

BOUQuET 🌸: dataset, Benchmark and Open initiative for Universal Quality Evaluation in Translation

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Abstract

BOUQuET is a multi-way, multicentric and multi-register/domain dataset and benchmark, and a broader collaborative initiative. This dataset is handcrafted in 8 non-English languages. Each of these source languages are representative of the most widely spoken ones and therefore they have the potential to serve as pivot languages that will enable more accurate translations. The dataset is multicentric to enforce representation of multilingual language features. In addition, the dataset goes beyond the sentence level, as it is organized in paragraphs of various lengths. Compared with related machine translation datasets, we show that BOUQuET has a broader representation of domains while simplifying the translation task for non-experts. Therefore, BOUQuET is specially suitable for crowd-source extension for which we are launching a call aiming at collecting a multi-way parallel corpus covering any written language.

1 Introduction

Although multilingual large language model (LLM) evaluation benchmarks are only starting (Dac Lai et al., 2023), there is a rich research history in multilingual evaluation datasets for natural language processing; e.g., (Sun and Duh, 2020; Malmasi et al., 2022; Yu et al., 2022), with Machine Translation (MT) being the task with the highest investment in multilinguality (Kocmi et al., 2024). This is evident from the nearly 20-year history of the Conference on Machine Translation (formerly a workshop, WMT), which has established an international evaluation campaign (Kocmi et al., 2024). The campaign has compiled a comprehensive collection of parallel corpus evaluations covering a broad range of language pairs, domains, tasks and recently, investing in a multi-way parallel dataset expanding in languages (Deutsch et al., 2025). However, the largest multi-way parallel evaluation dataset to date was introduced with FLORES-101

(Goyal et al., 2022), later expanded to FLORES-200 (NLLBTeam, 2024), FLORES+¹ and to 2M-FLORES (Costa-jussà et al., 2024).

These existing datasets and benchmarks fall short due to having an English-centric focus, a narrow selection of registers, compromised quality from automated construction and mining, limited language coverage, or a static nature, in addition to being prone to contamination (Sainz et al., 2023). Similarly, in parallel with the previous progress, there have been several initiatives that called for data annotation in a collaborative and open way, such as the translation data collection initiative (Singh et al., 2024).

Recently, Wu et al. (2025) evaluate multilingual benchmarking and make a call for action for the need for accurate, contamination-free, challenging, practically relevant, linguistically diverse, and culturally authentic evaluations. This call and the urgent need of progressing in multilingual benchmarking set the stage for the introduction of a new multilingual multi-way parallel evaluation dataset and benchmark. BOUQuET, which additionally combines community efforts, relies on text written from scratch (contamination-free²) by native speakers in 8 different major languages (linguistically diverse). Text includes a variety of 8 practical domains (practically relevant) that represent localised knowledge (culturally diverse). BOUQuET is aligned at the sentence and paragraph-level and it relies on a mixture of commissioned and openly collected human annotations to extend to any language.

The organisation of the paper is as follows. First, the paper details how we develop the Source-BOUQuET dataset (Section 3), which is the neces-

¹<https://oldi.org/>

²Note that BOUQuET is free from contamination in each initial state because it is originally created and not mined. However, from the moment we open-source certain splits, BOUQuET will risk to leak into training. Therefore, we keep one split hidden to avoid this.

sary stepping stone towards an open initiative. Second, we benchmark BOUQuET for the 8 pivot languages plus English (Section 4). Finally, Section 5 presents how we design the open initiative itself, which aims to build the Full-BOUQuET dataset; i.e., Source-BOUQuET translated into any written language. At the time of submission of this paper, BOUQuET includes 55 multi-way parallel completed languages (Table 6).

2 Definitions and background

Definitions Before describing the Source-BOUQuET dataset’s characteristics and building methodology, we define our use of some frequently encountered terms that may cover a variety of meanings.

Domain. By the term *domain*, we mean different spaces in which language is produced in speech, sign, or writing (e.g., books, social media, news, Wikipedia, organization websites, official documents, direct messaging, texting). In this paper, we focus solely on the written modality.

Register. We understand the term *register* as a functional variety of language that includes socio-semiotic properties, as expressed in Halliday and Matthiessen (2004), or more simply as a “contextual style,” as presented in Labov (1991, pp.79–99). In that regard, a register is a specific variety of language used to best fit a specific communicative purpose in a specific situation.

Background There is a large body of work in creating datasets for MT evaluation (e.g. WMT International Evaluation Campaigns (Deutsch et al., 2025)). However, the vast majority are limited to a few languages. we next discuss the main efforts to build massively multilingual MT benchmarks and one representation of multi-domain dataset.

FLORES+ FLORES+ (Maillard et al., 2024) is the largest multilingual extension of FLORES-200 (Goyal et al., 2022) and it covers the largest multi-way parallel dataset in terms of languages in 3 domains (Wikipedia, News, Travel guides). Even if FLORES+ has paragraph information, the translation has been done at the level of sentence without showing context to the annotators.

NTREX-128 Similarly to FLORES+ NTREX-128 covers a multi-way parallel dataset but for 128 languages. Unlike FLORES-200, translators had the full context of the document

available when translating sentences, but the authors did not know if (or to what extent) they used this information (Federmann et al., 2022).

NLLB-MD was motivated to complement FLORES-200 in terms of domains in the context of the NLLB (NLLBTeam, 2024) project. It covers chat, news and health domains in 6 languages and it includes a much larger number of sentences.

All these datasets are English-localised and English-centric, meaning that all languages have been translated from the original source English. They cover limited amount of domains (a maximum of 4) and do not differentiate among registers.

3 Dataset: Source-BOUQuET

In this section, we describe the creation criteria that have been followed to design Source-BOUQuET, as well as the languages it includes.

3.1 Main characteristics

As described in greater detail next, the Source-BOUQuET dataset is mainly characterized by its non-English-centric focus, its diverse range of registers and domains (which are complementary to FLORES-200), its manual and original composition, and its built-in dynamic extensibility. Table 1 provides a comparison of several relevant statistics from BOUQuET and the closest related datasets covered in the previous section.

Non-English-centric focus. Source-BOUQuET is handcrafted by proficient speakers of Egyptian Arabic and MSA, French, German, Hindi, Indonesian, Mandarin Chinese, Russian, and Spanish. Each of these languages contributes the same number of sentences to the final dataset. The languages for Source-BOUQuET (see Table 3 in Section 3.3) are all part of the top 20 languages in the world in terms of user population, as listed in Eberhard et al. (2024). In addition, they are also used by a large number of non-native speakers, which makes them good candidates for what we refer to as *pivot* languages; i.e., higher-resource languages that can facilitate—as source languages—the translation of datasets into lower-resource languages. English is often used as such a pivot language, since numerous people have a high degree of proficiency in English as a second language. English is not the only language in this situation, however, and is not always the best pivot language option. For example, it is much easier to find Guarani-Spanish bilingual

speakers than it is to find Guarani-English bilingual speakers. What is more, cultural proximity may also make translation slightly easier.

Diverse registers and domains. Registers derive from communicative purposes and, as such, are related to domains. However, the relationship between registers and domains is not one to one. See the register and domain correspondence in Figure 5 (Appendix B). For example, if we take a domain such as TV news, we can identify at least 3 registers: (1) the register used by the news anchor, which is represented by fully scripted language that is read from a teleprompter with a very specific and unnatural form of diction (e.g., hypercorrect enunciation, unnatural intonation, homogeneous pace); (2) The register produced by communication specialists (i.e., people who have been trained to be spokespersons or surrogates). The points they make have been scripted and rehearsed to the point of being known by heart. It sounds spontaneous but it is not structured like informal language; (3) the register represented in person-in-the-street segments, which is more informal and spontaneous (possibly colloquial). This example is taken from a domain where both speech and writing are used but the situation is not significantly different in the written modality only. Language users all commonly shift between registers, which is typically referred to as style-shifting. Style-shifting (i.e., register-shifting) occurs within domains; so the domain itself is not a fool-proof way of getting a specific register. Although the norms of the domain can impose the degree of formality and of lexical specialization, it is often the register (which derives from the communicative purpose), not the domain, that determines many aspects of linguistic structure (e.g., lexical density, pronoun use, syntax, etc.).

