

Enhancing Online Grooming Detection via Backtranslation Augmentation*

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Abstract

Grooming minors for sexual exploitation become an increasingly significant concern in online conversation platforms. For a safer online experience for minors, machine learning models have been proposed to tap into explicit *textual* remarks and automate detecting predatory conversations. Such models, however, fall short of real-world applications for the sparse distribution of predatory conversations. In this paper, we propose backtranslation augmentation to augment training datasets with more predatory conversations. Through our experiments on 8 languages from 4 language families using 3 neural translators, we demonstrate that backtranslation augmentation improves models' performance with fewer training epochs for better classification efficacy. Our code and experimental results are available at github.com/fani-lab/osprey/tree/coling25.

1 Introduction

An alarming problem in online conversation platforms is the presence of minors before legal age with little cognitive development and the prevalence of online grooming, where an adult sexual predator initiates a sexual relationship with a minor (victim) (Georgia M. Winters and Jeglic, 2017; Susi et al., 2019). Further, online grooming is underreported for lack of awareness, support, or trust in authorities, fear of retaliation from the predator or legal repercussions, and distress of being judged or blamed (Taylor and Gassner, 2010).

For a safer online experience, researchers have proposed neural models, including feed-forward (Villatoro-Tello et al., 2012; Escalante et al., 2013; Cheong et al., 2015), convolutional (Ebrahimi et al., 2016) and recurrent neural networks (Kim et al., 2020; Ngejane et al., 2021b),

and transformers (Vogt et al., 2021; Agarwal et al., 2021), to learn from explicit textual remarks of predators for online grooming detection and help warn minors, parents or police of such incidents while preserving minors' privacy. Such models, however, suffer from low recall due to the sparse distribution of predatory conversations; e.g., in pan (Inches and Crestani, 2012) benchmark dataset, merely 2.3% of conversations are predatory.

In this paper, we proposed to bridge the gap by natural language backtranslation augmentation to enrich training datasets with more predatory conversations. Specifically, we translate original predatory conversations from their original language, e.g., English, to a target language, e.g., French, and then translate them back to the original language using an off-the-shelf neural translator, e.g., meta's nllb (Costa-jussà et al., 2024), to generate new synthetic predatory conversations. While languages share underlying commonalities, they carry differences on the surface (Friederici, 2017), especially in an informal context like in online conversations, that can be leveraged via backtranslation to generate diverse paraphrases of a predatory conversation while withholding its predatory intent.

From Table 1, backtranslation can uncover latent terms in a predatory conversation as they may not be commonly known in a target language and, hence, should be explicitly generated through translation, like when '*having it with minor*' is translated to French as '*l'avoir avec mineur*' followed by a backtranslation to English, it brings up '*having sex*'. Moreover, backtranslation can augment *context-aware* synonymous terms from a target language to the original predatory conversation, as opposed to simple synonym replacement by a thesaurus (Shiri, 2004). For instance, when '*hooked up*' is translated to Chinese as '交过', followed by a backtranslation to English as '*to have sex*', it augments '*sex*' as opposed to other semantics like '*to plug in*' in electrical nomenclature. Finally, backtranslation can

***Warning:** This paper discusses online grooming that may be offensive or upsetting.

original message	language: translation	backtranslation
'having it with minor'	French: 'l'avoir avec mineur'	'having <u>sex</u> with a minor'
'i feel little aroused'	German: 'ich fühle mich ein wenig erregt'	'i'm feeling a little <u>turned on</u> '
'you ever hooked up with anybody...?'	Chinese: '你有没有和网上的人交过?'	'have you ever <u>had sex</u> with ...?'
'like two guys doing each other?'	German: 'wie zwei typen, die es miteinander treiben?'	'like two guys <u>having sex</u> ?'

Table 1: Backtranslation examples of predatory messages from pan (Inches and Crestani, 2012).

disambiguate polysemous collocations, like translating an ambiguous message 'doing each other' to German 'miteinander treiben', and backtranslating to English, maps the term 'each other' to 'sex'.

