The State of Profanity Obfuscation in Natural Language Processing
Scientific Publications

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Abstract
Work on hate speech has made considering rude and harmful examples in scientific publications inevitable. This situation raises various problems, such as whether or not to obscure profanities. While science must accurately disclose what it does, the unwarranted spread of hate speech can harm readers and increases its internet frequency. While maintaining publications’ professional appearance, obfuscating profanities makes it challenging to evaluate the content, especially for non-native speakers. We discuss the problems with obfuscation and suggest a multilingual community resource called PrOF with a Python module to standardize profanity obfuscation processes. We believe PrOF can help scientific publication policies to make hate speech work accessible and comparable, irrespective of language.

Warning: this paper contains unobfuscated examples some readers may find offensive.

1 Introduction
A major downside of unsavory research subjects is that they still need to be investigated and reported, especially if we want to improve matters. Hateful language poses this challenge in natural language processing. We first need to collect and annotate it to detect, classify, and mitigate it. Setting aside the ethical conundrum of subjecting annotators to hateful language (Kennedy et al., 2018; Vidgen et al., 2019), reporting on it presents researchers with various challenges.

On the one hand, science should unflinchingly report on its subject matter, no matter how unpleasant (Jane, 2014). On the other hand, if that subject matter is language, then reporting on it is almost equivalent to producing it. This issue presents two problems: 1) proliferation and 2) audience framing.

Table 1: Examples originally reported as unobfuscated in research papers. Here we obfuscate them.

| Obfuscated | Unobfuscated                                                                 | Reference                      |
|------------|-------------------------------------------------------------------------------|--------------------------------|
| *h*mo      | A political *h*mo? I am not listening to a fairy gay *t*ggot [...]             | (Zhu and Bhat, 2021)          |
| *ck*       | suck a pig *d*ck *c*nt                                                       | (Botelho et al., 2021)        |
| *g*gas     | Bruh im tired of n*ggas [...]                                                 | (Shvets et al., 2021)         |
| *pe*her    | Someone should *r*pe her                                                      | (Guest et al., 2021)          |

Context should disambiguate whether a word is used in its intended meaning or as a meta-function of talking about the word (Jakobson, 2010) without using its original intent. However, written content that is freely accessible online might appear in unexpected contexts. E.g., as training data for language models (Brown et al., 2020).

Open access also means it is unclear who will read a given text. Scientific readers will likely assume the meta-function and discount hateful language. However, there is no guarantee as to who other readers may be. Disclaimers can help frame this problem and give the reader a choice. However, readers who do not want to read unpleasant examples should not be excluded from conducting research in hate speech detection. Disregarding their personal feelings about an offensive term seems cruel and insensitive at best, especially if they are members of targeted groups or abuse victims (see Table 1).

A compromise solution is obfuscation, where one or more letters in an offensive term are replaced with stars or other symbols. This approach preserves the word shape and allows interested readers to reconstruct the original word without allowing it to proliferate or forcing it upon readers.

However, based on our survey of 150 NLP papers, there are several issues with obfuscation:

- **Obfuscated words are often not discernible**, especially for non-native (English) speakers. Profanities are not taught in school, and we
cannot expect people learning English to know and recognize them when characters are hid-
den (Dewaele, 2004). This kind of language changes more readily than more formal lan-
guage - even older native speakers might not recognize novel slurs. Moreover, it is ba-
sically impossible to search for obfuscated words without guessing their meaning (not to mention the impact on the search history).¹

• Authors have many choices when obfuscat-
ing words, e.g., obfuscate only vowels, keep or obfuscate only the first letter, etc. As a re-
result, profanities can be obfuscated in a wide variety of ways, making their interpretation even harder. E.g., cunt, c*nt, c**t, c***.

• There is no clear definition of what is a pro-
fanity and what should be obfuscated, espe-
cially if a word has other, more neutral, mean-
ings. E.g., retarded or r*tarded.

• Profanities in languages other than English tend not to be obfuscated.

This prompts one simple question: How can we use profanity obfuscation in scientific publication? Among the 150 *ACL publications from 2021 re-
porting profanities, a number of solutions emerge. Even if standardization has been made in specific venues², these solutions are not consistent.

