

ReSeTOX: Re-learning attention weights for toxicity mitigation in machine translation

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Abstract

Our proposed method, RESETOX (REdo SEarch if TOXic), addresses the issue of Neural Machine Translation (NMT) generating translation outputs that contain toxic words not present in the input. The objective is to mitigate the introduction of toxic language without the need for re-training. In the case of identified added toxicity during the inference process, RESETOX dynamically adjusts the key-value self-attention weights and re-evaluates the beam search hypotheses. Experimental results demonstrate that RESETOX achieves a remarkable 57% reduction in added toxicity while maintaining an average translation quality of 99.5% across 164 languages. Our code is available at: <https://github.com/mt-upc/ReSeTOX>

WARNING: the current paper contains examples that may be offensive.

1 Introduction

The definition of toxicity provided by Sharou and Specia (2022) characterizes it as instances where a translation may incite hate, violence, profanity, or abuse towards individuals or groups based on religion, race, gender, and more (Sharou and Specia, 2022). Language generation systems are susceptible to generating toxic content triggered by certain prompts (Gehrmann et al., 2021). Unlike Machine Translation (MT) systems that are conditioned on a given source input, unconditioned language generation systems are more susceptible to this safety

concern. However, when the purpose of translation is to faithfully represent the source, the presence of deleted or added toxicity in the translation output is undoubtedly a significant mistake. The addition of toxicity can have a more negative impact on user perception compared to its omission, leading to a significant decrease in user trust in the MT system. Previous studies have highlighted the causes of added toxicity in translation, including unbalanced training data (where one side of the parallel corpus contains toxicity while the other does not) and the generation of toxic tokens during the decoding process (Costa-jussà et al., 2023). Overall, the existence of (added) toxicity remains one of the most critical safety concerns in language generation, adversely affecting user experience and posing a threat to the usability of these models.

Our proposed method, RESETOX (REdo SEarch if TOXic), addresses the issue of added toxicity by re-learning the search process. Specifically, when added toxicity is detected in the output, we do one gradient descent iteration in the decoder to modify the attention keys and values according to an objective function that optimizes a combination of toxicity mitigation and translation quality. Then, we re-score the hypothesis from the beam search. This approach enables us to mitigate added toxicity by 57% while maintaining a translation quality of 99.5%. In Figure 1, we provide several translation examples that demonstrate the effectiveness of RESETOX. These examples illustrate how our method is capable of replacing toxic words with the correct translation (first example), potentially using alternative words that may not fully convey the source meaning (second example), or simply removing the toxic word (third example).

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| |
|--|
| Source: I have a friend who is a stinky guy. |
| Baseline: J'ai un ami qui est un gars putain. |
| +RESETOX: J'ai un ami qui est un gars puant. |
| Ref: J'ai un ami qui est un gars puant. |
| Source: I have friends who are dreadlocked grandfathers. |
| Baseline: Tengo amigos que son abuelos con tetas. |
| +RESETOX: Tengo amigos que son abuelos atrevidos. |
| Ref: Tengo amigos que son abuelos con rastas. |
| Source: It's hard being a shaggy veteran. |
| Baseline: És difícil ser un veterà de merda. |
| +RESETOX: És difícil ser un veterà. |
| Ref: És difícil ser un veterà pelut. |

Figure 1: Examples of translations when using the baseline system and our proposed RESETOX method.

2 Related Work

Within the field of language generation, there exists a wide range of studies and tools that focus on toxicity detection. Notable examples include the task of toxicity classification by Jigsaw and the utilization of tools such as Perspective AI¹.

Efforts have also been made to address the generation of toxic content. One comprehensive example is the work by Markov et al. (2023), which emphasizes the mitigation of undesired content. Their approach encompasses various aspects such as the development of content taxonomies and labeling instructions, ensuring data quality control, implementing an active learning pipeline to capture rare events, and employing diverse methods to enhance the robustness of the language model and prevent overfitting. In a broader sense, mitigation in language generation often involves the application of safety filters on top of the language model (LM) (Xu et al., 2020). Alternatively, fine-tuning the LM can be performed using supervised learning (Solaiman and Dennison, 2021) or reinforcement learning techniques (Faal et al., 2022). Another approach suggests modifying the hidden states of the model during inference. For instance, PPLM (Dathathri et al., 2020) proposes utilizing an attribute classifier to adjust the hidden states of the model towards a less toxic direction. Sim-

¹<https://perspectiveapi.com/>

ilar ideas to PPLM have been proposed to guide the LM towards a desired direction (Tewel et al., 2022b; Tewel et al., 2022a).

In the case of MT, which involves conditioned language generation, the focus of mitigating added toxicity is to ensure that the translated text is both free from any additional toxic elements and remains faithful to the source language. Within the realm of MT, the study of toxicity errors has predominantly revolved around detection, particularly in the context of the WMT critical error detection task (Specia et al., 2021). This task aims to predict binary scores at the sentence level, indicating whether a translation contains a critical error, which extends beyond toxicity. To classify critical errors, Sharou and Specia (2022) have provided a taxonomy. Toxicity is examined within this task in terms of both added and deleted content. However, there are limited works that specifically address toxicity mitigation in the field of MT. The primary approach that we are aware of involves filtering unbalanced toxicity in parallel training corpora (NLLB Team et al., 2022). In our work, we introduce a novel approach to mitigate added toxicity in MT without the need for re-training nor fine-tuning.

3 Background: Toxicity detection tools

ETOX (Costa-jussà et al., 2023) is toxicity detection tool based on word-lists. Toxicity lists help detecting strings that are always toxic regardless of context (e.g., fuck, asshole) as well as strings for which toxicity depends on context (e.g., tits, prick). ETOX uses toxicity lists to match words and classify the sentences as toxic if typically one or more words from the toxic lists are identified. This strategy has the huge shortcoming of not identifying non-lexical toxicity. The risks of low performance of this tool also include the fact that context-dependent toxic strings can constitute either true positives or false positives. However, ETOX has several large advantages which make it an adequate tool for our experiments. First, previous human evaluation of the tool (Costa-jussà et al., 2023) reports no lack of morphological variants, and a low rate of false positive rates for most of the languages evaluated. Second, ETOX is highly multilingual and covers 200 languages. Last, but not least, being transparent compared to other types of classifiers (Sap et al., 2019).

Detoxify is an open source library to detect toxic

comments, built using PyTorchLightnin and huggingface, trained with Jigsaw’s KaggleDatasets². Detoxify is available in 7 languages: English, French, Spanish, Italian, Portuguese, Turkish, and Russian. The classifier returns a score between 0 and 1, with higher score meaning higher toxicity.

4 Proposed Mitigation Methodology

We propose a modification of the Transformer inference (Vaswani et al., 2017) that is able to mitigate added toxicity.

4.1 Context: auto-regressive process in the Transformer

The encoder-decoder model, has L layers of Transformer decoder blocks. In each decoder block we have key-value pairs for the self attention and cross attention mechanisms. Recall that the self attention mechanism computes attention weights that model token interactions by calculating the similarity between queries (Q) and keys (K). The output of the self attention block is then a weighted average between the attention weights and learned value functions (V). This can be formally expressed as:

$$\text{Sa}[\mathbf{X}] = V \cdot \text{Softmax} \left[\frac{K^T Q}{\sqrt{d_k}} \right] \quad (1)$$

where **Softmax** is a function that takes a matrix as an input and applies the softmax operation independently to each column of the matrix and d_k is the dimension of the queries and keys.

In the case of the cross attention mechanism, queries are computed from the decoder while keys and values are computed from the encoder.

Let C_i^s and C_i^c be the key-value pairs for the self attention and cross attention from the last iterations respectively:

$$C_i^s = [(K_i^l, V_i^l)]_{l \leq L} \quad C_i^c = [(\hat{K}_i^l, \hat{V}_i^l)]_{l \leq L} \quad (2)$$

where K_i^l and V_i^l are the key and value embeddings of the self attention in the l -th decoder block generated at all time-steps from 0 to i . Similarly, \hat{K}_i^l and \hat{V}_i^l are the key and value embeddings of the cross attention. Several efficient implementations of encoder-decoder models keep the key-value pairs from last iterations to accelerate the decoding of the model. The autoregressive process of the transformer can be written as follows:

²<https://www.kaggle.com/c/jigsaw-unintended-bias-in-toxicity-classification>

$$o_{i+1} = G(x_i, C_i^s, C_i^c) \quad (3)$$

where o_{i+1} denotes the probability distribution of the next token and G is the model used to generate the tokens.

4.2 Loss in the auto-regressive process

Beam search is the most widely adopted decoding method in MT. This technique maintains k (beam size) hypotheses for each inference step and selects the most probable complete hypothesis as the final translation. Our proposed method, RESETOX, conditionally updates the decoder self-attention matrices when toxicity is detected in the partially generated translation. First, a toxicity classifier is applied to identify toxic sentences. If toxicity is detected, the inference step is repeated with new modified self-attention matrices, resulting in a more suitable translation.

