Multilingual Arbitration: Optimizing Data Pools to Accelerate Multilingual Progress

Ayomide Odumakinde*
Cohere
ayomideodumakinde@cohere.com

Daniel D'souza*
Cohere Labs
danieldsouza@cohere.com

Pat Verga
Cohere
pat@cohere.com

Beyza Ermis
Cohere Labs
beyza@cohere.com

Sara Hooker
Cohere Labs
sarahooker@cohere.com

Abstract

Synthetic data has driven recent state-of-the-art advancements, but reliance on a single oracle teacher model can lead to model collapse and bias propagation. These issues are particularly severe in multilingual settings, where no single model excels across all languages. In this study, we propose *multilingual arbitration*, which exploits performance variations among multiple models for each language. By strategically routing samples through a diverse set of models, each with unique strengths, we mitigate these challenges and enhance multilingual performance. Extensive experiments with state-of-the-art models demonstrate that our approach significantly surpasses single-teacher distillation, achieving up to 80% win rates over proprietary and open-weight models like Gemma 2, Llama 3.1, and Mistral v0.3, with the largest improvements in low-resource languages.

1 Introduction

Throughout life, we learn from multiple teachers, each offering unique expertise. Similarly, specialized fields rely on diverse mentors, yet synthetic data generation often depends on a single teacher model. This approach passively transfers both strengths and limitations, assuming one model can effectively teach all relevant skills (Shumailov et al., 2023; Magister et al., 2023; Shimabucoro et al., 2024; Gerstgrasser et al., 2024).

The limitations of the single oracle approach become particularly pronounced in multilingual settings, where high-performing large language models (LLMs) are often trained predominantly on a few data-rich languages (Singh et al., 2024; Joshi et al., 2020; Fan et al., 2021). This diverse landscape of multilingual model development has resulted in a variety of models: large-scale models that support multiple languages (Xue et al., 2020; Scao et al., 2022; Shliazhko et al., 2022; Li et al., 2023; Üstün et al., 2024), frontier models with some multilingual capabilities that are not specifically optimized (Armengol-Estapé et al., 2021; Chowdhery et al., 2022; Zhang et al., 2022; Team et al., 2024), and models focused on regional language families (Adelani et al., 2021; Mirzakhalov et al., 2021; Cahyawijaya et al., 2022). As a result, it is often unclear how to determine which model to use to maximize performance for a given language. Relying on a single model can also further amplify disparities in treatments between languages, as models may perform well on some language but not have coverage for others. Performance tends to be critical for the quality of synthetic data, which can enable further progress in those languages by making data more ubiquitous over time (Alaa et al., 2022; Gao et al., 2023; Bukharin and Zhao, 2023; Li et al., 2024; Zhang et al., 2024).

In this work, we take a wider view of synthetic data generation. Rather than treating model distillation as a single-teacher-to-student transfer, we reframe the problem within this heterogeneous landscape as learning how to optimize sampling for a desired part of the data distribution from an ensemble of teachers. Multilingual settings serve as an ideal case study for this approach due to the distinct boundaries between languages compared to tasks. We propose *multilingual arbitration*, leveraging model performance differences per language to strategically route sampling. This raises the question: *Can sampling from multiple models outperform any individual model?*

We evaluate this approach across 15 languages using 9 state-of-the-art multilingual models. Our key findings and contributions are as follows:

Multilingual arbitration significantly out-

* First authors.

Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 19142–19164
July 27 - August 1, 2025

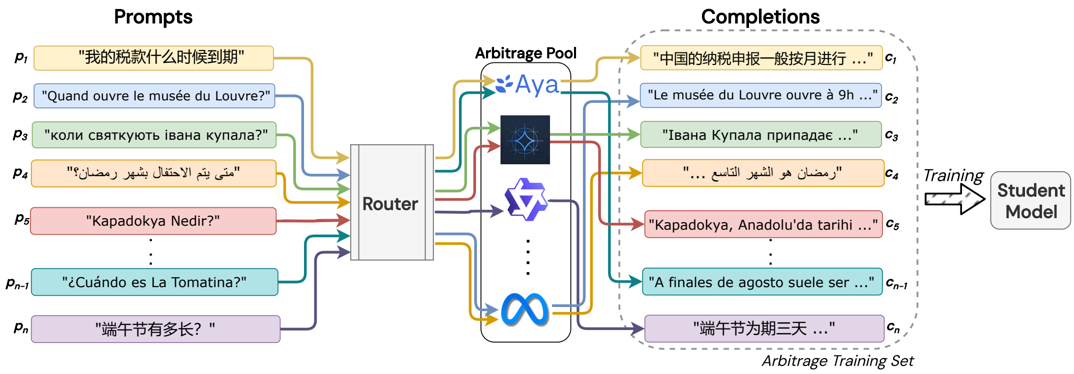


Figure 1: **Overview of *Multilingual Arbitration*.** Instead of relying on a single "oracle" teacher, multilingual arbitration re-frames the distillation as optimizing sampling for a desired part of the data distribution from an ensemble of teachers.

performs single-teacher distillation. Our experiments show that arbitration-based methods consistently surpass single-teacher models. Specifically, reward-based routing improves generative win rates by 56.5% and outperforms the best single-teacher model by 28.1%. Additionally, student models trained with this approach achieve an average absolute win rate gain of 32.02% (153.5% relative) over multiple state-of-the-art models. Compared to the strongest individual model, arbitration still delivers a 6.9% absolute (15.9% relative) improvement, underscoring its significant performance advantage.

Not all arbitration techniques are equal. We evaluate the performance of various arbitration techniques against a lower bound baseline of random routing. Reward-based routing, fixed routing with predefined set of expert teachers, and learned routing improved absolute performance by 30.6%, 22.9% and 13.4% (relative performance by 119.5%, 76.8%, and 40.6%) respectively. While reward-based routing, though resource-intensive, was the most effective, our results show that the more efficient reward-guided learned routing can achieve impressive performance gains without needing to generate all completions from each model.

Arbitration improves or maintains textual characteristics. We analyze the impact of instruction fine-tuning (IFT) with multilingual arbitration on text verbosity, readability, and lexical diversity. Reward-based routing increases token count by 14.1%, while learned routing leads to a 68.4% increase compared to both single-teacher and random routing baselines. Lexical diversity also improves: reward-based routing achieves a 6% gain, and learned routing 4.2%, relative to single teachers, with 13.4% and 11.5% gains over random routing, respectively. These results highlight arbitration's ability to enhance linguistic richness while maintaining coherence.

Arbitration produces a model checkpoint that outperforms state-of-the-art models. We scaled our arbitration approach and evaluated it against leading models, including Gemma 2 (Team et al., 2024), Llama 3.1 (Dubey et al., 2024), and Mistral v0.3[1]. Specifically, we observed an average absolute gain in win rates of 32.02% (a relative gain of 153.5%) compared to various state-of-the-art models, resulting in absolute win rates for our arbitration methods ranging from 50.1% to 80% against Gemma 2 and Mistral v0.3, respectively.

2 Methodology

Our primary goal is to train a high-performing multilingual student model S. Given a set of input prompts $P = \{p_i\}_{i=1}^{N}$, we generate a corresponding set of completions $C = \{c_i\}_{i=1}^{N}$ using a pool of potential teacher models $\mathcal{T} = \{T_j\}_{j=1}^{M}$. These prompt-completion pairs (p_i, c_i) will then be used to fine-tune S. For each prompt $p_i \in P$, we aim to identify the specific teacher model $T_j \in \mathcal{T}$ that produces the highest quality completion c_i.

We consider that each teacher model T_j may not perform uniformly across all regions of interest R in the data distribution. Therefore, we aim to minimize the empirical error $E[P_j(R)]$, where $P_j(R)$ represents the performance of teacher model T_j in region R, over the broader distribution D. This ensures robustness and generalization beyond the i.i.d. training sample D_{iid}.

[1] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

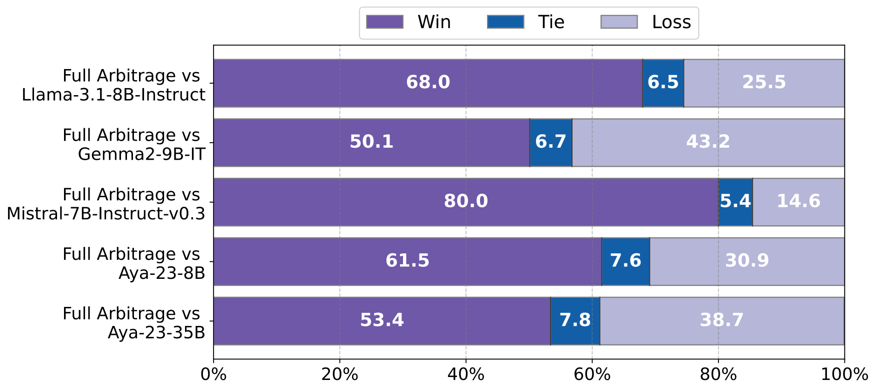


Figure 2: **Win rates (%) of student trained with arbitration data:** Comparison of reward-based routing trained students with state-of-the-art models. The largest gain is observed with a 65.4% win-loss difference against *Mistral-7B-instruct-v0.3*. Values are aggregated across 23 languages.

This approach allows us to select the most suitable teacher model for each prompt, optimizing the training of our student model S. We note that this amounts to optimization in the data space and allows for *on-the-fly* creation of dataset properties to minimize sensitivity to distribution drift.

2.1 Routing Methods

The crux of the problem of multilingual arbitration is: *how do you route prompts to the most calibrated teacher model for each prompt?* We explore and benchmark several routing strategies that aim to address this challenge. Table 1 presents a comparative overview of these strategies, highlighting their respective strengths and limitations, which we discuss in more detail below.

Fixed Routing. In practice, one might choose a fixed model, such as T_2, to process all input prompts in P. This can be reasonable if T_2 demonstrates significantly better overall performance for a majority of the prompts. In the multilingual case, this setting is one in which we can pre-determine the best model for each language based on their known strengths, enabling us to use a fixed routing strategy for each prompt deterministically by choosing the appropriate teacher model according to the prompt's language. However, in real-world settings it is not always possible to know what models are relatively strong at different languages in advance.

Reward-based Routing. Next we consider the more realistic setting which assumes that we cannot pre-determine a fixed routing strategy. Instead, we rely on a reward model for routing. For each p_i we generate a completion from each of the teacher models in $\mathcal{T}$ and then select c_i to be the completion with the highest score given by some ranking method. In our case, we use a proprietary reward model (Cohere May 2024) which is competitive with top-scoring state-of-the-art reward models on the RewardBench Leaderboard (Lambert et al., 2024)[2]. We intentionally use a separate reward model for routing from the model that we use for our LLM-as-a-judge evaluation (GPT-4-Turbo[3]) given the known biases incurred by using the same model for both (Bansal et al., 2023; Verga et al., 2024; Shimabucoro et al., 2024).

