

# Investigating Multi-Pivot Ensembling with Massively Multilingual Machine Translation Models

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## Abstract

Massively multilingual machine translation models allow for the translation of a large number of languages with a single model, but have limited performance on low- and very-low-resource translation directions. Pivoting via high-resource languages remains a strong strategy for low-resource directions, and in this paper we revisit ways of pivoting through multiple languages. Previous work has used a simple averaging of probability distributions from multiple paths, but we find that this performs worse than using a single pivot, and exacerbates the hallucination problem because the same hallucinations can be probable across different paths. We also propose MaxEns, a novel combination strategy that makes the output biased towards the most confident predictions, hypothesising that confident predictions are less prone to be hallucinations. We evaluate different strategies on the FLORES benchmark for 20 low-resource language directions, demonstrating that MaxEns improves translation quality for low-resource languages while reducing hallucination in translations, compared to both direct translation and an averaging approach. On average, multi-pivot strategies still lag behind using English as a single pivot language, raising the question of how to identify the best pivoting strategy for a given translation direction.<sup>1</sup>

## 1 Introduction

Early work on multilingual neural machine translation (NMT) has explored combining source segments in different source languages (Zoph and Knight, 2016; Firat et al., 2016a), an idea that is also compatible with pivoting through intermediate languages. For example, one could translate from Dutch to Ukrainian by first translating the Dutch source to English and Russian, and then

making a combined prediction to Ukrainian. In the simplest case, this combination is achieved by predicting probability distributions for each source language and averaging these predictions in an ensemble-like manner (Firat et al., 2016a).

With massively multilingual NMT models (NLLB Team et al., 2022; Mohammadshahi et al., 2022a; Goyal et al., 2022; Wenzek et al., 2021; Zhang et al., 2020; Fan et al., 2021; Aharoni et al., 2019; Arivazhagan et al., 2019), one can in principle translate directly in any translation direction. While early models relied on zero-shot generalization for many directions, recent improvements include massive data collection efforts (Schwenk et al., 2021; El-Kishky et al., 2020) and synthetic data creation via back-translation (Edunov et al., 2018; Sennrich et al., 2016). However, these models still have low performance on many low-resource translation directions<sup>2</sup> and pivoting via high-resource languages remains a strong baseline. Fan et al. (2021) also investigate the combination of multiple translation paths, which they call *multi-source self-ensemble*, that slightly improves over the direct translation and a single pivot for zero-shot language pairs.

In this paper, we investigate this multi-source self-ensembling strategy more closely, with a focus on preventing completely defunct translations such as hallucinations. However, we find that simple averaging is sub-optimal and may increase the number of hallucinations in the output, a typical failure case in low-resource settings. We relate this to a recent finding that hallucinations are *sticky*, meaning that different models trained on the same data and architecture may produce similar hallucinations (Guerreiro et al., 2023a). We also find evidence of such stickiness when combining multiple translation paths, and propose a new ensembling strategy that, instead of averaging probabilities, picks the

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<sup>1</sup>The implementation is publicly available at <https://github.com/ZurichNLP/MultiPivotNMT>.

<sup>2</sup>SentencePiece BLEU of 63% translation directions in M2M-100 is lower than 12 (Mohammadshahi et al., 2022b).

output with the maximum probability across different paths: **MaxEns**. This is partially inspired by the finding that model confidence is a good heuristic for avoiding hallucinations, which tend to be low-confidence predictions (Guerreiro et al., 2023b).

We perform experiments on the FLORES benchmark (Goyal et al., 2022) for 20 low-resource translation directions by using two massively multilingual NMT models, SMaLL100 (Mohammadshahi et al., 2022a) and M2M100 (Fan et al., 2021). Our results show that while the average ensemble outperforms the direct translation, it still underperforms using only English as a pivot, both in terms of spBLEU and the number of hallucinations. MaxEns performs significantly better than the averaging strategy for both translation performance and hallucination. Specially, MaxEns has competitive translation performance with English pivoting on average, but still lags behind it on the hallucination performance. To sum up, our contributions are:

- We explore why a naive multi-pivot strategy with massively multilingual models can underperform single-pivot translation. Then, we propose MaxEns, a more robust ensembling technique for multi-pivot translation with multilingual NMT models.
- We evaluate different ensembling strategies on 20 low-resource translation directions of FLORES benchmark, and demonstrate that multi-pivot ensembling still lags behind the English pivoting.

