# FLM-101B: An Open LLM and How to Train It with \$100K Budget

Xiang Li<sup>1†</sup>, Yiqun Yao<sup>1†</sup>, Xin Jiang<sup>1†</sup>, Xuezhi Fang<sup>1†</sup>, Xuying Meng<sup>2</sup>, Siqi Fan<sup>3</sup>, Peng Han<sup>3</sup>, Jing Li<sup>4</sup>, Li Du<sup>1</sup>, Bowen Qin<sup>1</sup>, Zheng Zhang<sup>1</sup>, Aixin Sun<sup>5</sup>, Yequan Wang<sup>1∗</sup>

<sup>1</sup>Beijing Academy of Artificial Intelligence, Beijing, China

<sup>2</sup>Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China

 $3$ University of Electronic Science and Technology of China, Chengdu, China

<sup>4</sup>Harbin Institute of Technology, Shenzhen, China

<sup>5</sup>School of Computer Science and Engineering, Nanyang Technological University, Singapore

#### Abstract

Large language models (LLMs) have achieved remarkable success in NLP and multimodal tasks. Despite these successes, their development faces two main challenges: (i) high computational cost; and (ii) difficulty in conducting fair and objective evaluations. LLMs are prohibitively expensive, making it feasible for only a few major players to undertake their training, thereby constraining both research and application opportunities. This underscores the importance of costeffective LLM training. In this paper, we utilize a *growth strategy* to significantly reduce LLM training cost. We demonstrate that an LLM with 101B parameters and 0.31TB tokens can be trained on a \$100K budget. We also adopt a systematic evaluation paradigm for the IQ evaluation of LLMs, in complement to existing evaluations that focus more on knowledge-oriented abilities. We introduce our benchmark including evaluations on important aspects of intelligence including *symbolic mapping*, *rule understanding*, *pattern mining*, and *anti-interference*. Such evaluations minimize the potential impact of memorization. Experimental results show that our model FLM-101B, trained with a budget of \$100K, achieves comparable performance to powerful and well-known models, *e.g.,* GPT-3 and GLM-130B, especially in the IQ benchmark evaluations with contexts unseen in training data. The checkpoint of FLM-101B will be open-sourced at [https:](https://huggingface.co/CofeAI/FLM-101B) [//huggingface.co/CofeAI/FLM-101B](https://huggingface.co/CofeAI/FLM-101B).

#### <span id="page-0-0"></span>1 Introduction

Large language models (LLMs), exampled by decoder-only structure (*e.g.,* GPT series [\[36;](#page-18-0) [37;](#page-18-1) [3\]](#page-15-0), LLAMA series [\[54;](#page-20-0) [55\]](#page-20-1)), encoder-only structure (*e.g.,* BERT [\[10\]](#page-16-0)), and encoder-decoder structure (*e.g.*, T5 [\[40\]](#page-18-2)) and their variants [\[27;](#page-17-0) [19;](#page-17-1) [51;](#page-19-0) [41\]](#page-18-3), have achieved remarkable success and are widely applied in various language processing [\[61;](#page-20-2) [60;](#page-20-3) [11;](#page-16-1) [28\]](#page-17-2) and multimodal tasks [\[77\]](#page-22-0).

Despite their great successes, the cost of training LLMs is so expensive that only a few companies can afford to train them. Moreover, current trend suggests to use larger amount of training data, which further pushes up the research cost of large models. For example, LLAMA-1 [\[54\]](#page-20-0) models use 1-1.4 TB tokens for training while LLAMA-2 [\[55\]](#page-20-1) uses 2TB tokens.

<sup>\*</sup>Corresponding author. Email: tshwangyequan@gmail.com

<sup>†</sup> Indicates equal contribution.

<span id="page-1-0"></span>

Figure 1: An overview of different growth strategies.

Another critical challenge in LLM research is evaluation. Mainstream evaluations fit into two categories: knowledge evaluation (*i.e.,* MMLU [\[15\]](#page-16-2) and C-Eval [\[18\]](#page-17-3)), and NLP tasks evaluation. Such evaluations may not truly reflect the model capability due to potential data leakage if some of the evaluation datasets were used in model training. In addition, we believe that knowledge-oriented evaluations are not enough for measuring intelligence. It would be more fair and objective to assess the Intelligence Quotient (IQ) of LLMs by generalizing to conditions and contexts unseen in the training data.

Growth Strategy. To address the training cost challenge, we make the very first attempt to train a 100B LLM by the *growth strategy*. Growth means that the number of parameters is not fixed in the training process, but expands from a smaller size to large ones.

Figure [1](#page-1-0) illustrates three typical scenarios for growth strategies. As the FLOPs of LLMs are approximately proportional to their number of parameters [\[17\]](#page-17-4), the area between the change curve of model parameters and the X-axis represents the computational cost of training. Figure [1\(](#page-1-0)a) shows the standard training strategy without model growth; with a straightforward linear growth strategy (Figure [1\(](#page-1-0)b)), the cost saving is equal to 50%; figure [1\(](#page-1-0)c) shows a modest growth strategy that reduces cost by less than 50%; in contrast, Figure [1\(](#page-1-0)d) represents an aggressive growth strategy, which reduces cost by more than 50%. This analysis informs our decision to employ the aggressive growth strategy, promising maximal computational savings.

Our growth operators are inspired by MSG [\[73\]](#page-21-0), which proposed a complete operation set that covers all the four growth dimensions for Transformer structure. More importantly, MSG achieves strict function-preservation when growing. Thus, while a small model learns quickly with smaller searching space for parameters, its knowledge can be inherited by the subsequent larger models. This makes a growth strategy potentially achieve better performance under equal or less computational cost.

The Open-source FLM-101B. In our study, we managed to train a 101B LLM with progressive growth, which will be open-sourced. Our model architecture is an evolution of FreeLM [\[23\]](#page-17-5). Thus, we name it F(ree)LM-101B. The FreeLM framework features two pre-training objectives guided by the language signals and teacher signals. In this work, we unify these objectives into a common language modeling paradigm.

IQ Evaluation Benchmark. In addition to the low-cost training paradigm, another contribution of ours is a systematic benchmark to evaluate the Intelligence Quotient (IQ) of LLMs. Previous study [\[59\]](#page-20-4) reveals that while PPL could reflect the generated text quality to some extent, it is unreliable. On the other hand, the training data of LLMs is so huge that it is hard to identify whether the model is merely reciting the knowledge data, or truly achieves human-like reasoning, analysing, and generalizing abilities, which combines into our definition of IQ here.

Some popular evaluations, *e.g.,* MMLU (for English) and C-Eval (for Chinese), are significantly knowledge-oriented, and could not holistically reflect the intelligence of the model. For sanity check, we conducted a test: five computer science researchers from world-renowned universities took an exam using C-Eval's chemistry test. We found their accuracy to be approximately equal to random guessing, as most volunteers have forgotten their chemistry knowledge. Hence, benchmarks that emphasize on professional knowledge are not adequate in measuring the IQ of models.

To fully gauge the IQ of LLMs, we develop an IQ evaluation benchmark that considers four pivotal facets of intelligence: *symbolic mapping*, *rule understanding*, *pattern mining*, and *anti-interference*.

- Language is intrinsically symbolic. There are studies [\[66\]](#page-21-1) that use symbols instead of category labels to evaluate the intelligence of LLMs. Similarly, we use a *symbolic mapping* approach to test the LLMs' generalization ability to unseen contexts.
- For human intelligence, one important ability is to understand given rules, and conduct corresponding actions. This kind of test method is widely used in various levels of examinations. Hence, we add *rule understanding* as a second test.
- Pattern mining, involving both induction and deduction, is also an important part of intelligence. This approach has played a crucial role in historical scientific developments. In addition, it is often used in various levels of competition. Motivated by this, we use *pattern mining* as our third evaluation metric.
- Last but not least, anti-interference ability is also the core of intelligence. Existing studies [\[5;](#page-15-1) [79\]](#page-22-1) point out that both language and image are easily affected by noise. To this point, we use *anti-interference* as our final assessment metric.

We aspire for our comprehensive IQ evaluation framework to stimulate subsequent research in this domain.

#### Our main contributions are as follows:

- To the best of our knowledge, this is the first attempt to use a *growth strategy* to train an LLM with 100B+ parameters from scratch. Simultaneously, this is the lowest-cost model with  $100B +$  parameters, costing only  $100,000$  US dollars.
- We solve several instability issues via improvements to FreeLM training objectives, promising approaches for hyperparameter search, and function-preserving growth. Our methodology holds potential benefits for the broader research community.
- We conduct experiments on both the prevalent knowledge-oriented benchmarks and our systematic IQ evaluation benchmark, to compare our model with strong baselines. Experimental results show that FLM-101B is competitive and robust.
- We release model checkpoints, code, related tools, *et al.* to promote research on bilingual Chinese and English LLMs at the scale of 100B+.

## <span id="page-2-0"></span>2 Design Overview of FLM-101B

In this section, we provide a comprehensive outline of the FLM-101B, detailing its architecture, pre-training methods, and configuration specifics.

## 2.1 FLM-101B Architecture

FreeLM as Backbone. The architecture of an LLM significantly determines its capabilities. However, current researches [\[75;](#page-21-2) [3\]](#page-15-0) underscore the high costs associated with experimenting on diverse architectures, making it less feasible for a majority of researchers and enterprises. Consequently, we adopt FreeLM [\[23\]](#page-17-5) as the core architecture for FLM-101B. FreeLM is based on GPT [\[37\]](#page-18-1), a transformer-based architecture with a decoder-only configuration known for its exceptional performance. FreeLM features two pre-training objectives: the language objective and the teacher objective. The latter employs teacher signals to instill task-oriented and factual verification knowledge. While the initial FreeLM [\[23\]](#page-17-5) introduces an additional classification module to utilize the teacher signal, it brings issues in training stability as the model scales up. To mitigate this, we unify these two training objectives, detailed further in Section [2.2.](#page-3-0) We preserve the transformer block designs inherent in both GPT and FreeLM, including the Pre-LayerNorm and the additional LayerNorm after the last transformer layer. We employ the tokenizer derived from GPT-4, characterized by a vocabulary size of 100, 256.

