CASTILLO: Characterizing Response Length Distributions of Large Language Models

Daniel F. Perez-Ramirez
RISE Computer Science
KTH Royal Institute of Technology
Stockholm, Sweden
daniel.perez@ri.se - dfpr@kth.se

Dejan Kostic
KTH Royal Institute of Technology
RISE Computer Science
Stockholm, Sweden
dmk@kth.se

Magnus Boman
Karolinska Institutet
Solna, Sweden
magnus.boman@ki.se

Abstract

Efficiently managing compute resources for Large Language Model (LLM) inference remains challenging due to the inherently stochastic and variable lengths of autoregressive text generation. Accurately estimating response lengths in advance enables proactive resource allocation, yet existing approaches either bias text generation towards certain lengths or rely on assumptions that ignore model- and prompt-specific variability. We introduce CASTILLO, a dataset characterizing response length distributions across 13 widely-used open-source LLMs evaluated on seven distinct instruction-following corpora. For each ⟨prompt, model⟩ sample pair, we generate 10 independent completions using fixed decoding hyper-parameters, record the token length of each response, and publish summary statistics (mean, std-dev, percentiles), along with the shortest and longest completions, and the exact generation settings. Our analysis reveals significant inter- and intra-model variability in response lengths (even under identical generation settings), as well as model-specific behaviors and occurrences of partial text degeneration in only subsets of responses. CASTILLO enables the development of predictive models for proactive scheduling and provides a systematic framework for analyzing model-specific generation behaviors. We publicly release the dataset and code to foster research at the intersection of generative language modeling and systems.

1 Introduction

Large Language Models (LLMs) have transformed natural language processing by enabling general-purpose language understanding and generation at unprecedented scale [Brown et al., 2020, Raffel et al., 2020, Chowdhery et al., 2023]. Instruction-tuned LLMs are now widely deployed across a range of applications—including question answering, dialogue systems, and code generation—powering production services used by millions of users daily [Ouyang et al., 2022, Chen et al., 2021, Achiam et al., 2023, Team et al., 2023]. However, their computational and memory demands pose significant challenges to scalable and cost-effective inference in production systems.

A central bottleneck in LLM serving systems is the difficulty of managing compute and memory resources efficiently, especially under high concurrency and latency constraints. Recent systems research has emphasized memory management of the attention Key-Value (KV) cache [Kwon et al., 2023] and reactive scheduling strategies that respond to runtime demand fluctuations [Duan
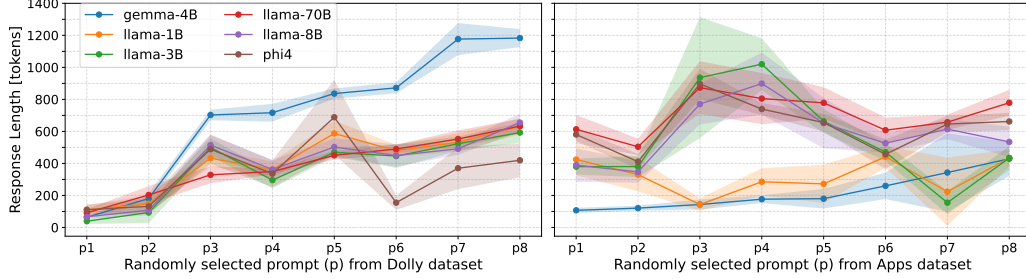
Figure 1: **LLM response lengths exhibit significant inter- and intra-model variability**. Points depict the mean response length for a ⟨prompt, model⟩ pair; shaded regions depict ±1 standard deviation over 10 independent responses under fixed decoding parameters. Significant variation both among different models and within the 10 sampled responses, even within the same model.

et al., 2024, Patel et al., 2024, Agrawal et al., 2024]. While effective to some degree, reactive methods are inherently limited by their inability to anticipate the variable and stochastic nature of autoregressive generation in transformer-based models [Vaswani et al., 2017, Holtzman et al., 2020]. This unpredictability leads to inefficient resource utilization and increased operational overhead.

Proactive scheduling strategies, with the aim to predict response lengths before generation, have the potential to significantly improve LLMs inference efficiency. Existing approaches often rely on strong assumptions, such as fixed-length outputs across prompts or models [Jin et al., 2023, Shahout et al., 2025], or introduce unwanted bias by implicitly conditioning the generation toward target lengths [Zheng et al., 2023]. Figure 1 highlights the substantial variability in response lengths across both prompts and models. Even under fixed decoding parameters, we observe that no model consistently produces longer or shorter outputs—one model may respond concisely to a particular prompt but verbosely to another. Even when fixing the model and prompt, we see cases of high variance among responses that can extend for hundreds of tokens for some models (see Apps-p3 in Figure 1). This unpredictability underscores the limitations of using only the text prompt alone to estimate response lengths.

In this work, we present **CASTILLO**–**C**har**A**cterizing re**S**ponse leng**T**h d**I**stributions in **L**arge **L**anguage m**O**dels–a large-scale dataset designed to empirically characterize LLM response length distributions across diverse models and tasks. CASTILLO spans 13 widely-used open-source LLMs and 7 instruction-following datasets, covering a diverse range of model architectures, sizes, and text corpora. For each ⟨prompt, model⟩ sample pair, we generate 10 independent completions using fixed decoding hyper-parameters and record the token length of each response. We release summary statistics (mean, standard deviation, percentiles), along with the shortest and longest completions and the exact generation settings.

Our analysis reveals several key insights:

1. **Inter-model variability**: Different models exhibit markedly different response length distributions, even when prompted with identical inputs (see Figures 3 and 4). This underscores the need for model-specific characterization of generation behavior.

2. **Intra-model variability**: within a single model, we observe high variance in response lengths across different prompts (see Figure 5), even with fixed decoding settings, highlighting the influence of prompt semantics on generation length.

3. **Partial text degeneration**: In some cases, a subset of the 10 completions for a given prompt-model pair exhibit text degeneration artifacts (e.g., repetition or incoherence), suggesting localized instability not captured by single-sample evaluations (see Figure 6).

CASTILLO serves as both a benchmarking resource and a foundation for building predictive models of response length. Such models could inform proactive scheduling strategies, reduce latency, and optimize resource allocation in LLM serving infrastructures. Additionally, CASTILLO provides a controlled framework for systematically analyzing and comparing generation behaviors across different models, prompts, and decoding settings. We release the dataset and codebase (see Appendix A) to support reproducibility and foster future work at the intersection of machine learning and systems.
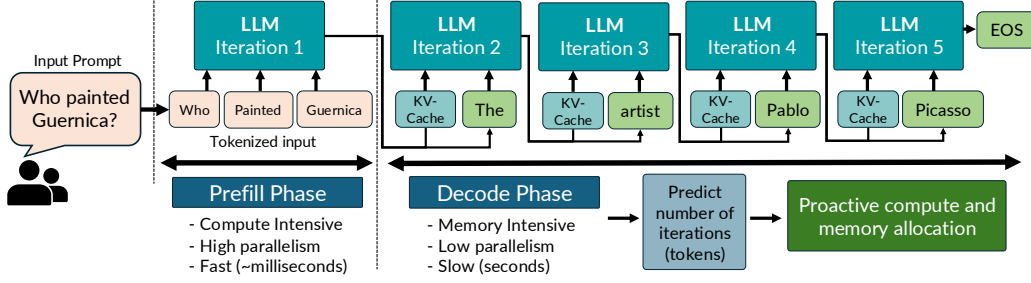
Figure 2: Transformer-based LLM inference in production is divided into a fast and compute intensive phase (prefill) and a time-consuming and memory intensive phase (decode).

2 Background and Related Work

To our knowledge, CASTILLO is the first publicly-available dataset to empirically characterize response length distributions across multiple LLMs and instruction-following datasets.

Transformer-based models Modern LLMs are predominantly based on the Transformer architecture [Vaswani et al., 2017], which models text as sequences of discrete tokens and generates outputs through an autoregressive process–predicting each token conditioned on the preceding context. This token-by-token generation is inherently stochastic and influenced by both the model parameters and sampling hyperparameters (such as temperature) and decoding configuration [Holtzman et al., 2020]. In this work, we focus exclusively on transformer-based LLMs, given their ubiquity and dominance in both academic and industrial deployments.

Efficient LLM inference In production systems, LLM inference can be decomposed into two distinct phases: a prefill phase and a decoding phase [Agrawal et al., 2023, Patel et al., 2024, Agrawal et al., 2024]. Figure 2 depicts the process: the prefill phase encodes the input prompt and computes the KV-Cache for the attention layers–a compute-intensive parallelizable operation that typically executes in the millisecond range. The decoding phase then generates tokens autoregressively, both using and augmenting the KV-Cache, incurring sequential dependencies and high memory overhead. This phase often dominates latency, stretching into seconds or even minutes for long responses. Meanwhile, scheduling decisions–such as request admission or GPU placement–typically occur in the microsecond range, creating a critical need for accurate, low-latency predictions of output length to enable proactive scheduling.

Recent work aims at improving LLM inference efficiency through systems-level innovations. Methods such as PagedAttention [Kwon et al., 2023] and FlashAttention [Dao et al., 2022] address memory locality and computation speed during attention computation. Inference engines like vLLM [Kwon et al., 2023], SplitWise [Patel et al., 2024], Sarathi [Agrawal et al., 2024], Flexgen [Sheng et al., 2023], and MuxServe [Duan et al., 2024] implement dynamic batching, cache eviction policies, and token-level scheduling. CASTILLO is orthogonal to these efforts: our work provides a standardized dataset to inform and augment such systems via better response length estimation.

Response Length Prediction Recent works attempt to directly predict response lengths in advance. Zheng et al. [2023] propose to fine-tune LLMs with an auxiliary task that predicts the number of output words before generating a response. However, this method introduces length biases and was evaluated on only a single dataset, limiting generality. Jin et al. [2023] introduce S^3, a classification-based predictor using DistilBERT to assign each input prompt to one of 10 output-length buckets. While efficient, S^3 ignores intra-model variability (each ⟨prompt, model⟩ pair has a single estimated length) and assumes inter-model homogeneity by using the same predictor for all LLMs. Moreover, the use of DistilBERT constrains prompt length to 512 tokens, and the fixed bucket resolution may be too coarse for fine-grained scheduling. Building on S^3, Shahout et al. [2025] propose TRAIL, which refines predictions during decoding by conditioning on *specific* intermediate activations from the LLM and updating estimates via a Bayesian model. While effective, TRAIL introduces communication overhead and requires in-depth layer-wise model-specific analysis, which limits its generalization.

CASTILLO contributes to this growing area by offering a large-scale dataset that captures both inter- and intra-model response variability under fixed decoding conditions. By releasing response statistics (mean, percentiles, extremes), generation hyperparameters, and evidence of partial degeneration, our dataset enables systematic study and benchmarking of predictive length estimation methods, and serves as a robust testbed for building more general and proactive inference schedulers.

3 CASTILLO Dataset Construction

This section details the construction of CASTILLO, including source dataset selection, open-source LLMs used, and the response generation framework. Our dataset is designed to enable empirical study of response length variability and support the development of predictor models for proactive inference scheduling.

3.1 Source Dataset Selection

To capture a diverse range of instruction-following behaviors, we consider seven publicly available and widely used open-source datasets spanning both general-purpose NLP tasks and code generation benchmarks. Our selection includes open-ended instruction datasets—**Dolly**, **ShareGPT**, and **Alpaca**—as well as structured problem-solving and code-oriented datasets such as **Mbpp**, **Apps**, **DS-1000**, and **BigCodeBench**. All selected datasets have seen prior adoption in peer-reviewed machine learning or systems research and are representative of real-world LLMworkloads.

