

OpenMLDB: Open-source Machine Learning Database Driving Real-time Intelligent Decision-making with Real-time Features

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About Me



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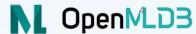


Contents

- 1. Engineering Challenges in Real-Time Intelligent Decision Making
- 2. OpenMLDB Provides Online-Offline Consistent Real-Time Feature Computation
- 3. Community Eco-System and Use-Cases



1. Engineering Challenges in Real-Time Intelligent Decision Making



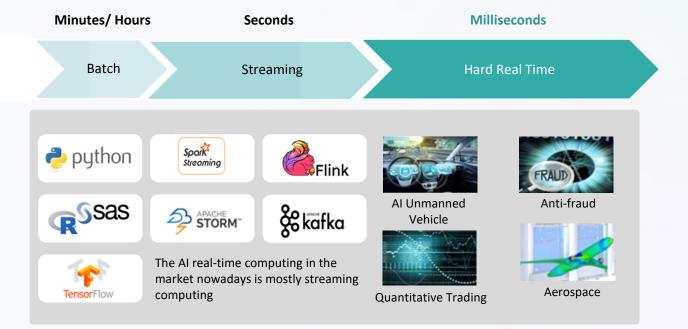
Real-time Intelligent Decision-making based on Machine Learning Requires Millisecond Level Real-time Computing Capability

Two major AI applications: Perception-based AI and Decision-based AI

Only hard real-time computing can truly meet real-time decision-making

requirements - Real-time Data, Real-time Computing

Streaming computing are mostly designed for Big Data and BI



Bank requires millisecond-level responses

Taking a certain bank's anti-fraud scenario as an example

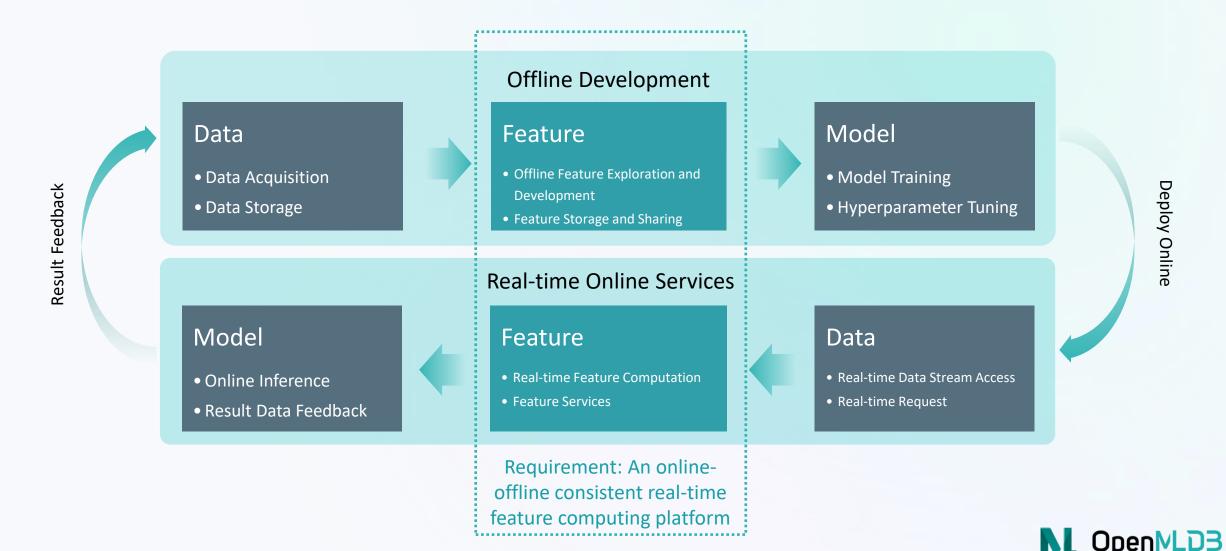
Customer Requirement: A highly-accurate anti-fraud system with a response time of 20ms for feature computation

Solution	Respone Time	Precision and Recall
Traditional Rule System	~200ms	Relatively Poor
Customer Self- Developed System	~50ms	Moderate
The Prophet of the Fourth Paradigm	<20ms	Excellent

Hard real-time scenarios contain enormous commercial value, and there are few universal commercial products available



Intelligent Decision-making based on Machine Learning from Offline Development to Online Deployment



Real-time Feature Computation for Anti-fraud Transactions

Swiping Records



Card Number	Swiping Amount	Swiping Time
012159	1000	2022/01/12 08:00:00

Virtual Insertion

Transaction History Table

	Card	Swiping	Swiping Time	Window
ı	Number	Amount	(Sorted)	Aggregation
	012112	223	2022/01/12 02:00:00	
	012159	15	2022/01/12 06:00:00	٦
	012159	1000	2022/01/12 07:59:55	-3h
	012159	2000	2022/01/12 07:59:57	- 10s
	012159	1000	2022/01/12 08:00:00	



Feature Computation

Generated Features

Card Number	Swiping Amount	In the past 10 seconds: Number of card swipes Maximum Amount Swiped Minimum Amount Swiped Average Amount	In the past 3 hours: Number of card swipes Maximum Amount Swiped Minimum Amount Swiped Average Amount	
012159	1000	3 2000 1000 1333	4 2000 14 1003	

