FSTs vs ICL: Generalisation in LLMs for an under-resourced language

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Abstract

The effectiveness of LLMs remains uncertain in scenarios where pre-trained models have limited prior knowledge of a language. In this work, we examine LLMs' generalization in under-resourced settings through the task of orthographic normalization across Otomi language variants. We develop two approaches: a rule-based method using a finite-state transducer (FST) and an in-context learning (ICL) method that provides the model with string transduction examples. We compare the performance of FSTs and the neural approach in low-resource scenarios, providing insights into their potential and limitations. Our results show that while FSTs outperform LLMs in zero-shot settings, ICL enables LLMs to surpass FSTs, stressing the importance of combining linguistic expertise with machine learning in current approaches for low-resource scenarios.[1]

1 Introduction

Large Language Models (LLMs) have been widely adopted to tackle many traditional NLP tasks. Part of their success is attributed to their extensive pretraining, which enables them to generalize well across different domains and diverse linguistic structures. The rapid advancement of the field has led to techniques like in-context learning (ICL), which have further showcased the impressive generalization capabilities of LLMs, allowing them to adapt to new tasks and domains with minimal training data, often requiring only a few examples.

However, the effectiveness of these approaches remains uncertain in scenarios where pretrained models have limited prior knowledge of a language. This is particularly relevant for under-resourced languages, where training data is scarce or highly non-homogeneous. The performance of LLMs in these situations is not yet well understood, and it is unclear whether their impressive generalization capabilities can be replicated in all type of scenarios. This raises critical questions about the extent to which in-context learning and other recent innovations can bridge the gap in multilingual coverage.

In this work, we examine the generalization of LLMs in under-resourced settings through the task of orthographic normalization across Otomi language variants. We develop two approaches: a rule-based method using a finite-state transducer (FST) and an ICL approach that provides the model with string transduction examples. We focus on the scenarios that are particularly difficult for a transducer-based approach.

In-context learning. A paradigm where LLMs learn to perform tasks by recognizing patterns from a few provided examples (demonstrations). Unlike supervised learning, it requires no parameter updates or separate training stage. ICL enables models to make predictions by drawing analogies from the given context (Brown et al., 2020). It can be considered a form of generalization, but it has nuances compared to traditional machine learning (ML).

Although the mechanisms that underlie and influence this type of learning are not fully understood (Dong et al., 2024), it has proven successful in several domains. ICL can be applied in domains with minimal training data, requiring only a few examples. For example, multilingual tasks involving under-resourced languages such as machine translation and interlinear glossing (Coleman et al., 2024; Clarke et al., 2024; Ginn et al., 2024; Aycock et al., 2025).

Orthographic normalization This is the process of converting written text into a standardized form within a language. For many dominant languages with long-established writing conventions, this task is either well-solved or of limited concern. However, for numerous other languages, particularly those lacking a long tradition of standard-

[1] Code and data available at https://github.com/MCL-Lab-mx/fstvsicl

Findings of the Association for Computational Linguistics: EMNLP 2025, pages 15998–16006

Norm	Description	Ref
INALI	Norm by the National Institute of Indigenous Languages of Mexico	(Inali, 2014)
OTS	Standard used in some texts from variants in the State of Mexico	(De la Vega, 2017)
OTQ	Standard proposed mainly for Querétaro variants.	(Hekking and de Jesús, 1989)

Norm	Example sentence
INALI	[...]bijúgígó escuela pero ndichichithóhó
OTQ	[...]bijúgígó escuela pero nditxitxithóhó
OTS	[...]bikjúgígó escuela pero ndichichitjójó

Table 1: Otomi orthographic standards

ization due to sociopolitical factors, normalization remains a significant challenge. These languages often exhibit high internal diversity, making the task even more complex.

Otomi is a group of languages spoken in central Mexico (see Appendix A for geographical distribution) that are part of the Oto-Manguean language family. There are around nine dialectal variants (Lewis, 2009; INALI, 2008). Otomi is an endangered language group (around 300,000 speakers) that faces a scarcity of NLP tools and digital resources, plus there is orthographic variability, with several standards in use by the speakers.

