

# ARCHON: An Architecture Search Framework for Inference-Time Techniques

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September 24, 2024

## Abstract

Inference-time techniques are emerging as highly effective tools to increase large language model (LLM) capabilities. However, there is still limited understanding of the best practices for developing systems that combine inference-time techniques with one or more LLMs, with challenges including: **(1)** effectively allocating inference compute budget, **(2)** understanding the interactions between different combinations of inference-time techniques and their impact on downstream performance, and **(3)** efficiently searching over the large space of model choices, inference-time techniques, and their compositions. To address these challenges, we introduce ARCHON<sup>1</sup>, an automated framework for designing *inference-time architectures*. ARCHON defines an extensible design space, encompassing methods such as generation ensembling, multi-sampling, ranking, fusion, critiquing, verification, and unit testing. It then transforms the problem of selecting and combining LLMs and inference-time techniques into a hyperparameter optimization objective. To optimize this objective, we introduce automated *Inference-Time Architecture Search (ITAS)* algorithms. Given target benchmark(s), an inference compute budget, and available LLMs, ITAS outputs optimized architectures. We evaluate ARCHON architectures across a wide range of instruction-following and reasoning benchmarks, including MT-Bench, Arena-Hard-Auto, AlpacaEval 2.0, MixEval, MixEval Hard, MATH, and CodeContests. We show that automatically designed inference-time architectures by ARCHON outperform strong models such as GPT-4o and Claude 3.5 Sonnet on these benchmarks, achieving an average increase of 14.1 and 10.3 percentage points with all-source models and open-source models, respectively. We make our code and datasets available publicly on Github: <https://github.com/ScalingIntelligence/Archon>.

## 1 Introduction

Inference-time techniques are gaining traction as effective methods for improving model capabilities. Examples include generation ensembling, ranking, and fusion, where models in the ensemble are queried in parallel, their responses are ranked, and the best ones are fused into a single, higher quality output, respectively [24, 56]. Other types of inference-time techniques are based on querying a single LLM successively (via multi-sampling) and using a voting strategy or unit tests to select the top generation [6, 7, 28]. We categorize these existing inference-time techniques into three components: *generative*, meaning that new candidate responses are drawn from the models (e.g. generation ensembling and multi-sampling), *reductive*, meaning that the existing responses are aggregated or filtered to keep the top responses (e.g. fusion and ranking), or *comparative*, meaning they provide analysis of candidate responses (e.g. critiquing and unit testing), as shown in (Table 1).

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<sup>1</sup>pronounced: Ark-On

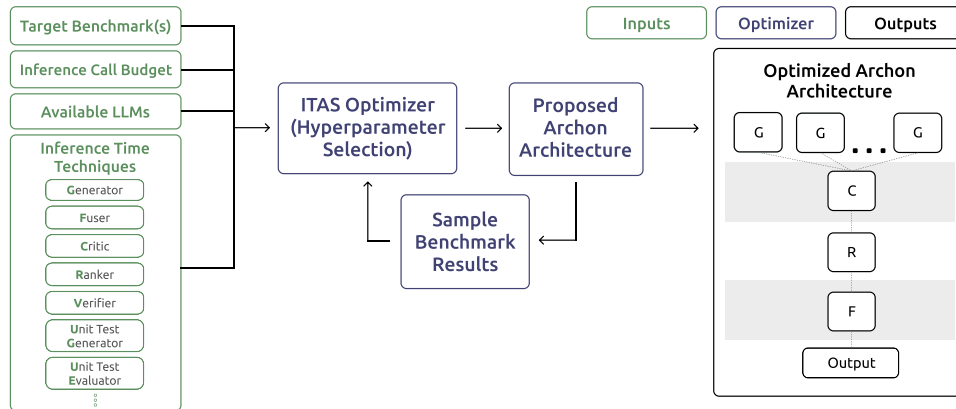


Figure 1: **Overview of ARCHON Framework:** Inference-Time Architecture Search (ITAS) requires the following inputs: target benchmarks, inference call budget, list of available LLMs, and available inference-time techniques (**left**). The ITAS algorithm uses Bayesian optimization [48] (Section A.6) to select and test different configurations of ARCHON (**middle**) before returning the optimized ARCHON architecture (**right**) for the target benchmarks (Section 3.4).

Recent work has made progress towards building robust *inference-time architectures*, which are systems composed of one or more large language models (LLMs) and inference-time techniques, such as Mixture-of-Agents (MoA) [56] and LLM-Blender [24] as well as single-model systems like LeanStar [32] and rStar [14]. However, our experiments show that existing architectures, such as MoA, still suffer from lack of generalization and become significantly less effective beyond the task(s) they were developed on (see Section 4.2). We argue that designing inference-time architectures that are generally effective across a wider range of tasks requires addressing the following challenges:

- **Effectively Utilizing Inference Compute:** Current inference-time architectures typically delegate their additional inference budget towards more model sampling calls [6, 7, 24], which can be effective for math and coding tasks [20, 31]. Other tasks such as instruction-following and reasoning are shown to benefit from additional inference-time techniques, including ranking and fusion [24, 56]. While all of these inference-time techniques are useful, the optimal inference-time architecture can widely differ depending on the tasks as well as the target compute budget and LLMs available.
- **Understanding Interactions Between Inference-Time Techniques:** While previous studies analyzed inference-time techniques individually (e.g. generation sampling in [7]), we need a more comprehensive understanding of the relationships between different inference-time architectures across different tasks (e.g. Is it better to have more models or more samples per model?) to design effective and generalizable inference-time architectures.
- **Efficiently and Automatically Building Inference-Time Architectures:** Given a set of LLMs and target tasks, there is currently no single prevailing inference-time architecture for maximizing downstream accuracy across all tasks (Table 3). When designing inference-time architectures, we must make several key configuration decisions: which LLMs to use, how many times to sample them, how to combine the candidate generations, what inference-time techniques to perform on the candidates, and more.

In our work, we address each of these challenges. Firstly, we demonstrate that by **combining a comprehensive set of existing and new inference-time techniques**, including *ensembling*, *fusion*, *ranking*, *critiquing*, *verification*, and *unit testing*, we can substantially improve the overall task performance (Table 2 and Table 3). This enables us to effectively utilize inference-time compute by building inference-time architectures with open-source models that surpass closed-source APIs, such as GPT-4o [40] and Claude-3.5-Sonnet [2]. We also show that our inference-time architectures outperform existing state-of-the-art open-source models, such as the Llama 3.1, Qwen2, and DeepSeek model families [15, 18, 43] and often do so by a large margin (Table 3).

Secondly, we **analyse the interactions between inference-time techniques**, and explore the benefits of adding new models and new techniques individually. We find that candidate fusion substantially improves the quality of the final response generation and, when combined with additional techniques like critiquing, verifying, and ranking, can improve generation quality beyond the oracle best candidate from individual (non-fused) responses (Table 2; Figure 4). Additionally, we find that candidate verification, unit test generation, and unit test evaluation are most effective for reasoning tasks, whereas critiquing and ranking is effective across instruction-following and reasoning tasks (Section 3.1; Table 2). Lastly, we also observe that model ensembling and repeated sampling boost overall performance, allowing us to effectively scale inference-time compute and emphasizing the importance of automated verification techniques (Figure 3; Figure 4; Figure 7).

Thirdly, drawing upon our analysis of inference-time architectures, we present **ARCHON**, a framework for building inference-time architectures. **ARCHON** utilizes automatic **inference-time architecture search (ITAS)** algorithms to maximize generation quality for a wide range of tasks, including instruction-following, reasoning, and coding. Our ARCHON framework and ITAS algorithms draw inspiration from neural architectures and neural architecture search (NAS) [33, 34, 45, 64], respectively. ARCHON is constructed of *layers of LLMs*, in which models in the same layer run in parallel but each layer runs sequentially. The layers perform different inference-time techniques, either transforming the number of candidate responses through generation and fusion (like linear transformations) or reducing the number of candidate responses to improve quality (like non-linearities) (Section 3.1). The number of generators, samples per model, fusion layers, fusion models per layer, and more are all treated as hyperparameters for optimization in our ITAS algorithms (Section 3.4). Our best ITAS algorithm utilizes Bayesian optimization to select ARCHON configurations for testing, allowing us to search the hyperparameter space efficiently and effectively [36, 48](Section 3.4). However, one notable difference with NAS is that our ARCHON framework requires no training or weight optimization.

Overall, our work makes the following contributions:

- We develop ARCHON, a modular framework for designing LLM systems that combine multiple inference-time techniques, including ensembling, multi-sampling, fusion, ranking, critiquing, unit testing, and verification (Section 3.1). ARCHON is plug-and-play, allowing users to select from existing inference-time techniques (or add new ones) and specify their desired objective functions to optimize for accuracy, latency, and cost. We make our code and datasets available at: <https://github.com/ScalingIntelligence/Archon>.
- We introduce ITAS, the underlying optimizer engine for ARCHON, which enables automated inference-time architecture search for target benchmarks, leveraging Bayesian optimization [36, 48](Section 3.4).
- We show that scaling the number of layers of inference-time architectures can be an effective approach for end-to-end performance optimization (Figure 5; Section 4.2).
- We discover efficient new combinations of test-time techniques. For example, we show that sequentially applying critique, ranking, top-k selection, and then fusion is a highly effective composition (Section 3.2). In addition, we demonstrate the effectiveness of model-based unit test generation and evaluation for improving coding capability (Figure 7). For example, we show that these techniques can be used to improve GPT-4o’s *Pass@1* performance on CodeContest problems by 11.4 percentage points.
- Our best all-source ARCHON architectures surpass both single-call LLMs (e.g. GPT-4o and Claude-3.5 Sonnet) and prior top-performing inference-time architectures (e.g. Mixture-of-Agents), boosting state-of-the-art performance by 14.1 percentage points, on average, across a diverse set of instruction-following, reasoning, and coding benchmarks (Table 3): MT-Bench, Arena-Hard-Auto, Alpaca-2.0 Eval, MixEval, MixEval Hard, MATH, and CodeContests [20, 29, 30, 31, 37, 63]. Even when just using open-source LLMs, ARCHON architectures surpass all-source single-call LLMs by 10.3 percentage points, on average. All of our stated gains are *Pass@1* results, meaning that we do not assume access to any external sources of grounding such as golden unit tests for coding problems.

## 2 Related Work

### 2.1 Scaling Laws of Language Models

Language models [22, 40, 50, 53] have transformed the field of artificial intelligence across a vast number of domains and tasks. LLMs are pretrained on substantial amounts of textual data before being further

aligned with human preferences through instruction fine-tuning [10, 57], direct policy optimization (DPO) [44], Kahneman-Tversky optimization (KTO) [16], reinforcement learning from AI feedback (RLAIF) [5], and other techniques. As language models continue to gain improved abilities with further scaling of data, parameters, and compute [17, 26], the cost of developing new LLMs is ever increasing, requiring the curation of trillions of new tokens as well as substantial GPU-hours for pretraining. Furthermore, as the current state-of-the-art in LLMs are primarily closed-source APIs, such as OpenAI’s GPT-4o [40], Google’s Gemini [51] and Anthropic’s Claude [2], it is difficult to effectively explore and push the frontier of existing LLMs without being able to manipulate the parameters of these closed-source models and employing techniques such as continual pretraining [25], instruction fine-tuning [57], data mixing [60], chain-of-thought [58], among others. A number of recent works show the effectiveness of scaling compute at test time [6, 7, 24, 47]. In particular, Large Language Monkeys [6] characterizes inference-time scaling laws, showing a log-linear relationship between coverage—the fraction of problems solved by at least one attempt—and the number of samples drawn from the model across a broad range of reasoning tasks and LLMs. We build on the inference-time compute scaling approaches and propose ARCHON, a formal framework for applying inference-time techniques, combining the strengths of multiple pretrained LLMs (Section 3.2), and exploring different inference-time architectures with ITAS (Section 3.4).

## 2.2 Inference-Time Techniques

By utilizing a single LLM or multiple LLMs, inference-time architectures allow us to combine multiple inference-time techniques (e.g. generation ensembling, sampling, ranking, and fusion), achieving superior performance compared to individual models. Notable works in this domain include the Mixture-of-Agents (MoA) [56], LLM Blender [24], and RouteLM [28, 38], which have demonstrated the efficacy of these techniques in improving generation quality, limiting API costs, and reducing query latency. LM frameworks, such as DSPy [27] and TextGrad [61], have even emerged for orchestrating LMs and other tool components (e.g. retrievers, search engines, calculators, compilers, etc.), optimizing prompt engineering for integrating these components. Even with a single LLM, various inference-time techniques can bolster downstream performance by building better reasoning strategies. These techniques include OpenAI’s o1, Chain of Thought, Branch-Solve-Merge, Rephrase and Respond, Lean-STaR, rStar, and more [14, 32, 39, 41, 46, 58].

