
Herd: Using multiple, smaller LLMs to match the performances of proprietary, large LLMs via an intelligent composer

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Abstract

Currently, over a thousand LLMs exist that are multi-purpose and are capable of performing real world tasks, including Q&A, text summarization, content generation, etc. However, accessibility, scale and reliability of free models prevents them from being widely deployed in everyday use cases. To address the first two issues of access and scale, organisations such as HuggingFace have created model repositories where users have uploaded model weights and quantized versions of models trained using different paradigms, as well as model cards describing their training process. While some models report performance on commonly used benchmarks, not all do, and interpreting the real world impact of trading off performance on a benchmark for model deployment cost, is unclear. Here, we show that a herd of open source models can match or exceed the performance of proprietary models via an intelligent router. We show that a Herd of open source models is able to match the accuracy of ChatGPT, despite being composed of models that are effectively 2.5x smaller. We show that in cases where GPT is not able to answer the query, Herd is able to identify a model that can, at least 40% of the time.

1 Introduction

Large language models have found novel ways to increase the number of use cases, such as by expanding the number of parameters, combining existing models to augment a single models' functionality and quantizing large models to fit on smaller devices [4, 12, 9, 18, 2, 8, 13, 3–5]. The rapid expansion of model availability has created a significant challenge in practice, where corporations want to expose performant LLM endpoints for their users, and have to spend time evaluating models to find the best one that works for them in practice. To overcome this problem, engineers often resort to proprietary models without knowing if there are open-source models available at a comparable performance standard.

This often leads to the problem elaborated in Figure 1, showing examples of questions taken from MMLU that ChatGPT (GPT 3.5 Turbo) answers incorrectly, but there is some open source model that can answer the question correctly. We use this insight to try and construct a herd of models such that at least one model in the herd can answer any incoming query correctly.

Question:	Closed source	Open source					
		Llama-2-7b-Chat-GPT Q	Spicyboros-13B-2.2-GPTQ	Vicuna 7B	ORCA_LLAMA_70B_QLoRA-GPT Q	Airoboros-L-2-13B-2.2-GPTQ	Airoboros-6-5B-GPT4-m-2.0-GPTQ
Within a substance, atoms that collide frequently and move independently of one another are most likely in a?	liquid.	gas.	gas	crystal.	gas.	liquid	gas.
Gavin has two rocks. Both rocks are made up entirely of the same mineral. What other property of his two rocks is most likely to be the same??	weight	weight	weight	color	weight	Weight	4. weight
Which food provides the most energy for the body in the shortest amount of time??	meat	meat	potato	Meat provides the most ...	fruit	Meat	milk
Which of the following is a chemical change? Element 1 is hammered into a thin sheet. Element 2 is heated and turns into a liquid. Element 3 turns a greenish color as it sits in air. Element 4 is ground up into a fine, slippery powder.	Option 2	Element 2 is heated and turns into a liquid.	Element 3 turns a greenish color as it sits in air.	Element 2 is heated and turns into a liquid.	Element 2 is heated and turns into a liquid.	Element 4 is ground up into a fine, slippery powder.	Element 4 is ground up into a fine, slippery powder.

Figure 1: In practice, not all models are able to answer all questions accurately (the ones that do answer the questions correctly have their answers boxed in green), which leads to the practical challenge in picking an ensemble of models that has at least one highly performant model for every question. Herd attempts to solve this problem by constructing a herd of large language models that collectively can answer the query accurately, and by learning the association between input text and performance of each LLM.

Recent model evaluation frameworks [6, 19] help users compare LLMs against each other, but the growing pace of model formats, outpaces one-size-fits-all comparison software suites. Empirical evidence in this work, reveals that open source models have caught up with leading proprietary models, but not all open source models feature on leaderboards, due to their vast number.

Deployment of models also remains a key challenge. The 70b parameter Llama-2, in 16-bit precision, requires 2 80Gb A100 GPUs, and in practice, users might want several models running in parallel. Sacrificing parameter count to cut costs risks performance degradation, the exact magnitude of which is unknown before deployment.

