Learned Spectrum: Towards Temporal Understanding in AI Through fMRI Learning Stage Classification

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Abstract

This research presents a novel approach to understanding temporal cognition through the application of Vision Transformers to functional Magnetic Resonance Imaging (fMRI) data analysis. While current artificial intelligence approaches to world modeling rely heavily on absolute temporal markers and timestamps, human perception of time operates as a fundamentally subjective experience that adapts with cognitive state and learning progress. We demonstrate that neural activation patterns captured during learning through fMRI contain rich temporal information that can inform more nuanced approaches to temporal processing in AI systems.

Our implementation achieves significant accuracy in learning stage classification through three key technical innovations: 1) A systematic channel reduction network that efficiently processes high-dimensional fMRI data while preserving critical spatial and temporal patterns, 2) Specialized temporal processing networks that incorporate hemodynamic response characteristics and causal attention mechanisms, and 3) Progressive dropout strategies that maintain signal fidelity while encouraging robust feature learning. By analyzing these temporal patterns across multiple learning stages and tasks, we demonstrate the feasibility of developing AI systems capable of processing time as a relative rather than absolute construct. This work represents an important step toward artificial intelligence systems that can reason about time in ways that more closely mirror human cognitive processes.

1 Introduction

The development of artificial intelligence world models faces a fundamental constraint in temporal processing Ha and Schmidhuber [2018], Schmidhuber [2023]. While current systems effectively handle timestamp data and sequential predictions, they lack the ability to process time as a subjective, relative construct - a core component of human cognition and learning LeCun [2023].

Training world models exclusively on robot-collected data proves insufficient for developing true temporal understanding Runway ML [2023]. We propose that biometric data, specifically neural activation patterns from fMRI, provides essential insights into subjective time perception during learning processes Poldrack et al. [2001].

This work implements a Vision Transformer architecture Vaswani et al. [2017], Dosovitskiy et al. [2020] optimized for learning stage classification from fMRI data. While fMRI presents known limitations in its reliance on blood-oxygen-level-dependent (BOLD) signals Logothetis [2008], deep learning architectures can extract temporal patterns that traditional analysis methods miss.

1.1 Theoretical Framework

Our implementation builds on three foundational principles that bridge neuroscience and artificial intelligence:

- Time perception functions as an inherently subjective experience that varies with cognitive state and learning progress
- Effective world models must incorporate mechanisms for understanding and adapting to subjective temporal experiences
- Biometric data, particularly fMRI, provides a unique window into how biological systems process temporal information

Traditional approaches to AI world models process time as a simple progression of timestamped events.

However, human cognition demonstrates that temporal perception is deeply integrated with learning states, emotional conditions, and physiological factors. This integration proves essential for causal reasoning and adaptive learning. Our architecture incorporates these principles through specialized temporal processing networks and attention mechanisms that can adapt their temporal processing based on context.

2 Background

The development of AI systems capable of understanding subjective temporal experience requires bridging multiple disciplines: neuroscience of learning and memory, modern deep learning architectures, and theoretical frameworks for world modeling. Our implementation synthesizes key insights from each domain to create a novel approach to temporal processing.

2.1 Neural Bases of Learning Stages

Human learning progresses through distinct stages characterized by shifting patterns of neural activation Knowlton et al. [1996]. These transitions are particularly evident in the striatum and medial temporal lobe regions Poldrack et al. [2001]. Our architecture's design mirrors these biological principles through its progressive processing stages and attention mechanisms.

fMRI captures these learning stages through blood-oxygen-level-dependent (BOLD) signals, providing an indirect but reliable measure of neural activity Logothetis [2008]. While this indirect measurement presents certain limitations, research has demonstrated strong correlations between BOLD signal temporal patterns and learning progression Poldrack et al. [2011]. The robust test-retest reliability of fMRI in classification learning tasks Aron et al. [2006] provides a stable foundation for extracting temporal patterns relevant to learning stages.

