Swayam

Distributed Autoscaling for Machine Learning as a Service

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Microsoft Research

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Google

Machine Learning as a Service (MLaaS)

Microsoft Azure Machine Learning

powered by aws Amazon Machine Learning

IBM® Data Science & Machine Learning

Google Cloud AI

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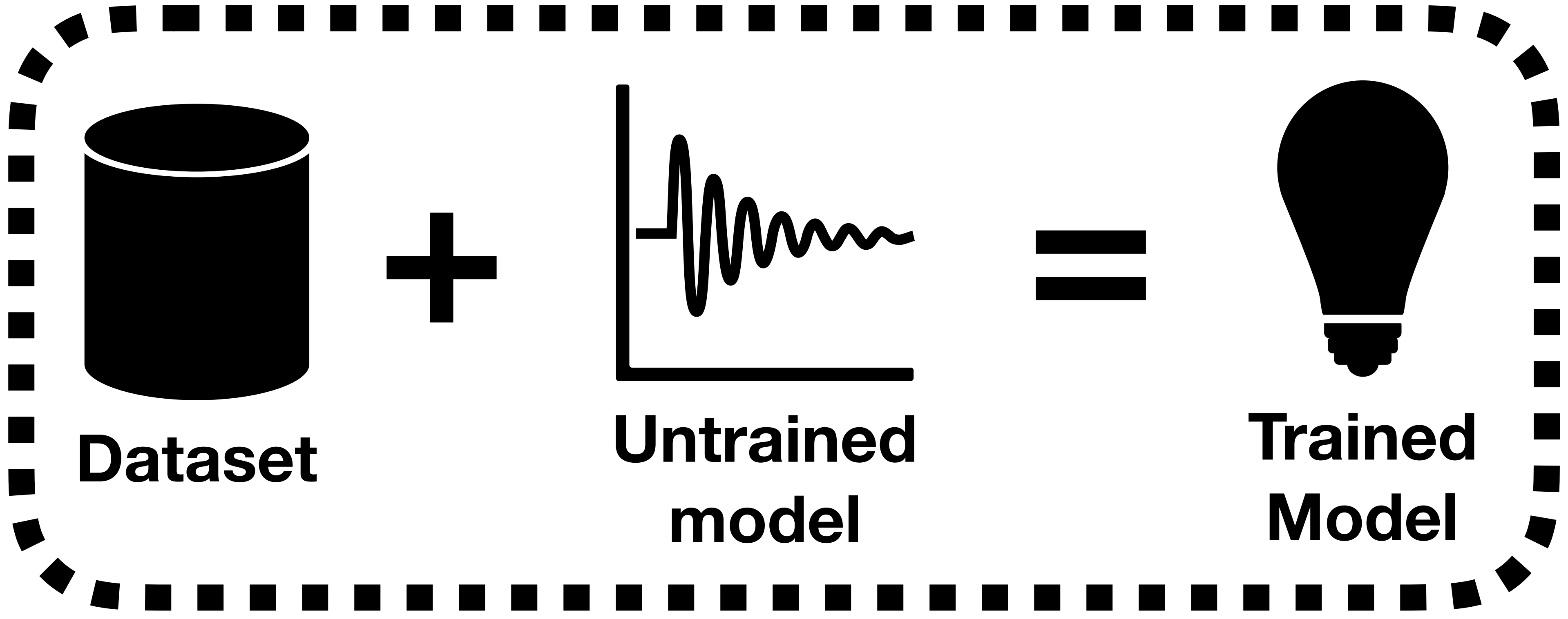
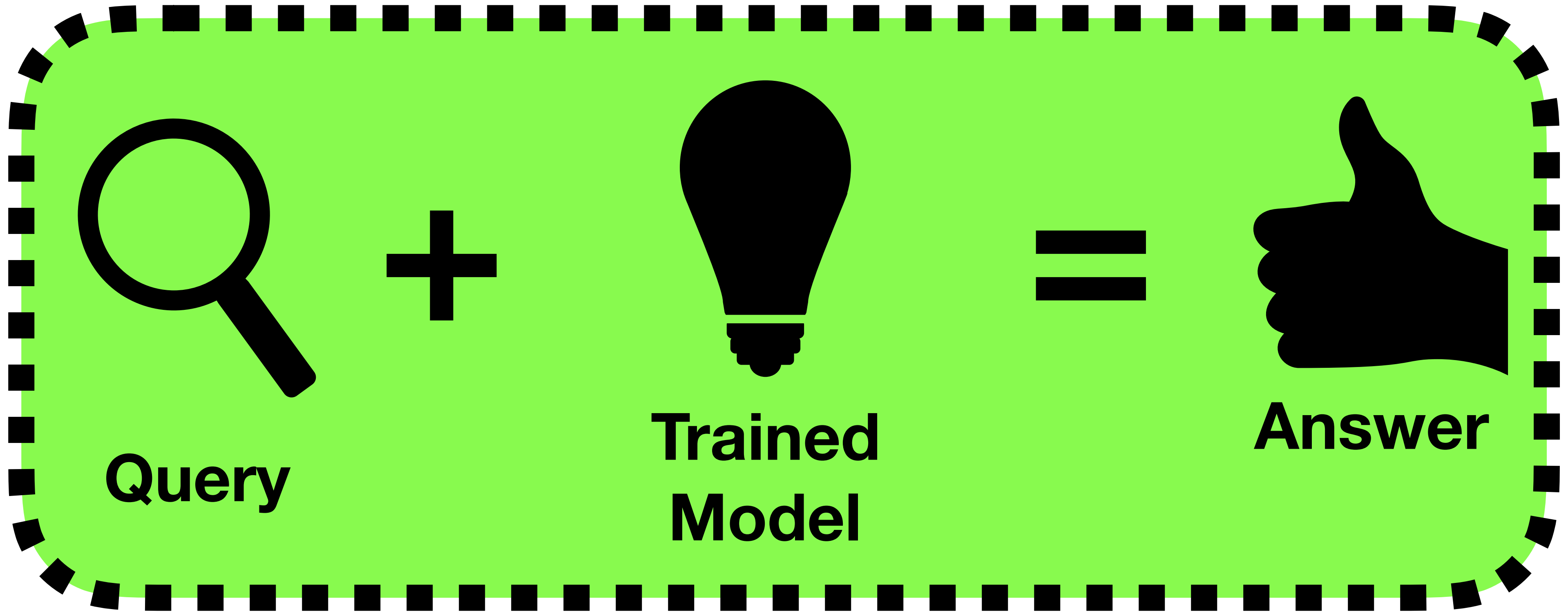
1. Training



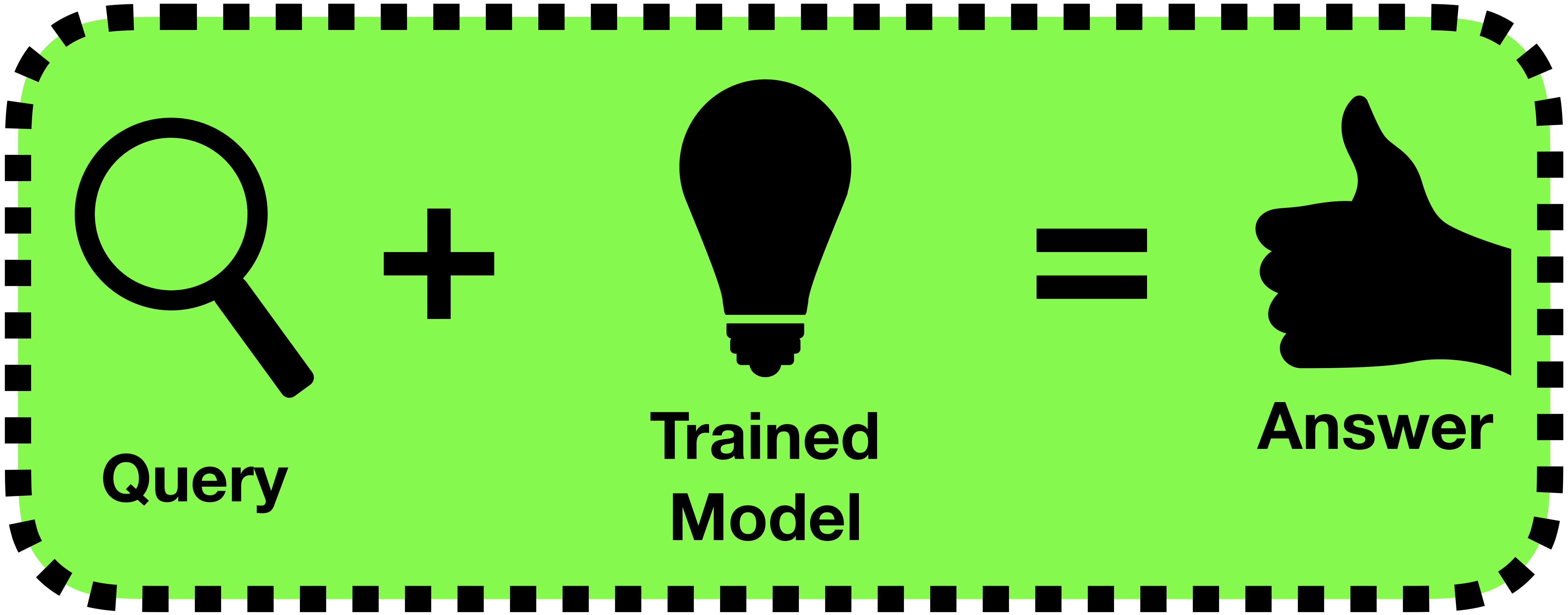
2. Prediction



Machine Learning as a Service (MLaaS)

This work

2. Prediction



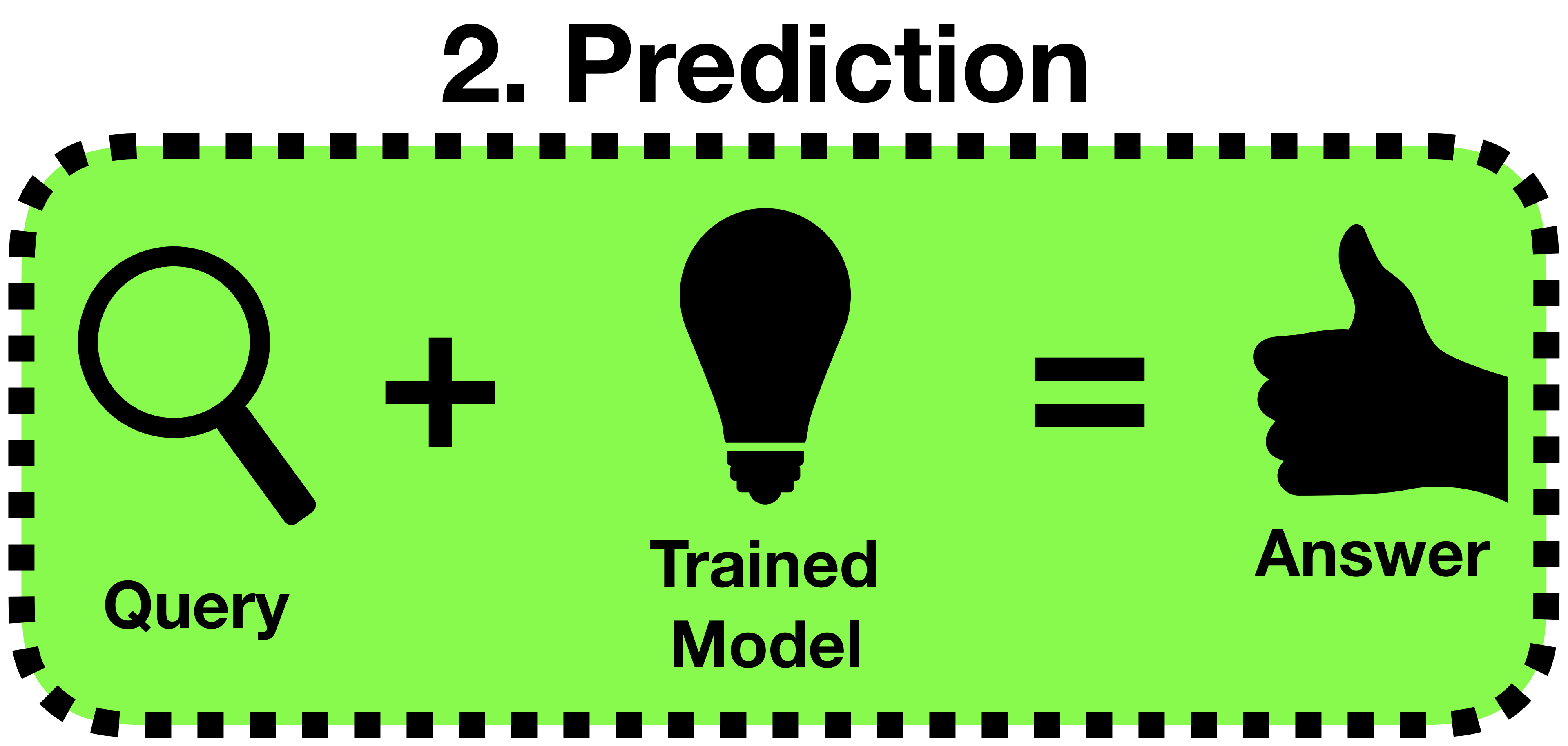
*Models are **already trained** and available for prediction*

Swayam

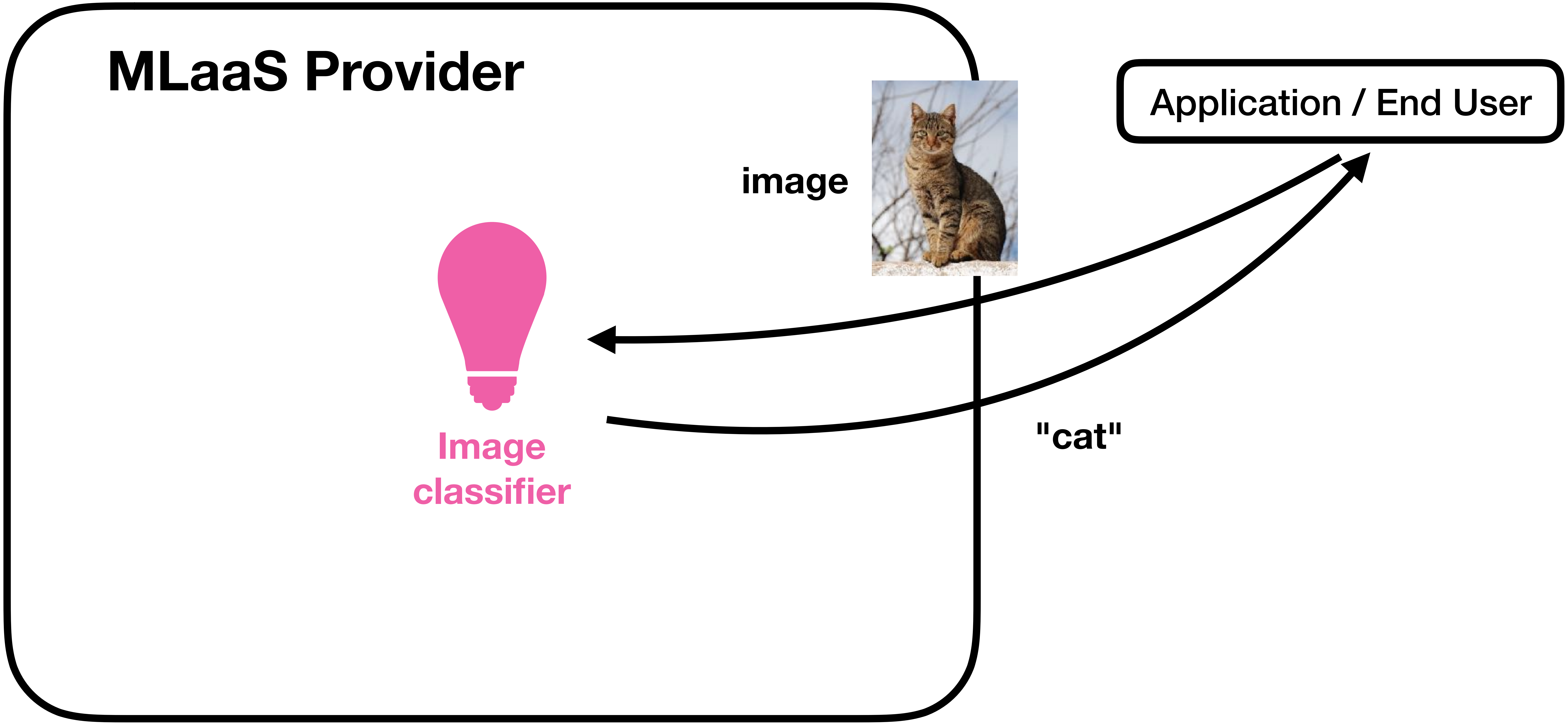
Distributed autoscaling

of the compute resources
needed for **prediction serving**

inside the MLaaS infrastructure



Prediction serving (application perspective)

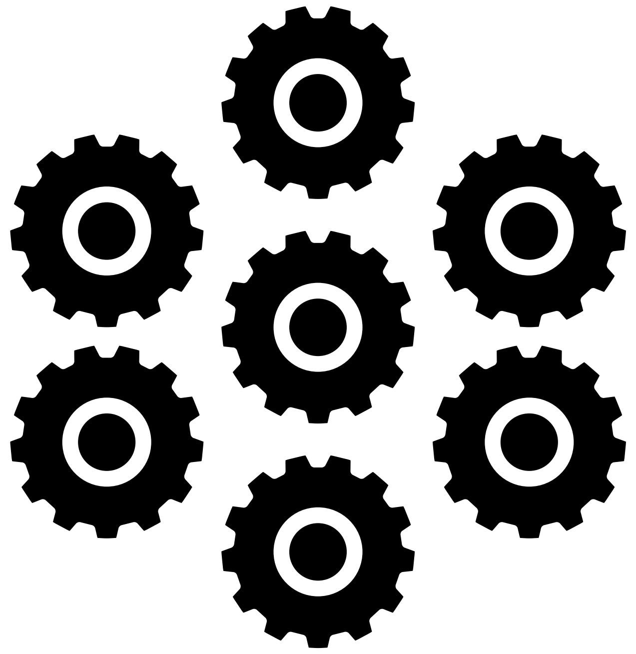


Prediction serving (provider perspective)

MLaaS Provider

Lots of trained models!

Finite compute resources
"Backends" for prediction



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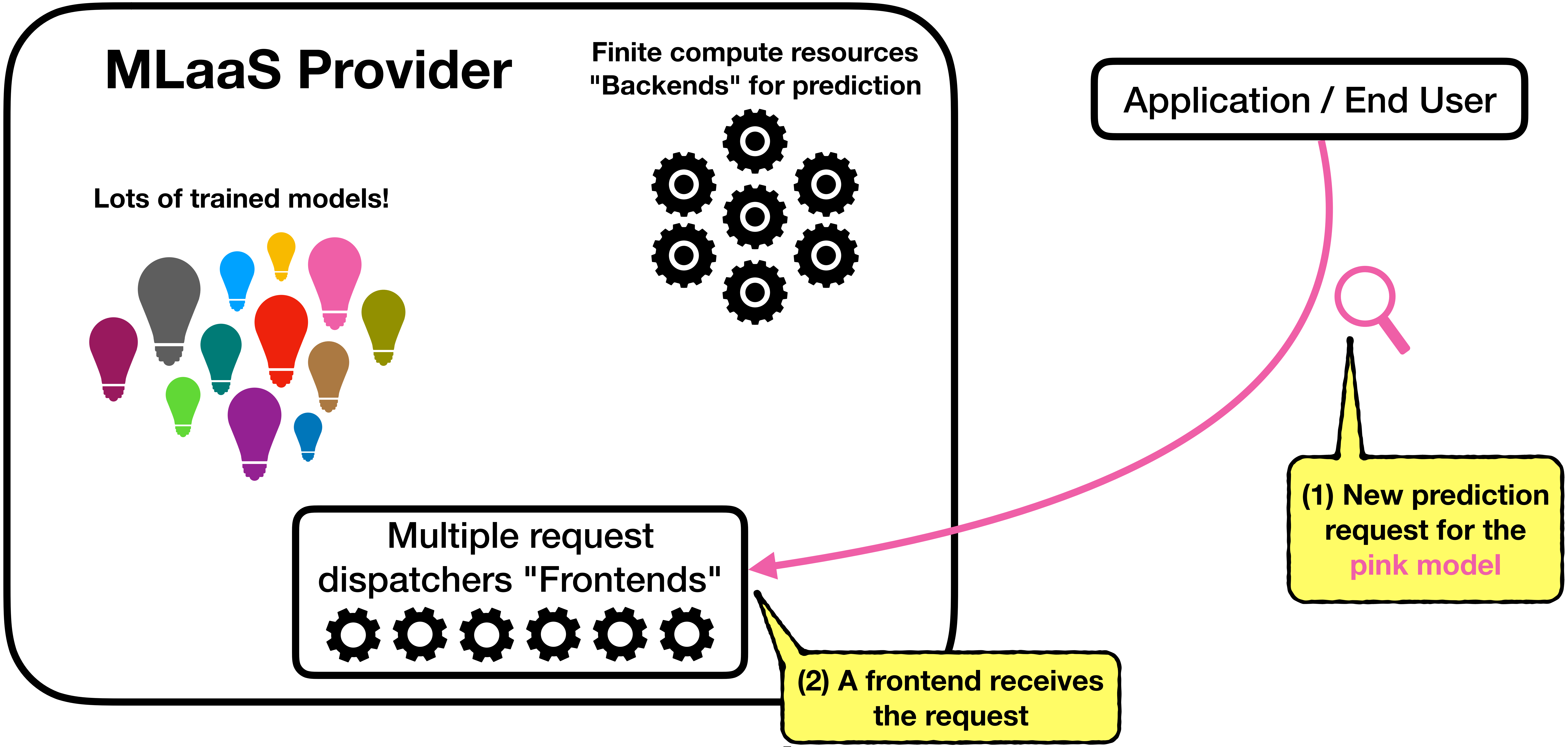

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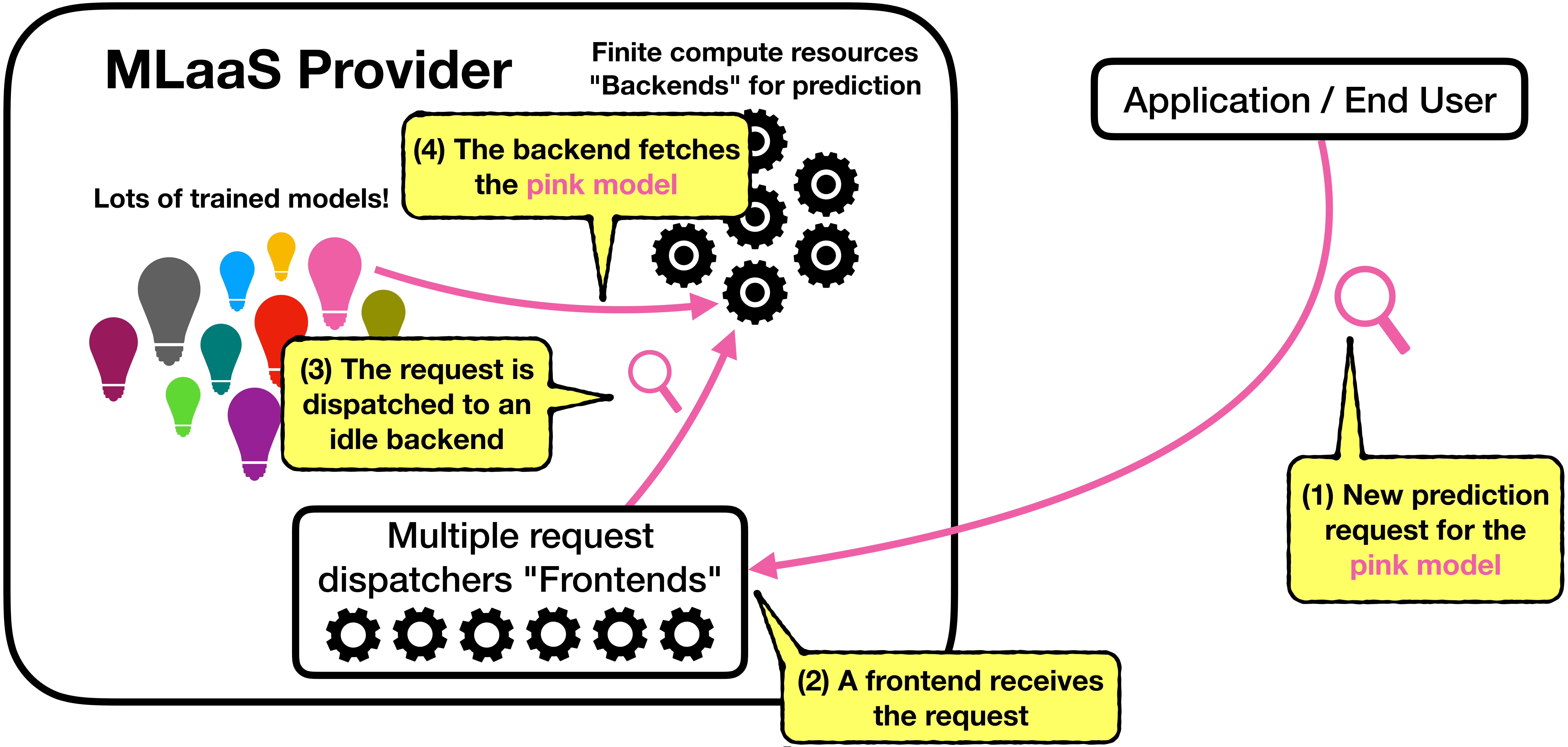

