MAKING, NOT TAKING, THE BEST OF N

Anonymous authors

000

001 002 003

004

006

008 009

010

011

012

013

014

016

018

019

021

025

026

027 028 029

030

032

033

034

037

038

040

041

042

043

044

045

046

047

048

051

052

Paper under double-blind review

ABSTRACT

Obtaining high-quality generations in modern LLMs has largely been framed as a selection problem: identifying a single winning generation from a diverse pool of N samples, the Best-of-N (BoN). Yet, this approach is inherently zero-sum, discarding diverse and potentially useful information from the pool. Instead, we explore a collaborative setup, where all candidates can potentially contribute to the final winning generation. To this end, we propose **Fusion-of-**N (FUSION): a method that uses a general LLM judge to synthesize the most informative elements of each sample into a single final answer. We compare FUSION to BON in two settings, (i) test-time scaling, where we sample and aggregate from a single model at test-time (ii) synthetic data generation, where we fuse samples from a pool of diverse teachers to improve a student model. We extensively benchmark both setups across 11 languages, 3 diverse benchmarks and varying model scales. Across the bench, FUSION consistently outperforms BON showing versatility and robustness both in test-time scaling and in downstream gains from synthetic data generation. We also perform extensive analysis on FUSION, where it shows surprising strengths and robustness under challenging settings. These results show that we should shift how we think about evaluating and utilizing LLM generations from a monolithic measure of quality, to embracing their polylithic nature. This shift allows us to integrate diverse strengths, unlock latent potential, and achieve improvements that were previously inaccessible through selection alone.

1 Introduction

Many of today's advances in LLMs rely heavily on aggregation at inference: The dominant approach, Best-of-N (BoN), involves generating multiple candidates and selecting one among them as the final output. This approach has proven highly effective for test-time scaling in tasks ranging from math reasoning and translation to open-ended tasks (Snell et al., 2025; Khairi et al., 2025; Yao et al., 2023; Wang et al., 2023a), and for producing synthetic data used in fine-tuning (Jayalath et al., 2025; Muennighoff et al., 2025), especially in multilingual setups (Grattafiori et al., 2024; Dang et al., 2024; Martins et al., 2025; Hernández-Cano et al., 2025; Lai & Nissim, 2024; Hwang et al., 2025; Odumakinde et al., 2025; Rei et al., 2025). However, existing aggregation methods treat generations as competitors in a *zero-sum game*. Whether through majority voting (Brown et al., 2024), self-consistency (Wang et al., 2023a), or reward-model scoring (Ouyang et al., 2022), the goal is to find the single best answer while discarding the rest. This hard **selection** step imposes clear limitations: it discards the diversity of reasoning paths that could be combined to produce stronger answers. It wastes much of the compute spent generating samples and risks reward hacking (Skalse et al., 2022b;a; Ichihara et al., 2025): the candidate that maximizes a judge's score is not always the most correct or useful.

In today's fast-shifting LLM landscape, where leaderboard wins change hands quickly, treating quality as a single monolithic dimension is increasingly outdated. In practice, there is rarely a single "best" answer; diverse outputs often complement one another. This motivates our central question: can we go beyond selection and design a method that makes fuller use of all generated samples? We propose FUSION, a simple synthesis-based alternative to BON that exploits the generative abilities of LLMs to integrate complementary signals across candidates—truly making, rather than merely taking, the best of N.

We treat aggregation as a **synthesis problem** rather than a selection problem. We use a strong LLM judge, the fusor, to integrate the complementary strengths of multiple candidates into a single an-

swer. Our proposed Fusion-of-*N* (FUSION) method is simple, general, versatile and can directly replace BON with no modifications beyond access to a reasonably strong generative LLM that acts as a fusor. The *polylithic* understanding of quality allows us to decompose complex problems into compositional ones that are more tractable. FUSION optimizes across samples and integrates complementary insights into a single, higher-quality answer. Going beyond the initial sample pool is especially valuable when the pool is strong and diverse, and for problems that naturally benefit from diversity. Intuitively, this mirrors how experts synthesize knowledge from multiple domains and perspectives.

We perform a comprehensive evaluation of FUSION as a replacement for BON across test-time scaling and data generation: For **test-time scaling**, we measure the effectiveness of FUSION with multiple samples from 8B and 111B models on open-ended generation and machine translation tasks. We evaluate the **impact of synthetic data** generated with FUSION in terms of data quality and downstream results after fine-tuning a 7B and a 111B model on open-ended prompts, math and factual reasoning tasks. In both setups our evaluations are spanning multiple languages to test FUSION under diverse and challenging conditions.

Our results show that synthesis is not only more effective, but also more sample-efficient: FUSION consistently outperforms BON under the same sampling budget, and in some cases even surpasses the oracle, revealing that selection is not the upper bound. It proves robust under weaker teacher pools, showing that diversity can be leveraged even when individual contributors are limited. We observe that fine-tuning on FUSION data enables models to outperform even the strongest single teacher, showing that synthesis distills collective knowledge in ways that selection cannot. Finally, our analysis provides the first detailed look into the mechanisms of synthesis, uncovering both its strengths—sample efficiency, robustness, and adaptability—and its limits on tightly constrained math tasks. To summarize, our contributions are:

Conceptual shift from selection to synthesis. We present compelling evidence for reframing aggregation as synthesis problem. In contrast to previous works in this direction (section 6), FUSION is simple, easily customizable and works out-of-the-box, making it an attractive substitute for BON.

Demonstrated gains across test-time scaling and data generation. FUSION consistently outperforms BoN in both settings where candidate aggregation is used today: (i) *test-time scaling*, where it yields substantial improvements (e.g., +3.8% win-rate vs GEMINI2.5-PRO on mArena-v2, +3.7 XCOMETXL on translation), and (ii) *synthetic data generation*, where it produces higher-quality datasets that drive downstream gains across diverse tasks (+2.5% on mArena-v2 vs GEMINI2.5-FLASH, +0.8 on WMT, +1.0% on GeoFactX answer accuracy and +0.8% on reasoning quality).

Robustness and efficiency across models and settings. Our analysis shows that FUSION is more sample-efficient and robust than BON. It maintains high performance with smaller or weaker teacher pools, benefits from larger fusor models, and scales effectively with added test-time compute. These properties make it a practical and generalizable approach for both test-time scaling and synthetic data generation, even under constrained or imperfect conditions.

This work redefines how we measure and leverage LLM outputs. Instead of treating generations as isolated candidates, we embrace their diversity and complementary strengths, synthesizing them into more powerful, coherent results. Our findings show that treating LLMs as collaborators and not competitors unlocks higher-quality outputs and more impact on downstream usecases, pointing toward a fundamentally more effective paradigm for large-scale language model deployment.

2 METHODOLOGY: From Selection to Synthesis

Selection with Best-of-N (BoN) Given a prompt x, a pool of candidates $y \in Y$, and a scoring function S, the BoN method selects the optimal candidate y^* by maximizing a scalar score:

$$y^* = \operatorname*{arg\,max}_{y \in Y} S(y, x)$$

The scoring function could be a specialized reward model as used in rejection sampling for synthetic data generation (Grattafiori et al., 2024), or test-time scaling (Cobbe et al., 2021). The score could also be produced by a generative LLM that is prompted to predict a scalar score (Kim et al., 2024), though in practice trained classifiers often perform better, for instance many top models on Reward-Bench (Malik et al., 2025) leaderboard are sequence classifiers. These type of scoring functions

are typically optimized on verifiable domains and pairwise human preferences (Cobbe et al., 2021; Ouyang et al., 2022).

Limitations of BoN The limiting factors for selection with BoN are (1) the alignment with the desired task (Lambert et al., 2020; Pan et al., 2022; Ichihara et al., 2025; Viswanathan et al., 2025), (2) and the quality of the generated sample pool (as per definition, the final generation can *only be as good as the best* of the candidates). For domains with verifiable problems, the alignment can easily be improved by scaling up training data for the reward model (Liu et al., 2025), but even with expensive ensembles (Eisenstein et al., 2024) risks of overfitting to an imperfect proxy remain (Stroebl et al., 2024). Scaling up reward model alignment is less transferrable to open domains like chat or open-ended question answering, where this signal needs to be obtained from human feedback (Huang et al., 2025; Viswanathan et al., 2025). Similarly, a poor initial sample pool can be improved by diversification (Chen et al., 2025) or optimized sampling (Khairi et al., 2025), or simply scaling up the number of samples, sometimes requiring thousands of samples for test-time scaling to be effective (Stroebl et al., 2024; Brown et al., 2024), which makes it extremely resource-intensive.

Synthesis with Fusion-of-N (FUSION) A fusor model F (a standard LLM) generates a *new* response y^* based on the input prompt X, and a pool of candidates Y:

$$y^* = F(x, Y), \quad y^* \notin Y$$

This means that the final generation y^* is conditionally dependent on the other candidates, and, can—in contrast to BoN—exceed the original pool in quality (see Section 5). It can be seen as a form of collaborative refinement: Rather than only selecting a sample according to a monolithic notion of quality, FUSION goes beyond and productively integrates a polylithic notion of quality into the synthesis of a better sample. The polylithic view, meaning that we acknowledge the existence of higher and lower-quality parts in each sample, is particularly well suited for long generations for complex prompts. FUSION can "mix and match" fragments of variable size (e.g. tokens, terms, sentences, ...) that stand out in quality in each of the provided samples (see the example in fig. 13). BoN is captured as a special case: the fusor still has the option to copy one whole generation if it outperforms all others for the entire sequence.

Components of FUSION The success of FUSION depends on the capabilities of the judge to comparatively evaluate, extract and aggregate the best parts of each generation. We will show in section 5 that there appears to be a threshold in model size that needs to be crossed for FUSION to work without any specialized training. Our analysis also shows that the choice of fusor, given a certain model size, seems less important than the composition of the sample pool. One major advantage over using a reward model, is that the FUSION prompt (ours in table 4) allows for incontext learning and adaptation without any training. It can be tuned to steer FUSION behavior in ambiguous cases, such as concerning safety standards (e.g. with a constitution (Bai et al., 2022)), tone or model identity, and how much it should attempt to integrate parts from all samples or also discard the worst ones entirely. With chain-of-thought prompting (Wei et al., 2022) or reasoning models as fusors, we also have the possibility to scale up FUSION compute where desired. In preliminary experiments we found it important to instruct the model to not only focus on the best, but also discard the worst parts. We have not conducted any prompt tuning beyond that, but practitioners are invited to tune their FUSION prompt to their use cases.

3 EXPERIMENTAL SETUP

Our experiments span two prominent environments for BoN, the first focused on **test-time scaling**, and the second focused on **synthetic data generation**. In both cases, our intervention of replacing BoN by Fusion is minimal: Both methods receive the *identical set of generations* for the same prompts, but aggregate it differently to produce the final generation.

3.1 Models for Test-Time Scaling

We study the test-time scaling behavior for multilingual models of two sizes: AYA EXPANSE 8B and COMMAND A at 111B. We use temperature sampling at T=0.7 to generate N=5 samples

from each model (see Figure 5 for various N). We use a competitive in-house multilingual Reward Model (RM)¹ for scoring the candidates in BoN and Command A as fusor in Fusion (ablation and comparison to GEMMA models (Team et al., 2025a) in fig. 4).

3.2 Models and Data for Synthetic Data Generation

Models. For synthetic data generation, we employ five open and strong models of varying size and families as teachers: GEMMA3-27B-IT, KIMI-K2-INSTRUCT, QWEN3-235B, DEEPSEEK-V3 and COMMAND A (Team et al., 2025a;b; Yang et al., 2025; DeepSeek-AI et al., 2025; Cohere et al., 2025). We sample a low temperature completion ($\tau=0.3$) from each of them to generate the pool of samples for each prompt. From this pool, we then select one completion for supervised fine-tuning (SFT), either with RM or COMMAND A as fusor. Ablations regarding pool composition and fusor model choice will follow in table 2. For fine-tuning, we choose an 111B instruction-tuned LLM as our baseline model for our main SFT experiments, and perform an ablation with a smaller 7B Base LLM baseline (Appendix G). Finetuning hyperparameters are listed in appendix B. We do not apply test-time scaling on top of our fine-tuned models.

General Fine-tuning Dataset. For our main fine-tuning experiments, we randomly sample 10k prompts from UltraFeedback Binarized (UFB) (Tunstall et al., 2023), an English preference dataset with 61k pairs that was previously used to measure the impacts of data composition in fine-tuning (Odumakinde et al., 2025; Li et al., 2025b). We translate the prompts automatically into 9 languages: German, French, Spanish, Chinese, Japanese, Arabic, Korean, Italian, Portuguese.

