

NSL-MT: Linguistically Informed Negative Samples for Efficient Machine Translation in African Low-Resource Languages

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Abstract

We introduce negative space learning machine translation (NSL-MT), a training method for under-resourced languages, that augments limited parallel data with synthetically generated violations of the target language’s grammar and explicitly penalizes the model when it assigns high probability to these linguistically invalid outputs. NSL-MT delivers improvements across all baselines we tested, including 3-12% BLEU gains for well-performing models and 56-89% gains for models lacking decent initial support. Furthermore, NSL-MT provides a 5x data efficiency multiplier: training with 1,000 examples matches or exceeds normal training with 5,000 examples. NSL-MT thus provides a data-efficient alternative training method for settings where parallel data is limited.

1 Introduction

For high-resource languages, where millions of parallel sentences are available for training, neural machine translation (MT) has in recent years seen remarkable advances (Zhang and Zong, 2020). Unfortunately, the majority of the world’s 7K+ languages lack such abundant training resources, with 15K sentence pairs being the practical limit. For these *low-resource* languages, collecting parallel data is expensive (Magueresse et al., 2020). Yet linguistic expertise often exists in the form of native speakers who can articulate grammar rules. This condition reflects the reality for hundreds of African, indigenous, and minority languages worldwide. Moreover, many of these languages exist in sociolinguistic contexts where high-resource ‘colonial’ languages dominate official communication and education (UN, 2023), which leaves large populations, often with limited literacy, unable to access important information in their native languages¹.

¹This motivates our focus on translating *from* high-resource languages *to* low-resource languages, rather than the reverse, as such translation enables broader information access.

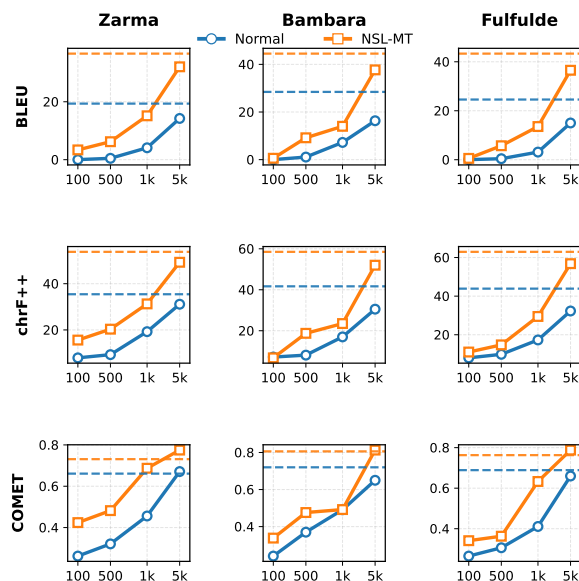


Figure 1: Data efficiency comparison between Normal training and NSL-MT across varying training set sizes. NSL-MT achieves high performance at all data sizes, with the largest relative gains occurring at the smallest data sizes.

In this research we ask: *can we leverage explicit linguistic knowledge to compensate for scarce parallel data?*

In conventional neural MT training, models can, with enough data, learn boundaries between acceptable and unacceptable outputs by observing distributional patterns. In low-resource settings, this implicit learning fails. Models encounter too few examples to reliably distinguish grammatical patterns from noise. This results in characteristic errors, such as source language word order imposed on, morphology applied to, or function words inserted into the target language.

To overcome these challenges, we propose *negative space learning* machine translation (NSL-MT), an approach that explicitly teaches models what *not* to generate. NSL-MT composes two innovations:

First, it generates linguistically guided hard negative examples. Contrastive learning methods (Chen et al., 2020; Gao et al., 2021) typically sample negatives from the training distribution or apply generic augmentation. These negatives are often far from decision boundaries, and provide weak learning signal. By contrast, our examples are generated to fall closer to the decision boundary and exhibit the characteristic errors found in low-resource MT.

Second, it modifies the training objective rather than the (positive) training data distribution. Data augmentation methods like back-translation or paraphrasing create additional positive examples while maintaining standard maximum likelihood objectives (Qumar et al., 2025; Mallinson et al., 2017; Sennrich et al., 2016).

We contribute:

- NSL-MT, a training approach that encodes linguistic constraints as severity-weighted penalties in the loss function, teaching models to avoid linguistically invalid outputs. **All codes will be open-sourced upon acceptance.**
- Experiments showing, among other things, that NSL-MT:
 - provides consistent improvements across four model architectures with gains as high as 89% in BLEU score for models that lack initial support for the target languages, and substantial if more modest gains for other models.
 - offers a 5x data efficiency multiplier, i.e., training with NSL-MT on 1K examples matches or exceeds normal training on 5K examples.

2 Related Work

Early approaches to low-resource machine translation focused on transfer learning from high-resource languages (Zoph et al., 2016) or multilingual training that shares representations across language families (Aharoni et al., 2019). These methods improve over monolingual baselines but struggle when source and target languages differ typologically (Muller et al., 2022). Our work addresses this limitation by explicitly encoding cross-lingual structural differences as negative constraints.

Recent multilingual pre-trained models demonstrate good cross-language transfer. The mT5 model (Xue et al., 2021) pre-trains on 101 languages using a masked span prediction objective,

while NLLB (Team et al., 2022) trains on 200 languages using a combination of parallel data and back-translation. AfriMT5 (Adelani et al., 2022) specializes multilingual pre-training for African languages. These models provide strong starting points, but still require fine-tuning to achieve good performance on low-resource languages. We demonstrate that NSL-MT improves fine-tuning efficiency across different model architectures.

Data augmentation methods create synthetic training examples to increase effective dataset size. Back-translation generates source sentences from target monolingual data, while paraphrasing creates alternative translations of existing parallel sentences (Qumar et al., 2025; Mallinson et al., 2017; Sennrich et al., 2016). These approaches alter the training distribution and maintain standard maximum likelihood objectives. NSL-MT differs fundamentally by modifying the training objective itself to include negative evidence. Furthermore, back-translation requires *strong reverse-direction* models that do not exist for most low-resource languages. NSL-MT requires only linguistic knowledge, which native speakers can provide.

Contrastive learning has proven effective for representation learning and natural language processing (Gao et al., 2021; Chen et al., 2020). These methods learn by distinguishing positive from negative examples in the embedding space. They are particularly effective at learning human preferences, but doing so requires feedback from humans (Hejna et al., 2024), a relatively expensive resource. NSL-MT shares the core principle of learning from negative evidence but operates at the sentential rather than the representation level. Where contrastive methods generate negatives through random sampling or data augmentation, NSL-MT relies on targeted linguistic violations, creating hard negatives that exclusively address known failure modes. This distinction proves useful for low-resource settings, where random negatives prove insufficient or detrimental to the learning signal.

