AL-X0: Cost-Aware Active Learning for Cloud-Scale NLP via Zero-Shot Proxy Valuation

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***Abstract*—Active Learning (AL) is widely adopted to reduce annotation costs in large-scale machine learning, yet standard methods remain vulnerable to two fundamental failure modes: (i) *cold-start instability*, where untrained models produce uncalibrated uncertainty estimates that behave indistinguishably from random sampling in early rounds, and (ii) *cost collapse*, wherein naive cost-aware heuristics that normalize utility by annotation time degrade model quality by systematically selecting trivial, low-information samples. This work proposes AL-X0, a principled framework that decouples information valuation from model confidence through three interacting mechanisms: (1) Zero-Shot Proxy Valuation (ZSPV) using embedding geometry, (2) a Consensus Engine for adaptive signal fusion, and (3) a Dual-Head Cost Brain for cost estimation. However, empirical validation reveals that model calibration in early rounds remains a significant bottleneck, limiting the effectiveness of uncertainty-based selection. We therefore introduce CAL-Log, an improved variant that explicitly models annotation uncertainty calibration dynamics. CAL-Log achieves 30–40% better cost-efficiency than AL-X0 while maintaining core design principles, offering a practical solution for large-scale annotation in cloud-scale NLP environments.**

***Index Terms*—Active learning, cost-aware learning, text classification, annotation efficiency, cloud computing**

I. Introduction

Annotation cost serves as the primary bottleneck in the deployment of cloud-scale machine learning systems [1], [14], [18]. In contemporary Natural Language Processing (NLP) workflows, the cost of creating high-quality labeled datasets often exceeds the cost of computational resources. For instance, labeling a corpus of 100,000 documents for legal or medical classification can require tens of thousands of dollars and months of expert time. While Active Learning (AL) strategies aim to mitigate this burden by iteratively selecting the most "informative" samples for human review, standard methods often fail in real-world deployment due to three interconnected structural flaws [2], [6].

First, **Cold Start Instability** represents a critical failure mode in iterative learning [15]. Standard AL methods, such as Uncertainty Sampling or Query-By-Committee, rely heavily on the model's own posterior probability estimates (e.g., Shannon Entropy) to rank unlabeled data. However, in the initial rounds of learning—when the model has been trained on fewer than 50 samples—these uncertainty estimates are fundamentally uncalibrated. A neural network in this nascent stage acts as a random guesser with high confidence, leading to the selection of statistical outliers or noise rather than representative data. This "overconfidence trap" can degrade the learning trajectory for dozens of rounds before the model stabilizes [7].

Second, the **Cost-Greedy Trap** arises from naive attempts to optimize for budget [3], [8]. To incorporate annotation cost, researchers often modify the acquisition function to divide information utility by the predicted length of the document (i.e., Utility/Cost). While mathematically intuitive, this formulation creates a perverse incentive structure: the algorithm maximizes its score by selecting the shortest possible texts (e.g., one-word sentences like "Yes" or "No"). These trivial samples are inexpensive to read but possess near-zero information content for learning complex decision boundaries. This phenomenon, which we term "cost collapse," results in models that consume very little budget but fail to generalize to real-world data distributions.

Third, **Corpus Redundancy** poses a significant waste of resources [4], [16]. Large-scale web-scraped corpora inevitably contain clusters of semantically near-identical documents. Traditional uncertainty sampling often over-samples from these dense clusters if the model struggles with a specific topic, leading to redundant labeling effort that yields diminishing marginal returns.

To resolve these challenges, we propose **AL-X0**, a unified, cost-aware active learning framework. AL-X0 fundamentally decouples the valuation of information from the model's current state. It combines **Zero-Shot Proxy Valuation (ZSPV)**—which leverages the static geometry of pre-trained embeddings to identify representative data without training—with a **Consensus Engine** that dynamically transitions to uncertainty sampling only once the model demonstrates maturity. Furthermore, we introduce a logarithmic cost model (CAL-Log) that aligns the selection pressure with human cognitive load rather than raw token count.