Manual construction and original composition (not crawled) with accurate revisions To develop Source-BOUQuET, we set a variety of linguistic criteria that need to be covered, including both unmarked and marked structures (e.g., expected and unexpected number agreement between subject and verb). Guidelines are then shared with linguists who manually craft sentences covering examples of these linguistic criteria and compose paragraphs ranging from 3 to 6 sentences in length. These paragraphs are then manually translated across all pivot languages.

The main strategies for open collaboration are

to design contribution guidelines and build an annotation tool that enables the free collection of translations in any language. BOUQuET is shared in a repository that allows language community to easily add a new language by translating it from one of the 8 pivot languages or the English translation. This repository contains detailed guidelines on how to do it. BOUQuET’s innovative approach ensures widespread language accessibility. This open collaborative initiative will enrich BOUQuET with the following characteristics.

Language coverage extensibility Using both private and community-driven initiatives, we could potentially support any written language, as long as there is individual interest in contributing to multilingual advancements.

Dynamic in nature Since BOUQuET includes the community, it can continuously evolve by constantly engaging it.

3.2 Creation criteria

For the design of the creation guidelines, detailed in Appendix A, we prepared a list of linguistic coverage requirements along with some statistical information.

Linguistic coverage requirements. In order for BOUQuET to be representative of various linguistic phenomena, linguistic coverage requirements are defined (as listed in Table 2), which are to be included in sentences that form paragraphs. Sentences are assigned a unique identifier that combines a unique paragraph ID number with a serial sentence number. Thus, paragraphs can be retrieved by concatenating sentences that share the same paragraph ID.

Variety of domains. Source-BOUQuET is intended to cover 8 domains: narration (as in fiction writing), dialog, social media posts, social media comments, how-to manuals and instructions, miscellaneous website content (excluding social media or news), opinion pieces, and other miscellaneous (such as written speeches or signage). The choice of these domains optimizes for variety and popular usefulness.

Variety of registers. Source-BOUQuET is built with register variety in mind, differently from FLORES-200, which covers a few different domains but remains largely within similar registers.

DATASET	SPLIT	#PARAG.	#SENT	AVG. WRD. PARAG/SENT	REG.	DOM.	LANG.	DYN.
FLORES+	Dev		997					
	Devtest	×	1,012	25	×	Wikipedia, News, Travel guides	220	✓
	Eval		992					
NTREX-128	Test	123	1,997	389/24	×	News	128	×
NLLB-MD	Dev		6,000					
	Devtest	×	1,310	25	×	Chat, News, Health	6	×
	Eval		1,500					
BOUQuET	Dev	120	504					
	Devtest	200	864	55/15	✓	Fiction, Conversation, Social media posts/comments, Tutorials, Website, Reflection pieces, Miscellaneous	55+ ^a	✓
	Eval	144	628					

^aSee Appendix D for language coverage details

Table 1: Main statistics from MT evaluation datasets including BOUQuET: number of sentences, number of paragraphs, average word per paragraph (or sentence), register information, domains, languages, dynamism.

PHENOMENA
Paragraph-like continuity
Variation in sentence lengths
Dominant (unmarked) and non-dominant (marked) word orders
Different emphasis or topicalization
Different sentence structures (affirmation, interrogation, negation, subordination, coordination)
Different verb moods, tenses, and aspects
Different morphosyntactic options
Different grammatical persons (1st, 2nd, 3rd, singular, plural)
Different grammatical genders
Different grammatical number agreement
Different grammatical case or forms of inflection
Most frequent words used in various registers
Presence of named entities, numbers, slang, and emojis

Table 2: Source-BOUQuET Linguistic Requirements

We characterize the registers through 3 main features (connectedness, preparedness, and social differential). Connectedness attempts to describe the type of interaction typically available in a given domain. Preparedness aims to gauge how much time is typically used to produce or edit language content. Social differential describes the relationship between the interlocutors involved in a given social situation (e.g., writer and reader, characters in a dialog, etc.). Each individual domain can present different combinations of features but become differentiated at the level of the sentence. There are a variety of feature combinations, which are mentioned in Figure 5 and defined in Appendix B.

By including new registers and domains, the new dataset is likely to be more generalizable to different contexts and applications.

Statistical guidance for domain representation.

In order to appropriately cover linguistic requirements and adequately represent domains, we performed a statistical analysis to understand the linguistic characteristics of each domain before creating BOUQuET. In particular, our analysis cov-

ers most domains that we are including in Source-BOUQuET by using diverse public datasets: narration (Books3, Gutenberg library (Gerlach and Font-Clos, 2018)); Social media posts (Reddit (Baumgartner et al., 2020)); Social media comments (Wikipedia comments³); Conversations / Dialogues (dialogsum (Chen et al., 2021), Open Orca (Lian et al., 2023)); Tutorials/how-to articles (how-to Wikipedia-lingua⁴); Website content (C4 (Raffel et al., 2020)); News / Reflection pieces (CNN-DailyMail (Nallapati et al., 2016), XSum (Narayan et al., 2018)) and Miscellaneous (Wikipedia). Note that we collect information from public data that do not always accurately match our categories but constitute a proxy. For each of these domains, we have analyzed dimensionality: characters per token; tokens per sentence and sentences per paragraph; and linguistic complexity with CEFR levels⁵.

Regarding tokens per sentence (Figure 1 left), we can see correlations between different domains, and clear differences in length, especially in dialogs which tend to be much shorter. Regarding sentences per paragraph (Figure 1 middle), we can find a correlation between different datasets representing the same domain, where fiction writing paragraphs tend to be much longer (averaging 5 but reaching up to 20), dialogs and news articles are much shorter (barely reaching 3-4 sentences in a paragraph), and the rest of the categories are somewhere in between (normally staying between 1-5 but reaching up to 10 in some cases).

To guide BOUQuET creators on the linguistic complexity required for each domain, we have assessed complexity using the distribution of CEFR

³<https://www.kaggle.com/competitions/jigsaw-multilingual-toxic-comment-classification>

⁴<https://huggingface.co/datasets/GEM/wiki-lingua>

⁵<https://rm.coe.int/common-european-framework-of-reference-for>

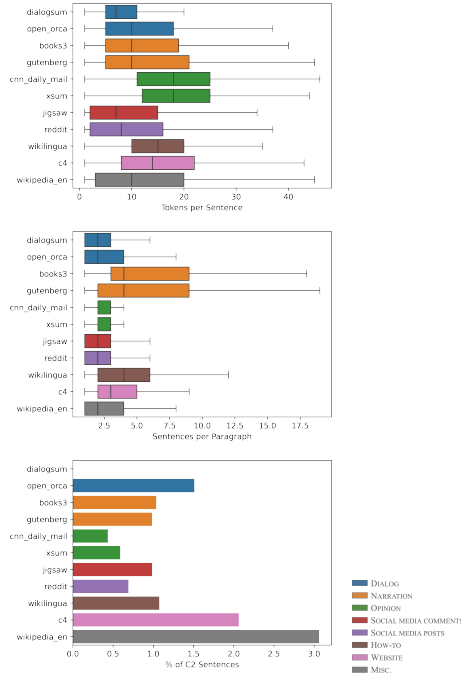


Figure 1: (Top) Tokens per sentence and (Middle) sentences per paragraph (Bottom) CEFR per dataset representative of BOUQuET domains.

levels as a proxy. This includes the % of C2 scores at the sentence level for each dataset. These scores were labeled by a SONAR-based model (Duquenne et al., 2023) trained on CEFR-SP data for CEFR Text Classification, which significantly outperformed LLAMA-3 (Touvron et al., 2023). See right side of Figure 1. Wikipedia seems to be the only dataset with a more considerable share of C2 sentences, with some others like dialogues having no samples scored as such.