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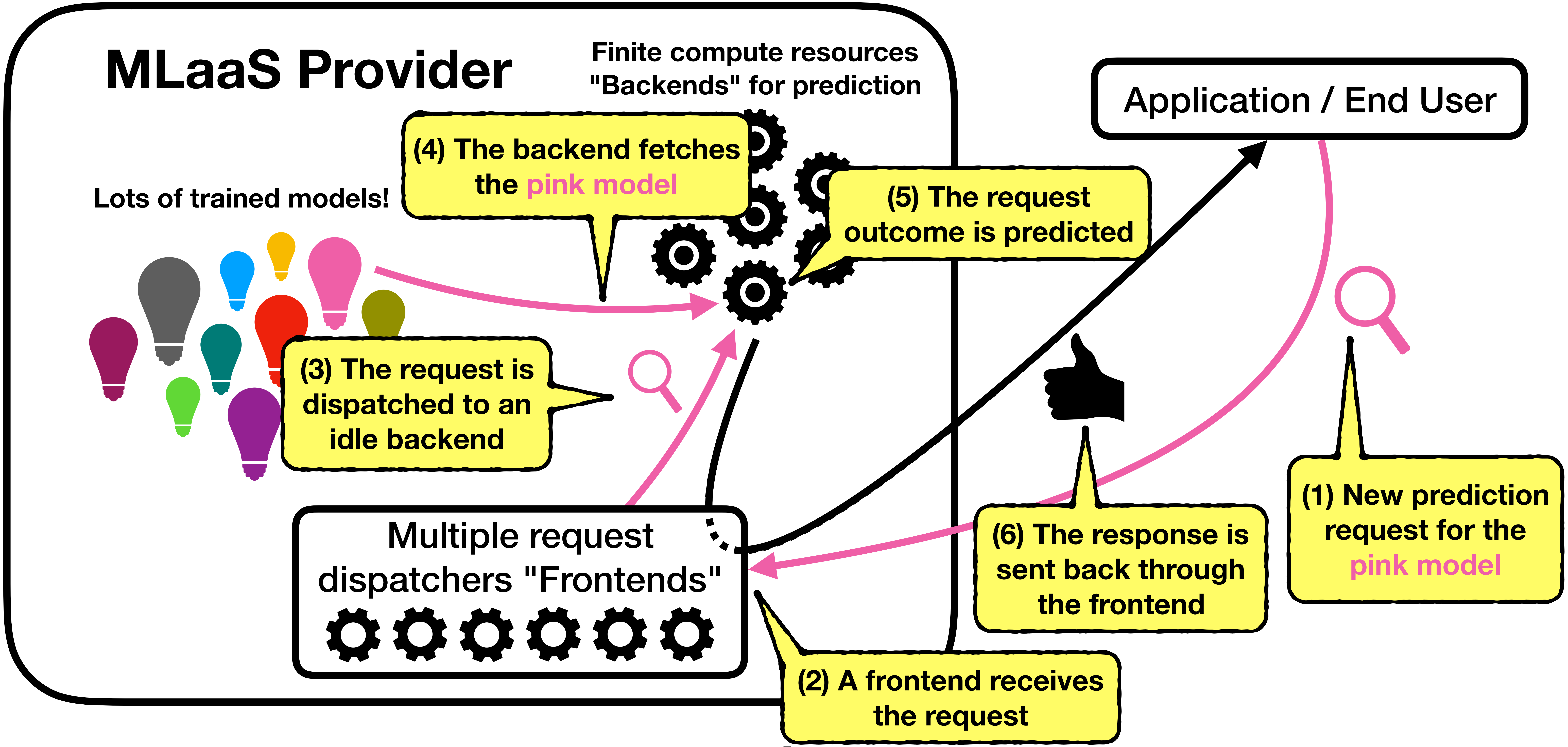
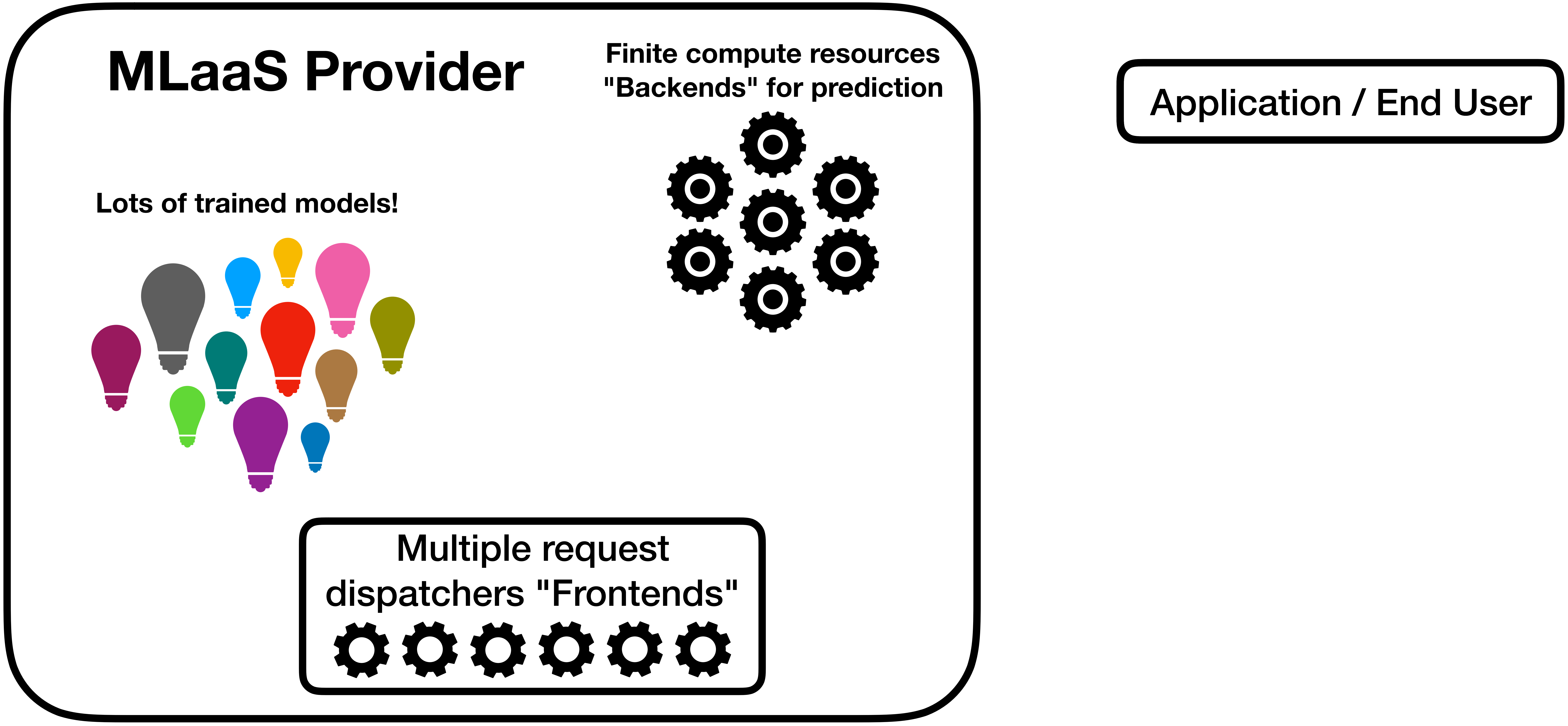


Prediction serving (objectives)



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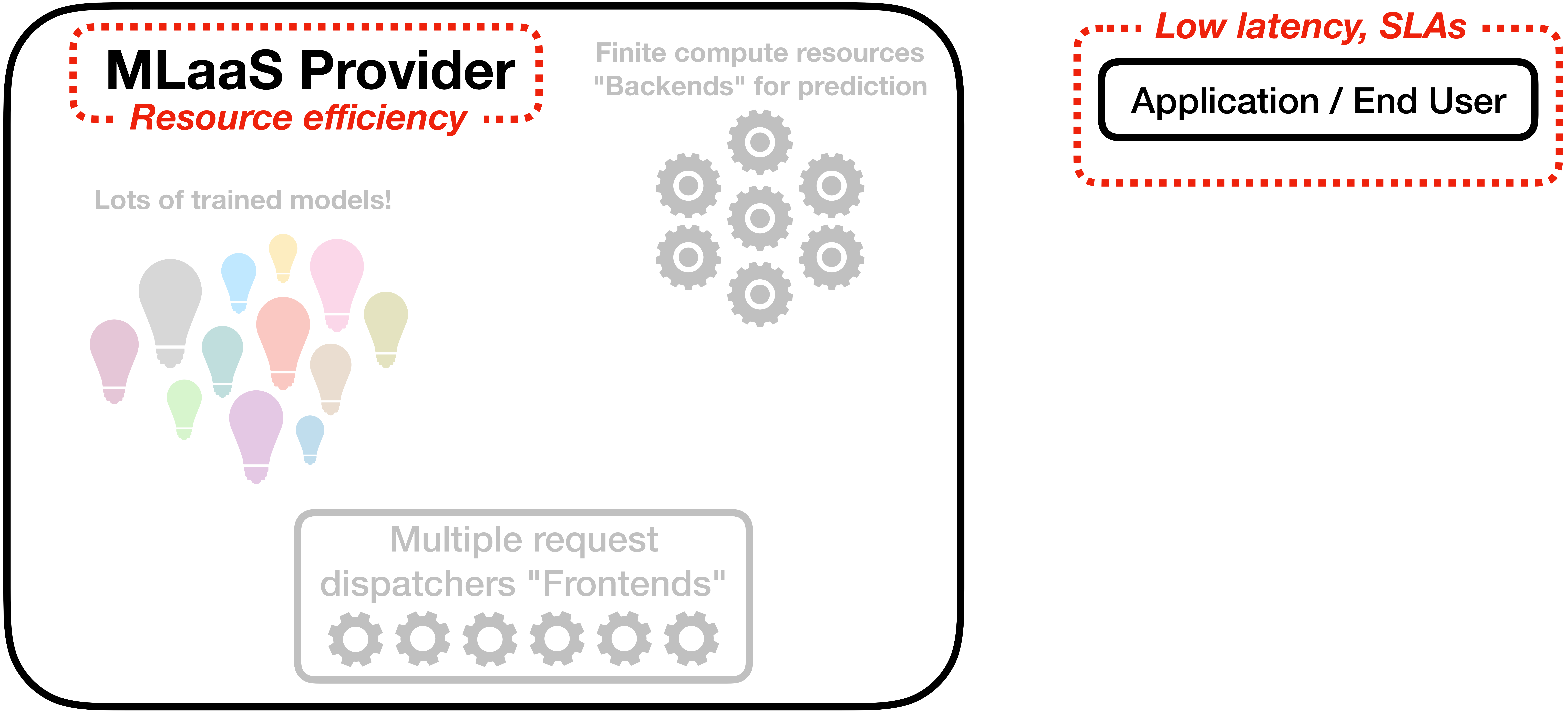

Static partitioning of trained models

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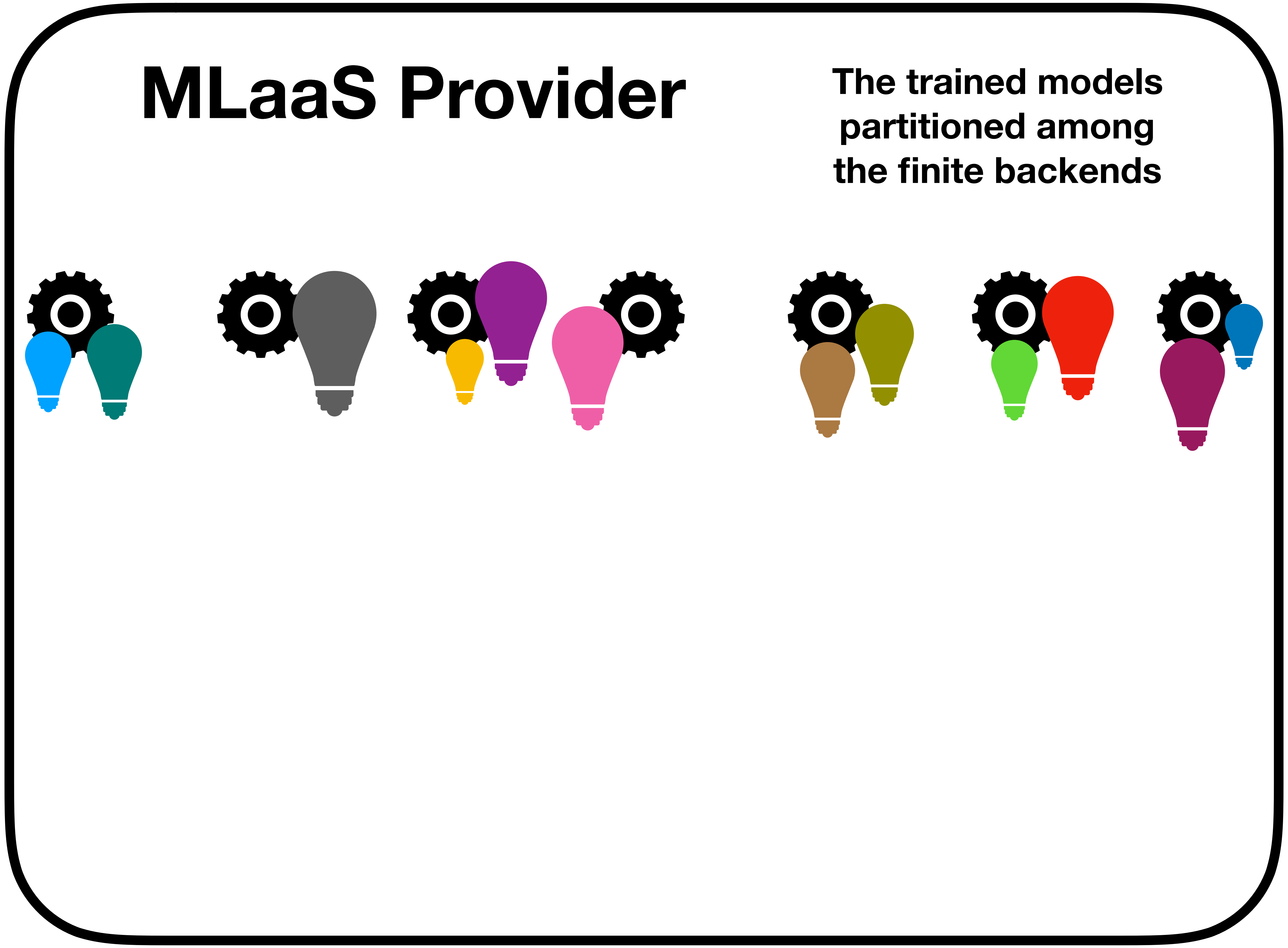

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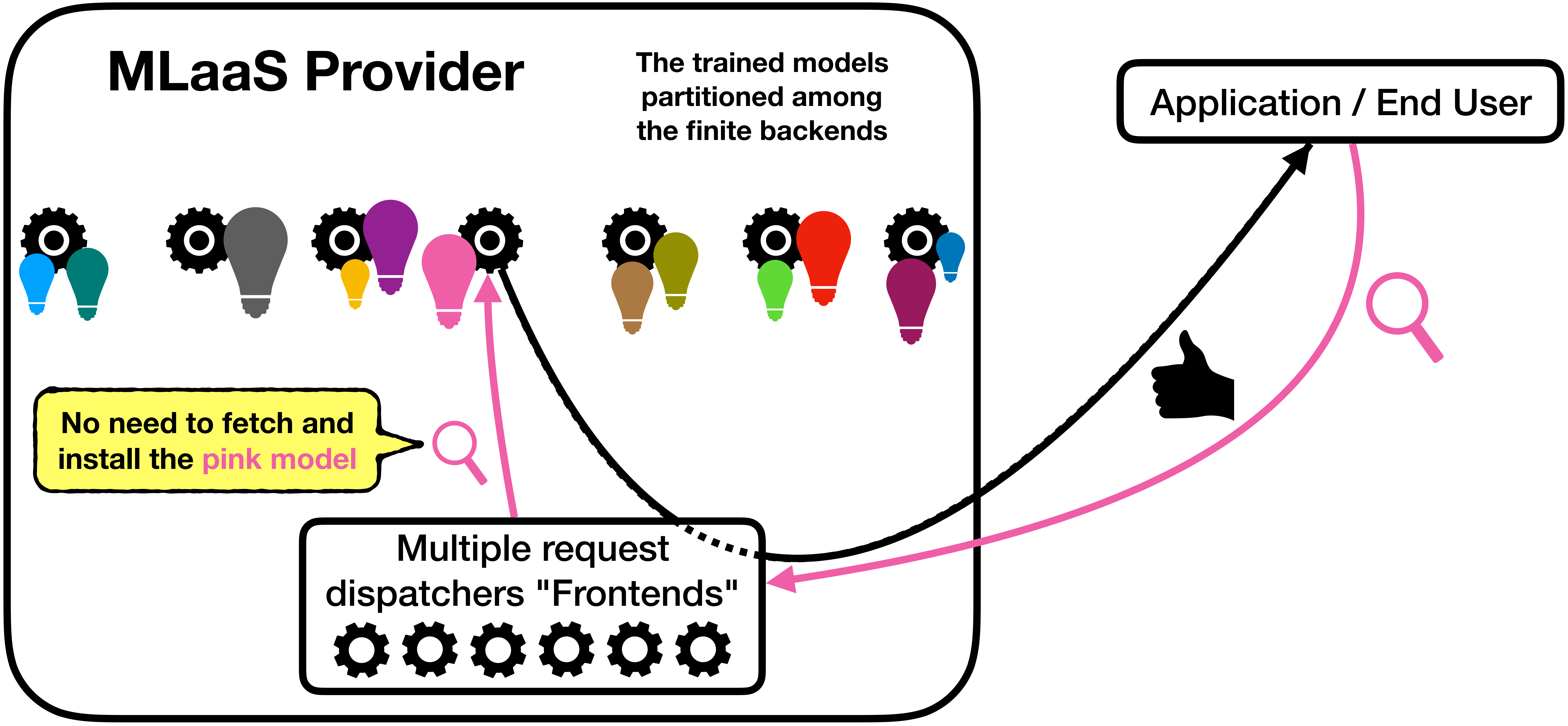

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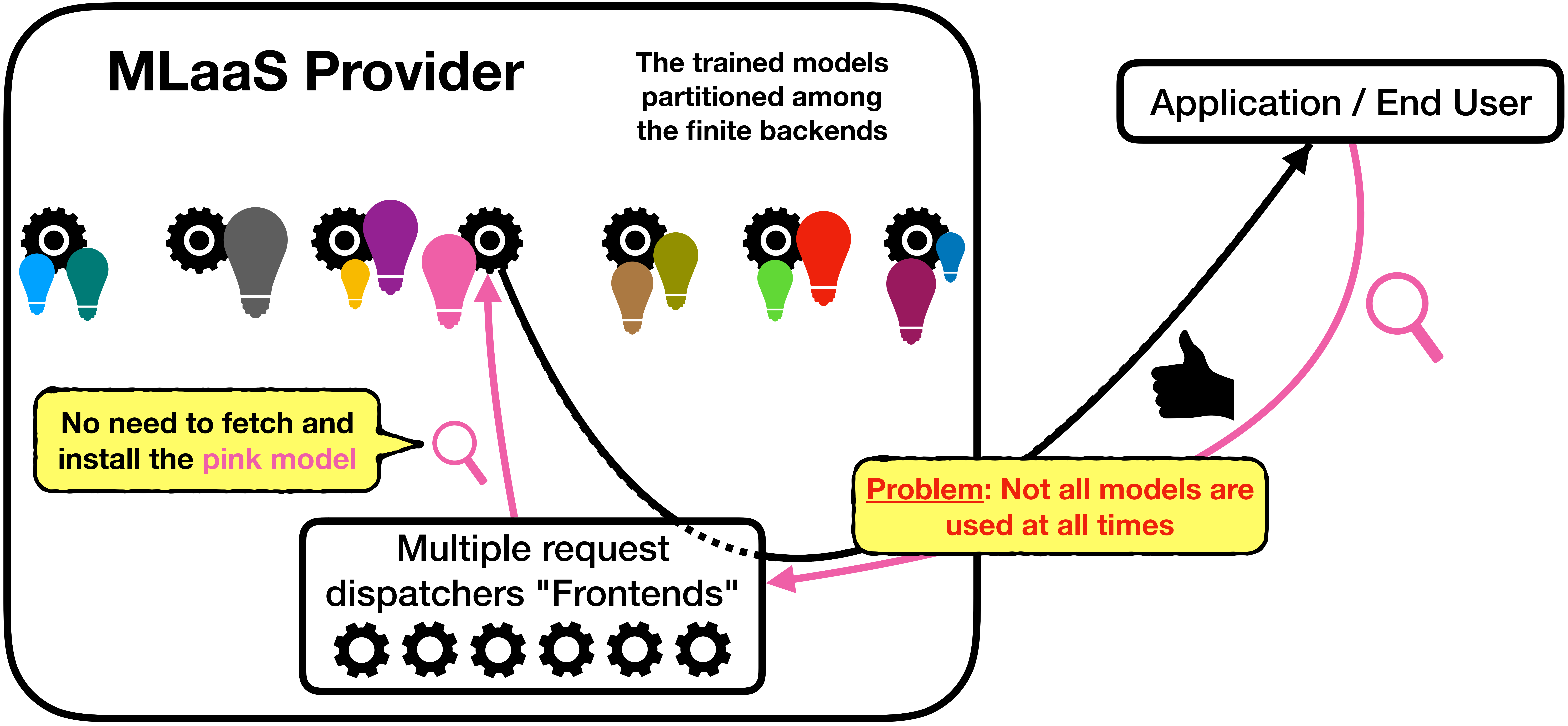

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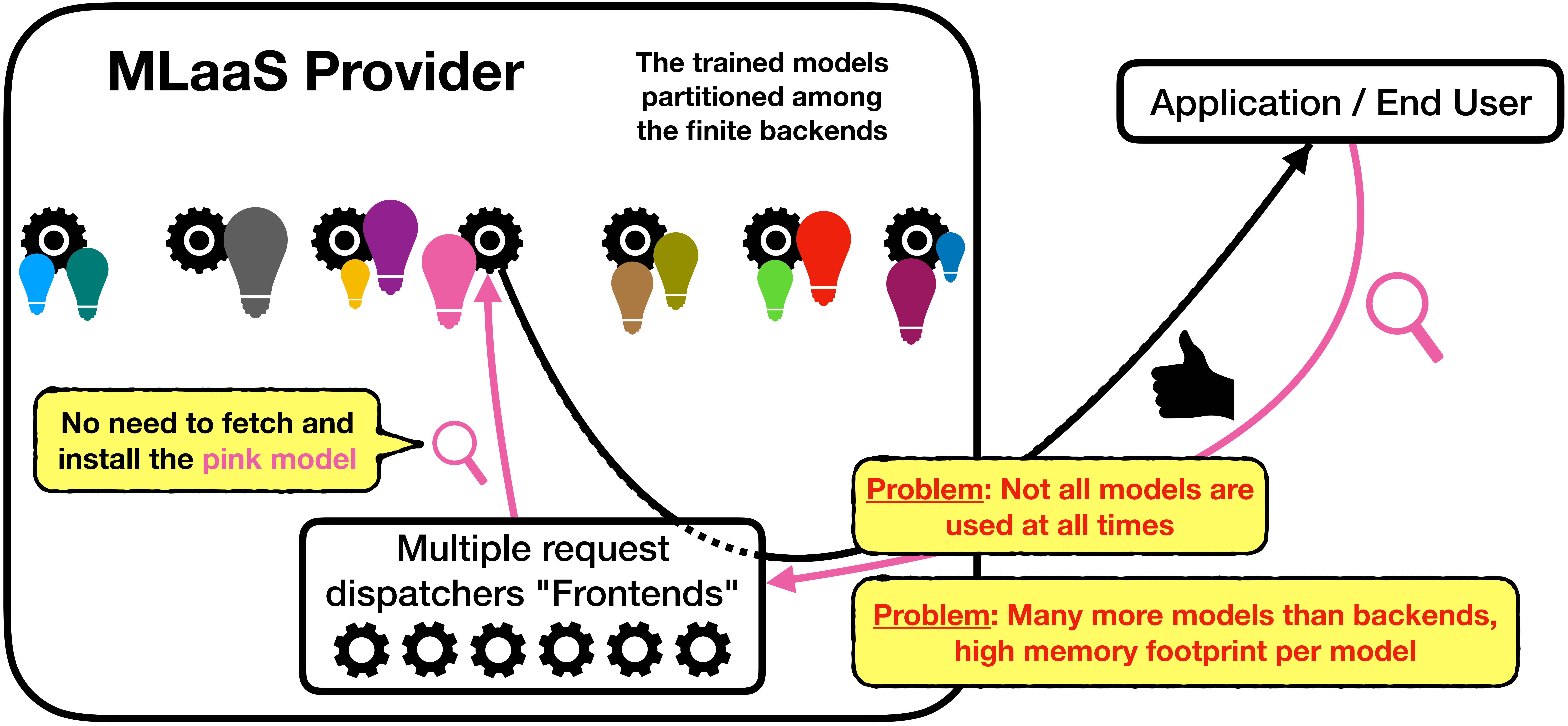

