Not-Just-Scaling Laws: Towards a Better Understanding of the Downstream Impact of Language Model Design Decisions

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Abstract

Improvements in language model capabilities are often attributed to increasing model size or training data, but in some cases smaller models trained on curated data or with different architectural decisions can outperform larger ones trained on more tokens. What accounts for this? To quantify the impact of these design choices, we meta-analyze 92 open-source pretrained models across a wide array of scales, including state-of-the-art open-weights models as well as less performant models and those with less conventional design decisions. We find that by incorporating features besides model size and number of training tokens, we can achieve a relative 3-28% increase in ability to predict downstream performance compared with using scale alone. Analysis of model design decisions reveal insights into data composition, such as the trade-off between language and code tasks at 15-25% code, as well as the better performance of some architectural decisions such as choosing rotary over learned embeddings. Broadly, our framework lays a foundation for more systematic investigation of how model development choices shape final capabilities.[1]

1 Introduction

The effectiveness of language model training depends critically on decisions made during pretraining. For instance, the effectiveness of scaling up data depends on its composition – processing even a trillion tokens would be ineffective if they all consisted of the word "the". Language model performance has been found to be fairly predictable through *scaling laws* (Kaplan et al. (2020), section 2) – extrapolations of model performance based on the parameter counts and number of tokens the models were trained on. However, scaling laws based on only these two aspects do not always explain downstream task performance (Diaz and Madaio, 2024; Isik et al., 2024).

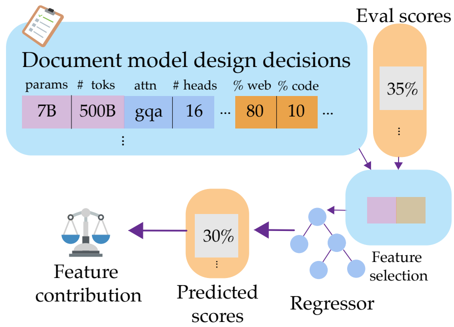


Figure 1: We document design decisions from open-weights models related to both architecture and data composition, and train predictors for downstream task performance. This allows us to examine the impact of model design choices individually.

The research community has made progress in understanding how training decisions impact downstream performance with respect to data composition. For instance, controlled studies have demonstrated that training on code data improves performance on certain reasoning benchmarks (Aryabumi et al., 2024; Petty et al., 2024), meta-features of data such as age and the use of toxicity filters affect performance on many QA tasks (Longpre et al., 2024), and the balance of multilingual data affects performance on English and other languages (Chang et al., 2023; Yue et al., 2025). These works uncover valuable insights, but they tend to focus on changing only a single aspect of the training recipe while keeping the rest fixed. Although rigorous, this is costly in compute and development time. We instead ask: can we leverage past findings from open language models to examine how training decisions jointly impact downstream performance?

To do so, we first *catalog* features regarding the model architecture, and data of 92 base pretrained LMs from varied families (§3). The result-

[1]Code and data are available at `https://github.com/nightingal3/llm-pretraining-behaviours` for the community to build upon.

ing database of model features spans most major original pretrained decoder-only models released open-weights between the years 2019-2024.

We then develop methodology to *predict performance* of these models across a wide array of benchmarks both based on traditional scaling factors as well as architectural decisions and data composition (§4). Specifically, we train regression models that take in the extracted features and predict the benchmark results, and further use model interpretability techniques to identify the most salient features in making these predictions.

We evaluate this methodology on predicting performance across 12 popular LLM benchmarks, and demonstrate that it is *not just scaling* that determines model performance – on all benchmarks the regressor with all features outperforms a regressor based solely on scaling model features (§5.1). Our analysis of feature importance reveals potential impacts of data domains on task performance, reconfirming empirical results such as the best ratio of code to use in pretraining (§5.2). Furthermore, we find that features extracted from a model's generated text – such as the frequency of question-related words or the proportion of web-like text—help predict performance on various benchmarks. This suggests that a model's generation patterns can reflect underlying biases from its pretraining data that, in turn, influence downstream performance.

By documenting open-source models trained by the entire community and extracting insights, we provide a practical resource for model developers to learn from collective experience. We discuss this and future work in (§7).

2 Scaling Laws

2.1 Definition

We define scaling laws here as a relationship between the number of parameters N and the number of tokens D of a language model family, and the expected language-modelling loss at convergence $L(N, D)$.[2] Importantly, these laws are typically examined while holding all other factors constant: keeping the same model architecture, training data, and model parameters. Originally, Kaplan et al. (2020) showed that over a wide range of transformer-based models, this relationship can be expressed as a power law:

[2] Please see §6.2 for more detailed discussion; scaling laws can and do take into account other factors in various works, but for simplicity we call N and D scale-related here, while all other decisions in §3.2 are contrasted with these.

$$L(N, D) = \left(\left(\frac{N_c}{N} \right)^{\frac{\alpha_N}{\alpha_D}} + \frac{D_c}{D} \right)^{\alpha_D} \tag{1}$$

Later, Hoffmann et al. (2022a) introduced a similar law, which differed in the coefficients fitted, but was also based on a power law.

However, scaling laws are not absolute, and the exact functional form and fitted coefficients may depend on the architecture type, size range (Pearce and Song, 2024), or other considerations such as inference costs. See (§6.2) for further discussion.

2.2 Maybe it's Not Just Scaling?

Are parameter count and number of training tokens really all that are needed to accurately predict a model's downstream performance? Intuitively the answer is "no" – there are a number of design decisions that go into model training, and all of them could have an effect on model performance.

Model Architecture Details While the majority of modern language models follow the transformer architecture, there are some details that differ. For instance, the variety (Zhang and Sennrich, 2019) and position (Xiong et al., 2020) of layer normalization, and the type of positional encoding (Su et al., 2021; Press et al., 2022) make significant differences in model performance. Previous work, such as Gu and Dao (2023), has demonstrated empirically that holding all other factors equal, models that make better architecture decisions (Touvron et al., 2023a) outperform those that make worse decisions (Vaswani et al., 2017).

Data Composition In addition, data composition and quality plays a major role in the final quality of a model. For instance, past work has demonstrated that training on some quantity of code improves performance on English reasoning tasks (Ma et al., 2023). Also, work has demonstrated that filtering for "educational" content allows for more efficient learning and higher performance on knowledge-based question answering tasks (Gunasekar et al., 2023).

Task Setting Finally, there is an interplay of all the above factors with how model performance is measured. While previous work on scaling laws has mostly measured loss values, downstream users usually care about task performance, rather than validation loss on a pretraining dataset. Although there is often a correlation between the two for many tasks, certain tasks may be harder to predict from a model's loss alone (Bhagia et al., 2024). Moreover, certain tasks exhibit pathological scaling behaviour, such as inverse or U-shaped scaling (Caballero et al., 2023; Wei et al., 2023; McKenzie et al., 2024), or simply more unpredictable performance (Isik et al., 2024).

We ask: *can we more effectively predict the performance of LLMs by devising a new set of "laws" that are not just reliant on scaling-based factors?*

3 Building a Database of Publicly-Available Language Models

To approach our research question, we built a comprehensive database of publicly available language models. Our database encompasses models spanning a wide range of sizes, from 11M to 110B parameters,[3] and includes only distinct pretrained base models with decoder-only architectures.[4] In this section, we describe the criteria used for model inclusion, how we featurized the models, as well as the evaluation suite we used.

3.1 Data Collection

To ensure that our analysis was consistent, we applied the following criteria:

Pretrained-only: Only base models that were pretrained from scratch were included. Fine-tuned variants, merged models, and models with additional post-training were excluded.

Architecture: Only transformer-based decoder-only models were included to maintain uniformity. Mixture-of-experts (MoEs) or other architectures were excluded.

Publicly available information: Only models with publicly available metadata, documented through configuration files or papers, were included. In particular, both the total number of parameters and total number of tokens trained on were required for inclusion. A full list of models and model families can be found in Appendix A.

