MOSEL: Inference Serving Using Dynamic Modality Selection

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Abstract

Rapid advancements over the years have helped machine learning models reach previously hard-to-achieve goals, sometimes even exceeding human capabilities. However, achieving desired accuracy comes at the cost of larger model sizes and increased computational demands. Thus, serving predictions from these models to meet any latency and cost requirements of applications remains a key challenge, despite recent work in building inference serving systems as well as algorithmic approaches that dynamically adapt models based on inputs. Our paper introduces a new form of dynamism, *modality selection*, where we adaptively choose modalities from inference inputs while maintaining the model quality. We introduce MOSEL, an automated inference serving system for multimodal ML models that carefully picks input modalities per request based on resource availability, as we as user-defined service level objectives (SLOs). MOSEL exploits modality configurations extensively, improving system throughput by 3.6× with an accuracy guarantee and shortening job completion times by 11× compared to modality-agnostic approaches.

1 Introduction

Recent advancements in Deep Learning has enabled Deep Neural Networks (DNNs), especially Transformers, to far exceed human capabilities in various Computer Vision and Natural Language Processing tasks (He et al., 2015; Wolf et al., 2019). However, the computational requirement of the largest machine learning (ML) models has doubled every few months, resulting in a 1,000,000× increase from 2012 to 2020 (Sevilla et al., 2021). The increasing size of the models presents fundamental challenges in terms of latency and cost when they are commissioned for inference (Romero et al., 2021a; Gunasekaran et al., 2022; Gujarati et al., 2020).

These challenges has driven the development of inference serving systems. These systems, hosted by cloud providers, deploy ML models to deliver fast and accurate responses to queries. Providers guarantee service level objectives (SLOs) for latency or accuracy while aiming to optimize hardware utilization and maximize throughput.

One approach to mitigate inference overheads and improve throughout is through *accuracy scaling*, which adapts model accuracy to varying query demands. An inference task involves three components: system, model, and input. Prior work focuses on optimizing the *system* and *model* aspects. System optimizations employ techniques such as batching (Ahmad et al., 2024; Choi et al., 2021; Crankshaw et al., 2017a; Shen et al., 2019a), sharing (LeMay et al., 2020; Romero et al., 2021a), and scheduling (Romero et al., 2021a; Ahmad et al., 2024; Crankshaw et al., 2017a). However, these techniques often require additional computational resources or powerful accelerators to handle higher query demands, which may not always be feasible due to the limited availability and flexibility of hardware resources. On the other hand, model optimizations often replace a large model with a more cost-effective variant, typically obtained using ML *compression techniques*, such as distillation (Sanh et al., 2019; Mullapudi et al., 2019), pruning (Lin et al., 2017; Gordon et al., 2020) and quantization (Polino et al., 2018). However, this approach necessitates multiple model replicas, wasting storage space and introducing overhead for switching between replicas and execution backends (Romero et al., 2021a; Ahmad et al., 2024).

In this paper, we propose an orthogonal and complementary perspective on accuracy scaling. In particular, we propose *modulating the input*, specifically via *selectively using* parts of it. We demonstrate its usefulness in the context of *multi-modal learning* (Ngiam et al., 2011; Baltrušaitis et al., 2018), an emerging and important class of ML techniques that combine data from different modalities to provide prediction cooperatively, enhancing prediction accuracy.

As we describe in Section 3, we empirically find that some modalities (e.g., the audio modality in the Textless Vision-Language Transformer (TVLT) model (Tang et al., 2022)) contribute significantly to prediction accuracy without major resource use (e.g., memory) and processing time. In contrast, other modalities (e.g., the video modality in TVLT) consume significant resources and incur latency while only marginally improving accuracy.

We leverage the above insight in inference settings and propose that modalities be selectively enabled or disabled based on application requirements and workload patterns, creating novel opportunities to exploit the trade-off between speed and accuracy that multi-modality presents. We refer to it as *modality selection*, which complements existing accuracy scaling techniques and can be directly applied to the original model.

We assume that queries generally favor higher accuracy whenever resource permits, but can tolerate reduced accuracy for timely responses under resource constraints, provided that SLOs are not violated. This assumption is particularly relevant to applications like recommendation systems (Fang et al., 2018) or real-time applications, where response time outweighs the need for accuracy (Huang et al., 2015).

We build MOSEL, an automated inference serving system for multi-modal models that selects input modalities per request based on user-defined latency and accuracy SLO and system load. Our approach ensures scaling and performance during inference by dividing it into offline and online components. The offline component is designed to quickly generate a rich repository of modality selection strategies, enabling the online component to make informed decisions. For the online component, we ensure that, at inference time, late-enqueued jobs meet their latency requirements. We facilitate jobs ahead in the inference queue by dynamically reselecting modalities to ease the queueing load; this allows later-enqueued jobs to run at the required accuracy without missing their latency targets.

We evaluate MOSEL on a set of representative multi-modal models that utilize commonly-seen architectures (Transformer (Vaswani et al., 2017), BERT (Devlin et al., 2019), CNN (LeCun et al., 2015)). We show that MOSEL outperforms modality-agnostic approaches in resource utilization and query spike tolerance, reducing job completion times by up to 11× and handling up to 3.6× more requests with accuracy guarantees. Moreover, MOSEL achieves up to 4.6× throughput when combined with quantization techniques.

