Vikhr: The Family of Open-Source Instruction-Tuned Large Language **Models for Russian**

Aleksandr Nikolich

Konstantin Korolev

Igor Kiselev

ITMO University

HSE University alexdragannikolich@gmail.com korolevko@icloud.com

Accenture example@mail.com

Artem Shelmanov MBZUAI

artem.shelmanov@mbzuai.ac.ae

Abstract

There has been a surge in the development of various Large Language Models (LLMs). However, text generation for languages other than English often faces significant challenges, including poor generation quality and the reduced computational performance due to the disproportionate representation of tokens in model's vocabulary. In this work, we address these issues and introduce Vikhr, a new state-of-the-art open-source instruction-tuned LLM designed specifically for the Russian language. "Vikhr" refers to the name of the Mistral LLM series and means "strong gust of wind." Unlike previous efforts for Russian that utilize computationally inexpensive LoRA adapters on top of English-oriented models, Vikhr features an adapted tokenizer vocabulary and undergoes the continued pre-training and instruction tuning of all weights. This approach not only enhances the model's performance but also significantly improves its computational and contextual efficiency. The remarkable performance of Vikhr across various Russian-language benchmarks can also be attributed to our efforts in expanding instruction datasets and corpora for continued pre-training. Vikhr not only sets the new state of the art among open-source LLMs for Russian, but even outperforms some proprietary closed-source models on certain benchmarks. The model weights, instruction sets, and code are publicly available¹.

Introduction

Instruction tuning has unlocked in Large Language Models (LLMs) vast zero-shot capabilities without the need of careful prompt engineering (Ouyang et al., 2022). The most rapid research and development efforts are currently devoted to English LLMs. There has been a surge in English open-source models: Llama series (Touvron et al., 2023a,b), Mistral series (Jiang et al., 2023), Vicuna series (Chiang et al., 2023), etc. This growth is driven

by the abundance of raw training data in English and dedicated efforts to create comprehensive sets of instruction-output pairs. Despite the fact that LLMs oriented on English have some multilingual capabilities (Zhao et al., 2024) due to small portions of texts in various languages leaked into their training datasets (Touvron et al., 2023a), their overall performance in these languages remains relatively low. Although they can usually generate portions of coherent texts, these models struggle with reasoning in non-English languages, lack culturespecific knowledge, and are highly inefficient in terms of tokenization. This inefficiency arises due to the way bite-pair tokenization algorithms work: they split the infrequent words into multiple tokens. Since multilingual data typically represents a small portion of the training dataset, non-English words are often split in many pieces. This leads to more steps during prompt processing and text generation, shorter effective context windows, and ultimately lower quality (Tikhomirov and Chernyshev, 2023; Petrov et al., 2024). This disparity places non-English languages at a disadvantage.

There is a research direction focused on developing multilingual LLMs that work well for multiple popular languages: BLOOMz (Muennighoff et al., 2023), mGPT (Shliazhko et al., 2022), Bactrian-X (Li et al., 2023), PALO (Maaz et al., 2024), Aya101 from CohereAI (Üstün et al., 2024), etc. These models are typically trained on rich multilingual datasets and are less skewed towards English. However, when aiming to perform well across multiple languages simultaneously, these models must still share their vocabulary and parameters. This often hinders their performance for each particular language in isolation, especially for the popular smaller model sizes, such as 7B and 13B.

The goal of maximizing the LLM performance for a specific language within a certain number of parameters has led researchers to develop bi-lingual LLMs. For example, Jais (Sengupta et al., 2023)

https://huggingface.co/Vikhrmodels

focus only on English and Arabic. The inclusion of English data in pre-training alongside Arabic data is motivated by the significantly larger volume of English data available. This helps LLMs substantially enhance skills such as logical and common sense reasoning, which are also applied when generating text in Arabic.