Each dataset is processed independently. When a dataset contains more than 2000 samples, we randomly downsample to a uniform cap of 2000 prompts. For datasets with internal categorization (e.g., by task type or domain), we apply stratified sampling to maintain representative distributions. Importantly, we verify that the downsampled subsets preserve the original distributions of input token lengths, as shown in Appendix B. The resulting prompts are partitioned into training, validation, and test splits using a 70/20/10 ratio, with optional stratification where applicable. The training and validation sets are intended for the development of response length predictors, while the test set is reserved for system-level evaluation.

Table 1 presents an overview of the seven datasets considered, including token-level statistics of the input prompts after tokenization using the `llama-3.2-1B` tokenizer. We report the mean, minimum, percentiles (P25, P50, P75, P99), and maximum token lengths. These statistics highlight the high diversity in prompt lengths across datasets–from compact, instruction-like inputs in Alpaca and Dolly, to longer, more verbose examples in Apps and DS-1000—underscoring the importance of considering a wide range of source datasets for building characterizing response lengths.

3.2 LLM Model Selection

To explore variability across models and architectures, CASTILLO includes 13 open-source instruction-tuned LLMs from four major organizations. We prioritize models that are (1) publicly available on Hugging Face, (2) used in recent systems and ML research focused on inference optimization, and (3) realistically deployable by research labs and Small- and Medium Enterpises (SMEs), particularly in the mid-size parameter range. Our selection includes models from the LLaMA, Mistral, Qwen, Phi, and Gemma families, ranging in size from 1B to 70B parameters. By including multiple sizes within families, we allow for both intra-family and inter-family comparisons of response behavior. We query each model using its instruction-tuned variant and standardized HuggingFace model configuration. Appendix C (Table 2) lists the specific model identifiers, their parameter sizes, organizations, and the number of H100 GPUs used for inference.

3.3 Response Generation Process

We implement dataset-specific prompt formatting routines to respect the schema and intended use cases of each source dataset. These routines generate consistent and model-compatible chat prompts, as detailed in the subsections of Appendix B.

To ensure compatibility with all models and control GPU memory usage, we cap input prompt lengths at 2500 tokens. This threshold was selected based on analysis of the input token distributions in Table 1, and strikes a balance between empirical coverage and feasibility of computing response

Table 1: Source datasets used by CASTILLO to generate input prompts for the LLMs, with sample counts and token length statistics after tokenization with Llama-3.2-1B. "PX" denotes the Xth percentile. More details about source dataset analysis and processing in Appendix B.

Name	Samples	Mean	Min.	P25	P50	P75	P99	Max.
DollyDataset [Conover et al., 2023]	2000	125.9	36	44	50	146	795.2	4003
ShareGPT [Chiang et al., 2023]	2000	260.5	36	48	64	168	2534.0	2534
Alpaca [Taori et al., 2023]	2000	53.7	39	45	49	57	114.0	397
Mbpp [Austin et al., 2021]	974	153.5	88	109	131	173	336.3	2265
Apps [Hendrycks et al., 2021]	2000	545.0	87	307.7	441	650	2105.0	2534
DS-1000 [Lai et al., 2023]	1000	317.2	67	170.5	283	395	1018.3	2109
BigCodeBench [Zhuo et al., 2025]	1140	179.8	87	137	164	205	398.4	1251

lengths with our available resources. Notably, this limit is significantly larger than the 99th percentile token length across all datasets and avoids out-of-memory failures while preserving most of the input space relevant for inference.

For each ⟨prompt, model⟩ pair, we first transform the text prompt into a `chat_template` using the respective model's tokenizer, we construct a batch of 10 identical prompt entries, and perform independent decoding for each using Hugging Face's Transformers interface [Wolf et al., 2020]. Generation is performed with `do_sample=True`, and the decoding parameters (`temperature`, `top-k`, `top-p`) are recorded and stored for each sample. Our codebase (see Appendix A) is designed to be extensible, allowing users to augment the dataset with additional models and decoding configurations by specifying them at runtime. To guard against resource exhaustion due to pathological completions (repeated test generation in loop), we cap the maximum output length at 15000 per response (approximately 11000 words). This decision was informed by early observations of text degeneration, where some LLMs entered repetitive loops or verbose rambling that consumed the full context window and available GPU memory.

After generation, each batch of 10 completions is post-processed to extract the *token length* of each response. For every ⟨prompt, model⟩ pair, we compute and store the following statistics: i) mean, standard deviation (std-dev), and percentile values (P25, P50, P75, P99) of response lengths, ii) the shortest and longest completions (cached as raw text, and iii) full decoding configuration (`temperature`, `top-k`, `top-p`). More details about the complete dataset schema can be found in Table 3 in the Appendix.

3.4 Sanitizing the CASTILLO Dataset

To support downstream analysis and robustness studies, we further partition the dataset into two complementary subsets:

1. A **sanitized version**, sanitizing or excluding all completions exhibiting degeneration artifacts (e.g., high repetition, loss of coherence, maximum-length responses), and

2. A **degeneration-only subset**, containing flagged cases for which at least one of the 10 completions showed evidence of text degeneration.

For full details and illustrative examples, see Appendix D. For identifying text degeneration in CASTILLO, we applied a two-stage filtering strategy based on output length statistics. Specifically, we flagged samples as degenerated if they contained any outputs that reached the generation cap of 15,000 tokens, or if they exhibited high variance in response lengths—defined as a standard deviation greater than twice the mean combined with at least one output exceeding 8,500 tokens. This approach enabled us to distinguish true degeneration from benign verbosity and to construct both degenerated and sanitized subsets of the dataset used in our analysis. These two versions allow researchers to isolate text-degeneration behavior or train predictors on clean, high-quality generations.

4 Characterizing LLM Response Distributions

In this section, we analyze the response length distributions in CASTILLO to characterize the generation behavior of different LLMs across the considered datasets. Our findings confirm expected
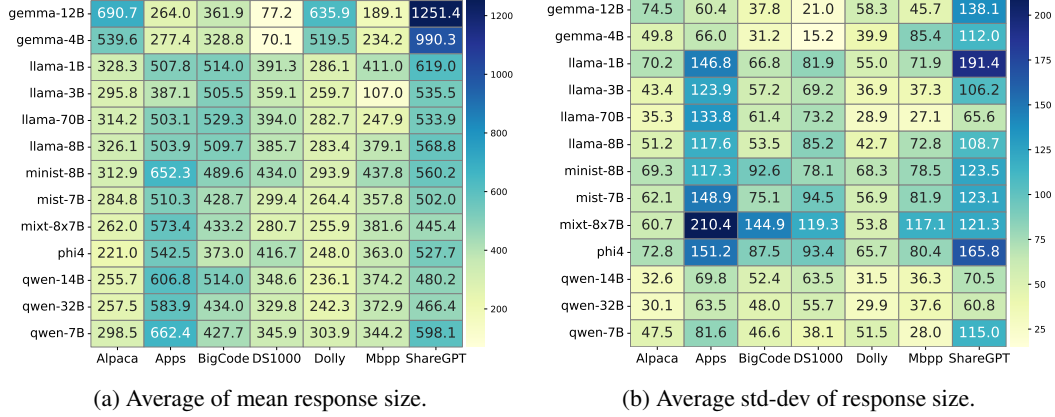
	Alpaca	Apps	BigCode	DS1000	Dolly	Mbpp	ShareGPT
gemma-12B	690.7	264.0	361.9	77.2	635.9	189.1	1251.4
gemma-4B	539.6	277.4	328.8	70.1	519.5	234.2	990.3
llama-1B	328.3	507.8	514.0	391.3	286.1	411.0	619.0
llama-3B	295.8	387.1	505.5	359.1	259.7	107.0	535.5
llama-70B	314.2	503.1	529.3	394.0	282.7	247.9	533.9
llama-8B	326.1	503.9	509.7	385.7	283.4	379.1	568.8
minist-8B	312.9	652.3	489.6	434.0	293.9	437.8	560.2
mist-7B	284.8	510.3	428.7	299.4	264.4	357.8	502.0
mixt-8x7B	262.0	573.4	433.2	280.7	255.9	381.6	445.4
phi4	221.0	542.5	373.0	416.7	248.0	363.0	527.7
qwen-14B	255.7	606.8	514.0	348.6	236.1	374.2	480.2
qwen-32B	257.5	583.9	434.0	329.8	242.3	372.9	466.4
qwen-7B	298.5	662.4	427.7	345.9	303.9	344.2	598.1

(a) Average of mean response size.

	Alpaca	Apps	BigCode	DS1000	Dolly	Mbpp	ShareGPT
gemma-12B	74.5	60.4	37.8	21.0	58.3	45.7	138.1
gemma-4B	49.8	66.0	31.2	15.2	39.9	85.4	112.0
llama-1B	70.2	146.8	66.8	81.9	55.0	71.9	191.4
llama-3B	43.4	123.9	57.2	69.2	36.9	37.3	106.2
llama-70B	35.3	133.8	61.4	73.2	28.9	27.1	65.6
llama-8B	51.2	117.6	53.5	85.2	42.7	72.8	108.7
minist-8B	69.3	117.3	92.6	78.1	68.3	78.5	123.5
mist-7B	62.1	148.9	75.1	94.5	56.9	81.9	123.1
mixt-8x7B	60.7	210.4	144.9	119.3	53.8	117.1	121.3
phi4	72.8	151.2	87.5	93.4	65.7	80.4	165.8
qwen-14B	32.6	69.8	52.4	63.5	31.5	36.3	70.5
qwen-32B	30.1	63.5	48.0	55.7	29.9	37.6	60.8
qwen-7B	47.5	81.6	46.6	38.1	51.5	28.0	115.0

(b) Average std-dev of response size.

Figure 3: **Both the average mean and std-dev across models and dataset can vary by several hundreds of tokens**. Heatmaps depict the average of both the mean (3a) and std-dev (3b) of response lengths across models and datasets for all generations performed.

trends—such as substantial variability across models and datasets—but also uncover significant variation in response lengths for the *same* prompt under fixed decoding settings. This highlights the challenges in accurately predicting response lengths. Moreover, our analysis reveals notable occurrences of text degeneration in a subset of generated completions.

4.1 Inter- and Intra-Model Variability

Figure 3 presents a heatmap of the average mean (3a) and standard deviation (3b) of response lengths across all ⟨model, dataset⟩ combinations. We observe pronounced disparities in both metrics. Models consistently produce longer responses for certain datasets, notably ShareGPT and Apps [Hendrycks et al., 2021], with mean response lengths varying by several hundred tokens across models. The standard deviation heatmap (Figure 3b) further illustrates intra-model variability, with response length variation ranging from a few dozen tokens (e.g., gemma-4B on DS-1000) to a couple hundreds of tokens (e.g., mixt-8x7B). These findings emphasize the inherent stochasticity of autoregressive generation, even under fixed sampling parameters, and underscore the difficulty of response length prediction.

Distributions Across Models and Datasets   To further explore the range of variability, Figure 4 presents boxplots of the mean (4a) and standard deviation (4b) of response lengths across all ⟨prompt, model⟩ pairs, grouped by dataset. The wide interquartile ranges and extended whiskers illustrate the breadth of generation behavior across LLMs.

We observe a consistent pattern in which code-related datasets (Mbpp, Apps, DS-1000, Big-CodeBench) elicit longer responses compared to instruction-tuned text datasets (e.g., Alpaca, Dolly). Interestingly, the Gemma models deviate from this trend, producing longer responses on text-based datasets. This inversion highlights the importance of model-specific tuning and architectural differences in influencing output characteristics.