2 Background

Multi-modal Learning: Multi-modal learning techniques are shown to surpass unimodal techniques by exploiting the complementary nature of different modalities, such as text, image, audio, and video (Ngiam et al., 2011; Baltrušaitis et al., 2018). The existing techniques can be broadly classified into two categories: early fusion (Snoek et al., 2005; Atrey et al., 2010; Katsaggelos et al., 2015) and late fusion (Snoek et al., 2005; Liu and Yuan, 2018; Abavisani et al., 2019). Early fusion combines modalities at an early stage, blending features before further processing, as seen in TVLT (Tang et al., 2022). Late fusion processes each modality separately and merges outcomes later, exemplified by the Temporal Binding Network (TBN) (Kazakos et al., 2019). Some methods attempt to combine properties from both early and late fusion (Nagrani et al., 2021; Joze et al., 2020; Perez-Rua et al., 2019; Vielzeuf et al., 2018; Xue and Marculescu, 2023; Nagrani et al., 2021). We demonstrate in Figure 1 that multi-modalities present complexities due to varied resource requirements and performance traits.

Inference and its challenges: Increased accuracy of DNNs has led to their wide adoption in real-world applications resulting in increased production costs (Hazelwood et al., 2018; Gupta et al., 2020; Romero et al., 2021b; aws). Inference serving systems use pre-trained ML models for predictions and manage resources to meet diverse user requests and application requirements (Crankshaw et al., 2017b; Reddi et al., 2020; Hsieh et al., 2018; Gog et al., 2022). Additionally, inference serving systems must manage dynamic workloads for cost and resource efficiency (Yadwadkar et al., 2019; Crankshaw et al., 2020, 2017b; Zhang et al., 2023a). The complexity increases when diverse services, each with unique Service Level Objectives (SLOs), contend for shared model resources. Comparing to serving systems that handle uni-modal models, serving multi-modal models with resource and latency-awareness has not been fully explored.

3 Opportunities & Challenges

Accuracy Across Modalities: In multi-modal DNNs, the importance of each modality can vary

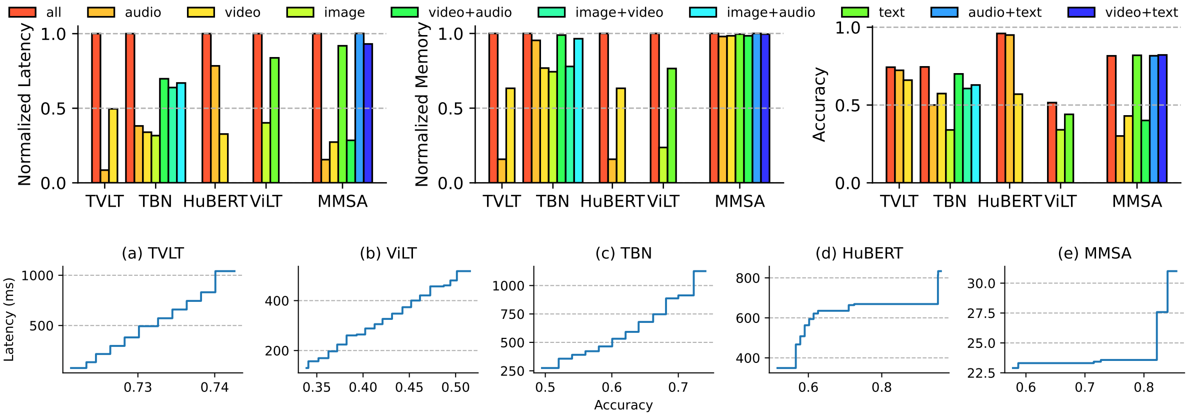
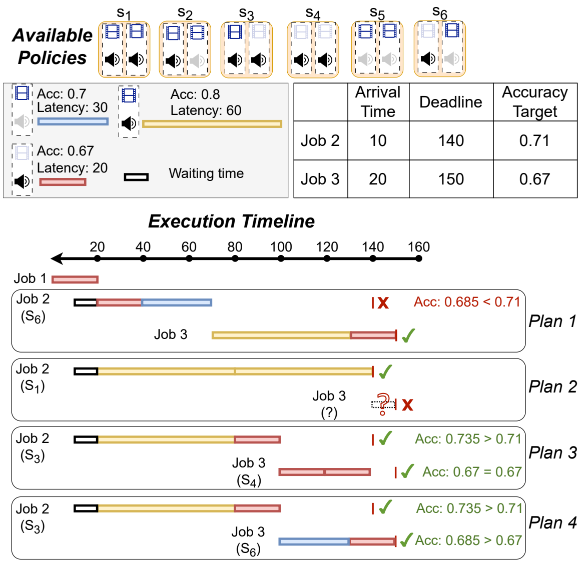


Figure 1: *Performance comparison of different modalities for models discussed in Table 1: (Upper Left) Normalized latency for modalities, obtained by dividing each modality's latency by the modality-agnostic baseline. (Upper Middle) The normalized memory footprint of different modalities. (Upper Right) Accuracy comparison using different modalities. (Bottom) Minimum latency required to achieve different levels of accuracy across various models using combinations of modalities.*

based on task, data, and model architecture (Ma et al., 2021, 2022; Tang et al., 2022; Nagrani et al., 2021). Figure 1(left) illustrates that some models, like TVLT, can achieve high accuracy without using all modalities. This shows data of different modalities contribute differently to the model accuracy.

