No Video Left Behind: A Utility-Preserving Obfuscation Approach for YouTube Recommendations

Jiang Zhang[1], Hadi Askari[2], Konstantinos Psounis[1], Zubair Shafiq[2]

[1]University of Southern California
[2]University of California, Davis

Abstract

Online content platforms optimize engagement by providing personalized recommendations to their users. These recommendation systems track and profile users to predict relevant content a user is likely interested in. While the personalized recommendations provide utility to users, the tracking and profiling that enables them poses a privacy issue because the platform might infer potentially sensitive user interests. There is increasing interest in building privacy-enhancing obfuscation approaches that do not rely on cooperation from online content platforms. However, existing obfuscation approaches primarily focus on enhancing privacy but at the same time they degrade the utility because obfuscation introduces unrelated recommendations. We design and implement DE-HARPO, an obfuscation approach for YouTube's recommendation system that not only *obfuscates* a user's video watch history to protect privacy but then also *denoises* the video recommendations by YouTube to preserve their utility. In contrast to prior obfuscation approaches, DE-HARPO adds a *denoiser* that makes use of a "secret" input (i.e., a user's actual watch history) as well as information that is also available to the adversarial recommendation system (i.e., obfuscated watch history and corresponding "noisy" recommendations). Our large-scale evaluation of DE-HARPO shows that it outperforms the state-of-the-art by a factor of 2× in terms of preserving utility for the same level of privacy, while maintaining stealthiness and robustness to de-obfuscation.

1 Introduction

Online content platforms, such as YouTube, heavily rely on recommendation systems to optimize user engagement on their platforms. For instance, 70% of the content watched on YouTube is recommended by its algorithm [1]. These recommendation systems provide personalized content recommendations by tracking and profiling user activity. For instance, YouTube tracks and profiles activities of its users on YouTube as well as off of YouTube to this end [2]. This tracking and profiling enables these platforms to predict relevant content that a user is likely to be interested in. On one hand, this tracking and profiling enables desirable utility to users by providing relevant content recommendations. On the other hand, this tracking and profiling poses a privacy issue because the platform might infer potentially sensitive user interests.

Some platforms, including YouTube, allow users to remove a subset of the tracked activity (e.g., remove a specific video from YouTube watch history) or even disable the use of certain profiled user interests (e.g., gambling) to influence the recommendations. However, these controls do not necessarily stop the platform from tracking and profiling user activities in the first place. Thus, these controls provided by the platforms may not provide much, if any, privacy benefit to users. Moreover, the exercising of these controls would hurt the quality of personalized recommendations. For example, if users employ these controls to curtail tracking or profiling then they will likely not receive personalized recommendations they are actually interested in.

The research community is increasingly interested in developing privacy-enhancing obfuscation approaches that do not rely on cooperation from online content platforms [3–6]. At a high level, these privacy-enhancing approaches work by adding fake activity to real user activity to lessen the ability of the recommendation system to infer sensitive information. However, the addition of fake activity for the sake of obfuscation also ends up impacting the utility users might derive from the recommendation system in terms of relevance of personalized recommendations. Prior obfuscation approaches attempt to navigate the trade-off between privacy and utility, for example [6], by carefully adding fake activity so as to obfuscate "private" interests but allow "non-private" interests.

In this work, we are interested in designing a privacy-enhancing *and* utility-preserving obfuscation approach for recommendation systems. In contrast to prior approaches that are typically limited to only obfuscating inputs to the recommendation system, our key idea is to design an obfuscation approach that can obfuscate inputs to preserve user privacy but at the same time remove "noise" from outputs to preserve the utility of recommendations. Since an adversarial recom-

mendation system might also attempt to remove "noise", it is crucial that the denoiser can only be used by the user and not by the recommendation system. To this end, our insight is that the denoiser uses a "secret" input (specifically, a user's actual browsing history), which is only available to the user and not the recommendation system. The recommendation system instead only has access to the obfuscated browsing history of the user. Therefore, by leveraging the knowledge of a user's actual browsing history, the denoiser allows the user to preserve the recommendations related to the users' actual interests while discarding the unrelated recommendations caused by obfuscation.

We design and implement DE-HARPO, an obfuscation approach for YouTube's recommendation system that not only obfuscates a user's video watch history to protect privacy but then also denoises the video recommendations by YouTube to preserve their utility. DE-HARPO uses an *obfuscator* to inject obfuscation videos into a YouTube user's video watch history and a *denoiser* to remove recommended videos that are unrelated to the user's actual interests.

The *obfuscator* is a RL model trained to insert YouTube videos in a users' watch history that will maximize the distortion in their interests being inferred by YouTube. We address two key issues in designing DE-HARPO's *obfuscator*, which is a non-trivial adaptation of Harpo [6] to YouTube. First, we build a surrogate of YouTube's recommendation system to efficiently train the RL model in a virtual environment. Second, we design the surrogate model to predict the distribution of hundreds of different classes of YouTube recommendation videos (we use the 154 affinity segments used by Google [7] as our video classes) rather than the sheer number (order of hundreds of millions) of individual YouTube videos.

The *denoiser* is a ML model that is trained to reproduce the original recommendations that would have been received in the absence of the *obfuscator*. We address two key issues in designing DE-HARPO's *denoiser*. First, *denoiser* makes use of a "secret" input (i.e., a user's actual watch history) as well as information that is also available to the adversarial recommendation system (i.e., obfuscated watch history and corresponding "noisy" recommendations). As we show later, this design ensures that only DE-HARPO is able to remove "noise' while the adversary is unable to de-obfusacte without prohibitive collateral damage. Second, we define new divergence-based metrics to measure privacy and utility in training *obfuscator* and *denoiser*.

We deploy and evaluate DE-HARPO's effectiveness on YouTube using 10,000 sock puppet based personas, 10,000 Reddit user personas, and 936 real-world YouTube users [8]. Our evaluation shows that DE-HARPO's *obfuscator* is able to degrade the quality of YouTube's recommendations by up to 87.23% (privacy) and its *denoiser* is able to recover up to 90.40% of the actual recommendations (utility). We show that DE-HARPO outperforms the state-of-the-art by a factor of $2\times$ in terms of improving utility for the same level of privacy. Crucially, we also demonstrate that DE-HARPO is stealthy and robust to de-obfuscation by an adversarial system. Our evaluation shows that the adversary incurs a prohibitively large number of false positives (order of tens/hundreds of millions) in attempting to undermine stealthiness and achieving de-obfuscating.

Our main contributions are summarized as follows:

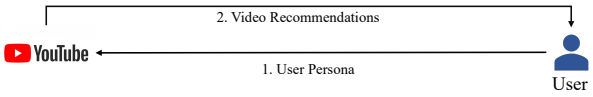
- We propose DE-HARPO, a privacy-enhancing *and* utility-preserving obfuscation approach for YouTube's recommendation system that employs an *obfuscator* to obfuscate users' video watching history and a *denoiser* to remove noise in video recommendations.
- We undertake a non-trivial adaptation of Harpo [6] to YouTube, which involved designing and implementing a purpose-built YouTube surrogate model.
- We demonstrate the effectiveness of DE-HARPO in both enhancing user privacy and preserving utility of YouTube's recommendation system using 10,000 sock puppet based personas, 10,000 Reddit user personas, and 936 real-world YouTube users.

2 Preliminaries

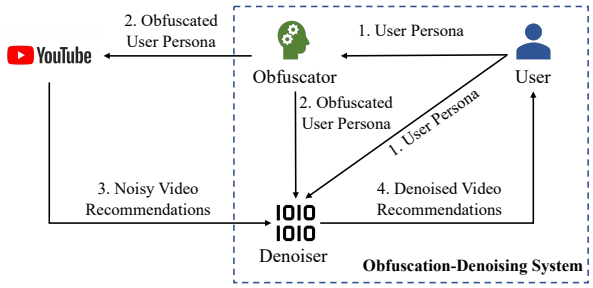
2.1 Problem Statement

Recommendation systems track users' browsing activity to provide personalized recommendations. YouTube, for example, tracks users' browsing activity on YouTube (e.g., videos watched, channel subscriptions) as well as off of YouTube (e.g., activity on other Google services such as Google Search and Google Analytics, or web pages opened in Chrome browser) to personalize homepage and up-next video recommendations [2]. Users can selectively remove certain videos from their YouTube watch history or clear their browsing activity altogether to influence personalized video recommendations. However, doing so does not necessarily mean that their browsing activity is not tracked in the first place, and thus there is no material privacy benefit to users. It will also hurt the quality of personalized recommendations because users will likely not receive recommendations for videos they are interested in. In summary, users are unable to exert meaningful control over recommendation systems to protect their privacy while preserving the utility of personalized recommendations.

Prior work has proposed obfuscation approaches to protect user privacy in personalized recommendation systems without relying on cooperation from online content platforms. Existing approaches obfuscate a user's browsing history by injecting fake activity (e.g., webpage visits) to manipulate a user's interest segments and targeted ads in online behavioral advertising [6, 9]. These obfuscation approaches are designed for recommendation systems (e.g., online behavioral advertising) where users are not necessarily interested in consuming the output of the recommendation system, rather users are mainly interested in subverting it. While these approaches aim



(a) Without obfuscation-denoising system.



(b) With obfuscation-denoising system.