Despite these advancements, several challenges remain for the development of inference-time architectures. Firstly, many inference-time architectures today delegate the vast majority of their inference calls towards additional generations [7, 13, 24]. For reasoning domains like coding and mathematics, additional repeated inference calls are shown to be effective in improving benchmark performance [6]. However, for other tasks such as chat and instruction-following, additional inference-time techniques such as generation fusion and ranking are shown to be useful [24, 56]. Additionally, for tasks without built-in verification (e.g. unit tests), it can be important to delegate additional compute towards reasoning generation and verification to improve downstream accuracy [13]. Within the set of inference-time architectures, we still do not understand the trade-offs between different inference-time techniques in these systems. Prior studies have only explored limited aspects of inference-time architecture configurations, often focusing on specific benchmarks without generalizing the findings to broader datasets [24, 56]. For example, both [7] and [28] explored the impact of LLM calls on downstream performance but they did not examine how other inference-time techniques, such as generation ensembling and fusion, might impact the trends found for LLM sampling. Beyond analysis of inference-time techniques, it is also crucial to thoroughly and efficiently develop inference-time architectures since the optimal configuration can differ widely based on the benchmark, the models available, and the maximum number of inference calls allowed (Section 4.2). To address these challenges, we analyzed multiple inference-time techniques (Section 3.1) and developed the ARCHON framework for automating the development of inference-time architectures with ITAS (Section 3.4).

## 3 Inference-Time Techniques for ARCHON

To better understand what inference-time techniques could be most effective for ARCHON, we test an array of different techniques, incorporating existing approaches for generating, ranking, and fusing candidates [24, 56] as well as constructing new approaches for critiquing, verifying, and unit testing candidates, inspired by a host of recent work [6, 13]. Below, we elaborate on the structure, inputs, and outputs of each of the inference-time techniques, which we also include in Table 1. Then, we discuss how to combine the different techniques into an inference-time architecture (Section 3.2) and the relationships between the different inference-time techniques (Section 3.3) before finally exploring automatic approaches for constructing inference-time architectures (Section 3.4).

Inference-time Technique	Definition	Input	Output	Inference Cost	Domains
Generator	Generates a candidate response from an instruction prompt	Instruction Prompt	Candidate Response(s)	1 call per cand.	All Domains
Fuser	Merges multiple candidate responses into a single response	Instruction Prompt + Candidate Response(s)	Fused Candidate Response(s)	1 call per cand.	All Domains
Critic	Generates strengths/weaknesses for each candidate response	Instruction Prompt + Candidate Response(s)	Candidate Response(s) Strengths/Weaknesses	1 call	All Domains
Ranker	Returns top-K candidate responses	Instruction Prompt + Candidate Response(s)	Ranked Candidate Response(s)	1 call	All Domains
Verifier	Returns the candidate responses with verified reasoning	Instruction Prompt + Candidate Response(s)	Verified Candidate Response(s)	2 calls per cand.	Reasoning Tasks
Unit Test Generator	Generates unit tests to evaluate the candidate responses	Instruction Prompt	Instruction Prompt + Unit Tests	1 call	Reasoning Tasks
Unit Test Evaluator	Uses generated unit tests to evaluate candidate response	Instruction Prompt + Unit Tests + Candidate Response(s)	Scored Candidate Response(s)	1 call per cand.	Reasoning Tasks

Table 1: **Overview of ARCHON’s Inference-time Techniques:** Definitions, Inputs, Outputs, Costs, and Application Domains.

### 3.1 LLM Components of ARCHON

In this section, we discuss the *LLM components* of ARCHON, which are LLMs that perform a specific inference-time technique. The components are summarized in Table 1.

**Generator:** The *Generator* module of ARCHON is a LLM that creates candidate responses. As input, the generator takes in the instruction prompt and outputs candidate responses. Generators can be called in parallel to perform *generation ensembling* [24, 56], or sampled multiple times [6, 7]. When calling the Generators in parallel, you can sample one or more LLMs one or more times. The exact number of models, samples, and temperature for generation can be varied based on model configuration. We provide the exact prompt used in the ARCHON generator in Table 5.

**Fuser:** The *Fuser* module of ARCHON is a LLM that combines multiple candidate responses to create one or more higher-quality responses. As input, the fuser takes in the instruction prompt and the set of proposed responses. As output, the fuser generates a fused response that combines the proposed responses into a higher-quality generation for addressing the instruction prompt. We provide the exact prompt used in the ARCHON fuser in Table 6.

**Ranker:** The *Ranker* module of ARCHON is a language model that ranks the current list of candidate generations based on their quality and the instruction prompt. As input, the ranker takes in the instruction prompt and the set of proposed responses. As output, the ranker produces a ranked list of the proposed responses. We provide the exact prompt used in the ARCHON ranker in Table 7.

**Critic:** The *Critic* module of ARCHON is a LLM that produces a list of strengths and weaknesses for each candidate response in a provided set. As input, the critic takes in the instruction prompt and the set of proposed responses. As output, the critic produces a list of strengths and weaknesses for each respective candidate response. We use the strengths and weaknesses to improve the quality of the final response (Section 3.2; Figure 5). We provide the exact prompt used in the ARCHON critic in Table 8.

**Verifier:** The *Verifier* module of ARCHON is a LLM that verifies whether a provided candidate response has appropriate reasoning for a given instruction prompt. It proceeds in two stages: **Stage #1** takes in the instruction prompt and a candidate response as input and outputs reasoning for why the candidate response is correct; **Stage #2** takes in the instruction prompt, candidate response, and produced reasoning before outputting reasoning and a verdict (i.e. binary [Correct] or [Incorrect]) for whether or not the candidate response is correct according to the provided instruction prompt and reasoning. We provide the exact prompt used in the ARCHON verifier in Table 9.

**Unit Test Generator:** The *Unit Test Generator* module of ARCHON is a LLM that generates a set of unit tests for a given instruction prompt. As input, the unit test generator solely takes in an instruction prompt. As output, the unit test generator produces a list of unit tests that are consequential for the accuracy and relevance of a candidate response. These generated unit tests are verified by the Unit Test Evaluator, allowing us to rank different candidate responses. Each unit test is formatted as a concise declarative statement that can either be

passed or failed. We make the number of unit tests generated a configurable choice for the unit test generator but we find 5-10 generated unit tests to be most effective with our set of LM prompts (Section 4.2; Figure 7). We include examples of unit tests for an instruction-following query and a reasoning query in Table 11. We provide the exact prompt used in the ARCHON unit test generator in Table 10.

**Unit Test Evaluator:** The *Unit Test Evaluator* module of ARCHON is a language model that evaluates each candidate generation against a generated set of unit tests. As input, the unit test evaluator takes in the instruction prompt, candidate response(s), and set of unit tests. As output, the unit test evaluator outputs the candidate response(s), ranked in descending order by how many unit tests they pass. We use model-based unit test evaluation by prompting the LLM to provide reasoning and verdicts for each unit test across each of the candidate responses. By aggregating the unit test verdicts for each candidate response, the unit test evaluator ranks the candidate responses. For reasoning tasks, particularly coding tasks, it can be useful to compare different candidate responses by the number of unit tests they pass to gauge for quality. Additionally, by generating many candidate responses and evaluating each one against the unit tests, we can better leverage increased inference time compute budgets while improving the quality of the final returned response (Figure 7). We provide the exact prompt used in the ARCHON unit test evaluator in Table 12.

### 3.2 Combining the LLM Components

**Overview:** Inspired by the structure of neural networks [21], ARCHON is constructed of layers of LLM components (Figure 1; Section 3.1). Each layer is composed of sets of these LLM components that are called in parallel, performing a text-to-text operation to the instruction prompt and the subsequently generated candidate responses. Furthermore, like a neural network, some layers perform *transformations* of the provided list of strings (e.g. the Generator and Fuser components), converting a list of strings into a different list of strings (the numbers of candidates can vary from the original number of candidates). Other components introduce non-linearities into the ARCHON structure, performing filtering of the list of strings (e.g. Ranker and Verifier). Ultimately, the inputs and outputs for each layer is always a list of strings, whether that is the instruction prompt (e.g. a list with a single string) or a list of candidate responses (e.g. a list of many strings). If a list of strings are outputted at the last layer of the ARCHON structure, the first string in the list is returned.

Unlike a classical neural network, no weights are learned between the LLM components and the layers; in turn the ARCHON architecture can be deployed off-the-shelf without any tuning. This distinction makes architecture search much cheaper and more efficient since a new configuration is tested without an inner optimization of the architecture’s weights, which we discuss in Section 3.4. Additionally, a single state is transformed sequentially from the input layer to the final output; this single state is the initial instruction prompt and the current candidate responses. In Figure 2, we provide an example ARCHON architecture composed of five layers: an ensemble layer of generators, an intermediate critic layer, an intermediate layer of fusers, an intermediate ranker layer, and a final fuser layer.

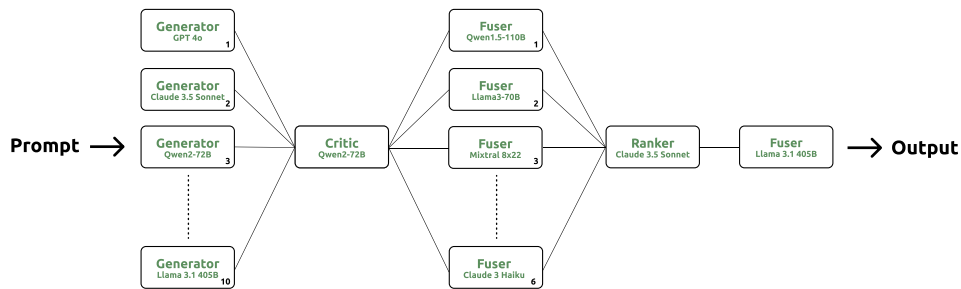


Figure 2: **Example Archon Architecture:** The architecture starts with ten generator models, followed by a critic model with one layer of 6 fuser models, and finishing with a ranker model and a final fuser model.

**Rules for Construction:** While ARCHON is a modular framework, the LLM components in Section 3.1 can only be placed in specific orders.

1. Only one type of module can be present in any given layer.

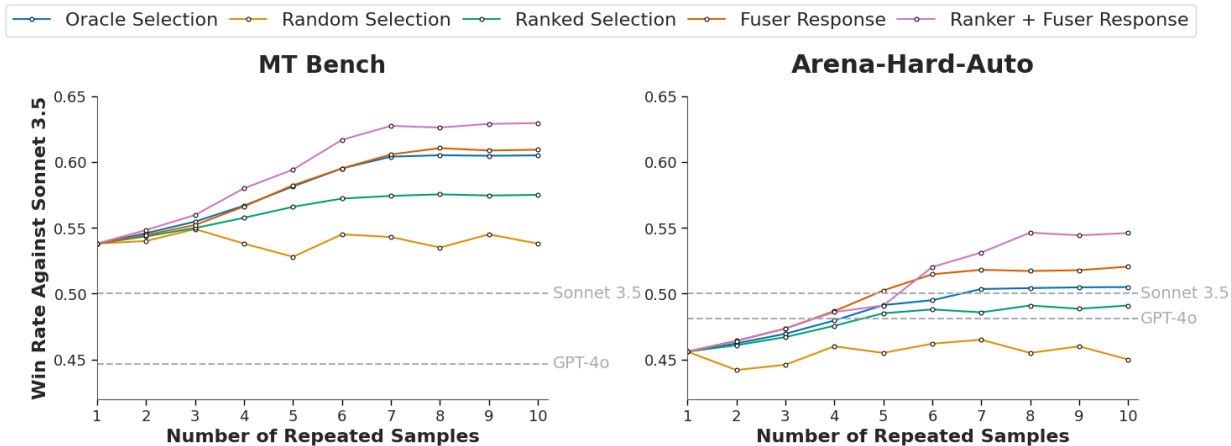


Figure 3: **Performance Gains from Applying Inference Time Techniques on a Single Model:** We repeatedly sample more responses for each individual query. For each sample count, we choose the best response in 5 different ways: (1) using an oracle (to get the upper bound for performance of best sample), (2) randomly, (3) using a ranker model, (4) by fusion, in which a model synthesizes a response based on all the samples, and (5) by ranking the top-5 best answers and then fusing them. For both MT Bench and Arena-Hard-Auto, we find that fusion is an effective technique. In particular, ranking the candidates first, and then selecting the top-5 and fusing them scores the highest. The best open-source model for these tasks across all the 70B+ models we are considering is WizardLM-2-8x22B [59] (see Table 14 for details). For both ranking and fusion, we use Qwen2 72B Instruct [43].

2. Generator components must and can only be placed in the first layer of ARCHON; you can put multiple Generators or a single Generator in the layer.
3. The Critic component must come before a Ranker or a Fuser, otherwise the generated strengths and weaknesses cannot be incorporated into generation ranking or fusion, respectively.
4. Ranker, Critic, Verifier, and Unit Test Generator/Evaluator layers can go anywhere in the ARCHON structure (besides the first layer); for each of these components (as well as the Unit Test Generator), it must be the one and only module in its layer.
5. Fuser components can also be placed anywhere in the ARCHON structure (besides the first layer); you can put multiple Fusers or a single Fuser in the layer.
6. Unit Test Generators and Evaluators are placed in layers next to each other: generator first, then evaluator.