System Implications: Different modalities uniquely impact latency and memory consumption due to their distinct data representations and processing methods. For example, in TVLT, the audio modality is more efficient than video in memory usage and latency, with minimal accuracy tradeoffs, shown by Figure 1 (left, middle). Memory consumption scales with sequence length in attention mechanisms (Vaswani et al., 2017), selectively using subset of input modalities means shorter sequences and reduced memory usage. Many recent works (Tang et al., 2022; Shi et al., 2021; Nagrani et al., 2021; Harwath et al., 2016; Lu et al., 2019; Sun et al., 2019) adopt similar attention-based multi-modal models, which can also benefit from using fewer modalities to reduce latency and memory consumption.

Opportunities: Applications provide inference systems with varying SLOs for *accuracy* and *latency*. These varying requirements offer opportunities for adaptive multi-modal selection, which previous systems haven't explored. Modalities can be enabled or disabled based on application needs (e.g., serving latency) and resource availability. For instance, under high load, prioritizing ultra-low latency to prevent resource contention is crucial. In such scenarios, employing only the audio modality in TVLT helps reduce latency by 11× with minimal accuracy loss, as shown in Figure 1. Conversely, under low load, using both video and audio ensured highest accuracy due to resource availability. We refer to this method as *accuracy scaling* (Ahmad et al., 2024), which adapts the inference accuracy to meet varying query demands. Fully achieving accuracy scaling raises the following challenges.



	Arrival Time	Deadline	Accuracy Target
Job 2	10	140	0.71
Job 3	20	150	0.67

Figure 2: *: Job 1 runs from timestamp 0 to 20. Job 2 arrives at timestamp 10 and starts at 20 after existing Job 1 finishes. One of Job 2's strategies, s_6, has an accuracy of $\frac{0.67+0.7}{2} = 0.685$, failing to meet its accuracy SLO (Plan 1). Similarly, s_4 also fails with an accuracy of 0.67. Job 3 arrives shortly after 20 with a deadline of 150. If Job 2 selects s_1, it occupies the system until 140, leaving Job 3 unable to meet its deadline (Plan 2). By selecting a lower accuracy modality, Job 2 can free up resources for Job 3 (Plan 3) allowing Job 3 to use a higher accuracy video modality (Plan 4).*

Challenge 1: find optimal modalities to use. Figure 2 illustrates the challenges of multi-modal inference. Each *job*, consisted of multiple requests submitted by an application, has specific *accuracy* and *latency* SLOs. Job 1 with an audio modality runs from time 0 to 20, Job 2 arrives at 10 and starts at 20, and Job 3 arrives shortly after 20. All jobs are executed in the order they arrive (a First-In-First-Out, FIFO, manner). Each job requires a *modality selection strategy* to determine the modalities to use for each request. Figure 2 shows six possible strategies for Job 2 or Job 3. For example, S_1 uses both modalities for both requests, while S_4 uses only the audio modality.

The number of strategies can be large and grow exponentially with the number of requests and the number of modalities. For a job with 20 requests and 3 modalities, there are 231 possible strategies. Some strategies may be infeasible, failing to meet accuracy or latency SLOs. For instance, only two of the six strategies for Job 2 satisfy the accuracy SLO (0.71) and the latency SLO (140). To achieve faster model deployment, efficient methods are needed to prune infeasible strategies and estimate latency for feasible ones.

Challenge 2: handle resource contention. Figure 2 illustrates that multiple strategies can yield valid accuracy. But we note that some strategies that create opportunities for a job potentially come at the cost of other jobs. In particular, greedily increasing accuracy for a job comes at the cost of increased resource consumption that may in turn hurt other jobs. This is illustrated by Plan 2 in Figure 2: it offers great accuracy for Job 2 by selecting both modalities for both requests (effective accuracy of 0.8) and finishing exactly by 140 time units. But, it leaves no room for Job 3 to finish by its deadline. On the other hand, by lowering accuracy for some jobs, we are left with extra resources that can be used to improve the outcomes for other jobs; e.g., in Plan 3, we use just the audio modality for one of Job 2's requests, yielding an effective accuracy of 0.735, which allows Job 3 to start at time 100 and use the audio modality for both its requests in order to finish by time 140 with an accuracy of 0.67. In fact, we can improve Job 3 – by picking a higher-accuracy modality (video) for one of its requests, Job 3 achieves an effective accuracy of 0.685 (Plan 4), while finishing at its deadline of 150.

The upshot is that we may have to look for less-than-optimal strategies for some jobs in the queue to enable other later-coming jobs to meet their objectives. To tackle the challenges for models that dynamically adapt to input data, we need techniques that adapt to the changing SLOs and query load across jobs. Existing inference serving systems leverage various techniques, including autoscaling (Microsoft Azure; Amazon Web Services), model switching (Romero et al., 2021a; Zhang et al., 2020), batching (Crankshaw et al., 2017a), predictive serving (Gujarati et al., 2020) and preemption (Zhang et al., 2023a). Inference systems for multi-modality such as (Li et al., 2021) focus on speculatively executing modalities using augmented data. All of these techniques are agnostic to input data modalities and to the possibility of exploiting them for efficiency.