For similar reasons, backtranslation has been employed in review analysis (Fei et al., 2021; Liesting et al., 2021; Hemmatizadeh et al., 2023), web search (Rajaei et al., 2024, 2025) and other natural language processing tasks like text summarization (Fabbri et al., 2021), question-answering (Bhaisaheb et al., 2023), and machine translation (Sennrich et al., 2016; Guo et al., 2021). Furthermore, the open-source accessibility to neural translators (Costa-jussà et al., 2024), capable of delivering high-quality translations between many languages, as well as their seamless integration into any pipeline with few lines of code, have already set off a surge of interest. Nonetheless, other augmentation techniques such as rule-based (Wei and Zou, 2019), synonym replacement (Kolomiyets et al., 2011), and structure-based (Min et al., 2020) fall short in online grooming detection due to the short, noisy and informal messages.

2 Related Works

The related works to this paper are centred around two areas: (1) online grooming detection and (2) data augmentation. We acknowledge yet exclude research on online grooming from a non-computational perspective in psychology (Schoeps et al., 2020; Chiu and Quayle, 2022), behavioral studies (Broome et al., 2020; Ringenberg et al., 2022), and forensics (Ngejane et al., 2021a).

2.1 Online Grooming Detection

The primary means of online grooming is *textual* messages. Hence, natural language processing techniques have been widely used to detect online grooming through machine learning classifiers on vector representations of conversations, which can be categorized into (1) sparse vector representation (Villatoro-Tello et al., 2012; Escalante et al., 2013; Cheong et al., 2015; Ebrahimi et al., 2016), (2) low-dimensional dense vector representations (Ebrahimi et al., 2016; Muñoz et al., 2020; Kim et al., 2020; Vogt et al., 2021; Chehbouni et al.,

2022; Waezi et al., 2024), and (3) hand-crafted feature representations from conversations (Waezi et al., 2024). Initially, sparse vector representations for conversations have been widely used, like bag-of-word representations of messages or conversations (Villatoro-Tello et al., 2012; Escalante et al., 2013; Cheong et al., 2015; Ebrahimi et al., 2016). Despite their simplicity, sparse representations suffer from out-of-vocabulary, loss of token order, and high dimensionality, to name a few. Next, pre-trained word embeddings from word2vec (Mikolov et al., 2013) and glove (Pennington et al., 2014) have been employed, following their success in various tasks like document classification (Ebrahimi et al., 2016; Muñoz et al., 2020). Such embeddings, however, performed poorly for being trained on corpora different from informal online chats. State-of-the-art methods use contextualized word embeddings for online grooming (Kim et al., 2020; Vogt et al., 2021; Chehbouni et al., 2022; Waezi et al., 2024). More recently, Waezi et al. (2024) proposed incorporating conversational features, such as the message's timestamp and the number of participants, to capture characteristic features of online grooming.

In terms of classifiers, earlier works used support vector machines (Villatoro-Tello et al., 2012; Escalante et al., 2013; Cheong et al., 2015; Bours and Kulrud, 2019), logistic regression (Cheong et al., 2015; Chehbouni et al., 2022), and other classical machine learning models, including k-nearest neighbors (Chehbouni et al., 2022), naive Bayes (Bogdanova et al., 2012), and decision trees (McGhee et al., 2011; Cheong et al., 2015). Recent works have increasingly adopted neural models, including feedforward (Villatoro-Tello et al., 2012; Escalante et al., 2013; Cheong et al., 2015), convolutional (Ebrahimi et al., 2016), and recurrent neural networks (Ngejane et al., 2021a; Waezi et al., 2024), and transformer-based models (Vogt et al., 2021), which enable considering larger or even the entire context of a conversation for classification. For example, Waezi et al. (2024) processed conversations as sequences of messages using recurrent neural networks, showing gru has a better gating strategy versus lstm for predatory

conversations, which are often long.

Nonetheless, to the best of our knowledge, no work has been proposed to address the highly sparse distribution of predatory conversations in training datasets.