Engineering Requirements

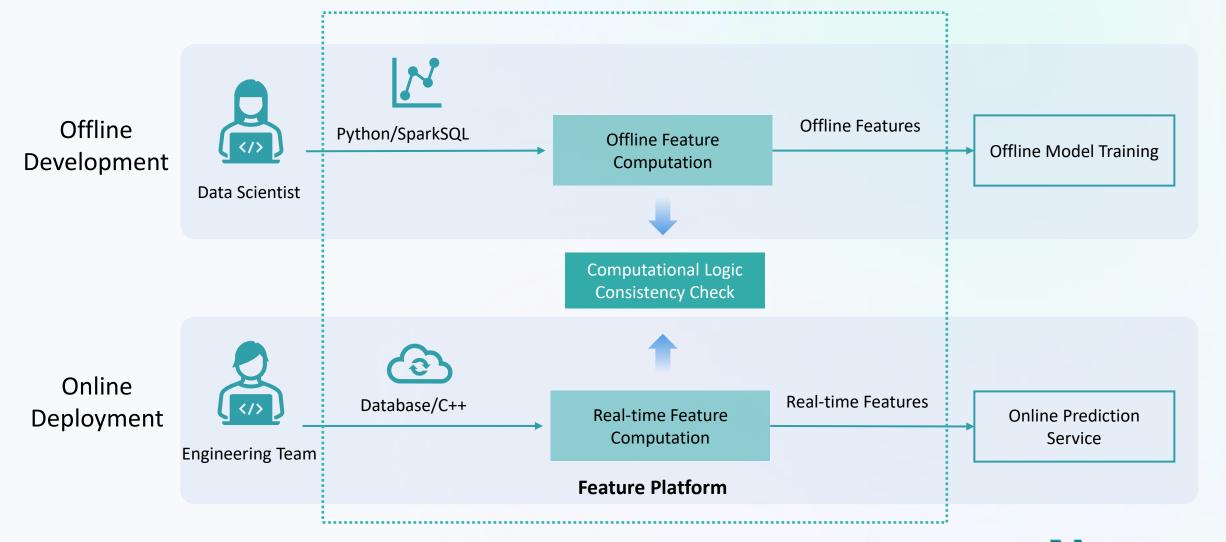
- 1. Online and offline consistency
- 2. Low latency, high concurrency, and high availability

Model Inference





Traditional Feature Development: Separation of Offline Development and Online Deployment Incurring High Investment Cost



Possible Reasons for Online and Offline Inconsistency

Inconsistency in tool capabilities

Offline Development





Python

$$\sum_{i=0}^{N} \frac{(x_i - \mu)^2}{N - 1}$$

standard deviation (Bessel's Correction)

Online Deployment







Different understanding of demands





A bank for all of us



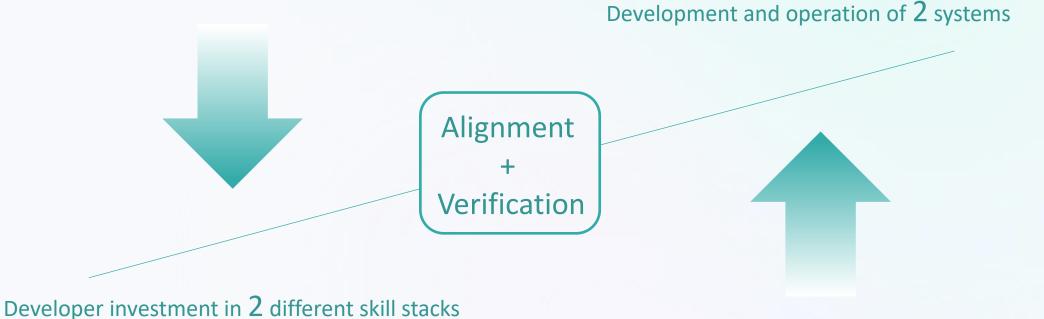
Money shouldn't just work for some of us. It should work for all of us

	Account Balance
Online Deployment	current "account balance"
Offline Development	"account balance" as of yesterday



The High Cost of Engineering Implementation Brought About by Online and Offline Consistency Verification

Offline Development



Online Deployment



2. OpenMLDB Provides Online-Offline Consistent Real-Time Feature Computation



OpenMLDB Development History: From Close-source to Open-source

2021.6

Past 5 Years

RTIDB/FEDB

(4Paradigm Close-source)

OpenMLDB

(Open-source/commercialization)

brought out within 4paradigm SageOne and implemented in over 100 scenarios, covering over 300 nodes.

After Open-source,

Before Open-source,

actively embraces community developers with an open attitude, integrates the opensource ecosystem, and provides commercial customization and support.













Main Usage Scenarios

Credit Card Cash Installment **Precise Marketing**

> **Credit Card Account Risk Warning**

Fraud and Card Retention **Prevention and Control**

Network Traffic Prediction

Pre-loan Risk Scoring

Compliance Quota **Decision-making**

Personalized Financial Recommendations

Transaction Fraud Scoring

Marketing Customer Acquisition

Risk Management

Anti-fraud Measures for Retail Loans

> Cash Installment Personalized Recommendation

Personalized Recommendation

Exploration of Investment Advisory Clients

> **Historical Customer** Activation

Credit Card Transaction Anti-fraud

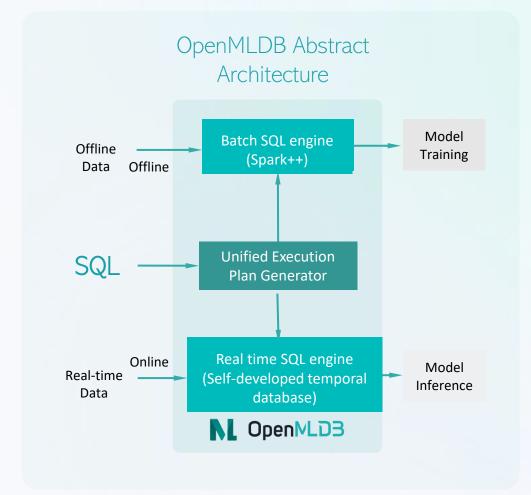
Intelligent Identification of Suspicious Transactions in **Anti-money Laundering**

Credit Card Application Anti-fraud Customer Loss Warning **Financial Product** Recommendations



OpenMLDB: Open-source Machine Learning Database, A Consistent Feature Platform both Online and Offline

