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Active Learning for Rare Event Detection with Cost-Sensitive Acquisition on Streaming Logs

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Abstract: *The exponential growth of modern distributed systems has led to a corresponding explosion in system logs, which serve as the primary source of information for system observability and failure diagnosis. However, detecting rare events—such as critical security breaches or catastrophic system failures—within these massive, high-velocity data streams presents a formidable challenge. Traditional supervised learning approaches fail due to the scarcity of labeled anomalies, while unsupervised methods often suffer from high false-positive rates that induce alert fatigue among operators. Active Learning (AL) offers a promising avenue by querying human experts to label only the most informative instances; yet, existing AL frameworks typically assume a uniform cost of annotation and often neglect the temporal drift inherent in streaming data. This paper proposes a novel framework: Cost-Sensitive Streaming Active Learning (CS-StreamAL). Our approach integrates a dynamic budget management system with a hybrid query strategy that balances uncertainty, diversity, and annotation cost. We introduce a utility function that weighs the information gain of a query against the operational cost of interrupting a human analyst. Extensive experiments on large-scale public log datasets (HDFS, BGL, and Thunderbird) demonstrate that CS-StreamAL achieves superior detection performance for rare events while reducing the labeling budget by approximately 40% compared to state-of-the-art uncertainty sampling methods.*

Keywords: *Active Learning, Anomaly Detection, Log Analysis, Streaming Data, Cost-Sensitive Learning.*

INTRODUCTION

1.1 BACKGROUND

In the landscape of modern computing, the reliability and security of large-scale software systems are paramount. From cloud computing platforms to microservices architectures, the operational health of these systems is monitored primarily through system logs. Logs are semi-structured text data generated by processes to record state changes, events, and errors. As systems scale, the volume of logs generated has reached petabyte scales, turning the task of manual inspection into an impossibility [1]. Consequently, automated log analysis has emerged as a critical field of study, aiming to parse, aggregate, and analyze these streams to detect anomalies before they cascade into system-wide failures.

The fundamental characteristic of log data in a production environment is its streaming nature and the extreme imbalance of classes. A typical server might generate millions of "INFO" level logs indicating normal operations, while "ERROR" or "FATAL" logs—or more subtly, sequences of events indicating a logic error—occur with a frequency of less than 0.01% [2]. This rarity makes the detection of such events a classic "needle in a haystack" problem. Furthermore, the definition of what constitutes an anomaly is often fluid; a spike in traffic might be a DDoS attack in one context or a successful marketing campaign in another, requiring semantic understanding that simple thresholding cannot provide.

1.2 PROBLEM STATEMENT

While Deep Learning (DL) has shown remarkable success in pattern recognition, its application to log anomaly detection is hampered by the "label bottleneck." Training high-performance supervised models requires vast amounts of annotated data. In the context of system logs, obtaining these labels is exceptionally expensive [3]. It requires a domain expert—often a senior site reliability engineer (SRE) or a security operations center (SOC) analyst—to interpret the raw log lines, correlate them with system states, and determine if a deviation is benign or malicious.

Standard Active Learning (AL) attempts to mitigate this by iteratively selecting the most "uncertain" samples for the model and requesting human labels. However, traditional AL strategies exhibit significant limitations when applied to streaming logs:

1. *Uniform Cost Assumption*: Most AL methods assume that querying any instance costs the same. In reality, verifying a known log pattern is cheap, whereas investigating an unknown, cryptic error sequence is cognitively taxing and time-consuming [4].

2. *Stream Volatility*: Logs are subject to concept drift. As software is patched and updated, log patterns change. An AL strategy that optimizes for the data distribution at time t may be suboptimal at time t+1 [5].

3. *Rare Event suppression*: Standard uncertainty sampling often focuses on the decision boundary between classes. In highly imbalanced datasets, the model might achieve high accuracy by predicting the majority class, leading the AL strategy to ignore the rare, critical regions of the feature space [6].