Annotations and Quality Checks Each entry of Source-BOUQuET includes the source text (in one of the 8 pivot languages of Table 3) and its translation into English, domain information and contextual information for better translation accuracy. To double-check that Source-BOUQuET does not contain repeated sentences, we explored the similarity across English sentences. For each English sentence, we computed SONAR embeddings (Duquenne et al., 2023) and we computed the cosine distance on the vectors. There were only 14 sentences with a cosine distance below 0.3. These sentences are reported in Appendix E.

3.3 Languages

As mentioned earlier, BOUQuET aims to be multi-centric and localized, in contrast to most existing

datasets that are English-centric. The motivation is mainly to be representative of linguistic phenomena. To this effect, it is created in 8 non-English languages (Table 3). Each language contributes with a similar number of sentences along with their English equivalents given by the sentence creators themselves.

3.4 Multi-way extension to Source-BOUQuET languages

Details Source-BOUQuET creators composed 250 sentences for each of the 8 pivot languages plus the corresponding English translation. The remaining 1,750 sentences for each pivot language are translated from English. The final Source-BOUQuET is composed of 2,000 sentences in 9 languages (8 pivot language plus its translation into English).

Quality checks Since multi-way parallel data is created from English, we manually checked that translations did not lose the linguistic information when translating from English. While translating BOUQuET, we had to make sure that the contextual information which was applicable to the whole paragraph was taken into consideration by the translators. To ensure this, we used a number of following QA strategies reported in Appendix C.

Additional contextual information The multi-centric nature of BOUQuET is also a reminder that English is not morphologically rich (e.g., it doesn't mark grammatical gender agreement between nouns, adjectives, and verbs) and displays relatively little information about formality in its written form (e.g., it uses only one second-person singular pronoun, regardless of who is addressing whom). As such, English isn't an ideal source language for translation purposes unless translators can be provided with additional contextual information. The BOUQuET dataset includes such additional information; for example, the grammatical gender of the first and second person (when this isn't obvious) or the linguistic markedness of some words or phrases (e.g., literary or archaic verb tenses, use of slang, infrequently used level of formality).

3.5 Overall Statistics

In total, BOUQuET currently contains 2,000 sentences. These sentences are split by making a stratified selection at the paragraph-level among source languages and domains into development,

ISO 6393	ISO 15924	LANGUAGE	FAMILY	SUBGROUP1
arb	Arab	Modern Standard Arabic	Afro-Asiatic	West Semitic
cmn	Hans	Mandarin Chinese	Sino-Tibetan	Sinitic
deu	Latn	German	Indo-European	West Germanic
fra	Latn	French	Indo-European	Italic
hin	Deva	Hindi	Indo-European	Indo-Aryan
ind	Latn	Indonesian	Austronesian	Malayic
rus	Cyrl	Russian	Indo-European	Balto-Slavic
spa	Latn	Spanish	Indo-European	Italic

Table 3: Source-BOUQuET Languages

test and evaluation sets. Initially, the evaluation set (632/144 sentences/paragraphs) is intended to be kept hidden. Figure 2 shows the representation of registers (top) and domains (bottom) in the non-hidden splits. Labels for each of the combinations of register options are created by concatenating the lowercase letters used as unique identifiers (see details of these register options in the Appendix B). For example, a register characterized as impersonal (in connectedness), composed (in preparedness), and equal-assumed (in social differential) is labeled: ica.

The results in the following section are presented with the test split of 864/200 sentences/paragraphs.

4 Benchmark

We benchmark BOUQuET in two dimensions: domain representation and machine translation. The former quantifies how representative BOUQuET is of public datasets of multiple domains compared to other evaluation datasets. The latter addresses how several MT systems are ranked with BOUQuET compared to other evaluation datasets.

Domain representation The performance of the model in a new or unseen dataset depends on the similarity between the dataset that was used to fit the model and the new dataset. We compare the domain coverage of BOUQuET with that of FLORES+, NTREX-128 and NLLB-MD. To do this comparison, we take a random sample of 2,000 sentences (which seems to be a sufficiently large sample of the embedding space for score stability) from each of the domain datasets from Figure 1; as well as 2000 from each alternative dataset FLORES+, NTREX-128, NLLB-MD, and BOUQuET. We create vector representations of each sentence in previous datasets with SONAR (Duquenne et al., 2023). From SONAR vectors, we do a PCA-dimensionality reduction, fitted upon the combined

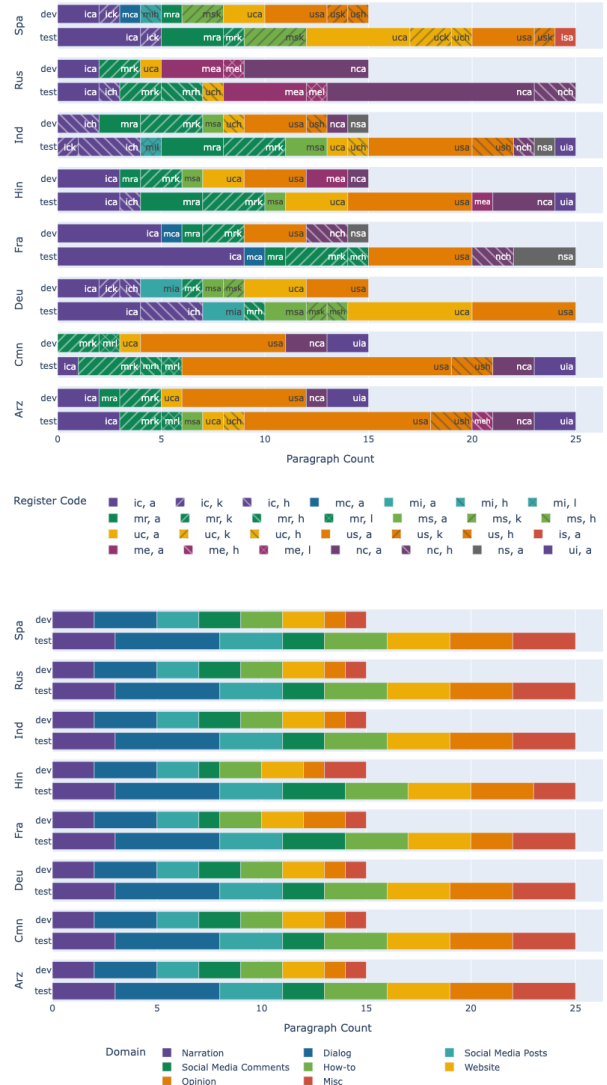


Figure 2: Registers (top) and domains (bottom) representations in development and test partitions.

multi-domain set, see Figure 6 (Appendix F). Public domains from Figure 1 are represented in grey; alternatives evaluation datasets are represented in blue and BOUQuET is represented in red. Figure 6, from top to down, compares BOUQuET against FLORES-200, NTREX-128, NLLB-MD, respectively. We qualitatively observe that BOUQuET covers a wider range of domains. Additionally, to quantify this coverage, we measure the overlap between each dataset with each of the domains using the Wasserstein distance (implemented with the POT library⁶). The Wasserstein Distance (WD), also known as the Earth Mover’s Distance (EMD), is a metric that measures the “effort” required to transform one probability distribution into

⁶<https://pythonot.github.io/>

another. Lower results indicate a higher similarity between clusters. This distance is run on the full 1024-dimensional SONAR embedding vectors, without applying any kind of dimensionality reduction (PCA). Some domain sets and evaluation sets were several orders of magnitude larger than each other. Sampling all down to the same size (2,000) makes the metric computable in a reasonable amount of time and removes any sensitivity to class imbalance in the distribution distance metric. Figure 3 shows that the lowest consistent results are obtained for all domains with BOUQuET.

