

# Understanding and Mitigating Language Confusion in LLMs

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## Abstract

We investigate a surprising limitation of LLMs: their inability to consistently generate text in a user’s desired language. We create the Language Confusion Benchmark (LCB) to evaluate such failures, covering 15 typologically diverse languages with existing and newly-created English and multilingual prompts. We evaluate a range of LLMs on monolingual and cross-lingual generation reflecting practical use cases, finding that Llama Instruct and Mistral models exhibit high degrees of language confusion and even the strongest models fail to consistently respond in the correct language. We observe that base and English-centric instruct models are more prone to language confusion, which is aggravated by complex prompts and high sampling temperatures. We find that language confusion can be partially mitigated via few-shot prompting, multilingual SFT and preference tuning. We release our language confusion benchmark, which serves as a first layer of efficient, scalable multilingual evaluation.<sup>1</sup>

## 1 Introduction

Large language models (LLMs) are increasingly used in a variety of applications across the globe (Kaddour et al., 2023). While early LLMs focused on English (Joshi et al., 2020; Hu et al., 2020), recent models are more multilingual. Nevertheless, LLMs do not provide equal utility to non-English speakers due to higher latency, increased costs, and reduced performance (Ahia et al., 2023; Asai et al., 2023; Held et al., 2023).

To be useful, an LLM must understand intent and provide a response that is appropriate in both form, e.g., correct grammar, style, tone, register, and content, e.g., truthful, coherent, concise (Grice,

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<sup>1</sup>The data is available at <https://github.com/for-ai/language-confusion>.

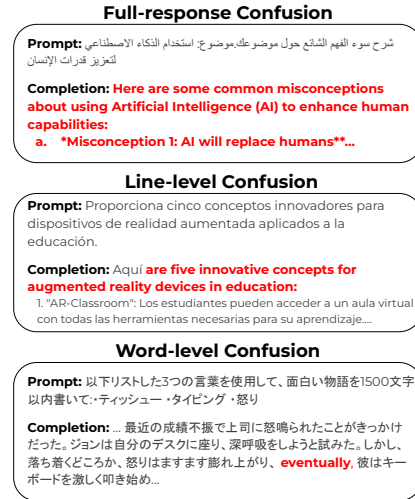


Figure 1: Language Confusion can occur at the word level, line level, or over the entire output response.

1975; Wilson and Sperber, 2012). While content-related issues such as hallucinations have attracted substantial attention (Ji et al., 2023; Bang et al., 2023), they are often subtle and difficult to evaluate (Gudibande et al., 2024; Hosking et al., 2024), particularly in multilingual settings (Guerreiro et al., 2023). Form-related errors indicate a more obvious failure to fulfill a request and—in extreme cases—may cause confusing or unintelligible responses.

We identify a surprising form limitation that drastically reduces LLMs’ utility for non-English languages: LLMs are often unable to consistently generate text in the user’s desired language, or the appropriate language given the context. We call this category of error “language confusion”.<sup>2</sup>

Take an Arabic prompt as an example: an LLM may inappropriately respond fully in English (full-response confusion), produce some lines in the desired language and some in another language (line-level confusion), or sporadically insert single

<sup>2</sup>We use this term to indicate that this is an *erroneous* behaviour rather than *natural* alternations between languages, i.e., code-switching (Doğruöz et al., 2021).

words or phrases in another language (word-level confusion). Figure 1 shows example errors. Even if such errors occur rarely, they cause a jarring user 经验 (experience).

We investigate language confusion on the line and word level in two practical settings: **a)** Monolingual generation, where a user queries the LLM in a given language, *implicitly* requesting an answer in the same language; and **b)** cross-lingual generation, where a user *explicitly* instructs a model to generate text in a different language.

We create and release a language confusion benchmark covering 15 typologically diverse languages, sourcing prompts from public English and multilingual instruction datasets, and additionally creating new data with more complex prompts. We evaluate a range of state-of-the-art LLMs including Llama, Command R, Mistral, and OpenAI family models. We find that Llama Instruct and Mistral LLMs exhibit severe language confusion in many languages. While Command R and OpenAI models fare much better on monolingual generation, even the strongest cannot consistently generate text in the correct language cross-lingually.

Our contributions are the following:

1. We identify and describe the issue of language confusion in LLMs.
2. We introduce a new benchmark and metrics to measure language confusion in LLMs.
3. We perform a systematic evaluation of various LLMs, investigating when language confusion occurs in practice.
4. We propose methods to mitigate language confusion in LLMs.

## 2 Language Confusion Benchmark

While some datasets to evaluate LLMs’ performance on *natural* code-switched data exist (Khanuja et al., 2020; Winata et al., 2023), there are none designed to assess language confusion in LLMs. We create the Language Confusion Benchmark (LCB) by collecting a diverse set of prompts reflecting realistic use cases across a typologically diverse set of languages. The benchmark is easily extensible, cheap, and efficient to evaluate.

### 2.1 Generation settings

We measure language confusion in two settings: monolingual and cross-lingual generation.

**Monolingual generation** A speaker queries a model in language  $l$  and expects a response in  $l$ .

This is the most common usage scenario as users often prefer to interact with technology in their native language (Kantar and IMAI, 2023).

**Cross-lingual generation** A user instructs a model in language  $l$  to fulfill a request in another language  $l'$ . In this challenging setting, the requested language  $l'$  is *different* from the instruction language  $l$ . This setting is relevant in applications where multilingual outputs are required, but optimizing a prompt for each input language is inefficient in practice or when a user requires a generation in a language they do not speak. We set the instruction language to English.

### 2.2 Language Confusion Metrics

To detect language confusion, we rely on off-the-shelf language identification (LID) tools. We employ fastText (Joulin et al., 2016) as a strong alternative to expensive LLM-based evaluation.

**Line-level detection** We split a response into lines (by newline character) and check each line against the user’s desired language with fastText.<sup>3</sup>

**Word-level detection** Off-the-shelf tools do not support word-level LID and LLMs only achieve 79–86 F1 detecting word-level code-switching (Zhang et al., 2023), too low for use as automatic evaluators. Consequently, we take a two-pronged heuristic approach to detecting word-level language confusion focusing on settings where it achieves high precision. For non-Latin script languages, we observe that word-level language confusion in top LLMs mainly occurs with English. To avoid natural code-switching false positives,<sup>4</sup> we check for English words that do not typically occur in target language text.<sup>5</sup> We evaluate word-level confusion in Arabic (ar), Hindi (hi), Japanese (ja), Korean (ko), Russian (ru), and Simplified Chinese (zh). For Latin script languages where word-level language confusion is rarer,<sup>6</sup> we detect tokens where any character is outside of the Unicode range of the language’s script. We evaluate word-level confusion in German (de), English (en), Spanish (es),

<sup>3</sup>We only apply fastText to sequences of more than 4 words as its LID predictions are less precise for shorter sequences.

<sup>4</sup>E.g., Japanese users may use English acronyms: AI に関する記事を書きます。 (“Write an article about AI.”)

<sup>5</sup>We source words from <https://gist.github.com/WChargin/8927565>, which is based on the Linux dictionary usually stored in /usr/share/dict/words. To reduce false positives, we exclude capitalized words from the dictionary (which are often proper nouns or acronyms).

<sup>6</sup>We show an example of such word-level confusion in A1.

	Dataset name	Reference	Nature of data	$ L $	$ D $	Languages	$W$
Mono-lingual	Aya	Singh et al. (2024)	Human-generated	100	500	en, tr, ar, zh, pt	9
	Dolly	Singh et al. (2024)	MT post-edited	100	500	hi, ru, fr, ar, es	10
	Okapi	Lai et al. (2023)	Synthetic + MT	100	1.2k	en, fr, it, de, zh, vi, ru, es, id, pt, ar, hi	13
	Native prompts	Ours	Human-generated	100	400	es, fr, ja, ko	19
Cross-lingual	Okapi	Lai et al. (2023)	Synthetic	100	1.5k	$\mathcal{L}$	15
	ShareGPT	<a href="https://sharegpt.com/">https://sharegpt.com/</a>	Human-generated	100	1.5k	$\mathcal{L}$	18
	Complex prompts	Ours	Human-generated	99	1.5k	$\mathcal{L}$	159

Table 1: **Data sources in the LCB for monolingual and cross-lingual generation.**  $|D|$  is the total number of examples per data source and  $|L|$  is the number of examples per language. For the cross-lingual setting, the model is instructed in English to generate in the target language  $l \in \mathcal{L}$  where  $\mathcal{L} = \{\text{fr, de, es, pt, it, ja, ko, zh, ar, tr, hi, ru, id, vi}\}$ .  $W$  is the median length in words of the prompts in each dataset.

French (fr), Indonesian (id), Italian (it), Portuguese (pt), Turkish (tr), and Vietnamese (vi).

**Binary evaluation** A response is only correct when entirely in the correct language, as even one instance of language confusion can damage intelligibility and cause a jarring user experience. We calculate binary metrics to indicate whether a response contains any instance of **a)** a line in an incorrect language and **b)** an isolated English word for languages using  $\rightarrow$  Latin scripts and an out-of-Unicode-range character for Latin script languages. These main metrics are defined below.

*Line-level pass rate (LPR)*: percentage of model responses that pass our line-level language confusion detector without error. A response is “correct” if all lines match the user’s desired language.

$$\text{LPR} = \frac{|R \setminus E_L|}{|R|}$$

where  $R$  is the set of all responses and  $E_L$  the set of responses that contain line-level errors.<sup>7</sup>

*Word-level pass rate (WPR)*: percentage of responses where all words are in the desired language. We exclude responses with line-level errors as most line-level errors would also be counted as word-level errors, making it difficult to disentangle the two error types. For languages that use a  $\rightarrow$  Latin script, we detect erroneous English words while for Latin script languages, we identify characters outside of the script’s Unicode range.

$$\text{WPR} = \frac{|(R \setminus E_L) \setminus E_W|}{|R \setminus E_L|}$$

<sup>7</sup>For completeness, we show results for “line-level language accuracy” (the fraction of lines in the correct language across all responses of an LLM) in Tables A1 and A2 at §A.1.

where  $R$  is the set of all responses,  $E_L$  the set of responses with line-level errors and  $E_W$  the set of responses with word-level errors.

*Language confusion pass rate (LCPR)*: harmonic mean<sup>8</sup> of LPR and WPR:

$$\text{LCPR} = 2 \times \frac{\text{LPR} \times \text{WPR}}{\text{LPR} + \text{WPR}}$$

LCPR is elucidating in cases of severe issues producing output in the correct language.<sup>9</sup>

### 2.3 Data sources

The monolingual and cross-lingual tasks respectively comprise 2600 and 4500 prompts in total, across 15 typologically diverse languages: English, French, German, Spanish, Portuguese, Italian, Japanese, Korean, Chinese, Arabic, Turkish, Hindi, Russian, Indonesian, and Vietnamese. Details are shown in Table 1.

The prompts are sourced from the datasets below, focusing on human-annotated or human-edited prompts. We filter each dataset to make it most useful for evaluating language confusion.

**Aya** 250 original human-written prompts in 7 languages each from the aya-human-annotated subset of the Aya Evaluation Suite (Singh et al., 2024).

**Dolly** 200 machine-translated Dolly (Conover et al., 2023) prompts post-edited by fluent speakers for 6 languages from the Aya Evaluation Suite’s dolly-human-edited subset (Singh et al., 2024).

<sup>8</sup>Similar to F1, this gives higher importance to low values.

<sup>9</sup>Imagine a model’s LPR for Arabic is a dismal 1% because only 1/100 responses are fully Arabic, the rest English. WPR is a deceptively high 100%: as outputs are fully English, no English word appears in an Arabic line. The model scores 2% LCPR, however, reflective of severe confusion.