Integration of xPos. To enhance the modeling of long sequences, we integrate the Extrapolatable Position Embedding (xPos) [\[52\]](#page-19-1). This innovation draws inspiration from the principles of RoPE [\[50\]](#page-19-2), which aims to improve the length extrapolation ability. By introducing an exponential decay into the rotation matrix, xPos strives to rectify this hurdle. To the best of our knowledge, FLM-101B is the largest model to date that incorporates the xPos technology.

Model Sizes. Benefiting from our *growth strategy*, the FLM series produces three models with 16B, 51B, and 101B (named FLM-101B) parameters in a single training. The training process is carried out in a sequential manner, starting from a smaller model and progressively growing to larger ones.

## <span id="page-3-0"></span>2.2 Pre-Training Setup

FLM-101B inherits the training strategy of FreeLM [\[23\]](#page-17-5). As we mentioned above, the original FreeLM [\[23\]](#page-17-5) incorporates two training objectives: language modeling objective guided by language signals and binary classification objective guided by teacher signals. As the model scales beyond 16B, this engenders training instability. To address this, we introduce one unified objective. This unified objective could handle both teacher and language signals using a masking strategy and two specialized tokens. These tokens facilitate the transformation of the binary classification objective into the language modeling format.

Language Signals in Unsupervised Textual Corpus. Like the GPT series [\[3;](#page-15-0) [33\]](#page-18-4), the training objective here is to maximize the token prediction likelihood. FLM-101B is an English-Chinese bilingual model. It mixes English and Chinese corpora at a ratio of approximately 53.5 : 46.5 for language modeling. Existing studies [\[34\]](#page-18-5) demonstrate that instruction data can augment LLMs' comprehension capabilities. Inspired by this, we integrate multi-task instructionally prompted data: OIG (Open Instruction Generalist)<sup>[1](#page-3-1)</sup> and COIG (Chinese Open Instruction Generalist)<sup>[2](#page-3-2)</sup>, in the pre-training stage.

Teacher Signals in Propositional Judgment. The original teacher objective of FreeLM aimed at minimizing cross-entropy in binary classification for proposition correctness judgment [\[23\]](#page-17-5). In the training of FLM-101B, we transform this binary classification into the formation of autoregressive language modeling. Specifically, we employ two emojis:  $\bullet$  (U+1F621) and  $\bullet$  (U+1F608)<sup>[3](#page-3-3)</sup>, from the vocabulary to replace the original binary labels of 1 and 0. We apply zero-masking to the loss for tokens in the propositions and predict one of these two special tokens at the end of each proposition. By this method, we unify the teacher objective and language modeling.

Moreover, we abandon the Iterative Training approach from FreeLM [\[23\]](#page-17-5) and completely mix the samples from both signals in every batch. This strategy can enhance the consistency of data sampling distribution as well as improve the training stability. Due to computational resource concerns, we only apply the teacher signal to eFLM-16B (Section [4.3\)](#page-8-0).

<span id="page-3-1"></span><sup>1</sup> <https://huggingface.co/datasets/laion/OIG>

<span id="page-3-2"></span> $^2$ <https://huggingface.co/datasets/BAAI/COIG>

<span id="page-3-3"></span> $^3$ <https://apps.timwhitlock.info/emoji/tables/unicode>

## 2.3 Growth Strategy

Contrary to common practices that train models with different sizes independently [\[54;](#page-20-0) [55\]](#page-20-1), we sequentially train three models with 16B, 51B, and 101B parameters, with each model inheriting knowledge from its smaller predecessor.

Function-preserving Growth. Function preservation is defined as: before and after growth, the models always yield consistent outputs given arbitrary inputs. This property has proven beneficial for both knowledge inheritance [\[8;](#page-16-3) [6;](#page-16-4) [47\]](#page-19-3) and training stability [\[73\]](#page-21-0). We use growth operators inspired by [\[73\]](#page-21-0) in our training process. To adapt to the multi-node 3D parallel framework, we implement it by extending the model structures off-line and reloading the checkpoint when the next stage starts.

Schedules and Cost-Effectiveness. Scheduling the model growth is a trade-off between the pros and cons inherent to models of different sizes [\[73\]](#page-21-0): a smaller model is faster in computing each training step, enabling more rapid consumption of training data for wider common-sense knowledge; conversely, a larger model is better in the decrease of loss per step, indicating a deeper understanding of the nuanced linguistic patterns, which is important for the acquisition of intelligence. We train the 16B model with 245.37B tokens, the 51B model with 39.64B tokens, and the 101B model with 26.54B tokens. The *billion tokens per day* of different sizes are listed in Table [2.](#page-5-0) Under this growth schedule, the total time cost for our 101B model is 21.54 days, which is 54.8% time-saving (or a 2.2x speedup) compared to training a 101B model from scratch (47.64 days). This is consistent with our motivations depicted in Figure [1.](#page-1-0)

## 2.4 The Parallelism Setup and Model Configurations

FLM-101B is trained on a cluster of 24 DGX-A800 GPU (8×80G) servers for less than 26 days. Based on the *growth* strategy, we sequentially completed the model training for sizes 16B, 51B, and 101B on this cluster.

The Parallel Strategies. Data parallelism [\[56\]](#page-20-5) and tensor model parallelism [\[48\]](#page-19-4) have become the standard approaches for training models at the billion scale. Nevertheless, an excessive amount of tensor parallelism may escalate GPU communication overheads, affecting training efficiency. To tackle this problem, we integrate pipeline model parallelism [\[32\]](#page-18-6) and employ a 3D parallel strategy for optimal throughput. Moreover, by employing sequence parallelism [\[22\]](#page-17-6), we sliced the inputs to the Transformer core's LayerNorm and Dropout layers along the sequence length dimension, leading to additional savings in GPU computational resources and memory utilization. We utilize the Megetron-LM<sup>[4](#page-4-0)</sup> implementation of a distributed optimizer [\[42\]](#page-19-5) to further reduce the GPU memory consumption, which is a technique that evenly distributes the optimizer states across data parallel ranks.

<span id="page-4-1"></span>Table 1: Parallel strategies and throughput for different growth stages. For NVIDIA A800 GPUs, the peak theoretical FLOPs per second is 312 teraFLOPs/sec. Gradient accumulation is applied for the large global batch size.



Table [1](#page-4-1) shows the parallelism configurations and training throughput in each stage of FLM-101B training under our growth strategy. In different growth stages, we configure different Tensor Parallel  $\times$  Pipeline Parallel sizes to achieve higher throughput. The single-GPU throughput for all three training stages consistently exceeds 160 teraFLOPs/sec with a utilization rate of at least 51.3%. As a comparison, GLM-130B achieved 135 teraFLOPs/sec [\[75\]](#page-21-2) with a 42.27% utilization rate. We also observed that FLM-101B has a higher FLOP utilization rate than Megatron-LM [\[22\]](#page-17-6) under a similar model size.

<span id="page-4-0"></span><sup>4</sup> <https://github.com/NVIDIA/Megatron-LM>

<span id="page-5-0"></span>

Params (billion)	Learning Rate	Warmup (samples)	<b>Batch Tokens</b> (million)	Time $\text{(day)}$	<b>Tokens</b> (billion)
16	$4e-4$	4608000	4.72	9.63	245.37
51	$3.4e-4$	230400	4.72	5.37	39.64
101	$2e-4$	230400	4.31	6.54	26.54

Table 2: Partial configuration for different growth stages.

FLM-101B Configurations. The FLM-101B model is structured with a hidden state dimension of 10240, a layer number of 80, a context window of 2048 tokens, 80 attention heads, and a vocabulary size of 100256. FLM-101B is trained utilizing the AdamW optimizer [\[29\]](#page-18-7) with  $\beta_1 = 0.9$ ,  $\beta_2 = 0.95$ . A cosine learning rate schedule is employed, leading to a final learning rate of 6e-6. We use a weight decay of 0.1 and gradient clipping of 1.0.

Table [2](#page-5-0) presents part of the hyperparameters used in different growth stages. In each growth stage, we approximately inherit the previous learning rate and stick to the same schedule. In Table [2,](#page-5-0) we report the learning rate at the beginning of each stage. In the 16B stage, 4,608k samples are used for learning rate warmup, while in later growth stages, we use fewer samples of 230.4k. We do not apply batch size warmup because we solved the stability issue in a more promising way (Section [3\)](#page-5-1).

Training durations and token consumption for each stage are also outlined in Table [2.](#page-5-0) We efficiently completed more training tokens in less time during the 16B phase, while dedicating additional time to the final 101B stage. In total, FLM-101B training was accomplished within 22 days using 311.54B tokens.