## 2 Related Work

Several approaches exploited different multi-pivoting methods to improve the performance of NMT models, specifically for low-resource language directions (Macháček et al., 2023; Dabre et al., 2021; Kim et al., 2019; Cheng et al., 2017; Firat et al., 2016b). Macháček et al. (2023) analyzed the robustness of multi-source NMT in transcription errors. Dabre et al. (2021) improved the performance of simultaneous NMT by translating the source language into pivot languages, then applying the multi-source translation method (Zoph and Knight, 2016). Firat et al. (2016b) proposed a novel zero-resource translation approach by exploiting the multi-way multilingual NMT model, introduced by Firat et al. (2016a), and improved the performance over traditional pivot-based translation (Wu and Wang,

2007; Utiyama and Isahara, 2007). Cheng et al. (2017) introduced the pivot-based NMT model by jointly training source-to-pivot and pivot-to-target directions. Currey and Heafield (2019) proposed an alternative method by applying a monolingual pivot-language data for zero-resource NMT via back-translation (Sennrich et al., 2016).

## 3 Ensembling Methods

When performing direct translation, the score of a translation  $Y$  given a source sequence  $X_{src}$  is computed as follows:

$$s(Y; X_{src}) = \sum_{i=1}^{|Y|} \log p(y_i | y_{<i}, X_{src}) \quad (1)$$

where  $p(y_i | y_{<i}, X_{src})$  is the predicted probability of the  $i$ -th target token  $y_i$  given the previous tokens  $y_{<i}$  and the source sequence  $X_{src}$ .

For multi-pivot ensembling, we select a set of pivot languages  $M = \{\mu_1, \mu_2, \dots, \mu_K\}$  and generate the corresponding pivot translations  $X_M = \{X_{\mu_1}, X_{\mu_2}, \dots, X_{\mu_K}\}$ . The final translation is generated by ensembling predictions, conditioned on the individual pivot translations.

In the following, we describe two approaches for such an ensembling: the multilingual averaging method and our MaxEns approach.

**Multilingual Average (MultiAvg).** Inspired by Fan et al. (2021); Firat et al. (2016b), we average the predicted probabilities of a token  $y_i$  across all pivot languages:<sup>3</sup>

$$s(Y; X_M) = \sum_{i=1}^{|Y|} \log \frac{1}{|M|} \sum_{k=1}^{|M|} p(y_i | y_{<i}, X_{\mu_k}). \quad (2)$$

where  $|Y|$  and  $|M|$  are the number of target tokens and pivots, respectively.

**Maximum Ensemble (MaxEns).** As novel combination strategy that biases the prediction towards the more confident pivot, we propose the following approach:

$$s(Y; X_M) = \sum_{i=1}^{|Y|} \max_{k=1}^{|M|} [\log p(y_i | y_{<i}, X_{\mu_k})]. \quad (3)$$

<sup>3</sup>We tried both averaging probabilities and log-probabilities in preliminary experiments, and averaging probabilities worked better in terms of translation performance and hallucination.