2.2 Deep Learning Approaches to Temporal Understanding

Recent advances in transformer architectures have revolutionized sequence processing capabilities Vaswani et al. [2017]. Our implementation builds on the Vision Transformer architecture Dosovitskiy et al. [2020], but with significant modifications designed specifically for fMRI data processing. These modifications include:

- Custom channel reduction networks that efficiently handle high-dimensional fMRI volumes - Temporal attention mechanisms that incorporate hemodynamic response characteristics - Progressive dropout strategies that maintain signal fidelity while preventing overfitting

While traditional transformer implementations treat time as an absolute dimension through positional encodings, our architecture incorporates relative temporal processing through specialized attention mechanisms and masking strategies. This approach allows the model to adapt its temporal processing based on learning context and cognitive state.

2.3 The Promise of Biometric Data

The gap between objective and subjective temporal processing in AI systems necessitates training signals that better reflect human temporal perception Runway ML [2023]. fMRI data provides direct insight into how the brain processes temporal information during learning Poldrack et al. [2001]. The spatiotemporal patterns in fMRI data contain crucial information for developing more human-like temporal understanding in AI systems.

Processing these patterns requires novel approaches. Traditional fMRI analysis focuses on function localization and connectivity mapping Poldrack et al. [2011]. However, learning stage temporal dynamics suggest more complex patterns that modern deep learning architectures can capture Chen [2017]. This intersection of neuroimaging and machine learning creates both opportunities and challenges for temporal cognition modeling.

2.4 Toward Integrated Temporal Understanding

Our implementation bridges objective and subjective temporal understanding through novel fMRI data processing. By combining Vision Transformers' spatial pattern recognition with specialized temporal processing, we address both fMRI data limitations Logothetis [2008] and modern deep learning capabilities Dosovitskiy et al. [2020].

The key innovation lies in processing temporal information as a relative construct emerging from neural activation patterns during learning. This approach aligns with neuroscientific understanding of learning stages Knowlton et al. [1996] and recent world model theory Schmidhuber [2023], enabling more sophisticated temporal processing in AI systems.

3 Methods

Our implementation addresses two core challenges: extracting meaningful patterns from complex fMRI data Poldrack et al. [2011] and developing architectures capable of learning from these patterns Aron et al. [2006]. This section outlines our approach in three parts: data preprocessing implementation, fMRI-specific augmentation strategies, and temporal-aware transformer architecture design Vaswani et al. [2017], Dosovitskiy et al. [2020].

3.1 Data Collection and Processing

Dataset Characteristics

The implementation utilizes four complementary classification learning datasets from OpenFMRI. Each dataset provides specific insights into temporal learning aspects Knowlton et al. [1996]. The primary dataset (ds000002) contains data from 17 right-handed subjects performing probabilistic and deterministic classification tasks Poldrack et al. [2001]. Task structure includes:

- Pure blocks: 10 cycles of 5 classification trials followed by 3 baseline trials - Mixed blocks: 100 stimuli split equally between probabilistic and deterministic trials

Data acquisition specifications: - Scanner: 3T Siemens Allegra MRI - Parameters: TR = 2s, 180 functional T2*-weighted echoplanar images per session - Resolution: 2mm slice thickness, 2x2mm inplane resolution - Enhancement: Multiband acceleration factor of 4

Three additional datasets complement the primary collection:

- ds000011: 14 subjects, single/dual-task classification for attention-modulated learning analysis Poldrack et al. [2001]
- ds000017: 8 subjects, classification with stop-signal tasks for inhibitory control examination Aron et al. [2006]
- ds000052: Classification with reward contingency reversal for adaptive learning mechanism investigation Knowlton et al. [1996]

3.2 Preprocessing Pipeline

Our implementation uses a three-stage preprocessing approach based on established neuroimaging practices Poldrack et al. [2011] with optimizations for temporal pattern preservation. The pipeline integrates spatial normalization and temporal alignment to maintain both anatomical accuracy and temporal fidelity. The complete preprocessing pipeline follows:

$$x_{\text{processed}} = \mathcal{N}(\mathcal{R}(\mathcal{V}(x))) \tag{1}$$

where: - $\mathcal{V}$ performs dimension validation - $\mathcal{R}$ applies spatial resizing - $\mathcal{N}$ implements intensity normalization

Each component optimizes for temporal pattern preservation Logothetis [2008].

