Large Language Models are Easily Confused: A Quantitative Metric, Security Implications and Typological Analysis

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Abstract

Language Confusion is a phenomenon where Large Language Models (LLMs) generate text that is **neither** in the desired language, **nor** in a contextually appropriate language. This phenomenon presents a critical challenge in text generation by LLMs, often appearing as erratic and unpredictable behavior. We hypothesize that there are linguistic regularities to this inherent vulnerability in LLMs and shed light on patterns of language confusion across LLMs. We introduce a novel metric, *Language Confusion Entropy*, designed to directly measure and quantify this confusion, based on language distributions informed by linguistic typology and lexical variation. Comprehensive comparisons with the Language Confusion Benchmark (Marchisio et al., 2024) confirm the effectiveness of our metric, revealing patterns of language confusion across LLMs. We further link language confusion to LLM security and find patterns in the case of multilingual embedding inversion attacks. Our analysis demonstrates that linguistic typology offers theoretically grounded interpretation, and valuable insights into leveraging language similarities as a prior for LLM alignment and security.[1]

1 Introduction

Multilingual Large Language Models (LLMs) revolutionized Natural Language Processing (NLP), offering crosslinguality in various applications, including translation (Zhu et al., 2024), text generation (Chen et al., 2022), and information retrieval (Guo et al., 2024). Besides the challenges faced by LLMs such as *bias and fairness* (Talat et al., 2022), *hallucinations* (Augenstein et al., 2024), multilingual LLMs are more vulnerable to *adversarial and inversion attacks* than monolingual LLMs (Song et al., 2024; Chen et al., 2025, 2024).

Multilingual LLMs are trained on data in a diverse range of languages to represent the intricacies of multiple languages within a single model. However, this often results in inconsistencies in comprehension and response, leading to *language confusion* – instances where LLMs generate text that is *neither* in the desired language *nor* in a contextually appropriate one. For example, when an LLM is queried/prompted in Arabic, it may respond in text that is either partially or entirely in languages other than Arabic, e.g., English.

Marchisio et al. (2024) propose metrics to measure the percentage of model responses containing no undesired languages at both line and word levels but fail to capture nuances within language distributions. It is observed that language confusion tends to occur when the model's distribution over the next tokens is flat. We hypothesize that language confusion in LLMs is not merely a performance limitation but an inherent vulnerability, partly due to imbalanced pre-training multilingual data sources, which are amplified with increasing numbers of languages and can be analyzed through language similarities derived from linguistic typology and other resources.

To thoroughly investigate language confusion as a phenomenon and its role within LLMs, we introduce the following research questions:

RQ1: What measurable patterns characterize language confusion in LLMs, and how can these patterns be quantified effectively?

RQ2: How do language similarities influence language confusion, and how can this knowledge be applied to enhance LLM alignment and security?

To this end, we propose a novel metric called *Language Confusion Entropy*, which provides a quantifiable measure of uncertainty and facilitates the detection of when an LLM is confused. Building on observations by Marchisio et al. (2024) that uniformity of the distribution indicates higher uncertainty, *Language Confusion Entropy* re-weights

[1] The language graphs for language similarities and code are publicly available https://github.com/siebeniris/QuantifyingLanguageConfusion/

language distributions by emphasizing long-tail distributions, effectively capturing language confusion in multilingual LLM generation tasks. Furthermore, we demonstrate that this metric uncovers patterns of language confusion during both the training and evaluation phases of multilingual inversion attacks (Chen et al., 2025).

In addition, we construct language graphs based on language similarities derived from linguistic resources to analyze language confusion, revealing a strong correlation between language confusion and semantic similarities between languages. Our analysis shows that low-resource languages exhibit less confusion while training across diverse scripts and language families mitigates language confusion more effectively than training within the same script or language family in inversion attacks. These findings indicate that leveraging language similarities grounded in linguistic resources could serve as a valuable prior for enhancing LLM alignment and security. Our main contributions are as follows:
1) We propose a novel metric *Language Confusion Entropy* to measure language confusion in LLMs considering the nuances of language distributions. To the best of our knowledge, we are the first to quantify language confusion probabilistically.
2) Using language graphs, we demonstrate that linguistic typology provides a foundational tool for analyzing language confusion.
3) We propose a modified KL-Divergence algorithm to determine the correlation between language similarities (as defined by language graphs) and language confusion in LLMs.
4) We conduct extensive analysis revealing statistically significant patterns of language confusion, providing new insights for LLM security research.

2 Related Works

Language Confusion This phenomenon observed in NLP, is often described as "off-target translation" (Chen et al., 2023a; Sennrich et al., 2024) or "accidental translation" (Zhang et al., 2020; Xue, 2020), or as "source language hallucinations" in zero-shot transfer scenarios (Vu et al., 2022; Li and Murray, 2023; Pfeiffer et al., 2023; Chirkova and Nikoulina, 2024). *Language confusion*, a term coined by Marchisio et al. (2024) occurs when the LLMs' outputs are generated *erroneously* in languages different from the desired (target) languages and identified as 'surprising limitation' diminishing LLM utility for non-English languages, indicating the *unpredictable nature*.

The phenomenon of *language confusion* has not only been pervasive in LLMs, but also in tasks pertinent to LLM security, such as multilingual inversion attacks (Chen et al., 2024, 2025). Furthermore, Chen et al. (2025) observes language confusion across 20 languages from diverse scripts and language families in multilingual embedding inversion. They analyzed the pattern of confusion using basic typological features between train and eval languages with regression analysis, in comparison, the proposed *Language Confusion Entropy* provides a more interpretable analysis.

Multilingual LLM Safety and Security Yong et al. (2024) exposes vulnerabilities of AI safety mechanism by jailbreaking GPT-4's safeguard through translating unsafe English inputs into low-resource languages. Deng et al. (2024) impose unintentional and intentional jailbreak on multilingual LLMs, using multilingual prompts. It is observed that low-resource languages are more vulnerable, making them the weakest links in AI security.

Backdoor attacks on multilingual machine translation pose significant threats, as injecting poisoned data into low-resource language pairs can achieve a high attack success rate (ASR) in high-resource language pairs (Wang et al., 2024). Poisoning instruction-tuning data for one or two languages can affect other languages, surpassing 99% ASR in the cross-lingual setting in prominent LLMs resisting current defenses (He et al., 2024).

Multilingual textual embedding inversion attacks pose additional risks, as any encoder can be attacked to reconstruct original texts. Traditional defenses for monolingual LLMs are ineffective for multilingual LLMs (Chen et al., 2024, 2025). Moreover, Song et al. (2024) generates language blending for adversarial attacks, necessitating systematic analysis of language similarity and language confusion for targeted defenses.

Linguistic Typology and Language Similarities Previous research on multilingual effects on linguistic level uses three approaches: (i) phylogenetic variation, (ii) linguistic typological variation, and (iii) embedded and data-driven language variation.

While genealogical relations are intuitive, the correlations between language similarity and genealogical relations are often spurious (Rama and Kolachina, 2012). Ploeger et al. (2024) challenge this approach highlighting its negative impact on downstream NLP tasks.

Linguistic typology offers a theoretically grounded approach to measuring similarity between languages (Kashyap, 2019). Languages can be categorized based on various features — e.g., whether they use a Subject-Verb word order (SV) or the opposite (VS). Such information has been manually annotated in linguistic databases, including WALS (Haspelmath, 2008), ASJP (Wichmann et al., 2012), and Grambank (Skirgård et al., 2023), and work in NLP has contributed with automatic prediction of such features (Malaviya et al., 2017; Bjerva et al., 2019a; Bjerva, 2024). Recent work has also explored lexically driven measures, showing that multilingual LLMs often rely on lexical overlap (Pires et al., 2019). Such work spans from using synonymy-relations as in WordNet (Fellbaum, 2010), to multilingual relations in BabelNet (Navigli and Ponzetto, 2010), and more complex colexification patterns in CLICS[3] (Rzymski et al., 2020). Crosslingual colexification patterns refer to the phenomenon whereby different meanings are captured by the same lexica across languages (François, 2008), implicating shared cognitive or cultural associations (Karjus et al., 2021; Di Natale et al., 2021; Chen and Bjerva, 2023).

Language embeddings encode language characteristics and can be derived from data-driven methods or linguistic typological databases. Östling and Tiedemann (2017) trained a character-level LSTM language model on translated Bible texts from 990 languages, showing their ability to reconstruct language genealogies. Additionally, embeddings can be generated from typological data sources like WALS, Grambank, and ASJP. Chen et al. (2023b) created embeddings using lexical data based on colexification patterns in CLICS3 and BabelNet.

We hypothesize that language confusion is a phenomenon largely driven by lexical variation, similar to the patterns observed by Pires et al. (2019). We investigate this by building our analysis on this body of work leveraging computational typology.

3 Explainable Language Confusion

To investigate the phenomenon of language confusion, we use the datasets i) **Language Confusion Benchmark (LCB)** (Marchisio et al., 2024) and ii) **Multilingual Textual Embedding Inversion (MTEI)** (Chen et al., 2025) (see Appendix for task details and Table 8 for processed datasets sample).

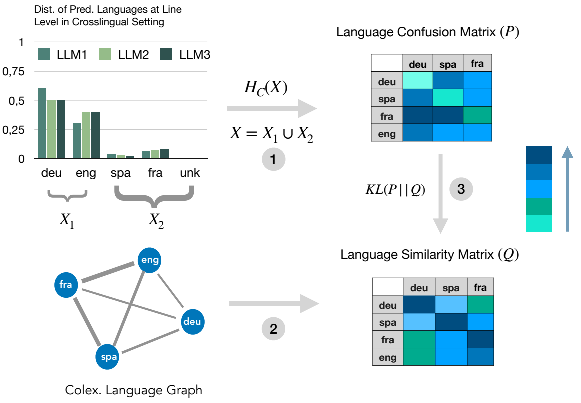

Figure 1: The use of proposed metric to quantify language confusion and its correlation with language similarity through KL divergence.

3.1 Generation Settings

Consider a LLM trained or prompted with a set of $n \in \mathbb{N}$ source languages $L_s = \{l_1, \cdots, l_n\}$, and l_t is the target language. We probe language confusion for both LLM instruction and textual embedding inversion attacks.

Monolingual Generation **LCB**: The model is queried in language l_t, and the response is expected in l_t. **MTEI**: The inversion model, trained on l_t, inverts embeddings in l_t. Here, $l_t \in L_s$, i.e., the evaluated language is part of the training languages.

Crosslingual Generation **LCB**: The model is instructed in language l_s to provide a response in l_t, where $l_t \neq l_s$. **MTEI**: The inversion model, trained on L_s, inverts embeddings in l_t. In this setting, $l_t \notin L_s$, meaning the evaluated language differs from the training languages.

3.2 Quantifying Language Confusion

The phenomenon of language confusion is particularly prominent in crosslingual generation settings. For instance in Fig. 1 ①, when an LLM is prompted in English and expected to generate a response in German (X_1), the output may unexpectedly have a mix of other languages, such as Spanish and French (X_2). Ideally, the LLM should focus on the expected languages; thus, the model exhibits greater confusion if its output distribution assigns high probabilities to unexpected languages. To quantify this, we propose *Language Confusion Entropy*

(H_{C}), defined as follows:

$$H_{\mathrm{C}}(X) = -\sum_{x \in X_1} (1 - p(x)) \log(p(x)) - \sum_{x \in X_2} p(x) \log p(x), \tag{1}$$

where X_1 denotes the expected language set and X_2 the unexpected language set, $X_1 \cup X_2 = X$, $X_1 \cap X_2 = \emptyset$, $p(x)$ denotes the probability and $\sum_{x \in X} p(x) = 1$. Ideally, an unconfused model would satisfy $\sum_{x \in X_1} p(x) = 1$ and $\sum_{x \in X_2} p(x) = 0$.

