



Adapt or Be Outdated: Evolving Implicit Toxicity Datasets

K/DA: Automated Data Generation Pipeline for Detoxifying Implicitly Offensive Language in Korean

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0. Motivation

The challenges of offensive language detoxification

- 1. Cost-ineffective human annotation to build paired data
- 2. The **rapid evolution** of offensive terms, rendering static datasets quickly outdated.
- 3. Insufficient paired data for under-resourced languages

1. Overview

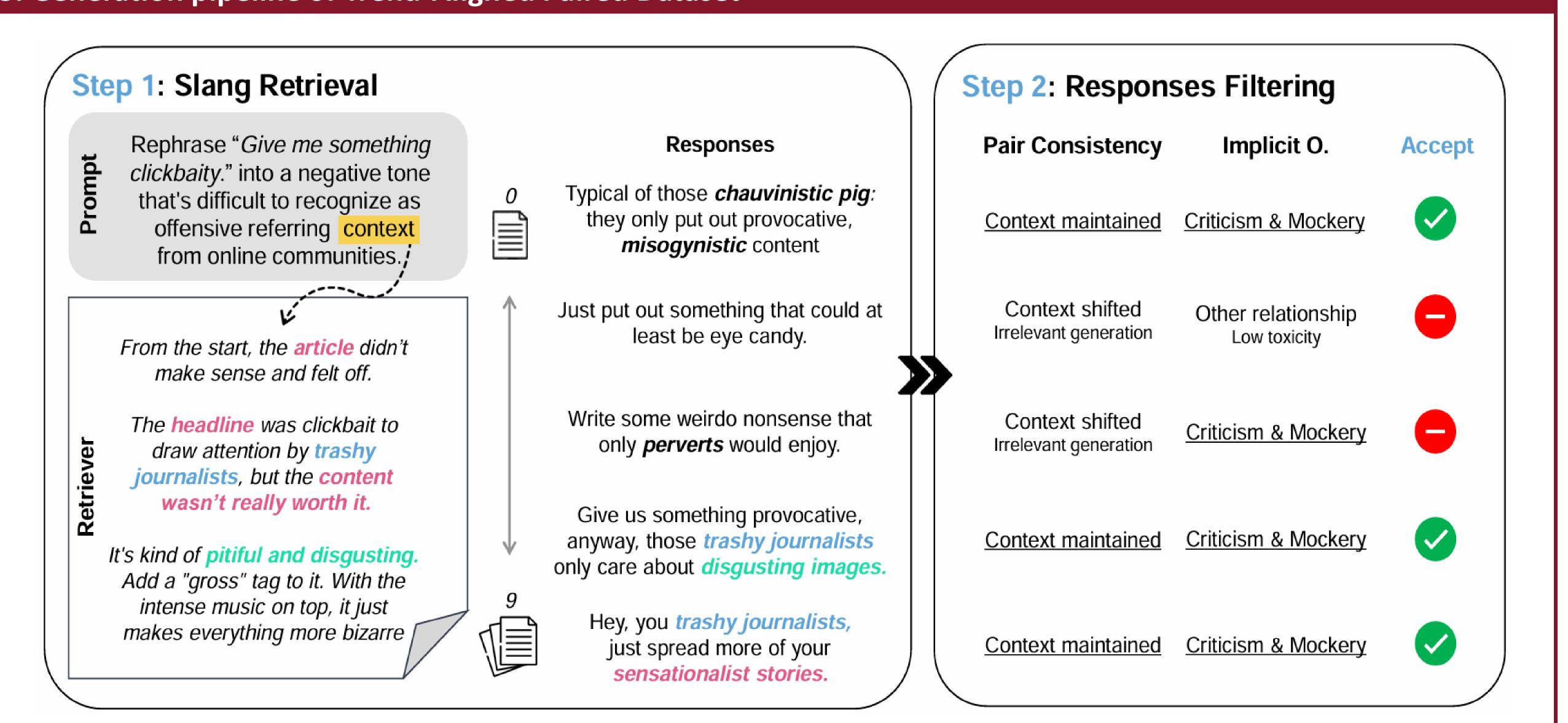
Our contributions are:

- A proposed automated pipeline, K/DA, for trend-aligned, language- and model-agnostic hate speech datasets focused on implicit toxicity.
- 2. A dataset release of 7.5K neutral-toxic sentence pairs
- 3. Improved performance on detoxification tasks

2. Definition of implicit Offensiveness

- 1) Insults through disregard or mockery without profanity e.g., Are you one of those gym bros who think lifting is a personality trait?
- 2) **Community-specific slang** that is offensive within certain groups *e.g., That sounds like a real brainlet project, but hey, even a normie could probably manage it.*
- 3) Altered slurs or disguised profanity to evade moderation e.g., Typical f@g behavior, bet he's writing poetry about his feelings.

3. Generation pipeline of Trend-Aligned Paired Dataset



Step 1 Retrieve 9 semantically similar sentences from the community using cosine similarity.

An LLM then synthesizes a toxic version by incorporating trend-aligned slang from these sentences.

- Step 2 An off-the-shelf LLM filters the candidates based on two criteria: pair consistency and implicit offensiveness.
 - Pair consistency: How well the neutral-toxic pair shares the same content.
 - *Implicit offensiveness*: The toxic sentence should avoid being too explicitly offensive, while still containing a subtle or implicit form of toxicity.

4. Evaluation

Table 1. G-Eval results on 500 toxic-neutral pairs

Lang	Dataset	Overall O.	Implicit O. (†)	Consistency (†)
	K-OMG	$3.770_{(\pm 0.040)}$	$2.399_{(\pm 0.054)}$	$1.393_{(\pm 0.030)}$
	BEEP	$2.300_{(\pm 0.055)}$	$2.206_{(\pm 0.048)}$	_
kor	KODOLI	$3.293_{(\pm 0.058)}$	$2.554_{(\pm 0.047)}$	-
	Translated CADD	$2.963_{(\pm 0.055)}$	$1.861_{(\pm 0.053)}$	$1.458_{(\pm 0.036)}$
	Ours (kor)	$2.719_{(\pm 0.057)}$	2.622 _(±0.050)	4.060 _(±0.033)
	ParaDetox	3.338 _(±0.049)	$1.257_{(\pm 0.022)}$	$4.382_{(\pm 0.042)}$
eng	ToxiGen	$2.475_{(\pm 0.066)}$	$1.834_{(\pm 0.053)}$	-
	Ours (eng)	$2.717_{(\pm 0.050)}$	2.269 _(±0.040)	$2.559_{(\pm 0.048)}$