Automatically converting text across the different standards is a crucial upstream task for developing more advanced language technologies. In low-resource settings, common approaches for building normalizers include designing FSTs based on linguistic expertise (Johny et al., 2021; O'neil et al., 2023) and applying neural models like seq2seq (Lusetti et al., 2018; Lutgen et al., 2025).

2 Data and Methods

2.1 Orthographic norms

This study focuses on the most common standards that can be found in Otomi written documents (Table 1).

Rule-based normalizer. We developed finite-state transducers (FST) to convert text between different Otomi orthographic standards (norms), using a two-step process: first, mapping source text to a phonetic alphabet (IPA), and then generating the target orthography. The transduction rules were informed by a linguist's expertise and existing documentation (Hernández-Green, 2016). The system was implemented using the HFST toolkit[2]. The FSTs converts text across standards without requiring a specified source norm. These rule-based normalizers have been integrated into an open repository[3] and a Python toolkit (Gutierrez-Vasques et al., 2025), allowing easy use.

Neural approaches (LLMs). If we already have rules for converting text across orthographic norms, costly neural network-based methods may be unnecessary. However, transducers have limitations, they lack flexibility and struggle to adapt to speakers' linguistic realities. We identify two key challenges where this approach falls short:

- Code-switching: Texts often include words from other languages, mainly Spanish and Nahuatl (e.g., *escuela* and *pero* in Table 1). Since FSTs apply rules that were specific for Otomi, handling these cases is challenging. Additionally, language identification tools for many indigenous languages are limited.

- Ambiguity: Instances where the same input can be mapped to multiple outputs. A transduction rule may be favored over others, sometimes leading to incorrect mappings. In Otomi, we observed that the same grapheme can be transcribed to different phonemes based on the orthographic norm of the source text. This phonological ambiguity can lead to errors, which can propagate to the target norm realization.

With these challenges in mind, we tried to leverage the generalization and adaptability of neural approaches to tackle these complex cases. Specifically, we focus on using LLMs with ICL.

2.2 Few shot examples and test set

To compare FSTs and neural approaches, we focus on two main settings: (a) OTS→INALI : OTS as the source norm and INALI as the target, and (b) OTS+OTQ→INALI : sentences in OTS or OTQ with INALI as the target[4]. The target norm is INALI as converting to this institutional standard is a common use case among speakers. It was therefore important to test how well computational methods handle this normalization.

To build the test datasets, we selected sentences[5] covering code-switching, ambiguity, and typical

[2]https://github.com/hfst/hfst/wiki

[3]https://github.com/ElotlMX/py-elotl/tree/master/elotl/otomi

[4]We omitted the OTQ→INALI case since both standards are similar. Instead, we created a more challenging setup

[5]Our dataset comes from a small Otomi corpus that compiles various sources and dialects: tsunkua.elotl.mx/

	OTS→INALI	OTS+OTQ→INALI
# sentences (test)	191	191
# sentences (few-shot)	10	10

Table 2: Datasets size for each normalization setting

transformations across written standards. The initial transduction for obtaining the different normalizations of the test sentences was performed using FSTs, followed by manual correction of errors. The test set contains 191 sentences, i.e., 4200 tokens. It is important to note that this dataset was specifically designed to include challenging cases. Although it is not huge, it focuses on difficult instances that we believe provide a meaningful evaluation of the different approaches.

Additionally, we manually selected 10 representative sentences as ICL demonstrations (Table 2). The selection was linguistically informed: we first applied a heuristic to filter sentences that cover the most common transduction changes across different norms. From this set, we prioritized those with code-switching and ambiguity.

Although our main focus is transduction to INALI, we also evaluated other directions using the same set of sentences converted across all norms.

The heuristic used to select these 10 examples (or demonstrations) is detailed in Appendix B.

2.3 LLMs

For the ICL neural approaches, we used the following base models: *GPT-3.5 Turbo, GPT-4o, LLaMA 3.1, and LLaMA 3.3*.

Zero-shot setting: We prompt the system to generate normalized test sentences without prior examples. For OTS→INALI, we explicitly specify the source and target norms. For OTS+OTQ→INALI, we do not specify the source norm, only that input sentences may come from either norm and should be transduced into INALI.