We provide an overview of the available placements and configurations for each LLM module in Table 4.

### 3.3 Utilities and Interactions of LLM Components

In this subsection, we present our analysis of the effectiveness of each LLM component (i.e. the *Utility*) and the relationships between each component (i.e. the *Component Interactions*) by evaluating on *instruction-following tasks* (MT Bench, AlpacaEval 2.0, Arena-Hard-Auto), *reasoning tasks* (MixEval, MixEval-Hard, MATH) and *coding tasks* (CodeContests) (Section 4.1). For our ARCHON models, we utilize a host of 70B+ open-source models (Section 4.1; Table 13).

#### 3.3.1 Generator

**Utility:** For our Generator module, we find additional model sampling to significantly boost performance (Figure 3), particularly for coding tasks (Figure 7). In settings with a limited inference call budget, additional model samples lead to the largest marginal benefit. We see a similar pattern for model ensembling, where sampling from additional models leads to continual performance increases (assuming the models are ordered from best to worst for the given task) (Figure 4).

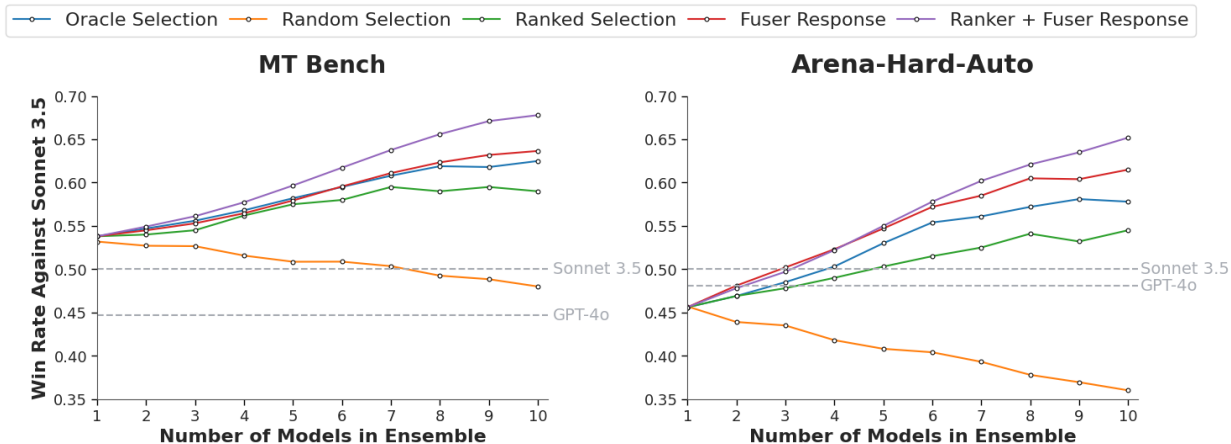


Figure 4: **Performance Gains from Applying Inference-Time Techniques on an Ensemble of Models:** We incrementally add more models to the ensemble, which consists of open-source 70B+ models. The models are added to the pool based on their performance for each task, from best to worse (see Table 14 for details). For each ensemble size, we choose the best response in 5 different modes: (1) using an oracle (to get the upper bound for performance of best individual response in the ensemble), (2) randomly, (3) using a ranker model, (4) by fusion, in which one model synthesizes a response based on all the responses of the ensemble models, and (5) ranking the top-5 best responses and then fusing them. For MT Bench and Arena-Hard-Auto, we find consistent performance improvements as we add more models to the ensemble. We find that fusion is beneficial across various ensemble sizes and in particular a fused candidate based on the top-5 ranked responses scores highest. The ensemble approach scores higher than applying the same techniques on repeated samples from a single best-performing model (see Figure 3). For both ranking and fusion, we use Qwen2 72B Instruct [43].

### 3.3.2 Fuser

**Utility:** For every benchmark explored, we found that the Fuser module substantially improved performance (Figure 3; Figure 4; Figure 5). For the single-generation 10-model ensemble of 70B+ models, the Fuser module improved downstream accuracy by 5.2 points, on average, compared to the single-generation best model (Figure 4). When combined with the Ranker module for ranking the top-5 candidate responses, the Fuser improved downstream accuracy by 7.3 points and 3.6 points, on average, compared to the single-sample best model and the oracle best candidate response, respectively (Figure 4). Overall, we found that Fuser efficacy increased as more candidate responses were provided, demonstrating that additional candidate generations can continue to bolster inference-time architecture performance when combined with a Fuser.

In previous work like Mixture-of-Agents (MoA) [56], multiple layers of Fusers was found to boost performance on some instruction-following tasks (i.e. MT Bench and Alpaca Eval 2.0). Across all the benchmarks explored, we observed similar benefits in the ARCHON framework when adding multiple layers of Fusers (Figure 5). However, based on our results in Figure 8, the number of Fuser layers needed to improve performance varied by task, with some tasks receiving limited benefits from added layers (1-2 point increase in accuracy for MixEval) while others experienced significant benefits with 3-4 fusion layers and more (2 to 5 point increase in win rate for MT Bench and Alpaca Eval 2.0). We attribute this distinction to the difference in task requirements, with chat and instruction following tasks benefiting more from multiple iterations of revisions through the multiple Fuser layers, leading to greater diversity in the final generation (Table 15).

**Component Interactions:** To better understand how the Fuser module works with the other LLM components, we took the single-sample 10-model ensemble of Generators with a Fuser and tried adding each of these components individually: a Critic, a Ranker, a Verifier, and a Unit Test Generator/Evaluator. Across all of the benchmarks, the added candidate response analyses from the Critic improved the Fuser’s ability to effectively merge the different candidate responses, increasing performance by an average of 3.1 percentage points (Figure 5). With the added Ranker, the ARCHON architecture improved the combined Ensemble + Critic + Fuser performance across all the benchmarks by 4.8 percentage points, on average (Figure 5). The Ranker proved most effective for style-



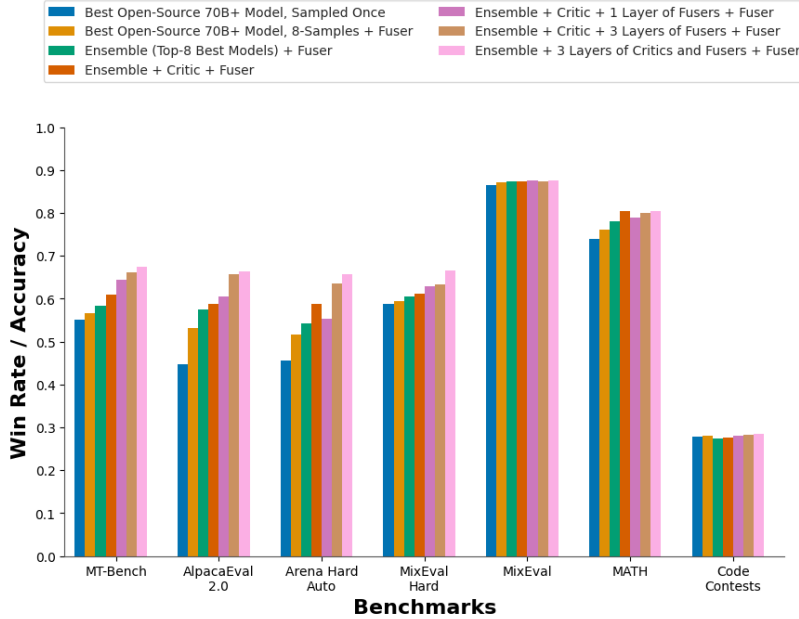


Figure 5: **Performance Gains from Scaling "Layers" of Inference-Time Techniques:** To better understand the impact of scaling inference-time techniques, we evaluate different ARCHON architectures on AlpacaEval 2.0 [30], Arena-Hard-Auto [29], MT-Bench [63], MixEval [37], MixEval Hard, MATH [20], and CodeContests [31]. For the ensemble, we use the top-8 70B+ open-source models (Table 14). We generally observe performance improvements as we scale the critic and fusion layers. Compared to sampling the best open-source model once, our inference-time architecture with an 8-model ensemble, 3 layers of critic and fusion (8 models in each layer), and a final fusion performs 17.3% higher, on average. For MixEval and CodeContests, we find that alternative inference-time architectures are more effective than generator ensembles and fusion layers. We break-down our results for MixEval and MixEval-Hard by subdataset in Section 4.2 (Table 25; Table 26). For CodeContests, we show the effectiveness of increased generator sampling combined with model-based unit test generation/evaluation in Figure 7.

oriented tasks (e.g. MT Bench and AlpacaEval 2.0) since the examples mostly focus on improving the instruction-guidance towards the provided prompt. With the added Verifier module (Figure 5), the performance of the Ensemble + Critic + Fuser configuration improved marginally for the instruction-following tasks (1.2 percentage points, on average, for MT Bench, AlpacaEval 2.0, and Arena-Hard-Auto). However, this configuration improved performance more on reasoning tasks (3.2 percentage points for MixEval and MixEval-Hard, on average), assisting generation by filtering out irrelevant or flawed answers before the final fusion step (Figure 5). The added Unit Test Generator and Evaluator was less effective for the instruction-following and reasoning tasks, only providing a 1.5 percentage points increase, on average, when added to the Ensemble + Critic + Fuser configuration (Table 2). However, for coding tasks, we found unit test generation and evaluation significantly improved performance, leading to a 10.7 percentage point increase (56% performance increase comparatively) as we scale model sampling (Figure 7).

### 3.3.3 Critic

**Utility:** The Critic module proved effective for every task we explored in Figure 5 and Table 2. With our 10-model 70B+ Generator ensemble and Fuser configuration of ARCHON, the added Critic improved performance on average by 3.1 percentage points across the benchmarks explored.

**Component Interactions:** While useful for most ARCHON architectures, the added strengths and weaknesses from the Critic module are particularly useful when combined with the Fuser module, helping guide generation fusion for a single layer and even useful when placed between multiple fusion layers (on average 3.2 percentage point boost across benchmarks in Figure 5). The Critic module was also effective with the Ranker module, providing additional information for comparing candidate responses (Figure 3) and leading to a 5.9 percentage point increase, on average (Table 2).

### 3.3.4 Ranker

**Utility:** From our results in Table 2, Figure 3, and Figure 4, we found the Ranker to be most effective for instruction-following tasks, where pair-wise comparisons of answers focus on style and adherence to the prompt. To examine the candidate selection improvement provided by candidate ranking, we compare three approaches to the Ranker: **(1)** random selection of candidate generation, **(2)** oracle selection of candidate generation, and **(3)** the top-ranked candidate selected by our Ranker. For MT Bench and Arena-Hard-Auto, we find that the ranker improves generation output quality by 3.8% compared to random candidate selection and performs within 2.7% of oracle selection (Figure 3).

**Component Interactions:** Based on our benchmark results in Table 2, the Ranker pairs well with the Critic module; the provided strengths and weaknesses helps guide ranking, particularly for instruction-following tasks, improving performance by 5.9 percentage points, on average. Furthermore, the Ranker was also effective when paired with the Fuser; the filtered list of candidate responses helped improve the final condensed response produced by the Fuser by 3.8 percentage points, on average (Figure 4). When paired with the Verifier and Unit Test Generator, the Ranker had neutral effects; performances changed marginally, either positively or negatively by 1-2 percentage points (Table 2).

Overall, our findings demonstrate the value of added Rankers for instruction-following and reasoning tasks when paired with Fusers. We find that when Rankers are used alone with an ensemble of Generators, their performance lags behind the 10-sample best single model configuration by 3.0 percentage points, on average (Table 2). Additionally, our findings show the importance of building better rankers for more complex reasoning tasks, such as math and coding, which is a challenge also raised by [6].

