Quantified Facial Temporal-Expressiveness Dynamics for Affect Analysis

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Affective Expression vs. Expressiveness

*Pain expression sequence. Neutral to low to high level pain*

Motivation

➔ Beyond expression, we need to understand the expressivity
➔ Unstructured visual expression data to structured data
➔ Making visual expression analysis accessible

TED based Visual Affect Analysis Framework

➔ Get visual dataset
➔ Track facial features (**facial action units, landmarks, headpose, gaze**)
➔ Compute TED on tracked features
➔ High level tasks
  ◆ Descriptive summary
  ◆ Model interpretation
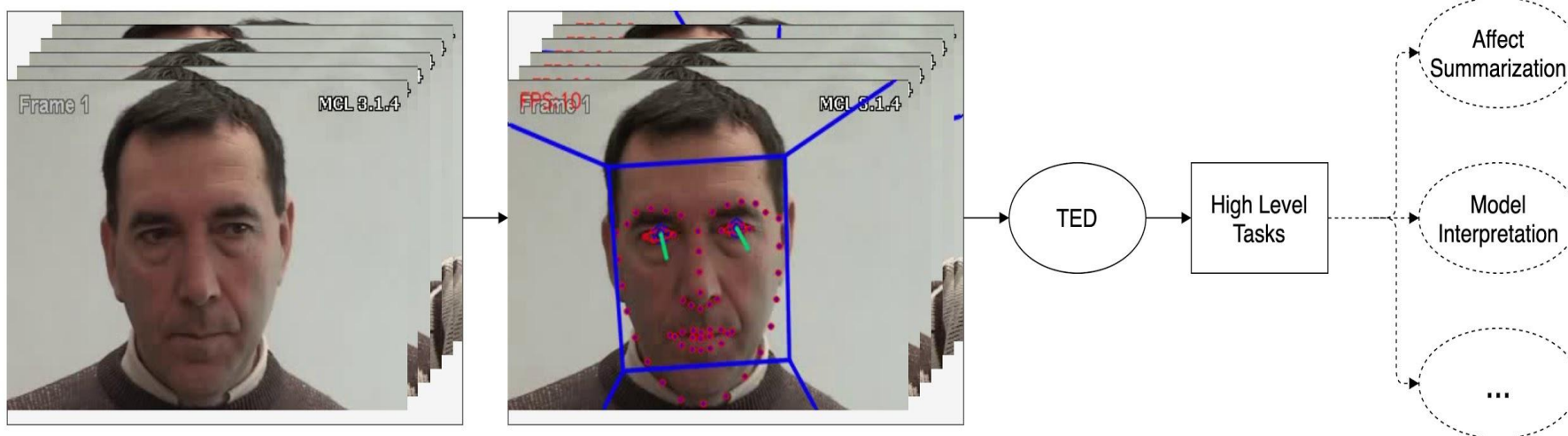
Proposed Affective Expressiveness Algorithm (TED)

Step #1: Compute static expressiveness emphasizing on the high intensity action units (AUs)

$$S = \sum_{1}^{n} e^v$$

Step #2: Capture dynamics by computing relative changes in AUs, landmarks, headpose & eyes' gaze

$$C_r = \begin{cases} 0 & \text{if } var(f_i) + var(f_{i+1}) = 0 \\ \frac{var(f_{i+1}, f_i)}{var(f_i) + var(f_{i+1})} & \text{otherwise} \end{cases}$$

$$D_s = \begin{cases} +1 & \text{if } \sum_{i=1}^{m} [f_{i+1} - f_i] \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

