TOWER: An Open Multilingual Large Language Model for Translation-Related Tasks

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While general-purpose large language models (LLMs) demonstrate proficiency on multiple tasks within the domain of translation, approaches based on open LLMs are competitive only when specializing on a single task. In this paper, we propose a recipe for tailoring LLMs to multiple tasks present in translation workflows. We perform continued pretraining on a multilingual mixture of monolingual and parallel data, creating TOWERBASE, followed by finetuning on instructions relevant for translation processes, creating TOWERINSTRUCT. Our final model surpasses open alternatives on several tasks relevant to translation workflows and is competitive with general-purpose closed LLMs. To facilitate future research, we release the TOWER models, our specialization dataset, an evaluation framework for LLMs focusing on the translation ecosystem, and a collection of model generations, including ours, on our benchmark.

1 Introduction

Many important tasks within multilingual NLP, such as quality estimation, automatic post-edition, or grammatical error correction, involve analyzing, generating or operating with text in multiple languages, and are relevant to various translation workflows — we call these **translation-related tasks**. Recently, general-purpose large language models (LLMs) challenged the paradigm of *per-task* dedicated systems, achieving state-of-the-art performance on several recent WMT shared tasks (Kocmi et al., 2023; Freitag et al., 2023; Neves et al., 2023). Unfortunately, strong capabilities for *multiple* translation-related tasks have so far been exhibited by *closed* LLMs only (Hendy et al., 2023; Kocmi & Federmann, 2023; Fernandes et al., 2023; Raunak et al., 2023). Perhaps because most *open* LLMs are English-centric, approaches leveraging these models still lag behind, having thus far achieved competitive results only when specializing on a *single* task (Xu et al., 2024a; 2023; Iyer et al., 2023).

In this paper, we bridge this gap with a detailed recipe to develop an LLM for *multiple* translation-related tasks. Our approach, illustrated in Figure 1 and inspired by Xu et al.

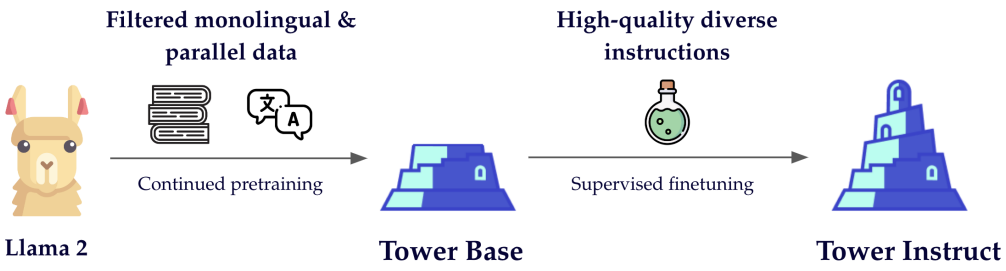


Figure 1: Illustration of our method for building TOWERBASE and TOWERINSTRUCT.

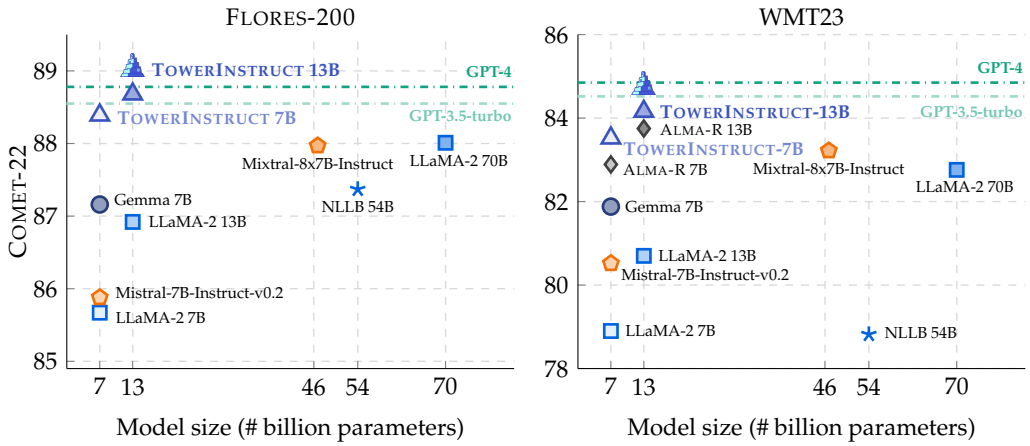


Figure 2: Translation quality on FLORES-200 and WMT23 for TOWERINSTRUCT models and a collection of open and close models across different scales. As the scale of GPT models is not known, we represent them with a horizontal line. TOWERINSTRUCT outperforms open alternatives — even of larger scales — and is competitive with GPT models.

(2024a), relies on three steps. First, we extend the multilingual capabilities of LLaMA-2 (Touvron et al., 2023b) through continued pretraining on a dataset comprising 20B tokens, creating TOWERBASE (§2.1). Importantly, while Xu et al. (2024a) employ a dataset exclusively composed by monolingual data, our approach includes parallel data as an additional cross-lingual signal. Second, we curate a dataset to specialize LLMs for translation-related tasks, TOWERBLOCKS (§2.2). Third, we perform supervised finetuning to obtain an instruction-following model tailored for the field of translation, TOWERINSTRUCT (§2.3).

We extensively evaluate all our models, comparing with open and closed alternatives on a wide range of tasks (§3). TOWERINSTRUCT consistently achieves higher translation quality than open alternatives and is competitive with the closed GPT-4 and GPT-3.5-turbo models — see Figure 2. Additionally, TOWERINSTRUCT outperforms open models in automatic post-edition, grammatical error correction, and named entity recognition. Careful ablations also outline the influence of each element in our recipe (§4). We highlight the importance of adding parallel data during continued pretraining for improved translation quality, and the effectiveness of including conversational and coding data on TOWERBLOCKS.

Accompanying this work, we release 1) the TOWER family, comprising our TOWERBASE and TOWERINSTRUCT models in the sizes of 7B and 13B; 2) our specialization dataset TOWERBLOCKS; 3) TOWEREVAL, the evaluation framework for LLMs for translation-related tasks that we used to perform all evaluations in this paper; 4) a collection of model of our benchmark to ensure reproducibility and encourage future exploration.[1]

2 TOWER: An Open Multilingual LLM for Translation-Related Tasks

Our backbone language model is LLaMA-2, which is very competitive on a wide range of tasks (Touvron et al., 2023b) and achieves the best zero-shot translation quality across available open LLMs (Xu et al., 2024a). Nevertheless, the LLaMA-2 family was exposed to relatively little non-English data during pretraining, limiting its potential for multilingual tasks, such as machine translation. We alleviate this effect by continuing the pretraining of LLaMA-2 on a highly multilingual corpus (§2.1). Afterwards, we introduce our dataset to tailor LLMs for translation-related tasks (§2.2) and finetune our continued pretrained model to obtain an instruction-following model centered around translation (§2.3).

[1]Links for the TOWER models; TOWERBLOCKS; TOWEREVAL; Zeno (Cabrera et al., 2023) project with model generations.

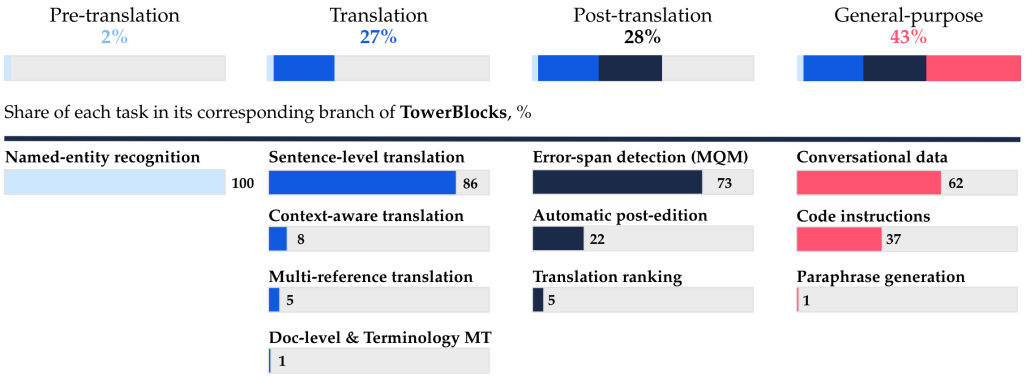


Figure 3: Tasks included in our supervised finetuning dataset TOWERBLOCKS.

2.1 TOWERBASE: Extending the multilingual capabilities of LLaMA-2

We extend LLaMA-2's training on a highly-multilingual dataset comprising 20 billion tokens — measured with the model's tokenizer — for 10 languages: English (en), German (de), French (fr), Dutch (nl), Italian (it), Spanish (es), Portuguese (pt), Korean (ko), Russian (ru), and Chinese (zh). While previous work exclusively leverages monolingual data (Xu et al., 2024b), we draw inspiration from Anil et al. (2023); Briakou et al. (2023), which include parallel data during pretraining. Specifically, we *mix parallel sentences* (one-third) along with monolingual data (two-thirds). Our results show that this approach greatly benefits translation quality (§4).

Monolingual data. We collect monolingual data from mC4 (Xue et al., 2021), a multilingual web-crawled corpus, uniformly sampling across our languages. Additionally, we *improve data quality* with standard cleaning procedures (Wenzek et al., 2019; Touvron et al., 2023a): deduplication, language identification, and perplexity filtering with KenLM (Heafield, 2011).

Parallel Data. We uniformly sample to-English (xx→en) and from-English (en→xx) language pairs from various public sources. Additionally, we *ensure translation quality* by removing sentence pairs below quality thresholds for Bicleaner (Sánchez-Cartagena et al., 2018; Ramírez-Sánchez et al., 2020) and COMETKIWI-22 (Rei et al., 2022b) — we detail parallel data sources and filtering thresholds for monolingual and parallel data in Appendix C.

