Towards Causal Psychophysiology in the Wild:

Probabilistic Programs for Skin Conductance Analysis

The problem

Changes in our mental state are reflected in our physiology. This psychophysiological link is frequently exploited under controlled, laboratory conditions as an objective measure of cognitive response to external stimuli. Observed differences in physiological state as a result of latent changes in psychological state are mediated through the Autonomic Nervous System (ANS), whose sympathetic ('fight-or-flight') and parasympathetic ('rest-and-digest') branches antagonistically drive us towards physiologically homeostasis. These two branches innervate and influence many physiological subsystems, including skin temperature, heart rate, blinking, breathing, and electrodermal activity (EDA)— a measure of sweat gland activity.

EDA is typically used as part of highly-controlled studies, alongside heavy, qualitative data pre-processing that removes anything outside of clear and expected EDA responses to predetermined stimuli. Attempts to move EDA out of the lab typically focus on situations where stimuli and contexts can still be anticipated and controlled; automated data artifact removal remains an area of active research.

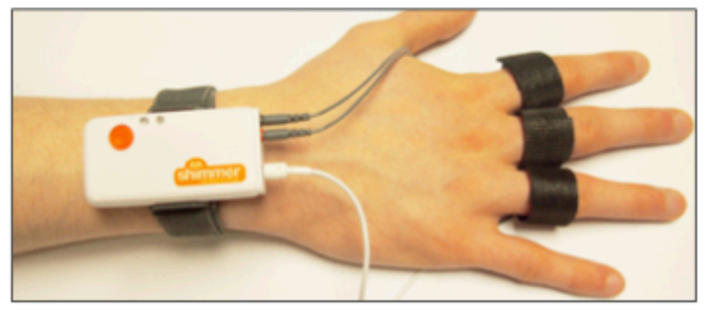
We want to measure and understand the impact of our technology, our environments, and other interventions on our psychology. State of the art for psychology uses surveys throughout the day (experience sampling); major issues with the current state-of-the-art approaches for psychophysiological modeling include:

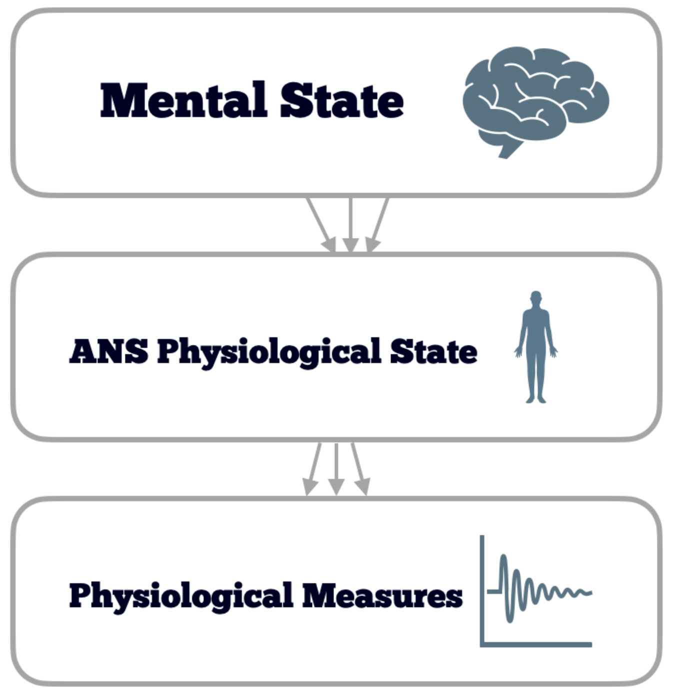
(1) **Laboratory Conditions**. Measurements made under laboratory conditions do not reflect or translate to naturalistic experiences — study participants are more alert, self-consciously aware of their performance, and have social pressure on them to meet expectations of the experimenter; psychological 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 it's injective relationship to physiology.

These all make it a great candidate for probabilistic modeling. Our work focuses on (1) unobtrusive hardware development for real-world, long-term measurement and (2) using that to derive continuous, robust insight into our mental states and their influences.





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 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.