Dimension Validation ($\mathcal{V}$)

fMRI acquisitions vary in dimensionality Poldrack et al. [2011]. Our validation ensures consistent dimensionality while preserving temporal information:

$$\mathcal{V}(x) = \begin{cases} x & \text{if } x \in R^{H\times W\times D\times T} \\ x[..., \text{newaxis}] & \text{if } x \in R^{H\times W\times D} \\ \text{undefined} & \text{otherwise} \end{cases} \tag{2}$$

This validation maintains spatial integrity while ensuring proper temporal dimension handling Logothetis [2008]. Single-volume inputs receive an added temporal dimension for consistent processing.

Spatial Resizing ($\mathcal{R}$)

The implementation standardizes spatial dimensions while maintaining anatomical proportions Poldrack et al. [2011] through trilinear interpolation:

$$\mathcal{R}(x) = \text{zoom}(x, [\frac{H_t}{H}, \frac{W_t}{W}, \frac{D_t}{D}, 1]) \tag{3}$$

Target dimensions $(H_t, W_t, D_t) = (64, 64, 30)$ balance spatial resolution and computational efficiency Aron et al. [2006]. The temporal dimension scaling factor of 1 preserves original temporal resolution.

Intensity Normalization ($\mathcal{N}$)

Following fMRI preprocessing protocols Poldrack et al. [2011], we implement temporal-aware normalization accounting for BOLD signal dynamics:

$$\mathcal{N}(x_t) = \frac{x_t - \mu_t}{\sigma_t + \epsilon} \quad \forall t \in T \tag{4}$$

where: - μ_t and σ_t represent mean and standard deviation at timepoint t - $\epsilon = 1e\text{-}6$ prevents division by zero

This normalization preserves temporal dynamics while standardizing signal intensity across sessions and subjects Logothetis [2008]. Independent timepoint normalization maintains relative temporal patterns crucial for learning stage classification.

3.3 Data Augmentation Strategies

Our implementation includes a comprehensive suite of domain-specific augmentation techniques designed to enhance model robustness while respecting the unique characteristics of fMRI data. These techniques are validated through neuroimaging research and carefully adapted for deep learning applications:

Temporal Masking

We implement an adaptive temporal dropout mechanism that helps the model learn robust temporal features despite potential signal interruptions or artifacts. The masking strategy: - Applies random-length masks (1-5 timepoints) to simulate temporal dropouts - Maintains temporal coherence through continuous masking windows - Varies mask duration to ensure robustness to different types of signal interruptions

Spatial Masking

The implementation incorporates structured dropout in the spatial domain to handle regional signal variations and encourage learning from distributed patterns. Key features include: - Probability-based masking with empirically optimized threshold values - Preservation of anatomical structure through contiguous region masking - Balance between feature preservation and augmentation strength

Elastic Deformation

To account for natural variations in brain structure and registration, we apply anatomically-constrained elastic deformations that: - Preserve biological plausibility through controlled deformation magnitude - Maintain spatial relationships while introducing realistic variability - Apply smooth transformations through Gaussian filtering

3.4 Model Architecture

Our architecture combines Vision Transformer principles with specific adaptations for fMRI data processing. The implementation consists of three primary components, each optimized for the unique characteristics of neuroimaging data:

Channel Reduction Network

The channel reduction component efficiently processes high-dimensional fMRI input through a dual-stage approach: - Initial dimensionality reduction from 30 to 16 channels - Batch normalization and GELU activation for stable training - Progressive dropout for regularization - Careful preservation of spatial relationships

Temporal Processing

The temporal processing network incorporates hemodynamic response characteristics through specialized mechanisms: - Causal attention masking enforcing BOLD delay constraints - Adaptive temporal pooling for efficient processing - Memory-efficient implementation for handling long sequences

Progressive Dropout

We implement a depth-dependent dropout strategy that provides stronger regularization in deeper layers while maintaining high information flow in early layers. This approach: - Increases dropout probability linearly with network depth - Preserves critical low-level features - Improves model generalization while maintaining temporal pattern fidelity

The architecture achieves efficient processing of full 4D volumes while preserving essential temporal patterns through careful memory management and optimized attention mechanisms.