	Prompt	Translation	Data source
Monolingual	問: 如何清洗和保养筷子?	Q: How to clean and maintain chopsticks?	Aya
	¿Cómo escapar de un helicóptero atrapado en el agua?	How to escape from a helicopter stuck in water?	Dolly
	Erklären Sie, wie der Gini-Index berechnet wird.	Explain how the Gini index is calculated.	Okapi
	日本で救急隊員を目指す人は、どのような教育やトレーニングを受ける必要がありますか。	What kind of education and training do people who want to become emergency workers in Japan need to undergo?	Native prompts (Ours)
Cross-lingual	Generate an essay <b>in Korean</b> of at least 500 words that argues in favor of regulating artificial intelligence.		Okapi
	<b>Respond in French.</b> You are a medical communications expert. Please provide a summary on how pharma companies are approaching diversity and inclusion, and health inequalities globally. Focus on the general approach and include information on clinical trials.		Share-GPT
	Based solely on the text below: 1. Extract the statistical techniques and machine learning algorithms analysts employ to uncover relationships and patterns within the data. 2. Generate 5 fill-in-the-blanks style questions 3. Summarize the text in 100 words [...] <b>Reply in Turkish.</b>		Complex prompts (Ours)

Table 2: **An example prompt from each dataset used for monolingual and cross-lingual generation.** English translations are shown for convenience. For cross-lingual generation, prompts are in English and have been amended with an instruction to generate the output in another language. The complex prompt example is truncated.

**Okapi** We use the multilingual-alpaca-52k subset of the Okapi data, which contains ChatGPT-generated translations of 52k English instructions from Alpaca (Taori et al., 2023) into 26 languages.

**ShareGPT** We use prompts from the first turn of 90,000 mostly English user conversations with ChatGPT, scraped via the ShareGPT API<sup>10</sup> before it was shut down.<sup>11</sup>

**Native prompts (Ours)** For Japanese and Korean, under-represented in the above datasets, as well as Spanish and French, we commission native annotators to collect our own prompts (see §A.2).

**Complex prompts (Ours)** As prompts from the above sources are relatively simple, we collect complex English prompts written by human annotators.

## 2.4 Data Filtering and Processing

**Suitability for LID** As LID tools underperform on short sequences and non-standard text, we manually filter out: **a)** examples answerable with a single word/phrase; **b)** multiple-choice questions and prompts asking for lists; **c)** prompts requiring code generation, math equations, or data formats such as HTML. For datasets where completions are available, we filter out prompts with very short completions (less than 5 words).

<sup>10</sup><https://sharegpt.com/>

<sup>11</sup><https://huggingface.co/datasets/RyokoAI/ShareGPT52K>

**Western-centric responses** Many datasets created via translation contain questions about Western-centric concepts (e.g., US National Parks, presidents or US-based brands) which can cause false positives with our word-level detector. We manually filter out such questions.

**Prompt format** For cross-lingual generation, we semi-automatically amend prompts with an instruction to generate in a target language (see §A.3 for details). Prompts are used as-is for monolingual generation. Some examples are shown in Table 2.

## 3 Experiments

**Models** We evaluate the following LLMs covering various scales and model families: Llama 2 70B Instruct (Touvron et al., 2023), Llama 3 and 3.1 70B Instruct (Dubey et al., 2024), Command R (35B),<sup>12</sup> Command R+ (104B parameters),<sup>13</sup> Command R Refresh (command-r-08-2024), Command R+ Refresh (command-r-plus-08-2024), Mixtral 8x7B (Jiang et al., 2024), Mistral Large,<sup>14</sup> GPT-3.5 Turbo (gpt-3.5-turbo-012524; Brown et al., 2020), GPT-4 Turbo (gpt-4-turbo-040924; Achiam et al., 2023), and GPT-4o (gpt-4o-2024-08-06). For Llama and Command models, we also evaluate base versions (see §4.5). We generate at most

<sup>12</sup><https://cohere.com/blog/command-r>

<sup>13</sup><https://cohere.com/blog/command-r-plus-microsoft-azure>

<sup>14</sup><https://mistral.ai/news/mistral-large/>



	Monolingual															
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Llama 2 70B-I	48.3	0.3	59.0	99.0	95.7	87.7	1.0	62.0	72.0	7.0	0.0	91.0	88.9	33.0	17.0	10.5
Llama 3 70B-I	46.0	21.7	31.0	<b>100.0</b>	98.3	88.7	23.0	21.0	88.0	10.0	0.0	95.5	77.0	18.0	10.0	8.0
Llama 3.1 70B-I	99.0	98.9	<b>100.0</b>	98.5	99.0	<b>100.0</b>	<b>100.0</b>	94.0	<b>100.0</b>	96.9	<b>100.0</b>	<b>99.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>99.0</b>
Mixtral 8x7B	73.0	48.3	90.9	99.5	89.3	95.3	71.0	58.0	72.0	66.7	61.2	85.0	65.0	90.0	57.0	45.5
Mistral Large	69.9	48.0	98.0	99.0	99.0	<b>100.0</b>	19.0	31.0	99.0	48.0	64.0	79.5	98.0	71.0	29.0	66.0
Command R	98.6	<b>100.0</b>	98.0	99.5	95.7	99.3	<b>100.0</b>	92.0	99.0	<b>100.0</b>	<b>100.0</b>	98.5	<b>100.0</b>	99.0	99.0	98.5
Command R+	99.2	99.7	<b>100.0</b>	<b>100.0</b>	99.3	99.7	<b>100.0</b>	<b>97.0</b>	<b>100.0</b>	99.0	<b>100.0</b>	97.5	<b>100.0</b>	<b>100.0</b>	99.0	97.5
Command R Refresh	98.9	99.6	<b>100.0</b>	99.5	99.3	99.7	<b>100.0</b>	92.0	<b>100.0</b>	99.0	<b>100.0</b>	98.0	<b>100.0</b>	99.0	<b>100.0</b>	98.0
Command R+ Refresh	<b>99.3</b>	99.0	<b>100.0</b>	<b>100.0</b>	99.3	<b>100.0</b>	<b>100.0</b>	96.0	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	97.5	99.0	<b>100.0</b>	<b>100.0</b>	98.0
GPT-3.5 Turbo	99.1	<b>100.0</b>	<b>100.0</b>	99.5	<b>99.7</b>	<b>100.0</b>	99.0	96.0	<b>100.0</b>	98.0	<b>100.0</b>	98.0	<b>100.0</b>	<b>100.0</b>	99.0	97.0
GPT-4 Turbo	<b>99.3</b>	99.0	<b>100.0</b>	<b>100.0</b>	99.3	99.3	<b>100.0</b>	96.0	99.0	<b>100.0</b>	<b>100.0</b>	98.0	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>99.0</b>
GPT-4o	98.9	99.7	<b>100.0</b>	<b>100.0</b>	99.3	99.3	99.0	94.0	<b>100.0</b>	99.0	<b>100.0</b>	97.5	99.0	<b>100.0</b>	99.0	98.0

	Cross-lingual															
	avg	ar	de	-	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Llama 2 70B-I	38.4	12.4	52.3	-	77.3	71.1	21.2	46.0	66.5	16.2	4.8	75.9	38.3	24.0	20.4	11.1
Llama 3 70B-I	30.3	31.1	34.7	-	61.1	53.1	46.4	25.4	36.4	1.4	0.8	54.4	38.4	17.4	18.7	4.3
Llama 3.1 70B-I	81.4	77.2	87.5	-	90.4	90.5	95.6	<b>97.1</b>	88.1	59.4	51.5	86.0	76.5	85.7	93.6	69.9
Mixtral 8x7B	69.0	59.1	76.4	-	79.1	79.0	39.2	72.8	85.0	57.9	56.9	79.4	72.4	76.0	75.8	57.5
Mistral Large	58.2	36.1	74.5	-	68.5	71.9	58.5	59.2	65.8	44.5	41.1	64.5	63.3	65.9	54.8	46.5
Command R	68.1	61.6	63.2	-	72.5	74.4	65.5	70.8	65.7	65.3	69.2	67.2	69.4	67.7	65.7	75.0
Command R+	91.2	93.4	91.6	-	91.7	91.5	90.2	85.9	93.8	93.8	91.1	88.5	93.0	92.0	91.1	89.5
Command R Refresh	93.1	91.9	96.1	-	96.4	94.0	95.0	85.1	93.8	95.0	93.8	<b>94.0</b>	92.2	93.4	94.1	88.9
Command R+ Refresh	<b>95.4</b>	<b>95.4</b>	<b>97.5</b>	-	<b>97.6</b>	<b>97.2</b>	<b>98.2</b>	88.9	<b>96.2</b>	<b>95.1</b>	<b>95.9</b>	91.7	<b>96.4</b>	<b>97.9</b>	<b>97.9</b>	90.2
GPT-3.5 Turbo	89.8	90.8	90.2	-	93.3	87.8	92.0	84.5	91.3	88.3	90.3	89.9	91.8	89.2	91.8	86.4
GPT-4 Turbo	90.3	88.9	93.0	-	93.1	90.7	91.0	87.3	91.8	87.7	89.7	91.0	90.0	91.4	90.0	87.9
GPT-4o	92.4	95.0	92.9	-	95.8	93.5	91.9	85.4	94.1	92.5	92.4	88.0	92.6	95.1	92.7	<b>91.3</b>

Table 3: Line-level pass rate (LPR) on monolingual and cross-lingual generation, by language.

	Monolingual	Cross-lingual
Llama 2 70B-I	97.9	84.2
Llama 3 70B-I	93.0	94.4
Llama 3.1 70B-I	99.5	95.0
Mixtral 8x7B	73.7	68.2
Mistral Large	98.4	93.8
Command R	96.3	94.0
Command R+	99.4	95.1
Command R Refresh	99.4	97.2
Command R+ Refresh	<b>99.8</b>	96.5
GPT-3.5 Turbo	<b>99.8</b>	<b>98.7</b>
GPT-4 Turbo	99.7	96.6
GPT-4o	99.7	98.1

Table 4: Average word-level pass rate (WPR) on non-Latin script languages. See Tables A3 and A4 for detailed WPR results on non-Latin and Latin script languages respectively.

100 tokens per prompt using nucleus sampling with  $p = 0.75$  and  $T = 0.3$ .

LPR, WPR, and LCPR results are in Tables 3, 4, and A5, respectively.<sup>15</sup> We show language confusion examples for different models in Table A6.

**Monolingual generation** Command and GPT models perform well on average on the line level (LPR in [98.6, 99.3]), but Llama 2 and 3 and Mistral models struggle to consistently generate text in the correct language (LPR in [48.3, 73.0]). Llama

3.1 performs much better, however. Mistral Large is better on some European languages while Llama 2 and 3 exhibit language confusion even for high-resource languages such as German. Most models have WPR within the same range and perform better on Latin script vs non-Latin script languages; however, Mixtral 8x7B is considerably worse. GPT-4 Turbo is strongest on LCPR, with Command R+ Refresh and GPT-4o only slightly behind. Llama models’ preference for English responses leads to very low LCPR.

**Cross-lingual generation** In the challenging cross-lingual setting, the best models have LPRs in the low 90s. The Command R and R+ Refresh models outperform their original versions, with Command R Refresh in particular showing a large improvement over Command R, which performs poorly cross-lingually. OpenAI and Command models perform best; Command R+ Refresh achieves the best performance overall. Llama 2 and 3 models perform poorly: both scoring in the 30s due to a tendency to respond in English. Llama 3.1 shows improved performance but still tends to generate in English for some languages. Mistral Large is worse than Mixtral, even in European languages. On LCPR, Command R+ Refresh performs best, followed by GPT-4o.

<sup>15</sup>We find results show little variance across runs (see §A.9).

