Is Your LLM Outdated? A Deep Look at Temporal Generalization

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Abstract

The rapid advancement of Large Language Models (LLMs) has led to the development of benchmarks that consider temporal dynamics, however, there remains a gap in understanding how well these models can generalize across temporal contexts due to the inherent dynamic nature of language and information. This paper introduces the concept of temporal generalization in LLMs, including bias in past and future generalizations. Then we introduce FreshBench, a new evaluation framework that employs fresh text and event prediction for assessing LLMs' temporal adaptability, ensuring the evaluation process free from data leakage and subjective bias. The experiment shows significant temporal biases and a decline in performance over time. Our findings reveal that powerful models, while initially superior, tend to decline more rapidly in future generalization. Additionally, powerful open-source models demonstrate better long-term adaptability compared to their closed-source counterparts. Our code is available at https://github.com/FreedomIntelligence/FreshBench

1 Introduction

Proprietary large language models (LLMs) OpenAI (2023); GoogleAI (2023); Anthropic (2023); Anil et al. (2023) has been paralleled by efforts in the open-source community to democratize LLMs. Meanwhile, the rapid advancement of LLM democratization Touvron et al. (2023) emphasizes the necessity for dynamic and robust benchmarks that accurately reflect their evolving capabilities. Traditional benchmarks, broadly classified into knowledge-based assessments and open-dialogue evaluations, each present unique challenges. Knowledge-based assessments, exemplified by MMLU Hendrycks et al. (2021) and C-Eval Huang et al. (2023), are prone to data manipulation, raising concerns about their real-world applicability and the risk of data leakage Wei et al. (2023); Golchin and Surdeanu (2024). Open-dialogue evaluations like MT-Bench Zheng et al. (2023) and Alpaca-Eval Li et al. (2023a), rely on subjective human or model-based judgments, making their outcomes susceptible to the influence of dialogue structure, and thereby, potentially compromising assessment validity.

Given the limitations of traditional methods, researchers are increasingly developing new approaches to evaluate models in diverse and dynamic contexts. For instance, recent efforts have introduced methods that assess models' abilities to handle temporal evolution, contextual understanding, and real-time information updates Fatemi et al. (2024); Kasai et al. (2024); Vu et al. (2023); Chen et al. (2021); Zhang and Choi (2021); Liška et al. (2022). While methods like RealTimeQA and FreshQA focus on continuously updating knowledge for real-time processing Kasai et al. (2024); Vu et al. (2023), others like LatestEval Li et al. (2023b) emphasize recent text-based comprehension. In contrast, our work shifts the focus to evaluating models' world understanding through prediction, using a fact-based approach that minimizes bias and ensures objectivity in assessment. This method enhances robustness against data contamination and focuses on the model's capacity for accurate, real-world event prediction.

We believe that the evaluation of LLMs should be conducted in scenarios that are resistant to hacking manipulation, with results that are objective and **free from evaluator biases** Chen et al. (2024). Additionally, time as a dynamic dimension, can also ensure robust and relevant evaluations. This paper explores an alternative way to **evaluate large language models**, i.e., **on temporal generalization** where time is considered as an important aspect. This approach significantly reduces the issue of data contamination by limiting access to future content. Moreover, a retrospective perspective on

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time could be beneficial for temporal bias analysis for LLMs.

To achieve this goal, we design two scenarios. The first is to have the model generate text based on recent data such as arXiv papers, news articles, new books, and Wikipedia content. An excellent model should be able to generalize these new texts with high language likelihood without data leakage. The second scenario focuses on future event prediction. An excellent model should be able to understand the current context, integrate world knowledge, and effectively generalize to future scenarios. In these two scenarios, temporal generalization evaluation has two main advantages: eliminating the possibility of data leakage through temporal boundaries and enabling objective evaluation results without relying on subjective interpretations.

Our analysis indicates that using validation loss of new text to evaluate models is mostly effective. However, we observe that while performance on language likelihood is a strong indicator of a model's linguistic capabilities, it does not always align with specific abilities measured by existing benchmarks, which may represent discrete knowledge or other capacities that are important but not directly related to language modeling.

Our **contributions** are as follows: 1) We define and quantify temporal generalization and bias, establishing a basis for understanding and assessing the capabilities of LLMs over time. 2) We proposed a benchmark Freshbench to test the capabilities of LLMs in predicting future events. This benchmark is dynamically updated to reflect the latest data, ensuring that our evaluations remain relevant and accurate in the face of rapidly evolving data environments. It experimentally assesses the performance of existing LLMs across various timeframes, providing insights into their historical and ongoing performance stability and adaptability.

2 Conceptualization of Temporal Generalization

In this section, we will first conceptualize *Temporal Generalization*, then *Temporal Biases* and *Temporal Degeneration* in Sec. 2.1. We will discuss ways to measure /textitTemporal Biases and Degeneration in 2.2.

2.1 Temporal Generalization

LLMs face the ongoing challenge of remaining applicable as new text evolves. Consequently, it is crucial for these models to not only understand and generate text based on seen (e.g., past) data but also to anticipate and adapt to future data. This inspires temporal generalization as below.

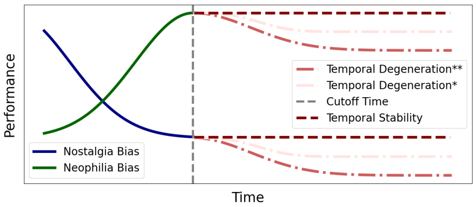

Figure 1: Schematic figure of temporal generalization. In general, prior to the cutoff time, an LLM might exhibit a Nostalgia bias that is skewed toward past dates (i.e., aligning better with historical data) or a Neophilia bias that is skewed toward future dates (favoring more recent information). However, after the cutoff time, the model's understanding of future trends declines, leading to temporal degeneration.

Definition 2.1. Temporal Generalization refers to the LLMs' ability to align with the contexts of the past, present, and future.

This requires the models to integrate and apply knowledge from historical and current data to adapt to the evolution of language and emerging trends. Temporal generalization highlights the challenge of designing models that remain effective and accurate over time, without the need for frequent re-training as new data is introduced. LLMs must maintain a delicate balance between leveraging historical data to understand long-standing language patterns and adapting to new expressions, terminology, and topics as they emerge.

2.1.1 For Models: Define Past, Present and Future

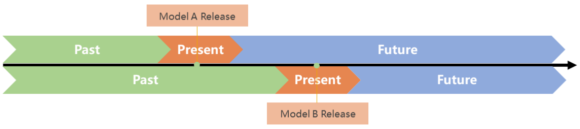

Figure 2: Schematic Diagram of 3 Periods of Models

To distinguish the *past* and the *future*, we define the cutoff time as the release date of the model. For instance, if an LLM is released in January 2024, then all events or information before January 2024 are considered part of the *past*, while everything after January 2024 is considered the *future*. Although the data after the cutoff time is not strictly future data, this approach ensures no data leakage for the model. As is shown in Figure 2, the period near the cutoff time can be referred to as the *present*. We evaluate the model's prediction accuracy across these time periods, denoted as acc_{past}, acc_{future}, and acc_{present}, respectively.

2.1.2 Define Temporal Bias and Temporal Degeneration

With the three time periods defined, we can define Temporal Bias and Temporal Degeneration for models.

Definition 2.2. Temporal Bias In this paper, we define temporal bias as the preferences of LLMs over time. [1]

There exist two biases, namely **Nostalgia Bias** and **Neophilia Bias**, which reflect two contrasting tendencies in how these models might predict or generate text about the past, present, or future. A visual representation of these biases is provided in Fig. 1, where the trends associated with Nostalgia and Neophilia biases are plotted over time.

Nostalgia Bias refers to the over-reliance on historical data when generating text. This bias causes models to reflect perspectives, styles, or information prevalent in past training data, leading to outputs that may not account for recent developments. Essentially, Nostalgia Bias can make a model seem 'stuck in the past', limiting its ability to accurately represent the present or predict the future.

Neophilia Bias implies a model's overemphasis on novelty and future trends, potentially at the expense of established information. This bias could result in predictions that are overly speculative and not well-grounded in historical data or current realities. Though less common due to LLM training on historical datasets, Neophilia Bias could be perceived from prompt structuring or interpretation of outputs that prioritize futuristic concepts over historical accuracy.

Definition 2.3. Temporal Degeneration refers to the decline in a model's performance in the future, that is, after it is released.

In conclusion, the illustration for the above concepts is in Figure 1.

2.2 Assessing Temporal Generalization

Based on definition in Sec. 2.1, we turn to assess temporal generalization through the lens of 1) I: compression intelligence in Sec. 2.2.1 and II): future event prediction in Sec. 2.2.2.

2.2.1 Case I: Compression Intelligence

In the assessment of compression intelligence, metrics such as perplexity (PPL) and bits per character (BPC) offer insights into model performance. We refine our focus to BPC for a more normalized comparison. Unlike traditional BPC which is specific to character-level language models, our **adapted Bits Per Character (BPC)** metric offers a comparison between models by normalizing the log likelihood based on character count, irrespective of the tokenization method, allowing for a more **equitable assessment of model performance** across different languages and tokenization schemes, the BPC is calculated as follows:

$$BPC(T) = \frac{-\sum_{i=1}^{N} \log p(w_i | w_1, \ldots, w_{i-1})}{\text{len-utf-8}(T)} \quad (1)$$

Here, T represents the text being analyzed, N is the number of tokens in T (which may vary depending on the tokenizer), and len-utf-8(T) is the length of T when encoded in UTF-8, measured in characters. The tokens w_i correspond to segments of text which may vary depending on the tokenizer used. This variance is due to different tokenization methods splitting the text into tokens at different granularities, ranging from subword units to characters. In this paper, we investigate the compression intelligence proposed in Huang et al. (2024) in a temporal manner,

2.2.2 Case II: Future Event Prediction

LLMs could perform *future event prediction*, as seen in Bonde (2022) which employed GPT-3 in a few-shot setting to tackle binary questions from the Metaculus platform. Further, Zou et al. (2022) enriched the discourse by introducing a comprehensive dataset that includes forecasting questions alongside a news corpus. This approach enhances model training by incorporating varied and relevant data contexts. Moreover, Halawi et al. (2024) showcased how integrating news content can significantly improve the accuracy of predictions in real-time scenarios.