As outlined above, obfuscation leads to sev-
eral unintended problems, predominantly for non-
native speakers. As the NLP community grows, an increasing number of readers face this conun-
 dram. N***ger is easy enough to guess, but p*rker is difficult without advanced knowledge. Or, if you are a native speaker of English, consider Danish p*rker, German F*rger, or Italian bo**rino. Now try googling them. Moreover, many slurs and ins-
ults are culture-specific. For example, without knowledge of the history of racism in America, it is almost impossible to even guess at the meaning of c***n. This issue is related to the bias towards work on English in NLP (Bender and Friedman, 2018).

Contributions We surveyed profanity reporting in 150 scientific publications. Based on our findings, we propose PrOF (Profanity ObFuscation), a multi-lingual resource to help researchers converge on common procedures for profanity obfuscation. PrOF will permit researchers to report profanities in scientific publications while ensuring formal ap-
pearance, readability, and accessibility.

2 Do we need a framework for profanity obfuscation?

Research in hate speech inevitably needs to face the use of profanities in language. These taboo words are known to be perceived negatively (John-
son, 2012; Coyne et al., 2012), leading to height-
ened states of emotional arousal (Jay et al., 2008), and potentially causing vicarious trauma (Vidgen et al., 2019). As scholars publishing on open ac-
cess platforms, we need on the one hand to protect readers from this content and, on the other hand, to report the message in its unexpurgated entirety (Jane, 2014) because euphemisms and generic de-
scriptors cannot convey the hostility. Obfuscation, if not ideal, is the best compromise to deal with the conundrum of hateful language in scientific literature: obfuscated words should be discernible to allow accessibility and replicability. How can a researcher test the same examples if it is not pos-
sible to discern the text? At the same time, while the content deciphering is left to the reader, the conveyed emotion is still negative (Stout, 2015).

3 Methodology and Results

We surveyed the ACL Anthology for proceedings of *ACL conferences that took place in 2021 and a workshop specifically focused on abuse detec-
tion, the Workshop on Online Abuse and Harms (WOAH). We searched this data for occurrences of “*” and “#”, used to obfuscate profanities.³ For each paper that included one or more profanities, we noted whether or not the authors notify the use of profanities in the title or abstract. Each conference’s profanity count is listed in Table 2.

| Proceedings | # obfuscated profanities |
|-------------|--------------------------|
| ACL 2021    | 67                       |
| EACL 2021   | 15                       |
| EMNLP 2021  | 11                       |
| WOAH 2021   | 57                       |

Table 2: Statistics of papers using obfuscation.

¹None of the authors of this paper are native speakers of English and all have faced this issue.

²https://www.workshopononlineabuse.com/resources-and-policies/reporting-examples

³When the proceedings did not include all papers in a single file, we searched in each paper the mention of abusehateloffensiveltoxic in the title or abstract.
3.1 Current practice
Several approaches can be used for obfuscation. To minimize the possibility of offending readers, it is possible to completely obfuscate the word or maintain only the first letter. E.g. *f*uck would result in “****” or “f****” or “f*”. However, this practice makes the words (almost) impossible to decipher.

The most common practice is to obfuscate vowels. For example, *f*ucking would become “*f*ck*ing” or “*f*uck*ng” or “*f*ck*ng”. This hypothetically makes the meaning intelligible by suppressing the fewest number of characters.

Summarizing the scientific publications in the *ACL* community, the current practice is: (1) Obfuscation is always performed via the “*” symbol, (2) there is no shared practice of which letters to obfuscate, and (3) there are different sensibility levels when choosing which words to obfuscate, especially in languages other than English.

3.2 Considerations regarding obfuscation
Lack of a uniform profanity obfuscation in scientific articles affects readability and accessibility.