## 4 Analyses

### 4.1 Impact of dataset

In creating the language confusion test sets, we aimed to include prompts covering various use cases and domains. We show differences of LPR by dataset in Tables 5 and A7 for cross-lingual and monolingual generation, with WPR and LCPR in Tables A8 and A9 in §A.4. Differences between datasets are small for monolingual generation. Cross-lingually, the difference is more pronounced: models perform fairly well on Okapi and ShareGPT, but are much worse on our Complex prompts, indicating their more challenging nature.

	avg	Okapi	ShareGPT	Complex (Ours)
Llama 2 70B-I	38.4	43.4	46.0	25.7
Llama 3 70B-I	30.3	35.0	39.5	16.3
Llama 3.1 70B-I	81.3	85.3	91.0	67.7
Mixtral 8x7B	69.0	77.4	79.8	49.9
Mistral Large	58.2	68.0	56.2	50.5
Command R	68.1	75.6	89.7	39.0
Command R+	91.2	96.1	98.7	78.9
Command R Refresh	93.1	<b>98.3</b>	<b>99.4</b>	81.7
Command R+ Refresh	<b>95.4</b>	98.0	98.7	<b>89.6</b>
GPT-3.5 Turbo	89.8	97.7	96.8	75.0
GPT-4 Turbo	90.3	96.6	96.4	77.7
GPT-4o	92.4	97.4	97.6	82.1

Table 5: **Line-level pass rate (LPR) by dataset on cross-lingual generation.**

### 4.2 Impact of prompt length

We analyze whether the difficulty of our Complex prompts is caused by their much higher length (see Table 1) by grouping the prompts into three length buckets: short, medium and long, each with one third of the prompts. Table A10 shows the LPR of several models over the different lengths. We find no clear pattern, suggesting that higher confusion is caused by prompt complexity rather than length.

### 4.3 Impact of instruction position

Cross-lingual prompts include an instruction with the desired output language at the beginning, at the end, or integrated in the prompt (e.g., “Write an essay in Korean [...]”). Table A11 shows that across all models, line-level confusion is low for isolated instructions, with similar performance whether they are at the start or the end. Integrated instructions cause more confusion: Command R has only 69% LPR on this type of prompt, versus ~85% for isolated types. This difficulty can be greatly reduced

with one-shot prompting (80.6% LPR; see §6.4).<sup>16</sup>

### 4.4 Impact of quantization

Quantization maps higher-precision LLM weights and activations to lower precision, reducing storage and inference costs, potentially at the cost of performance. We compare *FP16* with *W8*, *W8A8*, and *W4* variants of Command R+ on monolingual generation. Negative effects appear at *W4*, shown in Table A12. Details of quantization are in §A.6.

### 4.5 Impact of instruction tuning

We compare the base with instruction-tuned variants of Llama and Command models on monolingual generation in Table 6. While instruction-tuned Command R models exhibit less language confusion than their base versions, instruction-tuned Llama models are much more confused, indicating English-centric instruction tuning, which is confirmed by our mitigation experiments (see §6.4).

	avg	ar	hi	ja	ko	vi	zh
Llama 2 70B	<b>98.5</b>	<b>99.6</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>98.0</b>	<b>93.2</b>
Llama 2 70B-I	6.0	0.3	1.0	7.0	0.0	17.0	10.5
Llama 3 70B	<b>94.7</b>	<b>96.7</b>	<b>97.9</b>	<b>87.9</b>	<b>98.8</b>	<b>97.0</b>	<b>90.0</b>
Llama 3 70B-I	12.1	21.7	23.0	10.0	0.0	10.0	8.0
Command R base	85.9	94.9	81.0	93.9	94.2	83.0	68.1
Command R	<b>99.6</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>99.0</b>	<b>98.5</b>
Command R+ base	78.4	92.8	67.0	90.5	93.5	65.7	60.9
Command R+	<b>99.2</b>	<b>99.7</b>	<b>100.0</b>	<b>99.0</b>	<b>100.0</b>	<b>99.0</b>	<b>97.5</b>

Table 6: **Line-level pass rate (LPR) of base vs instruction-tuned LLMs on monolingual generation** for a subset of languages. Full results in Table A17, §A.8.

## 5 When does language confusion occur?

We study a sample of prompts to better understand where language confusion occurs. Intuitively, if a token in an undesired language is assigned sufficient probability, it may be sampled. We observe that language confusion typically occurs when the distribution over next tokens is flat and the nucleus is large (see §A.10 for background).

We generate responses to 15 Chinese prompts from Okapi with Command R.<sup>17</sup> We examine outputs to identify instances of English language confusion, finding it in 5 of 15 outputs. For each, we find the first position where an English token was

<sup>16</sup>Even though our demonstrations in few-shot prompting do not have integrated instructions.

<sup>17</sup> $k = 0, p = 0.75, t = 0.7$

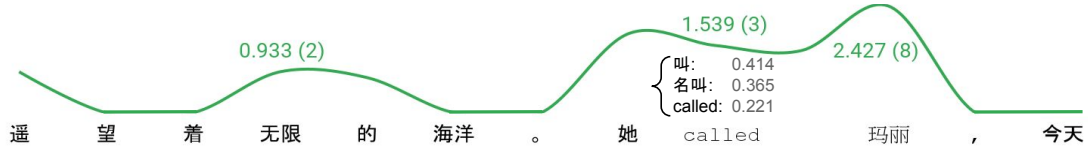


Figure 2: **A model is vulnerable to world-level language confusion when the number of tokens in the sampling nucleus is high, and the distribution is flat.** Metrics: Shannon entropy; in brackets: # of tokens in nucleus.

elicited, which we call the *confusion point* (CP).<sup>18</sup> There are 9 such CPs.<sup>19</sup>

We calculate Shannon entropy (Shannon, 1948) and nucleus size at each sampling point. We show an example output of Command R in Figure 2, indicating Shannon entropy and the number of tokens in the nucleus at select sampling points, and the next possible tokens with normalized probabilities at the confusion point. In the example, “called” was third most likely but occurred with sufficient probability to be sampled (0.221). We generate 100 tokens per prompt, so there are 1500 points: 9 of which are CPs. We refer to the others as  $\neg$ CPs.

We average nucleus size and entropy over examples containing no instances of language confusion (10 samples, 1000  $\neg$ CPs), at least one instance (5 examples, 9 CPs, 491  $\neg$ CPs), and overall (15 samples, 9 CPs, 1491  $\neg$ CPs). Results are in Table 7.<sup>20</sup> Outputs with and without language confusion show similar average nucleus size and entropy (1.64 vs. 1.61, and 0.353 vs. 0.365). At CPs, however, average nucleus size and entropy is considerably higher: 3.56 nucleus size and 1.228 entropy vs 1.61/0.356 at  $\neg$ CPs, indicating that confusion tends to occur when nucleus size and entropy are high.

	Avg. Nucleus Size			Avg. Entropy		
	Overall	@CP	$\neg$ @CP	Overall	@CP	$\neg$ @CP
Has CP	1.64	3.56	1.61	0.353	1.228	0.337
No CP	1.61	-	1.61	0.365	-	0.365
All	1.62	3.56	1.61	0.361	1.228	0.356

Table 7: **Avg. nucleus size, entropy at confusion points** (sampling points where language switch did [ $\text{@CP}$ ] or did not [ $\neg\text{@CP}$ ] occur) for 15 Chinese responses. Responses are split into those which had at least one CP (“Has CP”) or zero CPs (“No CP”).

<sup>18</sup>When intentional, such points are referred to in the code-switching literature as “*switch points*”. We coin a new term here to indicate that this switching is erroneous.

<sup>19</sup>There are 3 examples of line-level confusion. We label the initial switching point from Chinese to English as the CP.

<sup>20</sup>E.g., For outputs exhibiting language confusion, the average nucleus size @CP is:  $\frac{\text{sum of nucleus sizes at all CPs}}{9} = \frac{32}{9} = 3.56$ .

## 6 Mitigating Language Confusion

Based on the insights from our analyses in §4.5 and §5, we propose *inference-time* and *training-time* mitigations for language confusion.

### 6.1 Reducing temperature and nucleus size

Modifying sampling hyper-parameters affects which tokens are chosen at inference time. Section A.10 explains nucleus sampling with temperature, and Figure 3 has a toy example of manipulating the hyperparameter  $T$ . Framing language confusion as an undesired side-effect of sampling, it is intuitive that we might control it by sharpening the distribution over the next tokens at each timestep.

We try to reduce the chance of having a wrong-language token sampled by manipulating temperature and nucleus size. Table 8 shows the results on monolingual WPR for Command R, with cross-lingual and LPR results in Section A.7. Higher  $T$  encourages language confusion:  $T = 1$  shows an average WPR of only 83.5%, and as low as 72.0% and 69.5% for Japanese and Chinese. Increasing  $p$ , resulting in a smaller nucleus, has a smaller effect. Note that setting  $T = 0.0$  is equivalent to sampling with top-K = 1 (greedy search).

	avg	ar	hi	ja	ko	ru	zh
T=0.0	<b>97.2</b>	97.6	<b>100.0</b>	<b>96.9</b>	97.0	<b>96.0</b>	<b>95.9</b>
T=0.3	96.3	<b>99.3</b>	99.0	93.9	97.0	<b>96.0</b>	92.3
T=0.5	96.4	97.9	99.0	94.9	<b>99.0</b>	95.0	92.3
T=0.7	94.2	98.0	98.0	91.8	93.9	93.0	90.3
T=1.0	<b>86.5</b>	<b>95.9</b>	<b>93.8</b>	<b>74.5</b>	<b>92.8</b>	<b>87.5</b>	<b>74.7</b>
p=0.1	97.4	98.3	<b>100.0</b>	98.0	<b>97.0</b>	95.0	95.9
p=0.3	97.3	<b>98.0</b>	<b>100.0</b>	<b>99.0</b>	<b>97.0</b>	<b>94.0</b>	95.9
p=0.5	<b>97.6</b>	<b>98.0</b>	<b>100.0</b>	96.9	<b>96.0</b>	<b>98.0</b>	<b>96.9</b>
p=0.75	<b>96.3</b>	<b>99.3</b>	99.0	<b>93.9</b>	<b>97.0</b>	96.0	<b>92.3</b>

Table 8: **Effect of varying temperature ( $T$ ) or nucleus size ( $p$ ) on monolingual word-level language confusion (WPR) of Command R.** Default values are  $p = 0.75$  and  $T = 0.3$ . **Best score.** **Worst score.**

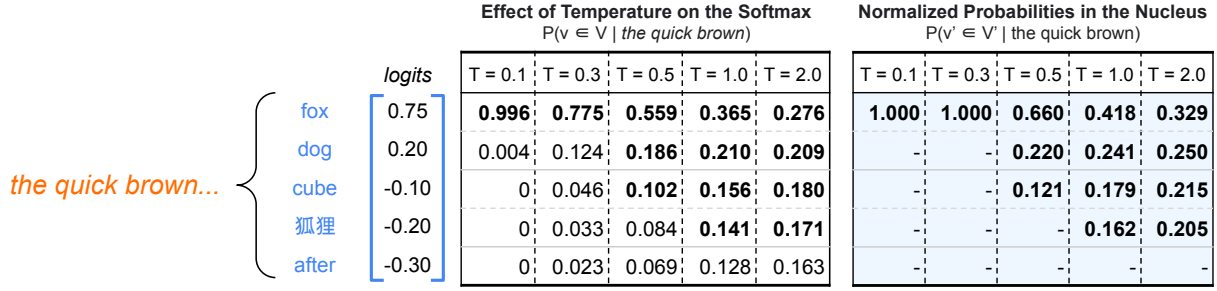


Figure 3: **Effect of Temperature ( $T$ ) in Nucleus Sampling.** Tokens in the nucleus at  $p = 0.75$  are **bold**. Middle: Effect of  $T$  on the softmax probabilities (Equation 1). Right: Effect of  $T$  on the probabilities of tokens in the nucleus right before sampling (Equation A.10). As  $T$  increases, the token 狐狸 has less chance to be sampled.

## 6.2 Beam search decoding

We explore the effect of beam search decoding on language confusion for Command R. Table 9 shows aggregate results for beam sizes 1 (greedy search) to 10, with full results in Section A.7. Increasing beam size helps moderately over greedy search on WPR, with little noticable effect on monolingual LPR. Increasing beam size consistently *hurts* cross-lingual LPR and is most pronounced for non-Indo-European languages, where average LPR drops from 73.9 with greedy search to 65.6 with beam size = 10.