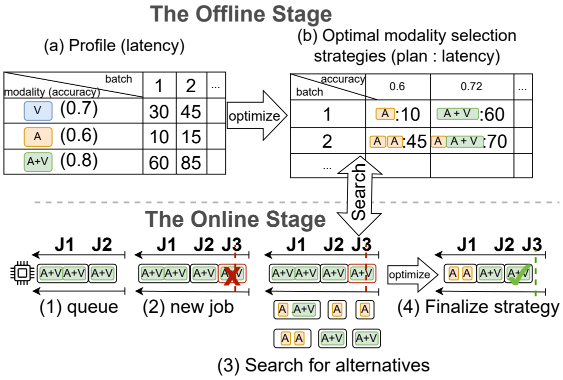


Figure 3: MOSEL *During the offline phase,* MOSEL *first (a) profiles latency for different accuracy-batch size pairs, then (b) constructs the optimized modality selection strategy matrix based on profile. In the online phase, it uses this matrix to dynamically derive modality selection strategies for different jobs.*

4 MOSEL Overview

4.1 Design Goals

We design MOSEL to achieve three key goals. First, MOSEL should automate modality selection, allowing users to only focus on high-level SLOs. Second, MOSEL should dynamically scale inference accuracy in response to varying system loads, maximize accuracy whenever possible while ensuring SLO compliance. Finally, MOSEL should easily integrate with existing inference systems for ease of use and adoption. This section provides an overview of our approach to meeting these goals and addressing the challenges outlined in Section 3.

Figure 3 illustrates the two stages of MOSEL's approach: *offline profiling* and *online optimization*. The offline stage generates potential modality selection strategies, thereby preparing the system for varying operational scenarios. During the online stage, the system selects from these precomputed strategies in real-time, adjusting modality choices to scale accuracy based on system load and SLOs of active jobs. This two-stage process ensures that MOSEL can minimize job deadline violations, enhance inference accuracy, and boost overall throughput - all without direct user intervention in modality selection.

4.2 The Offline Stage

MOSEL's offline stage generates a repository of potential modality selection strategies. As discussed in Section 3, each job has specific SLOs for *accuracy* and *latency*. Moreover, the number of requests submitted by different users can vary, resulting in variations in batch sizes. Consequently, MOSEL must prepare diverse modality strategies to accommodate diverse request volumes and accuracy demanded by users.

However, exhaustively exploring every potential possible modality selection strategy to identify those that fulfill the specified criteria is not practical. Consider a model with three modalities and jobs sizes ranging from 1 to 64; this results in approximately $400,000$ distinct strategies, taking up to 25 hours just for profiling. Moreover, increasing the jobs sizes and the number of modalities significantly escalates the complexity of the search space.

Therefore, we adopt an alternative approach: profiling *individual* modality combinations and leveraging the profiled data to *synthesize* optimized modality selection strategies. Taking the same model for example, we can form seven distinct combinations by selecting one, two, or three modalities. This requires profiling only $448 = 64 \times 7$ instances — a dramatic reduction from the exhaustive method. This approach decreases the profiling workload by a factor of $890\times$, making it significantly more efficient. We profile each instance for latency, documenting the accuracy and batch size. The latency for each batch-modality pair is stored as an entry in a profile table (Figure 3(a)).

MOSEL uses the profile table to construct a matrix of modality selection strategies for different job sizes and accuracy constraints for a given model, as shown in Figure 3(b). MOSEL first defines a range of possible job sizes, as well as a range of potential accuracy SLOs. Then, it uses an integer non-linear program (INLP) solver to generate an optimal strategy with minimal latency for a given accuracy-job size pair, represented by an entry in Figure 3(b). The construction happens in a one-time offline phase before the model is deployed. More details can be found in Section 5.1.

4.3 The Online Stage

MOSEL's online stage dynamically selects modality selection strategies, generated during offline stage, for each job in real-time. As outlined in Section 3, MOSEL's goal is to *scale* accuracy for all requests, **maximizing** it during low system load and **balancing** it against higher loads, ensuring compliance with user-defined accuracy and latency SLOs. This requires an *ongoing update* of modality strategies in response to the fluctuating system load and the SLOs of active jobs.

Once a model is deployed, the system queues all incoming jobs. MOSEL prioritizes and orders these jobs by their deadlines, as shown in Figure 3(1) (bottom half; leftmost panel). By default, Each new job adopts the strategy with the highest accuracy.

MOSEL monitors the queued jobs and detects if incoming new jobs may suffer from deadline violations. For a given job, MOSEL calculates the total latency by adding the latency of the existing modality selection strategy used by the job and the total latency of all preceding jobs. It then checks whether the sum would exceed the given job's latency SLO. If a job risks missing its deadline, as shown in Figure 3(2), MOSEL adjusts the modality selection strategies for all preceding jobs, potentially sacrificing accuracy, in order to reduce the wait time for the job at risk of a deadline violation.

When a job is detected to be at risk of a deadline violation, MOSEL considers the violator and all its preceding jobs as candidates for potential modality selection strategy changes. For each candidate job, MOSEL selects from the pre-computed modality strategies generated during the offline stage, whose accuracy are greater than the accuracy SLO specified for each job, as shown in Figure 3(3). MOSEL then takes all such strategies for all candidate jobs, and inputs them into an INLP solver, which reassigns a strategy for each candidate job, as shown in Figure 3(4). If the solver fails to find a solution, it means MOSEL is unable to reduce the queue time further without violating the accuracy SLO, and it will drop the job at risk of a deadline violation.