Russian is one of the high-resource languages and is typically represented in multilingual LLMs. Additionally, there are several proprietary closedsource LLMs, such as MTS AI, GigaChat, and YandexGPT, that meet or even surpass their Englishoriented flagship competitors when it comes to text processing and generation in Russian. However, controllable research often requires white-box access to LLM logits and layer outputs, the ability to modify weights and a model architecture, and consistent answers for reproducibility, which is often impossible in closed-source LLMs due to their constant development and retirement. There are only a few open-source LLMs designed for Russian (such as Saiga (Gusev, 2023), ruGPT (AI Forever, 2022), ruadapt (Tikhomirov and Chernyshev, 2023)). Of these, only Saiga and ruadapt are instruction-tuned.

This work aims to build an efficient and effective open-source instruction-following LLM for Russian facilitating multilingual natural language processing research. Building even a small LLM that targets a particular language from scratch requires a lot of computational resources. Consequently, many researchers simply fine-tune LoRA adapters (Hu et al., 2021) for English-oriented LLMs on some language-specific data. While this approach can improve model generation quality, it does not address computational inefficiency because the tokenizer and model vocabulary remain unchanged. In contrast, our approach not only fine-tunes a base LLM on Russian language data but also reconstructs its underlying tokenizer and vocabulary, alongside suggesting an improved method for continued pre-training. Additionally, we have significantly expanded the available Russian datasets for instruction tuning. The developed LLM achieves state-of-the-art results for the Russian language among other open-source counterparts across a wide range of benchmarks.

Contributions of the paper are the following:

 We have constructed Vikhr – a state-of-theart open-source instruction-following LLM oriented on the Russian language. In addition to its high generation quality, Vikhr features

- an efficient tokenizer that enables rapid text generation and good context utilization.
- We have developed a pipeline for adapting English-oriented LLMs to the Russian language. The pipeline implements vocabulary adaptation, continued pre-training with regularization to prevent "catastrophic forgetting", and instruction tuning.
- We have expanded the datasets for continued pre-training of Russian language models and previously available instruction datasets.
- We conducted an extensive evaluation of several open-source LLMs on evaluation benchmarks for Russian, demonstrating that Vikhr achieves new state-of-the-art results.

2 Related Work

One of the first notable series of generative LLMs for Russian is ruGPT (AI Forever, 2022; Zmitrovich et al., 2023). The authors created several models trained for the vanilla language modelling task with the sizes of up to 13b. The models were created from the scratch and trained on large Russian corpora. They are able to handle the linguistic nuances of Russian more effectively than multilingual models (Muennighoff et al., 2022). Since the training data was mostly in Russian, these models have efficient tokenization, but the lack of multilingual data (e.g. in English) limits their performance. ruGPT models are not instruction tuned.

Gusev (2023) suggests to leverage reasoning capabilities of existing English-oriented LLMs and adapt them to the Russian language by training LoRA adapters. They also create an Alpaca-like set of Russian instruction-output pairs and performed instruction tuning. They have established the Saiga model series, which has a competitive performance and used to be a reasonable choice for off-the-shelf open-source Russian LLM for the past year. However, the tokenizer in theses models is not adapted, so they experience issues with context and computational efficiency.

Tikhomirov and Chernyshev (2023) address these issues in Saiga. In addition to model tuning on Russian data, they also adapt the model tokenizer. They note that improving tokenization helps to both improve the efficiency of the model and its performance while reducing memory consumption. However, during continued pre-training,

Content	Length	Tokenization Result
Original Sentence	31	Машинное обучение изменяет мир
Mistral Tok- enizer	13	['Ma', 'шин', 'ное', 'об', 'у', 'чение', 'из', 'мен', 'я', 'ет', 'ми', 'р']
Vikhr Tok- enizer	7	['Ma', 'шин', 'ное', 'обуче- ние', 'изменяет', 'мир']

Table 1: Tokenizer comparisons between the original Mistral model and Vikhr

the authors freeze the model weights except LM heads and token embeddings, which probably results in the suboptimal performance.