Figure 1: Problem Overview.

to protect user privacy (e.g., inferred interest segments), they do not consider the utility of recommendations (e.g., whether targeted ads are of interest to the user). In contrast, in recommendation systems such as YouTube, these obfuscation tools would render the utility of YouTube's video recommendations useless to the user.

Can we design privacy-enhancing obfuscation approaches that can enhance privacy of users and at the same time preserve utility for users in recommendation systems? With this goal in mind, we propose to build a denoiser to remove the "noisy" videos injected as part of obfuscation. It is crucial that the denoiser can only be used by the user and not by the recommendation system. To this end, our insight is that the denoiser uses a "secret" (specifically, the user's actual browsing history), which is only available to the user and not the recommendation system. Therefore, by leveraging the knowledge of a user's actual browsing history, the denoiser may preserve the recommendations related to the users' actual interests while discarding the unrelated recommendations caused by obfuscation. Figure 1b illustrates this idea that we next operationalize in DE-HARPO.

2.2 Threat Model

User. The user's goal is to routinely browse YouTube videos and get high-quality recommendation videos fitting their interests, while misleading the YouTube recommendation system such that it can not accurately infer the user's interests. To achieve this goal, users install a local obfuscation-denoising system, which consists of an *obfuscator* and a *denoiser*. The *obfuscator* will obfuscate their video watching history by injecting fake video watches into the user's real video watches, and the *denoiser* will automatically remove "noisy" recommended videos from YouTube (i.e. caused by obfuscation) that do not fit user's interests. The obfuscation-denoising system is designed to satisfy the following properties:

- it is **privacy-preserving** in that the user's interests are protected from being inferred by YouTube recommendation system.
- it is **utility-preserving** in that the user can receive high-quality videos fitting their interests.
- it is **stealthy** in that it is impossible for YouTube to detect the usage of obfuscation-denoising system.
- it is **robust to deobfuscation** in that it is impossible for YouTube to distinguish fake video watches from real video watches.

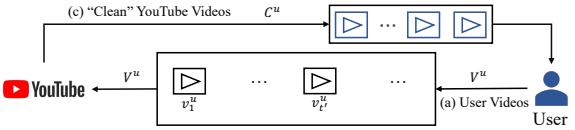
Recommendation system. The goal of the recommendation system is to track user activity for personalized recommendations to maximize user engagement (e.g., click rate and watch time). We assume that the recommendation system has full access to the user's video watching history and it recommends videos based on the user's video watching history, which is true for YouTube [10] (unless the user deletes their watching history). We also assume that the recommendation system has substantial computation resources to train a machine learning model for its recommendations. This assumption also holds for YouTube [11]. Moreover, we assume that the recommendation system has access to DE-HARPO once it is public, such that it can use it to analyze the obfuscation approach and possibly train adversarial detectors to detect and filter the usage of DE-HARPO. More specifically, we assume that the recommendation system has a two-step detection workflow. In the first step, the adversary will train a classifier to detect whether or not a user uses DE-HARPO. Then, in the second step, if DE-HARPO usage is detected, the adversary further attempts to achieve deobfuscation by filtering out obfuscation videos and keeping the remaining videos.

3 Proposed Approach

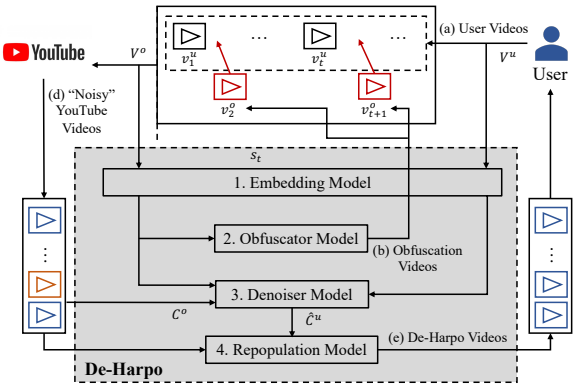
In this section, we present the proposed utility-preserving obfuscation approach DE-HARPO.

3.1 Overview

As already discussed, at a high-level DE-HARPO consists of an *obfuscator* designed for enhancing user privacy and a *denoiser* designed for preserving user utility, as demonstrated in Figure 2b. The DE-HARPO *obfuscator* is a non-trivial adaptation of Harpo's obfuscator [6] in the context of YouTube's recommendation system, which we will refer to as Y-Harpo. The *obfuscator* injects fake video playing records into a user's video playing history at random times. We refer to videos played by the user as *user videos* and to videos played by the *obfuscator* as *obfuscation videos*. Note that without any *obfuscation videos* in the user's video playing history (which is denoted by V^u in this case), YouTube will recommend a set of videos desired by the user. We refer to this set of videos as "clean" YouTube videos. However, with *obfuscation videos* in the user's video playing history (which is denoted by V^o in this case), YouTube will recommend a set of videos which include videos undesired by the user. We refer to this set of videos as "noisy" YouTube videos. The *denoiser* is designed



(a) Without obfuscation-denoising system.



(b) With obfuscation-denoising system.

Figure 2: Overview of DE-HARPO. Note that V^u denotes the non-obfuscated user persona, V^o denotes the obfuscated user persona generated by the *obfuscator*, C^u is the recommended video class distribution based on V^u, C^o is the recommended video class distribution based on V^o, $\hat{C}^u$ is the *denoiser*'s estimate of C^u, and v_i^u and v_i^o represent user video and obfuscation video respectively.

to predict the class distribution of "clean" YouTube videos from the class distribution of "noisy" YouTube videos, such that DE-HARPO can repopulate a new set of videos with the same class distribution as the "clean" YouTube videos. We refer to the repopulated videos as DE-HARPO videos. Note that each video class represents a video topic, and we use the 154 affinity segments used by Google [7] as our video classes.

In more detail, DE-HARPO starts by generating video embeddings of past played videos via an embedding model. It then uses an *obfuscator* model to select obfuscation videos based on the generated video embeddings. Note that we follow a similar methodology with that in [6] to formulate the process of inserting *obfuscation videos* as a Markov Decision Process (MDP), and use reinforcement learning (RL) to train the *obfuscator* model to maximize the divergence between the class distribution of "noisy" YouTube videos (denoted by C^o) and the class distribution of "clean" YouTube videos (denoted by C^u). After receiving the "noisy" YouTube videos, the *denoiser* outputs an estimate of the class distribution of "clean" YouTube videos (denoted by $\hat{C}^u$), by taking as inputs V^u, V^o, and C^u. Finally, DE-HARPO will use a repopulation model to generate the set of DE-HARPO videos with class distribution $\hat{C}^u$.

3.2 System Preliminaries

User persona. We define a user persona as a sequence of YouTube videos. Formally, we denote the non-obfuscated user persona as $V^u = [v_1^u, ..., v_n^u]$, where v_i^u represents the ith video played by the user, and n is the total number of videos played by the user. We denote the obfuscated user persona as $V^o = [v_1^j, ..., v_{n'}^j]$, where $j \in \{u, o\}$, v_i^u and v_i^o represent that the ith video is played by the user and *obfuscator* respectively, and n' is the total number of videos played by the user and *obfuscator* combined.

Recommended video class distribution. We define the recommended video class distribution of a non-obfuscated user persona V^u (i.e. the class distribution of "clean" YouTube videos) as $C^u = [c_1^u, ..., c_K^u]$, where $\sum_{k=1}^{k=K} c_k^u = 1$, c_k^u is the percentile of videos from the kth class among recommended videos for V^u, and K is the total number of classes. Similarly, we define the recommended video class distribution of an obfuscated user persona V^o (i.e. the class distribution of "noisy" YouTube videos) as $C^o = [c_1^o, ..., c_K^o]$, where $\sum_{k=1}^{k=K} c_k^o = 1$ and c_k^o is the percentile of videos from the kth class among the recommended videos for V^o. We use the recommended video class distribution as a representation of the user interest profile built by YouTube instead of directly using the recommended videos. This design choice is made to (i) mitigate the impact of non-determinism in YouTube's recommendations and (ii) alleviate the difficulty of making video-level recommendations given an incomplete set of available videos while still making reasonably fine-grained recommendations (among 154 different classes).

Privacy metric. At a high level, we want to distort the user interest profile built by YouTube for user personas to enhance user privacy. Motivated by the use of the recommended video class distribution as a representation of YouTube's user interest profile, we define the privacy metric as follows:

$$P = E[D_{KL}(C^o||C^u)] = E[\sum_{k=1}^{k=K} c_k^o \log \frac{c_k^o}{c_k^u}], \quad (1)$$

which measures the expected KL divergence between the two probability distributions (C^o and C^u)[1]. We use KL divergence since it is a well-established measure of the discrepancy between two distributions, and, together with the closely related mutual information measure they have been used as on-average privacy metrics in myriad of applications including recommendation systems [12–17]. We do not use stricter privacy metrics which provide worst-case privacy guarantees (e.g. differential privacy [18]), since in the context of our application one would need to inject a lot of obfuscation noise to satisfy such guarantees, leading to recommendations with very low utility.

