Apparate

Rethinking Early Exits to Tame Latency-Throughput Tensions in ML Serving

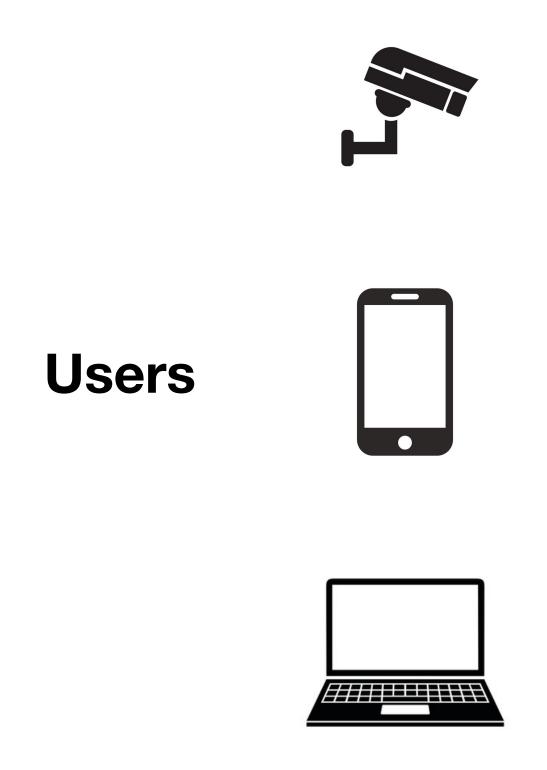
Yinwei Dai*, Rui Pan*, Anand Iyer, Kai Li, Ravi Netravali



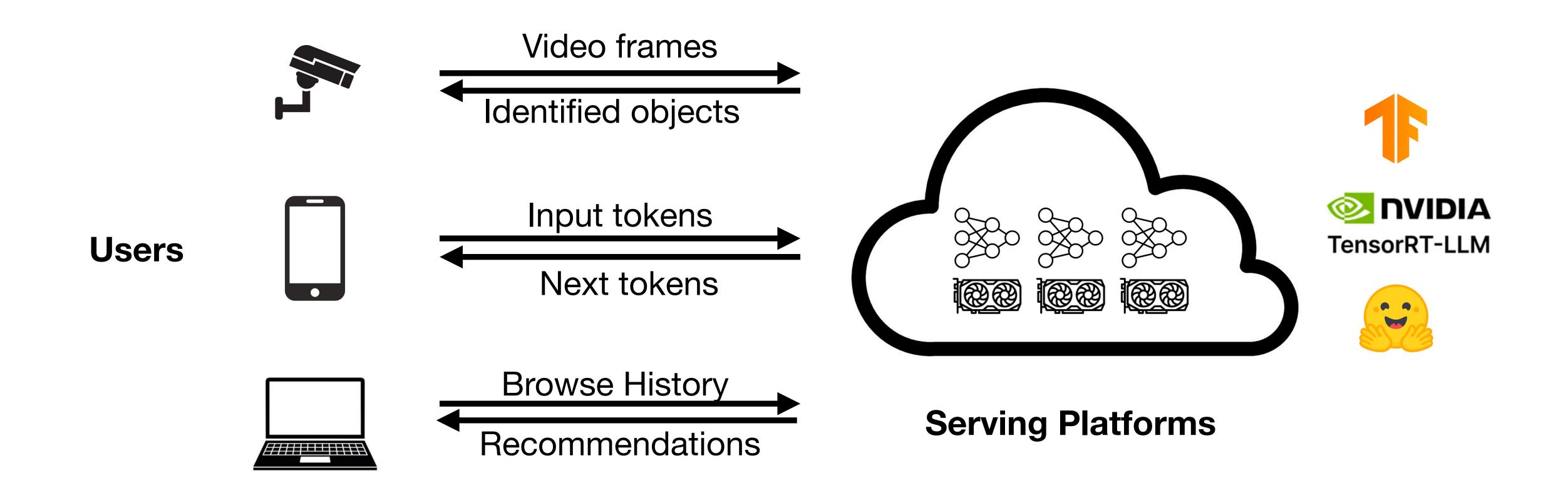


11/06/2024 SOSP 2024

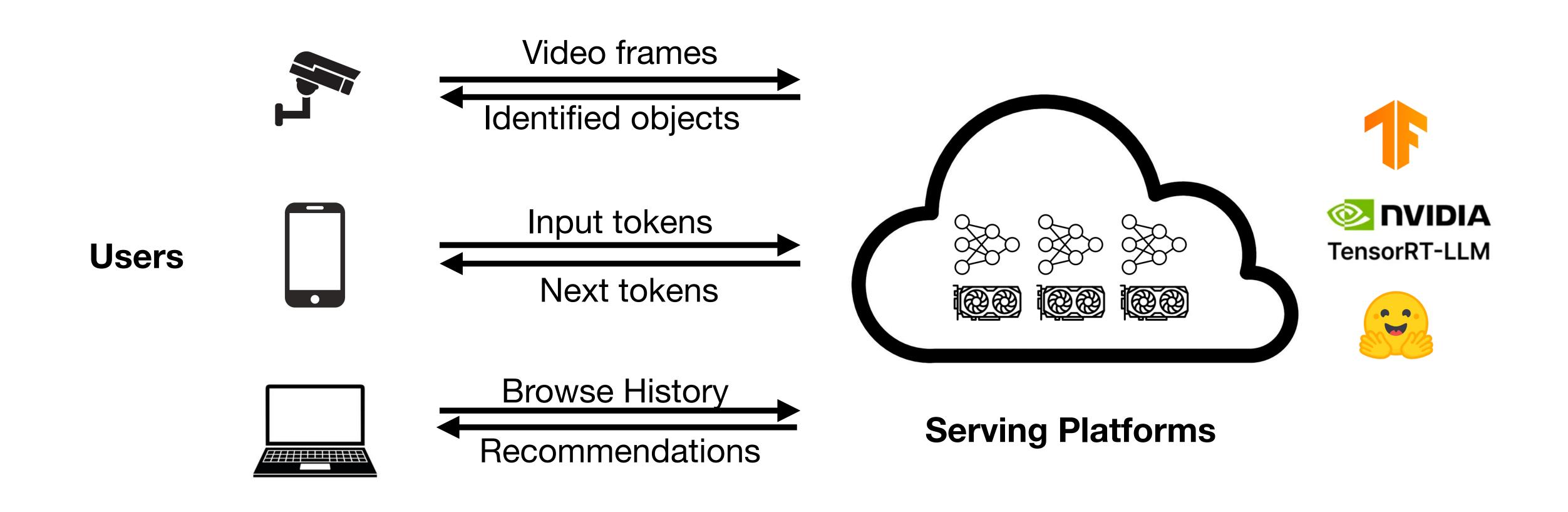
ML-Based Interactive Applications Are Pervasive



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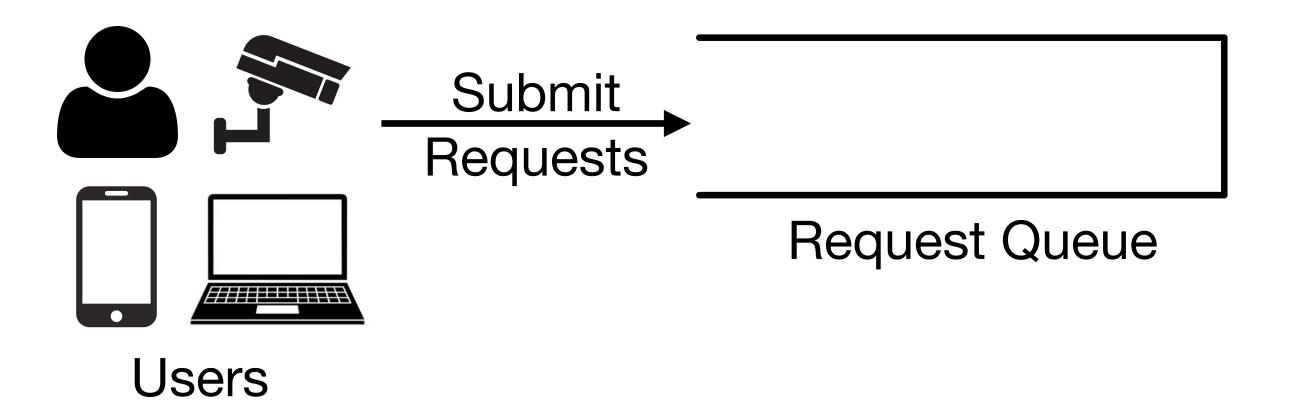


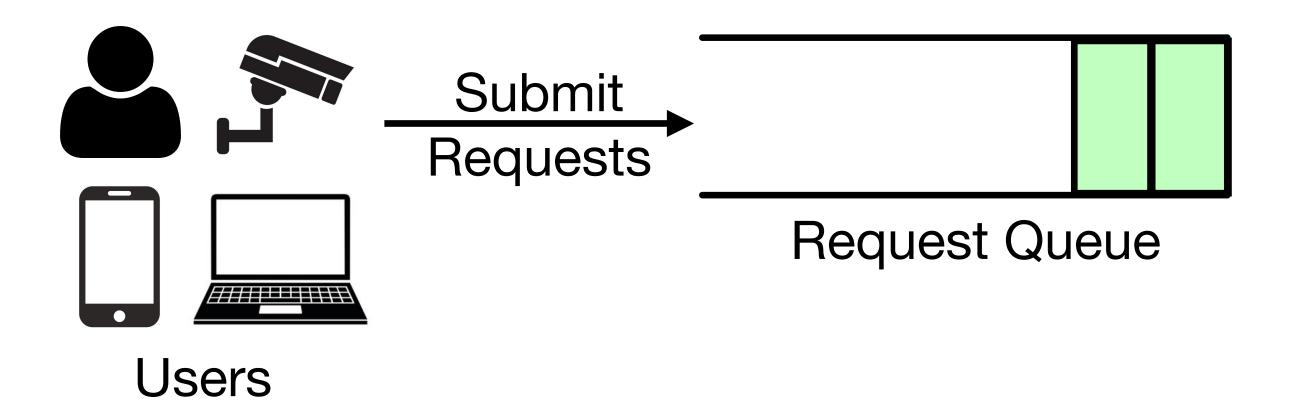
ML-Based Interactive Applications Are Pervasive

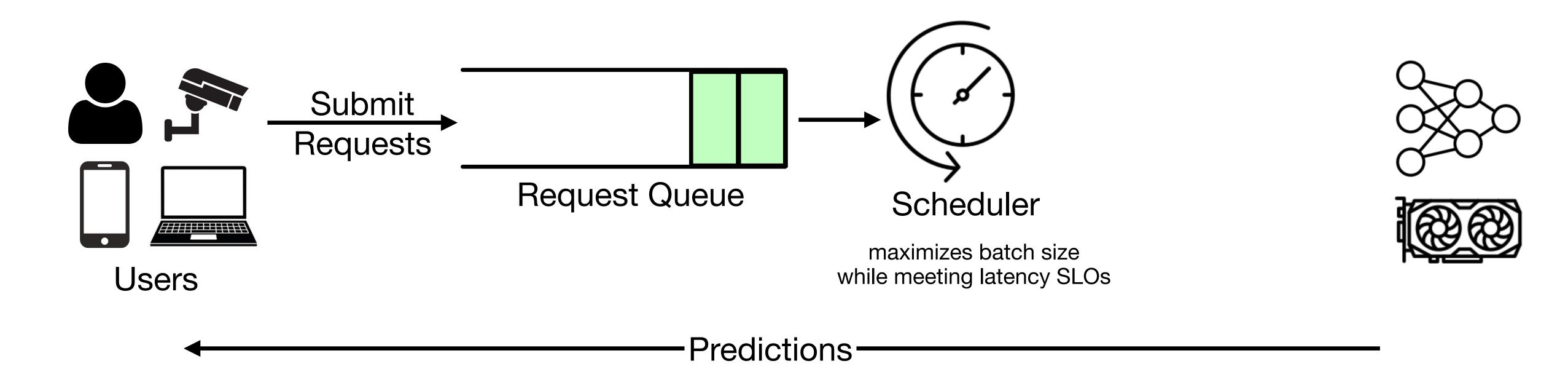


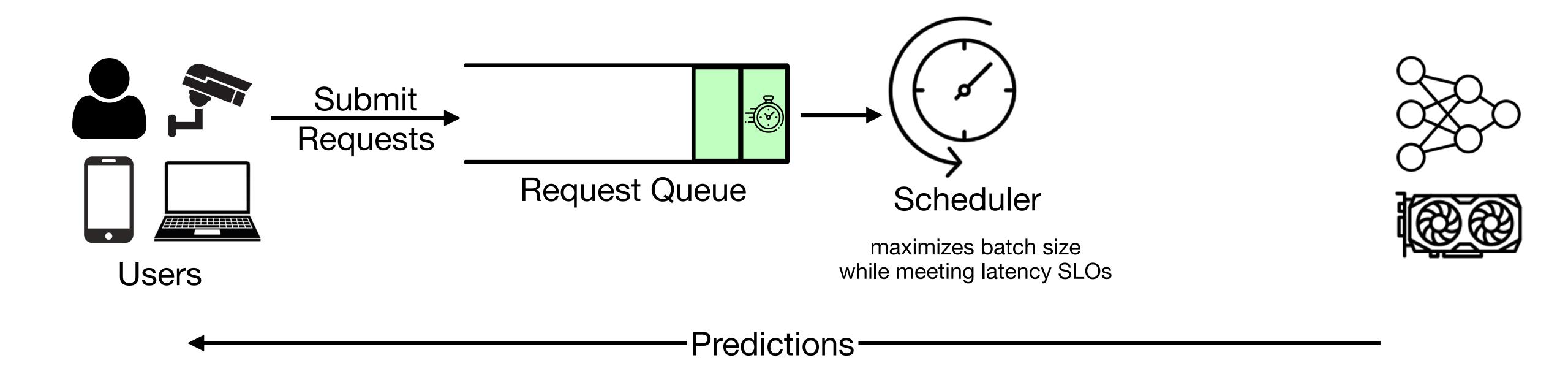
Goal: maximize throughput and meet latency SLOs

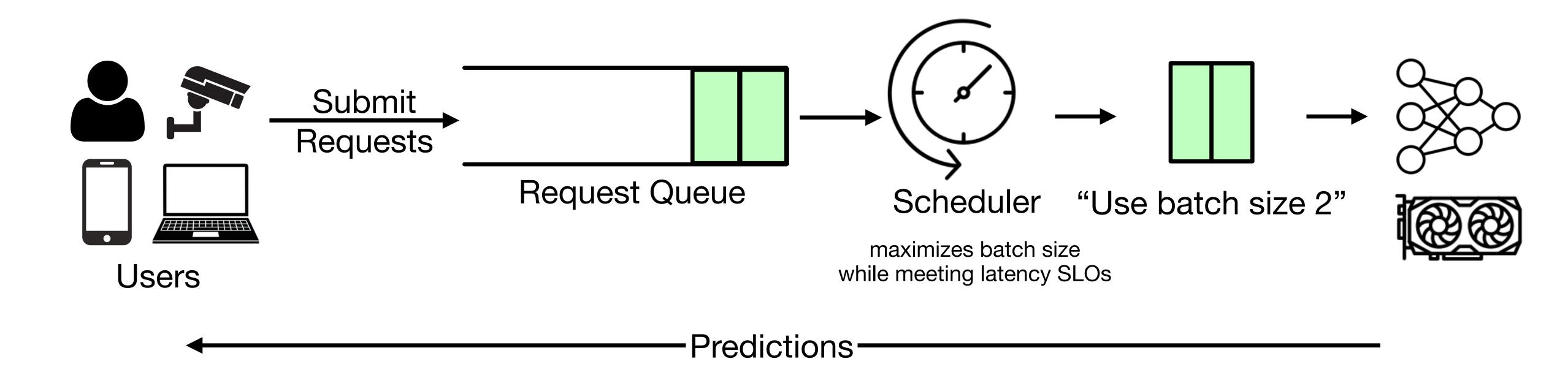


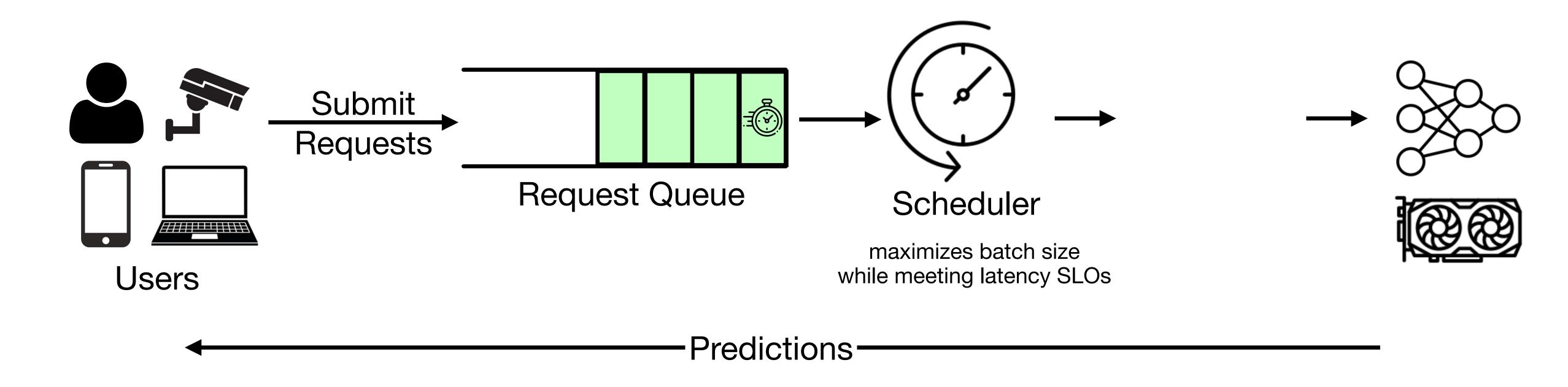


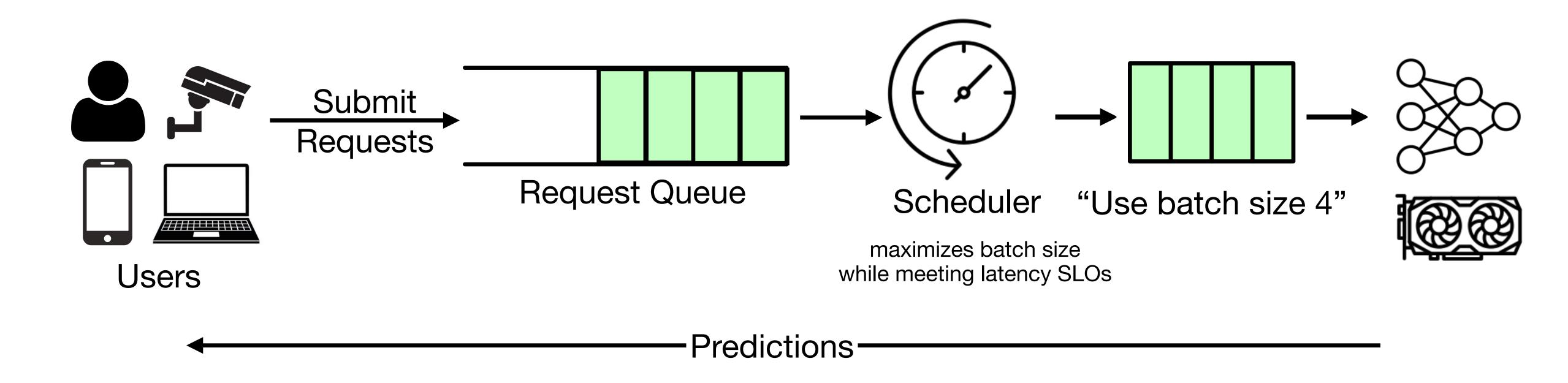




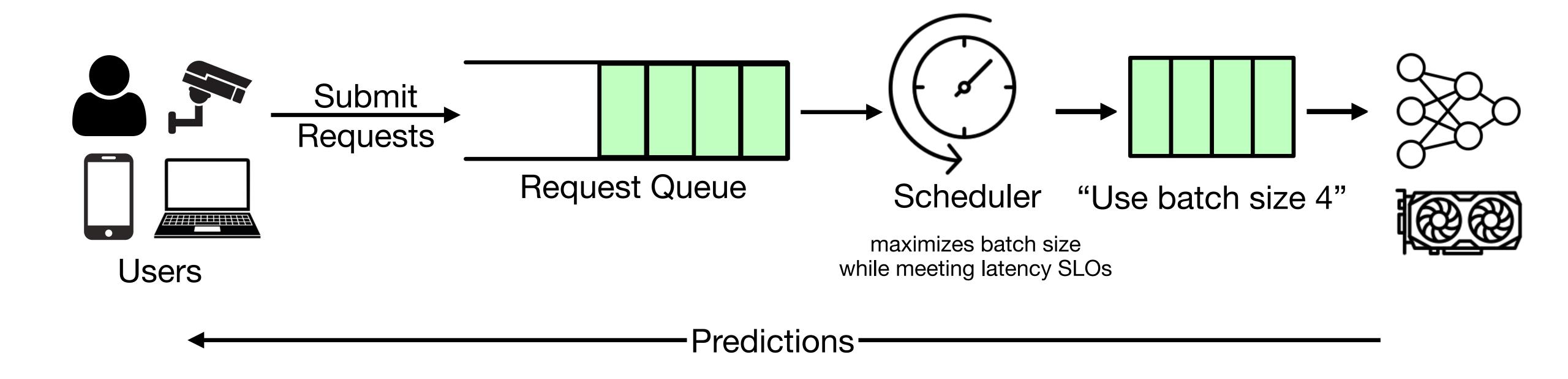








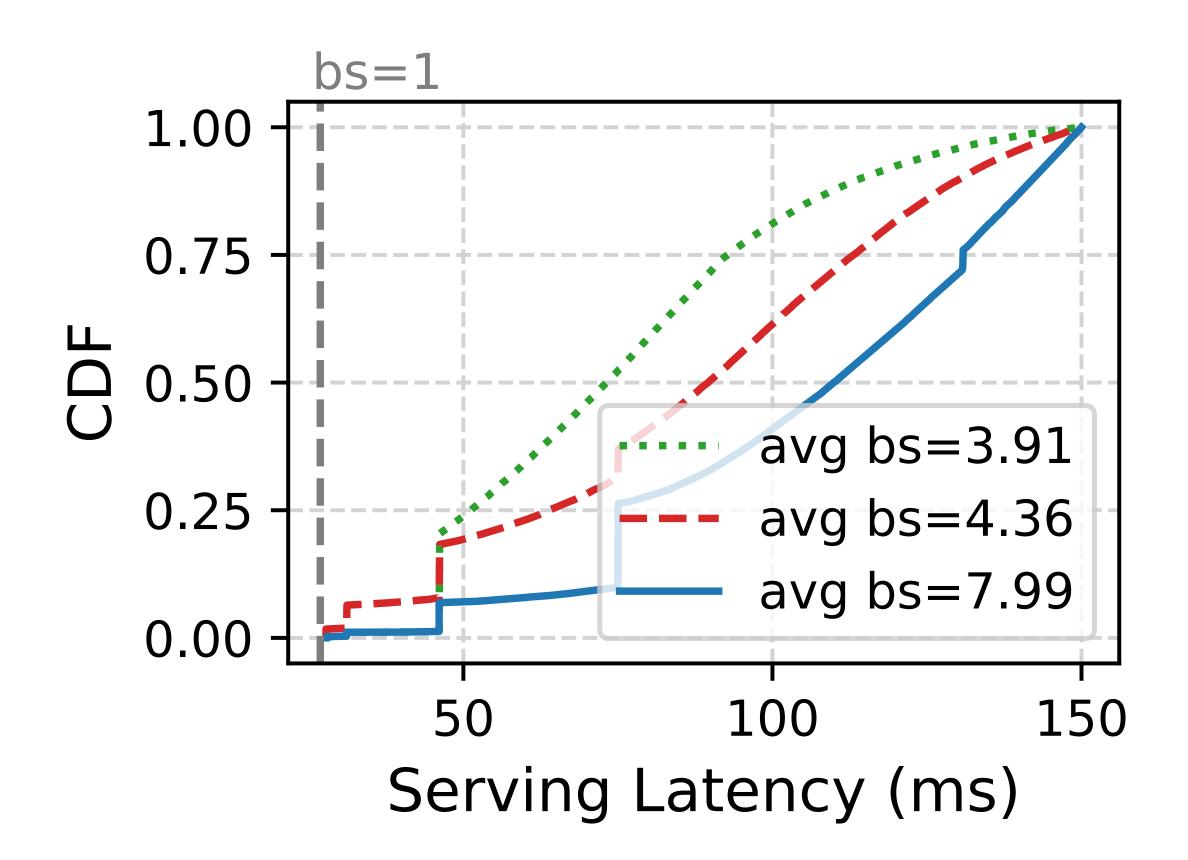
to maximize throughput and minimize SLO violations



Existing systems view latency utility as binary: meeting SLOs or not

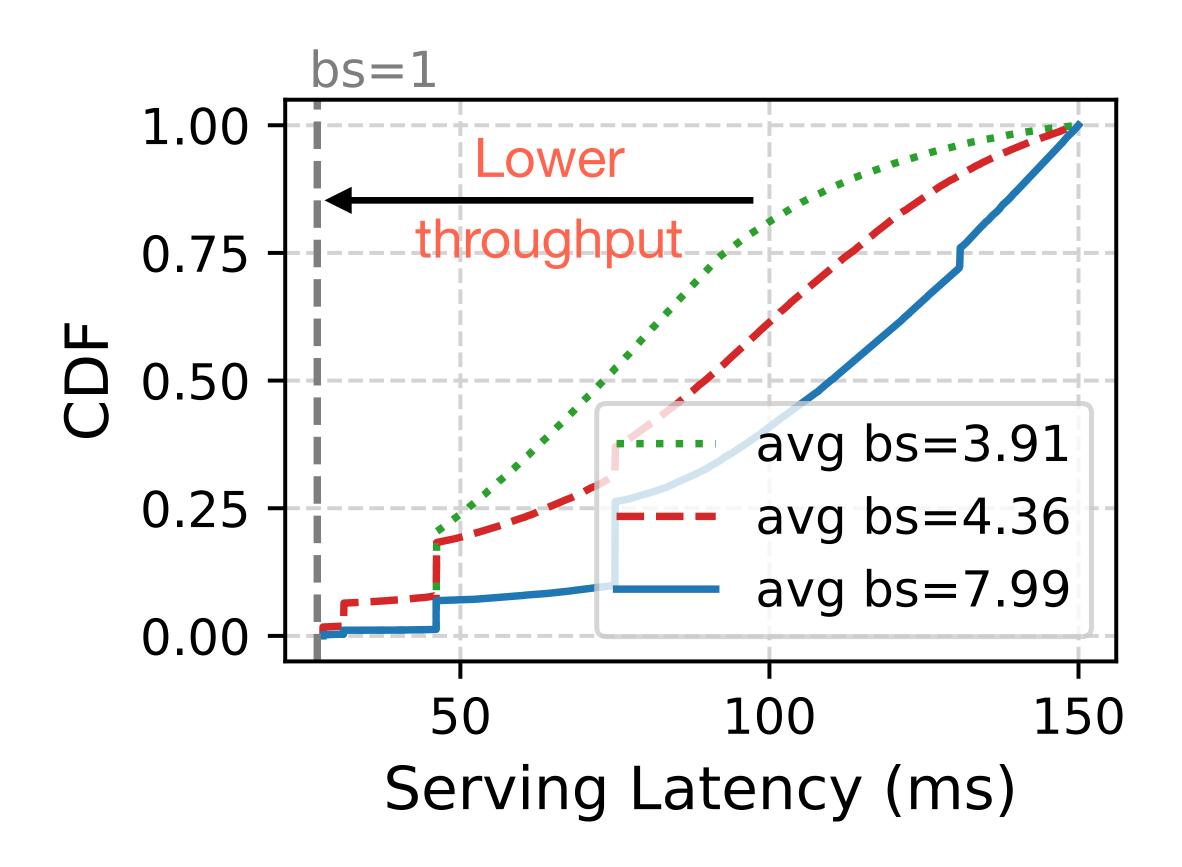
Batch Size Tuning

Presents harsh latency-throughput tradeoffs



Batch Size Tuning

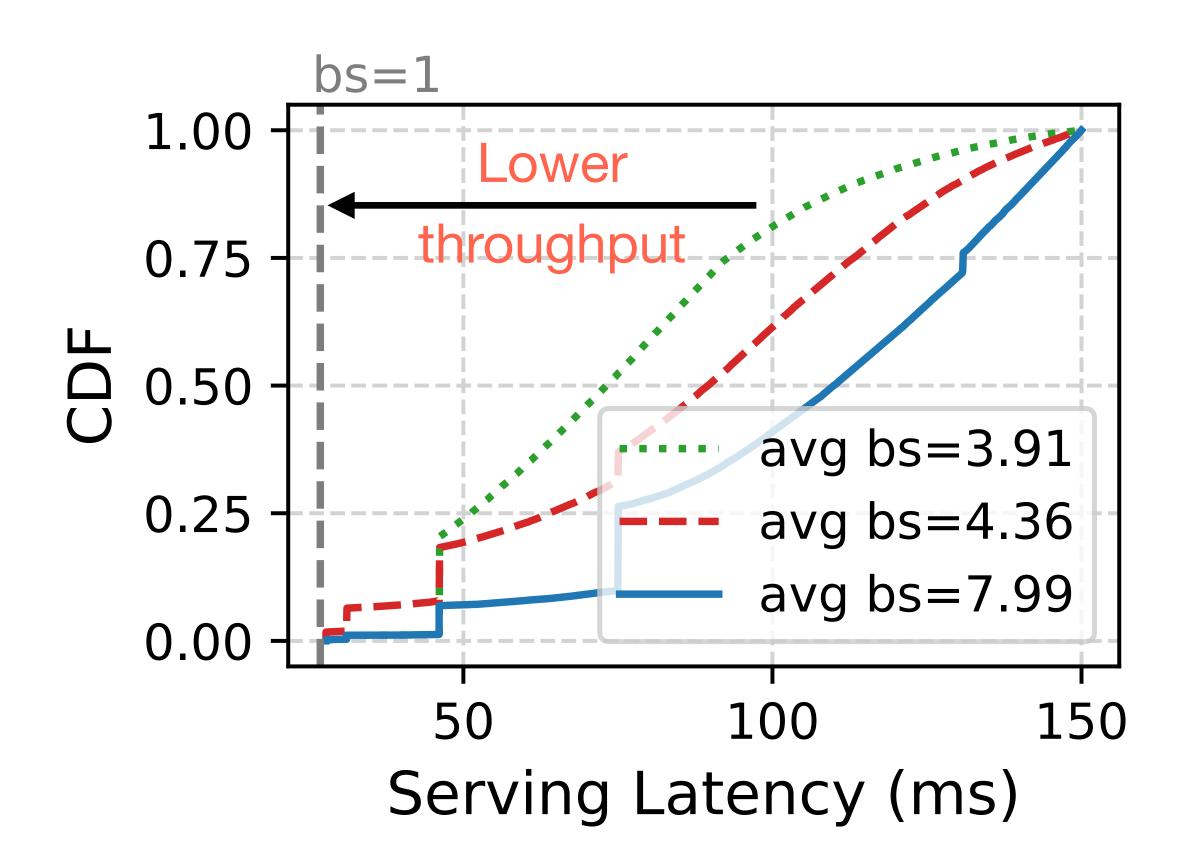
Presents harsh latency-throughput tradeoffs



Median latency improvements (17–39%) cause up to 3.6× throughput reductions

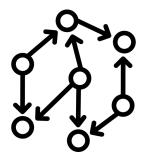
Batch Size Tuning

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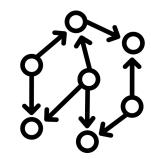


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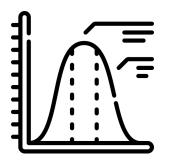
Batch size is too coarse-grained to trade off per-input latency

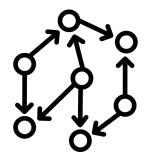


Models are over-parametrized

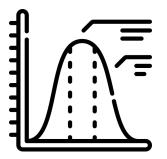


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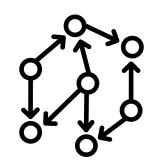