One of the challenges in EDA analysis is that the signal (Fig. 1A, top) often contains a large amount of drift, and may also contain movement artifacts that manifest as jumps in the signal. For this reason, EDA analysis typically incorporates a pre-processing step to separate the signal into a tonic Skin Conductance Level (SCL) that varies slowly over time (bottom), and a phasic Skin Conductance Response (SCR) that captures dynamic responses to external stimuli (middle). Various approaches are used to separate these two signal components. The SCR component is most common for affective analysis, and what we will focus on here.

Psychologically-driven SCR events are usually identified by human observation, as they have a distinctive log-normal shape characterized by an exponential decay that follows a rapid rise of at least 0.05 μSiemens occurring 1-3 seconds after the presentation of a stimulus event. These events are very difficult to programmatically separate from motion artifacts, which introduce sharp transients, as well as other true SCR events that result from deep breathing. Some references suggest cross-comparison with breathing measurements to identify suspect EDA responses, though this is rare in practice.

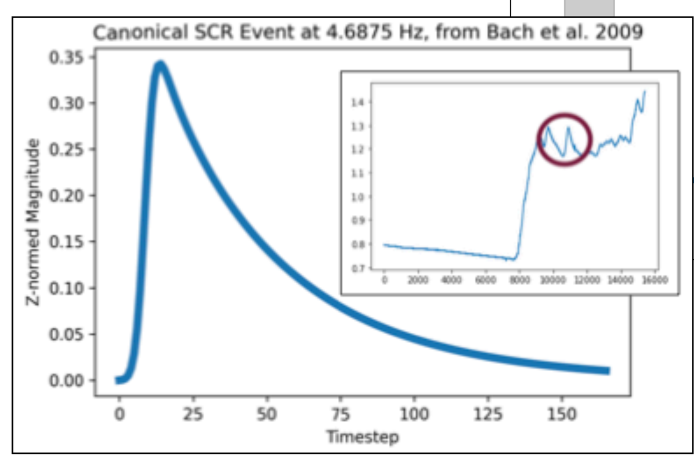
In lab, noise sources are addressed using 'best practice': allow the participant at least 15 minutes to acclimate to a temperature- and humidity-controlled room before the experiment, and provide strict guidance to limit motion and deep breathing. Stimuli are known and asserted with precise timing. Frequently, gel is used to improve electrode contact.

