EIFFEL: a novel benchmark to measure bias of English heavy training on French idiomatic expressions

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Abstract

Mainstream multilingual LLMs are generally trained on a much higher proportion of English than multilingual data, raising questions about their ability to capture linguistic features particular to non-English languages or to capture information important to non-anglophone cultures. We add to a growing effort to increase multilingual sensitivity in LLMs by developing a benchmark, EIFFEL, testing mastery of French idiomatic expressions in context. We fully explain the methodology, which exploits input from native French speakers, to make it reproducible for other languages. We compare mainstream multilingual LLMs with French-focused LLMs both on standard LLM benchmarks and EIFFEL; EIFFEL brings out the benefits of higher proportions of French data and shows limitations of standard benchmarks for measuring multilingual competence. We also train from scratch a series of 1B SLMs with different proportions of French and English pretraining data that confirm EIFFEL's lessons.

1 Introduction

While large language models (LLMs) are increasingly popular worldwide, many of the leading models are trained on disproportionate amounts of English data. For example, only 8% of Llama 3.1's training data come from non-English natural languages (Grattafiori et al., 2024). This raises the question of how anglocentricity shapes an LLM's ability to produce high-quality sequences in other languages and to represent knowledge and cultural norms central to non-anglophone cultures.

Answering this question is complicated by the potential for language transfer. Suppose that we have a bilingual model B trained on English and some non-English language L. If there is transfer from one language to another, then B's probability distribution over English tokens can inform its distribution over L tokens and vice versa. If we then apply B to a downstream task that is covered by knowledge transfer from English, B might do well having seen only a small proportion of data in L. Language transfer together with task relevant training is arguably what makes mainstream anglocentric LLMs surprisingly powerful in non-English languages. A more focused question is then: to what extent will culturally and linguistically sensitive aspects of L be overlooked if we rely on language transfer?

A complete answer to this question is beyond the scope of this paper, but we offer an important and first of its kind tool to explore this question: EIFFEL, **E**valuation of **I**diomatic **F**rench **F**ixed **E**xpressions for **L**arge Language Models, is a benchmark that showcases French idiomatic expressions.

Idiomatic expressions make a good test subject because they are a feature of everyday language that is highly language specific. While some idiomatic expressions can be translated word-for-word between French and English, such as "Not my cup of tea/Pas ma tasse de thé," others are less direct or even completely different. The expression "call a spade a spade " for example, has an obvious counterpart in French, literally "call a cat a cat"; but it is not a direct translation. The majority of expressions are even less easily translatable. "Avoir du chien," literally, "to have some dog," means to be charming. For a model to handle these latter expressions, we hypothesize that it needs more than a solid hold on English and a good capacity for translation; it needs to have seen either explicit translations of the idiomatic expressions or a fair amount of (non-translated) French data.

We test the impact of our benchmark by first comparing a series of models on French and English versions of standard benchmarks (ARC Challenge (Clark et al., 2018), Hellaswag (Zellers et al., 2019), MMLU (Hendrycks et al., 2020)) and then compare the results to those on EIFFEL and the French subset of INCLUDE (Romanou

et al., 2024), a dataset also originally in French that contains culturally sensitive and agnostic subsets that allow for interesting comparisons with EIFFEL. We consider pretrained models from two anglocentric model families,[1] Llama and Gemma (Team et al., 2024, 2025), as well as "gallocentric" models[2] trained on 1:2 and 1:1 ratios of French and English data: the Gaperon models (Godey et al., 2025), Lucie (Gouvert et al., 2025), and CroissantLLM (Faysse et al., 2024). We also look at EuroLLM models (Martins et al., 2025a,b), as they offer a middle case between anglocentric and gallocentric models and focus on translation capacities. Our study is restricted to pretrained models, as we are interested in basic linguistic mastery.

While standard LLM benchmarks in French do not reveal an advantage for gallocentric models over anglocentric ones, both EIFFEL and the culturally-sensitive subset of INCLUDE do. This suggests that EIFFEL captures features of French that benefit less from transfer or literal translation.

To further explore this trend, we train a series of 1 billion parameter models, each trained on 100 billion tokens of varying proportions of French and English web data. Even at this small scale, we see a trend on at least some standard benchmarks that the pretrained models with at least a 1:2 French to English ratio in pretraining perform better on French versions of standard benchmarks; they also perform significantly better on EIFFEL. This suggests that EIFFEL may serve as an early benchmark for training and that the trend observed with the larger models is already visible at a small scale, meaning that insights from our tests on EIFFEL could inform the training of full-scale LLMs.[3]

Insofar as idioms are just one example of everyday language likely found in French web data and also an example of a phenomenon important for a variety of downstream tasks—from summarizing conversation transcripts to speaking to users in a style that makes them feel comfortable—our benchmark results show that modulating the amount of French data may be important for downstream success of French LLMs more generally.

An additional factor uncovered by EIFFEL is the effect of translation data. Translation corpora, dictionaries, etc. imbue models with complex statistical relations between elements of English and French, from the word level up to the sentence, to the paragraph and potentially beyond. EIFFEL shows that a translational paradigm offers rather restricted correlations: models with translation data but not much French in pretraining excel at idioms with word-for-word translations in English, but their performance falls below that of gallocentric models on other idioms. This supports prior work that has shown that such data induces biases towards frequent or standardized forms over rare and non standard ones, structural simplification as well as reduced lexical and morphological diversity (Vanmassenhove et al., 2021; Laviosa, 1998).