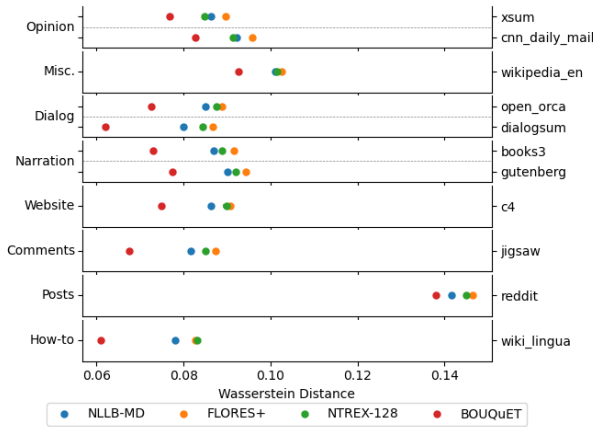


Figure 3: Wasserstein Distance (WD) for each domain and dataset. Lower WD indicate better representation of the domain.

Machine Translation To help the reader understand why the dataset is useful, we present preliminary results to demonstrate its use for its intended purpose: MT benchmarking. We evaluate 14 translation systems: LLAMA-3 (Llama3.1-8B, Llama3.2-3B, Llama3.3-70B) (Touvron et al., 2023), Tower (TowerInstruct-7B-v0.2) (Rei et al., 2024), Aya (Aya101-13B, Aya-Expanse-8B) (Dang et al., 2024), Babel (Babel-9B-Chat) (Zhao et al., 2025), Cohere (CohereLabs-command-r7b-12-2024), Eurollm (EuroLLM-9B-Instruct) (Martins et al., 2024), MADLAD (MADLAD-3B-MT and MADLAD-10B-MT) (Kudugunta et al., 2023), Mistral (Mistral-7B-Instruct-v0.3)⁷, Qwen (Qwen2.5-7B-Instruct) (Bai et al., 2023) and NLLB (NLLB-3.3B) (NLLBTeam, 2024). We select the models as ones with open weights, focusing primarily on moderate sizes (about 10B) and variety of architectures. Following the official evaluation metrics of WMT 2024 (Kocmi et al., 2024), we use

⁷<https://docs.mistral.ai/getting-started/models/models.overview/>

two automatic metrics: CometKiwi (CometKiwi-da-xl, range 0-1 and ↑ better, COM) (Chimoto and Bassett, 2022) and MetricX (MetricX-24-hybrid-xl-v2p6, range 0-25 and ↓ better, MetX) (Juraska et al., 2024). We include in the benchmarking datasets that cover Source-BOUQuET languages (FLORES+ and NTREX-128).

Table 4 shows that BOUQuET scores consistently higher than other datasets on average, suggesting that BOUQuET is easier to translate. This is an advantage for the open initiative, since the complexity of current MT test sets makes it harder to ask the community to participate in translations as it requires a high-level of expertise.

Rankings across models and datasets is not preserved, which hints that all datasets may be posing different challenges to the models. Rankings is computed as counting when a system is similar in the same position according to CometKiwi. This ranking and Pearson correlation on the CometKiwi is dissimilar for datasets evaluated at the sentence-level, with BOUQuET being the most different. This difference is enlarged when evaluating at the paragraph-level where number of swaps increases and, coherently, Pearson correlation decreases, meaning that datasets pose different challenges to models. We need to further investigate which linguistic challenges BOUQuET is adding. However, best two systems are consistent across datasets and level of evaluation (sentence and paragraphs) being those the largest model (Llama3.3-70B) and Aya-e-8B.

NLLB-3.3B has a higher variation between being evaluated at the sentence or paragraph-level, which makes sense since it is the only one trained with sentence-level data.

Figure 4 shows results of the 3 best systems averaged across language directions, evaluated at the sentence-level, per domains. Worse performing domains are comments, conversations, how-to and narration. Best performing domains are web and other miscellaneous, reflection and social posts. Appendix F reports more detailed results on BOUQuET per language and domains.

5 Beyond commissioning translations: Open initiative

Source-BOUQuET is intended to be translated into any written language. For this, we have commissioned an initial set of priority languages covering a variety of high and low-resource languages rep-

Model	BOUQUET		FLORES		NTREX		BOUQUETP		NTREXP	
	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX
NLLB-3B	0.68	2.1	0.66	2.56	0.65	2.97	0.59	3.71	0.29	14.1
aya101-13B	0.67	2.02	0.63	2.65	0.63	3.14	0.58	3.29	0.24	13.17
aya-e-8B	0.69	1.75	0.65	2.9	0.67	2.45	0.64	2.42	0.34	8.7
babel-9B	0.67	2.33	0.65	2.66	0.63	3.36	0.61	3.4	0.32	10.39
cohere-7B	0.67	2.15	0.65	2.89	0.64	3.01	0.61	3.2	0.32	9.61
eurollm-9B	0.67	2.33	0.65	2.89	0.61	3.64	0.61	3.64	0.31	10.08
madlad-10B	0.63	2.74	0.64	2.72	0.63	3.35	0.41	6.76	0.15	15.99
madlad-3B	0.63	2.85	0.63	2.94	0.61	3.67	0.37	6.71	0.49	5.29
mistral-7B	0.54	4.29	0.51	5.69	0.49	6.12	0.49	6.64	0.24	10.96
qwen-7B	0.59	3.25	0.6	3.75	0.59	4.21	0.57	4.5	0.52	4.93
Llama3.1-8B	0.66	2.36	0.64	2.82	0.63	3.27	0.6	3.33	0.32	10.17
Llama3.2-3B	0.59	3.59	0.57	4.34	0.55	4.89	0.52	5.52	0.27	12.67
Llama3.3-70B	0.7	1.85	0.68	2.21	0.67	2.59	0.63	2.72	0.35	9.76
Tower-7B	0.58	3.69	0.56	4.19	0.56	4.35	0.49	5.65	0.28	12.22
BOUQUET-FLORES		FLORES-NTREX		NTREX-BOUQUET		BOUQUETP-NTREXP				
Swaps		3		4		7		11		
Pearson Cor.		0.95		0.99		0.95		0.92		

Table 4: Averaged Results XX-to-XX 9 Source-BOUQuET (8 pivot plus English) languages for BOUQuET, FLORES+, NTREX-128 at the level of sentence 2 columns on the left and at the level of paragraph 3 columns on the right. Number of ranking swaps (a system not being in the same position according to CometKiwi) from each dataset compared to the other two (in similar sentence or paragraph-level) and Pearson correlation indicate that while datasets report similar results at sentence-level, being BOUQuET the most different, it is not the case for paragraph-level where the ranking of systems varies by a larger amount.

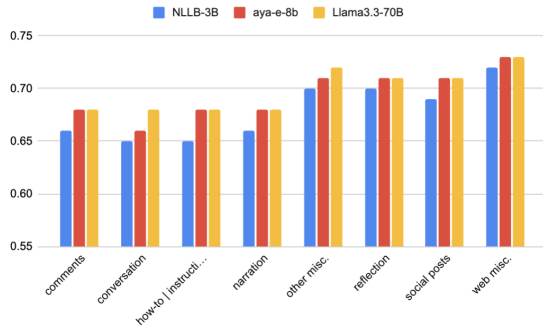


Figure 4: Best performing models and their results in each of the BOUQuET domains .

resenting different geographical regions, linguistic families and scripts. See the list of languages currently covered by BOUQuET in Appendix D.

