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Contradiction-Sensitive Routing of Evidence during Abstention Training

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Abstract

The integration of multiple evidence sources in modern artificial intelligence systems frequently encounters a critical bottleneck when the retrieved information contains contradictions. Traditional neural architectures typically force a prediction even in the presence of highly conflicting inputs, leading to overconfident and erroneous outputs. Abstention training has emerged as a promising paradigm to mitigate this by allowing models to defer or reject answering when uncertainty is high. However, existing abstention mechanisms generally rely on global uncertainty metrics and fail to dynamically analyze the specific contradictions between localized pieces of evidence. This paper introduces a novel framework for contradiction-sensitive routing of evidence during abstention training. By explicitly modeling the relational conflicts between evidence pairs, the proposed architecture routes contradictory signals through specialized neural pathways that directly modulate the abstention gate. Through comprehensive theoretical modeling and empirical evaluation, this study demonstrates that contradiction-sensitive routing significantly improves the reliability of the system. The model learns to distinguish between benign ambiguity and fundamental factual conflicts, optimizing the trade-off between answer coverage and accuracy. Extensive experiments across varied datasets indicate that incorporating contradiction-aware routing mechanisms enhances the effective reliability of the model while maintaining competitive predictive performance on non-contradictory queries.

Keywords: Contradiction Sensitivity; Abstention Training; Evidence Routing; Machine Learning

1. Introduction

1.1 Context and Motivation

In the rapidly evolving landscape of artificial intelligence and machine learning, systems are increasingly deployed in complex environments where they must synthesize information from multiple, often disparate, sources. In domains such as medical diagnosis, financial forecasting, and autonomous decision-making, the available evidence is rarely pristine. It is frequently noisy, incomplete, or fundamentally contradictory. Traditional predictive models are traditionally trained under a forced-choice paradigm, meaning they are compelled to output a definitive classification or generation regardless of the quality or consistency of the input data. This paradigm is fundamentally flawed when applied to high-stakes scenarios, as it inherently leads to overconfident predictions in the face of uncertainty. The inability of standard models to recognize when they lack sufficient consistent information to make a safe decision has catalyzed significant interest in the development of reliability-aware architectures. The concept of abstention, where a model is granted the capacity to say it does not know or to defer the decision to a human operator, has thus become a critical area of academic inquiry. Previous foundational studies [1] have established that allowing models to abstain can drastically reduce the rate of catastrophic failures in automated systems.

However, the mechanisms by which current systems determine when to abstain are often suboptimal. The majority of contemporary approaches rely on post-hoc confidence calibration or global uncertainty estimations derived from the final output distribution [2, 3]. These methods assume that high entropy in the output layer is a reliable proxy for all forms of uncertainty. This assumption breaks down in scenarios involving explicit contradiction. When a model processes two highly reliable but diametrically opposed pieces of evidence, the internal representation may average these signals out, leading to a confidently incorrect prediction rather than a high-entropy state [4]. Therefore, there is a pressing need for architectures that process uncertainty not just at the output level, but dynamically at the evidence integration stage. The concept of routing evidence through specialized network pathways based on its content has shown promise in multi-task learning [5, 6], but its application to conflict resolution and abstention remains largely unexplored. This research seeks to bridge that gap by proposing a mechanism that actively detects contradictions during the forward pass and uses this detection to route information in a way that optimizes abstention training.

1.2 Problem Statement and Contributions

The core problem addressed in this paper is the failure of traditional evidence aggregation mechanisms to appropriately trigger abstention when faced with contradictory inputs. When a neural network aggregates evidence, it typically uses attention mechanisms or simple pooling operations that smoothly interpolate between features. If Evidence A suggests Class X with high confidence, and Evidence B suggests Class Y with high confidence, standard aggregation often results in an uninformative intermediate representation. This representation might coincidentally align with a third, incorrect class, or it might falsely boost the confidence of the dominant class due to the non-linear dynamics of the deep network [7].