In sum, our main contributions are as follows:
(i) EIFFEL, a cultural French benchmark for idioms – the only one of its kind.
(ii) Detailed, reproducible methodology for building such a benchmark.
(iii) Six 1 billion parameter, open-source models trained from scratch on varying proportions of French and English web data.
(iv) Experiments on our test models to study the impact of different proportions of French data.

2 State of the Art

The impact of anglocentricity. Anglocentric multilingual models generally can produce reasonable quality non-English text. This does not mean, however, that the concepts and linguistic patterns thereby produced naturally represent concepts and patterns employed by native speakers.

Guo et al. (2025) show that the syntax and vocabulary distribution in non English-languages are affected by high proportions of English training data, resulting in outputs that are often less natural and less diverse than those of native speakers. The greater the typological difference between English and the target language, the more pronounced the gap of lexical naturalness. Karim et al. (2025) show that anglocentricity can impact model performance even in domains that do not seem culturally sensitive, such as math. In particular, they show a decline in performance on mathematical benchmarks when certain words in the math problems are replaced with words more relevant to a non-anglophone culture, such as replacing Western food names with those from Pakistan or Moldova.

Towards multilingual models. Recently, mainstream models including Gemma 3 (Team

[1] We take anglocentric models to be those with a high English/French ratio.

[2] Gallocentric models have higher proportions of French over English, typically at least 25%.

[3] We will openly release our entire dataset and our 1B models upon paper acceptance.

et al., 2025), Qwen 3 (Yang et al., 2025), and Mistral 3.1 (https://mistral.ai/fr/news/mistral-small-3-1) claim to have increased multilingual data, though we were unable to find statistics on data proportions (and we tried). Some models, such as Llama 3 (Grattafiori et al., 2024), Nemotron-H (Blakeman et al., 2025; Adler et al., 2024), and SmolLM3 (Bakouch et al., 2025), provide statistics for overall multilingual proportions, but we could not find a breakdown by language.[4]

Projects with a more explicit multilingual focus often provide more information. The EuroLLM models (Martins et al., 2025a,b) cover 24 languages and cite around 45-60% (depending on the training phase) non-English, natural language data with 5-6% in French; the Apertus models (Hernández-Cano et al., 2025) cover 1800 languages and use 40% non-English data with 7.28% French; and the Salamandra models (Gonzalez-Agirre et al., 2025) cover 35 languages and have 55% non-English data with 6.6% in French (and 16% Spanish).

Some projects focus on particular non-English languages; we focus on gallocentric projects here. CroissantLLM is a bilingual 1.3 billion parameter model trained from scratch on a 1:1 French-English ratio (Faysse et al., 2024) while Lucie 7B (Gouvert et al., 2025) and the Gaperon models (Godey et al., 2025) are trained on a roughly 1:2 ratio.

Standard benchmarks. Many benchmarks used to test multilingual performance are translated from datasets originally in English. Some are translated automatically, e.g.: XCODAH and XCSQA (Lin et al., 2021), based on CODAH (Chen et al., 2019) and CSQA (Talmor et al., 2019), as well as ARC (Clark et al., 2018), Hellaswag (Zellers et al., 2019), TruthfulQA (Lin et al., 2022), GSM8K (Cobbe et al., 2021) and MMLU (Hendrycks et al., 2020) translated by (Thellmann et al., 2024). Faysse et al. (2024) translated other benchmarks, including ARC and Hellaswag, into French.

A few benchmarks are multilingual through semi-automatic or manual translation, for example Belebele (Bandarkar et al., 2024), Mintaka (Sen et al., 2022) and Global MMLU (Singh et al., 2025). And only a few benchmarks are originally constructed in the target language, such as FQuAD2.0 (d'Hoffschmidt et al., 2020; Heinrich et al., 2021), a French reading comprehension dataset in the style of SQuAD (Rajpurkar et al., 2016).

Benchmarks targeting culture. Global MMLU (Singh et al., 2025) is a multilingual version of MMLU that extends the original benchmark by translating it and tagging questions as culturally-agnostic or culturally-sensitive. BLEnD (Myung et al., 2024) is a multilingual benchmark built by asking native speakers to fill in blanks of translated sentence templates with the names of, say, holidays or common food dishes. CulturalBench (Chiu et al., 2024) includes questions targeting 45 cultures although the questions are written in English.

For cultural benchmarks developed natively in the target language, AraDiCE (Mousi et al., 2025) includes seven Arabic dialogues annotated with associated cultural context. CLIcK (Kim et al., 2024) tests textual, grammatical, and functional knowledge in Korean. IOLBENCH (Goyal and Dan, 2025) poses questions in English about linguistic features of a variety of languages. INCLUDE (Romanou et al., 2024) is a multilingual benchmark built by extracting Q/A data from documents in the target languages that are then verified and corrected by native speakers. It includes culturally agnostic and culturally sensitive subsets. French Bench grammar-vocab-reading (Faysse et al., 2024) evaluates grammar rules, vocabulary, and basic reading comprehension. Of these, only INCLUDE and French Bench cover French, and only INCLUDE has culturally sensitive topics.