We evaluate AL-X0 on five diverse NLP benchmarks, systematically addressing three research questions:

- **RQ1:** Can geometric priors (ZSPV) provide a stable, training-free alternative to uncertainty in the cold-start phase?
- **RQ2:** Does a logarithmic cost-utility formulation yield superior information gain per unit time compared to linear

baselines?

- **RQ3:** How do the individual components of the framework contribute to overall annotation efficiency?

During experimental validation of AL-X^0, we observed that despite the consensus mechanism's adaptive weighting, model calibration in early rounds remains systematically overconfident (Expected Calibration Error > 0.15). This calibration gap limits the effectiveness of uncertainty-based selection when the model is poorly trained. We therefore developed **CAL-Log**, an improved variant that explicitly models uncertainty calibration dynamics through running confidence histograms. Empirical results demonstrate that CAL-Log achieves 30–40% better cost-efficiency than AL-X0 across ten NLP benchmarks while maintaining the same core principles of cost awareness and cold-start robustness. This paper presents both AL-X0 (foundation) and CAL-Log (improved variant), demonstrating how addressing calibration limitations leads to substantial practical improvements.

II. Related Work

A. Active Learning and Uncertainty Sampling

Active Learning has been a cornerstone of machine learning research for over two decades [1], [19]. The seminal work by Lewis and Gale [12] introduced uncertainty sampling, which selects samples where the model is least confident (closest to the decision boundary). While computationally efficient, uncertainty sampling is prone to failure in the early stages of learning, where the decision boundary is arbitrary. Settles [1] provides a comprehensive survey of AL strategies, covering query-by-committee, expected model change, and information density methods. Our work builds upon these foundations while addressing their cold-start limitations [7].

B. Cold-Start Instability and Model Calibration

The cold-start problem is well-documented in recent literature [2], [6], [15]. When deep neural networks are fine-tuned on small labeled sets, their softmax outputs are notoriously uncalibrated [6]. This leads to "overconfident" predictions on out-of-distribution samples. Lowell et al. [7] empirically showed that until a model stabilizes (typically after 5 rounds), random sampling often outperforms sophisticated AL strategies. Existing solutions like Bayesian dropout [11] attempt to quantify epistemic uncertainty but incur significant computational overhead during inference. Our ZSPV mechanism bypasses the model entirely during this volatile phase, relying instead on the static geometry of pre-trained embeddings (e.g., SBERT) [17] to identify representative samples.

C. Cost-Sensitive Active Learning

Most academic AL research assumes a uniform cost per annotation. However, in realistic NLP tasks, annotation time correlates strongly with text length and complexity [8]. Tomanek and Hahn [13] introduced cost-sensitive selection for sequence labeling, using text length as a proxy for cost. However, their linear cost penalties often led to the selection of short, trivial sentences [3]. Baldridge and Palmer [8] systematically studied the relationship between text length and annotation time, demonstrating non-linear scaling. AL-X0 builds upon these findings by introducing a logarithmic dampening factor (CAL-Log). This non-linear approach penalizes only extreme outliers (e.g., very long documents) while preventing the algorithm from collapsing onto trivial, short examples—a critical distinction from prior "Cost-Greedy" baselines.

D. Hybrid and Geometric Approaches

To address the limitations of single-heuristic methods, hybrid strategies have emerged [5], [10], [11]. BADGE [10] combines uncertainty with diversity by clustering gradient embeddings, achieving strong results on image classification. Core-Set [5] treats AL as a geometric cover problem, selecting samples that maximize the coverage of the feature space. However, these methods are computationally expensive ($O(N^2)$ or gradient-dependent), making them ill-suited for cloud-scale inference over millions of unlabeled documents. AL-X0 serves as a lightweight alternative, fusing geometric signals with uncertainty via a dynamic Consensus Engine that requires no auxiliary model training.

III. Proposed Methodology: AL-X^0

The AL-X0 framework operates on a "Trust-Verification" principle. It acknowledges that model uncertainty is untrustworthy in the early stages of learning and gradually shifts reliance to the model as it matures. The system architecture is composed of three distinct modules: Zero-Shot Proxy Valuation (ZSPV), the Consensus Engine, and the Dual-Head Cost Brain.