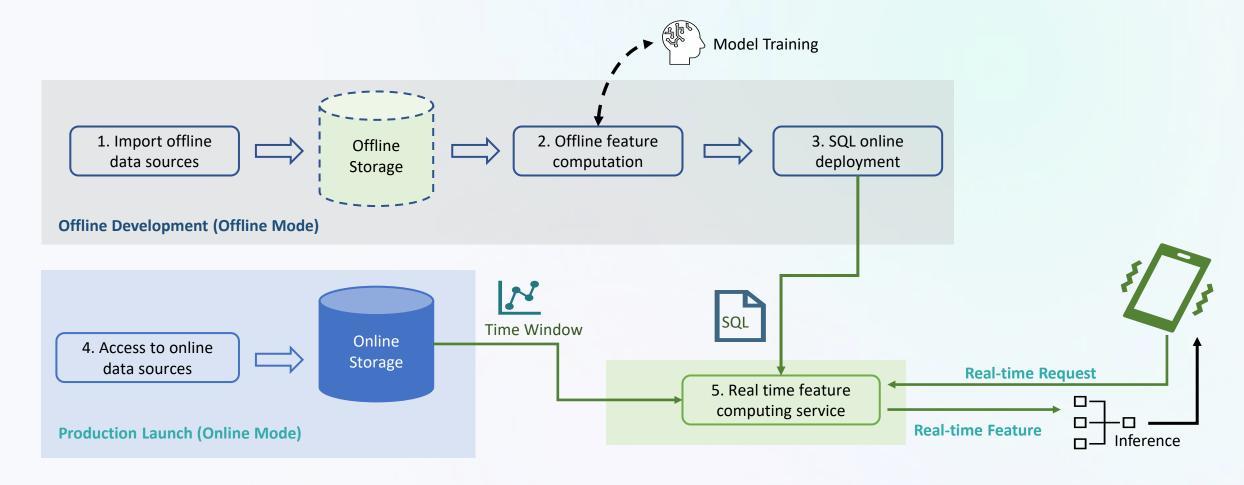
Original Process Step 1: Feature script development Scientist Step 2: Refactoring to meet online low latency, high Engineer throughput, and high availability Step 3: Online and offline consistency verification Scientist and Engineer Step 4: Production Engineer launch







Complete Process from Offline Development to Online Services



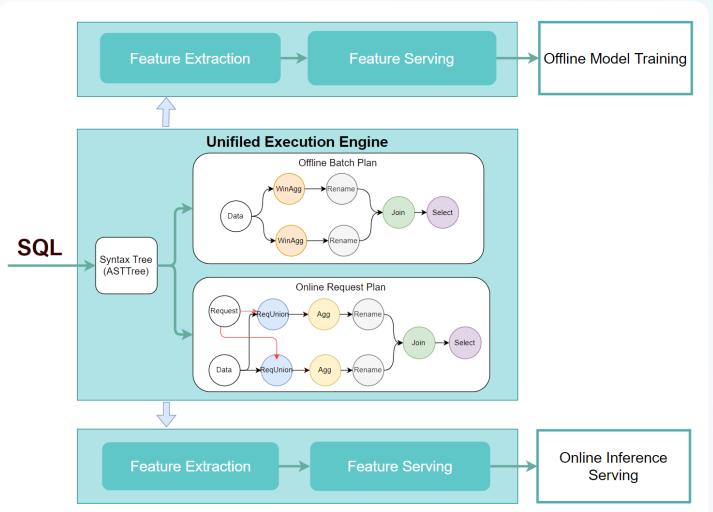


OpenMLDB provides a Consistent Millisecond Level realtime feature computing platform both Online and Offline

- On-demand computation based on real-time data
- Defining features based on SQL
- Production-level platform, distributed, scalable, and highly-available



Core Component 1: Online and Offline Consistent Unified Execution Engine



- Unified underlying computing functions
- Adaptive adjustment of online and offline execution modes from logical plan to physical plan



Consistency between online and offline is naturally guaranteed



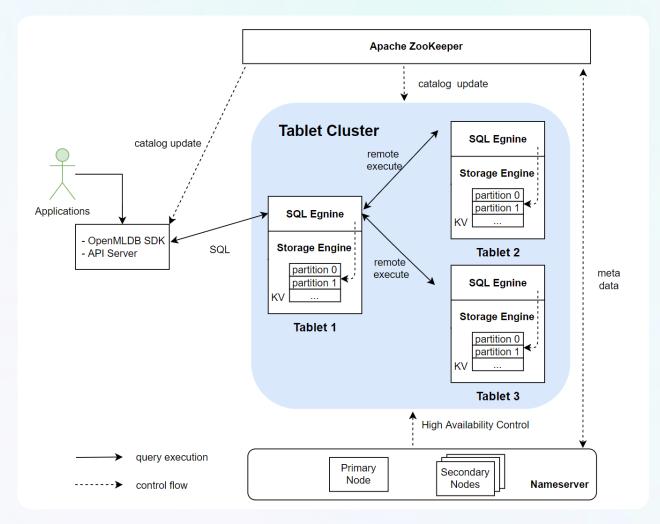
Core Component 2: High Performance Real-time SQL Engine

Main modules of distributed real-time SQL engine

- **ZooKeeper** Metadata storage and management
- Nameserver Tablet Management and Failover
- Tablets
 - Distributed SQL Execution Engine
 - Distributed storage engine:
 dual storage engine for memory and disk
- High performance, scalability, and high availability