Lack of * use consistency Obfuscation is highly inconsistent across different papers. Some authors remove the first vowel (Xu et al., 2021a; Chuang et al., 2021; Lucchioni and Viviano, 2021; Xu et al., 2021b; ElSherief et al., 2021), others obfuscate two letters (e.g., *f***king**) (Qian et al., 2021; Sheng et al., 2021b; Turcan et al., 2021; Bhat et al., 2021), or obfuscate the first letter (e.g., *s*tick-*ing*) (Kang and Hovy, 2021), or other customized choices (Ousidhoum et al., 2021; Gros et al., 2021; Sawhney et al., 2021; Mishra et al., 2021; Baheti et al., 2021). Some choices may lead to sentences that are not understandable, e.g., “*All you n* and *s*” (Du et al., 2021). A more important issue is the lack of consistency within the same paper, further compounding the confusion around profanity obfuscation practices. For example, in Sheng et al. (2021a); Mostafazadeh Davani et al. (2021), the authors obfuscate almost all letters for some words but few for others (e.g., *f*** and a**hole*), and Salawu et al. (2021) use both p**xy and pu**y. If the same word is obfuscated differently, though, readers may think they are actually different words, maybe unknown (e.g., *putty*).

Word obfuscation choices Another problem is the choice of whether to obfuscate a word. Some authors choose to also obfuscate words that are not vulgar per se, such as *dumb* or *queer* (Caselli et al., 2021; Röttger et al., 2021), but that may be offensive in a specific context, i.e., when used as an insult. Again, we found a lack of consistency in obfuscation choices in the same paper. This means that some authors decide to obfuscate some words (e.g., ni***r) but not others (e.g., *wh*ore) (Cheng et al., 2021; Vidgen et al., 2021; Bagga et al., 2021; Laugier et al., 2021; Zhou et al., 2021).

Typos We also observed typos in obfuscated words. This can generate confusion for readers who might misinterpret these mistakes as unknown profanities. For example, we found b**itch (Bertaglia et al., 2021) and *wh*ore (Kirk et al., 2021).

No obfuscation A number of papers reported profanities without any form of obfuscation (Shvets et al., 2021; Fortuna et al., 2021; Hahn et al., 2021; Nozza, 2021; Zampieri et al., 2020; Sen et al., 2021; Chiril et al., 2021; An et al., 2021; Cercas Curry et al., 2021; Xie et al., 2021; Dale et al., 2021; Mehrabi et al., 2021; Leonardelli et al., 2021; Zhu and Bhat, 2021; Botelho et al., 2021; Guest et al., 2021; Hede et al., 2021). Some of these works study other languages in addition to English. Since the scientific research is English-centric, the authors potentially found the profanities in other languages less hurtful (Gonzalez-Reigosa, 1972; Harris et al., 2003; Christianson et al., 2017).

A possible solution for not using obfuscation in hate speech detection is to select examples that do not contain profanities (Niraula et al., 2021). However, we argue that scholars are responsible for reporting hate speech as severe as it is, no matter how unpleasant (Jane, 2014). Note that offensive language can occur in other non-hateful contexts as well (Malmasi and Zampieri, 2018).

Multimodality A challenging issue is profanities in images containing text, such as memes or artifact figures. While the same procedures outlined above could be applied, a solution is that (1) images created by the authors should conform to the standards, while (2) they can report images from the internet in their original form, but with a disclaimer on the paper’s first page. We observe this procedure in several publications (Zia et al., 2021; Kougia and Pavlopoulos, 2021; Qian et al., 2021; ElSherief et al., 2021; Baheti et al., 2021). There are still exceptions where artifact figures report unobfuscated profanities (An et al., 2021; Bucur et al., 2021; Zhou et al., 2021).
3.3 Considerations regarding disclaimers

Less than 20% of NLP papers use disclaimers of offensive content. However, the community needs to reach a behavioral standard. Knowing where and how disclaimers should be placed is important to ensure every reader is aware of the use of offensive examples in the paper. The papers including disclaimers applied very different practices. Disclaimers are placed (1) before the abstract (Xu et al., 2021b; Mehrabi et al., 2021), (2) after the abstract (Cercas Curry et al., 2021), (3) as a footnote on the first page (Nozza, 2021; Zampieri et al., 2020), or (4) under the table of offensive examples (Kang and Hovy, 2021; ElSherief et al., 2021). Most papers warning users of offensive language do not use any form of obfuscation in the paper. We recommend authors add an italicized disclaimer at the end of the abstract to signal that a paper includes offensive terms. This practice should be implemented even when profanities are obfuscated.