While quantized models might alleviate some of the challenges associated with model deployment, finding performant quantized models, navigating their formats and knowing their training details, such as what datasets were used in their quantisation calibration, requires expertise.

In addition to quantized variants of models, specific model variants exist with chat capabilities, with different performance metrics from non-chat models. Others with more specific domain expertises such as science or code [17, 1], might be useful for some user applications but aren't fine-tuned for chat capability, making it harder to pick one model to use in production.

Today the Huggingface (HF) model repository contains ~24,000 machine learning models for text generation. While model cards might provide some insight into the dataset that a model is trained on, common practices such as fine-tuning models using inputs from other large language models or model merging [10, 16, 14, 11] has made it difficult to track what data was used to train the model. This has also made it challenging to track what datasets or tasks one can expect the models to be performant on. Further, not all open source models have detailed model cards, making trusting them in deployment even more challenging.

Together, it would be a useful service to expose an endpoint that would process an incoming users' request by abstracting away model selection. Here, we explore the advantage of exposing a model herd of open source models, which outperforms a larger, proprietary large language model, offering size advantages. We also train a Tryage router [7] to predict model performance, and show that the model herd is able to answer 74% of incoming queries with performance comparable to or better than ChatGPT.

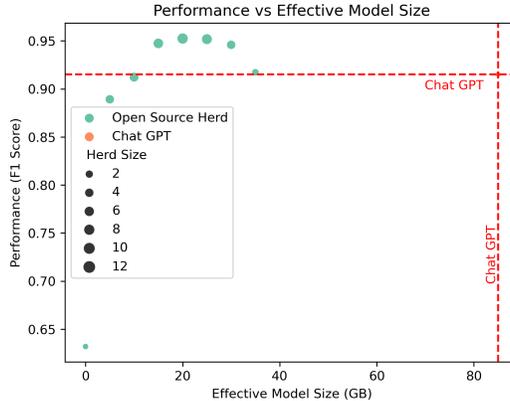


Figure 2: Open source model Herds outperform proprietary models such as ChatGPT on MMLU with decreased model size.

Herd Architecture

Define a model Herd M , which is a collection of models. In an oracle model system, incoming query z is assigned to $\arg \max_j M_j(z)$. However, in practice, evaluating $M_j(z)$ for all j , is expensive. To this end, we choose the model $\arg \max_j \hat{M}_j(z)$, where \hat{M}_j is learned by a router R [7]. We implement the router model as a language model. In practice, the router optimizes its weight set W over the following loss function.

$$\min_W \mathbb{E}_{z \sim p(z)} \left(\frac{1}{|M|} \sum_{M_i} D(R(z, M_i; W) || L(z, M_i)) \right) \quad (1)$$

where $D(\cdot || \cdot)$ is divergence between predicted loss $R(z, M_i; W)$ and ground truth loss $L(z, M_i)$ (here the L1 distance function was used between predicted and ground truth F1s measured character-wise) for prompts z drawn from data distribution $p(z)$ from the MMLU dataset.

In this work, we found that bert-medium [15] was the best performing router when a variety of router models were trained on 12,000 examples and validated on 3001 examples from MMLU, with a fixed batch size of 16, using the Adam optimizer with a learning rate of $2e - 5$.

In this work, we composed the herd by replicating realistic user constraints of models that would fit on an 8x48Gb cluster, using a mixture of 7B, 15B, 30B and 70B order models. We used a mix of quantized and non-quantized models, since their performances' were previously unknown.

Demonstrating Herd

We find that a herd of open source models is able to beat ChatGPT (Figure 2) despite being effectively less than 30% of the size (effective size measured as the average size of models weighted by the number of examples allocated to them). Further, none of the models in the herd were individually better than ChatGPT, but together, they were able to surpass ChatGPT's performance. Further, all the models are open source, and the herd can be seamlessly expanded, contracted or interchanged for other models.

