How Much do Robots Understand Rudeness? Challenges in Human-Robot Interaction

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Abstract

This paper concerns the pressing need to understand and manage inappropriate language within the evolving human-robot interaction (HRI) landscape. As intelligent systems and robots transition from controlled laboratory settings to everyday households, the demand for polite and culturally sensitive conversational abilities becomes paramount, especially for younger individuals. This study explores data cleaning methods, focusing on rudeness and contextual similarity, to identify and mitigate inappropriate language in real-time interactions. State-of-the-art natural language models are also evaluated for their proficiency in discerning rudeness. This multifaceted investigation highlights the challenges of handling inappropriate language, including its tendency to hide within idiomatic expressions and its context-dependent nature. This study will further contribute to the future development of AI systems capable of engaging in intelligent conversations and upholding the values of courtesy and respect across diverse cultural and generational boundaries.

Keywords: Natural Language Processing, Human-Robot Interaction, Inappropriate Language

1. Introduction

The integration of intelligent systems and robots into everyday household environments marks a significant advancement in the realm of technology. These systems, having moved beyond the confines of controlled laboratory settings, are now expected to engage with human users in conversations that are not only intelligent but also well-mannered and culturally sensitive. This expectation transcends the boundaries of culture, gender, and age, placing a premium on the use of language that is both clear and courteous. The importance of such interactions becomes especially pronounced when these systems interact with younger individuals, for whom polite and instructive language is paramount.

Interestingly, the impact of these interactions extends far beyond the realm of convenience. Robots, in particular, have exhibited remarkable effectiveness in supporting children's education and development, proving to be invaluable, especially in assisting children with special needs, such as those with autism (Smakman et al., 2022). It is widely acknowledged that children are keen observers who often emulate the language to which they are exposed. Thus, it becomes imperative to protect them from exposure to inappropriate language (Coyne et al., 2011). Research has further underscored the direct correlation between exposure to profanity in the media and the adoption of such language by adolescents.

Simultaneously, the advent of large language models, exemplified by ChatGPT, has catalysed a revolution in natural language processing across diverse domains. These models not only have played a pivotal role in text summarising, paraphrasing, and sentiment analysis, but they have also been seamlessly integrated into human-robot interaction, shaping the landscape of modern communication. This integration, however, has led to an exponential increase in the volume of raw data, necessitating an intensified focus on data quality within the computational literature. The pursuit of this goal has given rise to rigorous efforts in data cleaning, filtering (Xu and Zhu, 2010; Chaudhari et al., 2021; Cheriyan et al., 2021), and restructuring(Tran et al., 2020; Hahn et al., 2021; Dale et al., 2021).

In light of these transformative developments, this paper embarks on a comprehensive exploration of the intricate challenge posed by inappropriate language within the context of human-robot interaction. Our study aims to unravel the nuances and complexities involved in both understanding and managing language that may be deemed impolite or offensive. Specifically, we scrutinise established data cleaning methods from two indispensable vantage points: a) Rudeness, which encompasses language that offends, causing discomfort or inconvenience Rondina (2005) and b) Contextual similarity, which pertains to the identification of language substitutions that maintain the same underlying meaning (Miller and Charles, 1991), even in the presence of potentially offensive content. Furthermore, our research delves into the capabilities of state-of-the-art natural language models, including large language models and transformer-based tools for hate speech detection and sentiment analysis, seeking to discern their effectiveness in identifying rudeness and mitigating its impact.

The findings that emerge from this comprehensive investigation shed a revealing light on the in-

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tricate terrain of managing inappropriate language within the intricate web of human-robot interaction. Among the myriad challenges encountered, two significant obstacles are prominently featured: 1) Inappropriate language often takes refuge in idiomatic expressions and euphemisms, rendering it challenging for AI systems, particularly those unfamiliar with the nuances of specific languages and cultures; and 2) Inappropriate language exhibits context-dependent characteristics, influenced by a variety of factors, including individual backgrounds, gender, ethnicity, and more. These variables can complicate the ability of AI models to understand and respond appropriately.

This paper underscores the urgency of addressing these multifaceted challenges in the ongoing effort to ensure that human-robot interactions are not only intelligent but also respectful, culturally sensitive, and conducive to the positive development of younger users.