3.2 Characterizing Models and Data

We represent each model by the architectural choices it makes, as well as its choice of pretraining data. Formally, let $\mathcal{A}$ be the set of features related to model architecture, and $\mathcal{D}$ be the set of features related to the model's pretraining dataset. For each task T we want to approximate a model M's true score s_T with a prediction $\widehat{s_T}$:

$$\widehat{s_T}(M) = f_\theta([\mathcal{A}_M; \mathcal{D}_M]). \quad (2)$$

This reduces to typical scaling laws when $\mathcal{A} = \{\#\,\text{params}\}$, $\mathcal{D} = \{\#\,\text{tokens}\}$, and f_θ is a power law.

In total, we document 92 open models along the dimensions of model features, high-level dataset features, and features derived from that model's no-context generations. For the full set of features and definitions, please see Appendix B.

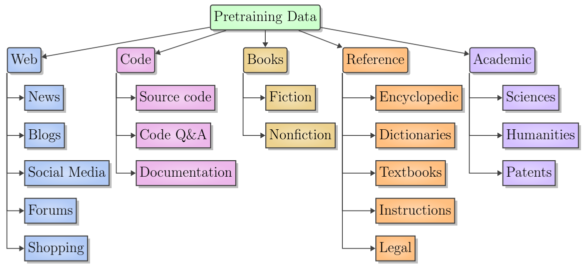


Figure 2: Taxonomy of pretraining data categories. We sorted data sources into this taxonomy based on model documentation.

3.2.1 Features from Model Documentation

We first collect information about each model by reading source papers/blogs when available (see Appendix A for original citations), as well as data listed on the Hugging Face Hub (Wolf et al., 2020).

Architectural Features: These features capture design decisions that determine model structure. For example, *total parameters* (including embedding parameters), the number of transformer layers, the embedding and feed-forward dimensions, and details such as the type of layer normalization or attention variant used.

Data Features: These features summarize pretraining data composition. Representative examples include *total tokens trained on* and the percentage breakdown of tokens sourced from various domains defined in Figure 2, as well as the proportion of English-language tokens. Our pretraining data domains were derived from common subdomains in open pretraining datasets (Gao et al., 2020; Soldaini et al., 2024). We use the top level domains (web, code, books, reference, academic) as this tends to be the granularity at which data composition is described in papers.

[3] Including embedding parameters.

[4] By distinct, we mean that each combination of training data and model architecture decisions should be unique. Variants of the same model trained on a deduplicated dataset are counted as separate, but not variants trained on the same data but with different curricula/initializations.

3.2.2 Exploring Data Composition via Generation

Although many models do document some details of their data composition, relatively few release their full pretraining corpus. Further, even when data composition statistics are provided, they are often presented at a high level of granularity. As a result, many models in our study have missing values for data composition.

To address this, we further propose an approach of estimating the data a model was trained on by generating from the model with a context containing just the beginning-of-sequence (BOS) token for that model (or end-of-sequence if that model lacked a BOS token). We use temperature-based sampling with $T = 1$, as this should in principle recover $P_{raw}(x_t \mid x_{<t}) \approx P(x_t \mid x_{<t})$ in the limit of sampling infinitely from an LM that captures its distribution perfectly.

We call this **free-generation**. However, this has important caveats: we cannot actually sample infinitely, and a model does not reflect its pretraining data perfectly. Therefore, we use this as a "fingerprint" of the model's training, but do not claim that this reflects a model's pretraining dataset exactly. In practice, we sample between 5-10k free-generations from each model (5k for larger models). In addition to categorizing them (see Appendix E) by the domains in Figure 2, we also extract lower-level features:

Low-level data features: We aggregate per-generation statistics that reflect data quality and linguistic structure. Examples include the words per sentence, the depth of the constituency tree for natural language text, and dependency length.

3.3 Evaluation Datasets and Metrics

To assess how design choices affect reasoning capabilities, we evaluated model performance on a curated suite of datasets derived from the first version of the Open LLM leaderboard (Myrzakhan et al., 2024), which was designed to capture diverse facets of reasoning (Table 1).[5] We collect results for some models directly from the leaderboard, and for models not on the leaderboard we use the Eleuther LM eval harness (Gao et al., 2023) to conduct evaluations with exactly the same setting. In addition, if there were multiple versions of a task or sub-tasks, we evaluated all of them and averaged them to get the overall task score. For the full list of evaluation datasets and settings, see Appendix C.

Commonsense Reasoning / NLI		
ANLI (Nie et al., 2020)	$\sim$ 163k	Brier Score
HellaSwag (Zellers et al., 2019)	$\sim$ 70k	Accuracy
Winogrande (Sakaguchi et al., 2019)	$\sim$ 44k	Accuracy
XNLI (Conneau et al., 2018)	$\sim$ 2.5k	Brier Score
Math / Logic		
GSM8K (Cobbe et al., 2021)	8 000	Accuracy
LogiQA2 (Wang et al., 2020)	$\sim$ 8k	Brier Score
MathQA (Saxton et al., 2019)	$\sim$ 37k	Brier Score
General Knowledge		
ARC Challenge (Clark et al., 2018)	$\sim$ 2.6k	Accuracy
Lambada (Paperno et al., 2016)	$\sim$ 10k	Accuracy
MMLU (Hendrycks et al., 2020)	$\sim$ 2.85k	Accuracy
Other		
TruthfulQA (Lin et al., 2021)	817	Accuracy
HumanEval (Chen et al., 2021)	164	Accuracy

Table 1: Overview of LM evaluation datasets with approximate sample counts, citations, and evaluation metrics. Datasets ANLI, XNLI, LogiQA2, and MathQA use Brier Score, while the others use Accuracy.

For an evaluation dataset T where the i-th sample is y_i and model M, we define $s_T(M)$ with:

Accuracy We use unnormalized, exact-match accuracy $s_{T,\text{acc}} = \frac{1}{|T|}\sum_{i=1}^{|T|} \mathbb{1}\{y_i = \hat{y}_i\}$ for the majority of tasks. We use pass@1 for Humaneval, but group it with accuracy tasks for convenience.

Brier score For tasks where smaller models struggle to achieve non-zero accuracy, we follow Schaeffer et al. (2023) in using multiclass brier score as an alternate continuous metric for multiple-choice tasks (Brier, 1950). For a task with K classes, let p_{ik} be the predicted probability for class k on sample i. Then $s_{T,BS} = \frac{1}{|T|}\sum_{i=1}^{|T|}\sum_{j=1}^{K}(p_{ik} - \mathbb{1}\{y_i = k\})$.[6]

3.4 Heterogeneity in Task-specific Scaling

Before adding in other factors, we examine differences in scaling along N and D between our selected tasks. We fit a Kaplan et al. (2020) style law to each task. As seen in Figure 3, we see that different tasks may exhibit marked differences both in how well they follow scaling trends, as well as their individual scaling contours. For instance, TruthfulQA appears to exhibit U-shaped scaling, while Humaneval has more "outlier" models. A full list

[5]Arithmetic and Minerva math ((Brown et al., 2020; Hendrycks et al., 2021)) tasks were also initially included in this leaderboard, but we excluded them as we focused solely on base (not instruction tuned) models, and very few were able to achieve non-zero scores.

[6]Note that lower is better for brier score. Multiclass brier score ranges between 0-2.

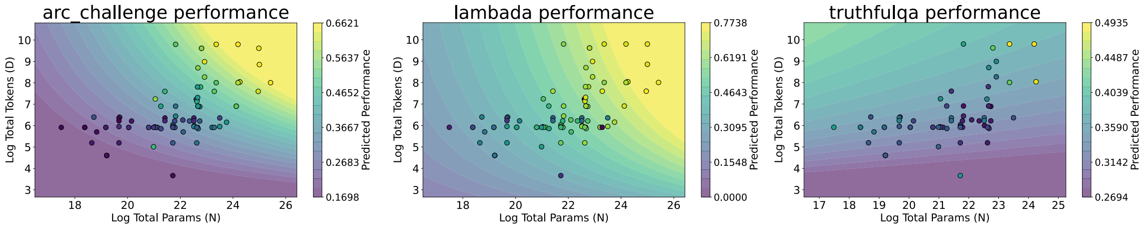


Figure 3: Performance of plotted against their total parameters and tokens. The background colour represents Equation 1 fitted to the task, and the marker colours indicate true performance. Some tasks have different performance trends with scale. Within each task, individual models may also perform unexpectedly.

of R^2 values for tasks can be found in Appendix D.

