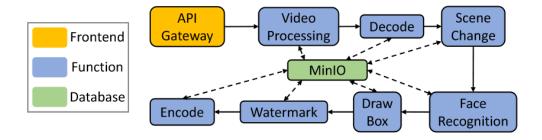
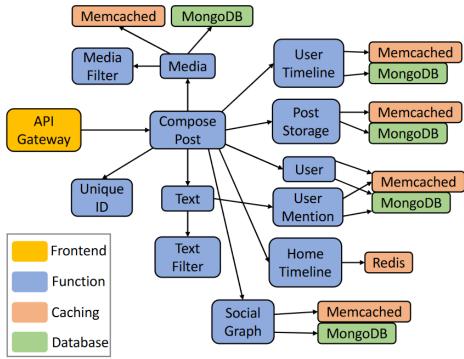


### BACKGROUND

### Multi-stage FaaS workflow

- Fine-grained scalability, parallel execution, etc.
- Challenges in resource management <-</li>(Cascade Cold Start)





## CHALLENGES

Cold starts: launching new container, setting up runtime environment, fetching and loading libraries, etc.

Resource allocation: resource requirements between functions vary a lot (CPU, Memory)

Uncertainty in FaaS: noise and uncertainty causes biased observations, impairing the performance of sampling-based resource management approaches

### AQUATOPE - ELIMINATING COLD STARTS

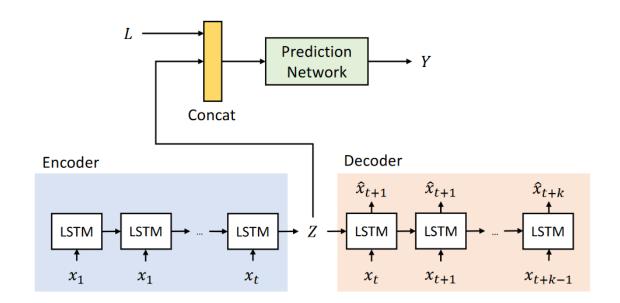
Using ML models to infer the total number of required containers for each active serverless application over the next time interval.

 $\{x_1, x_2, \dots, x_t\}$ : number of active containers in the past t time windows

L: external feature vector (time of day, ...)

#### **Hybrid Bayesian neural network**

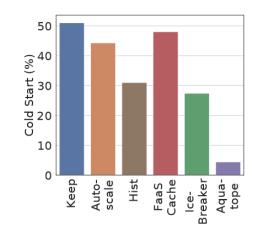
- utilize external features
- take system noises into account

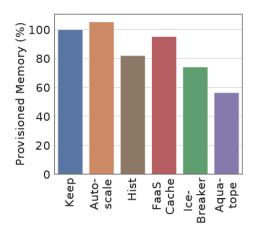


## AQUATOPE - ELIMINATING COLD STARTS

#### **Prediction-Based Container Pool**

Prediction	Prediction Models			
Error	Fixed Keep-Alive	ARIMA	LSTM	Aquatope
SMAPE	24.5%	18.6%	9.5%	5.7%



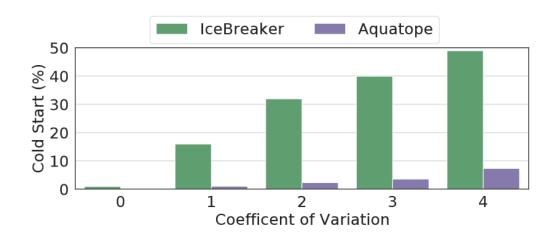


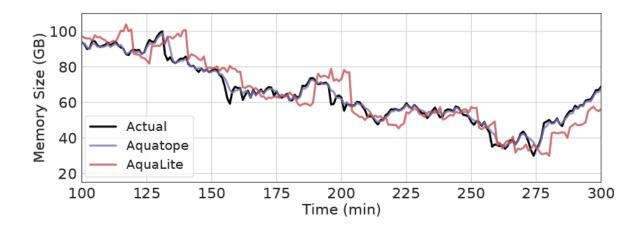
(a) Function cold starts.

(b) Provisioned memory time.