Building on this foundation, our research seeks to explore the temporal generalization capabilities

[1] Temporal bias are multifaceted in previous literature. For instance, can refer to the assumption of an incorrect sequence of events that misleads our reasoning about causality Dorsey (2021) or user preferences over time in point-of-interest recommendations Rahmani et al. (2022). Recently, biases have raised more challenges in pre-trained language models Yogarajan et al. (2023), particularly focusing on under-represented societies. Sarkar and Vafa (2024) examines lookahead bias in pre-trained language models, providing insights into how these biases affect model performance.

of LLMs: *how well they adapt and remain accurate as new data emerges and contexts evolve?* As an example of using LLMs to predict political outcomes, we gather new factual data about future events, such as "`What will President Biden's approval rating be as of 7 June 2024, according to FiveThirtyEight?`". To ensure objectivity in our predictions, answers are typically formatted as ranges within a prediction market scenario. For instance, President Biden's approval rating might be categorized into intervals such as `lower than 34%`, `at least 34.0%, but less than 36.0%`, `at least 36.0%, but less than 38.0%`, up to `46.0% or higher`.

However, since collecting actual future data is impossible, we adopt a retrospective study approach. We use data available after the event's question was posed and before the prediction market's closure, treating this as "future" data for model evaluation. This ongoing, online evaluation objectively assesses the model's predictive capability. We define prediction accuracy, denoted by Acc, as follows:

$$Acc = \frac{N_{\text{correct}}}{N_{\text{total}}} \tag{2}$$

where N_{correct} is the number of correct predictions among N_{total} future prediction questions. See. Sec. 4.1 for the collected future prediction question set over time. This metric evaluates the effectiveness of LLMs in predicting future events. This approach also allows continuous evaluation with the latest data, ensuring the assessment reflects the model's current capabilities and the evolving information landscape.

3 Temporal Generalization through the Lens of Compression Intelligence

This section discusses how various models handle data from different periods, showcasing their performance stability or volatility.

Key Findings

- In general, while the ranking of models varied slightly between datasets, the performance of individual models remained relatively stable over time within each dataset type, as can be seen in Figure 3 and 4. Here we made a discovery regarding the distinct characteristics of the Wikipedia and BBC datasets at 3.1.2.

- Another interesting observation was made in the arXiv dataset shown in Figure 5, where a sharp decrease in BPC occurred around March 2024. This timing coincides with the peak in ChatGPT usage, as reported by Exploding Topics[2], which saw over 1.8 billion visits in that month. In essence, it appears that humans may be adapting their writing to more closely resemble LLM outputs, rather than LLMs significantly enhancing their ability to model human language.

3.1 Temporal Bias

3.1.1 Protocol for Quantitative Measurement

Data sources Our system aggregates data from various platforms, including Yahoo for financial news, BBC for political insights, Reddit for discussions, Wikipedia for encyclopedic updates, arXiv for academic research, GitHub for software trends, and Quora for diverse questions and answers. Utilizing a Python-based crawling framework, it's designed for adaptability and efficient data collection, with Playwright addressing navigation and specific site challenges. We also did some basic data pre-processing, due to space limitation, details in Appendix F. An overview of the data volume and the average entry length from a single crawl is provided in Appendix G. Experiment settings are listed in Appendix A.

3.1.2 Observation of Temporal Bias in Compression Intelligence

To comprehensively explore the temporal generalization capabilities of models, we plot the BPC curve over time.

In text data before release, a negative slope indicates the presence of Neophilia Bias. Conversely, a positive slope would suggest that the model's performance is decreasing, which shows Nostalgia Bias.

ArXiv BPC has a huge decline after GPT is widely used, as mentioned in Key Findings. Models show stronger Nostalgia Bias when evaluated with BBC text than Wiki text. From the BPC charts, it's not easy to spot differences between models. However, our calculations in Appendix I reveal variations in how well each model can adapt specific text over time.

Difference of Text Feature An insightful reviewer helped us found the reason of the different patterns of Wiki an BBC text. New Wiki texts with

[2] `https://explodingtopics.com/blog/chatgpt-users`

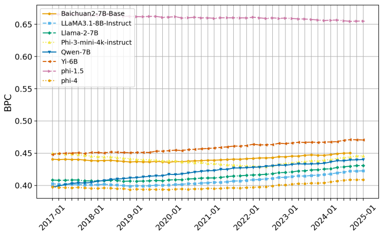

Figure 3: BPC on Wiki text

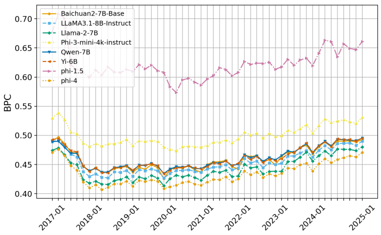

Figure 4: BPC on BBC news text

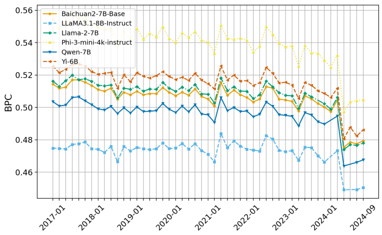

Figure 5: BPC on arXiv text

recent temporal markers do not necessarily imply that the content is new in a temporal context. For instance, in 2017-01, there was a Wiki article titled "History of India". However, the information within it was not new and could potentially have been sourced from other materials. Conversely, BBC texts are news articles and are highly time-sensitive.

To quantify the difference, we uniformly sampled approximately 500 data pieces from both the Wiki and BBC datasets (taking into account that news may also cover historical events) and asked gpt-4o to classify the content. The results are as follows:

- Wiki: Historical: 97.83%, Others [3] :2.17%.
- BBC: Recent: 91.86%, Historical: 8.14%.

So, it is reasonable that Wiki text has a flat curve in BPC.

Claim the Value of Wiki Dataset Since the Wikipedia dataset is continuously updated, it is not easily subject to direct contamination. Although a substantial portion of Wiki pertains to old information, this content still represents valuable knowledge that we need. An ideal model should consistently perform well on such knowledge. (If a model shows a decline in performance on Wikipedia, it is likely that the model is overfitting.)

3.2 Temporal Degeneration

3.2.1 Protocol for Quantitative Measurement

Definition 3.1. Temporal Bias Index (TBI) For each model in a certain period, we record BPC_i at n time points, forming n data points (i, BPC_i), where $i = 1, \dots, n$. Here the time interval between BPC_i and BPC_{i+1} is set as two month. We then fit a linear model:

$$BPC_i = a * i + b \tag{3}$$

then Temporal Bias Index (TBI) is defined as the coefficient a. TBI is crucial for understanding **the direction and rate of change in model performance over time**.

To quantify model temporal generalization, we computed the BPC for various models on the Wiki and BBC datasets and evaluated their performance using this index. Specifically, We established a base BPC using data from the six months prior to each model's release. After that, we measured the changes in BPC at 3, 6, 9 and 12 months post-release relative to the base BPC; and assessed the overall trend in model performance using TBI. The specific results are detailed in Appendix H.

3.2.2 Observation

Temporal generation pattern is mostly determined by the nature of data Models perform stably on Wikipedia but show more variation on BBC. This reveals their ability to handle well-structured and formal text like Wiki and insufficient adaptability to dynamic text like BBC text. The overall BPC for BBC texts shows an increasing trend, indicating gradual performance degeneration.

Individual models show considerable differences in performance on new data; for instance, Yi, and Baichuan2 series adapt relatively well to new texts, while Phi-1.5 and OPT series exhibit poorer generalization (see Appendix I). These findings indicate that in dynamic environments, different models have significantly varying adaptation capabilities.

Model performance positively correlates with performance decay. (see Tab. 1). There is a positive correlation between model attributes (such as model size and release date) and performance decay. A positive BPC slope indicates an increase in BPC over time, reflecting performance degeneration.

In the Wiki dataset, larger models deteriorate faster (correlation coefficient of 0.504), suggesting a trade-off between capability and flexibility.

[3] "Others" refers to content not associated with specific historical events, focusing instead on general, educational, and ever-relevant information.

Table 1: Correlation between Model Attributes and Their TBI on Wiki and BBC text

Correlation	Model Size	Release Date	MMLU	Humanities	Social-Sciences	STEM	MMLU Other	GSM8	Ar20c	Hellawasg	TrustfulQA	Winogrande	Longbench
Wiki	0.504	0.267	0.599	0.500	0.594	0.393	0.528	0.473	0.380	0.581	0.200	0.632	0.404
BBC	-0.044	0.313	0.384	0.317	0.311	0.186	0.153	0.188	-0.071	0.248	0.485	0.204	0.549

In more dynamic environments (such as the BBC dataset), the impact of model size on performance decay is smaller. Additionally, newer models show higher correlations, meaning that despite their advanced capabilities, they may deteriorate faster. These results emphasize the importance of designing models that can maintain robustness over time and across various data environments. As machine learning applications grow in complexity and scale, temporal generalization will become increasingly critical.

