

OPTIMIZING PRETRAINING DATA MIXTURES WITH LLM-ESTIMATED UTILITY

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ABSTRACT

Large Language Models improve with increasing amounts of high-quality training data. However, leveraging larger datasets requires balancing quality, quantity, and diversity across sources. After evaluating nine baseline methods under both compute- and data-constrained scenarios, we find token-count heuristics outperform manual and learned mixes, indicating that simple approaches accounting for dataset size and diversity are surprisingly effective. Building on this insight, we propose two complementary approaches: UtiliMax, which extends token-based heuristics by incorporating utility estimates from reduced-scale ablations, achieving up to a 10.6x speedup over manual baselines; and Model Estimated Data Utility (MEDU), which leverages LLMs to estimate data utility from small samples, matching ablation-based performance while reducing computational requirements by $\sim 200x^1$. Together, these approaches establish a new framework for automated, compute-efficient data mixing that is robust across training regimes.

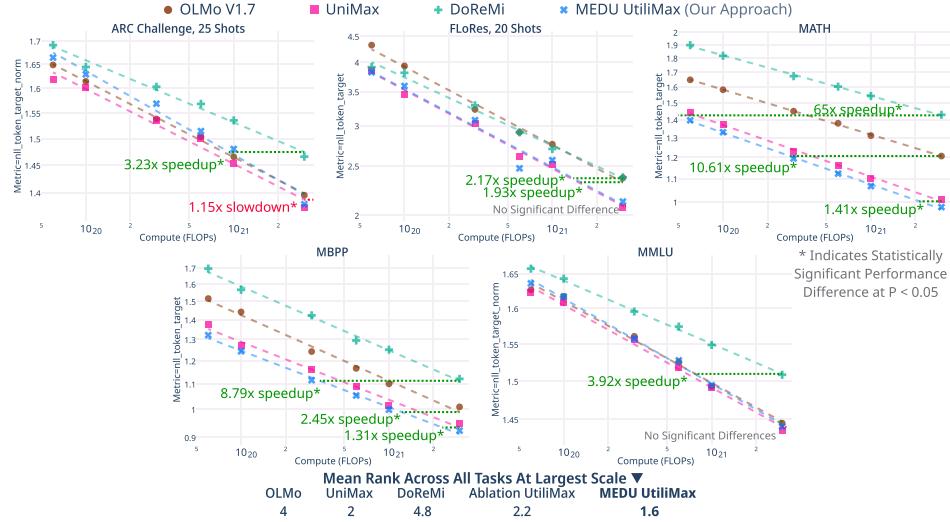


Figure 1: Scaling curves for data mixing methods for compute-optimal models trained for 6×10^{19} to 3×10^{21} Floating Point Operations (FLOPs). Compared to manual (Groeneveld et al., 2024, OLMo), heuristic (Chung et al., 2023, UniMax), and learned (Xie et al., 2024, DoReMi) data mixes, UtiliMax leads to more compute efficient models that perform better on average across tasks.

1 INTRODUCTION

Large Language Model (LLM) pretraining data increasingly consists of sub-corpora from many sources covering multiple domains and varying in size (Gao et al., 2020; Du et al., 2022; TogetherAI,

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¹Comparison between a training run using 6×10^{19} FLOPs and inference cost of 3×10^{17} FLOPs from Llama 70B on 2.1 million tokens needed for MEDU using the FLOP equations from Hoffmann et al. (2022)

2023; Laurençon et al., 2022; Dubey et al., 2024). Unlike traditional multi-task learning scenarios, datasets are not necessarily aligned with a specific intended use. Moreover, “intended usage” is often multi-functional as LLMs are being developed for general-purpose functionality (Eloundou et al., 2024; Qin et al., 2023). Given multiple training corpora and multiple downstream goals, how should we sample from each corpus to get the best possible model?

Prior work has explored heuristic (Rae et al., 2021; Soldaini et al., 2024) and learned (Xie et al., 2024; Albalak et al., 2023) approaches to solve this. However, there is minimal comparison between these methods using the same data and model configuration. Furthermore, it is unclear whether these approaches are robust to the impacts of epoching which is critical as frontier models are increasingly data-constrained (Villalobos et al., 2024; Longpre et al., 2024). We address both questions by training nine baselines across six compute scales, evaluating them under constrained and unconstrained data scenarios. We then propose a novel method to optimize data mixes for a target budget based on the Markowitz model of portfolio optimization (Markowitz, 1952; Boyd et al., 2024).

Research Questions & Findings

1. *How well do prior data mixing methods perform across compute scales and token budgets?* We re-implement and compare nine baselines in a unified setup across likely training scenarios. We find UniMax (Chung et al., 2023), an approach which maximizes diversity under epoching constraints, outperforms other heuristic, manual, and learned data mixes.
2. *Given a set of training runs on individual datasets, can we optimize a data mix effectively?* We propose UtiliMax, which combines utility estimates and dataset size to find data mixes using portfolio optimization. We show UtiliMax improves results by using reduced-scale ablations on individual datasets to estimate data utility.
3. *Can we further reduce the cost of data mixing using existing LLMs to estimate utility?* We prompt LLMs to describe useful training data based on benchmark development sets, then use these descriptions to classify utility for a sample of the training data. These estimates are effective utility estimates for UtiliMax, but are 200x less costly to compute.

2 BACKGROUND

Given an arbitrary utility function μ , data mix optimization aims to improve model performance by optimizing sampling weights \mathbf{w} over datasets $\mathbb{D} := \{d_1, d_2, \dots, d_n\}$. Based on external constraints such as computational resources or data, models are trained for a fixed budget B_e , in terms of a number of training examples. Given a budget, we want to find $\arg \max_{\mathbf{w}} \mu(\bigcup_{d \in \mathbb{D}} \{e_1, e_2, \dots, e_{w_d \cdot B_e}\} \sim d)$ where e_i represents an example from dataset d_i .

Clearly, the target budget is a core factor for this problem, as well as data curation broadly (Goyal et al., 2024). However, existing works run experiments at a single scale and budget (Rae et al., 2021; Soldaini et al., 2024; Xie et al., 2024; Albalak et al., 2023). To determine data mixes for the varying constraints of new models, data mixing methods must perform well across budgets and model scales. This makes evaluating this form of generalization critical for identifying effective methods.

With budget in mind, data mixing is a resource allocation problem. While resource allocation has been extensively studied in convex optimization (Boyd & Vandenberghe, 2004), optimizing utility μ directly is intractable given the cost of full-scale training runs. Furthermore, benchmarks only estimate μ based on a sample of the domain they represent. Instead, data mix optimization requires methods that are robust to error induced by *estimated* utility.

Most relevant is the Markowitz model (Markowitz, 1952), a portfolio optimization method that balances an expected reward $\mathbf{w}^\top \mu(\mathbb{D})$ with risk $\mathbf{w}^\top \Sigma \mathbf{w}$, where Σ is the covariance matrix across assets. Using this *risk-adjusted return*, data mix optimization can be formulated as:

$$\arg \max_{\mathbf{w}} \mathbf{w}^\top \mu(\mathbb{D}) - \mathbf{w}^\top \Sigma \mathbf{w} \quad \text{subject to} \quad \mathbf{1}^\top \mathbf{w} = 1, \quad \min(\mathbf{w}) > 0, \quad (1)$$

In applying this approach to data mix optimization, we make a few key assumptions. First, we assume the utility contributed by a dataset is linear with respect to its weight in the data mix. Second, we assume that the utility of each dataset is independent. Finally, to avoid compounding estimation

error, we approximate Σ as $|\mathbb{D}|I$, corresponding to an assumption that the risk associated with each individual dataset increases linearly with the total number of alternatives.

2.1 RELATED WORK

Token-Size Heuristic Data Mixes Data mixes are often found using heuristics using the number of tokens per dataset t , the target budget B_t in terms of tokens, and the sampling proportion $\frac{B_t \cdot w}{t}$.

Uniform sampling is the simplest baseline data mixing method and defines $w = \frac{1}{|\mathbb{D}|}$. Despite the simplicity, uniform sampling is a strong baseline in multi-task learning (Michel et al., 2021).

Proportional sampling is more common in efforts for large-scale training runs (Rae et al., 2021; Groeneveld et al., 2024) and defines $w = \frac{t}{t+1}$. This holds the sampling proportion constant across datasets at any budget, minimizing the maximum sampling proportion or number of epochs.

OLMo V1.7 utilizes near proportional weights, with Wikipedia up-sampled and CommonCrawl data down-sampled – both by a factor of two². A methodology for these adjustments is not released, but likely stems from a combination of researcher intuition and results from the data mix ablations shown in Soldaini et al. (2024). Since we use Dolma V1.7, we compare to this as a manual baseline.

UniMax (Chung et al., 2023) interpolates between proportional and uniform sampling by setting an epoch cap C and finding $\arg \min_w w^T w$ s.t. $\frac{B_t \cdot w}{t} \leq C$. Through the lens of portfolio optimization, UniMax purely minimizes risk under an assumption of uniform “linguistic utility” from the multilingual setting it was designed for (Blasi et al., 2022). UtiliMax is a generalization of UniMax which allows for arbitrary non-uniform utility functions over datasets.

Learning Data Mixes There is also significant appeal to methods that *learn* data mixes.

DoReMi (Xie et al., 2024) does this using a sequence of training runs. First, a reference model is trained using a prior data mix. Then, a proxy model is trained using Distributionally Robust Optimization (Sagawa et al., 2020) to find weights which minimize worst-case excess loss with respect to the reference model. w is defined as the average of these weights throughout training.

Online Data Mixing (Albalak et al., 2023, ODM) treats data mixing as a multi-armed bandit problem and uses a variant of the EXP3 algorithm (Auer et al., 2002) to dynamically sample data during training. Bandit methods are another natural formulation of data mixing, and have also been explored in works for multilinguality (Schioppa et al., 2023) and translation (Kreutzer et al., 2021).

Model Based Quality Filtering Related to MEDU, many prior works develop methods to filter out “low-quality” data points entirely. Albalak et al. (2024) offer a systematic survey of this area.

Perplexity filters use n-gram or other low-cost language models, such as KenLM (Heafield, 2011), trained on high-quality text to assess data quality in new data (Wenzek et al., 2020). High perplexity data points are excluded based on the assumption that they are likely not natural language.

Quality classifiers operate in a similar manner, but model both low and high quality data to distinguish the two. Brown et al. (2020) popularized this approach by using a classifier trained to distinguish high-quality web pages from random web pages. Recently, LLMs have been used to create zero-shot quality classifiers based on natural language specifications of high-quality data (Wettig et al., 2024; Penedo et al., 2024). This approach has been validated at frontier model scale by Llama 3 (Dubey et al., 2024), but requires a single manually-written specification of “high-quality” data.