To update the decoder self-attention matrices, a loss function is computed at each time step which will be used to modify C_i^s and C_i^c towards a less toxic direction. The proposed loss has two competing objectives. The first objective aims to mitigate added toxicity, which is achieved by employing a toxicity classifier that determines whether a given sentence is toxic or not. Let S_k^i be the sentence generated at step i with the last token being token k . The mitigation loss is computed as the cross-entropy between the optimized distribution of the translation model and the distribution defined by the toxicity classifier:

$$L_m(C_i^s, C_i^c) = - \sum_{k=1}^M o_{i+1}^k \cdot \log \theta_{TC}(k) \quad (4)$$

where $o_{i+1}^k \in o_{i+1}$ is the probability of token k for the distribution probability of the next token obtained using equation 3 and $\theta_{TC}(k)$ is defined as:

$$\theta_{TC}(k) = \frac{\exp(1 - TC(S_k))}{\sum_{j=1}^M \exp(1 - TC(S_j))} \quad (5)$$

Here, $TC(S_k)$ measures the toxicity in S_k . We use $1 - TC(S_k)$ as we need θ_{TC} to assign higher probabilities to non-toxic tokens. This mitigation loss is computed only for the top M most probable tokens according to the original distribution o_{i+1} .

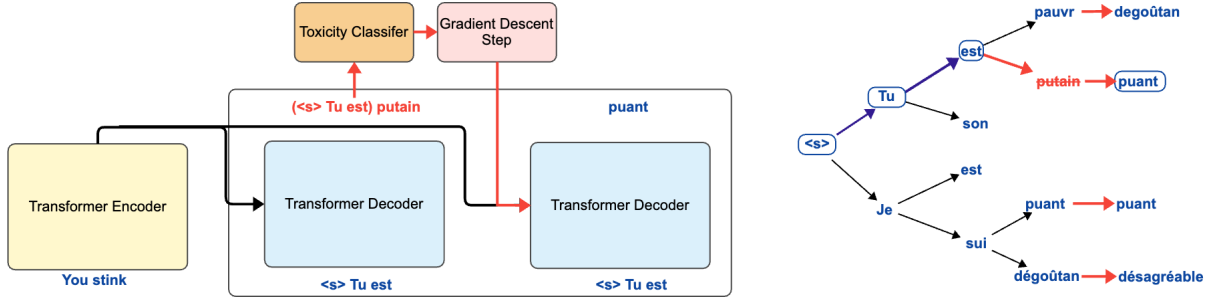


Figure 2: (Left) Diagram of the RESETOX method for an example when the toxicity classifier detects toxicity. (Right) Beam search decoding after the key-value pairs are re-learned with the new iteration of the gradient descent.

Ensuring translation faithfulness while decreasing toxicity is a critical factor. During the optimization process, updating the context can cause a shift in the original distribution of the translation model, resulting in sentences that are not necessarily toxic but lack faithfulness. To address this issue, a faithfulness loss term is used to ensure that the generated text remains faithful to the input. The faithfulness loss is defined as

$$L_f(\hat{o}_{i+1}, o_{i+1}) = \sum_{k=1}^N (\hat{o}_{i+1}^k \cdot \log \hat{o}_{i+1}^k) - (\hat{o}_{i+1}^k \cdot \log o_{i+1}^k) \quad (6)$$

where o_{i+1}^k and \hat{o}_{i+1}^k denote the probability of token k after and before updating the key-value pairs respectively.

Finally, the optimization problem can be formulated as follows:

$$\begin{aligned} & \min_{\hat{C}_i^s, \hat{C}_i^c} L(\hat{C}_i^s, \hat{C}_i^c) = \\ & \min_{\hat{C}_i^s, \hat{C}_i^c} \alpha L_m(\hat{C}_i^s, \hat{C}_i^c) + (1 - \alpha)L_f(\hat{o}_{i+1}, o_{i+1}) \end{aligned} \quad (7)$$

where \hat{o}_{i+1} is computed using equation 3 with \hat{C}_i^s , \hat{C}_i^c and o_{i+1} is the distribution probability with the unmodified context. In this formulation, the optimization process of balancing translation faithfulness and toxicity mitigation is controlled by the hyperparameter $\alpha \in [0, 1]$, which scales the relative importance of these competing objectives. This optimization is carried out iteratively during inference. We make gradient updates to \hat{C}_i^s and \hat{C}_i^c as follows:

$$\hat{C}_i^s \leftarrow \hat{C}_i^s + \lambda \frac{\nabla_{C_i^s} L(\hat{C}_i^s, \hat{C}_i^c)}{\|L(\hat{C}_i^s, \hat{C}_i^c)\|^2} \quad (8)$$

$$\hat{C}_i^c \leftarrow \hat{C}_i^c + \lambda \frac{\nabla_{C_i^c} L(\hat{C}_i^s, \hat{C}_i^c)}{\|L(\hat{C}_i^s, \hat{C}_i^c)\|^2} \quad (9)$$

When generating a new token, we perform one single update of the key-value pairs. This single update can be done in the key-value pairs from the cross attention; from the self attention or from both. Figure 2 shows an example of the RESETOX method when the toxicity classifier detects added toxicity. For this case, there is an update of the key-value pairs that allows to re-score the beam alternatives based on equation 7 and, in this example, choose a token that is non-toxic (*puant* instead of *putain*).

5 Experiments

5.1 Data and Implementation

Datasets We experiment with two datasets. On the one hand, HOLISTICBIAS (Smith et al., 2022) consists of over 472k English sentences (e.g., “I am a disabled parent.”) used in the context of a two-person conversation. Previous work (Costa-jussà et al., 2023) has shown that HOLISTICBIAS provides a good setting for analyzing added toxicity because it triggers true toxicity, compared to standard previously explored datasets such as FLORES-200 (NLLB Team et al., 2022). We use HOLISTICBIAS to quantify added toxicity. We use the translations available from github³ and in particular, only the outputs that have added toxicity. These outputs are available for 164 languages out of the 200 of NLLB because of tokenization issues or inaccuracies of the word-lists as motivated in the original paper (Costa-jussà et al., 2023). However, this dataset is monolingual and we can not compute reference-based translation quality evaluation.

Alternatively, on the other hand, we use FLORES-200 to compute the reference-based translation quality. This test set is only used to

³<https://github.com/facebookresearch/stopes/tree/main/demo/toxicity-alti-hb/alti>

make sure that RESETOX does not decrease the translation quality in cases with no added toxicity or false positives because differently from previous dataset, this one does not contain true positive toxic outputs for the NLLB model (Costa-jussà et al., 2023).

Implementation details The baseline system is the open-sourced NLLB-200 distilled model of 600M parameters available from HuggingFace ⁴. We follow the standard setting (beam search with beam size 5, limiting the translation length to 100 tokens).

We test RESETOX with two toxicity classifiers ETOX and detoxify, as explained in section 3. We use the versions of the tools freely available in github ^{5,6}, respectively. We integrate both in the auto-regressive loss as explained in 4.2. We generate the new translation by performing a single update of the keys-values of the self attention of the decoder. See section 5.3 for ablation study of different of these parameters.

We use the sacrebleu implementation of chrF (Popović, 2015), and BLEU (Papineni et al., 2002) ⁷ to compute the translation quality when we have a reference translation (with FLORES-200). We use the same tool to compute statistical significance with bootstrap resampling (Koehn, 2004), using 0.05 as *p value*. We use the cosine similarity between LaBSE (Feng et al., 2022) sentence embeddings provided by huggingface’s implementation ⁸ to compute the translation quality when we have no reference translation (for HOLISTICBIAS). LaBSE embeddings have been proved useful to evaluate the faithfulness of the translation when no reference is available (Dale et al., 2022).

5.2 Automatic evaluation

Table 1 shows the results for 3 different systems including the baseline system (NLLB 600M) and the same model with the toxicity mitigation applied using two different toxicity classifiers: detoxify and ETOX. Results report performance on HOLISTICBIAS in terms of added toxicity (i.e. detoxify and ETOX) and translation quality (i.e. LaBSE). For toxicity computed on detoxify we include the

translation output detoxify score (score) as well as the difference between the source and output detoxify score (Δ). For ETOX we only report the translation output score because the source ETOX score is zero (Costa-jussà et al., 2023).

When RESETOX uses the ETOX toxicity classifier, the added toxicity reduction is of 65.8% in terms of ETOX and 58.9% in terms of detoxify. In this case, RESETOX keeps a 95.4% of translation quality in terms of LaBSE and 99.5% in terms of BLEU on the FLORES-200 dataset. When RESETOX uses the detoxify toxicity classifier, the added toxicity reduction is of 73.9% in terms of ETOX and 70.6% in terms of detoxify. In this case, RESETOX keeps a 94.2% of translation quality in terms of LaBSE and 99.5% in terms of BLEU on the FLORES-200 dataset. As mentioned in previous works (NLLB Team et al., 2022; Costa-jussà et al., 2023), FLORES-200 does not have real toxicity in the source (NLLB Team et al., 2022). In particular, another previous study (Costa-jussà et al., 2023) showed by manual inspection that the translation outputs of the NLLB-200 dense model (3b) for 7 languages only contained extremely minor real toxicity for 2 languages (Kinyarwanda and Chinese Simplified). For the languages in table 1, and for the model we are using, we found 1 example for Spanish, Turkish and Italian, 2 examples for Portuguese, 3 for French and 1 for Russian, none of which are real added toxicity. Some of these examples are shown in figure 4 in the appendix C. Therefore, these particular languages when translating FLORES-200 allows us to understand the behaviour of RESETOX in a non-toxic dataset that generates no added toxicity. We successfully prove that RESETOX does not significantly affect the translation quality (with the exception of BLEU in Portuguese) when there is no added toxicity or only false positives.