2.2 Data Augmentation

Augmentation techniques have helped models’ robustness and generalization for out-of-vocabulary and out-of-distribution scenarios during inference, which can be categorized based on where augmentation happens in the machine learning pipeline (Bayer et al., 2023): (1) data space, which involves augmenting pieces of text directly in levels of character, word, phrase, and sentence, and (2) feature space, where the vector representations (embeddings) of input texts in a latent space are used to augment new data by, e.g., introducing noise to a vector or interpolating new vectors from existing ones (Kumar et al., 2019; Chen et al., 2020). In contrast to feature space augmentation, where the augmented vectors are not interpretable for humans (Bolukbasi et al., 2021) and their generation is often computationally costly, data space augmentations are simpler yet more effective and include noise addition (Belinkov and Bisk, 2018), rule-based transformations (Coulombe, 2018), synonym replacement (Kolomiyets et al., 2011), structure-based manipulation (Min et al., 2020), machine-generated text (Qiu et al., 2020), and backtranslation (Risch and Krestel, 2018; Hemmatizadeh et al., 2023). For example, Rizos et al. (2019) employed synonym substitution for hate speech detection, and Cao and Lee (2020) and Casula and Tonelli (2023) used machine-generated text to augment datasets of hate speech detection and offensive language detection, respectively.

Among data space augmentation methods, backtranslation has been used notably due to its ability to create new paraphrases of an existing text with new vocabulary and structure while controlling the semantic context (Aroyehun and Gelbukh, 2018; Xie et al., 2020; Qu et al., 2021). Specifically, backtranslation has been used in domains close but different from online grooming, like aggression (Aroyehun and Gelbukh, 2018) and offensive language detection (Ibrahim et al., 2020). However, in online grooming, where turn-taking conversations are involved, as opposed to an online post or comment, the effect of data augmentation, in general, and backtranslation augmentation, in particular, is yet to be studied.

3 Problem Definition

A conversation c in a language l is a sequence of $|c|$ timestamped messages m_i^c ; $1 \leq i \leq |c|$, each message of which includes id, text, author, and timestamp. Furthermore, as opposed to an online post or comment, an online conversation should have at least two different authors, each of whom has at least one message, i.e., $\exists m_i^c, m_j^c$ such that $m_i^c.\text{author} \neq m_j^c.\text{author}$. Let $\mathcal{C} = \{c\}$ be the set of conversations, our task is to learn $f_\theta : \mathcal{C} \rightarrow \{0 : \text{normal}, 1 : \text{predatory}\}$, a mapping function of parameters θ from the conversation set to the Boolean set, such that $f_\theta(c) = 1$ if c is predatory and 0 otherwise.

4 Backtranslation Augmentation

We learn the mapping function f_θ from a set of conversations $\mathcal{C}^+ = \mathcal{C} \cup \mathcal{C}^l$ that is augmented by backtranslated versions of predatory conversations via a language l . Let \mathcal{L} be the set of natural languages, τ be a two-way translator, and c be a predatory conversation. We *forward* translate each message of the predatory conversation m_i^c to a target language l and translate it *back* to the source language using the translator τ , resulting in the backtranslated version of each message, denoted by $m_i^{c \leftarrow l}$. We collect the backtranslated messages and form a new predatory conversation $c^{\leftarrow l}$ as the backtranslated version of c , keeping the same values in other attributes like timestamp and author. Finally, we augment the dataset with backtranslated versions of existing predatory conversations.

5 Experiments

5.1 Dataset

Access to training sets of online grooming remains challenging due to legal concerns. Previous datasets such as conversations from an online game for minors (Cheong et al., 2015), chat-coder (McGhee et al., 2011) and pan-chat-coder (Vogt et al., 2021), are inaccessible to researchers. The sole accessible dataset is pan (Inches and Crestani, 2012) (Appendix A), which extensively used in prior studies (McGhee et al., 2011; Bogdanova et al., 2012; Ebrahimi et al., 2016; Cardei and Rebedea, 2017; Aragón and López-Monroy, 2018). In our experiments, we removed conversations with only 1 participant or those with fewer than 6 message exchanges.