## <span id="page-5-1"></span>3 Training Stability of FLM-101B

Models beyond 100B parameters [\[45;](#page-19-6) [75\]](#page-21-2) usually suffer from a bunch of notorious stability issues including loss divergence, gradient explosion, and numerical overflow/underflow. This not only inflates the cost of searching for feasible hyperparameters–like optimal learning rates–but also amplifies ongoing maintenance during training, such as babysitting, issue addressing, data adjustment, and rebooting. Moreover, this makes the budget of the whole project unpredictable. Fortunately, we managed to provide a promising solution to mitigate all these aforementioned issues with the methodologies delineated below:

Loss Prediction. The Tensor Programs theories [\[70;](#page-21-3) [26\]](#page-17-7) have unveiled the universal relations across the training dynamics of a series of models with the *model width* tending to infinite. This results in a parameterized mapping for the optimal value of some hyperparameters between a small model and its larger counterparts, which is termed  $\mu$ P [\[71\]](#page-21-4). Two important insights are:

- *The wider, the better:* theoretically, under  $\mu$ P transfer, a wider model will always yield lower loss than its narrower counterparts when exposed to identical data [\[71\]](#page-21-4). As a direct corollary, if a narrow model converges, its wider counterparts will always converge.
- *Loss prediction*: the loss value of a large model is predictable using the loss of its smaller counterparts, as claimed in GPT-4 tech report [\[33\]](#page-18-4). For the first time in the open source world,  $\mu$ Scaling [\[72\]](#page-21-5) showed evidence that loss prediction can be achieved by combining  $\mu$ P [\[71\]](#page-21-4) and (a modified) scaling law [\[21;](#page-17-8) [16;](#page-17-9) [17\]](#page-17-4).

Based on the conclusions above, our method to solve training stability is as follows: we first decide the data distribution before the FLM-16B training starts. Next, we perform a grid search on three hyperparameters including the learning rate, initialization standard deviation, and the softmax temperature in the output layer. This grid search is performed by running a 40M *proxy model* with a hidden state dimension ("model width") of 256 and a head number of 2. All the other structural hyperparameters and training data of the proxy model are identical to FLM-16B. A single run of grid search takes 24.6 hours with data parallelism on 6 nodes, which is equivalent to 6 hours per run given our 24-node infrastructure. We found optimal hyperparameters (learning rate  $= 4e-4$ , standard deviation = 1.6e-2, softmax temperature =  $2.0$ ) through this grid search. Transferring these hyperparameters to the 16B model via  $\mu$ P [\[71\]](#page-21-4) led to a seamless training experience *devoid* of

instabilities. Combining with MSG [\[73\]](#page-21-0), we also experienced no post-growth divergence in FLM-51B and FLM-101B.

<span id="page-6-0"></span>

Figure 2: Training loss for FLM-101B models.

The full training loss curve is presented in Figure [2.](#page-6-0) The first stage (16B) stably throughputs 246B tokens. Immediately afterwards, FLM grows from 16B to 51B. As expected, the loss is stable. More importantly, we observe the loss curve becomes steeper. It meets the experience that a bigger model has a smaller loss. Followed by, FLM grows to 101B. Although the training data on 51B stage is only 40B, FLM grown again remains stable. More exciting, the loss curve slightly becomes steeper. This loss curve proves the effectiveness of *growth strategy*.

Most of our implementations of  $\mu$ P are the same as  $\mu$ Scaling [\[72\]](#page-21-5), with modifications to handle the rotary embedding. Thus, the intermediate loss ranges for FLM-16B are also predictable with the results from multiple proxy widths at the same steps.

**Mixed Precision with Bfloat16.** We apply mixed-precision training to save run-time memory and time costs. We choose Bfloat16 instead of FP16 due to its superior precision for values approaching zero, making it more suitable for  $\mu$ P. As a result, we do not encounter the FP16 underflow issue reported by [\[71\]](#page-21-4). Our FLM models are currently the largest ones successfully trained with mixed precision  $+\mu P$ . Moreover, Bfloat16 negates the need for loss scale adjustments, making our training procedure more promising and reproducible.

## <span id="page-6-1"></span>4 Benchmark Evaluation

Many current benchmarks (*e.g.,* Open LLM) focus on assessing the knowledge ability of LLMs. Indeed, knowledge ability is an critical part of human intelligence, but we argue that knowledge alone might not comprehensively represent LLM intelligence (see Section [4.3](#page-8-0) for more details). Thus, in addition to the benchmark evaluation in this section, we conduct the IQ evaluation for LLMs in Section [5.](#page-9-0)

#### 4.1 Cost Estimation Method

Due to the considerable computational expense of LLMs, we emphasize their associated costs in our experimental results. LLM infrastructures are significantly different. In addition, the cost of hardware is getting lower. Thus, it is hard to directly compare the actual cost for each LLM. To objectively compare computational costs during training, we use the number of floating-point operations for training as the cost estimation index, which can be estimated from the model's parameters, configuration and data for training [\[32\]](#page-18-6). Since many models do not release complete training configuration parameters (*e.g.,* GPT-3, LLAMA series), we estimate FLOPs within a range.

For monolingual LLMs, *e.g.,* GPT-3, the cost of monolingual is equal to the total cost. The computational cost of GPT-3 calculated is  $376.41$  ( $\pm 53.77$ ) zettaFLOPs. For LLAMA-2 (13B), the cost is 210.37 ( $\pm$ 28.77) zettaFLOPs. Because the cost is linear with both model parameters and training data, we could calculate the cost of the remaining LLAMA models easily. For bilingual or multilingual models, it is necessary to estimate based on the amount of data in the corresponding language. The total cost of GLM-130B is 421.60 zettaFLOPs. As the data ratio of English and Chinese is 1:1, the cost of GLM-130B for English is 210.80 zettaFLOPs, and the same for Chinese. The data ratio of FLM-101B is 53.5% : 46.5% for English and Chinese. The total cost of FLM-101B is 52.76 zettaFLOPs. According to the data ratio, the cost of English and Chinese is 28.22 zettaFLOPs and 24.54 zettaFLOPs.

### 4.2 Open LLM Evaluation

Open LLM is an open-source project <sup>[5](#page-7-0)</sup>. Its target is to track and evaluate the open LLMs and chatbots. Open LLM contains four tasks: ARC-Challenge, HellaSwag, MMLU, and TruthfulQA. The Open LLM Leaderboard applies the average score of these tasks as a metric.

ARC: The ARC [\[9\]](#page-16-5) dataset is proposed for graduate-school level closed book science questionanswering tasks. Most problems in ARC are solvable with life experiences and Wikipedia searches. Thus, a model is expected to perform better if exposed to more commonsense and factual data.

HellaSwag: This is a sentence completion task emphasizing commonsense inference [\[74\]](#page-21-6). We observe that the increase in HellaSwag performance is highly correlated with the decrease in training loss. This is intuitive because the training data is usually enriched with commonsense.

MMLU: MMLU includes 57 multiple-choice tasks covering subjects spanning STEM to social science [\[15\]](#page-16-2). The tasks differ significantly in complexity, with many STEM-oriented questions demanding domain-specific professional knowledge and intricate reasoning to be solved.

TruthfulQA: TruthfulQA contains 817 factual questions to detect model falsehoods caused by naively mimicking human language patterns [\[25\]](#page-17-10). The solutions to these questions are closely associated with English Wikipedia sources. The task probes a model's factual knowledge and resistance to popular misconceptions.

<span id="page-7-1"></span>



Table [3](#page-7-1) details the performance of FLM-101B and strong baselines (*i.e.,* LLAMA series and GLM-130B). Because GPT-3 is close-sourced, we could not get the probability value to compare fairly. As a result, we cannot list GPT-3 here. GLM-130B results are achieved by our run on an open-source checkpoint.

Observations. Among all the baseline models, FLM-101B ranks last with an average of 43.94. However, going deeper into the nature of these tasks, this does not indicate the inferiority of our model.

(i) MMLU typically requires domain knowledge to solve. Since no textbook or exam questions are intentionally added to the training data of FLM-101B, the achieved score is reasonable. Direct evidence for our claim is: in an FLM variant that incorporates this knowledge with FreeLM objectives (eFLM-16B, Section [4.3\)](#page-8-0), even a 16B model outperforms GLM-130B.

(ii) As mentioned above, TruthfulQA, ARC and HellaSwag emphasize commonsense and Wiki-level knowledge, and their performances improve with the amount of data and training loss. With less than 0.16TB English data (about  $1/10$  of LLAMA-2), FLM-101B already achieves the best accuracy of 41.47 among all the baselines. On ARC and HellaSwag, FLM-101B is comparable to GLM-

<span id="page-7-0"></span> $^5$ [https://huggingface.co/spaces/HuggingFaceH4/open\\_llm\\_leaderboard](https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard)

130B with a similar amount of English data (approximately 0.2TB). Moreover, the training data of GLM-130B includes ARC and Hellaswag, as expressly claimed in [\[75\]](#page-21-2).

Based on these evidences, we believe that the FLM-101B's abilities in factual knowledge are not superior at all, and will continue to improve if exposed to more data.

#### <span id="page-8-0"></span>4.3 Professional Knowledge Evaluation

To validate the effect of professional knowledge, we add professional knowledge data as FreeLM teacher signals (Section [2\)](#page-2-0) to enhance FLM. Due to computational cost, we apply the FreeLM objectives with this data to continue training FLM-16B, the smallest one. The knowledge-related data includes: (i) part of the auxiliary training set of MMLU; (ii) exam questions in similar domain and formats to C-Eval [\[18\]](#page-17-3); and (iii) other domain knowledge data. Sticking to the insights from FreeLM, we keep a portion of the original language modeling data to avoid damaging the generative ability. This professional-knowledge-enhanced FLM-16B is named as eFLM-16B.

MMLU Results. The incorporation of the teacher signals with professional knowledge data results in an MMLU score of 44.50 for eFLM-16B, which surpasses GLM-130B (42.59), a model also adds multi-task data in related domain [\[75\]](#page-21-2). As a reference, the score is 27.02 for un-enhanced GLM-16B.

C-Eval Results. C-Eval [\[18\]](#page-17-3) can be considered as a Chinese version of MMLU. Table [4](#page-8-1) shows the results of eFLM-16B and baselines. As a reference, for FLM-16B without knowledge enhancement, the average C-Eval score was 27.03. The scores are achieved on the test set by submitting to the C-Eval platform.