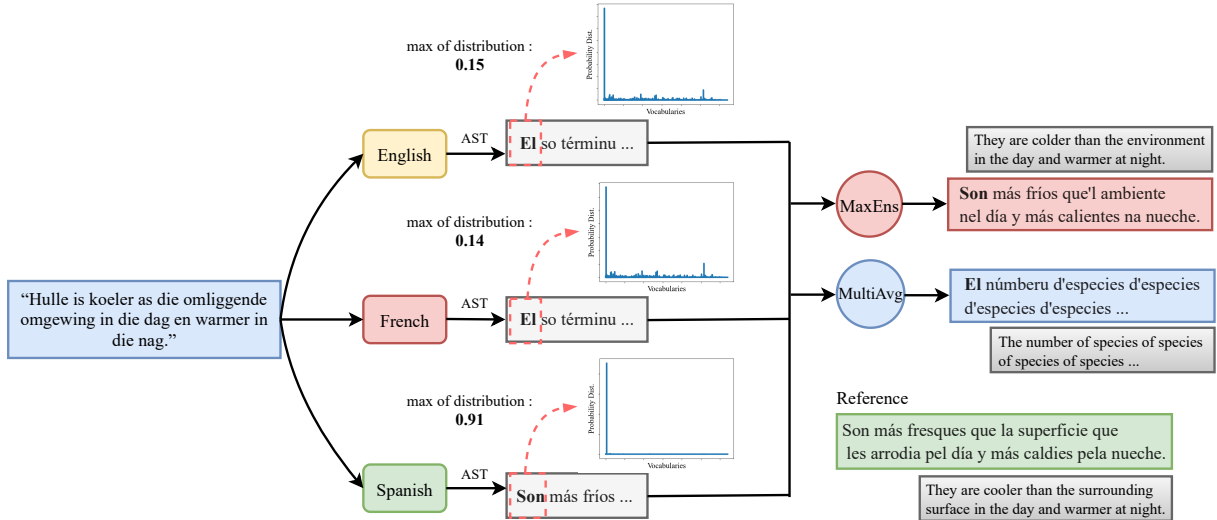


Figure 1: A sample translation of Afrikaans to Asturian by using SMA1100. Translations of individual pivots are shown in the middle, output translations of MaxEns and MultiAvg on the right. MaxEns method eliminates the hallucination, as it follows the more confident pivot (here, Spanish). Glosses in English are presented within gray boxes.

where it chooses the maximum score between predictions of pivots for token  $y_i$ . Intuitively, MaxEns selects the most confident pivot language when generating token  $y_i$ .

## 4 Results and Discussion

### 4.1 Experimental Setup

**Models.** We used M2M100 and SMA1100 as our massively multilingual NMT models. M2M100 is trained on large-scale multilingual corpora (Schwenk et al., 2021; El-Kishky et al., 2020) with a novel data mining procedure, that uses language similarities. We exploit M2M100 variant with 418M parameters. SMA1100 (Mohammadshahi et al., 2022a) is a distilled version of M2M100 12B with 330M parameters. It has been trained with uniform sampling across all language pairs on nearly 6% of M2M100 pre-training dataset, and achieved competitive performance with M2M100 with 1.2B parameters.

**Evaluation Setting.** Inspired by Fan et al. (2021), we use the FLORES-101 benchmark (Goyal et al., 2022). It contains 3,001 sentences derived from English Wikipedia, and translated into 101 languages by human. We use the *devtest* subset for the evaluation. To better understand the effect of multilingual pivoting, we chose five low-resource (or very low) languages from different branches of Indo-European, including Germanic, Romance, Slavic, Indo-Aryan, and Iranian. These languages are Afrikaans, Asturian, Croatian, Urdu, and

Pashto. We evaluate on all permutations of these languages, which results in 20 language pairs. As pivot languages, we use English, Spanish and French. English has the largest amount of bitext overall in the training data of M2M100, and Spanish and French have the largest amount of bitext with English (Fan et al., 2021).

**Evaluation Metrics.** spBLEU<sup>4</sup> is used to measure the translation performance (Goyal et al., 2022). For the hallucination measurement, we apply a coarse estimation method inspired by Lee et al. (2019); Müller and Sennrich (2021), counting the proportion of sentences with ChrF (Popović, 2015)<sup>5</sup> less than 20.<sup>6</sup> Additionally, we use top n-gram (TNG) (Guerreiro et al., 2023b; Raunak et al., 2022, 2021) for detecting oscillatory hallucinations.<sup>7</sup> We apply significance testing with  $p=0.05$ .<sup>8</sup> Beam size 5 is used for inference.

