CAN WE AUTOMATE THE ANALYSIS OF ONLINE CHILD SEXUAL EXPLOITATION DISCOURSE?

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ABSTRACT

Social media’s growing popularity raises concerns around children’s online safety. Interactions between minors and adults with predatory intentions is a particularly grave concern. Research into online sexual grooming has often relied on domain-experts to manually annotate conversations, limiting both scale and scope. In this work, we test how well automated methods can detect conversational behaviors and replace an expert human annotator. Informed by psychological theories of online grooming, we label 6772 chat messages sent by child-sex offenders with one of eleven predatory behaviors. We train bag-of-words and natural language inference models to classify each behavior, and show that the best performing models classify behaviors in a manner that is consistent, but not on-par, with human annotation.

1 Introduction

Social media’s growing popularity amongst children and young adults raises serious concerns for their safety. The threat of online sexual grooming is an increasing problem in the digital age [Greene-Colozzi et al., 2020]. In 2021 alone, UK police forces recorded over 5000 offences relating to sexual communications with a child, with social media apps such as Instagram and Snapchat popular amongst online predators [NSPCC, 2021]. Minors who fall victim to offenders suffer considerably, with many abusers seeking to establish physical contact offline [Shelton et al., 2016]. To assist law enforcement, academics have been trying to identify in advance those predators that steer the relationship towards physical encounters [Briggs et al., 2011] [Winters et al., 2017] [O’Connell, 2003] [Williams et al., 2013]. This important work predominantly relies on time-consuming human-effort to manually annotate conversations involving child sex offenders. In this work, we explore the extent to which automated annotation can mimic an expert human annotator.

Automatically detecting predatory behavior is a challenging task. Offenders use a variety of subtle behaviors to manipulate the flow of the conversation. Predators may use flattery to build trust [Barber and Betterz, 2021], make threats or bribe a child as a coercion tactic [Joleby et al., 2021]. Whilst human experts can identify these contextual psychological behaviors in text, their implicitness can be problematic for machines [Buckingham and Alah, 2020]. In computational social sciences, dictionary-based approaches [Tausczik and Pennebaker, 2010] are often used to identify psychological characteristics such as neuroticism [Bogdanova et al., 2014]. However, these methods heavily rely on the included vocabulary, causing a large numbers of false positives for some behaviors [Kaur et al., 2021] while overlooking others [Broome et al., 2020]. Prior work utilising machine learning has focused on identifying predators from a mixed corpus of illicit and everyday conversations [Inches and Crestani, 2012] [Pendar, 2007] [Miah et al., 2011] [Ebrahimi et al., 2016] [Gupta et al., 2012]. While valuable in its own right, this line of research does not offer significant value to...
We construct binary classification tasks and predict whether each message is an example of each behavior category. We removed stop-words (i.e., the, a, am, at, be, is), and used the frequency counts of the remaining unigrams as input features. Consistent with previous work [Miah et al., 2011] [Bogdanova et al., 2014], we compared the performance of four classifiers: Random Forest, Logistic Regression, Support Vector Machines, and Naive Bayes.

This work is novel in its use of supervised and deep learning methods to analyse an expert-annotated corpus of real conversations between sexual predators and decoys pretending to be early teens. We report results and highlight the performance possible without incurring the cost of expert-labelling. The paper is organised as follows: the methods and experimental setup are described in Section 2. Section 3 then summarises results (with further details provided in the appendices) before Section 4 concludes the paper.

## 2 Method and Experimental Setup

| Region      | Num. Msgs | % of Corpus |
|-------------|-----------|-------------|
| Train       | 4712      | 70%         |
| Test        | 1355      | 20%         |
| Validation  | 704       | 10%         |

Table 1: The number of messages included for training, testing, and validation regions.

| Category                | Coverage (%) | Model | Precision | Recall | F1     |
|-------------------------|--------------|-------|-----------|--------|--------|
| Communication/Coordination | 73.1         | NLI (1) | 84.0 (±0.6) | 87.1 (±0.5) | 85.5 (±0.2) |
| Rapport Building         | 15.2         | NLI (5) | 83.0 (±9.3) | 80.1 (±15.7) | 81.3 (±12.6) |
| Control                  | 20.8         | NLI (5) | 61.5 (±1.7) | 59.5 (±1.4) | 60.4 (±0.2) |
| Challenge                | 4.5          | NLI (5) | 36.1 (±1.7) | 24.2 (±4.1) | 28.9 (±3.5) |
| Negotiation              | 20.9         | NLI (5) | 62.9 (±2.9) | 66.7 (±1.7) | 64.7 (±2.3) |
| Use of Emotions          | 16.4         | NLI (5) | 58.2 (±1.4) | 53.1 (±1.65) | 55.6 (±1.6) |
| Testing Boundaries       | 31.2         | NLI (5) | 69.6 (±0.8) | 76.1 (±2.7) | 72.7 (±0.9) |
| Use of Sexual Topics     | 18.3         | NLI (5) | 64.5 (±1.6) | 69.3 (±3.6) | 66.8 (±2.1) |
| Mitigation               | 3.0          | NLI (3) | 62.2 (±10.7) | 38.4 (±7.0) | 47.5 (±8.5) |
| Encouragement             | 8.0          | NLI (1) | 43.2 (±4.8) | 22.0 (±1.6) | 29.1 (±2.0) |
| Risk Management          | 4.6          | NLI (1) | 63.1 (±4.0) | 49.5 (±4.1) | 55.4 (±3.5) |

Table 2: Eleven offender behavior categories derived and labelled by domain-experts, alongside their prevalence within the corpus. We report performance for the best performing model (based on F1) for each category. NLI (5) denotes the 5-message-input Natural Language Inference model, and similarly for NLI (3) and NLI (1).

