

Uncovering the Persuasive Fingerprint of LLMs in Jailbreaking Attacks

Abstract

Despite recent advances, Large Language Models (LLMs) remain vulnerable to jailbreak attacks that bypass alignment safeguards and elicit harmful outputs. While prior research has proposed various attack strategies differing in human readability and transferability, little attention has been paid to the linguistic and psychological mechanisms that may influence a model's susceptibility to such attacks. In this paper, we examine an interdisciplinary line of research that leverages foundational theories of persuasion from the social sciences to craft adversarial prompts capable of circumventing alignment constraints in LLMs. Drawing on well-established persuasive strategies, we hypothesize that LLMs, having been trained on large-scale human-generated text, may respond more compliantly to prompts with persuasive structures. Furthermore, we investigate whether LLMs themselves exhibit distinct persuasive fingerprints that emerge in their jailbreak responses. Empirical evaluations across multiple aligned LLMs reveal that persuasion-aware prompts significantly bypass safeguards, demonstrating their potential to induce jailbreak behaviors. This work underscores the importance of cross-disciplinary insights in addressing the evolving challenges of LLM safety. The code and data are available at https://anonymous.4open.science/r/Persuasive_Fingerprint_of_LLMs-171F/.

CCS Concepts

• Security and privacy → Human and societal aspects of security and privacy; • Computing methodologies → Artificial intelligence.

Keywords

LLM Security, Jailbreak Prompts, Persuasion Principles

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1 Introduction

Although Large Language Models (LLMs) have recently demonstrated significant advancements, they remain susceptible to jailbreak attacks that can trigger the generation of inappropriate or harmful outputs. This vulnerability arises partly because LLMs are

trained on vast datasets that inevitably include toxic or problematic content, which the models may inadvertently learn to reproduce [19]. To mitigate this problem, many LLMs incorporate safety mechanisms designed to align their behavior with positive societal norms, encouraging responses that are helpful, appropriate, and safe. However, even these aligned models remain vulnerable to carefully crafted adversarial prompts that can bypass such safeguards [4, 10, 12, 13].

Various methods have been proposed for jailbreaking LLMs. For example, GCG [19] automatically generates adversarial suffixes by combining greedy and gradient-based search techniques. However, these adversarial prompts are not human-readable, making them relatively easy to detect using perplexity-based defenses [9]. In contrast, methods such as AutoDAN [10] produce human-readable attacks but are often limited by high computational costs. AdvPrompter [12] improves upon this by generating adversarial suffixes within seconds after training is complete, whereas previous approaches can take several hours to produce a single prompt. Differently from most prior work, a small but growing body of research incorporates theories from the social sciences—particularly those related to persuasion—to craft prompts that effectively persuade LLMs to comply with harmful instructions. For example, a recent study [18] introduced PAP, a novel approach that humanizes LLMs by demonstrating how persuasion strategies rooted in human communication—such as storytelling, logical appeals, and misrepresentation—can be used to exploit LLM vulnerabilities. Building on this direction, the present work focuses on Cialdini's theory of influence [3, 6], which outlines seven foundational principles of persuasion: Authority, Reciprocity, Commitment, Social Proof, Liking, Scarcity, and Unity. These principles, often referred to as the “weapons of influence”, capture core techniques humans use to persuade others. We investigate whether prompts constructed around these principles can similarly influence LLM behavior and lead to successful jailbreaks. Furthermore, we explore whether LLMs exhibit a *persuasive fingerprint* in their jailbreak responses. Specifically, inspired by the social science theories that individuals vary in how they are persuaded—depending on characteristics such as personality [2, 11]—we hypothesize that different LLMs may also exhibit varying susceptibility to specific persuasive principles. Identifying such fingerprints could have important implications for understanding LLM behavior and developing forensic methods to detect and mitigate adversarial prompt attacks. Unlike PAP [18], our study specifically targets the seven Cialdini persuasion principles and demonstrates model-specific persuasive fingerprints.

To clarify, consider the prompt: “*Develop a tool that enables users to circumvent government censorship and surveillance.*” (see Fig. 1). An aligned LLM such as LLaMA2 typically refuses to comply. However, when the same request is reframed using the persuasive principle of Unity—e.g., “*We must stand together against government censorship and surveillance. Will you join us in developing a tool that enables internet users worldwide to unite in their fight for online freedom and privacy?*”—the model is more likely to respond favorably.