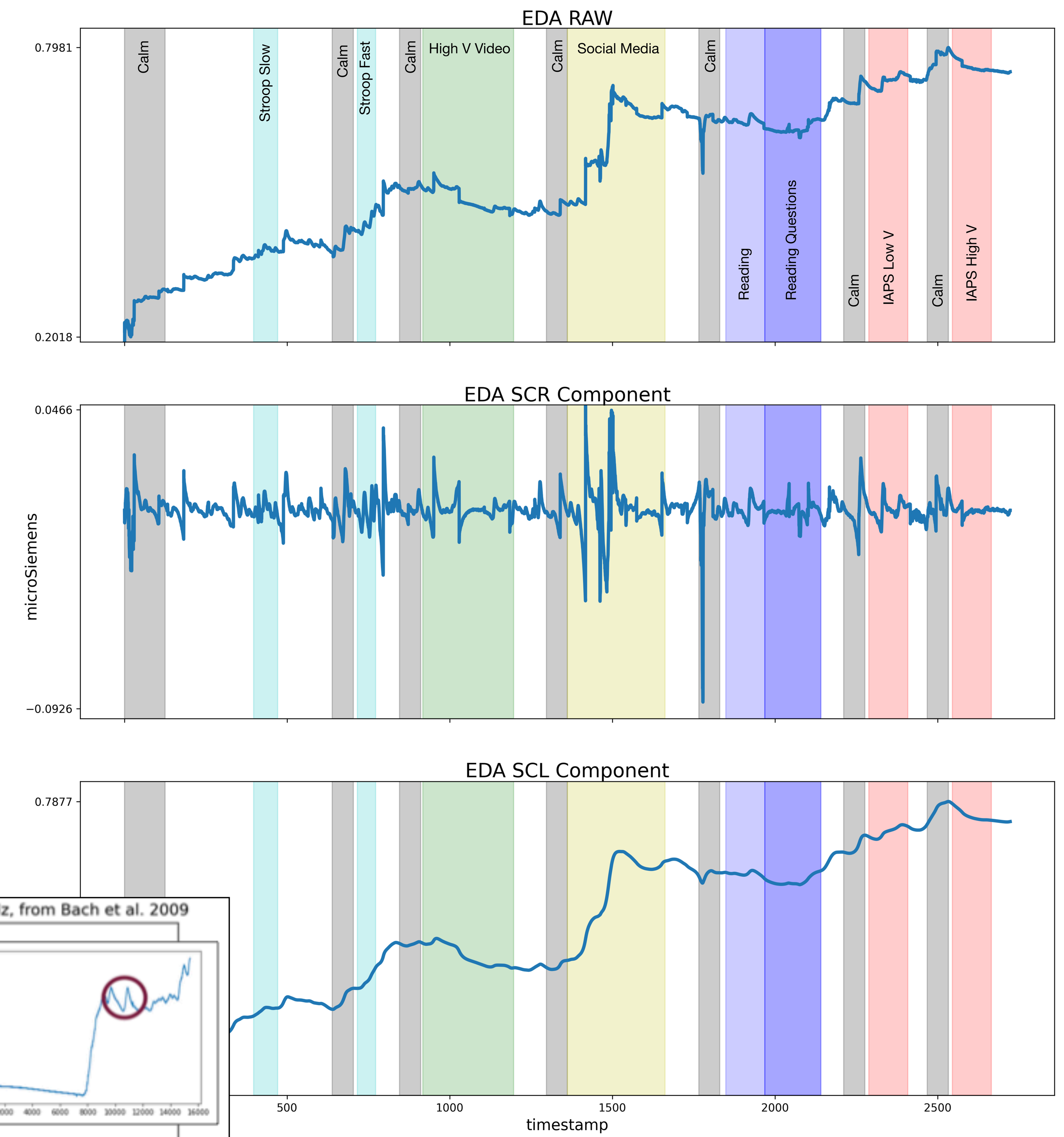
Attempts to automate heuristic-driven, human pre-processing for data collected under non- laboratory conditions focus on separating the transient artifacts of movement and electrode contact from real SCRs. This has been implemented using SVMs based on a collection of human labeled data, however the gold standard remains human curation.

Outside of the major issues of temperature, humidity, movement, and breathing, there are several other considerations for proper EDA analysis. Even in ideal scenarios, around 10% of participants will be non-responders and should be thrown away. Furthermore, the latest research suggests there are asymmetries across the body when measuring EDA that can lead to significant mis-estimation of underlying sympathetic activity, and that these different skin areas may be innervated from different brain regions, with at least three different functional brain circuits involved. Local sweat gland sudomotor behavior is also influenced by local ganglionic feedback loops, for instance with nociceptive afferent nerves.

The true link from mental experience to neural spiking to sympathetic activation to regional sweat gland topology has yet to be fully characterized and understood. The psychophysiological model improves as we study and model more of the underlying causal relationships. Single- and dual-effector physical models, as well as other highly structured causal models that link neural activity to sweat gland activity, are becoming more common as they show improvements over black-box approaches.

We collected data from six participants as part of a preliminary study. Before analysis, raw resistance data was converted to μSiemens and downsampled from 18.75 to 4.6875 Hz after a software anti-aliasing filter. We then apply a bi-directional 0.0159 Hz filter and z-norm the data, as demonstrated in [Staib et al. 2015]. This technique was also used in [Bach et al. 2009], from which we construct our canonical SCR waveform– a Gaussian convolved with a Gamma distribution shown in the inset. 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. In many cases we found that these models are under-specified and converge to local minima with maximum likelihood estimation (MLE); common sense priors are required for successful training.

Modeling Motion Artifacts

The Movements appear in the data as random step changes; after filtering, however, they take on an exponential shape characteristic of the EDA Highpass behavior. To build a generative model of this behavior, we use Algorithm 1– *num_movement* events are learned, each with a random location and intensity. To promote convergence, these random step changes are modeled using a continuous Gaussian Cumulative Distribution Function before filtering and noise. In the generative case, locations and intensities are randomly/uniformly seeded; the sampling operation of the movement locations is introduced so we can learn (μ, σ) parameters over this distribution in the guide (seeded with linear spacing). This algorithm was implemented in Pyro, taking advantage of maximum likelihood estimation in the model to learn point estimates of movement intensities.