Few-shot setting: We provide models with 10-shot examples of orthographic transductions. For OTS→INALI we show 10 examples and specify that test sentences are in OTS, requiring INALI orthographic normalization. For OTS+OTQ→INALI, examples include transductions across INALI, OTS, and OTQ. During testing, the source norm is unspecified (either OTS or OTQ), and the model must generate the INALI normalization.

In all settings, we state the language and alert the system that there might be cases of code-switching and challenging transductions. The examples were always presented in the same order. See Appendix C for prompts and details about the models.

3 Findings and Interpretation

To compare model performance, we measure the error rate between predicted orthographic normalizations and gold standards using Word Error Rate (WER) and Character Error Rate (CER), the latter being particularly useful for morphologically rich languages (James et al., 2024). The overall results are shown in Figure 1, with detailed error-rate values reported in Table 3.

Both settings, OTS→INALI and OTS+OTQ→INALI, exhibit a similar trend: the rule-based FST approach outperforms state-of-the-art LLMs in orthographic normalization of Otomi text when they are prompted in a zero-shot setting. This is notable since FSTs are computationally lightweight compared to the extensive resources (data and infrastructure) required for training large neural models. Despite their robustness across many tasks, these LLMs struggle to generalize to orthographic variations in an under-resourced language like Otomi

Surprisingly, providing neural models with few-shot examples drastically improves their performance. Models like GPT-4o show some of the worst performances in a zero-shot setting. Still, with just 10 examples provided, the error rate decreases, outperforming FSTs and becoming the best model for orthographic normalization. See for example, GPT-4o_zero (*WER: 31.5% CER: 10.1%*) vs. GPT-4o_few (*WER: 11.2% CER: 2.6%*) in OTS→INALI.

The plots show a clear trend: LLMs make more errors than FSTs but surpass them in a few-shot setting, highlighting the effectiveness of ICL. Interestingly, the most recent models perform worst in zero-shot, contrary to expectations given their sophistication. We conjecture that they may prioritize specialized reasoning capabilities over multilingual flexibility. However, their ICL capability remains remarkable. Further exploration is needed.

Despite expectations, the OTS+OTQ→INALI setting yielded lower error rates, suggesting it was easier. We anticipated greater difficulty since neural models lacked source orthography information at test time. A possible reason is that OTQ and INALI are similar, with few character transformations, making sentences in this norm relatively easy to normalize, even without source orthography information at test time.