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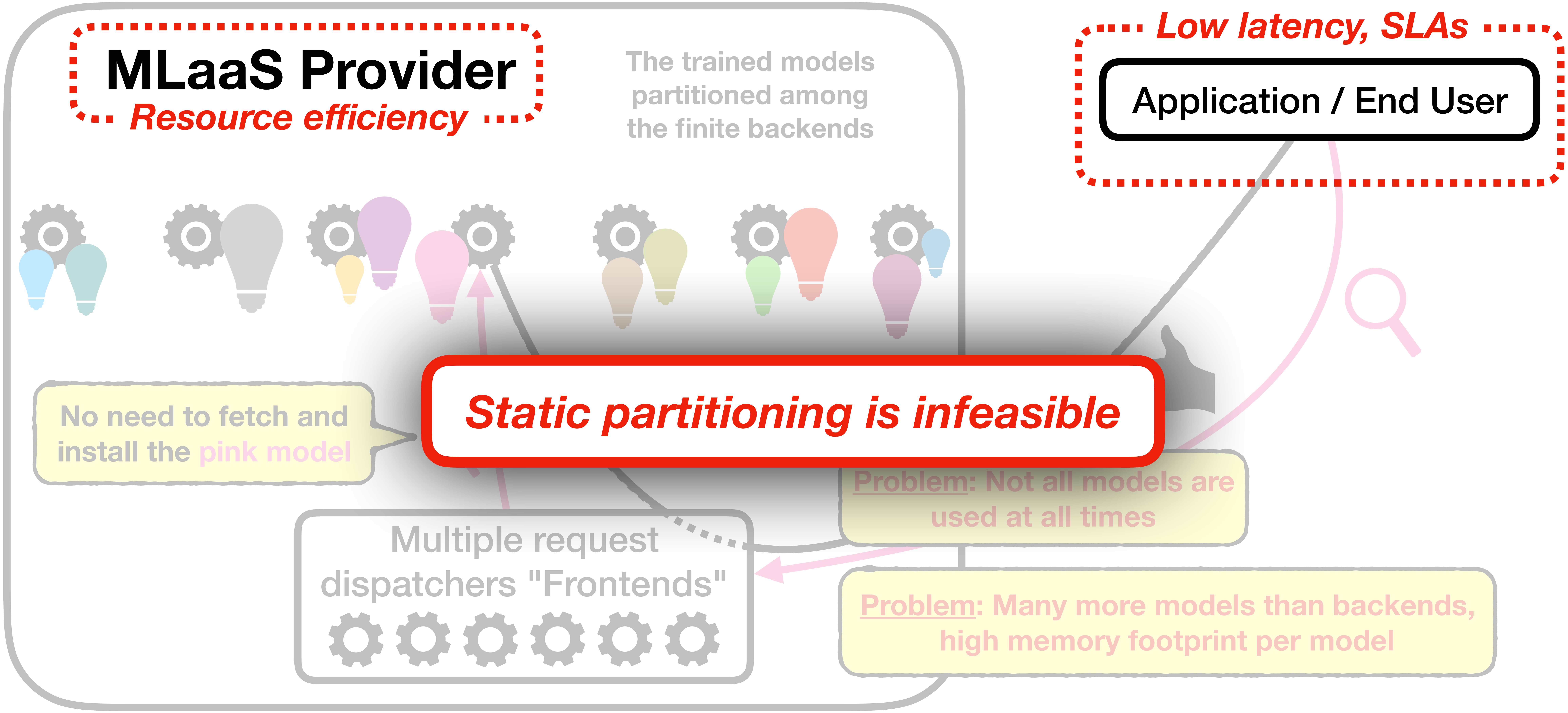
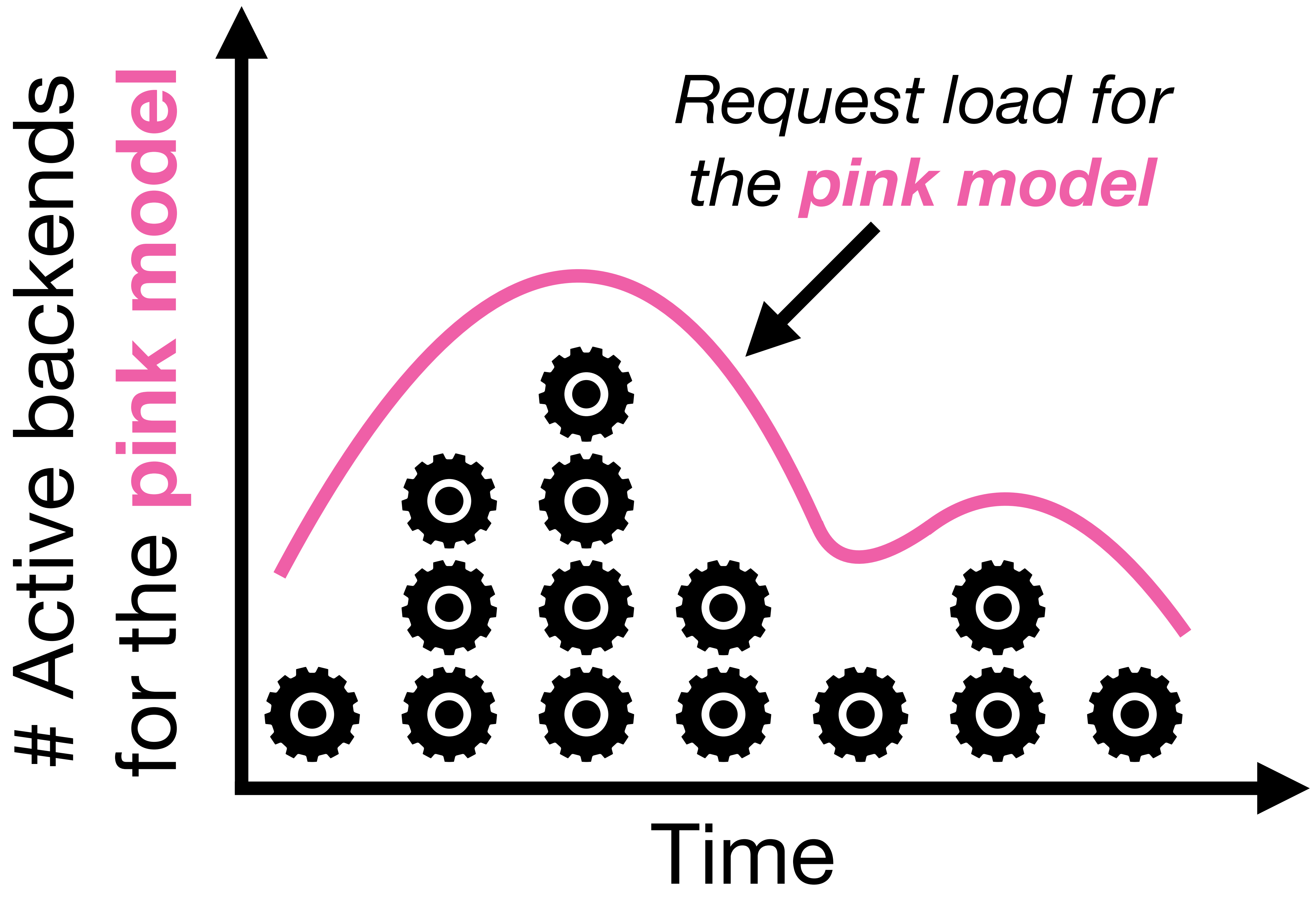


Classical approach: autoscaling



The number of active backends are automatically scaled up or down based on load

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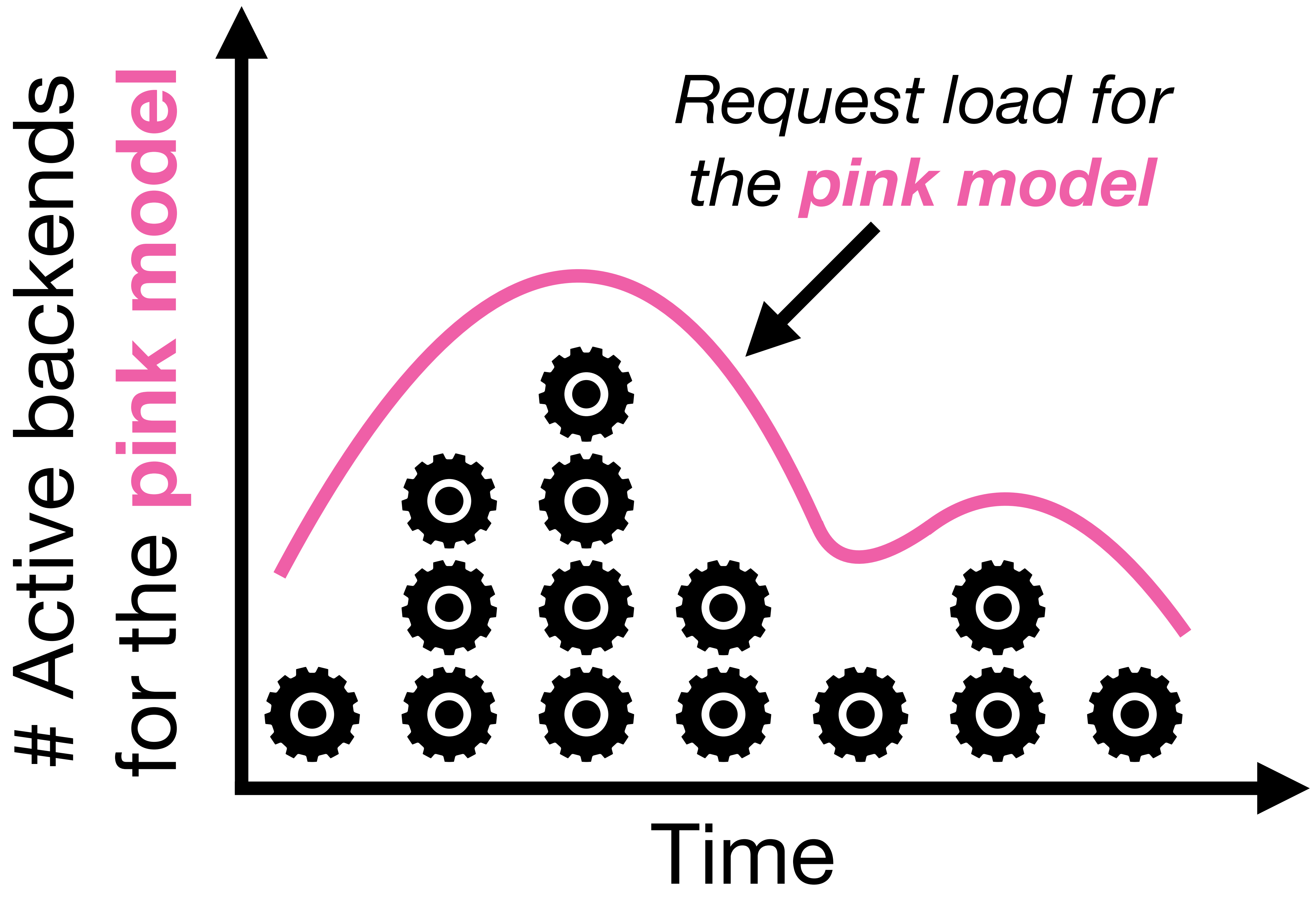

The number of active backends are automatically scaled up or down based on load

With **ideal autoscaling ...**

- ✔ Enough backends to guarantee **low latency**
- ✔ # Active backends over time is **minimized for resource efficiency**

Autoscaling for MLaaS is challenging [1/3]

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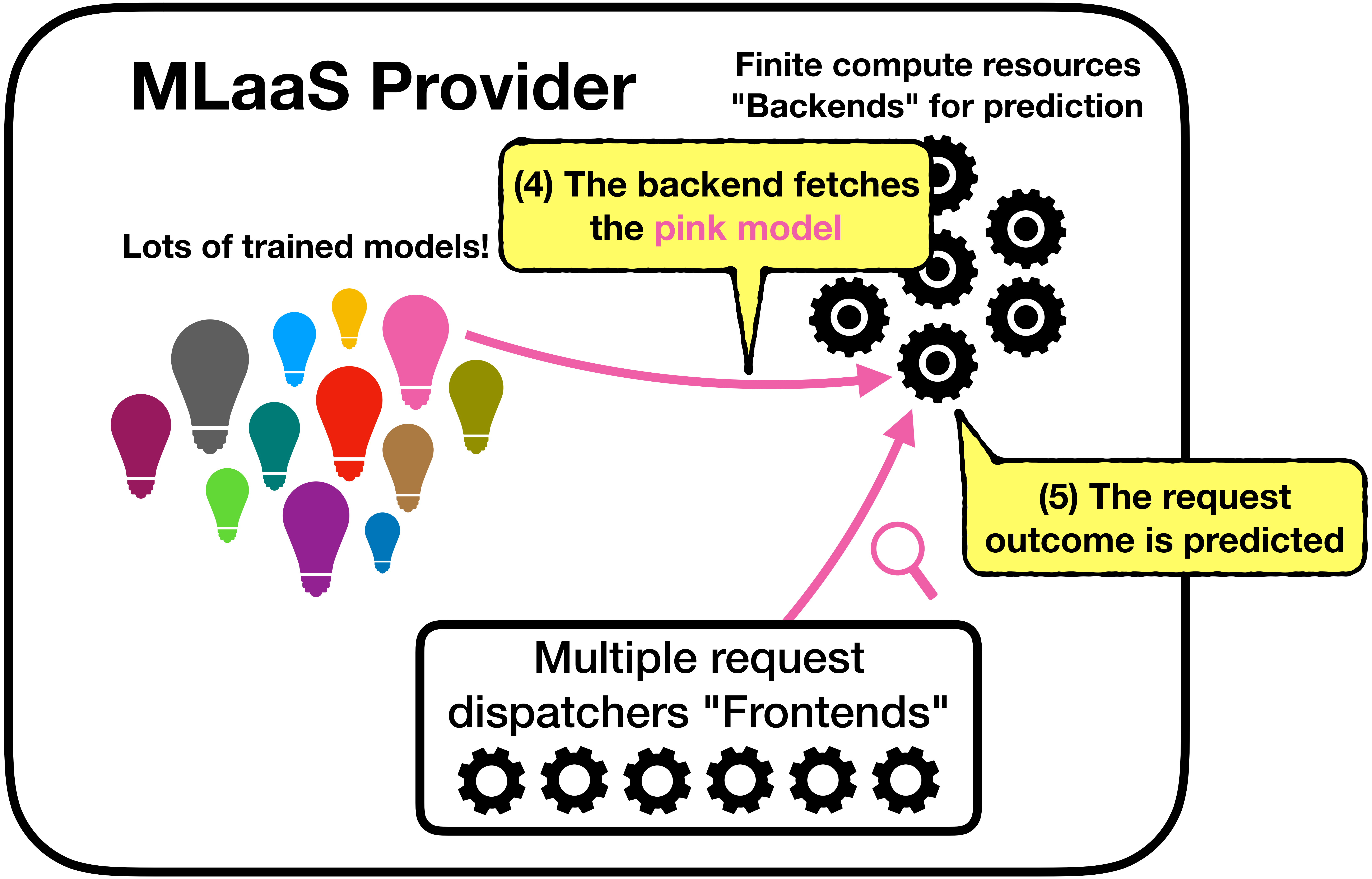

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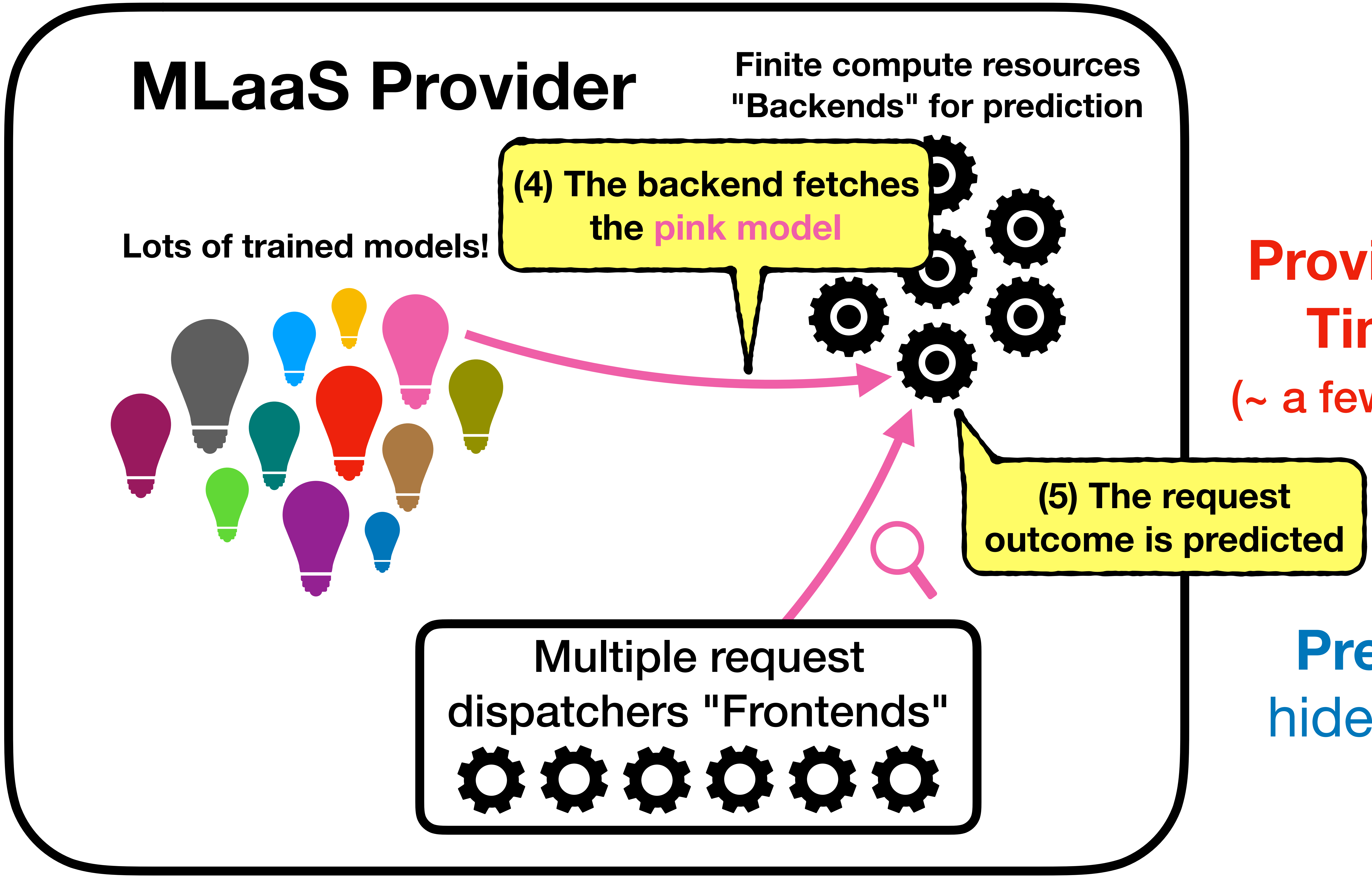


Challenge

Provisioning Time (4) >> Execution Time (5)

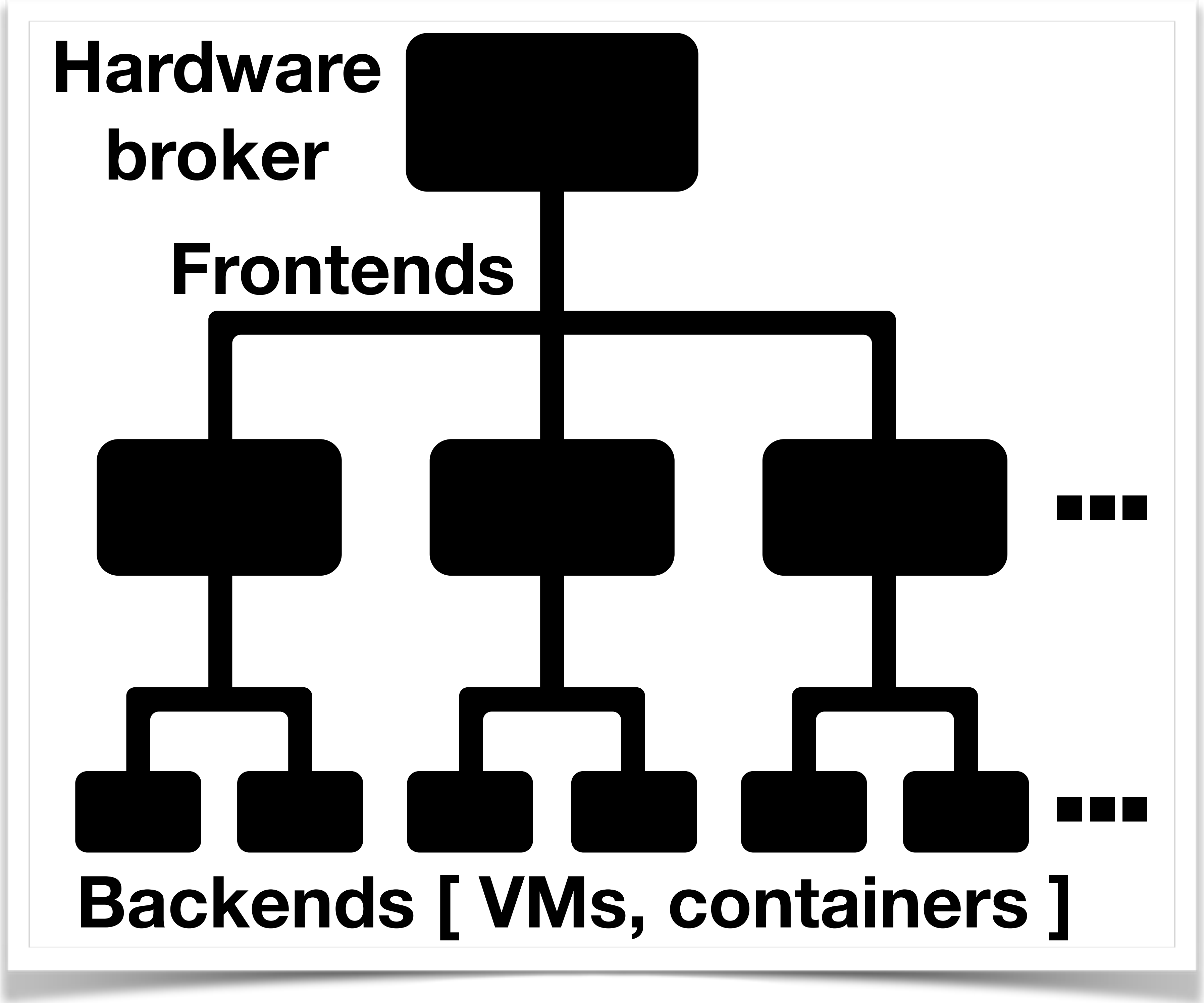
(~ a few seconds) (~ 10ms to 500ms)

Requirement

Predictive autoscaling to hide the provisioning latency

Autoscaling for MLaaS is challenging [2/3]

MLaaS architecture is
large-scale, multi-tiered



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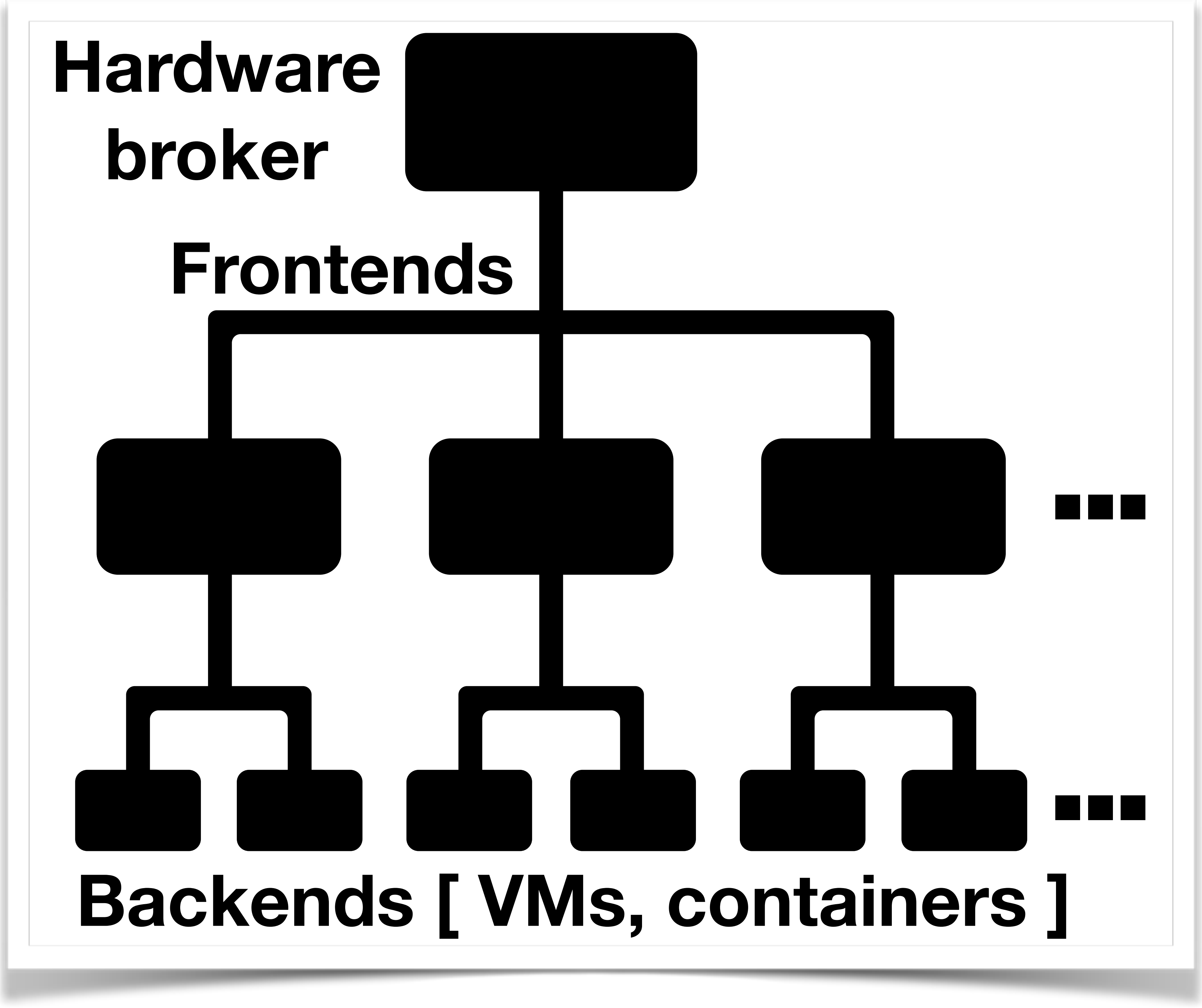