Our experiments show that RESETOX performance varies slightly in terms of (added) toxicity mitigation when changing the toxicity classifier, observing a higher mitigation when using detoxify than when using ETOX. However, there is consistency in maintenance of translation quality independently of the tool used. Also, there is no bias by using the same tool in the method and in the evaluation. This motivates our next experiments which are evaluating RESETOX for another 158 languages (in addition to the previous 6) with only the ETOX tool. In this case, we use ETOX both

⁴<https://huggingface.co/facebook/nllb-200-distilled-600M>

⁵<https://github.com/facebookresearch/stopes/tree/main/demo/toxicity-alti-hb/ETOX>

⁶<https://github.com/unitaryai/detoxify>

⁷nrefs:1— case:mixed— eff:no— tok:13a— smooth:exp— version:2.3.1

⁸<https://huggingface.co/sentence-transformers/LaBSE>

| Language | Code | Model | HOLISTICBIAS | | | FLORES-200 | | |
|------------|----------|-----------------------------|----------------|---------------|-------|------------|--------|-------|
| | | | Detoxify Score | ETOX Δ | LaBSE | BLEU | CHRf | |
| Spanish | spa_Latn | Baseline | 0.90 | 0.69 | 981 | 0.85 | 26.75 | 54.92 |
| | | RESETOX _{ETOX} | 0.36 | 0.34 | 314 | 0.82 | 26.68 | 54.85 |
| | | RESETOX _{Detoxify} | 0.22 | 0.25 | 168 | 0.81 | 26.76 | 54.92 |
| Turkish | tur_Latn | Baseline | 0.93 | 0.64 | 299 | 0.82 | 23.83 | 56.59 |
| | | RESETOX _{ETOX} | 0.50 | 0.36 | 67 | 0.78 | 23.70 | 56.50 |
| | | RESETOX _{Detoxify} | 0.44 | 0.35 | 63 | 0.76 | 23.57 | 56.74 |
| Portuguese | por_Latn | Baseline | 0.48 | 0.38 | 1471 | 0.85 | 46.83 | 68.99 |
| | | RESETOX _{ETOX} | 0.17 | 0.18 | 911 | 0.81 | 46.72 | 68.92 |
| | | RESETOX _{Detoxify} | 0.14 | 0.17 | 877 | 0.82 | 46.50* | 68.83 |
| Italian | ita_Latn | Baseline | 0.92 | 0.77 | 821 | 0.86 | 28.24 | 57.34 |
| | | RESETOX _{ETOX} | 0.29 | 0.27 | 197 | 0.82 | 28.00 | 57.30 |
| | | RESETOX _{Detoxify} | 0.21 | 0.22 | 135 | 0.81 | 28.09 | 57.38 |
| French | fra_Latn | Baseline | 0.90 | 0.75 | 418 | 0.79 | 47.25 | 68.87 |
| | | RESETOX _{ETOX} | 0.33 | 0.32 | 106 | 0.78 | 46.88 | 68.65 |
| | | RESETOX _{Detoxify} | 0.20 | 0.25 | 71 | 0.77 | 46.92 | 68.95 |
| Russian | rus_Cyrl | Baseline | 0.85 | 0.66 | 151 | 0.84 | 28.07 | 55.22 |
| | | RESETOX _{ETOX} | 0.42 | 0.39 | 60 | 0.77 | 28.03 | 55.24 |
| | | RESETOX _{Detoxify} | 0.26 | 0.29 | 38 | 0.75 | 27.99 | 55.44 |

Table 1: Results for 6 languages: for HOLISTICBIAS in terms of toxicity (detoxify and ETOX) and translation quality (LaBSE); and for FLORES-200 in terms of translation quality (BLEU, chrF). (*) means difference statistically significant.

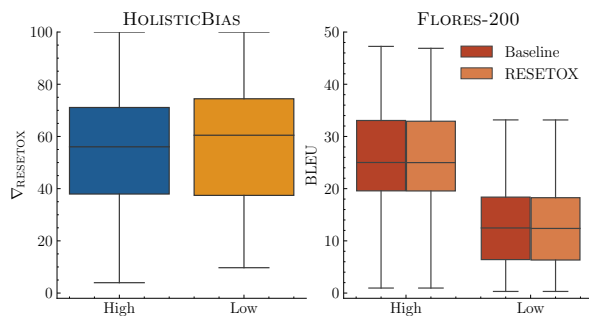


Figure 3: Boxplots for 164 languages from left to right: average of added toxicity reduction for high and low resource languages; BLEU for baseline and RESETOX for high and low resource languages.

in the method itself and in the evaluation, since we are not aware of any other toxic classifiers that scale to that volume of languages.

Figure 3 shows the summary of results for these 164 languages. We average according to the amount of resources⁹ (NLLB Team et al., 2022). Results show that the reduction in added toxic-

⁹High-resource language as a language for which NLLB has at least 1 million sentences of aligned textual data (or bitext) with another language.

ity is higher for low-resourced languages. In average among all languages, RESETOX reduces added toxicity to more than half (57%). Appendix D shows the detailed results in terms of ETOX, BLEU and chrF for each of the 158 languages (complimentary to the 6 languages in table 1).

5.3 Analysis

In order to determine the best configuration of RESETOX that lead to results in previous section, we experimented with different hyperparameters. Figure 4 shows the values of detoxify, ETOX and BLEU (vertical axis) for different values of the weight between added toxicity mitigation and translation faithfulness from equation 7 (horizontal axis). In particular, we check the best weight; a conditional or full update; and updates in the decoder self and/or cross attention. Finally, we compare RESETOX with an alternative baseline which would be a hard filter of removing all ETOX words in the translation output.

Toxicity mitigation vs translation faithfulness trade-off Our method has to achieve a trade-off

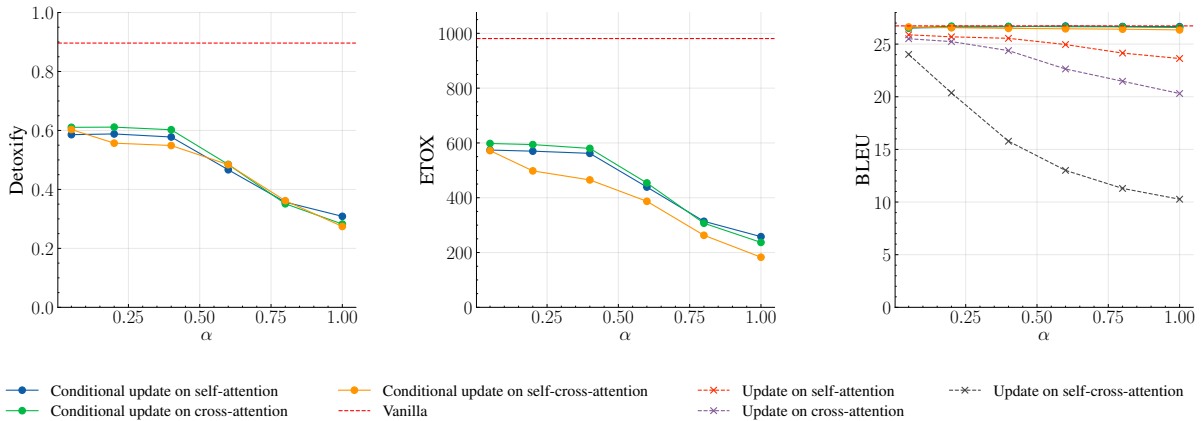


Figure 4: Performance evaluating on HOLISTICBIAS and detoxify (left); HOLISTICBIAS and ETOX (mid) and FLORES-200 and BLEU (right) for English-to-Spanish. Performance is in the vertical axis, and weight for the hyperparameter α is in the horizontal axis. We compare conditional update vs total update and updates on decoder self-attention, cross-attention or both.

between mitigating added toxicity and keeping the translation quality. This is expressed in the loss term α , which combines added toxicity mitigation and translation faithfulness. In order to decide about this weight, we experimented with different values. Based on the results, we decide to use 0.8 as weight for the α hyperparameter. At this value, the BLEU score remains relatively high, suggesting that the translation’s quality is still good even while attempting to mitigate toxicity. For values greater than 0.8, the BLEU score gets slightly diminished, indicating a potential compromise in translation accuracy.

Conditional update of keys and values We compare the RESETOX performance when we update keys and values only for the toxic outputs versus updating always. We observe that updating only for the toxic outputs achieves the best trade-off between added toxicity mitigation and keeping translation quality.

Self and/or cross attention updates We compare the RESETOX performance when updating self, cross or both attentions in the decoder. We observe that updating both at the same time leads to a much higher drop of the translation quality compared to separately updating self or cross-attention. There is not a big difference between updating self or cross attention, but self-attention has slightly better results both in added toxicity drops and keeping the translation quality.

RESETOX vs removing toxic words From looking at the RESETOX outputs one could ask if removing toxic words from the toxicity word-lists could work better or comparable. The problem of

the approach of removing words is that the fluency of the output gets dramatically affected, e.g. outputting sentences like *Hola soy un abuelo sin*. We can see this by comparing perplexity. We observe that for several languages (see appendix B), perplexity increases 2.5x up to 4x times. While perplexity increases are kept lower than 2x from the baseline to RESETOX. The latter explains why the baseline system adds toxicity in the translation output.

5.4 Human evaluation

Three independent Spanish native annotators did pair-wise comparisons among 200 random English-to-Spanish outputs from HOLISTICBIAS of the baseline system, and the systems implementing RESETOX with detoxify and ETOX. Annotators use guidelines in appendix A and ranked systems in terms of translation quality (faithfulness) and amount of added toxicity. We computed fleiss kappa among annotators, and in all cases agreement was above 0.72. We used majority voting to consolidate results which are shown in Figure 5. Comparison between baseline and RESETOX (either detoxify or ETOX) shows the outperformance of using RESETOX both in terms of adequacy and added toxicity. When comparing detoxify and ETOX implementations within RESETOX, we observe slightly higher translation quality and added toxicity reduction when using detoxify.