When INALI is not the target norm, ICL still

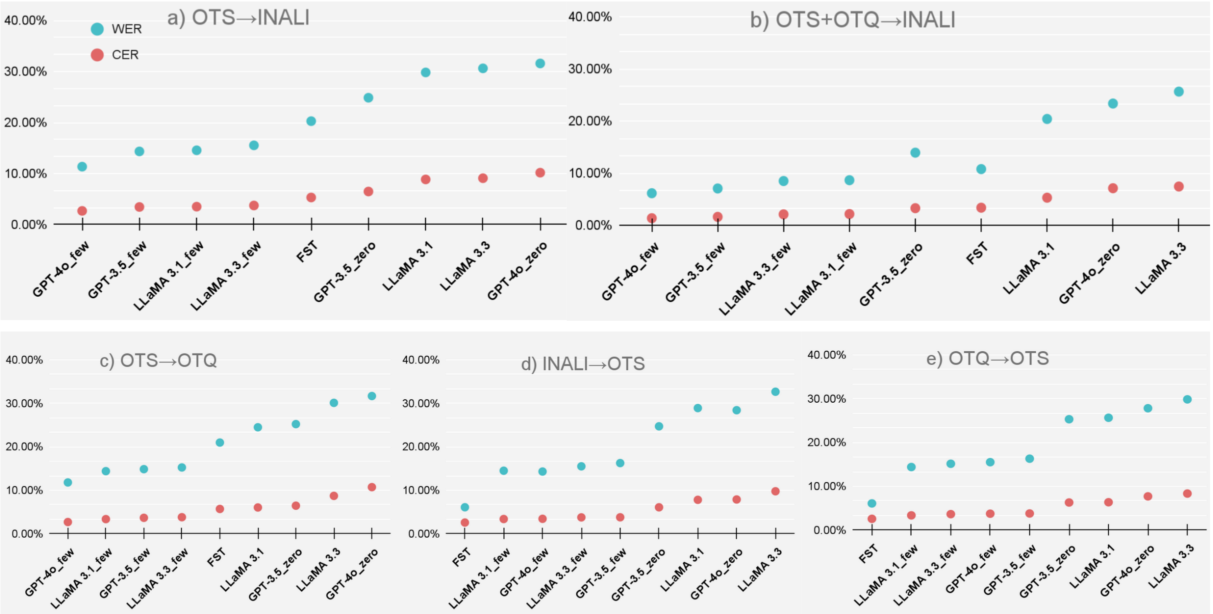

Figure 1: Performance of models for Otomi orthographic normalization. The Y-axis presents WER and CER, and the X-axis orders the models from the lowest to highest CER

helps, but LLMs don't consistently outperform the FST. In particular, LLMs struggle when the target is OTS. We conjecture this is likely due to the greater availability of digital data in INALI (a norm that represents an institutional effort to unify standards), whereas OTS is among the least represented norms online, limiting the effectiveness of pretrained models to generate text when OTS is the target.

Some studies suggest LLMs' sensitivity to input and target probabilities may affect their emergent capabilities, especially in rare languages and text sequences (McCoy et al., 2024).

3.1 Error analysis

We know that FSTs make mistakes when trying to normalize cases of code-switching and rule ambiguities since our approach has limited strategies to deal with that. But what errors are neural models most prone to? We analyzed test sentences with the highest CER and WER to answer this.

A key finding is that both zero-shot and few-shot neural models handle code-switching well, easily recognizing non-Otomi words and avoiding unnecessary transformations. This good handling performed by LLMs is expected for dominant languages like Spanish and English but also extends to proper names, place names, and loanwords of Nahuatl, an under-resourced language.

Errors in the few-shot setting mainly stemmed from failing to infer transduction rules (especially the ambiguous ones) and mixing up norms when

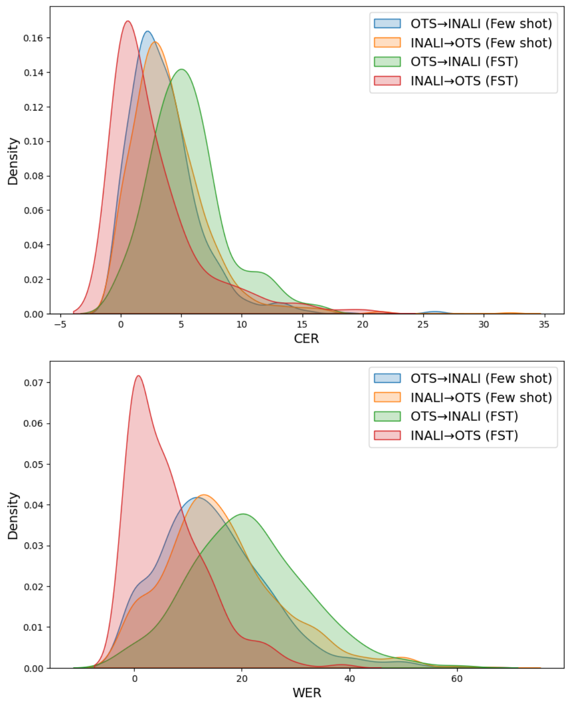

Figure 2: CER and WER distributions for test sentences under Few-shot and FST in OTS→INALI and INALI→OTS normalization tasks.