Learned-Routing. The disadvantage of reward-based routing is that it requires generating a full set of M completions for each prompt where $M = |\mathcal{T}|$. As a more efficient alternative, we explore the merits of a *learned router* which instead trains a router model based on scores produced by the reward model which is proposed by (Lu et al., 2024). In this method, the router model learns to predict the reward conditioned only on the prompt p_i, thereby determining the most suitable teacher model T_j without the need to generate multiple completions based upon historical routing trends. The router $R(p_i)$ is defined to select the teacher model T_j that maximizes the expected reward for a given prompt p_i. Formally, for each $p_i \in P$, the selected model T_j is given by:

$$T_j = \arg\max_{T \in \mathcal{T}} R(p_i, T).$$

This approach leverages the complementary strengths of the models in $\mathcal{T}$ and ensures that

[2] https://huggingface.co/spaces/allenai/reward-bench

[3] https://platform.openai.com/docs/models/gpt-4-turbo-and-gpt-4

	Fixed	Reward-Based	Learned
Works with Unknown Teachers	×	✓	✓
All models are considered for each prompt	×	✓	✓
Efficient Routing	✓	×	✓
New models can be added on-the-fly	×	✓	×

Table 1: **Comparison of Arbitration Techniques:** Summary of key features for each routing method. While reward-based routing is highly flexible, learned routing achieves a good balance between efficiency and adaptability.

each prompt is routed to the model most likely to produce the highest quality completion. By integrating reward model ranking with query routing, reward-guided Learned-Routing enhances the efficiency of the LLM ensemble, reducing computational overhead while ensuring effective training of the student model S.

To train our learned-routing model, we collect a training dataset of diverse prompts and then generate completions from each of the candidate models in the teacher pool. Given a prompt from our training set, we obtain a scalar reward for each candidate model generation as in the following:

$$\mathbf{r_i} = \{RM(p_i, T_j(p_i))\}_{j=1}^{|\mathcal{T}|}, \quad i = 1, \ldots, N \tag{1}$$

where $\mathbf{r_i} \in \mathcal{R}^{|\mathcal{T}|}$. We then train our router R on the training data with Kullback-Leibler (KL) divergence as the loss function:

$$\mathcal{L}(p_i, \mathbf{r}_i) = \mathrm{KL}(R(p_i), \mathrm{softmax}(\mathbf{r}_i)). \tag{2}$$

This approach improves the quality of synthetic data while maintaining computational efficiency during inference, introducing only minimal overhead compared to traditional reward model ranking methods, which is training the router model. However, this overhead is well compensated during inference because learned routing only generates samples from the routed model, rather than from each model in the pool. As a result, the generation cost is reduced to $1/M$, where M is the number of models in the pool.

3 Experimental Setup

3.1 Baselines

To evaluate *multilingual arbitration*, we compare against several baselines:

Single Teachers. This is the most widely adopted approach for incorporating synthetic data into training. In this paradigm a student model is trained on the generations from a single teacher model. We evaluate whether ***multilingual arbitration outperforms a single "oracle" teacher***.

We choose single teacher models based on their architecture, size, base model type, and language coverage. Our experiments are divided into two scales. For the basic set, we use widely adopted models with parameters ranging from 7B to 9B: Aya 23 (Aryabumi et al., 2024), Llama 3 (Dubey et al., 2024), and Gemma 2 (Team et al., 2024). For larger-scale experiments with expanded language coverage, we choose top-performing open-weight models: CommandR+, Gemma2 27B (Team et al., 2024), and Mistral Large 2. Detailed information about each model is provided in Appendix B.

Random Routing. Next, we consider a router that **randomly** assigns each prompt $p_i \in P$ to teacher model $T_j \in \mathcal{T}$, without accounting for language or any prompt-specific characteristics. This baseline allows us to explore: ***Is multilingual arbitration more effective than selecting models at random for a given data distribution?***

Translation. This baseline evaluates whether strategic sampling is superior to simply translating the outputs of a single English model into multiple languages. We investigate: ***Does generating synthetic data directly in the target language outperform translating the best English-only data?*** We generate completions for our English training prompts using our most capable English teacher model, Llama 3. We then translate each of the prompts and completions to the seven languages included in our router experiments.

3.2 Routing Teacher Pools

Fixed Router Model Pool. Our fixed router experiments assume prior knowledge of the best-performing models for specific languages. We train several geo-cluster models specialized in 15 languages, grouped as follows: ***Germanic*** (German, Dutch), ***Slavic*** (Czech, Russian, Ukrainian, Polish), ***Romance*** (French, Portuguese, Spanish, Italian, Romanian), and ***East-Asian*** (Turkish, Korean, Japanese, Chinese). This approach leverages linguistic and geographic similarities (Kohli et al., 2023; Kew et al., 2023; Tejaswi et al., 2024). Before student training, geo-cluster models outperform single-teacher models, achieving a 5.95% absolute (14.9% relative) win rate gain. Additional training and evaluation details are in Appendix C.

Reward-based and Learned Routing. These methods evaluate routing effectiveness in a diverse model pool with unknown multilingual performance. We include single-teacher models (§3.1), geo-cluster models (§3.2), and monolingual models for Chinese (Qwen2-7B-instruct) (Yang et al., 2024) and Turkish (Turkish-Llama-8b-Instruct-v0.1). Details on monolingual models are in Appendix B. This variety-from massively multilingual to geo-cluster and monolingual models – allows us to analyze model selection trends across different routing techniques.

Learned Routing. We train our learned router by fine-tuning Gemma2-2B (Team et al., 2024), selected for its compact size, strong performance, and multilingual capabilities. To further improve training efficiency, we also train an mT5-base (Xue et al., 2020) with 580M parameters. Comparative results for these models are presented in Appendix E. Our learned router models were trained using prompts from Dolly-15k which were translated using NLLB-3.3B (Team et al., 2022) into 7 languages covered by our routing experiments, and resulting in 60,419 prompts.

3.3 Student Model

We use Aya 23 8B (Aryabumi et al., 2024) as our student model for its state-of-the-art multilingual capabilities at its size. Experiments are conducted at two scales: (1) ***Basic Set*** - synthetic data is generated in 7 languages: *Arabic, Chinese, English, French, German, Turkish, Ukrainian* and (2) ***Larger Scale*** - synthetic data is generated in 23 languages, including the initial seven plus: *Dutch, Czech, Greek, Spanish, Persian, French, Hebrew, Hindi, Indonesian, Italian, Japanese, Korean, Polish, Portuguese, Russian, Vietnamese*. These languages cover diverse language families for comprehensive evaluation across various linguistic contexts (see Table 7 in Appendix D).

Training Details. For the basic set, student models are trained using 10,000 randomly sampled prompts from the *UltraFeedback Binarized Dataset* (UFB) (Tunstall et al., 2023), an English preference dataset with 61,135 pairs. These prompts are translated into 7 target languages using the NLLB-3.3B model, resulting in 70,000 prompts. For larger-scale experiments, 10,000 UFB prompts, 13,000 from Dolly (Conover et al., 2023), and 43,000 from ShareGPT [4] are translated into 23 languages, totaling 1,358,000 prompts. Completions for each prompt are generated by the assigned teacher model. Each student model is fine-tuned on these data points - 70,000 for the basic set and 1,358,000 for the larger scale - selected through multilingual arbitration.

3.4 Evaluations

Open-ended Generation Win rates. Beyond traditional NLP tasks, we aim to evaluate the open-ended generation capabilities of the student models, focusing on their ability to produce unstructured and long-form responses. For this evaluation, we use GPT-4 as an LLM-judge to measure pairwise win rates between two model generations. We evaluate on the target language subset of the Multilingual Dolly-200 Eval dataset (Singh et al., 2024; Üstün et al., 2024). This 200 instance evaluation dataset is a held-out curated sample from the Dolly-15k dataset (Conover et al., 2023). These prompts are open-ended and capture general-purpose non-code use cases. Hence, evaluation using this dataset is a valuable proxy for how multilingual arbitration impacts more fluid and often open-ended asks.

Discriminative Tasks. To evaluate our models on completely unseen tasks, we follow Muennighoff et al. (2023) and use XNLI (Conneau et al., 2018), XCOPA (Ponti et al., 2020), and XStoryCloze (Lin et al., 2021) datasets targeting natural language inference, commonsense reasoning and sentence completion respectively. These unseen tasks are crucial for evaluating the effectiveness of IFT in improving a model's reasoning and comprehension capabilities as they test the model's ability to discriminate between different possible interpretations or outcomes. For all unseen tasks, we report zero-shot performance.

4 Results and Discussion

4.1 Multilingual Arbitration Performance

Comparison against state-of-the-art models. Figure 2 shows the win rates of our reward-based routing strategy compared to several widely adopted models, with parameters ranging from 7B to 9B, as well as the Aya 23 model with 35B

[4] https://sharegpt.com/

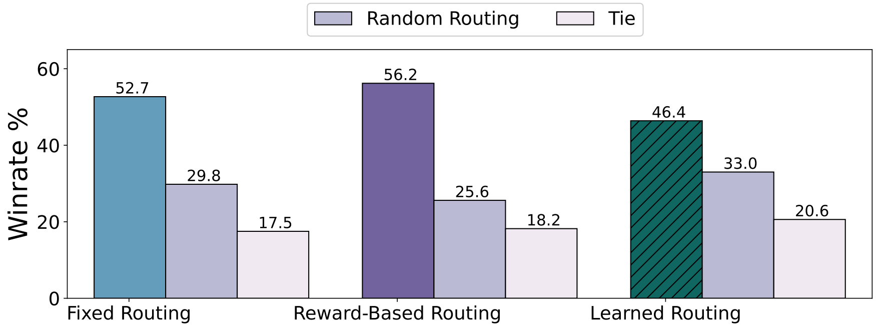


Figure 3: **Win rates (%) of students trained with different routing strategies:** Comparison of router-trained and random routing trained students. Reward-based routing shows the largest gains with a 30.6% win-loss difference. Values are percentages aggregated across 7 languages.

parameters. Our student models, trained using data derived from this strategy, demonstrated a significant performance advantage over all these state-of-the-art models. We observed an average absolute increase in win rates of 32.02% (relative gain of 153.5%) across all models, with improvements ranging from 6.9% (15.9% relative) for Gemma2 9B to 65.4% (447% relative) for Mistral-7B-instruct, based on results averaged across 23 languages.

Comparison against random routing. Our random routing baseline serves as a crucial lower bound that any proposed arbitration strategy should outperform. This baseline helps us evaluate: *Is our multilingual arbitration technique better than a random guess?* In Figure 3, we compare the win rates of each of the different routing methods against the random routing baseline. We observe that all the multilingual arbitration methods consistently outperformed the random baseline with average win rate of 51.8% and a notable absolute win rate improvement of 22.3% (78.9% relative) on average.

Comparison against single "oracle" teacher. In Figure 4, we show win rates comparing our routing strategies to single teacher models. Student models trained with data from these strategies significantly outperformed those using single teacher generations. Specifically, fixed routing achieves an absolute average winrate improvement of 13.3% (34.7% relative), reward-based routing shows a 19.5% absolute average improvement (56.5% relative), and learned routing has a 9.0% absolute improvement in average (25.6% relative) over all single teachers. Notably, Gemma 2 was the best-performing single teacher, yet learned routing still achieved an absolute average winrate improvement of 1.4% (3.2% relative gain) over it.