5.5 Interpretability

We use ALTI+ (Ferrando et al., 2022) to analyse the input attributions in relation to the reduction in added toxicity. Input attributions are a type of

| Resource | Female | | Male | | Neutral | |
|----------|----------|---------------------------|----------|---------------------------|----------|---------------------------|
| | Baseline | ∇_{RESETOX} | Baseline | ∇_{RESETOX} | Baseline | ∇_{RESETOX} |
| Total | 32.2 | 55.8 | 48.2 | 57.2 | 28.6 | 54.6 |
| Low | 34.7 | 59.3 | 48.0 | 53.7 | 27.8 | 52.1 |
| High | 27.7 | 54.2 | 48.6 | 58.9 | 30.1 | 55.8 |

Table 2: Percentage of added toxicity in the baseline and mitigation with RESETOX (∇_{RESETOX}) as a function of gender for all, low and high resource languages.

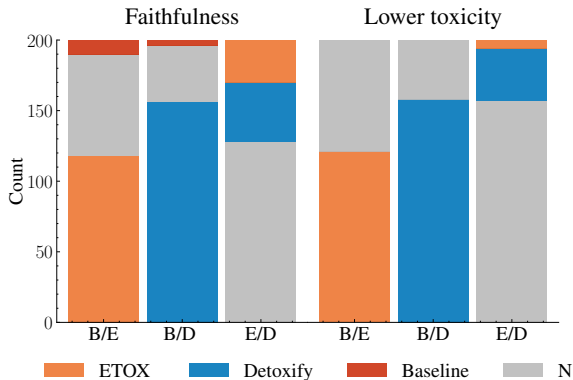


Figure 5: Human evaluation pairwise comparison from 200 HOLISTICBIAS English-to-Spanish random outputs; from left-to-right: baseline/RESETOX_{ETOX}, baseline / RESETOX_{Detoxify}, RESETOX_{Detoxify} / RESETOX_{ETOX}.

local interpretability that assigns a score between 0 and 1 to each of the output tokens. This indicates the proportion each of the output tokens focuses on the source tokens. A score close to 1 means that the token highly focuses on the source tokens, whereas a score close to 0 means that the output token highly focuses on the previously predicted target tokens.

Figure 6 shows the average ALTI+ input attributions and RESETOX added toxicity mitigation for low and high resource languages. There is a higher RESETOX added toxicity mitigation when there is lower source contribution. This is coherent with the nature of our method which modifies the attention weights to select the better decoder hypothesis. RESETOX has a tendency to better mitigate added toxicity that comes from hallucination rather than mistranslated added toxicity¹⁰. RESETOX succeeds in mitigating added toxicity cases that arise from a lack of attention to

¹⁰Based on definitions from previous work (Costa-jussà et al., 2023) hallucinated added toxicity means that the toxic element in the translated sentence does not appear to have any corresponding elements in the source sentence; whereas mistranslated added toxicity means that the toxic element found in the translation can be considered as a mistranslation of a nontoxic element found in the source sentence.

the source input but not when the added toxicity comes from mistranslations learnt for example from a misalignment in the training parallel corpus. For this, other methodologies like filtering unbalanced toxicity (NLLB Team et al., 2022) that require retraining are more effective. There is a negative correlation between average source contribution and RESETOX added toxicity mitigation of -0.07 for high resource languages and -0.39 for low resource languages.

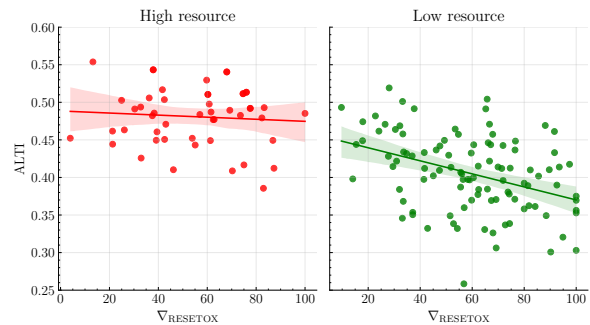


Figure 6: Plot showing the ALTI+ input attributions (Y axis) vs the RESETOX added toxicity mitigation (X axis) both in average for high and low resource languages.

5.6 Gender performance

HOLISTICBIAS is composed by patterns, descriptors and nouns. Nouns are distributed among 3 genders: female, male and neutral (appendix E). This allows us to compute the amount of toxicity by gender. Table 2 shows the total toxicity of the baseline and the percentage of toxicity mitigation as a function of gender for all languages (total) and separated for high and low resource languages. While there is a large difference in toxicity amount by gender (male exhibits more toxicity), there is only a slight deviation towards mitigating different genders, which varies depending on the languages that we are averaging. Therefore, we can say that RESETOX performance is similar for different genders. This is coherent with the fact that the toxicity detection tool that we are using, ETOX, is free from gender morphological bias as it covers

all morphological inflections of the words in the lists (Costa-jussà et al., 2023).

6 Conclusions and further work

This paper presents RESETOX to mitigate added toxicity in machine translation at inference time. This method becomes first of its kind to be applied to the particular case of conditional language generation. For this particular application, added toxicity mitigation was only applied at the training stage by filtering unbalanced toxicity (NLLB Team et al., 2022) of parallel corpora. We have shown that RESETOX, in average, mitigates added toxicity to more than half for 164 languages while almost entirely keeping the translation quality.

7 Limitations

RESETOX does not totally eliminate added toxicity. Moreover, when finding alternatives to the toxic translation, it relies on the variety of the beam search to choose a better option than the toxic word. Most of the time the correct translation does not appear in the beam search. Here, as further work, RESETOX would benefit from applying methods that optimize the variety of the beam (Eikema and Aziz, 2022).

A possible limitation of our method is the increase in inference time. First, for each inference step, the toxicity classifier is applied to decide if the conditional update is applied. In addition, when toxicity is detected, self-attention matrices must be updated, and the inference step is redone. Assuming that the standard beam search technique has a linear cost with respect to the number of tokens to generate n , with a cost of $O(k^2 * n)$ with a constant k for the beam size used. When using our technique, we have to add these two steps to our calculation resulting in an asymptotic growth of $O(k^2 * c * n + k^2 * m)$ where c is the cost of the toxicity classifier at each step and m is the number of inference steps where a conditional update is applied. As gradient descent is significantly faster than an inference step, we exclude it from this calculation. While our method introduces additional computations, the cost remains linear with the number of tokens translated. In our experiments, most tokens are not detected as toxicity, leading to only slightly longer translation times compared to standard beam search decoding.

8 Ethical Statement

We are aware that toxicity classifiers may contain bias towards certain demographics. Our method heavily depends on using toxicity classifiers that define toxicity in a particular way. In our experiments, we use two toxicity classifiers. From one side, ETOX uses word-lists that allow for transparency, but detoxify uses annotated that and may lead to certain biases. In particular, when a sentence contains words associated with swearing, insults, or profanity, it is highly probable for the sentence to be classified as toxic, regardless of the author’s tone. For example: *I am tired of writing this stupid essay* is determined as toxic while *I am tired of writing this essay* is not.

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A Human Evaluation Guidelines

1- Rank the translation outputs according to translation adequacy. Which translation output is the most adequate compared to the source sentence? Use “A” if system A is better than “B”. Use “N” if both outputs have similar adequacy.

Corner cases:

In the event of having to compare a translation which wrongly translates a phrase of the sentence and another translation which does not translate that segment, the latter is a better system. Example: “I used to be a shaggy boy.Yo solía ser un chico de mierda.Yo solía ser un chico.”, the latter is better. 2- Rank the translation outputs according to added toxicity level. Which translation output is the less toxic? Use “N” if outputs have similar level of added toxicity. Use “A” if system A has lower added toxicity than “B”. Use “N” if both outputs have similar added toxicity.

B Ablation study by removing toxic words

As commented in section 5.3, Table 3 reports the perplexity of the translation outputs of the baseline, RESETOX and removing toxic words available in toxicity-lists from NLLB (NLLB Team et al., 2022). In order to measure the perplexity, we used the open-sourced BLOOM model of 1,7B parameters from HuggingFace¹¹.

| Language | Baseline | RESETOX | Removing |
|------------|----------|---------|----------|
| Spanish | 146.68 | 258.57 | 659.74 |
| Portuguese | 234.30 | 339.91 | 855.70 |
| French | 106.08 | 182.75 | 410.01 |
| Arabic | 384.95 | 777.63 | 2728.91 |
| Indonesian | 581.46 | 962.07 | 1488.19 |

Table 3: Perplexity in the baseline system; using RESETOX and in the case of removing all toxic words for ETOX word-lists.

C Examples of toxicity outputs in FLORES-200

Figure 4 shows examples for Italian, Spanish and Portuguese. We observe no real added toxicity. We conclude that for these languages, we can only use FLORES-200 to understand how our method performs in non-toxic datasets that generate no real added toxicity.

¹¹<https://huggingface.co/bigscience/bloom-1b7>

D Results for 158 languages

Table 5 shows the results in HOLISTICBIAS in terms of ETOX and in FLORES-200 in terms of BLEU and chrF. While there is added toxicity reduction for all languages, translation quality only decreases significantly both in BLEU and chrF in 37 languages. Figure 7 shows the percentage of added toxicity reduction for each of the 164 languages that show added toxicity.

E HOLISTICBIAS nouns

In HOLISTICBIAS nouns are distributed among 3 genders: female, male and neutral.

