# Toward Pattern-based Model Selection for Cloud Resource Forecasting

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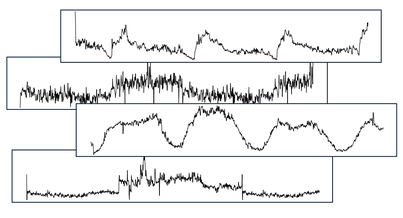
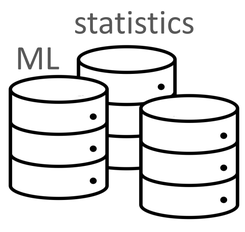
## 1. Problem Space

CPU Usage Patterns per Job

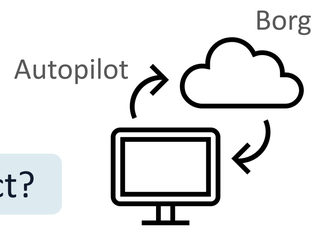


**Historical Data**




**Cloud Resource Prediction Models**

Which model to select?




**Cloud Resource Management System**

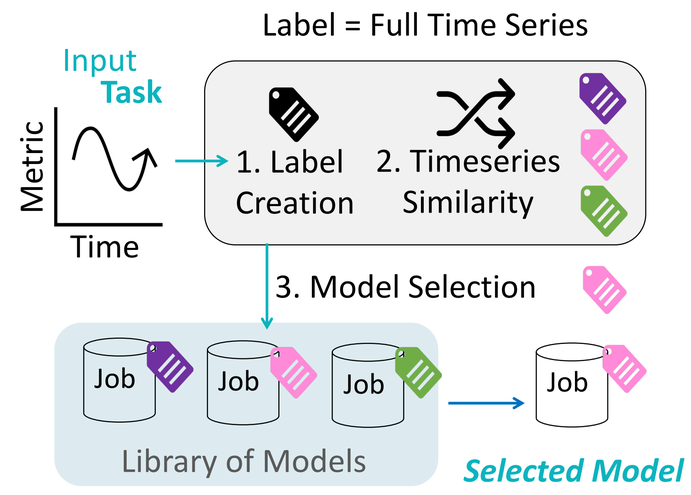
**Resource Scaling:** Choose Model with Highest Prediction Accuracy.

**Overcommitment Policies:** Choose Model that predicts Max value.

**Example Use Cases**

**Problem Statement**: Can we **select a model** based on the **pattern** of resource usage?

## 2. Proposed Approach




*1 ML-based Model per Job*

## 3. Pattern-based Comparison

### Data Representations

**Numeric**: Time Series Data "as-is"

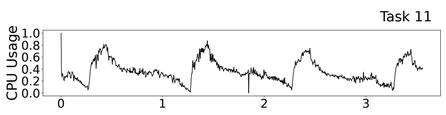
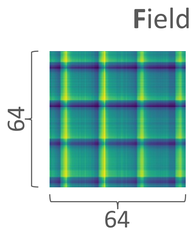



**Image**: **G**ramian **A**ngular **D**ifference **F**ield (GADF)




1 image / timeseries

### Comparison Metrics

- L2 Norm
- **D**ynamic **T**ime **W**arping (DTW)
- **S**tructural **S**imilarity **I**ndex **M**easure (SSIM)

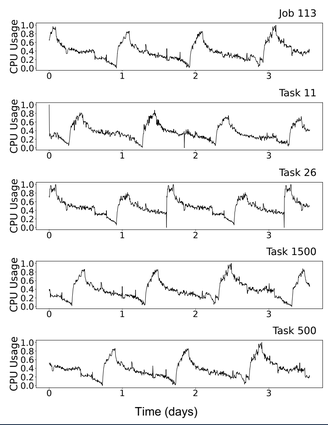
### Approach - Combinations

I. Numeric – L2
II. Numeric – DTW
III. GADF Image - L2
IV. GADF Image - SSIM

**Question:** Which **combination** of time series data representations and comparison metrics can **separate the tasks of a job** based on a pattern?

**Methodology:** Run k-means to cluster the time series of the tasks creating 1 cluster per job.

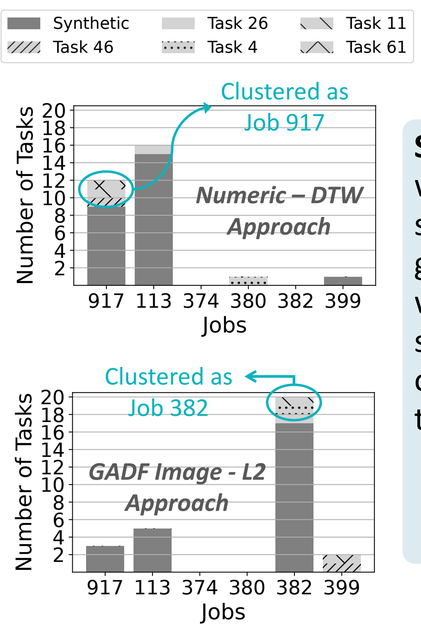
When using **homogeneous** (very similar) tasks, the clustering is successful for **all approaches.**




Representative Task of job 113 (Google Workload Traces)

