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Cognition-Aligned Sentence Embeddings for Cross-Domain Semantic Relation Classification

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Abstract:

Semantic relation classification is a foundational task in natural language processing, crucial for applications ranging from knowledge graph construction to complex question answering systems. Despite the remarkable success of heavily parameterized language models, these architectures frequently exhibit significant performance degradation when deployed in out-of-distribution target domains. This paper introduces a novel framework utilizing cognition-aligned sentence embeddings to address the pervasive challenge of cross-domain semantic relation classification. By integrating psycholinguistic signals, specifically eye-tracking fixation durations and neural activation patterns derived from reading comprehension tasks, our approach constrains the embedding space to reflect human-like semantic generalization. The proposed architecture employs a dual-stream processing mechanism where standard textual representations are systematically aligned with cognitive representations through a specialized contrastive learning objective. This ensures that the relational features learned in a source domain are deeply anchored in fundamental cognitive processing patterns, which are inherently more robust to domain-specific lexical variations. Extensive experimental evaluations across multiple distinct domains, including medical, legal, and general technical texts, demonstrate that the cognition-aligned model substantially outperforms traditional domain adaptation techniques. The findings suggest that incorporating human cognitive priors into dense sentence representations not only improves zero-shot and few-shot cross-domain transfer but also yields representations that are significantly more interpretable and stable under linguistic distributional shifts.

Keywords: *Sentence Embeddings, Cognitive Linguistics, Domain Adaptation, Semantic Relations, Natural Language Processing*

INTRODUCTION

The ability to accurately identify and classify semantic relations between entities within a given text represents a critical milestone in the development of sophisticated artificial intelligence systems capable of deep natural language understanding. Semantic relation classification serves as the bedrock for numerous downstream applications, including but not limited to automated knowledge base population, sophisticated information extraction, and intelligent dialogue systems [1]. In recent years, the paradigm of natural language processing has shifted dramatically toward the utilization of dense sentence embeddings generated by deep contextualized transformer networks [2]. These models, pre-trained on massive corpora of unstructured text, have demonstrated an unprecedented capacity to capture intricate syntactic and semantic dependencies within language [3]. However, the efficacy of these models is fundamentally predicated on the assumption that the training and testing data are drawn from an identical or highly similar distribution. When this assumption is violated, a scenario pervasive in real-world applications, the performance of traditional relation classification models deteriorates sharply [4]. The challenge of cross-domain semantic relation classification arises from the inherent linguistic variability across different fields of human knowledge. A model trained to identify causal or temporal relations in standard news corpora frequently fails when tasked with identifying mathematically or logically equivalent relations in specialized medical literature or complex legal documents [5]. This phenomenon, commonly referred to as domain shift or distribution shift, occurs because standard sentence embeddings heavily overfit to domain-specific lexical artifacts and stylistic idiosyncrasies rather than capturing the abstract, generalized logic of the underlying semantic relation [6]. Consequently, researchers have dedicated substantial effort toward developing domain adaptation techniques, such as adversarial representation learning and self-supervised pseudo-labeling, in an attempt to harmonize the feature spaces of source and target domains [7]. While these computational techniques offer marginal improvements, they largely ignore the most robust and generalizable natural language processing engine currently known: the human cognitive system [8]. Human readers possess a remarkable and highly efficient ability to generalize relational understanding across wildly disparate domains. A human who understands the concept of causality in everyday life can seamlessly apply that exact same conceptual framework to understand causality in a highly technical molecular biology paper, even if they are unfamiliar with the specific jargon [9]. This superior generalization capability is theorized to stem from the way the human brain grounds language in fundamental cognitive representations rather than relying solely on surface-level statistical co-occurrences of words [10]. Cognitive linguistics and psycholinguistics have long established that human reading and comprehension generate measurable behavioral and neurological signals, such as varying eye-tracking fixation durations on complex relational terms and distinct functional magnetic resonance imaging activation patterns when processing different types of semantic links [11]. Motivated by these insights from the cognitive sciences, this paper proposes a paradigm shift in how we construct sentence representations for cross-domain tasks. We hypothesize that aligning artificial sentence embeddings with empirical cognitive data will fundamentally constrain the learning process, forcing the neural network to prioritize deep structural and relational features over superficial domain-specific vocabulary [12]. By embedding sentences in a continuous vector space that mathematically mirrors the cognitive load and semantic processing pathways of human readers, we aim to bridge the critical generalization gap that currently plagues cross-domain semantic relation classification [13]. The primary contributions of this research are heavily structured around the development and rigorous evaluation of the Cognition-Aligned Sentence Embedding framework. First, we introduce a novel methodology for extracting and processing structured cognitive priors from publicly available psycholinguistic