During real-world experimentation on YouTube, we observe that the recommended video class distribution of the same persona may differ a bit due to an inherent randomness of the system. Since we are interested to measure the divergence thanks to obfuscation only, we define D^{Min} as the

[1]Note that if $c_k^i = 0$ ($i \in \{u, o\}$), we assign a small value to it to avoid getting ∞ in KL divergence calculation.

expected KL divergence between a random sample of C^u and its mean $\bar{C}^u$ (i.e., $D^{Min} = E[D_{KL}(\bar{C}^u, C^u)]$), and subtract from P the divergence caused by randomness, that is, we work with $P - D^{Min}$. Furthermore, since P is unbounded, we normalize the privacy metric as follows. Denote the user persona set as $\mathcal{V}$, which consists of all user personas. Let V^u and $V^{u'}$ be two user personas uniformly and randomly sampled from $\mathcal{V}$, and let their associated recommended video class distributions be C^u and $C^{u'}$ respectively. Then, we define the normalized privacy metric P^{Norm} by:

$$P^{Norm} = \frac{P - D^{Min}}{D^{Max} - D^{Min}}, \tag{2}$$

where $D^{Max} = E[D_{KL}(C^u, C^{u'})]$ is the expectation of the KL divergence between C^u and $C^{u'}$ and thus corresponds to the average "distance" between two video class distributions of two randomly selected users. Hence, P^{Norm} measures the fraction of the maximum possible divergence that obfuscation achieves, on average. Note that for both P and P^{Norm}, the higher their value is, the more effective the *obfuscator* is in enhancing user privacy (see Figure 3).

Utility metric. In our threat model, the user sends the obfuscated persona to YouTube and then receives a "noisy" recommended video list with class distribution C^o. However, the user desires the "clean" recommended video list with class distribution C^u. Our *denoiser* is designed to predict C^u from C^o, such that DE-HARPO can repopulate the "clean" recommended video list from C^u. With the above in mind, we define our utility loss metric as follows:

$$U_{Loss} = E[D_{KL}(\hat{C}^u || C^u)] = E[\sum_{k=1}^{k=K} \hat{c}_k^u \log \frac{\hat{c}_k^u}{c_k^u}], \tag{3}$$

where $\hat{C}^u$ is the output of the *denoiser*, representing its estimation of C^u. Smaller U_{Loss} means smaller divergence between the non-obfuscated recommended video class distribution C^u and the *denoiser*'s estimate of such distribution $\hat{C}^u$ and thus a better estimate. The theoretical minimum that this value can take is 0, representing two identical distributions i.e. the noise is perfectly removed. Note that without applying the *denoiser*, the utility loss equals the value of privacy P (since $\hat{C}^u = C^o$). The *denoiser* can reduce the utility loss caused by the *obfuscator* by $P - U_{Loss}$ which represents the *denoiser* utility gain. Similarly to above, because P is unbounded and YouTube's randomness causes, on average, a divergence of D^{Min}, we define the normalized utility gain metric as follows:

$$U_{Gain}^{Norm} = \frac{P - U_{Loss}}{P - D^{Min}}, \tag{4}$$

which represents the fraction of obfuscation noise reduced by the *denoiser*, on average. Higher U_{Gain}^{Norm} implies that the *denoiser* can reduce the utility loss caused by the *obfuscator* more effectively and a value of 100% indicates a complete removal of noise (see Figure 3).

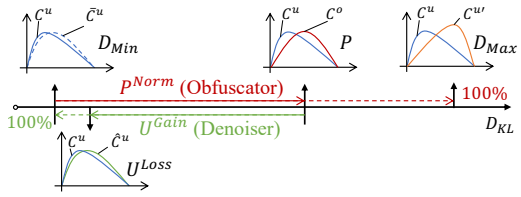


Figure 3: Privacy and utility metrics.

3.3 System Model

Obfuscator. The obfuscation video selection process of *obfuscator* can be formulated as a Markov Decision Process (MDP) defined as follows:

1) Obfuscation step: As shown in Figure 4, at the beginning of each time step, a video will be played. If the played video is an obfuscation video injected by the *obfuscator*, we refer to this time step as an obfuscation step. We denote the number of videos that have been played up to obfuscation step t by n_t. Note that we use the obfuscation budget α as a system parameter to control the percentile of obfuscation videos. At each time step, with probability α, an obfuscation video will be injected by *obfuscator* into the user persona.

2) State: We define state $s_t \in \mathcal{S}$ at obfuscation step t as $s_t = [v_1, ..., v_{n_t}]$, where n_t is the total number of videos played until the beginning of obfuscation step t, and $\mathcal{S}$ is the state space of the MDP.

3) Action: At obfuscation step t, an action a_t will be taken by the MDP. We define action $a_t \in \mathcal{A}$ as the obfuscation video selected by the MDP policy, where $\mathcal{A}$ is the action space of the MDP, i.e. the obfuscation videos set in our application.

4) State Transition: We define the state transition function as $\mathcal{T}(\cdot|\mathcal{S}, \mathcal{A}) : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$, which outputs the probability of $s_{t+1} = s'$ given $s_t = s$ and $a_t = a$ as $\mathcal{T}(s_{t+1} = s' | s_t = s, a_t = a)$. In our system, state s_{t+1} contains all videos played until state s_t, the action a_t (i.e. the obfuscation videos selected at obfuscation step t), and all the videos played by users between obfuscation step t and obfuscation step $t+1$. Note that the randomness of this MDP comes from the random injection of obfuscation videos.

5) Reward: We associate a reward r_t for the action a_t at obfuscation step t. Specifically, we define r_t as the difference of the privacy metric P (see Eq. (1)) between this obfuscation step and the previous one, i.e., $r_t = P_t - P_{t-1}$, where P_t represents the privacy metric value at obfuscation step t, calculated based on the recommended video class distributions of a non-obfuscated user persona and the corresponding obfuscated user persona at the end of obfuscation step t.

6) Policy: The policy of the MDP can be defined as $\pi(\cdot|\mathcal{S}) : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, which outputs the probability of $a_t = a$ given $s_t = s$ as $\pi(a_t = a | s_t = s)$. In our system, the *obfuscator* is modeled as the policy in MDP, which outputs the probability distribution of obfuscation video selection. Suppose we have M obfuscation videos in the obfuscation video set ($\mathcal{A}$), then we have $\sum_{i=1}^{i=M} \pi(a_t = i | s_t) = 1$, where $a_t = i$

represents the selection of i-th obfuscation video. At each obfuscation step t, we randomly choose one obfuscation video based on a multinomial distribution parameterized by $A_t = [\pi(a_t = 1|s_t), \cdots, \pi(a_t = M|s_t)]$, conditioning on the current state s_t. The goal of solving this MDP is to find the optimal policy, such that the accumulative rewards $\sum_{t=1}^{t=T} r_t$ can be maximized. Note that T is the total number of obfuscation steps since we consider a finite-horizon MDP.

Denoiser. At a high level, we model the *denoiser* as a mapping from the recommended video class distribution of the obfuscated user persona $C^o \in \mathbb{R}^K$ to the recommended video class distribution of the non-obfuscated user persona $C^u \in \mathbb{R}^K$ (K is the total number of video categories).

Estimating directly C^u from C^o can be challenging. In the extreme case, where the mutual information between C^u and C^o is zero [19], it is impossible for the *denoiser* to estimate C^u from C^o. To estimate C^u, the *denoiser* may leverage side information indicating how the obfuscation videos are injected into the user personas, as in this case it may be able to undo the effect of obfuscation videos in the recommendations list. In our application, such side information is explicitly available to users (V^u portion of V^o), since the *obfuscator* is installed locally and users know exactly how the obfuscation videos are injected into user personas. Therefore, our *denoiser* is modeled to be a functional mapping from (V^u, V^o, C^o) to C^u.

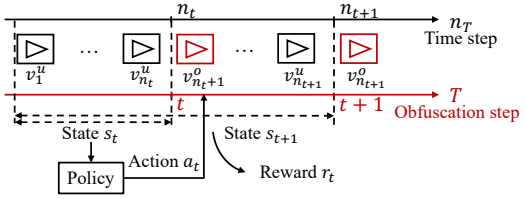


Figure 4: MDP for the *obfuscator*.

3.4 The Secret of the Denoiser

We use the information theory concept of mutual information (MI) to explain why the *denoiser* works. In our system, both V^u and V^o are random vectors, and V^o is generated from V^u by the *obfuscator*, which is a random function. Additionally, both C^u and C^o are random vectors, which are generated from V^u and V^o respectively by the YouTube recommendation system. By applying the chain rule of MI, we can derive the following equation:

$$I(C^o, V^o, V^u; C^u) = I(C^o, V^o; C^u) + I(V^u; C^u | C^o, V^o), \quad (5)$$

where $I(C^o, V^o, V^u; C^u)$ is the MI between (C^o, V^o, V^u) and C^u, $I(C^o, V^o; C^u)$ is the MI between (C^o, V^o) and C^u, and $I(V^u; C^u | C^o, V^o)$ is the MI between V^u and C^u conditioning on (C^o, V^o).

First, we show that the non-obfuscated user persona V^u can be leveraged by the *denoiser* to better estimate C^u. Since C^u is generated by YouTube recommendation system given V^u, V^u is correlated with C^u, thus $I(V^u; C^u | C^o, V^o) > 0$. Hence,

$$I(\underbrace{C^o, V^o, V^u}_{\text{with secret}}; C^u) > I(\underbrace{\ C^o, V^o\ }_{\text{without secret}}; C^u). \quad (6)$$

Since the MI between (V^u, V^o, C^o) and C^u is larger than the MI between (C^o, V^o) and C^u, (C^o, V^o, V^u) can reveal more information about C^u than (C^o, V^o), leading to a more accurate estimate of C^u. As an aside, note that YouTube may attempt to de-obfuscate V^u from V^o. We evaluate the robustness of the *obfuscator* against de-obfuscation in Section 6.6.