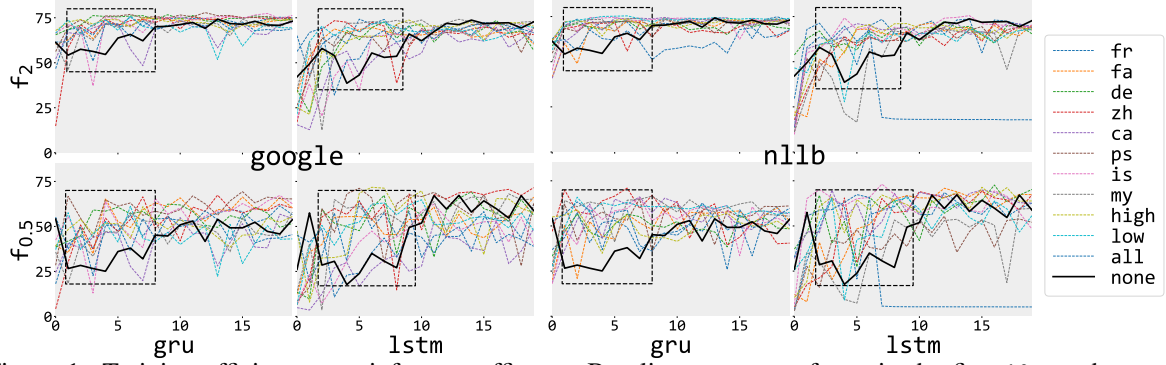


Figure 1: Training efficiency vs. inference efficacy. Baselines converge faster in the first 10 epochs on the augmented dataset (colored lines) for better f-measures on the test set compared to the lack thereof (black line). From Appendix C, m2m100 follows the same trend.

5.2 Backtranslation

We chose French, German, Icelandic, and Catalan from Indo-European, Farsi and Pashto from Iranic, and Chinese and Myanmar from Sino-Tibetan, among which Icelandic, Catalan, Pashto, and Myanmar are low-resource languages. For translation and backtranslation, we utilized three two-way neural translators: meta’s nllb (Costa-jussà et al., 2024) and m2m100 (Fan et al., 2021), and google’s translator. These translators can perform translations to and from over 100 languages with a single model, enabling a comprehensive study on a wide variety of languages. All three translators are based on transformers. However, while meta’s translators are open-sourced, google’s translator is closed, yet it is a well-known commercial translator. Regarding translation quality, nllb is the state-of-the-art on benchmark translation datasets (Costa-jussà et al., 2024).

5.3 Baselines

We trained state-of-the-art gru-based recurrent model by Waezi et al. (2024) and the strong lstm-based competitor by Kim et al. (2020) to estimate f_θ for online grooming detection on the backtranslated augmented dataset and lack thereof. Both models have a single layer with 512 units, utilizing the tanh activation function and the Adam optimizer. Each conversation was vectorized as a sequence of its message embeddings using pretrained 768-dimensional vectors of distilroberta (Sanh et al., 2019).

5.4 Evaluation Methodology

We performed 3-fold cross-validation. For each fold, we conducted two separate training sessions for a baseline model: one using the original fold and one using the augmented one. We evaluated

the performance of the trained models on the same test set using f-measures with $\beta = 2.0$ to favour recall over precision vs. $\beta = 0.5$ vice versa, and $\beta = 1.0$ for equal importance. We compared the average results over the folds. To study how backtranslation augmentation improves models’ efficiency during training, we reported the models’ performance on the test set at each training epoch.

5.5 Results

From Figure 1, we observe that baselines converge faster in fewer training epochs when the training set is augmented with backtranslations across different languages compared to the lack thereof in terms of f-measures. In terms of efficacy, Table 2 shows the performance delta before and after backtranslation augmentation of the training set for baselines after 20 epochs. As seen, backtranslation augmentation helps with the models’ efficacy overall. However, the performance gain depends on the language, translator, and baseline model.