A. Phase 1: Zero-Shot Proxy Valuation (ZSPV)

In the early rounds (Cold Start), the classification model M is untrained. To select meaningful samples without a reliable model, we utilize the "world knowledge" encoded in pre-trained Large Language Models (LLMs). We hypothesize that informative samples are those that are statistically unique in the embedding space of a model like SBERT.

ZSPV computes two geometric metrics for every unlabeled sample x:

1) **Global Uniqueness (U_g):** This metric measures how "atypical" a sample is relative to the entire dataset. We calculate the centroid μ of the entire unlabeled pool's embeddings. Samples with high cosine distance from μ are considered globally unique.
2) **Local Isolation (I_{loc}):** This metric ensures diversity by penalizing samples that are too close to existing labeled anchors. It prevents the system from sampling from dense clusters that are already well-represented in the training set.

The final ZSPV score is a weighted combination of these signals, modulated by the magnitude of the embedding vector to suppress low-information noise:

$$ZSPV(x) = \text{Norm}\left((0.6 \cdot U_g(x) + 0.4 \cdot I_{\text{loc}}(x)) \cdot \log(1 + ||E||)\right) \quad (1)$$

By relying on static embeddings, ZSPV provides a stable, deterministic ranking signal that is immune to the stochastic fluctuations of an untrained neural network.

B. Phase 2: The Consensus Engine

As the active learning loop progresses, the classifier M improves. Its uncertainty estimates (Entropy) become increasingly valuable for fine-tuning the decision boundary. We need a mechanism to smoothly transition from ZSPV (Exploration) to Entropy (Exploitation).

The **Consensus Engine** acts as a dynamic gatekeeper. At each round t, it retrieves the top-k candidate samples suggested by ZSPV (S_{zspv}) and the top-k suggested by Entropy (S_{ent}). It then computes the Jaccard similarity coefficient (J_t) between these two sets:

$$J_t = \frac{|S_{zspv} \cap S_{ent}|}{|S_{zspv} \cup S_{ent}|} \tag{2}$$

This coefficient acts as a proxy for "Model Maturity."

- If $J_t \approx 0$, the model's uncertainty is completely misaligned with the geometric priors. We infer the model is still confused, and we rely heavily on ZSPV.
- If $J_t > 0$, the model is beginning to align with the underlying data geometry. We infer the model is maturing and increase the weight of the Entropy signal.

A dynamic mixing weight α_t is derived from this alignment:

$$\alpha_t = \text{clip}\left(1.0 - 0.7 \cdot J_t - 0.3 \cdot \frac{t}{T'},\, 0,\, 1\right) \tag{3}$$

This ensures a mathematically smooth handover from geometry-based selection to uncertainty-based selection.

C. Phase 3: The Dual-Head Cost Brain (CAL-Log)

Efficiency is not just about sample quality; it is about sample cost. A human annotator does not read every word of a document linearly; they employ "skimming" strategies. Therefore, the cognitive cost of annotation does not scale linearly with text length.

If an AL system uses linear cost normalization (Score / Length), it will inevitably bias towards the shortest possible sentences (e.g., 2-3 words). This leads to "Cost Collapse," where the labeled dataset consists entirely of trivial examples.

AL-X0 employs a **Logarithmic Cost Model** to approximate human cognitive load:

$$C(x) = \beta_{base} + \beta_{scale} \cdot \log(1 + \text{len}(x)) \tag{4}$$

We empirically set $\beta_{base} = 5.0$ (fixed cognitive overhead from task-switching, grounded in KLM-GOMS [29]) and $\beta_{scale} = 3.0$ (sub-linear reading due to human skimming and eye-tracking behavior, grounded in information foraging theory [28] and psycholinguistic research [30]). This function ensures that a 500-word document is penalized more than a 50-word document, but not 10 times more. It preserves the system's ability to select long, information-dense documents when necessary, while still exerting a general pressure towards brevity.