Challenge

Multiple frontends with **partial information** about the workload

Requirement

Fast, coordination-free, globally-consistent autoscaling decisions on the frontends

Autoscaling for MLaaS is challenging [3/3]

Strict, model-specific SLAs
on response times

"99% of requests must complete under 500ms"

"99.9% of requests must complete under 1s"

"[A] 95% of requests must complete under 850ms"

"[B] Tolerate up to 25% increase in request rates without violating [A]"

Autoscaling for MLaaS is challenging [3/3]

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Challenge

No **closed-form solutions** to get response-time distributions for SLA-aware autoscaling

Requirement

Accurate **waiting-time** and **execution-time** distributions

Swayam: model-driven distributed autoscaling

Challenges

Provisioning Time (4) **>>** **Execution Time (5)**

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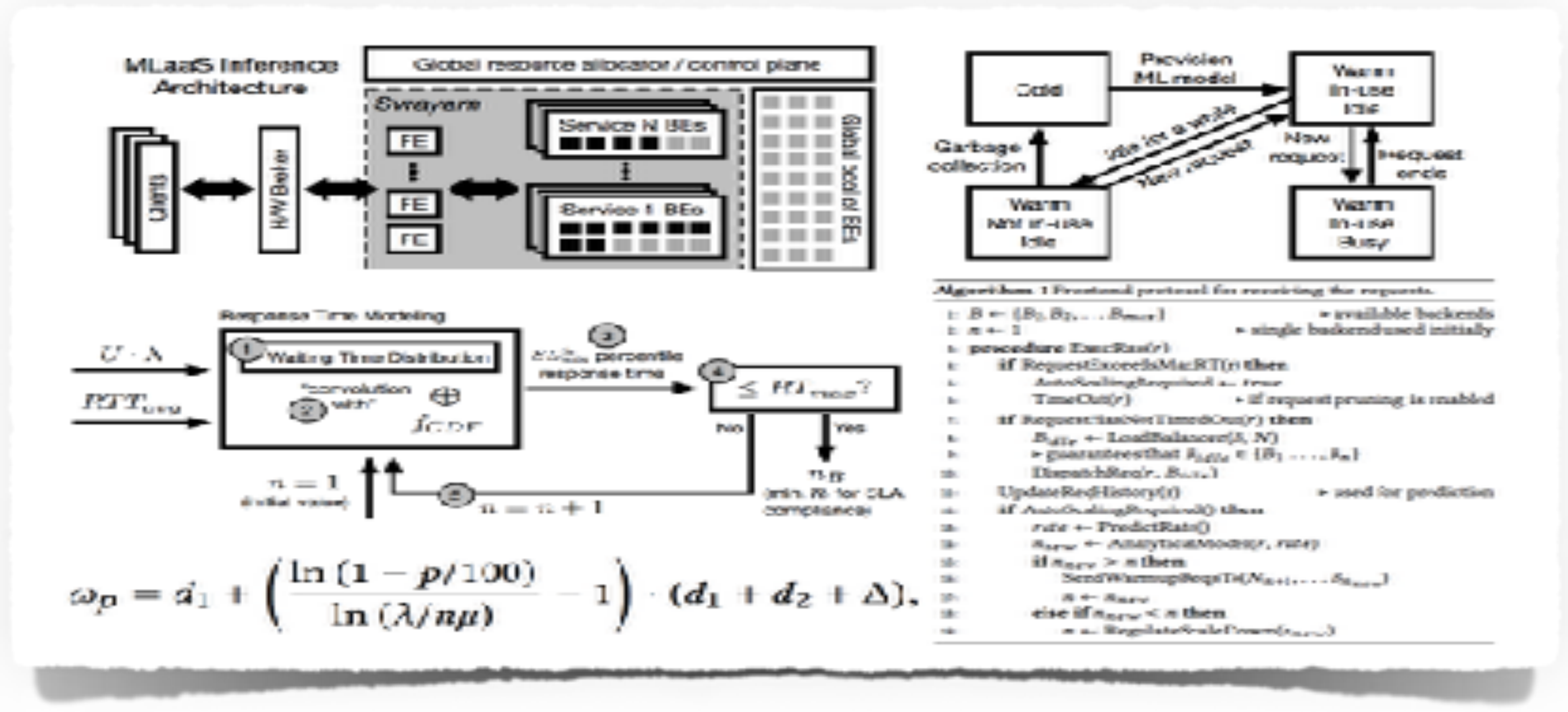

We address these **challenges**

by leveraging specific **ML workload characteristics**

and design an **analytical model** for resource estimation

that allows **distributed** and **predictive** autoscaling

Outline

1. **System architecture, key ideas**
2. Analytical model for resource estimation
3. Evaluation results

System architecture

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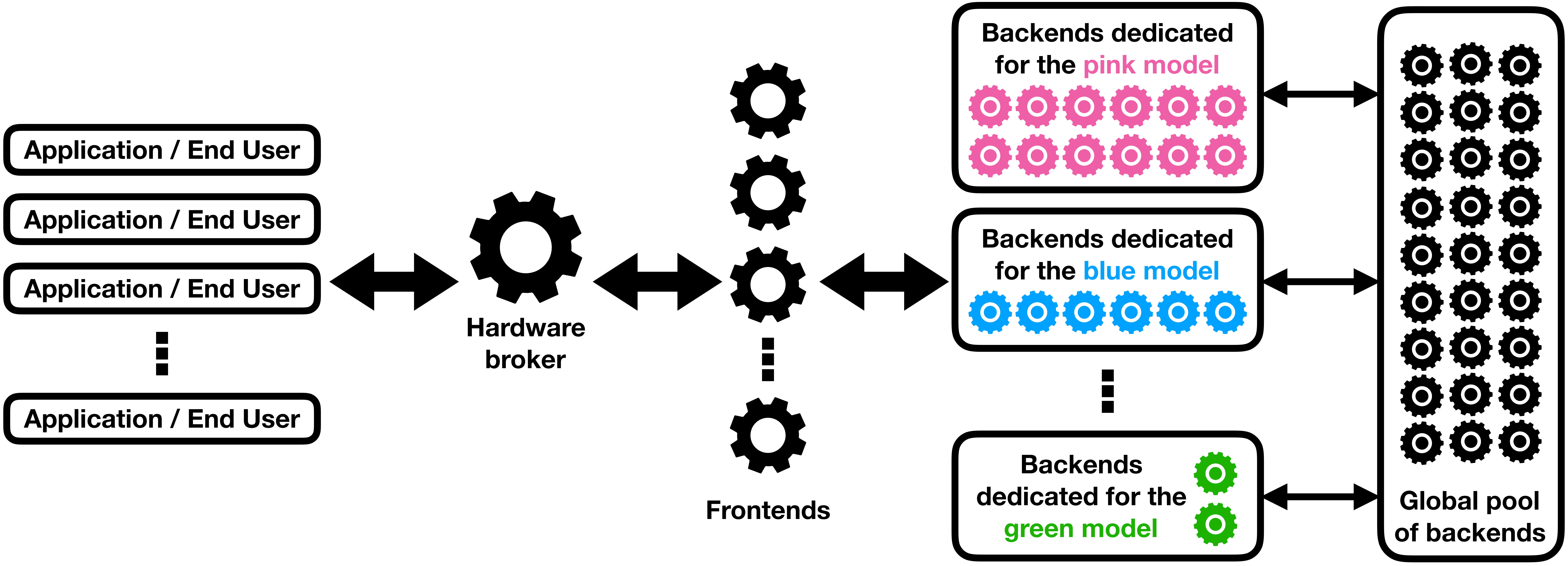

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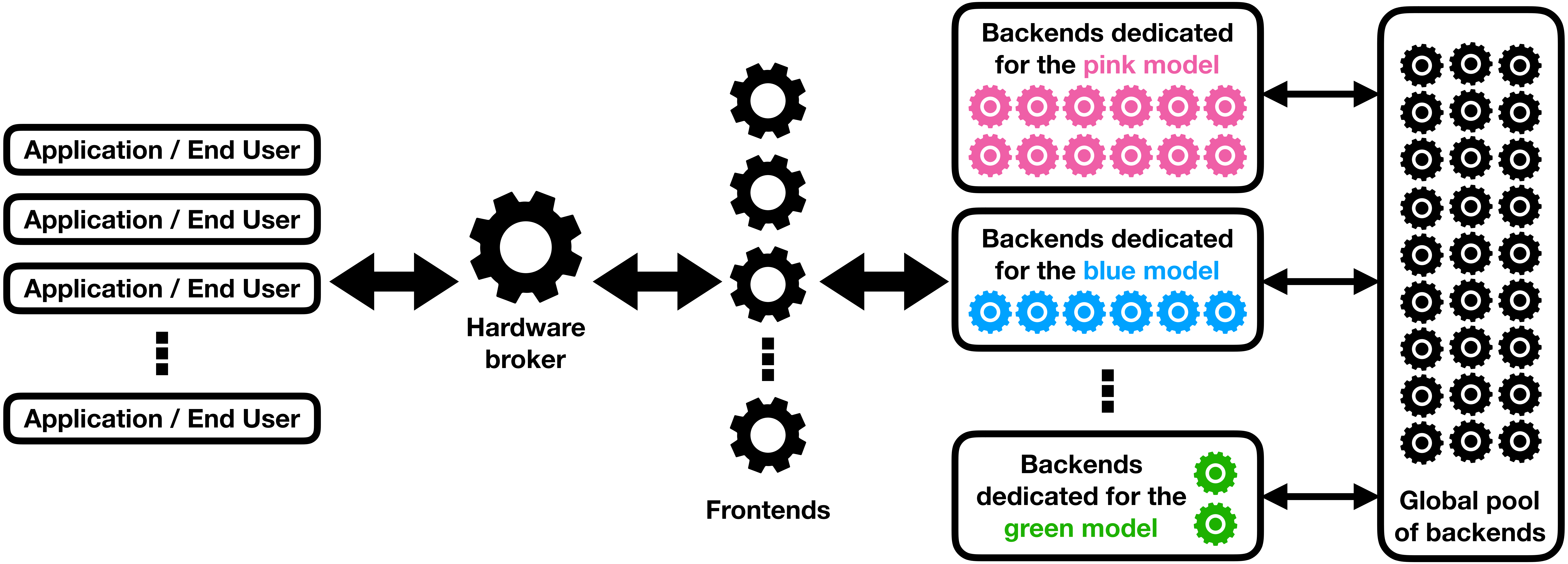


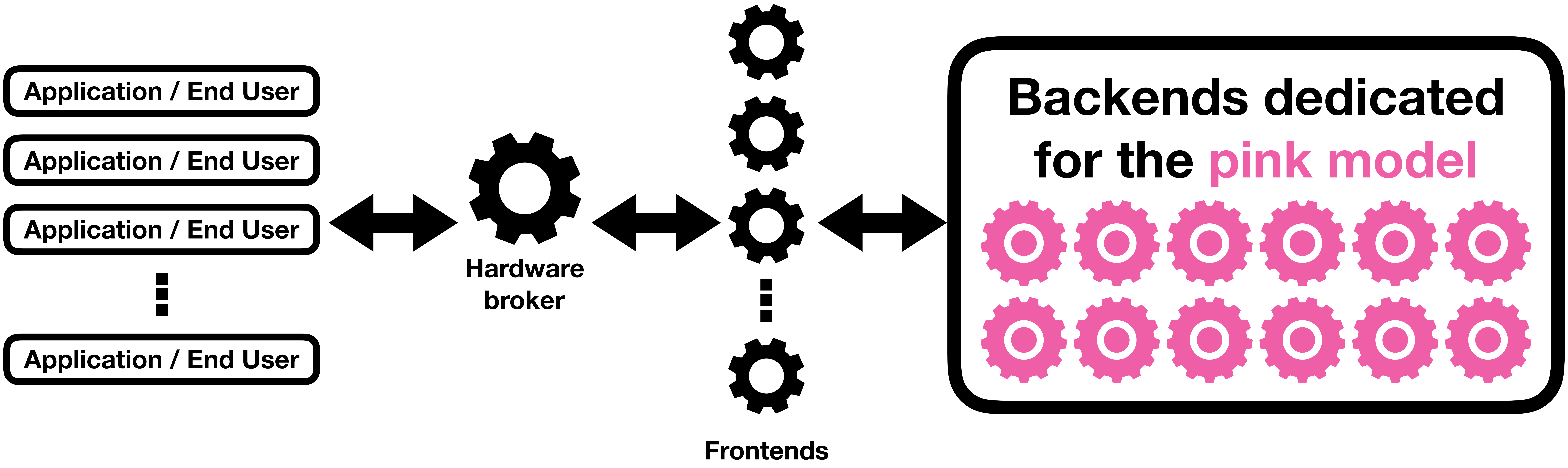
Objective: dedicated set of backends should dynamically scale

1. If load decreases, extra backends go back to the global pool ***(for resource efficiency)***

2. If load increases, new backends are set up in advance ***(for SLA compliance)***

System architecture

Let's focus on the pink model



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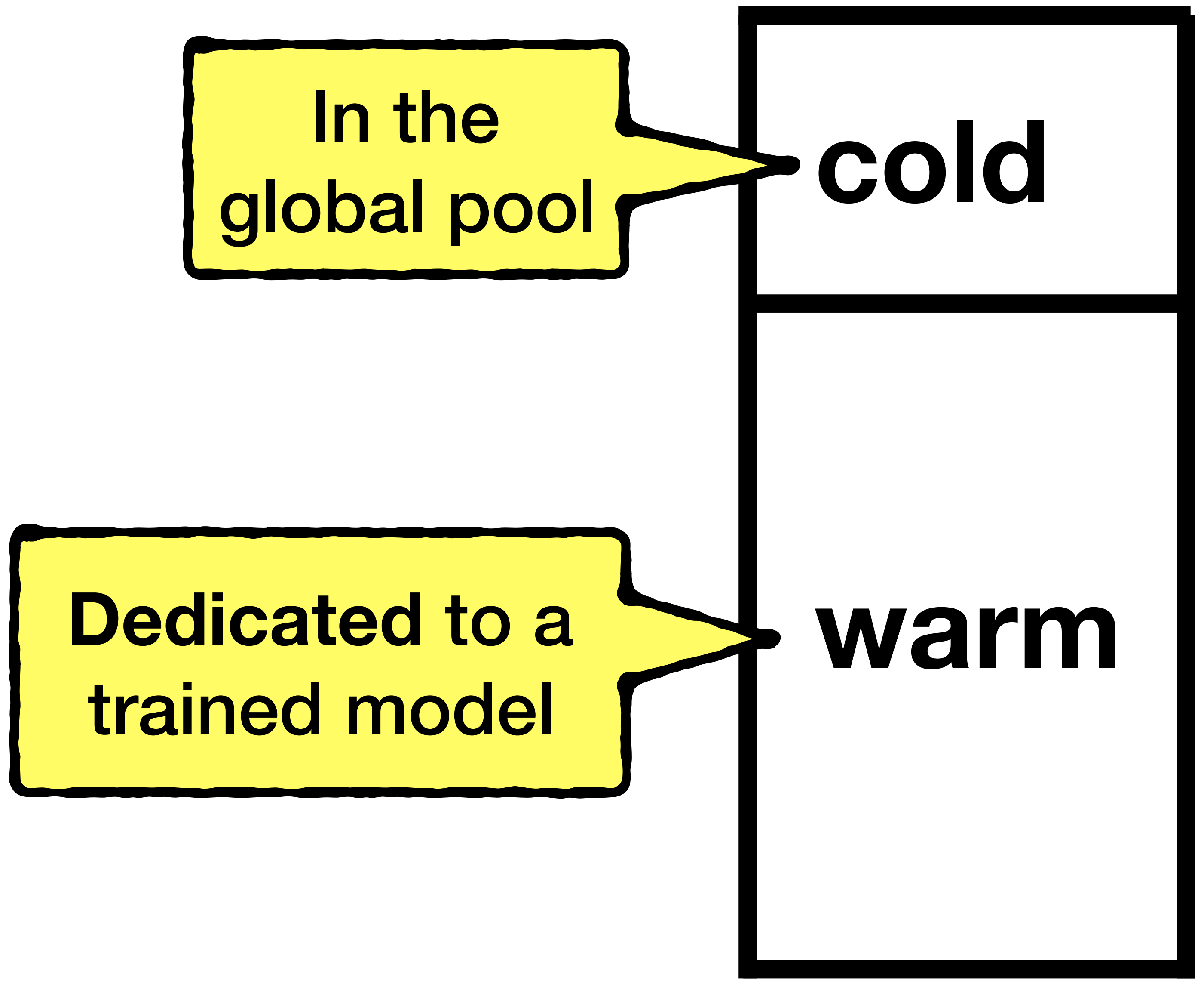

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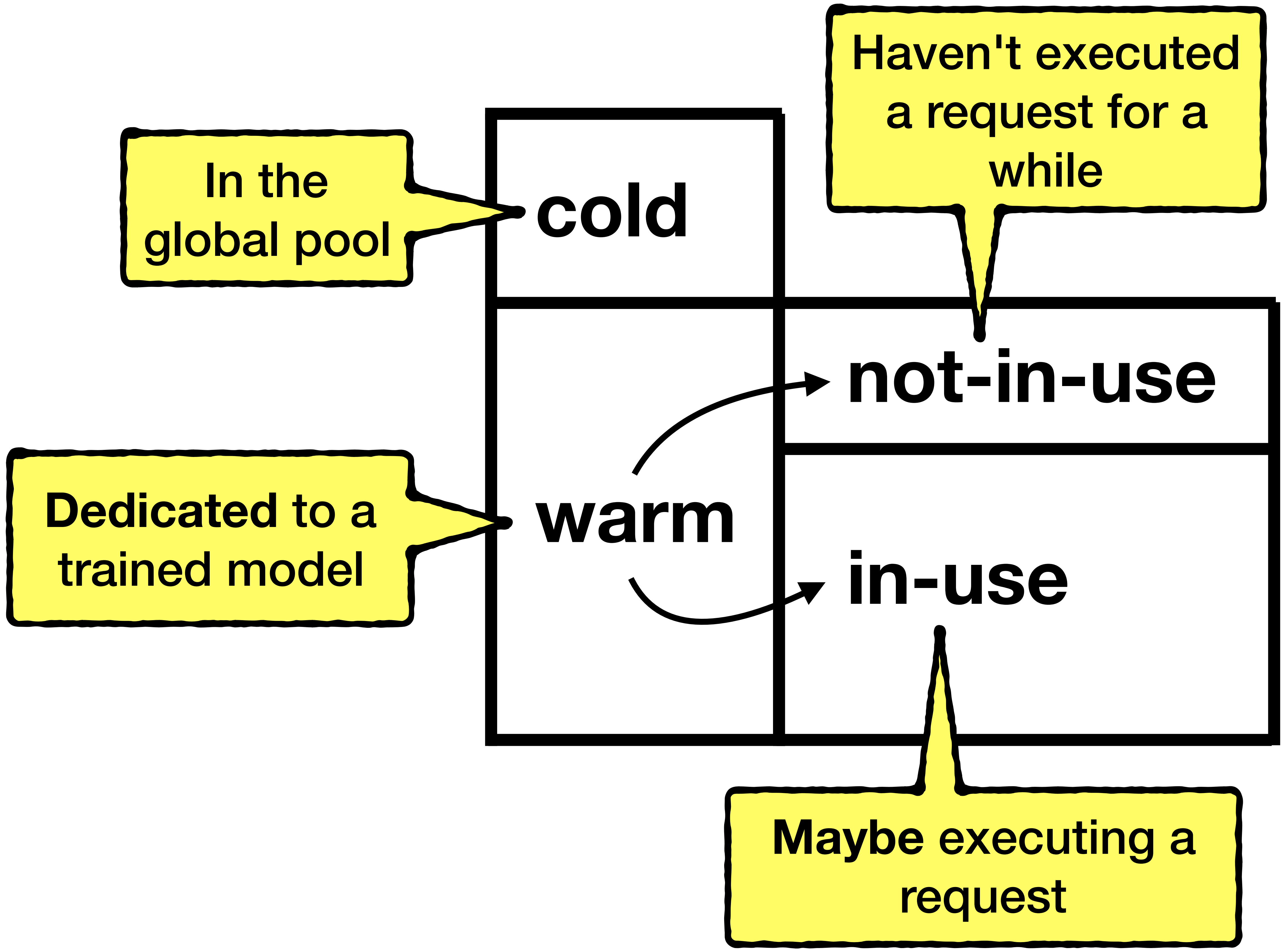

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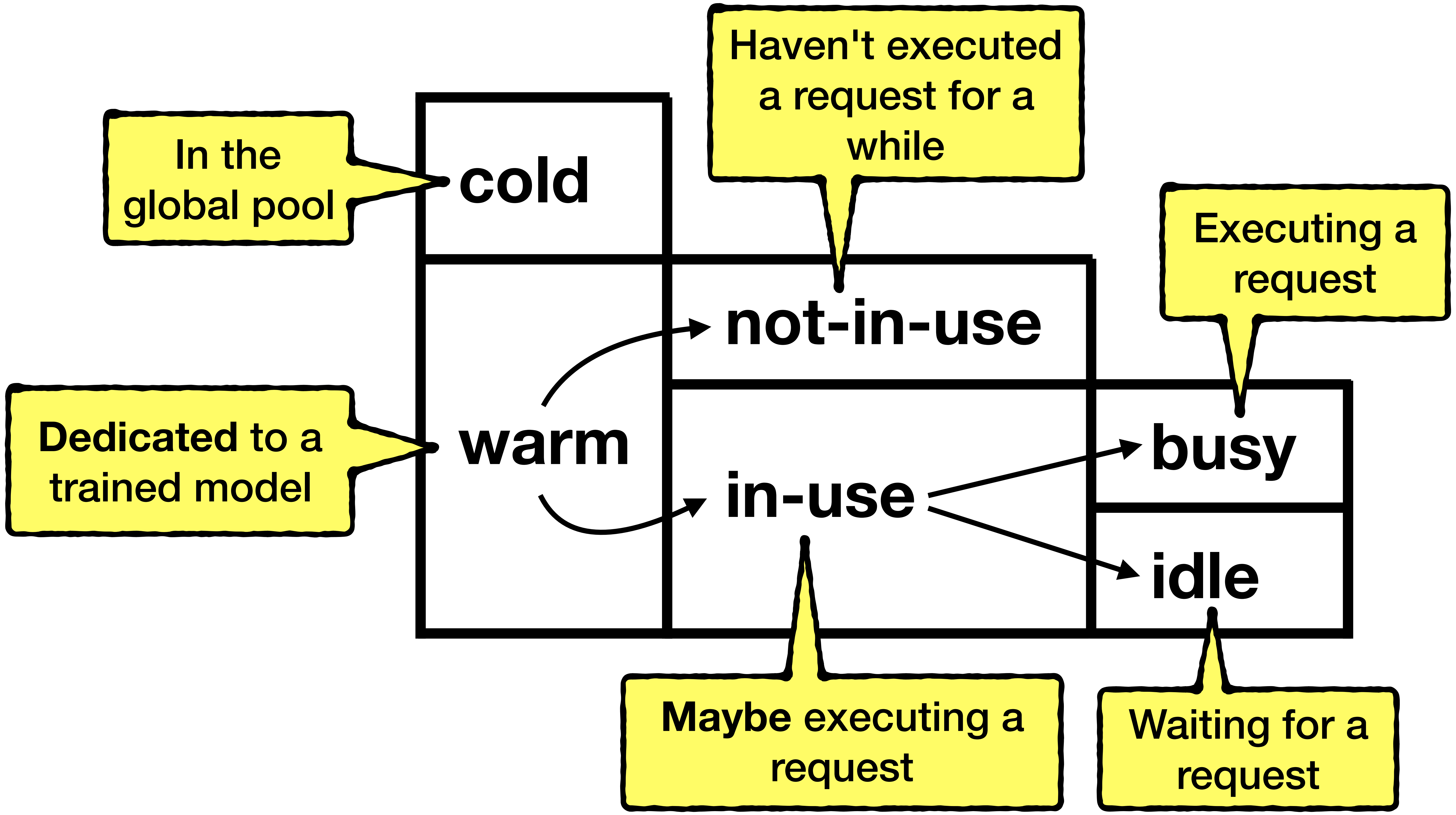

