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

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Abstract

Machine learning (ML) inference platforms are tasked with balancing two competing goals: ensuring high throughput given many requests, and delivering low-latency responses to support interactive applications. Unfortunately, existing platform knobs (e.g., batch sizes) fail to ease this fundamental tension, and instead only enable users to harshly trade off one property for the other. This paper explores an alternate strategy to taming throughput-latency tradeoffs by changing the granularity at which inference is performed. We present Apparate, a system that automatically applies and manages early exits (EEs) in ML models, whereby certain inputs can exit with results at intermediate layers. To cope with the time-varying overhead and accuracy challenges that EEs bring, Apparate repurposes exits to provide continual feedback that powers several novel runtime monitoring and adaptation strategies. Apparate lowers median response latencies by 40.5-91.5% and 10.0-24.2% for diverse CV and NLP workloads, respectively, without affecting throughputs or violating tight accuracy constraints.

1 Introduction

Machine Learning (ML) inference has become a staple for request handling in interactive applications such as traffic analytics, chatbots, and web services [24, 26, 33, 40, 55]. To manage these ever-popular workloads, applications typically employ serving platforms [4, 5, 17, 22, 39, 44] that ingest requests and schedule inference tasks with pre-trained models across large clusters of compute resources (typically GPUs). The overarching goals of serving platforms are to deliver sufficiently *high throughput* to cope with large request volumes – upwards of trillions of requests per day [37] – while respecting the service level objectives (SLOs) that applications specify for response times (often 10s to 100s of ms).

Unfortunately, in balancing these goals, serving platforms face a challenging tradeoff (§2.1): requests must be batched for high resource efficiency (and thus throughput), but larger batch sizes inflate queuing delays (and thus per-request latencies). Existing platforms navigate this *latency-throughput tension* by factoring only tail latencies into batching decisions and selecting max batch sizes that avoid SLO violations. Yet, this trivializes the latency sensitivity of many interactive applications whose metrics of interest (e.g., user retention [20, 54], safety in autonomous vehicles [52]) are also influenced by how far below SLOs their response times fall.

This paper explores the role that early exits (EEs) – an adaptation mechanism that has garnered substantial ML research interest in recent years [28, 36, 53, 56–58, 64] – can play in resolving this tension for existing serving platforms. With EEs, intermediate model layers are augmented with ramps of computation that aim to predict final model responses. Ramp predictions with sufficiently high confidence (subject to a threshold) exit the model, foregoing downstream layers and bringing corresponding savings in both compute and latency. The intuition is that models are often overparameterized (especially given recent model growth [31, 32, 48]), and certain 'easy' inputs may not require complete model processing for accurate results. Importantly, unlike existing platform knobs (e.g., batch size) that simply walk the steep latency-throughput tradeoff curve, EEs rethink the granularity of inference on a per-input basis. This, in turn, provides a path towards lowering request latencies without harming platform throughputs. Indeed, across different CV and NLP workloads, we find that optimal use of EEs brings 24.8-94.0% improvement in median latencies for the same accuracy and throughput.

Despite these potential benefits, EEs are plagued with practical challenges that have limited their impact to date (§2.3). The primary issue is that EE proposals have solely come in the context of specific model architectures that impose fixed ramp designs and locations [53, 57]. The lack of guidance for integrating EEs into arbitrary models is limiting, especially given the ever-growing number of model offerings in the marketplace today. Worse, even existing proposals lack any policy for *runtime adaptation* of EE configurations, i.e., the set of active ramps and their thresholds. Such adaptation is crucial since dynamic workload characteristics govern the efficacy of each ramp in terms of exiting capabilities and added overheads (to non-exiting inputs); accordingly, failure to continually adapt configurations can result in unacceptable accuracy drops of 8.3-23.9% for our workloads. However, devising adaptation policies is difficult: the space of configurations is massive, and it is unclear how to obtain a signal for accuracy monitoring once an input exits.

We present **Apparate**, the first system that automatically injects and manages EEs for serving with a wide range of models. Our main insight is that the above challenges are not fundamental to EEs, and instead are a byproduct of what we are trying to get out of them. Specifically, adaptation challenges largely stem from halting execution for an input upon an exit, which leaves uncertainty in the 'correct' response (as per the non-EE model). Instead, Apparate uses EEs *only to deliver latency reductions*; results for successful exits are immediately released, but *all* inputs continue to the end of the

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model. The key is in leveraging the (now) redundant computations to enable continual and efficient adaptation.

Guided by this philosophy, Apparate runs directly atop existing serving platforms and begins by automatically converting registered models into EE variants. Apparate's EE preparation strategy must strike a balance between supporting fine-grained runtime adaptation without burdening those time-sensitive algorithms with (likely) unfruitful options. To do so without developer effort, Apparate leans on guidance from the original model design, crafting ramp locations and architectures based on downstream model computations and data flow for intermediates around the model. Original model layers (and weights) are unchanged, and added ramps are trained in parallel (for efficiency), but in a manner that preserves their independence from other ramps.

Once deployed by serving platforms, Apparate continually monitors EE operation in GPUs, tracking computations and latency effects of each ramp, as well as outputs of the original model (for accuracy ground truth). To tackle the massive space of configuration options, Apparate judiciously decouples tunable EE knobs: thresholds for existing ramps are frequently and quickly tuned to ensure consistently high accuracy, while costlier changes to the set of active ramps occur only periodically as a means for latency optimization. For both control loops, Apparate leverages several fundamental properties of EEs to accelerate the tuning process. For instance, the monotonic nature of accuracy drops (and increases in latency savings) for higher thresholds motivates Apparate's greedy algorithm for threshold tuning which runs up to 3 orders of magnitude faster than grid search while sacrificing only 0-3.8% of the potential wins.

We evaluated Apparate across a variety of recent CV and NLP models (ranging from compressed to large language models), multiple workloads in each domain, and several serving platforms (TensorFlow-Serving [39], Clockwork [22]). Compared to serving without EEs, Apparate improves 25th percentile and median latencies by 70.2-94.2% and 40.5-91.5% for CV, and 16.0-37.3% and 10.0-24.2% for NLP, while imposing negligible impact on platform throughput. Importantly, unlike existing EE proposals that yield accuracy dips of 8.3-23.9%, we find that Apparate's adaptation strategies *always* met user-defined accuracy constraints.

2 Background and Motivation

We start by overviewing existing ML serving platforms (§2.1), highlighting the challenges they face in balancing metrics that are important for system performance (i.e., throughput, resource utilization) and application interactivity, i.e., per-request latencies. We then describe the promising role that early exits can play in alleviating those tensions (§2.2), and the challenges in realizing those benefits in practice (§2.3). Results here follow the methodology from §5.1, and presented trends hold for all workloads used in the paper.

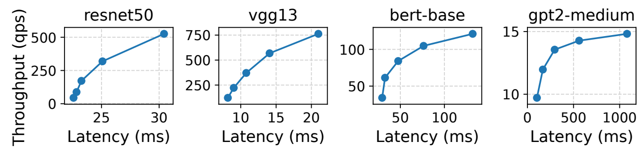


Figure 1: Throughput-latency tradeoff in model serving. Results show serving times with batch sizes of 1-16.

2.1 Model Serving Platforms

ML models are routinely used to service requests in interactive applications such as real-time video analytics [13, 49], recommendation engines [50], or speech assistants [12]. To manage such workloads, especially at large scale, applications employ serving platforms such as ONNX runtime [5], TensorFlow-Serving [39], PyTorch Serve [9], Triton Inference Server [4], among others [17,22,44,49,60]. These platforms ingest pre-trained model(s) from applications, often in graph exchange formats like ONNX [6] and NNEF [2], and are also granted access to a pool of compute resources (potentially with ML accelerators such as GPUs) for inference.

Given the latency-sensitive nature of interactive applications, requests are most often accompanied with *service level objectives* (SLOs) that indicate (un)acceptable response times for the service at hand. In particular, responses delivered after an SLO expires are typically discarded or yield severely degraded utility. Common SLOs are in the 10-100s of milliseconds, e.g., for live video analytics [40, 49].