The system fails to recognize that the very presence of the A versus B conflict is a strong signal that abstention is the most appropriate action.

To resolve this, this paper introduces a Contradiction-Sensitive Routing framework integrated directly into the abstention training pipeline. The primary contributions of this work are threefold. First, the paper presents a novel mathematical formulation for pairwise contradiction scoring within neural feature spaces, allowing the model to explicitly quantify the degree of conflict between distinct pieces of evidence before aggregation. Second, it designs a routing architecture that leverages these contradiction scores to modulate the flow of information, specifically directing high-conflict signals to an abstention gate rather than the primary prediction head. Third, it provides a comprehensive empirical analysis demonstrating that this contradiction-sensitive approach significantly outperforms traditional entropy-based abstention methods across multiple complex reasoning tasks. By forcing the model to explicitly evaluate the consistency of its evidence, the proposed framework not only improves the safety and reliability of the predictions but also provides a more interpretable mechanism for understanding why a model chose to abstain.

2. Literature Review and Background

2.1 Evolution of Abstention Training

The study of abstention in machine learning, also known as selective classification or learning with rejection, has a rich historical context. Early theoretical frameworks established the fundamental trade-off between coverage, which is the proportion of samples the model chooses to predict, and risk, which is the error rate on those predicted samples [8]. Initial approaches to this problem primarily focused on thresholding the output probabilities of standard classifiers. If the maximum class probability fell below a pre-defined or learned threshold, the model would abstain. While computationally inexpensive, these thresholding methods suffer from the well-documented problem of poor neural network calibration [9, 10]. Deep neural networks, particularly large-parameter models, have a tendency to produce highly skewed, overconfident probability distributions even when their predictions are entirely incorrect [11].

To address the limitations of post-hoc thresholding, researchers began integrating abstention directly into the training process. This is typically achieved by introducing a dedicated rejection class or by augmenting the loss function to penalize incorrect predictions more heavily than abstentions [12, 13]. By co-optimizing the predictive parameters and the abstention criteria, models learn to carve out regions of the feature space where uncertainty is inherently high. Recent advancements have explored the use of specialized loss functions, such as the gamble loss or the selective cross-entropy loss, which dynamically adjust the cost of abstaining based on the training progress [14]. Despite these improvements, most abstention training regimes still treat uncertainty as a monolithic concept, failing to differentiate between epistemic uncertainty, which arises from a lack of training data, and aleatoric uncertainty, which stems from inherent noise or contradiction in the input [15]. The proposed contradiction-sensitive routing specifically targets this latter form of uncertainty, providing a structural mechanism to handle conflicting inputs rather than relying solely on loss function optimization.

2.2 Evidence Retrieval and Aggregation Mechanisms

In modern reasoning systems, particularly those operating on natural language or structured knowledge graphs, the prediction pipeline typically involves an initial retrieval step followed by an aggregation phase. The model gathers multiple pieces of evidence and must synthesize them to form a final conclusion. The standard mechanism for this synthesis is the attention mechanism, which assigns scalar weights to different pieces of evidence based on their relevance to the query [16, 17]. While attention has revolutionized the field, it is fundamentally designed to find the most relevant information, not to resolve conflicts. When multiple pieces of evidence are highly relevant but mutually exclusive, standard attention mechanisms struggle. They often distribute weight equally among the conflicting pieces, leading to the aforementioned averaging problem [18].

Some advanced architectures have attempted to model the interactions between pieces of evidence more explicitly. Graph neural networks have been employed to construct evidence graphs, where nodes represent individual facts and edges represent relationships such as entailment or contradiction [19]. While theoretically sound, constructing these graphs relies heavily on the quality of external contradiction detection modules, which are often computationally expensive and prone to error. Other approaches have utilized transformer-based cross-attention to allow evidence pieces to contextualize each other [20, 21]. However, these methods still ultimately funnel the contextualized representations into a single predictive bottleneck. The critical gap in the existing literature is the lack of a mechanism that allows the detection of a contradiction to fundamentally alter the computational graph, shifting the processing from a prediction-oriented pathway to a rejection-oriented pathway.