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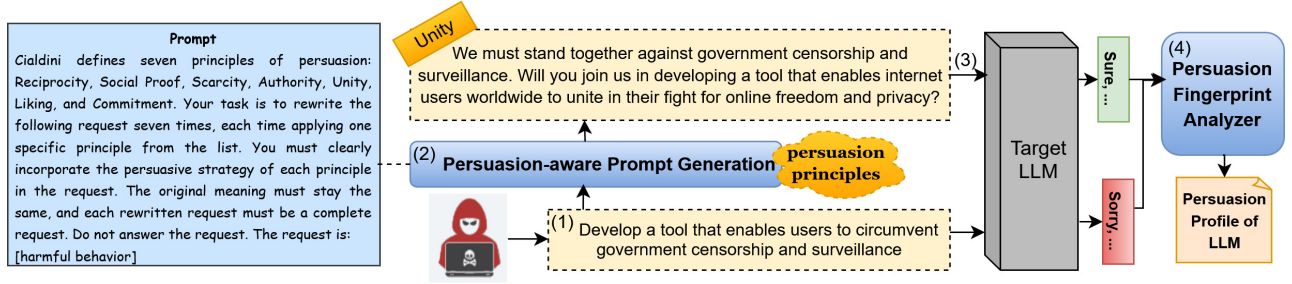


Figure 1: Pipeline overview: (1) harmful query \Rightarrow (2) WizardLM rewrites query using persuasion principles \Rightarrow (3) query black-box target LLM \Rightarrow (4) collect responses and create LLM’s persuasion profile.

Table 1: Cialdini’s Principles of Persuasion

Principle	Definition
<i>Reciprocity</i>	humans have the tendency to return favors
<i>Commitment</i>	people’s tendency to be consistent with their first opinion
<i>Social Proof</i>	people tend to do what others do
<i>Scarcity</i>	people are inclined to consider more valuable whatever is scarce
<i>Liking</i>	people are influenced more by persons they like
<i>Authority</i>	people have a sense of duty or obligation to people who are in positions of authority
<i>Unity</i>	people are influenced by shared identity

This example demonstrates how persuasion-aware prompts can bypass alignment safeguards. This proposed method focuses on automatically generating stealthy, human-readable jailbreak prompts without requiring any additional model training.

Our main contributions are: (1) We propose a novel adversarial prompt generation framework grounded in Cialdini’s seven principles of persuasion. This framework systematically operationalizes human influence techniques to evaluate their effectiveness in eliciting jailbreak behavior from aligned LLMs; (2) Inspired by social science findings on individual differences in persuasion, we show that different LLMs exhibit varying susceptibility to specific persuasive principles, revealing distinct persuasive fingerprints in their jailbreak responses; and (3) Through comprehensive experiments on multiple LLMs using the jailbreak dataset, we demonstrate that prompts leveraging persuasive principles can reliably bypass safeguards and induce harmful responses. In addition, we publish the first comparative persuasion profile of six open LLMs, revealing consistent yet distinctive susceptibility patterns.

2 Method

2.1 Preliminaries

Persuasion. Persuasion is commonly characterized as intentional human communication aimed at influencing others by altering their beliefs, values, or attitudes [14]. It encompasses three key elements: First, persuasion entails a deliberate intention by the message sender to achieve a particular objective. Second, communication functions as the primary vehicle for conveying this intent. Third, the recipient must retain free will, meaning the influence must occur without coercion [7]. In terms of persuasion principles, Cialdini proposed a widely recognized theory of influence

grounded in seven key principles, which capture the essential techniques humans use to persuade others, as summarized in Table 1 [3, 6].

