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The Research on Wildebeest Effect Based on MBTE Model

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Abstract

This paper analyzes the Wildebeest Effect on the African savannah, using the Emotional State Transition Model and Bayesian Emotional Transition to construct the MBTE model, and employing MCMC methods for simulation. This model contributes to the study of emotional transitions in psychology.

Keywords

Wildebeest Effect, State transition, MBTE model, MCMC, Bayesian inference.

1. Introduction

In the dynamic mosaic of human society, emotions are fundamental, acting as both immediate responses to stimuli and determinants of decisions and actions[1]. The absence of emotional control can lead to impulsive choices with unforeseen consequences[2]. This behavioral phenomenon, known as the "Wildebeest Effect," illustrates the profound impact of emotions on human conduct and emphasizes the critical need for effective emotional management, especially amidst challenges and pressures[3,4].

The Wildebeest Effect is a psychological concept inspired by the African savannah, where wildebeests, in response to minor blood loss from bat bites, react with rage and run incessantly, leading to exhaustion and death. This metaphor underscores the potential risks of uncontrolled emotional responses on individual health and survival. In human contexts, emotional fluctuations can similarly lead to irrational decisions, affecting personal and professional life, thus highlighting the necessity for emotional understanding and mastery.

This paper presents the MBTE model, a novel approach to understanding the Wildebeest Effect. The model uses a transition probability matrix and Bayesian inference to categorize and simulate emotional states—low, moderate, and high stress. The Metropolis-Hastings algorithm is employed to simulate transitions between these states, enabling a quantitative analysis of the impact of external events and individual response strategies on emotional states. Bayesian inference is integral to the MBTE model, allowing for the iterative updating of posterior probabilities based on observed emotional data. This method provides a deeper understanding of the relationship between emotional states and their frequency of occurrence, with implications for psychological research, sentiment analysis, and artificial intelligence in emotional recognition.

The structure of this article is as follows: Section 1 briefly introduces the problem. Section 2 provides a detailed explanation of the key steps of the MBTE model. Section 3 gives the experiments. Finally, we provide some conclusions and future research directions.

2. The MBTE model

The MBTE model introduces a Bayesian approach to emotional state transition analysis, enhancing traditional Markov chain models by incorporating uncertainty and new data. It defines a state space with assigned prior probabilities, reflecting initial beliefs about emotional states.

A Dirichlet distribution captures the variability of the transition probability matrix, while a likelihood function integrates observational data, enabling Bayesian updating. The posterior distribution updates beliefs about emotional states and transitions, facilitating simulations and predictions.

The model's iterative updating process adapts to emotional state changes and assesses the impact of emotional management strategies. By combining Markov chains and Bayesian inference, the MBTE model offers a precise and dynamic framework for analyzing emotional state transitions. The "Wildebeest Effect" is modeled as a Markov chain, representing an individual's emotional state transitions. The mathematical framework is as follows:

State Space: Define a state space $S = s_1, s_2, s_3$, where s_1 represents a low-stress state, s_2 represents a medium-stress state, and s_3 represents a high-stress state.

Transition Probability Matrix: Define a 3 × 3 transition probability matrix P, where P_{ij} represents the probability of transitioning from state s_i to state s_j .

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \tag{1}$$

Current State Probability Vector: Define a probability vector π_t representing the current state distribution at time t. Each element π_t of the vector π_{ti} represents the probability of being in state s_i at time t.

State Transition: At each time step t, update the state probability vector based on the current state probability vector π_t and the transition probability matrix P.

$$\pi_{t+1} = \pi_t + P. \tag{2}$$

The state probability distribution at time t is a 1 × 3 vector π_t , that is,

$$\pi_t = [\pi_{t1}, \pi_{t2}, \pi_{t3}] \tag{3}$$

Metropolis-Hastings sampling.

3. Experimental Results

3.1. Transition Probability Matrix

The emotional state transition probability matrix, denoted as base_transitionbase_transition, is structured with three rows, each representing transitions from a specific stress state: low, medium, and high. Each row corresponds to the probabilities of moving to low, medium, and high stress states, respectively.

$$\text{bse\_transition} = \begin{bmatrix} 0.7 & 0.3 & 0.0 \\ 0.4 & 0.5 & 0.1 \\ 0.0 & 0.3 & 0.7 \end{bmatrix} \tag{4}$$

Adjusting the transition probabilities for individual differences, denoted as $individual_{id}$, modifies the probabilities as follows:

Setting the adjustment to 1 raises the probability for individual 1 moving from "low-stress" to "medium-stress" from 0.3 to 0.6. Setting it to 2 increases the probability for individual 2 moving from "low-stress" to "high-stress" from 0.0 to 0.3.