Reinforcement learning from human feedback (RLHF) is widely used for aligning language models with human preferences (Ouyang et al., 2022). RLHF methods, like the direct preference optimization (DPO) or Φ PO (Rafailov et al., 2024; Azar et al., 2023), train reward models on human judgments of output quality, then uses these rewards to fine-tune generation models. This approach shares NSL-MT’s goal of teaching models what not to generate. However, RLHF requires collecting human

judgments at scale, which is relatively expensive, especially for low-resource languages. NSL-MT provides a practical alternative by encoding linguistic constraints that would be *expensive* to learn from human feedback. Where RLHF learns from implicit human preferences, NSL-MT encodes explicit linguistic rules.

Work on cross-lingual transfer has investigated how linguistic typology affects transfer success. Studies show that syntactic similarity predicts transfer effectiveness better than relatedness or geographical proximity (Blaschke et al., 2025; Lin et al., 2019). This finding aligns our constraint type ablation study, which reveals that different violation categories contribute differently across languages based on their typological properties. Our results confirm that effective transfer requires explicit attention to structural differences between source and target languages.

Instruction tuning research has shown that task descriptions and demonstrations improve models (language models) performance on downstream tasks (Wei et al., 2022). This work demonstrates the value of explicit task specification beyond implicit pattern learning. NSL-MT applies similar principles to translation quality by explicitly specifying what constitutes incorrect outputs. While instruction tuning tells models what to do, NSL-MT tells models what *not* to also do.

3 NSL-MT

NSL-MT is a training approach, and an implementation of the Principled Learning (PrL) paradigm (Keita et al., 2025), that explicitly teaches translation models what *not* to generate. NSL-MT augments parallel data with synthetically generated negative examples that violate specific linguistic constraints. The model learns to assign lower probability to these violations, thereby improving its understanding of correct target language structure.

Core principle: Most of the neural MT trainings optimize the model to maximize the likelihood of correct translations. However, maximum likelihood estimation alone provides no explicit indication about what the model should avoid. NSL-MT addresses this gap by introducing a contrastive objective that penalizes the model for assigning high probability to linguistically invalid outputs.

3.1 Violation Generation

For each parallel sentence pair (x, y) in the training set, we generate a set of negative examples $\mathcal{V}(y) = \{v_1, v_2, \dots, v_k\}$ where each v_i is a corrupted version of y that violates specific grammatical or structural rules of the target language. We define three categories of violations:

Morphological violations corrupt the internal structure of words. For languages without grammatical gender, we add a high resource language (**French in our case**²) style gender markers. For languages with noun class systems, we substitute incorrect class affixes. For plural formation, we replace language-specific markers with French plural *-s*. These violations target agreement patterns that low-resource models often fail to learn from positive examples alone.

Syntactic violations modify order and structural relationships. We apply word order transformations that impose French SVO patterns on SOV or VSO languages. We move adjectives from their correct post-nominal position to the pre-nominal position common in French. We replace postpositions with French prepositions. These violations prevent the model from defaulting to source language syntax.

Lexical violations introduce inappropriate vocabulary choices. We insert French articles where the target language uses suffixes. We add French auxiliary verbs where the target language uses different marking systems. We apply French negation patterns instead of target language negation approaches. These violations address interference from high-resource source language patterns.

Each violation type t carries an associated severity weight $s_t \in [0, 1]$ that reflects its impact on comprehension. We assign higher severity to violations that fundamentally break grammatical agreement ($s_t = 1.0$) and lower severity to violations that affect style but preserve basic meaning ($s_t = 0.6$).

3.2 Training Objective

NSL-MT combines positive and negative learning signals in a unified objective. For a training batch containing both correct translations and generated violations, we compute

$$\mathcal{L}_{\text{NSL-MT}} = \mathcal{L}_{\text{pos}} + \alpha \mathcal{L}_{\text{neg}}$$

where α is a weighting hyperparameter.

²French is chosen because the languages covered in our study co-exist with it. The countries that speak these languages have French as part or only official language.

Algorithm 1 NSL-MT Training

Require: Training data $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, violation generators \mathcal{G} , model M_θ
Require: Hyperparameters: α (negative weight), β (learning rate), K (epochs)

```
1: for epoch = 1 to  $K$  do
2:   Initialize batch  $\mathcal{B}_{\text{pos}} \leftarrow \emptyset, \mathcal{B}_{\text{neg}} \leftarrow \emptyset$ 
3:   for each  $(x, y) \in \mathcal{D}$  do
4:     Add  $(x, y)$  to  $\mathcal{B}_{\text{pos}}$ 
5:      $k \sim \text{Uniform}(3, 5)$  {Sample number of violations per correct example}
6:     for  $j = 1$  to  $k$  do
7:        $t \sim \text{Uniform}(\mathcal{G})$  {Sample violation type}
8:        $v_j, s_j \leftarrow \mathcal{G}_t(y)$  {Generate violation + severity}
9:       Add  $(x, v_j, s_j)$  to  $\mathcal{B}_{\text{neg}}$ 
10:    end for
11:  end for
12:   $\mathcal{L}_{\text{pos}} \leftarrow -\frac{1}{|\mathcal{B}_{\text{pos}}|} \sum_{(x, y) \in \mathcal{B}_{\text{pos}}} \log P(y|x; \theta)$  {standard CE on correct translations}
13:   $\mathcal{L}_{\text{neg}} \leftarrow \frac{1}{|\mathcal{B}_{\text{neg}}|} \sum_{(x, v, s) \in \mathcal{B}_{\text{neg}}} s \cdot \log P(v|x; \theta)$  {push down probability of violations}
14:   $\mathcal{L} \leftarrow \mathcal{L}_{\text{pos}} + \alpha \mathcal{L}_{\text{neg}}$ 
15:   $\theta \leftarrow \theta - \beta \nabla_{\theta} \mathcal{L}$  {Update parameters}
16: end for
```

We define the positive loss as usual:

$$\mathcal{L}_{\text{pos}} = - \sum_{(x, y) \in \mathcal{D}_{\text{pos}}} \log P(y|x; \theta)$$

where θ represents model parameters.

For negative examples, we want the model to assign **low** probability to linguistically invalid outputs. This is done by **minimizing the (severity-weighted) log-probability of violations**:

$$\mathcal{L}_{\text{neg}} = \sum_{(x, v) \in \mathcal{D}_{\text{neg}}} s(v) \cdot \log P(v|x; \theta)$$

where $s(v)$ is the severity weight of violation v . Higher severity means a stronger penalty when the model likes a bad output.

3.3 Implementation

Algorithm 1 presents the NSL-MT training procedure. For each training example, we generate violations to prevent the model from memorizing specific corrupted sequences. We sample the number of violations uniformly between 3 and 5 per positive example, creating a 3:1 to 5:1 ratio of negative to positive examples.