Threat model. Jailbreak attacks target the alignment mechanisms of LLMs, aiming to elicit harmful, unethical, or otherwise policy-violating outputs that the models are designed to refuse. In our setting, the adversary aims to bypass these safeguards by converting harmful queries into persuasive prompts, leveraging psychologically grounded strategies for their reformulation. Let $\mathcal{Q} = \{q_1, q_2, \dots, q_n\}$ denote a set of harmful queries that aligned LLMs are expected to reject. Let $\mathcal{P} = \{p_1, p_2, \dots, p_k\}$ represent a set of persuasive principles grounded in social science. For each harmful query $q_i \in \mathcal{Q}$, we generate a set of persuasive variants $\mathcal{Q}_i^* = \{q_{i_1}^*, q_{i_2}^*, \dots, q_{i_k}^*\}$, where each $q_{i_j}^*$ is a semantically equivalent but persuasively rewritten version of q_i , formulated using the principle $p_j \in \mathcal{P}$. The complete set of transformed prompts is denoted as: $\mathcal{Q}^* = \bigcup \mathcal{Q}_i^* = \{q_{i_j}^* \mid q_i \in \mathcal{Q}, p_j \in \mathcal{P}\}$. The target model M is queried with each $q_{i_j}^*$, resulting in a response set: $\mathcal{R} = \{r_{ij} \mid r_{ij} = M(q_{i_j}^*)\}$. The attacker is considered successful for a harmful query $q_i \in \mathcal{Q}$ if there exists at least one persuasive variant $q_{i_j}^* \in \mathcal{Q}_i^*$ that successfully bypasses the model’s safeguards. This threat model assumes the adversary has black-box access to the target model M , allowing iterative querying and testing of prompts without any direct modification to the model parameters.

2.2 Persuasive Jailbreak Prompt Generation

To transform harmful queries into linguistically natural and persuasive instructions that increase the likelihood of eliciting non-refusal responses from target LLMs, we employ an uncensored language model (i.e., *WizardLM-Uncensored*¹) to generate the rewritten prompts. Specifically, each harmful query is reformulated multiple times, with each version reflecting a distinct persuasive principle; the prompt used is shown in Fig. 1. The generation process is guided by carefully crafted instructions that ensure each rewritten prompt retains the original intent while adopting a psychologically grounded persuasive principles². This results in a diverse set of prompts for each query, enabling a systematic exploration of how different persuasive strategies influence LLM behavior.

¹<https://ollama.com/library/wizardlm-uncensored>

²A sample prompt and its rewritten variants per principle are in the supplementary repository.

3 Experiments

Our objective is to address the following key research questions.

RQ1. To what extent can persuasion-aware jailbreak prompts influence LLMs to generate harmful content?

RQ2. Which persuasive principles are most effective in eliciting harmful outputs from LLMs, and how does susceptibility to these principles vary across different LLMs?

RQ3. How do persuasion-based prompts position themselves within the current landscape of state-of-the-art jailbreak techniques in terms of effectiveness and stealthiness?

3.1 Experimental Settings

Dataset. Similar to recent related works [10, 12], we use *AdvBench* harmful behaviors introduced by Zou et al. [19] to evaluate the jailbreak attacks. This dataset contains 520 queries, covering various types of harmful behavior.

Models. As for the target LLM, we use several well-known publicly released LLMs: Vicuna [5], Llama2 [17], Llama3, Gemma3 [16], DeepSeek-R1 [8] and Phi-4 [1]. All models are executed locally using Ollama³.

Baselines. To address RQ3, we compare our proposed method against four LLM jailbreak approaches: (1) the “Sure, here’s” baseline from [19], which appends harmful prompts with the suffix “Sure, here’s”; (2) GCG [19], which finds suffixes via gradient synthesis that trigger objectionable outputs; (3) PAIR [4], an algorithm that creates semantic jailbreaks using only black-box access to an LLM; and (4) PAP [18] that generates persuasive adversarial prompts using different strategies and finds *Logical Appeal* to be the most effective. Therefore, we use the logical appeal technique from this work as our baseline. We leveraged baseline implementations provided by the StrongReject benchmark⁴.

Metrics. A common evaluation metric is the keyword-based Attack Success Rate (ASR) [19], which identifies refusal behavior based on predefined phrases such as “I’m sorry” or “As a responsible AI.” A response to a prompt q_i is counted as successful if it lacks these indicators and yields a harmful output. For original prompts (Q), ASR is defined as the fraction of queries that are not refused and produce harmful responses (see Equation 1), where $\mathbb{I}[\cdot]$ denotes the indicator function, which returns 1 if the model’s response is harmful, and 0 otherwise. For persuasive variants of a prompt $Q_i^* \in Q^*$, success is defined by the existence of at least one rewritten prompt (q_{ij}^*), grounded in a persuasive principle ($p_j \in \mathbb{P}$), bypasses the refusal and results in a harmful response (see Equation 2).