Second, we show that including C^o and V^o may help to further enhance the effectiveness of the *denoiser*, compared with using V^u only. Based on the chain rule of MI, we can rewrite Eq. (5) as follows:

$$\begin{aligned} &I(V^u, V^o, C^o; C^u) \\ &= I(V^u; C^u) + I(C^o; C^u | V^u) + I(V^o; C^u | C^o, V^u). \end{aligned} \quad (7)$$

Consider the term $I(C^o; C^u | V^u)$. C^o depends on V^u and the obfuscation videos, and C^u depends on V^u. Crucially, they both also depend on the (non deterministic) YouTube recommendation system. Hence, even when V^u is given, there is non-zero MI between C^o and C^u, that is, $I(C^o; C^u | V^u) > 0$, leading to the following inequality:

$$I(V^u, V^o, C^o; C^u) > I(V^u; C^u), \quad (8)$$

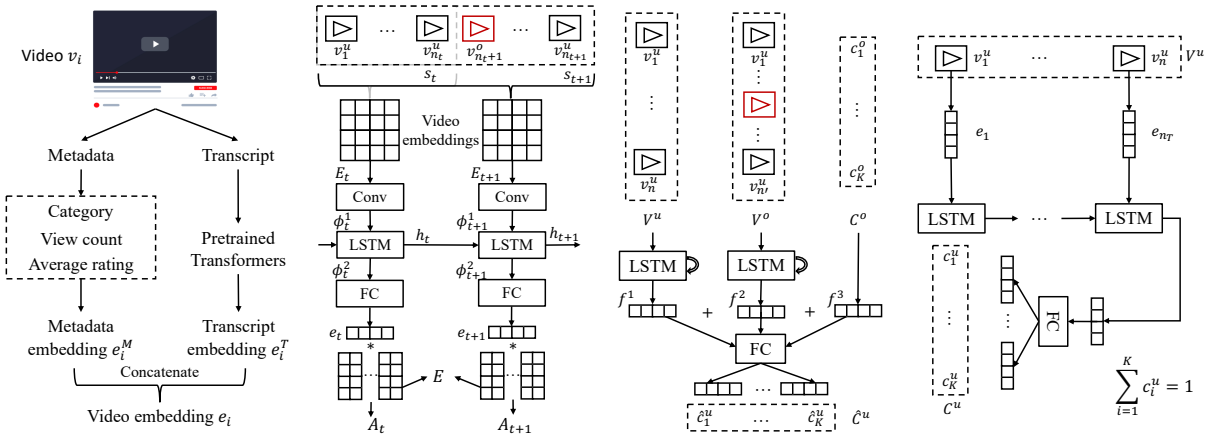
which means the MI between (V^u, V^o, C^o) and C^u is larger than the MI between V^u and C^u only. Intuitively, knowing the pair V^o, C^o reveals information about how the YouTube recommendation system selects videos to recommend given a user video watching history. Therefore, the *denoiser* taking C^o and V^o as additional inputs can learn more information about C^u, as compared to the *denoiser* taking only V^u as input. Our evaluation results in Section 6.2 empirically support the above analysis.

4 System Design and Implementation

In this section, we describe the detailed design of DE-HARPO and how we implement DE-HARPO as a browser extension. DE-HARPO consists of five modules: (1) a video embedding model that maps videos into embeddings; (2) a *obfuscator* model that selects obfuscation videos based on the video embeddings of played videos; (3) a *denoiser* model that estimates the class distribution of "clean" YouTube videos from the class distribution of "noisy" YouTube videos; (4) a repopulation model that outputs DE-HARPO videos with the estimated class distribution of "clean" YouTube videos; (5) a surrogate model used to train the *obfuscator* model offline efficiently (see Figure 2b for the workflow of modules (1)-(4)).

4.1 Video Embedding

To make our system scalable to millions of YouTube videos without being restricted to a fixed set, we represent each video by an embedding vector. A YouTube video typically consists



(a) Video embedding (b) *obfuscator* (c) *denoiser* (d) Surrogate model

Figure 5: Details of system design.

of metadata (e.g. title, description, view count, rating, thumbnail, etc), a sequence of image frames (i.e. the video), and the transcript for the video. Since a video's transcript is a good representation of its content and it is more computationally and spatially efficient to process the transcript compared to processing the original video stream, we use video metadata and transcript to generate the video embedding.

As demonstrated in Figure 5a, we start by extracting the category, view count and average rating of each video from its metadata. We then use an one-hot embedding to represent the category of each video (with dimension 18)[2], and use two real numbers to represent the standardized view count and average rating of each video. By combining them together, we derive the metadata embedding with 20 elements. We denote the metadata embedding for video v_i as $e_i^M \in \mathbb{R}^{20}$.

Next, we use a pretrained natural language processing (NLP) Transformer from [20] to generate the transcript embedding for the video transcript. Since the pretrained NLP Transformer has a constraint on the maximal number of words in the input text (256 words in our case), we firstly split video transcript with more than 256 words into multiple transcript chunks, each of which contains 256 words. Then, for each transcript chunk, we use it as input of the NLP model and get the output embedding vector. We take the average of these embedding vectors for these transcript chunks to derive the final transcript embedding. We denote the transcript embedding for video v_i as $e_i^T \in \mathbb{R}^{384}$, which is a real vector with dimension 384. Note that if a video does not contain any transcript (e.g. music videos), we use the video title and description as an alternative of transcript to generate the transcript embedding. Last, we concatenate the metadata and transcript embeddings and derive the complete video embedding vector $e_i = [e_i^M, e_i^T] \in \mathbb{R}^{404}$.

[2]Note that YouTube has 17 video categories, and we add an additional "none" category for videos without category metadata. Hence, the one-hot-embedding for category information has a dimension of 18.

4.2 Obfuscator Model

As discussed before, we model the process of injecting obfuscation videos as an MDP. Due to the prohibitively large state space of this MDP, we use RL, parameterized by a deep neural network, to learn the optimal policy for obfuscation video selection.

The *obfuscator* takes as input the state at each obfuscation step, and outputs a video embedding. Recall that we have M obfuscation videos as the action space of the MDP. By measuring the cosine similarity between the output video embedding and each obfuscation video embedding, the *obfuscator* derives the probability distribution of the obfuscation video selection, where an obfuscation video with more similar embedding as the output video embedding is assigned a higher probability. Specifically, as shown in Figure 5b, the *obfuscator* consists of a convolutional layer (Conv), a LSTM layer, and a fully-connected layer (FC). At step t, the convolutional layer takes the embeddings of the past n_t videos as input ($E_t \in \mathbb{R}^{n_t \times 404}$) and outputs a real vector with m_1 elements ($\phi_t^1 \in \mathbb{R}^{m_1}$). Next, the LSTM layer takes ϕ_t^1 and the hidden vector at obfuscation step $t-1$ with m_3 elements $h_{t-1} \in \mathbb{R}^{m_3}$ as input, and outputs a real vector with m_2 elements ($\phi_t^2 \in \mathbb{R}^{m_2}$) and the hidden vector $h_t \in \mathbb{R}^{m_3}$ for obfuscation step t ($m_1 = m_2 = m_3 = 128$ in our experiments). Finally, a linear layer converts ϕ_t^2 into a real vector with the same dimension as the video embedding. We denote this vector by $e_t \in \mathbb{R}^{404}$ as it represents the target embedding for the obfuscation video. Let $E = [e_1, ..., e_M]$ denote the embedding vectors of the M obfuscation videos at our disposal. Then, the probability of selecting the i-th obfuscation video, $i = 1 \ldots M$, is calculated proportionally to the similarity between its embedding and the target embedding after normalizing using a softmax function:

$$\pi(a_t = i | s_t) = \frac{e^{\langle e_t, e_i \rangle}}{\sum_{i=1}^{i=M} e^{\langle e_t, e_i \rangle}}, \tag{9}$$

where $\langle x, y \rangle$ denotes the inner product between x and y.

To train the *obfuscator*, we use the on-policy RL algorithm A2C (Advantage Actor and Critic) [21], which is one of the

state-of-the-art on-policy RL agorithms. Note that we choose the on-policy RL algorithm since it fits our application well, where the *obfuscator* (RL agent) needs to keep interacting with the YouTube recommendation system (environment) to improve the policy in an online fashion due to the dynamics of the YouTube recommendation system.

4.3 Denoiser Model

As mentioned in Section 3.3, the *denoiser* has three inputs: the non-obfuscated user persona V^u, the obfuscated user persona V^o, and the recommended video class distribution of obfuscated user persona C^o. The *denoiser* uses two LSTM layers and an FC layer to encode inputs, as shown in Figure 5c. Specifically, the first LSTM layer takes as input the embeddings of videos in the non-obfuscated user persona V^u recurrently and outputs its final hidden vector $f^1 \in \mathbb{R}^n$ (we use $n = 128$ in our experiments). Similarly, the inputs of the second LSTM layer are the embeddings of videos in the obfuscated user persona V^o and its output is its last hidden vector $f^2 \in \mathbb{R}^n$. Last, the FC layer converts the class distribution $C^o \in \mathbb{R}^K$ (where K represents the number of categories) into a real vector $f^3 \in \mathbb{R}^n$. By concatenating vectors f^1, f^2, and f^3 into a single vector with dimension $3n$, a final FC layer is used to map it into the estimated recommended video class distribution $\hat{C}^u \in \mathbb{R}^K$.

