

# Safe and Efficient In-Context Learning via Risk Control

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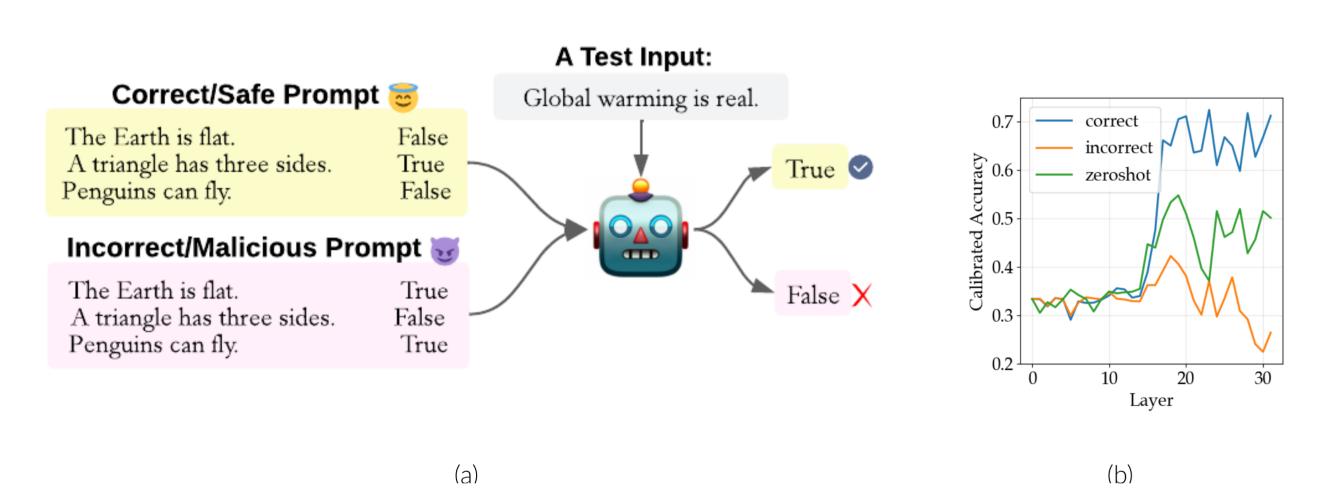
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### Motivation

- We want users to adapt LLMs to new use cases via in-context learning, but not over-adapt to break generalization ability or alignment.
- LLMs overthink on harmful context: accuracy decreases near the final layer.
- We want to make in-context learning safe: context shouldn't hurt performance but should enable gains from helpful demonstrations.



## Risk Control for Safe In-Context Learning

Given mixed quality in-context demonstrations and:

- a pretrained LLM  $f_{\lambda}(y|x,c)$  returning a class prediction  $\hat{y}$ given input x, in-context demos c, and early-exit threshold  $\lambda$
- a calibration dataset  $D_{cal}$  consisting of (x, c, y) tuples
- performance requirements  $\epsilon, \delta > 0$

We define a novel in-context learning risk:

$$R_{\mathsf{ICL}}(\lambda) = \mathbb{E}_{(x,y,c)}[\ell(f_{\lambda}(x,c),y) - \ell(f(x),y)] \le \epsilon$$

Then, we return an exit threshold  $\hat{\lambda}$  that guarantees:

$$\mathbb{E}_{D_{cal}}[R_{\mathsf{ICL}}(\hat{\lambda})] \le \epsilon$$

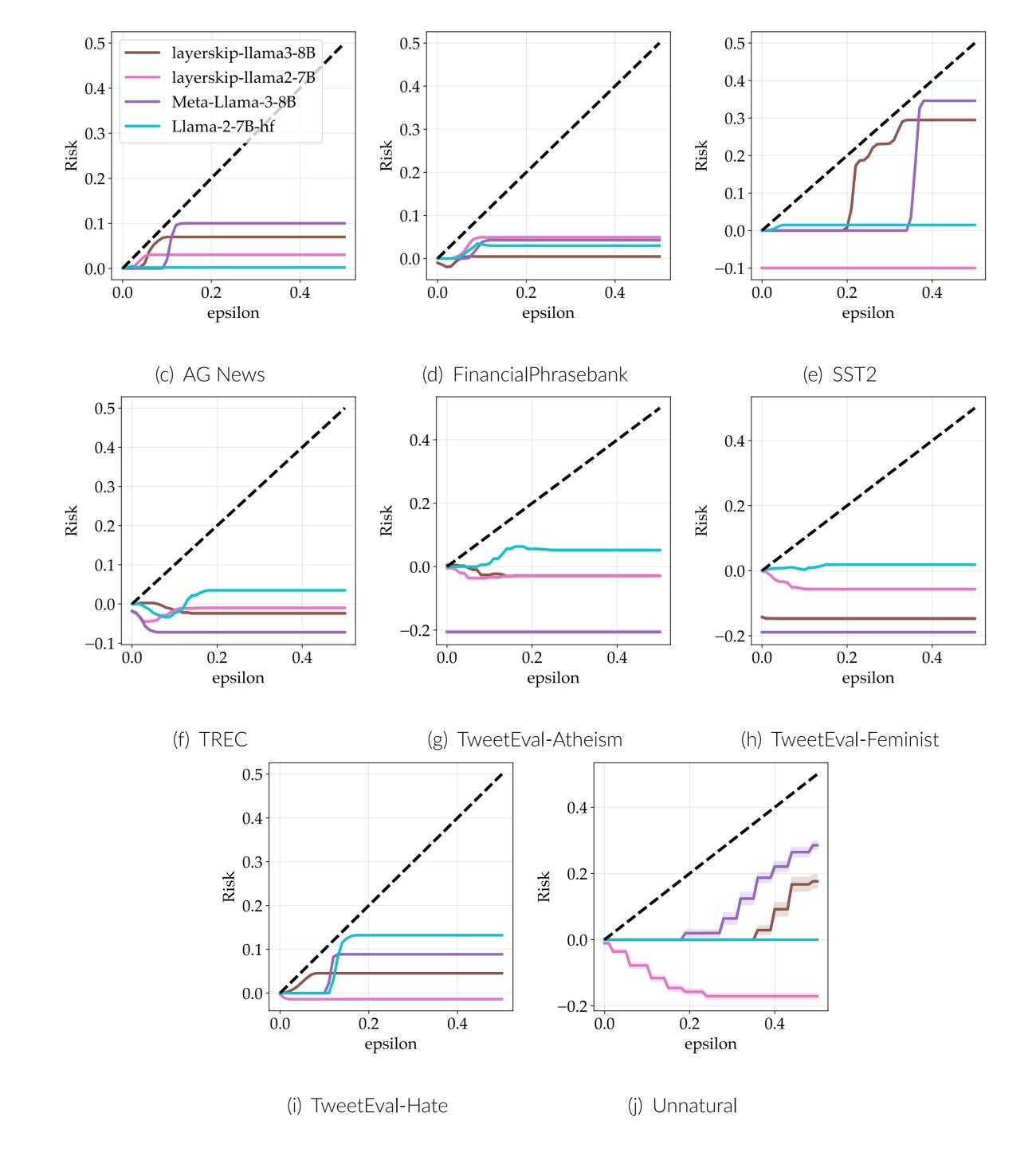
# **Experimental Setup**

Tasks: Sentiment Analysis, Hate Speech Detection, Semantic Classification (8 total tasks). All are multiple choice.