<span id="page-8-1"></span>Table 4: Performance of eFLM-16B and baselines on C-eval. In this table, eFLM-16B refers to the professional-knowledge-enhanced FLM-16B. Note that C-eval Leaderboard only keeps one demical place for the evaluation results.

Model	Average	Average (Hard)		STEM Social Science	Humanities	<b>Others</b>
$GPT-4$	68.7	54.9	67.1	77.6	64.5	67.8
<b>ChatGPT</b>	54.4	41.4	52.9	61.8	50.9	53.6
$GLM-130B$	44.0	30.7	36.7	55.8	47.7	43.0
$eFLM-16B$	46.1	28.9	38.3	53.7	46.8	52.6

Observations. A straightforward observation is that adding professional knowledge data in related domains significantly improves the scores on both MMLU (15.16 points) and C-Eval (19.07 points). On both tasks, eFLM-16B outperforms GLM-130B by around 2 points. This proves that the scores on datasets emphasizing professional knowledge could NOT reflect the intelligence of LLMs, since the contribution of some specific training data can be overwhelming.

#### 4.4 Evaluation on Growth Strategy

Our core method for reducing computational cost is the growth strategy. We would like to answer the question of whether our growth strategy is effective in knowledge inheritance, and the trajectory of how model capabilities increase with sizes. Hence, we evaluate the performance of FLM on all the stages: 16B, 51B and 101B. The training data for each stage is 0.246TB, 0.04TB and 0.026TB respectively. Table [5](#page-8-2) shows the performance of FLM models in each phase.

<span id="page-8-2"></span>Table 5: Performance of the three stages of FLM on Open LLM. To reduce the computational cost during evaluation, we sample 20% and 30% items for HellaSwag and MMLU tasks, respectively.

	Parameters Training Data Average ARC Hellaswag				MMLU	TruthfulOA
16B 51 <sub>B</sub>	246B 40B	39.19 41.79	32.25 35.32	58.57 64.04	27.02 27.66	38.92 40.12
101 <sub>B</sub>	26B	44.41	39.76	67.88	28.54	41.47

Observations. As expected, the performance of FLM improves along with the increase of model size. FLM-101B achieves the best performance on almost all tasks. This means that our model inherits knowledge from the privous stage after each growth. We also observe that the 101B model improves the performance scores more significantly than 51B model with less samples. This indicates that the models are successfully incorporating new weights in training after growth and take the advantage of model sizes when the loss is low. Interestingly, the performance of ARC and HellaSwag increases steadily and significantly, providing another evidence for our claims in Section [3.](#page-7-1) Hence, when more training data is processed, we can expect FLM-101B's performance on Open LLM to be much better, except on MMLU since it is domain-relevant as we discussed.

The above experiments evaluate the knowledge-related ability of FLM and how the performances depend on the amount and domain of training data. More importantly, knowledge could not reflect the *intelligence* of LLMs on its own. To this end, we further evaluate the intelligence of LLMs by IQ test in the following section.

# <span id="page-9-0"></span>5 IQ Experiments

Section [4](#page-6-1) details the evaluation of existing benchmarks, focusing on knowledge. As we discussed in Section [1,](#page-0-0) knowledge could not reflect the Intelligence Quotient (IQ) of LLMs. To this end, we use existing IQ-related datasets [\[66;](#page-21-1) [67;](#page-21-7) [49\]](#page-19-7) and make necessary modifications or generate new synthetic datasets for a more systematic evaluation for the IQ of LLMs.

Specifically, our IQ evaluation mainly considers four aspects: *symbolic mapping*, *rule understanding*, *pattern mining*, and *anti-interference*. A common key property of these tasks is that they are dependent on the inference and generalization in a new context, instead of the previously-learned knowledge. We re-organize the modified existing datasets and newly generated datasets under these topics. Next, we introduce the motivation for each aspect and the detailed execution method.

Compared Methods. As a milestone of LLM development, GPT-3 (175B) [\[3\]](#page-15-0) proposed in-context learning for the first time. GLM-130B [\[75\]](#page-21-2) is the first open English-Chinese bilingual LLM. Hence, we select them as baseline models. Both models are trained with 300 ~400 billion tokens, which are in the same range as ours. GPT-3 focuses on English, so it is not included in Chinese-related evaluation (*i.e.,* CLUE-IQ).

## 5.1 Symbolic Mapping Evaluation

Existing study [\[66\]](#page-21-1) points out that classification tasks (*e.g.,* document classification, sentiment classification) for given categories in the form of text often lack generalization. This is because there are so many public websites that include this kind of raw language text and labeled training datasets, *i.e.*, SemEval, IMDB [\[30\]](#page-18-8), and Yelp <sup>[6](#page-9-1)</sup> et al.. This leads a model to over-fit the semantics of the labels instead of inferring them from the new context, while real intelligence emphasizes the latter. Considering this, we use a symbolic mapping method to replace the original category labels with symbols that are unlikely seen in the training data. Hence, we could evaluate the LLMs' truthful understanding ability as well as the generalization abilities to a new context. Because the labels are from a given scope, we form our evaluation task as in-context learning.

## <span id="page-9-2"></span>5.1.1 Data Collection

We use the existing benchmark dataset (*e.g.,* SuperGLUE [\[57\]](#page-20-6), CLUE [\[69\]](#page-21-8)) as the data source and build new benchmarks for IQ by sampling up to 300 samples and replacing the original category with a random string. Figure [3](#page-10-0) shows the difference between the previous benchmark and the symbolic mapping benchmark. In this case, *entailment* category is replaced by random string <30mFC%4Z> while *not entailment* category is replaced by <?V9qP@Rx>. This processing also mitigates the problem that these datasets contaminates the  $\overline{\text{LIM}}$  pre-training data, since both benchmarks are public with lots of reproductions. Table [6](#page-10-1) presents the statistics and task types of our rebuilt datasets.

<span id="page-9-1"></span> $^6$ <https://www.yelp.com/dataset/documentation/main>

<span id="page-10-0"></span>

Figure 3: An example of symbolic mapping method. The main difference is that the symbolic mapping method replaces the original label with random strings. In this example, we use <30mFC%4Z> and <?V9qP@Rx> to replace *entailment* and *not entailment*, respectively.

<span id="page-10-1"></span>Table 6: Statistics for SuperGLUE-IQ and CLUE-IQ datasets. "WSD" stands for "Word Sense Disambiguation"; "SS" stands for "Sentence Similarity"; "KR" stands for "Keyword Recognition"; *coref.* stands for "coreference resolution".

						Source BoolQ WiC RTE WSC   AFQMC CSL OCNLI CLUEWSC2020
Samples 299 300 277 103			300	208	<b>300</b>	<b>300</b>
Task		QA WSD NLI <i>coref.</i>   SS			KR NLI	coref.

#### 5.1.2 SuperGLUE-IQ

SuperGLUE is a benchmark for evaluating a model's language understanding ability. So we build a new dataset named SuperGLUE-IQ based on the original dataset. Since the label of the testing set of SuperGLUE is not public, we use a validation set here. There are two rules for selecting the sub-tasks: (i) the number of data items exceeds 100; (ii) the classification categories are fixed sets. The building process is detailed in Section [5.1.1.](#page-9-2) Since we will release this dataset, to further avoid the label strings being mixed into the training set, we can update them regularly (*e.g.,* every week) and automatically. Table [7](#page-10-2) lists the performance of FLM-101B and the baselines.

<span id="page-10-2"></span>Table 7: Performance on SuperGLUE-IQ of GPT-3, GLM-130B and FLM-101B. The result of GPT-3 is evaluated by API. GLM-130B is evaluated with its open-source checkpoint.

Model	$Cost (zettaFLOPs)$ Average BoolO WiC			RTE	WSC.
GPT-3 $GLM-130B$	$376.41 \ (\pm 53.77)$ 210.80	47.60 48.19	50.84 40.13	53.33 48.38 37.86 48.67 47.65	56.31
$FLM-101B$	28.22	46.76	49.50	50.33 48.38	38.83

Observations. On BoolQ, WiC and RTE tasks, our FLM-101B and GPT-3 are at the same level, and both of them perform better than GLM-130B. Particularly, GPT-3 and FLM-101B are more than 9 points better than GLM-130B on BoolQ. On WSC task, FLM-101B and GPT-3 perform similarly. However, GLM-130B achieves the best result with about 18 points gap. The technical report of GLM-130B shows that they use both the WSC and RTE datasets in training, but the performance of GLM-130B on the two tasks is so different. Because the original label is replaced by a random

string, overfitting can be ruled out to a certain extent. We believe that it is caused by the structure. The difference is that the encoder method of the context is before the predicted token. GLM-130B is bidirectional while FLM-101B and GPT-3 are uni-directional. This feature makes GLM-130B perform better in coreference resolution tasks, while poor in reasoning-related tasks, *e.g.,* BoolQ. Importantly, the costs of the three models are so different. Our proposed FLM-101B achieves a comparable performance with GPT-3 using about 1/13 computational cost.

# 5.1.3 CLUE-IQ

CLUE [\[69\]](#page-21-8) is an open benchmark for Chinese NLP tasks. Similar to SuperGLUE-IQ, we build CLUE-IQ based on CLUE dataset. Because GPT-3 is unable to handle Chinese well, here we compare FLM-101B with GLM-130B. There are four tasks including AFQMC, CSL, OCNLI and CLUEWSC2020 to be evaluated. For the details of these tasks, please refer to the original work [\[69\]](#page-21-8). The same rules as used in SuperGLUE-IQ are applied to filter the original CLUE. Table [8](#page-11-0) lists the performance of FLM-101B and GLM-130B.