		Datasets								
		MT Bench	AlpacaEval 2.0		Arena Hard Auto	MixEval Hard	MixEval	MATH*	Code Contests*	
Judge Model		GPT-4 0314	GPT-4 Turbo	GPT-4 Turbo	GPT-4 Turbo	N/A	N/A	N/A	N/A	
Reference Model		Claude-3.5 Sonnet	GPT-4 Turbo	GPT-4 Turbo	Claude-3.5 Sonnet	N/A	N/A	N/A	N/A	
Model / LLM System		# of Infer. Calls	W.R.	L.C. W.R.	Raw W.R.	W.R.	Acc.	Acc.	Acc.	Acc.
Control	Best Open-Source 70B+ Model, Sampled Once	1	55.0%	44.7%	37.1%	45.6%	58.7%	86.5%	73.5%	<b>27.1%</b>
	Ensemble + Fuser	9	58.4%	57.5%	51.3%	54.3%	60.5%	87.3%	75.5%	22.0%
	Ensemble + Critic + Fuser	10	60.9%	58.7%	<u>65.8%</u>	58.8%	62.4%	87.4%	77.0%	24.5%
Ablations	Ensemble + Ranker	9	52.5%	54.7%	47.6%	50.5%	58.2%	86.8%	71.5%	23.5%
	Ensemble + Verifier	24	53.2%	56.2%	50.2%	52.4%	56.5%	85.6%	76.0%	24.9%
	Ensemble + Unit Test Gen./Eval.	17	51.5%	54.4%	49.4%	46.1%	55.2%	86.0%	75.0%	25.1%
	Ensemble + Ranker + Fuser	10	<u>62.5%</u>	<u>60.3%</u>	63.6%	57.2%	60.1%	87.6%	76.0%	23.6%
	Ensemble + Verifier + Fuser	25	60.5%	59.4%	58.7%	59.2%	65.1%	87.5%	78.0%	24.5%
	Ensemble + Unit Test Gen./Eval. + Fuser	17	61.4%	58.5%	55.1%	56.4%	62.8%	86.9%	77.0%	26.3%
	Ensemble + Critic + Verifier + Fuser	25	61.3%	60.0%	61.0%	59.5%	<u>65.5%</u>	<u>87.8%</u>	<u>78.0%</u>	24.8%
	Ensemble + Critic + Ranker + Fuser	11	<b>64.7%</b>	<b>62.6%</b>	<b>72.4%</b>	<b>60.9%</b>	<b>67.0%</b>	<b>88.3%</b>	<b>79.5%</b>	24.1%

Table 2: **Impact of Different Compositions of ARCHON’s Inference-Time Techniques:** For the ensemble configuration of ARCHON, we see added benefits from ranker, critic, verifier, fuser, and unit test generator/evaluator. In particular, a composition of ensemble generator, critic, ranker, and fuser components improves performance across the explored benchmarks. For CodeContests, we find that there is a single model (Llama 3.1 405B Instruct) that performs considerably better than the rest of the LLMs studied, making it more effective to build architectures that use multiple inference-time techniques on a single model and leverage additional model sampling (Figure 7; Table 14). For our ensemble, we use the best 8 open-source 70B+ models for the task. For our fuser, critic, ranker, and verifier components, we use the best fuser model found for the task (Table 14). \*For MATH and CodeContests, we use sampled subsets of their test sets (Section 4.1; Table 24).

### 3.3.5 Verifier

**Utility:** The Verifier was most effective for the reasoning benchmarks explored in Table 2. When just using a 70B+ Generator ensemble with Verifier module after generation, the ARCHON configuration lagged behind the ARCHON ensemble and fuser configuration by 1.5 percentage points, on average, across all benchmarks

explored. This suggests that the Verifier is most effective when combined with other inference-time techniques. **Component Interactions:** As noted in Section 3.3.2, the Verifier augmented the performance of the Critic and Fuser on reasoning tasks (e.g. Arena-Hard-Auto, MixEval, MixEval-Hard), boosting performance by 3.7 percentage points, on average, when combined together with these modules. Overall, the Verifier is most powerful when augmenting additional components for tasks requiring verification of intermediate steps and the final response (Table 2). Therefore, the Verifier was less helpful for instruction-following tasks (e.g. MT Bench and AlpacaEval) but more effective for reasoning tasks (e.g. Arena-Hard-Auto and MixEval).

### 3.3.6 Unit Test Generator and Evaluator

**Utility:** The Unit Test Generator and Evaluator were most effective on reasoning and coding tasks, improving performance on benchmarks that required more verification steps, such as Arena-Hard-Auto, MixEval, MixEval-Hard, MATH, and CodeContests (Table 2). For the reasoning tasks, we found the unit test generator and evaluator to be most effective when combined with other components. When the 70B+ ensemble of Generators was only combined with unit tests, it was less effective for reasoning tasks like Arena-Hard-Auto and MixEval, lagging behind the ensemble and fuser configuration by 3.1 percentage points. This inspired us to look into other inference-time techniques combinations for unit test generation, such as increased sampling and fusion. When we increased generation sampling and added unit test generation/evaluation for CodeContests, we see a 56% boost in Pass@1 performance (Figure 7), increasing from 17.9 to 29.3 Pass@1.

**Component Interactions:** When combined with the Fuser module, the Unit Test Generator and Evaluator improved performance by 2.1 percentage points across the benchmarks explored (Table 2). The combined ensemble, Unit Test Generator/Evaluator, and Fuser ARCHON configuration was most effective on the reasoning benchmarks, leading to a 2.5 percentage point boost, on average. For coding, the unit test generator and evaluator was most effective when combined with the best performing Generator (using large sample counts) and a final Fuser (subsection 4.2).

## 3.4 Inference-Time Architecture Search (ITAS)

In this section, we explore different approaches for finding the best inference-time architecture (for a given task) through *inference-time architecture search* (ITAS). Due to compute resources, we pre-filtered certain ways of combining LLM components to reduce the search space while still building effective inference-time architectures. While it is possible to expand the search space of potential ARCHON architectures (e.g. different temperatures for generative LLM components, alternative prompts for each LLM component, multiple layers of Generator modules, additional LLM components for ARCHON, etc.), we use our analysis from Section 3.2 to selectively limit our search space to configurations that fit our rules for ARCHON: starts with a layer of Generator modules, followed by layers performing fusing, ranking, critiquing, verifying, and unit testing.

**Search Hyperparameters:** With the studied LLM modules and their relationships within the ARCHON architecture, we selected five main axes for the hyperparameters in our search:

1. **Top- $K$  Generators for Ensemble:** The top- $K$  models to be used for the initial Generator ensemble, ranges from 1 to 10. The top- $K$  models are the best- $K$  LLMs for the given task, based on their individual performances (Table 14).
2. **Top- $K$  Generator Samples:** The number of samples gathered from each Generator in the ensemble (it is the same for all the models), ranges from 1 to 5. For MATH and Code-Contests, we also explore high sample settings over the following set of samples: [1, 10, 100, 500, 1000].
3. **Number of Fusion Layers:** The number of layers of Fusers, ranges from 1 to 4. The last fusion layer will always have a single Fuser.
4. **Top- $K$  Fusers for Fusion Layers:** The top- $K$  models used for each fusion layer, ranges from 2 to 10 and increases by 2 each time.

By combining all the hyperparameters, we create a search space of 6,250 configurations by multiplying each of the configuration option counts together ( $10 * 5 * 5^{(4-1)} = 6250$ ). However, we remove configurations that are not viable: configurations in which the number of initial generations exceeds the context window of the fusers (i.e. 24 candidate generations) and configurations with only one fuser layer but multiple fusers declared. This reduces our search space to 3192 configurations. For these configurations, we add critic and ranker layers before

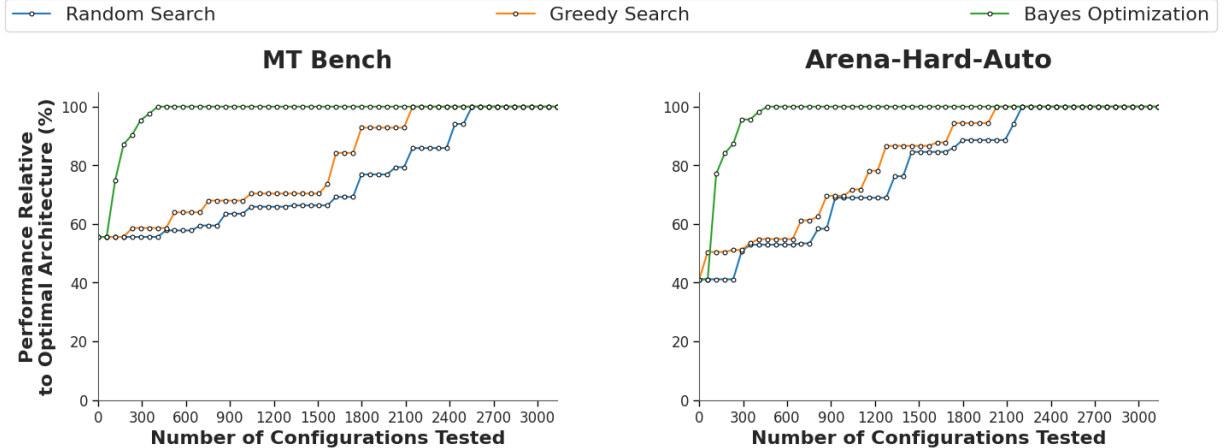


Figure 6: **Impact of Different Optimization Algorithms on Inference-Time Architecture Search (ITAS)**: On the benchmarks MT Bench and Arena-Hard-Auto, we compare four approaches for finding the optimal inference-time architecture: random search, greedy search, and Bayes optimization. We find Bayes optimization to be the most computationally efficient, finding the optimal architecture in 80.4% less iterations compared to greedy search and 87.1% less iterations compared to random search.

each fuser layer since they’ve been shown to have added benefits across the benchmarks explored (Figure 4; Figure 5). The ranker selects the top-5 candidate generations to send to the next layer. Additionally, for our coding tasks (i.e. CodeContests), we use unit test generators and evaluators after our initial generation layer, with a default setting of 10 unit tests generated. On our instruction-following and reasoning tasks (i.e. MT-Bench, AlpacaEval 2.0, Arena-Hard-Auto, MixEval, MixEval-Hard, and MATH), we also ablate adding a verifier before the final fuser layer (Table 2). Ultimately, we could increase the search space substantially more along various other axes, such as additional combinations of verifier, unit test generation, and fuser layers, but given our compute resource limitations, we did not scale further.

**Search Techniques:** Within the hyperparameter space, we explored four search algorithms for automating the development of inference-time architectures:

1. **Random Search:** Randomly selects a combination of hyperparameters for our ARCHON architecture.
2. **Greedy Search:** Starting with a base ARCHON configuration, marginally changes each hyperparameter and test if it improves performance or not. If it does, incorporate the change. If not, move on to the next hyperparameter.
3. **Bayesian Optimization:** Efficiently selects the most promising hyperparameter configurations for ARCHON by building a probabilistic surrogate model and leveraging an acquisition function for hyperparameter selection [36, 48] (Section A.6).

To get our model ranking for the benchmark, we calculate the model ranking by testing each model individually on the entire benchmark ( $K = 1$ ) in the first stage of the search. To get our fusion model ranking for the benchmark, we use the same approach, testing each model’s fusion performance with an ensemble of 10 randomly selected models from the available set. From our experiments, we found that the best generator and fusion models could vary widely dataset to dataset, making it beneficial to perform these rankings for new datasets (Table 14). For search, we use a 20% sample of each dataset for guiding architecture search to improve the evaluation speed while getting meaningful development signal. With the top 10 architectures evaluated in our search, we then evaluate on the complete benchmark to report results.

**Comparing Search Algorithms:** In Figure 6, we compare the effectiveness of each search algorithm on our explored benchmarks. While random search guarantees the optimal ARCHON configuration, we found Bayesian optimization to be most effective in terms of tradeoff between finding the optimal configurations and minimizing the number of configurations tested. For 95.2% percent of the search iterations tested in Figure 6, we found that

Bayesian optimization had the optimal configuration amongst the four explored search algorithms. We use 80 initial samples for our Bayes optimization architecture search (Section A.6). Bayesian optimization also found the best architecture configuration in 80.4% less evaluations than greedy search and 87.1% less evaluations than random search.

**Bayesian Optimization Analysis:** In Table 23, we explore how the number of initial testing points, the number of exploration iterations, and the ARCHON inference call budget impacts the effectiveness of Bayesian optimization. Additional initial testing points continue improving search efficacy up until 80-90 samples, where testing would be better delegated towards configuration search. For lower inference call budgets with ARCHON (e.g. <20 inference calls), Bayesian optimization proved less effective, performing more similarly to greedy search or random search given the limited search space (Table 20). Therefore, Bayesian optimization is more effective for more open-ended ITAS with larger inference call budgets (e.g. >20 inference calls) whereas traditional component engineering might be better for more limited inference call budgets.

## 4 Experiments

In our experimental evaluations, we focus on four questions: **(1)** how do ARCHON architectures compare to existing SOTA closed-source LLMs and other inference-time architectures? **(2)** how does ARCHON performance compare across tasks? **(3)** how does ARCHON performance compare when optimized for a set of tasks vs. an individual task? **(4)** what are the current limitations of ARCHON and plans for future work?

### 4.1 Benchmarks and Models

In this section, we discuss the benchmarks and models used in our LLM component analysis and development of ARCHON.

**Benchmarks:** We evaluate our models with several benchmarks for instruction-following and reasoning: MT-Bench [63], AlpacaEval 2.0 [30], Arena Hard Auto [29], MixEval [37], MixEval-Hard, MATH [20], and CodeContests [31]. We provide an overview of each dataset in Table 24, where we compare their query counts, scoring type, evaluation metrics, baseline models, and judge models. For MixEval and MixEval Hard, we use the 2024-06-01 dataset release. For MT Bench and Arena-Hard-Auto, we also include a configuration with Claude-3.5-Sonnet as the baseline model (in addition to the original setting with GPT-4-0314) to have a stronger model for comparing against ARCHON architecture performances (Table 3) and mitigate the GPT-4-Turbo judge bias towards GPT responses. Additionally, we chose not to use the single-scoring configuration for MT Bench due to the inconsistencies in LLM judge scoring on 1-10 scales [49, 52]. For MATH, we evaluate a random sample of 200 problems from the dataset’s test set. For CodeContests, we evaluate on the 140 test set questions that do not include image tags in the problem description.