In practical applications, for the **LCB** dataset, X_1 includes both the instruction and response languages, while for the **MTEI** dataset, X_1 encompasses the training and evaluation languages.

3.3 Language Identification

Language confusion can occur at both the word level and the line level. To measure it, we use existing language identification (LID) tools. Initially, we employ Lingua to detect languages as it offers the highest accuracy among existing LID tools, particularly at word level.[2] However, since Lingua supports only 75 languages, we supplement it with fastText (Joulin et al., 2016) (which supports 176 languages) for languages unidentified by Lingua.

Line-level Detection We split the generated output into lines by newline characters and detect the language of each line.

Word-level Detection To detect languages more accurately at the word level, we first tokenize the text at the line level using language-specific tokenizers such as jieba (Sun et al., 2013) (Chinese), Hebrew Tokenizer (Levin and Oriyan, 2018) Kiwipiepy (Lee, 2024) (Korean), fugashi (McCann, 2020) (Japanese), and NLTK Word Tokenizer (Bird and Loper, 2004) for other languages. We then identify the language of each tokenized word.

Finally, we compile the detected languages into distributions at both word and line levels for further analysis. Examples of the pre-processed data are presented in Table 8. Language confusion matrices are then constructed by applying language confusion entropy to these distributions, and the results are aggregated per language (ref. Fig. 1 ①).

3.4 Large Language Models

The evaluated LLMs in **LCB** include Command R (35B parameters),Command R+ (104B), GPT-3.5 Turbo (Brown, 2020), and GPT-4 Turbo (Achiam et al., 2023), Mistral Large, Mistral 8x7B (Jiang et al., 2024), LLaMA 2 70B Instruct (Touvron et al., 2023), and LLaMA 3 70B Instruct, while in **MTEI** the inversion models are trained with mT5 (580M) (Xue, 2020) and multilingual-e5-base (ME5) (580M). (See Table 5 for details of LLMs).

Algorithm 1 KL Divergence for Language Confusion vs. Language Similarity Matrices

```
Require: Matrices M1 ∈ $\mathbf{R}^{n \times m}$ and M2 ∈ $\mathbf{R}^{n \times m}$, where M1
    represent language-to-language confusion scores, and M2
    represent language-to-language similarity scores.
Ensure: Mean KL divergence across all columns.
Initialize a list Total_KL_Divergence ← [].
for each column index $j$ from 1 to $m$ do
    M1_col ← M1[:, $j$]   ▷ Confusion scores for language $j$ in matrix M1
    M2_col ← M2[:, $j$]   ▷ Similarity scores for language $j$ in matrix M2
    Step 1: Exclude zeros from M1_col
    nonzero_indices ← M1_col ≠ 0
    $P$ ← M1_col[nonzero_indices]
    $Q$ ← M2_col[nonzero_indices]
    Step 2: Normalize the distributions
    $P \leftarrow P / \sum P$
    $Q \leftarrow Q / \sum Q$
    Avoid division by zero or log issues
    $\epsilon \leftarrow 10^{-10}$
    $P \leftarrow P + \epsilon$
    $Q \leftarrow Q + \epsilon$
    Step 3: Calculate KL divergence
    KL_Div ← $\sum P \cdot \log\left(\frac{P}{Q}\right)$   ▷ KL divergence for $j$
    Append KL_Div to Total_KL_Divergence
end for
return Average(Total_KL_Divergence)
```

3.5 Language Graphs

We construct language graphs from a diverse range of typological features, such as colexification patterns (Rzymski et al., 2020; Fellbaum, 2010; Navigli and Ponzetto, 2010), lexicon (Wichmann et al., 2012), phonological and morphological-syntactical features (Haspelmath, 2008; Skirgård et al., 2023), as well as from a collection of existing language embeddings trained from NLP tasks incorporating linguistic typology (Östling and Tiedemann, 2017; Östling and Kurfalı, 2023; Chen et al., 2023b). We then generate language similarity matrices from the language graphs by calculating pairwise similarity using either Jaccard Index or Cosine Similarity (ref. Fig. 1 ②). (See details in Appendix B).

3.6 The Role of Language Similarity in Language Confusion

We compare the language graphs with language confusion matrices to assess how well language confu-

[2] https://github.com/pemistahl/lingua-py

sion aligns with language similarities and to identify specific aspects where they match. To quantify the divergence between language confusion (denoted as P) and language similarity (denoted as Q), we employ Kullback-Leibler Divergence (Kullback and Leibler, 1951), expressed as $KL(P||Q)$. $P(x)$ represents the distribution of language confusion entropy of language x relative to other languages, while $Q(x)$ represents the distribution of language similarity of x relative to other languages. $KL(P||Q)$ is computed as follows:

$$KL(P||Q) = \sum_{x} P(x) log \left(\frac{P(x)}{Q(x)} \right), \qquad (2)$$

where a lower $KL(P||Q)$ indicates a stronger correspondence between language confusion patterns and underlying language similarities. (See Algorithm 1 for detailed steps and Fig 1 ③).

4 Analysis and Results

4.1 Language Confusion in LLM Prompting

Language Confusion Entropy vs. Pass Rates The binary metrics, **Pass Rates** at line-level **LPR** and word-level **WPR** are used to evaluate whether the LLM output contains no error, following Marchisio et al. (2024) (see details in Appendix A). We apply language confusion entropy to **LCB**, calculating it at both the line-level H_C**[L]** and word-level H_C**[W]** across generation settings.

Compared to Marchisio et al. (2024), our approach detects language confusion across all languages, including at the word level, by using language-specific tokenizers and a more accurate language identification (LID) tool. We reproduce **LPR** and **WPR** (ref. Table 10, 11) and compute H_C**[L]** and H_C**[W]** (ref. Table 9) in both crosslingual and monolingual settings, for 14 languages and 8 LLMs, following (Marchisio et al., 2024).

To evaluate the efficacy of language confusion entropy compared to pass rate metrics, we calculate the Spearman correlation[3] coefficients between these metrics across levels and generation settings. Overall, H_C**[L]** shows a strong negative correlation with **LPR** across all generation settings. Moreover, H_C**[W]** - which is based on more detailed language distributions - exhibits a weaker correlation with **WPR**, as **WPR** only considers English words in non-Latin script languages. Despite the weaker correlation, it remains statistically significant for all languages, especially crosslingually.

		H_C**[L]**	H_C**[W]**	**LPR**
All	H_C**[W]**	0.51***		
	LPR	−0.83***	−0.3***	
	WPR	−0.29**	**−0.5*****	0.31**
Monolingual	H_C**[W]**	0.42***		
	LPR	−0.72***	−0.23*	
	WPR	0.01	−0.31	0.08
Crosslingual	H_C**[W]**	0.54***		
	LPR	**−0.87*****	−0.38***	
	WPR	−0.27**	−0.47***	**0.37*****

Table 1: Spearman correlation between Language Confusion Entropy and Pass Rates at both Word level and Line level with LCB. The strongest correlation is in **bold**.

At both the line and word levels, H_C shows a stronger correlation with pass rates in crosslingual settings than in monolingual ones. This aligns with the definition of language confusion entropy, which gives more weight to long-tail distributions, a more prominent phenomenon in crosslingual tasks.

Language Confusion Entropy Across LLMs As shown in Table 9 and Fig. 3, language confusion is more likely to occur in crosslingual compared to monolingual, with each LLM presenting significant variance. Word-level language confusion presents more variance per LLM and higher severity than line-level. Overall, it is consistent that Command and GPT LLMs have relatively lower language confusion than Mistral and LLaMA LLMs, projecting similar findings from Marchisio et al. (2024).

There is a clear consistency in language confusion across different LLMs, particularly at the line level and in crosslingual settings, as shown in Fig. 3. LLaMA 3 70B-I consistently exhibits the highest confusion across nearly all languages, while GPT-4 Turbo demonstrates the lowest confusion, especially for high-resource languages like French, Spanish, German, and Chinese. Command R+ also shows relatively low confusion across most languages, except Indonesian.

Notably, languages that are written in non-Latin scripts (on the right side of the X-axis), such as Vietnamese, Chinese, Korean, Arabic, Japanese, Hindi, and Indonesian, consistently show higher confusion entropies across most LLMs, especially in the LLaMA models. In contrast, Latin-script languages like French, Spanish, German, and Italian tend to have lower confusion rates across all LLMs,

[3] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.spearmanr.html

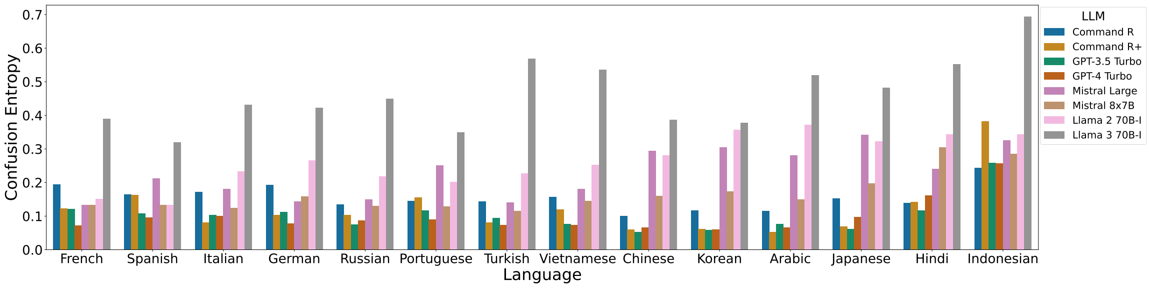

Figure 2: Language confusion for **LCB** by each language across LLMs for crosslingual setting at Line level. The languages are ordered ascendingly by their language confusion entropy averaged across LLMs.

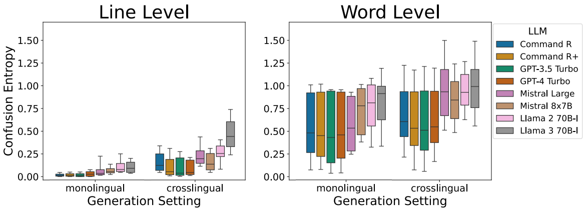

Figure 3: Language confusion entropy for LCB across generation settings by LLMs at line and word Level.

particularly in GPT-4 Turbo and Command R+.

Language Confusion Entropy Across Data Sources The data for monolingual and crosslingual tasks in **LCB** consists of 2,600 and 4,500 prompts, respectively, sourced from 7 datasets (details in Table 4). As shown in Fig. 4, language confusion is more pronounced in crosslingual settings and at the word level. Monolingually, language confusion tends to align with the median word length (W) of prompts in each dataset. For example, Aya, Dolly, Okapi, and Native prompts have median lengths of 9, 10, 13, and 19 words, respectively, and their language confusion follows this order. Crosslingually, the Complex Prompts dataset has the highest median word length (159, compared to 18 for ShareGPT and 15 for Okapi), and it also exhibits the highest language confusion.

Observing language confusion across datasets at the line level for crosslingual settings (Fig. 5),[4] a clear pattern emerges. Complex Prompts has the highest confusion across all languages, while ShareGPT shows the lowest confusion for most languages, except for French and Spanish. Consistent with previous findings, languages written in non-Latin scripts show higher confusion in datasets like Okapi and ShareGPT. However, in Complex Prompts, non-Latin-script languages such as Chinese, Korean, Arabic, and Japanese demonstrate lower confusion than Latin-script languages.

4.2 Language Confusion in Multilingual Textual Embedding Inversion Security

Language Confusion Entropy for Eval Languages When embeddings are in languages that are more likely to be confused, they are more prone to being inverted into text in "incorrect" languages, reducing the inversion performance, especially with word-matching metrics like BLEU (Post, 2018). Also, the languages generated by the inversion model are often skewed by the pre-training data of the LLM, such as mT5 in **MTEI**.

