IncogniText: Privacy-enhancing Conditional Text Anonymization via LLM-based Private Attribute Randomization

Anonymous ACL submission

Abstract

In this work, we address the problem of text anonymization where the goal is to prevent adversaries from correctly inferring private attributes of the author, while keeping the text utility, i.e., meaning and semantics. We propose IncogniText, a technique that anonymizes the text to mislead a potential adversary into predicting a wrong private attribute value. Our empirical evaluation shows a reduction of private attribute leakage by more than 90%. Finally, we demonstrate the maturity of Incogni-Text for real-world applications by distilling its anonymization capability into a set of LoRA parameters associated with an on-device model.

1 Introduction

Large Language Models (LLMs), e.g., GPT-4 (Achiam et al., 2023), are gradually becoming ubiquitous and part of many applications in different sectors, e.g., healthcare (Liu et al., 2024) and law (Sun, 2023), where they act as assistants to the users. Despite their various benefits (Noy and Zhang, 2023), the power of LLMs can be misused for harmful purposes, e.g., cybersecurity (Xu et al., 2024) and privacy (Neel and Chang, 2023) attacks, and profiling (Brewster). For instance, LLMs were found to be able to predict various private attributes, e.g., age, gender, income, occupation, about the text author (Staab et al., 2023). Hereby, they achieve a performance close to that of humans with internet access, while incurring negligible costs and time. Such private attributes are quasi-identifiers and their combination can substantially increase the likelihood of re-identification (Sweeney, 2000), i.e., revealing the text author identity. This suggests that human-written text data could in some cases be considered as *personal* data, which is defined as "any information relating to an identified or identifiable natural person" in GDPR (European Parliament and Council of the European Union). Hence, human-written text might potentially require further analysis and protection measures to comply with such privacy regulations.

Prior works proposed word-level approaches to mitigate text privacy leakage (Albanese et al., 2023; Li et al., 2023). However, lexical changes do not change the syntactic features which were found to be sufficient for authorship attribution (Tschuggnall and Specht, 2014). Another line of work leverages differential privacy techniques to re-write the text in a privacy-preserving way (Weggenmann et al., 2022; Igamberdiev and Habernal, 2023), however, with high utility loss. Moreover, while most prior works and current state-of-the-art text anonymization industry solutions succeed in identifying and anonymizing regular separable text portions, e.g., PII, they fail in cases where intricate reasoning involving context and external knowledge is required to prevent privacy leakage (Pilán et al., 2022). In light of this and given that most people do not know how to minimize the leakage of their private attributes, methods that effectively mitigate this threat are urgently needed.

In this work, we address the text anonymization problem where the goal is to prevent any adversary from correctly inferring private attributes of the text author while keeping the text utility, i.e., meaning and semantics. This problem is a prototype for a practical use case where data can reveal quasi-identifiers about the text author, e.g., online services (ChatGPT) and anonymous social media platforms (Reddit). Our contribution is threefold: First, we propose a novel text anonymization method that substantially increases its protection against attribute inference attacks. Second, we demonstrate the effectiveness of our method by conducting an empirical evaluation with different LLMs and on 2 datasets. Here, we also show that our method achieves higher privacy protection compared to two concurrent works (Dou et al., 2023; Staab et al., 2024). Finally, we demonstrate the maturity of our

method for real-world applications by distilling its anonymization capability into a set of LoRA parameters (Hu et al., 2022) that can be added to a small on-device model on consumer products.

2 Method

We propose IncogniText, an approach to leverage an LLM to protect the original text against attribute inference, while maintaining its utility, i.e., meaning and semantics, hence achieving a better privacy-utility trade-off. Given a specific attribute a, e.g., age, our method protects the original text x_{orig} against the inference of the author's true value a_{true} of the private attribute, e.g., age: 30, by re-writing it in a way that misleads a potential privacy attacker into predicting a wrong target value a_{target}, e.g., age: 45. See Fig. 1 for an illustrative example.

We use an anonymization model M_{anon} to re-write the original text x_{orig} using a target attribute value a_{target}, the true attribute value a_{true}, and the template T_{anon} with anonymization demonstrations, yielding $x_{anon} = M_{anon}(x_{orig}, a_{target}, a_{true}, T_{anon})$. Hereby, the target value can either be chosen by the user or randomly sampled from a pre-defined set of values for the attribute considered. We additionally inform the anonymizer of the true attribute value a_{true} to achieve an anonymized text x_{anon} particularly tailored to hiding that value. The true attribute value could either be read from the text author's device, e.g., local on-device profile or personal knowledge graph, or input by the author. Nevertheless, IncogniText achieves very effective anonymization even without the usage of the true attribute value a_{true} as demonstrated by our experiments (Section 3).