### 4.2 Results & Discussion

Figure 1 illustrates an example of multi-pivot translation of Afrikaans to Asturian by using English, French, and Spanish as pivots. Translations via English and French pivots are hallucinations, while the translation via the Spanish pivot is more related to the reference translation. The output of MaxEns

<sup>4</sup>BLEU is computed after tokenization with SentencePiece with 256K tokens (Goyal et al., 2022).

<sup>5</sup>sacrebleu 2.3.1 (Post, 2018) with ChrF3 is used.

<sup>6</sup>Threshold based on manual inspection.

<sup>7</sup>We follow Guerreiro et al. (2023b) and use  $n=4$  and  $t=2$ .

<sup>8</sup>Paired bootstrap resampling (Koehn, 2004) with sacrebleu.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	20.6	21.8	<b>22.5</b>	21.0
Afrikaans-Croatian	22.1	22.5	22.4	<b>22.8</b>
Afrikaans-Urdu	14.0	13.8	13.9	<b>14.4</b>
Afrikaans-Pashto	<b>5.9</b>	<b>5.8</b>	<b>6.0</b>	<b>6.0</b>
Asturian-Afrikaans	18.5	19.9	19.8	<b>21.0</b>
Asturian-Croatian	16.1	<b>20.4</b>	20.0	<b>20.4</b>
Asturian-Urdu	8.4	11.8	11.8	<b>12.6</b>
Asturian-Pashto	3.6	5.0	5.0	<b>5.4</b>
Croatian-Afrikaans	20.5	20.7	20.8	<b>21.2</b>
Croatian-Asturian	19.7	20.8	<b>21.6</b>	19.7
Croatian-Urdu	<b>13.5</b>	13.1	12.9	13.2
Croatian-Pashto	5.0	5.2	5.2	<b>5.6</b>
Urdu-Afrikaans	12.1	13.0	13.2	<b>13.8</b>
Urdu-Asturian	7.7	11.7	<b>12.8</b>	12.2
Urdu-Croatian	11.2	<b>12.0</b>	<b>11.9</b>	<b>12.2</b>
Urdu-Pashto	<b>4.7</b>	<b>4.4</b>	4.2	<b>4.6</b>
Pashto-Afrikaans	10.2	11.0	11.0	<b>11.4</b>
Pashto-Asturian	6.9	9.9	<b>10.9</b>	10.4
Pashto-Croatian	8.7	<b>9.9</b>	<b>10.0</b>	<b>9.8</b>
Pashto-Urdu	<b>10.0</b>	9.2	9.2	9.5
Average	12.0	13.1	<b>13.3</b>	<b>13.4</b>

Table 1: Average spBLEU (higher is better) of different pivoting methods for M2M100 and SMaLL100 on selected language pairs of FLORES-101. Best systems (not significantly outperformed by any other) in bold.

approach is closer to the translation achieved by using Spanish as the pivot language, since the NMT model is more confident for this pivot (maximum of output probability distributions for the first token of English, French, and Spanish pivots are 0.15, 0.14, and 0.91, respectively). In contrast, the output of the MultiAvg method is a hallucination. Tables 1 and 2 show translation and hallucination performances on 20 language directions, respectively.<sup>9</sup> TNG scores for measuring oscillatory hallucinations are provided in Appendix B. MultiAvg approach achieves better translation performance and lower hallucination compared to the direct translation. However, MultiAvg method lags behind the English pivoting approach in terms of both translation quality (13.4 vs. 13.1) and the occurrence of hallucinations (18.8% vs. 22.5%).<sup>10</sup> Applying the MaxEns method instead for combining pivots tightens this gap, and leads to better translation and reduces the occurrence of hallucinations. Specifically, MaxEns reaches competitive translation quality with English

<sup>9</sup>Average scores of M2M100 and SMaLL100 are shown in Table 1 and 2. Individual scores are provided in Appendix A.

