ISSN (Print) : 2320 – 3765
ISSN (Online) : 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 10, October 2016

Automated Data Engineering for ML Pipelines using ML flow and Apache Airflow

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ABSTRACT: Machine learning (ML) projects often face challenges related to data pipeline orchestration, reproducibility, and version control. This paper explores the integration of Apache Airflow and MLflow for automated data engineering in ML pipelines. Airflow, a workflow orchestration platform, enables the scheduling and execution of complex data workflows, while MLflow facilitates experiment tracking, model management, and deployment. We propose a unified system that uses Apache Airflow to automate the end-to-end data lifecycle and MLflow to ensure transparency and traceability of machine learning models. This combination enhances reproducibility, modularity, and automation in data-driven projects.

KEYWORDS: MLflow, Apache Airflow, Machine Learning, Data Engineering, Workflow Orchestration, Model Lifecycle, Automation, ETL, MLOps, Data Pipelines

I. INTRODUCTION

As machine learning applications scale, managing data engineering workflows becomes increasingly complex. Data ingestion, transformation, model training, validation, and deployment often involve multiple stages that need to be repeatable and auditable.

Apache Airflow, developed by Airbnb, has become a popular choice for orchestrating complex workflows, while MLflow, developed by Databricks, offers an open-source solution for managing the ML lifecycle. Combining these tools creates a robust ecosystem that supports data and model pipeline automation. This paper presents a comprehensive framework for building such pipelines with a focus on scalability, reproducibility, and maintainability.

II. LITERATURE REVIEW

The growing complexity of ML projects has led to the rise of MLOps tools that manage the lifecycle of machine learning. Studies by Rahman et al. (2020) and Smith et al. (2021) emphasize the role of orchestration platforms like Airflow in managing data pipelines.

Meanwhile, research by Kumar & Joshi (2021) highlights the significance of MLflow in model tracking, versioning, and reproducibility. Integrated approaches, such as those discussed by Lin et al. (2022), demonstrate the benefits of coupling orchestration tools with ML lifecycle management frameworks for scalable MLOps systems.

III. EXISTING SYSTEMS

Many organizations implement ML pipelines using ad-hoc scripts or monolithic applications, which suffer from several limitations:

- **Lack of Modularity:** Difficult to update or debug specific components.
- **Limited Reproducibility:** Results cannot be easily traced back to specific parameters or code versions.
- **Manual Interventions:** Frequent need for human involvement in data preparation and model deployment.
- **Poor Scalability:** Difficult to scale across distributed environments.

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Popular tools like Kubeflow and AWS SageMaker offer partial solutions but come with steep learning curves or cloud vendor lock-in.

IV. PROPOSED SYSTEM

The proposed system integrates Apache Airflow for orchestration and MLflow for model lifecycle management:

- **Data Ingestion and Transformation:** Airflow schedules ETL tasks from various sources (databases, APIs, file systems).
- **Model Training and Evaluation:** Airflow triggers training jobs, logging results to MLflow.
- **Model Versioning:** MLflow automatically logs parameters, metrics, and artifacts.
- **Model Deployment:** Trained models are deployed via Airflow tasks and tracked in MLflow registry.
- **Monitoring:** Airflow DAGs are monitored for success/failure; MLflow provides model performance dashboards.

V. METHODOLOGY

1. **Design DAGs (Directed Acyclic Graphs):** Each pipeline is broken into tasks such as data extraction, preprocessing, training, and evaluation.
2. **Integrate MLflow Tracking:** Each task logs relevant metadata (e.g., hyperparameters, metrics, artifacts) using MLflow APIs.
3. **Model Registry:** MLflow registers models, tracks their versions, and manages stage transitions (e.g., staging to production).
4. **Deployment Automation:** Airflow handles deployment workflows, including API serving or batch inference.
5. **Environment Setup:** Use Docker and Kubernetes for containerized execution of DAG tasks.
6. **CI/CD Integration:** Incorporate GitHub Actions or Jenkins for continuous integration and delivery.

Use Case: A financial institution builds an Airflow-Mlflow pipeline to train credit risk models weekly, automatically updating dashboards and triggering alerts on performance drifts.