During operation, serving platforms queue up incoming requests that can arrive at fixed or variable rates, and continually schedule jobs across the available compute resources. An inference task may be scheduled to run on a single node in a cluster, or may be distributed across multiple nodes [60]. State-of-the-art serving frameworks include optimizations such as response caching [17], intelligent job placement to aggressively pack GPU memory resources [49], or strategies to mitigate CPU-GPU communication overheads [60].

Latency-Throughput tension. Real-world inference deployments must handle large volumes of requests [25, 37]. To support the need for high *throughput*, serving platforms resort to *batching*, whereby inputs are grouped into a single high-dimensional tensor that moves through the model in lockstep, kernel by kernel, with final per-request responses being delivered at the same time. Larger batch sizes amortize the cost of loading a kernel into GPU memory across more inputs, and enable more effective use of the parallelism that ML-focused hardware affords [17, 62].

Unfortunately, delivering the throughput necessary to support high request rates is directly at odds with *per-request* latencies (Figure 1). On one hand, latency for an input is minimized by scheduling inference as soon as the request arrives with batch size of 1. On the other hand, throughput is maximized by creating large batches using a queuing system which directly inflates request latencies.

The problem. In navigating this tension, the key decision

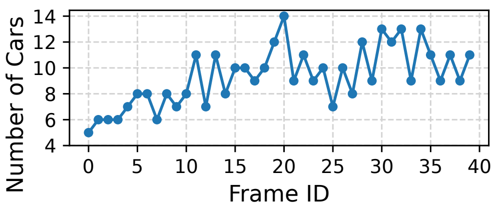
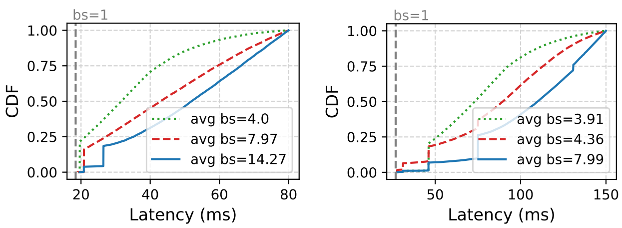


Figure 2: Object counts in videos vary frequently and thus need low-latency responses. Results use a random 30-fps video in our corpus and the FasterRCNN detector.



(a) ResNet50 **(b) BERT-base**

Figure 3: Tuning platform knobs lowers latencies but harms throughput. Results vary TF-Serve's *max_batch_size* from 4-16. Gray lines show min serving delay per model (batch of 1). CV uses a random video in our set; NLP uses Amazon reviews [10].

that serving platforms face is when to drain queued requests and schedule them for inference. Certain platforms [17, 22, 49] take an all-or-nothing viewpoint on latency, with adherence to SLOs considered complete success, and violations viewed as complete failure. Accordingly, these platforms schedule inference jobs in a work-conserving manner and select the *max* batch size that limits SLO violations for queued requests. However, many interactive applications present a more nuanced latency story where sub-SLO responses are not equally useful. For instance, live video analytics results can change every frame, i.e. 33 ms (Figure 2); faster responses ensure up-to-date perception of the environment. Similarly, for speech assistance, faster responses are favored to keep conversational interactivity high [26, 59].

Other platforms [4, 9, 39] provide more flexibility by exposing tunable knobs to guide queue management. For instance, applications can configure *max_batch_size* and *batch_timeout_micros* parameters that set a cap on batch size or inter-job scheduling durations. However, as shown in Figure 3, such knobs do little to ease the throughput-latency tension, and instead expose harsh tradeoffs: across both CV and NLP workloads, tuning these knobs for median latency improvements of 17.3-39.1% brings 1.1-3.6× reductions in average batch sizes (and proportional hits on throughput).

Takeaway. Existing platform configurations and knobs fail to practically remediate the throughput-latency tension, and instead simply navigate (often) unacceptable tradeoff points between the two goals. Given ever-growing request rates and the need for high throughput, we ask if there is a middle-ground: whereby new serving adaptations enable lower per-request latencies (moving closer to the lower-bound serving times in Figure 3) without harming platform throughput.

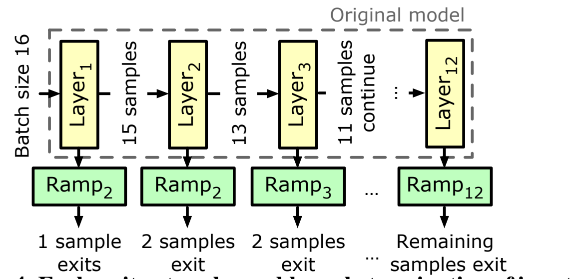
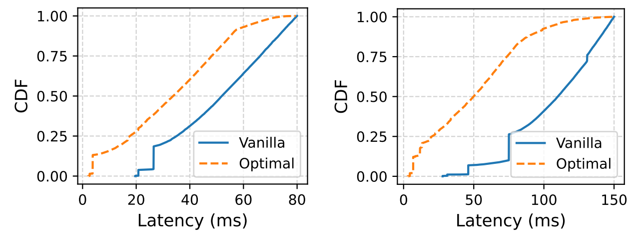


Figure 4: Early exit networks enable early termination of inputs at intermediate layers, lowering both compute and latency.



(a) ResNet50 **(b) BERT-base**

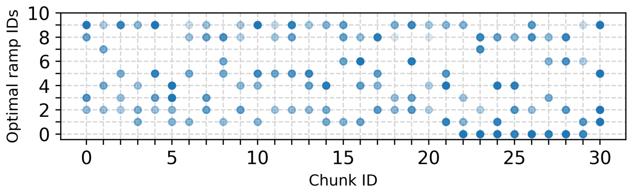
Figure 5: EEs can lower latencies without harming throughput. Results modulate latencies from TF-Serve with original/vanilla models (Figure 3) based on optimal exiting.

2.2 Early-Exit Models

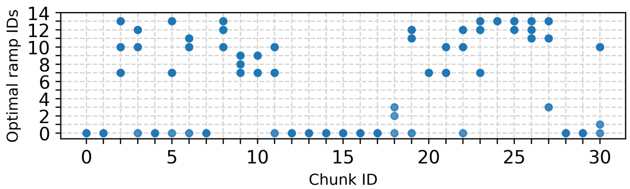
Early (or multi) exit models [53, 57] present an alternate way to address this tension by rethinking the granularity of inference. As shown in Figure 4, the key premise is that certain 'easy' inputs may not require the full predictive power of a model to generate an accurate result. Instead, results for such inputs may be predictable from the values at intermediate layers. In such cases, the foregone model execution can yield proportional reductions in both per-request latencies and compute footprints. Thus, the goal with early exits (EEs) is to determine, on a per-input basis, the earliest model layer at which an accurate response can be generated.

To use EEs, intermediate layers in a model are augmented with *ramps* of computation. These ramps ingest the values output by the layers they are attached to and parse them to predict the final model's result, e.g., a classification label. Ramps can perform arbitrary degrees of computation to arrive at a potential result. Exiting decisions at each ramp are made by comparing the entropy in the predicted result (or averaged over the past k ramps) to a preset *threshold*. Thresholds are set to balance latency and compute wins with potential dips in accuracy; a higher threshold implies lower required confidence for exiting, and thus more exiting.

Potential benefits. To understand the effect that EEs can have on the latency-throughput tension, we considered off-the-shelf EE variants for the models used in Figure 3: BranchyNet [53] (for CV) and DeeBERT [57] (for NLP). For each model-input pair, we identified the *optimal* exit point defined as the earliest exit ramp that predicted the correct response for the input, i.e., the ramp which assigned the maximum probability to the correct label. We then modified the



(a) BERT-base; Amazon reviews



(b) ResNet50; random corpus video

Figure 6: Optimal EE configurations change frequently. Streaming workloads were divided into chunks of 64 requests. Dot presence show a ramp that was part of the optimal config for a chunk, while transparencies indicate threshold values (opaque is higher).

highest-throughput results in Figure 3 to account for exiting by subtracting the time saved for each exiting input, i.e., the difference in time for passing an input to the end of its optimal ramp versus passing it to the end of the model (without any ramps present). Note that these results are conservative upper bounds in that they do not reduce queuing delays or alter job scheduling. As shown in Figure 5, without changing queueing decisions, EEs can bring 35-54.7% and 17.9-26% improvements in median and 95th percentile latencies relative to running existing serving systems alone.