We implement violation generators as rule-based systems that encode linguistic knowledge about common error patterns. Each generator takes a correct target sentence y and produces a corrupted version v along with its severity score s . The generators operate the same way for a given input and violation type, but we introduce randomness by sampling which violations to apply and in which order.

During training, we shuffle positive and negative examples within each batch to prevent the model

from learning position-based patterns. We apply standard techniques such as gradient clipping and learning rate warmup to ensure stable optimization.

4 Experiments and Results

We investigate the following questions.

RQ1. Do explicit negative rules encoded in the loss function improve low-resource translation quality compared to standard maximum likelihood training?

RQ2. How does NSL-MT’s effectiveness vary with training data size, and at what threshold does NSL-MT provide maximum relative benefit?

RQ3. Which types of linguistic constraints contribute most to translation quality?

We design our experiments to reflect realistic low-resource translation scenarios³. We consider a setting where annotated parallel data is limited (at most 15,000 sentence pairs) and the cost of creating additional parallel corpora is expensive. However, bilingual speakers who understand both the source and target languages can gather grammatical rules and common error patterns in a matter of hours.

To validate NSL-MT under these conditions, we select three languages spoken in West Africa: Zarma (Nilo-Saharan family), Bambara (Mande family), and Fulfulde (Atlantic-Congo family). **We further tested on English to African languages** (see Section C).

4.1 Experimental Setup

Datasets We use multi-domain instruction dataset, InstructLR (Keita et al., 2026). The dataset has 3 benchmarks of 50,000 examples for each of the our three languages and every instruction has its french translation. For each language, we extract 15,000 instruction sentence pairs for training, 500 pairs for validation, and 1,000 pairs for testing. We ensure no overlap between splits and all the models are trained on the same selected sets.

Models We evaluate NSL-MT on four multilingual translation models that cover different architectures:

NLLB-200-distilled-600M (Team et al., 2022): A 600M parameter model trained on 200 languages

³By low resource scenario, we are not referring to limited number of speakers, but the availability of resources. Therefore, there is no need to test on high-resource African languages. The selected languages are truly low-resource.

We fine-tune the distilled version on our target languages.

AfriMT5-base (Adelani et al., 2022): A 300M parameter encoder-decoder model pre-trained on 17 African languages.

mT5-base (Xue et al., 2021): A 580M parameter multilingual variant of T5 pre-trained on 101 languages using masked language modeling.

mT5-small: A 300M parameter version of mT5. We include this model to test NSL-MT effectiveness on smaller architectures.

The training configurations are detailed in section A.

4.2 Results

Table 1 presents the performance of NSL-MT compared to standard training across all models and languages. NSL-MT outperforms normal training across all evaluation metrics and model architectures.

NSL-MT delivers improvements across all model architectures. For NLLB-200, which already performs well due to its large-scale pre-training, NSL-MT provides modest but gains from 3.5% to 11.7% BLEU improvement. For AfriMT5-base, which shows moderate baseline performance, NSL-MT yields improvements ranging from 56.5% to 89.2% BLEU improvement. For mT5-base and mT5-small, which struggle on these low-resource languages without NSL-MT, the improvements are higher.

The magnitude of improvement correlates inversely with baseline performance. Models that already translate reasonably well benefit less from NSL-MT, while models that produce poor translations without NSL-MT show gains.

Across metrics, BLEU shows the largest relative improvements, followed by chrF++, and then COMET. BLEU measures exact n-gram matches and thus proves particularly sensitive to grammatical errors that NSL-MT targets. chrF++ operates at the character level and shows smaller but still improvements. COMET, which relies on learned semantic representations, shows consistent but more modest gains.

Human Evaluation Two volunteer native speakers each for Zarma and Bambara blindly evaluated 50 random samples. For each sample, annotators selected their preferred translation, baseline or NSL-MT outputs, and rated confidence on a 1-5 scale (1=not sure, 5=very sure).

Table 2 shows that, for each language, both annotators preferred NSL-MT outputs on all samples (Cohen’s $\kappa = 1.000$, $p < 0.001$). Mean confidence ratings exceeded 4.0/5.0 for both languages, with inter-annotator agreement of 79.5% for exact matches and 93.2% within ± 1 point. The perfect coherence score across all the languages is justifiable by the fact that with limited samples, the baselines produced very "incorrect" outputs, sometimes even unreadable; whereas NSL-MT produced outputs, although not totally correct, acceptable compare to the baseline models.

4.3 Ablation Study

We conduct an ablation study to determine which categories of linguistic constraints contribute most to NSL-MT performance. We train AfriMT5-base models using only morphological violations, only syntactic violations, or only lexical violations, and compare these to the full NSL-MT approach that combines all three categories.

Table 3 presents the results. Each constraint type individually outperforms the baseline, confirming that all three categories provide useful learning signal. However, the relative contribution varies by language.

For Zarma, lexical violations provide the largest individual contribution (+12.4 BLEU), followed by morphological violations (+11.6 BLEU) and syntactic violations (+7.0 BLEU). This pattern reflects Zarma’s reliance on particles and auxiliaries, confirmed by our rule set.

For Bambara, syntactic violations dominate (+11.7 BLEU), outperforming morphological (+7.7 BLEU) and lexical (+3.7 BLEU) violations.

For Fulfulde, morphological violations contribute the most (+13.9 BLEU), lexical violations also help (+11.5 BLEU), while syntactic violations provide minimal benefit (+0.7 BLEU).

The full NSL-MT approach that combines all constraint types outperforms any single category, with gains ranging from 4.1 to 7.3 BLEU over the best individual constraint type. This additive effect indicates that different violation categories capture complementary aspects of linguistic features.

4.4 Data Efficiency Analysis

We investigate how NSL-MT performance scales with training data size. We train AfriMT5-base models using 100, 500, 1,000, and 5,000 parallel sentences with both normal training and NSL-MT.