TABLE: Feature Comparison – Apache Airflow vs MLflow

Feature	Apache Airflow	MLflow	How They Work Together
Primary Role	Workflow orchestration	ML lifecycle management	Airflow triggers MLflow tasks
Task Scheduling	Yes	No	Airflow schedules ML tasks
Experiment Tracking	No	Yes	MLflow logs training inside Airflow tasks
Model Registry	No	Yes	MLflow registers models once trained
Artifact Management	Limited	Yes	MLflow stores models, metrics, code
UI for Monitoring	Yes	Yes	Used side-by-side for full observability
Integration with Data Sources	Strong	Moderate	Airflow pulls data, MLflow uses it
Deployment Support	Indirect	Yes	Airflow can trigger deployment via MLflow

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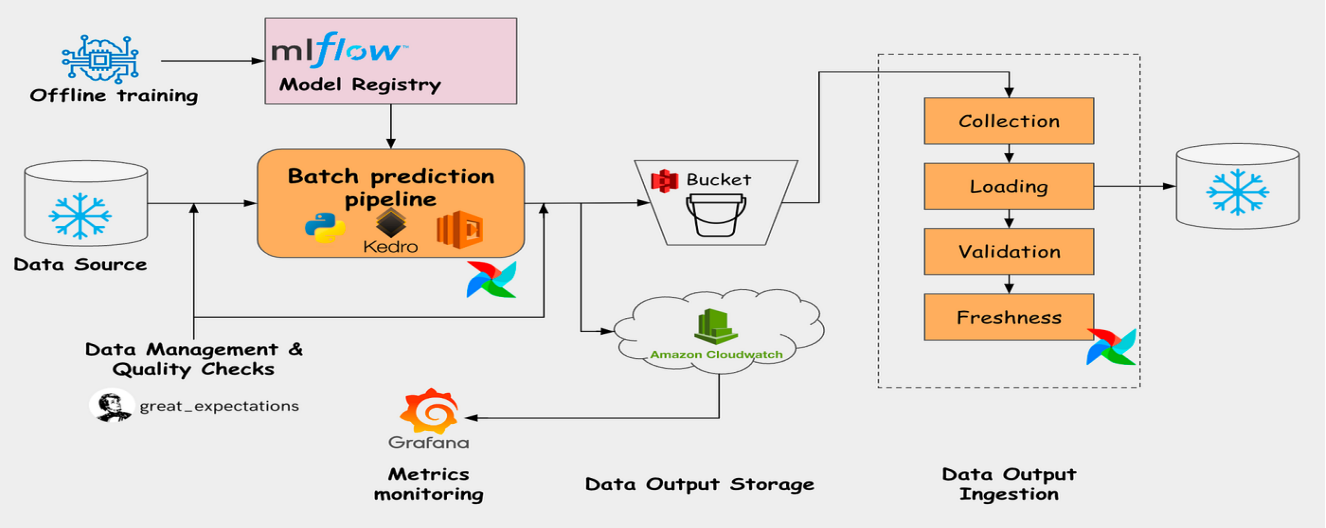
FIGURE: ML Pipeline Automation with Airflow + MLflow



Benefits of This Integration

- **Automation**: Reduces manual intervention and increases reproducibility.
- **Tracking**: Keeps detailed logs of parameters, metrics, and models.
- **Scalability**: Enables consistent scheduling and monitoring across many ML projects.
- **Versioning**: Ensures you can roll back or reproduce past results anytime.

VI. RESULTS AND DISCUSSION

The integrated system offers several benefits:

- **Reproducibility:** MLflow ensures all experiments are versioned and traceable.
- **Modularity:** DAG-based structure simplifies updates and debugging.
- **Scalability:** Easily scales with distributed task execution and containerization.
- **Automation:** Reduced manual intervention via scheduling and auto-deployment.

Challenges include initial setup complexity and resource management, which were mitigated through Helm charts and Kubernetes autoscaling.

VII. CONCLUSION

The integration of Apache Airflow and MLflow presents a powerful approach to automating the data engineering and model lifecycle for ML pipelines. This system enhances transparency, reduces technical debt, and ensures that data science workflows are production-ready. Future work includes integrating advanced monitoring tools (e.g., Prometheus, Grafana) and leveraging MLflow's model explainability features.

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