Reasoning Fine-tuning Dataset. Learning to reason is often approached through synthetic data, where models imitate reasoning traces from a single teacher (Shridhar et al., 2023; Muennighoff et al., 2025; Hwang et al., 2025). Here, we apply our FUSION approach to learn to reason from multiple teachers. We add a second, smaller, batch of prompts for domain-specific reasoning tasks: We add the prompts from the GeoFactX dataset (train split) for geography-based factual reasoning, and translated s1k prompts (Hwang et al., 2025) for mathematical reasoning. The prompts are machine-translated from English and cover five and ten languages, respectively. We prompt the teachers to generate chains-of-thought and answers for training a student model (details in appendix C).

3.3 EVALUATION BENCHMARKS

We focus on challenging, multilingual benchmarks that test our models' *generative* abilities and cover tasks of three domains (full details in appendix D):

Open-ended challenging prompts (Arena) are sourced from *mArenaHard V.*2 (Khairi et al., 2025) (11 languages). Quality of generations is measured in terms of win rates as determined by an LLM judge (gpt-4o-2024-05-13) (1) in direct comparison to the commercial GEMINI2.5-FLASH and GEMINI2.5-PRO models and (2) in head-to-head comparisons of FUSION vs BON.

Machine Translation (WMT) prompts are sourced from *WMT24++* (Deutsch et al., 2025; Kocmi et al., 2024a) (English to 10 languages). Quality of generations is measured with XCOMET-XL (Guerreiro et al., 2024), a state-of-the-art multilingual translation evaluation metric.

Reasoning evaluations target the reasoning fine-tuning mix and include the GeoFactX test split (Hwang et al., 2025) (5 languages) and math problems from *MGSM* (11 languages incl. English) (Shi et al., 2022). Both are evaluated in terms of accuracy of the final answers, and we additionally inspect reasoning quality for GeoFactX, following (Hwang et al., 2025).

4 RESULTS

4.1 TEST-TIME SCALING

FUSION brings substantial improvements in multilingual open-ended generation tasks. We evaluate both COMMAND A and AYA EXPANSE 8B on Arena when scaling test-time compute (Sec-

¹It scores an average score of 76.1 on the English RewardBench2 (Malik et al., 2025), which at the time of submission (24 Sept 2025), places it at 11th place. On multilingual RewardBench (Gureja et al., 2025) it scores an average of 87.6 across languages, beating all openly benchmarked models.

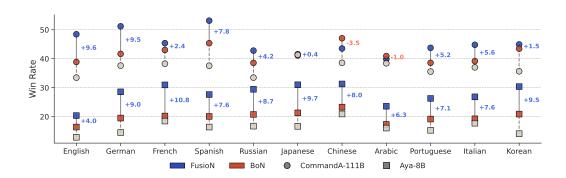


Figure 1: **Test-time scaling with** N=5: FUSION raises win rates against GEMINI2.5-PRO Arena across languages. It largely outperforms BON with the same set of samples, for both AYA EXPANSE 8B and COMMAND A models. Gray markers indicate greedy baseline performance.

tion 3.1) and comparing gains from using FUSION vs BON. The results in Figure 1 show significant gains in win-rate against GEMINI2.5-PRO across both languages and models. For AYA EXPANSE 8B we see impressive jumps in win-rate of up to +10.8% in French. Similarly, FUSION outperforms BON for COMMAND A in 9 out of 11 languages. Surprisingly, in cases like German (+9.5%) and Spanish (+7.8%) the gains from using FUSION on only 5 samples allow COMMAND A to win over GEMINI2.5-PRO (absolute win-rate > 50%), the top model in Arena. This special case, where fusor and sampling model are identical, FUSION can be seen as a form of very effective self-refinement (Ranaldi & Freitas, 2024). The gains from FUSION are also consistent at different scales (number of samples), tasks and in direct comparison which we investigate deeper in Section 5 and Appendix G.

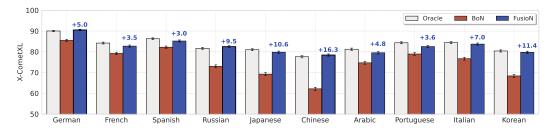


Figure 2: FUSION vs BON vs ORACLE (the highest scoring sample according to the ground truth) in Translation, error bar show std-err. Bars with bold border (German, Russian and Chinese) are cases where FUSION is outperforming the ORACLE

Synthesis beats selection in machine translation. When testing on WMT we can use the reference translation to score each candidate generation against it with the task metric XCOMETXL. We can thus identify the "oracle" among our samples, and compare its quality to the quality of samples selected by BoN with its (imperfect) RM, or the sample synthesized by FUSION. Figure 2 shows the comparison for N=5 generations from COMMAND A sampled at temperature $\tau=0.7$ for the WMT24++ test set. FUSION outperforms BoN with large margins across languages, reaching differences of +11.4 in Korean. More importantly, FUSION outperforms the ORACLE selection in the German, Russian and Chinese translation with gains of +0.8 in the latter, a meaningful improvement in terms of XCOMETXL scores. This confirms the utility of our proposed synthesis framework of aggregation. Instead of treating generations as competitors in a zero-sum game, we should treat them as collaborators whose strengths can be integrated.

4.2 SYNTHETIC DATA GENERATION

FUSION yields consistent multilingual gains with downstream impact. We compare generation and translation quality of the model fine-tuned on FUSION-generated data with the model

279

280

281

282

283284285

287

288

289

290

291

292

293

295296

297

298

299

300

301

302

303

304

305

306

307

308

309

310

311

312

313

314

315

316 317

318 319

320

321

322 323

		ar	de	en	es	fr	it	ja	ko	pt	ru	zh	Avg
ıa	BoN	43.9	43.1	42.7	43.3	44.5	44.2	43.6	45.1	43.4	43.7	44.8	43.8
rer	FUSION	45.1	44.3	48.0	46.2	48.3	48.4	43.8	48.4	45.0	45.2	46.3	46.3
<,	BON FUSION Δ	+1.2	+1.2	+5.3	+2.9	+3.8	+4.2	+0.2	+3.3	+1.6	+1.5	+1.5	+2.5
L	BoN	73.8	90.9	-	86.4	83.5	85.6	81.6	81.7	85.1	83.0	78.6	83.0
₹	$\begin{array}{c} \textbf{BoN} \\ \textbf{FusioN} \\ \Delta \end{array}$	74.6	91.2	-	87.2	84.3	86.2	83.1	82.8	85.5	83.5	79.8	83.8
>	Δ	+0.8*	+0.3*	-	+0.8*	+0.8*	+0.6	+1.5*	+1.1*	+0.4	+0.5	+1.2*	+0.8

Table 1: **Downstream evaluation** of BON/FUSION-fine-tuned 111B models on Arena (% win rate against GEMINI2.5-FLASH) and WMT (XCOMETXL, en \rightarrow : FUSION outperforms BON consistently across tasks and languages. * indicates significance for WMT results according to comet-compare (paired t-test and bootstrap resampling (Koehn, 2004)). The baseline starts at a 22.79% for Arena, and 82 for WMT.

trained on BoN-generated data in table 1 (see Appendix G for 7B results). All hyperparameters, prompts and teacher outputs are identical for both variants. Given that we only change the way we aggregate the samples, we find surprisingly notable and consistent improvements of FUSION over BoN, across languages and the two tasks. On average, the model fine-tuned on fused generations yields XCOMETXL scores +0.8 higher on WMT24++, a delta that can be expected to represent human preferences with around 73.6% accuracy, according to estimates in (Kocmi et al., 2024b).² Similarly, FUSION improves win-rates against GEMINI2.5-FLASH by +2.5% over BoN. With only minimal intervention in the data generation phase, the results reveal a remarkable downstream impact, underscoring the powerful ripple effect that even modest improvements in data generation can achieve. The 7B model finetuned with FUSION outperforms the one finetuned with BoN on WMT, but not Arena as we discuss in Appendix G.

FUSION leads to better multilingual factual reasoning Figure 3 demonstrates how the model fine-tuned on FUSION outputs outperforms the model fine-tuned on BoN in terms of answer correctness and reasoning score across four out of five languages, with a minor regression in English answer correctness. The fine-tuned models do not only outperform base model (by +8.1% in answer correctness on average for BoN, +9.1% for FUSION), but also the fusor model (by 3.4% and 4.4%, respectively, see full results in table 8). This validates our hypothesis that we can effectively leverage the wisdom of the crowd without being bounded by the model that performs the fusion (see also Appendix G). It is worth noting that this holds even for the languages that the fusor model (COMMAND A) officially does not support (Swahili and Thai). On MGSM, however, we found some cases where FUSION scores below BoN, which we discuss in appendix E.2.

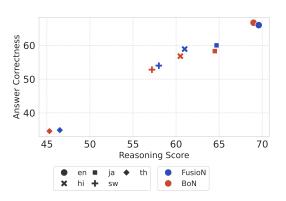


Figure 3: **Downstream evaluation on multilingual factual reasoning** on the GeoFactX test set. FUSION outperforms BON both in reasoning quality and answer correctness, with the exception of English answer correctness.

5 ANALYSIS

Our results reveal consistent improvements across setups and languages with an out-of-the box fusor and a small set of samples. To find out, *where and how* FUSION is working, we conduct a range of ablations, diving deeper into specific sub-questions.

²https://kocmitom.github.io/MT-Thresholds/

325

326

327

328

329

330

331

332

333

334

335

336

337

338

339

340

341

342

343

344 345 346

347

348

349

350

351

352

353

354

355

356

357

358

359

360

361

362

363

364 365

366

367

368

369

370

371

372

373

374

375

376

377

What makes the fusor work? In Figure 4 we approach this question from two angles: (i) the scale of the fusor (number of parameters), and (ii) how the fusor model is utilized. We evaluate the size effect by varying the fusor from the 4B Gemma-3 to the 111B COMMAND A measuring the resulting average win-rate of test-time scaling on Arena. We find that for FUSION (blue) a larger scale is needed for the fusor to work out of the box. Importantly, FUSION continuously benefits from increasing the scale of the fusor as we see an increase in win-rates of +5.5% as we go from the 27B fusor to a 111B fusor. When we use the same fusor models as a rater in BoN (red) (prompt in Appendix A), smaller models fare better, but these gains vanish at scale, which aligns with the observation that even the strongest generative models such as GEMINI2.5-PRO are still outperformed by classifier RMs on classic reward scoring benchmarks (Malik et al., 2025). Overall, FUSION utilizes the judge capabilities at larger scale more ef-

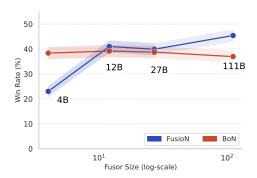


Figure 4: **Size of the fusor matters**: Small LLMs might serve well as scalar judges in BoN, but generative fusion capabilities get unlocked at larger scale, here measured in win-rates on Arena, averaged across languages, shaded areas represent std-err.

fectively than BoN. Smaller fusors likely need specialized training for FUSION, which related work has done for math (Qi et al., 2025b; Zhao et al., 2025).

Which method is more sample-efficient? compare the sample efficiency of BoN and FUSION under the same test-time scaling budget. In Figure 5 we measure win-rates on Arena across four languages (See appendix G for language breakdown). We observe that FUSION is more efficient at the lower scales (N < 10), improving win-rate against GEMINI2.5-PRO by +6% with only N=2, where BON needs twice more samples to achieve similar gains. Gains for both methods plateau beyond N=7, but FUSION consistently makes fuller use of each generated sample, making FUSION the more efficient choice for low-budget scaling. Note that BoN requires N independent samples, which are parallelizable, while FUSION encodes all samples together. Despite this, FUSION shines at small N, making every token count and turning even a few samples into high-quality, integrated solutions. With

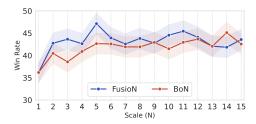


Figure 5: **Scaling test-time budget**: Winrates are shown against GEMINI2.5-PRO on 4 languages from m-ArenaHard-v2.0. Shaded areas are average std-err across languages.

an efficient long-context implementation, it can achieve strong scaling performance while fully leveraging the diversity in the sample pool.