Normalize the probabilities of each row to ensure that the sum of the prob- abilities in each row remains equal to 1.

In the Metropolis-Hastings algorithm, the proposal distribution is set by using `np.random.choice` to suggest new states from current transition probabilities. The process starts with an initial state and a state sequence list. Each iteration proposes a new state and

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calculates an acceptance probability, which ideally accounts for transition probability ratios and symmetry. An error exists in assuming symmetry in the transition matrix, which may not apply. The acceptance probability guides the decision to update the current state, which is then appended to the sequence if accepted.

Assume two individuals undergoing 1000 iterations of MCMC sampling. Customize transition matrices and set initial states for each, starting from low-pressure. Execute the Metropolis-Hastings algorithm to record state transition frequencies.

Convert transition counts to probabilities by dividing by (len($states_{sequence}$)- 1), excluding the initial state, to get the $transition_{probabilities}$ matrix.

Thus, we abtain the individual state transition probability Figure 1 and 2.

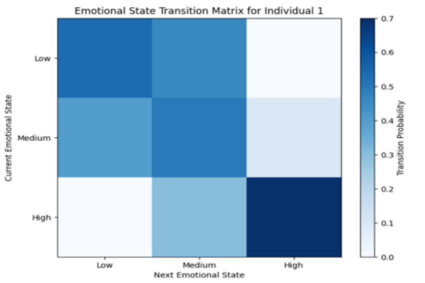

Figure 1: Individual state

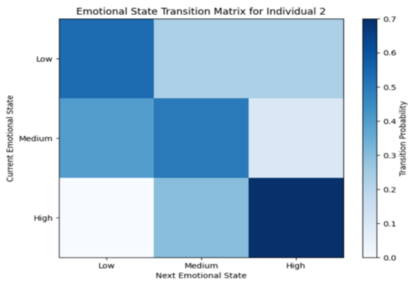

Figure 2: Next emotional state

3.2. Multidimensional Emotions and Integrating Bayesian Transition Probabilities

Bayesian models in emotional analysis involve setting priors, likelihoods, and updating posteriors with Bayes' theorem. This includes establishing prior emotional states, transition probabilities, and the likelihood of observations.

Define an expanded emotional state space with Low Stress, Medium Stress, High Stress, Anxious, Excited, and Content.

Start with a uniform transition probability matrix, suggesting equal change probabilities without additional info.

Set an impact matrix for external events—Good News, Bad News, Social Interaction—that adjusts emotional transition probabilities.

$$\text{Good\_News} = \begin{bmatrix} 1.1 & 0.9 & 0.8 & 0.5 & 1.0 & 1.0 \\ 0.9 & 1.1 & 0.9 & 0.6 & 0.9 & 0.9 \\ 0.8 & 0.9 & 1.1 & 0.7 & 0.8 & 0.8 \\ 0.5 & 0.6 & 0.7 & 1.2 & 0.7 & 0.6 \\ 1.0 & 0.9 & 0.8 & 0.5 & 1.2 & 1.0 \\ 1.1 & 0.9 & 0.8 & 0.6 & 0.7 & 1.3 \end{bmatrix} \quad \text{Bad\_News} = \begin{bmatrix} 1.2 & 1.0 & 1.1 & 1.5 & 0.8 & 0.7 \\ 1.0 & 1.2 & 1.0 & 0.8 & 1.1 & 1.0 \\ 1.1 & 1.0 & 1.3 & 0.9 & 0.9 & 0.9 \\ 1.5 & 0.8 & 0.9 & 1.0 & 1.2 & 0.8 \\ 0.8 & 1.1 & 0.9 & 1.2 & 1.0 & 1.2 \\ 0.7 & 1.0 & 0.9 & 0.8 & 1.3 & 1.0 \end{bmatrix} \tag{5}$$

$$\text{Social\_Interaction} = \begin{bmatrix} 1.0 & 1.1 & 1.0 & 1.1 & 1.0 & 1.0 \\ 1.1 & 1.2 & 1.1 & 0.9 & 1.1 & 1.0 \\ 1.0 & 1.1 & 1.3 & 1.0 & 0.9 & 0.8 \\ 1.1 & 0.9 & 1.0 & 1.2 & 1.1 & 0.7 \\ 1.0 & 1.0 & 0.9 & 1.1 & 1.3 & 1.0 \\ 1.0 & 1.0 & 0.8 & 0.7 & 0.8 & 1.3 \end{bmatrix} \tag{6}$$

The Metropolis-Hastings algorithm randomly proposes a new state, calculates the acceptance probability, and decides on acceptance. If rejected (np.random.rand() >= acceptance_ probability), the current state persists, but the sequence may still record the last state.