<span id="page-11-0"></span>

Observations. On CLUE-IQ, our proposed FLM-101B achieves the best average performance of 42.07. Among the evaluated tasks, FLM-101B has advantage on AFQMC, CSL, and CLUEWSC2020. The results show that FLM-101B has decent Chinese ability at the level of 100B parameters. Interestingly, FLM-101B performs better than GLM-130B on Chinese WSC, while worse than GLM-130B on English WSC. In addition, FLM-101B performs worse than GLM-103B on OCNLI. These results could reflect that Chinese and English are quite different. Finally, from a cost-effective perspective, our proposed FLM-101B model achieves better performance in Chinese IQ at about 12% of the cost.

#### 5.2 Rule Understanding Evaluation

For human intelligence, understanding and executing according to a given rule is a fundamental part of intelligence. To this end, we design the rule understanding evaluation. This test is different from reasoning which is based on the chain of thought. The former focuses on the understanding ability of simple rules and making the right action, while the latter focuses on reasoning ability. For example, "counting a sequence of numbers" is a typical task for rule understanding evaluation; the step-by-step reasoning by chain-of-thoughts would not be reachable before a model achieves this basic rule-understanding ability.

Detail of Selected Tasks and Data. *Counting* (0-shot) is the simplest test method for rule understanding ability. Here, we build a dataset with 150 items. A typical example is "Let's count from 10010 to 10035: 10010, 10011, 10012,". *String replacement* (4-shots) is another task that examines the model's capacity to edit the text precisely following human intention. Each of these two datasets contains 300 items. Each item starts with a clear instruction: for the "Replace-Word" task, it is like "In the following sentence, replace the specified word with the target word. word to replace: \*\*WQHF\*\* target word: \*\*<u>DFBB</u>\*\*"; for the "Replace-Lowercase" task, it is "For the following text, please modify all uppercase letters to lowercase". The counting range and words to replace are sampled with a uniform distribution. Table [9](#page-11-1) shows the performance of our proposed FLM-101B against GPT-3 and GLM-130B on both counting and string replacement tasks.

#### <span id="page-11-1"></span>Table 9: Performance of FLM-101B, GPT-3 and GLM-130B on rule understanding tasks.



Observations. On this rule understanding task, FLM-101B achieves the second-best performance. Unsurprisingly, GPT-3 wins the first place. This is because GPT-3 has the largest amount of English training data. On the counting task, GPT-3 outperforms the other models, and FLM-101B achieves 69.59%, about 9 points better than GLM-130B. For the string replacement task, GLM-130B performs better than FLM-101B, and GPT-3 again performs the best. On the word replacing task, FLM-101B achieves the best performance, while GPT-3 is the second best. This experiment shows that the advantages of each model are varied. Hence, in future work, rule understanding evaluation tasks should cover more scenarios. Finally, considering the cost of each model, the performance of our FLM-101B is satisfactory.

#### 5.3 Pattern Mining Evaluation

Pattern Mining is the induction and deduction of the patterns emerging in a new context. It is difficult even for humans and frequently used in intelligence tests. To this end, we build a benchmark with three tasks (*i.e.,* Head & Tail, Full Repeating, and Head Slicing) for evaluation. Specifically, *Head & Tail* is to add head and tail to the given input, and the two elements (*i.e.,* the head and tail) should be exactly the same as the ones in the given examples. As to *Full Repeating*, the input sequence should be fully repeated once. For *Head Slicing* task, the model needs to return the first fixed number of characters of the input. The number can be inferred from the preceding examples.

<span id="page-12-0"></span>

	<b>Pattern Mining Evaluation</b>		
	<b>Head &amp; Tail</b>	<b>Full Repeating</b>	<b>Head Slicing</b>
<b>Examples</b>	Input: IHFJd	Input: gEdcFa	Input: EgIdJ
	Output: JHcIIHFJdFgcB	Output: gEdcFagEdcFa	Output: Eq
	Input: BEgI	Input: IdcBq	Input: cqBaE
	Output: JHcIBEgIFgcB	Output: IdcBgIdcBg	Output: cq
	$\cdots$	$\cdots$	$\cdots$
	Input: JlgH	Input: dHqFa	Input: BcJ
	Output: JHclJlgHFgcB	Output: dHqFadHqFa	Output: Bc
Prompt			
	Input: BEH	Input: EqBJ	Input: gHdEla
	Output:	Output:	Output:

Figure 4: Examples of pattern mining evaluation.

Figure [4](#page-12-0) shows examples of this benchmark. For *Head & Tail* task, it's not hard to find that the inserted head and tail are "JHcl" and "FgcB". For *Full Repeating* task, we could find the pattern is repeating the given string one time. Hence, the right output is "EgBJEgBJ". For the *Head Slicing* task, human intelligence could see that the intention is to find the first two characters. We sample the input strings, heads, and tails from a uniform distribution. These tasks are actually the "alphabetical" versions of the *list\_functions* sub-task of Big-Bench [\[49\]](#page-19-7). The original numerical version is so simple that most existing LLMs could achieve 90%+ accuracy. As a result, the original version lacks distinctiveness. To alleviate this problem, we replace the numbers with characters. All these tasks require the model to discover the behavior patterns inside the given examples. Each task is 5-shot and contains 100 instances. Table [10](#page-12-1) lists the experiment results of our proposed FLM-101B against GPT-3 and GLM-130B on pattern mining tasks.

<span id="page-12-1"></span>Table 10: Performance of FLM-101B, GPT-3 and GLM-130B on pattern mining tasks.

Model	Average		Head & Tail Full Repeating Head Slicing	
GPT-3	70.00	61.00	92.00	57.00
$GLM-130B$	53.00	38.00	70.00	51.00
$FLM-101B$	64.67	52.00	79.00	63.00

Observations. On all three tasks of pattern mining, FLM-101B achieves the second-best performance. Similar to rule understanding evaluation, GPT-3 achieves the best performance due to more training data. FLM-101B outperforms GPT-3 and GLM-130B on the head slicing task. On the other two tasks, the performance of these three models are same: GPT-3 first, FLM-101B second, and GLM-130B third. In detail, FLM-101B achieves 14% and 9% increase compared to GLM-130B.

#### <span id="page-13-0"></span>**Anti-interference Evaluation**

#### **Multiple Key Retrival**

There is an important info hidden inside a lot of irrelevant text. Find it and memorize them. I will quiz you about the important information there Here we go. There and back again.

... Here we go. There and back again. Pass key 1 is **4`(\_8bLIB6**. Remember it. **I4kh-DMS8y** is pass key 2.<br>Here we go. There and back again.

...<br>Here we go. There and back again.

The pass key 1 I told you was

#### **Supporting Facts**



#### Figure 5: Examples of anti-interference evaluation.

Generally speaking, our model achieves performance comparable to GPT-3 and better than GLM-130B. Considering the computational cost, FLM-101B exhibits noticeable abilities in this area.

#### 5.4 Anti-interference Evaluation

Anti-interference capability is critical for finding and utilizing information that are truly related to a specific goal, in a brand-new noisy context (Figure [5\)](#page-13-0). We believe that in addition to generalization, anti-interference is also one of the important principles of AGI. For example, many LLMs will babble in cues with noisy input. Another famous hard problem, the cocktail party problem in speech recognition [\[35\]](#page-18-9), also supports the importance of the anti-interference ability of intelligent agents. To this end, we set this anti-interference evaluation.

Figure [5](#page-13-0) shows two typical examples of this test. Hence, the ability of anti-interference is a useful aspect to evaluate intelligent agents, such as LLMs.

Selected Tasks and Data Collection. We conduct anti-interference evaluation in three task types: multiple key retrievals, single supporting fact tracking and two supporting facts tracking. *Multiple key retrieval* is a kind of puzzle that hides some important information (refers to keys) inside a lot of irrelevant text. If the anti-interference ability of LLMs is not good enough, they will output the wrong or even meaningless words. Even if LLMs pass the first challenge, they may still fail in front of multiple relevant noises. We collect a multiple key retrieval dataset in similar formats as [\[7\]](#page-16-6) with at most 3 keys in each instance, exemplified in Figure [5.](#page-13-0) The *single supporting fact tracking* and *two supporting facts tracking* tasks test whether a model can find the chain of supporting facts to answer a question correctly, which is hidden inside a set of irrelevant statements. There are two sub-tasks in the babi-20 [\[67\]](#page-21-7) benchmark (qa1 and qa2 $^7$  $^7$ ) that are aligned with this setting. Thus, we directly modify them in a generative format with 3-shots. We randomly sampled 300 questions for each of these three tasks. Table [11](#page-14-0) shows the evaluation results on anti-interference.

Observations. Among all the baselines for this evaluation, FLM-101B achieves the second-best passing rates 89.00%, 59.00% and 32.33%, respectively, which is an advantage of about 11%, 3% and 6% compared to GLM-130B. Considering the computational cost, FLM-101B achieves exciting performance.

In conclusion, on our four aspects of IQ evaluation, FLM-101B obtains competitive results to GPT-3 and outperforms GLM-130B with much lower costs. Except for the impacts of training data, the

<span id="page-13-1"></span><sup>&</sup>lt;sup>7</sup>We drop qa3 due to the long context length and extraordinary difficulties for all the models

Model	Average		Multiple Key Retrieval Single Supporting Fact Two Supporting Facts	
$GPT-3$	70.11	92.67	78.33	39.33
GLM-130B	53.56	77.67	56.33	26.67
<b>FLM-101B</b>	60.11	89.00	59.00	32.33

<span id="page-14-0"></span>Table 11: Performance of FLM-101B, GPT-3 and GLM-130B on anti-interference evaluation.

superiority may be owed to that the smaller models in early stages refines a smaller search space, which keeps taking effects when the model grows bigger and wider with increased generalization ability.

