Towards Causal Psychophysiology in the Wild:
Probabilistic Programs for Skin Conductance Analysis

The problem

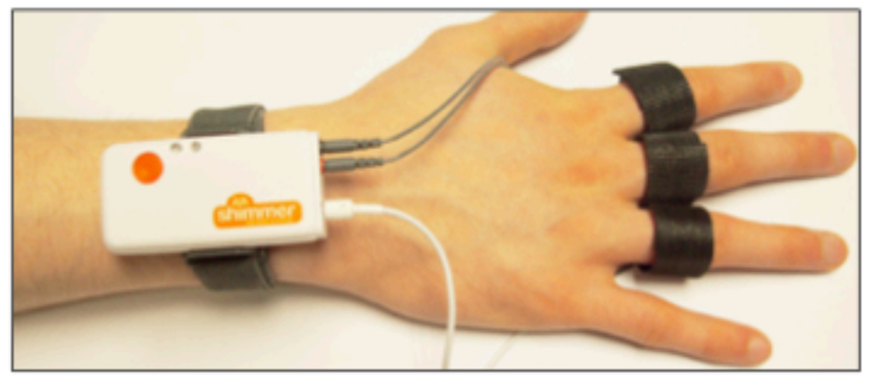
Our work focuses on (1) ***unobtrusive hardware development for real-world, long-term physiological measurement*** and (2) ***using these measurements to derive continuous, robust insight into our mental states and their influences***.

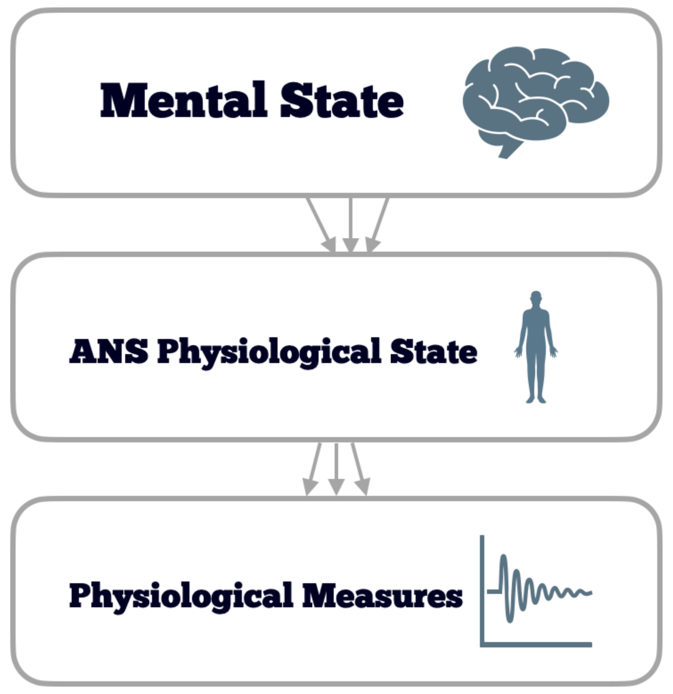
Major issues with the current state-of-the-art approaches for psychophysiological modeling include:

1. Laboratory Conditions. Measurements are almost always made in controlled situations with known stimuli, that do not reflect or translate to naturalistic experiences— study participants are more alert, self-consciously aware of their performance, and have social pressure on them to meet expectations of the experimenter; psychological stimuli are also contrived. These insights don't translate to the real world.

2. Noise. Measurements made in the lab are done with high quality equipment in environments where external noise sources are heavily controlled and participants under contrived conditions (at rest, no motion).

3. Decision Boundaries. In general, 'predictive modeling' psychophysiological modeling is done using standard machine learning approaches that don't take into account the irreducible uncertainty of mental phenomenology and its injective relationship to physiology.





