Osprey: A Reference Framework for Online Grooming Detection via Neural Models and Conversation Features*

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Abstract

Online grooming is the process of an adult initiating a sexual relationship with a minor through online conversation platforms. While neural models are developed to detect such incidents, their practical implications in real-world settings remain moot for their closed, irreproducible, and poor evaluation methodologies under the sparse distribution of grooming conversations in the training datasets, like undermining `recall` over `precision`. Furthermore, proposed models overlook characteristic features of grooming in online conversations, including the number of participants, message exchange patterns, and temporal signals, such as the elapsed times between messages. In this paper, we foremost contribute `Osprey`, an open-source library to support a standard pipeline and experimental details, incorporating canonical neural models and a variety of vector representation learning for conversations while accommodating new models and training datasets. Further, we incorporate conversation features into the models to improve `recall` while maintaining `precision`. Our experiments across neural baselines and vector representations of conversations demonstrated that recurrent neural models, particularly `gru`, on the sequence of pretrained transformer-based embeddings of messages in a conversation along with conversation features obtain state-of-the-art performance, winning the best `recall` with competitive `precision`. `Osprey` is available at `https://github.com/fani-lab/Osprey/tree/cikm24`.

CCS Concepts

• **Information systems → Chat**; **Content analysis and feature selection**; • **Social and professional topics → Children**.

Keywords

Online Grooming; Predatory Conversation Vectorization;

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

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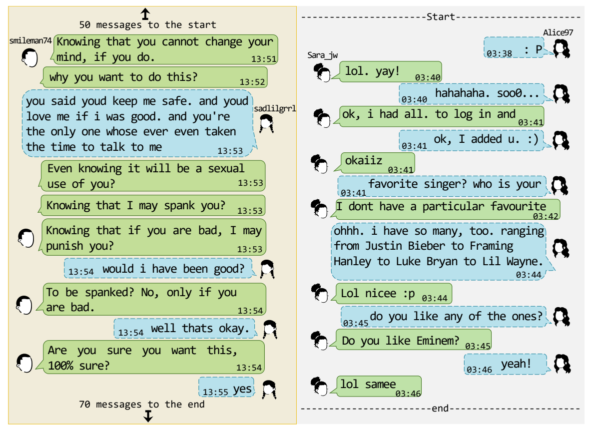

Figure 1: A predatory conversation between a 34-year-old predator and a 13-year-old victim (left) vs. a normal one.

1 Introduction

With the prevalence of more technology, minors access it before they are of legal age and with little cognitive development [18], facing an alarming problem of engaging with predators in online grooming [36]. Through grooming, the sexual predator tries to form an emotional relationship with a minor to get her trust and make her engage in sexual activities afterwards [14, 35, 37]. Recent stats show that 57% of girls and 48% of boys have experienced at least one online grooming, with some regions like north america and western europe being even higher [30]. Meanwhile, crimes involving minors are 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, among others [12, 38]. Such proceedings have stressed the development of computational models that plug into an online chat environment and help warn minors, parents or police of such incidents while preserving the minor's privacy [8].

In many cases of online grooming, as shown in Figure 1, the predators mix explicit textual remarks to give the minor a feeling of endearment and to lure her into their trap. Such remarks can be extracted by natural language processing techniques and tapped into machine learning models to detect predators or predatory conversations [22]. To this end, researchers have formulated online grooming detection problem as a Boolean classification task and have tackled it at two granularity levels of *i*) message or *ii*) entire conversation through machine learning models including support vector machine [4, 7, 9, 11, 40], logistic regression [6, 7, 25], k-nearest neighbors [6, 31], naïve Bayes [2, 25, 39], decision trees [7, 23, 25], and recently neural models, including feed-forward [7, 11, 40], convolutional [9], and recurrent [19, 29] neural networks, and transformers [41]. In predatory message classification, a message in a conversation is mapped into a sparse vector representation like an occurrence vector of tokens [7, 9–11, 27, 40] or a dense low-dimensional vector using distributional vector representation learning (embedding) techniques [3, 9, 28] like `glove` [32] and `word2vec` [26], or contextual pretrained vectors from large language models like `bert` [6, 19, 41] which is further classified into a Boolean value of *'predatory'* or *'normal'*. The proposed works for predatory message classification, however, overlooked the conversation context such as the messages before and after. To fill the gap, Kim et al. [19] fed messages of a conversation in sequence to `lstm` followed by a classifier and obtained state-of-the-art performance.