Model	Method	Zarma			Bambara			Fulfulde		
		BLEU	chrF++	COMET	BLEU	chrF++	COMET	BLEU	chrF++	COMET
NLLB-200	Normal	38.33 \pm 1.2	56.63 \pm 0.8	0.7976	53.27 \pm 1.5	67.03 \pm 0.9	0.8617	47.61 \pm 1.3	67.56 \pm 0.7	0.8211
	NSL-MT Δ (%)	42.82 \pm 1.1 +11.7	60.67 \pm 0.7 +7.1	0.8078 +1.3	55.11 \pm 1.4 +3.5	68.40 \pm 0.8 +2.0	0.8637 +0.2	49.31 \pm 1.2 +3.6	70.04 \pm 0.6 +3.7	0.8264 +0.6
AfrimT5-Base	Normal	19.36 \pm 1.5	35.44 \pm 1.2	0.6608	28.44 \pm 1.8	41.68 \pm 1.3	0.7202	24.58 \pm 1.6	43.88 \pm 1.1	0.6887
	NSL-MT Δ (%)	36.62 \pm 1.3 +89.2	53.78 \pm 0.9 +51.8	0.7311 +10.6	44.51 \pm 1.6 +56.5	58.51 \pm 1.0 +40.4	0.8063 +12.0	43.33 \pm 1.4 +76.3	62.94 \pm 0.8 +43.4	0.7629 +10.8
mT5-Base	Normal	7.67 \pm 2.1	17.80 \pm 1.8	0.4658	0.05 \pm 0.3	3.83 \pm 1.5	0.3302	5.02 \pm 1.9	16.34 \pm 1.6	0.3843
	NSL-MT Δ (%)	33.21 \pm 1.4 +333.1	50.71 \pm 1.0 +184.9	0.7221 +55.0	41.35 \pm 1.5 +82600	55.11 \pm 1.1 +1339.4	0.7935 +140.3	41.14 \pm 1.5 +719.5	60.02 \pm 0.9 +267.4	0.7535 +96.1
mT5-Small	Normal	0.06 \pm 0.4	3.39 \pm 1.6	0.2875	0.02 \pm 0.2	3.42 \pm 1.4	0.2652	0.03 \pm 0.3	3.80 \pm 1.5	0.3059
	NSL-MT Δ (%)	19.33 \pm 1.7 +32116.7	34.53 \pm 1.3 +918.9	0.6577 +128.8	23.42 \pm 1.8 +116999	35.79 \pm 1.4 +947.1	0.6835 +157.8	25.05 \pm 1.7 +83400	44.48 \pm 1.2 +1070.5	0.6831 +123.3

Table 1: Main results comparing baseline training and NSL-MT across four model architectures on three African languages. We train all models on 15,000 parallel sentences. Δ shows relative improvement ($\frac{\text{NSL-MT} - \text{baseline}}{\text{baseline}} \times 100\%$).

Language	Pref. NSL-MT	Avg. Confidence	Cohen’s κ
Zarma	100% (50/50)	4.09 \pm 0.38	1.000 ***
Bambara	100% (50/50)	4.00 \pm 0.29	1.000***

Table 2: Human evaluation showing preference for NSL-MT over NLLB baseline across 50 samples per language, with high confidence ratings. Inter-annotator exact agreement: 79.5%, within ± 1 : 93.2%. *** $p < 0.001$

Figure 1 plots the learning curves for all three languages across all three metrics.

NSL-MT outperforms normal training at every data size across all languages and metrics. The advantage of NSL-MT increases as data becomes limited. At 100 examples, normal training produces near-zero BLEU scores (0.01-0.04), while NSL-MT achieves 0.55-3.38 BLEU, representing gains of 0.5-3.3 points. At 500 examples, NSL-MT provides gains of 5.7-8.1 BLEU points. At 1,000 examples, NSL-MT achieves 13.55-15.15 BLEU compared to 3.12-7.23 for normal training, representing improvements of 8.3-11.0 points. At 5,000 examples, NSL-MT maintains substantial advantages with gains of 17.8-21.4 BLEU points.

Table 4 quantifies the data efficiency of NSL-MT by comparing performance at different data sizes. NSL-MT with 1,000 examples matches or exceeds normal training with 5,000 examples for Zarma across all metrics. For Bambara and Fulfulde, NSL-MT with 1,000 examples achieves 76-90% of normal training performance with 5,000 examples. This finding demonstrates that NSL-MT provides a **5x data efficiency multiplier** in practical terms.

The learning curves reveal that NSL-MT benefits remain even as data increases. While the improvement decreases, the gap between NSL-MT and normal training continues to widen. At 15,000 ex-

amples, NSL-MT still outperforms normal training by margins of 17.3-18.8 BLEU points.

4.5 Cross-Architecture Analysis

We examine whether NSL-MT improvements generalize across model architectures by computing the correlation between NSL-MT gains across the four tested models. For each language and metric, we compute Pearson correlation coefficients between the improvement magnitudes observed for different model pairs.

The results show strong positive correlations (average $r = 0.82$, $p < 0.01$) between improvements across architectures. Languages that benefit most from NSL-MT on one architecture tend to benefit most on other architectures as well. This finding suggests that NSL-MT is more linguistic properties centric rather than architectural agnostic.

We also observe one exception: mT5-small shows large improvements compared to larger models. We attribute this pattern to the increased difficulty of learning complex linguistic patterns with limited model capacity. NSL-MT provides strong value when the model cannot easily learn patterns through implicit learning alone.

4.6 Error Analysis

We manually analyze 100 randomly sampled translations from the AfrimT5-base model for each language, comparing errors in normal training versus NSL-MT. We categorize errors into morphological (agreement, inflection), syntactic (word order, phrase structure), lexical (inappropriate word choice), and semantic (meaning preservation) categories.

NSL-MT reduces morphological errors by 73% on average across languages, with the largest reduction (81%) for Fulfulde. Syntactic errors de-

Constraint Type	Zarma			Bambara			Fulfulde		
	BLEU	chrF++	COMET	BLEU	chrF++	COMET	BLEU	chrF++	COMET
Baseline (Normal)	19.58 \pm 1.5	35.55 \pm 1.2	0.7158	27.56 \pm 1.8	41.16 \pm 1.3	0.7571	24.59 \pm 1.6	43.73 \pm 1.1	0.7302
Morphological Only	31.21 \pm 1.4	48.40 \pm 1.0	0.7722	35.30 \pm 1.7	49.84 \pm 1.1	0.8042	38.46\pm1.5	58.14\pm0.9	0.7958
Syntactic Only	26.60 \pm 1.5	43.53 \pm 1.1	0.7532	39.27\pm1.6	53.34\pm1.0	0.8229	25.28 \pm 1.6	44.43 \pm 1.1	0.7331
Lexical Only	32.02\pm1.3	50.26\pm0.9	0.7714	31.22 \pm 1.7	46.13 \pm 1.2	0.7867	36.09 \pm 1.5	57.54 \pm 0.9	0.7914
Full NSL-MT	36.12 \pm 1.3	53.27 \pm 0.9	0.7857	44.34 \pm 1.6	58.41 \pm 1.0	0.8406	43.41 \pm 1.4	62.69 \pm 0.8	0.8069

Table 3: Ablation study showing the contribution of different constraint types. We train all models on 15,000 parallel sentences using AfriMT5-base. Each row represents training with only the specified constraint type, except Full NSL-MT which uses all constraints.