Within-Batch Variability and Coefficient of Variation   To quantify the variation within each batch of 10 generated responses per ⟨prompt, model⟩ pair, we compute the average coefficient of variation (CV = std-dev/mean) per model-dataset combination. Figure 5 shows CV values ranging from 7% to 45%, indicating substantial within-batch response length variation despite fixed decoding parameters for the batch. High intra-batch CV values suggest that LLM outputs can be highly unpredictable for certain models and datasets, particularly for code-oriented datasets like Apps, BigCode and DS-1000, where prompt structure and complexity likely amplify generation variance. This level of unpredictability presents a challenge for inference-time schedulers and systems that rely on deterministic or narrowly distributed response length estimates.
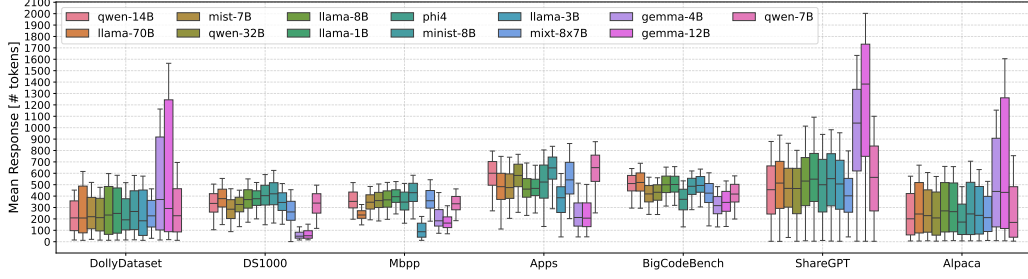
(a) Mean response length distribution across models and datasets depicts significant inter-model variation in response lengths. Box extents delimit inter-quartile range, whiskers depict 1st and 90st percentile.
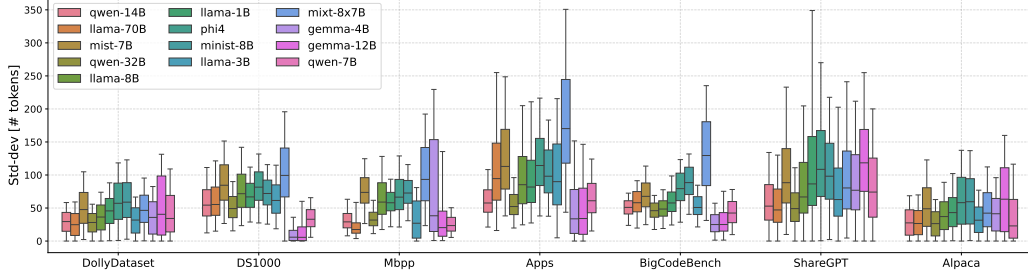
(b) Distribution of standard deviation of model response lengths across datasets. Box extents delimit inter-quartile range, whiskers depict 1st and 99st percentile.

Figure 4: **LLMs exhibit substantial variation in their distribution of both mean and std-dev of their responses.** Figure4a shows large disparities across both models and datasets, even under identical generation settings.
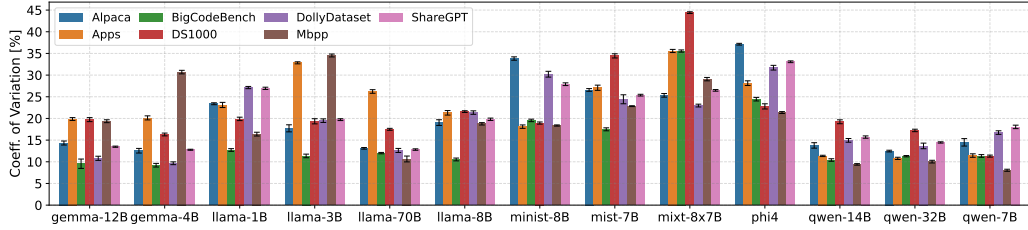

Figure 5: **High coefficient of variation between responses for the same prompt from an LLM.** Figure depicts average coefficients of variation (std-dev normalized by the mean) across datasets and models ranging from 7% to up to 45%. Hence, the std-dev can reach up to half of the value of the average response length in the batch.

(a) Number of samples suffering from test degeneration.

(b) Share in text degeneration set by model.

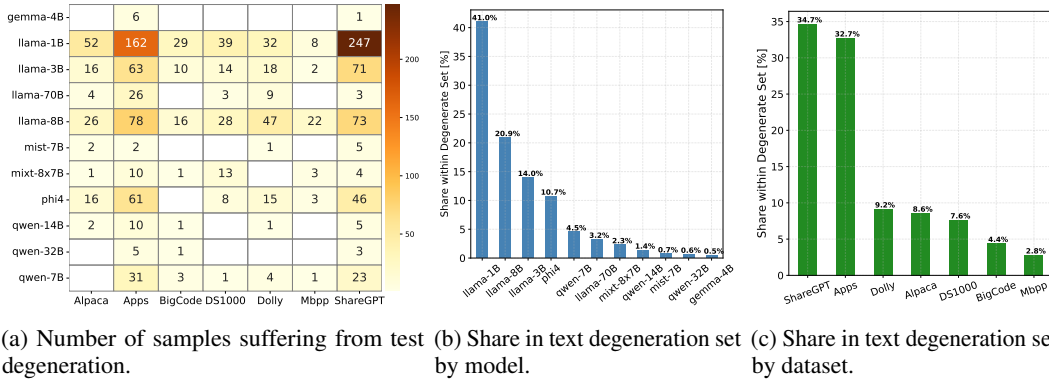(c) Share in text degeneration set by dataset.

Figure 6: **We identify a total of 956 text degeneration cases across all models and datasets.** Figure6a depicts a heatmap of the number of text degeneration cases by model and dataset. Figures 6b and 6c show the share of samples from the total 956 according to the model and dataset, respectively.

4.2 Text Degeneration Cases

We define *text degeneration* as cases where generated completions exhibit artifacts such as excessive repetition, incoherence, or abrupt verbosity, often reaching the maximum token limit. Figure 16 and 15 in Appendix D illustrate qualitative examples of such behavior. CASTILLO enables the identification of degeneration cases by generating 10 independent completions per prompt under fixed decoding settings. This design facilitates benchmarking the likelihood of encountering degeneration artifacts across models and datasets.

Our degeneration detection pipeline (described in Algorithm 1 in Appendix D) identified a total of 956 affected samples. Figure 6 provides a heatmap of degeneration counts across ⟨model, dataset⟩ combinations. Of the 13 LLMs evaluated, only two—minist-8B and gemma-12B—exhibited no degeneration cases. In contrast, three models (llama-1B, llama-3B, and llama-8B) showed degeneration across all datasets. A clear trend emerges within model families and their sizes: smaller variants (e.g., qwen-7B, llama-1B) are more prone to degeneration than their larger counterparts. Figures 6b and 6c summarize the distribution of degeneration cases across models and datasets. Notably, llama-1B alone accounts for over 40% of all degeneration cases, which may reflect the model's limited capacity to regulate generation under open-ended prompting. On the dataset side, ShareGPT and Apps contribute the majority of degeneration cases, likely due to their high diversity and prompt verbosity.

These findings support the inclusion of both sanitized and degeneration-only subsets in CASTILLO, enabling researchers to develop robust length predictors and to better understand model-specific vulnerabilities in generation stability.

5 Use Cases for CASTILLO

CASTILLO is designed to serve as a flexible and extensible benchmark for analyzing and predicting the output behavior of instruction-tuned LLMs. We outline several key use cases that highlight the dataset's applicability in both systems and machine learning research:

Length Prediction for Proactive Scheduling   In latency-sensitive LLM serving systems, the ability to predict output length prior to generation is critical for informed admission control, resource allocation, and scheduling. CASTILLO provides per-sample statistics (mean, std, percentiles) over multiple completions per prompt, which enables the training and evaluation of both regression-based and classification-based output length predictors. These models can be integrated into serving infrastructures to support proactive inference scheduling strategies.

Benchmarking Model-Specific Generation Behavior   CASTILLO enables researchers to compare how different open-source LLMs respond to the same prompt distribution under identical decoding parameters. By including models across diverse architecture families and parameter scales (1B–70B), our dataset supports detailed inter- and intra-model comparisons. This facilitates analyses of length variability, degeneration tendencies, and generation style, which can inform the selection and deployment of models for specific application domains.

Degeneration Detection and Filtering   The dataset includes both sanitized and degeneration-only subsets, enabling research into degeneration detection, mitigation strategies, and generation stability analysis. Degeneration patterns—such as token repetition, incoherence, or excessive verbosity—are often subtle and model-specific. Our dataset provides the necessary signals (e.g., outlier response lengths, high variance) to develop heuristics or learning-based detectors for pathological generations.

Downstream Integration for System Simulations   CASTILLO can serve as a simulation backend for system-level studies in LLM inference. For example, system designers can use the statistical length distributions to emulate response lengths in multi-tenant inference clusters, or to test token-level schedulers and memory managers under realistic generation profiles. By decoupling evaluation from online generation, researchers can prototype and benchmark new scheduling policies efficiently.

8

6 Limitations and Future Work

CASTILLO offers a comprehensive and empirically grounded foundation for analyzing LLM response length distributions, addressing a crucial gap in current benchmarking and systems design. However, we identify the following limitations and opportunities for future work.

Transformer-centric Scope　All models used for building our dataset are based on the transformer architecture, reflecting its current dominance in LLM research and deployment. While our findings are broadly applicable, they may not generalize to alternative architectures such as state-space models [Gu et al., 2022, Gu and Dao, 2023] or LSTM-based systems [Beck et al., 2024]. Future iterations of CASTILLO could incorporate such models to assess whether similar length variability patterns emerge beyond the transformer architecture.

Extensibility to More Models and Datasets　While CASTILLO includes a diverse range of 13 instruction-tuned LLMs and 7 datasets, the long tail of model and data heterogeneity in practice suggests significant room for growth. To support community-driven expansion, we publicly release the dataset and a modular codebase (see Appendix A) that enables seamless addition of new models, datasets, and generation settings. Notably, CASTILLO also supports optional caching of prefill-stage activations (hidden states and logits), opening new avenues for analysis of how input representations correlate with output length. We envision future work could systematically explore this relationship.

Chain-of-Thought Specific Extensions　Out dataset generation framework can be extended to accommodate reasoning-focused models that follow chain-of-thought framework [Wei et al., 2022, Yao et al., 2023]. In such settings, we propose partitioning the response into two measurable segments: (1) the reasoning trace delimited by `<think>` tokens and (2) the final answer. This would enable fine-grained prediction of intermediate vs. final response lengths, and support a deeper understanding of how models allocate tokens to reasoning versus conclusions. Given the demonstrated model-specific variation in generative behavior, we hypothesize that reasoning lengths may also reflect distinct architectural or model "personalities".

Generation-Configuration Interactions　While CASTILLO generates responses assuming the respective model's default decoding settings, generation configuration remains a powerful lever that modulates output variability. Our dataset includes metadata for temperature, top-k, and top-p settings, and can be extended to systematically study their interactions with both prompt structure and model identity. Future work could incorporate model-specific controlled ablation studies to quantify the marginal effect of each decoding parameter on response length distribution and degeneration likelihood. This process is model-dependent, and outside of our scope of inter-model variability.