Turning to idioms, ID10M (Tedeschi et al., 2022) tests for the ability to identify an idiom or other MWE (multiword expression) in a text. Other tasks focus on being able to provide or identify definitions or paraphrases of idioms and MWEs, such as MAPS (Haviv et al., 2023), IDIOMKB (Li et al., 2024) and MIDAS (Kim et al., 2025). Multilingual Idioms and Similes in LLMs (Khoshtab et al., 2025) tests for the ability to properly continue a text after an idiom is used. Only ID10M includes French, to our knowledge, although the PARSEME shared tasks, e.g., Ramisch et al. (2020), test ability to perform MWE classification and paraphrasing. The closest benchmark to ours is the Arabic benchmark Kinayat (Attia et al., 2025), which assesses the ability to complete idiomatic expressions by masking the last word of the expression.

Ablation studies. There have been few studies that investigate how proportions of data of different languages affect the performance of multilingual models. Han et al. (2025) trained ablation models

[4]Llama 3.1: 8% multilingual data, 8 supported languages; Nemotron-H: 3.7-5%, 9 languages; Nemotron 4 15%, 53 languages; SmolLM3 12%, 6 languages.

on 500 billion Chinese and English tokens in two different settings (1:1 zh-en, 1:9 zh-en). In each setting, they tested replacing both 10 billion and 40 billion regular tokens with the same amount of Chinese-English translation data to evaluate transfer between English and Chinese.

They show that in the 1:9 scenario, replacing 10 billion regular tokens with 10 billion parallel tokens brings Chinese performance to the level of a model trained in the 1:1 setting with no parallel data. This provides experimental evidence that even small amounts of $L1$-$L2$ translation data can improve $L2$ performance on standard benchmarks, even if the proportion of $L2$ data is small. Han et al. (2025)'s results thus support the multilingual strategy of EuroLLM (Martins et al., 2025a,b). As we show in Section 5, however, this strategy does not capture at least some culturally sensitive aspects of language.

3 Building a benchmark for French idiomatic expressions

The idiomatic meaning of an idiomatic expression cannot be inferred from the literal meanings of its parts: if you're at a party where no one is talking, and you tell your partner to "break the ice," you are not literally instructing them to break some block of ice but rather to get people talking. Understanding and properly using idiomatic expressions requires a subtle mastery of the target language and the context of use, making them a perfect subject for a benchmark on culturally-specific language.

EIFFEL draws on the expertise of native speakers. We detail below the steps for building it and illustrate them in Figure 1.

1. Collecting basic idiomatic expressions. Because idiomatic expressions are an important part of everyday language, it was relatively easy to assemble a decent size list by searching the web and discussing among native French and English speaking colleagues. Some expressions were found by starting with English expressions and searching for similar expressions in French.

2. Data categorization. Our hypothesis is that anglocentric multilingual LLMs will fare well on tasks where language transfer helps, but struggle on features that are difficult to capture through translation. Accordingly, we propose three categories of idiomatic expressions for our study:

Word-for-word: The French idiomatic expression has a *word-for-word* translation in English, e.g., "Ce n'est pas ma tasse de thé" = "It's not my cup of tea." We expect these expressions to be the easiest for anglocentric models because they can be inferred from knowledge of the English expression together with basic translation capacities.

Similar: There is an expression in English that is easily recognizable as a translation of the French expression, but is not *word-for-word*, e.g., "appeler un chat un chat" (lit. "call a cat a cat") vs. "call a spade a spade" or "d'autres chats à fouetter" (lit. "other cats to whip") vs. "other fish to fry." We expect anglocentric models to be more likely to confuse the target French expression with a direct French translation of the English expression.

Different: A French expression counts as *different* if we could not find an English counterpart ("de France et de Navarre") or if the counterpart is sufficiently different that we had to discuss between speakers to find or verify the translations, e.g., "en avoir ras le bol", which means "have it up to here" but uses the metaphor of a bowl filled to its rim. We hypothesize that these expressions will be the most difficult for models exposed to small percentages of French data.

Of the 602 idiomatic expressions targeted by EIFFEL, 63 are *word-for-word*, 114 are *similar* and 425 are *different*, meaning that EIFFEL emphasizes aspects of language that are particular to French and do not lend themselves to translation.

3. Selection of masking target. As shown in Figure 1, the benchmark is designed as a multiple choice test where the LLM has to fill in a blank ("<...>") with one of four proposed options to complete the target idiomatic expression. The next step is thus to choose where to put the blank.

This task depends on idiom category. For *word-for-word* expressions, we mask the noun phrase that is most central to the idiom, e.g.,"throw the baby out with the bathwater" becomes "throw <...> out with the bathwater". Note that because French requires adjectives and articles to agree with the head noun for gender (*le* bateau vs. *la* voiture) and number (*les* voiture*s*), these expressions could help the LLM find the correct response. We therefore mask the entire noun phrase.