In this work, we take advantage of pre-trained English-oriented LLMs, adapt LLM tokenizer for better computational efficiency, leverage continued pre-training on vast Russian-language corpora with regularization for preventing "catastrophic forgetting", construct a novel extended set of Russian instruction-output pairs, and perform instruction tuning. The created LLM adaptation pipeline along with the data for continued pre-training and instruction tuning enables Vikhr to achieve new state-of-the-art results for Russian, maintain high performance for English, and demonstrate high computational efficiency.

3 LLM Construction Pipeline

The construction of Vikhr starts from one of English-oriented LLMs. In this work, we discuss the Vikhr model based on Mistral 7B. The strong logical and common reasoning capabilities, as well as the extensive world knowledge present in these LLMs provide an excellent starting point for our model. These features partially transfer to Vikhr, enhancing its performance in generating text in Russian. The process of LLM adaptation to Russian starts with the vocabulary adaptation. Then we perform continued pre-training of the LLM on large Russian datasets to mitigate the vocabulary shift and introduce culture specific knowledge. Finally, we perform fine-tuning of Vikhr on a set of instruction-output pairs in Russian.

3.1 Vocabulary Adaptation

The big drawback of English-oriented LLMs is that each Russian word would be split into multiple tokens: a common case is when symbols in the word become an individual tokens (see example in Table 1). This slows down the generation by

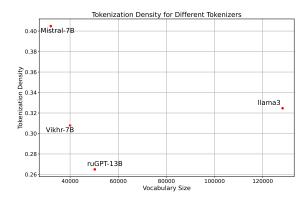


Figure 1: The Vikhr tokenizer efficiency in comparison to tokenizers of other models.

Data Source	Approx. size (GB)	Tokens (Billion)		
Scientific papers	20	2.5		
News articles	4	1		
Wikipedia	25	4		
Habr	6	1		
Other sources	20	2.5		

Table 2: The statistics of the Russian-language datasets for continued pre-training.

multiple times, reduces the amount of information that could be stored in the context, and drastically hurts the generation quality.

To mitigate this problem in Vikhr, we adopt the approach suggested in (Cui et al., 2023; Tikhomirov and Chernyshev, 2023), where authors rebuild the tokenizer using a language-specific corpus. In particular, we trained a SentencePiece tokenizer (Kudo and Richardson, 2018) with a 40k vocabulary on the RuLM dataset (Gusev, 2023). As can be seen from Figure 1, the resulting tokenizer for Russian is much more efficient than the tokenizer of the original English-oriented model.

3.2 Continued Pre-training

The new vocabulary requires also new embedding matrices and LM heads. The tokens that were present in the original vocabulary are initialized with the old embeddings, the new tokens are initialized by averaging the embeddings of their pieces in the original embedding matrix (Hewitt, 2021). The similar approach is also applied to LM heads. Training model with these modifications requires much more computational resources than the mainstream technique for adaptation of LLMs to new languages based on LoRA adapters (Hu et al., 2021), as it requires to perform continued

Hyperparam.	Value
LR	1×10^{-3}
AdamW eps	1×10^{-8}
Num warmup steps	10
AdamW betas	0.99, 0.95
Accumulation steps	128
Batch size	3
Epochs	1
Sequence length	1024

Table 3: The hyperparameters for continued pretraining.

pre-training of the whole model and on much more language-specific data to mitigate the shift in the vocabulary.

The dataset for continued pre-training is constructed from Russian Wikipedia, news articles, scientific papers, top 100k up-voted posts on Habr, and some other sources. The statistics of these datasets is presented in Table 2. The total number of tokens used for this step is 11 billion.

We note that the continued pre-training of a LLM might partially eliminate the reasoning capabilities present in the original English-oriented model. This drastically affects the model performance. In our preliminary experiments, continued pre-training may result even in worse performance on Russian benchmarks compared to the original model. To alleviate the "catastrophic forgetting", we use the loss regularization with KL penalty between the probability distribution of Vikhr and the reference English-oriented original LLM:

$$L_{\text{Vikhr}} = L_{\text{CE}} + KL\left(P_{\text{Vikhr}} || P_{\text{Ref}}\right). \tag{1}$$

In practice, we implement this approach using the SLERP interpolation of model losses (Goddard et al., 2024).