Step #3: Compute average changes using rolling window

$$M = \frac{1}{w} \sum_{i}^{w+i-1} D_s * C_r$$

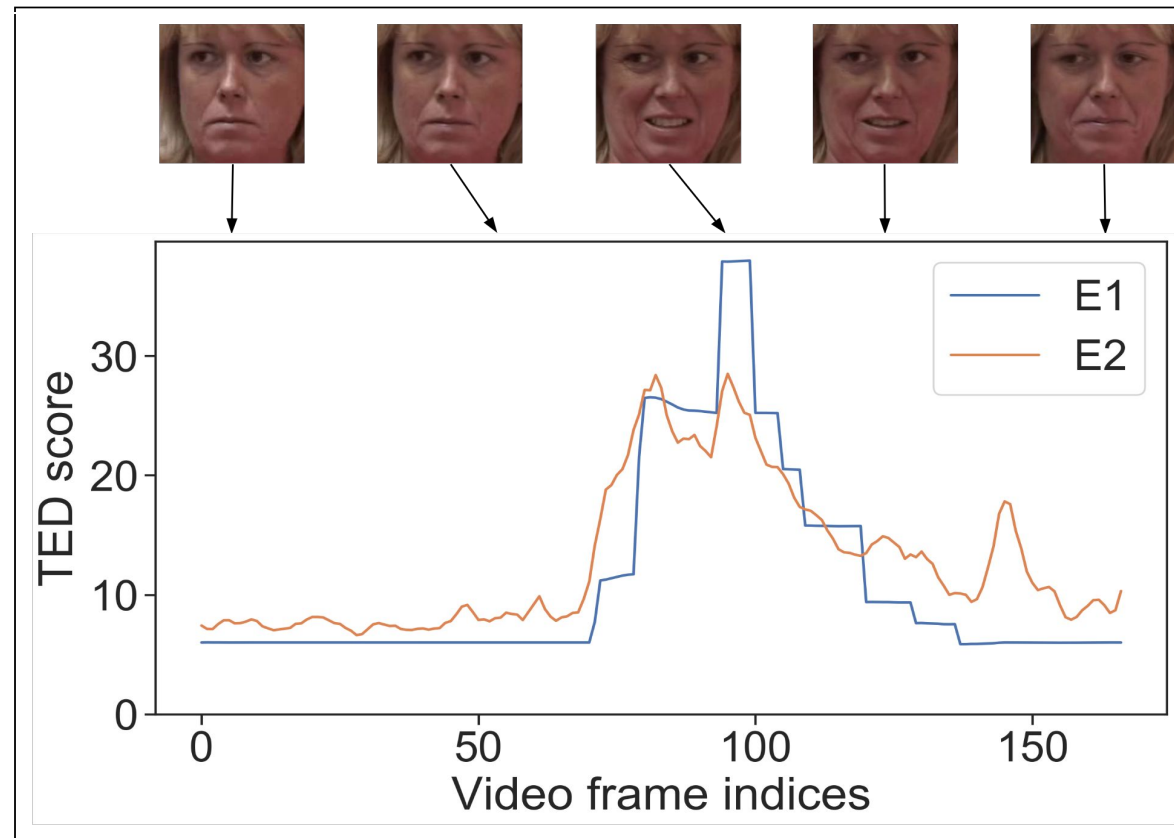Step #4: Expressiveness in a given moment of time combining static & dynamic expressiveness

