

Bielik 7B v0.1: A Polish Language Model – Development, Insights, and Evaluation

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Abstract

We introduce Bielik 7B v0.1, a 7-billion-parameter generative text model for Polish language processing. Trained on curated Polish corpora, this model addresses key challenges in language model development through innovative techniques. These include Weighted Instruction Cross-Entropy Loss, which balances the learning of different instruction types, and Adaptive Learning Rate, which dynamically adjusts the learning rate based on training progress. To evaluate performance, we created the Open PL LLM Leaderboard and Polish MT-Bench, novel frameworks assessing various NLP tasks and conversational abilities. Bielik 7B v0.1 demonstrates significant improvements, achieving a 9 percentage point increase in average score compared to Mistral-7B-v0.1 on the RAG Reader task. It also excels in the Polish MT-Bench, particularly in Reasoning (6.15/10) and Role-playing (7.83/10) categories. This model represents a substantial advancement in Polish language AI, offering a powerful tool for diverse linguistic applications and setting new benchmarks in the field.

1 Introduction

The rapid advancement in natural language processing (NLP) has led to the development of increasingly sophisticated language models that can understand and generate human-like text. These models have shown remarkable success in various linguistic tasks across multiple languages. However, the development of high-performing models for less-resourced languages remains a significant challenge due to the scarcity of large and diverse datasets and computational resources.

Existing Polish language models, such as TRURL 2 (Voicelab, 2023) and Qra (National Information Processing Institute and Gdańsk University of Technology, 2024), have made important strides in this domain. TRURL 2, a collection

of fine-tuned Llama 2 models with 7 billion and 13 billion parameters was trained on approximately 1 million conversational Polish and English samples, with a context size of 4,096 tokens. Another series of models is Qra, which comprises continuously pretrained models with 1, 7, and 13 billion parameters. The Qra models were trained on Polish data, totaling 90 billion tokens, and also employ a context size of 4,096 tokens. While numerous other Polish-focused language models exist, the majority of them are fine-tuned using significantly smaller datasets or fine-tuning approaches, which can limit their performance and versatility.

This paper introduces Bielik 7B v0.1, a state-of-the-art Polish language model developed as a collaborative effort between the open-science project SpeakLeash and the High Performance Computing (HPC) center: ACK Cyfronet AGH. Bielik 7B v0.1 is an evolution of the Mistral 7B v0.1 model (Jiang et al., 2023), enhanced to understand and generate Polish text with high accuracy. This model leverages a massive corpus of Polish texts and advanced machine learning techniques, making it a pioneering tool in the realm of Polish Natural Language Processing (NLP). The development of Bielik 7B v0.1 addresses several challenges, including the adaptation of a model trained primarily on English data to the Polish language, which involves significant linguistic and semantic adjustments.

In the following sections, we detail the architecture of Bielik 7B v0.1, describe the dataset preparation, discuss the training process, and evaluate the model’s performance on various NLP tasks. Our results demonstrate that Bielik 7B v0.1 not only advances the state of Polish language understanding but also serves as a valuable resource for further research and application in Polish NLP.

2 Model and Tokenizer

In this section, we introduce the model design and tokenizer, presenting architectural decisions and configurations.

2.1 Model Architecture

Parameter	Value
Layers	32
Model Dimension	4096
Attention Heads	32
Key/Value Heads	8
Head Size	128
Intermediate Size	14336
Activation Function	SwiGLU
Vocabulary Size	32000
Positional Embeddings	RoPE ($\theta = 10000$)
Context Length	8192
Sliding Window	4096

Table 1: Model architecture.

The Bielik 7B v0.1 model builds upon the Transformer architecture (Vaswani et al., 2017), with its key parameters detailed in Table 1, and incorporates a suite of advanced techniques to enhance its performance.

Self-attention with causal masks (Vaswani et al., 2017) allows the model to weigh the importance of different parts of the input sequence. The causal mask ensures that the model only attends to previous tokens, which is crucial for maintaining the autoregressive property in language modeling tasks.

Grouped-query attention (GQA) (Ainslie et al., 2023) reduces computational complexity and memory usage while maintaining model quality. It achieves this by using fewer key-value heads than query heads, allowing for more efficient processing of long sequences.

Sliding Window Attention (Child et al., 2019; Beltagy et al., 2020) limits the attention span to a fixed window size, reducing computational complexity from quadratic to linear in sequence length. It enables the model to process longer sequences more efficiently while still capturing local context effectively.

SwiGLU activation function (Dauphin et al., 2016; Shazeer, 2020) is a combination of the Swish activation function and Gated Linear Units (GLU), offering improved performance and train-

ability compared to traditional activation functions like ReLU.

Rotary Positional Embeddings (RoPE) (Su et al., 2024) allow the model to better capture the relative positions of tokens in the input sequence, offering advantages over absolute positional embeddings. It excels in tasks requiring nuanced understanding of token positions, providing better extrapolation to longer sequences and improving overall performance.

Root Mean Square Layer Normalization (RMSNorm) (Jiang et al., 2024) is used for normalizing activations within the network. It offers improved training stability and slightly faster computation compared to traditional Layer Normalization, contributing to more efficient training and inference.

Pre-normalization applies layer normalization before the self-attention and feed-forward layers, rather than after, resulting in improved model convergence and overall performance.

The Bielik 7B v0.1 model was adapted from the Mistral 7B v0.1 model and further pretrained. The decision to use an existing model instead of training our own from scratch was due to the lack of access to sufficient high-quality data. Additionally, training from scratch would have required significantly more resources, including GPU power and time. We chose the Mistral 7B v0.1 model because of its strong performance in benchmarks and its permissive Apache 2.0 license.