4 Predictive Modeling

Next, given our database we fit a regressor to try to predict performance. In traditional scaling laws, regressors are fit based on power laws. However, we are now dealing with a larger number of features, some of which may not be captured well by simple parametric forms. Hence, we follow previous work on performance prediction (Xia et al., 2020; Ye et al., 2021) utilizing tree-based regressors based on XGBoost (Chen and Guestrin, 2016).[7]

For each evaluation benchmark, we train a model to predict the performance metric on that task based on architectural features $\mathcal{A}$ and data features $\mathcal{D}$. For each task setting, we perform 3-fold cross-validation due to the relatively small number of models, with a nested inner cross-validation over the training set in each fold. The inner cross-validation conducted grid search over a small set of hyperparameters, allowing the model to slightly vary per task. See Appendix G for more details.

Evaluation To evaluate the predictors, we use Mean Absolute Error averaged across all models and folds. In other words, for a task with N models evaluated, $\text{MAE}_T = \frac{1}{|T|}\sum_{i=1}^{N} |s_T(M_i) - \widehat{s_T}(M_i)|$. We compare the scaling-laws predictor as well as the all-features predictor against each other, but also against the **median baseline**, which simply predicts the median score of the models in the training set for each model in the test set of that fold.

Iterative Feature Selection As the full set of features is very large, we sequentially selected features from the full set greedily based on which reduced MAE the most, averaged across 5 random seeds. Features were added until no reduction of at least 1×10^{-4} was observed. We started using only the two scaling laws features, and refer to this as the **scaling-laws** model, though it does not have the form of a traditional power law.[8] By then incorporating additional architectural or data features, we can then directly quantify the incremental predictive power afforded by these extra features. We refer to the model with the set of features as the **all-features** model. In all cases, we ran models with the same hyperparameter grid and the same random seeds and splits.

Significance Testing Because the relative difference between baselines is small, we test both predictors across many seeds (50). We then ran paired t-tests on the overall MAE values for each seed, and corrected for multiple comparisons across tasks with the False Discovery Rate (Benjamini and Hochberg, 1995).

5 Results

5.1 Predictor Performance

Incorporating scale-independent features consistently improves benchmark performance. We find that incorporating extra features alongside traditional scaling laws features leads to substantial improvements in prediction accuracy across multiple benchmarks, as seen in Table 2. The all-features predictor outperforms the scaling-laws-only predictor in all evaluated cases, with improvements ranging from approximately 3% (MathQA) to about 28% (Lambada) relative error reduction. Notably, the strongest improvements were observed in language modeling and common-sense reasoning tasks.

[7]We also performed preliminary experiments with LightGBM (Ke et al., 2017) but it yielded very similar results in both prediction accuracy and feature importance.

[8]Typically, scaling laws are used to extrapolate the performance of larger models. Because we use a decision-tree based predictor, our approach is less likely to extrapolate, a trade-off we opted to take to incorporate the array of scale-independent features we have, not all of which are numeric. Therefore, we moreso focus on interpolating performance within the size boundaries that we have (roughly 10M-100B parameters, and 50B-3T tokens). Examining results with a variety of other prediction methods is an interesting direction for future work.

Benchmark	Setting	Baseline MAE	Scaling Laws MAE	All Features MAE	p-val (corrected)
			Accuracy		
Arc Challenge	25-shot	13.23%	4.36% $\pm$ 0.12%	**3.67%** $\pm$ **0.09%***	4.89×10^{-19}
GSM8k	5-shot	15.65%	6.04% $\pm$ 0.21%	**5.10%** $\pm$ **0.23%***	6.49×10^{-14}
Hellaswag	10-shot	12.26%	3.93% $\pm$ 0.13%	**3.18%** $\pm$ **0.09%***	6.66×10^{-20}
Humaneval	0-shot	11.79%	8.08% $\pm$ 0.22%	**6.93%** $\pm$ **0.22%***	1.46×10^{-12}
Lambada	0-shot	16.89%	9.51% $\pm$ 0.33%	**6.85%** $\pm$ **0.25%***	2.87×10^{-22}
MMLU (0-shot)	0-shot	11.98%	4.76% $\pm$ 0.20%	**4.10%** $\pm$ **0.17%***	6.02×10^{-13}
MMLU (5-shot)	5-shot	12.25%	3.97% $\pm$ 0.18%	**3.54%** $\pm$ **0.14%***	2.09×10^{-10}
TruthfulQA	0-shot	3.72%	2.75% $\pm$ 0.08%	**2.29%** $\pm$ **0.06%***	1.27×10^{-17}
Winogrande	5-shot	10.14%	3.39% $\pm$ 0.08%	**3.09%** $\pm$ **0.07%***	6.02×10^{-13}
			Brier score		
XNLI	0-shot	7.22	6.68 $\pm$ 0.11%	**6.30**$\pm$ **0.11%***	3.16×10^{-9}
ANLI	0-shot	5.90	6.74 $\pm$ 0.19%	**6.53**$\pm$ **0.21%***	3.84×10^{-4}
MathQA	0-shot	7.57	2.83 $\pm$ 0.06%	**2.75**$\pm$ **0.07%***	1.63×10^{-4}
LogiQA2	0-shot	12.74	4.74 $\pm$ 0.12%	**4.60**$\pm$ **0.15%***	1.37×10^{-2}

Table 2: Comparison of MAE values (mean $\pm$ 95% CI) for Scaling Laws and All Features predictors alongside Baseline MAE. Lower MAE is bolded; * indicates significance ($p < 0.05$). Brier score values are multiplied by 100 to be on a similar scale to accuracy.

Certain tasks are more strongly dependent on non-scale features. This pattern of improvements suggests that architectural and training data features may be more informative for predicting performance on certain types of tasks more strongly linked to a particular "genre" of data. Large improvements were observed for both code generation (HumanEval, 15% improvement) as well as natural-language based reasoning tasks (e.g. Lambada, 28% improvement). Even tasks with narrower domains, such as mathematical reasoning (GSM8k, +16%) or knowledge-intensive evaluations (MMLU, +11–14%), see consistent, if more moderate, enhancements. The Brier score benchmarks, however, show smaller improvements (around 3–6%). This may be because the Brier score is inherently less sensitive to emergent effects in model performance, the specific choice of tasks limits the room for improvement, or a combination of both factors.

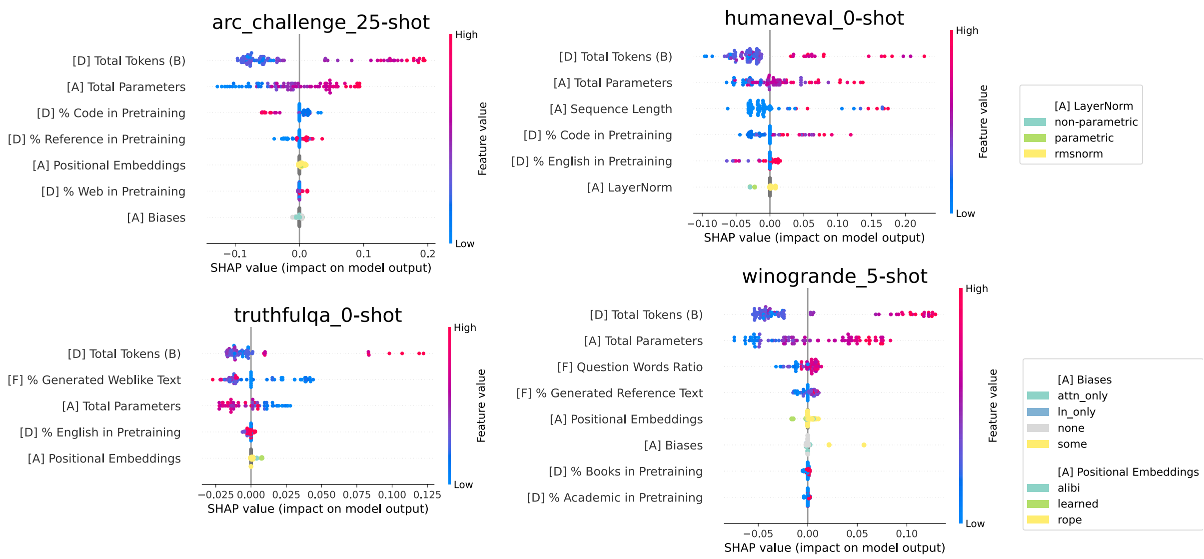
5.2 What Features Does Task Performance Depend On?