However, it would be challenging to achieve our language coverage target to any language. This ambition can only be achieved with the support of the community. For this, we have organized an open collaborative effort which involves language communities that are interested in contributing to this effort.

The purpose of this open initiative is to collect translations from Source-BOUQuET. To collect these annotations, we have set a tool to collect annotations. Together with setting Source-BOUQuET in this tool, we use the annotation guidelines from Section 3.4 which very much resemble those from FLORES-200 (NLLBTeam, 2024) and which are available in the 9 BOUQuET languages. One of the advantages is that annotators can choose the

source language from among one of the Source-BOUQuET languages. These languages have been chosen to cover a wide range of speakers, facilitating the task of annotation instead of depending on English bilingual speakers. This open initiative is available in HuggingFace BLIND.

6 Conclusions and Next Steps

In this paper, we have presented the Source-BOUQuET dataset and the attached open initiative. We have shown consistent gains in domain diversity in two different metrics while keeping complexity lower than its competitors. The latter is particularly relevant to simplify the translation for non-experts that may join the open initiative. We also provide MT results for the 8 languages in which Source-BOUQuET has been created. Although BOUQuET is currently totally completed for 55 languages (see list 6), this number is only a fraction of the language coverage ambition that we are pursuing by launching the open initiative for community efforts. Please join us in making Universal Quality Evaluation in Translation available in any language.

Beyond increasing in number of languages, BOUQuET is actively evolving, and we are currently working on designing quality control for each of the contributions and adding new languages to the incremental releases of BOUQuET and extending the benchmarking by further showing the capabilities of BOUQuET, e.g. increasing the evaluation of linguistic signals over its alternatives.

Limitations and Ethical Considerations

The BOUQuET dataset is still limited in the number of languages and translations. The benchmarking is quite complete (4 datasets comparison, 14 models and 2 metrics) but it can also be extended in several axes (linguistic analysis). However, the entire purpose of this work is to describe the dataset and open-initiative, while providing a minimal benchmarking. Authors expect the community to extend the benchmarking by further using this dataset for further exploration. Creators and commissioned translation’s annotators are paid a fair rate.

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817	Minghao Wu, Weixuan Wang, Sinuo Liu, Huifeng Yin,	3. Narration (creative writing that doesn't include	864
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823	and Eunsol Choi. 2022. Beyond counting datasets:	8. Miscellaneous (address to a nation, disaster re-	870
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825	necessary resources. In <i>Findings of the Association</i>	The creators had to produce the set number of sen-	872
826	for Computational Linguistics: EMNLP 2022, pages	tences for each of the domains; the structure of the	873
827	3725–3743, Abu Dhabi, United Arab Emirates. As-	template (domain / paragraph / sentence) could not	874
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830	Mahani Aljunied, Zhaodonghui Li, Lidong Bing,	When creating sentences, the creators had to make	877
831	Hou Pong Chan, Yu Rong, Deli Zhao, and Wenx-	sure that the register of language being used was	878
832	uan Zhang. 2025.	representative of the most expected and appropriate	879
833	A Specific guidance for paragraph and	register for the situation. When several registers were	880
834	sentence creation	possible, the creators were asked to use discretion	881
835	A.1 Overview	when selecting a register, while making sure that the	882
836	The Bouquet-source dataset comprises 250 unique	chosen register was among the most expected and	883
837	sentences in each of its source languages. This means	appropriate. To help them make a determination, we	884
838	that each linguist created (i.e., wrote from scratch,	defined 3 main functional areas of language register:	885
839	did not copy; see Section 2.4 above) 250 original	• Connectedness: What type of connection do	886
840	sentences. These sentences were requested to be:	language users who initiate the text have with	887
841	• Organized in logically structured paragraphs	other language users?	888
842	(see the Paragraphs section below)	• Preparedness: How much time do language	889
843	• Representative of the linguistic structures and	users who initiate the text had or took to prepare	890
844	features most frequently used in specific do-	the text?	891
845	main (see the Domains section below)	• Social differential: What is the relative social	892
846	• Representative of the most common register	status of the language users who initiate the text	893
847	of language used in similar situations (see the	towards other language users?	894
848	Registers section below)	A.5 Linguistic Features	895
849	• Accompanied by a gold-standard (i.e., best in	One of the main reasons for dividing the dataset into	896
850	class) human translation into English.	sections that correspond to domains is to attempt to	897
851	A.2 Paragraphs	cover as many registers and aspects of language as	898
852	The linguist received a template in the form of a	possible. For example, we know that:	899
853	spreadsheet, in which paragraph structures were de-	• Some pro-drop languages may drop the subject	900
854	signed and laid out. The template specified the exact	pronouns more often in some situations than in	901
855	number of paragraphs and the exact number of sen-	others.	902
856	tences for each of the paragraphs. Each paragraph	• Some case-marking languages may use some	903
857	was given a unique paragraph ID (e.g., P01, P02,	cases in specific situations but avoid them in	904
858	P15). Each sentence within each paragraph was also	others.	905
859	given a serial, non-unique ID (e.g., S1, S2, S3).		

906	• In English, lexical density increases when the	B Registers Details	951
907	level of formality increases.		
908	• Some languages use a specific past verb tense	We provide non-exclusive options for each of the 3	952
909	in storytelling, which stands out from other past	functional areas that characterize registers described	953
910	verb tenses used in casual conversations or other	in Section 3.2 and mentioned in Figure 5. By non-	954
911	situations.	exclusive, we mean that a domain may be character-	955
		ized by more than one option. The functional area /	956
912	• Some languages use specific verb moods in	option breakdown can be described as follows (the	957
913	some situations but avoid them in others.	bold lowercase letters in square brackets represent a	958
		unique identifier for each option):	959
914	A.6 Violating Content	Connectedness	960
915	While creating sentences, the creators were asked to	• Impersonal [i]: For example a text written for	961
916	avoid inserting violating content. Violating content	the purpose of giving definitions or explanations	962
917	is language that can fall under one (or more) of the	with no specific readership in mind; typi-	963
918	below categories:	cally written in the third person only (e.g., a	964
		contract).	965
919	• Toxicity	• Non-directional [n]: A text written with a read-	966
920	• Illegal activities	ership in mind but that doesn't address the read-	967
		ership specifically (e.g., an author recounting a	968
921	• Stereotypes and biases	story)	969
922	A.7 Step-by-Step Description of Tasks	• Uni-directional [u]: A text addressing a reader-	970
923	Please refer to Table 5 for the step-by-step description	ship who either cannot respond or is asked to	971
924	of the tasks.	refrain from responding at a given time (e.g.,	972
		the transcription of a presentation, such as a	973
925	A.8 Additional Guidance on	TED Talk)	974
926	Domain-Specific Content	• Multi-directional [m]: A text addressing a read-	975
927	Dialogues, especially those inserted in long creative	ership who can respond (e.g., SMS, DM) or	976
928	writing (such as novels), often include the name of	representing the transcription of a dialogue in-	977
929	the speaker or a cue mark (e.g., —), and sometimes	volving 2 or more language users.	978
930	quotation marks. When creating sentences for conver-		
931	sations, the creators were let free to invent names for	Preparedness	979
932	speakers or to label speaker turns (e.g., A, B); they	• Reactive (spontaneous) [r]: The production is	980
933	were also asked to place the names or speaker refer-	immediate either because it needs to be or be-	981
934	ence in markup tags, similarly to this: <Name:>or	cause the user wants it to be	982
935	<A:>.	• Improvised (coached) [i]: The production ap-	983
936	Emojis: As there are emojis frequently in some so-	pears spontaneous but takes place after a period	984
937	cial media and messaging domains, some representa-	of general training or coaching (e.g., spokes-	985
938	tion was also expected from the creators. However,	people who answer questions live but have had	986
939	the creators were asked to keep this representation	time to prepare and choose vocabulary to use	987
940	very limited, as there are no real agreed ways to trans-	or to avoid)	988
941	late them across hundreds of languages.	• Rehearsed (extemporaneous) [e]: The produc-	989
942	Social media comments: The creators were told that	tion is live but its overall structure has been	990
943	they could keep the structure of those comments flat,	carefully crafted and rehearsed (e.g., transcrip-	991
944	and that including tags was not absolutely necessary,	tions of 20-minute presentations or speeches	992
945	though it was permitted (even expected).	that aren't fully scripted and given from notes).	993
946	Disfluencies in informal conversations: Disfluen-	• Scripted (declaimed) [s]: The production	994
947	cies were permitted provided they were representa-	may or may not be live and has been fully	995
948	tative of conversations and they could be translated	scripted (e.g., transcriptions of speeches used	996
949	(i.e., there is some consensus on how to write them	in teleprompters)	997
950	in the language — ah, oh, um).	• Composed (frozen) [c]: The production is com-	998
		pletely offline, and goes through iterations of	999
		reviewing and editing (e.g., the text of a novel).	1000