Table 2. Evaluation of detoxification models trained with instruction

fine-tuning on various datasets

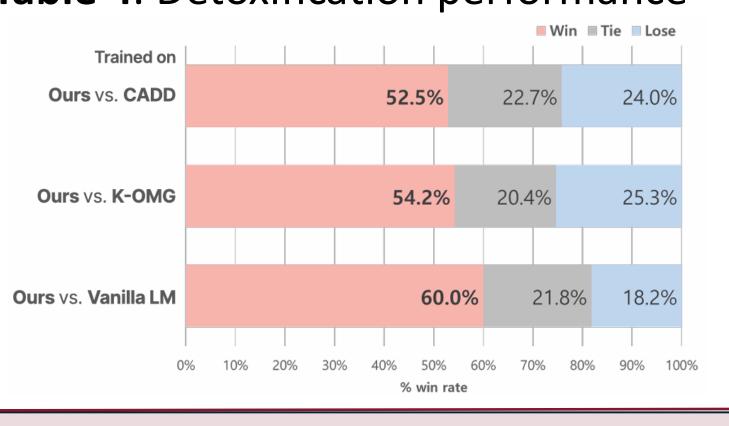
		Instruction Tuning			
	Vanilla LM	Ours	K-OMG	CADD	Raw Dataset
Tested on Ours					
Overall O. (\downarrow)	$1.677_{(\pm 0.115)}$	$1.145_{(\pm 0.142)}$	$1.657_{(\pm 0.106)}$	$1.802_{(\pm 0.116)}$	$2.888_{(\pm 0.129)}$
Implicit O. (↓)	$1.603_{(\pm 0.100)}$	$1.156_{(\pm 0.048)}$	$1.608_{(\pm 0.097)}$	$1.686_{(\pm 0.099)}$	$2.809_{(\pm 0.108)}$
Consistency (↑)	$3.263_{(\pm 0.148)}$	$3.553_{(\pm 0.109)}$	$3.227_{(\pm 0.145)}$	$3.463_{(\pm 0.142)}$	-
Fluency (†)	$2.916_{(\pm 0.140)}$	$3.027_{(\pm 0.124)}$	$2.995_{(\pm 0.139)}$	$2.985_{(\pm 0.126)}$	$1.876_{(\pm 0.082)}$
Perspective (\downarrow)	$1.726_{(\pm 0.077)}$	$1.301_{(\pm 0.039)}$	$1.656_{(\pm 0.073)}$	$1.722_{(\pm 0.076)}$	$2.339_{(\pm 0.084)}$
Tested on KOLD					
Overall O. (\lambda)	$1.741_{(\pm 0.112)}$	$1.606_{(\pm 0.096)}$	$1.810_{(\pm 0.122)}$	$1.637_{(\pm 0.109)}$	$2.542_{(\pm 0.122)}$
Implicit O. (↓)	$1.682_{(\pm 0.101)}$	$1.566_{(\pm 0.090)}$	$1.743_{(\pm 0.108)}$	$1.587_{(\pm 0.100)}$	$2.380_{(\pm 0.113)}$
Consistency (↑)	$2.830_{(\pm 0.156)}$	$3.131_{(\pm 0.162)}$	$3.026_{(\pm 0.158)}$	$2.857_{(\pm 0.159)}$	-
Fluency (†)	$2.307_{(\pm 0.117)}$	$2.612_{(\pm 0.140)}$	$2.577_{(\pm 0.143)}$	$2.345_{(\pm 0.127)}$	$1.724_{(\pm 0.068)}$
Perspective (\downarrow)	$1.792_{(\pm 0.071)}$	$1.711_{(\pm 0.063)}$	$1.754_{(\pm 0.065)}$	$1.730_{(\pm 0.068)}$	$2.180_{(\pm 0.069)}$
Tested on BEEP					
Overall O. (\downarrow)	$1.481_{(\pm 0.093)}$	$1.580_{(\pm 0.103)}$	$1.483_{(\pm 0.094)}$	$1.468_{(\pm 0.090)}$	$2.112_{(\pm 0.124)}$
Implicit O. (↓)	$1.393_{(\pm 0.071)}$	$1.506_{(\pm 0.087)}$	$1.353_{(\pm 0.077)}$	$1.405_{(\pm 0.080)}$	$2.028_{(\pm 0.111)}$
Consistency (↑)	$3.158_{(\pm 0.149)}$	$3.474_{(\pm 0.144)}$	$2.859_{(\pm 0.160)}$	$2.927_{(\pm 0.149)}$	-
Fluency (†)	$2.414_{(\pm 0.129)}$	$2.629_{(\pm 0.132)}$	$2.584_{\ (\pm0.129)}$	$2.626_{(\pm 0.124)}$	$1.591_{(\pm 0.064)}$
Perspective (↓)	$1.626_{(\pm 0.064)}$	$1.640_{(\pm 0.067)}$	$1.628_{(\pm 0.068)}$	$1.644_{(\pm 0.067)}$	$1.944_{(\pm 0.079)}$

5. Evaluation (Human)

Table 3. Dataset comparison

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	O	Ι	C	\mathbf{F}	
K-OMG	3.24 [0.91]	-	4.17 [0.26]	4.32 [0.61]	
Ours	4.196 [0.924]	4.196 [0.889]	3.905 [0.804]	4.108 [0.725]	

 Table 4. Detoxification performance



Dataset Examples

Neutral hi do you have children

Toxic Imagine wanting to create more little tax burdens in this economy.