7 Conclusion

We introduced CASTILLO, a large-scale dataset designed to empirically characterize response length distributions across open-source instruction-tuned LLMs. By systematically measuring response length variability across 13 models and 7 diverse datasets, it provides a rich foundation for building predictive models that support proactive inference scheduling. Beyond its utility for systems research, our dataset enables the investigation of model-specific generation behaviors, including intra-model variance and partial text degeneration phenomena. We release the dataset, codebase, and baseline tools to encourage reproducibility and community-driven extensions, and we envision CASTILLO as a versatile tool for research at the intersection of machine learning and systems.

References

J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

A. Agrawal, A. Panwar, J. Mohan, N. Kwatra, B. S. Gulavani, and R. Ramjee. Sarathi: Efficient llm inference by piggybacking decodes with chunked prefills, 2023. URL `https://arxiv.org/abs/2308.16369`.

A. Agrawal, N. Kedia, A. Panwar, J. Mohan, N. Kwatra, B. Gulavani, A. Tumanov, and R. Ramjee. Taming Throughput-Latency tradeoff in LLM inference with Sarathi-Serve. In *18th USENIX Symposium on Operating Systems Design and Implementation (OSDI 24)*, pages 117–134, Santa Clara, CA, July 2024. USENIX Association. ISBN 978-1-939133-40-3. URL `https://www.usenix.org/conference/osdi24/presentation/agrawal`.

J. Austin, A. Odena, M. Nye, M. Bosma, H. Michalewski, D. Dohan, E. Jiang, C. Cai, M. Terry, Q. Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.

M. Beck, K. Pöppel, M. Spanring, A. Auer, O. Prudnikova, M. K. Kopp, G. Klambauer, J. Brandstetter, and S. Hochreiter. xLSTM: Extended long short-term memory. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems (NeurIPS)*, 2024. URL `https://openreview.net/forum?id=ARAxPPIAhq`.

T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems (NeurIPS)*, volume 33, pages 1877–1901. Curran Associates, Inc., 2020. URL `https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf`.

M. Chen, J. Tworek, H. Jun, Q. Yuan, H. P. de Oliveira Pinto, J. Kaplan, H. Edwards, Y. Burda, N. Joseph, G. Brockman, A. Ray, R. Puri, G. Krueger, M. Petrov, H. Khlaaf, G. Sastry, P. Mishkin, B. Chan, S. Gray, N. Ryder, M. Pavlov, A. Power, L. Kaiser, M. Bavarian, C. Winter, P. Tillet, F. P. Such, D. Cummings, M. Plappert, F. Chantzis, E. Barnes, A. Herbert-Voss, W. H. Guss, A. Nichol, A. Paino, N. Tezak, J. Tang, I. Babuschkin, S. Balaji, S. Jain, W. Saunders, C. Hesse, A. N. Carr, J. Leike, J. Achiam, V. Misra, E. Morikawa, A. Radford, M. Knight, M. Brundage, M. Murati, K. Mayer, P. Welinder, B. McGrew, D. Amodei, S. McCandlish, I. Sutskever, and W. Zaremba. Evaluating large language models trained on code. 2021.

W.-L. Chiang, Z. Li, Z. Lin, Y. Sheng, Z. Wu, H. Zhang, L. Zheng, S. Zhuang, Y. Zhuang, J. E. Gonzalez, I. Stoica, and E. P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality, March 2023. URL `https://lmsys.org/blog/2023-03-30-vicuna/`.

A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, H. W. Chung, C. Sutton, S. Gehrmann, P. Schuh, K. Shi, S. Tsvyashchenko, J. Maynez, A. Rao, P. Barnes, Y. Tay, N. Shazeer, V. Prabhakaran, E. Reif, N. Du, B. Hutchinson, R. Pope, J. Bradbury, J. Austin, M. Isard, G. Gur-Ari, P. Yin, T. Duke, A. Levskaya, S. Ghemawat, S. Dev, H. Michalewski, X. Garcia, V. Misra, K. Robinson, L. Fedus, D. Zhou, D. Ippolito, D. Luan, H. Lim, B. Zoph, A. Spiridonov, R. Sepassi, D. Dohan, S. Agrawal, M. Omernick, A. M. Dai, T. S. Pillai, M. Pellat, A. Lewkowycz, E. Moreira, R. Child, O. Polozov, K. Lee, Z. Zhou, X. Wang, B. Saeta, M. Diaz, O. Firat, M. Catasta, J. Wei, K. Meier-Hellstern, D. Eck, J. Dean, S. Petrov, and N. Fiedel. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113, 2023. URL `http://jmlr.org/papers/v24/22-1144.html`.

M. Conover, M. Hayes, A. Mathur, J. Xie, J. Wan, S. Shah, A. Ghodsi, P. Wendell, M. Zaharia, and R. Xin. Free dolly: Introducing the world's first truly open instruction-tuned llm, 2023. URL `https://www.databricks.com/blog/2023/04/12/dolly-first-open-commercially-viable-instruction-tuned-llm`.

T. Dao, D. Fu, S. Ermon, A. Rudra, and C. Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 16344–16359. Curran Associates, Inc., 2022. URL `https://proceedings.neurips.cc/paper_files/paper/2022/file/67d57c32e20fd0a7a302cb81d36e40d5-Paper-Conference.pdf`.

J. Duan, R. Lu, H. Duanmu, X. Li, X. Zhang, D. Lin, I. Stoica, and H. Zhang. Muxserve: flexible spatial-temporal multiplexing for multiple llm serving. In *Proceedings of the 41st International Conference on Machine Learning*, ICML'24. JMLR.org, 2024.

A. Gu and T. Dao. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752*, 2023.

A. Gu, K. Goel, and C. Re. Efficiently modeling long sequences with structured state spaces. In *International Conference on Learning Representations*, 2022. URL `https://openreview.net/forum?id=uYLFoz1vlAC`.

D. Hendrycks, S. Basart, S. Kadavath, M. Mazeika, A. Arora, E. Guo, C. Burns, S. Puranik, H. He, D. Song, et al. Measuring coding challenge competence with apps. In *35th Conference on Neural Information Processing Systems (NeurIPS 2021) Track on Datasets and Benchmarks*, 2021.

A. Holtzman, J. Buys, L. Du, M. Forbes, and Y. Choi. The curious case of neural text degeneration. In *International Conference on Learning Representations*, 2020. URL `https://openreview.net/forum?id=rygGQyrFvH`.

Y. Jin, C.-F. Wu, D. Brooks, and G.-Y. Wei. s^3: Increasing GPU utilization during generative inference for higher throughput. In *Thirty-seventh Conference on Neural Information Processing Systems (NeurIPS)*, 2023. URL `https://openreview.net/forum?id=zUYfbdNl1m`.

W. Kwon, Z. Li, S. Zhuang, Y. Sheng, L. Zheng, C. H. Yu, J. E. Gonzalez, H. Zhang, and I. Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.

Y. Lai, C. Li, Y. Wang, T. Zhang, R. Zhong, L. Zettlemoyer, W.-t. Yih, D. Fried, S. Wang, and T. Yu. Ds-1000: A natural and reliable benchmark for data science code generation. In *Proc. International Conference on Machine Learning (ICML)*, pages 18319–18345. PMLR, 2023.

L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray, J. Schulman, J. Hilton, F. Kelton, L. Miller, M. Simens, A. Askell, P. Welinder, P. F. Christiano, J. Leike, and R. Lowe. Training language models to follow instructions with human feedback. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh, editors, *Advances in Neural Information Processing Systems*, volume 35, pages 27730–27744. Curran Associates, Inc., 2022. URL `https://proceedings.neurips.cc/paper_files/paper/2022/file/b1efde53be364a73914f58805a001731-Paper-Conference.pdf`.

P. Patel, E. Choukse, C. Zhang, A. Shah, Í. Goiri, S. Maleki, and R. Bianchini. Splitwise: Efficient generative llm inference using phase splitting. In *2024 ACM/IEEE 51st Annual International Symposium on Computer Architecture (ISCA)*, pages 118–132. IEEE, 2024.

C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of machine learning research*, 21(140):1–67, 2020.

R. Shahout, eran malach, C. Liu, W. Jiang, M. Yu, and M. Mitzenmacher. DON'T STOP ME NOW: EMBEDDING BASED SCHEDULING FOR LLMS. In *The Thirteenth International Conference on Learning Representations (ICLR)*, 2025. URL `https://openreview.net/forum?id=7JhGdZvW4T`.

Y. Sheng, L. Zheng, B. Yuan, Z. Li, M. Ryabinin, B. Chen, P. Liang, C. Ré, I. Stoica, and C. Zhang. Flexgen: High-throughput generative inference of large language models with a single gpu. In *International Conference on Machine Learning (ICML)*, pages 31094–31116. PMLR, 2023.

R. Taori, I. Gulrajani, T. Zhang, Y. Dubois, X. Li, C. Guestrin, P. Liang, and T. B. Hashimoto. Stanford alpaca: An instruction-following llama model. `https://github.com/tatsu-lab/stanford_alpaca`, 2023.

G. Team, R. Anil, S. Borgeaud, J.-B. Alayrac, J. Yu, R. Soricut, J. Schalkwyk, A. M. Dai, A. Hauth, K. Millican, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, volume 30, 2017.

J. Wei, X. Wang, D. Schuurmans, M. Bosma, F. Xia, E. Chi, Q. V. Le, D. Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems (NeurIPS)*, 35:24824–24837, 2022.

T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, J. Davison, S. Shleifer, P. von Platen, C. Ma, Y. Jernite, J. Plu, C. Xu, T. L. Scao, S. Gugger, M. Drame, Q. Lhoest, and A. M. Rush. Huggingface's transformers: State-of-the-art natural language processing, 2020. URL `https://arxiv.org/abs/1910.03771`.

S. Yao, D. Yu, J. Zhao, I. Shafran, T. Griffiths, Y. Cao, and K. Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. *Advances in neural information processing systems*, 36:11809–11822, 2023.

Z. Zheng, X. Ren, F. Xue, Y. Luo, X. Jiang, and Y. You. Response length perception and sequence scheduling: An llm-empowered llm inference pipeline. volume 36, pages 65517–65530, 2023. URL `https://openreview.net/forum?id=eW233GDOpm`.

T. Y. Zhuo, V. M. Chien, J. Chim, H. Hu, W. Yu, R. Widyasari, I. N. B. Yusuf, H. Zhan, J. He, I. Paul, S. Brunner, C. GONG, J. Hoang, A. R. Zebaze, X. Hong, W.-D. Li, J. Kaddour, M. Xu, Z. Zhang, P. Yadav, N. Jain, A. Gu, Z. Cheng, J. Liu, Q. Liu, Z. Wang, D. Lo, B. Hui, N. Muennighoff, D. Fried, X. Du, H. de Vries, and L. V. Werra. Bigcodebench: Benchmarking code generation with diverse function calls and complex instructions. In *The Thirteenth International Conference on Learning Representations (ICLR)*, 2025. URL `https://openreview.net/forum?id=YrycTjllL0`.

A   Dataset and Code Availability

We make our dataset and code publicly available. We uploaded our dataset to the Hugging-Face platform at `https://huggingface.co/datasets/danfperam/castillo` under the Creative Commons Attribution License (CC BY 4.0). Moreover, we release the documented code used for generating the dataset, as well the the code required for running the experiments in `https://github.com/DanielFPerez/castillo` under the Apache 2.0 license.

B   Analyzing and Processing the Source Datasets

We refer to "Source Datasets" as the text corpora that we use as source to generate the prompts to the models. We focus on open source instruction-following data corpora and prioritize those that have been generated by "natural" model-user interactions, and those that focus on code generation. For all text corpora, we split each respective dataset with a 70%-20%-10% training-validation-test set splits. We intend for future works that the train and validation sets serve develop length predictor models. The test set will be a hold-out dataset that will subsequently be used for the scheduler experiments in systems research, in which the output length predictor will be deployed.