How UtiliMax Differs Prior data mixing work avoids making assumptions about use-cases to improve generality. On the other hand, most practitioners have a set of *intended* use-cases measured by benchmarks which have strong correlation with various LLM capabilities (Ruan et al., 2024). UtiliMax maintains generality by optimizing for *multiple* downstream tasks with terms for data utility, diversity, and size. This is applicable to any estimator, such as concurrent work which identifies loss correlations across open-source models (Thrush et al., 2024). Separately, MEDU proposes an approach to automatically construct quality specifications for each downstream task and then leverages this specification to provide more compute efficient utility estimates to UtiliMax.

²Information drawn from the OLMo V1.7 Release blog post.

Table 1: Training Corpora Statistics From Dolma V1.7 using the Llama 3 Tokenizer.

Corpus	Tokens	Corpus	Tokens	Corpus	Tokens
Refined Web	440B	PeS2o	58B	CC News Head	8.5B
CC Head	346B	Arxiv	27B	CC News Middle	3.7B
CC Middle	436B	StackExchange	17B	CC News Tail	1.5B
CC Tail	371B	Tulu Flan	13B	MegaWika	4.4B
StarCoder	215B	Algebraic Stack	11B	Wiki	3.7B
C4	133B	Open Web Math	5.1B	Total	
Reddit	76B	Books	5B		2.1T

3 EXPERIMENTAL SETUP

3.1 TRAINING SETUP

Training Data Overview We use Dolma V1.7 (Soldaini et al., 2024), which is released under the Open Data Commons License, for our experiments. While prior works have used the Pile (Gao et al., 2020) for data mixing experiments, it has since had sections removed due to copyright issues which prevents direct comparison. Dolma is made up of 15 separate corpora including 2 corpora which are bucketed at higher granularity using KenLM (Heafield, 2011) perplexity. We report the names and sizes of the Dolma corpora using the Llama tokenizer in Table 1.

Importantly, Dolma is large-enough for and has been validated through large-scale training runs through OLMo (Groeneveld et al., 2024). Dolma has also undergone document filtering, deduplication, and cleaning, which allows this work to focus solely on *mixing* similarly preprocessed corpora.

General Hyperparameters We train compute-optimal models from 6×10^{19} to 3×10^{21} FLOPs based on the scaling law presented in the Llama 3 paper (Dubey et al., 2024), using the same architecture and tokenizer. The models range in size from 550M to 4.1B parameters and are trained on 14B to 110B tokens across compute scales. Across all training runs, we use a cosine learning rate schedule with a linear warmup for 2,000 training steps decaying to 0.1 of the peak learning rate. The peak learning rate is 2×10^{-4} for all models, except for the largest run which uses 3×10^{-4} . Examples are packed to a sequence length of 8192 and batch size increases from 32 to 256 such that models train for approximately the same number of steps (58k on average, $\pm 9.2k$)³.

3.2 EVALUATING ACROSS TRAINING BUDGET CONSTRAINTS

In this work, we explore two realistic settings corresponding to different budgets discussed in Section 2. In the *compute-constrained* scenario, we have less compute than data, so any data mix discards much of the available data. In the *data-constrained* scenario, we have more compute than we have data, so most data mixes will require epoching over at least one of, if not all of, our datasets.

Compute-Constrained Experiments Prior works on learned data mixes have focused on this setting Xie et al. (2024); Albalak et al. (2023), training for 50-100B tokens. Our first set of experiments aligns with this as our largest model is trained for 100B out of 2.1T tokens. However, frontier models are increasingly trained longer and becoming “data-constrained” (Muennighoff et al., 2024).

Data-Constrained Experiments To identify data mixing methods applicable to frontier models, understanding the effects of epoching is essential for optimal performance (Goyal et al., 2024). Since training for the full 2.1T tokens in Dolma is infeasible for a large number of baselines, we instead simulate data constraints using sub-sampling.

Our simulation sub-samples each dataset to have $T \cdot \frac{D_t}{D_s}$ tokens where T is the total tokens in the dataset, D_t is the number of tokens we will actually train for, and D_s is the number of tokens we are simulating constraints for. This causes the epoching behaviour in the experiment to behave as it

³We describe how examples are constructed, shuffled, and sampled in A.7.

would at the target budget. In this paper, we target a 1.6T token budget - the number of tokens seen using the OLMo V1.7 weights adjusted for the Llama tokenizer.

3.3 EVALUATION TASKS AND METRICS

Per-Task Evaluation Metrics Evaluating methods of Large Language Model pretraining with respect to downstream performance is often challenging, since discrete metrics like accuracy can be noisy at smaller scales (Wei et al., 2022; Schaeffer et al., 2024a). On the other hand, negative log-likelihood (NLL) on pretraining data may not correlate with model utility for downstream tasks.

To strike a balance between scaling predictability and correlation with downstream performance, we utilize the NLL per token *on the correct answers from downstream benchmarks* as our metric across tasks. For multiple-choice tasks, we normalize the NLL by the probability assigned to all options to produce a metric that correlates with accuracy improvements but improves predictably with scale (Schaeffer et al., 2024b; Dubey et al., 2024).

We evaluate the impacts of data mixing on these metrics across benchmarks in 5 commonly-tested LLM capabilities: coding (Chen et al., 2021; Austin et al., 2021, HumanEval; MBPP), mathematics (Hendrycks et al., 2021b, MATH), translation (Goyal et al., 2022, FLoRes), reasoning (Clark et al., 2018, ARC), and general knowledge (Hendrycks et al., 2021a, MMLU). We use the NLL over the correct answer for MBPP, HumanEval, MATH, and FLoRes and normalized NLL over the correct answer for ARC and MMLU.

Across-Task Evaluation Metrics We also report measures to ease comparison across tasks.

Speedup or *slowdown* is the ratio of FLOPs it takes to achieve the same performance as a baseline at a specific point based on the fit scaling curve for each task. In our experiments, we provide this measure with comparison to the performance at the largest scale of 3×10^{21} .

Mean rank is a metric across all tasks. First each approach is ranked based on performance within each task, these ranks are then averaged across all tasks. We draw this metric from Thrush et al. (2024) as a way to succinctly capture the relative performance of methods across several tasks.

4 GENERALIZATION OF DATA MIXING METHODS

Model configuration, tokenizers, and shuffling are all likely to impact data mix experiments. To control for these confounders, we re-implement⁴ and re-compute data mixes for Dolma using a unified setup and consistent random seed. In Figure 2, we plot the comparison of all baselines.

4.1 BASELINES

We compute Proportional and Uniform data mixes using the formulas from Section 2.1. For OLMo V1.7, we use the sampling proportions shared by the authors. We re-implement the UniMax algorithm using CVXPY (Diamond & Boyd, 2016) and compute two data mixes: one for our “compute-constrained” scenario and another for our “data-constrained” scenario. In the 100B scenario, we use a single epoch cap while for the 1.6T token budget we use the two epoch cap used by OLMo V1.7.

We use DoReMi and Online Data Mixing (ODM) as our baselines for learned data mixes. While DoReMi uses the Proportional prior for reference models, it is unclear whether this is the optimal prior for Dolma. To account for this, we train three DoReMi variants with Uniform, Proportional, and OLMo V1.7 priors. Reference and proxy models are trained for 6×10^{19} FLOPs and are trained separately for compute- and data-constrained experiments.

In the ODM paper, given reward \hat{R} , the weights w_t at step t are computed as $(1 - K\mathcal{E}_t)\sigma(\mathcal{E}_{t-1}\hat{R}) + \mathcal{E}_t$, where σ denotes the softmax. We call this variant “ODM Paper”. However, $\mathcal{E}_{t-1} \rightarrow 0$ as $t \rightarrow \infty$ which causes the softmax to become uniform independent of the rewards across datasets. We noted that the open-source release of ODM removes \mathcal{E}_{t-1} from the softmax, and confirm with the first author that the reported experiments used this code. We call this variant “ODM Github”.

⁴For learned data mixes, we reference the following open-source code released by authors to verify our re-implementations in addition to the released papers: ODM Github and DoReMi GitHub.

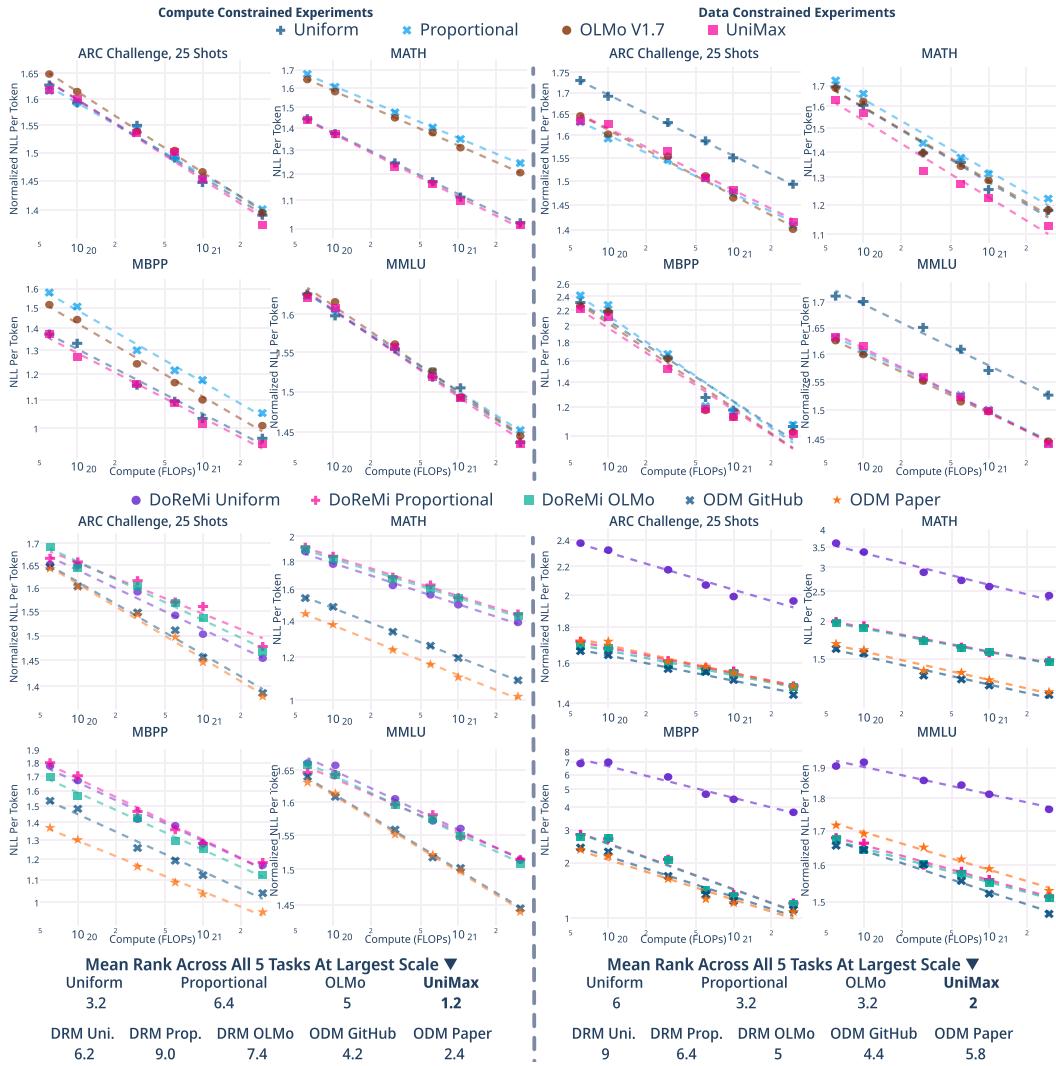


Figure 2: Comparison of baseline data mixing methods. The model with the top average rank at 3×10^{21} FLOPs is in **bold**. UniMax consistently outperforms all other baselines in both settings.