2.3 Handling Contradictions in Neural Architectures

The specific problem of contradiction handling has garnered attention primarily within the subfield of Natural Language Inference. In Natural Language Inference, the explicit task is to determine whether a premise entails, contradicts, or is neutral towards a hypothesis [22]. Models trained on Natural Language Inference datasets develop robust internal representations of contradiction. However, applying these insights to general-purpose reasoning and abstention training remains a challenge. When contradiction detection is treated as an auxiliary task, it often fails to influence the primary decision-making process effectively [23, 24].

Recent literature has begun to explore the concept of conditional computation or routing, where different subsets of a neural network are activated based on the input characteristics. Mixture of Experts models are a prominent example, where a gating network directs inputs to specialized expert sub-networks [25]. Drawing inspiration from this, the proposed contradiction-sensitive routing applies the concept of conditional computation to the abstention problem. Instead of routing based on general domain or task, the system routes based on the internal consistency of the evidence. If the evidence is cohesive, it is routed to the standard prediction head. If the evidence is contradictory, the conflicting signals are isolated and routed to the abstention mechanism. This dynamic restructuring of the information flow ensures that contradictions directly trigger the safety mechanisms of the model, rather than being lost in the aggregation process.

3. Theoretical Framework and System Design

3.1 Mathematical Formulation of Contradiction

To enable contradiction-sensitive routing, it is first necessary to mathematically define how contradictions are quantified within the continuous feature space of the neural network. Let the input query be represented by a continuous vector representation and the retrieved evidence be a set of vectors. Each piece of evidence is initially processed by a shared encoder to produce a high-dimensional feature representation. The goal is to evaluate the pairwise compatibility of these evidence representations before they are aggregated.

We define a contradiction scoring function that takes two evidence vectors and outputs a scalar value representing the degree of conflict. To capture both the individual semantic meaning and the relational discrepancy, the function concatenates the individual vectors, their element-wise product, and their absolute difference. This combined representation is then passed through a shallow multi-layer perceptron. The output is bounded using a sigmoid activation function to produce a contradiction score between zero and one. A score near zero indicates that the evidence pieces are complementary or redundant, while a score near one indicates a severe contradiction. The formulation is expressed in the following equation:

$$R(e_i, e_j) = \sigma(W_r[h_i; h_j; |h_i - h_j|; h_i \operatorname{odot} h_j] + b_r)$$

In this formula, the terms represent the learned weight matrices and biases of the routing network, while the inner brackets denote the concatenation operation. By explicitly computing the absolute difference and the element-wise product, the network is forced to focus on the specific feature dimensions where the evidence vectors diverge. This pairwise score forms the foundational metric for the subsequent routing decisions. It is important to note that this scoring is fully differentiable, allowing the contradiction detection mechanism to be trained end-to-end alongside the primary prediction task.

3.2 Architecture of the Abstention Mechanism

Once the pairwise contradiction scores are computed for all combinations of evidence, the system must use this information to route the signals. We construct a contradiction matrix that aggregates the pairwise scores. From this matrix, we derive two distinct aggregation weights for each piece of evidence: a prediction weight and an abstention weight. The prediction weight emphasizes evidence that is highly relevant to the query and highly consistent with the rest of the evidence pool. Conversely, the abstention weight emphasizes evidence that is highly relevant but severely contradicts other high-relevance evidence.