For *similar* expressions, we aim to mask the most important words that differ between French and English. In general, this involves a noun phrase; "appeler un chat un chat" becomes "appeler <...>". In rare cases, as when a verb is not widely used in contexts outside the given idiomatic

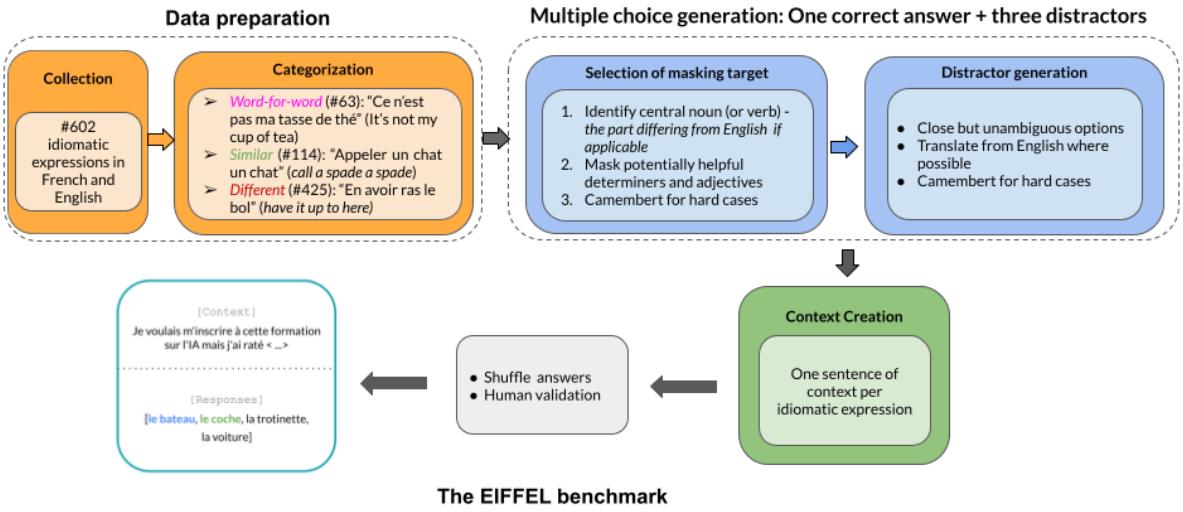

Figure 1: The EIFFEL benchmark building pipeline illustrated here on an example from the *similar* category. The context translates to "I wanted to sign up for this class on AI but I missed <...>". The possible responses translate as: "the boat," "the coach," "the scooter," "the car". The correct response is in green; the direct translation of the corresponding English expression is given in blue.

expression or when the verb is the item that differs between the English and French expressions, e.g.,"Plonger dans les livres" (lit. "Plunge/dive into the books") vs. "Hit the books," we target the verb.

The expressions in the *different* category were more difficult. When we were unable to decide where to put the blank, for any of the categories, we appealed to embeddings by the French model Camembert (Martin et al., 2020). For each alternative under consideration, we looked at the first 15 words whose embeddings were the closest via cosine similarity and chose the alternative with the most pertinent closest neighbors. Impertinent neighbors were those that were close to a non-targeted sense of a polysemous alternative or those whose similarity was not apparent to a native speaker, as can happen for alternatives whose embeddings were clearly not well learned by Camembert. When choosing between two alternatives with pertinent neighbors, we chose the alternative that had the closest neighbors.

4. Distractor generation. Each multiple choice question in the benchmark has one correct answer and three distractors. The latter are crucial for the effectiveness of multiple choice questions and must be both sufficiently credible and unambiguous (Alhazmi et al., 2024).

Given the hypothesis that anglocentric LLMs will have English biases (Guo et al., 2025; Tian et al., 2018), we include the English translation of masked expressions as distractors when possible, as in "le bateau" ("the boat") in Figure 1.

When we struggled to choose distractors, we again resorted to Camembert embeddings,[5] pulling distractors from among the top 15 closest neighbors of the head noun or verb of the masked expression, controlling for grammatical agreement, gender, and semantic compatibility. We avoided neighbors that were so similar that they could lead to answers synonymous with the target expression.

All distractors are human validated for grammar and fluency. To ensure randomness of response order, we shuffled the answers and distractors so that the correct answer is equally likely to show up in any of the four positions.

5. Adding context to idiomatic expressions. Despite our efforts to produce quality, unambiguous distractors, a common issue is that the target sentence could naturally be filled with one or more distractors to make an acceptable French expression. "It's not my cup of coffee" is a perfect sentence in English (as is its translation in French), but it is not idiomatic. To restrict the task to one of testing for idiomatic expressions, we created contexts for each example that motivated the idiomatic completion. For example: "I don't like dark chocolate. It's not

[5]We also tried creating distractors with Mixtral-8x22B-Instruct (https://huggingface.co/mistralai/Mixtral-8x22B-Instruct-v0.1) but this approach required significant manual intervention and was generally less satisfying than our Camembert method, so we rejected it.

my cup of <...>." We constructed and validated all contexts manually. Appendix A provides examples of each of the three categories of EIFFEL.

4 Evaluation of out of the box models

To see whether our benchmark captures performance differences missed by standard benchmarks, we evaluated a series of foundation models on a set of standard benchmarks translated into French and then tested the same models on EIFFEL and the French subset of INCLUDE.

4.1 Models and benchmarks

We restrict our study to base or pretrained models, as we are interested the basic knowledge and linguistic capacities of LLMs. We compare pretrained models in two size ranges, 1-2B and 7-9B, and from three categories: anglocentric, gallocentric, and intermediate. For anglocentric models, we choose Llama 3.1 8B, Llama 3.2 1B, Gemma 2 9B and Gemma 3 1B. For gallocentric models, we consider Lucie 7B, Gaperon 1B and 8B, and CroissantLLM (1.3B). As intermediate models, we take EuroLLM 9B and 1.7B, which are trained on less English then anglocentric models, but much less French than more gallocentric ones.