Column A: Lang-ID	This column should have the same 3-lowercase-letter code representing the source language of the sentences being created followed by an underscore character (_) and a 4-letter code representing the script.
Column B: Domain	This is 1 of the 8 domains represented in the dataset (see Section 3.1).
Column C: Subdomain	Please insert your description of the subdomain or topic.
Column D: P-ID	This is the unique code identifying a paragraph (e.g., P01, P02, ..., P58).
Column E: S-ID	This is the non-unique code identifying the sequential place of the sentence within a paragraph.
Column F: Sentence	In this cell, please type a sentence you created.
Column G: Translation into English	After entering a sentence in your language in Column F, please provide a gold-standard human translation in this cell.
Column H: S-Nchars	This represents a count of the number of characters in the sentence.
Column I: S Comment_src.lang	To help other linguists expand this dataset by translating your sentences into their own languages, please add any comments that bring more context about the sentence.
Column J: S Comment_English	Please provide an English translation of the comment you inserted in Column I.
Column K: Linguistic features	Please list the register- or domain-specific linguistic features you tried to showcase in the sentence.
Column L: Connectedness	Please use any of the options best describing the register area of Connectedness.
Column M: Preparedness	Please use 1 of the options best describing the register area of Preparedness.
Column N: Social differential	Please use any of the options best describing the register area of Social differential.
Column O: Formality	Please indicate the level of formality best characterizing the sentence.
Column P: Relationship	Please insert the intended relationship between the language users involved in the situation.
Column Q: Idea origin	Please insert the name of the media type or platform that inspired the sentence.
Column R: P Comment_src.lang	To help other linguists expand this dataset by translating your sentences into their own languages, please add any comments that bring more context about the entire paragraph.
Column S: P Comment_English	Please provide a translation into English for the comment you inserted in Column R.
Column T: P-Nchars	This represents a count of the number of characters in the current paragraph.
Column U: Creator_Translator-ID	Please insert your ID here, if it isn't pre-populated.

Table 5: Step-by-step guidance.

Domains	Connectedness				Preparedness					Social differential			
	Impersonal (3P only)	Non- directional (1Ps only)	Uni- directional	Multi- directional	Reactive Spontaneous	Improvised Coached	Rehearsed Extemporaneous	Scripted Declaimed	Composed Frozen	Equal (known)	Equal (assumed)	Higher- to-lower	Lower- to-higher
Narration	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Dialog	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Social media posts	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Social media comments	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
How-to	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
Website misc.	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
Opinion	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>
Other misc.	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 5: Register functional areas and breakdowns within each functional areas and their representations across domains.

Social differential

- Equal (known) [k]: The readership or addressees are known to be peers; this can include a very informal or colloquial attitude
- Equal (assumed) [a]: The readership or addressees are not known but assumed to be peers; this can include a casual or informal attitude but likely excludes a very colloquial one
- Higher-to-lower [h]: The readership or addressees are considered to be at a lower social level than the producer (e.g., the producer is arrogant or assumes a position of higher authority)
- Lower-to-higher [l]: The readership or addressees are considered to be at a higher social level than the producer (e.g., the producer wants to express deference, respect, or admiration)

1. Checking the correct co-referencing. The Bouquet dataset is a representation of natural language, and the usage of personal and possessive pronouns as a substitute for the nouns is a typical occurrence. If the internal co-referencing in the paragraph is broken (the wrong pronoun is used or the noun is repeated where the noun should be), it indicates that the paragraph was treated as a collection of sentences not linked to each other, rather than a paragraph of text.
2. Checking the lexical consistency. We made sure to check that vocabulary used to translate word denoting objects or events is appropriate in tone, style and register and is used consistently throughout each paragraph. For example, when checking, we found out that translations from Indonesian into Russian did not keep consistency for “potato fritters” (“perkedel kentang”), using three different ways to translate it in P-292. We later applied the necessary corrections.
3. Checking the grammatical consistency. Since the Bouquet dataset contains examples of different domains, we needed to check whether the verb tenses and syntax were appropriate for a given domain and used consistently throughout each paragraph. For example, when checking translated into German paragraphs which im-

C Quality Checks Details in Multi-way extension

In order to make sure that the BOUQuET contextual information was taken into account while translating BOUQuET, we used the following QA strategies:

1050 itate fiction narration, we made sure that Ger-
1051 man Präteritum tense is used appropriately, not
1052 Perfekt.

1053 4. Checking the special symbols such as emojis
1054 and numbers.

1055 **D Priority Languages**

1056 Table 6 shows the languages in which BOUQuET
1057 exists at the time of submission of this paper (May
1058 2025).

1059 **E Dataset Examples**

1060 Table 7 reports the sentences with highest similar-
1061 ity score computed with cosine distance of SONAR
1062 vectors across all 2,000 Source-BOUQuET English
1063 sentences.