2.2 Tokenizer

One measure of the effectiveness of the tokenization process is the count of tokens generated for the input text. A lower number of tokens indicates faster and more efficient text generation by the language model. The tokenizer from the Mistral 7B model was not specifically trained for the Polish language. Therefore, we conducted a series of experiments aimed at expanding the original tokenizer to include Polish tokens. Our approach to expanding the tokenizer involved incorporating tokens from the Polish APT3 model (Ociepa and Azurro Team, 2024) by extending the model’s edge layers (embeddings and language model head) and continuing the training process. We chose the preamble of the Constitution of the Republic of Poland as the benchmark text because it effectively captures the essence of Polish writing and includes official English versions for compar-

Tokenizer	Vocab Size	Avg tokens	Polish			English		
			Tokens	CpT	TpW	Tokens	CpT	TpW
APT3	31980	480	344	5.22	1.48	615	3.15	1.93
Llama2	32000	554	681	2.63	2.94	427	4.53	1.34
Mistral v0.1	32000	578	747	2.40	3.22	408	4.75	1.28
Llama2 + APT3	57362	442	441	4.07	1.90	442	4.38	1.39
Mistral v0.1 + APT3	58690	450	493	3.64	2.12	407	4.76	1.28

Table 2: Comparison of token count, characters per token (CpT), and tokens per word (TpW) for the preamble of the Constitution of the Republic of Poland in Polish and English versions, processed by various tokenizers: APT3 (dedicated Polish language tokenizer), Llama2 and Mistral v0.1 (multilingual tokenizers with minimal Polish support), and merged tokenizers Llama2 + APT3 and Mistral v0.1 + APT3.

ative analysis. Table 2 presents a detailed comparison of various metrics, including token count, characters per token (CpT), and tokens per word (TpW). These metrics illustrate the performance of different tokenizers when applied to both the Polish and English versions of the preamble.

Despite achieving good results on benchmarks with the trained models, we observed issues in text generation, which occasionally manifested as incorrect token combinations for Polish words. This problem arose partly due to the ambiguity that occurs when merging pairs of tokens during the tokenization process (Imamura and Sumita, 2022). This process utilizes the byte pair encoding (BPE) algorithm (Sennrich et al., 2016), which is implemented through SentencePiece (Kudo and Richardson, 2018). Since the tokens from the APT3 model tokenizer and the Mistral 7B model tokenizer are not mutually exclusive (their vocabularies overlap), ambiguity arises during the merging of token pairs, making it impossible to directly combine both tokenizers.

In light of these issues, we decided to retain the original tokenizer from the Mistral 7B model, which has a vocabulary size of 32,000 tokens, while continuing to explore potential expansion options for future model versions.

3 Pre-training

The primary objective of the pre-training phase was to enhance the model’s Polish language capabilities, focusing on both accuracy and fluency. To accomplish this, we employed a diverse selection of high-quality Polish texts. These materials were subjected to rigorous cleaning procedures and meticulous quality evaluations, ensuring the highest standard of training data.

3.1 Pre-training Data

The pre-training of the Bielik model involved constructing a novel, diverse, and high-quality dataset, primarily made up of Polish language texts. We leveraged resources from the SpeakLeash project (SpeakLeash Team, 2024). Using metadata assigned to each document, which included information about its topic and various stylometric features, we selected 18 million documents from different datasets that offered high quality and topic diversity. These selected texts underwent thorough cleaning and quality assessment procedures, detailed in sections 3.1.1 and 3.1.2. Additionally, we removed documents where, although robots.txt did not prohibit scraping, the terms and conditions explicitly forbade using them for training language models. Only documents meeting our stringent quality criteria were retained for training and subsequently tokenized. This meticulous process yielded a training dataset comprising 22 billion tokens. To improve the model’s adaptation to a new language and mitigate catastrophic forgetting (Li et al., 2022; Ostapenko et al., 2022; Ibrahim et al., 2024), we supplemented our training dataset with English texts, sourced from the SlimPajama dataset (Soboleva et al., 2023), known for its diverse and high-quality English content. Ultimately, our final training dataset consisted of 36 billion tokens.

3.1.1 Data Cleanup

To improve the quality of the documents, we implemented a series of heuristics aimed at removing damaged and unwanted text fragments, anonymizing personal data (such as physical addresses, email addresses, phone numbers, and URLs), and fixing encoding or formatting issues. As a result of this process, we obtained higher-quality texts,

which allowed for further quality assessment.

3.1.2 Quality Evaluation

To create the training dataset for text quality evaluation, we manually selected and annotated 9,000 documents, assigning each to one of three quality classes: HIGH, MEDIUM, or LOW. The HIGH class represented documents of superior quality, LOW denoted poor-quality texts, while MEDIUM was reserved for documents where the quality was ambiguous to the annotator, falling between high and low standards. This classification scheme allowed for a nuanced approach to quality assessment, accounting for the inherent complexities in determining text quality.

For each document, we calculated 266 stylistic features, including metrics such as the frequency of verbs, nouns, sentences, and punctuation marks. This comprehensive set of features was derived based on the methodology outlined in the StyloMetrix tool (Okulska et al., 2023). These linguistic and structural attributes provided a multifaceted representation of each text’s stylistic properties.

Using these stylistic features as input, we trained an XGBoost classifier model. This machine learning approach allowed us to leverage the complex interactions between various textual characteristics to predict document quality effectively, as presented in Table 3 and Figure 1.

Precision	Recall	F1
0.8640	0.8285	0.8431

Table 3: Validation results for the XGBoost classifier model.

To determine an appropriate threshold for identifying high-quality documents, we conducted a manual analysis of 1,000 documents. Based on this thorough examination, we established a cut-off point for the HIGH category at a probability score exceeding 90%. Documents that did not meet this threshold were excluded from the target training dataset of the Bielik model.

3.2 Training Hyperparameters

We utilized the AdamW optimizer (Loshchilov and Hutter, 2017) with hyperparameters $\beta_1 = 0.9$, $\beta_2 = 0.95$, and weight decay = 0.1. The learning rate followed a cosine decay schedule, starting at $3e-05$ and decreasing to $2e-05$, with a warmup

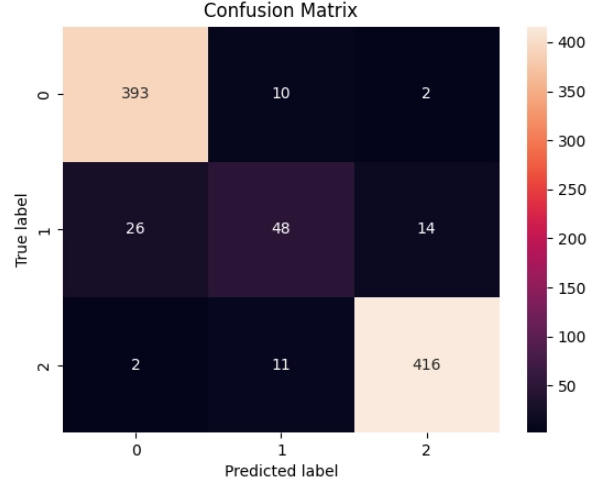


Figure 1: Confusion matrix illustrating validation results for the XGBoost classifier model.

period of 2000 iterations. Training continued for a total of 17350 iterations. We employed a global batch size of 256, composed of local batches of size 4. The gradient clipping norm was set to 1.0, and we used mixed precision with bfloat16. The model was trained on 36B tokens over 2 epochs, with a maximum context length of 4096. The training loss and accuracy over the training tokens for the base model are presented in Figures 2 and 3.

