

AKAMAS

# Automating Performance Tuning with Machine Learning

USENIX SRECon 21

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# Agenda

- 1 **Why SREs should care about system configurations**
- 2 **A new approach: ML-driven performance tuning**
- 3 **Real-world example: optimize Kubernetes and JVM**
- 4 **Conclusions**



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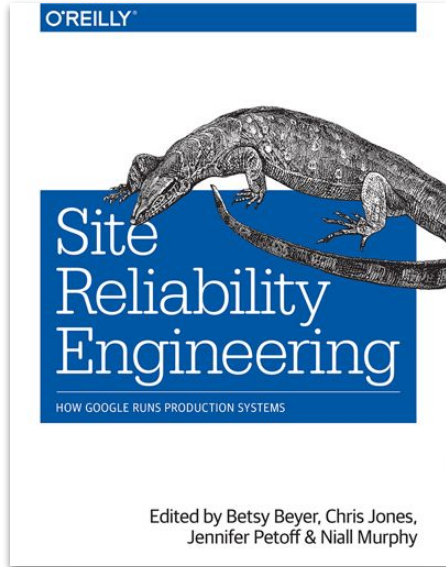
15 years in performance engineering

2015 CMG Best Paper Award Winner

# Why SREs should care about system configurations



# SREs care about efficiency and performance



*“an **SRE team** is responsible for the availability, latency, performance, efficiency, change management, monitoring, emergency response, and capacity planning of their service(s)”*

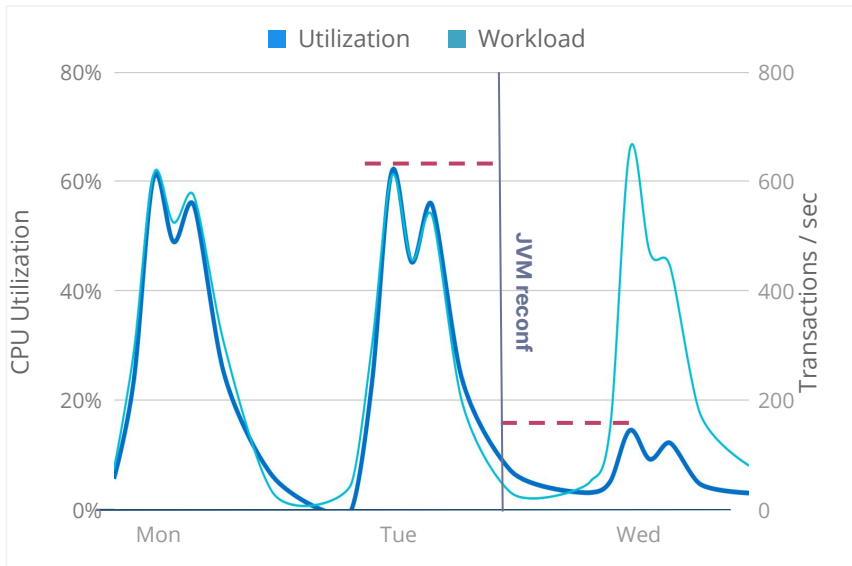
The **core SRE tenets** include:

- Pursuing maximum change velocity without violating SLOs
- Demand Forecasting and Capacity Planning
- Efficiency and performance

<https://sre.google/books>

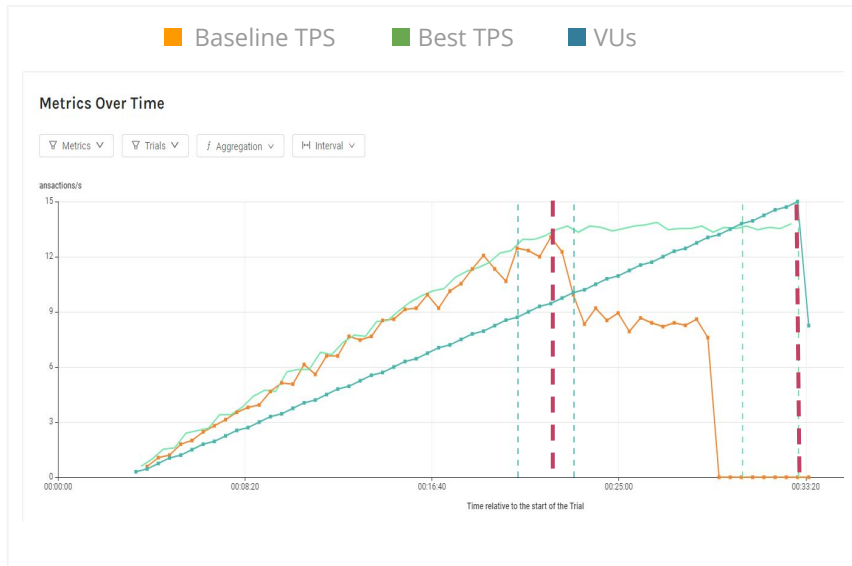
# Tuning system configuration matters...