<sup>10</sup>4.5% vs. 7.3% based on the TNG metric, as shown in Table 7.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	5.9	6.4	4.0	4.3
Afrikaans-Croatian	1.7	2.2	2.2	1.9
Afrikaans-Urdu	11.3	13.9	13.4	11.1
Afrikaans-Pashto	49.5	54.1	53.2	49.8
Asturian-Afrikaans	8.8	6.2	7.8	2.1
Asturian-Croatian	19.5	5.3	8.2	3.5
Asturian-Urdu	40.7	23.4	22.9	18.0
Asturian-Pashto	66.7	62.2	62.2	55.9
Croatian-Afrikaans	1.1	1.5	1.2	1.3
Croatian-Asturian	6.1	6.3	3.8	5.0
Croatian-Urdu	13.2	16.5	16.3	12.7
Croatian-Pashto	54.7	58.4	56.6	53.1
Urdu-Afrikaans	9.8	9.2	9.4	4.9
Urdu-Asturian	31.5	19.9	14.7	12.5
Urdu-Croatian	14.1	15.4	15.5	11.8
Urdu-Pashto	56.8	66.0	66.8	60.1
Pashto-Afrikaans	9.1	10.5	10.0	6.6
Pashto-Asturian	26.9	21.2	15.7	15.6
Pashto-Croatian	18.4	18.5	18.7	16.7
Pashto-Urdu	24.7	33.2	33.3	28.9
Average	23.5	22.5	21.8	18.8

Table 2: Average percentage (100%) of hallucinations (chrF < 20; lower is better) of different pivoting methods for M2M100 and SMaLL100 on selected language pairs of FLORES-101.

pivoting on average (13.3 vs. 13.4), while still underperforming on hallucinations, as most of the parallel sentences of pre-training data for M2M100 and SMaLL100 are paired with English.

In general, the optimal strategy differs across translation directions, highlighting the potential for future research on determining the most effective translation strategy for each direction without depending on the development data for each.

## 5 Conclusion

We investigate more closely the multi-source self-ensembling method of Fan et al. (2021) for combining multiple translation paths to improve translations of low-resource (or very-low) language pairs. Specifically, this approach (named MultiAvg, here) averages the predictions of probability distributions of each source language in an ensemble-like manner. We evaluated it on 20 low-resource language pairs of FLORES-101 benchmark by using two massively multilingual NMT models, SMaLL100 and M2M100. The MultiAvg method performs better than direct translation in terms of both translation quality and hallucinations, however it lags behind applying only English as pivot. Then, we proposed MaxEns method, a novel combination

method that chooses the maximum of prediction probabilities of pivots for each designated target token. This approach results in a better translation quality compared to MultiAvg, while reducing hallucinations. On average, it achieves competitive performance with English pivoting with regard to the translation quality metric, but performs worse with regard to the hallucination metric. The most effective translation strategy varies depending on the translation direction, suggesting the need for future research to identify the optimal strategy for each direction independently of the specific development data. We hope our findings are a starting point for the broader integration of ensemble techniques within the context of massively multilingual NMT.

The insights of our experiments, specifically the stickiness of hallucinations with different inputs, have inspired our follow-up work on source-contrastive decoding (Sennrich et al., 2024), which has empirically shown to be an effective strategy to mitigate hallucinations. Future work could revisit multi-pivot ensembling in combination with source-contrastive decoding.

## Limitations

We apply our method to two common massively multilingual NMT models, SMALL100 and M2M100; future work can extend our work to more recent large models e.g. NLLB200 (NLLB Team et al., 2022) and LLMs (Touvron et al., 2023; Workshop et al., 2022). We tested our approach on a subset of 20 low-resource language directions, future research can study the method for further language directions, including medium-resource language pairs.