Successful as they are, proposed neural methods forego distinctive features of a predatory conversation, including *i*) the number of participants in a conversation; little to no predatory conversation has more than two participants, *ii*) the message exchange pattern; predatory conversations lack a fair exchange of messages through turn-taking, and *iii*) the elapsed times of the message exchanges. From `pan` benchmark dataset [17, 18], as seen in Table 1, all predatory conversations are one-on-one (binary); i.e., only two participants are involved. Further, the average number of consecutive messages from the same participant, referred to as a *segment*, for predatory conversations and normal ones are `2.12±0.64` vs. `2.00±2.50`, respectively, and the average time elapsed for message exchange between a predator and a minor is `1.43±8.61` minutes compared to `0.91±1.41` in normal conversations. Moreover, to the best of our knowledge, no proposed method is publicly available except that of Vogt et al. [41], which includes only their proposed method falling short of being a benchmark library. With regard to the evaluation methodology, existing work reported `accuracy`, which is misleading in online grooming detection where predatory conversations are very scarce in training datasets; e.g., in `pan`, merely `2.3%` of conversations are predatory. Also, studies forego the critical precedence of `recall` and the dire consequences of misclassifying even one online grooming in the real world.

In this paper, foremost, (1) we contribute `Osprey`, an open-source benchmark library to foster reproducibility, and sound evaluation methodology, which literature of this field lacks. `Osprey` sets forth sparse and dense vector representations of conversations at both levels of the message and the entire conversation along with neural and non-neural models with a one-click pipeline that orchestrates the standard flow of machine learning with no human in the loop. (2) We then propose to incorporate features from the conversation context, including message timestamps and the number of participants, to improve the efficiency of neural models during training while improving inference efficacy. (3) Moreover, through a cross-study of vector representations at levels of a message or the entire conversation with conversation features and lack thereof on neural and non-neural models, we systematically addressed research questions that are yet to be answered in online grooming detection, including *i*) conversation features show synergistic impact across all models and all varieties of vector representations, and more importantly, they help models prioritize `recall` while maintaining `precision`, *ii*) recurrent models outperform other baselines across all varieties of vector representations; specifically, `gru` outperforms `lstm` [19], becoming the state of the art, and *iii*) the sequence of pretrained *contextual* vectors of messages yields the best results.

Table 1: Statistics of pan [17] dataset.

	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/ 1 participant	12,773	29,561	**0**	**0**
#conversations w/ 2 participants	45,741	105,862	9,474	21,722
#binary ***predatory*** conversations	2,016	3,737	957	1,698
#non-binary ***predatory*** conversations	**0**	**0**	**0**	**0**
avg #msgs in a ***predatory*** conversation	**60.73**	**90.07**	**80.68**	**71.48**
avg #msgs in a normal conversation	**12.74**	**12.86**	**41.73**	**41.78**

2 Problem Definition

A conversation c is a sequence of $|c|$ messages $[m_i]; 1 < i \leq |c|$, such that each message includes `id`, `text`, `participant`, and `timestamp`. Furthermore, as opposed to an online post or a comment, an online conversation should have at least two different participants, each of whom has at least one message, i.e., $\exists m_i, m_j \in c, i \neq j$ such that $m_i.\texttt{participant} \neq m_j.\texttt{participant}$. Given $C = \{c\}$ be the set of conversations, online grooming detection is to learn $f_\theta : C \rightarrow \{\texttt{0}:\texttt{normal}, \texttt{1}:\texttt{predatory}\}$, a mapping function of parameters θ from the conversation set to the Boolean set, such that $f_\theta(c) = \texttt{1}$ if c is predatory and `0` otherwise. We estimate f_θ based on different vector representations of a conversation in a d-dimensional space through a function $g_\phi : c \rightarrow \mathcal{R}^d$ such that $f_\theta(c) \approx f_\theta(g_\phi(c))$.