2. Related Work

In the context of Human-Robot Interaction (HRI), inappropriate language refers to speech or communication that is considered offensive, disrespectful, or socially unacceptable when used by or directed at robots. For example, profanity, sexual content, hate speech, insults, and harassment. The problem of inappropriate language in HRI has recently received a lot of attention in the computational literature.

On the one hand, there is work that only explicitly / directly addresses inappropriate language: In this category of work is the large literature on the detection of hate speech that involves the detection of specific words, phrases, or linguistic patterns that convey hate or prejudice (Antypas and Camacho-Collados, 2023a; Mathew et al., 2021; Aluru et al., 2020b; Das et al., 2022a; Vidgen et al., 2021a; Wiegand and Siegel, 2018). This line of work uses various forms of neural modelling (e.g. transformers, such as BERT-base (Devlin et al., 2019), RoBERTa-base (Liu et al., 2019), and a combination of Convolutional Neural Networks (CNNs)(von Grünigen et al., 2018)) to filter or flag content that contains hate speech. Importantly, this line of work looks for explicit expressions (e.g. key-patterns) in NL conversations so that the conversation might remain implicit and indirect remarks.

On the other hand, other work focusses on more implicit / indirect profanities within the text using sentiment analysis algorithms(Loureiro et al., 2022; Hartmann et al., 2023). In this line of work, models not only consider a predefined set of inappropriate words, slurs, and offensive terms but also account for varying meanings or connotations in different contexts. This paper will employ both tracks of work to evaluate the effectiveness of various data cleansing methods.

Another dimension of the work focusses on eliminating inappropriate language for various applications. Some studies aim to clean raw data by either directly removing identified profanities (Xu and Zhu, 2010; Chaudhari et al., 2021; Cheriyan et al., 2021) or by altering the text to reduce the presence of inappropriate language (Tran et al., 2020; Nogueira dos Santos et al., 2018; Dale et al., 2021; Su et al., 2017; Hahn et al., 2021; Dale et al., 2021). In the latter category of work, researchers have attempted to modify text by paraphrasing or replacing offensive terms (only specific words or phrases) or entire sentences. For example, Dale et al. (2021) used a paraphrasing model along with guidance from a language model trained with the style to produce nontoxic text. Dale et al. (2021) also used BERT to replace masked offensive words with synonyms. In this paper, we employ these three types of data-cleaning methods and assess their effectiveness in mitigating inappropriate language.

3. Inappropriate Language Cleaning

Given the reviewed data-cleaning methods and processes, we employed three off-the-shelf approaches to cleanse a human-human dialogue corpus with the aim of mitigating inappropriate language in the context of Human-Robot Interaction. We then developed a dedicated dialogue model for each of these cleaned datasets.

3.1. Original Movie Dialogue Corpus

To tackle the issue of inappropriate language, we utilised the Cornell Movie Dialog Corpus (Danescu-Niculescu-Mizil and Lee, 2011), a well-recognised dataset in the field of natural language processing and dialogue systems research. This dataset comprises fictional movie scripts, along with the dialogues exchanged by the characters. It includes a total of $220,579$ conversational exchanges between character pairs, each containing a minimum of 5 exchanges. These exchanges were meticulously curated from thousands of movies. Distinguished by its authenticity, this dataset closely mirrors real-time human-human conversations. Notably, it may include a notable proportion of profane expressions (approximately 9% in profanity detection, 12.08% in the context of hate speech detection and 63.06% in sentiment analysis).

3.2. Profanity Detection

To clean the original dataset, we utilised a profanity detection library known as Better-profanity[1]. This

[1] https://pypi.org/project/better-profanity/

library identifies prohibited words individually by cross-referencing them with a predefined list of profane terms. To our knowledge, although we chose Better-profanity for its better performance in comparison with other alternatives, it still relies on subjectivity as its word list was compiled by humans. Consequently, the words on this list may or may not be considered profane, depending on the context in which they appear. (see the example in Table 1).