4.2 RESULTS

Generalization to data-constraints Our results emphasize the importance of simulating data constraints that occur in frontier training. Methods behave dramatically differently at different budgets. Data mixes which are close to uniform perform well in compute-constrained settings and perform poorly in data-constrained settings, while the opposite is true for near proportional data mixes. Reliable data mixing methods should perform well in both settings.

The Unreasonable Effectiveness of Uniform Utility Our second finding is that UniMax outperforms other methods in *both* settings. Given the simplicity of UniMax it may be surprising that it outperforms learned and manual baselines. However, the effectiveness of assuming uniform utility is consistent with results in portfolio optimization (DeMiguel et al., 2009).

The superior performance of UniMax suggests that maintaining data diversity and scale is the major driver of performance, particularly as training runs become data-constrained. Furthermore, it makes no assumptions of downstream tasks and can be computed at near zero cost. Due to these results we compare primarily to UniMax throughout the rest of this work for clarity, with full results across all baselines and experiments reported in A.8.

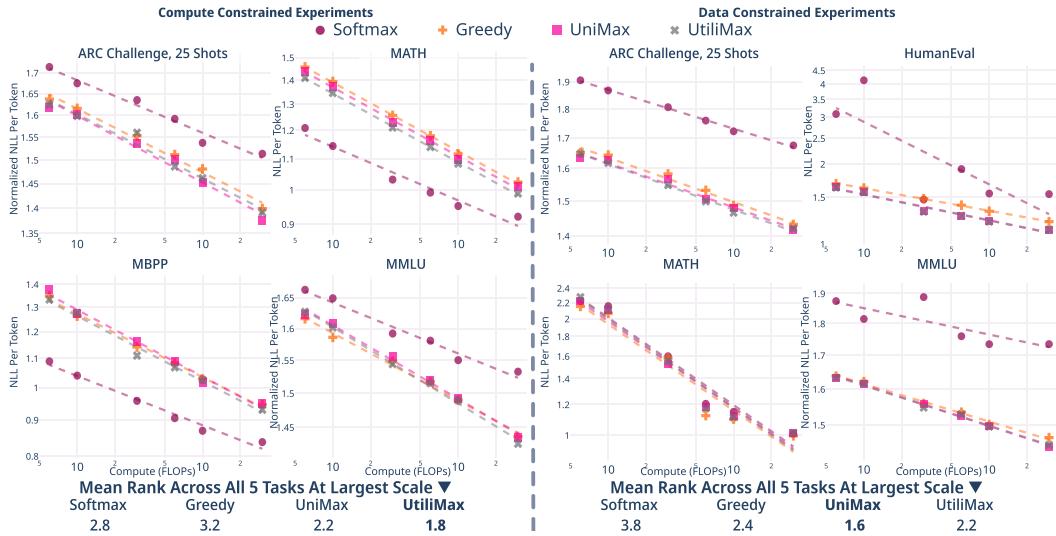


Figure 3: Comparison of utility optimization methods. The model with the top average rank at 3×10^{21} FLOPs is in **bold**. UtiliMax outperforms alternative optimization procedures in both settings.

5 ESTIMATED DATA UTILITY OPTIMIZATION

Despite the effectiveness of UniMax, it is reasonable to believe that data sources have non-uniform utility for downstream tasks. The challenge is in estimating these utilities accurately and robustly handling estimation errors. In Figure 3, we compare our proposed method, UtiliMax, using performance on validation sets as an estimate of utility.

5.1 ISOLATED DATA ABLATIONS

As an intrinsic measure of utility, we train proxy models for 6×10^{19} FLOPs and evaluate on downstream tasks. We use the released held-out validation splits for this, except for MBPP where we use HumanEval as held-out validation data. We estimate utility for each Dolma dataset, treating each perplexity bucket of CommonCrawl data separately, resulting in seventeen proxy models.

Given a set of \mathbb{D} datasets and \mathbb{T} downstream evaluations, this gives us a metric matrix $M \in \mathbb{R}^{|\mathbb{D}| \times |\mathbb{T}|}$. Since NLL metrics for each task vary significantly in scale we normalize the range of values for each task to a normal distribution with mean 0.5 and range [0, 1] creating a utility matrix U .

5.2 UTILIMAX OPTIMIZATION METHODOLOGY

In equation 1, we formulate data mix optimization as maximizing risk-adjusted utility in abstract. Here, we describe the specific problem that we solve using the Splitting Conic Solver (O’Donoghue et al., 2016; O’Donoghue, 2021) through CVXPY (Diamond & Boyd, 2016).

UtiliMax maximizes utility by minimizing the L_2 distance between the expected utility vector $w^\top U$ of our data mix across tasks and a theoretical optimal data mix which has a utility of 1 for all tasks.

In this work, we estimate risk associated by assuming that increasing allocation to a single dataset linearly corresponds to the number of alternative datasets. Therefore we set the risk term to $|\mathbb{D}|w^\top w$. This could also be interpreted in two ways: (1) as maximizing utility with a specific L_2 regularization or (2) as interpolating between the utility maximizing solution and UniMax dependent on $|\mathbb{D}|$.

Finally, following UniMax, we set an epoching cap C on each dataset. With all of this established, UtiliMax is formulated concretely as follows:

$$\arg \max_{\mathbf{w}} \|\mathbf{w}^\top \mathbf{U} - \mathbf{1}\|_2 + |\mathbb{D}| \mathbf{w}^\top \mathbf{w} \quad \text{subject to} \quad \mathbf{1}^\top \mathbf{w} = 1, \quad \min(\mathbf{w}) > 0, \quad \frac{B_T \cdot \mathbf{w}}{t} \leq C \quad (2)$$

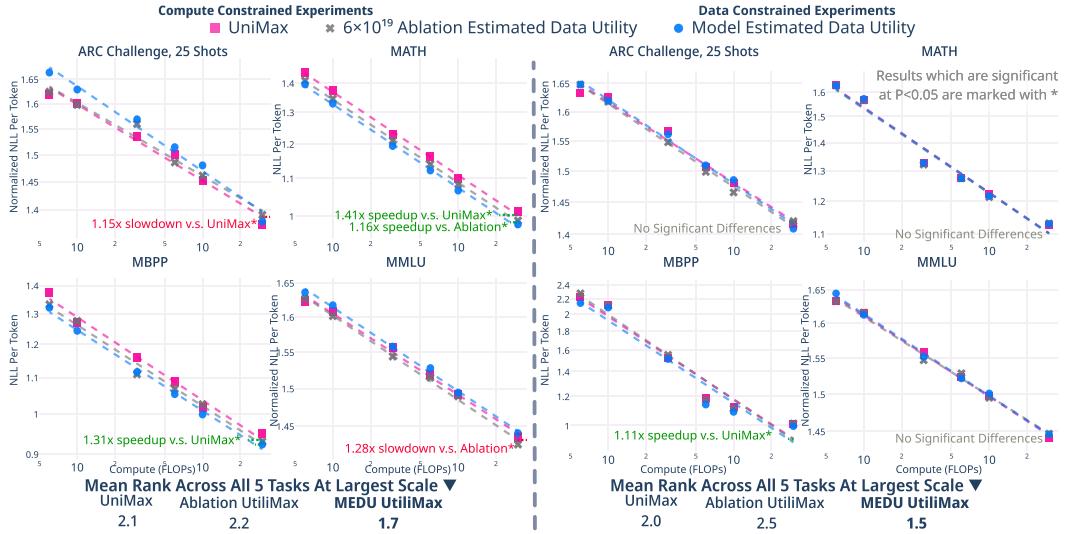


Figure 4: Scaling curves comparing MEDU, Ablation Estimates, and UniMax. The model with the best mean rank at 3×10^{21} FLOPs is marked in **bold**. Speedup indicates cases where using MEDU improves over Ablation-Based Utility, while slowdowns indicates the opposite.

We compare this approach to three alternative optimization procedures. First, simply projecting our NLL results to a valid distribution using the softmax function $\sigma(\mathbf{1}^\top \mathbf{M})$. Second, using utility optimization without risk-adjustment, removing the $|\mathbb{D}| \mathbf{w}^\top \mathbf{w}$ term in equation 2. Finally, considering only risk-minimization, which is equivalent to UniMax.

5.3 RESULTS

Our experimental results show that diversity, in addition to utility, is integral to effective data mixing. Using either the softmax or greedy optimization leads to poor results in at least one setting, despite using natural estimates of dataset utility at significant computational cost. Only with the added risk-adjustment in UtiliMax does the information from ablations lead to consistent performance and improve over UniMax in either setting.

However, using ablations to estimate utility has major shortcomings compared to assuming uniform utility. First, the quality of ablation utility estimates depends on the validation set of the benchmark. Increasingly, high-quality LLM benchmarks, such as GPQA (Rein et al., 2023) or HumanEval (Chen et al., 2021), have either very small or non-existent validation sets. Furthermore, even when large high-quality validation sets do exist, running these ablations can be prohibitively expensive.

6 REDUCING COST OF UTILITY ESTIMATION WITH LLMs

In order to address these shortcomings, we propose a method to use existing LLMs to estimate data utility at a vastly reduced cost, similar to the model-based quality filtering described in Dubey et al. (2024). Beyond reducing costs by removing the need for ablations, model-based utility estimates have the advantage of being able to generalize specific validation data into a more general description of desirable data formats and domains. In Figure 4, we compare **Model Estimated Data Utility (MEDU)** to ablation-based and uniform utility estimates.

6.1 MODEL ESTIMATED DATA UTILITY METHODOLOGY

Our method prioritizes the following requirements. First, it must be end-to-end automated such that there is minimal prompt engineering required to incorporate new benchmarks. Secondly, it must provide estimates that are effective for UtiliMax at a fraction of the cost of ablations.

Table 2: Mean rank across all methods and all evaluation tasks at our largest compute scale (3×10^{21}) and averaged across all compute scales. Best rank in **bold** and the second best rank marked with *.

