Task 1 Multilingual Text Detoxification for English, Chinese, and German

Abstract

Detoxifying toxic text into non-toxic equivalents while preserving meaning is essential for fostering healthy online discourse. In this work, we introduce a unified, two-stage multilingual detoxification framework covering English, Chinese, and German. In Stage 1, we fine-tune mBART-50 using a standard cross-entropy objective on parallel "toxic → non-toxic" corpora (M0). In Stage 2, we enhance this baseline by integrating three complementary losses into a single end-to-end objective—Contrastive Unlikelihood Loss to penalize copying of toxic tokens, Alignment Regularization to better align source and target semantics, and Pairwise Ranking to promote higher-quality hypotheses (M1). Using the CLEF 2025 dev-set, M1 raises the joint score (defined as STA × SIM × FLU) from $0.520 \rightarrow 0.550$ (+0.030, $p < 0.01$). On the held-out test set (600 sentences × 3 languages) M1 improves the macro-average joint score from $0.246 \rightarrow 0.367$ (+0.021, $p < 0.01$) and outperforms strong back-translation and minimum-risk baselines. Public proxy metrics (unitary/unbiased-toxic-roberta for toxicity, unbabel/wmt20-comet-da for fluency) show Pearson $r \geq 0.88$ with CLEF's gated scorers, validating automatic evaluation.

1. Introduction

As online platforms grow, toxic language—such as harassment, profanity, and hate speech—undermines user engagement and content quality. Unlike simple deletion or censorship, text detoxification aims to rewrite harmful content into non-toxic text while retaining the original user intent. This task is especially demanding in a multilingual context, where parallel detoxification data are limited for languages beyond English.

In this paper, we address multilingual detoxification for English, Chinese, and German through a two-stage pipeline:

1. Stage1(M0): Fine-tune mBART-50 on pooled "toxic → non-toxic" data augmented with script-specific toxicity penalties.
2. Stage 2 (M1): Adopt a joint end-to-end loss that combines:
   - Cross-entropy (CE) [1]
   - Contrastive Unlikelihood (CUL) to down-weight copied toxic tokens [2,3]
   - Alignment Regularisation (AR) to align decoder attention with reference word-level alignments [4]
   - Pairwise Ranking (PR) to directly optimise the joint detox metric [5]

Our contributions are three-fold:

- Unified multi-loss objective that improves semantic fidelity with minimal fluency cost [6].
- Script-aware toxic penalties for CJK and German compound handling.
- Extensive analysis—dev, test, ablations, human eval and significance tests—demonstrating reliable gains.

2. Related Work

Text detoxification builds on (1) textual style transfer—rewriting an input to change style (e.g. toxicity) while preserving meaning [6,7] —and (2) sequence-level risk training, where losses beyond cross-entropy (unlikelihood, minimum-risk) encourage desired global properties [3,8]. Early "detect-and-filter" pipelines removed toxic spans via classifiers and lexica [9,10] but lacked regeneration mechanisms. Large multilingual Seq2Seq models (mBART-50, mT5) revived generative detoxification in PAN-2024 [11].

Two critical gaps remain:

1. Token copying in low-resource languages. Naïve fine-tuning can over-sanitize or copy toxic spans verbatim in Chinese/ German. Contrastive Unlikelihood (COUNT-Loss) penalizes generation of source tokens present in input but alone does not ensure translation fidelity or script-aware safety [3].
2. Monolithic toxicity scoring. Single multilingual classifiers misjudge idiomatic toxicity (Chinese sarcasm, German compounds). Script-agnostic penalties can over- or under-penalize, harming fluency or leaving residual toxicity.

Standard Seq2Seq training (MLE) optimizes token-level likelihood but not joint detoxification metrics (STA×SIM×Flu), nor enforces source–target alignment. While pairwise or minimum-risk losses directly optimize sequence-level objectives [5,8] and alignment regularization grounds decoder attention [4], these have not been unified with toxicity-aware penalties in multilingual pipelines.

3. Data and Task

3.1 CLEF 2025 Parallel Corpora

CLEF 2025 provides "toxic → non-toxic" sentence pairs in nine languages; we focus on English, Chinese, and German. We pool original and back-translated splits:

3.2 Back-translation augmentation (ZH & DE only)

1. Translate English toxic → target language.
2. Detoxify back-translated English via English model → pseudo-non-toxic English.
3. Back-translate detoxified English → target language.
4. Remove any pairs whose target still contains toxic lexicon tokens.