Model Training. We train our models with a codebase based on Megatron-LLM (Cano et al., 2023) on 8 A100-80GB GPUs, an effective batch size of 1.57 million tokens per gradient step, and a cosine scheduler with initial and final learning rates of 3×10^{-5} and 3×10^{-6}, respectively. The training times for TOWERBASE 7B and 13B were 10 and 20 days.

2.2 TOWERBLOCKS: A dataset to tailor LLMs for translation-related tasks

We build TOWERBLOCKS prioritizing data *diversity* and *quality*. Figure 3 illustrates all tasks in the dataset. They include tasks important to translation workflows, applied before or after translation, and datasets to improve multilingual understanding and instruction-following.

Diversity. We collect records from existing datasets for all translation-related tasks, promoting *domain diversity* by including multiple datasets for each task — we detail all data sources in Appendix D. We then reformulate all records as question-answer pairs. Similar to Wei et al. (2022), we focus on *template diversity* with multiple manually curated zero- and few-shot templates for each task. Afterwards, we follow the insights from Longpre et al. (2023), constructing 75% of the records as zero-shot instructions. For the remaining records, we include either 1, 3, or 5 in-context examples uniformly sampled from the respective dataset. Finally, we increase *task diversity*, which improves held-in performance up to a

moderate number of tasks (Longpre et al., 2023), by adding a paraphrasing task, dialog data from UltraChat (Ding et al., 2023), and coding instructions from Glaive-Code-Assistant.[2]

Quality. Similar to Xu et al. (2024a), we construct our question-answer pairs from *human-annotated records*,[3] prioritizing validation or older test sets. Importantly, we ensure that records from 2023 onwards are excluded from the training data. We also *avoid reference quality issues* (Xu et al., 2024b) for tasks with reference translations, such as translation and automatic post-edition, by scoring source-reference pairs with XCOMET-QE-ENSEMBLE (Guerreiro et al., 2023) and discarding records with quality scores below 0.85. Additionally, we *avoid translationese* on the source side, which is associated with numerous quality issues (Zhang & Toral, 2019; Riley et al., 2020), by only including translation pairs in their original direction. Finally, we adopt the UltraChat (Ding et al., 2023) dialogues filtered by Tunstall et al. (2023) and additionally exclude records respective to translation requests, conversations with formatting issues (e.g., instructions starting with punctuation, and others), and instances where the assistant refuses to answer.

2.3 TOWERINSTRUCT: Specializing TOWERBASE for Translation-Related Tasks

As a final step, we obtain TOWERINSTRUCT by finetuning TOWERBASE on TOWERBLOCKS.

Dialog template. We format each dialog as a single tokenizable string using the `chatml` template (Open AI, 2023); we provide an example in Appendix E.2. This template clearly separates between instructions and answers, and allows for mutli-turn dialog. The template has three special identifiers (control tokens) to delimit messages: `<|im_start|>user` and `<|im_start|>assistant` preempt the beginning of a turn, and `<|im_end|>` marks its end. We avoid the separation of `<|im_start|>` and `<|im_end|>` into multiple tokens by extending the tokenizer for TOWERINSTRUCT with two dedicated tokens. We do not explicitly add new tokens for `user` and `assistant`, as both strings already have dedicated tokens. Additionally, we overwrite the end-of-sequence token with the `<|im_end|>` token.

Model training. We finetune the model with the standard cross-entropy loss, enabling bfloat16 mixed precision and packing (Raffel et al., 2020). We only calculate the loss on target (answer) tokens. We train for 4 epochs using a low learning rate and a large batch size — we detail all hyperparameters in Appendix E.1. We found that this combination performed the best and eliminated step-wise training losses that have been observed in recent models (Tunstall et al., 2023; Lv et al., 2023).[4] Our training took around 50h on 4 NVIDIA A100-80GB GPUs and leveraged the Axolotl framework[5] and DeepSpeed (Rasley et al., 2020) for model parallelism.

3 Experiments

3.1 Experimental Setup

Datasets and Tasks. We analyze translation capabilities using FLORES-200 (NLLB Team et al., 2022), WMT23 (Kocmi et al., 2023), and TICO-19 (Anastasopoulos et al., 2020). Additionally, we examine three translation-related tasks. First, we evaluate automatic post-edition (APE) by measuring final translation quality after post-editing NLLB-3.3B (NLLB Team et al., 2022) translations for WMT23. Second, we evaluate named entity recognition

[2] https://huggingface.co/datasets/glaiveai/glaive-code-assistant

[3] For named entity recognition, we did not find a permissively licensed human-annotated dataset, so we use MultiCoNER (Malmasi et al., 2022; Fetahu et al., 2023). For general translation, we include a small amount of parallel data from OPUS to cover all language pairs. Nevertheless, we apply Bicleaner using a threshold of 0.85 followed by the quality filtering procedure described in this section.

[4] One hypothesis put forward in Howard & Whitaker (2023) is that LLMs can rapidly memorize examples during training with one gradient step. In fact, the sudden downward shifts in loss occur precisely when a new epoch starts.

[5] https://github.com/OpenAccess-AI-Collective/axolotl

(NER), useful for entity anonymization, using the test split from MultiCoNER 2023 (Fetahu et al., 2023).[6] Third, we evaluate grammatical error correction (GEC), which is *held out* from our training data and can be applied to correct the source sentence before translation. We test GEC on CoNLL-2014 (Ng et al., 2014) (English), COWSL2H (Yamada et al., 2020) (Spanish), and mlconvgec2018 (Chollampatt & Ng, 2018) (German).

Baselines. On all tasks, we compare the TOWER models with the open models LLaMA-2 70B (Touvron et al., 2023b) and Mixtral-8x7B-Instruct (Jiang et al., 2024), and the closed-source models GPT-3.5-turbo and GPT-4.[7] For the task of machine translation, we also compare with dedicated systems NLLB-54B (NLLB Team et al., 2022) and ALMA-R (Xu et al., 2024b). We also report numbers on other open alternatives — Gemma 7B (Gemma Team, 2024), Mistral-7B-Instruct-v0.2 (Jiang et al., 2023) and Qwen1.5 72B (Bai et al., 2023) — in Appendix F.[8] All model generations are performed with greedy decoding — we explore alternative decoding methods in Appendix A. For LLaMA-2 70B and Mixtral-8x7B-Instruct, we always provide 5 in-context learning examples randomly selected from the development set in the prompt. Unless specified, we evaluate all other models in a 0-shot fashion.

Evaluation. We evaluate translation quality with COMET-22 (Rei et al., 2022a) for both MT and APE. For translation, we also report XCOMET (Guerreiro et al., 2023), COMETKIWI-22 (Rei et al., 2022b), BLEURT (Sellam et al., 2020), and CHRF (Popović, 2015) in Appendix F.[9] For GEC, we measure edit rate (ER) (Snover et al., 2006) and report ERRANT(Bryant et al., 2017; Felice et al., 2016) in Appendix G. For NER, we measure sequence F1 score. On all tasks, we also report performance clusters based on statistically significant performance gaps. For a given language, we verify whether measured differences between all system pairs are statistically different.[10] Afterwards, we create *per-language* groups for systems with similar performance by following the clustering procedure in Freitag et al. (2023). Finally, we obtain system-level rankings across multiple languages using a normalized Borda count (Colombo et al., 2022), which is defined as an average of the obtained clusters. Note that a first cluster will not exist if no model significantly outperforms all others on a majority of languages.

3.2 Translation

We report aggregated results for all models on FLORES-200, WMT23 and TICO-19 in Table 1. In Table 2, we study the translation quality on all languages in our training set using FLORES-200, considering both en→xx and xx→en translation directions.

TOWERINSTRUCT 13B is the open system with highest translation quality. TOWERINSTRUCT 13B consistently outperforms the larger open models LLaMA-2 70B and Mixtral-8x7B-Instruct, as well as the dedicated systems NLLB-54B and ALMA-R across the board. On FLORES-200, TOWERINSTRUCT 13B is often ranked first, and is close to GPT-4 performance on WMT23 and TICO-19. Upon inspecting both systems' outputs, we verified that the gap between them increases with longer sentences, as is shown in Figure 4.[11] Notably, this

[6] We uniformly sample 1000 of the more than 200k records due to the computational costs of evaluating all models on the whole test set.

[7] We use `gpt-3.5-turbo-0613` and `gpt-4-0613` available from the official OpenAI API.

[8] TOWERINSTRUCT outperforms all these open alternatives.

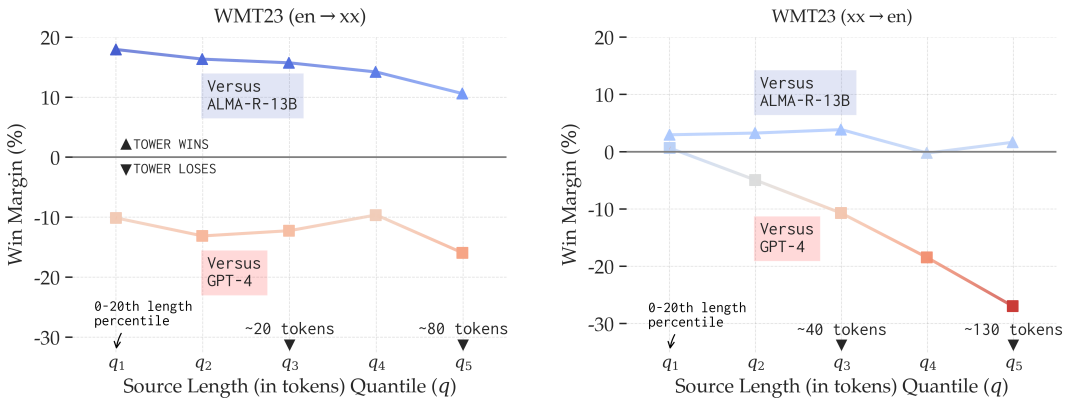
[9] We find that performance trends largely hold across metrics. Yet, there is a significant quality gap between ALMA-R and TOWER models in terms of CHRF — e.g., over 7 points in en→xx directions on WMT23 — which is not found with neural metrics. We posit that ALMA-R's alignment process on translations preferred by COMETKIWI-XXL (Rei et al., 2023) and XCOMET may inadvertently degrade performance on lexical metrics. Exploring evaluation dynamics after alignment with translation quality metrics is a promising direction for future work.