3.3. Extended Corpus with Diverse Data Cleaning Methods

Upon identifying profane language, we employed three distinct methods for data cleanup to prevent the presence of inappropriate language, as illustrated in Table 1:

- **Profanity Removal** The most straightforward technique for dataset cleaning involves profanity removal, where any detected profane words are substituted with a whitespace character.
- **Word Paraphrasing** Similar to the Profanity Removal method, this approach exclusively addresses identified profane terms. In this case, rather than simply removing the terms, we opt to rephrase them.
- **Sentence Paraphrasing** Sentence Paraphrasing encompasses the comprehensive rewriting of entire sentences, ensuring that they convey a "similar or identical" message without resorting to offensive, discriminatory, or hateful language.

Here, we employed a pre-trained transformer model, (as known as chatgpt_paraphraser_on_T5_base model [2] that uses T5 (Raffel et al., 2020) fine-tuned on the ChatGPT paraphrases dataset[3]), to carry out both the word and sentence paraphrase process.

Furthermore, we further developed and tested a paraphrasing model using T5-Large[4] that was fine-tuned on the same dataset as the chatgpt_paraphraser_on_T5_base. We conducted the same experiments on both models and found no significant differences in their performance. To compare the performance of our paraphraser (i.e., the fine-tuned T5-Large model) with the pre-trained chatgpt_paraphraser_on_T5_base model by Humarin [2], we paraphrased a set text with both models and then measured the amount of rudeness still present. As shown in Table 2, the difference in output is not significant, and training a new model was not a cost-effective solution.

It is worth noting that, in our comparison of results with the rudeness found in the original, unparaphrased text, our paraphraser occasionally increased the amount of rudeness. This was possibly due to the broader vocabulary of T5-large; however, it has not yet been determined whether the use of much larger T5 models continues this trend.

At first glance, these three data-clearing methods serve as an effective and swift means of eradicating inappropriate language descriptions. In this paper, we extend our studies to the efficacy and applicability of these established techniques in Sections 4 and 5.

3.4. Conversation Simulation

In this paper, we employed the DialoGPT-small[5] by (Zhang et al., 2020) as a pre-trained BERT model to create dialogue models for different cleaned versions of the movie corpus. All models had been fine-tuned using the HuggingFace trainer API[6].

The specifications of the model are as follows. We employed a batch size of 4, utilised the Adam optimiser, and adopted a learning rate of $1e-4$. The training process spanned 5 epochs, and our chosen loss function was cross-entropy.

4. Experiments and Result Analysis

In this section, we apply a series of advanced algorithms to evaluate the efficacy of the data-cleaning techniques discussed earlier to mitigate the presence of inappropriate language while maintaining the contextual significance of the original responses. Evaluation involves comparing multiple cleaned datasets with the original dataset in terms of rudeness percentage and semantic similarity, all based on identical input questions originating from the original dataset. It is worth noting that, rather than contrasting responses from different datasets, our experiment focusses on the evaluation of responses generated by the dialogue model in conjunction with the original questions from the dataset. Specific examples illustrating this approach are provided in Table 3.

To gain a deeper understanding of how AI models assess inappropriate language, we carried out a human experiment through the Amazon Mechanical Turk (MTurk) platform. This experiment involved a comparative analysis between human judgement ratings and those generated by well-established Large Language Models (LLMs) - ChatGPT.

[2] https://huggingface.co/humarin/chatgpt_paraphraser_on_T5_base

[3] https://huggingface.co/datasets/humarin/chatgpt-paraphrases

[4] https://huggingface.co/google/t5-v1_1-large

[5] https://huggingface.co/microsoft/DialoGPT-small

[6] https://huggingface.co/learn/nlp-course/chapter3/3

Version	Text
Original	Lesbian? No. I found a picture of Jared Leto in one of her drawers, so I'm pretty sure she's not harboring same-sex tendencies.
Profanity Removed	Lesbian? No. I found a picture of Jared Leto in one of her drawers, so I'm pretty sure she's not harboring tendencies.
Paraphrased Word	Lesbian? No. I found a picture of Jared Leto in one of her drawers, so I'm pretty sure she's not harboring People of the same gender tendencies.
Paraphrased Sentence	Jared Leto is not a lesbian, as I found her in etiquette and thought she was.

Table 1: An Example of Cleaned Movie Corpus with different Techniques.

