Model Drift Detection and Automated Retraining in Production ML System

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Abstract - This paper presents DRIFT-ACT (Drift-Aware Continuous Training), a practical and modular framework designed to tackle the persistent challenge of model performance degradation in real-world AI systems. DRIFT-ACT combines real-time drift detection using lightweight statistical monitoring techniques with automated retraining pipelines powered by MLOps tools. Instead of modifying the core model architecture, DRIFT-ACT operates as a thin, flexible layer on top of existing systems—monitoring, detecting, and adapting to shifts in data or concept distributions without human intervention. Tested across synthetic and real-world production scenarios, DRIFT-ACT significantly improves model robustness over time, reduces manual maintenance effort, and ensures sustained performance consistency. Beyond the technical solution, this work serves as a practical blueprint for deploying resilient ML systems in dynamic, high-impact environments.

Key Words: Model Drift, Concept Drift, Data Drift, Automated Retraining, MLOps, Monitoring, CI/CD, MLflow, Evidently AI

1.INTRODUCTION

Large language models (LLMs) like OpenAI's GPT-4.1 have demonstrated remarkable capabilities across a wide range of tasks such as question answering, summarization, and code generation. However, in real-world deployments, not just LLMs but a wide spectrum of machine learning (ML) models suffers from a more general but equally critical issue: performance degradation over time due to model drift. This drift arises when data distributions change—either subtly or significantly—from the original training conditions, leading to inaccurate or unreliable predictions. In high-stakes domains such as finance, healthcare, and transportation, such degradation can introduce serious operational and ethical risks.

Model drift manifests in different forms, such as data drift, where the input distribution changes; concept drift, where the relationship between features and target labels evolves; and label drift, where the distribution of output classes shifts. These edge scenarios often go undetected in conventional monitoring systems, leading to models making outdated, inconsistent, or illogical predictions—especially when exceptions or rare conditions dominate decision-making.

To address this persistent challenge, we present DRIFT-ACT, a modular and production-ready framework aimed at enhancing the robustness of deployed ML systems against drift-induced failures. DRIFT-ACT is grounded in two pillars: [1] a real-time drift detection layer that leverages lightweight statistical tests and data profiling to identify shifts in feature distributions and prediction outcomes; and [2] an automated retraining pipeline, powered by MLOps tools such as MLflow and DVC, that continuously adapts the model using fresh, versioned datasets without requiring full model reengineering.

There are three main contributions of this paper. We first break down the typical forms of model drift and study the effects of model drift in the context of different domain specific production systems. Second, we present and deploy the DRIFT-ACT framework that automatically identifies drift events and responds to them with a minimum human involvement. Third, we test our method on synthetic and real-world tests, and show significant better performance with respect to long-term model accuracy, stability, and maintainability.

In contrast to the previous techniques of reducing drifts that have separated detection and retraining into two separate operations, the DRIFT-ACT framework offers a single and end-to-end pipeline that features a lightweight statistical drift identification, which is directly linked to automatic retraining. It is a generalization strategy across the various fields, such as finance, healthcare, and IoT, with low retraining cost provided by parameter-efficient fine-tuning via LoRA.

All of these features allow DRIFT-ACT to be a viable, transparent method of maintaining model accuracy and reliability in real-life dynamically changing settings.

2. RELATED WORKS

Several studies have explored the limitations and mitigation techniques for model drift in deployed machine learning (ML) systems, particularly under dynamic data conditions. The challenge of maintaining model performance over time has sparked numerous advancements in drift detection, monitoring, and automated retraining strategies.

Robustness LoRA-based Fine-tuning on Drifted Data

In [1], the authors demonstrated that even high-performing models degrade significantly when exposed to evolving input data distributions, highlighting the urgent need for real-time monitoring mechanisms. In response, [2] introduced DDM and EDDM—adaptive drift detection methods that flag statistically significant deviations in prediction error rates, although they require careful threshold tuning and may underperform on gradual drifts. However, they frequently fail in complex production setups where the data changes in non-obvious ways.

In [3], a comprehensive framework for data and concept drift was proposed using KL divergence and PSI (Population Stability Index), offering interpretability and deployment ease. Yet, these methods often lack tight integration with retraining mechanisms, making them suitable only for offline analysis. To bridge the monitoring-to-action gap, [4] presented an MLOps-based solution that couples drift detection with scheduled retraining pipelines using tools like MLflow and Airflow. However, the approach demands substantial infrastructure and lacks flexibility across domains.

The work presented in [5] introduces Evidently AI, an open-source library that tracks model performance, drift metrics, and data quality in a real-time dashboard, enhancing transparency but lacking out-of-the-box retraining triggers. Similar to this, [6] proposed a lightweight framework that integrates drift detection with automated model updating using online learning strategies, although it struggles with model version control and rollback safety in high-risk applications.

In [7], the authors applied domain-specific retraining to fraud detection and demonstrated that frequent micro-batch retraining boosts accuracy, but increases computational overhead and complexity in model governance.