[10] We apply significance testing at a confidence threshold of 95%. For segment-level metrics such as COMET-22 we can perform significance testing at the segment level. However, for corpus-level metrics such as ER and Sequence F1, we follow Koehn (2004) and perform bootstrapping with 100 samples of size 500 each, applying significance testing on the sample scores.

[11] A similar domain-level analysis did not find any domain dissimilar from the others.

Models	FLORES-200 en→xx	FLORES-200 xx→en	WMT 23 en→xx	WMT 23 xx→en	TICO 19 en→xx
Closed					
GPT-3.5-turbo	88.95 2	88.14 3	85.56 2	83.48 2	87.36 2
GPT-4	**89.13** 1	**88.42** 1	**86.01** 1	**83.69** 1	**87.52** 1
Open					
NLLB 54B	86.79 4	87.95 3	78.60 7	79.06 6	87.05 2
LLaMA-2 70B	87.82 4	88.19 2	82.95 6	82.56 4	86.46 4
Mixtral-8x7B-Instruct	87.76 3	88.17 2	83.60 5	82.84 3	86.60 4
ALMA-R 7B	—	—	83.40 5	82.39 4	—
ALMA-R 13B	—	—	84.46 3	83.03 3	—
TOWERINSTRUCT 7B	88.51 3	88.27 2	84.28 3	82.77 4	87.01 3
TOWERINSTRUCT 13B	88.88 2	**88.47** 1	85.14 2	83.18 2	87.32 2

Table 1: Results for machine translation aggregated by language pair. Models with statistically significant performance improvements are grouped in quality clusters. We highlight the best ranked models in bold and underline the best ranked open models.



(a) en→xx directions.

(b) xx→en directions.

Figure 4: Win rates margin of TOWERINSTRUCT-13B by length of the tokenized source for (a) en→xx and (b) xx→en language pairs for the WMT23 test set. We compare against GPT-4 (□) and ALMA-R (△). We define a (sentence-level) win if the delta between two systems is superior to 1 COMET-22 point.

trend vanishes when comparing TOWERINSTRUCT 13B to ALMA-R. We posit this difference stems from a prevalence of shorter sentence-level translations in the training data of both TOWERINSTRUCT 13B and ALMA-R. In future work, we would like to explore how to better leverage longer contexts, which can benefit instruction-following (Zhao et al., 2024).

TOWERINSTRUCT 13B achieves high translation quality across all language directions. In Table 2, TOWERINSTRUCT 13B is ranked first for the majority of en→xx directions, and is among the top performing models for all but one xx→en language pair. Notably, TOWERINSTRUCT stands out as the best overall model — outperforming GPT-4 — for both pt→en and ru→en language pairs. This outcome likely stems from the English-centric pretraining of the LLaMA-2 family. A longer, *more expensive* continued pretraining might improve performance on en→xx directions further. In fact, we show in Section 4 that the translation quality gains from LLaMA-2 are larger for en→xx language directions.

Models	FLORES-200 (en→xx) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	88.78 2	**87.08** 1	**89.02** 1	**89.06** 1	89.36 2	**88.63** 1	**90.46** 1	89.56 3	88.58 2
GPT-4	**88.98** 1	**87.10** 1	**88.93** 1	**89.05** 1	**90.06** 1	**88.56** 1	**90.43** 1	**90.19** 1	**88.87** 1
Open									
NLLB 54B	87.18 5	85.92 4	87.71 3	88.10 3	89.00 3	87.33 3	88.72 5	88.89 4	78.26 7
LLaMA-2 70B	87.31 5	86.41 3	87.82 3	88.22 3	88.07 4	87.47 3	89.11 4	88.65 5	87.32 5
Mixtral-8x7B-Instruct	87.99 3	86.80 2	88.53 2	88.77 2	85.63 5	87.57 3	89.45 3	89.09 4	85.99 6
TOWERINSTRUCT 7B	87.82 4	86.76 2	88.44 2	88.73 2	89.41 2	88.38 2	89.60 3	89.53 3	87.90 4
TOWERINSTRUCT 13B	88.16 3	**87.06** 1	**88.92** 1	**89.21** 1	**89.92** 1	**88.63** 1	89.78 2	89.95 2	88.29 3

Models	FLORES-200 (xx→en) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	89.60 2	87.26 3	89.46 3	88.03 3	87.83 3	87.71 2	89.78 3	86.69 4	86.92 2
GPT-4	**89.76** 1	**87.57** 1	**89.61** 1	88.21 2	**88.58** 1	**87.88** 1	89.94 2	86.94 2	**87.29** 1
Open									
NLLB 54B	89.17 4	87.25 3	89.29 4	87.91 3	87.86 3	87.49 3	89.38 4	86.66 4	86.55 3
LLaMA-2 70B	89.44 3	87.49 2	89.55 2	88.18 2	87.91 3	87.52 3	89.84 2	86.87 2	86.91 2
Mixtral-8x7B-Instruct	89.57 2	**87.65** 1	89.56 2	**88.44** 1	87.37 4	87.54 3	89.73 3	86.81 3	86.88 2
TOWERINSTRUCT 7B	89.48 3	87.48 2	89.50 2	**88.39** 1	88.16 2	87.66 2	89.92 2	86.90 2	86.96 2
TOWERINSTRUCT 13B	89.61 2	**87.62** 1	**89.67** 1	**88.42** 1	**88.48** 1	**87.92** 1	**90.07** 1	**87.20** 1	**87.27** 1

Table 2: Translation quality on FLORES-200 by language pair. Models with statistically significant performance are grouped in quality clusters. Best ranked models are in bold and best ranked open models are underlined.

Models	APE↑ en→xx	xx→en	GEC↓ Multilingual	NER↑ Multilingual
Baseline (no edits)	76.80	79.99	16.66	—
Closed				
GPT-3.5-turbo	81.47 4	78.68 5	15.06 2	50.22 4
GPT-4	**85.20** 1	**84.30** 1	15.08 2	59.88 3
Open				
LLaMA-2 70B	78.34 5	81.03 4	21.74 5	44.62 5
Mixtral-8x7B-Instruct	82.64 3	82.81 2	17.10 4	41.77 6
TOWERINSTRUCT 7B	82.69 2	81.56 4	15.13 3	71.68 2
TOWERINSTRUCT 13B	83.31 2	82.26 2	15.68 2	**74.70** 1

Table 3: Results for translation-related tasks aggregated by language or language pair. Models with statistically significant performance improvements are grouped in quality clusters. We highlight the best ranked models in bold and underline the best ranked *open* models. Since GEC is a held out task, we evaluate all models with 5 in-context examples.

TOWERINSTRUCT 7B achieves a trade-off between performance and scale. The smaller TOWERINSTRUCT 7B, although behind TOWERINSTRUCT 13B, is competitive with other open systems and achieves GPT-3.5-turbo translation quality for some language pairs. Importantly, it outperforms the only system of the same size, ALMA-R 7B.

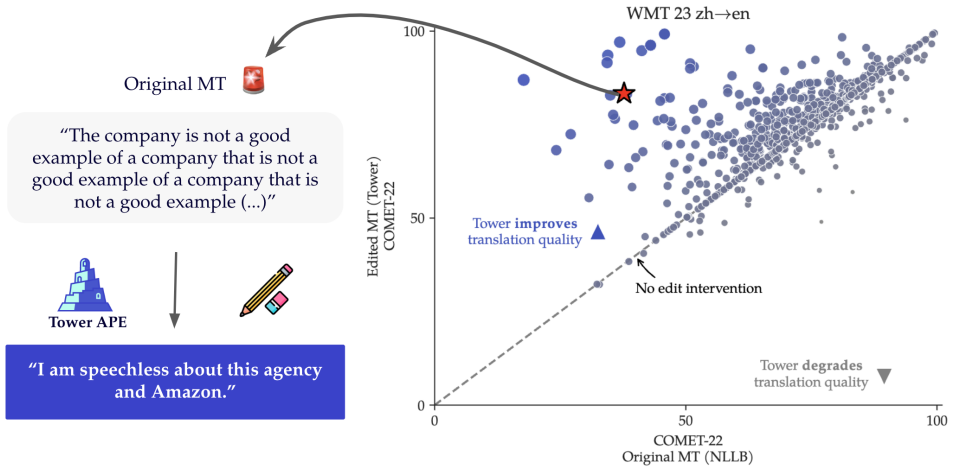


Figure 5: Comparison of NLLB 3B original translation quality (x-axis) with TOWERINSTRUCT 13B post edition quality (y-axis), and a concrete example (left). Each dot is a WMT 23 zh→en translation. Marker size and hue represent the difference between post-edition and original translation qualities. The source and reference of the highlighted post edition are "对这个代理公司和亚马逊实在是很无语。" and "As it relates to this agency and Amazon, I am truly stunned.", respectively. Similar patterns hold on other LPs.