4.4 Repopulating Recommended Videos

Recall that the *denoiser* in DE-HARPO outputs a target video class distribution $\hat{C}^u$. In order to go from a target video class distribution back to actual videos on the user's screen, we repopulate the recommendations using a browser extension.

For efficiency, we maintain a "bank" of videos per class and use it to repopulate the recommendations. This leads to the question of how often should we refresh this bank in order to get a suitable trade-off between the recency of the videos and the overhead required to collect the videos. To ascertain what the optimal time period would be to refresh this bank we run a 24-hour experiment where we query the name of a class in the YouTube search bar as a proxy for the explicit class and collect statistics for each class's most popular recommended videos. Specifically, we run the same query each hour, collect the top 20 search results per query, and compute the percentile of top queries that remain the same. The results indicate that for most classes about 70-80% of the top search results remain the same. Motivated by this, we use a 24 hour delay in re-crawling videos to re-populate our bank. Note that the "noisy" recommended videos removed during the repopulation process will be included into our obfuscation video sets such that they can be played later to augment the obfuscation effect.

4.5 Surrogate Model

The training of the *obfuscator* requires frequent interactions with the YouTube recommendation system. However, directly interacting with YouTube is time-consuming, since it takes more than 30 minutes to construct a single persona (as described in Section 5.2). To train the *obfuscator* efficiently, we build a surrogate model as a replication of the actual YouTube recommendation system.

Prior approaches to learn latent user-item relationships for recommendation systems (e.g., matrix factorization [22–29], neural MF [30–37]) are not scalable because they rely on a fixed set of users and items. To address this limitation, recent work has focused on embedding based recommendation systems that predict the next item clicked by users from their item-click history and thus can scale to a large and dynamic set of users and items [11, 38]. YouTube, deals with a large influx of videos and users everyday [10] and thus uses a scalable recommendation system that predicts the next watched videos based on the embeddings of the past watched videos and other factors [11]. Similar to YouTube's embedding based recommendation architecture, our surrogate model also takes as input the video embeddings. Slightly different from YouTube's embedding based recommendation architecture and as explained in Section 3.2, our surrogate model is designed to predict the recommended video class distribution, instead of making video-level recommendations.

Figure 5d demonstrates the architecture of our surrogate model, which consists of a LSTM layer and a FC layer. The LSTM layer takes as input the embeddings of videos in a user persona recurrently and outputs its last hidden vector, which will be used as the input of the FC layer. Then, the FC layer will output the recommended video class distribution $C^i \in \mathbb{R}^K$ ($i \in \{u, o\}$). We train the surrogate model via supervised learning with stochastic gradient descent (see Section 5.3).

4.6 DE-HARPO Implementation

We implement DE-HARPO as a browser extension, which consists of two components: *obfuscator* and *denoiser*.

Obfuscator. The *obfuscator* is a lightly modified version of Harpo's browser extension [6]. The browser extension plays the selected obfuscation videos in a background tab that is hidden from users. In order to determine the timing of playing obfuscation videos, the *obfuscator* component uses a background script to keep monitoring the URLs visited by the user and estimating the arrival rate of YouTube videos watched by user as λ^u. Then, given obfuscation budget α, the *obfuscator* component will use a Poisson Process with rate $\lambda^o = \frac{\lambda^u \alpha}{1-\alpha}$ to inject randomly select obfuscation videos. In order to avoid detection by YouTube's anti-fraud mechanisms (i.e., users typically watch one video at a time), the selected obfuscation videos can be stored in a queue and only played when the user stops watching YouTube.

Denoiser. The *denoiser* has two modules: HTML modification and the denoising. The HTML modification module is implemented in the background script. Whenever the user visits YouTube homepage, the HTML modification module sends

the "noisy" homepage recommendation video list requested from the content script to the denoising module. Once HTML modification module receives the "clean" homepage recommended video list from the denoising module, it will modify the HTML of YouTube homepage to show "clean" homepage recommended videos. The denoising module is implemented in the back-end, which is responsible for accessing the metadata of the received "noisy" homepage recommended videos, running the *denoiser* model to convert the "noisy" homepage recommended video list into a "clean" one, and then sends the "clean" video list back to the HTML modification module. We evaluate the implementation overhead of the *obfuscator* and *denoiser* components in Section 6.4.

5 Experimental Setup

5.1 User Personas

To train and evaluate DE-HARPO, we need to construct realistic user personas. However, it is challenging to have access to real-world YouTube users' video watch history in a large scale as our training data. To address this concern, we design two approaches that can generate a large number of synthetic user personas to simulate real-world users: 1) the first approach creates sock puppet based personas by following the "up next" videos recommended by YouTube; 2) the second approach leverages the YouTube videos publicly posted by Reddit users as an approximation of their YouTube user personas. We use these synthetic user persona datasets to train DE-HARPO. Then, we evaluate it on both synthetic user persona datasets and a real user persona dataset that contains YouTube video watch history collected from real-world users. We describe these three datasets in detail below.

Sock Puppet Based Personas. According to YouTube, about 70% of the videos viewed on the platform are sourced from its recommendation system [39]. Accordingly, given the current video, the "up next" videos recommended by YouTube are good representations of the potential subsequent videos watched by real-world YouTube users. Based on this insight, we build a sock puppet user persona model that generates random *recommendation trails* from a single *seed video* to model realistic YouTube user personas, by keeping playing one of the "up next" videos recommended by YouTube randomly with uniform probability.

Specifically, we denote this model as $G(D,T)$ parameterized by D, the depth of the recommendation trail, and T, the total number of videos in the watch history, and we define the *recommendation trail* as a sequence of videos that are recommended and subsequently watched by a user starting from the given seed video. At each step of the recommendation trail, we randomly select one "up next" video to watch from the list of recommended videos with uniform probability. We repeat this process until the *recommendation trail* reaches the depth D at which point we check if the user has watched T videos. If not, we randomly select another seed video from the user's homepage and repeat the process until T videos have been watched. Note that we randomly select around 20,000 popular videos from a set of popular YouTube channels as our *seed videos*. For each *seed video*, we randomly generate a *recommendation trail* and use it as a synthetic user persona.

Since these personas are synthetically built, we are able to exercise more control over the distribution of watched videos. This leads to simpler watch histories, as compared to real-world personas, that is expected to help with the training of our surrogate model. In total, we generate 10,000 sock puppet based personas with 40 videos each. Note that we set the length of each user persona as 40, since we empirically observe that 40 videos can trigger enough personalized recommended videos on the YouTube homepage and the average time it takes to watch them is close to the average daily time spent by each YouTube user (35 min) [10].

Reddit User Personas. As a second way of simulating real-world user personas in a large scale, we gather YouTube links publicly posted by social media users as an approximation of their YouTube personas. While there are various social media platforms where users can share YouTube videos, we choose to collect data from Reddit, since it is one of the largest and most popular communities where users post links related to their interests, and millions of Reddit's user submissions[3] are publicly available.

Specifically, we download Reddit user submissions from 2017 to 2021 using APIs provided by `pushshift.io` [40]. For each user submission, we first extract the username and all YouTube links posted by this Reddit account. Next, we filter out any duplicate or broken links. Then, we extract the YouTube video ids from these remaining links in order, as the YouTube persona of this Reddit user. Finally, we remove users with less than 40 YouTube video posts, since a small number of videos is not a fair approximation of the user's actual YouTube persona. In total, we collect 10,000 Reddit user personas with length 40.

Real-world YouTube Users. To conduct a more realistic evaluation of DE-HARPO, we use a real-world user dataset from [8]. This dataset contains the web browsing histories of 936 real users collected through Web Historian [41] for three months. It is a good representative of real YouTube users, since: 1) the demographic distribution of these users, including their gender, age (18-65+), and education level (from less than high school to Doctoral degree), are relatively uniform; 2) on average 650 YouTube video URLs are watched by each user in three months; 3) the first 40 videos watched by these users have different video class distribution, indicating diverse user interests. Considering that the dataset is collected over a long period, we select the first 40 YouTube videos watched by

[3] A Reddit user submission is a json file storing metadata of a Reddit user's posts, including the username, the timestamp, the URL of post, the text, etc.

each of these 936 users as our real user personas, to evaluate DE-HARPO.

5.2 Data Collection and Preparation

User Persona Construction. We use a fresh Firefox browser based on Selenium to construct each user persona. For each sock puppet based persona, we start with a seed video and then follow the "up next" video recommendations to generate a *recommendation trail*. We play each video in a user persona for 30 seconds before playing the next video. Note that we clear any pop-up windows and skip the ads before playing the video. For each Reedit user and real user persona, since we already known the video ids in each persona, we visit these videos sequentially[4]. Similar to constructing synthetic user personas, if there are any pop-up windows or ads, we clear them and then play the video for 30 seconds.

