Toward ML-Centric Cloud Platforms

Exploring the opportunities to use ML, the possible designs, and our experience with Microsoft Azure.

BY RICARDO BIANCHINI, MARCUS FONTOURA, ELI CORTEZ, ANAND BONDE, ALEXANDRE MUZIO, ANA-MARIA CONSTANTIN, THOMAS MOSCIBRODA, GABRIEL MAGALHAES, GIRISH BABLANI, AND MARK RUSSINOVICH.

MATTIA MAFFONGELLI 1941528

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"Toward ML-Centric Cloud Platforms"

Cloud platforms such as **Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform (GCP)** operate many infrastructures composed of physical and virtual resources. These include:

- **Virtual Machines (VMs)** and **Containers:** For running applications.
- **Storage Systems:** To store and retrieve data efficiently.
- **Networking Components:** To provide connectivity and performance.

However, the complexity and cost is very high. Indeed, Cloud providers aim to optimize operations by improving:

- **Resource allocation efficiency:** Reducing over-provisioning and underutilization.
- **Operational costs:** Minimizing energy consumption and infrastructure maintenance.
- **Performance:** Ensuring high availability and low latency for customers.

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Why Traditional Methods Fall Short?

Lack of adaptability

Static policies do not adjust to real-time changes in workload patterns.

Reactive rather than proactive

They respond only after issues occur, such as over-utilization of servers.

Manual tuning is error-prone

Thresholds for resource usage often require manual adjustment, which can be inaccurate.

Machine Learning Advantages:

- **Adaptive decision-making:** ML models can dynamically adjust resource allocation based on predictions.
- **Proactive optimizations:** Identifying trends before resource shortages occur.
- **Improved accuracy:** ML models outperform traditional rule-based approaches in predicting workload behavior.

ML in Cloud Resource Management

Container Scheduling

Selecting the best server to run a container without causing resource contention (e.g., CPU, memory, disk).

ML Solution:

- Predict future resource usage based on historical data.
- Avoid deploying containers that might interfere with each other.

Server Defragmentation & VM Migration

As workloads change, servers may become fragmented with unused capacity.

ML Solution:

- Predict which VMs or containers can be safely migrated to free up space.
- Optimize server usage by consolidating workloads.

Power and Energy Management

Cloud data centers consume massive amounts of power. Overuse can lead to outages.

ML Solution:

- Predict power consumption trends.
- Dynamically scale down workloads to prevent overloading power circuits.

Server Health Prediction

Hardware failures lead to service disruptions.

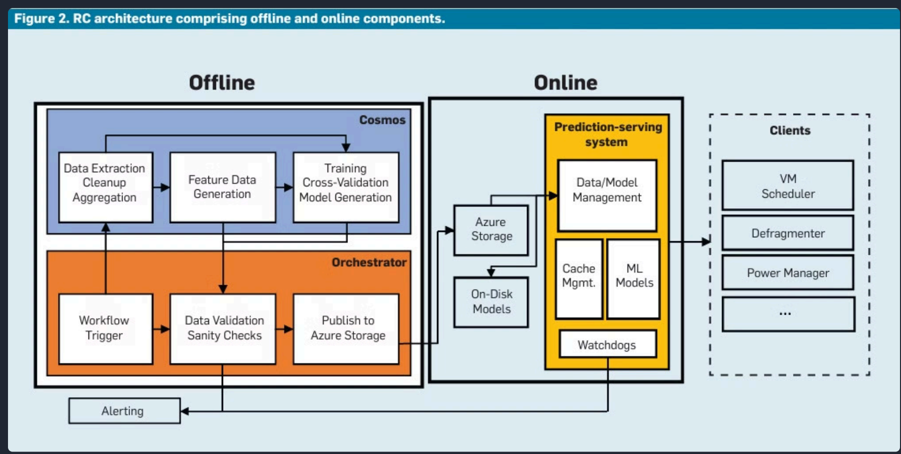
ML Solution:

- Monitor hardware performance metrics.
- Predict failures before they happen and schedule proactive maintenance.

Resource Central (RC): A Practical ML Implementation in Azure

To address these challenges, Microsoft implemented **Resource Central (RC)**, an ML-based system integrated into Azure's cloud platform. RC is designed to provide accurate **predictions** to Azure's resource management systems.

RC Architecture



Offline Component (Model Training)

- Collects **telemetry data** from VMs and containers.
- Cleans, aggregates, and processes data.
- **Trains** ML models (e.g., Gradient Boosted Trees).
- Stores models in **Azure Storage** for later use.

Online Component (Prediction Phase)

- Provides real-time **predictions** via a REST API.
- **Cloud managers** (e.g., the scheduler) query RC for insights.
- RC **fetches** necessary historical data and returns predictions.

Example Workflow: A VM scheduler can request a prediction for CPU utilization by providing details like VM type and previous usage patterns. RC responds with an estimated utilization value and confidence score.

What Are Gradient Boosted Trees (GBT)?

Gradient Boosted Trees (GBT) is the primary ML technique used by RC. It is an ensemble learning method that builds multiple **decision trees**, where each tree attempts to correct the errors made by the previous ones. The process consists of:

1

Training phase

- The first decision tree is built to predict the outcome (e.g., CPU usage).
- The residual errors (differences between predicted and actual values) are calculated.
- A new tree is trained to minimize these residuals.
- This process continues iteratively, improving accuracy over time.

2

Advantages of GBT

- High prediction accuracy.
- Works well with large and complex datasets.
- Handles non-linear relationships effectively.
- Resistant to overfitting when properly tuned.

3

Why GBT in cloud management?

It provides reliable predictions for CPU/memory utilization and helps in better resource allocation.

ML vs Traditional Resource Management

Then, the paper compares the effectiveness of ML-based approaches with traditional resource management techniques. We can resume it:

Feature	Traditional Approach	ML-Based Approach
Decision-Making	Static thresholds/rules	Dynamic adaptation via ML
Accuracy	Low (fixed parameters)	High (continuous learning)
Efficiency	Reactive	Proactive
Complexity	Easier to debug	Requires tuning and monitoring
Resource Optimization	Generalized for all workloads	Personalized per workload

Results from RC in Microsoft Azure

The paper presents empirical results from RC, like as:

1.5B

Daily Queries

RC handles 1.5 billion queries daily, helping optimize resource allocation.

87%

Prediction Accuracy

CPU utilization predictions achieved an accuracy of 74-87%, improving over time with more data.

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Cost Savings

RC has reduced unnecessary live migrations, allowing better resource packing and savings in power and infrastructure.

Open Research Areas and Future Directions

Finally the paper highlights areas for further research:

1

Integrating application-level data

Many workloads don't provide internal performance data; more automated ways to extract meaningful insights are needed.

2

Action-prescribing ML frameworks

More research is required to safely implement ML systems that autonomously manage cloud resources.

3

Debugging complex ML models

Developing tools to explain ML decisions transparently to cloud operators.

4

Cross-service optimizations

ML could be expanded to areas like security, network traffic, and reliability improvements.

Conclusion

ML has the potential to change in a global way cloud resource management, but there are also some challenges in terms of scalability, transparency, and integration.

Key Points:

Efficiency and Cost

ML can improve cloud efficiency and reduce costs.

Promising Results

RC has shown promising results but requires further refinement.

Future Investment

Cloud providers must continue investing in ML-driven automation to stay competitive.