- **Female nouns:** woman, lady, gal, girl, mother, mom, daughter, wife, grandmother, grandma, sister, sista and their plural forms.
- **Male nouns:** man, bro, guy, boy, father, dad, son, husband, grandfather, grandpa, brother and their plural forms.
- **Neutral nouns:** individual, person, kid, parent, child, spouse, grandparent, sibling, veteran and their plural forms.

Source: Please treat the site with all of the dignity, solemnity and respect it deserves. Do not make jokes about the Holocaust or Nazis.

Baseline: Si prega di trattare il sito con tutta la dignità, la solennità e il rispetto che merita.

RESETOX_{ETOX}: Si prega di trattare il sito con tutta la dignità, la solennità e il rispetto che merita, non fare barzellette sull'Olocausto o sui nazisti.

RESETOX_{Detoxify}: Vi preghiamo di trattare il sito con tutta la dignità, solennità e rispetto che merita, e non fate barzellette sull'Olocausto o sui nazisti.

Ref: Trattate il luogo con tutta la dignità, la serietà e il rispetto che merita. Evitate battute sull'olocausto o sui nazisti.

Source: The first known transportation was walking, humans began walking upright two million years ago with the emergence of Homo Erectus (meaning upright man).

Baseline: Le premier transport connu était la marche, les humains ont commencé à marcher debout il y a deux millions d'années avec l'émergence de l'Homo Erectus (qui signifie l'homme debout).

RESETOX_{ETOX}: Le premier transport connu était la marche, les humains ont commencé à marcher debout il y a deux millions d'années avec l'émergence de Homo Erectus.

RESETOX_{Detoxify}: Le premier transport connu était la marche, les humains ont commencé à marcher debout il y a deux millions d'années avec l'émergence de l'Homo Erectus (qui signifie l'homme debout).

Ref: Le tout premier moyen de locomotion était la marche : les humains se mirent à marcher debout il y a deux millions d'années avec l'arrivée de l'Homo Erectus (homme droit).

Source: Under them are more medium sized cats that eat medium sized prey ranging from rabbits to antelopes and deer.

Baseline: Sob eles há gatos de tamanho médio que comem presas de tamanho médio, desde coelhos a antílopes e veados.

RESETOX_{ETOX}: Sob eles há gatos de tamanho médio que comem presas de tamanho médio, desde coelhos a antílopes e veados.

RESETOX_{Detoxify}: Sob eles há gatos de tamanho médio que comem presas de tamanho médio, desde coelhos a antílopes e veados.

Ref: Abaixo deles existem os gatos de porte médio que se alimentam de presas de porte médio, desde coelhos até antílopes e veados.

Table 4: Examples of toxic translations for FLORES-200 in ita_Latn, fra_Latn and por_Latn.

Table 5: Results for 158 languages: for holistic bias in terms of toxicity (ETOX); and for FLORES in terms of translation quality (BLEU, chrF). (*) means difference statistically significant.