Win-rate Gains are largest for Reward-Based Routing. Reward-based routing achieves the highest win-rate gains of 56.5% against single teachers but is the least efficient, requiring inference and generation from all models in the pool for each prompt. In contrast, fixed and learned routing, though slightly less effective, are far more efficient, needing only one generation per prompt. In a 9-model pool, reward-based routing generates and scores 9 completions per prompt, while fixed and learned routing require just one. Learned routing adds a lightweight router call, but this overhead is negligible compared to full model inference. Notably, learned routing is the most flexible, 9× more efficient than reward-based routing, and unlike fixed routing, it does not require prior knowledge of model strengths.

Discriminative tasks. Table 9 shows zero-shot performance on unseen discriminative tasks, highlighting similar gaps between single teachers and arbitration techniques. Single teachers improve performance by 0.57 absolute (0.98% relative) over the base student model (Aya 23), while arbitration achieves a 1.14 absolute (1.95% relative) gain. Among arbitration methods, Fixed Routing performs best, with a 1.46 absolute (2.50% relative) improvement, followed by Reward-Based Routing (1.12 absolute, 1.91% relative), demonstrating their superior impact on cross-lingual and commonsense reasoning. Interestingly, Fixed Routing ranks highest in discriminative tasks but second in win rates, reflecting a broader tension between academic benchmarks and open-ended generation performance. Recent studies suggest that as LLMs improve in conversational and instruction-following abilities, their performance

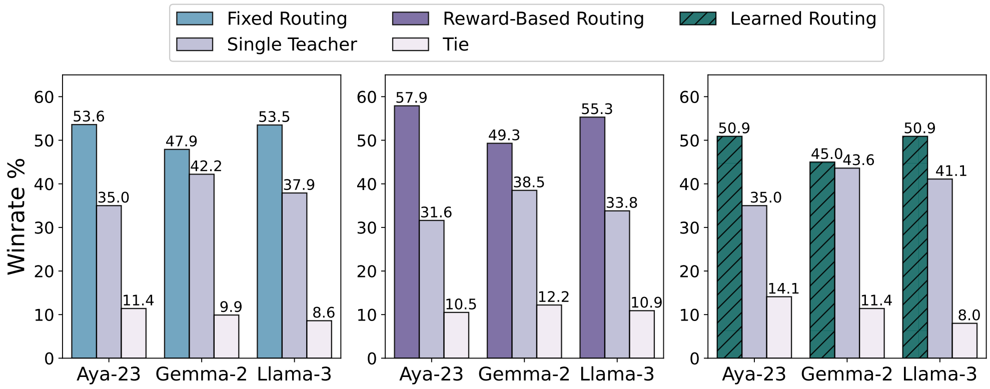


Figure 4: **Win rate (%) comparison of Fixed, Reward-Based and Learned Routing against Single Teacher Models.** The x-axis shows the single teacher model used for synthetic data generation. All multilingual arbitration strategies outperform single teachers, with reward-based routing achieving the largest gains. Values are aggregated across seven languages: *Arabic, Chinese, English, French, German, Turkish, and Ukrainian*.

	XCOPA	**XNLI**	**XStoryCloze**	**Average**
AYA23 (Base Model)	64.1	42.9	68.23	58.41
SINGLE TEACHERS	65.5	43.96	67.41	58.98 ↑ 0.98
RANDOM ROUTING	65.9	44.01	67.25	59.05 ↑ 1.09
FIXED ROUTING	**67.4**	43.89	68.33	**59.87** ↑ 2.50
REWARD BASED ROUTING	66.2	**44.21**	68.20	59.53 ↑ 1.91
LEARNED ROUTER	65.8	43.62	**68.36**	59.25 ↑ 1.43

Table 2: **Performance of Student Models on held-out Discriminative Tasks:** Results are averaged over 7 languages, showing performance changes relative to the base model Aya23. Single teacher results are averaged across Aya23, Llama 3, and Gemma 2. 'Average' column shows the percentage increase over the base model.

on traditional benchmarks may decline (Iyer et al., 2023; Üstün et al., 2024; Aakanksha et al., 2024). For full results, see Table 9 in Appendix G.

4.2 Language and Routing Analysis

Difference in per-language gains. Figure 5 compares performance gains in medium- vs. high-resource languages using reward-based and learned routing against single teachers - Aya 23, Llama 3, Gemma 2. Medium-resource languages, Turkish and Ukrainian, experience greater benefits, with reward-based routing achieving an absolute gain of 19.2% (56.1% relative) and learned routing achieving a 18.1% (52.2% relative) over single teachers. In contrast, high-resource languages (Joshi et al., 2020), English, German, French, Chinese, and Arabic see an absolute gain of 13.2% (35.7% relative) with reward-based routing and 6% (14.3% relative) with learned routing. These results suggest routing strategies benefit medium-resource languages more than single teachers. Detailed per-language gains are in Table 8, Appendix F.

Routed Dataset Distribution Across Models. Figure 6 shows the distribution of the training dataset prompts routed to each model by the reward-based router. We observed a balanced routing strategy with different models favored for each language, which highlights the benefits of combining the strengths of a pool of models with varying strengths. For instance, Llama 3, a strong English model, receives 60% of English prompts but is less frequently used for other languages. Meanwhile, 30.7% of Chinese prompts are directed to the Chinese monolingual expert, whereas the Turkish monolingual expert is rarely selected, with only 0.6% of prompts routed to it. Overall, Aya 23 emerges as the leading multilingual model, predominantly chosen for Ukrainian, Turkish, and Arabic, with 53% of Arabic prompts routed to it. Geo-cluster models, included for all languages except Arabic (as there is no Geo-cluster model for it), handle an average of 18.7% of the prompts.

Comparison of in-language generation vs translation. We investigate whether generating

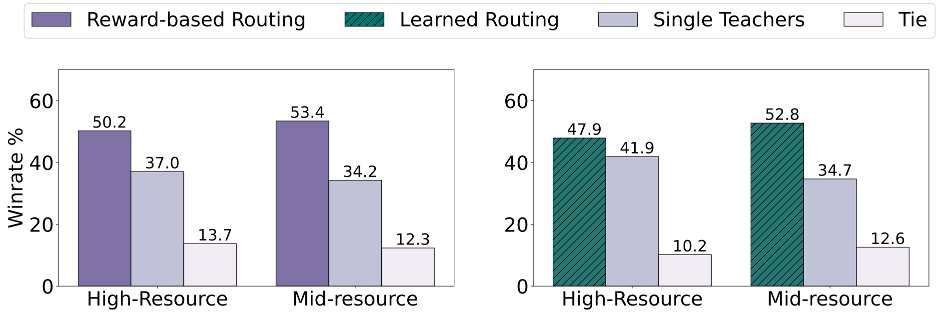


Figure 5: **Win rate Changes by Language Resource Level:** Comparison of the Mid- and High-Resource Language win rates against Single Teachers (average of Aya 23, Llama 3 and Gemma 2). Mid-resource languages are Turkish and Ukrainian and high-resource languages are English, German, French, Chinese and Arabic.

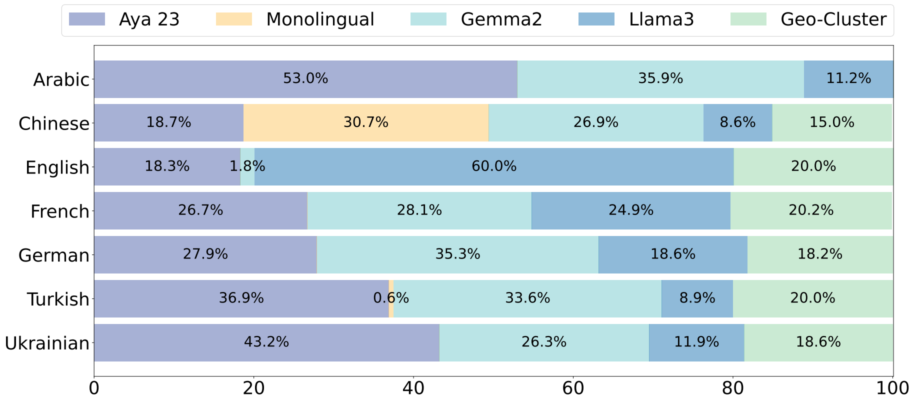


Figure 6: **Model Composition per Language:** Here we analyze the model routing distribution of a dataset constructed with Reward-Based Routing. The values represent the percentage of prompts routed to a given model for the particular language.

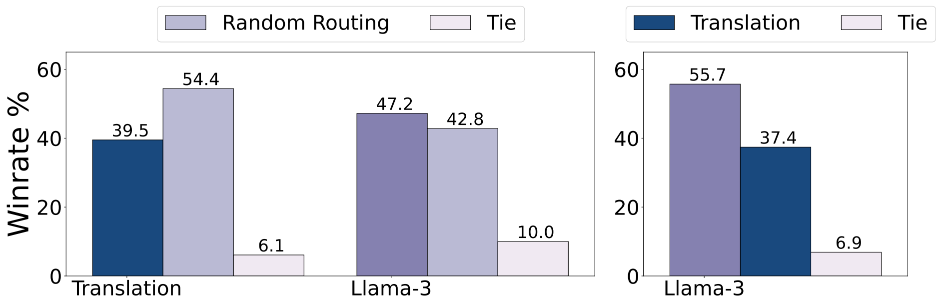


Figure 7: **Win rates (%) for Llama 3 translations vs. generations:** Comparison of translation, in-language generation by single teacher and router-trained students to those trained with random routing. The largest gains are observed for in-language data generation with a win-loss diff of 18.3%.

synthetic data directly in the target language is more effective than translating English-only data. Using Llama 3, we generate English data, translate it into 6 languages, and train a student model on the translated dataset. We then compare its performance to students trained on Llama 3's in-language generations and random routing. Figure 7 shows that random routing (54.4% win rate) outperforms translation, while the Llama 3 single-teacher model surpasses random routing with a 4.4% absolute (10.3% relative) gain. Notably, Llama 3 translation performs worse than Llama 3 in-language generations, with a 18.3% absolute (48.9% relative) win rate gap. These results confirm that translation is the least effective synthetic data method, as even random routing performs better. Generating data within the target language provides substantial advantages, even when the original model excels in English.

Textual Characteristics. To gain a holistic view of how multilingual arbitration affects model generation characteristics, we use the

Student Models	# Tokens	Gunning-Fog	Rix	MLTD
AYA23 (Base)	76.74	15.83	4.7	43.98
SINGLE TEACHER STUDENTS				
AYA23	151.83	17.67	5.92	46.51
LLAMA-3	141.71	17.33	5.87	49.5
GEMMA-2	140.59	15.67 ↓	4.28 ↓	52.48
TRANSLATION	197.05	16.62	5.22	**53.01**
MULTILINGUAL ARBITRATION				
RANDOM ROUTING	144.16	17.16	5.81	45.81
FIXED ROUTING	160.75	17.71	5.94	50.79
REWARD BASED ROUTING	164.4	17.01	5.69	51.95
LEARNED ROUTING	**242.56**	**19.11**	**7.74**	51.08

Table 3: **Textual characteristics of student models across four languages (ENGLISH, GERMAN, FRENCH, AND UKRAINIAN).** The results reflect how different routing strategies and model choices influence verbosity (# Tokens), readability (Gunning-Fog and Rix indices), and lexical richness (MLTD). Notably, all student models except GEMMA-2 exhibit increases across the evaluated metrics.