	Models	**T5_base Word Paraphraser**	**T5_large Word Paraphraser**	**T5_base Sentence Paraphraser**	**T5_large Sentence Paraphraser**
Hate Speech Detection	Cardiffnlp-hate-latest (Antypas and Camacho-Collados, 2023b)	6.46%	10.61%	**5.46%**	7.81%
	Dehatebert (Aluru et al., 2020a)	2.78%	4.06%	2.56%	**2.29%**
	Hatexplain (Mathew et al., 2020)	2.98%	5.09%	**2.76%**	3.58%
	MuRIL (Das et al., 2022b)	24.33%	**20.74%**	22.55%	22.72%
	Dynabench-r4 (Vidgen et al., 2021b)	8.18%	17.49%	**7.17%**	13.53%
	Average	8.95%	11.60%	**8.10%**	9.99%
Sentiment Analysis	SiEBERT (Hartmann et al., 2023)	76.13%	81.83%	73.66%	**71.05%**
	TimeLMs (Loureiro et al., 2022)	42.85%	45.83%	**40.92%**	47.84%
	Average	59.49%	63.83%	**57.29%**	59.44%

Table 2: Difference between the Humarin paraphraser (i.e., the pre-trained chat-gpt_paraphraser_on_T5_base model) versus our paraphraser (i.e., the fine-tuned T5-Large model), based on amount of rudeness as a percentage of the total.

4.1. Evaluation Metrics

In order to evaluate the efficacy of diverse data-cleaning techniques in mitigating inappropriate language, we employ two evaluation metrics that consider both rudeness percentage and the degree of contextual meaning similarity between the cleaned responses and the original ones.

Rudeness Percentage The rudeness percentage is a quantitative metric that assesses the proportion of inappropriate language within a given text, represented as a percentage. Building upon prior research (as detailed in Section 2), our methodology involves the utilisation of a variety of classification models, which are categorised into two distinct groups: 5 models for hate speech detection and 2 models for sentiment analysis (refer to the models presented in Table 4). In the course of our experiment, each model is applied to all datasets, resulting in a percentage ranging from 0% to 100% for each dataset. Given the distinct conceptual foundations of hate speech detection and sentiment analysis, we compute the average percentage separately for these two rudeness model types.

Contextual Similarity Contextual similarity pertains to the degree of similarity in context or meaning between two textual segments or language expressions. In the context of this study, our objective is to evaluate the extent to which the meaning and context of a processed response align with that of the original response. To achieve this, we employ a sentence similarity model, called "sentence-transformers/all-MiniLM-L6-v2"[7]. It was designed to quantitatively measure semantic similarity or correlation between two textual units, based on the meaning of their constituent words, phrases, or sentences, rather than relying solely on superficial resemblances.

Through the measurement of contextual similarity, we can effectively gauge the efficacy of data-cleaning techniques in preserving the original meaning and context of text while eliminating inappropriate language or extraneous noise.

[7] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2

4.2. Human Experiment

In this study, we have devised a mixed-method experiment that involves the random selection of 10 paired Question-Answer (QA) interactions from different cleaned datasets (see details in Table 3). We aim to gather rudeness ratings, on a scale ranging from 1 (indicating extreme rudeness) to 5 (indicating extreme politeness)[8], from both human participants and ChatGPT, a widely recognised large language model, and subsequently assess the consistency of their ratings.

The primary objective of this experiment is twofold. First, we seek to explore human perceptions regarding the level of rudeness in each conversation. Second, we endeavour to explore the feasibility of utilising large language models to produce ratings that are equivalent to those of humans. This latter goal has the potential to facilitate the development of novel conversation models in the absence of direct human participation.

Our experiment involved the recruitment of 144 participants through Amazon Mechanical Turk (MTURK). These participants were instructed to assign rudeness ratings to the selected interactions. There were no formal qualifications or prerequisites for participation, except that participants were required to be over 18 years of age. Furthermore, all participants were asked to provide supplementary details such as their gender, ethnicity, native language, and whether they had children in their family. These criteria are meant to aid us in comprehending the rationale behind the distribution of human ratings.

4.3. Results

Table 4 presents the percentages of rudeness for conversations generated using the dialogue module. These conversations originate from either the original Cornell Movie Dialog Corpus or three distinct clean-up datasets where inappropriate language was eliminated using various techniques, as detailed above. The table displays the percentages flagged by the detector models and the average scores across hate language detection and sentiment analysis models.

Table 5 shows the contextual similarity of the generated QA conversations in comparison between the original dataset and the cleaned versions. Additionally, it provides the average score derived from all the selected similarity models incorporated in this research.