## performance and efficiency



*higher application performance and lower infrastructure cost*

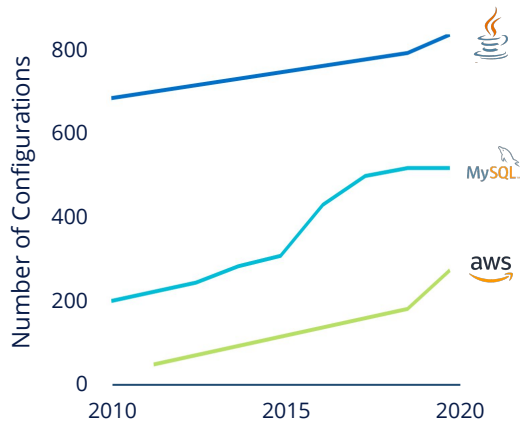
## ... and service availability



*higher transaction throughput and improved service resilience*

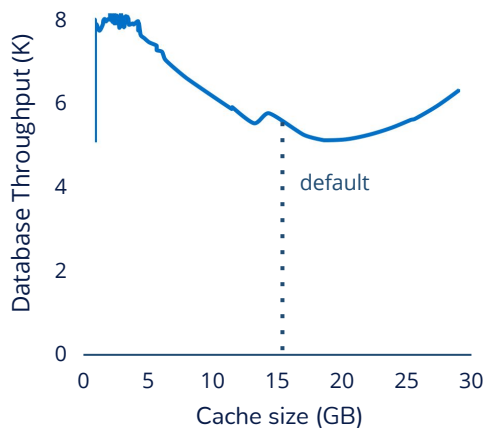
# ... but it is getting harder and harder

## Configuration Explosion



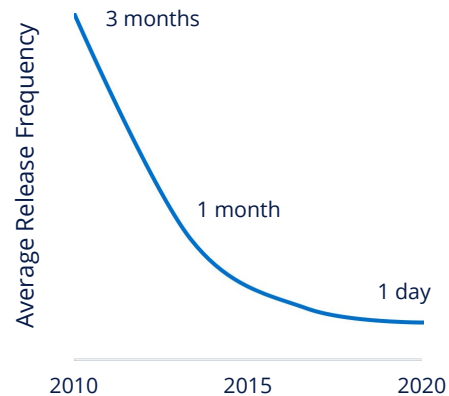
*properly configuring the IT stack requires analyzing thousands of configurations*

## Unpredictable Effects



*effect of changes can be counterintuitive + default values not always appropriate*

## Faster Deployments



*acceleration of release pace makes manual approach infeasible/useless*

# **A new approach: ML-driven performance tuning**



# Key requirements for a new approach

## Full-Stack



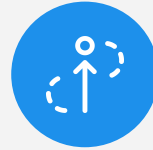
*Optimize multiple technologies and layers at the same time*

## Smart Exploration



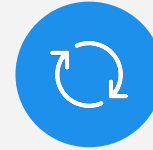
*Explore huge space of configurations in a time and cost-effective way*

## Goal-oriented



*Define tailored goals and constraints driving the optimization*

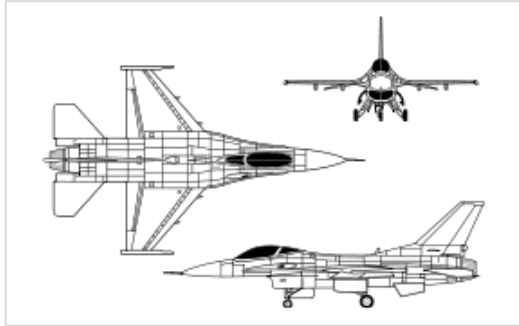
## Fully Automated



*Execute the entire optimization process in a fully automated way*



# ML techniques for smart exploration



## Model Based

Queuing Networks  
Petri Networks  
Linear Programming



## Simulation Based

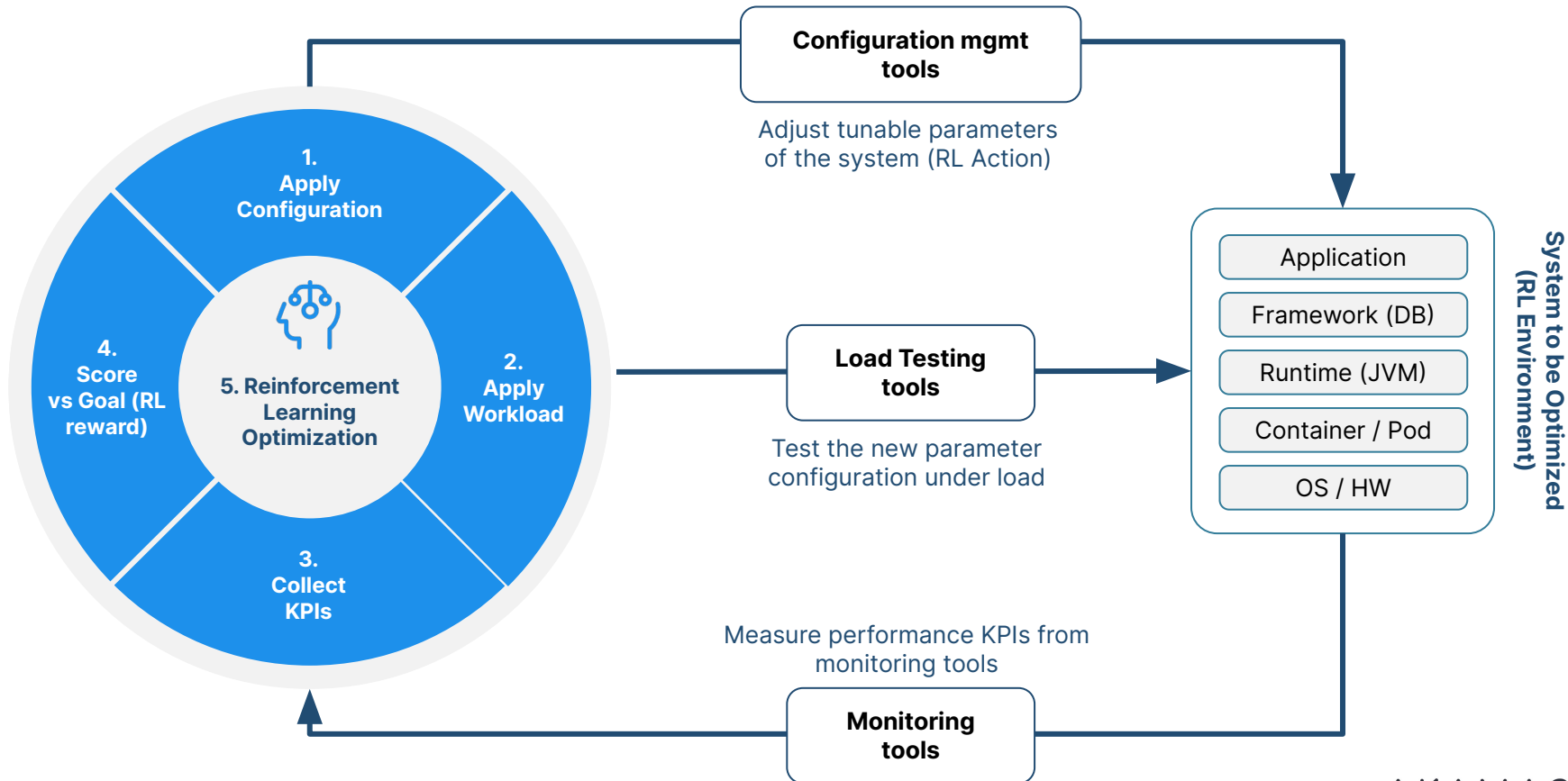
Random Forests  
Statistical Machine Learning