Emotions

Regions	Stress	Fear	Startle	Sexual arousal	Anxiety	Joy	Pain	Guilt
Nose	↓	↓		↑		↓		↓
Cheeks			↓					
Periorbital			↑	↑	↑			
Supraorbital			↑		↑			
Forehead	↓↑	↓		↑	↑		↓	
Maxillary	↓	↓	↓				↓	↓
Neck–carotid			↑					
Nose	↓							
Tail		↓					↓	
Fingers/palm		↓					↓	
Lips/mouth				↑				

from: Thermal infrared imaging in psychophysiology: Potentialities and limits (2014)

EDA is the Simplest Physiological Marker

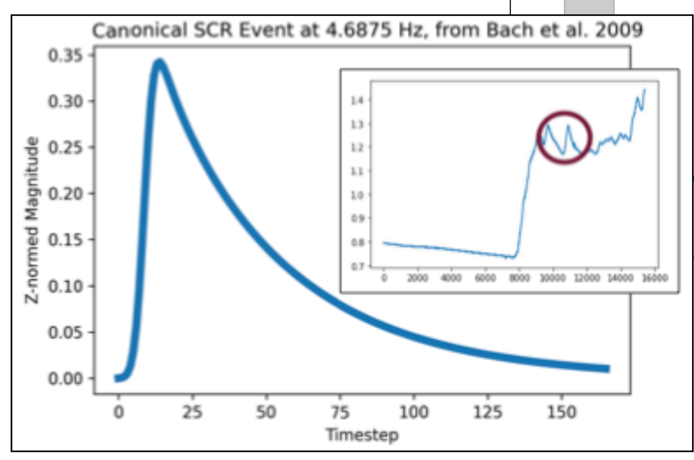
EDA is one of the simplest physiological markers to measure and predict; it is primarily driven by the Sympathetic branch of the ANS (most have both Sympathetic and Parasympathetic), and is used to measure emotional engagement at live performances, stress in call centers, alertness in the classroom, and motivation in advertising.

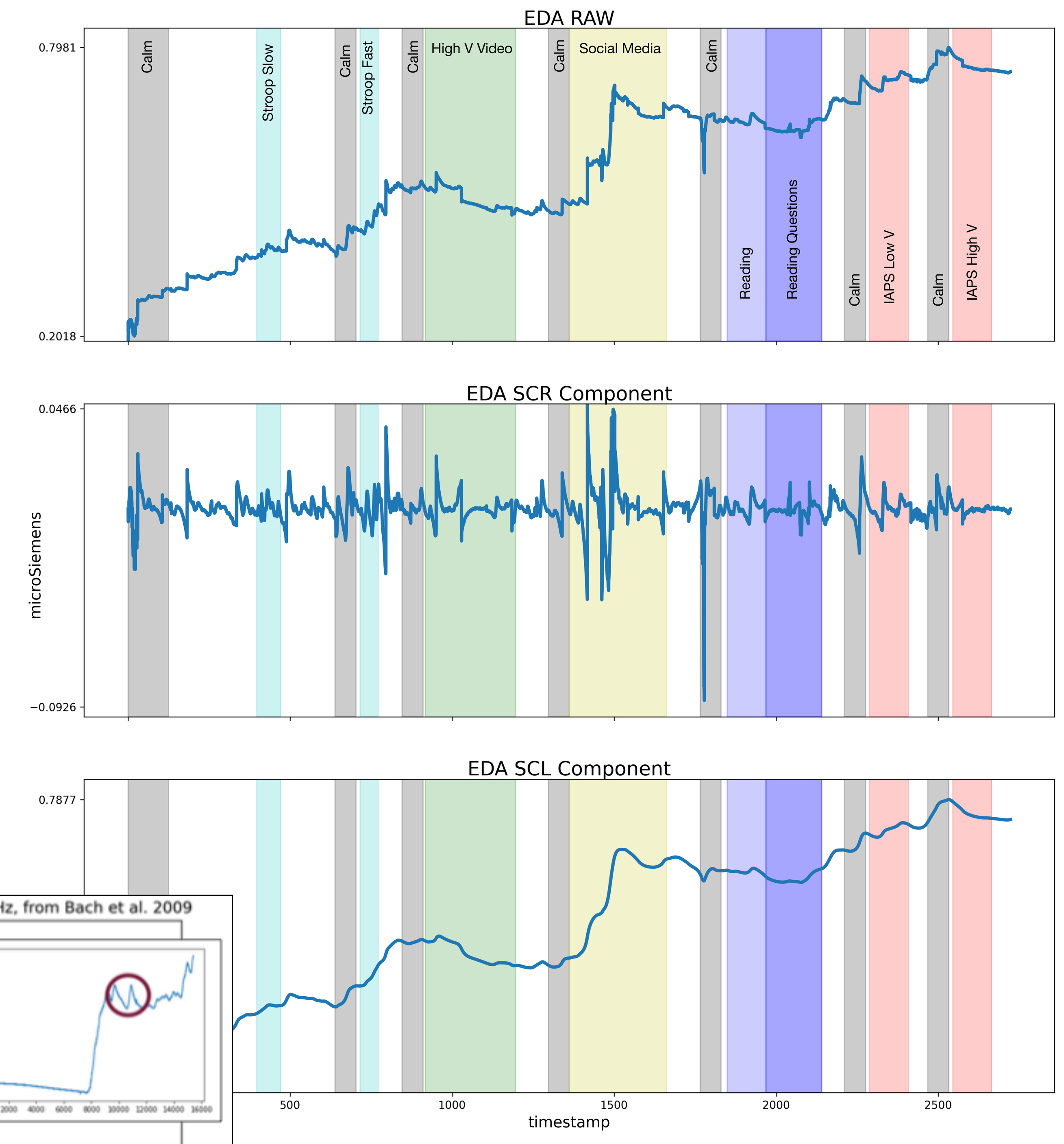
EDA is Still Very Difficult to Measure and Model