How is synthetic data quality affected by the fusor and teacher pool? The quality of the synthetic data generated is dependent on the quality of the pool of the samples and the fusor used. We measure quality of the data averaged across 10 languages using win-rates against GEMINI2.5-FLASH for 1k examples of UFB, and report in table 2 how modifications to the teacher pool and fusor affect data quality. Across all modifications we see that FUSION-generated synthetic data is of higher quality compared to the BoN data with +4.4% in the default setup with all five teachers. Even when we perform FUSION with—on this benchmark—weaker DEEPSEEK-V3 (based on reward scores from our internal RM) (#3), we see only a small drop in quality while still outperforming BoN. When we replace GEMMA3-27B-IT with GEMMA3-4B-IT in the teacher pool (weaker teacher pool) (#4+#5), both methods are minimally affected—however, using a smaller pool of only four teachers (without KIMI-K2-INSTRUCT, #6+#7) affects FUSION proportionally more, but it still wins over BoN. If we sample only from a single teacher (here DEEPSEEK-V3, #8+#9) win-rates drop substantially, highlighting the importance of diversity in the teacher pool. Overall, these ablations show that FUSION is more robust under weaker ensembles than BoN.

#	Candidate Pool	Method	WR
0	CMD: 1 Sample	-	57.9
1	All 5 Teachers	Fusion	65.4
2		BoN	61.0
3		Fusor=DS	63.9
4	Weaker Pool	FusioN	65.0
5		BoN	60.9
6	Smaller Pool	FusioN	62.9
7		BoN	60.2
8 9	DS: 5 Samples	FusioN BoN	59.0 58.9

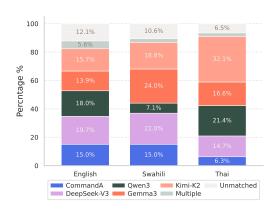


Table 2: **Ablation on pool size and diversity**: win-rates (*WR*) vs. GEMINI2.5-FLASH using 1k random UFB samples, averaged over 10 languages. *DS*: DEEPSEEK-V3. *CMD*: CommandA.

Figure 6: **Diverse teacher contributions**: Analysis of teacher contributions to the final output of FUSION on a subset of GeoFactX (50 samples per language) across unsupported languages.

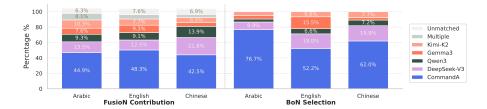


Figure 7: **Contributions to the final generation:** Analysis of different teachers in the pool contributing to the final output of FUSION or BON. For the multi-teacher we look at FUSION outputs on subset of UFB (50 samples per language) with a 5-teachers pool.

How does FUSION balance its pool? We track the sources of contribution in FUSION by surface-level sequence matching (details and more bias probes in appendix F, with an example in fig. 13). We see that a large proportion of the FUSION output is directly taken from the teachers' outputs, forming a coherent synthesis. **Only a small fraction of words is** *unmatched*, where the fusor adds "glue" or reformulates teacher outputs. In Figure 7, we compare contribution to fused outputs and selections of BoN on a random sub-sample of UFB. While both methods show similar high-level preferences (favoring COMMAND A the most and GEMMA3-27B-IT the least), FUSION integrates even the less preferred ones. Finally, we inspect the contributions in the GeoFactX data, because it contains languages not officially covered by the fusor (COMMAND A). Figure 6 shows that FUSION remains robust, with its preferences shifting to utilize GEMMA3-27B-IT the most.

Is the fusor putting a ceiling on the quality? In Table 3, we compare the outputs of FUSION, BON, and all teachers on various metrics on the GeoFactX train set. For answer correctness, FUSION achieves the highest accuracy with 58.6%, despite the fusor (COMMAND A) scoring the lowest. FUSION also obtains the highest reward score, from our internal RM, on the GeoFactX mix—the very metric BON is optimizing. We note that FUSION has a low 98.9% language correctness, likely due to our fusion prompt being English-only (Appendix A), but leave studying these effects to future work. These results show that FUSION is not limited by the fusor and is in fact more dependent on the sample pool.

Model	Reward Score	Answer Correctness	Language Correctness		
FusioN	7.86	58.56	98.86		
BoN	7.11	49.77	99.05		
CommandA	6.30	40.52	99.61		
DeepSeek	6.43	48.89	98.99		
Qwen-3	6.46	41.06	99.58		
Gemma-3	6.52	41.89	92.11		
Kimi-K2	6.64	46.62	99.56		

Table 3: **Data analysis** for teachers and aggregation outputs on GeoFactX samples, averaged across languages.

Opportunities for strengthening FUSION. During test-time scaling we find that FUSION benefits English more than other languages. It is likely that the skills that are required to perform successful FUSION are not evenly present in all languages. Although we do find gains of FUSION over BON in unsupported languages of the fusor for GeoFactX, BON might be the safer choice for cross-lingual transfer to lower-resource languages (Hong et al., 2025), while generative model capabilities are still lacking behind. We also found more mixed results when testing on MGSM (appendix E.2), which might indicate that close-ended tasks are either just not well suited to be addressed by generative ensembling, or that the fusor would need specialized training for such a specialized domain that RMs are usually well trained on.

6 RELATED WORK

The principle of learning from ensembles has led to advances in many areas of machine learning, and can be integrated into LLMs in various forms (Wang et al., 2023b; Lee et al., 2023; Huang et al., 2024; Wan et al., 2024). In this work, we focus on *integrative output ensembling*. This approach can be seen as an instance of *Mixture-of-Agents* (MoA) (Wang et al., 2024), a framework where multiple agents organized in layers iteratively enhance the output. Our approach stands out through simplicity: We show that FUSION becomes effective already in a *single aggregation step* with a single fusor, even in diverse and challenging setups, thereby constituting an attractive alternative for BoN, which is—thanks to its simplicity—a much more widely adopted framework than MoA.

LLM-Blender (Jiang et al., 2023) follows a similar idea, but requires two separate modules, one for pairwise ranking, and one for fusing top-ranking outputs. It operates on the basis of pairwise comparisons (which require training a specialized model), while we pass all outputs at once to the fusor, so that it can evaluate them in context. Other contemporaneous related works also require training such specialized aggregator modules (Qi et al., 2025b; Zhao et al., 2025; Li et al., 2025b), while our approach is effective without any training. These works focus primarily on reinforcement learning or reasoning for verifiable tasks like math and code. For such specific scenarios with available expert raters, Li et al. (2025a) warn that MoA might not be sufficiently robust to lower-quality inputs. For our diverse open-ended evaluations, however, we find FUSION fairly robust to the teacher pool, and sampling from a single teacher—the proposed solution by Li et al. (2025a)—performs significantly worse. Jayalath et al. (2025) find that fused single-teacher roll-outs can nevertheless provide valuable supervision in RL training, even without any fusor training.

Our approach can also be cast as *combination of parallel and sequential* test-time-scaling (Welleck et al., 2024; Snell et al., 2025), with N parallel steps and one refinement step. Balancing these options can be seen as a search problem (Inoue et al., 2025). This poses an interesting avenue for future work, where FUSION operates with adaptive compute (rather than a fixed N+1) customized for each input. This flexibility might be needed for mimicking human cognitive processes more closely (Zhang et al., 2024). Overall, our work complements very recent advancements discovering collaborative synthesis at inference, enhancing understanding of its benefits and limitations. Even in its simplest form, our approach demonstrates gains across diverse applications, including test-time scaling and model supervision.

7 Conclusion

Our work thoroughly investigates and challenges the to-date standard practice of BoN in test-time scaling and synthetic data generation. Our experiments strongly support replacing it by FUSION in these scenarios to make most of the costs that are already incurred from generating and evaluating multiple samples. Across a range of challenging multilingual tasks, FUSION consistently outperforms traditional winner-takes-all approaches like BoN, delivering higher-quality outputs, greater sample efficiency, and stronger downstream performance. Importantly, FUSION leverages the strengths of multiple models, even when some are weaker, showing robustness and adaptability. These results highlight a shift in how we should think about evaluating and utilizing LLM generations: rather than measuring quality monolithically, embracing their polylithic nature allows us to integrate diverse strengths, unlock latent potential, and achieve improvements that were previously inaccessible through selection alone. FUSION points toward a more effective and sustainable paradigm for leveraging the collective capabilities of today's leading LLMs.

ETHICS STATEMENT

Training on synthetic data comes with inherent risks of propagating and amplifying biases (Ahn et al., 2022; Shimabucoro et al., 2024; Mohammadshahi & Ioannou, 2025). We hope that by increasing diversity in the teacher pool, we can reduce model-specific biases to propagate (as opposed to learning from one teacher only), and prevent loss of diversity the generated data (Briesch et al., 2024).

Regardless, we cannot strictly protect the student model from adversarial teachers, probably even less so with FUSION than BON because they might be more prone to prompt injections. Our tests revealed robustness with respect to the quality of the teacher pool (section 5), but we have not tested truly adversarial inputs. We rely on the user to verify teacher suitability and potentially add any sanity checks. In contrast to BON, the FUSION framework allows for flexible instructions that could include e.g., a constitution (Bai et al., 2022) or specific safety guidelines. In practice, FUSION could also be prepended with a hard filter for unsafe or lowest-quality samples (e.g. language compliance via language identification), so that the undesired information does not even get to the aggregation stage.

We also perform additional analyses for typical LLM judge biases in appendix F, and find no evidence for self-preference, but a slight position bias, i.e. the fusor preferring samples that it is presented first more than those that come later.

We would also like to emphasize that any use of such ensembling needs to respect all terms of use and licenses of the individual teachers, which lies in the responsibility of the user.

REPRODUCIBILITY STATEMENT

Fusor and teacher models that we use in this work are publicly available (section 3), as well as the prompts for fine-tuning. We transparently report prompts and instruction templates for LLM evaluation (appendix A), and benchmark metric implementations (section 3. Where models are not public (student model in the experiments on synthetic data generation, and reward model), we report scores on public benchmarks that allow to anchor our experiments. The data generation pipeline that we describe in detail in appendix C is not perfectly reproducible due to inherent randomness in the sampling process. Therefore, we will release synthetic data for BON and FUSION where licenses allow. In addition, we follow the recommended practice for generative multilingual LLM evaluations (Kreutzer et al., 2025) and release our pairwise evaluations that rely on LLM judges.

REFERENCES

Jaimeen Ahn, Hwaran Lee, Jinhwa Kim, and Alice Oh. Why knowledge distillation amplifies gender bias and how to mitigate from the perspective of DistilBERT. In Christian Hardmeier, Christine Basta, Marta R. Costa-jussà, Gabriel Stanovsky, and Hila Gonen (eds.), *Proceedings of the 4th Workshop on Gender Bias in Natural Language Processing (GeBNLP)*, pp. 266–272, Seattle, Washington, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022. gebnlp-1.27. URL https://aclanthology.org/2022.gebnlp-1.27/.

Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional ai: Harmlessness from ai feedback, 2022. URL https://arxiv.org/abs/2212.08073.

Martin Briesch, Dominik Sobania, and Franz Rothlauf. Large language models suffer from their own output: An analysis of the self-consuming training loop, 2024. URL https://arxiv.org/abs/2311.16822.

541

542

543

544

546

547 548

549

550

551

552

553

554

558

559

561

562

565

566

567

568

569

570

571

572

573

574

575

576

577

578

579

580

581

582

583

584

585

586

588

590

592

Bradley Brown, Jordan Juravsky, Ryan Ehrlich, Ronald Clark, Quoc V. Le, Christopher Ré, and Azalia Mirhoseini. Large language monkeys: Scaling inference compute with repeated sampling, 2024. URL https://arxiv.org/abs/2407.21787.

Jianhao Chen, Zishuo Xun, Bocheng Zhou, Han Qi, Hangfan Zhang, Qiaosheng Zhang, Yang Chen, Wei Hu, Yuzhong Qu, Wanli Ouyang, and Shuyue Hu. Do we truly need so many samples? multi-llm repeated sampling efficiently scales test-time compute, 2025. URL https://arxiv.org/abs/2504.00762.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.