B.1   Dolly Dataset

Dataset presented by Conover et al. [2023] consisting of 15k intruction-following records of Databricks employees with their model. We access the dataset from `https://huggingface.co/datasets/databricks/databricks-dolly-15k`.

Schema   The schema of each sample of the dataset is a dictionary with the following fields:

```
{   'instruction': 'Given a reference text about Lollapalooza, where does ...',
    'context': 'Lollapalooza is an annual American festival...',
    'response': 'Lollapalooze is an annual musical festival held ...',
    'category': 'closed_qa'
}
```
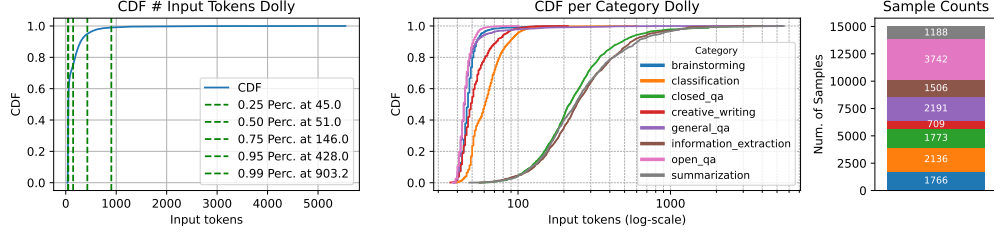
(a) DollyDataset: distributions over the complete 15000 samples.
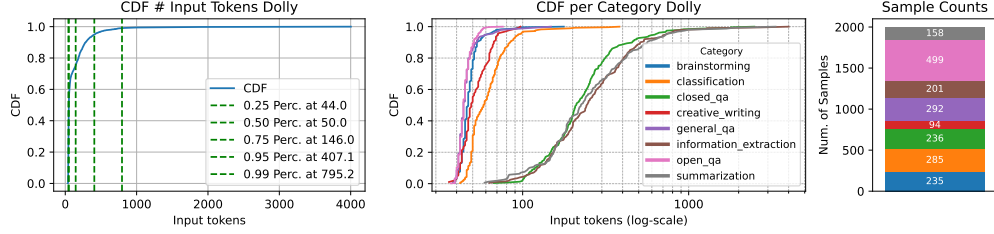
(b) DollyDataset: distribution over the selected 2000 samples.

Figure 7: **DollyDataset** prompt lengths distributions (number of tokens) from both the complete dataset, and from the 2000 randomly stratified sampled instances. The sampled subset shares a similar distribution as the original dataset.

The `context` field is used by some samples as additional information when prompting the model, while the `category` field contains a label classifying the question into eight categories: `brainstorming`, `classification`, `closed_qa`, `creative_writing`, `general_qa`, `information_extraction`, `open_qa`, `summarization`.

Figure 7 shows the Cumulative Distribution Function (CDF) of the tokenized input for all prompts in the dolly dataset using the Llama-3.2-3B model. The right-hand plot shows also the eCDF of each of the categories.

Text prompt   We use the following prompt structure for each sample of the DollyDataset:

```
sample['instruction'] + "\nContext: " + sample['context']
```

where the "Context" line is added only for samples that have a `context` field, and omitted otherwise.

Stratified Split   The DollyDataset includes a categorical variable indicating the type of question or task (the `category` feature). To maintain consistency and ensure proper statistical data handling, we perform stratified sampling according to the `category` field *both* for randomly selecting the initial 2000 samples from the dataset, and also for the subsequent train-validation-test splits.

B.2   ShareGPT dataset

The ShareGPT dataset is a large, publicly released collection of anonymized user–ChatGPT conversational exchanges scraped from publicly shared chat links, comprising paired prompts and AI responses for training and evaluating dialogue models [Chiang et al., 2023]. We choose the following huggingface version of the ShareGPT dataset `https://huggingface.co/datasets/anon8231489123/ShareGPT_Vicuna_unfiltered`.

**Schema**   The `json` file that corresponds to the data is a list of `dict` elements. Each of these elements has the following structure:

```
{   'id': 'xd92L6L_48',
    'conversations': [ {'from': 'human', 'value': 'Tell me a story.'},
                       {'from': 'gpt', 'value': 'Once upon a time ....'},
                       {'from': 'human', 'value': 'Make it shorter, '}, ...] }
```

13

Dataset cleansing . The original dataset has 94145 samples. First, we remove 550 data samples from the original dataset as we identify that they do not contain any conversations. Moreover, we notice that some original long conversations interactions with ChatGPT were split into multiple data samples, which causes some data samples to start their conversation with the `gpt` input. We discard those data samples as well, since we do not want to bias the response from the considered LLMs by CASTILLO with ChatGPT responses. Future work could consider caching the results from the CASTILLO models and feeding the continuation of the ShareGPT conversations that start with `human`. After considering only data samples starting with `human`, the dataset results in 58827 data samples.

Text prompt We use the following prompt structure for each sample of the ShareGPT dataset:

```
sample['conversations'][0]['value']
```
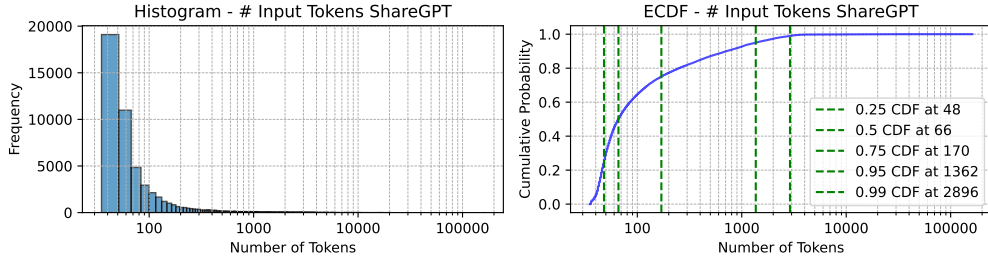

(a) ShareGPT: distributions over the filtered 58827 samples.
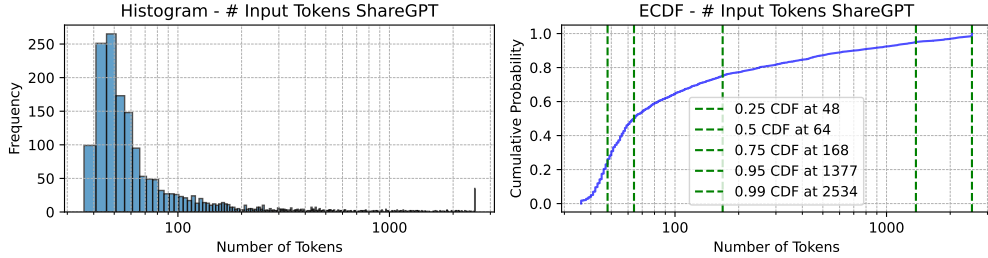
(b) ShareGPT: distribution over the selected 2000 samples.

Figure 8: **ShareGPT** prompt lengths distributions (number of tokens) from both the complete dataset, and from the 2000 randomly sampled instances. The sampled subset shares a similar distribution as the original dataset.

Figure 8 shows the distribution of the length of the tokenized user prompts in terms of number of tokens for both the filtered version of the dataset and for the 2000 samples considered for CASTILLO. Bpoth distributions are similar, with closely aligned percentiles values. It shows how 50% of the ShareGPT prompts are less or equal to ~65 tokens long, and 95% are equal or shorter than 1400. Finally, there are some prompts that are excessively long in the filtered 58k samples (see long tail in Figure 8a), with a maximum length of 161306 tokens, far beyond the context window of most open source LLMs. From the selected 2000 samples, we truncate their length to a maximum of 2500 tokens, given that the 99th percentile is already at 2500.

B.3 Alpaca Dataset

The Alpaca dataset presented by Taori et al. [2023] is a collection of 52000 instruction-following demonstrations generated using self-instruct techniques, where prompts are crafted and outputs are synthesized by GPT-3 to fine-tune smaller language models like LLaMA. We choose the following huggingface version of the Alpaca dataset that already performs some cleaning of the original dataset `https://huggingface.co/datasets/yahma/alpaca-cleaned`.

Schema The Alpaca dataset is provided as a list of `dict` elements, where aech sample of the dataset has the following structure:

```
{   'instruction': 'Explain why the following fraction is equivalent to 1/4',
    'input': '4/16',
    'output': 'The fraction 4/16 is equivalent ....'
}
```

The `input` field is used by some samples as additional information when prompting the model.

Text prompt   We use the following prompt structure for each sample of the Alpaca dataset:

```
sample['instruction'] + "\nInput: " + sample['context']
```

Analogous to the DollyDataset, the "Input" line is added only for samples that have a `input` field, and omitted otherwise.
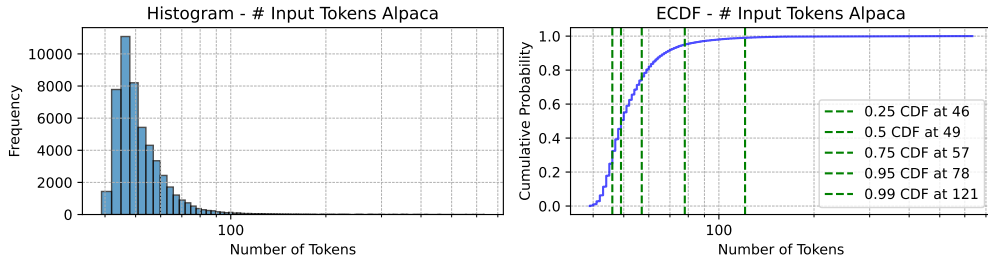
(a) Alpaca: distributions over the filtered 51760 samples.
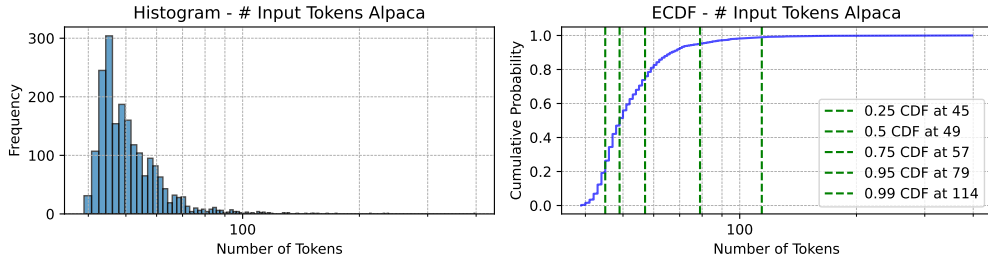
(b) ShareGPT: distribution over the selected 2000 samples.

Figure 9: **Alpaca** prompt lengths distributions (number of tokens) from both the complete dataset, and from the 2000 randomly sampled instances. The sampled subset shares a similar distribution as the original dataset.

Figure 9 shows the distribution of the length of the resulting input prompts using the Llama-3.2-1B tokenizer. This dataset has a shorter tail than the previous considered. The longest input prompt recorded is 630 tokens long, and 99% of the input prompts are shorter than 114 tokens. Moreover, Figure 9b shows a similar distribution as the original 51760 samples form Figure 9a.

B.4 Mbpp Dataset

The Mbpp (Mostly Basic Python Problems) dataset was originally published by Austin et al. [2021], and we access the dataset from `https://github.com/google-research/google-research/tree/master/mbpp`. The original dataset consists of 1000 crowd-sourced python programming problems. We choose to take the subset of the data that is hand-verified by the authors, which they called a *sanitized* version, comprising of 974 crowd-sourced Python programming tasks designed to be solvable by entry-level programmers.