We trained a tryage router [7] to model the performances of a herd and found that the router was able to successfully allocate incoming queries to models that produced aggregate performance comparable to GPT 3.5 Turbo despite being effectively 2.5x smaller ¹. Further, some models in the herd are quantized, meaning they can be run on edge compute / cloud compute - a user can trade off the size of a herd for compute cost.

¹exact number of parameters in ChatGPT (GPT 3.5 Turbo) unknown, based on reported information

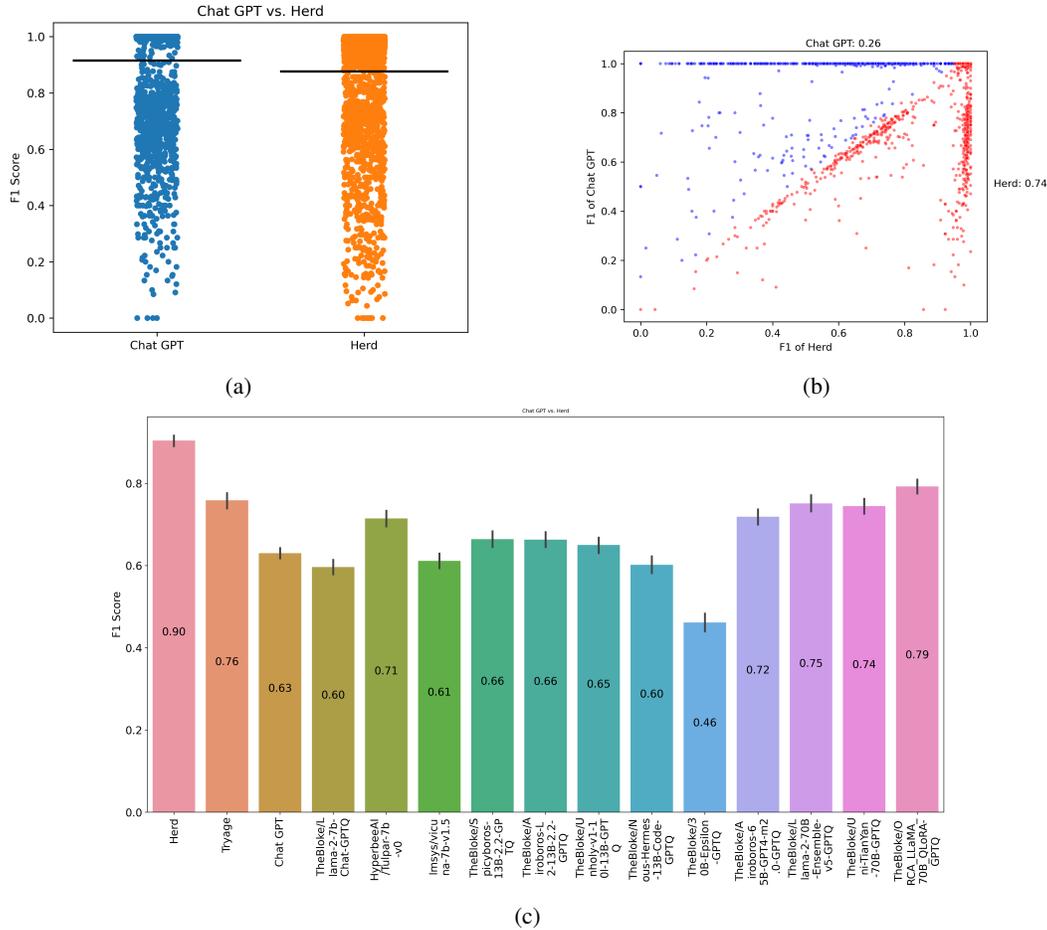


Figure 3: a) A router trained to model the performance of a herd offers comparable performance to GPT 3.5 Turbo (mean performances shown as horizontal lines). b) GPT exceeds the performance of the Herd in only 26% of incoming queries, implying 74% of incoming queries can be answered by open source models in the Herd. c) In questions that ChatGPT gets wrong the Herd can find models that perform correctly (Average of 0.9 F1). A routing model, achieves an aggregate of 0.76 F1 on these questions.

