Augmenting ESM-based Mental Health Assessment using Affective Ising Model

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Abstract. This study presents a novel approach to augment the accuracy and granularity of mental health assessment using a combination of Experience Sampling Methodology (ESM) and the Affective Ising Model. Traditional methods often lack the ability to capture the dynamic and nuanced nature of an individual's mental health. We propose a data-driven framework that leverages ESM data to construct an individual's positive and negative affect space, thus enabling a comprehensive analysis of their emotion landscape. To achieve this, we utilize the Affective Ising Model, a statistical physics-based framework that extracts the energy landscape of an individual's affect space, providing insights into their underlying mental state dynamics. We illustrate our approach using synthetic data generated from existing ESM datasets, ensuring a controlled yet realistic representation of affective states. Parameter estimates of the Affective Ising Model were shown to categorize different potential mental health states. This characterization aids in identifying potential markers or indicators of specific mental health challenges, thus facilitating early diagnosis and possible personalized interventions. The proposed method is hoped to provide a robust framework for augmenting mental health assessment, offering a more comprehensive understanding of an individual's emotional experiences and their potential mental health states.

Keywords: Mental health, Assessment, Experience sampling method, Affective Ising model, Energy landscape, Emotional experience, Model-based analysis

1 Introduction

In recent years, the recognition of mental health as a critical component of overall well-being has gained significant momentum. The global prevalence of mental health disorders underscores the urgent need for effective and innovative diagnostic methodologies that can better address the complex nature of human emotional experiences. Mental health concerns have become a global challenge, with statistics indicating that approximately 1 in 4 individuals worldwide will be affected by mental health disorders at some point in their lives (World Health Organization, 2021). As mental health and well-being are explicitly integrated into the United Nations Sustainable Development Goals (SDGs), the imperative to develop advanced diagnostic techniques is more pressing than ever before.

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Traditionally, mental health diagnosis has relied upon clinical assessments and subjective evaluations, leading to several limitations. This approach often necessitates a case-to-case examination, making it challenging to capture the dynamic and transient nature of affective states. Moreover, the individualized nature of mental health requires customized therapeutic interventions that are tailored to each person's unique emotional landscape [1]. The inadequacies of these conventional diagnostic methods hinder the timely identification of mental health issues and limit the efficacy of treatment strategies. On the other hand, although artificial intelligence has been directed towards achieving highly accurate diagnosis and treatment of mental health conditions [2], being mechanism-agnostic, it lacks a comprehensive understanding of the underlying disorders and caution is necessary in the interpretation of its results.

To address these challenges, computational models have emerged as a promising avenue for augmenting mental health diagnosis [3, 4]. These models harness the power of data-driven analysis to capture the intricate interplay of affective states within an individual's emotional spectrum. By integrating computational methodologies with established psychological frameworks, such as Experience Sampling Methodology (ESM), new horizons are opened for a more comprehensive and precise understanding of human emotional experiences. ESM allows for the collection of real-time data on individuals' emotional experiences in their natural environment, offering a unique opportunity to capture the dynamics of affective states as they unfold. On the other hand, the Affective Ising Model is a computational framework rooted in statistical physics, which provides a formalized approach to understanding the dynamic interactions between positive and negative affective states within an individual's emotional landscape, enabling a deeper analysis of emotional transitions and fluctuations. In this paper, we present the approach that combines the principles of ESM with the Affective Ising Model to augment mental health diagnosis. This may shed light into the possible shortcomings of traditional diagnostic techniques, highlighting the need for a more nuanced and data-driven methodology. By harnessing the capabilities of such computational models, we aspire to bridge the gap between traditional diagnostic practices and the evolving landscape of mental health assessment.

As mental health continues to take center stage in the global agenda, the integration of computational models holds the potential to redefine how we approach and address mental health challenges. Through this interdisciplinary endeavor, we seek to contribute to a more comprehensive understanding of mental health and well-being, fostering early detection and personalized interventions that are rooted in empirical data and advanced computational analyses.

2 Affective Ising Model

The Affective Ising Model (AIM) [5] is a computational framework used to study and analyze the dynamics of affective states, particularly in the context of psychology, social sciences, and neuroscience. It draws inspiration from the Ising model, a fundamental concept in statistical physics that is used to describe the behavior of magnetic spins in a lattice structure. The Affective Ising Model extends this idea to describe the interactions between positive and negative affective states within an individual's emotional landscape. The positive and negative affective states are processed each by a population of neurons modelled as Ising spins as shown in Figure 1. The populations receive self-excitation and mutual inhibition from each other and may also receive external excitation from other sources.