Recommended Video Collection. After we complete the construction of each user persona, we go back to the YouTube homepage and refresh it for 50 times to collect all the recommended videos into a list. Note that we refresh the homepage multiple times since we want to collect enough homepage recommended videos to estimate the recommended video class distribution. We choose the number of refresh times as 50 since we empirically observe that it is a good tradeoff between collecting enough samples and minimizing the quantity of crawls to be performed. Because extremely popular videos are common across many users regardless of their profile, we remove them to underscore personalized recommendations. With this in mind, we filter out videos which appear in more than 1% of personas' homepage recommended video lists. Then, for each recommended video, we extract the associated tags (i.e. a list of keywords) from its metadata, and map each of them into one of the 154 topic-level video classes we have (note that a video may belong to multiple video classes). Last, for each persona, we count the number of recommended videos in each class and divide it by the sum of videos in all classes to derive the recommended video class distribution of each persona.

Video Data Collection and Embedding Preparation. We use `youtube-dl`, a free command-line software for downloading YouTube videos [42], to collect metadata and transcripts of videos. For metadata, we extract the category, average rating, view count, title, and description of each video, which is then used to generate the metadata embedding of each video. For a transcript, after we download it, we extract the transcript text, split it into text chunks with 256 words each, and use the pretrained Transformer `all-MiniLM-L6-v2` from [20] to convert them into transcript embeddings. As described in Section 4.1, we combine the metadata and transcript embeddings to generate the final video embedding.

User Persona Dataset Collected for Surrogate Model. We construct 10,000 sock puppet based personas and 10,000 Reddit user personas with 40 videos each. For each of these personas, we collect the YouTube homepage recommended videos and derive the recommended video class distribution. We use these constructed personas as inputs (V^u) and the associated recommended video class distributions as labels (C^u) to build the dataset for surrogate model training and testing. As discussed in Section 5.3, we use supervised learning to train the surrogate model.

User Persona Dataset Collected for Obfuscator and Denoiser. To evaluate the effectiveness of the *obfuscator* model against the real-world YouTube recommendation system, we need to construct both non-obfuscated and obfuscated user personas. Specifically, for each *obfuscator* model under an obfuscation budget α, we first construct 2,936 non-obfuscated user personas [5] with 40 videos each and the corresponding 2,936 obfuscated user personas generated by the *obfuscator* with on average $40 * \frac{\alpha}{1-\alpha}$ videos each. Then for each pair of non-obfuscated and obfuscated user persona (V^u and V^o), we collect their associated recommended videos from the YouTube homepage and derive their recommended video class distribution (C^u and C^o).

Moreover, we use the same user persona data collected for the *obfuscator* evaluation to create the dataset for the *denoiser* training and testing (see Section 5.3). Specifically, each input of this dataset consists of one non-obfuscated user personas (V^u), the corresponding obfuscated user persona generated by the *obfuscator* (V^o), and its associated recommended video class distribution (C^o). Each label of this dataset is the recommended video class distribution of the non-obfuscated user persona (C^u).

Obfuscation Video Set. We create our obfuscation video set by combining played videos during persona construction and videos appearing in homepage recommendations of all personas. In total, we collect approximately one million YouTube videos and use them as the obfuscation video set. Note that the *obfuscator* will select one obfuscation video from the obfuscation video set at each obfuscation step.

5.3 Training and Testing

Surrogate Model. We split the user persona dataset collected for the surrogate model in 80% for training and 20% for testing. We use stochastic gradient descent for the surrogate model to minimize its loss, which is defined as the KL divergence between its output distribution and the actual recommended video category distribution of input user persona. We train our surrogate model for 50 epochs, where all the training samples are used once at each training epoch. We report that

[4] Note that directly visiting the URL of each video doesn't trigger cookies from YouTube and hence no personal recommendation can happen. To address this, we first search the video id at YouTube and then click the first search result.

[5] Note that 2,936 non-obfuscated user personas consist of 1,000 sock puppet based personas, 1,000 Reddit user personas, and the 936 real user personas from real-world users.

the average loss of our surrogate model on the testing dataset is 0.55.

Obfuscator. Recall that the *obfuscator* needs to take as input the non-obfuscated user personas. We use the training and testing user personas in the dataset collected for the surrogate model as the non-obfuscated user personas, and train the *obfuscator* to generate obfuscated user personas that maximize privacy (see Section 3.3). Specifically, we train the *obfuscator* against the surrogate model for 50 epochs, where all the training user personas are used once at each epoch. After that, we use the testing user personas to evaluate the *obfuscator* against both the surrogate model and the real-world YouTube recommendation system, and report the average privacy metrics (P and P^{Norm}). Note that to evaluate the performance of the *obfuscator* against YouTube, we construct non-obfuscated and obfuscated user personas to collect real-world data from YouTube (see Section 5.2).

Denoiser. As described in Section 5.2, we create a dataset with 1,800 samples to train and test the *denoiser*, where 80% of the samples are used for training and 20% are used for testing. Specifically, the *denoiser* is trained via stochastic gradient descent to minimize the KL divergence between the output of the *denoiser* $\hat{C}^u$, i.e. the estimated recommendation video category distribution of a non-obfuscated user persona, and the actual distribution C^u. We train the *denoiser* for 50 epochs, where all the training samples are used once at each training epoch. We test the *denoiser* using the remaining 20% samples and report the average utility metrics (U^{Norm}_{Gain} and U^{Loss}).

5.4 Baselines

Obfuscator. We compare the privacy-enhancing performance of DE-HARPO *obfuscator* with two baselines:

1) Rand-Obf: At each obfuscation step, we randomly select one obfuscation video from the obfuscation video set, and the probability of selecting each obfuscation video is equal to $\frac{1}{M}$ (M is the total number of obfuscation videos in the set).

2) Bias-Obf: At each obfuscation step, we randomly select one obfuscation video from the obfuscation video set. However, the probability of selecting each obfuscation video is proportional to the reward triggered by each obfuscation video. To create such non-uniform distribution, we firstly use Rand-Obf to randomly select obfuscation videos and then record the reward after injecting them into non-obfuscated user personas. We repeat this experiment for 50 epochs and count the accumulative reward of each obfuscation video, normalize it by the sum of the accumulative rewards of all obfuscation videos, and use the normalized rewards as the non-uniform probability distribution.

Denoiser. We compare the utility-preserving performance of the *denoiser* in DE-HARPO with the *Surro-Den* baseline, where we use the same architecture as the surrogate model to predict C^u directly from a non-obfuscated user persona V^u, without taking the obfuscated persona V^o and the associated recommended video class distribution C^o as inputs. Ideally, if the surrogate model is a perfect replication of YouTube's recommendation system, then users could directly use it to get recommended videos based on their non-obfuscated user personas. Clearly this is unrealistic in practice since the surrogate model does not have access to the complete universe of YouTube videos which are updated constantly, and the model is merely an approximation of the actual YouTube recommendation system.

6 Evaluation

In this section, we evaluate the effectiveness of DE-HARPO from six perspectives: privacy, utility, overhead, stealthiness, robustness to de-obfuscation, and personalization.

6.1 Privacy

We first evaluate the effectiveness of DE-HARPO in enhancing privacy using three user persona datasets, and report the results in TABLE 1. Note that we test the obfuscator of DE-HARPO and other obfuscator baselines against the real-world YouTube recommendation system.

As shown in TABLE 1a, DE-HARPO can trigger 0.91 KL divergence in the recommended video class distribution after obfuscation (P) on sock puppet based personas, which translates into triggering 41.63% of the maximal potential KL divergence in the recommended video class distribution (P^{Norm}). Compared with other baselines, DE-HARPO can increase P^{Norm} by up to 2.01× and at least 1.93×. Similarly, on Reddit user personas, DE-HARPO outperforms all baselines by up to 1.57× and at least 1.50×, as reported in TABLE 1b.

Moreover, we evaluate whether the effectiveness of DE-HARPO in enhancing privacy can be transferred to real-world user personas. Specifically, we use the same obfuscator trained on sock puppet based personas to inject obfuscated videos into real-world user's video watch history, and then test it against YouTube. As reported in TABLE 1c, DE-HARPO can trigger 87.23% of the maximal potential KL divergence in the recommended video class distribution (P^{Norm}), which outperforms all baselines against YouTube by up to 1.92× and at least 1.82× in terms of P^{Norm}.

6.2 Utility

Next, we evaluate the effectiveness of DE-HARPO in preserving user utility. TABLE 2a reports our evaluation results in terms of U_{Loss} and U^{Norm}_{Gain} using sock puppet based personas. Compared with Surro-Den, the DE-HARPO *denoiser* achieves on average 26% better performance in terms of decreasing U_{Loss} (i.e. increasing U^{Norm}_{Gain}). Recall that different from Surro-Den, the DE-HARPO *denoiser* also takes as inputs the obfuscated user persona V^o, and the associated recommended video class distribution C^o which comes directly from the actual YouTube system. In contrast, the surrogate model is merely

Table 1: Privacy evaluation results against YouTube w.r.t. P and P^{Norm}.

Obfuscator	Rand-Obf	Bias-Obf	DE-HARPO
P	0.71	0.70	**0.91**
P^{Norm}	21.55%	20.76%	**41.63%**

(a) Using sock puppet based personas (D^{Min}:0.49, D^{Max}:1.51).