Team Cohere, :, Aakanksha, Arash Ahmadian, Marwan Ahmed, Jay Alammar, Milad Alizadeh, Yazeed Alnumay, Sophia Althammer, Arkady Arkhangorodsky, Viraat Aryabumi, Dennis Aumiller, Raphaël Avalos, Zahara Aviv, Sammie Bae, Saurabh Baji, Alexandre Barbet, Max Bartolo, Björn Bebensee, Neeral Beladia, Walter Beller-Morales, Alexandre Bérard, Andrew Berneshawi, Anna Bialas, Phil Blunsom, Matt Bobkin, Adi Bongale, Sam Braun, Maxime Brunet, Samuel Cahyawijaya, David Cairuz, Jon Ander Campos, Cassie Cao, Kris Cao, Roman Castagné, Julián Cendrero, Leila Chan Currie, Yash Chandak, Diane Chang, Giannis Chatziveroglou, Hongyu Chen, Claire Cheng, Alexis Chevalier, Justin T. Chiu, Eugene Cho, Eugene Choi, Eujeong Choi, Tim Chung, Volkan Cirik, Ana Cismaru, Pierre Clavier, Henry Conklin, Lucas Crawhall-Stein, Devon Crouse, Andres Felipe Cruz-Salinas, Ben Cyrus, Daniel D'souza, Hugo Dalla-Torre, John Dang, William Darling, Omar Darwiche Domingues, Saurabh Dash, Antoine Debugne, Théo Dehaze, Shaan Desai, Joan Devassy, Rishit Dholakia, Kyle Duffy, Ali Edalati, Ace Eldeib, Abdullah Elkady, Sarah Elsharkawy, Irem Ergün, Beyza Ermis, Marzieh Fadaee, Boyu Fan, Lucas Fayoux, Yannis Flet-Berliac, Nick Frosst, Matthias Gallé, Wojciech Galuba, Utsav Garg, Matthieu Geist, Mohammad Gheshlaghi Azar, Ellen Gilsenan-McMahon, Seraphina Goldfarb-Tarrant, Tomas Goldsack, Aidan Gomez, Victor Machado Gonzaga, Nithya Govindarajan, Manoj Govindassamy, Nathan Grinsztajn, Nikolas Gritsch, Patrick Gu, Shangmin Guo, Kilian Haefeli, Rod Hajjar, Tim Hawes, Jingyi He, Sebastian Hofstätter, Sungjin Hong, Sara Hooker, Tom Hosking, Stephanie Howe, Eric Hu, Renjie Huang, Hemant Jain, Ritika Jain, Nick Jakobi, Madeline Jenkins, JJ Jordan, Dhruti Joshi, Jason Jung, Trushant Kalyanpur, Siddhartha Rao Kamalakara, Julia Kedrzycki, Gokce Keskin, Edward Kim, Joon Kim, Wei-Yin Ko, Tom Kocmi, Michael Kozakov, Wojciech Kryściński, Arnav Kumar Jain, Komal Kumar Teru, Sander Land, Michael Lasby, Olivia Lasche, Justin Lee, Patrick Lewis, Jeffrey Li, Jonathan Li, Hangyu Lin, Acyr Locatelli, Kevin Luong, Raymond Ma, Lukáš Mach, Marina Machado, Joanne Magbitang, Brenda Malacara Lopez, Aryan Mann, Kelly Marchisio, Olivia Markham, Alexandre Matton, Alex McKinney, Dominic McLoughlin, Jozef Mokry, Adrien Morisot, Autumn Moulder, Harry Moynehan, Maximilian Mozes, Vivek Muppalla, Lidiya Murakhovska, Hemangani Nagarajan, Alekhya Nandula, Hisham Nasir, Shauna Nehra, Josh Netto-Rosen, Daniel Ohashi, James Owers-Bardsley, Jason Ozuzu, Dennis Padilla, Gloria Park, Sam Passaglia, Jeremy Pekmez, Laura Penstone, Aleksandra Piktus, Case Ploeg, Andrew Poulton, Youran Qi, Shubha Raghvendra, Miguel Ramos, Ekagra Ranjan, Pierre Richemond, Cécile Robert-Michon, Aurélien Rodriguez, Sudip Roy, Sebastian Ruder, Laura Ruis, Louise Rust, Anubhay Sachan, Alejandro Salamanca, Kailash Karthik Saravanakumar, Isha Satyakam, Alice Schoenauer Sebag, Priyanka Sen, Sholeh Sepehri, Preethi Seshadri, Ye Shen, Tom Sherborne, Sylvie Shang Shi, Sanal Shivaprasad, Vladyslav Shmyhlo, Anirudh Shrinivason, Inna Shteinbuk, Amir Shukayev, Mathieu Simard, Ella Snyder, Ava Spataru, Victoria Spooner, Trisha Starostina, Florian Strub, Yixuan Su, Jimin Sun, Dwarak Talupuru, Eugene Tarassov, Elena Tommasone, Jennifer Tracey, Billy Trend, Evren Tumer, Ahmet Ustün, Bharat Venkitesh, David Venuto, Pat Verga, Maxime Voisin, Alex Wang, Donglu Wang, Shijian Wang, Edmond Wen, Naomi White, Jesse Willman, Marysia Winkels, Chen Xia, Jessica Xie, Minjie Xu, Bowen Yang, Tan Yi-Chern, Ivan Zhang, Zhenyu Zhao, and Zhoujie Zhao. Command a: An enterprise-ready large language model, 2025. URL https://arxiv.org/abs/2504.00698.

John Dang, Shivalika Singh, Daniel D'souza, Arash Ahmadian, Alejandro Salamanca, Madeline Smith, Aidan Peppin, Sungjin Hong, Manoj Govindassamy, Terrence Zhao, Sandra Kublik, Meor Amer, Viraat Aryabumi, Jon Ander Campos, Yi-Chern Tan, Tom Kocmi, Florian Strub, Nathan Grinsztajn, Yannis Flet-Berliac, Acyr Locatelli, Hangyu Lin, Dwarak Talupuru,

595

596

597

598

600

601

602

603

604

605

606

607

608

609

610

611

612

613

614

615

616

617

618

619

620

621

622

623

624

625

626

627 628

629

630

631

632

633

634

635

636

637

638 639

640

641

642

645

646

Bharat Venkitesh, David Cairuz, Bowen Yang, Tim Chung, Wei-Yin Ko, Sylvie Shang Shi, Amir Shukayev, Sammie Bae, Aleksandra Piktus, Roman Castagné, Felipe Cruz-Salinas, Eddie Kim, Lucas Crawhall-Stein, Adrien Morisot, Sudip Roy, Phil Blunsom, Ivan Zhang, Aidan Gomez, Nick Frosst, Marzieh Fadaee, Beyza Ermis, Ahmet Üstün, and Sara Hooker. Aya expanse: Combining research breakthroughs for a new multilingual frontier, 2024. URL https://arxiv.org/abs/2412.04261.

DeepSeek-AI, Aixin Liu, Bei Feng, Bing Xue, Bingxuan Wang, Bochao Wu, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Daya Guo, Dejian Yang, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Haowei Zhang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Li, Hui Qu, J. L. Cai, Jian Liang, Jianzhong Guo, Jiaqi Ni, Jiashi Li, Jiawei Wang, Jin Chen, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, Junxiao Song, Kai Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Lei Xu, Leyi Xia, Liang Zhao, Litong Wang, Liyue Zhang, Meng Li, Miaojun Wang, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Mingming Li, Ning Tian, Panpan Huang, Peiyi Wang, Peng Zhang, Qiancheng Wang, Qihao Zhu, Qinyu Chen, Qiushi Du, R. J. Chen, R. L. Jin, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, Runxin Xu, Ruoyu Zhang, Ruyi Chen, S. S. Li, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shaoqing Wu, Shengfeng Ye, Shengfeng Ye, Shirong Ma, Shiyu Wang, Shuang Zhou, Shuiping Yu, Shunfeng Zhou, Shuting Pan, T. Wang, Tao Yun, Tian Pei, Tianyu Sun, W. L. Xiao, Wangding Zeng, Wanjia Zhao, Wei An, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, X. Q. Li, Xiangyue Jin, Xianzu Wang, Xiao Bi, Xiaodong Liu, Xiaohan Wang, Xiaojin Shen, Xiaokang Chen, Xiaokang Zhang, Xiaosha Chen, Xiaotao Nie, Xiaowen Sun, Xiaoxiang Wang, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xingkai Yu, Xinnan Song, Xinxia Shan, Xinyi Zhou, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, Y. K. Li, Y. Q. Wang, Y. X. Wei, Y. X. Zhu, Yang Zhang, Yanhong Xu, Yanhong Xu, Yanping Huang, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Li, Yaohui Wang, Yi Yu, Yi Zheng, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Ying Tang, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yu Wu, Yuan Ou, Yuchen Zhu, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yukun Zha, Yunfan Xiong, Yunxian Ma, Yuting Yan, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Z. F. Wu, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhen Huang, Zhen Zhang, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhibin Gou, Zhicheng Ma, Zhigang Yan, Zhihong Shao, Zhipeng Xu, Zhiyu Wu, Zhongyu Zhang, Zhuoshu Li, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Ziyi Gao, and Zizheng Pan. Deepseek-v3 technical report, 2025. URL https://arxiv.org/abs/2412.19437.

Daniel Deutsch, Eleftheria Briakou, Isaac Caswell, Mara Finkelstein, Rebecca Galor, Juraj Juraska, Geza Kovacs, Alison Lui, Ricardo Rei, Jason Riesa, Shruti Rijhwani, Parker Riley, Elizabeth Salesky, Firas Trabelsi, Stephanie Winkler, Biao Zhang, and Markus Freitag. Wmt24++: Expanding the language coverage of wmt24 to 55 languages & dialects, 2025. URL https://arxiv.org/abs/2502.12404.

Jacob Eisenstein, Chirag Nagpal, Alekh Agarwal, Ahmad Beirami, Alexander Nicholas D'Amour, Krishnamurthy Dj Dvijotham, Adam Fisch, Katherine A Heller, Stephen Robert Pfohl, Deepak Ramachandran, Peter Shaw, and Jonathan Berant. Helping or herding? reward model ensembles mitigate but do not eliminate reward hacking. In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=5u1GpUkKtG.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, 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, Danny Wyatt, 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, Francisco

650

651

652

653

654

655

656

657

658

659

660

661

662

666

667

668

669

670

671

672

673

674

675

676

677

679

680

683

684

685

687

688

689

690

691

692

693

696

699

700

Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind Thattai, 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, Jack Zhang, 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, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal Lakhotia, 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, Maria Tsimpoukelli, 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, Ning Zhang, 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, Rohan Maheswari, 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, Vítor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan, Xide Xia, 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, Aayushi Srivastava, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco, Anuj Goyal, 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, Ce Liu, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, 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, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Filippos Kokkinos, Firat Ozgenel, Francesco Caggioni, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan Inan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Ilias Leontiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Janice Lam, 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, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh, Kun Huang, Kunal Chawla, 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, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao Liu, Michael L.

704

705

706

708

709

710

711

712

713

714

715

716

717

718

719

720

721

722

723

724

725 726

727

728

729 730

731

732

733

734

735

736

738739

740

741

742

743

744

745

746

747

748

749

750

751

752

754

755

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, Nikhil Mehta, Nikolay Pavlovich Laptev, Ning Dong, 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, Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shishir Patil, 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, Summer Deng, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Koehler, 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, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaojian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. The llama 3 herd of models, 2024. URL https://arxiv.org/abs/2407.21783.

Nuno M. Guerreiro, Ricardo Rei, Daan van Stigt, Luisa Coheur, Pierre Colombo, and André F. T. Martins. xcomet: Transparent machine translation evaluation through fine-grained error detection. *Transactions of the Association for Computational Linguistics*, 12:979–995, 2024. doi: 10.1162/tacl_a_00683. URL https://aclanthology.org/2024.tacl-1.54/.

Srishti Gureja, Lester James Validad Miranda, Shayekh Bin Islam, Rishabh Maheshwary, Drishti Sharma, Gusti Triandi Winata, Nathan Lambert, Sebastian Ruder, Sara Hooker, and Marzieh Fadaee. M-RewardBench: Evaluating reward models in multilingual settings. In Wanxiang Che, Joyce Nabende, Ekaterina Shutova, and Mohammad Taher Pilehvar (eds.), *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 43–58, Vienna, Austria, July 2025. Association for Computational Linguistics. ISBN 979-8-89176-251-0. doi: 10.18653/v1/2025.acl-long.3. URL https://aclanthology.org/2025.acl-long.3/.