	Monoling.			Crosslingual		
	WPR	LPR		WPR	LPR	
					Overall	$\neg IE$
1	97.8	<b>99.0</b>	94.9	<b>74.1</b>	-	<b>73.9</b>
2	98.6	<b>99.0</b>	95.4	72.2	(-1.9)	71.1 (-2.8)
3	98.6	98.7	<b>97.1</b>	71.5	(-2.5)	70.1 (-3.8)
5	<b>99.0</b>	<b>99.0</b>	96.7	70.3	(-3.8)	68.3 (-5.6)
10	<b>99.0</b>	98.5	96.7	68.4	(-5.7)	65.6 (-8.3)

Table 9: **Effect of beam search decoding on language confusion metrics for Command R.** Beam sizes: 1-10.

Table 10 aggregates the best average score achieved for beam search and nucleus sampling from Tables 8, A13, A14, A15, A16. Beam search is always better than nucleus sampling for WPR and for cross-lingual LPR, and both methods seem equally effective for monolingual LPR, suggesting that beam search may be an effective decoding strategy for lessening language confusion (though at higher computational cost).

## 6.3 Few-shot prompting

Non-instruction-tuned LLMs often do not answer instructions as expected. When prompted with an instruction in a non-English language, for instance, Command R Base often translates it instead of answering. We thus employ few-shot prompting to

	WPR				LPR			
	Beam S.	Nuc. Samp.	Beam S.	Nuc. Samp.	Beam S.	Nuc. Samp.	Beam S.	Nuc. Samp.
	max	min	max	min	max	min	max	min
Mono.	<b>99.0</b>	97.8	97.6	86.5	<b>99.0</b>	98.5	98.9	96.8
Cross.	<b>97.1</b>	94.9	94.6	80.1	<b>74.1</b>	68.4	68.2	64.0

Table 10: Beam Search vs. Nucleus Sampling. Shown: **best** and *second-best* overall average score.

guide Command R Base towards the correct behavior. We cherry-pick 5 prompt/answer pairs in English and translate them with Google Translate.<sup>21</sup>

For cross-lingual generation, we use a similar format to the test sets. Figure A2 shows the template used to prompt the base model. For comparison, we also apply one-shot prompting to Command R where the example is presented as turns in a conversation. Table 11 shows the results. Tables A19 and A18 in Appendix show the detailed results per language for monolingual and cross-lingual language confusion respectively.

Few-shot prompting greatly reduces Command R Base’s language confusion and almost completely eliminates the problem in the monolingual setting. While one-shot prompting with Command R is detrimental monolingually—indicating a difficulty of dealing with demonstrations in other languages—it enables the model to better follow the cross-lingual instructions.

## 6.4 Multilingual instruction tuning

We additionally study the impact of English-centric and multilingual instruction tuning by fine-tuning Command R Base with several techniques:

**English-only tuning** We fine-tune the base model with English-only publicly available instruc-

<sup>21</sup>Few-shot demonstrations are in different languages than the current task’s target language. The goal is to help a model understand the task, not find the language to generate into.



	Monolingual		Cross-lingual	
	LPR	WPR	LPR	WPR
Command R Base	86.2	98.7	1.1	<b>100.0</b>
+ Q/A template (0-shot)	85.3	99.7	20.9	97.0
+ 1-shot	94.1	<b>100.0</b>	90.7	98.6
+ 5-shot	<b>99.0</b>	<b>100.0</b>	<b>95.0</b>	99.7
+ English SFT	77.8	96.2	78.3	91.7
+ English pref. tuning	74.3	90.9	85.7	87.4
+ Multilingual SFT	98.3	95.5	78.2	90.0
+ Multi. pref. tuning	98.9	93.4	89.4	86.9
<i>Command R</i>	98.6	96.3	68.1	94.0
+ 1-shot	68.3	92.7	82.9	92.3

Table 11: **Effect of few-shot prompting and instruction tuning on language confusion.**

tion data (SFT; Touvron et al., 2023), then apply English-only preference tuning to this model.

**Multilingual tuning** We extend the English data with multilingual data, most of which comes from machine-translated Dolly and ShareGPT (Üstün et al., 2024). Due to the scarcity of multilingual data, our SFT data mixture is 90% English. For preference tuning, we use 50% multilingual data. Results are in Table 11.

English-only tuning (both SFT and pref. tuning) exacerbates language confusion monolingually: likely the reason for high language confusion of Llama-Instruct models (see §4.5). English-only preference tuning has a strong negative impact on word-level confusion. However, SFT with just 10% multilingual data is enough to almost eliminate the problem of line-level confusion monolingually. Cross-lingually, multilingual tuning does not give better line-level performance than English-only tuning. This may be because cross-lingual datasets only have English prompts and it is more important for the model to learn to follow English instructions (e.g., “Reply in French”).

## 7 Discussion

We discuss several aspects that raise important questions including the behavior of base models, the English centrality of models, the impact of preference tuning, and the importance of other factors in Appendix A.11.

## 8 Related Work

**Code-switching** There has been much research on *natural* alternations between languages, i.e., code-switching (Doğruöz et al., 2021) in natural

language processing (NLP). Prior work focused on evaluating capabilities on standard NLP tasks using code-switching data (Khanuja et al., 2020; Winata et al., 2023) including sentiment analysis, machine translation, summarization and word-level language identification. These tasks typically employ data created by humans where word-level code-switching occurs between English and another language such as Hindi, Spanish, or Arabic. Current models still struggle to generate and understand code-switched text in some languages (Yong et al., 2023; Zhang et al., 2023). In contrast, we investigate *unnatural* and *erroneous* code-switching—or language confusion—in the LLM’s generations.

**Language confusion** Prior work has observed ‘source language hallucinations’ in zero-shot cross-lingual transfer (Vu et al., 2022; Li and Murray, 2023; Pfeiffer et al., 2023; Chirkova and Nikoulina, 2024) when models are fine-tuned on English data and applied to generate text in another language. The problem of language confusion is known in the machine translation field as ‘off-target translation’ (Chen et al., 2023; Sennrich et al., 2024). It typically occurs on English-centric multilingual models, when used in a zero-shot manner (to translate between two languages unseen at training). For LLMs, there is no source language per se. A few studies (Kew et al., 2023; Faisal and Anastasopoulos, 2023; Chen et al., 2024) have provided evidence of LLMs generating in an incorrect language on the response level. Holtermann et al. (2024) analyze which languages are confused on the response level using mainly smaller LLMs. To the best of our knowledge, we are the first to show results on the line and word level and the first to systematically study language confusion in LLMs.

## 9 Conclusion

We have introduced the Language Confusion Benchmark. We have shown that some LLMs exhibit severe language confusion and even the strongest LLMs do not achieve perfect performance cross-lingually. We observed that base and English-centric instruct models are particularly susceptible to language confusion, which is exacerbated by complex prompts. Finally, we proposed measures to mitigate language confusion at inference and training. Our benchmark is efficient to evaluate and easy to extend and can help ensure that models achieve equal utility across languages.

## Acknowledgements

We thank Sander Land, Florian Strub, Mo Gheshlaghi Azar, and Olivier Pietquin for early discussions on language confusion. We are grateful to Sander Land for help with an initial version of a script to analyze nucleus sampling generations. We thank our internal annotators and the team at Cohere.

## Limitations

As this is to our knowledge, the first systematic study on language confusion in LLMs, there are several natural research directions that we were not able to cover:

**Conversations** We focus on single-turn inputs, and do not consider the impact of multiple turns of a conversation or users employing different languages across different turns.

**Code-switched input** We focus on the setting where a user’s prompt is in a single language (the target language in the monolingual setting and English in the cross-lingual setting). We do not consider inputs that are naturally code-switched.

**Inputs with cross-lingual context** Content may not always be available in a user’s language, which is relevant for applications such as cross-lingual summarization or cross-lingual QA.

**Language varieties** We evaluate generation into standardized languages. Future work may expand to language varieties and dialects, styles, and registers.

Our metrics are applied to model outputs of at most 100 tokens. But what is a token depends on the model’s tokenizer. Models with more aggressive tokenization could be advantaged with regard to the binary metrics (LPR and WPR). Likewise, because we allow models to stop their generation early (by producing an end-of-sequence token), models which are less verbose could have an advantage. Furthermore, because current LID tools do not support word-level language identification, our WPR metric is currently limited to assessing non-Latin script languages for unintended switching into English. As LID tools

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## A Appendix

### A.1 Extended Results

**Prompt:** que partes tiene una noticia?

**Completion:** Una noticia típica suele tener las siguientes partes: ...

**Prompt:** y los epígrafes?

**Completion:** ... Los epígrafes **瓦解** también se pueden utilizar para resaltar citas importantes, proporcionar transiciones entre temas o simplemente dividir el texto en secciones más manejables y digeribles.

Figure A1: Example of non-English word-level language confusion produced by an LLM.

Monolingual																
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Llama 2 70B-I	49.8	3.2	60.3	99.7	96.7	89.8	2.3	65.6	73.0	7.3	0.7	92.5	91.2	35.5	17.7	11.7
Llama 3 70B-I	47.3	27.7	31.0	<b>100.0</b>	98.8	89.1	25.4	21.5	88.9	11.2	2.3	97.8	77.0	19.6	10.4	9.4
Mixtral 8x7B	74.2	49.5	90.9	99.8	90.0	95.3	72.2	60.2	72.0	70.6	62.1	86.2	65.7	90.0	59.4	49.2
Mistral Large	70.3	48.7	98.0	99.6	99.5	<b>100.0</b>	19.5	31.0	99.0	48.0	64.3	80.9	98.7	71.5	29.0	67.0
Command R	99.5	100.0	99.3	99.9	98.7	99.9	100.0	96.8	99.7	100.0	100.0	99.7	100.0	99.0	<b>99.9</b>	99.6
Command R+	<b>99.8</b>	99.9	<b>100.0</b>	<b>100.0</b>	99.8	99.9	<b>100.0</b>	99.0	<b>100.0</b>	99.8	<b>100.0</b>	99.4	<b>100.0</b>	<b>100.0</b>	99.5	99.1
GPT-3.5 Turbo	99.5	<b>100.0</b>	<b>100.0</b>	99.8	99.8	<b>100.0</b>	99.5	98.3	<b>100.0</b>	98.7	<b>100.0</b>	<b>99.5</b>	<b>100.0</b>	<b>100.0</b>	99.0	98.3
GPT-4 Turbo	99.7	99.2	<b>100.0</b>	<b>100.0</b>	<b>99.8</b>	99.7	<b>100.0</b>	98.0	99.7	<b>100.0</b>	<b>100.0</b>	99.4	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>99.7</b>

Table A1: **Line-level language ID accuracy of different LLMs on *monolingual* generation.** Line accuracy is calculated by  $\frac{\text{\# lines responded in correct language}}{\text{Total \# of lines generated}}$

Cross-lingual																
	avg	ar	de	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	
Llama 2 70B-I	46.0	23.5	58.3	80.5	74.6	31.4	51.1	73.4	26.9	15.9	79.9	47.0	28.1	30.0	23.3	
Llama 3 70B-I	53.4	60.3	65.8	77.4	73.8	69.7	58.2	65.5	6.2	2.8	75.8	65.2	55.2	61.4	10.4	
Mixtral 8x7B	72.7	61.5	79.7	82.5	82.5	41.7	78.9	85.9	64.1	61.3	83.0	75.2	78.1	79.4	64.6	
Mistral Large	65.7	45.4	79.8	74.9	76.7	63.3	68.6	73.5	58.2	51.9	72.4	68.7	69.5	61.4	56.1	
Command R	75.7	67.5	75.4	80.0	81.7	69.7	78.9	74.1	75.4	76.3	73.2	76.0	76.3	72.3	83.1	
Command R+	<b>95.3</b>	<b>95.9</b>	<b>95.5</b>	<b>95.8</b>	<b>95.3</b>	<b>94.0</b>	<b>93.2</b>	<b>95.9</b>	<b>96.4</b>	<b>95.4</b>	<b>94.5</b>	<b>96.1</b>	<b>94.9</b>	<b>95.8</b>	<b>95.0</b>	
GPT-3.5 Turbo	91.5	91.5	91.5	94.9	90.9	92.2	88.0	92.7	89.7	91.3	93.9	92.6	90.5	92.5	89.4	
GPT-4 Turbo	92.4	91.0	94.0	94.7	93.1	92.6	92.0	93.2	90.5	91.5	94.4	92.0	92.4	91.5	90.3	

