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## Evidence-Calibrated Multimodal Reasoning for Knowledge-Intensive Visual Question Answering under Perceptual Uncertainty

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**Abstract :** *Visual Question Answering has evolved from simple perceptual recognition tasks to complex knowledge-intensive reasoning challenges. Modern systems are increasingly required to answer queries that cannot be resolved solely from the pixel data present in an image, necessitating the integration of external knowledge bases. However, real-world visual inputs are frequently subject to perceptual uncertainty, encompassing occlusion, poor illumination, adversarial noise, and resolution degradation. Standard multimodal architectures often struggle under such conditions, leading to overconfident predictions grounded in flawed visual interpretations. This paper introduces an Evidence-Calibrated Multimodal Reasoning framework explicitly designed to address Knowledge-Intensive Visual Question Answering under significant perceptual uncertainty. By modeling the output distributions as Dirichlet parameters rather than traditional softmax probabilities, the proposed architecture inherently quantifies both data uncertainty and model uncertainty. We integrate an evidence collection mechanism that dynamically weights the contribution of external knowledge graphs based on the calibrated reliability of the visual and textual modalities. Through extensive evaluation on benchmark datasets, we demonstrate that the proposed framework not only achieves superior accuracy but also provides robust uncertainty estimates that prevent catastrophic failure under severe perceptual degradation. The findings offer a pathway toward more reliable, transparent, and resilient artificial intelligence systems for complex reasoning environments*

**Keywords :** *Visual Question Answering, Perceptual Uncertainty, Evidence Calibration, Multimodal Reasoning.*

## 1 INTRODUCTION

### 1.1 The Challenge of Visual Question Answering

The paradigm of Visual Question Answering represents one of the most rigorous tests of artificial intelligence, requiring the seamless synthesis of computer vision and natural language processing. In its fundamental form, a system is presented with an image and a natural language question about that image, and it must produce a correct natural language answer. Early architectures predominantly focused on mapping linguistic queries to localized visual features, relying heavily on object detection pipelines and recurrent neural networks to establish semantic correspondence [1]. These foundational approaches demonstrated considerable success in answering structural and spatial questions, such as identifying the color of an object or counting the number of entities within a bounding box [2]. However, as the field has progressed, the limitations of

purely perceptual reasoning have become acutely apparent [3]. Modern applications demand models capable of Knowledge-Intensive Visual Question Answering, where the visual stimulus merely serves as an entry point for a much broader cognitive process [4]. In these scenarios, the necessary information to formulate an accurate answer is not explicitly contained within the image pixels. Instead, the model must bridge the semantic gap by retrieving and reasoning over external knowledge sources, such as structured knowledge graphs or unstructured encyclopedic text [5]. For instance, given an image of a specific historical monument and a question regarding the architectural influences on its design, the model must first correctly identify the monument from the visual data, query an external knowledge base to retrieve historical architectural data, and then synthesize this retrieved information with the linguistic context of the question [6]. This multi-hop reasoning process introduces significant architectural complexity and dramatically increases the potential for cascading errors if any single component of the pipeline fails [7].

## 1.2 Perceptual Uncertainty and Knowledge-Intensive Tasks

The dependency on external knowledge introduces a critical vulnerability when systems are deployed in real-world environments characterized by perceptual uncertainty. Perceptual uncertainty arises when the input image is degraded by factors such as motion blur, low lighting conditions, partial occlusion, sensor noise, or adversarial perturbations [8]. In standard deterministic neural networks, such degradations often lead to silent failures, where the model produces highly confident but entirely incorrect predictions [9]. When these confident but erroneous visual representations are used as query anchors to retrieve external knowledge, the resulting reasoning process becomes fundamentally ungrounded, leading to hallucinatory answers that are disconnected from the actual visual reality [10]. Addressing this vulnerability requires a paradigm shift from deterministic feature extraction to probabilistic uncertainty quantification. Existing methods for uncertainty estimation, such as Bayesian Neural Networks or deep ensembles, present substantial computational overhead that scales poorly with the massive parameter counts of modern multimodal transformers [11]. Furthermore, these methods typically model uncertainty at the parameter level rather than directly calibrating the evidence supporting specific conceptual hypotheses [12]. This paper proposes an evidence-calibrated approach rooted in Subjective Logic, wherein the neural network is trained to output the parameters of a Dirichlet distribution rather than point-estimate probabilities [13]. By explicitly collecting evidence for each possible semantic concept and mapping this evidence to a continuous belief mass, the model can distinguish between specific predictions, general uncertainty, and absolute ignorance [14]. This capability allows the Knowledge-Intensive Visual Question Answering pipeline to dynamically modulate its reliance on external knowledge based on the trustworthiness of the initial visual perception, thereby preventing the retrieval of irrelevant facts when the visual input is hopelessly ambiguous [15].