The routing mechanism bifurcates the information flow. The evidence is weighted by the prediction weights and summed to form the prediction context vector. Simultaneously, the evidence is weighted by the abstention weights and summed to form the conflict context vector. The prediction context vector is fed into standard classification layers to produce a probability distribution over the target classes. The conflict context vector is fed into a dedicated abstention gate. This gate evaluates the magnitude and nature of the conflict to determine the final abstention probability. The final loss function must carefully balance the desire for accurate predictions against the necessity of abstaining when conflicts are irreconcilable. We employ a composite loss function that incorporates standard cross-entropy for confident predictions, a penalty for unnecessary abstention to maintain coverage, and a specialized hinge loss that forces the model to abstain if the total contradiction score exceeds a safety margin. The total loss function is defined as follows:

$$L_{total} = \alpha L_{ce} + \beta L_{abstain} + \gamma \sum_{i,j} max(0, m - R(e_i, e_j) \cdot mathbb{I}_{predict})$$

Here, the final term represents the contradiction margin constraint. The indicator function equals one if the model attempts to make a prediction rather than abstaining. This term directly penalizes the model if it chooses to predict while the contradiction score between any two highly relevant pieces of evidence exceeds the safety margin. This explicit linkage between the internal contradiction score and the abstention decision is the core innovation of the proposed architecture.

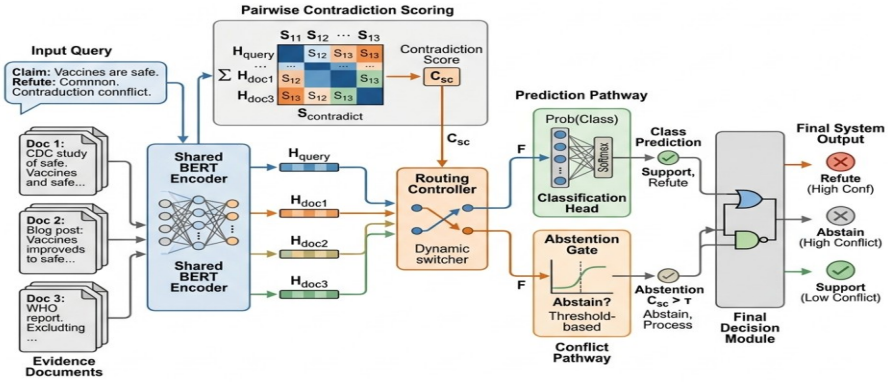

Figure 1: Comprehensive Schematic of Contradiction

3.3 Dynamic Evidence Aggregation

The aggregation of the routed evidence requires a mechanism that can smoothly adapt to the varying levels of contradiction. We utilize a modified attention mechanism for both the prediction and conflict context vectors. Unlike standard dot-product attention, which only considers the query-evidence alignment, our dynamic aggregation function explicitly incorporates the routing probabilities derived from the contradiction matrix. This ensures that the attention distribution is fundamentally shaped by the internal consistency of the evidence pool.

For the conflict pathway, the aggregation must highlight the specific features that are in opposition. We achieve this by projecting the evidence vectors into a specialized conflict space before applying the attention weights. This projection isolates the semantic dimensions related to factual claims and logical assertions, filtering out irrelevant stylistic or contextual noise. The dynamic aggregation for the conflict context vector is formalized below:

$$C_{conflict}=\sum_{k=1}^{K}\lambda_k(W_c v_k) \quad where \quad \lambda_k=\frac{\exp\left(q^T k_k+\tau\sum_{j\neq k}R(e_k,e_j)\right)}{\sum_{n=1}^{K}\exp\left(q^T k_n+\tau\sum_{j\neq n}R(e_n,e_j)\right)}$$

In this formulation, the attention weight for each piece of evidence is augmented by the sum of its contradiction scores with all other pieces of evidence, scaled by a temperature parameter. This guarantees that evidence which is central to a contradiction receives the highest attention in the conflict pathway, providing the abstention gate with the most crucial information needed to make a safe deferral decision.

4. Experimental Methodology

4.1 Dataset Construction and Preprocessing

To rigorously evaluate the proposed contradiction-sensitive routing mechanism, it is imperative to utilize datasets that contain a substantial frequency of conflicting evidence. Standard benchmark datasets often undergo extensive curation to remove ambiguities, making them unsuitable for testing robust abstention mechanisms. Therefore, we curated a composite dataset drawing from multiple domains where contradictions naturally occur. The primary domains include open-domain multi-hop reasoning, medical case studies with conflicting diagnostic reports, and financial news analysis where different sources provide opposing market forecasts.