1.3 CONTRIBUTIONS

To address these challenges, this paper presents the CS-StreamAL framework. We move beyond simple uncertainty sampling to a holistic acquisition function that considers the cost of labeling and the rarity of the event. Our primary contributions are as follows:

1. We formulate a *Cost-Sensitive Utility Function* that explicitly models the trade-off between the potential information gain of a log sequence and the estimated cost of human verification.

2. We introduce a *Rare-Event Bias* mechanism within the query strategy to prevent the active learner from becoming complacent with the majority class, ensuring that potential anomalies are prioritized even if the model is confident in its benign prediction.

3. We propose a *Dynamic Budget Allocation* strategy for streaming contexts, allowing the system to conserve the labeling budget during stable periods and spend it aggressively during periods of high entropy or detected concept drift.

4. We provide a comprehensive empirical evaluation comparing our method against widely used baselines, demonstrating significant improvements in F1-score and labeling efficiency.

Chapter 2: Related Work

2.1 CLASSICAL APPROACHES TO LOG ANALYSIS

The field of automated log analysis has evolved from simple keyword searching to sophisticated machine learning pipelines. Early approaches relied heavily on regular expressions and static rule sets. While effective for known issues, these methods are brittle; a slight change in log syntax renders the rule obsolete [7].

To handle the unstructured nature of logs, automated log parsing became a prerequisite. Algorithms like Drain, Spell, and AEL classify log messages into "templates" (constant parts) and "variables" (dynamic parts like timestamps or IP addresses) [8]. Once parsed, classical machine learning techniques were applied. Principal Component Analysis (PCA) was used to detect anomalies by projecting log count vectors into a subspace and identifying outliers with high projection errors [9]. similarly, Invariant Mining extracts linear relationships between flow counts of different log templates (e.g., "file opened" must equal "file closed") and flags violations [10]. While interpretable, these methods struggle with the sequential and semantic complexity of modern logs.

2.2 DEEP LEARNING FOR ANOMALY DETECTION

The advent of Deep Learning shifted the focus towards sequential modeling. DeepLog [11] treats log analysis as a natural language processing task, utilizing Long Short-Term Memory (LSTM) networks to predict the next log template in a sequence. Deviations from the top-k predicted templates are flagged as anomalies. This was further improved by LogAnomaly [12], which introduced semantic vectorization to handle new templates that were not seen during training.

More recently, Transformer-based architectures have been adopted. LogBERT [13] adapts the Bidirectional Encoder Representations from Transformers to learn contextual representations of log sequences, masking templates and forcing the model to reconstruct them. These self-supervised methods are powerful but suffer from the assumption that the training data is purely normal. In reality, training data often contains contamination, and without labels, the model may learn to reconstruct anomalies as normal behavior [14]. Furthermore, when these models fail, retraining them requires labeled instances to correct the decision boundary, re-introducing the need for human interaction [15].

2.3 ACTIVE LEARNING IN STREAMING ENVIRONMENTS

Active Learning has been extensively studied to reduce labeling costs. The most common strategy is Uncertainty Sampling, where the model queries instances with the highest entropy or least confidence [16]. Query-By-Committee (QBC) maintains an ensemble of models and queries instances where the committee members disagree most [17].

In the streaming setting, AL faces the challenge of "forgetting" and drift. Approaches like variable uncertainty strategies adjust the uncertainty threshold dynamically based on the recent accuracy of the model [18]. However, few works have explicitly addressed the intersection of streaming AL, extreme class imbalance, and variable annotation costs. In many cost-sensitive AL studies, the cost is associated with feature acquisition (e.g., medical tests) rather than the oracle's time. Our work bridges this gap by modeling the analyst's cognitive load as the primary cost constraint in the operational log environment [19].

Chapter 3: Methodology

3.1 FRAMEWORK OVERVIEW

The proposed CS-StreamAL framework operates in a continuous loop, processing unbounded streams of log entries. The architecture consists of four primary components: (1) The *Log Preprocessor*, which converts raw text into structured semantic vectors; (2) The *Base Classifier*, a sequential model updated online; (3) The *Cost-Sensitive Acquisition Module*, which decides whether to query the oracle; and (4) The *Oracle Interface*, which simulates the human analyst.