4 Temporal Generalization through the Lens of Future Event Prediction

Advantages of Future Event Prediction over Compression Intelligence Compression Intelligence is limited by its inapplicability to closed-source models, where key indicators like logits or losses are inaccessible. This exclusion narrows comparative analysis and hinders a comprehensive understanding of the language technology landscape. Additionally, language likelihood can be biased by models finely tuned to specific formats or domains, skewing overall evaluation and presenting a distorted view of a model's general performance.

This motivated us to research temporal generalization and bias from the perspective of future prediction. In this section, we investigate temporal generalization (in Sec. 4.1) and biases (Sec. 4.2) through the Lens of Future Event Prediction.

Key Findings

- Models prefer older knowledge, with non-uniform knowledge distribution skewed towards the past. This poses a risk as users expect up-to-date knowledge close to the model's release date.

- Within model series such as Claude,Gemini, and GPT, newer versions are becoming more powerful but also experience more rapid performance decline. Miniature models significantly underperform compared to their full -sized counterparts in temporal tasks.

- Newer models generally exhibit stronger performance. Closed-source models tend to perform slightly better at the beginning, yet open-source models demonstrate superior generalization capabilities.

4.1 Temporal Biases

4.1.1 Protocol for Quantitative Measurement: a Hypothesis Testing Method

We discussed generally what is past, present, and future for a model in Sec 2.1.1. Now, let's clarify the context of the prediction problem. For each prediction task, there is an initiation time (when the question is posed) and a close time (when the answer is revealed). If a question's closure time precedes the model's release date (for instance, by more than three months), then that question is considered part of the *past* for that model. The *present* refers to questions whose close time is near the release time of the model, capturing the period around when the model was launched.

To investigate the two mentioned temporal biases in Sec. 2.1.2, we propose two hypothesis testings as follows. These tests help practitioners make informed decisions despite the randomness inherent in the question datasets.

Hypothesis Testing 1. Neophilia Bias:

$$\begin{aligned} T_1: \quad & H_0: \mathbf{E}[acc_{\text{past}}] = \mathbf{E}[acc_{\text{present}}], \\ & H_1: \mathbf{E}[acc_{\text{past}}] < \mathbf{E}[acc_{\text{present}}] \end{aligned} \tag{4}$$

This hypothesis tests if there is a significant increase in model accuracy for current questions compared to past questions, suggesting a bias towards newer content. The p-value $\widehat{p}$ quantifies the strength of evidence against the null hypothesis.

Hypothesis Testing 2. Nostalgia Bias:

$$\begin{aligned} T_2: \quad & H_0': \mathbf{E}[acc_{\text{past}}] = \mathbf{E}[acc_{\text{present}}], \\ & H_1': \mathbf{E}[acc_{\text{past}}] > \mathbf{E}[acc_{\text{present}}] \end{aligned} \tag{5}$$

Conversely, this hypothesis tests if there is a significant increase in model accuracy for past questions, indicating a preference for older or historical content. The p-value $\widehat{p}'$ quantifies the strength of evidence against the null hypothesis.

P-Value Computation The p-values for assessing the shifts in accuracy are computed using the standard normal cumulative distribution function Φ as follows:

$$\widehat{p} = 1 - \Phi\left(\frac{acc_1 - acc_2}{\sqrt{\frac{acc_1(1-acc_1)}{n_1} + \frac{acc_2(1-acc_2)}{n_2}}}\right), \quad (6)$$

acc_1 and acc_1 could be either acc_{past} or acc_{present}, which is based on which Hypothesis Testing is used. Note that the two Hypothesis Testings are symmetrical.

Detailed experiment settings are listed in Appendix D.

4.1.2 Observation

Models tend to be stronger in earlier periods before release, with performance gradually declining over time. Using the -20 to 0 months period as an anchor, if we assign the three periods to represent the near past (20 to 40 months before release), the middle past (40 to 60 months before release), and the distant past (60 to 80 months before release), we observe that the further back in time we go, the more pronounced the Nostalgia Bias becomes, and it is also more significant. This suggests that the models gradually degrade during the pre-release period, rather than experiencing a rapid decline around the cutoff period.

Nostalgia Bias is prevalent. As shown in Tab. 2, among the biases, Nostalgia is the most common, followed by periods where neither bias is significant (shown as -), with Neophilia Bias being the least frequent. Phi-1.5 and Baichuan2-13B series show Nostalgia Bias in all three periods before release. Mistral-7B-v0.1 show Neophilia Bias in 20 to 40 months before release but show more significant Nostalgia in another two periods, which we attribute to random fluctuations rather than a consistent trend.

This observation reveals that models generally favor older knowledge and prefer information from more distant past periods. The distribution of knowledge is not uniform, nor does it tend to be closer to the present. This poses a potential risk in our utilization of these models because there is an expectation that the knowledge utilized should be as up-to-date as possible, ideally close to the model's release date.

4.2 Temporal Degeneration

4.2.1 Protocol

We discussed generally *Temporal Degeneration* in 2.1.2, here we need to define specifically.

Definition 4.1. Temporal Degeneration The capability of future event prediction might be degraded over time due to the larger generalization gap brought by time.

To qualitatively measure Temporal Degeneration, we propose a hypothesis testing like 4.1.1.

Hypothesis Testing 3. Temporal Degeneration

$$\begin{aligned} T_3: \quad & H_0: \mathbf{E}[acc_{\text{future}}] = \mathbf{E}[acc_{\text{present}}], \\ & H_1: \mathbf{E}[acc_{\text{future}}] < \mathbf{E}[acc_{\text{present}}] \end{aligned} \quad (7)$$

Similar to Sec 4.1.1, acc_{future} represents the model accuracy on questions proposed after the model's release. This hypothesis assesses whether there is a significant decline in model accuracy, indicating a degeneration over time. The hypothetical p-value is similar to that of Eq. 6.

4.2.2 Observation

Earlier models perform worse, while newer advanced models perform better in future predictions. As the latest scores in Table 3 show, earlier models, show a significant performance decline across multiple time periods. For example, LLaMA-7B's accuracy dropped from 0.11 in March 2023 to 0.08 by March 2024, with no improvement in later evaluation periods. In contrast, newer models exhibit much stronger future prediction capabilities.

Close-source models perform well initially but struggle with temporal generalization, while open-source models show better stability. As is shown in Appendix C, in both pre- and post-release scenarios, proprietary models such as GPT-4 and Claude-3.5 slightly outperform their open-source counterparts. However, when predicting outcomes for events known only post-release, all models exhibited substantial declines in performance.

Our analysis highlights models with less than 31% decline in post-release accuracy in **bold**, illustrating relatively stable performance. Conversely, models that experienced declines greater than 39% are marked by underline, indicating substantial performance degeneration. Notably, models such as Command R+, Mixtral-8x22B-Instruct-v0.1, DeepSeek-V2-Chat, and LLaMA-3.1-405B-Instruct demonstrate slower declines in accuracy

Table 2: Comparison of Model Performance in Different Pre-Release Periods (Compared to 0-20 months before Release), uses asterisks to denote significance levels:† ($p < 0.05$), ††($p < 0.01$), and ††† ($p < 0.001$), → refers to Neophilia Bias, ← refers to Nostalgia Bias.

Models	20-40 Months Before Release	40-60 Months Before Release	60-80 Months Before Release
OPT-13B	–	← †††	← ††
OPT-2.7B	–	→ †	–
LLaMA-7B	–	← †††	← ††
Pythia-12B	→ ††	← †††	← †††
Falcon-rw-1B	–	–	–
Baichuan-7B-Chat	–	–	← †
LLaMA-2-13B	–	← †††	← †††
LLaMA-2-7B	← †††	← †	–
LLaMA-2-7B-Chat	–	← †††	← †††
Zhongjing-Base	–	–	← †††
InternLM-Chat-7B	← ††	–	–
Baichuan2-7B-Chat	← ††	–	–
Mistral-7B-v0.1	→ †	← ††	← †††
Phi-1.5	← †	← ††	← †††
Baichuan2-13B-Base	← ††	← †††	← †††
Baichuan2-13B-Chat	← †	← †††	← †††
Colossal-LLaMA-2-7B-Base	← ††	–	← †
Qwen-14B-Chat	← ††	← ††	← †††
Qwen-7B	–	–	–
Skywork-13B-Base	–	–	–
Zephyr-7B-beta	← †	← †††	← †††
Yi-6B	–	–	–
Yi-6B-Chat	← †	← †	← †
Qwen-1.8B	–	–	← ††
RWKV-v5-Eagle-7B	–	–	–
Phi-2	← ††	–	← †
Command R+	← ††	← †††	← †††
Mixtral-8x22B-Instruct-v0.1	–	← †††	← †††
Phi-3-mini-4k-instruct	–	← †††	← ††
Qwen1.5-110B-Chat	← †	← †††	← †††

post-release. Conversely, models like Claude-3.5-Sonnet-20240620, GPT-4-231106, and GPT-4o show rapid declines in performance,

The case studies of model iterations within the Claude series and the GPT models illustrate the dynamics of model evolution and generalization capabilities over time. Notably, the Claude-3-opus-20240229 model shows the least decline, indicating a potentially better tuning for broader applications or general datasets. This contrasts with the more significant declines seen in Claude-3-sonnet-20240229 and Claude-3.5-Sonnet-20240620, suggesting that these iterations may have undergone specific architectural tweaks, utilized different training data scopes, or implemented optimization strategies that did not generalize as effectively.

Similarly, the progression from GPT-3.5-turbo-230613 to GPT-4-231106 shows an increasing trend in both pre-release accuracy and the magnitude of decline post-release, with the GPT-4-231106 model experiencing the largest drop (39.39%). This trend could indicate a push towards optimizing these models for higher initial accuracy, possibly at the expense of their ability to generalize effectively over time.