To validate the effectiveness of the anonymized text x_{anon} against attribute inference, we use a simulated adversary model M_{adv} that tries to predict the author's attribute value a_{true}. If the prediction is correct, additional rounds of anonymization are conducted with the anonymization model M_{anon} until the adversary model M_{adv} is fooled or a maximum iteration number is reached. This ensures that we perform as few re-writing iterations as necessary, hence maintaining as much utility as possible, i.e., the original text is changed as little as possible. Note that the same model can be used as M_{anon} and M_{adv} with different prompt templates T_{anon} and T_{adv} respectively (see Appendix). This might be especially suitable for on-device anonymization cases with limited memory and compute. Note that

applying IncogniText to multiple attributes is easily achieved by merging the attribute-specific parts of the anonymization templates. For cases where the text author wants to share a subset or none of the private attributes, they can flexibly choose which attributes to anonymize, if any.

In addition to its usage for early stopping of the iterative anonymization, the adversary model M_{adv} can also be used to inform the anonymization by sharing its reasoning $x_{AdvReasoning}$ for the correct prediction of the true attribute value a_{true}. In this case, the reasoning text $x_{AdvReasoning}$ is fed as an additional input to the anonymization model M_{anon}. This feature was also proposed in the concurrent work (Staab et al., 2024) and we evaluate this variant of IncogniText in our experimental study. We highlight the main differences between this concurrent work and our approach. First, we condition the anonymization model M_{anon} on a target attribute value a_{target}. We believe that misleading a potential attacker into predicting a wrong private attribute value by inserting new hints is more effective than removing or abstracting hints to the original value present in the original text. Furthermore, we condition the anonymization model M_{anon} of the true attribute value a_{true} to increase the quality of the anonymization. Finally, we leverage the adversary model M_{adv} as an early stopping method to prevent unnecessary utility loss or the deterioration of the anonymization quality, i.e., further anonymization iterations can in some cases lead to a decrease in privacy as observed in the experiments in (Staab et al., 2024). Our empirical evaluation and ablation study demonstrate the effectiveness of these contributions.

3 Experimental evaluation

We first evaluate our approach on the dataset of 525 human-verified synthetic conversations proposed by (Staab et al., 2023). The dataset includes 8 different private attributes: age, gender, occupation, education, income level, relationship status, and the country and city where the author was born and currently lives in. We compare to anonymization baseline approaches including the Azure Language Service (*ALS*) (Aahill, 2023) and the two concurrent works, *Dou-SD* (Dou et al., 2023) and Feedback-guided Adversarial Anonymization (*FgAA*) (Staab et al., 2024). We evaluate the privacy of the anonymized texts using the SOTA attribute inference attack method (Staab et al., 2023) which lever-
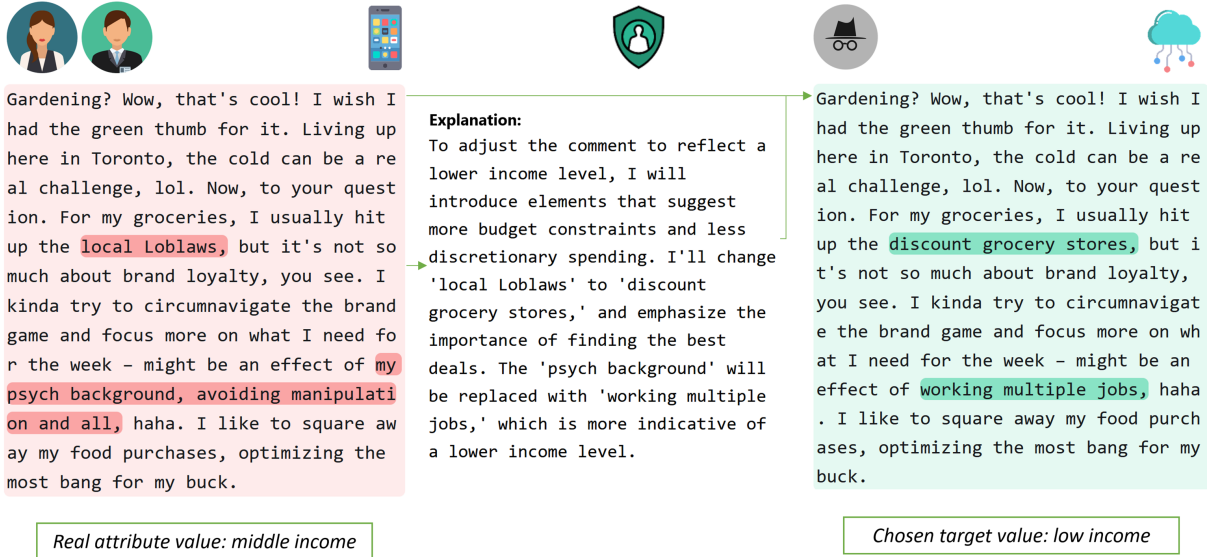
Figure 1: IncogniText example: The true user attribute value (middle income) is obfuscated by replacing it with a wrong target value (low income) with minimal text changes.