We show that Herd can capture knowledge in cases where ChatGPT fails to answer an incoming query. While any single model might not be able to answer all the incoming queries, Herd is able to find a model that can answer each query, based on the input text of the prompt. ChatGPT is only able to beat a herd of open source models 26% of the time, implying 74% of the queries can be answered by open source models (Fig. 3b, ‘beat’ is defined as F1 in excess of 5%).

In the cases where ChatGPT was wrong, defined as when ChatGPT had an F1 score of less than 0.9, Herd was able to achieve a correct answer (defined as when any model in the Herd had an F1 score greater than 0.95), 69.3% of the time. A predictive router, was able to identify a model that can answer the query correctly, 40% of the time (Tryage bar in Fig. 3c). The mean of the F1s of the answers from each model, as well as the aggregate F1s from Herd and the predictive router, are shown in Figure 3c.

Conclusion and discussion

In this work we present the result that a Herd of open-sourced models can achieve performance comparable or better than ChatGPT, at a fraction of the compute cost and zero query cost. Further, when proprietary models cannot answer a query, a herd of open source models, are able to cover a

significant portion of the deficit. This system offers a new model paradigm to compete against closed source models, by leveraging widely available open source technology.

References

- [1] Introducing Code Llama, an AI Tool for Coding, August 2023.
- [2] Haoli Bai, Lu Hou, Lifeng Shang, Xin Jiang, Irwin King, and Michael R Lyu. Towards Efficient Post-training Quantization of Pre-trained Language Models.
- [3] Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.
- [4] 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.
- [5] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. *arXiv preprint arXiv:2305.14314*, 2023.
- [6] Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, September 2021.
- [7] Surya Narayanan Hari and Matt Thomson. Tryage: Real-time, intelligent Routing of User Prompts to Large Language Models, August 2023. arXiv:2308.11601 [cs].
- [8] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16000–16009, 2022.
- [9] Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-Rank Adaptation of Large Language Models, October 2021. arXiv:2106.09685 [cs].
- [10] Xisen Jin, Xiang Ren, Daniel Preotiuc-Pietro, and Pengxiang Cheng. Dataless Knowledge Fusion by Merging Weights of Language Models, June 2023. arXiv:2212.09849 [cs].
- [11] Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Awadallah. Orca: Progressive learning from complex explanation traces of gpt-4, 2023.
- [12] OpenAI. Gpt-4 technical report, 2023.
- [13] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Stanford alpaca: An instruction-following llama model, 2023.
- [14] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.
- [15] Iulia Turc, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Well-Read Students Learn Better: On the Importance of Pre-training Compact Models, September 2019. arXiv:1908.08962 [cs].
- [16] Guan Wang, Sijie Cheng, Qiyang Yu, and Changling Liu. OpenChat: Advancing Open-source Language Models with Imperfect Data, 7 2023.
- [17] BigScience Workshop, Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, 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, Dragomir Radev, Eduardo González Ponferrada, Efrat Levkovizh, Ethan Kim, Eyal Bar Natan, Francesco De Toni, Gérard Dupont, Germán Kruszewski, Giada Pistilli, Hady Elshahar, Hamza Benyamina, Hieu Tran, Ian Yu, Idris Abdulmumin, Isaac Johnson, Itziar Gonzalez-Dios, Javier de la Rosa, Jenny Chim, Jesse Dodge, Jian Zhu, Jonathan Chang, Jörg Froberg, Joseph Tobing, Joydeep Bhattacharjee, Khalid Almubarak, Kimbo Chen, Kyle Lo, Leandro Von Werra, Leon Weber, Long Phan, Loubna Ben allal, Ludovic Tanguy, Manan Dey, Manuel Romero Muñoz, Maraim Masoud, María Grandury, Mario Šaško, Max Huang, Maximin Coavoux, Mayank Singh, Mike Tian-Jian Jiang, Minh Chien Vu, Mohammad A. Jauhar, Mustafa Ghaleb, Nishant Subramani, Nora Kassner, Nurulaqilla Khamis, Olivier Nguyen, Omar Espejel, Ona de Gibert, Paulo