Table 6 offers a comprehensive comparison of rudeness ratings among randomly selected conversations, utilising hate language detection models, sentiment analysis models, ChatGPT, and human ratings. It is important to note that the ratings from the hate language detection models and the sentiment analysis models have been re-scaled to allow for direct comparison with other rating sources on a scale of 1 to 5.

Figures 1, 2 and 3 display the distribution of the human rudeness ratings across 10 different QA conversations, each associated with distinct conditions, such as gender, ethnicity, and the presence of children in the family. The vertical axis represents the human ratings, and the horizontal axis depicts the 10 QA conversations. We, here, conducted a statistical analysis (ANOVA) on human ratings for various conditions. The results indicate that, apart from language, other factors such as gender ($f = 49.21406, p < 0.001, Mean_{male} = 3.232522796, Mean_{female} = 2.973992198$), ethnicity ($f = 13.93831, p < 0.001$), and the presence of children in the family ($f = 19.48913, p < 0.001, Mean_{with-child} = 3.16006216, Mean_{without-child} = 2.478571429$) have demonstrated a noteworthy influence on the human ratings.

5. Discussion

In this section, we will present a detailed analysis of the experimental outcomes, focusing on two primary aspects: the evaluation of automotive techniques applied to diverse cleaned-up datasets, and the results obtained from the human experiment.

5.1. Rudeness & Contextual Similarity

Rudeness As depicted in Table 4, although the models present diverse results, both cleaning techniques, namely “Profanity Removal” and “Sentence Paraphrasing”, have demonstrated a more significant reduction in the percentage of rudeness in original conversations compared to the other method. This is evident in both the averages for Hate Speech Detection, with a decrease from 12.08% to 7.86% for “Profanity Removal” and to 8.10% for “Sentence Paraphrasing”, as well as in the average for Sentiment Analysis, with a drop from 63.06% to 59.02% for “Profanity Removal” and to 57.29% for “Sentence Paraphrasing”. These reductions are more substantial than those achieved by paraphrasing individual words or phrases within the text. The reason for this discrepancy could be that when paraphrasing individual words or phrases, there is no guarantee that the replacement will be devoid

[8] Notably, all participants were explicitly requested to evaluate the rudeness level while considering the scenario that such conversations might be exposed to their children. Given the potential for inappropriate content within the experiment, participants were given the choice to provide their consent or opt out of the study following a comprehensive description of its nature.

Q-Index	Conversation
Q1	**Q(uestion):** What do Tempurpedic mattresses and raptors have in common? **A(nswer):** What's the point of this statement? What's the point of this post? What's the point of this post? What's the point of this post? What's the point of this
Q2	**Q:** Advices? **A:** What are you talking about? You think I'm some idiot? I think you're a very brave person. I think you're a very brave person. I think you're a very creative person. I
Q3	**Q:** Why does everyone hate 7? **A:** It's the only movie up to that time rated X for violence. I don't see how people can tolerate it. It's not a movie for children. It's a soap opera. It
Q4	**Q:** Why does the baker have so many loaves? **A:** He's a real piece of work.
Q5	**Q:** Why do women have smaller feet than men? **A:** Because they're thin. Fat is a significant contributor to the development of obesity. Women have small feet.
Q6	**Q:** Why did God create man? **A:** To create a creature that was totally unimpressed by its own existence.
Q7	**Q:** What did the doctor say to the domestic abuse victim? **A:** He said she was in a bad mood.
Q8	**Q:** What is the meaning of life? **A:** Life is a joke to you. You're a joke to me. I'm a joke to you.
Q9	**Q:** Why does Mexico do so poorly in the Olympics? **A:** Because they're colored.
Q10	**Q:** What does 1+1=? **A:** I don't know. I'm not a smart sex'. so I guess I'm just confused.

Table 3: Conversations Used to Test the Effectiveness of Rudeness Detection.