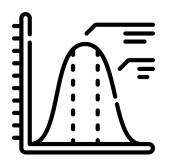
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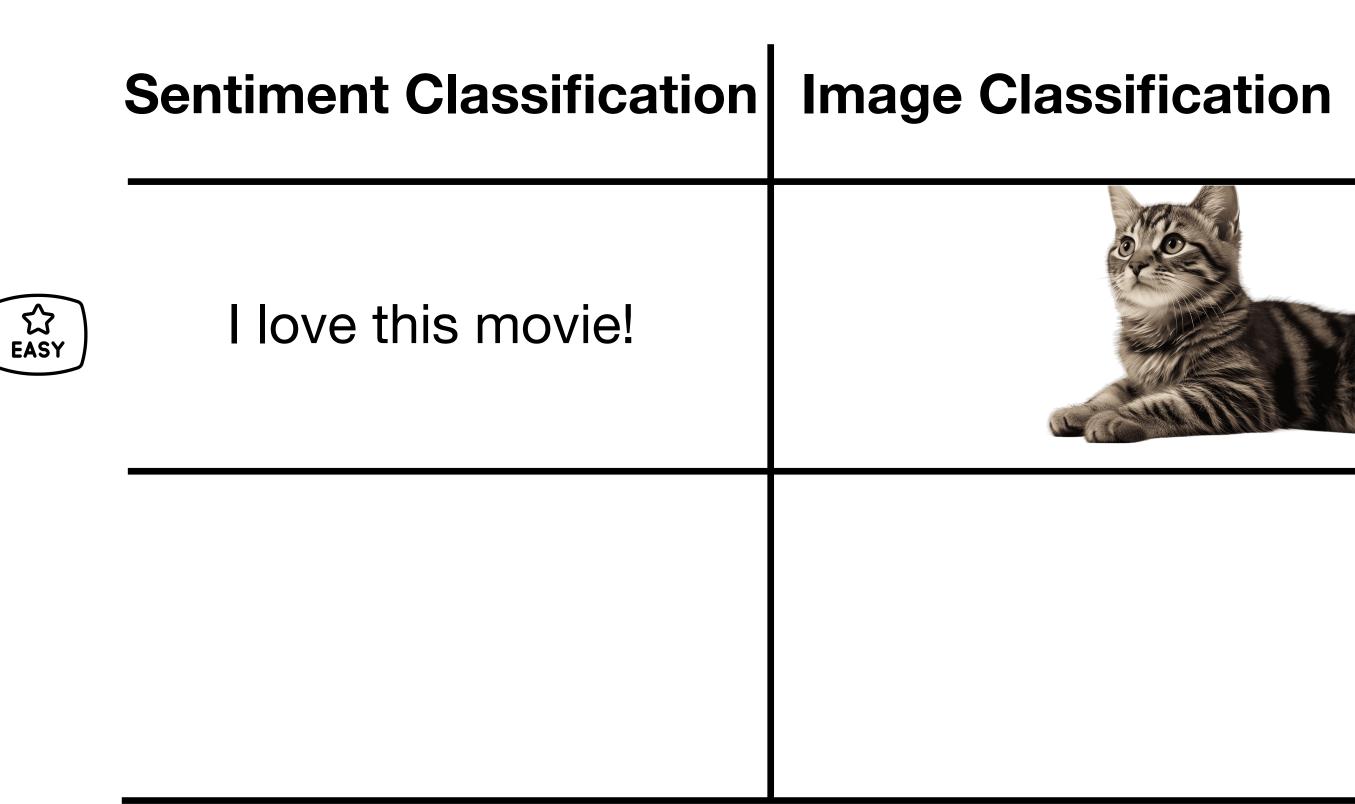


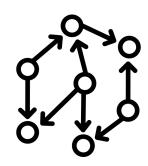
Sentiment Classification	Image Classification



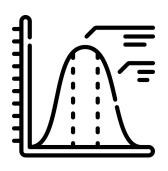
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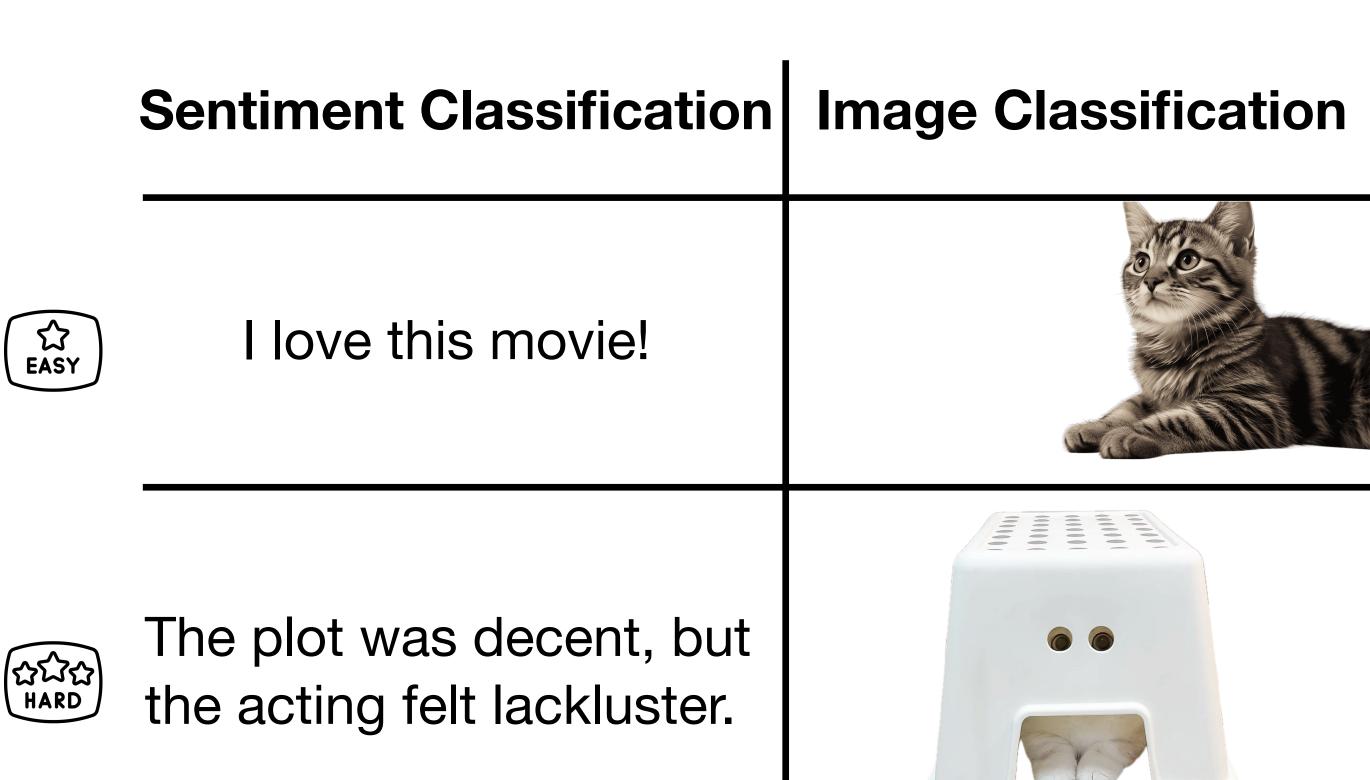


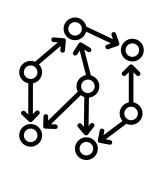




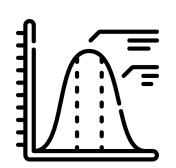
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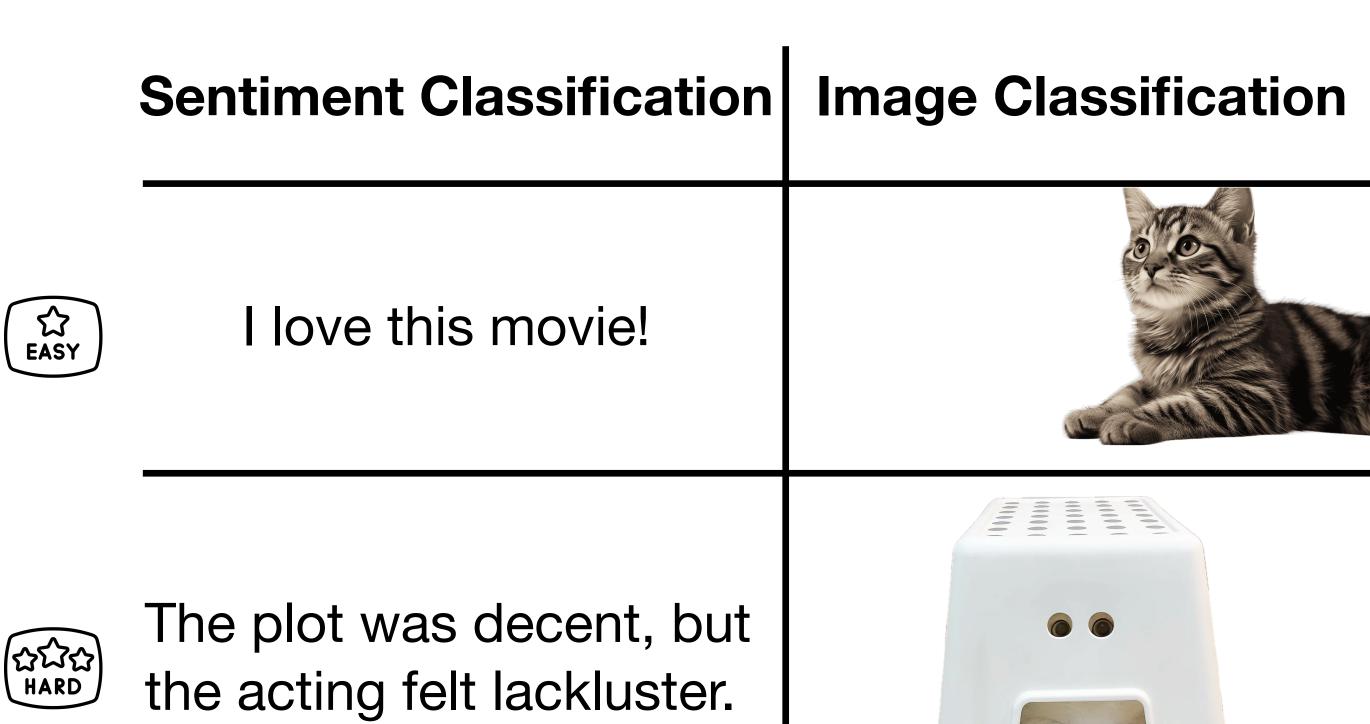
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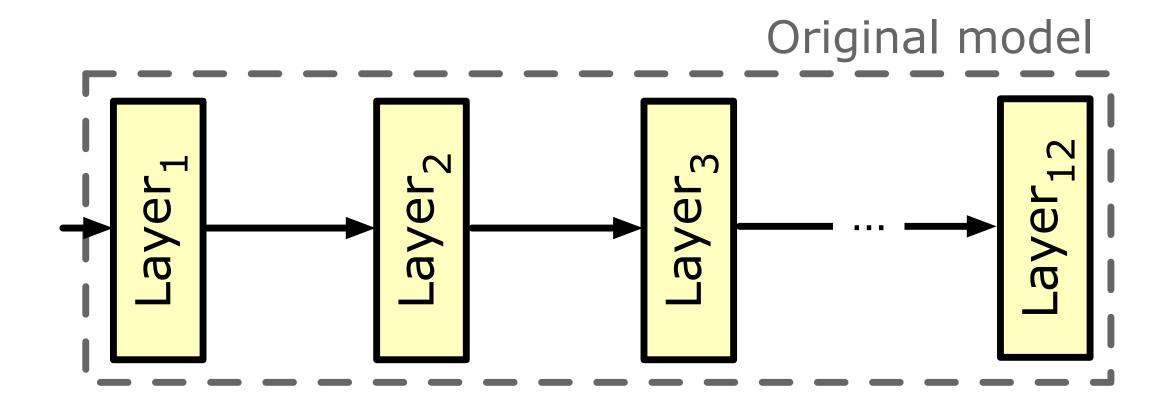


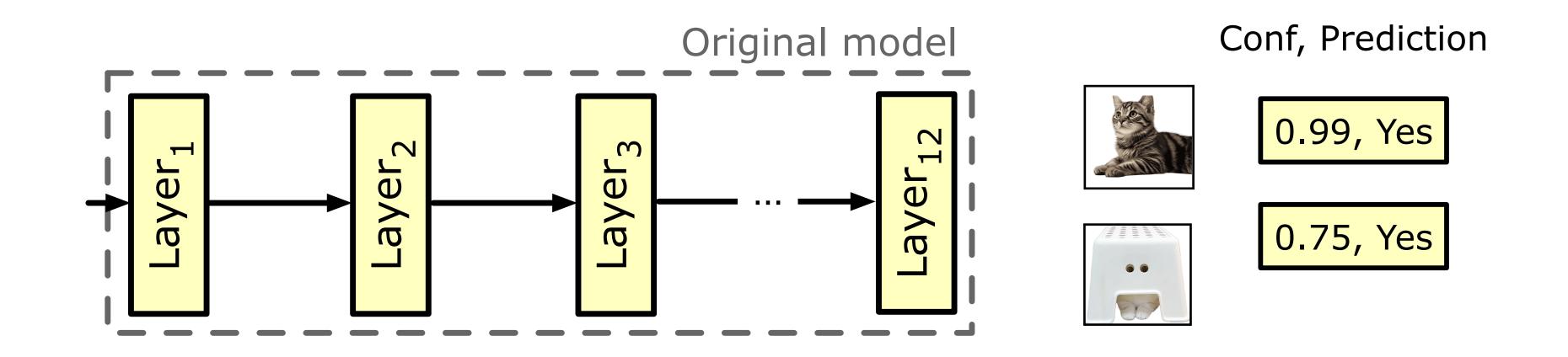
Input easiness varies



Adapt per-input compute!

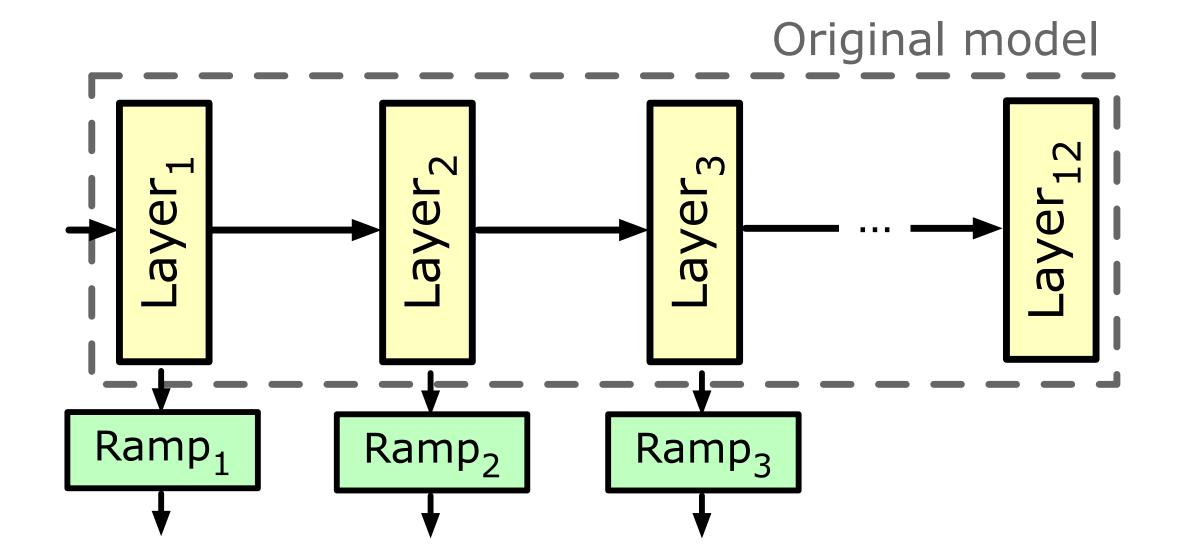




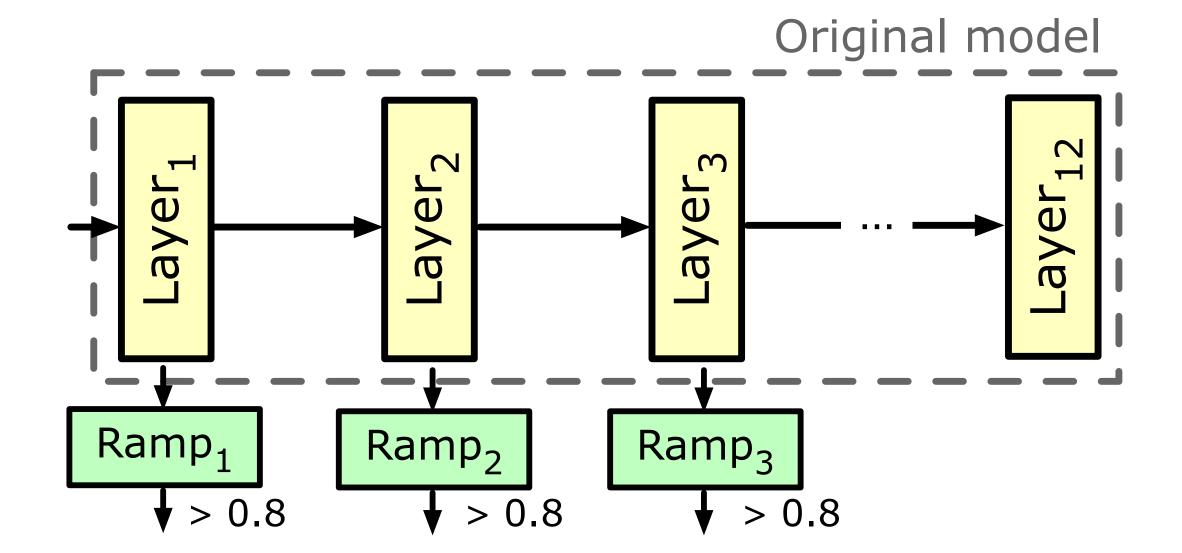


by allowing "easy" inputs to exit early

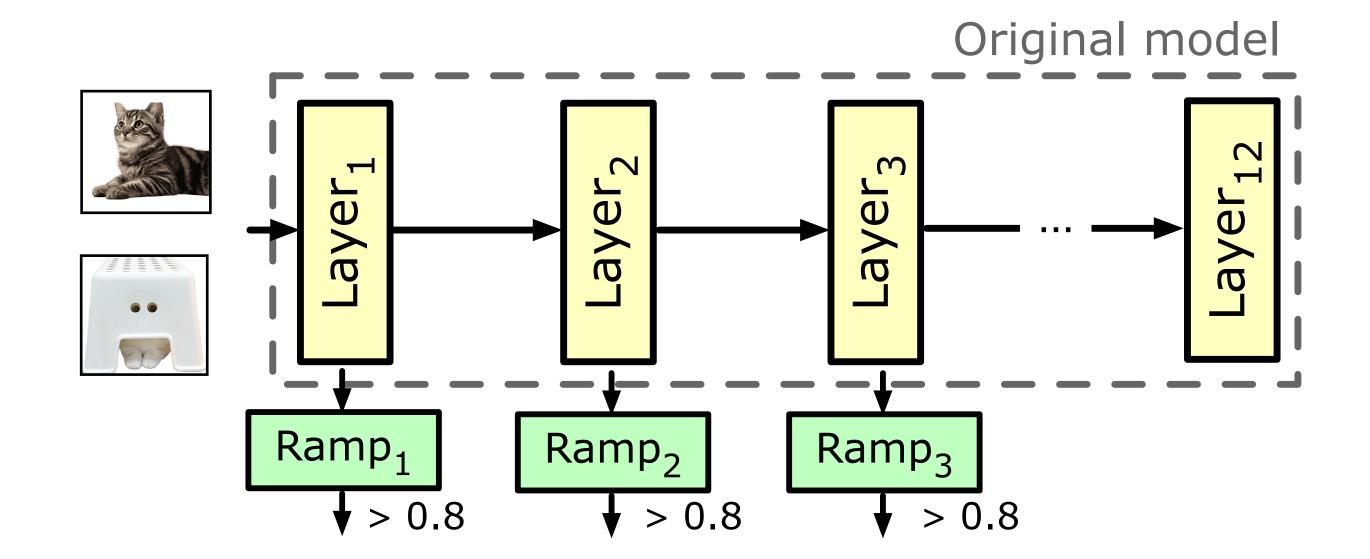
Augment intermediate layers with ramps (intermediate classifiers)



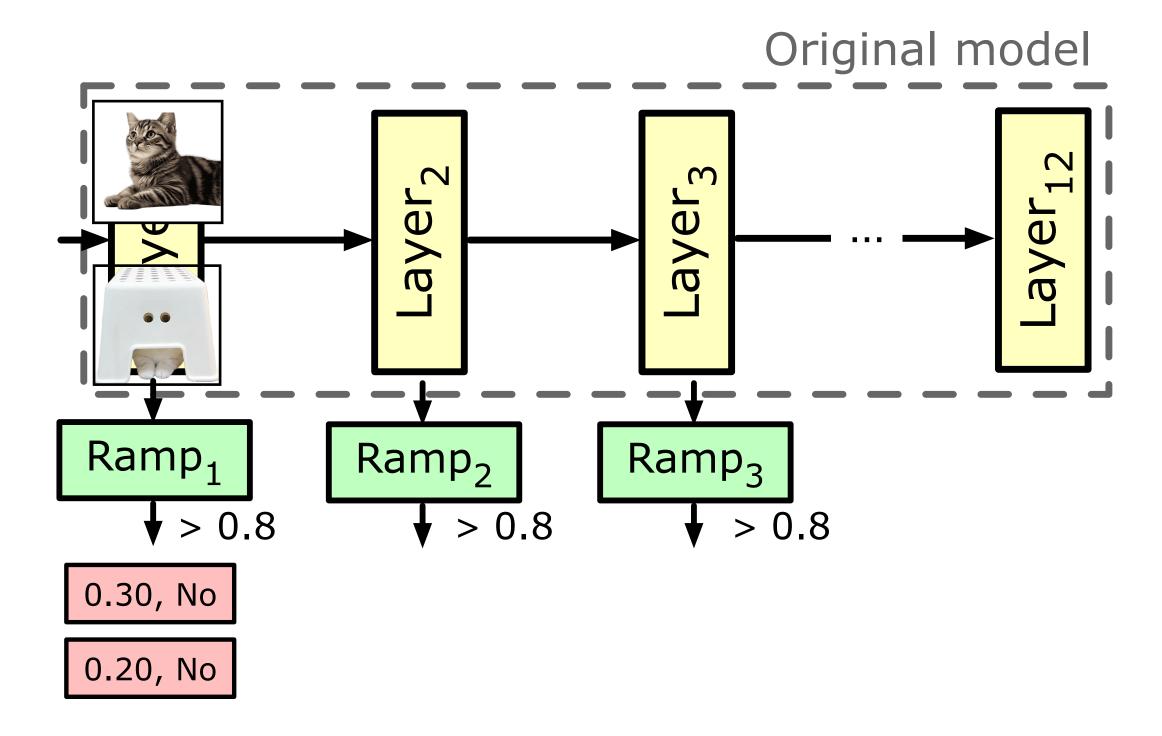
- Augment intermediate layers with ramps (intermediate classifiers)
- Exiting decisions: confidence > threshold (e.g., 0.8)



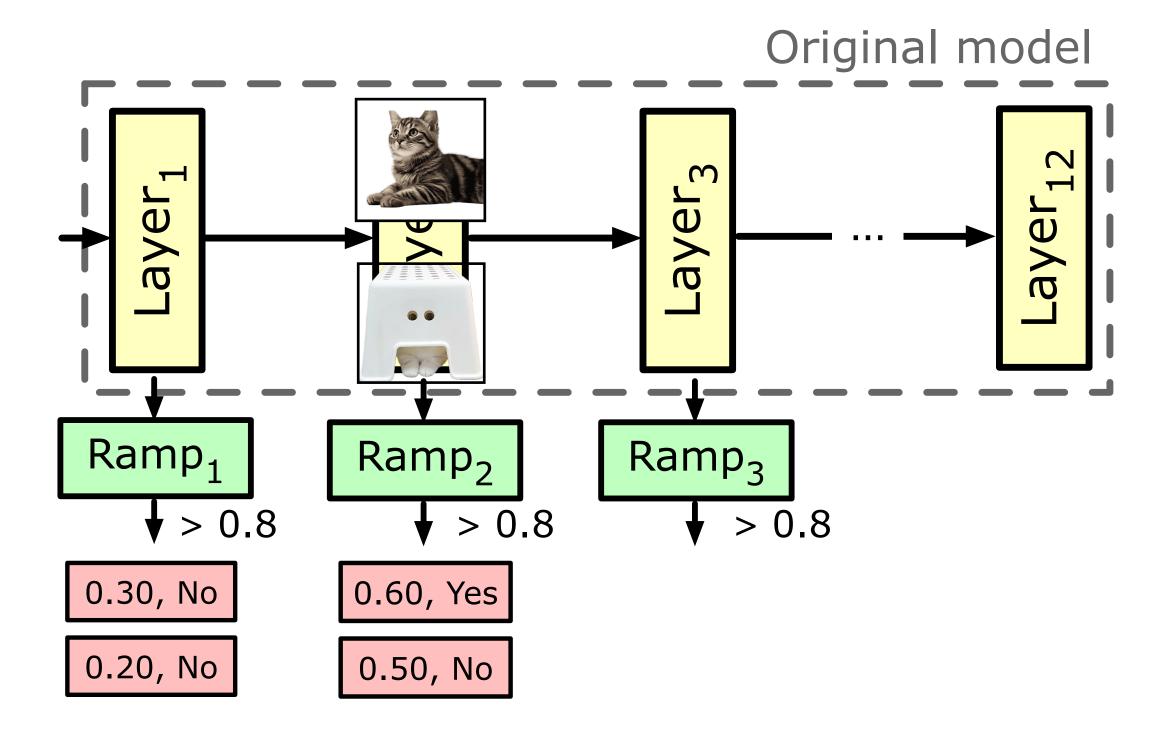
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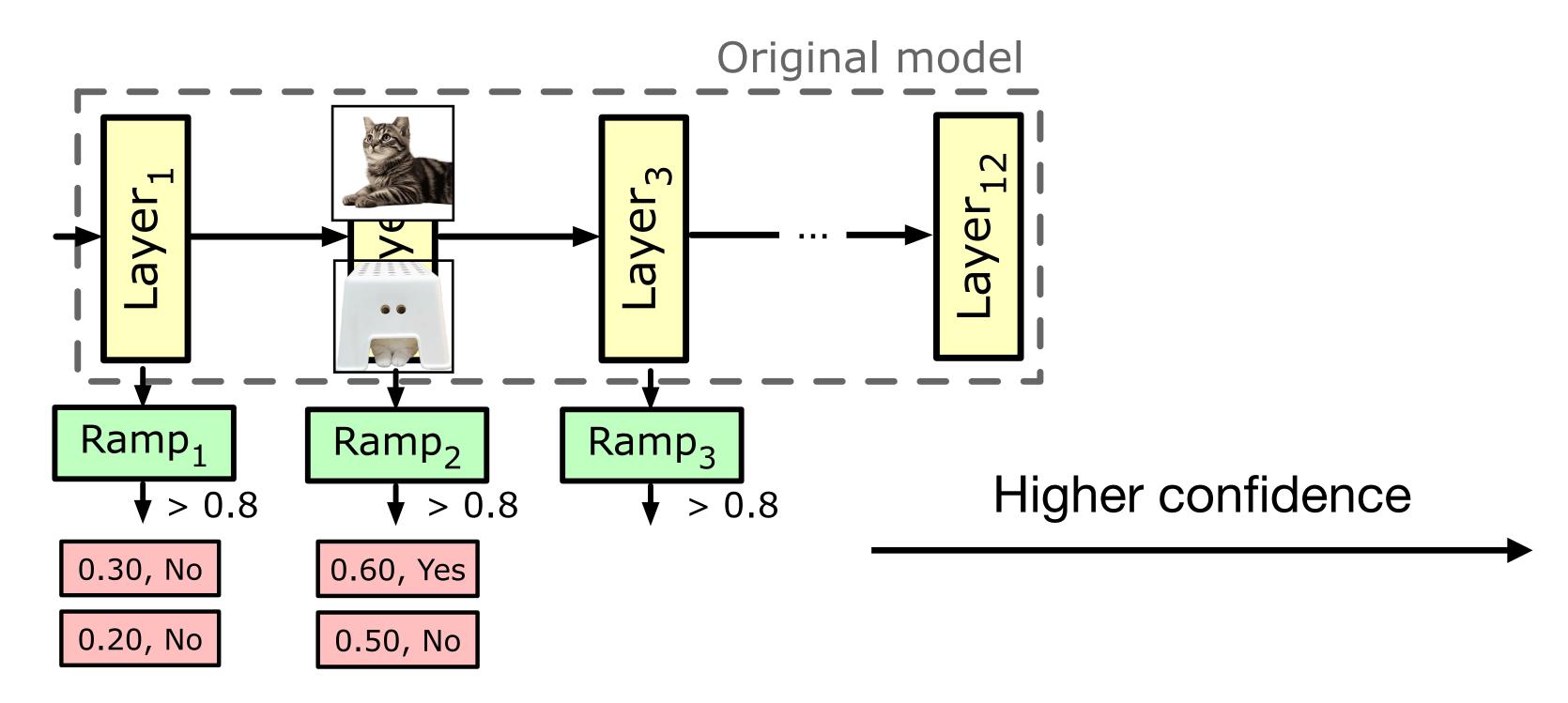
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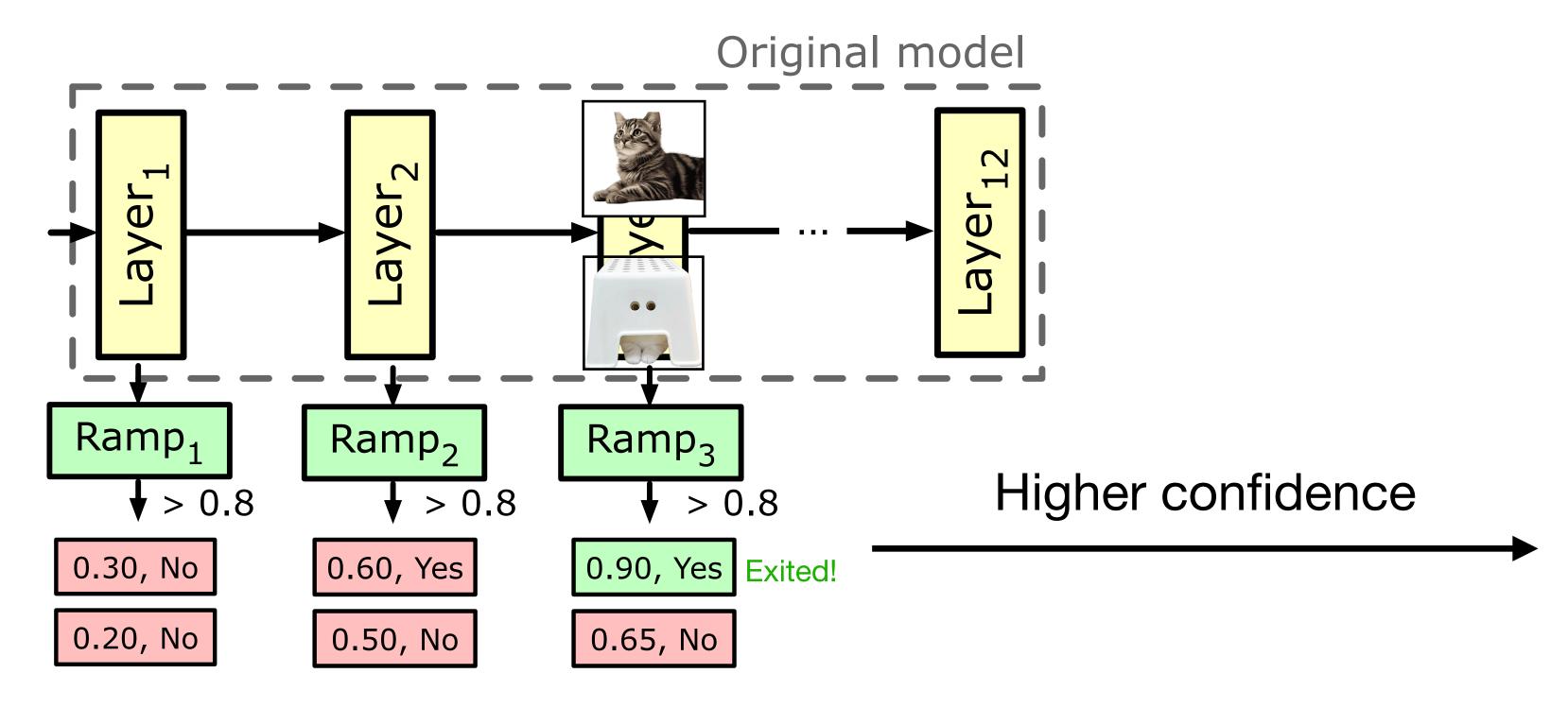
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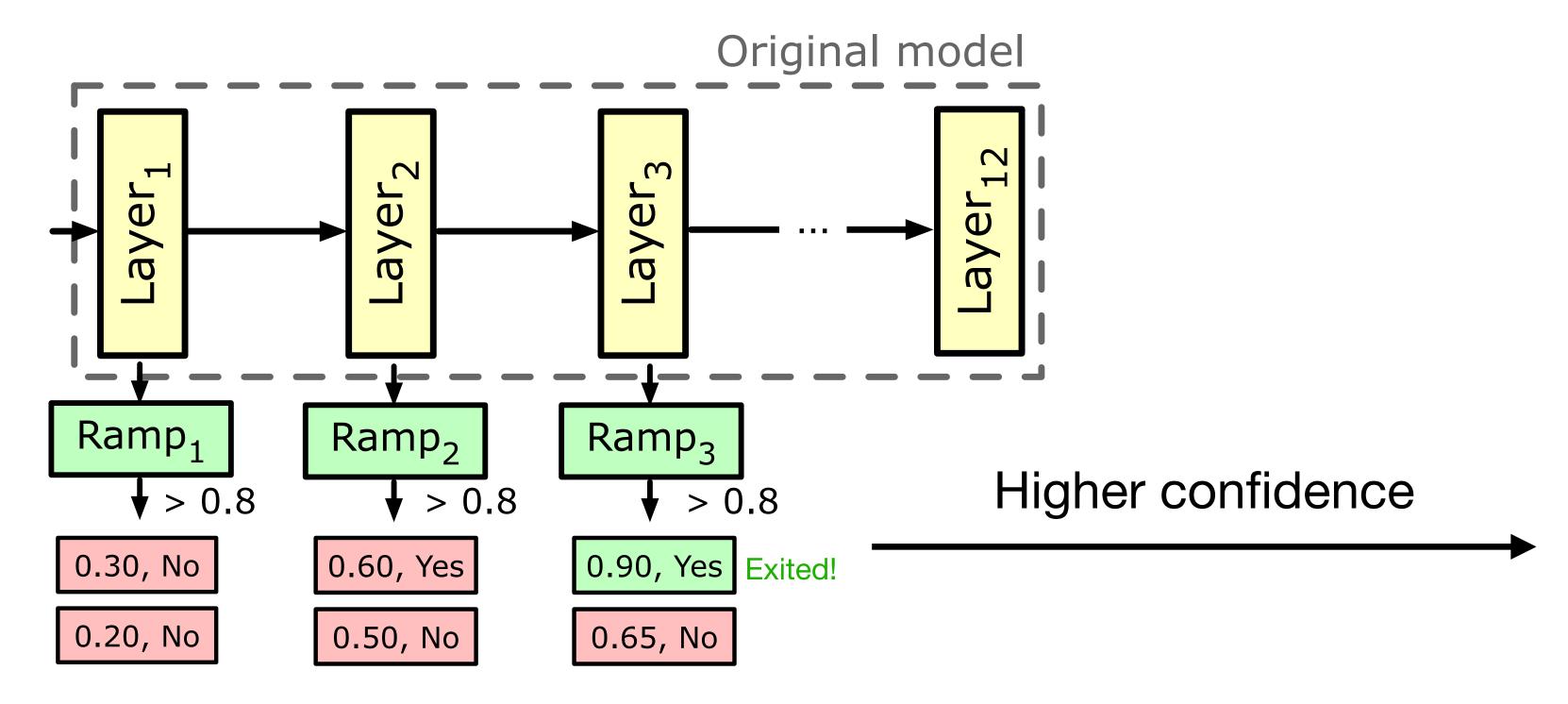
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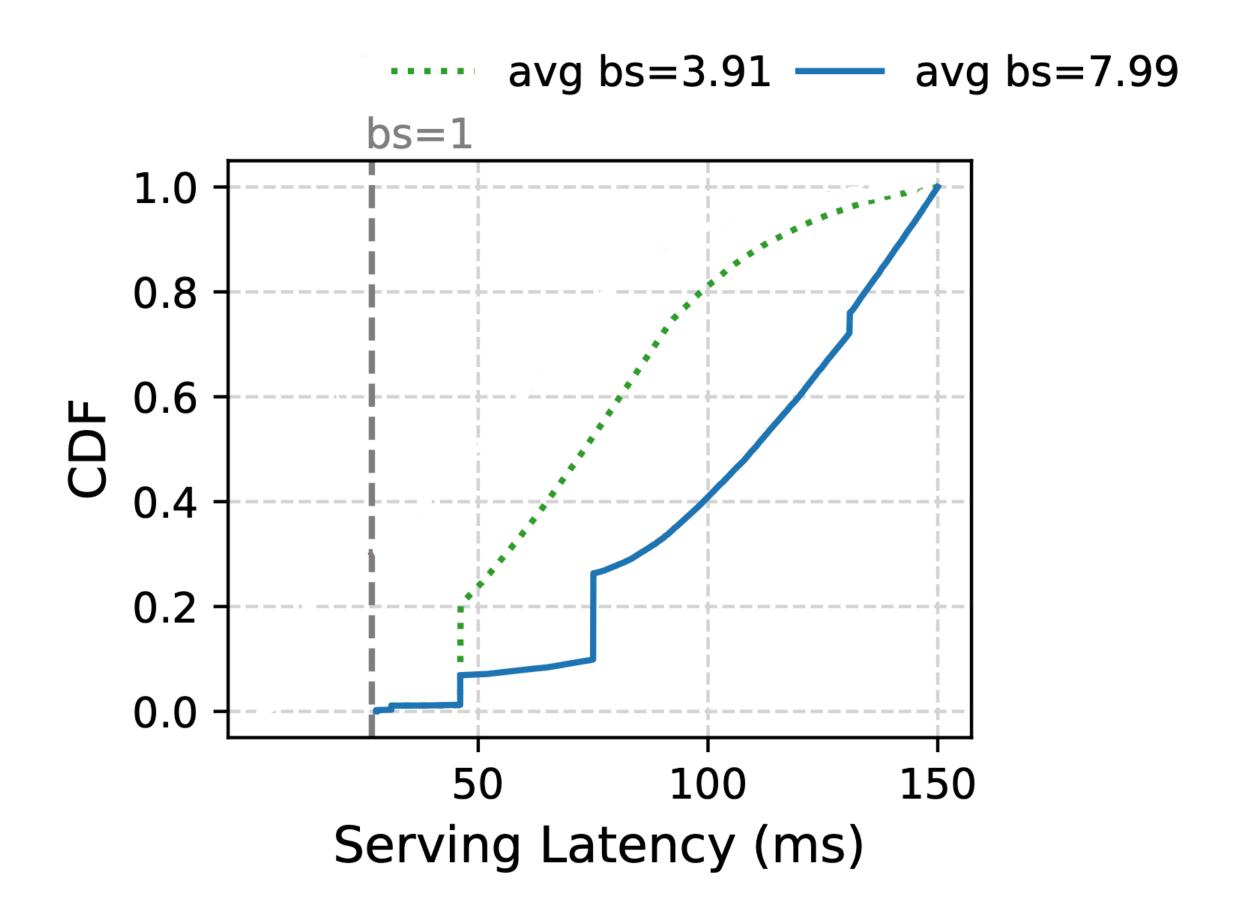


