LLäMmlein 🐑: Transparent, Compact and Competitive German-Only Language Models from Scratch

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Abstract

We transparently create two German-only decoder models, LLäMmlein 120M and 1B[1], from scratch and publish them, along with training data, for the (German) NLP research community to use[2]. The model training involved several key steps, including data preprocessing/filtering, the creation of a German tokenizer, the training itself, as well as the evaluation of the final models on various benchmarks, also against existing models. Throughout the training process, multiple checkpoints were saved in equal intervals and analyzed using the German SuperGLEBer benchmark to gain insights into the models' learning process.

Compared to state-of-the-art models on the SuperGLEBer benchmark, both LLäMmlein models performed competitively, consistently matching or surpassing models with similar parameter sizes. The results show that the models' quality scales with size as expected, but performance improvements on some tasks plateaued early during training, offering valuable insights into resource allocation for future models.

1 Introduction

Large Language Models (LLMs) have achieved remarkable success, yet this progress is predominantly centered on English. Other languages, including German, lag behind due to limited competition, reduced investment, and a lack of transparency in training data, code, and detailed results (also see Pfister and Hotho, 2024). While smaller German-only models do exist, such as BERTs or smaller GPTs (Chan et al., 2020; Scheible et al., 2020), or the contemporaneous effort by Idahl (2024), many are closed or undocumented, and few robust, openly accessible German LLMs have been built from scratch with full transparency. Most German-capable LLMs are either multilingual models (e.g., mGPT (Shliazhko et al., 2024)) or English models adapted to German (e.g., LeoLM (Plüster, 2023b), BübleLM (Delobelle et al., 2024), or bloom-clp (Ostendorff and Rehm, 2023)). Others, like Mistral (Jiang et al., 2023), share little about their (German) training data, making it difficult to understand which resources and pretraining strategies are most suitable for developing strong German LLMs from scratch. This lack of traceability hampers the community's ability to identify, curate, and refine German data, and to examine how corpus and training choices affect model quality. Subtle issues – such as performance deteriorations on non-English downstream tasks (Virtanen et al., 2019) or poor handling of German's complex grammar and morphology (Mielke et al. (2019), also Appendix A) – remain common, even in state-of-the-art models like Llama 3 (Dubey et al., 2024), which can revert to English despite a German context, or sometimes sound like machine-translated from English[3].

We present *LLäMmlein*, the first German-only LLM family trained entirely from scratch with full transparency, providing a foundation for systematically analyzing the relationship between training data and model outputs. To this end, we share the model, code, and dataset to foster reproducibility and collaboration. Although our evaluation is primarily illustrative, it offers insights into the model's German capabilities and enables further research and development. We accompany training with iterative benchmark evaluations, tracking the learning progress of our 120M and 1B model to illuminate scaling effects and guide future research.

To achieve this, we: (1) clean and filter a large German dataset derived from RedPajama V2 (Weber et al., 2024), ensuring high-quality input,

🐑 These authors contributed equally to this work.

[1] After submission we also released a new 7B model

[2] `https://professor-x.de/lm/LLaMmlein`

[3] `https://www.reddit.com/r/LocalLLaMA/comments/1bfce18/still_didnt_found_a_better_small_german_llm_anyone/`

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(2) construct a dedicated German tokenizer (32k tokens) fitted on varying data amounts to compare against existing German tokenizers, (3) pretrain two exclusively German autoregressive LLMs (120M and 1B) and release incremental checkpoints, inspired by Biderman et al. (2023), to inform efficient stopping criteria and shed light on learning dynamics, and (4) evaluate the models on a range of tasks (SuperGLEBer (Pfister and Hotho, 2024), lm-evaluation-harness-de (Plüster, 2023a; Gao et al., 2021)) to benchmark performance against existing models.

In doing so, we directly demonstrate and address the pressing need for dedicated German-centric LLM research, establishing a transparent foundation for understanding, improving, and expanding the German LLM ecosystem.

> 🐑 : Throughout the paper, we highlight interesting findings and insights we gained during the process in little boxes like this one.

2 Methodology

Pretraining and evaluating a German LLM from scratch, end-to-end involves several steps, including dataset preprocessing (section 2.1.2), tokenizer fitting (section 3.1), model pretraining (section 2.2), model evaluation using a comprehensive German benchmark, as well as multiple translated prompt-based few-shot QA tasks (section 2.3), and exemplary downstream adaptations (section 2.4).

2.1 Dataset

RedPajama V2 is an open[4], multilingual dataset designed for training large language models (Weber et al., 2024). It consists of over 100 billion text documents collected from 84 CommonCrawl snapshots between 2014 and 2023 and encompasses multiple languages, including English, German, French, Italian, and Spanish. The dataset was originally preprocessed using the CCNet pipeline (Wenzek et al., 2020) leading to about 30 billion overall documents further enriched with quality signals and duplicate indicators. Using perplexity of a language model, the RedPajama dataset was divided into three quality categories, in descending order of quality: head, middle, and tail. Following a manual inspection of a randomly selected subset, the head and middle partitions were deemed to contain sufficiently high-quality German texts suitable for continued use. In contrast, the tail partition exhibited inconsistent quality and was consequently excluded from further training.

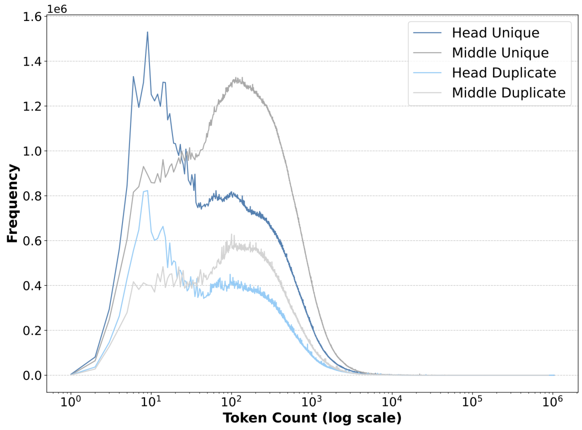

Figure 1: Token count distribution for each partition separately: head unique, middle unique, head duplicate and middle duplicate based on gbert-large tokenizer

2.1.1 Dataset Analysis

The aim of the following preliminary dataset analysis is to gain a deeper understanding of the German portion of the dataset used. The "official" estimate of the size of the German segment within the RedPajamaV2 dataset, derived through extrapolation from a smaller sample analyzed with Mistral-7B, is approximately 3 trillion German tokens (Weber et al., 2024). Following, we first perform an exploratory analysis of the dataset to gain a clearer understanding of the actual amount of German data it contains, alongside its domain distribution and the most prevalent data sources.

Statistics Our own count using the gbert-large tokenizer, led to a token count of 2.7 trillion German tokens for head and middle combined, before document-level deduplication.

Figure 1 breaks down the distribution of each partition, i.e. head unique, middle unique, head duplicate and middle duplicate separately. The first occurence of a document is considered unique, while all subsequent appearances are marked as duplicates. The middle unique partition contains the largest amount of data, with approximately 1.2 billion samples, which corresponds to 45% of the full dataset. The head unique partition, by comparison, includes around 400 million fewer samples.

Overall, most samples are unique (1.9 billion samples) and only significantly less are marked as duplicates, appearing a second or more times (777 million samples) across the entire dataset. The

[4] https://commoncrawl.org/terms-of-use

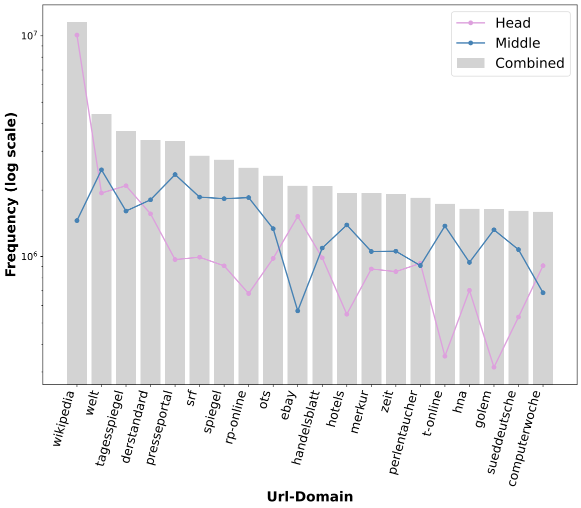

Figure 2: Top 20 most frequent domains across the full dataset in gray with frequencies in head and middle partitions separately.

most common token-per-document count can be found at nine, with approximately 3.6 million occurrences in the dataset. A second peak (most prominent for the unique split) occurs at around 100 tokens per document. In total, the 2.7 trillion German tokens are distributed across samples with lengths ranging from 1 to 1 034 799 tokens, averaging approximately 1000 tokens per sample.

Domain Analysis The dataset contains content crawled from various domain names. Figure 2 displays the top 20 sources from which the data was collected, with the overall count illustrated as gray bars and separate plots for the head (pink) and middle (blue) unique splits.

Wikipedia clearly stands out as the largest contributor, with a combined total of over 11.5 million samples. Among these, about 10 million entries belong to the head category, while about 1.45 million stem from the middle partition. This distribution aligns with the fact that the split into head, middle and tail was created using a perplexity score criterion based on a language model trained on Wikipedia (Weber et al., 2024) – consequently, texts closer in style to Wikipedia tend to be ranked higher. Besides Wikipedia, it is evident that news websites also constitute a significant portion of the dataset. For the middle split, "welt.de" emerges as the most frequent domain, contributing around 2.47 million samples. With the exception of domains like eBay, hotels and Perlentaucher, the list is largely dominated by general news outlets.