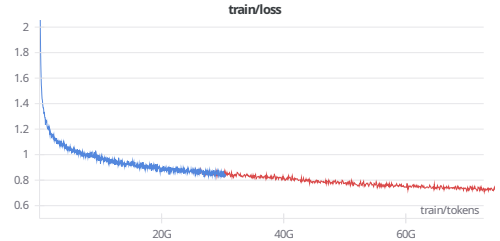


Figure 2: Training loss over the training tokens for the base model.



Figure 3: Training accuracy over the training tokens for the base model.

4 Post-training

After finishing the pre-training phase, we moved on to the post-training phase, which focused on improving the model’s capabilities across various areas, such as coding, mathematics, logical reasoning, and following instructions.

4.1 Post-training Data

There was no sufficiently large and open dataset of instructions and dialogues for the Polish language, which is why we have begun creating our own dataset that is continuously expanded and refined by annotators. This dataset was being manually developed through the writing of instructions and dialogues by annotators, ensuring high-quality and relevant content tailored to the needs of the Polish language.

To supplement the manually annotated data, we also generated instructions based on the data used in pre-training (see Section 3.1). For this purpose, we selected a collection of 1 million articles from various categories, and then generated an instruction and response based on each article. A portion of these instructions was manually verified and corrected before being used for training purposes.

To further increase the number and diversity of instructions, we utilized publicly accessible collections of English instructions, such as the OpenHermes-2.5 (Teknium, 2023) and orca-math-word-problems-200k (Mitra et al., 2024) datasets, which accounted for half of the instructions used in training. As a result, we obtained a training dataset containing over 2.3 million instructions, amounting to more than 700 million tokens.

4.2 Supervised Fine-Tuning

The varying quality of training instructions negatively impacts a model’s benchmark performance, as demonstrated in previous studies, which found that poor-quality instructions degrade model capabilities (Zhou et al., 2023). These studies showed that smaller, higher-quality instruction datasets often yield better results than larger, noisier datasets. To address this, we introduced several improvements, summarized below, while still utilizing the previously mentioned datasets.

4.2.1 Masked Tokens

We employed a masked token approach, selectively applying loss only to certain parts of the

output. Specifically, we masked the loss on user instruction and control tokens (Shi et al., 2024). This technique ensures that these tokens do not contribute to the overall loss during training, allowing the model to focus on learning from the content tokens.

4.2.2 Adaptive Learning Rate

The lengths of instructions can vary significantly, leading to fluctuations in the number of tokens used in computing the loss function. To ensure consistent influence from each instruction, we implemented an adaptive learning rate (ALR). This approach is based on prior research that links learning rates to batch sizes (Granzio et al., 2020). In particular, the learning rate (LR) is scaled according to the square root of the ratio between the number of tokens in the batch (T) and the baseline batch size (BS):

$$\text{ALR} = \text{LR} \cdot \sqrt{\frac{T}{\text{BS}}} \quad (1)$$

4.2.3 Weighted Instruction Cross-Entropy Loss

This strategy, inspired by weighted cross-entropy loss (Wu et al., 2024), offline reinforcement learning (Xu et al., 2022) and C-RLFT (Wang et al., 2024), enabled us to effectively utilize mixed-quality training data annotated with fine-grained weight labels.

Given the SFT conversation dataset $\mathcal{D} = (x_i, y_i)$, where x_i indicates the instruction, y_i is its corresponding response, we assign a weight $w_i \in (0, 1]$ to each instruction-response pair (x_i, y_i) that is representing the quality of the pair. This allows us to construct a weighted dataset, \mathcal{D}_w , where the highest quality pairs are assigned a weight of 1.0, while lower quality instructions have smaller weights ($w_i < 1.0$). We can express the relationship between weights and quality as:

$$w_i = \begin{cases} 1.0, & \text{highest quality} \\ \alpha, & \text{lower quality} \end{cases} \quad (0 < \alpha < 1) \quad (2)$$

This weighting scheme guides the model to favor high-quality responses while still learning from a diverse range of instruction-response pairs. We labeled our dataset, as described in Section 4.1, and assigned weights to the instruction-response pairs

based on predefined rules:

$$w_i = \begin{cases} 1.0, & \text{high quality} \\ 0.7, & \text{medium quality} \\ 0.5, & \text{low quality} \end{cases} \quad (3)$$

where:

high quality - instructions and dialogues manually written by annotators, the OpenHermes-2.5 (Teknium, 2023) and orca-math-word-problems-200k (Mitra et al., 2024) datasets.

medium quality - generated instructions based on pre-training data, which have been manually verified and corrected.

low quality - generated instructions based on pre-training data without manual verification.

Supervised Fine-Tuning (SFT) methods are designed to adapt a pre-trained language model π_0 into a fine-tuned model π_{SFT} using a high-quality instruction dataset \mathcal{D} and supervised learning. We use $\pi(y|x)$ to represent the probability of generating response y given instruction x in the dataset \mathcal{D} . The objective of SFT can be expressed as a maximum likelihood estimate (MLE):

$$J_{\text{SFT}} = \mathbb{E}_{(x,y) \sim \mathcal{D}} [\log \pi_{\text{SFT}}(y|x)] \quad (4)$$

To ensure optimal fine-tuning performance, SFT requires the instruction dataset \mathcal{D} to be of the highest possible quality, as it treats all training data uniformly (Zhou et al., 2023; Chen et al., 2024). However, assembling a sufficiently large and high-quality dataset can be both time-consuming and financially expensive.

In practice, the quality of available instructions often varies. It is possible that valuable and informative instructions may have lower quality than desired. To leverage the potential of such mixed-quality data, we introduce the weighted instruction cross-entropy loss, which guides the learning process to prioritize more preferred answers while still allowing the model to learn valuable insights from lower-quality instructions.

