

Motivation

Challenge: Deploying large language models in high-stakes settings (e.g. healthcare, finance, education) requires balancing :

- **accuracy, cost, and reliability.**

Problem:

- Larger models offer superior reasoning but incur high computational cost.
- Smaller models are cheaper but struggle on complex tasks.
- Current systems lack mechanisms to decide when to defer to stronger models or humans.

Goal: Build AI systems that make cost-aware and risk-sensitive decisions, learning *when to trust themselves, when to escalate to stronger models, and when to abstain for human review.*

Key Idea:

A cascaded human-AI decision framework that:

- Uses a base model for low-complexity queries.
- Defers to a more capable model when uncertainty is high.
- Abstains and seeks human input when confidence remains low.
- Learns online from feedback to improve over time.



Read the full paper:



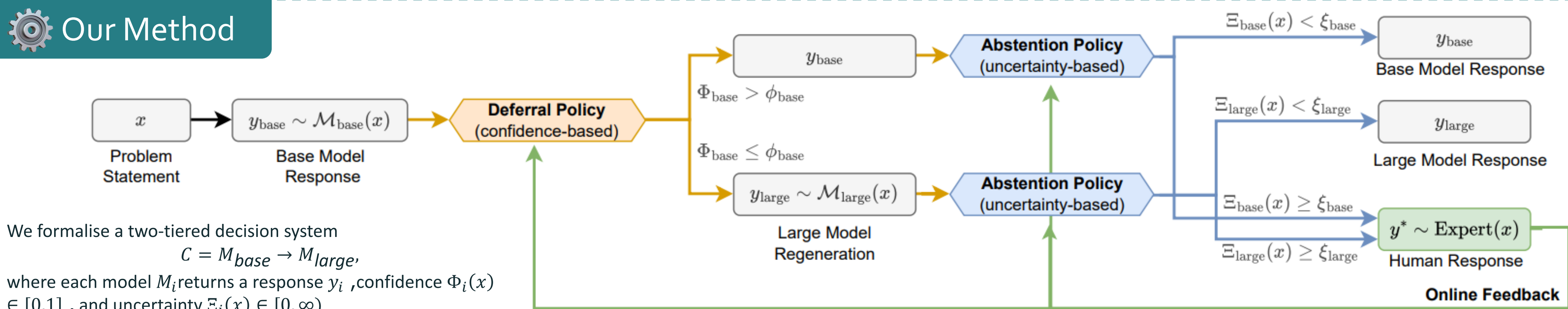
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Our Method



1 Efficient Deferral

Only defer when $\Phi_{base}(x)$ is low to minimise unnecessary regeneration cost:
 M_{large} used iff $\Phi_{base}(x) \leq \phi_{base}$

2 Safe Abstention

Escalate to human experts only when model uncertainty is high.
Abstain iff $\Xi_i(x) > \xi_i$

3 Online Adaption

Update thresholds $\phi_{base}, \xi_{base}, \xi_{large}$ via stochastic gradient descent on $R(C)$ incorporating feedback from human-labelled abstentions.
 $\theta_{t+1} = \theta_t - \eta \nabla_{\theta} R(C)$

Verification & Uncertainty Estimation

Verification Strategies

Given an input-response pair (x, y_i) from model M_i :

- **Self-Verification (SV):**

M_i re-evaluates its own answer with a verification prompt.

- **Surrogate Token Probability (STP):**

Extract next-token probability for YES/NO with verification question:

$$p_i(x) = \frac{M_i(\text{YES} | x, y_i)}{M_i(\text{YES} | x, y_i) + M_i(\text{NO} | x, y_i)}$$

Bayesian Calibration

We fit a **Bayesian Logistic Regression** on a small calibration set (≈ 100 samples):

