Mapping 1,000+ Language Models via the Log-Likelihood Vector

Anonymous ACL submission

Abstract

To compare autoregressive language models at scale, we propose using log-likelihood vectors computed on a predefined text set as model features. This approach has a solid theoretical basis: when treated as model coordinates, their squared Euclidean distance approximates the Kullback–Leibler divergence of text-generation probabilities. Our method is highly scalable, with computational cost growing linearly in both the number of models and text samples, and is easy to implement as the required features are derived from cross-entropy loss. Applying this method to over 1,000 language models, we constructed a "model map," providing a new perspective on large-scale model analysis.

1 Introduction

Language models have been evolving rapidly, and their community has grown substantially. To understand the community's structure and future directions, it is essential to systematically analyze model similarity and positioning based on language modeling principles. On the Hugging Face Hub, models are categorized based on their names and attributes, while other studies measure model similarity by outputs (Yax et al., 2024) or activations (Zhou et al., 2025). Leaderboards (Beeching et al., 2023; Fourrier et al., 2024; Chiang et al., 2024) are commonly used to assess model standings.

Since language models are probability models, we propose representing each model with coordinates that reflect the structure of the corresponding probability distribution space. Concretely, we define a language model's coordinates as its log-likelihood vector across a large collection of texts. Figure 1 shows a model map obtained through dimensionality reduction applied to the coordinates of 1,018 language models. This visualization reveals that models of the same type tend to cluster together, while text categories with the highest relative log-likelihoods appear as a continuous distribution across the map.

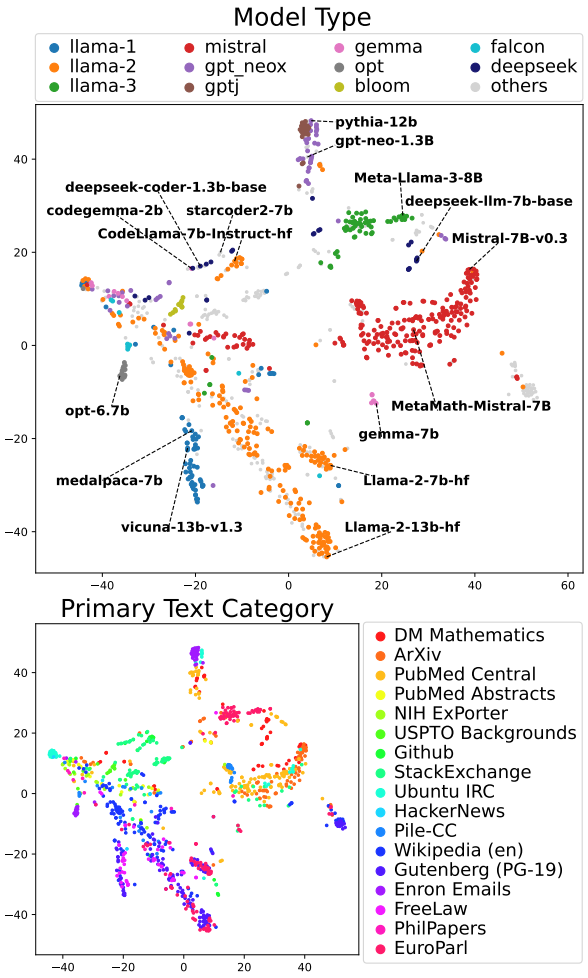

Figure 1: Map of 1,018 language models. Their log-likelihood vectors are visualized using t-SNE. (Top) Colors indicate model types. (Bottom) Colors indicate the model's "primary text category," the text category where the model achieves the highest relative log-likelihood among 17 categories. See Section 4 for details.

We find that the distances in our defined coordinate system accurately capture relationships among language models. On this map, each point represents a single model, with those having similar

meta-llama/Meta-Llama-3-8B	KL	mistralai/Mistral-7B-v0.3	KL	google/codegemma-2b	KL	deepseek-ai/deepseek-llm-7b-base	KL
Undi95/Meta-Llama-3-8B-hf	0.003	MaziyarPanahi/Mistral-7B-v0.3	0.000	deepseek-ai/deepseek-coder-1.3b-instruct	1654.767	deepseek-ai/deepseek-moe-16b-base	130.715
dfurman/Llama-3-8B-Orpo-v0.1	6.994	mistral-community/Mistral-7B-v0.2	7.221	bigcode/starcoderbase-1b	1812.768	deepseek-ai/deepseek-llm-7b-chat	245.408
migtissera/Tess-2.0-Llama-3-8B	28.829	unsloth/mistral-7b-v0.2	7.222	deepseek-ai/deepseek-coder-1.3b-base	2115.462	deepseek-ai/deepseek-moe-16b-chat	247.889
freewheelin/free-llama3-dpo-v0.2	67.783	mistralai/Mistral-7B-v0.1	22.038	bigcode/gpt_bigcode-santacoder	2644.348	deepseek-ai/DeepSeek-V2-Lite	306.530
jondurbin/bagel-8b-v1.0	110.365	Cartinoe5930/Llama2_init_Mistral	29.819	deepseek-ai/deepseek-coder-6.7b-instruct	2675.004	deepseek-ai/ESFT-vanilla-lite	307.487
migtissera/Llama-3-8B-Synthia-v3.5	128.141	Locutusque/Hercules-3.1-Mistral-7B	32.099	Qwen/CodeQwen1.5-7B-Chat	2759.243	deepseek-ai/DeepSeek-V2-Lite-Chat	585.090
nvidia/Llama3-ChatQA-1.5-8B	128.776	migtissera/Synthia-7B-v3.0	33.418	NTQAI/Nxcode-CQ-7B-orpo	2767.578	mistralai/Mistral-7B-Instruct-v0.1	913.708
ruslanmv/Medical-Llama3-8B	138.566	uukuguy/speechless-zephyr-code-functionary-7b	35.723	Salesforce/codegen-6B-multi	2859.701	statking/zephyr-7b-sft-full-orpo	1089.127
FairMind/Llama-3-8B-4bit-UltraChat-Ita	199.748	uukuguy/zephyr-7b-alpha-dare-0.85	35.745	bigcode/starcoderbase-7b	2990.326	Severian/ANIMA-Phi-Neptune-Mistral-7B	1140.161
NousResearch/Hermes-2-Theta-Llama-3-8B	222.357	crumb/apricot-wildflower-20	40.907	deepseek-ai/deepseek-coder-6.7b-base	3282.352	sethuiyer/Medichat-Llama3-8B	1157.599

Table 1: Top 10 nearest neighbors among the 1,018 language models for each model listed in the first row. The KL divergence is computed using formula (3).

text-generation probability distributions appearing closer together and those with more distinct distributions positioned farther apart. In Section 2, we show that the squared Euclidean distance in this coordinate system approximates the Kullback-Leibler (KL) divergence among models. Table 1 lists the nearest neighbors for each language model. For example, many of the closest neighbors of `meta-llama/Meta-Llama-3-8B` (AI@Meta, 2024) also contain `Llama-3` in their names.

Several studies have explored methods for comparing language models (see Appendix A). In particular, prior work on comparing generated text includes approaches that construct phylogenetic trees based on model-generated text (Yax et al., 2025) and approaches that measure differences in text-generation probabilities conditioned on given prompts using KL divergence (Melamed et al., 2024). However, these methods require generating text with each model, thus incurring the cost of pairwise distance computations, which becomes prohibitively expensive at large scale. By contrast, our method does not involve actual text generation; instead, we compute generation probabilities on a predefined text corpus. This enables us to derive model coordinates without pairwise comparisons, allowing efficient large-scale comparison of many models.

A language model's log-likelihood vector can be treated as its feature vector. In Section 4, we discuss the insights gleaned from analyzing these features. Then, in Section 5, we show how this feature vector can be leveraged to predict benchmark performance.

2 Mapping Language Models into the Space of Text Probability Distributions

In this section, we present our proposed method. Sections 2.2 and 2.3 introduce model feature vectors derived from text-generation probabilities. Section 2.4 demonstrates that the squared Euclidean distance in the coordinate system built using these features approximates the KL divergence between models. Section 2.5 offers an interpretation of the resulting model coordinates. An extension of this method, which defines model coordinates using the sequence of conditional probabilities for generating a given token sequence, is presented in Appendix E.

2.1 Autoregressive language models

Let $\mathcal{X}$ be the set of all possible texts, and let $\mathcal{V}$ be the token vocabulary. A text $x \in \mathcal{X}$ is represented as a sequence of tokens:

$$x = (y_1, \ldots, y_n), \quad y_t \in \mathcal{V}.$$

Denoting the maximum text length by $n_{\max}$, we have $\mathcal{X} = \bigcup_{n=0}^{n_{\max}} \mathcal{V}^n$. We consider a set of K language models $\{p_i\}_{i=1}^K$. With y_0 denoting the beginning-of-sequence (BOS) token, each language model p_i predicts the next token y_t given the preceding token sequence $y^{t-1} = (y_0, \ldots, y_{t-1})$. Thus, the conditional probability defined by p_i is given by

$$y_t \sim p_i(y_t \mid y^{t-1}), \quad t = 1, \ldots, n.$$

Accordingly, the probability of a text x under model p_i, denoted $x \sim p_i$, is

$$p_i(x) = \prod_{t=1}^{n} p_i(y_t \mid y^{t-1}).$$

In addition to the K language models $p_1, \ldots, p_K$, we introduce a language model p_0 that represents an underlying distribution for theoretical purposes. We assume we have a dataset (corpus)

$$D = (x_1, x_2, \ldots, x_N) \in \mathcal{X}^N,$$

consisting of N texts, where each text is independently drawn from p_0.

2.2 Log-likelihood vector

For a model p_i, the probability of generating a text x is denoted $p_i(x)$. Following the convention in

statistical model selection, we refer to $p_i(x)$ as the likelihood of model p_i given the text x. The log-likelihood is then defined as

$$\ell_i(x) = \sum_{t=1}^{n} \log p_i(y_t \mid y^{t-1}).$$

In language model implementations, $-\ell_i(x)$ corresponds to the cross-entropy loss for the text x, and $\exp(-\ell_i(x)/n)$ is known as the perplexity.

Our approach is straightforward. Given that the dataset D consists of N texts, we use the log-likelihood vector

$$\boldsymbol{\ell}_i = (\ell_i(x_1), \ldots, \ell_i(x_N))^\top \in \mathbb{R}^N$$

as the feature vector for model p_i. The first step in our model analysis is to construct the log-likelihood matrix

$$\boldsymbol{L} = (\boldsymbol{\ell}_1, \ldots, \boldsymbol{\ell}_K)^\top \in \mathbb{R}^{K \times N}$$

by stacking the vectors $\boldsymbol{\ell}_i$ for the K models.

2.3 Double centering

As a preprocessing step for model analysis, we apply a technique called double centering (Borg and Groenen, 2005) to $\boldsymbol{L}$. First, we perform row-wise centering. The mean of each row, referred to as the mean log-likelihood, is given by

$$\bar{\ell}_i = \sum_{s=1}^{N} \ell_i(x_s)/N.$$

Subtracting this value from each component of $\boldsymbol{\ell}_i$, we define the centered log-likelihood vector $\boldsymbol{\xi}_i = (\xi_{i1}, \ldots, \xi_{iN})^\top \in \mathbb{R}^N$, where

$$\xi_{is} := \ell_i(x_s) - \bar{\ell}_i, \quad s = 1, \ldots, N.$$

Next, we apply column-wise centering to the matrix of centered feature vectors $(\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_K)^\top$. The mean vector is $\bar{\boldsymbol{\xi}} = \frac{1}{K}\sum_{i=1}^{K} \boldsymbol{\xi}_i$, and by subtracting this vector from each $\boldsymbol{\xi}_i$, we define the double-centered log-likelihood vector

$$\boldsymbol{q}_i = \boldsymbol{\xi}_i - \bar{\boldsymbol{\xi}}.$$

For further details, see Appendices B and C.

2.4 Kullback–Leibler divergence

The Kullback–Leibler (KL) divergence is often used to measure how far apart two models p_i and p_j are in the space of probability distributions.[1] It is defined as

$$\begin{aligned} \mathrm{KL}(p_i, p_j) &= \sum_{x \in \mathcal{X}} p_i(x) \log \frac{p_i(x)}{p_j(x)} \\ &= \mathbb{E}_{x \sim p_i}\big(\ell_i(x) - \ell_j(x)\big). \end{aligned} \tag{1}$$

We assume the dataset D is generated from an unknown underlying model p_0 and that the models p_i and p_j provide good approximations of p_0. Under this assumption, the KL divergence can be approximated as follows:

$$2\,\mathrm{KL}(p_i, p_j) \approx \mathrm{Var}_{x \sim p_0}\big(\ell_i(x) - \ell_j(x)\big). \tag{2}$$

While the definition of KL divergence in (1) involves the expectation of $\ell_i(x) - \ell_j(x)$, the approximation in (2) takes the form of a variance. This result is somewhat surprising yet quite insightful. Notably, although KL divergence is not symmetric in the two models, the approximation in (2) is symmetric. We estimate (2) from the dataset D as

$$2\,\mathrm{KL}(p_i, p_j) \approx \|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2/N. \tag{3}$$

Thus, if we regard the model coordinates of p_i as $\boldsymbol{q}_i/\sqrt{N}$ by scaling with N, then the squared Euclidean distance between two points approximates $2\,\mathrm{KL}(p_i, p_j)$.

The main results, namely (2) and (3), are proved in Appendix D using the theory of exponential family of distributions (Barndorff-Nielsen, 2014; Efron, 1978, 2022; Amari, 1982), similar to the discussion on the relationship between the norm of embeddings and KL divergence (Oyama et al., 2023). Although the concept of model coordinates has been discussed in statistics (Shimodaira, 2001), and there have been a few applications of model maps (Shimodaira and Hasegawa, 2005; Shimodaira and Terada, 2019), they have seldom been utilized in practice.

2.5 Model coordinates

We primarily use $\boldsymbol{q}_i$ as the feature vector of model p_i and refer to it as the model coordinates. As shown in (3), the squared Euclidean distance in the $\boldsymbol{q}$-coordinate system approximates the KL divergence between language models,[2] indicating that $\boldsymbol{q}_i$ represents the position of p_i in the space of probability distributions. Since $\boldsymbol{\xi}_i$ differs from $\boldsymbol{q}_i$ only

[1] $\mathbb{E}(\cdot)$ denotes expectation and $\mathrm{Var}(\cdot)$ denotes variance.

[2] That is, $\|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2 \approx 2N\,\mathrm{KL}(p_i, p_j)$. For simplicity, we omit the constant scaling factor in expressions of this type.

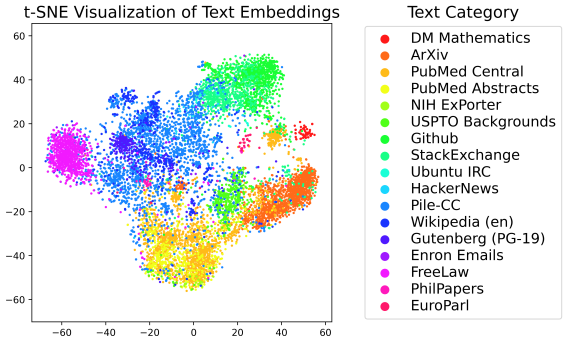

Figure 2: Text embeddings for 10,000 texts in dataset D, computed via `simcse-roberta-large` (Gao et al., 2021b) and visualized with t-SNE. Colors indicate 17 text categories.

by an offset from the origin, $\boldsymbol{\xi}_i$ also serves as a model coordinate, and $\|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2 = \|\boldsymbol{\xi}_i - \boldsymbol{\xi}_j\|^2$. However, we prefer $\boldsymbol{q}_i$ for its more interpretable components and thus adopt it throughout this paper.

For visualization purposes, we mainly use $\boldsymbol{\ell}_i$ as the coordinates of the model map, as $\boldsymbol{\ell}_i$ can be intuitively interpreted as encoding $\sqrt{N}\,\bar{\ell}_i$ in the "height" dimension and $\boldsymbol{q}_i$ in the "horizontal" dimensions. As shown in Appendix D.6,

$$\|\boldsymbol{\ell}_i - \boldsymbol{\ell}_j\|^2 = \|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2 + N(\bar{\ell}_i - \bar{\ell}_j)^2, \quad (4)$$

which means the squared Euclidean distance in the $\boldsymbol{\ell}$-coordinate system can be decomposed into the sum of $2N\,\mathrm{KL}(p_i, p_j)$ and $N\,(\bar{\ell}_i - \bar{\ell}_j)^2$.

3 Experimental Setup

We describe the key components of our experiment. In particular, Section 3.1 explains the procedure for selecting the 10,000 texts used to compute the model coordinates, and Section 3.2 discusses how we selected the 1,018 language models. Further details are given in Appendix G.

3.1 Selection of text data

The texts used for computing the language models' coordinates were extracted from the Pile (Gao et al., 2020), with five categories of copyrighted material removed.[3] This yielded a dataset D consisting of 10,000 texts, each tagged with a category label from the Pile. Figure 2 visualizes these texts.

To build the dataset, we began by dividing the first 1M texts from the Pile Uncopyrighted corpus into 1,024-byte chunks (UTF-8 encoded). In cases where decoding errors occurred, we truncated by one byte at a time. Chunks smaller than 256 bytes were discarded, resulting in about 5.7M valid chunks. From these, we randomly sampled 10,000 texts to create the final dataset used for computing model coordinates.

3.2 Selection of language models

We used $K = 1{,}018$ language models in total. Of these, 1,000 were selected from models listed on Open LLM Leaderboard v1. Specifically, we considered CausalLM models ranging from 1B to 13B parameters and ranked them by their number of downloads over the 30 days preceding February 1, 2025.[4] We initially selected the top 1,100 models by download count and attempted log-likelihood calculations. Among these, 1,011 successfully produced valid log-likelihood values, and we chose the 1,000 most frequently downloaded from that set. In addition, we included 18 models from the DeepSeek language model series. We obtained information on model parameter sizes and architectures from the Leaderboard. Appendix G provides basic information on the selected models and details on how model types were defined. A complete list of models used in this study is given in Appendix K.

3.3 Computation of the Log-Likelihood

The log-likelihood matrix $\boldsymbol{L}$ was computed in float16 precision, with the bottom 2% of values clipped. This clipping mitigates the large impact of extremely low likelihoods on (3). After computing $\boldsymbol{L}$, we applied row-wise and column-wise centering to obtain the double-centered log-likelihood matrix $\boldsymbol{Q}$. Figure 3 visualizes $\boldsymbol{Q}$. Each value in the matrix can be interpreted in two ways: as the relative probability of a text for each model or as the relative likelihood of a model for each text. Both models and texts exhibit clustering patterns. Figure 4 shows a dendrogram of the top 100 models. We examined the effective dimension from the perspective of feature vector dimensionality reduction and found that the cumulative contribution ratio, based on the sum of squared singular values of $\boldsymbol{Q}$, reached 90% at 42 dimensions and 95% at 82 dimensions.

3.4 Obtaining the leaderboard scores

We obtained benchmark scores for the language models used in our experiments from Open LLM

[3] https://huggingface.co/datasets/monology/pile-uncopyrighted

[4] Hugging Face's API provides the total number of downloads in the past 30 days.

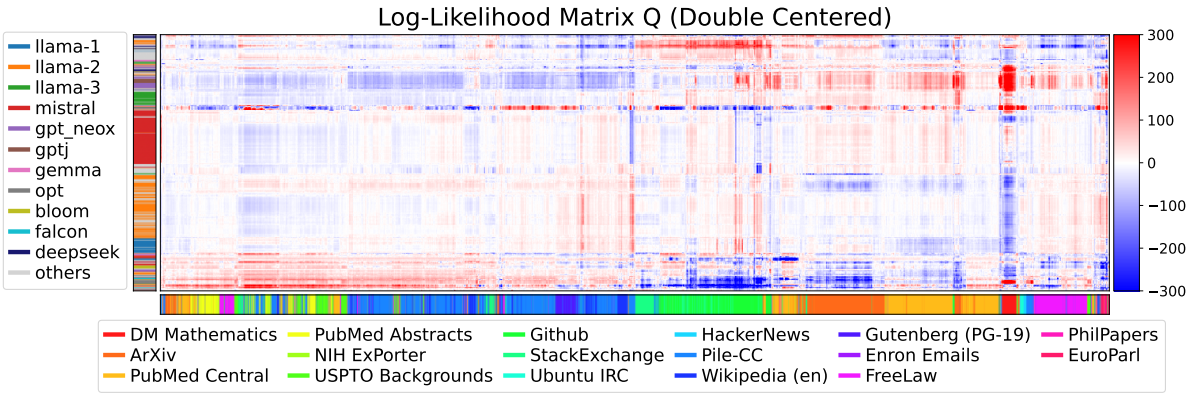

Figure 3: The double-centered log-likelihood matrix $\boldsymbol{Q}$, with rows and columns reordered by hierarchical clustering. Each row corresponds to one of the 1,018 models, color-coded by model type. Each column represents one of the 10,000 texts, color-coded by text category.

Figure 4: Hierarchical clustering of the top 100 most-downloaded models, based on their feature vectors $\boldsymbol{q}_i$. Model names are color-coded by model type.

Leaderboard v1.[5] Between April 2023 and June 2024, this leaderboard evaluated language models on six tasks: AI2 Reasoning Challenge (ARC) (Clark et al., 2018), HellaSwag (Zellers et al., 2019), MMLU (Hendrycks et al., 2021a), TruthfulQA (Lin et al., 2022a), Winogrande (Sakaguchi et al., 2019), and GSM8K (Cobbe et al., 2021). Along with individual task scores, we also use the average score across all six tasks, referred to as 6-TaskMean.

4 Map of Language Models

We applied t-SNE (van der Maaten and Hinton, 2008) to the log-likelihood matrix $\boldsymbol{L}$ for dimensionality reduction[6]. Using this visualization, we analyze the insights gained from the model map in this section. While this paper presents model maps using $\boldsymbol{L}$, alternative maps using the double-centered log-likelihood matrix $\boldsymbol{Q}$, as well as a model map with labels for all language models, are available in Appendix H.

4.1 Visualizing attributes on the model map

Model type. The top panel of Fig. 1 visualizes the distribution of model types, with each model color-coded according to its type. We observe that models belonging to the same type tend to cluster together, forming distinct regions on the map (e.g., `llama-2`, `mistral`, and `gemma`). In particular, models optimized for coding tasks[7] appear in a relatively compact region, suggesting that these models share notable similarities in their probability distributions.

Text category. The bottom panel of Fig. 1 shows the model map with each model color-coded according to the text category in which it achieves the highest relative likelihood. From this figure, we see that models exhibiting high likelihoods for the same text category are grouped together. Notably, the cluster containing coding-specialized models in the top panel aligns with the GitHub/StackExchange region in the bottom panel, suggesting that these models have relatively high likelihoods for text originating from GitHub and StackExchange.

Model performance. Figure 5 visualizes two evaluation metrics: mean log-likelihood and benchmark task performance. From the left and central

[5] https://huggingface.co/spaces/open-llm-leaderboard-old/open_llm_leaderboard

[6] The perplexity value was set to 30, and we used the scikit-learn implementation (Varoquaux et al., 2015).

[7] For example, `starcoder2-7b` (Lozhkov et al., 2024), `deepseek-coder-1.3b-base` (Guo et al., 2024), `codegemma-2b` (CodeGemma Team et al., 2024) and `CodeLlama-7b-Instruct-hf` (Rozière et al., 2024).

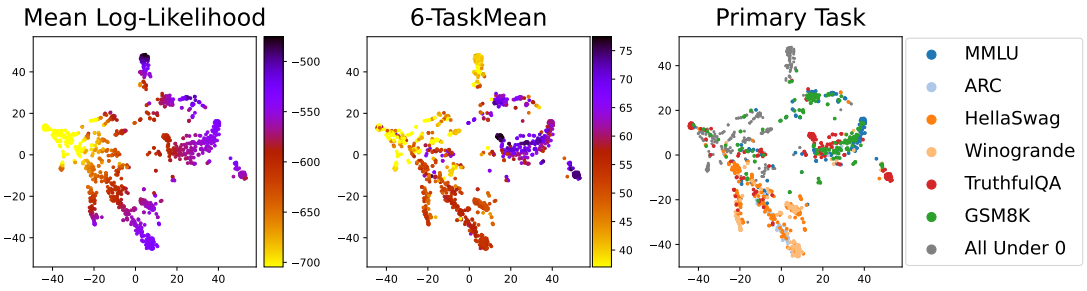

Figure 5: Model maps illustrating model performance. From left to right, the panels show each model's mean log-likelihood, 6-TaskMean score, and the "primary task," meaning the task for which each model achieves its highest standardized score among the six tasks. The color bar is clipped at the 10th percentile for mean log-likelihood and 6-TaskMean, with darker colors indicating better performance. In the primary task panel, models with standardized scores below zero on all six tasks are labeled "All Under 0."

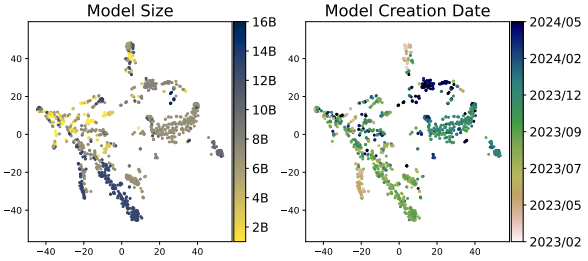

Figure 6: A model map color-coded by (Left) model size and (Right) model creation date.

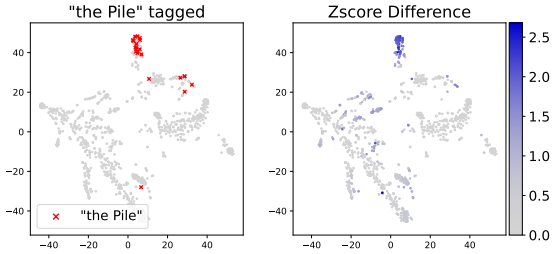

Figure 7: (Left) Models tagged with "the Pile." (Right) Difference between the standardized mean log-likelihood and the standardized 6-TaskMean score.

panels, we see that both metrics exhibit similar trends on the map, where models that lie close together tend to show similar metric values. Additionally, in the right panel, the GSM8K/MMLU region corresponds to the ArXiv/PubMed Central region in the bottom panel of Fig. 1, suggesting that models with high likelihoods on academic and scientific texts also tend to perform well on mathematical reasoning and academic knowledge-intensive tasks.

Model size and creation date. Figure 6 shows the distribution of models by size and creation date. Compared to Fig. 5, newer models generally perform better, but model size does not always correlate with performance, as some smaller models perform comparably to larger ones.

4.2 Detection of data leakage

Since the text data we used was extracted from the Pile corpus, models that were pre-trained on the Pile are likely to exhibit higher log-likelihood values than their actual capabilities measured by benchmarks. We analyze this effect using the model map in Fig. 7. The left panel highlights models that used the Pile for pre-training. The right panel shows models with high mean log-likelihood relative to their 6-TaskMean score. The alignment between these two distributions suggests that models pre-trained on the Pile tend to achieve higher likelihoods on our text data, while their benchmark performance remains comparatively lower.

5 Predicting Model Performance from Model Coordinates

As shown in the central panel of Fig. 5, the positioning of models on the map suggests that a model's benchmark performance may be inferred from its coordinates. In this section, we conduct a regression analysis using the $\boldsymbol{q}$-coordinates to predict benchmark scores and evaluate predictive performance.

5.1 Benchmark scores and models

We use six benchmark scores from Open LLM Leaderboard v1, as described in Section 3.4. Our experiments are conducted on 996 models for which these benchmark scores are available[8].

[8]From the 1,018 models, we excluded four that lacked TruthfulQA scores and 18 from `deepseek-ai`, as their bench-

	ARC	HellaSwag	MMLU	TruthfulQA	Winogrande	GSM8K	6-TaskMean	mean log-likelihood
Pearson's r	0.972	0.948	0.963	0.958	0.965	0.935	0.976	0.994
Spearman's ρ	0.976	0.974	0.969	0.937	0.973	0.899	0.978	0.990

Table 2: Results of ridge regression for predicting benchmark scores from model coordinates. Predictions for 6-TaskMean and mean log-likelihood are also included. High correlation coefficients are observed across all settings.

5.2 Setting for regression analysis

For each benchmark task, the dataset is given as $\{(\boldsymbol{q}_1, f_1), \ldots, (\boldsymbol{q}_K, f_K)\}$, where $\boldsymbol{q}_i \in \mathbb{R}^N$ is the double-centered log-likelihood vector of the language model p_i, and $f_i \in [0, 100]$ is its corresponding benchmark score. We use ridge regression to predict each benchmark score. Let $\boldsymbol{Q} \in \mathbb{R}^{K \times N}$ be the matrix of explanatory variables, and let $\boldsymbol{f} = (f_1, \ldots, f_K) \in \mathbb{R}^K$ be the vector for the target variable. The objective function with parameter $\boldsymbol{w} \in \mathbb{R}^N$ is given by:

$$L(\boldsymbol{w}) = \|\boldsymbol{f} - \boldsymbol{Q}\boldsymbol{w}\|^2 + \alpha\|\boldsymbol{w}\|^2,$$

where $\alpha \in \mathbb{R}_{>0}$ is a hyperparameter that controls the strength of regularization. Since the number of variables N is much larger than the sample size K ($N \gg K$), making this a high-dimensional regression setting, we carefully set α using cross-validation to avoid overfitting.

We split the set of models into five folds and perform parameter training[9] and benchmark score prediction. To mitigate the effect of randomness, we repeat the data splitting with five different seeds and take the average of the predictions as the final predicted score. As evaluation metrics, we compute Pearson's r and Spearman's ρ to measure the correlation between the predicted and benchmark scores. Additionally, we conduct experiments by replacing the target variable with 6-TaskMean and mean log-likelihood, leading to a total of eight experimental settings. See Appendix J.1 for details.

5.3 Results

Table 2 presents the results of the regression analysis. For all benchmark tasks, the correlation coefficients are high, demonstrating that ridge regression achieves strong predictive performance. Similarly, for 6-TaskMean, the correlation remains high, as also illustrated by the scatter plot in Fig. 8. Even for mean log-likelihood, the regression model attains a high correlation, despite the explanatory variables being double-centered.