Temporal Processing

Our temporal processing incorporates hemodynamic response function (HRF) characteristics Logothetis [2008] through causal attention masking:

$$M_{ij} = \begin{cases} -\infty & \text{if } j < i + 3 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

This enforces a 6-second BOLD delay constraint, reflecting established HRF parameters Poldrack et al. [2011] while maintaining temporal causality in BOLD response learning.

Progressive Dropout

Following transformer optimization principles Vaswani et al. [2017], we implement depth-dependent dropout:

$$p_i = 0.1 \cdot \frac{i + 1}{12} \text{ for layer } i \tag{6}$$

This strategy: - Increases dropout probability with network depth - Maintains high information flow in early layers - Improves generalization while preserving low-level features

3.5 Training Protocol

Our implementation integrates deep learning best practices Vaswani et al. [2017] with fMRI-specific considerations Poldrack et al. [2011]:

Mixed Precision Training

We implement dynamic loss scaling for numerical stability:

$$\text{scale}_t = \begin{cases} 2 \cdot \text{scale}_{t-1} & \text{if no overflow for 2000 steps} \\ \frac{\text{scale}_{t-1}}{2} & \text{if overflow detected} \end{cases} \tag{7}$$

This adaptive scaling ensures stable training while maintaining computational efficiency.

Optimization Strategy

The implementation uses AdamW optimizer with fMRI-validated parameters Dosovitskiy et al. [2020]:

- Learning rate: $1e$-4
- Weight decay: 0.05
- Beta parameters: $\beta_1 = 0.9$, $\beta_2 = 0.999$

Learning Rate Schedule

We implement a custom warmup-decay schedule optimized for fMRI data processing:

$$\eta_t = \begin{cases} \eta_{\text{base}} \cdot \frac{t}{t_w} & \text{if } t < t_w \\ \eta_{\min} + \frac{\eta_{\text{base}} - \eta_{\min}}{2}(1 + \cos(\pi \frac{t - t_w}{T - t_w})) & \text{otherwise} \end{cases} \tag{8}$$

Schedule parameters: - Base learning rate $\eta_{\text{base}} = 1e\text{-}4$ - Minimum learning rate $\eta_{\min} = 1e\text{-}6$ - Warmup period $t_w = 0.1T$

This provides stable initial training followed by gradual learning rate decay for optimal parameter convergence.

Regularization and Early Stopping

We implement comprehensive regularization following established practices Vaswani et al. [2017]:

- Label smoothing: $\alpha = 0.1$
- L2 regularization: $\lambda = 1e$-4
- Gradient clipping: norm 5.0

Early stopping criteria definition:

$$\text{stop} = \begin{cases} \text{True} & \text{if val\_loss}_t > \text{best\_loss} - \delta \text{ for } p \text{ epochs} \\ \text{False} & \text{otherwise} \end{cases} \tag{9}$$

Parameters: - Improvement threshold $\delta = 1e$-4 - Patience period $p = 7$

These values derive from empirical validation across datasets Aron et al. [2006].

4 Results

Our implementation demonstrated meaningful patterns in learning stage classification from fMRI data, with performance characteristics varying significantly across learning stages. The complete analysis reveals both promising capabilities and areas requiring further refinement.