$$\Phi_i(x) = \mathbb{E}[\text{correctness}],$$

$$\Xi_i(x) = \text{STD}[\text{correctness}],$$

yielding calibrated

- **confidence** $\Phi_i(x)$
- **uncertainty** $\Xi_i(x)$

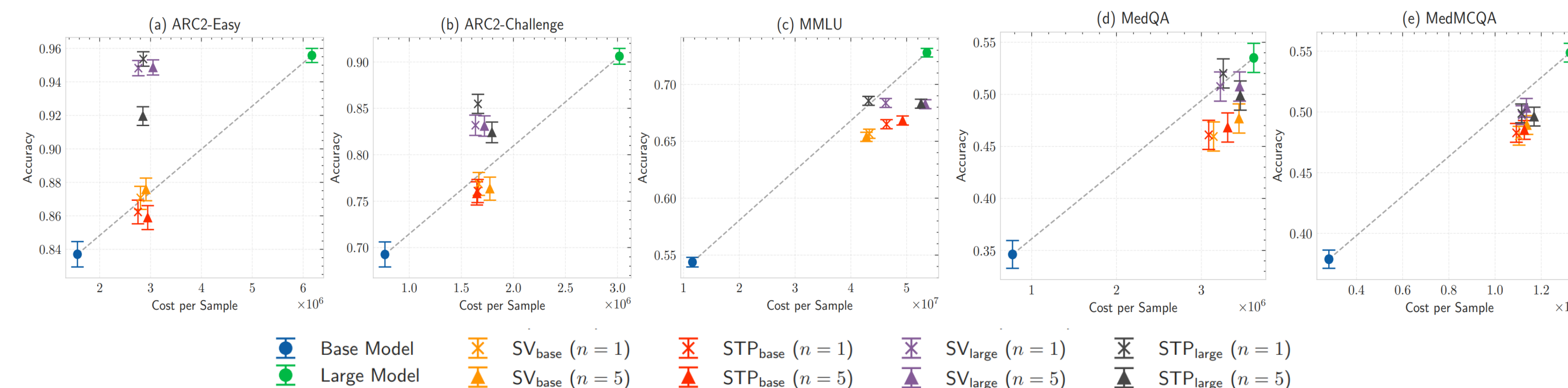
Deferral: if $\Phi_{base}(x) < \phi_{base}$
Abstention: if $\Xi_i(x) > \xi_i$

💡 **Purpose:** This module converts model outputs into **calibrated probabilities** that the system uses to decide **when to defer or abstain**, making the cascade statistically grounded and cost-aware.

Results & Insights

Verification Experiment: Large-model evaluation improves cost-accuracy trade-offs

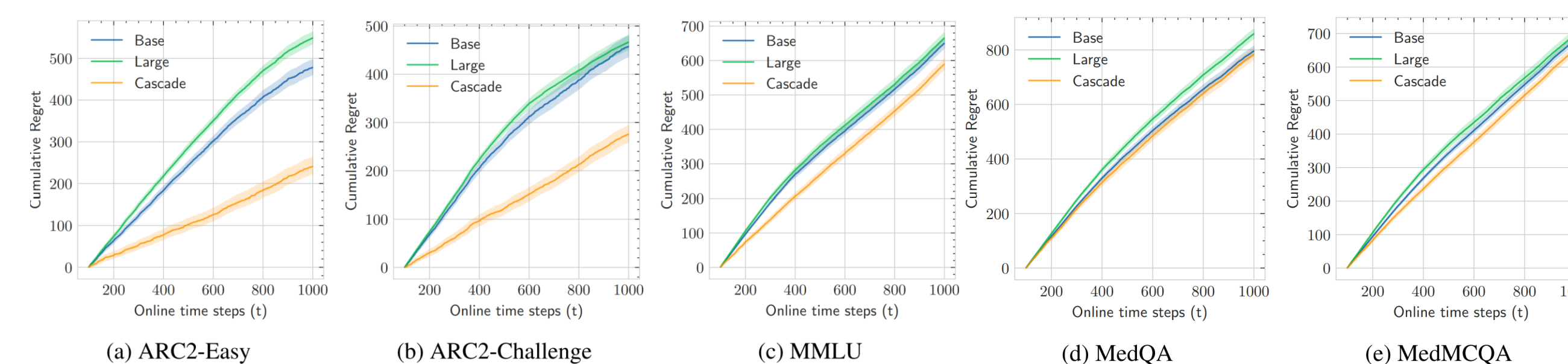
- When using large-on-small model verification the cascaded system achieves higher accuracy per unit cost.
- Surrogate Token Probability (STP) yields the best balance across datasets.



💡 Verifying with a stronger model is cheaper than regenerating responses and yields better calibration.

Online learning Experiment: Online learning reduces cumulative regret

- Introduce a soft-gate (sigmoid) for the decision thresholds, so the optimisation becomes differentiable.
- Updating thresholds $\phi_{base}, \xi_{base}, \xi_{large}$ via SGD on $R(C)$ improves decision efficiency over time.



💡 The cascade learns when to defer or abstain, achieving lower long-term cost-risk.