2.1.2 Further Dataset Preprocessing

To remove common web boilerplate, such as EU-specific "General Data Protection Regulation" (GDPR) notices or similar repetitive content, we utilize a paragraph-level deduplication scheme powered by Dolma – a framework that enables efficient deduplication through a Rust-based Bloom filter (Soldaini et al., 2024). A Bloom filter is a probabilistic method that works similarly to a hash table, determining whether an element has already been previously encountered or not. This ensures that highly redundant text is filtered out, improving the overall quality and diversity of the dataset. This approach may inadvertently over-remove valid and relevant content, such as short texts mistakenly treated as entire paragraphs being removed across the dataset. To mitigate this, and to preserve meaningful short text sections – such as lists or frequently occurring itemized phrases that are contextually significant – we excluded paragraphs containing fewer than three words from the deduplication process.

Despite these efforts, we found that some unusual artifacts, such as long sequences of guitar chords, remained, as they scored low perplexity (41.2) compared to the average perplexity of 206.35 in the respective snapshot (2014_52) and were therefore not removed by the preliminary quality filter. To address this, we built a token-to-word ratio filter. Here, we compared the word count (whitespace separated) with the token count using the German GPT-2 tokenizer (Schweter, 2020). According to our intuition, a usual ratio between the two counts indicates abnormal or low-quality text, whereas a close match suggests valid German content. A simple example illustrates this clearly: The phrase "Der Himmel ist blau" consists of 4 words and 4 tokens, so it is not removed by our filter. In contrast, "/de/c/trebic-unesco" counts as 1 word but 11 tokens, and should therefore be excluded by this token-to-word ratio filter.

Preliminary examinations and manual review suggested a ratio of tokens to words of eight as a valid threshold. Thus, paragraphs exceeding this threshold were excluded from the dataset.

Interesting: Regular patterns of non-textual data, such as guitar chords, can yield a low perplexity and therefore remain in the dataset through quality filtering processes.

2.2 Model Pretraining Framework

While there are several existing resources and repositories for training an LLM from scratch[5], we chose the TinyLlama GitHub repository as the backbone of our project (Zhang et al., 2024). It was used to pretrain the 1B English Llama 2-based (Touvron et al., 2023) TinyLlama model from scratch before and builds upon the lit-gpt repository (AI, 2023), which provides robust tooling for data preparation, fine-tuning, pretraining, and deploying LLMs using PyTorch Lightning.

It includes all key features such as multi-GPU and multi-node distributed training with FSDP as well as FlashAttention-2 (Dao, 2024). In addition, it provides scripts to convert the models into HuggingFace format for easier use and distribution.

We modified the codebase[6] for our requirements: 1. We significantly improved the data loader speed by adding various layers of caching. 2. We enable training directly from a directory of jsonl-files, without any prior preprocessing. 3. Most importantly, inspired by our reviewers' feedback, we retrained our models logging exact datapoints as they enter the model. This allows us to correlate the training data and its order for each of our published (intermediate) checkpoints[7].

2.3 Model Evaluation Setup

2.3.1 Intermediate Checkpoint Evaluation

To get a better understanding of the training, we monitor the progress and regularly evaluate intermediate checkpoints on six representative SuperGLEBer tasks (Pfister and Hotho, 2024) following a finetuning to the task from the respective checkpoint. These tasks were selected to encompass a range of problem types to assess our model's performance. Within classification, (1) Natural Language Inference(NLI) (Conneau et al., 2018) requires determining whether a hypothesis is entailed, neutral, or contradictory to a premise; (2) FactClaiming Comments (Risch et al., 2021) involves binary classification of fact-checkable claims; (3) DB Aspect (Wojatzki et al., 2017) addresses multi-label categorization and polarity detection in input sentences; and (4) WebCAGe (Henrich et al., 2012) tests if a given word's sense aligns across two contexts. For sequence tagging, (5) EuroParl (Faruqui and Padó, 2010) evaluates Named Entity Recognition on European Parliament data. Finally, in the sentence similarity domain, (6) PAWSX (Liang et al., 2020) challenges the model to detect paraphrases via vector representations.

2.3.2 Final Model Evaluation

To assess general knowledge and abilities, we evaluated our final models on the full SuperGLEBer benchmark (29 tasks across classification, sequence tagging, question answering, and sentence similarity) (Pfister and Hotho, 2024), as well as machine-translated, prompt-based, few-shot QA tasks using the lm-evaluation-harness-de by Plüster (2023a) (if not stated otherwise, they are evaluated measuring unnormalized and Byte-length normalized accuracy (Gao et al., 2021)): (1) ARC-Challenge-DE (Clark et al., 2018): Grade-school science questions (1471 samples). Few-shot evaluation with 25 samples. (2) MMLU-DE (Hendrycks et al., 2021): 6829 multiple-choice questions across 57 topics (e.g., math, medicine, law). Few-shot evaluation with five samples. (3) HellaSwag-DE (Zellers et al., 2019): Commonsense reasoning dataset with 11 000 translated samples, featuring incomplete sentences with multiple-choice completions. Few-shot evaluation with ten samples. (4) TruthfulQA-DE (Lin et al., 2022): 817 questions across 38 categories designed to evaluate model truthfulness, particularly in handling misconceptions in a zero-shot evaluation setting. Performance here is measured using MC1 (Single-true): accuracy in selecting a single correct answer and MC2 (Multi-true): the normalized probability assigned to all correct answers (Gao et al., 2021).

To assess the impact of checkpoint averaging on model performance (Vaswani et al., 2017; Dubey et al., 2024), we also evaluate averaged checkpoints on the SuperGLEBer benchmark.

2.4 Exemplary Downstream Adaptations

As examples of downstream adaptation, we finetune our model with LoRA (Hu et al., 2022) in two settings: instruct-tuning (adapting the model to respond to user prompts) and for demonstration purposes on Bavarian and Swiss in Appendix H.

3 Experiments

3.1 Tokenizer

We follow the TinyLlama setup and fit an Llama 2 Byte-Pair Encoding (BPE) tokenizer with a 32 000-

[5] a small subset: `https://github.com/Hannibal046/Awesome-LLM#llm-training-frameworks`

[6] `https://github.com/LSX-UniWue/LLaMmlein`

[7] Since the performance of the original model (without data logging) and the new model (with data logging) did not differ significantly, we kept the original scores throughout the paper.

token vocabulary (Touvron et al., 2023). We trained three tokenizers on different amounts of data:

(1) 1TB: Spans backward from the most recent data until 1TB of data is processed (2) 2023-2021: Includes all splits of the high quality data split from years 2023 to 2021 (847GB) (3) 2023_14: Consists of the most recent 2023_14 split (67GB)

3.2 Model Pretraining

We trained two models, LLäMmlein 120M and LLäMmlein 1B, using filtered subsets of our preprocessed dataset (section 2.1). Detailed configurations for both models are provided in Table 6, and Figures 3 and 4 display the model's loss curve, where each training resume is distinguished by a unique color.

3.2.1 LLäMmlein 120M

LLäMmlein 120M was trained on the filtered head unique partition, comprising 1T pretraining tokens (2 epochs). The training setup included a maximum learning rate of 6e-4, grouped query attention of 4, a sequence length of 2048, and a global batch size of 1024. We employed the full-shard FSDP strategy across 32 L40 GPUs on 16 nodes, completing training in approximately 10 000 GPU hours.

3.2.2 LLäMmlein 1B

LLäMmlein 1B was trained on the filtered, head and middle unique partitions, resulting in a dataset of 1.3T unique tokens, and 3T overall tokens seen during training. The training setup featured a maximum learning rate of 6e-4, a global batch size of 1024 (per device batch size of 16), and was executed on 64 A100 80GB GPUs across 8 nodes over 32 days (50 000 GPU hours).

3.3 Downstream Adaptations

For instruct-tuning, we use LoRA (Hu et al., 2022) with supervised finetuning, PEFT (Mangrulkar et al., 2022) and default hyperparameters for three epochs on the following datasets from huggingface: "LSX-UniWue/Guanako", "FreedomIntelligence/alpaca-gpt4-deutsch", "FreedomIntelligence/evol-instruct-deutsch", and "FreedomIntelligence/sharegpt-deutsch". We train and publish a separate adapter for each dataset, and also a combined model across all datasets.

Tokenizer	Head	Middle
word count	46 509 357	80 782 685
german-gpt2	1.68	1.72
gbert-large	1.72	1.74
ours 1TB	2.27	2.27
ours 2023-2021	2.07	2.10
ours 2023_14	1.76	1.80

Table 1: Fertility of our three tokenizers with different training data sizes in comparison to other German tokenizers on two unseen training data samples: one from head and one from middle partition.

4 Evaluation

4.1 Tokenizer

We evaluate our custom Llama2-based tokenizers by measuring their fertility on random samples and training splits, comparing them to two established German tokenizers: german-gpt2 (vocab size: 50 266) and gbert-large (vocab size: 31 102). Fertility measures how many subwords represent a single original word, with a value of 1 indicating perfect segmentation (Rust et al., 2021; Ali et al., 2024). Although differing vocabulary sizes complicate direct comparisons, the results still provide relative performance insights.