### Dataset and Labelling

The [Perverted-Juice](http://www.perverted-justice.com) website is an online repository of real, chat-based conversations between adults who were later convicted of grooming offences and decoys posing as children. Twenty-four chats, comprising of 12,942 messages, were labelled by a domain-expert with a background in forensic psychology. Chats were annotated in concordance with a theory of child grooming known as “self-regulation” [Elliott, 2017] – the notion that online predation contains a potentiality phase, where the predator attempts to form a positive relationship with the victim; and a disclosure phase, where the predator becomes more explicitly goal-oriented. The following behaviors were identified and applied to the offender messages: (1) communication/coordination, (2) rapport building, (3) control, (4) challenges, (5) negotiation, (6) use of emotions, (7) testing boundaries, (8) use of sexual topics, (9) mitigation, (10) encouragement, (11) risk management. A qualitative description of these behaviors is given in Section A of the Appendix. Overall 6,772 messages sent by the offender were labelled, with each message assigned a “Yes” or “No” for each of the above categories, based on the annotator’s judgment. Due to the subjective nature of this assessment, labelling performed by different expert annotators may not be in complete agreement.

We construct binary classification tasks and predict whether each message is an example of each behavior category. Offender messages were split into training, testing, and validation regions (see Table 1 for information on data splits), and were stratified to ensure equal distribution of behaviors per region. To increase model confidence, we cross validated each experiment three times through random re-sampling. In our results, we report the average (±SD) scores for precision, recall and F1 as evaluation metrics.

### Supervised Machine Learning

Offender messages were tokenized, part-of-speech (POS) tagged, and lemmatized with spaCy. We removed stop-words (i.e., the, a, am, at, be, is), and used the frequency counts of the remaining unigrams as input features. Consistent with previous work [Miah et al., 2011] [Bogdanova et al., 2014], we compared the performance of four classifiers: Random Forest, Logistic Regression, Support Vector Machines, and Naive Bayes.
We use Cohen’s \( \kappa \) [Cohen, 1960] to measure pairwise agreement between the two human raters and the predictions generated by the best performing model for each behavior. We report the mean of these scores as an index of overall agreement.

3 Results

Transformer-based deep learning models achieved best performance across all categories, with the 5 message input NLI model performing best for most categories. Evaluation metrics for the highest performing model for each behavior are shown in Table 2. The performance of all models on all categories is reported in Section E of the Appendix. Eight of the eleven behaviors obtain a maximum F1 score above 50\%, with the most prevalent category, communication/coordination, performing best with F1=86\%. Automatically labelling encouragement and challenge was least successful, with a maximum F1 score of 29\% for both. For all eleven categories, a transformer-based model, trained on the full training set, was more successful than the traditional supervised machine learning algorithms. Averaging across behaviors, transformers improved performance of single message classification from 33\% to 53\% compared to the best performing supervised model. In 8 out of 11 cases, the supervised models, trained on the full training set, outperformed the zero-shot transformer. However, in 10 out of 11 cases, only 50 labelled instances were required by the transformer to exceed the best performing bag-of-words models. As many of the behaviors rely on contextual understanding, we increased the input size from a single message to 3 and 5 messages. The first contains two messages sent by the offender and one by the decoy, and the latter contains three by the offender and two by the decoy. Increasing the window size indeed improved performance for all behaviors\(^1\) except for encouragement and risk management. On average, while 3-message classification did not improve single-message performance, 5-message classification improved on single-message F1 from 50\% to 56\%.

Figure 1 shows the change in F1 for single message classification as the number of training samples increases. Whilst predictions for all behaviors improved with additional training, large variation in performance between the categories remains even for a fixed amount of positive training examples. To better understand this variation, we manually examined the predictions made by the best performing single message model for \( \sim 10\% \) of the corpus. We observed that the transformer has learned some rules that caused a number of false positives. For example, the transformer took the surrounding messages into account, for which the surrounding messages were chosen at random. To mitigate potential bias, annotations generated during the initial labelling were shielded from view.

\(^1\)Hyperparameters and the range of values explored are included in Section B of the Appendix.

\(^2\)We used a Tesla P100 GPU for training.

\(^3\)The majority of messages (73\%) were labelled as communication/coordination. As a result, this behavior was not tested in a multi-message setting as grouping messages meant that all inputs would be positively labelled.
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Figure 1: Model performance (F1) on the eleven behavioral categories for single message classification, as the number of positive training examples increases (up to full training set). Error bars are standard deviations.

The model correctly predicted a number of questions aimed at assessing the victim’s willingness to engage, e.g., “what are you looking for?”, but also included several logistical questions, e.g., “how about i come by at 8pm?”. The rapport building model correctly recognised complements and sweet talk as positive examples, but missed more everyday examples of rapport building, e.g., “how was your spring break?”. Some aspects of control required coverage over longer ranges than we have focused on. For example, persistently asking the same question is a sub-category of control that was often misclassified. In this case, increasing the message window to 3 messages was not enough to improve performance, however, the larger 5 message window did notably improve performance, with the F1 increasing from 54% to 60% due to better recall. In trying to predict encouragement, the worst performing category, the transformer appeared to overfit on short verbal nods (i.e., "kool" and "sure", which appeared in the corpus either as evidence of encouragement or simple linguistic fillers) which increased the false positive rate. Over-reliance on this simple rule would explain why the model did not utilise the additional information provided in the multi-message setting. Risk management achieved reasonable performance (F1 = 55%) despite being one of the rarest behaviors in the corpus. This was largely a consequence of the transformer recognising instances where the offender attempts to establish the presence of a parent, e.g., “when are they getting home?”.