## AQUATOPE - ELIMINATING COLD STARTS

#### Handling fluctuating load



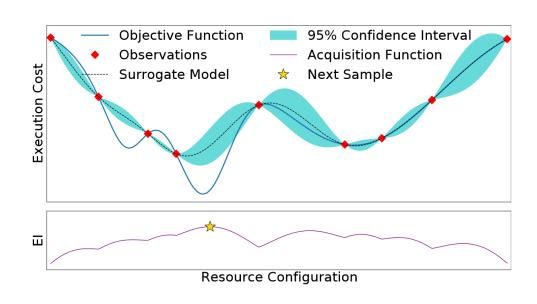


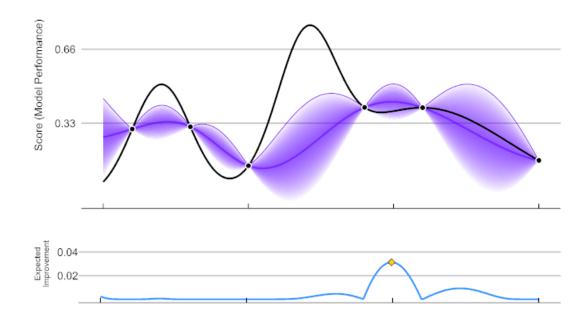
Pre-warmed container pool manager ensures that the majority of function invocations are handled by warm containers.

Consider the diverse resource requirements of each function

- Manually deriving an analytical performance model -> difficult
- Exhaustively searching the entire configuration space -> time consuming & expensive

#### Bayesian Optimization (BO) Workflow





### Challenges for conventional BO

Cloud noise: previous BO-based resource managers assume a noiseless setting

**QoS constraint:** previous resource managers rely on manually crafted objective functions with a penalty term that is triggered upon QoS violation -> *slow convergence & performance degradation* 

Batch sampling: conventional BO samples and evaluates one configuration at a time

### **Customized Bayesian Optimization**

**Customized surrogate models:** Gaussian process (GP)

#### Cloud noise:

Inherent noise (Gaussian noise)
Irregular noise (non-Gaussian noise)

Builds independent GP models for the cost target f and the QoS constraint  $\ell$ 

- Converge faster and more accurate
- Performance model narrows down the search space

### **Customized Bayesian Optimization**

Customized acquisition function: constrained noisy expected improvement (NEI) + quasi-Monte Carlo sampling (QMC)

**NEI:** take Gaussian observation noise into consideration, doesn't require noiseless observations

Constrained NEI: multiply NEI of reducing cost with the probability of satisfying QoS

**QMC:** enables batch sampling

### **Customized Bayesian Optimization**

Anomaly Detection: builds diagnostic GP model using data points other than the one under evaluation, computing the confidence interval to identify possible anomaly

#### Cloud noise:

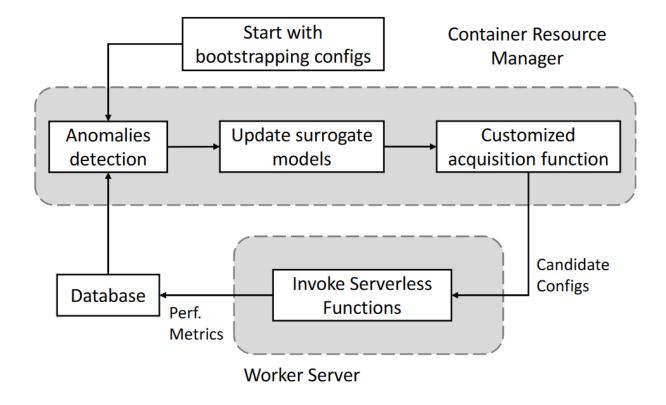
Inherent noise (Gaussian noise)

Irregular noise (non-Gaussian noise)

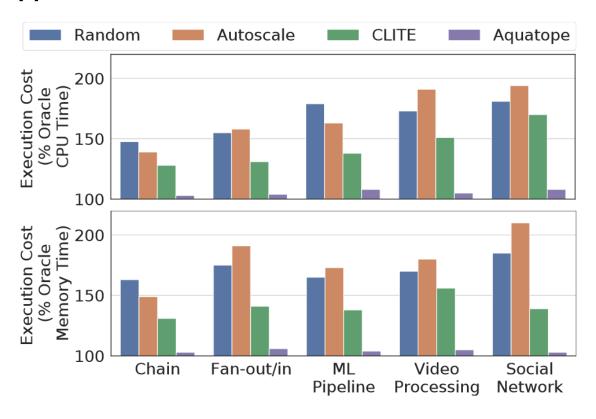
**Incremental retraining:** the anomaly detection mechanism allows Aquatope to detect changes in the performance behaviors. These deviations can be caused by changes in the input workload, function updates, etc.

