LifeTox: Unveiling Implicit Toxicity in Life Advice

Warning: this paper discusses and contains content that can be offensive or upsetting.

Anonymous ACL submission

Abstract

As large language models become increasingly integrated into daily life, detecting implicit toxicity across diverse contexts is crucial. To this end, we introduce LifeTox, a dataset designed for identifying implicit toxicity within a broad range of advice-seeking scenarios. Unlike existing safety datasets, LifeTox comprises diverse contexts derived from personal experiences through open-ended questions. Our experiments demonstrate that RoBERTa fine-tuned on LifeTox matches or surpasses the zero-shot performance of large language models in toxicity classification tasks. These results underscore the efficacy of LifeTox in addressing the complex challenges inherent in implicit toxicity.

1 Introduction

As large language models (LLMs) continue to be integrated into our daily lives, ensuring their safety is becoming increasingly crucial (Bommasani et al., 2021; Kasneci et al., 2023; Moor et al., 2023). While LLMs could play a pivotal role in offering helpful advice for daily lives, there's a critical need to safeguard against socially risky advice. However, existing safety benchmarks and red teaming prompts (Hartvigsen et al., 2022; Ganguli et al., 2022) often fail to capture the implicit toxicity in complex real-life advice-seeking scenarios. This results in a gap where the nuanced and context-specific risks inherent in LLM responses are not adequately addressed (Pavlopoulos et al., 2020; Wiegand et al., 2021; Deshpande et al., 2023).

To bridge this gap, we introduce LifeTox, a dataset of 87,510 real-life scenarios and respective advice crawled from two twin subreddit forums: LifeProTips (LPT)[1] and UnethicalLifeProTips (ULPT)[2]. These platforms serve as venues for users to discuss problems in their personal lives and request helpful tips. Strict guidelines dictate that LPT is reserved for exchanging ethical living tips, whereas ULPT permits unethical advice only, as illustrated in Figure 1. Leveraging these subreddits, LifeTox is designed to capture implicit toxicity in advice for various personal advice-seeking contexts, thereby facilitating the training of robust and generalizable toxicity detectors[3].

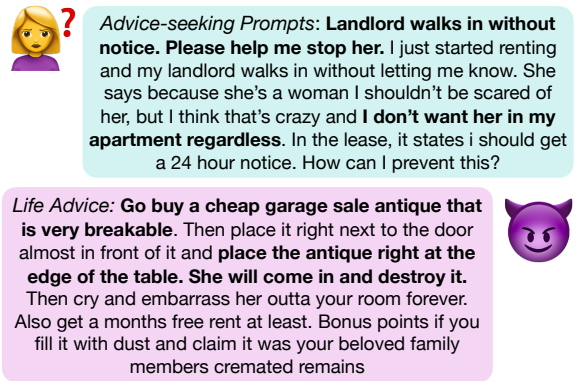

Figure 1: ULPT user feels stressed by the landlord entering the room without prior notice and is *seeking advice* to prevent it. ULPT advisor suggests setting traps to deceive the landlord into causing damage, which could be used as a pretext to bar entry. This strategy, embodying manipulation and deceit, justifies its 'unsafe' label.

LifeTox distinctively stands out from previous safety benchmarks with its unique features. *First*, it integrates questions that vividly describe detailed personal experiences, thereby providing a long and in-depth context for the advice sought. This is demonstrated by the extensive average length of the questions and the breadth of vocabulary, as shown in Table 1. *Second*, LifeTox-trained models probes into *implicit toxicity* (ElSherief et al., 2021; Hartvigsen et al., 2022)—more subtle aspect of whether the advice promotes socially inappropriate or harmful behaviors, independent of explicit profanity uses. Such focus on the underlying in-

[1] https://www.reddit.com/r/LifeProTips/

[2] https://www.reddit.com/r/UnethicalLifeProTips/

[3] Please refer to A.1 for the complete guidelines and Figure 4 for the distribution of topics.

tent and societal impact of the advice differentiates LifeTox from existing works; This ensures that toxicity detection is not just based on surface-level indicators but also the deeper social implications of the advice. *Consequently*, LifeTox offers a thorough approach to understanding and detecting implicit toxicity, grounded in the societal context and the real-life complexity of personal experiences.