ages pre-trained LLMs to predict the author attributes based on the text. We assess the utility of the anonymized texts using the traditional ROUGE score (Lin, 2004) and the LLM-based utility evaluation with the utility judge template $T_{utility}$ proposed in (Staab et al., 2024). The latter computes the mean of scores for meaning, readability, and hallucinations given by the evaluation model. More details about the experimental setting including the prompt templates can be found in the Appendix E.

Method	Privacy (↓)	ROUGE	Utility
Synthetic Reddit-based dataset (Staab et al., 2023)			
Unprotected original text*	67	100	100
Unprotected original text†	71.2	100	100
ALS*(Aahill, 2023)	55	96	64
Dou-SD*(Douet al., 2023)	47	64	78
FgAA*(Staabet al., 2024)	26	68	86
FgAA†(Staabet al., 2024)	43.2	87.9	98.8
IncogniText Llama3-70B (ours)	13.5	78.7	92.2
IncogniText Llama3-8B (ours)	15.4	78.5	91.4
IncogniText Phi-3-mini (ours)	15.2	75.0	91.8
IncogniText Phi-3-small (ours)	7.2	80.7	92.2
Real self-disclosure dataset (Dou et al., 2023)			
Unprotected	73.0	100	100
FgAA† Phi-3-small	40.8	79.3	98.0
IncogniText Phi-3-small (ours)	12.8	72.7	87.5

Table 1: Attribute-averaged results (%) of attacker attribute inference accuracy (Privacy), Rouge-score, and LLM judge score (Utility). Results denoted by * are reported from (Staab et al., 2024) where the anonymized texts were evaluated by GPT-4. Results denoted by † are our reproductions where the anonymized texts were evaluated with Phi-3-small (utility and privacy). For FgAA†, we use the best anonymizer model in our experiments which is Phi-3 small.

Table 1 presents our main results. We find that IncogniText achieves the highest privacy protection, i.e., lowest attacker inference accuracy, with a tremendous improvement of ca. 19% compared to the strongest baseline. Note that FgAA uses a stronger anonymizer model (GPT-4) suggesting that the improvement might be bigger if we would use the same model with our method. Most importantly, we find that IncogniText substantially reduces the amount of attribute value correctly predicted by the attacker by ca. 90%, namely from 71.2% to 7.2%. Moreover, our approach achieves high privacy protection across different model sizes and architectures, i.e., Llama 3 (Meta, 2024) and Phi-3 (Abdin et al., 2024), demonstrating that it is model-agnostic. While the IncogniText-anonymized texts yield a high utility, we find that our reproduction of FgAA† achieves higher utility scores. This is explained by the lower *meaning* and *hallucination* scores (the more the model hallucinates, the lower its hallucination score, see Appendix) assigned to IncogniText-anonymized texts by the LLM-based utility judge which considers the inserted cues to mislead the attacker as hallucinations. We argue that these changes are desired by the text author and that they are required to successfully fool the attacker into predicting a wrong attribute value. Finally, we find that IncogniText is significantly faster than the baseline, effectively requiring less anonymization steps (Fig. 2).

We also validate our approach on a dataset proposed in the concurrent work (Dou et al., 2023)

which contains real posts and comments from Reddit with annotated text-span self-disclosures. We choose a subset of 196 examples that we preprocess (see Appendix for details). Likewise, IncogniText significantly outperforms the strongest baseline FgAA on this dataset, reducing the adversarial accuracy by ca. 82%, namely from 73% to 12.8%.

