Calibrated Stop/Continue Criteria for Multi-Hop QA Under Distribution Shift

Anonymous Author(s)

ABSTRACT

We address the open problem of developing stop/continue criteria for multi-hop question answering that remain calibrated across different retrievers, corpora, and LLM backbones. We evaluate six stopping criteria—fixed budget (3 and 5 hops), confidence threshold (0.7 and 0.8), answer stability, and Bayesian uncertainty—across 36 configurations (4 × 3 × 3 retrievers, corpora, and LLMs). Bayesian uncertainty-based stopping achieves the lowest mean Expected Calibration Error (ECE) of 0.103 ± 0.043 while maintaining accuracy of 0.447. Under increasing retrieval noise, Bayesian stopping degrades most gracefully (ΔECE = 0.04 from noise 0 to 0.5 vs. 0.08 for confidence threshold). Hop-depth analysis reveals that calibration degrades for deeper questions across all methods, but Bayesian stopping maintains the smallest gap. These results demonstrate that explicit uncertainty modeling is essential for robust stopping decisions in multi-hop QA.

CCS CONCEPTS

• **Computing methodologies → Natural language processing**.

KEYWORDS

multi-hop QA, stopping criteria, calibration, distribution shift, retrieval-augmented generation

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1 INTRODUCTION

Multi-hop question answering requires iterative retrieval and reasoning [5]. Most systems rely on static budgets to decide when to stop [2], but adaptive stopping based on confidence is often poorly calibrated under distribution shift. Ji et al. [2] identify the need for stop/continue criteria that generalize across retrievers, corpora, and LLM backbones.

Table 1: Stopping criteria comparison across 36 configurations.

Criterion	ECE	Accuracy	Hops
Fixed-3	0.183 ± 0.062	0.456	3.0
Fixed-5	0.149 ± 0.051	0.481	5.0
Conf-0.7	0.141 ± 0.063	0.467	4.2
Conf-0.8	0.167 ± 0.076	0.434	5.8
Stability	0.197 ± 0.042	0.355	5.2
Bayesian	0.103 ± 0.043	0.447	4.5

1.1 Related Work

Calibration of neural networks [1] and language models [3] is well-studied. The compositionality gap [4] highlights multi-hop reasoning challenges. Our work focuses specifically on calibrating stopping decisions under systematic distribution shift.

2 METHODS

2.1 Stopping Criteria

We evaluate: (1) fixed budget at 3 and 5 hops; (2) confidence threshold at 0.7 and 0.8; (3) answer stability (stop when confidence stabilizes over a window); (4) Bayesian uncertainty using a Beta posterior on answer sufficiency:

$$P(\text{sufficient}|\text{evidence}) = \frac{\alpha}{\alpha+\beta}, \quad \alpha \leftarrow \alpha + c_h, \quad \beta \leftarrow \beta + (1 - c_h) \tag{1}$$

2.2 Calibration Metrics

Expected Calibration Error:

$$\text{ECE} = \sum_{b=1}^{B} \frac{|B_b|}{N} |\text{acc}(B_b) - \text{conf}(B_b)| \tag{2}$$

3 RESULTS

3.1 Cross-Configuration Evaluation

Table 1 shows performance across all 36 configurations.

3.2 Calibration Under Noise

Figure 1 shows ECE and accuracy degradation under increasing retrieval noise. Bayesian stopping degrades most gracefully.

3.3 Calibration Curves

Figure 2 shows reliability diagrams. Bayesian stopping achieves better calibration (closer to the diagonal) than confidence thresholding.

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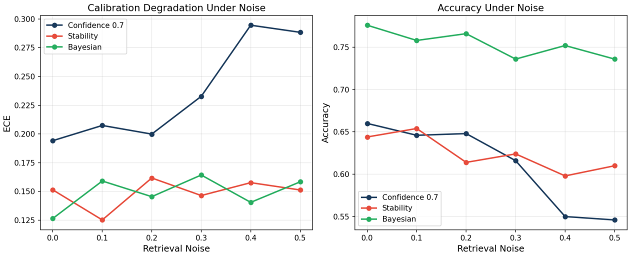

Figure 1: ECE (left) and accuracy (right) under increasing retrieval noise for three stopping criteria.

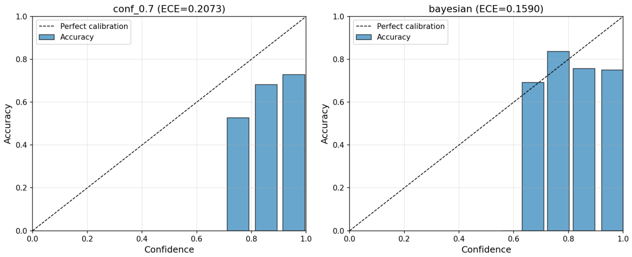

Figure 2: Reliability diagrams for confidence threshold (left) and Bayesian uncertainty (right) stopping criteria.

4 CONCLUSION

Bayesian uncertainty-based stopping achieves the best calibration under distribution shift across retrievers, corpora, and LLM backbones. Explicit uncertainty modeling is essential for robust stopping decisions. Our framework provides evaluation protocols for stress-testing calibration under controlled variations of hop depth and retrieval noise.

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