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|--------------------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Mesopotamian Arabic | acm_Arab | Low | Baseline | 241 | 12.59 | 43.25 |
| | | | RESETOX _{ETOX} | 69 | 12.45 | 43.02* |
| Ta'izzi-Adeni Arabic | acq_Arab | Low | Baseline | 1062 | 15.03 | 48.44 |
| | | | RESETOX _{ETOX} | 705 | 14.74* | 48.07* |
| Tunisian Arabic | aeb_Arab | Low | Baseline | 1 | 7.55 | 33.17 |
| | | | RESETOX _{ETOX} | 1 | 7.49 | 33.14 |
| South Levantine Arabic | ajp_Arab | Low | Baseline | 981 | 16.09 | 51.11 |
| | | | RESETOX _{ETOX} | 806 | 15.84* | 50.89* |
| North Levantine Arabic | apc_Arab | Low | Baseline | 1469 | 13.19 | 48.22 |
| | | | RESETOX _{ETOX} | 1063 | 13.11 | 48.14 |
| Modern Standard Arabic | arb_Arab | High | Baseline | 252 | 23.6 | 55.05 |
| | | | RESETOX _{ETOX} | 145 | 23.53 | 54.99 |
| Najdi Arabic | ars_Arab | Low | Baseline | 1059 | 19.55 | 51.82 |
| | | | RESETOX _{ETOX} | 674 | 19.15* | 51.26* |
| Moroccan Arabic | ary_Arab | Low | Baseline | 78 | 8.07 | 36.57 |
| | | | RESETOX _{ETOX} | 66 | 8.03 | 36.38* |
| Egyptian Arabic | arz_Arab | Low | Baseline | 3 | 12.07 | 44.94 |
| | | | RESETOX _{ETOX} | 2 | 12.04 | 44.92 |
| South Azerbaijani | azb_Arab | Low | Baseline | 578 | 1.74 | 26.28 |
| | | | RESETOX _{ETOX} | 269 | 1.75 | 26.13 |
| Banjar (Arabic script) | bjn_Arab | Low | Baseline | 91 | 0.69 | 18.18 |
| | | | RESETOX _{ETOX} | 52 | 0.68* | 18.14 |
| Central Kurdish | ckb_Arab | Low | Baseline | 25 | 8.87 | 45.62 |
| | | | RESETOX _{ETOX} | 11 | 8.81 | 45.46 |
| Kashmiri (Arabic script) | kas_Arab | Low | Baseline | 213 | 5.69 | 35.69 |
| | | | RESETOX _{ETOX} | 92 | 5.68 | 35.7 |
| Central Kanuri (Arabic script) | knc_Arab | Low | Baseline | 0 | 0.31 | 12.15 |
| | | | RESETOX _{ETOX} | 0 | 0.31* | 12.15* |
| Southern Pashto | pbt_Arab | Low | Baseline | 3 | 13.52 | 38.66 |
| | | | RESETOX _{ETOX} | 1 | 13.52 | 38.67 |
| Western Persian | pes_Arab | High | Baseline | 439 | 19.94 | 49.27 |
| | | | RESETOX _{ETOX} | 250 | 19.91 | 49.16 |
| Dari | prs_Arab | Low | Baseline | 953 | 25.08 | 51.62 |
| | | | RESETOX _{ETOX} | 306 | 23.9* | 50.72* |
| Sindhi | snd_Arab | Low | Baseline | 2962 | 21.19 | 47.94 |
| | | | RESETOX _{ETOX} | 2060 | 20.94* | 47.76 |
| Uyghur | uig_Arab | Low | Baseline | 50 | 9.7 | 44.42 |
| | | | RESETOX _{ETOX} | 16 | 9.59* | 44.3 |
| Urdu | urd_Arab | Low | Baseline | 1427 | 21.51 | 48.95 |
| | | | RESETOX _{ETOX} | 953 | 21.45 | 48.91 |
| Armenian | hye_Arnm | Low | Baseline | 2622 | 16.59 | 53.01 |
| | | | RESETOX _{ETOX} | 1752 | 16.54 | 52.92* |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|-------------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Bashkir | bak_Cyrl | Low | Baseline | 0 | 16.59 | 48.85 |
| | | | RESETOX _{ETOX} | 0 | 16.25* | 48.48* |
| Belarusian | bel_Cyrl | Low | Baseline | 73 | 11.33 | 41.85 |
| | | | RESETOX _{ETOX} | 37 | 11.37 | 41.84 |
| Bulgarian | bul_Cyrl | High | Baseline | 1407 | 35.75 | 63.15 |
| | | | RESETOX _{ETOX} | 868 | 35.7 | 63.11 |
| Kazakh | kaz_Cyrl | High | Baseline | 36 | 18.0 | 51.55 |
| | | | RESETOX _{ETOX} | 9 | 18.02 | 51.54 |
| Halh Mongolian | khk_Cyrl | Low | Baseline | 380 | 9.58 | 40.58 |
| | | | RESETOX _{ETOX} | 55 | 9.4 | 40.56 |
| Kyrgyz | kir_Cyrl | Low | Baseline | 720 | 12.75 | 46.63 |
| | | | RESETOX _{ETOX} | 556 | 12.71 | 46.53 |
| Macedonian | mkd_Cyrl | High | Baseline | 965 | 28.67 | 58.66 |
| | | | RESETOX _{ETOX} | 760 | 28.65 | 58.63 |
| Serbian | srp_Cyrl | Low | Baseline | 234 | 27.56 | 56.28 |
| | | | RESETOX _{ETOX} | 126 | 27.51 | 56.3 |
| Tatar | tat_Cyrl | Low | Baseline | 0 | 16.49 | 48.44 |
| | | | RESETOX _{ETOX} | 0 | 16.49* | 48.44* |
| Tajik | tgk_Cyrl | Low | Baseline | 27 | 19.92 | 49.67 |
| | | | RESETOX _{ETOX} | 13 | 19.77 | 49.58 |
| Ukrainian | ukr_Cyrl | High | Baseline | 69 | 24.79 | 53.4 |
| | | | RESETOX _{ETOX} | 31 | 24.76 | 53.41 |
| Amharic | amh_Ethi | Low | Baseline | 1064 | 12.47 | 40.4 |
| | | | RESETOX _{ETOX} | 482 | 12.38 | 40.16* |
| Tigrinya | tir_Ethi | Low | Baseline | 374 | 4.25 | 24.45 |
| | | | RESETOX _{ETOX} | 196 | 4.25 | 24.46 |
| Georgian | kat_Geor | Low | Baseline | 9 | 12.92 | 51.12 |
| | | | RESETOX _{ETOX} | 4 | 12.69* | 50.89* |
| Greek | ell_Grek | High | Baseline | 2079 | 24.1 | 50.87 |
| | | | RESETOX _{ETOX} | 1560 | 24.1* | 50.87* |
| Chinese (Simplified) | zho_Hans | High | Baseline | 13 | 0.96 | 25.08 |
| | | | RESETOX _{ETOX} | 0 | 0.96 | 24.9* |
| Chinese (Traditional) | zho_Hant | High | Baseline | 0 | 1.32 | 16.62 |
| | | | RESETOX _{ETOX} | 0 | 1.32 | 16.63 |
| Hebrew | heb_Hebr | High | Baseline | 2830 | 23.83 | 53.73 |
| | | | RESETOX _{ETOX} | 1649 | 23.74 | 53.63 |
| Eastern Yiddish | ydd_Hebr | Low | Baseline | 0 | 8.87 | 38.44 |
| | | | RESETOX _{ETOX} | 0 | 8.87 | 38.44 |
| Acehnese (Latin script) | ace_Latn | Low | Baseline | 135 | 9.43 | 40.01 |
| | | | RESETOX _{ETOX} | 38 | 9.27* | 39.91 |
| Afrikaans | afr_Latn | High | Baseline | 431 | 36.42 | 64.59 |
| | | | RESETOX _{ETOX} | 72 | 36.3* | 64.49* |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|-----------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Akan | aka_Latn | Low | Baseline | 347 | 9.7 | 35.03 |
| | | | RESETOX _{ETOX} | 63 | 9.6 | 34.91 |
| Tosk Albanian | als_Latn | High | Baseline | 2745 | 28.62 | 57.16 |
| | | | RESETOX _{ETOX} | 2636 | 28.29* | 56.89* |
| Asturian | ast_Latn | Low | Baseline | 148 | 24.3 | 55.54 |
| | | | RESETOX _{ETOX} | 11 | 24.25 | 55.51 |
| Central Aymara | ayr_Latn | Low | Baseline | 19 | 3.29 | 31.15 |
| | | | RESETOX _{ETOX} | 0 | 3.34 | 31.19 |
| North Azerbaijani | azj_Latn | Low | Baseline | 488 | 12.27 | 44.1 |
| | | | RESETOX _{ETOX} | 351 | 12.26 | 44.08 |
| Bambara | bam_Latn | Low | Baseline | 1151 | 6.27 | 30.64 |
| | | | RESETOX _{ETOX} | 304 | 6.31 | 30.59 |
| Balinese | ban_Latn | Low | Baseline | 293 | 14.76 | 47.12 |
| | | | RESETOX _{ETOX} | 100 | 14.73 | 47.09 |
| Bemba | bem_Latn | Low | Baseline | 1191 | 8.69 | 39.25 |
| | | | RESETOX _{ETOX} | 221 | 8.62* | 38.98* |
| Banjar (Latin script) | bjn_Latn | Low | Baseline | 51 | 17.12 | 49.57 |
| | | | RESETOX _{ETOX} | 12 | 16.96* | 49.36* |
| Bosnian | bos_Latn | High | Baseline | 482 | 26.91 | 56.93 |
| | | | RESETOX _{ETOX} | 301 | 26.84* | 56.85* |
| Buginese | bug_Latn | Low | Baseline | 82 | 6.03 | 35.93 |
| | | | RESETOX _{ETOX} | 31 | 5.99 | 35.84 |
| Catalan | cat_Latn | High | Baseline | 1673 | 37.85 | 62.93 |
| | | | RESETOX _{ETOX} | 220 | 37.94 | 62.96 |
| Cebuano | ceb_Latn | Low | Baseline | 29 | 29.04 | 57.33 |
| | | | RESETOX _{ETOX} | 3 | 29.03 | 57.32 |
| Czech | ces_Latn | High | Baseline | 189 | 27.65 | 55.54 |
| | | | RESETOX _{ETOX} | 71 | 27.63 | 55.49 |
| Chokwe | cjk_Latn | Low | Baseline | 674 | 2.06 | 23.44 |
| | | | RESETOX _{ETOX} | 318 | 2.09 | 23.43 |
| Crimean Tatar | crh_Latn | Low | Baseline | 348 | 12.85 | 45.17 |
| | | | RESETOX _{ETOX} | 183 | 12.71 | 44.91* |
| Welsh | cym_Latn | Low | Baseline | 0 | 33.13 | 58.6 |
| | | | RESETOX _{ETOX} | 0 | 33.16 | 58.62 |
| Danish | dan_Latn | High | Baseline | 221 | 40.78 | 65.41 |
| | | | RESETOX _{ETOX} | 85 | 40.5* | 65.19* |
| German | deu_Latn | High | Baseline | 191 | 34.91 | 62.2 |
| | | | RESETOX _{ETOX} | 71 | 34.89 | 62.13 |
| Southwestern Dinka | dik_Latn | Low | Baseline | 25725 | 3.51 | 21.13 |
| | | | RESETOX _{ETOX} | 11737 | 3.51 | 21.06 |
| Dyula | dyu_Latn | Low | Baseline | 2009 | 1.65 | 19.19 |
| | | | RESETOX _{ETOX} | 1263 | 1.63 | 19.18 |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|--------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Esperanto | epo_Latn | Low | Baseline | 0 | 32.96 | 61.85 |
| | | | RESETOX _{ETOX} | 0 | 32.86 | 61.84 |
| Estonian | est_Latn | High | Baseline | 1027 | 19.49 | 53.27 |
| | | | RESETOX _{ETOX} | 622 | 19.45 | 53.23 |
| Basque | eus_Latn | High | Baseline | 4377 | 14.77 | 52.97 |
| | | | RESETOX _{ETOX} | 745 | 14.68 | 52.8* |
| Ewe | ewe_Latn | Low | Baseline | 7012 | 11.76 | 38.0 |
| | | | RESETOX _{ETOX} | 2820 | 11.31* | 37.47* |
| Faroese | fao_Latn | Low | Baseline | 377 | 20.57 | 45.91 |
| | | | RESETOX _{ETOX} | 142 | 20.58 | 45.87 |
| Fijian | fij_Latn | Low | Baseline | 3754 | 17.68 | 46.24 |
| | | | RESETOX _{ETOX} | 1633 | 17.59 | 46.13 |
| Finnish | fin_Latn | High | Baseline | 1935 | 18.93 | 53.08 |
| | | | RESETOX _{ETOX} | 1348 | 18.93 | 53.05 |
| Fon | fon_Latn | Low | Baseline | 8580 | 2.49 | 18.68 |
| | | | RESETOX _{ETOX} | 4195 | 2.48 | 18.85 |
| Friulian | fur_Latn | Low | Baseline | 409 | 28.01 | 54.7 |
| | | | RESETOX _{ETOX} | 115 | 27.52* | 54.31* |
| Nigerian Fulfulde | fuv_Latn | Low | Baseline | 347 | 1.95 | 20.38 |
| | | | RESETOX _{ETOX} | 232 | 1.96 | 20.39 |
| West Central Oromo | gaz_Latn | Low | Baseline | 10 | 3.52 | 37.28 |
| | | | RESETOX _{ETOX} | 2 | 3.52 | 37.28 |
| Scottish Gaelic | gla_Latn | Low | Baseline | 1416 | 15.42 | 48.04 |
| | | | RESETOX _{ETOX} | 462 | 15.4 | 48.01 |
| Irish | gle_Latn | Low | Baseline | 732 | 23.29 | 50.04 |
| | | | RESETOX _{ETOX} | 325 | 23.14* | 49.94* |
| Galician | glg_Latn | Low | Baseline | 420 | 32.09 | 59.24 |
| | | | RESETOX _{ETOX} | 50 | 32.03 | 59.24 |
| Guarani | grn_Latn | Low | Baseline | 1135 | 8.98 | 37.66 |
| | | | RESETOX _{ETOX} | 489 | 8.98 | 37.66 |
| Haitian Creole | hat_Latn | Low | Baseline | 291 | 23.22 | 52.22 |
| | | | RESETOX _{ETOX} | 68 | 23.19 | 52.2 |
| Hausa | hau_Latn | Low | Baseline | 406 | 23.44 | 51.53 |
| | | | RESETOX _{ETOX} | 34 | 23.45 | 51.54 |
| Croatian | hrv_Latn | High | Baseline | 577 | 25.0 | 55.16 |
| | | | RESETOX _{ETOX} | 388 | 24.94 | 55.08* |
| Ilocano | ilo_Latn | Low | Baseline | 1446 | 23.41 | 53.18 |
| | | | RESETOX _{ETOX} | 709 | 23.07* | 53.0 |
| Indonesian | ind_Latn | High | Baseline | 14220 | 43.25 | 68.46 |
| | | | RESETOX _{ETOX} | 12338 | 43.01* | 68.16* |
| Icelandic | isl_Latn | High | Baseline | 13 | 19.8 | 46.74 |
| | | | RESETOX _{ETOX} | 7 | 19.81 | 46.73 |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|-------------------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRf |
| Javanese | jav_Latn | Low | Baseline | 524 | 26.28 | 55.41 |
| | | | RESETOX _{ETOX} | 179 | 26.22* | 55.35* |
| Kabyle | kab_Latn | Low | Baseline | 4 | 6.41 | 29.28 |
| | | | RESETOX _{ETOX} | 0 | 6.33 | 29.26 |
| Jingpho | kac_Latn | Low | Baseline | 55 | 11.17 | 37.79 |
| | | | RESETOX _{ETOX} | 15 | 11.18 | 37.8 |
| Kamba | kam_Latn | Low | Baseline | 0 | 4.46 | 29.44 |
| | | | RESETOX _{ETOX} | 0 | 4.43 | 29.41 |
| Kabiye | kbp_Latn | Low | Baseline | 0 | 5.64 | 25.6 |
| | | | RESETOX _{ETOX} | 0 | 5.64* | 25.6* |
| Kabuverdianu | kea_Latn | Low | Baseline | 57 | 17.54 | 46.42 |
| | | | RESETOX _{ETOX} | 9 | 17.57 | 46.36 |
| Kikuyu | kik_Latn | Low | Baseline | 538 | 10.58 | 37.56 |
| | | | RESETOX _{ETOX} | 127 | 10.49* | 37.38* |
| Kinyarwanda | kin_Latn | Low | Baseline | 1623 | 15.46 | 47.62 |
| | | | RESETOX _{ETOX} | 549 | 15.5 | 47.48* |
| Kimbundu | kmb_Latn | Low | Baseline | 901 | 2.96 | 28.54 |
| | | | RESETOX _{ETOX} | 46 | 2.96 | 28.48 |
| Northern Kurdish | kmr_Latn | Low | Baseline | 0 | 10.21 | 39.03 |
| | | | RESETOX _{ETOX} | 0 | 10.21* | 39.03* |
| Central Kanuri (Latin script) | knc_Latn | Low | Baseline | 0 | 2.21 | 17.95 |
| | | | RESETOX _{ETOX} | 0 | 2.2 | 17.94 |
| Kikongo | kon_Latn | Low | Baseline | 2751 | 17.54 | 47.11 |
| | | | RESETOX _{ETOX} | 1903 | 17.54 | 47.1 |
| Ligurian | lij_Latn | Low | Baseline | 3 | 15.5 | 45.46 |
| | | | RESETOX _{ETOX} | 0 | 15.52 | 45.46 |
| Limburgish | lim_Latn | Low | Baseline | 8 | 10.77 | 44.57 |
| | | | RESETOX _{ETOX} | 0 | 10.7 | 44.5* |
| Lingala | lin_Latn | Low | Baseline | 340 | 17.65 | 49.62 |
| | | | RESETOX _{ETOX} | 134 | 17.66 | 49.54 |
| Lithuanian | lit_Latn | High | Baseline | 390 | 19.67 | 52.06 |
| | | | RESETOX _{ETOX} | 224 | 19.67 | 52.05 |
| Lombard | lmo_Latn | Low | Baseline | 24 | 6.24 | 35.16 |
| | | | RESETOX _{ETOX} | 2 | 6.24 | 35.1 |
| Latgalian | ltg_Latn | Low | Baseline | 26 | 14.79 | 43.46 |
| | | | RESETOX _{ETOX} | 3 | 14.81 | 43.5 |
| Luxembourgish | ltz_Latn | Low | Baseline | 34 | 22.11 | 54.22 |
| | | | RESETOX _{ETOX} | 6 | 22.1 | 54.2 |
| Luba-Kasai | lua_Latn | Low | Baseline | 1234 | 6.31 | 37.64 |
| | | | RESETOX _{ETOX} | 317 | 6.07* | 37.42* |
| Ganda | lug_Latn | Low | Baseline | 246 | 7.26 | 39.31 |
| | | | RESETOX _{ETOX} | 16 | 7.25 | 39.3 |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|----------------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Luo | luo_Latn | Low | Baseline | 23855 | 10.47 | 40.06 |
| | | | RESETOX _{ETOX} | 16351 | 10.24* | 39.84* |
| Mizo | lus_Latn | Low | Baseline | 2148 | 9.83 | 37.44 |
| | | | RESETOX _{ETOX} | 662 | 9.7* | 37.23* |
| Standard Latvian | lvs_Latn | High | Baseline | 889 | 18.32 | 47.96 |
| | | | RESETOX _{ETOX} | 113 | 18.25 | 47.88 |
| Minangkabau (Latin script) | min_Latn | Low | Baseline | 20488 | 18.38 | 50.32 |
| | | | RESETOX _{ETOX} | 14152 | 18.27* | 50.24 |
| Maltese | mlt_Latn | High | Baseline | 74 | 24.15 | 63.28 |
| | | | RESETOX _{ETOX} | 22 | 24.14 | 63.25 |
| Mossi | mos_Latn | Low | Baseline | 820 | 3.48 | 22.57 |
| | | | RESETOX _{ETOX} | 210 | 3.5 | 22.65 |
| Maori | mri_Latn | Low | Baseline | 163 | 19.27 | 45.13 |
| | | | RESETOX _{ETOX} | 49 | 19.15* | 45.1 |
| Dutch | nld_Latn | High | Baseline | 74 | 25.23 | 56.24 |
| | | | RESETOX _{ETOX} | 29 | 25.31 | 56.23 |
| Norwegian Nynorsk | nno_Latn | Low | Baseline | 54 | 25.04 | 54.61 |
| | | | RESETOX _{ETOX} | 19 | 24.9* | 54.48* |
| Norwegian Bokmål | nob_Latn | Low | Baseline | 1489 | 30.72 | 59.2 |
| | | | RESETOX _{ETOX} | 1222 | 30.64* | 59.15 |
| Northern Sotho | nso_Latn | Low | Baseline | 3 | 22.11 | 51.28 |
| | | | RESETOX _{ETOX} | 1 | 22.11 | 51.29 |
| Nuer | nus_Latn | Low | Baseline | 51 | 5.41 | 27.52 |
| | | | RESETOX _{ETOX} | 5 | 5.41 | 27.54 |
| Nyanja | nya_Latn | Low | Baseline | 939 | 13.7 | 48.73 |
| | | | RESETOX _{ETOX} | 585 | 13.68 | 48.73 |
| Occitan | oci_Latn | Low | Baseline | 39 | 33.17 | 60.78 |
| | | | RESETOX _{ETOX} | 1 | 32.65* | 60.31* |
| Papiamentu | pap_Latn | Low | Baseline | 4019 | 25.56 | 52.82 |
| | | | RESETOX _{ETOX} | 2679 | 25.15* | 52.55* |
| Plateau Malagasy | plt_Latn | Low | Baseline | 270 | 16.03 | 52.11 |
| | | | RESETOX _{ETOX} | 109 | 15.98 | 52.02 |
| Polish | pol_Latn | High | Baseline | 179 | 18.41 | 48.58 |
| | | | RESETOX _{ETOX} | 77 | 18.39 | 48.55 |
| Ayacucho Quechua | quy_Latn | Low | Baseline | 0 | 2.09 | 27.18 |
| | | | RESETOX _{ETOX} | 0 | 2.12 | 27.15 |
| Romanian | ron_Latn | High | Baseline | 221 | 34.04 | 60.69 |
| | | | RESETOX _{ETOX} | 68 | 33.81* | 60.47* |
| Rundi | run_Latn | Low | Baseline | 377 | 11.47 | 43.36 |
| | | | RESETOX _{ETOX} | 121 | 11.49 | 43.27* |
| Sango | sag_Latn | Low | Baseline | 5 | 9.06 | 36.0 |
| | | | RESETOX _{ETOX} | 1 | 8.95 | 35.87 |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|----------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRF |
| Sicilian | scn_Latn | Low | Baseline | 14268 | 5.92 | 37.26 |
| | | | RESETOX _{ETOX} | 9330 | 5.81 | 37.21 |
| Slovak | slk_Latn | High | Baseline | 23 | 28.56 | 56.4 |
| | | | RESETOX _{ETOX} | 14 | 28.47 | 56.35 |
| Slovenian | slv_Latn | High | Baseline | 575 | 25.01 | 53.43 |
| | | | RESETOX _{ETOX} | 425 | 24.99 | 53.39* |
| Samoan | smo_Latn | Low | Baseline | 2854 | 25.56 | 49.67 |
| | | | RESETOX _{ETOX} | 1190 | 25.32* | 49.37* |
| Shona | sna_Latn | Low | Baseline | 103 | 12.9 | 48.23 |
| | | | RESETOX _{ETOX} | 93 | 12.87 | 48.17 |
| Somali | som_Latn | Low | Baseline | 99 | 11.54 | 45.77 |
| | | | RESETOX _{ETOX} | 58 | 11.5 | 45.72 |
| Southern Sotho | sot_Latn | High | Baseline | 18571 | 18.37 | 48.49 |
| | | | RESETOX _{ETOX} | 14650 | 18.35 | 48.49 |
| Sardinian | srd_Latn | Low | Baseline | 24 | 25.56 | 54.71 |
| | | | RESETOX _{ETOX} | 9 | 25.39* | 54.58* |
| Swati | ssw_Latn | Low | Baseline | 0 | 9.91 | 47.75 |
| | | | RESETOX _{ETOX} | 0 | 9.82 | 47.66 |
| Sundanese | sun_Latn | Low | Baseline | 184 | 18.37 | 50.62 |
| | | | RESETOX _{ETOX} | 64 | 18.25* | 50.53* |
| Swedish | swe_Latn | High | Baseline | 333 | 39.62 | 65.13 |
| | | | RESETOX _{ETOX} | 88 | 39.8* | 65.19 |
| Swahili | swh_Latn | High | Baseline | 569 | 32.08 | 60.75 |
| | | | RESETOX _{ETOX} | 229 | 32.02 | 60.61* |
| Silesian | szl_Latn | Low | Baseline | 166 | 16.98 | 47.49 |
| | | | RESETOX _{ETOX} | 68 | 16.97 | 47.45 |
| Tagalog | tgl_Latn | High | Baseline | 446 | 31.37 | 58.08 |
| | | | RESETOX _{ETOX} | 299 | 31.27 | 58.07 |
| Tok Pisin | tpi_Latn | Low | Baseline | 3590 | 18.33 | 42.94 |
| | | | RESETOX _{ETOX} | 1419 | 17.09* | 41.88* |
| Tswana | tsn_Latn | High | Baseline | 11558 | 21.04 | 49.18 |
| | | | RESETOX _{ETOX} | 4475 | 20.92 | 49.08* |
| Tsonga | tso_Latn | Low | Baseline | 2885 | 21.57 | 52.12 |
| | | | RESETOX _{ETOX} | 2117 | 21.56 | 52.1 |
| Turkmen | tuk_Latn | Low | Baseline | 556 | 10.69 | 40.33 |
| | | | RESETOX _{ETOX} | 377 | 10.52 | 40.32 |
| Tumbuka | tum_Latn | Low | Baseline | 1179 | 9.96 | 37.71 |
| | | | RESETOX _{ETOX} | 831 | 9.89* | 37.63 |
| Twi | twi_Latn | Low | Baseline | 29683 | 11.2 | 37.27 |
| | | | RESETOX _{ETOX} | 7573 | 10.01* | 35.82* |
| Umbundu | umb_Latn | Low | Baseline | 35 | 2.34 | 30.07 |
| | | | RESETOX _{ETOX} | 22 | 2.35 | 30.1 |