1064 Table 8 shows complete entries examples of the
1065 Source-BOUQuET dataset.

1066 **F Domain representation details**

1067 Figures 6 shows the domain representation and over-
1068 lap across datasets.

1069 **G Detailed results**

ISO 639-3	ISO 15924	LANGUAGE	FAMILY	SUBGROUP	Class
arz (+ arb)	Arab	Egyptian Arabic +Modern Stan. Arabic)	Afro-Asiatic	Central Semitic	Pivot
arz	Latn	Romanized Egyptian Arabic	Afro-Asiatic	Semitic	P1-HR
aar	Latn	Afar	Afro-Asiatic	Cushitic	P1-LR
agr	Latn	Aguaruna	Chicham	–	P1-LR
ami	Latn	Amis	Austronesian	East Formosan	P1-LR
ben	Beng	Bengali	Indo-European	Indo-Aryan	P1-HR
cmn	Hans	Mandarin Chinese	Sino-Tibetan	Sinitic	Pivot
ces	Latn	Czech	Indo-European	Balto-Slavic	P1-HR
crk	Cans	Plains Cree	Algic	Algonquian	P1-LR
deu	Latn	German	Indo-European	West Germanic	Pivot
dje	Arab, Latn	Zarma	Songhay	Eastern Songhay	P1-LR
ell	Grek	Modern Greek	Indo-European	Hellenic	P1-HR
fra	Latn	French	Indo-European	Italic	Pivot
gaz	Latn	West Central Oromo	Afro-Asiatic	Cushitic	P1-LR
gil	Latn	Gilbertese	Austronesian	Micronesian	P1-LR
guc	Latn	Wayuu	Arawakan	Caribbean Arawakan	P1-LR
hin	Deva	Hindi	Indo-European	Indo-Aryan	Pivot
hin	Latn	Romanized Hindi	Indo-European	Indo-Aryan	P1-HR
hrv	Latn	Croatian	Indo-European	Balto-Slavic	P1-HR
hun	Latn	Hungarian	Uralic	Hungaric	P1-HR
ind	Latn	Indonesian	Austronesian	Malayic	Pivot
ita	Latn	Italian	Indo-European	Italic	P1-HR
jav	Latn	Javanese	Austronesian	Javanese	P1-HR
jpn	Jpan	Japanese	Japonic		P1-HR
kaa	Cyrl	Karakalpak	Turkic	Kipchak	P1-LR
kal	Latn	Kalaallisut	Eskimo-Aleut	Eskimo	P1-LR
khm	Khmr	Central Khmer	Austroasiatic	Mon-Khmer	P1-HR
kor	Kore	Korean	Korean	Koreanic	P1-HR
kru	Deva	Kurukh	Dravidian	North Dravidian	P1-LR
lij	Latn	Ligurian	Indo-European	Italic	P1-LR
lin	Latn	Kinshasa Lingala	Atlantic-Congo	Central West. Bantu	P1-LR
mya	Mymr	Burmese	Sino-Tibetan	Burmo-Qiangic	P1-LR
nld	Latn	Standard Dutch	Indo-European	West Germanic	P1-HR
pes	Arab	Western Persian	Indo-European	Iranian	P1-HR
pol	Latn	Polish	Indo-European	Balto-Slavic	P1-HR
rus	Cyrl	Russian	Indo-European	Balto-Slavic	Pivot
ron	Latn	Romanian	Indo-European	Italic	P1-HR
sba	Latn	Ngambay	Central Sudanic	Sara-Bongo-Bagirmi	P1-LR
spa	Latn	Spanish	Indo-European	Italic	Pivot
por	Latn	Portuguese (Brazilian)	Indo-European	Italic	P1-HR
swe	Latn	Swedish	Indo-European	North Germanic	P1-HR
swb	Latn	Coastal Swahili	Atlantic-Congo	N.E. Coastal Bantu	P1-HR
tha	Thai	Thai	Tai-Kadai	Southwestern Tai	P1-HR
tir	Ethi	Tigrinya	Afro-Asiatic	Semitic	P1-LR
tgl	Latn	Tagalog	Austronesian	Greater Central Philippine	P1-HR
tur	Latn	Turkish	Turkic	Oghuz	P1-HR
ukr	Cyrl	Ukrainian	Indo-European	Balto-Slavic	P1-HR
urd	Arab	Urdu	Indo-European	Indo-Aryan	P1-HR
vie	Latn	Vietnamese	Austroasiatic	Vietic	P1-HR
yor	Latn	Yoruba	Atlantic-Congo	Defoid	P1-LR
zlm +zsm	Latn	Colloquial Malay + Standard Malay	Austronesian	Malayic	P1-HR

Table 6: Source-BOUQuET Languages (Pivot) and Priority languages (P) both high-resource (HR) and low-resource (LR) included in BOUQuET at the time of submission. Note that these languages have been commissioned, we do not include updates in annotations collected from the open-initiative, which we will include in later versions of the paper.

cosinedist	lang-A	lang-B	Domain-A	Text-A	UNIQID-A	DomainB	Text-B	UNIQID-B
0.19	ind	arz	conversation	What time do we meet?	P304-S4	conversation	when will we meet?	P017-S1
0.20	fra	cmn	web misc.	About us	P220-S1	web misc.	About our team	P098-S1
0.22	rus	deu	conversation	<B:> Which one?	P363-S2	conversation	<B:> When and where?	P134-S2
0.24	rus	fra	conversation	<B:> Nah, I am sick	P360-S2	conversation	<B:> You're sick?	P185-S4
0.25	rus	fra	conversation	<A:> You know what I mean!	P362-S4	conversation	<A:> Did you hear?	P183-S1
0.28	fra	arz	web misc.	Send us your résumé and motivation letter at the below address.	P215-S6	web misc.	Please send your CV with letters of recommendation to this email address	P043-S5
0.28	spa	rus	comments	<B:> WHAT IS THIS???	P443-S2	conversation	<B:> What do you mean?	P362-S2
0.29	rus	fra	conversation	<A:> Get well soon	P360-S3	conversation	<A:> Not doing very well.	P185-S3
0.29	rus	fra	conversation	<B:> What do you mean?	P362-S2	conversation	<A:> Did you hear?	P183-S1
0.29	rus	fra	conversation	<B:> What do you mean?	P362-S2	conversation	<B:> You're sick?	P185-S4
0.29	rus	fra	conversation	<B:> Nothing is working for me.	P366-S2	conversation	<A:> Not doing very well.	P185-S3

Table 7: Source-BOUQuET sentences with closest similarity score (cosine distance lower than 0.3)

LangID	Domain	Subdomain	PID	SID	Sentence	English	Linguistic label	Reg.
spa_Latn	conversation	text message chain	P417	S1	<Guillermo:> Habéis cenado ya?	<Guillermo:> Have you had dinner already?	word:named-entity	mrk
spa_Latn	conversation	text message chain	P417	S2	<Jaime:> No, estábamos pensando en salir ahora, te apuntas?	<Jaime:> No, we were thinking about going out now. Are you in?	word:named-entity	mrk
spa_Latn	conversation	text message chain	P417	S3	<Guillermo:> Sí, me estoy muriendo de hambre.	<Guillermo:> Yes, I'm starving.	word:named-entity, miscellaneous:collocation	mrk
spa_Latn	conversation	text message chain	P417	S4	<Jaime:> Guai, salimos en cinco, te esperamos en la parada del metro.	<Jaime:> Cool, we're leaving in five, we'll wait for you at the metro station.	word:named-entity, word:slang	mrk
spa_Latn	conversation	text message chain	P417	S5	<Guillermo:> Perfecto, me cambio y salgo.	<Guillermo:> Perfect, I'll change and head out.	word:named-entity	mrk
fra_Latn	social posts	Integrity	P204	S1	Choses que j'aurais aimé savoir plus tôt	Things I wish I had known earlier	sentence:fragment	usa
fra_Latn	social posts	Integrity	P204	S2	Si tu ne prends pas de décision pour toi-même, d'autres les prendront pour toi.	If you don't make decisions for yourself, others will take them for you.	word:impersonal-pronoun	usa
fra_Latn	social posts	Integrity	P204	S3	Quand on te submerge de généralités, demande plusieurs exemples spécifiques.	When you are getting submerged in generalities, request several specific examples.	word:impersonal-pronoun	usa
ind_Latn	narration	Folklore / Fable	P310	S1	Pada suatu masa, hiduplah sepasang suami istri di sebuah pedesaan.	Once upon a time, there lived a husband and wife in a village.	Third person, impersonal, narration	ica
ind_Latn	narration	Folklore / Fable	P310	S2	Mereka belum juga dikarunia anak setelah sekian lama menikah.	They have not yet been blessed with children after being married for so long.	Third person, impersonal, narration	ica
ind_Latn	narration	Folklore / Fable	P310	S3	Keduanya bermimpi bahwa mereka harus menanam timun, jika mereka ingin memiliki anak.	Both of them dreamed that they had to plan cucumbers, if they wanted to have a child.	Third person, impersonal, narration	ica
ind_Latn	narration	Folklore / Fable	P310	S4	Kemudian ditanamlah timun-timun itu.	Then they planted the cucumbers.	Third person, impersonal, narration	ica