The standard Weighted Cross-Entropy Loss (King and Zeng, 2001), originating from the weighted exogenous sampling maximum-likelihood estimator, is frequently used in multi-class classification problems (Wu et al., 2024). It is commonly employed, for instance, to address imbalanced class distributions (Rezaei-Dastjerdehei et al., 2020). We can formulate standard Weighted Cross-Entropy Loss as

follows:

$$l(o_i, y_i) = - \sum_{c=1}^C w_c \cdot y_{i,c} \cdot \log p_{i,c} \quad (5)$$

where C is the number of classes, $\mathbf{y}_i = (y_{i,1}, \dots, y_{i,C}) \in \{0, 1\}^C$ is the one-hot encoding of the ground truth label for sample x_i , and $y_{i,c} = 1$ indicates that x_i belongs to class c . Meanwhile, $\mathbf{p}_i = (p_{i,1}, \dots, p_{i,C}) \in \mathbb{R}_+^C$ represents the predicted probability vector for sample x_i across C classes. In multi-class classification problems using deep neural networks, p_i corresponds to the softmax values of the logits for each class produced by the last layer of the network. Specifically, $p_{i,c} = \frac{\exp(o_{i,c})}{\sum_{j=1}^C \exp(o_{i,j})}$, where $o_{i,c}$ is the logit for class c for sample x_i .

To integrate fine-grained weights from the dataset \mathcal{D}_w , we modify Eq. 5 as follows:

$$l(o_i, y_i) = -w_i \cdot \sum_{c=1}^C y_{i,c} \cdot \log p_{i,c} \quad (6)$$

where w_i represents the weight assigned to the instruction-response pair (x_i, y_i) . This learning objective provides a flexible framework for fine-tuning language models, offering more granular control over the importance of each instruction during training. It can capture subtle differences in data quality while maintaining computational efficiency.

4.3 Training Hyperparameters

We applied the AdamW optimizer, using $\beta_1 = 0.9$, $\beta_2 = 0.95$, and a weight decay of 0.05. The adaptive learning rate followed a cosine decay, starting at $7e-6$ and tapering down to $6e-7$, with 50 warmup iterations. The training process spanned a total of 55,440 iterations. Our setup used a global batch size of 128, made up of local batches with a size of 1. Gradient clipping was enforced with a threshold of 1.0, and the model was trained in mixed precision using bfloat16. We trained the model for 3 epochs with a maximum context length of 4,096, processing a total of 2.1 billion tokens. The training loss, accuracy, and adaptive learning rate over the training iterations for the instruction model are presented in Figures 4, 5, and 6.

4.4 Efficient Implementation

For our training needs, we utilized the ALLaMo framework (Ociepa, 2023), developed by a co-

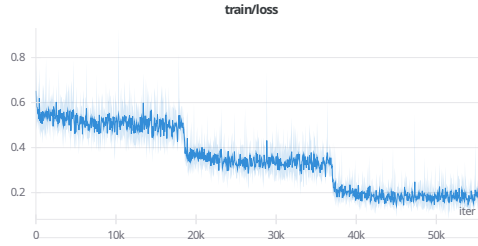


Figure 4: Training loss over the training iterations for the instruction model.

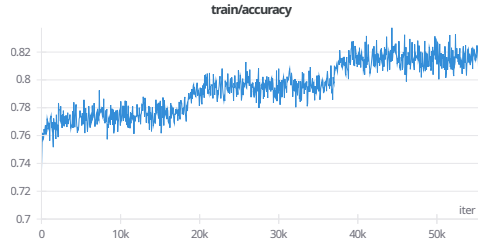


Figure 5: Training accuracy over the training iterations for the instruction model.

author of the Bielik model to optimize training throughput. This framework allowed us to maximize the computational resources of the supercomputer, enabling faster calculations and reducing overall training time. ALLaMo achieves high efficiency through numerous optimizations at the dataloader, model, and training process levels, along with a strong reliance on `torch.compile` in conjunction with an efficient attention implementation using PyTorch SDPA and the PyTorch Fused AdamW optimizer (Ansel et al., 2024). A significant advantage of ALLaMo is its primary reliance on PyTorch, without dependencies on other popular frameworks or libraries, which allows for better optimization and easier implementation of functionalities not available in other frameworks. For post-training, we implemented the weighted instruction cross-entropy loss and adaptive learning rate strategies, detailed in sections 4.2.3 and 4.2.2. These improvements enabled us to efficiently conduct numerous experiments and successfully complete the final model training. During the base model training, we utilized 256 NVIDIA GH200 GPUs, achieving a throughput of over 9,200 tokens per GPU per second.

To validate the performance of the ALLaMo framework, we conducted a comparison with the implementation used in training the TinyLlama

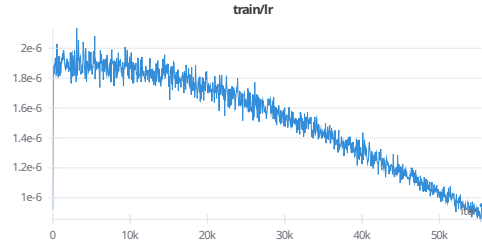


Figure 6: Adaptive learning rate over the training iterations for the instruction model.

model (Zhang et al., 2024). The authors of this model introduced numerous improvements to accelerate training, including FlashAttention-2 (Dao, 2023), fused LayerNorm, fused SwiGLU, fused Cross-Entropy Loss, and fused Rotary Positional Embeddings. The experiment was carried out on A100 40GB GPUs in 8x and 16x A100 configurations, using a model with parameters identical to the TinyLlama 1.1B model. When using ALLaMo, it was possible to increase the local batch size from 8 to 9, which further enhanced training throughput. Table 4 illustrates the performance differences between the TinyLlama implementation and the ALLaMo framework.

5 Evaluations

5.1 Open PL LLM Leaderboard

The Open PL LLM Leaderboard, based on the Open LLM Leaderboard v1 (Beeching et al., 2023), evaluates models on various NLP tasks, including: sentiment analysis, categorization, and text classification, but does not test their conversational capabilities (Wróbel et al., 2024). The leaderboard utilizes the lm-evaluation-harness framework for model evaluation (Gao et al., 2024).