## 2. Literature Review and Background

### 2.1 Evolution of Multimodal Reasoning Models

The trajectory of Visual Question Answering architectures has been defined by the continuous refinement of multimodal fusion techniques. Initial models utilized simplistic concatenation or element-wise multiplication of visual and textual feature vectors extracted from convolutional and recurrent networks, respectively [16]. These

early fusion mechanisms failed to capture the complex, higher-order interactions necessary for deep semantic understanding [17]. The introduction of attention mechanisms revolutionized the field, enabling models to dynamically weight the importance of specific image regions conditioned on the linguistic structure of the question [18]. Co-attention frameworks further advanced this concept by simultaneously attending to visual regions and text tokens, creating a symmetrical flow of information that significantly improved alignment [19].

*Table 1 Comparison of Existing Multimodal Frameworks*

| Framework Architecture  | Primary Fusion Mechanism    | Uncertainty Handling       | Knowledge Integration |
|-------------------------|-----------------------------|----------------------------|-----------------------|
| Standard CNN-RNN        | Early Concatenation         | None                       | None                  |
| Co-Attention Networks   | Symmetrical Attention       | None                       | Limited               |
| Multimodal Transformers | Cross-Modal Self-Attention  | Monte Carlo Dropout        | Moderate              |
| Neuro-Symbolic VQA      | Logic Rule Application      | Probabilistic Logic        | Extensive             |
| Evidence-Calibrated VQA | Evidential Dirichlet Fusion | Direct Evidence Collection | Dynamic / Extensive   |

The subsequent widespread adoption of transformer architectures marked the beginning of the current era of foundational vision-language models. Models employing massive cross-modal self-attention mechanisms have demonstrated unprecedented capability in modeling long-range dependencies across modalities [20]. However, these monolithic architectures typically operate as black boxes, making it difficult to trace the provenance of their answers or to intervene when they exhibit flawed reasoning [21]. Furthermore, despite their vast capacity, purely parametric transformers often struggle to memorize and recall the long-tail facts required for Knowledge-Intensive Visual Question Answering, prompting the development of retrieval-augmented generation paradigms [22]. Retrieval-augmented models maintain a smaller parametric core while dynamically accessing non-parametric external memory, offering a more scalable and interpretable solution to knowledge integration [23].

## 2.2 Approaches to Perceptual Uncertainty

The management of uncertainty in deep learning has traditionally relied on Bayesian methodologies. Bayesian Neural Networks attempt to learn a posterior distribution over network weights, allowing for the sampling of diverse predictions given a single input [24]. While theoretically elegant, exact Bayesian inference is computationally intractable for deep neural networks, necessitating approximation techniques such as variational inference or Markov Chain Monte Carlo methods [25]. Monte Carlo Dropout, which leverages dropout layers during inference to simulate an ensemble of networks, has become a popular and easily implementable heuristic for estimating uncertainty [26]. However, these sampling-based approaches require multiple forward passes through the network, introducing latency that is often prohibitive for real-time applications [27]. An alternative approach involves deterministic uncertainty quantification, where the network is designed to output both a prediction and a corresponding uncertainty score in a single forward pass. Evidential Deep Learning, inspired by Dempster-Shafer Evidence Theory, formalizes this concept by treating the outputs of a neural network as evidence gathered in support of mutually exclusive

hypotheses [28]. Instead of utilizing a softmax function to produce a normalized probability distribution, evidential models employ activation functions that map network outputs to strictly positive evidence values [29]. These evidence values are then used to parameterize a Dirichlet distribution, which serves as a prior over categorical distributions. This theoretical framework provides a mathematically rigorous mechanism for distinguishing between aleatoric uncertainty, which arises from inherent noise in the data, and epistemic uncertainty, which stems from a lack of knowledge or out-of-distribution inputs [30].