3 Conversation Features

Predatory conversations embody distinctive characteristics; almost *all* are one-on-one (binary) conversations, lack a fair distribution of messages between participants via turn-taking, and have long elapsed times in message exchanges, the capture of which presumably improve the performance of online grooming detection methods. In this paper, we propose incorporating the timestamp of a message and the number of participants to improve upon neural and non-neural estimators for f_θ. Specifically, we cross-examine (1) neural models trained on (2) a variety of conversation vector representation methods g_ϕ(c), (3) fused with conversation features, including message timestamp and the number of participants via (4) `Osprey`'s unified framework followed by (5) the *stratified* k-fold cross-validation training and test evaluation methodology, considering the highly skewed distributions of classes. To estimate f_θ, we integrated vanilla (`rnn`) and gated recurrent neural models, including `lstm` and `gru` as the cutting-edge class of approaches to learn from the sequence of messages within the context of a conversation followed by a final classification. We also used feedforward and non-neural classifiers to classify the entire conversation at once. We vectorize conversations at two levels:

Message-level Embeddings. Given a conversation $c = [m_i]_{i=1}^{|c|}$, we map each message m_i onto a vector using bag-of-word, distributional, and contextual embeddings, as our g_ϕ, such that $g_\phi(c) \approx [g_\phi(m_i)]_{i=1}^{|c|}$, that is, a conversation becomes a list of vector representations of its constituents messages. Distributional and contextual embeddings can be transferred from a pretrained model on an external corpus, finetuned, or trained from scratch on an online grooming dataset. For distributional embeddings, we used `word2vec` [26, 32] to map the message's words onto embeddings whose average yields the embedding for the message. For contextual embeddings, we used `roberta` [20] to map the message onto

Table 2: Comparative results for 3-fold train-validation of models with conversation features and lack thereof on pan's test set. Bold and underlined numbers indicate the *column-wise* highest and second highest, respectively.