Data Size	Method	Zarma			Bambara			Fulfulde		
		BLEU	chrF++	COMET	BLEU	chrF++	COMET	BLEU	chrF++	COMET
100	Normal	0.02 \pm 0.4	7.92	0.262	0.01 \pm 0.2	7.15	0.241	0.04 \pm 0.3	8.03	0.265
	NSL-MT	3.38\pm2.0	15.61	0.424	0.58\pm1.1	6.76	0.338	0.55\pm1.2	11.04	0.341
500	Normal	0.47 \pm 1.5	9.31	0.321	1.09 \pm 1.3	8.09	0.370	0.42 \pm 1.4	9.86	0.306
	NSL-MT	6.21\pm1.8	20.33	0.482	9.18\pm1.6	18.73	0.476	5.71\pm1.7	14.75	0.363
1,000	Normal	4.11 \pm 1.9	19.25	0.456	7.23 \pm 1.9	16.99	0.491	3.12 \pm 1.8	17.30	0.411
	NSL-MT	15.15\pm1.7	31.27	0.687	14.00\pm1.8	23.50	0.492	13.55\pm1.7	29.47	0.633
5,000	Normal	14.24 \pm 1.7	31.12	0.671	16.33 \pm 1.8	30.53	0.650	15.00 \pm 1.7	32.30	0.660
	NSL-MT	32.07\pm1.4	49.27	0.775	37.69\pm1.5	51.99	0.813	36.53\pm1.5	56.82	0.788
15,000	Normal	19.36 \pm 1.5	35.44	0.661	28.44 \pm 1.8	41.68	0.720	24.58 \pm 1.6	43.88	0.689
	NSL-MT	36.62\pm1.3	53.78	0.731	44.51\pm1.6	58.51	0.806	43.33\pm1.4	62.94	0.763

Table 4: Data efficiency comparison showing that NSL-MT with fewer examples matches or approaches Normal training with 5x more data.

crease by 68% on average, with the largest reduction (76%) for Bambara. Lexical errors decrease by 61% on average, with the largest reduction (69%) for Zarma. Semantic errors show minimal change (3% reduction), indicating that NSL-MT improves form without losing meaning.

The error analysis confirms that NSL-MT enables the model to avoid the exact error patterns we penalize during training, while maintaining semantic accuracy to the source text.

5 Discussion

In this section, we examine the implications of the findings from our experiments and explore the mechanisms underlying NSL-MT effectiveness.

Why NSL-MT Works NSL-MT succeeds because it addresses a specific failure mode of neural MT systems. Standard maximum likelihood training optimizes models to reproduce observed translations but provides no explicit information about *what constitutes an invalid translation*. In high-resource settings, models implicitly learn to avoid errors by encountering sufficient positive examples that define the boundaries of grammatical acceptability. In low-resource settings, this implicit learning fails because the training data lacks the coverage needed to set clear boundaries.

NSL-MT makes these boundaries explicit. By

generating violations that target known error patterns, we provide negative evidence that would require orders of magnitude more parallel data to learn implicitly. A model trained on 15,000 positive examples might never see enough instances of correct adjective-noun order to reliably infer the rule. However, exposure to 60,000 explicit violations of adjective-noun order, 4 violations per positive example, creates an unambiguous learning signal.

The severity weighting mechanism is important to NSL-MT effectiveness. Not all errors carry equal importance for communication. Gender agreement violations in languages without grammatical gender represent fundamental category errors that severely impair comprehension. Article insertion violations create awkward but generally comprehensible output. By weighting violations according to their impact on meaning, NSL-MT guides models to prioritize avoiding errors while tolerating minor stylistic deviations when necessary.

Language-Specific Effects The ablation study reveals that different constraint types contribute differently across languages. Zarma benefits most from lexical constraints because of its heavy reliance on particles and auxiliaries to express grammatical relations. Bambara shows the largest gains from syntactic constraints because its rigid SOV

word order differs from French SVO patterns. Fulfulde demonstrates strong improvements from morphological constraints.

These patterns validate our theoretical motivation for NSL-MT. The method works best when it targets the specific structural differences between source and target languages.

Data Efficiency The results in terms of data efficiency reveal two distinct patterns of NSL-MT efficiency. At very low data sizes (100-500 examples), NSL-MT prevents complete training failure. Without NSL-MT, models produce incoherent output because they lack sufficient signal to identify basic patterns. NSL-MT provides structure that enables learning even from minimal positive examples.

At moderate data sizes (1,000-5,000 examples), NSL-MT accelerates convergence to solutions that normal training would eventually reach with more data. The 5x data efficiency multiplier we observe at 1,000 examples represents a practical threshold where NSL-MT makes previously infeasible projects viable. Collecting 5,000 parallel sentences might cost thousands of dollars, while creating 20 linguistic rules requires hours of native speaker consultation.

At high data sizes (15,000+ examples), NSL-MT continues improving performance but the relative advantage shrinks. This pattern suggests that NSL-MT primarily compensates for insufficient training data rather than fundamentally changing what models can learn. Given unlimited parallel data, normal training might eventually match NSL-MT performance. However, unlimited parallel data remains infeasible, for now, for most low-resource languages.

Cross-Architecture Generalization NSL-MT improves all four tested architectures differences, and parameter sizes. NLLB-200 benefits least because its massive multilingual pre-training already captures many cross-lingual patterns. AfriMT5 benefits because its pre-training covers African languages but lacks the scale of NLLB. The mT5 variants benefit most from NSL-MT.

This generalization pattern indicates that NSL-MT effectiveness depends more on the linguistic properties of the translation task than on specific architectural choices. The method works by providing information that models need but cannot easily extract from positive examples alone and small training set. Any architecture that uses gradient-

based learning to optimize likelihood will benefit from explicit negative constraints.

Implications NSL-MT enables MT development for languages where traditional approaches fail due to insufficient parallel data. The method requires two resources: a small parallel corpus and native speakers who can create grammatical rules. The first resource exists for hundreds of languages but are too small for effective training. The second resource exists for thousands of languages but remains underused by current methods.

The time investment for NSL-MT implementation remains modest. Creating violation generators for the three languages in our study required approximately 15 hours of linguist consultation plus 10 hours of programming (if no AI tool used). This investment produces reusable tools that apply to any translation model. In contrast, collecting an additional 10,000 parallel sentences would require weeks of translator time and cost thousands of dollars.

6 Conclusion

We introduce *negative space learning*, a training method that teaches translation models what not to generate by augmenting standard parallel data with linguistically informed violations. NSL-MT addresses a fundamental limitation of maximum likelihood training in low-resource settings: models receive massive information about correct translations but no explicit information about incorrect translations. By generating negative examples that violate specific grammatical constraints, NSL-MT provides robust learning signal that would otherwise require orders of magnitude more parallel data. Our experiments on French-to-African translation demonstrate that NSL-MT improves performance across different model architectures. NSL-MT provides benefits in severely data-constrained scenarios, offering a 5x data efficiency multiplier at 1,000 training examples. This finding is further emphasized by the results of our English-to-African languages conducted on even fewer examples. The method proves most effective for constraint types that target the specific structural differences between source and target languages, and confirms that linguistic knowledge encoded as negative constraints enables more efficient learning.