Alejandro Hernández-Cano, Alexander Hägele, Allen Hao Huang, Angelika Romanou, Antoni-Joan Solergibert, Barna Pasztor, Bettina Messmer, Dhia Garbaya, Eduard Frank Durech, Ido Hakimi, Juan García Giraldo, Mete Ismayilzada, Negar Foroutan, Skander Moalla, Tiancheng Chen, Vinko Sabolčec, Yixuan Xu, Michael Aerni, Badr AlKhamissi, Ines Altemir Marinas, Mohammad Hossein Amani, Matin Ansaripour, Ilia Badanin, Harold Benoit, Emanuela Boros, Nicholas Browning, Fabian Bösch, Maximilian Böther, Niklas Canova, Camille Challier, Clement Charmillot, Jonathan Coles, Jan Deriu, Arnout Devos, Lukas Drescher, Daniil Dzenhaliou, Maud Ehrmann, Dongyang Fan, Simin Fan, Silin Gao, Miguel Gila, María Grandury, Diba Hashemi, Alexander Hoyle, Jiaming Jiang, Mark Klein, Andrei Kucharavy, Anastasiia Kucherenko, Frederike Lübeck, Roman Machacek, Theofilos Manitaras, Andreas Marfurt, Kyle Matoba, Simon Matrenok, Henrique Mendoncça, Fawzi Roberto Mohamed, Syrielle Montariol, Luca Mouchel, Sven Najem-Meyer, Jingwei Ni, Gennaro Oliva, Matteo Pagliardini, Elia Palme, Andrei Panferov, Léo Paoletti, Marco Passerini, Ivan Pavlov, Auguste Poiroux, Kaustubh Ponkshe, Nathan Ranchin, Javi Rando, Mathieu Sauser, Jakhongir Saydaliev, Muhammad Ali Sayfiddinov, Marian Schneider, Stefano Schuppli, Marco Scialanga, Andrei Semenov, Kumar Shridhar, Raghav Singhal, Anna Sotnikova, Alexander Sternfeld, Ayush Kumar Tarun, Paul Teiletche, Jannis Vamvas, Xiaozhe Yao, Hao Zhao Alexander Ilic, Ana Klimovic, Andreas Krause, Caglar Gulcehre, David Rosenthal, Elliott Ash, Florian Tramèr, Joost VandeVondele, Livio Veraldi, Martin Rajman, Thomas Schulthess, Torsten Hoefler, Antoine Bosselut, Martin Jaggi, and Imanol Schlag.

- Apertus: Democratizing open and compliant llms for global language environments, 2025. URL https://arxiv.org/abs/2509.14233.
 - Jiwoo Hong, Noah Lee, Rodrigo Martínez-Castaño, César Rodríguez, and James Thorne. Crosslingual transfer of reward models in multilingual alignment. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 2: Short Papers)*, pp. 82–94, 2025.
 - Audrey Huang, Adam Block, Qinghua Liu, Nan Jiang, Akshay Krishnamurthy, and Dylan J Foster. Is best-of-n the best of them? coverage, scaling, and optimality in inference-time alignment. In *Forty-second International Conference on Machine Learning*, 2025. URL https://openreview.net/forum?id=QnjfkhrbYK.
 - Yichong Huang, Xiaocheng Feng, Baohang Li, Yang Xiang, Hui Wang, Ting Liu, and Bing Qin. Ensemble learning for heterogeneous large language models with deep parallel collaboration. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL https://openreview.net/forum?id=7arAADUK6D.
 - Jaedong Hwang, Kumar Tanmay, Seok-Jin Lee, Ayush Agrawal, Hamid Palangi, Kumar Ayush, Ila Fiete, and Paul Pu Liang. Learn globally, speak locally: Bridging the gaps in multilingual reasoning, 2025. URL https://arxiv.org/abs/2507.05418.
 - Yuki Ichihara, Yuu Jinnai, Tetsuro Morimura, Kenshi Abe, Kaito Ariu, Mitsuki Sakamoto, and Eiji Uchibe. Evaluation of best-of-n sampling strategies for language model alignment. *Transactions on Machine Learning Research*, 2025. ISSN 2835-8856. URL https://openreview.net/forum?id=H4S4ETc8c9.
 - Yuichi Inoue, Kou Misaki, Yuki Imajuku, So Kuroki, Taishi Nakamura, and Takuya Akiba. Wider or deeper? scaling llm inference-time compute with adaptive branching tree search, 2025. URL https://arxiv.org/abs/2503.04412.
 - Dulhan Jayalath, Shashwat Goel, Thomas Foster, Parag Jain, Suchin Gururangan, Cheng Zhang, Anirudh Goyal, and Alan Schelten. Compute as teacher: Turning inference compute into reference-free supervision, 2025. URL https://arxiv.org/abs/2509.14234.
 - Dongfu Jiang, Xiang Ren, and Bill Yuchen Lin. LLM-blender: Ensembling large language models with pairwise ranking and generative fusion. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 14165–14178, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.792. URL https://aclanthology.org/2023.acl-long.792/.
 - Ammar Khairi, Daniel D'souza, Ye Shen, Julia Kreutzer, and Sara Hooker. When life gives you samples: The benefits of scaling up inference compute for multilingual llms, 2025. URL https://arxiv.org/abs/2506.20544.
 - Seungone Kim, Juyoung Suk, Shayne Longpre, Bill Yuchen Lin, Jamin Shin, Sean Welleck, Graham Neubig, Moontae Lee, Kyungjae Lee, and Minjoon Seo. Prometheus 2: An open source language model specialized in evaluating other language models. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 4334–4353, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.248. URL https://aclanthology.org/2024.emnlp-main.248/.
 - Tom Kocmi, Eleftherios Avramidis, Rachel Bawden, Ondřej Bojar, Anton Dvorkovich, Christian Federmann, Mark Fishel, Markus Freitag, Thamme Gowda, Roman Grundkiewicz, Barry Haddow, Marzena Karpinska, Philipp Koehn, Benjamin Marie, Christof Monz, Kenton Murray, Masaaki Nagata, Martin Popel, Maja Popović, Mariya Shmatova, Steinthór Steingrímsson, and Vilém Zouhar. Findings of the WMT24 general machine translation shared task: The LLM era is here but MT is not solved yet. In Barry Haddow, Tom Kocmi, Philipp Koehn, and Christof Monz (eds.), *Proceedings of the Ninth Conference on Machine Translation*, pp. 1–46, Miami, Florida, USA, November 2024a. Association for Computational Linguistics. doi: 10.18653/v1/2024.wmt-1.1. URL https://aclanthology.org/2024.wmt-1.1/.

- Tom Kocmi, Vilém Zouhar, Christian Federmann, and Matt Post. Navigating the metrics maze: Score magnitudes and implications for machine translation evaluation, 2024b.
 - Philipp Koehn. Statistical significance tests for machine translation evaluation. In Dekang Lin and Dekai Wu (eds.), *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing*, pp. 388–395, Barcelona, Spain, July 2004. Association for Computational Linguistics. URL https://aclanthology.org/W04-3250/.
 - Julia Kreutzer, Eleftheria Briakou, Sweta Agrawal, Marzieh Fadaee, and Tom Kocmi. Déjà vu: Multilingual LLM evaluation through the lens of machine translation evaluation. In *Second Conference on Language Modeling*, 2025. URL https://openreview.net/forum?id=yxzVanFoij.
 - Huiyuan Lai and Malvina Nissim. mCoT: Multilingual instruction tuning for reasoning consistency in language models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 12012–12026, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.649. URL https://aclanthology.org/2024.acl-long.649/.
 - Nathan Lambert, Brandon Amos, Omry Yadan, and Roberto Calandra. Objective mismatch in model-based reinforcement learning. *Proceedings of Machine Learning Research vol*, 120:1–15, 2020.
 - Young-Suk Lee, Md Sultan, Yousef El-Kurdi, Tahira Naseem, Asim Munawar, Radu Florian, Salim Roukos, and Ramón Astudillo. Ensemble-instruct: Instruction tuning data generation with a heterogeneous mixture of LMs. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 12561–12571, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.836. URL https://aclanthology.org/2023.findings-emnlp.836/.
 - Wenzhe Li, Yong Lin, Mengzhou Xia, and Chi Jin. Rethinking mixture-of-agents: Is mixing different large language models beneficial?, 2025a. URL https://arxiv.org/abs/2502.00674.
 - Yafu Li, Zhilin Wang, Tingchen Fu, Ganqu Cui, Sen Yang, and Yu Cheng. From drafts to answers: Unlocking Ilm potential via aggregation fine-tuning, 2025b. URL https://arxiv.org/abs/2501.11877.
 - Zihan Liu, Yang Chen, Mohammad Shoeybi, Bryan Catanzaro, and Wei Ping. AceMath: Advancing frontier math reasoning with post-training and reward modeling. In Wanxiang Che, Joyce Nabende, Ekaterina Shutova, and Mohammad Taher Pilehvar (eds.), *Findings of the Association for Computational Linguistics: ACL 2025*, pp. 3993–4015, Vienna, Austria, July 2025. Association for Computational Linguistics. ISBN 979-8-89176-256-5. doi: 10.18653/v1/2025. findings-acl.206. URL https://aclanthology.org/2025.findings-acl.206/.
 - Keming Lu, Hongyi Yuan, Runji Lin, Junyang Lin, Zheng Yuan, Chang Zhou, and Jingren Zhou. Routing to the expert: Efficient reward-guided ensemble of large language models. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 1964–1974, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.109. URL https://aclanthology.org/2024.naacl-long.109/.
 - Saumya Malik, Valentina Pyatkin, Sander Land, Jacob Morrison, Noah A. Smith, Hannaneh Hajishirzi, and Nathan Lambert. Rewardbench 2: Advancing reward model evaluation, 2025. URL https://arxiv.org/abs/2506.01937.
 - Pedro Henrique Martins, João Alves, Patrick Fernandes, Nuno M. Guerreiro, Ricardo Rei, Amin Farajian, Mateusz Klimaszewski, Duarte M. Alves, José Pombal, Nicolas Boizard, Manuel Faysse, Pierre Colombo, François Yvon, Barry Haddow, José G. C. de Souza, Alexandra Birch, and André F. T. Martins. Eurollm-9b: Technical report, 2025. URL https://arxiv.org/abs/2506.04079.

- Aida Mohammadshahi and Yani Ioannou. What's left after distillation? how knowledge transfer impacts fairness and bias. *Transactions on Machine Learning Research*, 2025. ISSN 2835-8856. URL https://openreview.net/forum?id=xBbj46Y2fN.
- Niklas Muennighoff, Zitong Yang, Weijia Shi, Xiang Lisa Li, Li Fei-Fei, Hannaneh Hajishirzi, Luke Zettlemoyer, Percy Liang, Emmanuel Candès, and Tatsunori Hashimoto. s1: Simple test-time scaling, 2025. URL https://arxiv.org/abs/2501.19393.
- Ayomide Odumakinde, Daniel D'souza, Pat Verga, Beyza Ermis, and Sara Hooker. Multilingual arbitration: Optimizing data pools to accelerate multilingual progress. In Wanxiang Che, Joyce Nabende, Ekaterina Shutova, and Mohammad Taher Pilehvar (eds.), *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 19142–19164, Vienna, Austria, July 2025. Association for Computational Linguistics. ISBN 979-8-89176-251-0. doi: 10.18653/v1/2025.acl-long.939. URL https://aclanthology.org/2025.acl-long.939/.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 27730–27744. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/blefde53be364a73914f58805a001731-Paper-Conference.pdf.
- Alexander Pan, Kush Bhatia, and Jacob Steinhardt. The effects of reward misspecification: Mapping and mitigating misaligned models. In *International Conference on Learning Representations*, 2022. URL https://openreview.net/forum?id=JYtwGwIL7ye.
- Jianing Qi, Xi Ye, Hao Tang, Zhigang Zhu, and Eunsol Choi. Learning to reason across parallel samples for llm reasoning. *arXiv preprint arXiv:2506.09014*, 2025a.
- Jianing Qi, Xi Ye, Hao Tang, Zhigang Zhu, and Eunsol Choi. Learning to reason across parallel samples for llm reasoning, 2025b. URL https://arxiv.org/abs/2506.09014.
- Leonardo Ranaldi and Andre Freitas. Self-refine instruction-tuning for aligning reasoning in language models. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 2325–2347, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.139. URL https://aclanthology.org/2024.emnlp-main.139/.
- Ricardo Rei, Nuno M. Guerreiro, José Pombal, João Alves, Pedro Teixeirinha, Amin Farajian, and André F. T. Martins. Tower+: Bridging generality and translation specialization in multilingual llms, 2025. URL https://arxiv.org/abs/2506.17080.
- Freda Shi, Mirac Suzgun, Markus Freitag, Xuezhi Wang, Suraj Srivats, Soroush Vosoughi, Hyung Won Chung, Yi Tay, Sebastian Ruder, Denny Zhou, et al. Language models are multilingual chain-of-thought reasoners. *arXiv preprint arXiv:2210.03057*, 2022.
- Luísa Shimabucoro, Sebastian Ruder, Julia Kreutzer, Marzieh Fadaee, and Sara Hooker. LLM see, LLM do: Leveraging active inheritance to target non-differentiable objectives. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 9243–9267, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.521. URL https://aclanthology.org/2024.emnlp-main.521/.
- Kumar Shridhar, Alessandro Stolfo, and Mrinmaya Sachan. Distilling reasoning capabilities into smaller language models. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 7059–7073, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023. findings-acl.441. URL https://aclanthology.org/2023.findings-acl.441/.

Joar Skalse, Nikolaus Howe, Dmitrii Krasheninnikov, and David Krueger. Defining and characterizing reward gaming. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), Advances in Neural Information Processing Systems, volume 35, pp. 9460-9471. Curran Associates, Inc., 2022a. URL https://proceedings.neurips.cc/paper_files/paper/2022/file/3d719fee332caa23d5038b8a90e81796-Paper-Conference.pdf.