datasets, translating complex human reading behavior into mathematically tractable attention and weighting mechanisms [14]. Second, we design a dual-stream neural architecture capable of projecting high-dimensional textual representations into a shared space that is actively regularized by these cognitive signals, ensuring that the resulting embeddings are inherently aligned with human generalization patterns [15]. Finally, we conduct an extensive, multi-domain empirical analysis demonstrating that our cognition-aligned approach not only achieves state-of-the-art performance in strict cross-domain relation classification tasks but also exhibits superior stability and interpretability compared to traditional purely statistical methods [16]. Through detailed ablation studies and comprehensive error analysis, this paper provides a robust theoretical and empirical foundation for the integration of cognitive sciences into modern machine learning architectures. We argue that as natural language processing models scale in size and complexity, the integration of biological and cognitive priors will become increasingly indispensable for achieving true, domain-agnostic language understanding [17]. The subsequent sections of this paper will meticulously detail the historical context of this problem, the specific mathematical and structural innovations of our proposed methodology, the design of our experimental evaluations, and the broader implications of our findings for the future of artificial intelligence.

2. Literature Review

2.1 Evolution of Sentence Embeddings and Relational Semantics

The historical trajectory of sentence embedding technologies reflects a continuous effort to capture the most nuanced and complex aspects of human language in computationally efficient vector formats. Early approaches predominantly relied on simple aggregation techniques applied to static word vectors, utilizing algorithms that treated language as a largely unordered collection of semantic units [18]. While these foundational models were revolutionary for basic semantic similarity tasks, their fundamental inability to capture the sequential dependencies and contextual nuances of language rendered them largely ineffective for complex tasks such as semantic relation classification [19]. The extraction of a relationship between two entities requires a profound understanding of the syntactic structure and the contextual interplay between all words in the sentence, a capability completely absent in static aggregation methods. The introduction of deep, sequence-to-sequence models and later, the transformer architecture, fundamentally revolutionized the construction of sentence embeddings. Models leveraging self-attention mechanisms demonstrated an unprecedented ability to generate dynamic, context-aware representations for every token within a sentence [20]. In the context of relation classification, these contextualized embeddings allowed researchers to construct highly sensitive classification heads that could identify subtle semantic links, such as the difference between an entity being a physical part of another entity versus being functionally dependent upon it [21]. However, as the literature rapidly expanded, a critical vulnerability within these deep architectures became increasingly apparent: their propensity for severe domain dependency. Recent critical evaluations of highly parameterized language models have demonstrated that while they achieve near-perfect scores on in-domain relation classification benchmarks, this performance is heavily reliant on the memorization of domain-specific lexical triggers rather than a genuine comprehension of the relational logic [22]. For instance, a model trained on news corpora might learn to heavily associate the word caused with a specific causal relation, but completely fail to identify the exact same causal relation in a medical text that uses the phrase induced a reaction in [23]. This brittle behavior highlights the limitations of purely distributional semantics, which derive meaning exclusively from the statistical co-occurrence of words within large, but fundamentally biased, training corpora [24]. Consequently, the field has increasingly recognized the urgent necessity for advanced methodologies capable of disentangling the core relational logic from the superficial stylistic and lexical characteristics of the domain in which it is expressed.