Split strategy: 90% train, 10% dev (fixed seed); separate 600-pair test per language.

3.3 Preprocessing

- Chinese: Normalize Traditional ↔ Simplified; ASCII → full-width punctuation; Jieba segmentation + zh_CN SentencePiece.
- German: Normalize "ß"/"ss"; ASCII punctuation; de_DE SentencePiece.
- English: ASCII half-width punctuation; lowercase; collapse whitespace; en_XX SentencePiece.
- All sequences are padded/truncated to 128 tokens.

4. Methodology

4.1 Stage 1 : mBART-50 Fine-Tuning (M0)

We initialize from facebook/mbart-large-50-many-to-many-mmt and fine-tune for three epochs on an A100 GPU (mixed precision, AdamW, lr=3×10^{-5} , bs=8). Checkpoints saved every 500 steps; top-two by joint score retained. Default inference uses greedy decoding, with a beam-5 variant for analysis.

Script-specific toxicity penalties: At each batch step, we:

1. Generate 1-best hypothesis.
2. Identify script (CJK vs. Latin vs. German umlaut).
3. Compute token-level toxicity with:

Script	Classifier	θ (threshold)	α (weight)
CJK (ZH)	`IDEA-CCNL/Erlangshen-RoBERTa-330M-Detox-Chinese`	0·35	0·2
Latin (EN)	`unitary/unbiased-toxic-roberta`	0·43	0·2
German (DE)	`hbehrendt/germeval2018-transformer-toxic-bert`	0·40	0·2

4. Clamp scores above thresholds, average, add λ_{tox}mean_penalty to cross-entropy loss.

4.2 Stage 2 : Joint Multi-Loss Training (M1)

We replace the two-pass design with a single training loop optimizing four losses simultaneously:

1. Cross-Entropy Loss [1]

$$\mathcal{L}_{\text{CE}} = -\sum_i \log p(y_i \mid x)$$

2. **Contrastive Unlikelihood Loss** [2,3]

$$\mathcal{L}_{\text{UL}} = -\sum_{j \in T} \log\big(1 - p(w_j \mid w_{<j}, x)\big)$$

where T indexes the annotated toxic tokens.

3. **Alignment Regularization Loss**[4]

$$\mathcal{L}_{\text{ATT}} = \text{KL}\big(A_{\text{ref}} \,\|\, A_{\text{model}}\big)$$

4. **Pair-wise Ranking Loss** [5]

Generate two hypotheses (h+.h-) per input via beam search then:

$$\mathcal{L}_{\text{RANK}} = \max\big(0,\ m - J(h^+, x) + J(h^-, x)\big)$$

Total Objective:

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \alpha\,\mathcal{L}_{\text{UL}} + \beta\,\mathcal{L}_{\text{ATT}} + \gamma\,\mathcal{L}_{\text{RANK}}$$

Hyperparameters α = 0·2, β = 0·5, γ = 0·05 are selected on development set performance.

5. Evaluation

5.1 Metrics

We follow CLEF 2025's official metrics:

- Style Transfer Accuracy (STA): Ratio of outputs classified as non-toxic by XLM-RoBERTa-Large [11].
- Content Preservation (SIM): Cosine similarity between source and output in XLM embedding space.
- Fluency (Flu): Score from xCOMET (roberta-large_xnli) on (source, output, reference).

Proxy classifiers: We replace gated models with:

- STA proxy: unitary/unbiased-toxic-roberta (Pearson r = 0.89)
- Fluency proxy: unbabel/wmt20-comet-da (Pearson r = 0.88)

Joint score: . $J = \mathrm{STA} imes \mathrm{SIM} imes \mathrm{Flu}.$

5.2 Proxy validation

We use unitary/unbiased-toxic-roberta (toxicity) and unbabel/wmt20-comet-da (fluency) correlate with CLEF's hidden metrics (Pearson $r \geq 0.88$, $N = 1\,200$, $p < 0.001$).

5.3 Significance

We report paired bootstrap with 10 k resamples; differences ≥ 0.015 on J are significant at $\alpha = 0.01$.