- Joar Max Viktor Skalse, Nikolaus H. R. Howe, Dmitrii Krasheninnikov, and David Krueger. Defining and characterizing reward gaming. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho (eds.), *Advances in Neural Information Processing Systems*, 2022b. URL https://openreview.net/forum?id=yb3HOXO31X2.
- Charlie Victor Snell, Jaehoon Lee, Kelvin Xu, and Aviral Kumar. Scaling Ilm test-time compute optimally can be more effective than scaling parameters for reasoning. In *International Conference on Learning Representations*, 2025. URL https://api.semanticscholar.org/CorpusID:278498044.
- Benedikt Stroebl, Sayash Kapoor, and Arvind Narayanan. Inference scaling flaws: The limits of llm resampling with imperfect verifiers, 2024. URL https://arxiv.org/abs/2411.17501.
- Gemma Team, Aishwarya Kamath, Johan Ferret, Shreya Pathak, Nino Vieillard, Ramona Merhej, Sarah Perrin, Tatiana Matejovicova, Alexandre Ramé, Morgane Rivière, et al. Gemma 3 technical report. *arXiv preprint arXiv:2503.19786*, 2025a.
- Kimi Team, Yifan Bai, Yiping Bao, Guanduo Chen, Jiahao Chen, Ningxin Chen, Ruijue Chen, Yanru Chen, Yuankun Chen, Yutian Chen, Zhuofu Chen, Jialei Cui, Hao Ding, Mengnan Dong, Angang Du, Chenzhuang Du, Dikang Du, Yulun Du, Yu Fan, Yichen Feng, Kelin Fu, Bofei Gao, Hongcheng Gao, Peizhong Gao, Tong Gao, Xinran Gu, Longyu Guan, Haiqing Guo, Jianhang Guo, Hao Hu, Xiaoru Hao, Tianhong He, Weiran He, Wenyang He, Chao Hong, Yangyang Hu, Zhenxing Hu, Weixiao Huang, Zhiqi Huang, Zihao Huang, Tao Jiang, Zhejun Jiang, Xinyi Jin, Yongsheng Kang, Guokun Lai, Cheng Li, Fang Li, Haoyang Li, Ming Li, Wentao Li, Yanhao Li, Yiwei Li, Zhaowei Li, Zheming Li, Hongzhan Lin, Xiaohan Lin, Zongyu Lin, Chengyin Liu, Chenyu Liu, Hongzhang Liu, Jingyuan Liu, Junqi Liu, Liang Liu, Shaowei Liu, T. Y. Liu, Tianwei Liu, Weizhou Liu, Yangyang Liu, Yibo Liu, Yiping Liu, Yue Liu, Zhengying Liu, Enzhe Lu, Lijun Lu, Shengling Ma, Xinyu Ma, Yingwei Ma, Shaoguang Mao, Jie Mei, Xin Men, Yibo Miao, Siyuan Pan, Yebo Peng, Ruoyu Qin, Bowen Qu, Zeyu Shang, Lidong Shi, Shengyuan Shi, Feifan Song, Jianlin Su, Zhengyuan Su, Xinjie Sun, Flood Sung, Heyi Tang, Jiawen Tao, Qifeng Teng, Chensi Wang, Dinglu Wang, Feng Wang, Haiming Wang, Jianzhou Wang, Jiaxing Wang, Jinhong Wang, Shengjie Wang, Shuyi Wang, Yao Wang, Yejie Wang, Yiqin Wang, Yuxin Wang, Yuzhi Wang, Zhaoji Wang, Zhengtao Wang, Zhexu Wang, Chu Wei, Qianqian Wei, Wenhao Wu, Xingzhe Wu, Yuxin Wu, Chenjun Xiao, Xiaotong Xie, Weimin Xiong, Boyu Xu, Jing Xu, Jinjing Xu, L. H. Xu, Lin Xu, Suting Xu, Weixin Xu, Xinran Xu, Yangchuan Xu, Ziyao Xu, Junjie Yan, Yuzi Yan, Xiaofei Yang, Ying Yang, Zhen Yang, Zhilin Yang, Zonghan Yang, Haotian Yao, Xingcheng Yao, Wenjie Ye, Zhuorui Ye, Bohong Yin, Longhui Yu, Enming Yuan, Hongbang Yuan, Mengjie Yuan, Haobing Zhan, Dehao Zhang, Hao Zhang, Wanlu Zhang, Xiaobin Zhang, Yangkun Zhang, Yizhi Zhang, Yongting Zhang, Yu Zhang, Yutao Zhang, Yutong Zhang, Zheng Zhang, Haotian Zhao, Yikai Zhao, Huabin Zheng, Shaojie Zheng, Jianren Zhou, Xinyu Zhou, Zaida Zhou, Zhen Zhu, Weiyu Zhuang, and Xinxing Zu. Kimi k2: Open agentic intelligence, 2025b. URL https://arxiv.org/abs/2507.20534.
- Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro Von Werra, Clémentine Fourrier, Nathan Habib, et al. Zephyr: Direct distillation of lm alignment. *arXiv preprint arXiv:2310.16944*, 2023.
- Vijay Viswanathan, Yanchao Sun, Shuang Ma, Xiang Kong, Meng Cao, Graham Neubig, and Tongshuang Wu. Checklists are better than reward models for aligning language models, 2025. URL https://arxiv.org/abs/2507.18624.
- Fanqi Wan, Xinting Huang, Deng Cai, Xiaojun Quan, Wei Bi, and Shuming Shi. Knowledge fusion of large language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=jiDsk12qcz.

- Junlin Wang, Jue Wang, Ben Athiwaratkun, Ce Zhang, and James Zou. Mixture-of-agents enhances large language model capabilities, 2024.
 - Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc V Le, Ed H. Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-consistency improves chain of thought reasoning in language models. In *The Eleventh International Conference on Learning Representations*, 2023a. URL https://openreview.net/forum?id=1PL1NIMMrw.
 - Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 13484–13508, Toronto, Canada, July 2023b. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.754. URL https://aclanthology.org/2023.acl-long.754/.
 - Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824–24837, 2022.
 - Sean Welleck, Amanda Bertsch, Matthew Finlayson, Hailey Schoelkopf, Alex Xie, Graham Neubig, Ilia Kulikov, and Zaid Harchaoui. From decoding to meta-generation: Inference-time algorithms for large language models. *Transactions on Machine Learning Research*, 2024. ISSN 2835-8856. URL https://openreview.net/forum?id=eskQMcIbMS. Survey Certification.
 - An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, Chujie Zheng, Dayiheng Liu, Fan Zhou, Fei Huang, Feng Hu, Hao Ge, Haoran Wei, Huan Lin, Jialong Tang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jing Zhou, Jingren Zhou, Junyang Lin, Kai Dang, Keqin Bao, Kexin Yang, Le Yu, Lianghao Deng, Mei Li, Mingfeng Xue, Mingze Li, Pei Zhang, Peng Wang, Qin Zhu, Rui Men, Ruize Gao, Shixuan Liu, Shuang Luo, Tianhao Li, Tianyi Tang, Wenbiao Yin, Xingzhang Ren, Xinyu Wang, Xinyu Zhang, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yinger Zhang, Yu Wan, Yuqiong Liu, Zekun Wang, Zeyu Cui, Zhenru Zhang, Zhipeng Zhou, and Zihan Qiu. Qwen3 technical report, 2025. URL https://arxiv.org/abs/2505.09388.
 - Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. *Advances in neural information processing systems*, 36:11809–11822, 2023.
 - Kaiyan Zhang, Biqing Qi, and Bowen Zhou. Towards building specialized generalist ai with system 1 and system 2 fusion, 2024. URL https://arxiv.org/abs/2407.08642.
 - Wenting Zhao, Pranjal Aggarwal, Swarnadeep Saha, Asli Celikyilmaz, Jason Weston, and Ilia Kulikov. The majority is not always right: RI training for solution aggregation, 2025. URL https://arxiv.org/abs/2509.06870.

Based on the provided Instruction and Generated Texts in language, fuse them into a better generation that combines the strength of each of them. Do so in two steps: First, compare the Generated Text with a focus on what sets them apart in terms of content, language quality and responsibility, highlighting strengths and weaknesses. Second, fuse them into a new final generation that combines the best aspects of each of them while avoiding the weaknesses.

The fused generation should be adequately responding to the instruction, sound natural to a native speaker, and be focused on conveying the most relevant and accurate information in a responsible and ethical way.

Output Format

Comparison: (short explanation of the strengths and weaknesses of each generation)
Answer: [[The final fused generation]]

Context

Instruction

prompt

Generated Texts

generations

Please analyse the Generated Texts, discarding any unsafe or unethical generations and provide your fused text. Remember to stick to the requested Output Format, providing first a short explanation and then putting the final fused generation inside double brackets [[]].

Table 4: Prompt used for FUSION, including placeholders. Generations are randomly shuffled and enumerated, presented one per line.

A PROMPTS

A.1 FUSION

We provide the prompt used by the fusor in Table 4. We use the same prompt across all tasks, setups, fusors and languages. Table 5 shows the pormpt for using the fusor model as scaler rater. We also provide the *English Version* of the instruction prompts used in our evaluation in Table 6.

B FINE-TUNING HYPERPARAMETERS

We train the 111B baseline on the synthetic data generated from our UFB mix with a batch size of 16, cosine decay with peak learning rate of 5e-6 using Adam optimizer across 64 Nvidia H100 GPUs for 250 steps. For the extended mix (UFB and Math+GeoFactX) we use the same hyperparameter with increased number of steps of 323. We train the 7B models on the UFB mix with 16 GPUs with the same parameters.

C SYNTHETIC REASONING DATA

Hwang et al. (2025) build two datasets for improving multilingual reasoning abilities: s1k-X for multilingual mathematical reasoning and GeoFactX for geography-based multilingual factual reasoning. The multilinguality stems from automatic translation of the prompts, of the s1k dataset from (Muennighoff et al., 2025), and of synthetically created English prompts that designed to cover a variety of regions. For s1k-X the reasoning traces and answers from Qwen-2.5-Instruct 72B in s1k are also translated (via the Google Translate API). This has some undesired side effects where the mathematical notation or the answer formatting gets corrupted, e.g. with white spaces around LaTeX math symbols. For both datasets, we only work with the translated prompts, and use our pool of teachers to generate multilingual responses. For analysis and for evaluation, we use the "silver" answers of Gemini provided in the GeoFactX dataset as ground truth for the evaluation of accurateness of answers. For s1k-X, a correctness analysis of the data is hindered by the inconsistencies in format for the (translated) silver answers of Qwen, which makes the extraction of answers non-trivial. We leave this analysis for future work.

Please act as a fair judge. Based on the provided Instruction and Generated Text, analyse the Generated Text and provide a 1-5 integer score. The given instruction is in language and the response should also be in language Your selection should be based on your judgment as well as the following guidelines for each possible score:

- 1. The Generated Text is unintelligibly written (incomplete sentences, leaps in logic, flagrant mechanical errors) or has majorly incorrect or unverifiable information.
- 2. The Generated Text is occasionally difficult to understand, dotted with minor factual or mechanical errors, or missing crucial formatting elements.
- 3. The Generated Text expresses useful information, is readable, has no factual errors, and has no more than a minor mechanical error or two. Though it may be informative to those unfamiliar with the subject matter, it is not overly insightful, engaging, or likely to hold up to expert scrutiny.
- 4. The Generated Text clearly expresses useful information at an expert level, is readable, and has no factual or mechanical errors. It could just use a quick adjustment with tone or length.
- 5. The Generated Text clearly expresses useful information at an expert level, is readable, has no factual or mechanical errors, and is the perfect length and tone with regard to the prompt.

Output Format

Analysis: xxx Answer: [[SCORE]] (this should be an integer from 1-5 and nothing else; the score should be enclosed in double brackets as indicated)

Evaluation Information

Instruction

message

Generated Text

generation

Please analyse the Generated Text and provide a 1-5 integer score according to the guidelines. Remember to stick to the requested Output Format, providing analysis and putting your final score (an INTEGER in 1-5) inside double brackets [[]].