To speed up the process of continued pretraining, we use an optimized Flash attention implementation². As an optimization algorithm, we leverage AdamW as it trades some memory efficiency in favor of robustness to the hyperparameter choice. The hyperparameters used for continued pre-training are presented in Table 3.

3.3 Instruction Tuning

Instruction tuning is an essential step in reaching high zero-shot performance with LLMs. It also allows to obtain more natural communication

Instruction Set	Language	# instances
Veles	Russian	30k
Nectar	English	50k
Saiga	Russian	100k
ruFLAN	Russian	500k

Table 4: The statistics of instruction datasets.

with the model without complex prompting. Further fine-tuning techniques such as RLHF (Ouyang et al., 2022), which require input from the assessors, are also crucial for such tasks as multicriteria alignment. However, the most significant performance gains are still achieved through instruction tuning (Jha et al., 2023).

Previously, Gusev (2023) constructed an opensource set of instruction-output pairs for the Russian language (Saiga). The core Saiga dataset was created similar to Alpaca by querying ChatGPT (gpt-3.5-turbo) (Taori et al., 2023). In this work, we extend this set by translating two English instruction datasets. First, we translated instructions for the FLAN model (Wei et al., 2021) and generated answers in Russian using ChatGPT. Originally, FLAN instructions were constructed automatically from annotated datasets using templates to facilitate multitask and zero-shot capabilities of seq2seq models. Later, it was shown that this data also helps to improve decoder-only chat-oriented models as well. Second, we construct Veles³ by translating the English OpenHermes (Teknium, 2023) instruction dataset. We also include without translation Nectar⁴ (Zhu et al., 2023) – the English instruction dataset. It helps to keep the performance of Vikhr high also for English. Since the majority of the outputs were machine generated there are many low quality outputs. To mitigate this problem, we filtered out low quality pairs using a reward model trained on human data. The statistics of the Vikhr instruction datasets is presented in Table 4.

Contrary to Saiga, we do not use LoRA adapters and just as in the phase of continued pre-training, we update all model parameters. The hyperparameters for the instruction tuning phase are presented in Table 5.

²https://huggingface.co/docs/optimum/ bettertransformer/tutorials/convert

³https://huggingface.co/datasets/Vikhrmodels/ Veles-2.5

⁴https://huggingface.co/datasets/berkeley-nest/Nectar

Hyperparam.	Value
LR	1×10^{-5}
AdamW, eps	1×10^{-8}
Num warmup steps	10
AdamW, betas	0.99, 0.95
Accumulation steps	64
Batch size	3
Num epochs	3
Sequence length	1024

Table 5: The hyperparameters for instruction tuning.

3.4 Hardware

Vikhr was trained on eight NVIDIA A100 GPUs 80GB. We spend approximately 1,000 GPU hours for the continued pre-training phase and 60 hours for instruction tuning.

4 Experiments

4.1 Experimental Setup

Benchmarks. The evaluation was performed on MMLU (Hendrycks et al., 2021), Ru-MMLU⁵, CheGeKa, Russian SuperGLUE (Shavrina et al., 2020), and MERA (Fenogenova et al., 2024). MMLU (En-MMLU) evaluates LLMs across 57 subjects with multiple-choice questions, assessing a model's broad knowledge and reasoning abilities. We use this benchmark to verify that the model retains bi-lingual capabilities. In the results, we report the accuracy@1 score. RuMMLU is a translation of MMLU with GPT-3.5 to Russian. Just as for MMLU, we report the accuracy@1 score. CheGeKa is based on questions from the game "What? Where? When?". This benchmark contains challenging open-ended questions, requiring logical reasoning and world knowledge. It includes 29,376 training and 416 test instances. The reported evaluation metric is the F1 score. Russian SuperGLUE is a benchmark similar to well-known English SuperGLUE (Wang et al., 2019). It tests LLMs on various natural language understanding tasks like reading comprehension and textual entailment. The metric reported in the results is accuracy@1. The MERA benchmark encompasses 21 evaluation tasks for generative LLMs in 11 skill domains. Note that among other tasks MERA also includes CheGeKa, RuMMLU, and one of the subtasks of SuperGLUE (RWSD). The reported evaluation metric is the total score, which is the average of scores across all non-diagnostic tasks.