This approach allows MOSEL to dynamically adjust modality selection strategies to accommodate varying system loads. If the queue becomes relatively empty or contains few jobs, MOSEL will attempt to increase the accuracy for all queued jobs by progressively trying higher-accuracy modality strategies for each queued job. The modality strat-

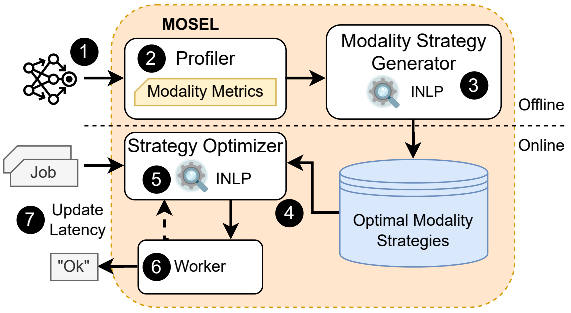


Figure 4: MOSEL *Workflow*

egy reassignment process is formulated as an INLP, detailed in Section 5.2.

5 Formulation

This section outlines how we identify optimal modality selection strategies to minimize latency while meeting accuracy SLOs for different job sizes. We also explain how we dynamically adjust these strategies in real-time to adapt to varying system resources.

5.1 Offline Optimal Strategy Generation

For a given model supporting n modalities and batch size from 1 to b, we profile the latency for each modality combination and batch size, yielding, in total, $b(2^n - 1)$ results, collectively denoted as the set $\mathcal{D}$ (represented by Figure 3 (a)). $\mathcal{D}_{ij}$ represents the latency using modality combination i with batch size j.

The submitted requests, with an accuracy SLO α, and the number of requests $|\mathcal{R}|$, are divided into multiple batches, denoted as $\mathcal{J}$, each using a different modality selection strategy from $\mathcal{D}$. For each batch, we aim to find the modality combination $\mathcal{I}$, such that the total latency of all batches $\sum_{i,j\in\mathcal{I},\mathcal{J}} D_{ij}$ is **minimized**, subject to two **constraints**: (**1**) The sum of all batches sizes must be equal to the total number of requests: $\mathcal{R}| = \sum_{j\in\mathcal{J}} j$, and (**2**) The average accuracy of all batches must exceed the user-specified accuracy SLO α. We use $acc(i)$ to denote the accuracy achieved by a modality selection strategy i. Formally, we have: $\sum_{i,j\in\mathcal{I},\mathcal{J}} acc(i)j \geq \alpha|\mathcal{R}$

The INLP solver requires only three components to function: the profiled results $\mathcal{D}$, the request size $\mathcal{R}$, and the accuracy SLO α. This enables us to precompute the modality selection strategies completely offline, reducing the risk of deadline violations once a model is deployed. Formally, given N possible request sizes and A accuracy requirements, we optimize for each of the $N \cdot A$ combinations. The optimal strategies are denoted as $\mathcal{P}$, where $\mathcal{P}_{ij}$ represents the optimal strategy for a request of size i with accuracy SLO j) (shown by Figure 3 (b)). This process has negligible overheads.

5.2 Online Modality Selections and Adjustment

Once a model is deployed, incoming requests are enqueud. To ensure no job misses its deadline (shown in Figure 3), we use T to represent the maximum allowed time budget. If MOSEL detects a deadline violation, T is set to the difference between the violator's deadline and the start time of the most recently executed job. Otherwise, T is set to the difference between the last job's deadline and the start time of the most recent job.

MOSEL selects one strategy from $\mathcal{P}$ for each job in the queue, based on the available time budget T. We denote the set of all such strategies as S, and the set of all involved jobs as J. Our goal is to select a strategy for each job in J such that the total accuracy is **maximized**: $\sum_{s,j\in S,J} acc(s) \cdot |j|$.

We use $l(s)$ to represent the execution latency of a strategy. To ensure the total latency fits within the budget T, wee add this **constraint** to our INLP: $\sum_{s\in S} l(s) \leq T$.

6 MOSEL Implementation

MOSEL is implemented in 3k lines of Python code. The offline profiler uses Pytorch (Paszke et al., 2019) to execute ❶ DNNs on the GPU and profile ❷ system metrics through CUDA API. We use GEKKO (Beal et al., 2018) to generate ❸ the offline modality selection strategies. GEKKO is an optimizer that solves large-scale mixed-integer and differential algebraic equations with nonlinear programming solvers. The generated strategies are stored in a single pickle object. During model deployment, the monitor process buffers incoming jobs, ❹ retrieves the generated modality plans, ❺ uses GEKKO to finalize the modality plan for each job, and puts the job into a FIFO queue shared with the worker process. To handle the GEKKO's overhead (which takes up to 80 ms), the monitor process enqueues enough jobs to compensate for the optimizer overhead. The worker process polls the FIFO queue, executes ❻ the jobs, and reports the latest ❼ execution latency metrics back to the monitor process for accurate resource estimation.

7 Evaluation

To evaluate our implementation, we conduct experiments using realistic workloads and address the following questions:

Q1*: What are the benefits of modality-aware optimizations?* (Section 7.1)

Q2*: Is* MOSEL *resilient towards profiling error?* (Section 7.2)

Unless specified otherwise, our experiments use the following configurations. We explore MOSEL's compatibility with existing model optimization techniques in Appendix C.