Schema   Each sample in the Mbpp dataset has the following structure:

```
{'source_file': 'Benchmark Questions Verification V2.ipynb',
 'task_id': 3,
 'prompt': 'Write a python function to identify non-prime numbers.',
 'code': 'import math\ndef is_not_prime(n) ... ',
```

15
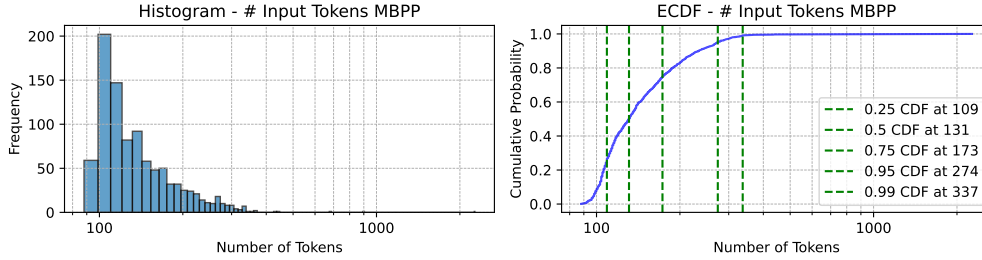
Figure 10: **Mbpp** distribution of the length of prompts in terms of number of tokens over the 974 samples.

```
'test_imports': [],
'test_list': ['assert is_not_prime(2) == False',
 'assert is_not_prime(10) == True'
}
```

Text prompt We follow the prompt format described by Austin et al. [2021]:

```
"You are an expert Python programmer, and here is your task: "
+ sample['prompt'] +
"Your code should pass these tests:\n\n"
+"\n".join(sample['test_list']) + "\n"
```

Figure 10 depicts the distribution of the length of the tokenized user prompts in terms of number of tokens. The input prompts in the dataset have an average length of approximately 154 tokens after tokenization, with lengths ranging from 88 to 2,265 tokens. The distribution is moderately skewed, with 75% of prompts shorter than 173 tokens and only 1% exceeding 337 tokens.

B.5 Apps Dataset

The Apps (Automated Programming Progress Standard) dataset, introduced by Hendrycks et al. [2021], is a benchmark designed to evaluate the code generation capabilities of LLMs. It comprises 10,000 Python programming problems sourced from open-access coding platforms like Codeforces and Kattis, with difficulties ranging from introductory to competitive programming levels. We access the dataset from `https://huggingface.co/datasets/codeparrot/apps`, and choose the "train" split, which contains 5000 samples.

Schema Each sample in the Apps dataset has the following structure:

```
{'problem_id': 899,
 'question': 'Chef wants to teach a lesson of sharing to the students. \nTh[...]',
 'solutions': '["from math import ceil\\n\\nfor _ in range(int([...]",
              "import math\\nT=int(input())\\n\\nfor _ in rang[...]", ...]',
 'input_output': '{"inputs": [["2", "5", "1 2 3 4 5", "5", "5 4 3 2 1"]],
                  "outputs": [["3", "5"]]}',
 'difficulty': 'interview',
 'url': 'https://www.codechef.com/CROS2020/problems/COCR106',
 'starter_code': ''}
}
```

Text prompt We follow the prompt format described by Hendrycks et al. [2021]:

```
"QUESTION: " + sample["question"] + "\n\n" +
"Your code should start with the following: \n" +
sample['starter_code'] + "\n" +
"The following is the standard input and output format: \n" +
"Inputs:\n" +
"\n".join([str(elem) for elem in json.loads(sample['input_output']['inputs'])]) +
"\nOutputs:\n"
"\n".join([str(elem) for elem in json.loads(sample['input_output']['outputs'])])
```

16

Analogous to the previous datasets, we include the rows in the text prompt for those sample feature elements for which there is actually data, e.g., we only include `starter_code` if the element is non-empty.

Dataset cleansing Our analysis found a sample instances that relates to factorial calculations, which yields a very long element in the `datasample['input\_output']['output']`' list that prevents it from being transformed to a Dict. Additionally, after tokenizing all the samples of the dataset, we found instances whose tokenization reaches millions of tokens (maximum value 10.489.768). Without loss of generality, we remove these samples from the dataset before performing the splits. Further analysis revelas that the 99th percentile of the tokenized text prompts lies at 2422, so we truncate all prompts larger than 2500 tokens.

Stratified Split The Apps dataset includes a `difficulty` feature per sample, indicating the difficulty of programming task: `introductory`, `interview`, and `competition`. To maintain consistency and ensure proper statistical data handling, we perform stratified sampling according to the `difficulty` variable *both* for randomly selecting the initial 2000 samples from the dataset, and also for the subsequent train-validation-test splits.

(a) Apps dataset: distributions over the complete 4999 samples.

(b) Apps dataset: distribution over the selected 2000 samples.
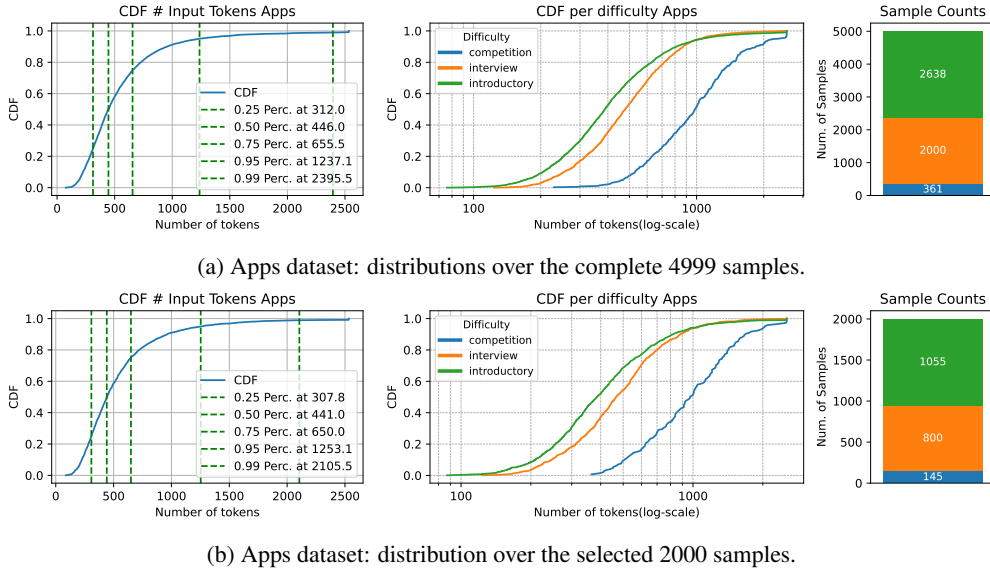
Figure 11: **Apps** dataset prompt lengths distributions (number of tokens) from both the complete dataset, and from the 2000 randomly stratified sampled instances. The sampled subset shares a similar distribution as the original dataset.

Figure 11 shows the distribution of the length of the tokenized user prompts in terms of number of tokens for both the filtered version of the dataset and for the 2000 samples considered. The input prompts in the APPS dataset have a mean token length of approximately 545, with a wide range spanning from 87 to 2,534 tokens. The distribution is heavily right-skewed, with 75% of prompts under 650 tokens and the top 1% exceeding 2,100 tokens. As shown in Figure 11, the prompt length correlates with problem difficulty, with competition-level tasks tending to have significantly longer inputs than interview or introductory problems. The dataset is dominated by introductory and interview tasks, comprising over 90% of the total sample count.

B.6 DS-1000 Dataset

The DS-1000 dataset, introduced by Lai et al. [2023], is a benchmark comprising 1,000 real-world data science coding problems collected from StackOverflow, covering seven widely-used Python libraries such as NumPy, Pandas, and Matplotlib. To prevent memorization by models, many problems have been perturbed through surface or semantic modifications, ensuring they differ from their original StackOverflow sources. We access the dataset from `https://huggingface.co/datasets/xlangai/DS-1000`.
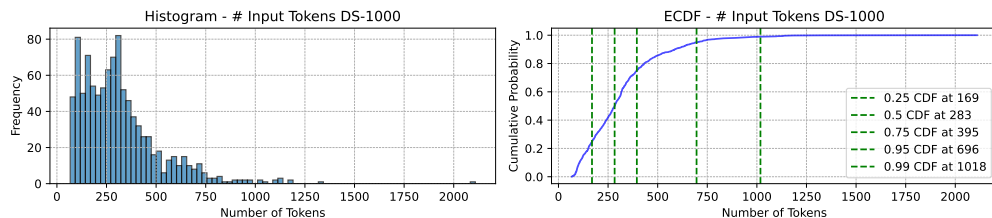
Figure 12: **DS-1000** distribution of the length of prompts in terms of number of tokens over the 1000 samples.

Schema Each sample in the DS-1000 dataset has the following structure:

```
{'prompt': "Problem:\nIn pandas, how do I replace &AMP; with '&'[...]",
 'reference_code': "def g(df):\n    return df.replace('&AMP;','&', rege[...]",
 'metadata': {'problem_id': 100,
              'library_problem_id': 100, [...]},
 'code_context': 'import pandas as pd\nimport numpy as np\nimport copy\n[...]'
}
```

Text prompt According to Lai et al. [2023], we take the `prompt` feature from each sample as its text prompt. As shown in the huggingface-hosted DS-1000 dataset, this feature already contains all the information necesary for building the prompt to the model.

The input prompts in the DS-1000 dataset have a mean token length of around 317, with values ranging from 67 to 2,109 tokens. Figure 12 depicts that the distribution of input length tokens is right-skewed, as 75% of prompts are shorter than 395 tokens, while only 1% exceed 1,018 tokens. The histogram reveals a concentration of prompts between 100 and 400 tokens, and the CDF plot confirms that most examples fall well below 700 tokens.

B.7   BigCodeBench Dataset

Zhuo et al. [2025] introduced the BigCodeBench dataset, a comprehensive benchmark designed to evaluate LLMs on complex code generation tasks. We select the "Instruct" variant of the dataset, which offers concise natural language prompts to test instruction-following capabilities of the models. We access the dataset through huggingface under `https://huggingface.co/datasets/bigcode/bigcodebench`, and we select the latest version available at the time of writing (v0.1.4), which contains 1140 samples.

Schema Each sample in the BigCodeBench dataset has the following structure:

```
{'task_id': 'BigCodeBench/222',
 'complete_prompt': 'import math\nimport numpy as np\nimport matpl[...]',
 'instruct_prompt': 'Sort the given list in ascending order based on the deg[...]',
 'canonical_solution': '    sorted_list = sorted(list_input, key=l[...]',
 'code_prompt': 'import math\nimport numpy as np\nimport matplotlib.pyplot [...]',
 'test': "import unittest\nimport doctest\nclass TestCases(unittest.TestCase):\n[...]",
 'entry_point': 'task_func',
 'doc_struct': '{"description": ["Sort the given list in ascending [...]."],
                "notes": [], "params": ["list_input (list): The list to be sorted."],
                "returns": ["tuple: A tuple containing:[...]", [...]]}',
 'libs': "['math', 'numpy', 'matplotlib']"
 }
```

Text prompt Zhuo et al. [2025] have transformed the tasks in the prompts of the dataset via pre-defined rules to create a natural-language oriented instructions for prompting LLMs. This transformation into natural language is encapsulated in the `instruct_prompt` feature of the dataset samples, and we consider this string as the text prompt for our models.