Tasks:

- **polemo2:** Sentiment analysis of online consumer reviews across four domains (medicine, hotels, products, university) with four-class labeling (positive, negative, neutral, ambiguous) (Kocoń et al., 2019); metric: accuracy.
- **klej-ner:** Named entity recognition in sentences containing single-type entities, classifying into six categories (no entity, place, person, organization, time, geographical name) (Rybak et al., 2020); metric: accuracy.
- **8tags:** Topic classification of social media headlines into eight categories (film, history,

Framework	Configuration	Total Batch Size	Throughput
TinyLlama	8xA100 40GB	2,097,152 tokens	24,390 tokens/GPU/sec
ALLaMo	8xA100 40GB	2,097,152 tokens	26,150 tokens/GPU/sec (+7.2%)
ALLaMo	8xA100 40GB	2,359,296 tokens	26,550 tokens/GPU/sec (+8.8%)
TinyLlama	16xA100 40GB	2,097,152 tokens	24,000 tokens/GPU/sec ¹
ALLaMo	16xA100 40GB	2,097,152 tokens	25,850 tokens/GPU/sec (+7.7%)
ALLaMo	16xA100 40GB	2,359,296 tokens	26,000 tokens/GPU/sec (+8.3%)

¹ The value reported by the authors of the model.

Table 4: A comparison of the training performance between the TinyLlama implementation and the ALLaMo framework.

food, medicine, motorization, work, sport, technology) (Dadas et al., 2020); metric: accuracy.

- **belebele:** Machine reading comprehension for question answering (Bandarkar et al., 2024); metric: accuracy.
- **dyk:** Question answering based on human-annotated pairs from Wikipedia’s "Did You Know" section (Marcinczuk et al., 2013); metric: binary F1.
- **ppc:** Text similarity assessment using manually labeled sentence pairs (exact paraphrases, close paraphrases, non-paraphrases) (Dadas, 2022); metric: accuracy.
- **psc:** Summarization of news articles (Ogrodniczuk and Kopeć, 2014); metric: binary F1.
- **cbd:** Text classification for cyberbullying and hate-speech detection (Ptaszynski et al., 2023); metric: macro F1.
- **polqa:** Open-domain question answering from the "Jeden z dziesięciu" TV show, with and without context (abstractive QA/RAG) (Rybak et al., 2024); metric: accuracy, levenshtein.
- **poquad:** Context-based extractive question answering (QA/RAG) (Tuora et al., 2023); metric: levenshtein.

Most of the tasks are multiple-choice tests, which means that the model chooses the correct answer from a set of options. They are implemented as two types of tests:

- **Loglikelihood:** We choose the highest probability token from the given set, e.g., ABCD. These tests are suitable for base models.
- **Generate:** Model generates answer freely.

All tasks are evaluated in both 0-shot and 5-shot settings.

Evaluation scores:

- **All tasks:** The average score across all tasks, normalized by baseline scores.
- **Reranking:** The score of reranking task, commonly used in Retrieval-Augmented Generation (RAG).
- **Reader (Generator):** The score of open-book question-answering task, also commonly used in RAG.
- **Perplexity:** A bonus metric that does not correlate with other scores and should not be used for direct model comparison (lower is better).

As of April 3, 2024, Table 5 presents the current scores of both pretrained and continuously pretrained models, as evaluated on the Open PL LLM Leaderboard in a 5-shot setting.

The Bielik 7B v0.1 model achieved one of the highest scores in the RAG Reader task, demonstrating a notable improvement of nearly 9 percentage points in average score compared to Mistral-7B-v0.1. In our subjective evaluations of conversational abilities, our models outperformed others that had higher average scores. The results presented in Table 5 were obtained without employing instruction templates for the instructional models, treating them instead as base models. This approach may have skewed the results, as instructional models are specifically optimized to follow particular instructions.

5.2 Polish MT-Bench

MT-bench (Zheng et al., 2023) is a tool designed to test the ability of language models (LLMs) to conduct two-step conversations and follow instructions. It covers typical use cases and focuses on challenging questions to differentiate the capabilities of various models. Eight main categories of user queries were identified, which were used to construct MT-bench:

Model	All tasks	RAG Reranking	RAG Reader	Perplexity
7B parameters models:				
berkeley-nest/Starling-LM-7B-alpha	47.46	75.73	82.86	1438.04
openchat/openchat-3.5-0106	47.32	74.71	83.60	1106.56
Nexusflow/Starling-LM-7B-beta	45.69	74.58	81.22	1161.54
openchat/openchat-3.5-1210	44.17	71.76	82.15	1923.83
teknium/OpenHermes-2.5-Mistral-7B	42.64	70.63	80.25	1463.00
mistralai/Mistral-7B-Instruct-v0.2	40.29	72.58	79.39	2088.08
<u>Bielik-7B-Instruct-v0.1</u>	39.28	61.89	86.00	277.92
internlm/internlm2-chat-7b	37.64	72.29	71.17	3892.50
internlm/internlm2-chat-7b-sft	36.97	73.22	69.96	4269.63
HuggingFaceH4/zephyr-7b-alpha	33.97	71.47	73.35	4464.45
HuggingFaceH4/zephyr-7b-beta	33.15	71.65	71.27	3613.14
szymonrucinski/Curie-7B-v1	26.72	55.58	85.19	389.17
mistralai/Mistral-7B-Instruct-v0.1	26.42	56.35	73.68	6909.94
meta-llama/Llama-2-7b-chat-hf	21.04	54.65	72.93	4018.74
Voicelab/trurl-2-7b	18.85	60.67	77.19	1098.88
Baseline (majority class)	0.00	53.36	-	-
Models with different sizes:				
upstage/SOLAR-10.7B-Instruct-v1.0 (10.7B)	46.07	76.93	82.86	789.58
Voicelab/trurl-2-13b-academic (13B)	29.45	68.19	79.88	733.91
Azuro/APT3-1B-Instruct-v1 (1B)	-13.80	52.11	12.23	739.09
7B parameters pretrained and continuously pretrained models:				
alpindale/Mistral-7B-v0.2-hf	33.05	60.23	85.21	932.60
internlm/internlm2-7b	33.03	69.39	73.63	5498.23
mistralai/Mistral-7B-v0.1	30.67	60.35	85.39	857.32
<u>Bielik-7B-v0.1</u>	29.38	62.13	88.39	123.31
internlm/internlm2-base-7b	20.68	52.39	69.85	3110.92
meta-llama/Llama-2-7b-hf	12.73	54.02	77.92	850.45
OPI-PG/Qra-7b	11.13	54.40	75.25	203.36

Table 5: Detailed comparison among Bielik 7B v0.1 and other representative open-source models

- writing
- role-playing
- information extraction
- reasoning
- mathematics
- coding
- knowledge / hard sciences / stem
- knowledge / humanities / social sciences

For each category, two-step questions were manually developed.