Experimental Setup All measurements are conducted on real hardware using a NVIDIA Tesla A100 GPU (80GB DRAM) and an Intel Xeon Silver 4314 CPU (2.40GHz, 128GB DRAM). We used NVIDIA driver version 525.85, CUDA 12.0, and PyTorch 2.1.0. The operating system is Ubuntu 22.04.1 LTS with 5.15.0 kernel.

Models. Table 1 summarizes the five pretrained PyTorch models used for evaluation. The models differ in size and fusion strategy. All models are fine-tuned on the task-specific datasets and preloaded onto the GPU before evaluation.

Workloads. We conducted experiments using both synthetic and real-world query patterns. For synthetic workloads, we generated queries with constant loads at fixed intervals. For real-world workloads, we used timing information from a month-long 2018 Twitter trace (twi, 2018), which reflects realistic inference workloads with diurnal patterns and spikes (Zhang et al., 2019). For each experiment, we randomly selected a day from the Twitter trace.

7.1 MOSEL with production workload

Here we show that dynamic modality selection enables MOSEL to improve throughput and utilization while reducing SLO violations under heavy load.

Experimental setup. We evaluated various models summarized in Table 1. To account for the varying processing latency, we adjusted the query per second (QPS) for each model. The Twitter trace was mapped to a minimum of 5 QPS. We set the maximum QPS based on each model's capacity to process requests within one second without missing deadlines: TVLT (60), AVHuBERT (20), TBN (40), MMSA (100), and ViLT (40). These values are twice the maximum requests each model can process per second. Requests were generated following a normal distribution, with a mean of 1 and a standard deviation of 6, until the total number of requests matches the QPS. We randomly assigned each job an accuracy SLO within the model's performance range, based on the lowest and highest achievable accuracy using different modalities.

We used four different policies: **(a)** optimized: (Section 5.2) uses available resources to achieve the highest accuracy for all enqueued jobs; **(b)** random (Algorithm 1) selects jobs randomly from the queue and applies the fastest strategy meeting the accuracy SLO, repeating until no deadline violations occur; **(c)** aggressive applies the fastest strategy satisfying the accuracy SLO to all enqueued jobs, **regardless** of deadline violations; and **(d)** none (modality-agnostic) performs **no** modality modification and serves as the baseline.

Results and discussion. Figure 5 shows dynamic modality selection results in higher throughput for all models compared to the modality-agnostic approach. TVLT, AvHUBERT, TBN, MMSA, and ViLT achieved throughput increase of $5.3\times$ $2.2\times$, $3.1\times$, $1.12\times$, and $4.3\times$, respectively. At low request arrival rate, both the modality-aware and modality-agnostic approaches have similar throughput. However, the modality-aware methods can handle higher request arrival rates, while the modality-agnostic method suffers from high processing latency and fluctuation. Note that MMSA has consistently low processing latency across all modalities, resulting in similar performance among different modality strategies.

Figure 5 also shows that all modality-aware techniques have significantly fewer SLO violations compared to the modality-agnostic approach. The optimized policy achieves 25%, 18%, 17%, 15%, and 4% lower average SLO violation ratios for TVLT, VilT, TBN, AVHuBERT, MMSA, respectively. Note the optimized policy has a slightly higher SLO violation ratio compared to the aggressive and random policy for models like TVLT and MMSA, due to processing latency being close the online optimizer latency. MOSEL compensates for this with higher accuracy and more consistency accuracy distributions across jobs, as shown in Figure 6. For larger models, the online optimizer overhead is negligible.

7.2 Resilience to Variations

In this section, we show how variations in offline and online optimizations can affect the inference process.

Experimental setup. To evaluate the impact of the offline optimization on accuracy and throughput, we generate optimized modality selection strategies, discussed in Section 4.2. We then vary the latency from 20% to 250% of the original latency

Task	Dataset	Model	Modalities	Fusion
Sentiment Analysis	MOSEI (Zadeh et al., 2018)	TVLT (Tang et al., 2022)	audio, video	Early
Speech Recognition	LRS3 (Afouras et al., 2018)	AVHuBERT (Shi et al., 2022)	audio, video	Early
Action Recognition	EPIC-KITECHENS (Damen et al., 2022)	TBN (Kazakos et al., 2019)	audio, video, image	Late
Sentiment Analysis	MOSEI (Zadeh et al., 2018)	Self-MM (Yu et al., 2021)	text, audio, video	Late
Multi-Label Classification	MM-IMDb (Ovalle et al., 2017)	ViLT (Kim et al., 2021)	text, image	Early

Table 1: *Tasks, datasets used for finetuning and evaluation, model architectures, model sizes, modalities used, fusion strategy*