Despite these advancements, most existing solutions treat drift detection and retraining as separate components. A cohesive framework that integrates real-time detection with adaptive, automated retraining across domains remains underexplored. The DRIFT-ACT framework addresses this gap by combining statistical drift analysis with fully automated retraining workflows to ensure model reliability and robustness in dynamic environments. The other related works are tabulated as in Table 1.

Table -1:COMPARISON OF SOME EXISTING WORKS IN THE LITERATURE.

	Model Type	Task Focus	Methodology
[1]	Supervised ML Models	Concept Drift Detection	Statistical Analysis of Prediction Shifts
[2]	Online Learning Models	Real-time Drift Detection	DDM, EDDM Algorithms
[3]	General ML Pipelines	Feature Distribution Monitoring	KL Divergence, PSI, KS-Test
[4]	MLOps-integrated Models	Automated Retraining Pipelines	MLflow, Airflow Integration
[5]	Python-based Monitoring Tool	Production Monitoring & Alerts	Evidently AI Framework
[6]	Incrementally Retrained Models	Online Model Updating	Micro-batch Retraining
[7]	Fraud Detection Systems	Domain-Specific Drift Adaptation	Frequent Retraining with Feedback Loops
[8]	Deep Learning Models (Healthcare)	Clinical Model Robustness	LoRA-based Fine-tuning on Drifted Data

IJSREM sample template format ,Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

Limitations of the Existing Systems

1. Delayed Drift Detection: Many existing systems detect model drift only after significant performance degradation, limiting timely intervention in production environments.
2. Isolated Components: Drift detection and retraining are often treated as separate, disconnected processes, causing inefficiencies and slow adaptation to evolving data distributions.
3. Limited Domain Adaptability: Current drift detection methods may not generalize well across diverse domains, especially when shifts involve subtle, context-dependent feature changes.
4. Lack of Automation: Manual triggers for retraining and model updates increase operational overhead and delay response to drift events, risking prolonged exposure to inaccurate predictions.
5. Poor Explainability: Drift alerts frequently lack interpretable explanations about the nature or impact of detected shifts, making it difficult for practitioners to assess severity or prioritize actions.

3. METHODOLOGY USED

1)Real-Time Drift Detection (RDD)

A lightweight monitoring mechanism that continuously evaluates incoming data and model predictions to identify distributional shifts.

- Statistical-Drift-Detection:
  Techniques like Population Stability Index (PSI), Kolmogorov-Smirnov Test (KS), and KL Divergence are applied to input and prediction distributions.
- Context-Aware-Triggers:
  Drift is assessed not only on raw data but also with domain-aware metrics (e.g., concept drift in time-sensitive features).

2) Automated Retraining Pipeline (ARP)

Once drift is detected and validated, the system automatically initiates a fine-tuning or retraining routine.

- Synthetic or Historical Data Use:
  The model is retrained using a mix of recent drifted data and domain-specific synthetic examples to ensure robustness.
- Efficient Model Update:
  Low-resource strategies such as LoRA or adapter layers are used to reduce computational overhead while improving adaptability.

4. EXPERIMENTAL RESULTS

Datasets:

The proposed drift-aware framework was evaluated using diverse datasets selected to simulate real-world drift scenarios across multiple domains. Each dataset contains built-in temporal or contextual shifts, making them ideal for assessing the robustness and adaptability of continuous learning systems:

- FinanceDrift-X: Transaction data with temporal drift reflecting policy changes, user behavior shifts, and economic factors.

- IoTSensorStream: Time-series data from smart devices with seasonal, environmental, and hardware-induced drifts.
- E-CommerceClick: User clickstream data showing concept drift due to marketing campaigns or changing product catalogs.
- HealthMonitor-Drift: Patient vitals and diagnostics with gradual drift based on demographics or treatment evolution.
- TextStreamQA: Streaming text classification data simulating semantic drift in topics and terminology over time.

Metrics:
The metrics used to measure the performance of the method used are

- Detection Accuracy
- Contradiction Rate
- Consistency Score
- Justification Quality (JQ)

The result of the experiment is shown in Table2.

1. Detection Accuracy

$$\frac{\text{True Positives + True Negatives}}{\text{Total Drift Events}} \times 100\%$$

2. Retraining Efficiency

$$\frac{\text{Baseline Retrain Time} - \text{Actual Retrain Time}}{\text{Baseline Retrain Time}} \times 100\%$$

3. Post-Drift Accuracy

$$\frac{\text{Correct Predictions After Drift}}{\text{Total Predictions After Drift}} \times 100\%$$

4. Adaptability Score (A)

$$\frac{1 - \text{Inconsistent Outputs}}{\text{Total Compared Outputs}} \times 100\%$$

5. Explainability Score (ES)

Subjective evaluation of how interpretable the drift alerts and retraining decisions are to human operators.
$ES \in \{1,2,3,4,5\}$(average of human evaluator ratings)
Where:

- 1 = Unclear or unhelpful
- 5 = Fully transparent and actionable

Table 2. Performance Analysis

Metric	Average Score	Best Performing Dataset
Drift Detection Accuracy	92.3%	FinanceDrift-X (94.7%)
Post-Drift Accuracy	90.1%	IoTSensorStream (91.0%)
Retraining Efficiency	65.4% time saved	E-CommerceClick
Adaptability Score (A)	0.88	TextStreamQA
Explainability Score (ES)	4.2 / 5	HealthMonitor-Drift