Table 1 shows the fertility of all tokenizers on two unseen dataset snapshots. Both german-gpt2 and gbert-large achieve the lowest fertility. Notably, among our own tokenizers, the one trained on the smallest dataset (2023_14) produces fewer tokens on average than those trained on larger datasets. This suggests that a smaller dataset may enable more efficient tokenization by concentrating on the most frequent tokens, while larger datasets introduce greater variability and less efficient segmentation. As seen in Table 5, the tokenizer trained on less data also appears to yield more meaningful subword segments. Consequently, we selected the tokenizer trained on the 2023_14 snapshot.

> **Interesting**: Fitting a tokenizer on "too much" data can reduce its efficiency, possibly due to having to account for variation in the data.

To validate this finding, we repeated the experiment using a variety of disjoint training datasets and different test sets, including snapshots from different time periods as well as random internet texts. Interestingly, we consistently observed the same outcome across all variations.

Model	FactCl.	EUParl	PAWSX	NLI	DB Asp.	WebCAGe
10 000	0.711	0.531	0.427	0.549	0.454	0.689
100 000	0.708	0.532	0.464	0.559	0.479	0.700
200 000	0.705	0.497	0.497	0.575	0.464	0.703
300 000	0.712	0.525	0.497	0.615	0.498	0.682
400 000	0.713	0.522	0.488	0.627	0.511	**0.695**
466 509	0.711	0.538	0.489	**0.629**	**0.517**	0.687
german-gpt2	0.707	0.533	0.394	0.479	0.429	0.645
gbert-base	**0.751**	**0.616**	**0.561**	0.436	0.478	0.693
bert-ger-cased	0.721	0.607	0.537	0.490	0.480	0.679

Table 2: Results of LLäMmlein 120M checkpoints on six SuperGLEBer tasks compared to similarly sized german-gpt2, gbert-base and bert-base-german-cased

4.2 Pretraining Process

During training, we regularly saved and evaluated checkpoints to monitor the training process (section 2.3.1). Intermediate checkpoints will be published to enable further analysis and comparison with other models .

4.2.1 LLäMmlein 120M

We evaluated LLäMmlein 120M against german-gpt2, gbert-base, and bert-base-german-cased. While it consistently outperformed the decoder-only german-gpt2 model, BERT-based models excelled in the first three tasks (FactClaiming, EuroParl, PAWSX), reflecting known limitations of autoregressive architectures in tasks like sequence tagging and sentence similarity (Pfister and Hotho, 2024). However, LLäMmlein 120M demonstrated superiority in complex classification tasks, outperforming all models in NLI from checkpoint 10 000 onward, with its best checkpoint exceeding bert-base-german-cased by 14%. It also closely matches the top scores for DB Aspect and WebCAGe classification.

Performance trends during pretraining varied by task. We calculate the Spearman correlation coefficient r to measure the strength and direction of the relationship between pretraining steps and task performance, and the corresponding p-value to assess the statistical significance of the correlation. FactClaiming and EuroParl showed minimal variation, but PAWSX (r = 0.607, p = 0.04), NLI (r = 0.947, p < 0.0001), and DB Aspect (r = 0.909, p < 0.0001) displayed significant linear improvements.

Despite this, an Analysis of Variance (ANOVA) across all 29 SuperGLEBer benchmark tasks revealed no statistically significant performance improvements beyond the 300 000 training checkpoint (Figure 5). In particular, average performance at checkpoints 300 000 (0.693) and 466 509 (0.699) only demonstrated small gains of 0.06 (Figure 5), despite additional 166 509 training steps (≈349 billion tokens). These findings problematize the marginal returns of extended training on downstream tasks, suggesting potential early convergence or benchmark limitations in capturing nuanced model improvements on average across tasks. While LLäMmlein quickly reached a plateau for certain tasks, i.e. those that might require more basic structure recognition (FactClaiming/EuroParl), it continued to learn and improve on some more complex tasks. Interestingly, contrary to the “curse of monolingual models” posited by Kydlíček et al. (2024), which suggests monolingual models excel at LM but lack reasoning, our model demonstrates strong performance on deeper semantic tasks such as NLI and WebCAGe.

Model	FactCl.	EUParl	PAWSX	NLI	DB Asp.	WebCAGe
10 000	0.735	0.708	0.461	0.642	0.563	0.677
100 000	0.734	0.662	0.511	0.709	0.607	0.699
500 000	0.733	0.712	0.539	0.734	0.613	0.720
1 000 000	0.750	0.697	0.540	0.740	0.629	0.756
1 430 512	0.736	0.713	0.526	0.749	0.623	0.765
Llama 3.2. 1B	0.665	0.537	0.551	0.603	0.557	0.689
EuroLLM-1.7B	0.724	0.654	0.585	0.529	0.587	0.662
gbert-base	**0.751**	0.616	0.561	0.436	0.478	0.693
mbart-large-50	0.723	**0.727**	0.358	0.336	0.471	0.651
gbert-large	0.747	0.636	**0.654**	0.736	0.550	0.716
leo-mistral-7b	0.741	0.649	-	**0.807**	0.664	-
leo-hessianai-7b	0.747	-	-	-	**0.669**	**0.781**

Table 3: Results of LLäMmlein 1B across multiple training checkpoints on six SuperGLEBer tasks, in comparison to the best-performing models and models with similar parameter size. Following SuperGLEBer, results of models that experienced out-of-memory (OOM) errors on an A100 80 GB are indicated with a “-”.

Contradiction: Kydlíček et al. (2024) suggests monolingual models excel at LM but often lack reasoning; ours appear strong in both.

4.2.2 LLäMmlein 1B

We compared LLäMmlein 1B’s performance on the SuperGLEBer benchmark to the best-performing models for each task and similarly sized models (Table 3). All models and checkpoints are evaluated after a task-specific finetuning, following SuperGLEBer evaluation protocol. While not always securing the top spot, it remains competitive across tasks, even against much larger models. As with the 120M model, LLäMmlein 1B trails in sentence similarity tasks like PAWSX. However, it achieves competitive results for EuroParl. Examining task progress over time reveals noticeable improvements across all tasks, except for FactClaiming. Compared to the LLäMmlein 120M model, Spearman correlation analysis indicated significant positive relationships between training time and performance for all remaining tasks. In particular, also for EuroParl (r = 0.431, p = 0.009) and WebCAGe (r = 0.92, $p < 0.0001$), suggesting that LLäMmlein 1B continues to benefit from extended training. Nevertheless, across all SuperGLEBer tasks, the advantage of extended pretraining diminished after roughly 30% of the pretraining data was processed. From this state, despite a slow decline in loss, no significant improvements were observed across the 29 downstream tasks (Figure 6). To investigate further, we evaluated the checkpoint where SuperGLEBer performance plateaued, along with its instruction-tuned variants on generative tasks (Plüster, 2023a). Interestingly, while SuperGLEBer performance stagnated, generative benchmark results (Table 9) continued to improve on average, likely due to enhanced autoregressive language modeling capabilities.

> **Interesting**: While generative tasks benefit from further pretraining, other task types do no longer after about 30% of the pretraining data.

4.3 Final Model Evaluation

Detailed results for all SuperGLEBer tasks can be found in Table 7, and on the official website `https://lsx-uniwue.github.io/SuperGLEBer-site/leaderboard_v1`.

4.3.1 LLäMmlein 120M

After evaluating LLäMmlein's performance across pretraining, we compared its final results against other models on the full SuperGLEBer benchmark, including pairwise t-tests to compare results with other models on the SuperGLEBer benchmark. As shown in Table 2 and fig. 7a, the final checkpoint of LLäMmlein significantly outperforms german-gpt2, establishing itself as the leading German decoder model in this size range. Against BERT-based models (gbert-base and bert-german-cased), no significant differences were found (Table 2 and figs. 7b and 7c), despite BERT's known strengths in sequence tagging and similarity tasks (Pfister and Hotho, 2024). This highlights LLäMmlein's ability to compete effectively with established BERT models, even with their architectural advantages.

We further evaluated our results on the lm-evaluation-harness-de evaluation benchmark for autoregressive models against german-gpt2, the only other German-only decoder model available at this parameter size (Table 4), and find that we outperform or closely match this model for all tasks, except for TruthfulQA.

Model	**Truth.QA**	**ARC-Chal.**	**HellaSwag**	**MMLU**
german-gpt2	0.432	0.236	0.268	0.238
ours 120M	0.404	0.238	0.320	0.245
Llama 3.2 1B	0.407	0.310	0.412	0.284
Llama 3.2 1B Inst.	**0.440**	0.296	0.411	**0.343**
ours 1B	0.365	0.311	0.483	0.253
ours 1B Guanako	0.375	0.313	**0.502**	0.258
ours 1B Alpaka	0.397	**0.323**	0.499	0.258
Llama 2 7b	0.422	0.381	0.513	0.400
leo-hessianai-7b-chat	0.452	0.442	0.624	0.401
Disco-Llama3-Ger-8B Inst.	**0.530**	**0.538**	**0.664**	**0.559**
em-german-7b-v01	0.427	0.233	0.276	0.241

Table 4: Performance of our (instruction tuned) models on the lm-evaluation-harness-de, with TruthfulQA (mc2), ARC-Challenge (acc_norm), HellaSwag (acc_norm), MMLU (acc). Short version of Table 8.