2.3 Challenges

Despite numerous EE proposal from the ML community [28, 36, 46, 53, 57, 58, 64], and their potential benefits for serving platforms, multiple issues complicate their use in practice, leading to low adoption rates. We describe them in turn.

C1: Latency and resource overheads. Although exiting can enable certain inputs to eschew downstream model computations, exit ramps impose two new overheads on model serving. First, to be used, ramps must also be loaded into GPU memory which is an increasingly precious resource as models grow in size [31, 48, 60] and inference shifts to resource-constrained settings [23, 40]. For instance, DeeBERT inflates overall memory requirements by 6.56% compared to BERT-base. Second, certain inputs may be too "hard" to accurately exit at an intermediate ramp. In these cases, overall serving latency mildly grows as unsuccessful exiting decisions are made, e.g., inputs that cannot exit at any ramp slow by 22.0% and 19.5% with BranchyNet and DeeBERT.

C2: Frequent and costly adaptation. As shown in Figure 6, the evolving nature of workloads for interactive applications [35, 51] brings frequent changes in the best EE configuration at any time, i.e., the set of active ramps (and their thresholds) that maximize latency savings without sacrificing response accuracy or exceeding available memory. Unfortunately, the large body of EE literature is unaccompanied by any policy for tuning ramps and thresholds during serving. Instead, proposed EE models are equipped with the max number of ramps, and mandate users to perform one-time tuning of thresholds. Such tuning is non-trivial and fails to cope with workload dynamism. For example, Table 1 shows how one-time tuning on initial or sampled data brings 8.3-14.5% drops in accuracy relative to continual tuning. Worse, the space of configurations is untenably large, with many ramp options (i.e., at any layer, with any computation) and a continuous space of possible threshold values for each.

Strategy\Workload	CV	NLP
Initial Only	84.5% (74.3%)	86.8% (73.6%)
Uniformly Sampled	90.3% (64.2%)	87.7% (69.4%)
Continual Tuning	98.6% (43.5%)	98.3% (26.6%)

Table 1: Thresholds need frequent tuning to avoid accuracy loss. Continual tuning kicks in when chunk accuracy $<$ 99%. Results list avg accuracy (median latency wins).

C3: Lack of accuracy feedback. EE ramp decisions are ultimately confidence-driven and may result in accuracy degradations (as shown above). In production scenarios, serving optimizations that deliver accuracy reductions of more than 1-2% are generally considered unacceptable [14]. Yet, despite this strict constraint, once deployed, EE models do not provide any indication of accuracy drops; indeed, when an exit is taken, the corresponding input does not pass through the remaining model layers, and the original (non-EE) model's prediction is never revealed. Thus, with early exiting, we lack mechanisms to determine when accuracy degradations are arising and EE tuning is required.

C4: Incompatibility with batching. Lastly, although EE decisions do not directly conflict with queuing decisions in serving platforms, combining exiting and batching presents practical challenges. In particular, as inputs exit at ramps, batch sizes for *already scheduled inference tasks* naturally shrink, leading to resource underutilization for the rest of the model's execution. Batch reforming [4] could help, but adds undue latency from added CPU-GPU data transfers; recent proposals [29, 38] aim to address these communication overheads but fail to generalize across hardware configurations.[1]

3 Design

Apparate is an end-to-end system that automatically integrates early exits into models and manages their operation throughout the inference process. Its overarching goal is to optimize per-request latencies while adhering to tight accuracy constraints and throughput goals. Our key insight is in rethinking the way that EEs are configured and the benefits they are expected to deliver. In particular, rather than using EEs in the traditional way – where inputs exit model inference to provide *both* latency and computational benefits –

[1] Solving this challenge directly is outside the scope of this paper. We note that this would bring latency and compute wins from EEs, but would forego accuracy feedback (and thus, adaptation).

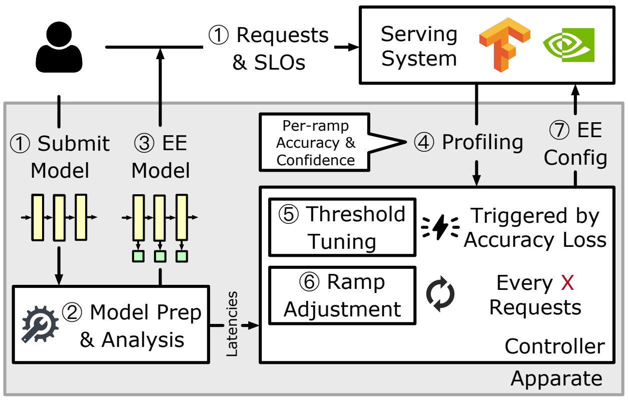


Figure 7: System architecture.

Apparate focuses solely on latency savings by allowing *results* to exit, with inputs still running to completion. Foregoing true exiting (and thus, compute savings) eliminates batch size changes during inference (C4), while also granting Apparate with direct and continual feedback on EE accuracy (C3). This feedback, in turn, provides the requisite signals for Apparate's strategy to continually adapt EE configurations to maximize latency savings while catering to resource constraints and workload dynamics (C1, C2).

Figure 7 overviews Apparate's workflow, which runs atop existing serving platforms. Users register inference jobs as normal ❶, providing models and SLOs. In addition, Apparate introduces two parameters: (1) *ramp aggression*, which (along with compute restrictions) bounds the number of active ramps in terms of % impact on worst-case latency (and throughput), and (2) *accuracy constraint* which indicates how much (if any) accuracy loss is acceptable relative to running the submitted model on all inputs without exiting. With these inputs, Apparate's controller begins by configuring the provided model with EEs ❷, performing a graph-level assessment to determine suitable positions for ramps, and training those ramps on bootstrap data (§3.1). The resulting model is passed to the serving platform for deployment ❸, after which Apparate shifts to management mode. In this phase, as requests arrive and inference tasks are scheduled, Apparate's controller gathers real-time feedback on both the utility of each ramp (overheads vs. latency savings) and achieved accuracies (relative to the original model) ❹. This information is continually used to adapt the EE configuration ❼ at different time scales: rapid threshold tuning for accuracy preservation (§3.2) ❺, and less frequent ramp adjustments for latency optimization (§3.3) ❻.

Note that Apparate's controller runs on a CPU, with GPUs streaming per-ramp/batch profiling information in a *non-blocking* fashion. This is possible since inputs pass to the end of models with Apparate, irrespective of exiting decisions. Further, tasks associated with model handling and serving are handled by the underlying serving platform, e.g., loading from disk, queuing.

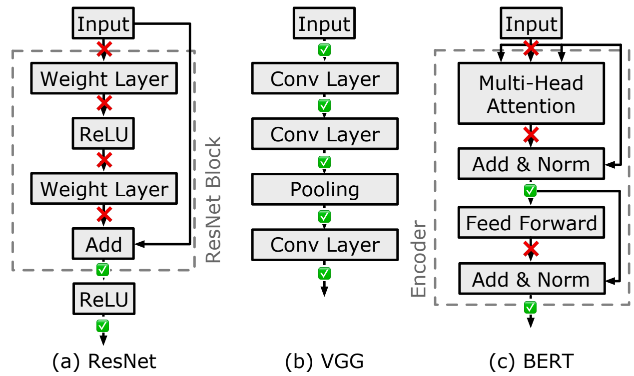


Figure 8: Apparate only injects ramps that make full use of available data flows at that part of the model.

3.1 Preparing Models with Early Exits

Upon job registration with a generic DNN, Apparate's initial task is to automatically prepare that model to leverage EEs, without requiring any developer effort. This phase repeats any time the submitted model changes, e.g., continual retraining to cope with data drift [13,35,51].