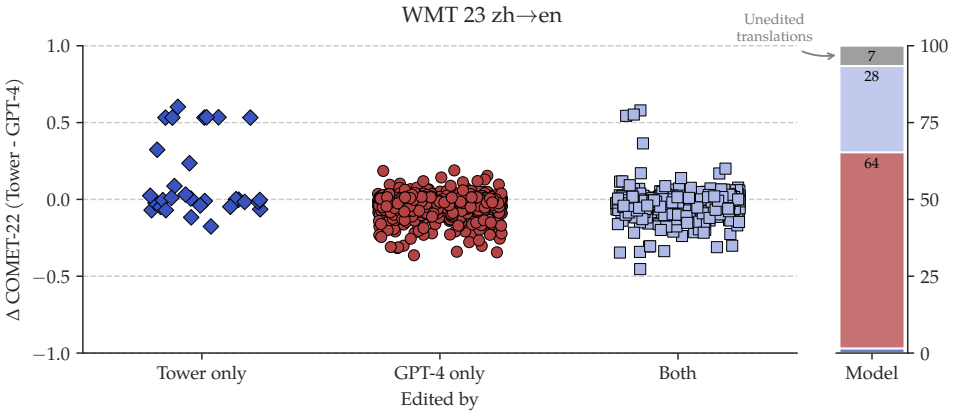


Figure 6: Difference in translation quality after post-edition for cases where only TOWERINSTRUCT 13B edits (◇), only GPT-4 edits (○), or both models edit (□). The bar to the right represents the percentage of instances corresponding to each case. Each dot is a WMT23 zh→en NLLB 3.3B translation, and similar patterns are observed on other LPs.

3.3 Translation-Related Tasks

In Table 3, we report the results for all translation-related tasks, for both open and closed models, aggregated by language or language pair.[12]

TOWERINSTRUCT is an effective translation post editor. TOWERINSTRUCT outperforms open models and GPT-3.5-turbo on APE. The model's post editions consistently and significantly improve the quality of NLLB 3B translations, going as far as converting oscillatory hallucinations into high-quality translations (Figure 5). However, GPT-4 is still the top performer on this task. One factor that could be behind this gap is that GPT-4 edits much more often than TOWERINSTRUCT, as shown by Figure 6: almost 90% of instances are edited

[12]Appendix G.1 details evaluated languages and provides results for APE and GEC.

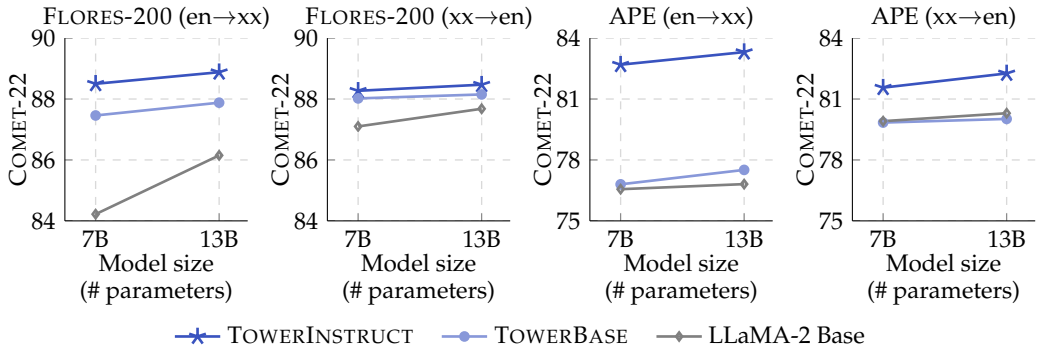


Figure 7: Recipe ablation across TOWER scales on FLORES-200 and APE for en→xx and xx→en directions. Numbers with pretrained models are obtained in a 5-shot setup; TOWERINSTRUCT, on the other hand, is obtained in a 0-shot fashion.

by GPT-4, compared to the 30% of TOWERINSTRUCT.[13] We posit that TOWERINSTRUCT learns a tendency for more minimal editing from the relative abundance — roughly 38% — of unedited segments in TOWERBLOCKS.

There is room for improvement on grammatical error correction. On this task, no model significantly outperforms the others on the majority of languages considered. We hypothesize the relatively average performance of TOWERINSTRUCT is caused by the absence of GEC data in TOWERBLOCKS.

TOWERINSTRUCT can identify named entities in multiple languages. TOWERINSTRUCT 13B shows promising performance on NER, surpassing GPT-4 by about 15 F1 points. Similar to APE, most of these improvements are already reflected on TOWERINSTRUCT 7B, highlighting its capabilities despite the smaller parameter scale. Other open models do not perform well on this task, even with 5 in-context examples. We hypothesize these results stem from NER being a token-level classification task, as opposed to a generative one. While the models can learn the expected output format from the examples or task description, they struggle to grasp the classification function itself. Conversely, TOWERINSTRUCT can learn the task from the records in TOWERBLOCKS.

4 Dissecting the training recipe

We performed multiple ablations to provide insights on the impact of the several design choices made in the development of the TOWER models.

Continued pretraining and supervised finetuning yield independent performance gains. The two leftmost plots of Figure 7 illustrate translation quality after continued pretraining and supervised finetuning. Both steps bring performance improvement at both model scales. Remarkably, TOWERBASE 7B and TOWERINSTRUCT 7B outperform LLaMA-2 13B, and TOWERINSTRUCT 7B outperforms TOWERBASE 13B. In the two rightmost plots, we analyze APE. For this task, while supervised finetuning yields better performance, continued pretraining — and in particular parallel data — does not improve performance as observed for translation. In future work, we would like to explore additional training signals during continued pretraining to increase performance for translation-related tasks.

Parallel data during continued pretraining improves translation quality. Figure 8 reports 5-shot translation quality on FLORES-200 for multiple continued pretraining data recipes. Mixing monolingual and parallel data achieves the highest quality, outperforming both monolingual only and parallel only data. In general, improvements are more noticeable on

[13]This result suggests that GPT-4 is over-editing, which we further analyze in Appendix §B

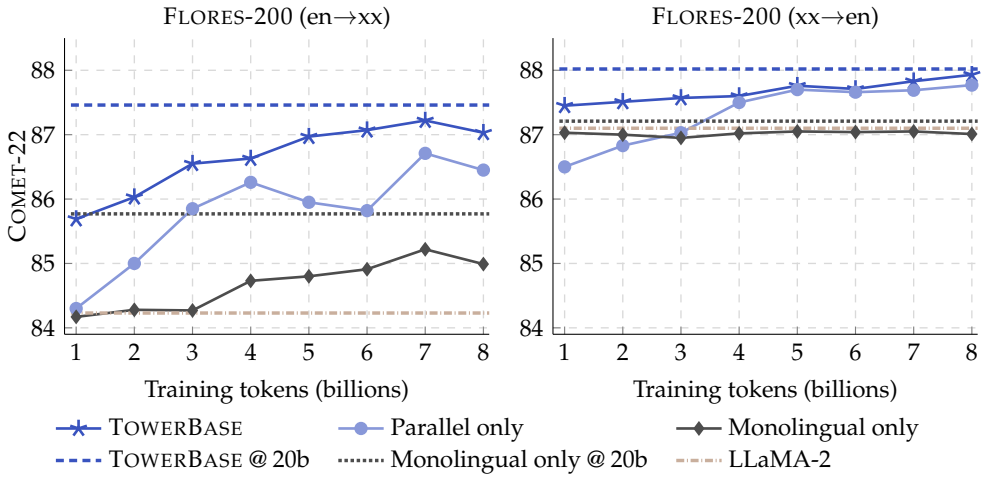


Figure 8: Translation quality on FLORES-200 for continue pretraining data recipes. The TOWERBASE recipe, outlined in Section 2.1, mixtures monolingual with parallel data. The "Parallel only" recipe only processed 8 billion tokens due to compute constraints.

Model	MT en→xx	MT xx→en	APE↑ en→xx	APE↑ xx→en	GEC↓ Multilingual	NER↑ Multilingual
LLaMA-2 7B	84.23	87.10	76.56	79.91	15.95	20.09
TOWERBASE 7B	87.46	88.02	76.79	79.83	15.41	20.51
Supervised Finetuning						
+ MT	88.45	**88.28**	79.19	79.36	54.76	0.00
+ Pre-MT + Post-MT	87.92	87.96	81.95	**81.73**	17.44	**74.92**
+ General-Purpose	**88.51**	88.27	**82.69**	81.56	**15.13**	71.68

Table 4: Ablation results for the components of TOWERBLOCKS. Results for pretrained models are obtained with 5 in-context examples while results for supervised models are obtained in a 0-shot setup. We consider FLORES-200 to evaluate translation quality.

en→xx directions, likely due to the English-centric nature of LLaMA-2's training. Nevertheless, while monolingual only data improves over the base LLaMA-2 by 0.1 COMET-22 points on xx→en directions, our recipe gains nearly a full point.[14]

Parallel data during continued pretraining is sample efficient, but quality continues to improve with more tokens. At the 2 billion tokens mark, combining parallel sentences with monolingual data (i) yields more than 50% of the improvement over the base model, and (ii) surpasses the recipe leveraging solely monolingual data. Additionally, while training on more tokens has diminishing returns — 85% of the total performance gains appear by the 5 billion tokens mark — it continues to improve translation quality.

Transfer/interference relations between tasks are complex. Table 4 ablates the components of TOWERBLOCKS. We finetune on translation data, translation-related tasks including pre- and post-translation, and the full dataset with general-purpose tasks. While adding translation-related tasks improves their performance, it decreases translation quality. We hypothesize that the reduced number of tasks encourages the model to "split" its capacity, independently learning each task. Remarkably, introducing general-purpose instructions recovers translation quality, possibly due to the difficulty of "splitting" capacity for a large

[14]While 0.1 COMET-22 points translates to 54.9% human agreement, one COMET-22 point translates to 90.9% (Kocmi et al., 2024).

number of tasks. In future work, we would like to explore transfer/interference between tasks using scaling laws.