**Models:** For ARCHON, we test across three model categories: 8B or less parameter models, 70B or more parameter models, and closed-source model APIs. For our 8B models, we selected the top-10 performing chat models on the Chatbot Arena Leaderboard [9] as of July 2024. For our 70B+ models, we selected the existing state-of-the-art open-source chat models as of July 2024. For our closed-source model APIs, we include GPT-4o, GPT-4-Turbo, Claude Opus 3.0, Claude Haiku 3.0, and Claude Sonnet 3.5. We list and compare all of the models tested in the ARCHON framework in Table 13 and Table 14.

### 4.2 ARCHON vs. Closed-Source LLMs and Other Inference-Time Architectures

We start by comparing ARCHON architectures to existing SOTA closed-source LLMs and inference-time architectures across a set of instruction-following, reasoning, and coding tasks with either pairwise ranking or accuracy metrics, as described in Section 4.1. Based on our results in Table 3, we find that ARCHON architectures consistently match or surpass existing SOTA approaches across all the benchmarks explored. On the evaluation suite, our ARCHON architectures with open-source models experience a 10.2 point increase, on average, above SOTA open-source approaches; for its worst performance, our open-source ARCHON architectures are only 1.6% above SOTA open-source approaches on AlpacaEval 2.0. For our ARCHON architectures with closed-source models, we set SOTA performance across MT Bench, Arena-Hard-Auto, MixEval, and MixEval-Hard, leading to a 18.3 point increase, on average, compared to closed-source approaches. Lastly, for approaches that use all models available, both open and closed-source, ARCHON achieves an increase of 14.1 points, on average, over existing SOTA approaches.

		Datasets								
		MT Bench	Alpaca Eval 2.0	Arena Hard Auto	Arena Hard Auto	MixEval Hard	MixEval	MATH*		
Judge Model		GPT-4 0314	GPT-4 Turbo	GPT-4 Turbo	GPT-4 Turbo	N/A	N/A	N/A		
Reference Model		Claude 3.5 Sonnet	GPT-4 Turbo	Claude 3.5 Sonnet	GPT-4 Turbo	N/A	N/A	N/A		
Model / LLM System	Infer. Calls	W.R.	L.C. W.R.	Raw W.R.	W.R.	W.R.	Acc.	Acc.	Pass @1	
GPT-4o - 2024-05-13	1	44.7%	57.5%	51.3%	48.1%	80.3%	63.6%	88.0%	72.0%	
Claude 3.5 Sonnet	1	N/A	52.4%	40.6%	N/A	80.9%	68.9%	89.7%	72.0%	
Llama 3.1 405B Instruct	1	44.7%	40.3%	37.7%	28.4%	64.1%	66.2%	88.9%	74.0%	
MoA	19	51.6%	65.1%	59.8%	52.2%	84.2%	62.5%	87.3%	72.5%	
MoA Lite	7	45.6%	59.3%	57.0%	40.6%	87.8%	61.1%	87.1%	70.5%	
Open Source	General-purpose ARCHON Architecture	35	67.5%	63.0%	68.3%	66.2%	85.1%	65.5%	86.9%	75.5%
	Task-specific ARCHON Architectures	44	71.6%	66.7%	70.7%	69.0%	89.5%	67.5%	89.6%	<b>80.5%</b>
Closed Source	General-purpose ARCHON Architecture	32	73.1%	63.5%	69.1%	70.5%	85.8%	67.7%	88.2%	77.0%
	Task-specific ARCHON Architectures	40	77.5%	68.4%	72.1%	74.4%	90.2%	<b>72.9%</b>	90.4%	79.0%
All Source	General-purpose ARCHON Architecture	35	76.8%	65.8%	70.2%	72.5%	89.3%	70.1%	88.1%	78.0%
	Task-specific ARCHON Architectures	39	<b>80.4%</b>	<b>68.8%</b>	<b>73.3%</b>	<b>76.1%</b>	<b>92.1%</b>	<b>72.9%</b>	<b>90.6%</b>	<b>80.5%</b>

Table 3: **ARCHON’s Strong Performance with ITAS Optimization on Open-Source, Closed-Source, and All-Source Models:** We find that ARCHON’s inference-time architectures consistently outperform single-call state-of-the-art LLMs, both open-source and closed-source baselines. We explore two configurations: ITAS for building custom ARCHON configurations for each individual benchmark and ITAS for building a single general-purpose ARCHON configuration for all the benchmarks (Section 4.4). We find that a general ARCHON configuration lags behind the custom ones by only 3.2 percentage points, on average, across our all-source settings, which suggests the efficacy of general-purpose inference-time architectures created with our framework. For Arena-Hard-Auto, we also include a configuration with Claude 3.5 Sonnet as a stronger reference model for comparison against ARCHON inference-time architectures and to mitigate bias from GPT judges towards GPT generations. For MT Bench, we use a GPT-4-0314 judge model instead of newer LLM judges to be consistent with previous results on this benchmark. For our task-specific ARCHON architectures, we also provide the average inference calls across the given benchmarks. For our full-list of models explored, please see Table 13. For MATH, we use a randomly sampled subset of size 200 for evaluation (Section 4.1; Table 24).

### 4.3 ARCHON by Task

We analyze ARCHON performance by task style: instruction-following tasks that use pairwise ranking for scoring, reasoning tasks that use accuracy-based metrics for scoring, and coding tasks that use Pass@1. On instruction-following tasks like MT Bench, AlpacaEval 2.0, and Arena-Hard-Auto, open-source ARCHON architectures outperform current open-source baselines by 12.8 percentage points, on average, while closed-source ARCHON outperforms current closed-source baselines by 22.2 percentage points (Table 3). On reasoning tasks like MixEval, MixEval-Hard, and MATH, open-source ARCHON architectures outperform existing open-source baselines by 5.1 percentage points while closed-source ARCHON architectures outperform current closed-baselines by 4.7 percentage points (Table 3). On coding tasks (i.e. CodeContests), open-source ARCHON architectures match existing open-source baselines (0.2 percentage points difference) and all-source ARCHON architectures outperform all-source baselines by 2.5 percentage points (Figure 7). All-source architectures of ARCHON outperforms existing all-source baselines by 21.8 and 3.8 percentage points, on average, for instruction-following tasks and for reasoning tasks, respectively (Table 3).

**Instruction-Following and Reasoning:** With ARCHON, multiple models used for Generators and the depth of fusion layers lead to performance boosts on instruction-following tasks, increasing the richness of responses and allowing multiple iterations for step-by-step instruction-following (Table 15). For reasoning,

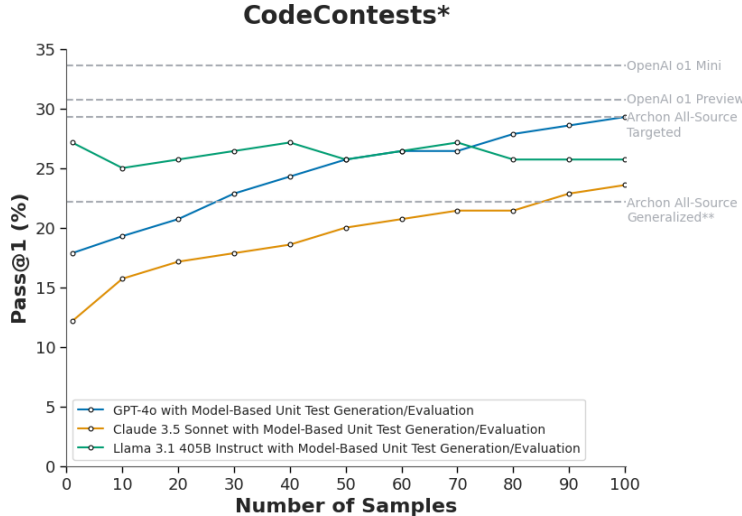


Figure 7: **Performance Gains from Combining Multi-Sampling with LLM-based Unit-test Generation/Evaluation:** In this architecture, each sample is evaluated against (the same) 5 model-generated unit tests and the first sample that passes all the unit tests is considered as the model’s final response. We use model-based evaluation for the unit tests, passing the prompt, query, and unit tests to the LLM directly for evaluation. For unit test generation and evaluation, we use the same LLM as we do for sampling. We observe strong performance improvements in Pass@1 performance as we scale the number of samples for GPT-4o and Claude 3.5 Sonnet. Our ARCHON all-source targeted architecture is included in Figure 12, which utilizes Llama 3.1 405B Instruct for generation (1000 samples) and uses GPT-4o for model-based unit test generation/evaluation. \*We use the subset of 140 CodeContests problems that do not require image handling. \*\*Our ARCHON all-source generalized architecture baseline (also found in Table 3) was optimized for instruction-following and reasoning tasks, not coding tasks (Section 4.4).

while the performance boost from ARCHON is smaller when we consider the *aggregate* scores for MixEval and MixEval-Hard, we do see meaningful increases in performance when we create inference-time architectures for each individual task under MixEval and MixEval-Hard (Table 25; Table 26). When we create individual ARCHON architectures for each subtask, we see 3.7 and 8.9 percentage point increases in accuracy, on average, for MixEval and MixEval-Hard, respectively. This finding suggests that reasoning tasks (e.g. mathematics, sciences, logic) require more individualized inference-time architectures for their particular queries.

**Coding:** We have observed that ensembling, fusion, and ranking techniques have limited impact on CodeContests (Table 2). For example, when we apply the general all-source architecture from Table 24 to CodeContests problems, we achieve small gains from ARCHON (see Figure 7). One contributing factor is that, unlike the distribution of instruction-following/reasoning tasks, coding tasks tend to have one or two LLMs that perform substantially better than the rest of models (Table 14). However, when we add unit test generation/evaluation, and increase the number of samples, ARCHON’s performance on CodeContests improves significantly (Figure 7), allowing us to boost GPT-4o Pass@1 performance by 56% for Pass@1 (from 25 to 41 out of 140 questions). Future work should focus on developing better ARCHON modules for handling the multi-step reasoning that is implemented in various code agents [42, 62]. For model-based unit test generation/evaluation, we generate 5 unit tests and use the LM to evaluate each candidate response against the generated unit tests, allowing us to rank the different candidate responses. Lastly, we explored several additional benchmarks for math and code (GSM8K [11], MMLU Math [20], HumanEval [8], and MBPP [3]) but existing approaches already reach fairly high performances (>90% Pass@1)(Table 27).

#### 4.4 Task-Specific and General-Purpose ARCHON Architectures

**Task-Specific vs. General-Purpose:** We also compare custom ARCHON architectures, specifically configured to a single evaluation dataset ("Task-specific ARCHON Architectures"), and a generalized ARCHON architecture configured to handle all the evaluation datasets ("General-purpose ARCHON Architectures") (Table 3). We

utilize ITAS to find the generalized ARCHON architectures in Table 3 (subsection 3.4), maximizing performance over all of the benchmarks explored except CodeContests. We exclude CodeContests from the generalized ARCHON architecture search since we found that ARCHON architectures for coding tasks are most effective with a different set of inference-time techniques compared to instruction-following and reasoning tasks (i.e. increased model sampling combined with model-based unit test generation/evaluation) (Section 3.2; Table 2). For open-source models, we find that our generalized ARCHON architecture only lags behind the specialized ARCHON architectures by 3.4 percentage points, on average, across all the benchmarks, demonstrating the robustness of the ARCHON architecture found by the ITAS algorithms (Table 3). We see similar gaps between the generalized and specialized ARCHON architectures for closed-source models (3.8 percentage points) as well as the all-source models (3.2 percentage points) (Table 3).

**Insights from Architecture Construction:** We include examples of our learned effective generalized ARCHON architectures constructed by ITAS in Section A.3, where we breakdown the exact LM components used for constructing each architecture. For instruction-following and reasoning tasks, we found a generalizable ARCHON architecture to be most effective with multiple layers of critic-ranker-fuser, chained sequentially to improve candidate generation (Figure 9). However, the specific models chosen for these LLM components could change task by task, with some tasks benefiting from using a single SOTA closed-source LLM for all the components (e.g. Arena-Hard-Auto and MixEval) (Figure 11) whereas others benefited from a diversity of LLMs in their ensemble (e.g. MT Bench and MixEval-Hard) (Figure 9; Figure 10). Regardless of models used, we found that scaling inference layers including critics, rankers, and fusers improved performance on instruction-following and reasoning tasks (Figure 5; Section A.3). For instruction-following and reasoning tasks, the verifier module is more effective than the unit test generation/evaluation module for task-specific ARCHON architectures (Section 3.2; Table 2). For coding tasks, we found a high-sample setting to be the most effective, with added layers of unit test generation and evaluation to boost the quality of the final candidate generation (Figure 12; Figure 7). Overall, our findings demonstrate the benefits of scaling inference-time compute through layering of techniques, showing the importance of effectively and efficiently constructing inference-time architectures.