Real Heterogeneous (slightly dissimilar) Tasks

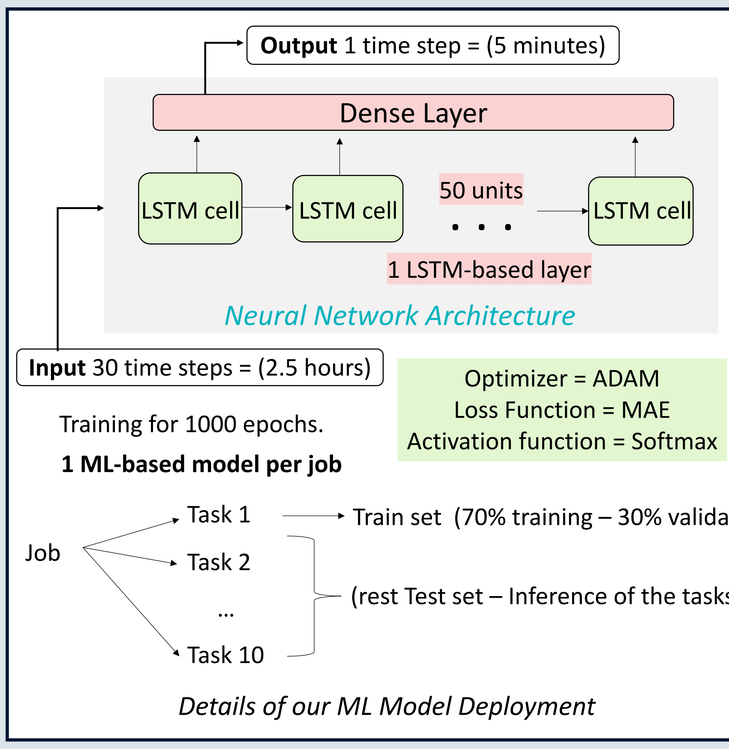
Synthetic Time Shifted Tasks




**Slightly dissimilar** tasks with spikes or time shifted patterns are not grouped together. Even when using DTW, a sophisticated method, or when using images to reveal more features.

**No single winner approach!**

## 4. Model Selection



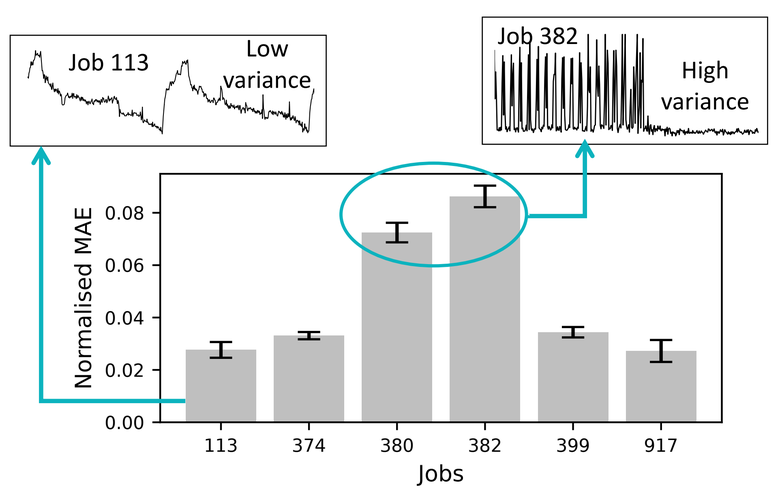

Optimizer = ADAM
Loss Function = MAE
Activation function = Softmax

Training for 1000 epochs.

**1 ML-based model per job**




*Details of our ML Model Deployment*

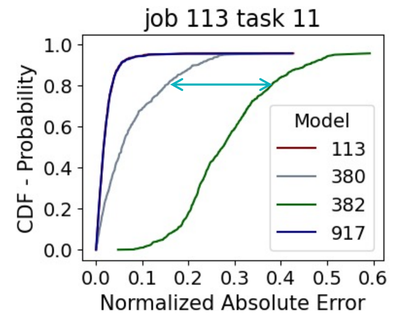



*Prediction Error (MAE) across tasks of a job. Model trained on the job.*

ML models can **generalize** across job tasks.

| Approach | Model |
|---|---|
| Numeric – L2 | 380 |
| Numeric – DTW | 917 |
| GADF Image - L2 | 382 |
| GADF Image - SSIM | 917 |

*Models selected across approaches to predict **task 11 of job 113.***




*Distribution of Prediction Error (MAE).*

- **Model 113** lowest overall error. Importance of choosing the right model.
- **Model 917** exactly same curve. Opportunity for stronger generalizability?
- **Models 380, 382** deliver 10% - 40% error with probability 0.8. Impact of not choosing the right model.

Effective Pattern-based Model Selection is important to deliver **high prediction accuracy**.

## 5. Main Insights

1. **Effective pattern-based model selection** unlocks highly **generalizable and accurate** model inference across tasks of a job. Ineffective selection reveals significant loss in inference quality.

2. Pattern-based comparisons using **distance-based metrics** are effective for very similar timeseries, but **break** when patterns become **slightly disimillar** (e.g., time shifted), even with more sophisticated approaches (DTW, image-based). Opportunity for new contributions!

## 6. Future Directions

- **Expand dataset** to more jobs, tasks, patterns, resources, and finer granularity across time windows.
- Explore more sophisticated **ML-based pattern matching**.
- Use **explainable AI** to understand model generalizability.
- Explore **other forecasting models** (ML, statistical).
- **Integrate** pattern-based model selection in **use case** e.g., resource autoscaler, overcomitment policy.

## References

Scan for Paper

Scan for Code