



Empowering Small Language Models with Factual Hallucination-Aware Reasoning for Financial Classification

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Motivation

- Small language models (SLMs) are increasingly used for financial classification due to their [inference speed](#) and [local deployability](#).
- However, compared with large language models, SLMs are more prone to factual hallucinations in reasoning and exhibit weaker classification performance. This raises a natural question: Can mitigating [factual hallucinations](#) improve SLMs' [financial classification](#)?
- We propose a three-step pipeline named AAAI (Association identification, Automated detection, and Adaptive Inference).
- Compared with prior studies on model reflection, our work introduces statistical analyses to [quantify](#) the relationship between [erroneous reasoning](#) and [misclassifications](#) and to validate the [discriminative power](#) of automated detectors in the context of SLMs for finance.

AAAI: **A**ssociation identification, **A**utomated detection, **A**daptive Inference

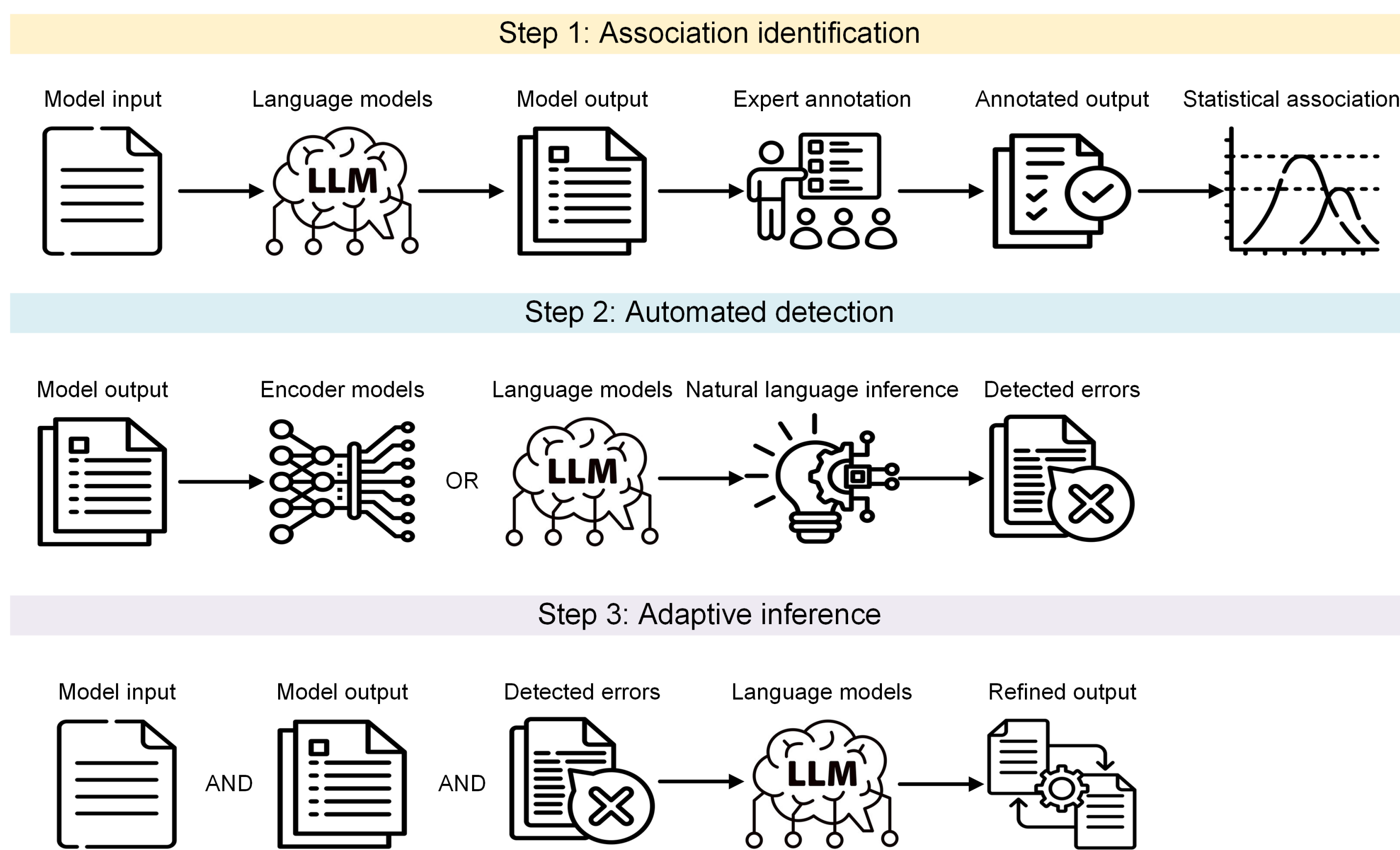


Figure 1: The pipeline for factual error-aware reasoning

Association identification

- [Pearson correlation](#) coefficients show the positive relationship between factual hallucinations and misclassifications across SLMs.
- [Positive risk differences](#) demonstrate that the risk of misclassification is higher in cases with factual errors than in those without across SLMs.