To better understand the factors that influence task performance, we examine Shapley (1953) (SHAP) values of the predictor, which provide a local view of how individual feature values influence predictions. The results and feature descriptions for Arc Challenge, HumanEval, Winogrande, and TruthfulQA are shown in Figure 4, and results for remaining benchmarks are shown in Appendix I.

A little code goes a long way, but too much is harmful to NLI. One of the most important non-scaling features is the percentage of code data in pretraining. Higher code composition results in positive Shapley values (i.e. higher predicted performance) for Humaneval, but it negatively affects Arc Challenge, Hellaswag, Winogrande, and Lambada. In the scatterplots of Figure 5, we compare the code percentage against SHAP impact for both small and large models. We see that models trained with more than roughly 20–25% code are predicted to have large gains on tasks like Humaneval, but start to incur penalties on standard natural language benchmarks. By contrast, a moderate code proportion in the 15–25% range appears to balance these competing demands, yielding a more neutral or slightly positive effect overall.

Other domains of data can occasionally yield task-specific effects. While the percentage of code in pretraining is consistently selected as an impactful feature, with clear trade-offs, this other pretraining domains are selected less frequently. From the fine-grained features from free generations, we also observed that many recent models (particularly those trained on synthetic data such as the Phi (Gunasekar et al., 2023) and SmolLM (Allal et al., 2024)) generate a relatively large number of question words, indicating extensive training on data related to question answering. A higher percentage of reference-like or question-loaded generations resulted in better model accuracy on some tasks such as Arc Challenge and Winogrande. Additionally, models that generate more web-like data tend to do worse on TruthfulQA (Figure 4).

Non-scale architectural decisions have minor effects. Most highly influential features were data-related or architectural features related to scale



Feature Name	Description
[D] Total Tokens (B)	Total number of tokens used during pretraining, measured in billions (log scale).
[A] Total Parameters	Total number of parameters in the model (log scale).
[D] % Code in Pretraining	Percentage of pretraining data that consists of code.
[F] Question Words Ratio	Ratio of question-related words generated by the model.
[A] Dimension	Embedding dimension.
[A] Sequence length	Sequence length.
[A] LayerNorm	Type of layer normalization used (non-parametric, parametric, rmsnorm).
[A] Biases	Presence of bias parameters in the model.
[A] Positional Embeddings	Type of positional embedding used (alibi, learned, rope).
[F] % English Generated	Percentage of English text generated by the model.
[D] % Academic in Pretraining	Percentage of pretraining data from academic sources.
[D] % Reference in Pretraining	Percentage of pretraining data from reference sources.
[F] % Generated Weblike Text	Percentage of web-like text generated by the model.
[F] % Generated Reference Text	Percentage of reference-like text generated by the model.
[D] % Books in Pretraining	Percentage of pretraining data from books.
[D] % English in Pretraining	Percentage of English text in the pretraining data.

Figure 4: In all tasks, the number of parameters and pretraining tokens heavily influences the predictions made by the regressor. The percentage of code in pretraining often influences predictions negatively for NLI tasks but positively for Humaneval. [D], [A] and [F] denote features derived from data, architecture, or free-generations of a model respectively.

(e.g., dimension). However, both the type of layer norm and the positional embedding were deemed to have a significant effect in some cases.

6 Related Work

6.1 Empirical Data Composition Results

Prior work has examined the effects of including code during pretraining (Ma et al., 2023; Aryabumi et al., 2024) and ablating domains such as C4 or books from The Pile (Longpre et al., 2024). Data filtering has also been shown to improve performance beyond scaling alone by removing low-quality data (Sorscher et al., 2023; Goyal et al., 2024). Our results align with prior findings, indicating that code can enhance natural language reasoning at moderate proportions but degrades performance at higher percentages. We estimate an optimal code ratio of 15-25%, refining prior work suggesting 25% (Aryabumi et al., 2024), though intermediate ranges were not tested in their study. Our approach—first pooling insights from existing models—complements empirical ablations by identifying useful axes of variation for further testing.

6.2 Observational and Task-Specific Scaling Law Fitting

Previous works have examined task-specific scaling laws. In machine translation, parameter allocation between encoder and decoder affects outcomes, and incorporating machine-translated data can be detrimental (Ghorbani et al., 2021). Multilingual studies reveal that language similarity doesn't impact scaling trends; however, multitasking offers greater benefits when English is the target language (Fernandes et al., 2023). Scaling

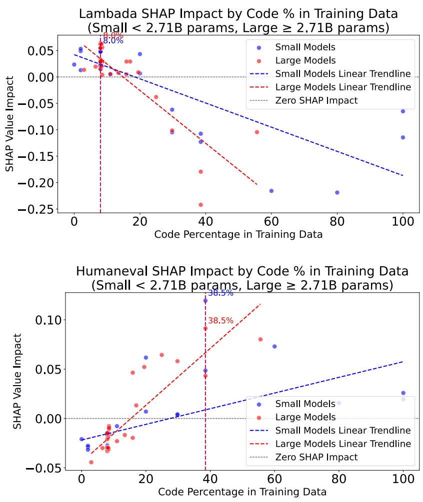


Figure 5: SHAP impact of code percentage on Lambada (reprentative NL task) and Humaneval on our regressors.

laws for downstream tasks and transfer learning have been proposed, emphasizing that alignment between pretraining data and downstream tasks is crucial for performance prediction (Hernandez et al., 2021; Isik et al., 2024). Data repetition has been considered, especially in data-constrained domains (Muennighoff et al., 2024), with extensions to multiple data domains (Goyal et al., 2024). Alternative scaling formulations address factors like sparsity (Frantar et al., 2023), precision (Kumar et al., 2024), and inference costs (Hoffmann et al., 2022b). In contrast, some studies find stable performance across various batch sizes and learning rates (DeepSeek-AI et al., 2024a).

Ruan et al. (2024) also use observations from open-source models to predict task performance, but derive their predictions of one task's performance from performance on other tasks. We find a similar result in identifying two axes of performance– general natural language ability and coding ability but are motivated instead by tracing these capabilities back to pretraining decisions.

6.3 Pretraining Data Selection

Domain mixing has been studied in pretraining, and other works have formulated this as a regression problem (Ye et al., 2024; Liu et al., 2025) or used proxy models to select domain weights in the course of training (Xie et al., 2023; Albalak et al., 2023; Jiang et al., 2024b; Yu et al., 2025). In contrast, we retrospectively analyze how domain composition and training decisions influence performance across tasks, which is a complementary perspective to optimizing data weights for a single model during training.

6.4 Tracing Capabilities to Data

Specific language model capabilities have been linked to patterns in pretraining data. Performance on numerical reasoning and syntactic rule learning depends on frequency of numerical terms in the training data (Kassner et al., 2020; Wei et al., 2021). Ruis et al. (2024) found that influential data for reasoning is dispersed across numerous documents and is associated with procedural content. Similarly, Chen et al. (2024) observed that "parallel structures" are closely tied to in-context learning abilities. We currently focus on broader data domains, but our framework can be extended with more granular tasks or refined data features.