For benchmarks, we choose a set of standard benchmarks targeting natural language tasks that have both English and French versions: Hellaswag for commonsense reasoning, ARC Challenge for general knowledge and reasoning, MMLU (Global MMLU translations) for general knowledge, and Flores (Costa-Jussà et al., 2022) for translation. For French-centered benchmarks, we consider EIFFEL as well as INCLUDE, whose culturally sensitive subset comes from original French documents (in contrast to Global MMLU for example).

4.2 Evaluation setup

For all of our evaluations, we use the lighteval library (Habib et al., 2023) with the vLLM backend and 0-shot settings. For ARC Challenge, Hellaswag and MMLU, we use normalized accuracy; for FLORES, we use the BLEU metric. When we had an option between cloze or multiple choice formulation, as in MMLU, we chose cloze, which is simpler for pretrained models.

We integrated both INCLUDE and EIFFEL as custom tasks in lighteval with cloze formulation and evaluated on accuracy. For EIFFEL, we consider the log-likelihood of the sequences resulting from completing the context with each response.

4.3 Standard benchmark results

Table 1 shows that all models, even models with substantial French pretraining, tend to do better on the English version of a given benchmark than on its French translation. This tendency is especially marked for anglocentric models Llama3 8B and Gemma 9B with improvements of 7-14 points. We also see a clear improvement with Gaperon 8B, which while trained on the same amount of French data as Lucie 7B, is trained on much more English.

For Lucie and Croissant, the relative improvement on English benchmarks is less pronounced. Given that these models have a 1:1 English French training ratio, switching the language of the benchmark might well have less of an effect.

Perhaps more surprisingly, while anglocentric models tend to be stronger on English versions of the benchmarks than more gallocentric models, we do not observe the reverse trend in Table 1. Llama and Gemma models tend to have comparable if not slightly better results than Gaperon, Lucie and Croissant on the French benchmarks. Additionally, the EuroLLM models, with an 8:1 to 10:1 English to French ratio, perform more strongly on French benchmarks than the gallocentric models.

These results suggest several hypotheses. First, given the fact that the French versions of ARC-C, Hellaswag and MMLU are translated from English, one might expect models trained on parallel data to do well on them even if French is not particularly emphasized during training, echoing the results of Han et al. (2025). A second point pertains to the anglocentric orientation of benchmark content: translation should not change the meaning of the original data, so a French version of MMLU will retain the anglocentric biases present in the original dataset. This will give anglocentric models with already high scores on the English versions an advantage even on the French versions.

With regards to Flores, unsurprisingly, the EuroLLM models do very well. The most gallocentric models Lucie and Croissant are close seconds, however, indicating that a higher French/English ratio does help in translation. More surprisingly, a large majority of the models, including the gallocentric ones, do better at translating from English to French than vice-versa.

4.4 French-focused benchmarks

The results in Table 1 and our explanatory hypotheses above seem to point to the conclusion that hav-

Pretrained Models	French datasets			English datasets			Translation	
	ARC-C	MMLU	Hellswg	ARC-C	MMLU	Hellswg	En-Fr	Fr-En
Gaperon 8b	.44	.37	.64	.51	.42	.72	.49	.45
Lucie 7b	.40	.35	.65	.39	.41	.67	**.51**	.47
EuroLLM 9b	.46	.38	.67	.46	.41	.78	**.51**	**.49**
Llama-3 8b	.47	.39	.65	.55	.48	.79	.45	.46
Gemma-2 9B	**.54**	**.43**	**.70**	**.66**	**.53**	**.80**	.50	.48
Croissant 1.3b	.28	.28	.50	.27	.31	.53	.45	42
Gaperon 1.7b	.28	.29	.46	.34	.33	.52	.41	.40
EuroLLM 1.7b	**.35**	**.31**	**.51**	.36	**.36**	.58	.44	.44
Llama-3 1b	.29	.29	.45	.37	**.36**	.64	.30	.36
Gemma-3 1b	.30	.30	.50	**.38**	**.36**	**.62**	.26	.39

Table 1: Evaluation of selected models on a set of standard benchmarks with French translations. Models are divided into two categories by size, 1-2 billion parameters and 7-9 billion parameters. High scores are in bold; low scores are underlined. Benchmarks: ARC Challenge (ARC-C), Global MMLU, Hellaswag, FLORES 200 (for translation).

ing high proportions of French data is simply not important for good performance on these datasets. However, another possibility, made more plausible by our hypotheses, is that performing well on the standard benchmarks may not translate to good performance in French on various downstream tasks, requiring, say, conversational fluency.

This possibilty motivated us to evaluate our models on the INCLUDE and the EIFFEL benchmarks. As shown in Table 2, less anglocentric models (Gaperon, Lucie, and EuroLLM) tend to outperform more anglocentric models on INCLUDE data judged to be culturally sensitive but not on the culturally agnostic examples. On the sensitive data, Gaperon 8B leads Llama 3 8B by 6 points, while the 1B version comes out 10 points ahead over its Llama counterpart. We note, however, that models with a higher French English data ratio do not always do better on culturally sensitive data; CroissantLLM with 1:1 ratio fares worse than the other gallocentric models with less French data.

On the EIFFEL benchmark, however, overall scores indicate that a higher proportion of French data tends to lead to better performance. When we break down the scores by category, several interesting patterns emerge. We would expect models with a special focus on translation training, such as EuroLLM (Martins et al., 2025b,a) and CroissantLLM (Faysse et al., 2024), to perform well in the *word-for-word* category, and they do. We also expect, however, that models with lower proportions of French data should lose this advantage in the *similar* and *different* categories, where translation is less relevant. Indeed, for these categories, the gallocentric models beat the EuroLLM models, which in turn beat the anglocentric models.