Miniature versions of models show significant declines in temporal performance. The data reveals that miniature versions of models underperform compared to their full-sized counterparts in temporal tasks. For instance, Gemini.pro had an accuracy of 0.37 in March 2024, but this dropped sharply to 0.17 by July 2024, indicating a significant loss in precision for temporal tasks. Similarly, the mini version of GPT-4 showed considerably lower performance across multiple time periods, particularly in April 2024, where its accuracy was just 0.21, around 0.1 lower than the full-sized GPT-4 in the same period. This illustrates that while mini models improve inference efficiency, they exhibit poor generalization over time, with perfor-

Table 3: Accuracy performance of various models across different periods. The presence of asterisks (*) denotes statistically significant decreases in performance during specific periods (p < 0.05 for *, p < 0.01 for **, and p < 0.001 for ***), benchmarked against their accuracy before release. Grey cells indicate the models have not been released in this period and represent the average scores of the models prior to their release.

Model	23/1 -23/2	23/3 -23/4	23/5 -23/6	23/7 -23/8	23/9 -23/10	23/11 -23/12	24/1 -24/2	24/3 -24/4	24/5 -24/6	24/7 -24/8
Baichuan-13B-Chat	0.52		0.26**	0.20**	0.36**	0.32**	0.33**	0.20**	0.23**	0.17**
GPT-3.5-turbo-230613	0.49		0.29**	0.37*	0.45	0.44	0.37*	0.29**	0.28**	0.26**
GPT-4-230613	0.6		0.39**	0.43*	0.41**	0.38**	0.48	0.40**	0.35**	0.36**
Llama-2-13B	0.52			0.43	0.48	0.36**	0.39*	0.40*	0.28**	0.34**
Llama-2-7B	0.27			0.26	0.27	0.22	0.26	0.33	0.18**	0.24
LLaMA2-7B-Chat	0.45			0.30*	0.46	0.35**	0.37	0.38	0.27**	0.28**
Baichuan2-13B-Base	0.49			0.30**	0.46	0.42*	0.28**	0.39*	0.27**	0.27**
Baichuan2-13B-Chat	0.5			0.33**	0.43	0.41*	0.26**	0.29**	0.29**	0.33**
Baichuan2-7B-Base	0.42			0.26**	0.30*	0.24**	0.33	0.33*	0.25**	0.22**
Baichuan2-7B-Chat	0.37			0.35	0.43	0.31	0.37	0.40	0.23**	0.27*
Colossal-LLaMA-2-7B-Base	0.42				0.43	0.37	0.28*	0.33*	0.25**	0.26**
Mistral-7B-v0.1	0.44				0.41	0.35*	0.28*	0.34*	0.25**	0.24**
Phi-1.5	0.41				0.38	0.38	0.30	0.26**	0.32*	0.27**
Qwen-14B-Chat	0.39				0.25**	0.24**	0.33	0.27**	0.28**	0.19**
Zephyr-7B-beta	0.4				0.32	0.32*	0.28*	0.28**	0.31*	0.19**
Yi-6B	0.29				0.27	0.16**	0.22	0.33	0.21*	0.21*
Gemini	0.43					0.20**	0.37	0.24**	0.21**	0.17**
Qwen-1.8B	0.35					0.22**	0.37	0.29	0.20**	0.20**
GPT-4-231106	0.66					0.45**	0.39**	0.36**	0.47**	0.43**
Phi-2	0.31					0.23*	0.22	0.29	0.18**	0.15**
Claude-3-opus-20240229	0.53						0.52	0.37**	0.47	0.36**
Claude-3-sonnet-20240229	0.23						0.24	0.13**	0.10**	0.07**
Command R+	0.54							0.37**	0.43*	0.33**
DeepSeek-V2-Chat	0.58							0.49**	0.46**	0.35**
Mixtral-8x22B-Instruct-v0.1	0.56							0.39**	0.43**	0.35**
Phi-3-mini-4k-Instruct	0.38							0.26**	0.24**	0.26**
Qwen1.5-110B-Chat	0.56							0.40**	0.45*	0.36**
Claude-3.5-Sonnet-20240620	0.63								0.48**	0.23**
Gemini-1.5-Pro	0.5								0.47	0.35**
Gemini-1.5-flash	0.39								0.23**	0.22*
Qwen2-72B-Instruct	0.6								0.45**	0.40**
LLaMA-3.1-405B-Instruct	0.5									0.41
GPT-4o	0.62									0.39**
GPT-4o-mini-2024-07-18	0.48									0.28**

mance rapidly declining in long-term prediction tasks.

5 Conclusion and Community Call to Action

We rigorously define and quantify temporal generalization and bias within LLMs, uncovering significant challenges in predicting and adapting to future contexts. Our experiments reveal that LLMs often struggle with temporal biases, affecting reliability in dynamic scenarios requiring accurate forecasting. The evaluation framework and datasets we introduce allow for an in-depth assessment of model performance over time. The findings highlight shortcomings in existing benchmarks related to temporal shifts and underscore the urgent need for improvements in LLM training and updating processes to enhance adaptability and mitigate biases.

Specifically, we urge the community to take note of this phenomenon: models tend to better comprehend earlier events. Cheng et al. (2024) suggests that models are most familiar with knowledge up to the year 2020. However, our findings indicate that the understanding of world events (even in cases where models can remember) lingers around 2015, with a trend towards even earlier years (beyond the time range of our test data). This observation is contrary to our initial hypothesis that models may overfit current events, which is significantly more concerning. It suggests that caution is needed, especially for those hoping to use model judgments directly.

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Future Work

Moving forward, it is crucial to refine LLM development and evaluation techniques to better handle evolving informational environments, ensuring their continued relevance and utility in various applications.

Looking ahead, we suggest future work includes several ambitious goals aimed at enhancing the versatility and depth of our evaluation framework. Key among these objectives are:

- Exploring mitigation strategies, through we conducted preliminary investigations into prompt engineering strategies that could potentially mitigate temporal performance degradation, see Abstract B.
- Integrating a wider array of models, particularly focusing on those based on the Transformer architecture, such as Griffin and Mamba models.
- Expanding the number of checkpoints accessed for a more comprehensive temporal analysis of model performance.
- Delving into the relationship between token-level loss metrics and overall scores, which could offer more granular insights into model capabilities.
- Developing methodologies to assess the obsolescence of benchmarks and models, potentially offering a dynamic approach to evaluating the relevance and efficiency of language models over time.

These initiatives represent our commitment to advancing the state of the art in language model evaluation, ensuring that our tools remain at the forefront of technological progress and innovation.

Limitations

While we strive to collect textual data from a variety of sources such as news articles, scientific papers, and forum discussions, the proportion and diversity of the texts may still fall short of fully reflecting the diversity and complexity of language. Also, the English-centric nature of the questions and answers limits the benchmark's applicability to non-English speaking regions and global events. Moreover, such evaluations on text loss require access to the model's logits, which is challenging for closed-source models or models accessed via APIs.

Potential Risks

Bias and Fairness Risks: When used to make predictions about future events, language models can inadvertently perpetuate or amplify biases present in their training data. This could lead to biased forecasts that reflect and potentially exacerbate existing societal prejudices. Such biased outputs may result in models that are unfair or discriminatory, which could harm individuals or groups and damage the reputation of the organizations involved.

Ethics Statement

We fully acknowledge the need to adhere to ethical standards in handling and generating textual data. Hence, we commit to:

- We utilize various datasets in our experiments, including publicly available sources like news articles and academic papers, which do not contain personally identifiable information or offensive content. However, some datasets created or used during our study contain sensitive information or are bound by specific usage agreements that prevent public sharing. Therefore, these datasets are utilized strictly within our experiments and are not released as part of our open-source materials, adhering to ethical guidelines and agreements.
- **Responsibility for Content Generated by Open-Source Models:** We recognize that content generated by our system or through the use of open-source models involved in the evaluation might reflect or amplify biases. While efforts are made to minimize these biases and improve the fairness of the content,

we cannot take responsibility for the generated content. We encourage users and developers to critically engage with these models and remain vigilant of their outputs.

- **Addressing Data Leak Issues:** Our system aims to tackle data leak issues by dynamically generating benchmarks and ensuring models generalize to new or future texts. We commit to continuously monitoring and updating our evaluation methods to avoid potential data leakage, ensuring the validity and reliability of our assessment results.
- **Transparency:** We are committed to maintaining the highest level of transparency in our work, including our evaluation methods, data sources used, and assessment outcomes. We encourage open critique and suggestions for improvement of our methodology, aiming to foster knowledge sharing and technological advancement.

We believe that through this approach, we can offer a valuable resource to the research and development community, while fostering deep reflection and discussion on ethical issues in the artificial intelligence field.

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Other text will not be released.

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A Related Work

Given the limitations of traditional methods, researchers are exploring new ways to measure model performance more comprehensively. Recently, several methods have been proposed to evaluate models at different times and in various contexts Fatemi et al. (2024); Kasai et al. (2024); Vu et al. (2023). TimeQA Chen et al. (2021) evaluates a model's ability to handle temporal evolution, while Situated QA Zhang and Choi (2021) focuses on a model's performance in specific contexts. StreamingQA Liška et al. (2022) introduces the concept of continuous information flow, while RealTimeQA Kasai et al. (2024) and FreshQA Vu et al. (2023) emphasize real-time and up-to-date information processing capabilities. LatestEval Li et al. (2023b) utilizes the most recent text to construct questions and answers, covering six most frequently queried categories including explanation, summary, reason, demonstrations, existence, and possible usage.