7 Conclusion and Future Work

We perform the first systematic analysis of the performance of open language models across diverse tasks and tie their performance to architectural and data-compositional design decisions. Looking into the future, there are a number of clear directions. First, our database (§3) can be further expanded as new models and benchmarks are released, and we will release the code and data to help spur community efforts for more systematic data documentation. Second, we hope our work will help discover hypotheses to be tested in more controlled settings – existing models intertwine a number of design decisions, and further controlled pre-training experiments that only involve one axis of variation could further clarify the effect of each feature. Finally, within our study, the great majority of pretrained models focused on dense transformer architectures, while alternative architectures such as mixture-of-experts (Jiang et al., 2024a; DeepSeek-AI et al., 2024b) and state-space models (Gu and Dao, 2023) have also seen significant research interest. How to appropriately featurize these more various model architectures and use the information in performance prediction is an interesting challenge that may uncover further insights. Lastly, although pretraining data analysis and selection has mainly been focused on empirical findings so far, building a better understanding of how training impacts model capabilities through large-scale empirical studies could also facilitate interpretability experiments and possible interventions on learned representations, with controlled axes of variation providing case studies.

Limitations

Our current work has several limitations that can be improved in future work. First, although we document many open models, our sample size remains limited, particularly for larger (>50B) parameter models. This limits our ability to draw robust conclusions about scaling behaviour in large models. Additionally, the models that we have are not evenly distributed across number of parameters, data size, and data distributions, with certain size ranges and data distributions being overrepresented. There are also likely selection effects in which models are made open-weights, as well as likely time effects in popular architectural decisions or data compositions in different time periods.

Second, our methodology also imposes some limitations. Because we do not systematically train all our own models (though we have a few of our own in Appendix A), our analyses are observational in nature. While we can observe interesting relationships between design choices and performance, making causal claims requires experimental validation. Additionally, while tree-based regressors are effective for capturing complex feature interactions, they limit our ability to extrapolate beyond the range of model sizes (in parameters and tokens) seen in our dataset.

Last, we note that the scope of our work also has limitations. Namely, we focus on base pretrained decoder-only dense transformer models, which excludes significant architectural variants such as mixture-of-experts models, non-transformer based architectures, as well as post-trained models. Additionally, we examine mostly English-language models as we do not focus on multilinguality in this work. Our feature set, while extensive, may also not capture all relevant details of model design and training, particularly optimization details as of now.

These limitations suggest directions for future work: expanding the database to include more diverse model types and language coverage, developing more targeted functional forms that allow better extrapolation while also taking as input a heterogeneous feature set, as well as conducting targeted experiments with new pretrained models to validate the impact of specific design choices.

Ethical Considerations

In this work, we focus on understanding why models may perform well on standard benchmarks, but do not focus on other important considerations such as safety or societal bias.

Furthermore, our analysis focuses on English-language models and benchmarks. This limitation reflects but may also reinforce the field's existing bias toward English, potentially contributing to underinvestment in developing effective architectures for other languages.

Author Contribution Statement

We follow a slightly modified version of the CRediT author statement.

- **EL**: conceptualization (lead), data curation (equal), methodology/software (lead), writing – original draft (lead), writing – review and editing (lead), visualization (lead), funding acquisition (supporting)
- **AB**: conceptualization (supporting), methodology/software (supporting), data curation (equal), writing – review and editing (supporting)
- **LS**: conceptualization (supporting), methodology/software (supporting), data curation (equal)
- **LT**: conceptualization (supporting), methodology/software (supporting), data curation (equal)
- **PF**: conceptualization (supporting), methodology/software (supporting), data curation (equal), writing – review and editing (supporting)
- **LM**: methodology/software (supporting), data curation (equal)
- **MC**: methodology/software (supporting), data curation (equal)
- **SS**: methodology/software (supporting), data curation (equal)
- **CL**: writing – review and editing (supporting), project administration (supporting)
- **AR**: conceptualization (supporting), writing – review and editing (supporting), supervision (supporting)
- **KG**: conceptualization (supporting), writing – review and editing (supporting), supervision (supporting), project administration (supporting)

- **GN**: conceptualization (lead), methodology/software (supporting), writing – review and editing (supporting), supervision (lead), project administration (lead), funding acquisition (lead)

Acknowledgments

This work was supported by a fellowship from NEC Laboratories Europe and the BRIDGE CMU-AIST research project. EL was supported by the Natural Science and Engineering Research Council of Canada (NSERC), [funding reference number 578085]. AB was supported by a grant from the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE2140739. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the sponsors.

We thank Xiang Yue for providing useful feedback and advice on this work, as well as Simran Khanuja for providing helpful edits. We also thank Brendon Boldt and David Mortensen for help with LaTeX formatting.

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A List of all models

All models are listed in Table 3:

Table 3: Model Parameter Counts by Organization (sorted by size)

Organization	Model Name	Parameters
EleutherAI (Biderman et al., 2023)	pythia-14m	14M
EleutherAI	pythia-70m-deduped	70M
EleutherAI	pythia-70m	70M
facebook (Meta AI, 2022a)	opt-125m	125M
EleutherAI (Black et al., 2021)	gpt-neo-125m	125M
HuggingFaceTB (Allal et al., 2024)	SmolLM-135M	135M
EleutherAI	pythia-160m	160M
EleutherAI	pythia-160m-deduped	160M
None (this paper)	llama2_220M_nl_100_code_0	220M
None (this paper)	llama_220M_nl_80_code_20	220M
None (this paper)	llama2_220M_nl_40_code_60	220M
None (this paper)	llama2_220M_nl_20_code_80	220M
None (this paper)	llama2_220M_nl_0_code_100	220M
Salesforce (Nijkamp et al., 2023)	codegen-350M-mono	350M
Salesforce	codegen-350M-multi	350M
Salesforce	codegen-350M-nl	350M
facebook	opt-350m	350M
HuggingFaceTB	SmolLM-360M	360M
EleutherAI	pythia-410m-deduped	410M
EleutherAI	pythia-410m	410M
facebook (Meta AI, 2022b)	xglm-564M	564M
EleutherAI	pythia-1b-deduped	1B
bigscience (BigScience Workshop et al., 2023)	bloom-1b7	1B
EleutherAI	pythia-1b	1B
cerebras (Cerebras Systems, 2023)	Cerebras-GPT-1.3B	1.3B
microsoft (Li et al., 2023)	phi 1.5	1.3B
EleutherAI	gpt-neo-1.3B	1.3B
EleutherAI	pythia-1.4b	1.4B
EleutherAI	pythia-1.4b-deduped	1.4B
HuggingFaceTB	SmolLM-1.7B	1.7B
Salesforce	codegen-2B-mono	2B
Salesforce	codegen-2B-nl	2B
Salesforce	codegen-2B-multi	2B
google (Gemma Team et al., 2024b)	gemma-2-2b	2B
cerebras	Cerebras-GPT-2.7B	2.7B
EleutherAI	gpt-neo-2.7B	2.7B
NinedayWang (Xu et al., 2022)	PolyCoder-2.7B	2.7B
facebook	opt-2.7b	2.7B
microsoft (Abdin et al., 2023)	phi 2	2.7B
EleutherAI	pythia-2.8b	2.8B
EleutherAI	pythia-2.8b-deduped	2.8B
facebook	xglm-2.9B	2.9B
Qwen (Qwen et al., 2025)	Qwen2.5-3B	3B
cerebras (Dey et al., 2023)	btlm-3b-8k-base	3B

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Table 3 – Continued from previous page

