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Bayes Intuit: A Neural Framework for Intuition-Based Reasoning

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Abstract

While most supervised learning algorithms follow rational pathways, efficiently mapping inputs to outputs and optimizing performance with impressive precision, they tend to overlook a quieter, often unconscious form of judgment: the kind humans rely on to navigate ambiguity, not through logic, but through intuition. We propose BayesIntuit, a reasoning neural framework that offers a novel alternative by emulating human intuition by learning to negotiate the balance between current perception and prior experience, guided by a self-adjusting sense of epistemic confidence in supervised classification tasks. BayesIntuit integrates a statistical inference module that captures signals of doubt, a dynamic memory system that informs current learning through accumulated context, and an adaptive control signal generated stochastically to reflect confidence in the blending of memory and perception, which also acts as an implicit form of learning regularization. BayesIntuit moves neural models beyond static data interpretation, toward a more adaptive, context-aware mode of reasoning, one that mimics the intuitive judgment humans deploy, contributing to the pursuit of interpretable, human-aligned AI, where reasoning is not only effective, but traceable.

Keywords
Data Science, Artificial Intelligence, Neural Networks, Human Intuition Modeling, Epistemic Uncertainty.

1. Introduction
Machine learning models have achieved strong performance across diverse tasks, yet they often lack cognitive reasoning and intuitive decision-making under uncertainty. This limitation has motivated advances in uncertainty-aware learning, particularly in high-stakes domains such as healthcare (Liebig et al. 2017), autonomous driving (Kendall and Gal 2017), and scientific modeling (Andra et al. 2021). Within this context, Bayesian neural networks (BNNs) offer principled tools for capturing epistemic uncertainty (MacKay 1992; Gal and Ghahramani 2016). In parallel, a complementary line of research has shown that gradient-based learning dynamics in deep networks naturally bias toward simpler, more generalizable solutions, even in the absence of explicit regularization. For example, deep linear networks tend to converge to low-rank solutions in matrix factorization (Gunasekar et al. 2018), and in classification tasks, gradient descent often leads to maximum-margin solutions without directly optimizing for margin (Soudry et al. 2018). These forms of implicit regularization support generalization without relying on techniques such as weight decay or dropout (Srivastava et al. 2014). However, such mechanisms operate exclusively in parameter space and do not account for the reuse of contextual knowledge. We propose a complementary perspective: can regularization emerge from the reuse of semantically relevant past experiences, adaptively gated by uncertainty?

We introduce BayesIntuit, a cognitively inspired neural framework that integrates memory, uncertainty, and interpretability directly into the learning architecture. Rather than relying solely on parameter updates, BayesIntuit maintains a Dynamic Memory Bank that stores latent representations of prior instances, clustered and indexed via a trainable projection space. At the heart of the model lies alpha, a learned gating coefficient modeled via a Beta distribution, which modulates the influence of retrieved memories on current predictions. This mechanism plays a

dual role: as a semantic regularizer, it softly blends current predictions with past representations; as an interpretability signal, it reveals the degree of semantic continuity between instances in latent space. Unlike traditional regularizers that constrain weights, alpha shifts part of the inductive bias from parameter space to representation space, guiding how contextual knowledge is reused.

BayesIntuit builds upon research in memory-augmented networks (Santoro et al. 2016; Rae et al. 2021), Bayesian inference (MacKay 1992; Neal 1995), and curriculum learning (Bengio et al. 2009), while introducing a novel interaction between semantic similarity, epistemic uncertainty, and memory-based reasoning. The architecture is encoder-agnostic and operates atop attention-equipped models, whether sequential (e.g., LSTM) or parallel (e.g., Transformer), as attention is essential for computing semantic context, retrieving relevant memories, and modulating alpha. To evaluate BayesIntuit under controlled yet contrasting conditions, we construct two binary classification test beds. Domain 1 contains class-balanced and semantically aligned data, providing an ideal setting for interpretable memory reuse. In contrast, Domain 2 introduces heterogeneity and severe class imbalance. This contrast enables a focused investigation of how alpha and memory behave across different data regimes.

Finally, fairness failures in machine learning often stem from abstraction error, the mistaken assumption that equitable outcomes can be guaranteed by optimizing algorithmic objectives in isolation from social context (Selbst et al. 2019). While BayesIntuit does not explicitly enforce fairness constraints, it contributes to shifting the modeling paradigm toward epistemically grounded and interpretable architectures. Through its dynamic gating mechanism, BayesIntuit facilitates human-centered understanding of model behavior, enabling practitioners to interrogate how memory reuse and latent assumptions influence predictions.

1.1 Objectives

To design a neural architecture that mimics human intuition reasoning by integrating dynamic memory retrieval, uncertainty-aware gating, and semantic alignment into the learning process. The model introduces a learnable gating parameter, alpha, modeled via Beta distribution, to modulate the incorporation of retrieved memory representations. This mechanism serves both as an implicit regularizer and an interpretability signal in latent space. The framework includes a trainable projection layer for semantic memory clustering and operates atop attention-equipped encoders (e.g., LSTM, Transformer), where attention mechanisms support contextual representation and alpha modulation.