Ramp locations. Apparate accepts a model in the ONNX format, a widely used IR that represents the computation as a directed acyclic graph [6]. Once ingested, Apparate must first identify candidate layers for ramp addition. The goal is to maximize ramp coverage across the model (to provide more configuration options for Apparate's runtime management), while avoiding ramps that are unlikely to be fruitful (but add complexity adaptation decisions). To balance these aspects for diverse models, Apparate marks feasible ramp locations as those where operators are *cut vertices*, i.e., a vertex whose removal would disconnect a graph into two or more disjoint sub-graphs. In other words, no edge can start before a ramp and re-enter the model's computation after the ramp.

The idea is that such ramps take advantage of all available data outputs from the original model's processing to that point, boosting their chance at accurate predictions. As an example, consider families like ResNet or BERT which enable deep models by stitching together series of residual blocks, i.e., ResNet blocks for convolutions, or BERT encoders that each embed multi-head attention and feed-forward network residual blocks. To avoid performance degradations late in the model, the output of each block is ultimately a combination of its processing results and its input. In such scenarios, Apparate injects ramps between blocks, but not within each block to avoid ramps making decisions on partial data, i.e., ignoring block inputs. In contrast, for VGG models, ramps are feasible at all layers since their intermediates represent the full extent of data flow throughout the model. Figure 8 depicts these examples.

Overall, this strategy results in 9.2-68.4% of layers having ramps for the models in our corpus, which we empirically observe is sufficient to adapt to dynamic workloads (§5.2). However, we note that Apparate can directly support any other ramp configuration strategy, and offers a simple

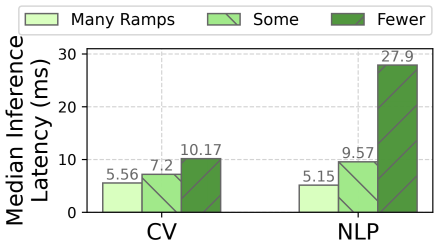


Figure 9: More lightweight ramps boost EE savings. Results compare Apparate's default ramps (many ramps) with versions that use fewer, more expensive ramps, i.e., adding convolutional layers for CV, or more fully-connected/pooling layers for NLP.

API for developers to express ramp policies or restrictions. Moreover, for each feasible ramp, Apparate's runtime monitoring (§3.2-3.3) ultimately monitors its accuracy and utility (and thus, if it is ever activated) for the workload at hand.

Ramp architectures. For each feasible ramp location, Apparate must determine the style of ramp computations to use. Recall from §2 that ramps can ultimately be composed of arbitrary layers and computations, with the only prerequisite being that the final layer sufficiently mimics that of the original model to ensure that response formats match. Determining the appropriate ramp complexity in this large space presents a tradeoff: additional computation can improve the exit capabilities of a ramp, but comes at the expense of (1) increased ramp latency, and (2) coarser flexibility and coverage at runtime since ramps become illogical if their computation exceeds that in the original model up until the next ramp.

Apparate opts for the shallowest ramps that can transform the intermediates at any layer into a final model prediction. Specifically, ramps comprise the model's final fully-connected (fc) layer, prepended with a lightweight pooling operation that reduces the dimensionality of intermediates to ensure compatability with the fc layer. This manifests differently for various model types. For instance, for vision models like ResNet, pooling is simply the model's penultimate layer. In contrast, for BERT, only the basic operator is drawn from the BERT pooler module, i.e., extracting the hidden state corresponding to the first token [19]. Note that, for all models, the input width of the fc layer is modified to match that of the intermediates at each ramp location; the output remains unchanged to preserve result formats.

Figure 9 evaluates this methodology by comparing Apparate's ramps with two, more expensive alternatives. With ResNet, to mimic model operations following each ramp, we add 1-2 convolution layers prior to pooling. For BERT, we consider two approaches: (1) add two fc layers after pooling, each with reduced width to shrink inputs to the final fc, and (2) inspired by DeeBERT [57], replacing the simple pooling operator with the entire BERT pooler block (which also includes dense linear and activation layers) and adding a dropout after pooling as in the original model. In all cases, the number of ramps is subject to the same ramp budget (i.e., Apparate's default uses the most ramps), ramps are uniformly spaced across feasible positions in each model, and thresholds are optimally selected as in §2.2.

As shown, and in line with reflections from prior hand-designed EE models [53], we observe that the additional computation has minimal effect on ramp effectiveness. For example, median latencies are 1.3-1.8× and 1.9-5.4× larger with Apparate's default ramps than the more complex alternatives for CV and NLP. Nonetheless, to showcase Apparate's generality, we consider other ramp styles in §5.4.

Training ramps and deploying models. To determine the appropriate weights for each ramp, Apparate relies on an initial dataset that can either be user-provided or auto-generated by running the original model on historical data. Regardless, during training, Apparate freezes the original model weights to ensure that non-EE behavior and feedback for tuning EEs is unchanged from the user's original intentions. In addition, Apparate enforces that *all* inputs are used to train all ramps, i.e., exiting is prohibited during training. This ensures that ramps are trained *independently* of the presence (or behavior) of any upstream ramps, which is crucial since the set of active ramps can vary at runtime. Further, such independence and the model freezing enable loss calculations to be backwards propagated *in parallel* across ramps, rapidly speeding up training despite Apparate's use of many lightweight ramps. §4 details the training process.

For initial deployment, Apparate evenly spaces the max number of allowable ramps (based on the budget and GPU resources) across the model. To avoid accuracy dips due to discrepancies between training data and the current workload, each ramp begins with a threshold of 0, i.e., no exiting. The updated model definition (with enabled ramps) is passed to the serving platform which operates as normal, e.g., profiling expected model runtimes for different batch sizes [22].

3.2 Accuracy-Aware Threshold Tuning

To avoid accuracy drops as workload characteristics change over time, Apparate's controller employs frequent and fast tuning of thresholds for already-enabled ramps. The reason is that threshold tuning for any set of ramps is sufficient to ensure that user-specified accuracy constraints are not violated – at the extreme, all thresholds could be set to zero, which precludes any early exiting. Altering only the set of active ramps fails to provide this property.

To enable threshold tuning, as requests pass through a model, Apparate's controller continually records exiting information at each active ramp, as well as the final result that the original model predicts. More precisely, for each ramp, Apparate records the result (e.g., classification label) with the lowest error rate, i.e., the highest-confidence result for the ramp, even if the error exceeds the ramp's threshold (precluding exiting). Importantly, since inputs always pass fully through models with Apparate, this information is recorded for all inputs at each active ramp, irrespective of upstream exiting decisions. This is paramount since the information

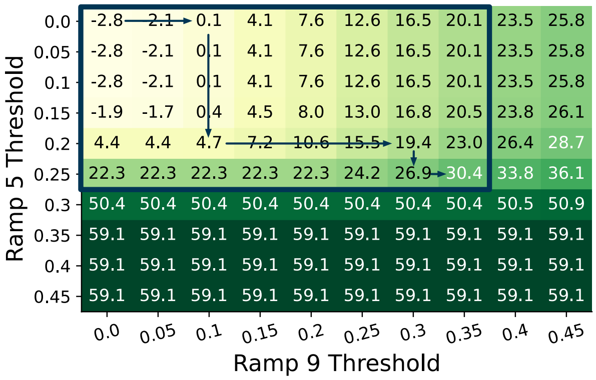


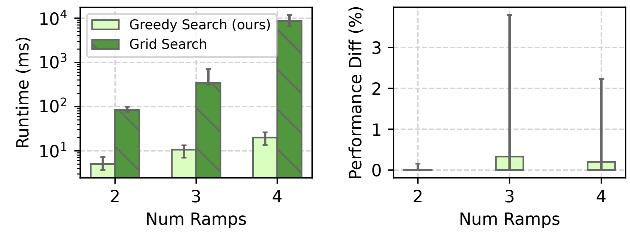
Figure 10: Threshold tuning example with two active ramps for ResNet50 and a random video. Configurations within the boundary have <1% accuracy loss; cell values list latency wins. Arrows show the path taken by Apparate's hill climbing algorithm (without fine-grained step changes).

serves not only as a signal for when to tune thresholds, but also provides guidance for how to do so.