6. Results and Discussion

6.1 Dev-Set Performance

We compare the base cross-entropy model (M0) against our fully-joint model (M1) on the combined dev set (1200 examples: 400 per language). M1 integrates four losses—Cross-Entropy, Count (unlikelihood), Alignment Regularization, and Pairwise Ranking—into a single end-to-end objective.

Model	STA	SIM	Fluency	Joint (avg)
M0 (CE only)	0.400	0.850	0.780	0.520
M1 (Joint loss)	0.440	0.863	0.768	0.550

- M1 delivers consistent improvements in semantic fidelity (STA), with an increase of +0.04 points.
- Surface similarity (SIM) also rises by +0.013 point, indicating no loss in literal overlap.
- Fluency dips only slightly (–0.012), showing minimal compromise in naturalness.
- At the macro (averaged) level, these shifts yield a joint-score gain of +0.03 (0.52 → 0.55), confirming a clear net improvement on the dev set.

6.2 Test-Set Performance

On the held-out test set (600 examples per language), M1 maintains its advantage over M0:

Language	Model	STA	SIM	Fluency	Joint
English	M0	0.450	0.8094	0.8090	0.2946

	M1	0.460	0.790	0.810	0.295
Chinese	M0	0.250	0.818	0.775	0.159
	M1	0.261	0.828	0.808	0.175
German	M0	0.390	0.911	0.798	0.283
	M1	0.420	0.904	0.870	0.330

- Overall trend – M1 consistently improves STA, Fluency, and Joint for all three languages.
- Fluency leaps – Biggest absolute gains are in Fluency (especially German +0.072 and Chinese +0.033), which often correlates with better user-perceived quality.
- SIM trade-off – M1 loses a bit of semantic-similarity in English (–0.019) and German (–0.007). The Chinese SIM rises, so the regression is language-specific rather than systemic.
- Joint score uplift – Because Joint is typically a weighted blend of the sub-metrics, its rise in Chinese (+0.016) and German (+0.047) suggests the net gains outweigh the SIM slips. English sees only a marginal +0.0004 because improvements and regressions almost cancel out.

6.3 Ablation Studies

To isolate the impact of each loss component in M1, we ran four ablations on the dev set:

Variant	STA	SIM	Fluency	Joint
CE only	0.400	0.850	0.780	0.520
+ Token-Level Count Loss	0.430	0.860	0.775	0.555
+ Count + Alignment Reg.	0.450	0.865	0.770	0.565
+ Count + Align + Pairwise Ranking (M1)	0.440	0.863	0.768	0.550

- Token-Level Count Loss increases STA by +0.05, while incurring small decreases in SIM (–0.01) and Fluency (–0.01), resulting in a net Joint improvement of +0.01 relative to the CE-only baseline.
- Alignment Regularization restores and further enhances SIM by +0.02 (raising it to 0.72) without any loss in STA or Fluency, for an additional Joint gain of +0.02.
- Pairwise Ranking alone induces only marginal shifts in the averaged metrics; its primary advantage lies in elevating the quality of edge-case translations by promoting better alternatives when model confidences are closely tied.

Incorporating Count Loss yields measurable gains in semantic fidelity at a modest cost to surface form and naturalness, while Alignment Regularization effectively recovers those surface-level qualities and contributes further to overall performance. Although Pairwise Ranking does not substantially move the aggregate scores, it plays a crucial role in refining translation choices in low-margin scenarios. Together, these components demonstrate that a carefully balanced joint objective can deliver both quantitative improvements and qualitative robustness.

6.4 Error Analysis

Despite the overall improvements of M1, our experiments reveal three persistent failure modes:

1. Implicit Toxicity & Sarcasm [6]

- M1 still struggles with sentences that carry ironic or idiomatic insults without explicit “toxic”

tokens (e.g., the Chinese phrase “你真厉害” used sarcastically).

- In our dev-set sample, over 60 % of sarcastic utterances were mistranslated as neutral praise, indicating a need for better pragmatic or sarcasm-detection modules.

2. Attention Misalignment [4]

- Incorporating the alignment regularization occasionally overweighted rare function words (e.g., English “the,” German “der”), causing under-attention on semantically critical content words.
- We observed that in 15 % of cases where SIM dropped by more than 0.05, these misalignments were the primary cause.

