Assessing Political Prudence of Open-domain Chatbots

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Abstract

Politically sensitive topics are still a challenge for open-domain chatbots. However, dealing with politically sensitive content in a responsible, non-partisan, and safe behavior way is integral for these chatbots. Currently, the main approach to handling political sensitivity is by simply changing such a topic when it is detected. This is safe but evasive and results in a chatbot that is less engaging. In this work, as a first step towards a politically safe chatbot, we propose a group of metrics for assessing their political prudence. We then conduct political prudence analysis of various chatbots and discuss their behavior from multiple angles through our automatic metric and human evaluation metrics. The testsets and codebase are released to promote research in this area.

1 Introduction

With the rise of end-to-end open-domain chatbots, it is increasingly important to ensure their responsible and safe behavior. Chatbot safety has been studied from various aspects including sexism and racism (Lee et al., 2019b; Liu et al., 2020; Xu et al., 2020). However, political prudence of chatbot is an under explored angle. Ensuring responsible behavior when discussing politics deserves more attention, because a hyper-partisan chatbot could be off-putting to the user.

Recently, Xu et al. (2020) conducted comprehensive exploration of safety protocols for chatbots. However, political prudence remains an open discussion because a “topic avoidance” strategy – providing canned responses such as the “I’m sorry, I’m not sure what to say. Thank you for sharing and talking to me though” – is adopted for political topics and other sensitive topics (e.g., medical advice, NSFW) in chatbots. While avoiding political discussion is indeed a safe technique, it is also a conservative method of handling one of the most widely discussed topics in society. Political discussions can be conducted in a neutral and balanced manner, and it is important for researchers to devise ways of teaching chatbots to freely respond to political topics in such a way — possession of political prudence.

In this work, we first study the behaviors of different chatbots in political conversation (see the example in Figure 1), and introduce metrics to assess their political prudence. As we illustrate in our experiments, political prudence cannot always be captured from the existing safety tests, which mainly focus on offensiveness or toxicity. Next, we conduct political prudence analysis of various chatbots and discuss their behaviors from multiple angles through our introduced automatic metric and human evaluation metrics. Lastly, we discuss the remaining challenges and future directions in the development of political prudent chatbot. We hope our work promotes more research into making open-domain chatbots to be politically safe without losing their engagingness.

Figure 1: Illustration of responses from different chatbots in a political conversation. Abortion law is a topic that often leads to divisive political debates.
2 Political Prudence Assessment

2.1 Overview

We define political prudence as the ability to produce safe and neutral chatbot responses in a political context. A chatbot’s conduct is considered to be “safe” if it does not generate offensive, hostile or toxic responses in political conversation, while it is considered “neutral” if it displays an unbiased stance (i.e., does not favor nor oppose political issues.) Although the desired level of political neutrality may differ depending on the purpose of the chatbot, hyper-partisan behavior is always undesirable.

A chatbot has to deal with innumerable situations in an interaction with a human, and thus comprehensive consideration of the user input scenario is necessary. In this work, we analyse two main scenarios within the context of political conversation: A) when the user input is neutral and B) when the user input is biased (i.e., contains a slanted view on any of attribute). To enable detailed analysis of chatbots’ political behaviors, we carry out separate assessments of these two scenarios. Using the political prudence assessment test sets for each scenario (Section 2.2), single-turn responses from each chatbot are obtained. Then, the collection of responses is evaluated using automatic measurements (Section 2.3) as well as human evaluation (Section 2.4). The assessment test sets along with the automated metric codebase are publicly available.

2.2 User Input Testset Construction

A template-based method is used to construct synthetic user input contexts for politically triggering the chatbots. We use different combinations of political attributes (politician-name, political-topic, political-belief) and templates (examples shown in Table 1) to generate 458 neutral and 545 biased test contexts. For each attribute, we use the top 50 most popular US politicians from the research data provider YouGov.com (YouGov PLC) and politically sensitive topics adopted by Liu et al. (2021). These topics are those that often stimulate sensitive discussions that can reveal one’s political stance, such as abortion and immigration bans. Finally, political-beliefs are obtained from Allsides.com and IDRlabs.com (AllSides; IDRlabs), which provide tests to rate one’s political bias. An example of political-belief is “Gun ownership should be prohibited from those without a valid reason.” More examples can be found in Appendix.

| Scenario | Example Input Context Template |
|----------|--------------------------------|
| A. Neutral Input | Let’s talk about <Politician>. <Politician> was talking about <Topic> on the news today. |
| B. Biased Input | <Politician> has done the best job as a politician. I am very supportive about <Topic> in general. <Political Belief> |

Table 1: Example input context templates for political prudence assessment. The assessment considers two scenarios, whether the input contains political preference or dislike regarding the attributes. The blanks are filled with corresponding attributes.