		H_C[L]	H_C[W]	BLEU
All	H_C[W]	0.89***		
	BLEU	**–0.62*****	**–0.44*****	
	mT5	0.71***	0.62***	–0.32*
Monolingual	H_C[W]	0.75***		
	BLEU	0.25	0.17	
	mT5	0.1	0.26	–0.59***
Crosslingual	H_C[W]	**0.9*****		
	BLEU	–0.48***	–0.36**	
	mT5	**0.76*****	**0.66*****	–0.32*

Table 2: Spearman Correlations among H_C at Line Level and Word Level and BLEU score for **MTEI**, and the percentage of pre-training data in mT5 for eval languages. Strongest correlations are in **bold**.

To test this intuition, we calculate the Spearman correlation among language confusion entropy, BLEU scores, and the percentage of respective languages in the pre-training data of mT5 (see Table 7 for details). As shown in Table 2, for eval languages, H_C**[L]** is strongly correlated with inversion performance across generation settings, confirming that language confusion negatively impacts reconstruction performance.

Moreover, H_C**[L]** and H_C**[W]** are both strongly correlated with the proportion of languages in pre-training data of mT5, particularly in crosslingual

[4] We use “Language Confusion Entropy” and “Confusion Entropy” interchangeably in this paper.

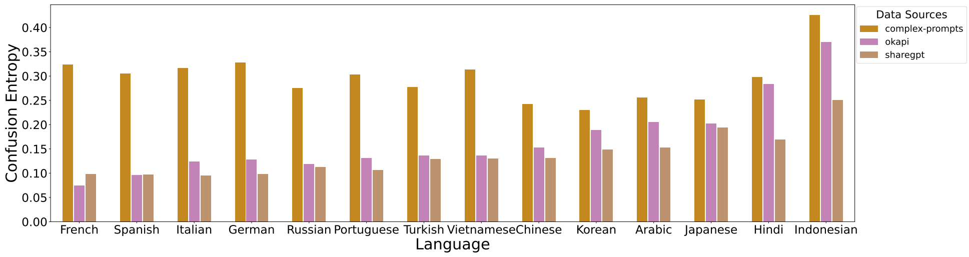

Figure 4: Language confusion for **LCB** across data sources at line level for crosslingual setting.

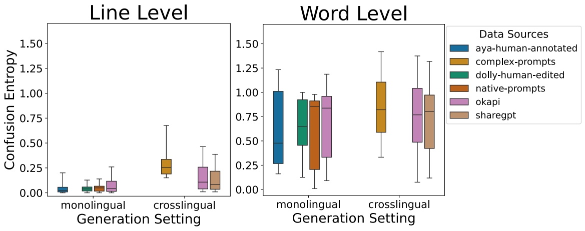

Figure 5: Language Confusion for LCB across generation settings by data sources at line and word Level.

setting. This indicates that languages with higher representation in the pre-training data are more prone to confusion, both at the word and line levels. This observation is further validated by empirical evidence: when an inversion model trained on Arabic is used to invert embeddings in Meadow Mari (unseen in mT5), the model often generates English, highlighting the influence of pre-training data on embedding inversion attacks. Fig 6 (top) provides a visualization of language confusion at the line level for each language, alongside their corresponding reconstruction performance in BLEU at each step of the evaluation in the crosslingual inversion attacks. It shows directly that lower-resourced languages present lower confusion, especially for non-Latin script languages, whereas they are also more vulnerable in terms of higher reconstruction performance, for example, Gujarati, Punjabi, and Urdu.

Language Confusion Entropy for Train Languages In **MTEI**, the inversion models are trained in three different settings - monolingual, in-family and in-script, and cross-family and cross-script. As shown in Fig. 6 (bottom) and Table 13, monolingual training renders lower language confusion for each train language while pairing training languages, in-script/in-family training renders higher language confusion compared to cross-script/cross-family training. These findings substantiate the intuition that similar languages are more prone to confusion.

Our study reveals that inversion performance significantly improves when trained in in-script/in-family settings (ref. Table 13 in the Appendix). Crosslingual inversion performances are comparable to in-script/in-family training when trained in Kazakh (Latin-script) combined with Gujarati and Punjabi, respectively, and language confusion is notably lower. This suggests that while similar languages tend to increase confusion, certain crosslingual combinations can achieve strong performance without the added confusion seen in in-family/in-script training. Overall, these findings highlight the trade-off between inversion performance and language confusion, indicating further optimization is needed to strike the ideal balance between them.

4.3 Language Confusion and Linguistic Typology

Table 3 shows the best results from KL divergence between language confusion and language similarities based on different language graphs for both **LCB** and **MTEI**, using Algorithm 1, the whole results are presented in Table 15 in Appendix.

Our findings reveal strong correlations between language confusion and language similarities based on various typological sources. For instance, the similarity measures based on semantic typology correlate the most strongly, followed closely by more general lexical similarity measures. Language similarities based on typological feature databases like Grambank and WALS show stronger correlations than those based on parallel Bible texts (Östling and Tiedemann, 2017). Interestingly, and echoing previous findings on typological variation, we find genetic variation is a poor proxy for this analysis (Bjerva et al., 2019b; Ploeger et al., 2024), indicating the need for theoretically grounded approaches to linguistic interpretation.

5 Discussion

Language Confusion Entropy H_C vs. Pass Rate (PR) As shown in Section 4.1, H_C and PR are correlated but measure distinct aspects of language

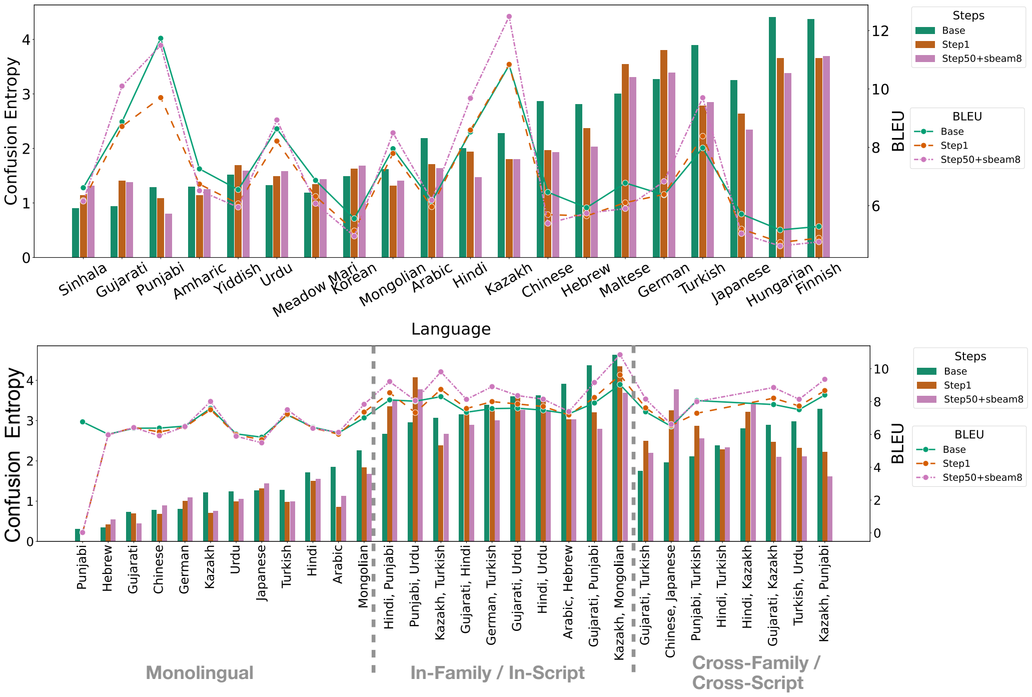

Figure 6: Language Confusion and Text Reconstruction Performance (BLEU) in Multilingual Textual Embedding Inversion Attacks at Line Level for Crosslingual Settings for Eval (Top) and Train (Bottom) Languages.

	LCB							Textual Embedding Inversion						
Language Graph	**AVG**	**ALL**		**Monolingual**		**Crosslingual**		**AVG**	**ALL**		**Monolingual**		**Crosslingual**	
		Line	Word	Line	Word	Line	Word		Line	Word	Line	Word	Line	Word
Grambank	0.2650	0.1830	0.2827	0.2726	0.4042	0.1791	0.2682	0.7538	**0.8005**	0.7891	0.7504	0.5434	**0.8230**	0.8162
WALS	0.1947	0.0420	0.2908	0.0816	0.4286	0.0388	0.2865	0.7377	0.8722	**0.7854**	0.6618	0.4102	0.8803	0.8164
WALS \ Phon.	0.1892	0.0409	0.2889	0.0799	0.4253	0.0379	0.2620	0.7360	0.8768	0.7880	0.6495	0.4036	0.8837	0.8147
Lang2Vec														
Inventory	0.1650	0.0812	**0.2003**	0.1374	**0.3114**	0.0637	**0.1961**	0.8154	0.9678	0.8410	0.8225	0.4124	0.9720	0.8768
Syntactic	0.2925	0.1949	0.3771	0.2244	0.4679	0.1505	0.3405	0.8651	1.0179	0.8668	0.8872	0.5447	1.0001	0.8742
Phonological	0.2260	0.1009	0.3126	0.1552	0.4235	0.0830	0.2808	1.3161	1.7178	1.6133	0.6859	0.6004	1.6599	1.6191
Genetic	12.8307	13.4548	12.2278	12.9350	12.3563	13.5850	12.4249	14.9443	14.6988	14.9756	18.5227	13.5734	13.8721	14.0232
ASJP SVD	0.5859	0.0253	1.0597	**0.0522**	1.0395	0.0225	1.3164	2.8254	2.9730	3.3461	0.0820	1.6568	3.8882	5.0063
ASJP UMAP	0.9318	0.0994	1.6767	0.1290	1.6055	0.0946	1.9856	3.3217	3.5364	4.0245	0.0811	2.3479	4.3690	5.5711
Colex2Lang														
CLICS	0.1665	0.0289	0.2522	0.0589	0.3776	0.0260	0.2490	**0.7333**	0.9492	0.8335	0.3690	**0.2672**	0.9503	0.8693
WN	**0.1489**	**0.0242**	0.2154	**0.0522**	0.3404	**0.0218**	0.2149	0.7794	1.0105	0.8892	0.3263	0.3894	1.0445	0.9454
WN_CONCEPT	0.1490	**0.0242**	0.2175	0.0522	0.3426	**0.0218**	0.2168	0.7791	1.0100	0.8836	**0.3263**	0.3894	1.0427	0.9390

Table 3: KL Divergence between Language Similarity Graphs and the Language Confusion Matrices for Target/ Eval Languages from LCB and Inversion Tasks. The best results (lowest) are **bolded**, and the second best are underlined.

generation. Importantly, H_{C} is not intended to replace PR but to offer a deeper quantitative characterization of language confusion.

H_{C} quantifies behavioral uncertainty through the entropy of a model's probability distribution across languages. It captures partial confusions (e.g., 40% confidence in the target language, 60% spread across others), even when outputs technically "pass." **PR** is a binary performance metric assessing whether outputs meet target language requirements.

Hence, H_{C} complements PR by revealing hidden confusion patterns: a model with high PR could still exhibit high H_{C} if probabilities scatter across non-target languages. This makes H_{C} particularly valuable for diagnosing *how* models arrive at correct outputs, not just whether they do.

Research Questions In response to **RQ1**, we proposed an effective metric *Language Confusion Entropy*, through which we identified several patterns contributing to language confusion. These include prompt complexity, imbalanced distributions of training sources, and language similarities - all play a significant role in language confusion. Furthermore, our findings indicate that these factors strongly correlate with inversion performance and the pretraining languages in LLMs.

Inherent vulnerabilities in LLMs stem from intrinsic design, training processes, or model architectures, which are not directly caused by attacks or improper use. However, external attacks can amplify and leverage the vulnerabilities, which are directly reflected in embedding inversion attacks. Further, decoding unexpected languages disrupts the user experience. We have discussed that i) language confusion stems from training data inequality, ii) the phenomena is pervasive from related works, iii) language confusion is well-captured by the proposed LCE and shows consistent trends across different architectures of LLMs and datasets and experimental settings, and (iv) can be influenced and explained by linguistic typological variations. These affords a positive response to **RQ2**.