EDA is typically processed as SCL and SCR; there are many heuristics used to clean up data. 10% of people are thrown out, and there are many confounding noise sources embedded in the underlying signal, due to changes in temperature, humidity, breathing, motion, and electrode contact. Even pristine signals are known to have complex asymmetries across the body and are driven by three different brain circuits.

Our Method

- Six participants as part of a preliminary study.
- Raw resistance data was converted to μSiemens and downsampled from 18.75 to 4.6875 Hz after anti-aliasing.
- Bi-directional 0.0159 Hz filter and z-norm the data, as demonstrated in [Staib et al. 2015].
- We construct a canonical SCR waveform– a Gaussian convolved with a Gamma distribution shown in the inset, based on [Bach et al. 2009]. These techniques have been optimized empirically.





Raw EDA is processed into SCR and SCL components; a 'true' response can be hard to disambiguate from measurement artifact.

The solution

Our models are implemented in Pyro, taking advantage of Stochastic Variational Inference (SVI) and the standard trace evidence lower bound (ELBO) loss function. Here we model ***Motion Artifacts*** and ***True SCR Events***.

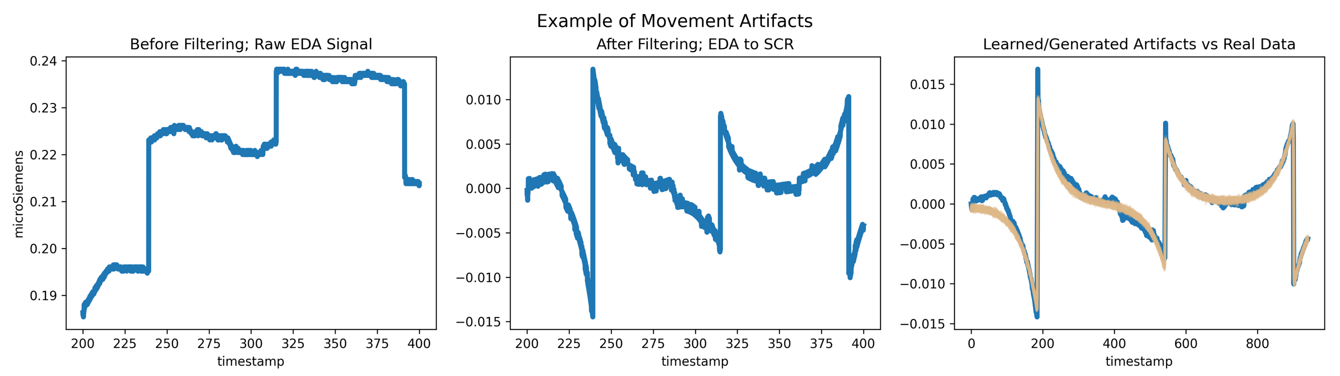
Algorithm 1: Movement Artifact Generative Model

```
Model(num_movements, movement_init_std, noise_init_std, obs)
    noise_std = noise_init_std // trainable
    output = Zeroes(Len(obs))
    // all trainable parameters with shape [num_movements, 1]:
    movement_intensities ~ Uniform(−1, 1)
    movement_location_mus ~ Uniform(0, Len(obs))
    movement_location_stds = [movement_init_std, movement_init_std, ...]
    movement_locations ~ Normal(movement_location_mus, movement_location_stds)
    For move_location, move_intensity in movement_locations, movement_intensities:
        movement_dist = Normal(move_location, movement_slope)
        output += move_intensity * movement_dist.CDF(Indices(obs))
    filtered_output = EDA_BiDirect_IIR_HPF (output)
    observations ~ Normal(filtered_output, noise_std)
```