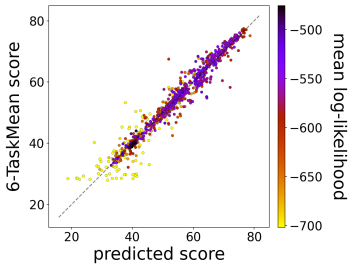

Figure 8: Scatter plot of predicted scores versus 6-TaskMean scores for test sets. Pearson's r is 0.976, and Spearman's ρ is 0.978. Each point is color-coded by the mean log-likelihood, with higher values generally corresponding to higher 6-TaskMean scores. However, some models with extremely high mean log-likelihood due to data leakage (Section 4.2) appear in the lower score region, deviating from the general trend. Despite this, the regression-based predictions remain highly accurate, as reflected in the strong correlation coefficients. The color bar is clipped at the 10th percentile. Scatter plots for individual benchmark tasks are provided in Fig. 14 in Appendix J.2.

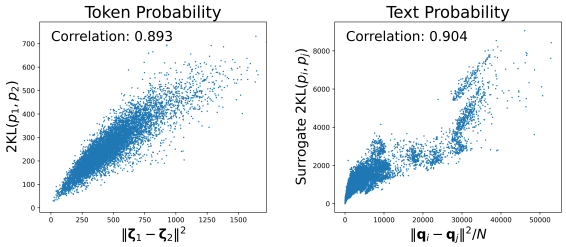

Figure 9: Relationship between the squared Euclidean distance of model coordinates and KL divergence. (Left) In the token-level experiment (Section 6.1), each point represents a text. (Right) In the text-level experiment (Section 6.2), each point represents a pair of models.

6 Empirical Validation of Theory

In Section 2, we discussed model coordinates for text probability models. Appendix E extends this framework to token-sequence probability models. These theoretical results state that the squared Euclidean distance in the model-coordinate space approximates the KL divergence between models. To validate this, we first evaluate token-level condi-

mark scores were incomplete due to the models being relatively new, leaving 996 for analysis. For simplicity, we denote the number of models as K.

[9]We used scikit-learn (Varoquaux et al., 2015) `RidgeCV`.

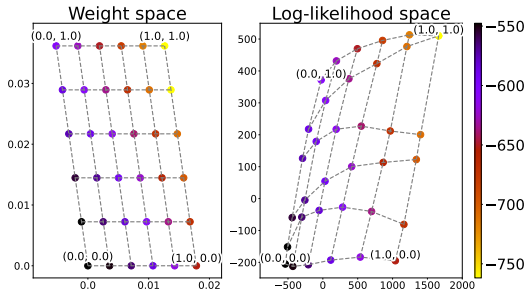

Figure 10: Visualization of 36 language models obtained by linearly interpolating pretrained model weights. Each point is color-coded according to its mean log-likelihood. (Left) Models in the weight parameter space. (Right) Models in the probability distribution space, represented by the $\boldsymbol{q}$-coordinate system.

tional probability models (Section 6.1), since token-level experiments are generally easier to conduct than text-level experiments. We then extend our analysis to text probability models (Section 6.2). Additionally, in Section 6.3, we explore the relationship between model weight parameters and model coordinates.

6.1 Validation of (26) for token-level models

Settings. Two models with a shared tokenizer `Llama-2-7b-hf` and `Llama-2-7b-chat-hf` (Touvron et al., 2023b), denoted as p_1 and p_2, were used. Following the method described in Appendix E.1, we computed the model coordinates $\boldsymbol{\zeta}_1(x)$ and $\boldsymbol{\zeta}_2(x)$ for each text $x = (y_1, \cdots, y_n) \in D$, where these coordinates are centered vectors with elements $\log p_i(y_t|y^{t-1})$ as defined in (22). We then calculated the squared Euclidean distance between these coordinates, $\|\boldsymbol{\zeta}_1(x) - \boldsymbol{\zeta}_2(x)\|^2$. To obtain the exact KL divergence between models, we used the outputs of the softmax function in the language models. We computed the sum of per-token KL divergences: $\sum_{t=1}^{n} \mathrm{KL}(p_1(y_t|y^{t-1}), p_2(y_t|y^{t-1}))$, which is also used in Lv et al. (2023).

Results and discussion. The left panel of Fig. 9 shows a scatter plot of the squared Euclidean distance and KL divergence for $x \in D$, with a correlation coefficient of 0.893. This result indicates that (26) provides a good approximation in actual language models.

6.2 Validation of (3) for text-level models

Settings. Among the 292 language models sharing the tokenizer with `Llama-2-7b-hf` (Touvron et al., 2023b), we excluded the five models with the largest values of $\sum_{x \in D} \|\boldsymbol{\zeta}_i(x)\|^2$, leaving 287 models for our experiment. Using the approach described in Section 2, we computed the model coordinates for each model and calculated the squared Euclidean distance $\|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2$ between every pair of models. Because it is extremely difficult to directly compute $\mathrm{KL}(p_i, p_j)$, we instead used $\frac{1}{N}\sum_{x \in D} \left\|\boldsymbol{\zeta}_i(x) - \boldsymbol{\zeta}_j(x)\right\|^2$ as a proxy. For a theoretical justification that this quantity approximates $\mathrm{KL}(p_i, p_j)$, see (27) in Appendix E.

Results and discussion. As shown in the right panel of Fig. 9, the scatter plot of squared Euclidean distance versus KL divergence exhibits a correlation coefficient of 0.904. This finding confirms that the relationship in (3) holds approximately in practical language models.

6.3 Relationship between model weights and model coordinates

For language models with the same architecture, comparison can also be conducted via weight parameters. We investigated how the structure of the model-coordinate space aligns with the structure of the weight-parameter space. We generated 36 new language models by linearly interpolating the weights of `Llama-2-7b-hf`, `Llama-2-7b-chat-hf` (Touvron et al., 2023b), and `vicuna-7b-v1.5` (Zheng et al., 2023). For these 36 models, we computed text-generation log-likelihoods and visualized the resulting model coordinates in two dimensions using Principal Component Analysis (PCA). Figure 10 shows these 36 models in both weight space and model coordinate space. We observe that the two-dimensional grid structure in the weight space is mapped continuously into the model coordinate space. This finding supports the validity of (6) and (14) in Appendix D, especially for models that are close to one another. Further details on this experiment can be found in Appendix I.

7 Conclusion

We propose a method to compare autoregressive language models using log-likelihoods from a predefined text set. By treating these as model coordinates, we show that the squared Euclidean distance approximates KL divergence, enabling efficient large-scale comparisons. Experiments with over 1,000 models confirm its effectiveness in structuring model relationships and predicting benchmark task performance, while also validating the theoretical foundations.

Limitations

- Changing the text data will alter the analysis results of the model map. This is both a limitation and an advantage of the proposed method, because it allows us to choose text data according to the analysis objective. For example, if we want to investigate code-focused language models in more detail, we can increase the proportion of code data from GitHub, thereby increasing the resolution of code-focused models on the model map.

- The proof (Section 2 and Appendix D) that the squared Euclidean distance in the model coordinate system approximates the KL divergence assumes that the language model's text-generation probabilities closely match the distribution of the text data. When this assumption does not hold, the approximation accuracy decreases. However, even under such circumstances, the model coordinates should still function sufficiently as model features.

- If the text data used for the model coordinates is contained in a language model's pre-training corpus, that model's mean log-likelihood may be overestimated. This data leakage is generally non-negligible, as shown in Fig. 7 in Section 4.2, which illustrates the effect of using the Pile corpus. However, comparing it against benchmark scores makes it possible to detect such data leakage, and one can remove models that are affected.

- Beyond the data leakage mentioned above, other systematic errors introduced into the model coordinates can also affect the model map. As noted in Appendix C, $\boldsymbol{\ell}_i$ and $\bar{\ell}_i$ are susceptible to systematic biases. However, thanks to double centering, $\boldsymbol{q}_i$ is less influenced by bias terms.

- Although the calculation of model coordinates is linear time $O(KN)$ in the number of models K and the number of texts N, it still requires a non-negligible amount of computation. In our experiments, it took about 10 minutes on a single GPU (RTX 6000 Ada) to compute coordinates ($N = 10^4$, float16) for a single 7B model.

- Computing the model map visualization from the model coordinates is generally not linear in K. For example, t-SNE requires a distance matrix, incurring $O(K^2N)$ computational cost. However, in modern computing environments, as long as K is not extremely large (e.g., in the millions), the cost of visualization is negligible compared to the cost of calculating the model coordinates.

- A sufficiently large number of text samples, N, is desirable for the model coordinates. We used $N = 10^4$. Since the error in the KL divergence estimate due to randomness decreases proportionally to $N^{-1/2}$, N must be increased according to the desired resolution of the model map.

- When using model coordinates as feature vectors, $N = 10^4$ can be unwieldy. According to the experiment in Section 3.3, applying PCA to reduce the dimensionality of $\boldsymbol{q}$-coordinates to 82 dimensions still retains 95% of the information. However, the predictive performance of such dimension-reduced features has not yet been tested.

- Since the language models used in our experiments were obtained from the Open LLM Leaderboard v1 (which ran from April 2023 to June 2024), our discussion of models released after June 2024 is limited.

- The results of the task-performance prediction in Section 5 should be interpreted conservatively. While we use a proper cross-validation setup to prevent data leakage (splitting the training set, validation set, and test set), if very similar models appear in both training and test sets (for example, models that share a base model and differ only slightly by fine-tuning), it might become easier to predict task performance. Also, we have not evaluated models that are not listed on the leaderboard.

- The theoretical validation experiment in Section 6 is limited. Currently, it is difficult to directly compute exact KL divergence values among text-generation probability models, so conducting more precise validation experiments remains a future challenge.

- In the method of computing model coordinates from token-sequence conditional probabilities (Appendix E and Appendix F), the proof that the squared Euclidean distance in

the model coordinate system approximates the KL divergence requires additional assumptions (Appendix F.3). In practice, Assumption 2 does not hold, and due to the variations in (33), $\|\boldsymbol{\zeta}_i - \boldsymbol{\zeta}_j\|^2$ in (26) tends to overestimate the KL divergence. Nonetheless, even in such situations, token-level model coordinates will still likely function sufficiently as features.

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A Related Work

In recent years, research on comparing large language models (LLMs) has gained attention. This section provides an overview of existing studies from three perspectives: model parameters, activations[10], and probability distributions.

Comparison of model parameters. One approach to comparing LLMs is to analyze their parameters. Zhu et al. (2025) proposed a statistical framework for evaluating parameter similarity between different models and introduced a method for determining whether these models were trained independently. Additionally, Yadav et al. (2023b) focused on parameter changes due to task adaptation, specifically analyzing task vectors[11]. They proposed a method to mitigate interference when integrating task vectors from different models. Specifically, by reducing redundant numerical components and adjusting for conflicting signs, their approach enables effective model merging.

Comparison of activations. Comparisons of LLMs based on activations have also been studied. Zhou et al. (2025) quantified the similarity between LLMs by measuring the cosine similarity of activations for linguistic minimal pairs. In particular, they used datasets such as BLiMP (Warstadt et al., 2020) and showed that model similarity is significantly influenced by the pre-training dataset.

Comparison of probability distributions. Several approaches compare LLMs using probability distributions. Lv et al. (2023) proposed a method for computing coefficients in parameter ensembling by providing the same input text to two models and comparing the softmax probability distributions at each token. Specifically, they used KL divergence and summed the results to derive appropriate coefficients. Furthermore, Yax et al. (2025) proposed a similarity metric based on the conditional probabilities of LLMs and introduced a method for calculating the phylogenetic distance between different models. Additionally, a method has been proposed for measuring differences in conditional probabilities based on prompts using KL divergence (Melamed et al., 2024).

B Double Centering

We confirm the notation and computational operations. The matrices $\boldsymbol{L}$, $\boldsymbol{\Xi}$, and $\boldsymbol{Q}$ are all of size $K \times N$, and their elements are denoted by

[10] In general, "activations" refer to the intermediate outputs of Transformer models (e.g., the residual stream or neurons) (Bereska and Gavves, 2024).

[11] The difference in parameters before and after fine-tuning is referred to as a task vector, and arithmetic operations on these vectors function effectively (Ilharco et al., 2023).

$\ell_{is}, \xi_{is}, q_{is}$, respectively. In particular, we have $\ell_{is} = \ell_i(x_s)$. First, row-wise centering of $\boldsymbol{L}$ is performed by subtracting the mean log-likelihood $\bar{\ell}_i$ of each model from each row $(\ell_{i1}, \ldots, \ell_{iN})$, resulting in $\boldsymbol{\Xi} = (\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_K)^\top$. Next, column-wise centering of $\boldsymbol{\Xi}$ is performed by subtracting the coordinate component $\bar{\xi}_s$ of the mean vector $\bar{\boldsymbol{\xi}}$ from each column $(\xi_{1s}, \ldots, \xi_{Ks})^\top$, yielding $\boldsymbol{Q} = (\boldsymbol{q}_1, \ldots, \boldsymbol{q}_K)^\top$. Thus, this process involves *double centering*, where column-wise centering follows row-wise centering. Notably, even after column-wise centering, the row-wise mean of $\boldsymbol{Q}$ remains zero:

$$\begin{aligned}\frac{1}{N}\sum_{s=1}^{N} q_{is} &= \frac{1}{N}\sum_{s=1}^{N}(\xi_{is} - \bar{\xi}_s) \\ &= \frac{1}{N}\sum_{s=1}^{N}\xi_{is} - \frac{1}{NK}\sum_{i=1}^{K}\sum_{s=1}^{N}\xi_{is} \\ &= 0 - 0 = 0. \end{aligned} \tag{5}$$

The column-wise centering can be interpreted as follows. In the $\boldsymbol{\xi}$-coordinate system, the mean vector $\bar{\boldsymbol{\xi}}$ of the K model coordinates $\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_K$ can be regarded as representing an "average model." By redefining this average model as the new origin, we obtain the $\boldsymbol{q}$-coordinate system. From the definition $\boldsymbol{q}_i = \boldsymbol{\xi}_i - \bar{\boldsymbol{\xi}}$, its mean satisfies

$$\sum_{i=1}^{K} \boldsymbol{q}_i / K = \boldsymbol{0}.$$

The row-wise centering can be interpreted as follows. Let $\mathbf{1}_N = (1, \ldots, 1)^\top \in \mathbb{R}^N$. Since $\bar{\ell}_i = \mathbf{1}_N^\top \boldsymbol{\ell}_i / N$, we have $\boldsymbol{\xi}_i = \boldsymbol{\ell}_i - \bar{\ell}_i \mathbf{1}_N$. Thus,

$$\mathbf{1}_N^\top \boldsymbol{\xi}_i = \mathbf{1}_N^\top \boldsymbol{\ell}_i - \bar{\ell}_i N = 0,$$

and furthermore, $\mathbf{1}_N^\top \bar{\boldsymbol{\xi}} = 0$. From this, equation (5) is actually trivial, as

$$\mathbf{1}_N^\top \boldsymbol{q}_i = \mathbf{1}^\top (\boldsymbol{\xi}_i - \bar{\boldsymbol{\xi}}) = 0 - 0 = 0.$$

The row-wise centering implies that $\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_K$ and $\boldsymbol{q}_1, \ldots, \boldsymbol{q}_K$ lie in the subspace orthogonal to $\mathbf{1}_N$.

C Effect of errors in model coordinates

We analyze the impact of additive errors ϵ_{is} in the log-likelihood vector components ℓ_{is} for $i = 1, \ldots, K$ and $s = 1, \ldots, N$. Denoting the true values with an asterisk as ℓ^*_{is}, the observed values can be expressed as

$$\ell_{is} = \ell^*_{is} + \epsilon_{is}.$$

We decompose the error as follows:

$$\epsilon_{is} = a + b_i + c_s + d_{is},$$

where we assume, without loss of generality, the constraints

$$\sum_{i=1}^{K} b_i = \sum_{s=1}^{N} c_s = \sum_{i=1}^{K} d_{is} = \sum_{s=1}^{N} d_{is} = 0.$$

Here, a, b_i, and c_s are bias terms, while d_{is} represents interaction terms. Using simple calculations, we obtain:

$$\begin{aligned}\bar{\ell}_i &= \frac{1}{N}\sum_{s=1}^{N} \ell_{is} = \bar{\ell}^*_i + a + b_i, \\ \xi_{is} &= \ell_{is} - \bar{\ell}_i = \xi^*_{is} + c_s + d_{is}, \\ \bar{\xi}_s &= \frac{1}{K}\sum_{i=1}^{K} \xi_{is} = \bar{\xi}^*_s + c_s, \\ q_{is} &= \xi_{is} - \bar{\xi}_s = q^*_{is} + d_{is}. \end{aligned}$$

Additionally, for the differences between two models, which are crucial for the model map, we obtain:

$$\begin{aligned}\ell_{is} - \ell_{js} &= \ell^*_{is} - \ell^*_{js} + b_i - b_j + d_{is} - d_{js}, \\ \xi_{is} - \xi_{js} &= \xi^*_{is} - \xi^*_{js} + d_{is} - d_{js}, \\ q_{is} - q_{js} &= q^*_{is} - q^*_{js} + d_{is} - d_{js}. \end{aligned}$$

Thus, the terms affected by the error are $\bar{\ell}_i$, which is influenced by $a + b_i$, and $\ell_{is} - \ell_{js}$, which is affected by $b_i + d_{is}$, meaning it is influenced by the bias terms. However, in the centered values $\xi_{is} - \xi_{js}$ and $q_{is} - q_{js}$, only the interaction term d_{is} contributes to the error.

D Theory of Model Coordinates for Text Probability Distributions

In this section, we prove the main results of Section 2, namely (2) and (3). Our discussion applies not only to text probability distributions but also more generally to any setting where i.i.d. observations $x_1, \ldots, x_N \sim p_i(x)$ are available. Compared to the previous study that proposed model maps (Shimodaira and Cao, 1998), we conduct a more precise analysis in this paper. Specifically, the previous study provided only a rough evaluation of the approximation and omitted the centering argument in the proof of (2). In the next section, as the starting point of our discussion, we construct a *super model* that includes the K models p_i, $i = 1, \ldots, K$, as submodels. This model is introduced as a mathematical tool to rigorously prove the main theorem of this paper, and we do not compute it numerically in practice.

D.1 Exponential family of distributions

We first consider a model in the exponential family of distributions parameterized by a K-dimensional parameter $\boldsymbol{\theta} \in \mathbb{R}^K$:

$$p(x;\boldsymbol{\theta}) = p_0(x)\exp(\boldsymbol{\theta}^\top \boldsymbol{b}(x) - \psi(\boldsymbol{\theta})). \quad (6)$$

Here, the function $\boldsymbol{b}(x) = (b_1(x),\dots,b_K(x))^\top$ will be defined later using the K models. The normalization constant is given by

$$Z(\boldsymbol{\theta}) = \sum_{x\in\mathcal{X}} p_0(x)\exp(\boldsymbol{\theta}^\top \boldsymbol{b}(x)),$$
$$\psi(\boldsymbol{\theta}) = \log Z(\boldsymbol{\theta}),$$

which ensures that $\sum_{x\in\mathcal{X}} p(x;\boldsymbol{\theta}) = 1$. For $\boldsymbol{\theta} = \mathbf{0}$, where $\mathbf{0} = (0,\dots,0)^\top$, we obtain

$$p(x;\mathbf{0}) = p_0(x).$$

To associate the K models with (6), we define $\boldsymbol{b}(x)$. For a constant $\lambda > 0$, we set

$$\lambda b_i(x) := \ell_i(x) - \ell_0(x). \quad (7)$$

The constant λ is an order parameter introduced for theoretical convenience, and in our theoretical framework, we assume that $b_i(x)$ is of constant order and that λ is sufficiently small[12]. Thus, we essentially assume that $|\ell_i(x) - \ell_0(x)| = O_p(\lambda)$ is sufficiently small, implying that each model p_i provides a good approximation of the true generative model p_0. In the proof of the main theorem, we consider the asymptotic theory as $\lambda \to 0$, retaining terms up to $O(\lambda^2)$ while ignoring those of $O(\lambda^3)$.

A one-hot vector is defined as $\boldsymbol{e}_i = (0,\dots,0,1,0,\dots,0)^\top \in \mathbb{R}^K$ for $i = 1,\dots,K$, where only the i-th element is 1. Then, setting $\boldsymbol{\theta} = \lambda\boldsymbol{e}_i$ gives

$$p(x;\lambda\boldsymbol{e}_i) = p_i(x). \quad (8)$$

Indeed, substituting (7) into (6) yields

$$\begin{aligned}
&p(x;\lambda\boldsymbol{e}_i)\\
=&p_0(x)\exp(\lambda\boldsymbol{e}_i^\top\boldsymbol{b}(x) - \psi(\lambda\boldsymbol{e}_i))\\
=&p_0(x)\exp(\ell_i(x) - \ell_0(x) - \psi(\lambda\boldsymbol{e}_i))\\
=&p_0(x)(p_i(x)/p_0(x))\exp(-\psi(\lambda\boldsymbol{e}_i))\\
=&p_i(x)\exp(-\psi(\lambda\boldsymbol{e}_i))\\
=&p_i(x),
\end{aligned}$$

where $\psi(\lambda\boldsymbol{e}_i) = 0$.

[12] If numerical computation were to be performed, λ could be set to any arbitrary value (e.g., $\lambda = 1$).

D.2 Properties of the exponential family of distributions

This section outlines some well-known basic properties of the exponential family of distributions, which have been established in the literature (Barndorff-Nielsen, 2014; Efron, 1978, 2022; Amari, 1982). We define the expectation and covariance matrix of $\boldsymbol{b}(x)$ as follows:

$$\begin{aligned}
\boldsymbol{\eta}(\boldsymbol{\theta}) &:= \mathop{\mathbb{E}}_{x\sim p(\boldsymbol{\theta})}\big(\boldsymbol{b}(x)\big) = \sum_{x\in\mathcal{X}} \boldsymbol{b}(x)p(x;\boldsymbol{\theta}),\\
G(\boldsymbol{\theta}) &:= \mathop{\mathbb{E}}_{x\sim p(\boldsymbol{\theta})}\big\{(\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))(\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))^\top\big\}\\
&= \mathop{\mathrm{Var}}_{x\sim p(\boldsymbol{\theta})}\big(\boldsymbol{b}(x)\big).
\end{aligned}$$

These quantities can be expressed in terms of $\psi(\boldsymbol{\theta})$ as follows:

$$\boldsymbol{\eta}(\boldsymbol{\theta}) = \frac{\partial\psi(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}, \quad (9)$$
$$G(\boldsymbol{\theta}) = \frac{\partial^2\psi(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}^\top}. \quad (10)$$

We now derive these two equations. First, from

$$\frac{\partial Z(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}} = \sum_{x\in\mathcal{X}} \boldsymbol{b}(x)p_0(x)e^{\boldsymbol{\theta}^\top\boldsymbol{b}(x)},$$

we obtain

$$\begin{aligned}
\frac{\partial\psi(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}} =& \frac{\partial\log Z}{\partial\boldsymbol{\theta}} = \frac{1}{Z(\boldsymbol{\theta})}\frac{\partial Z}{\partial\boldsymbol{\theta}}\\
=& \frac{1}{Z(\boldsymbol{\theta})}\sum_{x\in\mathcal{X}} \boldsymbol{b}(x)p_0(x)e^{\boldsymbol{\theta}^\top\boldsymbol{b}(x)}\\
=& \sum_{x\in\mathcal{X}} \boldsymbol{b}(x)p(x;\boldsymbol{\theta}) = \boldsymbol{\eta}(\boldsymbol{\theta}).
\end{aligned}$$

Thus, we have established (9). Next, using

$$\begin{aligned}
\frac{\partial p(x;\boldsymbol{\theta})}{\partial\boldsymbol{\theta}} =& \Big(\boldsymbol{b}(x) - \frac{\partial\psi}{\partial\boldsymbol{\theta}}\Big)p(x;\boldsymbol{\theta})\\
=& (\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))p(x;\boldsymbol{\theta}),
\end{aligned}$$

we obtain

$$\begin{aligned}
&\frac{\partial^2\psi(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}^\top} = \frac{\partial\boldsymbol{\eta}(\boldsymbol{\theta})^\top}{\partial\boldsymbol{\theta}}\\
=&\frac{\partial}{\partial\boldsymbol{\theta}}\sum_{x\in\mathcal{X}} \boldsymbol{b}(x)^\top p(x;\boldsymbol{\theta})\\
=&\sum_{x\in\mathcal{X}} (\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))\boldsymbol{b}(x)^\top p(x;\boldsymbol{\theta})\\
=&\sum_{x\in\mathcal{X}} (\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))(\boldsymbol{b}(x) - \boldsymbol{\eta}(\boldsymbol{\theta}))^\top p(x;\boldsymbol{\theta})\\
=&G(\boldsymbol{\theta}).
\end{aligned}$$

Thus, we have established (10).

D.3 Approximation of the KL divergence

The Kullback-Leibler (KL) divergence between the models $p(\boldsymbol{\theta})$ and $p(\boldsymbol{\theta}')$ at parameter values $\boldsymbol{\theta}, \boldsymbol{\theta}' \in \mathbb{R}^K$ is given by

$$\begin{aligned}
&\mathrm{KL}(p(\boldsymbol{\theta}), p(\boldsymbol{\theta}')) \\
=&\sum_{x \in \mathcal{X}} p(x; \boldsymbol{\theta}) \log \frac{p(x; \boldsymbol{\theta})}{p(x; \boldsymbol{\theta}')} \\
=&\sum_{x \in \mathcal{X}} p(x; \boldsymbol{\theta}) \big\{ (\boldsymbol{\theta} - \boldsymbol{\theta}')^\top \boldsymbol{b}(x) - \psi(\boldsymbol{\theta}) + \psi(\boldsymbol{\theta}') \big\} \\
=&(\boldsymbol{\theta} - \boldsymbol{\theta}')^\top \boldsymbol{\eta}(\boldsymbol{\theta}) - \psi(\boldsymbol{\theta}) + \psi(\boldsymbol{\theta}'). \qquad (11)
\end{aligned}$$

Here, we assume that the parameter values $\boldsymbol{\theta}$ and $\boldsymbol{\theta}'$ are sufficiently close to $\mathbf{0}$. In particular, we assume $\|\boldsymbol{\theta}\| = O(\lambda)$ and $\|\boldsymbol{\theta}'\| = O(\lambda)$. Substituting (9) and (10) into the Taylor expansion of $\psi(\boldsymbol{\theta})$ gives

$$\begin{aligned}
&\psi(\boldsymbol{\theta}') \\
=&\psi(\boldsymbol{\theta}) + \frac{\partial \psi}{\partial \boldsymbol{\theta}^\top}(\boldsymbol{\theta}' - \boldsymbol{\theta}) \\
&+ \frac{1}{2}(\boldsymbol{\theta}' - \boldsymbol{\theta})^\top \frac{\partial^2 \psi(\boldsymbol{\theta})}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^\top}(\boldsymbol{\theta}' - \boldsymbol{\theta}) \\
&+ O(\|\boldsymbol{\theta}' - \boldsymbol{\theta}\|^3) \\
=&\psi(\boldsymbol{\theta}) + \boldsymbol{\eta}(\boldsymbol{\theta})^\top (\boldsymbol{\theta}' - \boldsymbol{\theta}) \\
&+ \frac{1}{2}(\boldsymbol{\theta}' - \boldsymbol{\theta})^\top G(\boldsymbol{\theta})(\boldsymbol{\theta}' - \boldsymbol{\theta}) + O(\lambda^3). \qquad (12)
\end{aligned}$$

Substituting (12) into (11) gives

$$\begin{aligned}
&\mathrm{KL}(p(\boldsymbol{\theta}), p(\boldsymbol{\theta}')) \\
&= \frac{1}{2}(\boldsymbol{\theta}' - \boldsymbol{\theta})^\top G(\boldsymbol{\theta})(\boldsymbol{\theta}' - \boldsymbol{\theta}) + O(\lambda^3). \qquad (13)
\end{aligned}$$

This corresponds to eq. (9) of Oyama et al. (2023). Here, the equation holds approximately by ignoring higher-order terms of $O(\lambda^3)$. For more details, refer to Amari (1982, p. 369) and Efron (2022, p. 35). More generally, $G(\boldsymbol{\theta})$ represents the Fisher information metric, and (14) holds for a wide class of probability models (Amari, 1998). Furthermore, since $G(\boldsymbol{\theta}) = G(\mathbf{0}) + O(\|\boldsymbol{\theta}\|) = G(\mathbf{0}) + O(\lambda)$, we obtain

$$\begin{aligned}
&\mathrm{KL}(p(\boldsymbol{\theta}), p(\boldsymbol{\theta}')) \\
&= \frac{1}{2}(\boldsymbol{\theta}' - \boldsymbol{\theta})^\top G(\mathbf{0})(\boldsymbol{\theta}' - \boldsymbol{\theta}) + O(\lambda^3). \qquad (14)
\end{aligned}$$

D.4 The variance representation of the KL divergence

Substituting $p_i = p(\lambda \boldsymbol{e}_i)$ into (14) gives

$$\begin{aligned}
&2\mathrm{KL}(p_i, p_j) = 2\mathrm{KL}(p(\lambda \boldsymbol{e}_i), p(\lambda \boldsymbol{e}_j)) \\
&= \lambda^2 (\boldsymbol{e}_i - \boldsymbol{e}_j)^\top G(\mathbf{0})(\boldsymbol{e}_i - \boldsymbol{e}_j) + O(\lambda^3). \qquad (15)
\end{aligned}$$

Here, we have

$$\begin{aligned}
&\boldsymbol{e}_i^\top G(\mathbf{0}) \boldsymbol{e}_j = G_{ij}(\mathbf{0}) \\
&= \mathop{\mathbb{E}}_{x \sim p_0} \Big\{ (b_i(x) - \eta_i(\mathbf{0}))(b_j(x) - \eta_j(\mathbf{0})) \Big\}. \qquad (16)
\end{aligned}$$

Next, we substitute (16) and (7) into the right-hand side of (15) to derive an alternative expression for the KL divergence:

$$\begin{aligned}
&\lambda^2 (\boldsymbol{e}_i - \boldsymbol{e}_j)^\top G(\mathbf{0})(\boldsymbol{e}_i - \boldsymbol{e}_j) \\
=&\lambda^2 \mathop{\mathbb{E}}_{x \sim p_0} \Big[\Big\{ (b_i(x) - \eta_i(\mathbf{0})) \\
&\qquad - (b_j(x) - \eta_j(\mathbf{0})) \Big\}^2 \Big] \\
=& \mathop{\mathbb{E}}_{x \sim p_0} \Big[\Big\{ (\ell_i(x) - \ell_0(x)) - (\ell_j(x) - \ell_0(x)) \\
&\qquad - \mathop{\mathbb{E}}_{x' \sim p_0} \Big((\ell_i(x') - \ell_0(x')) \\
&\qquad\qquad - (\ell_j(x') - \ell_0(x')) \Big) \Big\}^2 \Big] \\
=& \mathop{\mathbb{E}}_{x \sim p_0} \Big[\Big\{ \ell_i(x) - \ell_j(x) \\
&\qquad - \mathop{\mathbb{E}}_{x' \sim p_0} \Big(\ell_i(x') - \ell_j(x') \Big) \Big\}^2 \Big] \\
=& \mathop{\mathrm{Var}}_{x \sim p_0} \Big(\ell_i(x) - \ell_j(x) \Big).
\end{aligned}$$

Finally, substituting this result into (15) yields

$$2\mathrm{KL}(p_i, p_j) = \mathop{\mathrm{Var}}_{x \sim p_0} \Big(\ell_i(x) - \ell_j(x) \Big) + O(\lambda^3). \qquad (17)$$

This establishes (2). Furthermore, since $|\ell_i(x) - \ell_j(x)| = O_p(\lambda)$, the magnitude of (17) is $O(\lambda^2)$.