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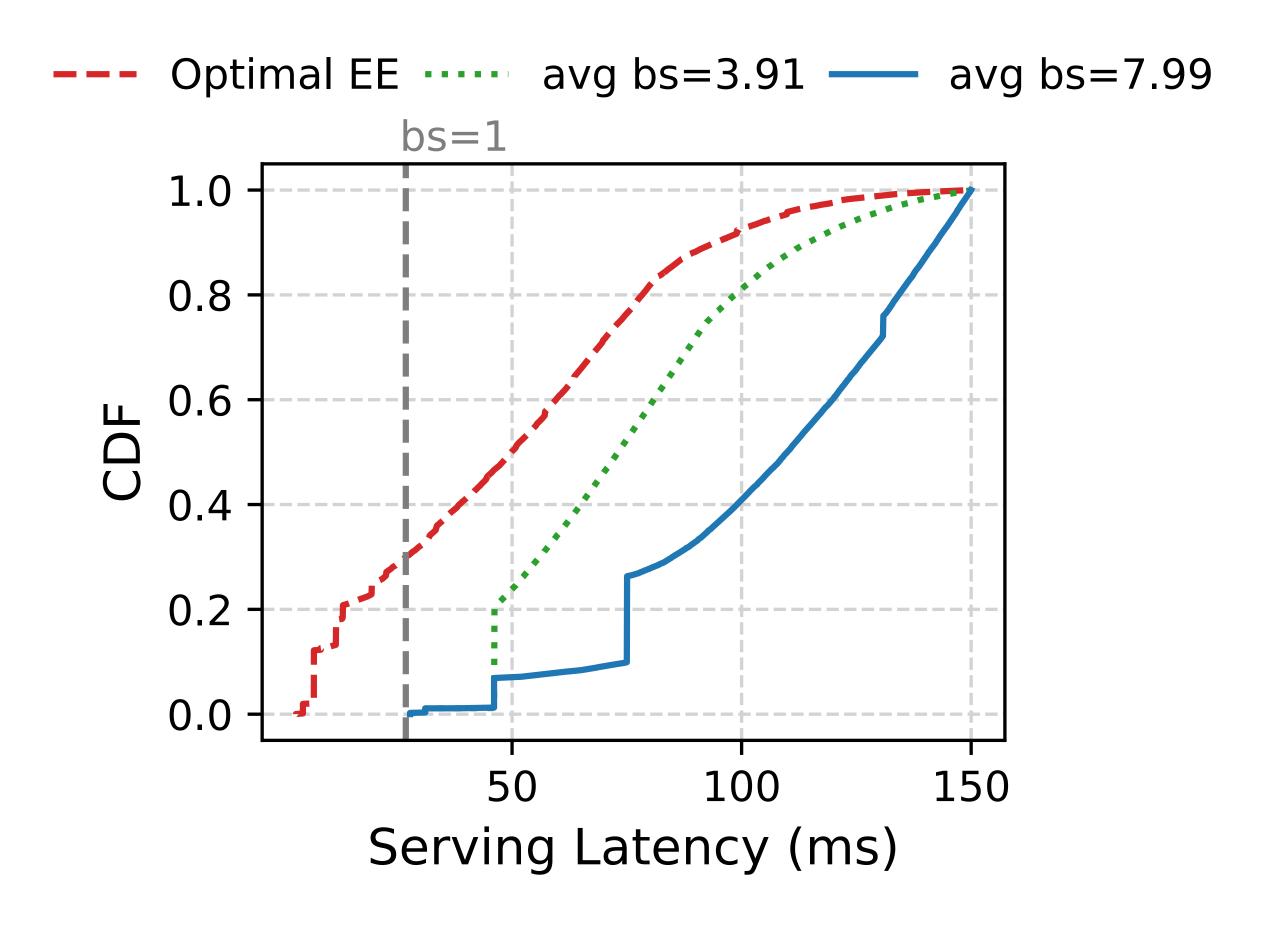


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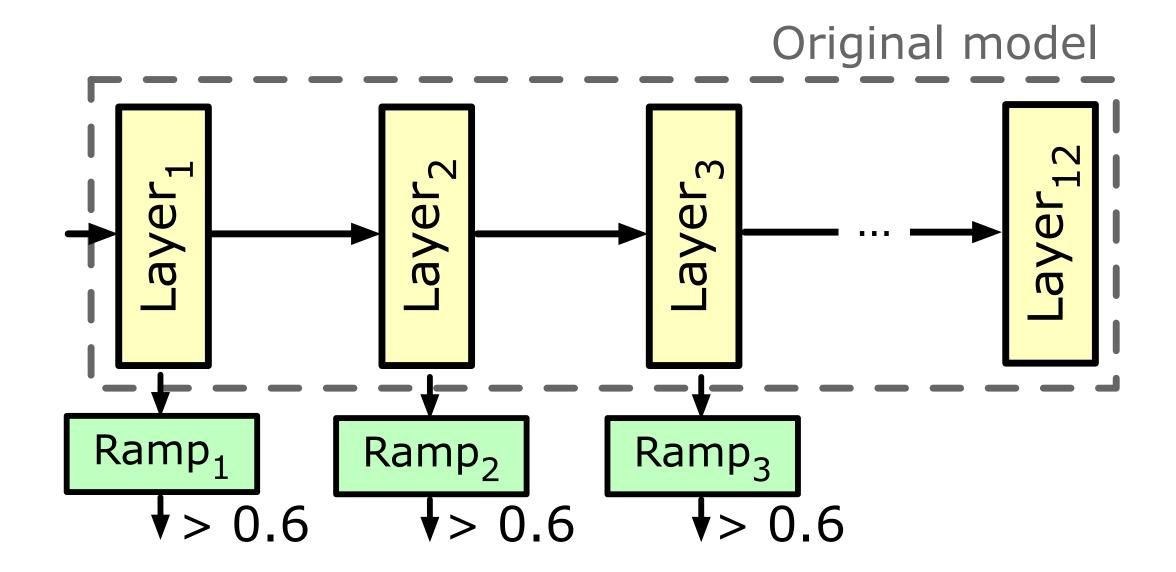


Optimal Early Exits minimize

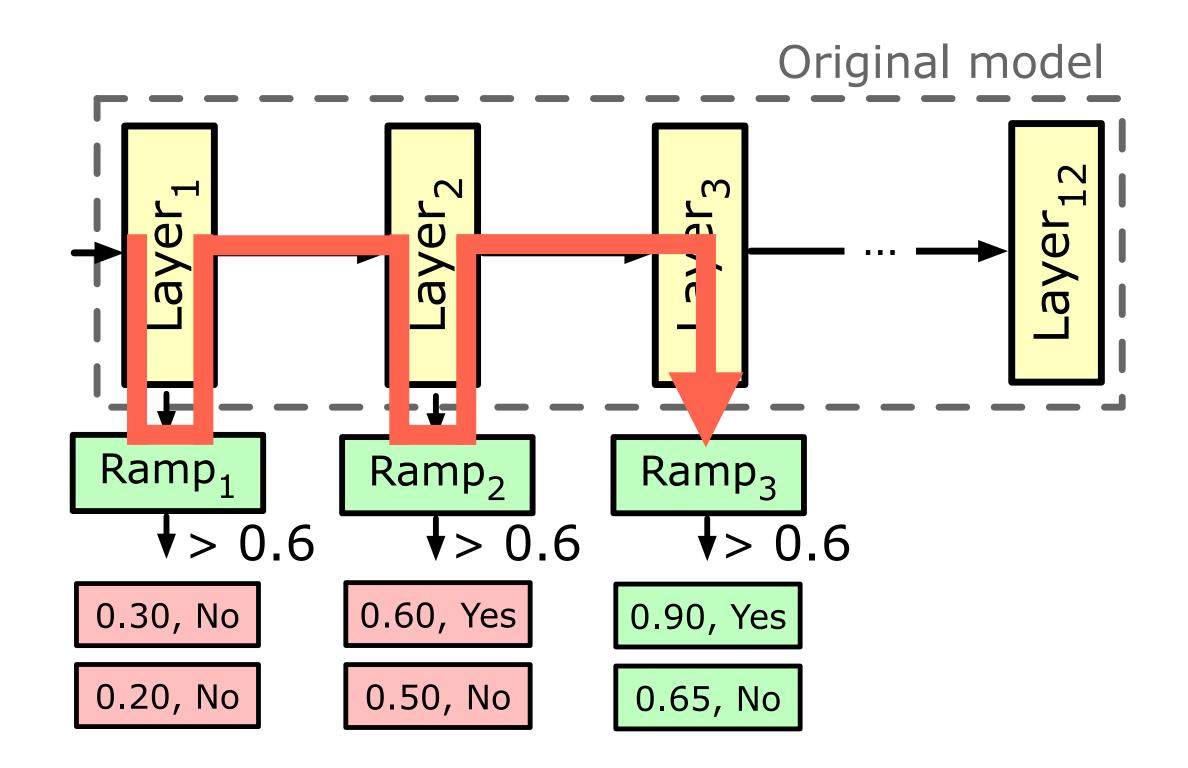
latency without sacrificing throughput

Early Exits: Practical Challenges

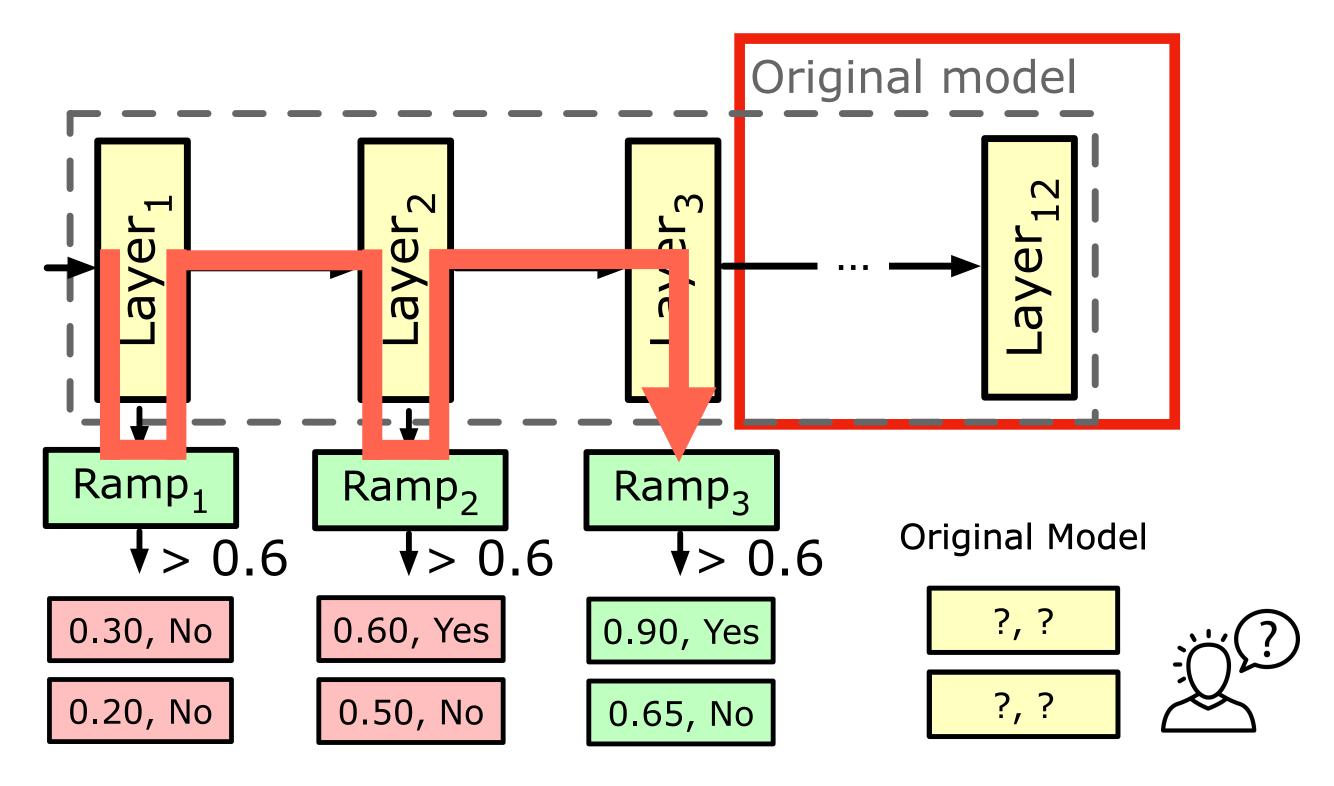
low accuracy and high overheads



low accuracy and high overheads

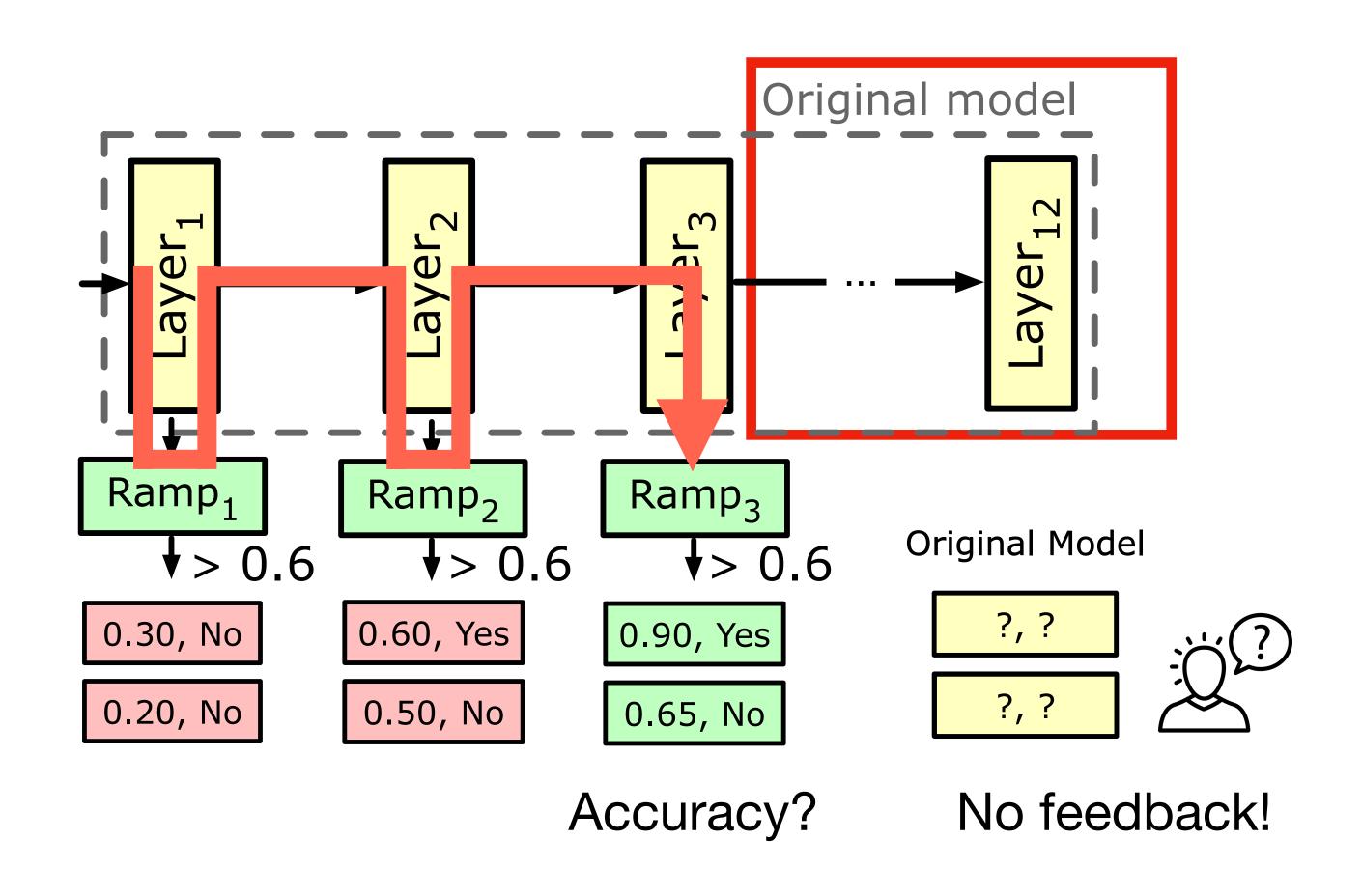


low accuracy and high overheads

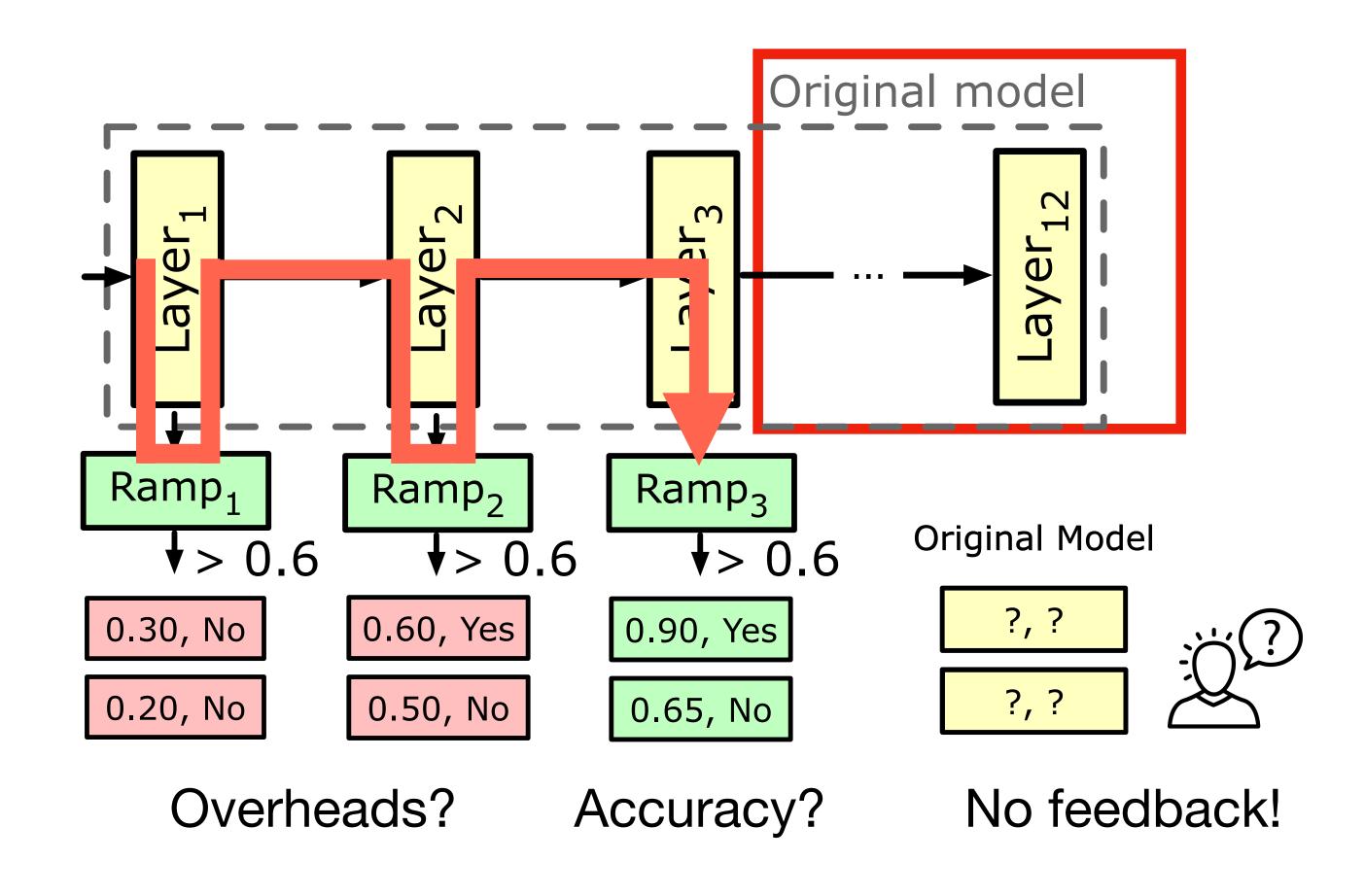


No feedback!

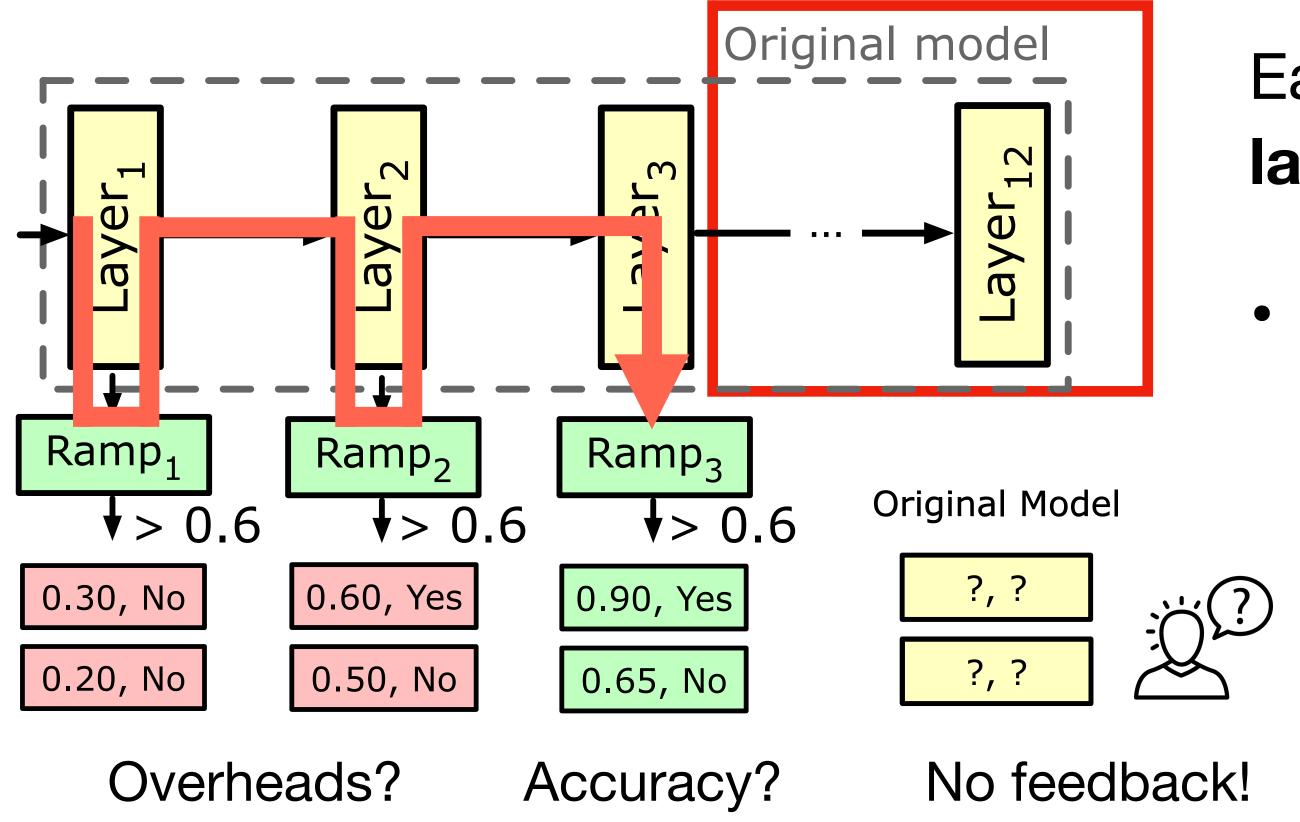
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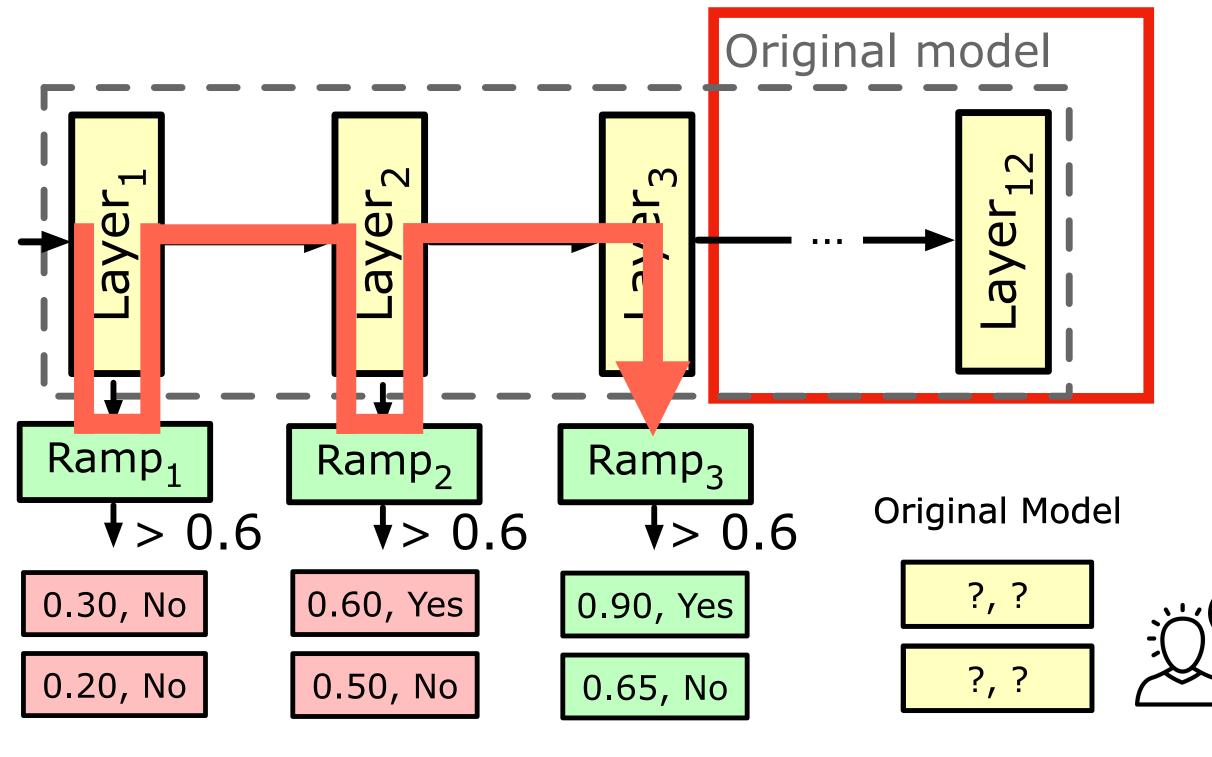


Early Exits aim for saving both latency and computation

No feedback for online adaptation

low accuracy and high overheads

Overheads?