	aucroc			f_2 (favours recall)			$f_{0.5}$ (favours precision)		
	−ctx	+ctx	Δ	−ctx	+ctx	Δ	−ctx	+ctx	Δ
conversation as a sequence of message embeddings ($c = [g_\phi(m_i)]_{i=1}^{\lvert c\rvert}$)									
bow-rnn	54.04±01.16	58.40±02.56	+04.36	10.65±00.92	12.38±02.22	+01.73	03.30±00.09	05.01±01.51	+01.71
word2vec-rnn	54.65±04.25	57.62±01.92	+02.97	10.98±01.71	11.73±00.37	+00.75	10.37±09.49	18.23±10.38	+07.87
word2vec†-rnn	57.97±01.46	65.13±06.27	+07.16	12.91±00.60	14.98±03.90	+02.06	11.59±10.55	11.30±08.82	−00.28
roberta-rnn	59.11±02.79	67.01±05.83	+07.90	11.69±00.41	12.87±01.89	+01.18	8.06±06.53	10.72±09.79	+02.66
roberta†-rnn	54.75±00.41	55.79±00.44	+01.04	10.80±00.30	11.22±00.22	+00.42	11.48±05.58	22.85±00.15	+11.37
bow-lstm	94.36±01.89	96.24±00.16	+01.88	62.44±03.36	60.69±04.75	−01.75	62.48±05.05	60.35±05.23	−02.13
word2vec-lstm	91.79±03.37	90.51±03.42	−01.28	53.38±00.96	54.13±02.65	+00.74	59.54±03.32	55.76±07.37	−03.77
word2vec†-lstm	90.96±00.59	93.02±01.52	+02.05	47.20±02.66	51.69±01.63	+04.50	34.23±06.31	45.91±09.76	+11.68
roberta-lstm [19]	96.08±00.28	97.98±00.48	+01.90	64.07±04.28	<u>70.74</u>±01.89	+06.68	<u>63.69</u>±04.38	64.43±03.14	+00.74
roberta†-lstm	81.95±13.88	93.87±02.53	+11.91	39.23±19.27	49.22±02.42	+09.99	37.43±18.14	29.14±13.06	−08.29
bow-gru	96.69±00.54	97.09±00.74	+00.40	<u>67.95</u>±01.38	62.75±02.55	−05.21	48.84±02.42	<u>67.20</u>±03.90	+18.36
word2vec-gru	95.38±00.85	96.00±00.45	+00.62	55.63±02.13	54.66±02.17	−00.97	51.35±06.13	50.63±10.51	−00.72
word2vec†-gru	92.18±00.58	92.98±00.39	+00.80	48.49±01.49	47.91±01.49	−00.58	50.71±03.21	45.52±13.83	−05.19
roberta-gru	<u>97.04</u>±00.82	**98.29**±00.22	+01.25	67.30±00.97	**74.00**±01.25	+06.71	59.04±06.97	54.87±03.90	−04.17
roberta†-gru	95.53±01.18	97.09±00.39	+01.56	45.66±17.29	63.80±04.22	+18.15	23.16±12.93	38.89±07.76	+15.73
conversation as a single embedding ($c = g_\phi(m_c^*)$)									
bow-svm [40]	49.97±00.01	50.10±00.06	+00.13	00.03±00.00	00.28±00.15	+00.24	00.12±00.00	01.06±00.58	+00.94
word2vec-svm	50.23±00.02	82.26±00.31	+32.02	00.59±00.04	61.77±00.17	+61.18	02.28±00.15	51.42±01.43	+49.13
word2vec†-svm	50.02±00.01	50.04±00.02	+00.03	00.04±00.02	00.11±00.04	+00.07	00.18±00.06	00.44±00.16	+00.26
roberta-svm	82.49±00.26	82.78±00.42	+00.29	65.92±00.24	66.83±00.55	+00.91	**66.31**±00.91	**68.51**±00.60	+02.20
roberta†-svm	83.85±00.81	55.48±02.07	−28.36	62.18±00.23	13.18±04.57	−49.00	46.75±02.16	24.33±04.56	−22.43
bow-ff [9]	48.50±00.43	96.17±00.21	+47.67	04.00±00.42	68.39±00.39	+64.38	01.88±00.16	39.73±00.65	+37.85
word2vec-ff	48.69±06.92	95.89±00.49	+47.20	11.03±01.04	59.10±00.51	+48.08	03.04±00.32	29.80±00.76	+26.77
word2vec†-ff	91.46±00.21	92.52±00.79	+01.06	46.55±03.12	48.70±01.88	+02.16	21.33±02.82	22.54±01.88	+01.21
roberta-ff	**97.84**±00.16	<u>98.25</u>±00.00	+00.41	**68.20**±01.00	70.33±00.69	+02.13	44.20±02.76	47.29±02.84	+03.09
roberta†-ff	93.77±00.44	94.88±00.45	+01.11	56.73±06.46	58.99±00.62	+02.27	32.78±11.55	30.39±00.53	−02.39

an embedding. Our choices of distributional and contextual embedding methods are without loss of generality to other recent and advanced transformer-based language models. Yet, our goal is to study the effect of different embedding types using pioneering methods, distributional vs. contextualized embeddings, toward grooming detection; a better model most likely shows similar findings. The sequence of message-level embeddings for a conversation, each of which is concatenated with their timestamp and the number of participants to signal the unique features of predatory conversations, is fed to the recurrent neural models in order to classify the entire conversation as predatory or else.

Conversation-level Embeddings. To represent a conversation c as an embedding, we concatenate all its constituent messages into a long synthetic message, that is, $c \approx m_c^* = m_1 : \ldots : m_i : \ldots : m_{|c|}$, and apply one of our message-level embedding methods such that $g_\phi(c) \approx g_\phi(m_c^*)$. Herein, we add only the number of participants since the entire conversation becomes a single synthetic message. Such embeddings are fed to feedforward or non-neural classifiers.

4 Experiments

In this section, we aim to address the following research questions:

RQ1: Does the inclusion of conversation features improve the efficacy of online grooming detection across models and different vector representations of conversations?