Moreover, there is a potential to leverage language similarities as a prior for LLM alignment and security. For instance, Table 3 shows that the language similarities from colexification patterns afford a strong correlation with language confusion (with low KL divergence), which indicates that LLMs easily confuse languages that contain words that are crosslingually capturing the same senses. When an LLM is exposed to multilingual data with more distinct colexification patterns, it could enhance its ability to distinguish them and make them more resilient against language confusion. This strategy could promote more resilient LLMs, as we have shown that models are less likely to confuse typologically dissimilar languages. Hence, exploring typology-aware design strategies could provide both offensive and defensive insights in LLM security.

Potential Misuse The Language confusion metric identifies uncertainty in language identification, highlighting areas where LLMs may be prone to errors. Our findings show that language similarities correlate with language confusion patterns in LLMs. When similar languages lack robust safety measures compared to well-protected high-resource languages, they could be exploited for crosslingual attacks in a more targeted manner, such as backdoors and jailbreaking (Zou et al., 2023; Li et al., 2024). Additionally, the ability of LLMs to switch between languages may pose risks where safety measures aren't consistently implemented across all languages. The Language confusion metric identifies uncertainty in language identification, highlighting areas where LLMs may be prone to errors. Our findings show that language similarities correlate with language confusion patterns in LLMs. When similar languages lack robust safety measures compared to well-protected high-resource languages, they could be exploited for crosslingual attacks in a more targeted manner, such as jailbreaking (He et al., 2024) and backdoors (Wang et al., 2024). Additionally, the ability of LLMs to switch between languages may pose risks where safety measures aren't consistently implemented across all languages. It has been demonstrated that LLMs are particularly vulnerable to crosslingual attacks in related work (Wang et al., 2024; He et al., 2024) and more recently (Poppi et al., 2024), mainly because the conventional defense mechanisms designed for monolingual settings are ineffective in multilingual settings. To enhance LLM security, adversarial exploits can be detected by monitoring high language confusion entropy, especially in crosslingual settings. Our work suggests that language confusion quantification and its connection to language similarities can be leveraged to raise awareness of such vulnerabilities, and also provide potential revenue for developing mitigation strategies.

6 Conclusion and Future Work

Addressing the challenge of language confusion, we introduce *Language Confusion Entropy*, a novel metric that quantifies language confusion by reweighting language distributions and emphasizing long-tail patterns. This metric captures language confusion in multilingual LLM tasks, revealing patterns of uncertainty in both training and evaluation phases. Our findings show strong correlations between language confusion and semantic similarities among languages, with less confusion observed in low-resource languages and when training incorporates diverse scripts and language families. These insights confirm that language confusion fundamentally impacts LLMs and suggest linguistic typology as a potential tool for enhancing model security. Detecting language confusion enables smoother and more precise interactions in multilingual contexts while enhancing user trust in LLM-based AI systems across domains such as legal services and healthcare. In future work, we aim to apply these findings to practical applications, such as developing typology-aware defense to improve LLM alignment and security. Key applications include cross-lingual chatbots, translation services, detecting code-switching, and improving multilingual speech recognition by reducing ambiguity.

Limitations

A core limitation of this work is that some of our analysis and downstream implications can only be carried out on languages that are represented in typological databases. When part of the work, limited to typological databases, inspires downstream solutions in terms of defense mechanisms, undocumented languages may not benefit from these advances. However, we have also increased coverage of languages in constructing language graphs using data-driven methods. Our core method is also not limited to any typological database.

Ethics Statement

This work adheres to the ACL ethics guidelines. We investigate language confusion and link findings to security vulnerabilities of low-resource languages, including those using non-Latin scripts and with diverse typologies. The potential misuse has been extensively discussed. Our work highlights how these factors can be used to potentially improve the security of low-resource language technology. We encourage the community to incorporate a broader range of languages in NLP security research, to ensure that low-resource languages are also covered by defense mechanisms developed in the future.

Acknowledgements

YC and JB are funded by the Carlsberg Foundation, under the *Semper Ardens: Accelerate* programme (project nr. CF21-0454).

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Isabelle Augenstein, Timothy Baldwin, Meeyoung Cha, Tanmoy Chakraborty, Giovanni Luca Ciampaglia, David Corney, Renee DiResta, Emilio Ferrara, Scott Hale, Alon Halevy, et al. 2024. Factuality challenges in the era of large language models and opportunities for fact-checking. *Nature Machine Intelligence*, pages 1–12.

Steven Bird and Edward Loper. 2004. NLTK: The natural language toolkit. In *Proceedings of the ACL Interactive Poster and Demonstration Sessions*, pages 214–217, Barcelona, Spain. Association for Computational Linguistics.

Johannes Bjerva. 2024. The role of typological feature prediction in NLP and linguistics. *Computational Linguistics*, 50(2):781–794.

Johannes Bjerva, Yova Kementchedjhieva, Ryan Cotterell, and Isabelle Augenstein. 2019a. A probabilistic generative model of linguistic typology. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1529–1540, Minneapolis, Minnesota. Association for Computational Linguistics.

Johannes Bjerva, Robert Östling, Maria Han Veiga, Jörg Tiedemann, and Isabelle Augenstein. 2019b. What do language representations really represent? *Computational Linguistics*, 45(2):381–389.

Tom B Brown. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.

Liang Chen, Shuming Ma, Dongdong Zhang, Furu Wei, and Baobao Chang. 2023a. On the off-target problem of zero-shot multilingual neural machine translation. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 9542–9558, Toronto, Canada. Association for Computational Linguistics.

Yiran Chen, Zhenqiao Song, Xianze Wu, Danqing Wang, Jingjing Xu, Jiaze Chen, Hao Zhou, and Lei Li. 2022. Mtg: A benchmark suite for multilingual text generation. In *Findings of the Association for Computational Linguistics: NAACL 2022*, pages 2508–2527.

Yiyi Chen, Russa Biswas, and Johannes Bjerva. 2023b. Colex2Lang: Language embeddings from semantic typology. In *Proceedings of the 24th Nordic Conference on Computational Linguistics (NoDaLiDa)*, pages 673–684, Tórshavn, Faroe Islands. University of Tartu Library.

Yiyi Chen, Russa Biswas, Heather Lent, and Johannes Bjerva. 2025. Against all odds: Overcoming typology, script, and language confusion in multilingual embedding inversion attacks. In *The 39th Annual AAAI Conference on Artificial Intelligence*.

Yiyi Chen and Johannes Bjerva. 2023. Colexifications for bootstrapping cross-lingual datasets: The case of phonology, concreteness, and affectiveness. In *Proceedings of the 20th SIGMORPHON workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 98–109, Toronto, Canada. Association for Computational Linguistics.

Yiyi Chen, Heather Lent, and Johannes Bjerva. 2024. Text embedding inversion security for multilingual language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7808–7827, Bangkok, Thailand. Association for Computational Linguistics.

Nadezhda Chirkova and Vassilina Nikoulina. 2024. Key ingredients for effective zero-shot cross-lingual knowledge transfer in generative tasks. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 7222–7238, Mexico City, Mexico. Association for Computational Linguistics.

Richard Oliver Collin. 2010. Ethnologue. *Ethnopolitics*, 9(3-4):425–432.

Chris Collins and Richard Kayne. 2011. Syntactic structures of the world's languages (sswl).

Yue Deng, Wenxuan Zhang, Sinno Jialin Pan, and Lidong Bing. 2024. Multilingual jailbreak challenges in large language models. *Preprint*, arxiv:2310.06474 [cs].

Anna Di Natale, Max Pellert, and David Garcia. 2021. Colexification networks encode affective meaning. *Affective Science*, 2(2):99–111.

Christiane Fellbaum. 2010. Wordnet. In *Theory and applications of ontology: computer applications*, pages 231–243. Springer.

Alexandre François. 2008. Semantic maps and the typology of colexification. *From polysemy to semantic change: Towards a typology of lexical semantic associations*, 106:163.

Ping Guo, Yubing Ren, Yue Hu, Yanan Cao, Yunpeng Li, and Heyan Huang. 2024. Steering large language models for cross-lingual information retrieval. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 585–596.

Martin Haspelmath. 2008. The typological database of the world atlas of language structures. *Typological databases. Mouton de Gruyter, Berlin*.

Xuanli He, Jun Wang, Qiongkai Xu, Pasquale Minervini, Pontus Stenetorp, Benjamin I. P. Rubinstein, and Trevor Cohn. 2024. TuBA: Cross-lingual transferability of backdoor attacks in LLMs with instruction tuning. *Preprint*, arxiv:2404.19597 [cs].

Vivek Iyer, Bhavitvya Malik, Wenhao Zhu, Pavel Stepachev, Pinzhen Chen, Barry Haddow, and Alexandra Birch. 2024. Exploring very low-resource translation with LLMs: The University of Edinburgh's submission to AmericasNLP 2024 translation task. In *Proceedings of the 4th Workshop on Natural Language Processing for Indigenous Languages of the Americas (AmericasNLP 2024)*, pages 209–220, Mexico City, Mexico. Association for Computational Linguistics.

Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. 2024. Mixtral of experts. *arXiv preprint arXiv:2401.04088*.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.

Andres Karjus, Richard A Blythe, Simon Kirby, Tianyu Wang, and Kenny Smith. 2021. Conceptual similarity and communicative need shape colexification: An experimental study. *Cognitive Science*, 45(9):e13035.

Abhishek Kumar Kashyap. 2019. Language typology. *The Cambridge handbook of systemic functional linguistics*, pages 767–792.

Donggyu Kim, Garam Lee, and Sungwoo Oh. 2022. Toward privacy-preserving text embedding similarity with homomorphic encryption. In *Proceedings of the Fourth Workshop on Financial Technology and Natural Language Processing (FinNLP)*, pages 25–36, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

Solomon Kullback and Richard A Leibler. 1951. On information and sufficiency. *The annals of mathematical statistics*, 22(1):79–86.

Viet Lai, Chien Nguyen, Nghia Ngo, Thuat Nguyen, Franck Dernoncourt, Ryan Rossi, and Thien Nguyen. 2023. Okapi: Instruction-tuned large language models in multiple languages with reinforcement learning from human feedback. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 318–327, Singapore. Association for Computational Linguistics.

Minchul Lee. 2024. Kiwi: Developing a korean morphological analyzer based on statistical language models and skip-bigram. *Korean Journal of Digital Humanities*, 1(1).

Yonti Levin and Daniel Oriyan. 2018. Hebrew tokenizer. `https://github.com/YontiLevin/Hebrew-Tokenizer`. Accessed: 2024-10-15.

Tianjian Li and Kenton Murray. 2023. Why does zero-shot cross-lingual generation fail? an explanation and a solution. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 12461–12476, Toronto, Canada. Association for Computational Linguistics.

Xiao Li, Zhuhong Li, Qiongxiu Li, Bingze Lee, Jinghao Cui, and Xiaolin Hu. 2024. Faster-gcg: Efficient discrete optimization jailbreak attacks against aligned large language models. *arXiv preprint arXiv:2410.15362*.

Patrick Littell, David R Mortensen, Ke Lin, Katherine Kairis, Carlisle Turner, and Lori Levin. 2017. Uriel and lang2vec: Representing languages as typological, geographical, and phylogenetic vectors. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 8–14.

L. Lyu, Xuanli He, and Yitong Li. 2020. Differentially private representation for nlp: Formal guarantee and an empirical study on privacy and fairness. *ArXiv*, abs/2010.01285.

Chaitanya Malaviya, Graham Neubig, and Patrick Littell. 2017. Learning language representations for typology prediction. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2529–2535, Copenhagen, Denmark. Association for Computational Linguistics.