The evaluation of responses is performed by a metamodel. In the case of MT-Bench, this is the GPT-4 model. By using a metamodel, we can verify responses from open-ended questions, e.g., write an article about hybrid cars. The model evaluates the content of the response, the quality of facts used, creativity, etc.

The Polish MT-Bench (Kinas et al., 2024) has been completely polonized. Each task was first machine-translated and then verified. Additionally, we introduced Polish accents, e.g., instead of describing a vacation in Hawaii, we suggested the location - Masuria. In our language version, many changes were introduced to transfer the test into Polish linguistic realities.

Table 6 presents the results of the Polish MT-Bench evaluation for various language models. The table shows three key metrics: the Polish score (pl_score), the proportion of responses in Polish (responses_pl), and the average score. The Bielik 7B v0.1 model has a pl_score of 5.40, demonstrating competitive performance among larger models.

Table 7 provides a more detailed breakdown of the Polish MT-Bench results, showing scores across eight different categories for each model. The Bielik 7B v0.1 model shows competitive performance in several categories, notably excelling in Reasoning (6.15) and Role-playing (7.83). These results demonstrate the model’s versatility across various tasks, despite its smaller size compared to some of the top-performing models.

Model	pl_score	responses_pl	Average Score
Mixtral-8x7b	7.64	1.00	7.64
Mistral-Nemo-Instruct-2407	7.37	1.00	7.37
openchat-3.5-0106-gemma	6.51	0.96	6.81
Meta-Llama-3.1-8B-Instruct	6.24	1.00	6.24
Starling-LM-7B-alpha	6.05	0.93	6.49
openchat-3.5-0106	6.03	0.94	6.39
Mistral-7B-Instruct-v0.3	5.75	0.98	5.82
Bielik-7B-Instruct-v0.1	5.40	0.89	6.08
dolphin-2.9.1-llama-3-8b	5.24	0.89	5.86
Polka-Mistral-7B-SFT	4.43	0.98	4.52
trurl-2-7b	2.75	0.99	2.76
Mistral-7B-Instruct-v0.2	2.05	0.31	6.56

Table 6: Polish MT-Bench results for various language models

Model	Coding	Extraction	Humanities	Mathematics	Reasoning	Role-playing	Stem	Writing
Mixtral-8x7b	5.20	8.15	9.45	5.65	5.80	8.95	8.55	9.35
Mistral-Nemo-Instruct-2407	5.85	8.95	9.50	6.70	5.80	7.45	8.30	6.40
openchat-3.5-0106-gemma	5.35	6.90	8.80	4.55	5.40	7.97	8.47	7.05
Meta-Llama-3.1-8B-Instruct	4.60	9.10	8.82	5.30	2.50	5.60	6.30	7.70
Starling-LM-7B-alpha	4.75	7.35	8.50	4.15	3.90	6.90	8.85	7.55
openchat-3.5-0106	5.05	6.90	9.30	3.80	3.90	6.00	8.40	7.75
Mistral-7B-Instruct-v0.3	4.30	7.30	6.75	2.35	3.80	7.25	7.45	7.35
Bielik-7B-Instruct-v0.1	3.00	4.35	8.47	4.10	6.15	7.83	6.90	7.85
dolphin-2.9.1-llama-3-8b	4.60	6.15	8.80	4.80	3.30	7.40	6.35	5.50
Polka-Mistral-7B-SFT	2.95	5.25	5.60	2.95	2.45	4.90	6.80	5.25
trurl-2-7b	1.80	3.50	3.95	1.70	2.05	3.30	2.65	3.15
Mistral-7B-Instruct-v0.2	4.25	7.40	8.40	3.20	5.00	-	-	-

Table 7: Polish MT-Bench results for various language models by category

5.3 Bias, Toxicity and Misinformation

Language models have been shown to reproduce and amplify biases present in the training data, and can generate toxic or offensive content. Since our training dataset contains a large proportion of data from the web, Bielik-7B-v0.1 may produce factually incorrect output and should not be relied upon for producing accurate information. Despite significant efforts to clean the training data, it is still possible for this model to generate lewd, false, biased, or otherwise offensive content.

6 Model Quantization

In our work on the Bielik 7B v0.1 model, our primary objective was to create quantized versions that could be accessible to users with limited computational resources. This effort was driven by a vision to democratize advanced language models and make them available to those who do not have access to powerful computing infrastructure. By optimizing our model for low-resource environments, we aimed to facilitate deployment on various devices, including edge devices such as mobile phones and embedded systems.

To achieve this, we developed and delivered several quantized versions of Bielik 7B v0.1, including GGUF (GPT - Generated Unified Format)¹, HQQ (Half-Quadratic Quantization) (Badri and Shaji, 2023), AWQ (Activation-aware Weight Quantization) (Lin et al., 2024), MLX (Apple MLX Framework) (Hannun et al., 2023), EXL2 (ExLlamaV2)², GPTQ (Accurate Post-Training Quantization for Generative Pre-trained Transformers) (Frantar et al., 2022), and IQ2_XXS (GGUF IQ)³. Each quantization technique offered different trade-offs in terms of performance, memory usage, and computational requirements, allowing for flexibility depending on the intended use case and hardware capabilities. The IQ2_XXS version, in particular, was specifically designed for edge devices, with a bit-per-weight quantization of 2.06 bpw, providing an efficient solution for deployment on resource-constrained platforms such as mobile phones.

¹<https://github.com/gganganov/ggml>

²<https://github.com/turboderp/exllama> v2

³<https://github.com/gganganov/llama.cpp>

6.1 Calibration and Evaluation of Quantized Models

In addition to the standard quantization process, we created calibrated versions of the imatrix (Importance Matrix) GGUF model. Calibration plays a crucial role in minimizing performance degradation, which is often a concern during quantization. To support this process, we developed a multilingual (Polish-English) calibration dataset with a specific emphasis on the Polish language. This multilingual approach aimed to improve the model’s generalization capabilities across languages while ensuring high fidelity in its Polish-language outputs.

To assess the impact of calibration, we conducted a thorough comparison between the uncalibrated and calibrated versions of the model for the Polish language. Our evaluation metrics focused on both the accuracy of language understanding and the quality of generated text. The results showed that the calibration process improved the model’s performance, particularly in language-specific contexts where nuances and subtleties are crucial.