4.3.2 LLäMmlein 1B

We evaluated LLäMmlein 1B against similarly sized and larger models. Compared to Llama 3.2 (1B) and EuroLLM (1.7B), LLäMmlein 1B consistently outperformed both (Figures 8a and 8b). Leo-hessianai-7b , showed superior performance, reaffirming the size advantage of 7B models (Table 4 and fig. 8c). Interestingly, LLäMmlein 1B showed no significant difference in performance compared to other, larger models like the Disco-Llama3-German (8B), Llama 3.1 (8B), and gbert-large (Table 4 and figs. 8d to 8f), highlighting its efficiency and competitiveness.

Table 4 compares LLäMmlein 1B and its instruction-tuned variants with Llama 3.2 1B and larger models. Notably, the German-finetuned Disco-Llama 3 (8B) instruct model achieved the highest scores overall, showing the benefit of increased size and instruction tuning. However, this model had no significant advantage over LLäMmlein 1B on SuperGLEBer, suggesting that on average model size matters more for generative tasks than for this benchmark.

For smaller models, Llama 3.2 (1B) achieved the best TruthfulQA score. However, in completion tasks like ARC-Challenge and HellaSwag, LLäMmlein 1B Instruct models consistently outperformed both the base LLäMmlein model and Llama 3.2 1B, indicating that instruct-tuning enhances performance on structured completion tasks. Conversely, Llama 3.2 1B Instruct excelled in the broader knowledge-focused MMLU benchmark. Interestingly, instruct-tuning improved LLäMmlein scores across all tasks, a trend not observed for the Llama 3.2 model.

Task-specific results highlighted structural differences. While ARC-Challenge and HellaSwag focus on commonsense reasoning, TruthfulQA and MMLU emphasize factual understanding. Smaller models, even when finetuned, struggle more with question-answering tasks. Comparing the 120M and 1B versions, the latter consistently outperformed the smaller model by 10%, except for MMLU and TruthfulQA. Interestingly, the 120M model outperforms the 1B model on TruthfulQA, aligning with Lin et al. (2022), who found smaller models often beat their larger counterparts.

> **Confirmation**: 120M model is better at TruthfulQA than 1B model, confirming the findings of Lin et al. (2022).

We observed that scaling from 120M to 1B parameters yields only marginal improvements in sentence similarity and question answering tasks (GermanQuAD and MLQA), with performance differences below 2% and 4%, respectively (Table 7). This contrasts with SuperGLEBer, where these tasks showed more significant scaling benefits.

> **Contradiction**: Scaling provides fewer benefits for tasks like QA and sentence similarity, contradicting prior results from SuperGLEBer (Pfister and Hotho, 2024).

4.4 Checkpoint Averaging

Checkpoint averaging did not improve – or even change – downstream task performance on SuperGLEBer for either the 120M or 1B model (see Figure 9 for the 1B model). This was unexpected, but we hypothesize the checkpoints being too far apart, as Vaswani et al. (2017) averaged checkpoints written every 10 minutes near the end of training, while our checkpoints are about 6-8 hours apart.

> **Interesting**: Checkpoint averaging ineffective, possibly checkpoints are too far apart.

5 Related Work

5.1 German LLMs and Their Limitations

While several language models include German, relatively few have been trained exclusively on German data, and even fewer have transparently documented the process and model capabilities.

German-only Models Early German-focused models were predominantly encoder-based (e.g., BERT variants) trained on corpora up to 163.4GB (Chan et al., 2020). A GPT-2 style German model was trained on 16GB of mixed-domain data (Schweter, 2020). Contemporaneous to our work, DOSMo (Idahl, 2024) introduced a Mistral-7B model trained on 1T tokens of German text from a variety of sources. However, little details about DOSMo's training process, data filtering, and evaluation is publicly known. Furthermore, after acceptance two ModernBERT models have been trained using our dataset (Ehrmanntraut et al., 2025).

Multi-/Crosslingual Models Including German Several multilingual models incorporate German data, including Büble (Delobelle et al., 2024), bloom-6b4-clp-german (Ostendorff and Rehm, 2023), GerPT2 (Minixhofer, 2020), DiscoLlama3-German-8B (DiscoResearch and Occiglot, 2024), EuroLLM-1.7B (Martins et al., 2024), and leo-hessianai-7b (Plüster, 2023b), as well as mGPT (Shliazhko et al., 2024), a multilingual variant of GPT-2. While these models demonstrate the feasibility of German (transfer) language modeling, they typically offer limited transparency in German data preprocessing, training conditions, and systematic evaluation. In contrast, our work is the first to (1) train a German-only LLM fully from scratch, (2) provide a detailed, transparent description of the training pipeline and data sources, and (3) rigorously evaluate the resulting model's German capabilities.

5.2 Comparable Efforts in Other Languages

Transparent training and comprehensive evaluation have become more common in other language contexts. Pythia (Biderman et al., 2023), for example, released a suite of English models with detailed training logs, and Latxa (Etxaniz et al., 2024) continued pretraining Llama 2 models on Basque data (4.2B tokens), thus significantly improving the models' Basque language modelling capabilities, while openly documenting its setup and performance. Furthermore, Virtanen et al. (2019) show that explicitly pretraining models monolingually on Finnish is able to outperform multilingually trained models. Our approach extends this ethos of openness and thorough evaluation to the German language, advancing both model quality and reproducibility.

6 Conclusion

We developed two German-only decoder models, LLäMmlein 120M and 1B, trained from scratch with tailored tokenization and preprocessing. Throughout training, we evaluated intermediate checkpoints to analyze task-specific learning dynamics, noting varied speeds of improvement and early plateaus for some tasks.

On the SuperGLEBer benchmark, LLäMmlein 1B consistently matched or outperformed comparable models, including multilingual Llama 3.2 1B, highlighting the potential benefits of monolingual training for language-specific tasks. While generative question answering revealed limitations of smaller models, our 1B model performed comparably to larger models in most tasks.

Future work includes deeper analysis of training dynamics using our published checkpoints and data, creating high-quality German instruct datasets, and exploring domain-specific fine-tuning for further improvement.

7 Limitations

While the LLäMmlein models represent a significant contribution to German NLP research, several limitations remain: 1. **Limited Capabilities on some domains** Due to the scarcity of high-quality German resources for e.g. coding, we found the models perform poorly on such tasks. 2. **Monolingual Focus** While being considered a strength in the context of this setup, LLäMmlein lacks the ability to leverage multilingual contexts or perform cross-lingual tasks, which could limit usability in certain scenarios. 3. **Evaluation Scope** While evaluated extensively on the SuperGLEBer benchmark and lm-evaluation-harness, other domains such as literature, spoken language, or dialects were not tested, leaving gaps in the understanding of model capabilities. 4. **Long-Context Handling** The models were trained with a maximum sequence length of 2048 tokens, which limits their applicability to tasks requiring extended contexts, such as processing long documents or legal texts.

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References

Lightning AI. 2023. Lit-gpt.

Mehdi Ali, Michael Fromm, Klaudia Thellmann, Richard Rutmann, Max Lübbering, Johannes Leveling, Katrin Klug, Jan Ebert, Niclas Doll, Jasper Buschhoff, Charvi Jain, Alexander Weber, Lena Jurkschat, Hammam Abdelwahab, Chelsea John, Pedro Ortiz Suarez, Malte Ostendorff, Samuel Weinbach, Rafet Sifa, Stefan Kesselheim, and Nicolas Flores-Herr. 2024. Tokenizer choice for LLM training: Negligible or crucial? In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 3907–3924, Mexico City, Mexico. Association for Computational Linguistics.

Stella Biderman, Hailey Schoelkopf, Quentin Anthony, Herbie Bradley, Kyle O'Brien, Eric Hallahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, Aviya Skowron, Lintang Sutawika, and Oskar Van Der Wal. 2023. Pythia: a suite for analyzing large language models across training and scaling. In *Proceedings of the 40th International Conference on Machine Learning*, ICML'23. JMLR.org.

Branden Chan, Stefan Schweter, and Timo Möller. 2020. German's next language model. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 6788–6796, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *ArXiv*, abs/1803.05457.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. XNLI: Evaluating cross-lingual sentence representations. In *Proceedings of* *the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2475–2485, Brussels, Belgium. Association for Computational Linguistics.

Tri Dao. 2024. FlashAttention-2: Faster attention with better parallelism and work partitioning. In *International Conference on Learning Representations (ICLR)*.

Pieter Delobelle, Alan Akbik, et al. 2024. BübleLM: A small German LM.

DiscoResearch and Occiglot. 2024. Llama3-discoleo-instruct-8b-v0.1. Instruction-tuned German language model developed with support from DFKI and hessian.AI.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Lauren Rantala-Yeary, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin Kardas, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Raparthy, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaoqing Ellen Tan, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aaron Grattafiori, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alex Vaughan, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Franco, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, Danny Wyatt, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Firat Ozgenel, Francesco Caggioni, Francisco Guzmán, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Govind Thattai, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Karthik Prasad, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kun Huang, Kunal Chawla, Kushal Lakhotia, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manav Avalani, Manish Bhatt, Maria Tsimpoukelli, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikolay Pavlovich Laptev, Ning Dong, Ning Zhang, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Rohan Maheswari, Russ Howes, Ruty Rinott, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Kohler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vítor Albiero, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaofang Wang, Xiaojian Wu, Xiaolan Wang, Xide Xia, Xilun Wu, Xinbo Gao, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yuchen Hao, Yundi Qian, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, and Zhiwei Zhao. 2024. The llama 3 herd of models. *Preprint*, arXiv:2407.21783.