D.5 Estimation of the KL divergence

If the expected value $\mathbb{E}_{x \sim p_0}(f(x))$ of a function $f(x)$ exists and is bounded, then by the law of large numbers, the sample mean[13] converges to the expected value as $N \to \infty$, and we have

$$\mathop{\mathbb{E}}_{x \sim D}(f(x)) = \mathop{\mathbb{E}}_{x \sim p_0}(f(x)) + O_p(N^{-1/2}).$$

Applying this to (17) and ignoring the terms of order $O_p(\lambda^3 + \lambda^2 N^{-1/2})$, we obtain the following approximation:

$$2\mathrm{KL}(p_i, p_j) \approx \mathop{\mathrm{Var}}_{x \sim D} \Big(\ell_i(x) - \ell_j(x) \Big). \qquad (18)$$

[13] $\mathbb{E}_{x \sim D}(f(x)) = \frac{1}{N} \sum_{x \in D} f(x) = \frac{1}{N} \sum_{s=1}^{N} f(x_s)$ represents the sample mean, and $\mathrm{Var}_{x \sim D}(\cdot)$ represents the sample variance.

We define the coordinates $\boldsymbol{\xi}_i \in \mathbb{R}^N$ of model p_i as

$$\boldsymbol{\xi}_i = (\xi_{i1}, \ldots, \xi_{iN})^\top$$

with

$$\xi_{is} := \ell_i(x_s) - \mathop{\mathbb{E}}_{x\sim D}(\ell_i(x))$$

for $s = 1, \ldots, N$. From (18), we obtain

$$\begin{aligned} 2\mathrm{KL}(p_i, p_j) \approx & \frac{1}{N}\sum_{s=1}^{N}(\xi_{is} - \xi_{js})^2 \\ = & \frac{1}{N}\|\boldsymbol{\xi}_i - \boldsymbol{\xi}_j\|^2. \end{aligned} \tag{19}$$

Since

$$\|\boldsymbol{\xi}_i - \boldsymbol{\xi}_j\|^2 = \|(\boldsymbol{q}_i + \bar{\boldsymbol{\xi}}) - (\boldsymbol{q}_j + \bar{\boldsymbol{\xi}})\|^2 = \|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2,$$

this establishes (3).

D.6 Relationships among the three types of model coordinates

Let $\mathbf{1}_N = (1, \ldots, 1)^\top \in \mathbb{R}^N$. From the definitions of the $\boldsymbol{\xi}$-coordinate system and the $\boldsymbol{q}$-coordinate system, we have

$$\begin{aligned} \boldsymbol{\xi}_i &= \boldsymbol{q}_i + \bar{\boldsymbol{\xi}}, \\ \boldsymbol{\ell}_i &= \boldsymbol{\xi}_i + \bar{\ell}_i \mathbf{1}_N \\ &= \boldsymbol{q}_i + \bar{\ell}_i \mathbf{1}_N + \bar{\boldsymbol{\xi}}. \end{aligned} \tag{20}$$

Additionally, equation (5) in Appendix B can be rewritten as

$$\mathbf{1}_N^\top \boldsymbol{q}_i = 0. \tag{21}$$

Thus, we obtain

$$\begin{aligned} & \|\boldsymbol{\ell}_i - \boldsymbol{\ell}_j\|^2 \\ = & \|(\boldsymbol{q}_i - \boldsymbol{q}_j) + (\bar{\ell}_i - \bar{\ell}_j)\mathbf{1}_N\|^2 \\ = & \|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2 + N(\bar{\ell}_i - \bar{\ell}_j)^2 \\ & + 2(\bar{\ell}_i - \bar{\ell}_j)\mathbf{1}_N^\top(\boldsymbol{q}_i - \boldsymbol{q}_j) \\ = & \|\boldsymbol{q}_i - \boldsymbol{q}_j\|^2 + N(\bar{\ell}_i - \bar{\ell}_j)^2, \end{aligned}$$

where (20) and (21) are used in the first and last equations, respectively. This establishes (4).

Moreover, since $\bar{\ell}_i = \mathbf{1}_N^\top \boldsymbol{\ell}_i / N$, it is straightforward that the component of the $\boldsymbol{\ell}$-coordinate system in the $\mathbf{1}_N$ direction is given by

$$(\mathbf{1}_N/\sqrt{N})^\top \boldsymbol{\ell}_i = \sqrt{N}\bar{\ell}_i.$$

E Mapping Language Models into the Space of Token Probability Distributions

In Section 2, we discussed model maps based on the probability distributions $p_i(x)$ of texts generated by language models. This approach requires computing probabilities for a large number of texts in the dataset $D = (x_1, \ldots, x_N)$, leading to high computational costs. To mitigate this issue, we focus on the fact that a text $x = (y_1, \ldots, y_n)$ is a sequence of tokens. Instead of using text probabilities, we discuss model maps based on the conditional probability distributions of token generation, $p_i(y_t|y^{t-1})$. In this approach, model coordinates are computed using only a single text x. A limitation of this approach is that it can only be used for comparing models that share the same tokenizer. Furthermore, the current estimation method ignores the variance of the expected log-likelihood ratio of conditional probabilities, resulting in a rough approximation. Thus, the estimated values should be regarded only as reference values rather than precise measurements.

E.1 Model coordinates

For a text $x = (y_1, \ldots, y_n)$, the coordinates of model p_i

$$\boldsymbol{\zeta}_i = (\zeta_{i1}, \ldots, \zeta_{in})^\top \in \mathbb{R}^n$$

are defined as

$$\zeta_{it} := \log p_i(y_t|y^{t-1}) - \ell_i(x)/n \tag{22}$$

for $t = 1, \ldots, n$. This is centered for each i and for each text, satisfying $\sum_{t=1}^{n} \zeta_{it} = 0$.

E.2 Kullback-Leiber divergence

The KL divergence for next-token generation in language models, where $y_t \sim p_i(y_t|y^{t-1})$, is given by

$$\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})) = \tag{23}$$

$$\sum_{y_t \in \mathcal{V}} p_i(y_t|y^{t-1}) \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})}. \tag{24}$$

We apply the results for text probability distributions from Section 2 and Appendix D to the conditional probability distributions of token generation. The equation corresponding to (2) is

$$\begin{aligned} & 2\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})) \approx \\ & \mathop{\mathrm{Var}}_{y_t \sim p_0(y_t|y^{t-1})} \left\{ \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})} \right\}. \end{aligned} \tag{25}$$

The squared Euclidean distance in the ζ-coordinate system provides an estimate of the sum of (25) over all tokens in the text x:

$$\|\zeta_i - \zeta_j\|^2$$
$$\approx 2\sum_{t=1}^{n} \mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})) \quad (26)$$
$$\approx 2\mathrm{KL}(p_i, p_j). \quad (27)$$

The proof is provided in Appendix F. To justify the estimation in (26), we assume the following:

$$\mathop{\mathbb{E}}_{y_t \sim p_0(y_t|y^{t-1})} \left\{ \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})} \right\} \quad (28)$$

takes a constant value independent of t. In reality, this assumption is not entirely correct, and the degree of variation affects the accuracy of the approximation in (26)[14]. On the other hand, the approximation in (27) holds more generally and is demonstrated in Appendix F.5.

F Theory of Model Coordinates for Token Probability Distributions

In this section, we provide a more detailed explanation of the content discussed in Appendix E. We extend the discussion of text probability distributions in Appendix D to the case of conditional probability distributions for token generation.

F.1 Exponential family of distributions

We apply the same setting as for $p_i(x)$ in Section D to the conditional probability distributions of tokens:

$$y_t \sim p_i(y_t|y^{t-1}), \quad t = 1, \ldots, n.$$

The exponential family of distributions incorporating K models, corresponding to (6), is given here as

$$p(y_t|y^{t-1}; \boldsymbol{\theta}) := p_0(y_t|y^{t-1}) \exp(\boldsymbol{\theta}^\top \boldsymbol{b}(y_t|y^{t-1}) - \psi(\boldsymbol{\theta}|y^{t-1})). \quad (29)$$

The setting (7), which associates the K models with (29), is given here as

$$\lambda b_i(y_t|y^{t-1}) := \log p_i(y_t|y^{t-1}) - \log p_0(y_t|y^{t-1}). \quad (30)$$

Thus, we have

$$p_i(y_t|y^{t-1}) = p(y_t|y^{t-1}; \lambda \boldsymbol{e}_i)$$

for $i = 1, \ldots, K$.

[14] Since this assumption does not affect (3), there is no concern regarding the use of model maps based on text probabilities.

F.2 The variance representation of the KL divergence

The KL divergence is given by (24). Applying the result for the model $p(x; \boldsymbol{\theta})$ in (17) to the token-level conditional distribution model $p(y_t|y^{t-1}; \boldsymbol{\theta})$, we obtain

$$2\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})) = \mathop{\mathrm{Var}}_{y_t \sim p_0(y_t|y^{t-1})} \left\{ \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})} \right\} + O(\lambda^3). \quad (31)$$

F.3 Two additional assumptions

To estimate the KL divergence from a single text x, two additional assumptions are required, as described below. Such assumptions were not necessary when estimating the KL divergence from the dataset D in Appendix D. In reality, these two assumptions are not strictly satisfied, and the discrepancy between these assumptions and reality affects the accuracy of the KL divergence approximation.

Assumption 1: We assume that the probability distribution of y_t depends only on the past k tokens, denoted as $y_{t-k}^{t-1} = (y_{t-k}, y_{t-k+1}, \ldots, y_{t-1})$. That is,

$$p_i(y_t|y^{t-1}) = p_i(y_t|y_{t-k}^{t-1}),$$

which allows us to regard y_{t-k}^{t} as the state of a Markov chain. More generally, we use the notation y^k to represent a state variable. We consider a function f of the state variable y^k. Furthermore, we assume that this Markov chain is positive Harris recurrent, has a stationary distribution π, and that f is absolutely integrable, i.e.,

$$\mathop{\mathbb{E}}_{y^k \sim \pi}(|f(y^k)|) < \infty.$$

Then, by the strong law of large numbers for Markov chains (Meyn and Tweedie, 2009, Theorem 17.0.1 (i)), in the limit $n \to \infty$,

$$\frac{1}{n}\sum_{t=1}^{n} f(y_{t-k}^{t}) \to \mathop{\mathbb{E}}_{y^k \sim \pi}(f(y^k)) \quad \text{a.s.}$$

For simplicity in notation and discussion, we assume that $y_{-k+1}, \ldots, y_0$ are appropriately defined. Since the Markov chain converges to π, we also have

$$\frac{1}{n}\sum_{t=1}^{n} f(y_{t-k}^{t}) \to \frac{1}{n}\sum_{t=1}^{n} \mathop{\mathbb{E}}_{y^t \sim p_0}(f(y_{t-k}^{t})) \quad (32)$$

almost surely as $n \to \infty$.

Assumption 2:

$$\mathop{\mathbb{E}}_{y_t\sim p_0(y_t|y^{t-1})} \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})} = c \qquad (33)$$

for some $c \in \mathbb{R}$ that can depend on the indices i and j but not on t. In other words, (33) takes a constant value independent of t.

F.4 Estimation of the KL divergence

Define

$$h(y^t) := \log \frac{p_i(y_t|y^{t-1})}{p_j(y_t|y^{t-1})}.$$

From Assumption 1, $h(y^t)$ can be written in the form $h(y^t) = f_1(y^t_{t-k})$ for some f_1, so applying (32), for sufficiently large n, we obtain

$$\frac{1}{n}\sum_{t=1}^{n} h(y^t) \approx \frac{1}{n}\sum_{t=1}^{n} \mathop{\mathbb{E}}_{y^t\sim p_0}(h(y^t)).$$

Applying (33) to the right-hand side gives

$$\frac{1}{n}\sum_{t=1}^{n} h(y^t) \approx c.$$

Next, since $(h(y^t)-c)^2$ can be written in the form of $f_2(y^t_{t-k})$ for some function f_2, applying (32) again yields

$$\begin{aligned}
&\frac{1}{n}\sum_{t=1}^{n}(h(y^t)-c)^2 \\
\approx&\frac{1}{n}\sum_{t=1}^{n} \mathop{\mathbb{E}}_{y^{t-1}\sim p_0}\left\{\mathop{\mathrm{Var}}_{y_t\sim p_0(y_t|y^{t-1})}(h(y^t))\right\} \\
\approx&\frac{1}{n}\sum_{t=1}^{n} \mathop{\mathrm{Var}}_{y_t\sim p_0(y_t|y^{t-1})}(h(y^t)).
\end{aligned}$$

In the final equation, we applied (32) using the fact that $\mathrm{Var}_{y_t\sim p_0(y_t|y^{t-1})}(h(y^t)) = f_3(y^t_{t-k})$ for some f_3. Using (31), we obtain

$$\begin{aligned}
&\sum_{t=1}^{n}(h(y^t)-c)^2 \approx \\
&\qquad 2\sum_{t=1}^{n}\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})). \qquad (34)
\end{aligned}$$

Meanwhile, the components of the model coordinate $\boldsymbol{\zeta}_i$ are given by

$$\zeta_{it} = \log p_i(y_t|y^{t-1}) - c_i$$

where

$$c_i = \frac{1}{n}\sum_{t=1}^{n} \log p_i(y_t|y^{t-1}).$$

Since

$$\zeta_{it} - \zeta_{jt} = h(y^t) - (c_i - c_j)$$

with $c_i - c_j \approx c$, equation (34) can be rewritten as

$$\begin{aligned}
&\|\boldsymbol{\zeta}_i - \boldsymbol{\zeta}_j\|^2 \approx \\
&\qquad 2\sum_{t=1}^{n}\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})).
\end{aligned}$$

Thus, (26) is established.

F.5 Connecting the KL divergence of token and text probability distributions

Here, we fix the sequence length of the text $x = (y_1, \ldots, y_n)$ as n, i.e., we set $\mathcal{X} = \mathcal{V}^n$. For notational simplicity, we define

$$g_i(y^t) = \log p_i(y_t|y^{t-1}).$$

Noting that

$$p_i(x) = \prod_{t=1}^{n} p_i(y_t|y^{t-1}) = \prod_{t=1}^{n} e^{g_i(y^t)},$$

we obtain

$$\begin{aligned}
&\mathrm{KL}(p_i, p_j) \\
=&\sum_{x\in\mathcal{X}}\prod_{t'=1}^{n} e^{g_i(y^{t'})}\sum_{t=1}^{n}(g_i(y^t)-g_j(y^t)) \\
=&\sum_{t=1}^{n}\sum_{y^t\in\mathcal{V}^t}\prod_{t'=1}^{t} e^{g_i(y^{t'})}(g_i(y^t)-g_j(y^t)) \\
=&\sum_{t=1}^{n}\sum_{y^{t-1}\in\mathcal{V}^{t-1}}\prod_{t'=1}^{t-1} e^{g_i(y^{t'})} \\
&\qquad\sum_{y_t\in\mathcal{V}} e^{g_i(y^t)}(g_i(y^t)-g_j(y^t)) \\
=&\sum_{t=1}^{n}\sum_{y^{t-1}\in\mathcal{V}^{t-1}} p_i(y^{t-1}) \\
&\qquad\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})) \\
=&\sum_{t=1}^{n}\mathop{\mathbb{E}}_{y^{t-1}\sim p_i}\left\{\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1}))\right\} \\
=&\mathop{\mathbb{E}}_{x\sim p_i}\left\{\sum_{t=1}^{n}\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1}))\right\}.
\end{aligned}$$

Thus, for sufficiently large n, by the strong law of large numbers for Markov chains, we obtain

$$\mathrm{KL}(p_i, p_j) \approx \sum_{t=1}^{n}\mathrm{KL}(p_i(y_t|y^{t-1}), p_j(y_t|y^{t-1})). \qquad (35)$$

This corresponds to (27). Assumption 1 from Appendix F.3 is used in (35), but Assumption 2 is not needed in the discussion of this subsection.

G Details of Experiments

G.1 Information obtained via the Hugging Face Hub API

We used the Hugging Face Hub API to retrieve information about each language model's tags, the date the model was created, the number of downloads over the past 30 days, and the model's configuration details. All of this information is current as of February 1, 2025.

Among the model tags, we specifically used `llama2`, `llama-2`, `license:llama2`, `llama3`, `llama-3`, and `license:llama3` to determine the model type (llama-1, llama-2, or llama-3). Furthermore, to identify language models that were pre-trained on the Pile in Section 4, we employed tags such as `dataset:eleutherai/pile`, `dataset:eleutherai/the_pile`, `dataset:eleutherai/the_pile_deduplicated`, and `arxiv:2101.00027`.

G.2 How the model type was determined

In principle, we used the value of `model_type` in the config retrieved from the Hugging Face Hub API as the model type. However, out of the 1,018 language models we examined, there were 587 whose config `model_type` was listed as `llama`. For these, we used the following procedure to determine whether they were the original Llama (llama-1), Llama-2, or Llama-3; if we were able to identify which version they were, we reclassified them as `llama-1`, `llama-2`, or `llama-3` accordingly.

1. We checked the tags assigned to each model. Of these, 136 models that included any of `llama2`, `llama-2`, or `license:llama2` were classified as `llama-2`. Similarly, 39 models that included any of `llama3`, `llama-3`, or `license:llama3` were classified as `llama-3`.

2. For the remaining 412 models whose classification was not determined by tags alone, we used the creation date and the model name (converted to lowercase) to make a decision. First, 69 models that were created prior to July 18, 2023 (the Llama-2 release date) were classified as `llama-1`. Next, 88 models whose lowercase model name contained either `llama2` or `llama-2` were classified as `llama-2`. Among those whose lowercase model name contained `llama3` or `llama-3`, 22 models whose creation date was after April 18, 2024 (the Llama-3 release date) were classified as `llama-3`.

3. After following the steps above, the 217 models that could not be classified were left as `llama`.

Furthermore, any model whose name prior to the slash (`/`) was `deepseek-ai` was defined as `deepseek`. In addition, even though `abacusai/Llama-3-Smaug-8B` was tagged with `license:llama2`, we manually reclassified it as `llama-3`.

Table 3 shows the number of models classified

Model type	Models
`llama-1`	69
`llama-2`	223
`llama-3`	62
`llama`	217
`mistral`	232
`gpt_neox`	54
`deepseek`	26
`gptj`	19
`gemma`	18
`opt`	15
`bloom`	12
`falcon`	11
`qwen2`	10
`mixtral`	9
`mpt`	6
`stablelm`	6
`gpt_neo`	3
`phi`	3
`gpt_bigcode`	3
`phi3`	3
`xglm`	3
`rwkv`	3
`starcoder2`	2
`olmo`	2
`camelidae`	2
`codegen`	2
`deci`	1
`recurrent_gemma`	1
`stablelm_alpha`	1
Total	1,018

Table 3: Number of models by model type.

Text category	Texts
Pile-CC	2,353
PubMed Central	1,763
ArXiv	1,172
Github	925
FreeLaw	837
StackExchange	712
Wikipedia (en)	567
USPTO Backgrounds	487
PubMed Abstracts	464
Gutenberg (PG-19)	251
DM Mathematics	151
EuroParl	83
HackerNews	67
Ubuntu IRC	54
PhilPapers	51
NIH ExPorter	41
Enron Emails	22
Total	10,000

Table 4: Number of texts in each text category.

into each model type.

G.3 Basic information on the dataset

The dataset used in our experiments consists of a total of 10,000 texts, which are divided into 17 text categories. Table 4 shows the number of texts in each category.

To assign colors to the text categories, we first compute the average text embedding for each category in the Pile using `simcse-roberta-large` (Gao et al., 2021b). Next, we calculate a tour over the 17 average embedding vectors by solving the traveling salesman problem. Based on the adjacency relationships along this tour, we segment the hue circle at equal intervals and color each category accordingly.

G.4 Standard scores

In the three experiments described below, we use standardized values[15], or Z-score normalization, of both the log-likelihood and the benchmark scores calculated for the K language models.

- In Figure 1, where we define each language model's primary text category, we use the average log-likelihood for each category, standardized across all models.
- In Section 4, to determine each language model's primary task, we standardize each task's score across the K models.
- Furthermore, in the data leakage detection described in Section 4, we use the difference between the standardized mean log-likelihood and the standardized 6-TaskMean score as the indicator.

[15] By subtracting the mean from each value and dividing by the standard deviation, the data is transformed to have a mean of 0 and a variance of 1.

G.5 Hierarchical clustering settings

In Fig. 3, which visualizes the double-centered log-likelihood matrix $\boldsymbol{Q}$, hierarchical clustering is applied to both the rows and the columns of $\boldsymbol{Q}$. We use `correlation` as the metric and `average` as the linkage method. For the hierarchical clustering shown in Fig. 4, which presents a dendrogram of 100 language models, we use `euclidean` as the metric and `ward` as the linkage method.

H Additional Model Maps

In this section, we present additional model maps, including a figure that lists all the model names and a map obtained through dimensionality reduction of the double-centered log-likelihood matrix $\boldsymbol{Q}$.

H.1 Model map with model names

Figure 11 shows the model map defined in Section 4, with each point labeled with its corresponding model name.

H.2 Model map via the double centered log-likelihood matrix

In the main text, we use a model map generated by dimensionality reduction of the log-likelihood matrix $\boldsymbol{L}$. Here, in Figs. 12 and 13, we present model maps obtained by dimensionality reduction of the double-centered log-likelihood matrix $\boldsymbol{Q}$.

I Details of Weight Interpolation

In this section, we describe the experimental details concerning the relationship between model coordinates and model weights, as introduced in Section 6.3.

Constructing the weight grid. Let p_0 denote the base model, and p_1 and p_2 denote the fine-tuned models derived from p_0. We denote the weight parameter vectors of these models as W_0, W_1, and

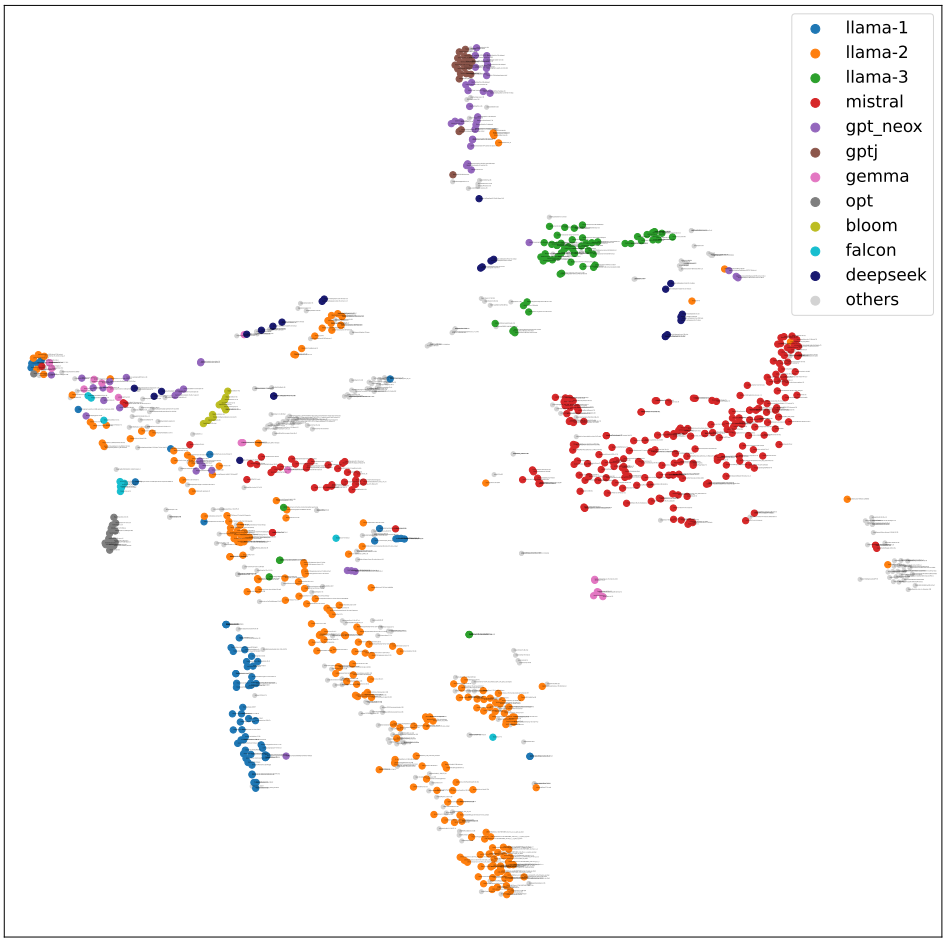

Figure 11: Each point on the model map is labeled with the corresponding model name.

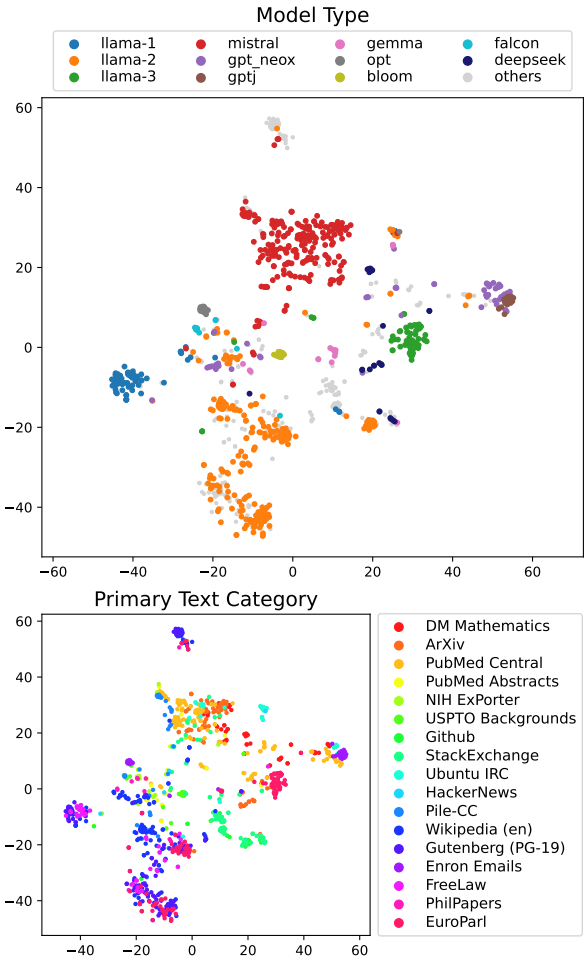

Figure 12: Model maps obtained by double centered log-likelihood matrix $\boldsymbol{Q}$. These maps correspond to Figure 1. (Top) Colors indicate model types. (Bottom) Colors indicate the text category in which each model attains the highest relative log-likelihood among 17 categories.

W_2, respectively. To construct the weight grid, we merged the model weights using the following linear operation:

$$W_{\alpha,\beta} = W_0 + \alpha(W_1 - W_0) + \beta(W_2 - W_0), \quad (36)$$

where the merge ratios $\alpha, \beta \in \mathbb{R}$ were chosen from 36 evenly spaced combinations within the interval $[0, 1]$: $\{0.0, 0.2, 0.6, 0.8, 1.0\}$. The original models W_0, W_1, and W_2 correspond to $W_{0,0}$, $W_{1,0}$, and $W_{0,1}$, respectively. When $\alpha + \beta \leq 1$, the operation corresponds to linear interpolation between models. Even among models with the same architecture, the sizes of the embedding/unembedding matrices may differ. In such cases, we truncated or reshaped the weight parameters to match the base model.

Computing model coordinates. For each composed model $p_{\alpha,\beta}$ with weight $W_{\alpha,\beta}$, we computed the model coordinates $\boldsymbol{q}_{\alpha,\beta}$ following the method described in Section 2. The tokenizer of the base model was used to ensure consistency. The text data consists of 1,000 randomly sampled sentences from the dataset of 10,000 sentences created in Section 3.1.

Selection of models. We set the base model p_0 as `Llama-2-7b-hf`. Among the fine-tuned models based on `Llama-2-7b-hf`, we selected the two most downloaded models: `vicuna-7b-v1.5` and `Llama-2-7b-chat-hf`, denoted as p_1 and p_2, respectively.

Visualization. Figure 10 shows the linearly merged models, visualized in both weight space and log-likelihood space. The corners of the grid are labeled with their corresponding (α, β) values.

In the left panel, we visualized $W_{\alpha,\beta}$ in the weight space. Since the dimensionality of $W_{\alpha,\beta}$, i.e., the number of model parameters, is extremely high, we employed a 2D projection method using the norms of the difference vectors $r_1 = \|W_1 - W_0\|_2$, $r_2 = \|W_2 - W_0\|_2$, and the angle between them, $\phi = \arccos((W_1 - W_0)^\top (W_2 - W_0)/r_1 r_2)$. Each point was placed at $(\alpha r_1 + \beta r_2 \cos\phi, \beta r_2 \sin\phi)$.

In the right panel, we visualized the model coordinates $\boldsymbol{q}_{\alpha,\beta}$ by Principal Component Analysis (PCA). Each model $p_{\alpha,\beta}$ was mapped onto the $\boldsymbol{q}$-coordinate system to analyze the structure of the interpolated models.

J Details of Model Performance Prediction

This section provides additional details on the prediction of benchmark scores using model coordinates, as discussed in Section 5.

J.1 Details of ridge regression

As described in Section 5.2, ridge regression requires setting a regularization strength parameter, α. To determine α from $\{10^1, \ldots, 10^9\}$, we performed a five-fold cross-validation within each training dataset[16]. As a post-processing step, we clipped the predicted scores to the range $[0, 100]$.

For the setting where the target variable $\mathbf{f}$ was replaced with the mean log-likelihood $(\bar{\ell}_1, \ldots, \bar{\ell}_K) \in \mathbb{R}^K$, we searched for α within

[16]The training dataset consisted of four out of the five folds obtained by splitting the dataset for each benchmark task.