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To determine state transition probabilities, iterate the model. Simulate external event effects, modify the transition matrix, normalize probabilities, and create bar charts for Figures 3, 4, and 5.

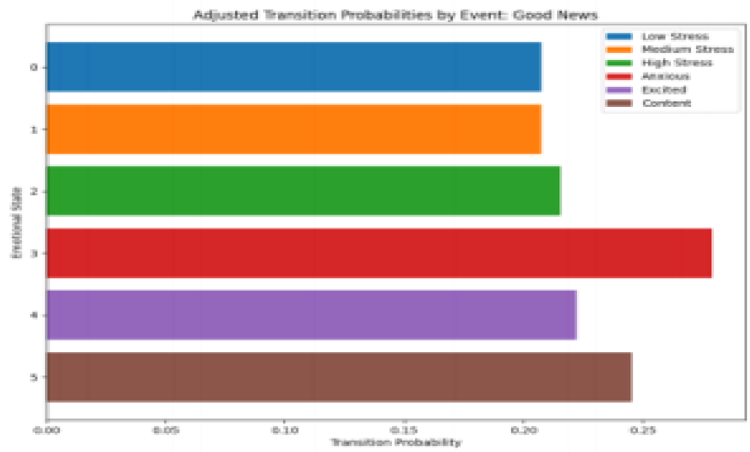

Figure 3: Transition Probability 2.

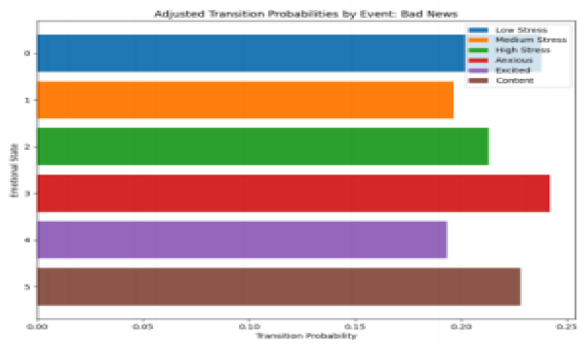

Figure 4: Transition Probability 2.

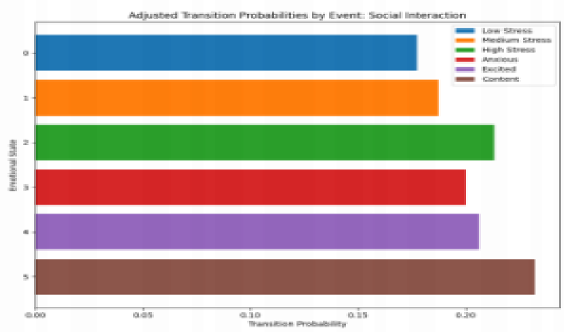

Figure 5: Transition Probability 3

3.3. The modelling

The steps for the MBTE model are follows.

Define the emotional state space as Low Stress, Medium Stress, High Stress, Anxious, Excited, and Content.

Initial probability distribution: With $n = 6$ states, $P(S_0)$ is uniform across Low Stress, Medium Stress, High Stress, Anxious, Excited, and Content.

Define the transition probability matrix T where t_{ij} denotes the probability of moving from state i to state j.

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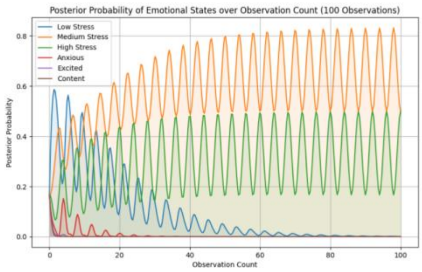
$$T = \begin{bmatrix} 0.5 & 0.3 & 0.1 & 0.05 & 0.03 & 0.02 \\ 0.2 & 0.5 & 0.2 & 0.05 & 0.03 & 0.02 \\ 0.1 & 0.2 & 0.5 & 0.1 & 0.05 & 0.05 \\ 0.05 & 0.1 & 0.2 & 0.5 & 0.1 & 0.05 \\ 0.03 & 0.05 & 0.1 & 0.2 & 0.5 & 0.12 \\ 0.02 & 0.03 & 0.05 & 0.1 & 0.2 & 0.60 \end{bmatrix} \quad (7)$$