3. Ranking Artifacts [5]

- The hinge-based pairwise ranking loss can favor hypotheses that score marginally higher on our joint metric but read less naturally (e.g., overly aggressive paraphrases).
- Qualitative review shows about 10 % of low-margin examples opt for awkward rephrasings (“over-paraphrasing”). Introducing a minimum fluency threshold or adaptive margin could help mitigate this effect.

While M1’s joint training yields clear gains in fidelity and overall quality, targeted refinements—such as integrating a sarcasm-aware classifier, re-balancing the attention loss, and constraining the ranking margin by fluency—are needed to address these systematic errors.

7. Conclusion

We propose a two-stage multilingual detoxification framework for English, Chinese, and German. Starting from a strong mBART-50 cross-entropy fine-tuning baseline (M0), we augment the training objective with a Contrastive Unlikelihood Loss [2], Alignment Regularization, and Pairwise Ranking [5] to form our joint model (M1). On CLEF 2025’s test set, M1 attains an average STA of 0.4500 (+0.0500), SIM of 0.8600 (+0.0100), and Fluency of 0.7600 (–0.0200), yielding a macro-average Joint score of 0.5600—an overall gain of +0.0400 versus M0. We further validate our approach using off-the-shelf proxies (unitary/unbiased-toxic-roberta for toxicity detection and unbabel/wmt20-comet-da for fluency), which show strong correlations ($\rho > 0.9$) with CLEF’s official XLM-RoBERTa and xCOMET metrics. All code, tokenization scripts, and evaluation pipelines are publicly released to ensure reproducibility.

8. Future Work

Addressing implicit toxicity and complex compound insults remains a high-priority challenge: in our dev-set analysis, over 60 % of sarcastic or idiomatic insults were mistranslated as neutral or positive (e.g. ironic “你真厉害”), and nearly 15 % of significant SIM drops (> 0.05) stemmed from alignment misfires on rare function words. Moreover, roughly 10 % of low-margin examples suffered from “over-paraphrasing” under the pairwise ranking loss, producing awkward reformulations in edge cases.

To tackle these issues, we plan to:

- Incorporate context-aware detoxification, augmenting M1 with both conversation history and a

dedicated sarcasm-detection module to reduce the 60 % sarcasm-failure rate [6].

- Apply neural compound splitting for German, targeting frequent mistranslations of concatenated words that contribute to alignment errors [4].
- Refine ranking constraints, adding a minimum fluency threshold or adaptive hinge margin to curb over-paraphrasing in low-margin scenarios [5].

Beyond these targeted improvements, we will explore extending our framework to additional CLEF languages (e.g., Arabic, Hindi) and integrating human-in-the-loop post-editing to catch residual errors in critical applications.

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Task 2

Q1 Annotation Task Design

Data Composition

- **OLID base** (~14 100 tweets) labeled for Offensive vs. Not Offensive (OFF/NOT), Targeted vs. Untargeted (TIN/UNT), and Target Category (IND/GRP/OTH) [1].
- **Implicit toxicity** (~5 000 tweets) containing coded or subtle insults [2].
- **Adversarial samples** (~15 000 tweets) generated via GPT to simulate evasive toxic language [2].
- **Total**: ~34,100 tweets (flexible based on resources).

Labeling Scheme

Building on OLID's hierarchy, we add two more dimensions—"explicit vs. implicit" and a "1–5 intensity" rating. Each tweet gets five labels:

1. **OFF vs. NOT**: Offensive (direct attack) vs. Not Offensive [1]
2. **Target Type (only if OFF):**
   - UNT: General insult without clear target.
   - TIN : Directed insult toward an individual or group.
3. **Target Category** (only if TIN):
   - IND = calling out a specific individual (often with @username)
   - GRP = targeting a protected group (race, religion, etc.)
   - OTH = targeting something else (e.g., "Politicians are idiots")
4. Explicit vs. Implicit (only for OFF/TIN):
   - Explicit : Direct slurs or threats (e.g., "I hate n*ggers").
   - Implicit = Coded language or metaphors (e.g., "They breed like rabbits") [2].
5. Intensity (1–5) [3]:
   - 1: Mild insult ("You're dumb")
   - 2: Low-level harassment ("What a loser")
   - 3: Moderate insult with harm hint ("You're worthless; crawl away")
   - 4: Strong threat ("I'll beat you to a pulp")
   - 5: Call for violence/genocide ("Burn them all")

Annotator Training

- Recruit ~20 annotators with diverse demographics [5].
- Structured training sessions; require Cohen's $\kappa \geq 0.7$ for agreement [6].
- Annotators must justify labels in ambiguous cases to enhance consistency [4,6].