Regarding the effects of each language, language families, and their combinations on the baselines’ efficacy, we observe that low-resource languages individually have shown an overall better performance like Catalan (ca), Pashto (pa), and Myanmar (my), which can be attributed to their better paraphrasing (Appendix B). Low-resource languages have shown relatively higher semantic similarities for the relatively low bleu scores. In contrast, Chinese (zh), a high-resource language, yielded a lower performance in Table 2 due to its poor backtranslations with the lowest bleu and semantic similarities. From the results of integrating the backtranslations from languages of the same family, we observe that *not* all language families show synergy. While integrating backtranslations of French (fr) + Catalan (ca) from the Western Ro-

			$\Delta f0.5$			$\Delta f1$			$\Delta f2$		
			google	m2m100	n11b	google	m2m100	n11b	google	m2m100	n11b
gru	none		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	+fr		+8.76	+2.61	+2.65	+7.08	+2.84	+2.63	+5.80	+2.46	+3.35
	+fa		+1.68	+3.50	+4.05	+1.88	+3.64	+3.39	+2.43	+5.42	+3.04
	+de		+4.10	+3.81	+9.00	+3.76	+2.97	+6.39	+4.22	+2.92	+2.27
	+zh		-8.97	+1.55	+5.63	-5.87	+2.14	+4.27	-3.92	+4.89	+2.61
	+ca		+7.29	+7.44	+11.03	+6.73	+5.40	+8.04	+5.01	+2.67	+4.70
	+ps		9.57	-5.32	+13.60	+6.48	-3.79	+7.58	+3.04	+1.56	+0.52
	+is		+3.73	-2.24	+10.14	+4.04	-0.68	+6.98	+6.27	+2.25	+3.24
	+my		+12.51	-3.13	+9.34	+9.13	-1.66	+6.06	+4.63	+1.46	+2.00
	+fr+ca	Western Romance	+8.07	-4.40	+15.29	+7.02	-2.35	+9.94	+6.76	-0.81	+3.52
	+fa+ps	Iranic	-3.31	-6.71	+2.91	-1.88	-4.75	+2.62	+0.34	+0.78	+3.60
	+de+is	West Germanic	+11.84	+5.94	+9.43	+9.39	+5.60	+7.65	+6.98	+6.63	+6.16
	+zh+my	Sino-Tibetan	+8.83	-8.76	-3.15	+6.80	-6.33	-1.21	+4.55	-7.05	+0.66
	+fr+fa+de+zh	high-resource	+5.88	-1.36	+10.14	+4.62	-0.40	+7.63	+3.94	+3.01	+4.97
	+ca+ps+is+my	low-resource	+8.10	-1.38	+10.41	+6.61	-0.52	+5.26	+5.63	+2.64	-1.00
	all		+4.25	-0.32	+6.51	+4.30	+0.06	+5.20	+6.02	+2.16	+4.64
lstm	none		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	+fr		+8.42	-2.78	+5.30	+1.79	-2.10	+2.55	-6.71	-2.64	-1.43
	+fa		+1.99	+4.06	-6.82	-0.03	+0.65	-5.59	-3.53	-4.19	-7.95
	+de		+2.14	+4.16	-0.58	+1.78	-0.17	-0.70	+1.21	-5.75	-3.90
	+zh		+5.80	+2.04	-6.30	-0.02	-0.40	-2.66	-7.02	-4.87	-13.18
	+ca		-2.09	+2.83	+8.03	-0.74	-0.08	+1.97	+0.69	-5.70	-5.46
	+ps		-9.05	+4.32	+1.68	-7.05	+2.06	-1.89	-6.36	-0.82	-9.89
	+is		+1.83	-10.86	+6.64	+1.66	-8.07	+1.10	-2.03	-3.81	-6.26
	+my		-3.94	+0.28	+8.86	-3.15	-2.63	+4.52	-7.74	-6.91	-0.87
	+fr+ca	Western Romance	-0.08	-12.39	+0.96	-0.67	-8.89	-1.16	-2.02	-4.14	-4.55
	+fa+ps	Iranic	+8.68	-11.79	+2.90	+2.38	-8.87	-0.33	-5.59	-4.43	-6.13
	+de+is	Western Germanic	-13.23	-0.62	+1.70	-9.32	-0.97	-0.18	-8.14	-2.33	-3.62
	+zh+my	Sino-Tibetan	-1.32	+4.27	+0.57	-0.04	+0.52	-2.88	+0.91	-4.26	-9.11
	+fr+fa+de+zh	high-resource	+1.44	-8.80	+9.38	-1.60	-6.98	+2.91	-5.55	-8.82	-5.00
	+ca+ps+is+my	low-resource	-11.90	+0.56	+7.01	-8.57	-1.17	+1.67	-4.89	-3.87	-5.78
	all		+3.24	+3.28	+4.54	+0.69	-0.17	+1.51	-2.85	-4.60	-3.39