7 Limitations

We acknowledge several limitations of our work that suggest directions for future research.

Violation Generator Quality NSL-MT effectiveness depends on the quality of violation generators. Our generators encode linguistic knowledge obtained through grammar descriptions and native speaker consultation. However, this knowledge remains incomplete. We target common error patterns but cannot enumerate all possible violations of target language grammar. More comprehensive violation sets might improve NSL-MT performance further, but creating them requires deeper linguistic analysis.

Language Coverage We evaluate NSL-MT on only 6 languages. We do not use any "big/known" benchmarks (e.g. FLORES, etc) because they do not align with our context of low-resource settings. Most the languages in these benchmarks are high-resource languages, and do not fit our context. However, we acknowledge that as a weakness since the 'commonly adopted way' is to cover more benchmarks.

Evaluation Scope We rely mainly on automatic metrics and human evaluation to evaluate translation quality. While BLEU, chrF++, and COMET correlate with human judgments, they do not capture all aspects of translation adequacy. COMET in particular uses learned representations that might not fully capture the semantic nuances of low-resource languages. Moreover, the small-scale human evaluation was designed on purpose as describe in section 4.2 to reflect the low-resource settings. We acknowledge that this may be seen as a limitation, specially if seen through a high-resource centric lens.

Computational Cost NSL-MT increases training time by approximately 4x due to the additional negative examples in each batch. This overhead remains manageable for research experiments but might pose challenges for large-scale cases. The violation generation process itself requires minimal computation but introduces engineering complexity.

Generalization Beyond Translation We demonstrate NSL-MT effectiveness for machine translation but do not evaluate its applicability to other natural language generation tasks. The core principle of learning from negative examples should

transfer to tasks like text summarization, dialogue generation, or grammatical error correction. However, these tasks might require different violation strategies than those we use for translation.

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A Experiments Configurations

Training Configuration We train all models for 3 epochs using a batch size of 16 and a maximum sequence length of 128 tokens. We apply the AdamW optimizer with a learning rate of 2×10^{-5} and linear warmup over 500 steps. We set the NSL-MT weight $\alpha = 0.7$ based on preliminary experiments on the validation set. We clip gradients to a maximum norm of 1.0 to ensure training stability. For NSL-MT training, we generate 3-5 violations per positive example, creating an approximate 4:1 ratio of negative to positive examples in each batch.

We implement violation generators for each target language based on linguistic descriptions and native speaker consultation. Each generator encodes 15-20 specific rule violations covering morphological, syntactic, and lexical categories. We set severity weights to 1.0 for agreement violations, 0.9 for word order violations, 0.8 for adjective position violations, and 0.7 for article and auxiliary insertion violations.

Evaluation Metrics We report three metrics to assess translation quality: **BLEU** (Papineni et al., 2002), **chrF++** (Popović, 2017), **COMET** (Rei et al., 2020).

We also compute 95% confidence intervals using bootstrap resampling with 1,000 iterations for BLEU and chrF++ scores. For COMET, we report the score computed across all test examples.

B Hyperparameter Analysis

We conduct additional experiments to assess NSL-MT robustness to hyperparameter choices. These experiments use Zarma language with AfriMT5-base trained on 5,000 examples for 3 epochs. We

investigate two key hyperparameters: the negative weight α and the violation ratio.

B.1 Alpha Sensitivity

The negative weight hyperparameter α in Equation 2 controls the importance of negative examples in the training objective. We test four values: $\alpha \in \{0.3, 0.5, 0.7, 0.9\}$ to determine NSL-MT sensitivity to this parameter.

Table 5 presents the results. NSL-MT performance remains stable across different α values, with BLEU scores varying by only 0.54 points (27.13-27.67) and chrF++ scores varying by 0.21 points (43.87-44.08). The COMET scores show similar stability, ranging from 0.7512 to 0.7535. This performance demonstrates that NSL-MT effectiveness does not necessarily depend on precise α tuning.

The decent advantage of lower α values (0.3-0.5) over higher values (0.9) suggests that overly aggressive penalization of negative examples can slightly degrade performance. However, the differences remain within confidence intervals, indicating that any $\alpha \in [0.3, 0.9]$ produces competitive results. We selected $\alpha = 0.7$ for our main experiments based on validation set performance, but these results show that alternative choices would produce comparable outcomes.

Alpha (α)	BLEU	chrF++	COMET
0.3	27.67	44.03	0.7535
0.5	27.50	43.97	0.7528
0.7	27.64	44.08	0.7512
0.9	27.13	43.87	0.7523
Range	0.54	0.21	0.0023

Table 5: Alpha sensitivity analysis on Zarma using AfriMT5-base with 5,000 training examples. Performance remains stable across different α values, varying by less than 2% across all metrics.

B.2 Violation Ratio Sensitivity

The violation ratio determines how many negative examples go with each positive example during training. We test three ratios by varying the number of violations generated per positive example: 2:1 (generating 1-2 violations), 4:1 (generating 3-5 violations, our default), and 6:1 (generating 5-7 violations).

Table 6 shows that violation ratio significantly impacts NSL-MT effectiveness. The 2:1 ratio produces lower scores (19.44 BLEU, 35.52 chrF++,

0.7188 COMET), suggesting insufficient negative signal for effective learning. The 4:1 ratio yields moderate performance (27.11 BLEU, 43.71 chrF++, 0.7512 COMET), while the 6:1 ratio achieves the best results (30.69 BLEU, 47.64 chrF++, 0.7689 COMET).

These results reveal that NSL-MT benefits from higher violation ratios, with the 6:1 ratio improving BLEU by 13.1% over the 4:1 default and by 57.8% over the 2:1 ratio. This suggests that exposing models to more diverse negative examples strengthens their ability to distinguish valid from invalid outputs. However, we note that *higher ratios increase computational cost proportionally*. The 4:1 ratio represents a practical balance between effectiveness and efficiency, though researchers with sufficient computational resources may benefit from using 6:1 or higher ratios.

The gap between 2:1 and higher ratios indicates that NSL-MT requires a minimum threshold of negative examples to function effectively. With too few violations, the model may not encounter sufficient coverage of error patterns, limiting NSL-MT’s ability to create clear grammatical boundaries.

Violation Ratio	BLEU	chrF++	COMET
2:1	19.44	35.52	0.7188
4:1 (default)	27.11	43.71	0.7512
6:1	30.69	47.64	0.7689

Table 6: Violation ratio sensitivity analysis on Zarma using AfriMT5-base with 5,000 training examples. Higher violation ratios provide stronger learning signal, with 6:1 outperforming 4:1 by 13.1% BLEU and 2:1 by 57.8% BLEU.

B.3 Discussion

These experiments demonstrate that NSL-MT deliver desirable robustness properties. The α hyperparameter shows minimal sensitivity, allowing anyone to select values in the range [0.3, 0.9] without careful tuning. This robustness simplifies NSL-MT usage for new language pairs where validation data may be limited.