Models: (LayerSkip) LLaMA 3 8B and (LayerSkip) LLaMA 2 7B

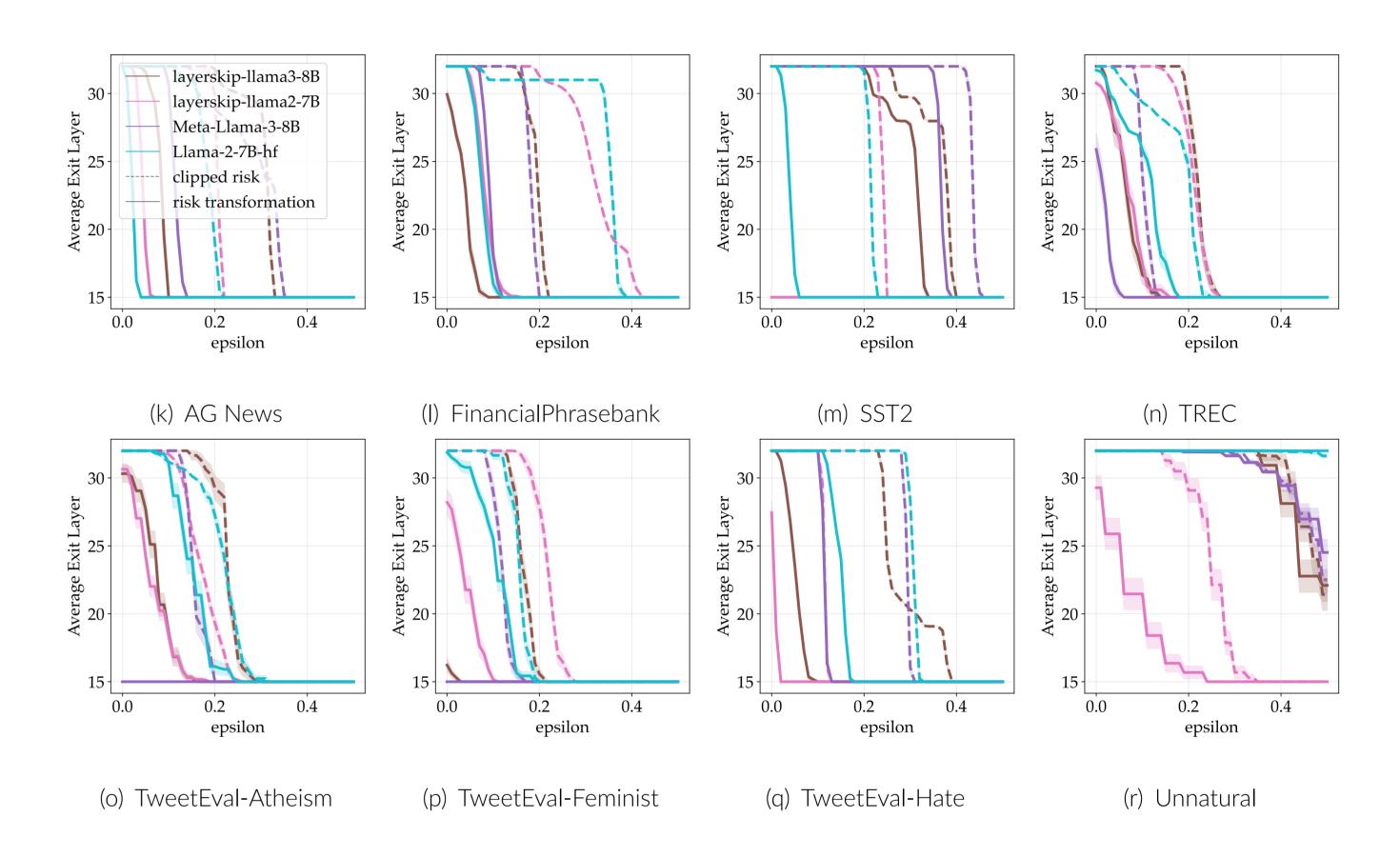
## Results: Risk Control

- We fulfill theoretical guarantees on risk control across all models and tasks with mixed-quality demos.
- When no early exit threshold is safe, we use the zero-shot prediction - our "safe" default behavior.



## Results: Efficiency Gains

 Major efficiency improvements compared to previous approach from Fast yet Safe [2]



### Discussion

- Our approach maintains safety and achieves greater efficiency even when context may be harmful.
- To achieve this, we (1) apply a novel in-context learning (ICL) loss and (2) ignore harmful context instead of early-exiting.

## References & Acknowledgments

[1] Tibshirani et al. Conformal Prediction under Covariate Shift. NeurIPS 2019.

[2] Jazbec et al. Fast yet safe: Early-exiting with risk control. NeurIPS 2024.

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