Baselines. We compare Vikhr to six open-source and two proprietary closed-source competitors of the similar size. Open-source models: aya101 – a massively multilingual LLM from CohereAI that follows instructions in 101 languages⁶, it shows state-of-the-art results among massively multilingual LLMs; Mistral-7B-0.2-instruct – an Englishoriented LLM that was used as the base model for Vikhr; rccmsu/ruadapt_mistral_saiga_7b_v0.1 – a Russian-oriented LLM that was constructed from the Mistral model using similar adaptations of the tokenizer, token embeddings, and the LM head (Tikhomirov and Chernyshev, 2023); saiga-mistral-7b-lora and saiga-llama3-8b – two versions of the Saiga models based on English-oriented LLMs and obtained by fine-tuning LoRA adapters on the Saiga instruction dataset⁷. Closed-source proprietary models for Russian: MTS AI Chat⁸ and GigaChat-7b. The access to GigaChat weights is closed, so the reported results are taken from the leaderboards⁹. The results of MTS AI Chat are also taken from the leaderboard¹⁰.

4.2 Results

The evaluation results are presented in Table 6. As we can see, Vikhr outperforms all open-source models, including the ones that were built specifically for Russian. It also slightly outperforms its parent model Mistral on the En-MMLU benchmark, which might be the result of longer pre-training. The second place with close scores for all 4 Russian language benchmarks is obtained by the Saiga model based on recently released Llama-3. The high scores of this model probably are the result of the transfer of the outstanding performance of Llama-3. Since Saiga based on Llama-3 outperforms Saiga based on Mistral, we expect that applying our adaptation pipeline to Llama-3 would also help further improving the state of the art.

We note that the original Mistral-7B-0.2-instruct, despite being an English-oriented model, demonstrates competitive performance in 3 out of 4 Russian benchmarks. This indicates demonstrates that such models could be viable alternatives. The only dataset, where its performance is very low is CheGeKa, which is related to open-ended question-

⁵https://github.com/NLP-Core-Team/mmlu_ru

⁶https://huggingface.co/CohereForAI/aya-101

⁷https://huggingface.co/collections/IlyaGusev

⁸https://huggingface.co/MTSAIR/multi_verse_ model

⁹https://mera.a-ai.ru/ru/submits/10257

¹⁰https://mera.a-ai.ru/ru/submits/10290

LLM	Pre-train on Russian	Training Method	En-MMLU	Ru-MMLU	CheGeKa	Russian SuperGLUE	MERA
MTS AI Chat 7B (closed-source) ♦	false	sft+dpo	-	0.689	0.083	0.56	0.479
GigaChat-7B (closed-source) ♦	true	sft+dpo	-	0.67	0.451*	0.71*	0.479
aya101	false	pt+sft	0.41	0.37	0.005	0.36	0.320
Mistral-7B-Instruct-v0.2	false	none	0.60	0.78	0.005	0.57	0.400
rccmsu/ruadapt-mistral-7b-v0.1	false	pt+sft	0.61	0.72	0.005	0.64	0.421
rugpt13b	true	none	0.25	0.25	0.132	0.52	0.208
saiga-mistral-7b-lora	false	sft	0.60	0.76	0.223	0.64	0.442
saiga-llama3-8b	false	sft	0.59	0.78	0.225	0.66	0.476
Vikhr-7B-instruct_0.2	true	pt+sft	0.62	0.80	0.231	$\overline{0.67}$	0.485

Table 6: Evaluation results for Russian and multilingual LLMs. Pre-train on Russian means that the model underwent (continued) pre-training on Russian data. The following abbreviations are used: sft – instruction tuning, pt – (continued) pre-training; dpo – direct preference optimization.