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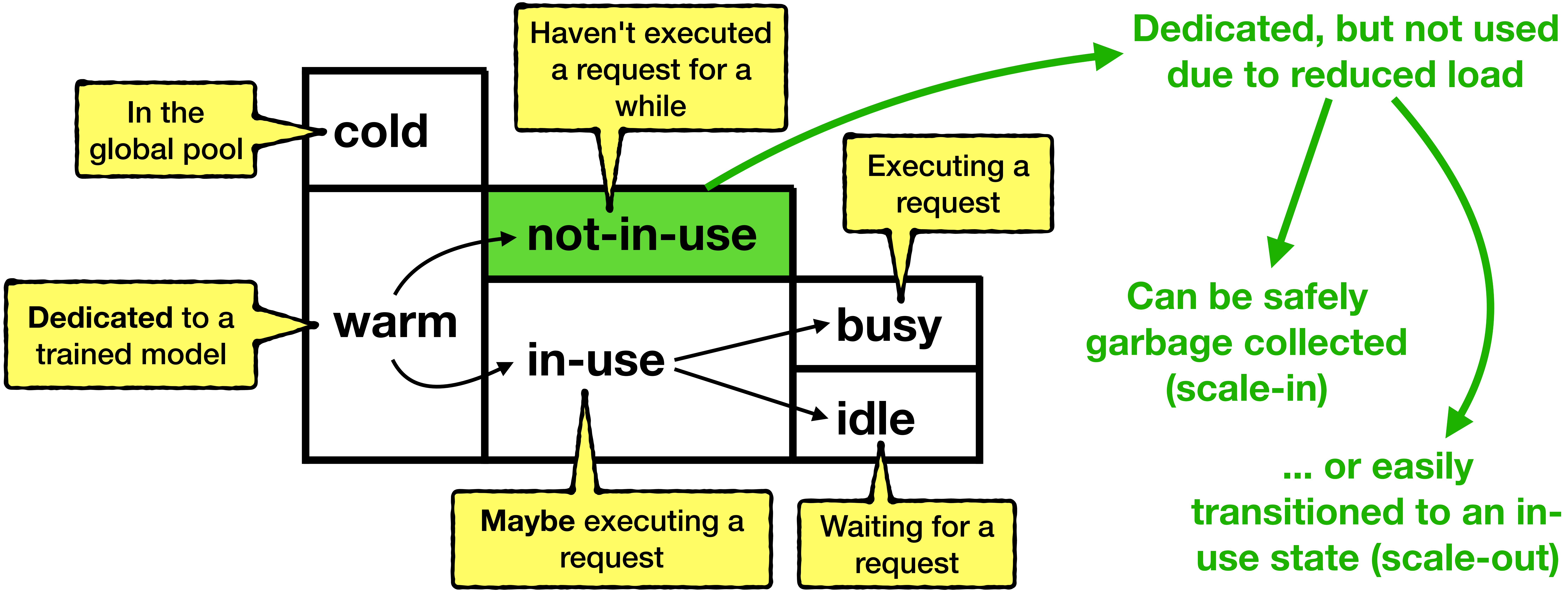

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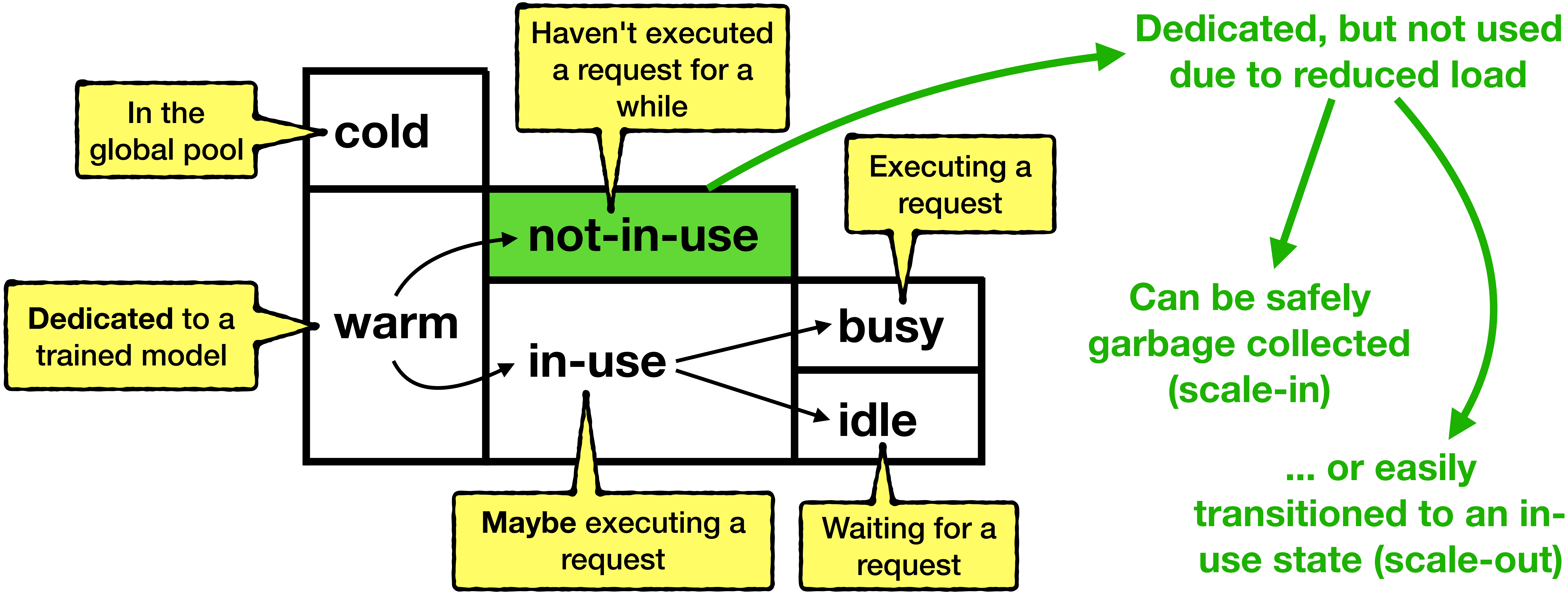
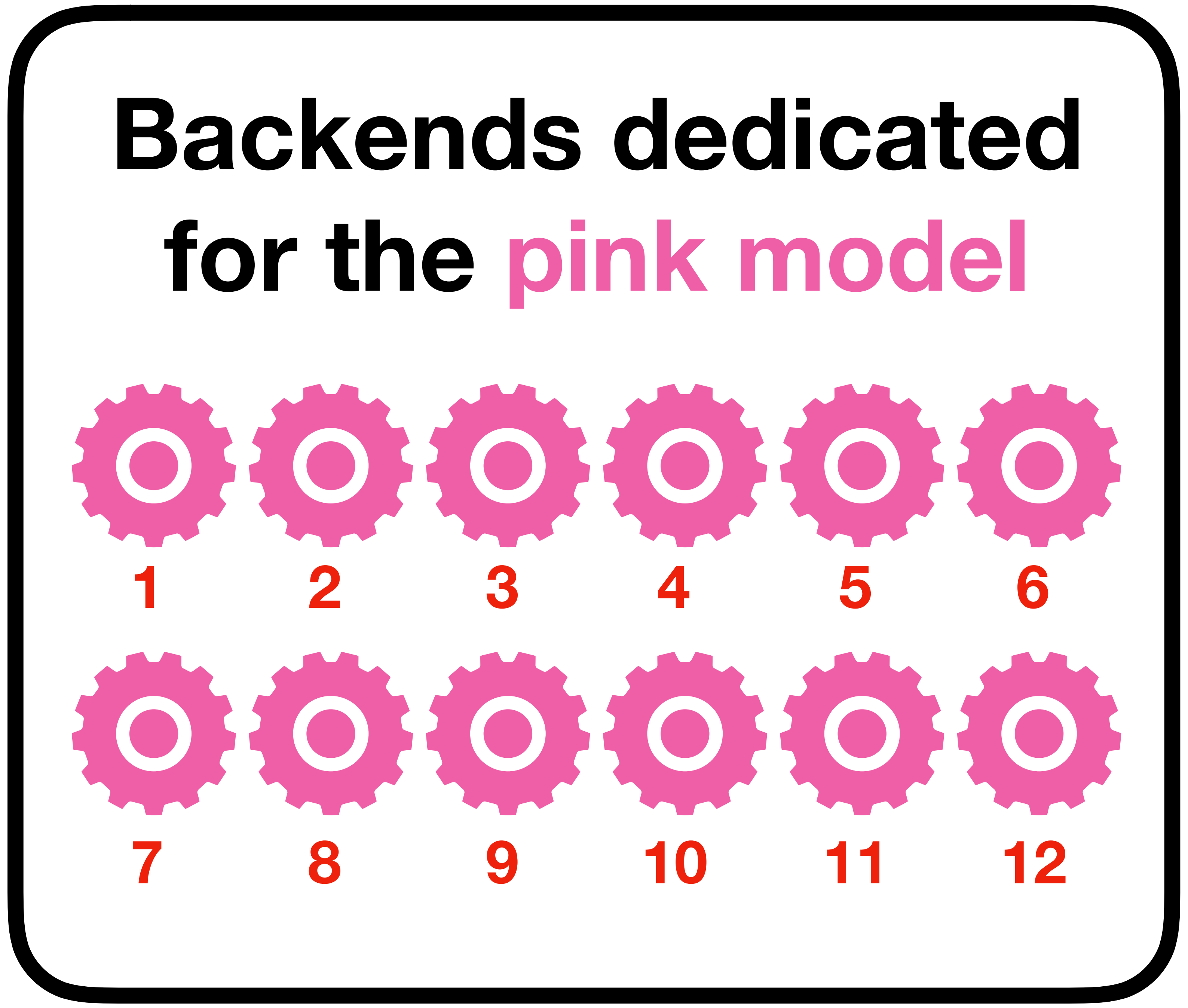


How do frontends know which dedicated backends to use, and which to not use?

Key idea 2: Order the dedicated set of backends



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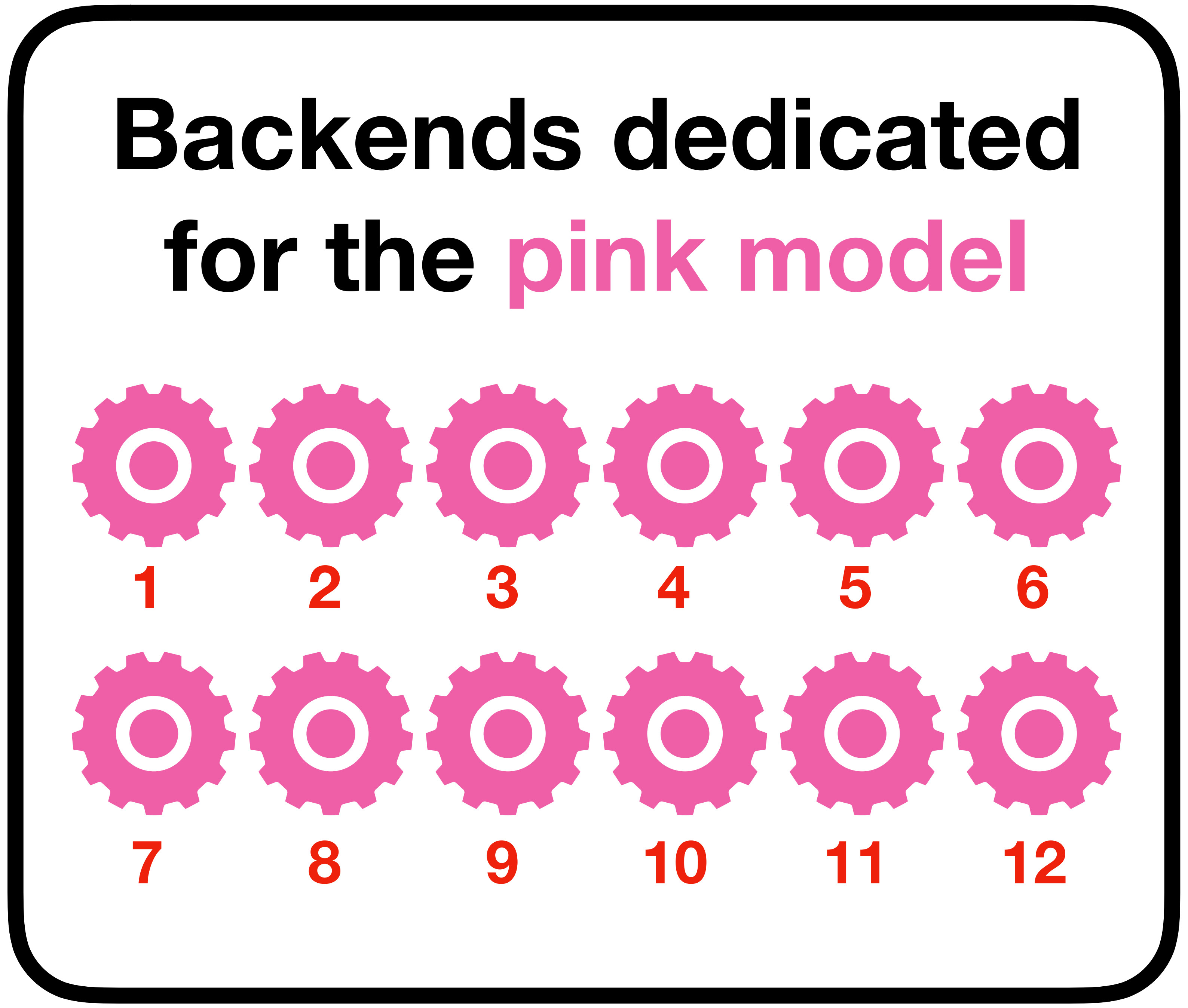
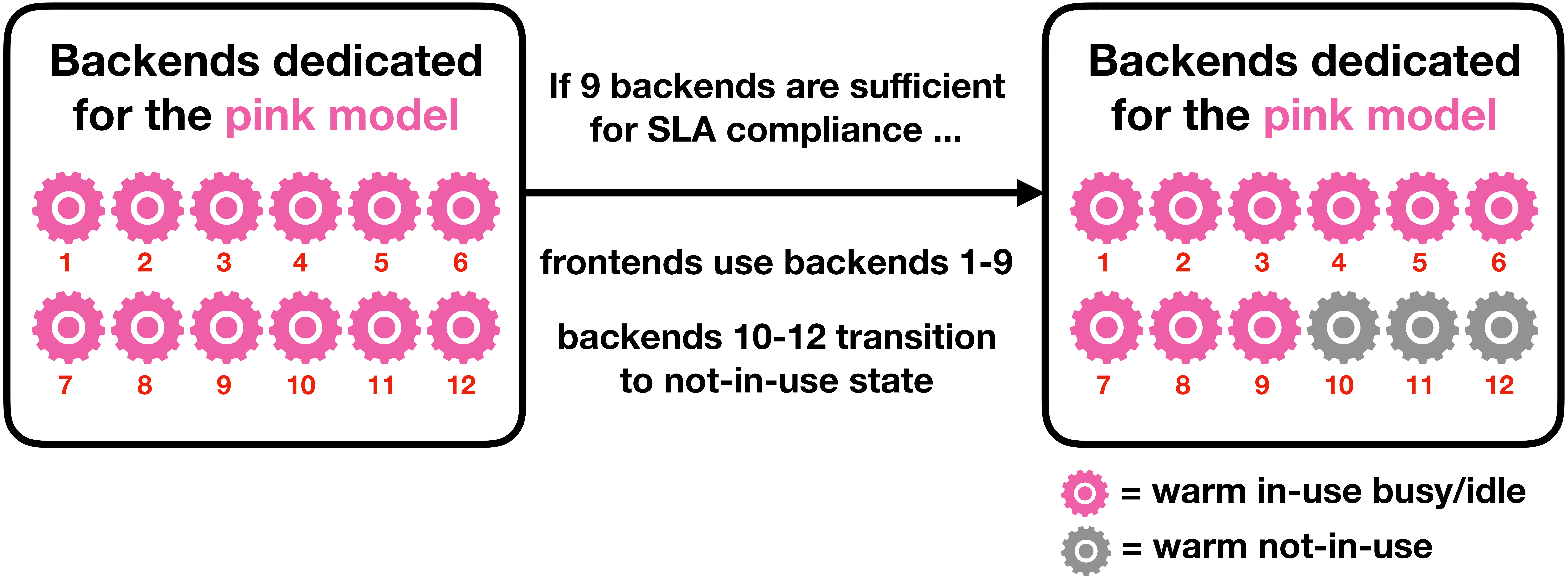


If 9 backends are sufficient for SLA compliance ...

Key idea 2: Order the dedicated set of backends



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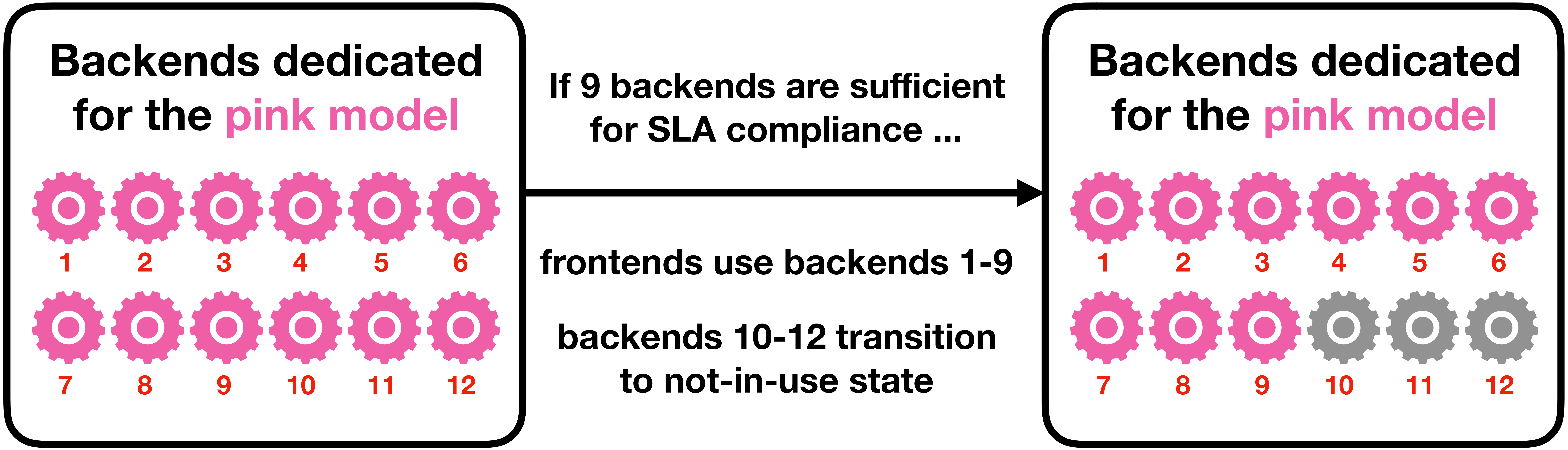
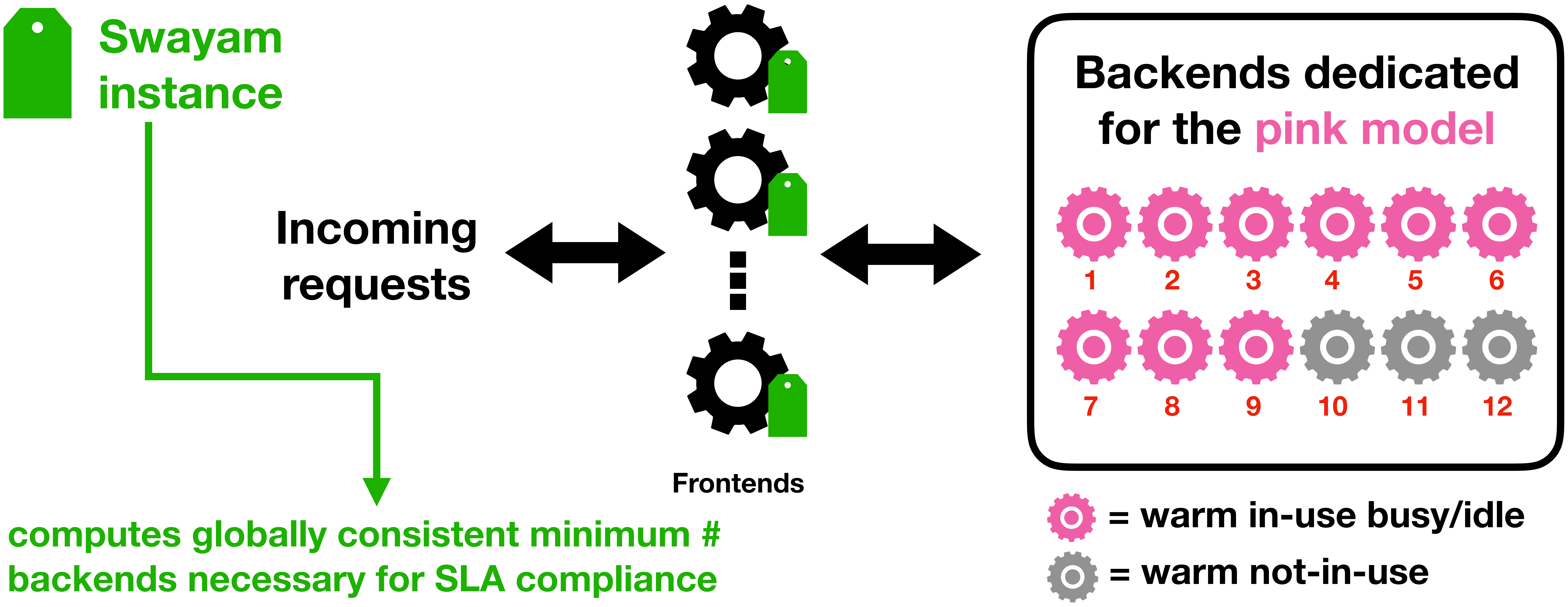


How do frontends know how many backends are sufficient?

Key idea 3: Swayam instance on every frontend



Outline

1. System architecture, key ideas

2. Analytical model for resource estimation

3. Evaluation results

Making globally-consistent decisions

at each frontend (Swayam instance)

What is the minimum # backends required for SLA compliance?

Making globally-consistent decisions

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1. Expected request execution time
2. Expected request waiting time
3. Total request load

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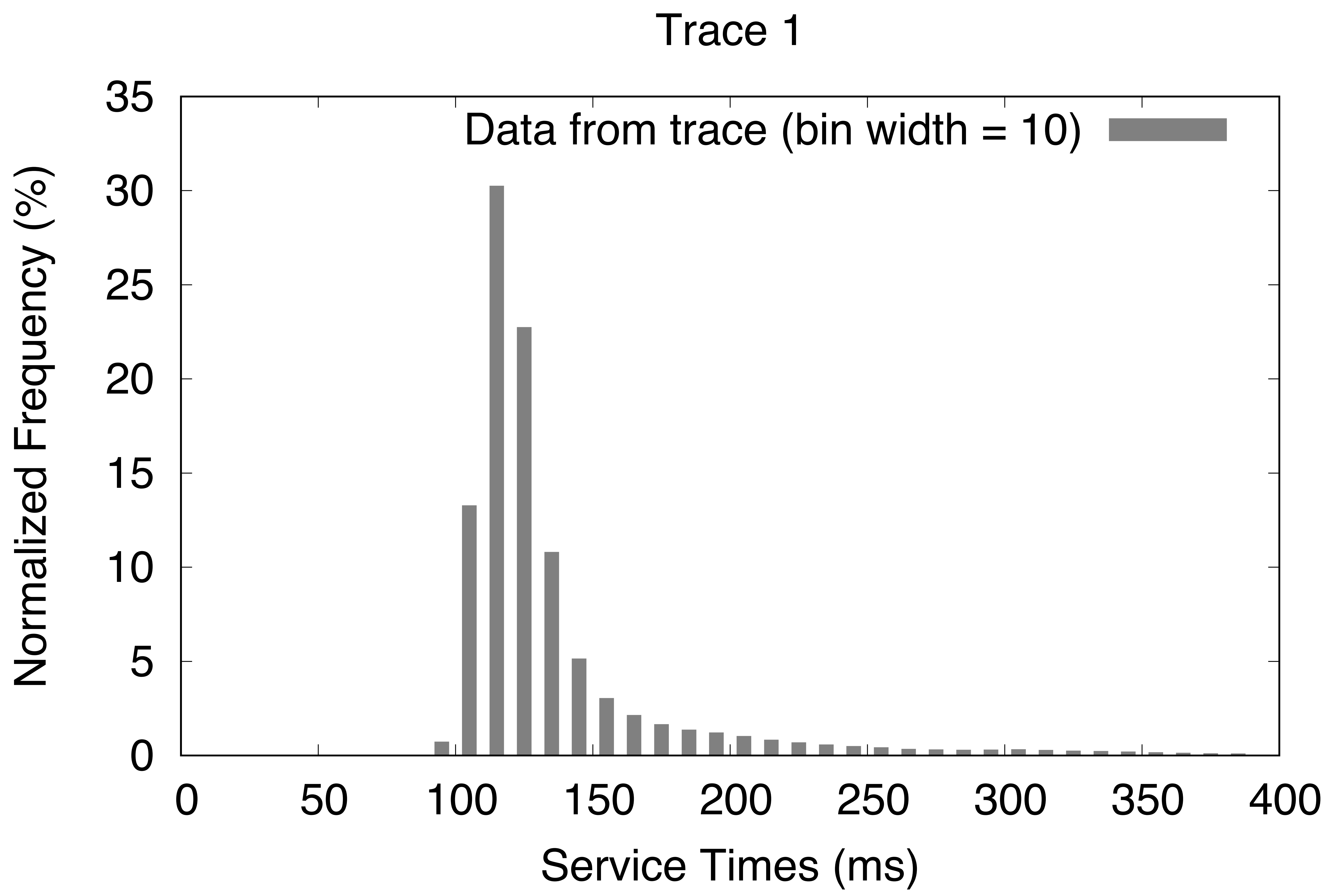
leverage ML workload characteristics

Determining expected request execution times

Studied execution traces of 15 popular services hosted on Microsoft Azure's MLaaS platform