TextDescriptives framework from Hansen et al. (2023) to calculate various textual features. Table 3 presents the average statistics across student models, including token count, readability (Gunning-Fog (Gunning, 1968) and Rix (Anderson, 1983) indices), and lexical diversity (MLTD (Shen, 2022)) scores. For a more detailed analysis of the textual characteristics of generations, please refer to Appendix H.

5 Conclusion

We introduce multilingual arbitration, a strategy that leverages model performance variations to optimize sampling from a teacher model pool, generating superior training data for student models. Our experiments across 23 languages show that routing strategies significantly enhance performance across all benchmarks, outperforming traditional single-teacher methods in both open-ended generation and discriminative tasks. Analysis of textual characteristics and unseen tasks confirms that instruction fine-tuned students not only retain their capabilities but also improve multilingual generation. Our findings highlight the value of strategic sampling, especially for handling out-of-distribution challenges and underrepresented data. We anticipate arbitration techniques will drive substantial gains in these areas.

6 Limitations

While our approach covers a broad range of languages, most are still considered mid- or high-resource by global standards. Extremely low-resource languages, where minimal training data or teacher models are available, remain challenging. The lack of suitable experts for routing and the increased risk of generating poor-quality synthetic data make such cases currently infeasible. Additionally, as discussed in Section 2.1, our reward-based routing method requires generating completions from all candidate models for each prompt. While this approach enhances performance, it also significantly increases inference costs.

References

Aakanksha, Arash Ahmadian, Beyza Ermis, Seraphina Goldfarb-Tarrant, Julia Kreutzer, Marzieh Fadaee, and Sara Hooker. 2024. The multilingual alignment prism: Aligning global and local preferences to reduce harm. *Preprint*, arXiv:2406.18682.

David Ifeoluwa Adelani, Jade Abbott, Graham Neubig, Daniel D'souza, Julia Kreutzer, Constantine Lignos, Chester Palen-Michel, Happy Buzaaba, Shruti Rijhwani, Sebastian Ruder, et al. 2021. Masakhaner: Named entity recognition for african languages. *Transactions of the Association for Computational Linguistics*, 9:1116–1131.

Ahmed Alaa, Boris Van Breugel, Evgeny S Saveliev, and Mihaela van der Schaar. 2022. How faithful is your synthetic data? sample-level metrics for evaluating and auditing generative models. In *International Conference on Machine Learning*, pages 290–306. PMLR.

Ateret Anaby-Tavor, Boaz Carmeli, Esther Goldbraich, Amir Kantor, George Kour, Segev Shlomov, Naama Tepper, and Naama Zwerdling. 2019. Not enough data? deep learning to the rescue! *Preprint*, arXiv:1911.03118.

Jonathan Anderson. 1983. Lix and rix: Variations on a little-known readability index. *Journal of Reading*, 26(6):490–496.

Jordi Armengol-Estapé et al. 2021. On the multilingual capabilities of very large-scale english language models. *arXiv preprint arXiv:2108.13349*.

Viraat Aryabumi, John Dang, Dwarak Talupuru, Saurabh Dash, David Cairuz, Hangyu Lin, Bharat Venkitesh, Madeline Smith, Kelly Marchisio, Sebastian Ruder, et al. 2024. Aya 23: Open weight releases to further multilingual progress. *arXiv preprint arXiv:2405.15032*.

Hritik Bansal, John Dang, and Aditya Grover. 2023. Peering through preferences: Unraveling feedback acquisition for aligning large language models. *arXiv preprint arXiv:2308.15812*.

Quentin Bertrand, Avishek Joey Bose, Alexandre Duplessis, Marco Jiralerspong, and Gauthier Gidel. 2024. On the stability of iterative retraining of generative models on their own data. *Preprint*, arXiv:2310.00429.

Martin Briesch, Dominik Sobania, and Franz Rothlauf. 2023. Large language models suffer from their own output: An analysis of the self-consuming training loop. *Preprint*, arXiv:2311.16822.

Alexander Bukharin and Tuo Zhao. 2023. Data diversity matters for robust instruction tuning. *arXiv preprint arXiv:2311.14736*.

Samuel Cahyawijaya, Holy Lovenia, Alham Fikri Aji, Genta Indra Winata, Bryan Wilie, Rahmad Mahendra, Christian Wibisono, Ade Romadhony, Karissa Vincentio, Fajri Koto, et al. 2022. Nusacrowd: Open source initiative for indonesian nlp resources. *arXiv preprint arXiv:2212.09648*, pages 13745–13818.

Lingjiao Chen, Matei Zaharia, and James Zou. 2023. Frugalgpt: How to use large language models while reducing cost and improving performance. *arXiv preprint arXiv:2305.05176*.

Aakanksha Chowdhery et al. 2022. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.

Alexis Conneau, Guillaume Lample, Ruty Rinott, Adina Williams, Samuel R Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. Xnli: Evaluating cross-lingual sentence representations. *arXiv preprint arXiv:1809.05053*.

Mike Conover, Matt Hayes, Ankit Mathur, Jianwei Xie, Jun Wan, Sam Shah, Ali Ghodsi, Patrick Wendell, Matei Zaharia, and Reynold Xin. 2023. Free dolly: Introducing the world's first truly open instruction-tuned llm. *Company Blog of Databricks*.

Marta R Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, et al. 2022. No language left behind: Scaling human-centered machine translation. *arXiv preprint arXiv:2207.04672*.

Elvis Dohmatob, Yunzhen Feng, and Julia Kempe. 2024. Model collapse demystified: The case of regression. *Preprint*, arXiv:2402.07712.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.

Angela Fan, Shruti Bhosale, Holger Schwenk, Zhiyi Ma, Ahmed El-Kishky, Siddharth Goyal, Mandeep Baines, Onur Celebi, Guillaume Wenzek, Vishrav Chaudhary, et al. 2021. Beyond english-centric multilingual machine translation. *Journal of Machine Learning Research*, 22(107):1–48.

Yunzhen Feng, Elvis Dohmatob, Pu Yang, Francois Charton, and Julia Kempe. 2024. Beyond model collapse: Scaling up with synthesized data requires reinforcement. *arXiv preprint arXiv:2406.07515*.

Jiahui Gao, Renjie Pi, Yong Lin, Hang Xu, Jiacheng Ye, Zhiyong Wu, Weizhong Zhang, Xiaodan Liang, Zhenguo Li, and Lingpeng Kong. 2023. Self-guided noise-free data generation for efficient zero-shot learning. *Preprint*, arXiv:2205.12679.

Matthias Gerstgrasser, Rylan Schaeffer, Apratim Dey, Rafael Rafailov, Henry Sleight, John Hughes, Tomasz Korbak, Rajashree Agrawal, Dhruv Pai, Andrey Gromov, Daniel A. Roberts, Diyi Yang, David L. Donoho, and Sanmi Koyejo. 2024. Is model collapse inevitable? breaking the curse of recursion by accumulating real and synthetic data. *Preprint*, arXiv:2404.01413.

Robbie Gunning. 1968. The technique of clear writing.

Yanzhu Guo, Guokan Shang, Michalis Vazirgiannis, and Chloé Clavel. 2024. The curious decline of linguistic diversity: Training language models on synthetic text. *Preprint*, arXiv:2311.09807.

Lasse Hansen, Ludvig Renbo Olsen, and Kenneth Enevoldsen. 2023. Textdescriptives: A python package for calculating a large variety of metrics from text. *arXiv preprint arXiv:2301.02057*.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *Preprint*, arXiv:1503.02531.

Srinivasan Iyer, Xi Victoria Lin, Ramakanth Pasunuru, Todor Mihaylov, Daniel Simig, Ping Yu, Kurt Shuster, Tianlu Wang, Qing Liu, Punit Singh Koura, Xian Li, Brian O'Horo, Gabriel Pereyra, Jeff Wang, Christopher Dewan, Asli Celikyilmaz, Luke Zettlemoyer, and Ves Stoyanov. 2023. Opt-iml: Scaling language model instruction meta learning through the lens of generalization. *Preprint*, arXiv:2212.12017.

Dongfu Jiang, Xiang Ren, and Bill Yuchen Lin. 2023. Llm-blender: Ensembling large language models with pairwise ranking and generative fusion. *arXiv preprint arXiv:2306.02561*.

Pratik Joshi, Sebastin Santy, Amar Budhiraja, Kalika Bali, and Monojit Choudhury. 2020. The state and fate of linguistic diversity and inclusion in the nlp world. *arXiv preprint arXiv:2004.09095*.

Jean Kaddour and Qi Liu. 2023. Text data augmentation in low-resource settings via fine-tuning of large language models. *arXiv preprint arXiv:2310.01119*.

Tannon Kew, Florian Schottmann, and Rico Sennrich. 2023. Turning english-centric llms into polyglots: How much multilinguality is needed? *Preprint*, arXiv:2312.12683.

Guneet Singh Kohli, Shantipriya Parida, Sambit Sekhar, Samirit Saha, Nipun B Nair, Parul Agarwal, Sonal Khosla, Kusumlata Patiyal, and Debasish Dhal. 2023. Building a llama2-finetuned llm for odia language utilizing domain knowledge instruction set. *Preprint*, arXiv:2312.12624.

Nathan Lambert, Valentina Pyatkin, Jacob Morrison, LJ Miranda, Bill Yuchen Lin, Khyathi Chandu, Nouha Dziri, Sachin Kumar, Tom Zick, Yejin Choi, et al. 2024. Rewardbench: Evaluating reward models for language modeling. *arXiv preprint arXiv:2403.13787*.

Haonan Li, Fajri Koto, Minghao Wu, Alham Fikri Aji, and Timothy Baldwin. 2023. Bactrian-x: Multilingual replicable instruction-following models with low-rank adaptation. *arXiv*, abs/2305.15011.

Haoran Li, Qingxiu Dong, Zhengyang Tang, Chaojun Wang, Xingxing Zhang, Haoyang Huang, Shaohan Huang, Xiaolong Huang, Zeqiang Huang, Dongdong Zhang, et al. 2024. Synthetic data (almost) from scratch: Generalized instruction tuning for language models. *arXiv preprint arXiv:2402.13064*.

Xi Victoria Lin, Todor Mihaylov, Mikel Artetxe, Tianlu Wang, Shuohui Chen, Daniel Simig, Myle Ott, Naman Goyal, Shruti Bhosale, Jingfei Du, Ramakanth Pasunuru, Sam Shleifer, Punit Singh Koura, Vishrav Chaudhary, Brian O'Horo, Jeff Wang, Luke Zettlemoyer, Zornitsa Kozareva, Mona Diab, Veselin Stoyanov, and Xian Li. 2021. Few-shot learning with multilingual language models. *arXiv*, abs/2112.10668.

Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V. Le, Barret Zoph, Jason Wei, and Adam Roberts. 2023. The flan collection: Designing data and methods for effective instruction tuning. *arXiv*, abs/2301.13688.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization. *Preprint*, arXiv:1711.05101.