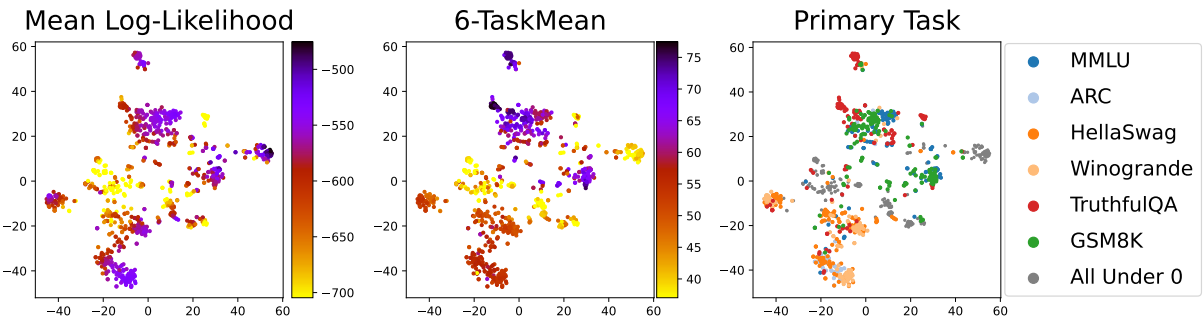

Figure 13: Model maps obtained by double centered log-likelihood matrix $\boldsymbol{Q}$. These maps correspond to Figure 5. These maps are illustrating model performance. From left to right, the panels show each model's mean log-likelihood, 6-TaskMean score, and the "primary task," which refers to the task where each model achieves the highest standardized score among the six tasks, color-coded accordingly. The color bar is clipped at the 10th percentile for mean log-likelihood and 6-TaskMean, with darker colors indicating better performance. In the primary task panel, models with standardized scores below zero across all six tasks are labeled as "All Under 0."

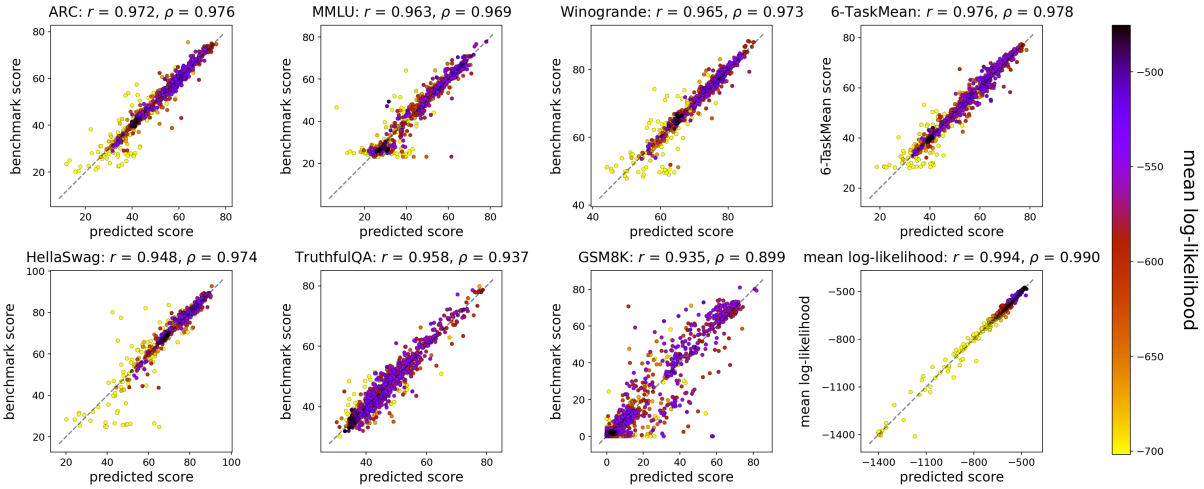

Figure 14: Scatter plots of predicted scores and benchmark scores for six benchmark tasks. Additionally, results for predicting 6-TaskMean (identical to Fig. 8) and the mean log-likelihood are also shown. Each point is color-coded by the mean log-likelihood, with higher mean log-likelihood values generally corresponding to higher task scores. For better visualization, the color bar range is clipped to the 10th–100th percentile.

	ARC	HellaSwag	MMLU	TruthfulQA	Winogrande	GSM8K	Average	mean log-likelihood
Pearson's r	0.969±0.002	0.943±0.004	0.959±0.003	0.954±0.001	0.961±0.002	0.930±0.002	0.973±0.001	0.993±0.001
Spearman's ρ	0.975±0.001	0.971±0.002	0.966±0.003	0.933±0.001	0.971±0.002	0.892±0.001	0.976±0.001	0.989±0.001

Table 5: This table presents the mean and standard deviation of correlation coefficients between predicted and actual benchmark scores. These coefficients were computed using ridge regression across five different data splits. Results for predicting 6-TaskMean and the mean log-likelihood are also included.

$\{10^{-4}, \ldots, 10^{4}\}$ and did not apply clipping as a post-processing step.

J.2 Details of prediction results

Figure 14 shows scatter plots of predicted scores and actual benchmark scores for each benchmark task, as well as for 6-TaskMean and the mean log-likelihood. As in Fig. 8, the scatter plots show strong correlations for all six benchmark tasks and for the mean log-likelihood.

To account for randomness, we ran five different data splits when predicting each benchmark score. The final predicted score was the average of these five runs. For each split, we computed the correlation coefficients between the predicted scores and the actual benchmark scores. Table 5 presents their mean and standard deviation, and shows a similar trend as Table 2.

K Model List

Table 6 lists the 1,018 models used in this study. The BibTeX entries cited for each model were determined through the following procedure.

First, we extracted the BibTeX entries available in each model's Hugging Face model card[17]. If the BibTeX entry was missing a year of publication, we filled it in with the model's creation date[18]. Additionally, we generated BibTeX entries using the arXiv IDs found in the model card tags by querying the arXiv API[19]. This process resulted in a set of BibTeX entries for each model.

Next, we manually checked pairs of different BibTeX entries where the title similarity[20] was high, or the authors matched, to determine whether they corresponded to the same source. This step allowed us to create groups of BibTeX entries that were considered identical.

Then, for each BibTeX group, we selected a representative entry as follows. Within each group, the entry most frequently cited by the models was chosen as the representative. If multiple candidates met this criterion, we prioritized BibTeX entries generated from arXiv IDs when available. If no such entry existed, we selected the one with the longest string.

Finally, we replaced each model's BibTeX entry with the representative entry from its corresponding group. Any selected BibTeX entry that contained typos or formatting errors was manually corrected based on compilation errors. If the author information was incomplete, we corrected it manually by checking the source.

Note that for `mistralai/Mistral-7B-v0.3`, `google/codegemma-2b`, `deepseek-ai/deepseek-llm-7b-base` in Table 1, as well as for the example `deepseek-ai/deepseek-coder-1.3b-base`, we manually prepared the BibTeX entries for citation based on their respective sources. We also used the same BibTeX entries for all other models that were considered to be of the same type.

[17] https://github.com/huggingface/huggingface_hub.

[18] https://github.com/sciunto-org/python-bibtexparser.

[19] https://github.com/lukasschwab/arxiv.py.

[20] We used Python's `difflib.SequenceMatcher`.

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
1	01-ai/Yi-1.5-6B (01. AI et al., 2025)	llama	6B	2024-05-11	5102	-525.57	61.57
2	01-ai/Yi-1.5-6B-Chat (01. AI et al., 2025)	llama	6B	2024-05-11	19443	-645.33	66.17
3	01-ai/Yi-1.5-9B (01. AI et al., 2025)	llama	8B	2024-05-11	20252	-513.39	66.73
4	01-ai/Yi-1.5-9B-32K (01. AI et al., 2025)	llama	8B	2024-05-15	9287	-510.38	55.22
5	01-ai/Yi-1.5-9B-Chat (01. AI et al., 2025)	llama	8B	2024-05-10	20108	-626.90	69.56
6	01-ai/Yi-1.5-9B-Chat-16K (01. AI et al., 2025)	llama	8B	2024-05-15	14262	-601.39	66.98
7	01-ai/Yi-6B (Zhang et al., 2024b; Yue et al., 2024a; 01. AI et al., 2025)	llama	6B	2023-11-01	6997	-515.62	54.02
8	01-ai/Yi-6B-200K (Zhang et al., 2024b; Yue et al., 2024a; 01. AI et al., 2025)	llama	6B	2023-11-06	8370	-529.12	56.76
9	01-ai/Yi-9B-200K (Zhang et al., 2024b; Yue et al., 2024a; 01. AI et al., 2025)	llama	8B	2024-03-15	8915	-517.82	61.94
10	42dot/42dot_LLM-PLM-1.3B (42dot Inc., 2023)	llama	1B	2023-09-04	1268	-600.03	35.70
11	42dot/42dot_LLM-SFT-1.3B (42dot Inc., 2023)	llama	1B	2023-09-04	1453	-605.30	36.61
12	922-CA/monika-ddlc-7b-v1	llama-2	7B	2023-10-13	1191	-635.19	50.49
13	AIChenKai/TinyLlama-1.1B-Chat-v1.0-x2-MoE	mixtral	1B	2024-01-03	1217	-619.71	36.98
14	AIJUUD/juud-Mistral-7B	mistral	7B	2024-01-31	1312	-564.68	61.72
15	AIJUUD/juud-Mistral-7B-dpo (Lacoste et al., 2019)	mistral	7B	2024-02-07	3217	-567.00	60.89
16	AlekseyKorshuk/pygmalion-6b-vicuna-chatml	gptj	6B	2023-06-22	1169	-564.90	42.08
17	Andron00e/YetAnother_Open-Llama-3B-LoRA	llama	3B	2023-07-21	1163	-646.46	–
18	Artples/L-MChat-7b	mistral	7B	2024-04-02	9634	-557.41	69.57
19	Artples/L-MChat-Small	phi	2B	2024-04-11	2793	-640.49	63.14
20	Aspik101/StableBeluga-13B-instruct-PL-lora_unload	llama-2	13B	2023-08-04	1244	-544.64	56.24
21	Aspik101/WizardVicuna-Uncensored-3B-instruct-PL-lora_unload	llama-2	3B	2023-08-07	1161	-626.59	39.95
22	Aspik101/vicuna-13b-v1.5-PL-lora_unload	llama-2	13B	2023-08-03	1263	-566.80	55.24
23	AtAndDev/CapybaraMarcoroni-7B	mistral	7B	2024-01-03	1162	-541.33	70.32
24	Austism/chronos-hermes-13b-v2	llama-2	13B	2023-08-02	1225	-585.56	56.10
25	Azazelle/Argetsu	mistral	7B	2023-12-30	1208	-560.37	69.64
26	Azazelle/Dumb-Maidlet	mistral	7B	2023-12-30	1201	-548.86	68.34
27	Azazelle/Half-NSFW_Noromaid-7b	mistral	7B	2023-12-29	1208	-547.63	62.32
28	Azazelle/Maylin-7b	mistral	7B	2024-01-04	1198	-575.94	70.26
29	Azazelle/Silicon-Medley	mistral	7B	2023-12-29	1200	-566.66	69.49
30	Azazelle/SlimMelodicMaid	mistral	7B	2023-12-30	1205	-577.28	69.70
31	Azazelle/Tippy-Toppy-7b	mistral	7B	2024-01-03	1197	-560.94	69.58
32	Azazelle/Yuna-7b-Merge	mistral	7B	2024-01-05	1201	-580.65	71.46
33	Azazelle/smol_bruin-7b	mistral	7B	2023-12-29	1207	-572.80	71.05
34	Azazelle/xDAN-SlimOrca	mistral	7B	2023-12-29	1206	-575.20	68.04
35	Azure99/blossom-v1-3b	bloom	3B	2023-07-29	1228	-641.52	36.90
36	Azure99/blossom-v2-3b	bloom	3B	2023-08-08	1237	-654.44	35.98
37	Azure99/blossom-v2-llama2-7b	llama-2	7B	2023-09-06	1241	-572.17	51.71
38	Azure99/blossom-v3-mistral-7b	mistral	7B	2023-11-20	1319	-565.31	62.95
39	Azure99/blossom-v3_1-mistral-7b	mistral	7B	2023-11-27	1320	-567.17	62.53
40	Azure99/blossom-v4-mistral-7b	mistral	7B	2023-12-26	1315	-550.37	63.61
41	BEE-spoke-data/Mixtral-GQA-400m-v2	mixtral	2B	2023-12-20	1182	-794.25	28.45
42	BarryFutureman/NeuralTurdusVariant1-7B	mistral	7B	2024-01-22	1170	-592.94	74.83
43	BioMistral/BioMistral-7B (Labrak et al., 2024)	mistral	7B	2024-02-14	11349	-652.04	52.33
44	BioMistral/BioMistral-7B-DARE (Yadav et al., 2023a; Labrak et al., 2024; Yu et al., 2024a)	mistral	7B	2024-02-05	1209	-586.37	57.03
45	BlueNipples/TimeCrystal-l2-13B	llama-2	13B	2023-11-11	1282	-567.72	59.26
46	BramVanroy/GEITje-7B-ultra (Vanroy, 2024)	mistral	7B	2024-01-27	1597	-674.95	52.61
47	Brouz/Slerpeno	llama	13B	2023-09-08	1201	-545.39	56.59
48	CHIH-HUNG/llama-2-13b-FINETUNE2_TEST_2.2w	llama-2	13B	2023-09-04	1174	-530.90	53.20
49	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r16-gate_up_down	llama-2	13B	2023-09-20	1171	-533.48	54.32
50	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r4-gate_up_down	llama-2	13B	2023-09-19	1166	-535.81	53.35
51	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r4-q_k_v_o	llama-2	13B	2023-09-19	1170	-536.50	53.62
52	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r8-gate_up_down	llama-2	13B	2023-09-20	1165	-533.51	53.71
53	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r8-q_k_v_o	llama-2	13B	2023-09-20	1170	-535.00	53.99
54	CHIH-HUNG/llama-2-13b-FINETUNE3_3.3w-r8-q_k_v_o_gate_up_down	llama-2	13B	2023-09-24	1165	-536.24	53.43
55	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r16-gate_up_down	llama-2	13B	2023-09-22	1165	-533.56	53.52
56	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r16-gate_up_down-test1	llama-2	13B	2023-10-07	1165	-531.27	53.66
57	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r16-q_k_v_o	llama-2	13B	2023-09-22	1164	-534.36	53.68
58	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r4-gate_up_down	llama-2	13B	2023-09-21	1174	-537.05	53.48
59	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r4-q_k_v_o_gate_up_down	llama-2	13B	2023-09-25	1163	-540.47	53.23
60	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r8-gate_up_down	llama-2	13B	2023-09-21	1171	-533.65	53.58
61	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r8-q_k_v_o	llama-2	13B	2023-09-21	1171	-533.89	54.06
62	CHIH-HUNG/llama-2-13b-FINETUNE4_3.8w-r8-q_k_v_o_gate_up_down	llama-2	13B	2023-09-25	1165	-537.12	52.88
63	CHIH-HUNG/llama-2-13b-FINETUNE4_addto15k_4.5w-r16-gate_up_down	llama-2	13B	2023-10-08	1161	-531.46	54.88
64	CHIH-HUNG/llama-2-13b-FINETUNE4_compare15k_4.5w-r16-gate_up_down	llama-2	13B	2023-10-08	1169	-532.00	53.94
65	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r16-gate_up_down	llama-2	13B	2023-10-04	1167	-534.88	53.44
66	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r16-q_k_v_o	llama-2	13B	2023-10-04	1161	-533.84	54.63
67	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r4-q_k_v_o	llama-2	13B	2023-10-01	1172	-536.02	53.32
68	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r4-q_k_v_o_gate_up_down	llama-2	13B	2023-10-02	1163	-541.64	53.38
69	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r8-gate_up_down	llama-2	13B	2023-10-03	1163	-534.71	54.02
70	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r8-q_k_v_o	llama-2	13B	2023-10-02	1167	-534.88	54.64
71	CHIH-HUNG/llama-2-13b-FINETUNE5_4w-r8-q_k_v_o_gate_up_down	llama-2	13B	2023-10-04	1164	-540.68	53.69
72	CHIH-HUNG/llama-2-13b-OpenOrca_5w	llama-2	13B	2023-08-24	1178	-533.15	55.80
73	CHIH-HUNG/llama-2-13b-Open_Platypus_and_ccp_2.6w-3_epoch	llama-2	13B	2023-09-05	1165	-533.19	53.80
74	CHIH-HUNG/llama-2-13b-dolphin_20w	llama-2	13B	2023-08-29	1187	-533.73	55.06
75	CHIH-HUNG/llama-2-13b-dolphin_5w	llama-2	13B	2023-08-25	1175	-533.03	55.53
76	CalderaAI/13B-BlueMethod	llama-1	13B	2023-07-07	1193	-569.51	54.12
77	CalderaAI/13B-Legerdemain-L2	llama-2	13B	2023-08-03	1200	-551.69	55.13
78	CalderaAI/13B-Ouroboros	llama	13B	2023-07-20	1197	-1133.56	49.54
79	CalderaAI/13B-Thorns-l2	llama	13B	2023-09-06	1207	-580.08	54.72
80	Cartinoe5930/Llama2_init_Mistral	llama-2	7B	2024-01-16	1174	-528.82	60.98
81	Changgil/K2S3-SOLAR-11b-v1.0	llama	10B	2024-03-03	2290	-811.23	36.67
82	Changgil/k2s3_test_24001	llama-2	13B	2024-02-14	2346	-561.61	56.67

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
83	CobraMamba/mamba-gpt-3b-v4 (chiliu, 2023)	llama	3B	2023-09-05	1183	-605.83	41.24
84	ContextualAI/archangel_sft-kto_llama13b (Ethayarajh et al., 2023)	llama	13B	2023-12-03	1214	-542.49	52.87
85	Corianas/gpt-j-6B-Dolly	gptj	6B	2023-03-28	1173	-502.52	39.60
86	DBCMLAB/Llama-3-instruction-constructionsafety-layertuning (AI@Meta, 2024; Lee, 2024a; Lee and Ahn, 2024)	llama-3	8B	2024-05-22	2712	-658.58	56.32
87	Dampish/Dante-2.8B	gpt_neox	2B	2023-05-09	1237	-671.96	–
88	Dampish/StellarX-4B-V0 (Black et al., 2022)	gpt_neox	4B	2023-05-27	1268	-722.64	37.31
89	Dampish/StellarX-4B-V0.2 (Black et al., 2022)	gpt_neox	4B	2023-06-03	1245	-866.96	36.15
90	Danielbrdz/Barcenas-13b	llama-2	13B	2023-09-09	1178	-558.81	55.83
91	Danielbrdz/Barcenas-3b	llama-2	3B	2023-11-15	1167	-554.05	41.74
92	Danielbrdz/Barcenas-7b	llama	7B	2023-08-25	1175	-603.96	50.87
93	Danielbrdz/Barcenas-Llama3-8b-ORPO	llama-3	8B	2024-04-29	12814	-557.50	72.50
94	Danielbrdz/CodeBarcenas-7b	llama-2	7B	2023-09-03	1174	-656.68	40.09
95	Deathsquad10/TinyLlama-1.1B-Remix-V.2	llama	1B	2024-01-05	1192	-670.53	34.91
96	Deathsquad10/TinyLlama-Remix	llama	1B	2023-11-26	1213	-812.12	34.00
97	Deathsquad10/TinyLlama-repeat	llama	1B	2024-01-06	1191	-622.61	37.09
98	Deci/DeciLM-7B-instruct (DeciAI Research Team, 2023)	deci	7B	2023-12-10	9769	-570.53	63.19
99	DeepMount00/Llama-3-8b-Ita	llama-3	8B	2024-05-01	179401	-578.66	73.65
100	DeepMount00/Mistral-Ita-7b	mistral	7B	2023-11-08	2927	-579.30	58.26
101	Delcos/Mistral-Pygmalion-7b	llama-2	7B	2023-10-09	1185	-556.74	51.02
102	Doctor-Shotgun/CalliopeDS-L2-13B (Yadav et al., 2023a)	llama-2	13B	2023-09-16	1428	-568.72	56.34
103	Doctor-Shotgun/CalliopeDS-v2-L2-13B	llama-2	13B	2023-09-28	1250	-572.65	57.12
104	DopeorNope/You_can_cry_Snowman-13B	llama	13B	2023-12-27	1203	-577.68	69.46
105	EleutherAI/gpt-j-6b (Gao et al., 2020; Wang, 2021; Wang and Komatsuzaki, 2021; Su et al., 2023a)	gptj	6B	2022-03-02	241435	-479.14	40.10
106	EleutherAI/gpt-neo-1.3B (Gao et al., 2020; Black et al., 2021)	gpt_neo	1B	2022-03-02	243332	-545.00	33.58
107	EleutherAI/gpt-neo-2.7B (Gao et al., 2020; Black et al., 2021)	gpt_neo	2B	2022-03-02	205503	-520.30	36.20
108	EleutherAI/llemma_7b (Azerbayev et al., 2024)	llama-2	7B	2023-09-12	4671	-554.43	48.75
109	EleutherAI/polyglot-ko-12.8b (Kim et al., 2022; Ko et al., 2023; Su et al., 2023a)	gpt_neox	13B	2022-10-14	2941	-967.65	33.33
110	EleutherAI/pythia-1.4b (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	1B	2023-02-09	22152	-531.68	34.75
111	EleutherAI/pythia-1.4b-deduped (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	1B	2023-02-09	12730	-534.52	35.00
112	EleutherAI/pythia-12b (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	12B	2023-02-28	9192	-475.42	38.82
113	EleutherAI/pythia-12b-deduped (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	12B	2023-02-27	9737	-477.81	39.70
114	EleutherAI/pythia-1b-deduped (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	1B	2023-02-14	17983	-551.07	32.78
115	EleutherAI/pythia-2.8b-deduped (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	2B	2023-02-10	11649	-507.42	36.72
116	EleutherAI/pythia-6.9b-deduped (Gao et al., 2020; Biderman et al., 2022, 2023)	gpt_neox	6B	2023-02-25	9824	-490.70	39.30
117	Enno-Ai/ennodata-raw-pankajmathur-13b-peft	llama	13B	2023-09-29	1215	-613.07	55.40
118	Eurdem/Defne_llama3_2x8B	mixtral	13B	2024-05-10	9076	-571.19	71.73
119	Expert68/llama2_13b_instructed_version2	llama-2	13B	2023-10-14	1184	-561.35	55.41
120	FairMind/Llama-3-8B-4bit-UltraChat-Ita	llama-3	8B	2024-05-03	5014	-543.07	61.54
121	FairMind/Phi-3-mini-4k-instruct-bnb-4bit-Ita	mistral	4B	2024-05-02	2746	-634.71	66.61
122	FelixChao/CodeLlama13B-Finetune-v1	llama	13B	2023-09-13	1188	-647.40	47.19
123	FelixChao/llama2-13b-math1.1	llama-2	13B	2023-08-12	1181	-602.88	54.18
124	FelixChao/llama2-13b-math1.2	llama-2	13B	2023-08-15	1197	-607.07	54.19
125	FinancialSupport/saiga-7b	mistral	7B	2023-12-28	3902	-558.71	64.51
126	FlagAlpha/Llama2-Chinese-7b-Chat	llama-2	7B	2023-07-23	1383	-627.19	51.13
127	FlagAlpha/Llama3-Chinese-8B-Instruct	llama-3	8B	2024-04-23	1978	-557.17	63.50
128	Fredithefish/Guanaco-3B-Uncensored-v2	gpt_neox	2B	2023-08-27	2189	-632.46	38.98
129	FreedomIntelligence/AceGPT-7B	llama	7B	2023-09-14	2982	-565.76	49.47
130	FreedomIntelligence/phoenix-inst-chat-7b	bloom	7B	2023-04-11	1296	-693.44	43.03
131	GeneZC/MiniChat-1.5-3B (Jain et al., 2023; Zhang et al., 2024a; Rafailov et al., 2024)	llama	3B	2023-11-26	1601	-599.51	50.23
132	GeneZC/MiniChat-2-3B (Jain et al., 2023; Zhang et al., 2024a; Rafailov et al., 2024)	llama	3B	2023-12-27	4167	-607.10	51.49
133	GeneZC/MiniChat-3B (Zhang et al., 2024a)	llama	3B	2023-11-11	1633	-585.38	45.31
134	GeneZC/MiniMA-2-3B (Zhang et al., 2024a)	llama	3B	2023-12-27	1492	-526.37	44.75
135	GeneZC/MiniMA-3B (Zhang et al., 2024a)	llama	3B	2023-11-11	1494	-537.57	41.44
136	GritLM/GritLM-7B (Muennighoff et al., 2024)	mistral	7B	2024-02-11	72991	-564.58	61.41
137	Gryphe/MythoLogic-L2-13b	llama	13B	2023-08-03	1198	-570.07	56.19
138	Gryphe/MythoMax-L2-13b	llama	13B	2023-08-10	14308	-583.80	56.00
139	Gryphe/MythoMix-L2-13b	llama	13B	2023-08-08	1174	-566.44	56.31
140	HWERI/Llama2-7b-sharegpt4	llama-2	7B	2023-08-04	1200	-660.22	51.05
141	HWERI/pythia-1.4b-deduped-sharegpt	gpt_neox	1B	2023-08-10	1200	-557.93	35.11
142	HenryJJ/Instruct_Mistral-7B-v0.1_Dolly15K	mistral	7B	2024-01-02	1166	-577.98	60.45
143	HenryJJ/Instruct_Yi-6B_Dolly15K	llama	6B	2024-01-06	1170	-524.87	56.85
144	HenryJJ/Instruct_Yi-6B_Dolly_CodeAlpaca	llama	6B	2024-01-07	1177	-527.06	56.11
145	HiTZ/GoLLIE-7B (Sainz et al., 2024)	llama-2	7B	2023-09-25	1394	-632.52	37.48
146	HuggingFaceFW/ablation-model-fineweb-v1 (Lacoste et al., 2019)	llama	1B	2024-04-20	2238	-771.42	36.76
147	HuggingFaceH4/mistral-7b-sft-beta	mistral	7B	2023-10-26	7408	-553.64	59.78
148	HuggingFaceH4/zephyr-7b-alpha (Ding et al., 2023; Tunstall et al., 2023; Cui et al., 2024; Rafailov et al., 2024)	mistral	7B	2023-10-09	12911	-559.73	59.50
149	HuggingFaceH4/zephyr-7b-beta (Ding et al., 2023; Tunstall et al., 2023; Cui et al., 2024; Rafailov et al., 2024)	mistral	7B	2023-10-26	294019	-570.40	59.08
150	IDEA-CCNL/Ziya-LLaMA-13B-Pretrain-v1 (IDEA-CCNL, 2021; Zhang et al., 2022a; Yang et al., 2022)	llama-1	13B	2023-06-01	1171	-1397.30	29.96
151	IDEA-CCNL/Ziya-LLaMA-13B-v1 (IDEA-CCNL, 2021; Zhang et al., 2022a; Yang et al., 2022)	llama-1	13B	2023-05-16	1244	-1397.34	29.82
152	INSAIT-Institute/BgGPT-7B-Instruct-v0.2	mistral	7B	2024-03-03	3265	-594.56	63.08
153	IkariDev/Athena-v1	llama	13B	2023-08-30	1225	-566.12	54.11
154	IkariDev/Athena-v4	llama	13B	2023-10-07	1214	-555.80	57.23
155	Intel/neural-chat-7b-v3-1 (Mukherjee et al., 2023)	mistral	7B	2023-11-14	3976	-563.71	59.90