Test Models	INCLUDE			EIFFEL			
	Ave	Agn	Sens	Ave	W-W	Sim	Diff
Gaperon 8b	.42	.27	**.54**	**.94**	.94	.93	**.94**
Lucie 7b	.37	.23	.51	**.94**	.94	**.94**	**.94**
Eurollm 9b	.39	.25	.51	.93	**.98**	.88	.92
Llama 3.1 8b	.41	.31	.48	.88	.97	.82	.85
Gemma 9b	**.44**	**.33**	.49	.89	.97	.80	.89
Croissant 1.3b	.29	.23	.39	**.94**	**.95**	**.92**	**.93**
Gaperon 1b	**.35**	**.25**	**.45**	.92	**.95**	.90	.90
Eurollm 1.7b	.33	.23	.42	.85	.91	.80	.81
Llama 3 1b	.28	.19	.35	.74	.78	.71	.74
Gemma 3 1b	.31	.23	.38	.78	.89	.69	.75

Table 2: Evaluation of selected models on culturally sensitive benchmarks in French. Avg: average, Agn: culturally agnostic, Sens: culturally sensitive, W-W: word for word, Sim: similar, Diff: different.

5 Testing bilingual proportions

Given the difference in performance on standard, translated benchmarks and benchmarks designed for French, we decided to delve deeper into the question of language proportions by training a series of 1 billion parameter models. In addition to monolingual English and French models, we trained four others on varying proportions of French and English web data: 1:100 (fr-en), 1:20, 1:2, and 1:1 (for training details see the Appendix B). The 1:100 and 1:20 mixes represent what we suppose is roughly a minimum and maximum for mainstream LLMs that include, but do not focus on, French. The 1:1 ratio allows for a bilingual

model that is not anglo- (or gallo-) centric, while 1:2 is the proportion of French data used for Lucie and Gaperon. We chose a bilingual approach to limit the number of factors to test and took English as the pivot language, as it plays that role in all mainstream models (as far as we know).

As seen in Table 3, our 1B models fail to provide results significantly beyond a random baseline for French/English ARC challenge except when the models are completely monolingual (French or English). We added ARC-Easy in English[6] to give the 1B models an easier benchmark, and which with MMLU presents a somewhat less bleak picture. The Hellaswag data set also presents more conclusive results. For these datasets Table 3 shows a performance drop for models below a 1:2 French/English ratio on the French data sets and a corresponding improvement on English datasets once we hit a 1:1 ratio (unfortunately we did not have the resources to test a 2:1 French-English ratio, but we assume the results would be symmetric with the French side).

	French datasets			English datasets			
Fr:En Models	AC	MMLU	HS	AC	AE	MMLU	HS
100% Fr	**.26**	**.26**	**.38**	.20	.32	.25	.28
1:1	**.26**	**.26**	**.38**	.25	.42	.27	.38
1:2	.25	**.26**	.37	.24	.42	.27	.40
1:20	.25	.25	.32	.24	.44	.27	.42
1:100	.23	.25	.29	.25	**.45**	**.28**	**.43**
0% Fr	.25	.25	.26	**.26**	.43	.28	.42

Table 3: Evaluation of our 1B models with different ratios of French/English on standard datasets (AC:ARC challenge, AE: ARC Easy, HS: Hellaswag) and their French translations.

Our 1B models' results on INCLUDE and EIFFEL in Table 4 show that high French to English ratios clearly help with language and culturally sensitive data. Once again below the 1:2 French-English ratio, we see a significant drop in performance on EIFFEL across all categories. INCLUDE reveals a less clear boundary; still, less anglocentric models perform better on the culturally sensitive data than more anglocentric ones.

Performance on EIFFEL, unlike that on INCLUDE, is quite stable and breaks away from random at a low scale. It also includes very high scores and performance improves smoothly throughout training as shown in Figure 5 in the Appendix, indicating that EIFFEL can serve as an early signal benchmark (Penedo et al., 2024). We leave a more challenging version for future work.

[6]Unfortunately we could not find a French version.

	INCLUDE			EIFFEL			
Fr:En Models	Ave	Agn	Sens	Ave	W-W	Sim	Diff
100% Fr	.27	.19	**.35**	**.89**	**.89**	**.89**	**.89**
1:1	.24	.19	.31	.87	**.89**	.85	.87
1:2	.25	.21	.28	.86	.87	**.89**	.84
1:20	**.28**	**.23**	.33	.70	.79	.68	.63
1:100	.22	.17	.27	.50	.56	.47	.46
0% Fr	.25	.19	.29	.34	.30	.32	.39

Table 4: Results of our 1B models with varying French English training ratios on INCLUDE and EIFFEL.

6 Error analysis on the *similar* category

We did an error analysis of both standard and our 1B models' performance on the *similar* expressions in EIFFEL. We investigated the total number of errors and looked at how many of these errors resulted from choosing the distractor translated from English as seen in Table 6 in the Appendix. The small anglocentric models Llama, Gemma 1B and our 1B models with ratios of 1:20 Fr-En or less had the most errors (overall and coming from translation) but the lowest *proportion* of literal translation errors. The gallocentric models had lower numbers of overall and translation errors but the number of translation errors varied according to the French/English ratio. Lucie and Croissant with a 1:1 ratio had the lowest number of errors; in Lucie's case, almost 90% of those errors came from choosing the distractor from English. We also note that our 1B models with a French/English ratio of 1:2 or higher were competitive with EuroLLM 9B. This suggests that a higher French/English training ratio not only improves performance on EIFFEL but allows even the small models to have a fall-back literal translation strategy for difficult idioms.