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## Appendix A Individual Scores of M2M100 and SMaLL100 Models

### A.A M2M100 Results

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	19.3	20.2	<b>21.0</b>	20.2
Afrikaans-Croatian	<b>20.8</b>	<b>21.1</b>	<b>21.0</b>	<b>21.4</b>
Afrikaans-Urdu	14.0	13.6	13.8	<b>14.4</b>
Afrikaans-Pashto	<b>5.4</b>	<b>5.4</b>	<b>5.5</b>	<b>5.6</b>
Asturian-Afrikaans	14.2	16.5	16.1	<b>18.0</b>
Asturian-Croatian	11.1	<b>19.0</b>	18.3	<b>19.4</b>
Asturian-Urdu	6.3	11.4	11.4	<b>12.6</b>
Asturian-Pashto	2.4	4.4	4.5	<b>5.0</b>
Croatian-Afrikaans	17.6	<b>17.9</b>	<b>17.9</b>	<b>18.2</b>
Croatian-Asturian	18.8	19.5	<b>20.6</b>	19.1
Croatian-Urdu	<b>13.6</b>	13.3	13.1	<b>13.4</b>
Croatian-Pashto	4.4	4.9	4.9	<b>5.4</b>
Urdu-Afrikaans	9.0	9.8	10.0	<b>10.6</b>
Urdu-Asturian	7.1	9.9	<b>10.8</b>	<b>10.9</b>
Urdu-Croatian	8.9	<b>10.0</b>	<b>9.8</b>	<b>10.1</b>
Urdu-Pashto	<b>4.2</b>	3.8	3.6	<b>4.2</b>
Pashto-Afrikaans	8.3	<b>9.3</b>	8.9	<b>9.3</b>
Pashto-Asturian	7.8	9.6	<b>10.4</b>	9.7
Pashto-Croatian	8.0	<b>9.0</b>	<b>9.0</b>	8.5
Pashto-Urdu	<b>9.8</b>	8.9	8.9	9.0
Average	10.6	11.9	12.0	<b>12.2</b>

Table 3: spBLEU (higher is better) of different pivoting methods for M2M100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark. Best systems (not significantly outperformed by any other) in bold.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	7.0	8.8	5.0	3.6
Afrikaans-Croatian	2.6	2.6	2.4	2.3
Afrikaans-Urdu	12.2	15.5	14.5	11.5
Afrikaans-Pashto	53.6	59.7	57.0	54.8
Asturian-Afrikaans	15.7	10.0	13.0	2.8
Asturian-Croatian	35.0	7.3	12.6	4.4
Asturian-Urdu	55.8	26.7	27.3	18.4
Asturian-Pashto	73.4	68.0	67.8	58.6
Croatian-Afrikaans	1.4	1.9	1.5	1.7
Croatian-Asturian	6.5	8.4	4.5	3.9
Croatian-Urdu	13.3	17.0	16.4	13.6
Croatian-Pashto	59.1	62.0	58.8	57.5
Urdu-Afrikaans	15.2	14.5	14.8	7.7
Urdu-Asturian	38.9	28.0	21.5	15.9
Urdu-Croatian	20.3	22.3	22.2	17.9
Urdu-Pashto	60.2	72.7	73.3	65.1
Pashto-Afrikaans	11.5	12.8	12.7	9.0
Pashto-Asturian	23.1	25.1	17.9	18.0
Pashto-Croatian	20.5	21.6	22.5	21.1
Pashto-Urdu	26.6	35.9	35.5	31.9
Average	27.6	26.0	25.0	21.0

Table 4: The percentage of hallucinations ( $\text{chrF} < 20$ ; lower is better) of different pivoting methods for M2M100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark.