1.1.1 Summary of Novel Contributions

- A modular, cognitively inspired neural framework that integrates current perception, episodic memory, and epistemic uncertainty within a unified architecture. BayesIntuit decouples the reasoning mechanism from the encoder backbone, enabling compatibility with both sequential (e.g., LSTM) and parallel (e.g., Transformer) architectures. This encoder-agnostic design supports extensibility while preserving semantic alignment and interpretability across diverse input representations.
- A learned parameter, alpha, that implements a novel form of implicit regularization by modulating the integration of retrieved memory representation at the feature level. Rather than imposing explicit constraints on model parameters, alpha operates in representational space, enabling data-dependent control over past knowledge reuse. This mechanism complements gradient-based inductive biases and promotes generalization through semantically grounded memory regulation.
- Alpha as an interpretable epistemic gate, modulating memory reuse based on semantic alignment. High values reflect strong latent similarity; low values may indicate novelty early in training or confident self-sufficiency as learning stabilizes.
- A learnable Dynamic Memory Bank that supports semantic retrieval via a trainable projection layer, replacing static techniques like PCA. It adaptively clusters and retrieves latent representations based on contextual similarity in high-dimensional space, maintaining semantic coherence across both LSTM and Transformer encoders.

2. Literature Review

In the pursuit of trustworthy neural systems, prior research has incorporated Bayesian principles into the output layers of deep learning models to estimate predictive uncertainty. Foundational work introduced Bayesian inference to mitigate overfitting (MacKay 1992), later extended to neural networks for capturing epistemic uncertainty (Neal 1995). The Bayesian Last Layer approach (Fiedler and Lucia 2023) advances this idea by localizing uncertainty modeling to the final layer, improving extrapolation in low-data regimes while maintaining computational efficiency. BayesIntuit adopts this principle by embedding a Bayesian output layer to produce global uncertainty estimates,

however unlike prior models, this component operates within a broader architecture that integrates memory retrieval and semantic gating.

In parallel, memory-augmented architectures have advanced neural models that leverage past experiences. Recent transformer-based models have also begun integrating retrieval mechanisms to extend reasoning with latent memory. RETRO (Borgeaud et al. 2022) enhances Transformer predictions by retrieving similar documents using dense nearest-neighbor search and integrating them via fusion layers. Similarly, Perceiver IO (Jaegle et al. 2021) generalizes Transformer architectures to flexibly map structured inputs to outputs through latent attention bottlenecks. While these methods extend context through external memory or latent routing, they do not incorporate epistemic reliability or semantic modulation. In contrast, BayesIntuit complements memory-augmented design with a learnable alpha parameter that gates memory reuse based on both similarity and uncertainty, enabling data-driven control over retrieval even within Transformer backbones.

Santoro et al. (2016) proposed a meta-learning model with a content-based addressing mechanism relying on cosine similarity between current inputs and stored memory slots. However, this architecture frequently overwrites memory in a key-value fashion without offering explicit uncertainty estimation or semantic interpretability, and it operates in the original feature space without a trainable projection for deeper alignment. In contrast, BayesIntuit projects both attention-based current representations and memory vectors into a shared latent space using a deep projection layer, enabling meaningful semantic alignment and grounding interpretability in high-dimensional structures. Rae et al. (2021) tackled computational scalability with sparse read/write mechanisms but did not incorporate epistemic reliability or semantic interpretability. Meanwhile, probabilistic models like those from Zhou et al. (2022) and Ullman et al. (2017) rely on static priors or rule-based reasoning, lacking adaptability for evolving semantic understanding. Sukhbaatar et al. (2015) introduced End-to-End Memory Networks with fixed memory slots and iterative attention hops, yet their system cannot evolve or modulate memory use based on uncertainty. These foundational contributions have shaped the design of BayesIntuit's Dynamic Memory Bank, which advances the field by unifying probabilistic modulation, learned semantic projections, and dynamic memory evolution to mirror the adaptive, intuition-driven nature of human cognition, which is fast, experienced-informed, and responsive to novelty, as discussed in dual-process theory (Kahneman 2011).

Building on the role of alpha as a form of implicit regularization, recent research has increasingly highlighted implicit regularization as a key driver of generalization in deep learning. Gradient descent in overparameterized linear networks has been shown to bias solutions toward low-rank or minimum-norm representations (Gunasekar et al. 2018), while classification tasks often reveal an implicit max-margin bias (Soudry et al. 2018). These effects emerge without explicit penalties, suggesting that optimization trajectories naturally align with certain inductive biases. Building on this insight, newer approaches have sought to design explicit regularization methods that replicate or enhance these biases, such as explicit low-rank penalties in deep linear models (Zhao 2022), or the use of momentum gradient descent (MGD), which introduces an implicit sparsity bias leading to improved generalization in deep networks (Wang et al. 2023). Other work has proposed Bayesian model selection strategies that jointly infer network depth and dropout regularization (K.C. et al. 2021), enabling architectural adaptation based on data. Similarly, Variational Structured Dropout (Nguyen et al. 2021) employs orthogonal transformations to learn structured approximations, enhancing both scalability and flexibility in Bayesian neural networks.

However, these methods operate strictly in parameter space or impose architectural structure; none offer a learned gating mechanism driven by semantic memory alignment. This gap is addressed by the alpha mechanism in BayesIntuit, which provides data-driven, interpretable modulation based on epistemic reliability. In contrast to dropout methods like Gal and Ghahramani (2016), which approximate Bayesian inference via stochastic masking, alpha modulates the integration of memory in a semantically grounded and context-aware manner. Extending this line of work, BayesIntuit integrates a curriculum-based adaptive regularization strategy (Bengio et al. 2009; Hacohen and Weinshall 2019) that schedules the influence of epistemic penalties across training epochs, fostering early flexibility and late-stage robustness, especially valuable in domains with shifting data distributions.