4 PROF

We propose PROF, a multi-lingual community resource for the obfuscation of profanities in scientific publications. It allows for the uninterrupted reading of papers with profanities while allowing non-native speakers to look up words and definitions if they desire. For the definition, we use the multi-lingual BabelNet (Navigli and Ponzetto, 2012). PROF consists of a table reporting: 1) the unobfuscated profanity (e.g., f*ck) 2) first-vowel obfuscation (e.g., f*ck) 3) the language (e.g., English) 4) the part-of-speech (POS) tag (e.g., NOUN) 5) the BabelNet multi-lingual synset (e.g., https://babelnet.org/synset?id=bn:00006453n&lang=EN) or other resources if the synset does not exist.

We suggest the obfuscation practice of removing the first vowel. For compound words, we obfuscate the first vowel of the element with an offensive meaning (e.g., femin*zis).

We extend PROF to other languages with the help of native speakers, reaching a total of 203 profanities: 50 in English, 44 in French, 19 in German, 42 in Italian, and 48 in Spanish. Details about PROF construction are given in Appendix 4.

We understand that our work is currently limited to the profanities of the languages we speak and the set of profanities we cover. However, we currently cover all the profanities reported in ~3000 published papers. As we advance, we hope that PROF will be used as a community-based research tool that evolves in conjunction with the research conducted on it. Therefore, we aim for a crowdsourcing strategy. We recommend that researchers submit their entries to the project repository, which the authors of this paper will maintain. This method ensures the repository is comprehensive and up-to-date while also facilitating access.

PROF construction PROF construction starts with the list of English profanities surveyed from recent proceedings of *ACL conferences (see Section 3). This starting list comprises 50 entries, of which 37 unique terms and 4 unique POS tags (ADJ, ADV, NOUN, VERB). Note that profanities can be associated with different POS tags (e.g., f*ck can be a noun, a verb, and an adverb). Table 3 lists the most common English profanities and their associated obfuscated version.

We used these 50 English profanities as a seed for creating German, Italian, French, and Spanish PROF. Using BabelNet, we retrieve all associated concepts in other languages for each profanity. Note that each language is characterized by a different number of profanities that can be associated with a target group (e.g., women). Using BabelNet instead of a translation tool enables us to retrieve all these terms instead of just one exact translation.

The limitation of this approach is that the number of retrieved concepts starting from one term is very high and not all relevant. For example, some terms can be used to refer to profane acts in some contexts, but their main meaning is non-profane (e.g., avvitare (screw) is a word that can also refer to the act of having sexual intercourse). In other cases, the profanities related concepts in BabelNet are still in English or are literally translated, resulting in nonsense terms in the target language (e.g., piece of tail4 is literally translated in Italian with the non-existing idiom pezzo di coda). For this reason, we use a hurtful lexicon to filter retrieved related concepts (Bassignana et al., 2018).

Finally, we asked native speakers to validate the resulting filtered list of terms by removing terms that were not unambiguous profanities. We also permit native speakers to include additional profanities if they felt some popular ones were missing, on average they added 4 profanities.

4https://www.urbandictionary.com/define.php?term=Piece%20of%20Tail
Table 3: Most common obfuscated profanities in 2021 ACL proceedings with their counts.

| obfuscated word | count |
|-----------------|-------|
| f*ck            | 20    |
| n*gga           | 14    |
| b*tch           | 13    |
| f*cking         | 9     |
| f*g             | 8     |
| n*gger          | 8     |
| sh*t            | 8     |
| sl*t            | 7     |

5 Related Work

Profanities have been investigated in NLP for discovering how to automatically filter them or how to prevent their obfuscation. These issues can be solved straightforwardly with a forbidden word list. However, preparing this list is difficult, as people are constantly creating new forms to avoid filtering via dictionary lookups, such as $h!t, shIt, or s.h.i.t. I.e., introducing spacing or punctuation between letters, swapping or removing characters, and 0–9 substitutions. Approaches to automatically filter variations of vulgar words are based on string matching techniques (Yoon et al., 2010; Ghauth and Sukhur, 2015). The research on de-obfuscation of profanities is much larger. This is due to NLP tools’ need to access the content of a sentence. Several studies (Mishra et al., 2018a,b; Eger et al., 2019; Mehdad and Tetreault, 2016) showed that obfuscated words are often ignored or treated as out-of-vocabulary impacting tasks like sentiment analysis or hate speech detection. Methods range from sequence alignment algorithms used in genomics (Rojas-Galeano, 2017) to word embeddings (Lee et al., 2018; Renwick and Barbosa, 2021). Our work differs from this literature in that we focus on scientific publications, not on social media. In this setting, the use of a dictionary is feasible.