Obfuscator	Rand-Obf	Bias-Obf	DE-HARPO
P	1.05	1.07	**1.30**
P^{Norm}	48.79%	50.99%	**76.49%**

(b) Using Reddit user personas (D^{Min}:0.60, D^{Max}:1.51).

Obfuscator	Rand-Obf	Bias-Obf	DE-HARPO
P	0.98	1.00	**1.39**
P^{Norm}	45.45%	48.01%	**87.23%**

(c) Using real-world user personas (D^{Min}:0.53, D^{Max}:1.51).

Table 2: Utility evaluation results w.r.t. U_{Loss} and U^{Norm}_{Gain}. Note that each cell in the table reports U_{Loss}/U^{Norm}_{Gain}. For the results in the column where denoiser is DE-HARPO, it represents that we use the DE-HARPO *denoiser* for different obfuscators.

Obfuscator \ Denoiser	Surro-Den	DE-HARPO
Rand-Obf	0.60 / 50.91%	0.54 / 79.09%
Bias-Obf	0.60 / 49.06%	0.53 / 82.08%
DE-HARPO	0.60 / 74.59%	**0.53 / 90.35%**

(a) Using sock puppet based personas (D^{Min}:0.49).

Obfuscator \ Denoiser	Surro-Den	DE-HARPO
Rand-Obf	0.68 / 83.26%	0.64 / 91.18%
Bias-Obf	0.68 / 83.98%	0.66 / 88.96%
DE-HARPO	0.68 / 89.32%	**0.65 / 93.80%**

(b) Using Reddit user personas (D^{Min}:0.6).

Obfuscator \ Denoiser	Surro-Den	DE-HARPO
Rand-Obf	0.66 / 59.01%	0.62 / 81.12%
Bias-Obf	0.66 / 45.45%	0.61 / 82.34%
DE-HARPO	0.66 / 86.05%	**0.61 / 90.40%**

(c) Using real-world user personas (D^{Min}:0.53).

a "first-order" model of the actual, quite complex YouTube system. We also evaluate the effectiveness of DE-HARPO in preserving user utility using both Reddit user personas and real-world users. As reported in TABLE 2b-2c, the DE-HARPO *denoiser* can consistently preserve the utility well, reducing the utility loss by 93.80% and 90.40% respectively.

It is worth noting that the effectiveness of the denoiser in preserving utility does not depend on the effectiveness of the obfuscator in enhancing privacy. As shown in Table 2a-2c, the same denoiser can achieve almost the same utility loss U_{Loss} under different obfuscators, which implies the denoiser does not need to sacrifice privacy in order to preserve utility. We discuss the privacy-utility tradeoff in the next subsection.

6.3 Privacy-Utility Tradeoff

To further illustrate the effectiveness of the DE-HARPO *denoiser* in preserving utility, we plot the privacy-utility tradeoff of different obfuscators with/without the denoiser in Figure 6. Specifically, we combine the Rand-Obf obfuscator with the DE-HARPO *denoiser*, denoted by Rand-Obf/DE-HARPO, and combine the Bias-Obf obfuscator with the DE-HARPO *denoiser*, denoted by Bias-Obf/DE-HARPO.

As demonstrated in Figure 6, with the DE-HARPO *denoiser*, the utility loss caused by different obfuscators can be significantly reduced without sacrificing privacy. Note that since our denoiser is designed to work after obfuscation, it does not hurt the performance of the obfuscator. Moreover, with the DE-HARPO *denoiser*, the utility loss remains almost the same as we keep increasing the obfuscation budget to get higher privacy. For example, compared with baselines without using the DE-HARPO *denoiser*, DE-HARPO can reduce the utility loss by 2.12× when $\alpha = 0.5$. Note that without the DE-HARPO *denoiser*, the obfuscator needs to sacrifice utility (higher utility loss) to achieve higher privacy. This is a key difference between DE-HARPO and prior works that consider privacy-utility tradeoff (see Section 8).

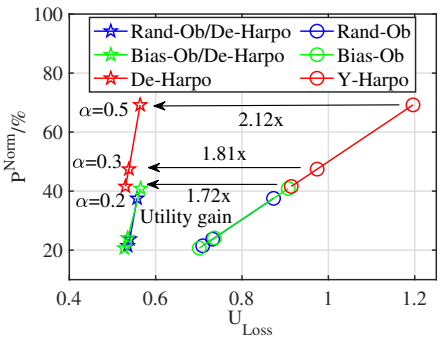


Figure 6: Privacy-utility tradeoff w.r.t. P^{Norm} and U_{Loss} under different obfuscation budget α. Note that Rand-Obf/DE-HARPO represents the combination of Rand-Obf obfuscator and the DE-HARPO *denoiser*, and Bias-Obf/DE-HARPO represents the combination of Bias-Obf obfuscator and the DE-HARPO *denoiser*. Top left of figure represent both high privacy and high utility.

6.4 Overhead

Obfuscation budget. So far, the obfuscation budget α is set to 0.2 in our evaluation (with the exception of Figure 6 that we further discuss below). To evaluate how the obfuscation budget (i.e. the percentile of obfuscation videos in a user persona) can affect the performance of DE-HARPO, we select α from $\{0.2, 0.3, 0.5\}$ and evaluate DE-HARPO under different α w.r.t. both privacy (P^{Norm}) and utility (U_{Loss}). We also consider two baselines: Rand-Obf/DE-HARPO (i.e. the combination of Rand-Obf and the DE-HARPO *denoiser*) and Bias-Obf/DE-HARPO (i.e. the combination of Bias-Obf and the DE-HARPO *denoiser*).

Figure 6 shows the privacy-utility tradeoff between P^{Norm} and U_{Loss} with varying α, where the top left region corresponds to both high privacy and high utility. We observe that with increasing obfuscation budget α, the privacy (P^{Norm}) will increase for all obfuscators. Among them, DE-HARPO can

achieve the best privacy-enhancing performance under different α values in terms of P^{Norm}. Specifically, with $\alpha = 0.2$, DE-HARPO can achieve the same level of privacy as other baselines achieve with $\alpha = 0.5$. That is, DE-HARPO can be as effective as baseline obfuscator in terms of enhancing privacy with 2.5× less obfuscation budget.

System overhead. We evaluate the system overhead of DE-HARPO in terms of CPU and memory usage and the video page load time using a an Intel i7 workstation with 64GB RAM on a campus WiFi network. As described in Section 4.6, DE-HARPO consists of an *obfuscator* component that always runs in the background and a *denoiser* component that only runs when the user visits the YouTube homepage. We separately report their overhead below.

1) Obfuscator: We select an obfuscation budget α from $\{0.0, 0.2, 0.3, 0.5\}$, where $\alpha = 0.0$ is used as the baseline (i.e. no obfuscation videos). For each obfuscation budget α we construct 10 user personas with 15 user videos each, and the browser extension visits $15 \cdot \alpha$ obfuscation videos in the background. We find that the increased CPU usage is less than 5% and the increased memory usage is less than 2%, even for obfuscation budget $\alpha = 0.5$. Moreover, the change in video page load time of user videos is less than 2% as α increases. Hence, we conclude that the *obfuscator* component in DE-HARPO has a negligible impact on the user experience overall.

2) Denoiser: The YouTube's homepage load time with DE-HARPO is 1.79 seconds, which represents just a 37.8 millisecond increase as compared to the homepage load time without DE-HARPO. Specifically, it takes less than 24.6 millisecond to get the "noisy" recommended videos from the homepage, 13.0 millisecond for the *denoising* module to get "clean" recommended videos, and 0.2 millisecond for showing these videos in the homepage. In terms of the CPU and memory usage, the *denoiser* of DE-HARPO will increase them by 27.1% and 2.2% respectively, which is mainly due to running the ML model in the *denoising* module. Note that the increase of the CPU usage (from 12.9% to 40.0%) lasts for just 13 milliseconds while the ML model runs and returns to the normal level right after that. It is worth noting that the aforementioned measurements are conducted for the *live* version of DE-HARPO. In practice, we can reduce the overhead even further by implementing a *cached* version of DE-HARPO, which caches the YouTube homepage periodically in the background and simply shows the cached homepage when the user navigates to the YouTube homepage. Hence, we conclude that the *denoiser* component in DE-HARPO has a negligible impact on the user experience overall.

6.5 Stealthiness

In this subsection, we evaluate whether an adversary can train an ML classifier to accurately detect the usage of obfuscators. We use the precision and recall of this adversarial detector to measure stealthiness of obfuscation. If the detector achieves high precision and recall, then it means that an obfuscator is less stealthy. Specifically, the input of the adversary is a user persona consisting of a sequence of videos and the binary output indicates whether or not the user persona contains at least one obfuscation video.

Table 3: Stealthiness of DE-HARPO under different obfuscation budget α. Note that we choose α from $\{0.2, 0.3, 0.5\}$ and report (Precision, Recall) of the adversarial detector for different obfuscators.