7 Conclusions

Our experiments with EIFFEL indicate that current multilingual LLMs are often evaluated with tools that insufficiently capture how training data composition shapes model behavior, because of non open data models or lack of testing on multilingual mixes. The dominance of anglocentric resources makes it difficult to disentangle genuine multilingual capabilities from artifacts induced by disproportionate exposure to English. EIFFEL helps correct this imbalance.

Limitations

Our study focuses on pretrained models, but it would also be relevant to study our question at other stages of model training.

A question for our bilingual models that we have not addressed is the question of regional variation. For instance, in Belgian French, the number ninety is expressed as *nonante*, whereas in France, it is *quatre-vingt-dix*. How should we treat these variants is something we leave for future research.

Our approach to improving multilingual performance focuses on a smaller subset of languages, and among high-resource ones rather than attempting to cover all languages simultaneously. This can help to optimize performance for specific languages without diluting training resources. But it is not clear how our approach affects or even transfers to mid or low resource languages. Especially since French and English are close typologically. Our approach also has tested various proportions of the two languages, but absolute counts might matter too. And we have concentrated only on pretraining; different strategies might also be relevant.

Another limitation of our work is that the established benchmarks are not always clean, and even EIFFEL could be improved: many expressions are missing and could be added. We also do not have an English version of EIFFEL to see if the results transfer to English. EIFFEL also takes English as a pivot language, another common assumption but one that may limit the generalizability of the approach.

Finally, we did not have the resources to do multiple training runs for our 1B models.

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A Benchmark examples

Target expression	Context	Answer A	Answer B	Answer C	Answer D
Battre le fer quand il est encore chaud *Strike while the iron is hot*	Tu as eu raison de prendre la parole, il fallait battre < ...> quand il était encore chaud *You were right to speak up, we had to strike while < ...> was hot.*	**le métal** *the metal*	le fer *the iron*	l'acier *the steel*	le cuivre *the copper*
Ce n'est pas ma tasse de thé *It's not my cup of tea.*	Le chocolat noir ce n'est pas trop ma tasse < ...>. *Dark chocolate isn't really my cup <...>.*	**de thé** *of tea*	d'infusion *of infusion*	de café *of coffee*	de tisane *of herbal tea*
Chercher une aiguille dans une botte de foin *Looking for a needle in a haystack*	Chercher ce restaurant dans Paris sans GPS c'est comme chercher < ...> dans une botte de foin. *Looking for this restaurant in Paris without GPS is like looking for < ...> in a haystack.*	une seringue *a syringe*	une épingle *a pin*	**une aiguille** *a needle*	une ficelle *a string*
Avoir la tête sur les épaules *Have a good head on your shoulders*	Il s'agirait d'agir comme un adulte et d'avoir < ...> sur les épaules. *It would be a matter of acting like an adult and having < ...> on your shoulders.*	le cerveau *the brain*	**la tête** the head	le cou *the neck*	la nuque *the back of the neck*

Figure 2: Examples of the *word-for-word* category of idiomatic expressions. The correct answers are in blue.

Target expression	Context	Answer A	Answer B	Answer C	Answer D
Avoir un chat dans la gorge *To have a cat in the throat*	Je suis malade depuis samedi, je suis enrhumé et j'ai < ...> dans la gorge. *I've been sick since Saturday, I have a cold and I have < ...> in the throat.*	une grenouille *a frog*	un crapaud *a toad*	un chien *a dog*	**un chat** *a cat*
Appeler un chat un chat *To call a cat a cat*	Arrête de prendre des pincettes, au bout d'un moment il faut appeler <...> *Stop beating around the bush, at some point you have to call < ...>*	un chien un chien *a dog a dog*	une bêche une bêche *a spade a spade*	**un chat un chat** *a cat a cat*	une pelle une pelle *a shovel a shovel*
Boire comme un templier *To drink like a templar*	Il a une sacrée descente, il boit comme un < ...> *He can really hold his liquor, he drinks like <...>*	chevalier *a knight*	**templier** *a templar*	dauphin *a dolphin*	poisson *a fish*
Être au septième ciel *To be in the seventh sky*	C'est mon parfum de glace préféré, à chaque fois que j'en mange je suis au < ...> *It's my favorite ice cream flavor. Every time I eat it, I'm in <...>*	**septième ciel** *seventh sky*	neuvième nuage *ninth cloud*	cinquième ciel *fifth sky*	huitième nuage *eighth cloud*