Table 2: Average 3-fold cross-validation results of baselines for 20 training epochs using backtranslation augmentations and lack thereof (none) on the same test set based on the performance delta (Δ). Best viewed in color.

mance family boosts the baselines’ performance, Chinese (zh) + Myanmar (my) from the Sino-Tibetan have a discounting effect. However, when we integrate more languages based on their high or low-resource richness, or integrating all languages, backtranslation augmentation shows positive impacts in general.

For the quality of neural translators on the performance gain, from Table 2, we see that the translation by n11b and google have resulted in the best and runner-up performance improvements, respectively, while m2m100 has shown less effectiveness. Specifically, in low-resource languages, m2m100’s backtranslations have shown subpar performance compared to n11b and google. Our results are also aligned with translation benchmarks, and the fact that n11b has been developed with low-resource languages in mind (Costa-jussà et al., 2024).

To see whether backtranslation augmentation consistently benefits the performance of the baseline models, we clearly observe that gru’s performance improvement has been positive overall

across different languages and metrics. Surprisingly, lstm’s performance is *not* following a similar trend; while lstm’s f0.5 has been improved across high-resource languages, its performance drops in other languages for f1 and f2. Our results are in line with Waezi et al. (2024)’s work where gru outperformed lstm due to its better gating strategy to retain dependencies from earlier messages in long conversations as in predatory conversations.

6 Concluding Remarks

In this paper, we proposed backtranslation augmentation of predatory conversations for online grooming detection. We showed that (1) backtranslation augmentation improves models’ performance with fewer training epochs for better classification efficacy; (2) low-resource languages have shown better performance; (3) higher quality neural translators yield more performance gain; and (4) finally, the underlying model architecture matters where gru consistently improves upon backtranslation augmentation across all languages while lstm improves only across high-resource languages.

7 Limitations

The main limitation of this study lies in the benchmark dataset, pan, which is solely in English. This restricts the generalizability of our findings to other languages. We acknowledge that online grooming occurs across other languages, highlighting the critical need for non-English training datasets. Expanding research to include multilingual datasets would allow for a more comprehensive evaluation of online grooming detection techniques, including the effectiveness of our backtranslation augmentation. Additionally, the victims in pan are trained adult decoys rather than actual minors, which may affect the quality and reliability of results. Finally, while the ultimate objective of online grooming detection is to identify predators before they can harm potential victims, our study requires the entire conversation for classification. In future work, we plan to focus on the task of *early* detection, that is, identifying grooming behaviors at early stages based on the first few messages before the conversation escalates into serious exploitation or abuse.

8 Ethical Considerations

The researchers involved in this study were all adults who were warned and fully informed about the harmful content of predatory conversations in the benchmark dataset. Additionally, the use or distribution of pan dataset could violate laws in certain jurisdictions, leading to potential legal consequences for the researchers involved. Moreover, the work undertaken in this paper, as well as pan dataset, must not be exploited for malicious purposes like reverse study or re-engineering of predatory behaviours to *fool* detection methods by adversarial or behavioural manipulation. Finally, predatory conversations in pan dataset have been obtained from Perverted-Justice¹ whose method of decoy operations has raised controversy for being *entrapment*. Hence, the labels for predatory conversation may contain noise and inconsistency to correctly interpret the real-world situations.