5 Related Work

Previous work explored various approaches for adapting open models to *single* tasks within the field of machine translation (Xu et al., 2024a; 2023; Iyer et al., 2023), yielding results competitive with closed models or dedicated systems. Notably, Xu et al. (2024a) proposes a two-step approach to adapt LLaMA-2 for translation. Their approach first extends the multilingual capabilities of LLaMA-2 with continued pretraining on *monolingual* data and then specializes for translation by finetuning on high quality parallel data.

Our work also adopts a similar approach, but introduces *parallel* data during continued pretraining and leverages LLMs' instruction-following capabilities to build a system capable of performing *multiple* translation-related tasks.

Multilinguality in LLMs. While English-centric LLMs can solve tasks in non-English languages, their potential is often limited by the lack of multilingual data in their training corpus. Works on building more multilingual LLMs bridge this gap in one of two ways: either by training a model "from scratch" on more multilingual data (Wei et al., 2023; Faysse et al., 2024), or by continuing the pretraining on data for the language(s) of interest, possibly with vocabulary extension (Cui et al., 2023; Xu et al., 2024a; Pires et al., 2023).

Our multilingual extension approach builds upon insights showcasing the effectiveness of parallel data during pretraining (Anil et al., 2023; Wei et al., 2023) and includes *parallel* sentences during continued pretraining of LLaMA-2 without vocabulary extension, as preliminary experiments yielded negative results.

Specialization of LLMs. Recent research also highlights the efficacy of tailoring LLMs for subsets of closely-related tasks. Again, works are split into training models "from scratch" with domain-specific data (Taylor et al., 2022; Wu et al., 2023), continued pretraining with data tailored to increase knowledge of the field (Lewkowycz et al., 2022; Chen et al., 2023), supervised finetuning on domain-specific datasets (Yue et al., 2024) or a combination of the last two (Rozière et al., 2023; Liu et al., 2023).

Our specialization approach is broadly inspired by instruction tuning (Wei et al., 2022; Sanh et al., 2022),[15] which finetunes language models on a collection of tasks formatted as natural language instructions. Specifically, we curate a dataset for supervised finetuning to specialize LLMs for translation-related tasks. We also leverage the findings from Longpre et al. (2023); Wang et al. (2023); Zhou et al. (2023); Xu et al. (2024a), and prioritize data quality and diversity in our dataset.

6 Conclusion

We propose a new recipe for specializing LLMs to *multiple* translation-related tasks. First, we expand the multilingual capabilities of LLaMA-2 with continued pretraining on a highly multilingual corpus. Then, we finetune the model on a dataset of high-quality and diverse instructions for translation-related tasks. Our final model consistently outperforms *open* alternatives on multiple translation-related tasks, and is competitive with *closed-source* models such as GPT-4.

We release the TOWER models, as well as TOWERBLOCKS. Moreover, we also make available all the code used for this paper's benchmark, TOWEREVAL, as well as all model generations for the translation benchmark. The Github repository comes with instructions on how to reproduce the paper's results, and the generations are available on the Zeno platform to allow for interactive exploration.

[15] In this paper, we adopt the nomenclature of supervised finetuning to refer to instruction tuning.

Acknowledgments

We thank António Farinhas and Manuel Faysse for the fruitful discussion throughout the project. Part of this work was supported by the EU's Horizon Europe Research and Innovation Actions (UTTER, contract 101070631), by the project DECOLLAGE (ERC-2022-CoG 101088763), by the Portuguese Recovery and Resilience Plan through project C645008882-00000055 (Center for Responsible AI), and by Fundação para a Ciência e Tecnologia through contract UIDB/50008/2020. We also thank GENCI-IDRIS for the technical support and HPC resources — Jeanzay grants 101838, 103256, 103298 and Adastra grants C1615122, CAD14770, CAD15031 — used to partially support this work.

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A Analysis of alternative decoding strategies

Models	FLORES-200 en→xx	FLORES-200 xx→en	WMT 23 en→xx	WMT 23 xx→en	TICO 19 en→xx
GPT-3.5-turbo	77.08	78.12	72.06	**72.50**	75.91
GPT-4	77.26	78.51	**72.54**	**72.91**	**76.16**
TOWERINSTRUCT 13B					
Greedy	76.89	78.67	70.87	71.75	75.40
Beam	77.40	**78.87**	71.31	71.88	75.66
MBR	**77.79**	**78.96**	72.29	72.36	76.13

Table 5: Impact of beam search and minimum Bayes risk (MBR) decoding in translation quality for TOWERINSTRUCT 13B. In bold, we highlight systems in the first quality cluster. For TICO-19 there is no first cluster since no model significantly outperforms the others on a majority of the language pairs.

In this section, we analyse the performance of TOWERINSTRUCT 13B with beam-search (Reddy, 1977) using beam size of 5 and minimum Bayes risk (MBR) decoding (Eikema & Aziz, 2020; Fernandes et al., 2022; Freitag et al., 2022) with 20 hypotheses and COMET-22 as an utility function. We generate hypotheses using temperature and nucleus sampling (Holtzman et al., 2020), with $t = 0.9$ and $p = 0.6$. We avoid "optimizing" the evaluation metric (Fernandes et al., 2022) by measuring translation quality with BLEURT.

Table 5 reports translation quality across all test sets. Both decoding strategies consistently improve translation quality over greedy decoding, with MBR decoding achieving higher quality. Additionally, for both WMT23 and TICO-19, decoding strategies close the gap to GPT-4. Notably, on FLORES-200, TOWERINSTRUCT 13B appears isolated in the first cluster.

B Further analysis on TOWERINSTRUCT and GPT-4 editing tendencies

Figure 9 shows that differences between GPT-4 and TOWERINSTRUCT edit rates are not strongly correlated to differences in COMET-22 (0.34 Spearman ρ). This means that GPT-4 edits often do not correspond to gains in performance. This finding, allied with the discussion in Section 3.3 about GPT-4 editing considerably more than TOWERINSTRUCT, suggests that GPT-4 may be editing too much.

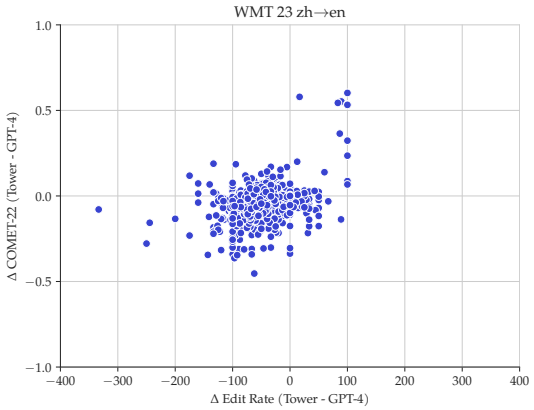

Figure 9: Difference between TOWERINSTRUCT 13B and GPT-4 edit rate (compared to the original NLLB translation) (x-axis), and difference between TOWERINSTRUCT 13B and GPT-4 post-edition COMET-22 (y-axis). The correlation between the two variables is 0.34 Spearman ρ. Similar patterns are observed for other language pairs.

C Details of the continued pretraining dataset

In Table 6, we report the perplexity floors and ceilings used to filter the monolingual data in the continued pretraining corpus, as well as the Bicleaner and CometKiwi-22 thresholds used to filter the parallel data. In Table 7, we also detail all sources of the parallel sentences used in the continued pretraining dataset.

	en	de	fr	nl	es	pt	ru	zh	ko
Min. perplexity ∗	50	50	50	50	50	50	50	50	50
Max. perplexity ∗	516	611	322	649	275	257	334	2041	198
Bicleaner †	-	0.5	0.5	0.5	0.5	0.5	0.5	0.0	0.5
COMETKIWI-22 †	-	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75

Table 6: Quality filtering thresholds applied on monolingual data (∗) and parallel data (†) by language. On the latter, the to-English language pair's threshold is the same as the corresponding from-English one.

Dataset	Version
Europarl (Koehn, 2005)	v8
ParaCrawl (Esplà et al., 2019)	v9
MultiParaCrawl (Esplà et al., 2019)	v7.1
CCMatrix (Schwenk et al., 2020)	v1
CCAligned (El-Kishky et al., 2020)	v1
MultiCCAligned (El-Kishky et al., 2020)	v1
WikiTitles (Tiedemann, 2012)	v2014
WikiMatrix (Schwenk et al., 2019)	v1
News-Commentary (Tiedemann, 2012)	v16
OPUS100 (Zhang et al., 2020)	v1
TildeModel (Rozis & Skadiņš, 2017)	v2018
Bible (Mayer & Cysouw, 2014)	v1
Ubuntu (Tiedemann, 2012)	v14.10
Tatoeba (Tiedemann, 2012)	v2
GNOME (Tiedemann, 2012)	v1
GlobalVoices (Tiedemann, 2012)	v2018q4
KDE4 (Tiedemann, 2012)	v2
KDE-Doc (Tiedemann, 2012)	v1
PHP (Tiedemann, 2012)	v1
Wikipedia (Wołk & Marasek, 2014)	v1.0
Wikimedia (Tiedemann, 2012)	v20210402
JRC (Tiedemann, 2012)	v3.0
DGT (Tiedemann, 2012)	v2019
EuroPat (Europat)	v3
EUbookshop (Tiedemann, 2012)	v2
EMEA (Tiedemann, 2012)	v3
EUConst (Tiedemann, 2012)	v1
tico-19 (Anastasopoulos et al., 2020)	v20201028
ECB (Tiedemann, 2012)	v1
Elitr-ECA (Williams & Haddow, 2021)	v1
MultiUN (Eisele & Chen, 2010)	v1
OpenOffice (Tiedemann, 2012)	v3
Ada83 (Tiedemann, 2012)	v1
infopankki (Tiedemann, 2012)	v1
Scielo (Soares et al., 2018)	v1
giga-fren (Tiedemann, 2012)	v2
UNPC (Ziemski et al., 2016)	v1.0

Table 7: The various data sources used to create the parallel data with the number of available language pairs.

