Master Thesis

Title: Predictive Auto-Scaling for Cloud Applications,

Machine Learning Driven Framework using E-Commerce Data Workloads

Master of Science
Applied Computer Science

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Agenda

Introduction to Cloud Predictive Auto-Scaling

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Introduction to Cloud Predictive Auto-Scaling

What is Auto-Scaling?

Automatic adjustment of computing resources based on system load.

Traditional scaling reacts *after* overload.

Why Predictive Auto-Scaling?

Predictive scaling *foresees* load and adjusts *before* performance drops.

Motivation and Problem Definition

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Motivation

Motivation

- Online retail workloads fluctuate rapidly during events (sales, campaigns).
- Delayed scaling causes latency and revenue loss.
- Predictive auto-scaling ensures proactive resource readiness.
- Machine learning enables workload forecasting and uncertainty estimation.

Research Objectives

- **Delayed Scaling:** Reactive methods adjust resources only *after* overload, increasing latency and harming user experience.
- **Resource Inefficiency:** Over-provisioning wastes cost; under-provisioning slows performance.
- **No Adaptive Forecasting:** Traditional approaches fail to learn complex, nonlinear workload patterns.
- **No Uncertainty Handling:** Existing models ignore prediction uncertainty, causing unstable scaling decisions.

Tools and Technology

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Tools and Technology Used

- **Dataset:** Alibaba Cluster Trace 2018 (real cloud workload data)
- **Languages:** Python (for ML pipeline), Node.js (for controller)
- **Libraries:** pandas, numpy, scikit-learn, TensorFlow/Keras
- **Monitoring Stack:**
  - Prometheus (metrics collection)
  - Alertmanager (notifications)
- **Containerization:** Docker & Docker Compose

Proposed Architecture diagram

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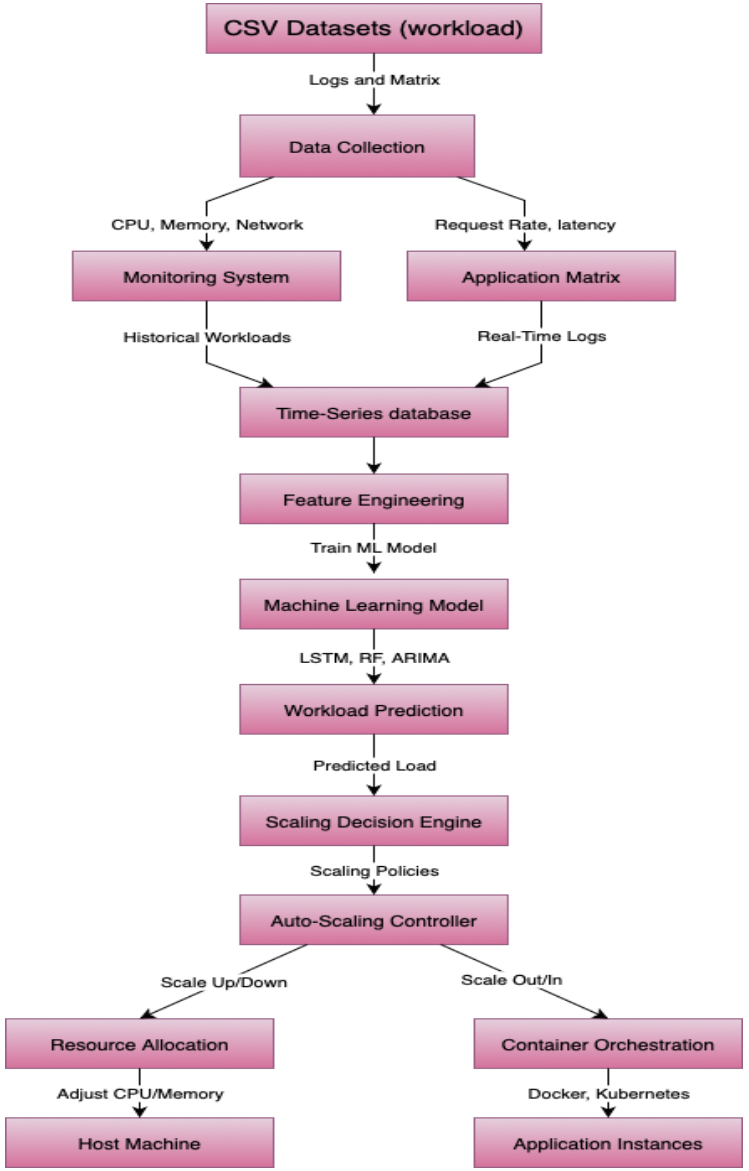
Architecture diagram



Data Input: Alibaba 2018 workload CSVs provide real historical logs such as CPU, memory, network, and execution time, used to understand real cloud behavior.