Anton Ehrmanntraut, Julia Wunderle, Jan Pfister, Fotis Jannidis, and Andreas Hotho. 2025. ModernGBERT: German-only 1B Encoder Model Trained from Scratch. *Preprint*, arXiv:2505.13136.

Julen Etxaniz, Oscar Sainz, Naiara Miguel, Itziar Aldabe, German Rigau, Eneko Agirre, Aitor Ormazabal, Mikel Artetxe, and Aitor Soroa. 2024. Latxa: An open language model and evaluation suite for Basque. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14952–14972, Bangkok, Thailand. Association for Computational Linguistics.

Manaal Faruqui and Sebastian Padó. 2010. Training and evaluating a german named entity recognizer with semantic generalization. In *Conference on Natural Language Processing*.

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. 2021. A framework for few-shot language model evaluation.

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)*.

Verena Henrich, Erhard Hinrichs, and Tatiana Vodolazova. 2012. WebCAGe – a web-harvested corpus annotated with GermaNet senses. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 387–396, Avignon, France. Association for Computational Linguistics.

Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*.

Maximilian Idahl. 2024. DOSMo-7B: A Large Language Model Trained Exclusively on German Text. In *Proceedings of the Konferenz der deutschen KI-Servicezentren 2024 (KonKIS 24)*. Accessed: 2024-12-10.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. *Preprint*, arXiv:2310.06825.

Hynek Kydlíček, Guilherme Penedo, Clémentine Fourier, Nathan Habib, and Thomas Wolf. 2024. Finetasks: Finding signal in a haystack of 200+ multilingual tasks.

Yaobo Liang, Nan Duan, Yeyun Gong, Ning Wu, Fenfei Guo, Weizhen Qi, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, Xiaodong Fan, Ruofei Zhang, Rahul Agrawal, Edward Cui, Sining Wei, Taroon Bharti, Ying Qiao, Jiun-Hung Chen, Winnie Wu, Shuguang Liu, Fan Yang, Daniel Campos, Rangan Majumder, and Ming Zhou. 2020. XGLUE: A new benchmark dataset for cross-lingual pre-training, understanding and generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6008–6018, Online. Association for Computational Linguistics.

Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. TruthfulQA: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3214–3252, Dublin, Ireland. Association for Computational Linguistics.

Sourab Mangrulkar, Sylvain Gugger, Lysandre Debut, Younes Belkada, Sayak Paul, and Benjamin Bossan. 2022. Peft: State-of-the-art parameter-efficient fine-tuning methods. `https://github.com/huggingface/peft`.

Pedro Henrique Martins, Patrick Fernandes, João Alves, Nuno M. Guerreiro, Ricardo Rei, Duarte M. Alves, José Pombal, Amin Farajian, Manuel Faysse, Mateusz Klimaszewski, Pierre Colombo, Barry Haddow, José G. C. de Souza, Alexandra Birch, and André F. T. Martins. 2024. Eurollm: Multilingual language models for europe. *Preprint*, arXiv:2409.16235.

Sabrina J. Mielke, Ryan Cotterell, Kyle Gorman, Brian Roark, and Jason Eisner. 2019. What kind of language is hard to language-model? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4975–4989, Florence, Italy. Association for Computational Linguistics.

Benjamin Minixhofer. 2020. GerPT2: German large and small versions of GPT2.

Malte Ostendorff and Georg Rehm. 2023. Efficient language model training through cross-lingual and progressive transfer learning. *arXiv preprint*.

Jan Pfister and Andreas Hotho. 2024. SuperGLEBer: German language understanding evaluation benchmark. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 7904–7923, Mexico City, Mexico. Association for Computational Linguistics.

Björn Plüster. 2023a. German benchmark datasets - translating popular llm benchmarks to german.

Björn Plüster. 2023b. LeoLM: Igniting German-Language LLM Research. Accessed: 2024-11-15.

Julian Risch, Anke Stoll, Lena Wilms, and Michael Wiegand, editors. 2021. *Proceedings of the GermEval 2021 Shared Task on the Identification of Toxic, Engaging, and Fact-Claiming Comments*. Association for Computational Linguistics, Duesseldorf, Germany.

Phillip Rust, Jonas Pfeiffer, Ivan Vulić, Sebastian Ruder, and Iryna Gurevych. 2021. How good is your tokenizer? on the monolingual performance of multilingual language models. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3118–3135, Online. Association for Computational Linguistics.

Raphael Scheible, Fabian Thomczyk, Patric Tippmann, Victor Jaravine, and Martin Boeker. 2020. Gottbert: a pure german language model. *ArXiv*, abs/2012.02110.

Stefan Schweter. 2020. German gpt-2 model.

Oleh Shliazhko, Alena Fenogenova, Maria Tikhonova, Anastasia Kozlova, Vladislav Mikhailov, and Tatiana Shavrina. 2024. mGPT: Few-shot learners go multilingual. *Transactions of the Association for Computational Linguistics*, 12:58–79.

Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Jha, Sachin Kumar, Li Lucy, Xinxi Lyu, Nathan Lambert, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew Peters, Abhilasha Ravichander, Kyle Richardson, Zejiang Shen, Emma Strubell, Nishant Subramani, Oyvind Tafjord, Evan Walsh, Luke Zettlemoyer, Noah Smith, Hannaneh Hajishirzi, Iz Beltagy, Dirk Groeneveld, Jesse Dodge, and Kyle Lo. 2024. Dolma: an open corpus of three trillion tokens for language model pretraining research. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15725–15788, Bangkok, Thailand. Association for Computational Linguistics.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models. *Preprint*, arXiv:2307.09288.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

Antti Virtanen, Jenna Kanerva, Rami Ilo, Jouni Luoma, Juhani Luotolahti, Tapio Salakoski, Filip Ginter, and Sampo Pyysalo. 2019. Multilingual is not enough: Bert for finnish. *Preprint*, arXiv:1912.07076.

Maurice Weber, Daniel Y. Fu, Quentin Anthony, Yonatan Oren, Shane Adams, Anton Alexandrov, Xiaozhong Lyu, Huu Nguyen, Xiaozhe Yao, Virginia Adams, Ben Athiwaratkun, Rahul Chalamala, Kezhen Chen, Max Ryabinin, Tri Dao, Percy Liang, Christopher Ré, Irina Rish, and Ce Zhang. 2024. Redpajama: an open dataset for training large language models. *NeurIPS Datasets and Benchmarks Track*.

Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. 2020. CCNet: Extracting high quality monolingual datasets from web crawl data. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 4003–4012, Marseille, France. European Language Resources Association.

Michael Wojatzki, Eugen Ruppert, Sarah Holschneider, Torsten Zesch, and Chris Biemann. 2017. Germeval 2017: Shared task on aspect-based sentiment in social media customer feedback.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*.

Peiyuan Zhang, Guangtao Zeng, Tianduo Wang, and Wei Lu. 2024. Tinyllama: An open-source small language model. *Preprint*, arXiv:2401.02385.

A Exemplary Shortcoming of Current Multilingual Models in German

Llama 3.1 8B:

Was haben David Hasselhoff und Markus Söder gemein?
Die beiden haben in den 1980er Jahren die Fernsehserie "Miami Vice" gemeinsam gespielt. Hasselhoff spielte **Kraftedurch** die Figur von Ricardo Montalban, der **Cobrai** im Film "Zorba the Greek" gespielt hat; Söder war Lieutenant Vincent Lopiano und **wurde während des Drehprozesses an einen Verletzung erkrankt**.

Issues:

- **Kraftedurch:** This name is nonsensical and seems like a verbatim translation of two English words.
- **Cobrai:** Like Kraftedurch a nonsensical name.
- **wurde während des Drehprozesses an einen Verletzung erkrankt:** Grammatically incorrect, mixing verb forms and incorrect article use.

Ours 1B chat_selected:

Was haben David Hasselhoff und Markus Söder gemein?
Sowohl David Hasselhoff als auch Markus Söder sind zwei berühmte deutsche Persönlichkeiten, die sich in der Unterhaltungs- und Politikwelt einen Namen gemacht haben. Sie teilen einige gemeinsame Merkmale wie ihren Erfolg bei den Fans, ihre Popularität und ihren Sinn für Humor.

Ignoring the possibly absurd content of this query, the responses highlight underlying issues with the German language of existing multilingual open-source LLMs. The response from Llama 3.1 8B contains glaring grammatical errors and nonsensical phrases, such as "Kraftedurch" (a meaningless word) and "wurde während des Drehprozesses an einen Verletzung erkrankt" (grammatically incoherent), which highlight a lack of robust German language training. These issues, which required minimal effort to uncover, exemplarily show the inadequacy of current large-scale LLMs for German[8], where even basic grammatical rules are frequently violated. This demonstrates the critical importance of dedicated, large-scale German LLM pretraining to address these shortcomings.