## 4.5 ARCHON by Inference Budget

Finally, we compare different ARCHON architectures across inference budgets for both open-source models and closed-source models (Table 16). For instruction-following and reasoning tasks, we find consistent improvements in downstream performance as we scale from 1 to 50 inference calls, increasing by 14.3 percentage points, on average, across our selected evaluation benchmarks (Table 16). However, after roughly 50 inference calls, performance gains plateau. The results suggest that the early addition of LLM components in ARCHON (e.g. critic, ranker, layers of fusers) led to the most substantial gains in performance and after that, additional LLM components did not ultimately enhance the final generated response. We see the trend most apparent for the MixEval and MixEval-Hard benchmarks, where additional layers of Critic, Rankers, and Fusers do not benefit performance beyond a 30 inference call budget (Table 16). Notably, for math and coding tasks, we see continued improvements with additional inference calls by using generated unit tests to evaluate candidate responses, leading to a 56% increase in Pass@1 (Figure 7).

## 4.6 Limitations and Future Work of ARCHON

**Parameter Count:** The ARCHON framework is most effective with LLM with 70B parameters or more. When we utilize the ARCHON architecture with only 7B open-source models, we get a notable decrease in performance (Table 17). The best 7B ARCHON configurations lag behind single SOTA (and much larger) models by 15.7% on across all the benchmarks, on average; 7B models work well for ranking but are less effective for critic and fusion. While this is expected, as small models generally exhibit lower performance, their weaker instruction following ability is a compounding factor.

**Latency and Costs:** ARCHON is not ideal for tasks that prefer the latency of a single LLM call, such as certain consumer chatbots. Since ARCHON architectures often make multiple LLM calls successively for different operations (e.g. ensembling, critiquing, ranking, fusion, etc.), it can often take 5+ more time than a single LLM call (Section A.3). Furthermore, it can require calling multiple API endpoints for a single query, leading to increased expenditures compared to single-call LLMs (Table 18; Table 19). Note that these increases in compute costs and latency translate to higher quality responses, and can be justified in many application domains, such as science, math, and programming, or for addressing complex customer service issues.

**ARCHON Components:** While ARCHON is a modular framework, allowing the easy incorporation of new



LLMs, new inference-time techniques, and even tool use, we only explore seven LLM inference time techniques in our work (Section 3.1). The addition of new techniques is a promising avenue for future research. Furthermore, while different queries can be best suited by different ARCHON architectures (Table 25; Table 26), the ITAS algorithm selects the best single architecture for the evaluation set queries combined. Future architecture search could focus on dynamic selection of components on a query-by-query basis.

## 5 Conclusion

This paper presents ARCHON, a modular framework for optimizing inference-time architectures by integrating multiple inference-time techniques, such as ensembling, ranking, fusion, critique, verification, and unit test generation. Extensive experiments demonstrate that ARCHON consistently matches or exceeds the performance of leading closed-source LLMs, such as GPT-4 and Claude-3.5-Sonnet, while only using open-source models across diverse benchmarks, including MT-Bench, AlpacaEval 2.0, Arena-Hard-Auto, MixEval, MixEval-Hard, MATH, and CodeContests. We attribute ARCHON’s boost in benchmark performance to two main factors. The first factor is the ability to leverage inference-time compute towards utilizing multiple LLMs and additional operations (e.g. fusing, ranking, critiquing, verification, unit testing), leading to amplified benefits that scale with additional inference calls (Sections 3.1 and 3.3). The second factor is the automatic approach for iteratively testing different ARCHON architectures with ITAS, guaranteeing the optimal configuration given enough exploration steps (Section 3.4). These results underscore the potential of ARCHON and ITAS algorithms in advancing the development of high-performing and generally capable inference-time architectures. The framework and datasets are publicly available on Github: <https://github.com/ScalingIntelligence/Archon>.

## 6 Acknowledgements

We thank Simran Arora, Bradley Brown, Ryan Ehrlich, Jordan Juravsky, Jerry Liu, Benjamin Spector, Alyssa Unell, Benjamin Viggiano, and Michael Zhang for their constructive feedback during the composition of the paper. We would also like to thank our collaborators at the Stanford Artificial Intelligence Laboratory (SAIL) and TogetherAI.

We gratefully acknowledge the support of NIH under No. U54EB020405 (Mobilize), NSF under Nos. CCF2247015 (Hardware-Aware), CCF1763315 (Beyond Sparsity), CCF1563078 (Volume to Velocity), and 1937301 (RTML); US DEVCOM ARL under Nos. W911NF-23-2-0184 (Long-context) and W911NF-21-2-0251 (Interactive Human-AI Teaming); ONR under Nos. N000142312633 (Deep Signal Processing); Stanford HAI under No. 247183; NXP, Xilinx, LETI-CEA, Intel, IBM, Microsoft, NEC, Toshiba, TSMC, ARM, Hitachi, BASF, Accenture, Ericsson, Qualcomm, Analog Devices, Google Cloud, Salesforce, Total, the HAI-GCP Cloud Credits for Research program, the Stanford Data Science Initiative (SDSI), and members of the Stanford DAWN project: Meta, Google, and VMWare. The U.S. Government is authorized to reproduce and distribute reprints for Governmental purposes notwithstanding any copyright notation thereon. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views, policies, or endorsements, either expressed or implied, of NIH, ONR, or the U.S. Government.

# A Appendix

## A.1 ARCHON LLM Components

Module	Initial Layer Placement	Placement after Initial Layer	>1 Module in Layer	Increase Candidate Responses	Decrease Candidate Responses
Generator	Yes	No	Yes	Yes	No
Fuser	No	Yes	Yes	Yes	Yes
Ranker	No	Yes	No	No	Yes
Critic	No	Yes	No	No	No
Verifier	No	Yes	No	No	Yes
Unit Test Generator	No	Yes	No	No	No
Unit Test Evaluator	No	Yes	No	No	No

Table 4: **Rules of ARCHON Construction:** Allowed combinations of each LLM component from Section 3.1.

<instruction here>.

Table 5: **Generator Prompt**

You have been provided with a set of responses with their individual critiques of strengths/weaknesses from various open-source models to the latest user query. Your task is to synthesize these responses into a single, high-quality response. It is crucial to critically evaluate the information provided in these responses and their provided critiques of strengths/weaknesses, recognizing that some of it may be biased or incorrect. Your response should not simply replicate the given answers but should offer a refined, accurate, and comprehensive reply to the instruction. Ensure your response is well-structured, coherent, and adheres to the highest standards of accuracy and reliability.

Responses from models:

```
1. <response #1>
Critique: <critique #1>
2. <response #2>
Critique: <critique #2>
...
N. <response #N>
Critique: <critique #N>
<instruction here>
```

(a) With Critiques

You have been provided with a set of responses from various open-source models to the latest user query. Your task is to synthesize these responses into a single, high-quality response. It is crucial to critically evaluate the information provided in these responses, recognizing that some of it may be biased or incorrect. Your response should not simply replicate the given answers but should offer a refined, accurate, and comprehensive reply to the instruction. Ensure your response is well-structured, coherent, and adheres to the highest standards of accuracy and reliability.

```
1. <response #1>
2. <response #2>
...
N. <response #N>
<instruction here>
```

(b) Without Critiques

Table 6: **Fuser Prompt: Without and With Critiques**

I will provide you with N responses, each indicated by a numerical identifier []. Rank the responses based on their relevance to the instruction: <instruction here>.

[1] <response #1>

[2] <response #2>

...

[N] <response #N>

Instruction: <instruction here>.

Rank the N responses above based on their relevance to the instruction. All the responses should be included and listed using identifiers, in descending order of relevance to the instruction. The output format should be [] > [], e.g., [4] > [2]. Only respond with the ranking results, do not say any word or explain.

Table 7: **Decoder-Based Ranking Prompt**

You are a helpful assistant. I will provide you with N responses, each indicated by a numerical identifier (e.g., [1], [2], etc.). Rank the responses based on their relevance to the instruction: <instruction here>.

[1] <response #1>  
 [2] <response #2>  
 ...  
 [N] <response #N>

Instruction: <instruction here>.

Evaluate the N responses above based on their relevance to the instruction. All the responses should be included and listed using identifiers. For each response, start the critique with the numerical identifier (e.g., [1]) followed by the strengths and weaknesses. You must include both strengths and weaknesses, even if there are more of one than the other. At the end of each response's analysis, include two new lines to separate the critiques. Do not include any preface or text after the critiques. Do not include any references to previous critiques within a critique. Start with the analysis for the first response and end with the analysis for the last response. All of the N responses should be included and evaluated using identifiers. Structure each response's analysis as follows:

**Strengths:**

- <strength #1>
- <strength #2>
- <strength #n>

**Weaknesses:**

- <weakness #1>
- <weakness #2>
- <weakness #n>

Table 8: **Critic Prompt**

I will provide you with a response indicated by the identifier 'Response'. Provide reasoning for why the response accurately and completely addresses the instruction: <instruction here>.

Response: <response>

Instruction: <instruction here>.

Provide the reasoning for the response above based on its relevance, completeness, and accuracy when compared to the instruction. Do not include any preface or text after the reasoning.

Table 9: **Verifier Prompt**

**Instruction Prompt:** Given the following query, generate a set of N unit tests that would evaluate the correctness of responses to this query.

- The unit tests should cover various aspects of the query and ensure comprehensive evaluation.
- Each unit test should be clearly stated and should include the expected outcome.
- The unit tests should be in the form of assertions that can be used to validate the correctness of responses to the query.
- The unit test should be formatted like 'The answer mentions...', 'The answer states...', 'The answer uses...', etc. followed by the expected outcome.
- Solely provide the unit tests for the question below. Do not provide any text before or after the list. Only output the unit tests as a list of strings (e.g., ['unit test #1', 'unit test #2', 'unit test #3']).

Query: <instruction here>

(a) With Unit Test Cap

**Instruction Prompt:** Given the following query, generate a set of unit tests that would evaluate the correctness of responses to this query.

- The unit tests should cover various aspects of the query and ensure comprehensive evaluation.
- Each unit test should be clearly stated and should include the expected outcome.
- The unit tests should be in the form of assertions that can be used to validate the correctness of responses to the query.
- The unit test should be formatted like 'The answer mentions...', 'The answer states...', 'The answer uses...', etc. followed by the expected outcome.
- Solely provide the unit tests for the question below. Do not provide any text before or after the list. Only output the unit tests as a list of strings (e.g., ['unit test #1', 'unit test #2', 'unit test #3']).

Query: <instruction here>

(b) Without Unit Test Cap

Table 10: **Unit Test Generator Prompt: With and Without Unit Test Cap**

**Instruction Prompt:** Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.

1. Unit Test #1: The blog post mentions at least two cultural experiences specific to Hawaii.
2. Unit Test #2: The blog post highlights at least three must-see attractions in Hawaii.
3. Unit Test #3: The tone of the blog post is engaging and uses descriptive language that would appeal to readers interested in travel.
4. Unit Test #4: The blog post includes factual information about Hawaii's culture, such as local customs, festivals, or historical facts.
5. Unit Test #5: The blog post contains a clear narrative structure, including an introduction, main body, and a conclusion.

(a) Instruction-Following Query

**Instruction Prompt:** Alice and Bob have two dice. They roll the dice together, note the sum of the two values shown, and repeat. For Alice to win, two consecutive turns (meaning, two consecutive sums) need to result in 7. For Bob to win, he needs to see an eight followed by a seven. Who do we expect to win this game?

1. Unit Test #1: The response correctly identifies the winning condition for Alice (two consecutive sums of 7).
2. Unit Test #2: The response correctly identifies the winning condition for Bob (a sum of 8 followed by a sum of 7).
3. Unit Test #3: The response explains the probability of achieving two consecutive 7s when rolling two dice.
4. Unit Test #4: The response explains the probability of achieving an 8 followed by a 7 when rolling two dice.
5. Unit Test #5: The response provides a conclusion on who is more likely to win based on the probability analysis.

(b) Reasoning Query

Table 11: **Unit Test Examples**

Given the following query, candidate response, and unit tests, evaluate whether or not the response passes each unit test.

- In your evaluation, you should consider how the response aligns with the unit tests, retrieved documents, and query.
- Provide reasoning before you return your evaluation.
- At the end of your evaluation, you must finish with a list of verdicts corresponding to each unit test.
- You must include a verdict with one of these formatted options: '[Passed]' or '[Failed]'.
- Here is an example of the output format:  
Unit Test #1: [Passed]  
Unit Test #2: [Failed]  
Unit Test #3: [Passed]
- Each verdict should be on a new line and correspond to the unit test in the same position.

Here is the query, response, and unit tests for your evaluation:

Query: <instruction here>.