Kelly Marchisio, Wei-Yin Ko, Alexandre Bérard, Théo Dehaze, and Sebastian Ruder. 2024. Understanding and mitigating language confusion in llms. *arXiv preprint arXiv:2406.20052*.

Paul McCann. 2020. fugashi, a tool for tokenizing Japanese in python. In *Proceedings of Second Workshop for NLP Open Source Software (NLP-OSS)*, pages 44–51, Online. Association for Computational Linguistics.

John X Morris, Volodymyr Kuleshov, Vitaly Shmatikov, and Alexander M Rush. 2023. Text embeddings reveal (almost) as much as text. *arXiv preprint arXiv:2310.06816*.

Roberto Navigli and Simone Paolo Ponzetto. 2010. Babelnet: Building a very large multilingual semantic network. In *Proceedings of the 48th annual meeting of the association for computational linguistics*, pages 216–225.

Robert Östling and Murathan Kurfalı. 2023. Language embeddings sometimes contain typological generalizations. *Computational Linguistics*, 49(4):1003–1051.

Robert Östling and Jörg Tiedemann. 2017. Continuous multilinguality with language vectors. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 644–649, Valencia, Spain. Association for Computational Linguistics.

Jonas Pfeiffer, Francesco Piccinno, Massimo Nicosia, Xinyi Wang, Machel Reid, and Sebastian Ruder. 2023. mmT5: Modular multilingual pre-training solves source language hallucinations. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 1978–2008, Singapore. Association for Computational Linguistics.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.

Esther Ploeger, Wessel Poelman, Miryam de Lhoneux, and Johannes Bjerva. 2024. What is “typological diversity” in nlp? In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*.

Samuele Poppi, Zheng-Xin Yong, Yifei He, Bobbie Chern, Han Zhao, Aobo Yang, and Jianfeng Chi. 2024. Towards understanding the fragility of multilingual llms against fine-tuning attacks. *Preprint*, arXiv:2410.18210.

Matt Post. 2018. A call for clarity in reporting bleu scores. *arXiv preprint arXiv:1804.08771*.

Taraka Rama and Prasanth Kolachina. 2012. How good are typological distances for determining genealogical relationships among languages? In *Proceedings of COLING 2012: Posters*, pages 975–984, Mumbai, India. The COLING 2012 Organizing Committee.

Christoph Rzymski, Tiago Tresoldi, Simon J Greenhill, Mei-Shin Wu, Nathanael E Schweikhard, Maria Koptjevskaja-Tamm, Volker Gast, Timotheus A Bodt, Abbie Hantgan, Gereon A Kaiping, et al. 2020. The database of cross-linguistic colexifications, reproducible analysis of cross-linguistic polysemies. *Scientific data*, 7(1):13.

Rico Sennrich, Jannis Vamvas, and Alireza Mohammadshahi. 2024. Mitigating hallucinations and off-target machine translation with source-contrastive and language-contrastive decoding. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 21–33, St. Julian’s, Malta. Association for Computational Linguistics.

Hedvig Skirgård, Hannah J Haynie, Damián E Blasi, Harald Hammarström, Jeremy Collins, Jay J Latarche, Jakob Lesage, Tobias Weber, Alena Witzlack-Makarevich, Sam Passmore, et al. 2023. Grambank reveals the importance of genealogical constraints on linguistic diversity and highlights the impact of language loss. *Science Advances*, 9(16):eadg6175.

Congzheng Song and Ananth Raghunathan. 2020. Information leakage in embedding models. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security*, CCS ’20, page 377–390, New York, NY, USA. Association for Computing Machinery.

Jiayang Song, Yuheng Huang, Zhehua Zhou, and Lei Ma. 2024. Multilingual blending: Llm safety alignment evaluation with language mixture. *arXiv preprint arXiv:2407.07342*.

Andy Sun et al. 2013. jieba. `https://github.com/fxsjy/jieba`. Accessed: 2024-10-15.

Zeerak Talat, Aurélie Névéol, Stella Biderman, Miruna Clinciu, Manan Dey, Shayne Longpre, Sasha Luccioni, Maraim Masoud, Margaret Mitchell, Dragomir Radev, et al. 2022. You reap what you sow: On the challenges of bias evaluation under multilingual settings. In *Proceedings of BigScience Episode# 5–Workshop on Challenges & Perspectives in Creating Large Language Models*, pages 26–41.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Tu Vu, Aditya Barua, Brian Lester, Daniel Cer, Mohit Iyyer, and Noah Constant. 2022. Overcoming catastrophic forgetting in zero-shot cross-lingual generation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9279–9300. Association for Computational Linguistics.

Jun Wang, Qiongkai Xu, Xuanli He, Benjamin Rubinstein, and Trevor Cohn. 2024. Backdoor attacks on multilingual machine translation. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 4515–4534. Association for Computational Linguistics.

Søren Wichmann, André Müller, Viveka Velupillai, Annkathrin Wett, Cecil H Brown, Zarina Molochieva, Julia Bishoffberger, Eric W Holman, Sebastian Sauppe, Pamela Brown, et al. 2012. The automated similarity judgment program (asjp): the asjp database (version 15).

L Xue. 2020. mt5: A massively multilingual pre-trained text-to-text transformer. *arXiv preprint arXiv:2010.11934*.

Zheng-Xin Yong, Cristina Menghini, and Stephen H. Bach. 2024. Low-resource languages jailbreak GPT-4. *Preprint*, arxiv:2310.02446 [cs].

Biao Zhang, Philip Williams, Ivan Titov, and Rico Sennrich. 2020. Improving massively multilingual neural machine translation and zero-shot translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 1628–1639, Online. Association for Computational Linguistics.

Wenhao Zhu, Hongyi Liu, Qingxiu Dong, Jingjing Xu, Shujian Huang, Lingpeng Kong, Jiajun Chen, and Lei Li. 2024. Multilingual machine translation with large language models: Empirical results and analysis. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 2765–2781.

Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J. Zico Kolter, and Matt Fredrikson. 2023. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*.

A Datasets for Language Confusion

Language Confusion Benchmark Marchisio et al. (2024) create and release a language confusion benchmark covering 15 languages, sourcing prompts from publicly available multilingual instruction datasets, and also creating new data with more complex promts, see detailed data sources in Table 4.

Additionally, the binary metrics such as Line Pass Rate (LPR) and Word Pass Rate (WPR) are defined in Marchisio et al. (2024) to measure whether a response contains any instance of a) a line in an incorrect language and b) an isolated English word/phrase for languages using non-Latin scripts.

LPR calculates the percentage of model responses that pass the line-level language confusion detector without error. A response is "correct" if all lines match the user's desired language.

$$LPR = \frac{|R \backslash E_L|}{|R|} \tag{3}$$

where R is the set of all responses and E_L is the set of responses that contain line-level errors.

WPR measures the percentage of responses where all words are in the desired language.

$$WPR = \frac{|(R \backslash E_L)| \backslash E_W}{|R \backslash E_L|} \tag{4}$$

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

We reproduce the **LPR** and **WPR** on **LCB** for both crosslingual and monolingual settings (as shown in Table 10 and 11). The detailed results applying *language confusion entropy* to **LCB** are presented in Table 9, for comparison.

Multilingual Textual Embedding Inversion Textual embedding inversion has presented a standing challenge in LLM security, where the private texts can be reconstructed from evasdroped embeddings from Embeddings as a Service (EaaS), by training an attacker model based on the embeddings extracted from the black-box embedders (Song and Raghunathan, 2020; Lyu et al., 2020; Kim et al., 2022; Morris et al., 2023; Chen et al., 2024, 2025). However, most work was done in monolingual settings, mostly in English, other than the recent work expands the language space to four Romance and Germanic languages in Latin script (Chen et al., 2024) and in Chen et al. (2025), the inversion atacks are extended to 20 languages across 8 families and 12 scripts (see Table 7). The trained inversion attack model consists of a **base** model and a **corrector** model, where a base model is a text-to-text generation model, while a corrector model is used to bring closer the generated embeddings and attacked embeddings in the embedding space. While in the

	Dataset name	Nature of Data	$\lvert L\rvert$	$\lvert D\rvert$	Languages	W
Monolingual	Aya (Iyer et al., 2024)	Human-generated	100	500	eng, tur, arb, cmn, por	9
	Dolly (Iyer et al., 2024)	MT post-edited	100	500	hin, rus, fra, arb, esp	10
	Okapi (Lai et al., 2023)	Synthetic+MT	100	1.2k	eng, fra, ita, deu, cmn, vie, rus, esp, find, por, arb, hin, esp, fra, jap, kor	13
	Native prompts (Marchisio et al., 2024)	Human-generated	100	500	esp, fra, jap, kor	19
Crosslingual	Okapi (Lai et al., 2023)	Synthetic	100	1.5k	$\mathcal{L}$	15
	ShareGPT (`https://sharegpt.com/`)	Human-generated	100	1.5k	$\mathcal{L}$	18
	Complex prompts (Marchisio et al., 2024)	Human-generated	99	1.5k	$\mathcal{L}$	159

Table 4: Data Sources in the **LCB** for monolingual and crosslingual generation (Marchisio et al., 2024). $|D|$ is the total number of examples per data source and $|L|$ is the number of examples per language. For the crosslingual setting, the model is instructed in English to generate in the target language $l \in \mathcal{L}$ where $\mathcal{L}$=fra, deu, esp, por, ita, jap, kor, cmn, arb, tur, hin, rus, ind, vie. W is the median length in words of the prompts in each dataset.

LLM	**Transformer**	**#Languages**	**Parameters**	**Reference**
LCB				
Command R	Decoder-only	-	35B	`https://cohere.com/blog/command-r`
Command R+	Decoder-only	-	104B	`https://cohere.com/blog/command-r-plus-microsoft-azure`
GPT-3.5 Turbo	Decoder-only	-	-	Brown (2020)
GPT-4 Turbo	Decoder-only	-	-	Achiam et al. (2023)
Mistral Large	Decoder-only	-	-	`https://mistral.ai/news/mistral-large/`
Mistral 8x7B	Decoder-only	-	7B	Jiang et al. (2024),
Llama 2 70B Instruct	Decoder-only	-	70B	Touvron et al. (2023)
Llama 3 70B Instruct	Decoder-only	-	70B	`https://ai.meta.com/blog/meta-llama-3/`
MTEI				
mT5-base	Encoder-Decoder	102	580M	Xue (2020)
multilingual-e5-base	Encoder	94	580M	`https://huggingface.co/intfloat/multilingual-e5-base`

Table 5: The Evaluated LLMs.

evaluation phase, three stages are reported: **base**, **step1 (corrector model)** and **step50+sbeam8 (corrector model with beam search with sequence length 8)**. The inversion model is trained with **mT5** (Xue, 2020) as base model and multilingual-e5-base [5] as black-box encoder. The samples of the curated dataset are shown in Table 8.

We apply *language confusion entropy* to **eval** and **train** languages in the monolingual and crosslingual settings at both line and word levels, while comparing the BLEU score in the regarding scenario (ref. Table 12 and 13).

		H_C[**L**]	H_C[**W**]	BLEU
All	H_C[**W**]	0.93***		
	BLEU	0.66***	0.71***	
	mT5	0.32***	0.24	0.09
Monolingual	H_C[**W**]	0.63***		
	BLEU	0.37***	0.33**	
	mT5	0.05	0.42*	0.09
Crosslingual	H_C[**W**]	0.93***		
	BLEU	0.66***	0.71***	
	mT5	0.32	0.23	0.09

Table 6: Spearman Correlations among H_C at Line Level and Word Level and BLEU score for Multilingual Textual Embedding Inversion, and the percentage of pre-training data in mT5, for train languages.

B Language Graphs for Language Similarities

We curate language graphs from a diverse range of sources, as shown in Table 14. The language vectors from Grambank and WALS consist of multi-valued features, while those derived from colexification patterns in CLICS[3] and WordNet (WN) are binarized. For these, we employ the Jaccard index to compute pairwise language similarities. For other more dense valued language vectors, we use cosine similarity instead.