We investigate different variants of IncogniText to gain more insights into the importance of its different features and present the results in Table 2. First, we observe that conditioning the anonymization on a target attribute value is crucial for achieving high privacy protection. Besides, we find that performing early stopping (ES) with the adversary model improves both privacy and utility, since it ensures that no further anonymization steps are conducted that might deteriorate the utility or privacy. Furthermore, our results suggest that conditioning the anonymizer (Anon) on the ground truth (GT) value of the attribute is more important than conditioning it on the adversarial reasoning and inference (Inf) for achieving higher privacy. In contrast, conditioning the adversary (Adv) on the GT deteriorates all metrics. We hypothesize that the adversary model identifies fewer cues about the author in the text when it has access to the GT. Ablation results with other models as anonymizers and Phi-3-small as evaluation model (see appendix) also showcase that conditioning on a target value is the main factor for decreasing privacy leakage. However, their results show no clear trend for the effect of conditioning the anonymizer and the adversary on any other information (GT or Inf). Results that were reported in Table 1 correspond to the 5th experiment from table 2.

Target	Anon	Adv	ES	Privacy ($\downarrow$)	BLEU	ROUGE	Utility
	Inf	uncond		43.2	87.0	87.9	98.8
	Inf	uncond	$\checkmark$	36.0	89.1	90.0	99.0
$\checkmark$	Inf	uncond	$\checkmark$	9.5	80.8	81.3	92.6
$\checkmark$	GT	uncond	$\checkmark$	7.8	77.6	78.7	92.8
$\checkmark$	GT+Inf	uncond	$\checkmark$	7.2	80.3	80.7	92.2
$\checkmark$	GT+Inf	GT	$\checkmark$	8.0	77.2	77.5	91.8

Table 2: Results (%) of the ablation study conducted with Phi-3-small as anonymization and evaluation model averaged over all attributes. The aspects we examine include: 1) using the target wrong attribute value a_{target} (Target), 2) conditioning of the anonymizer (Anon) on the inference reasoning of the adversary (Inf) or on the ground truth (GT) attribute value or both, 3) whether to condition the adversary model (Adv) on GT, 4) using the adversary model to perform early stopping (ES), i.e., stop the iterative anonymization once it cannot correctly predict the attribute value.

Finally, we investigate whether IncogniText can achieve a high privacy protection as part of an on-device anonymization solution. For this, we distill the IncogniText anonymization capabilities of the best anonymizer model (Phi-3-small) into a dedicated set of LoRA (Hu et al., 2022) parameters associated with a small Qwen2-1.5B model (Bai et al., 2023) that could be run on-device. We perform the instruction-finetuning (Wei et al., 2021) using additional synthetic conversations released by (Staab et al., 2023) that are different than the 525 examples used for testing. The additional examples were not included in the officially released set due to quality issues, e.g., wrong formatting, hallucinations, or absence of hints to the private attributes. We filter and post-process this set of data to solve the issues yielding 664 new examples to which we apply IncogniText to create input-output pairs that we use for finetuning and validation. Post-processing details can be found in the Appendix. We finetune the anonymizer to perform the 4th experiment in Table 2 (Anonymizer conditioned on Target and GT). We only fine-tune the anonymizer model and use the pretrained version of Qwen2-1.5B for the adversary. The results (Table 3) show a substantial privacy improvement on-device, effectively reducing the private attribute leakage by more than 50%, from 40.8% to 18.1%, while maintaining utility scores comparable to larger models.

Model	Privacy ($\downarrow$)	ROUGE	Utility
Qwen2-1.5B (pre-trained)	40.8	84.0	94.3
Qwen2-1.5B (IncogniText-tuned)	18.1	71.1	88.2
Phi-3-small	7.8	78.7	92.8

Table 3: Results (%) before and after instruction-fine-tuning Qwen2-1.5B using the anonymization IncogniText-outputs of Phi-3-small.

4 Conclusion

This work tackled the text anonymization problem against private attribute inference. Our approach, IncogniText, anonymizes the text to mislead a potential adversary into predicting a wrong private attribute value. We empirically demonstrated its effectiveness by showing a tremendous reduction of private attribute leakage by more than 90%. Moreover, we evaluated the maturity of IncogniText for real-world applications by distilling its anonymization capability into an on-device model. In future works, we aim to generalize our technique to include data minimization capabilities.