Candidate Response: <response>

Unit Tests:  
Unit Test #1: <Unit Test #1>  
Unit Test #2: <Unit Test #2>  
...  
Unit Test #N: <Unit Test #N>

Table 12: Unit Test Evaluator Prompt

## A.2 ARCHON LLM Analysis

Model	Source Code	Parameter Count	Max Sequence Length
GPT-4o [40]	Closed-Source	—	128K
GPT-4-Turbo [40]	Closed-Source	—	128K
Claude-3-Opus [2]	Closed-Source	—	200K
Claude-3.5-Sonnet [2]	Closed-Source	—	200K
Claude-3-Haiku [2]	Closed-Source	—	200K
Llama-3.1-70B-Instruct [15]	Open-Source	70B	8k
Llama-3.1-405B-Instruct [15]	Open-Source	70B	8k
DeepSeek LLM 67B Chat [18]	Open-Source	67B	32k
Qwen2 72B Instruct [43]	Open-Source	72B	32k
Qwen1.5 110B Chat [4]	Open-Source	110B	32k
Qwen1.5 72B Chat [4]	Open-Source	72B	32k
Mixtral 8x22B v0.1 [23]	Open-Source	176B	32k
WizardLM 8x22B [59]	Open-Source	176B	32k
dbrx-instruct [12]	Open-Source	132B	32k
princeton-nlp/Llama-3-Instruct-8B-SimPO [35]	Open-Source	8B	8k
princeton-nlp/Llama-3-Instruct-8B-DPO [35]	Open-Source	8B	8k
princeton-nlp/Llama-3-Instruct-8B-RDPO [35]	Open-Source	8B	8k
princeton-nlp/Llama-3-Instruct-8B-IPO [35]	Open-Source	8B	8k
Llama-3.1-8B-Instruct [15]	Open-Source	8B	8k
Qwen2-7B-Instruct [43]	Open-Source	7B	32k
Qwen/Qwen1.5-7B-Chat [4]	Open-Source	7B	32k
mistralai/Mistral-7B-Instruct-v0.2 [22]	Open-Source	7B	32k
cognitivecomputations/dolphin-2.2.1-mistral-7b [19]	Open-Source	7B	32k
microsoft/Phi-3-mini-4k-instruct [1]	Open-Source	4B	4k
HuggingFaceH4/zephyr-7b-beta [55]	Open-Source	7B	32k
microsoft/Phi-3-small-8k-instruct [1]	Open-Source	7B	8k
snorkelai/Snorkel-Mistral-PairRM-DPO [54]	Open-Source	7B	32k
mistralai/Mistral-7B-Instruct-v0.3 [22]	Open-Source	7B	32k

Table 13: Models Tested with ARCHON.

Inference-Time Architecture	Jaccard Similarity (%)						
	MT Bench	AlpacaEval 2.0	Arena-Hard Auto	MixEval	MixEval Hard	MATH	Code Contests
Best Open-Source 70B+ Model, Sampled 8 Times + Fuser	45.3%	52.1%	48.4%	55.2%	58.9%	65.2%	63.7%
Ensemble (8 Top Models), Sampled Once Each + Fuser	31.6%	34.1%	28.9%	38.6%	40.9%	57.1%	53.4%

Table 15: Jaccard Similarities between Candidates Responses and Fused Response by Benchmark: For the fuser, we use the best-performing 70B+ model for benchmark.



Models	MT Bench		Alpaca Eval 2.0		Arena Hard Auto		MixEval		MixEval Hard		MATH		CodeContests	
	Gen	Fusion	Gen	Fusion	Gen	Fusion	Gen	Fusion	Gen	Fusion	Gen	Fusion	Gen	Fusion
GPT-4o	44.7%	61.9%	<b>57.5%</b>	64.5%	<b>48.1%</b>	69.2%	88.0%	<b>89.4%</b>	63.6%	65.4%	72.0%	75.5%	17.9%	19.4%
GPT-4-Turbo	42.2%	<b>63.1%</b>	55.0%	<b>65.8%</b>	<b>48.1%</b>	61.9%	88.9%	89.0%	64.1%	64.4%	74.5%	76.5%	9.3%	14.2%
Claude 3 Opus	30.9%	57.2%	40.5%	N/A	27.0%	47.9%	88.3%	88.2%	63.6%	64.0%	72.5%	71.0%	10.0%	12.5%
Claude 3.5 Sonnet	N/A	71.9%	52.37%	63.6%	N/A	<b>73.2%</b>	<b>89.7%</b>	89.3%	<b>68.9%</b>	<b>69.5%</b>	72.0%	74.5%	12.1%	15.5%
Qwen 2 72B Instruct	35.0%	59.7%	37.48%	56.0%	14.5%	49.5%	86.5%	87.5%	58.7%	61.1%	<b>76.0%</b>	<b>78.5%</b>	3.6%	5.2%
DeepSeek LLM 67B Instruct	18.4%	20.0%	17.8%	17.1%	N/A	N/A	79.2%	N/A	42.5%	N/A	45.0%	N/A	5.7%	N/A
Qwen 1.5 72B Chat	24.7%	46.3%	36.6%	55.7%	14.4%	36.4%	84.5%	82.1%	50.3%	52.2%	62.5%	65.5%	15.0%	13.9%
Qwen 1.5 110B Chat	34.4%	50.3%	43.6%	55.9%	21.9%	39.7%	85.3%	86.5%	51.8%	55.6%	67.0%	72.5%	3.6%	7.8%
Wizard 8x22B	<b>53.8%</b>	57.2%	44.7%	50.6%	45.6%	51.2%	83%	78.1%	54.3%	50.4%	69.0%	58.5%	7.1%	10.4%
Llama 3.1 8B Instruct	33.1%	45.9%	25.6%	34.9%	11.9%	28.6%	75.0%	57.5%	41.3%	46.5%	59.0%	60.5%	8.6%	7.8%
Llama 3.1 70B Instruct	45.0%	51.9%	35.6%	40.2%	23.8%	37.2%	85.7%	83.5%	61.1%	65.5%	69.0%	71.5%	20.7%	<b>23.4%</b>
Llama 3.1 405B Instruct	44.7%	N/A	40.3%	N/A	28.4%	N/A	88.9%	N/A	66.2%	N/A	74.5%	N/A	<b>27.1%</b>	N/A

Table 14: **ARCHON Generation and Fusion Performances for Single Models:** For Alpaca Eval 2.0, we use the length-controlled win rate (LC WR). For fusion, we gather one candidate from each of the top-10 generator models.

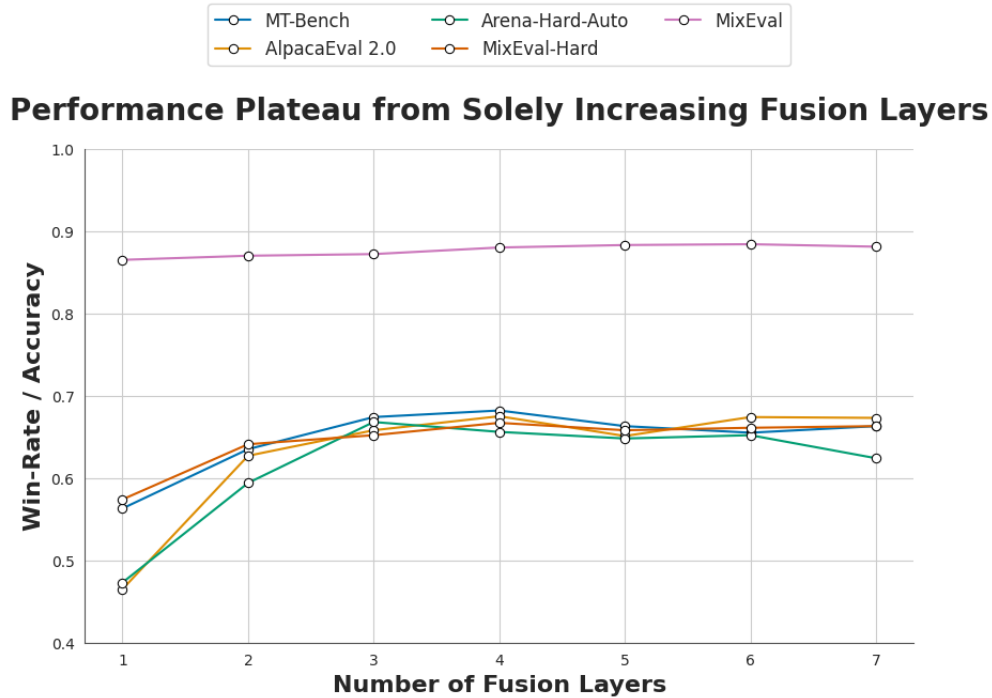


Figure 8: **Fusion Layer Efficacy by Benchmark:** From solely scaling the fusion layers, we see limited benefits across the benchmarks explored but when we add other inference-time techniques, such as Critic and Ranker, we see increased downstream performance as we continue scaling inference-time compute (Figure 5). We use an 8-model ensemble of the top Generator models for each benchmark (Table 14). For our Fuser layers, we use the best Fuser model for the final fuser layer (Table 14). For the intermediate layers, we use the top-8 Fuser models for each benchmark.

### A.3 ARCHON Architectures

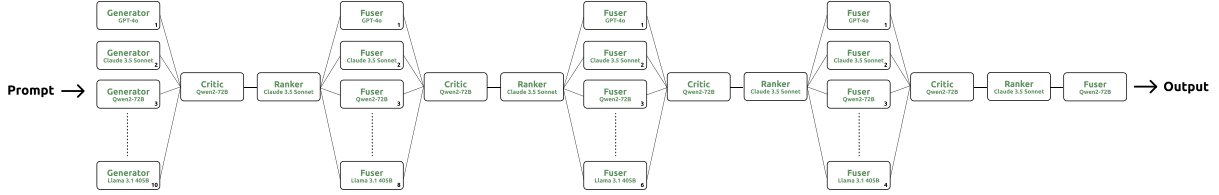


Figure 9: **All-Source Generalizable ARCHON Architecture:** Using ITAS, we found this all-source ARCHON configuration to be effective across the benchmarks explored (except for CodeContests). In the diagram above, we use 10 SOTA all-source LLMs to create multiple successive layers of critic, ranker, and fusers, with each successive fuser layer having less fusers to produce a "funneling" effect as the candidate generations are processed. The layers of critic, ranker, and fuser led to better candidate generations through iterative critique and rewriting. Each of the initial Generator models were sampled once.

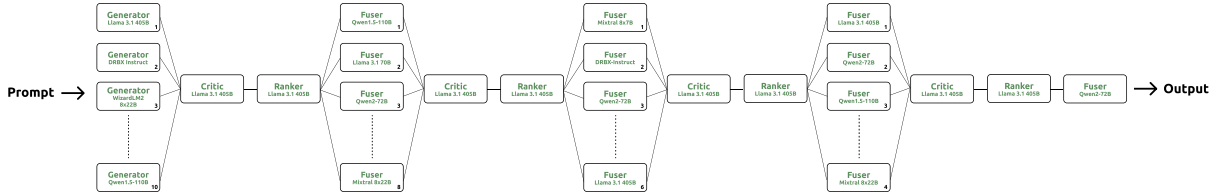


Figure 10: **Open-Source Generalizable ARCHON Architecture:** Using ITAS, we found this open-source ARCHON configuration to be effective across the benchmarks explored (except for CodeContests). In the diagram above, we use 10 SOTA open-source LLMs to create multiple successive layers of critic, ranker, and fusers, with each successive fuser layer having less fusers to produce a "funneling" effect as the candidate generations are processed. The layers of critic, ranker, and fuser led to better candidate generations through iterative critique and rewriting. Each of the initial Generator models were sampled once.

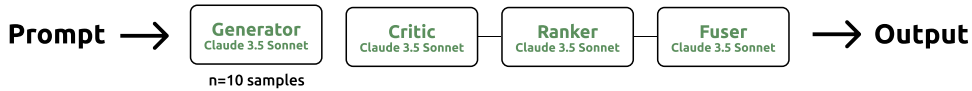


Figure 11: **All-Source ARCHON Architecture for Instruction-Following:** Using ITAS, we found Claude-3.5-Sonnet as a generator, critic, ranker, and fuser to be an effective targeted architecture for instruction-following tasks, such as MT Bench and AlpacaEval 2.0. The ranker picks the top-5 candidate responses to send to the fuser. Each of the initial Generator models were sampled once.

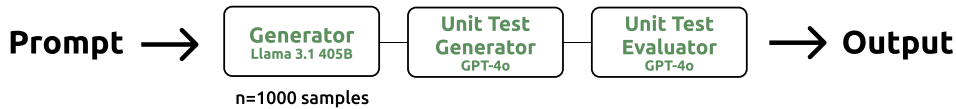


Figure 12: **All-Source ARCHON Architecture for CodeContests:** By using Llama 3.1 405B for generation and GPT-4o for unit testing, we were able to get improved code generation on CodeContests (Figure 7). The unit test generator produces 10 unit tests for evaluation. Each of the initial Generator models were sampled once.