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
156	Intel/neural-chat-7b-v3-2 (Yu et al., 2024b)	mistral	7B	2023-11-21	2102	-554.92	68.29
157	Intel/neural-chat-7b-v3-3 (Yu et al., 2024b)	mistral	7B	2023-12-09	166226	-575.02	69.83
158	Jayant9928/orpo_med_v3	llama	8B	2024-05-01	2705	-557.53	62.21
159	Jiayi-Pan/Tiny-Vicuna-1B	llama	1B	2023-11-22	3094	-647.57	34.76
160	Josephgflowers/TinyLlama-3T-Cinder-v1.2	llama	1B	2023-12-31	1413	-777.50	35.26
161	JosephusCheung/Qwen-LLaMAfied-7B-Chat	llama-2	7B	2023-08-04	1221	-646.77	51.99
162	JosephusCheung/Qwen-VL-LLaMAfied-7B-Chat	llama-2	7B	2023-08-30	1186	-788.30	45.00
163	Kabster/Bio-Mistralv2-Squared	mistral	7B	2024-03-09	2762	-603.34	57.73
164	Kabster/BioMistral-Zephyr-Beta-SLERP	mistral	7B	2024-03-09	2758	-597.30	56.35
165	KnutJaegersberg/LLongMA-3b-LIMA	llama	3B	2023-09-03	2010	-617.15	38.51
166	KnutJaegersberg/MistralInstructLongish	mistral	7B	2023-11-15	1970	-543.74	53.62
167	KnutJaegersberg/Qwen-1_8B-Llamafied	llama	1B	2024-01-03	2839	-760.12	44.75
168	KnutJaegersberg/Walter-Falcon-1B	falcon	1B	2023-12-09	2014	-1010.10	34.07
169	KnutJaegersberg/deacon-13b	llama	13B	2023-09-20	2018	-533.27	53.63
170	KnutJaegersberg/deacon-3b	llama	3B	2023-09-18	2016	-621.85	39.05
171	KnutJaegersberg/falcon-1b-t-sft	falcon	1B	2023-12-04	2029	-978.54	35.02
172	KnutJaegersberg/webMistral-7B	mistral	7B	2023-11-17	1972	-554.62	53.97
173	KoboldAI/GPT-J-6B-Adventure	gptj	6B	2022-03-02	1297	-661.77	35.95
174	KoboldAI/GPT-J-6B-Janeway (Gao et al., 2020; Wang and Komatsuzaki, 2021)	gptj	6B	2022-03-02	4382	-496.37	39.54
175	KoboldAI/GPT-J-6B-Shinen (Gao et al., 2020; Wang and Komatsuzaki, 2021)	gptj	6B	2022-03-02	1498	-498.02	39.60
176	KoboldAI/GPT-J-6B-Skein (Lacoste et al., 2019; Wang, 2021)	gptj	6B	2022-03-02	1236	-509.27	40.02
177	KoboldAI/LLaMA2-13B-Holomax	llama-2	13B	2023-08-14	1255	-563.47	54.52
178	KoboldAI/LLaMA2-13B-Tiefighter	llama-2	13B	2023-10-18	2321	-599.88	54.51
179	KoboldAI/OPT-13B-Erebus (Zhang et al., 2022b)	opt	13B	2022-09-09	6998	-652.81	39.61
180	KoboldAI/OPT-13B-Nerybus-Mix (Zhang et al., 2022b)	opt	13B	2023-02-13	1657	-646.08	39.61
181	KoboldAI/OPT-13B-Nerys-v2 (Zhang et al., 2022b)	opt	13B	2022-09-19	4259	-652.01	39.53
182	KoboldAI/OPT-2.7B-Erebus (Zhang et al., 2022b)	opt	2B	2022-09-19	5559	-692.73	36.96
183	KoboldAI/OPT-2.7B-Nerybus-Mix	opt	2B	2023-02-09	1464	-686.59	36.88
184	KoboldAI/OPT-6.7B-Erebus (Zhang et al., 2022b)	opt	6B	2022-09-15	5587	-641.11	39.09
185	KoboldAI/OPT-6.7B-Nerybus-Mix	opt	6B	2023-02-13	1585	-642.68	38.83
186	KoboldAI/OPT-6B-nerys-v2 (Zhang et al., 2022b)	opt	6B	2022-06-26	4974	-656.62	38.72
187	Korabbit/Llama-2-7b-chat-hf-afr-100step-flan	llama-2	7B	2023-11-30	1208	-650.87	52.88
188	Korabbit/Llama-2-7b-chat-hf-afr-100step-flan-v2	llama-2	7B	2023-12-03	1208	-650.96	52.92
189	Korabbit/Llama-2-7b-chat-hf-afr-100step-v2	llama-2	7B	2023-11-22	1205	-655.71	50.89
190	Korabbit/Llama-2-7b-chat-hf-afr-200step-flan	llama-2	7B	2023-11-30	1201	-647.72	52.62
191	Korabbit/Llama-2-7b-chat-hf-afr-200step-flan-v2	llama-2	7B	2023-12-03	1211	-648.67	52.75
192	Korabbit/Llama-2-7b-chat-hf-afr-200step-merged	llama-2	7B	2023-11-21	1222	-653.05	52.26
193	Korabbit/Llama-2-7b-chat-hf-afr-200step-v2	llama-2	7B	2023-11-22	1203	-658.69	50.21
194	Korabbit/Llama-2-7b-chat-hf-afr-300step-flan-v2	llama-2	7B	2023-12-03	1208	-647.99	52.41
195	Korabbit/Llama-2-7b-chat-hf-afr-441step-flan-v2	llama-2	7B	2023-12-03	1209	-647.85	52.28
196	Kukedlc/NeuralExperiment-7b-MagicCoder-v7.5	mistral	7B	2024-03-07	4044	-569.72	74.28
197	Kukedlc/NeuralLLaMa-3-8b-DT-v0.1	llama-3	8B	2024-05-11	5707	-571.65	72.52
198	Kukedlc/NeuralLLaMa-3-8b-ORPO-v0.3	llama-3	8B	2024-05-14	7985	-562.41	72.66
199	Kukedlc/NeuralSynthesis-7B-v0.1	mistral	7B	2024-04-06	8910	-596.75	76.80
200	Kukedlc/NeuralSynthesis-7B-v0.3	mistral	7B	2024-04-07	3114	-597.52	76.70
201	Kukedlc/NeuralSynthesis-7b-v0.4-slerp	mistral	7B	2024-04-12	3067	-597.78	76.76
202	LDCC/LDCC-SOLAR-10.7B (Kim et al., 2024b)	llama	10B	2024-01-03	3267	-549.97	71.40
203	LTC-AI-Labs/L2-7b-Base-WVG-Uncensored	llama	7B	2023-09-23	1241	-556.11	50.63
204	LTC-AI-Labs/L2-7b-Beluga-WVG-Test	llama	7B	2023-10-03	1222	-567.10	52.04
205	LTC-AI-Labs/L2-7b-Hermes-Synthia	llama-2	7B	2023-11-23	1232	-562.42	52.21
206	LTC-AI-Labs/L2-7b-Hermes-WVG-Test	llama	7B	2023-09-27	1225	-570.23	51.35
207	LTC-AI-Labs/L2-7b-Synthia-WVG-Test	llama	7B	2023-09-28	1233	-576.22	51.25
208	Lazycuber/L2-7b-Base-Guanaco-Uncensored	llama	7B	2023-09-19	1172	-555.04	50.45
209	LeoLM/leo-hessianai-7b	llama	7B	2023-08-22	4502	-592.31	47.72
210	LeoLM/leo-hessianai-7b-chat	llama	7B	2023-09-10	3924	-735.02	49.29
211	LinkSoul/Chinese-Llama-2-7b	llama-2	7B	2023-07-20	40799	-584.42	52.59
212	Locutusque/Hercules-2.5-Mistral-7B	mistral	7B	2024-02-10	1953	-533.73	63.59
213	Locutusque/Hercules-3.1-Mistral-7B	mistral	7B	2024-02-19	2780	-528.16	62.09
214	Locutusque/Orca-2-13b-SFT-v4	llama	13B	2023-11-25	2345	-617.05	59.75
215	Locutusque/Orca-2-13b-SFT-v6	llama	13B	2023-12-22	2319	-674.35	56.15
216	Locutusque/Orca-2-13b-SFT_v5	llama	13B	2023-12-13	2191	-602.83	56.77
217	MTSAIR/multi_verse_model	mistral	7B	2024-03-07	6357	-598.96	76.74
218	MayaPH/FinOPT-Franklin	opt	1B	2023-05-26	1207	-1380.66	29.78
219	MayaPH/opt-flan-iml-6.7b (Iyer et al., 2023)	opt	6B	2023-08-15	1193	-729.78	35.84
220	MaziyarPanahi/Llama-3-8B-Instruct-v0.4	llama-3	8B	2024-05-01	1407	-569.34	70.30
221	MaziyarPanahi/Llama-3-8B-Instruct-v0.8	llama-3	8B	2024-05-01	7281	-576.95	73.17
222	MaziyarPanahi/Llama-3-8B-Instruct-v0.9	llama-3	8B	2024-05-30	6241	-575.60	73.29
223	MaziyarPanahi/Mistral-7B-Instruct-v0.3	mistral	7B	2024-05-22	5230	-549.67	65.21
224	MaziyarPanahi/Mistral-7B-v0.3	mistral	7B	2024-05-22	5758	-531.44	60.40
225	MediaTek-Research/Breeze-7B-Instruct-v1_0 (Hsu et al., 2024)	mistral	7B	2024-03-05	3065	-559.49	63.40
226	Mihaiii/Metis-0.3	mistral	7B	2023-12-16	1279	-567.64	65.44
227	Minirecord/Mini_DPO_test02	mistral	7B	2023-11-30	3470	-547.90	61.23
228	MoaData/Myrrh_solar_10.7b_3.0	llama	10B	2024-04-26	9855	-673.46	67.61
229	NExtNewChattingAI/shark_tank_ai_7_b	mistral	7B	2023-12-17	1224	-546.93	71.10
230	NExtNewChattingAI/shark_tank_ai_7b_v2	mistral	7B	2023-12-23	1208	-618.14	66.54
231	NTQAI/Nxcode-CQ-7B-orpo (Hong et al., 2024)	qwen2	7B	2024-04-24	12700	-685.73	42.98
232	Neko-Institute-of-Science/metharme-7b	llama-1	6B	2023-04-30	1161	-562.36	47.48
233	Neko-Institute-of-Science/pygmalion-7b	llama-1	6B	2023-04-30	1188	-562.13	46.04
234	NekoPunchBBB/Llama-2-13b-hf_Open-Platypus-QLoRA-multigpu	llama-2	13B	2023-09-15	1208	-536.60	54.40
235	NeverSleep/Llama-3-Lumimaid-8B-v0.1	llama-3	8B	2024-04-30	1499	-545.48	66.55
236	NeverSleep/Noromaid-7b-v0.2	mistral	7B	2023-12-21	1179	-552.34	61.78
237	NewstaR/Koss-7B-chat	llama	7B	2023-10-01	1180	-660.75	50.37
238	NewstaR/Starlight-7B (Clark et al., 2018; Zellers et al., 2019; Hendrycks et al., 2021a; Gao et al., 2021a; Lin et al., 2022a; Beeching et al., 2023)	llama-2	7B	2023-09-11	1180	-549.87	49.73

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
239	Nexusflow/NexusRaven-V2-13B (Nexusflow.ai team, 2023; Rozière et al., 2024)	llama	13B	2023-12-04	3966	-593.55	48.21
240	Nexusflow/Starling-LM-7B-beta (Ziegler et al., 2020; Zhu et al., 2023a)	mistral	7B	2024-03-19	4847	-559.22	69.88
241	NickyNicky/Mistral-7B-OpenOrca-oasst_top1_2023-08-25-v2 (Xiao et al., 2024)	mistral	7B	2023-10-11	1236	-560.11	61.65
242	NickyNicky/Mistral-7B-OpenOrca-oasst_top1_2023-08-25-v3 (Dao et al., 2022; Xiao et al., 2024)	mistral	7B	2023-10-13	1227	-568.73	61.26
243	Norquinal/Mistral-7B-claude-instruct	mistral	7B	2023-09-28	1248	-534.14	59.27
244	Norquinal/llama-2-7b-claude-chat	llama-2	7B	2023-08-11	1221	-557.34	50.98
245	Norquinal/llama-2-7b-claude-chat-rp	llama-2	7B	2023-08-14	1218	-557.09	51.25
246	NousResearch/CodeLlama-13b-hf	llama	13B	2023-08-24	6299	-582.02	43.35
247	NousResearch/CodeLlama-7b-hf	llama	7B	2023-08-24	9428	-597.05	39.81
248	NousResearch/Hermes-2-Pro-Llama-3-8B ("Teknium" et al., 2024b)	llama-3	8B	2024-04-30	26797	-576.90	68.73
249	NousResearch/Hermes-2-Pro-Mistral-7B ("interstellarninja" et al., 2024)	mistral	7B	2024-03-11	14586	-620.93	67.35
250	NousResearch/Hermes-2-Theta-Llama-3-8B ("Teknium" et al., 2024a)	llama-3	8B	2024-05-05	12392	-565.47	69.21
251	NousResearch/Meta-Llama-3-8B-Instruct (AI@Meta, 2024)	llama-3	8B	2024-04-18	104388	-573.95	67.10
252	NousResearch/Nous-Hermes-13b	llama-1	13B	2023-06-03	1536	-605.76	54.04
253	NousResearch/Nous-Hermes-2-Mistral-7B-DPO ("Teknium" et al., 2024c)	mistral	7B	2024-02-18	8725	-565.26	68.10
254	NousResearch/Nous-Hermes-2-SOLAR-10.7B	llama	10B	2024-01-01	9918	-542.37	71.00
255	NousResearch/Nous-Hermes-Llama2-13b	llama-2	13B	2023-07-20	39412	-586.34	55.75
256	NousResearch/Nous-Hermes-llama-2-7b	llama-2	6B	2023-07-25	12019	-569.93	51.87
257	NousResearch/Yarn-Mistral-7b-128k (Peng et al., 2023b)	mistral	7B	2023-10-31	20727	-532.22	59.42
258	NousResearch/Yarn-Mistral-7b-64k (Peng et al., 2023b)	mistral	7B	2023-10-31	10368	-532.16	59.63
259	OEvortex/EMO-2B	gemma	2B	2024-04-28	4137	-976.17	44.26
260	Open-Orca/LlongOrca-13B-16k (Mukherjee et al., 2023; Wang et al., 2023a; Dale et al., 2023; Longpre et al., 2023; Touvron et al., 2023b)	llama-2	13B	2023-08-16	1217	-551.07	56.59
261	Open-Orca/LlongOrca-7B-16k (Mukherjee et al., 2023; Wang et al., 2023a; Longpre et al., 2023; Touvron et al., 2023b; Lian et al., 2023c)	llama-2	7B	2023-08-05	1223	-583.06	53.02
262	Open-Orca/Mistral-7B-OpenOrca (Mukherjee et al., 2023; Longpre et al., 2023; Lian et al., 2023d)	mistral	7B	2023-09-29	18070	-575.75	60.17
263	Open-Orca/Mistral-7B-SlimOrca (Mukherjee et al., 2023; Lian et al., 2023f,e; Longpre et al., 2023)	mistral	7B	2023-10-08	3696	-569.42	60.37
264	Open-Orca/OpenOrca-Platypus2-13B (Hu et al., 2022; Mukherjee et al., 2023; Wang et al., 2023a,b; Lee et al., 2023; Longpre et al., 2023; Touvron et al., 2023b; Lee et al., 2024)	llama	13B	2023-08-11	6853	-557.72	57.28
265	Open-Orca/OpenOrca-Preview1-13B (Mukherjee et al., 2023; Lian et al., 2023a; Longpre et al., 2023; Touvron et al., 2023a)	llama-1	13B	2023-07-12	1240	-679.87	51.38
266	Open-Orca/OpenOrcaxOpenChat-Preview2-13B (Mukherjee et al., 2023; Wang et al., 2023a,b; Longpre et al., 2023; Touvron et al., 2023b)	llama-2	13B	2023-07-31	2172	-547.85	56.70
267	OpenAssistant/codellama-13b-oasst-sft-v10	llama-2	13B	2023-08-26	2122	-591.56	44.85
268	OpenAssistant/llama2-13b-orca-8k-3319 (Mukherjee et al., 2023)	llama-2	13B	2023-07-24	1270	-531.87	55.09
269	OpenAssistant/oasst-sft-1-pythia-12b	gpt_neox	12B	2023-03-09	22359	-615.25	40.77
270	OpenAssistant/oasst-sft-4-pythia-12b-epoch-3.5	gpt_neox	12B	2023-04-03	458718	-572.27	41.31
271	OpenAssistant/pythia-12b-sft-v8-7k-steps	gpt_neox	12B	2023-05-07	1323	-524.99	42.21
272	OpenAssistant/stablelm-7b-sft-v7-epoch-3	gpt_neox	7B	2023-04-20	1215	-764.93	34.85
273	OpenBuddy/openbuddy-atom-13b-v9-bf16	llama	13B	2023-08-05	1206	-625.44	52.31
274	OpenBuddy/openbuddy-llama2-13b-v11-bf16	llama-2	13B	2023-08-23	1199	-606.17	52.93
275	OpenBuddy/openbuddy-llama2-13b-v11.1-bf16	llama-2	13B	2023-08-24	1210	-595.93	55.28
276	OpenBuddy/openbuddy-llama2-13b-v8.1-fp16	llama-2	13B	2023-07-25	7339	-587.40	57.76
277	OpenBuddy/openbuddy-llama3-8b-v21.1-8k	llama-3	8B	2024-04-20	2293	-578.14	65.31
278	OpenBuddy/openbuddy-mistral-7b-v13	mistral	7B	2023-10-10	1335	-643.47	53.50
279	OpenBuddy/openbuddy-mistral-7b-v13-base	mistral	7B	2023-10-11	1197	-677.88	51.99
280	OpenBuddy/openbuddy-mistral-7b-v13.1	mistral	7B	2023-10-11	1217	-638.68	52.62
281	OpenBuddy/openbuddy-mistral2-7b-v20.3-32k	mistral	7B	2024-03-27	2302	-642.78	62.73
282	OpenBuddy/openbuddy-openllama-13b-v7-fp16	llama-1	13B	2023-07-03	1209	-654.65	49.31
283	OpenBuddy/openbuddy-openllama-3b-v10-bf16	llama	3B	2023-08-10	1206	-794.41	36.87
284	OpenBuddy/openbuddy-openllama-7b-v12-bf16	llama	7B	2023-09-19	3153	-854.52	45.28
285	OpenBuddy/openbuddy-zephyr-7b-v14.1	mistral	7B	2023-11-06	3392	-657.03	51.86
286	OpenModels4all/gemma-1.1-7b-it (Joshi et al., 2017; Zhao et al., 2018; Mihaylov et al., 2018; Clark et al., 2019; Talmor et al., 2019; Sap et al., 2019; Bisk et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Zellers et al., 2019; Austin et al., 2021; Cobbe et al., 2021; Hendrycks et al., 2021a; Chen et al., 2021; Parrish et al., 2022; Srivastava et al., 2023; Zhong et al., 2023; Gemini Team et al., 2024)	gemma	8B	2024-04-06	5128	-1355.60	59.78
287	OpenPipe/mistral-ft-optimized-1218	mistral	7B	2023-12-17	1405	-546.73	71.94
288	OpenPipe/mistral-ft-optimized-1227	mistral	7B	2023-12-27	6273	-564.28	70.54
289	Orenguteng/Llama-3-8B-Lexi-Uncensored	llama-3	8B	2024-04-23	9653	-564.93	66.18
290	PathFinderKR/Waktaverse-Llama-3-KO-8B-Instruct (AI@Meta, 2024; AI@Waktaverse, 2024)	llama-3	8B	2024-04-19	2305	-552.92	66.77
291	Pirr/pythia-13b-deduped-green_devil	gpt_neox	13B	2023-02-09	1351	-505.96	40.31
292	PistachioAlt/Synatra-MCS-7B-v0.3-RP-Slerp	mistral	7B	2023-12-11	1162	-549.18	69.18
293	PracticeLLM/SOLAR-tail-10.7B-Merge-v1.0	llama	10B	2023-12-26	2264	-530.70	71.68
294	PygmalionAI/metharme-1.3b	gpt_neox	1B	2023-06-02	1235	-541.84	35.04
295	PygmalionAI/mythalion-13b	llama-2	13B	2023-09-05	2383	-552.46	56.48
296	PygmalionAI/pygmalion-1.3b	gpt_neox	1B	2022-12-25	1519	-963.99	31.14
297	PygmalionAI/pygmalion-2-13b	llama-2	13B	2023-09-04	2083	-540.27	55.12
298	PygmalionAI/pygmalion-2-7b	llama-2	6B	2023-09-04	2063	-559.12	51.11
299	PygmalionAI/pygmalion-2.7b	gpt_neo	2B	2023-01-05	1986	-659.52	33.98
300	PygmalionAI/pygmalion-6b	gptj	6B	2023-01-07	4312	-555.36	38.47
301	Q-bert/Bumblebee-7B	mistral	7B	2023-12-03	1226	-549.82	67.73
302	Q-bert/Optimus-7B	mistral	7B	2023-12-03	1237	-550.18	69.09
303	Q-bert/Terminis-7B	mistral	7B	2023-12-12	1233	-564.26	70.73
304	Qwen/CodeQwen1.5-7B-Chat (Bai et al., 2023)	qwen2	7B	2024-04-15	77169	-691.05	43.26
305	Qwen/Qwen1.5-1.8B (Bai et al., 2023)	qwen2	1B	2024-01-22	137256	-610.58	46.55
306	Qwen/Qwen1.5-1.8B-Chat (Bai et al., 2023)	qwen2	1B	2024-01-30	10856	-673.92	43.99
307	Qwen/Qwen1.5-4B (Bai et al., 2023)	qwen2	3B	2024-01-22	6431	-553.86	57.05

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
308	Qwen/Qwen1.5-4B-Chat (Bai et al., 2023)	qwen2	3B	2024-01-30	5525	-601.85	46.79
309	Qwen/Qwen1.5-7B (Bai et al., 2023)	qwen2	7B	2024-01-22	122768	-533.48	61.76
310	Qwen/Qwen1.5-7B-Chat (Bai et al., 2023)	qwen2	7B	2024-01-30	26143	-608.59	55.15
311	Qwen/Qwen2-1.5B (Yang et al., 2024a)	qwen2	1B	2024-05-31	46510	-581.07	55.80
312	Qwen/Qwen2-7B (Yang et al., 2024a)	qwen2	7B	2024-06-04	37173	-507.30	68.40
313	RWKV/rwkv-raven-1b5	rwkv	1B	2023-05-04	1570	-526.30	33.56
314	RoversX/llama-2-7b-hf-small-shards-Samantha-V1-SFT	llama-2	7B	2023-08-11	1164	-558.46	49.96
315	RubielLabarta/LogoS-7Bx2-MoE-13B-v0.2	mixtral	12B	2024-01-21	3055	-589.76	77.15
316	S4sch/zephyr-neural-chat-frankenmerge11b	mistral	11B	2023-11-28	1181	-618.27	58.57
317	SJ-Donald/SJ-SOLAR-10.7b-DPO	llama	10B	2024-01-25	2306	-533.83	72.67
318	SJ-Donald/SOLAR-10.7B-slerp	llama	10B	2024-01-12	2296	-533.67	72.58
319	SJ-Donald/llama3-passthrough-chat	llama-3	11B	2024-05-17	2241	-607.16	60.15
320	Salesforce/codegen-6B-multi (Nijkamp et al., 2023)	codegen	6B	2022-04-13	1651	-733.14	32.43
321	Salesforce/codegen-6B-nl (Nijkamp et al., 2023)	codegen	6B	2022-04-13	1176	-478.78	40.00
322	SanjiWatsuki/Kunoichi-7B	mistral	7B	2024-01-04	1230	-579.35	72.13
323	SanjiWatsuki/Kunoichi-DPO-v2-7B	mistral	7B	2024-01-13	1216	-586.90	72.40
324	SanjiWatsuki/Loyal-Macaroni-Maid-7B	mistral	7B	2023-12-24	1297	-575.31	71.68
325	SanjiWatsuki/Silicon-Maid-7B	mistral	7B	2023-12-27	1578	-580.90	70.31
326	SanjiWatsuki/Sonya-7B	mistral	7B	2023-12-31	5399	-594.55	68.48
327	SciPhi/SciPhi-Self-RAG-Mistral-7B-32k (Mukherjee et al., 2023; Longpre et al., 2023; Asai et al., 2023)	mistral	7B	2023-10-27	1214	-664.82	56.46
328	SeaLLMs/SeaLLM-7B-v2 (Kojima et al., 2023; Zheng et al., 2023; Zhang et al., 2023; Nguyen et al., 2024)	mistral	7B	2024-01-29	6294	-548.56	67.57
329	SeaLLMs/SeaLLM-7B-v2.5 (Zhang et al., 2023; Nguyen et al., 2024)	gemma	8B	2024-04-03	13928	-565.35	69.07
330	Severian/ANIMA-Phi-Neptune-Mistral-7B	mistral	7B	2023-10-11	1191	-631.73	55.54
331	StudentLLM/Alpagasus-2-13b-QLoRA-merged (Chen et al., 2024a)	llama	13B	2023-09-02	1303	-533.28	54.31
332	SuperAGI/SAM	mistral	7B	2023-12-22	1235	-550.64	59.30
333	TIGER-Lab/MAmmoTH2-7B-Plus (Yue et al., 2024b)	mistral	7B	2024-05-06	10155	-673.56	67.75
334	TIGER-Lab/MAmmoTH2-8B-Plus (Yue et al., 2024b)	llama	8B	2024-05-06	12819	-595.71	67.49
335	TIGER-Lab/TIGERScore-13B (Jiang et al., 2024)	llama	13B	2023-11-26	1429	-548.56	56.79
336	TaylorAI/Flash-Llama-13B	llama	13B	2023-08-19	1181	-530.82	53.67
337	TaylorAI/Flash-Llama-3B	llama	3B	2023-08-13	1177	-578.13	40.13
338	TaylorAI/Flash-Llama-7B	llama	7B	2023-08-19	1184	-549.87	49.73
339	TeeZee/Bielik-SOLAR-LIKE-10.7B-Instruct-v0.1	mistral	10B	2024-04-10	1566	-854.79	53.50
340	TehVenom/Dolly_Malion-6b	gptj	6B	2023-03-27	1201	-486.77	39.77
341	TehVenom/Dolly_Shygmalion-6b	gptj	6B	2023-03-29	1195	-491.76	39.89
342	TehVenom/Dolly_Shygmalion-6b-Dev_V8P2 (Wang and Komatsuzaki, 2021)	gptj	6B	2023-05-23	1197	-487.65	40.11
343	TehVenom/GPT-J-Pyg_PPO-6B	gptj	6B	2023-03-05	1203	-495.88	39.60
344	TehVenom/GPT-J-Pyg_PPO-6B-Dev-V8p4	gptj	6B	2023-03-26	1191	-493.17	39.61
345	TehVenom/Metharme-13b-Merged	llama-1	13B	2023-05-18	1199	-561.32	54.15
346	TehVenom/Moderator-Chan_GPT-JT-6b	gptj	6B	2023-03-19	1185	-502.43	42.17
347	TehVenom/PPO_Pygway-V8p4_Dev-6b (Wang and Komatsuzaki, 2021)	gptj	6B	2023-03-17	1191	-489.49	39.85
348	TehVenom/PPO_Shygmalion-6b	gptj	6B	2023-03-23	1199	-489.16	39.35
349	TehVenom/PPO_Shygmalion-V8p4_Dev-6b	gptj	6B	2023-03-23	1188	-490.13	39.85
350	TehVenom/Pygmalion-13b-Merged	llama-1	13B	2023-05-18	1207	-588.35	48.49
351	TehVenom/Pygmalion-Vicuna-1.1-7b	llama-1	6B	2023-05-02	1246	-572.52	49.25
352	TehVenom/Pygmalion_AlpacaLora-7b	llama-1	7B	2023-04-30	1195	-605.84	46.49
353	Telugu-LLM-Labs/Indic-gemma-7b-finetuned-sft-Navarasa-2.0	gemma	8B	2024-03-17	2025	-650.29	55.74
354	TencentARC/LLaMA-Pro-8B	llama-2	8B	2024-01-05	1319	-557.58	51.67
355	TencentARC/LLaMA-Pro-8B-Instruct	llama-2	8B	2024-01-06	1423	-634.71	58.06
356	TheBloke/CodeLlama-13B-Instruct-fp16	llama-2	13B	2023-08-24	2193	-579.86	45.82
357	TheBloke/CodeLlama-13B-Python-fp16	llama-2	13B	2023-08-24	2114	-587.68	37.52
358	TheBloke/Llama-2-13B-fp16	llama-2	13B	2023-07-18	6470	-530.82	53.67
359	TheBloke/Nous-Hermes-13B-SuperHOT-8K-fp16	llama-1	13B	2023-06-26	1225	-633.76	52.18
360	TheBloke/Planner-7B-fp16	llama-1	7B	2023-06-05	1219	-562.04	45.65
361	TheBloke/UltraLM-13B-fp16 (Ding et al., 2023)	llama-1	13B	2023-06-29	1211	-567.38	54.62
362	TheBloke/Vicuna-13B-CoT-fp16 (Lacoste et al., 2019)	llama-1	13B	2023-06-08	1219	-646.61	53.28
363	TheBloke/Wizard-Vicuna-13B-Uncensored-HF	llama-1	13B	2023-05-13	1648	-579.62	54.14
364	TheBloke/Wizard-Vicuna-7B-Uncensored-HF	llama-1	7B	2023-05-18	1976	-607.14	48.27
365	TheBloke/WizardLM-13B-V1-1-SuperHOT-8K-fp16 (Xu et al., 2023a)	llama-1	13B	2023-07-07	1225	-626.40	53.16
366	TheBloke/airoboros-13B-HF	llama-1	13B	2023-05-23	1214	-581.17	54.05
367	TheBloke/airoboros-7b-gpt4-fp16	llama-1	7B	2023-06-04	1208	-603.39	47.70
368	TheBloke/gpt4-alpaca-lora-13B-HF	llama-1	13B	2023-04-17	1181	-547.42	53.98
369	TheBloke/guanaco-13B-HF	llama-1	13B	2023-05-25	1222	-588.92	53.54
370	TheBloke/guanaco-7B-HF	llama-1	7B	2023-05-25	1267	-586.15	47.34
371	TheBloke/koala-13B-HF	llama-1	13B	2023-04-07	2501	-594.23	51.16
372	TheBloke/koala-7B-HF	llama-1	7B	2023-04-07	1238	-617.95	44.29
373	TheBloke/stable-vicuna-13B-HF (von Werra et al., 2023; Anand et al., 2023; Chiang et al., 2023; Taori et al., 2023; Touvron et al., 2023a)	llama-1	13B	2023-04-28	1337	-590.21	51.64
374	TheBloke/tulu-13B-fp16 (Köpf et al., 2023; Conover et al., 2023; Wang et al., 2023c; Peng et al., 2023a; Longpre et al., 2023; Chaudhary, 2023; Touvron et al., 2023a)	llama-1	13B	2023-06-10	1231	-583.06	53.58
375	TheBloke/tulu-7B-fp16 (Köpf et al., 2023; Conover et al., 2023; Wang et al., 2023c; Peng et al., 2023a; Longpre et al., 2023; Chaudhary, 2023; Touvron et al., 2023a)	llama-1	7B	2023-06-10	4079	-616.51	50.24
376	TheBloke/wizard-vicuna-13B-HF	llama-1	13B	2023-05-04	1219	-610.98	52.75
377	TheTravellingEngineer/llama2-7b-chat-hf-dpo	llama-2	7B	2023-08-14	1201	-659.39	50.38
378	TheTravellingEngineer/llama2-7b-chat-hf-guanaco	llama-2	6B	2023-08-02	1209	-597.96	50.02
379	TheTravellingEngineer/llama2-7b-chat-hf-v2	llama-2	6B	2023-08-08	1208	-549.87	49.73
380	TheTravellingEngineer/llama2-7b-chat-hf-v3	llama-2	6B	2023-08-10	1203	-557.97	48.81
381	TheTravellingEngineer/llama2-7b-chat-hf-v4	llama-2	6B	2023-08-10	1213	-549.87	49.78
382	TheTravellingEngineer/llama2-7b-hf-guanaco	llama-2	6B	2023-07-25	1206	-554.41	50.12
383	TigerResearch/tigerbot-7b-base	llama	7B	2023-08-19	1228	-587.17	47.93
384	TinyLlama/TinyLlama-1.1B-Chat-v0.6	llama	1B	2023-11-20	15745	-642.54	34.94
385	TinyLlama/TinyLlama-1.1B-Chat-v1.0	llama	1B	2023-12-30	1078500	-619.71	37.17