$$Score = S_i * [1 + M_L * M_{H_o} * M_{H_r} * M_{G_l} * M_{G_r} * M_I]$$

Example: **Quantified expressiveness of pain affect**

E1 - Expert (human) coded AUs were used in experiments

E2 - ML model predicted AUs were used in experiments

Expressiveness dynamics for a given pain sequence
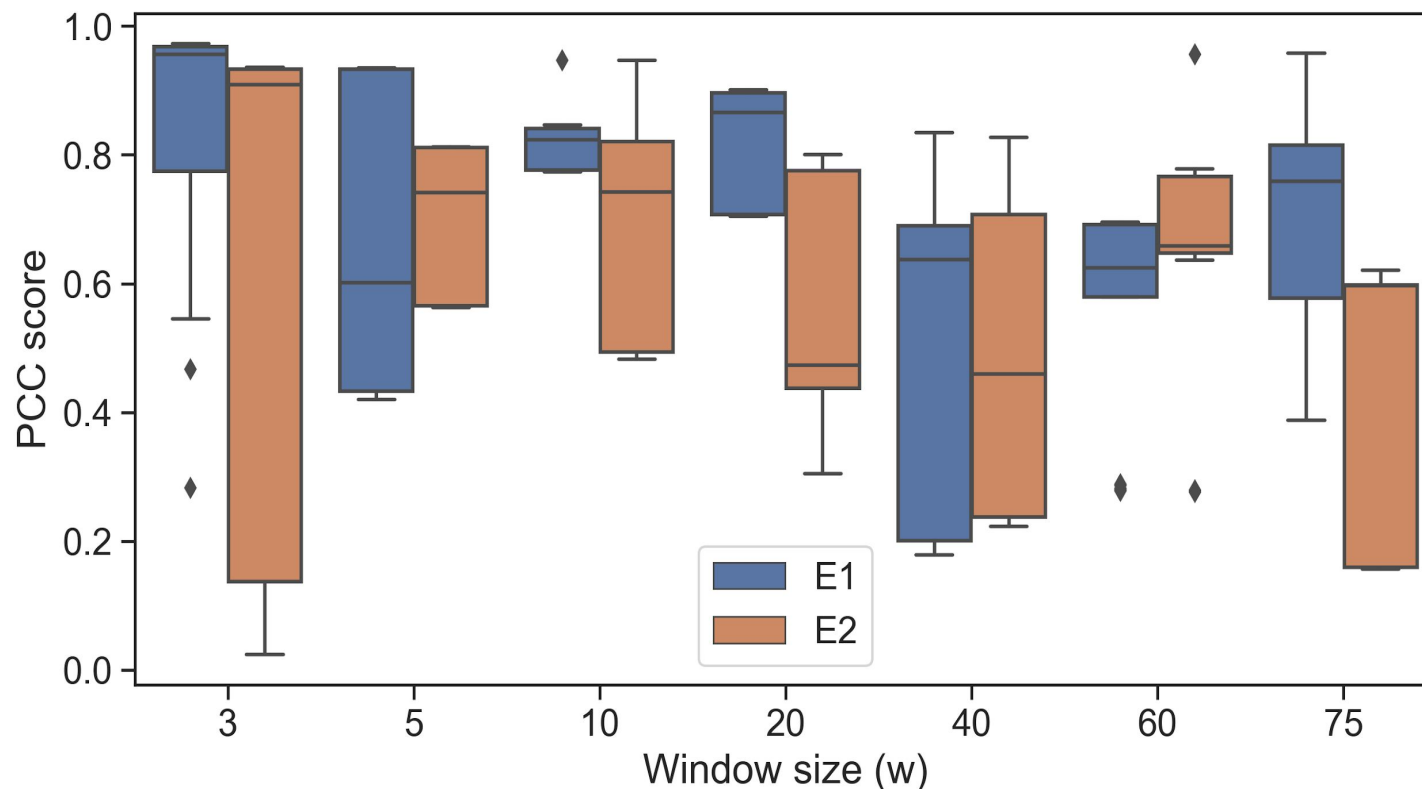
Experiments and Analysis

TED based pain expressiveness is strongly correlated with PSPI scale scored pain level

Comparison: *Expressiveness (TED) scores vs. PSPI pain scores*
Experimented dataset: UNBC-McMaster shoulder pain dataset (IEEE FG 2011)
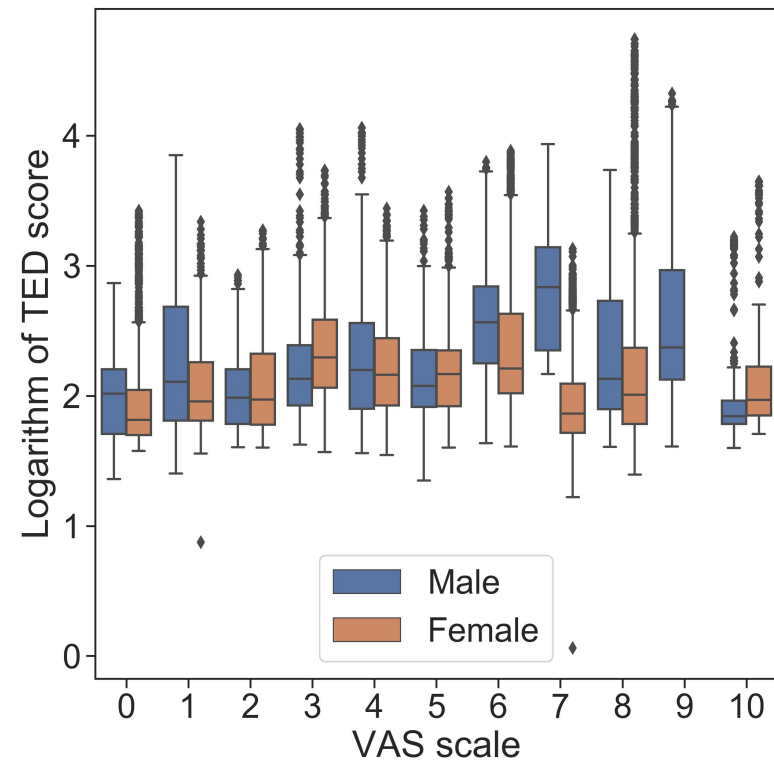Evaluation metric: PCC (Pearson correlation coefficient). Higher is Better.