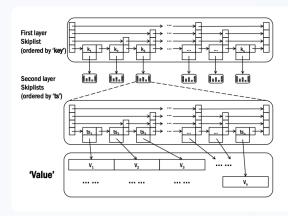
For a detailed description of the online engine architecture, please refer to:

https://openmldb.feishu.cn/wiki/wikcnavULzxKH5Aka3ox0871R2f

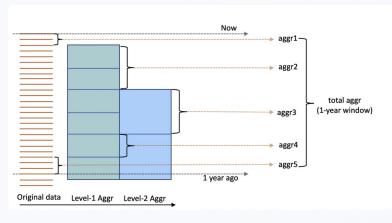




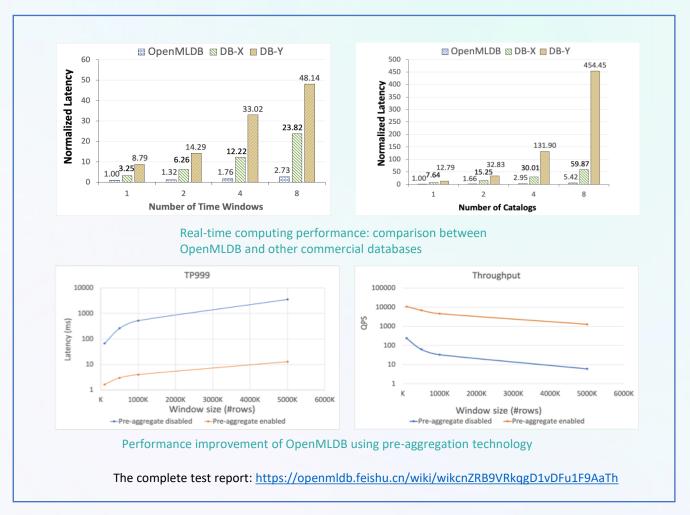
Core Component 2 (Continued): High Performance Real-time SQL Engine - Core Optimization Technology



Core optimization: Double layer skip list (memory engine)



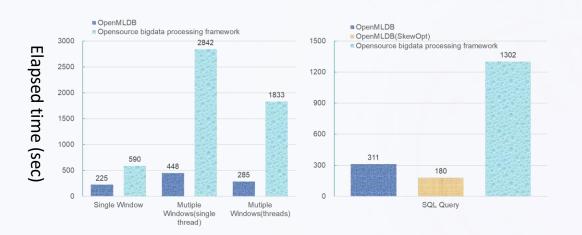
Core optimization technology: Pre-aggregation

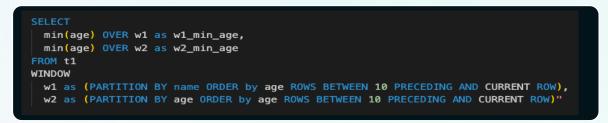


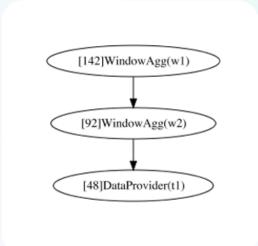


Core Component 3: An Optimized Offline Computing Engine for Feature Computing

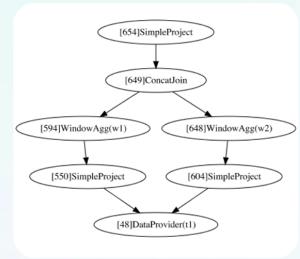
- Multi-window parallel computing optimization
- Optimization of data skew computation
- SQL syntax extension
- OpenMLDB Spark distribution optimized for feature computing











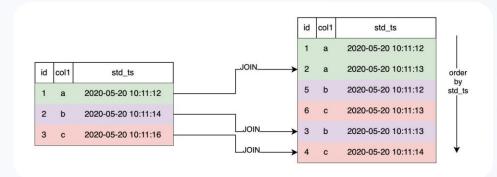
OpenMLDB



Core Component 4: SQL Extension for Feature Engineering

LAST JOIN

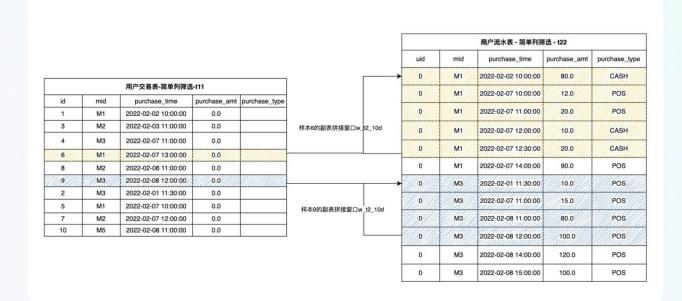
When matching multiple rows, only matches the latest record



id	col1	std_ts	id	col1	std_ts
1	а	2020-05-20 10:11:12	2	а	2020-05-20 10:11:13
2	b	2020-05-20 10:11:14	3	b	2020-05-20 10:11:13
3	С	2020-05-20 10:11:16	4	С	2020-05-20 10:11:14

WINDOW UNION

Cross table join and window aggregation operations (point-in-time) to avoid feature traversal