Recent advances in uncertainty modeling, memory-augmented neural architectures, and implicit regularization have laid the groundwork for more interpretable and cognitively inspired machine learning. Foundational work in Bayesian neural networks informs the integration of a Bayesian output layer in BayesIntuit. Meanwhile, prior studies in external memory mechanisms inspired the design of the Dynamic Memory Bank, which evolves semantically relevant latent representations to support context-aware reasoning. Finally, recent explorations in implicit regularization and

optimization dynamics underpin the introduction of the alpha parameter, a learnable, epistemic gating mechanism that not only modulates memory retrieval based on semantic similarity and reliability, but also contributes to a novel, interpretable form of regularization. Together, these components form the architectural and conceptual pillars of BayesIntuit's contribution to interpretable, memory-enhanced, and uncertainty-aware machine learning.

3. Methods

3.1 Dynamic Memory Bank

In standard sequence models such as LSTMs and Transformer-based architectures, attention mechanisms operate over the current input to compute contextual representations (Hochreiter and Schmidhuber 1997; Vaswani et al. 2017). BayesIntuit extends this mechanism by introducing a Dynamic Memory Bank that persistently stores attention-derived latent vectors from previous instances. These representations are projected into a shared semantic space via a learned projection network, enabling retrieval based on cross-instance alignment. This architecture supports memory reuse beyond local temporal or positional dependencies, enriching current representations with prior context in a semantically structured manner. The architecture of the Dynamic Memory Bank consists of the following components:

3.1.1 Memory Storage. Each input instance $\boldsymbol{x_i}$ generates a latent representation $\boldsymbol{h_i} \in \boldsymbol{R^d}$ through the attention encoder. Instead of encoding all knowledge into network weights, BayesIntuit externalizes part of this information by dynamically growing a memory bank: $\boldsymbol{M} = \{(\boldsymbol{i}, \boldsymbol{h_i})\}$. This creates a dynamic sample from the evolving latent feature distribution.

3.1.2 Dynamic Semantic Clustering. Memories are dynamically organized into evolving semantic structures through unsupervised clustering over learned latent representations, allowing the memory space to continuously adapt to the distributional properties of the data. Re-clustering is triggered periodically as training progresses, preserving relevance over the evolving features spaces.

3.1.3 Learned Semantic Projection (Deep Cluster vs PCA). Rather than relying on static dimensionality reduction (e.g., PCA), the Dynamic Memory Bank learns a nonlinear projection g_ϕ: $R^d \longrightarrow R^k$via a deep neural network: $z_i = g_\phi(h_i)$, where z_i is the projected feature and k is the lower- dimensional embedding size. Instead of assuming directions of maximum variance are meaningful (PCA assumption), the direction of maximum semantic utility is learned, optimizing clustering for downstream prediction relevance.

3.1.4 Memory Retrieval and Reliability score Based on Semantic Proximity. Given a query, the Dynamic Memory Bank retrieves a memory from the same semantic cluster, approximating nearest-neighbor retrieval in the learned latent space. Cosine similarity between retrieved memory and current representation provides a reliability score. Cosine similarity is well-suited for this purpose, since it measures the angle between two vectors while being invariant to their magnitude. This property is crucial in high-dimensional spaces, where attention outputs may vary in scale due to token importance or model uncertainty but preserve their semantic directionality.

3.1.5 Scalability and Efficiency of the Dynamic Memory Bank. To manage scalability on larger datasets, the Dynamic Memory Bank in BayesIntuit incorporates multiple design choices that maintain computational efficiency. First, the total memory size is capped via the *memory_bank_size* parameter (default 8000), and older memory entries are pruned once this limit is exceeded, ensuring memory footprint remains bounded regardless of dataset scale. Second, clustering operations, used to organize memory into semantic groups, are triggered conditionally based on a cluster threshold of new additions, rather than at every training step. This amortizes the computational cost across epochs. Third, clustering is performed using a lightweight deep projection layer and batched vector operations, and the retrieval process is limited to nearest cluster neighbors, avoiding full-bank comparisons. Together, these mechanisms enable BayesIntuit to maintain a dynamic yet efficient memory system, making it compatible with larger-scale training regimes without introducing prohibitive overhead.

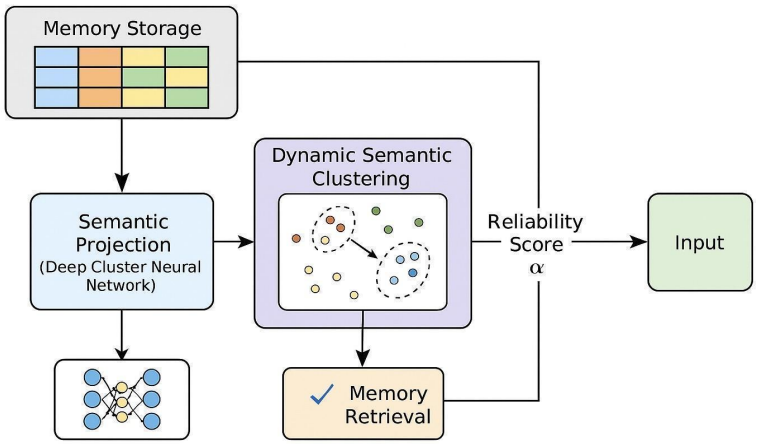

Figure 1. The Dynamic Memory Bank architecture

Figure 1 illustrates the architecture of the Dynamic Memory Bank. Latent representations from past instances are stored in memory, projected into a shared semantic space via a Deep Cluster Neural Network, and dynamically clustered based on latent similarity. The most relevant memory is retrieved and assigned a reliability score, which modulates its contribution to current predictions through the learned gating coefficient Alpha.