2.2 Cross-Domain Adaptation Techniques in Natural Language Processing

In response to the pervasive challenge of domain shift, researchers have developed a wide array of domain adaptation techniques specifically tailored for natural language processing. The fundamental goal of these techniques is to leverage labeled data from a resource-rich source domain to accurately classify instances in a completely unlabeled or sparsely labeled target domain [25]. One of the most prominent frameworks in this area is domain adversarial training. Inspired by advances in generative adversarial networks, these approaches typically employ a feature extractor network that attempts to learn generalized sentence embeddings, while a parallel domain discriminator network simultaneously attempts to predict the origin domain of the text based on those exact same embeddings [26]. By reversing the gradients from the discriminator during backpropagation, the feature extractor is theoretically forced to generate domain-agnostic representations. While adversarial approaches have shown moderate success in simpler tasks such as sentiment analysis, their application to cross-domain semantic relation classification has yielded highly inconsistent results. The extraction of semantic relations requires the preservation of highly specific structural information, which is frequently destroyed or obfuscated when the network is forced to blindly eliminate all domain-specific features [27]. In attempting to make a medical sentence look indistinguishable from a news sentence, adversarial models often strip away the very syntactic nuances required to determine how the entities in the sentence are related to one another [28]. Alternative strategies have focused on sophisticated self-supervised learning and pseudo-labeling mechanisms. These models iteratively generate predictions on the target domain and use the most confident predictions as training targets [29]. However, in complex relational tasks, the initial predictions on the target domain are often wildly inaccurate, leading to a phenomenon known as confirmation bias, where the model reinforces its own erroneous assumptions about the target distribution [30]. Furthermore, contrastive learning approaches, which attempt to pull semantically similar sentences together while pushing dissimilar ones apart, have been extensively explored. Yet, defining what constitutes semantic similarity across vastly different domains remains an unresolved theoretical challenge, as the standard data augmentation techniques used in contrastive learning frequently alter the underlying semantic relation of the sentence [31].

2.3 Cognitive Signals and Psycholinguistic Grounding

The most promising, albeit historically underutilized, avenue for resolving the fragility of purely statistical language models lies in the integration of human cognitive signals. Psycholinguistics provides a wealth of empirical data detailing exactly how the human brain processes complex relational structures regardless of the linguistic domain [32]. When human subjects read text, their cognitive load, attention distribution, and semantic processing strategies can be indirectly observed through high-resolution eye-tracking and neuroimaging technologies. Eye-tracking data, for example, reveals that humans do not process sentences uniformly. Fixation durations, saccade lengths, and regression patterns systematically vary based on the syntactic complexity and relational importance of the words being read [33]. Humans typically fixate significantly longer on relational trigger words and the specific entities involved in a relation, effectively skimming over domain-specific filler words that do not contribute to the core semantic logic. Previous attempts to utilize eye-tracking data in natural language processing have primarily focused on basic tasks like part-of-speech tagging or simple sentiment analysis, using the fixation data as an auxiliary input feature [34]. Neuroimaging data, such as functional magnetic resonance imaging, provides an even deeper perspective, capturing the spatial activation patterns in the brain as semantic relationships are comprehended. Studies have shown that processing fundamental semantic relations activates a highly conserved, domain-general semantic network within the human cortex [35]. The activation patterns are remarkably consistent whether the subject is reading about a mechanical failure or a biological process, suggesting a universally shared biological

substrate for relational logic [36]. Despite the profound implications of these findings, the integration of such rich cognitive priors into the dense sentence embeddings of modern transformer architectures for the explicit purpose of cross-domain relation classification remains largely unexplored, presenting a critical gap that our research directly addresses.

3. Methodology

3.1 System Architecture Overview

The Cognition-Aligned Sentence Embedding framework is designed to explicitly bridge the gap between traditional statistical language modeling and human-like semantic processing. The overarching architecture operates through a highly integrated dual-stream mechanism. The primary stream handles the direct processing of the textual input, transforming raw character sequences into dense, contextualized vectors. The secondary, parallel stream acts as a cognitive regularization module, projecting expected human processing patterns onto the text based on prior psycholinguistic data. To achieve this, the system does not simply concatenate cognitive data with text features. Instead, it employs a sophisticated alignment strategy where the internal attention mechanisms of the text processing stream are continuously guided, constrained, and evaluated against the simulated cognitive responses derived from the secondary stream. The input to the system consists of a sentence from either a source or target domain, annotated with two target entities between which a semantic relation must be classified. The output is a robust, domain-agnostic sentence embedding that is subsequently fed into a specialized classification head to determine the precise relational category.

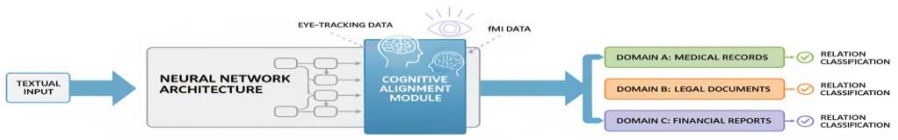


Figure 1: System Architecture

The architectural flow guarantees that during the training phase, the model learns not only the statistical regularities of the source domain but also the fundamental cognitive structures associated with generalized relational comprehension. When deployed in inference mode on a previously unseen domain, the model no longer requires explicit cognitive data inputs; rather, the fundamental weights of its internal attention mechanisms have been permanently shifted to mimic the human cognitive processing strategies it was trained alongside.