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
386	TinyLlama/TinyLlama-1.1B-intermediate-step-1195k-token-2.5T	llama	1B	2023-12-11	1365	-613.87	36.26
387	TinyLlama/TinyLlama-1.1B-intermediate-step-1431k-3T	llama	1B	2023-12-28	798206	-608.46	36.42
388	TinyLlama/TinyLlama-1.1B-intermediate-step-955k-token-2T	llama	1B	2023-11-19	8119	-646.34	34.56
389	TomGrc/FusionNet	llama	10B	2023-12-31	1166	-561.26	74.38
390	TomGrc/FusionNet_linear	llama	10B	2023-12-31	1167	-561.26	74.43
391	Toten5/Marcoroni-neural-chat-7B-v2	mistral	7B	2023-12-12	1201	-557.34	72.50
392	TsinghuaC3I/Llama-3-8B-UltraMedical (Zhang et al., 2024c)	llama-3	8B	2024-04-27	3949	-558.79	63.73
393	Unbabel/TowerBase-7B-v0.1 (Alves et al., 2024)	llama	6B	2024-01-03	1856	-582.06	49.11
394	Unbabel/TowerInstruct-7B-v0.1 (Alves et al., 2024)	llama	6B	2024-01-04	2230	-590.30	52.39
395	Undi95/MLewd-Chat-v2-13B	llama	13B	2023-09-26	1187	-569.88	57.23
396	Undi95/MLewd-L2-13B	llama	13B	2023-09-04	1172	-666.07	53.12
397	Undi95/MLewd-L2-Chat-13B	llama	13B	2023-09-16	1177	-551.09	57.75
398	Undi95/MLewd-v2.4-13B	llama	13B	2023-09-26	1280	-571.03	56.37
399	Undi95/MLewdBoros-L2-13B	llama	13B	2023-09-09	1224	-542.84	56.51
400	Undi95/Meta-Llama-3-8B-hf (AI@Meta, 2024)	llama-3	8B	2024-04-18	11376	-514.33	62.35
401	Undi95/Mistral-11B-v0.1	mistral	10B	2023-10-09	1196	-556.96	58.05
402	Undi95/Nous-Hermes-13B-Code	llama	13B	2023-09-02	1207	-602.47	55.93
403	Undi95/OpenRP-13B	llama	13B	2023-09-11	1242	-536.49	56.57
404	Undi95/ReMM-SLERP-L2-13B	llama	13B	2023-09-04	1511	-585.33	56.03
405	Undi95/ReMM-v2-L2-13B	llama	13B	2023-09-09	1207	-565.06	56.99
406	Undi95/ReMM-v2.1-L2-13B	llama	13B	2023-09-12	1217	-564.83	56.71
407	Undi95/ReMM-v2.2-L2-13B	llama	13B	2023-09-21	1384	-567.22	57.10
408	Undi95/UndiMix-v1-13b	llama	13B	2023-08-31	1220	-649.19	55.50
409	Undi95/UndiMix-v4-13B	llama	13B	2023-09-12	1212	-569.06	56.93
410	Undi95/Unholy-v1-12L-13B	llama	13B	2023-09-10	1210	-541.04	57.47
411	Undi95/X-MythoChronos-13B	llama	13B	2023-11-18	1203	-604.69	58.43
412	VAGOsolutions/Llama-3-SauerkrautLM-8b-Instruct	llama-3	8B	2024-04-19	55400	-579.40	73.74
413	VAGOsolutions/SauerkrautLM-7b-HerO	mistral	7B	2023-11-24	1226	-553.88	64.49
414	VAGOsolutions/SauerkrautLM-Gemma-7b	gemma	8B	2024-02-27	5691	-561.27	67.83
415	VAGOsolutions/SauerkrautLM-SOLAR-Instruct	llama	10B	2023-12-20	1175	-560.76	74.21
416	VMware/open-llama-0.7T-7B-open-instruct-v1.1	llama-1	7B	2023-05-31	1161	-652.26	41.11
417	VMware/open-llama-7b-open-instruct	llama-1	7B	2023-06-08	6470	-642.10	42.59
418	Voicelab/trurl-2-13b-academic	llama-2	13B	2023-09-18	2774	-568.46	53.94
419	Voicelab/trurl-2-7b	llama-2	7B	2023-08-16	2861	-602.32	50.58
420	Weyaxi/ChatAYT-Lora-Assamble-Marcoroni	llama	13B	2023-09-14	1203	-569.45	57.76
421	Weyaxi/Dolphin2.1-OpenOrca-7B	mistral	7B	2023-10-11	1221	-557.64	60.47
422	Weyaxi/Instruct-v0.2-Seraph-7B	mistral	7B	2023-12-12	1203	-574.63	68.48
423	Weyaxi/Luban-Marcoroni-13B-v2	llama	13B	2023-09-13	1212	-566.43	57.92
424	Weyaxi/Luban-Marcoroni-13B-v3	llama	13B	2023-09-13	1214	-566.44	57.94
425	Weyaxi/MetaMath-Chupacabra-7B-v2.01-Slerp	mistral	7B	2023-12-08	1210	-546.54	70.26
426	Weyaxi/MetaMath-NeuralHermes-2.5-Mistral-7B-Linear	mistral	7B	2023-12-05	1205	-560.95	67.60
427	Weyaxi/MetaMath-NeuralHermes-2.5-Mistral-7B-Ties	mistral	7B	2023-12-05	1212	-604.36	67.03
428	Weyaxi/MetaMath-OpenHermes-2.5-neural-chat-v3-3-Slerp	mistral	7B	2023-12-10	1224	-548.15	69.92
429	Weyaxi/MetaMath-Tulpar-7b-v2-Slerp	mistral	7B	2023-12-08	1217	-555.63	70.07
430	Weyaxi/MetaMath-neural-chat-7b-v3-2-Slerp	mistral	7B	2023-12-08	1208	-544.26	69.79
431	Weyaxi/MetaMath-neural-chat-7b-v3-2-Ties	mistral	7B	2023-12-05	1212	-590.97	67.54
432	Weyaxi/MetaMath-una-cybertron-v2-bf16-Ties	mistral	7B	2023-12-06	1218	-602.74	68.88
433	Weyaxi/OpenHermes-2.5-neural-chat-7b-v3-1-7B	mistral	7B	2023-11-24	1230	-567.74	67.84
434	Weyaxi/OpenHermes-2.5-neural-chat-7b-v3-2-7B	mistral	7B	2023-12-03	1221	-576.02	68.71
435	Weyaxi/OpenOrca-Zephyr-7B	mistral	7B	2023-10-11	1208	-564.12	64.97
436	Weyaxi/Samantha-Nebula-7B	mistral	7B	2023-10-05	1166	-584.51	54.58
437	Weyaxi/SauerkrautLM-UNA-SOLAR-Instruct	llama	10B	2023-12-21	1225	-561.98	74.26
438	Weyaxi/Seraph-7B	mistral	7B	2023-12-11	1214	-546.73	71.86
439	Weyaxi/Seraph-openchat-3.5-1210-Slerp	mistral	7B	2023-12-27	1210	-567.06	70.89
440	Weyaxi/SlimOpenOrca-Mistral-7B	mistral	7B	2023-10-11	1220	-587.26	60.84
441	Weyaxi/neural-chat-7b-v3-1-OpenHermes-2.5-7B	mistral	7B	2023-12-01	1205	-570.29	67.19
442	Weyaxi/openchat-3.5-1210-Seraph-Slerp	mistral	7B	2023-12-27	1210	-553.81	71.82
443	WhiteRabbitNeo/WhiteRabbitNeo-13B-v1	llama-2	13B	2023-12-17	2090	-615.73	49.11
444	Xwin-LM/Xwin-LM-13B-V0.1 (Xwin-LM Team, 2023)	llama-2	13B	2023-09-15	1401	-559.13	55.29
445	Xwin-LM/Xwin-LM-7B-V0.1 (Xwin-LM Team, 2023)	llama-2	7B	2023-09-15	1474	-592.93	52.08
446	Yhyu13/LMCocktail-10.7B-v1 (Xiao et al., 2023)	llama-2	10B	2023-12-20	3332	-556.38	74.06
447	Yhyu13/chimera-inst-chat-13b-hf	llama-1	13B	2023-05-11	1295	-582.39	52.86
448	Yukang/Llama-2-7b-longlora-32k-ft (Chen et al., 2024b)	llama-2	7B	2023-09-12	2423	-1387.05	29.20
449	Yukang/LongAlpaca-13B (Chen et al., 2023b, 2024b)	llama	13B	2023-10-08	1896	-832.57	41.74
450	Yukang/LongAlpaca-7B (Chen et al., 2023b, 2024b)	llama	6B	2023-10-07	2773	-794.46	39.36
451	aaditya/Llama3-OpenBioLLM-8B (Singhal et al., 2022; Nori et al., 2023; Singhal et al., 2023; Pal and Sankarasubbu, 2024a,b; Rafailov et al., 2024)	llama-3	8B	2024-04-20	9308	-590.14	54.06
452	aari1995/germeo-7b-laser	mistral	7B	2024-01-09	2351	-686.18	62.82
453	abacusai/Giraffe-13b-32k-v3	llama-2	13B	2023-12-06	1214	-546.12	57.24
454	abacusai/Llama-3-Smaug-8B (Pal et al., 2024)	llama-3	8B	2024-04-19	12873	-565.82	64.61
455	abacusai/Slerp-CM-mist-dpo	mistral	7B	2024-01-03	4030	-553.48	73.10
456	abacusai/bigstral-12b-32k	mistral	12B	2024-03-06	5216	-632.41	62.17
457	abhinand/Llama-3-OpenBioMed-8B-slerp-v0.3	llama-3	8B	2024-05-02	2713	-558.51	62.08
458	abhinand/tamil-llama-7b-base-v0.1 (Balachandran, 2023)	llama-2	7B	2023-11-08	1382	-877.00	44.52
459	abhinand/tamil-llama-7b-instruct-v0.1 (Balachandran, 2023)	llama-2	7B	2023-11-08	3507	-708.97	45.52
460	abhishekchohan/Yi-9B-Forest-DPO-v1.0	llama	9B	2024-03-18	2755	-528.97	64.11
461	abhishekchohan/mistral-7B-forest-dpo	mistral	7B	2024-01-21	1961	-561.51	63.28
462	acrastt/Bean-3B	llama	3B	2023-09-02	1191	-592.51	40.18
463	acrastt/Griffin-3B	llama	3B	2023-08-18	1198	-584.63	41.13
464	acrastt/Marx-3B	llama	3B	2023-08-15	2006	-603.32	41.71
465	acrastt/Marx-3B-V2	llama	3B	2023-08-22	1234	-609.79	42.08
466	acrastt/OmegLLaMA-3B	llama	3B	2023-08-26	1201	-640.98	38.28
467	acrastt/Puma-3B	llama	3B	2023-08-16	1198	-584.54	41.02
468	acrastt/RedPajama-INCITE-Chat-Instruct-3B-V1	gpt_neox	2B	2023-07-27	1202	-565.14	39.23
469	adamo1139/Mistral-7B-AEZAKMI-v1	mistral	7B	2023-11-27	1199	-596.56	54.92

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
470	adonlee/LLaMA_2_13B_SFT_v0	llama	13B	2023-10-03	1268	-556.59	57.31
471	adonlee/LLaMA_2_13B_SFT_v1	llama	13B	2023-11-06	1265	-546.75	63.04
472	aerdincdal/CBDDO-LLM-8B-Instruct-v1	llama	8B	2024-05-02	4114	-613.44	56.94
473	ahnyeonchan/OpenOrca-AYT-13B	llama-2	13B	2023-09-07	1184	-569.10	–
474	ajibawa-2023/Code-13B	llama	13B	2023-12-08	1181	-604.28	54.81
475	ajibawa-2023/Python-Code-13B	llama	13B	2023-11-11	1201	-582.71	53.61
476	ajibawa-2023/SlimOrca-13B	llama	13B	2023-11-27	1177	-608.08	60.39
477	ajibawa-2023/Uncensored-Frank-13B	llama	13B	2023-09-14	1192	-577.46	55.64
478	ajibawa-2023/Uncensored-Frank-7B	llama	7B	2023-09-14	1178	-654.45	47.90
479	ajibawa-2023/Uncensored-Jordan-13B	llama	13B	2023-10-23	1174	-578.48	56.27
480	ajibawa-2023/Uncensored-Jordan-7B	llama	7B	2023-10-23	1174	-636.79	49.95
481	ajibawa-2023/carl-7b	llama	7B	2023-07-22	1212	-599.09	46.16
482	akjindal53244/Mistral-7B-v0.1-Open-Platypus	mistral	7B	2023-10-05	1286	-543.69	58.92
483	alignment-handbook/zephyr-7b-sft-full	mistral	7B	2023-11-09	11605	-569.88	57.52
484	allbyai/ToRoLaMa-7b-v1.0 (Do et al., 2023)	llama-2	7B	2023-12-19	1185	-732.57	47.87
485	allenai/OLMo-1B-hf (Touvron et al., 2023a; Groeneveld et al., 2024)	olmo	1B	2024-04-12	15221	-619.51	36.78
486	allenai/OLMo-7B-hf (Touvron et al., 2023a; Groeneveld et al., 2024)	olmo	6B	2024-04-12	5407	-554.02	43.36
487	allknowingroger/MultiverseEx26-7B-slerp	mistral	7B	2024-03-30	3034	-599.87	76.80
488	alnrg2arg/blockchainlabs_7B_merged_test2_4	mistral	7B	2024-01-17	1455	-577.39	75.28
489	alnrg2arg/blockchainlabs_7B_merged_test2_4_prune	mistral	7B	2024-01-18	1939	-673.45	57.91
490	aloobun/bun_mistral_7b_v2	mistral	7B	2023-12-20	1305	-558.93	59.76
491	aloobun/falcon-1b-cot-t2	falcon	1B	2024-01-07	2161	-735.39	28.56
492	aloobun/open-llama-3b-v2-elmv3	llama	3B	2023-12-08	1207	-604.18	41.14
493	andreaskoepf/llama2-13b-megacode2_min100	llama-2	13B	2023-08-14	1162	-571.36	56.92
494	argilla/notus-7b-v1	mistral	7B	2023-11-16	7660	-564.14	60.22
495	athirdpath/NSFW_DPO_Noromaid-7b	mistral	7B	2023-12-12	1280	-546.50	61.59
496	augmxnt/shisa-7b-v1 (Jain et al., 2023; Rafailov et al., 2024)	mistral	7B	2023-11-27	1195	-643.26	55.01
497	augmxnt/shisa-base-7b-v1	mistral	7B	2023-11-19	1188	-648.62	51.64
498	augmxnt/shisa-gamma-7b-v1	mistral	7B	2023-12-23	151426	-590.25	55.50
499	automerger/YamshadowExperiment28-7B	mistral	7B	2024-03-18	3152	-595.65	76.86
500	beaugogh/Llama2-7b-openorca-mc-v1	llama-2	7B	2023-08-20	1177	-613.56	52.24
501	beaugogh/Llama2-7b-openorca-mc-v2-dpo	llama-2	7B	2023-10-06	1173	-608.74	52.32
502	beaugogh/Llama2-7b-sharegpt4	llama-2	7B	2023-08-12	1183	-660.22	51.05
503	beaugogh/pythia-1.4b-deduped-sharegpt	gpt_neox	1B	2023-07-25	1293	-557.93	35.11
504	beomi/KoAlpaca-KoRWKV-6B	rwkv	6B	2023-06-02	2288	-1099.15	28.57
505	beomi/KoAlpaca-Polyglot-5.8B	gpt_neox	6B	2023-03-16	4198	-1309.35	29.46
506	beomi/KoRWKV-6B	rwkv	6B	2023-05-26	2127	-1148.78	28.19
507	beomi/Yi-Ko-6B (Lee, 2024b)	llama	6B	2023-11-30	4261	-589.43	50.27
508	beomi/llama-2-ko-7b (Lee, 2023)	llama-2	6B	2023-07-20	5226	-907.04	45.32
509	beowolx/CodeNinja-1.0-OpenChat-7B	mistral	7B	2023-12-20	6300	-555.93	67.40
510	berkeley-nest/Starling-LM-7B-alpha (Zhu et al., 2023b,a)	mistral	7B	2023-11-25	18366	-571.63	67.05
511	bhavinjawade/SOLAR-10B-OrcaDPO-Jawade	llama	10B	2024-01-06	1224	-563.19	74.27
512	bigcode/gpt_bigcode-santacoder	gpt_bigcode	1B	2023-04-06	40198	-861.42	28.49
513	bigcode/starcoder2-3b (Beltagy et al., 2020; Bavarian et al., 2022; Dao et al., 2022; Ainslie et al., 2023; Lozhkov et al., 2024)	starcoder2	3B	2023-11-29	445316	-620.70	39.25
514	bigcode/starcoder2-7b (Beltagy et al., 2020; Bavarian et al., 2022; Dao et al., 2022; Ainslie et al., 2023; Lozhkov et al., 2024)	starcoder2	7B	2024-02-20	11834	-584.03	42.95
515	bigcode/starcoderbase-1b (Shazeer, 2019; Dao et al., 2022; Bavarian et al., 2022; Li et al., 2023a)	gpt_bigcode	1B	2023-07-03	5247	-734.99	30.06
516	bigcode/starcoderbase-7b (Shazeer, 2019; Dao et al., 2022; Bavarian et al., 2022; Li et al., 2023a)	gpt_bigcode	7B	2023-07-26	3566	-652.23	33.75
517	bigscience/bloom-1b1 (Shoeybi et al., 2020; Press et al., 2022; Dettmers et al., 2022)	bloom	1B	2022-05-19	11054	-687.97	32.47
518	bigscience/bloom-1b7 (Shoeybi et al., 2020; Press et al., 2022; Dettmers et al., 2022)	bloom	1B	2022-05-19	40840	-657.05	33.98
519	bigscience/bloom-3b (Shoeybi et al., 2020; Press et al., 2022; Dettmers et al., 2022)	bloom	3B	2022-05-19	13914	-633.79	36.07
520	bigscience/bloom-7b1 (Shoeybi et al., 2020; Press et al., 2022; Dettmers et al., 2022)	bloom	7B	2022-05-19	21428	-604.20	39.18
521	bigscience/bloomz-3b (Muennighoff et al., 2023)	bloom	3B	2022-10-08	7975	-701.42	37.03
522	bigscience/bloomz-7b1 (Muennighoff et al., 2023)	bloom	7B	2022-09-27	12152	-652.34	42.21
523	bigscience/bloomz-7b1-mt (Muennighoff et al., 2023)	bloom	7B	2022-09-28	2427	-653.08	42.14
524	bofenghuang/vigogne-2-13b-instruct	llama-2	13B	2023-07-26	1203	-534.88	55.14
525	bofenghuang/vigogne-2-7b-chat	llama-2	7B	2023-07-29	1170	-558.60	52.45
526	bofenghuang/vigogne-2-7b-instruct	llama-2	7B	2023-07-20	1243	-555.11	52.02
527	bofenghuang/vigogne-7b-instruct	llama-1	7B	2023-03-22	1167	-570.61	47.76
528	bofenghuang/vigostral-7b-chat	mistral	7B	2023-09-29	4118	-535.15	59.18
529	budecosystem/boomer-1b	llama	1B	2023-10-03	1267	-846.13	28.44
530	castorini/rank_vicuna_7b_v1_fp16 (Touvron et al., 2023b; Pradeep et al., 2023)	llama-2	7B	2023-09-27	1165	-720.69	44.36
531	ceadar-ie/FinanceConnect-13B (CeADAR, 2023)	llama	13B	2023-11-28	1270	-661.62	49.34
532	chargoddard/storytime-13b	llama-2	13B	2023-09-22	1166	-599.45	56.64
533	chickencaesar/llama2-platypus-llama2-chat-13B-hf	llama-2	13B	2023-09-28	1216	-536.92	54.11
534	chinoll/Yi-6b-200k-dpo	llama	6B	2023-12-01	1187	-573.79	51.93
535	circulus/Llama-2-13b-orca-v1	llama-2	13B	2023-08-01	1228	-540.82	57.05
536	circulus/Llama-2-7b-orca-v1	llama-2	7B	2023-08-01	1235	-565.19	53.56
537	clibrain/Llama-2-7b-ft-instruct-es	llama-2	7B	2023-08-09	2062	-559.81	49.63
538	codellama/CodeLlama-13b-Instruct-hf (Rozière et al., 2024)	llama-2	13B	2023-08-24	25248	-579.86	45.82
539	codellama/CodeLlama-13b-Python-hf (Rozière et al., 2024)	llama-2	13B	2023-08-24	2537	-587.68	37.00
540	codellama/CodeLlama-13b-hf (Rozière et al., 2024)	llama-2	13B	2023-08-24	8432	-582.07	43.35
541	codellama/CodeLlama-7b-Instruct-hf (Rozière et al., 2024)	llama-2	6B	2023-08-24	133523	-598.06	40.05
542	codellama/CodeLlama-7b-Python-hf (Rozière et al., 2024)	llama-2	6B	2023-08-24	5138	-605.60	36.42
543	codellama/CodeLlama-7b-hf (Rozière et al., 2024)	llama-2	6B	2023-08-24	66040	-597.05	39.81
544	cognitivecomputations/Llama-3-8B-Instruct-abliterated-v2	llama-3	8B	2024-05-09	8728	-581.93	66.00
545	cognitivecomputations/TinyDolphin-2.8-1.1b	llama	1B	2024-01-21	1678	-683.06	36.34
546	cognitivecomputations/WestLake-7B-v2-laser	mistral	7B	2024-01-26	3980	-591.19	74.78

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
547	cognitivecomputations/dolphin-2.2.1-mistral-7b	mistral	7B	2023-10-30	7292	-546.22	65.01
548	cognitivecomputations/dolphin-2.6-mistral-7b	mistral	7B	2023-12-27	1418	-559.17	64.92
549	cognitivecomputations/dolphin-2.6-mistral-7b-dpo	mistral	7B	2023-12-31	1236	-565.34	67.20
550	cognitivecomputations/dolphin-2.6-mistral-7b-dpo-laser (Sharma et al., 2023)	mistral	7B	2024-01-01	2070	-558.72	67.28
551	cognitivecomputations/dolphin-2.9-llama3-8b	llama-3	8B	2024-04-20	130977	-640.39	65.92
552	cognitivecomputations/dolphin-2.9.1-llama-3-8b	llama-3	8B	2024-05-10	7575	-647.01	66.23
553	cognitivecomputations/dolphin-2.9.1-yi-1.5-9b	llama	8B	2024-05-18	4880	-598.79	68.92
554	cognitivecomputations/openchat-3.5-0106-laser	mistral	7B	2024-01-27	6155	-554.46	69.46
555	cookinai/BruinHermes	mistral	7B	2023-12-17	1193	-551.19	73.42
556	cookinai/CatMacaroni14	mistral	7B	2023-12-31	1186	-552.22	72.68
557	crumb/apricot-wildflower-20	mistral	7B	2023-12-19	1179	-531.99	59.74
558	cyberagent/open-calm-7b (Andonian et al., 2021)	gpt_neox	7B	2023-05-15	24168	-1002.50	28.21
559	cypienai/cymist-2-v02-SFT (Lacoste et al., 2019)	mistral	7B	2024-05-22	2717	-537.73	62.57
560	cypienai/cymist2-v01-SFT (Lacoste et al., 2019)	mistral	7B	2024-05-12	2754	-628.53	51.71
561	danielpark/gorani-100k-llama2-13b-instruct	llama-2	13B	2023-10-04	1176	-1410.79	29.69
562	databricks/dolly-v2-12b (Conover et al., 2023)	gpt_neox	12B	2023-04-11	3860	-566.95	39.46
563	databricks/dolly-v2-3b (Conover et al., 2023)	gpt_neox	3B	2023-04-13	21443	-556.97	–
564	databricks/dolly-v2-7b (Conover et al., 2023)	gpt_neox	7B	2023-04-13	10069	-555.60	39.24
565	deepseek-ai/DeepSeek-Coder-V2-Lite-Base (Dai et al., 2024)	deepseek	16B	2024-06-14	13642	-527.73	–
566	deepseek-ai/DeepSeek-Coder-V2-Lite-Instruct (Dai et al., 2024)	deepseek	16B	2024-06-14	142758	-569.70	–
567	deepseek-ai/DeepSeek-Prover-V1 (Xin et al., 2024a)	deepseek	7B	2024-08-16	114	-791.21	–
568	deepseek-ai/DeepSeek-Prover-V1.5-Base (Xin et al., 2024b)	deepseek	7B	2024-08-15	230	-554.13	–
569	deepseek-ai/DeepSeek-Prover-V1.5-RL (Xin et al., 2024b)	deepseek	7B	2024-08-15	12223	-672.91	–
570	deepseek-ai/DeepSeek-Prover-V1.5-SFT (Xin et al., 2024b)	deepseek	7B	2024-08-15	6459	-670.56	–
571	deepseek-ai/DeepSeek-R1-Distill-Llama-8B (DeepSeek-AI et al., 2025)	deepseek	8B	2025-01-20	199313	-693.69	–
572	deepseek-ai/DeepSeek-R1-Distill-Qwen-1.5B (DeepSeek-AI et al., 2025)	deepseek	2B	2025-01-20	290094	-854.97	–
573	deepseek-ai/DeepSeek-R1-Distill-Qwen-14B (DeepSeek-AI et al., 2025)	deepseek	14B	2025-01-20	139489	-605.82	–
574	deepseek-ai/DeepSeek-R1-Distill-Qwen-7B (DeepSeek-AI et al., 2025)	deepseek	7B	2025-01-20	201118	-758.13	–
575	deepseek-ai/DeepSeek-V2-Lite (DeepSeek-AI et al., 2024b)	deepseek	16B	2024-05-15	25474	-533.54	–
576	deepseek-ai/DeepSeek-V2-Lite-Chat (DeepSeek-AI et al., 2024b)	deepseek	16B	2024-05-15	18056	-588.92	–
577	deepseek-ai/ESFT-vanilla-lite (Wang et al., 2024c)	deepseek	16B	2024-07-04	270	-550.46	–
578	deepseek-ai/deepseek-coder-1.3b-base (Guo et al., 2024)	deepseek	1B	2023-10-28	48960	-718.82	–
579	deepseek-ai/deepseek-coder-1.3b-instruct (Guo et al., 2024)	deepseek	1B	2023-10-29	28984	-785.33	32.40
580	deepseek-ai/deepseek-coder-6.7b-base (Guo et al., 2024)	deepseek	6B	2023-10-23	38348	-647.51	40.87
581	deepseek-ai/deepseek-coder-6.7b-instruct (Guo et al., 2024)	deepseek	6B	2023-10-29	28828	-686.56	43.57
582	deepseek-ai/deepseek-coder-7b-base-v1.5 (Guo et al., 2024)	deepseek	7B	2024-01-25	895	-570.98	–
583	deepseek-ai/deepseek-coder-7b-instruct-v1.5 (Guo et al., 2024)	deepseek	6B	2024-01-25	28928	-604.47	50.89
584	deepseek-ai/deepseek-llm-7b-base (DeepSeek-AI et al., 2024a)	deepseek	7B	2023-11-29	19180	-552.39	–
585	deepseek-ai/deepseek-llm-7b-chat (DeepSeek-AI et al., 2024a)	deepseek	7B	2023-11-29	34271	-594.23	59.38
586	deepseek-ai/deepseek-math-7b-base (Shao et al., 2024)	deepseek	7B	2024-02-05	37614	-566.93	57.61
587	deepseek-ai/deepseek-math-7b-instruct (Shao et al., 2024)	deepseek	7B	2024-02-05	8352	-593.77	51.48
588	deepseek-ai/deepseek-math-7b-rl (Shao et al., 2024)	deepseek	6B	2024-02-05	1633	-607.25	49.54
589	deepseek-ai/deepseek-moe-16b-base (Dai et al., 2024)	deepseek	16B	2024-01-08	13924	-544.49	–
590	deepseek-ai/deepseek-moe-16b-chat (Dai et al., 2024)	deepseek	16B	2024-01-09	8852	-578.23	–
591	dfurman/Llama-3-8B-Orpo-v0.1	llama-3	8B	2024-04-26	5146	-515.13	64.67
592	dhmeltzer/Llama-2-13b-hf-ds_eli5_1024_r_64_alpha_16_merged	llama-2	13B	2023-09-14	1188	-542.35	54.16
593	dhmeltzer/Llama-2-13b-hf-ds_wiki_1024_full_r_64_alpha_16_merged	llama-2	13B	2023-09-14	1198	-536.93	52.94
594	dhmeltzer/Llama-2-13b-hf-eli5-wiki-1024_r_64_alpha_16_merged	llama-2	13B	2023-09-14	1192	-538.52	53.57
595	dhmeltzer/llama-7b-SFT_eli5_wiki65k_1024_r_64_alpha_16_merged	llama	6B	2023-08-25	1257	-568.38	50.00
596	diffnamehard/Psyfighter2-Noromaid-ties-13B	llama	13B	2023-12-28	1215	-569.13	59.47
597	digitous/13B-Chimera	llama-1	13B	2023-05-23	1359	-562.36	54.92
598	digitous/Alpacino13b	llama-1	13B	2023-04-13	1182	-547.35	52.39
599	dotvignesh/perry-7b	llama	7B	2023-09-28	1171	-618.90	49.55
600	dreamgen/WizardLM-2-7B (Luo et al., 2023; Xu et al., 2023a; Luo et al., 2025)	mistral	7B	2024-04-16	2533	-641.93	63.75
601	dvruette/oasst-pythia-12b-flash-attn-5000-steps	gpt_neox	12B	2023-03-12	1175	-602.37	40.73
602	dvruette/oasst-pythia-12b-pretrained-sft	gpt_neox	12B	2023-04-03	1170	-552.58	41.48
603	dvruette/oasst-pythia-12b-reference	gpt_neox	12B	2023-04-03	1174	-557.88	40.33
604	eachadea/vicuna-13b-1.1	llama-1	13B	2023-04-13	1336	-646.61	53.29
605	eachadea/vicuna-7b-1.1	llama-1	7B	2023-04-13	1388	-613.88	50.37
606	eldogbbhed/Peagle-9b	mistral	8B	2024-03-10	10180	-581.92	73.30
607	elinas/chronos-13b-v2	llama-2	13B	2023-08-02	1944	-595.38	55.25
608	elliotthwang/elliott_Llama-2-7b-hf	llama-2	6B	2023-10-09	1181	-553.66	50.20
609	elyza/ELYZA-japanese-Llama-2-13b (Touvron et al., 2023b; Sasaki et al., 2023b)	llama-2	13B	2023-12-25	1200	-587.25	56.14
610	elyza/ELYZA-japanese-Llama-2-13b-instruct (Touvron et al., 2023b; Sasaki et al., 2023b)	llama-2	13B	2023-12-25	1710	-594.98	54.72
611	elyza/ELYZA-japanese-Llama-2-7b (Touvron et al., 2023b; Sasaki et al., 2023a)	llama-2	7B	2023-08-28	2356	-630.66	48.70
612	elyza/ELYZA-japanese-Llama-2-7b-fast (Touvron et al., 2023b; Sasaki et al., 2023a)	llama-2	7B	2023-08-28	1766	-640.71	47.67
613	elyza/ELYZA-japanese-Llama-2-7b-fast-instruct (Touvron et al., 2023b; Sasaki et al., 2023a)	llama-2	7B	2023-08-28	2387	-629.72	49.15
614	elyza/ELYZA-japanese-Llama-2-7b-instruct (Touvron et al., 2023b; Sasaki et al., 2023a)	llama-2	7B	2023-08-28	6296	-625.45	49.78
615	ericzzz/falcon-rw-1b-chat	falcon	1B	2023-12-05	1319	-722.18	37.37
616	ericzzz/falcon-rw-1b-instruct-openorca	falcon	1B	2023-11-24	1585	-752.98	37.63
617	euclaise/Ferret_7B	mistral	7B	2023-10-28	1172	-634.24	53.87
618	euclaise/falcon_1b_stage1	falcon	1B	2023-09-15	2119	-734.28	37.25
619	euclaise/falcon_1b_stage2	falcon	1B	2023-09-17	4016	-717.40	37.59
620	facebook/opt-1.3b (Brown et al., 2020; Zhang et al., 2022b)	opt	1B	2022-05-11	139758	-700.64	34.60
621	facebook/opt-13b (Brown et al., 2020; Zhang et al., 2022b)	opt	13B	2022-05-11	19130	-625.38	40.06
622	facebook/opt-2.7b (Brown et al., 2020; Zhang et al., 2022b)	opt	2B	2022-05-11	61450	-673.03	36.74
623	facebook/opt-6.7b (Brown et al., 2020; Zhang et al., 2022b)	opt	6B	2022-05-11	44909	-641.13	39.08
624	facebook/opt-iml-max-1.3b (Iyer et al., 2023)	opt	1B	2023-01-26	8604	-712.07	35.21
625	facebook/xglm-1.7B (Lin et al., 2022b)	xglm	1B	2022-03-02	2388	-723.91	31.42