Figure 3: Examples of the *similar* category of idiomatic expressions

Target expressions	Context	Answer A	Answer B	Answer C	Answer D
Aller se faire cuire un œuf *Go fly a kite*	Il m'agaçait tellement avec ses remarques que je lui ai dit d'aller se faire cuire < ...> *He annoyed me so much with his comments that I told him to go to boil an < ...>*	un poulet. *a chicken*	une soupe. *a soup*	**un œuf.** *an egg*	un gâteau. *a cake*
Appuyer sur le champignon *To step on the gas*	Nous étions déjà en retard, alors il a appuyé sur < ...>. *We were already late, so he pressed <...>.*	l'aubergine *the eggplant*	**le champignon** *the mushroom*	la courgette *the zucchini*	la tomate *the tomato*
Avaler des couleuvres *make people believe lies*	On me fait avaler des < ...> toute la journée, répétait le baron. *They make me swallow < ...> all day long, the baron repeated.*	**couleuvres** *grass snakes*	grenouilles *frogs*	lézards *lizards*	vipères *vipers*
Avoir des oursins dans les poches *To have deep pockets but short arms.*	Il refuse toujours de payer un café, ce type a vraiment < ...> dans les poches ! *He still refuses to pay for coffee, that guy really has <...> in his pockets!*	**des oursins** *earwigs*	des poissons *fish*	des coquillages *seashells*	des épines *thorns*

Figure 4: Examples of the *different* category of idiomatic expressions

B Training details for bilingual test models

English data are randomly selected[7] from the split "sample-350BT" of the FineWeb dataset (Penedo et al., 2024), while French data are taken from the French subset of FineWeb-2 (Penedo et al., 2025). We focus on web data due to their diversity and the fact that they provide the foundation of LLM pretraining. Web data capture a range of everyday language and we assume that they are likely to passively include examples of idiomatic expressions.

We chose the FineWeb and FineWeb-2 datasets because they are relatively recent and have been filtered by similar pipelines. While we could have chosen better filtered datasets, English datasets such as FineWeb-edu (Lozhkov et al., 2024) would have introduced a clear quality difference between the English data and the French data from FineWeb-2. A highly filtered dataset for French, such as FineWeb-2-HQ (Messmer et al., 2025), would have resulted in a dataset too small to train our ablation models on a single epoch.

To tokenize our datasets, we use a custom in-house tokenizer with a vocabulary size of 128,000 that is trained on multilingual data: 20% French, 20% English, 20% Arabic, 20% programming languages and 20% divided between smaller proportions of other European languages. The tokenizer will be made openly available.

Each model is trained on 100 billion tokens and has Llama 3.2 1B architecture except that we adopt a sequence length of 2048 tokens. We use the NeMo library[8] and the default configuration for the Llama 3.2 1B architecture except that we adopt a sequence length of 2048 tokens. This yields:

number layers	16
hidden size	2048
ffn hidden size	8192
attention heads	32
query groups	8
activation	SwiGLU
normalization	RMS norm

Table 5: Architecture details for our test models.

We adopt a cosine scheduler with a maximum learning rate of $3e^{-4}$ and a minimum learning rate of $3e^{-5}$.

Each model was trained on 64 H100 GPUs (16 nodes) on the Jean Zay supercomputer run by GENCI-IDRIS. Training for each model took around 555 GPU hours.

[7] One exception is that we retroactively apply robots.txt protocols, so some samples are excluded off the bat.

[8] https://github.com/NVIDIA-NeMo/NeMo.

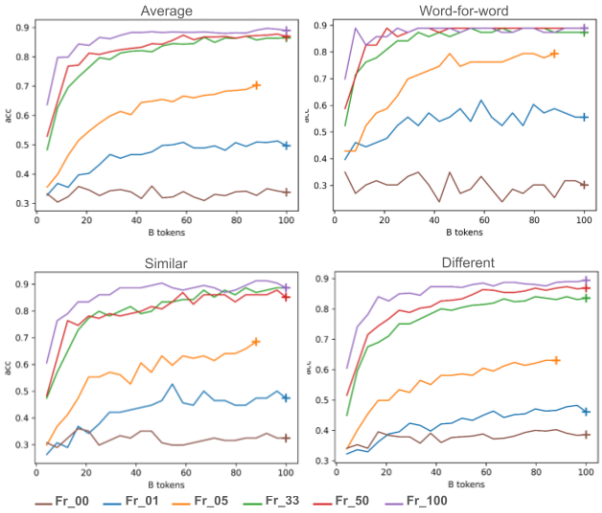

Figure 5: Performance of bilingual test models on the different subsets of EIFFEL. Top left: average scores; top right: performance on *word-for-word* expressions; bottom left: performance on *similar* expression; bottom right: performance on *different* expressions.

C Evolution of model training

The four graphs in Figure 5 show how performance of our 1B models evolved on the EIFFEL benchmark throughout training. We see a clear separation between the performance of models with at least a 1:2 ratio of French to English and those with less French. Performance improves fairly smoothly to rise above random performance, indicating that EIFFEL is a good candidate for an early signal benchmark (Penedo et al., 2024).

D Error analysis data

Models below the midline in the Table 6 are our 1B models given in terms of their French:English proportions. The second column in Table 6 provides the total number of errors. The third column indicates the number of errors that result from choosing the distractor coming from the translation of English.

Models	Nb Errors	English Bias
Llama 3 1b	45	23
Gemma 3 1b	35	17
Gemma 9b	23	15
Eurollm 1.7b	23	13
Llama 3.1 8b	20	10
Eurollm 9b	14	10
Gaperon 1b	11	6
Croissant 1.3b	9	6
Gaperon 8b	8	4
Lucie 7b	8	7
0% Fr	77	28
1:100	65	25
1:20	36	14
1:2	13	8
1:1	17	9
100% Fr	13	5

Table 6: Error analysis on the *similar* category of EIF-FEL for all models.