Triggering tuning. Apparate maintains an average achieved accuracy over the past 16 samples by comparing exiting results with the deployed configuration to results of the original model. Threshold tuning is triggered any time a window's accuracy falls below the user-specified accuracy constraint. The threshold tuning process (described below) runs asynchronously on a CPU, without any disruptions to ongoing jobs. This is possible since thresholds are anyway enforced only by Apparate's controller; GPUs are agnostic to threshold values, and instead simply stream ramp results to the Apparate controller which determines exiting decisions.

Evaluating threshold configurations. Threshold tuning requires insight into how any alterations to active ramp thresholds would affect overall model exiting behavior (and accuracies). The aforementioned per-request, per-ramp monitoring information grants this visibility, enabling Apparate to rapidly evaluate any threshold values across active ramps without requiring additional inference, and while accounting for inter-ramp dependencies. In particular, to evaluate new threshold values, Apparate simply identifies the earliest ramp whose top prediction now has an error rate below its threshold. Comparing these results with those of the original model indicates the achieved accuracy for the new configuration; latency wins for these exit patterns are computed using the one-time profiling data described in §3.3.

Greedy search. The goal of tuning is to identify a new set of thresholds that maximize latency savings while adhering to accuracy constraints for the last window of data. The challenge is that the space of thresholds to consider is massive, precluding a grid search (especially given how frequently adaptation is needed - §2.3). Indeed, even with discretized threshold values in [0, 1] with a step size of S, computation costs are $O(C \times (\frac{1}{S})^R)$, where R is the number of active ramps, and C is the cost to evaluate a given configuration.



(a) Threshold tuning speed. **(b) Optimality of tuning results.**

Figure 11: Apparate's tuning vs. optimal tuning on runtime and latency of selected configurations. Bars list medians across all model-workload pairs, with error bars for min-max.

Instead, Apparate employs a greedy heuristic (Algorithm 1 in §A) that leverages a fundamental property of EEs when evaluated against an original model: *higher thresholds result in monotonic decreases in accuracy and monotonic increases in latency savings*. This prunes the space of threshold values to consider by providing a clear boundary in the R-dimensional space that separates configurations that are sufficiently accurate from those that are not. Additionally, for accurate configurations, maximum latency savings must fall on that boundary. Figure 10 illustrates this.

These properties inform Apparate's hill climbing strategy [47] for threshold tuning. Starting with threshold values of 0 for each active ramp, and a step size of 0.1, threshold tuning runs in a series of (incremental) exploration rounds. In each round, we increase the threshold of each ramp in isolation (leaving the others unchanged), and evaluate the achieved accuracy and latency savings as described above. Apparate then chooses the single ramp threshold change that delivered the largest additional latency savings per unit of additional accuracy loss. This process repeats until no ramp's threshold can be increased without an accuracy violation.

To enhance this process, Apparate follows a multiplicative increase, multiplicative decrease policy on step sizes to balance search speed and granularity. Specifically, each time a step increase results in an accuracy violation, Apparate halves that ramp's step size for subsequent rounds to hone in on the boundary at fine granularity; step sizes are lower-bounded at 0.01. Conversely, selection of a ramp for threshold alteration suggests a potentially promising path of exploration; in this case, for a speedup, Apparate doubles that ramp's step size for the following round.

Overall, as shown in Figure 11, Apparate's threshold tuning algorithm runs up to 3 orders of magnitude faster than a pure grid search (11.9ms vs. 3.0s on average). Note that these results maximally parallelize grid search across a 30-core machine. Further, selected threshold values achieve within 0-3.8% of the latency savings of the optimal configurations.

3.3 Latency-Focused Ramp Adjustments

The set of active ramps ultimately dictates where inputs can exit, and thus provides bounds on potential latency savings. Unlike threshold tuning which runs reactively (since accuracy is a constraint) and uses only recent profiling data to evaluate new configurations, ramp adjustment is strictly an optimization (for latency savings), and requires deployment to evaluate the impact of any new ramp. Thus, Apparate's ramp tuning runs periodically (every 128 samples by default) and conservatively alters the set of active ramps to incrementally converge on high-performing configurations.

Evaluating active ramps. In each round, Apparate's controller starts by computing a utility score for each active ramp that evaluates its overall impact on workload latency. To do so, Apparate couples per-ramp exit rates (based on profiling data from threshold tuning in §3.2) with two additional inputs that are collected once per model during bootstrapping: (1) the latency overhead per ramp, and (2) a layer-wise breakdown of time spent during model inference (for different batch sizes [22]). The latter is necessary since different models can exhibit wildly different latency characteristics that govern the impact of any exits. For instance, latency of CV models is often heavily skewed towards early layers given the high dimensionality of the input data [40], while NLP transformers exhibit more consistent latency values across coding blocks. Note that, in the case of distributed serving, latency breakdowns are updated to account for network delays between serving nodes.

Using these inputs, Apparate defines the utility of ramp R as `savings - overheads`, where `savings` represents the sum of raw latency that exiting inputs avoided by using ramp R, and `overheads` is the sum of raw latency that R added to inputs that it was unable to exit. A negative (positive) utility value means a ramp is causing more (less) harm than benefit to overall latencies for the current workload.

Adding new ramps. If any negative utility values exist, Apparate applies a fast threshold tuning round to see if ramp utilities become entirely positive without harming overall latency savings. If not, Apparate immediately deactivates all negative-utility ramps. From there, the key question to address is what ramps (if any) should be added to make use of the freed ramp budget. The main difficulty is in predicting the utility of each potential addition. Indeed, while per-exit latency savings for each potential ramp are known (using the latency breakdown from above), exit rates are not.

To cope with this uncertainty, our guiding intuition is that, subject to the same accuracy constraint, *later ramps almost always exhibit higher exit rates than earlier ones*.[2] The reason is that late ramps have the luxury of leveraging more of an original model's computations when making a prediction. Importantly, this implies that a candidate ramp's exit rate is bound by the exit rate of the closest downstream ramp.

Building on this, Apparate's controller computes an upper bound on the utility of candidate ramps as follows. To avoid inter-ramp dependencies harming ramps that are already performing well, we only consider additions after the latest positive ramp P in the model. In particular, Apparate divides the range following P into intervals separated by any negative ramps deactivated in this round. The first round of candidate ramps are those in the middle of each interval.

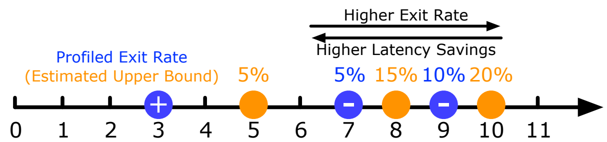


Figure 12: Computing upper-bound exit rates for candidate ramps. Blue dots show previously active ramps (+/− indicates positive/negative utility), while orange dots show candidates.

For each candidate ramp, we compute its upper-bound exit rate as the sum of profiled exit rates for the following deactivated ramp and any earlier deactivations (Figure 12); the idea is that inputs from earlier deactivations would have reached the following deactivated ramp and *might* have exited there. Utility scores are then computed as above, and the ramp with the highest positive utility score is selected for trial. If all ramps have negative projected utilities, Apparate repeats this process for later candidate ramps in each interval. Once a ramp is selected for trial, Apparate adds it to the deployed model definition, while removing deactivated ramps. Trialed ramps start with threshold=0 to prevent inaccurate exiting, but are soon updated in the next round of threshold tuning.

Until now, we have only discussed how Apparate handles scenarios with at least one negative ramp utility. In the event that all ramps exhibit positive utilities, Apparate enters a low-risk probing phase to determine if latency savings can grow by injecting (or shifting to) earlier ramps. There are two scenarios for this. If ramp budget remains, we add a ramp immediately before the existing ramp with *highest* utility (while keeping that ramp to preserve its exiting wins). In contrast, if no ramp budget remains, we shift the ramp with the *lowest* utility score one position earlier, leaving the most positive ramp untouched. Additions are incorporated into the configuration using the same process as above.