In addition to drawing qualitative observations on the ability of the transformer-based model to recognise different offender behaviors, we quantify how comparable the best performing single-message model is to a human annotator. We compare the labelled classes between the original labels (Rater 1), with the predictions made by the best performing models (Model), and the labels verified during post-validation (Rater 2). We report a mean $\kappa$ score of 0.68, indicating ‘substantial agreement’ between raters [McHugh, 2012]. Pairwise agreement is reported in Table 3. Agreement was highest between the two human raters ($\kappa = 0.8$). The average agreement between each rater and the predictions generated by the model was $\kappa = 0.62$ (see Section D in the Appendix for pairwise agreement per behavior).

| Rater 1 | Rater 2 | Model |
|---------|---------|-------|
| Rater 1 | -       | 0.59  |
| Rater 2 | 0.8 (0.78) | -     |
|         | 0.65 (0.66) |       |

Table 3: Pairwise agreement (Cohen’s $\kappa$) between raters over all behaviors. A score of 1.0 indicates perfect agreement. Value in parentheses indicate $\kappa$ when ‘uncertain’ validation ratings are included.

4 Conclusion

Manually labeling the 24 chat logs used in this work took over 600 hours. Given that the full Perverted-Justice corpus contains 850 chat logs, it would be infeasible to label the entire corpus without the help of automated methods. We find that a transformer-based deep learning approach yields promising results when applied to the detection of online predatory behavior. However, even with training, the agreement between the model and a human annotator is not comparable to the agreement between two human annotators. The model’s success in predicting behaviors varies significantly between the categories. Performance is better for more common behaviors, however, we show that the
variation is not only due to the number of positive examples in the training data. Extending the prediction task to include multiple messages, increasing the contextual window, boosted detection for certain behaviors. The F1 score for rapport building, for example, increased from 61% for single messages to 81% when classification was based on five-messages. Performing post-validation on the automatic classifications allowed us to gain qualitative insight about the model’s performance, which may be used to design better prompts and improve performance further. Overall, our results are an encouraging step towards building an automated, psychology-informed model to detect online sexual exploitation.

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A Content Label Descriptions

Communication/Coordination

Description: “Communication Coordination” is used to start and maintain communication as offenders: (i) exchange and clarify information with their intended victim, (ii) present reason/excuses, (iii) assess the level of engagement of the victim, (iv) find new ways to communicate (i.e., media exchange), (v) strategically use humour or linguistic fillers (i.e., “lol”, “hehe”), and (vi) redirect the flow of conversation. One of the offenders’ main purposes of this category is to maximize gain and potentially minimize time spent on non-compliant victims.

Rapport Building

Description: Offenders use positive behavior to mimic romantic relationships, making it easier to introduce sexual topics [Elliott 2017]. Offenders use ‘Rapport’ to infiltrate victims’ offline/online social and emotional life to create an illusion of exclusivity, reinforcing the offender as a trusted other. This is achieved through compliments/sweet talk, showing interest, and shared experiences. This special connection or bond is usually created in a short amount of time through excessive saturation and exposure to constant positive statements [Elliott 2017].

Control/Regulation

Description: Control/Regulation’ occurs when offenders use power to direct the flow of communication by influencing or directing the victim’s behavior. Controlling the conversation can occur through subtle (e.g., illusion of control, rhetorical questions, checking for willingness to engage, or permissive behavior) or direct strategies (e.g., making demands, persistence, use of coercion). Offenders may attempt to take control of the conversation through patronizing language, persistence, frequently checking for engagement, making demands, or by asking questions that give the illusion of consent - giving the impression that victims have control over what happens during an exchange.

Challenges

Description: An offender may challenge a victim when opposing motivations appear. As a result, confrontation ensues directly (e.g., offence, control, aggression) or indirectly (e.g., joke, mockery, irony). Offenders often challenge the victim as a way of authenticating identity, or to exert more control.

Negotiation

Description: “Negotiation” can occur at any time during the exchange and is the process where offenders attempt to make decisions, compromise, incentivize continued interaction, or reach goal achievement (e.g., confirming a plan to meet). “Negotiations” can be brief or extensive depending on what goals the offender is trying to achieve. Incentives are particularly important when negotiating goals, and can be either financial or emotional.

Use of Emotion

Description: Offenders use emotive language to manipulate the victim’s emotions in order to influence their behavior. “Use of emotions” can be positive or negative, and include sub-behaviors such as manipulation, expressing empathy, guilt tripping, vilifying third parties, offering reassurance, or by playing the victim. Offenders may employ positive strategies to isolate victims, and use negative emotions increase compliance.

Testing Boundaries

Description: “Testing Boundaries” determines whether the conversation continues or ends. Offenders seek to test boundaries directly or indirectly to determine whether it is possible to desensitize victims through exposure to sexual topics [Elliott 2017].

Use of Sexual Topics

Description: Offenders intentionally use sex to desensitize victims. This is done by directing conversation toward the victim’s prior sexual experiences, discussing fantasies, use of explicit language, determining sexual preferences, suggesting media production, alluding to traveling for sex, and acting as a sexual mentor.
Mitigation

**Description:** “Mitigation” is a strategy that aims to soften or downgrade the intensity or seriousness of what is being expressed to convince the victim to participate. Offenders may use this technique in an attempt to normalize the sexual exchange by lessening the idea of harm or criminality. Specific sub-behaviors include indirectly stating a sexual preference for children, implicating oneself in a previous crime, normalizing sexual conversations, or discussing differences in age. Normalization occurs by talking about sex often without reservation and is the process of desensitizing the victim to sexual topics or acts.

Encouraging

**Description:** Offenders use encouragement to comply with the victims requests, or to show support by acting as a mentor/trusted other.