# 6 Related Work

Scaling Up Language Models to 100B. The burgeoning advancements in hardware and computational techniques in recent years [\[43;](#page-19-8) [48\]](#page-19-4) have laid a robust groundwork for the expansion of language models. The benefits of scaling up LLMs include discernible advantages in language perplexity supported by studies on scaling laws [\[21;](#page-17-8) [16;](#page-17-9) [17;](#page-17-4) [72\]](#page-21-5), as well as the emergent cognitive competencies in models [\[64;](#page-21-9) [4\]](#page-15-2).

In the realm of 100+ billion parameters, examples of closed-source pre-trained LLMs include GPT-3 [\[3\]](#page-15-0), Gopher [\[38\]](#page-18-10), and Palm [\[1\]](#page-15-3). For closed-source models trained on Chinese data, notable mentions are Ernie 3.0 [\[58\]](#page-20-7), Pangu- $\Sigma$  [\[44\]](#page-19-9), and InternLM [\[53\]](#page-19-10). Turning our attention to open-source variants, OPT [\[76\]](#page-22-2) and BLOOM [\[45\]](#page-19-6) are among the counterparts to GPT-3; the Llama [\[54;](#page-20-0) [55\]](#page-20-1) series strategically operates on a slightly reduced scale (approximately 70B parameters) but amplifies the data to 2TB. GLM-130B [\[75\]](#page-21-2) is an open-source bilingual model with decent performance in both Chinese and English tasks. Nevertheless, the development trajectory and cost of GLM-130B remain largely inaccessible to many academic and industrial entities. FLM-101B is an exemplary paradigm for achieving comparable performance with only \$100K budget. It is our aspiration that this model serves as a catalyst, expediting research advancements and making them more economically feasible in this domain.

Aligning with Humans. Despite the evidence that foundation LLMs present reasoning abilities in zero/few-shot learning and chain-of-thought prompting [\[3;](#page-15-0) [65\]](#page-21-10), further refinement is needed to enhance their abilities to follow instructions [\[63\]](#page-21-11) and aligning to human preferences [\[34;](#page-18-5) [33;](#page-18-4) [13;](#page-16-7) [2\]](#page-15-4). Supervised fine-tuning releases the potential of LLMs to imitate the instruction-following formats and provide human-like responses in dialogical and problem-solving contexts [\[62;](#page-20-8) [68;](#page-21-12) [31;](#page-18-11) [24\]](#page-17-11). Meanwhile, policy optimization methods [\[46;](#page-19-11) [39\]](#page-18-12) lead LLMs to generate responses that maximize rewards congruent with human preferences, *e.g.,* being helpful and harmless [\[12\]](#page-16-8).

On the other hand, although these post-training techniques have proven effective and successful in industrial applications, the scaling laws regarding model sizes persist even after alignment with humans: larger models provide more factual and reasonable responses [\[14\]](#page-16-9), as well as being better calibrated with their confidence probabilities [\[20\]](#page-17-12). We hereby release FLM-101B as a large foundation model with both generative and IQ abilities, making it an accessible starting point for subsequent alignment studies.

LLM Evaluation. Widely-used approaches to evaluation LLMs include natural language processing benchmarks [\[69;](#page-21-8) [57\]](#page-20-6), commonsense knowledge benchmarks [\[9;](#page-16-5) [74;](#page-21-6) [25\]](#page-17-10), and professional knowledge benchmarks [\[15;](#page-16-2) [18\]](#page-17-3). Although knowledge ability is important, it does not reflect the generalization and reliability in new domains and contexts, which is another key requirement for intelligent systems. Existing research like Big-Bench [\[49\]](#page-19-7) and babi-20 [\[67\]](#page-21-7) include some sub-tasks relevant to this topic, while others are still only related to NLP and knowledge. In this work, we develop a more systematic IQ evaluation paradigm by re-organizing existing datasets as well as creating new ones while proper. For chatbots after fine-tuning, automatic and semi-automatic playgrounds are developed to evaluate their human alignment abilities [\[78\]](#page-22-3).

# 7 Conclusion and Lessons

The power of LLMs is very exciting. We believe that LLMs are one of the important possible technical paths to AGI. However, the computational cost is so high that limits the research of LLMs. For the sustainable development of LLMs, we believe that it may be an effective path to construct a basic LLM with a high IQ but less knowledge (to save cost), and then expand the knowledge of the LLM in different domains (to fit domain).

In this paper, we introduce FLM-101B, an open-source LLM that is successfully trained from scratch within \$100,000 budget. The key idea of reducing the training cost is to utilize the *growth strategy* to break through the fixed number of model parameters. Experimental results show that FLM-101B outperforms strong baseline models under much lower computational costs.

Another key challenge for LLMs is the evaluation. Traditional evaluation methods (*i.e.,* MMLU, SuperGLUE, CLUE *et al.*) could not reflect the intelligence of LLMs. Chain of thought evaluation alleviates this issue to some extent. However, the generated results are hard to evaluate automatically. We develop a systematic IQ evaluation benchmark that reflects four critical aspects of intelligence, as well as practical for automatic evaluation. We believe that along this pathway, better IQ evaluation methods will continue to emerge in future studies.

# Acknowledgments

This work was supported by the National Key R&D Program of China (2022ZD0116300) and the National Science Foundation of China (NSFC No. 62106249). We would like to thank Hanxiao Qu, Yan Tian, Xigang Cao, Xiaolong Zhang, Kailong Xie and Conghui Guo for their help on computational resources, Quanyue Ma, Hanyu Zhao, Yihui Guo and Jiahong Leng for their help on data, and all other colleagues' strong supports for this project.

# References

- <span id="page-15-3"></span>[1] Rohan Anil, Andrew M. Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H. Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernández Ábrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan A. Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A. Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vladimir Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, and et al. Palm 2 technical report. CoRR, abs/2305.10403, 2023.
- <span id="page-15-4"></span>[2] Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom B. Brown, Jack Clark, Sam McCandlish, Chris Olah, Benjamin Mann, and Jared Kaplan. Training a helpful and harmless assistant with reinforcement learning from human feedback. CoRR, abs/2204.05862, 2022.
- <span id="page-15-0"></span>[3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. Advances in neural information processing systems, 33:1877–1901, 2020.
- <span id="page-15-2"></span>[4] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott M. Lundberg, Harsha Nori, Hamid Palangi, Marco Túlio Ribeiro, and Yi Zhang. Sparks of artificial general intelligence: Early experiments with GPT-4. CoRR, abs/2303.12712, 2023.
- <span id="page-15-1"></span>[5] Yupeng Chang, Xu Wang, Jindong Wang, Yuan Wu, Kaijie Zhu, Hao Chen, Linyi Yang, Xiaoyuan Yi, Cunxiang Wang, Yidong Wang, Wei Ye, Yue Zhang, Yi Chang, Philip S. Yu, Qiang

Yang, and Xing Xie. A survey on evaluation of large language models. CoRR, abs/2307.03109, 2023.