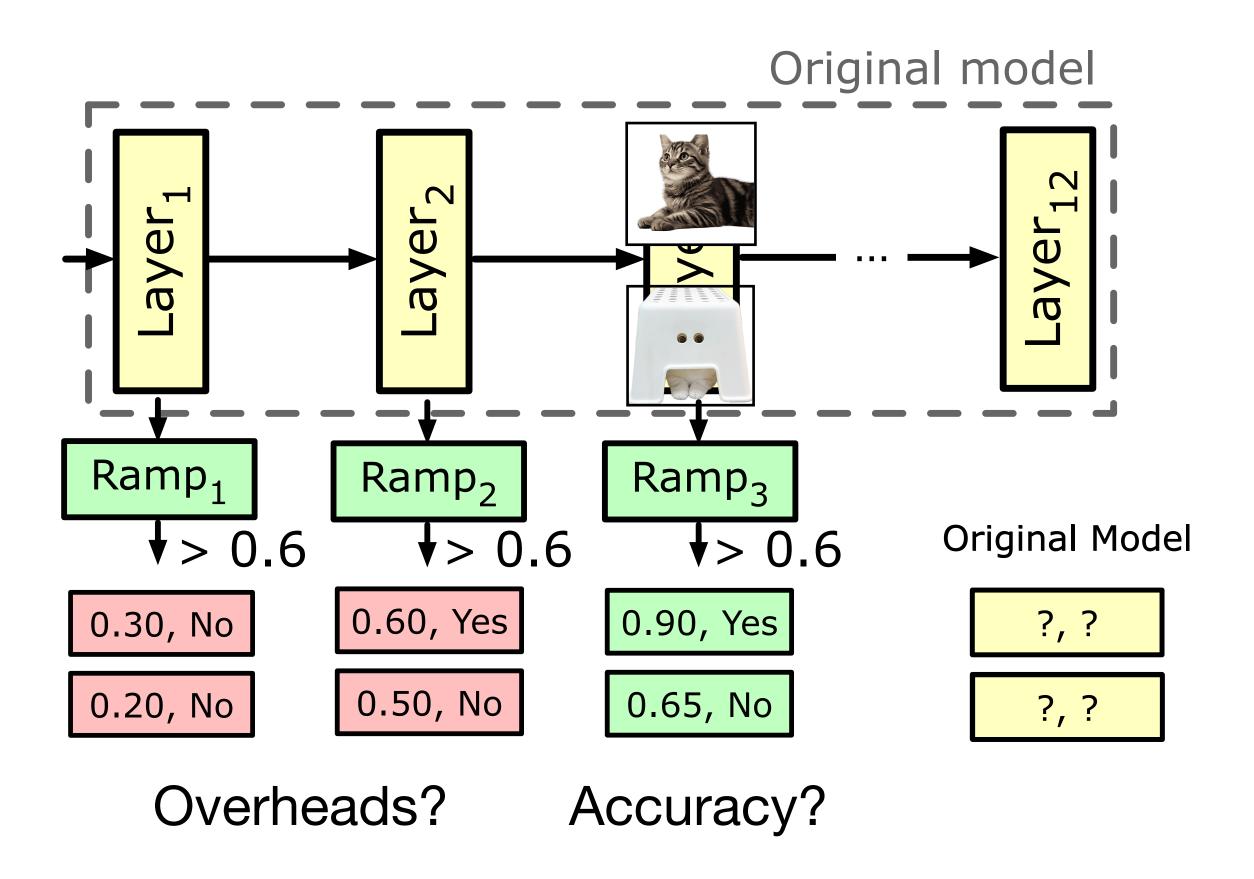


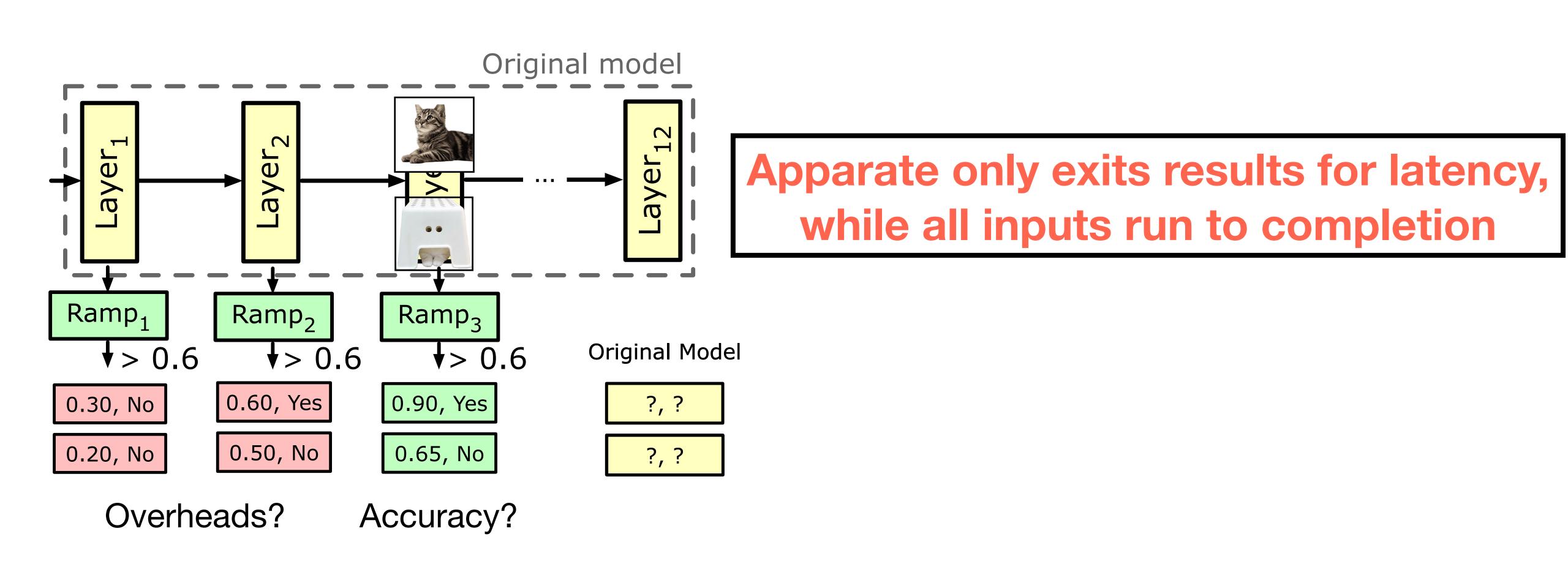
Accuracy?

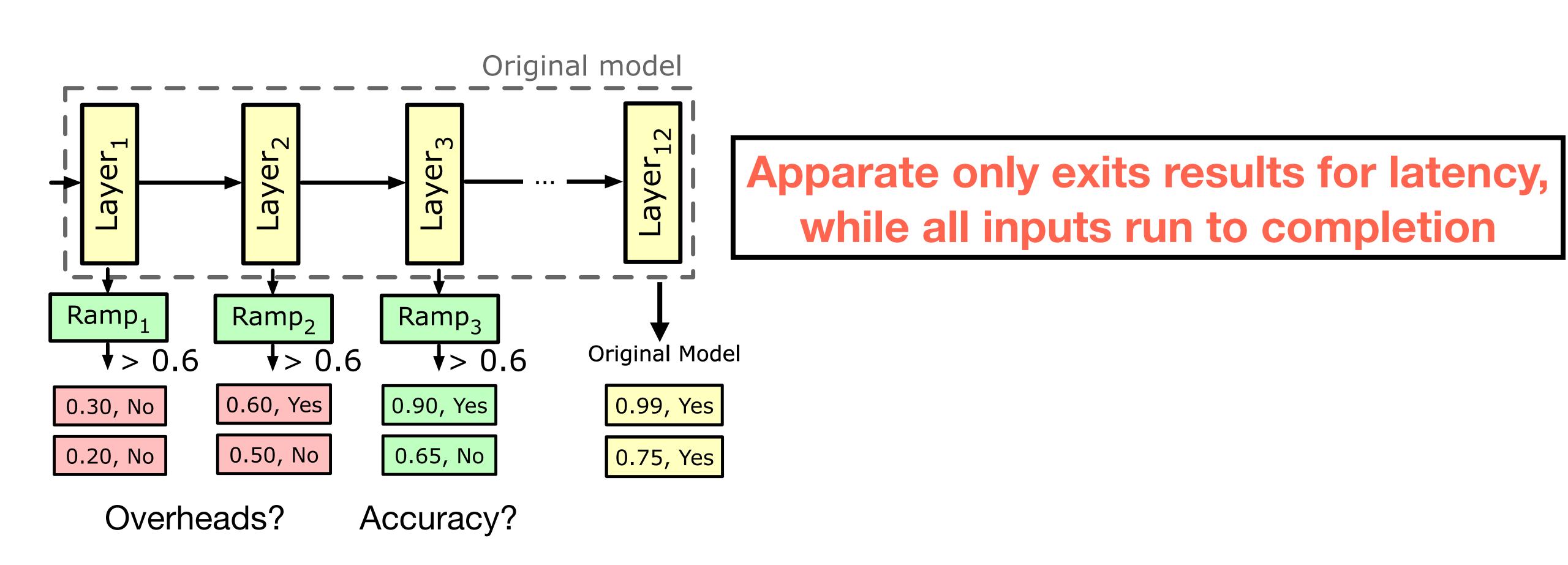
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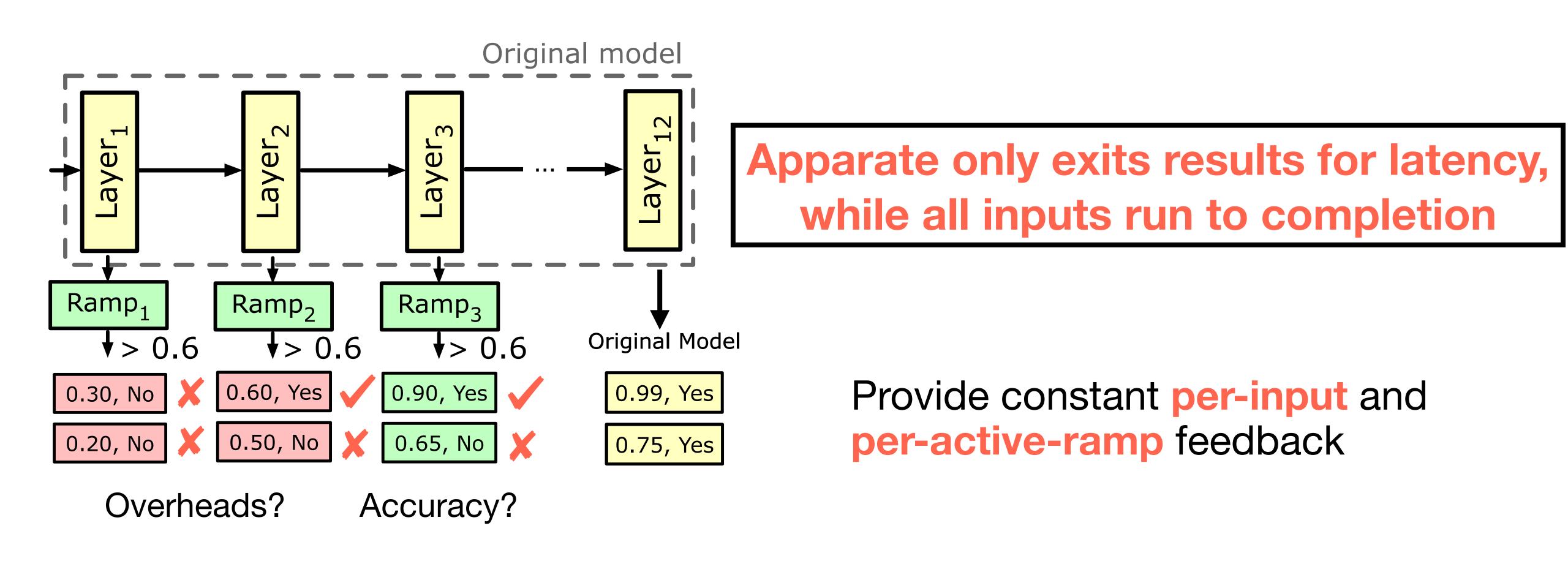
- No feedback for online adaptation
- Up to 24% accuracy loss and 22% latency overheads

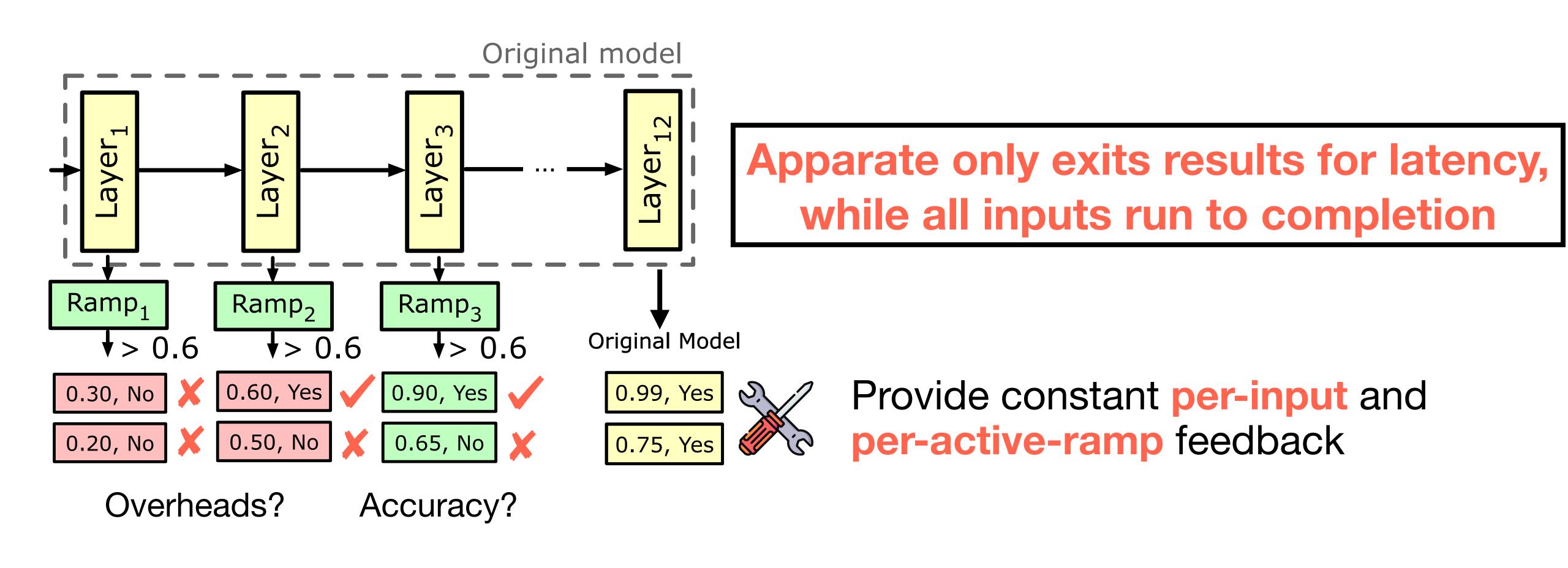
No feedback!

