 ± 0.35	0.65 ± 0	54.35 ± 0.30	0.59 ± 0.01	49.43 ± 0.32	0.26 ± 0.01
	Random Forest	75.88 ± 0.35	0.69 ± 0.01	**61.66 ± 1.93**	**0.70 ± 0**	49.27 ± 0.42	0.18 ± 0.01
	LDA	**81.08 ± 0**	**0.78 ± 0**	58.96 ± 1.73	0.67 ± 0.06	54.47 ± 3.72	0.40 ± 0.02
	XGBoost	49.44 ± 0	0.68 ± 0	57.26 ± 0.76	0.64 ± 0.01	47.89 ± 7.57	0.26 ± 0.13
	SVM	80.48 ± 0	0.75 ± 0	59.86 ± 1.91	0.70 ± 0.05	47.99 ± 3.78	0.32 ± 0.10
	MLP	78.68 ± 0	0.75 ± 0	56.76 ± 0	0.66 ± 0	54.16 ± 0	0.38 ± 0
PPG + EDA	**Logistic Regression**	85.89 ± 0	0.82 ± 0	60.06 ± 0	0.69 ± 0	55.23 ± 0	0.41 ± 0
	Decision Tree	83.78 ± 0.80	0.83 ± 0.01	**62.77 ± 0.30**	0.66 ± 0	**58.13 ± 0.70**	0.40 ± 0.01
	Random Forest	**90.69 ± 0**	**0.89 ± 0**	61.06 ± 1.35	0.70 ± 0.01	56.78 ± 1.56	0.26 ± 0.01
	LDA	84.89 ± 1.39	0.82 ± 0.01	57.56 ± 2.95	0.66 ± 0.06	55.48 ± 1.04	**0.42 ± 0.01**
	XGBoost	87.19 ± 2.73	0.85 ± 0.03	61.36 ± 4.79	0.67 ± 0.04	58.0 ± 1.66	0.36 ± 0.06
	SVM	87.29 ± 1.39	0.84 ± 0.02	62.16 ± 2.08	**0.72 ± 0.02**	55.97 ± 3.44	0.38 ± 0.04
	MLP	83.48 ± 0	0.81 ± 0	58.86 ± 0	0.63 ± 0	56.89 ± 1.47	0.36 ± 0.03
Text	**DistillBert**	**97.44 ± 0.69**	**0.97 ± 0.01**	**91.73 ± 1.73**	**0.88 ± 0.02**	**89.94 ± 1.17**	**0.88 ± 0.02**
	XLMBert-a Base	97.32 ± 0.34	0.97 ± 0	89.46 ± 1.60	0.70 ± 0.15	76.50 ± 9.59	0.70 ± 0.15

Baseline with Text-supervision





- We introduce the **Contrastive Language-Signal Pre-training** (CLSP) method for extracting more contextualized representations.
- The model was trained on physiological signals and text pairs to learn a joint embedding space, where both modalities are closely aligned using a **contrastive loss function**.

Results

Modality	Model	Stimulus-label		Valence		Arousal	
		Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score
EDA	**HC+NN**	**87.39**	**0.85**	61.86	0.68	57.27	0.39
PPG	**HC+NN**	78.68	0.75	56.76	0.66	54.16	0.38
EDA+PPG	**HC+NN**	83.48	0.81	58.86	0.63	58.58	0.40
EDA+Text	**CLSP**	64.19	0.68	**70.38**	**0.73**	**77.25**	**0.81**
PPG+Text	**CLSP**	56.95	0.53	64.74	0.64	69.91	0.62
EDA+PPG+Text	**CLSP**	53.50	0.48	64.87	0.60	69.64	0.64

Zero-shot Transfer

Dataset (Signal Type)	Method	Arousal Accuracy	Arousal F1 Score	Valence Accuracy	Valence F1 Score
Emognition (EDA)	MLP	52.80	0.57	**61.89**	0.36
	Zero-shot CLSP	**53.23**	**0.59**	50.32	**0.49**
Emognition (PPG)	MLP	49.94	0.53	50.63	0.28
	Zero-shot CLSP	48.19	0.47	51.88	0.41
Emognition (EDA + PPG)	MLP	51.53	0.54	55.12	0.34
	Zero-shot CLSP	50.94	0.52	53.58	0.41
WESAD (EDA)	MLP	85.00	0.84	96.67	0.97
	Zero-shot CLSP	53.33	0.67	51.67	0.67
WESAD (PPG)	MLP	80.00	0.80	75.00	0.75
	Zero-shot CLSP	70.00	0.68	66.67	0.72
WESAD (EDA + PPG)	MLP	**91.67**	**0.91**	**98.33**	**0.98**
	Zero-shot CLSP	75.00	0.71	86.67	0.86
Nurse (EDA)	MLP	39.88	0.32	71.83	0.03
	Zero-shot CLSP	**55.48**	**0.58**	**84.93**	0.20
Nurse (PPG)	MLP	45.10	0.38	72.08	0.05
	Zero-shot CLSP	53.08	0.48	75.34	0.23
Nurse (EDA + PPG)	MLP	48.35	0.43	76.04	0.23
	Zero-shot CLSP	53.08	0.45	84.59	**0.42**

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Takeaways

- Objective annotations based supervised learning algorithms often **fail** to capture the **subtle complexities** of emotion data.

- **Incorporating subjective annotations**, such as textual descriptions, provides a new opportunity to enhance the quality of representations learned from physiological signals.

Thank You :)

Pragya Singh

email: pragyas@iiitd.ac.in

Github: https://github.com/alchemy18/EEVR/

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