Monitoring & Preprocessing: These raw logs are collected, cleaned, and turned into continuous time-series data for model training.

Machine Learning Core: Models like LSTM, Random Forest, and ARIMA learn workload patterns and predict future latency (p95) with uncertainty.

Decision & Scaling: The controller applies the predictive rule mean + σ > SLO → Scale Up, mean + σ < SLO → Scale Down to manage resources proactively.

Execution Layer: The system automatically adjusts CPU/memory or container replicas through Docker/Kubernetes, keeping latency low and cost efficient.

Dataset and Preprocessing

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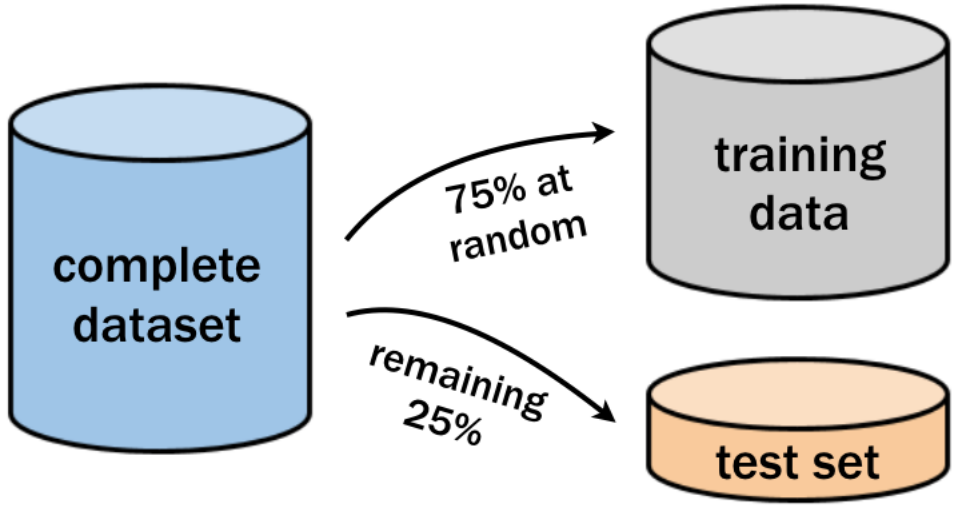
Dataset and Preprocessing

Dataset: Alibaba Cluster Trace (2018)

- Real traces from Alibaba's e-commerce cloud infrastructure.
- Contains CPU, memory, job, and container usage logs.
- Sampled 2000 rows for modeling and evaluation.
- Reflects realistic e-commerce resource dynamics.



Preprocessing:

- Loaded and time-sorted Alibaba CSV data by timestamp.
- Output → clean csv data used by pipeline.
- Aligned timestamps and handled missing values.
- Generated latency target (response_time_p95) using rolling 95th percentile of execution time.
- Added lag and rolling features for CPU, memory, network, and execution time.

Feature Engineering and Models

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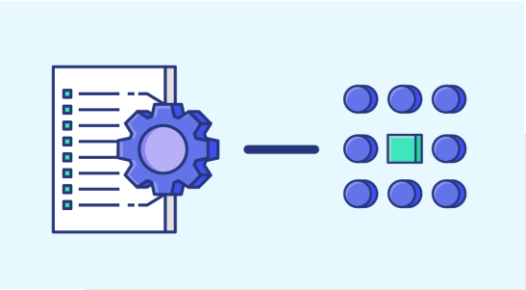
Feature Engineering and Models

Feature engineering:

- Converted all metrics to numeric time-series.
- Added lag features (t-1, t-2, t-3) for workload history.
- Added rolling averages (3 & 5 points) for CPU, memory, and network.
- Created response_time_p95 as latency target.
- Removed missing data and scaled features using MinMaxScaler.



Models:

- **LSTM:** Learns time-based workload patterns to predict future latency (response_time_p95), Monte Carlo dropout gives uncertainty (σ).
- **Random Forest:** Predicts future latency and provides quantile predictions (p50, p90, p95) for scaling decisions.
- **ARIMA:** Baseline time-series model that forecasts latency using past trends.