Table A2: **Line-level language ID accuracy of different LLMs on *cross-lingual* generation.** Line accuracy is calculated by  $\frac{\text{\# lines responded in correct language}}{\text{Total \# of lines generated}}$

	Monolingual							Cross-lingual						
	Avg	ar	hi	ja	ko	ru	zh	Avg	ar	hi	ja	ko	ru	zh
Llama 2 70B-I	97.9	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	93.2	94.4	84.2	91.4	85.3	84.4	86.7	81.5	75.9
Llama 3 70B-I	93.0	95.6	95.7	80.0	<b>100.0</b>	93.5	93.3	94.4	95.7	97.7	91.7	<b>100.0</b>	89.1	92.3
Llama 3.1 70B-I	99.5	<b>100.0</b>	<b>100.0</b>	99.0	<b>100.0</b>	98.0	<b>100.0</b>	95.0	95.7	98.5	90.3	97.4	93.4	94.4
Mixtral 8x7B	73.7	86.0	78.9	68.2	61.7	83.1	64.7	68.2	76.3	71.5	51.5	67.3	80.5	62.1
Mistral Large	98.4	<b>100.0</b>	94.7	97.9	<b>100.0</b>	99.0	98.9	93.8	93.5	95.4	91.5	92.0	92.8	97.7
Command R	96.3	99.3	99.0	93.9	97.0	96.0	92.3	94.0	94.3	98.6	88.5	97.2	94.0	91.1
Command R+	99.4	99.7	<b>100.0</b>	99.0	<b>100.0</b>	98.0	<b>100.0</b>	95.1	97.9	96.0	95.5	96.1	89.7	95.6
Command R Refresh	99.4	99.7	<b>100.0</b>	99.0	<b>100.0</b>	99.0	99.0	97.2	97.0	98.8	96.7	96.6	95.5	98.5
Command R+ Refresh	<b>99.8</b>	99.0	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	96.5	97.3	97.8	96.6	96.9	94.5	95.7
GPT-3.5 Turbo	<b>99.8</b>	<b>100.0</b>	<b>100.0</b>	99.0	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>98.7</b>	99.0	<b>99.1</b>	<b>98.6</b>	98.5	<b>98.3</b>	<b>99.0</b>
GPT-4 Turbo	99.7	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	99.0	<b>100.0</b>	99.0	96.6	97.4	97.3	95.6	96.8	95.7	97.1
GPT-4o	99.7	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	99.0	99.0	<b>100.0</b>	98.1	<b>99.2</b>	97.0	97.5	99.1	98.0	97.6

Table A3: **Word-level pass rate (WPR) on *monolingual* and *cross-lingual* generation in non-Latin script languages** (% of responses containing no English words). Llama models are instruction-tuned variants.

	Monolingual										Cross-lingual									
	Avg	de	en	es	fr	id	it	pt	tr	vi	Avg	de	es	fr	id	it	pt	tr	vi	
Llama 3 70B-I	99.0	100.0	99.7	100.0	100.0	100.0	100.0	100.0	100.0	90.9	99.7	100.0	99.0	100.0	100.0	100.0	100.0	100.0	98.7	
Llama 3.1 70B-I	99.6	100.0	99.7	100.0	100.0	98.9	100.0	100.0	99.0	99.0	99.1	100.0	99.2	99.6	99.1	100.0	99.6	98.0	97.5	
Command R	99.2	100.0	99.7	100.0	100.0	100.0	100.0	100.0	96.9	96.0	97.9	98.9	100.0	100.0	96.4	100.0	98.5	97.4	92.2	
Command R+	99.6	100.0	100.0	100.0	100.0	99.0	100.0	100.0	100.0	97.0	98.6	100.0	100.0	100.0	98.6	99.6	100.0	97.9	93.1	
Command R Refresh	99.9	100.0	100.0	99.7	100.0	100.0	100.0	99.5	100.0	100.0	99.9	100.0	100.0	100.0	99.5	100.0	100.0	100.0	100.0	
Command R+ Refresh	99.9	100.0	99.9	100.0	100.0	100.0	100.0	100.0	100.0	99.0	99.7	100.0	100.0	100.0	99.1	100.0	100.0	99.0	99.6	
GPT-3.5 Turbo	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0	100.0	99.2	100.0	
GPT-4o	99.8	100.0	99.7	100.0	100.0	98.9	100.0	99.5	100.0	100.0	99.7	100.0	100.0	100.0	99.1	100.0	100.0	99.6	99.1	

Table A4: **Word-level pass rate (WPR) on *monolingual* and *cross-lingual* generation in Latin script languages** (% of responses containing no characters that are outside the corresponding script’s Unicode range). Llama models are instruction-tuned variants.

	Monolingual							Cross-lingual						
	Avg	ar	hi	ja	ko	ru	zh	Avg	ar	hi	ja	ko	ru	zh
Llama 2 70B-I	20.9	0.7	2.0	13.1	0.0	91.0	18.9	27.2	21.8	33.9	27.2	9.0	52.1	19.3
Llama 3 70B-I	31.6	35.3	37.1	17.8	0.0	84.5	14.7	29.3	46.9	62.9	2.7	1.5	53.7	8.3
Llama 3.1 70B-I	99.3	99.4	<b>100.0</b>	97.9	<b>100.0</b>	99.0	<b>99.5</b>	81.0	85.5	97.0	71.7	67.4	84.1	80.3
Mixtral 8x7B	65.3	61.9	74.7	67.4	61.4	72.9	53.4	61.6	66.6	50.6	54.5	61.7	76.2	59.7
Mistral Large	69.4	64.9	31.7	64.4	78.0	98.5	79.2	63.3	52.1	72.5	59.9	56.9	75.3	63.0
Command R	98.0	99.7	99.5	96.9	98.5	98.0	95.3	78.6	74.5	78.7	75.1	80.9	79.9	82.3
Command R+	99.4	99.7	<b>100.0</b>	99.0	<b>100.0</b>	99.0	98.7	93.4	95.6	93.0	94.6	93.5	91.3	92.5
Command R Refresh	99.4	99.6	<b>100.0</b>	99.0	<b>100.0</b>	99.5	98.5	94.9	94.4	96.9	95.8	95.2	93.8	<b>93.5</b>
Command R+ Refresh	99.6	99.0	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	99.5	99.0	<b>95.8</b>	96.4	<b>98.0</b>	95.8	<b>96.4</b>	<b>95.4</b>	92.9
GPT-3.5 Turbo	99.4	<b>100.0</b>	99.5	98.5	<b>100.0</b>	<b>100.0</b>	98.5	94.1	94.7	95.4	93.2	94.2	94.9	92.3
GPT-4 Turbo	<b>99.7</b>	99.5	<b>100.0</b>	<b>100.0</b>	99.5	<b>100.0</b>	99.0	92.8	93.0	94.1	91.5	93.1	92.8	92.3
GPT-4o	99.6	99.8	<b>100.0</b>	<b>100.0</b>	99.2	99.2	99.5	95.1	<b>97.0</b>	94.9	<b>96.7</b>	96.2	94.9	91.1

Table A5: **Aggregate language confusion pass rate (LCPR) of LLMs on *monolingual* and *cross-lingual* tasks.**

models	prompt	generation	confusion type
Llama 3 70B-I	ロイングエクササイズの果について じる事を1,000文字以内で いてくださ	<b>**The Effects of Rowing Exercise: A Comprehensive Review**</b> Rowing exercise has gained popularity in recent years due to its numerous benefits for physical and mental health. As a low-impact, full-body workout, rowing has been shown to improve cardiovascular fitness, increase muscle strength and endurance, and enhance overall well-being. In this article, we will discuss the effects of rowing exercise and explore its advantages for individuals of all fitness levels. <b>**Cardiovascular Benefits**</b> Rowing is an excellent cardiovascular	Full response
Mixtral 8x7B	问题：油在生 活中有 哪些用途？	油在我们的日常生活中有许多用途，主要包括： 1. 烹饪：油是烹饪中不可或缺的一种原料，它可以用来油炸、煎炸、烧烤等 <b>verschiedenen Kochtechniken</b> . Es kann auch als Salatöl oder Dressing verwendet werden.	Line level
Command R	교실에서 시작하는 디지털 시민성 교육에 관한 교육 자료를 초등 학교 수준으로 쉬운 말투를 사용하여 200단어 이내로 작성해줘.	디지털 시민이란 인터넷과 디지털 기술로 연결된 세상에서 다른 사람들과 상호작용하고, 소통하는 방법을 아는 사람을 말해. 디지털 세상에서 우리는 좋은 친구들이나 가족들처럼 행동해야 해. 교실에서 디지털 시민이 되는 법을 배워보아요! 우리는 먼저 인터넷에서 주의해야 할 점을 알아볼 거야. 디지털 세상에서 우리 <b>would</b> 안전한 웹사이트만 방문하고, 우리 개인정보를 소중히 지켜야 해.	Word level

Table A6: Examples of different types of language confusion across models.

## A.2 Annotator statistics

Prompts were written by native-level speakers of the respective languages, each of whom is also fluent in English. Annotators were paid by the hour, with compensation above the federal minimum wage of the country of employment.

## A.3 Cross-lingual prompt generation

In order to generate prompts for the cross-lingual setting, we semi-automatically amend English prompts with an English instruction to generate text in the target language. For each English prompt and target language, we randomly choose an English instruction (e.g., “Respond in French”, “Reply in Turkish”). To control for the position of the instruction in the prompt, for each prompt separate examples are created where an instruction is inserted at the beginning and at the end respectively. For each prompt, we additionally generate another example where an instruction is manually integrated into the prompt, e.g., “Generate an essay **in Korean**”. The same process is applied to Okapi, ShareGPT, and our complex prompts. Table 2 shows representative examples where instructions are integrated in the middle, inserted at the beginning and at the end of the original prompts.



## A.4 Dataset Language Confusion Metrics

	Avg	Okapi	Aya	Dolly	Native (Ours)
Llama 2 70B-I	54.0	57.2	49.6	55.2	49.0
Llama 3 70B-I	56.2	56.0	50.8	61.8	47.0
Llama 3.1 70B-I	<b>99.7</b>	<b>100.0</b>	<b>100.0</b>	99.3	99.5
Mixtral 8x7B	74.9	70.7	78.3	75.8	78.2
Mistral Large	75.6	68.4	82.0	76.4	77.8
Command R	98.7	97.8	99.4	99.0	98.8
Command R+	99.3	99.0	99.0	99.8	99.2
Command R Refresh	99.2	98.4	99.0	<b>100.0</b>	99.5
Command R+ Refresh	99.2	99.2	98.6	99.4	<b>99.8</b>
GPT-3.5 Turbo	99.1	99.0	98.6	99.8	99.5
GPT-4 Turbo	99.4	98.9	99.4	99.8	99.2
GPT-4o	99.1	98.8	98.8	99.2	99.5

Table A7: **Line-level pass rate (LPR) by dataset on monolingual generation.**

	Monolingual					Cross-lingual			
	Avg	Okapi	Aya	Dolly	Native (Ours)	Avg	Okapi	ShareGPT	Complex (Ours)
Llama 2 70B-I	97.4	<b>100.0</b>	94.4	97.7	<b>100.0</b>	84.2	90.0	78.9	83.7
Llama 3 70B-I	95.1	<b>100.0</b>	93.3	91.9	90.0	94.4	98.9	87.9	96.4
Llama 3.1 70B-I	99.7	<b>100.0</b>	<b>100.0</b>	99.3	99.5	95.0	97.7	93.3	94.0
Mixtral 8x7B	78.0	77.9	74.8	81.3	64.9	68.2	75.8	68.0	60.8
Mistral Large	98.9	<b>100.0</b>	98.9	97.9	99.0	93.8	98.7	95.4	87.3
Command R	96.5	97.4	93.8	98.3	95.5	94.0	95.3	93.7	92.9
Command R+	99.7	<b>100.0</b>	<b>100.0</b>	99.0	99.5	95.1	97.4	97.6	90.3
Command R Refresh	99.5	<b>100.0</b>	99.0	99.3	99.5	98.8	99.6	99.6	97.1
Command R+ Refresh	99.6	<b>100.0</b>	99.5	99.0	<b>100.0</b>	98.3	99.3	99.1	96.6
GPT-3.5 Turbo	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>	99.5	98.7	<b>100.0</b>	<b>99.8</b>	96.4
GPT-4 Turbo	99.7	<b>100.0</b>	99.0	<b>100.0</b>	99.5	96.6	99.8	99.5	90.6
GPT-4o	99.8	<b>100.0</b>	<b>100.0</b>	99.5	99.7	<b>99.0</b>	<b>100.0</b>	99.6	<b>97.4</b>

Table A8: WPR by dataset for *monolingual* and *cross-lingual* generation.