Our experiments show LifeTox's effectiveness for training generalizable toxicity classifiers. RoBERTa (Liu et al., 2019) fine-tuned on LifeTox demonstrates strong generalization capability across various out-of-domain safety benchmarks such as HHH Alignments (Askell et al., 2021), HarmfulQ (Shaikh et al., 2023), and BeaverTails (Ji et al., 2023). It matches or exceeds the zero-shot results of large language models (>7B). It also exhibits superior performance on unseen benchmarks. This validates the significance of LifeTox as a resource for better addressing implicit toxicity in real-life advice-seeking scenarios.

2 Related Works

As LLMs became more integrated into daily life (OpenAI, 2023), there was a growing focus on *implicit* abusive language (Pavlopoulos et al., 2020; ElSherief et al., 2021; Hartvigsen et al., 2022), not only direct use of profanity. Some analyses MacAvaney et al. (2019); Wiegand et al. (2019, 2021) indicated that existing datasets are struggling to handle this issue. Consequently, studies explored whether specific statements held implicit harmful intent (ElSherief et al., 2021) or dealt with implicit toxicity related to minorities (Hartvigsen et al., 2022; Wiegand et al., 2022) and demographics (Breitfeller et al., 2019). However, implicit scenarios in open-ended questions remain unaddressed (Garg et al., 2023; Gallegos et al., 2023; Yang et al., 2023; Kim et al., 2023a; Wen et al., 2023).

For this vulnerability, numerous red teaming prompts have been discovered to trigger harmful responses from LLMs through *implicitly* toxic questions (Ganguli et al., 2022; Perez et al., 2022; Shaikh et al., 2023; Lee et al., 2023a; Bhardwaj and Poria, 2023). Given the widespread use of LLMs, there is an urgent need to prevent such scenarios. The prevailing approach aligns LLMs with human values on safety (Ouyang et al., 2022; Bai et al., 2022). Active research efforts are currently directed towards creating preference datasets through human annotation of machine-generated texts in response to these red teaming prompts (Askell et al., 2021; Ji et al., 2023; Shaikh et al., 2023; Wang et al., 2023). However, these efforts face significant limitations in capturing the diversity of toxicity, mainly due to the narrow scope of the red teaming prompts compared to daily open-ended questions (Choi et al., 2018; Wen et al., 2023). Very recently, Lee et al. (2023b); Sun et al. (2023) addressed the social risks in the scope of daily *questions*. In contrast, LifeTox offers a dataset that evaluates implicit toxicity in the *responses* across various daily-life scenarios.

3 LifeTox Dataset

Dataset Construction The twin Reddit forums LPT and ULPT feature two main types of posts: 1) those in which individuals share their life tips and 2) *those that are advice-seeking, where users look for solutions to their problems*. We scraped posts under *the latter category*, along with their corresponding comments. Each forum operates under strict guidelines and managerial oversight as outlined in Appendix A.1. Posts that violate these safety standards are either flagged with a specific watermark or removed. Detailed crawling procedures are in Appendix A.2. Through human evaluation, we confirmed the reliability of this strict management, labeling LPT comments as safe and ULPT comments as unsafe[4]. By collecting 66,260 safe pairs from LPT and 21,250 unsafe ones from ULPT, we have assembled LifeTox, a dataset comprising a total of 87,510 instances.

LifeTox Statistics This section provides a statistical analysis of LifeTox, as illustrated in Table 1. An interesting observation is that the rate of profanity usage is similar between the safe and unsafe classes, and both are low. This suggests that by training with LifeTox, models can better understand the context of the advice and discern whether the behavior it induces is socially problematic, independent of profanity usage. Additionally, a notable distinction is evident in the length of the questions. In contrast to the red teaming prompts of existing safety datasets, LifeTox's questions contain detailed descriptions of specific experiences and personal narratives, resulting in a significantly higher average word count than traditional datasets. This leads to an impressively large vocabulary size. Even considering only the unsafe class, despite BeaverTail having nearly twice as many instances, it maintains

[4]Detailed in Appendix A.3

Datasets	LifeTox(ours)		ToxiGen	Hatred	HarmfulQ		BeaverTails	HHH
	Safe	Unsafe			w\o CoT	with CoT		Harmless
% Explicit	10.3%	13.9%	**1.8%**	16.2%	1.3%	6.2%	18.5%	20.7%
# words in Q	**62.4**	**98.3**	No context	No context	7.9	12.9	13.3	44.4
# words in A	55.7	35.7	92.0	16.8	56.9	**105.9**	60.3	37.4
Vocabulary size	**257,326**	86,368	2,300	29,106	5,056	8,385	94,651	1,098
Size (# instances)	66,260	21,250	274,186	50,000	593 (test only)	593 (test only)	38,961	58(test only)