When there are fewer movement events than seeded with *num_movements*, we expect and see that intensities for redundant events trend toward zero.

Modeling Motion Artifacts

SCR events are modeled without a priori information of when stimuli occur in the signal. Here we predict, by examining several different people responding to the same event, when and how intensely an emotional event occurs. This shared underlying 'true emotional event signal' is modulated by user specific variables-- how long someone might take to show an SCR response, how noisy their signal is, and how reactive they are to that specific emotional event. These modifications, along with the canonical SCR response, are used to generate realistic SCR data traces.

This model incorporates complex numerical operations (convolutions); PPLs are a useful tool for building these deterministic operations into a generative model. In this case, user specific parameters (delays, noise floors, offsets, and individual reaction probabilities to each event) are learned using variational distributions; parameters for underlying events are trained using MLE point estimates.

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

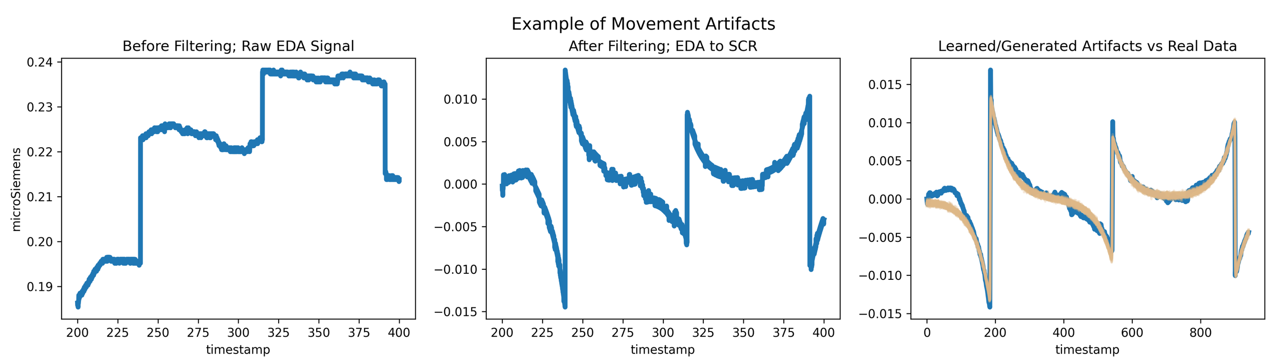
```
Model(num_events, event_std, obs)
    // trainable parameters with shape [num_events, 1]:
    event_locations ~ Uniform(0, Len(obs))
    event_intensities ~ Uniform(0, 1)
    // trainable parameters with shape [num_users, 1]:
    user_delays ~ Uniform(1, 3) // seconds
    user_noise_levels ~ Uniform(0.01, 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])
```

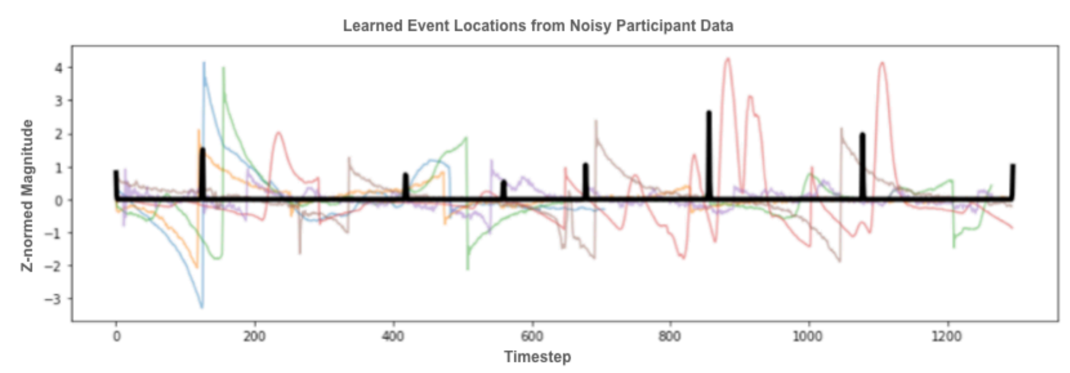
Pseudocode from Pyro to generate movement artifacts and noise in EDA baseline (top), as well as to learn emotional event locations and intensities given multiple participant reactions.