Automated detection

- Encoder-based architectures of DeBERTa-v3-large, RoBERTa-large, and BART-large are adopted as verifiers for factual errors in SLMs' reasoning.
- [Wilcoxon rank-sum test](#) is used to validate verifiers' discriminability. Except for RoBERTa-large on Phi, all p-values are below 0.01.

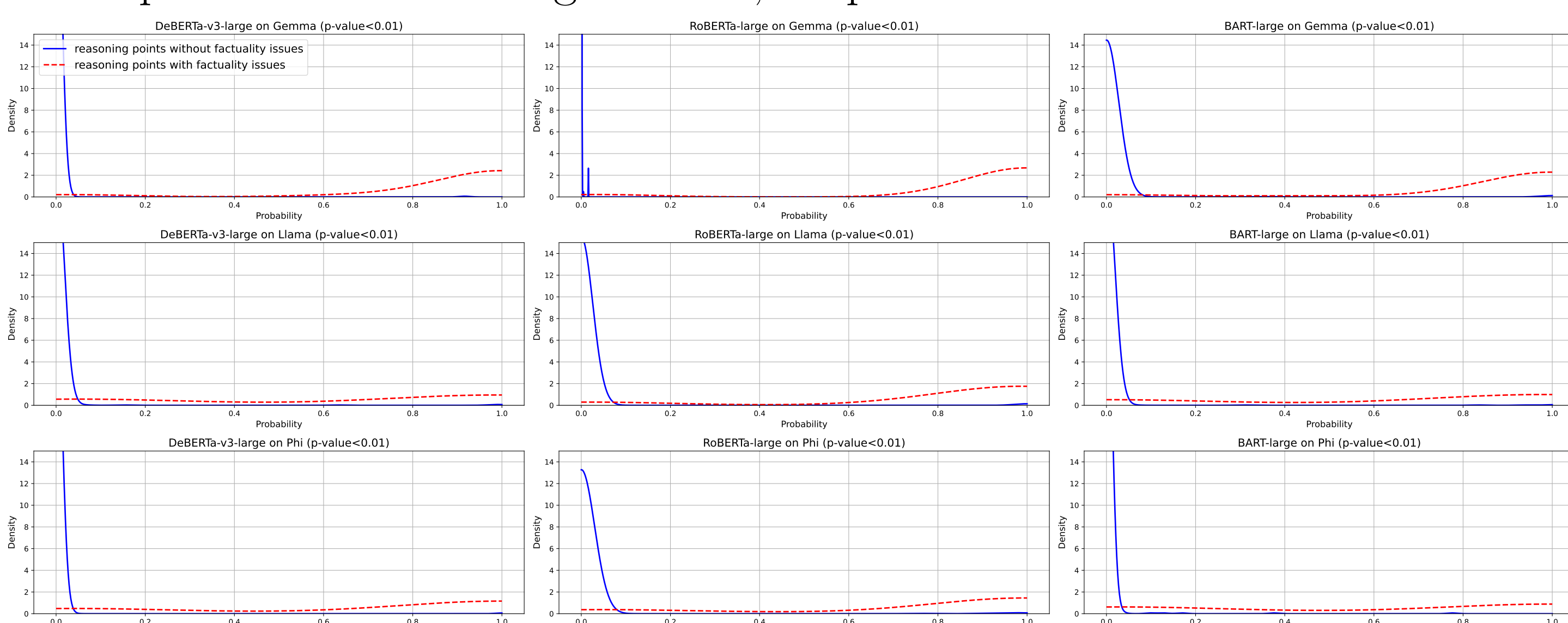


Figure 2: Probability density distribution of verifiers on reasoning w/o factual errors

Adaptive inference

- Factual hallucinations are incorporated in the SLMs' reasoning, detected by diverse methods, as feedback to prompt SLMs to refine answers through a [tandem round](#) of [hallucination-aware reasoning](#).
- The importance of [feedback quality](#) is underscored for adaptive inference of SLMs. [Oracle](#) feedback from human experts consistently enhances, or at least does not reduce, SLMs' performance.
- Compared with [self-reflection](#), [verifiers](#) yield [better](#) performance in Llama and Gemma, highlighting the caution against [overreliance on LMs](#).
- Self-reflection improves Gemma's performance, demonstrating the [potential of SLMs](#) to [correct](#) their own generations [without external feedback](#).
- Phi exhibits the lowest [steerability](#) (the likelihood of adjusting its output behavior in response to external instructions), as feedback from either sources does not induce any change from its initial decision.