RQ2: Does representing conversations as sequences of message-level embeddings yield better model performance than single embedding for the entire conversation?

RQ3: Do methods of online grooming detection prioritize `recall` while maintaining `precision`?

RQ4: Amongst the recurrent neural model, which gating strategy yields the best performance?

4.1 Setup

4.1.1 Dataset. Despite the significant societal benefit of computational models for online grooming detection, access to training sets of online conversations has remained challenging due to privacy and legal concerns. All few datasets in prior work, including chat-coder [23] and pan-chat-coder [41] are *in*accessible except that of pan [17], which has become the sole benchmark dataset in the literature [1, 2, 5, 9, 15, 23, 24]. In pan, cases of online grooming were obtained from trained volunteers (decoys) posing as minors in public chatrooms to catch and convict predators[13] and the normal conversations are from omegle[21] online chatrooms. For our experiments, we filtered out the conversations with 1 participant or an exchange of fewer than 6 messages. Table 1 shows the dataset's statistics. As seen, the number of predatory conversations with more than two participants is `0`, signifying predators approach their victims in private. Also, predatory conversations are notably longer, extending to around `80` messages on average. Such characteristics can be leveraged by a model to improve the performance of online grooming detection.

4.1.2 Baselines. We benchmarked `Osprey` using `svm` as a non-neural and a feedforward neural classifier (`ff`) when an entire conversation has been vectorized as a single embedding ($c = g_\phi(m_c^*)$), and vanilla (`rnn`), `lstm` [16], and `gru` recurrent neural models when a conversation is vectorized as a sequence of its messages' embeddings ($c = [g_\phi(m_i)]_{i=1}^{|c|}$). We used the `rbf` kernel for `svm` from scikit[34] with default values for hyperparameters. The feedforward neural model has a single layer of size `256` with `relu` activation function. The recurrent neural models have a single layer of size `512` with `tanh` as the activation function. `Adam` is the optimizer for all our neural models. To vectorize our conversations, we used

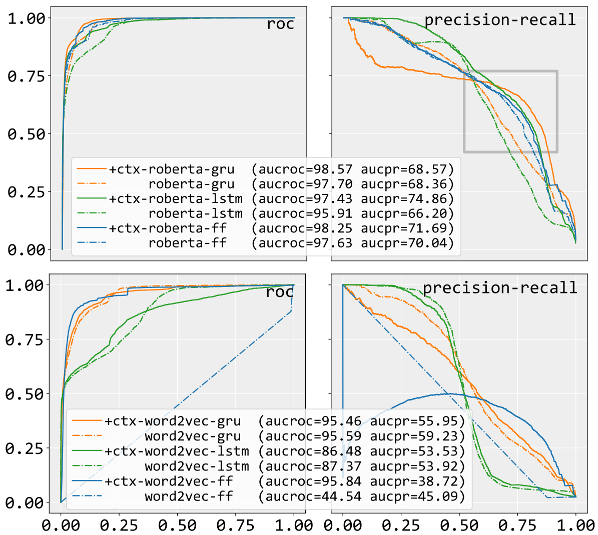

Figure 2: Efficacy at different classification thresholds.

bag-of-word (bow), `300`-dimensional embeddings from pretrained `word2vec` on google news as the *distributional* vectors, and `768`-dimensional vectors from pretrained roberta-base on openwebtext [33] (`roberta`) as the *contextual* vectors. We also trained word2vec (`word2vec`†) and finetuned roberta-base (`roberta`†) on `pan`. In total, we compare {5 models} × {5 embeddings} = 25 baselines.

4.1.3 Evaluation. Via 3-fold cross-validation procedure, we trained our baselines for `30` epochs, which results in one trained model per each fold for a baseline. We finally evaluated the per-fold trained models of a baseline on the `pan`'s test set and reported the recognized metrics under highly imbalanced class distributions, including `roc` and `precision-recall` curves along with `f-measure` with $\beta = 2.0$ to favour `recall` over `precision` vs. $\beta = 0.5$ vice versa.