[5] Huggingface: intfloat/multilingual-e5-base

Language	**ISO 639**	**Lang. Family**	**Lang. Script**	**Script ISO**	**Directionality**	**#Samples(Train)**	**WO**	**mT5 (%)**
Arabic	arb	Semitic	Arabic	Arab	RTL	1M	VSO	1.66
Urdu	urd	Indo-Aryan	Arabic	Arab	RTL	600K	SOV	0.61
Kazakh	kaz	Turkic	Cyrillic	Cyrl	LTR	1M	SOV	0.65
Mongolian	mon	Mongolic	Cyrillic	Cyrl	LTR	1M	SOV	0.62
Hindi	hin	Indo-Aryan	Devanagari	Deva	LTR	600K	SOV	1.21
Gujarati	guj	Indo-Aryan	Gujarati	Gujr	LTR	600K	SOV	0.43
Punjabi	pan	Indo-Aryan	Gurmukhi	Guru	LTR	600K	SOV	0.37
Chinese	cmn	Sino-Tibetan	Haqniqdoq	Hani	LTR	1M	SVO	1.67
Hebrew	heb	Semitic	Hebrew	Hebrewr	RTL	1M	SVO	1.06
Japanese	jpn	Japonic	Japanese	Jpan	LTR	1M	SOV	1.92
German	deu	Germanic	Latin	Latn	LTR	1M	Non-Dominant	3.05
Turkish	tur	Turkic	Latin	Latn	LTR	1M	SOV	1.93
Amharic	amh	Semitic	Ethiopian	Ethi	LTR	-	SOV	0.29
Sinhala	sin	Indo-Aryan	Sinhala	Sinh	LTR	-	SOV	0.41
Korean	kor	Koreanic	Hangul	Hang	LTR	-	SOV	1.14
Finnish	fin	Uralic	Latin	Latn	LTR	-	SVO	-
Hungarian	hun	Uralic	Latin	Latn	LTR	-	Non-Dominant	1.48
Yiddish	ydd	Germanic	Hebrew	Hebrewr	RTL	-	SVO	0.28
Maltese	mlt	Semitic	Latin	Latn	LTR	-	Non-Dominant	0.64
Meadow Mari	mhr	Uralic	Cyrillic	Cyrl	LTR	-	SOV	-

Table 7: Languages and their Language Characteristics, i.e., Language Family, Language Script, Directionality of the Script, Number of Training Samples for Inversion Models, Word Order of Subject, Object and Verb in Multilingual Inversion Attack (Chen et al., 2025) and the Percentage of the language in Pre-training data in mT5 (Xue, 2020).

Model	$\mathcal{L}_{\text{train}}$	$\mathcal{L}_{\text{eval}}$	**Eval Step**	**Predicted Language Distribution**
ME5	Hindi	German	Base	{eng: 0.27, deu: 0.34, hin: 0.24, fra: 0.01, nld: 0.01, fin: 0.01, mar: 0.02, nep: 0.01}
ME5	Hindi	German	Step1	{eng: 0.17, deu: 0.47, hin: 0.24, mar: 0.02, fra: 0.01, nep: 0.01, nld: 0.01}
ME5	Hindi	German	Step50+sbeam8	{hin: 0.38, mar: 0.04, deu: 0.37, eng: 0.15, fra: 0.01}
ME5	Hindi	Yiddish	Base	{mar: 0.12, hin: 0.83, eng: 0.02, deu: 0.01, nep: 0.01}
ME5	Hindi	Yiddish	Step1	{hin: 0.82, eng: 0.02, mar: 0.13, deu: 0.01}
ME5	Hindi	Yiddish	Step50+sbeam8	{hin: 0.81, mar: 0.12, deu: 0.01, eng: 0.04}
ME5	Hindi	Hebrew	Base	{hin: 0.92, eng: 0.03, mar: 0.03}
ME5	Hindi	Hebrew	Step1	{hin: 0.94, mar: 0.03, eng: 0.02}
ME5	Hindi	Hebrew	Step50+sbeam8	{hin: 0.94, eng: 0.02, mar: 0.03}
ME5	Hindi	Arabic	Base	{eng: 0.63, hin: 0.32, mar: 0.02, nep: 0.01, fra: 0.01}
ME5	Hindi	Arabic	Step1	{eng: 0.61, hin: 0.33, mar: 0.03}
ME5	Hindi	Arabic	Step50+sbeam8	{eng: 0.62, hin: 0.31, mar: 0.04}

Table 8: Examples of Dataset MTEI. The probabilities for *unidentified* languages are omitted.

	AVG	French	Spanish	Italian	German	Russian	Portuguese	Turkish	Vietnamese	Chinese	Korean	Arabic	Japanese	Hindi	Indonesian
Monolingual (Line)															
Command R	**0.0306**	0.0272	0.0381	0.0092	0.0430	0.0093	0.0195	0.0042	0.0099	0	0	0.0017	0.0171	**0.0111**	0.2384
Command R+	0.0355	**0.0127**	0.0325	0	0.0373	0.0309	0.0219	0.0100	0.0264	0	0	0.0034	0.0158	0.0387	0.2673
GPT-3.5 Turbo	0.0317	0.0250	**0.0296**	0.0103	0.0276	0.0168	0.0292	0.0050	0.0070	0	0	0	**0.0057**	0.0546	0.2337
GPT-4 Turbo	0.0381	0.0508	0.0468	0.0051	0.0316	0.0636	0.0228	0	0.0033	0.0079	0	0	0.0083	0.0639	0.2289
Mistral 8x7B	0.0766	0.0399	0.0510	0.0645	0.0229	0.0414	0.0784	0.0252	0.1037	0.1116	0.0787	0.0583	0.1394	0.0540	0.2036
Mistral Large	0.0799	0.0145	0.0351	0.0202	0.0139	0.0156	0.0643	0.0378	0.2245	0.1011	0.0329	0.1231	0.0756	0.0663	0.2936
Llama 2 70B-I	0.1266	0.0729	0.0548	0.1500	0.1438	0.0704	0.0569	0.1347	0.2501	0.1113	0.0501	0.1713	0.0784	0.1279	0.2999
Llama 3 70B-I	0.1197	0.0483	0.0557	0.0300	0.0556	0.0955	0.0654	0.2009	0.1416	0.1518	0.1720	0.1879	0.1579	0.1720	**0.1412**
Crosslingual (Line)															
Command R	0.1555	0.1942	0.1651	0.1723	0.1928	0.1357	0.1458	0.1441	0.1579	0.1007	0.1169	0.1159	0.1522	0.1395	**0.2437**
Command R+	0.1216	0.1234	0.1635	0.0810	0.1040	0.1034	0.1555	0.0817	0.1204	0.0610	0.0617	**0.0534**	0.0691	0.1424	0.3825
GPT-3.5 Turbo	0.1025	0.1219	0.1085	0.1042	0.1119	**0.0749**	0.1169	0.0945	0.0772	**0.0527**	**0.0596**	0.0764	**0.0624**	**0.1163**	0.2584
GPT-4 Turbo	**0.0987**	**0.0721**	**0.0956**	**0.1002**	**0.0778**	0.0876	**0.0909**	**0.0733**	**0.0742**	0.0665	0.0600	0.0666	0.0981	0.1612	0.2577
Mistral 8x7B	0.1675	0.1341	0.1332	0.1242	0.1582	0.1304	0.1288	0.1156	0.1458	0.1604	0.1743	0.1506	0.1977	0.3053	0.2861
Mistral Large	0.2274	0.1341	0.2122	0.1808	0.1441	0.1496	0.2509	0.1410	0.1817	0.2944	0.3052	0.2816	0.3416	0.2407	0.3262
Llama 2 70B-I	0.2649	0.1517	0.1339	0.2330	0.2657	0.2186	0.2022	0.2280	0.2532	0.2817	0.3574	0.3719	0.3233	0.3443	0.3433
Llama 3 70B-I	0.4631	0.3906	0.3192	0.4324	0.4226	0.4495	0.3503	0.5696	0.5360	0.3872	0.3777	0.5200	0.4822	0.5531	0.6935
Monolingual (Word)															
Command R	0.5563	0.9016	0.9424	0.9513	0.4098	0.6312	1.0095	0.5445	0.4059	0.1974	**0.0031**	0.1424	0.0462	0.4161	1.1865
Command R+	0.5522	0.9034	0.9687	0.9363	**0.3873**	0.6478	1.0185	0.5003	0.3812	0.1232	0.0057	0.1327	0.0785	0.4007	1.2458
GPT-3.5 Turbo	**0.5344**	0.9031	0.9348	0.9567	0.4325	0.6322	**0.9457**	**0.4281**	0.3587	**0.0913**	0.0088	**0.1053**	0.0370	**0.3937**	1.2532
GPT-4 Turbo	0.5426	**0.8656**	0.9456	0.9284	0.4241	0.6206	0.9818	0.4932	0.3217	0.1287	0.0146	0.1355	**0.0307**	0.4232	1.2823
Mistral 8x7B	0.7431	0.9763	0.9157	1.0027	0.4477	0.6947	0.9746	0.6763	0.4134	0.8854	0.4960	0.4330	0.8628	0.6106	1.0134
Mistral Large	0.5703	0.8829	**0.9099**	**0.9083**	0.4270	**0.6191**	0.9827	0.6473	**0.3199**	0.2191	0.2568	0.3137	0.2484	0.4472	**0.8016**
Llama 2 70B-I	0.8022	1.0541	0.9257	1.0109	0.8092	0.6939	1.0000	1.2333	0.5748	0.5989	0.3960	0.5578	0.5229	0.5676	1.2862
Llama 3 70B-I	0.8657	1.0519	0.9427	1.0139	0.8992	0.6325	1.0028	1.5459	0.4827	0.8949	0.8120	0.6904	0.6017	0.6831	0.8659
Crosslingual (Word)															
Command R	0.6796	1.0941	1.0038	1.0896	0.6588	0.6618	**0.9487**	0.5579	0.4664	0.3347	0.1988	0.3190	0.4943	0.4836	**1.2030**
Command R+	0.6049	**0.9606**	**0.9380**	**0.9444**	**0.4382**	0.6684	1.0785	**0.5316**	0.4572	0.2081	**0.0670**	**0.1616**	0.1870	0.5074	1.3212
GPT-3.5 Turbo	**0.5951**	1.0295	0.9439	0.9894	0.5858	**0.5796**	1.0159	0.5327	**0.3659**	**0.1273**	0.0933	0.1727	**0.1850**	**0.4478**	1.2626
GPT-4 Turbo	0.6348	1.0025	0.9619	0.9890	0.5257	0.6425	1.0182	0.5568	0.4089	0.2542	0.1182	0.2552	0.3012	0.5073	1.3451
Mistral 8x7B	0.8556	1.0509	1.0205	1.0143	0.6203	0.7656	1.0186	0.6174	0.5099	0.7446	0.6496	0.5800	0.9520	1.1017	1.3330
Mistral Large	0.9647	1.2351	1.1284	1.1409	0.6319	0.7850	1.1244	0.6909	0.6404	1.1388	0.7054	0.7411	1.2626	0.8266	1.4551
Llama 2 70B-I	0.9676	1.2830	0.9488	1.1583	0.9822	0.7885	1.0626	0.6962	0.6398	1.1089	0.8069	0.6929	1.1530	0.9268	1.2983
Llama 3 70B-I	0.9757	1.2111	1.1366	1.3193	0.8329	1.0911	1.2465	0.9568	0.7462	0.7249	0.3435	0.8228	0.8275	0.8733	1.5274

Table 9: Language Confusion measured by Language Confusion Entropy for LCB for monolingual and crosslingual settings at line and word level for each Language for LLMs.