	Monolingual					Cross-lingual			
	Avg	Okapi	Aya	Dolly	Native (Ours)	Avg	Okapi	ShareGPT	Complex (Ours)
Llama 2 70B-I	69.4	72.8	65.0	70.5	65.8	52.0	58.6	58.1	39.3
Llama 3 70B-I	70.5	71.8	65.8	73.9	61.8	44.7	51.7	54.5	27.9
Llama 3.1 70B-I	99.4	99.5	99.3	99.4	99.3	87.3	91.1	92.1	78.7
Mixtral 8x7B	76.4	74.1	76.5	78.5	71.0	68.3	76.6	73.4	54.8
Mistral Large	85.6	81.2	89.7	85.8	87.1	71.7	80.5	70.8	64.0
Command R	97.6	97.6	96.5	98.7	97.1	76.9	84.3	91.6	54.9
Command R+	99.5	99.5	<b>99.5</b>	99.4	99.4	93.0	96.7	98.2	84.2
Command R Refresh	99.4	99.2	99.0	99.7	99.5	95.7	<b>98.9</b>	<b>99.5</b>	88.7
Command R+ Refresh	99.4	<b>99.6</b>	99.0	99.2	<b>99.9</b>	<b>96.8</b>	98.6	98.9	<b>93.0</b>
GPT-3.5 Turbo	<b>99.6</b>	99.5	99.3	<b>99.9</b>	99.5	93.8	98.8	98.3	84.4
GPT-4 Turbo	99.5	99.4	99.2	<b>99.9</b>	99.4	93.3	98.2	97.9	83.7
GPT-4o	99.4	99.4	99.4	99.3	99.6	95.5	98.7	98.6	89.1

Table A9: LCPR by dataset for *monolingual* and *cross-lingual* generation.

## A.5 Extended Impacts

	Short [21, 65]	Medium [68, 224]	Long [227, 2971]
Command R	42.7	28.1	38.0
+ one-shot	59.5	49.1	67.7
Command R+	82.1	74.8	79.8
GPT-4	89.3	72.9	71.8

Table A10: **Line-level pass rate (LPR) on our “Complex prompts” dataset for cross-lingual generation, depending on length of the prompts.** We sort the prompts by length and split them into 3 length buckets of the same size (each containing one third of the prompts). [a, b]: min and max length in words of each bucket’s prompts.

	Start	Integrated	End
Command R	86.7	69.0	85.1
+ one-shot	88.7	80.6	90.6
Command R+	94.4	90.3	95.2
GPT-4	93.0	91.7	95.0

Table A11: **Line-level pass rate (LPR) on crosslingual generation depending on the position of the language control instruction.** “Integrated” corresponds to instructions of the form “Write an essay of 100 words in Korean about artificial intelligence.” “Start” and “End” are isolated instructions of the form “Reply in French.” placed either at the start or at the end of the prompt.

## A.6 Quantization

It is common to train at half-precision floating-point (FP16), where weights and activations of a network use 16 bits (2 bytes) to represent a floating-point value. It is common to quantize weights to INT8 (8-bit integers), often referred to as *W8*. More extreme quantization of weights to INT4 (4-bit) is called *W4*. Quantizing both weights and activations to INT8 is commonly called *W8A8*. In Section 4.4, we compare *FP16* with *W8*, *W8A8*, and *W4*<sup>22</sup> variants of Command R+ on monolingual generation.

Line-level Pass Rate (LPR)								
	avg	ar	hi	ja	ko	ru	zh	id
<b>FP16</b>	99.3	99.0	100.0	99.0	100.0	100.0	97.5	97.0
<b>W8</b>	99.3	99.7	100.0	98.0	100.0	100.0	99.0	97.0
<b>W8A8</b>	99.5	100.0	100.0	100.0	100.0	100.0	98.5	98.0
<b>W4-g</b>	98.8	99.3	99.0	98.0	100.0	100.0	98.5	91.0
Word-level Pass Rate (WPR)								
<b>FP16</b>	98.2	99.3	100.0	100.0	99.0	95.0	96.0	-
<b>W8</b>	98.3	99.3	99.0	99.0	100.0	96.0	96.5	-
<b>W8A8</b>	98.7	99.3	99.0	100.0	100.0	97.0	97.0	-
<b>W4-g</b>	98.1	99.3	100.0	98.0	99.0	93.9	98.5	-

Table A12: **Effect of quantization on LPR and WPR on monolingual generation.**

<sup>22</sup>W4 with group-wise scaling using GPTQ (Frantar et al., 2022).

## A.7 Extended Beam Search and Nucleus Sampling Results

	avg	ar	hi	ja	ko	ru	zh
T=0.0	93.3	<b>98.9</b>	94.6	86.4	96.7	93.0	90.0
T=0.3	94.0	94.3	<b>98.6</b>	88.5	<b>97.2</b>	94.0	91.1
T=0.5	94.2	<b>98.9</b>	96.1	87.1	95.2	<b>95.5</b>	<b>92.3</b>
T=0.7	<b>94.6</b>	97.9	99.1	<b>90.8</b>	95.7	94.6	89.6
T=1.0	80.1	93.5	88.6	70.5	85.5	71.0	71.2
p=0.1	93.6	97.4	96.6	<b>89.0</b>	97.5	93.3	87.6
p=0.3	<b>94.0</b>	<b>98.0</b>	97.6	85.7	98.4	92.0	<b>92.3</b>
p=0.5	<b>94.0</b>	95.0	97.3	<b>89.0</b>	<b>98.8</b>	93.8	90.1
p=0.75	<b>94.0</b>	94.3	<b>98.6</b>	88.5	97.2	<b>94.0</b>	91.1

Table A13: **Effect of varying temperature ( $T$ ) or nucleus size ( $p$ ) on cross-lingual word-level language confusion (WPR) of *Command R*.** Default values are  $p = 0.75$  and  $T = 0.3$ . Best score is in **bold**.

Monolingual							
	avg	ar	hi	ja	ko	ru	zh
1	97.8	98.6	<b>100.0</b>	97.0	97.0	98.0	96.4
2	98.6	98.2	<b>100.0</b>	98.0	<b>100.0</b>	98.0	97.4
3	98.6	98.9	<b>100.0</b>	<b>100.0</b>	98.0	98.0	96.9
5	<b>99.0</b>	<b>99.3</b>	<b>100.0</b>	99.0	98.0	<b>100.0</b>	97.4
10	<b>99.0</b>	98.5	<b>100.0</b>	99.0	98.0	<b>100.0</b>	<b>98.4</b>
Cross-lingual							
	avg	ar	hi	ja	ko	ru	zh
1	94.9	98.9	97.2	89.4	97.5	95.8	90.4
2	95.4	99.2	97.1	91.1	95.7	<b>97.2</b>	92.4
3	<b>97.1</b>	<b>100.0</b>	97.9	95.7	98.0	96.4	94.5
5	96.7	99.7	<b>98.3</b>	95.1	96.4	96.2	<b>94.7</b>
10	96.7	98.3	<b>98.3</b>	<b>96.7</b>	<b>98.4</b>	94.5	93.7

Table A14: **Monolingual and Cross-lingual word-level pass rate (WPR) of *Command R* using beam search** with beam sizes 1–10. ( $\neg$ ) *IE* = (non-) *Indo-European* language. ( $\neg$ ) *Latin* = (non-) *Latin* script.



	Monolingual																			
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	¬ IE	IE	¬ Latin	Latin
T=0.0	98.8	100.0	98.0	99.0	96.7	99.0	100.0	96.0	99.0	99.0	100.0	98.0	100.0	99.0	100.0	99.0	99.1	98.5	99.7	98.3
T=0.3	98.6	100.0	98.0	99.5	95.7	99.3	100.0	92.0	99.0	100.0	100.0	98.5	100.0	99.0	99.0	98.5	98.6	98.6	99.7	97.8
T=0.5	98.7	99.0	98.0	99.0	96.3	99.7	100.0	94.0	99.0	100.0	100.0	98.5	100.0	99.0	99.0	98.5	98.7	98.6	99.6	98.1
T=0.7	98.9	100.0	98.0	99.0	95.7	99.0	99.0	99.0	100.0	99.0	100.0	99.0	100.0	99.0	99.0	98.5	99.3	98.5	99.4	98.6
T=1.0	96.8	100.0	96.0	99.5	95.0	99.7	98.0	91.9	98.0	99.0	98.0	97.0	97.0	92.9	93.0	97.5	96.2	97.6	98.2	95.9
p=0.1	98.9	100.0	98.0	99.0	96.7	99.0	100.0	96.0	99.0	100.0	100.0	98.5	100.0	99.0	100.0	99.0	99.2	98.6	99.8	98.3
p=0.3	98.9	100.0	98.0	99.0	96.3	99.0	100.0	96.0	99.0	99.0	100.0	98.5	100.0	99.0	100.0	99.0	99.1	98.5	99.7	98.3
p=0.5	98.8	100.0	98.0	99.0	96.3	98.7	100.0	96.0	99.0	99.0	100.0	98.5	100.0	99.0	100.0	98.5	99.1	98.5	99.6	98.3
p=0.75	98.6	100.0	98.0	99.5	95.7	99.3	100.0	92.0	99.0	100.0	100.0	98.5	100.0	99.0	99.0	98.5	98.6	98.6	99.7	97.8
	Cross-lingual																			
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	¬ IE	IE	¬ Latin	Latin
T=0.0	68.1	61.7	61.9	-	70.7	74.6	65.2	70.4	65.9	68.1	70.8	68.8	68.8	65.6	65.7	74.8	68.2	67.8	68.2	67.9
T=0.3	68.1	61.6	63.2	-	72.5	74.4	65.5	70.8	65.7	65.3	69.2	67.2	69.4	67.7	65.7	75.0	68.1	68.1	67.7	68.4
T=0.5	67.9	60.7	62.5	-	72.1	74.3	64.3	69.6	66.2	67.1	70.2	67.8	67.1	67.0	65.6	76.2	67.9	67.9	67.6	68.1
T=0.7	67.9	60.7	63.2	-	72.1	74.3	65.6	68.8	66.2	68.1	69.7	68.4	68.4	64.4	65.7	75.5	67.7	68.3	68.0	67.9
T=1.0	64.0	63.3	63.0	-	70.6	72.4	63.3	63.9	62.0	65.4	65.2	66.1	62.7	57.1	51.7	69.8	62.4	66.2	64.9	63.3
p=0.1	68.0	61.3	62.5	-	71.1	75.0	65.1	70.1	66.9	67.8	70.2	68.4	68.3	65.9	65.7	74.2	67.9	68.2	67.8	68.2
p=0.3	68.1	61.3	62.5	-	70.7	74.6	65.4	69.7	66.6	67.7	69.8	68.1	68.4	67.2	65.7	75.2	68.1	68.0	68.0	68.1
p=0.5	68.2	61.1	62.9	-	71.4	75.3	65.1	69.2	66.6	68.1	70.1	68.8	69.5	66.8	65.9	74.5	68.2	68.3	68.1	68.4
p=0.75	68.1	61.6	63.2	-	72.5	74.4	65.5	70.8	65.7	65.3	69.2	67.2	69.4	67.7	65.7	75.0	68.1	68.1	67.7	68.4

Table A15: **Effect of varying temperature ( $T$ ) or nucleus size ( $p$ ) on *monolingual* and *crosslingual* line-level language confusion (LPR) of *Command R*.** Default values are  $p = 0.75$  and  $T = 0.3$ . **Best score.** ( $\neg$ ) *IE* = (*non-*) *Indo-European language*. ( $\neg$ ) *Latin* = (*non-*) *Latin script*.