Organization	Model Name	Parameters
openlm-research (Geng and Liu, 2023)	open_llama_3b_v2	3B
rinna (Sawada et al., 2024)	bilingual-gpt-neox-4b	4B
Dampish	StellarX-4B-V0	4B
facebook	xglm-4.5B	4.5B
Salesforce	codegen-6B-multi	6B
EleutherAI (Wang and Komatsuzaki, 2021)	gpt-j-6b	6B
Salesforce	codegen-6B-nl	6B
Salesforce	codegen-6B-mono	6B
cerebras	Cerebras-GPT-6.7B	6.7B
facebook	opt-6.7b	6.7B
EleutherAI	pythia-6.9b-deduped	6.9B
EleutherAI	pythia-6.9b	6.9B
Qwen (Bai et al., 2023)	Qwen-7B	7B
aisingapore (Lowphansirikul et al., 2021)	sea-lion-7b	7B
bigscience	bloom-7b1	7B
google (Gemma Team et al., 2024a)	gemma-7b	7B
mosaicml (MosaicML NLP Team, 2023)	mpt-7b	7B
openlm-research	open_llama_7b	7B
tiiuae (Institute, 2023)	falcon-7b	7B
allenai (for AI, 2024)	OLMo-7B-hf	7B
huggyllama (Touvron et al., 2023a)	llama-7b	7B
LLM360 (Liu et al., 2023)	Amber	7B
LLM360	CrystalCoder	7B
facebook	xglm-7.5B	7.5B
meta-llama (AI, 2023)	Meta-Llama-3-8B	8B
google	gemma-2-9b	9B
01-ai (01. AI et al., 2025)	Yi-9B	9B
EleutherAI	pythia-12b	12B
EleutherAI	pythia-12b-deduped	12B
cerebras	Cerebras-GPT-13B	13B
meta-llama (Touvron et al., 2023b)	Llama-2-13b-hf	13B
Qwen	Qwen1.5-14B	14B
Qwen	Qwen2.5-14B	14B
Salesforce	codegen-16B-nl	16B
Salesforce	codegen-16B-mono	16B
EleutherAI	gpt-neox-20b	20B
mosaicml	mpt-30b	30B
Qwen	Qwen2.5-32B	32B
Qwen	Qwen1.5-32B	32B
AbacusResearch	Jallabi-34B	34B
01-ai	Yi-34B	34B
01-ai	Yi-34B-200K	34B
meta-llama	Llama-2-70b-hf	70B
meta-llama (AI, 2023)	Meta-Llama-3.1-70B	70B

Continued on next page

Table 3 – Continued from previous page

Organization	Model Name	Parameters
meta-llama	Meta-Llama-3-70B	70B
Qwen (Qwen et al., 2025)	Qwen2-72B	72B
Qwen	Qwen2.5-72B	72B
Qwen	Qwen1.5-110B	110B

B List of all architectural and data features

B.1 Architectural Features

Note that features in this section are collected from official documentation (e.g. huggingface model/-data cards or original papers).

- **Total parameters** - the total number of parameters (embedding included) in the model. Note that we only include decoder-only dense models.
- **Dimension** - the embedding dimension.
- **Num heads** - the number of attention heads.
- **MLP ratio** - the ratio of $\frac{\text{FFN dimension}}{\text{embedding dimension}}$.
- **Positional Embeddings** - the type of positional embedding. This is either non-parametric (sinusoidal or fixed embeddings), learned (just learned as a vector per position), rope (rope embeddings), or alibi (technically not an embedding, but included here due to its functional purpose)
- **LayerNorm** - the type of layernorm applied. This is either non-parametric (just an arithmetic based normalization), parametric (similar, but with some learnable parameters such as scaling/biases), and RMSNorm (a simplified version of parametric)
- **Attention variant** - The broad type of attention used. This is either full (vanilla attention), local (each token position only attends to positions around it), mqa (multi-query attention), or gqa (grouped-query attention)
- **Biases** - whether or not bias terms are present in parts of the model. Either none (no biases), attn only (only in attention layers), ln only (only in layer norm)
- **Block type** - whether or not the transformer blocks are computed in parallel at all. Sequential indicates not, while parallel indicates some parallelism in attention or FFN layers.
- **Activation** - the activation function used. Either relu, gelu/gelu variations, silu, or swiglu.
- **Sequence length** - the sequence length.
- **Batch instances** - the batch size used during pretraining.

B.2 Data Features

Note that features in this section are collected from official documentation (e.g. huggingface model/-data cards or original papers).

- **Total tokens (B)** - total number of tokens used during pretraining, measured in billions (converted to log scale)
- **% Web in Pretraining** - Percentage of pretraining data from general web sources.
- **% Code in Pretraining** - Percentage of pretraining data that consists of code.
- **% Books in Pretraining** - Percentage of pretraining data from books.
- **% Reference in Pretraining** - Percentage of pretraining data from reference sources.
- **% Academic in Pretraining** - Percentage of pretraining data from academic sources.
- **% English in Pretraining** - Percentage of English text in the pretraining data.

B.3 Freegen-derived Features

These features are derived from model generations. For each model, 5–10k generations are extracted and the following metrics are aggregated (by mean and standard deviation). However, bigram entropy, the educational classifier score, and domain classifications are exceptions, as they are computed once across all generations.

We use Stanza (Qi et al., 2020) to generate the parse-based features after classifying generations by language. We only include languages that are supported by stanza in the final set of generations that the parse features are based on.

B.3.1 Generation Length & Basic Statistics

- **Mean Character Length** – Average number of characters per generation (capped at 2048).
- **Mean Tokens Generated** – Average number of tokens per generation.
- **Mean Sentences** – Average number of sentences per generation.
- **Mean Words** – Average number of words per generation.
- **Mean Words per Sentence** – Average number of words per sentence.

B.3.2 Constituency Parse Features

- **Mean Depth of Deepest Parse Tree** – Average maximum constituency tree depth per generation.
- **Mean Depth of Parse Trees** – Average constituency tree depth across all sentences/phrases.
- **Mean Word Depth** – Average depth of words within constituency trees.
- **Mean Word Depth Variation** – Average standard deviation of word depths across sentences/phrases.

B.3.3 Dependency Parse Features

- **Mean 90th-Percentile Dependency Head Distances** – For each generation, compute the 90th-percentile of the linear distances between words and their dependency head, then average these values.
- **Mean Maximum Dependency Head Distances** – Average maximum distance from any word to its dependency head per generation.
- **Mean Median Dependency Head Distances** – Average median dependency-head distance per generation.
- **Mean Maximum Dependency Root Distances** – Average maximum distance from any word to the sentence root per generation.
- **Mean Mean Dependency Root Distances** – Average of the mean distances from words to the sentence root per generation.
- **Mean Median Dependency Root Distances** – Average of the median distances from words to the sentence root per generation.

B.3.4 Domain Classification Features

- **% Generated Academic-like Text** – Percentage of generations classified as academic-like.
- **% Generated Books-like Text** – Percentage of generations classified as books-like.
- **% Generated Code-like Text** – Percentage of generations classified as code-like.
- **% Generated Reference-like Text** – Percentage of generations classified as reference-like.
- **% Generated Specialized Text** – Percentage of generations classified as specialized (e.g., music scores, chess PGNs, biomedical data).
- **% Generated Web-like Text** – Percentage of generations classified as web-like.

B.3.5 Classifier and Language Metrics

- **Mean Educational Classifier Score** – Average score assigned by the educational classifier.
- **% Generated English Text** – Average percentage of text generated in English.

B.3.6 Lexical Diversity and Entropy Metrics

- **Mean Bigram Entropy** – Average entropy computed on bigrams across generations.
- **Type-Token Ratio** – Average ratio of unique tokens to total tokens.
- **Unique Tokens** – Average number of unique tokens per generation.

B.3.7 Lexical and Stylistic Features

- **Content-Function Ratio** – Ratio of content words (nouns, verbs, adjectives, adverbs) to function words.
- **Question Words Ratio** – Ratio of question-related words (e.g. how, what, why, when, where, who, which, whose) per 100k words.
- **Imperative Words Ratio** – Ratio of imperative words (e.g. do, make, consider, take, use, ensure, check, build, apply, run, create, find, go, try, turn, start, stop, put, keep, leave, get, move) per 100k words.
- **Conjunctions Ratio** – Ratio of conjunction words (e.g. and, but, or, so, because, although, however, therefore, yet) per 100k words.
- **Instruction Words Ratio** – Ratio of instruction-oriented phrases (e.g. “Question:”, “Answer:”, “Instruction:”, “User:”, “Assistant:”, “Q:”, “A:”) per 100k words.
- **Numbers Ratio** – Ratio of numerical tokens in the generated text.

Task Name	# Models Evaluated
Commonsense Reasoning / NLI	
ANLI	82
HellaSwag	92
Winogrande	92
XNLI	82
Math / Logic	
GSM8K	92
LogiQA2	82
MathQA	82
General Knowledge	
ARC Challenge	92
Lambada	92
MMLU	92
Other	
TruthfulQA	92
HumanEval	91

Table 4: Number of models evaluated for each benchmark task. Note that some models encountered technical errors when being loaded or in lm-eval-harness. The number of models will continue to be updated.