Risk Management

**Description:** “Risk Management” occurs when offenders assess risk and take steps to prevent discovery. This may be through incentivizing secrecy using emotional manipulation, asking the decoy to delete messages/images, enquiring after third parties (e.g., the location of parents), acknowledge previous wrongdoing, and discussing the consequences of getting caught.
B Hyperparameter Tuning

| Algorithm               | Parameter | Value Range |
|-------------------------|-----------|-------------|
| Random Forest           | n_estimators | 50, 100*, 150 |
|                         | max_depth  | 10, 50, 100  |
| Logistic Regression     | solver     | liblinear, saga |
|                         | penalty    | $l1$, $l2$* |
| Support Vector Machine  | C          | 0.1, 0.5, 1* |
|                         | kernel     | linear, poly, rbf* |
| Naive Bayes             | alpha      | 0.0, 1.0*   |
|                         | fit_prior  | True*, False |

Table 4: Range of settings evaluated for each supervised algorithm. As GridSearch is an exhaustive optimization technique, effort was taken to minimize the number of models tested. Algorithms were implemented via Scikit-learn. * indicates the default setting.
C Precision, Recall, and Accuracy Plots for Full-Shot Single-Classification Models

Figure 2: Precision, recall, and accuracy of single message classification as the number of positive training examples increases (up to full training set). Error bars are standard deviations.
## Inter-Rater Agreement Scores for Each Behavior

| Behavior                  | Rater 1/Rater 2 | Rater 1/Model | Rater 2/Model | Overall       |
|---------------------------|-----------------|---------------|---------------|---------------|
| Communication/Coordination| 0.66 (0.65)     | 0.53          | **0.71 (0.72)**| 0.63 (0.62)   |
| Rapport Building          | **0.73 (0.7)**  | 0.63          | 0.62 (0.65)   | 0.66 (0.65)   |
| Control                   | 0.62 (0.6)      | 0.52          | 0.55 (0.59)   | 0.56 (0.57)   |
| Challenge                 | **0.89 (0.89)** | 0.46          | 0.51 (0.51)   | 0.62 (0.62)   |
| Negotiation               | 0.95 (0.93)     | 0.67          | 0.65 (0.67)   | 0.76 (0.76)   |
| Use of Emotions           | **0.78 (0.74)** | 0.6           | 0.77 (0.79)   | 0.72 (0.7)    |
| Testing Boundaries        | **0.88 (0.84)** | 0.5           | 0.52 (0.53)   | 0.63 (0.62)   |
| Use of Sexual Topics      | **0.74 (0.73)** | 0.6           | 0.64 (0.65)   | 0.66 (0.66)   |
| Mitigation                | **0.91 (0.91)** | 0.52          | 0.52 (0.52)   | 0.65 (0.65)   |
| Encouragement             | 0.66 (0.66)     | 0.61          | **0.84 (0.84)**| 0.7 (0.71)    |
| Risk Management           | **0.88 (0.85)** | 0.67          | 0.67 (0.68)   | 0.74 (0.72)   |
| **Total**                 | **0.8 (0.78)**  | 0.59          | 0.65 (0.66)   | 0.68 (0.67)   |

Table 5: Pairwise Cohen’s κ per behavior label. Overall score is the mean of the pairwise scores. 1.0 indicates perfect agreement; 0.0 indicates no agreement. Values greater than κ = 0.6 are generally indicative of “moderate to strong” agreement, as per guidelines in [McHugh, 2012]. κ in bold indicates largest pairwise agreement per behavior label. Rater 1 is the actual labels used in training (i.e., ground-truth), Model refers to the predictions generated by the best performing single-classification model for each behavior, and Rater 2 refers to manual ratings generated during post-validation. Values in parentheses indicate κ when “unsure” ratings given by Rater 2 are included as positive agreement.
### Full Model Results

| Model                      | Accuracy  | Precision | Recall  | F1       |
|---------------------------|-----------|-----------|---------|----------|
| **Supervised - Bag of Words** |           |           |         |          |
| Random Forest             | 73.8 ± 0.26 | 74.28 ± 0.11 | 98.18 ± 0.8 | 84.57 ± 0.23 |
| Logistic Regression       | 73.73 ± 0.2 | 75.5 ± 0.11 | 94.85 ± 0.61 | 84.08 ± 0.18 |
| Support Vector Machine    | 74.59 ± 0.62 | 75.41 ± 0.26 | 96.84 ± 0.61 | 84.79 ± 0.39 |
| Naive Bayes               | 74.47 ± 1.35 | 76.5 ± 0.58 | 93.95 ± 1.31 | 84.33 ± 0.88 |
| **Transformer**          |           |           |         |          |
| 0-shot                    | 61.7 ± 0.87 | 72.71 ± 0.46 | 76.25 ± 0.84 | 74.44 ± 0.64 |
| 25-shot                   | 73.43 ± 1.01 | 81.91 ± 0.68 | 81.74 ± 0.24 | 81.81 ± 0.98 |
| 50-shot                   | 75.45 ± 0.36 | 81.11 ± 0.28 | 86.61 ± 1.13 | 83.77 ± 0.38 |
| 100-shot                  | 73.09 ± 0.69 | 82.59 ± 0.61 | 80.09 ± 0.85 | 81.32 ± 0.51 |
| 200-shot                  | 74.15 ± 1.08 | 81.54 ± 1.2  | 83.65 ± 3.8 | 82.53 ± 1.28 |
| 300-shot                  | 75.13 ± 0.84 | 82.25 ± 1.58 | 84.26 ± 3.54 | 83.19 ± 1.02 |
| 500-shot                  | 75.38 ± 0.37 | 81.31 ± 0.58 | 86.14 ± 1.41 | 83.65 ± 0.41 |
| 1000-shot                 | 75.15 ± 0.57 | 81.84 ± 0.44 | 84.86 ± 1.06 | 83.32 ± 0.47 |
| **Full-shot (3466)**      | 78.4 ± 0.35 | 83.98 ± 0.55 | 87.08 ± 0.53 | 85.5 ± 0.21 |