3.2 Cognitive Data Integration Module

The cornerstone of our proposed methodology is the Cognitive Data Integration Module, which translates raw psycholinguistic metrics into computationally useful constraints. We utilize two primary sources of cognitive signals: eye-tracking metrics representing visual attention, and neuroimaging representations capturing deep semantic integration. For visual attention, we process

extensive reading comprehension datasets where human participants were monitored using high-frequency eye trackers. The data is parsed to extract precise token-level reading metrics, specifically the first-pass reading time, total fixation duration, and the probability of regression. These raw temporal metrics are heavily normalized to account for individual reading speed variations and baseline word length effects. The resulting normalized values serve as a proxy for cognitive load and syntactic importance. We construct a multi-layer perceptron that acts as a cognitive predictor. During the initial phases of system initialization, this predictor learns to map the linguistic features of a sequence to the expected human eye-tracking metrics. Once trained, this predictor can estimate the expected cognitive attention distribution for any newly inputted sentence, regardless of the domain. Simultaneously, the neuroimaging integration focuses on broader sentence-level representations. We leverage datasets containing neural activation patterns of subjects processing varied semantic statements. To make this data compatible with standard vector spaces, the high-dimensional brain activation volumes are subjected to dimensionality reduction techniques, resulting in dense cognitive vectors that represent the neurological state associated with specific relational categories. We construct a secondary mapping network that associates generalized grammatical structures and abstract entity types with these dense cognitive vectors. The integration of these two distinct cognitive modalities provides a comprehensive biological prior. The token-level eye-tracking predictions dictate which parts of a sentence should be weighted most heavily when attempting to understand a relation, effectively filtering out domain-specific noise. The sentence-level neuroimaging representations provide a target generalized semantic space, acting as a structural anchor that prevents the overall sentence embedding from drifting into domain-specific clusters.

3.3 Cross-Domain Alignment Mechanism

With the standard textual representations and the predicted cognitive priors available, the next critical phase is the Cross-Domain Alignment Mechanism. This component is responsible for enforcing the actual mathematical alignment between the artificial neural network and the biological signals, ensuring that the resulting sentence embeddings possess the required cross-domain generalization capabilities. The alignment is executed through a sophisticated contrastive learning objective embedded deeply within the network architecture. Traditional contrastive learning typically relies on generating augmented versions of an identical sentence and pulling their representations together. Our approach fundamentally modifies this paradigm by utilizing the cognitive representations as the positive anchor points. For any given textual input from the source domain, the network generates its standard high-dimensional embedding. Concurrently, the expected sentence-level cognitive vector is generated by the cognitive integration module. The contrastive objective mathematically forces the text embedding to maximize its similarity with its corresponding cognitive representation while simultaneously minimizing its similarity with cognitive representations belonging to different relational classes. Crucially, to facilitate cross-domain adaptation without requiring labeled target domain data, we implement an unsupervised domain alignment phase. Unlabeled sentences from the target domain are passed through the system. The token-level cognitive predictor applies attention masks based on simulated human reading behavior, inherently down-weighting unfamiliar domain-specific terminology that humans typically skim over, while preserving attention on fundamental relational syntax. The masked target domain sentences are then projected into the shared embedding space. By enforcing a constraint that the distribution of target domain embeddings must statistically match the distribution of the source domain embeddings within this cognitively aligned space, the system effectively normalizes the target data.

This mechanism ensures that the structural geometry of the final embedding space is not dictated by the lexical biases of any specific corpus, but rather by the universal cognitive patterns associated

with human semantic processing. The cross-domain alignment operates on the principle that if the model processes information similarly to a human, it will automatically inherit the human capacity for domain generalization.