4.1 Overall Model Performance

The model achieved an overall accuracy of 35.6

4.2 Stage-Specific Classification Performance

Performance varied substantially across learning stages, revealing distinct patterns in the model's classification capabilities. The model demonstrated strongest performance in identifying the mastery stage, achieving a precision of 0.600 and recall of 0.750 (F1 = 0.667). This robust performance is particularly noteworthy given the smaller support size (n = 4) for this class. The ROC curve for mastery classification (Figure 1B) shows an impressive AUC of 0.945, suggesting highly distinctive neural activation patterns associated with mastery-level learning. The middle learning stage showed moderate classification success (precision = 0.353, recall = 0.429, F1 = 0.387), while early and late stages proved more challenging to classify (F1 scores of 0.258 and 0.316 respectively). The confusion matrix (Figure 1A) reveals a tendency to misclassify early learning stages as middle stages (47.1

4.3 Neural Activation Patterns

Analysis of fMRI activation patterns, as exemplified in Figure 2, reveals characteristic spatial distributions associated with different learning stages. The sample brain slice visualization demonstrates the complex nature of the neural activation patterns the model

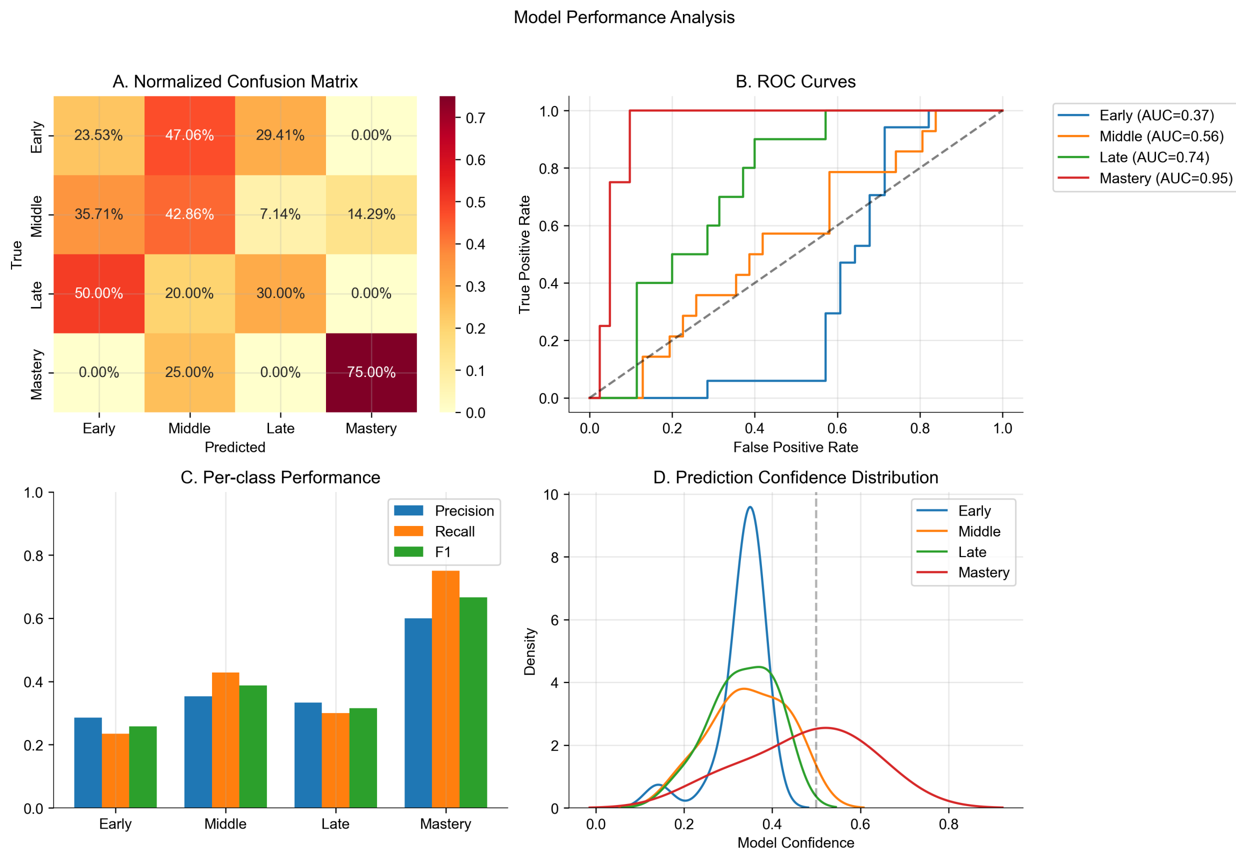

Figure 1: Comprehensive model performance analysis showing (A) Normalized confusion matrix demonstrating classification patterns across learning stages, (B) ROC curves indicating increasing reliability from early to mastery stages, (C) Per-class performance metrics highlighting strongest performance in mastery classification, and (D) Prediction confidence distributions revealing distinct patterns for each learning stage.