Table 5: Prompt used for BoN with generative models, including placeholders

Task	Prompt
MGSM (en)	Solve this math problem. Give the reasoning steps before giving the final answer on the last line by itself in the format of "Answer:". Do not add anything other than the integer answer after "Answer":
WMT24++	You are a professional src_lang to tgt_lang translator, tasked with providing translations suitable for use in tgt_lang (tgt_country). Your goal is to accurately convey the meaning and nuances of the original src_lang text while adhering to tgt_lang grammar, vocabulary, and cultural sensitivities. Produce only the tgt_lang translation, without any additional explanations or commentary. Please translate the following src_lang text into tgt_lang (tgt_country): source_text

Table 6: Instruction prompts used for evaluation, including task-specific placeholders. MGSM prompts are taken from the simple-evals library, we only list the English one here but use them in the respective target languages.

For evaluation of fine-tuned models on the test split on GeoFactX, we follow the procedure in (Hwang et al., 2025). We prompt a LLM judge (here GPT-40, deviating from (Hwang et al., 2025) which uses Qwen, as we wanted avoid self-bias) to (1) score the reasoning traces for quality, and (2) compare the final answer in the generation agains the list of the correct answers provided in the task. For data analysis in table 3, we implement a cheaper approach where we use fuzzy string matching to estimate the correctness of answers, which likely underestimates the true correctness.

D EVALUATION

We describe our set of evaluation benchmarks in more detail.

mArenaHard V.2 (short: *Arena*):³ This data contains 498 translated challenging prompts from ArenaHard v2.0⁴ across 23 languages (Khairi et al., 2025). Quality of generations is measured in terms of win rates in direct comparison to the commercial GEMINI2.5-FLASHand GEMINI2.5-PROmodels in addition to head-to-head comparison of FUSION vs BON. We mainly compare against GEMINI2.5-PRO in the test-time scaling environment where we use production ready LLMs with extra compute. In the synthetic data generation environment, we benchmark weaker LLMs fine-tuned on a small synthetic dataset, hence we switch to GEMINI2.5-FLASH. The pairwise comparison is as done by a LLM judge, here GPT-40. We focus on a subset of 11 languages: English (en), German (de), French (fr), Spanish (es), Russian (ru), Japanese (ja), Chinese (zh), Arabic (ar), Korean (ko), Portuguese (pt), and Italian (it).

WMT24++ (short: *WMT*):⁵ This dataset contains translation problems sourced from the WMT 2024 machine translation shared task (Kocmi et al., 2024a) expanded to more languages (Deutsch et al., 2025). Quality of generations is measured with XCOMET-XL,⁶ a state-of-the-art multilingual translation evaluation metric (Guerreiro et al., 2024). We use the prompt in Appendix A and we focus on translating from English to the following languages: Arabic (ar), German (de), Spanish (es), French (fr), Italian (it), Japanese (ja), Korean (ko), Portuguese (pt), Russian (ru), Chinese (zh).

MGSM: This benchmark contains 250 mathematical problems at grade-school level in 11 languages (bn, de, en, es, fr, ja, ru, sw, te, th, zh), originally translated from English (Shi et al., 2022). We prompt models to think step by step before outputting the final answer, following the simple-evals implementation,⁷. The evaluation metric is the accuracy of the final answer.

GeoFactX We follow the prompting and evaluation process recommended by Hwang et al. (2025) and evaluate reasoning traces and final answers with an LLM judge and against gold answers, respectively (details in appendix C).

E ADDITIONAL RESULTS

E.1 TEST-TIME SCALING

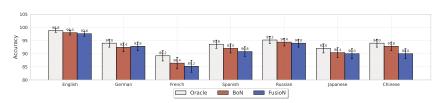


Figure 8: **Test-time Performance on MGSM**. We find that BoN has the best performance across languages, showing that FUSION might be the ideal fit for math task compared BoN with a specialized RM. Both method performance is close to the *Oracle*.

³https://huggingface.co/datasets/CohereLabs/m-ArenaHard-v2.0

https://github.com/lmarena/arena-hard-auto/tree/main/data/ arena-hard-v2.0

⁵https://huggingface.co/datasets/google/wmt24pp

⁶https://huggingface.co/Unbabel/XCOMET-XL

⁷https://github.com/openai/simple-evals/tree/main

Continuing our exploration of FUSION in test-time scaling, we look at performance across language on MGSM math benchmark in Figure 8. We find that FUSION performs well in this as it is relatively close to *Oracle* performance. However, BoN has a slight but consistent edge over FUSION in all languages in this task.

E.2 SYNTHETIC DATA GENERATION

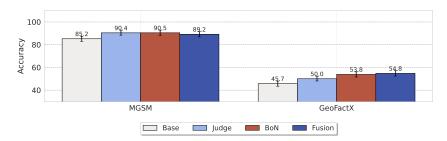


Figure 9: Comparison of downstream performance on close-ended tasks MGSM and Geo-FactX. We find while on math BoN has the best performance, FUSION has higher accuracy on GeoFactX, outperforming the fusion judge as well. Error bars show std-err averaged across languages.

Reasoning tasks Figure 9 compares the performance on the two reasoning tasks for the models trained on FUSION vs BON in relation to the performance of the JUDGE model, i.e., the fusor model (COMMAND A) and also the BASE model that we start fine-tuning from. For MGSM, we find that the FUSION accuracy lags behind both BON -1.2% and the JUDGE performance of -1.5%, indicating that while FUSION is overall beneficial for improving downstream math accuracy (+3.6% above BASE), it is not the optimal choice in this case (similar to the test-time scaling experiment in appendix E.1. Other works Qi et al. (2025a) have shown that it is possible to train specialized LLMs to perform synthesis in the math reasoning domain, which might help to remedy that. But the facts that (1) BoN does not improve the performance of the fine-tuned model beyond the fusor's performance, and that (2) the baseline model performs already surprisingly strong, make us wonder whether these results could also be due to the interplay between data seen in prior training steps, in fine-tuning, and also in the fusor model. Since the s1k dataset is quite popular, it might have been part of training (in English) of the fusor and the baseline already. For the factual QA domain we see in stark contrast, that with clearly unseen data, FUSION effects stand out more. The model fine-tuned on FUSION achieves the best accuracy with +1.0% gains over BON and an impressive +4.8% compared to fusor JUDGE.

F CONTRIBUTION ANALYSIS

Measuring contributions We inspect FUSION outputs and compare them with the teacher outputs with string matching. While this does not capture semantic rephrasings, it does give us an idea how much the fusor can directly copy and paste blocks of the teacher outputs. Parts of the FUSION output that we cannot directly find in any teacher's output, we mark as "unmatched"—this is where we might have some close semantic matches or also just some "glue" work to connect parts from different teachers. The matching procedure works as follows:

- 1. Finds all matching blocks between the fused string and each teacher string. We make use of the difflib library⁸ and use their SequenceMatcher to detect the longest contiguous matching subsequences.
- 2. Resolve attribution for each character: Retrieve matching blocks that cover it, assume the teacher with the longest match wins. If there is a tie: mark it as "multiple". If there is no match, mark it as "unmatched".

⁸https://docs.python.org/3/library/difflib.html

3. Calculate contribution statistics for each teacher: Count how many characters of the fused generation it was attributed to.

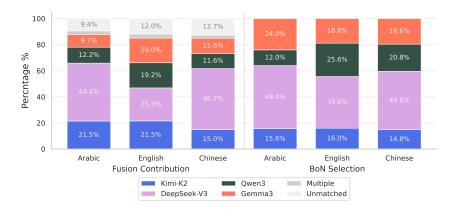
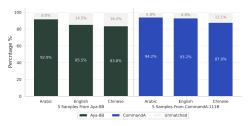


Figure 10: **FUSION contributions without fusor in the teacher pool:** Analysis of different teachers in the pool contribution to the final output of FUSION when the fusor model is *not* in the pool. We look at FUSION outputs on subset of UFB (50 samples per language)

Disentangling fusor and teacher pool The resulting contribution statistics can be compared with BoN selections that chooses one teacher for each sequence. In Figure 10 we do this on a small subset of the UFB data mix covering languages Arabic, English and Chinese. We look at pool of teachers that does not include the fusor (COMMAND A) to study the effect of the fusor self-bias. Similar to what we found in Figure 7 where FUSION and BON had their highest contribution from COMMAND A (the teacher that we now removed), in Figure 10 the methods also have same preference, agreeing on DEEPSEEK-V3 as their favorite (previously second-ranking when COMMAND A was in the pool). This consistent preference lets us conclude that FUSION does not suffer from self-bias with the fusor able to reliably find the best samples in the pool, whether or not the fusor samples is one of them.





- (a) Across Aya Expanse 8B and Command A
- (b) Across samples from COMMAND A

Figure 11: **FUSION contributions in test-time scaling:** Analysis of how different samples in test-time scaling contribute to the final output of FUSION: (a) with different candidate models (b) based on samples order. We look at FUSION outputs on subset of m-AreanHard-v2. (50 samples per language)

Contributions in test-time scaling In Figure 11 we perform the contribution analysis on the test-time scaling setup, where the samples in the pool are coming from a single model. First, we examine the effect of changing this single model on the FUSION preference. We are mostly interested in the case when the fusor is much larger than the candidate model as one would assume the fusor may opt to replace all of the weaker model outputs with its own preference in the fusion which would result in higher *unmatched* rate. However, in Figure 11a we see that for both the small candidate model AYA EXPANSE 8B and the larger one COMMAND A the fusor has a small *unmatched* rate. Albeit larger for AYA EXPANSE 8B, it demonstrate the fusor outputs are almost always more than 80% from the content in the samples.

	2.0	WMT24++					
Language	(w	in-rate, in %	6)	$(XCOMETXL; en \rightarrow \cdot)$			
(+region for WMT)	BoN	FUSION	Δ	BoN	FUSION	Δ	
ar (SA)	18.3	15.6	-2.7	65.4	66.3	+0.9	
de (DE)	16.8	16.8	0.0	86.8	87.1	+0.3	
en	14.9	14.1	-0.8	-	-	-	
es (MX)	19.6	17.6	-2.0	81.0	81.5	+0.5	
fr (FR)	22.4	17.2	-5.2	77.4	77.5	+0.1	
it (IT)	19.4	17.2	-2.2	80.1	80.4	+0.3	
ja (JP)	17.0	19.5	+2.5	70.8	72.1	+1.3	
ko (KR)	17.9	14.0	-3.9	72.0	72.5	+0.5	
pt (PT)	16.9	16.6	-0.3	79.8	80.2	+0.4	
ru (RU)	12.8	19.0	+6.2	74.8	74.5	-0.3	
zh (CN)	19.8	20.9	+1.1	70.9	71.6	+0.7	
Avg	17.8	17.1	-0.7	75.6	76.4	+0.5	

Table 7: **Downstream evaluation results on 7B Models** of BoN/FusioN-fine-tuned 7B models on mArenaHard v2.0 (win rate against GEMINI2.5-PRO as judged by GPT-40) and WMT24++ (XCOMETXL).

			soning					er Corr				
		(LLM score, in %)					(Accuracy, in %)					
	BoN	FUSION	Δ	Baseline	Fusor	BoN	FUSION	Δ	Baseline	Fusor		
en	69.0	69.6	+0.6	63.0	66.1	66.7	66.0	-0.7	68.8	68.5		
hi	60.5	61.0	+0.5	51.4	58.7	56.8	58.9	+2.1	48.5	57.0		
ja	64.5	64.7	+0.2	53.1	59.2	58.3	60.0	+1.7	49.9	56.5		
sw	57.2	58.0	+0.8	30.7	43.6	52.8	54.0	+1.2	37.2	43.0		
th	45.3	46.5	+0.2	31.6	35.9	34.6	34.9	+0.2	24.3	25.2		
Avg	59.3	60.0	+0.7	46.0	52.7	53.8	54.8	+1.0	45.7	50.4		

Table 8: **Downstream evaluation on multilingual factual reasoning**, as measured on the Geo-FactX test set. FUSION outperforms BON both in terms of reasoning quality and answer correctness, with the exception of English answer correctness. *Baseline* is model we used to finetune and *Fusor* is the model used for fusing the generations.

Position bias We consider another type of possible bias in Figure 11b, where we visualize the contribution analysis based on the order of the samples in the FUSION prompt. The samples are always shuffled before being formatted (see Table 4) and we analyze the order based on what the order the fusor sees. We find while not large in magnitude, across the three languages, the fusor outputs have the highest contribution rations in the first and second samples.

Finally in Figure 12 and we provide an example prompt with excerpts from teachers outputs, and in Figure 13 we show the full FUSION output color coded according to our contribution analysis.

G EVALUATION RESULTS COMPARISON

To evaluate the effectiveness of our method and generated data across different scales, we applied our synthetic data generation and SFT pipeline to a smaller baseline. We followed the same setup as used for the 111B model. The 7B baseline is a base model that have not undergone any post-training stages. As shown in Table 7, the downstream results vary. While FUSION remains more effective than BoN in WMT24, improving performance in every language, we observed no gains significant over BoN in m-ArenaHard-v2.0. This suggests that the smaller model requires more parameter tuning to achieve an optimal setup for SFT to be effective in downstream performance, especially the relatively small size of out synthetic dataset.