## A.4 ARCHON by Inference Compute Budget, Model Size, and Cost

	Number of Inference Calls	Datasets				
		MT Bench	Alpaca Eval 2.0	Arena Hard Auto	MixEval	MixEval Hard
70B+ Models	1	55.0%	44.7%	45.6%	86.5%	61.1%
	10	52.5%	50.6%	45.6%	86.5%	63.9%
	20	65.3%	60.4%	59.4%	89.0%	65.0%
	30	69.2%	64.5%	<b>69.0%</b>	<b>89.5%</b>	<b>67.5%</b>
	40	69.5%	<b>66.7%</b>	<b>69.0%</b>	<b>89.5%</b>	<b>67.5%</b>
	50	<b>71.6%</b>	<b>66.7%</b>	<b>69.0%</b>	<b>89.5%</b>	<b>67.5%</b>
Closed Models	1	45.0%	57.5%	48.1%	88.9%	68.9%
	10	57.1%	63.2%	68.4%	90.0%	70.1%
	20	59.4%	66.5%	75.5%	<b>90.6%</b>	70.5%
	30	70.2%	<b>68.8%</b>	<b>77.4%</b>	<b>90.6%</b>	<b>72.9%</b>
	40	75.5%	<b>68.8%</b>	<b>77.4%</b>	<b>90.6%</b>	<b>72.9%</b>
	50	<b>80.4%</b>	<b>68.8%</b>	<b>77.4%</b>	<b>90.6%</b>	<b>72.9%</b>

Table 16: **ARCHON with Different Inference Budgets:** For AlpacaEval 2.0, we use the length-controlled win rate (LC WR).

Models / LLM Systems	Datasets				
	MT Bench	Alpaca Eval 2.0	Arena Hard Auto	MixEval	MixEval Hard
SOTA Single-Model	<b>44.7%</b>	<b>57.5%</b>	<b>48.1%</b>	68.9%	<b>89.7%</b>
Best Model, 1-Sample	15.7%	41.0%	18.3%	76.2%	46.1%
Best Model - 10-Sample + Ranking	16.5%	43.2%	18.9%	78.4%	48.5%
10-Model, 1-Sample Ensemble + Ranking	22.4%	48.2%	25.6%	<b>81.5%</b>	52.9%
10-Model, 1-Sample Ensemble + Fusion	14.3%	39.4%	17.5%	73.2%	45.2%
10-Model, 1-Sample Ensemble + Top-5 Ranking + Fusion	15.9%	41.2%	18.0%	75.1%	46.9%
10-Model, 1-Sample Ensemble + Critic + Fusion	10.5%	38.4%	16.5%	71.4%	42.5%

Table 17: **ARCHON with 7B Open-Source Models:** For AlpacaEval 2.0, we use the length-controlled win rate (LC WR). We use open-source 7B models for testing from Table 13.

<b>Models</b>	<b>Cost (\$) per Million Input Tokens</b>	<b>Cost (\$) per Million Output Tokens</b>
Claude 3.5 Sonnet	\$3	\$15
Claude 3.0 Opus	\$15	\$75
GPT-4o	\$5	\$15
GPT-4-Turbo	\$10	\$30
TogetherAI - Llama 3.1 405B Instruct	\$5	\$5
TogetherAI - Llama 3.1 70B Instruct	\$0.88	\$0.88
TogetherAI - Other Models	\$0.90	\$0.90

Table 18: **Model API Costs as of August 2024**

<b>Model / LLM System</b>	<b>Cost (\$) per Query for Benchmark</b>						
	MT Bench	AlpacaEval 2.0	Arena-Hard Auto	MixEval	MixEval Hard	MATH	Code Contests
Claude 3.5 Sonnet	0.0305	0.0171	0.0212	0.0231	0.0226	0.0325	0.384
GPT-4o	0.0481	0.0236	0.0324	0.0357	0.0361	0.514	0.562
Llama 3.1 405B Instruct	0.0281	0.0174	0.0185	0.0212	0.0205	0.305	0.372
General Purpose ARCHON Architecture	0.364	0.189	0.195	0.284	0.252	0.375	0.461
Task Specific ARCHON Architecture	0.401	0.210	0.221	0.295	0.265	0.425	0.448

Table 19: **ARCHON Costs per Query by Benchmark**

## A.5 ITAS Algorithms Comparisons

Inference Budget	Iterations to Convergence				
	10	20	30	40	50
Random Selection	310	643	1153	2062	2695
Greedy Search	222	576	787	1607	1685
Bayes Optimization	<b>166</b>	<b>256</b>	<b>340</b>	<b>387</b>	<b>415</b>

Table 20: **ITAS Algorithms Comparison by Inference Call Budget:** For our comparison, we evaluate on MT Bench.

# of Init. Points	% of Total Configs	Iter. till Max. Config.	Comb. Iter.
50	1.57%	389	439
60	1.88%	321	381
70	2.19%	287	357
80	2.51%	268	<b>348</b>
90	2.82%	265	355
100	3.13%	258	358
110	3.45%	262	372
120	3.76%	253	373

Table 21: MT Bench

# of Init. Points	% of Total Configs	Iter. till Max. Config.	Comb. Iter.
50	1.57%	658	708
60	1.88%	575	635
70	2.19%	502	572
80	2.51%	453	<b>533</b>
90	2.82%	451	541
100	3.13%	455	555
110	3.45%	442	552
120	3.76%	437	557

Table 22: Arena-Hard-Auto

Table 23: **Bayesian Optimization Hyperparameter Comparisons:** On MT Bench and Arena-Hard-Auto, we compare Bayesian optimization configurations for the number of initial sample points. We find that 80 to 90 initial sample points minimizes the combined number of iterations (both initial sampling and exploring) to find the optimal configuration. For the configurations explored, the total number of hyperparameter choices is 3192.

## A.6 Bayesian Optimization

Bayesian Optimization is a sequential design strategy for global optimization of black-box functions that are expensive to evaluate [48]. It is particularly useful when dealing with functions that have unknown forms and are costly to evaluate, such as hyperparameter tuning in machine learning.

### A.6.1 Basic Idea of Bayesian Optimization

The core idea behind Bayesian Optimization is to build a probabilistic model of the objective function and use it to select the most promising points to evaluate next. This process involves two main components:

1. **Surrogate Model:** A probabilistic model (often a Gaussian Process) that approximates the unknown objective function.
2. **Acquisition Function:** A function that guides the search for the optimum by suggesting the next point to evaluate, based on the surrogate model.

### A.6.2 Steps in Bayesian Optimization

1. **Initialization:** Begin with a set of initial points  $\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_n, y_n)\}$ , where  $\mathbf{x}_i$  is the input, and  $y_i = f(\mathbf{x}_i)$  is the objective function value at  $\mathbf{x}_i$ .
2. **Model Building:** Fit a surrogate model (e.g., Gaussian Process) to the observed data  $\mathcal{D}$ .
3. **Acquisition:** Use the acquisition function to select the next point  $\mathbf{x}_{n+1}$  to evaluate:

$$\mathbf{x}_{n+1} = \underset{\mathbf{x}}{\operatorname{argmax}} a(\mathbf{x} | \mathcal{D})$$

where  $a(\mathbf{x} | \mathcal{D})$  is the acquisition function.

4. **Evaluation:** Evaluate the objective function at  $\mathbf{x}_{n+1}$  to get  $y_{n+1} = f(\mathbf{x}_{n+1})$ .
5. **Update:** Add the new data point  $(\mathbf{x}_{n+1}, y_{n+1})$  to the dataset  $\mathcal{D}$ .
6. **Repeat:** Repeat steps 2-5 until convergence or a stopping criterion is met (e.g., budget exhausted, no significant improvement).

### A.6.3 Gaussian Process as a Surrogate Model

A Gaussian Process (GP) is commonly used as a surrogate model in Bayesian Optimization. It is defined by a mean function  $\mu(\mathbf{x})$  and a covariance function (kernel)  $k(\mathbf{x}, \mathbf{x}')$ :

$$f(\mathbf{x}) \sim \mathcal{GP}(\mu(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$

Given a set of observations  $\mathcal{D}$ , the GP provides a predictive distribution for the objective function at a new point  $\mathbf{x}$ :

- **Predictive Mean:** The expected value of the function at  $\mathbf{x}$ :

$$\mu(\mathbf{x} | \mathcal{D}) = \mathbf{k}_n(\mathbf{x})^T \mathbf{K}_n^{-1} \mathbf{y}$$

where  $\mathbf{k}_n(\mathbf{x})$  is the covariance vector between  $\mathbf{x}$  and the training points, and  $\mathbf{K}_n$  is the covariance matrix of the training points.

- **Predictive Variance:** The uncertainty in the function value at  $\mathbf{x}$ :

$$\sigma^2(\mathbf{x} | \mathcal{D}) = k(\mathbf{x}, \mathbf{x}) - \mathbf{k}_n(\mathbf{x})^T \mathbf{K}_n^{-1} \mathbf{k}_n(\mathbf{x})$$

### A.6.4 Acquisition Functions

Acquisition functions guide the search for the optimum by balancing exploration (trying out areas with high uncertainty) and exploitation (focusing on areas with high predicted values). Common acquisition functions include:

1. **Expected Improvement (EI):**

$$\text{EI}(\mathbf{x}) = \mathbb{E}[\max(0, f(\mathbf{x}) - f(\mathbf{x}^+))]$$

where  $f(\mathbf{x}^+)$  is the best observed value so far.

2. **Probability of Improvement (PI):**

$$\text{PI}(\mathbf{x}) = \mathbb{P}(f(\mathbf{x}) > f(\mathbf{x}^+) + \xi)$$

where  $\xi$  is a small positive number.

### 3. Upper Confidence Bound (UCB):

$$\text{UCB}(\mathbf{x}) = \mu(\mathbf{x} | \mathcal{D}) + \kappa \sigma(\mathbf{x} | \mathcal{D})$$

where  $\kappa$  controls the trade-off between exploration and exploitation.

#### A.6.5 Summary of Bayesian Optimization

Bayesian Optimization iteratively uses a surrogate model to approximate the objective function and an acquisition function to decide where to sample next. By focusing on promising areas of the search space and systematically exploring uncertain regions, it efficiently optimizes complex, expensive-to-evaluate functions.

## A.7 ARCHON Benchmarks and Results

Benchmark	Example Count	Baseline Model	Judge Model	Scoring Type	Metric
AlpacaEval 2.0	805	GPT-4-Turbo	GPT-4-Turbo	Pairwise Comparison	L.C. & Raw Win Rates
Arena-Hard-Auto	500	Claude-3.5-Sonnet GPT-4-0314	GPT-4-Turbo	Pairwise Comparison	Win Rate
MT-Bench	80	Claude-3.5-Sonnet	GPT-4-0314	Pairwise Comparison	Adjusted Win Rate
MixEval	2000	N/A	N/A	Ground Truth	Accuracy
MixEval-Hard	500	N/A	N/A	Ground Truth	Accuracy
MATH	200 (sampled from 5000)	N/A	N/A	Ground Truth	Pass@1
CodeContests	140 (non-visual queries)	N/A	N/A	Ground Truth	Pass@1

Table 24: **Benchmark Overview:** Evaluation configurations for AlpacaEval 2.0 [30], Arena-Hard-Auto [29], MT-Bench [63], MixEval [37], MixEval Hard, MATH [20], and CodeContests [31]

Model / LLM System	Infer. Calls	MixEval - Sub-Datasets							Average
		GSM8K	TriviaQA	DROP	MATH	BBH	AGIEval		
GPT-4o - 2024-05-13	1	94.9	89.1	88.2	<b>98.5</b>	98.3	71.5	90.3	
Claude 3.5 Sonnet	1	98.0	92.0	92.6	96	95.6	78.0	92.0	
Llama 3.1 405B Instruct	1	<b>98.2</b>	87.9	89.6	91.5	95.8	73.2	89.6	
General-purpose ARCHON Architecture	29	98.3	94.8	94.6	98.1	97.3	82.1	94.2	
Task-specific ARCHON Architectures	34	<b>98.2</b>	<b>96.7</b>	<b>95.6</b>	<b>98.5</b>	<b>98.8</b>	<b>84.2</b>	<b>95.7</b>	

Table 25: **MixEval Results by Sub-Dataset:** For the average computed, we do not introduce any weighting for each dataset.



Model / LLM System	Infer. Calls	MixEval - Sub-Datasets						Average
		GSM8K	TriviaQA	DROP	MATH	BBH	AGIEval	
GPT-4o - 2024-05-13	1	72.3	70.5	70.2	94.4	80.0	53.5	73.5
Claude 3.5 Sonnet	1	87.3	75.5	79.3	82.5	80.0	74.6	79.9
Llama 3.1 405B Instruct	1	98.7	71.2	70.7	86.9	78.8	62.0	78.1
General-purpose ARCHON Architecture	33	96.7	82.7	83.2	93.4	82.0	76.7	85.8
Task-specific ARCHON Architectures	37	<b>98.9</b>	<b>86.2</b>	<b>85.2</b>	<b>96.2</b>	<b>86.0</b>	<b>80.1</b>	<b>88.8</b>

Table 26: **MixEval-Hard Results by Sub-Dataset:** For the average computed, we do not introduce any weighting for each dataset.

	GSM8K	MMLU Math	HumanEval Python	MBPP
Model	Pass@1	Pass@1	Pass@1	Pass@1
GPT-4o	97.1%	84.8%	89.0%	87.5%
Claude 3.5 Sonnet	96.8%	90.9%	90.2%	88.9%
Llama 3.1 405B Instruct	95.9%	85.4%	90.2%	88.6%

Table 27: **Additional Math and Code Benchmarks Explored**

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