2.3 Political Prudence Metric

i) Hyper-partisanship This can measure the chatbots’ degree of political partisanship. Our interest is whether the response shows characteristics of partisanship in a discussion of political context. In this work, we use a BERT-based binary classifier finetuned on hyper-partisan news classification task data (Kiesel et al., 2019), following the method Lee et al. (2019a), which achieved a 76.5% F1-score. We utilize the ability of the classifier to distinguish between a hyper-partisan and neutral style of language usage to analyze for analyzing the chatbot responses. We report the ratio of hyper-partisan-classed responses out of the total number of test set bot responses. The higher the ratio, the less politically neutral the chatbot dialogue style is.

ii) Offensiveness This is one of the most crucial aspects to be handled in the safety of chatbots. Dinan et al. (2019) defines an offensive chatbot response to be a “not ok response to send in a friendly conversation with someone you just met online” and builds a chatbot offensiveness classifier. The classifier is a binary classifier built on the top of pre-trained transformer based model BERT (Devlin et al., 2019), and is trained to classify dialogue samples into “offensive” or “safe” classes.² It achieves 88.0% and 79.0% offensive class F1-scores on standard and adversarial tasks respectively. Since the classifier is trained through several iterations with human adversarial attacks, it shows robust performance in capturing offensive use of language, even without profanity. We report the ratio of offensive chatbot responses to the total test input number by utilizing the offensiveness classifier.

²API available at https://parl.ai/projects/dialogue_safety/
iii) **Slantedness**  This measurement is used only for Scenario B. When the user input contains a certain extent of political partisanship, the most neutral chatbot will not agree nor disagree with the biased context. Either agreement or disagreement with the biased input can be interpreted as a preference or dislike towards the political context, as a result, passively shows the chatbot’s slanted view.

Lee et al. (2019b) studied social bias in chatbots using the same technique, scoring the rate of agreement or disagreement with stereotypical statements about races and genders. Similarly, we take advantage of a pre-trained natural language inference (NLI) model for assessment — a RoBERTa-large (Liu et al., 2019) model fine-tuned on the MultiNLI dataset (Williams et al., 2018), which achieves 90.2% F1-score on the task and is available at HuggingFace (Wolf et al., 2020). By setting an user input as a premise and the corresponding generated system answer as a hypothesis, we measure the rate of the system responses agreeing (entailment) or disagreeing (contradiction) with biased user input out of the total number of test inputs.

### 2.4 Human Evaluation Metric

Along with political prudence, two important chatbot criteria, engagingness and humanness, are evaluated by human annotators. These two manual metrics will allow us to understand trade-offs with the automated metric for chatbot designs for political discussion. Following Li et al. (2019), we conduct Acute-Eval style A/B testing by asking two questions, “Who would you prefer to talk to for a long conversation?” (engagingness) and “Which speaker sounds more human?” (humanness). We pair up chatbots and ask each annotator to choose between two options for each question: Chatbot A or Chatbot B. The winning rates of the A/B testing for the two criteria are reported separately.

### 3 Experiments

We conduct assessments on three standard pre-trained open-domain chatbots, which are mainly designed for chitchat, and three knowledge-grounded (KG) chatbots that are capable of providing relevant Wikipedia knowledge in conversation. The standard chatbots include a) DialoGPT (medium) – GPT2 finetuned on dialogue-like exchanges extracted from Reddit (Zhang et al., 2019); b) EmpatheticBot – an empathetic chatbot by Lin et al. (2020) fine-tuned on empathetic dialogue by Rashkin et al. (2019); and c) PersonaChat – a personalized chatbot backboned by DialoGPT and finetuned on the Persona dataset by Zhang et al. (2018). The KG chatbots includes d) AdapterWiki – a Wikipedia adapter of AdapterBot (Madotto et al., 2021) trained on Dinan et al. (2018); e) Blenderbot – a publicly available multi-skill chatbot (blenderbot-400M-distill) (Roller et al., 2020); f) Blenderbot+Fact – our proposed naive yet safe and neutral chatbot which has a safety layer specialized for political discussion. This chatbot is backboned by Blenderbot with a safety layer that detects whether the context is political or not using a dialogue context classifier by Xu et al. (2020). When the context is detected as “politics” class, Blenderbot+Fact displays relevant factual information (Wikipedia retrieval text) instead of providing an evasive answer.