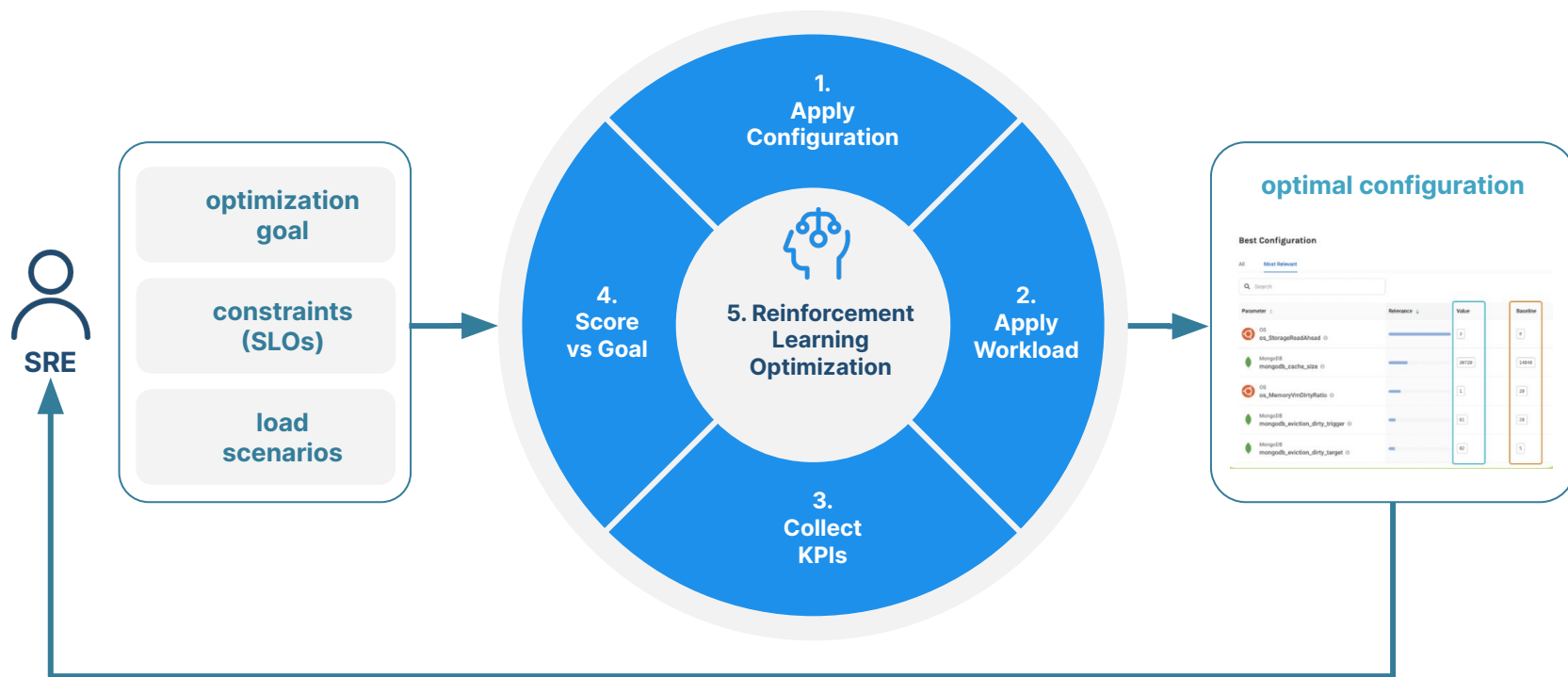
## Test Based

Random Search  
Reinforcement Learning  
Parzen Trees

# ML enables automated performance tuning...



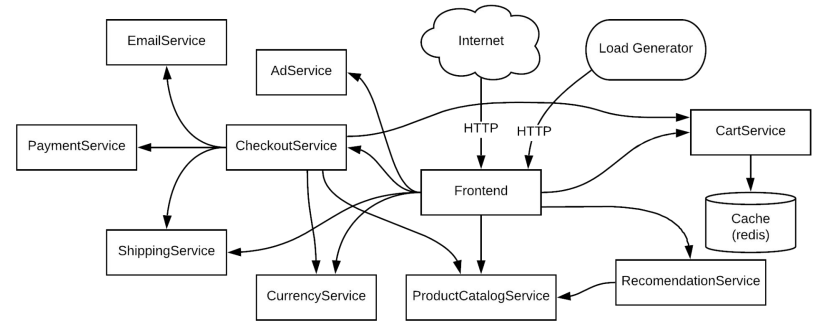
# ... and a new performance tuning process