4 Implementation

Apparate is implemented as a layer atop TensorFlow-Serving [39] and Clockwork [22] (using PyTorch [7]) and includes the components described in 3 written as Python modules in ∼7500 lines of code. Although we chose these platforms for our current implementation, we note that Apparate is not limited to them and its techniques can be implemented in any inference platform. Importantly, Apparate entirely leverages the scheduling and queuing mechanisms of the underlying framework. Original models are ingested in the ONNX format [6] and compiled for performance. Ramp training (during bootstrapping) uses the first 10% of each dataset following a 1:9 split for training and validation; the remaining 90% of each dataset is used for evaluation.

[2] For a single input, being able to exit at an early ramp does not guarantee exit capabilities at later ramps [34]. However, later-ramp exit rates were always higher than earlier ones for our workloads, and we note that Apparate only uses this property for search efficiency, not correctness.

5 Evaluation

We evaluated Apparate across a wide range of NLP and CV workloads and serving platforms. Our key findings are:

- Apparate lowers 25th percentile and median latencies by 40.5-91.5% and 70.2-94.2% for CV, and 16.0-37.3% and 10.0-24.2% for NLP workloads, compared to original (non-EE) models.
- Unlike existing EE models that unacceptably worsen accuracies and tail latencies by up to 23.9% and 11.0%, Apparate consistently meets specified accuracy and tail latency constraints.
- Apparate automatically generalizes to different model architectures (e.g., compressed) and EE configurations (e.g., ramp style), and its wins gracefully shrink as accuracy or tail-latency constraints grow.

5.1 Methodology

Models. We consider 10 models (across 4 families) that cover popular architectures and a variety of model sizes in both CV and NLP. For CV, we use the ResNet{18, 50, 101} residual models, as well VGG{11, 13, 16} models that follow a chained (linear) design. All of these models are pretrained on ImageNet and from the PyTorch Model Zoo [43]; we further fine-tune the models to our video scenes using a random sampling of 10% of frames across our dataset. For NLP, we consider 3 encoder-only transformers from the BERT family – BERT-base, BERT-large, and Distilbert [45] (a variant of BERT-base that was compressed via distillation) – as well as a decoder-only large language model: GPT2-medium. These models span 66-345 million parameters, were collected from HuggingFace [30], and were pretrained (without more fine-tuning) on Yelp reviews [8] that are separate from any evaluation dataset we use.

Workloads. CV workloads comprise real-time object classification (people, cars) on 8 one-hour videos used in recent video analytics literature [11, 27]. The videos were sampled at 30 frames per second, and collectively span day/night from diverse urban scenes; for each, we perform classification.

NLP workloads focus on sentiment analysis using two datasets: Amazon product reviews [10] and IMDB movie reviews [41]. To the best of our knowledge, there do not exist public streaming workloads for NLP classification, so we convert these datasets into streaming workloads as follows. For Amazon, we follow the order of product categories in the original dataset, but within each category, we keep reviews only from frequent users (i.e., those with >1k reviews) and order streaming by user (250k requests in total). For IMDB, we follow the order of reviews in the original dataset, but stream each in sentence by sentence (180k requests in total). We then define arrival patterns for these ordered requests by using the Microsoft Azure Functions (MAF) as in prior serving work [22]. Specifically, to ensure meaningful and realistic workloads despite the high degree of variation

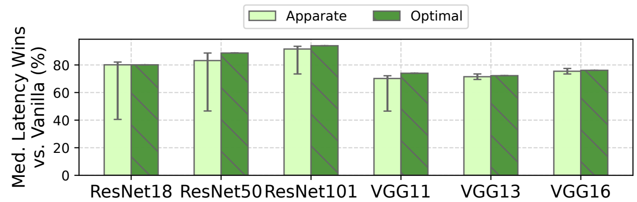


Figure 13: Median latency savings compared to vanilla models. Bars show median workload with error bars for min-max.

in runtime across our models, we paired each model with a randomly selected trace snippet from the set that met the following criteria: (1) number of requests match that in our largest dataset, and (2) queries per second should not result in >20% dropped requests with vanilla serving for the given model and selected SLO (described next).

Parameter configurations. Given our focus on interactivity, we cope with heterogeneity in model runtimes by setting SLOs to be 2× each model's inference time with batch size 1 in our main experiments. This results in SLOs between 13-204 ms, which match the ranges considered in prior work [22, 40, 49]; Table 5 in §A lists the specific SLO values per model, and we study the effect of SLO on Apparate in §5.4. Unless otherwise noted, results use 1% for Apparate's accuracy constraint (in line with industry reports [42]) and a ramp budget of 2% impact on worst-case latency; we consider other values for both parameters in §5.4.

Setup. Experiments were conducted on a dedicated server with one NVIDIA RTX A6000 housing 48GB of memory, one AMD EPYC 7543P 32-Core CPU, and 256GB DDR4 RAM. We run experiments with two serving platforms: TensorFlow-Serving [39] and Clockwork [22]. We primarily present results with Clockwork due to space constraints, but note that report trends hold for both platforms; we compare cross-platform results in §5.4.

Metrics and baselines. Our main metrics of evaluation are classification accuracy and per-request latencies. Accuracy is defined as the percentage of inputs that are assigned the correct label as defined by each original (i.e., non-EE) model. Per-request latency is measured as the time between when a request arrives at a serving platform, and when its response is released by the platform. We mainly compare Apparate with two baselines: (1) original models without EEs (*vanilla*) running in serving platforms, and (2) *optimal* EEs as defined in §2.2, i.e., assuming all inputs exit at their earliest possible ramps with non-exiting inputs incurring no ramp overheads. We compare Apparate to existing EE strategies in §5.3.

5.2 Overall Results

Figures 13- 16 compare Apparate with vanilla model serving and optimal exiting across our workloads. Overall, Apparate significantly lowers latencies compared to serving vanilla models, while always adhering to the imposed 1% accuracy constraint. For instance, median speedups range from

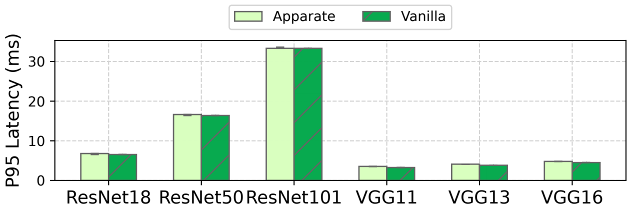


Figure 14: Evaluating Apparate's impact on tail latency (running with 2% budget) compared to vanilla serving. Bars show median workload, with error bars spanning min-max.

40.5-91.5% (2.7-30.5 ms) for CV workloads, and jump to 70.2-94.2% (5.2-31.4 ms) at the 25th percentiles. NLP workloads follow a similar pattern, with median and 25th percentile savings ranging from 10.0-24.2% (3.9-25.3 ms) and 16.0-37.3% (4.8-53.2 ms), respectively. Importantly, across all workloads, Apparate's tail latency (and thus impact on throughput) always falls within its granted budget (2% here) and is most often negligible (Figure 14).

Beyond this, there are several important trends to note. First, Apparate's raw latency savings grow with increased model sizes, e.g., 25th percentile wins of 53.2ms, 28.4ms, 14.3ms, 5.5ms for GPT-2, BERT-large, BERT-base, and Distilbert-base on the Amazon dataset. This is because only the results exit models with Apparate, with inputs running to completion; thus, latency savings pertain entirely to serving times (not queuing delays), with exit impact being higher as model size (and thus, runtime) grows. Relative (%) latency savings follow the same pattern for CV workloads, e.g., Apparate's median wins grow by 13.8% and 5.3% moving from the smallest to the biggest models in the ResNet and VGG families. However, relative wins remain relatively stable in NLP models, e.g., 15.8% and 13.7% for GPT2 and BERT-large on Amazon Reviews. The reason for this difference is in the effectiveness of the models in each domain. Results and task performance are largely similar across the considered CV models, enabling Apparate to inject ramps early in (even larger) models. In contrast, results and task efficacy are far better with the larger models in NLP; thus, Apparate's ramps fall in similar (relative) positions across the models.