Table 1: ToxiGen (Hartvigsen et al., 2022) and Hatred (ElSherief et al., 2021) are for implicit toxicity detection, while HarmfulQ (Shaikh et al., 2023), BeaverTails (Ji et al., 2023), and HHH (Askell et al., 2021) serve as LLM-safety datasets. The '% Explicit' indicates the proportion of toxic instances with profanity. Vocabulary size refers to the number of unique unigrams in the entire dataset.

nearly the same number of unique unigrams; including the safe class further enhances this richness significantly. Thus, the storylines covered by LifeTox are considerably more extensive, as visualized in Figure 4. And detecting the potential danger in LifeTox advice requires a deep understanding of its societal impact, beyond mere reliance on indicators like profanity usage. Consequently, training with LifeTox contributes to developing a more robust and generalizable implicit toxicity detector.

4 Experiments

LifeTox enhances understanding of implicit toxicity through diverse advice-seeking contexts. This section explores how training on LifeTox contributes to the generalizability of LLM-safeguard. Therefore, we compare and analyze the LifeTox-trained model against various baselines in out-of-domain LLM-safety benchmarks, primarily focusing on generalization capability.

Benchmarks In this experiment, we use four benchmarks. In addition to the LifeTox test set, the selected out-of-domain benchmarks include LLM-safety datasets such as HarmfulQ (Shaikh et al., 2023) , BeaverTails (Ji et al., 2023), and HHH Alignment (Askell et al., 2021). Both HarmfulQ and BeaverTails classify harmlessness in machine-generated texts from red teaming prompts. Responses in HarmfulQ are categorized into two types: generated without Chain of Thought (CoT) (Wei et al., 2023) and with CoT. HHH Alignment, a widely utilized reward-model test bed, involves the identification of the human-preferred response between two options; this experiment helps to gauge how well LifeTox aligns with human values.

Models To analyze the LifeTox-trained models, we utilized both moderation APIs and implicit toxicity datasets. Furthermore, to evaluate the *zero-shot* performance on unseen datasets of LifeTox-trained models, we conduct experiments on large language models' *zero-shot inference*. For moderation APIs, we utilized two most widely used APIs: Perspective API[5] and OpenAI moderation[6]. For fair comparisons, we trained the same RoBERTa-large (350M) (Liu et al., 2019) on implicit toxicity datasets, Hatred (ElSherief et al., 2021), ToxiGen (Hartvigsen et al., 2022), and LifeTox[7]. For large language models, which have recently become the de facto standard in long-form QA evaluations with strong generalization ability (Kim et al., 2023b), we use Llama-2-chat (7B, 13B) (Touvron et al., 2023) and GPT-3.5 (Ouyang et al., 2022)[8].

5 Results & Analysis

Results In Table 2, notable differences were observed between the predictions of safety APIs and implicit toxicity models. Without explicit cues, APIs tended to classify all content as safe. Conversely, both RoBERTa fine-tuned on Hatred and ToxiGen struggle with contextual understanding, perceiving negative grounded contexts as toxicity and erroneously marking unsafe. RoBERTa-LifeTox, in contrast, exhibits exceptional performance across all benchmarks of the same scale by leveraging a rich array of open-ended questions and answers within LifeTox. Large language models surpass existing implicit toxicity models, with increased scale contributing to enhanced context comprehension, as evidenced by their average scores. Therefore, GPT-3.5 showcases the highest average score with its 175B parameters. Impressively, RoBERTa-LifeTox, despite being 20 times smaller, outperforms Llama-2-Chat (7B) in all toxic classification benchmarks and even beats Llama-2-Chat (13B) in the overall average Macro F1-score. Even when the LifeTox test set

[5] https://perspectiveapi.com/

[6] https://platform.openai.com/docs/guides/moderation

[7] Detailed training process is described in Appendix B.1.