Pain frames are likely to be outlier as high scored self-reported pain sequences may contain very few highly expressive pain frames

Sequence level pain expressiveness analysis using self-reported pain scores (**VAS**)
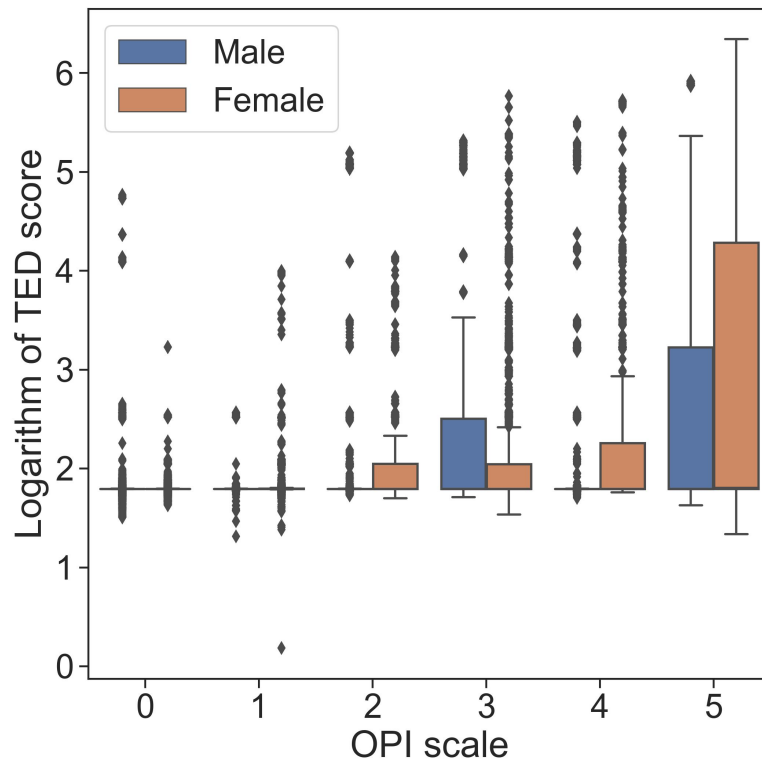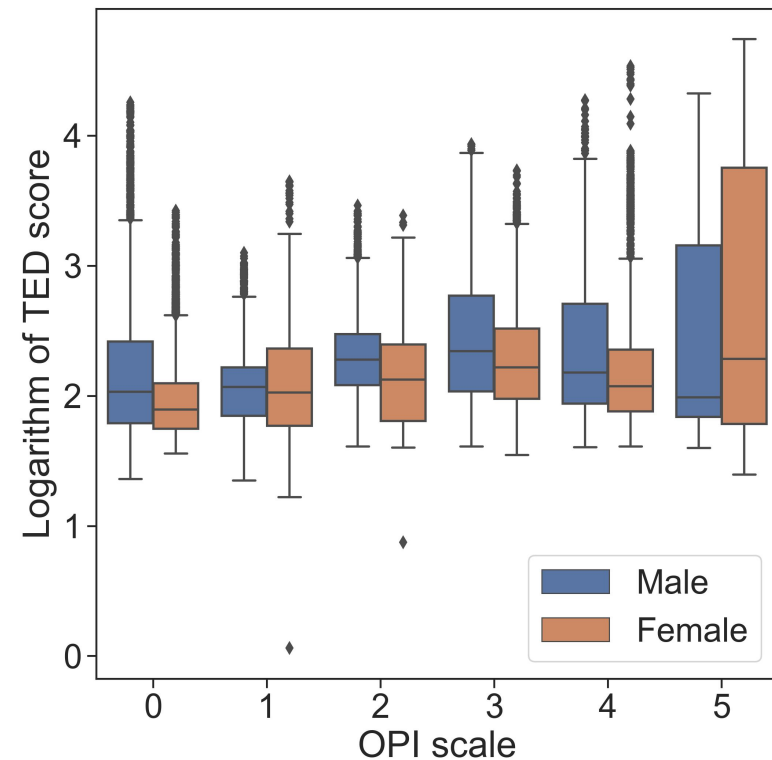
Experiment E1
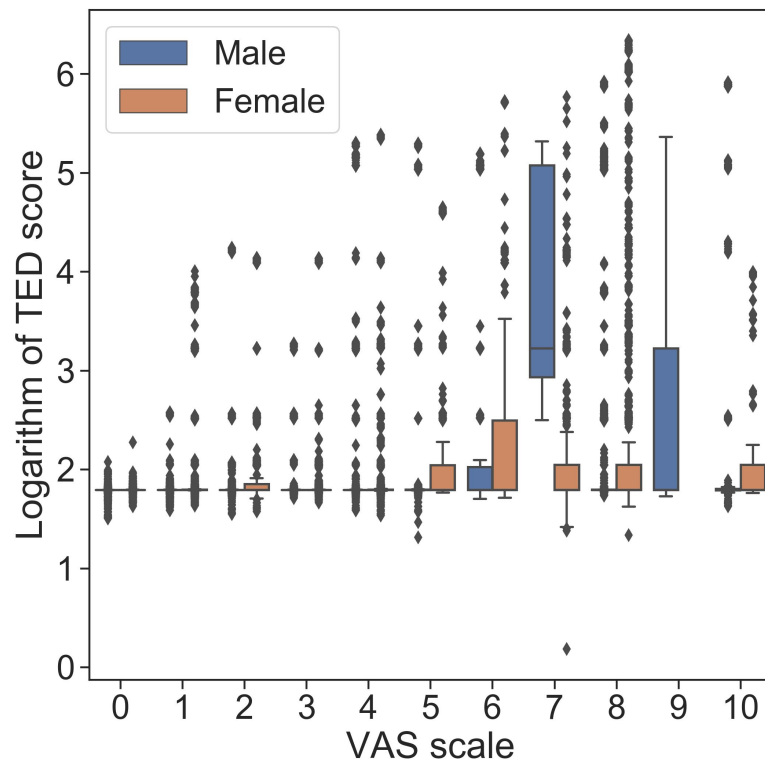
Experiment E2