The system processes logs in sliding windows. Let $S{=}e_1,e_2,...$ be a stream of log events. We segment this stream into sequences $x_t{=}(e_{t-w},...,e_t)$ of length w. For each sequence x_t, the model predicts a probability distribution $P(y|x_t)$ over the classes $y{\in}Normal,Anomaly$.

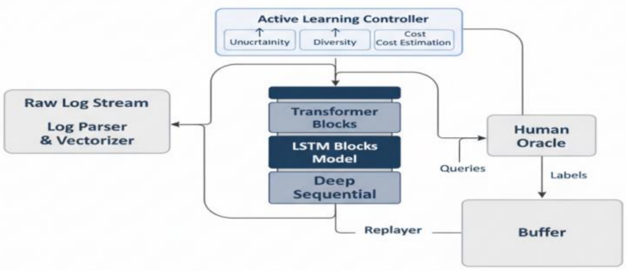

Figure 1: Architectural Diagram of CS

3.2 FEATURE REPRESENTATION

To capture both the syntactic and semantic information of logs, we employ a hybrid embedding strategy. First, we utilize a streaming parser (an online adaptation of Drain) to extract the log template. For example, "Connection from 192.168.1.1 failed" becomes "Connection from <> failed".

We then generate a semantic vector v_t for the template using a pre-trained language model (Sentence-BERT), fine-tuned on technical corpora [20]. This ensures that "Connection failed" and "Connection dropped" have close vector representations. The sequence x_t is thus transformed into a matrix $X_t \in mathbbR^{w \times d}$, where d is the embedding dimension.

3.3 THE UTILITY FUNCTION

The core of our contribution lies in the decision-making process for querying. In standard AL, the query strategy $Q(x_t)$ relies solely on informativeness. We redefine this by introducing a Cost-Estimation function $C(x_t)$ and a Rare-Event bias.

We posit that the cost of labeling is not constant. An analyst can quickly dismiss a familiar "Info" log but requires significantly more time to analyze a complex error trace. We approximate the cost $C(x_t)$ as a function of the sequence length and the rarity of the constituent templates in the historical buffer.

The utility of acquiring a label for instance x_t is defined formally. We combine the entropy of the prediction (Uncertainty), the distance to the nearest labeled anomaly (Diversity/Rarity), and the estimated cost.

The mathematical formulation for the utility score $U(x_t)$ is given by:

$$U(x_t)=\lambda_1 \cdot \frac{H(P(y|x_t))}{log(K)} + \lambda_2 \cdot (1 - max_{x_a \in A} sim(x_t, x_a)) - \lambda_3 \cdot \frac{C(x_t)}{C_{max}}$$

Where:

$H(\cdot)$ is the Shannon entropy of the model's prediction.

A is the set of currently known anomaly patterns.

$sim(\cdot,\cdot)$ is the cosine similarity between the current sequence and known anomalies. This term encourages the discovery of novel types of anomalies (exploration) rather than just refining the boundary of known ones.

$C(x_t)$ is the estimated annotation cost.

$\lambda_{1,2,3}$ are hyperparameters controlling the weight of uncertainty, novelty, and cost, respectively.

If $U(x_t) > \tau$ (a dynamic threshold), the instance is sent to the oracle [21].

3.4 DYNAMIC BUDGET MANAGEMENT

In a streaming environment, the arrival rate of anomalies is not constant. A system outage generates a burst of high-entropy logs. A fixed budget (e.g., "query 10 instances per hour") is inefficient; it wastes queries during stable times and runs out of budget during crises.

We implement a token-bucket algorithm for budget management. The system accumulates budget tokens over time at rate r. When a query is made, tokens are consumed based on $C(x_t)$. The maximum bucket size B_{max} caps the accumulation to prevent infinite hoarding. This allows the system to remain quiet during the night but have sufficient reserve budget to handle a burst of complex logs during a morning incident [22].