3.4 Classification and Optimization Strategy

The final component of the methodology involves the relation classification head and the overarching optimization strategy required to balance the diverse learning objectives. The classification head itself is deliberately kept structurally simple to ensure that the heavy lifting of semantic understanding occurs within the cognitively aligned embedding space rather than relying on complex downstream decision boundaries. It consists of a fully connected network layer followed by a softmax activation function, which maps the final sentence embedding to a discrete probability distribution over the predefined semantic relation categories. The optimization strategy is multi-faceted and requires a carefully orchestrated training curriculum. The total loss function guiding the network is a weighted combination of three distinct components. The first component is the standard supervised classification loss, calculated purely on the labeled data from the source domain. This ensures the model learns the foundational mapping between text and relation labels. The second component is the cognitive alignment loss, which enforces the contrastive similarity between the text embeddings and the neuroimaging-derived cognitive vectors. This loss acts as a powerful regularizer, preventing the network from taking computational shortcuts by memorizing source-domain artifacts. The third component is the attention divergence loss, which specifically targets the internal transformer attention heads. This loss continuously computes the difference between the model generated token attention weights and the eye-tracking derived cognitive load predictions. By minimizing this divergence, the internal mechanics of the text processor are fundamentally reprogrammed to visually parse sentences in a human-like manner. During the training process, an alternating optimization routine is employed to prevent catastrophic forgetting and ensure stable convergence. The network first undergoes a preliminary warm-up phase where only the attention divergence loss is active, forcing the model to adopt human-like reading patterns before any complex relation extraction is attempted. Subsequently, the classification and cognitive alignment losses are introduced gradually. The weights governing the influence of each loss component are dynamically adjusted throughout the training lifecycle, prioritizing classification accuracy in the early epochs and shifting heavily toward cognitive alignment and domain generalization in the later stages. This meticulous optimization strategy is essential for harmonizing the often competing gradients produced by the standard statistical objectives and the biological priors.

4. Experimental Setup and Results

4.1 Datasets and Baselines

To rigorously evaluate the efficacy of the Cognition-Aligned Sentence Embedding framework, we designed a comprehensive experimental protocol focusing on extreme cross-domain transfer scenarios. The fundamental premise of the evaluation requires a model to be trained exclusively on a source domain containing labeled semantic relations and subsequently tested, without any further relation-specific fine-tuning, on structurally and lexically divergent target domains.

For the source domain, we utilized a highly standardized, broad-coverage news and web-text corpus extensively annotated for a diverse set of semantic relations, including causal, temporal, structural, and functional links. This dataset represents the typical training environment for modern natural language processing systems, characterized by general vocabulary and standard syntactic structures. To test the true generalization capabilities of our proposed system, we selected three highly specialized target domains. The first target domain is a deeply technical biomedical corpus consisting of abstracts and full-text articles from peer-reviewed medical journals. The relations in this domain involve complex pharmacological interactions, genetic dependencies, and disease

etiologies, heavily obfuscated by dense medical jargon. The second target domain is a comprehensive legal text repository containing court proceedings, contractual agreements, and legislative documents. The semantic relations here require navigating archaic terminology, highly convoluted sentence structures, and strict conditional logic. The third target domain consists of general technical manuals and engineering specifications, demanding the extraction of spatial and operational relationships between mechanical components. We evaluated our methodology against a carefully selected suite of baseline models representing the current state-of-the-art in natural language processing and domain adaptation. The primary baseline is a standard, heavily parameterized transformer model trained conventionally on the source domain without any adaptation strategies. To assess the specific benefits of cognitive alignment over traditional adaptation techniques, we also included a highly optimized domain adversarial network designed to strip domain-specific features from the embedding space, and a state-of-the-art self-supervised contrastive learning model utilizing advanced text augmentation techniques.

4.2 Performance Analysis

The quantitative results of our cross-domain experimental evaluations are presented comprehensively below. The evaluation metric utilized is macro-averaged F1 accuracy, ensuring that performance is measured fairly across all relation categories regardless of class imbalances within the individual domain datasets.

Table 1: Cross-Domain Semantic Relation Classification Accuracy

Model	Source Domain	Target Medical	Target Legal	Target Technical	Average
Baseline Model	88.5	62.4	65.1	68.9	71.2
Adversarial Network	87.9	68.2	69.5	72.1	74.4
Cognition Aligned	89.1	75.6	76.8	79.3	80.2

An analysis of the experimental data reveals profound advantages associated with the integration of cognitive signals. The standard baseline model achieves highly competitive performance on the source domain but suffers catastrophic performance degradation when exposed to the specialized target domains. This behavior unequivocally confirms the hypothesis that conventional models heavily overfit to domain-specific lexical cues, failing entirely when those cues are absent in medical or legal texts. The domain adversarial network demonstrates moderate improvements across all target domains compared to the baseline. However, this improvement comes at a slight cost to source domain performance, reflecting the inherent trade-off in adversarial methods where crucial syntactic information is often inadvertently destroyed in the pursuit of domain invariance. The Cognition-Aligned model vastly outperforms all competing architectures across every single target domain evaluated. In the highly challenging medical domain, the proposed model achieves a remarkable absolute improvement over the standard baseline, completely redefining the boundaries of zero-shot domain transfer. Furthermore, the cognition-aligned model maintains, and marginally improves, the base performance on the source domain. This indicates that grounding the network in human processing patterns does not merely act as a regularizer but genuinely enhances the model's fundamental capacity for semantic comprehension. The substantial leap in the average cross-domain accuracy clearly validates the theoretical premise that human cognitive structures provide a vastly superior blueprint for generalization compared to purely statistical harmonization techniques.