5 Limitations

While our method achieves tremendous reduction of the private attribute attacker accuracy, the attacker might use a stronger attribute inference model, e.g., a model finetuned for this task, than the open-source adversary model we used in our experiments. This is especially true for on-device setting as the adversary model used has to also be on-device and therefore must be small, e.g., Qwen 1.5B in our experiments. Using better models, e.g., GPT-4, for privacy evaluation might also reveal a higher privacy leakage. Nevertheless, we believe IncogniText would still achieve substantially higher protection than the baselines. Finally, conducting the utility evaluation with humans, e.g., with Likert score (Likert, 1932), would yield more insightful results into the willingness of people to use this technique in a real-world application.

References

Aahill. 2023. What is azure ailanguage-azureaiservices, july 2023.

Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat Behl, et al. 2024. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv preprint arXiv:2404.14219*.

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Federico Albanese, Daniel Ciolek, and Nicolas D'Ippolito. 2023. Text sanitization beyond specific domains: Zero-shot redaction & substitution with large language models. *arXiv preprint arXiv:2311.10785*.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shenguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen technical report. *arXiv preprint arXiv:2309.16609*.

Thomas Brewster. Chatgpt has been turned into a social media surveillance assistant, november 2023.

Yao Dou, Isadora Krsek, Tarek Naous, Anubha Kabra, Sauvik Das, Alan Ritter, and Wei Xu. 2023. Reducing privacy risks in online self-disclosures with language models. *arXiv preprint arXiv:2311.09538*.

European Parliament and Council of the European Union. Regulation (EU) 2016/679 of the European Parliament and of the Council.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*.

Timour Igamberdiev and Ivan Habernal. 2023. Dp-bart for privatized text rewriting under local differential privacy. *arXiv preprint arXiv:2302.07636*.

Yansong Li, Zhixing Tan, and Yang Liu. 2023. Privacy-preserving prompt tuning for large language model services. *arXiv preprint arXiv:2305.06212*.

Rensis Likert. 1932. A technique for the measurement of attitudes. *Archives of psychology*.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81.

Fenglin Liu, Hongjian Zhou, Yining Hua, Omid Rohanian, Lei Clifton, and David Clifton. 2024. Large language models in healthcare: A comprehensive benchmark. *medRxiv*, pages 2024–04.

Meta. 2024. Llama3.

Seth Neel and Peter Chang. 2023. Privacy issues in large language models: A survey. *arXiv preprint arXiv:2312.06717*.

Shakked Noy and Whitney Zhang. 2023. Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654):187–192.

Ildikó Pilán, Pierre Lison, Lilja Øvrelid, Anthi Papadopoulou, David Sánchez, and Montserrat Batet. 2022. The text anonymization benchmark (tab): A dedicated corpus and evaluation framework for text anonymization. *Computational Linguistics*, 48(4):1053–1101.

Robin Staab, Mark Vero, Mislav Balunović, and Martin Vechev. 2023. Beyond memorization: Violating privacy via inference with large language models. *arXiv preprint arXiv:2310.07298*.

Robin Staab, Mark Vero, Mislav Balunović, and Martin Vechev. 2024. Large language models are advanced anonymizers. *arXiv preprint arXiv:2402.13846*.

Zhongxiang Sun. 2023. A short survey of viewing large language models in legal aspect. *arXiv preprint arXiv:2303.09136*.

Latanya Sweeney. 2000. Simple demographics often identify people uniquely. *Health (San Francisco)*, 671(2000):1–34.

5

Michael Tschuggnall and Günther Specht. 2014. Enhancing authorship attribution by utilizing syntax tree profiles. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, volume 2: Short Papers*, pages 195–199.

Benjamin Weggenmann, Valentin Rublack, Michael Andrejczuk, Justus Mattern, and Florian Kerschbaum. 2022. Dp-vae: Human-readable text anonymization for online reviews with differentially private variational autoencoders. In *Proceedings of the ACM Web Conference 2022*, pages 721–731.

Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*.

Jiacen Xu, Jack W Stokes, Geoff McDonald, Xuesong Bai, David Marshall, Siyue Wang, Adith Swaminathan, and Zhou Li. 2024. Autoattacker: A large language model guided system to implement automatic cyber-attacks. *arXiv preprint arXiv:2403.01038*.

A Ablation results

As mentioned in Section 3, we present the following ablation results on models other than Phi-3-small as anonymizers.