B Removed Datapoints…

To improve the overall quality and diversity of the dataset, we applied additional paragraph-level deduplication, to remove repetitive and redundant boilerplate texts (Appendix B.1) and a token-to-word ratio filter (Appendix B.2), to further exclude low-quality content. For instance, the following paragraphs were removed by our additional preprocessing steps:

B.1 …from deduplication

{ "raw_content": ...Die Nutzung der im Rahmen des Impressums oder vergleichbarer Angaben veroeffentlichten Kontaktdaten wie Postanschriften,

[8] https://www.reddit.com/r/LocalLLaMA/comments/1bfce18/still_didnt_found_a_better_small_german_llm_anyone/

Telefon- und Faxnummern sowie Emailadressen durch Dritte zur Uebersendung von nicht ausdruecklich angeforderten Informationen ist nicht gestattet..., ...}

{ "raw_content": ...5) Datenverarbeitung bei Eröffnung eines Kundenkontos Gemäß Art. 6 Abs. 1 lit. b DSGVO werden personenbezogene Daten im jeweils erforderlichen Umfang weiterhin erhoben und verarbeitet, wenn Sie uns diese bei der Eröffnung eines Kundenkontos mitteilen. Welche Daten für die Kontoeröffnung erforderlich sind, entnehmen Sie der Eingabemaske des entsprechenden Formulars auf unserer Website. ... }

B.2 ...from tokenizer filtering

{"raw_content": "Home > B > Bamboo > Masaya 1Masaya 1 Guitar Tabs Masaya 1 Guitar Tabs Bamboo Do you like Masaya 1? Share with your friends now Bass TabsBass Tabs v2ChordsChords v2Chords v3Chords v4TabsTabs v2Ukulele Artist/band: Bamboo e|—-3—3—3—3—3—3-3-3—0-0—0-0-0-0-0-0-0-0-0-0-0-0-0-0-0————-| B|—-3—3—3—3—3—3-3-3—0-0—1-1-1-3-3-3-3-p1-1-1-3-3-3-3-3————|G|——————0-0-0—0-0—2-2-2-2-2-2-2-2-2-2-2-2-2-2————-|..., "doc_id": "2014-52/0086/de_head.json.gz/84", "quality_signals": {"ccnet_perplexity": 41.2, ...}}

{"raw_content": DogsTootsie You are not logged in: Owner: merrier_with_a_terrierBreed: Wire Fox Terrier Gender: Female Jun 20, 2008twolfgirl66 Cute little girl!!!!!!!!!!!!!!!!!!!!!!! Jun 20, 2008 ttontosmommy aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa aaaaaaaaaaaaaaaaaaaaaaaaaaaaa aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa aaaaaaaaaaaaaawwwwwwwwwwwwwwwwww wwwwwwwwwwwwwwwwwwwww wwwwwwwwwwwwwwwwwwww wwwwwwwwwwwwwwww wwwwwwwwwwwwwwwwwwwwwwwww..., "doc_id":2014-52/0058/de_head.json.gz/309, ...}

C Tokenizer

To investigate the performance differences of our three trokenizer variants trained on different amounts of data, we analyzed the most frequently used tokens and the total number of unique subwords produced by each tokenizer on the head snapshot of 2014_15 (Table 5). As expected, all tokenizers shared common punctuation tokens (e.g., "." and ",") among their most frequent entries. However, notable distinctions emerged in how frequently used German words were tokenized. The 2023_14 tokenizer captures frequent German words like "der" and "und", whereas 2023-2021 and 1TB, exhibited a higher frequency of single-character tokens (e.g., "e", "r"). This pattern supports the hypothesis that the smaller dataset allows for a more efficient representation of frequently used tokens, while the larger datasets introduce more variability, leading to tokenization into smaller subunits. Remarkably, the frequent tokens of 2023_14 closely resembled those of german-gpt2 (vocab size (50 266), reinforcing its alignment with established baselines in capturing essential German vocabulary. Notably, the 2023_14 tokenizer utilized nearly its entire vocabulary (31 959 out of 32 000 tokens) when processing the unseen data, suggesting an effective distribution.

	2023_14		**2023-2021**		**1TB**		**german-gpt2**	
Rank	Token	Frequency	Token	Frequency	Token	Frequency	Token	Frequency
1.	.	2.967.221	Ġ	3.520.850	e	6.129.204	.	2.964.871
2.	,	2.535.194	.	2.967.544	Ġd	4.474.530	,	2.538.127
3.	Ċ	1.941.957	e	2.736.916	n	3.586.091	Ċ	1.941.957
4.	Ġder	1.510.132	,	2.535.765	.	2.967.544	Ġder	1.509.384
5.	Ġund	1.247.787	r	2.256.061	i	2.926.354	Ġund	1.247.544
6.	Ġdie	1.140.601	Ċ	1.941.957	r	2.724.928	Ġdie	1.140.601
7.	-	1.017.930	in	1.808.081	,	2.535.904	-	1.022.213
8.	Ġin	826.190	Ġde	1.547.525	Ġ	2.061.515	Ġin	822.906
9.	Ġ(	600.305	nd	1.281.432	Ċ	1.941.957	Ġ(	599.928
10.	Ġvon	588.567	Ġu	1.264.085	s	1.791.900	Ġvon	588.567
unique	31.959		31.568		31.328		49.723	

Table 5: Comparison of the most frequently used tokens on the "2014_52" head snapshot. "Unique" gives the count of distinct tokens used to encode the unseen data.

D Training

	LLäMmlein 120M	LLäMmlein 1B
Parameters	124 668 672	1 035 638 784
Heads	12	32
Layer	12	22
Tokens	1T	3T
Training steps	466 509	1 430 512
Learning rate	6e-4	6e-4
Batch size	1024	1024
Context length	2048	2048

Table 6: Architectural and training details of LLäMmlein models

Architectural and training details for both LLäMmlein models can be found in Table 6. In addition, we provide the loss curves for both models in Figures 3 and 4. For LLäMmlein-120M over-

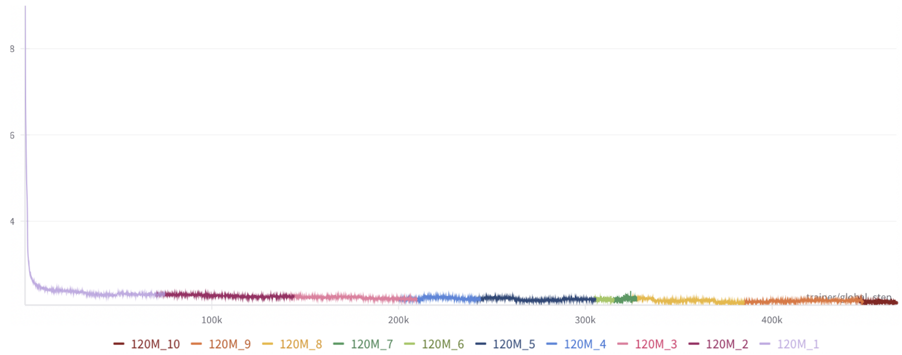


Figure 3: Loss curve of LLäMmlein 120M model. Each color indicates a run, resumed after a training interruption.

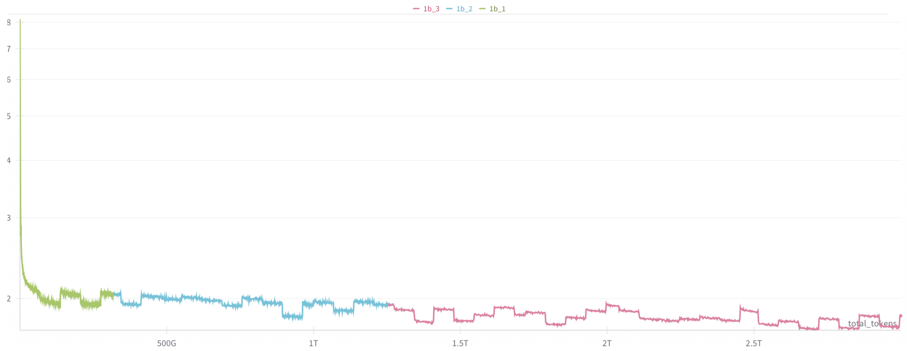


Figure 4: Loss curve of LLäMmlein 1B model. Each color indicates a run, resumed after an interruption. The visible jumps correspond to different chunks of training data, each sampled from a distinct part of the dataset.

all, ten restarts were necessary: Due to cluster settings, training was resumed at least every two days, and additionally, training had to be restarted a few times to address GPU and NCCL errors. Before starting the training run for LLäMmlein-1B, we preliminary attempted to estimate the runtime for replicating the original TinyLlama training settings on our hardware as a sanity check. Based on our extrapolations, the process would have taken over 200 days using 16 A100 GPUs, compared to the 90 days reported for TinyLlama on the same hardware. After suspecting sharding configuration issues, we adapted the Fully Sharded Data Parallel (FSDP) strategy to a hybrid sharding approach. This reduced the extrapolated runtime to approximately 100 days, which we deemed satisfactory. Next, we scaled our training to the final 64 GPUs, bringing the extrapolated runtime down to 36 days. Early in the training run, we identified further inefficiencies related to improper use of the available InfiniBand. We halted the training, corrected the configuration, switched back to full sharding, and implemented dataset pre-caching in RAM on each node. After these optimizations, we restarted the training, achieving a final overall runtime of 32 days (already including a few slower initial days before the final configuration change (green in Figure 4)), with a total of two restarts, illustrated in different colors in Figure 4. We will publish the code including all mentioned fixes/adaptations upon publication.