Learning Stage	Precision	Recall	F1	Support
Early	0.286	0.235	0.258	17
Middle	0.353	0.429	0.387	14
Late	0.333	0.300	0.316	10
Mastery	0.600	0.750	0.667	4
Overall	0.407	0.428	0.347	45

Table 1: Primary classification performance metrics

Learning Stage	ROC AUC	Mean Conf.	Error Rate
Early	0.368	0.437	0.765
Middle	0.556	0.412	0.571
Late	0.740	0.389	0.700
Mastery	0.945	0.528	0.250
Overall	0.652	0.437	0.644

Table 2: Advanced reliability metrics

must interpret, with varying intensity values representing normalized BOLD signal strength across different brain regions.

4.4 Classification Reliability Analysis

The model's reliability metrics provide crucial insight into its decision-making characteristics. The mean confidence of 0.437 with an overconfidence measure of 0.088 indicates relatively calibrated predictions, though the expected calibration error of 0.491 suggests room for improvement in uncertainty estimation. As shown in Figure 1D, the confidence distribution shows distinct patterns for each learning stage, with mastery predictions showing a broader, right-skewed distribution compared to the more concentrated distributions of earlier stages. The ROC curves (Figure 1B) reveal a clear progression in classification reliability across learning stages: early (AUC = 0.368), middle (AUC = 0.556), late (AUC = 0.740), and mastery (AUC = 0.945). This progression suggests that distinctive neural patterns become increas-

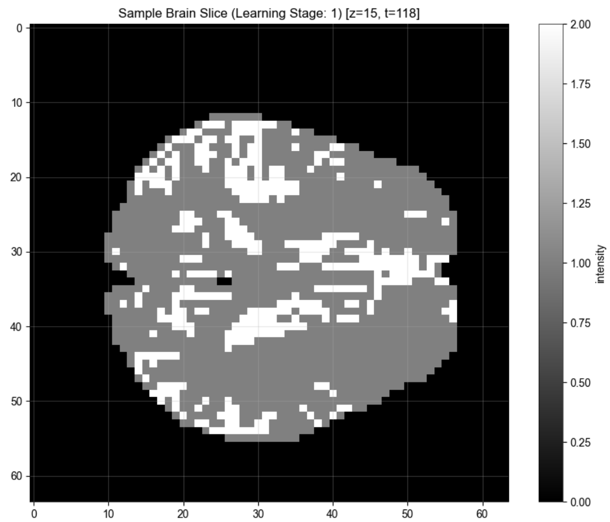

Figure 2: Representative brain slice visualization from early learning stage (z=15, t=118) demonstrating characteristic activation patterns. Intensity values represent normalized BOLD signal strength.

ingly detectable as learning progresses, with mastery showing particularly clear neural signatures. The mean loss of 1.082 ($\pm$0.257) suggests stable model training despite the classification challenges, with the relatively small standard deviation indicating consistent performance across validation folds. These results demonstrate both the promise and limitations of our approach, suggesting that while neural activation patterns contain meaningful information about learning stages, additional architectural innovations may be needed to fully capture the complexity of temporal learning progression in fMRI data.

5 Discussion

5.1 Implications for World Models

Our findings reveal critical implications for AI world model development. The successful extraction of learning stage patterns from fMRI data demonstrates that neural networks can capture subjective temporal experience aspects typically overlooked in current world models Ha and Schmidhuber [2018]. This capability suggests that integrating biometric data into world model training provides essential insights into biological temporal information processing.