5. RESULTS AND DISCUSSION

- The proposed drift-aware retraining framework achieved strong results across all evaluated domains, with detection accuracy exceeding 90%, showcasing robust drift recognition even under sudden and recurring shifts.
- Leveraging LoRA-based parameter-efficient fine-tuning, the system maintained high Post-Drift Accuracy and reduced retraining overhead by over 65%, supporting its use in dynamic, real-time environments.
- The HealthMonitor-Drift and FinanceDrift-X domains demonstrated significant recovery of model performance after drift, confirming the value of synthetic, edge-case-aware corpora in recalibration.
- High Adaptability Scores (average 0.87) reflect the system's ability to maintain logical consistency under varied and rephrased prompt conditions.
- An average Explainability Score of 4.2/5 demonstrates the human-centered transparency of retraining triggers and prediction rationales, essential in high-stakes fields like healthcare and finance.

The suggested drift-sensitive retraining concept exhibits a good performance in various areas. Accuracy on drift detection According to the results of the study, the drift detection accuracy is more than 90 percent, which shows that the system is able to identify abrupt and slow changes in data distributions, as reported previously in the literature on real-time drift detection [2], [3]. The post-drift accuracy was also high, indicating that the LoRA-based fine-tuning model is an efficient way to recalibrate weights of models without full retraining, significantly decreasing the computational load (more than 65 percent).

In task-oriented assessments, e.g., Health Monitor-Drift and FinanceDrift-X, model performance was restored rapidly following drift instances, which supports the importance of synthetic and edge-case-sensitive corpora in retraining. The Adaptability Score (0.87) indicates that the framework is easy to be logically consistent even when the prompts are formulated in different ways or offered in a form that has never been used before. In the meantime, Explainability Score (4.2/5) indicates the anthropocentrism of retraining triggers and prediction causes that is of paramount importance in high-stakes areas such as healthcare and finance.

On the whole, these findings suggest that parameter-efficient retraining in combination with real-time drift detection can greatly increase the strength and efficiency of deployed machine learning models. Future directions can look into the adaptive thresholding of drift and additional gains on the explainability measures.

6. CONCLUSIONS

This paper tackled one of the most critical challenges in modern language modeling—ensuring logical consistency, contextual clarity, and reliability in edge-case reasoning scenarios. While large language models such as GPT-4.1 perform impressively on common, well-structured inputs, they often struggle with complex, ambiguous, or rare prompts, which are frequent in high-stakes domains like law, medicine, and ethics, as highlighted by Wei et al. in Chain of Thought Prompting [4] and Lu et al. in Formal Reasoning Capabilities of LLMs [13].

To address these shortcomings, RECAP (Reasoning Enhancement through Context-Aware Prompting) was introduced—a lightweight, modular framework that integrates structured prompt engineering with parameter-efficient fine-tuning, building on LoRA-based fine-tuning techniques described by Huynh et al. [9] and prompt engineering strategies surveyed by Singh and Yamada [10]. Through rigorous testing on five diverse benchmark datasets (LegalBench-X, ARC-Challenge+, LAMBADA-Edge, BioMedQA-Hard, and EthicsQ-Edge), RECAP demonstrated measurable improvements in accuracy, consistency, and justification quality, consistent with findings in Self-Ask: A Prompting Technique for Improving Reasoning in Language Models [6].

Beyond quantitative metrics, qualitative analysis confirmed that RECAP-generated responses are more transparent, logically grounded, and domain-sensitive. Importantly, the framework remains highly deployable and adaptable, leveraging tools like LoRA adapters and API-level integration without altering foundational model weights, in line with approaches described in Bai et al.'s Constitutional AI [11].

Looking ahead, RECAP opens several exciting research avenues:

- Retrieval-augmented generation (RAG) could further enhance factual accuracy, as suggested in Yao et al.'s ReAct: Synergizing Reasoning and Acting in Language Models [5].
- Multilingual edge-case adaptation can extend its utility across diverse global contexts, building on surveys by Kiciński et al. [14].
- Meta-learning for dynamic prompt construction may offer real-time reasoning adaptability in rapidly evolving environments, as explored in Gao et al.'s PAL: Program-Aided Language Models [7].

As LLMs continue to be deployed in real-world, decision-critical systems, RECAP provides a timely, scalable, and robust approach to making them smarter, safer, and more trustworthy (Wei et al., 2022; Yao et al., 2022; Huynh et al., 2023) [4], [5], [9].

Although these results are encouraging, several limitations remain. RECAP can exhibit performance variations with completely unseen or highly domain-specific edge cases, and current evaluations rely primarily on selected benchmarks rather than large-scale industrial deployments, as noted in Lu et al., 2023 [13]. Furthermore, although reasoning quality is significantly improved, explainability could be further formalized using standardized interpretability metrics (Bai et al., 2022; Kiciński et al., 2023) [11], [14]. Computational costs and integration complexity, while minimized, still require consideration in production environments [9], [10].

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