Keming Lu, Hongyi Yuan, Runji Lin, Junyang Lin, Zheng Yuan, Chang Zhou, and Jingren Zhou. 2024. Routing to the expert: Efficient reward-guided ensemble of large language models. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 1964–1974, Mexico City, Mexico. Association for Computational Linguistics.

Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. 2023. Wizardcoder: Empowering code large language models with evol-instruct. *arXiv preprint arXiv:2306.08568*.

Lucie Charlotte Magister, Jonathan Mallinson, Jakub Adamek, Eric Malmi, and Aliaksei Severyn. 2023. Teaching small language models to reason. *Preprint*, arXiv:2212.08410.

Philip M. McCarthy and Scott Jarvis. 2010. Mtld, vocd-d, and hd-d: A validation study of sophisticated approaches to lexical diversity assessment. *Behavior Research Methods*, 42:381–392.

Sewon Min, Mike Lewis, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2021. Metaicl: Learning to learn in context. *arXiv preprint arXiv:2110.15943*, pages 2791–2809.

Jamshidbek Mirzakhalov, Anoop Babu, Duygu Ataman, Sherzod Kariev, Francis Tyers, Otabek Abduraufov, Mammad Hajili, Sardana Ivanova, Abror Khaytbaev, Antonio Laverghetta Jr, et al. 2021. A large-scale study of machine translation in turkic languages. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 5876–5890, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Swaroop Mishra, Daniel Khashabi, Chitta Baral, and Hannaneh Hajishirzi. 2021. Cross-task generalization via natural language crowdsourcing instructions. *arXiv preprint arXiv:2104.08773*, pages 3470–3487.

Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng Xin Yong, Hailey Schoelkopf, Xiangru Tang, Dragomir Radev, Alham Fikri Aji, Khalid Almubarak, Samuel Albanie, Zaid Alyafeai, Albert Webson, Edward Raff, and Colin Raffel. 2023. Crosslingual generalization through multitask finetuning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15991–16111, Toronto, Canada. Association for Computational Linguistics.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744.

Edoardo Maria Ponti, Goran Glavaš, Olga Majewska, Qianchu Liu, Ivan Vulić, and Anna Korhonen. 2020. Xcopa: A multilingual dataset for causal commonsense reasoning. *arXiv preprint arXiv:2005.00333*.

Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. 2021. Multitask prompted training enables zero-shot task generalization. *ICLR 2022*.

Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. 2022. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*.

Lucas Shen. 2022. LexicalRichness: A small module to compute textual lexical richness.

Luísa Shimabucoro, Sebastian Ruder, Julia Kreutzer, Marzieh Fadaee, and Sara Hooker. 2024. Llm see, llm do: Guiding data generation to target non-differentiable objectives. *Preprint*, arXiv:2407.01490.

Oleh Shliazhko, Alena Fenogenova, Maria Tikhonova, Vladislav Mikhailov, Anastasia Kozlova, and Tatiana Shavrina. 2022. mgpt: Few-shot learners go multilingual. *arXiv preprint arXiv:2204.07580*.

Tal Shnitzer, Anthony Ou, Mírian Silva, Kate Soule, Yuekai Sun, Justin Solomon, Neil Thompson, and Mikhail Yurochkin. 2023. Large language model routing with benchmark datasets. *arXiv preprint arXiv:2309.15789*.

Ilia Shumailov, Zakhar Shumaylov, Yiren Zhao, Yarin Gal, Nicolas Papernot, and Ross Anderson. 2023. The curse of recursion: Training on generated data makes models forget. *arXiv preprint arXiv:2305.17493*.

Ilia Shumailov, Zakhar Shumaylov, Yiren Zhao, Yarin Gal, Nicolas Papernot, and Ross Anderson. 2024. The curse of recursion: Training on generated data makes models forget. *Preprint*, arXiv:2305.17493.

Shivalika Singh, Freddie Vargus, Daniel Dsouza, Börje F. Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura OMahony, Mike Zhang, Ramith Hettiarachchi, Joseph Wilson, Marina Machado, Luisa Souza Moura, Dominik Krzemiński, Hakimeh Fadaei, Irem Ergün, Ifeoma Okoh, Aisha Alaagib, Oshan Mudannayake, Zaid Alyafeai, Vu Minh Chien, Sebastian Ruder, Surya Guthikonda, Emad A. Alghamdi, Sebastian Gehrmann, Niklas Muennighoff, Max Bartolo, Julia Kreutzer, Ahmet Üstün, Marzieh Fadaee, and Sara Hooker. 2024. Aya dataset: An open-access collection for multilingual instruction tuning. *Preprint*, arXiv:2402.06619.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. 2023. Stanford alpaca: An instruction-following llama model.

Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, et al. 2024. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295*.

NLLB Team, Marta R Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, et al. 2022. No language left behind: Scaling human-centered machine translation (2022). *URL https://arxiv. org/abs/2207.04672*.

Atula Tejaswi, Nilesh Gupta, and Eunsol Choi. 2024. Exploring design choices for building language-specific llms. *Preprint*, arXiv:2406.14670.

Jeanine Treffers-Daller, Patrick Parslow, and Shirley Williams. 2016. Back to Basics: How Measures of Lexical Diversity Can Help Discriminate between CEFR Levels. *Applied Linguistics*, 39(3):302–327.

Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clémentine Fourrier, Nathan Habib, et al. 2023. Zephyr: Direct distillation of lm alignment. *arXiv preprint arXiv:2310.16944*.

Ahmet Üstün, Viraat Aryabumi, Zheng-Xin Yong, Wei-Yin Ko, Daniel D'souza, Gbemileke Onilude, Neel Bhandari, Shivalika Singh, Hui-Lee Ooi, Amr Kayid, et al. 2024. Aya model: An instruction finetuned open-access multilingual language model. *arXiv preprint arXiv:2402.07827*.

Pat Verga, Sebastian Hofstatter, Sophia Althammer, Yixuan Su, Aleksandra Piktus, Arkady Arkhangorodsky, Minjie Xu, Naomi White, and Patrick Lewis. 2024. Replacing judges with juries: Evaluating llm generations with a panel of diverse models. *arXiv preprint arXiv:2404.18796*.

Hongyi Wang, Felipe Maia Polo, Yuekai Sun, Souvik Kundu, Eric Xing, and Mikhail Yurochkin. 2023a. Fusing models with complementary expertise. *arXiv preprint arXiv:2310.01542*.

Yizhong Wang, Hamish Ivison, Pradeep Dasigi, Jack Hessel, Tushar Khot, Khyathi Raghavi Chandu, David Wadden, Kelsey MacMillan, Noah A Smith, Iz Beltagy, et al. 2023b. How far can camels go? exploring the state of instruction tuning on open resources. *arXiv preprint arXiv:2306.04751*.

Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*.

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. 2023. Wizardlm: Empowering large language models to follow complex instructions. *arXiv preprint arXiv:2304.12244*.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2020. mt5: A massively multilingual pre-trained text-to-text transformer. *arXiv preprint arXiv:2010.11934*.

An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. 2024. Qwen2 technical report. *Preprint*, arXiv:2407.10671.

Dylan Zhang, Justin Wang, and Francois Charton. 2024. Instruction diversity drives generalization to unseen tasks. *arXiv preprint arXiv:2402.10891*.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. 2022. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*.

Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. 2023. Lima: Less is more for alignment. *arXiv preprint arXiv:2305.11206*.

A Related Work

LLM circularity. The issue of LLM circularity, where models influence others through distilled data, has gained attention, focusing on model degradation and self-preference (Dohmatob et al., 2024; Briesch et al., 2023; Shumailov et al., 2023). Recursive training impairs performance by neglecting long-tail knowledge (Briesch et al., 2023; Bertrand et al., 2024; Shumailov et al., 2024), leading to a loss of diversity (Guo et al., 2024; Feng et al., 2024). (Shimabucoro et al., 2024) explore how the transfer of characteristics via passive inheritance occurs when synthetic data generated by different LLMs is involved. By considering the issues highlighted in these studies, we aim to optimize synthetic data generation by selecting the most calibrated teacher model from a pool of LLMs in a multilingual setting.

Instruction Fine-tuning (IFT) and Multilingual Synthetic Data. IFT enhances LLM performance and generalization (Sanh et al., 2021; Wei et al., 2021; Mishra et al., 2021; Min et al., 2021; Ouyang et al., 2022), relying on task diversity (Longpre et al., 2023; Wang et al., 2023b; Chung et al., 2022), complexity (Xu et al., 2023; Luo et al., 2023), and quality (Zhou et al., 2023; Taori et al., 2023). While validated mainly for English tasks, there is a growing focus on multilingual contexts (Üstün et al., 2024). Efforts address multilingual instruction dataset scarcity (Singh et al., 2024). Research on English synthetic data generation is extensive (Gao et al., 2023; Anaby-Tavor et al., 2019), but its multilingual impact is less understood (Kaddour and Liu, 2023). Recent studies explore multilingual data with a single teacher model (Aryabumi et al., 2024) and for preference training (Aakanksha et al., 2024). In this work, we strategically sample from a diverse pool of models, each with unique strengths across different languages, to generate high-quality synthetic instruction data. Our research diverges by concentrating on multilingual synthetic instruction data generation from an ecosystem view rather than a single teacher.

Large Language Model Ensemble. Ensembling LLMs leverages individual strengths, but limited research exists on these effective strategies. Frameworks combine LLMs using pairwise ranking and generative fusion (Jiang et al., 2023), sequential inference (Chen et al., 2023), and supervised learning for output fusion (Wang et al., 2023a). Routers select the best LLM candidate based on benchmarks (Shnitzer et al., 2023). Relevant work proposes reward model-guided routing for task strengths (Lu et al., 2024). Our work explores various routing strategies beyond reward-based routing, in multilingual contexts.

B Teacher Model Pool Details

Single Teacher Models. We include additional details about each of the single teacher models we benchmark below:
Aya-23-8B (Aryabumi et al., 2024) is an 8B parameter model and a part of the Aya-23 family of multilingual instruction-tuned language models that supports 23 languages, and are based on Cohere's Command model[5] and multilingual instruction-style collection (Singh et al., 2024).
Llama-3-8B-instruct (Dubey et al., 2024) is an open-source instruction-tuned version of the Llama-3-8B pre-trained model. The model is trained on over 15 trillion tokens of publicly available data, with a focus on optimizing the performance across various real-world scenarios, including reasoning and code generation.
Gemma-2-9B-it (Team et al., 2024) is a 9B parameter instruction fine-tuned model on 8T tokens of data from web documents, code, and science articles. In particular, the 9B model was trained with knowledge distillation (Hinton et al., 2015) instead of next token prediction.
Gemma-2-27B-it (Team et al., 2024) is a 27B parameter instruction fine-tuned model on 13T tokens of data from web documents, code, mathematics.
Command-r-plus-08-2024 [6] is a 104B parameter multilingual model optimized for 10 languages: English, French, Spanish, Italian, German, Brazilian Portuguese, Japanese, Korean, Arabic, and Simplified Chinese.
Mistral Large 2[7] is a 123B parameter instruction fine-tuned model, supports dozens of languages including French, German, Spanish, Italian, Portuguese, Arabic, Hindi, Russian, Chinese, Japanese, and Korean.