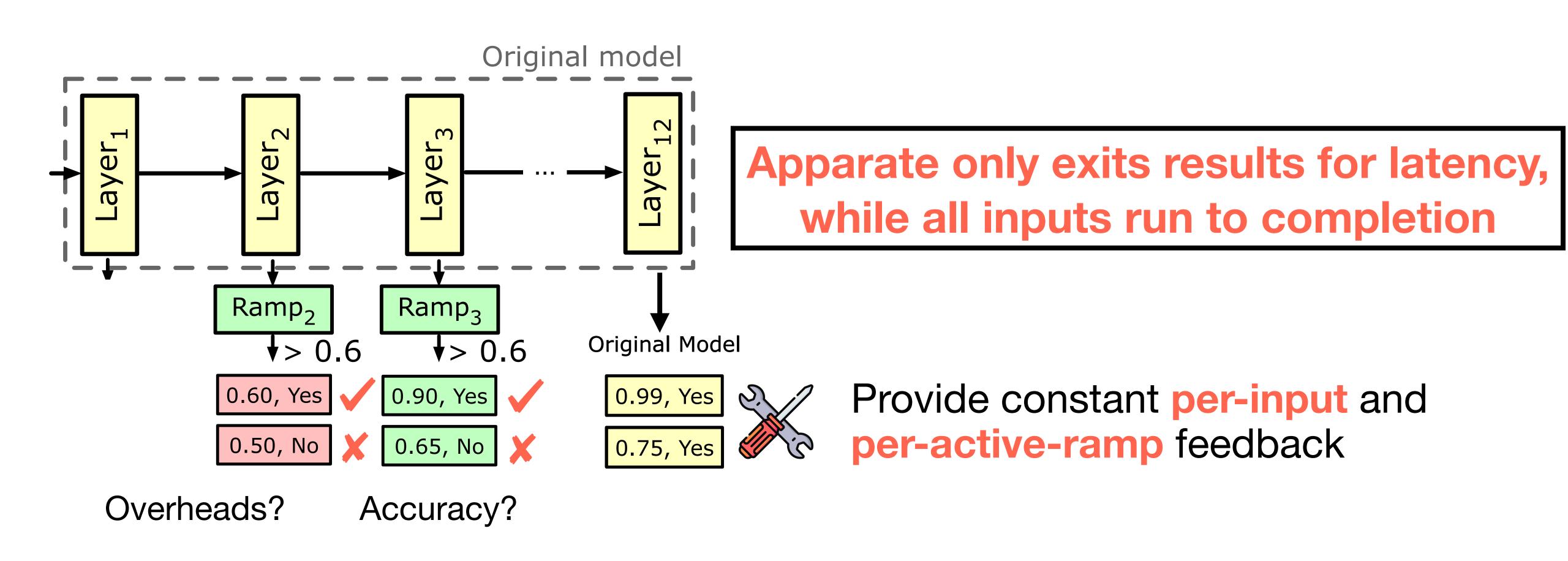


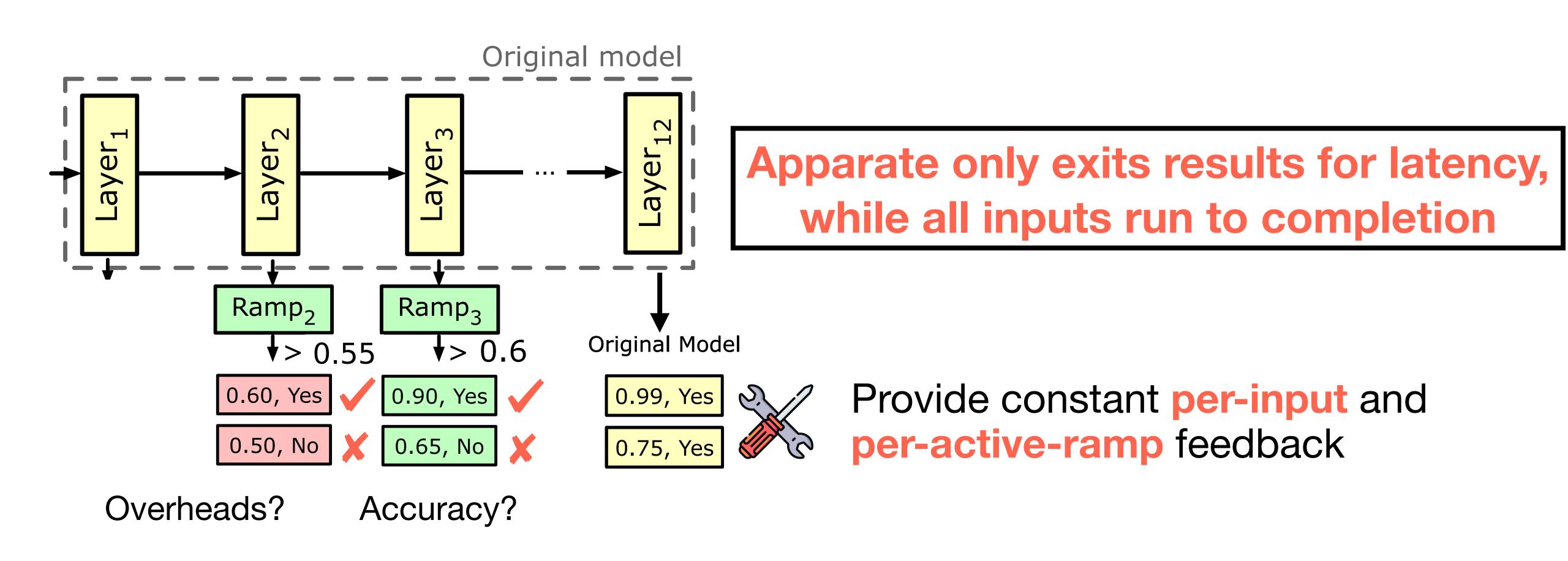


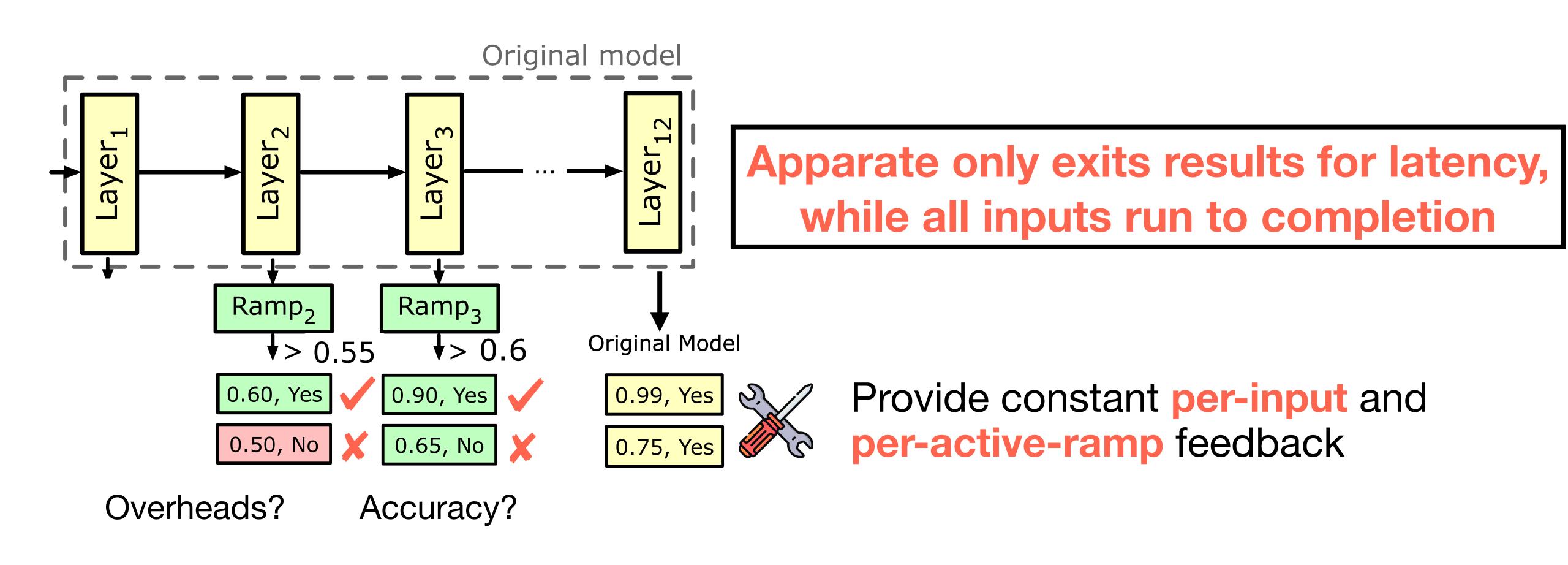


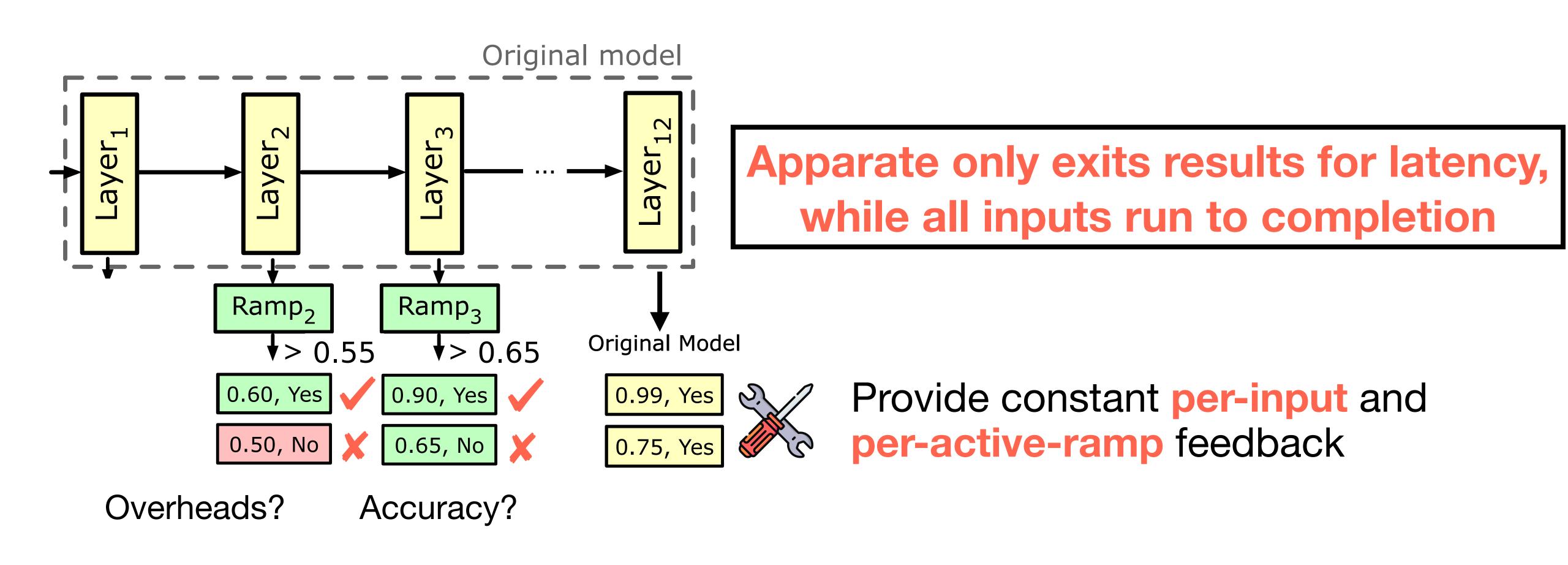


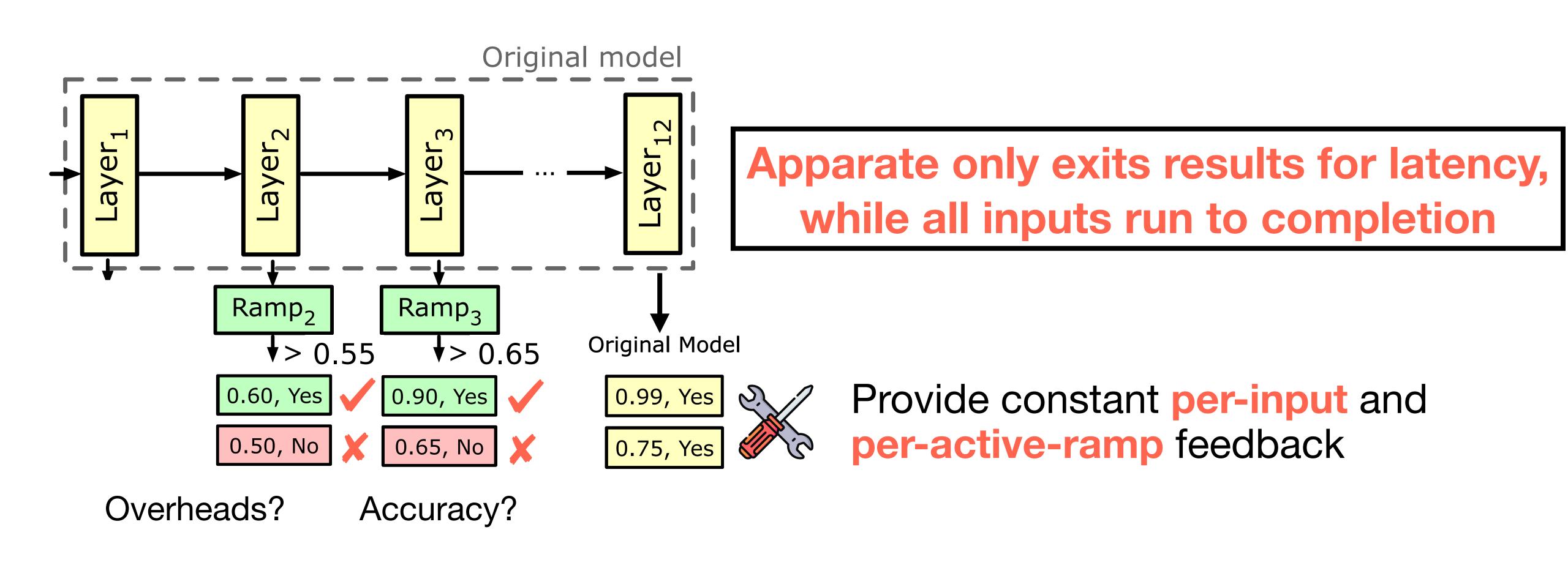


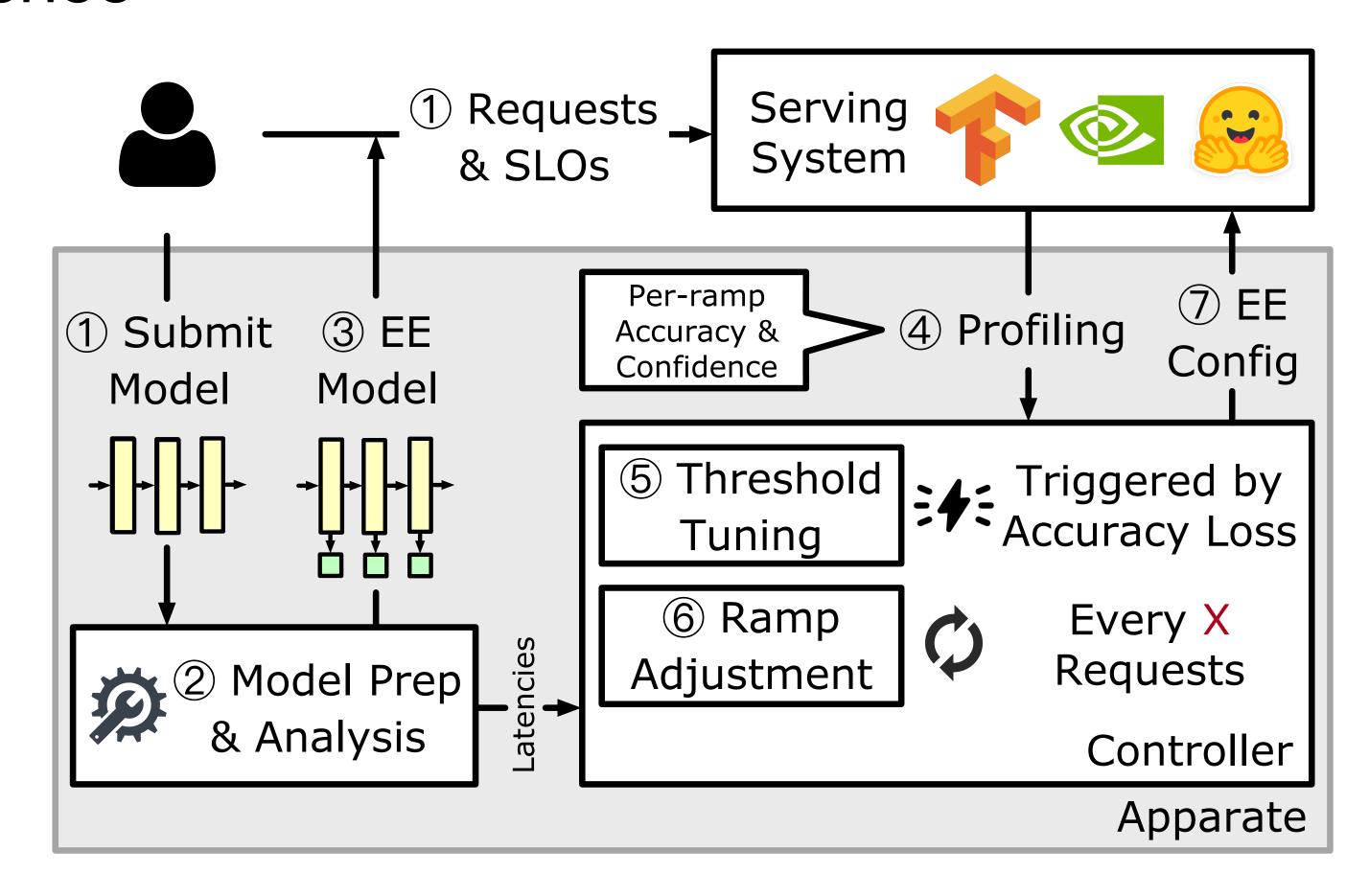


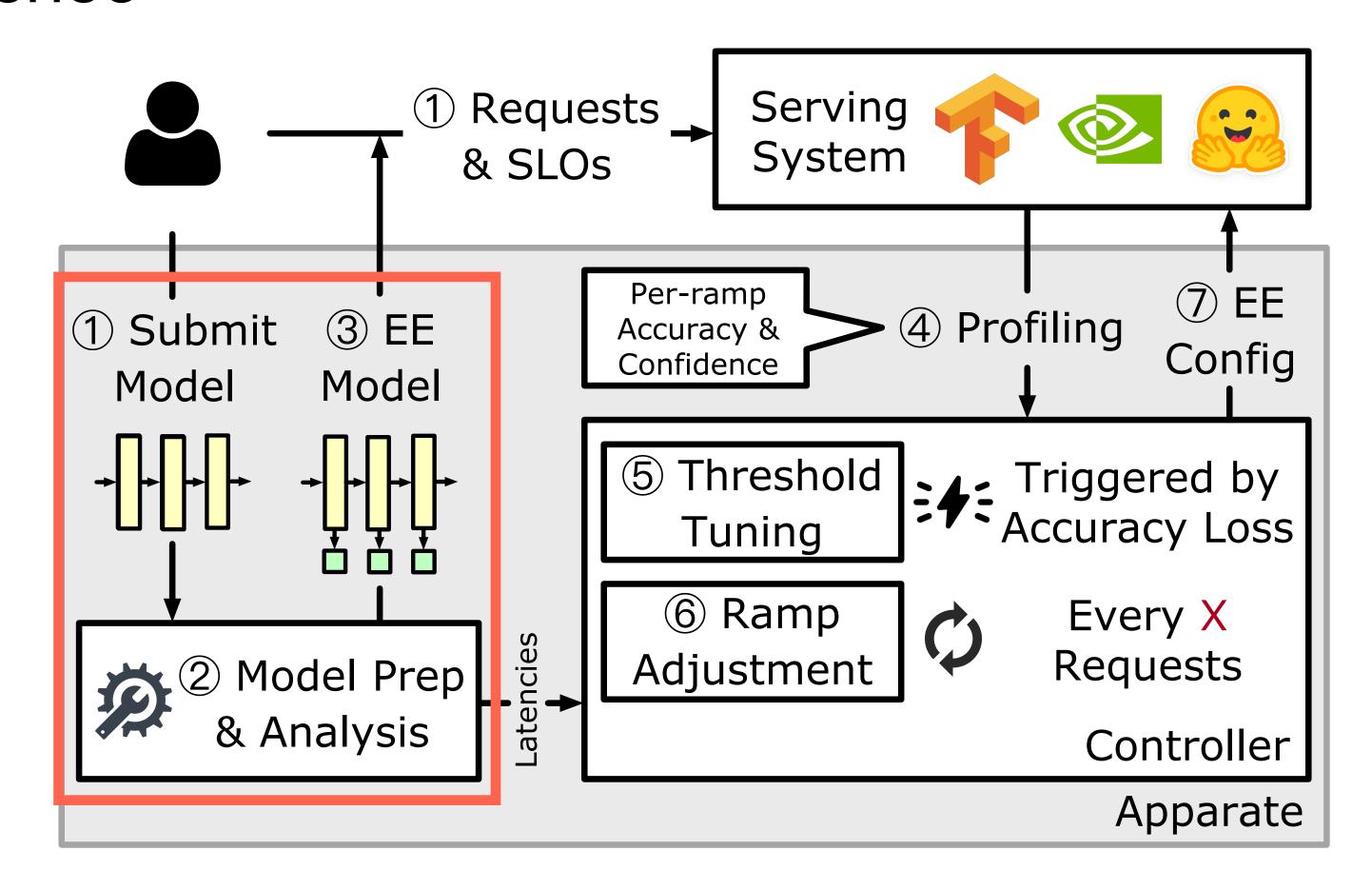


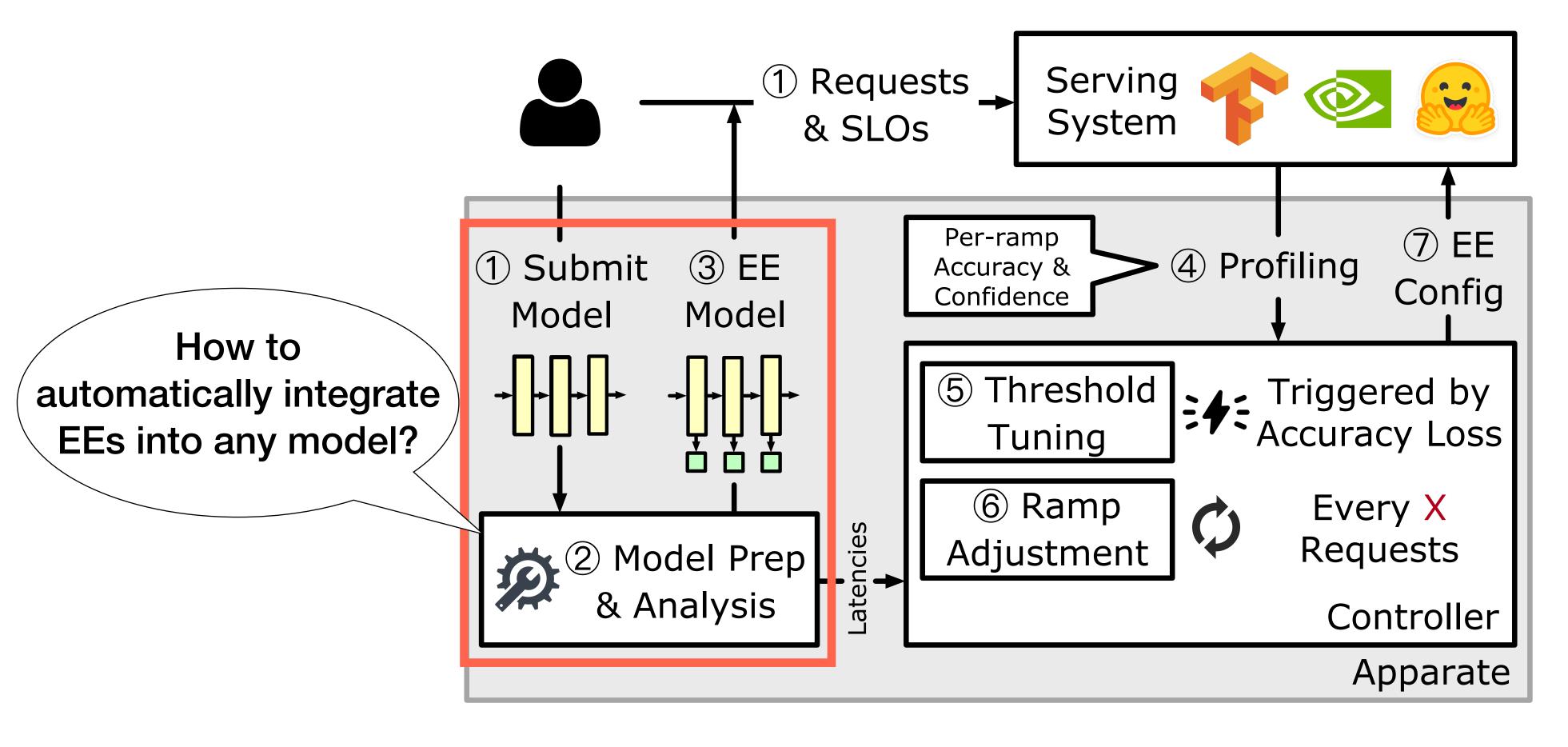


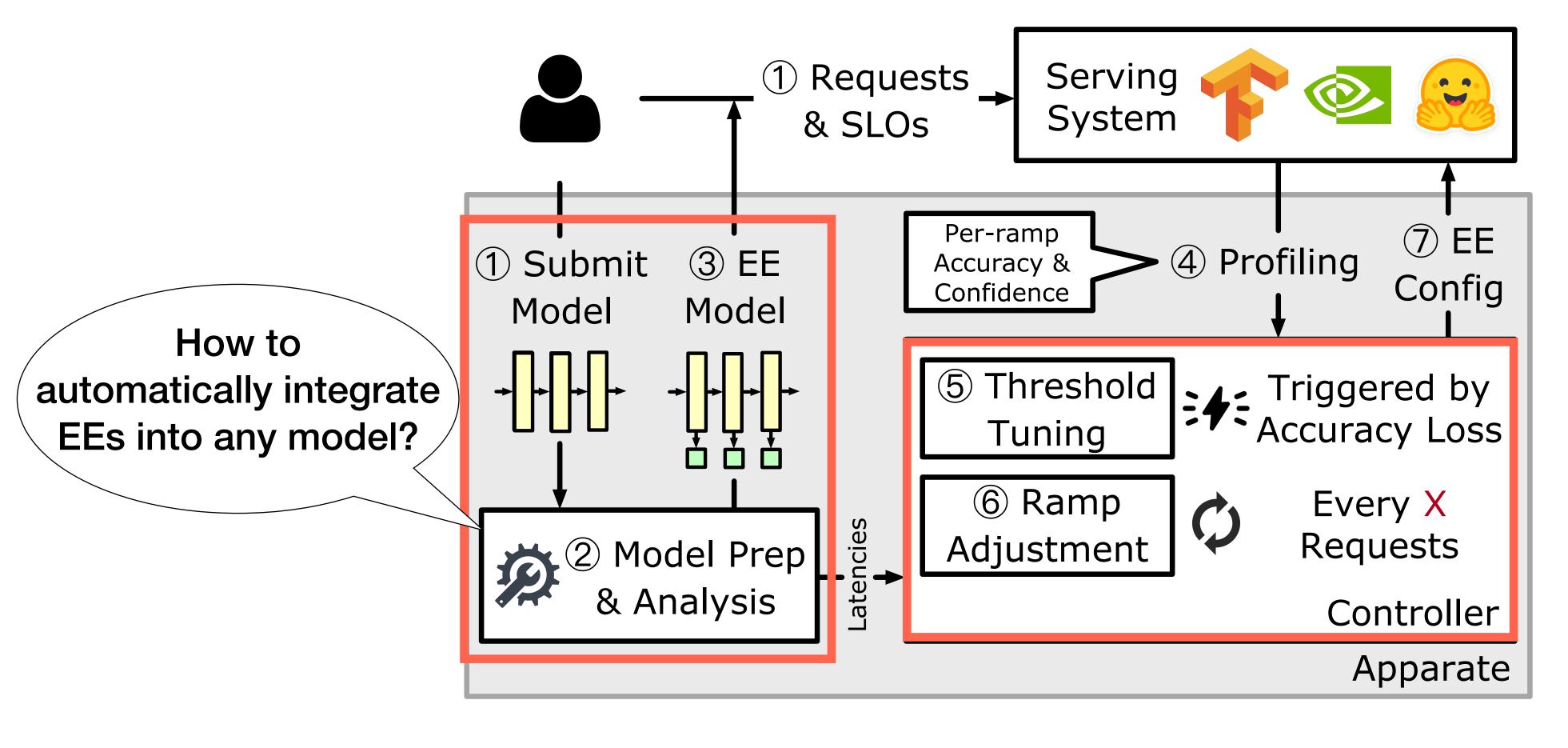


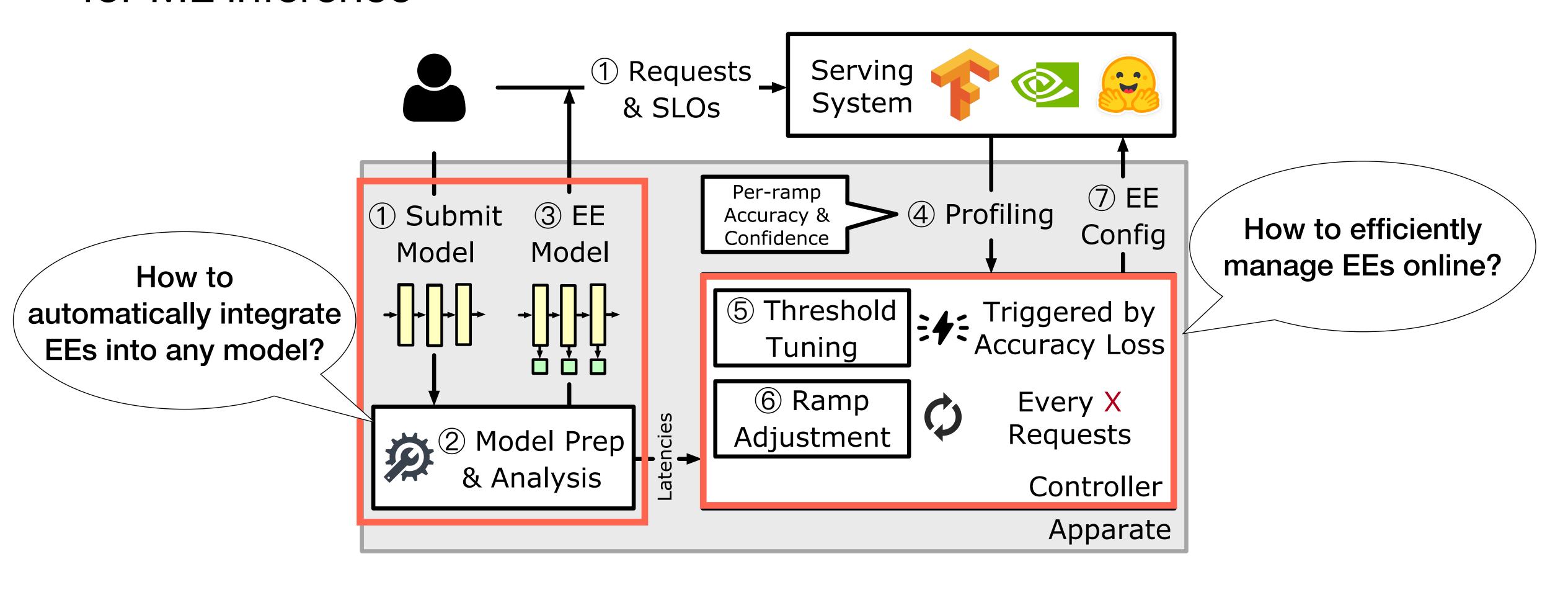




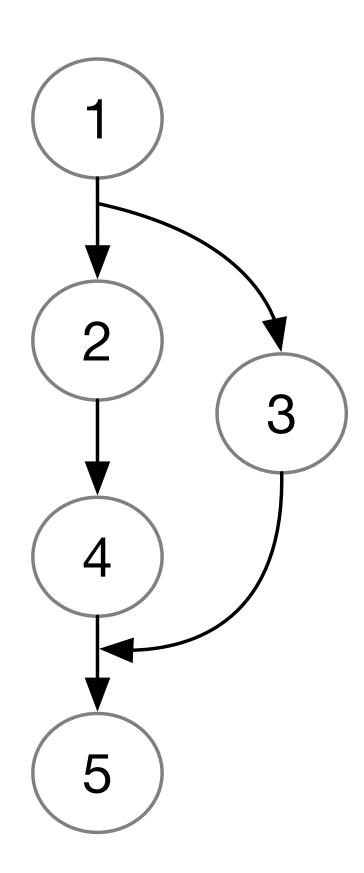




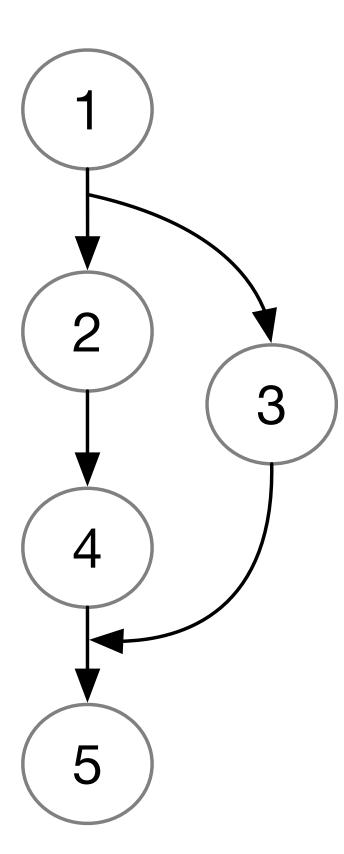




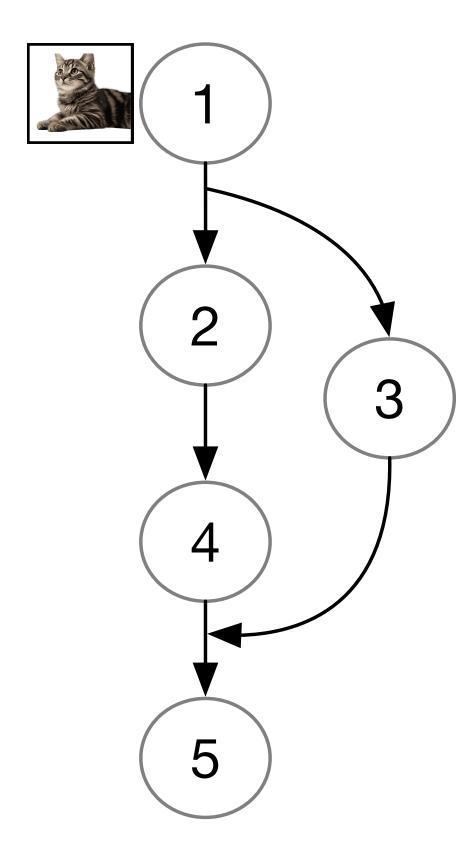
challenge: ramp location, architecture, and weights



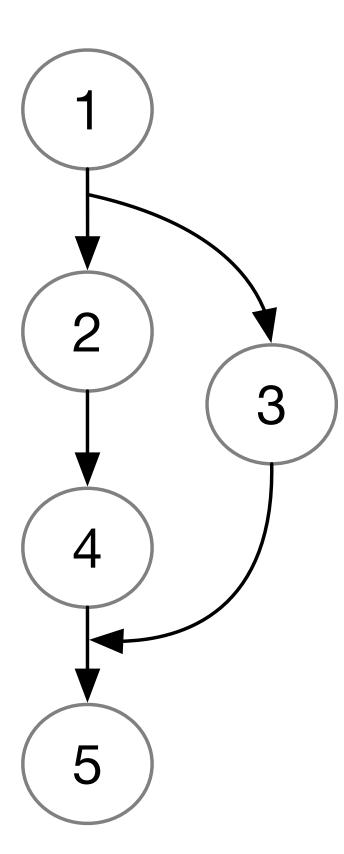
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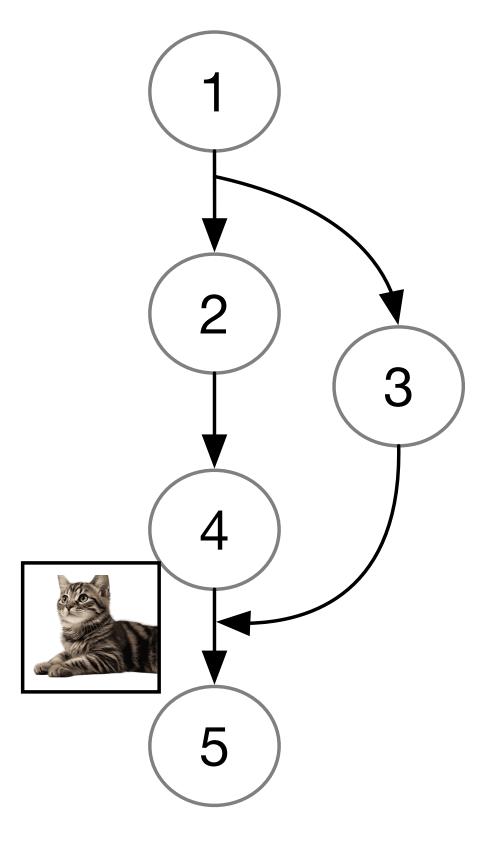
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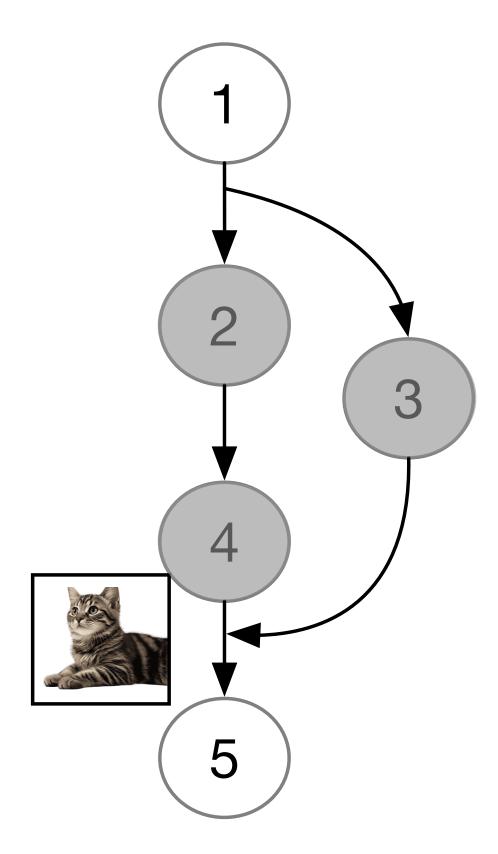


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Ramp Location

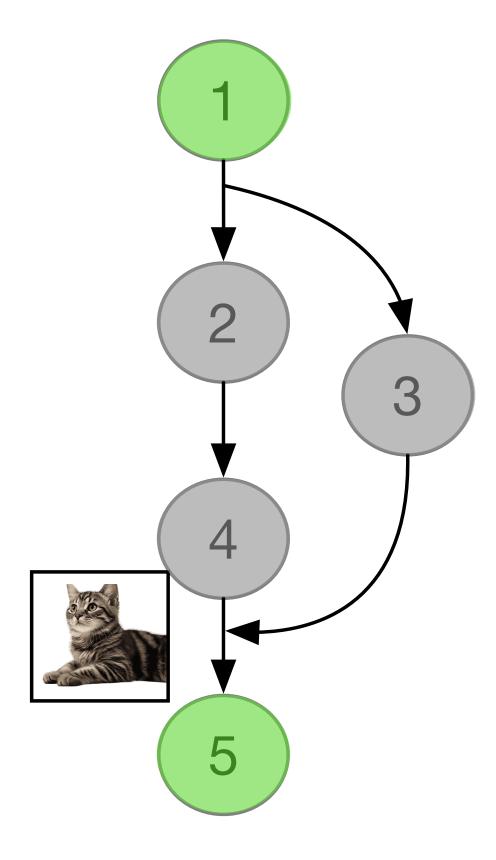


Partial features result in low ramp accuracy!

challenge: ramp location, architecture, and weights

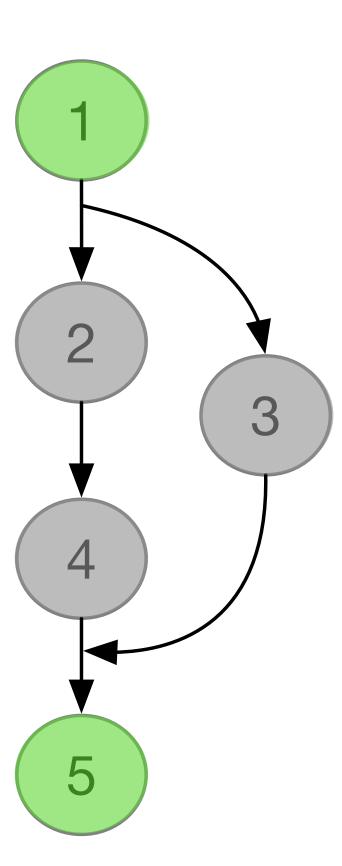
Ramp Location

cutting vertices



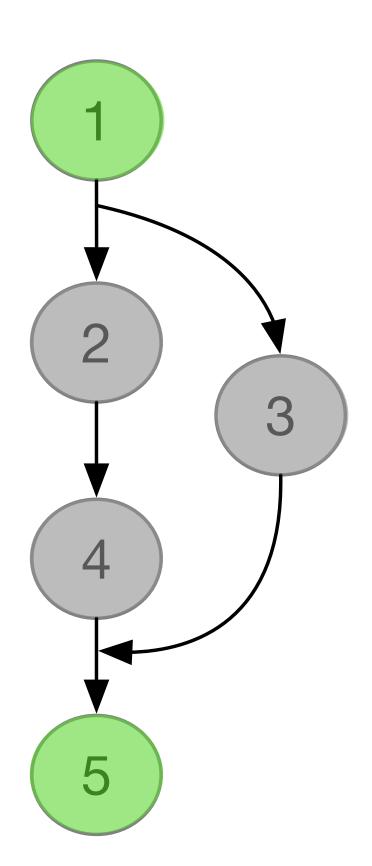
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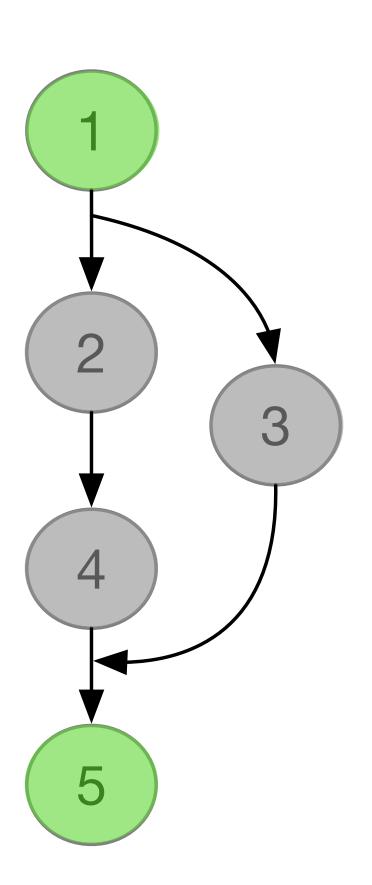


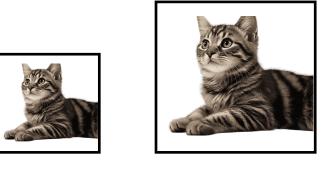


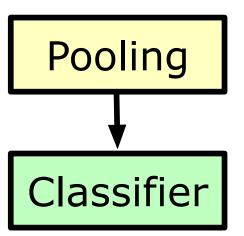


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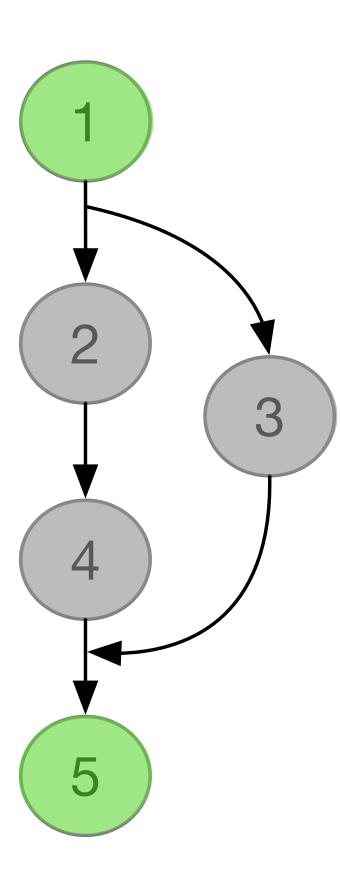


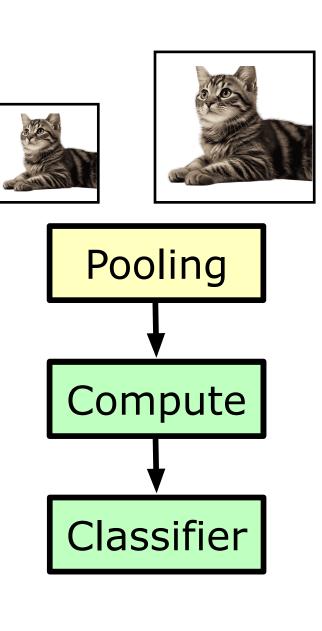




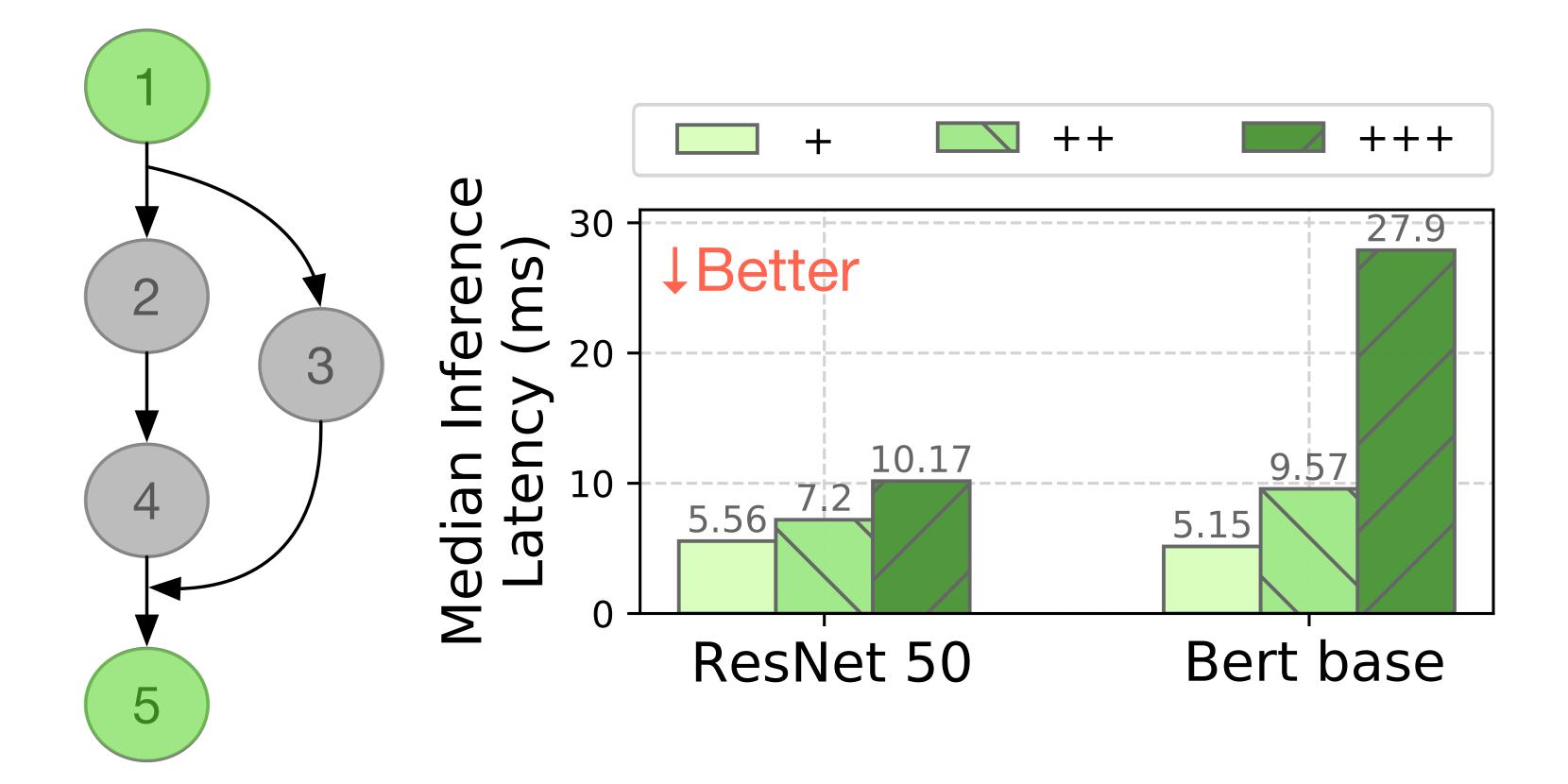


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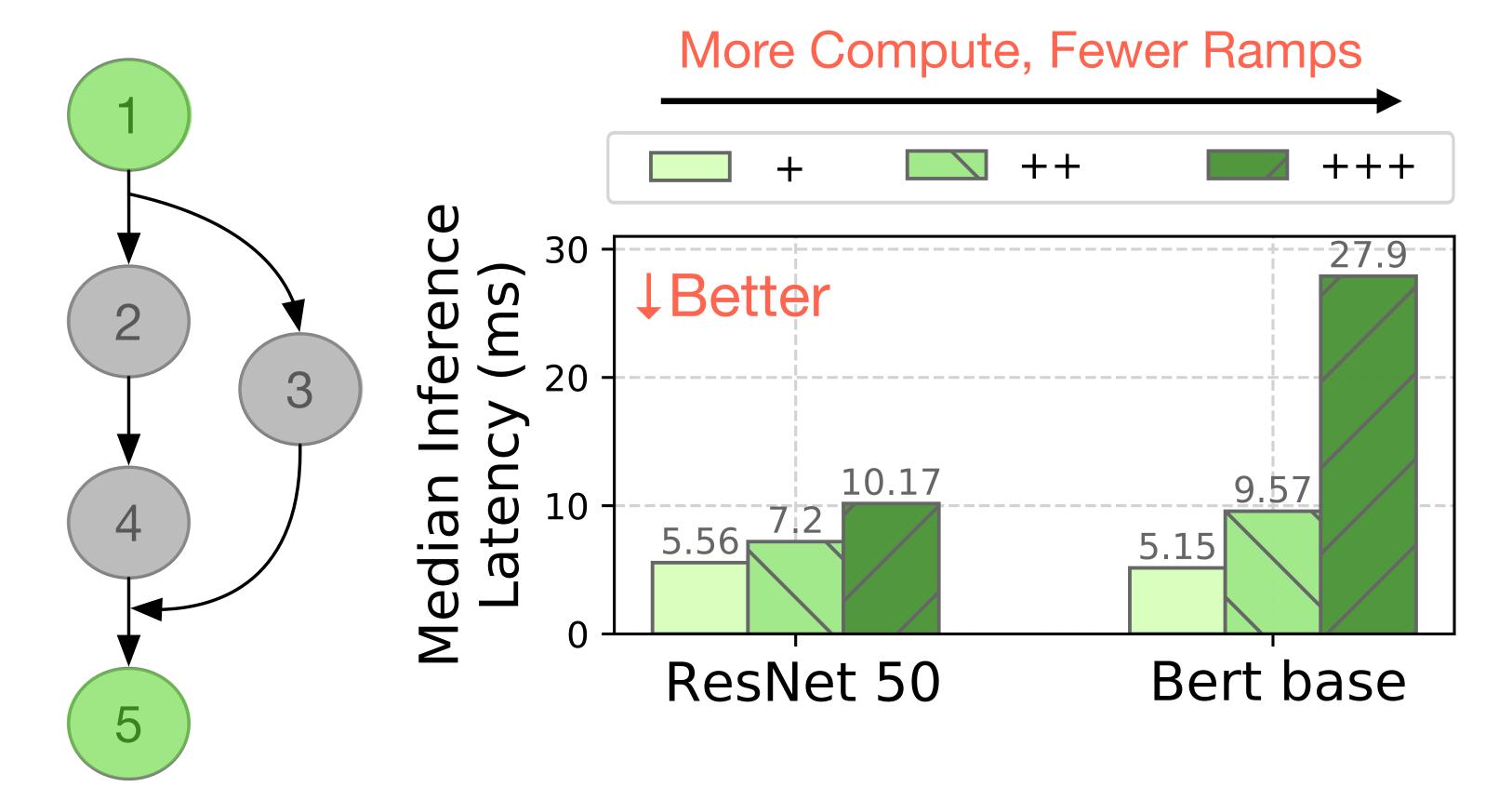