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
626	facebook/xglm-4.5B (Lin et al., 2022b)	xglm	5B	2022-03-02	1436	-669.92	34.31
627	facebook/xglm-7.5B (Lin et al., 2022b)	xglm	7B	2022-03-02	4654	-663.87	36.38
628	failspy/Meta-Llama-3-8B-Instruct-abliterated-v3	llama-3	8B	2024-05-20	9975	-572.33	67.27
629	failspy/Phi-3-medium-4k-instruct-abliterated-v3	phi3	13B	2024-05-22	5430	-569.05	70.12
630	fblgit/LUNA-SOLARkrautLM-Instruct	llama	10B	2023-12-22	1180	-582.98	73.79
631	fblgit/UNA-POLAR-10.7B-InstructMath-v2	llama	10B	2024-01-02	1180	-560.34	74.07
632	fblgit/una-cybertron-7b-v2-bf16 (Murias, 2023)	mistral	7B	2023-12-02	1440	-568.27	69.67
633	feidfoe/Metamath-reproduce-7b	llama-2	7B	2023-11-24	1198	-724.03	55.81
634	fireballoon/baichuan-vicuna-chinese-7b	llama-1	7B	2023-06-18	1210	-702.08	46.06
635	freewheelin/free-llama3-dpo-v0.2 (Kim et al., 2024b)	llama-3	8B	2024-05-09	3896	-499.17	62.69
636	gagan3012/MetaModelv2	llama	10B	2024-01-03	1203	-560.16	74.24
637	gagan3012/MetaModelv3	llama	10B	2024-01-05	1207	-561.14	74.39
638	garage-bAInd/Platypus2-13B (Hu et al., 2022; Touvron et al., 2023b; Lee et al., 2024)	llama	13B	2023-08-05	3716	-533.92	54.89
639	garage-bAInd/Platypus2-7B (Hu et al., 2022; Touvron et al., 2023b; Lee et al., 2024)	llama	6B	2023-08-22	6198	-554.08	49.97
640	georgesung/llama2_7b_chat_uncensored	llama-2	7B	2023-07-20	2602	-568.34	49.67
641	ghost-x/ghost-7b-alpha	mistral	7B	2024-04-13	4854	-662.59	57.65
642	glaiveai/glaive-coder-7b	llama-2	7B	2023-09-17	1222	-692.31	41.56
643	google/codegemma-2b (CodeGemma Team et al., 2024)	gemma	2B	2024-03-21	8798	-793.92	32.19
644	google/codegemma-7b (CodeGemma Team et al., 2024)	gemma	8B	2024-03-21	3779	-556.79	56.73
645	google/codegemma-7b-it (CodeGemma Team et al., 2024)	gemma	8B	2024-03-21	11227	-1040.98	58.28
646	google/gemma-1.1-7b-it (Joshi et al., 2017; Zhao et al., 2018; Mihaylov et al., 2018; Clark et al., 2019; Talmor et al., 2019; Sap et al., 2019; Bisk et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Zellers et al., 2019; Austin et al., 2021; Cobbe et al., 2021; Hendrycks et al., 2021a; Chen et al., 2021; Parrish et al., 2022; Srivastava et al., 2023; Zhong et al., 2023; Gemini Team et al., 2024)	gemma	8B	2024-03-26	19835	-1355.60	60.09
647	google/gemma-2b (Joshi et al., 2017; Mihaylov et al., 2018; Rudinger et al., 2018; Zhao et al., 2018; Sap et al., 2019; Bisk et al., 2019; Zellers et al., 2019; Clark et al., 2019; Talmor et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Gehman et al., 2020; Cobbe et al., 2021; Hendrycks et al., 2021a; Dhamala et al., 2021; Chen et al., 2021; Austin et al., 2021; Hartvigsen et al., 2022; Parrish et al., 2022; Lin et al., 2022a; Srivastava et al., 2023; Zhong et al., 2023; Gemini Team et al., 2024)	gemma	2B	2024-02-08	256798	-581.35	46.51
648	google/gemma-2b-it (Joshi et al., 2017; Mihaylov et al., 2018; Rudinger et al., 2018; Zhao et al., 2018; Sap et al., 2019; Bisk et al., 2019; Zellers et al., 2019; Clark et al., 2019; Talmor et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Gehman et al., 2020; Cobbe et al., 2021; Hendrycks et al., 2021a; Dhamala et al., 2021; Chen et al., 2021; Austin et al., 2021; Hartvigsen et al., 2022; Parrish et al., 2022; Lin et al., 2022a; Srivastava et al., 2023; Zhong et al., 2023; Gemini Team et al., 2024)	gemma	2B	2024-02-08	103851	-886.70	42.75
649	google/gemma-7b (Joshi et al., 2017; Mihaylov et al., 2018; Rudinger et al., 2018; Zhao et al., 2018; Sap et al., 2019; Bisk et al., 2019; Zellers et al., 2019; Clark et al., 2019; Talmor et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Gehman et al., 2020; Cobbe et al., 2021; Hendrycks et al., 2021a; Dhamala et al., 2021; Chen et al., 2021; Austin et al., 2021; Hartvigsen et al., 2022; Parrish et al., 2022; Lin et al., 2022a; Srivastava et al., 2023; Zhong et al., 2023; Dettmers et al., 2023; Gemini Team et al., 2024)	gemma	8B	2024-02-08	72047	-539.12	63.75
650	google/gemma-7b-it (Joshi et al., 2017; Mihaylov et al., 2018; Rudinger et al., 2018; Zhao et al., 2018; Sap et al., 2019; Bisk et al., 2019; Zellers et al., 2019; Clark et al., 2019; Talmor et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Gehman et al., 2020; Cobbe et al., 2021; Hendrycks et al., 2021a; Dhamala et al., 2021; Chen et al., 2021; Austin et al., 2021; Hartvigsen et al., 2022; Parrish et al., 2022; Lin et al., 2022a; Srivastava et al., 2023; Zhong et al., 2023; Gemini Team et al., 2024)	gemma	8B	2024-02-13	66776	-1327.43	53.56
651	google/recurrentgemma-2b-it (Joshi et al., 2017; Mihaylov et al., 2018; Rudinger et al., 2018; Zhao et al., 2018; Sap et al., 2019; Bisk et al., 2019; Zellers et al., 2019; Clark et al., 2019; Talmor et al., 2019; Chollet, 2019; Sakaguchi et al., 2019; Gehman et al., 2020; Cobbe et al., 2021; Hendrycks et al., 2021a; Dhamala et al., 2021; Chen et al., 2021; Hendrycks et al., 2021b; Austin et al., 2021; Hartvigsen et al., 2022; Parrish et al., 2022; Lin et al., 2022a; Srivastava et al., 2023; Zhong et al., 2023; De et al., 2024; Griffin Team et al., 2024)	recurrent_gemma	2B	2024-04-08	4046	-1033.09	40.86
652	gradientai/Llama-3-8B-Instruct-262k (Peng et al., 2023b; Ding et al., 2023; Pekelis et al., 2024; AI@Meta, 2024; Liu et al., 2025)	llama-3	8B	2024-04-25	12536	-555.17	60.26
653	gradientai/Llama-3-8B-Instruct-Gradient-1048k (Peng et al., 2023b; Ding et al., 2023; Pekelis et al., 2024; AI@Meta, 2024; Liu et al., 2025)	llama-3	8B	2024-04-29	6854	-564.98	59.84
654	guardrail/llama-2-7b-guanaco-instruct-sharded	llama-2	6B	2023-07-21	1320	-647.09	50.58
655	gywy/llama2-13b-chinese-v2	llama-2	13B	2023-08-22	1163	-719.40	49.58
656	h2oai/h2ogpt-gm-oasst1-en-1024-12b	gpt_neox	12B	2023-05-02	1185	-495.39	40.65
657	h2oai/h2ogpt-gm-oasst1-en-2048-open-llama-7b-preview-300bt	llama-1	7B	2023-05-04	1185	-1042.98	34.32
658	h2oai/h2ogpt-gm-oasst1-en-2048-open-llama-7b-preview-300bt-v2	llama-1	7B	2023-05-10	1190	-746.41	37.55
659	h2oai/h2ogpt-oasst1-512-12b	gpt_neox	12B	2023-04-17	1319	-484.68	40.48
660	h2oai/h2ogpt-oig-oasst1-256-6_9b	gpt_neox	9B	2023-04-17	1191	-492.94	38.62
661	h2oai/h2ogpt-oig-oasst1-512-6_9b	gpt_neox	9B	2023-04-18	1749	-521.42	38.52
662	habanoz/TinyLlama-1.1B-intermediate-step-715k-1.5T-lr-5-1epch-airoboros3.1-1k-instruct-V1	llama	1B	2023-11-22	1279	-658.65	34.98
663	habanoz/TinyLlama-1.1B-intermediate-step-715k-1.5T-lr-5-2.2epochs-oasst1-top1-instruct-V1	llama	1B	2023-11-20	1283	-648.88	35.45
664	habanoz/TinyLlama-1.1B-intermediate-step-715k-1.5T-lr-5-3epochs-oasst1-top1-instruct-V1	llama	1B	2023-11-21	1277	-651.34	35.42
665	habanoz/TinyLlama-1.1B-intermediate-step-715k-1.5T-lr-5-4epochs-oasst1-top1-instruct-V1	llama	1B	2023-11-21	1288	-646.55	35.28
666	habanoz/tinyllama-oasst1-top1-instruct-full-lr1-5-v0.1	llama	1B	2023-11-19	1178	-679.96	35.58
667	hakurei/instruct-12b	gpt_neox	12B	2023-04-09	1177	-602.56	38.63
668	hakurei/mommygpt-3B	llama	3B	2023-11-12	1177	-598.84	41.36
669	haoranxu/ALMA-13B (Xu et al., 2024b,a)	llama	13B	2023-09-17	2012	-563.34	50.16

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
670	haoranxu/ALMA-13B-Pretrain (Xu et al., 2024b,a)	llama	13B	2023-09-17	5510	-558.03	51.68
671	haoranxu/ALMA-7B (Xu et al., 2024b,a)	llama	7B	2023-09-17	1292	-599.26	45.32
672	harborwater/open-llama-3b-claude-30k	llama	3B	2023-11-21	1200	-603.17	40.93
673	health360/Healix-1.1B-V1-Chat-dDPO	llama	1B	2023-11-05	2790	-796.10	33.00
674	heegyu/LIMA-13b-hf	llama	13B	2023-08-01	3325	-544.21	52.61
675	heegyu/LIMA2-13b-hf (Touvron et al., 2023b)	llama-2	13B	2023-08-07	3330	-596.33	52.98
676	heegyu/LIMA2-7b-hf (Touvron et al., 2023b)	llama-2	7B	2023-08-04	3463	-651.31	49.27
677	heegyu/RedTulu-Uncensored-3B-0719	gpt_neox	3B	2023-07-23	1187	-703.96	39.19
678	heegyu/WizardVicuna-3B-0719	llama	3B	2023-07-23	3356	-655.31	39.48
679	heegyu/WizardVicuna-Uncensored-3B-0719	llama	3B	2023-07-23	1168	-638.46	39.73
680	heegyu/WizardVicuna-open-llama-3b-v2	llama	3B	2023-08-25	9364	-671.17	38.77
681	heegyu/WizardVicuna2-13b-hf (Touvron et al., 2023b)	llama-2	13B	2023-08-07	6481	-612.15	51.05
682	hfl/chinese-alpaca-2-13b	llama	13B	2023-08-14	1308	-592.75	57.41
683	hfl/chinese-llama-2-1.3b	llama-2	1B	2023-10-08	2269	-1132.44	28.59
684	hfl/chinese-llama-2-13b	llama-2	13B	2023-08-11	1176	-665.69	52.00
685	hiyouga/Baichuan2-7B-Base-LLaMAfied	llama-2	7B	2023-09-08	1218	-530.80	48.99
686	hiyouga/Baichuan2-7B-Chat-LLaMAfied	llama-2	7B	2023-09-09	1211	-609.32	51.42
687	hoskinson-center/proofGPT-v0.1-6.7B	gpt_neox	6B	2023-02-04	1187	-974.98	29.72
688	hpcai-tech/Colossal-LLaMA-2-7b-base (Li et al., 2023b; Touvron et al., 2023b; Dao, 2023)	llama-2	7B	2023-09-18	1192	-690.99	51.39
689	huggyllama/llama-13b	llama-1	13B	2023-04-03	6345	-541.90	51.33
690	huggyllama/llama-7b	llama-1	6B	2023-04-03	192383	-562.04	46.37
691	hyunseoki/ko-en-llama2-13b	llama-2	13B	2023-10-02	3351	-550.60	51.27
692	hyunseoki/ko-ref-llama2-13b	llama-2	13B	2023-10-04	3364	-775.26	43.62
693	hyunseoki/ko-ref-llama2-7b	llama-2	7B	2023-10-04	3312	-851.38	40.75
694	hywu/Camelidae-8x13B (Houlsby et al., 2019; Komatsuzaki et al., 2023; Dettmers et al., 2023; Wu et al., 2024)	camelidae	13B	2024-01-10	1886	-535.46	59.40
695	hywu/Camelidae-8x7B (Houlsby et al., 2019; Komatsuzaki et al., 2023; Dettmers et al., 2023; Wu et al., 2024)	camelidae	7B	2024-01-10	1901	-565.23	54.47
696	ibivibiv/llama-3-nectar-dpo-8B (Lacoste et al., 2019)	llama-3	8B	2024-05-14	6085	-576.43	67.92
697	ibm/merlinite-7b (Sudalairaj et al., 2024)	mistral	7B	2024-03-02	11156	-541.12	64.00
698	ibndias/NeuralHermes-MoE-2x7B	mixtral	12B	2024-01-03	1172	-533.10	64.08
699	ibranze/araproje-llama2-7b-hf	llama-2	7B	2023-10-06	1161	-549.87	49.73
700	ignos/LeoScorpius-GreenNode-Alpaca-7B-v1	mistral	7B	2023-12-15	1206	-558.75	74.74
701	ignos/LeoScorpius-GreenNode-Platypus-7B-v1	mistral	7B	2023-12-15	1188	-540.87	68.96
702	ignos/Mistral-T5-7B-v1	mistral	7B	2023-12-18	1266	-557.24	72.47
703	ikala/bloom-zh-3b-chat	bloom	3B	2023-05-07	1352	-722.56	37.58
704	invalid-coder/Sakura-SOLAR-Instruct-CarbonVillain-en-10.7B-v2-slerp	llama	10B	2024-01-10	12810	-560.73	74.45
705	itsliupeng/llama2_7b_code	llama-2	7B	2023-09-28	1236	-538.58	49.05
706	itsliupeng/openllama-7b-base	llama	7B	2023-12-08	1200	-536.60	47.09
707	itsliupeng/openllama-7b-icl (Shi et al., 2024)	llama	7B	2023-12-08	1186	-535.25	47.93
708	jae24/openhermes_dpo_norobot_0201	mistral	7B	2024-01-02	1161	-562.15	63.78
709	jan-hq/trinity-v1	mistral	7B	2023-12-14	1192	-559.84	74.80
710	jeonsworld/CarbonVillain-en-10.7B-v1	llama	10B	2023-12-28	1164	-561.74	74.28
711	jeonsworld/CarbonVillain-en-10.7B-v4	llama	10B	2023-12-30	12898	-561.44	74.52
712	jerryjalapeno/nart-100k-7b	llama-1	7B	2023-07-14	1194	-585.01	46.39
713	jingyeom/freeze_KoSoLAR-10.7B-v0.2_1.4_dedup	llama	10B	2024-01-29	2287	-594.17	60.06
714	johnsnowlabs/BioLing-7B-Dare	mistral	7B	2024-04-08	2682	-591.07	60.32
715	johnsnowlabs/JSL-MedLlama-3-8B-v2.0	llama-3	8B	2024-04-30	11813	-569.39	61.93
716	jondurbin/airoboros-gpt-3.5-turbo-100k-7b	llama-1	7B	2023-05-12	1473	-614.18	47.05
717	jondurbin/airoboros-l2-13b-2.1	llama-2	13B	2023-08-28	2322	-565.56	53.34
718	jondurbin/airoboros-l2-13b-gpt4-2.0	llama	13B	2023-07-27	1395	-575.42	52.49
719	jondurbin/airoboros-l2-13b-gpt4-m2.0	llama	13B	2023-07-28	1378	-614.41	52.66
720	jondurbin/bagel-8b-v1.0	llama-3	8B	2024-04-24	7960	-512.36	67.84
721	jphme/Llama-2-13b-chat-german (Touvron et al., 2023b)	llama-2	13B	2023-07-21	1265	-572.28	55.07
722	jphme/em_german_leo_mistral	mistral	7B	2023-10-07	1900	-625.44	51.69
723	jphme/orca_mini_v2_ger_7b (Conover et al., 2023; Mathur, 2023a; Su et al., 2023b; Harries, 2023; Taori et al., 2023; Touvron et al., 2023a; Xu et al., 2023a)	llama-1	7B	2023-07-04	1181	-603.44	47.65
724	junelee/wizard-vicuna-13b	llama-1	13B	2023-05-03	2196	-610.98	52.73
725	kaist-ai/mistral-orpo-capybara-7k (Hong et al., 2024)	mistral	7B	2024-03-23	4821	-540.67	63.36
726	kekmodel/StopCarbon-10.7B-v5	llama	10B	2023-12-30	13910	-560.12	74.41
727	kevin009/llamaRAGdrama	mistral	7B	2024-02-04	4248	-610.94	74.65
728	kfkas/Llama-2-ko-7b-Chat (Touvron et al., 2023b)	llama-2	7B	2023-07-25	3436	-767.03	40.27
729	kingbri/airolima-chronos-grad-l2-13B	llama-2	13B	2023-08-04	1174	-587.96	55.50
730	kingbri/chronolima-airo-grad-l2-13B	llama-2	13B	2023-08-04	1182	-582.73	55.50
731	klyang/MentaLLaMA-chat-7B (Yang et al., 2024b)	llama	7B	2023-09-26	2634	-640.26	51.17
732	kodonho/Solar-OrcaDPO-Solar-Instruct-SLERP	llama	10B	2024-01-12	3266	-560.31	74.35
733	kodonho/SolarM-SakuraSolar-SLERP	llama	10B	2024-01-12	3254	-562.65	74.29
734	kyujinpy/Sakura-SOLAR-Instruct	llama	10B	2023-12-24	4271	-559.44	74.40
735	kyujinpy/Sakura-SOLAR-Instruct-DPO-v2	llama	10B	2023-12-24	3298	-560.08	74.14
736	kyujinpy/Sakura-SOLRCA-Math-Instruct-DPO-v1	llama	10B	2023-12-25	3284	-562.45	74.13
737	l3utterfly/llama2-7b-layla	llama-2	7B	2023-08-07	1182	-561.12	52.05
738	l3utterfly/minima-3b-layla-v1	llama-2	3B	2023-12-12	1178	-548.62	43.21
739	l3utterfly/minima-3b-layla-v2	llama-2	3B	2023-12-19	1176	-547.03	43.39
740	l3utterfly/mistral-7b-v0.1-layla-v1	mistral	7B	2023-10-31	1206	-602.61	57.56
741	l3utterfly/mistral-7b-v0.1-layla-v2	mistral	7B	2023-12-16	1199	-567.42	57.60
742	l3utterfly/open-llama-3b-v2-layla	llama	3B	2023-08-18	1172	-832.18	40.25
743	lcw99/llama-3-10b-it-ko-2024-0527	llama-3	9B	2024-05-27	2236	-564.03	63.70
744	lcw99/llama-3-10b-it-kor-extented-chang	llama-3	9B	2024-05-15	2230	-558.58	54.76
745	lcw99/llama-3-10b-it-kor-extented-chang-pro8	llama-3	9B	2024-05-21	2234	-561.88	63.76
746	lcw99/llama-3-8b-it-kor-extented-chang	llama-3	8B	2024-05-02	2259	-527.86	66.27
747	lemon-mint/gemma-7b-openhermes-v0.80	gemma	8B	2024-04-09	4867	-691.34	56.91
748	lemon-mint/gemma-ko-1.1-2b-it	gemma	2B	2024-04-26	2337	-1058.64	30.92
749	lemon-mint/gemma-ko-7b-instruct-v0.62	gemma	8B	2024-04-03	7543	-589.67	69.25

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
750	lemon-mint/gemma-ko-7b-instruct-v0.71	gemma	8B	2024-04-09	2232	-711.63	59.23
751	leveldevai/TurdusBeagle-7B	mistral	7B	2024-01-18	1926	-577.38	75.15
752	lex-hue/Delexa-7b	mistral	7B	2024-04-05	11797	-575.31	70.86
753	lgaalves/llama-2-13b-chat-platypus	llama-2	13B	2023-09-06	1193	-570.00	53.92
754	lgaalves/llama-2-7b-hf_open-platypus	llama-2	6B	2023-08-30	1204	-564.27	49.73
755	lgaalves/mistral-7b-platypus1k	mistral	7B	2023-10-10	1183	-539.54	58.19
756	lgaalves/mistral-7b_open_platypus	mistral	7B	2023-10-13	1259	-557.93	56.29
757	lgaalves/tinyllama-1.1b-chat-v0.3_platypus	llama	1B	2023-10-09	1193	-665.44	34.50
758	lightblue/suzume-llama-3-8B-multilingual (Devine, 2024)	llama-3	8B	2024-04-23	16442	-557.50	65.55
759	lighteternal/Llama3-merge-biomed-8b (Yadav et al., 2023a; Yu et al., 2024a)	llama-3	8B	2024-05-28	2731	-575.20	66.30
760	liminerity/M7-7b	mistral	7B	2024-03-07	4186	-599.03	76.82
761	llm-agents/tora-7b-v1.0 (Gou et al., 2024)	llama-2	7B	2023-10-08	1177	-628.41	48.50
762	llm-agents/tora-code-7b-v1.0 (Gou et al., 2024)	llama-2	7B	2023-10-08	1242	-682.23	40.21
763	lmsys/longchat-13b-16k	llama-1	13B	2023-06-28	12228	-621.21	49.64
764	lmsys/longchat-7b-v1.5-32k	llama	7B	2023-08-01	5114	-650.92	47.95
765	lmsys/vicuna-13b-delta-v1.1 (Zheng et al., 2023; Touvron et al., 2023a)	llama-1	13B	2023-04-12	1216	-1396.42	53.28
766	lmsys/vicuna-13b-v1.1 (Zheng et al., 2023; Touvron et al., 2023a)	llama-1	13B	2023-04-12	2662	-646.61	53.28
767	lmsys/vicuna-13b-v1.3 (Zheng et al., 2023; Touvron et al., 2023a)	llama-1	13B	2023-06-18	11951	-604.80	54.27
768	lmsys/vicuna-13b-v1.5 (Touvron et al., 2023b; Zheng et al., 2023)	llama-2	13B	2023-07-29	48653	-585.07	55.41
769	lmsys/vicuna-13b-v1.5-16k (Touvron et al., 2023b; Zheng et al., 2023)	llama-2	13B	2023-08-01	29580	-595.73	54.97
770	lmsys/vicuna-7b-delta-v1.1 (Zheng et al., 2023; Touvron et al., 2023a)	llama-1	7B	2023-04-12	1330	-1396.42	50.37
771	lmsys/vicuna-7b-v1.3 (Zheng et al., 2023; Touvron et al., 2023a)	llama-1	7B	2023-06-18	31436	-621.79	49.78
772	lmsys/vicuna-7b-v1.5 (Touvron et al., 2023b; Zheng et al., 2023)	llama-2	7B	2023-07-29	368410	-608.63	52.06
773	lmsys/vicuna-7b-v1.5-16k (Touvron et al., 2023b; Zheng et al., 2023)	llama-2	7B	2023-07-31	3362	-622.49	51.42
774	lu-vae/llama2-13B-sharegpt4-orca-openplatypus-8w	llama-2	13B	2023-09-14	1190	-544.97	55.75
775	lu-vae/llama2-13b-sharegpt4-test	llama-2	13B	2023-09-07	1195	-557.27	55.69
776	luffycodes/nash-vicuna-13b-v1dot5-ep2-w-rag-w-simple (Sonkar et al., 2023)	llama-2	13B	2023-08-21	1165	-603.30	55.40
777	luffycodes/vicuna-class-shishya-13b-ep3 (Sonkar et al., 2023)	llama-2	13B	2023-12-21	2092	-633.43	48.52
778	luffycodes/vicuna-class-shishya-7b-ep3 (Sonkar et al., 2023)	llama-2	7B	2023-12-14	3501	-649.39	46.14
779	luffycodes/vicuna-class-tutor-13b-ep3 (Sonkar et al., 2023)	llama-2	13B	2023-12-21	1514	-605.75	55.88
780	luffycodes/vicuna-class-tutor-7b-ep3 (Sonkar et al., 2023)	llama-2	7B	2023-12-15	3735	-643.38	51.45
781	lyogavin/Anima-7B-100K	llama-2	7B	2023-09-14	1207	-611.20	42.98
782	macadeliccc/WestLake-7B-v2-laser-truthy-dpo	mistral	7B	2024-01-27	5064	-593.71	75.37
783	macadeliccc/laser-dolphin-mixtral-2x7b-dpo (Gao et al., 2021a; Sharma et al., 2023)	mixtral	12B	2024-01-08	1275	-594.20	67.16
784	malhajar/Mistral-7B-v0.2-meditron-turkish	mistral	7B	2024-01-05	3865	-641.84	63.34
785	martyn/llama2-megamerge-dare-13b-v2	llama-2	13B	2023-12-17	1213	-594.59	57.94
786	martyn/mistral-megamerge-dare-7b	mistral	7B	2023-12-14	1203	-638.88	48.93
787	martyn/solar-megamerge-dare-10.7b-v1	llama	10B	2023-12-31	1190	-533.45	68.79
788	matsuo-lab/weblab-10b	gpt_neox	10B	2023-08-04	1596	-485.56	38.59
789	matsuo-lab/weblab-10b-instruction-sft	gpt_neox	10B	2023-08-04	1235	-515.77	39.13
790	maywell/PiVoT-0.1-early	mistral	7B	2023-11-24	3267	-681.01	64.58
791	maywell/PiVoT-10.7B-Mistral-v0.2	mistral	10B	2023-12-13	3228	-578.51	64.25
792	maywell/Synatra-10.7B-v0.4	llama	10B	2023-12-27	3282	-532.85	65.48
793	maywell/Synatra-7B-v0.3-RP	mistral	7B	2023-10-29	8360	-582.37	59.26
794	maywell/Synatra-7B-v0.3-dpo	mistral	7B	2023-11-08	4302	-575.15	60.55
795	maywell/Synatra-RP-Orca-2-7b-v0.1	llama	6B	2023-11-21	3278	-632.02	59.65
796	maywell/Synatra-V0.1-7B-Instruct	mistral	7B	2023-10-09	3381	-623.00	55.86
797	medalpaca/medalpaca-7b (Li et al., 2023d)	llama-1	7B	2023-03-29	8136	-628.90	48.45
798	meta-llama/Llama-2-13b-chat-hf (Touvron et al., 2023b)	llama-2	13B	2023-07-13	266090	-616.08	54.91
799	meta-llama/Llama-2-13b-hf (Touvron et al., 2023b)	llama-2	13B	2023-07-13	120871	-530.82	55.69
800	meta-llama/Llama-2-7b-chat-hf (Touvron et al., 2023b)	llama-2	6B	2023-07-13	1402244	-656.64	50.74
801	meta-llama/Llama-2-7b-hf (Touvron et al., 2023b)	llama-2	6B	2023-07-13	1294737	-549.87	50.97
802	meta-llama/Meta-Llama-3-8B (AI@Meta, 2024)	llama-3	8B	2024-04-17	675850	-514.33	62.62
803	meta-llama/Meta-Llama-3-8B-Instruct (AI@Meta, 2024)	llama-3	8B	2024-04-17	2058011	-573.95	66.87
804	meta-math/MetaMath-Llemma-7B (Azerbayev et al., 2024; Yu et al., 2024b)	llama	7B	2023-11-19	1322	-612.21	53.19
805	meta-math/MetaMath-Mistral-7B (Jiang et al., 2023; Yu et al., 2024b)	mistral	7B	2023-10-22	3022	-571.33	65.78
806	microsoft/Orca-2-13b (Mitra et al., 2023)	llama	13B	2023-11-14	13616	-651.29	58.64
807	microsoft/Orca-2-7b (Mitra et al., 2023)	llama	7B	2023-11-14	11084	-684.33	54.55
808	microsoft/Phi-3-medium-128k-instruct	phi3	13B	2024-05-07	34054	-544.42	73.00
809	microsoft/Phi-3-medium-4k-instruct	phi3	13B	2024-05-07	35987	-552.43	73.45
810	microsoft/phi-1_5 (Li et al., 2023c)	phi	1B	2023-09-10	112476	-724.13	47.69
811	microsoft/phi-2	phi	2B	2023-12-13	237268	-621.44	61.33
812	migtissera/Llama-3-8B-Synthia-v3.5	llama-3	8B	2024-05-17	3310	-533.92	67.15
813	migtissera/SynthIA-7B-v1.3 (Mukherjee et al., 2023; Tissera, 2023)	mistral	7B	2023-09-28	3336	-541.46	59.34
814	migtissera/SynthIA-7B-v1.5	mistral	7B	2023-10-07	1228	-537.68	59.59
815	migtissera/Synthia-7B-v3.0	mistral	7B	2023-12-08	1204	-531.17	61.99
816	migtissera/Tess-2.0-Llama-3-8B	llama-3	8B	2024-05-05	3314	-523.68	64.81
817	migtissera/Tess-7B-v1.4	mistral	7B	2023-12-04	1234	-599.60	62.19
818	migtissera/Tess-XS-v1.1	mistral	7B	2023-11-22	1213	-546.97	59.39
819	mindy-labs/mindy-7b-v2	mistral	7B	2023-12-14	1238	-550.38	72.11
820	mistral-community/Mistral-7B-v0.2	mistral	7B	2024-03-23	30074	-532.63	60.41
821	mistralai/Mistral-7B-Instruct-v0.1 (Jiang et al., 2023)	mistral	7B	2023-09-27	1370245	-593.06	54.96
822	mistralai/Mistral-7B-Instruct-v0.2 (Jiang et al., 2023)	mistral	7B	2023-12-11	3565248	-574.91	65.71
823	mistralai/Mistral-7B-v0.1 (Jiang et al., 2023)	mistral	7B	2023-09-20	1750089	-527.60	60.97
824	mistralai/Mistral-7B-v0.3 (Jiang et al., 2023)	mistral	7B	2024-05-22	1443065	-531.44	60.28
825	mlabonne/AlphaMonarch-7B	mistral	7B	2024-02-14	12804	-593.46	75.99
826	mlabonne/Beagle14-7B	mistral	7B	2024-01-15	1986	-563.97	74.76
827	mlabonne/ChimeraLlama-3-8B-v2	llama-3	8B	2024-04-22	2806	-565.81	69.69
828	mlabonne/ChimeraLlama-3-8B-v3	llama-3	8B	2024-05-01	5718	-568.78	70.06
829	mlabonne/Daredevil-8B-abliterated	llama	8B	2024-05-26	9010	-565.64	71.82
830	mlabonne/GML-Mistral-merged-v1	mistral	8B	2023-12-27	1166	-1384.76	48.54
831	mlabonne/Marcoro14-7B-slerp	mistral	7B	2023-12-29	3792	-554.34	73.01
832	mlabonne/NeuralMarcoro14-7B	mistral	7B	2024-01-06	2015	-566.69	73.57
833	mlabonne/NeuralMonarch-7B	mistral	7B	2024-02-14	13486	-591.01	76.15