- <span id="page-16-4"></span>[6] Cheng Chen, Yichun Yin, Lifeng Shang, Xin Jiang, Yujia Qin, Fengyu Wang, Zhi Wang, Xiao Chen, Zhiyuan Liu, and Qun Liu. bert2bert: Towards reusable pretrained language models. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022, pages 2134–2148. Association for Computational Linguistics, 2022.
- <span id="page-16-6"></span>[7] Shouyuan Chen, Sherman Wong, Liangjian Chen, and Yuandong Tian. Extending context window of large language models via positional interpolation. arXiv preprint arXiv:2306.15595, 2023.
- <span id="page-16-3"></span>[8] Tianqi Chen, Ian J. Goodfellow, and Jonathon Shlens. Net2net: Accelerating learning via knowledge transfer. In Yoshua Bengio and Yann LeCun, editors, 4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings, 2016.
- <span id="page-16-5"></span>[9] 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. CoRR, abs/1803.05457, 2018.
- <span id="page-16-0"></span>[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171– 4186. Association for Computational Linguistics, 2019.
- <span id="page-16-1"></span>[11] Siqi Fan, Yequan Wang, Jing Li, Zheng Zhang, Shuo Shang, and Peng Han. Interactive information extraction by semantic information graph. In Luc De Raedt, editor, Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI 2022, Vienna, Austria, 23-29 July 2022, pages 4100–4106. ijcai.org, 2022.
- <span id="page-16-8"></span>[12] Deep Ganguli, Liane Lovitt, Jackson Kernion, Amanda Askell, Yuntao Bai, Saurav Kadavath, Ben Mann, Ethan Perez, Nicholas Schiefer, Kamal Ndousse, Andy Jones, Sam Bowman, Anna Chen, Tom Conerly, Nova DasSarma, Dawn Drain, Nelson Elhage, Sheer El Showk, Stanislav Fort, Zac Hatfield-Dodds, Tom Henighan, Danny Hernandez, Tristan Hume, Josh Jacobson, Scott Johnston, Shauna Kravec, Catherine Olsson, Sam Ringer, Eli Tran-Johnson, Dario Amodei, Tom Brown, Nicholas Joseph, Sam McCandlish, Chris Olah, Jared Kaplan, and Jack Clark. Red teaming language models to reduce harms: Methods, scaling behaviors, and lessons learned. CoRR, abs/2209.07858, 2022.
- <span id="page-16-7"></span>[13] Amelia Glaese, Nat McAleese, Maja Trebacz, John Aslanides, Vlad Firoiu, Timo Ewalds, Maribeth Rauh, Laura Weidinger, Martin J. Chadwick, Phoebe Thacker, Lucy Campbell-Gillingham, Jonathan Uesato, Po-Sen Huang, Ramona Comanescu, Fan Yang, Abigail See, Sumanth Dathathri, Rory Greig, Charlie Chen, Doug Fritz, Jaume Sanchez Elias, Richard Green, Sona Mokrá, Nicholas Fernando, Boxi Wu, Rachel Foley, Susannah Young, Iason Gabriel, William Isaac, John Mellor, Demis Hassabis, Koray Kavukcuoglu, Lisa Anne Hendricks, and Geoffrey Irving. Improving alignment of dialogue agents via targeted human judgements. CoRR, abs/2209.14375, 2022.
- <span id="page-16-9"></span>[14] Arnav Gudibande, Eric Wallace, Charlie Snell, Xinyang Geng, Hao Liu, Pieter Abbeel, Sergey Levine, and Dawn Song. The false promise of imitating proprietary llms. CoRR, abs/2305.15717, 2023.
- <span id="page-16-2"></span>[15] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net, 2021.
- <span id="page-17-9"></span>[16] Tom Henighan, Jared Kaplan, Mor Katz, Mark Chen, Christopher Hesse, Jacob Jackson, Heewoo Jun, Tom B. Brown, Prafulla Dhariwal, Scott Gray, Chris Hallacy, Benjamin Mann, Alec Radford, Aditya Ramesh, Nick Ryder, Daniel M. Ziegler, John Schulman, Dario Amodei, and Sam McCandlish. Scaling laws for autoregressive generative modeling. CoRR, abs/2010.14701, 2020.
- <span id="page-17-4"></span>[17] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katherine Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Oriol Vinyals, Jack W. Rae, and Laurent Sifre. An empirical analysis of compute-optimal large language model training. In NeurIPS, 2022.
- <span id="page-17-3"></span>[18] Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Jiayi Lei, Yao Fu, Maosong Sun, and Junxian He. Ceval: A multi-level multi-discipline chinese evaluation suite for foundation models. CoRR, abs/2305.08322, 2023.
- <span id="page-17-1"></span>[19] Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S. Weld, Luke Zettlemoyer, and Omer Levy. Spanbert: Improving pre-training by representing and predicting spans. Trans. Assoc. Comput. Linguistics, 8:64–77, 2020.
- <span id="page-17-12"></span>[20] Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, Scott Johnston, Sheer El Showk, Andy Jones, Nelson Elhage, Tristan Hume, Anna Chen, Yuntao Bai, Sam Bowman, Stanislav Fort, Deep Ganguli, Danny Hernandez, Josh Jacobson, Jackson Kernion, Shauna Kravec, Liane Lovitt, Kamal Ndousse, Catherine Olsson, Sam Ringer, Dario Amodei, Tom Brown, Jack Clark, Nicholas Joseph, Ben Mann, Sam McCandlish, Chris Olah, and Jared Kaplan. Language models (mostly) know what they know. CoRR, abs/2207.05221, 2022.
- <span id="page-17-8"></span>[21] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. CoRR, abs/2001.08361, 2020.
- <span id="page-17-6"></span>[22] Vijay Korthikanti, Jared Casper, Sangkug Lym, Lawrence McAfee, Michael Andersch, Mohammad Shoeybi, and Bryan Catanzaro. Reducing activation recomputation in large transformer models, 2022.
- <span id="page-17-5"></span>[23] Xiang Li, Xin Jiang, Xuying Meng, Aixin Sun, and Yequan Wang. Freelm: Fine-tuning-free language model. CoRR, abs/2305.01616, 2023.
- <span id="page-17-11"></span>[24] Hunter Lightman, Vineet Kosaraju, Yura Burda, Harrison Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's verify step by step. CoRR, abs/2305.20050, 2023.
- <span id="page-17-10"></span>[25] Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022, pages 3214–3252. Association for Computational Linguistics, 2022.
- <span id="page-17-7"></span>[26] Etai Littwin and Greg Yang. Adaptive optimization in the  $\infty$ -width limit. In The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023. OpenReview.net, 2023.
- <span id="page-17-0"></span>[27] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692, 2019.
- <span id="page-17-2"></span>[28] Yiyi Liu, Yequan Wang, Aixin Sun, Xuying Meng, Jing Li, and Jiafeng Guo. A dual-channel framework for sarcasm recognition by detecting sentiment conflict. In Marine Carpuat, Marie-Catherine de Marneffe, and Iván Vladimir Meza Ruíz, editors, Findings of the Association for Computational Linguistics: NAACL 2022, Seattle, WA, United States, July 10-15, 2022, pages 1670–1680. Association for Computational Linguistics, 2022.
- <span id="page-18-7"></span>[29] Ilya Loshchilov and Frank Hutter. Fixing weight decay regularization in adam. CoRR, abs/1711.05101, 2017.
- <span id="page-18-8"></span>[30] Andrew Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies, pages 142–150, 2011.
- <span id="page-18-11"></span>[31] Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Hassan Awadallah. Orca: Progressive learning from complex explanation traces of GPT-4. CoRR, abs/2306.02707, 2023.
- <span id="page-18-6"></span>[32] Deepak Narayanan, Mohammad Shoeybi, Jared Casper, Patrick LeGresley, Mostofa Patwary, Vijay Korthikanti, Dmitri Vainbrand, Prethvi Kashinkunti, Julie Bernauer, Bryan Catanzaro, Amar Phanishayee, and Matei Zaharia. Efficient large-scale language model training on GPU clusters. CoRR, abs/2104.04473, 2021.
- <span id="page-18-4"></span>[33] OpenAI. GPT-4 technical report. CoRR, abs/2303.08774, 2023.
- <span id="page-18-5"></span>[34] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In NeurIPS, 2022.
- <span id="page-18-9"></span>[35] Yanmin Qian, Chao Weng, Xuankai Chang, Shuai Wang, and Dong Yu. Past review, current progress, and challenges ahead on the cocktail party problem. Frontiers Inf. Technol. Electron. Eng., 19(1):40–63, 2018.
- <span id="page-18-0"></span>[36] Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever, et al. Improving language understanding by generative pre-training. 2018.
- <span id="page-18-1"></span>[37] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019.
- <span id="page-18-10"></span>[38] Jack W. Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, H. Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, Eliza Rutherford, Tom Hennigan, Jacob Menick, Albin Cassirer, Richard Powell, George van den Driessche, Lisa Anne Hendricks, Maribeth Rauh, Po-Sen Huang, Amelia Glaese, Johannes Welbl, Sumanth Dathathri, Saffron Huang, Jonathan Uesato, John Mellor, Irina Higgins, Antonia Creswell, Nat McAleese, Amy Wu, Erich Elsen, Siddhant M. Jayakumar, Elena Buchatskaya, David Budden, Esme Sutherland, Karen Simonyan, Michela Paganini, Laurent Sifre, Lena Martens, Xiang Lorraine Li, Adhiguna Kuncoro, Aida Nematzadeh, Elena Gribovskaya, Domenic Donato, Angeliki Lazaridou, Arthur Mensch, Jean-Baptiste Lespiau, Maria Tsimpoukelli, Nikolai Grigorev, Doug Fritz, Thibault Sottiaux, Mantas Pajarskas, Toby Pohlen, Zhitao Gong, Daniel Toyama, Cyprien de Masson d'Autume, Yujia Li, Tayfun Terzi, Vladimir Mikulik, Igor Babuschkin, Aidan Clark, Diego de Las Casas, Aurelia Guy, Chris Jones, James Bradbury, Matthew J. Johnson, Blake A. Hechtman, Laura Weidinger, Iason Gabriel, William Isaac, Edward Lockhart, Simon Osindero, Laura Rimell, Chris Dyer, Oriol Vinyals, Kareem Ayoub, Jeff Stanway, Lorrayne Bennett, Demis Hassabis, Koray Kavukcuoglu, and Geoffrey Irving. Scaling language models: Methods, analysis & insights from training gopher. CoRR, abs/2112.11446, 2021.
- <span id="page-18-12"></span>[39] Rafael Rafailov, Archit Sharma, Eric Mitchell, Stefano Ermon, Christopher D. Manning, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. CoRR, abs/2305.18290, 2023.
- <span id="page-18-2"></span>[40] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21:140:1–140:67, 2020.
- <span id="page-18-3"></span>[41] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21:140:1–140:67, 2020.
- <span id="page-19-5"></span>[42] Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. Zero: Memory optimization towards training A trillion parameter models. CoRR, abs/1910.02054, 2019.
- <span id="page-19-8"></span>[43] Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. Zero: memory optimizations toward training trillion parameter models. In Christine Cuicchi, Irene Qualters, and William T. Kramer, editors, Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis, SC 2020, Virtual Event / Atlanta, Georgia, USA, November 9-19, 2020, page 20. IEEE/ACM, 2020.