	OTS→INALI		OTS+OTQ→INALI		OTS →OTQ		INALI→OTS		OTQ→OTS	
	WER	CER	WER	CER	WER	CER	WER	CER	WER	CER
LLaMA 3.3_zero	30.62%	9.09%	25.65%	7.44%	30.11%	8.70%	32.67%	9.76%	29.85%	8.33%
LLaMA 3.3_few	15.53%	3.74%	8.49%	2.10%	15.24%	3.79%	15.50%	3.75%	15.14%	3.63%
LLaMA 3.1_zero	29.82%	8.85%	20.40%	5.29%	24.49%	6.03%	28.91%	7.79%	25.65%	6.35%
LLaMA 3.1_few	14.56%	3.51%	8.65%	2.16%	14.39%	3.35%	14.49%	3.37%	14.39%	3.35%
GPT-4o_zero	31.58%	10.17%	23.36%	7.11%	31.68%	10.71%	28.42%	7.87%	27.82%	7.69%
GPT-4o_few	**11.35%**	**2.68%**	**6.15%**	**1.36%**	**11.79%**	**2.68%**	14.30%	3.42%	15.50%	3.73%
GPT-3.5_zero	24.86%	6.48%	13.93%	3.28%	25.22%	6.44%	24.71%	6.07%	25.31%	6.29%
GPT-3.5_few	14.34%	3.45%	7.06%	1.61%	14.85%	3.65%	16.25%	3.77%	16.30%	3.78%
FST	20.27%	5.31%	10.78%	3.37%	20.97%	5.69%	**6.08%**	**2.56%**	**6.08%**	**2.56%**

Table 3: Detailed WERs and CERs for each orthographic normalization direction

trying to generate the target norm. In zero-shot, additional errors introduced noise, e.g., difficulty in handling the graphemes that correspond to vowels and tones of Otomi, the systems often modified them or added accent marks even though this was not required for the normalization (e.g., ä→aa, o̲→o, umbabihe →ūmbábihé), and hypercorrections that treated Otomi words as Spanish.

When changing the normalization direction where the target is not INALI, even with ICL, the LLMs' few-shot settings struggle to correctly capture some orthographic changes. For example, in the OTS→OTQ direction, the grapheme tj was erroneously replaced by ts (e.g., tjuts'i→tsuts'i instead of thuts'i). A particularly challenging case was the representation of tx in OTQ, which corresponds to ch in INALI and OTS. This convention, unique to OTQ, often caused LLMs to preserve the ch form (e.g., nchúi→nchúi instead of ntxúi). Conversely, false positives also appeared, such as normalizing tjo to txo when the expected form was tho.

Overall, FSTs make fewer errors when INALI is not the target norm, particularly when OTS is the target. This is probably because the transduction rules handle those specific cases more efficiently. However, when the target is INALI, FSTs tend to produce significantly more errors than LLMs (see Figure 2).

Original sentences vs gold standard: As a sanity check, we calculated error rates (WER, CER) between the source text and its INALI-standardized form (gold standard). These rates are typically high due to differences in written forms and should decrease when a normalization tool is applied. However, our case is unique since many test sentences contain code-switching, where several words should remain unchanged. This results in lower-than-expected error rates, making it unsuitable as a baseline. Still, few-shot models outperformed this measure. See Appendix D for details.

4 Conclusions

We explored the generalization limits of LLMs in an orthographic normalization task, which included building a rule-based system for converting Otomi text across norms and compared its performance against the neural approaches.

The test set was designed to assess the models capacity to normalize cases that are difficult for a rule-based approach, i.e., code-switching and ambiguous orthographic rules.

One of the main takeaways is that when working in a limited resource scenario, one can leverage knowledge of the language to build an FST, and this can be more effective than simply doing zero-shot prompting with sophisticated LLMs. However, once you have a FST you can use it to generate demonstrations of orthographic transductions across orthographic norms and use them to improve a neural model. Our results showed that LLMs surpass FSTs with just 10 examples in few-shot settings, they were particularly good in code-switching cases. However, we found that when the target orthography has very limited digital representation, even with ICL, LLMs struggle to produce normalized text with fewer errors than the FST.

In summary, this highlights the potential of ICL to generalize from limited data, reducing the reliance on extensive labeled datasets while reaffirming the value of linguistically informed data. This could be promising for many practical applications, including developing technologies for under-resourced languages.

Limitations

In this work, we examine the limits of LLMs' generalization through an orthographic normalization task using ICL approaches. While our conclusions are based on experimental results, a more comprehensive understanding of these limits may require testing across additional languages and tasks.

Although we cover the main orthographic norms used for this language, we excluded some lesser-used variants and phonological transcriptions. Phonological transcriptions were used for building the FSTs but not for the LLM approach.