Algorithm 2: SCR Generative Model

```
Model(num_events, event_std, obs)
    // trainable parameters with shape [num_events, 1]:
    event_locations ~ Uniform(0, Len(obs))
    event_intensities ~ Uniform(0, 1)
    // trainable parameters with shape [num_users, 1]:
    user_delays ~ Uniform(1, 3) // seconds
    user_noise_levels ~ Uniform(0.01, 0.05)
    user_offsets ~ Uniform(−3, 0)
    // trainable parameters with shape [num_events, num_users]:
    user_alphas = user_betas ~ Uniform(1.1, 5)
    For u in num_users:
        event_pulsetrain = Zeroes(Len(obs [u]))
        For e in num_events:
            react_intensity ~ Beta(user_alphas [u, e], user_betas [u, e])
            intensity = event_intensities [e ] * [3.0 * (react_intensity- 0.5)]
            pulse_dist += Normal (event_locations [e ] + user_delays [u ], event_std)
            event_pulsetrain += intensity * pulse_dist.PDF(Indices(obs [u]))
        SCR_clean = Convolve(event_pulsetrain, Canonical_SCR)
        observations ~ Normal(SCR_clean + user_offsets [u], user_noise_levels [u])
```

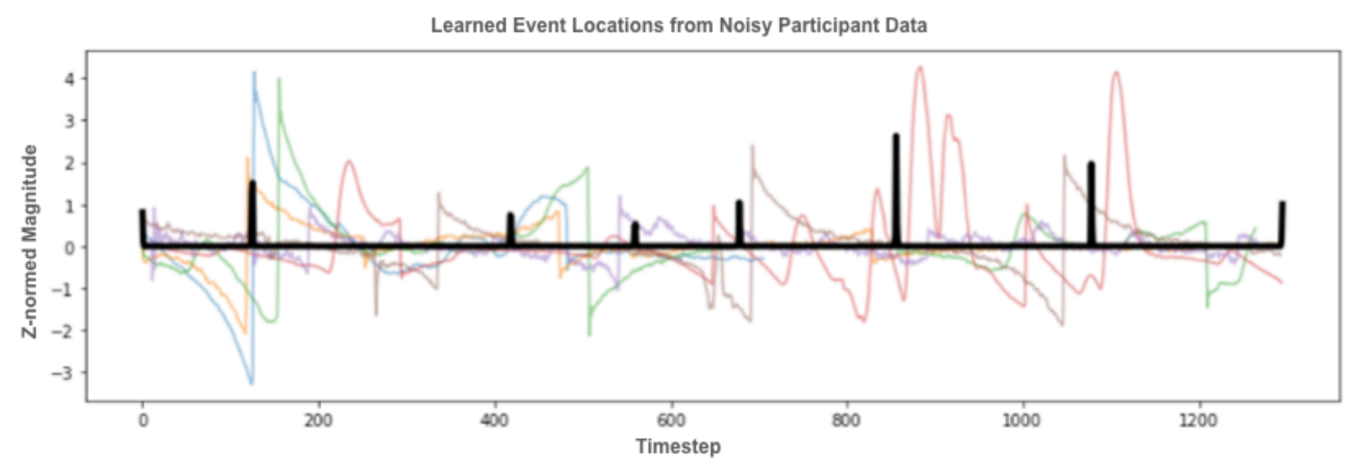
Pseudocode from Pyro to generate movement artifacts and noise in EDA baseline (left), as well as to learn emotional event locations and intensities given multiple participant reactions.