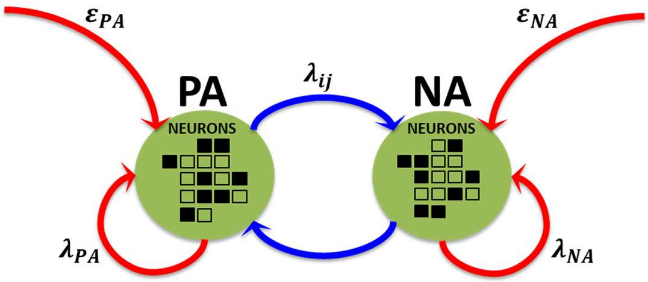

Figure 1. The Affective Ising Model consists of two interacting populations of neurons, one processing the positive affect, and the other, the negative affect of an individual. Excitatory feedback is shown in red while inhibitory feedback is shown in blue.

Let's denote the populations of neurons as PA and NA, which are processing the positive and negative affective states, respectively. The PA and NA populations respectively consist of N_1 and N_2 stochastic binary neurons. While the neurons toggle their states over time, the average activations also undergo temporal variations, resulting in noticeable fluctuations in the affective state $y(t) = (y_1(t), y_2(t))$. The probability density function (pdf) of $y(t)$ is given by:

$$p(y) = e^{\frac{-\beta F(y)}{Z}} \tag{1}$$

where $F(y)$ is the free energy function given by

$$F(y) = \sum_{i=1}^{2} \left(-\lambda_i {y_i}^2 + \theta_i y_i + \frac{N_i}{\beta} (y_i \, ln \, ln \, y_i \,) + (1 - y_i) \, ln \, ln \, (1 - y_i) \,) \right)$$
$$+\lambda_{12} y_1 y_2 \tag{2}$$

while Z is the partition function or the normalization constant of the pdf. The parameter β is associated with the inverse temperature in statistical mechanics. Within the AIM framework, the parameter is arbitrary and is assigned a value of 1 for simplicity. Other parameters of the free energy equation are summarized in Table 1.

Generally, higher N_{PA} and λ_{PA} (than N_{NA} and λ_{NA}, respectively) and lower θ_{PA} values (than θ_{NA}) would imply that the individual's affect state is more positive. On the other hand, a high value of λ_{12} indicates that the strengthening of one affective state inhibits the growth of the other. In simpler terms, if positive affect is high, it would tend to inhibit the persistence of negative affect, and vice versa. Finally, with the assumption of stochastic binary neurons, the dynamics of the affect states are given by

$$dy_i(t) = -\beta \frac{\partial F}{\partial y_i} dt + \sqrt{2D} dW_i(t) \tag{3}$$

where $\{W_i(t)\}$ are the associated Wiener processes that are uncorrelated to each other [6]. The diffusion parameter $D = \frac{2}{e(N_1+N_2)^2\Delta t}$ determines how an affect state moves across the energy landscape. Lower D value would indicate that an individual would linger longer on its current affect state.

Table 1. Internal parameters of the AIM

Parameter	Description
N_{PA}	population of PA neurons
N_{NA}	population of NA neurons
λ_{PA}	strength of self-excitation of PA
λ_{NA}	strength of self-excitation of NA
λ_{ij}	strength of mutual inhibition
θ_{PA}	activation threshold of PA
D	diffusion parameter

3 Method

3.1 Synthetic Data

The data used in this study were synthesized from the data based on Experience Sampling Methodology (ESM) used in [7]. ESM are generally considered to be the golden standard to study affect dynamics in an ecologically valid manner - a participant's affect state is measured repeatedly throughout the day during several days, giving researchers a window into their affective experiences during their daily lives.

An example of an ESM-based affect data is shown in Figure 2. The positive and negative affect values were calculated based on the participant's responses during the experiment. The data was synthesized from actual data [1] to illustrate a 70-30 PANA landscape. This implies that 70% of the responses showed higher positive than negative affect state and 30% of the responses showed higher negative than positive affect state.