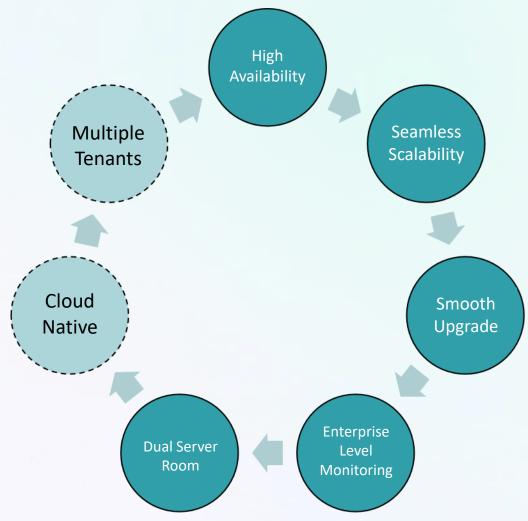


Enterprise Level Feature Support

Born for large-scale Enterprise

Level applications

Implemented in Hundreds of Scenarios

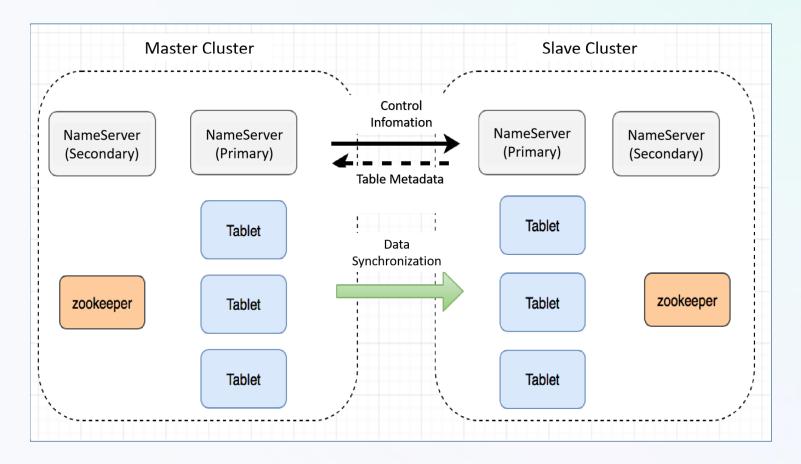




Advanced Feature: Cross Data Center Disaster Recovery

Deploy multiple OpenMLDB clusters in master-slave replication mode to achieve disaster recovery

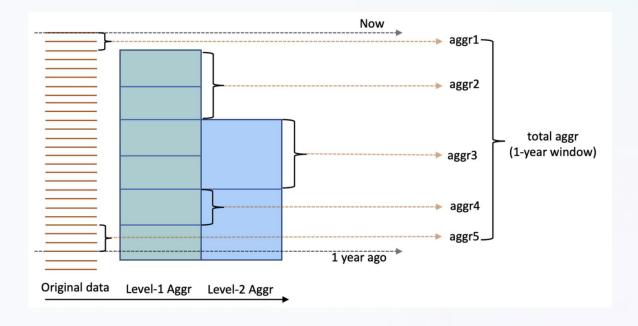
Master cluster: A cluster that can support read and write, and can synchronize data with the slave cluster Slave cluster (one or more): A cluster that only serves read requests, with data consistent with the master cluster



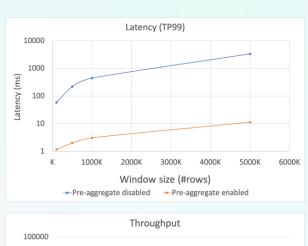


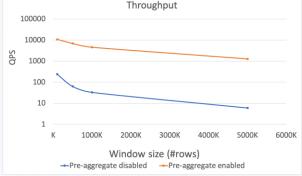
Advanced Features: Pre-aggregation

When the amount of data in the window is huge (millions), enabling pre-aggregation significantly optimizes the latency



Real-time window computation with a span of one year based on a two-layer pre-aggregated table



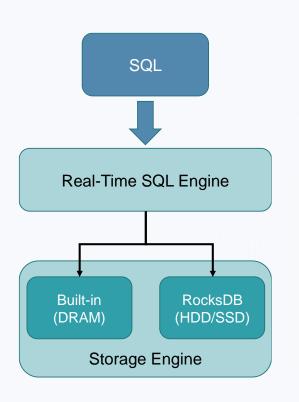


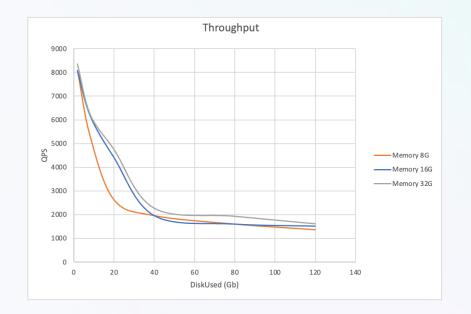
Pre-aggregation technology improves performance by 1-2 orders of magnitude



Advanced Features: Dual Storage Engine Architecture

The disk-based storage engine of the online engine provides a cost-saving solution that is more than 5 times that of the memory-based storage engine, but it will bring certain performance degradation. In practical scenarios, performance and cost requirements should be considered when selecting a solution





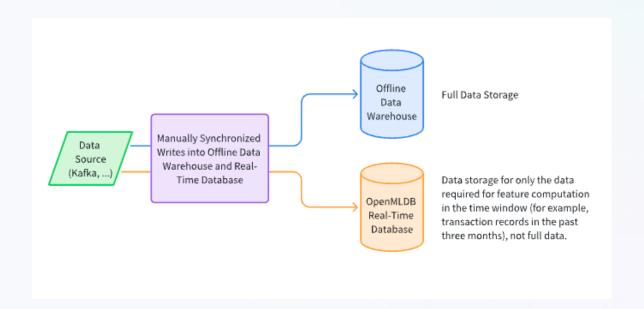


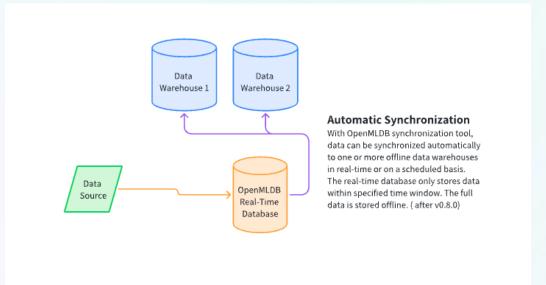
QPS/TP99 both have a performance degradation of 4-5x. Choose the architecture depending on the application scenario.



Advanced Features: Automated Online and Offline Data Synchronization

Online and offline data source synchronization, evolved from manual synchronization mechanism to automated synchronization mechanism





Manually establishing offline and online data synchronization

Automated online to offline data synchronization (Available after v0.8.0)



Advanced Features: Intelligent Operation and Maintenance Diagnostic Tool

Intelligent diagnostic tools: Automated service exception status check, intelligent log collection, ...

Intelligent operation and maintenance tool: openmldb_ops, one-click data and table recovery, automatic scaling and sharding balance, ...

Service Status Check

Automated abnormal state diagnosis (Version verification, configuration file check,...)

One-click Data Recovery

Rapid data recovery under abnormal conditions (Network exception, auto_failover=false,...)