C List of all evaluations and settings

Although we ideally would evaluate the full cross-product of models and tasks, we found that due to some models being incompatible with LM Evaluation Harness and compute constraints we could not evaluate all 92 models on every dataset. We list in Table 4 the number of evaluations we currently have for each benchmark and will continue to fill out evaluations in the database.

D Task Deviations from Kaplan-style Scaling Laws

In Table 5, we document the R^2 value for a fitted power law on the performance of each model.

E Free-generation Domain Classification

We classify model generations into top-level domains with GPT-4o-mini. We found that this multi-stage prompt Listing 1, Listing 2 had reasonable precision on a sample of Dolma by domain (Soldaini et al., 2024), so use it to classify free-generations.

Benchmark	R^2
gsm8k	0.85
arc challenge	0.82
hellaswag	0.80
winogrande	0.80
mmlu 5-shot	0.80
mmlu 0-shot	0.74
mathqa	0.70
ANLI	0.61
humaneval	0.61
lambada	0.55
LogiQA2	0.50
XNLI	0.41
truthfulqa	0.29

Table 5: Overview of R^2 values by benchmark.

F Free-generation Examples

Llama-2-70B, web-like: Gwen Stefani Couldn't Recognize Her First Song at an Event with Blake Shelton What's the first song you ever wrote and or recorded? And how would you feel if you never heard it again until you were Facetiming with hundreds of thousands of people while attending a big country music event? That's exactly what happened to Gwen Stefani, when she was honored at the Country Radio Seminar event this week. In Nashville, . One can only imagine that when you've had as crazy a career as she's had, it may be a chore to actually remember all of the milestones over the years, but just imagine also doing it on the spot, for everyone to see. Well, as it turns out, the doubly talented Dolly Parton was set to introduce Gwen as "an artist who broke barriers" when she cited the lyrics from one of Stefani's first-ever "country" songs…"year 3,000." The diplomatic "The Voice" coach Blake Shelton interjected at the video she was showing at that moment, asking "was there other work done ....

phi-2, books-like: The sun glistened brightly in the evening sky, casting warm rays across the quaint little kitchen where a pair of diligent parents were preparing a scrumptious meal. The air was filled with anticipation as they embarked on a culinary adventure, their hearts filled with love and joy.

With their sleeves rolled up, the parents deftly wielded an assortment of sharp knives, each one an extension of their skill and precision. Like artists with their brushes, they delicately maneuvered through the ingredients, dancing with knives as their partners. The blades moved with a swiftness that defied the physics of everyday movements, gliding through the air with grace and purpose.

...

Qwen2-72B, reference (instruct)-like: Children: Family ticket (at most 2 adults and 2 children) $23.00 (1) Mr Black wants to see the film with his wife and two sons (they're both over 9), how much should he pay?____ A. $23. B. $46. C. $48. D. $49. (2)Mr Brown wants to see the film with his 5-year-old twin sons, how much should he pay____. A. $18. B. $23. C. $28.5 D. $32 (3)Lisa can't see snow in this film.____ A. True B. False (4). Jane is a maths teacher and she has two daughters (she's 12 and her sister is 8). They want to see the film. How much should she pay?____ A. $28.5 B. $27 C. $33 D. $26.5 (5) Mike is sixteen. Today is Saturday and he wants to see the film with his 40-year-old parents. They will pay____ for the tickets. A. $22.

OPT-6.7B, web-like: I don't think this is a question. It's a statement. I say get a dog, the world is better with dogs.

I said to myself the exact same thing. I don't know why you were down-voted.

because reddit is a bunch of people who hate dogs.

Codegen-16B-mono, code-like:

```
from typing import Optional

from fastapi import FastAPI
from pydantic import BaseModel

app = FastAPI()


class Item(BaseModel):
    name: str
    price: float
    is_offer: Optional[bool] = None


@app.get("/")
def read_root():
    return {"Hello": "World from FastAPI"}


@app.get("/items/{item_id}")
def read_item(item_id: int, q: Optional[str] = None):
    return {"item_id": item_id, "q": q}


@app.put("/items/{item_id}")
def update_item(item_id: int, item: Item):
    return {"item_name": item.name, "item_id": item_id}
```

Pythia-410M, academic-like (patent): This invention relates to new and improved methods and apparatus for removing solid waste material from the waste stream of a power station where the solid waste material is intended for disposal after completion of the power plant.

Various attempts have previously been made to remove solid waste from the waste stream of plants. This is true, for example, to the discharge of sludge which is generally collected into a sludge tank and washed out of the plant in a washing tank which is generally connected to an open drain outlet of the plant. This prior art is discussed by U.S. Pat. No. 3,623,579 which issued to G. R. Clark and described a method for treating the waste stream to remove solid waste by flocculating and flocculating and agitating the solids in a tank to break bonds between the solid particles.

Furthermore, an apparatus was described by U.S. Pat. No. 4,016,823 which describes a method in which liquid sewage is removed from the waste stream and from the sewage treatment plant where the solid waste being removed is to be treated to produce ammonia-purified water for use in bathing baths or soaps and where the sewage from the wastewater treatment plant is removed to the sewage processing plant where this sewage is mixed with water or treated as a fertilizer.

...

G XGBoost Settings

For the inner grid search, the maximum depth of trees was in $[2, 3, 5]$, while the learning rate was in $[0.01, 0.1, 0.3]$ and the number of trees was in $[50, 100]$.

H Selected Features by Task

In Table 6, we show the selected features per benchmark.

I SHAP Plots for remaining benchmarks

SHAP plots for the remaining benchmarks can be found in Figure 6 – Figure 14. Please note that lower scores are better for Brier score tasks (ANLI, XNLI, MathQA, LogiQA2)