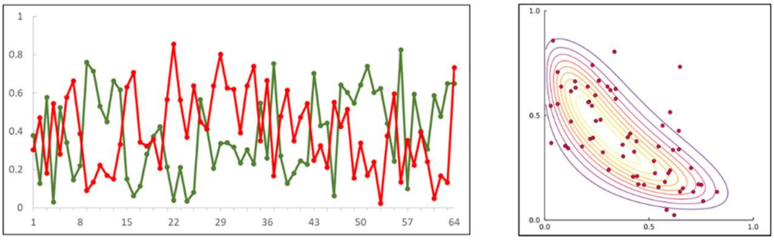

Figure 2. An example of an ESM-derived data consisting of 64 records of a participant's positive (green) and negative (red) affect based on his/her responses. The left plot shows the data in sequence while the right plot shows the participant's affect scatter plot from which the emotion landscape is derived.

3.2 Parameter Estimation

We employed GradientDiffusion [5] developed by Loossens et al. to estimate the parameters of the AIM from data using maximum likelihood estimation. The method specifically estimates an individual's affect dynamics in the absence of an external stimulus, focusing solely on the internal system. This is implemented using Julia, a platform for fast scientific computing [8]. In most cases, there are numerous local minima, thus, a global optimum is sought using a differential evolution heuristic [9].

4 Results and Discussion

Using the synthetic data, we performed parameter estimation of the AIM. From the estimated parameters, we can plot the emotion landscapes given by the free energy function in Equation (1). The contour plots in Fig. 3 show these free energy landscapes. Using an individual’s emotional landscape, we can see the affect state that is frequently experienced by an individual which is the mode of the distribution. Moreover, we can also derive the conditional probability given an observed state of the individual, and its temporal evolution, which gives us the most likely affect state that the individual will experience in the succeeding future.

In this study, we investigated the case of hypothetical individuals with probability density functions that non-Gaussian. This is interesting as it may have implications about an individual experiencing different mental states such as in persons with borderline personality disorder [10]. However, in the absence of actual data, we generated synthetic data derived from actual ESM data. We kept the percentage of PA-NA states but added constants such that the PA-NA states become more separated until a multimodal landscape is obtained as shown in the right plots of Figure 3. By looking into the results of the parameter estimation of each of the generated data in Figure 3, we may be able to derive insights regarding the observed transition from unimodal to multimodal emotion landscape of an individual.

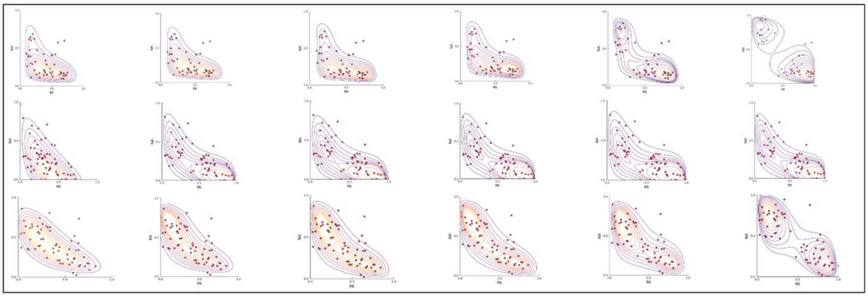

Figure 3. Transition of the free energy landscapes from unimodal to multimode. From top to bottom: PA states are higher than NA states in 70%, 60%, and 50% of the ESM responses, respectively. From left to right: Increasing separation of PA - NA states by adding constants to PA and NA values.

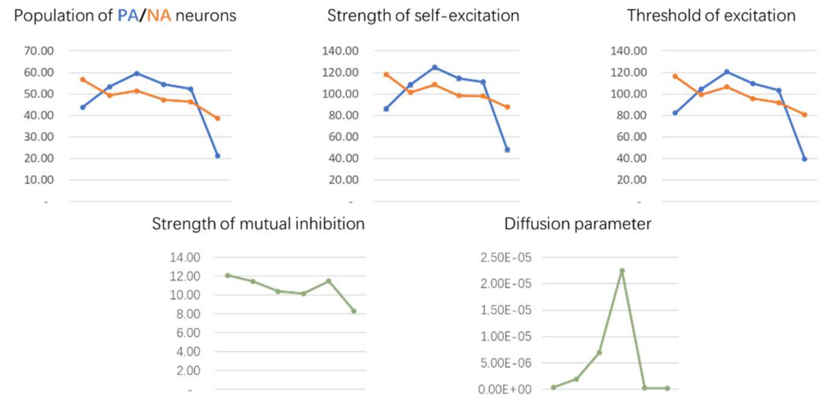

Figure 4. Parameter estimation results derived with the 70% PA - 30% NA data. The x-axis corresponds to increasing separation of PA-NA states by adding constants to PA and NA values (refer to Figure 3).