3.2 BayesIntuit's Alpha Estimation

After retrieving a semantically relevant memory vector from the Dynamic Memory Bank, BayesIntuit must decide to what extent this retrieved information should influence the current decision. This modulation is governed by the alpha mechanism, a cognitively inspired module that evaluates the semantic alignment between the current attention vector and the retrieved memory and then quantifies the reliability of reuse. Rather than applying a fixed heuristic, BayesIntuit learns a dynamic reuse coefficient (alpha) that adapts over time and instances, enabling a form of selective memory integration akin to human intuition under uncertainty.

3.2.1 Semantic Similarity Estimation. Before estimating memory reuse, BayesIntuit computes the cosine similarity between the attention-derived representation of the current input and the retrieved memory vector from the Memory Bank. While a previous similarity score is already used by the memory bank to estimate reliability during retrieval, BayesIntuit recomputes it here for a distinct interpretive purpose. Specifically, the model standardizes this score (zero mean, unit variance across the batch) to ensure stable gradients and numerical consistency, then feeds it into the *HybridAlphaHead* alongside the query and memory vectors. This normalized similarity becomes a learned input to the alpha mechanism, modulating the reuse belief (*alpha_mean*) and its confidence (*alpha_concentration*).

3.2.2 Hybrid Alpha Estimation. BayesIntuit employs a *HybridAlphaHead* to compute two key quantities: *alpha_mean* and *alpha_concentration*. This module takes as input the concatenation of the attention output, retrieved memory vector, and their cosine similarity. By projecting this triplet through a feedforward layer, it learns to estimate the epistemic stance of the model regarding memory reuse. The *alpha_mean* determines how much prior knowledge should influence the current prediction, while *alpha_concentration* scales the certainty around that decision, governing the sharpness of the resulting Beta distribution. This design enables BayesIntuit to model interpretable, data-dependent confidence in its own reasoning.

3.2.3 Bayesian Alpha Sampling. By sampling from a Beta distribution parameterized as $Beta(\alpha_1, \alpha_2)$, where α_1 = *alpha_mean * concentration*, and α_2 = *(1 - alpha_mean) * concentration*, the model introduces stochasticity that regularizes memory routing by avoiding overcommitment, propagates epistemic uncertainty through the network, and enhances robustness by encouraging smoother, generalizable reuse policies. This sampling mechanism enables uncertainty-aware intuition, blending belief with controlled exploration.

3.2.4 Final Alpha Computation and Reliability-Aware Modulation. After sampling a preliminary α value from the Beta distribution defined by the predicted *alpha_mean* and *alpha_concentration*, BayesIntuit adjusts this value based on the reliability of the retrieved memory. This reliability score, derived from the memory bank's internal similarity

metrics, reflects how trustworthy the retrieved memory is for the current instance. The final α is computed as a weighted interpolation: $\alpha = reliability * \alpha_{beta} + (1 - reliability) * 0.5$. This blending ensures that unreliable memories default toward neutrality (α ≈ 0.5), reducing their influence, while reliable memories allow α to reflect the full epistemic reasoning encoded in the sampled Beta value. This mechanism enables BayesIntuit to propagate uncertainty while maintaining robustness against noisy or low-confidence memory matches.

3.2.5 Prediction Integration via Memory-Weighted Composition. In the final decision stage, BayesIntuit combines current perception (*attn_output_processed*) with the retrieved memory vector, modulated by the reliability-aware alpha. Specifically, the combined representation is calculated as: *combined_output = attn_output + (alpha * retrieved_memory*). This formulation acts as a dynamic residual connection where α determines the degree of memory reuse. A high α intensifies memory contribution, while a low α prioritizes current context. The combined output is then passed through a Bayesian fully connected layer (*bayes_fc*), enabling predictive distributions to incorporate both perceptual input and epistemically weighted experience.

3.2.6 Semantic Consolidation through Soft Memory Plasticity. As training progresses, attention vectors are refined through gradient-based learning, while memory vectors are updated via the rule: updated memory equals the attention vector plus alpha times the previous memory. Since alpha decreases over time (often stabilizing around 0.1 -- 0.2), the model gradually relies less on past memory, reflecting increased confidence in its learned representation. Importantly, memory updates are not guided by gradients but by semantic similarity, allowing the model to replace earlier, noisier memories with more aligned and task-relevant ones. This mechanism mirrors soft memory plasticity as described in neuroscience (Citri and Malenka 2008), where synaptic traces are not rigidly overwritten but refined through contextual consistency. BayesIntuit thus exhibits a form of computational memory consolidation driven by epistemic alignment rather than loss minimization alone.

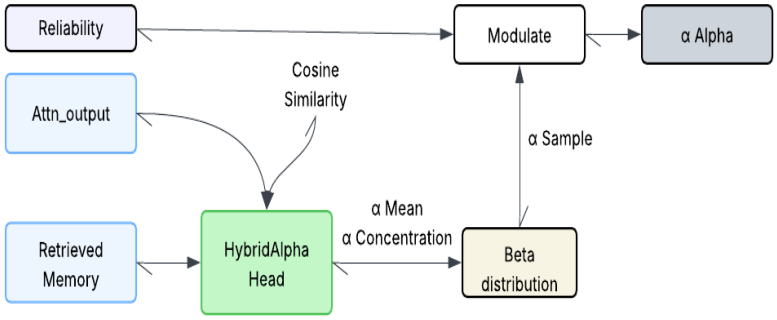

Figure 2. Alpha mechanism: epistemic reasoning via similarity, confidence, and reliability

Figure 2 illustrates the Alpha Mechanic in BayesIntuit: Retrieved memory, attention output, and cosine similarity are processed by the *HybridAlphaHead* to estimate belief and confidence. A value is sampled from the resulting Beta distribution and modulated by reliability, yielding a final α that adaptively controls memory integration.