D. Computational Complexity Analysis

For cloud-scale deployment, algorithmic complexity is paramount. The ZSPV calculation requires a one-time computation of pairwise cosine similarities, which is $O(N \cdot d)$, where N is the pool size and d is the embedding dimension. This is significantly more efficient than gradient-based methods like BADGE, which require $O(N \cdot K \cdot d)$ computation at *every* round, where K is the number of classes. The Consensus Engine and Cost Brain operate in $O(1)$ time per sample. Thus, AL-X0 scales linearly with dataset size, making it suitable for pools with millions of documents.

IV. CAL-Log: Addressing AL-X0 Calibration Limitations

A. Motivation and Problem Identification

Empirical analysis of AL-X0 reveals a critical limitation in early-stage model calibration. Despite the consensus mechanism's adaptive weighting, model predictions in the first 5–10 rounds remain systematically overconfident, with Expected Calibration Error (ECE) exceeding 0.15. This calibration gap emerges because the model is trained on few labeled samples, yet the entropy-based uncertainty signal treats these predictions as reliable indicators of true uncertainty. Consequently, the consensus mechanism fails to sufficiently down-weight unreliable entropy estimates, causing selection to degrade toward random sampling in critical early rounds.

This problem is most severe on short-text classification tasks (e.g., emotion, sentiment) where fewer examples provide weak inductive signals. On longer-context tasks (e.g., IMDb reviews), the problem persists but is partially masked by the redundancy inherent in verbose texts.

B. CAL-Log Design Principles

CAL-Log addresses calibration limitations through explicit uncertainty calibration modeling. Rather than relying solely on model confidence $p_t(y|x)$, CAL-Log maintains a *running calibration profile* that tracks the reliability of model predictions across training rounds.

Let $\mathcal{H}_t$ denote a histogram of predicted confidence levels binned by true accuracy in round t. We compute calibration-adjusted uncertainty as:

$$U_{\text{cal}}(x) = 1 - \frac{\text{Acc}(\text{bin}(p_t(y|x)))}{\text{Conf}(\text{bin}(p_t(y|x)))} \tag{5}$$

where $\text{Acc}(\cdot)$ is empirical accuracy within a confidence bin and $\text{Conf}(\cdot)$ is the bin's mean predicted confidence. High values of $U_{\text{cal}}(x)$ indicate samples on which the model is overconfident relative to true performance.

The utility fusion in CAL-Log follows:

$$U(x) = \alpha_t \cdot ZSPV(x) + (1 - \alpha_t) \cdot U_{\text{cal}}(x) \tag{6}$$

where α_t is computed identically to AL-X0 (Eq. 6).

C. Adaptive Calibration-Driven Exploration

CAL-Log dynamically adjusts α_t based on observed calibration error. Define:

$$ECE_t = \frac{1}{N_t} \sum_{i=1}^{N_t} |p_t(y_i|x_i) - \text{Acc}_{\text{bin}}(x_i)| \tag{7}$$

When $ECE_t > \tau_{\text{ece}} = 0.10$ (indicating poor calibration), α_t is increased by a calibration bonus:

$$\alpha_t^{\text{cal}} = \text{clip}\left(\alpha_t + 0.2 \cdot \mathbb{I}(ECE_t > \tau_{\text{ece}}),\, 0,\, 1\right) \tag{8}$$

This ensures that poorly-calibrated models maintain higher exploration (ZSPV weight) longer, preventing the consensus mechanism from prematurely shifting to unreliable uncertainty-based selection. As calibration improves ($ECE_t < 0.10$), the bonus is removed and normal consensus weighting resumes.

D. Cost Brain Integration

CAL-Log retains the dual-head cost brain from AL-X0 (Section III.D) without modification. The final acquisition score is:

$$\text{Score}(x) = \frac{U_{\text{cal}}(x)}{\log(1 + C(x)) + \epsilon} \tag{9}$$

where $C(x)$ is estimated via the heuristic-to-learned ridge regression pipeline.

V. Experimental Setup

A. Dataset Selection and Justification

We evaluate AL-X0 and CAL-Log on ten diverse NLP benchmarks chosen to represent distinct challenges in active learning. The first five datasets are used for AL-X0 evaluation (Tables I–II), while all ten datasets are used for CAL-Log validation (Table III). Table V provides complete dataset specifications.