Finally, while we demonstrated that combining LLMs with ICL and linguistic knowledge is a promising approach for orthographic normalization in under-resourced languages, practical considerations remain. The cost-benefit of using large models for relatively simple tasks should be evaluated, especially regarding accessibility for speakers and researchers working with these languages. Additionally, concerns about data handling in commercial systems must be addressed to ensure ethical and practical deployment.

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A Map

Figure 3: Geographical distribution of Otomi

B Selection of few-shot examples

Support set selection. First, we obtained sets of sentences grouped by phenomena of interest (code-switching and ambiguity). For each set, we manually ranked and selected sentences that were particularly informative, e.g., those sentences containing multiple instances of the phenomenon.

Besides covering problematic cases, we also wanted these examples to include the graphemes that can change across different orthographies. Therefore, we applied a second filter: we ranked the previously selected sentences by the count of graphemes that may vary between norms, so we can cover as many graphemes as possible.

Finally, we picked the top 10 sentences from the ranked candidates. This constitutes our few-shot examples (support set or demonstrations).

C Models and prompts

GPT-3.5 Turbo, GPT-4o, LLaMA 3.1, and *LLaMA 3.3* were used with default hyperparameters, setting a temperature of 0.2 via the API.

The LLaMA models were trained with 70B parameters, while the exact parameter count for GPT models is not publicly available.

Our choice of temperature was somewhat arbitrary, following prior ICL studies on underrepresented languages that used this hyperparameter —though not specifically for orthographic normalization (Ginn et al., 2024). We acknowledge that this methodological decision could be refined to ensure greater statistical robustness and reproducibility.

The choice of models was guided primarily by their availability through an API, which was necessary for seamless integration into our experimental pipeline. OpenAI and Meta are two leading providers offering robust APIs and hosting widely used large language models. We selected the most recent models available at that time.

- Prompt for OTS→INALI (few-shot)

```
Below are examples of orthographic conversions
    of strings from the OTS standard (State of
    Mexico Otomi) to the INALI standard for the
    Otomi language. Note that some loanwords
    retain their original orthography, and
    certain linguistic phenomena may affect the
    transformations.

Examples:

1. OTS: r'atsa noya ra sahagún: ndäxkjua k'oi
    florentino. j̲em'i xiii, x̲eni xiii (versión
    del náhuatl por ángel ma. garibay k.).
 INALI: r'atsa noya ra sahagún: ndäxjua k'oi
    florentino. h̲em'i xiii, x̲eni xiii (versión
    del náhuatl por ángel ma. garibay k.).

2. [...]
```

Task:

Using these examples as a guide, predict the INALI orthographic standardization for the following sentence. Return only the standardized sentence without any explanation.

OTS: (test sentence)

INALI: [Your prediction here]

- Prompt for OTS+OTQ→INALI (few-shot)

Below are examples of orthographic conversions of strings from the OTS standard (State of Mexico Otomi) and the OTQ standard (Otomi of Queretaro) to the INALI standard for the Otomi language. Note that some loanwords retain their original orthography, and certain linguistic phenomena may affect the transformations.

Examples:

1. OTS: r’atsa noya ra sahagún: ndäxkjua k’oi florentino. je̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).
   OTQ: r’atsa noya ra sahagún: ndäxjua k’oi florentino. he̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).
   INALI: r’atsa noya ra sahagún: ndäxjua k’oi florentino. he̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).

2. [...]

Task:

Using these examples as a guide, predict the INALI orthographic standardization for the following sentence. The sentence originates from either the OTS or OTQ standards, but its source is unspecified. Return only the standardized sentence without any explanation.

Sentence: (test sentence)

INALI: [Your prediction here]

- Prompt for OTS→INALI (zero-shot)

Predict the INALI orthographic standardization for the following Otomi sentence written in the OTS standard (State of Mexico Otomi) (please return only the normalized sentences, no explanations). Note that some loanwords retain their original orthography, and certain linguistic phenomena may affect the transformations.

OTS: (test sentence)

INALI: [Your prediction here]

- Prompt for OTS+OTQ→INALI (zero-shot)

predict the INALI orthographic standardization for the following sentence. The sentence originates from either the OTS (State of Mexico Otomi) or OTQ (Queretaro Otomi) standards, but its source is unspecified. Return only the standardized sentence without any explanation.