D Details of TOWERBLOCKS

This appendix details all datasets utilized in TOWERBLOCKS:

- **WMT14 to WMT21**[16] — Evaluation sets for the general machine translation shared task;
- **WMT22 with quality-shots** (Hendy et al., 2023) — Evaluation set from WMT23 with high quality in-context examples;
- **NTREX** (Federmann et al., 2022) — Professional translations of the WMT19 test set;
- **FLORES-200** (NLLB Team et al., 2022) — Development set of the FLORES-200 dataset for all languages included in training;
- **FRMT** (Riley et al., 2022) — Human translations of English Wikipedia sentences into regional variants;
- **OPUS** (Tiedemann, 2012) — Parallel corpora from which we sampled very high-quality samples for all language pairs;
- **QT21** (Specia et al., 2017) and **ApeQuest**[17] — Translation data with post-edits utilized for general translation and automatic post-editing;
- **MT-GenEval** (Currey et al., 2022) — Gender translation benchmark which we leveraged for general translation and context-aware translation;
- **WMT20 to WMT22 Metrics MQM**[18] — MT evaluation data annotated with multidimensional quality metrics (Lommel et al., 2014) that we used to perform error span detection;
- **WMT17 to WMT22 Metrics DAs**[19] — MT evaluation data annotated with direct assessements (DAs) (Graham et al., 2013) which we utilized for translation ranking.
- **WMT21 Terminology**[20] — Development set for the WMT21 terminology task;
- **Tatoeba** (Tiedemann, 2020) — Development set of the Tatoeba dataset which we used to generate translations in different languages for the same source — we identified this task as multi-reference translation;
- **MultiCoNER 2022 and 2023** (Malmasi et al., 2022; Fetahu et al., 2023) — Development sets of the named entity recognition MultiCoNER datasets. For MultiCoNER 2023, we adopted the coarse-grained entity categorization;
- **PAWS-X** (Yang et al., 2019) — Development set of the PAWS-X dataset which we used as paraphrase generation;
- **UltraChat** (Ding et al., 2023) — Filtered version of the UltraChat dataset used in Tunstall et al. (2023);
- **Glaive Code Assistant**[21] — Coding questions and answers across a wide range of programming languages.

[16] https://www2.statmt.org/wmt23/translation-task.html
[17] https://apequest.wordpress.com/
[18] https://www.statmt.org/wmt22/results.html
[19] https://www.statmt.org/wmt22/results.html
[20] https://www.statmt.org/wmt21/terminology-task.html
[21] https://huggingface.co/datasets/glaiveai/glaive-code-assistant

E Details of TOWERINSTRUCT

E.1 Hyperparameters

Table 8 details the full hyperparameters configuration for the training of TOWERINSTRUCT. We also utilized bfloat16 mixed precision and packing.

Global train batch size	256
Number of Epochs	4
Learning rate	7e-6
LR Scheduler	cosine
Warmup Steps	500
Weight Decay	0.01
Optimizer	Adam (Kingma & Ba, 2015)
Adam β_1	0.9
Adam β_2	0.999
Adam ϵ	1e-8
Maximum Sequence Length	2048

Table 8: Hyperparameter configuration to finetune TOWERINSTRUCT on TOWERBLOCKS.

E.2 Chat Template

We finetuned TOWERINSTRUCT with the `chatml` template (Open AI, 2023). Table 9 provides an example of an interaction using the aforementioned template.

User	<|im_start|>user Translate the following text from Portuguese into English. Portuguese: Ontem, a minha amiga foi ao supermercado mas estava fechado. Queria comprar legumes e fruta. English: <|im_end|> <|im_start|>assistant
Model	Yesteday, my friend went to the supermarket but it was closed. She wanted to buy vegetables and fruit.<|im_end|>
User	<|im_start|>user Can you now translate it into Spanish? <|im_end|> <|im_start|>assistant
Model	Ayer mi amiga fue al supermercado, pero estaba cerrado. Quería comprar verduras y fruta.<|im_end|>

Table 9: Example of a dialogue with TOWERINSTRUCT's user and model control tokens.

F Translation full results

On Tables 10 to Tables 13, we tables equivalent to Table 1, but with different metrics (one per table): XCOMET, COMETKIWI-22, BLEURT, and CHRF. The equivalent for Table 2 is done in Tables 14 to 17. On Tables 18, 19, and 20, we present translation results for a wider variety of models, broken down by language pair.

	FLORES-200		WMT 23		TICO 19
Models	en→xx	xx→en	en→xx	xx→en	en→xx
Closed					
GPT-3.5-turbo	94.41 2	**95.54** 1	88.99 2	89.75 2	91.19 2
GPT-4	**94.75** 1	**96.01** 1	**89.46** 1	**90.28** 1	91.38 2
Open					
NLLB 54B	90.04 4	93.78 4	78.99 6	81.38 6	90.11 3
LLaMA-2 70B	92.80 4	94.15 4	84.85 6	87.21 5	89.02 5
Mixtral-8x7B-Instruct	91.90 3	94.40 3	85.67 6	87.81 4	89.30 4
ALMA-R 7B	—	—	86.50 4	87.67 4	—
ALMA-R 13B	—	—	88.88 2	88.97 3	—
TOWERINSTRUCT 7B	93.85 2	94.67 3	87.20 4	87.88 4	90.56 3
TOWERINSTRUCT 13B	**94.80** 1	95.22 2	88.71 2	88.65 3	91.30 2

Table 10: Translation quality on WMT23 and TICO-19 by language pair measured by XCOMET. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

	FLORES-200		WMT 23		TICO 19
Models	en→xx	xx→en	en→xx	xx→en	en→xx
Closed					
GPT-3.5-turbo	86.25 2	85.64 2	80.82 2	80.35 2	85.65 2
GPT-4	**86.42** 1	**85.77** 1	**81.20** 1	**80.54** 1	85.79 2
Open					
NLLB 54B	82.93 5	84.89 4	70.96 6	76.69 5	85.16 3
LLaMA-2 70B	85.30 4	84.97 4	78.43 5	79.36 4	84.66 5
Mixtral-8x7B-Instruct	85.24 3	85.32 3	79.01 5	79.82 3	84.81 4
ALMA-R 7B	—	—	79.25 4	79.79 4	—
ALMA-R 13B	—	—	80.12 3	80.21 2	—
TOWERINSTRUCT 7B	85.96 3	85.41 3	79.80 4	79.95 3	85.32 3
TOWERINSTRUCT 13B	86.19 2	85.51 2	80.57 2	80.25 2	85.59 2

Table 11: Translation quality on WMT23 and TICO-19 by language pair measured by COMETKIWI-22. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 en→xx	FLORES-200 xx→en	WMT 23 en→xx	WMT 23 xx→en	TICO 19 en→xx
Closed					
GPT-3.5-turbo	**77.08** 1	78.12 3	72.06 2	**72.50** 1	75.91 2
GPT-4	**77.26** 1	78.51 2	**72.54** 1	**72.91** 1	76.16 2
Open					
NLLB 54B	74.29 3	77.99 3	62.73 6	66.46 5	75.49 2
LLaMA-2 70B	75.04 4	78.28 2	68.03 5	71.01 3	74.00 4
Mixtral-8x7B-Instruct	74.78 3	78.10 2	68.81 5	71.32 3	74.22 4
ALMA-R 7B	—	—	68.64 5	70.66 4	—
ALMA-R 13B	—	—	70.09 4	71.47 3	—
TOWERINSTRUCT 7B	76.10 3	78.26 2	69.77 4	71.11 3	74.83 4
TOWERINSTRUCT 13B	76.89 2	**78.67** 1	70.87 2	71.75 2	75.40 3

Table 12: Translation quality on WMT23 and TICO-19 by language pair measured by BLEURT. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 en→xx	FLORES-200 xx→en	WMT 23 en→xx	WMT 23 xx→en	TICO 19 en→xx
Closed					
GPT-3.5-turbo	**58.20** 1	63.75 3	**56.38** 1	60.92 2	64.18 2
GPT-4	**58.61** 1	64.35 2	**56.94** 1	**61.33** 1	64.34 2
Open					
NLLB 54B	54.70 4	63.87 2	42.98 6	52.08 6	63.84 2
LLaMA-2 70B	55.19 4	64.15 2	52.31 4	59.66 2	61.65 4
Mixtral-8x7B-Instruct	54.50 4	63.38 3	51.22 4	58.63 4	61.34 4
ALMA-R 7B	—	—	45.20 7	57.33 4	—
ALMA-R 13B	—	—	46.52 6	58.37 3	—
TOWERINSTRUCT 7B	56.16 3	64.08 2	52.25 4	58.88 4	62.07 4
TOWERINSTRUCT 13B	57.19 2	**64.79** 1	54.10 3	59.78 2	62.81 3

Table 13: Translation quality on WMT23 and TICO-19 by language pair measured by CHRF. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 en→xx	FLORES-200 xx→en	WMT 23 en→xx	WMT 23 xx→en	TICO 19 en→xx
Closed					
GPT-3.5-turbo	94.41 2	**95.54** 1	88.99 2	89.75 2	91.19 2
GPT-4	**94.75** 1	**96.01** 1	**89.46** 1	**90.28** 1	91.38 2
Open					
NLLB 54B	90.04 4	93.78 4	78.99 6	81.38 6	90.11 3
LLaMA-2 70B	92.80 4	94.15 4	84.85 6	87.21 5	89.02 5
Mixtral-8x7B-Instruct	91.90 3	94.40 3	85.67 6	87.81 4	89.30 4
ALMA-R 7B	—	—	86.50 4	87.67 4	—
ALMA-R 13B	—	—	88.88 2	88.97 3	—
TOWERINSTRUCT 7B	93.85 2	94.67 3	87.20 4	87.88 4	90.56 3
TOWERINSTRUCT 13B	**94.80** 1	95.22 2	88.71 2	88.65 3	91.30 2