Observer reported pain scores go up, expressiveness scores go up as well. Observers pay attention to the visual facial responses of pain.

Sequence level pain expressiveness analysis using observer reported pain scores (**OPI**)
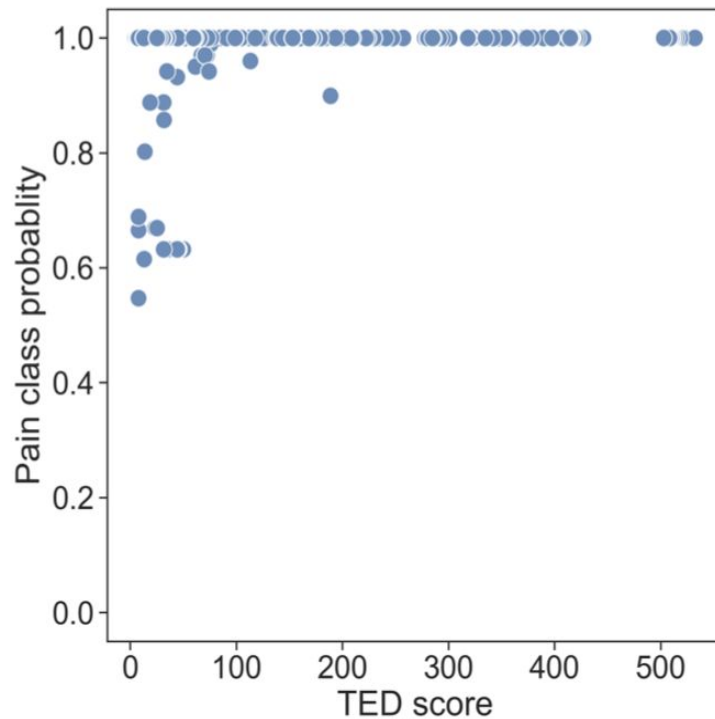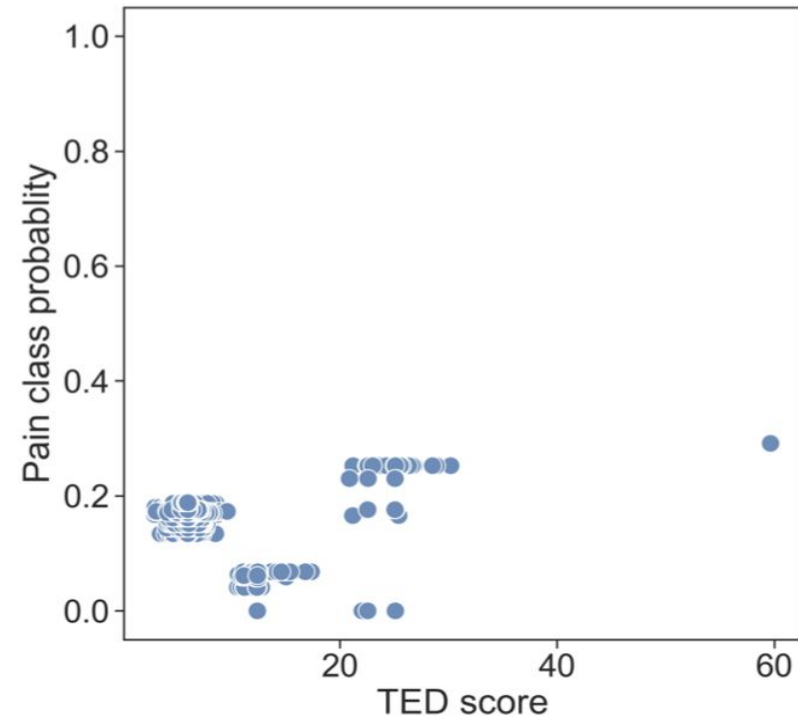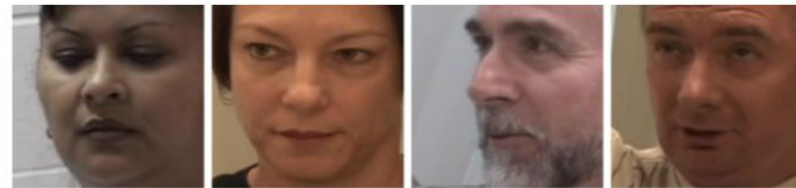
Experiment E1