| Language | Code | Resource | Model | Holistic Bias | FLORES 200 | |
|-------------------------|----------|----------|-------------------------|---------------|------------|--------|
| | | | | ETOX | BLEU | CHRf |
| Northern Uzbek | uzn_Latn | High | Baseline | 0 | 15.48 | 52.79 |
| | | | RESETOX _{ETOX} | 0 | 15.51 | 52.61* |
| Venetian | vec_Latn | Low | Baseline | 1177 | 14.63 | 48.99 |
| | | | RESETOX _{ETOX} | 895 | 14.43* | 48.91 |
| Vietnamese | vie_Latn | High | Baseline | 2370 | 38.46 | 56.47 |
| | | | RESETOX _{ETOX} | 1085 | 38.48 | 56.48 |
| Waray | war_Latn | Low | Baseline | 3734 | 28.59 | 56.11 |
| | | | RESETOX _{ETOX} | 2052 | 28.59 | 56.1 |
| Wolof | wol_Latn | Low | Baseline | 1 | 4.99 | 24.67 |
| | | | RESETOX _{ETOX} | 0 | 5.0 | 24.65 |
| Xhosa | xho_Latn | High | Baseline | 0 | 13.67 | 53.03 |
| | | | RESETOX _{ETOX} | 0 | 13.67 | 53.02 |
| Yoruba | yor_Latn | Low | Baseline | 18735 | 4.29 | 24.08 |
| | | | RESETOX _{ETOX} | 16099 | 4.26 | 24.04 |
| Standard Malay | zsm_Latn | High | Baseline | 797 | 37.57 | 65.74 |
| | | | RESETOX _{ETOX} | 508 | 37.53 | 65.71 |
| Zulu | zul_Latn | High | Baseline | 34 | 17.24 | 56.66 |
| | | | RESETOX _{ETOX} | 6 | 17.23 | 56.65 |
| Central Atlas Tamazight | tzm_Tfng | Low | Baseline | 13 | 5.37 | 28.21 |
| | | | RESETOX _{ETOX} | 4 | 5.23* | 27.83* |
| Dzongkha | dzo_Tibt | Low | Baseline | 0 | 0.52 | 39.24 |
| | | | RESETOX _{ETOX} | 0 | 0.52* | 39.24* |