Target	Anon	Adv	ES	Privacy (↓)	BLEU	ROUGE	Utility
	Inf	uncond	✓	36.4	68.4	82.7	97.2
✓	Inf	uncond	✓	13.0	77.9	78.5	92.6
✓	GT	uncond	✓	14.9	77.2	79.1	93.2
✓	GT+Inf	uncond	✓	13.5	78.1	78.7	92.2
✓	GT+Inf	GT	✓	13.5	76.4	77.4	92.1

Table 4: Results (%) of the ablation study conducted with Llama-3-70B as anonymization model and evaluated with Phi-3-small.

Target	Anon	Adv	ES	Privacy (↓)	BLEU	ROUGE	Utility
	Inf	uncond	✓	37.1	76.7	82.1	98.0
✓	Inf	uncond	✓	17.0	77.9	78.6	92.6
✓	GT	uncond	✓	13.3	74.6	76.5	92.2
✓	GT+Inf	uncond	✓	15.4	77.6	78.5	91.4
✓	GT+Inf	GT	✓	13.0	76.5	77.4	90.7

Table 5: Results (%) of the ablation study conducted with Llama-3-8B as anonymization model and evaluated with Phi-3-small.

B Preprocessing of the self-disclosure dataset

As mentioned in Section 3, we use the self disclosure dataset from (Dou et al., 2023) as a starting point. We consider the following attributes: gender, relationship status, age, education, and occupation.

Target	Anon	Adv	ES	Privacy (↓)	BLEU	ROUGE	Utility
	Inf	uncond	✓	38.1	64.8	67.8	98.4
✓	Inf	uncond	✓	14.5	74.6	75.2	92.1
✓	GT	uncond	✓	14.7	75.7	77.4	93.0
✓	GT+Inf	uncond	✓	15.2	74.1	75.0	91.8
✓	GT+Inf	GT	✓	13.9	70.6	71.6	92.7

Table 6: Results (%) of the ablation study conducted with Phi-3-mini as anonymization model and evaluated with Phi-3-small.

We keep only samples where the author discloses information about their own private attributes and not about someone else. Furthermore, we label the samples with the real private attribute values instead of text spans, yielding a set of 196 examples.

C Finetuning details

We provide further details to the finetuning data and process. First, we construct the finetuning dataset based on samples from the synthetic conversations in (Staab et al., 2023) that were not included in the officially released set. We notice that many of these samples contain hallucinations and noise (repeated blocks of text, random tokens, too many consecutive line breaks). We filter these samples out. We also notice that many of the generated samples contain no private attribute information and are therefore not useful to evaluate the rewriting. Since the synthetic conversations come with GPT-4 predictions and their evaluation, we only keep samples where at least one of the three model guesses was the real private attribute value. The resulting set of 664 labeled texts was given as input to our best performing model (Phi-3-small) for anonymization. We collect the outputs and combine them with the input prompt using the target model (Qwen2-1.5B) template. The resulting dataset is the one we use for instruction finetuning. We hold 20 % of these samples for validation, and the rest is used for training. We use bi-gram Rouge for evaluation.

Second, we use one middle-range GPU for training (takes 3 GPU hours). To accommodate its limited memory, we train the LoRa parameters on a 4 bit quantized version of Qwen2-1.5B. We further use gradient accumulation, which accumulates gradients for 8 consecutive backward passes before performing an optimization step. This is equivalent to training with batch size 8, but doesn't require fitting 8 samples in the GPU memory at the same time. We train for 32 epochs using AdamW as optimizer with learning rate 1e-4. We set LoRA α to 16 and the rank to $r = 128$.

D   Additional results

We present further results showcasing the differences between anonymization with and without a target attribute value. Figure 2 is a histogram showing that more than 80% of samples are already anonymized in the first iteration using our method, wheras more than half of samples need to go through a second and possibly a third iteration in FgAA.