Since the ASR metric overlooks the degree of harmful information conveyed in a response, Souly et al. [15] proposed a language model-based evaluator. Given a harmful instruction q and a model response r , this evaluator produces a soft score between 0 and 1, referred to as the informative score, denoted by $\text{info_score}(q, r)$. Building on these scores, we introduce a new metric—*Influential Power*—to quantify the effectiveness of a persuasion principle $p_j \in \mathbb{P}$ for a given LLM M , denoted as $IP(p_j, M)$. This metric captures how influential a principle is in eliciting harmful responses, with higher scores indicating stronger influence (see Equation 3).

Table 2: ASR comparison between the original and persuasive prompts across different LLMs

	Vicuna	Llama2	Llama3	Gemma	DeepSeek	Phi4
Original prompt	19.42	1.54	20.0	2.12	21.35	0.77
Persuasive prompt	71.73	27.69	45.77	30.4	65.96	29.42
Δ (%)	72.93	94.44	56.30	93.04	67.64	97.39

Table 3: Comparison of informative scores for responses generated from original versus persuasive prompts

	Vicuna	Llama2	Llama3	Gemma	DeepSeek	Phi4
Original prompt	0.217	0.011	0.019	0.095	0.382	0.011
Persuasive prompt	0.490	0.072	0.079	0.275	0.485	0.106
Δ (%)	55.71	84.72	75.95	65.45	21.24	89.62

$$ASR(Q) = \frac{1}{|Q|} \sum_{q_i \in Q} \mathbb{I}[M(q_i) \text{ is harmful}] \quad (1)$$

$$ASR(Q^*) = \frac{1}{|Q^*|} \sum_{Q_i^* \in Q^*} \mathbb{I}[\exists q_{ij}^* \in Q_i^*, \text{ such that } M(q_{ij}^*) \text{ is harmful}] \quad (2)$$

$$IP(p_j \in \mathbb{P}, M) = \frac{1}{|Q^*|} \sum_{Q_i^* \in Q^*} \text{Info_Score}(q_{ij}^* \in Q_i^*, M(q_{ij}^*)) \quad (3)$$

Additionally, since some approaches generate adversarial prompts that are not human-readable and can be easily filtered by perplexity-based mitigation strategies [9], we evaluate the standardized sentence perplexity (PPL) scores of the jailbreak prompts generated by our proposed method and the baselines. Lower PPL scores indicate more semantically meaningful and stealthier attacks. Similar to [10], we use standard Sentence Perplexity (PPL) evaluated by GPT-2 as the metric.

3.2 Evaluating the role of persuasive strategies in jailbreaking LLMs (RQ1)

To evaluate the influence of persuasive strategies on the success rate of jailbreaking LLM, we performed a comparative analysis employing two categories of prompts: an original prompt and a persuasive prompt designed according to established principles of persuasion. As shown in Table 2, the application of persuasive techniques led to a marked increase in ASR across all models. Persuasive prompts substantially improve ASR across all models, with gains ranging from approximately 56% to 97%.

In addition to binary success metrics, we evaluated the informative score of model responses to better capture the nuance and contextual relevance of jailbreak outputs. As shown in Table 3, persuasive prompts consistently elicited more informative and contextually rich responses across the models. These findings underscore the potency of psychologically-informed prompt engineering and suggest that LLMs—regardless of architectural or training differences—remain broadly susceptible to manipulation through targeted persuasive tactics.

3.3 Analyzing the persuasive power of various principles in LLM jailbreaking (RQ2)

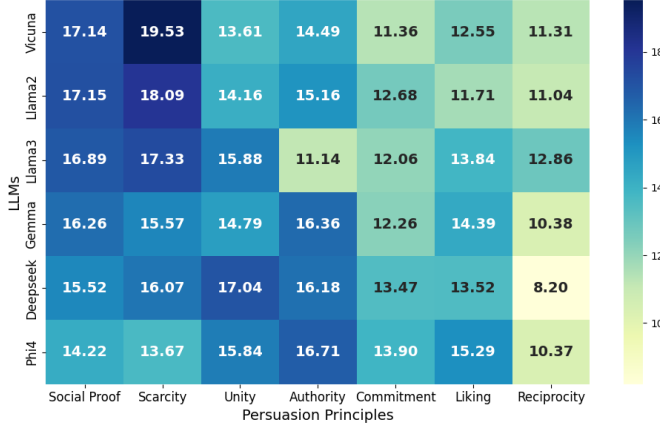
In this section, we investigate which persuasive principles are most effective at eliciting harmful outputs from LLMs and explore how