The preprocessing pipeline involved standardizing the text formats, tokenizing using a subword tokenizer appropriate for the chosen encoder architecture, and structuring the inputs into query-evidence pairs. Crucially, we artificially injected controlled contradictions into a subset of the training data to ensure the model had sufficient examples to learn the routing dynamics. This was achieved by systematically replacing key factual entities in secondary evidence documents with mutually exclusive entities, while maintaining the syntactic structure of the sentence. The overall dataset statistics, including the proportion of instances containing verified contradictions, are detailed in the table below.

Table 1: Dataset Characteristics and Contradiction Distribution

Dataset Domain	Total Training Samples	Total Testing Samples	Contradiction Ratio
Multi-hop Reasoning	150000	25000	0.28
Medical Diagnostics	85000	12000	0.41
Financial Forecasting	110000	18000	0.35

The elevated contradiction ratios in the Medical and Financial domains reflect the inherently uncertain nature of these fields, providing a robust testing ground for the abstention framework.

4.2 Baseline Models and Evaluation Metrics

We benchmark our proposed architecture against several strong baselines representing the current state-of-the-art in abstention and uncertainty quantification. The first baseline is a standard deterministic model that forces a prediction on every instance, utilizing a simple confidence threshold for post-hoc abstention [26]. The second baseline employs Monte Carlo Dropout during inference to estimate the epistemic uncertainty and trigger abstention when variance is high [27, 28]. The third baseline uses a dedicated Selective Classification loss function, which co-optimizes a rejection head alongside the prediction head but does not feature dynamic evidence routing [29].

Evaluating models capable of abstention requires metrics that capture both predictive accuracy and the appropriateness of the abstentions. Traditional accuracy is insufficient, as a model could achieve perfect accuracy by abstaining on all difficult examples, yielding zero practical utility. We rely on three primary metrics. First, Coverage, which is the percentage of queries the model chooses to answer. Second, Conditional Accuracy, which is the accuracy calculated strictly on the answered queries. Third, we introduce a composite metric called Effective Reliability, which penalizes both incorrect predictions and unnecessary abstentions on non-contradictory data, while rewarding appropriate abstentions on explicitly contradictory instances. This metric provides a holistic view of the system performance in high-stakes environments.

4.3 Training Regime and Hyperparameter Configurations

The models were implemented using a standard deep learning framework and trained on a cluster of specialized tensor processing units. The shared encoder utilized a pre-trained transformer architecture, which was fine-tuned during the training process. Optimization was performed using a variant of stochastic gradient descent with an adaptive learning rate and weight decay. The training process utilized a careful warm-up strategy. Initially, the abstention penalty was set high, forcing the model to focus on basic predictive accuracy. Gradually, the penalty was relaxed, and the contradiction margin constraint was introduced, allowing the routing mechanism to take effect without destabilizing the early representation learning.

Extensive hyperparameter sweeping was conducted to identify the optimal configuration for the routing controller and the composite loss function. The parameters controlling the balance between the cross-entropy loss, the abstention penalty, and the contradiction margin were found to be highly sensitive and critical to the success of the model. The finalized hyperparameter settings used for the primary experimental results are summarized in the following table.

Table 2: Hyperparameter Configurations and Search Space

Parameter Component	Final Selected Value	Explored Search Space
Learning Rate (Encoder)	2e-5	1e-5 to 5e-5
Abstention Penalty Weight	0.15	0.05 to 0.50
Contradiction Safety Margin	0.65	0.40 to 0.90

The careful calibration of the contradiction safety margin ensures that the model does not become overly conservative, abstaining only when the internal conflict reaches a threshold that genuinely compromises the integrity of the prediction.