Villegas, Peter Henderson, Pierre Colombo, Priscilla Amuok, Quentin Lhoest, Rheza Harliman, Rishi Bommasani, Roberto Luis López, Rui Ribeiro, Salomey Osei, Sampo Pyysalo, Sebastian Nagel, Shamik Bose, Shamsuddeen Hassan Muhammad, Shanya Sharma, Shayne Longpre, Somaieh Nikpoor, Stanislav Silberberg, Suhas Pai, Sydney Zink, Tiago Timponi Torrent, Timo Schick, Tristan Thrush, Valentin Danchev, Vassilina Nikoulina, Veronika Laippala, Violette Lepercq, Vrinda Prabhu, Zaid Alyafeai, Zeerak Talat, Arun Raja, Benjamin Heinzerling, Chenglei Si, Davut Emre Taşar, Elizabeth Salesky, Sabrina J. Mielke, Wilson Y. Lee, Abheesh Sharma, Andrea Santilli, Antoine Chaffin, Arnaud Stiegler, Debajyoti Datta, Eliza Szczechla, Gunjan Chhablani, Han Wang, Harshit Pandey, Hendrik Strobelt, Jason Alan Fries, Jos Rozen, Leo Gao, Lintang Sutawika, M. Saiful Bari, Maged S. Al-shaibani, Matteo Manica, Nihal Nayak, Ryan Teehan, Samuel Albanie, Sheng Shen, Srulik Ben-David, Stephen H. Bach, Taewoon Kim, Tali Bers, Thibault Fevry, Trishala Neeraj, Urmish Thakker, Vikas Raunak, Xiangru Tang, Zheng-Xin Yong, Zhiqing Sun, Shaked Brody, Yallow Uri, Hadar Tojarieh, Adam Roberts, Hyung Won Chung, Jaesung Tae, Jason Phang, Ofir Press, Conglong Li, Deepak Narayanan, Hatim Bourfoune, Jared Casper, Jeff Rasley, Max Ryabinin, Mayank Mishra, Minjia Zhang, Mohammad Shoeybi, Myriam Peyrounette, Nicolas Patry, Nouamane Tazi, Omar Sanseviero, Patrick von Platen, Pierre Cornette, Pierre François Lavallée, Rémi Lacroix, Samyam Rajbhandari, Sanchit Gandhi, Shaden Smith, Stéphane Requena, Suraj Patil, Tim Dettmers, Ahmed Baruwa, Amanpreet Singh, Anastasia Cheveleva, Anne-Laure Ligozat, Arjun Subramonian, Aurélie Névéal, Charles Lovering, Dan Garrette, Deepak Tunuguntla, Ehud Reiter, Ekaterina Taktasheva, Ekaterina Voloshina, Eli Bogdanov, Genta Indra Winata, Hailey Schoelkopf, Jan-Christoph Kalo, Jekaterina Novikova, Jessica Zosa Forde, Jordan Clive, Jungo Kasai, Ken Kawamura, Liam Hazan, Marine Carpuat, Miruna Clinciu, Najoung Kim, Newton Cheng, Oleg Serikov, Omer Antverg, Oskar van der Wal, Rui Zhang, Ruochen Zhang, Sebastian Gehrmann, Shachar Mirkin, Shani Pais, Tatiana Shavrina, Thomas Scialom, Tian Yun, Tomasz Limisiewicz, Verena Rieser, Vitaly Protasov, Vladislav Mikhailov, Yada Pruksachatkun, Yonatan Belinkov, Zachary Bamberger, Zdeněk Kasner, Alice Rueda, Amanda Pestana, Amir Feizpour, Ammar Khan, Amy Faranak, Ana Santos, Anthony Hevia, Antigona Unldreaj, Arash Aghagol, Arezoo Abdollahi, Aycha Tammour, Azadeh HajiHosseini, Bahareh Behroozi, Benjamin Ajibade, Bharat Saxena, Carlos Muñoz Ferrandis, Daniel McDuff, Danish Contractor, David Lansky, Davis David, Douwe Kiela, Duong A. Nguyen, Edward Tan, Emi Baylor, Ezinwanne Ozoani, Fatima Mirza, Frankline Ononiwu, Habib Rezanejad, Hessie Jones, Indrani Bhattacharya, Irene Solaiman, Irina Sedenko, Isar Nejadgholi, Jesse Passmore, Josh Seltzer, Julio Bonis Sanz, Livia Dutra, Mairon Samagaio, Maraim Elbadri, Margot Mieskes, Marissa Gerchick, Martha Akinlolu, Michael McKenna, Mike Qiu, Muhammed Ghauri, Mykola Burynok, Nafis Abrar, Nazneen Rajani, Nour Elkott, Nour Fahmy, Olanrewaju Samuel, Ran An, Rasmus Kromann, Ryan Hao, Samira Alizadeh, Sarmad Shubber, Silas Wang, Sourav Roy, Sylvain Viguier, Thanh Le, Tobi Oyebade, Trieu Le, Yoyo Yang, Zach Nguyen, Abhinav Ramesh Kashyap, Alfredo Palasciano, Alison Callahan, Anima Shukla, Antonio Miranda-Escalada, Ayush Singh, Benjamin Beilharz, Bo Wang, Caio Brito, Chenxi Zhou, Chirag Jain, Chuxin Xu, Clémentine Fourrier, Daniel León Perrián, Daniel Molano, Dian Yu, Enrique Manjavacas, Fabio Barth, Florian Fuhrmann, Gabriel Altay, Giyaseddin Bayrak, Gully Burns, Helena U. Vrabc, Imane Bello, Ishani Dash, Jihyun Kang, John Giorgi, Jonas Golde, Jose David Posada, Karthik Rangasai Sivaraman, Lokesh Bulchandani, Lu Liu, Luisa Shinzato, Madeleine Hahn de Bykhovetz, Maiko Takeuchi, Marc Pàmies, Maria A. Castillo, Marianna Nezhurina, Mario Sängler, Matthias Samwald, Michael Cullan, Michael Weinberg, Michiel De Wolf, Mina Mihaljcic, Minna Liu, Moritz Freidank, Myungsun Kang, Natasha Seelam, Nathan Dahlberg, Nicholas Michio Broad, Nikolaus Muellner, Pascale Fung, Patrick