Mixing Method	Mean 3×10^{21} Rank		Mean Rank Across All Scales	
	Compute Constrained	Data Constrained	Compute Constrained	Data Constrained
Uniform	6.5	10.5	5.93	10.15
Proportional	10.4	5.6	8.88	5.88
OLMo	9.5	5.4	9.03	4.92
UniMax	3.8*	3.7*	4.68*	4.32*
DoReMi Uniform	10.3	15.	10.62	14.88
DoReMi Proportional	13.7	10.2	13.43	9.65
DoReMi OLMo	12.2	9.1	12.62	8.98
ODM Github	8.4	8.5	8.7	7.88
ODM Paper	5.1	10.	5.7	10.03
Ablation Softmax	4.	10.8	4.8	11.95
MEDU Softmax	9.2	12.2	9.03	12.22
Ablation Greedy	8.2	6.7	7.75	5.92
MEDU Greedy	11.2	4.4	9.12	5
Ablation UtiliMax	4.1	5.	4.37	4.35
MEDU UtiliMax	3.4	2.9	5.33	3.87

To achieve our first goal, we prompt an LLM to describe a benchmark based on the examples from the development set, then to describe the skills and knowledge required, and finally to describe documents that are likely to contain this content. In Figure 5, we refer to this as "benchmark description".

However, many LLMs cannot fit more than a few examples at a time in their context window which could lead to sampling bias in descriptions. Therefore, we utilize hierarchical merging as proposed in Chang et al. (2024). First, we generate many descriptions based on separate batches of examples.

Then, we prompt the LLM to synthesize a new description from pairs of existing descriptions until only a single description remains. In Figure 5, we describe this as "description merging".

To achieve our second goal, we use the generated description to prompt an LLM to classify which of the following utility classes best describes an individual training documents utility for the benchmark: Great, Good, Okay, Poor, or Useless. For long documents, we take a random chunk of the document using the sampling algorithm from Rae et al. (2021, A.1.2). We map these classifications to numerical values 1, 0.75, 0.5, 0.25, 0 respectively. We call this "utility prediction" in Figure 5.

We utilize Llama 3 70B as the LLM for MEDU and classify relevance for a fixed random sample of documents. In practice, we find 256 documents from each corpus is effective⁵. At the upper-bound, where each classification uses the full context length, this process requires 2.1 Million tokens. This reduces computation from 6×10^{19} FLOPs to 3×10^{17} FLOPs for MEDU, a 200x reduction.

6.2 RESULTS

Our comparison of UniMax, Ablation-Based UtiliMax, and MEDU-Based UtiliMax in Figure 4 shows that MEDU does not significantly change results: UtiliMax outperforms UniMax using either MEDU or ablations⁶. The largest regressions from MEDU are for MMLU and ARC Challenge, both multiple choice tasks. Furthermore, in data-constrained settings, using MEDU improves results on average at the largest scale compared to running ablations.

In Table 2, we show that across *all* methods both UtiliMax approaches achieve the best mean ranks, both in the largest scales and across all scales. Given that MEDU is much cheaper to compute, combining MEDU with UtiliMax is a pareto-optimal data mixing approach.

⁵In A.4, we study the variance of MEDU and sensitivity to random sampling and to LLM choice with Llama 8B, 405B, Claude Sonnet 3.5, and GPT-4o

⁶In A.3, we repeat the UtiliMax ablations from Figure 3 and reconfirm each term is essential.

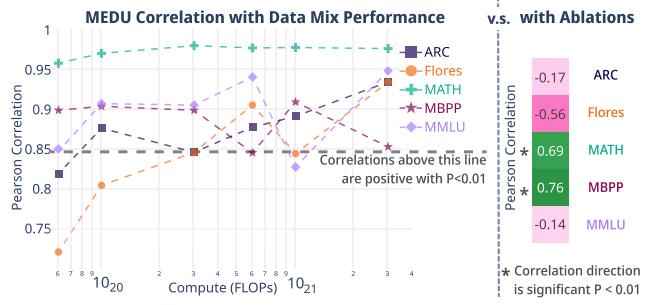


Figure 6: (left) Correlation between true performance and MEDU for all static baseline data mixes from Section 4.1. (right) Correlation between MEDU and ablation estimates. Correlation is positive for MATH and MBPP, with no other significant correlation in either direction ($P > 0.05$).

In Figure 6, we assess MEDU as a proxy for ablation results intrinsically through correlations. While the Pearson correlation between MEDU and individual dataset ablations are inconclusive, with correlations from only two out of five tasks excluding the null hypothesis⁷, correlations between MEDU and the ground-truth performance of a data mix are consistently positive.

We use our baseline methods from Section 4.1 as the sample population and compute the Pearson Correlation between the weighted average of MEDU scores based on the data mix weights w and the actual results. MEDU has consistently strong positive correlation (22/30 $P < 0.01$, 30/30 $P < 0.05$) with ground truth performance in these full mix ablations.

7 CONCLUSION

We highlight four takewaways from this work, both broadly for experiments on data mixing methods and for the methods we propose: UtiliMax and MEDU.

- *Effective data mixing requires balancing utility, diversity, and scale.* While token-heuristic methods focus on diversity and scale, learned data mixing approaches focus primarily on data utility. UtiliMax succeeds largely because the optimization procedure it leverages considers all three factors, allowing to produce effective data mixes in a pareto-optimal fashion when combined with MEDU. Future work should consider improving the measures of each of these factors, such as Σ derived from multiple proxy models as in Thrush et al. (2024) with principled covariance estimators (Ledoit & Wolf, 2017). As our understanding of the utility of data increases, we see the potential of UtiliMax to serve as a principled approach for converting any utility estimate into a data mix to help train better LLMs faster.
- *Scalable text analysis from LLMs can improve LLMs themselves.* Across disciplines (Dubois et al., 2023; Ziems et al., 2024; Demszky et al., 2023; Guha et al., 2024), LLM-based data analysis is becoming a common approach to scale “qualitative” data analysis into quantifiable metrics. Although these likely contain measurement error and variance (Messeri & Crockett, 2024), as with all metrics, we show that they can be combined with principled approaches which account for this to improve the models themselves.
- *Data mixing experiments must consider intended token-budget.* At small token budgets, some data mixes, such as uniform sampling, are very effective. However, only some of these approaches generalize to data mixes at higher budgets. Similar is true in reverse, with some methods which are weak at small-scales performing well at larger budgets. For data mixing methods to deliver predictable value, they must be tested under varied constraints.
- *An extremely simple baseline, UniMax, outperforms subsequent data mixing work.* This result is consistent across settings. UniMax even performs on par with UtiliMax for multiple benchmarks which makes it a good baseline comparison candidate for those introducing new methods.

⁷In A.5, we show that this is likely driven by MEDU making comparatively sparse utility estimations.

REFERENCES

- Alon Albalak, Liangming Pan, Colin Raffel, and William Yang Wang. Efficient Online Data Mixing for Language Model Pre-Training. In *R0-FoMo: Robustness of Few-shot and Zero-shot Learning in Large Foundation Models*, 2023.
- Alon Albalak, Yanai Elazar, Sang Michael Xie, Shayne Longpre, Nathan Lambert, Xinyi Wang, Niklas Muennighoff, Bairu Hou, Liangming Pan, Haewon Jeong, Colin Raffel, Shiyu Chang, Tatsunori Hashimoto, and William Yang Wang. A Survey on Data Selection for Language Models, 2024. URL <https://arxiv.org/abs/2402.16827>.
- Peter Auer, Nicolò Cesa-Bianchi, and Paul Fischer. Finite-Time Analysis of the Multiarmed Bandit Problem. *Mach. Learn.*, 47(2–3):235–256, may 2002. ISSN 0885-6125. doi: 10.1023/A:1013689704352. URL <https://doi.org/10.1023/A:1013689704352>.
- Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.
- Damian Blasi, Antonios Anastasopoulos, and Graham Neubig. Systematic inequalities in language technology performance across the world’s languages. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 5486–5505, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.376. URL <https://aclanthology.org/2022.acl-long.376>.
- Stephen Boyd and Lieven Vandenberghe. *Convex Optimization*. Cambridge university press, 2004.
- Stephen Boyd, Kasper Johansson, Ronald Kahn, Philipp Schiele, and Thomas Schmelzer. Markowitz Portfolio Construction at Seventy. *arXiv preprint arXiv:2401.05080*, 2024.
- Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners, 2020. URL <https://arxiv.org/abs/2005.14165>.
- Yapei Chang, Kyle Lo, Tanya Goyal, and Mohit Iyyer. BoookScore: A Systematic Exploration of Book-Length Summarization in the Era of LLMs. In *The Twelfth International Conference on Learning Representations*, 2024.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating Large Language Models Trained on Code. *arXiv preprint arXiv:2107.03374*, 2021.
- Hyung Won Chung, Xavier Garcia, Adam Roberts, Yi Tay, Orhan Firat, Sharan Narang, and Noah Constant. UniMax: Fairer and More Effective Language Sampling for Large-Scale Multilingual Pretraining. In *The Eleventh International Conference on Learning Representations*, 2023. URL <https://openreview.net/forum?id=kXwdL1cWOAi>.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think You Have Solved Question Answering? Try ARC, the AI2 Reasoning Challenge. *arXiv preprint arXiv:1803.05457*, 2018.
- Victor DeMiguel, Lorenzo Garlappi, and Raman Uppal. Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy? *The review of Financial studies*, 22(5):1915–1953, 2009.
- Dorottya Demszky, Diyi Yang, David S Yeager, Christopher J Bryan, Margaret Clapper, Susannah Chandhok, Johannes C Eichstaedt, Cameron Hecht, Jeremy Jamieson, Meghann Johnson, et al. Using Large Language Models in Psychology. *Nature Reviews Psychology*, 2(11):688–701, 2023.

Steven Diamond and Stephen Boyd. CVXPY: A Python-Embedded Modeling Language for Convex Optimization. *Journal of Machine Learning Research*, 17(83):1–5, 2016.

Nan Du, Yanping Huang, Andrew M Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, et al. GLaM: Efficient Scaling of Language Models with Mixture-of-Experts. In *International Conference on Machine Learning*, pp. 5547–5569. PMLR, 2022.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mihadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasudevan Alwala, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Lauren Rantala-Yeary, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin Kardas, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Raparthi, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaoqing Ellen Tan, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aaron Grattafiori, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alex Vaughan, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Franco, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, Danny Wyatt, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Firat Ozgenel, Francesco

Caggioni, Francisco Guzmán, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Govind Thattai, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Karthik Prasad, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kun Huang, Kunal Chawla, Kushal Lakhota, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manav Avalani, Manish Bhatt, Maria Tsimpoukelli, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keaneally, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikolay Pavlovich Laptev, Ning Dong, Ning Zhang, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghatham Murthy, Raghu Nayani, Rahul Mitra, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Rohan Maheswari, Russ Howes, Ruty Rinott, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Sadru Pan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Kohler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vítor Albiero, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaofang Wang, Xiaojian Wu, Xiaolan Wang, Xide Xia, Xilun Wu, Xinbo Gao, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yuchen Hao, Yundi Qian, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, and Zhiwei Zhao. The Llama 3 Herd of Models. *arXiv preprint arXiv:2407.21783*, 2024. URL <https://arxiv.org/abs/2407.21783>.