Across all quantization schemes examined (Q8_0, Q6_K, Q5_K_M, Q4_K_M, Q3_K_M, Q2_K) (see table 8), models quantized with imatrix consistently outperform their counterparts without imatrix quantization. This is evident through multiple evaluation metrics, indicating that imatrix quantization effectively preserves model quality even at lower bit-widths. The KLD values are consistently lower for imatrix-quantized models, indicating a closer alignment of the probability distributions between the quantized and the original FP16 models. Imatrix quantization results in Mean Δp values closer to zero, indicating less degradation in the model’s ability to predict the correct token. At Q3_K_M, the Mean Δp improves from -0.9160 without imatrix to -0.3860 with imatrix. The advantages of imatrix quantization become more pronounced at lower bit-width quantization levels. The reduction in performance metrics such as PPL, KLD, Mean Δp , and RMS Δp is more significant when comparing imatrix and non-imatrix models at Q2_K and Q3_K_M levels, demonstrating imatrix’s effectiveness in mitigating the adverse effects of aggressive quantization.

The application of imatrix quantization to the Polish language model leads to significant im-

provements in maintaining model quality across various quantization levels. These findings support the adoption of imatrix quantization as an effective technique for compressing language models without substantially compromising their performance.

Quant.	imatrix	Size [GiB]	PPL	Δ PPL	KLD	Mean Δp	RMS Δp	Same top p [%]
FP16	-	13.49	3.9393	-	-	-	-	-
Q8_0	No	7.17	3.9422	0.0029	0.0010	-0.0070	0.9800	98.6890
Q8_0	Yes	7.17	3.9422	0.0029	0.0010	-0.0070	0.9800	98.6890
Q6_K	No	5.53	3.9450	0.0057	0.0051	-0.0420	2.1850	97.2410
Q6_K	Yes	5.53	3.9406	0.0013	0.0037	-0.0030	1.8490	97.6130
Q5_K_M	No	4.78	3.9520	0.0127	0.0106	-0.0680	3.1320	96.0510
Q5_K_M	Yes	4.78	3.9473	0.0080	0.0086	-0.0250	2.8320	96.4670
Q4_K_M	No	4.07	3.9876	0.0483	0.0286	-0.2690	5.1300	93.6550
Q4_K_M	Yes	4.07	3.9727	0.0333	0.0220	-0.1440	4.4880	94.4700
Q3_K_M	No	3.28	4.0915	0.1522	0.0826	-0.9160	8.6880	89.5780
Q3_K_M	Yes	3.28	4.0458	0.1065	0.0683	-0.3860	7.8390	90.6290
Q2_K	No	2.53	4.7045	0.7652	0.2852	-3.8050	16.3760	81.1100
Q2_K	Yes	2.53	4.3522	0.4128	0.1939	-1.8980	13.4190	84.5580

Table 8: Comparison of quantization results for the Bielik 7B v0.1 model using imatrix: PPL - Perplexity, Δ PPL - change in perplexity, KLD - Kullback-Leibler Divergence, Mean Δp - mean change in correct token probability, RMS Δp - root mean square of change in token probabilities, Same top p - the percentage of instances where the quantized model and the FP16 model assign the highest probability to the same token.

7 Conclusion

In this paper, we introduced Bielik 7B v0.1, a language model specifically trained for the Polish language. We demonstrated that it is possible to significantly enhance the linguistic capabilities of an already trained model by fine-tuning it on texts exclusively in that language. Without changing the tokenizer, we achieved a high quality of responses generated by the model, which resembled texts written by native Polish speakers. Furthermore, the model performed well in various tasks, opening up intriguing possibilities for its further development.

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A Examples of Tasks

A.1 polemo2

Task: Sentiment analysis of online consumer reviews across four domains (medicine, hotels, products, university) with four-class labeling (positive, negative, neutral, ambiguous).

Example:

Opinia: "Leczyłam się u niej parę lat i nic mi nie pomogła, a jak zmieniła m lekarza po krótkim czasie zobaczyła m już poprawę a w tej chwili jestem już bez leków 6 lat i jest wszystko dobrze . Dr Ciborska leczyła mnie na depresję a potem przez dr Kopystecką miała m rozpoznany zespół maniakałno depresyjny i odtąd zmianę leków i przede wszystkim wysłuchała mnie z zaangażowaniem a nie jak dr Ciborska aby mnie zbyć"

Określ sentyment podanej opinii. Możliwe odpowiedzi:

A - Neutralny, B - Negatywny, C - Pozytywny, D - Niejednoznaczny

Prawidłowa odpowiedź: B

A.2 klej-ner

Task: Named entity recognition in sentences containing single-type entities, classifying into six categories (no entity, place, person, organization, time, geographical name).

Example:

Zdanie: "Ulewne deszcze nawiedziły także Słupsk."

Pytanie: Jakiego rodzaju jest nazwana jednostka, jeżeli występuje w podanym zdaniu?

Możliwe odpowiedzi: A - Brak nazwanej jednostki, B - Nazwa miejsca, C - Nazwa osoby, D - Nazwa organizacji, E - Czas, F - Nazwa geograficzna

Prawidłowa odpowiedź: B

A.3 8tags

Task: Topic classification of social media headlines into eight categories (film, history, food, medicine, motorization, work, sport, technology).

Example:

Tytuł: "Czy bateria zrobiona z 1000 cytryn jest w stanie uruchomić silnik?."

Pytanie: jaka kategoria najlepiej pasuje do podanego tytułu?

Możliwe odpowiedzi:

A - film, B - historia, C - jedzenie, D - medycyna, E - motoryzacja, F - praca, G - sport, H - technologie

Prawidłowa odpowiedź: E

A.4 belebele

Task: Machine reading comprehension for question answering.

Example:

Fragment: "Atom może być uważany za jeden z fundamentalnych elementów budujących całą materię. To bardzo złożona jednostka, która składa się, według uproszczonego modelu Bohra, z centralnego jądra, wokół którego znajdują się elektrony, co nieco przypomina planety krążące wokół Słońca – patrz rysunek 1.1. W skład jądra wchodzi dwa typy cząsteczek: neutrony i protony. Pod względem ładunku elektrycznego protony są dodatnie, elektrony są ujemne, a neutrony nie mają żadnego ładunku."

Pytanie: "Jaki ładunek mają cząstki krążące wokół jądra?"

Możliwe odpowiedzi: A - Ładunek dodatni, B - Bez ładunku, C - Ładunek ujemny, D - Ładunek dodatni i ujemny

Prawidłowa odpowiedź: C

A.5 dyk

Task: Question answering based on human-annotated pairs from Wikipedia's "Did You Know" section.