Haller, Ramya Chandrasekhar, Renata Eisenberg, Robert Martin, Rodrigo Canalli, Rosaline Su, Ruisi Su, Samuel Cahyawijaya, Samuele Garda, Shlok S. Deshmukh, Shubhanshu Mishra, Sid Kiblawi, Simon Ott, Sinee Sang-aaronsiri, Srishti Kumar, Stefan Schweter, Sushil Bharati, Tanmay Laud, Théo Gigant, Tomoya Kainuma, Wojciech Kusa, Yanis Labrak, Yash Shailesh Bajaj, Yash Venkatraman, Yifan Xu, Yingxin Xu, Yu Xu, Zhe Tan, Zhongli Xie, Zifan Ye, Mathilde Bras, Younes Belkada, and Thomas Wolf. BLOOM: A 176B-Parameter Open-Access Multilingual Language Model, June 2023. arXiv:2211.05100 [cs].

- [18] Guangxuan Xiao, Ji Lin, Mickael Seznec, Hao Wu, Julien Demouth, and Song Han. SmoothQuant: Accurate and Efficient Post-Training Quantization for Large Language Models. In *Proceedings of the 40th International Conference on Machine Learning*, pages 38087–38099. PMLR, July 2023. ISSN: 2640-3498.
- [19] 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, 2023.