Monolingual Teacher Models. These models are specifically tailored for individual languages, specifically Chinese and Turkish: **Qwen2-7B-instruct** (Yang et al., 2024) is an open-source 7B parameter model pretrained on 7T tokens of data from code, mathematics, and multilingual data. Qwen2-7B-instruct is a multilingual model supporting approximately 30 languages, and showing strong performance on Chinese. **Turkish-Llama-8b-Instruct-v0.1**[8] is a fully fine-tuned version of the Llama-3-8B-instruct model with a 30GB Turkish dataset. It currently tops the Turkish leaderboard on HuggingFace[9] for text generation tasks.

C Geo-Cluster Training Details

To train highly performant Geo-clusters, we train an 8B parameter Cohere command model on a data mix of the 15 languages covered by the Geo-Clusters as shown in Table 4.

For this data mix, we used both ShareGPT dataset and the Dolly-15k dataset as described by (Aryabumi et al., 2024). First these two datasets' prompts and completions were translated into these 15 languages, and translations were done using the NLLB-3.3B model (Costa-jussà et al., 2022). In addition, we also included what we call the ShareGPT CommandR+ dataset and the Dolly-15k CommandR+ dataset. For these variants, we use the translated prompts generated completions for the translated prompts using Command R+[10]. Our datasets cover 15 languages shown in Table 4. Table 5 shows the training data distribution in terms of number of samples used for each Geo-Cluster model training.

Before using the geo-clusters as teacher models, we validate performance of our trained Geo-cluster models. We compute average win rates in each language cluster using the held-out multilingual Dolly-200 evaluation dataset (Üstün et al., 2024).

D Language Families

As we present in Section 3.3, we generate synthetic data in 23 diverse languages: *Arabic, Chinese, English, French, German, Turkish,*

[5] https://cohere.com/command
[6] https://huggingface.co/CohereForAI/c4ai-command-r-plus
[7] https://huggingface.co/mistralai/Mistral-Large-Instruct-2407
[8] https://huggingface.co/ytu-ce-cosmos/Turkish-Llama-8b-Instruct-v0.1
[9] https://huggingface.co/spaces/malhajar/OpenLLMTurkishLeaderboard_v0.2
[10] https://huggingface.co/CohereForAI/c4ai-command-r-plus

Language Cluster	Languages
GERMANIC	German, Dutch
SLAVIC	Czech, Russian, Ukrainian, Polish
ROMANCE	French, Portuguese, Spanish, Italian, Romanian
EAST-ASIAN	Korean, Japanese, Chinese, Turkish

Table 4: **Language composition of Geo-clusters:** To evaluate fixed routing, we control apriori for the strength of a model on each language in our pool by training Geo-cluster models which are specialized on different groups of languages.

	Number of Samples Per Dataset			
Language Cluster	Original ShareGPT	ShareGPT CommandR+	Original Dolly15k	Dolly15k CommandR+
GERMANIC	155,480	157,699	40,466	42,447
SLAVIC	259,217	263,488	67,721	71,121
ROMANCE	309,708	314,513	80,295	84,345
EAST ASIAN	230,848	235,369	58,864	61,743

Table 5: Number of Training Samples Per Language Cluster

Ukrainian, Dutch, Czech, Greek, Spanish, Persian, French, Hebrew, Hindi, Indonesian, Italian, Japanese, Korean, Polish, Portuguese, Russian, Vietnamese. These languages, representing different language families, are selected to ensure a comprehensive evaluation across various linguistic contexts, detailed in Table 7.

E Router Model Details

Training Details. We chose Gemma2-2B[11] as our router model for its compact size, performance, and multilingual capabilities. We fine-tuned Gemma2-2B model using the AdamW (Loshchilov and Hutter, 2019) optimizer with an initial learning rate of 5×10^{-5}. We used a linear learning rate scheduler with a 200 warmup steps. We set weight decay to 0 and fine-tuned for 2 epochs.

To further improve training efficiency, we also evaluate a smaller mT5-base[12] variant with 580M parameters. We finetuned the mT5-base using the Adafactor optimizer with 1×10^{-3} as the learning rate. We fine-tuned for 5 epochs with a train batch size of 32.

Comparison of mT5 and Gemma 2 as Router Model. We chose Gemma2-2B as the final candidate for our learned router model. The student model trained on the dataset routed by Gemma2-2B demonstrated significant improvements, particularly against the strong Gemma2-9B single teacher model. Gemma2-2B was used as the learned router in all our experiments.

Figure 9 shows Gemma2-2B and mT5-base router performances compared to random routing and single teachers. Despite its smaller size, mT5-base also achieved remarkable results, out-

[11] https://huggingface.co/google/gemma-2-2b

[12] https://huggingface.co/google/mt5-base

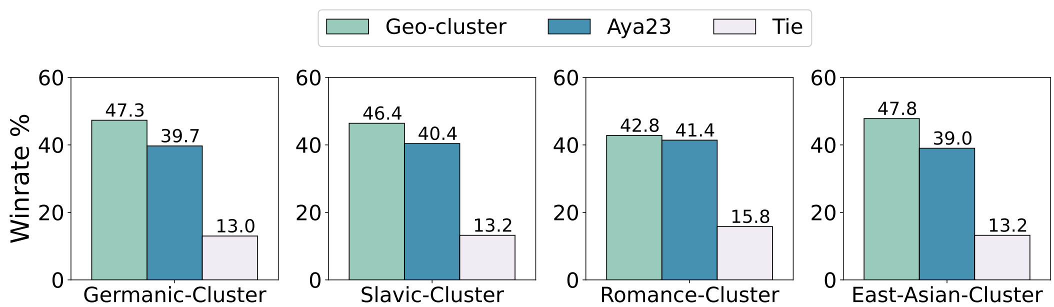


Figure 8: Geo-cluster win-rates against Aya 23 Single Teacher Model after training. All values are percentages, and aggregated over number of languages in each language cluster. Geo-cluster are powerful teacher models relative to the capabilities of the base Aya model.

Language	Model Pool
Arabic	Base Pool
Chinese	Base Pool, East Asian + Turkish Cluster, Qwen2-7B
English	Base Pool, Germanic Cluster
French	Base Pool, Romance Cluster
German	Base Pool, Germanic Cluster
Turkish	Base Pool, East Asian + Turkish Cluster, Turkish-Llama-8b
Ukrainian	Base Pool, Slavic Cluster

Table 6: Teacher model pool available for each language. The *Base Pool* consists of those outlined in Section 3.1: Aya 23, Llama 3, Gemma 2.

ISO Code	Language	Script	Family	Subgrouping	Resources
ara	Arabic	Arabic	Afro-Asiatic	Semitic	High
zho	Chinese	Han	Sino-Tibetan	Sinitic	High
eng	English	Latin	Indo-European	Germanic	High
fra	French	Latin	Indo-European	Italic	High
deu	German	Latin	Indo-European	Germanic	High
tur	Turkish	Latin	Turkic	Common Turkic	Mid
ukr	Ukrainian	Cyrillic	Indo-European	Balto-Slavic	Mid
nld	Dutch	Latin	Indo-European	Germanic	High
ces	Czech	Latin	Indo-European	Balto-Slavic	High
ell	Greek	Greek	Indo-European	Graeco-Phrygian	Mid
spa	Spanish	Latin	Indo-European	Italic	High
pes	Persian	Arabic	Indo-European	Iranian	High
fra	French	Latin	Indo-European	Italic	High
heb	Hebrew	Hebrew	Afro-Asiatic	Semitic	Mid
hin	Hindi	Devanagari	Indo-European	Indo-Aryan	High
ind	Indonesian	Latin	Austronesian	Malayo-Polynesian	Mid
ita	Italian	Latin	Indo-European	Italic	High
jpn	Japanese	Japanese	Japonic	Japanesic	High
kor	Korean	Hangul	Koreanic	Korean	Mid
pol	Polish	Latin	Indo-European	Balto-Slavic	High
por	Portuguese	Latin	Indo-European	Italic	High
rus	Russian	Cyrillic	Indo-European	Balto-Slavic	High
vie	Vietnamese	Latin	Austroasiatic	Vietic	High

Table 7: **Lineage for Cluster Languages.** 23 languages covered by our main experiments, each language's corresponding script, family, subgrouping, and if it is classified as higher or mid-resourced according to (Joshi et al., 2020).

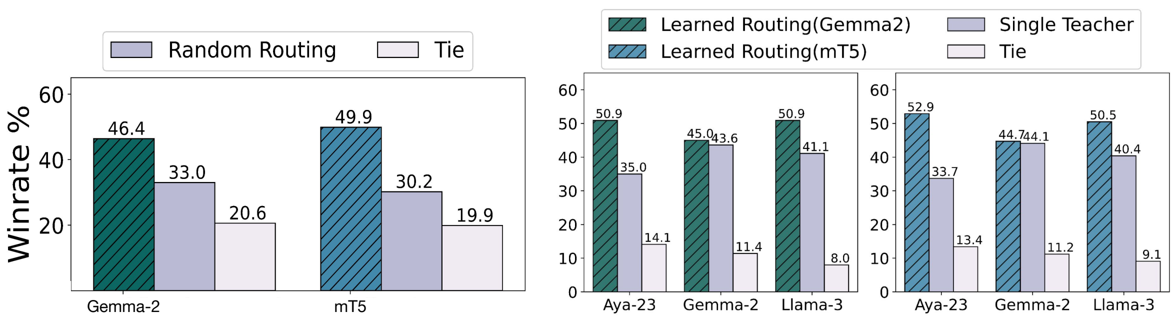


Figure 9: Win-rate % comparison of Learned Routing (mT5) and Learned Routing (Gemma2) against Random Routing (left) and multiple Single Teacher Models (right).

performing all baseline approaches with a notable 65.2% gain over random routing and an average gain of 27.7% over single teacher models.

F Difference in per-language gains.

In Figure 10, we compare both reward-based routing and learned routing strategies against random routing for medium-resource and high-resource languages.

High-resource languages (Joshi et al., 2020), English, German, French, Chinese, and Arabic see a 127.6% gain with reward-based routing and a 42.4% gain with learned routing. Medium-resource languages that includes Turkish and Ukrainian, experience greater benefits, with reward-based routing achieving a 134.7% gain and learned routing achieving a 57.1% gain over random routing. These findings suggest that medium-resource languages gain more from strategic sampling than from random routing. Detailed per-language gains are provided in Table 8.

The results indicate that reward-based routing leads to larger gains across all languages compared to learned routing, whether against single teachers or random routing. Mid-resource languages, Turkish and Ukrainian, consistently show high gains in all scenarios, followed by Arabic. However, no distinct pattern emerges for high-resource languages. Notably, reward-based routing results in significant gains for Chinese against both random routing and single teachers. Additionally, both reward-based and learned routing achieve substantial gains for English when compared to random routing.

G Discriminative tasks.

Table 9 presents the performance of various student models on three held-out discriminative tasks: XCOPA, XNLI, and XStoryCloze. The results, averaged across seven languages, highlight the relative improvements or declines in accuracy compared to the base model (AYA23).