We also report the detailed breakdown of results on downstream gains in the multilingual factual reasoning benchmark from the finetuned 111B model in Table 8. The *Fusor* and *Baseline* help anchor the gain and provide context about the magnitude of the finetuning gains in general. We find that fine-

1350 1351 1352 Can a comedian's use of audience interaction enhance their delivery and stage presence? 1353 ====Qwen3==== 1354 Yes, a comedian's use of audience interaction can significantly enhance both their delivery and 1355 stage presence. When used effectively, audience interaction can transform a standard stand-up 1356 performance into a more dynamic, engaging, and memorable experience. Here's how: 1357 1358 1359 ### Enhances Delivery 1360 Creates Natural Rhythm and Pacing Interacting with the audience can break up the monotony of a scripted set, allowing for natural pauses, laughs, and transitions. This variation in pacing can make the performance feel more 1363 spontaneous and alive. 1364 1365 2. Provides Real-Time Feedback Audience reactions during interactions give the comedian immediate feedback, helping... ====Gemma3== 1367 Absolutely! A comedian's use of audience interaction can *significantly* enhance their delivery and stage presence. It's a powerful tool, and when done well, it's a huge part of what separates 1369 a good comedian from a *great* one. Here's a breakdown of how it works, and the benefits: 1370 **How** Audience Interaction Enhances Delivery & Stage Presence: 1371 1372 * Breaks the Fourth Wall: It immediately makes the performance less of a one-way lecture and 1373 more of a shared experience. This creates a more intimate and engaging atmosphere. 1374 Improves Timing & Reactivity: Good audience work forces a comedian to be present* and react in the moment. This sharpens their comedic timing, as they have to... 1375 ======DeepSeek-V3======== 1376 Absolutely! A comedian's use of audience interaction can significantly enhance their delivery and stage presence in several ways: ### 1. Engagement & Connection - Direct interaction makes the audience feel involved, creating a personal connection that boosts 1380 - It breaks the "fourth wall," making the performance feel more spontaneous and alive. 1382 ### 2. Adaptability & Improvisation - Skilled crowd work demonstrates quick wit, making the material feel fresh and unique to each - It allows comedians to riff off real-time reactions, adding unpredictability and excitement. 1386 1387 ### 3. **Energy** & Authenticity 1388 - A dynamic back-and-forth keeps the energy high... =====CommandA==== 1389 Absolutely, a comedian's use of audience interaction can significantly enhance their delivery 1390 and stage presence in several ways: 1391 1392 1. Engagement and Connection: Interacting with the audience creates a sense of inclusion 1393 and connection. When a comedian involves the audience directly, it breaks the fourth wall and makes the performance feel more personal and intimate. This engagement can lead to a more 1394 receptive and responsive crowd, which in turn boosts the comedian's confidence and energy on 1395 stage. **Example:** Asking for volunteers or incorporating audience members into bits can create memorable moments that resonate with the entire crowd. 1399

Figure 12: An excerpt of the outputs of teachers to the FUSION example show in Figure 13

2. Improvisation and Adaptability: Au...

1400 1401

Can a comedian's use of audience interaction enhance their delivery and stage presence?

Yes, a comedian's use of **audience** interaction can significantly enhance both their **delivery** and **stage** presence. When executed skillfully, it **transforms** a standard stand-up performance into a dynamic, engaging, and personalized experience. Here's how:

Enhancing Delivery

- 1. **Improves** Timing & Reactivity: Audience interaction forces comedians to be present and adapt in real-time, sharpening their comedic timing and improvisation skills.
- 2. Creates Natural Rhythm: It breaks up scripted material, adding spontaneity and keeping the performance lively.
- 3. **Allows** for Callbacks & Customization: Referencing earlier interactions or tailoring jokes to the crowd's responses makes the material feel fresh and relevant.

Boosting Stage Presence

- 1. **Builds** Connection & Trust: Breaking the "fourth wall" fosters intimacy and makes the audience feel valued, strengthening the comedian's presence.
- 2. Showcases Confidence & Control: Handling unpredictable responses with humor demonstrates quick thinking and professionalism.
- 3. **Humanizes** the Performer: Sharing moments with the audience makes the comedian more relatable and approachable.

Types of Audience Interaction

- Call & Response: Builds energy and involvement.
- Heckle Responses: Risky but rewarding when handled with wit.
- Playful Banter: Engages specific audience members while maintaining sensitivity.
- Improvised Bits: High-level crowd work that showcases exceptional skills.

Potential Pitfalls

- Bombing: Interactions can fall flat, killing momentum.
- Offending Someone: Missteps can alienate audience members.
- Losing Control: Disruptive audience members can derail the performance.
- Forcing It: Unnatural interactions feel awkward and contrived.

Great Examples

- Dave Chappelle: Masters crowd work with charm and wit.
- **Jerry** Seinfeld: Uses subtle, observational interactions seamlessly.
- Hannah Gadsby: Deepens emotional impact through audience engagement.

Conclusion

When done well, audience interaction is a vital tool that elevates a comedian's delivery, strengthens their stage presence, and creates a memorable, shared experience. It requires practice, sensitivity, and a good read of the room, but the rewards are well worth the effort.

Figure 13: Contribution analysis for a sample FUSION ouput with text colored based on the respective source: CommandA, DeepSeek-V3, Qwen3, Gemma3, multiple, and unmatched. Individual teacher generations are in Figure 12.

tuning consistently improve performance over the baseline - with one exception in english. More importantly FUSION also outperform the *Fusor* in all non-English results.

In Figure 14, we move from comparing against GEMINI2.5-PRO as our reference and directly evaluate FUSION against BON in pairwise head-to-head setup judge by GPT-40. We use AYA EXPANSE 8B and COMMAND A to generate 5 samples on Arena, and aggregate with either one of our methods. We find significant gain that resemble what we observe in Figure 1: FUSION outperform BON across languages with large gains in magnitude for AYA EXPANSE 8B and lower but also impressive margins in for COMMAND A (up to +55.2% win-rate in Italian).

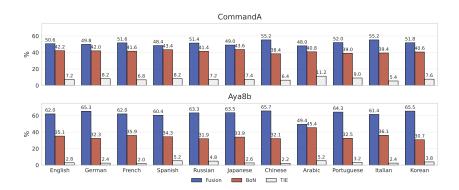


Figure 14: **Test Time Scaling** Head-to-Head Comparison of FUSION vs BON on m-ArenaHard-v2, Judged by GPT-40. We consistently see that FUSION results in better final sample compared to FUSION for both AYA EXPANSE 8B and COMMAND A.

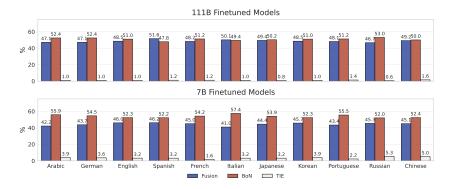


Figure 15: **Synthetic Data Finetuning** Head-to-Head Comparison of og the models finetuned with FUSION vs BON on m-ArenaHard-v2, Judged by GPT-40. We see varying results across languages in the 111B case, while BON is better on the 7B level.

We perform a similar comparison in Figure 15 between the finetuned models at the 111B and 7B. We see varying results across languages in direct head-to-head comparison between the FUSION finetuned and BON finetuned 111B models. For the 7B we see that BON scores better across all languages.

In Figure 16 we provide a breakdown on the scaling plots (win-rates on m-ArenaHard-v2.0 vs GEMINI2.5-PRO) across languages. We can see that in all subplots that FUSION grows faster than BON, with magnitudes depending on the language.

H EXTENDED RELATED WORK

Learning from Ensembles The principle of learning from ensembles has led to advances in many areas of machine learning, and can be integrated into training LLMs in various forms: For example, Huang et al. (2024) fuse multiple models via their output probabilities, Lee et al. (2023) learn from a consensus of multiple teachers in self-instructing (Wang et al., 2023b), and Wan et al. (2024) propose a continual pretraining objective for knowledge distillation from multiple teachers. In this work, we focus on *integrative output ensembling*, where we simply provide a LLM (the fusor) the ensemble of outputs as input to integrate their strengths into a *fused* output.

Synthesis-based ensembling Our approach can be seen as an instance of *Mixture-of-Agents* (MoA) (Wang et al., 2024), a framework where multiple agents organized in layers iteratively enhance the output. Our approach stands out through simplicity: We show that FUSION becomes effective already in a *single aggregation step* with a single fusor, even in diverse and challenging

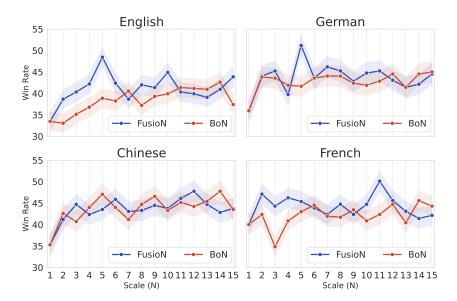


Figure 16: Head-to-Head Comparison of FUSION vs BON on m-ArenaHard-v2, Judged by GPT-40. We consistently see that FUSION results in better final sample compared to FUSION for both AYA EXPANSE 8B and COMMAND A.

setups, thereby constituting an attractive alternative for BoN, which is—thanks to its simplicity—a much more widely adopted framework than MoA.

LLM-Blender (Jiang et al., 2023) follows a similar idea, but requires two separate modules, one for pairwise ranking, and one for fusing top-ranking outputs. In contrast to our work, this framework operates on the basis of pairwise comparisons (which require training a specialized model), while we argue that the fusor should receive *all outputs at once* to best comparatively evaluate them.

Other contemporaneous related works also require training such specialized aggregator modules (Qi et al., 2025b; Zhao et al., 2025; Li et al., 2025b), while our approach is effective without any training. These works focus primarily on verifiable tasks like math and code targeting RL or reasoning. For such specialized scenarios with expert models available, Li et al. (2025a) warn that MoA might not be sufficiently robust to lower-quality inputs. For the more diverse generative evaluation scenarios that we are targeting, however, we find that FUSION is fairly robust with respect to the teacher pool (section 5), and sampling from a single teacher—the proposed solution by Li et al. (2025a)—performs significantly worse. Jayalath et al. (2025) find that fused single-teacher rollouts can nevertheless provide valuable supervision in RL training, even without any fusor training. Overall, our work fits nicely in a stream of very recent developments discovering new possibilities of synthesis as part of the inference process. Even though the idea of FUSION is so intuitive and shared among recent works, our work advances the understanding of the inner workings and limitations of this principle. We show that implemented even in its simplest form, it brings gains in highly diverse applications for both at test-time and for driving model supervision.

Test-time scaling Our approach can also be cast as combination of parallel and sequential test-time-scaling (Welleck et al., 2024; Snell et al., 2025), with N parallel steps and one refinement step. Inoue et al. (2025) formulate this combination as a search problem where in a each step either more samples can be requested, or existing ones can be revisited. This poses an interesting avenue for future work, where FUSION operates with adaptive compute (rather than a fixed N+1) based on each input sample. This flexibility might be needed for attempts to mimic human cognitive processes more closely (Zhang et al., 2024).

Synthetic data generation In the development of multilingual LLMs in particular, synthetic data generation has played a core role to reduce language disparities. For example, two recent models

Apertus (Hernández-Cano et al., 2025) and EuroLLM (Martins et al., 2025), rely on EuroBlocks, a collection of synthetic fine-tuning data obtained from various sources and individual teachers. Such synthetic data has also been key in improving mathematical reasoning, both monolingually (Muennighoff et al., 2025) and multilingually (Lai & Nissim, 2024; Hwang et al., 2025). Involving and ensembling multiple generations from either the same or multiple teachers in the process, as we study here, is still underexplored. For Llama 3, Grattafiori et al. (2024) report using rejection sampling (i.e. BoN) for multilingual data generation. For Aya Expanse, Dang et al. (2024) report routing samples to multiple teachers (Lu et al., 2024) via multilingual BoN as proposed in (Odumakinde et al., 2025), a strategy also adopted for building Tower+ (Rei et al., 2025).

I LLM USAGE DISCLOSURE

In this paper, we used AI in several auxiliary functions:

• Formatting of result tables in LATEX.

 • Shortening the text to fit into space limits.

Implementation aid for the contribution analysis.

• Polishing text by finding English correspondences to our non-English ideas.

 • Expansion of our initial list of related works, which we then read and carefully curated into the final related work discussion.

⁹https://huggingface.co/datasets/utter-project/EuroBlocks-SFT-Synthetic-1124