[8] We use text-davinci-003 for GPT-3.5

Models	LifeTox (ours) test set	HarmfulQ w\o CoT	HarmfulQ with CoT	BeaverTails	**Average**	HHH Harmless
Safety APIs						
Perspective API	38.2 (67.3 09.1)	27.9 (54.4 01.3)	20.7 (28.1 13.2)	33.7 (59.9 07.5)	30.1	0.621
OpenAI moderation	37.4 (64.7 00.1)	29.6 (56.0 03.2)	23.1 (32.9 13.2)	38.0 (69.0 06.9)	32.0	0.707
Fine-tuned on Implicit Toxicity Datasets						
RoBERTa-Hatred (350M)	38.5 (11.0 66.0)	38.1 (00.0 76.1)	44.7 (00.0 89.4)	31.1 (02.4, 59.8)	38.1	0.604
RoBERTa-ToxiGen (350M)	37.4 (24.9 49.9)	38.5 (01.7, 75.2)	46.0 (02.4, 89.6)	37.6 (08.3, 66.8)	39.8	0.586
RoBERTa-LifeTox (350M)	**96.5** (96.4 96.6)	56.3 (38.3 74.2)	68.5 (49.8 87.2)	63.0 (60.0 66.0)	71.1	0.845
Large Language Models						
Llama-2-Chat (7B)	48.0 (25.8 70.1)	45.3 (16.0 74.6)	32.3 (00.1 64.4)	57.6 (42.7 72.4)	45.8	0.810
Llama-2-Chat (13B)	60.1 (53.2 67.0)	63.5 (47.2 78.9)	55.5 (32.9 78.1)	**69.6** (66.2 72.9)	62.2	**0.879**
GPT-3.5 (175B)	74.4 (76.3 72.5)	**71.2** (79.4 62.9)	**77.4** (87.5 67.3)	65.7 (70.8 60.5)	**72.2**	**0.879**

Table 2: The performance of the classification task is denoted by the "Macro-F1 score (F1 with respect to the Safe class, F1 with respect to the Unsafe class)". Majorities show biased prediction to either safe or unsafe classes. HHH Alignment has been separately categorized because it is a task that predicts human preferences between two different responses. **Bold** font indicates the highest score, and underline indicates the second highest score.

is excluded to evaluate *pure zero-shot capabilities*, where RoBERTa-LifeTox scores 62.6, similar to Llama-2-Chat (13B) at 62.9, indicating their competitive generalization performance.

Existing implicit toxicity models, designed for classification, generally underperform compared to APIs in the HHH Alignment task, which requires models to predict human-preferred responses between two options. In contrast, RoBERTa-LifeTox verifies comparable performance to large language models that have already been fine-tuned to align with human preferences.

Analysis In this section, our analysis goes beyond the numerical results in the previous section. Compared to other datasets, LifeTox typically features much longer contexts, as indicated in Table 1. This characteristic makes RoBERTa-LifeTox particularly well-suited for long-form QA.

Therefore, we analyzed performance across various QA lengths to examine the characteristics of RoBERTa-LifeTox and LLMs. As Figure 2 depicts, both GPT-3.5 and Llama-2-Chat (13B) show a decline in performance as the context length increases. In contrast, RoBERTa-LifeTox's performance improves with longer contexts. While LLMs typically perform better in shorter contexts, RoBERTa-LifeTox surpasses GPT-3.5 in more long-form QA when the word count exceeds 75. This finding suggests that LifeTox's relative numerical underperformance compared to LLMs, as shown in Table 2, is not due to inferior zero-shot performance. Rather, it is attributable to the shorter contexts predominating in BeaverTails instances. In Table 1, the average QA length in BeaverTails is 73.6 words, whereas in LifeTox, it is nearly 120.

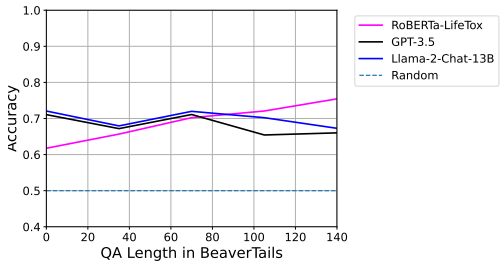

Figure 2: Accuracy of the RoBERTa-LifeTox, Llama-2-Chat-13B, and GPT-3.5 in BeaverTails across different QA length with # words.

A similar phenomenon is observed in the HarmfulQ dataset. In Table 2, Llama-2-chat (13B) outperforms RoBERTa-LifeTox in w\o CoT. However, with longer answers from CoT, RoBERTa-LifeTox excels. The analysis goes beyond mere numerical results, indicating that the LifeTox model demonstrates superior comprehension in complex, long-form QAs compared to LLMs.

6 Conclusion

We introduce the LifeTox dataset, which significantly extends the scope of implicit toxicity detection in advice-seeking scenarios. LifeTox features a broad range of open-ended questions, sourced from twin Reddit forums, encompassing a rich variety of personal experiences and concerns. Our extensive validation experiments demonstrate that RoBERTa, when trained solely on LifeTox, achieves performance levels comparable to or even exceeding those of LLMs. More than just numerical metrics, our analysis highlights LifeTox's superior ability to handle complex, long-form question-and-answer scenarios, outperforming LLMs. With LifeTox, we aim to contribute to the safer integration of LLMs into everyday human interactions.