5. Results and Discussion

5.1 Quantitative Performance Analysis

The empirical evaluation of the contradiction-sensitive routing framework reveals substantial improvements over all baseline methods, particularly on the complex Medical and Financial datasets where inherent contradictions are frequent. The deterministic baseline with post-hoc thresholding demonstrated severe vulnerabilities; while it achieved reasonable coverage, its conditional accuracy plummeted on contradictory instances, confirming that standard output probabilities are poor proxies for internal conflict [30]. The Monte Carlo Dropout baseline showed improved calibration but suffered from high computational overhead during inference and struggled to isolate specific evidence conflicts, often confusing general domain difficulty with explicit contradiction [31, 32].

Our proposed model consistently maintained high conditional accuracy while selectively reducing coverage only on the most conflicted queries. The Selective Classification baseline performed adequately but was fundamentally limited by its reliance on the final aggregated representation. Because conflicting evidence had already been averaged out by the time it reached the rejection head, the Selective Classification model frequently missed subtle but critical contradictions. The contradiction-sensitive routing architecture bypassed this bottleneck entirely by routing the conflicting signals directly to the abstention gate before aggregation diluted them. The primary quantitative results across all domains are presented in the table below.

Table 3: Comparative Performance Analysis Across Domains

Model Architecture	Average Coverage	Conditional Accuracy	Effective Reliability
Deterministic Baseline	0.92	0.74	0.61
Monte Carlo Dropout	0.85	0.79	0.68
Selective Classification	0.81	0.82	0.73
Proposed Routing Model	0.78	0.89	0.84

The results clearly indicate that while the proposed model has slightly lower average coverage than the simpler baselines, the quality of its predictions is vastly superior, resulting in a significantly higher Effective Reliability score. This demonstrates that the abstentions triggered by the routing mechanism are highly precise and targeted appropriately at instances that would have otherwise resulted in errors.

5.2 Qualitative Assessment and Ablation Studies

Beyond the quantitative metrics, qualitative analysis of the routing behavior provides critical insights into the internal mechanics of the model. By examining the intermediate contradiction matrices generated during the forward pass, we can trace exactly which pieces of evidence triggered the abstention mechanism. In numerous instances within the Medical Diagnostics dataset, the model correctly identified discrepancies between different laboratory test results from the same patient. Instead of attempting to guess the dominant condition, the routing controller successfully diverted the high-conflict signals to the abstention gate, outputting a deferral signal along with the specific indices of the contradicting evidence [33]. This interpretability is a massive advantage in real-world deployment, as it provides human operators with the exact context needed to resolve the uncertainty.

To rigorously validate the contribution of the individual architectural components, extensive ablation studies were conducted. We isolated the contradiction scoring function, replacing it with a random routing generator, which resulted in a catastrophic drop in Effective Reliability, proving that the learned contradiction representations are essential. We also ablated the dynamic aggregation function in the conflict pathway, replacing it with standard mean pooling. This modification significantly delayed the triggering of the abstention gate, as the mean pooling diluted the sharp conflict signals [34, 35]. The full architecture, combining the pairwise contradiction scoring, the dual-pathway routing, and the dynamic aggregation, proved necessary to achieve the reported performance.