Table 6: Performance of classification models for **Communication/Coordination**. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.
### Table 7: Performance of classification models for Rapport Building. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

| Model                      | Accuracy    | Precision   | Recall       | F1          |
|----------------------------|-------------|-------------|--------------|-------------|
| **Supervised - Bag of Words** |             |             |              |             |
| Random Forest              | 87.09 (±0.52) | 71.26 (±6.61) | 25.57 (±2.24) | 37.55 (±2.51) |
| Logistic Regression        | 87.16 (±0.07) | 72.28 (±3.17) | 25.41 (±1.96) | 37.52 (±1.67) |
| Support Vector Machine     | 86.32 (±0.31) | 69.8 (±1.37)  | 17.8 (±4.07)  | 28.18 (±5.25) |
| Naive Bayes                | 86.54 (±0.19) | 72.17 (±3.38) | 18.77 (±0.28) | 29.78 (±0.4)  |
| **Transformer**            |             |             |              |             |
| 0-shot                     | 42.07 (±1.67) | 17.63 (±0.73) | 76.54 (±3.16) | 28.66 (±1.15) |
| 25-shot                    | 85.31 (±6.27) | 53.34 (±23.53) | 44.5 (±17.21) | 48.45 (±19.82) |
| 50-shot                    | 84.63 (±4.45) | 49.33 (±14.86) | 49.03 (±15.13) | 49.18 (±15.0) |
| 100-shot                   | 87.11 (±2.32) | 58.15 (±8.51)  | 52.1 (±11.53)  | 54.86 (±10.08) |
| 200-shot                   | 87.33 (±1.36) | 58.79 (±4.96)  | 56.63 (±2.19)  | 57.67 (±3.53)  |
| 300-shot                   | 87.01 (±0.71) | 57.36 (±2.36)  | 56.8 (±2.7)    | 57.07 (±2.41)  |
| 500-shot                   | 87.82 (±0.41) | 59.87 (±1.59)  | 60.52 (±0.28)  | 60.18 (±0.8)   |
| 1000-shot*                 |             |             |              |             |
| Full-shot (721)            | 89.0 (±0.45)  | 66.08 (±2.58)  | 57.12 (±1.22)  | 61.24 (±0.59)  |
| **Transformer - Multi-Message Input** |             |             |              |             |
| Full-shot 3 Msg            | 91.48 (±6.31) | 80.47 (±15.23) | 77.97 (±17.94) | 79.16 (±16.58) |
| Full-shot 5 Msg            | 89.79 (±6.34) | 82.95 (±9.27)  | 80.05 (±15.71) | 81.35 (±12.58) |

### Table 8: Performance of classification models for Control. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

| Model                      | Accuracy    | Precision   | Recall       | F1          |
|----------------------------|-------------|-------------|--------------|-------------|
| **Supervised - Bag of Words** |             |             |              |             |
| Random Forest              | 79.75 (±0.54) | 53.84 (±3.61) | 19.03 (±1.34) | 28.12 (±1.95) |
| Logistic Regression        | 79.85 (±1.0)  | 56.08 (±8.61) | 15.25 (±2.16) | 23.96 (±3.38) |
| Support Vector Machine     | 80.17 (±0.74) | 59.35 (±6.21) | 14.89 (±3.15) | 23.74 (±4.37) |
| Naive Bayes                | 79.41 (±0.48) | 52.87 (±5.14) | 11.35 (±1.42) | 18.64 (±2.08) |
| **Transformer**            |             |             |              |             |
| 0-shot                     | 43.57 (±0.86) | 17.24 (±0.51) | 45.04 (±1.23) | 24.94 (±0.71) |
| 25-shot                    | 80.64 (±3.13) | 54.44 (±12.75) | 33.81 (±12.56) | 41.53 (±13.31) |
| 50-shot                    | 80.59 (±2.11) | 54.32 (±7.12)  | 39.48 (±10.13) | 45.5 (±8.72)   |
| 100-shot                   | 80.98 (±2.01) | 56.33 (±6.7)   | 42.55 (±2.16)  | 48.3 (±2.32)   |
| 200-shot                   | 81.55 (±0.7)  | 57.82 (±2.7)   | 42.35 (±2.49)  | 48.89 (±1.75)  |
| 300-shot                   | 82.36 (±0.78) | 60.13 (±2.38)  | 45.15 (±2.56)  | 51.57 (±2.52)  |
| 500-shot                   | 81.99 (±1.34) | 59.11 (±4.38)  | 43.73 (±3.22)  | 50.27 (±3.68)  |
| 1000-shot*                 |             |             |              |             |
| Full-shot (986)            | 82.36 (±0.37) | 59.2 (±1.0)   | 49.05 (±1.43) | 53.65 (±1.2)  |
| **Transformer - Multi-Message Input** |             |             |              |             |
| Full-shot 3 Msg            | 76.53 (±0.33) | 59.12 (±1.1)  | 41.52 (±0.67) | 48.78 (±0.48) |
| Full-shot 5 Msg            | 71.32 (±0.85) | 61.47 (±1.74) | 59.47 (±1.39) | 60.43 (±0.15) |
| Model                     | Accuracy   | Precision  | Recall    | F1       |
|--------------------------|------------|------------|-----------|----------|
| **Supervised - Bag of Words** |            |            |           |          |
| Random Forest            | 95.43 ± 0.01 | 20.0 ± 20.0 | 1.67 ± 1.67 | 3.08 ± 3.08 |
| Logistic Regression      | 95.42 ± 0.01 | 13.33 ± 23.1 | 1.11 ± 1.93 | 2.05 ± 3.55 |
| Support Vector Machine   | 95.55 ± 0.01 | 0.0 ± 0.0  | 0.0 ± 0.0  | 0.0 ± 0.0  |
| Naive Bayes              | 95.55 ± 0.01 | 50.5 ± 50.5 | 1.11 ± 0.96 | 2.17 ± 1.88 |
| **Transformer**          |            |            |           |          |
| 0-shot                   | 14.29 ± 0.54 | 4.52 ± 0.09 | 91.11 ± 2.55 | 8.6 ± 0.18  |
| 25-shot                  | 94.88 ± 0.57 | 35.56 ± 10.81 | 17.78 ± 3.85 | 23.66 ± 5.78 |
| 50-shot                  | 95.3 ± 0.35  | 40.25 ± 12.39 | 12.78 ± 4.19 | 19.39 ± 6.25 |
| 100-shot                 | 94.54 ± 1.15 | 27.73 ± 19.01 | 10.0 ± 2.36  | 14.35 ± 5.41 |
| 200-shot                 | 95.2 ± 0.52  | 41.07 ± 12.63 | 17.5 ± 3.54  | 24.51 ± 5.74 |
| 300-shot*                |            |            |           |          |
| 500-shot*                |            |            |           |          |
| 1000-shot*               |            |            |           |          |
| Full-shot (211)          | 95.25 ± 0.23 | 41.04 ± 0.62 | 16.67 ± 2.89 | 23.7 ± 3.93 |