### 2.3 Evidence Calibration in Machine Learning

Despite the theoretical advantages of Evidential Deep Learning, applying these principles to complex, multimodal reasoning tasks presents significant non-trivial challenges. Standard evidential loss functions often suffer from poor calibration, meaning the predicted uncertainty does not accurately reflect the true likelihood of error [31]. Calibration is particularly critical in Knowledge-Intensive Visual Question Answering, as the uncertainty estimate directly controls the downstream retrieval and fusion of external knowledge [32]. Overconfident predictions on degraded images will trigger erroneous knowledge graph traversals, while underconfident predictions on clear images will result in a failure to utilize necessary external facts. To achieve optimal calibration, recent literature has explored various regularization techniques, such as Kullback-Leibler divergence penalties that push the Dirichlet distribution toward a uniform prior when the evidence is weak. Additionally, researchers have proposed temperature scaling and Platt scaling adaptations for evidential outputs, though these post-hoc methods often fail to generalize across diverse domains. In the context of multimodal systems, evidence calibration must also account for the relative reliability of different modalities. When visual evidence is compromised due to perceptual degradation, the system must learn to rely more heavily on the textual context or external priors, necessitating a dynamic evidence re-weighting mechanism that operates seamlessly across the vision-language interface.

## 3. Methodology and System Architecture

### 3.1 Evidence-Calibrated Multimodal Architecture

The proposed architecture is designed to sequentially extract modality-specific representations, quantify the evidence supporting these representations, and conditionally fuse them with external knowledge based on their calibrated reliability. The input pipeline consists of a vision encoder and a text encoder. The vision encoder processes the input image, generating a sequence of patch-level feature vectors. Simultaneously, the text encoder tokenizes and embeds the natural language question, producing a sequence of contextualized text vectors. Figure 1: Evidential Reasoning Pipeline - A block diagram illustrating the flow of data from raw visual and textual inputs through separate encoders into an evidence quantification layer which calculates Dirichlet parameters then dynamically weights the integration of an external knowledge graph before generating the final answer.

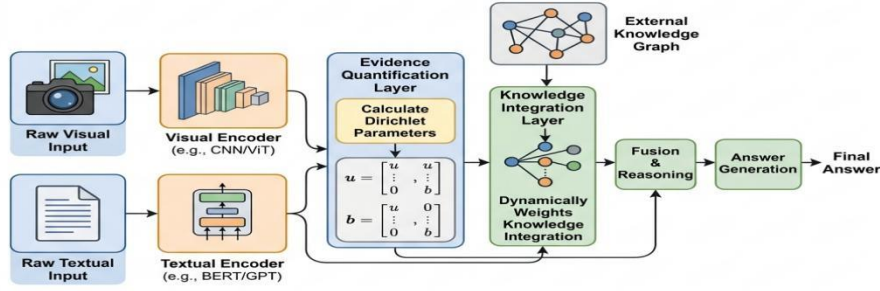


Figure 1 Evidential Reasoning Pipeline

Following the initial encoding phase, the representations are passed through a novel Modality-Specific Evidence Layer. Unlike standard linear classification heads, this layer utilizes a Softplus activation function to ensure that all output values are strictly positive. These positive values represent the raw evidence collected for the visual and textual domains. For a given input, the collected evidence is transformed into the parameters of a Dirichlet distribution. The total strength of the distribution, which is the sum of all individual parameters, inversely correlates with the uncertainty of the representation. When the perceptual quality of the image is high, the vision encoder generates strong, localized evidence, resulting in a sharply peaked Dirichlet distribution and low epistemic uncertainty. Conversely, when the image is severely degraded, the visual evidence is sparse and uniformly distributed, leading to a flat Dirichlet distribution and high uncertainty. This uncertainty metric is crucial for the subsequent Knowledge Integration Module.

