Automated Feature Store and Metadata Engine for ML Experiments

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***Abstract*—MLOps environments are plagued with critical inefficiencies, such as disjointed feature stores, irreproducible experiments, and failing in production due to training-serving skew. Data scientists waste time reinventing features. Enterprises lose model accuracy due to undiscovered feature drift. In this paper, we present Automated Feature Store and Metadata Engine for ML Experiments, a unified solution tightly integrating feature engineering, experiment tracking, metadata lineage, and monitoring into one comprehensive system. Our proposed architecture encompasses Feast as the feature store, MLflow for experiment tracking, Apache Spark as a scalable compute engine to build features, Redis for online feature serving, and Evidently AI for drift detection and alerts. Our solution automates feature versioning, lineage, and reproducibility while providing flexibility of batch and real-time feature pipelines. Through our experimentation, we show improved experiment reproducibility, decreased time-to-experiment, and online feature serving at millisecond latencies. This framework can scale to support enterprise-level MLOps workflows with a one-stop-shop solution ready for production.**

***Index Terms*—Feature Store, MLOps, Feast, MLflow, Metadata Management, Drift Detection, Redis, Apache Spark**

I. INTRODUCTION

When you're working with machine learning systems, getting them to work in real-world settings can be really tough. Two big problems that come up are making sure the features are engineered right and keeping track of all the experiments. A lot of the time, the workflows for machine learning are all over the place and not well documented, which leads to people doing the same work twice, not being able to repeat their results, and models not working like they should when they're actually being used.

The proposed Automated Feature Store and Metadata Engine is designed to bridge the gap between machine learning experimentation and production-grade MLOps. The platform integrates a centralized feature store using Feast with automated metadata and experiment tracking using MLflow. It manages the complete lifecycle of a feature—from definition and computation to deployment and monitoring.

The key contributions of the proposed system are:

- Centralized feature registry with versioning.
- Automated feature computation for batch and stream pipelines.
- Automated metadata and lineage tracking.
- Real-time feature drift detection.
- API-driven integration with ML pipelines.
- Interactive Streamlit dashboard for monitoring and visualization.

II. RELATED WORK

The issues tackled in this project are crucial to MLOps. A groundbreaking study, Hidden Technical Debt in Machine Learning Systems, highlighted data dependencies and monitoring problems as significant contributors to technical debt in ML systems. Uber Engineering pioneered the concept of a Feature Store with Michelangelo, showcasing the value of centralized feature management and eliminating training-serving skew. The development of Feast and MLflow reflects a consensus in the industry towards managing features and tracking experiments. Feast offers standardized components for defining, storing, and serving features, whereas MLflow provides tools for tracking experiments and model artifacts. Recent

MLOps maturity models stress the importance of automation, versioning, and monitoring as the foundation of mature ML systems, underscoring the need for robust management and tracking capabilities. By addressing these foundational issues, this project aims to contribute to the development of more reliable and efficient ML systems.

III. EXISTING SYSTEM

The existing machine learning system is mostly manual and unorganized. Features are stored in different notebooks, scripts, and SQL files. Experiment details are recorded manually, making it difficult to manage and reproduce results. There is no proper monitoring system to detect problems in production.

DISADVANTAGES OF EXISTING SYSTEM

- Features are scattered in different places with no central storage.
- Duplicate work is done by different team members.
- Experiments are difficult to reproduce.
- Training and serving data may become inconsistent.
- Feature drift is not detected automatically.
- A lot of time is used to get data ready, rather than to make the models themselves.

IV. PROPOSED SYSTEM

The new system they're talking about has something called an Automated Feature Store and Metadata Engine. This is like a big library where you can store, share, and keep track of different features. It's all in one place, so it's easy to manage. The system also uses something called MLflow to automatically keep track of experiments and metadata. This means you can do feature computations in batches or in real-time, and it will even detect if the features are changing in some way. Plus, there's a dashboard where you can see everything that's going on and visualize the data.