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	raw		filtered	
	train	test	train	test
#conversations	66,927	155,128	16,529	38,246
# predatory conversations	2,016	3,737	957	1,698
#conversations w/ single participant	12,773	29,561	0	0
# predatory conversations w/ 2+ participants	0	0	0	0
avg #msgs in a predatory conversations	60.73	90.07	80.68	71.48
avg #msgs in a normal conversations	12.74	12.86	41.73	41.78
avg #words in a msg of a predatory conversations	4.47	4.63	4.38	4.51
avg #words in a msg of a normal conversations	6.39	6.77	6.91	7.16

Table 3: Statistics of pan (Inches and Crestani, 2012) dataset.

	google	m2m100	n11b
#languages	133	101	196
model card	×	✓	✓
#parameters	unknown	1.2 billion	3.3 billion
license	closed source	mit	cc-by-nc
owner	google	meta	meta
architecture	transformer +rnn	transformers	transformers

Table 4: Details of neural translators.

A Dataset

The pan dataset includes cases of online grooming about 10 years obtained from trained volunteers (decoys) posing as minors in public conversation platforms to catch and convict predators. The normal conversations in this dataset are sourced from omegle online chatrooms² and internet relay chat logs³. It also includes conversations with a single participant and a small number of messages. We filter such conversations and those with less than 6 messages. Table 3 shows the statistics of the datasets before and after filtering. As seen, the dataset is extremely imbalanced against predatory conversations, which include only 2 participants and are generally longer.

B Effective Backtranslation for Augmentation

Table 4 summarizes the neural translators used in this paper, where google is closed-source yet a well-known commercial translator, widely used by the general public, industry, and academia (Patil and Davies, 2014; Yu et al., 2018; Madisetty and Desarkar, 2018), and m2m100 and n11b are open-source from meta. We presume backtranslation is effective for augmentation if it paraphrases the original predatory messages of a conversation into new wordings while keeping the semantic context of grooming. We opt for bleu to measure the n-gram overlap in wordings between the original and backtranslated messages. Meanwhile, we measure

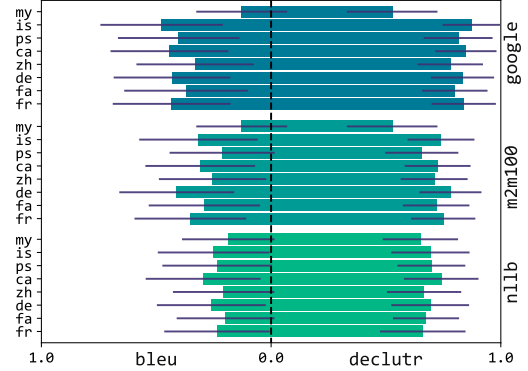


Figure 2: bleu and semantic similarity (declutr) of backtranslated messages against the original ones.

the semantic similarity between the original and backtranslated messages by declutr as the state-of-the-art model-based method (Giorgi et al., 2021), which calculates the semantic similarity of a pair of texts based on their cosine similarity in a vector space. From Figure 2, the semantic similarity of most backtranslations (paraphrases) to the original text typically falls between 40% and approximately 95%, indicating that, on average, the backtranslations retain the grooming intent of the conversations. Meanwhile, the bleu scores exhibit a lower range of values, indicating that word choices differ, which, together with semantic similarity, suggests a high-quality backtranslation for augmentation. Conversely, a higher bleu implies that the original text and the paraphrase are very similar in terms of word usage and could even be identical, yielding poor backtranslation for augmentation.

C Complementary Results

Figure 3 shows the trade-offs between the training efficiency and inference efficacy for baselines when the dataset is augmented with backtranslations using m2m100. As seen, a similar trend is followed as in other translators, including n11b and google (Figure 1). Furthermore, Table 5 shows the values of metrics for the baselines whose delta (Δ) were presented in Table 2.

²omegle.inportb.com

³krijnhoetmer.nl/irc-logs

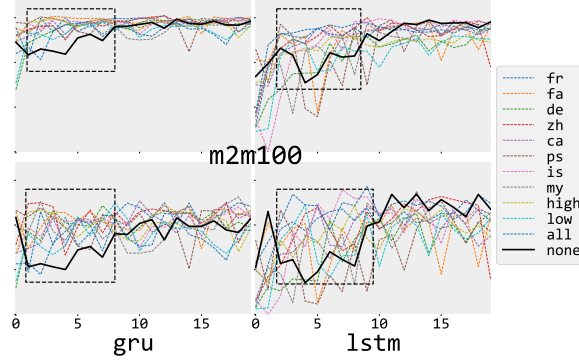


Figure 3: Training efficiency vs. inference efficacy for m2m100. Baselines converge faster in the first 10 epochs on the augmented dataset (colored lines) for better f-measures on the test set compared to the lack thereof (black line), a similar trend as in nllb and google.