Table 14: Translation quality on FLORES-200 by language pair measured by XCOMET. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 (en→xx) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	85.15 2	**87.04** 1	**87.18** 1	**87.47** 1	86.92 3	**86.88** 1	85.69 2	85.58 2	84.37 2
GPT-4	**85.27** 1	**87.07** 1	**87.25** 1	**87.51** 1	**87.47** 1	**86.90** 1	85.68 2	**85.99** 1	**84.68** 1
Open									
NLLB 54B	82.59 6	85.18 4	85.23 4	85.66 4	86.11 4	84.71 4	83.45 5	83.56 4	69.88 7
LLaMA-2 70B	84.19 5	86.40 3	86.68 3	86.77 3	85.46 5	85.87 3	84.57 4	84.59 3	83.13 5
Mixtral-8x7B-Instruct	84.72 3	86.74 2	87.04 2	87.18 2	83.49 6	85.95 3	84.99 3	84.78 3	82.30 6
TOWERINSTRUCT 7B	84.41 4	86.77 2	87.08 2	87.31 2	86.70 3	86.48 2	85.57 2	85.50 2	83.78 4
TOWERINSTRUCT 13B	84.73 3	**86.94** 1	**87.18** 1	**87.45** 1	87.22 2	86.60 2	**85.85** 1	85.68 2	84.09 3

Models	FLORES-200 (xx→en) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	84.64 2	86.27 2	**86.48** 1	86.84 2	85.69 2	86.18 2	**85.31** 1	84.59 2	84.76 2
GPT-4	**84.71** 1	**86.39** 1	**86.50** 1	**86.95** 1	**86.15** 1	**86.25** 1	**85.31** 1	**84.75** 1	**84.92** 1
Open									
NLLB 54B	84.09 5	85.51 5	86.04 3	86.06 4	85.13 4	85.59 5	84.45 4	83.95 4	83.18 6
LLaMA-2 70B	84.29 4	85.78 4	86.05 3	86.38 3	84.45 6	85.56 5	84.87 3	83.77 4	83.57 5
Mixtral-8x7B-Instruct	84.45 3	86.07 3	86.34 2	86.78 2	84.74 5	85.78 4	85.13 2	84.45 3	84.14 4
TOWERINSTRUCT 7B	84.41 3	86.12 3	86.35 2	86.79 2	85.21 4	85.98 3	85.17 2	84.47 2	84.16 4
TOWERINSTRUCT 13B	84.44 3	86.09 3	86.39 2	86.83 2	85.47 3	86.04 3	85.17 2	**84.69** 1	84.47 3

Table 15: Translation quality on FLORES-200 by language pair measured by COMETKIWI-22. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 (en→xx) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	**79.09** 1	**76.75** 1	**79.54** 1	79.83 2	69.39 2	**77.79** 1	**80.31** 1	77.31 2	73.69 2
GPT-4	**79.13** 1	**76.64** 1	**79.29** 1	80.00 2	**70.31** 1	77.58 2	**80.22** 1	**78.16** 1	**73.98** 1
Open									
NLLB 54B	77.71 3	75.37 4	77.96 3	79.26 3	68.95 2	76.47 3	77.80 4	76.81 3	58.32 6
LLaMA-2 70B	76.75 4	75.28 5	76.96 4	78.70 4	67.01 3	75.98 4	77.50 4	75.79 4	71.41 4
Mixtral-8x7B-Instruct	77.73 3	76.08 3	78.39 3	79.57 3	61.77 4	76.35 3	78.14 3	76.06 4	68.94 5
TOWERINSTRUCT 7B	77.61 3	75.71 4	78.03 3	79.58 3	69.25 2	**77.73** 1	78.43 3	77.02 2	71.53 4
TOWERINSTRUCT 13B	78.15 2	76.42 2	78.96 2	**80.39** 1	**70.53** 1	**77.93** 1	78.78 2	**77.97** 1	72.85 3

Models	FLORES-200 (xx→en) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	80.38 2	77.27 3	80.55 3	77.91 3	75.22 3	77.02 2	80.86 3	77.73 3	76.12 2
GPT-4	**80.74** 1	77.61 2	80.72 2	78.14 2	**76.51** 1	**77.23** 1	81.11 2	78.02 2	**76.54** 1
Open									
NLLB 54B	80.12 3	77.09 3	80.64 2	77.79 3	75.32 2	76.99 2	80.81 3	77.95 2	75.19 4
LLaMA-2 70B	80.38 2	**77.65** 1	80.79 2	78.05 2	75.58 2	76.77 3	81.16 2	78.18 2	75.96 2
Mixtral-8x7B-Instruct	80.40 2	**77.79** 1	80.75 2	**78.53** 1	74.15 4	76.87 2	80.85 3	78.02 2	75.57 3
TOWERINSTRUCT 7B	80.17 3	77.47 2	80.67 2	**78.40** 1	75.62 2	76.96 2	81.30 2	78.10 2	75.68 3
TOWERINSTRUCT 13B	**80.55** 1	**77.65** 1	**81.03** 1	**78.54** 1	**76.53** 1	**77.22** 1	**81.51** 1	**78.51** 1	**76.46** 1

Table 16: Translation quality on FLORES-200 by language pair measured by BLEURT. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 (en→xx) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	67.22 2	**57.39** 1	**72.79** 1	**60.67** 1	35.49 2	59.57 2	**72.96** 1	58.48 2	**39.21** 1
GPT-4	**67.89** 1	57.13 2	**72.89** 1	**60.60** 1	**37.18** 1	**59.97** 1	**72.98** 1	**59.50** 1	**39.32** 1
Open									
NLLB 54B	63.18 5	55.30 5	70.25 3	58.83 3	**36.54** 1	56.99 5	68.19 4	57.28 3	25.73 5
LLaMA-2 70B	63.43 5	55.39 5	69.54 4	58.20 3	32.07 3	56.53 5	69.61 2	56.58 4	35.38 3
Mixtral-8x7B-Instruct	64.14 4	56.14 4	70.91 2	59.01 2	27.54 4	56.22 6	69.43 2	56.07 4	31.01 4
TOWERINSTRUCT 7B	63.87 4	56.04 4	70.23 3	59.45 2	35.44 2	58.16 4	68.74 4	57.77 3	35.78 3
TOWERINSTRUCT 13B	65.16 3	56.58 3	71.26 2	**60.32** 1	**37.10** 1	59.04 3	69.06 3	58.77 2	37.40 2

Models	FLORES-200 (xx→en) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	69.31 2	60.46 3	69.54 2	62.76 3	57.50 3	60.75 2	72.56 3	62.80 3	58.07 2
GPT-4	**69.74** 1	61.09 2	**69.94** 1	62.75 3	**59.55** 1	60.88 2	72.91 2	63.40 2	**58.87** 1
Open									
NLLB 54B	68.54 3	60.72 2	69.70 2	62.95 3	58.55 2	60.67 2	72.26 3	62.66 3	**58.83** 1
LLaMA-2 70B	69.22 2	**61.34** 1	**70.08** 1	63.51 2	57.82 2	60.90 2	72.96 2	63.61 2	57.94 2
Mixtral-8x7B-Instruct	69.00 2	**61.29** 1	69.32 2	63.38 2	55.56 4	59.98 3	72.18 4	62.77 3	56.97 3
TOWERINSTRUCT 7B	68.94 2	**61.39** 1	69.56 2	63.59 2	58.48 2	60.65 2	73.00 2	63.37 2	57.79 2
TOWERINSTRUCT 13B	**69.39** 1	**61.50** 1	**70.07** 1	**64.06** 1	**59.81** 1	**61.40** 1	**73.54** 1	**64.41** 1	**58.90** 1

Table 17: Translation quality on FLORES-200 by language pair measured by CHRF. Models with statistically significant performance are grouped in quality clusters. Best performing models are in bold and best performing open models are underlined.

Models	FLORES-200 (en→xx) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	88.78	87.08	89.02	89.06	89.36	88.63	90.46	89.56	88.58
GPT-4	88.98	87.10	88.93	89.05	90.06	88.56	90.43	90.19	88.87
Open									
NLLB 54B	87.18	85.92	87.71	88.10	89.00	87.33	88.72	88.89	78.26
LLaMA-2 7B	84.03	84.37	85.18	85.18	80.20	84.48	87.01	85.09	82.50
LLaMA-2 13B	85.60	85.45	86.74	87.02	84.22	86.11	88.33	87.02	84.83
LLaMA-2 70B	87.31	86.41	87.82	88.22	88.07	87.47	89.11	88.65	87.32
Mistral-7B-Instruct-v0.2	84.27	84.87	86.16	85.86	79.20	84.43	87.53	85.78	82.41
Mixtral-8x7B	87.95	86.64	88.39	88.44	85.72	87.26	89.34	88.89	86.23
Mixtral-8x7B-Instruct	87.99	86.80	88.53	88.77	85.63	87.57	89.45	89.09	85.99
Qwen1.5 72B	87.20	86.46	87.78	88.19	87.64	87.40	89.13	88.41	88.85
Gemma 7B	86.13	85.84	87.09	87.03	84.89	86.03	88.60	87.24	85.75
ALMA-PRETRAIN 7B	86.47	83.18	84.23	83.59	68.06	81.05	84.80	87.96	85.80
ALMA-PRETRAIN 13B	87.07	84.90	86.05	86.09	77.10	84.36	87.47	88.91	86.58
TOWER									
TOWERBASE 7B	86.91	85.95	87.76	87.93	86.55	87.37	89.47	88.72	86.48
TOWERBASE 13B	87.21	86.01	88.34	88.25	88.78	87.52	89.36	88.30	87.14
TOWERINSTRUCT 7B	87.82	86.76	88.44	88.73	89.41	88.38	89.60	89.53	87.90
TOWERINSTRUCT 13B	88.16	87.06	88.92	89.21	89.92	88.63	89.78	89.95	88.29