	Monolingual																			
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	¬ IE	IE	¬ Latin	Latin
1	99.0	100.0	98.0	99.5	96.0	99.3	100.0	97.0	99.0	100.0	100.0	99.5	100.0	97.9	100.0	99.0	99.2	98.8	99.8	98.5
2	99.0	99.6	98.0	99.5	95.6	99.7	100.0	96.0	99.0	100.0	100.0	99.0	100.0	98.9	100.0	99.0	99.2	98.7	99.8	98.4
3	98.7	99.6	98.0	99.0	95.7	99.7	99.0	96.0	99.0	99.0	100.0	99.0	100.0	98.9	100.0	98.0	98.9	98.5	99.3	98.3
5	99.0	99.3	98.0	99.5	96.0	99.7	100.0	96.0	100.0	100.0	100.0	99.5	100.0	98.9	100.0	98.5	99.1	98.9	99.6	98.6
10	98.5	98.9	98.0	99.5	95.7	99.3	100.0	96.0	100.0	99.0	100.0	98.0	100.0	97.8	99.0	96.9	98.4	98.6	99.1	98.1

	Cross-lingual																			
	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	¬ IE	IE	¬ Latin	Latin
1	74.1	68.4	70.9	-	76.9	77.2	74.7	74.9	72.0	73.5	76.4	73.7	73.6	73.8	73.0	77.8	73.9	74.2	74.1	74.0
2	72.2	67.0	70.5	-	76.5	75.7	74.0	72.5	70.8	70.9	73.8	74.3	70.8	69.5	70.8	73.5	71.1	73.6	71.6	72.6
3	71.5	67.2	69.8	-	76.5	76.4	75.0	69.8	71.6	69.2	73.1	71.1	69.3	67.6	70.1	74.8	70.1	73.4	71.4	71.6
5	70.3	65.0	69.6	-	76.2	76.3	75.1	67.0	71.0	68.2	72.4	69.1	67.6	65.5	66.7	73.8	68.3	72.9	70.4	70.2
10	68.4	65.0	68.6	-	75.9	75.7	75.7	66.2	70.2	66.1	68.8	66.7	63.7	60.6	64.7	69.6	65.6	72.1	68.1	68.6

Table A16: ***Monolingual* and *Cross-lingual* line-level pass rate (LPR) of *Command R* using beam search with beam sizes 1-10.** ( $\neg$ ) *IE* = (*non-*) *Indo-European language*. ( $\neg$ ) *Latin* = (*non-*) *Latin script*.

## A.8 Base vs Instruction Tuning comparison

**Q:** Write your answer in French. How should I choose what cheese to buy?  
**A:** Il existe de nombreux types de fromages différents, donc le choix du fromage à acheter dépend des préférences personnelles, de la disponibilité et de l'utilisation prévue. [...]  
**Q:** What is the difference between pets and cattle? Reply in Arabic.  
**A:**

Figure A2: Template used for few-shot prompting the base models. The model’s answers are truncated to prevent the generation of new questions. For the instruct variants, we use similar prompting, except that the Q/A examples are formatted as User/Chatbot turns using the model’s chat template.

	Avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Llama 2 70B	<b>97.5</b>	<b>100.0</b>	<b>92.9</b>	<b>99.5</b>	<b>98.0</b>	<b>96.5</b>	<b>98.9</b>	<b>91.9</b>	<b>98.0</b>	<b>100.0</b>	<b>100.0</b>	<b>95.8</b>	<b>100.0</b>	<b>98.7</b>	<b>98.0</b>	<b>93.6</b>
Llama 2 70B-I	48.3	0.3	59.0	99.0	95.7	87.7	1.0	62.0	72.0	7.0	0.0	91.0	88.9	33.0	17.0	10.5
Llama 3 70B	<b>94.8</b>	<b>95.6</b>	<b>96.9</b>	99.0	96.6	<b>97.6</b>	<b>97.9</b>	<b>82.8</b>	<b>93.9</b>	<b>88.9</b>	<b>100.0</b>	<b>96.2</b>	<b>100.0</b>	<b>94.4</b>	<b>93.9</b>	<b>89.1</b>
Llama 3 70B-I	46.0	21.7	31.0	<b>100.0</b>	<b>98.3</b>	88.7	23.0	21.0	88.0	10.0	0.0	95.5	77.0	18.0	10.0	8.0
Command R base	86.3	94.5	83.8	98.5	89.6	86.6	81.0	69.4	79.0	98.0	94.3	83.9	93.6	91.0	79.6	71.1
Command R	<b>98.6</b>	<b>100.0</b>	<b>98.0</b>	<b>99.5</b>	<b>95.7</b>	<b>99.3</b>	<b>100.0</b>	<b>92.0</b>	<b>99.0</b>	<b>100.0</b>	<b>100.0</b>	<b>98.5</b>	<b>100.0</b>	<b>99.0</b>	<b>99.0</b>	<b>98.5</b>
Command R+ base	82.1	93.2	71.4	98.0	81.9	86.7	68.7	80.8	65.0	92.7	92.1	79.8	93.5	95.0	70.7	62.4
Command R+	<b>99.2</b>	<b>99.7</b>	<b>100.0</b>	<b>100.0</b>	<b>99.3</b>	<b>99.7</b>	<b>100.0</b>	<b>97.0</b>	<b>100.0</b>	<b>99.0</b>	<b>100.0</b>	<b>97.5</b>	<b>100.0</b>	<b>100.0</b>	<b>99.0</b>	<b>97.5</b>

Table A17: LPR of base vs instruction-tuned LLMs for *monolingual* generation.

Model	Crosslingual WPR							Crosslingual LPR														
	avg	ar	hi	ja	ko	ru	zh	avg	ar	de	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Command R Base	100.0	100.0	100.0	100.0	100.0	100.0	100.0	1.1	0.0	0.9	1.2	1.6	0.8	1.4	0.3	2.4	0.0	0.9	0.0	0.4	1.6	3.6
+ Q/A template	97.0	95.2	100.0	99.0	97.9	91.7	98.4	20.9	3.3	19.9	27.6	27.5	5.3	25.8	23.2	42.5	13.5	17.5	8.0	19.6	14.9	44.0
+ 1-shot	98.6	98.5	98.8	98.6	98.3	98.4	99.2	90.7	83.8	93.3	95.0	93.2	84.2	86.7	93.0	93.2	92.5	91.1	88.3	89.6	91.9	93.3
+ 5-shot	99.7	100.0	99.2	100.0	99.5	100.0	99.6	95.0	91.0	96.3	96.8	95.9	96.0	92.8	96.5	93.8	95.5	95.4	93.8	96.8	95.6	94.5
+ English SFT	91.7	95.5	98.7	77.9	94.8	94.3	89.0	78.3	70.0	77.7	82.7	76.6	78.4	77.7	74.8	80.8	80.7	79.3	74.4	82.4	83.9	77.1
+ English pref. tuning	87.4	91.2	97.7	70.4	92.9	88.5	83.6	85.7	86.4	87.4	86.2	82.1	87.7	80.2	83.9	87.6	84.3	83.2	86.7	90.1	89.6	84.6
+ Multilingual SFT	90.0	96.0	97.6	76.0	92.1	89.0	89.7	78.2	89.1	62.4	76.8	69.4	82.8	77.3	72.6	77.7	81.1	76.8	79.5	82.3	85.1	82.4
+ Multi. pref. tuning	86.9	94.1	96.6	71.2	87.7	84.9	87.0	89.4	94.1	80.9	91.9	88.7	91.2	85.6	88.9	89.2	93.0	83.7	92.3	91.7	93.0	87.8
Command R	94.0	94.3	98.6	88.5	97.2	94.0	91.1	68.1	61.6	63.2	72.5	74.4	65.5	70.8	65.7	65.3	69.2	67.2	69.4	67.7	65.7	75.0
+ 1-shot	92.3	97.2	98.3	87.6	89.7	91.6	89.5	82.9	80.0	79.5	85.6	82.6	84.7	79.9	82.4	78.0	87.2	81.5	84.4	84.5	84.5	85.2

Table A18: Effect of few-shot prompting and instruction tuning on cross-lingual language confusion, detailed per-language results.

Model	Monolingual WPR							Monolingual LPR															
	avg	ar	hi	ja	ko	ru	zh	avg	ar	de	en	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh
Command R Base	98.7	97.9	95.1	100.0	100.0	100.0	99.4	86.2	94.9	85.0	99.5	90.5	85.3	81.0	72.2	74.0	93.9	94.2	84.0	94.8	92.0	83.0	68.1
+ Q/A template	99.7	100.0	100.0	100.0	100.0	98.5	100.0	85.3	87.6	73.2	100.0	89.8	86.3	98.9	49.0	91.9	97.9	93.5	96.8	86.7	96.3	49.0	82.4
+ 1-shot	100.0	100.0	100.0	100.0	100.0	100.0	100.0	94.1	93.0	99.0	100.0	99.3	47.5	96.9	93.8	99.0	99.0	96.8	99.0	97.3	95.1	96.6	99.0
+ 5-shot	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.0	99.6	99.0	100.0	100.0	98.3	98.0	96.9	100.0	100.0	99.0	99.5	98.9	98.8	99.0	97.9
+ English SFT	96.2	98.4	100.0	88.1	98.5	100.0	92.3	77.8	54.1	83.8	100.0	80.3	86.9	59.6	89.0	96.0	67.7	66.7	84.4	68.0	64.0	85.0	82.0
+ English pref. tuning	90.9	93.5	97.8	88.4	95.4	89.6	85.0	74.3	54.4	81.0	100.0	82.7	85.6	46.0	80.0	95.0	64.0	65.0	81.4	67.7	51.0	82.0	78.5
+ Multilingual SFT	95.5	97.9	100.0	86.6	97.9	99.0	91.6	98.3	99.7	100.0	100.0	99.7	98.7	100.0	90.0	99.0	98.0	98.0	98.4	100.0	96.8	100.0	97.0
+ Multi. pref. tuning	93.4	97.9	100.0	86.7	93.0	91.8	91.2	98.8	99.6	97.0	99.5	99.3	99.3	100.0	92.0	100.0	99.0	100.0	99.0	100.0	100.0	100.0	98.0
Command R	96.3	99.3	99.0	93.9	97.0	96.0	92.3	98.6	100.0	98.0	99.5	95.7	99.3	100.0	92.0	99.0	100.0	100.0	98.5	100.0	99.0	99.0	98.5
+ 1-shot	92.7	94.4	95.7	93.8	88.9	90.5	92.9	68.3	51.8	53.0	5.5	83.2	98.3	23.7	88.0	94.0	65.0	95.7	66.0	95.5	90.3	97.8	17.0

Table A19: Effect of few-shot prompting and instruction tuning on monolingual language confusion, detailed per-language results.

## A.9 Metric Variability

We find there is little variability LPR and WPR between runs. We run monolingual and crosslingual language confusion tasks on the FP16 and W4g variants of Command R/R+ 5 times each, and report the minimum, maximum, and mean of LPR and WPR in Table A20.