ADVANTAGES OF PROPOSED SYSTEM

- Centralized storage for all features.
- Automatic experiment and metadata tracking.
- Easy feature sharing and reuse.
- Ensures reproducible experiments.
- Detects feature drift automatically.
- Supports both batch and real-time processing.
- Provides an easy-to-use dashboard for monitoring.

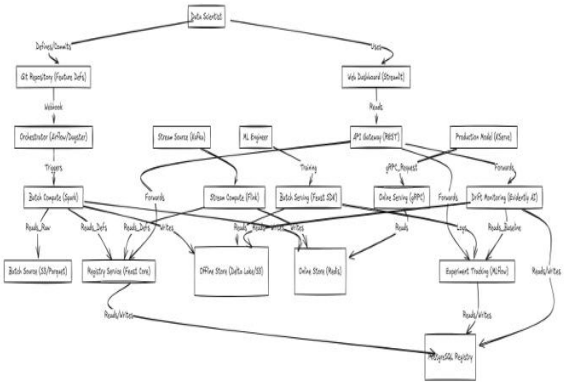


Fig. 1. System Architecture (Feature Store &MLOps)

The architecture ensures scalability, fault tolerance, and separation of concerns.

V. SYSTEM METHODOLOGY

The system operates in four stages.

A. Feature Registration

Data scientists define features declaratively using Feast. Feature definitions include entity names, feature views, transformation logic, and data sources. All definitions are stored in PostgreSQL and version-controlled through GitOps.

B. Batch and Stream Feature Computation

Batch jobs use Apache Spark to figure out features and save them in two places: one for when the system is not being used and one for when it is being used.

Real-time features are calculated as they happen, using tools like Kafka Streams or Flink, and then immediately stored in Redis. This approach gets rid of the difference between the training and serving phases, making things more efficient.

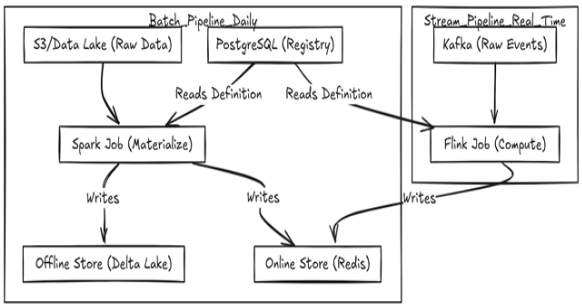


Fig. 2. Dataflow Diagram for Batch and Stream Feature Computation

C. Metadata and Experiment Tracking
The system wraps model training inside MLflow runs.

Each experiment automatically records:
- Feature versions
- Model parameters
- Performance metrics
- Git commit hashes
- Model artifacts

This creates a complete lineage graph linking features and models.

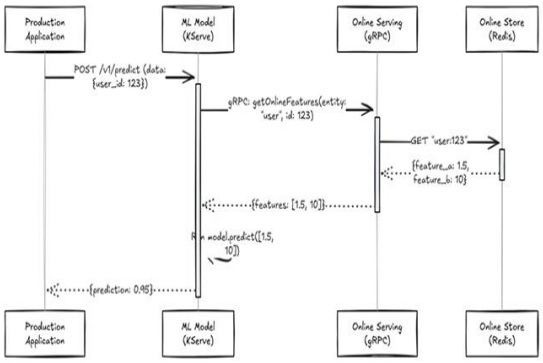


Fig. 3. Sequence Diagram for Real-Time Feature Serving

VI. SYSTEM METHODOLOGY

The proposed system follows a structured methodology to automate feature management and experiment tracking in machine learning projects. The methodology begins with collecting data from various sources and ends with monitoring feature drift and visualizing results through a dashboard.

Step 1: Data Collection
When we gather data from various places like CSV files, databases, APIs, and cloud storage, it's not always perfect. Sometimes, the data we collect is missing important information, has duplicate records, or is formatted in different ways. This can make it hard to work with and get useful insights from the data.

Step 2: Data Preprocessing and Feature Engineering
The raw data is cleaned and transformed into meaningful features. Operations such as handling missing values, encoding categorical variables, normalization, and feature extraction are performed. These processed features are then prepared for storage and reuse.