Yann Dubois, Chen Xuechen Li, Rohan Taori, Tianyi Zhang, Ishaan Gulrajani, Jimmy Ba, Carlos Guestrin, Percy S Liang, and Tatsunori B Hashimoto. AlpacaFarm: A Simulation Framework for Methods that Learn from Human Feedback. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine (eds.), *Advances in Neural Information Processing Systems*, volume 36, pp. 30039–30069. Curran Associates, Inc., 2023. URL https://proceedings.neurips.cc/paper_files/paper/2023/file/5fc47800ee5b30b877fdd30abcaaf3b-Paper-Conference.pdf.

Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock. GPTs are GPTs: Labor Market Impact Potential of LLMs. *Science*, 384(6702):1306–1308, 2024.

Leo Gao, Stella Biderman, Sid Black, Laurence Golding, Travis Hoppe, Charles Foster, Jason Phang, Horace He, Anish Thite, Noa Nabeshima, et al. The Pile: An 800gb Dataset of Diverse Text for Language Modeling. *arXiv preprint arXiv:2101.00027*, 2020.

Naman Goyal, Cynthia Gao, Vishrav Chaudhary, Peng-Jen Chen, Guillaume Wenzek, Da Ju, Sanjana Krishnan, Marc’Aurelio Ranzato, Francisco Guzmán, and Angela Fan. The FLoRes-101 Evaluation Benchmark for Low-Resource and Multilingual Machine Translation. *Transactions of the Association for Computational Linguistics*, 10:522–538, 2022.

Sachin Goyal, Pratyush Maini, Zachary C Lipton, Aditi Raghunathan, and J Zico Kolter. Scaling Laws for Data Filtering—Data Curation Cannot be Compute Agnostic. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22702–22711, 2024.

Dirk Groeneveld, Iz Beltagy, Evan Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, Shane Arora, David Atkinson, Russell Arthur, Khyathi Chandu, Arman Cohan, Jennifer Dumas, Yanai Elazar, Yuling Gu, Jack Hessel, Tushar Khot, William Merrill, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew Peters, Valentina Pyatkin, Abhilasha Ravichander, Dustin Schwenk, Saurabh Shah, William Smith, Emma Strubell, Nishant Subramani, Mitchell Wortsman, Pradeep Dasigi, Nathan Lambert, Kyle Richardson, Luke Zettlemoyer, Jesse Dodge, Kyle Lo, Luca Soldaini, Noah Smith, and Hannaneh Hajishirzi. OLMo: Accelerating the Science of Language Models. In Lun-Wei Ku, Andre Martins, and Vivek Srikanth (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 15789–15809, Bangkok, Thailand, August 2024. Association for Computational Linguistics. URL <https://aclanthology.org/2024.acl-long.841>.

Neel Guha, Julian Nyarko, Daniel Ho, Christopher Ré, Adam Chilton, Alex Chohlas-Wood, Austin Peters, Brandon Waldon, Daniel Rockmore, Diego Zambrano, et al. LegalBench: A Collaboratively Built Benchmark for Measuring Legal Reasoning in Large Language Models. *Advances in Neural Information Processing Systems*, 36, 2024.

Kenneth Heafield. KenLM: Faster and Smaller Language Model Queries. In Chris Callison-Burch, Philipp Koehn, Christof Monz, and Omar F. Zaidan (eds.), *Proceedings of the Sixth Workshop on Statistical Machine Translation*, pp. 187–197, Edinburgh, Scotland, July 2011. Association for Computational Linguistics. URL <https://aclanthology.org/W11-2123>.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2021a.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring Mathematical Problem Solving With the MATH Dataset. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*, 2021b. URL <https://openreview.net/forum?id=7Bywt2mQsCe>.

Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. In *Proceedings of the 36th International Conference on Neural Information Processing Systems*, pp. 30016–30030, 2022.

Julia Kreutzer, David Vilar, and Artem Sokolov. Bandits don't follow rules: Balancing multi-facet machine translation with multi-armed bandits. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2021*, pp. 3190–3204, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.274. URL <https://aclanthology.org/2021.findings-emnlp.274>.

Hugo Laurençon, Lucile Saulnier, Thomas Wang, Christopher Akiki, Albert Villanova del Moral, Teven Le Scao, Leandro Von Werra, Chenghao Mou, Eduardo González Ponferrada, Huu Nguyen, et al. The BigScience Roots Corpus: A 1.6 TB Composite Multilingual Dataset. *Advances in Neural Information Processing Systems*, 35:31809–31826, 2022.

Olivier Ledoit and Michael Wolf. Nonlinear Shrinkage of the Covariance Matrix for Portfolio Selection: Markowitz meets Goldilocks. *The Review of Financial Studies*, 30(12):4349–4388, 2017.

Shayne Longpre, Robert Mahari, Ariel Lee, Campbell Lund, Hamidah Oderinwale, William Bran-non, Nayan Saxena, Naana Obeng-Marnu, Tobin South, Cole Hunter, et al. Consent in Crisis: The Rapid Decline of the AI Data Commons. *arXiv preprint arXiv:2407.14933*, 2024.

Harry Markowitz. Portfolio selection. *The Journal of Finance*, 7(1):77–91, 1952. ISSN 00221082, 15406261. URL <http://www.jstor.org/stable/2975974>.

-
- Lisa Messeri and MJ Crockett. Artificial intelligence and illusions of understanding in scientific research. *Nature*, 627(8002):49–58, 2024.
- Paul Michel, Sebastian Ruder, and Dani Yogatama. Balancing Average and Worst-case Accuracy in Multitask Learning. *arXiv preprint arXiv:2110.05838*, 2021.
- Niklas Muennighoff, Alexander Rush, Boaz Barak, Teven Le Scao, Nouamane Tazi, Aleksandra Piktus, Sampo Pyysalo, Thomas Wolf, and Colin A Raffel. Scaling Data-Constrained Language Models. *Advances in Neural Information Processing Systems*, 36, 2024.
- Brendan O’Donoghue. Operator splitting for a homogeneous embedding of the linear complementarity problem. *SIAM Journal on Optimization*, 31:1999–2023, August 2021.
- Brendan O’Donoghue, Eric Chu, Neal Parikh, and Stephen Boyd. Conic optimization via operator splitting and homogeneous self-dual embedding. *Journal of Optimization Theory and Applications*, 169(3):1042–1068, June 2016. URL <http://stanford.edu/~boyd/papers/scs.html>.
- Guilherme Penedo, Hynek Kydlíček, Loubna Ben allal, Anton Lozhkov, Margaret Mitchell, Colin Raffel, Leandro Von Werra, and Thomas Wolf. The FineWeb Datasets: Decanting the Web for the Finest Text Data at Scale, 2024. URL <https://arxiv.org/abs/2406.17557>.
- Chengwei Qin, Aston Zhang, Zhuosheng Zhang, Jiaao Chen, Michihiro Yasunaga, and Diyi Yang. Is ChatGPT a General-Purpose Natural Language Processing Task Solver? In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 1339–1384, 2023.
- Jack W Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, et al. Scaling Language Models: Methods, Analysis & Insights from Training Gopher. *arXiv preprint arXiv:2112.11446*, 2021.
- David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. GPQA: A Graduate-level Google-Proof Q&A Benchmark. *arXiv preprint arXiv:2311.12022*, 2023.
- Yangjun Ruan, Chris J Maddison, and Tatsunori Hashimoto. Observational Scaling Laws and the Predictability of Language Model Performance. *arXiv preprint arXiv:2405.10938*, 2024.
- Shiori Sagawa, Pang Wei Koh, Tatsunori B. Hashimoto, and Percy Liang. Distributionally Robust Neural Networks. In *International Conference on Learning Representations*, 2020. URL <https://openreview.net/forum?id=ryxGuJrFvS>.
- Rylan Schaeffer, Brando Miranda, and Sanmi Koyejo. Are Emergent Abilities of Large Language Models a Mirage? *Advances in Neural Information Processing Systems*, 36, 2024a.
- Rylan Schaeffer, Hailey Schoelkopf, Brando Miranda, Gabriel Mukobi, Varun Madan, Adam Ibrahim, Herbie Bradley, Stella Biderman, and Sanmi Koyejo. Why Has Predicting Downstream Capabilities of Frontier AI Models with Scale Remained Elusive? *arXiv preprint arXiv:2406.04391*, 2024b.
- Andrea Schioppa, Xavier Garcia, and Orhan Firat. Cross-Lingual Supervision Improves Large Language Models Pre-Training. *arXiv preprint arXiv:2305.11778*, 2023.
- Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Arthur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Jha, Sachin Kumar, Li Lucy, Xinxi Lyu, Nathan Lambert, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew Peters, Abhilasha Ravichander, Kyle Richardson, Zejiang Shen, Emma Strubell, Nishant Subramani, Oyvind Tafjord, Evan Walsh, Luke Zettlemoyer, Noah Smith, Hannaneh Hajishirzi, Iz Beltagy, Dirk Groeneveld, Jesse Dodge, and Kyle Lo. Dolma: an Open Corpus of Three Trillion Tokens for Language Model Pretraining Research. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 15725–15788, Bangkok, Thailand, August 2024. Association for Computational Linguistics. URL <https://aclanthology.org/2024.acl-long.840>.

-
- Tristan Thrush, Christopher Potts, and Tatsunori Hashimoto. Improving Pretraining Data Using Perplexity Correlations. *arXiv preprint arXiv:2409.05816*, 2024.
- TogetherAI. Redpajama-data-1t, 2023. URL <https://huggingface.co/datasets/togethercomputer/RedPajama-Data-1T>.
- Pablo Villalobos, Anson Ho, Jaime Sevilla, Tamay Besiroglu, Lennart Heim, and Marius Hobbahn. Will We Run Out of Data? Limits of LLM Scaling Based on Human-Generated Data. In *Forty-first International Conference on Machine Learning*, 2024.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. Emergent Abilities of Large Language Models. *Transactions on Machine Learning Research*, 2022.
- Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. CCNet: Extracting High Quality Monolingual Datasets from Web Crawl Data. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 4003–4012, Marseille, France, May 2020. European Language Resources Association. ISBN 979-10-95546-34-4. URL <https://aclanthology.org/2020.lrec-1.494>.
- Alexander Wettig, Aatmik Gupta, Saumya Malik, and Danqi Chen. QuRating: Selecting High-Quality Data for Training Language Models, 2024. URL <https://arxiv.org/abs/2402.09739>.
- Sang Michael Xie, Hieu Pham, Xuanyi Dong, Nan Du, Hanxiao Liu, Yifeng Lu, Percy S Liang, Quoc V Le, Tengyu Ma, and Adams Wei Yu. DoReMi: Optimizing Data Mixtures Speeds Up Language Model Pretraining. *Advances in Neural Information Processing Systems*, 36, 2024.
- Caleb Ziems, William Held, Omar Shaikh, Jiaao Chen, Zhehao Zhang, and Diyi Yang. Can Large Language Models Transform Computational Social Science? *Computational Linguistics*, 50(1): 237–291, March 2024. doi: 10.1162/coli_a_00502. URL <https://aclanthology.org/2024.c1-1.8>.