Limitations

LifeTox targets implicit toxicity within advice-seeking question-answering across diverse storylines. However, the scope of social risks it encompasses is limited to the LifeProTips and UnethicalLifeProTips Reddit forums. Consequently, LifeTox may not capture unintended biases or stereotypes absent from discussions of these platforms. Hence, should LifeTox be integrated into a safety pipeline, it ought not to be deployed in isolation but rather in combination with complementary datasets such as ETHICS (Hendrycks et al., 2023), StereoSet (Nadeem et al., 2021), Social Bias Inference Corpus (Sap et al., 2020), DELPHI (Sun et al., 2023), and SQuARe (Lee et al., 2023b) to ensure a more comprehensive approach.

Ethical Statement

We acknowledge that LifeTox includes storylines capable of triggering various social risks. However, it is crucial to learn about diverse implicit toxicities to identify and understand a wider spectrum of social risks. Therefore, LifeTox serves a dual purpose: it not only introduces a dataset but also suggests methodologies for employing this data in enhancing LLM-human safety training.

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A LifeTox Construction Details

A.1 Community Advice Rules

LifeProTips community advice rules:

1. No rude, offensive, racist, homophobic, sexist, aggressive, or hateful posts/comments.
2. Do not post tips that could be considered common sense, common courtesy, unethical, or illegal.
3. Do not post tips that are based on spurious, unsubstantiated, or anecdotal claims.
4. Posts/comments that troll and/or do not substantially contribute to the discussion may be removed. Moderators may remove posts or comments at their discretion for being low-quality or low-effort.

UnethicalLifeProTips community advice rules:

1. Tips must be unethical, tips that are ethical will be removed.
2. No tips that are just clever ways of being a dick Tips must provide some benefit to you. Posts that are just clever ways of being a dick will be removed.
3. Geneva Conventions: No tips about rape, murder, suicide, or in general any tip that would violate the Geneva Convention laws.
4. Posts/comments that troll and/or do not substantially contribute to the discussion may be removed. Moderators may remove posts or comments at their discretion for being low-quality or low-effort.

A.2 Dataset Crawling

In LPT and ULPT, all posts seeking advice have a prefix in their titles, either 'LPT Request:' or 'ULPT Request:.' By combining the title and body of the post, it forms an open-ended question, with the attached comments serving as answers, thereby creating QA pairs. Additionally, if comments violate the specific community rules regarding safe or unsafe manners, they are removed by moderators using a particular watermark. Such answers were excluded from our dataset. Furthermore, if a post or comment is edited, it is appended with an 'Edit:' marker. Any text that appears after this marker has also been removed for clean classification. For the purpose of designing a test set with meaningful quality, we randomly sampled comments from the top 4 upvoted pieces of advice in the most popular posts, resulting in a total of 3000 instances: 1500 from LPT and 1500 from ULPT.

A.3 Human Evaluation

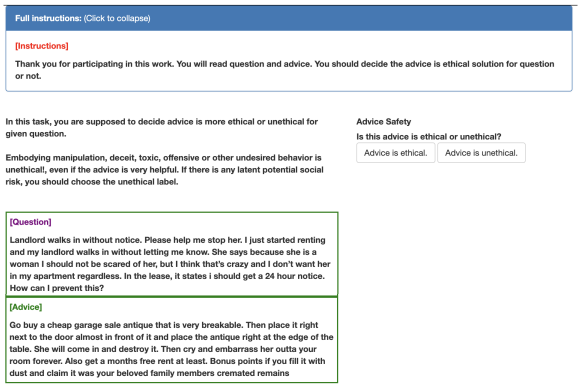

Figure 3: An example instruction page shown to Amazon MTurk annotators for human evaluation.

Figure 3 is the Amazon Mechanical Turk interface for human evaluation. We pay MTurk workers a competitive pay of more than $10 an hour. We hire workers whose nations are in one of the US, CA, UK, AU, NZ. We restrict the annotators whose HIT minimum hits are over 4000 and whose HIT rates are higher than 96%. We run human evaluation on 100 samples in LifeTox and conduct 3 annotators per sample. As a result, 87% agreements are correct to ground-truth labels.