Models	FLORES-200 (xx→en) de	es	fr	it	ko	nl	pt	ru	zh
Closed									
GPT-3.5-turbo	89.60	87.26	89.46	88.03	87.83	87.71	89.78	86.69	86.92
GPT-4	89.76	87.57	89.61	88.21	88.58	87.88	89.94	86.94	87.29
Open									
NLLB 54B	89.17	87.25	89.29	87.91	87.86	87.49	89.38	86.66	86.55
LLaMA-2 7B	88.47	86.63	88.78	87.48	85.52	86.67	88.98	85.87	85.53
LLaMA-2 13B	89.01	86.98	89.14	87.87	86.95	87.23	89.26	86.37	86.35
LLaMA-2 70B	89.44	87.49	89.55	88.18	87.91	87.52	89.84	86.87	86.91
Mistral-7B-Instruct-v0.2	88.83	87.07	88.81	87.69	85.16	86.93	89.05	86.21	85.65
Mixtral-8x7B	89.55	87.57	89.58	88.35	87.03	87.54	89.80	86.79	86.63
Mixtral-8x7B-Instruct	89.57	87.65	89.56	88.44	87.37	87.54	89.73	86.81	86.88
Qwen1.5 72B	89.67	87.66	89.58	88.41	88.42	87.72	89.88	87.13	87.94
Gemma 7B	89.17	87.09	89.12	87.81	87.28	87.23	89.48	86.59	86.59
ALMA-PRETRAIN 7B	89.23	86.84	89.01	87.68	83.35	86.92	89.05	86.81	86.59
ALMA-PRETRAIN 13B	89.81	87.42	89.42	88.18	86.26	87.59	89.70	87.23	87.16
TOWER									
TOWERBASE 7B	89.26	87.15	89.47	88.14	87.80	87.45	89.77	86.41	86.72
TOWERBASE 13B	89.54	87.42	89.55	88.11	88.24	87.61	89.71	86.18	87.02
TOWERINSTRUCT 7B	89.48	87.48	89.50	88.39	88.16	87.66	89.92	86.90	86.96
TOWERINSTRUCT 13B	89.61	87.62	89.67	88.42	88.48	87.92	90.07	87.20	87.27

Table 18: COMET-22 on FLORES-200 for a wide variety of models.

Models	WMT23 en→de	en→ru	en→zh	de→en	ru→en	zh→en
Closed						
GPT-3.5-turbo	84.61	85.38	86.70	85.91	83.02	81.52
GPT-4	84.89	86.07	87.08	86.17	83.63	81.27
Open						
NLLB 54B	77.40	83.91	74.48	80.06	80.52	76.60
LLaMA-2 7B	75.02	77.87	79.16	83.36	80.58	77.40
LLaMA-2 13B	78.29	80.44	81.30	83.92	81.54	78.73
LLaMA-2 70B	81.62	83.04	84.19	85.12	82.84	79.73
Mistral-7B-Instruct-v0.2	76.78	80.27	81.26	84.18	81.52	79.11
Mixtral-8x7B	81.92	83.39	83.81	85.04	82.70	79.50
Mixtral-8x7B-Instruct	83.07	83.79	83.94	85.45	83.02	80.04
Qwen1.5 72B	81.44	83.31	86.48	85.54	83.01	80.60
Gemma 7B	79.56	82.20	83.56	84.60	82.14	79.24
ALMA-PRETRAIN 7B	80.20	83.01	82.68	83.51	81.82	78.66
ALMA-PRETRAIN 13B	81.18	83.72	83.83	84.32	82.71	79.22
ALMA-R 7B	82.41	84.28	83.51	84.55	82.50	80.13
ALMA-R 13B	83.59	85.37	84.43	85.39	83.23	80.48
TOWER						
TOWERBASE 7B	81.03	83.25	84.00	84.09	80.08	78.92
TOWERBASE 13B	81.18	83.46	84.03	83.89	80.03	78.94
TOWERINSTRUCT 7B	83.22	84.73	84.89	85.24	82.94	80.13
TOWERINSTRUCT 13B	83.98	85.51	85.92	85.62	83.21	80.72

Table 19: COMET-22 on WMT23 for a wide variety of models.

Models	TICO-19 en→es	en→fr	en→pt	en→ru	en→zh
Closed					
GPT-3.5-turbo	88.67	81.86	90.30	87.88	88.09
GPT-4	88.76	81.85	90.30	88.36	88.32
Open					
NLLB 54B	88.74	82.01	89.84	88.67	85.97
LLaMA-2 7B	85.77	78.08	86.97	82.99	81.86
LLaMA-2 13B	86.94	79.83	88.48	85.44	84.89
LLaMA-2 70B	87.84	80.67	89.24	87.12	87.44
Mistral-7B-Instruct-v0.2	86.25	79.18	87.87	84.35	84.13
Mixtral-8x7B	88.12	81.15	89.27	87.14	86.58
Mixtral-8x7B-Instruct	88.23	81.39	89.48	87.04	86.84
Qwen1.5 72B	86.08	80.32	88.20	80.53	86.68
Gemma 7B	87.30	78.20	88.66	86.16	86.78
ALMA-PRETRAIN 7B	84.42	76.74	84.92	86.53	85.27
ALMA-PRETRAIN 13B	86.17	79.09	87.56	87.27	86.54
ALMA-R 7B	84.63	76.02	82.92	87.80	85.41
ALMA-R 13B	85.93	79.90	87.41	88.58	86.22
TOWER					
TOWERBASE 7B	87.90	81.20	89.45	86.94	86.97
TOWERBASE 13B	87.90	81.48	89.54	87.26	87.57
TOWERINSTRUCT 7B	88.34	81.60	89.38	88.11	87.63
TOWERINSTRUCT 13B	88.63	81.82	89.48	88.49	88.20

Table 20: COMET-22 on TICO-19 for a wide variety of models.

G Translation-related tasks full results

G.1 Languages considered

For APE, on Table 3, we consider 4 language pairs: en→de, en→zh, de→en, and ru→en. We leave out en→ru and zh→en, because we had no post editions to serve as fewshot examples for LLaMA-2 and Mixtral-8x7B-Instruct. In any case, we provide results for TOWERINSTRUCT, GPT-3.5-turbo, and GPT-4 on the 6 language pairs in Table 21.

For NER, we consider English, German, French, Spanish, Italian, Portuguese, Russian, and Chinese. Finally, we evaluate GEC on English, German, and Spanish. For this task, besides the numbers shown in Table 3, we also measure ERRANT in Table 22.

Results broken down by language may be found in Tables 23, 24, and 25.

	APE	
Models	en→xx	xx→en
Baseline (no edits)	78.84 4	78.80 4
GPT-3.5-turbo	82.32 3	77.91 5
GPT-4	**85.52** 1	**83.12** 1
TOWERINSTRUCT 7B	83.10 3	80.19 3
TOWERINSTRUCT 13B	83.65 2	80.89 2

Table 21: APE results for the 6 WMT23 LPs considered. NLLB corresponds to the translations that were subject to editing, so their quality serves as the baseline for the task. Table 3 did not include zh-en and en-ru to guarantee a fair comparison with open models — there were no fewshot examples available for these LPs.

Models	GEC Multilingual
Closed	
GPT-3.5-turbo	**0.49** 1
GPT-4	0.48 3
Open	
LLaMA-2 70B	0.43 4
Mixtral-8x7B-Instruct	0.43 4
TOWERINSTRUCT 7B	0.42 4
TOWERINSTRUCT 13B	0.43 4

Table 22: GEC ERRANT results.

Models	WMT23 en→de	en→ru	en→zh	de→en	ru→en	zh→en
Baseline (no edits)	77.87	82.93	75.72	79.92	80.05	76.44
Closed						
GPT-3.5-turbo	80.67	84.03	82.27	78.48	78.88	76.37
GPT-4	84.65	86.15	85.75	85.39	83.21	80.75
Open						
GPT-3.5-turbo	80.67	84.03	82.27	78.48	78.88	76.37
GPT-4	84.65	86.15	85.75	85.39	83.21	80.75
LLaMA-2 70B	78.49	—	78.20	81.30	80.76	—
Mixtral-8x7B-Instruct	82.12	—	83.15	83.40	82.22	—
TOWER						
TOWERINSTRUCT 7B	81.86	83.92	83.52	82.29	80.82	77.45
TOWERINSTRUCT 13B	82.03	84.34	84.59	83.22	81.30	78.15

Table 23: APE COMET-22 results by language pair.

Models	en	de	es
Baseline (no edits)	13.75	18.23	18.00
Closed			
GPT-3.5-turbo	14.71	13.19	17.29
GPT-4	16.48	12.89	15.86
Open			
LLaMA-2 70B	17.46	20.67	27.09
Mixtral-8x7B-Instruct	16.44	15.38	19.47
TOWER			
TOWERINSTRUCT 7B	13.39	14.77	17.23
TOWERINSTRUCT 13B	13.13	14.42	19.48

Table 24: GEC edit rate results by language.

Models	en	de	es	fr	it	pt	zh
Closed							
GPT-3.5-turbo	55.43	60.12	56.82	53.34	55.46	52.57	17.82
GPT-4	63.61	66.58	65.24	58.72	63.39	61.74	39.88
Open							
LLaMA-2 70B	46.34	48.79	50.69	47.50	53.96	45.60	19.44
Mixtral-8x7B-Instruct	45.74	46.94	46.03	46.11	50.86	40.21	16.51
TOWER							
TOWERINSTRUCT 7B	75.09	78.01	74.89	70.35	76.39	73.88	53.13
TOWERINSTRUCT 13B	77.52	79.73	76.69	74.55	80.36	77.47	56.57

Table 25: NER F1 results by language.