Second, Apparate's wins are larger for CV workloads than NLP workloads for two reasons. As previously noted, CV workloads use lighter models and lower request rates (bound by video fps), and thus incur far lower queuing delays. More importantly, in contrast to CV where spatiotemporal similarities across frames (and thus, requests) are high due to physical constraints of object motion in a scene, NLP requests exhibit less continuity, e.g., back-to-back reviews are not constrained in semantic similarity. The effects on Apparate's adaptation of EE configurations are that (1) past data is less representative of future data, and (2) the duration until subsequent adaptation is shorter.

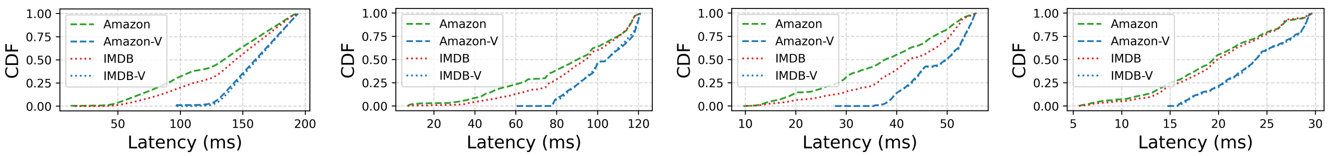
Lastly, Apparate's wins for NLP are consistently higher with the Amazon dataset versus the IMDB dataset. The reason is that the IMDB dataset exhibits 'harder' inputs that require later-ramp exits. For instance, for GPT-2, average exit locations for the offline optimal exit strategy are at layers 2.2 and 2.7 for Amazon and IMDB, respectively; these numbers are 2.1 and 2.5 for BERT-base.

Comparisons with optimal. As shown in Figure 13, latency savings with Apparate for CV workloads largely mirror those of the optimal that tunes exiting decisions based on perfect knowledge of the upcoming workload, e.g., median savings are within 20.5% of the optimal. In contrast, building on the discussion above, the limited continuity across inputs in NLP workloads leads to a wider gap of 73.1-83.2% at the median (Figure 16). To further characterize Apparate's performance on these workloads, we also consider a more realistic *online optimal* algorithm that relaxes the following elements. First, rather than per-sample adaptation of thresholds and ramps, ramp adjustments are set to operate only as fast as model definitions in the GPU can be updated. Second, rather than using perfect knowledge of upcoming inputs, decisions are made using only recent (historical) data; for each threshold or ramp adaptation decision, we tune based on the past {20, 40, 80} batches of inputs and select the decision that performs best on the upcoming data. As shown in Figure 16, Apparate's median latency savings are within 16.9-52.1% of this (more) realistic optimal exiting strategy.

Varying SLOs. SLOs affect serving system batching and queuing decisions, and thus Apparate's benefits. To study this effect, we considered SLOs for each model that were 2× and 4× those in our default experiments (Table 5). Generally, higher SLOs induce larger serving batch sizes and higher per-request queuing delays (as inputs wait for the previous, slower inference batch to complete); this dampens Apparate's relative latency savings which target model runtimes, but not queuing delays. Figure 17 illustrates this effect. For instance, median latency savings for GPT-2 drop from 16.3% to 6.8% as SLO grows by 4×. Note that, to illustrate this trend for CV workloads, we upsampled each video to 120 fps. The reason is that our serving platforms are work-conserving and, at 30 fps, they are able to consistently schedule jobs with batch size 1 and low queuing delays given the low runtimes of the considered CV models.

5.3 Comparison with Existing EE Strategies

We compare Apparate with two off-the-shelf EE models: BranchyNet [53] and DeeBERT [57]. BranchyNet extends ResNet models with ramps of the same style as Apparate, while DeeBERT extends BERT-base with deeper ramps (using the entire BERT pooler, as described in §3.1). For each, we follow their prescribed architectures, with ramps after every layer that are always active. We perform one-time tuning of thresholds as recommended by both works, and consider two variants: the default recommendation where all ramps must use the same threshold, and a more flexible version



(a) GPT2 (b) BERT-large (c) BERT-base (d) Distilbert-base

Figure 15: Apparate (with 2% budget) vs. vanilla models on NLP workloads. "-V" indicates serving using the vanilla model. Note that "-V" curves per plot mostly overlap since they use the same timing trace and no exiting; minor discrepancies are only due to the varying number of inputs across workloads.

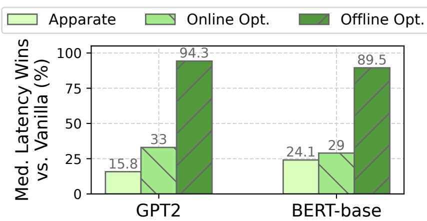
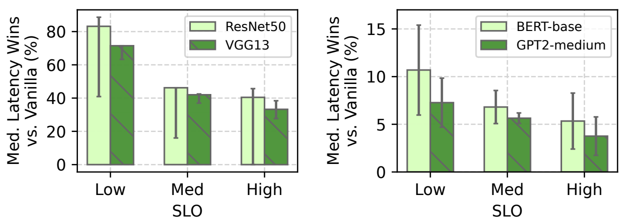


Figure 16: Apparate vs. optimal exiting on NLP workloads with the Amazon dataset.

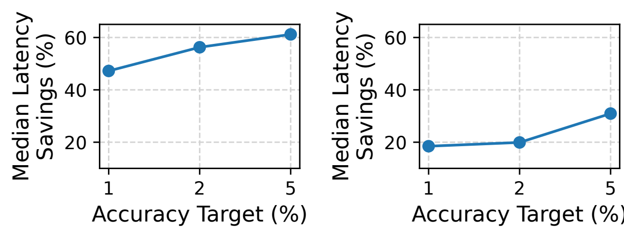


(a) CV (b) NLP

Figure 17: Impact of SLOs on Apparate's wins.

	Avg Acc	Median Wins	P95 Wins
Apparate (ResNet50)	99.0-99.2%	40.9-88.6%	-1.6-0.0%
BranchyNet	85.8-99.8%	-11.0-88.3%	-11.0%
BranchyNet+	76.1-99.9%	-11.0-88.3%	-11.0%
BranchyNet-opt	99.0-99.7%	-11.0-74.5%	-11.0%
Apparate (BERT-base)	99.1-99.3%	9.1-24.1%	0.7-1.8%
DeeBERT	91.7-97.1%	13.2-36.1%	-1.3-6.4%
DeeBERT+	82.2-90.3%	31.7-36.1%	5.9-6.4%
DeeBERT-opt	99.0%	9.8-36.1%	-1.4-6.4%

Table 2: Comparison with existing EE models. Results list ranges of accuracies or latency wins across all CV (top row) or NLP (bottom row) workloads. '+' and 'opt' pertain to optimized tuning strategies described in §5.3.



(a) ResNet50 (b) GPT2

Figure 18: Apparate's wins for different accuracy constraints.

that removes this restriction (+). For both, threshold tuning is done optimally (via grid search), and is based on uniformly sampled data across the workload. For fair comparison, Apparate's ramp budget is configured to support ramps at all layers (though it never does so).

Table 2 presents our results. The main takeaway is that existing EE approaches, even when favorably tuned, yield unacceptable drops in average accuracy up to 23.9% and 17.8% for CV and NLP. In contrast, Apparate consistently meets the imposed accuracy constraint (1% in this experiment) for both workloads. Further, even with such accuracy violations, tail latencies are 0.9-9.4% lower with Apparate than with these systems. The reason is again lack of adaptation: all ramps are always active despite their current efficacy which vary dramatically over time (§2.3), yielding undue overheads for large numbers of non-exiting inputs. In contrast, throughout these experiments, despite having a full ramp budget, Apparate maintained only 9.1-27.2% of all possible ramps.

For fair median latency comparison, we consider an optimally-tuned (opt) version of existing EE models that perform one-time tuning on the actual test dataset, picking the best (latency-wise) thresholds that ensure <1% accuracy drop. As shown, due to its regular and less-constrained adaptation, Apparate outperforms even this oracle version of existing EEs with up to 14.1% higher median latency savings.

5.4 Microbenchmarks

To ease presentation, results in this section use representative CV and NLP models (ResNet50, GPT2-medium) running on a random corpus video and Amazon reviews, respectively. All reported trends hold for all considered workloads.