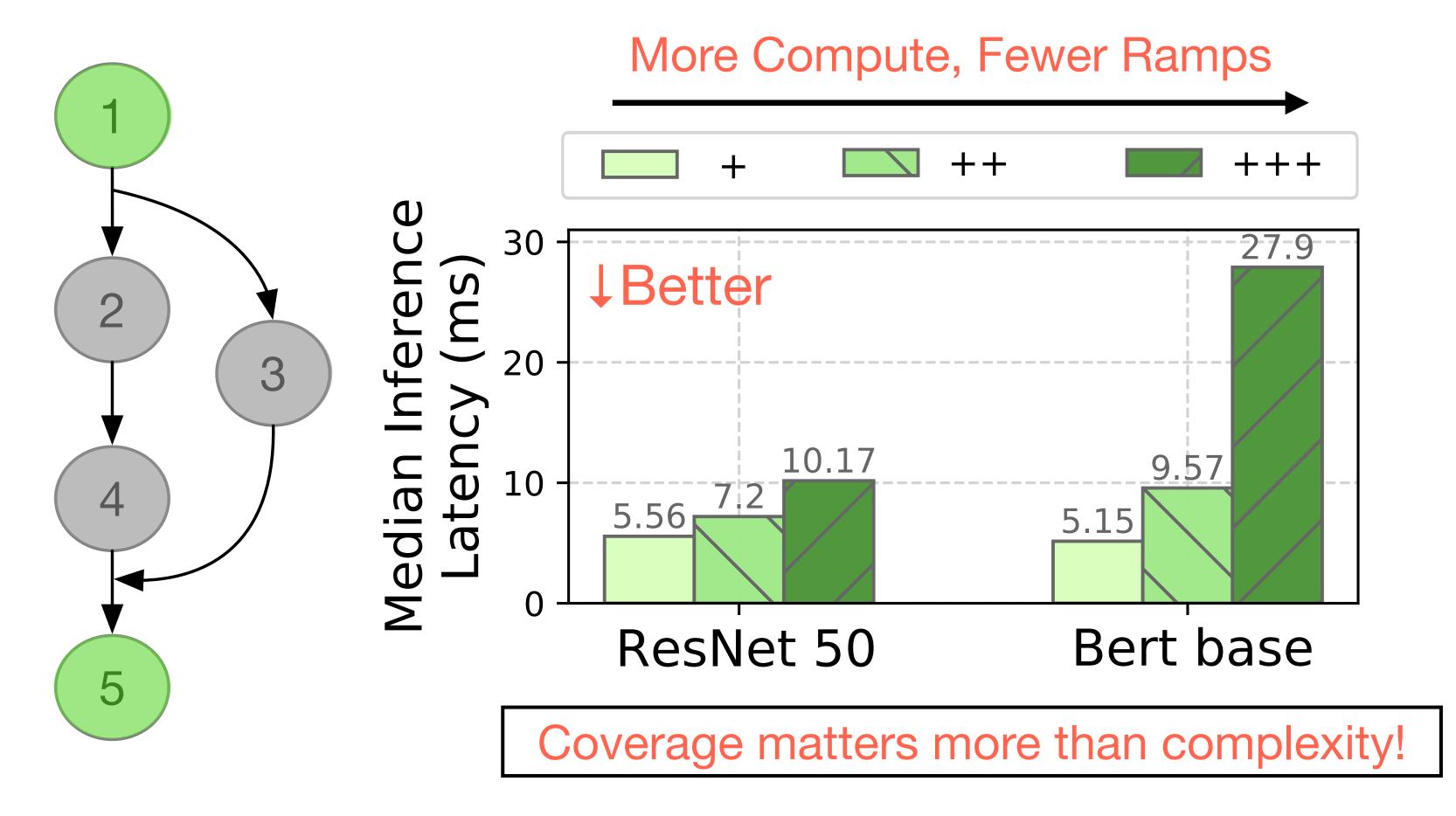
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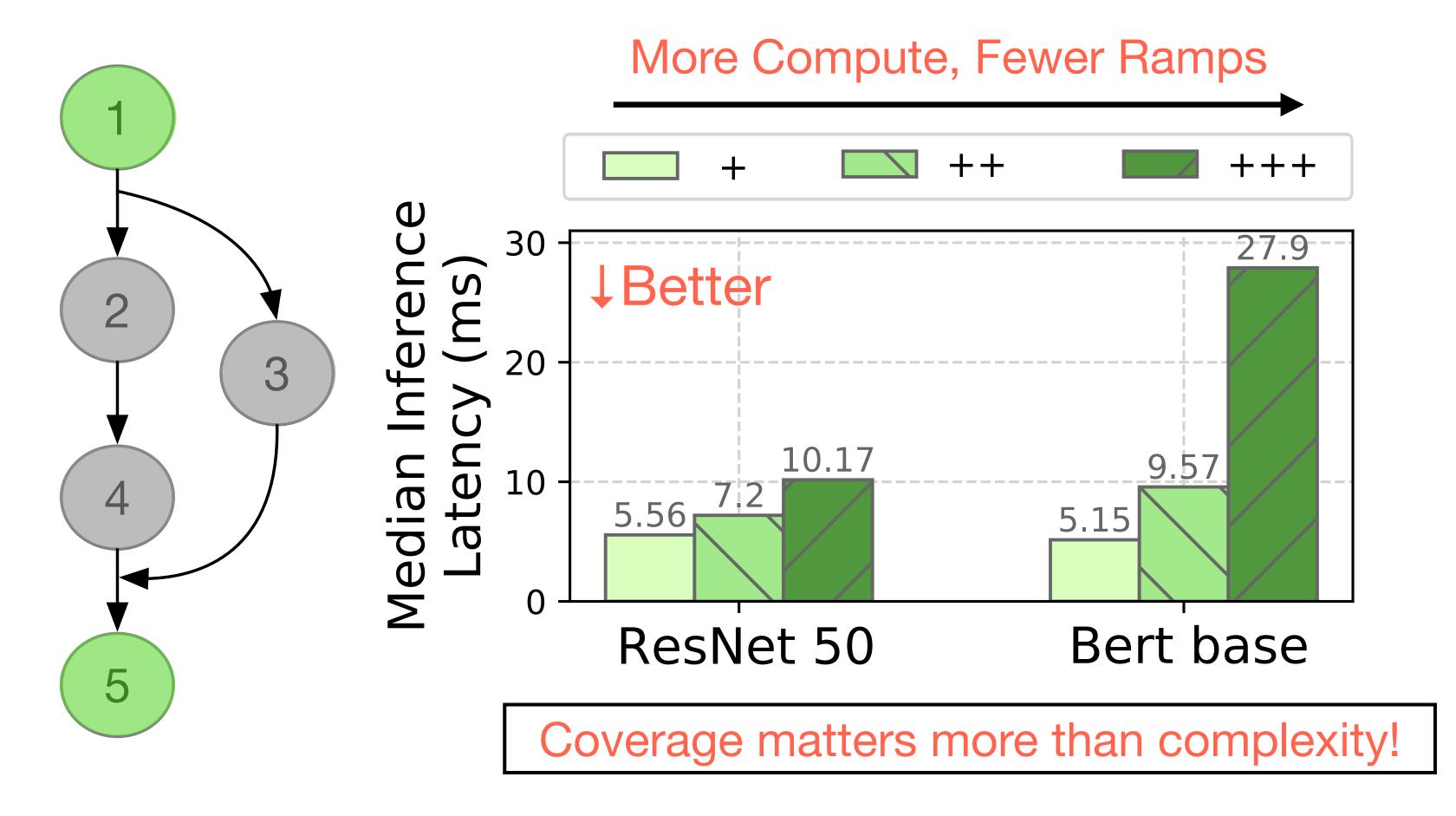
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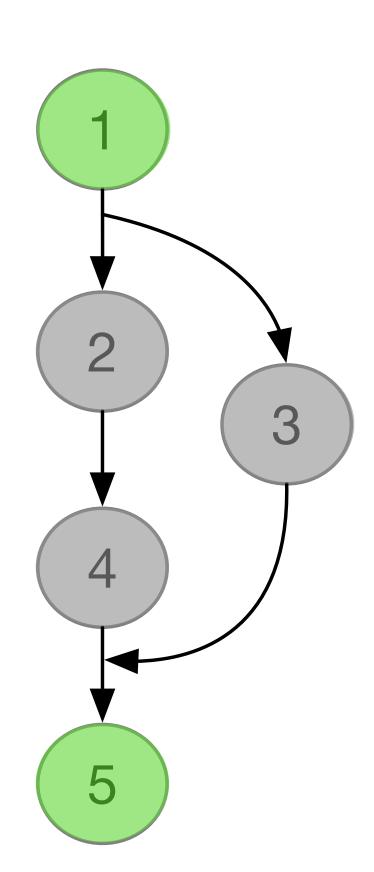
Ramp Architecture

cheapest ramps



Apparate: Automatic integration for EEs

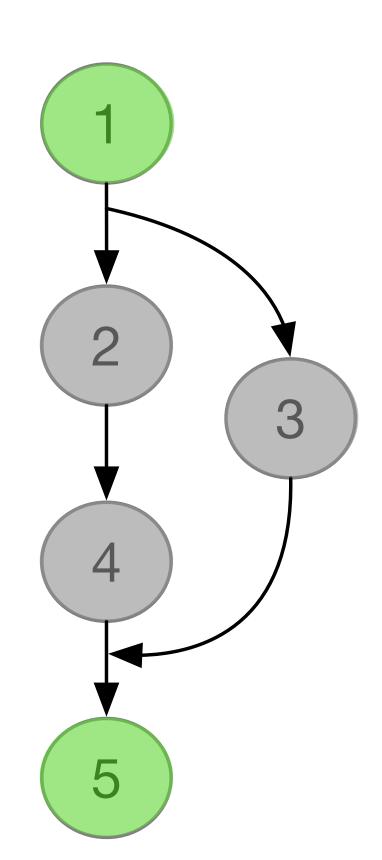
challenge: ramp location, architecture, and weights



Ramp weights

Apparate: Automatic integration for EEs

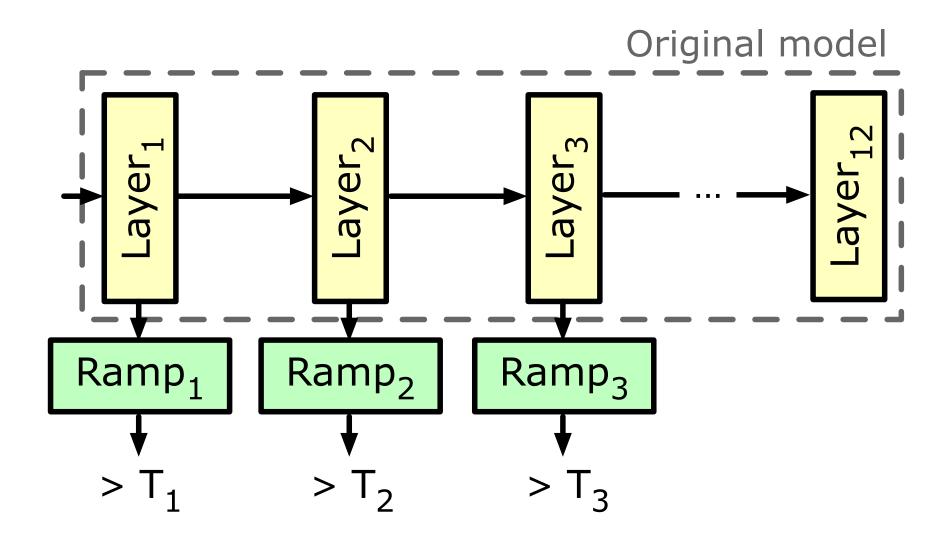
challenge: ramp location, architecture, and weights



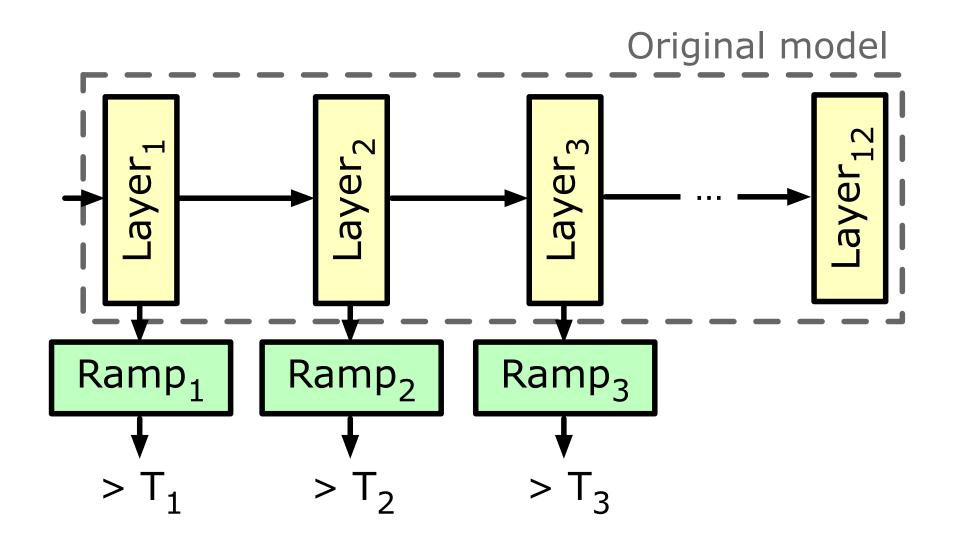
Ramp weights

parallel training

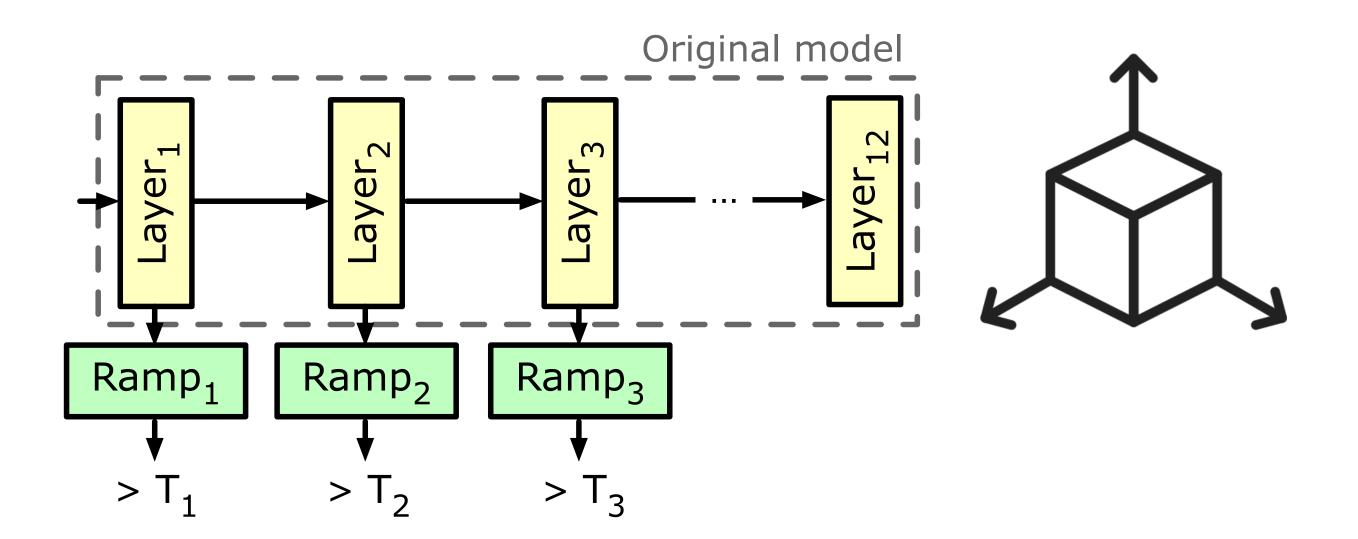
challenge: massive space of EE configurations



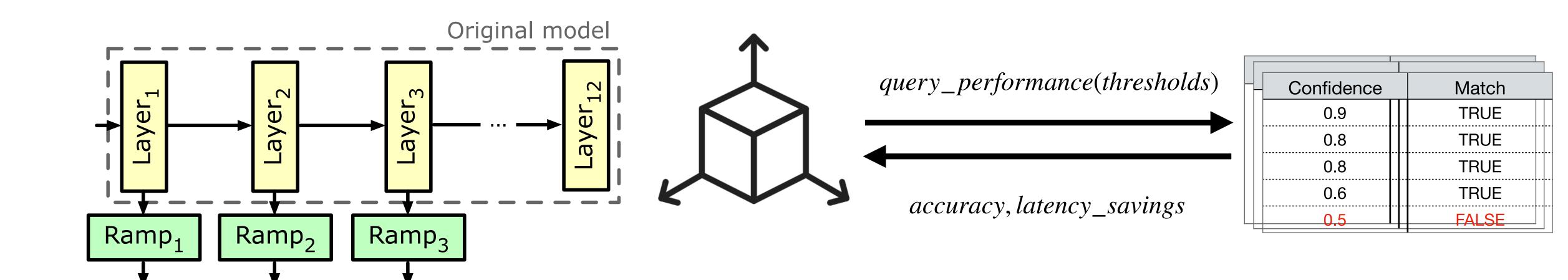
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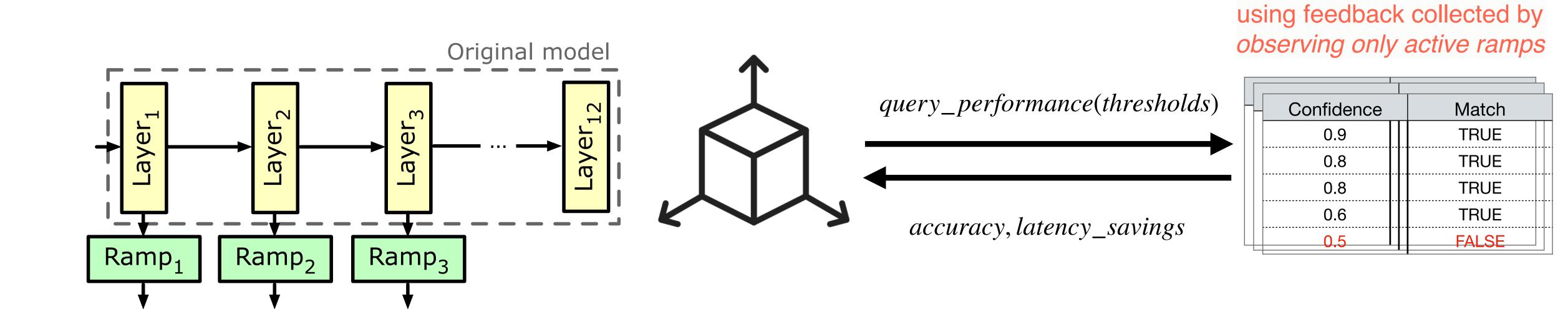
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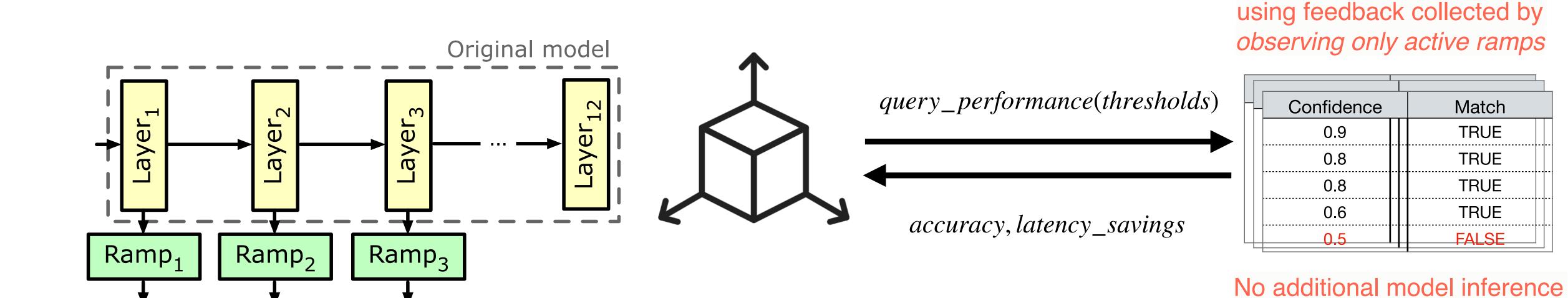
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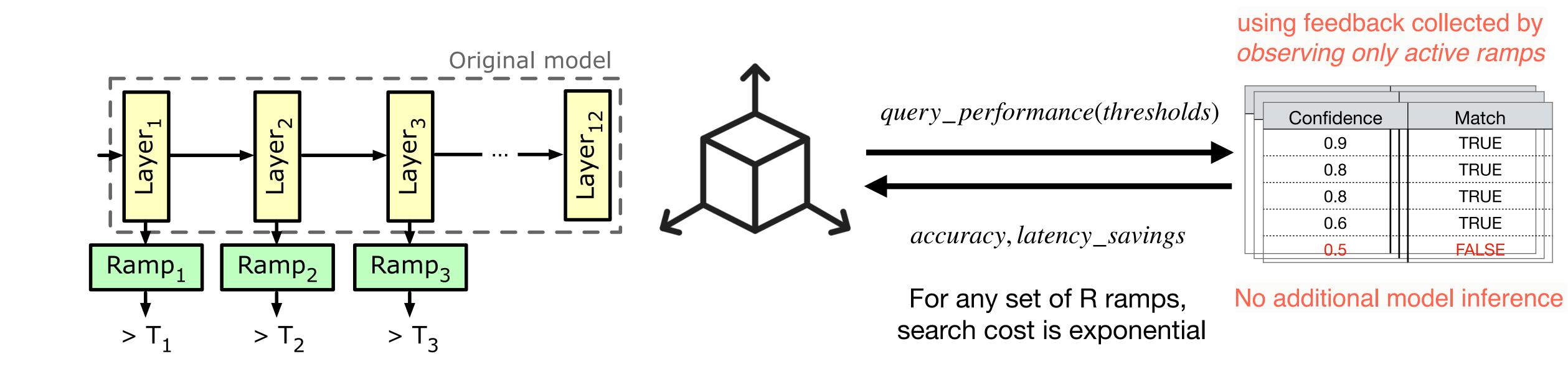
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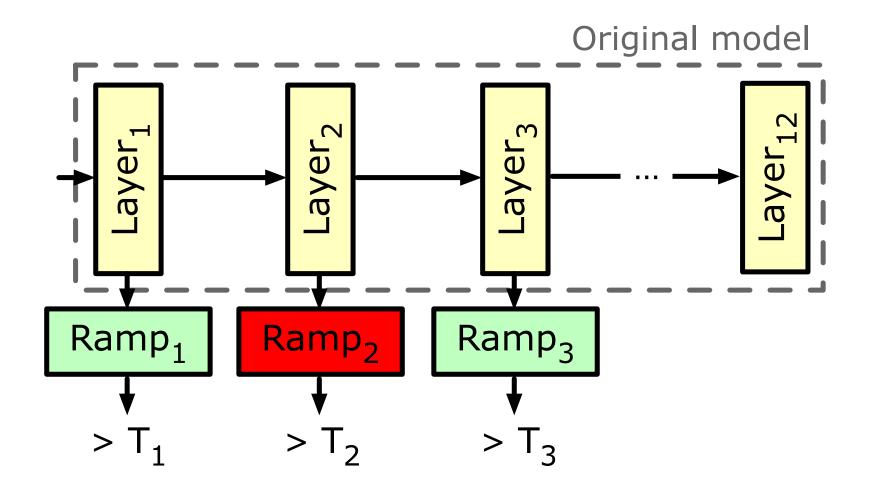


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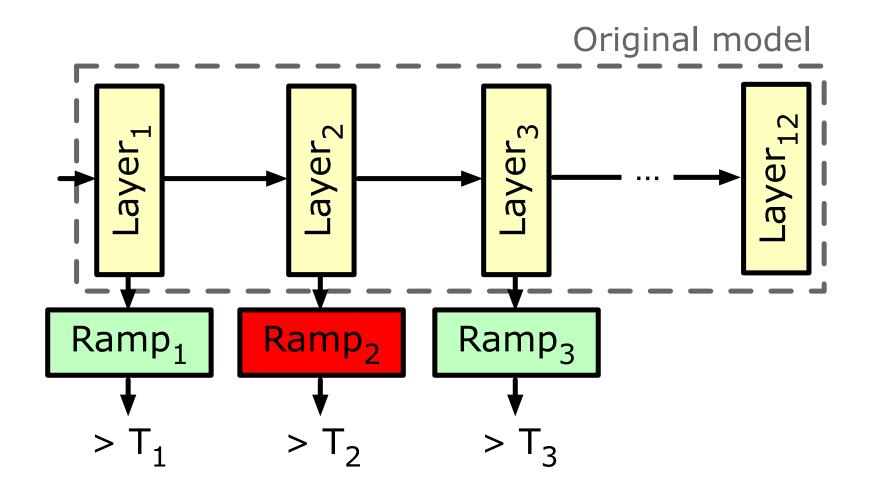


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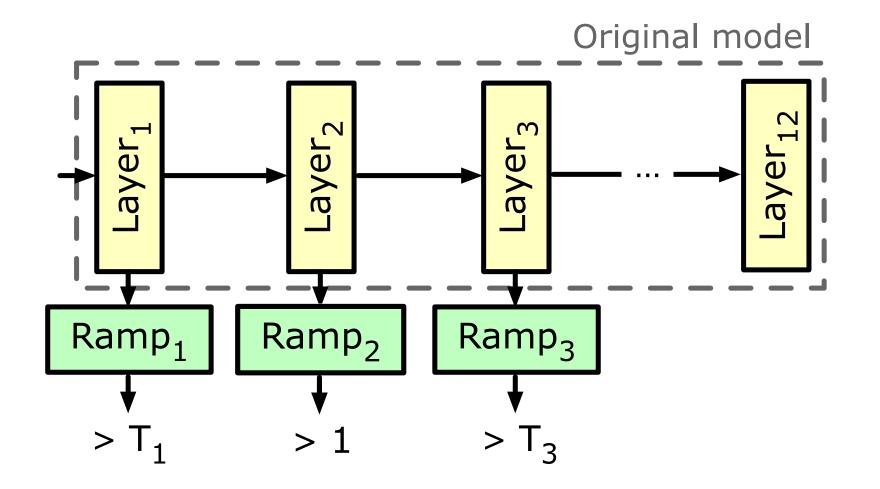




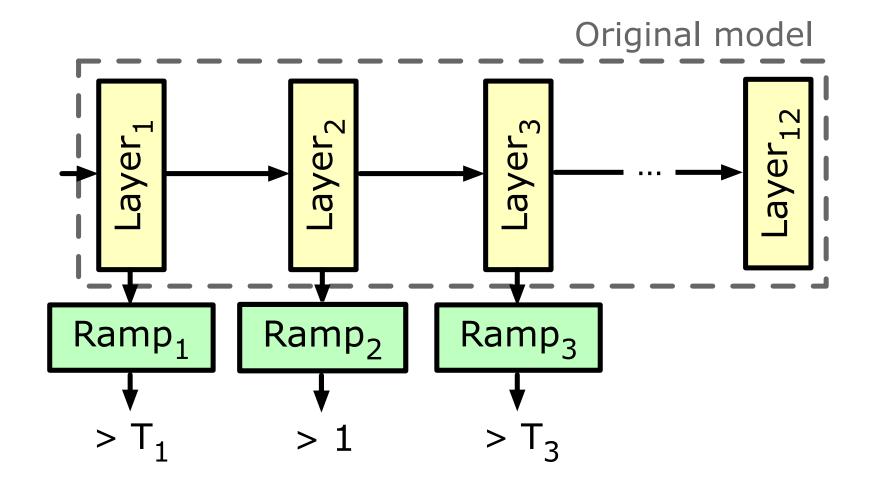
- Threshold Tuning:
 - Cheap and controls accuracy

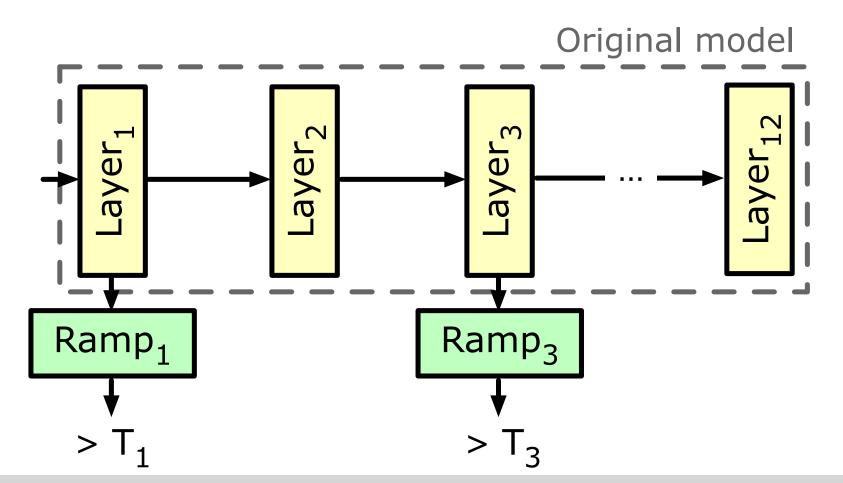


- Threshold Tuning:
 - Cheap and controls accuracy
 - Adjusts immediately to bound accuracy loss

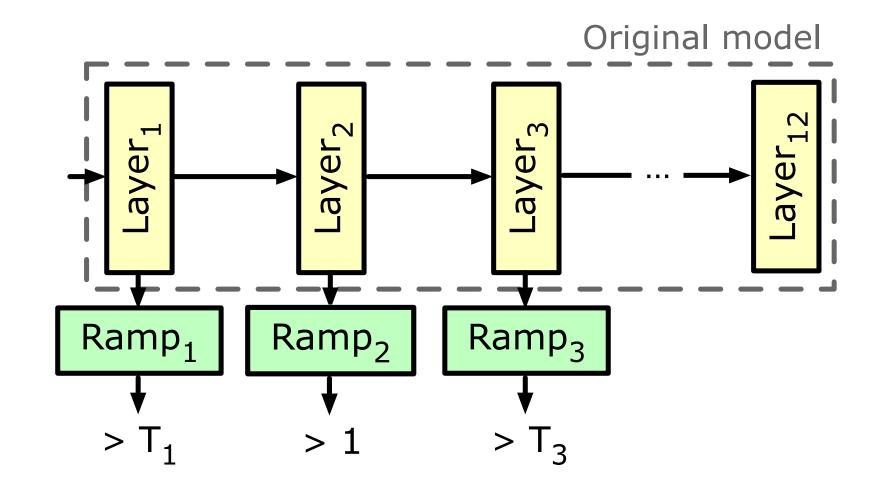


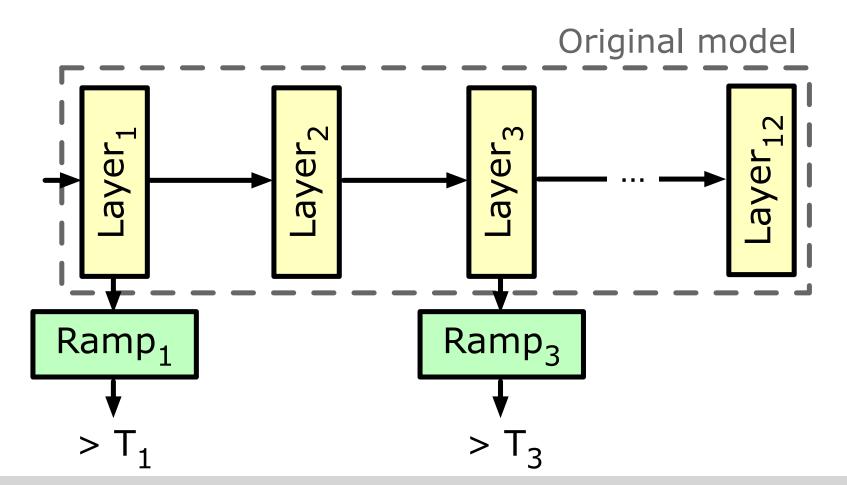
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 - Adjusts immediately to bound accuracy loss





- Threshold Tuning:
 - Cheap and controls accuracy
 - Adjusts immediately to bound accuracy loss
- Ramp Tuning:
 - Expensive and bounds latency
 - Adjusts periodically to optimize latency savings