6 Conclusion

Our work highlights the lack of obfuscation standards for reporting profanities in scientific publications. Prevailing practice allows for dangerous procedures and restricted access. We introduce PROF, a resource to standardize profanity obfuscation in scientific publications. PROF allows researchers to prevent offending readers while ensuring that information is readable and accessible. We plan to expand to more languages. As researchers add new words featured in their papers, PROF will grow along with the number of publications.

Limitations

We consider as profanities words that have highly offensive or vulgar connotations. We acknowledge that readers may have different sensibilities with respect to profanities. Obscene words depend on different factors, such as culture, social or religious background, and more (Hovy and Yang, 2021). Consequently, some words may be disturbing for a number of people, and should be obfuscated, while other readers may not have any issue with reading them. Moreover, we should consider that there is typically a hierarchy of offense, whereby some words are more severe than others; for example, f*ck is often socially accepted while the n-word usually is not (Sap et al., 2019).

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A Data Statement

We follow Bender and Friedman (2018) on providing a Data Statement for the proposed PROF resource.

Language-specific profanities have been validated by native speakers of each language (French, German, Italian, and Spanish). The annotators are in the age group of 25-35 and have experience in computational linguistics. Annotators were chosen from among colleagues and instructed on the research objective. The data we share is not sensitive to personal information, as it does not contain information about individuals.

B Python package

We released PROF as a Python package under the MIT license. We report some code snippets for demonstrating how the library can be used to obfuscate a profanity from a string (Figure 1) or from a text file, like a LaTeX source (Figure 2). Figure 3 shows how our library can be used for revealing a profanity from its obfuscated version. Finally, Figure 4 demonstrates the use of PROF as a web application for obfuscating and de-obfuscating profanities.
Proanity Obfuscation

Obfuscate

| A political homo? I am not listening to a fairy gay faggot for anyone. |

The obfuscated sentence is: A political h*mo? I am not listening to a fairy gay f*ggot for anyone.

Deobfuscate

| A political h*mo? I am not listening to a fairy gay f*ggot for anyone. |

The obfuscated sentence is: A political homo? I am not listening to a fairy gay faggot for anyone.

Figure 4: Usage examples of the web-app for obfuscating and revealing obfuscated profanities using the example in Table 1.
ACL 2023 Responsible NLP Checklist

A For every submission:

✔ A1. Did you describe the limitations of your work?
   Limitations section

✔ A2. Did you discuss any potential risks of your work?
   Limitations section

✔ A3. Do the abstract and introduction summarize the paper’s main claims?
   Abstract and Introduction

✘ A4. Have you used AI writing assistants when working on this paper?
   Left blank.

B ✔ Did you use or create scientific artifacts?

4

☐ B1. Did you cite the creators of artifacts you used?
   Not applicable. Left blank.

✔ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
   GitHub webpage

☐ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?
   Not applicable. Left blank.

☐ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?
   Not applicable. Left blank.

✔ B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?
   Appendix B

✔ B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.
   Section 4

C ☐ Did you run computational experiments?

Left blank.

☐ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
   No response.

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.
C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
No response.

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
No response.

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
No response.

D  ✓ Did you use human annotators (e.g., crowdworkers) or research with human participants?
Appendix A

X D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
Annotators were asked to validate a limited set of profanities, and instructions were communicated via short in-person discussion.

✓ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants’ demographic (e.g., country of residence)?
Appendix A

✓ D3. Did you discuss whether and how consent was obtained from people whose data you’re using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
Appendix A

☐ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
Not applicable. Left blank.

✓ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
Appendix A