## A.B SMaLL100 Results

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	22.0	23.4	<b>24.0</b>	21.7
Afrikaans-Croatian	23.5	<b>23.9</b>	<b>23.8</b>	<b>24.1</b>
Afrikaans-Urdu	13.9	14.0	14.0	<b>14.4</b>
Afrikaans-Pashto	<b>6.4</b>	6.1	<b>6.4</b>	<b>6.4</b>
Asturian-Afrikaans	22.8	<b>23.3</b>	<b>23.4</b>	<b>23.8</b>
Asturian-Croatian	21.1	<b>21.8</b>	<b>21.6</b>	<b>21.4</b>
Asturian-Urdu	10.5	12.1	12.2	<b>12.5</b>
Asturian-Pashto	4.8	<b>5.6</b>	<b>5.5</b>	<b>5.7</b>
Croatian-Afrikaans	23.4	23.4	23.7	<b>24.2</b>
Croatian-Asturian	20.6	<b>22.1</b>	<b>22.5</b>	20.2
Croatian-Urdu	<b>13.3</b>	12.8	12.6	<b>13.0</b>
Croatian-Pashto	<b>5.6</b>	<b>5.4</b>	<b>5.4</b>	<b>5.8</b>
Urdu-Afrikaans	15.1	16.1	16.3	<b>17.0</b>
Urdu-Asturian	8.3	13.4	<b>14.8</b>	13.4
Urdu-Croatian	13.4	14.0	13.9	14.3
Urdu-Pashto	<b>5.1</b>	<b>5.0</b>	<b>4.8</b>	<b>5.0</b>
Pashto-Afrikaans	12.0	12.7	12.9	<b>13.5</b>
Pashto-Asturian	6.0	10.2	<b>11.3</b>	<b>11.1</b>
Pashto-Croatian	9.4	<b>10.8</b>	<b>11.0</b>	<b>11.0</b>
Pashto-Urdu	<b>10.2</b>	9.5	9.4	9.9
Average	13.4	14.3	<b>14.5</b>	<b>14.4</b>

Table 5: spBLEU (higher is better) of different pivoting methods for SMaLL100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark. Best systems (not significantly outperformed by any other) in bold.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	4.7	4.1	2.9	5.0
Afrikaans-Croatian	0.9	1.9	2.1	1.5
Afrikaans-Urdu	10.4	12.3	12.2	10.8
Afrikaans-Pashto	45.4	48.4	49.4	44.8
Asturian-Afrikaans	1.9	2.5	2.6	1.5
Asturian-Croatian	4.1	3.3	3.9	2.7
Asturian-Urdu	25.6	20.1	18.5	17.5
Asturian-Pashto	59.9	56.5	56.7	53.3
Croatian-Afrikaans	0.8	1.1	0.9	0.9
Croatian-Asturian	5.6	4.2	3.1	6.1
Croatian-Urdu	13.2	16.0	16.1	11.8
Croatian-Pashto	50.3	54.7	54.5	48.7
Urdu-Afrikaans	4.4	4.0	4.0	2.1
Urdu-Asturian	24.1	11.8	7.9	9.0
Urdu-Croatian	7.9	8.5	8.8	5.7
Urdu-Pashto	53.4	59.3	60.3	55.2
Pashto-Afrikaans	6.7	8.3	7.3	4.2
Pashto-Asturian	30.7	17.3	13.6	13.2
Pashto-Croatian	16.4	15.4	14.9	12.4
Pashto-Urdu	22.7	30.5	31.1	25.9
Average	19.5	19.0	18.5	16.6

Table 6: The percentage of hallucinations ( $\text{chrF} < 20$ ; lower is better) of different pivoting methods for SMaLL100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark.

## Appendix B Results of oscillatory hallucinations based on TNG metric

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	2.2	2.1	0.7	1.3
Afrikaans-Croatian	0.3	0.3	0.2	0.2
Afrikaans-Urdu	1.2	1.5	1.1	0.6
Afrikaans-Pashto	6.7	6.7	5.1	4.7
Asturian-Afrikaans	5.1	3.0	3.9	0.2
Asturian-Croatian	11.9	1.5	3.0	0.4
Asturian-Urdu	15.7	4.1	4.3	0.7
Asturian-Pashto	20.9	12.8	11.6	5.0
Croatian-Afrikaans	0.1	0.2	0.2	0.0
Croatian-Asturian	2.2	2.0	1.0	1.2
Croatian-Urdu	1.5	1.3	1.1	0.5
Croatian-Pashto	7.2	6.4	4.9	4.3
Urdu-Afrikaans	8.2	3.3	3.3	0.9
Urdu-Asturian	15.8	6.2	4.0	2.4
Urdu-Croatian	2.5	2.6	2.8	0.8
Urdu-Pashto	9.3	11.7	9.5	4.2
Pashto-Afrikaans	2.7	3.6	3.5	0.8
Pashto-Asturian	16.0	6.2	4.1	2.0
Pashto-Croatian	3.6	2.9	3.0	1.0
Pashto-Urdu	2.5	4.8	4.3	1.6
Average	7.3	4.5	4.0	1.9