H Textual Characteristics

To obtain a more holistic view of how multilingual arbitration impacts model generation characteristics, we report average statistics, including the number of tokens along with readability and lexical diversity scores. Metrics like length are straightforward to compute and serve as positively correlated proxies for quality (Singh et al., 2024). These metrics are calculated from model generations over 100 instances from the Dolly200 Eval set (Singh et al., 2024). We standardize comparisons across models by allowing for a maximum output length of 600 tokens.

In addition to basic statistics like length, we also compute:

Gunning Fog Index (Gunning, 1968) is a readability test that estimates the years of formal education required to understand a piece of text on the first reading. Gunning-Fog uses sentence length and prevalence of complex words to estimate the complexity of the text and assign a grade level between 0 and 20. A score of 17-18 indicates college graduate-level text.

Rix (Anderson, 1983) calculates readability based on the number of words with more than six characters divided by the number of sentences in the text. A score of 5 corresponds to a grade level of around 10, while a score of 7 or higher indicates the need for a higher educational level to comprehend.

Measure of Textual Lexical Diversity (MTLD) score (Shen, 2022) helps tracking changes in vocabulary by reflecting the average number of words in a sequence that maintains a certain type-token ratio (TTR), a measure of vocabulary variety (McCarthy and Jarvis, 2010). An MLTD score of 50 can be considered as moderate lexical diversity. All the results are presented in Table 3 and Figure 11.

Average number of tokens per generation. The most significant change is observed in the average number of tokens per generation. The base model generates an average of 76 tokens per generation, whereas routing approaches produce substantially longer outputs, ranging from 160 tokens with Fixed Routing to 242 tokens with Learned Routing. In contrast, both random routing and single teacher models (averaged across Aya 23, Llama 3, and Gemma 2) generate around 144 tokens on average. These findings demonstrate that arbitration methods result in longer text generations compared to both random routing and single teacher models.

Textual properties. The readability metrics show smaller absolute changes compared to the average number of tokens. For the Gunning-Fog index, changes range from a decrease of 0.16 for Gemma 2 to an increase of 3.28 for Learned Routing, relative to the base student model. Similarly, the Rix index varies from a decrease of 0.42 for

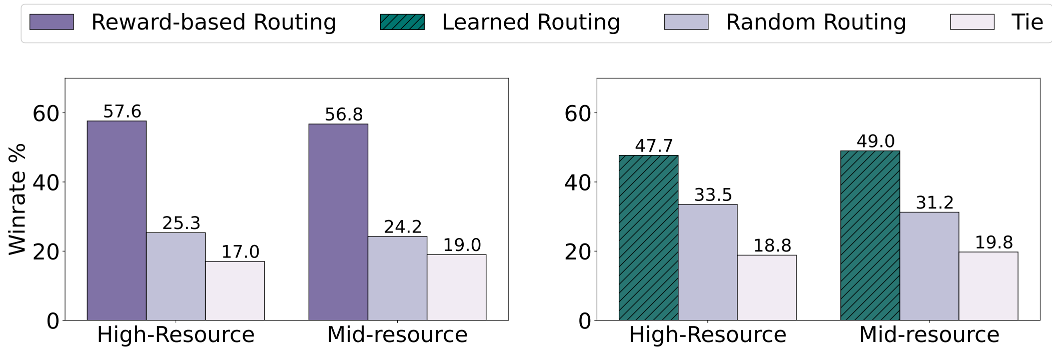


Figure 10: **Win-rate Changes Across Language Resource Level.** We compare the win rates of Mid-Resource Languages and High-Resource Languages against random-routing. Mid-resource languages consist of Turkish and Ukrainian and high-resource languages are English, German, French, Chinese and Arabic.

	% gain (Single Teachers)		% gain (Random Routing)	
Language	**Reward-based**	**Learned**	**Reward-based**	**Learned**
Arabic	75.7	43.4	115.1	43.5
Chinese	**114.5**	2.9	101.8	-4.6
English	55.2	0.4	116.0	**115.7**
French	22.5	-4.4	79.3	39.1
German	31.7	28.8	76.7	88.7
Turkish	52.2	**59.6**	**228.9**	94.5
Ukrainian	59.9	43.7	172.9	87.2

Table 8: **Win-rate gains across languages.** This table presents the percentage gain of reward-based routing and learned routing compared to single teachers and random routing across seven languages. The highest gain in each column is highlighted in **bold**, while the second highest gain is indicated in blue.

	XCOPA	XNLI	XStoryCloze	Average
BASE MODEL				
AYA23 (Base)	64.1	42.9	68.23	58.41
SINGLE TEACHER				
AYA23	65.5 ↑ 2.18	43.86 ↑ 2.23	68.05 ↓ 0.27	59.13 ↑ 1.23
LLAMA-3	65.1 ↑ 1.56	44.04 ↑ 2.65	66.46 ↓ 2.60	58.53 ↑ 0.20
GEMMA-2	66.1 ↑ 3.12	43.98 ↑ 2.51	67.74 ↓ 0.72	59.3 ↑ 1.52
TRANSLATION	64.6 ↑ 0.78	43.46 ↑ 1.30	66.77 ↓ 2.14	58.27 ↓ 0.24
MULTILINGUAL ARBITRATION				
RANDOM ROUTING	65.9 ↑ 2.80	44.01 ↑ 2.58	67.25 ↓ 1.44	59.05 ↑ 1.09
FIXED ROUTING	**67.4** ↑ 5.14	43.89 ↑ 2.30	68.33 ↑ 0.14	**59.87** ↑ 2.50
REWARD BASED ROUTING	66.2 ↑ 3.27	**44.21** ↑ 3.05	68.20 ↓ 0.05	59.53 ↑ 1.91
LEARNED ROUTER	65.8 ↑ 2.65	43.62 ↑ 1.67	**68.36** ↑ 0.19	59.25 ↑ 1.43

Table 9: Performance of Student Models on held-out Discriminative Tasks: XCOPA, XNLI, and XStoryCloze. The results are averaged over seven languages, highlighting the improvements or declines in performance compared to the base model AYA23.

Gemma 2 to an increase of 3.04 for Learned Routing. Both metrics reveal that arbitration methods result in higher scores. The Gunning-Fog index shows an absolute difference of 1.05 between arbitration methods and single teacher models, whereas the difference is 0.78 for random routing. For the Rix index, the absolute difference is 1.11 between arbitration methods and single teachers, compared to 0.65 for random routing.

These indices serve as proxies for evaluating

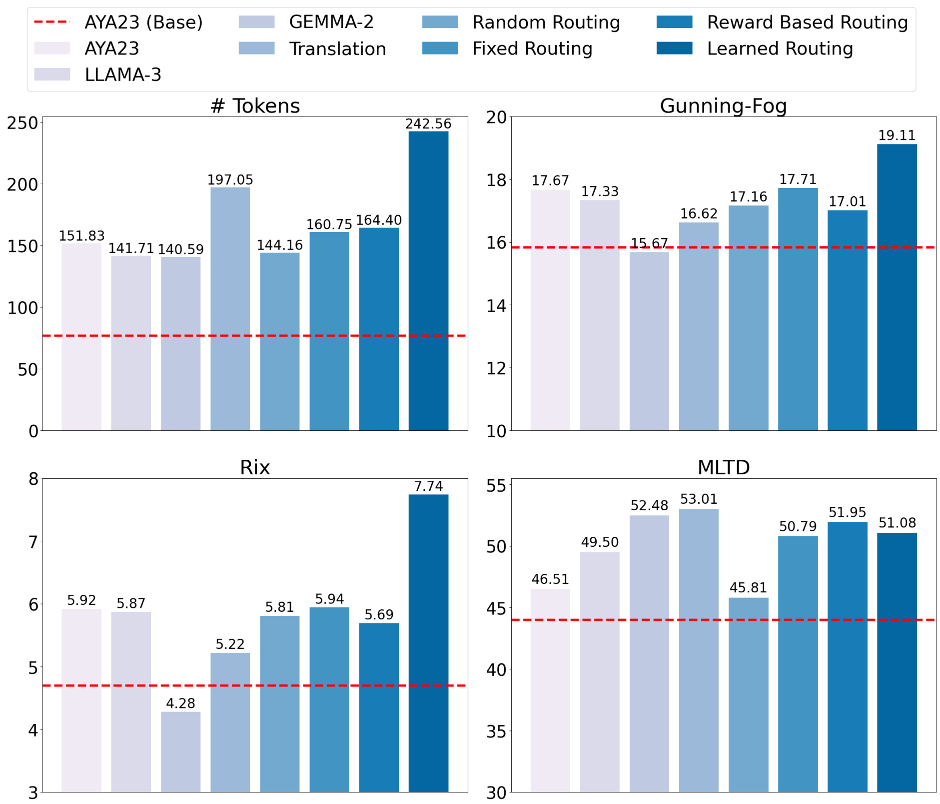


Figure 11: **Evaluation of Textual Characteristics:** We analyze characteristics of student models in four languages: ENGLISH, GERMAN, FRENCH AND UKRANIAN. The number of tokens, Gunning-Fog, Rix Index, and MLTD for each model highlights the differences in verbosity, readability and lexical diversity.

text complexity. There is a clear trend indicating that multilingual arbitration strategies, especially the learned routing approach, lead to higher readability metrics. In contrast, single teacher models, especially Gemma 2, generally result in lower values.

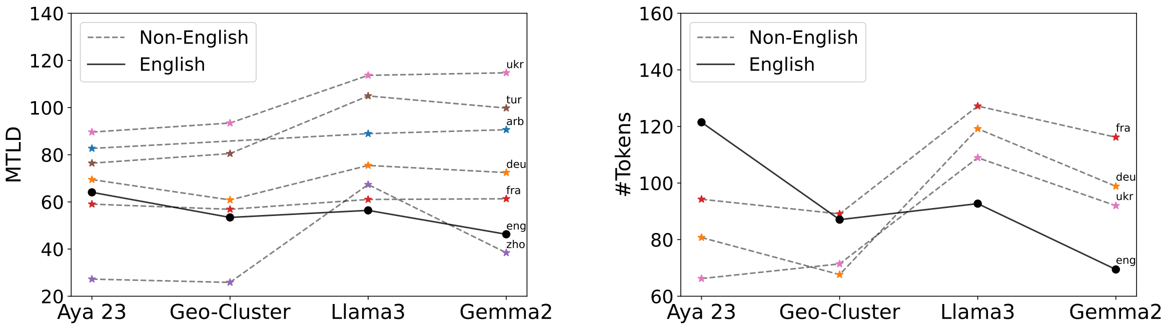
Regarding the MLTD score, we observe significant changes, with Reward-based routing showing an increase of up to 7.97 and Learned routing showing an increase of 7.1 relative to the base student model, which are considered substantial improvements (Treffers-Daller et al., 2016). Arbitration methods result in higher MLTD scores compared to both random routing and single teacher results. The average absolute difference is 1.77 between arbitration (averaged over all 3 methods) and single teacher models (averaged over Aya 23, Llama 3 and Gemma 2), while the difference is 5.46 for random routing.

Overall, multilingual arbitration strategies significantly increase the number of tokens in generations, readability metrics and improve lexical diversity compared to single teacher models. This suggests that multilingual arbitration enhances data quality and diversity, which in turn leads to improvements in student model performance and explains the significant increase in win rates.