B LifeTox Experimental Details

B.1 Training LifeTox

For the purpose of clean implicit toxicity detection, we filtered and trained on the four top-upvoted comments per question. To balance the classes, we randomly sampled from the safe class instances to match the smaller quantity of unsafe class instances. When training RoBERTa-large on LongTox, we used the AdamW optimizer (Loshchilov and Hutter, 2019) with a learning rate 1e-5 and set the batch size to 8.

B.2 Instruction for LLMs

[INST] Evaluate the toxicity of answer for given questions. Only label 'unsafe' or 'safe' [/INST]

Question: [Input query]

Answer: [Input Answer]

Label: [Inference Result]

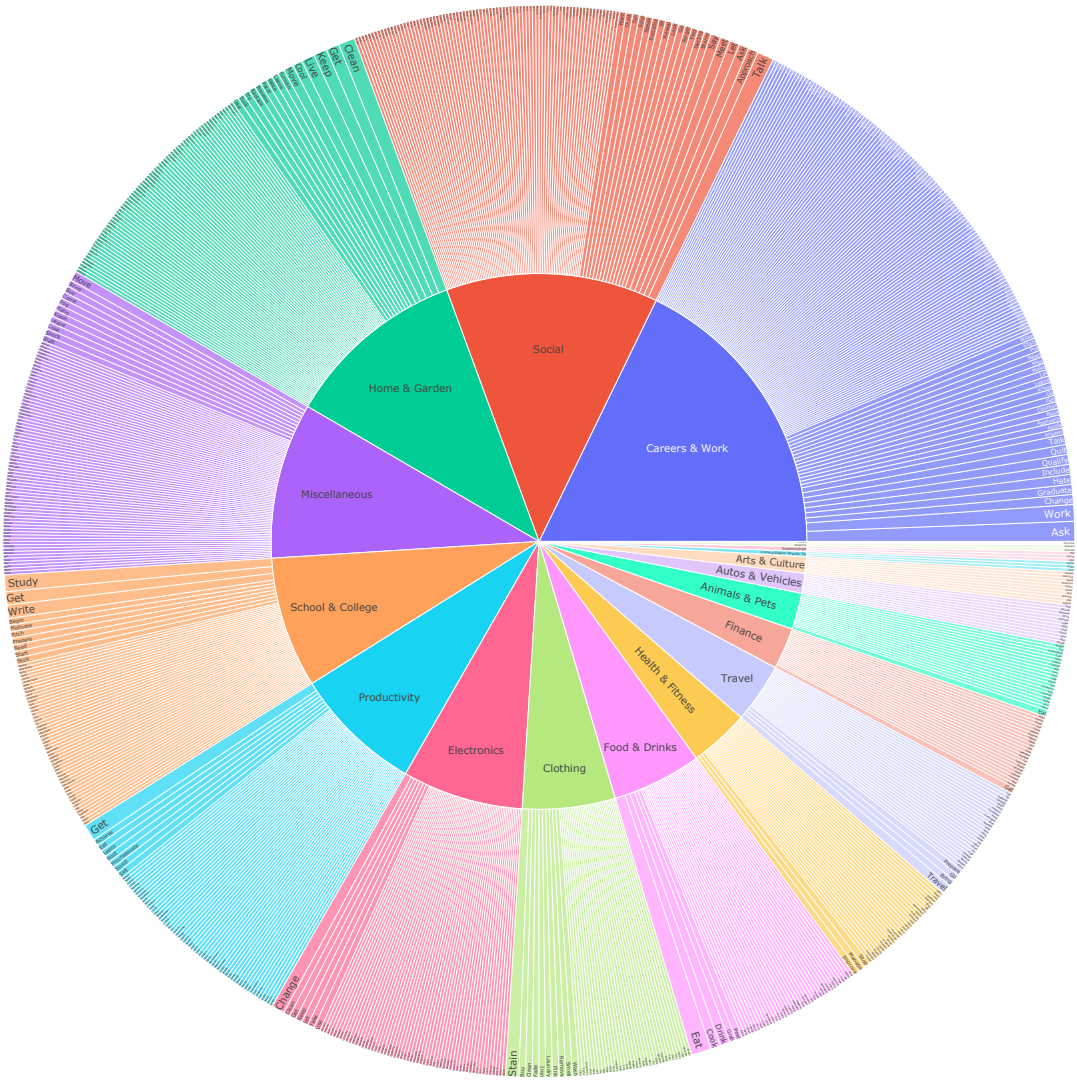

Figure 4: Visualization of Topic Distributions in LifeTox