However, it's essential to clarify that RealTimeQA Kasai et al. (2024) and FreshQA Vu et al. (2023), which continuously update topics, are inclined towards knowledge. For example, RealTimeQA Kasai et al. (2024) has such a sample in their paper, "Which wildly popular show was recently greenlit for a new season?" (Answer: Squid Game). These methods are typically used for evaluating retrieval-augmented generation (rag) series models. On the other hand, methods like LatestEval Li et al. (2023b), which construct questions using the most recent information, lean towards enhancing reading comprehension.

In contrast to these approaches, our focus is on testing the model's understanding of the world, as demonstrated through prediction. Our method of evaluation is based on facts and computation loss. This ensures that our evaluation is resistant to data contamination, objective, and free from biases in question construction and judgment. This approach allows us to examine the model's ability to process and predict real-world events accurately and efficiently.

Future-knowledge Prediction Previous research has focused on how to automatically predict real-world events. For instance, Zou et al. (2022) constructed a dataset of questions obtained from tournament predictions as an evaluation benchmark for automatic forecasting. However, this dataset may already be outdated because its knowledge is likely already embedded within current LLMs. Recently, studies have shown that LLMs can match human performance in the task of forecasting the future. For example, Schoenegger et al. (2024) demonstrates that the predictive performance of an ensemble of multiple LLMs is superior to that of a single LLM, and it even surpasses the performance of a group of human forecasters.

Model selection and Experimental Setting We selected a set of models due to their diversity and significance in advancing the capabilities of NLP systems. They are not only benchmarks of their respective sizes, ranging from 1 billion to 40 billion parameters, but also exemplify the rapid progression in NLP technology. We set the context size to 2048, then compute the sum of the negative logarithms of each segment. We then divide the computed sum by the length of the text under UTF-8 encoding. Throughout this experiment, approximately 300 GPU hours on NVIDIA A800 were consumed.

B Exploring Mitigation Strategies

While our primary focus is temporal evaluation rather than solution development, we conducted preliminary investigations into prompt engineering strategies that could potentially mitigate temporal performance degradation.

B.1 Try Different Prompt to Mitigate

Motivated by observed safety constraints and refusal patterns in base models and the result of Pham and Cunningham (2024), we designed five specialized prompts to investigate how different framing strategies affect temporal prediction:

- **Base**: Used direct incentivization ("tip of $200") and explicit guessing encouragement to counter safety-driven refusals.
- **Dream Framework (v1)**: Encourages speculative thinking by positioning the model as a visionary oracle.
- **Time Travel (v2)**: Frames predictions as historical memories from a future perspective.
- **Multiverse (v3)**: Leverages parallel universe observations to bypass temporal constraints.
- **Precise Thinking (v4)**: Emphasizes structured temporal reasoning chains.
- **Future Recall (v5)**: Simulates retrospective analysis from a future vantage point.

See Figure 6, 7, 8 and 9. Specifically, different models respond variably to the designed prompts. For Yi-6B, there were scarcely any discernible differences in performance across the several prompts we employed. In contrast, for the Qwen2.5-7B model, all modified prompts generally outperformed the base prompt in most scenarios. Analyzing the results from Llama3.1-8B-Instruct, Qwen2.5-7B and Baichuan2-7B-Chat, we found that prompts v5(Future Recall) and v4(Precise Thinking) demonstrated relatively better effectiveness. The specific impacts vary from model to model, which is closely related to the model's instruction-following capabilities.

In addition, our exploratory analysis revealed significant performance variations across question categories, with the model achieving lowest accuracy on "Finance" (58.1%), "Business" (55.4%). and "Economic Indicators" (62.3%) categories, compared to stronger performance on "Foreign Policy", (81.2%), "Security and Conflict" (79.6%) and "Leader Entry/Exit" (83.7%) categories.

It is plausible that fine-tuning models with analysis and prediction data (especially in these weak areas) could fully unlock their inner predictive potential.

C Full Table of Decline in Prediction Accuracy

See Table 4.

D Experimental setting

For this experiment, we sourced all questions from Good Judgment Open using web scraping. The data collected includes initiation and conclusion dates, domains, questions, descriptions, and answers, which were appropriately ordered for further processing. Approximately 50 GPU hours on NVIDIA A800 were consumed during this experiment.

Up to 2024.10.1, we collected a total of 2769 questions from Good Judgment Open. The earliest question was proposed on 2015-09-01: "Will Congress pass a resolution disapproving the Joint Comprehensive Plan of Action?" The most recent question was closed on 2024-10-01: "What will be the 12-month percentage change in the US Consumer Price Index (CPI) for September 2024?" Question samples and most common tags are in Appendix J.

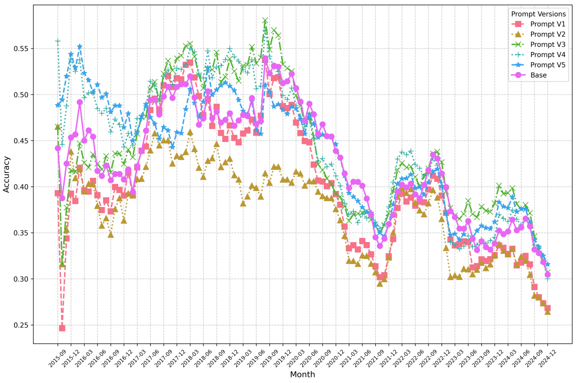


Figure 6: Accuracy of LlaMA3.1-8B-Instruct with different prompts

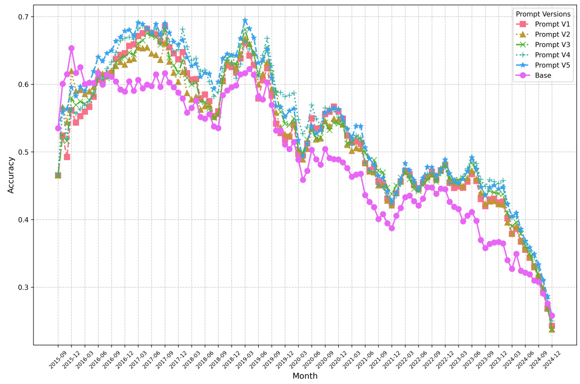


Figure 7: Accuracy of Qwen2.5-7B with different prompts

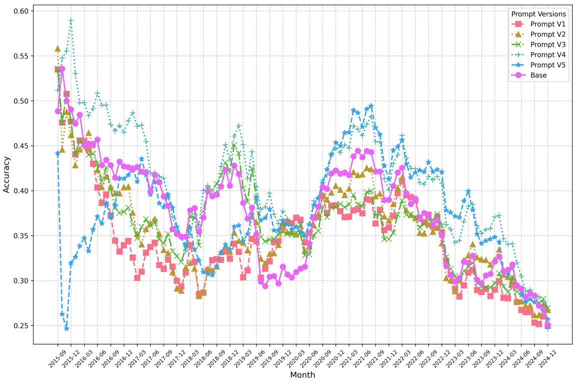


Figure 8: Accuracy of Baichuan2-7B-Chat with different prompts

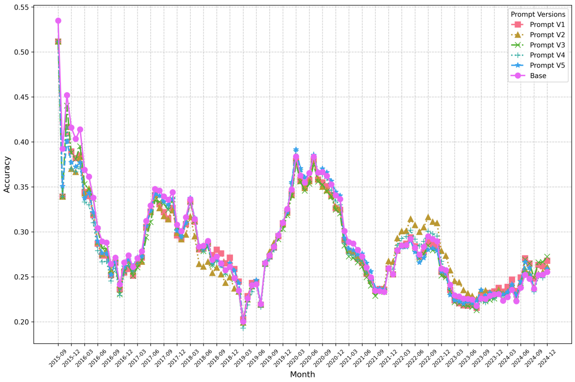


Figure 9: Accuracy of Yi-6B with different prompts

E Testing Statistical Hypothesis

Due to the inherent randomness in data, directly comparing outcomes of two experiments is insufficient to justify the superiority of one outcome over the other. To address this issue, practitioners often resort to hypothesis testing to make convincing decisions, like those demonstrated in Zhou et al. (2016). A board application of hypothesis testing lies in the A/B testing literature, which assesses the performance of various features of a product and performs post-experiment inferences, as introduced in Russac et al. (2021).

F Details of Data Collection

The data for our system is sourced from a diverse set of online platforms, each selected for its relevance to different data types and domains. We utilize a Python-based crawling framework, which is detailed in our publicly available repository. This framework is designed to be adaptable, allowing for the inclusion of additional sources as they become relevant.

The primary data sources include:

- **Financial News**: Crawled from Yahoo, providing up-to-date information on global financial trends.
- **Political News**: BBC News is used to gather the latest political developments worldwide.
- **Discussion Forums**: Reddit is scraped to capture current discussions across a variety of tofigures.
- **Online Literature**: Wattpad offers a rich source of contemporary fiction and non-fiction.
- **Encyclopedia**: Wikipedia's latest changes feed is monitored for updates across all domains.
- **Academic Papers**: arXiv is used to access the newest research across multiple scientific fields.
- **Code Repositories**: GitHub Trending provides insights into the latest developments in software engineering.