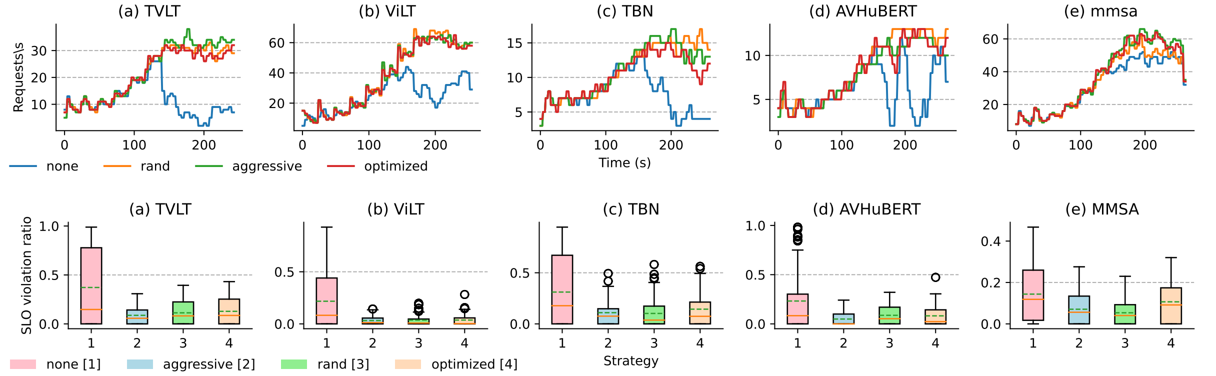


Figure 5: *Throughput and SLO violation ratio (number of SLO violations by total number of requests), profiled every 4 seconds. Each box shows the outlier, median, mean, 25%, and 75% quartiles.*

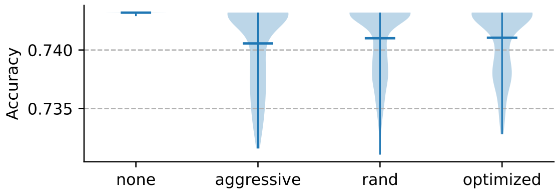


Figure 6: Accuracy distribution of TVLT with average accuracy of all jobs using different modality strategies.

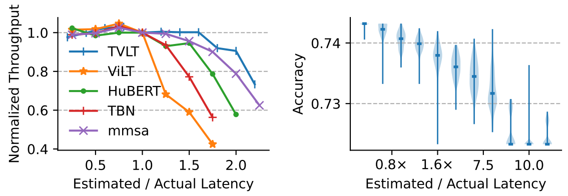


Figure 7: *Left: demonstrating the effect of the deviation between the expected and actual execution latency on models' normalized throughput. The discrepancy is calculated by estimated latency over actual latency. Right: accuracy distribution under different discrepancy between estimated and actual execution latency for TVLT. The discrepancy is calculated by estimated latency over actual latency.*

to simulate discrepancies between estimated and actual inference latency on real hardware. Using TVLT with a fixed QPS of 40, we apply `optimized` strategy for all experiments.

Results and discussion. As Figure 7 shows, all models can tolerate underestimated latency and maintain throughput. TVLT, AVHuBERT, and MMSA and tolerate up to 50% latency overestimation with negligible sacrifice in throughput. Since it's rare to obverse such discrepancy in inference infrastructures (Gujarati et al., 2020), we believe `MOSEL` is robust against estimation errors in most scenarios. The changing accuracy, as shown in Figure 7, is attributed to the system having false impression of resources due to overestimation, thus dropping jobs prematurely.

8 Conclusions

We modulate the input to a model at inference time to achieve accuracy scaling. We show the benefits of this approach in multi-modal inference. We highlight the key challenges and present practical solutions within `MOSEL`. We believe that input data modulation, combined with model and system optimization, opens new possibilities in inference literature. Modifying the input data can lead to significant benefits across the inference serving stack, including reduced network bandwidth, lower preprocessing costs, energy efficiency, and reduced operating costs. We envision `MOSEL` being applied to many scenarios with high input data variability that require adaptive optimizations.

Limitations

MOSEL presents two limitations in order to leverage the opportunity (§3) in a profitable way. First, MOSEL only considers the strategies that select the same modality for every request in a single job. This may lead to sub-optimal decisions. For example, Plan 4 in Figure 2 cannot be chosen. However, this design choice is inevitable otherwise the offline phase incurs prohibitive profiling costs. In the online phase, MOSEL may adopt a greedy heuristic that could be sub-optimal. We introduce it because solving the optimization problem online imposes a non-negligible latency overhead. We empirically show that the proposed heuristic works well and is close to the solver-based approach.

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A Greedy Heuristic

Algorithm 1 Random modality strategy selection

```
function RAND($jobQ, \mathcal{P}$)
    $S \leftarrow \{\}$
    if deadlineViolation($jobQ$) then
        $J \leftarrow$ jobsBeforeViolator($jobQ$)
    else
        $J \leftarrow jobQ$
    end if
    $deadline \leftarrow$ overhead($J$) $+ \, currTime$
    while $deadline > violatorDeadline$ do
        $j \leftarrow$ randomJob($J$)
        $s \leftarrow \mathcal{P}_{|j|,\ \mathtt{accuracy}(j)}$
        $deadline \leftarrow$ update($deadline, s$)
        $S$.append($s$)
    end while
    return S
end function
```

During the online stage (discussed in Section 5.2), the INLP solver may take up to 70 ms to assign modality selection strategies for each enqueued job, posing challenges for jobs with extremely low latency SLOs, such as MMSA. To address this issue, we propose a greedy heuristic that adapts the accuracy of enqueued jobs by randomly applying the fasted modality selection strategies meeting the minimum SLO for jobs preceding the deadline violator. We repeat this process until the total queue wait time is within the violator's deadline. The steps are described in Algorithm 1. We present the evaluation setup and the performance of the `random` heuristic in Section 7.

B Related Work

System-level dynamic optimization (Crankshaw et al., 2017a) proposes dynamic input batching to improve serving throughput by amortizing GPU kernel execution costs across multiple requests. It dynamically selects the largest profitable batch size that meets latency constraints.