# Real world example: optimize Kubernetes and JVM

# The target system: Online Boutique

- **Cloud-native application** by Google made of **10 microservices**
- Realistic sample web-based **e-commerce service**
- Features a **modern software stack** (Go, Node.js, Java, Python, Redis)
- Includes a Load Generator (Locust) to inject **realistic workloads**



<https://github.com/GoogleCloudPlatform/microservices-demo>

# Use Case: optimizing cost of K8s microservices while ensuring reliability

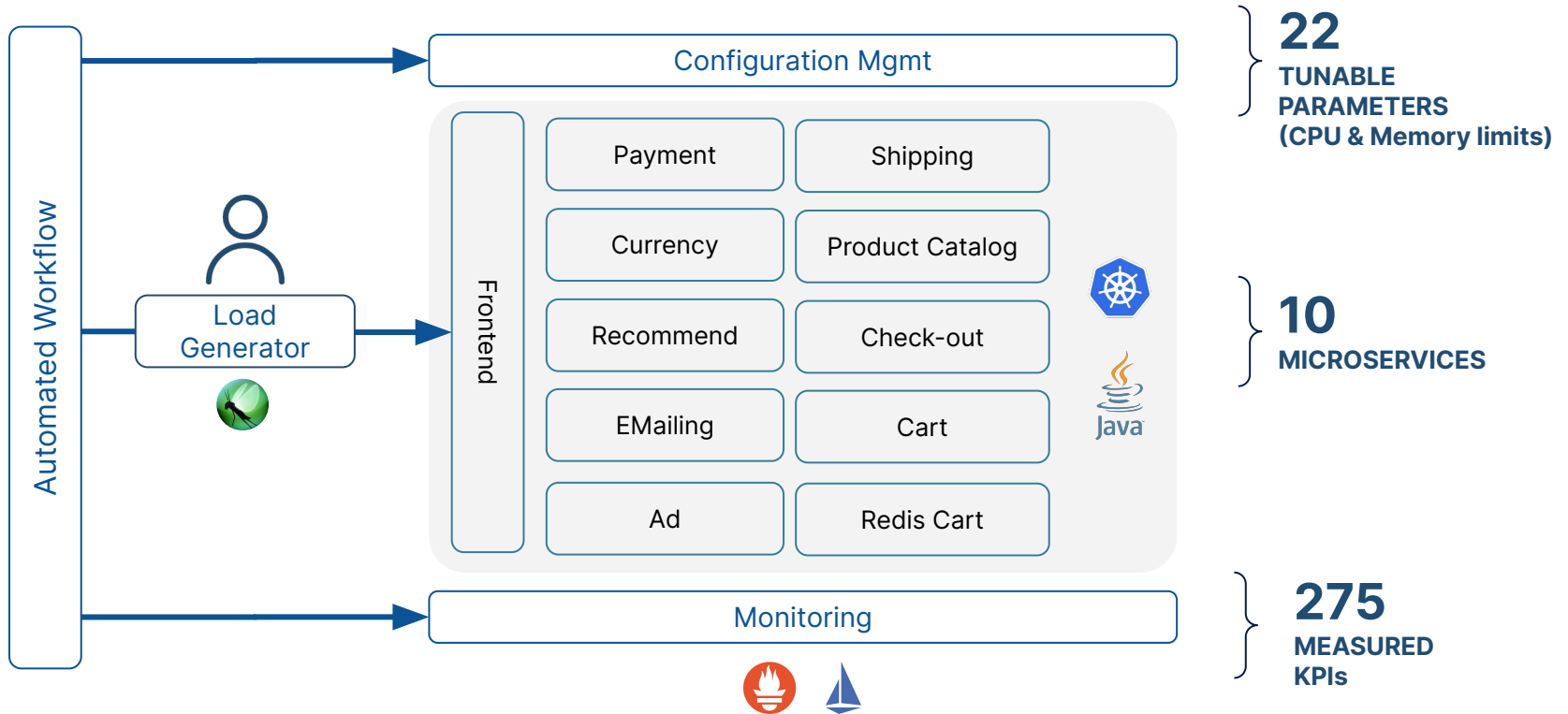
## Challenge for SRE

How to provision the optimal resources to your application made of several **Kubernetes** microservices, so that you can trust the overall service

- will sustain the expected **target load**
- while matching the defined **Service-Level Objectives** (SLOs)
- at the **minimum cost**
- while minimizing the operational effort
- and matching delivery milestones