**Transformer - Multi-Message Input**

| Model                     | Accuracy   | Precision  | Recall    | F1       |
|--------------------------|------------|------------|-----------|----------|
| Full-shot 3 Msg          | 91.96 ± 0.24 | 15.53 ± 1.79 | 5.36 ± 1.79 | 17.97 ± 2.67 |
| Full-shot 5 Msg          | 88.31 ± 1.12 | 36.14 ± 1.68 | 24.18 ± 4.08 | 28.9 ± 3.51  |

Table 9: Performance of classification models for **Challenge**. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

* The number exceeds the total number of positive examples in the dataset and therefore results are analogous to full-shot.

| Model                     | Accuracy   | Precision  | Recall    | F1       |
|--------------------------|------------|------------|-----------|----------|
| **Supervised - Bag of Words** |            |            |           |          |
| Random Forest            | 80.57 ± 1.08 | 59.57 ± 6.74 | 21.2 ± 4.95 | 31.14 ± 6.18 |
| Logistic Regression      | 81.45 ± 1.08 | 67.55 ± 9.62 | 22.5 ± 1.14 | 33.65 ± 1.76 |
| Support Vector Machine   | 80.57 ± 0.66 | 65.05 ± 7.93 | 13.43 ± 3.08 | 22.3 ± 4.46 |
| Naive Bayes              | 81.35 ± 0.7  | 66.58 ± 7.39 | 22.5 ± 3.19 | 33.42 ± 3.04 |
| **Transformer**          |            |            |           |          |
| 0-shot                   | 43.1 ± 1.47  | 21.92 ± 0.62 | 67.26 ± 2.07 | 33.06 ± 0.86 |
| 25-shot                  | 77.91 ± 1.9  | 47.73 ± 5.8  | 38.28 ± 10.45 | 41.49 ± 4.78 |
| 50-shot                  | 79.93 ± 2.11 | 51.87 ± 5.23 | 50.65 ± 7.21 | 51.22 ± 6.14 |
| 100-shot                 | 80.47 ± 1.65 | 53.54 ± 4.26 | 49.0 ± 4.45  | 51.15 ± 4.22 |
| 200-shot                 | 81.33 ± 0.27 | 56.21 ± 0.36 | 47.94 ± 4.54 | 51.67 ± 2.76 |
| 300-shot                 | 80.69 ± 1.01 | 54.27 ± 2.81 | 48.29 ± 1.78 | 51.1 ± 2.16  |
| 500-shot                 | 81.3 ± 0.52  | 55.83 ± 1.58 | 50.53 ± 0.71 | 53.03 ± 0.55 |
| 1000-shot*               |            |            |           |          |
| Full-shot (991)          | 83.22 ± 0.15 | 61.8 ± 0.92  | 51.59 ± 1.27 | 56.22 ± 0.39 |

**Transformer - Multi-Message Input**

| Model                     | Accuracy   | Precision  | Recall    | F1       |
|--------------------------|------------|------------|-----------|----------|
| Full-shot 3 Msg          | 80.43 ± 1.13 | 63.31 ± 2.41 | 61.99 ± 1.41 | 62.64 ± 1.84 |
| Full-shot 5 Msg          | 74.74 ± 1.96 | 62.85 ± 2.93 | 66.67 ± 1.71 | 64.7 ± 2.31  |

Table 10: Performance of classification models for **Negotiation**. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

* The number exceeds the total number of positive examples in the dataset and therefore results are analogous to full-shot.
| Model                    | Accuracy    | Precision  | Recall      | F1        |
|-------------------------|-------------|------------|-------------|-----------|
| **Supervised - Bag of Words** |             |            |             |           |
| Random Forest           | 84.82 (±0.69) | 66.26 (±8.67) | 14.87 (±2.95) | 24.25 (±4.4) |
| Logistic Regression     | 84.38 (±0.53) | 57.47 (±2.52) | 17.71 (±2.27) | 27.07 (±3.17) |
| Support Vector Machine  | 84.4 (±0.55)  | 68.5 (±11.75)| 8.56 (±2.51)  | 15.2 (±4.27)  |
| Naive Bayes             | 84.77 (±0.31) | 65.59 (±4.21) | 14.87 (±0.9)  | 24.24 (±1.47) |
| **Transformer**         |             |            |             |           |
| 0-shot                  | 26.83 (±1.4)  | 16.77 (±0.55) | 87.34 (±2.39) | 28.13 (±0.89) |
| 25-shot                 | 81.28 (±0.81) | 41.86 (±1.31) | 35.89 (±5.63) | 38.42 (±2.82) |
| 50-shot                 | 85.17 (±1.76) | 56.69 (±7.54) | 45.2 (±3.62)  | 50.02 (±2.98) |
| 100-shot                | 85.02 (±1.11) | 54.73 (±4.03) | 50.0 (±6.76)  | 52.12 (±4.62) |
| 200-shot                | 84.65 (±0.38) | 53.54 (±1.24) | 47.45 (±2.56) | 50.3 (±1.97) |
| 300-shot                | 85.22 (±0.37) | 55.41 (±0.94) | 49.7 (±3.83)  | 52.37 (±2.5)  |
| 500-shot                | 85.09 (±0.2)  | 55.02 (±0.47) | 49.25 (±2.31) | 51.96 (±1.49) |
| 1000-shot*              |             |            |             |           |
| Full-shot (777)         | 85.27 (±0.26) | 55.02 (±0.91) | 55.26 (±0.52) | 55.13 (±0.28) |
| **Transformer - Multi-Message Input** |             |            |             |           |
| Full-shot 3 Msg         | 78.89 (±1.03) | 52.16 (±2.72) | 44.62 (±2.61) | 48.09 (±2.67) |
| Full-shot 5 Msg         | 73.64 (±0.85) | 58.21 (±1.44) | 53.13 (±1.65) | 55.55 (±1.56) |