Predictive Decision Rule

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Predictive Decision Rule

Formula:

mean + σ > SLO → Scale Up

mean + σ < SLO → Scale Down

Interpretation:

- **mean:** Predicted future latency
- **σ:** Prediction uncertainty (safety margin)
- **SLO:** Latency limit (e.g., 0.09 s)

Why It's Unique:

- Adds **risk awareness** using prediction uncertainty.
- **Proactively scales** before performance drops

Implementation of the Pipeline

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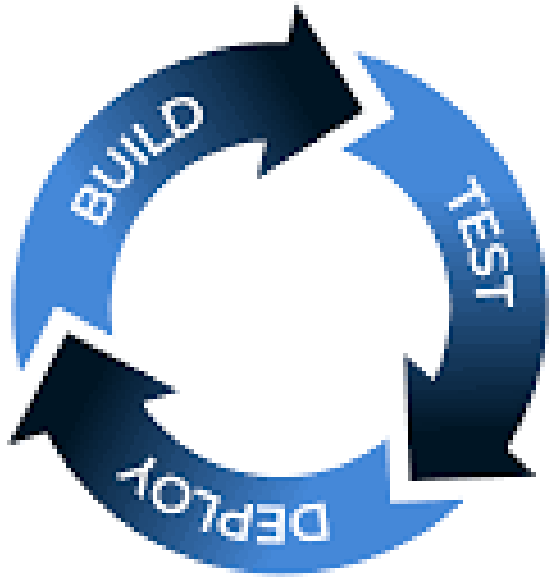
Implementation Pipeline

- **Training Pipeline:** Runs ML workflow → outputs predictive_signal.json.
- **Controller:** Reads predictive signal and applies scaling rule (mean + σ > SLO).
- **Prometheus:** Continuously scrapes system metrics from /metrics endpoint.
- **Docker Compose:** Orchestrates all components (ML, controller, monitoring stack).



Results and Evaluation

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Model Evaluation

Models trained: LSTM, Random Forest, ARIMA.

Metrics used:

- MAE (Mean Absolute Error)
- RMSE (Root Mean Square Error)

Observation:

LSTM achieved the most accurate time-series prediction of latency (response_time_p95).

[LSTM] MAE=0.004 RMSE=0.006

```
Evaluation started ...
[LSTM] MAE=0.0040  RMSE=0.0051  N=1976
[RF] MAE=0.0002  RMSE=0.0004  N=1996
[ARIMA] MAE=0.0046  RMSE=0.0058  N=1995
Evaluation completed ✅
```

Auto-Scaling Controller Logs

The controller read the predictive signal and **initiated scaling** when:

mean + σ > SLO

```
chaithratelkar@Mac cloud1 % docker logs --since=30m --tail=500 -f cloud1-scaling-controll
er-1 \
  | egrep -E "predictive read|Initiating scaling|Scaling completed"

info: predictive read: metric=response_time_p95 mean=0.0928 sigma=0.0019 alpha=1 decision
=0.0946 threshold(SLO p95 (seconds))=0.09 {"service":"auto-scaling-controller","timestamp
":"2025-10-22T22:06:00.478Z"}
info: Initiating scaling to 3 replicas. Reason: predictive_response_time_p95: value=0.094
6 threshold=0.09 (mean=0.0928, σ=0.0019, α=1) {"service":"auto-scaling-controller","times
tamp":"2025-10-22T22:06:00.479Z"}
info: Scaling completed: 2 -> 3 replicas in 2.001s {"service":"auto-scaling-controller","
timestamp":"2025-10-22T22:06:02.482Z"}
```

mean=0.0928, sigma=0.0019, decision=0.0946 > threshold=0.09

Scaling completed: 2 → 3 replicas

Interpretation: The system predicted that latency will exceed SLO and scaled up *proactively* before degradation occurred.

Prometheus Visualization

Prometheus metrics confirmed multiple scaling decisions:

- Query: scaling_decisions_total
- Shows 8 scaling events over time.

Graph indicates system responsiveness and predictive scaling trend.

Conclusion & Future Outlook:

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Conclusion

Developed a **predictive auto-scaling framework** combining machine learning, observability, and intelligent control to maintain optimal cloud performance.

Integrated a **complete data pipeline** using **LSTM, Random Forest, and ARIMA** models to forecast **p95 response time** and guide scaling actions.

Implemented a **safety-aware decision rule** (mean + σ > SLO) for proactive scaling, with tunable **α** and **SLO_P95_SEC** for balancing reliability and efficiency.

Ensured **transparency and traceability** through **Prometheus metrics and controller logs**, proving a scalable and reproducible approach for modern cloud systems.

Future Outlook

Integrate **multi-metric prediction** (CPU, memory, latency) jointly.

Implement **reinforcement learning-based scaling** for adaptive threshold tuning.

Extend to **Kubernetes cluster-level scaling** for production use.

Demo

Q & A

Thanks for your attention
Danke für Ihre Aufmerksamkeit..