Automatic Balance

Automatic migration and rebalancing of shards after expansion and contraction (Based on heuristic algorithms)

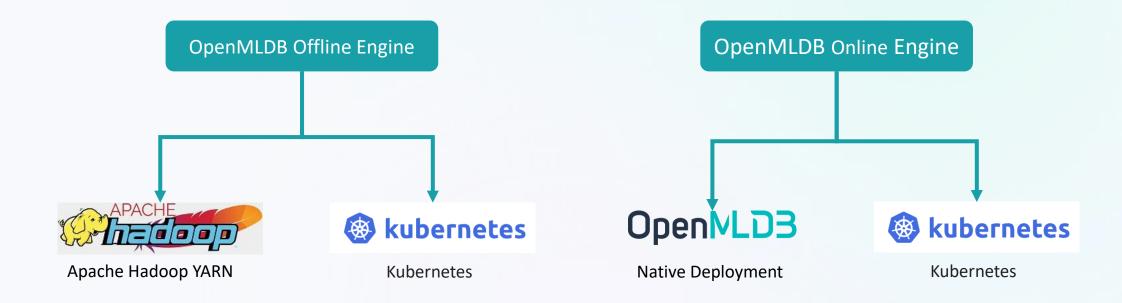








Advanced Features: Multi Form Deployment Support

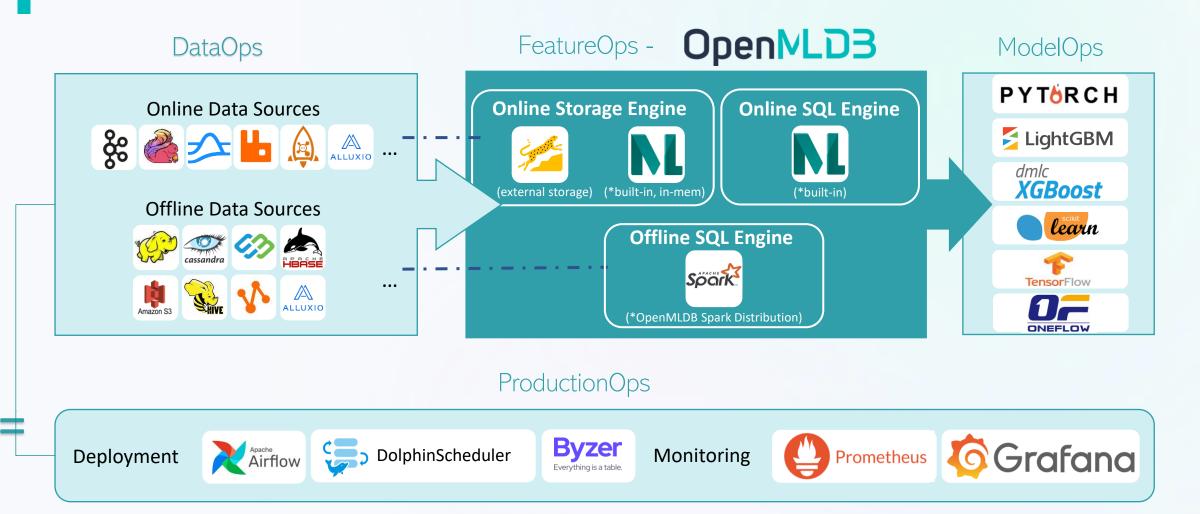




3. Community Eco-System and Use-Cases



OpenMLDB Upstream and Downstream Open-source Ecosystem

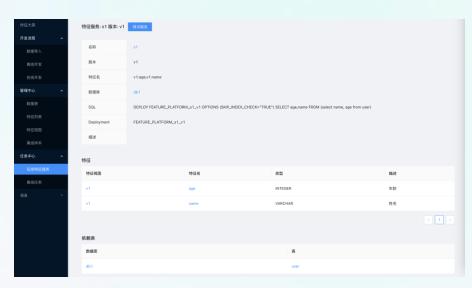


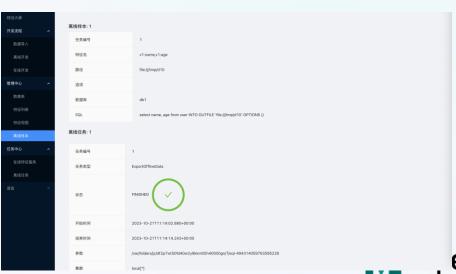


OpenMLDB Application Ecosystem - FeatInsight Feature Platform

- Visual feature development and management interface
- Development Assistance for Large Complex Features Based on DAG
- Flexible feature reuse
- Feature lineage management and version management
- Millisecond-level real-time feature and pre-computed feature support

Beta version has been released: https://github.com/4paradigm/FeatInsight





OpenMLDB Usecase - Feature Platform in Akulaku Intelligent Computing Architecture

Intelligent **Applications** **Behavioral Scoring**

Anti-money Laundering Model **Group Model**

Risk Equipment Label

Geotag

Address Rating

Device Unique ID

Intelligent Customer Service

Abnormal Text Recognition Intelligent Investment Advisor

Model Computation

Layer

Feature Computation Layer

Microservices and Container Management

Graph Database

Distributed Locks

Model Training

Heterogeneous Computing Scheduling Parameter Search and Optimization

Online Feature

Database

Offline Feature Database

Offline Computing Engine

Model Deployment

Microservices and Container Management

> **High Performance** Storage

Streaming **Computing Engine**

High Performance Storage

Knowledge Inference Engine

Knowledge Graph Inference Component

Graph Database

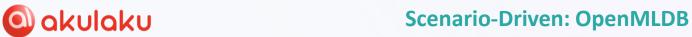
Recall Components

Coarse Arrangement

Components

Queue







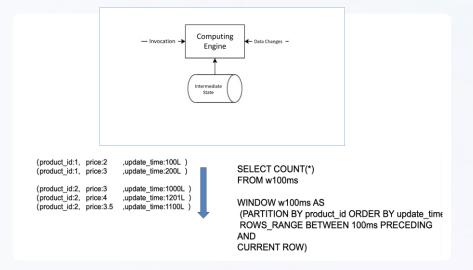
Akulaku Intelligent Risk Control Scenario, Performs Window Feature Computation on 1 Billion Orders, Achieving a Delay Performance of 4 Milliseconds