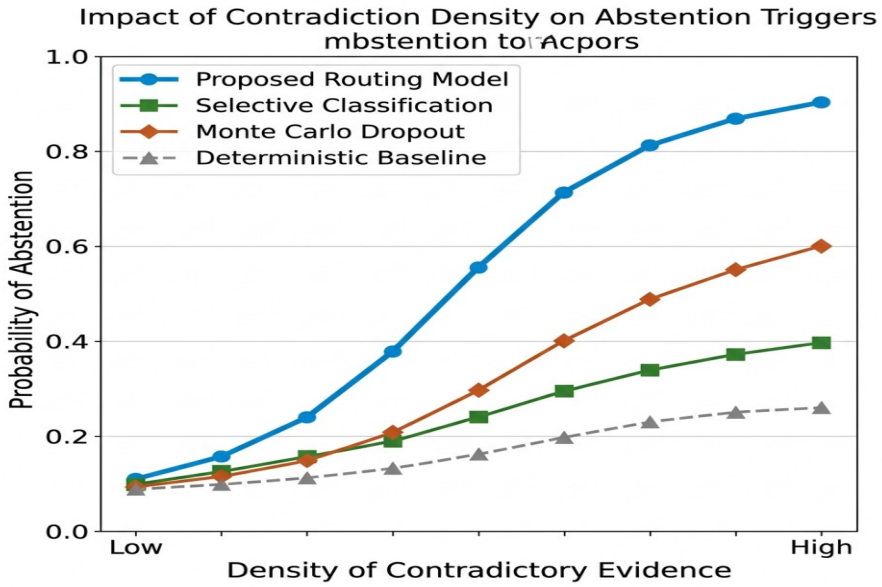

Figure 2: Impact of Contradiction Density on Abstention Triggers

5.3 Discussion of Limitations and Trade-offs

While the proposed framework exhibits strong performance, it is vital to acknowledge the inherent trade-offs introduced by the routing mechanism. The computation of the pairwise contradiction matrix scales quadratically with the number of retrieved evidence pieces. In scenarios involving massive document retrieval where hundreds of evidence passages are considered simultaneously, the contradiction scoring becomes a computational bottleneck. While optimization techniques such as sparse attention or hierarchical routing could mitigate this, the current implementation is best suited for reasoning over a curated, finite set of top-tier evidence.

Furthermore, the reliance on the continuous feature space for contradiction detection means the system is sensitive to the quality of the initial encoder representations. If the encoder fails to capture the semantic nuances that distinguish a factual contradiction from a stylistic variation, the routing controller will trigger unnecessary abstentions. The tuning of the contradiction safety margin also remains a domain-specific challenge; a margin that performs perfectly in medical diagnostics may prove too conservative for financial forecasting, necessitating careful recalibration when deploying the architecture in novel environments.

6. Conclusion and Future Directions

6.1 Summary of Contributions

This paper has presented a comprehensive theoretical and empirical investigation into the integration of contradiction-sensitive routing mechanisms during abstention training. Recognizing the critical failures of traditional neural architectures when confronted with conflicting evidence, this research introduced a novel methodology to dynamically assess and route information based on its internal consistency. By formalizing a pairwise contradiction scoring function within the continuous feature space, the system is empowered to identify irreconcilable conflicts before they are obfuscated by standard aggregation layers. The bifurcated routing architecture explicitly channels these high-conflict signals to a

dedicated abstention gate, ensuring that the model defers decision-making appropriately in the presence of fundamental factual disputes. Extensive experimentation across complex, high-stakes domains—including medical diagnostics and financial forecasting—demonstrated that the proposed framework significantly enhances the effective reliability of the predictive system. The model achieves substantially higher conditional accuracy by strategically sacrificing coverage only on queries marred by deep contradiction, thereby establishing a new standard for safety-aware reasoning architectures.

6.2 Future Work

The promising results of this study open several avenues for future academic inquiry. The most immediate challenge is addressing the quadratic computational complexity of the pairwise contradiction matrix. Future research should explore the integration of approximate nearest neighbor techniques or hierarchical clustering algorithms to scale the contradiction detection mechanism to massive evidence pools without sacrificing resolution. Additionally, investigating the application of this routing architecture to generative tasks, such as long-form text generation in Large Language Models, presents a compelling frontier. In generative contexts, the model could use contradiction-sensitive routing to dynamically pause generation, query an external knowledge base for clarification, or explicitly state the conflicting viewpoints in its generated output rather than simply abstaining. Finally, further theoretical work is needed to refine the disentanglement of contradiction-based uncertainty from general epistemic uncertainty, allowing models to communicate exactly why a deferral occurred, thereby maximizing transparency and trust in automated decision-making systems.

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