Updates the model by collecting new samples using a sliding window, gradually adapts to changes.

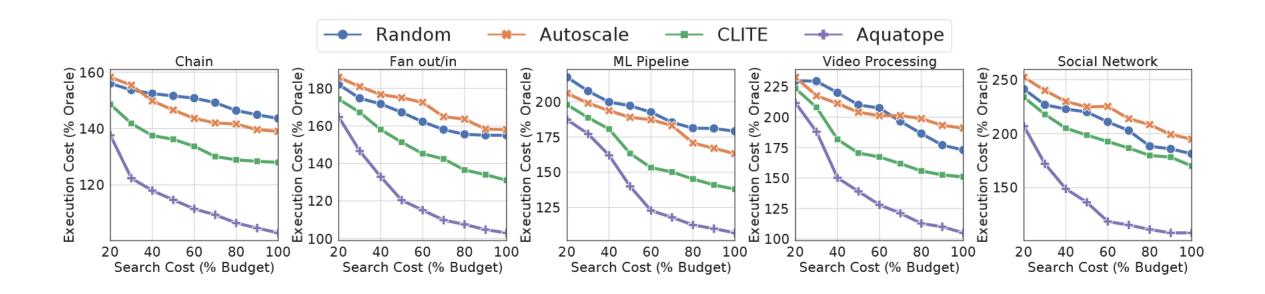
#### Workflow



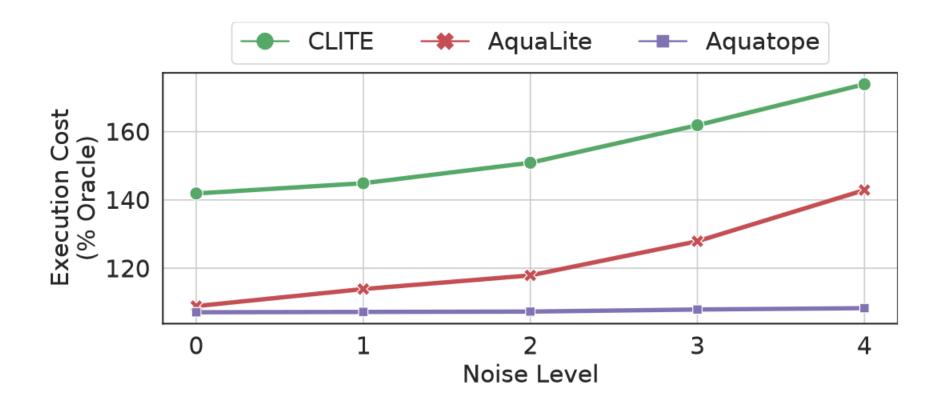
#### Multi-stage serverless applications



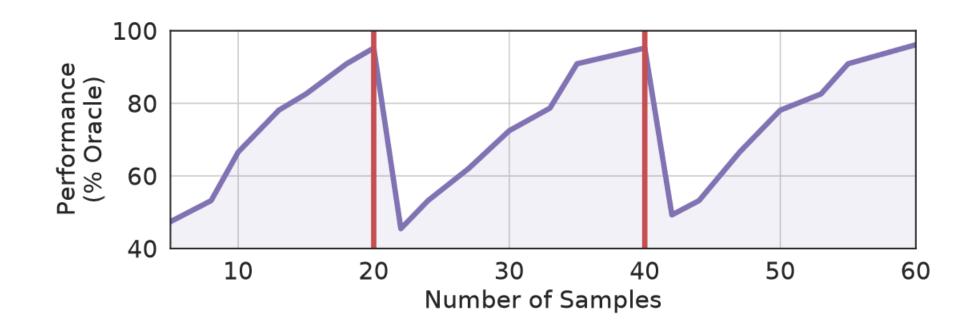
#### Fast and accurate convergence



#### Robustness to cloud noise



#### **Automatic retraining**



# EVALUATION

#### **End-to-End performance**