The results for GigaChat and MTS AI are taken from the leaderboards. The best result among open-source models is highlighted with bold, the second best is underscored. The best result among closed-source proprietary models is marked with *.

answering. This may be due to the lack of culture-specific knowledge, as the English-oriented model has not seen much Russian texts. Note that the MTS AI Chat also shows very low results on CheGeKa, which might also indicate the lack of culture-specific knowledge.

The proprietary model GigaChat substantially outperforms Vikhr on CheGeKa and notably on Russian SuperGLUE. We assume this is due to the use of much larger Russian datasets for pre-training. However, surprisingly, it falls behind Vikhr on Ru-MMLU. On all benchmarks, Vikhr outperforms the the proprietary competitor from MTS AI.

5 Conclusion

We have presented Vikhr – a new state-of-the-art open-source instruction-following LLM oriented on the Russian language. To create Vikhr, we developed a comprehensive pipeline for adapting English-oriented LLMs to Russian. The pipeline includes the adaptation of the tokenizer vocabulary, continued pre-training of the entire model, and instruction tuning. We have also constructed a new dataset for instruction tuning by expanding the Saiga dataset with automatically translated and cleaned English instruction datasets. Our extensive work enabled Vikhr to outperform the known baselines, while maintaining computational efficiency.

We hope that the published models will foster the research on LLMs and enhance the diversity of languages incorporated into research agendas.

Limitations

We do not introduce additional restrictions to the usage of our models. However, the users must

comply with the license of the base model and instruction datasets.

We do not implement RLHF / DPO fine-tuning of Vikhr due to the lack of the resources for human annotation. We expect further performance improvements from these techniques.

We do not introduce additional instructionoutput pairs to facilitate LLM alignment. However, we note that the majority of the data for supervised fine-tuning of Vikhr are obtained from the Chat-GPT model series, so our model partially inherits its alignment.

References

AI Forever. 2022. ru-gpts: Generative pre-trained transformer models for russian. https://github.com/ai-forever/ru-gpts.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality.

Yiming Cui, Ziqing Yang, and Xin Yao. 2023. Efficient and effective text encoding for chinese llama and alpaca. *arXiv preprint arXiv:2304.08177*.

Alena Fenogenova, Artem Chervyakov, Nikita Martynov, Anastasia Kozlova, Maria Tikhonova, Albina Akhmetgareeva, Anton Emelyanov, Denis Shevelev, Pavel Lebedev, Leonid Sinev, et al. 2024. Mera: A comprehensive llm evaluation in russian. *arXiv* preprint arXiv:2401.04531.

Charles Goddard, Shamane Siriwardhana, Malikeh Ehghaghi, Luke Meyers, Vlad Karpukhin, Brian Benedict, Mark McQuade, and Jacob Solawetz. 2024. Arcee's mergekit: A toolkit for merging large language models. *arXiv preprint arXiv:2403.13257*.

- Ilya Gusev. 2023. rulm: A toolkit for training neural language models. https://github.com/IlyaGusev/rulm.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2021. Measuring massive multitask language understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*.
- John Hewitt. 2021. Initializing new word embeddings for pretrained language models.
- Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. 2021. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*.
- Aditi Jha, Sam Havens, Jeremy Dohmann, Alex Trott, and Jacob Portes. 2023. Limit: Less is more for instruction tuning across evaluation paradigms. *arXiv* preprint arXiv:2311.13133.
- Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. 2023. Mistral 7b. arXiv preprint arXiv:2310.06825.
- Taku Kudo and John Richardson. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71.
- Haonan Li, Fajri Koto, Minghao Wu, Alham Fikri Aji, and Timothy Baldwin. 2023. Bactrian-x: A multilingual replicable instruction-following model with low-rank adaptation. *arXiv preprint arXiv:2305.15011*.
- Muhammad Maaz, Hanoona Rasheed, Abdelrahman Shaker, Salman Khan, Hisham Cholakal, Rao M Anwer, Tim Baldwin, Michael Felsberg, and Fahad S Khan. 2024. Palo: A polyglot large multimodal model for 5b people. *arXiv preprint arXiv:2402.14818*.
- Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng-Xin Yong, Hailey Schoelkopf, et al. 2022. Crosslingual generalization through multitask finetuning. *arXiv preprint arXiv:2211.01786*.
- Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng Xin Yong, Hailey Schoelkopf, et al. 2023. Crosslingual generalization through multitask finetuning. In *The 61st Annual Meeting Of The Association For Computational Linguistics*.

- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. Advances in neural information processing systems, 35:27730–27744.
- Aleksandar Petrov, Emanuele La Malfa, Philip Torr, and Adel Bibi. 2024. Language model tokenizers introduce unfairness between languages. *Advances in Neural Information Processing Systems*, 36.
- Neha Sengupta, Sunil Kumar Sahu, Bokang Jia, Satheesh Katipomu, Haonan Li, Fajri Koto, Osama Mohammed Afzal, Samta Kamboj, Onkar Pandit, Rahul Pal, et al. 2023. Jais and jais-chat: Arabic-centric foundation and instruction-tuned open generative large language models. *arXiv preprint arXiv:2308.16149*.
- Tatiana Shavrina, Alena Fenogenova, Emelyanov Anton, Denis Shevelev, Ekaterina Artemova, Valentin Malykh, Vladislav Mikhailov, Maria Tikhonova, Andrey Chertok, and Andrey Evlampiev. 2020. Russiansuperglue: A russian language understanding evaluation benchmark. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4717–4726.
- Oleh Shliazhko, Alena Fenogenova, Maria Tikhonova, Vladislav Mikhailov, Anastasia Kozlova, and Tatiana Shavrina. 2022. mgpt: Few-shot learners go multilingual. arXiv preprint arXiv:2204.07580.
- Rohan Taori, Ishaan Shum, Pieter Abbeel, Carlos Guestrin, and Percy Liang. 2023. Stanford alpaca: An instruction-following language model. *GitHub*.
- Teknium. 2023. Openhermes 2.5: An open dataset of synthetic data for generalist llm assistants.
- Mikhail Tikhomirov and Daniil Chernyshev. 2023. Impact of tokenization on llama russian adaptation. *arXiv preprint arXiv:2312.02598*.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023a. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023b. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. *Advances in neural information processing systems*, 32.

- Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*.
- Jun Zhao, Zhihao Zhang, Qi Zhang, Tao Gui, and Xuanjing Huang. 2024. Llama beyond english: An empirical study on language capability transfer. *arXiv* preprint arXiv:2401.01055.
- Banghua Zhu, Evan Frick, Tianhao Wu, Hanlin Zhu, and Jiantao Jiao. 2023. Starling-7b: Improving Ilm helpfulness & harmlessness with rlaif.
- Dmitry Zmitrovich, Alexander Abramov, Andrey Kalmykov, Maria Tikhonova, Ekaterina Taktasheva, Danil Astafurov, Mark Baushenko, Artem Snegirev, Tatiana Shavrina, Sergey Markov, et al. 2023. A family of pretrained transformer language models for russian. arXiv preprint arXiv:2309.10931.
- Ahmet Üstün, Viraat Aryabumi, Zheng-Xin Yong, Wei-Yin Ko, Daniel D'souza, Gbemileke Onilude, Neel Bhandari, Shivalika Singh, Hui-Lee Ooi, Amr Kayid, Freddie Vargus, Phil Blunsom, Shayne Longpre, Niklas Muennighoff, Marzieh Fadaee, Julia Kreutzer, and Sara Hooker. 2024. Aya model: An instruction finetuned open-access multilingual language model. arXiv preprint arXiv:2402.07827.