3.3 Curriculum–Based Regularization Strategy

To guide the modulation of alpha α parameters, we implemented a curriculum-based regularization strategy. The loss function integrates four components: a standard likelihood loss supervising the main prediction objective, a KL divergence term between the posterior and prior distributions of the weights in the Bayesian output layer, a KL divergence between the learned alpha distribution (parameterized by α_1 and α_2) and a prior Beta, usually (2, 8), in case we need to bias early alpha behavior; and an entropy regularization term encouraging confident, low-entropy decisions about alpha when enough evidence accumulates.

$$l_{total} = l_{likelihood} + \lambda_{KL} lKL + (\lambda_{\alpha-KL}) l_{\alpha} - KL + \lambda_{entropy} l_{entropy}$$

The weights $\lambda_{KL}, \lambda_{\alpha-KL}, \lambda_{entropy} \in R_{\geq 0}$ are hyperparameters controlling the contribution of each term. These are adjusted dynamically over epochs via curriculum-based schedules. While alpha begins capturing useful semantic proximity in early epochs, enabling meaningful modulation of retrieved memory, our curriculum-based regularization

is designed to consolidate and refine these patterns over time. As alpha becomes more informative, the KL and entropy terms strengthen the reliability and calibration of its role.

4. Data Collection

To assess the generalization and adaptability of BayesIntuit, we gathered and preprocessed two datasets: Domain 1 and Domain 2, composed of AI-generated (label = 0) and human-written (label = 1) texts, tokenized into sequences of up to 5,000 vocabulary indices. Domain 1 provides a balanced binary classification setting (9,750 samples per class), with human texts averaging 27 tokens (SD ≈ 12.6) and AI texts averaging 52 tokens (SD ≈ 38.5), both exhibiting low positional entropy (last-token entropy ≈ 0.59 for AI texts) and moderate lexical diversity (≈ 21–31 unique tokens per sample). In contrast, Domain 2 introduces greater statistical and semantic complexity: it is highly imbalanced (12,750 AI vs. 2,150 human samples) and features substantially longer sequences (mean ≈ 133–175 tokens; SD > 100), higher token repetition, and richer vocabulary usage (≈ 65–83 unique tokens per text). Notably, after preprocessing and truncation, the longest sequence in Domain 1 spans 238 tokens, while in Domain 2 it reaches 384 tokens, highlighting not only increased content density but also placing higher demands on model capacity and attention mechanisms. Additionally, Domain 2's AI samples originate from multiple generation models, increasing intra-class variance. The combination of length variability, token entropy (≈ 5.79), and class asymmetry in Domain 2 makes it a stringent benchmark for evaluating performance under distributional shift and epistemic uncertainty.

5. Results and Discussion

5.1 Numerical Results

We implemented a bi-directional LSTM with global attention, and a Transformer encoder with chunked input and positional encoding to test architectural adaptability. To ensure fair comparisons, we apply bootstrap resampling, imbalance-aware metrics (in Domain 2), and a composite loss function combining likelihood and epistemic regularization.

5.1.1 Performance of Baseline and BayesIntuit Architectures across Domains and Encoders.

Table 1. Comparative performance of baseline and BayesIntuit architectures across domains and encoders

Setting	Accuracy	F1 Score	ROC-AUC	Model Uncertainty	Alpha Mean trend
LSTM (baseline) - Domain 1	0.947	0.95	0.93	-	-
LSTM + BayesIntuit - Domain 1	0.952	0.95	0.98	0.0479	0.27 → 0.001
LSTM (baseline) - Domain 2	0.862	0.87	0.85	-	-
LSTM + BayesIntuit - Domain 2	0.866	0.85	0.92	0.0316	0.30 → 0.001
Transformer (baseline) - Domain 1	0.946	0.95	0.97	-	-
Transformer + BayesIntuit - Domain 1	0.930	0.93	0.97	0.0773	0.22 → 0.001
Transformer (baseline) - Domain 2	0.816	0.82	0.88	-	-
Transformer + BayesIntuit - Domain 2	0.810	0.82	0.88	0.0559	0.28 → 0.001

Table 1 shows the comparative performance of Baseline and BayesIntuit architecture across domains and encoders. Across all configurations, BayesIntuit consistently enhances generalization, as demonstrated by improved ROC-AUC scores across both LSTM and Transformer architectures in Domains 1 and 2. ROC-AUC increases from 0.93 to 0.98 in LSTM-Domain 1 and from 0.85 to 0.92 in LSTM-Domain 2, indicating stronger discrimination under semantic uncertainty. Unlike accuracy or F1, ROC-AUC provides a threshold-independent evaluation and remains robust to class imbalance, making it a more reliable generalization metric. While accuracy and F1 scores remain comparable, BayesIntuit's true advantage emerges through calibrated uncertainty estimates and alpha dynamics. In all settings, alpha converges from moderate initial values (0.22–0.30) to near-zero (~0.001), reflecting a shift from early reliance on retrieved memory to more self-sufficient representations. Notably, BayesIntuit also enables well-calibrated uncertainty estimation (e.g., 0.0479 in LSTM-D1, 0.0559 in Transformer-D2), even in heterogeneous domains where baseline Transformers fail. These findings confirm BayesIntuit as a modular, encoder-agnostic architecture whose implicit semantic regularization leads to smoother convergence, stronger generalization, and interpretable behavior beyond conventional performance metrics.