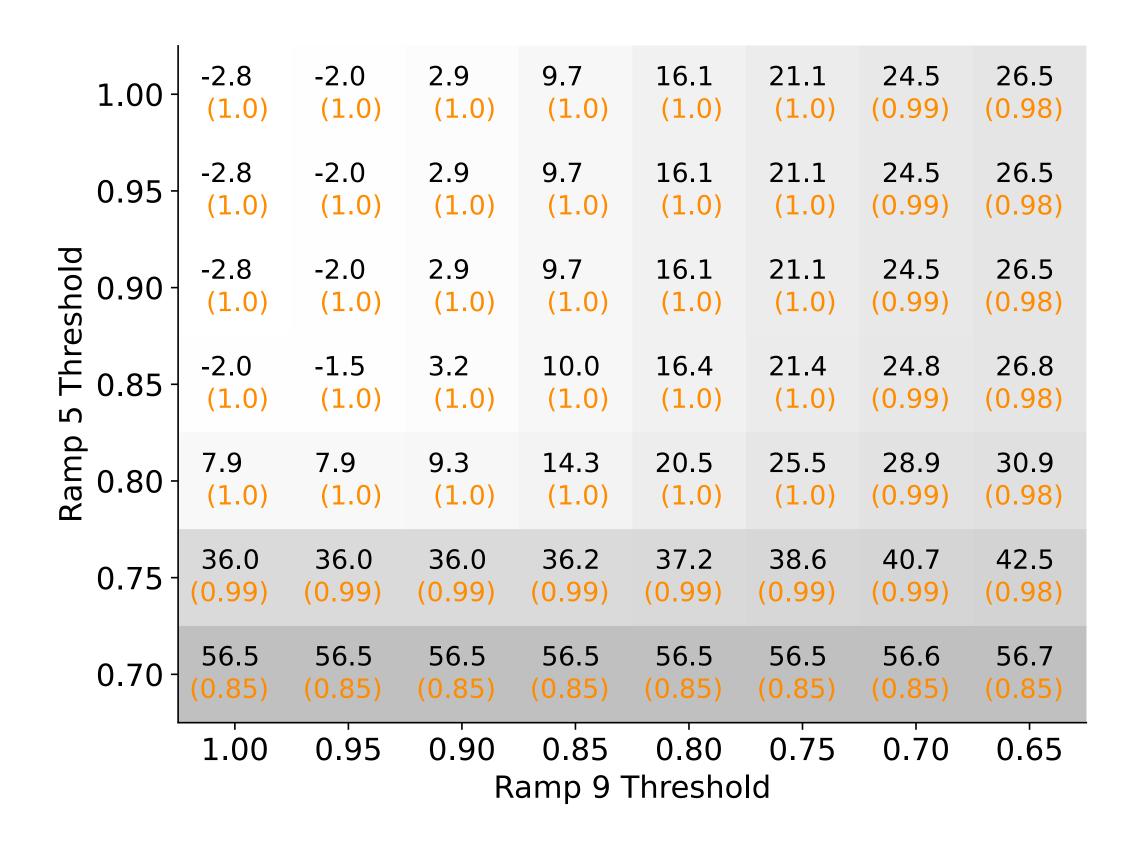




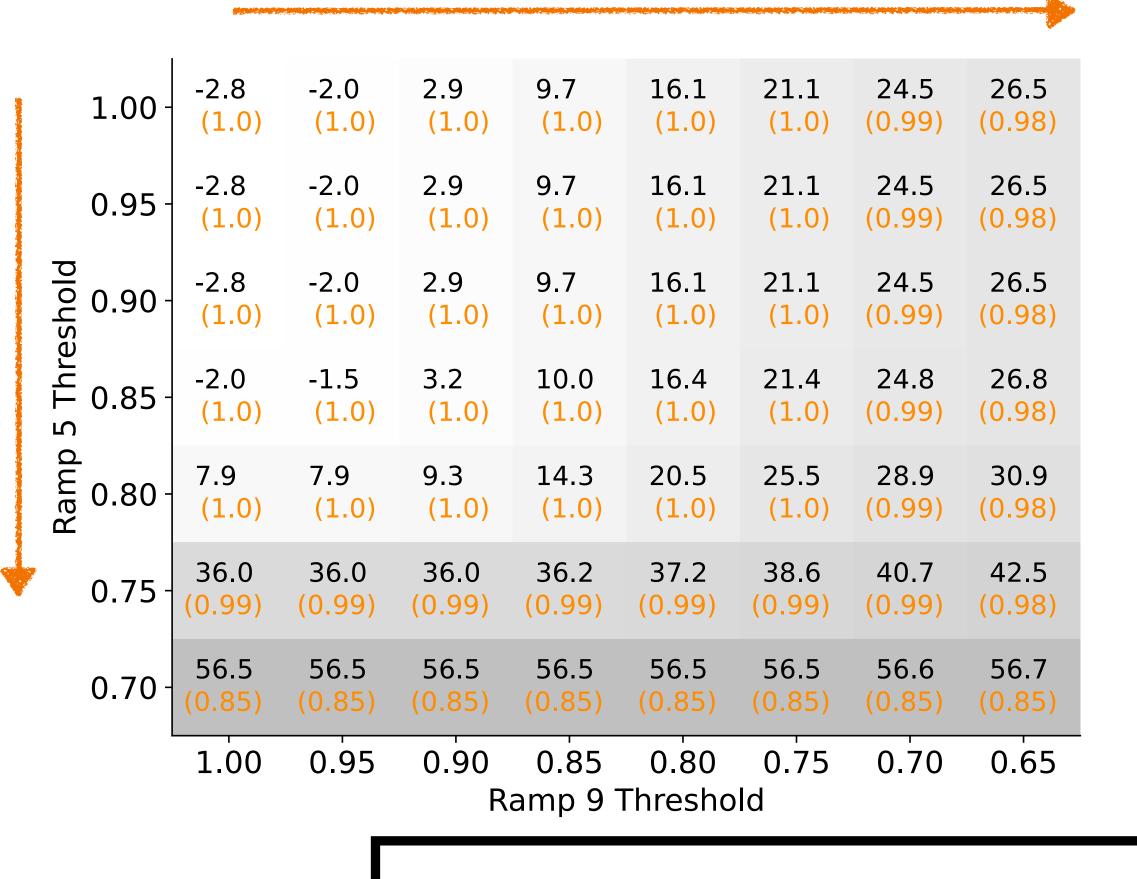
- Threshold Tuning:
 - Cheap and controls accuracy
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- Ramp Tuning:
 - Expensive and bounds latency
 - Adjusts periodically to optimize latency savings
 - Multiple lightweight ramps reduce the impact of missing highly effective ramps

insight 2: leverage EE properties for fast tuning

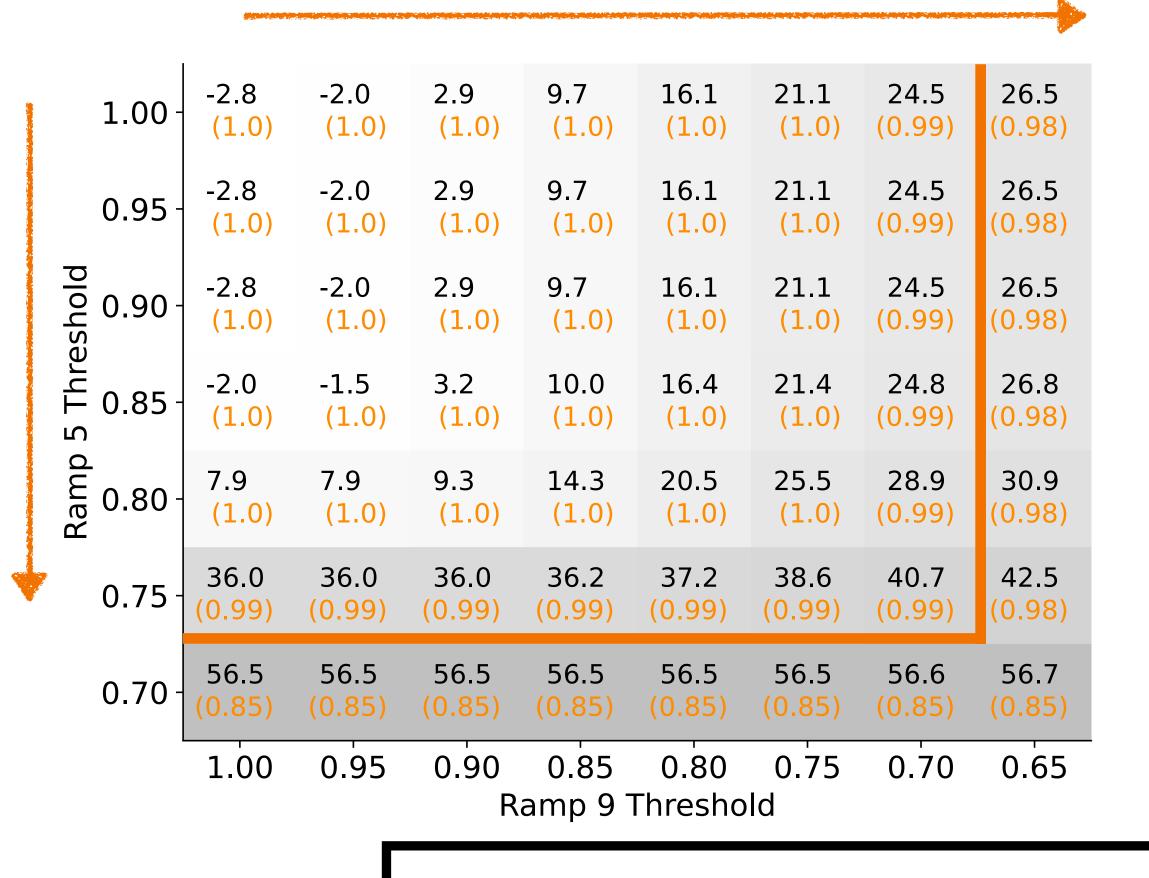
insight 2: leverage EE properties for fast tuning



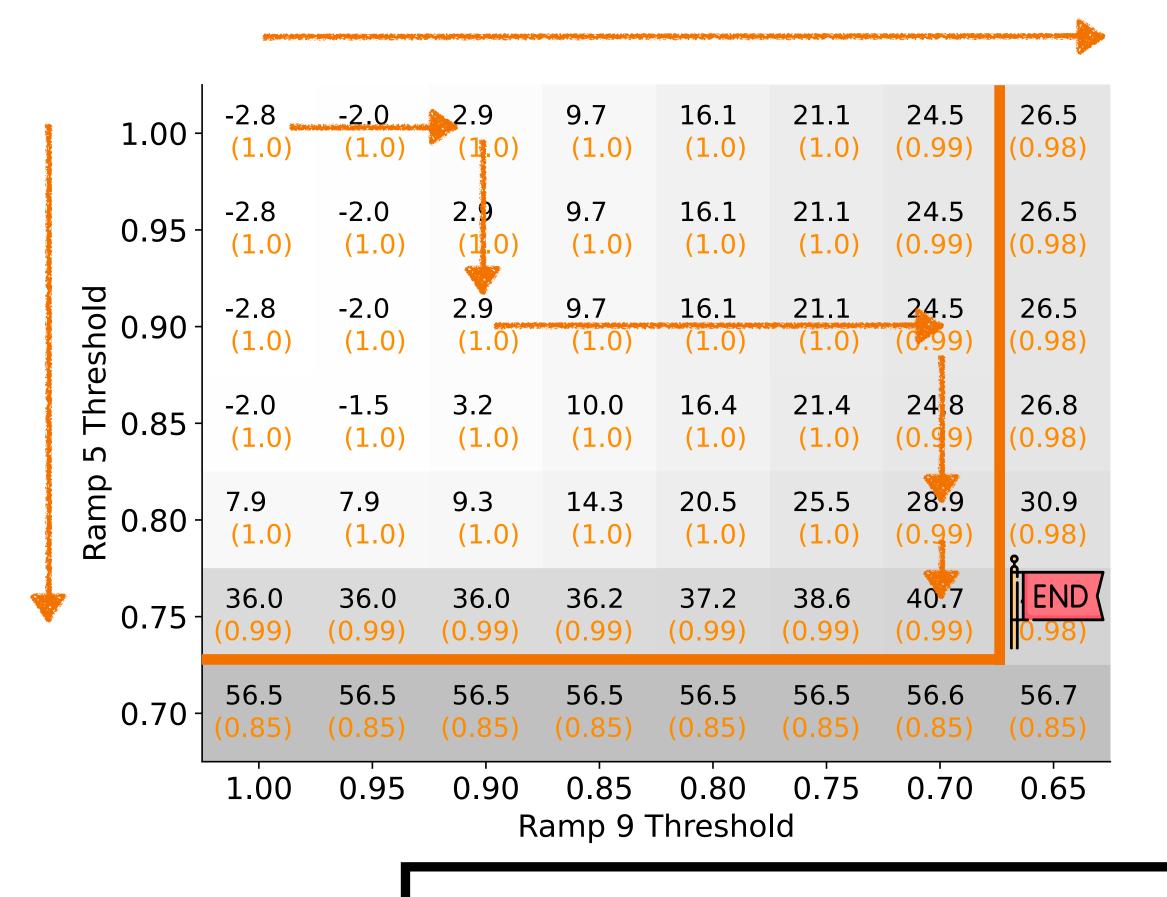
insight 2: leverage EE properties for fast tuning



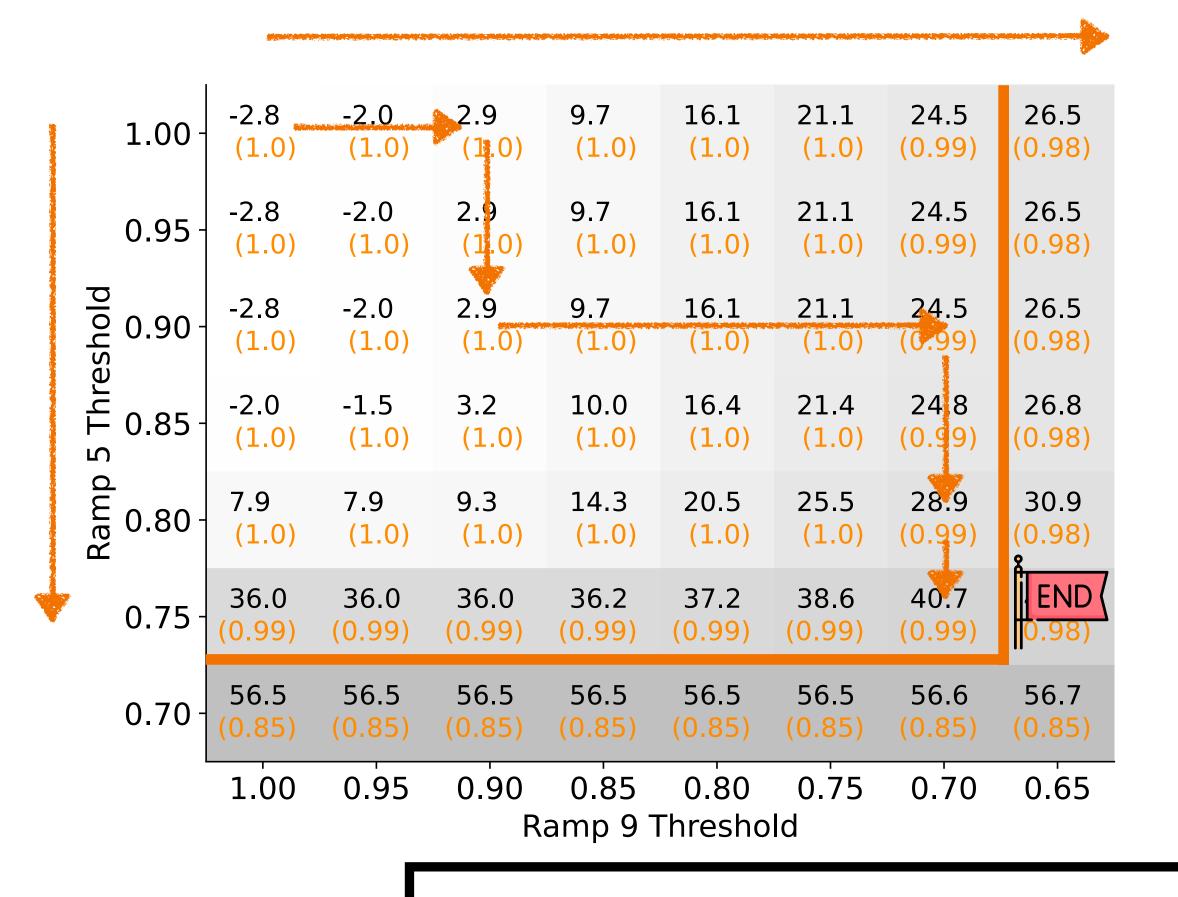
insight 2: leverage EE properties for fast tuning

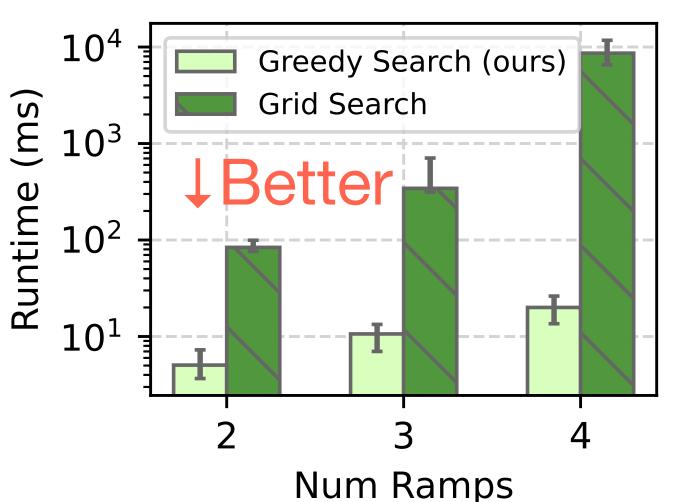


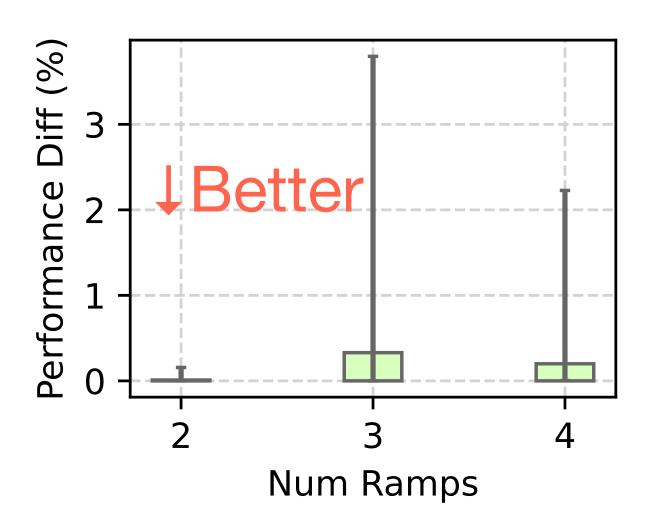
insight 2: leverage EE properties for fast tuning



insight 2: leverage EE properties for fast tuning

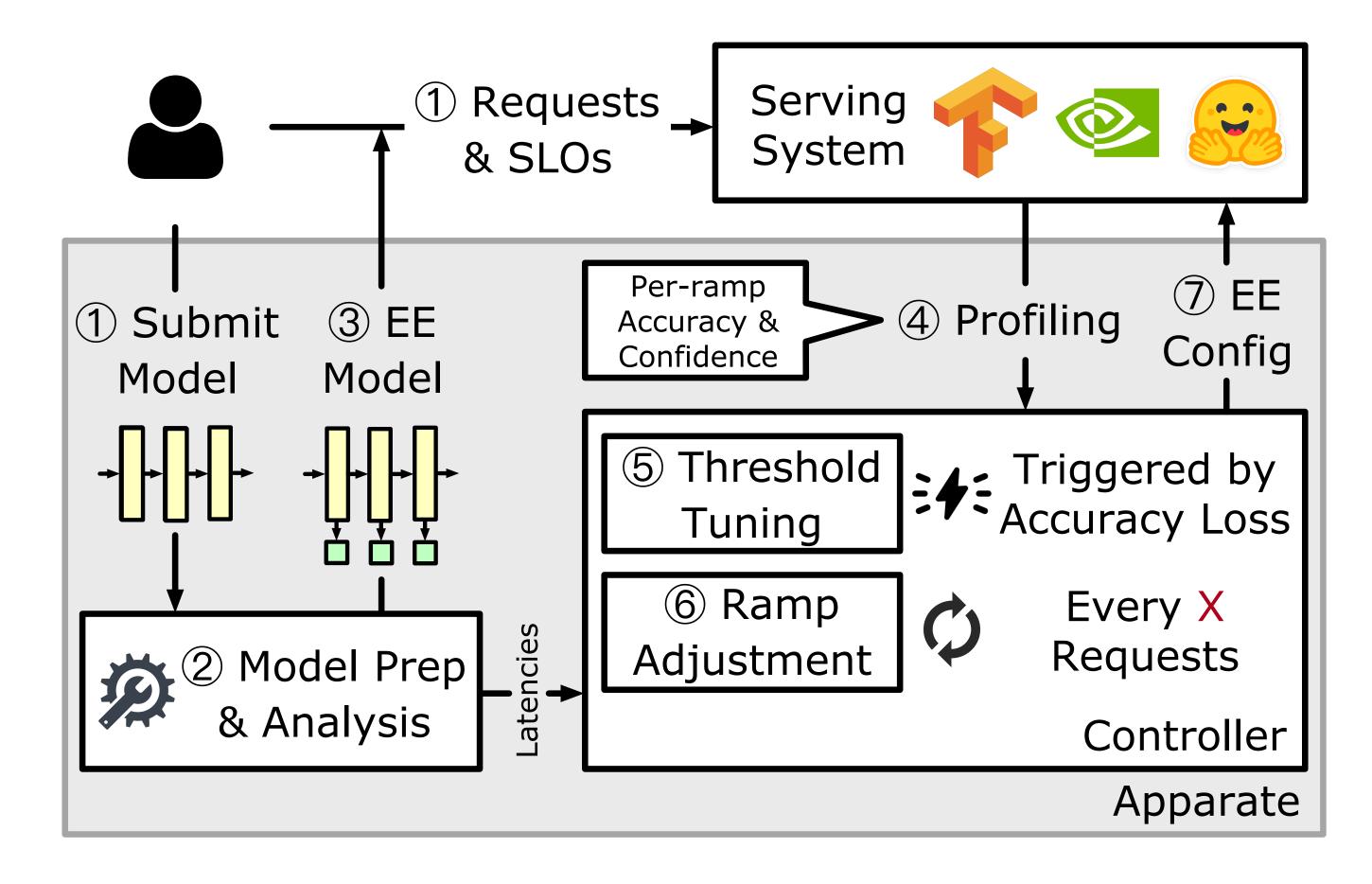




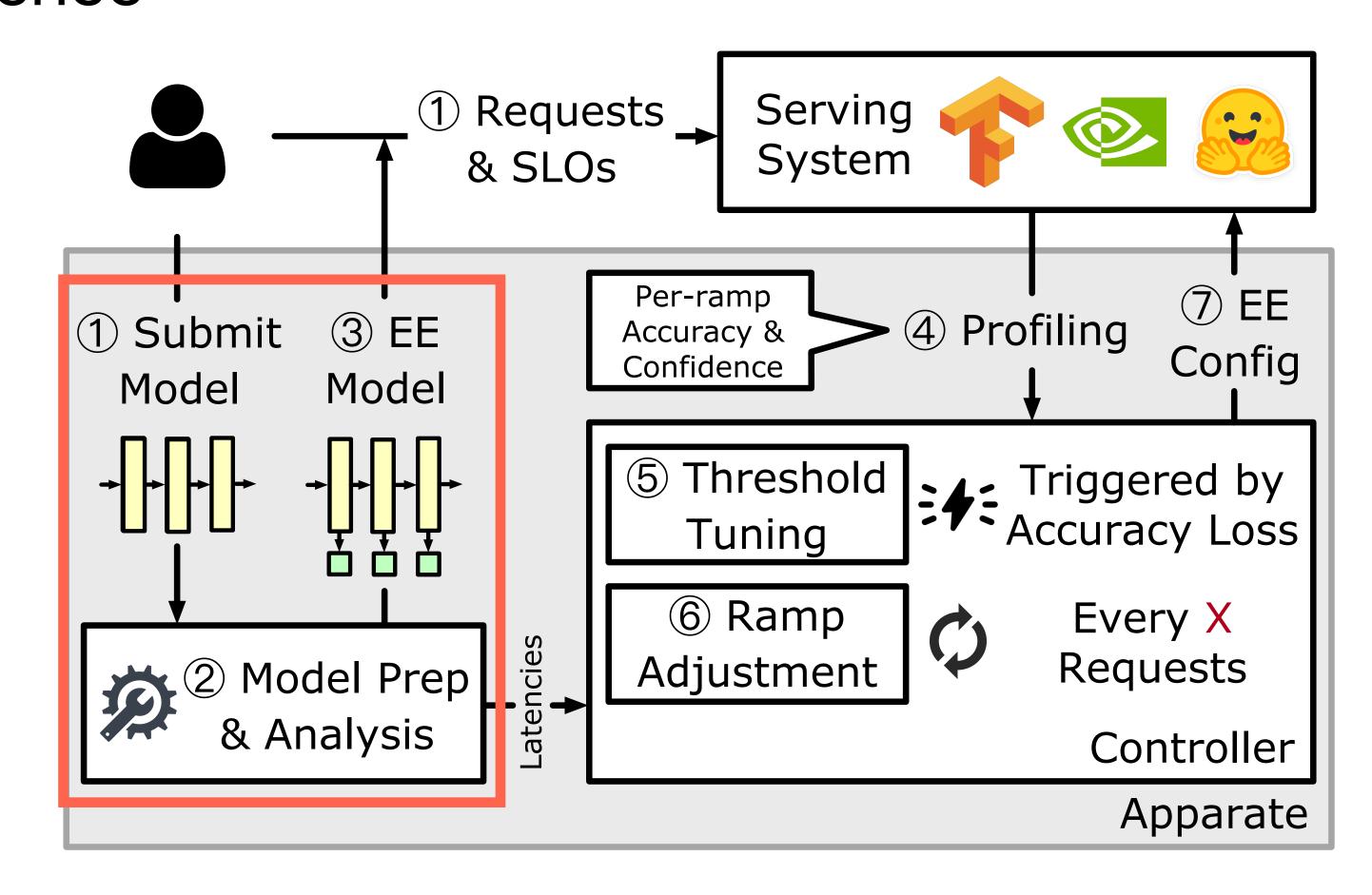


Threshold tuning is quick and achieves nearoptimal latency savings

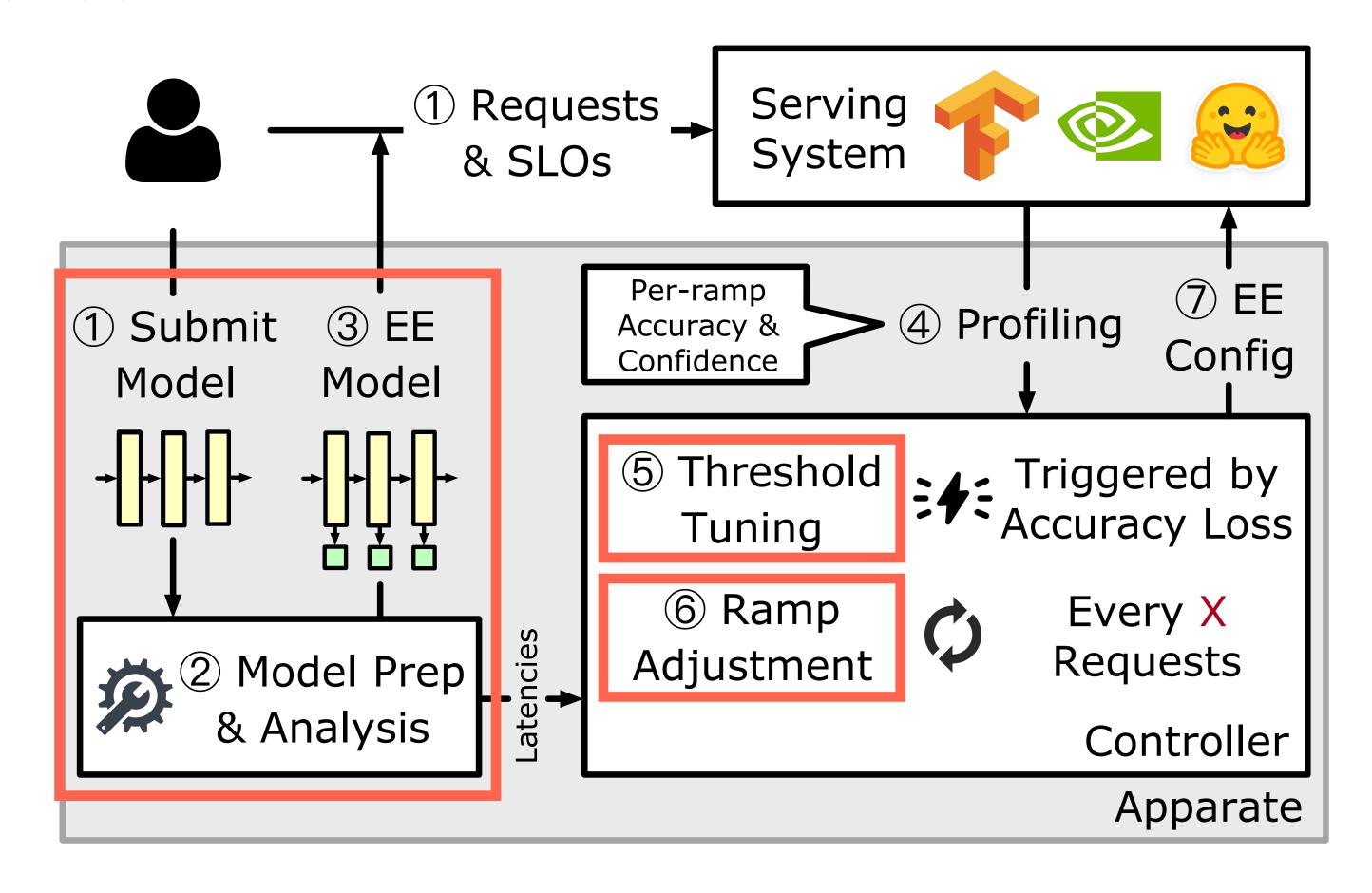
the first system that automatically integrates and manages EEs for ML inference



the first system that automatically integrates and manages EEs for ML inference



the first system that automatically integrates and manages EEs for ML inference

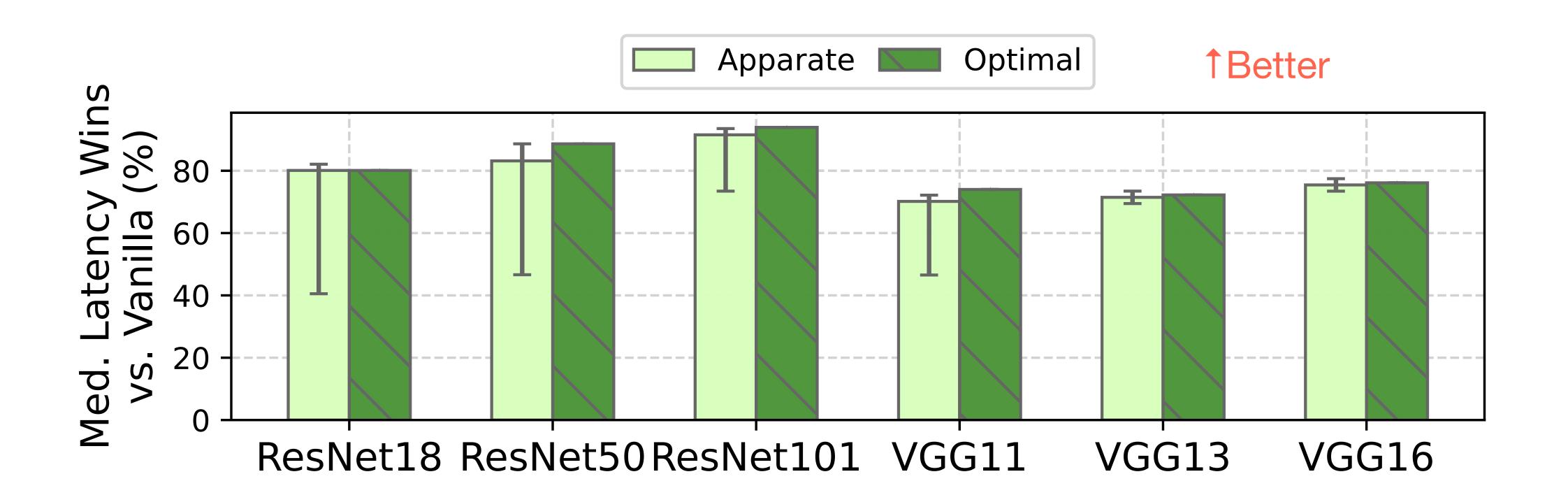


- How does Apparate compare with vanilla model inference?
 - Non-generative workloads
 - Generative workloads
- How does Apparate compare with baselines
- How does Apparate perform under different SLOs?
- How dose Apparate perform under different latency/acc budget?
- What's the runtime overhead?