Observation data O is a sequence of states. To find posterior probabilities $P(S_t|O_{1:t})$, we focus on the current observation o_t and the previous state, simplifying the computation without prior observations. The likelihood $P(O_t|S_t)$ is from matrix T, and $P(S_t|O_{1:t-1})$ is the previous step's posterior.

$$P(S_t|O_{1:t}) = \frac{P(O_t|S_t)P(S_t|O_{1:t-1})}{\sum S_i P(O_t|S_i)P(S_t|O_{1:i-1})}. \quad (8)$$

3.4. The Probability Envelope



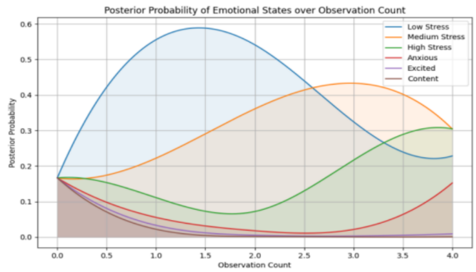


Figure 6: Posterior Probability (1) Figure 7: Posterior Probability (2)

Figures 6 and 7 show the evolution of posterior probabilities for various emotional states with increasing observations. In Figure 6, the "Observation Count" axis spans 20 to 100, with "Posterior Probability" ranging 0.0 to 0.8. Figure 7 adjusts the count from 0.0 to 4.0 and probability from 0.0 to 0.6, reflecting the impact of observation frequency on emotional state probabilities.

The charts reveal that posterior probabilities for various emotional states—low stress, medium stress, high stress, anxiety, excitement, and satisfaction—fluctuate with observation count. Notably, the probability for low stress rises from 0.2 to approximately 0.8, suggesting growing confidence in this state with more data. In contrast, medium and high stress probabilities show a decline, indicating a reduced likelihood with increased observations. Anxiety starts high at 0.6 but decreases, suggesting a reassessment of this state as more information is gathered. Excitement and satisfaction probabilities remain stable but low, implying persistently lower likelihoods.

These insights can enhance psychological research, emotional analysis, and AI-driven emotional recognition, aiding in understanding emotional dynamics and informing predictions and decisions. The model simulates emotional transitions, offering a lens into the Wildebeest Effect's narrative—where better emotional stewardship could mitigate stress escalation. Beyond this story, the model is versatile for examining emotional shifts across psychology and sociology, allowing for the exploration of emotional management strategies and their behavioral implications.

By tweaking the transition probability matrix, we can model diverse emotional responses and assess their outcomes, providing a robust tool for emotional state analysis and its practical applications.

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4. The Conclustion

In this study, we delve into the emotional dysregulation observed in the Wildebeest Effect by integrating a transition probability matrix, the Metropolis-Hastings algorithm, and Bayesian inference to develop the MBTE model. We categorized emotional states into low (S1), medium (S2), and high stress (S3), and mapped their transition probabilities. Utilizing the Metropolis-Hastings algorithm, we simulated emotional state transitions, examining the influence of external stimuli and individual coping mechanisms. Concurrently, Bayesian inference iteratively refined the posterior probabilities, uncovering emotional state dynamics across observations.

Our findings indicate that under high stress, external triggers and ineffective responses can escalate emotional instability, increasing the likelihood of remaining in a high-stress state with reduced recovery to low stress. Conversely, proactive strategies can sustain emotional equilibrium in low-stress states.

The synthesis of the transition probability matrix and the Metropolis-Hastings algorithm offers a nuanced simulation of emotional transitions, accounting for external and individual-specific factors, enhancing the realism of our models. Bayesian inference, in turn, dynamically updates emotional state probabilities with new data, providing insights into the evolution of emotional control over time.

References

[1] Shihuan Xia, The Influence of Emotion on Decision-Making and Its Neural Mechanism, Advances in Psychology, 2022, 12(2), 381-389.

[2] Xudong Song, Zheng Ruan, Kangyue Yan, Qiuhong Wu, Yu Hu, The Existence and Mechanism of Intergenerational Transmission Effect, Advances in Psychology, 2019, 9(4), 701-707.

[3] Yueling Zhou, Analysis of the Positive and Negative Effects of the Pressure Transmission Mechanism in the Organization and Its Improvement Path, Modern Management, 2020, 10(6), 1013-1020.

[4] Hongming Ye, Discussion on Post-Error Slowing Effect and Its Adaptability, Advances in Psychology, 2024, 14(4), 575-583.