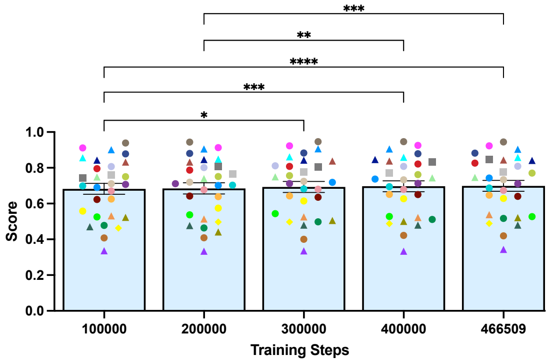


Figure 5: Statistical analysis of performance progress of 120M LLäMmlein over several checkpoints evaluated on the full SuperGLEBer dataset. Although all pairwise comparisons were calculate, non-significant connections (ns) were excluded for clarity.

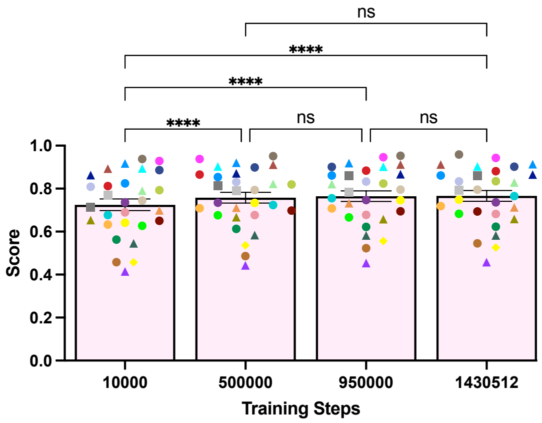


Figure 6: Statistical analysis of performance progress of 1B LLäMmlein over several checkpoints evaluated on the full SuperGLEBer dataset.

E Evaluation on SuperGLEBer

To investigate the influence of training steps on the model performance, we performed an Analysis of Variance (ANOVA) across multiple checkpoints that we evaluated on all 29 benchmark tasks. For the 120M model no significant improvements were observable after the 300 000 checkpoint (Figure 5), while average performance plateaued after the 500 000 checkpoint for the 1B model (Figure 6), raising questions whether training could have been concluded earlier, or if further training still provides improvements uncaptured by the benchmark.

Table 7 depicts concrete numbers for the SuperGLEBer benchmark comparing the reported encoder and decoder models with our final LLäMmlein 120M and 1B models, as well as their respective saturated variants. LLäMmlein is competitive with models of the same parameter size and particularly excels in classification tasks, where the 1B model achieves the highest average score. Notably, there is no significant difference observed between our models and its saturated counterparts. Comparing the 120M and 1B model it is noticeable that the 1B LLäMmlein model shows clear superiority for classification and sequence tagging tasks compared to the 120M version. However, this performance gap is smaller for question answering and sentence similarity tasks.

E.1 120M vs. other models

Figure 7 illustrates comparisons (incl. t-tests) of our model against existing models of the same size on the SuperGLEBer benchmark. LLäMmlein clearly outperforms german-gpt2, confirming its superiority among German decoder models of similar size. When comparing LLäMmlein with the two BERT models – gbert-base and bert-base-german-cased – no statistically significant differences were found, which makes our 120M model the first to match the average performance of a similarly sized encoder on the SuperGLEBer benchmark.

E.2 1B vs. other Models

Figure 8 compares our 1B model against models (using t-tests) of similar sizes and larger on the SuperGLEBer benchmark. To ensure comparability, we excluded tasks in pairwise analysis, where one model lacked a score due to CUDA out-of-memory errors. Among models with similar parameter sizes, we compare LLäMmlein 1B to Llama 3.2 with 1B parameters and EuroLLM with 1.7B parameters and significantly outperform them both. While we were (expectedly) outperfomed by the seven times larger leo-hessianai-7b model, no significant performance differences were found between LLäMmlein 1B and other much larger models, such as the German-finetuned Diso-Llama 3 with 8B parameters, Llama3.1 8B and gbert-large.

F lm-evaluation-harness-de

As decoder-only models are effective for generative tasks we further evaluated our models on the lm-evaluation-harness-de (Table 8).

During analysis of the training process, we found no siginificant average performance improvement on the SuperGLEBer benchmark for the 1B model starting from the 500 000 checkpoint. To further investigate, we evaluated this checkpoint on the lm-eval-harness as well (Table 9 and section 4.2.2).

A finding of the translated lm-evaluation-harness-de: During testing, we identified several instances of residual English text. For example, in the "high_school_computer_science" section:

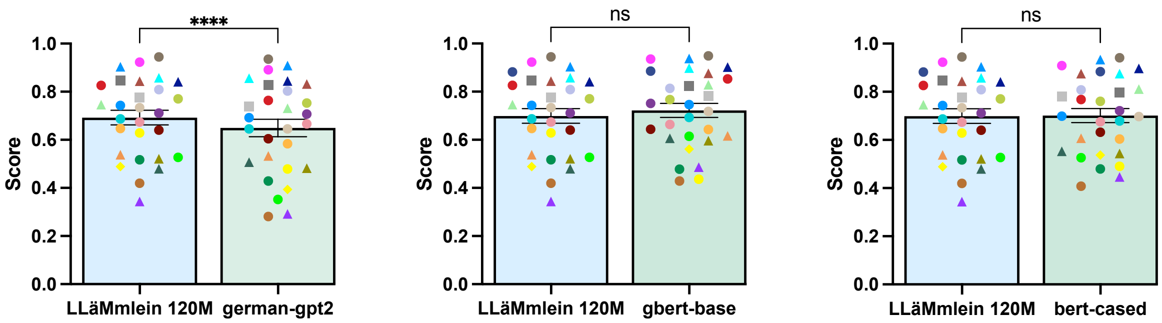
{'question': 'In Python 3, which of the following function convert a string to an int in python?', 'choices': ['int(x [,base])', 'long(x [,base])', 'float(x)', 'str(x)'], 'answer': 0, 'question_de': 'In Python 3, which of the following function convert a string to an int in python?', 'choices_de': ['int(x [,base])', 'long(x [,base])', 'float(x)', 'str(x)'], ...}

and in the "machine_learning" section:

{'question': '_ refers to a model that can neither model the training data nor generalize to new data.', 'choices': ['good fitting', 'overfitting', 'underfitting', 'all of the above'], 'answer': 2, 'ques-

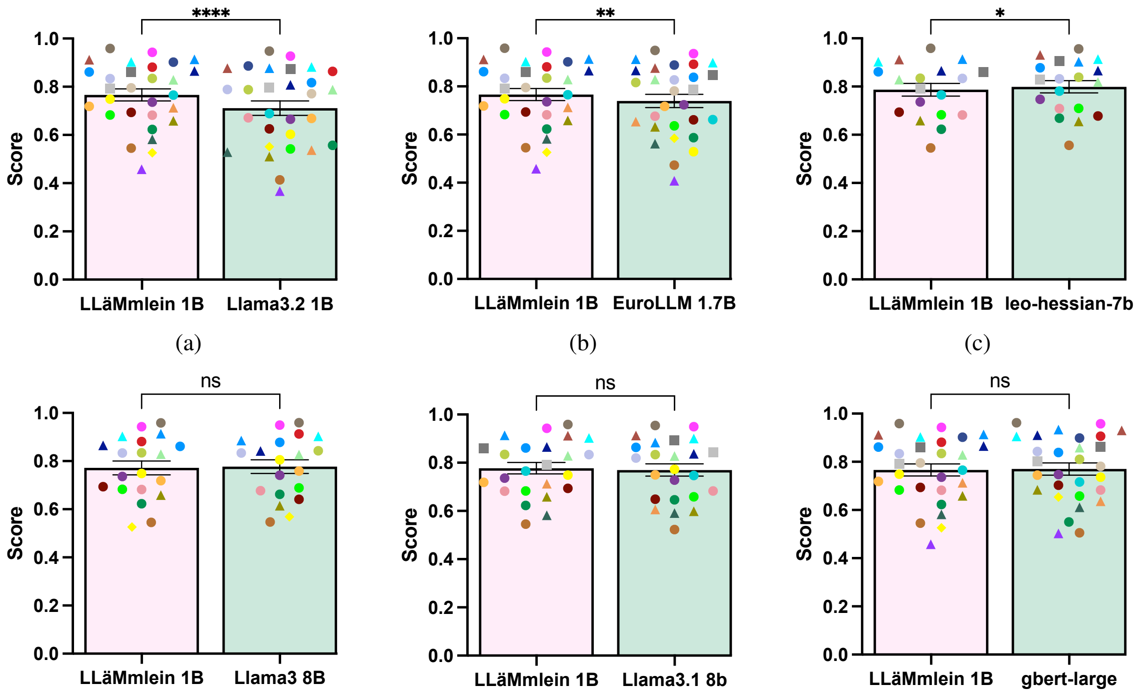
type	model	classification						tagging			similarity	QA
		tox. macro F1	sent. micro F1	match ACC	WSD micro F1	other mixed	avg mixed	NER micro F1	other micro F1	avg micro F1	pearson corr	m. t. F1
encoder	gbert-base	0.537	0.620	0.738	0.814	0.749	0.723	0.705	0.806	0.786	0.561	0.803
	gbert-large	0.604	0.673	0.811	0.837	0.816	0.785	0.744	0.813	0.799	0.654	0.833
	gottbert	0.553	0.607	0.753	0.806	0.609	0.635†	0.666†	0.794	0.768	0.553	0.795
	bert-base-german-cased	0.520	0.589	0.690	0.794	0.745†	0.710†	0.678	0.788	0.766	0.537	0.789
decoder	german-gpt2	0.443	0.511	0.664	0.768	0.612	0.606	0.617	0.725	0.704	0.394	0.784
	bloomz-560m	0.440	0.472	0.748	0.730	0.562†	0.575†	0.388	0.638	0.588	0.459	0.788
	leo-hessianai-7b	0.617	0.739	0.000†	0.391†	0.589†	0.534†	0.481†	0.671†	0.633†	0.000†	0.867
ours	LLäMmlein 120M	0.530	0.605	0.736	0.805	0.770	0.734	0.626	0.737	0.714	0.489	0.811
	saturated 120M	0.518	0.599	0.725	0.803	0.767	0.728	0.620	0.736	0.713	0.497	0.790
	LLäMmlein 1B	0.619	0.714	0.798	0.854	0.818	0.792	0.739	0.785	0.776	0.526	0.826
	saturated 1B	0.592	0.703	0.789	0.831	0.812	0.781	0.739	0.784	0.775	0.536	0.802