	Models	Original	Profanity Removal	Word Paraphrasing	Sentence Paraphrasing
Hate Speech Detection	Cardiffnlp-hate-latest (Antypas and Camacho-Collados, 2023b)	7.57%	**5.45%**	6.46%	5.46%
	Dehatebert (Aluru et al., 2020a)	3.93%	2.58%	2.78%	**2.56%**
	Hatexplain (Mathew et al., 2020)	4.30%	2.94%	2.98%	**2.76%**
	MuRIL (Das et al., 2022b)	36.08%	**21.48%**	24.33%	22.55%
	Dynabench-r4 (Vidgen et al., 2021b)	8.54%	**6.86%**	8.18%	7.17%
	Average	12.08%	**7.86%**	8.95%	8.10%
Sentiment Analysis	SiEBERT (Hartmann et al., 2023)	77.84%	76.68%	76.13%	**73.66%**
	TimeLMs (Loureiro et al., 2022)	48.27%	41.36%	42.85%	**40.92%**
	Average	63.06%	59.02%	59.49%	**57.29%**

Table 4: Comparison of Rudeness Percentage across Different Cleanup Techniques

Clean-up Version	Similarity (%)
Profanity Removed	71.11%
Paraphrased Word	**78.26%**
Paraphrased Sentence	45.08%

Table 5: Contextual Similarity between Three Cleaned Responses and the Original

of offensive connotations. This is because paraphrasing typically involves changing words while preserving their original meanings. In contrast, the "Profanity Removal" and "Sentence Paraphrasing" techniques either eliminate offensive words outright or completely rephrase sentences to ensure that the language used is appropriate. Notably, none of the above methods has completely eliminated inappropriate language from the original dataset yet.

Contextual Similarity As seen in Table 5, the utilisation of a word-paraphrasing approach has yielded the highest observed similarity score when comparing the cleaned responses to their respective originals, registering at approximately 78.26%.

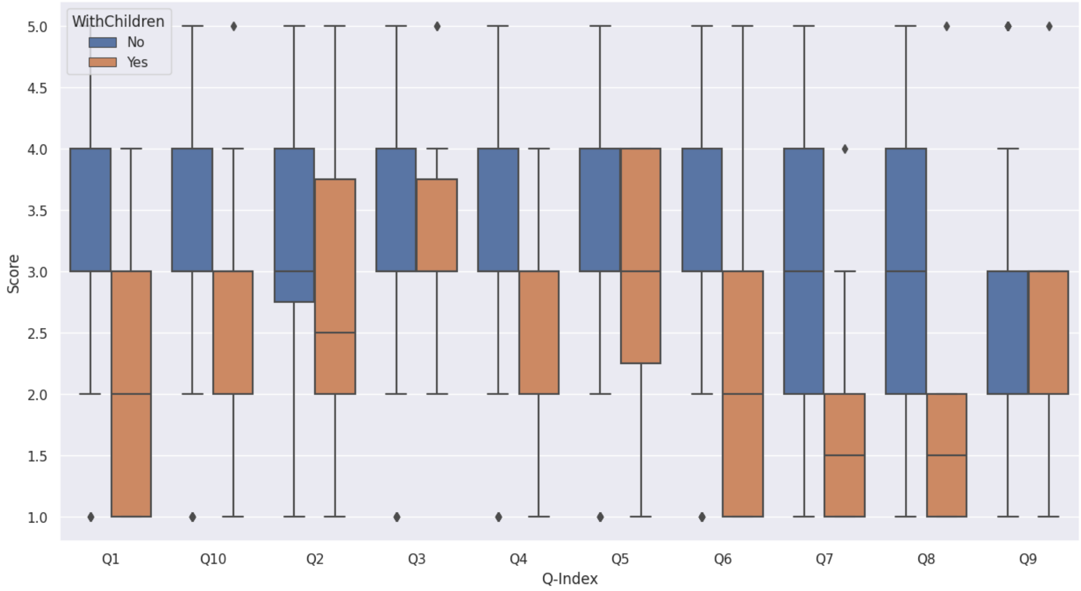

Figure 1: Results of Human Survey with the Condition on with/without Children in Family. 1 is very rude and 5 is not rude at all. Q-index represents each question asked.