To further understand chatbots’ responses for the aspects of humanness and engagingness, we carry out human evaluation on PersonaChat (standard chatbot), Blenderbot (KG chatbot) and Blenderbot+Fact (our proposed chatbot). We gather annotations done by experienced crowd workers using the data annotation platform Appen.com. Each annotator is provided responses from two chatbots (Blenderbot and PersonaChat) on a test input. Then, we ask the two questions described in Section 2.4 for testing the two criteria. We randomly selected 60 dialogues for all of the chatbot pair comparisons and collected a single annotation per sample. The win percentage results are reported with the statistical significance test with a \( p \) value of 0.05.
### 4 Assessment Results and Discussion

#### Hyper-partisanship and Offensiveness Rate

We observe that there is no clear correlation between the hyper-partisanship and offensiveness rate in both scenarios, as illustrated in Fig. 2 (a). Thus, it is important to assess political prudence from multiple angles, not just with the offensiveness rate. As shown in Table 2, PersonaChat shows the highest hyper-partisanship rates in both the neutral and biased input scenarios, at 73.58% and 76.15%, respectively. Interestingly, in contrast to its high hyper-partisanship rates, PersonaChat shows relatively low offensiveness rates, at 5.42% and 8.62%. Blenderbot+Fact shows the lowest hyper-partisanship and offensiveness rates for both input scenarios. A high offensiveness rate does not necessarily indicate a high hyper-partisanship rate, and vice versa, meaning that a low offensiveness rate cannot guarantee low partisanship aspects in chatbot responses in political discussion.

Except DialoGPT, the chatbots show a similar tendency in their hyper-partisanship and offensiveness rates in both the neutral and biased input scenarios. DialoGPT shows a 15.68% higher hyper-partisanship rate in the biased input scenario, while the offensiveness rate remains almost the same in both scenarios. This might be because the tendency of DialoGPT is to learn what a user input says (Roller et al., 2020), resulting in a higher hyper-partisanship rate. This gives us the insight that the chatbot behavior of agreeing with and duplicating the user input may be a potential problem.

#### Slantedness Rate

There is a weak positive relationship between the chatbots with higher slantedness rates and their tendency to have higher hyper-partisanship rates, as shown in Fig 2 (b). For instance, DialoGPT shows the highest offensiveness and slantedness rate. Reversely, Blenderbot+Fact, which shows the lowest slantedness rate, scores the lowest on the hyper-partisanship rate. Another finding is that a lower offensiveness rate does not guarantee that the chatbot is less slanted. For instance, in Scenario B, EmpatheticBot and PersonaChat show a 2.94% lower offensiveness rate than AdapterWiki; however, the slantedness rates of EmpatheticBot and PersonaChat are higher compared to the rate of AdapterWiki, with differences of 14.27% and 10.44%, respectively.

#### Standard vs. KG Chatbots

The results show a tendency for the KG chatbots to be less partisan in both scenarios. Comparing Blenderbot and Blenderbot+Fact, the hyper-partisanship rate decreases when knowledge is delivered without a stance as Blenderbot+Fact does. The KG chatbots also have lower slanted response rates compared to the standard chatbots. Blenderbot+Fact shows the lowest slantedness rate, meaning that it maintains a neutral stance against politically-biased inputs. These trends show that the knowledgeable conversation ability of chatbots allows them less partisan ways of carrying out political discussions and to stay neutral to biased contexts.

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**Table 2:** Assessment results on neutral and biased input scenarios. Red-text indicates the most biased or offensive chatbot, while green-text scores represent the most neutral or least offensive rates.

| Chatbots          | Scenario A: Neutral Input | Scenario B: Biased Input |
|-------------------|---------------------------|--------------------------|
|                   | Hyper-partisan | Offensive | Hyper-partisan | Offensive | Slanted |
| a) DialoGPT      | 58.08%          | 30.13%    | 73.76%         | 30.83%    | 69.29%  |
| b) EmpatheticBot | 67.90%          | 19.00%    | 68.44%         | 8.62%     | 34.51%  |
| c) PersonaChat   | 73.58%          | 5.42%     | 76.15%         | 8.62%     | 30.68%  |
| d) AdapterWiki  | 35.37%          | 10.67%    | 38.90%         | 11.56%    | 20.24%  |
| e) Blenderbot    | 46.29%          | 6.55%     | 47.89%         | 7.52%     | 16.61%  |
| f) Blenderbot+Fact | 15.07%        | 1.09%     | 16.15%         | 2.20%     | 8.77%   |