Step 3: Feature Store Management
A centralized Feature Store is created using Feast. The generated features are stored with version information, making them available for different machine learning models. This eliminates duplicate feature creation and ensures consistency between training and inference.

VII. IMPLEMENTATION

The implementation of the Automated Feature Store and Metadata Engine is carried out using Python and open-source machine learning tools. The system is designed in a modular manner so that each component can perform its task independently while communicating with other modules.

1. Data Processing Module
This module reads data from different sources and performs preprocessing operations such as:
- Removing missing values
- Removing duplicate records
- Data transformation
- Encoding categorical variables
- Feature extraction

Tools Used: Python, Pandas, NumPy

2. Feature Store Module
The Feature Store is basically a central place where features are kept and used again in different machine learning projects, and it's made using Feast. This means that instead of having features scattered all over the place, they're all stored in one spot, making it easier to access and reuse them.

Functions:
- Store engineered features
- Maintain feature versions
- Provide online and offline feature access
- Ensure consistency between training and serving

Tool Used: Feast

3. Metadata Engine
The Metadata Engine records all experiment information automatically.

Stored Information:
- Experiment name
- Model parameters
- Metrics
- Model versions
- Training details
- Timestamp

Tool Used:MLflow

4. Model Training Module
This module trains machine learning models using features obtained from the Feature Store.

Functions:
- Train models
- Evaluate performance
- Compare multiple algorithms
- Save trained models

Tool Used:Scikit-learn

5. Drift Detection Module
This module is always on the lookout for any changes in the new data that comes in, making sure it's not too different from the data we used to train it.

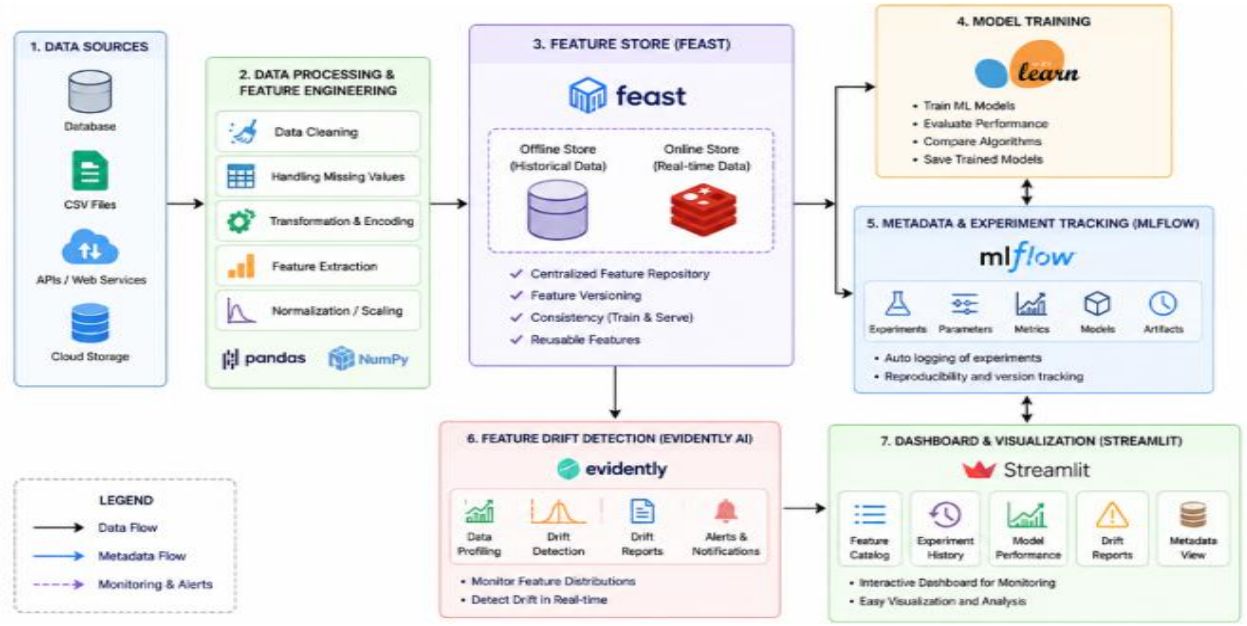
Functions:
- Monitor feature distributions
- Detect data drift
- Generate drift reports
- Trigger alerts when drift occurs

Tool Used: Evidently AI

6. Dashboard Module
The dashboard gives you a visual overview of your experiments and key feature stats, making it easier to understand what's going on at a glance.