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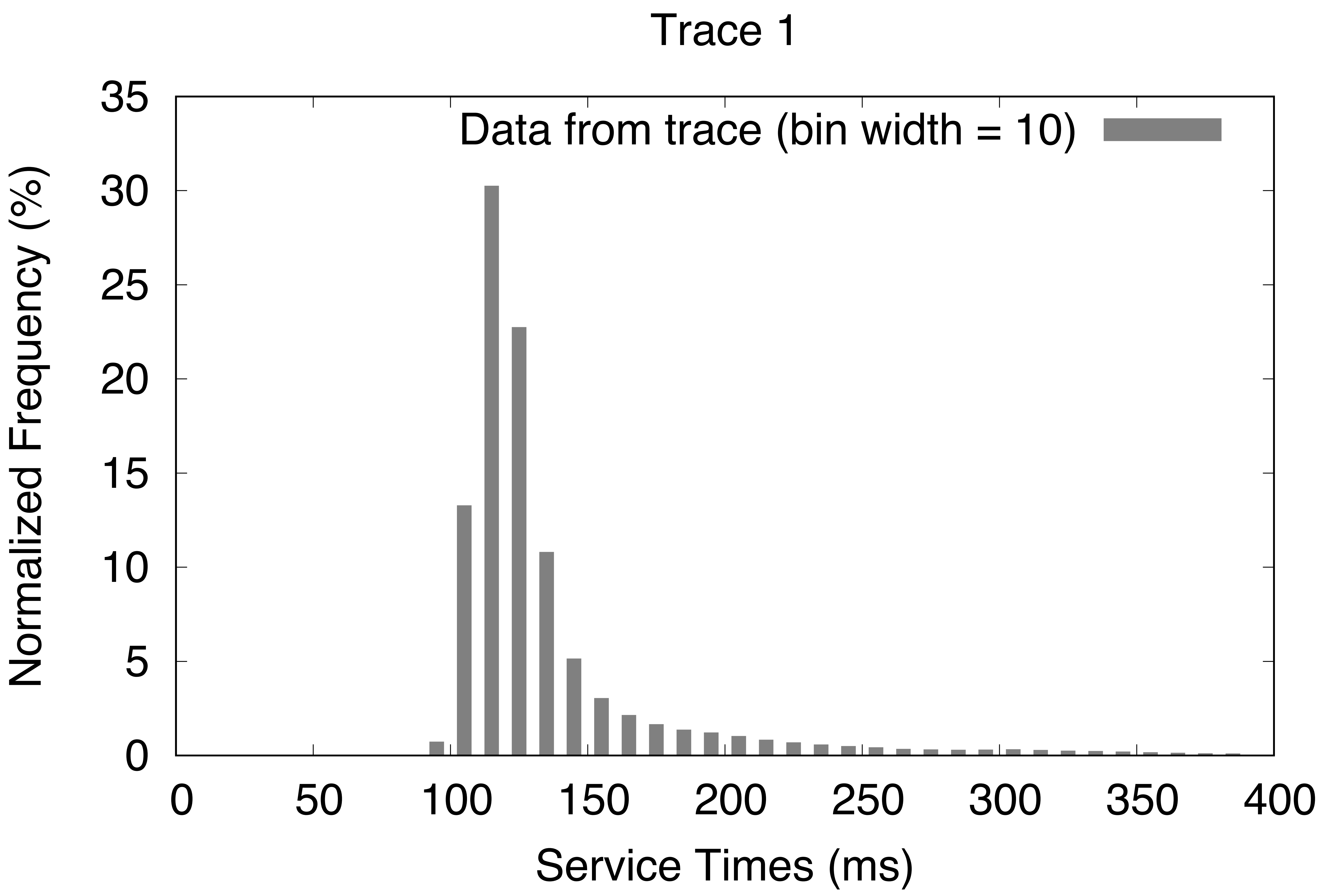
Variation is low

- Fixed-sized feature vectors
- Input-independent control flow
- Non-deterministic machine & OS events main sources of variability



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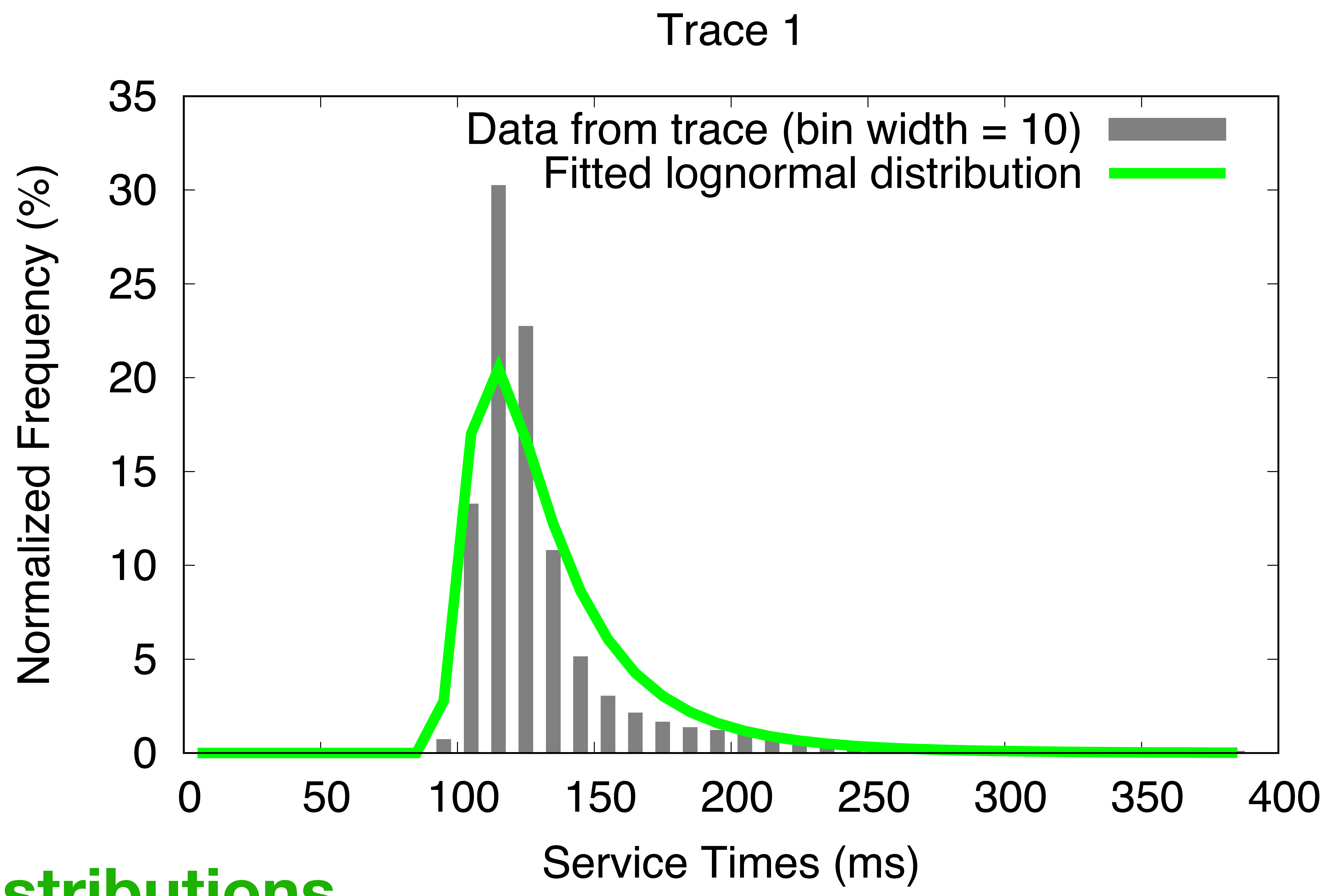

Modeled using log-normal distributions

Determining expected request waiting times

load balancing (LB)

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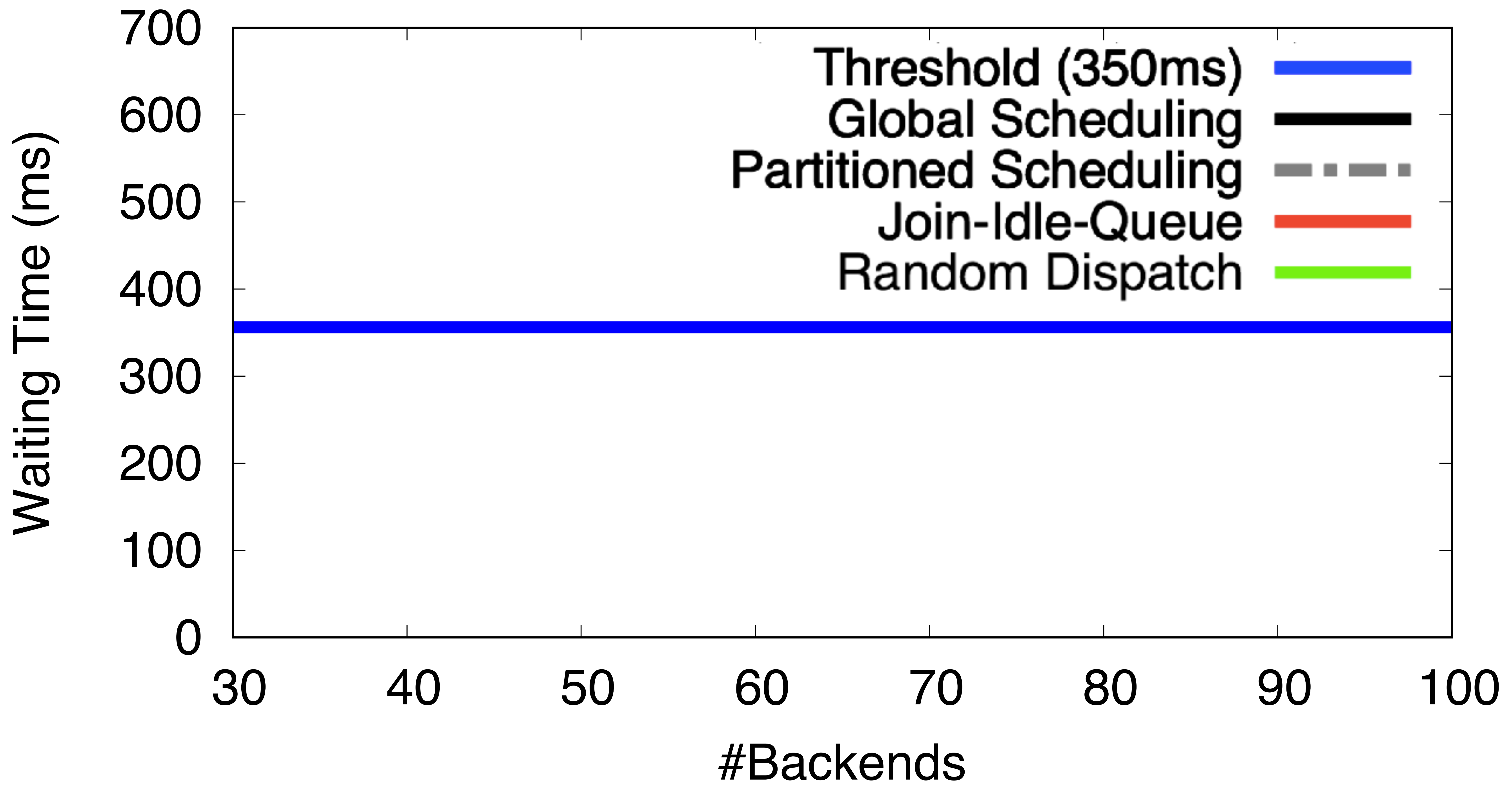

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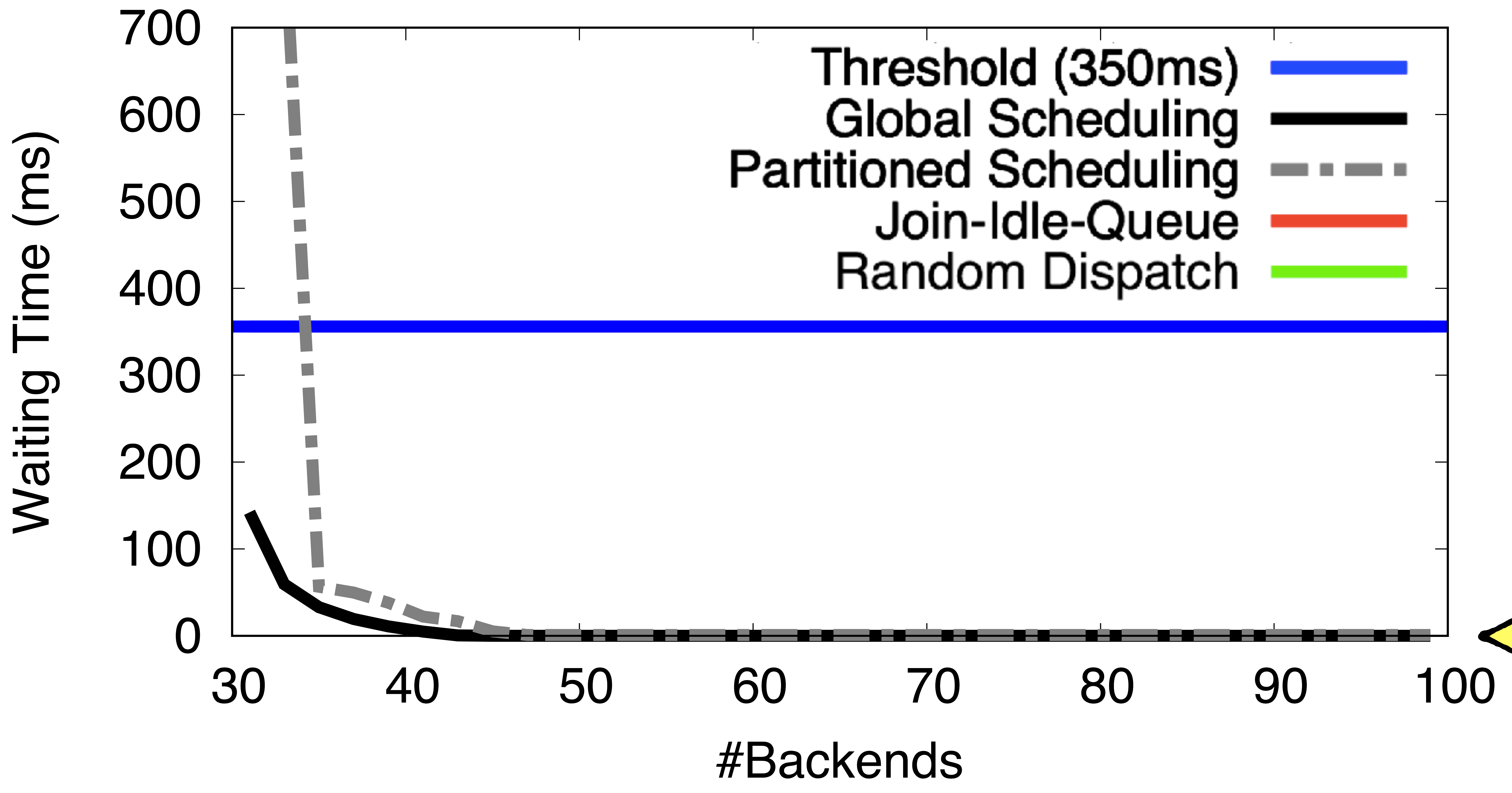

Global and partitioned perform well, but there are implementation tradeoffs

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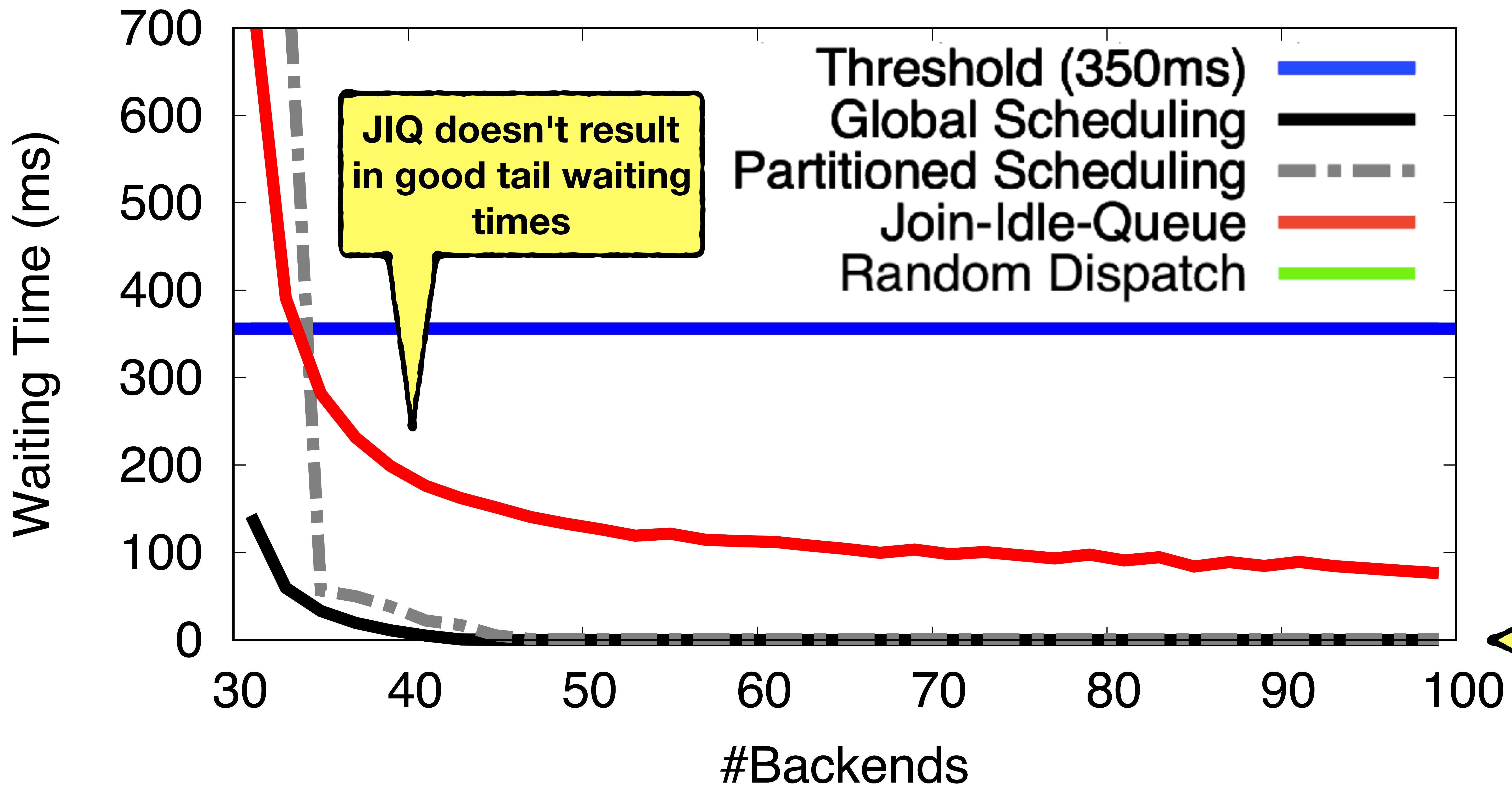

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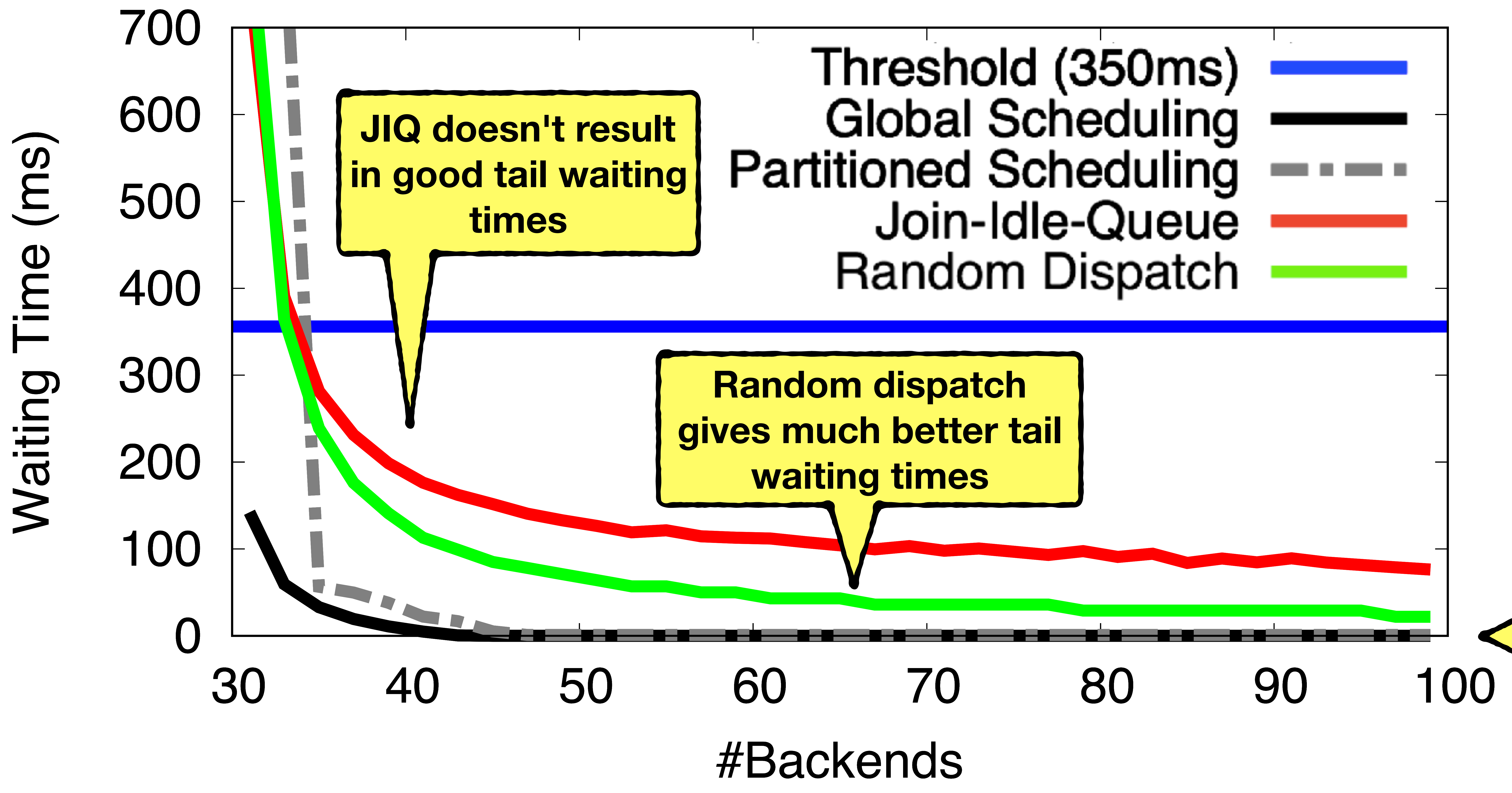

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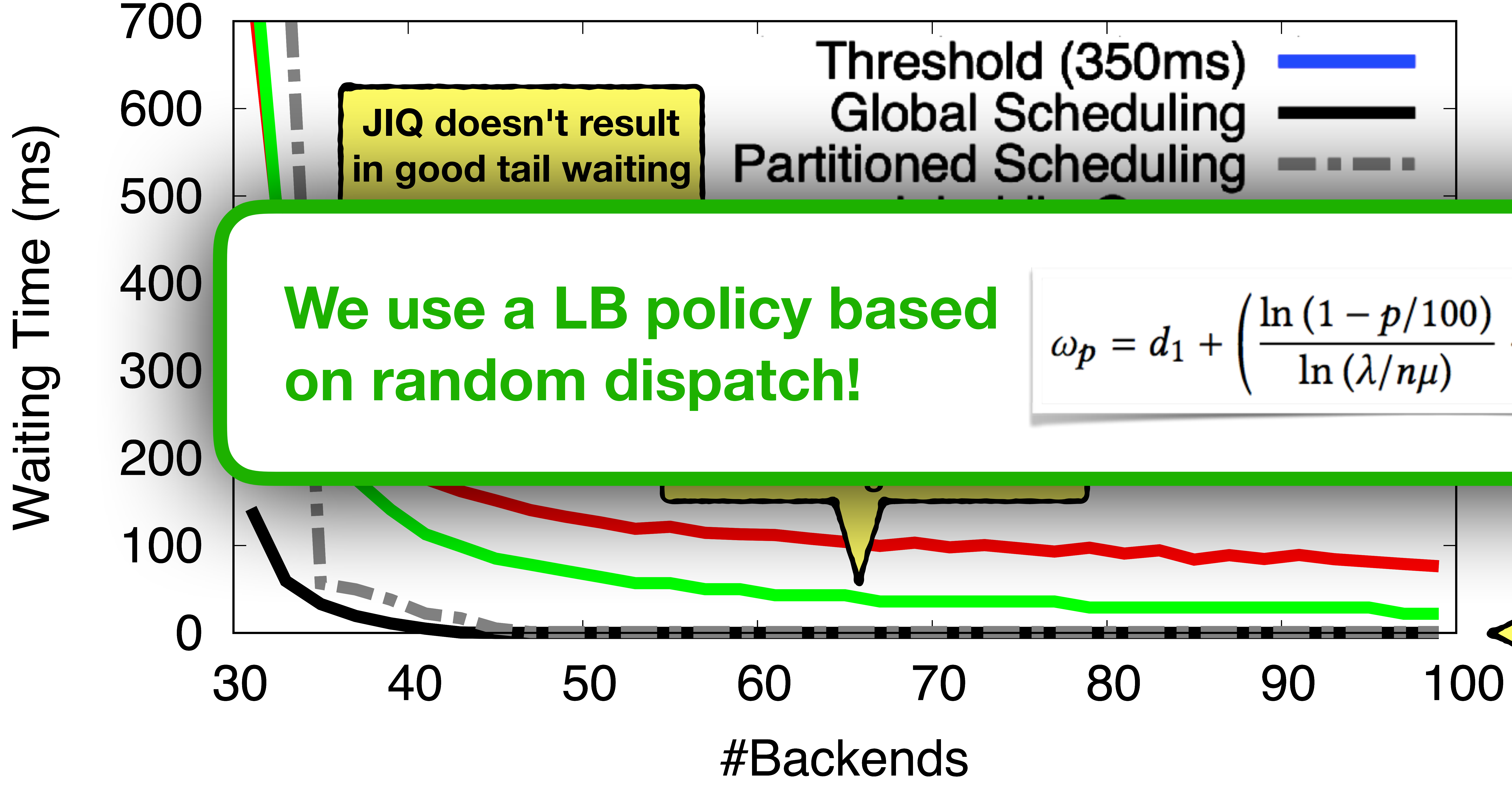

We use a LB policy based on random dispatch!

$$\omega_p = d_1 + \left(\frac{\ln(1 - p/100)}{\ln(\lambda/n\mu)} - 1 \right) \cdot (d_1 + d_2 + \Delta),$$