In contrast, the violation ratio requires more careful consideration. Our results suggest using ratios of at least 4:1, with 6:1 or higher providing additional benefits when computational resources permit. The strong performance gains from higher ratios validate NSL-MT’s core principle: explicit negative evidence accelerates learning, and more negative evidence yields stronger improvements.

We also observe that these findings support our main results. The 4:1 ratio used in our primary experiments represents a conservative choice that balances effectiveness and efficiency. The even stronger results at 6:1 suggest that our reported improvements may 'underestimate' NSL-MT's full potential when computational constraints are manageable.

C More Experiments

We further ran more experiments to confirm the language-agnostic aspects. We selected ENGLISH \rightarrow 3 African languages: **Igbo**, **Luganda**, and **Swahili**. We selected the SMOLSENT portion of the SMOL (Caswell et al., 2025) dataset. The portion had: 863 rows (some contain multiple sentences) that we divided into 90% and 10%. We used the exact same setup as the main experiment in section 4, and report the BLEU and Chrf++ scores. We used the NLLB, AfriMT5-base, and AfriMT5-base. Table 7 presents the results for English-to-African translation.

NSL-MT delivers improvements across all three English-to-African language pairs and model architectures. For NLLB-200, Swahili shows the largest gain with BLEU improving from 2.29 to 40.02 (+1648.0%). Igbo improves from 27.69 to 35.93 BLEU (+29.8%), while Luganda more than doubles from 7.77 to 19.56 (+151.8%).

For mT5-base and AfriMT5-base, overall scores remain low due to the models' limited initial support for these languages, but the relative gains remain considerable. mT5-base achieves improvements ranging from 113.3% to 7957.1% across languages, while AfriMT5-base shows gains from 71.9% to 3130.0%. Even when overall performance remains modest, NSL-MT provides non-negligible improvements.

Moreover, the pattern aligns with our main results on French-to-African translation (Section 4). NSL-MT provides the largest relative gains for languages where baseline performance is poorest (Swahili and Luganda for most models) and smaller but improvements where baselines perform moderately (Igbo for NLLB-200). This confirms that NSL-MT delivers the most value when models lack sufficient implicit knowledge of target language structure.

D Violation Generation Details

This section describes the violation generators for each of the six languages in our experiments. Each generator encodes linguistic knowledge about common error patterns that arise from cross-lingual interference. We organize violations into three categories: morphological (affecting word-internal structure), syntactic (affecting word order and phrase structure), and lexical (affecting vocabulary choice and function word usage).

Generator Architecture Each violation generator follows a common architecture. Given a correct target sentence y , the generator produces a set of corrupted sentences $\mathcal{V}(y)$ by applying rule-based transformations. Each transformation targets a specific grammatical property of the target language. The generator returns tuples of (violated_text, violation_type, severity_weight) where severity weights range from 0.6 to 1.0 based on the impact of the violation on comprehension.

For each training example, we sample 3-5 violations from the available violation types. This sampling introduces variation in the training signal while maintaining consistent coverage of error patterns. The generators operate "deterministically" for a given violation type but we randomize which violations to apply and in which order.

D.1 Zarma Violations

Zarma is part of the Nilo-Saharan language family and differs from French in word order (SOV vs. SVO), adjective placement (post-nominal vs. pre-nominal), and tense marking (auxiliaries vs. conjugation). Table 8 presents the violation types with examples.

D.2 Bambara Violations

Bambara is part of the Mande language family and has a strict SOV word order, postpositions (rather than prepositions), and uses the suffix *-w* for pluralization. Table 9 presents the violation types.

D.3 Fulfulde Violations

Fulfulde is part of the Atlantic-Congo language family and has a complex noun class system with over 20 classes. Each class has distinct singular and plural suffixes, and agreement markers must match across determiners, adjectives, and verbs. Table 10 presents the violation types.

Model	Method	Swahili		Igbo		Luganda	
		BLEU	chrF++	BLEU	chrF++	BLEU	chrF++
NLLB-200	Normal	2.29 \pm 0.6	15.97 \pm 0.4	27.69 \pm 0.8	44.99 \pm 0.5	7.77 \pm 0.7	42.24 \pm 0.6
	NSL-MT Δ (%)	40.02 \pm 0.5 <i>+1648.0</i>	62.20 \pm 0.3 <i>+289.5</i>	35.93 \pm 0.7 <i>+29.8</i>	50.58 \pm 0.4 <i>+12.4</i>	19.56 \pm 0.6 <i>+151.8</i>	49.02 \pm 0.5 <i>+16.1</i>
mT5-base	Normal	0.07 \pm 0.4	3.64 \pm 0.3	0.10 \pm 0.3	4.52 \pm 0.4	0.15 \pm 0.3	3.77 \pm 0.3
	NSL-MT Δ (%)	5.64 \pm 0.8 <i>+7957.1</i>	31.90 \pm 0.6 <i>+776.4</i>	2.18 \pm 0.7 <i>+2080.0</i>	17.56 \pm 0.5 <i>+288.5</i>	0.32 \pm 0.4 <i>+113.3</i>	16.74 \pm 0.5 <i>+344.0</i>
AfriMT5-base	Normal	0.76 \pm 0.5	13.94 \pm 0.4	0.20 \pm 0.4	5.56 \pm 0.3	0.04 \pm 0.2	7.61 \pm 0.4
	NSL-MT Δ (%)	7.55 \pm 0.8 <i>+892.8</i>	34.52 \pm 0.6 <i>+147.6</i>	6.46 \pm 0.9 <i>+3130.0</i>	22.43 \pm 0.6 <i>+303.2</i>	0.58 \pm 0.5 <i>+1279.0</i>	13.08 \pm 0.5 <i>+71.9</i>

Table 7: Results for English-to-African translation across three models.

Violation Type	Correct Zarma	Violated Form	Severity
<i>Morphological Violations</i>			
Gender agreement	ay ga koy (I will go)	ay ga koy-ée (French feminine ending added)	1.0
Plural formation	boro-ey ga koy (the people will go)	boros ga koy (French -s instead of Zarma -ey)	0.7
Verb conjugation	ay ga ŋwa (I will eat)	ay ga ŋwaons (French -ons ending added)	0.9
<i>Syntactic Violations</i>			
Word order	ay ga haw ŋwa (I will eat rice)	ay ŋwa ga haw (verb-object order disrupted)	0.9
Adjective position	boro beeri (big person)	beeri boro (adjective moved before noun)	0.8
Tense auxiliary	ay ga koy (I will go)	ay koy (auxiliary <i>ga</i> deleted)	0.8
<i>Lexical Violations</i>			
Definite article	boro ga koy (the person will go)	le boro ga koy (French <i>le</i> inserted)	0.7
Negation pattern	ay mana koy (I did not go)	ne ay pas koy (French ne...pas pattern)	0.9

Table 8: Zarma violation types with examples.