Serving systems dynamically assign GPUs to jobs based on their SLOs and request rates. Some of them (Shen et al., 2019b; Yu and Chowdhury, 2020; Choi et al., 2022) consider GPU sharing to improve GPU utilization and goodput. (Zhang et al., 2023a) proposes burst-tolerant resource provisioning by mapping multiple jobs to a group of resources at runtime. (Zhang et al., 2023a) argues that preemption is necessary to maximize a serving system's goodput and their system makes preemption decisions at runtime providing formal guarantees on goodput.

(Romero et al., 2021a) introduces a new dynamism layer, model-variants. A user specifies a task, accuracy, and latency requirements, and the proposed serving system automatically and dynamically explores the accuracy-latency tradeoff space of model-variants for the same task. (Chen et al., 2023) generates cost-effective LLM cascade execution plans, leveraging different cost-accuracy characteristics of different LLMs.

(Li et al., 2021) focused on dealing with the delayed communication of input data in the case of multi-modal inference on streaming sensor data. Their proposed approach generates an input modality that is delayed based on the available input using a generative adversarial network (GAN) instead of waiting for the delayed input. They assume that dropping a modality always causes a significant accuracy drop.

Model-level optimization A number of ML compression techniques (Cheng et al., 2017) including pruning (Xia et al., 2023; sem) and quantization (Nagel et al., 2021) reduce both a model's memory and computational costs by reducing model weights or precision. They are usually applied before deployment, but recent work shows that runtime quantization bit-width decision is beneficial (Liu et al., 2022).

Early exiting (Xin et al., 2020; Zhou et al., 2020; Teerapittayanon et al., 2017; Xin et al., 2021) adds task-specific layers (e.g. classification) to existing models, and stops inference early based on a given confidence level. (Zhang et al., 2023b) uses layer skipping and output verification for LLMs. It dynamically skips layers to reduce per-token inference time.

In mixture-of-experts (MoE) models (Shazeer et al., 2017), a model is partially activated during its forward pass. A gating network selects the expert networks that will be activated based on input. This architecture allows a model's parameters to

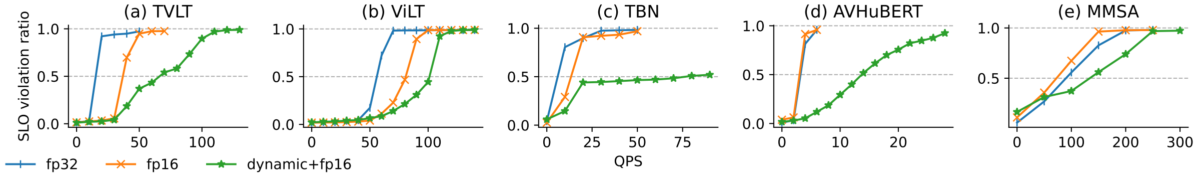

Figure 8: *SLO violation ratio using FP32, FP16, and dynamic modality selection combined with FP16.*

scale while avoiding the prohibitive forward pass execution costs of a dense model with the same number of parameters.

Data multiplexing (Murahari et al., 2022) adds multiplexing and demultiplexing layers at the beginning and end of the original model. The former transforms inputs into a succinct encoding and the latter does the opposite at the output. This improves throughput as the original model only runs on the more succinct encoding space. This technique is complementary to our approach that *drops* portions of the input data.

C Complimenting Existing Approaches

We show that MOSEL can be seamlessly incorporated into existing model optimization techniques to further improve inference throughput.

Experiment Setup. We use quantization to show how modality-aware techniques can be combined with other model optimization techniques to further reduce inference latency and satisfy SLOs. Quantization reduces the precision of numerical values in a model (Nagel et al., 2021), reducing memory footprint and speed up the inference process. We perform evaluation using two data types: `float32`, and `float16`. To study the effects under varying system loads, we select a range of QPS for each model. For modality selection, we use the `optimized` policy, employing the INLP solver during the online stage (as discussed in Section 5.2). The maximum QPS is set where the deadline violation ratio reaches 99%.

Results and discussion. Figure 8 shows that quantization allows all models to handle higher QPS before the deadline violation ratio increases significantly. For instance, AVHuBERT, when solely using quantization, fails to increase its processing throughput. However, with the combined use of quantization and dynamic modality selection, AVHuBERT can process up to 7× more requests before reaching a 99% violation ratio. This shows our approach is complimentary to existing model optimization techniques and can significantly improve inference processing throughput.

D MOSEL's decision overheads

In the offline profiling stage, MOSEL performs two tasks: (a) it measures the latency of different modalities under various batch sizes, and (b) it generates the optimal modality selection strategies for each batch size. Table 2 shows the median latency of these tasks and the speedup achieved by MOSEL over a brute-force search. Generating a single optimal modality offline selection strategy takes only 12ms.

Profile(s)	**Optimize(s)**	**Speedup**
32	45	31×

Table 2: The amoutnt of time TVLT spends in both system metrics profiling and modality generations, as well as speedup compared to brute force search for optimal modality generations.

In the online stage, MOSEL does two things: (a) it searches for the pre-computed optimal modality strategies that match the SLOs of each enqueued job, and (b) it finds the best modality selection strategy for each job. The optimizer's overhead varies from 12 ms to 80 ms. Note that this not on the critical path on job execution, as we overlap the optimization process with the job execution by having enough jobs enqueued by worker, as discussed in Section 6. For models with extremely low processing latency, we also propose a heuristic based method with lower latency, discussed in Appendix A.