Table 4: Comparison of Powerful Open-source and Closed-source LLMs

Model	Pre-release Accuracy	First Post-release Accuracy	Decline	Percentage Decline
Baichuan-13B-Chat	0.52	0.23	0.29	55.77%
GPT-3.5-turbo-230613	0.49	0.33	0.16	32.65%
GPT-4-230613	0.60	0.41	0.19	31.67%
Llama-2-13B	0.52	0.45	0.07	12.50%
Llama-2-7B	0.27	0.27	0.01	1.85%
LLaMA2-7B-Chat	0.45	0.38	0.07	15.56%
Baichuan2-13B-Base	0.49	0.38	0.11	22.45%
Baichuan2-13B-Chat	0.50	0.38	0.12	24.00%
Baichuan2-7B-Base	0.42	0.28	0.14	33.33%
Baichuan2-7B-Chat	0.37	0.39	-0.02	-5.41%
Colossal-LLaMA-2-7B-Base	0.42	0.40	0.02	4.76%
Mistral-7B-v0.1	0.44	0.38	0.06	13.64%
Phi-1.5	0.41	0.38	0.03	7.32%
Qwen-14B-Chat	0.39	0.24	0.15	37.18%
Zephyr-7B-beta	0.40	0.32	0.08	20.00%
Gemini	0.43	0.29	0.14	33.72%
Yi-6B	0.29	0.22	0.07	25.86%
Qwen-1.8B	0.35	0.29	0.05	15.71%
GPT-4-231106	0.66	0.42	0.24	36.36%
Phi-2	0.31	0.23	0.08	27.42%
Command R+	0.54	0.40	0.14	25.93%
Claude-3-opus-20240229	0.53	0.45	0.09	16.04%
Claude-3-sonnet-20240229	0.23	0.18	0.05	19.57%
DeepSeek-V2-Chat	0.58	0.47	0.10	18.10%
Mixtral-8x22B-Instruct-v0.1	0.56	0.41	0.15	26.79%
Phi-3-mini-4k-Instruct	0.38	0.25	0.13	34.21%
Qwen1.5-110B-Chat	0.56	0.43	0.14	24.11%
Claude-3.5-Sonnet-20240620	0.63	0.35	0.28	43.65%
Gemini-1.5-Pro	0.50	0.41	0.09	18.00%
Gemini-1.5-flash	0.39	0.23	0.17	42.31%
Qwen2-72B-Instruct	0.60	0.43	0.17	29.17%
LLaMA-3.1-405B-Instruct	0.50	0.41	0.09	18.00%
GPT-4o	0.62	0.39	0.23	37.10%
GPT-4o-mini-2024-07-18	0.48	0.28	0.20	41.67%

- **Question and Answer Forums**: Quora, focusing on popular topics such as Technology, Mathematics, Health, and Movies.

To facilitate efficient and effective data collection, our system's environment is configured with a specific Python package index URL and utilizes Playwright for web navigation and content extraction. This setup addresses potential challenges, such as page refresh requirements on Yahoo and hostname verification issues encountered with certain websites.

Our system employs a combination of tools and libraries, including Requests, Playwright, and various PDF processing utilities, to collect the latest textual data from the internet. This approach enables us to dynamically update our benchmark datasets with fresh information, ensuring that our evaluation reflects current language use and information trends.

Data Pre-processing For some raw content clean the text by removing these tags to ensure that only the content text is analyzed.

Filtering out short texts: Extremely short texts may not provide enough contextual information for analysis or model training. Setting a minimum text length threshold of 100 chars to filter out such instances.

External Dataset For the analysis of text likelihood and bias, we employed not only our own collection of historical arXiv data but also sampled entries from two additional datasets. We incorporated data from the BBC News and Wikitext datasets, which are publicly available through the Hugging Face datasets repository. Specifically, the datasets used were *bbc_news_alltime* and *wikitext_alltime*, accessible via the following URLs:

- BBC News: https://huggingface.co/datasets/RealTimeData/bbc_news_alltime
- Wikitext: https://huggingface.co/datasets/RealTimeData/wikitext_alltime

Sampling from these datasets was carried out every three months, with each instance involving the collection of 50 entries per dataset. This structured sampling approach was designed to ensure a consistent and representative analysis of content over time, enabling an effective assessment of textual bias and likelihood trends.

G Data Overview of One Crawl

Tab. 9 presented below offers a comprehensive overview of the diverse sources and categories of texts that were analyzed in one data crawl. Classified into distinct groups such as Academic STEM, Academic Non-STEM, Internet QA, and Internet articles, the table delineates the number of texts extracted from each source along with their average length. This includes detailed counts from different academic archives like arXiv, various categories from Internet question and answer platforms like Reddit and Quora, and articles from well-known online platforms including Wiki and BBC.

H Detailed results of BPC generalization on Wiki and BBC dataset

See Table 6.

Table 5: Most common tags of the Gjo questions

Topic	Count
Business	648
Non-US Politics	453
Security and Conflict	446
Society	425
US Politics	363
Technology	359
Finance	299
Elections and Referenda	288
Economic Indicators	273
Foreign Policy	271
US Policy	247
Health	245
Leader Entry/Exit	219
Economic Policy	160
Sports	148
Entertainment	148
Environment	80
Open	16

I TBI of Models across the arXiv, BBC, and Wiki datasets

See Table 8.

J Gjo data samples and most common tags of the Gjo questions

Gjo data samples see Table 5 and Gjo questions see Table 10.

K Analysis of Language Likelihood Values and Benchmark Correlation Across Text and Model Groups

From Fig. 12 we can conclude that the scale of models being observed does not significantly alter outcomes, suggesting that performance correlations across benchmarks are generally consistent regardless of model size.

L Correlation with Existing Benchmarks

The Selected Existing Benchmarks We explored the correlation between BPC and existing benchmarks, particularly focusing on how specific content types, such as GSM, influence model performance. The selected benchmarks encompass common sense reasoning, depth and breadth of knowledge across diverse subjects, truthfulness, natural language understanding, and mathematical

Table 6: Percentage Change in BPC Following Release, measured by BBC news data from 2020 to 2024.3. Dash ("-") symbols in the table indicate missing data points due to the later release dates of some models, which means there is no available data for those specific time intervals.

Model	Base BPC	BPC Change at 3 months (%)	BPC Change at 6 months (%)	BPC Change at 9 months (%)	BPC Change at 12 months (%)	mean
OPT-13B	0.450	2.273	-2.087	1.265	0.839	0.572
OPT-2.7B	0.475	1.970	-2.228	1.192	1.143	0.519
LLaMA-7B	0.450	1.270	0.177	-7.776	3.266	-0.766
Pythia-12B	0.480	-0.233	-3.888	-2.612	-1.012	-1.936
Falcon-rw-1B	0.510	0.459	-7.814	1.201	-1.474	-1.907
Baichuan-13B-Chat	0.467	-3.645	-1.078	0.413	-	-1.436
LLaMA-2-13B	0.416	-6.928	3.502	1.683	-	-0.581
LLaMA-2-7B	0.434	-7.314	3.092	1.279	-	-0.981
LLaMA-2-7B-Chat	0.505	-8.308	2.695	0.664	-	-1.650
Zhongjing-Base	0.465	-8.488	2.662	-1.290	-	-2.372
InternLM-Chat-7B	0.515	-2.476	-1.344	0.236	-	-1.195
Baichuan2-7B-Base	0.451	-3.059	0.595	-4.649	-	-2.371
Baichuan2-7B-Chat	0.517	-3.571	-0.038	-5.315	-	-2.975
Mistral-7B-v0.1	0.398	1.110	5.347	-0.661	-	1.932
Phi-1.5	0.602	-1.772	1.131	-1.837	-	-0.826
Baichuan2-13B-Base	0.439	-2.943	0.882	-4.390	-	-2.150
Baichuan2-13B-Chat	0.495	-3.541	-0.995	0.232	-	-1.435
Colossal-LLaMA-2-7B-Base	0.618	2.825	3.715	-	-	3.270
Qwen-14B-Chat	0.445	2.682	4.847	-	-	3.764
Qwen-7B	0.441	1.892	3.689	-	-	2.791
Qwen-7B-Chat	0.466	1.809	3.606	-	-	2.708
Skywork-13B-Base	0.429	7.163	3.261	-	-	5.212
ChatGLM3-6B	0.832	5.567	1.684	-	-	3.626
Zephyr-7B-beta	0.435	7.340	3.928	-	-	5.634
Yi-6B	0.427	6.478	3.144	-	-	4.811
Yi-6B-Chat	0.446	3.030	-2.798	-	-	0.116
Qwen-1.8B	0.520	1.899	-2.082	-	-	-0.091
Qwen-1.8B-Chat	0.599	1.635	-2.033	-	-	-0.199
RWKV-v5-Eagle-7B	0.440	4.956	2.278	-	-	3.617
TinyLLaMA-1.1B-Chat-v0.6	0.513	2.539	-3.678	-	-	-0.569
Phi-2	0.487	1.882	-	-	-	1.882

reasoning, ensuring a well-rounded assessment of the model's performance.

Base vs. Chat Models Tab. 12 shows the comparative analysis of base and tuned models. Our findings suggest that: 1) Base models exhibit a stronger correlation with established benchmarks, implying that these models, in their fundamental form, possess a robust capacity for modeling language. This observation advocates for conducting initial evaluations using base models to capture their intrinsic language modeling capabilities. 2) The exploration of tuned models reveals potential deeper patterns in model tuning, suggesting that specific tuning strategies may unlock further enhancements in model performance across different tasks and domains.

Correlation alone Text Length Tab. 13 is about a long text understanding benchmark Longbench.

For chat models in this task, the correlation between BPC and scores is logical—higher probabilities of generating the text correlate with higher scores, and this correlation strengthens with longer text lengths. This suggests a consistent alignment between the model's language likelihood in long text and its scoring, reinforcing the chat model's robustness in handling extensive text inputs.

However, an inverse trend is observed with base models, where a familiar text paradoxically results in lower scores on related comprehension tasks. This indicates that fine-tuning may alter the base models' understanding of the texts, perhaps shifting their processing in ways that do not favor traditional comprehension metrics.