- <span id="page-19-9"></span>[44] Xiaozhe Ren, Pingyi Zhou, Xinfan Meng, Xinjing Huang, Yadao Wang, Weichao Wang, Pengfei Li, Xiaoda Zhang, Alexander Podolskiy, Grigory Arshinov, Andrey Bout, Irina Piontkovskaya, Jiansheng Wei, Xin Jiang, Teng Su, Qun Liu, and Jun Yao. Pangu-Σ: Towards trillion parameter language model with sparse heterogeneous computing. CoRR, abs/2303.10845, 2023.
- <span id="page-19-6"></span>[45] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilic, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, Jonathan Tow, Alexander M. Rush, Stella Biderman, Albert Webson, Pawan Sasanka Ammanamanchi, Thomas Wang, Benoît Sagot, Niklas Muennighoff, Albert Villanova del Moral, Olatunji Ruwase, Rachel Bawden, Stas Bekman, Angelina McMillan-Major, Iz Beltagy, Huu Nguyen, Lucile Saulnier, Samson Tan, Pedro Ortiz Suarez, Victor Sanh, Hugo Laurençon, Yacine Jernite, Julien Launay, Margaret Mitchell, Colin Raffel, Aaron Gokaslan, Adi Simhi, Aitor Soroa, Alham Fikri Aji, Amit Alfassy, Anna Rogers, Ariel Kreisberg Nitzav, Canwen Xu, Chenghao Mou, Chris Emezue, Christopher Klamm, Colin Leong, Daniel van Strien, David Ifeoluwa Adelani, and et al. BLOOM: A 176b-parameter open-access multilingual language model. CoRR, abs/2211.05100, 2022.
- <span id="page-19-11"></span>[46] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. CoRR, abs/1707.06347, 2017.
- <span id="page-19-3"></span>[47] Sheng Shen, Pete Walsh, Kurt Keutzer, Jesse Dodge, Matthew E. Peters, and Iz Beltagy. Staged training for transformer language models. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato, editors, International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA, volume 162 of Proceedings of Machine Learning Research, pages 19893–19908. PMLR, 2022.
- <span id="page-19-4"></span>[48] Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. Megatron-lm: Training multi-billion parameter language models using model parallelism. CoRR, abs/1909.08053, 2019.
- <span id="page-19-7"></span>[49] Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. Transactions on Machine Learning Research, 2023.
- <span id="page-19-2"></span>[50] Jianlin Su, Yu Lu, Shengfeng Pan, Bo Wen, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. CoRR, abs/2104.09864, 2021.
- <span id="page-19-0"></span>[51] Yu Sun, Shuohuan Wang, Yu-Kun Li, Shikun Feng, Xuyi Chen, Han Zhang, Xin Tian, Danxiang Zhu, Hao Tian, and Hua Wu. ERNIE: enhanced representation through knowledge integration. CoRR, abs/1904.09223, 2019.
- <span id="page-19-1"></span>[52] Yutao Sun, Li Dong, Barun Patra, Shuming Ma, Shaohan Huang, Alon Benhaim, Vishrav Chaudhary, Xia Song, and Furu Wei. A length-extrapolatable transformer. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023, pages 14590–14604. Association for Computational Linguistics, 2023.
- <span id="page-19-10"></span>[53] InternLM Team. Internlm: a multilingual language model with progressively enhanced capabilities, 2023. [https://github.com/InternLM/InternLM-techreport/blob/main/](https://github.com/InternLM/InternLM-techreport/blob/main/InternLM.pdf) [InternLM.pdf](https://github.com/InternLM/InternLM-techreport/blob/main/InternLM.pdf),.
- <span id="page-20-0"></span>[54] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. CoRR, abs/2302.13971, 2023.
- <span id="page-20-1"></span>[55] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton-Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurélien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. Llama 2: Open foundation and fine-tuned chat models. CoRR, abs/2307.09288, 2023.
- <span id="page-20-5"></span>[56] Leslie G. Valiant. A bridging model for parallel computation. Commun. ACM, 33(8):103–111, aug 1990.
- <span id="page-20-6"></span>[57] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d'Alché-Buc, Emily B. Fox, and Roman Garnett, editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada, pages 3261– 3275, 2019.
- <span id="page-20-7"></span>[58] Shuohuan Wang, Yu Sun, Yang Xiang, Zhihua Wu, Siyu Ding, Weibao Gong, Shikun Feng, Junyuan Shang, Yanbin Zhao, Chao Pang, Jiaxiang Liu, Xuyi Chen, Yuxiang Lu, Weixin Liu, Xi Wang, Yangfan Bai, Qiuliang Chen, Li Zhao, Shiyong Li, Peng Sun, Dianhai Yu, Yanjun Ma, Hao Tian, Hua Wu, Tian Wu, Wei Zeng, Ge Li, Wen Gao, and Haifeng Wang. ERNIE 3.0 titan: Exploring larger-scale knowledge enhanced pre-training for language understanding and generation. CoRR, abs/2112.12731, 2021.
- <span id="page-20-4"></span>[59] Yequan Wang, Jiawen Deng, Aixin Sun, and Xuying Meng. Perplexity from PLM is unreliable for evaluating text quality. CoRR, abs/2210.05892, 2022.
- <span id="page-20-3"></span>[60] Yequan Wang, Xiang Li, Aixin Sun, Xuying Meng, Huaming Liao, and Jiafeng Guo. Cofenet: Context and former-label enhanced net for complicated quotation extraction. In Nicoletta Calzolari, Chu-Ren Huang, Hansaem Kim, James Pustejovsky, Leo Wanner, Key-Sun Choi, Pum-Mo Ryu, Hsin-Hsi Chen, Lucia Donatelli, Heng Ji, Sadao Kurohashi, Patrizia Paggio, Nianwen Xue, Seokhwan Kim, Younggyun Hahm, Zhong He, Tony Kyungil Lee, Enrico Santus, Francis Bond, and Seung-Hoon Na, editors, Proceedings of the 29th International Conference on Computational Linguistics, COLING 2022, Gyeongju, Republic of Korea, October 12-17, 2022, pages 2438–2449. International Committee on Computational Linguistics, 2022.
- <span id="page-20-2"></span>[61] Yequan Wang, Hengran Zhang, Aixin Sun, and Xuying Meng. CORT: A new baseline for comparative opinion classification by dual prompts. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, Findings of the Association for Computational Linguistics: EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022, pages 7064–7075. Association for Computational Linguistics, 2022.
- <span id="page-20-8"></span>[62] Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki, editors, Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023, pages 13484–13508. Association for Computational Linguistics, 2023.
- <span id="page-21-11"></span>[63] Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. Finetuned language models are zero-shot learners. In The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022. OpenReview.net, 2022.
- <span id="page-21-9"></span>[64] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. Emergent abilities of large language models. Trans. Mach. Learn. Res., 2022, 2022.
- <span id="page-21-10"></span>[65] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In NeurIPS, 2022.
- <span id="page-21-1"></span>[66] Jerry W. Wei, Le Hou, Andrew K. Lampinen, Xiangning Chen, Da Huang, Yi Tay, Xinyun Chen, Yifeng Lu, Denny Zhou, Tengyu Ma, and Quoc V. Le. Symbol tuning improves in-context learning in language models. CoRR, abs/2305.08298, 2023.
- <span id="page-21-7"></span>[67] Jason Weston, Antoine Bordes, Sumit Chopra, Alexander M Rush, Bart Van Merriënboer, Armand Joulin, and Tomas Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. arXiv preprint arXiv:1502.05698, 2015.
- <span id="page-21-12"></span>[68] Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. Wizardlm: Empowering large language models to follow complex instructions. CoRR, abs/2304.12244, 2023.
- <span id="page-21-8"></span>[69] Liang Xu, Hai Hu, Xuanwei Zhang, Lu Li, Chenjie Cao, Yudong Li, Yechen Xu, Kai Sun, Dian Yu, Cong Yu, Yin Tian, Qianqian Dong, Weitang Liu, Bo Shi, Yiming Cui, Junyi Li, Jun Zeng, Rongzhao Wang, Weijian Xie, Yanting Li, Yina Patterson, Zuoyu Tian, Yiwen Zhang, He Zhou, Shaoweihua Liu, Zhe Zhao, Qipeng Zhao, Cong Yue, Xinrui Zhang, Zhengliang Yang, Kyle Richardson, and Zhenzhong Lan. CLUE: A chinese language understanding evaluation benchmark. In Donia Scott, Núria Bel, and Chengqing Zong, editors, Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020, pages 4762–4772. International Committee on Computational Linguistics, 2020.
- <span id="page-21-3"></span>[70] Greg Yang and Edward J. Hu. Tensor programs IV: feature learning in infinite-width neural networks. In Marina Meila and Tong Zhang, editors, Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event, volume 139 of Proceedings of Machine Learning Research, pages 11727–11737. PMLR, 2021.
- <span id="page-21-4"></span>[71] Greg Yang, Edward J. Hu, Igor Babuschkin, Szymon Sidor, Xiaodong Liu, David Farhi, Nick Ryder, Jakub Pachocki, Weizhu Chen, and Jianfeng Gao. Tuning large neural networks via zero-shot hyperparameter transfer. In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan, editors, Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual, pages 17084–17097, 2021.
- <span id="page-21-5"></span>[72] Yiqun Yao and Yequan Wang. Research without re-search: Maximal update parametrization yields accurate loss prediction across scales. CoRR, abs/2304.06875, 2023.
- <span id="page-21-0"></span>[73] Yiqun Yao, Zheng Zhang, Jing Li, and Yequan Wang. 2x faster language model pre-training via masked structural growth. CoRR, abs/2305.02869, 2023.
- <span id="page-21-6"></span>[74] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In Anna Korhonen, David R. Traum, and Lluís Màrquez, editors, Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers, pages 4791–4800. Association for Computational Linguistics, 2019.
- <span id="page-21-2"></span>[75] Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. GLM-130B: an open bilingual

pre-trained model. In The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023. OpenReview.net, 2023.

- <span id="page-22-2"></span>[76] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona T. Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. OPT: open pre-trained transformer language models. CoRR, abs/2205.01068, 2022.
- <span id="page-22-0"></span>[77] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A survey of large language models. CoRR, abs/2303.18223, 2023.
- <span id="page-22-3"></span>[78] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena. CoRR, abs/2306.05685, 2023.
- <span id="page-22-1"></span>[79] Terry Yue Zhuo, Zhuang Li, Yujin Huang, Fatemeh Shiri, Weiqing Wang, Gholamreza Haffari, and Yuan-Fang Li. On robustness of prompt-based semantic parsing with large pre-trained language model: An empirical study on codex. In Andreas Vlachos and Isabelle Augenstein, editors, Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2023, Dubrovnik, Croatia, May 2-6, 2023, pages 1090–1102. Association for Computational Linguistics, 2023.