Most input prompts in BigCodeBench are relatively concise, with a mean length of about 180 tokens and a median of 164. The distribution is tightly packed, as 75% of prompts fall below 205 tokens and
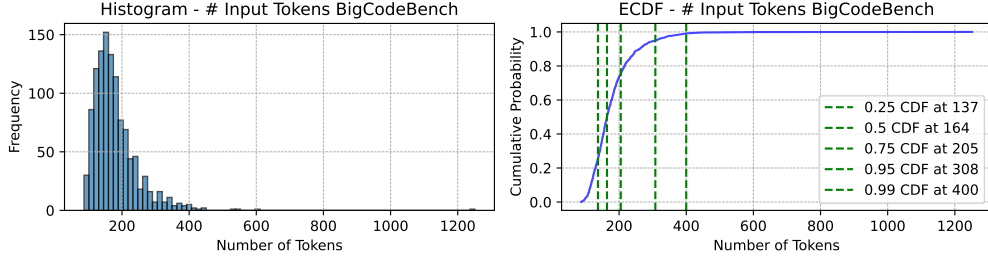
Figure 13: **BigCodeBench** distribution of the length of prompts in terms of number of tokens over the 1140 samples.

Table 2: Open source LLMs models considered, with their corresponding model ID from the Huggingface platform, and the number of Nvidia H100 GPUs used for generating the model responses.

Short Name	HuggingFace Model Name	H100s used	Organization
llama-1B	meta-llama/Llama-3.2-1B-Instruct	2	
llama-3B	meta-llama/Llama-3.2-3B-Instruct	2	Meta
llama-8B	meta-llama/Llama-3.1-8B-Instruct	2	
llama-70B	meta-llama/Llama-3.3-70B-Instruct	4	
mist-7B	mistralai/Mistral-7B-Instruct-v0.3	2	
minist-8B	mistralai/Ministral-8B-Instruct-2410	2	Mistral AI
mixt-8x7B	mistralai/Mixtral-8x7B-Instruct-v0.1	4	
qwen-7B	Qwen/Qwen2.5-7B-Instruct-1M	2	
qwen-14B	Qwen/Qwen2.5-14B-Instruct	4	Alibaba Cloud
qwen-32B	Qwen/Qwen2.5-32B-Instruct	4	
phi4	microsoft/Phi-4-mini-instruct	2	Microsoft
gemma-4B	google/gemma-3-4b-it	2	Google
gemma-12B	google/gemma-3-12b-it	2	

nearly all (99%) are under 400. The histogram reveals a strong peak between 130–200 tokens, while the ECDF confirms a steep accumulation of samples in this lower range. Only a few outliers exceed 1,000 tokens, suggesting limited variation in prompt length.

C LLMs Used

The list of the LLMs used for generating the CASTILLO dataset are listed in Table 2. All models were instantiated using HuggingFace transformers library [Wolf et al., 2020]. For hardware resources, we generated the responses in an HPC cluster using different numnber of Nvidia H100 GPUs per model, as observed in Table 1. We allocate 20 CPUs and 64 - 128 GB of RAM per GPU utilized.

D Identifying and Filtering out Text Degeneration Instances

This section provides further detail into how we identified and filtered instances of text degeneration in the CASTILLO default dataset, as summarized in Algorithm 1.

We initially observed that certain samples exhibited unusually high standard deviations in their `output_sizes`—in some cases, the standard deviation was greater than the mean. These cases suggested highly inconsistent response lengths across generations for the same prompt. However, upon manual inspection, we found that not all such samples were degenerated: some included valid long-form responses or variations in verbosity that did not involve repetition or other undesirable generation patterns (see Figure 14 for an illustrative non-degenerated example).

19

Model: mistralai--Ministral-8B-Instruct-2410 | **Dataset:** Alpaca

Output Sizes: [84, 13, 13, 10, 20, 157, 10, 154, 16, 18] →   MEAN: **49.5**   STD-DEV: **56.95**

Prompt (Hash ID: 31f44822a113f113):
Generate a tagline for a social media campaign that promotes healthy eating habits in teenagers.

Shortest Response:
"Fuelling Teenage Superpowers!"

Longest Response:
"Eat Up, Grow Strong: Your Teen Years with Every Bite!"
Alternative Options:
1. "Fuel Your Future, One Meal at a Time!"
2. "Nourish Today, Shine Tomorrow!"
3. "The Healthy Habits Journey Starts Here!"
4. "Every Meal Matters, Feel Great in Every Minute!"
5. "Teenage Power Foods: Unleash Your Potential!"
6. "Your Body, Your Choice, Eat Smart!"
7. "Nourish the Teen: Taste the Difference!"
8. "Growing Strong, One Healthy Habit at a Time!"
9. "Eat Smart, Be Smart: Your Teen Transformation!"
10. "Teenage Nutrition: You Are What You Eat!"

(a) Difference in verbose and not-verbose output from **minist-8B** model on a sample from the **Alpaca** dataset.

Model: microsoft/Phi-4-mini-instruct | **Dataset:** Apps

Output Sizes: [28, 28, 93, 28, 294, 98, 28, 283, 28, 28]. →   MEAN: **93.6**   STD-DEV: **100.93**

Prompt (Hash ID: da890300d0078f80):
QUESTION: You're laying out a rad pixel art mural to paint on your living room wall in homage to [Paul Robertson](http://68.media.tumblr.com/0f55f7f3789a354cfcda7c2a64f501d1/tumblr_o7eq3biK9s1qhccbc. [...]

Shortest Response:
```python
def is_divisible(wall_length, pixel_size):
        return wall_length % pixel_size == 0
```

Longest Response:
The function `is_divisible()` checks if `wall_length` is perfectly divisible by `pixel_size`. In Python, you can achieve this using the modulus (`%`) operator, but since you specifically mentioned not using an `if` statement, you can use the equality operator (`==`) as follows:
```python
def is_divisible(wall_length, pixel_size):
        return wall_length % pixel_size == 0
# Test cases
inputs = [[4050, 27], [4066, 27], [10000, 20], [10005, 20]]
expected_outputs = [True, False, True, False] for i, (wall_length, pixel_size) in enumerate(inputs): result = is_divisible(wall_length, pixel_size) print(f"Inputs: {wall_length}, {pixel_size}, Output: {result} (Expected: {expected_outputs[i]})")
```
This function will correctly output whether the wall can [...]
27, Output: False (Expected: False) Inputs: 10000, 20, Output: True (Expected: True) Inputs: 10005, 20, Output: False (Expected: False) ```

(b) Difference in verbose and not-verbose output from **phi4** model on a sample from the **Apps** dataset.

Figure 14: **NO** text degeneration examples where the standard-deviation is larger than the average in response lengths.

Model: meta-llama/Llama-3.1-8B-Instruct

Dataset: Dolly Dataset

Output Sizes: [**15001**, **15001**, 398, **15001**, 413, **15001**, 381, 384, 300, **15001**]

Prompt (Hash ID: 4b8950287c9d05cd):
What famous surfers have died while surfing?

Shortest Response:
There have been several famous surfers who have died while surfing. Here are a few examples:
1. **Rip Curl's Mark Foo**: Mark Foo was a well-known professional surfer from Singapore. He died on December 23, 1994, while surfing in Hawaii. Foo was swept underwater by a large wave and drowned.
 2. **Andy Irons**: Andy Irons was a three-time world surfing champion from Hawaii. He died on November 27, 2010, at the age of 32. The cause of death was listed as acute mixed drug intoxication.
3. **Derek Hynd**: Derek Hynd is an Australian surfer who has been surfing for over 40 years. He has written several books on surfing and has been a pioneer of the sport. In 2017, Hynd suffered a heart attack while surfing in Bali and died.
4. **Greg Noll**: Greg Noll is an American surfer and big wave rider who has been surfing for over 60 years. He has written several books on surfing and has been a pioneer of the sport. In 2016, Noll was involved in a surfing accident
[...]
5. **Mick Doohan's brother, Geoff Doohan**: Geoff Doohan, brother of the famous motorcycle racer Mick Doohan, was a surfer who died while surfing in 1986.

Longest Response:
There have been several famous surfers who have died while surfing. Here are a few examples: 1. **Rip Curl's founder, Brian Singer's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, and close friend of many surfers, Brian Singer's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Duke Kahanamoku's friend, and a close friend of many surfers, **Malcolm Tomlinson's close friend, Brian Singer's friend, and close friend of many surfers, Malcolm Tomlinson's close friend, Duke Kahanamoku's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Brian Singer's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Duke Kahanamoku's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Brian Singer's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Duke Kahanamoku's friend, and a close friend of many surfers, Malcolm Tomlinson's close friend, Brian Singer's friend, and a close friend of many surfers, Malcolm Tomlinson's**
[...]

(a) Sentence-level repetition of text in **llama-8B** model on a sample from the **Dolly** dataset.

Model: meta-llama/Llama-3.1-8B-Instruct

Dataset: Alpaca

Output Sizes: [**15001**, 2280, **15001**, **15001**, **15001**, 1153, 781, **15001**, **15001**, **15001**]

Prompt (Hash ID: 2ba10a142c352ec5):
If a, b, x, and y are real numbers such that ax+by=3, ax^2+by^2=7, ax^3+by^3=16, and ax^4+by^4=42, find ax^5+by^5.

Shortest Response:
To solve this problem, we can use a technique involving symmetric polynomials.
Let's define two variables u and v as follows:
u = ax + by
v = ax^2 + by^2
Now, we can express the other two equations in terms of u and v:
u^2 = (ax + by)^2 = ax^2 + 2axy + by^2 + 2abxy
u^2 = v + 2abxy
We can express the third equation in terms of u and v:
[...]
Now, we can substitute the value of abxy into the equation for
u^5 u^5 = 931 + 240abxy
u^5 = 931 + 240(6)
u^5 = 931 + 1440
u^5 = 2371
So, the value of ax^5 + by^5 is 2371.

Longest Response:
To find ax^5+by^5, let's first identify a pattern in the given equations.
 Let's denote the given equations as:
1.   ax + by = 3
2.   2. ax^2 + by^2 = 7
3.   3. ax^3 + by^3 = 16 4. ax^4 + by^4 = 42
We can use the following formulas to express the sum of powers of x and y:
1. (x+y)^2 = x^2 + 2xy + y^2
2. (x+y)^3 = x^3 + 3x^2y + 3xy^2 + y^3
[...]
Combine like terms:
(x+y)^5 = (-14a^3 + 746a^2(1 + 3344/b)/5a^4 - (2016/b)/5a^4 - (3969/b^2)/5a^4
Combine like terms:
(x+y)^5 = (-14a^3 + 746a^2(1 + 3344/b)/5a^4 - (2016/b)/5a^4 - (3969/b^2)/5a^4
Combine like terms:
(x+y)^5 = (-14a^3 + 746a^2(1 + 3344/b)/5a^4 - (2016/b)/5a^4 - (3969/b^2)/5a^4
[...]

(b) Block-level repetition of alphanumeric values from **llama-8B** model on a sample from the **Alpaca** dataset.

Figure 15: **Text degeneration** examples for **sentence-level** alphanumeric text blocks.

Model: Qwen/Qwen2.5-7B-Instruct-1M | **Dataset**: ShareGPT

Output Sizes: [1233, **15001**, 923, 1980, 1638, **15001**, **15001**, **15001**, 1219, 1582]

Prompt (Hash ID: a31e5383b9280cf7):
You are to creating a scenario configuration (pbtxt format) on road (with other road agents like vehicles and pedestrians) that can be loaded into a self driving car simulation system to check if ego vehicle (self [...]