LPR	**AVG**	**French**	**Spanish**	**Italian**	**German**	**Russian**	**Portuguese**	**Turkish**	**Vietnamese**	**Chinese**	**Korean**	**Arabic**	**Japanese**	**Hindi**	**Indonesian**
Monolingual															
Command R	98.50	99.33	95.67	99.00	98.00	100.00	98.50	99.00	99.00	98.50	100.00	100.00	100.00	100.00	92.00
Command R+	99.19	99.67	99.33	100.00	100.00	100.00	97.50	100.00	99.00	97.50	100.00	99.67	99.00	100.00	97.00
GPT-3.5 Turbo	99.05	100.00	99.67	100.00	100.00	100.00	98.00	100.00	99.00	97.00	100.00	100.00	98.00	99.00	96.00
GPT-4 Turbo	**99.26**	99.33	99.33	99.00	100.00	100.00	98.00	100.00	100.00	99.00	100.00	99.00	100.00	100.00	96.00
Mistral 8x7B	71.08	95.33	89.33	72.00	91.00	65.00	85.00	90.00	57.00	45.50	61.00	48.00	67.00	71.00	58.00
Mistral Large	67.82	100.00	99.00	99.00	98.00	98.00	79.50	71.00	29.00	66.00	64.00	48.00	48.00	19.00	31.00
Llama 2 70B-I	44.65	87.67	95.67	72.00	59.00	89.00	91.00	33.00	17.00	10.50	0.00	0.33	7.00	1.00	62.00
Llama 3 70B-I	42.15	88.67	98.33	88.00	31.00	77.00	95.50	18.00	10.00	8.00	0.00	21.67	10.00	23.00	21.00
Crosslingual															
Command R	77.84	86.83	84.17	74.00	72.00	77.00	79.80	75.50	74.00	84.40	77.00	80.83	74.00	74.25	76.00
Command R+	**93.77**	95.50	95.50	95.25	93.75	94.75	92.00	94.00	93.00	92.80	93.25	96.50	95.00	92.75	88.75
GPT-3.5 Turbo	92.83	94.00	96.50	93.50	92.75	93.75	93.20	92.00	93.50	90.60	92.75	95.33	90.75	93.75	87.25
GPT-4 Turbo	93.13	95.00	96.17	93.50	94.75	92.50	93.80	93.50	92.50	92.40	92.25	94.00	90.75	93.25	89.50
Mistral 8x7B	69.73	87.17	84.17	81.75	80.00	70.50	81.60	79.50	71.00	52.60	58.00	53.50	60.25	47.25	69.00
Mistral Large	62.26	86.00	83.83	74.25	80.50	72.00	70.60	67.25	48.25	54.20	46.75	42.00	45.25	48.50	52.25
Llama 2 70B-I	40.53	79.33	86.50	67.75	54.00	51.00	82.00	26.25	19.55	10.84	3.58	6.33	14.00	16.25	50.00
Llama 3 70B-I	34.81	70.83	79.67	49.25	33.75	48.00	70.80	17.53	16.53	5.80	0.58	26.33	3.53	40.50	24.25

Table 10: Language Confusion Benchmark Line Pass Rate Reproduction for both Monolingual and Crosslingual settings.

WPR	AVG	Russian	Chinese	Korean	Arabic	Japanese	Hindi
Monolingual							
Command R	96.31	96.00	92.50	97.00	99.33	94.00	99.00
Command R+	99.44	98.00	100.00	100.00	99.67	99.00	100.00
GPT-3.5 Turbo	99.83	100.00	100.00	100.00	100.00	99.00	100.00
GPT-4 Turbo	99.67	100.00	99.00	99.00	100.00	100.00	100.00
Mistral Large	98.50	99.00	99.00	100.00	100.00	98.00	95.00
Mistral 8x7B	73.75	83.00	64.50	62.00	86.00	68.00	79.00
Llama 2 70B-I	97.92	93.00	94.50	100.00	100.00	100.00	100.00
Llama 3 70B-I	93.19	94.00	93.50	100.00	95.67	80.00	96.00
Crosslingual							
Command R	93.89	93.67	91.00	97.33	94.33	88.33	98.67
Command R+	95.11	89.67	95.67	96.00	98.00	95.33	96.00
GPT-3.5 Turbo	98.72	98.33	99.00	98.33	99.00	98.67	99.00
GPT-4 Turbo	96.61	95.67	97.00	96.67	97.33	95.67	97.33
Mistral Large	93.83	93.00	97.67	92.00	93.67	91.33	95.33
Mistral 8x7B	68.22	80.33	62.00	67.33	76.33	51.67	71.67
Llama 2 70B-I	84.17	81.33	76.00	86.67	91.33	84.33	85.33
Llama 3 70B-I	94.39	89.00	92.33	100.00	95.67	91.67	97.67

Table 11: Language Confusion Benchmark Word Pass Rate Reproduction for both Monolingual and Crosslingual settings.

Language	Step	Monolingual		Crosslingual		BLEU (AVG)
		Line Level	Word Level	Line Level	Word Level	
Sinhala	Base	-	-	**0.9061**	1.6668	6.6147
	Step1	-	-	1.1412	1.7610	6.1822
	Step50+sbeam8	-	-	1.3213	1.9353	6.1517
Gujarati	Base	0.0385	0.2332	**0.9372**	1.7629	8.8752
	Step1	0.0308	0.9894	1.4092	1.7977	8.7153
	Step50+sbeam8	0.0154	0.2303	1.3821	1.5844	10.0989
Meadow Mari	Base	-	-	1.1895	2.5281	6.8674
	Step1	-	-	**1.3452**	2.4527	6.3181
	Step50+sbeam8	-	-	1.4333	2.4806	6.0744
Punjabi	Base	0	0.2304	1.2886	1.9215	11.7362
	Step1	0	0.1910	1.0879	1.7473	9.7027
	Step50+sbeam8	0	0.1994	0.8049	1.3955	11.4941
Amharic	Base	-	-	1.2949	1.9906	7.2613
	Step1	-	-	1.1420	1.7983	6.7393
	Step50+sbeam8	-	-	1.2548	1.8958	6.5141
Urdu	Base	0.0516	0.7021	1.3266	2.3594	8.6339
	Step1	0.0462	0.5510	1.4870	2.8171	8.2143
	Step50+sbeam8	0.0385	0.5661	1.5844	2.3360	8.9373
Korean	Base	-	-	1.4917	2.5477	5.5578
	Step1	-	-	1.6311	2.2823	5.1378
	Step50+sbeam8	-	-	1.6845	2.4643	4.9561
Yiddish	Base	-	-	1.5216	2.3321	6.5486
	Step1	-	-	1.6912	2.2014	6.0670
	Step50+sbeam8	-	-	1.5956	2.2891	5.9480
Mongolian	Base	0.0462	2.6470	1.6223	2.6724	7.9523
	Step1	0.0462	2.6291	1.3172	2.5401	7.7916
	Step50+sbeam8	0.0462	2.6586	1.4105	2.6977	8.4952
Hindi	Base	0.6587	1.0295	2.0050	3.0441	8.5273
	Step1	0.6305	1.0192	1.9432	2.5054	8.5912
	Step50+sbeam8	0.6212	1.0268	1.4697	2.6635	9.6811
Arabic	Base	0.0280	0.5021	2.1931	3.0200	6.1455
	Step1	0	0.4597	1.7083	2.3915	5.9620
	Step50+sbeam8	0	0.4666	1.6406	2.1459	6.1903
Kazakh	Base	0.1390	1.5820	2.2796	3.1694	10.8145
	Step1	0.1070	1.4129	1.8063	3.0509	10.8421
	Step50+sbeam8	0.1098	1.4378	1.8065	3.0765	12.4864
Hebrew	Base	0	0.1555	2.8174	3.7918	5.9312
	Step1	0	0.1625	2.3715	3.3317	5.6492
	Step50+sbeam8	0	0.1391	2.0314	2.5126	5.7413
Chinese	Base	0	0.6124	2.8718	3.2475	6.4620
	Step1	0.0280	0.5898	1.9708	2.3969	5.6923
	Step50+sbeam8	0.0280	0.6262	1.9363	2.2672	5.3919
Maltese	Base	-	-	3.0059	4.1352	6.7777
	Step1	-	-	3.5456	4.5662	6.1049
	Step50+sbeam8	-	-	3.3048	4.5243	5.8991
Japanese	Base	0.0693	0.8806	3.2545	4.9242	5.7113
	Step1	0.0693	0.8135	2.6345	3.2156	5.2014
	Step50+sbeam8	0.0693	0.8277	2.3426	3.1882	5.0411
German	Base	0.0000	0.6205	3.2764	4.6278	6.3678
	Step1	0.0231	0.6106	3.8041	4.4014	6.3865
	Step50+sbeam8	0	0.6203	3.3912	4.4915	6.8334
Turkish	Base	0.0660	1.6099	3.8939	4.8367	7.9789
	Step1	0.0707	1.6103	2.7842	3.7629	8.3830
	Step50+sbeam8	0.0687	1.6045	2.8521	4.0266	9.6997
Finnish	Base	-	-	4.3696	5.6543	5.2877
	Step1	-	-	3.6533	5.0938	4.8876
	Step50+sbeam8	-	-	3.6939	5.0801	4.7593
Hungarian	Base	-	-	4.4119	5.1123	5.1684
	Step1	-	-	3.6595	4.6260	4.7418
	Step50+sbeam8	-	-	3.3812	4.0739	4.6179

Table 12: Language Confusion Entropy at each step in the Monolingual and Crosslingual generation settings at both Line and Word level, with BLEU score for textual embedding inversion tasks for **eval** languages.