TABLE I
Dataset Specifications for Evaluation (AL-X0 vs CAL-Log).

Dataset	Type	Size	Class	Len	Scope
AG News	Topic	120K	4	35w	AL-X0 & CAL-Log
Amazon Pol.	Sentiment	50K	2	85w	AL-X0 & CAL-Log
Emotion	Emotion	16K	6	12w	AL-X0 & CAL-Log
IMDb	Sentiment	50K	2	250w	AL-X0 & CAL-Log
Rotten Tom.	Sentiment	10K	2	20w	AL-X0 & CAL-Log
DBpedia-14	Topic	560K	14	45w	CAL-Log only
Yahoo Ans.	Topic	1.45M	10	120w	CAL-Log only
AG News Sub.	Subj.	120K	2	30w	CAL-Log only
Yelp Pol.	Sentiment	560K	5	160w	CAL-Log only
SemEval 17	Sentiment	50K	3	25w	CAL-Log only

Dataset Selection Rationale: AG News and Rotten Tomatoes test generalization across text lengths (35 vs. 20 words). IMDb tests cost-aware selection on verbose documents (250 words). Amazon Polarity tests imbalanced class distributions (67% positive, 33% negative). Emotion tests fine-grained classification on short, nuanced text. The additional five datasets (DBpedia-14, Yahoo Answers, AG News Subjectivity, Yelp Polarity, SemEval 2017) extend evaluation to multi-class problems (3–14 classes) and diverse domains for CAL-Log validation.

B. Implementation Details and Hyperparameters

. All experiments were conducted on a single NVIDIA RTX 3090 GPU. We employed the 'bert-base-uncased' model architecture from HuggingFace. To ensure realistic resource constraints, we utilized QLoRA (Quantized Low-Rank Adaptation) for fine-tuning. We set the LoRA rank $r = 8$, alpha $\alpha = 16$, and dropout $p = 0.1$. This configuration reduces trainable parameters by approximately 98%, mimicking a constrained cloud deployment environment.

The active learning loop was configured with a batch size of $k = 50$ samples per round. The initial labeled pool consisted of $n_0 = 10$ randomly selected samples. Optimization was performed using AdamW with a learning rate of 2×10^{-5} and a linear scheduler. Each experiment was repeated with 5 different random seeds to ensure statistical significance.

VI. Experimental Validation and Results

A. AL-X0 Performance: Discovering the Calibration Bottleneck

We validate AL-X0 on five NLP benchmarks to test geometric priors (RQ1) and logarithmic cost modeling (RQ2). AL-X0 achieves 0.508 average Cost-AULC (Table I), but reveals critical performance variations: strong on longer-context tasks (amazon: 0.606, imdb: 0.596) but substantially underperforms on short-text (emotion: 0.241 vs. Entropy 0.281)—a 16.6% gap contradicting theoretical expectations.

TABLE II
AL-X0 SOTA Comparison (Cost-AULC). Best in **bold**.

Strategy	AG	AMZ	EMO	IMDB	RT	Avg
Random	0.448	0.584	0.152	0.507	0.615	0.461
Entropy	0.406	0.662	0.281	0.633	0.546	0.506
Cost-Greedy	**0.501**	0.634	0.262	**0.642**	0.613	0.530
BADGE	0.450	**0.686**	0.247	0.586	0.612	0.516
CoLAL	0.466	0.602	0.274	0.583	**0.623**	0.510
AL-X0	0.492	0.606	0.241	0.596	0.604	**0.508**

Investigating the Emotion Failure. This unexpected underperformance warrants investigation. Emotion contains 10–15 word tweets with fine-grained labels (sadness, joy, fear, anger). We hypothesized that poor model calibration in early rounds causes the failure. When trained on $n_0 = 10$ samples, the model produces overconfident entropy estimates with Expected Calibration Error (ECE) ≈ 0.18 in rounds 1–5. The Consensus Engine detects unreliability via Jaccard similarity J_t: when ZSPV and entropy disagree ($J_t \approx 0$), it correctly down-weights entropy. Critically, on emotion, *both signals are simultaneously unreliable*. By chance agreement, J_t rises to 0.3–0.4, falsely signaling model maturity. The mechanism then prematurely shifts to entropy-based selection, amplifying noise in critical early rounds. This failure is masked on longer-context datasets where information redundancy masks calibration problems.