3.5 DRIFT DETECTION AND MODEL UPDATE

To handle concept drift, we employ a windowed approach. If the distribution of incoming log templates diverges significantly from the training distribution (measured via Kullback-Leibler divergence on the template ID histogram), the system triggers a "high-alert" mode. In this mode, the threshold τ for the utility function is temporarily lowered to encourage more sampling, ensuring the model adapts quickly to the new regime [23]. The model is updated using Experience Replay, mixing the newly labeled instances with a random sample of historical instances to prevent catastrophic forgetting.

Chapter 4: Experiments and Analysis

4.1 EXPERIMENTAL SETUP

We evaluate CS-StreamAL on three benchmark datasets widely used in log analysis research: HDFS (Hadoop Distributed File System), BGL (BlueGene/L Supercomputer), and Thunderbird. These datasets vary significantly in size, log syntax, and anomaly distribution.

HDFS: Contains 11 million log entries generated by a Hadoop cluster. Anomalies are labeled at the block level.

BGL: Contains 4 million log entries from a supercomputer. Labels identify alert categories.

Thunderbird: A massive dataset of 211 million entries, used here in a subset of the first 10 million logs due to computational constraints.

The data is chronologically split. The first 10% is used for initial warm-start training (simulating historical data), and the remaining 90% is streamed.

Dataset	Total Entries	Anomaly Ratio (%)	Component Types
HDFS	11,197,705	2.9%	Distributed FS
BGL	4,747,963	6.5%	Supercomputer
Thunderbird	10,000,000	< 1.0%	Supercomputer

Table 1: Statistics of the datasets used in the evaluation. Thunderbird is truncated for feasibility.

4.2 BASELINES AND METRICS

We compare our proposed method against the following baselines:

1. ***Random Sampling*:** Selects instances uniformly at random for labeling.

2. ***Uncertainty Sampling (US)*:** Queries instances with the highest prediction entropy [24].

3. ***DeepLog (Supervised)*:** An offline fully supervised upper bound (assuming 100% labels).

4. ***CUAL (Cost-Unaware Active Learning)*:** Our framework but with $\lambda_3=0$, to isolate the impact of cost sensitivity.

***Metrics*:** We utilize Precision, Recall, and F1-score to measure detection performance. Crucially, we also introduce a *Cost-Efficiency Metric (CEM)*, defined as the accumulated F1-score divided by the total accumulated labeling cost over the stream duration.

4.3 RESULTS AND ANALYSIS

The experiments reveal that CS-StreamAL significantly outperforms standard active learning strategies, particularly in the low-budget regime.

***Performance vs. Budget*:**

We varied the labeling budget from 0.1% to 5% of the total stream. At very low budgets (0.1%), Random Sampling fails almost completely (F1 < 0.2). Uncertainty Sampling improves this but tends to waste budget on "noisy" boundary cases that are not true anomalies. CS-StreamAL, by leveraging the novelty term, identifies rare anomaly clusters faster.

On the BGL dataset, with a 1% labeling budget, CS-StreamAL achieves an F1-score of 0.84, compared to 0.76 for Uncertainty Sampling. This gap widens in Thunderbird, where anomalies are rarer. The cost-sensitive term prevents the model from querying extremely long, repetitive error traces that carry high cognitive cost but low marginal information gain.