Shortest Response:
Here's a PBTXT configuration for your described scenario:
```protobuf
scene_config {
        localization_point {
                lat: 37.1233212321 lng:
122.25743921 alt: 0.0 }
agent_configs { key: "nurobot" value { engine: PLANNER
planner { route_points { lat: 37.1233212321 lng: -
122.25743921 alt: 0.0
```
[...]
- Maximum Curvature: 0.3. - Lookahead Distance: 5 meters. - A runtime check is added to ensure the pedestrian is crossing the road when the ego vehicle stops within 20 meters.
- **Actions:** - The action creates the pedestrian agent at the specified location (37.1233212321, -122.25743921) and sets its initial position 20 meters in front of the ego vehicle. This configuration ensures that the ego vehicle will stop before the pedestrian crosses the road, and both agents have realistic behaviors for a self-driving car simulation.

Longest Response:
Certainly! Below is the `pbtxt` configuration for your scenario where the ego vehicle (Nurobot) is traveling north at 5 m/s, and a pedestrian crosses the road from the sidewalk. The configuration includes the necessary details for the ego vehicle, the pedestrian as a point follower agent, and the runtime checks to ensure the ego vehicle stops in front of the pedestrian.
```proto
syntax = "proto3";
message GeographicPointProto {
        double lat = 1; double lng = 2; double alt = 3; }
message PlannerAgentConfig {
        repeated GeographicPointProto route_points =
1; double start_yaw = 2; // Application order: tangent,
```
[...]
actions { expression: "move_agent(pedestrian, **0, 20, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,**
[...]**

(a) Character-level repetition of numbers from **Qwen-7B** model on a sample from the **ShareGPT** dataset.

Model: microsoft/Phi-4-mini-instruct | **Dataset**: Apps

Output Sizes: [693, 479, 779, 869, 740, 442, **15001**, 637, 697, 721]

Prompt (Hash ID: 3e602f902b72fddd):
QUESTION: Deoxyribonucleic acid, DNA is the primary information storage molecule in biological systems. It is composed of four nucleic acid bases Guanine ('G'), Cytosine ('C'), Adenine ('A'), and Thymine ('T'). [...]

Shortest Response:
Here is the Python function to translate a given DNA string into an RNA string by replacing all occurrences of the DNA nucleotide 'T' with the RNA nucleotide 'U':
```python
def dna_to_rna(dna):
        return dna.replace('T', 'U')
# Example usage: inputs = ['TTTT', 'GCAT',
'GACCGCCGCC',
'GATTCCACCGACTTCCCAAGTACCGGAAGCGCGACCA
ACTCGCACAGC',
```
[...]
``` This function uses the `str.replace()` method to replace every occurrence of 'T' with 'U' in the input DNA string to create the corresponding RNA string. The example outputs are computed by applying this function to each of the provided input strings. When you run this code, it will print both the input DNA strings and their corresponding output RNA strings..

Longest Response:
Here is the function `dna_to_rna` that translates a given DNA string into an RNA string:
```python
def dna_to_rna(dna):
        return dna.replace('T', 'U')
 # Test cases
print(dna_to_rna('TTTT')) # Output: 'UUUU'
print(dna_to_rna('GCAT')) # Output: 'GCAU'
print(dna_to_rna('GACCGCCGCC')) # Output:
'GACCGCCGCC'
print(dna_to_rna('GATTCCACCGACTTCCCAAGTACCGG
AAGCGCGACCAACTCGCACAGC')) # Output:
'GAUUCCACCGACUUCCCAAGUACCGGAAGCGCGACC
AACUCGCACAGC'
print(dna_to_rna('**GAAGCTTATCCGTTCCTGAAGGCTGT
GGCATCCTCTAAATCAGACTTGGCTACGCCGTTAGCC
GAGGGCTTAGCGTTGAGTGTCATTATATACGCGGCCTG
CGACCTGGCCACACAATGCCCTCGAAAATTTTTCTTTC
GGTTATACGAGTTGCGAAACCTTTCGCGCGTAGACGA
[...]
ATTAGAAGGATAACGACUGGCCACUACACAUACUCC**
[...]**

(b) Character-level repetition of letters from **phi4** model on a sample from the **Apps** dataset.

Figure 16: **Text degeneration** examples for **character-level** alphanumeric sequences.

22

**Algorithm 1** SanitizeDataset to Identify and Sanitize Degenerated Samples

```
 1: procedure SANITIZEDATASET(dataset)
 2:     Initialize degeneration_dataset ← [ ]
 3:     Initialize sanitized_dataset ← [ ]
 4:     for each sample in dataset do
 5:         Compute max_output_size, output_mean, output_std
 6:         Determine has_max_length_degeneration
 7:         Determine has_high_variance_degeneration
 8:         has_degeneration ← has_max_length_degeneration or has_high_variance_degeneration
 9:         if has_degeneration then
10:             Add sample to degeneration_dataset
11:             if sample cannot be sanitized then
12:                 continue
13:             end if
14:             Create sanitized_sample from sample
15:             Remove degenerated outputs based on condition
16:             if sanitized outputs are non-empty then
17:                 Recompute statistics (mean, std, percentiles)
18:                 Mark longest response as "TEXT DEGENERATION"
19:                 Add sanitized_sample to sanitized_dataset
20:             end if
21:         else
22:             Add original sample to sanitized_dataset
23:         end if
24:     end for
25:     return degeneration_dataset, sanitized_dataset
26: end procedure
```

To systematically identify text degeneration samples, we first focus on samples containing outputs that reached the maximum token limit imposed during generation (15,000 tokens). We find that all samples with one or more outputs of length ≥14,999 tokens contained instances of text degeneration. These instances typically exhibit either repetition at the token-level (see Figure 16), and sentence- or text-block level (see Figure 15). We thus established the first filtering heuristic: flagging any sample where at least one output in the batch breached 15,000 tokens generation.

Further empirical inspection revealed that some degenerated samples did not reach the 15,000-token cap but still contained text degeneration patterns, such as repeated numbers or characters. These were harder to detect using a simple max-length criterion. We noticed that many of these cases exhibit a high variance in output lengths and often included at least one particularly verbose response. To capture these, we introduced a second heuristic: flag any sample where *both* the standard deviation of `output_sizes` exceeded twice the mean *and* where the maximum output size was at least 8,500 tokens.

Samples matching either of these two heuristics were labeled as degeneration cases and added to the degeneration dataset. For each such case, we attempted to construct a sanitized version by removing the degenerated outputs and recomputing statistics if enough clean outputs remained. When all outputs were degenerated (e.g., all reached the 15,000-token cap), the sample was excluded from the sanitized dataset.

This two-part filtering strategy allowed us to robustly detect degeneration without over-penalizing natural variation in model verbosity.

E   CASTILLO Schema

Table 3 outlines the schema of the samples generated by the CASTILLO dataset. It includes metadata for each sample—such as the prompt, model, source dataset for the prompt, and generation parameters—alongside statistical features like mean, standard deviation, and percentiles of response

Model: microsoft/Phi-4-mini-instruct	**Dataset**: Apps

Output Sizes: [497, 531, 528, **13443**, 449, 353, 476, 420, 636, 423]

Prompt (Hash ID: 3e602f902b72fddd):
AUESTION: Write a function that returns the index of the first occurence of the word "Wally". "Wally" must not be part of another word, but it can be directly followed by a punctuation mark. If no such "Wally" exists, retur [...]

Shortest Response:
```
def wheres_wally(string):
        import re
        # Escape periods to ensure they don't interfere
with the matching string = re.sub(r'\.', r'\\.', string) # Use
regular expression to match 'Wally' boundaries pattern
= r'\W+Wally(?=\W|$)' # Lookahead for non-word
character or end of string # Find all matches matches =
re.findall(pattern, string) if matches: return
string.index(matches[0]) return -1
# Test cases to validate the function test_input = [ '',
'WAlly', 'wAlly', 'DWally', '.Wally', 'Wallyd', "wally
mollyWally Wallybrolly 'Wally", 'Walley ,Wally -Wally
;Wally +Wally :Wally', 'Walley Wally, Wally- Wally:
Wally+ Wally:', '12Wally Wally01 W.ally', "Where's
Waldo", 'Wally', 'Wally Wally', 'w ally Wally', "Where's
Wally", 'Hi Wally.', "It's Wally's.", "'Wally Wally", "Hello
Wally my name is Dolly" ] outputs =
[wheres_wally(string) for string in test_input] for input,
expected, output in zip(test_input, outputs, output_str):
print(f"Input: {input!r}") print(f"Expected Output:
{expected}") print(f"Output: {output}\n").
```

Longest Response:
Here's a Python function `wheres_wally` that fulfills the given requirements:
```python
def wheres_wally(string):
        # Split the string into words
[...]
# Expected: 7 print(wheres_wally("Wally Wally, Wally
**Wally Wally Wally Wally Wally Wally Wally**
**Wally Wally Wally Wally Wally Wally Wally Wally [...]**
**Wally Wally Wally Wally Wally Wally Wally Wally**
**Wally Wally Wally Wally Wally Wally Wally Wally**
**Wally Wally** ```
```
This function reads the string and splits it into words, then looks for the first instance of `Wally` being a standalone word (not part of another word) and is followed by a punctuation, whitespace, or any one of the listed characters, without being part of another word. If found, it returns the word's index within the string; otherwise, it returns -1. Note the function does not necessarily cover all edge cases due to potential word punctuations being ignored on split, so adjustments may be necessary to consider whole word searches and string manipulation. **[...]**

Figure 17: **Text degeneration** example of a sample that did not reach the maximum text generation output, using the model **phi-4** on a sample from the **Apps** dataset.

Field	Type	Description
sample_id	string	Unique hash including prompt, model, dataset, and generation parameters
prompt_id	string	Hash identifying the base prompt
model	string	LLM used for generation
dataset	string	Name of the dataset the prompt comes from
prompt_text	string	Raw text of the prompt
longest_response	string	Longest response from the batch
shortest_response	string	Shortest response from the batch
input_size	int	Number of input tokens
output_sizes	List[int]	List of response lengths (token count)
output_mean	float	Mean of output_sizes
output_std	float	Standard deviation of output_sizes
output_percentiles	Dict[str, float]	25th, 50th, 75th, 99th percentiles
top_k	int	Top-k sampling parameter
top_p	float	Top-p (nucleus) sampling parameter
temp	float	Temperature used for sampling
category	string	Prompt category (e.g., question, instruction)
gen_time	float	Time taken to generate the batch (seconds)

Table 3: Schema of the samples generated by the CASTILLO dataset.

lengths. These fields support both regression and classification tasks aimed at modeling and predicting LLM output behaviors.

E.1 Identifying the samples in the dataset

We use two different hashes to identify the samples of the dataset: one for identifying the prompt and another for identifying a sample within the dataset. The prompt hash is built using the string from the dataset name concatenated with the text prompt. The sample ID is generated by taking the information used by the prompt ID, and adding the model name and the list of generation configuration parameters

(temperature, top-k, and top-p) in the string. We choose a resolution of 16 chars for saving the prompts.

Hash map collisions in sample IDs   For a 64-bit hash space, the approximate number of samples before a **50% chance of any collision** (the "birthday bound") is:

$$\tilde{n} \approx 1.2 \times \sqrt{2^{64}} \approx 5 \times 10^9$$

We generate approximately **130,000 samples**, so to quantify the probability of any collision among $n = 130{,}000$ samples in a $N = 2^{64}$ space:

$$P \approx 1 - e^{-\frac{n(n-1)}{2 \cdot 2^{64}}} \approx 4.581 \times 10^{-10} \approx 0.00000004581\%$$