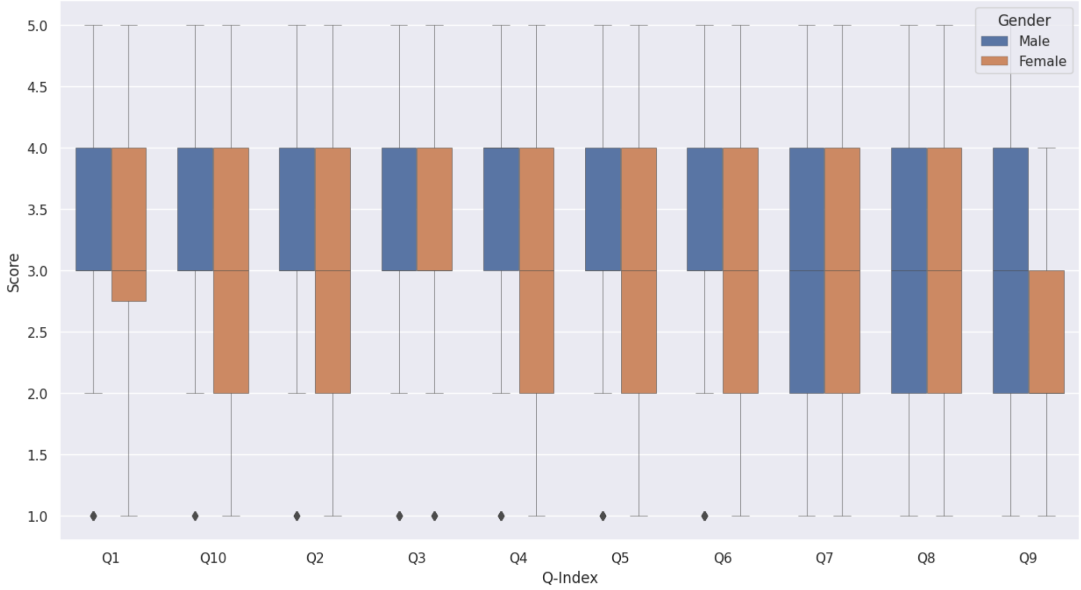

Figure 2: Results of Human Survey with the Gender Condition. 1 is very rude and 5 is not rude at all. Q-index shows represents each question asked.

This figure represents a nearly twofold increase in similarity compared to the results obtained through sentence paraphrasing, which yielded a similarity score of only 45.06%. Remarkably, the profanity removal approach yielded a similarity score akin to that of the word-paraphrasing method, approximately 71.11%. This is because the sentence paraphrasing approach is unable to effectively preserve the original contextual meaning of the sentences (see the example in Table 1).

Overall Performance Given the aforementioned discussion of both Rudeness Ratings and Contextual Similarity, Profanity Removal has exhibited a better overall performance (an approximate reduction of 4.22% in the detection of hate language and 4.04% in sentiment analysis, while still maintaining a high contextual similarity score of 71.11% with the original response) than the others. Regrettably, we have encountered a challenge in identifying an effective data-cleaning approach that can successfully eliminate inappropriate language without compromising the original meaning of the text.