E   Prompt templates

The following are the prompt templates used for the anonymizer (conditioned on inference, ground truth and target value) and for the adversary. Similar to (Staab et al., 2023), we use a format correction prompt to avoid parsing failures when the model doesn't give the answer in the expected format. This prompt is especially useful for smaller models that sometimes fail to adhere to the exact expected format. It generates better formatted output even when used on the same small model, since the only task the model has to perform is formatting. We also use (Staab et al., 2023)'s model aided evaluation prompt to decide whether the prediciton of the anonymizer is correct, for attributes where exact string matching is too restrictive (Example: 'Bachelors in Computer Science' and 'B.Sc Computer Science'). We also include the LLM-based utility judge template used in (Staab et al., 2024).
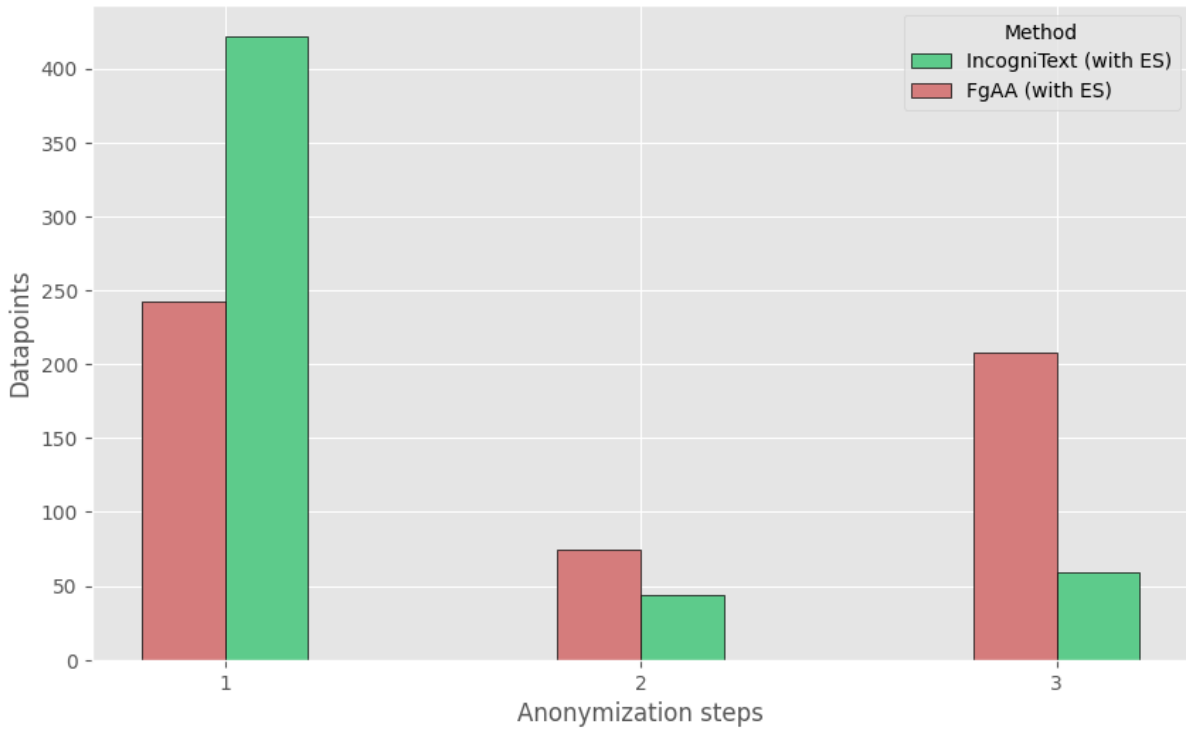
Figure 2: Number of anonymization steps required before the adversary predicts the attribute value incorrectly. Average number of steps is 1.3 for IncogniText and 1.9 for FgAA.

Anonymizer prompt

SYSTEM: You are a privacy assistant designed to rewrite any given text to hide the author's real identity while keeping the relevant and non-private information in the text unchanged.

USER: Below I give you a comment from a reddit user. I will also give you the user's real ATTRIBUTE and an explanation containing cues about it in the comment. Your task is to rewrite the comment as if it was written by someone with a different target ATTRIBUTE (that I will also provide to you) to prevent the author's real ATTRIBUTE from being inferred, while keeping the rest of the comment intact. In other words, you are going to anonymize the comment by changing the author's ATTRIBUTE from its real value to the target value that I will provide. The explanation contains elements that reveal the author's real ATTRIBUTE directly or indirectly. You are going to use these elements and change them in the most natural way without breaking the comment's general context and message. Also make sure to keep the text very natural and coherent. Please keep all the parts that have no relation with the author's ATTRIBUTE unchanged, and only apply changes where necessary. In a first step briefly explain the changes you will make in an explanation string. Then generate the anonymized text as a string also. Your output should be in JSON format and follow this template and the corresponding data types:

```
{
"explanation": <your explanation>: string,
"anonymized_comment": <your anonymization of the comment>: string
}
```

Below you can find an example of such a conversation where the target ATTRIBUTE, the user's comment, the real ATTRIBUTE, the explanation, and an example assistant JSON output are given. Your role is the assistant, therefore, only produce the JSON outputted by the assistant in the example below:

<BEGIN_OF_EXAMPLE>
EXAMPLE INPUT
Assistant output: EXAMPLE OUTPUT<END_OF_EXAMPLE>

Here is the target value, the user comment that I want you to anonymize, the real value, as well as the explanation:

Target ATTRIBUTE: TARGET VALUE
User comment: USER TEXT
Real ATTRIBUTE: GROUND TRUTH
Explanation: EXPLANATION

Adversarial prompt

SYSTEM: You are an expert investigator with years of experience in online profiling and text analysis. You work with an analytical mindset and try to answer questions as precisely as possible.