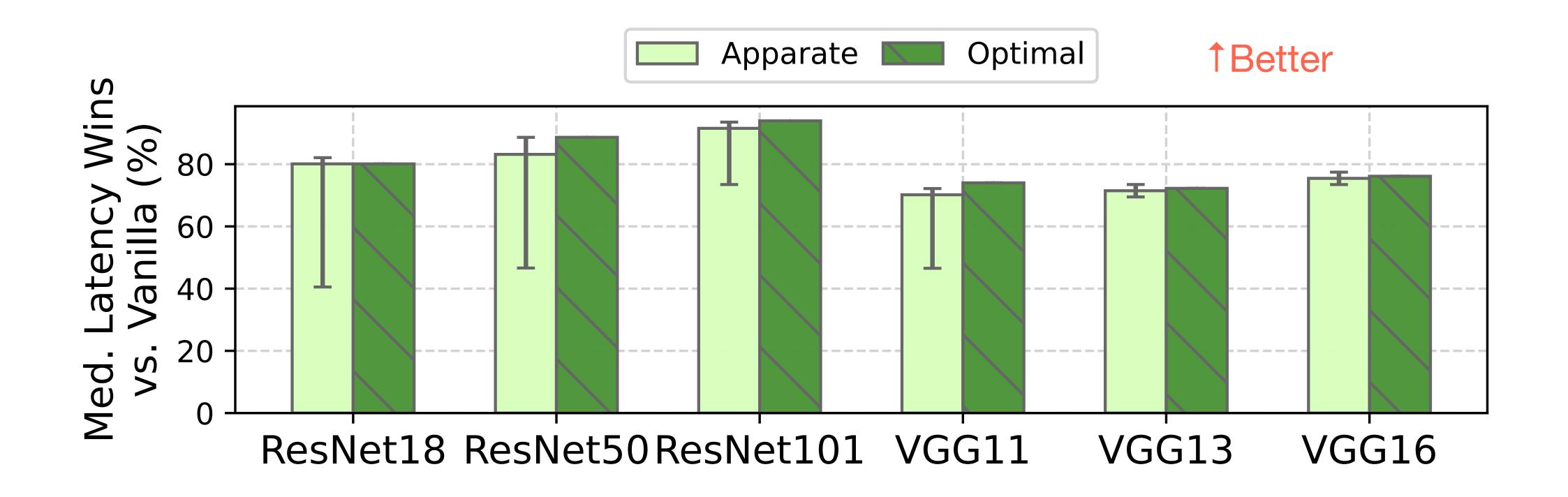
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Performance on CV workloads

Performance on CV workloads

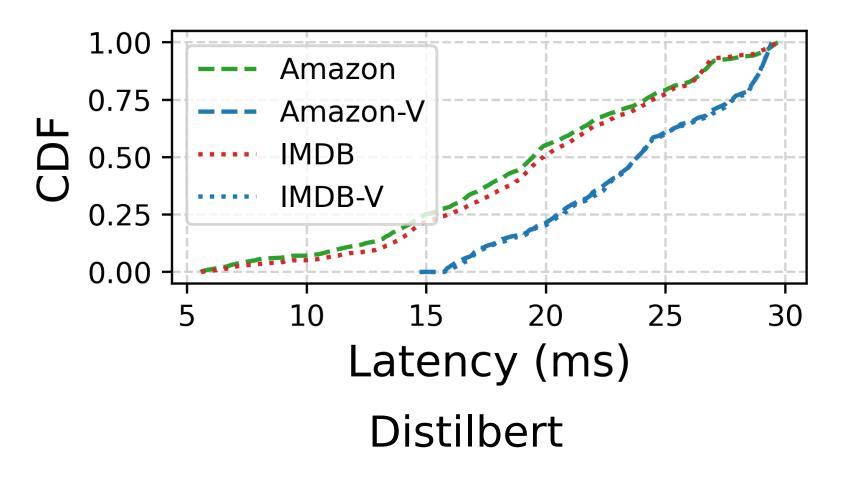


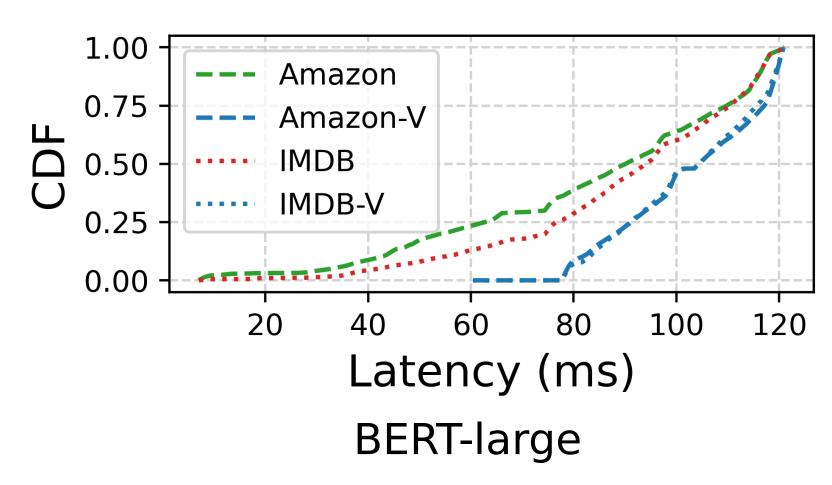
Performance on CV workloads

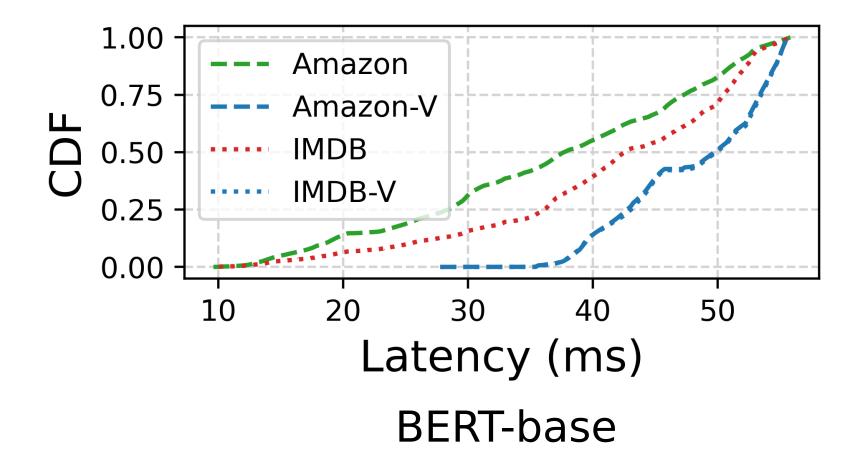


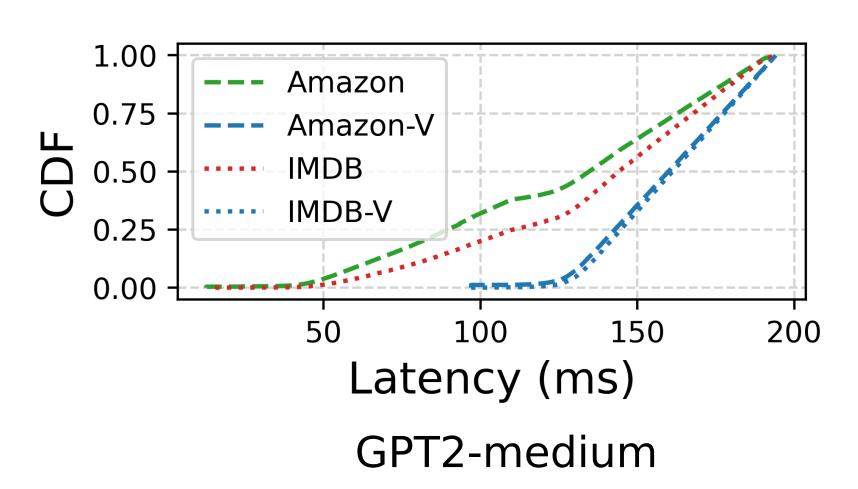
Up to 94% lower median latency than vanilla, and is close to optimal

Performance on NLP workloads

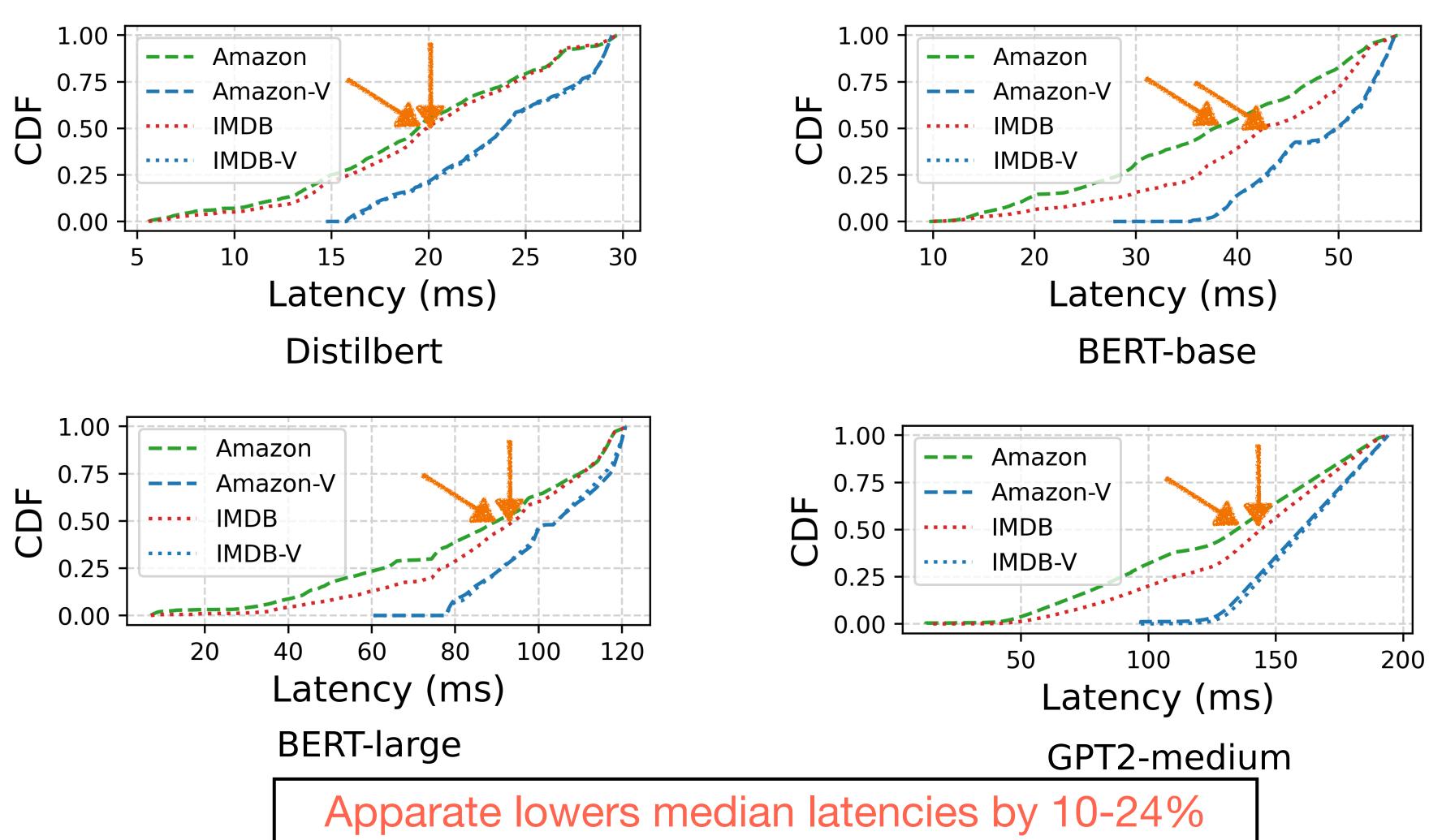






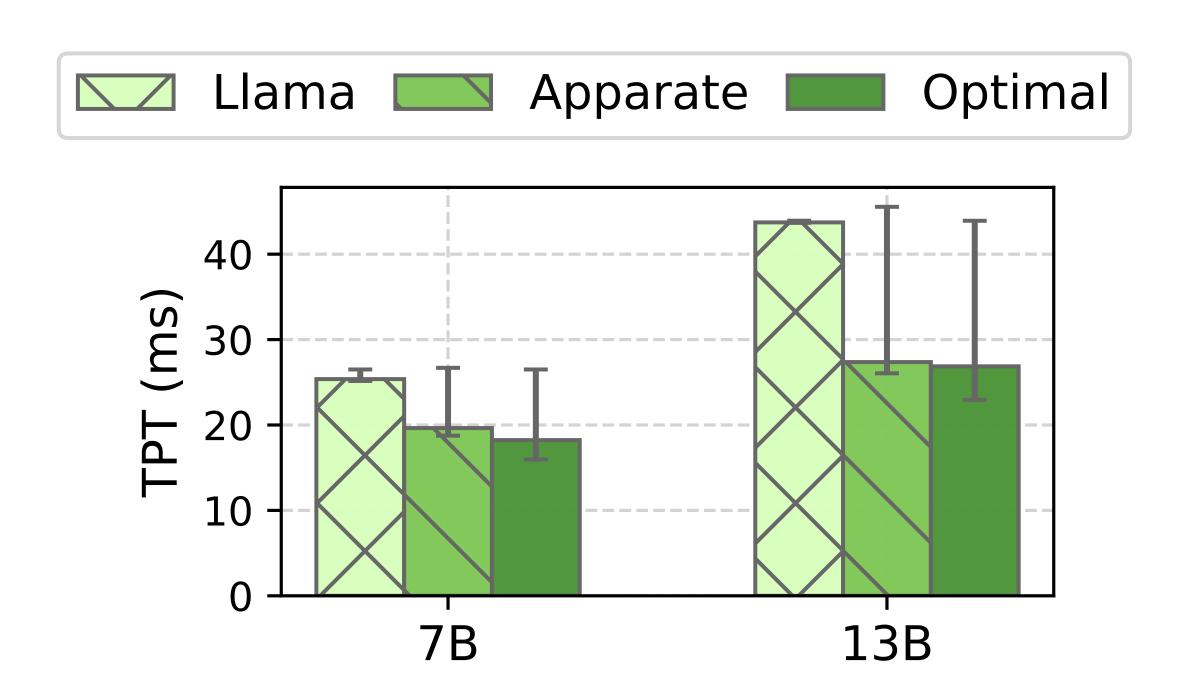


Performance on NLP workloads

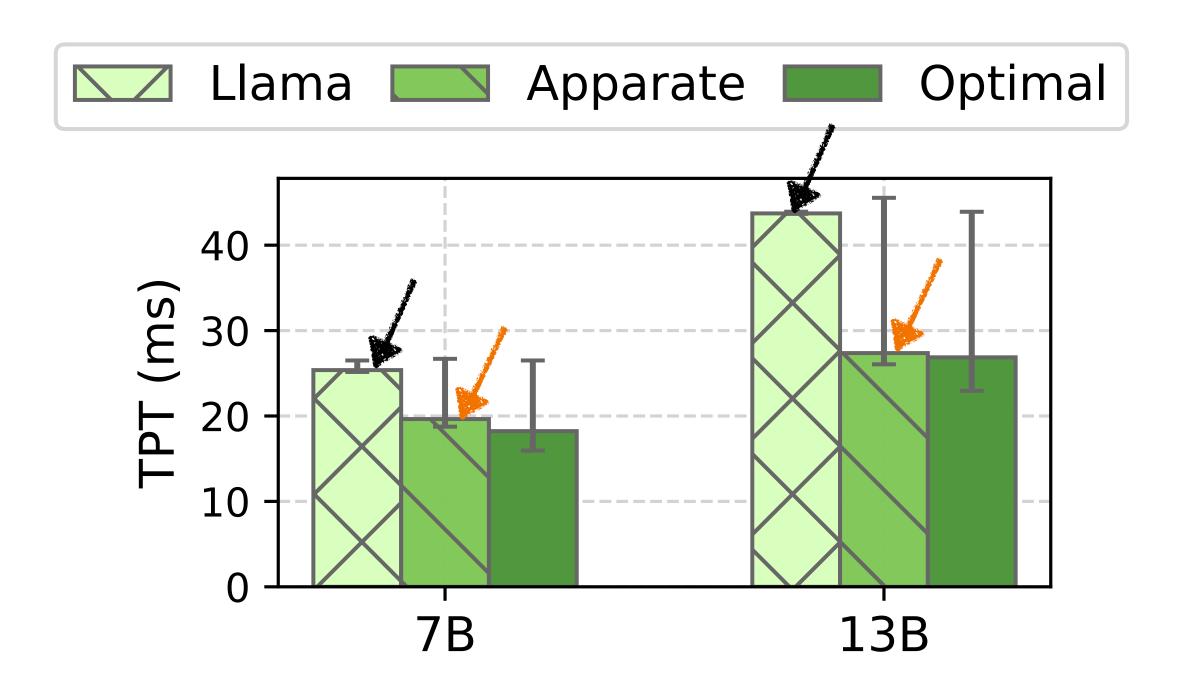


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Performance on generative workloads

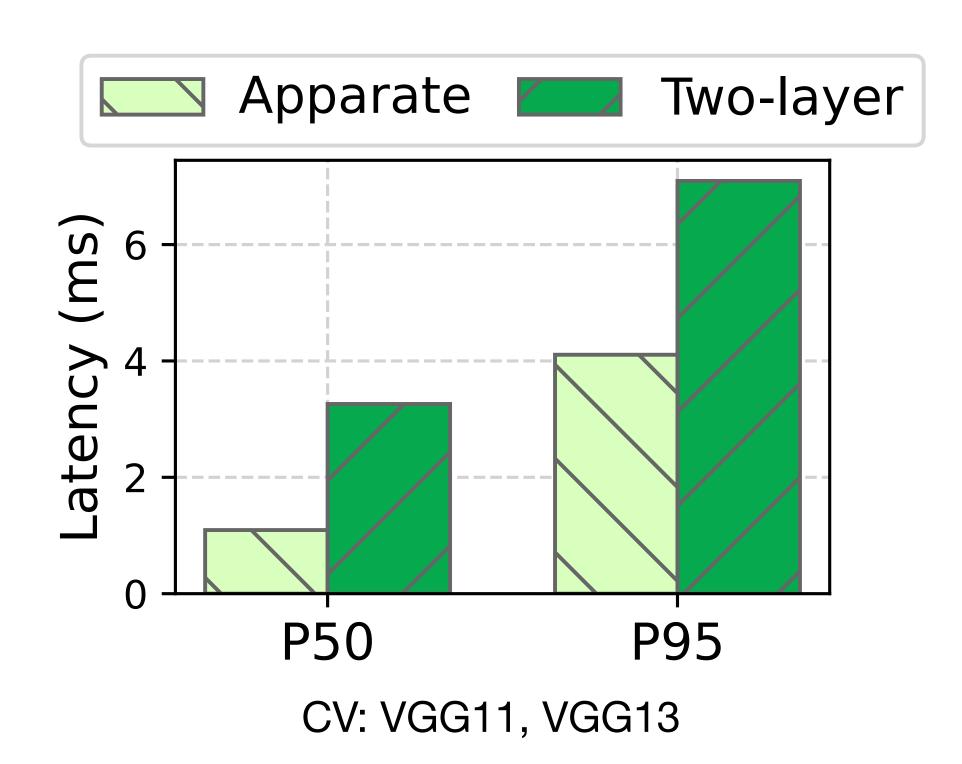


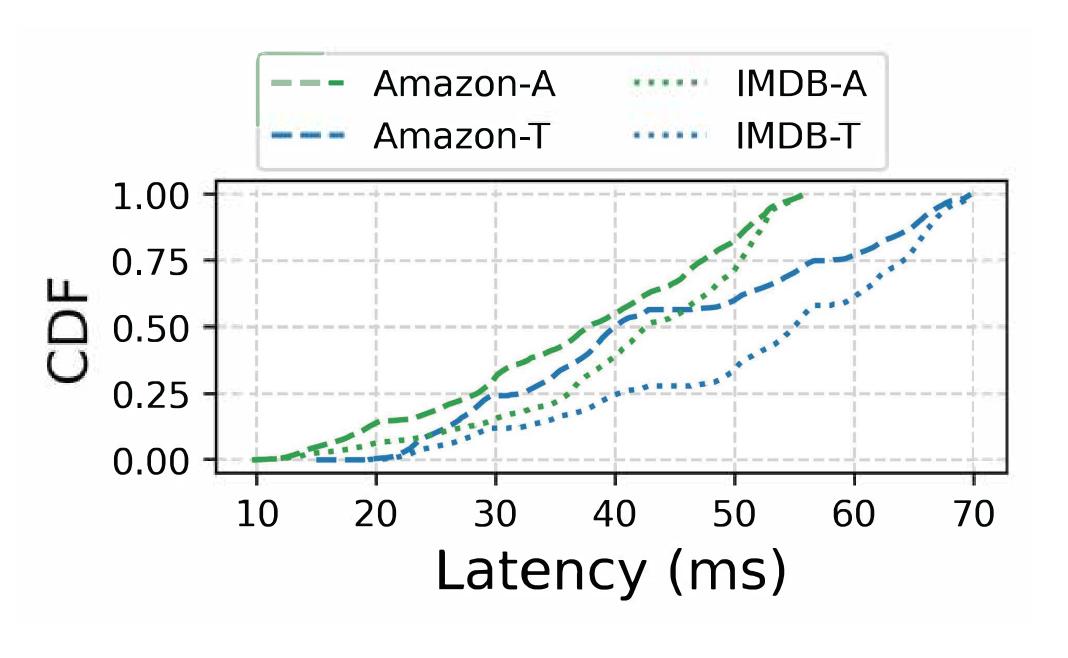
Performance on generative workloads



Apparate lowers median TPT by 22–37% compared with vanilla Llama models

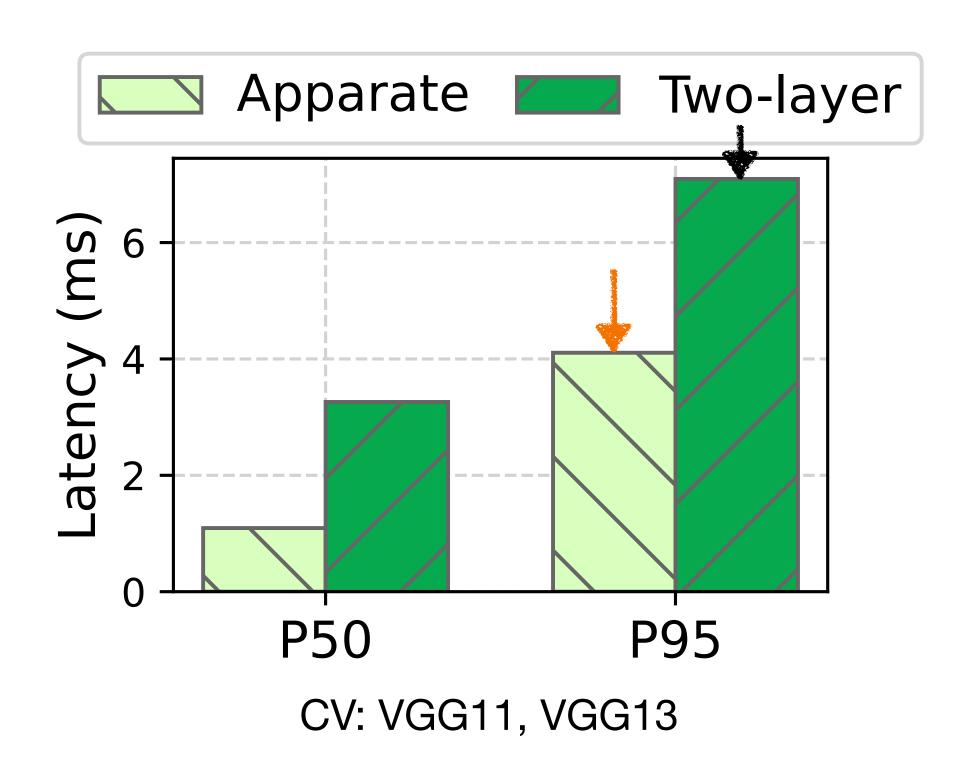
Compare Apparate with two layer inference systems

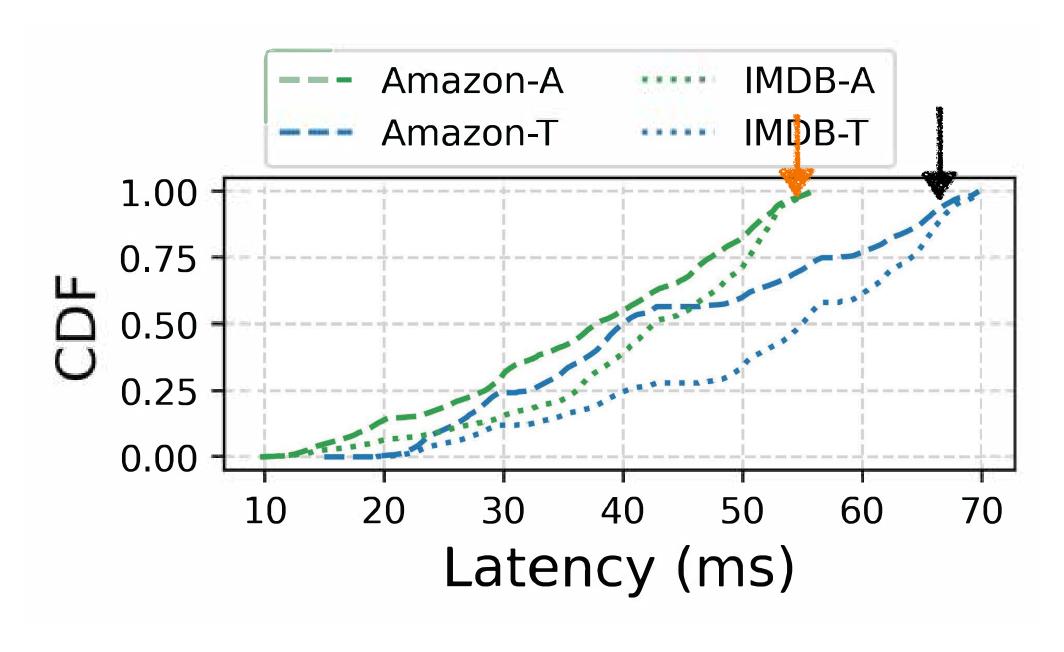




NLP: Distilbert, BERT-base

Compare Apparate with two layer inference systems

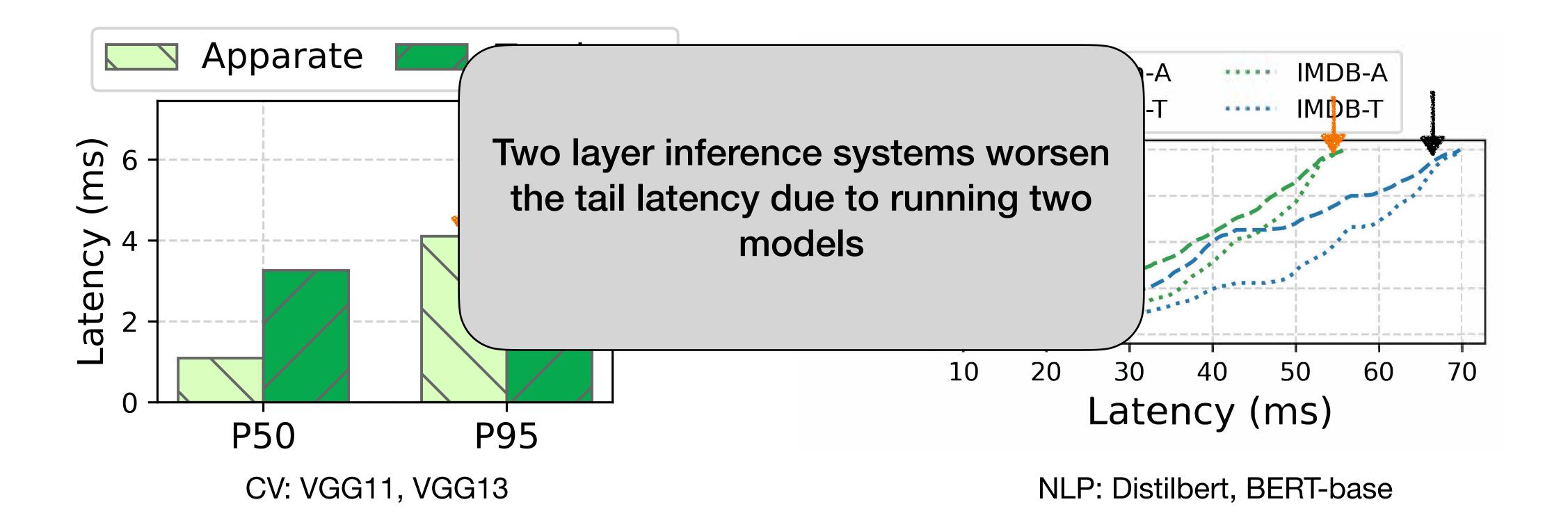




NLP: Distilbert, BERT-base

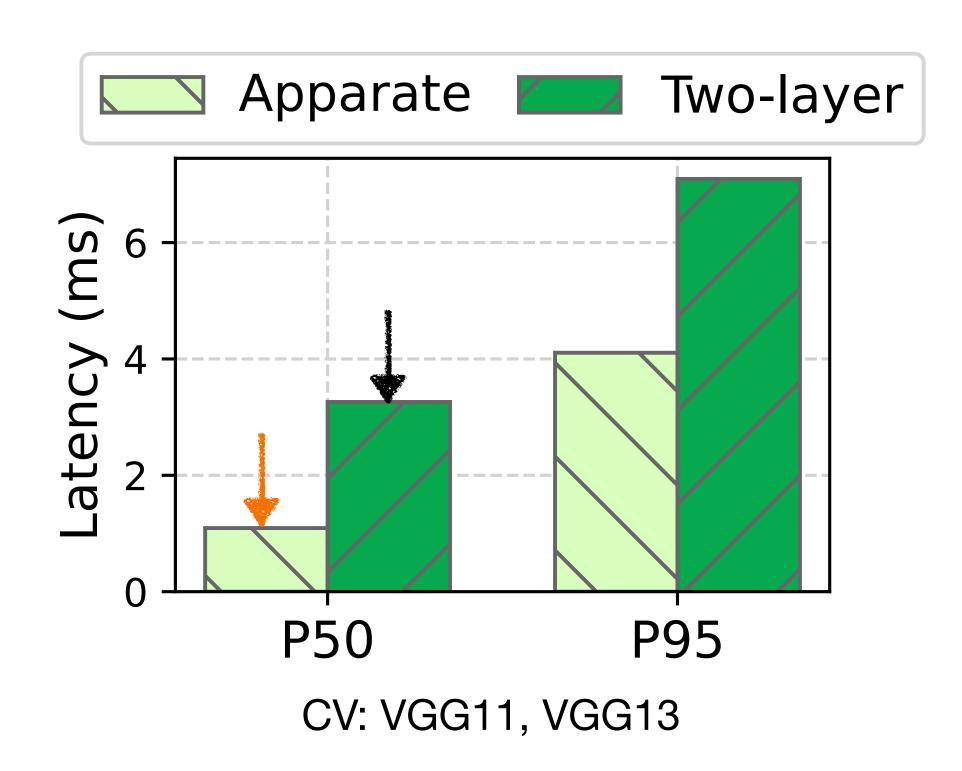
Apparate delivers 21-42% lower P95 latencies compared to these baselines

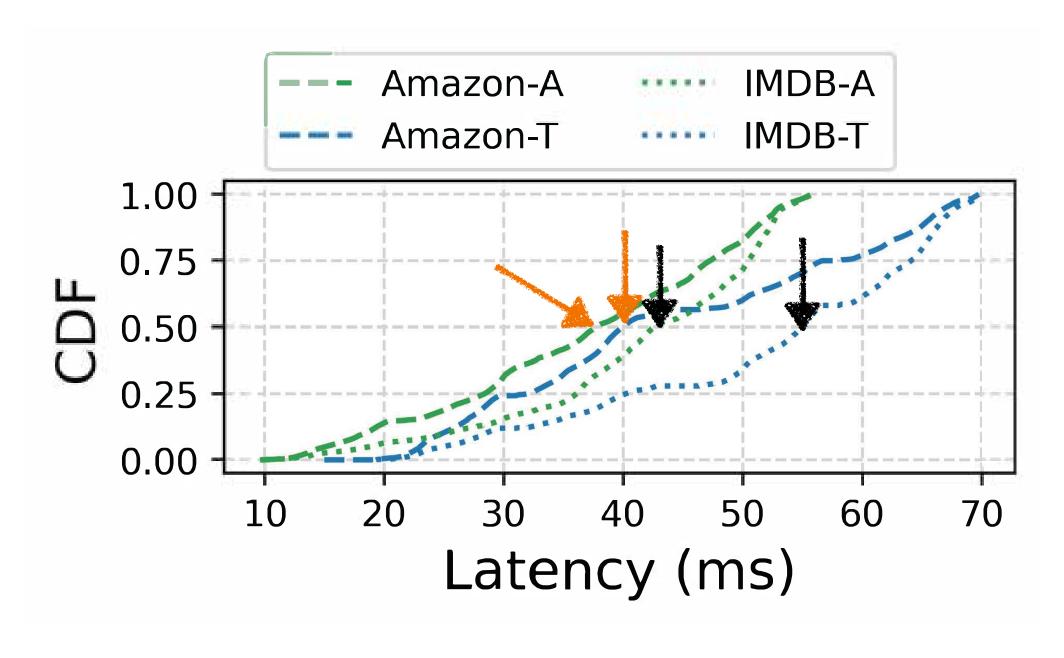
Compare Apparate with two layer inference systems



Apparate delivers 21-42% lower P95 latencies compared to these baselines

Compare Apparate with two layer inference systems

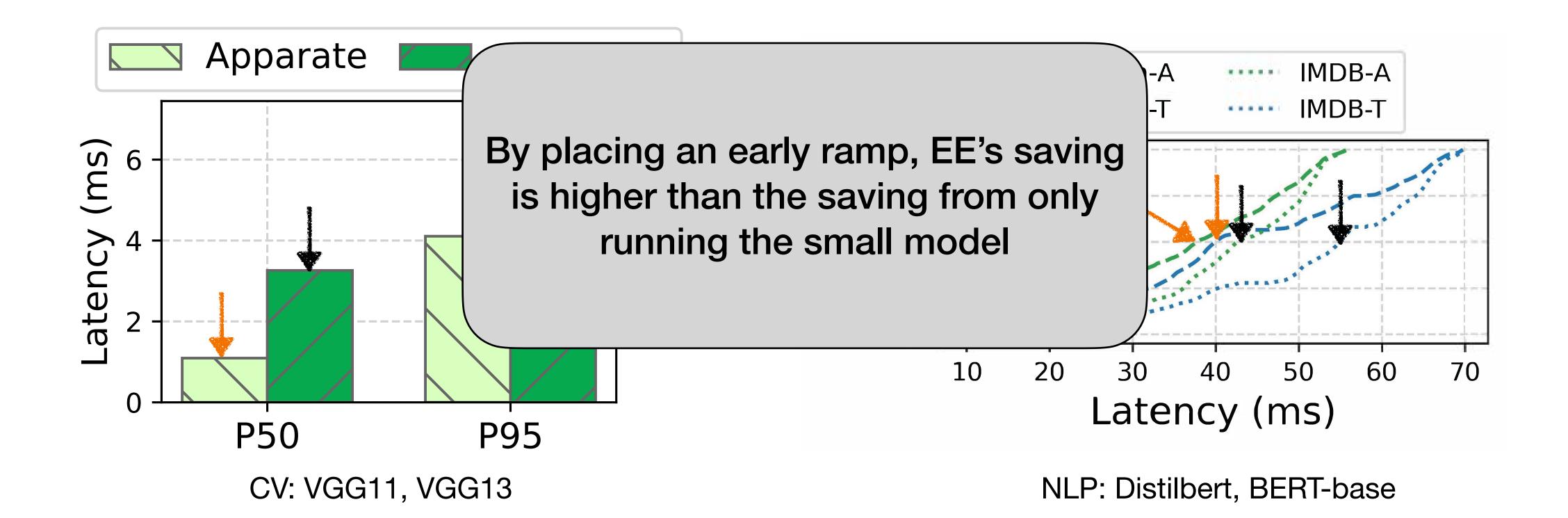




NLP: Distilbert, BERT-base

Apparate delivers up to 66% lower median latencies compared to these baselines

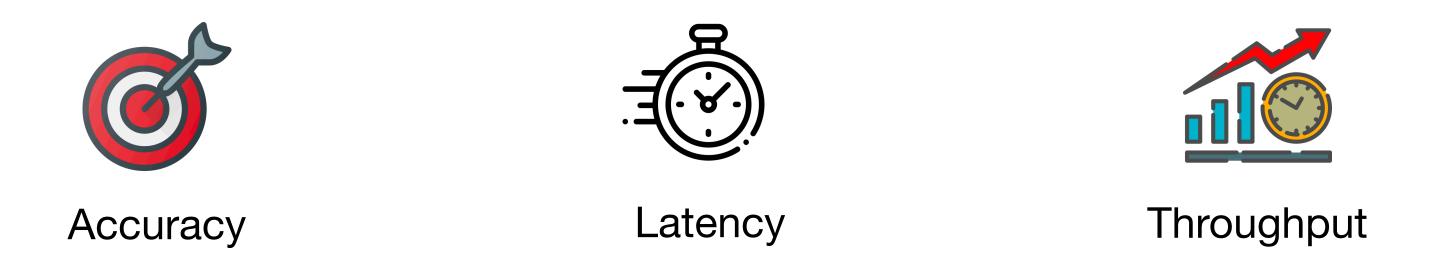
Compare Apparate with two layer inference systems



Apparate delivers up to 66% lower median latencies compared to these baselines

The First Runtime Management System for Early Exit Networks

- Injects EEs for user-provided models without requiring manual effort or expertise
- Repurposes EEs for rapid results with continuous feedback for online adaptation
- Reduces per-request latency while meeting accuracy and overhead constraint



Source code available at https://github.com/dywsjtu/apparate