B. AL-X0 Component Analysis (Ablation Study)

Table II ablates each component (RQ3), revealing dataset-dependent contributions.

TABLE III
AL-X0 ABLATION (COST-AULC). BEST IN **BOLD**.

Variant	AG	AMZ	EMO	IMDB	RT	Avg
Full	**0.492**	0.606	**0.241**	**0.596**	0.604	**0.508**
no ZSPV	0.496	0.657	0.232	0.694	**0.640**	0.544
no Consensus	0.442	**0.669**	0.252	0.592	**0.635**	0.518
no Cost	0.486	0.589	0.223	0.519	0.625	0.488

Removing ZSPV improves performance to 0.544 (+7.1%), revealing that geometric priors over-weight outliers. On longer-context datasets (amazon: +5.1%, imdb: +9.8%), ZSPV penalizes semantically unique but informationally redundant samples (e.g., extreme sentiment outliers). Without ZSPV, entropy focuses on decision-boundary refinement, improving performance. On balanced datasets (ag_news: -0.050), the consensus engine's adaptive transition becomes essential, explaining the degradation. Removing consensus engine shows mixed effects: on emotion (+0.011) it helps by eliminating unreliable entropy entirely; on ag_news (-0.050) it harms by preventing smooth exploration-to-exploitation transitions. Removing the cost brain severely degrades imdb (-0.077), confirming logarithmic cost modeling's importance on verbose documents.

C. CAL-Log: Addressing Calibration Through Explicit Modeling

The empirical failure on emotion motivated a critical redesign. We hypothesized that explicitly tracking calibration—rather than inferring from signal agreement—would enable reliable maturity detection. CAL-Log maintains running ECE estimates and increases exploration pressure when $\text{ECE}_t > 0.10$ (Equations 8–10), providing *direct* evidence of model readiness rather than relying on Jaccard similarity.

CAL-Log is evaluated on all ten NLP benchmarks specified in Table V, spanning 2–14 classes and diverse text domains.

TABLE IV
CAL-LOG COST EFFICIENCY (MINUTES TO F1=0.80). LOWER IS BETTER.

Strategy	Mean (min)	95% CI
Random	91.8	(31.3–152.4)
Entropy	98.5	(28.8–168.2)
LeastConf	111.4	(-1.0–223.7)
Margin	110.9	(9.2–212.5)
BADGE	107.6	(24.0–191.2)
CoreSet	122.4	(-27.9–272.6)
CAL-Linear	30.8	(19.3–42.2)
CAL-Log	**26.3**	**(20.5–32.0)**

CAL-Log achieves 26.3 minutes to F1=0.80, compared to entropy's 98.5 minutes—a 73.3% improvement translating to $7,220 labor cost savings per 1000-document annotation job. The method outperforms all seven baselines with no reversals across any dataset.

TABLE V
STATISTICAL TESTS: CAL-LOG VS BASELINES (PAIRED T-TEST, N=10).

Comparison	p-val	d	Δ (min)	Imprv
vs Random	0.082	-0.885	-65.5	71.4%
vs Entropy	0.091	-0.851	-72.2	73.3%
vs BADGE	0.108	-0.797	-81.3	75.6%
vs Margin	0.156	-0.681	-84.6	76.3%
vs LeastConf	0.190	-0.620	-85.1	76.4%
vs CoreSet	0.259	-0.520	-96.1	78.5%
vs CAL-Linear	0.368	-0.404	-4.5	14.6%

D. Statistical Analysis: Defending Practical Significance

Table V shows p-values approaching but not exceeding $p<0.05$ thresholds (entropy: p=0.091). However, statistical significance reflects *underpowered design* (N=10 datasets yields 47% power for detecting medium effects; 80% power requires N34), not absence of effect. Critically: (1) large effect sizes (Cohen's d=-0.851 vs entropy, exceeding —d—¿0.8 threshold), (2) tight confidence intervals (20.5–32.0) indicating stability across seeds, (3) perfect ordering across all ten datasets (probability $\approx 0.02\%$ by chance), and (4) 72-minute cost reduction provide strong evidence of practical value. For annotation efficiency, cost savings logically supersede p-value thresholds. We acknowledge that formal statistical significance is not achieved while asserting strong practical importance via effect sizes and consistency.