Difficulties in Feature Computation Process

- Online Deployment: Low latency, high timeliness, reflecting data changes as much as possible
- Offline Analysis: High throughput
- Logical Consistency: The logic for offline analysis and online deployment needs to be completely consistent

OpenMLDB Solution

- Scenario-driven: Business call process driven, real-time calculation results, and on-demand calculation
- Solution: 1) Use SQL as a bridge between offline and online; 2) Online time sliding window based on temporal database



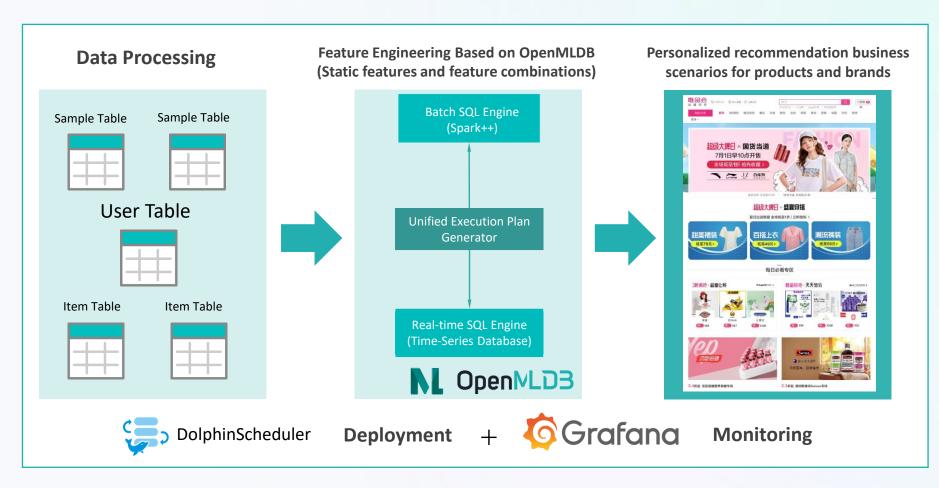
Business Implementation Based on OpenMLDB

- Scenario: Real-time computation of the number of orders in the past day
- Data Volume: 1 billion order data/day
- Requirements: Real-time updates, realtime sliding of time windows, and complex related requirements
- Test Result: 4 millisecond delay





Vipshop Applies OpenMLDB to Personalized Product and Brand Recommendation Scenarios, Resulting in a 60% Improvement in Feature Development Iteration Speed





Feature Development Iteration Speed

5 person-days



Note:

- · Sample Table: User behavior table in different scenarios, including exposure, clicking, and bookmarking
- User Table: User profile information for all users
- Item Table: Full quantity information table for different materials



VMALL Adopts OpenMLDB for Real-time Personalized Product Recommendation

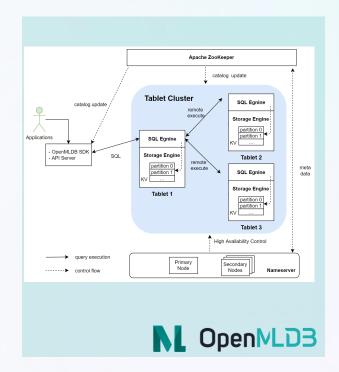
Online Real-time Data

- Data Updates in Minutes
- 720 Million Order Data/ day

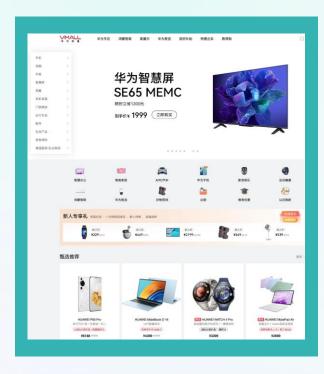
Client Data Table



Real-time Feature Extraction with OpenMLDB



Online Feature Deployment in Hours



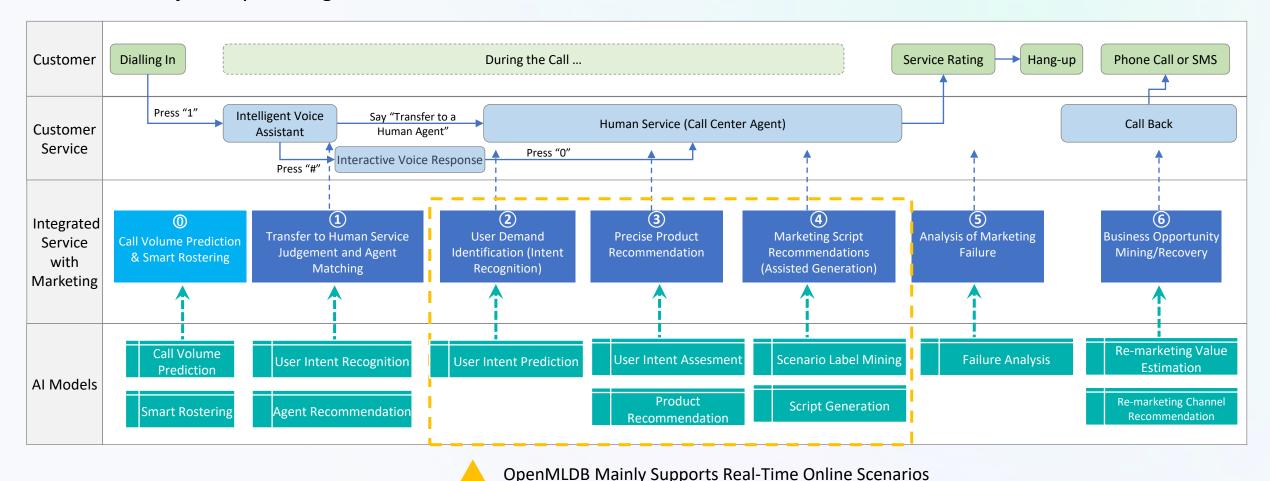






Leading Telecommunication Operator - Integrated Service with Marketing for Customer Service Hotline Channel