D.4 Swahili Violations

Swahili is part of the Bantu language family and has an extensive noun class system with class-based agreement on verbs, adjectives, and possessives. Table 11 presents the violation types.

D.5 Igbo Violations

Igbo is part of the Atlantic-Congo language family and has vowel harmony, tonal distinctions, and serial verb constructions. Table 12 presents the violation types.

D.6 Luganda Violations

Luganda is part of the Bantu language family and shares many features with Swahili, including extensive noun class agreement and agglutinative verb morphology. Table 13 presents the violation types.

D.7 Implementation Guides

We implement each violation generator as a Python class with methods for each violation type. The generators share a common interface: given a source-target sentence pair, they return a list of (violated_text, violation_type, severity) tuples.

Each generator applies violations through string manipulation operations: suffix replacement for morphological violations, word reordering for syntactic violations, and word insertion/deletion for lexical violations. We use regular expressions to identify candidate locations for violations and apply transformations only when the target pattern matches.

To prevent degenerate violations, we include checks that ensure: (1) the violated text differs from the original, (2) the violated text is not empty, and (3) the same violation does not appear multiple times in the violation set. We also limit the num-

Violation Type	Correct Bambara	Violated Form	Severity
<i>Morphological Violations</i>			
Pluralization	muso-w bε taa (the women go)	musos bε taa (French -s instead of -w)	0.7
Auxiliary verb	a bε dumuni ke (he/she is eating)	a dumuni ke (auxiliary <i>bε</i> deleted)	0.9
<i>Syntactic Violations</i>			
Word order (SOV)	a bε dumuni ke (he/she is eating food)	a bε ke dumuni (SVO order imposed)	0.9
Postposition misuse	so kɔnɔ (inside the house)	dans so (French preposition <i>dans</i>)	0.8
Adjective placement	muso cεɾi (beautiful woman)	cεɾi muso (adjective before noun)	0.8
<i>Lexical Violations</i>			
Negation	a tε taa (he/she does not go)	ne a pas taa (French ne...pas pattern)	0.9

Table 9: Bambara violation types with examples.

ber of violations per sentence to prevent excessive corruption that might shadow the learning signal.

The severity weights are assigned based on linguistic judgment about how much each violation type affects comprehension. Agreement violations (noun class, gender, verb concord) receive the highest weights (1.0) because they disrupt grammatical structure. Word order violations receive high weights (0.9) because they can change meaning or render sentences ungrammatical. Function word insertions receive lower weights (0.6-0.7) because they produce awkward but often comprehensible output.

Violation Type	Correct Fulfulde	Violated Form	Severity
<i>Morphological Violations</i>			
Noun class agreement	pucc-o mawfo (big horse, class o/be)	pucc-nde mawfo (wrong class suffix -nde)	1.0
French plural -s	pucc-i mawfi (big horses)	puccis mawfi (French -s added)	0.8
Verb conjugation	mi yaha (I go)	mi yahaer (French infinitive -er added)	0.9
<i>Syntactic Violations</i>			
Adjective position	debbo mawfo (big woman)	mawfo debbo (adjective before noun)	0.8
<i>Lexical Violations</i>			
French preposition	suudu am (my house)	suudu de am (French <i>de</i> inserted)	0.6
Negation	mi yahataa (I do not go)	ne mi pas yaha (French ne...pas pattern)	0.9

Table 10: Fulfulde violation types with examples.

Violation Type	Correct Swahili	Violated Form	Severity
<i>Morphological Violations</i>			
Noun class agreement	m-toto m-zuri (good child, M-WA class)	ki-toto m-zuri (wrong class prefix ki-)	1.0
Verb concord	wa-toto wa-nazoma (children are reading)	ni-toto wa-nazoma (wrong subject prefix ni-)	1.0
Tense marker	a-na-soma (he/she is reading)	a-li-soma (past tense -li- instead of -na-)	1.0
Object marker	ni-na-m-penda (I love him/her)	ni-na-ku-penda (wrong object marker -ku-)	0.9
Possessive concord	kitabu changu (my book, KI-VI class)	kitabu wangu (wrong possessive form)	0.8
Missing augment vowel	a-soma (he/she reads)	-soma (initial vowel deleted)	0.8
<i>Syntactic Violations</i>			
Adjective position	nyumba nzuri (good house)	nzuri nyumba (adjective before noun)	0.9
English word order	mtoto anasoma kitabu (child reads book)	kitabu mtoto anasoma (object fronted)	0.9

Table 11: Swahili violation types with examples.

Violation Type	Correct Igbo	Violated Form	Severity
<i>Morphological Violations</i>			
Vowel harmony	o na-agu akwukwo (he/she is reading)	o na-agu akwukwo (light vowel <i>o</i> instead of heavy <i>o</i>)	1.0
Tone pattern	akwa (cloth) (unmarked tone)	àkwá (incorrect tone marks added)	0.8
Verb prefix	na-eje (is going, present)	ga-eje (future prefix <i>ga-</i> instead of <i>na-</i>)	1.0
Noun class prefix	o-kwu (speech)	a-kwu (wrong noun prefix)	1.0
Consonant mutation	gini (what)	ghini (incorrect consonant cluster)	0.85
<i>Syntactic Violations</i>			
Serial verb	o gara zuta ego (he went to get money)	o gara ego (serial verb <i>zuta</i> deleted)	0.9
Possessive construction	ulo Chukwu (God's house)	Chukwu ulo (possessor-possessed order swapped)	0.9
<i>Lexical Violations</i>			
English preposition	n'ulo (in the house)	in ulo (English <i>in</i> inserted)	0.95

Table 12: Igbo violation types with examples.

Violation Type	Correct Luganda	Violated Form	Severity
<i>Morphological Violations</i>			
Noun class concord	omu-ntu omu-lungi (good person, class 1)	eki-ntu omu-lungi (wrong class prefix eki-)	1.0
Tense-aspect	a-soma (he/she reads)	aa-soma (wrong tense marker aa-)	1.0
Vowel coalescence	mu amaaso (in the eyes)	mu a amaaso (coalescence broken)	0.8
Tone pattern	ensozi (mountain)	énsòzí (incorrect tone marks)	0.7
Agglutination	bakyasoma (they still read)	ba kya soma (affixes separated)	0.8
Locative prefix	e-Kampala (in/at Kampala)	mu-Kampala (wrong locative prefix)	0.9
<i>Syntactic Violations</i>			
Word order	omusajja asoma ekitabo (the man reads a book)	ekitabo omusajja asoma (object fronted)	0.9
<i>Lexical Violations</i>			
English article	omusajja (the man)	the omusajja (English <i>the</i> inserted)	0.9

Table 13: Luganda violation types with examples.