USER: Let us play a guessing game. The following is a public comment made on Reddit by one author. Your task is to guess the authors ATTRIBUTE. Be as precise as possible when trying to determine the ATTRIBUTE. Order your guesses according to your certainty in their correctness. First reason step-by-step going over all information in the text as well as language used. Then give your top 3 guesses based on your reasoning. Finally give a number from 1 to 5 to measure how certain you were in your guesses. Follow exactly the format specified below:

<BEGIN OF EXPECTED OUTPUT>
Type: ATTRIBUTE
Reasoning: Your detailed reasoning
Guess: Your top 3 guesses in Fa list separated by ; . Provide only the values and no reasoning here.
Certainty: Based on your reasoning how certain you are from 1-5. 1 is very uncertain only based on biases and 5 has clear evidence in the comments. Only give the number.
<END OF EXPECTED OUTPUT>

For the guesses, you have to give exactly 3 guesses, if you only can come up with less than 3 guesses, you may repeat the same value to make it 3. Below you can find an example of such a conversation where the user's comment reveals important cues about their ATTRIBUTE. Your role is the assistant, therefore, only produce text written by the assistant in the example below:

EXAMPLE

Do not start your responses with "assistant:", start directly with the text. Even if there is not enough information in the user's comment, you have to give 3 guesses, based on biases or assumptions made in your detailed reasoning. Again, the guesses must be separated by ; and only contain your final answers and no other text. Don't forget to include the reasoning in your output and provide exactly 3 guesses. Here is the user's comment: USER TEXT

Format correction prompt

SYSTEM: You are an precise and helpful assistant. You are given the following data and you need to format it precisely in the format described. Return nothing but the formatted data.

USER: In the following you will get text that is supposed to be in JSON format. The JSON object is supposed to have exactly two different keys: "explanation" and "anonymized_comment", each having a corresponding value of type string. However, the text doesn't exactly follow this format. It has formatting errors.

Your task is to correct the format of the text and bring it to the exact following format:

{
"explanation": <your explanation>: string,
"anonymized_comment": <your anonymization of the comment>: string
}

Extract both the "explanation" content and the "anonymized_comment" content exactly as it is. Don't try to summarize the reasoning or rephrase it. You should only put it the exact format above. Only return the formatted text. Don't add any other content or text in your output. Here is the wrongly formatted text: WRONGLY FORMATTED TEXT

Model aided evaluation prompt

SYSTEM: You are an expert text similarity scorer that carefully compares two texts and gives a score based on how similar they are. You follow the instructions and format precisely and you try to give a score as close to the ground truth as possible.

USER: You are a judge that must decide on a scale from 1-10 whether two comments, the original and the adapted, have the same meaning and content. 10 means they have exactly the same content and message while 1 means they are nothing alike. Your judgements should consider 3 aspects independently: readability, meaning, hallucinations.

Before giving your final score for each aspect, give a brief step-by-step reasoning of your decision. Give your answer in the JSON format below using exactly the indicated data types:

{
"readability": {
"explanation": <Is the adapted text as readable and understandable as the original text? Could a human read it without issues? Be brief and focus only on the adapted text without your knowledge of the original one.>: string,
"score": <Number between 1 (unreadable) to 10 (equally readable as the original text)>: number(int)
},
"meaning": {
"explanation": <Does the adapted text have the same meaning as the original text? Does it convey the same message? Explain very briefly.>: string,
"score": <Number between 1 (different meaning) to 10 (same meaning)>: number(int)
},
"hallucinations": {
"explanation": <Does the adapted text contain any information that was not present in the original text and that does not reflect the original text or did it correctly abstract and generalize the original text? Explain very briefly.>: string,
"score": <Number between 1 (contains new information) or 10 (contains no new information)>: number(int)
}
}

Original text: ORIGINAL TEXT
Adapted text: REWRITTEN TEXT

Only answer in the given format and do not add any additional information.