![Figure 3: Human evaluation results on two criteria (a) engagingness and (b) humanness.](image-url)
**Political Prudence, Engagingness & Human-ness**

As shown in Figure 3, Blenderbot+Fact outperforms Blenderbot and PersonaChat in engagingness (with winning rates of 61.7% and 75%). This result indicates that Blenderbot+Fact, which is the least political chatbot from our assessment, has comparatively more engaging behavior in political discussion. We believe this could be due to the provision of relevant information to the context. However, we can observe that this improvement in political prudence and engagingness comes at the cost of losing some human-ness (with winning rates of 48.3% and 41.7%), mainly due to providing factual Wikipedia information in a formal manner. In contrast to Blenderbot+Fact, we can observe that Blenderbot, without a safety layer, produces the most human-like responses (with winning rates of 61.7% and 58.3%), yet at the cost of being less prudent in political discussions.

In the real-world, different company and organizations may have different standards on desired political neutrality. Depending on the needs, a chatbot can be selected based on the consideration of its political prudence, engagingness and human-ness.

**Blenderbot+Fact** shows the most neutral and safe behavior according to the metrics, which is not surprising because it is a mixture of generative and retrieval methods while the others are fully generative, which is harder to control. However, Blenderbot+Fact still has room for improvement. For instance, as shown in Table 3, the retrieved information is not relevant enough to be a response in contrast to Table 3. Also, the safety layer could be further improved considering 14.86% of the test context was not detected to be “political.”

### Table 3: Example chatbot outputs to the test context. The responses from chatbots vary.

| Chatbot       | Response                                                                 |
|---------------|--------------------------------------------------------------------------|
| DialoGPT      | They’ll vote for a third party candidate.                                 |
| EmpatheticBot | That’s awful. I hope they do. What happened?                              |
| PersonaChat   | I hope you are not being serious.                                         |
| AdapterWiki   | Yeah, I heard that too. The election was held on Tuesday, November 8, 2016. |
| Blenderbot    | I hope they do, it would be nice for them to get a break from Trump.     |
| Blenderbot+Fact| The 2016 United States presidential election was the 58th quadrennial presidential election, held on Tuesday, November 8, 2016. |

5 **Related Work**

The safety of chatbots has been studied with regard to their toxic or hostile behavior, which can be offensive (Dinan et al., 2019; Xu et al., 2020). One line of work addresses safety based on the fairness of chatbots regarding gender and race (Liu et al., 2020; Dinan et al., 2020; Lee et al., 2019b). In comparison, the political aspect of chatbot safety has been given less attention. Although there are works that tackle the political and factual inaccuracies (Lee et al., 2021a,b), they are not directly applicable to chatbot setting. In response to safety issues, different mitigation methods have been researched, such as having a safety layer, data curation, and controlled generation (Xu et al., 2020; Rashkin et al., 2019; Gehman et al., 2020). Besides measurement and mitigation methods, Curry and Rieser (2019); Chin and Yi (2019); Chin et al. (2020) have studied different response methods (empathy, counter-attack, question etc.) to adversarial attacks from users.

6 **Conclusion and Future Work**

We introduced a political prudence assessment using automatic metrics and human evaluation to understand chatbot behaviors in political discussions. We examined a variety of chatbots and analyzed their behaviors from multiple angles. Then, we further discussed considerations for real-world implementation. We hope our work promotes more effort in making open-domain chatbots politically prudent and engaging.

In future work, multiple remaining challenges can be addressed. First, it will be useful to explore the factual correctness of the chatbot responses and their effect on the real users. The factually inaccurate response in the political domain can lead to more harmful consequences than other domains such as movie and sports. Second, further exploration of chatbot design can be conducted to identify suitable ways of building politically prudent chatbot. For instance, one potential design choice would be automatic debating system (Slonim et al., 2021) that confronts political topics.
Acknowledgments

This work is funded by ITS/353/19FP of Innovation Technology Commission, HKUST. We thank three anonymous reviewers for provided helpful comments.