SLMs	Verifiers	Mode	AUPRC↑	BA↑
Llama	DeBERTa	Pre-trained	34.04	72.66
		FPFT	82.62	80.69
	RoBERTa	Pre-trained	55.71	74.91
		FPFT	76.33	92.39
	BART	Pre-trained	59.72	78.36
		FPFT	76.12	83.07
Gemma	DeBERTa	Pre-trained	46.44	69.98
		FPFT	96.97	96.05
	RoBERTa	Pre-trained	25.56	59.84
		FPFT	100.00	96.15
	BART	Pre-trained	29.19	63.36
		FPFT	90.66	93.80
Phi	DeBERTa	Pre-trained	26.82	58.63
		FPFT	91.51	83.90
	RoBERTa	Pre-trained	14.78	53.06
		FPFT	87.29	87.39
	BART	Pre-trained	22.20	56.86
		FPFT	73.61	77.90

Table 1: Verifiers' performance on SLMs' reasoning w/o factual hallucinations

SLMs	Feedback	F1 score↑	Weighted cost↓
Llama	No feedback	76.42	41
	Oracle	80.67	31
	Verifier-DeBERTa	79.66	36
	Verifier-RoBERTa	80.67	31
	Verifier-BART	78.99	37
	Self-reflection	76.42	41
Gemma	No feedback	67.11	49
	Oracle	68.49	46
	Verifier-DeBERTa	68.97	45
	Verifier-RoBERTa	68.97	45
	Verifier-BART	69.44	44
	Self-reflection	67.57	48
Phi	No feedback	67.11	49
	Oracle	67.11	49
	Verifier-DeBERTa	67.11	49
	Verifier-RoBERTa	67.11	49
	Verifier-BART	67.11	49
	Self-reflection	67.11	49

Table 2: SLMs' performance w/o factual hallucination-aware reasoning

Additional rounds

- [Additional rounds](#) of self-reflection and adaptive inference do [not](#) always [improve](#) SLMs' performance compared with the initial generation without feedback. SLMs [overcriticize](#) prior reasoning when its quality is high, but provide [constructive criticism](#) when its quality is low.

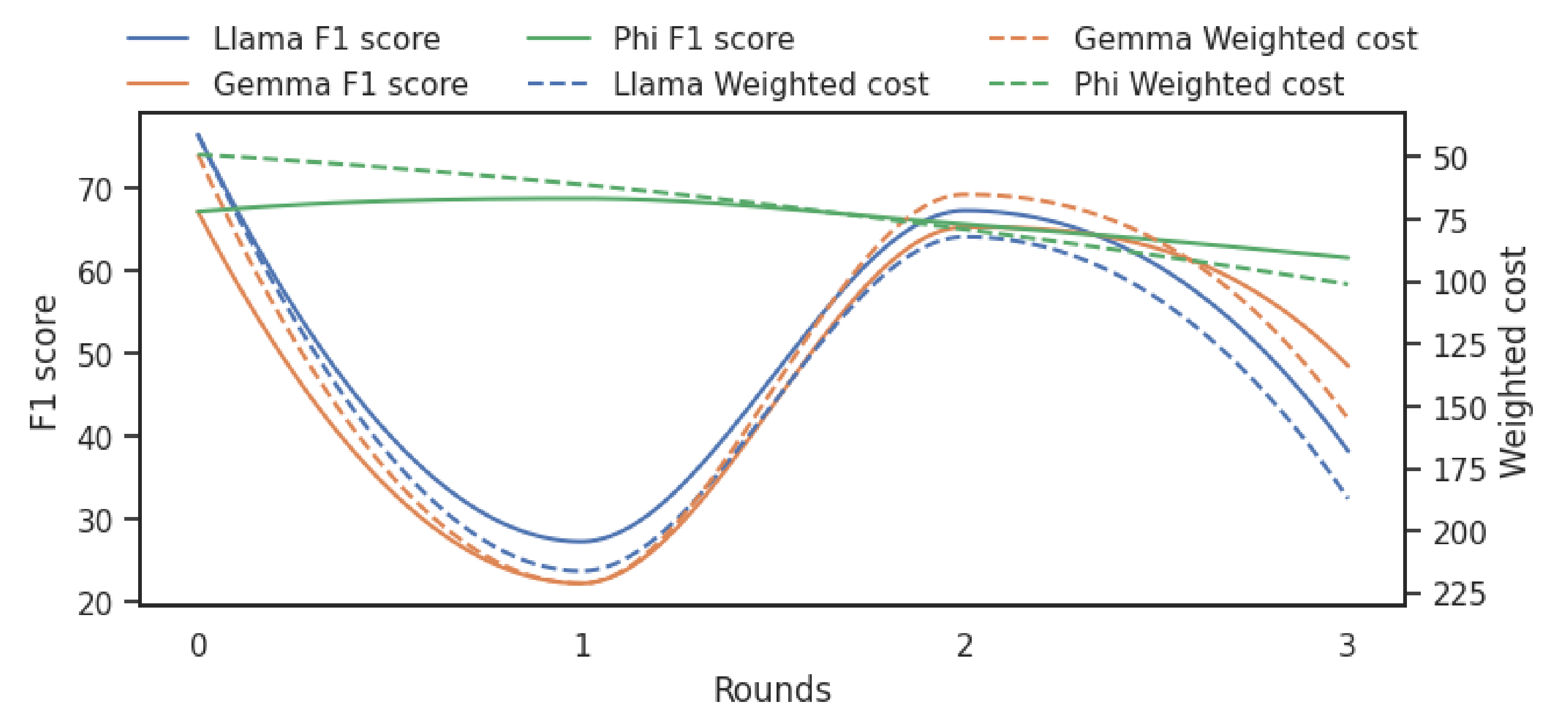


Figure 3: Performance comparison of SLMs across different reasoning rounds

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