Parameter sensitivity. Recall that Apparate ingests values for two key parameters: ramp aggression (i.e., a ramp budget) and accuracy constraint (i.e., acceptable accuracy loss). Fig. 18 and Tab. 3 studies the effect that these parameters have on Apparate's latency wins. The findings are intuitive: Apparate's latency savings over vanilla models decrease as ramp budgets shrink or accuracy constraints tighten. Both trends are a result of Apparate being granted less flexibility for adaptation, either via smaller acceptable threshold ranges (that meet accuracy targets), or active ramp capacity (and thus potential ramp configurations). Importantly, accuracy constraint has a larger impact on Apparate's wins. The reason is that inter-ramp dependencies result in overlap in the set of inputs that can exit at any ramp when run in isolation; thus, wins from using more ramps eventually hits diminishing returns. Indeed, Apparate begins by using the full budget,

Ramp Budget	ResNet50	GPT2
2%	48.9%	18.5%
5%	49.6%	22.2%
10%	50.4%	24.9%

Table 3: Apparate's median latency wins vs. ramp budget.

System\Workload	ResNet50	GPT2
Clockwork	(20.2, 37.8)	(689.2, 779.4)
TF-Serve	(24.5, 37.8)	(709.3, 793.1)

Table 4: Apparate on different serving platforms. Results show (median, p95) latency over vanilla models in ms.

only to quickly disable many ramps that have a net negative effect on serving latencies.

Ramp architectures. Although Apparate opts for using many lightweight ramps, it's adaptation algorithms can support any ramp architecture. To illustrate this, we ran Apparate with DeeBERT's more expensive ramps (described above). Overall, on the Amazon Reviews dataset, we find that these costlier ramps dampen Apparate's latency savings by 4% since they constrain Apparate's runtime adaptation in terms of feasible configurations, i.e., fewer active ramps at any time. Crucially, we note that accuracy constraints were still entirely met due to Apparate's frequent threshold tuning.

Impact of serving platform. Apparate runs atop existing serving platforms, responding to overall serving (and exiting patterns) rather than altering platform decisions, e.g., for queuing. Table 4 shows that, despite the discrepancies in platform scheduling strategies and knobs, Apparate's performance wins are largely insensitive to the underlying platform when CV or NLP workloads are configured with the same SLO goal. For example, Apparate's median latency savings for the Amazon workload and GPT-2 are within 2.9% when using Clockwork or TensorFlow-Serving.

Profiling Apparate. Figure 11 in §3.2 analyzes the runtime and optimality of Apparate's threshold tuning algorithm. Beyond that, Apparate includes two other overheads while running: ramp adjustment and coordination between its CPU controller and serving GPUs. Ramp adjustment rounds take an average of 0.5 ms. Coordination overheads are also low because of Apparate's small ramp sizes (definitions and weights consume only $\sim$10KB) and profiling data (simply a top-predicted result with an error score, collectively consuming around $\sim$1KB). Thus, CPU-GPU coordination delays take an average of 0.5ms per communication, 0.4ms of which comes from fixed PCIe latencies in our setup.

Importance of Apparate's techniques. Apparate's runtime adaptation considers frequent (accuracy-guided) threshold tuning, with periodic ramp adjustments. Table 2 highlights the importance of threshold tuning on average accuracies. Here, we evaluate the importance of ramp adjustment on Apparate's latency improvements by comparing versions with and without this optimization. Overall, disabling ramp adjustment results in 20.8-33.4% lower median latency wins, though worst-case latency (and throughput) and accuracy constraints remain continually met.

6 Additional Related Work

A number of **model-serving systems** have been proposed [4, 5, 7, 17, 22, 39, 44, 49] where the focus is on serving large volumes of inference requests within a pre-defined SLO. Existing systems favor maximizing the system throughput while adhering to the latency constraints (2) by the use of intelligent placement [22, 49], batching [4] and routing [44]. To the best of our knowledge, no existing serving proposals focus on alleviating the latency-throughput tension.

The ML community has been actively working on **early-exit networks**, with several proposals focusing on the EE's *ramp architecture* and *exit strategy* [28, 36, 46, 53, 57, 58, 64]. The architecture of the ramp depends on the domain, but it typically consists of one or more layers that provide information necessary to make an exit decision by emulating the original model. Replicating the last (few) layers is the common [57, 58], Apparate builds on this approach and prefers shallow ramps in its workflow (3). Once a ramp architecture is chosen, the exit strategy could be based on *confidence* of the labels [36] or *entropy* of the prediction [57]. More sophisticated approaches exist, e.g., instead of considering the ramps as fully independent, [64] uses *counter-based* exiting. Apparate's focus is on leveraging EEs to resolve the latency-throughput tension in serving systems with a design that generalizes to a large class of EE architectures.

Optimizing model serving objectives based on workload characteristics has been discussed in recent works [15, 16, 21, 44, 49, 62, 63]. Inferline [16] optimizes cost in serving pipelines of models while adhering to strict latency constraints using intelligent provisioning and management. Shepherd [63] maximizes goodput and resource utilization in highly unpredictable workloads. Despite their impressive results, these works still optimize their metric of choice at the expense of latency and do not resolve the latency-throughput tension, which is the focus of our (complementary) work.

A recent line of work has focused on creating *variants* of an ML model to optimize serving performance. Some of these works look at execution graph level optimizations such as quantization and fusing to reduce inference latency [1, 3], while others replace the model with an equivalent one that meets the provided constraints. Solutions like Mystify [23] and INFaaS [44] generates and chooses model variants based on their intent and constraints (including performance). As shown in §5.2, Apparate's wins persist even on compressed models, and is thus complementary to these works in that it can operate on their outputs. Finally, optimizing the execution of **dynamic neural networks** that alter NN execution (e.g., EEs, mixture of experts) was proposed in [18, 61]. These are low-level optimizations (e.g., at the GPU) which can benefit Apparate and improve its performance.

7 Conclusion

We present Apparate, the first system that automatically injects and manages early exiting for ML inference. Key to Apparate's ability to alleviate latency-throughput tensions in serving is its use of exiting only for fast results (not compute savings). This provides continual feedback on exits, and powers Apparate's novel adaptation strategies for EE ramps and thresholds. Apparate lowers median latencies by 40.5-91.5% for CV and 10.0-24.2% for NLP workloads, while meeting accuracy constraints and preserving throughputs.

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Model	bs=1	Small	Medium	Large
ResNet18	9	1×	2×	4×
ResNet50	22.7	1×	2×	4×
ResNet101	52.8	1×	2×	4×
VGG11	6.9	1×	2×	4×
VGG13	8.2	1×	2×	4×
VGG16	10.2	1×	2×	4×
Distilbert-base	15.5	2×	4×	8×
BERT-Base	29.4	2×	4×	8×
BERT-Large	63.2	2×	4×	8×
GPT2-medium	103	2×	4×	8×

Table 5: Different SLOs used. All numbers are in ms, measured on the A6000.

A Appendix

Algorithm 1: Threshold tuning algorithm

Input: *ramps*, list of ordered active ramp IDs
Input: *acc_loss_budget*, max accuracy loss tolerable
Input: *smallest_step_size*, smallest step size for incrementing thresholds
Output: *thresholds*, thresholds associated with each ramp
Output: *latency_savings*, latency savings with searched thresholds

```
/* all thresholds start at 0, i.e. no EE */
thresholds ← [0.0] ∗ len(ramps)
/* each ramp has its own step size */
step_sizes ← [smallest_step_size] ∗ len(ramps)
while True do
    best_ramp, overstepped_ramps, latency_savings ←
        pick_ramp(ramps, thresholds, acc_loss_budget)
        /* find next ramp to update thresholds */
    if best_ramp is valid then
        /* increment threshold of the selected ramp */
        thresholds[best_ramp] + = step_sizes[best_ramp]
        /* double step_size */
        step_sizes[best_ramp] ∗= 2
    else
        if step_sizes.all() ≤ smallest_step_size then
            return thresholds, latency_savings
    /* half step_size for overstepped ramps,
       double step_size for the rest */
    for ramp in overstepped ramps do
        step_sizes[ramp] / = 2
```