Example:

Pytanie: "za co Iwanowi Tyszkiewiczowi ucięto dłoń?"

Sugerowana odpowiedź: "Tyszkiewicz był torturowany – wyrwano mu język za "błuznierstwo przeciw Bogu", a za rzucenie krucyfiks na ziemię ucięto mu dłoń i nogę."

Czy sugerowana odpowiedź na zadane pytanie jest poprawna? Możliwe opcje: A - brakuje sugerowanej odpowiedzi, B - nie, sugerowana odpowiedź nie jest poprawna, C - tak, sugerowana odpowiedź jest poprawna, D - brakuje pytania

Prawidłowa opcja: C

A.6 ppc

Task: Text similarity assessment using manually labeled sentence pairs (exact paraphrases, close paraphrases, non-paraphrases).

Example:

Zdanie A: "Piasek nad Chinami."

Zdanie B: "Burza piaskowa w Chinach."

Pytanie: jaka jest zależność między zdaniem A i B?

Możliwe odpowiedzi: A - wszystkie odpowiedzi poprawne, B - znaczą dokładnie to samo, C - mają podobne znaczenie, D - mają różne znaczenie

Prawidłowa odpowiedź: C

A.7 psc

Task: Summarization of news articles.

Example:

Fragment 1: "Zwykle zaczyna się od siąkających nosami kilku osób. Jednak choroba postępuje lawinowo. Wirus grypy przenosi się drogą kropelkową - podczas rozmowy, kaszlu i kichania. Jedna zagrypiona osoba, która pojawi się w towarzystwie, może zakażać wielu ludzi. Lekarz dyżurny kraju Michał Sobolewski uspokaja: w Polsce jeszcze nie ma epidemii grypy. Wybuchnie, kiedy będzie dużo źródeł zakażenia."

Fragment 2: "W niedzielę przychodnie w Warszawie zalała fala pacjentów z objawami grypy. Lekarz dyżurny kraju uspokaja, że w Polsce nie ma jeszcze epidemii grypy. Podkreśla też, że Polacy lekceważą profilaktyczne szczepienia przeciwko tej chorobie, a tylko one zapobiegają rozprzestrzenianiu się schorzeń zakaźnych. W Europie epidemia grypy dociera do kolejnych państw. Odnotowano już przypadki śmiertelne."

Pytanie: jaka jest zależność między fragmentami 1 i 2?

Możliwe odpowiedzi: A - wszystkie odpowiedzi poprawne, B - dotyczą tego samego artykułu, C - dotyczą różnych artykułów, D - brak poprawnej odpowiedzi

Prawidłowa odpowiedź: B

A.8 cbd

Task: Text classification for cyberbullying and hate-speech detection.

Example:

Wypowiedź: "Ty wiesz lepiej. Ja wiem, że nawet wiceprezydentem nie będziesz na 100%"

Pytanie: Jaka kategoria najlepiej pasuje do podanej wypowiedzi?

Możliwe odpowiedzi: A - nieszkodliwa, B - sztyderstwo, C - obelga, D - insynuacja, E - groźba, F - molestowanie

Prawidłowa odpowiedź: B

A.9 polqa

Task: Open-domain question answering from the "Jeden z dziesięciu" TV show, with and without context (abstractive QA/RAG).

Example:

Kontekst: Przymiotnik. Przymiotniki, podobnie jak w języku polskim, odmieniały się przez liczby, rodzaje i przypadki. Wyraz określający następował zawsze po wyrazie określanym, tak jak w innych językach semickich, np. "ezzūtu šārū" „porywiste wiatry”, dosłownie „wiatry porywiste”

Pytanie: Czy przymiotniki odmienia się przez przypadki?

Czy kontekst jest relewantny dla pytania?

Odpowiedz krótko "Tak" lub "Nie". Prawidłowa odpowiedź: Tak

Kontekst: Alibi (łac. gdzie indziej) – dowód w postępowaniu karnym na okoliczność, że podejrzany albo oskarżony znajdował się w miejscu innym niż miejsce popełnienia zarzucanego mu przestępstwa.

Pytanie: Jak z łaciny nazywa się dowód sądowy polegający na wykazaniu, że osoba oskarżona nie przebywała na miejscu przestępstwa w chwili gdy je popełniono?

Prawidłowa odpowiedź: alibi

A.10 poquad

Task: Context-based extractive question answering (QA/RAG). **Example:**

Tytuł: Miszna

Kontekst: Pisma rabiniczne – w tym Miszna – stanowią kompilację poglądów różnych rabinów na określony temat. Zgodnie z wierzeniami judaizmu Mojżesz otrzymał od Boga całą Torę, ale w dwóch częściach: jedną część w formie pisanej, a drugą część w formie ustnej. Miszna – jako Tora ustna – była traktowana nie tylko jako uzupełnienie Tory spisanej, ale również jako jej interpretacja i wyjaśnienie w konkretnych sytuacjach życiowych. Tym samym Miszna stanowiąca kodeks Prawa religijnego zaczęła równocześnie służyć za jego ustnie przekazywany podręcznik.

Pytanie: Czym są pisma rabiniczne?

Prawidłowa odpowiedź (krótki cytat z Kontekstu): kompilację poglądów różnych rabinów na określony temat

B Evaluation Reproducibility

To reproduce our results, you need to clone the repository:

```
git clone https://github.com/speakleash/lm-evaluation-harness.git -b polish3cd
cd lm-evaluation-harness
pip install -e .
```

and run benchmark for 0-shot and 5-shot:

```
lm_eval --model hf --model_args
    pretrained=speakleash/Bielik-7B-
    Instruct-v0.1 --tasks
    polish_generate --num_fewshot 0 --
    output_path results/ --log_samples

lm_eval --model hf --model_args
    pretrained=speakleash/Bielik-7B-
    Instruct-v0.1 --tasks polish_mc --
    num_fewshot 0 --output_path results/
    --log_samples

lm_eval --model hf --model_args
    pretrained=speakleash/Bielik-7B-
    Instruct-v0.1 --tasks
    polish_generate_few --num_fewshot 5
    --output_path results/ --log_samples

lm_eval --model hf --model_args
    pretrained=speakleash/Bielik-7B-
    Instruct-v0.1 --tasks polish_mc --
    num_fewshot 5 --output_path results/
    --log_samples
```