A APPENDIX

A.1 CONTRIBUTIONS

Will and Todor were the project leads for this work. Todor scoped the project, conceptualized MEDU, and oversaw the project from start to finish. Will made MEDU concrete, conceptualized UtiliMax, and ran all experiments presented in this work. Bhargavi, Mike, and Frank all contributed core ideas resulting in the UtiliMax algorithm. Bhargavi debugged and refined early UtiliMax implementations. Frank led efforts which identified and defined the evaluation methodology for scaling experiments. Punit implemented the simulated epoching sub-sampler to enable data-constrained experiments. All authors contributed to writing and refining the paper.

A.2 ACKNOWLEDGEMENTS

This work was made possible by the collective expertise of the entire Llama team at Meta AI, especially the Pretraining Data team. Additionally, experiments would not have been possible without the Meta ML infrastructure teams which made running large-scale training runs and Llama inference jobs a smooth process.

We are grateful to Sang Michael Xie and Alon Albalak for their helpful discussion of details on their related works. Furthermore, we would like to thank Kushal Tirumala, Niladri Chatterji, Tristan Thrush, and Mirac Suzgun for conversations and comments which improved this work.

A.3 OPTIMIZER ABLATIONS ON RELEVANCE SCORES

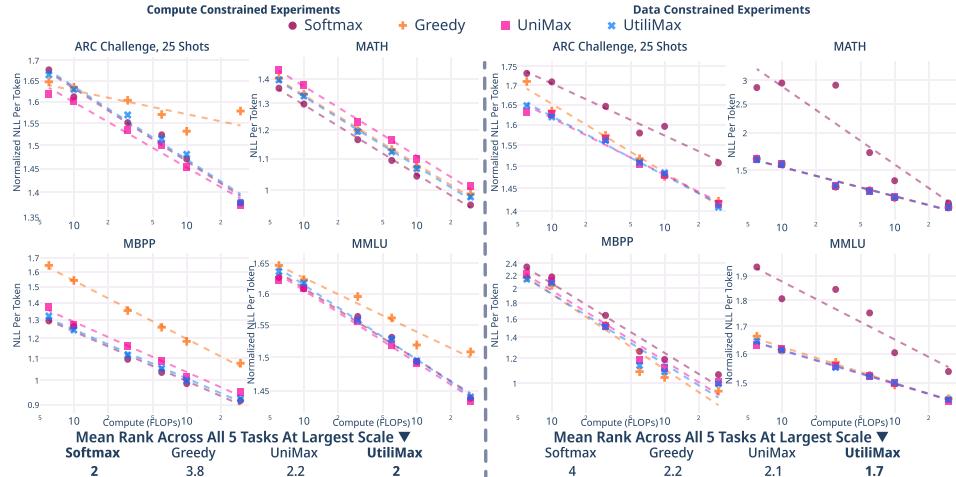


Figure 7: Scaling curves across utility optimization methods for MEDU. The model with the top average rank for ARC, MBPP, MATH, MMLU, and FloRes at 3×10^{21} FLOPs is in **bold**. UniMax outperforms greedy optimization when compute-constrained, but UtiliMax performs best in both settings, re-validating the results in Figure 3

A.4 MEDU VARIANCE AND SENSITIVITY ANALYSIS

A.4.1 VARIANCE INDUCED BY RANDOM SAMPLING

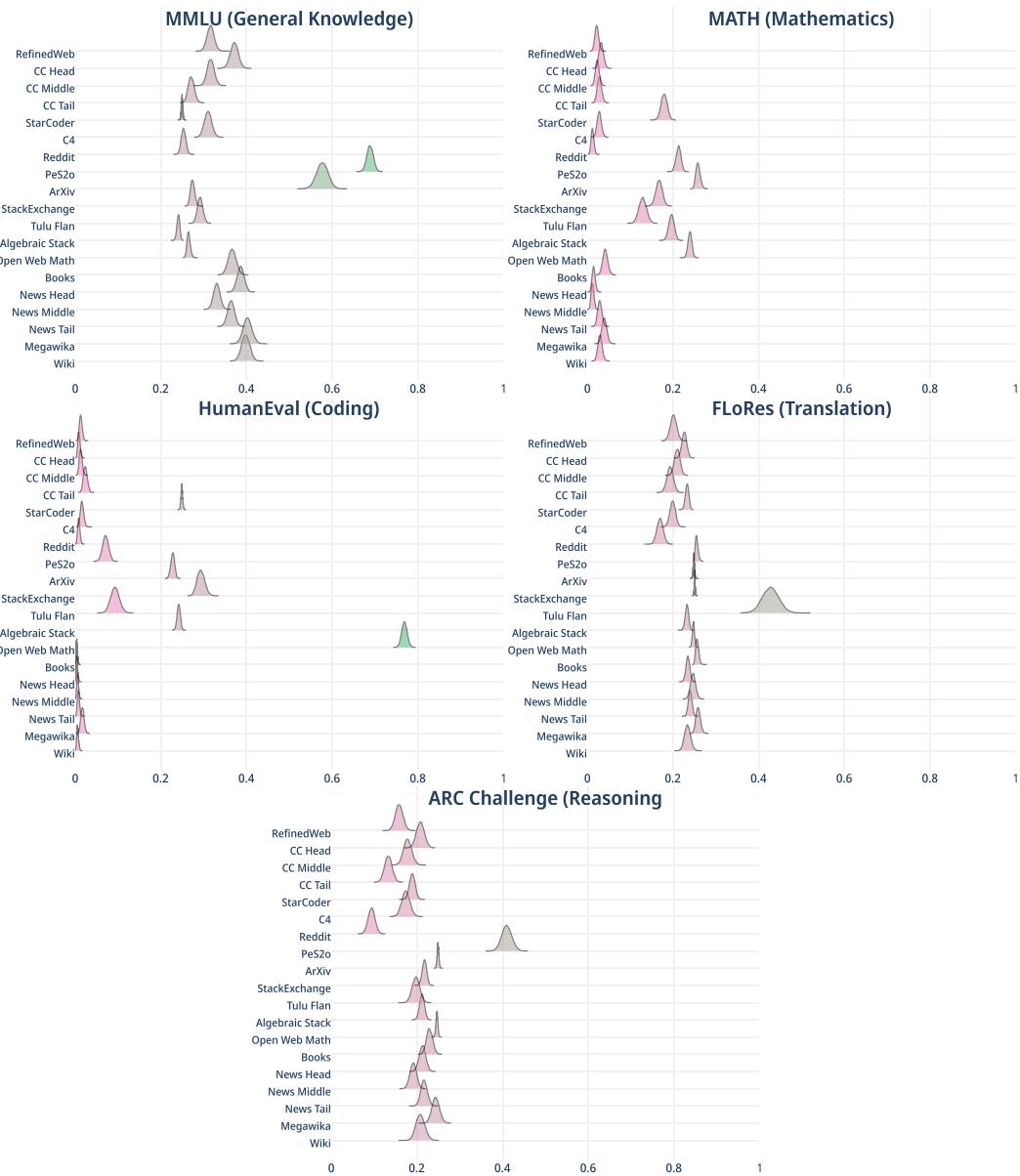


Figure 8: Distribution of MEDU Scores for a sample of 256 documents using the Llama 70B model. To compute these distributions, we run MEDU on a sample of 1024 documents, then recompute the mean 10,000 times using bootstrap sampling. At 256 examples, the distributions are tight enough that larger sample size would minimally impact the data mixes produced by UtiliMax.

A.4.2 VARIANCE ACROSS MODEL CHOICES

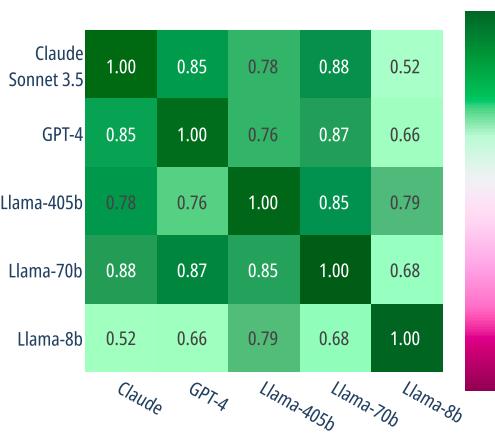


Figure 9: Pearson correlations of model-estimated data utility using different language models and different samples of data. In general, except for the 8B Llama model, we see strong correlation (> 0.75) across tested models.

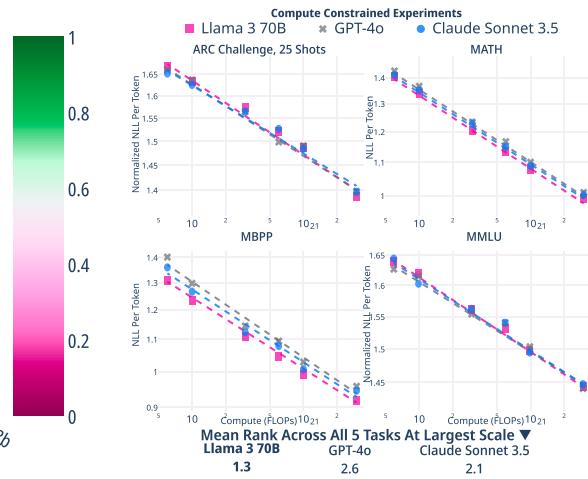


Figure 10: Scaling curves across different classifier models methods for MEDU. Results are extremely similar across models suggesting that there is not a significant amount of bias injected by a specific LLM.

For the core experiments in the paper, we utilize the Llama 3.1 70B model. This scale was selected as it offers strong performance, but can still be run on a single node for inference. Furthermore, since it is open-access it makes it easier to reproduce our results, while API models are subject to break reproducibility with version changes.

However, in order to assess how sensitive MEDU may be to the selection of an underlying language model we did further analysis on several different language models. First, we assess the effects of scale comparing Llama 3.1 8B, 70B, and 405B. Then, we assess the variance across frontier model families by comparing Llama, GPT, and Claude models.

For each model, we use the same prompts provided in Appendix A.6. This means that each model is used for the entire process, including generating benchmark descriptions which are then used for utility classification.