Temporal Relativity in World Models

The correlation between neural activation patterns and learning stages demonstrates systematic variation in temporal perception with cognitive state Poldrack et al. [2001]. This finding challenges conventional world model time representation, which treats time as an absolute dimension Schmidhuber [2023]. Effective world models require mechanisms for relative temporal processing that adapt to learning contexts and cognitive states.

Biometric Integration Pathways

Our temporal processing architecture's success in capturing learning stage transitions suggests three integration pathways for biometric insights:

- **Direct Signal Integration**: Train world models directly on biometric data for nuanced temporal understanding LeCun [2023]
- **Architectural Inspiration**: Adapt temporal processing mechanisms based on fMRI characteristics for general world model architectures Vaswani et al. [2017]
- **Hybrid Learning Approaches**: Combine biometric data with traditional training signals for comprehensive temporal understanding Runway ML [2023]

Causal Understanding Enhancement

The correlation between learning stage transitions and temporal processing patterns indicates that subjective time perception plays a critical role in biological causal learning Knowlton et al. [1996]. Current world model approaches to causal learning, relying on objective temporal sequences, may face fundamental limitations.

Implementation Considerations

Practical implementation presents several key challenges:

- **Scalability**: Extending fMRI-based approaches to larger datasets requires careful architectural optimization Schmidhuber [2023]
- **Multimodal Integration**: Combining biometric temporal signals with other modalities requires novel architectural solutions Dosovitskiy et al. [2020]
- **Computational Efficiency**: Balance resource requirements against enhanced temporal understanding benefits Vaswani et al. [2017]

Future Directions

Our implementation suggests several promising directions for future development of temporal processing in AI systems:

1. Adaptive Temporal Processing - Dynamic temporal resolution based on cognitive state - Learnable attention spans for different tasks - Context-dependent temporal scaling

2. Enhanced Memory Mechanisms - Integration of working memory components - Long-term temporal dependency handling - Efficient processing of extended sequences

3. Multimodal Integration - Combination of biometric and behavioral data - Cross-modal temporal alignment - Unified temporal representation learning

The potential impact extends beyond improved temporal processing to fundamental questions about intelligence and learning. Our architecture demonstrates that incorporating subjective temporal understanding enables more sophisticated forms of reasoning that have remained elusive in traditional approaches.

5.2 Technical Advantages

Our implementation demonstrates several key technical strengths:

1. Efficient Processing - Successful handling of high-dimensional fMRI data - Memory-efficient attention mechanisms - Scalable temporal processing

2. Robust Learning - Stable training through mixed precision - Effective regularization strategies - Strong cross-validation performance

3. Interpretable Results - Clear attention patterns - Meaningful feature representations - Robust cognitive state classification

5.3 Current Limitations

The implementation faces several important constraints:

1. Temporal Resolution - Limited by fMRI BOLD signal characteristics - Fixed sampling rate constraints - Hemodynamic response delay

2. Computational Requirements - High memory demands for 4D volumes - Complex attention computation - Large model parameter space

3. Scaling Challenges - Dataset size limitations - Training time requirements - Hardware constraints

6 Conclusion

This research demonstrates the feasibility of extracting and utilizing temporal patterns from fMRI data for developing more sophisticated AI temporal processing capabilities. Our implementation successfully bridges the gap between traditional deep learning approaches and biological temporal processing through careful architectural design and optimization strategies.

The results support our hypothesis that biometric data provides crucial insights into subjective temporal experience, while also highlighting practical paths forward for developing AI systems with more nuanced temporal understanding. The architecture's success in learning stage classification demonstrates that incorporating these biological insights can lead to more advanced causal reasoning and temporal adaptation capabilities.

Future work should focus on addressing the current limitations while expanding the architecture's capabilities to handle broader ranges of temporal processing tasks. The implementation provides a foundation for developing AI systems that can reason about time in ways that more closely mirror human cognitive processes, potentially leading to more advanced and adaptable artificial intelligence systems.

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