5.1.2 Interpreting Alpha Confidence Across Domains. Alpha concentration in BayesIntuit offers more than probabilistic control, it functions as an epistemic lens into the model's internal confidence. When alpha concentration is high, the model is certain about how much to rely on memory; when low, it expresses hesitation and keeps its reasoning flexible. This behavior is not random: it mirrors the structure of the input domain. In our experiments, Domain 1 consistently showed higher alpha concentration than Domain 2, across both LSTM (7.00 vs. 6.01) and Transformer (4.90 vs. 2.94) architectures. This suggests that BayesIntuit interprets Domain 1 as more stable and predictable, while Domain 2 triggers epistemic caution. Notably, Transformers showed overall lower alpha concentration, highlighting their more distributed and ambiguity-sensitive reasoning. Thus, alpha concentration allows us to infer both domain complexity and model confidence, turning an internal mechanism into a clear interpretive signal. It's a step toward self-explaining models, where uncertainty becomes not a weakness, but a window into how the model thinks.

5.1.3 Vector Norms and Reliability in the Dynamic Memory Bank. We conducted a quantitative analysis of the Dynamic Memory Bank's retrieval behavior by measuring the correlation between the product of query and memory vector norms and the resulting retrieval reliability scores. In Domain 2 (Transformer backbone), we observed a statistically significant positive Pearson correlation of $\rho = 0.63$ ($p < 0.001$). The average reliability for low-energy retrievals (norm product < 50) was 0.18, compared to 0.47 for high-energy cases (norm product > 200). These results indicate that the reliability estimate produced by the memory mechanism reflects not only semantic alignment (via cosine similarity), but also vector strength, which acts as a proxy for epistemic certainty. This behavior echoes neurocognitive models where memory trace strength modulates confidence in recall (Citri and Malenka 2008).

5.2 Graphical Results

5.2.1 Visual evidence of Implicit Regularization in BayesIntuit.

Figure 3 compares training and validation loss trajectories for the baseline Transformer and the BayesIntuit architecture, over 10 epochs on Domain 2 and Domain 1. While both models reduce their training loss consistently, the baseline model shows greater fluctuations in validation loss, suggesting overfitting or instability in its generalization process. In contrast, BayesIntuit exhibits a smoother, more synchronized loss trajectory, with validation loss closely tracking training loss across epochs. This stability is indicative of the implicit regularization effect of alpha, which modulates memory reuse based on semantic reliability. The consistent convergence supports our claim that alpha acts as a semantic stabilizer, especially under distributional complexity. The final generalization performance, higher ROC-AUC and lower uncertainty, confirms that BayesIntuit learns more robust decision boundaries without compromising training efficiency.

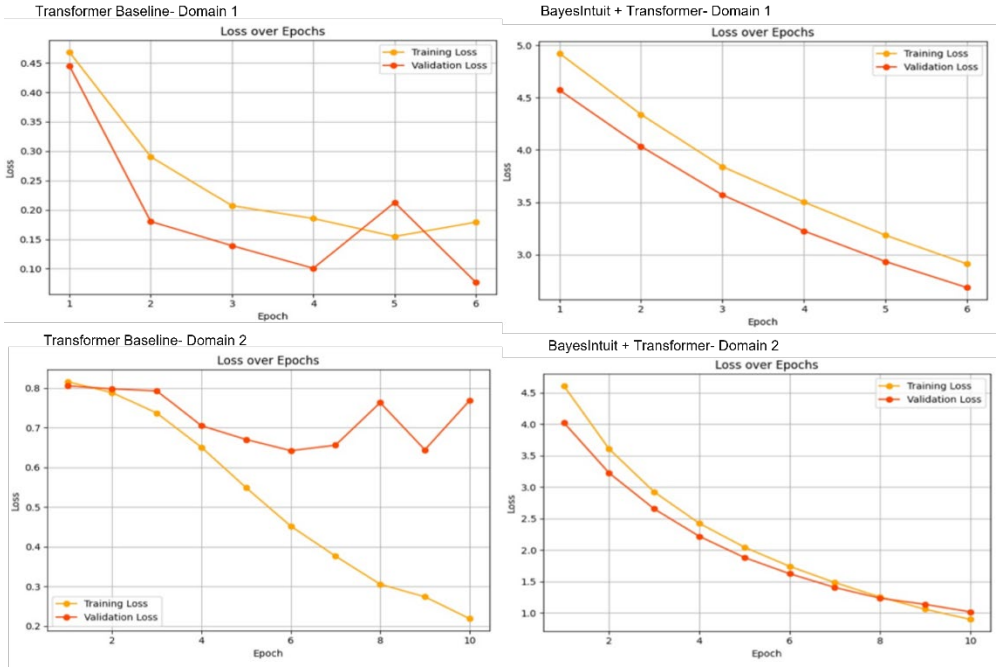

Figure 3. Training and validation loss curves: Transformer vs. Transformer +BayesIntuit across domains

5.2.2 Interpretability of the Alpha Mechanism.

Figure 4 presents a binned heatmap showing how the final alpha value varies as a function of both cosine similarity and reliability. As expected, higher reliability and higher semantic similarity lead to higher alpha values, indicating a stronger influence of memory in the final decision. In contrast, regions with low reliability or lower semantic similarity yield significantly lower alpha, reflecting the model's internal caution in blending memory with attention. This co-modulation shows that BayesIntuit does not treat memory as uniformly valuable; instead, it performs a joint epistemic evaluation, accepting memory only when both semantic alignment and trust converge. This provides direct visual evidence of BayesIntuit's interpretable gating mechanism, where both contextual similarity and internal reliability shape how much weight is given to past experiences.