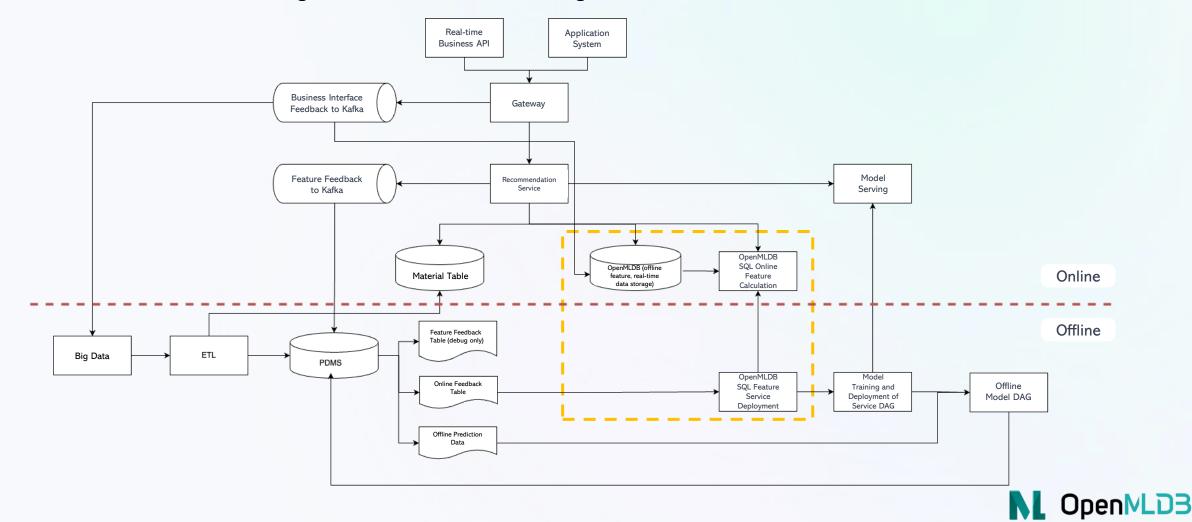
Customer's "journey" through the customer service hotline channel:





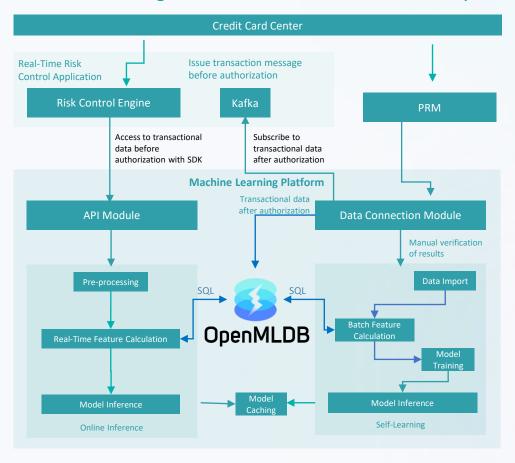
Leading Telecommunication Operator (Continued) – OpenMLDB Offers Millisecond Level Latency and Guarantees Online and Offline Consistency

Basic architecture of the integrated service with marketing



Leading Bank Builds Real-time Anti-fraud Transaction System with OpenMLDB

Architecture diagram of in-transaction risk control system



Bank requires millisecond-level responses

Customer Requirement: A real-time anti-fraud system with a response time of within 20ms and high recall rate

Solution	Response Time	Admission Rate
Traditional Rule-based	~200ms	Relatively Poor
Client Self-developed System	50ms	Moderate
OpenMLDB-based	<20ms	Excellent

OpenMLDB provides distributed, scalable online prediction services with rapid response capabilities, incorporating millisecond-level changes as features for modeling.

- Integration with real-time stream computing engines and message queues
- High-performance real-time time series data extraction
- Real-time transaction closed-loop data writing back
- Real-time high-concurrency read-write separation support



FEBench: First Benchmark for Real-time Feature Computation in Machine Learning

FEBench is the first industrial benchmark model for real-time feature computation in machine learning. It is developed in collaboration with Tsinghua University, the National University of Singapore, and the OpenMLDB community.

- Selected 6 typical scenarios from 118 typical use-case scenarios through modeling as benchmarks
- Compared several common features that support real-time feature computing platforms, including OpenMLDB,
 Flink, etc. OpenMLDB has significant advantages in handling real-time feature computing scenarios.
- Accepted to the top international database academic conference VLDB 2023 and awarded Best Industry Paper Runner-Up.

Table 4: The statistics of selected datasets.

Cluster	Task	Tables	Columns	Tuples
Q0	Ride Prediction	1	11	2.62×10^{6}
Q1	Flu Forecast	1	6	3.54×10^6
Q2	Energy Forecast	8	61	8.0×10^{6}
Q3	Sales Prediction	7	85	1.5×10^{10}
Q4	Loan Evaluation	9	245	1.0×10^{9}
Q5	Fraud Detection	10	773	1.3×10^{11}

6 typical scenarios from 118 typical scenarios as benchmark for testing

GitHub Open-source:

https://github.com/decis-bench/febench



VLDB 2023: Overview

VLDB is a premier annual international forum for data management and database researchers, vendors, practitioners, application developers, and users. The









Welcome to the OpenMLDB community

WeChat Group (Chinese)



OpenMLDB Official Website

Slack



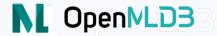
https://openmldb.ai/

LinkedIn Group



GitHub: https://github.com/4paradigm/OpenMLDB





Thanks

OpenMLDB Official Website

https://openmldb.ai/

GitHub: https://github.com/4paradigm/OpenMLDB