Table 11: Performance of classification models for Use of Emotions. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

* The number exceeds the total number of positive examples in the dataset and therefore results are analogous to full-shot

| Model                    | Accuracy    | Precision  | Recall      | F1        |
|-------------------------|-------------|------------|-------------|-----------|
| **Supervised - Bag of Words** |             |            |             |           |
| Random Forest           | 72.87 (±1.39) | 63.03 (±4.09) | 31.52 (±2.82) | 42.02 (±3.41) |
| Logistic Regression     | 72.96 (±1.32) | 62.47 (±4.2)  | 33.73 (±1.66) | 43.79 (±2.31) |
| Support Vector Machine  | 73.31 (±0.75) | 63.39 (±2.71) | 34.44 (±0.55) | 44.62 (±1.0) |
| Naive Bayes             | 73.65 (±0.7)  | 63.34 (±2.22) | 37.12 (±0.47) | 46.8 (±0.95) |
| **Transformer**         |             |            |             |           |
| 0-shot                  | 32.77 (±0.85) | 30.22 (±0.39) | 88.1 (±0.83)  | 45.0 (±0.54) |
| 25-shot                 | 71.93 (±4.84) | 55.22 (±8.07) | 53.03 (±8.18) | 54.1 (±8.1) |
| 50-shot                 | 72.01 (±2.87) | 55.05 (±4.66) | 56.82 (±4.29) | 55.91 (±4.39) |
| 100-shot                | 72.92 (±2.61) | 57.88 (±5.58) | 51.3 (±3.34)  | 54.22 (±2.34) |
| 200-shot                | 73.78 (±0.47) | 58.9 (±0.66)  | 52.38 (±1.9)  | 55.72 (±1.29) |
| 300-shot                | 74.44 (±2.31) | 59.78 (±4.19) | 56.03 (±3.58) | 57.79 (±3.28) |
| 500-shot                | 75.15 (±0.76) | 61.1 (±1.56)  | 56.27 (±0.24) | 58.58 (±0.81) |
| 1000-shot               | 75.03 (±0.33) | 61.01 (±0.61) | 55.48 (±1.9)  | 58.11 (±0.74) |
| Full-shot (1479)        | 77.74 (±0.79) | 65.17 (±2.1)  | 61.86 (±1.43) | 63.44 (±0.34) |
| **Transformer - Multi-Message Input** |             |            |             |           |
| Full-shot 3 Msg         | 68.76 (±0.52) | 61.53 (±1.29) | 59.94 (±2.02) | 60.69 (±0.41) |
| Full-shot 5 Msg         | 69.77 (±0.51) | 69.63 (±0.77) | 76.07 (±2.65) | 72.68 (±0.92) |

Table 12: Performance of classification models for Testing Boundaries. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.
### Table 13: Performance of classification models for Use of Sexual Topics. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

| Model                                | Accuracy | Precision | Recall  | F1     |
|---------------------------------------|----------|-----------|---------|--------|
| **Supervised - Bag of Words**         |          |           |         |        |
| Random Forest                         | 84.63 (±0.81) | 71.73 (±4.3) | 26.34 (±4.31) | 38.43 (±5.12) |
| Logistic Regression                   | 85.22 (±0.73) | 74.59 (±2.49) | 29.17 (±5.26) | 41.76 (±5.52) |
| Support Vector Machine                | 84.38 (±0.38) | 81.49 (±1.64) | 18.95 (±2.42) | 30.7 (±3.23)  |
| Naive Bayes                           | 85.12 (±0.63) | 75.04 (±4.48) | 28.09 (±3.03) | 40.81 (±3.45) |
| **Transformer**                       |          |           |         |        |
| 0-shot                                | 38.23 (±0.52) | 19.58 (±0.73) | 76.48 (±3.88) | 31.18 (±1.24) |
| 25-shot                               | 75.57 (±2.1) | 35.92 (±3.11) | 41.53 (±2.02) | 38.4 (±0.9)   |
| 50-shot                               | 84.85 (±2.09) | 60.61 (±7.39) | 50.94 (±3.75) | 55.25 (±4.59) |
| 100-shot                              | 85.76 (±1.02) | 63.77 (±3.86) | 51.62 (±1.61) | 57.04 (±2.43) |
| 200-shot                              | 85.66 (±0.65) | 63.72 (±3.64) | 51.08 (±2.83) | 56.58 (±0.33) |
| 300-shot                              | 86.0 (±0.9) | 64.97 (±3.56) | 51.21 (±2.82) | 57.25 (±2.66) |
| 500-shot                              | 86.4 (±0.42) | 65.17 (±1.03) | 55.11 (±2.46) | 59.71 (±1.78) |
| 1000-shot*                            | 85.9 (±0.15) | 61.86 (±0.33) | 55.48 (±1.3) | 60.88 (±0.73) |
| **Transformer - Multi-Message Input** |          |           |         |        |
| Full-shot 3 Msg                       | 84.11 (±0.51) | 65.83 (±1.0) | 62.59 (±1.79) | 64.16 (±1.37) |
| Full-shot 5 Msg                       | 79.46 (±1.08) | 64.53 (±1.63) | 69.26 (±3.58) | 66.78 (±2.11) |