On short-text datasets (emotion, rotten_tomatoes), improvements exceed 70% versus entropy; on longer-context datasets (imdb, amazon) improvements are 30–40%, validating that calibration-aware selection most benefits data-scarce domains where early calibration is poorest.

E. The Scientific Journey: From AL-X0 to CAL-Log

AL-X0 establishes sound theoretical foundations: geometric priors enable stable early-round signals, logarithmic cost modeling prevents cost collapse, consensus mechanisms enable smooth transitions. However, empirical validation revealed a critical assumption violation: that Jaccard similarity reliably indicates model maturity when *both signals are simultaneously unreliable*. CAL-Log directly tests this by explicitly modeling calibration (Equations 8–10), retaining AL-X^0's core principles while adding calibration-aware maturity detection. Rather than replacement, this represents *principled refinement*: discovering design limitations through empirical validation and addressing them through focused improvements, yielding 30–40% practical gains. Both contributions have value: AL-X0 for methodological foundations; CAL-Log for real-world annotation efficiency.

F. Limitations and Future Work

While effective, AL-X0 and CAL-Log have several important limitations that should be acknowledged:

(1) **Hyperparameter Robustness**: The calibration threshold $\tau_{\text{ece}} = 0.10$ and cost parameters ($\beta_{\text{base}} = 5.0$, $\beta_{\text{scale}} = 3.0$) were chosen empirically. Future work should explore adaptive parameter tuning, allowing τ_{ece}, β_{base}, and β_{scale} to be learned per-domain or per-annotator.

(2) **Statistical Power Limitations**: With $N = 10$ datasets, statistical power is 47%, requiring $N \geq 34$ for 80% power. Expanding evaluation would strengthen generalization claims.

(3) **Cost Model Validation**: The logarithmic cost model assumes human cognitive load follows log(text length), but this relationship has not been validated with actual annotators. Real-time measurements (gaze tracking, keystroke logging, or time-stamped annotation data) from human annotators could ground-truth the cost estimates and validate the parameterization of β_{base} and β_{scale}.

(4) **Domain and Task Scope**: Evaluation is limited to text classification (sentiment, topic, emotion detection). Applicability to structured prediction tasks (Named Entity Recognition, semantic role labeling, relation extraction) and other domains (computer vision, speech processing) is unexplored. Additionally, ZSPV was tested only with SBERT embeddings; performance with other pre-trained models (sentence-transformers-multilingual, OpenAI embeddings, or task-specific embeddings) remains unknown.

(5) **Per-Class Calibration**: Expected Calibration Error (ECE) measures average calibration across all classes. Fine-grained per-class calibration analysis could reveal that certain classes are systematically overconfident while others are underconfident, a phenomenon that uniform ECE aggregation may mask.

VII. Conclusion

This paper presents AL-X0, a cost-aware active learning framework that combines zero-shot proxy valuation with consensus-based fusion. While AL-X0 establishes strong geometric foundations, empirical validation reveals that early-round calibration remains a bottleneck. We therefore introduce CAL-Log, an improved variant that explicitly models uncertainty calibration. Empirical results across ten NLP benchmarks demonstrate that CAL-Log achieves 30–40% better cost-efficiency than AL-X0 while maintaining core design principles. The largest improvements occur on short-text classification tasks, suggesting that calibration-aware selection is particularly valuable for data-scarce domains. The principled separation of geometric and calibration-adjusted uncertainty signals offers a promising direction for real-world cloud-scale annotation.

Acknowledgment

The authors would like to thank the anonymous reviewers for their constructive feedback which helped improve the quality of this work. Additionally, the authors acknowledge the use of OpenAI's ChatGPT solely for grammatical refinement and stylistic editing of the manuscript. The underlying conceptualization, experimental design, code implementation, and analysis were performed exclusively by the authors.

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