This indicates scenarios where a model scores high on language likelihood due to its text-generation skills but may not perform equally well on tasks that require deep semantic understanding or critical thinking. Thus, relying solely on language likelihood as an indicator of overall per-

Table 7: Percentage Change in Language Likelihood Following Release, measured by wiki data from 2020 to 2024.3. Dash ("-") symbols in the table indicate missing data points due to the later release dates of some models, which means there is no available data for those specific time intervals.

Model	Base BPC	BPC Change at 3 months (%)	BPC Change at 6 months (%)	BPC Change at 9 months (%)	BPC Change at 12 months (%)	mean
OPT-13B	0.075	-0.623	0.105	-0.413	-0.818	-0.437
OPT-2.7B	0.082	-0.658	0.024	-0.528	-0.915	-0.519
LLaMA-7B	0.052	0.214	-0.425	0.379	-0.067	0.025
Pythia-12B	0.071	-0.578	-0.933	-0.859	-0.903	-0.818
Falcon-rw-1B	0.083	-1.272	-1.113	-1.131	-1.207	-1.181
Baichuan-13B-Chat	0.058	0.019	0.124	-0.125	-	0.006
LLaMA-2-13B	0.041	1.700	1.446	1.796	-	1.647
LLaMA-2-7B	0.050	0.774	0.349	0.517	-	0.547
LLaMA-2-7B-Chat	0.060	0.132	-0.186	-0.093	-	-0.049
Zhongjing-Base	0.050	0.756	0.269	0.569	-	0.531
InternLM-Chat-7B	0.080	-0.482	-0.301	-0.250	-	-0.344
Baichuan2-7B-Base	0.059	0.523	0.157	0.185	-	0.289
Baichuan2-7B-Chat	0.068	0.343	-0.035	-0.073	-	0.078
Mistral-7B-v0.1	0.053	0.381	-0.028	0.018	-	0.124
Phi-1.5	0.098	0.066	-0.125	-0.248	-	-0.102
Baichuan2-13B-Base	0.053	1.019	0.797	0.900	-	0.905
Baichuan2-13B-Chat	0.062	0.299	0.628	0.512	-	0.480
Colossal-LLaMA-2-7B-Base	0.065	-0.042	-0.199	-	-	-0.121
Qwen-14B-Chat	0.049	1.301	1.939	-	-	1.620
Qwen-7B	0.061	0.428	0.430	-	-	0.429
Qwen-7B-Chat	0.065	0.302	0.226	-	-	0.264
Skywork-13B-Base	0.050	0.075	0.276	-	-	0.175
ChatGLM3-6B	0.105	-0.187	-0.245	-	-	-0.216
Zephyr-7B-beta	0.059	-0.049	-0.033	-	-	-0.041
Yi-6B	0.058	-0.071	0.022	-	-	-0.024
Yi-6B-Chat	0.060	-0.028	0.023	-	-	-0.003
Qwen-1.8B	0.080	-0.131	-0.251	-	-	-0.191
Qwen-1.8B-Chat	0.091	-0.331	-0.496	-	-	-0.414
RWKV-v5-Eagle-7B	0.065	0.149	0.220	-	-	0.184
TinyLLaMA-1.1B-Chat-v0.6	0.070	-0.332	-0.473	-	-	-0.403
Phi-2	0.072	-0.037	-	-	-	-0.037

formance might overlook crucial aspects of cognitive and interpretative abilities that are essential for more complex applications.

M Details of Model Accuracy Peaks

Tab. 14 captures the peak performance periods of various models on Freshbench. It lists specific models along with their respective dates when they achieved the best performance.

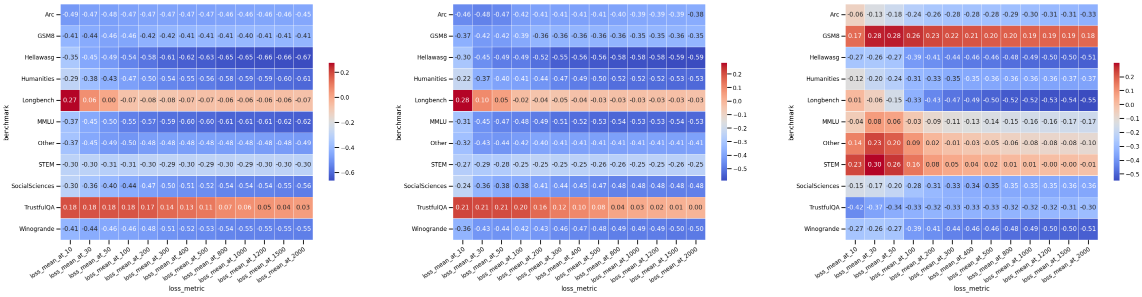
N Analysis of Best-Achieved Accuracy and Cutoff Time

Tab. 15 shows an analysis covering the period from 2015 to 2024, with the year 2019 serving as a pivotal midpoint, a distinct pattern emerges from the performance data of various language models: all models reached their peak accuracy before 2020. This observation points to a notable trend toward "Nostalgia", where models demonstrate optimal performance on data from the earlier part of the timeline analyzed. This tendency highlights the models' alignment with the informational characteristics prevalent prior to the latter half of the observed period, suggesting their training data may disproportionately reflect earlier times.

The peak accuracy periods analyzed are based on the average accuracy of all questions within three-month intervals, to provide a stable and robust assessment of each model's performance.

Table 8: Comprehensive list of models with their release dates and metrics for TBI (multiplied by 1000) across the arXiv, BBC, and Wiki datasets. Negative TBI values indicate a trend of increasing BPC, which refers to decreasing performance on MMLU.

Model Name	**Released Date**	**TBI*1000 (arXiv)**	**TBI*1000 (BBC)**	**TBI*1000 (Wiki)**
OPT-13B	May 2022	-19.4	1689.0	-30.2
OPT-2.7B	May 2022	-18.8	1080.7	-46.9
LLaMA-7B	Feb 2023	-15.3	713.0	52.0
Pythia-12B	Mar 2023	-8.1	802.7	-11.1
Falcon-rw-1B	Apr 2023	-26.8	607.4	-47.7
Baichuan-13B-Chat	Jun 2023	-11.7	685.7	4.8
Baichuan-7B-Chat	Jun 2023	-14.6	726.6	-16.5
LLaMA-2-13B	Jul 2023	-11.1	769.6	65.9
LLaMA-2-7B	Jul 2023	-12.6	684.6	23.2
Baichuan-13B-Chat	Jul 2023	-7.0	717.2	12.1
Zhongjing-Base	Jul 2023	-15.0	759.7	56.9
InternLM-Chat-7B	Jul 2023	-19.3	574.0	-22.0
Baichuan2-7B-Base	Aug 2023	-9.5	687.5	3.7
Baichuan2-7B-Chat	Aug 2023	-8.4	781.8	-11.6
Mistral-7B-v0.1	Sep 2023	-15.1	756.8	10.4
Phi-1.5	Sep 2023	-26.0	1212.9	-60.7
Baichuan2-13B-Base	Sep 2023	-9.1	747.9	15.8
Baichuan2-13B-Chat	Sep 2023	-7.0	717.2	12.1
Colossal-LLaMA-2-7B-Base	Sep 2023	-21.2	696.3	-36.2
Qwen-14B-Chat	Sep 2023	-7.9	762.2	51.5
Qwen-7B	Sep 2023	-11.7	662.4	7.4
Qwen-7B-Chat	Sep 2023	-13.2	705.7	-3.6
Skywork-13B-Base	Oct 2023	-16.3	549.1	30.8
ChatGLM3-6B	Oct 2023	-25.5	412.6	-70.4
Zephyr-7B-beta	Oct 2023	-21.1	506.9	3.7
Yi-6B	Nov 2023	-9.4	451.7	24.6
Yi-6B-Chat	Nov 2023	-9.4	506.5	20.2
Qwen-1.8B	Nov 2023	-22.7	374.0	-46.2
Qwen-1.8B-Chat	Nov 2023	-25.3	426.8	-50.3
RWKV-v5-Eagle-7B	Nov 2023	-12.8	511.3	4.2
TinyLLaMA-1.1B-Chat-v0.6	Dec 2023	-25.0	300.1	-45.3
Phi-2	Dec 2023	-21.2	669.3	-44.7



(a) STEM: base models

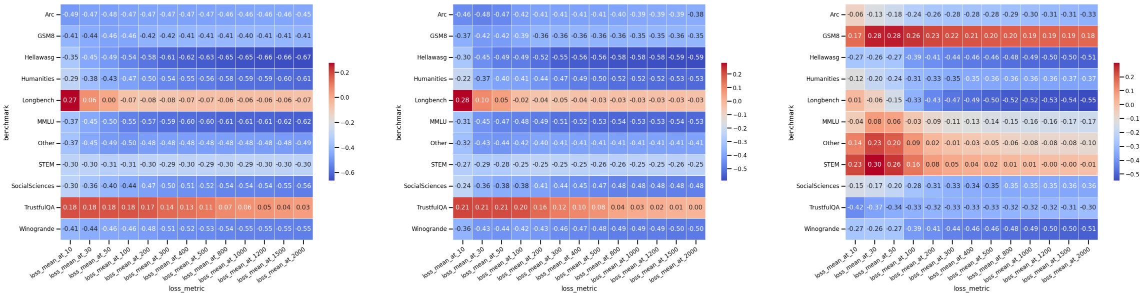
(b) non-STEM: base models

(c) Non-STEM: chat models

Figure 10: The heatmaps display the correlations by loss for a group of models across different text chunk lengths and different benchmark scores. Each row represents a specific truncation length, while the columns represent different benchmark score categories. The values in the cells indicate the corresponding correlation coefficients. (a) presents the correlations by loss for all 18 base models on STEM Academia texts. (b) presents the correlations by loss for all 18 base models on non-STEM Academia texts. (c) presents the correlations by loss for all 15 chat models on non-STEM Academia texts.