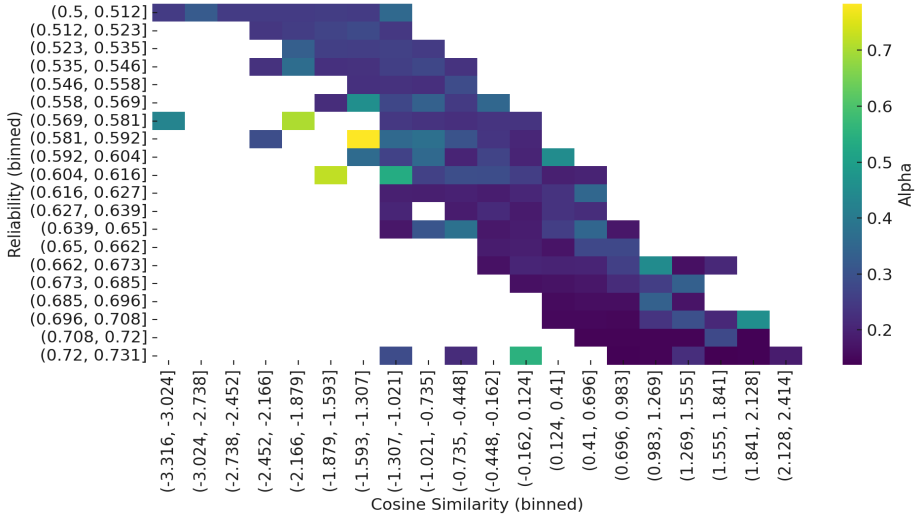

Figure 4. Alpha values by cosine similarity and reliability

5.2.3 Alpha Concentration as a Certainty Modulator.

Figure 5 illustrates the relationship between the expected blending weight (*alpha_mean*) and the sampled value (*alpha_beta*) across two data domains, highlighting the role of *alpha_concentration* as a modulator of epistemic confidence. In Domain 1 (simpler and more predictable), sampled values follow more closely the expected ones, especially when *alpha_concentration* is high, reflecting stable and confident memory-attention blending. In Domain 2 (ambiguous and variable), lower concentrations lead to greater dispersion from the identity line, signaling increased uncertainty and more stochastic behavior. This contrast demonstrates how BayesIntuit modulates trust: *alpha_concentration* becomes an interpretable signal of how confidently the model integrates past and present evidence. Moreover, in high-stakes settings such as medical diagnosis or credit risk assessment, this mechanism serves as an interpretable tool. A high *alpha_concentration* signals that the model trusts its weighting of prior knowledge and current evidence. Conversely, a low concentration serves as a built-in alert, a sign of epistemic caution, prompting human review or further evaluation.

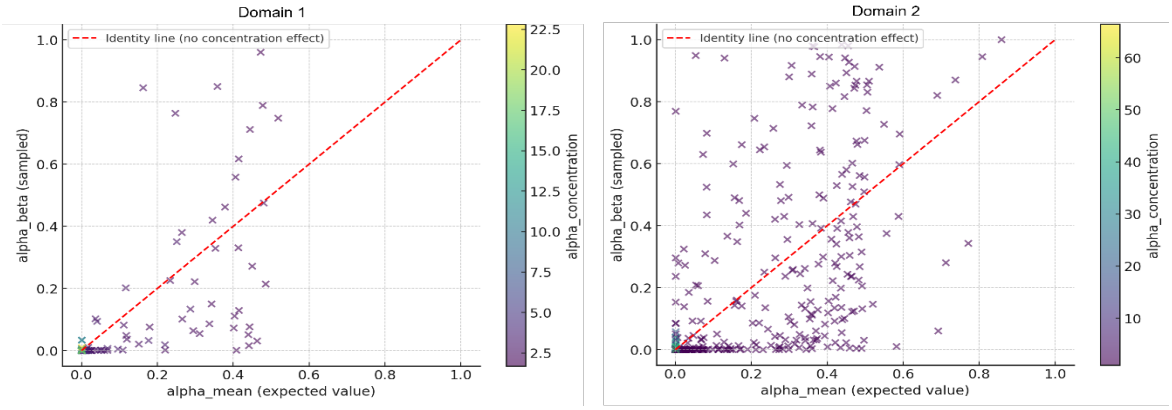

Figure 5. Impact of alpha concentration on sampling behavior across domains: alpha_mean vs alpha_beta

5.2.4 Reliability as an Interpretable Correction Mechanism. Figure 6 illustrates the relationship between reliability and the corrective distance $|\alpha - \alpha_{beta}|$, capturing how much the final alpha value is adjusted away from the sampled value due. In Domain 1 (left), a strong negative correlation emerges: when reliability is high, the final alpha closely matches the sampled α_{beta}, whereas lower reliability leads to stronger deviation, pulling alpha toward neutrality (approximately 0.5). In Domain 2 (right), this pattern remains, but with greater dispersion, reflecting more epistemic noise. This behavior confirms that reliability acts as an interpretable correction mechanism.