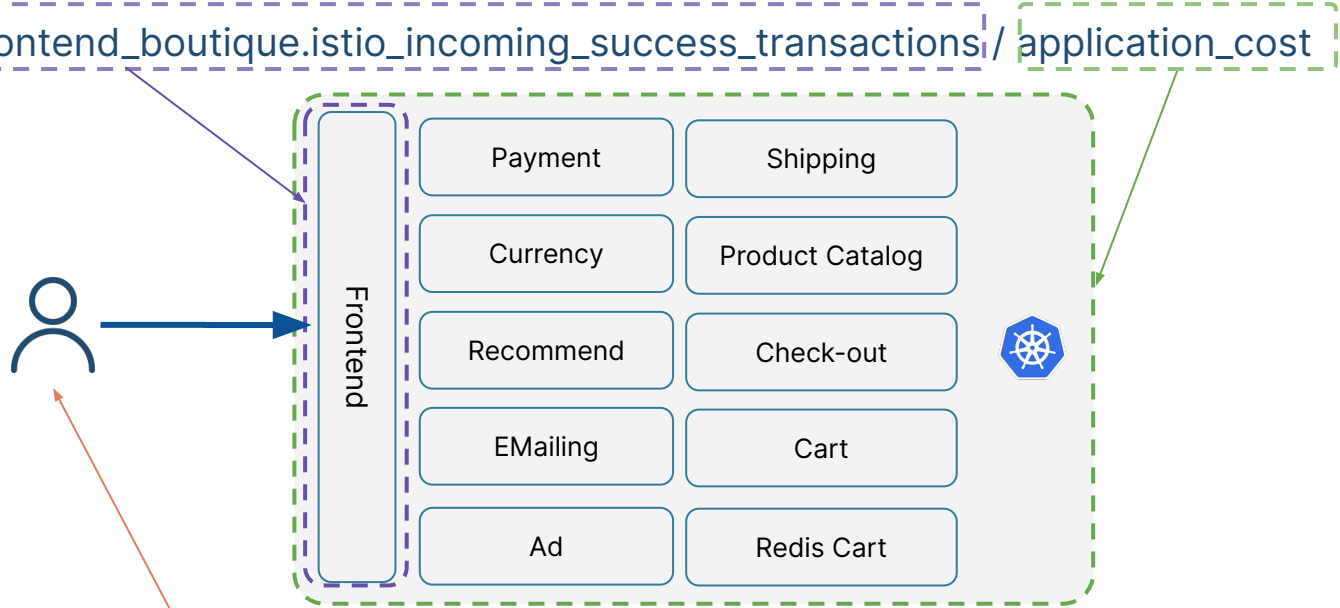
# The reference architecture



# The optimization goals & constraints

GOAL:

**MAXIMIZE**  $\text{frontend\_boutique.istio\_incoming\_success\_transactions}$  /  $\text{application\_cost}$

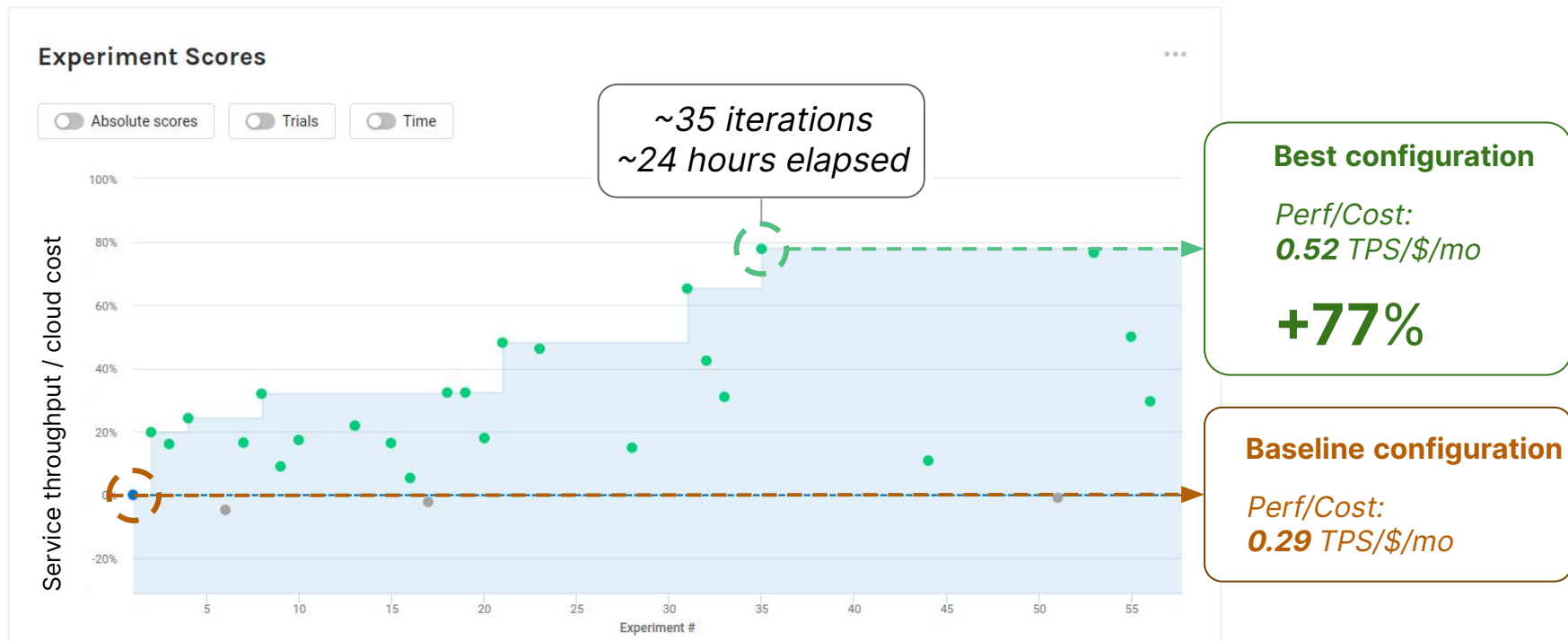


**CONSTRAINTS:**

$\text{loadgenerator\_locust.locust\_fail\_ratio} \leq 2\%$  **AND**  
 $\text{frontend\_boutique.istio\_incoming\_response\_time\_90pct} \leq 500\text{ms}$