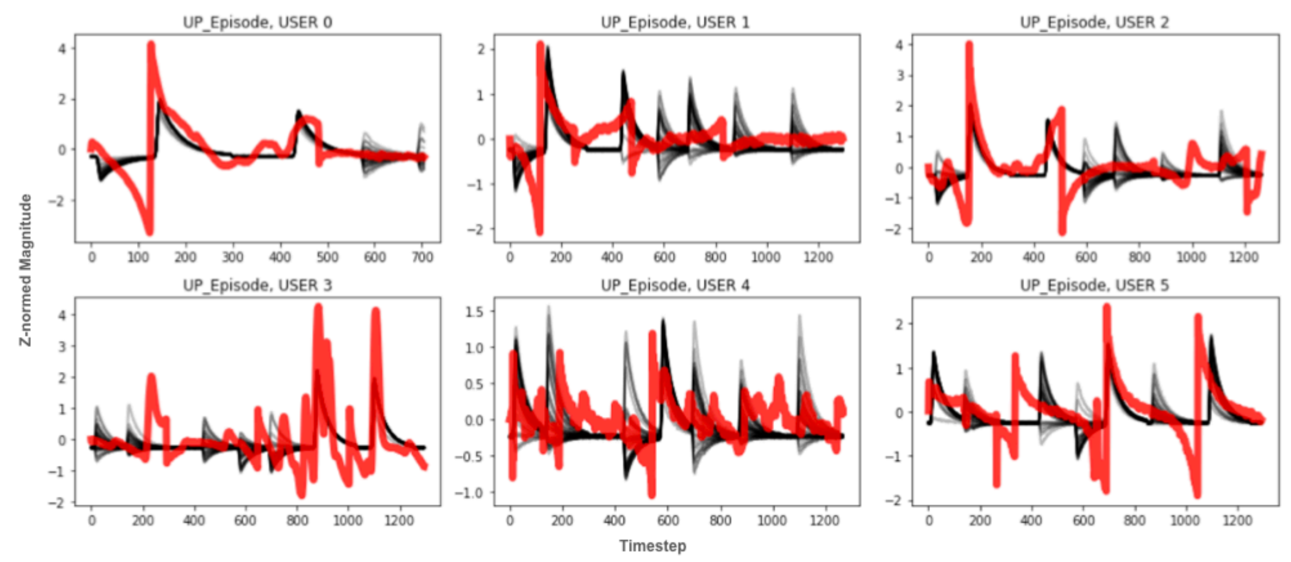
We can see that the model learns plausible event locations across all users, and captures some of the more obvious SCR events that have shared timing across users. It does not handle noise and artifacts well because this model is limited to a noise baseline and convolutions with the canonical SCR response. Additionally, some events are predicted in signals where they clearly do not occur; this illustrates tuning of the model to trade off individual variation and common, shared events. If we allow individuals to vary widely in the strength of their reactions (or not have a reaction at all), any SCR-shaped event in a single participant's data will likely converge to a 'true' emotional event. The more we bias the model so that all users must have a measurable reaction to shared events, the more we bias the model to rely on shared trends across users at the expense of an individual's trace accuracy. Finally, we also notice that our model has learned offsets, noise levels, and delays (user 4 is offset slightly below zero and noisier; each user response is slightly time shifted).

Future

Many scientists focus on a deep understanding of our sweat glands or our neural firing patterns at the lowest levels. Others look at high-level correlation between EDA data and stimuli. We contend that a middle approach-- 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 like ambient temperature, humidity, and motion measurements. Our hope is that a combination of these physiological markers with better indicators of user phenomenology will lead to a large improvement in our ability to measure and predict the impact of our UIs, our tools, and our environments on our inner experience.







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

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