			f0.5			f1			f2		
			google	m2m100	nllb	google	m2m100	nllb	google	m2m100	nllb
gru	none		50.95	50.95	50.95	59.03	59.03	59.03	68.15	68.15	68.15
	+fr		59.72	53.56	53.61	66.11	61.87	61.66	73.96	70.62	71.51
	+fa		52.63	54.45	55.01	60.91	62.68	62.42	70.59	73.58	71.20
	+de		55.05	54.77	59.96	62.79	62.00	65.42	72.38	71.07	70.42
	+zh		41.99	52.50	56.59	53.17	61.17	63.30	64.24	73.05	70.77
	+ca		58.24	58.40	61.99	65.76	64.44	67.07	73.17	70.83	72.85
	+ps		60.53	45.63	64.55	65.51	55.24	66.61	71.20	69.72	68.68
	+is		54.68	48.72	61.09	63.07	58.36	66.01	74.42	70.41	71.40
	+my		63.46	47.82	60.30	68.16	57.38	65.09	72.79	69.62	70.16
	+fr+ca	west romance	59.03	46.55	66.25	66.05	56.68	68.97	74.92	67.35	71.68
	+fa+ps	iranica	47.65	44.24	53.87	57.15	54.28	61.65	68.50	68.93	71.76
	+de+is	western germanic	62.80	56.90	60.38	68.43	64.64	66.68	75.14	74.79	74.32
	+zh+my	sino-tibetan	59.79	42.20	47.81	65.83	52.70	57.82	72.70	61.10	68.82
	+fr+fa+de+zh	high-resource	56.83	49.59	61.09	63.65	58.63	66.66	72.10	71.17	73.13
	+ca+ps+is+my	low-resource	59.05	49.58	61.37	65.64	58.51	64.29	73.79	70.80	67.16
	all		55.20	50.64	57.47	63.33	59.09	64.23	74.18	70.32	72.80
lstm	none		58.39	58.39	58.39	64.51	64.51	64.51	71.76	71.76	71.76
	+fr		66.82	55.62	63.70	66.31	62.42	67.07	65.06	69.12	70.33
	+fa		60.39	62.46	51.57	64.49	65.17	58.93	68.23	67.57	63.81
	+de		60.53	62.56	57.82	66.30	64.35	63.82	72.97	66.01	67.86
	+zh		64.19	60.44	52.10	64.50	64.11	61.86	64.74	66.89	58.59
	+ca		56.30	61.23	66.43	63.78	64.44	66.49	72.46	66.06	66.31
	+ps		49.35	62.72	60.08	57.47	66.58	62.63	65.40	70.94	61.88
	+is		60.23	47.54	65.03	66.18	56.45	65.61	69.74	67.95	65.50
	+my		54.46	58.68	67.25	61.36	61.89	69.03	64.02	64.86	70.89
	+fr+ca	west romance	58.48	46.00	59.36	63.85	55.63	63.36	69.74	67.62	67.21
	+fa+ps	iranica	67.08	46.61	61.29	66.90	55.65	64.19	66.17	67.34	65.63
	+de+is	western-germanic	45.17	57.78	60.10	55.19	63.55	64.34	63.62	69.43	68.14
	+zh+my	sino-tibetan	57.08	62.67	58.97	64.48	65.04	61.64	72.67	67.50	62.65
	+fr+fa+de+zh	high-resource	59.83	49.60	67.78	62.92	57.54	67.42	66.22	62.94	66.76
	+ca+ps+is+my	low-resource	46.50	58.96	65.41	55.95	63.35	66.19	66.87	67.89	65.98
	all		61.64	61.68	62.94	65.21	64.35	66.02	68.91	67.17	68.37

Table 5: Average 3-fold cross-validation results of baselines for 20 training epochs using backtranslation augmentations and lack thereof (none) on the same test set.