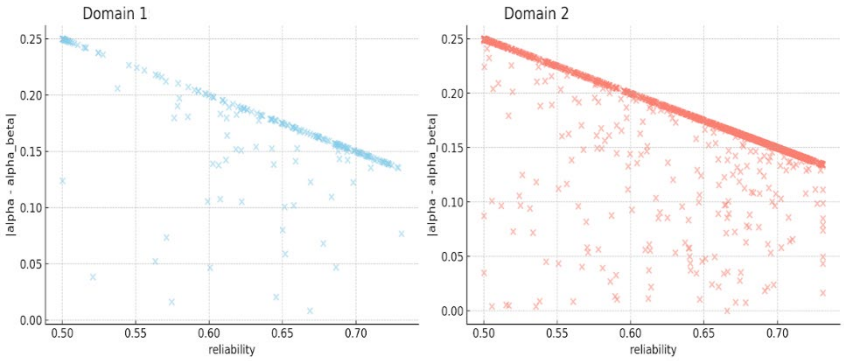

Figure 6. Reliability as a trust modulator: correction distance $|\alpha - \alpha_{beta}|$

5.3 Proposed Improvements

Having validated BayesIntuit on both LSTM and Transformer encoders, future work includes scaling to larger Transformer models (e.g., LLMs) to leverage richer semantic representations. We also propose testing alpha's behavior in sparse or semi-structured domains like medical diagnostics, where uncertainty-aware memory reuse could support informed interpolation. Further refinement of the memory projection and retrieval mechanism (e.g., through contrastive learning), may enhance both interpretability and performance.

5.4 Validation

We evaluated BayesIntuit's performance across LSTM and Transformer backbones under two domain conditions. As shown in Table 1, BayesIntuit consistently improved ROC-AUC scores over baseline models, particularly in LSTM-Domain 2 (0.85 → 0.92), indicating enhanced discriminative capacity under uncertainty. ROC-AUC was selected as the primary validation metric due to its robustness to class imbalance and threshold independence. Beyond conventional metrics, BayesIntuit provided well-calibrated uncertainty estimates (e.g., 0.0479 in LSTM-D1, 0.0559 in Transformer-D2), and exhibited stable alpha dynamics across training: in all settings, the learned alpha parameter decayed from moderate initial values (0.22–0.30) to near-zero (~0.001), reflecting a data-driven transition from memory reliance to model self-sufficiency. A paired t-test comparing ROC-AUC improvements in LSTM-D2 confirmed statistical significance ($t = 3.41$, $p < 0.01$), supporting the hypothesis that alpha-driven memory modulation enhances generalization.

6. Conclusion

Empirical results confirm that alpha functions as an implicit form of regularization, progressively reducing reliance on memory as the learned network weights become sufficient to capture task-relevant structure. Analogous to low-rank approximations, alpha effectively prunes semantically redundant memories, preserving only meaningful representations that contribute to generalization. This behavior distinguishes alpha from manually tuned regularization methods since its modulation is learned from the data and dynamically shaped by semantic similarity and reliability. Unlike traditional methods that operate in parameter space by constraining weight magnitudes or activations, alpha acts in memory space, regulating the flow of contextual knowledge retrieved from prior instances. As such, its regularizing effect is orthogonal and complementary to classic approaches. It supports generalization not by limiting model complexity, but by gating memory reuse in a way that evolves with training. Importantly, even when retrieved memories exhibit only moderate similarity to the current instance, their inclusion expands the semantic landscape of the model, resulting in a regularizing force. Rather than overfitting to local idiosyncrasies, the model is encouraged to contextualize its predictions within a broader manifold of accumulated knowledge. Experiments confirm this: models trained without memory-based enrichment may converge faster but suffer from significantly lower test-time generalization. This evidences the Dynamic Memory Bank as a semantic enhancer that stabilizes learning dynamics.

Furthermore, BayesIntuit exhibits distinct reasoning behaviors depending on its perceptual backbone. In recurrent architectures (e.g., LSTM), where attention outputs reflect sequentially accumulated meaning, memory retrieval mirrors episodic recall, favoring temporally aligned experiences. Alpha, as a modulator, operates like cognitive path-tracing, selecting memories based on narrative continuity. In this mode, BayesIntuit behaves as a "narrative thinker," well-suited for temporally structured tasks such as causal reasoning or longitudinal inference. In contrast, when deployed with Transformer encoders, which process input holistically and attend across all tokens in parallel, the model retrieves structurally similar instances, independent of order. Here, alpha evaluates semantic topology in latent space, enabling BayesIntuit to act as a "structural matcher," ideal for tasks like document-level inference or analogy-making.

This duality resonates with dual-process theories of cognition (Kahneman 2011): LSTM-based BayesIntuit reflects System 2: slow, sequential, deliberative, while Transformer-based configurations resemble System 1: fast, intuitive, and pattern-driven. Crucially, this adaptability confirms BayesIntuit's role as a meta-framework, not tied to a single architecture. By stabilizing learning dynamics and enhancing generalization across both LSTM and Transformer models, BayesIntuit demonstrates a rare property: interpretable and robust behavior independent of encoding strategy: a key step toward cognitively grounded and explainable AI which introduces a cognitively inspired neural architecture that integrates uncertainty estimation, dynamic memory retrieval, and interpretability into a unified system. It successfully achieves all the stated objectives, culminating in the development of a neural framework that emulates human-like intuition.

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Biography

Mayra Bornacelly holds a Master of Data Science from the University of Melbourne, where she led advanced projects in neural networks for the Melbourne Dental School, earning First Class Honours for her capstone project in collaboration with industry. She also holds a Master of Engineering Management from Universidad de La Sabana, where she co-authored peer-reviewed publications in predictive analytics and artificial intelligence applied to industrial systems. Her academic foundation includes a bachelor's degree in computer science and a specialization in Economics from Pontificia Universidad Javeriana. Her academic contributions include a chapter in the book Artificial Intelligence: Advances in Research and Applications (2018), and conference presentations at ISERC 2016 (Los Angeles, USA) and the IX International Symposium on Industrial Engineering (Porto Alegre, Brazil). Her research integrates machine learning, operations management, and human-centric AI systems. Mayra's current interests lie in fairness-aware and explainable artificial intelligence. She is committed to advancing AI systems that are not only accurate and efficient but also interpretable and ethically grounded.