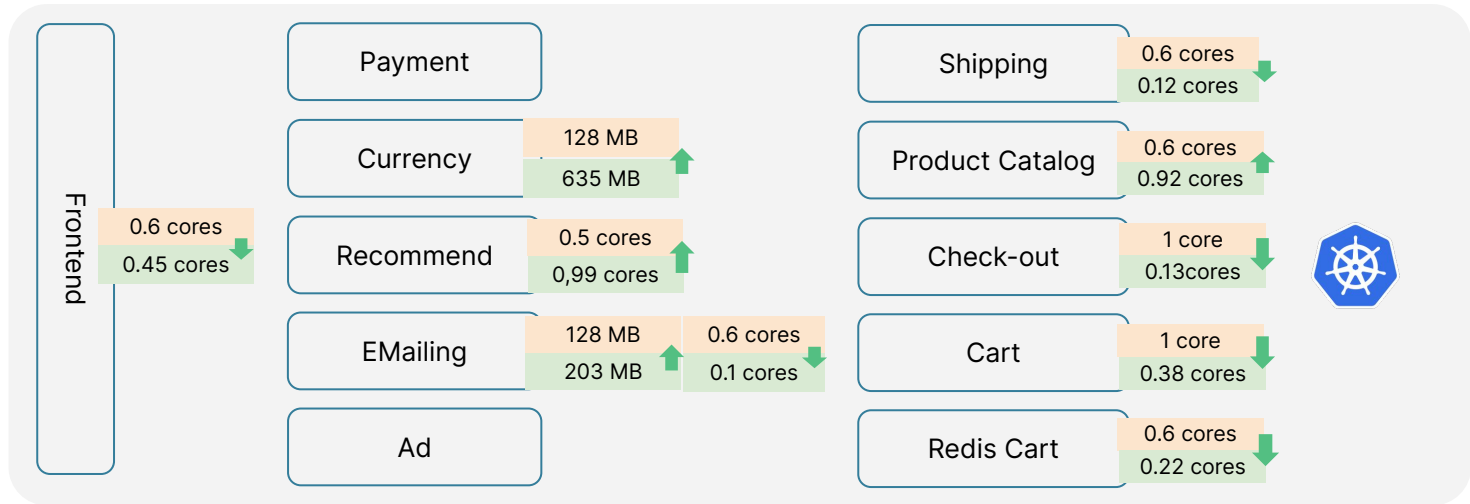
# Best configuration found by ML in 24H improves cost efficiency by 77%



# Best config: optimal resources assigned to microservices

10  
TOP IMPACT  
PARAMETERS

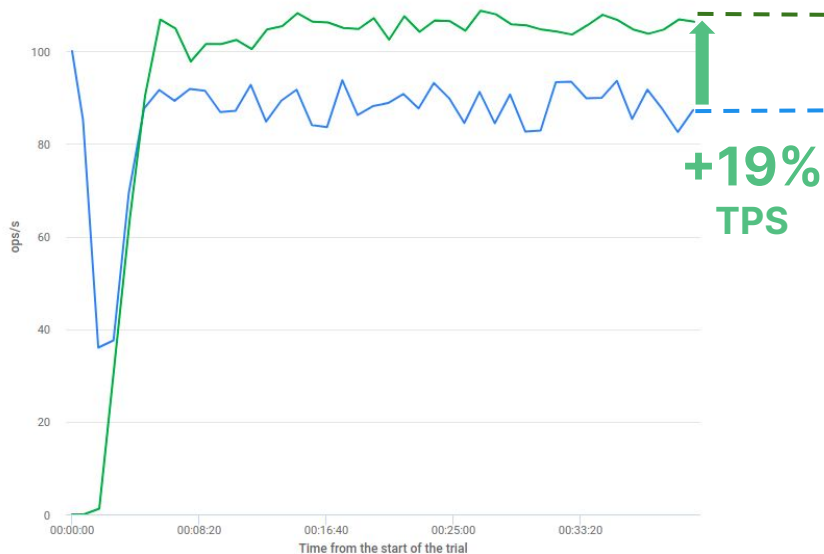
Baseline
Best



- decreased CPU limits set for almost all containers
- increased CPU assigned to 2 microservices
- all these changes to achieve max cost efficiency and match SLOs

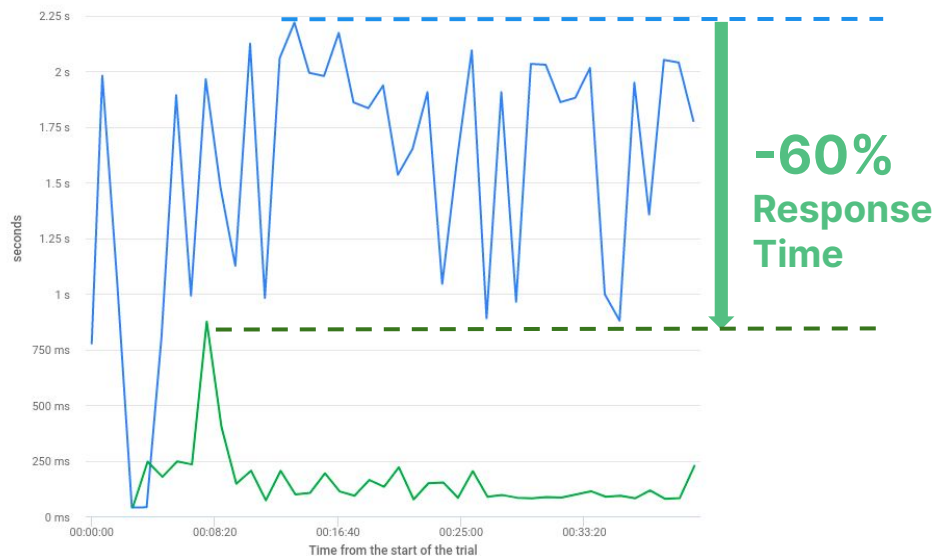
# Best config: higher performance & efficiency for the overall service

## Baseline vs Best: Service throughput



— Baseline, Trial 1, frontend\_boutique.istio\_incoming\_success\_transactions  
— Exp 31, Trial 1, frontend\_boutique.istio\_incoming\_success\_transactions