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
834	mncai/agiin-13.6B-v0.1	mistral	13B	2023-12-15	3317	-595.75	68.40
835	monology/openinstruct-mistral-7b	mistral	7B	2023-11-20	1191	-537.83	63.64
836	mosaicml/mpt-7b (Henry et al., 2020; Shoeybi et al., 2020; Press et al., 2022; Dao et al., 2022; Chen et al., 2023a; MosaicML NLP Team, 2023b; Touvron et al., 2023a)	mpt	7B	2023-05-05	31480	-548.53	44.28
837	mosaicml/mpt-7b-8k (Henry et al., 2020; Shoeybi et al., 2020; Press et al., 2022; Dao et al., 2022; Chen et al., 2023a; MosaicML NLP Team, 2023b; Touvron et al., 2023a)	mpt	7B	2023-06-30	2106	-546.57	47.24
838	mosaicml/mpt-7b-8k-chat (Henry et al., 2020; Dao et al., 2022; Press et al., 2022; MosaicML NLP Team, 2023a)	mpt	7B	2023-06-22	1304	-586.09	47.78
839	mosaicml/mpt-7b-chat (Henry et al., 2020; Dao et al., 2022; Press et al., 2022; MosaicML NLP Team, 2023b)	mpt	7B	2023-05-04	88069	-647.13	45.39
840	mosaicml/mpt-7b-instruct (Henry et al., 2020; Dao et al., 2022; Press et al., 2022; MosaicML NLP Team, 2023b)	mpt	7B	2023-05-05	8599	-569.62	44.83
841	mosaicml/mpt-7b-storywriter (Dao et al., 2022; Press et al., 2022; Chen et al., 2023a; MosaicML NLP Team, 2023b)	mpt	7B	2023-05-04	1920	-650.05	39.31
842	mrm8488/llama-2-coder-7b (Manuel Romero, 2023)	llama-2	7B	2023-07-26	1313	-572.92	49.95
843	mwitiderrick/open_llama_3b_code_instruct_0.1	llama	3B	2023-12-11	1252	-598.99	39.72
844	nlpguy/ColorShadow-7B	mistral	7B	2023-12-30	1214	-552.87	68.34
845	nlpguy/ColorShadow-7B-v2	mistral	7B	2023-12-30	1214	-569.63	66.88
846	nlpguy/ColorShadow-7B-v3	mistral	7B	2023-12-30	1222	-561.80	67.29
847	nvidia/Llama3-ChatQA-1.5-8B (Liu et al., 2024)	llama-3	8B	2024-04-28	10608	-515.82	56.71
848	occultml/CatMarcoro14-7B-slerp	mistral	7B	2024-01-06	1234	-551.33	73.25
849	occultml/Helios-10.7B	llama	7B	2023-12-31	1215	-1381.38	42.19
850	occultml/Helios-10.7B-v2	llama	7B	2023-12-31	1218	-1381.35	42.25
851	oh-yeontaek/llama-2-13B-LoRA-assemble	llama-2	13B	2023-09-13	3303	-568.38	57.91
852	oh-yeontaek/llama-2-7B-LoRA-assemble	llama-2	7B	2023-09-13	1337	-614.33	52.26
853	openaccess-ai-collective/DPOpenHermes-11B	mistral	10B	2023-12-03	1185	-591.33	66.83
854	openaccess-ai-collective/jackalope-7b (Mukherjee et al., 2023; Lian et al., 2023b; Longpre et al., 2023)	mistral	7B	2023-10-07	1198	-550.33	61.16
855	openaccess-ai-collective/manticore-13b	llama-1	13B	2023-05-17	1224	-553.22	54.86
856	openaccess-ai-collective/manticore-13b-chat-pyg	llama-1	13B	2023-05-22	2148	-553.85	54.13
857	openaccess-ai-collective/minotaur-13b	llama-1	13B	2023-06-06	1202	-577.38	53.97
858	openaccess-ai-collective/minotaur-13b-fixed	llama-1	13B	2023-06-12	1194	-568.52	55.19
859	openaccess-ai-collective/mistral-7b-slimorcaboros	mistral	7B	2023-10-13	1186	-569.20	61.18
860	openaccess-ai-collective/wizard-mega-13b	llama-1	13B	2023-05-14	2168	-565.46	54.27
861	openbmb/UltraLM-13b-v2.0	llama	13B	2023-09-22	1174	-554.24	58.72
862	openchat/openchat-3.5-0106 (Wang et al., 2024a; OpenAI et al., 2024)	mistral	7B	2024-01-07	26858	-554.42	69.30
863	openchat/openchat-3.5-0106-gemma (Wang et al., 2024a)	gemma	8B	2024-03-09	7817	-937.52	69.42
864	openchat/openchat-3.5-1210 (Wang et al., 2024a; OpenAI et al., 2024)	mistral	7B	2023-12-12	2123	-583.16	68.89
865	openchat/openchat-3.6-8b-20240522 (Wang et al., 2024a)	llama-3	8B	2024-05-07	10464	-561.80	68.14
866	openlm-research/open_llama_13b (Geng and Liu, 2023; Together Computer, 2023; Touvron et al., 2023a)	llama-1	13B	2023-06-15	2373	-582.20	47.26
867	openlm-research/open_llama_3b (Geng and Liu, 2023; Together Computer, 2023; Touvron et al., 2023a)	llama-1	3B	2023-06-07	157405	-612.46	38.26
868	openlm-research/open_llama_3b_v2 (Geng and Liu, 2023; Together Computer, 2023; Touvron et al., 2023a)	llama-1	3B	2023-07-16	21275	-578.08	40.28
869	openlm-research/open_llama_7b (Geng and Liu, 2023; Together Computer, 2023; Touvron et al., 2023a)	llama-1	7B	2023-06-07	44968	-610.20	42.31
870	openlm-research/open_llama_7b_v2 (Geng and Liu, 2023; Together Computer, 2023; Touvron et al., 2023a)	llama-1	7B	2023-07-06	2792	-556.22	44.26
871	openthaigpt/openthaigpt-1.0.0-beta-13b-chat-hf	llama	13B	2023-12-18	1225	-712.61	50.45
872	openthaigpt/openthaigpt-1.0.0-beta-7b-chat-ckpt-hf	llama	7B	2023-08-14	1291	-772.50	45.35
873	pankajmathur/orca_mini_v3_13b (Mukherjee et al., 2023; Touvron et al., 2023b; Mathur, 2023b)	llama	13B	2023-08-09	4717	-546.48	57.24
874	pankajmathur/orca_mini_v3_7b (Mukherjee et al., 2023; Touvron et al., 2023b; Mathur, 2023c; Touvron et al., 2023a)	llama	7B	2023-08-07	2338	-572.18	53.47
875	pe-nlp/llama-2-13b-vicuna-wizard	llama-2	13B	2023-08-11	1176	-549.39	51.94
876	pillowtalks-ai/delta13b	llama-1	13B	2023-04-14	1168	-646.61	53.29
877	princeton-nlp/Sheared-LLaMA-1.3B (Xia et al., 2024)	llama	1B	2023-10-10	28905	-646.81	35.95
878	princeton-nlp/Sheared-LLaMA-1.3B-ShareGPT (Xia et al., 2024)	llama	1B	2023-11-22	1737	-721.70	37.14
879	princeton-nlp/Sheared-LLaMA-2.7B (Xia et al., 2024)	llama-2	2B	2023-10-10	2590	-610.74	40.84
880	princeton-nlp/Sheared-LLaMA-2.7B-ShareGPT (Xia et al., 2024)	llama-2	2B	2023-11-22	1866	-681.47	42.11
881	project-baize/baize-v2-13b (Xu et al., 2023b)	llama-1	13B	2023-05-23	2149	-578.69	52.94
882	project-baize/baize-v2-7b (Xu et al., 2023b)	llama-1	7B	2023-05-23	1212	-638.05	46.72
883	qnguyen3/Master-Yi-9B	llama	8B	2024-05-18	8810	-522.22	67.44
884	quantumaikr/QuantumLM-7B	llama	7B	2023-07-22	1192	-625.18	49.51
885	quantumaikr/llama-2-7b-hf-guanaco-1k	llama-2	7B	2023-08-06	1186	-605.93	50.13
886	quantumaikr/quantum-v0.01	mistral	7B	2023-12-17	1192	-559.84	74.68
887	refuelai/Llama-3-Refueled	llama-3	8B	2024-05-03	1246	-582.52	63.62
888	revolutionarybukhari/Llama-2-7b-chat-finetune-AUTOMATE	llama-2	7B	2023-10-14	1166	-613.72	50.68
889	rinna/bilingual-gpt-neox-4b (Zhao et al., 2023b; Sawada et al., 2024)	gpt_neox	3B	2023-07-31	3267	-594.93	32.14
890	rinna/japanese-gpt-neox-3.6b (Zhao and Sawada, 2023; Sawada et al., 2024)	gpt_neox	3B	2023-05-17	6042	-1117.39	29.28
891	rinna/llama-3-youko-8b (Andonian et al., 2021; AI@Meta, 2024; Sawada et al., 2024; Mitsuda et al., 2024)	llama-3	8B	2024-05-01	1468	-502.57	57.55
892	rinna/youri-7b (Andonian et al., 2021; Touvron et al., 2023b; Zhao et al., 2023a; Sawada et al., 2024)	llama-2	7B	2023-10-30	2512	-545.03	47.11
893	rishiraj/CatPPT-base (Acharya, 2023)	mistral	7B	2023-12-17	4392	-558.36	72.25
894	ruslanmv/Medical-Llama3-8B	llama-3	8B	2024-04-21	5457	-514.00	60.61
895	ruslanmv/ai-medical-model-32bit	llama	8B	2024-05-13	2810	-557.43	67.67
896	rwitz2/go-bruins-v2.1 (Murias, 2023)	mistral	7B	2023-12-14	1193	-561.68	74.50
897	rwitz2/go-bruins-v2.1.1 (Murias, 2023)	mistral	7B	2023-12-14	1205	-562.22	74.95
898	saberai/Zro1.5_3B	gpt_neox	2B	2023-12-25	1200	-695.87	38.02
899	samir-fama/FernandoGPT-v1	mistral	7B	2023-12-30	1209	-551.17	72.87
900	samir-fama/SamirGPT-v1	mistral	7B	2023-12-28	1215	-552.06	73.11
901	sarvamai/OpenHathi-7B-Hi-v0.1-Base	llama-2	6B	2023-12-13	1766	-673.13	46.64
902	scaledown/ScaleDown-7B-slerp-v0.1	mistral	7B	2024-01-01	1206	-538.58	71.57

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
903	scb10x/llama-3-typhoon-v1.5-8b-instruct (Pipatanakul et al., 2023)	llama-3	8B	2024-05-06	6088	-590.46	65.62
904	scb10x/typhoon-7b (Pipatanakul et al., 2023)	mistral	7B	2023-12-20	1908	-617.60	58.05
905	selfrag/selfrag_llama2_7b (Asai et al., 2023)	llama-2	7B	2023-10-18	4388	-605.61	51.30
906	senseable/WestLake-7B-v2	mistral	7B	2024-01-22	1189	-594.85	74.68
907	sethuiyer/Medichat-Llama3-8B	llama-3	8B	2024-04-22	4542	-535.77	66.03
908	shadowml/BeagSake-7B	mistral	7B	2024-01-31	11842	-562.99	75.38
909	shanchen/llama3-8B-slerp-biomed-chat-chinese	llama-3	8B	2024-04-30	2708	-591.11	63.00
910	shanchen/llama3-8B-slerp-med-262k	llama-3	8B	2024-04-30	2697	-599.35	53.65
911	shanchen/llama3-8B-slerp-med-chinese	llama-3	8B	2024-04-30	8028	-593.26	58.99
912	shenzhi-wang/Llama3-8B-Chinese-Chat (Wang et al., 2024b)	llama-3	8B	2024-04-21	55718	-550.92	67.10
913	shibing624/chinese-alpaca-plus-7b-hf (Ming, 2023)	llama-1	7B	2023-05-01	1527	-741.70	44.77
914	shitshow123/tinylamma-20000	llama	1B	2024-01-09	1195	-1213.36	27.95
915	skfrost19/BioMistralMerged	mistral	7B	2024-04-21	4013	-600.14	57.44
916	speakleash/Bielik-7B-Instruct-v0.1 (Levine et al., 2020; Granziol et al., 2021; Ociepa et al., 2024b; Wang et al., 2024a; Ociepa et al., 2024c)	mistral	7B	2024-03-30	3573	-871.06	51.24
917	speakleash/Bielik-7B-v0.1 (Ociepa et al., 2024a,c)	mistral	7B	2024-03-30	2822	-721.18	50.01
918	stabilityai/StableBeluga-13B (Touvron et al., 2023b; Mukherjee et al., 2023)	llama	13B	2023-07-27	6154	-540.85	57.05
919	stabilityai/StableBeluga-7B (Touvron et al., 2023b; Mukherjee et al., 2023)	llama	6B	2023-07-27	6691	-565.19	53.56
920	stabilityai/japanese-stablelm-base-gamma-7b (Jiang et al., 2023)	mistral	7B	2023-10-16	2072	-581.58	52.59
921	stabilityai/japanese-stablelm-instruct-gamma-7b (Jiang et al., 2023)	mistral	7B	2023-10-16	1412	-584.50	52.82
922	stabilityai/stable-code-3b (Rajbhandari et al., 2020; Black et al., 2022; Li et al., 2023a; Su et al., 2023a; Touvron et al., 2023b; Pinnaparaju et al., 2024; Azerbayev et al., 2024; Yu et al., 2024b)	stablelm	2B	2024-01-09	5670	-616.25	41.53
923	stabilityai/stablelm-2-12b-chat (Stability AI Language Team, 2024; Rafailov et al., 2024)	stablelm	12B	2024-04-04	4843	-588.55	68.38
924	stabilityai/stablelm-2-1_6b-chat (Stability AI Language Team, 2024; Rafailov et al., 2024)	stablelm	1B	2024-04-08	4156	-683.91	50.71
925	stabilityai/stablelm-2-zephyr-1_6b (Stability AI Language Team, 2024; Rafailov et al., 2024)	stablelm	1B	2024-01-19	18239	-660.56	49.99
926	stabilityai/stablelm-3b-4e1t (Ba et al., 2016; Zhang and Sennrich, 2019; Rajbhandari et al., 2020; Gao et al., 2020; Black et al., 2022; Li et al., 2023a; Su et al., 2023a; Tow et al., 2023; Touvron et al., 2023b)	stablelm	2B	2023-09-29	11112	-510.56	46.58
927	stabilityai/stablelm-base-alpha-3b (Andonian et al., 2021)	gpt_neox	3B	2023-04-17	1728	-677.47	31.50
928	stabilityai/stablelm-base-alpha-7b (Andonian et al., 2021)	gpt_neox	7B	2023-04-11	1750	-623.09	34.37
929	stabilityai/stablelm-base-alpha-7b-v2 (Shazeer, 2020; Rajbhandari et al., 2020; Gao et al., 2020; Li et al., 2023a; Su et al., 2023a; Tow, 2023)	stablelm_alpha	6B	2023-08-04	2209	-505.45	46.18
930	stabilityai/stablelm-tuned-alpha-3b (Taori et al., 2023; Anand et al., 2023; Chiang et al., 2023)	gpt_neox	3B	2023-04-19	2145	-736.44	32.14
931	stabilityai/stablelm-tuned-alpha-7b (Taori et al., 2023; Anand et al., 2023; Chiang et al., 2023)	gpt_neox	7B	2023-04-19	3765	-694.37	34.04
932	stabilityai/stablelm-zephyr-3b (Zheng et al., 2023; Rafailov et al., 2024)	stablelm	2B	2023-11-21	8261	-777.98	53.43
933	starmpcc/Asclepius-Llama2-13B (Kweon et al., 2024)	llama-2	13B	2023-09-19	1175	-645.45	50.25
934	starmpcc/Asclepius-Llama2-7B (Kweon et al., 2024)	llama-2	7B	2023-09-19	1231	-688.58	47.15
935	statking/zephyr-7b-sft-full-orpo	mistral	7B	2024-05-18	2278	-548.89	53.16
936	swap-uniba/LLaMAntino-3-ANITA-8B-Inst-DPO-ITA (Basile et al., 2023; AI@Meta, 2024; Polignano et al., 2024)	llama-3	8B	2024-04-29	5995	-635.92	75.12
937	teilomillet/MiniMerlin-3B	llama	3B	2023-12-15	1168	-681.62	47.63
938	teknium/OpenHermes-13B	llama-2	13B	2023-09-06	1594	-543.02	55.24
939	teknium/OpenHermes-2.5-Mistral-7B	mistral	7B	2023-10-29	100997	-560.57	61.45
940	tiiuae/falcon-7b (Shazeer, 2019; Brown et al., 2020; Gao et al., 2020; Dao et al., 2022; Su et al., 2023a; Penedo et al., 2023; Almazrouei et al., 2023)	falcon	7B	2023-04-24	104010	-549.44	44.17
941	tiiuae/falcon-7b-instruct (Shazeer, 2019; Brown et al., 2020; Dao et al., 2022; Su et al., 2023a; Penedo et al., 2023; Almazrouei et al., 2023)	falcon	7B	2023-04-25	179952	-621.07	43.16
942	tiiuae/falcon-rw-1b (Brown et al., 2020; Dao et al., 2022; Press et al., 2022; Penedo et al., 2023)	falcon	1B	2023-04-26	22921	-688.36	37.07
943	timpal0l/Mistral-7B-v0.1-flashback-v2	mistral	7B	2023-12-04	1275	-578.05	57.53
944	togethercomputer/GPT-JT-6B-v0	gptj	6B	2022-11-22	1422	-484.70	44.05
945	togethercomputer/GPT-JT-6B-v1 (Tay et al., 2022, 2023)	gptj	6B	2022-11-24	5765	-503.02	43.13
946	togethercomputer/LLaMA-2-7B-32K	llama-2	7B	2023-07-26	8884	-530.20	47.07
947	togethercomputer/Llama-2-7B-32K-Instruct (Liu et al., 2023)	llama-2	7B	2023-08-08	5596	-564.83	50.02
948	togethercomputer/Pythia-Chat-Base-7B	gpt_neox	7B	2023-03-22	7040	-522.45	39.81
949	togethercomputer/RedPajama-INCITE-7B-Base	gpt_neox	7B	2023-05-04	1487	-560.75	41.49
950	togethercomputer/RedPajama-INCITE-7B-Chat	gpt_neox	7B	2023-05-04	1583	-931.82	39.37
951	togethercomputer/RedPajama-INCITE-7B-Instruct	gpt_neox	7B	2023-05-05	1274	-525.00	42.38
952	togethercomputer/RedPajama-INCITE-Base-3B-v1	gpt_neox	3B	2023-05-04	2635	-590.97	38.54
953	togethercomputer/RedPajama-INCITE-Chat-3B-v1	gpt_neox	3B	2023-05-05	1647	-610.76	39.53
954	togethercomputer/RedPajama-INCITE-Instruct-3B-v1	gpt_neox	3B	2023-05-05	2014	-552.27	39.06
955	totally-not-an-llm/EverythingLM-13b-16k	llama-2	13B	2023-08-12	2132	-557.79	52.33
956	totally-not-an-llm/PuddleJumper-13b-V2	llama	13B	2023-09-21	1162	-633.45	54.19
957	unsloth/Phi-3-medium-4k-instruct	mistral	13B	2024-05-23	3994	-552.43	73.57
958	unsloth/Phi-3-mini-4k-instruct	mistral	3B	2024-04-29	12224	-575.74	69.86
959	unsloth/mistral-7b-v0.2	mistral	7B	2024-03-24	4119	-532.63	60.34
960	unsloth/tinyllama-chat	llama	1B	2024-02-14	5959	-619.71	37.24
961	upstage/SOLAR-10.7B-Instruct-v1.0 (Kim et al., 2024b,a)	llama	10B	2023-12-12	67725	-557.67	74.20
962	upstage/SOLAR-10.7B-v1.0 (Kim et al., 2024b)	llama	10B	2023-12-12	24478	-525.51	66.04
963	uukuguy/speechless-code-mistral-7b-v1.0	mistral	7B	2023-10-10	4393	-540.50	58.85
964	uukuguy/speechless-llama2-hermes-orca-platypus-13b (Touvron et al., 2023b)	llama-2	13B	2023-09-01	1368	-587.97	57.17
965	uukuguy/speechless-llama2-hermes-orca-platypus-wizardlm-13b (Touvron et al., 2023b)	llama-2	13B	2023-09-01	2101	-609.55	57.52
966	uukuguy/speechless-zephyr-code-functionary-7b	mistral	7B	2024-01-23	4098	-529.18	62.93
967	uukuguy/zephyr-7b-alpha-dare-0.85	mistral	7B	2023-11-23	6141	-529.44	62.35
968	uygarkurt/llama-3-merged-linear	llama-3	8B	2024-05-09	12676	-570.63	73.93
969	v1olet/v1olet_marcoroni-go-bruins-merge-7B	mistral	7B	2023-12-11	1225	-559.92	72.81
970	v1olet/v1olet_merged_dpo_7B	mistral	7B	2023-12-12	1210	-592.71	70.26
971	varox34/Bio-Saul-Dolphin-Beagle-Breadcrumbs	mistral	7B	2024-05-01	2679	-610.01	48.72
972	vibhorag101/llama-2-13b-chat-hf-phr_mental_therapy	llama-2	13B	2023-09-17	1269	-630.34	42.50

ID	Model Name	Model Type	Size	Date	DLs	$\bar{\ell}_i$	Task
973	vicgalle/CarbonBeagle-11B (Wortsman et al., 2022)	mistral	10B	2024-01-21	6696	-549.83	74.64
974	vicgalle/CarbonBeagle-11B-truthy	mistral	10B	2024-02-10	13887	-554.84	76.10
975	vicgalle/Configurable-Hermes-2-Pro-Llama-3-8B (Gallego, 2024)	llama-3	8B	2024-05-02	10273	-580.31	70.10
976	vicgalle/Configurable-Llama-3-8B-v0.3 (Gallego, 2024)	llama-3	8B	2024-04-20	6030	-555.07	68.79
977	vicgalle/Configurable-Yi-1.5-9B-Chat (Gallego, 2024)	llama	8B	2024-05-12	6537	-633.71	70.50
978	vicgalle/ConfigurableBeagle-11B (Gallego, 2024)	mistral	10B	2024-02-17	6045	-548.90	75.40
979	vicgalle/ConfigurableHermes-7B (Gallego, 2024)	mistral	7B	2024-02-17	6085	-572.68	68.89
980	vicgalle/ConfigurableSOLAR-10.7B (Gallego, 2024)	llama	10B	2024-03-10	5135	-559.06	73.94
981	viethq188/LeoScorpius-7B	mistral	7B	2023-12-12	1194	-552.34	72.21
982	viethq188/Rabbit-7B-v2-DPO-Chat	mistral	7B	2023-12-12	1181	-579.23	69.36
983	vihangd/dopeyplats-1.1b-2T-v1	llama	1B	2023-11-26	1191	-682.92	35.28
984	vihangd/dopeyshearedplats-1.3b-v1	llama-2	1B	2023-12-12	1168	-766.02	36.74
985	vihangd/dopeyshearedplats-2.7b-v1	llama-2	2B	2023-12-16	1173	-709.66	42.90
986	vihangd/neuralfalcon-1b-v1	falcon	1B	2023-12-17	1185	-895.18	29.72
987	vihangd/shearedplats-1.3b-v1	llama-2	1B	2023-11-16	1184	-706.16	35.97
988	vihangd/shearedplats-2.7b-v2	llama-2	2B	2023-11-18	2081	-647.66	41.61
989	vihangd/smartyplats-3b-v1	llama	3B	2023-09-11	1180	-600.04	40.00
990	vihangd/smartyplats-3b-v2	llama	3B	2023-09-14	1179	-597.07	40.29
991	vikash06/llama-2-7b-small-model-new	llama-2	6B	2023-12-22	1174	-925.37	46.62
992	vmajor/Orca2-13B-selfmerge-26B	llama	13B	2023-12-01	2041	-653.10	62.24
993	vmajor/Orca2-13B-selfmerge-39B	llama	13B	2023-12-01	1208	-653.10	62.24
994	vonjack/Qwen-LLaMAfied-HFTok-7B-Chat	llama-2	7B	2023-08-09	1189	-839.96	50.64
995	w601sxs/b1ade-1b	gpt_neox	1B	2023-07-17	1204	-929.29	32.59
996	wang7776/Llama-2-7b-chat-hf-10-sparsity (Sun et al., 2024)	llama-2	6B	2023-12-11	1178	-660.87	52.48
997	wang7776/Llama-2-7b-chat-hf-20-sparsity (Sun et al., 2024)	llama-2	7B	2023-12-13	1175	-668.34	52.01
998	wang7776/Llama-2-7b-chat-hf-30-sparsity (Sun et al., 2024)	llama-2	6B	2023-12-11	1179	-676.50	51.02
999	webbigdata/ALMA-7B-Ja-V2 (Xu et al., 2024a)	llama-2	7B	2023-10-21	1177	-599.69	47.85
1000	wei123602/Llama-2-13b-FINETUNE4_TEST	llama-2	13B	2023-09-18	1174	-538.02	53.62
1001	wenbopan/Faro-Yi-9B (OpenAI et al., 2024)	llama	8B	2024-03-27	6127	-594.07	66.37
1002	wenbopan/Faro-Yi-9B-DPO (OpenAI et al., 2024)	llama	8B	2024-04-07	6121	-597.40	68.77
1003	wenge-research/yayi-7b	bloom	7B	2023-06-02	1192	-653.40	41.88
1004	wenge-research/yayi-7b-llama2	llama-2	7B	2023-07-21	1195	-562.60	49.88
1005	winglian/Llama-2-3b-hf	llama-2	3B	2023-09-19	1565	-1376.16	29.53
1006	winglian/llama-2-4b	llama-2	4B	2023-09-19	1193	-676.31	34.23
1007	xDAN-AI/xDAN-L1-Chat-RL-v1	mistral	7B	2023-12-20	1178	-574.92	68.38
1008	yam-peleg/Hebrew-Mistral-7B	mistral	7B	2024-04-26	5993	-625.28	58.76
1009	yanolja/Bookworm-10.7B-v0.4-DPO (Mukherjee et al., 2023; Lian et al., 2023g; Cui et al., 2024)	llama	10B	2024-01-18	2239	-586.77	66.59
1010	yanolja/EEVE-Korean-Instruct-10.8B-v1.0 (Lian et al., 2023g; Mukherjee et al., 2023; Kim et al., 2024c; Cui et al., 2024)	llama	10B	2024-02-22	13241	-555.03	66.48
1011	yeen214/llama2_7b_small_tuning_v1	llama-2	7B	2023-10-02	3289	-1402.04	28.56
1012	yeen214/test_llama2_7b	llama-2	7B	2023-09-30	3289	-549.87	49.73
1013	yeen214/test_llama2_ko_7b	llama-2	7B	2023-10-02	3285	-1405.43	29.99
1014	yhyhy3/open_llama_7b_v2_med_instruct	llama-1	7B	2023-07-09	1197	-561.62	46.24
1015	yulan-team/YuLan-Chat-2-13b-fp16 (YuLan-Team, 2023)	llama	13B	2023-08-04	1165	-645.56	57.01
1016	yunconglong/DARE_TIES_13B (Yadav et al., 2023a; Yu et al., 2024a)	mixtral	12B	2024-01-30	7029	-611.23	77.10
1017	yunconglong/MoE_13B_DPO	mixtral	12B	2024-01-28	3939	-603.88	77.05
1018	yunconglong/Truthful_DPO_TomGrc_FusionNet_7Bx2_MoE_13B	mixtral	12B	2024-01-21	7965	-598.84	77.44

Table 6: List of 1018 models. "ID" denotes the alphabetical index; "Model Name" denotes the name of the model; "Model Type" denotes the classification defined in this paper; "Size" denotes the size of the model (B: billion); "Date" denotes the date of model creation; "DLs" denotes the total number of downloads; $\bar{\ell}_i$ denotes the mean log-likelihood; "Task" denotes the mean of the 6 benchmark scores (i.e., 6-TaskMean).