Routed Dataset Composition Characteristics. Here, we analyze how prompt characteristics affect the reward-based router decision, using the same subset of the UltraFeedback Binarized Dataset (UFB) as depicted in Figure 6. The average MLTD score and number of tokens of the prompts routed to a particular model is shown in Figure 12.

Figure 12a shows that the average MLTD scores *for English prompts* routed to different models range from 46.28 to 64.07. Aya 23 receives English prompts with the highest MLTD score of 64.07, while Llama 3 has an average MLTD score of 56.41, and Gemma 2 has the lowest score of 46.28. In contrast, for non-English prompts, Aya 23 has an average MLTD score of 67.42, Llama 3 scores 79.66, and Gemma 2 achieves the highest MLTD score of 85.24.

Figure 12b shows that the longest English prompts are routed to Aya 23, with an average of 121.5 tokens, while Gemma 2 receives the short-



Average MTLD per model.

Average number of tokens per model.

Figure 12: **Characteristics of Prompts Routed to Given Models:** We analyze the MTLD (a) and number of tokens (b) for the set of prompts routed to each of the teacher models as selected by Reward-Based Routing. Each line represents a different language and each column is a particular teacher model.

est English prompts, averaging 69.4 tokens. English prompts routed to Geo-clusters and Llama 3 have average token counts of 87.1 and 92.7, respectively. *For non-English prompts, the pattern differs.* Geo-clusters receive the shortest prompts, averaging 78.8 tokens. Aya 23 receives prompts with an average of 90.7 tokens, Gemma 2 with 94.1 tokens, and Llama 3 receives the longest non-English prompts, averaging 112.0 tokens.

We can conclude, for English prompts, those that are more lexically diverse and longer tend to be routed to Aya 23. In contrast, for non-English prompts, Gemma 2 and Llama 3 are preferred for handling more lexically diverse and longer prompts.

I Full Budget Comparison

To show the effectiveness of reward-based routing, we also compare it against a variant, we refer to as *Full Budget*. In this variant, we include the completions generated by all M teacher models in the pool for each prompt. This results in a dataset with M times more data points than the other variants presented in the paper. The results shown in Table 10 demonstrate that strategic sampling outperforms even the version where all generations from all models are used.

J Language-Specific Win Rates

In Table 11, we present the language-specific win rates (%) for 23 languages, comparing the *Reward-Based Routing* model against the best-performing state-of-the-art model in our experiments, *Gemma2-9B-IT*. In 19 of these languages, the model trained with the reward-based routing approach achieves higher win rates than *Gemma2-9B-IT*.

Language	Reward-Based Routing	All Completions	Tie
ENGLISH	**54.0**	31.5	14.5
GERMAN	**47.5**	33.5	19.0
FRENCH	**50.0**	34.0	16.0
ARABIC	**46.5**	34.5	19.0
CHINESE	**51.0**	39.0	10.0
TURKISH	**54.5**	27.5	18.0
UKRAINIAN	**45.0**	34.0	21.0

Table 10: **Win rates (%) Comparison** of Reward-based routing trained student with all completions trained student model. The Reward-based routing variant consistently outperforms the latter with the highest gain in Turkish.

Language Code	Reward-Based Routing	Gemma2-9B-IT	Tie
ar	**57.5**	36.0	6.5
cs	**50.5**	42.5	7.0
de	**50.0**	46.0	4.0
el	**57.0**	37.5	5.5
en	37.0	**57.0**	6.0
es	41.0	**52.5**	6.5
fa	**57.0**	35.5	7.5
fr	35.0	**55.5**	9.5
he	**65.0**	29.0	6.0
hi	**50.0**	44.0	6.0
id	**53.0**	42.0	5.0
it	**49.5**	42.0	8.5
ja	44.0	**45.5**	10.5
ko	**53.0**	34.5	12.5
nl	**49.0**	46.0	5.0
pl	**49.0**	45.0	6.0
pt	**46.5**	45.5	8.0
ro	**58.0**	37.5	4.5
ru	**50.5**	44.5	5.0
tr	**47.5**	45.0	7.5
uk	**48.5**	44.5	7.0
vi	**53.5**	42.5	4.0
zh	**50.5**	44.5	5.0

Table 11: **Language-Specific Win Rates (%)** of Reward-Based Routing Compared to Gemma2-9B-IT Across 23 Languages.

K Student Model Generations

Examples of model generations in English from different student models can be found in Table 12.

Prompt: *Cats have relatively few taste buds compared to humans (470 or so versus more than 9,000 on the human tongue). Domestic and wild cats share a taste receptor gene mutation that keeps their sweet taste buds from binding to sugary molecules, leaving them with no ability to taste sweetness. Their taste buds instead respond to acids, amino acids like protein, and bitter tastes. Cats also have a distinct temperature preference for their food, preferring food with a temperature around 38 °C (100 °F) which is similar to that of a fresh kill and routinely rejecting food presented cold or refrigerated (which would signal to the cat that the "prey" item is long dead and therefore possibly toxic or decomposing). Why are cats so picky about what they eat?*

Student Model	**Generation**
Single Llama 3	Cats are known for being picky eaters, and their unique taste preferences are due to a combination of factors. The main reason is that cats have a specific temperature preference for their food, which is around 38°C (100°F). This temperature is similar to the temperature of a fresh kill, which is around 37°C (98°F) to 40°C (104°F). Cats are also born with a natural instinct to hunt and kill prey, and they are trained to associate certain temperatures with food that is fresh and safe to eat. In addition, cats have a limited number of taste buds compared to humans, which is around 470 taste buds on the tongue. This is because cats have a unique taste receptor gene mutation that prevents their sweet taste buds from binding to sugary molecules. Instead, their taste buds respond to acids, amino acids, and bitter tastes. This means that cats are not as sensitive to sweet tastes as humans are, and they are more likely to be attracted to foods that have a strong flavor or aroma. Another factor that contributes to cats' picky eating habits is their ability to detect and avoid potential toxins. Cats have a natural instinct to avoid food that is toxic or decomposed, and they are trained to associate certain temperatures and textures with potential toxins. This is why cats often reject food that is presented cold or refrigerated, as it may indicate that the food is no longer fresh or safe to eat. Overall, cats' picky eating habits are a result of their unique biological and behavioral characteristics, including their temperature preference, limited number of taste buds, and ability to detect and avoid potential toxins.
Random Routing	They have a distinct temperature preference for their food.
Reward-Based Routing	According to the text, cats are picky about what they eat because they have a distinct temperature preference for their food. They prefer food with a temperature around 38 °C (100 °F), which is similar to that of a fresh kill and routinely reject food presented cold or refrigerated. This is because cats have a genetic mutation that prevents their sweet taste buds from binding to sugary molecules, leaving them with no ability to taste sweetness. Their taste buds instead respond to acids, amino acids like protein, and bitter tastes.
Learned Routing	Cats are picky eaters due to several factors related to their biological and evolutionary traits: **Taste Sensitivity:** Cats have fewer taste buds than humans and cannot taste sweetness due to a genetic mutation. Their taste buds are more responsive to acids, amino acids, and bitter tastes, aligning with their carnivorous diet. **Temperature Preference:** Cats prefer food at around 38°C (100°F), similar to a fresh kill, and often reject cold or refrigerated food, which they may perceive as old and potentially unsafe. These factors ensure that cats consume food that meets their nutritional needs and is safe, reflecting their evolutionary adaptations as obligate carnivores.

Table 12: Comparison of student model responses trained using different methods: Single Llama 3 (best English teacher), random routing, reward-based routing, and learned routing. The Single Llama 3 student's answer is too long and includes a lot of irrelevant details, while random routing generates responses that are too brief and insufficient.

Examples of model generations in Turkish from different student models can be found in Table 13.

Prompt: *Kedilerin, insanlara kıyasla nispeten az sayıda tat alma tomurcuğu vardır (insan dilindeki 9.000'den fazla ile karşılaştırıldığında yaklaşık 470). Evcil ve yabani kediler tat alıcı gen mutasyonunu paylaşıyor. Bu da tatlı tat alma tomurcuklarının şekerli moleküllere bağlanmasını engelliyor ve tatlı tadı alma yeteneklerini kaybediyor. Onun yerine tat alma tomurcukları asitlere, protein gibi amino asitlere ve acı tatlara tepki verir. Kediler ayrıca yiyecekleri için belirgin bir sıcaklık tercihine sahiptir, taze bir öldürme ile benzer olan yaklaşık 38 °C (100 °F) sıcaklığındaki yiyecekleri tercih eder ve rutin olarak soğuk veya buzdolabında sunulan yiyecekleri reddeder (ki bu, "av" öğesinin uzun zamandır ölü olduğunu ve bu nedenle muhtemelen toksik veya çürümeye başladığını kedilere işaret eder). Neden kediler yemek konusunda bu kadar seçicidir?*

Student Model	**Generation**
Single Aya 23	Kediler, yiyecekleri için belirgin bir sıcaklık tercihine sahiptir ve taze bir avın sıcaklığını tercih ederler.
Random Routing	Kediler, yiyecekleri için belirgin bir sıcaklık tercihine sahiptir ve taze bir öldürme ile benzer olan yaklaşık 38 °C (100 °F) sıcaklığındaki yiyecekleri tercih ederler. Bu, kedilerin yiyecekleri için belirli bir sıcaklık aralığına sahip oldukları ve bu sıcaklıkta yiyecekleri tercih ettikleri anlamına gelir. Kediler ayrıca soğuk veya buzdolabında sunulan yiyecekleri reddederler, bu da yiyecekleri için belirli bir sıcaklık aralığına sahip oldukları ve bu sıcaklıkta yiyecekleri tercih ettikleri anlamına gelir. Bu, kedilerin yiyecekleri için belirli bir sıcaklık aralığına sahip oldukları ve bu sıcaklıkta yiyecekleri tercih ettikleri anlamına gelir.
Reward-Based Routing	Kediler, yiyecekleri için belirgin bir sıcaklık tercihine sahiptir ve taze bir öldürme ile benzer olan yaklaşık 38 °C (100 °F) sıcaklığındaki yiyecekleri tercih ederler. Bu, kedilerin yiyecekleri için bir sıcaklık tercihine sahip oldukları ve bu sıcaklıkta yiyecekleri tercih ettikleri anlamına gelir. Kediler ayrıca soğuk veya buzdolabında sunulan yiyecekleri reddederler, bu da yiyeceklerin "av" öğesinin uzun zamandır ölü olduğunu ve bu nedenle muhtemelen toksik veya çürümeye başladığını kedilere işaret ettiği anlamına gelir. Bu nedenle, kediler yiyecek konusunda bu kadar seçici olabilirler.
Learned Routing	Kediler, yiyecekleri için belirgin bir sıcaklık tercihine sahiptir ve taze bir öldürme ile benzer olan yaklaşık 38 °C (100 °F) sıcaklığındaki yiyecekleri tercih ederler. Bu, yiyeceklerin taze ve toksik olmamasını garanti eder.

Table 13: Comparison of student model responses trained using different methods: Single Aya 23 (best Turkish teacher), random routing, reward-based routing, and learned routing. The Aya 23 student's answer is too short and inadequate, while random-routing generates responses that are repetitive.