In Figure 9, we visualize the Pearson correlations between utility-scores estimated using each model. Overall, the correlation is strong (> 0.75) for all models, except for Llama 3.1 8B. This suggests that, even with different models, MEDU tends to capture similar signal from the underlying data. While this signal may not be optimal, this consistency is important as it suggests that methods built on top of model-estimated data utility are unlikely to see significant shifts due to model selection, at least within the current generation of frontier models.

To add further evidence to this, in Figure 10, we run full experiments of MEDU UtiliMax with Claude Sonnet 3.5 and GPT-4o. Since our experiments showed that data mixing methods have the largest impact in compute constrained settings, we run this set of experiments only in that setting. Overall, we see that the performance of MEDU UtiliMax is robust to model selection, with Llama 3.1 70B performing the best by a small margin overall but very little variance in downstream performance in any individual task.

A.5 COMPARING MEDU AND ABLATION-BASED UTILITY ESTIMATES

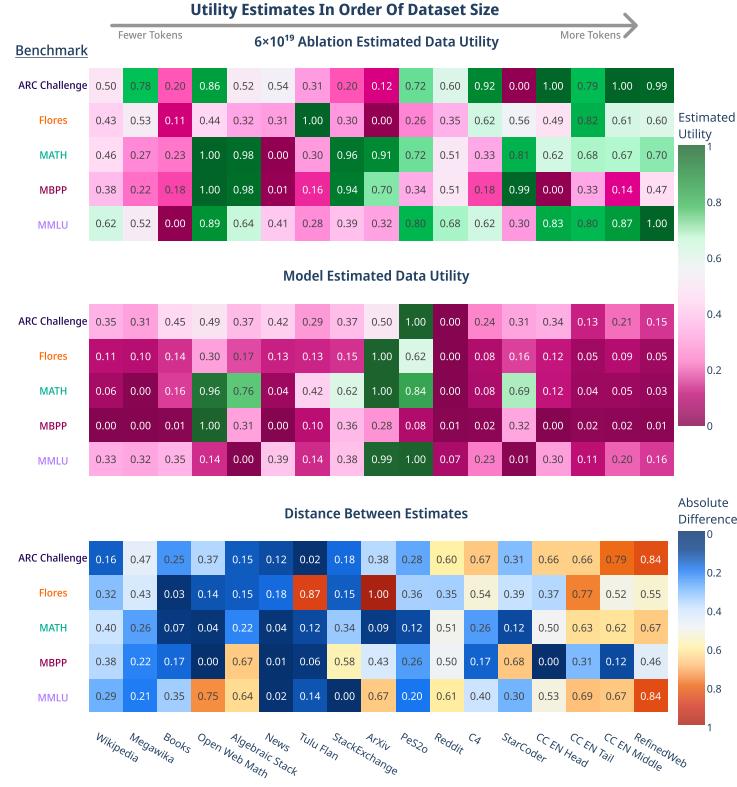


Figure 11: Heatmaps of utility scores across the two methods, with increasingly large datasets placed to the right. While ablations provide a set of estimates closer to a normal distribution, MEDU assigns high utility to just a few outliers for each task, with the rest of values skewing below the mean. MEDU also seems to systematically give lower scores to large web-corpora.

A.6 PROMPTS

A.6.1 BENCHMARK DESCRIPTION

```
f """
{corpus}
Help me decide the types of training data to look for to train a
language model for an evaluation with data similar to the
above.
You should keep the description brief and it is okay to generalize
or abstract specific details to do so.
Give your answer in three sections, first write what type of test
this might be from, then write out the languages, skills and
knowledge the language model would need, and finally write a
description of the ideal training data for the evaluation.
"""
```

A.6.2 DESCRIPTION MERGING

```
f """
<BEGIN CORPUS DESCRIPTION A>
{description_a}
<END CORPUS DESCRIPTION A>
<BEGIN CORPUS DESCRIPTION B>
```

```
{description_b}
<END CORPUS DESCRIPTION B>
{comparison}
The above analyses were written about a NLP evaluation used for
Large Language Models by two different people based on equally
sized random samples of examples from the evaluation.
Help me synthesize them into a more complete analyses based on
both of them. You should keep the description brief and it is
okay to generalize or abstract specific details to do so.
Give your answer in three sections, first write what type of test
this might be from, then write out the languages, skills and
knowledge the language model would need, and finally write a
description of the ideal training data for the evaluation.
"""

```

A.6.3 UTILITY CLASSIFICATION

```
f """
The following document is being considered as training data for a
Large Language Model.

Provide a concise description of the document and an assessment of
the quality of the text or code in the document.
```

Key Attributes to Mention

- Languages contained in the document
- The coherence of the document
- The skills the document demonstrates
- The topics the document contains facts and information about

```
Document{prompt_addition}:
"""
{example}
"""
```

Based on your previous reasoning, give me a concrete decision about the utility of the document as training data for the following benchmark. If a benchmark is Multilingual, you should assume a high-degree of importance is placed on high-quality content in languages other than English.

```
{test_description}

Output your decision about the utility of the data as one of the
following single words Great/Good/Okay/Poor/Useless without
formatting.==

"""

```

A.7 DATA SHUFFLING, SAMPLING, AND PACKING

Consider a data mix containing a list of datasets D_i with their associated weights w_i , where $i \in \{1..n\}$. We assume here that the weights w_i have been normalized to 1. Additionally, let us suppose that the overall batch size is B and sequence length is S . Therefore, in each step, we need to sample B sequences, each of length S tokens, from the different datasets D_i .

In the beginning of training, we initialize a dataset iterator for each dataset D_i , denoted as $\text{Iter}(D_i)$, which is responsible for packing together S tokens from dataset D_i into a dense sequence. A seed $\text{seed}(\text{epoch})$ which is a function of the epoch count is specified to determine how the dataset is

shuffled. $\text{Iter}(D_i)$ will sample as many complete documents as necessary from D_i to fill in S tokens, keeping any remaining tokens in a buffer to be used in the next iteration.

The overall batch creation process for the next step can be summarized below

Algorithm 1 Batch creation process

```
1: Input: A list of dataset iterators  $\text{Iter}(D_i)$  along with their associated weights  $w_i$ .
2: Output: The next batch
3: weightsVector =  $[w_1, w_2 \dots w_n]$ 
   batch = []
4: for batchIndex in range(1 ..  $B$ ) do
5:   # Sample from a multinomial distribution based on weightsVector.
6:   chosenDatasetIndex = np.random.choice(len(weightsVector), p = weightsVector)
7:   sequence = next( $\text{Iter}(D_{\text{chosenDatasetIndex}})$ )
8:   batch.append(sequence)
9: end for
10: return batch
```

As we can see, each dataset can epoch at different times based on their own dataset weights and the number of tokens in the dataset. At the end of an epoch, we reinitialize $\text{Iter}(D_i)$ with a new $\text{seed}(epoch + 1)$ for the next epoch so that we get a shuffled view of the dataset.

A.8 FULL EXPERIMENTAL RESULTS

Table 3: NLL Metrics for each individual run without simulated epoching. NLL Per Token is used for MATH, HumanEval, Flores, and GPQA. Normalized NLL Per Token is used for ARC Challenge and MMLU, since they are Multiple-Choice Tasks. Best results in **bold**.

Training Run Setup		Downstream Evaluation				
Mixing Method	FLOPs	ARC	Flores	MATH	MBPP	MMLU
DoReMi OLMo	6×10^{19}	1.69	3.91	1.90	1.70	1.66
	1×10^{20}	1.64	3.81	1.82	1.57	1.64
	3×10^{20}	1.60	3.29	1.67	1.42	1.60
	6×10^{20}	1.57	2.91	1.60	1.29	1.57
	1×10^{21}	1.54	2.70	1.54	1.25	1.55
	3×10^{21}	1.47	2.37	1.43	1.12	1.51
DoReMi Prop.	6×10^{19}	1.67	4.00	1.91	1.80	1.65
	1×10^{20}	1.66	3.76	1.84	1.70	1.64
	3×10^{20}	1.62	3.21	1.68	1.47	1.60
	6×10^{20}	1.57	2.95	1.63	1.36	1.58
	1×10^{21}	1.56	2.74	1.54	1.28	1.55
	3×10^{21}	1.48	2.44	1.44	1.18	1.51
DoReMi Uniform	6×10^{19}	1.65	3.04	1.88	1.77	1.66
	1×10^{20}	1.65	2.93	1.78	1.67	1.66
	3×10^{20}	1.59	2.41	1.63	1.42	1.61
	6×10^{20}	1.54	2.18	1.56	1.38	1.57
	1×10^{21}	1.50	1.99	1.50	1.28	1.56
	3×10^{21}	1.45	1.73	1.39	1.17	1.51
ODM GitHub	6×10^{19}	1.65	3.86	1.54	1.53	1.64
	1×10^{20}	1.60	3.94	1.48	1.48	1.61
	3×10^{20}	1.55	3.26	1.34	1.26	1.56
	6×10^{20}	1.51	2.94	1.26	1.19	1.52
	1×10^{21}	1.46	2.59	1.20	1.12	1.50
	3×10^{21}	1.39	2.24	1.09	1.04	1.45
ODM Paper	6×10^{19}	1.64	3.86	1.44	1.37	1.63
	1×10^{20}	1.60	3.60	1.38	1.30	1.61
	3×10^{20}	1.54	3.19	1.24	1.16	1.55
	6×10^{20}	1.50	2.79	1.16	1.09	1.52
	1×10^{21}	1.45	2.50	1.10	1.04	1.50
	3×10^{21}	1.38	2.11	1.02	0.96	1.44
OLMo Sampling	6×10^{19}	1.65	4.32	1.65	1.52	1.63
	1×10^{20}	1.61	3.93	1.58	1.44	1.62
	3×10^{20}	1.54	3.23	1.45	1.24	1.56
	6×10^{20}	1.50	2.91	1.38	1.17	1.53
	1×10^{21}	1.47	2.76	1.31	1.10	1.49
	3×10^{21}	1.40	2.37	1.21	1.01	1.45
Greedy Ablation	6×10^{19}	1.64	4.56	1.46	1.35	1.62
	1×10^{20}	1.62	4.30	1.39	1.26	1.59
	3×10^{20}	1.55	3.56	1.26	1.14	1.55
	6×10^{20}	1.51	3.23	1.18	1.08	1.52
	1×10^{21}	1.48	2.98	1.12	1.03	1.49
	3×10^{21}	1.40	2.65	1.02	0.95	1.44

Table 4: (Cont.) NLL Metrics for each individual run without simulated epoching. NLL Per Token is used for MATH, HumanEval, Flores, and GPQA. Normalized NLL Per Token is used for ARC Challenge and MMLU, since they are Multiple-Choice Tasks. Best results in **bold**.