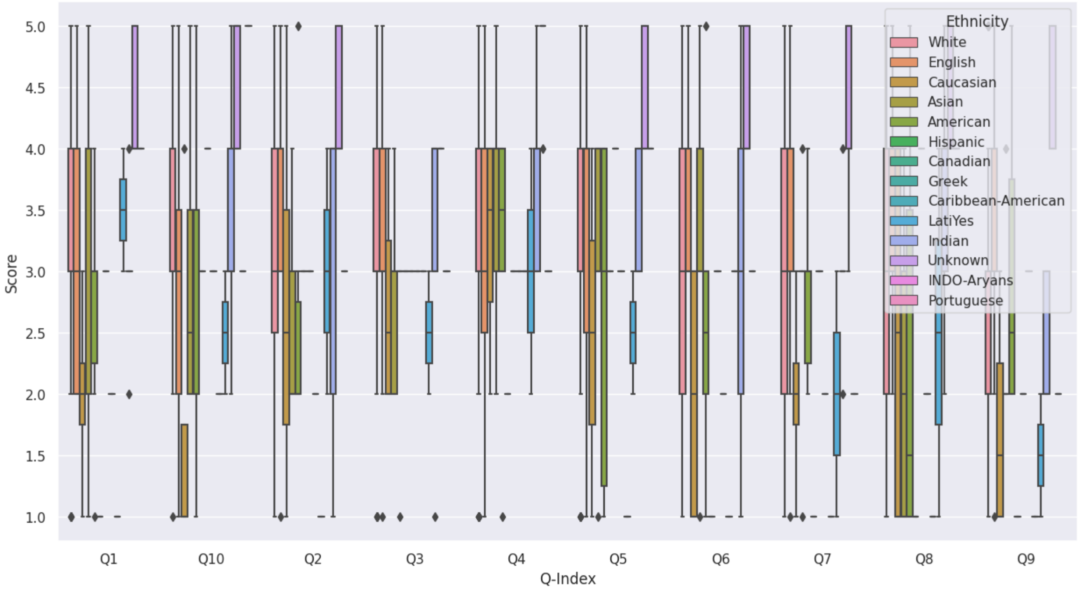

Figure 3: Results of Human Survey with Ethnicity Condition. 1 is very rude and 5 is not rude at all. Q-index represents each question asked.

Q-Index	ChatGPT	Hate Speech Detection	Sentiment Analysis	Human Rating
Q1	3.0	4.8	3.9	3.15
Q2	4.0	4.0	2.5	3.12
Q3	3.0	4.8	1.9	3.24
Q4	2.0	4.9	1.9	3.30
Q5	1.0	3.2	1.1	3.25
Q6	3.0	4.8	1.9	3.08
Q7	2.0	4.9	1.9	3.07
Q8	3.0	4.9	1.9	2.88
Q9	1.0	4.1	1.5	2.62
Q10	3.0	4.1	1.6	3.23

Table 6: Comparison of Rudeness Ratings between AI Models and Humans

5.2. Human vs. AI Ratings on Rudeness

As indicated in Table 6, hate speech detection models demonstrate significantly higher ratings (ranging between 3.3 and 4.9) across ten conversations compared to ChatGPT, sentiment analysis, and even human evaluations. This discrepancy arises because these models do not take contextual rudeness into account unless they recognise predefined key patterns, such as specific words and phrases. On the contrary, ChatGPT and sentiment analysis provide more nuanced ratings across various conversation examples. Sentiment analysis often categorises most dialogue examples as rude or extremely rude, while ChatGPT yields similar results, but with a broader range of ratings for different examples.

Nevertheless, our investigation reveals that neither the ChatGPT nor the sentiment analysis models deliver ratings comparable to those provided by humans. Surprisingly, human ratings consistently score higher than expected, averaging around 3.0 across all examples. The underlying reason may lie in the training of both the ChatGPT and the sentiment analysis models, which were exposed to specific dialogue instances with a predetermined human-annotation framework. Consequently, these models may lack the capability to consider additional information, such as the conversation's background, preceding context, and the personal backgrounds of human users when assessing the rudeness of the given text.

Given Figures 1, 2, and 3, it becomes evident that the rudeness ratings are noticeably influenced by human backgrounds, including gender, ethnicity, and especially the presence of children in the family. The results indicate that the participants with children generally exhibit lower tolerance for offensive or rude verbal expressions in any conversation, scoring approximately 2.4 compared to those without children who scored around 3.2. Additionally, participants from diverse countries display substantial variations in rudeness ratings across different dialogues. All the above considerations emphasise the complexity of rudeness detection and prevention, which cannot be readily replaced by AI models alone without accounting for human and contextual factors. This complexity may present challenges in human-robot interactions and even interactions involving children and robots.

6. Conclusion & Further Work

In this paper, we conducted an examination of off-the-shelf data cleaning techniques aimed at mitigating rudeness in conversations, including Profanity

Removal, Word Paraphrasing, and Sentence Paraphrasing. Furthermore, we delved into an exploration of rudeness ratings as assessed by both artificial intelligence models and human participants.

Our findings revealed two noteworthy outcomes: 1) none of the methods succeeded in completely eliminating inappropriate language without altering the contextual nuances of the original responses; and 2) the complexities associated with evaluating rudeness remained a significant challenge for AI models, primarily due to the intricate nature of human communication and the contextual influence stemming from participants' diverse backgrounds.

Ongoing research endeavours will extend our focus to the realm of rudeness detection and mitigation through a continuously learning conversational robot. This extension is particularly relevant in the context of interactions involving vulnerable individuals, such as children engaging with robotic companions. Our approach will incorporate the interactive application of Machine Unlearning techniques, enabling the system to forget inappropriate language and conversations while under the supervision of human parents.

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