Table 9: Overview of text categories with their sources counts, and average lengths in one sample crawl.

Category	Source	Count	Length
Academic STEM	arXiv Mathematics	50	42850
	arXiv Computer Science	50	43336
	arXiv Physics	50	42580
	arXiv Statistics	50	42619
	arXiv Electrical Engineering and Systems Science	50	43027
Academic Non-STEM	arXiv Economics	50	42592
	arXiv Quantitative Finance	50	43969
	arXiv Quantitative Biology	50	42974
Code	GitHub	30	21849
Internet QA	Reddit	583	643
	Quora Health	20	1150
	Quora Movies	69	1349
	Quora Mathematics	70	1365
	Quora Technology	80	1674
Internet article	Wiki	220	4091
	Wattpad	38	6615
	BBC	45	4792
	Yahoo	41	5373



(a) STEM: base models

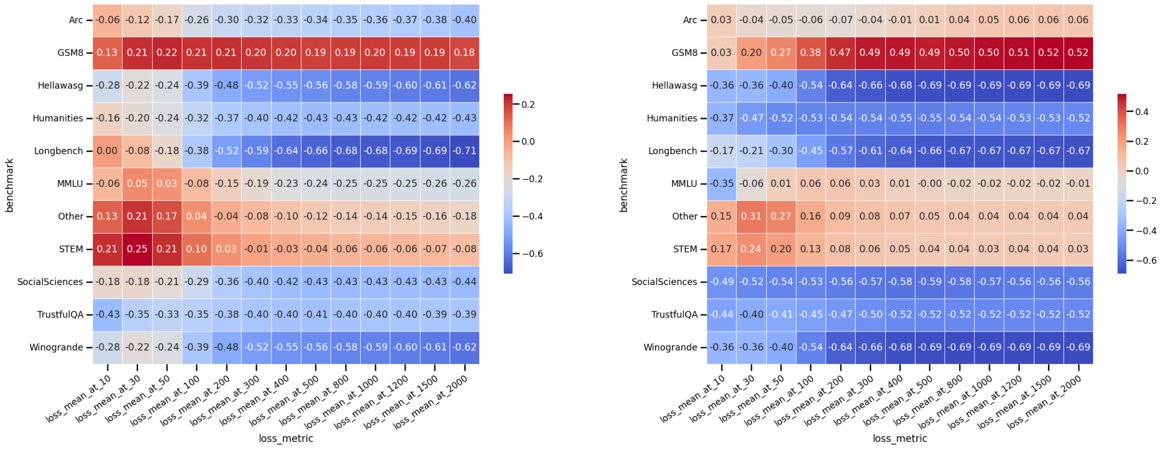
(b) non-STEM: base models

(c) Non-STEM: chat models

Figure 11: The heatmaps display the correlations by loss for a group of models across different text chunk lengths and different benchmark scores. Each row represents a specific truncation length, while the columns represent different benchmark score categories. The values in the cells indicate the corresponding correlation coefficients. (a) presents the correlations by loss for all 18 base models on STEM Academia texts. (b) presents the correlations by loss for all 18 base models on non-STEM Academia texts. (c) presents the correlations by loss for all 15 chat models on non-STEM Academia

Table 10: Sample of Questions and Their Respective Answers (Correct Answer in Bold): The percentages represent the proportion of forecasters' votes on a prediction website.

Question	**Start Time**	**End Time**	**Possible Answers**
What will be the 12-month percentage change in the US Consumer Price Index (CPI) for September 2024?	May 31, 2024 05:00PM UTC	Oct 01, 2024 07:01AM UTC	Up by less than 1.200% or down: 0% Up by at least 1.200%, but less than 1.800%: 0% Up by at least 1.800%, but less than 2.400%: 53% **Up by at least 2.400%, but less than 3.000%: 44%** Up by at least 3.000%, but less than 3.600%: 3% Up at least 3.600%, but less than 4.200%: 0% Up by 4.200% or more: 0%
If Israeli Defense Forces (IDF) ground forces invade the Gaza Strip before 7 November 2023, when will Israel publicly announce or acknowledge that IDF ground forces have left the Gaza Strip?	Oct 17, 2023 05:00PM UTC	Oct 10, 2024 07:01AM UTC	Before 30 November 2023: 0% Between 30 November 2023 and 13 January 2024: 0% Between 14 January 2024 and 13 March 2024: 0% Between 14 March 2024 and 11 June 2024: 0% Between 12 June 2024 and 9 October 2024: 2% **Not before 10 October 2024: 96%** IDF ground forces will not invade the Gaza Strip before 7 November 2023: 2%
What will Kamala Harris' favorability rating be as of 3 October 2024, according to FiveThirtyEight?	Sep 17, 2024 08:00AM UTC	Oct 03, 2024 07:01AM UTC	Lower than 42.0%: 1% At least 42.0%, but less than 44.0%: 4% At least 44.0%, but less than 46.0%: 7% **At least 46.0%, but less than 48.0%: 70%** At least 48.0%, but less than 50.0%: 15% At least 50.0%, but less than 52.0%: 2% At least 52.0%, but less than 54.0%: 1% 54.0% or higher: 0%



(a) STEM: all chat models

(b) STEM: 7B level chat models

Figure 12: (a) presents the correlations by loss for all 15 chat models on STEM Academia texts. (b) presents the correlations by loss for all 9 7B level chat models on STEM Academia texts.

Table 11: Overview of AI Benchmarks and Their Evaluation Focus

Benchmark	**Description**
HellaSwag	Tests an AI's common sense reasoning by requiring it to complete sentences or narratives that reflect everyday logic, highlighting the model's ability to predict logical continuations. Zellers et al. (2019)
MMLU	Evaluates an AI's breadth and depth of understanding across a diverse range of subjects, from science to literature, showcasing its versatility and comprehensive grasp of human language. Hendrycks et al. (2021)
TruthfulQA	Focuses on the model's capacity to provide honest and accurate responses, particularly to questions where the truth may not be intuitive, testing its commitment to truthfulness and its proficiency in avoiding misinformation. Lin et al. (2022)
Winogrande	Assesses common sense reasoning and natural language understanding through sentence completion tasks, measuring an AI's ability to apply common sense knowledge in language processing. Sakaguchi et al. (2019)
GSM8K	Challenges AI models with elementary-level math problems, testing their mathematical reasoning capabilities and their understanding and application of basic math concepts. Cobbe et al. (2021)

Table 12: Correlation with Different Benchmarks, Base vs. Chat Models

Benchmarks	Loss of Base Model	Loss of Chat Model	Delta
MMLU	-0.61	-0.22	0.39
MMLU:Humanities	-0.59	-0.42	0.17
MMLU:SocialSciences	-0.54	0.42	0.96
MMLU:STEM	-0.29	0.02	0.31
MMLU:Other	-0.47	-0.1	0.37
Arc	-0.46	0.34	0.8
Hellawasg	-0.66	-0.57	0.09
Wnogrande	-0.56	0.57	1.13
Longbench	-0.04	-0.65	-0.61
GSM8K	-0.4	0.22	0.62
TrustfulQA	0.05	0.39	0.34

Table 13: Correlation with Longbench values across different lengths

Length	10	30	50	100	200	300	400	500	800	1000	1200	1500	2000
Base Models	0.35	0.13	0.06	-0.03	-0.05	-0.06	-0.05	-0.05	-0.04	-0.04	-0.04	-0.04	-0.04
Chat Models	0.01	-0.07	-0.16	-0.39	-0.53	-0.58	-0.61	-0.63	-0.65	-0.65	-0.67	-0.67	-0.68

Table 14: Detailed Record of Model Accuracy Peaks

Date	Models
2015-01	Skywork-13B-Base, Phi-1.5
2015-07	Skywork-13B-Base, Phi-1.5
2016-01	Baichuan2-7B-Chat, Colossal-LLaMA-2-7B-Base, LLaMA-2-7B, Qwen-14B-Chat, Qwen-1.8B, Qwen-1.8B-Chat, Yi-6B, Yi-6B-Chat, Baichuan-13B-chat, Baichuan-7B-chat, ChatGLM3-6B, falcon-1B, InternLM-chat-7B, OPT-13B, Phi-2
2016-07	RWKV5-Eagle-7B
2017-01	GPT-3.5-turbo-0613
2017-07	Baichuan2-7B-Base
2018-01	Baichuan2-13B-Base
2018-07	Baichuan2-13B-Chat, LLaMA-2-13B-hf, Qwen-7B, GPT4-0613, GPT4-1106, LLaMA2-7B-Chat, LLaMA-7B, mistral-7B-v0.1, OPT-2.7B, Pythia-12B, Zephyr-7B-beta
2019-07	TinyLLaMA-1.1B-Chat
2020-01	
2020-07	
2021-01	
2021-07	
2022-01	
2022-07	
2023-01	
2023-07	
2024-01	
2024-07	

Table 15: Analysis about the time of the best-achieved accuracy and its cutoff time.

Peak Period	Model	Peak Time of Accuracy	Cutoff Time	Interpolation
Post-2019	TinyLLaMA1.1B	2019-07	2023-11	52
2017 to 2018	GPT4-1106	2018-07	2023-06	59
	LLaMA2-13B	2018-07	2023-02	55
	Baichuan2-13B-Base	2018-01	2023-06	65
2015 to 2016	Baichuan2-7B-Chat	2016-01	2023-08	91
	Colossal-LLaMA-2-7B-Base	2016-01	2023-09	92
	LLaMA2-7B	2016-01	2023-02	85