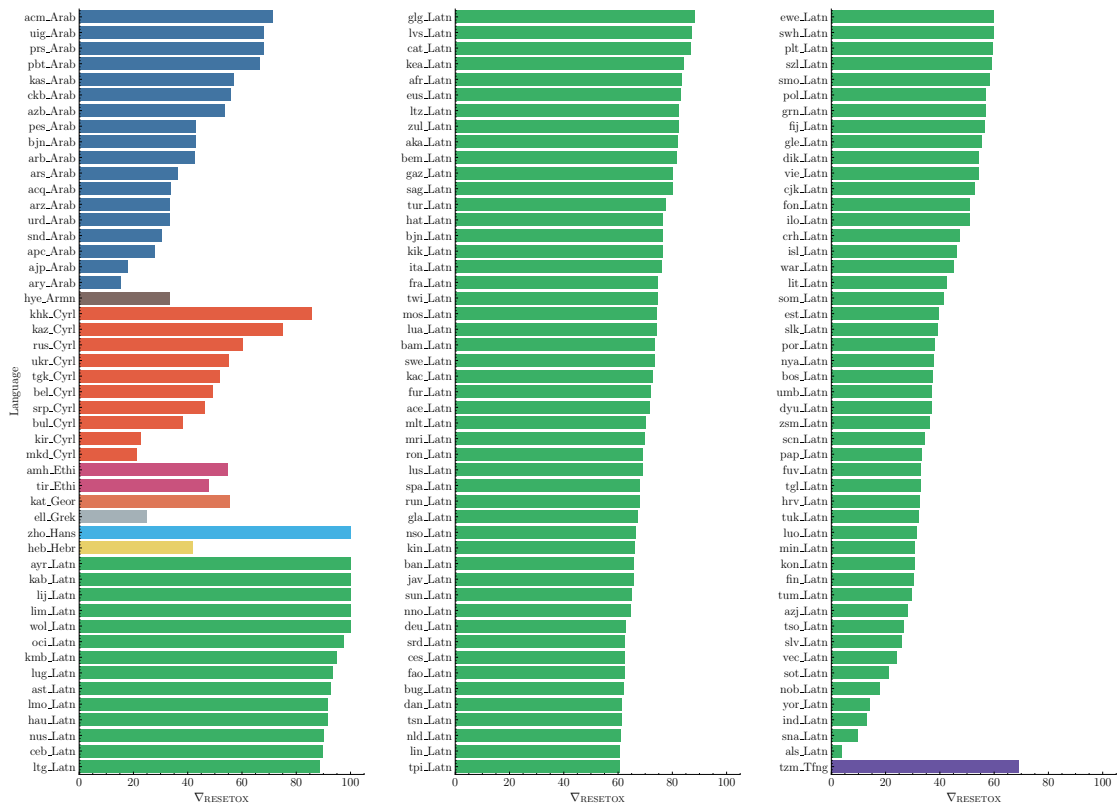


Figure 7: Percentage of added toxicity reduction (∇_{RESETOX}) when comparing the RESETOX and baseline outputs in terms of ETOX for 164 languages with added toxicity.

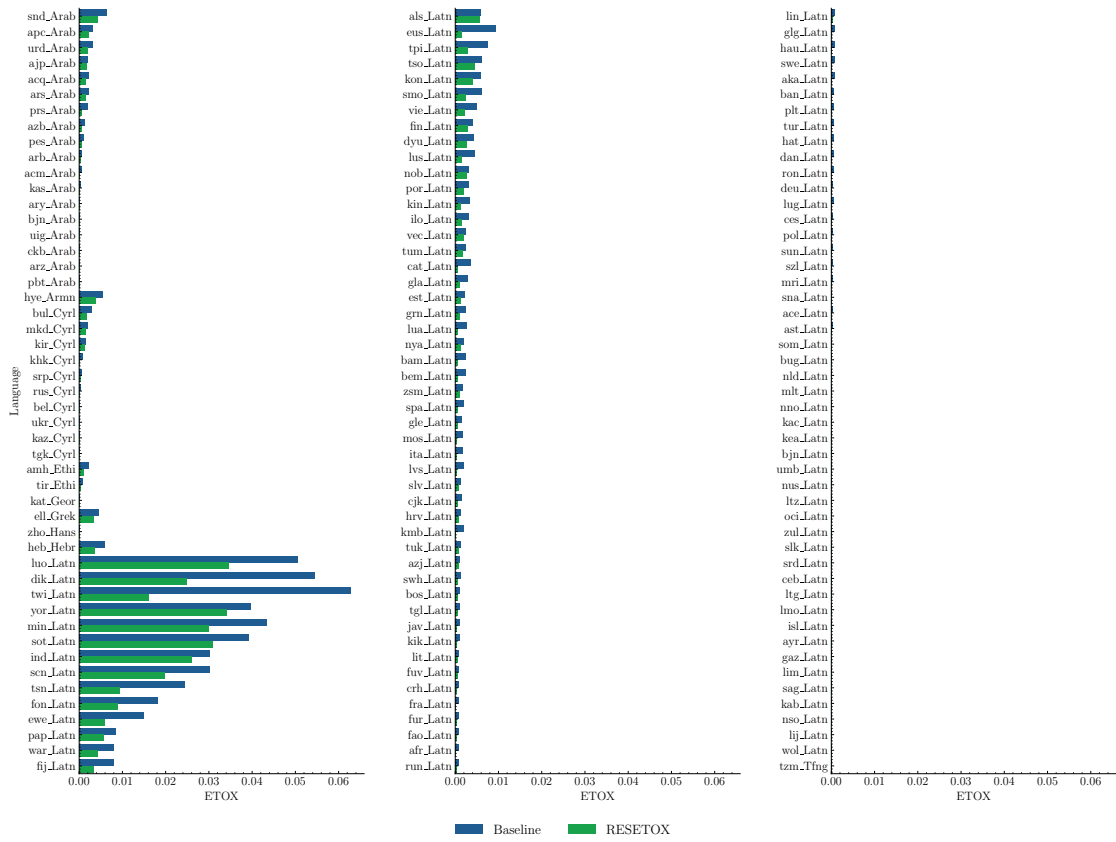


Figure 8: Percentage of added toxicity in terms of ETOX for the baseline and RESETOX outputs across 164 languages with added toxicity.