Training Run Setup		Downstream Evaluation				
Mixing Method	FLOPs	ARC	Flores	MATH	MBPP	MMLU
UtiliMax Ablation	6×10^{19}	1.62	3.76	1.41	1.33	1.63
	1×10^{20}	1.60	3.67	1.35	1.28	1.60
	3×10^{20}	1.56	2.94	1.21	1.11	1.54
	6×10^{20}	1.49	2.70	1.14	1.07	1.52
	1×10^{21}	1.46	2.58	1.08	1.03	1.49
	3×10^{21}	1.39	2.17	0.99	0.93	1.43
	6×10^{19}	1.71	4.86	1.21	1.09	1.66
Softmax Ablation	1×10^{20}	1.67	4.58	1.14	1.04	1.65
	3×10^{20}	1.63	3.81	1.03	0.96	1.59
	6×10^{20}	1.59	3.49	0.99	0.91	1.58
	1×10^{21}	1.54	3.29	0.95	0.87	1.55
	3×10^{21}	1.51	2.86	0.92	0.84	1.53
Proportional	6×10^{19}	1.62	4.30	1.68	1.58	1.62
	1×10^{20}	1.59	3.96	1.61	1.51	1.61
	3×10^{20}	1.54	3.33	1.48	1.30	1.56
	6×10^{20}	1.49	2.94	1.40	1.22	1.53
	1×10^{21}	1.45	2.73	1.35	1.18	1.49
	3×10^{21}	1.40	2.39	1.25	1.05	1.45
Greedy MEDU	6×10^{19}	1.65	3.75	1.40	1.64	1.65
	1×10^{20}	1.63	3.67	1.34	1.54	1.62
	3×10^{20}	1.60	3.08	1.20	1.35	1.60
	6×10^{20}	1.57	2.80	1.13	1.26	1.56
	1×10^{21}	1.53	2.53	1.07	1.18	1.52
	3×10^{21}	1.58	2.40	0.99	1.08	1.51
UtiliMax MEDU	6×10^{19}	1.66	3.82	1.40	1.32	1.64
	1×10^{20}	1.63	3.59	1.33	1.24	1.62
	3×10^{20}	1.57	3.08	1.19	1.12	1.56
	6×10^{20}	1.51	2.47	1.12	1.05	1.53
	1×10^{21}	1.48	2.57	1.07	1.00	1.49
	3×10^{21}	1.38	2.13	0.98	0.92	1.44
Softmax MEDU	6×10^{19}	1.68	3.81	1.36	1.29	1.63
	1×10^{20}	1.61	3.70	1.30	1.26	1.61
	3×10^{20}	1.55	3.06	1.16	1.10	1.56
	6×10^{20}	1.52	2.84	1.09	1.04	1.53
	1×10^{21}	1.47	2.49	1.04	0.99	1.49
	3×10^{21}	1.38	2.28	0.96	0.92	1.44
UniMax	6×10^{19}	1.62	3.86	1.44	1.38	1.62
	1×10^{20}	1.60	3.46	1.37	1.27	1.61
	3×10^{20}	1.54	3.03	1.23	1.16	1.56
	6×10^{20}	1.50	2.61	1.16	1.09	1.52
	1×10^{21}	1.45	2.52	1.10	1.02	1.49
	3×10^{21}	1.37	2.07	1.01	0.95	1.44
Uniform	6×10^{19}	1.63	3.87	1.44	1.37	1.63
	1×10^{20}	1.59	3.72	1.37	1.33	1.60
	3×10^{20}	1.55	3.05	1.25	1.16	1.55
	6×10^{20}	1.49	2.73	1.17	1.10	1.52
	1×10^{21}	1.45	2.56	1.11	1.03	1.50
	3×10^{21}	1.39	2.19	1.02	0.97	1.44

Table 5: NLL Metrics for each individual run with simulated epoching. NLL Per Token is used for MATH, HumanEval, Flores, and GPQA. Normalized NLL Per Token is used for ARC Challenge and MMLU, since they are Multiple-Choice Tasks. Best results in **bold**.

Training Run Setup		Downstream Evaluation				
Mixing Method	FLOPs	ARC	Flores	MATH	MBPP	MMLU
DoReMi OLMo	6×10^{19}	1.69	4.24	1.97	2.75	1.67
	1×10^{20}	1.68	3.91	1.89	2.72	1.64
	3×10^{20}	1.59	3.38	1.72	2.07	1.60
	6×10^{20}	1.56	2.93	1.62	1.42	1.57
	1×10^{21}	1.55	2.83	1.57	1.32	1.55
	3×10^{21}	1.48	2.48	1.46	1.19	1.51
DoReMi Proportional	6×10^{19}	1.72	4.16	1.99	2.84	1.68
	1×10^{20}	1.68	3.86	1.92	2.69	1.66
	3×10^{20}	1.61	3.42	1.72	2.08	1.60
	6×10^{20}	1.57	2.95	1.64	1.40	1.58
	1×10^{21}	1.56	2.81	1.57	1.34	1.56
	3×10^{21}	1.48	2.54	1.47	1.20	1.51
DoReMi Uniform	6×10^{19}	2.38	7.77	3.61	6.88	1.90
	1×10^{20}	2.32	8.35	3.37	7.00	1.92
	3×10^{20}	2.18	7.04	2.89	5.82	1.86
	6×10^{20}	2.07	6.96	2.72	4.69	1.84
	1×10^{21}	1.99	6.46	2.59	4.40	1.81
	3×10^{21}	1.96	6.02	2.42	3.74	1.77
ODM GitHub	6×10^{19}	1.66	4.84	1.62	2.41	1.66
	1×10^{20}	1.64	4.51	1.56	2.29	1.64
	3×10^{20}	1.57	3.93	1.32	1.69	1.60
	6×10^{20}	1.55	3.44	1.28	1.34	1.56
	1×10^{21}	1.51	3.32	1.22	1.24	1.52
	3×10^{21}	1.44	2.84	1.14	1.11	1.47
ODM Paper	6×10^{19}	1.72	5.23	1.68	2.35	1.72
	1×10^{20}	1.72	4.93	1.60	2.17	1.69
	3×10^{20}	1.61	4.30	1.37	1.63	1.65
	6×10^{20}	1.58	3.79	1.35	1.27	1.62
	1×10^{21}	1.55	3.63	1.28	1.21	1.59
	3×10^{21}	1.48	3.01	1.16	1.08	1.53
OLMo Sampling	6×10^{19}	1.65	4.78	1.69	2.26	1.63
	1×10^{20}	1.60	4.33	1.62	2.18	1.60
	3×10^{20}	1.55	3.66	1.40	1.62	1.55
	6×10^{20}	1.51	3.14	1.34	1.17	1.51
	1×10^{21}	1.46	2.98	1.29	1.12	1.50
	3×10^{21}	1.40	2.55	1.18	1.02	1.45
Greedy Ablation	6×10^{19}	1.65	4.69	1.68	2.15	1.64
	1×10^{20}	1.64	4.44	1.62	2.06	1.62
	3×10^{20}	1.58	3.63	1.48	1.58	1.56
	6×10^{20}	1.53	3.15	1.40	1.12	1.53
	1×10^{21}	1.49	2.95	1.33	1.10	1.50
	3×10^{21}	1.43	2.56	1.21	0.99	1.47
UtiliMax Ablation	6×10^{19}	1.65	4.91	1.63	2.27	1.63
	1×10^{20}	1.62	4.42	1.57	2.11	1.62
	3×10^{20}	1.55	3.70	1.32	1.55	1.55
	6×10^{20}	1.50	3.20	1.27	1.17	1.53
	1×10^{21}	1.47	3.01	1.21	1.11	1.49
	3×10^{21}	1.42	2.57	1.13	1.01	1.45

Table 6: (Cont.) NLL Metrics for each individual run with simulated epoching. NLL Per Token is used for MATH, MBPP, Flores. Normalized NLL Per Token is used for ARC Challenge and MMLU, since they are Multiple-Choice Tasks. Best results in **bold**.

Training Run Setup		Downstream Evaluation				
Mixing Method	FLOPs	ARC	Flores	MATH	MBPP	MMLU
Softmax Ablation	6×10^{19}	1.90	6.35	3.08	2.22	1.87
	1×10^{20}	1.87	6.10	4.13	2.15	1.81
	3×10^{20}	1.81	5.48	1.47	1.60	1.89
	6×10^{20}	1.76	4.72	1.91	1.20	1.76
	1×10^{21}	1.72	4.59	1.55	1.15	1.73
	3×10^{21}	1.67	3.82	1.54	1.01	1.73
Proportional	6×10^{19}	1.63	4.70	1.73	2.42	1.63
	1×10^{20}	1.59	4.22	1.66	2.28	1.60
	3×10^{20}	1.55	3.61	1.44	1.67	1.56
	6×10^{20}	1.51	3.19	1.38	1.20	1.53
	1×10^{21}	1.48	2.92	1.31	1.17	1.50
	3×10^{21}	1.41	2.52	1.22	1.07	1.44
Greedy MEDU	6×10^{19}	1.71	5.29	1.63	2.16	1.66
	1×10^{20}	1.63	4.95	1.57	2.05	1.61
	3×10^{20}	1.57	4.24	1.32	1.53	1.57
	6×10^{20}	1.52	3.40	1.28	1.09	1.52
	1×10^{21}	1.48	3.28	1.21	1.04	1.49
	3×10^{21}	1.42	2.71	1.13	0.94	1.45
UtiliMax MEDU	6×10^{19}	1.65	4.77	1.63	2.14	1.64
	1×10^{20}	1.62	4.49	1.57	2.08	1.61
	3×10^{20}	1.56	3.72	1.33	1.51	1.55
	6×10^{20}	1.51	3.18	1.27	1.14	1.52
	1×10^{21}	1.49	3.00	1.22	1.09	1.50
	3×10^{21}	1.41	2.50	1.13	1.00	1.45
Softmax MEDU	6×10^{19}	1.73	5.43	2.84	2.34	1.94
	1×10^{20}	1.71	5.04	2.94	2.17	1.81
	3×10^{20}	1.65	4.46	2.89	1.64	1.84
	6×10^{20}	1.58	3.95	1.72	1.26	1.75
	1×10^{21}	1.60	3.70	1.38	1.19	1.60
	3×10^{21}	1.51	3.13	1.16	1.06	1.54
UniMax	6×10^{19}	1.63	4.87	1.63	2.22	1.63
	1×10^{20}	1.63	4.36	1.57	2.11	1.62
	3×10^{20}	1.57	3.62	1.32	1.52	1.56
	6×10^{20}	1.51	3.19	1.28	1.18	1.52
	1×10^{21}	1.48	2.98	1.22	1.12	1.50
	3×10^{21}	1.42	2.54	1.13	1.01	1.44
Uniform	6×10^{19}	1.73	5.32	1.69	2.31	1.71
	1×10^{20}	1.69	4.85	1.61	2.18	1.70
	3×10^{20}	1.63	4.28	1.40	1.63	1.65
	6×10^{20}	1.59	3.77	1.36	1.27	1.61
	1×10^{21}	1.55	3.62	1.25	1.17	1.57
	3×10^{21}	1.49	3.02	1.18	1.06	1.53