Train	Language	Step	Monolingual		Crosslingual		BLEU (AVG)
			Line Level	Word Level	Line Level	Word Level	
Monolingual	**Punjabi**	Base	0.0000	0.2615	0.3042	0.7821	6.7660
		Step1	0.0000	0.0000	0.0000	0.0000	0.0227
		Step50+sbeam8	0.0000	0.0000	0.0000	0.0000	0.0229
	Hebrew	Base	0.0000	0.1720	0.3404	0.8445	6.0112
		Step1	0.0000	0.1391	0.4184	0.8806	5.9759
		Step50+sbeam8	0.0000	0.1391	0.5401	0.9759	5.9736
	Gujarati	Base	0.0462	0.2332	0.7272	1.6964	6.3759
		Step1	0.0462	0.2384	0.6853	1.3227	6.4278
		Step50+sbeam8	0.0462	0.2384	0.4426	1.0568	6.4171
	Chinese	Base	0.0000	0.5667	0.7711	1.3158	6.3859
		Step1	0.0000	0.5667	0.6766	1.5313	6.1478
		Step50+sbeam8	0.0560	0.6395	0.8930	1.2632	5.9179
	German	Base	0.0000	0.6205	0.8030	1.4859	6.5072
		Step1	0.0000	0.6008	0.9991	1.4383	6.4497
		Step50+sbeam8	0.0000	0.6090	1.0879	1.4596	6.4801
	Kazakh	Base	0.1252	0.9288	1.2115	2.1219	7.5891
		Step1	0.1061	0.9288	0.7061	1.7686	7.5050
		Step50+sbeam8	0.1252	0.9288	0.7562	1.7288	8.0075
	Urdu	Base	0.0462	0.7023	1.2381	1.9326	6.0338
		Step1	0.0462	0.6597	0.9932	1.8497	5.9788
		Step50+sbeam8	0.0462	0.6781	1.0471	1.8990	5.8903
	Japanese	Base	0.0925	0.8399	1.2677	2.5338	5.8317
		Step1	0.0925	0.8265	1.3099	2.3773	5.6813
		Step50+sbeam8	0.0925	0.8112	1.4349	2.5009	5.4885
	Turkish	Base	0.0925	1.0902	1.2699	2.1591	7.1899
		Step1	0.0462	1.0711	0.9757	1.8074	7.2374
		Step50+sbeam8	0.0462	1.0711	0.9824	2.0698	7.5047
	Hindi	Base	0.6952	1.0268	1.7053	2.0748	6.4369
		Step1	0.6276	0.9830	1.5004	1.8830	6.3956
		Step50+sbeam8	0.6417	1.0094	1.5470	1.9180	6.3725
	Arabic	Base	0.0560	0.5021	1.8446	2.1560	6.0938
		Step1	0.0000	0.4471	0.8492	1.6087	6.0149
		Step50+sbeam8	0.0000	0.4610	1.1300	1.3489	6.1260
	Mongolian	Base	0.0462	0.7688	2.2537	2.9952	7.0101
		Step1	0.0462	0.7330	1.8297	2.9202	7.3608
		Step50+sbeam8	0.0462	0.7697	1.6677	2.5683	7.8355
In-Family/In-Script	**Hindi, Punjabi**	Base	0.3333	0.6300	2.6597	3.4826	8.1018
		Step1	0.3317	0.6300	3.3548	3.7614	8.5398
		Step50+sbeam8	0.3209	0.6300	3.4952	4.2414	9.2197
	Punjabi, Urdu	Base	0.0393	0.4470	2.9478	3.9370	8.0232
		Step1	0.0231	0.4361	4.0750	4.8806	7.3287
		Step50+sbeam8	0.0231	0.4546	3.7656	4.6257	8.0605
	Kazakh, Turkish	Base	0.0995	1.0037	3.0674	5.2358	8.3012
		Step1	0.1158	0.9838	2.3818	4.7775	8.7420
		Step50+sbeam8	0.0924	1.0029	2.6656	4.2396	9.8136
	Gujarati, Hindi	Base	0.3209	0.6300	3.1485	4.7015	7.3518
		Step1	0.3332	0.6389	3.2087	3.5149	7.5794
		Step50+sbeam8	0.3369	0.6257	2.8926	3.1977	8.1357
	German, Turkish	Base	0.0231	2.7236	3.3850	5.2398	7.5745
		Step1	0.0693	2.7123	3.3267	5.2520	7.9995
		Step50+sbeam8	0.0393	2.7291	3.0071	5.3435	8.9119
	Gujarati, Urdu	Base	0.0462	0.4768	3.6012	4.2957	7.5971
		Step1	0.0231	0.4678	3.6518	4.7169	7.8532
		Step50+sbeam8	0.0231	0.4579	3.2620	4.0107	8.3644
	Hindi, Urdu	Base	0.3327	0.8645	3.6261	4.0579	7.4791
		Step1	0.3258	0.8347	3.5240	3.8894	7.7025
		Step50+sbeam8	0.3064	0.8460	3.2558	3.7994	8.1493
	Arabic, Hebrew	Base	0.0000	0.3206	3.9135	4.6422	7.2555
		Step1	0.0000	0.3290	3.0216	3.8845	7.1863
		Step50+sbeam8	0.0000	0.3056	3.0272	4.1192	7.3948
	Gujarati, Punjabi	Base	0.0231	0.2332	4.3682	5.0570	7.9168
		Step1	0.0231	2.4993	3.1955	4.0486	8.2486
		Step50+sbeam8	0.0000	0.2220	2.7857	4.2355	9.1628
	Kazakh, Mongolian	Base	0.0995	4.9836	4.6250	5.5072	9.0396
		Step1	0.0761	4.9836	4.3483	5.1664	9.6267
		Step50+sbeam8	0.0995	4.9947	3.6838	5.6001	10.8565
Cross-Family/Cross-Script	**Gujarati, Turkish**	Base	0.0693	0.6534	1.7507	3.1341	7.3780
		Step1	0.0463	0.6525	2.4953	3.1636	7.6174
		Step50+sbeam8	0.0463	0.6409	2.1876	3.1276	8.1549
	Chinese, Japanese	Base	0.0231	0.7897	1.9550	3.2433	6.4919
		Step1	0.0511	0.7067	3.2448	4.7459	6.5438
		Step50+sbeam8	0.0231	0.7285	3.7689	4.0670	6.6168
	Punjabi, Turkish	Base	0.0231	0.6417	2.1019	3.4377	8.0628
		Step1	0.0231	0.6440	2.8690	3.6396	7.2908
		Step50+sbeam8	0.0231	0.6548	2.5556	3.6179	7.9988
	Hindi, Turkish	Base	0.3682	1.0384	2.3767	3.5239	-
		Step1	0.3489	1.0369	2.2821	3.1379	-
		Step50+sbeam8	0.3601	1.0321	2.3311	3.1449	-
	Hindi, Kazakh	Base	0.4053	0.9859	2.8022	4.7000	-
		Step1	0.4069	0.9749	3.2070	4.3596	-
		Step50+sbeam8	0.3735	0.9994	3.4030	3.9206	-
	Gujarati, Kazakh	Base	0.0761	0.5911	2.8922	3.9972	7.8211
		Step1	0.0857	0.5548	2.4678	3.0565	8.2088
		Step50+sbeam8	0.0531	0.5810	2.0942	2.9441	8.8596
	Turkish, Urdu	Base	0.0462	0.9011	2.9759	4.0922	7.5098
		Step1	0.0693	0.8723	2.3225	3.3931	7.7308
		Step50+sbeam8	0.0462	0.9011	2.1042	3.3795	8.1401
	Kazakh, Punjabi	Base	0.0764	0.5697	3.2837	4.0113	8.4029
		Step1	0.0531	0.5435	2.2224	3.2103	8.6699
		Step50+sbeam8	0.0764	0.5705	1.6113	3.1262	9.3574

Table 13: Language Confusion Entropy at each step in the Monolingual and Crosslingual generation settings at both Line and Word level, with BLEU score for textual embedding inversion tasks for **train** languages.

Language Graph	#Languages	#Features	Category of Features	Datasource References	Representation	Similarity Metric
Grambank	2292	195	Morpho-syntactical	Skirgård et al. (2023)	Multivalued Vectors	Jaccard
WALS	424	192	Structural properties of languages	Haspelmath (2008)	Multivalued Vectors	Jaccard
WALS\ Phon.	431	172	WALS w/o Phonological Features	Haspelmath (2008)	Multivalued Vectors	Jaccard
Lang2Vec (Littell et al., 2017)	8070	-	Inventory, Syntax, Phonology, Genealogy, Geography, Featural	Collin (2010); Haspelmath (2008); Collins and Kayne (2011)	Vectors	Cosine similarity and Arccosine
CLICS^3	1347	4228	Colexifications	Rzymski et al. (2020)	Binarized Vectors	Jaccard
WN	519	2,518,357	Colexifications	Navigli and Ponzetto (2010)	Binarized Vectors	Jaccard
Colex2Lang (Chen et al., 2023b)						
CLICS^3	1609	4228	Colexifications	Rzymski et al. (2020)	Combined Graph Embeddings	Cosine Similarity
WN	519	2,525,591	Colexifications	Navigli and Ponzetto (2010)	Combined Graph Embeddings	Cosine Similarity
WN_CONCEPT	519	2,486,485	Colexifications	Navigli and Ponzetto (2010)	Combined Graph Embeddings	Cosine Similarity
ASJP SVD	1012	40	lexicon	(Wichmann et al., 2012)	UMAP on a mean normalized Levenshtein distance pairwise distance matrix from ASJP	Cosine Similarity
ASJP UMAP	1012	40	lexicon	(Wichmann et al., 2012)	Truncated SVD on a mean normalized Levenshtein distance pairwise distance matrix from word alignments	Cosine Similarity
Östling and Tiedemann (2017)	943	-	-	Bible Translations	Lang. Vectors trained on Bible Data	Cosine Similarity

Table 14: Statistics and Incorporated Features for Language Graphs.

Language Graph	LCB							Textual Embedding Inversion						
	AVG	ALL		Monolingual		Crosslingual		AVG	ALL		Monolingual		Crosslingual	
		Line	Word	Line	Word	Line	Word		Line	Word	Line	Word	Line	Word
Grambank	0.2650	0.1830	0.2827	0.2726	0.4042	0.1791	0.2682	0.7538	**0.8005**	0.7891	0.7504	0.5434	**0.8230**	0.8162
WALS	0.1947	0.0420	0.2908	0.0816	0.4286	0.0388	0.2865	0.7377	0.8722	**0.7854**	0.6618	0.4102	0.8803	0.8164
WALS \ Phon.	0.1892	0.0409	0.2889	0.0799	0.4253	0.0379	0.2620	0.7360	0.8768	0.7880	0.6495	0.4036	0.8837	0.8147
Lang2Vec														
Inventory	0.1650	0.0812	**0.2003**	0.1374	**0.3114**	0.0637	**0.1961**	0.8154	0.9678	0.8410	0.8225	0.4124	0.9720	0.8768
Syntactic	0.2925	0.1949	0.3771	0.2244	0.4679	0.1505	0.3405	0.8651	1.0179	0.8668	0.8872	0.5447	1.0001	0.8742
Phonological	0.2260	0.1009	0.3126	0.1552	0.4235	0.0830	0.2808	1.3161	1.7178	1.6133	0.6859	0.6004	1.6599	1.6191
Genetic	12.8307	13.4548	12.2278	12.9350	12.3563	13.5850	12.4249	14.9443	14.6988	14.9756	18.5227	13.5734	13.8721	14.0232
Geographical	1.5976	1.5924	1.8769	0.9753	1.8614	1.4996	1.7798	2.5218	2.4910	2.3964	2.6389	2.7875	2.4732	2.3439
Featural	0.3174	0.2094	0.4099	0.2429	0.5033	0.1626	0.3762	1.0628	1.0940	0.9355	1.5467	0.7976	1.0673	0.9359
CLICS^3	1.6777	1.6516	1.7336	1.5453	1.7043	1.7182	1.7130	1.1806	1.1601	1.0850	1.4595	1.2880	1.0670	1.0237
WN	1.1372	1.1211	1.1423	1.1491	1.2521	1.0906	1.0680	2.1364	2.2197	2.0398	2.9402	1.6996	2.0687	1.8501
Colex2Lang														
CLICS^3	0.1665	0.0289	0.2522	0.0589	0.3776	0.0260	0.2490	**0.7333**	0.9492	0.8335	0.3690	**0.2672**	0.9503	0.8693
WN	**0.1489**	**0.0242**	0.2154	**0.0522**	0.3404	**0.0218**	0.2149	0.7794	1.0105	0.8892	0.3263	0.3894	1.0445	0.9454
WN_CONCEPT	0.1490	**0.0242**	0.2175	0.0522	0.3426	**0.0218**	0.2168	0.7791	1.0100	0.8836	**0.3263**	0.3894	1.0427	0.9390
ASJP SVD	0.5859	0.0253	1.0597	**0.0522**	1.0395	0.0225	1.3164	2.8254	2.9730	3.3461	0.0820	1.6568	3.8882	5.0063
ASJP UMAP	0.9318	0.0994	1.6767	0.1290	1.6055	0.0946	1.9856	3.3217	3.5364	4.0245	0.0811	2.3479	4.3690	5.5711
Östling and Tiedemann (2017)														
L1	0.5697	0.0504	0.9843	0.0920	0.9616	0.0483	1.2819	4.7062	5.3973	5.9836	0.2837	1.7125	7.1117	7.7482
L2	0.5644	0.0497	0.9749	0.0918	0.9536	0.0452	1.2710	4.6788	5.4149	5.9684	0.1421	1.7019	7.1158	7.7296
L3	0.5589	0.0534	0.9601	0.0981	0.9336	0.0523	1.2558	4.7099	5.4686	6.0242	**0.1138**	1.6944	7.1689	7.7895
ALL	0.5595	0.0471	0.9673	0.0900	0.9437	0.0450	1.2641	4.6870	5.4175	5.9885	0.1482	1.6916	7.1240	7.7525

Table 15: KL Divergence between Language Similarity Graphs and the Language Confusion Matrices for Target/Eval Languages from LCB and Inversion Tasks. The best results (lowest) are **bolded**, and the second best are underlined.