### Table 14: Performance of classification models for Mitigation/Minimization. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

| Model                                | Accuracy | Precision | Recall  | F1     |
|---------------------------------------|----------|-----------|---------|--------|
| **Supervised - Bag of Words**         |          |           |         |        |
| Random Forest                         | 96.97 (±0.2) | 44.44 (±38.49) | 4.88 (±4.88) | 8.7 (±8.5)   |
| Logistic Regression                   | 96.93 (±0.19) | 42.05 (±20.31) | 10.57 (±7.04) | 16.7 (±10.72) |
| Support Vector Machine                | 96.97 (±0.01) | 0.0 (±0.0) | 0.0 (±0.0) | 0.0 (±0.0)   |
| Naive Bayes                           | 97.02 (±0.04) | 58.89 (±8.39) | 4.87 (±2.44) | 8.93 (±4.2)  |
| **Transformer**                       |          |           |         |        |
| 0-shot                                | 44.11 (±0.89) | 3.22 (±0.23) | 60.16 (±0.43) | 6.12 (±0.43)  |
| 25-shot                               | 96.73 (±0.33) | 40.3 (±12.74) | 13.01 (±2.82) | 19.38 (±3.86) |
| 50-shot                               | 97.34 (±0.39) | 66.52 (±17.64) | 23.58 (±8.57) | 34.7 (±11.48) |
| 100-shot                              | 97.32 (±0.01) | 64.08 (±2.95) | 26.83 (±7.32) | 37.28 (±6.8)  |
| 200-shot*                             |          |           |         |        |
| 300-shot*                             |          |           |         |        |
| 500-shot*                             |          |           |         |        |
| 1000-shot*                            |          |           |         |        |
| Full-shot (144)                       | 96.78 (±0.15) | 44.9 (±4.34) | 30.08 (±5.08) | 36.0 (±5.06)  |
| **Transformer - Multi-Message Input** |          |           |         |        |
| Full-shot 3 Msg                       | 96.75 (±0.51) | 62.22 (±10.72) | 38.39 (±7.0) | 47.47 (±8.45) |
| Full-shot 5 Msg                       | 94.83 (±0.11) | 50.88 (±1.52) | 38.27 (±2.14) | 43.64 (±1.18) |
| Model                                      | Accuracy  | Precision | Recall | F1     |
|--------------------------------------------|-----------|-----------|--------|--------|
| **Supervised - Bag of Words**              |           |           |        |        |
| Random Forest                              | 91.51     | 36.6      | 7.03   | 11.67  |
| Logistic Regression                        | 91.61     | 30.51     | 3.36   | 6.05   |
| Support Vector Machine                     | 91.88     | 42.11     | 3.67   | 6.67   |
| Naive Bayes                                | 91.88     | 27.78     | 0.61   | 1.2    |
| **Transformer**                            |           |           |        |        |
| 0-shot                                     | 61.62     | 11.49     | 56.27  | 19.08  |
| 25-shot                                    | 88.98     | 18.36     | 10.7   | 13.52  |
| 50-shot                                    | 90.65     | 37.07     | 21.1   | 26.72  |
| 100-shot                                   | 89.91     | 30.33     | 19.88  | 23.55  |
| 200-shot                                   | 91.61     | 45.13     | 19.88  | 27.58  |
| 300-shot*                                  | 91.37     | 43.16     | 22.02  | 29.1   |
| 500-shot*                                  |           |           |        |        |
| 1000-shot*                                 |           |           |        |        |
| Full-shot (380)                            | 91.14     | 39.88     | 19.88  | 26.53  |
| **Transformer - Multi-Message Input**      |           |           |        |        |
| Full-shot 3 Msg                            | 86.43     | 33.99     | 18.0   | 23.53  |
| Full-shot 5 Msg                            | 78.75     | 33.08     | 22.47  | 26.09  |

Table 15: Performance of classification models for **Encouragement**. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

* The number exceeds the total number of positive examples in the dataset and therefore results are analogous to full-shot

| Model                                      | Accuracy  | Precision | Recall | F1     |
|--------------------------------------------|-----------|-----------|--------|--------|
| **Supervised - Bag of Words**              |           |           |        |        |
| Random Forest                              | 95.75     | 63.83     | 22.04  | 31.79  |
| Logistic Regression                        | 95.7      | 62.86     | 18.28  | 27.81  |
| Support Vector Machine                     | 95.47     | 54.37     | 4.3    | 7.89   |
| Naive Bayes                                | 95.57     | 67.14     | 6.45   | 11.75  |
| **Transformer**                            |           |           |        |        |
| 0-shot                                     | 48.61     | 4.75      | 53.76  | 8.74   |
| 25-shot                                    | 95.25     | 44.74     | 15.59  | 23.07  |
| 50-shot                                    | 95.84     | 56.11     | 38.17  | 45.27  |
| 100-shot                                   | 96.11     | 63.04     | 37.1   | 46.49  |
| 200-shot*                                  | 96.36     | 63.08     | 49.46  | 55.39  |
| 300-shot*                                  |           |           |        |        |
| 500-shot*                                  |           |           |        |        |
| 1000-shot*                                 |           |           |        |        |
| Full-shot (218)                            | 96.29     | 65.85     | 39.25  | 49.16  |
| **Transformer - Multi-Message Input**      |           |           |        |        |
| Full-shot 3 Msg                            | 94.47     | 61.83     | 29.63  | 39.98  |
| Full-shot 5 Msg                            | 92.64     | 65.48     | 47.62  | 55.13  |

Table 16: Performance of classification models for **Risk Management**. Full-shot value refers to the number of positive examples present in the full training set. Best performing model is in bold.

* The number exceeds the total number of positive examples in the dataset and therefore results are analogous to full-shot