Table 7: Average percentage (100%) of hallucinations (TNG metric; lower is better) of different pivoting methods for M2M100 and SMaLL100 on selected language pairs of FLORES-101.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	1.8	2.6	1.1	0.5
Afrikaans-Croatian	0.5	0.49	0.2	0.3
Afrikaans-Urdu	1.9	2.7	1.6	0.9
Afrikaans-Pashto	10.4	11.6	9.1	8.0
Asturian-Afrikaans	9.8	5.6	6.8	0.2
Asturian-Croatian	22.6	2.5	5.2	0.4
Asturian-Urdu	25.3	7.6	7.7	1.2
Asturian-Pashto	36.8	23.6	21.3	9.2
Croatian-Afrikaans	0.1	0.2	0.2	0.0
Croatian-Asturian	2.3	2.7	1.1	0.2
Croatian-Urdu	2.2	2.1	1.7	0.7
Croatian-Pashto	11.8	11.1	8.5	7.5
Urdu-Afrikaans	15.2	6.1	6.1	1.5
Urdu-Asturian	18.2	9.0	6.8	2.1
Urdu-Croatian	4.1	4.8	4.9	1.2
Urdu-Pashto	13.3	21.0	16.8	7.4
Pashto-Afrikaans	4.2	4.3	4.7	1.1
Pashto-Asturian	12.7	6.9	5.1	1.2
Pashto-Croatian	4.2	3.7	3.7	1.6
Pashto-Urdu	3.3	7.5	6.2	2.8
Average	10.9	7.6	6.7	2.8

Table 8: The percentage of hallucinations (TNG metric; lower is better) of different pivoting methods for M2M100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark.

Language Pairs	Direct	MultiAvg	MaxEns	EN Pivot
Afrikaans-Asturian	2.5	1.6	0.2	2.1
Afrikaans-Croatian	0.0	0.1	0.2	0.1
Afrikaans-Urdu	0.4	0.3	0.6	0.2
Afrikaans-Pashto	2.9	1.8	1.2	1.3
Asturian-Afrikaans	0.4	0.5	0.9	0.2
Asturian-Croatian	1.2	0.4	0.7	0.4
Asturian-Urdu	6.1	0.7	0.9	0.2
Asturian-Pashto	5.0	2.0	1.9	0.9
Croatian-Afrikaans	0.0	0.1	0.1	0.0
Croatian-Asturian	2.1	1.3	0.8	2.2
Croatian-Urdu	0.8	0.4	0.4	0.3
Croatian-Pashto	2.6	1.7	1.3	1.2
Urdu-Afrikaans	1.1	0.6	0.4	0.3
Urdu-Asturian	13.4	3.3	1.2	2.6
Urdu-Croatian	0.8	0.4	0.7	0.4
Urdu-Pashto	5.3	2.3	2.1	1.0
Pashto-Afrikaans	1.2	2.9	2.2	0.4
Pashto-Asturian	19.4	5.4	3.1	2.7
Pashto-Croatian	3.0	2.1	2.3	0.3
Pashto-Urdu	1.6	2.2	2.4	0.4
Average	3.6	1.5	1.2	0.9

Table 9: The percentage of hallucinations (TNG metric; lower is better) of different pivoting methods for SMALL100 model on selected language pairs of FLORES-101 (Goyal et al., 2022) benchmark.