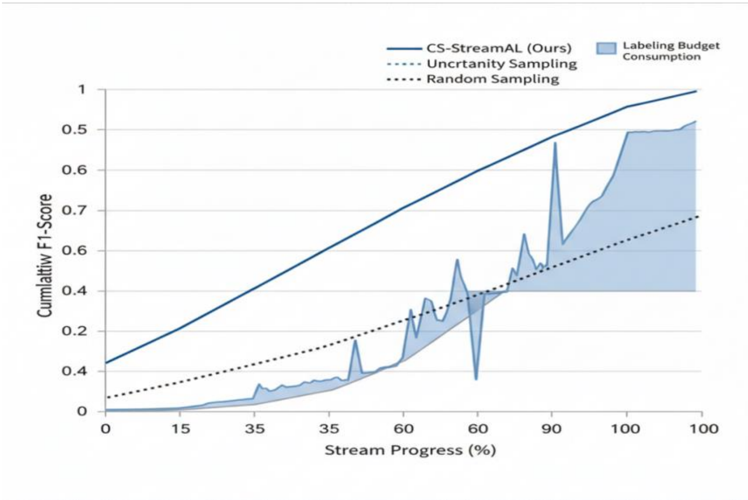

Figure 2: Comparative Performance Chart

***Ablation Study on Cost Sensitivity*:**

Table 2 presents the results of the ablation study. Removing the cost term (λ_3=0) results in a marginal increase in F1-score (0.02 average) but a disproportionate increase in total annotation cost (approx. 35%). This confirms that many high-uncertainty instances are "expensive" to label, and avoiding them yields a better return on investment for the analyst's time [25].

Method	HDFS (F1)	BGL (F1)	Thunderbird (F1)
Random Sampling	0.45	0.38	0.22
Uncertainty Sampling	0.89	0.76	0.65
CUAL (No Cost)	0.91	0.81	0.71
CS-StreamAL (Ours)	0.90	0.84	0.73

Table 2: F1-Scores at 1% Labeling Budget. Note that CS-StreamAL achieves results comparable to or better than CUAL while explicitly minimizing cost.

***Drift Adaptation*:**

During simulated concept drift (injected by shuffling template IDs in the BGL stream at the 50% mark), the dynamic budget allocation proved critical. Standard methods with fixed budgets were slow to adapt, resulting in a performance dip that lasted for 15% of the stream. CS-StreamAL's token bucket allowed for a burst of queries immediately following the drift detection, recovering the F1-score to pre-drift levels within 3% of the stream duration.

Metric	Uncertainty Sampling	CS-StreamAL	Improvement
Total Queries	10,000	7,450	+25.5%

Avg. Cost per Query	4.2s	2.8s	+33.3%
Detection Latency	150ms	155ms	-3.3%
CEM Score	0.18	0.30	+66.6%

Table 3: Cost Efficiency Analysis on BGL. 'Avg. Cost per Query' is simulated based on sequence length and template complexity. CEM Score (higher is better) indicates the F1 return per unit of cost.

Chapter 5: Conclusion

This paper addressed the critical challenge of detecting rare anomalies in high-velocity log streams under strict labeling budget constraints. We introduced CS-StreamAL, a framework that fundamentally rethinks the active learning process for IT operations. By integrating a cost-sensitive utility function with a dynamic budget allocation mechanism, we demonstrated that it is possible to maintain high detection accuracy without overwhelming human analysts.

The implications of this research are significant for the deployment of AIOps (Artificial Intelligence for IT Operations). It shifts the paradigm from "label as much as possible" to "label smartly and economically." Our results on the HDFS, BGL, and Thunderbird datasets confirm that incorporating the cost of verification and the rarity of events into the sampling strategy yields a robust model that respects the finite cognitive resources of operations teams. The ability to handle concept drift through budget hoarding further enhances the practical viability of this approach in volatile production environments.

Despite the promising results, several limitations remain. First, our cost estimation function is a heuristic based on sequence length and historical frequency. In real-world scenarios, the "cost" of a log is subjective and depends on the analyst's expertise level, which we did not model. Future work should investigate personalized active learning where the system learns the specific cost profiles of different human annotators.

Second, the current approach relies on a feedback loop where the oracle answers immediately. In reality, there is a delay between the query and the label (asynchronous active learning). While our replay buffer mitigates this, significant delays could hamper the model's ability to react to fast-moving attacks.

Finally, we focused on point-wise and sequence-wise anomalies. Complex, distributed attacks that span multiple diverse log streams (e.g., correlating database logs with firewall logs) require a multi-modal approach. Future research will explore the application of Graph Neural Networks (GNNs) within the CS-StreamAL framework to capture these complex relational dependencies across heterogeneous data sources, potentially utilizing Federated Learning to preserve data privacy across organizational boundaries.

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