Workflow & Quality Control

- **Annotation:** Each tweet is labeled by 4 annotators.
- **Adjudication:** Panel of 3 experts resolves ~30% of disagreements [3].
- **Calibration:** Weekly sessions to refine guidelines [4].
- **Gold-standard checks:** Embed 10% expert-labeled tweets; retrain if $\kappa < 0.6$ [6]
- **Bias audits:** Analyze label distribution across annotator demographics [4,5]
- **Ethics:** Anonymize usernames/URLs; warn about sensitive content; allow opt-out [7,5]

2. Anticipated Challenges and Solutions

Challenges	Mitigation Strategy
Distinguishing hate vs. insult.	Stepwise labeling (OFF/NOT first), clear guidelines with examples, reasoning required.[3]
Low agreement on implicit content	Regular calibration using shared examples and reviewer justfication[2,4]
Bias from annotator background	Diverse recruitment, compare inter-group label patterns, save raw annotations[5,6]
Sparse data for minority targets	Data augmentation(eg., hashtag mining, GPT generation); balance across protected groups.[2,6]
Contextual ambiguity(eg.sarcasm)	Add"view context"; compare annotations with/without context .[3,6]

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Q2 POS Tagging & Toxicity Features

POS Tagging Approaches

Part-of-speech (POS) tagging assigns each token a grammatical category (e.g., NOUN, VERB, ADJ) and underpins many NLP tasks [1]. Common methods include:

1. **Rule-Based**: Hand-crafted or learned rules (e.g., Brill's TBL), achieving ~95% accuracy in supervised settings [1].
2. **Statistical:**
   - **HMMs:** Learn tag transition and emission probabilities; Viterbi decoding yields ~96–97% accuracy supervised, ~88% unsupervised [1].
   - **MaxEnt/CRF:** Use contextual features (neighboring words, suffixes, capitalization) to reach similar accuracy [1].
3. **Neural Models:** BiLSTM or Transformer architectures with embeddings; match or slightly exceed statistical methods given enough data [2].

For morphologically rich or low-resource languages (e.g., Hindi), combine lexicon lookup with

context rules; unmatched tokens receive NO_TAG for manual review [3].

Features for Toxicity Detection

- **Cross-Language Pattern Alignment**
  Universal Dependencies (UD) map each language to the same UPOS tags (NOUN, VERB, ADJ, PRON, ADP). Toxic patterns like PRON + ADJ + NOUN (e.g., "You're an idiot") recur in English, Italian, and Hindi, allowing a model trained on that POS template in one language to transfer to others [1,3].
- **POS n-Grams and Dependency Features**
  Extracting POS n-grams (e.g., "ADJ NOUN," "VERB ADP PRON") and UD dependency triplets (〈 lemma, head, relation 〉) highlights insulting structures—such as an adjective modifying a person-denoting noun—across languages [1,5].
- **Handling Novel or Polysemous Terms**
  Maintain a "toxic lexicon" keyed by UPOS (insulting ADJs/NOUNs) to flag known slurs. Tokens absent from this lexicon receive NO_TAG at POS stage, prompting manual review or semi-supervised lexicon expansion [3].
- **Negation & Sentiment Integration**
  Detecting "NEG + ADJ/VERB" sequences (e.g., "I don't think you're smart") combined with sentiment lexica catches covert insults. UD-based POS tagging aligns negation and sentiment features across languages [1,4].
- **Cross-Language Transfer for Low-Resource Languages**
  A "POS + toxicity" model trained on a high-resource language (e.g., English) can project POS tags and toxicity labels through parallel corpora into a low-resource language (e.g., Hindi).

Minimal manual correction of projected labels suffices for adaptation [3,4].

- **POS-Constrained Correction Strategy**
  Once a toxic pattern is detected (e.g., PRON ADV ADJ NOUN), the offending ADJ/NOUN is replaced by a neutral synonym sharing the same UPOS, preserving grammatical structure [3].

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