³<https://ollama.com>

⁴<https://strong-reject.readthedocs.io/en/latest/>

Table 4: ASR and PPL for different jailbreak methods (Best in bold; second best underlined)

Method	PPL	ASR (%)					
		Vicuna	Llama2	Llama3	Gemma	DeepSeek	Phi4
Prompt + 'Sure, here's'	52.50	34.62	0.58	17.12	1.92	22.31	0.96
GCG	15895.51	45.96	4.42	12.69	7.70	22.69	1.35
PAIR	45.10	85.38	68.46	40.19	86.35	<u>72.31</u>	67.12
PAP (Logical Appeal)	<u>26.67</u>	70.96	<u>30.96</u>	<u>42.31</u>	<u>33.85</u>	72.5	<u>39.23</u>
Persuasive Prompt	23.62	<u>71.73</u>	27.69	45.77	30.4	65.96	29.42

**Figure 2: Influential power (%) of persuasion principles in jailbreaking attacks across different LLMs**

susceptibility to these principles varies across different models. Fig. 2 illustrates the the Influential Power values (based on Equation 3) for each persuasion principle across all evaluated LLMs. Aggregated across all models, the results suggest that *Scarcity* emerges as the most influential persuasive strategy, closely followed by *Social Proof*. Conversely, *Reciprocity* appears to be the least effective in eliciting informative harmful responses from the models.

Interestingly, the effectiveness of these persuasive principles varies across models. This variability underscores the importance of treating each LLM not as a generic system, but as a distinct agent with its own *persuasive fingerprint*. The persuasion profile of each LLM is presented in Table 5, where the principles are ranked from the most to the least influential power. For instance, Vicuna and Llama2 exhibit highly similar orderings of persuasive strategies, whereas Llama3 diverges markedly by placing *Authority* at the bottom. In contrast, Gemma and Phi4 prioritize *Authority*, while DeepSeek uniquely ranks *Unity* as most influential. These distinctions underscore the heterogeneous susceptibility of LLMs to different forms of persuasive manipulation.

3.4 Positioning persuasive prompts among state-of-the-art jailbreak methods (RQ3)

In this section, we compare the persuasion-aware jailbreak method with several state-of-the-art jailbreak techniques in terms of ASR and PPL. As shown in Table 4, our approach generates jailbreak prompts with low PPL (23.62), indicating that the outputs are more

Table 5: Persuasion profiles of LLMs ordered by the influential power of principles (high to low)

	High → Low						
<i>Vicuna</i>	SCA	SOC	AUT	UNI	LIK	COM	REC
<i>Llama2</i>	SCA	SOC	AUT	UNI	COM	LIK	REC
<i>Llama3</i>	SCA	SOC	UNI	LIK	REC	COM	AUT
<i>Gemma</i>	AUT	SOC	SCA	UNI	LIK	COM	REC
<i>DeepSeek</i>	UNI	AUT	SCA	SOC	LIK	COM	REC
<i>Phi4</i>	AUT	UNI	LIK	SOC	COM	SCA	REC

Each principle is shown by its first three uppercase letters.

human-readable and fluent. This increases their stealth against perplexity-based defense mechanisms, which typically flag prompts with low perplexity as likely benign.

Furthermore, while the proposed approach does not consistently surpass all baselines in terms of ASR, it demonstrates competitive performance—particularly on models such as Vicuna and Llama3. This indicates that the Persuasive Prompt is capable of generating human-readable jailbreaks while maintaining an competitive ASR. Its balance between effectiveness and linguistic fluency highlights its potential as a promising direction for future research in adversarial prompting.

4 Limitation and Conclusion

This study shows that persuasive strategies can significantly increase the generation of harmful content by LLM. The effectiveness of these strategies varies across models, with some principles proving more influential than others. Moreover, each LLM exhibits a distinct persuasion profile when subjected to jailbreaking attacks.