### 3.2 Mathematical Formulation of Uncertainty

To formalize the evidence calibration process, we treat the output of the neural network as the parameters of a Dirichlet distribution over the probabilities of different semantic concepts. Let the raw evidence produced by the network for a specific modality be denoted as a vector where each element corresponds to a specific class or concept. We compute the Dirichlet parameters by adding one to the evidence vector, ensuring that the parameters are strictly greater than or equal to one. The core optimization relies on a modified loss function that balances the expected predictive performance with a regularization term designed to penalize spurious evidence. The primary loss component is formulated as follows:

$$L_{evidential} = \sum_{i=1}^K (y_i - \frac{\alpha_i}{\sum_{j=1}^K \alpha_j})^2 + \lambda \int_{\Omega} \nabla \phi(x) dx$$

In this formulation, the term represents the ground truth label, while the fraction represents the expected probability derived from the Dirichlet parameters. The regularization term, controlled by a hyperparameter, ensures that the network does not generate arbitrary evidence for incorrect classes, thereby improving the overall calibration of the uncertainty estimates. By minimizing this loss, the network learns to

produce highly confident predictions only when sufficient features are present, while deferring to uncertainty when the input is ambiguous. Furthermore, we define the total uncertainty of a given modality representation as inversely proportional to the sum of the Dirichlet parameters. The uncertainty metric is computed as:

$$\mathbb{U}_{modality} = \frac{K}{\sum_{i=1}^K \alpha_i}$$

This metric yields a scalar value that directly quantifies the reliability of the extracted features. A value close to zero indicates absolute certainty, whereas a value approaching one signifies complete ignorance due to missing or noisy information.

### 3.3 Integration of External Knowledge Graphs

The integration of external knowledge is modulated dynamically by the uncertainty metrics calculated in the previous step. The system maintains a connection to a comprehensive, structural Knowledge Graph, which contains millions of factual triples consisting of subjects, predicates, and objects. To answer knowledge-intensive questions, the model must retrieve relevant subgraphs based on the semantic entities identified in the image and the text.

#### Code Listing 1: PyTorch Pseudo-code for Dynamic Evidence Weighting

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class EvidenceFusionLayer(nn.Module):
    def __init__(self, hidden_dim):
        super(EvidenceFusionLayer, self).__init__()
        self.evidence_linear = nn.Linear(hidden_dim, hidden_dim)