4.2 Results

RQ1: Improvement upon inclusion of conversation features. From Table 2, we observe the general positive effects (+Δ) of including conversation features (`+ctx`) in all models in terms of `aucroc`, f_2, and $f_{0.5}$ compared to the lack thereof (`-ctx`). Specifically, substantial performance gains were obtained when conversation features were in tandem with the conversation as a single embedding. On a per-model basis, from a row-wise view, while recurrent baselines `*-lstm` and `*-gru` show the best performance overall, as expected, their gains from conversation features are marginal, which can be attributed to their ability to capture the conversation features through sequence processing of message embeddings. It is worth noting that even marginal improvement in online grooming detection, particularly in terms of f_2, leads to major positive societal contributions. On a per-metric basis, comparing f_2 and $f_{0.5}$, we see the overall positive impact of conversation features on both `recall` and `precision` and the few negatively impacted $f_{0.5}$ are negligible in favour of `recall` in online grooming detection.

RQ2: Comparing message- vs. conversation-level embeddings. From Table 2, it is evident that conversations as sequences of embeddings for their constituent messages are better representations than single embeddings for the entire conversations, enabling recurrent models to capture the message exchange patterns of online

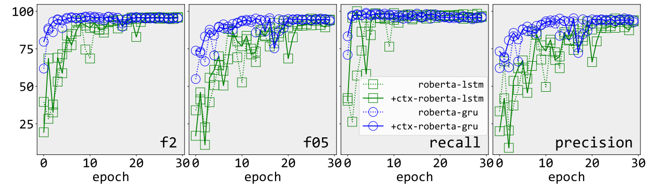

Figure 3: Efficacy vs. training efficiency of `gru` vs. `lstm`.

grooming and yield superior performance across metrics. Not unexpectedly, dense embeddings (`roberta-*` and `word2vec-*`) are better representations vs. sparse bag-of-word vectors (bow-*), and contextual embeddings (`roberta-*`) are of higher quality compared to distributional embeddings (`word2vec-*`). In terms of pretrained vs. trained or finetuned embeddings, *oddly*, pretrained embeddings on external corpora yield better performance compared to training or finetuning on `pan`, which calls for more investigation.

RQ3: Prioritizing `recall` while maintaining `precision`. We draw the `roc` and `precision-recall` curves for strong baselines in Figure 2. Interestingly, we observe no baseline favours `recall` unless their inputs are augmented with conversation features. As indicated in Figure 2 (top), almost all neural models whose `roberta` embeddings are augmented with conversation features yield higher `recall` for competitive `precision`, which is the prime focus in online grooming detection. Further, from Figure 2, while neural models on `word2vec` embeddings obtained higher `recall`, this came at the substantial cost of lower `precision`. Indeed, for `*-word2vec-lstm`, `precision` and `recall` are *inversely* correlated, rendering `word2vec` moot for conversation vectorization.

RQ4: Best gating strategy for recurrent neural models. Amongst recurrent models, from Table 2, we see that `*-gru` models are the best and `*-lstm` models [19] are runners up. Also, Figure 3 shows that `*-roberta-gru` outperforms `*-roberta-lstm` with much less training epochs. As already shown in the literature, vanilla recurrent models (`*-rnn`) are the poorest, even in comparison with `feedforward` and `svm`, which is attributed to their lack of gates and vanishing gradient problem; they fall short of retaining dependencies from earlier messages when processing long conversations as it is the case in predatory conversations.

5 Concluding Remarks

In this paper, we addressed online grooming, a disturbing practice where adults initiate inappropriate relationships with minors on online chat platforms. We contributed `Osprey`, an open-source reproducible library that hosts conversation vectorizations along with conversation features for neural classifiers. We benchmarked vector representations of conversations with conversation features and lack thereof via different neural models and showed that (1) conversation features have consistent synergistic effects across all baselines, (2) vectorizing a conversation through a sequence of message embeddings is of higher quality, (3) conversation features help models to prioritize `recall` while maintaining `precision`, and (4) `gru` is the best gating strategy for recurrent models in online grooming detection where the conversations are long and lack turn-taking. For future work, we are investigating the oddly low performance of finetuned embeddings as well as online grooming detection in other languages.

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