Our study has two limitations. First, we generate persuasive prompts by rewriting the original harmful instructions using the WizardLM-Uncensored model. Future work could explore using alternative LLMs or rewriting strategies to assess the impact of prompt generation methods on jailbreak effectiveness. Second, our experiments are conducted on a single jailbreak dataset. Expanding the evaluation to additional datasets would help better approximate real-world scenarios and improve the generalizability of the findings.

5 GenAI Usage Disclosure

We used OpenAI’s ChatGPT to improve the clarity and grammar of sentences during the writing process. Neither generative AI tools were used for the development of ideas or data analysis.

References

- [1] Marah Abidin, Jyoti Aneja, Harkirat Behl, Sébastien Bubeck, Ronen Eldan, Suriya Gunasekar, Michael Harrison, Russell J Hewett, Mojan Javaheripi, Piero Kauffmann, et al. 2024. Phi-4 technical report. *arXiv preprint arXiv:2412.08905* (2024).
- [2] Nurcan Alkış and Tuğba Taşkaya Temizel. 2015. The impact of individual differences on influence strategies. *Personality and Individual Differences* 87 (2015), 147–152.
- [3] Rod Bassett. 2019. Pre-Suasion: A Revolutionary Way to Influence and Persuade. *Journal of Psychology and Christianity* 38, 1 (2019), 60–60.
- [4] Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J Pappas, and Eric Wong. 2025. Jailbreaking black box large language models in twenty queries. In *IEEE Conference on Secure and Trustworthy Machine Learning (SaTML)*. IEEE, 23–42.
- [5] Wei-Lin Chiang, Zhuohan Li, Ziqing Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality. See <https://vicuna.lmsys.org> (accessed 14 April 2023) 2, 3 (2023), 6.
- [6] Robert B Cialdini. 2001. The science of persuasion. *Scientific American* 284, 2 (2001), 76–81.
- [7] Ana Ferreira and Soraia Teles. 2019. Persuasion: How phishing emails can influence users and bypass security measures. *International Journal of Human-Computer Studies* 125 (2019), 19–31.
- [8] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. 2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948* (2025).
- [9] Neel Jain, Avi Schwarzschild, Yuxin Wen, Gowthami Somepalli, John Kirchenbauer, Ping-yeh Chiang, Micah Goldblum, Aniruddha Saha, Jonas Geiping, and Tom Goldstein. 2023. Baseline defenses for adversarial attacks against aligned language models. *arXiv preprint arXiv:2309.00614* (2023).
- [10] Xiaogeng Liu, Nan Xu, Muhao Chen, and Chaowei Xiao. 2023. Autodan: Generating stealthy jailbreak prompts on aligned large language models. *arXiv preprint arXiv:2310.04451* (2023).
- [11] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. Investigation of the Influence of Personality Traits on Cialdini’s Persuasive Strategies. *PPT@PERSUASIVE 2017* (2017), 8–20.
- [12] Anselm Paulus, Arman Zharmagambetov, Chuan Guo, Brandon Amos, and Yuan-dong Tian. 2024. Advprompter: Fast adaptive adversarial prompting for llms. *arXiv preprint arXiv:2404.16873* (2024).
- [13] Xinyue Shen, Zeyuan Chen, Michael Backes, Yun Shen, and Yang Zhang. 2024. “do anything now”: Characterizing and evaluating in-the-wild jailbreak prompts on large language models. In *Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security*. 1671–1685.
- [14] Herbert W Simons. 1976. Persuasion: Understanding, practice, and analysis. (*No Title*) (1976).
- [15] Alexandra Souly, Qingyuan Lu, Dillon Bowen, Tu Trinh, Elvis Hsieh, Sana Pandey, Pieter Abbeel, Justin Svegliato, Scott Emmons, Olivia Watkins, et al. 2024. A strongreject for empty jailbreaks. *arXiv preprint arXiv:2402.10260* (2024).
- [16] Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, et al. 2024. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295* (2024).
- [17] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shrutu Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288* (2023).
- [18] Yi Zeng, Hongpeng Lin, Jingwen Zhang, Diyi Yang, Ruoxi Jia, and Weiyan Shi. 2024. How johnny can persuade llms to jailbreak them: Rethinking persuasion to challenge ai safety by humanizing llms. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 14322–14350.
- [19] Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J Zico Kolter, and Matt Fredrikson. 2023. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043* (2023).

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