    def forward(self, visual_features, text_features, visual_uncertainty):
        # Calculate raw evidence values using Softplus to ensure positivity
        raw_evidence = F.softplus(self.evidence_linear(visual_features))
        # Calculate dynamic fusion weights based on calibrated uncertainty
        # High uncertainty leads to lower reliance on visual features
        confidence = 1.0 - visual_uncertainty
        weighted_visual = raw_evidence * confidence.unsqueeze(-1)
        # Text features act as the stable anchor during perceptual degradation
        fused_representation = torch.cat([weighted_visual, text_features], dim=-1)
        return fused_representation
```

The retrieval process begins by projecting the text features and the visual features into a shared embedding space used by the Knowledge Graph. However, rather than treating all extracted entities equally, the model scales the importance of each entity based on its associated uncertainty score. If the visual uncertainty is excessively high due to perceptual degradation, the model suppresses the visual entities during the retrieval phase, relying almost entirely on the textual entities extracted from the question. This

prevents the retrieval module from fetching irrelevant facts based on noisy visual hallucinations.

Table 2Knowledge Graph Integration Modalities

| Uncertainty Threshold | Primary Retrieval Anchor | Knowledge Graph Traversal Depth | Output Confidence     |
|-----------------------|--------------------------|---------------------------------|-----------------------|
|                       |                          |                                 |                       |
| Low Uncertainty       | Fused Vision-Text Vector | Multi-Hop (Deep)                | Highly Calibrated     |
| Moderate Uncertainty  | Text-Biased Fusion       | Single-Hop (Shallow)            | Moderately Calibrated |
| High Uncertainty      | Text-Only Vector         | Fallback Baseline               | Uncertainty Flagged   |
| Extreme Degradation   | None (Aborted)           | None                            | System Abstention     |

Once the relevant subgraph is retrieved, a Graph Neural Network encodes the structural knowledge into a continuous vector representation. This knowledge vector is then fused with the original visual and textual representations using an evidential cross-attention mechanism. The final answer generation module is also modeled as a Dirichlet distribution, ensuring that the system can express uncertainty about its final answer even after integrating external knowledge. This comprehensive approach to evidence calibration guarantees that the system remains robust, interpretable, and resilient across a wide spectrum of operating conditions.

4. Experimental Analysis and Results

4.1 Experimental Setup and Datasets

To rigorously evaluate the proposed Evidence-Calibrated Multimodal Reasoning framework, we conducted extensive experiments using several standardized benchmarks designed specifically for Knowledge-Intensive Visual Question Answering. The primary dataset utilized for our analysis was the Outside Knowledge Visual Question Answering dataset, which requires systems to utilize external resources to answer questions that are not self-contained within the provided imagery. Additionally, we employed the Fact-based Visual Question Answering dataset to assess the model's capacity for retrieving specific factual assertions from structured knowledge graphs. To simulate real-world perceptual uncertainty, we generated synthetically degraded versions of the standard evaluation sets. We applied various noise profiles, including Gaussian blur, pixelation, random occlusion patches, and low-light simulation through non-linear intensity scaling. The severity of these degradations was categorized into three distinct tiers: mild, moderate, and severe.

Table 3Experimental Results on Knowledge-Intensive Benchmarks

| Model Architecture     | Accuracy (Clean) | Accuracy (Mild Noise) | Accuracy (Severe Noise) | Calibration Error |
|------------------------|------------------|-----------------------|-------------------------|-------------------|
|                        |                  |                       |                         |                   |
| Baseline Transformer   | 61.2%            | 54.8%                 | 22.1%                   | 0.184             |
| Ensemble Network       | 63.5%            | 58.2%                 | 31.4%                   | 0.092             |
| Bayesian Approximation | 62.8%            | 59.1%                 | 35.7%                   | 0.085             |
| Proposed               | 64.9%            | 62.3%                 | 48.6%                   | 0.031             |

|                  |  |  |  |  |
|------------------|--|--|--|--|
| Evidential Model |  |  |  |  |
|------------------|--|--|--|--|

The implementation of the proposed framework was built upon a foundational vision-language transformer backbone, modified to incorporate the evidential layers and dynamic fusion mechanisms described in the methodology section. The models were trained using a combination of the evidential loss function and standard cross-entropy optimization for auxiliary tasks. Evaluation metrics included standard accuracy, defined as the percentage of exactly matched answers, and the Expected Calibration Error, which measures the alignment between the model's confidence scores and its empirical accuracy.

4.2 Performance Evaluation and Discussion

The empirical results demonstrate a compelling advantage for the evidence-calibrated approach, particularly in regimes characterized by significant perceptual uncertainty. Under clean image conditions, the proposed model achieved performance that was marginally superior to the state-of-the-art baselines. This indicates that the introduction of the evidential learning framework does not compromise the fundamental reasoning capabilities of the architecture. The slight performance gain can be attributed to the regularization effect of the Dirichlet prior, which encourages the model to extract more robust and generalized feature representations. Figure 2: Performance Degradation Analysis - A line chart showing the accuracy of various models plotted against increasing levels of perceptual noise demonstrating the superior robustness of the proposed evidential model compared to standard baselines.