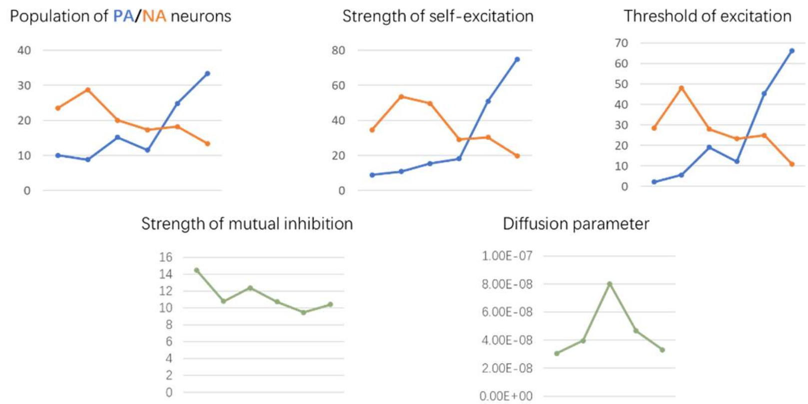

Figure 5. Parameter estimation results derived with the 50% PA - 50% NA data.

For discussion, we look at the results on the hypothetical landscapes with 70% more positive-, 30% more negative- affect state (these correspond to the first row of Figure 3). The results of the parameter estimation for this data are shown in Table 2 above. Several nonlinearities can be observed based on the results of the parameter estimation. For example, the number of positive affect neurons or processing units increases as the landscape transitions from unimodal to multimodal but decreases again as the second mode becomes more apparent. This observation is the same with the strength of self-excitation and threshold of excitation of the PA population. On the other hand, the number of negative affect neurons, the strength of self-excitation, and the threshold of self-excitation of the negative affect neurons generally decreases as the emotion landscape transitions from one to two mode modes. From these results, we can generalize that at the transition point, the estimated values of the parameters for the positive affect processing units are high while that for the negative affect processing units are lower compared to when the landscape is unimodal. When the values of the NA parameters continue to decrease along with decrease in the values of the PA parameters and together with a decreased mutual inhibition, a multimodal landscape appears. This observed physio-biological mechanism based on AIM may augment our understanding of how an individual who previously manifested a generally normal mental behavior would suddenly exhibit a distinct mental state. Finally, we look into the diffusion parameter, which tells how the emotion landscape is explored. Generally, a low diffusion parameter means that an individual's mental state is stable and vice versa. From the estimated values in Figure 4, we can say that the hypothetical individual likely experiences an unstable mental state at the point of transition in which the diffusion parameter is highest. When the individual's emotion landscape becomes multimodal, the diffusion parameter becomes lower, which could imply that the individual lingers at one mental health state longer before they exhibit a different mental health state corresponding to the second mode. Similar observations were found with the 60% PA - 40% NA data. However, with the 50% PA - 50% NA data, the trend is different for the population of PA/NA neurons, strength of self-excitation and threshold of excitation. Interestingly, the same trend was found for the strength of mutual inhibition and the diffusion parameter. This suggests that these parameters are possible indicators of transition from unimodal to multimodal affect landscape.

5 Conclusion and Recommendations

This study illustrates how to augment mental health assessment of clinicians using a model-based approach. The model uses mutually inhibiting populations of stochastic Ising neurons that are processing the positive and negative affect of an individual. By performing maximum likelihood of a free energy function, we may be able to get insights regarding the observed mental states of an individual. We demonstrated the ability of the model to give insights regarding individuals who may be experiencing transitioning from generally normal to a mental health disorder that may be characterized by a multimodal emotion landscape such as in individuals with borderline personality or bipolar disorder. Specifically, we found that decreasing strength of mutual inhibition and high diffusion parameter seem to be a possible indicator of transition.

While the approach may be promising, the study is hoped to be validated using actual data and consultations with psychologists and clinicians. The study shall be extended to include external excitations that are hypothesized to be events or situations experienced by individuals that could critically affect their mental health state and could be the reason for transitioning to a multimodal emotion landscape. With this computational approach, it may be possible to reverse engineer an individual's mental health state by providing appropriate interventions.

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