Global and partitioned perform well, but there are implementation tradeoffs

Determining the total request load

in the near future, to account
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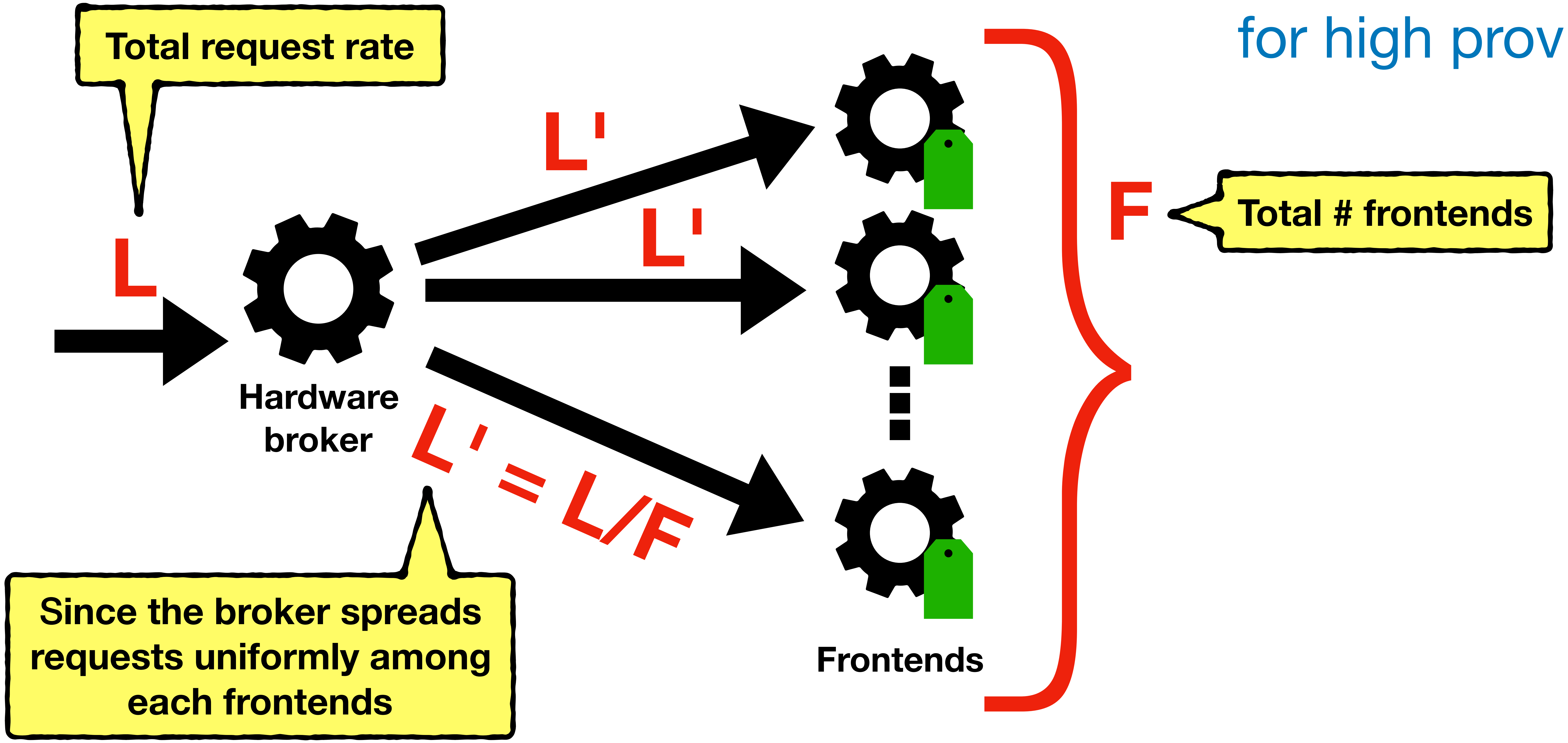

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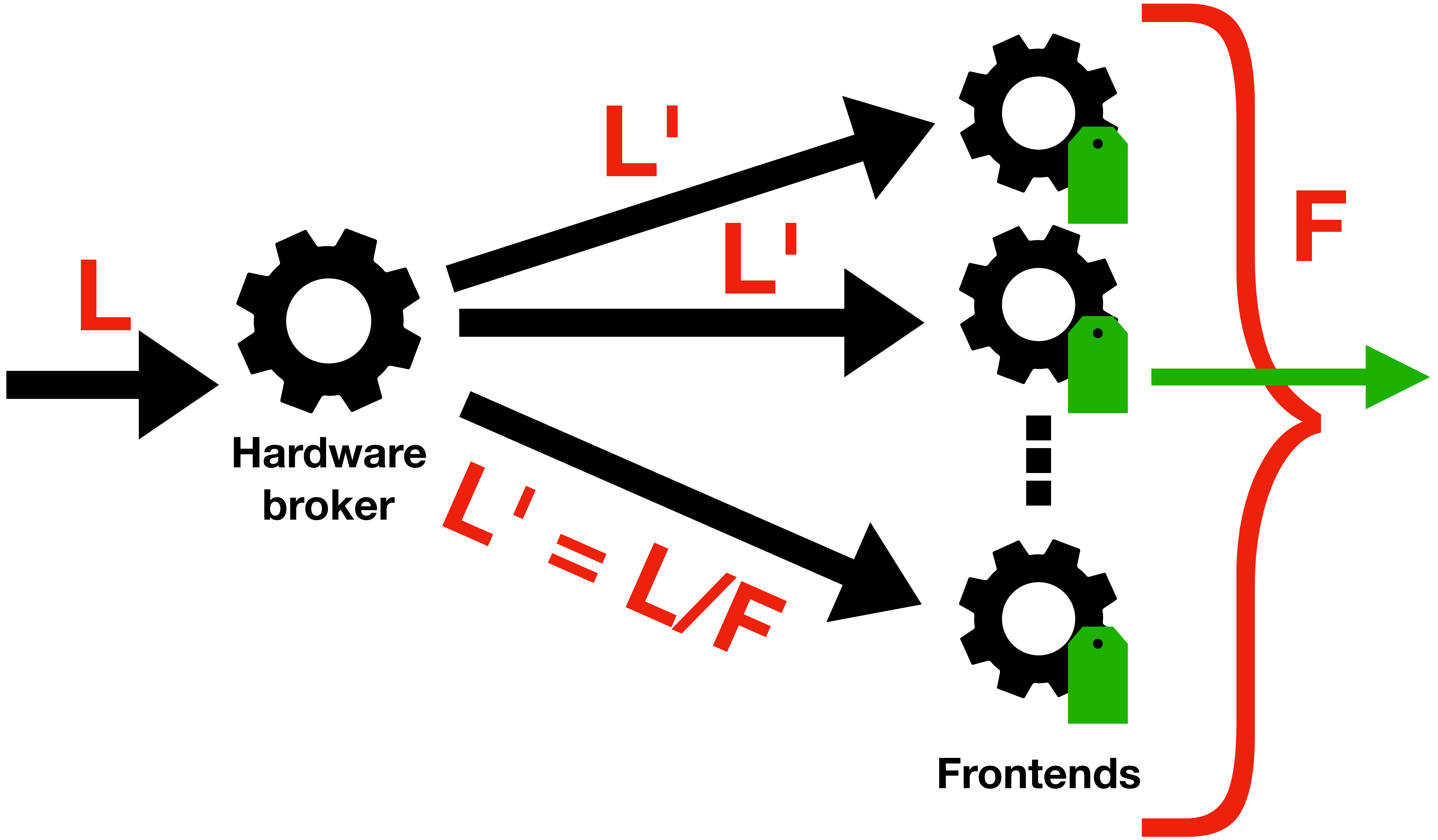


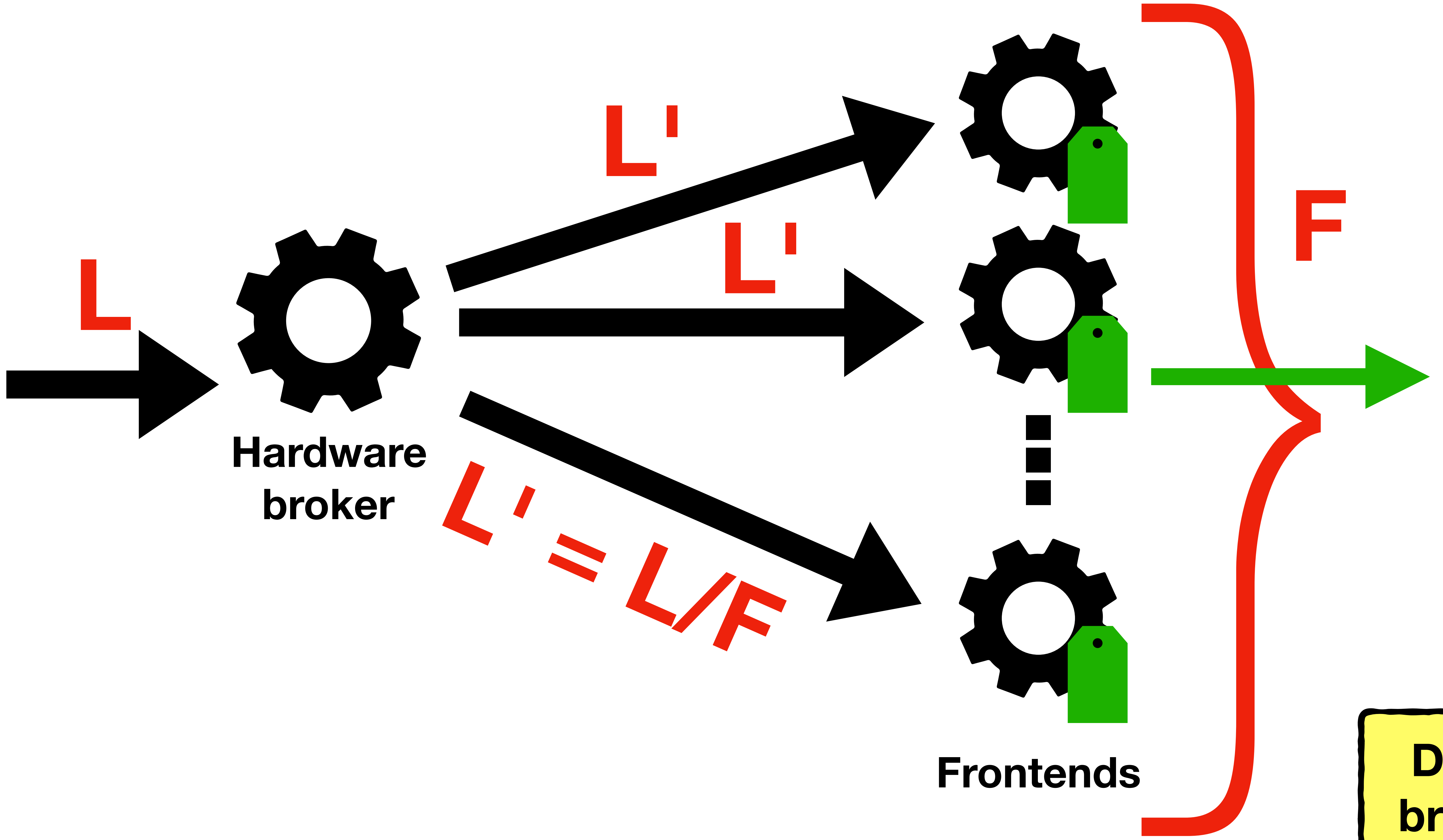
Each Swayam instance

- **Predicts L' for <u>near future</u>**

Depends on the time to setup a new backend

Determining the total request load

in the near future, to account for high provisioning times



Each Swayam instance

- Predicts L' for near future
- Given F, computes L = F x L'

Determined from broker / through a gossip protocol

Making globally-consistent decisions

at each frontend (Swayam instance)

What is the minimum # backends required for SLA compliance?

1. Expected request execution time ✓
2. Expected request waiting time ✓
3. Total request load ✓

SLA-aware resource estimation

For each trained model

n = min # backends

Response-Time Threshold

RT_{max}

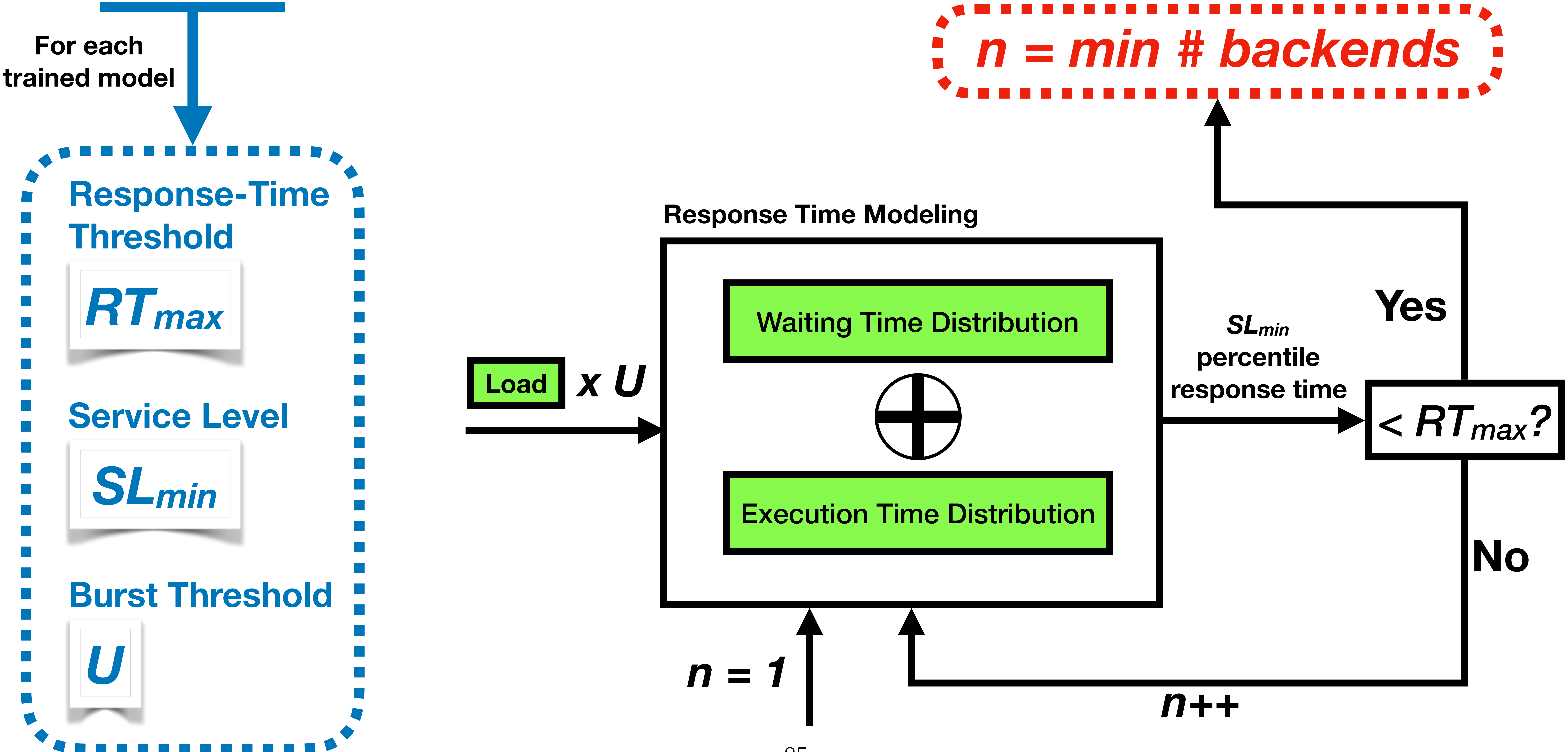
Service Level

SL_{min}

Burst Threshold

U

SLA-aware resource estimation



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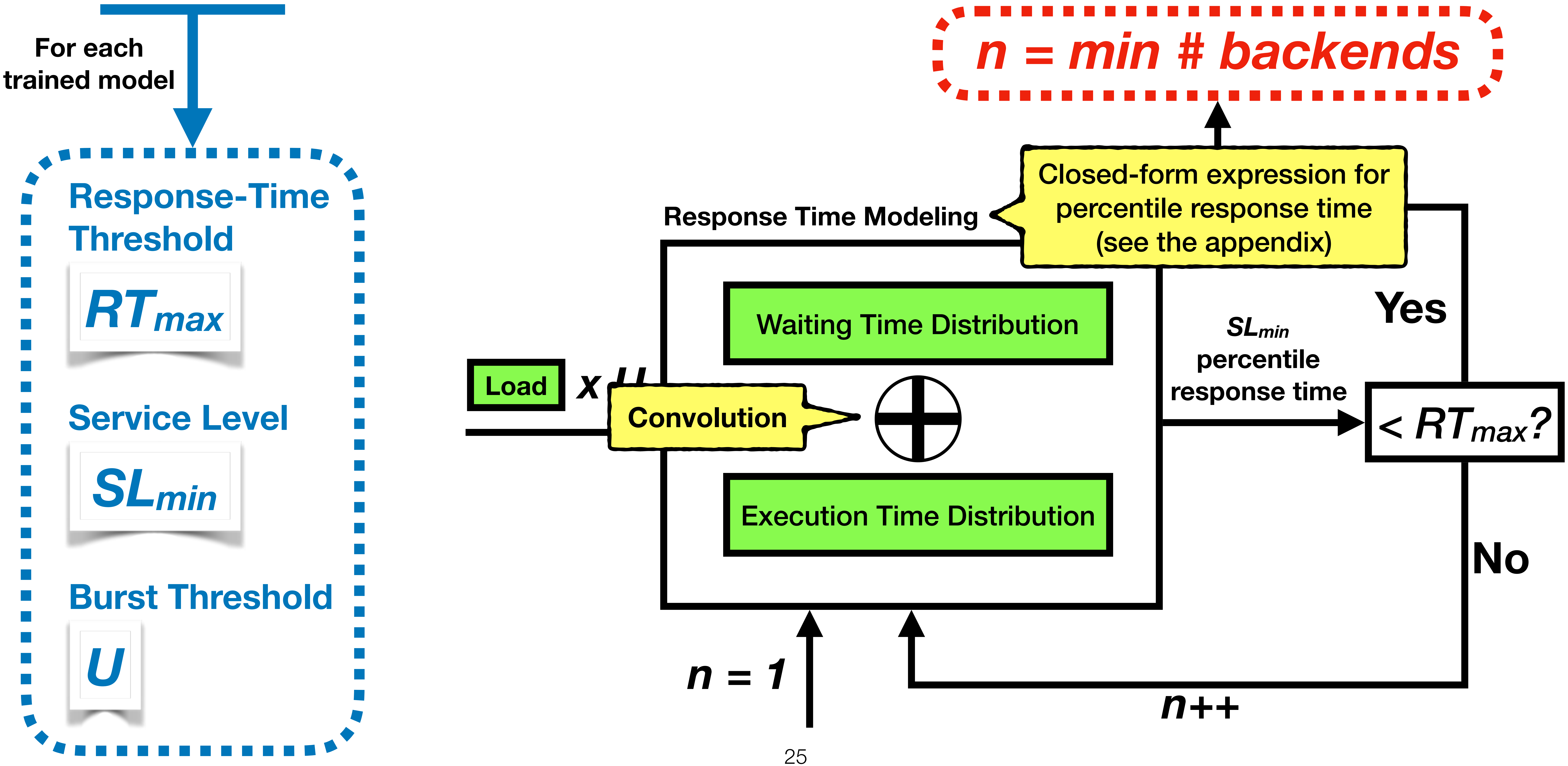

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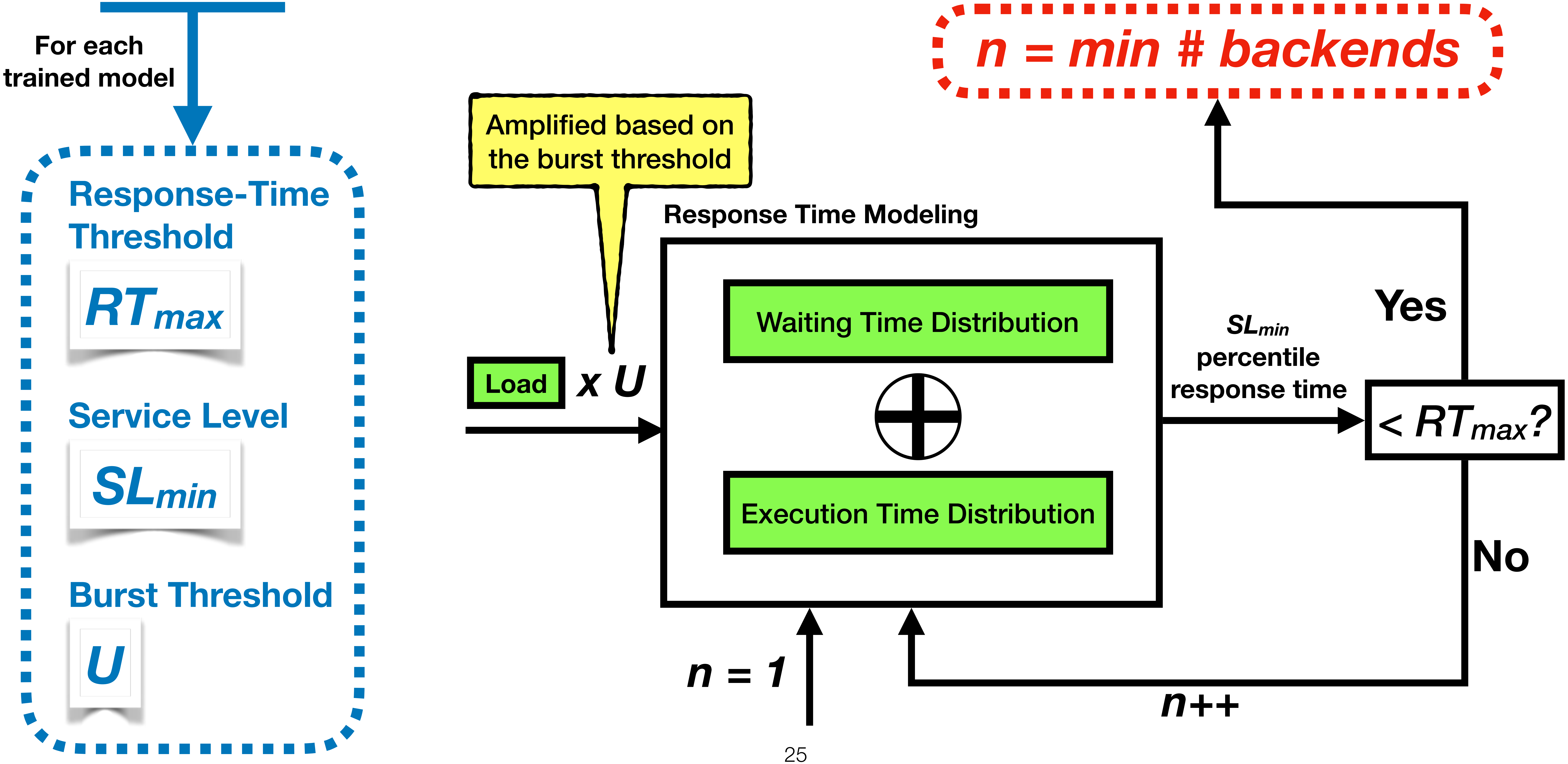