Sentence: (test sentence)

INALI: [Your prediction here]

- Prompt for OTQ→OTS (few-shot)

Below are examples of orthographic conversions of strings from the OTQ standard (Queretaro Otomi) to the OTS standard (State of Mexico Otomi) for the Otomi language. Note that some loanwords retain their original orthography, and certain linguistic phenomena may affect the transformations.

Examples:

1. OTQ: r’atsa noya ra sahagún: ndäxjua k’oi florentino. he̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).
   OTS: r’atsa noya ra sahagún: ndäxkjua k’oi florentino. je̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).

2. [...]

Task:

Using these examples as a guide, predict the OTS orthographic standardization for the following sentence. Return only the standardized sentence without any explanation.

OTQ: (test sentence)

OTS: [Your prediction here]

- Prompt for INALI→OTS (few-shot)

Below are examples of orthographic conversions of strings from the INALI standard to the OTS standard (State of Mexico Otomi) for the Otomi language. Note that some loanwords retain their original orthography, and certain linguistic phenomena may affect the transformations.

Examples:

1. INALI: r’atsa noya ra sahagún: ndäxjua k’oi florentino. he̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).
   OTS: r’atsa noya ra sahagún: ndäxkjua k’oi florentino. je̱m’i xiii, xe̱ni xiii (versión del náhuatl por ángel ma. garibay k.).

2. [...]

Task:

```
Using these examples as a guide, predict the OTS
     orthographic standardization for the
     following sentence. Return only the
     standardized sentence without any
     explanation.

INALI: ( test sentence )

OTS: [Your prediction here]
```

- Prompt for OTS→OTQ (few-shot)

```
Below are examples of orthographic conversions
     of strings from the OTS standard (State of
     Mexico Otomi) to the OTQ standard (Queretaro
     Otomi) for the Otomi language. Note that
     some loanwords retain their original
     orthography, and certain linguistic
     phenomena may affect the transformations.

Examples:

1. OTS: r'atsa noya ra sahagún: ndäxkjua k'oi
     florentino. jem'i xiii, xeni xiii (versión
     del náhuatl por ángel ma. garibay k.).
OTQ: r'atsa noya ra sahagún: ndäxjua k'oi
     florentino. hem'i xiii, xeni xiii (versión
     del náhuatl por ángel ma. garibay k.).

2. [...]

Task:

Using these examples as a guide, predict the OTQ
     orthographic standardization for the
     following sentence. Return only the
     standardized sentence without any
     explanation.

OTS: ( test sentence )

OTQ: [Your prediction here]
```

- Prompt for OTQ→OTS (zero-shot)

```
Predict the OTS orthographic standardization (
     State of Mexico Otomi) for the following
     Otomi sentence written in the OTQ standard (
     Queretaro Otomi) (please return only the
     normalized sentences, no explanations). Note
     that some loanwords retain their original
     orthography, and certain linguistic
     phenomena may affect the transformations.

OTQ: ( test sentence )

OTS: [Your prediction here]
```

- Prompt for INALI→OTS (zero-shot)

```
Predict the OTS orthographic standardization (
     State of Mexico Otomi) for the following
     Otomi sentence written in the INALI standard
     (please return only the normalized
     sentences, no explanations). Note that some
     loanwords retain their original orthography,
     and certain linguistic phenomena may affect
     the transformations.

INALI: ( test sentence )

OTS: [Your prediction here]
```

- Prompt for OTS→OTQ (zero-shot)

```
Predict the OTQ orthographic standardization (
     Queretaro Otomi) for the following Otomi
     sentence written in the OTS standard (State
     of Mexico Otomi) (please return only the
     normalized sentences, no explanations). Note
     that some loanwords retain their original
     orthography, and certain linguistic
     phenomena may affect the transformations.

OTS: ( test sentence )

OTQ: [Your prediction here]
```

D Original sentences vs gold standard

The following plots show the WER and CER for the different models. We have added a dotted line that indicates the error rate when comparing the source text and its INALI standardized form (gold standard), i.e., how dissimilar the source and target sentence are when no normalizer has been applied.