## Baseline vs Best: Service p90 response time



— Baseline, Trial 1, frontend\_boutique.istio\_incoming\_response\_time\_90\_ms  
— Exp 31, Trial 1, frontend\_boutique.istio\_incoming\_response\_time\_90\_ms

# Use Case: maximizing service performance & efficiency with JVM tuning

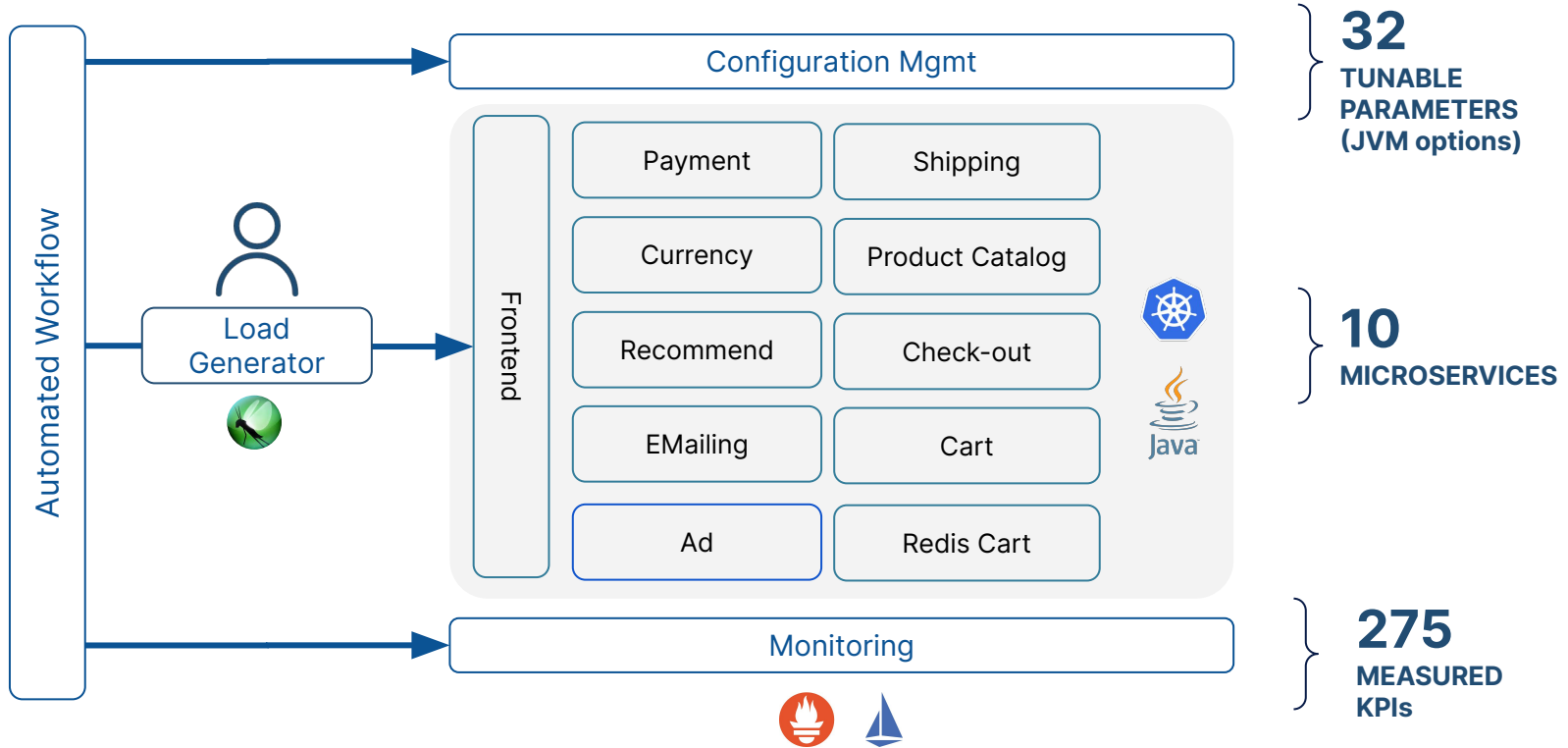
## Challenge for SRE

How to ensure a reliable product launch, by properly configuring JVM options, so that you can trust the overall service



- will sustain the expected **target load**
- while matching the defined **Service-Level Objectives** (SLO)
- at the **minimum cost**
- while minimizing the operational effort
- and staying aligned product launch milestones