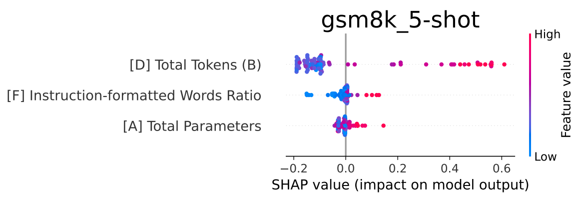

Figure 6: SHAP values for GSM8k

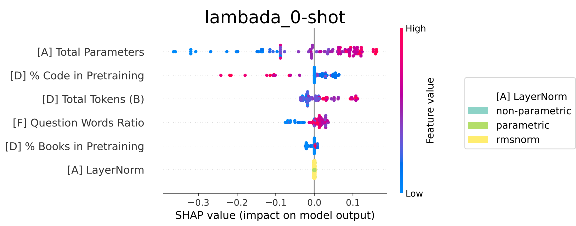

Figure 7: SHAP values for Lambada

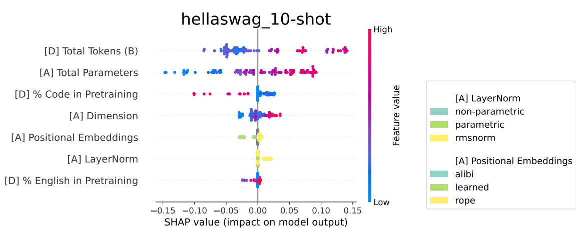

Figure 8: SHAP values for Hellaswag

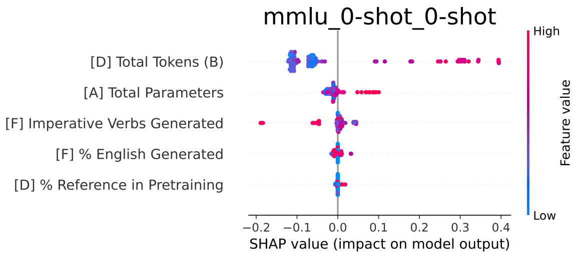

Figure 9: SHAP values for MMLU 0-shot

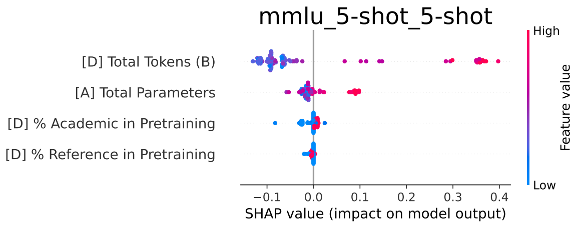

Figure 10: SHAP values for MMLU 5-shot

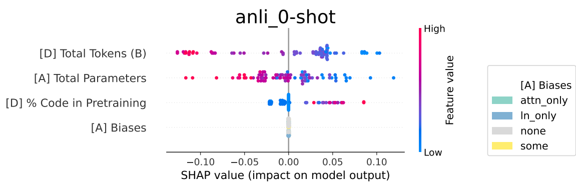

Figure 11: SHAP values for ANLI

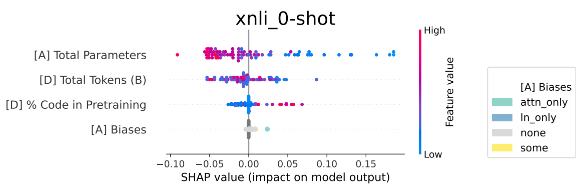

Figure 12: SHAP values for XNLI

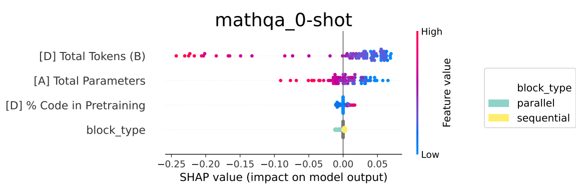

Figure 13: SHAP values for MathQA

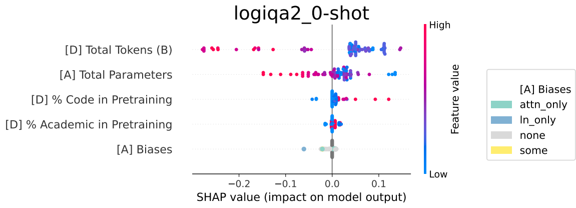

Figure 14: SHAP values for LogiQA2

Listing 1: Multistage classification prompt.

```
<PROMPT 1>. [SYSTEM] You are a system tasked with classifying documents. First, determine if this
     document is relatively coherent. These documents are generated by language models, so they may
     not make sense. Classify a document as incoherent ONLY if it shows extreme repetition, code
     mixes in a way that does not make sense (such as different languages referencing entirely
     different subjects), or if it is mostly gibberish. Don't worry about logic errors or factual
     inconsistencies. If multiple documents are mixed into one, classify it as incoherent. Respond
     ONLY with "incoherent" if the document is incoherent, otherwise respond with "not_incoherent"
[USER] Please classify the document as incoherent or not_incoherent.\nDocument: {document}

If not incoherent...
<PROMPT 2>. [SYSTEM] Determine if this document contains programming code. Look for:
1. Programming language keywords (def, class, import, etc)
2. Code blocks (marked with backticks, indentation patterns)
3. Stack Overflow-style Q&A about programming
4. File extensions (.py, .js, etc)
5. Documentation about code/config files

Respond ONLY with:
- "code" if ANY of these are present
- "not_code" otherwise
[USER] Please classify the document as code or not_code.\nDocument: {document}

If not code...
<PROMPT 3> [SYSTEM] For documents WITHOUT programming code, determine if this is web content. Web
     content includes news articles, social media and online forums, blog posts, shopping websites,
     and other general websites. This includes a wide variety of content, and anything that looks
     like it may be a web article at all should be included. Look for:
1. URLs or hyperlinks
2. Social media formatting (@mentions, #hashtags)
3. "Click here" or UI elements
4. Comment threads or forum posts
5. Shopping/e-commerce language
6. Bylines or author names
7. Descriptions of products or product features

Respond ONLY with:
- "web" if ANY of these are present
- "not_web" otherwise

[USER] Please classify the document as web or not_web.\nDocument: {document}

If not web...
<PROMPT 4> [SYSTEM] For documents WITHOUT programming code, determine if this is academic or
     patent-related content. Academic content consists of research papers and snippets of research
     in both sciences and humanities, as well as patent applications. Student essays or assignments
     should also be included in this category. Look for:
1. Citations or references
2. Latex formatting such as equations or tables
3. Formal academic language, not aimed at educating a general audience
4. Technical jargon or domain-specific terminology
5. Patent numbers or legal language (but not court documents, only patents)

Do NOT classify as academic if the document:
- Only uses occasional technical terms
- Is a popular science article or description of a scientific study, rather than the study itself
- Is educational but aimed at a general audience

Respond ONLY with:
- "academic" if ANY of these are present
- "not_academic" otherwise
[USER] Please classify the document as academic or not_academic.\nDocument: {document}
```

Listing 2: Multistage classification prompt (contd).

```
If not academic...
<PROMPT 5> [SYSTEM] For documents WITHOUT programming code, determine if this is a book, reference
    material (including media content), or a specific dataset. Books include literary works,
    fiction, and narrative nonfiction. Reference material includes wikipedia, dictionaries,
    textbooks and textbook like content, and encyclopedias. Please note that reference should also
    include instruction or human preference datasets for language model training. Media content
    includes podcasts, subtitles, and other media-related text. Specific datasets are unique and
    not covered by the other categories, such as biomedical datasets or molecules, chess PGNs or
    specific data formats not covered by any other category. Look for:

For the books category:
1. Chapter headings or book titles
2. Fictional character names or dialogue
3. For literary nonfiction, look for a more narrative and less didactic tone
4. Extended narrative prose or dialogue
Do NOT classify as books if the document:
- Only has a single dialogue snippet
- Could be a web article
- Is primarily informational or educational (use reference instead)

For the reference category:
1. Definitions or explanations of terms
2. Encyclopedic formatting
3. Textbook-like language
4. Explanations or examples meant to educate a reader
5. Chat formatting like 'User:/Assistant:' or similar tokens
6. Court documents or legal language (NOT patents)
7. Wikipedia headers such as 'references' or 'external links'

For the media category (should be classified as reference):
1. Audio or video timestamps
2. Subtitles or captions

For the specific datasets category:
1. Unique names or identifiers
2. Dataset-specific formatting
3. Data or metadata descriptions

If this seems to be a web document (social media, news, blogs, forums, shopping), you can also back
    off to the 'web' category.

Respond ONLY with:
- "books" if the document is a book
- "reference" if the document is reference material
- "specific_datasets" if the document is a specific dataset
- "web" if the document is web content
- "unknown" if none of these are present

[USER] Please classify the document as books, reference, media, specific_datasets, or
    unknown.\nDocument: {document}"
```

Table 6: Greedily-selected features per benchmark.

Benchmark	**Selected Features**
arc challenge (25-shot)	total params, pretraining summary total tokens billions, question words ratio, layer norm type, dimension, pretraining summary percentage code
gsm8k (5-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage reference, edu classifier std, pretraining summary percentage books
hellaswag (10-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage code, pretraining summary percentage reference, positional embeddings, pretraining summary percentage academic
mmlu 0-shot (0-shot)	total params, pretraining summary total tokens billions, layer norm type, activation, pretraining summary percentage code
truthfulqa (0-shot)	total params, pretraining summary total tokens billions, domain web pct mean, dep parse dep root dist max mean, pretraining summary percentage english, entropy mean, layer norm type
winogrande (5-shot)	total params, pretraining summary total tokens billions, question words ratio, layer norm type, pct english mean, positional embeddings, pretraining summary percentage books, pretraining summary percentage code, block type
anli (0-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage code, pretraining summary percentage web, pretraining summary percentage books, positional embeddings
logiqa2 (0-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage web, domain reference pct mean, dep parse dep root dist mean std, dep parse dep root dist median std
mathqa (5-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage books, num heads
xnli (0-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage web
lambada (0-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage code, block type
mmlu 5-shot (5-shot)	total params, pretraining summary total tokens billions, sequence length, biases, num heads, dimension, edu classifier mean, pretraining summary percentage academic
gsm8k (5-shot)	total params, pretraining summary total tokens billions, instructions words ratio, pretraining summary percentage academic, sequence length, mlp ratio
humaneval (0-shot)	total params, pretraining summary total tokens billions, pretraining summary percentage code, layer norm type, pretraining summary percentage english, biases