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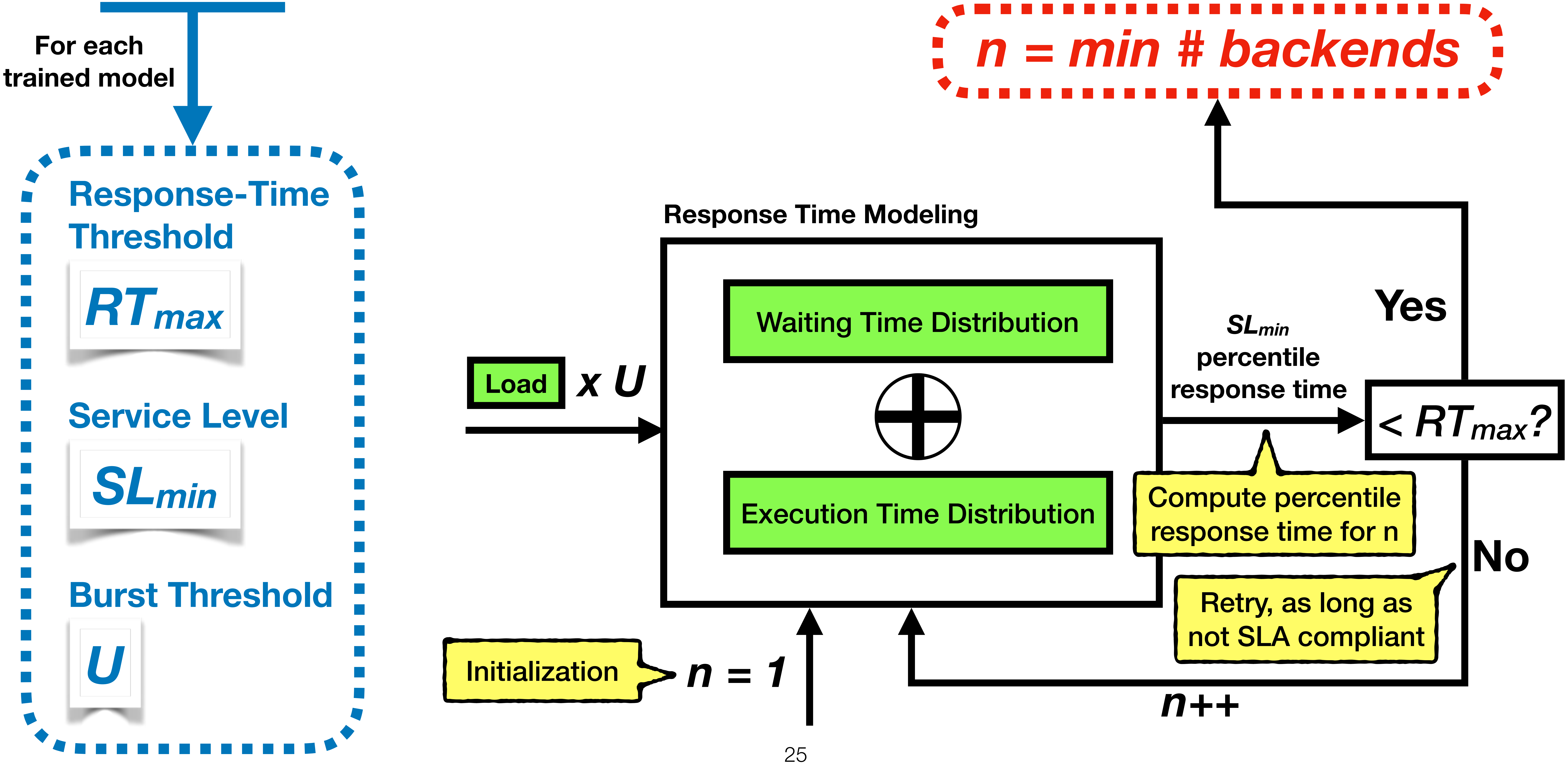
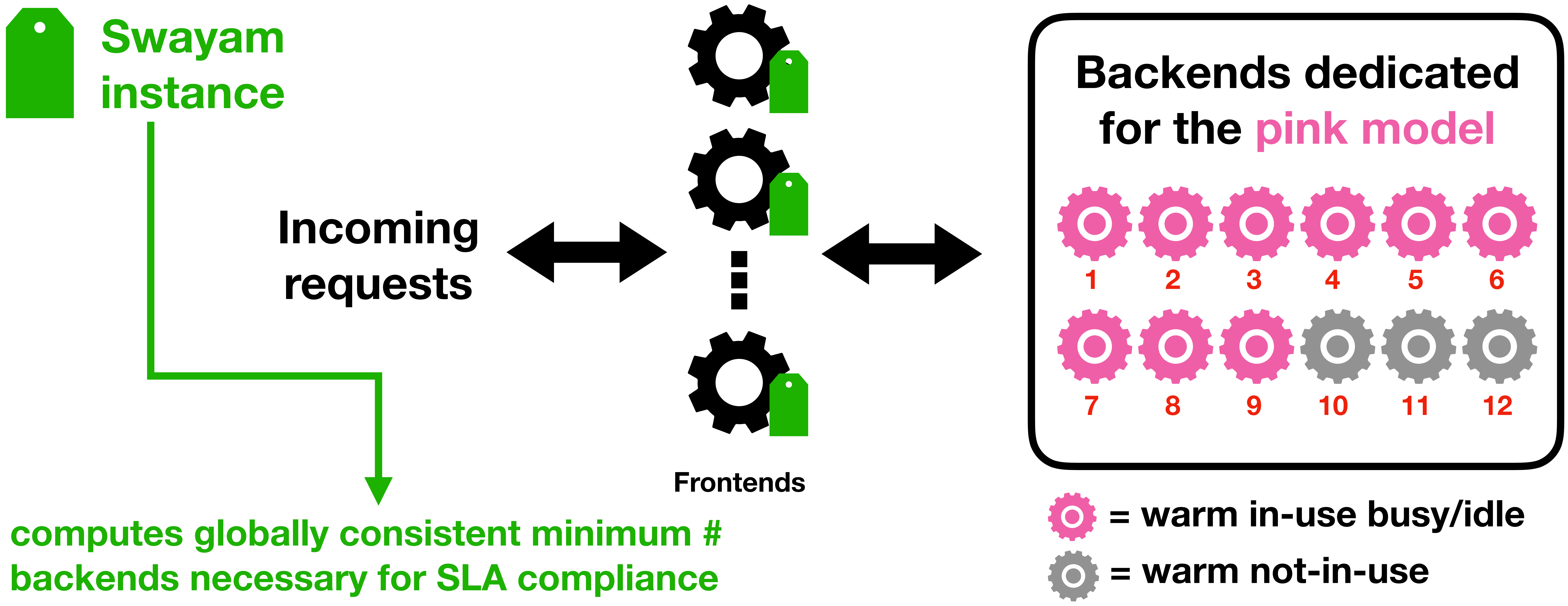


Swayam Framework



Outline

1. System architecture, key ideas
2. Analytical model for resource estimation
3. **Evaluation results**

Evaluation setup

- Prototype in C++ on top of Apache Thrift
  ➡ 100 backends per service
  ➡ 8 frontends
  ➡ 1 broker
  ➡ 1 server (for simulating the clients)

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  - ➡ 100 backends per service
  - ➡ 8 frontends
  - ➡ 1 broker
  - ➡ 1 server (for simulating the clients)
- Workload
  - ➡ 15 production service traces (Microsoft Azure MLaaS)
  - ➡ Three-hour traces (request arrival times and computation times)
  - ➡ Query computation & model setup times emulated by spinning

SLA configuration for each model

- Response-time threshold RT_{max} = $5C$

  ➡ C denotes the mean computation time for the model

- Desired service level SL_{min} = 99%

  ➡ 99% of the requests must have response times under RT_{max}

- Burst threshold $U = 2x$

  ➡ Tolerate increase in request rate by up to 100%

- Initially, 5 pre-provisioned backends

Baseline: Clairvoyant Autoscaler (ClairA)

➡ It knows the processing time of each request beforehand

➡ It can travel back in time to provision a backend

➡ "Deadline-driven" approach to minimize resource waste

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➡ **It knows the processing time of each request beforehand**

➡ **It can travel back in time to provision a backend**

➡ **"Deadline-driven" approach to minimize resource waste**

- ClairA1 assumes zero setup times, immediate scale-ins

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➡ **It can travel back in time to provision a backend**

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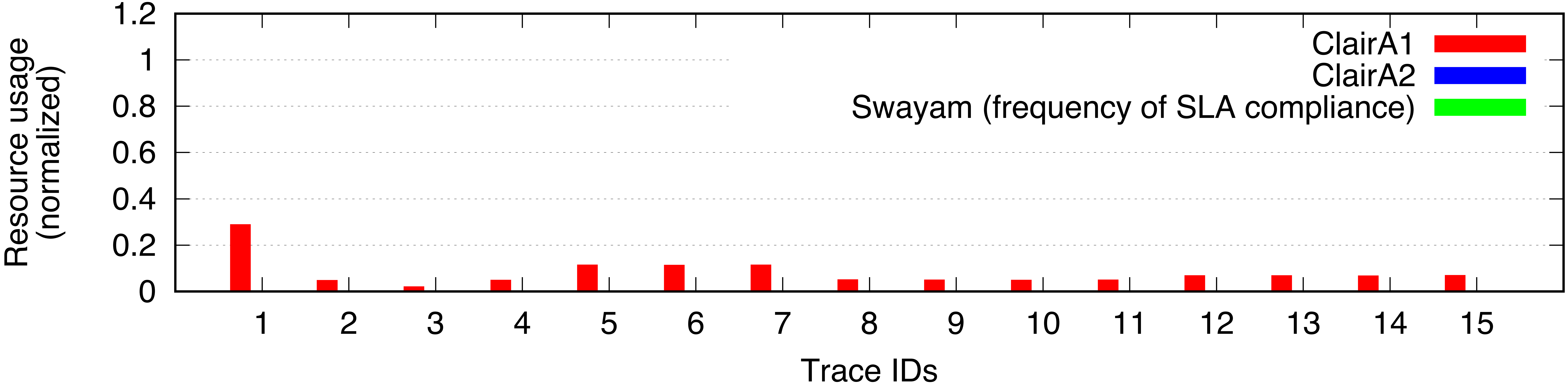
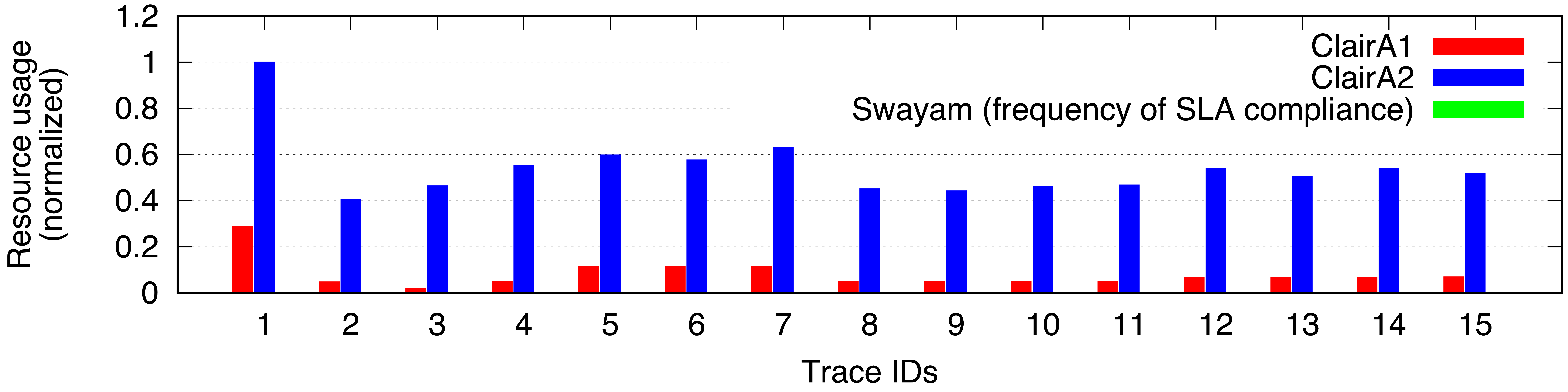
- Both ClairA1 and ClairA2 depend on RT_{max}, but not on SL_{min} and U

Resource usage vs. SLA compliance

Resource usage vs. SLA compliance



Resource usage vs. SLA compliance



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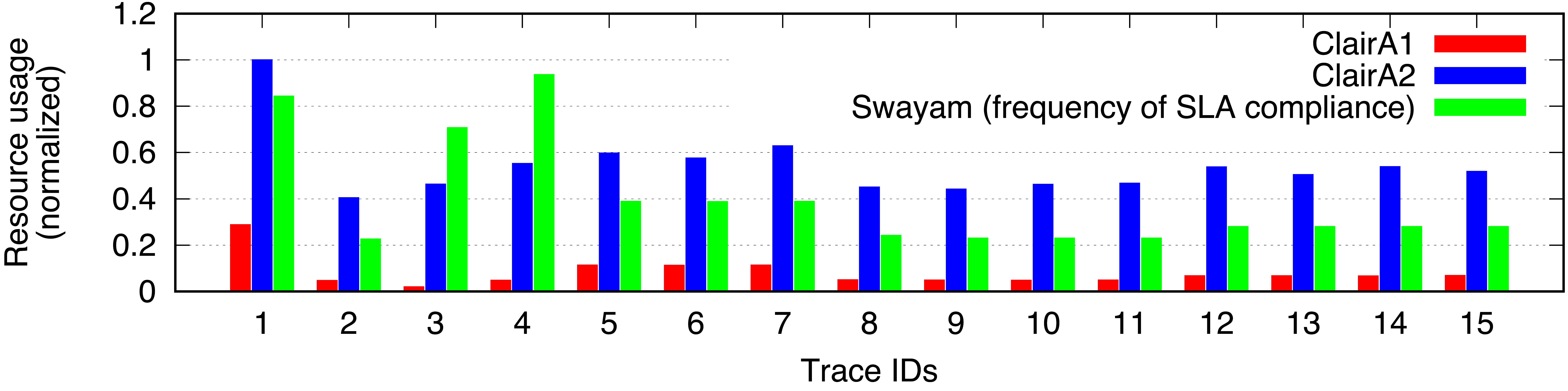

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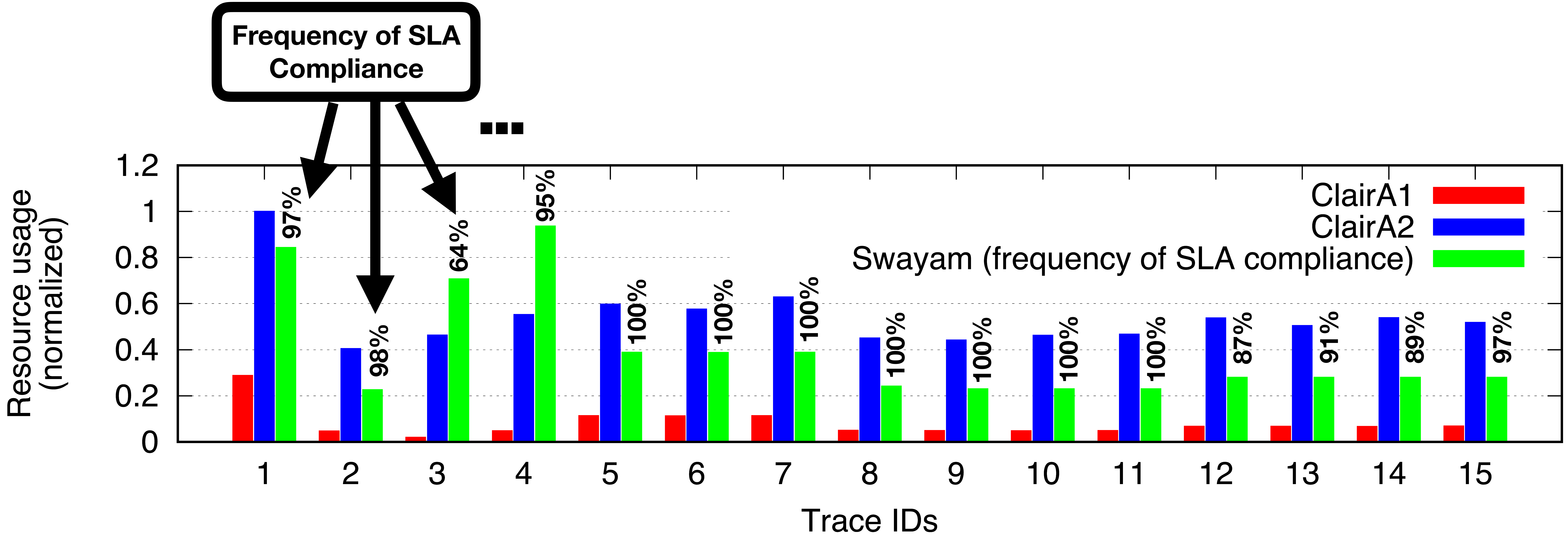

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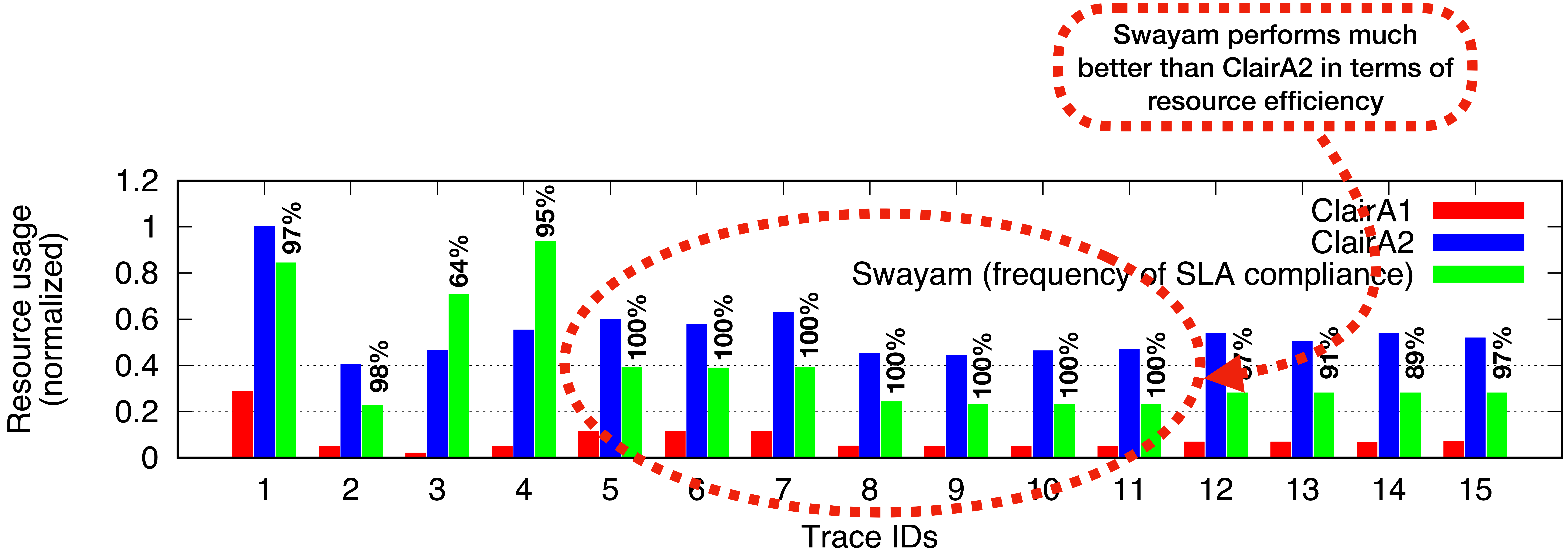

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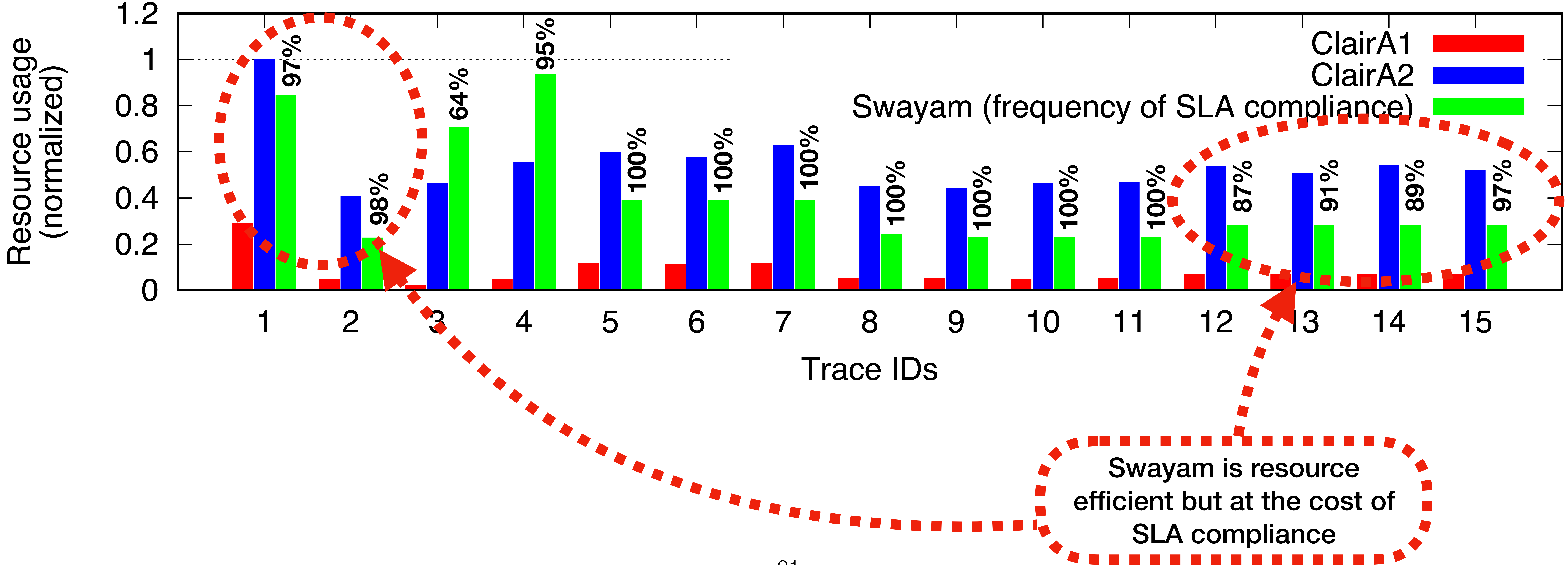

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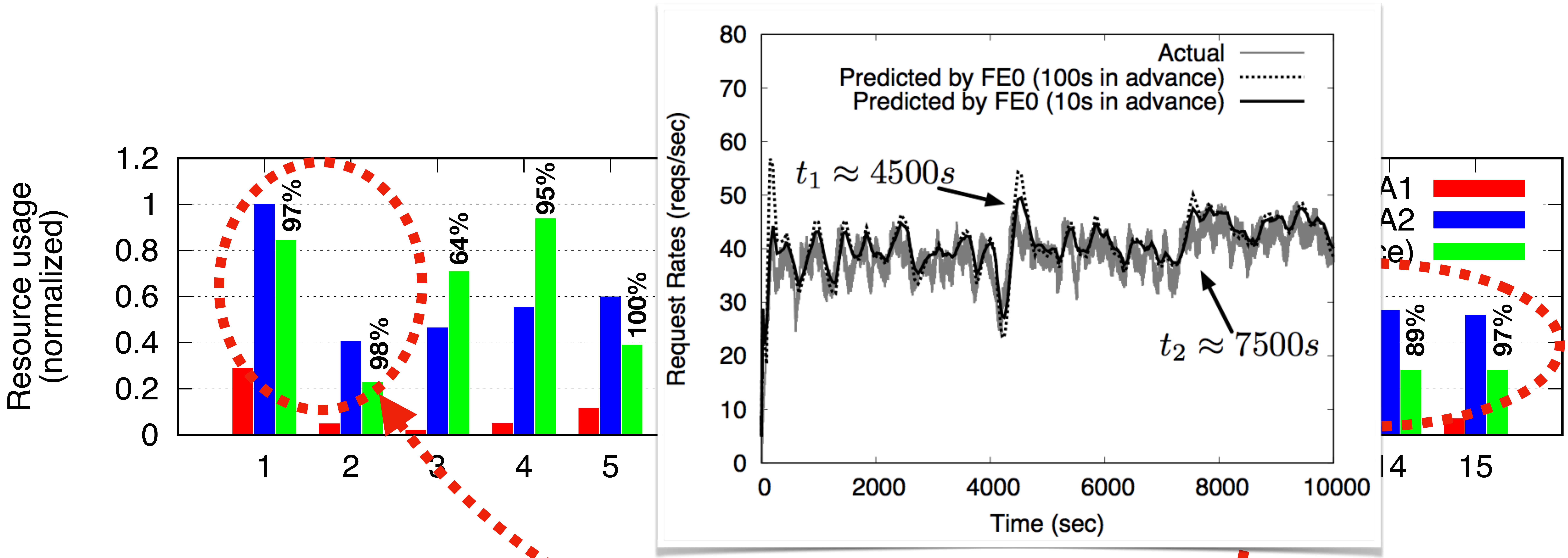
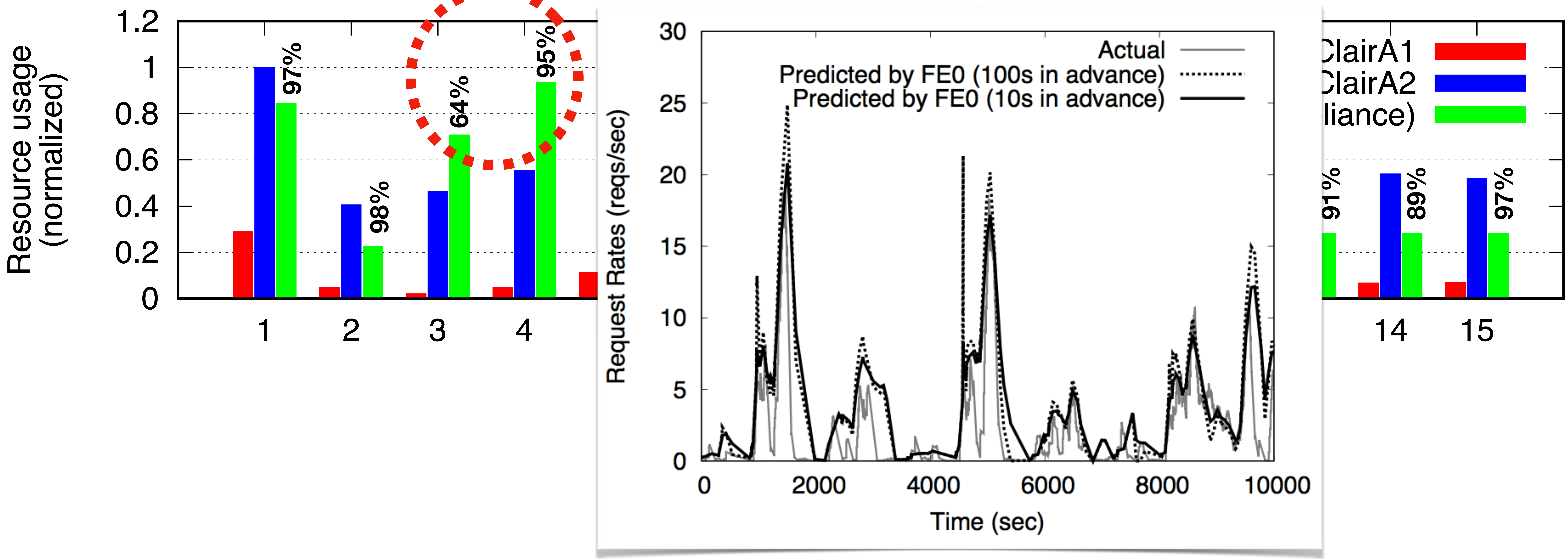


Swayam is resource efficient but at the cost of SLA compliance

Resource usage vs. SLA compliance

Swayam seems to perform poorly
because of a very bursty trace



Summary

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- Swayam strikes a good balance, for MLaaS prediction serving
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  ➡ at the cost of occasional SLA violations
- Easy integration into any existing request-response architecture

Thank you. Questions?