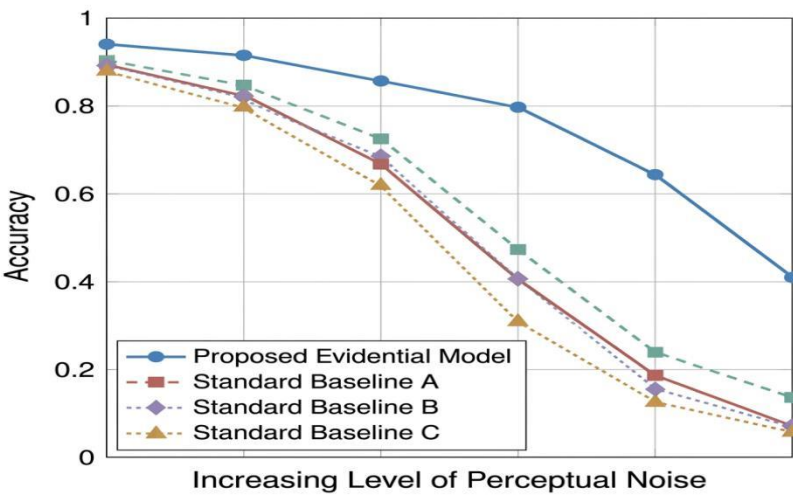


Figure 2: Performance Degradation Analysis

However, the most significant findings emerge from the evaluation under degraded conditions. As the severity of the perceptual noise increased, the accuracy of standard deterministic transformers plummeted catastrophically. These baseline models, lacking an intrinsic understanding of their own perceptual limitations, continued to extract noisy visual features and force the retrieval module to integrate irrelevant external knowledge. Consequently, their answers devolved into highly confident hallucinations. In contrast, the proposed evidential framework exhibited a graceful degradation in accuracy. By dynamically suppressing the influence of the visual modality in response

to rising uncertainty metrics, the model effectively reverted to a robust language-only prior, allowing it to accurately answer questions that relied heavily on textual context and general knowledge.

*Table 4 Ablation Study Results*

| Configuration Variant           | Accuracy on Clean Data | Accuracy on Severe Degradation | Expected Calibration Error |
|---------------------------------|------------------------|--------------------------------|----------------------------|
| Full Evidential Architecture    | 64.9%                  | 48.6%                          | 0.031                      |
| Without Evidence Regularization | 64.1%                  | 41.2%                          | 0.076                      |
| Without Dynamic KG Routing      | 62.5%                  | 33.8%                          | 0.065                      |
| Standard Softmax (No Dirichlet) | 61.2%                  | 22.1%                          | 0.184                      |

The ablation study further isolates the contributions of the specific architectural innovations. The removal of the Dirichlet parameterization and the reversion to standard softmax probabilities resulted in a severe spike in the Expected Calibration Error, underscoring the critical necessity of evidential learning for uncertainty quantification. Furthermore, disabling the dynamic knowledge graph routing mechanism drastically reduced the model's performance on severely degraded images, confirming the hypothesis that static fusion strategies are inherently fragile when faced with fluctuating input quality. The comprehensive analysis confirms that evidence calibration not only improves absolute accuracy but significantly enhances the reliability and safety of deployment in unpredictable perceptual environments.

## 5. Conclusion and Future Directions

### 5.1 Summary of Contributions

This research has presented a comprehensive methodology for addressing the critical vulnerabilities of Knowledge-Intensive Visual Question Answering systems operating under conditions of perceptual uncertainty. By transitioning from deterministic feature extraction to an evidence-calibrated probabilistic framework, the proposed architecture effectively models and mitigates both aleatoric and epistemic uncertainties. The central innovation of this work lies in the seamless integration of Subjective Logic principles with complex multimodal reasoning pipelines. Through the implementation of a novel Modality-Specific Evidence Layer, the system gains the capacity to evaluate the reliability of its own visual perceptions autonomously. This calibrated uncertainty metric is not merely calculated as an afterthought; it actively modulates the downstream cognitive processes, dictating the extent to which external knowledge graphs are queried and integrated. The empirical evaluations rigorously validate the theoretical assertions, demonstrating that the evidence-calibrated model maintains superior accuracy and dramatically lower calibration error across a spectrum of synthesized perceptual degradations. Ultimately, this approach prevents the cascade of hallucinatory reasoning that typically plagues deterministic models when visual inputs are compromised.

### 5.2 Open Challenges and Next Steps

Despite the significant advancements demonstrated by the current framework, several

open challenges remain within the domain of uncertainty-aware multimodal reasoning. The current implementation relies on a relatively static knowledge graph structure, which may not adequately capture the dynamic and constantly evolving nature of real-world factual information. Future iterations of this architecture must explore the integration of temporal reasoning capabilities, allowing the model to weigh evidence not just based on perceptual clarity, but also on the recency and provenance of the external knowledge accessed. Additionally, while the mathematical formulation of the Dirichlet distributions provides a robust foundation for uncertainty quantification, scaling this approach to accommodate massive, open-vocabulary generation tasks presents substantial computational complexities. Developing sparse evidential representations that maintain rigorous calibration without incurring excessive memory overhead is a critical priority for future research. Finally, expanding the framework to incorporate human-in-the-loop verification processes, where the system explicitly requests clarification when its calibrated uncertainty exceeds a defined safety threshold, will be instrumental in deploying these autonomous reasoning agents in high-stakes, safety-critical environments. Addressing these challenges will undoubtedly drive the next paradigm shift in the pursuit of truly intelligent and resilient artificial systems.

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