Table 7: SuperGLEBer results, averaged at varying levels of granularity, following (Pfister and Hotho, 2024). The columns reading “avg” have been averaged across the averages of the respective task types, in order to not overweight any task type for which more datasets exist, i.e. all “NER” tasks have been averaged into a single value before averaging across all tagging tasks. The second row gives the type of metric used for the respective task type. Here “mixed” means that at least two kind of metrics have been averaged together. The results marked with † have been averaged over tasks for which a “Cuda OOM” error occured on an A100 80GB GPU as well at all averages this affects transitively. All missing values have been treated as a 0.0 when calculating the average. “saturated” indicates our models at a checkpoint from which no more significant improvement on SuperGLEBer could be measured (Sections 4.2.1 and 4.2.2 and figs. 5 and 6.



(a) (b) (c)

Figure 7: Comparison of LLäMmlein 120M across the full SuperGLEBer benchmark with: (7a) german-gpt2, (7b) gbert-base and (7c) bert-base-german-cased. The asterisks indicate the level of statistical significance: "ns" denotes not significant ($p > 0.05$), while increasing significance is represented as follows: * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$), and **** ($p \leq 0.0001$).



(a) (b) (c)

(d) (e) (f)

Figure 8: Performance comparison of LLäMmlein 1B accross the full SuperGLEBer benchmark with: (8a) Llama 3.2 1B, (8b) EuroLLM-1.7B, (8c) leo-hessianai-7b, (8d) on German-finetuned Disco-Llama 3 8B, (8e) Llama 3.1 8B and (8f) gbert-large. The asterisks indicate the level of statistical significance: "ns" denotes not significant ($p > 0.05$), while increasing significance is represented as follows: * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$), and **** ($p \leq 0.0001$). For consistency, we entirely excluded tasks from the pairwise t-tests, where a larger model lacked a score due to a cuda out of memory error.

Model	TruthfulQA	ARC-Challenge	HellaSwag	MMLU
german-gpt2	0.261|0.432	0.195|0.236	0.262|0.268	0.238|0.263
ours 120M	0.247|0.404	0.194|0.238	0.291|0.320	0.245|0.276
Llama 3.2 1B	**0.280**|0.407	0.265|0.310	0.339|0.412	0.284|0.302
Llama 3.2 1B Instruct	0.279|**0.440**	0.259|0.296	0.340|0.411	**0.343|0.343**
ours 1B	0.239|0.365	0.266|0.311	0.390|0.483	0.253|0.270
ours 1B full	0.257|0.388	0.282|0.318	0.395|0.499	0.254|0.273
ours 1B Alpaka	0.268|0.397	0.279|0.323	0.399|0.499	0.258|0.273
ours 1B Evol	0.255|0.378	**0.284|0.323**	0.397|0.498	0.250|0.268
ours 1B Guanako	0.257|0.385	0.280|0.314	0.394|0.498	0.260|0.275
ours 1B Sharegpt	0.242|0.371	0.275|0.317	**0.398|0.504**	0.250|0.270
Llama 2 7b	0.268|0.422	0.333|0.381	0.396|0.513	0.400|0.396
leo-hessianai-7b-chat	0.301|0.452	0.405|0.442	0.485|0.624	0.401|0.401
Disco-Llama3-Ger-8B	0.331|0.495	0.456|0.497	0.491|0.654	0.545|0.529
Disco-Llama3-Ger-8B Inst.	**0.364|0.530**	**0.506|0.538**	**0.515|0.664**	**0.559|0.555**
em-german-7b-v01	0.225|0.427	0.197|0.233	0.258|0.276	0.241|0.263

Table 8: Performance comparison of (instruction tuned) LLäMmlein variants as well as similar sized and various larger models on the lm-evaluation-harness-de including the: TruthfulQA (mc1|mc2), ARC-Challenge (acc|acc_norm), HellaSwag (acc|acc_norm) and MMLU (acc|acc_norm). This is the full table of Table 4, including all metrics and all trained instruct adapters.

Model	TruthfulQA	ARC-Challenge	HellaSwag	MMLU
ours 1B_sat. full	0.256|0.495	0.205|0.247	0.252|0.258	0.227|0.250
ours 1B_sat. Alpaka	0.273|0.494	0.213|0.255	0.253|0.259	0.229|0.251
ours 1B_sat. Evol	0.261|0.501	0.211|0.249	0.254|0.256	0.229|0.253
ours 1B_sat. Guanako	0.264|0.501	0.224|0.246	0.251|0.261	0.231|0.255
ours 1B_sat. Sharegpt	0.262|0.495	0.202|0.243	0.255|0.261	0.230|0.249

Table 9: Performance comparison of "saturated" LLäMmlein 1B instruction tuned variants from checkpoint 500 000, from which no significant improvement was noticeable on the SuperGLEBer benchmark (has to be compared to Table 8).

tion_de': '_______ refers to a model that can neither model the training data nor generalize to new data.', 'choices_de': ['gute Anpassung', 'Überanpassung', 'Unteranpassung', 'alle oben genannten'], ...}'}

Thus, the results and their information value about German language capabilities may not be completely accurate.

G Checkpoint Averaging

Aiming to boost our performance, we experimented with checkpoint averaging (Section 4.4). However, no significant differences were observable when comparing the final 1B LLäMmlein model with averaged checkpoints from the last five or ten checkpoints on the SuperGLEBer benchmark (Figure 9). A possible reason for this could be, that the checkpoints were saved with too large intervals between them, as we recorded approximately three checkpoints per day. In contrast, in the transformer paper (Vaswani et al., 2017), where this technique was successfully used, checkpoints were saved every ten minutes.

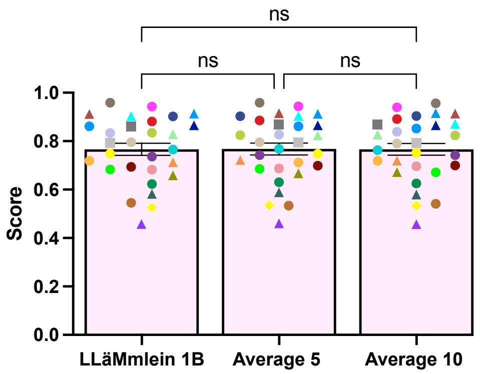


Figure 9: Comparison of results for the LLäMmlein 1B model and its five and ten checkpoints-averaged versions.

H Exemplarily Dialectic Analysis

To showcase the model's versatility, we finetuned adapters on specific dialectal data. For Bavarian, we used approximately 25 700 Wikipedia pages from the Bavarian column of the "cis-lmu/bavarian_to_english" dataset on HuggingFace. For Swiss German, we finetuned an adapter on 206 047 documents from the "HuggingFaceFW/fineweb-2" dataset. Following the setup in Section 3.3, these experiments, though not quantitatively evaluated, highlight the model's adaptability and potential, as illustrated in Appendix F.

Prompt	Variant	Output
In Berlin…	German	In Berlin-Mitte ist ein Mann mit einem Messer angegriffen und schwer verletzt worden.
	Bavarian	In Berlin is a Stod in da Bundesstod Berlin.
	Swiss	In Berlin ist es heute Nacht zu einem Brand gekommen.
In Minga…	German	In Minga, der Stadt der Münchner, gibt es viele Sehenswürdigkeiten, die man sich anschauen kann.
	Bavarian	In Minga is a Gmoa in Bayern.
	Swiss	In Minga Minga ([mɪŋɡa]) isch en Begriff, wo im südliche Afrika, in de südliche Sahara und in de südliche Halbinse, wo in de Sahelzone liegt, gebräuchlig isch.
In Züri…	German	In Züri West, dem neuen Album von Züri West.
	Bavarian	In Züri is a Stod in der Schweiz.
	Swiss	In Züri isch es nid so heiss wie in Basel.

Table 10: Example outputs in German, Bavarian, and Swiss dialects for the base model and two adapter variants, when being asked about the “regional captial”, showcasing linguistic adaptability across regional varieties. The outputs demonstrate varying levels of accuracy in adapting to the target dialects. While some results capture the linguistic characteristics effectively, others fall short, highlighting the challenges of fine-tuning models for nuanced regional variations. The tendency of the Bavarian adapter to adhere to the Wikipedia style is pronounced as it starts with a short descriptive sentence every time.