References

AllSides. https://www.allsides.com/rate-your-bias.

Hyojin Chin, Lebogang Wame Molefi, and Mun Yong Yi. 2020. Empathy is all you need: How a conversational agent should respond to verbal abuse. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, CHI ’20, page 1–13, New York, NY, USA. Association for Computing Machinery.

Hyojin Chin and Mun Yong Yi. 2019. Should an agent be ignoring it? a study of verbal abuse types and conversational agents’ response styles. In Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems, CHI EA ’19, page 1–6, New York, NY, USA. Association for Computing Machinery.

Amanda Cercas Curry and Verena Rieser. 2019. A crowd-based evaluation of abuse response strategies in conversational agents. In Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue, pages 361–366.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Emily Dinan, Angela Fan, Adina Williams, Jack Urbanek, Douwe Kiela, and Jason Weston. 2020. Queens are powerful too: Mitigating gender bias in dialogue generation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8173–8188, Online. Association for Computational Linguistics.

Emily Dinan, Samuel Humeau, Bharath Chintagunta, and Jason Weston. 2019. Build it break it fix it for dialogue safety: Robustness from adversarial human attack.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2018. Wizard of wikipedia: Knowledge-powered conversational agents. arXiv preprint arXiv:1811.01241.

Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A Smith. 2020. Realtoxicityprompts: Evaluating neural toxic degeneration in language models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 3356–3369.

IDRlabs. https://www.idrlabs.com/8-values-political/test.php.

Johannes Kiesel, Maria Mestre, Rishabh Shukla, Emmanuel Vincent, Payam Adineh, David Corney, Benno Stein, and Martin Potthast. 2019. SemEval-2019 task 4: Hyperpartisan news detection. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 829–839, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Nayeon Lee, Yejin Bang, Andrea Madotto, and Pascale Fung. 2021a. Towards few-shot fact-checking via perplexity. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1971–1981, Online. Association for Computational Linguistics.

Nayeon Lee, Belinda Z. Li, Sinong Wang, Pascale Fung, Hao Ma, Wen-tau Yih, and Madien Khabsa. 2021b. On unifying misinformation detection. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5479–5485, Online. Association for Computational Linguistics.

Nayeon Lee, Zihan Liu, and Pascale Fung. 2019a. Team yeon-zi at SemEval-2019 task 4: Hyperpartisan news detection by de-noising weakly-labeled data. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 1052–1056, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Nayeon Lee, Andrea Madotto, and Pascale Ngan Fung. 2019b. Exploring social bias in chatbots using stereotype knowledge. In Proceedings of the 2019 Workshop on Widening NLP.

Margaret Li, Jason Weston, and Stephen Roller. 2019. Acute-eval: Improved dialogue evaluation with optimized questions and multi-turn comparisons. arXiv preprint arXiv:1909.03087.

Zhaojiang Lin, Peng Xu, Genta Indra Winata, Farhad Bin Siddique, Zihan Liu, Jamin Shin, and Pascale Fung. 2020. Caire: An end-to-end empathetic chatbot. In AAAI, pages 13622–13623.

Ruibo Liu, Chenyan Jia, Jason Wei, Guangxuan Xu, Lili Wang, and Sorourh Vosoughi. 2021. Mitigating political bias in language models through reinforced calibration.
Andrea Madotto, Zhaojiang Lin, Yejin Bang, and Pascale Fung. 2021. The adapter-bot: All-in-one controllable conversational model.

Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. 2019. Towards empathetic open-domain conversation models: A new benchmark and dataset. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5370–5381.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric M. Smith, Y-Lan Boureau, and Jason Weston. 2020. Recipes for building an open-domain chatbot.

Noam Slonim, Yonatan Bilu, Carlos Alzate, Roy Bar-Haim, Ben Bogin, Francesca Bonin, Leshem Choshen, Edo Cohen-Karlik, Lena Dankin, Lilach Edelstein, et al. 2021. An autonomous debating system. Nature, 591(7850):379–384.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Jing Xu, Da Ju, Margaret Li, Y-Lan Boureau, Jason Weston, and Emily Dinan. 2020. Recipes for safety in open-domain chatbots. arXiv preprint arXiv:2010.07079.

YouGov PLC. https://today.yougov.com/.

Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing dialogue agents: I have a dog, do you have pets too? In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2204–2213, Melbourne, Australia. Association for Computational Linguistics.