		Monolingual LPR														Monolingual WPR							
		avg	ar	de	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	avg	ar	hi	ja	ko	ru	zh
Command R+ fp16	min	99.1	98.6	100.0	99.0	98.7	100.0	95.0	100.0	98.0	100.0	97.5	100.0	100.0	99.0	97.0	99.1	99.3	100.0	99.0	98.0	97.0	100.0
	mean	99.3	99.3	100.0	99.3	99.6	100.0	96.6	100.0	98.6	100.0	98.3	100.0	100.0	99.8	97.9	99.4	99.7	100.0	99.8	99.4	97.6	100.0
	max	99.5	100.0	100.0	99.7	100.0	100.0	99.0	100.0	99.0	100.0	99.0	100.0	100.0	100.0	99.0	99.6	100.0	100.0	100.0	100.0	99.0	100.0
Command R+ w4g	min	99.3	98.6	100.0	99.3	99.7	100.0	97.0	100.0	97.0	100.0	97.5	100.0	100.0	100.0	98.5	99.5	100.0	100.0	99.0	99.0	99.0	98.5
	mean	99.4	99.1	100.0	99.6	99.9	100.0	97.8	100.0	97.4	100.0	98.1	100.0	100.0	100.0	98.9	99.7	100.0	100.0	99.8	99.8	99.4	99.2
	max	99.5	99.6	100.0	99.7	100.0	100.0	99.0	100.0	98.0	100.0	98.5	100.0	100.0	100.0	99.5	99.8	100.0	100.0	100.0	100.0	100.0	100.0
Command R fp16	min	98.3	98.6	97.0	98.0	98.7	100.0	92.0	99.0	98.0	99.0	98.5	99.0	98.0	100.0	96.5	95.1	97.3	95.0	90.7	97.0	93.9	92.3
	mean	98.6	99.2	97.0	98.1	99.2	100.0	93.6	99.6	99.6	99.0	99.0	99.8	98.6	100.0	97.7	95.6	97.8	96.0	92.5	97.6	96.2	93.4
	max	98.8	99.3	97.0	98.3	99.3	100.0	95.0	100.0	100.0	99.0	99.5	100.0	99.0	100.0	98.5	96.5	98.7	97.0	96.0	98.0	97.0	94.4
Command R w4g	min	98.5	99.0	95.0	96.3	99.7	99.0	96.0	100.0	99.0	97.0	98.0	100.0	98.0	99.0	98.0	95.7	98.3	97.0	86.9	95.9	96.0	93.9
	mean	98.6	99.4	95.0	96.5	99.9	99.8	97.2	100.0	99.8	97.0	98.3	100.0	98.8	99.8	98.6	95.9	98.4	97.6	89.1	96.7	98.4	95.2
	max	98.7	100.0	95.0	97.0	100.0	100.0	98.0	100.0	100.0	97.0	98.5	100.0	99.0	100.0	99.5	96.2	98.6	98.0	91.9	97.9	100.0	96.0
		Crosslingual LPR														Crosslingual WPR							
		avg	ar	de	es	fr	hi	id	it	ja	ko	pt	ru	tr	vi	zh	avg	ar	hi	ja	ko	ru	zh
Command R+ fp16	min	90.8	92.5	90.3	90.0	91.1	88.1	87.8	92.4	92.4	90.6	87.5	89.8	91.5	90.1	90.2	94.8	97.5	94.4	94.7	94.6	90.2	94.4
	mean	91.0	93.0	90.6	91.2	91.6	88.8	88.2	93.0	93.1	91.1	88.3	91.3	92.0	90.8	91.3	95.1	97.9	95.2	95.7	95.1	91.1	95.9
	max	91.2	93.6	91.0	92.4	91.9	89.2	88.6	93.4	94.1	91.3	89.6	92.4	92.9	91.5	92.5	95.4	98.3	95.7	96.6	95.6	92.0	96.5
Command R+ w4g	min	90.0	89.9	89.2	90.4	91.6	87.5	85.6	92.5	92.4	89.8	84.1	90.6	89.8	90.4	89.2	94.8	97.2	94.2	96.0	94.9	88.7	95.7
	mean	90.1	90.6	89.9	90.7	91.7	88.4	86.5	93.1	92.8	90.6	85.4	91.0	90.7	90.7	89.6	95.3	97.7	94.8	96.5	95.8	90.3	96.5
	max	90.2	91.1	90.7	91.0	91.7	89.1	87.4	93.8	93.4	91.1	85.9	91.4	91.5	91.0	90.5	95.6	98.2	95.9	97.3	96.4	91.1	97.6
Command R fp16	min	66.3	57.9	58.6	68.8	72.1	63.9	68.7	62.9	65.1	68.6	63.8	67.4	63.6	64.2	74.2	92.9	97.5	97.6	88.6	90.5	86.6	90.2
	mean	66.4	58.8	59.6	69.0	73.0	64.0	69.3	63.6	66.3	69.2	64.2	68.8	64.2	65.1	74.6	93.6	98.5	98.4	90.5	93.3	88.7	92.1
	max	66.6	59.5	60.0	69.5	73.8	64.3	69.8	63.9	67.4	69.6	64.4	69.7	64.8	66.3	74.8	94.4	99.2	99.6	92.1	95.1	91.0	93.4
Command R w4g	min	67.0	60.3	58.9	72.4	73.0	67.3	66.6	64.2	65.0	69.5	64.1	68.9	64.2	65.7	72.5	92.5	96.3	94.8	89.2	92.8	86.5	90.8
	mean	67.2	60.4	59.3	72.8	73.3	67.7	67.9	64.8	65.4	70.4	64.6	69.7	64.6	66.1	73.0	93.0	97.5	95.6	90.3	94.8	88.0	92.3
	max	67.3	60.6	59.6	73.0	73.8	68.0	68.6	65.2	66.0	71.1	65.1	70.6	65.2	66.4	73.8	93.6	98.4	96.2	91.6	95.9	89.3	93.6

Table A20: Variability in LPR & WPR metrics for Command R/R+ models over 5 evaluation runs.

### A.10 Nucleus Sampling with Temperature

Previous work shows that greedy search empirically leads to repetition and generally low-quality generations. One solution is adding stochasticity to decoding, such as by sampling the next token from the top-K next most likely tokens or from the top-P of the probability distribution over next tokens. The latter is called “nucleus sampling” (Holtzman et al., 2019), and can be combined with top-K and temperature sampling.

Let  $\mathbf{x} = [x_0, x_1, x_2, \dots, x_{n-1}]$  be a sequence of tokens. We describe how to sample the next token in the sequence via *nucleus sampling with temperature* given a language model with vocabulary  $V$ .

The *nucleus* of a probability distribution for  $0 < p \leq 1$  is the smallest subset  $V' \subset V$  such that the summed probabilities of  $V'$  are greater than or equal to  $p$ .<sup>23</sup> *Nucleus sampling* samples the next token  $x_n$  at random from this set. The function *top\_p* returns  $V'$ :

$$\text{top\_p}(\mathbf{x}, V, p) = v \in V \text{ s.t. } \sum_i P(v_i|\mathbf{x}) \geq p$$

Let  $z \in \mathbb{R}^{|V|}$  be an output vector of logits. We apply the softmax function over element  $z_i$  given temperature  $T$  to transform its logit  $z_i$  to a probability over vocabulary tokens, as below. Let  $v_i$  be the vocabulary token corresponding to logit  $z_i$ .

$$P(v_i|\mathbf{x}) = \text{softmax}(z_i, T) = \frac{e^{\frac{z_i}{T}}}{\sum_j e^{\frac{z_j}{T}}} \quad (1)$$

The next token  $x_n$  is chosen at random from normalized probabilities in the nucleus:

$$P_{\text{normalized}}(v'_i|\mathbf{x}) = \frac{P(v'_i|\mathbf{x})}{\sum_{v'_j \in V'} P(v'_j|\mathbf{x})}$$

$T$  controls the peakiness of the distribution at the sampling point. As  $T$  increases, the distribution becomes more uniform. Figure A3 shows the effect on Equation 1 for a toy example. As  $T$  increases, previously unlikely words become more likely, and highly likely words have lower probabilities.

We walk through Figure 3 as an example.

**Lowering Temperature** Imagine we run inference with  $p = 0.75, T = 1$ . Given previous tokens ‘the’, ‘quick’, and ‘brown’, the next token options

are ‘fox’, ‘dog’, ‘cube’, ‘狐狸’, and ‘after’ with logits  $[0.75, 0.20, -0.10, -0.20, -0.30]$ . Applying the softmax, ‘fox’, ‘dog’, ‘cube’, and ‘狐狸’ remain in the nucleus with respective likelihoods  $[0.418, 0.241, 0.179, 0.162]$ . ‘狐狸’ has an over 16% chance of being sampled at the next step—a high risk for language confusion. Increasing  $T$  to 2.0, ‘狐狸’ has an over 20% chance of being elicited. Reducing  $T$  to 0.5, however, we sharpen the distribution by shifting probability mass to ‘fox’, ‘dog’, and ‘cube’ such that ‘狐狸’ falls out of the nucleus and cannot be sampled, thus eliminating the risk of language confusion at this timestep.

**Reducing Nucleus Size** The distribution may also be sharpened by decreasing nucleus size. Keeping  $T = 1$  but reducing nucleus size to  $p = 0.7$ , ‘狐狸’ is not in the nucleus. The probabilities over next tokens in the nucleus are then: “fox” : 0.499, “dog” : 0.287, “cube” : 0.213, and the risk of language confusion is eliminated.

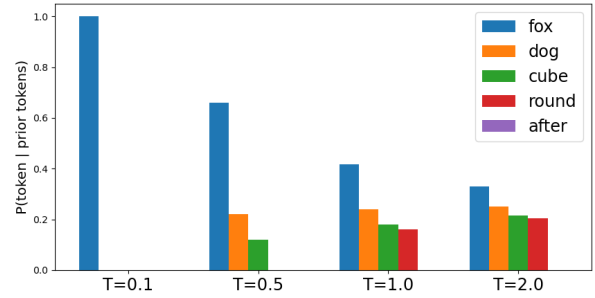


Figure A3: **Effect of increasing temperature  $T$  on output distribution.** As  $T \uparrow$ , the distribution flattens.

<sup>23</sup>Some implementations will define  $V'$  as the *largest subset*  $V' \subset V$  s.t. the summed probabilities of  $V'$  is *less-than-or-equal-to*  $p$ . We use the definition from the original work.

## A.11 Discussion

**Behavior of base models** As observed in §4.5, language confusion in base models is not correlated with their downstream performance. Stronger base models such as Command R+ and Llama 3 70B are more confused than Command R and Llama 2 70B respectively. Given the occurrence of translations and token in other languages in pre-training (Blevins and Zettlemoyer, 2022), we expect base models to exhibit some degree of language switching while instruction tuning then reinforces the desired behavior.

**English-centricity** Despite LLMs in general exhibiting impressive multilingual generative capabilities, the fact that they are most likely to switch to English—both on the sentence and word level—is another example of their English-centric nature (Hu et al., 2020; Zhao et al., 2024). Our experiments in §6.4 further highlight the negative impact of overly English-centric instruction tuning, which is also illustrated by Llama Instruct models’ high language confusion.

**Preference Tuning** In Table 11, we observe that WPR decreases after preference tuning. Citing similar observations by Yuan et al. (2024),<sup>24</sup> Yan et al. (2024) observe a decrease in the likelihood of both preferred and unpreferred data points as DPO (Rafailov et al., 2023) training progresses, and propose a theoretical explanation. Xu et al. (2024) remark that “DPO is prone to generating a biased policy that favors out-of-distribution responses, leading to unpredictable behaviors.” It is plausible that if preference learning decreases token likelihoods for examples seen during its training (e.g. common English words), then the relative likelihoods of unseen/rare tokens increases, explaining the large decrease in WPR we see for +English SFT +English pref. tuning. The hypothesis that preference learning encourages unfavorable behaviors such as language confusion is worthy of further exploration.

**Other factors** There are other factors that may affect language confusion. We suspect that word-level confusion is related to under-training. Certain non-English tokens, particularly in low-density regions that are rarely encountered during pre-training, may be under-trained and lack calibration.

This can then lead to English tokens being sampled due to the absence of in-language tokens with higher likelihood as seen in §5. Future work might investigate this hypothesis.

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<sup>24</sup>Also, [https://wandb.ai/eric\\_anthony\\_mitchell/dpo-demos/runs/og8q3euz?nw=nwusereric\\_anthony\\_mitchell](https://wandb.ai/eric_anthony_mitchell/dpo-demos/runs/og8q3euz?nw=nwusereric_anthony_mitchell)