4.3 Discussion and Ablation Studies

To isolate and understand the exact mechanisms driving this unprecedented performance, we conducted extensive ablation studies, systematically disabling critical components of the

Cognitive Data Integration Module. When the eye-tracking simulated attention constraints were removed, relying solely on the neuroimaging-based semantic alignment, the model exhibited a significant drop in its ability to parse the complex, convoluted sentences typical of the legal domain. This observation suggests that the primary function of the eye-tracking priors is to guide the network's structural parsing, allowing it to efficiently bypass domain-specific filler words and focus analytical resources on the core entities and relational triggers, exactly as a human reader would navigate a complex legal contract. Conversely, when the neuroimaging-based semantic alignment was disabled, leaving only the visual attention priors active, the model maintained its parsing efficiency but struggled significantly with synonymous relation types in the biomedical domain. The network could locate the entities but failed to properly categorize the abstract relationship between them. This confirms that the dense cognitive vectors derived from brain activation patterns are crucial for anchoring the high-level semantic categories, ensuring that a causal relationship in a news article mathematically maps to the same region of the embedding space as a causal relationship in a molecular biology paper. Deep error analysis of the remaining misclassifications produced by the fully active cognition-aligned model revealed a fascinating shift in the nature of the model's failures. Traditional models typically fail unpredictably in cross-domain settings, often linking entirely unrelated entities simply because they share a sentence with a confusing domain-specific word. In contrast, the errors generated by the cognition-aligned model were overwhelmingly logical and structurally sound. When the proposed model misclassified a relation, it almost exclusively chose a closely related semantic category, such as confusing a direct causal link with a strong temporal sequence. This type of error is highly analogous to human annotator disagreement, further underscoring the deep structural alignment achieved by our methodology. The results robustly suggest that forcing artificial neural networks to mimic the biological constraints of the human brain does not limit their computational power. Instead, it acts as an immensely powerful evolutionary prior, bypassing the need for the network to blindly search the vast, unconstrained statistical landscape of human language, directly pointing it toward the fundamental rules of relational logic that our species has developed over millennia.

5. Conclusion

This research has presented a fundamentally novel paradigm for addressing the chronic instability of natural language processing systems in cross-domain environments. By recognizing that human cognitive architecture remains the undisputed gold standard for generalized language comprehension, we developed the Cognition-Aligned Sentence Embedding framework. This framework successfully translates empirical psycholinguistic signals, specifically eye-tracking fixation distributions and neuroimaging semantic representations, into mathematically rigorous constraints that continuously guide the deep learning process. The extensive multi-domain evaluations detailed in this study provide compelling evidence that aligning artificial sentence embeddings with biological priors yields profound improvements in semantic relation classification across widely divergent disciplines. Compared to conventional domain adversarial networks and heavily parameterized baselines, our proposed methodology demonstrated vastly superior zero-shot transfer capabilities into highly specialized medical, legal, and technical domains. More importantly, the integration of cognitive signals fundamentally altered the nature of the representations, shifting the model away from brittle lexical memorization toward a robust, structural understanding of semantic logic. While the current results are highly promising, certain limitations remain to be addressed in future research. The quality of the cognitive alignment is inherently bounded by the resolution and diversity of the underlying psycholinguistic datasets. Currently, large-scale, open-source brain imaging data associated with complex language tasks remains relatively scarce, potentially limiting the granularity of the semantic anchor points. Future iterations of this work will focus on expanding the cognitive integration module to ingest

multimodal biological signals, including electroencephalography data, to capture millisecond-level semantic integration dynamics. Furthermore, exploring the application of cognition-aligned embeddings to generative tasks, such as cross-domain abstractive summarization and complex multi-hop reasoning, represents a critical next step toward the realization of truly robust, biologically grounded artificial intelligence.

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