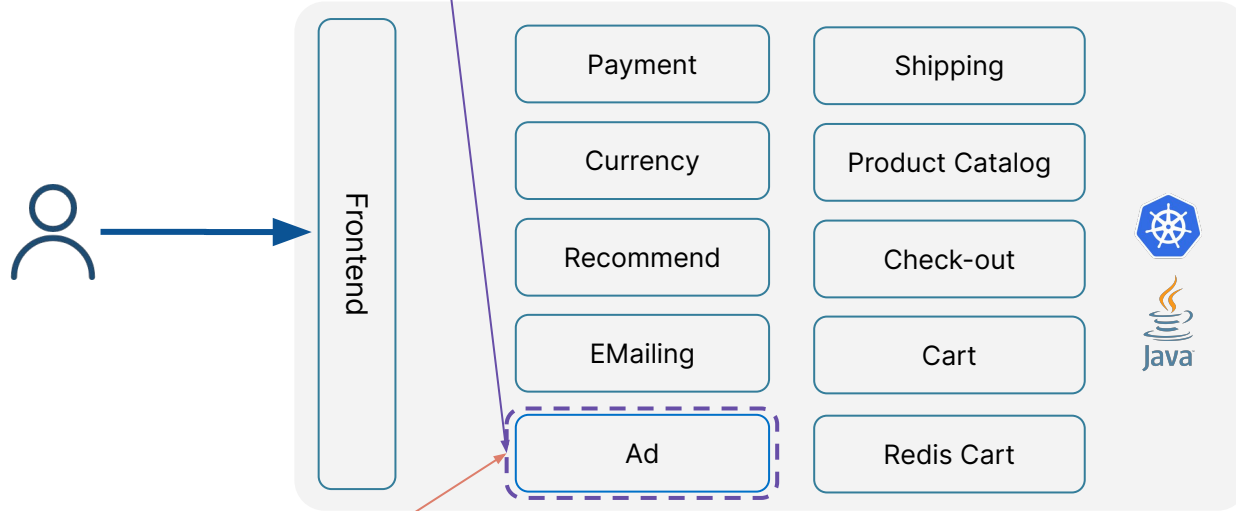
# The reference architecture



# The optimization goals & constraints

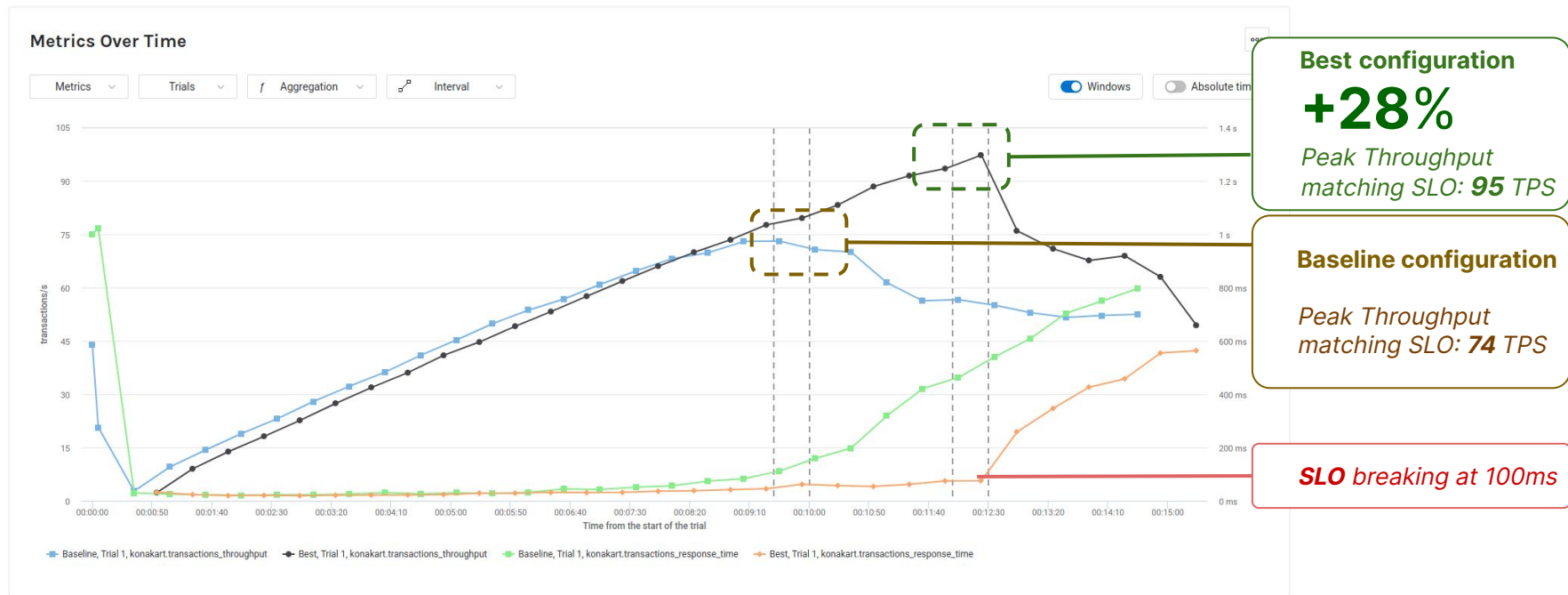
GOAL:

MAXIMIZE `ad.istio_incoming_success_transactions`



CONSTRAINTS: `ad.transaction_response_time <= 100ms`

















# Best config: +28% throughput, and meeting SLOs



# Best config: optimal JVM options

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### TOP IMPACT PARAMETERS

Parameter	Relevance	Best	Baseline
 jvm jvm_newSize		550 MB (+83.3%)	300 MB
 jvm jvm_GCTimeRatio		100 (+1%)	99
 jvm jvm_concurrentGCThreads		1 threads (-87.5%)	8 threads
 jvm jvm_gcType		Parallel	G1
 jvm jvm_maxHeapSize		901 MB (+252%)	256 MB
 jvm jvm_maxTenuringThreshold		6 (-60%)	15
 jvm jvm_parallelGCThreads		3 threads (-62.5%)	8 threads
 jvm jvm_survivorRatio		100 (+1,150%)	8

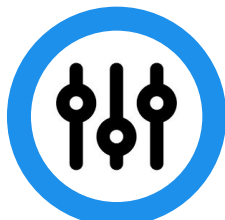
- increased max heap memory
- changed Garbage Collector type
- decreased number of Garbage Collector threads
- adjusted heap regions & object aging thresholds



# Conclusions



# Key takeaways



**Tuning modern applications** for increasing their efficiency, performance and reliability is a **complex problem** that represent a **relevant toil** for SRE teams



A new approach leveraging fully-automated **ML-based optimization** enables SRE teams to ensure applications will have **higher performance & reliability**



Leveraging this new **ML-based optimization** approach, SRE teams can **reduce the operational toil** and **stay aligned to release milestones**

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# BACKUP SLIDES