Experiment E2

Strong association between expressiveness scores & model confidence

Pain detection using random forests. Performance: 0.86 F-measure
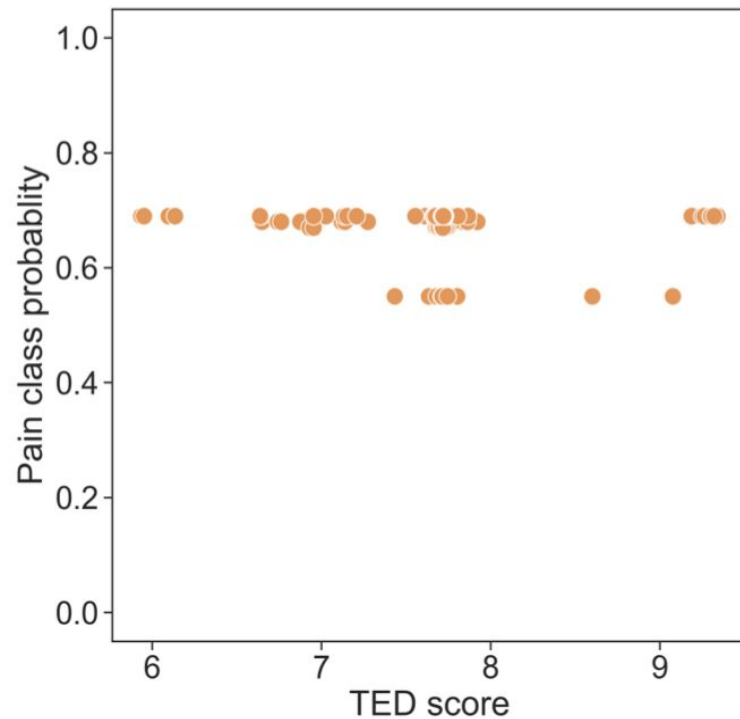
True Positive (Success)

True Negative (Success)

Pain detection model made mistakes in gray area (low pain intensity pain frames, i.e. neutral is similar to pain samples)

False Positive (Failure)

False Negative (Failure)

Summary

➔   Quantifying facial expressiveness at video frame level
➔   Automated unstructured affective data analysis
➔   Better predictive modeling via additional expressiveness analysis

Thanks for watching :)

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Q/A