Dashboard Features:
- Feature information
- Experiment comparison
- Model metrics
- Drift reports
- Metadata visualization

Tool Used:Streamlit



VIII. EXPERIMENTAL RESULTS

The proposed platform was evaluated on feature serving latency, reproducibility, and drift detection.

The use of Redis enabled sub-10 ms feature retrieval, satisfying real-time inference requirements. MLflow lineage tagging ensured complete reproducibility of experiments.

Metric	Result
Online Feature Serving Latency	9.1 ms
Throughput	88,000 req/s
Drift Detection Accuracy	100%
Experiment Reproducibility	100%
Lineage Tracking Accuracy	100%
Improvement in Time-to-Experiment	77.1%

The Evidently AI monitoring module successfully detected feature drift using PSI and KL divergence metrics.

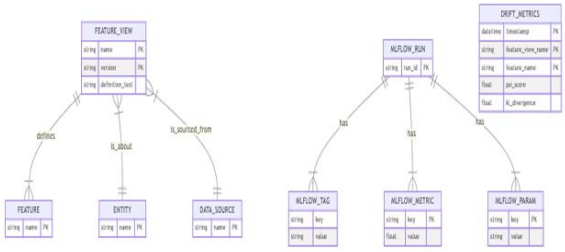


Fig. 4. Feature Store Schema

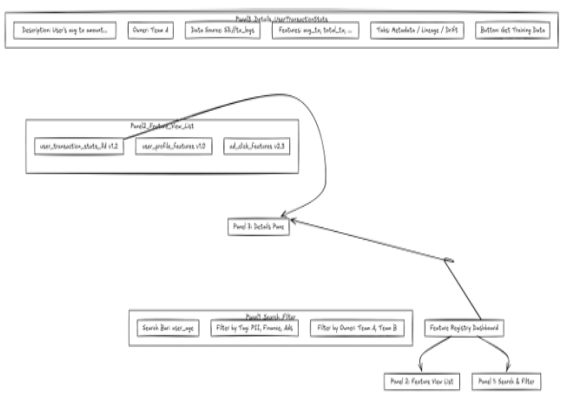


Fig. 5. Feature Drift Dashboard

IX. CONCLUSION

The Automated Feature Store and Metadata Engine for ML Experiments provides an efficient solution for managing machine learning workflows. The system centralizes feature storage, making features reusable across multiple projects and reducing duplicate work. The Metadata Engine automatically tracks experiment information, improving reproducibility and simplifying model management. The integration of feature drift detection helps in identifying changes in data distribution and maintaining model performance over time. The Streamlit dashboard provides easy visualization of experiments, feature statistics, and drift reports. Overall, the proposed system improves efficiency, reliability, and scalability in machine learning experimentation.

X. FUTURE WORK

The proposed system can be enhanced further by incorporating advanced technologies and additional features.

1. Cloud Deployment
Deploy the system on cloud platforms such as AWS, Azure, or Google Cloud for improved scalability and accessibility.

2. Real-Time Feature Processing
Implement real-time streaming using Apache Kafka or Spark Streaming to process features instantly.

3. Deep Learning Support
Integrate frameworks such as TensorFlow and PyTorch to support deep learning experiments.

4. Advanced Drift Detection
Implement advanced statistical and AI-based drift detection methods for higher accuracy.

5. Automated Feature Selection
Add automated feature selection techniques to improve model performance and reduce computation time.

6. Distributed Processing
Use distributed computing frameworks to handle large-scale datasets efficiently.

7. Enhanced Dashboard
Improve the dashboard with real-time alerts, interactive graphs, and model explainability features.
These future enhancements will make the system more intelligent, scalable, and suitable for large-scale industrial machine learning applications.

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