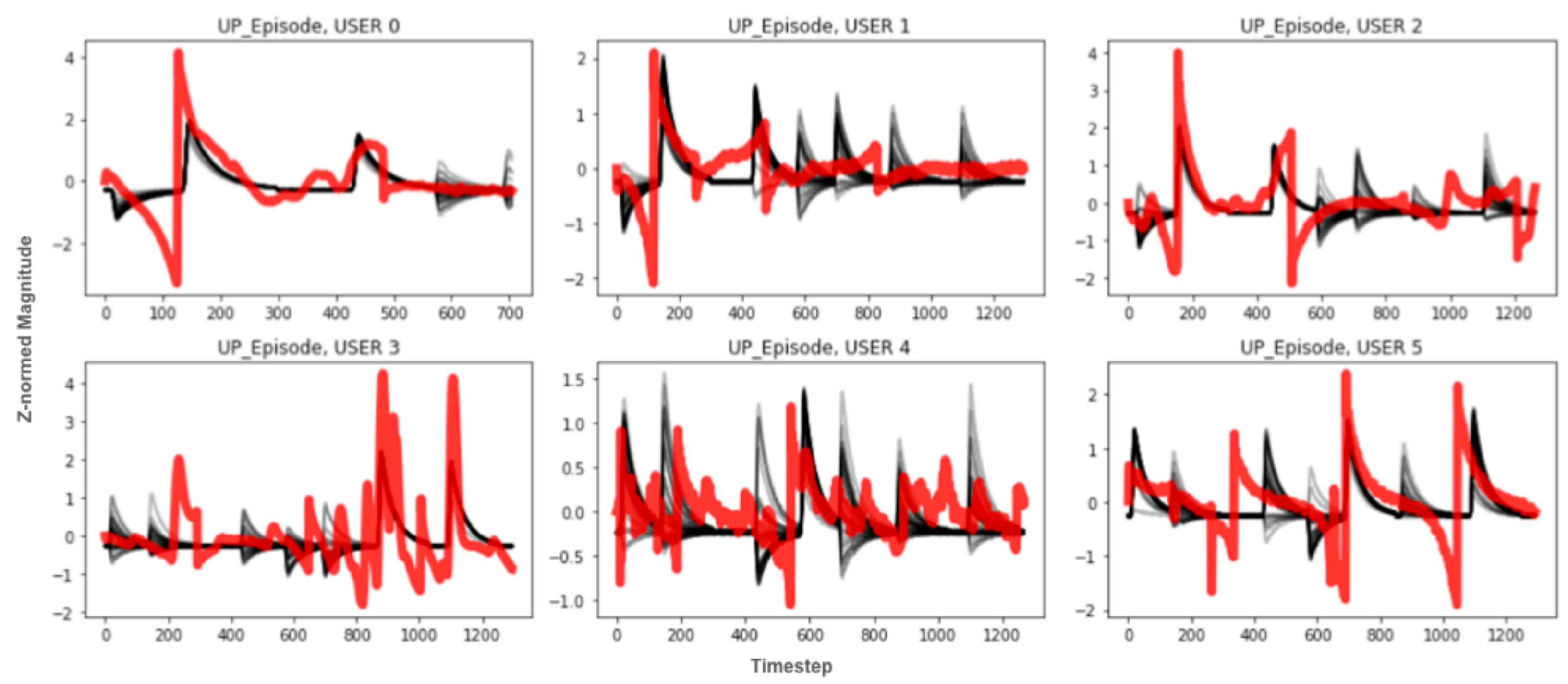


The model trades off ***individual accuracy*** with ***shared priors over event identification***, and this is tunable. There are many degrees of freedom in the model, and thus common sense priors are required for successful training.

Future

Modeling the basic underlying physical processes to serve higher level prediction, especially by fusing many disparate noisy streams of data— is the best way to form predictions about the inner experience of users under real-world conditions. In the future we will extend this concept beyond EDA to other ANS markers; we will also incorporate contextual information about noise sources, finally bringing robust predictions of mental experience to everyday life.





Examples of generative models trained on real data for learning movement artifacts (top left) and emotional events (right)

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