Table 8: BOUQuET examples including main fields

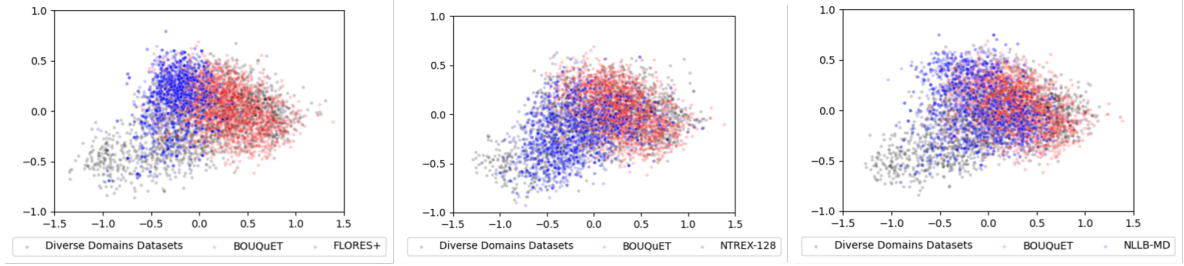


Figure 6: Domain representation and overlap across FLORES+ (left), NTREX-128 (middle), NLLB-MD (right)(in blue) with diverse domains datasets (in grey) and BOUQuET (in red).

Src-lang	arz-Arab		cmn-Hans		deu-Latn		eng-Latn		fra-Latn		hin-Deva		ind-Latn		rus-Cyrl		spa-Latn	
	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX
nllb-3B	0.59	2.31	0.66	1.39	0.72	2.39	0.75	1.86	0.69	2.11	0.61	2.33	0.69	2.03	0.67	2.33	0.72	2.13
aya101-13B	0.59	2.23	0.65	1.32	0.71	2.31	0.75	1.76	0.67	2.07	0.6	2.32	0.69	1.88	0.67	2.26	0.71	1.99
aya-e-8B	0.6	2.04	0.68	1.09	0.73	2.06	0.77	1.47	0.7	1.77	0.62	1.94	0.7	1.69	0.69	1.94	0.73	1.76
babel-9B	0.57	2.78	0.66	1.61	0.72	2.58	0.75	1.92	0.68	2.47	0.59	2.54	0.69	2.16	0.67	2.47	0.71	2.46
cohere-r7B	0.58	2.38	0.66	1.28	0.72	2.45	0.75	1.87	0.66	2.52	0.61	2.18	0.7	1.86	0.66	2.65	0.71	2.16
eurollm-9B	0.58	2.55	0.66	1.59	0.71	2.68	0.75	2.04	0.68	2.38	0.61	2.41	0.66	2.37	0.67	2.58	0.71	2.36
madlad-10B	0.52	3.71	0.62	1.8	0.66	3.23	0.73	2.0	0.64	2.61	0.58	2.75	0.62	3.06	0.63	3.08	0.69	2.39
madlad-3B	0.51	3.93	0.62	1.76	0.63	3.51	0.72	2.26	0.63	2.82	0.59	2.63	0.61	3.25	0.63	3.1	0.7	2.4
mistral-7B	0.44	5.32	0.54	3.53	0.59	4.52	0.6	3.83	0.55	4.2	0.46	4.95	0.59	3.81	0.56	4.31	0.59	4.11
qwen-7B	0.5	3.83	0.58	2.55	0.63	3.49	0.68	2.79	0.6	3.25	0.52	3.45	0.61	3.16	0.59	3.47	0.62	3.29
Llama-3.1-8B	0.56	2.77	0.64	1.58	0.7	2.63	0.75	1.88	0.66	2.46	0.58	2.77	0.68	2.24	0.66	2.52	0.7	2.38
Llama3.2-3B	0.46	4.88	0.58	2.56	0.63	3.86	0.67	3.02	0.58	3.77	0.53	3.78	0.61	3.35	0.59	3.46	0.63	3.62
Llama3.3-70B	0.61	1.96	0.68	1.18	0.74	2.14	0.77	1.62	0.71	1.94	0.62	2.1	0.71	1.73	0.69	2.05	0.74	1.91
Tower-7B	0.4	6.07	0.62	1.5	0.63	3.23	0.66	3.48	0.56	4.21	0.49	4.42	0.62	3.26	0.6	3.61	0.64	3.46
Trg-lang	arz-Arab		cmn-Hans		deu-Latn		eng-Latn		fra-Latn		hin-Deva		ind-Latn		rus-Cyrl		spa-Latn	
	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX	COM	METX
NLLB-3B	0.62	3.08	0.59	2.99	0.71	0.99	0.76	2.22	0.69	2.01	0.61	2.55	0.7	1.53	0.71	1.77	0.72	1.76
aya101-13B	0.64	2.61	0.63	1.82	0.69	1.07	0.76	2.26	0.68	2.14	0.56	2.94	0.69	1.55	0.69	1.85	0.7	1.89
aya-e-8B	0.7	1.9	0.65	1.81	0.72	0.85	0.77	2.01	0.71	1.82	0.53	3.02	0.71	1.3	0.72	1.47	0.73	1.59
babel-9B	0.64	3.06	0.66	1.96	0.68	1.31	0.76	2.1	0.69	2.06	0.53	3.74	0.68	2.42	0.69	2.42	0.71	1.91
cohere-7B	0.68	2.38	0.65	1.87	0.7	1.0	0.76	2.13	0.69	1.95	0.51	3.99	0.66	2.08	0.68	2.24	0.72	1.72
eurollm-9B	0.7	1.99	0.66	1.65	0.72	0.89	0.77	2.13	0.7	1.87	0.6	2.65	0.45	6.53	0.72	1.57	0.72	1.67
madlad-10B	0.65	2.67	0.59	2.61	0.67	1.64	0.75	2.47	0.66	2.71	0.41	5.12	0.62	2.64	0.66	2.66	0.7	2.1
madlad-3B	0.65	2.8	0.58	2.77	0.66	1.73	0.73	2.79	0.64	2.81	0.42	5.1	0.62	2.64	0.65	2.83	0.69	2.2
mistral-7B	0.32	8.73	0.55	3.12	0.62	1.85	0.73	2.7	0.62	2.96	0.3	8.42	0.52	4.52	0.61	3.38	0.65	2.89
qwen-7B	0.53	4.74	0.64	2.09	0.63	1.76	0.72	2.39	0.64	2.63	0.25	7.38	0.64	2.65	0.61	3.12	0.66	2.49
Llama3.1-8B	0.54	4.68	0.64	1.91	0.69	1.17	0.76	2.25	0.68	2.17	0.57	3.05	0.68	1.81	0.68	2.18	0.7	2.01
Llama3.2-3B	0.43	6.84	0.55	3.11	0.63	1.76	0.73	2.62	0.62	2.86	0.49	4.5	0.62	2.7	0.54	5.27	0.66	2.66
Llama3.3-70B	0.6	3.32	0.68	1.62	0.73	0.85	0.77	2.04	0.71	1.84	0.63	2.41	0.72	1.35	0.72	1.55	0.73	1.64
Tower-7B	0.3	7.96	0.61	2.33	0.67	1.44	0.74	2.74	0.66	2.6	0.41	6.54	0.51	4.62	0.66	2.52	0.68	2.5

Table 9: Averaged results on CometKiwi (COM) and MetricX (etx) at the sentence-level from 9 BOUQuET languages (top) and into (bottom). Best results are in bold (before rounding to 2 decimals). Best results on CometKiwi tend to be with Llama-3.3-70B (the largest model) and best results in MetricX tend to be with Aya-expanse-8B. Best direction is from and into English .