Obfuscator	(Precision, Recall)		
	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.5$
Rand-Obf	(52%, 94%)	(53%, 98%)	(83%, 94%)
Bias-Obf	(55%, 94%)	(87%, 84%)	(93%, 93%)
DE-HARPO	(97%, 98%)	(97%, 99%)	(98%, 99%)

We train the adversarial classifier via supervised learning. To create the labeled dataset, we use the same set of non-obfuscated and obfuscated personas used for evaluation in Section 6.4 as inputs, and assign the corresponding labels to the personas (0: non-obfuscated, 1: obfuscated). For each obfuscator and obfuscation budget α, we get a dataset with 1,800 non-obfuscated personas and 1,800 obfuscated personas, and we split them into 80% for training and 20% for testing.

Table 3 reports the precision and recall of the adversarial detector under different α values. We observe that as α increases, both the precision and recall of detector also increase. This is expected as larger α represents more obfuscation videos, which makes it easier for the adversarial detector to distinguish obfuscated personas from non-obfuscated personas. Moreover, while both the Rand-Obf and the Bias-Obf are a bit more stealthy than DE-HARPO, we observe that DE-HARPO can still achieve reasonable stealthiness even when $\alpha = 0.5$. For example, it leads to 99% recall (1% false negative rate) and 98% precision (2% false positive rate) even with $\alpha = 0.5$. It is noteworthy that while the 2% false positive rate seems low at surface, it actually presents the major obstacle in deployment of the adversarial detector due to base-rate fallacy [43]. Specifically, since we expect a small fraction of billions of YouTube users to employ DE-HARPO, the adversarial detector would incur a prohibitively large number of false positives (order of tens/hundreds of millions, despite only 2% false positive rate). Essentially, the adversarial detector will have to achieve exceptionally high precision to be useful in practice.

Note that such a binary detector may be used as a first step of the detection workflow. Once the adversary detects the usage of DE-HARPO, it may further attempt to de-obfuscate the obfuscated user personas. That is, the adversary may attempt to identify obfuscation videos in the obfuscated user persona such that it may remove them to retrieve the non-obfuscated user personas. We evaluate this de-obfuscation performance of an adversary next.

Table 4: De-obfuscation robustness of DE-HARPO under different obfuscation budget. Note that we set $\alpha \in \{0.2, 0.3, 0.5\}$ and report (Precision, Recall) of adversarial detector under different obfuscation approaches.

Obfuscator	(Precision, Recall)		
	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.5$
Rand-Obf	(62%, 97%)	(67%, 91%)	(69%, 99%)
Bias-Obf	(67%, 89%)	(71%, 89%)	(77%, 92%)
DE-HARPO	(79%, 93%)	(83%, 97%)	(84%, 97%)

6.6 De-obfuscation Robustness

Once the adversary detects the usage of DE-HARPO in a user persona, it can conduct de-obfuscation. To evaluate whether an obfuscator is robust to de-obfuscation, we train a second adversarial detector to distinguish the obfuscation videos from the actual user videos. Specifically, we build a second ML classifier to detect the type of each video (user versus obfuscation video) in each user persona, and use its precision and recall to measure the de-obfuscation robustness. Smaller precision and recall represents higher de-obfuscation robustness.

We use the same set of obfuscated personas as in Section 6.4 as inputs. For each video in an obfuscated user persona, we assign a binary label, where 0 represents it is watched by the user while 1 represents that it is injected by the obfuscator. The detector model takes as input the obfuscated user persona, and predicts a label for each video in the user persona. We use a recurrent neural network (LSTM layer) to model this adversarial detector.

As shown in Table 4, the precision of this adversarial detector is lower than 85%, which means more than 15% of the obfuscated videos identified by the adversary are false positives (they are actual user videos). Similar to stealthiness, false positives present a bigger challenge to the adversary in deploying this detector in practice. Therefore, we conclude that DE-HARPO is robust to de-obfuscation by an adversary.

6.7 Personalization

The *obfuscator* in DE-HARPO so far is trained to maximize the KL divergence in the recommended video class distribution after obfuscation, by either increasing or reducing the probability of each video class. However, a YouTube user may have a list of *sensitive* video classes (e.g. health or wellness related), where they do not want the YouTube recommendations containing videos from these classes after obfuscation (i.e. reducing their probability to zero).

Motivated by this, we design a mechanism that can treat *sensitive* video classes and *non-sensitive* video classes differently based on user preferences. Without loss of generality, suppose the first L classes of the recommended video class distribution are *non-sensitive* and the remaining $K-L$ classes are *sensitive*. We then train the *obfuscator* in DE-HARPO to maximize the following privacy metric, which aims to treat non-sensitive classes like before (maximize divergence before and after obfuscation) and eliminate sensitive class videos:

Table 5: Personalization results. $D_{KL}^{NonSens}$ and D_{KL}^{Sens} denote the divergence in *non-sensitive* classes and *sensitive* classes respectively.

	D_{KL}^{NonSen}	D_{KL}^{Sen}
DE-HARPO	1.18	0.26
Personalized DE-HARPO	0.81 (↓ 31.36%)	0.05 (↓ 80.77%)

$$P^{Personalized} = E[\underbrace{D_{KL}(C^o_{1:L}, C^u_{1:L})}_{D_{KL}^{NonSens}} - \lambda \underbrace{D_{KL}(C^o_{L+1:K}, [\varepsilon]_{L+1:K})}_{D_{KL}^{Sens}}], \tag{10}$$

where $[\varepsilon]_{L+1:K} \in \mathbb{R}^{K-L}$ indicates a close-to-zero vector filled with ε, which is a small positive number (e.g. 0.0001), and $\lambda > 0$ is an adjustable parameter for controlling the relative importance of $D_{KL}^{NonSens}$ versus D_{KL}^{Sens}. Specifically, the term $D_{KL}^{NonSens}$ aims to maximize the distance between the distribution of *non-sensitive* classes before and after obfuscation, like we did before for all classes. The term $-\lambda D_{KL}^{Sens}$ aims to minimize the distance between the distribution of the sensitive classes and a distribution of very small probabilities.[6]

Table 5 reports our evaluation results of personalized DE-HARPO against surrogate models, where we select 27 out of 154 video classes related to Beauty & Wellness and Sports & Fitness as *sensitive* classes. Compared with non-personalized DE-HARPO, personalized DE-HARPO can reduce the divergence between *sensitive* video class distribution and a zero vector (D_{KL}^{Sens}) by more than 80%, while still triggering high divergence in *non-sensitive* class distribution ($D_{KL}^{NonSens}$).

7 Discussion

7.1 Ethical Considerations

We outline the potential benefits and harms to the user and the recommendation system. We argue that the potential benefits of DE-HARPO outweigh its potential harms.

Users. DE-HARPO provides a clear privacy benefit to its users, especially when platforms such as YouTube do not provide any meaningful control over its tracking and profiling of users. Crucially, DE-HARPO is able to enhance privacy while mostly preserving the utility of personalized recommendations. Thus, DE-HARPO does not degrade user experience on YouTube. However, users of DE-HARPO potentially violate YouTube's Terms of Service (TOS) [44] because YouTube might interpret obfuscation as "fake engagement". Therefore, if a user is signed-in to YouTube, their YouTube account might be suspended if YouTube is able to detect DE-HARPO's usage (though we showed that YouTube would be unable to do so without risking significant collateral damage). More seriously, the violation of TOS might be considered possible violation of the Computer Fraud and Abuse Act (CFAA, 18 U.S. Code § 1030) [45]. However, given that DE-HARPO users only

[6] Notice that we are somewhat abusing the "distribution" term above, because we do not re-normalize the corresponding probabilities to sum up to 1, as this would (i) de-emphasize the contrast between the patterns of interest and (ii) is not required to meaningfully use the KL divergence formula.

watch videos that they are authorized to (i.e., publicly available videos), we argue that the videos injected to the watch history for obfuscation nor the videos injected to the recommendations for repopulation exceed authorized access that could be a violation of CFAA [46].

YouTube. Since DE-HARPO aims to preserve utility of recommendations to YouTube users, we argue that it will not directly hurt user engagement on YouTube. DE-HARPO's *obfuscator* and *denoiser* would, however, contribute to additional traffic to YouTube servers and may have some indirect impact on the effectiveness of YouTube's recommendation system. Overall, as compared to extant privacy-enhancing obfuscation tools, we conclude that DE-HARPO is more favorable since it specifically aims to preserve utility and user engagement on YouTube.

7.2 Limitations & Future Work

Side channels. DE-HARPO's stealthiness can be undermined by exploiting various implementation side channels. For example, YouTube could use Page Visibility API [47] or the Performance API [48] to detect whether obfuscation videos are unusually not being played in the foreground. However, there are patches such as wpears [49] to avoid detection. Additionally, the *obfuscator* plays the obfuscation videos in full in a background tab while disabling background throttling (or other such optimizations [50, 51]) to prevent detection by such side channels. As another example, the repopulation of recommendations on the homepage after denoising would entail manipulation of the HTML DOM [52], which might be detectable. However, such an attach would be infeasible in practice, because the detection approaches would add an overhead of up to several seconds [53, 54].

Deployment on mobile devices. DE-HARPO is currently implemented as a browser extension for desktops and cannot be readily used on mobile apps or mobile browser apps. Since browsers extensions are not supported on iOS or Android, the only option for users to benefit from DE-HARPO on their mobile phone is to use other Chromium based browsers that allow extensions [55, 56]. Another option for mobile users is to use a remote desktop utility [57] to access YouTube with DE-HARPO on a desktop. Finally, users might still be able to reap the obfuscation benefits of DE-HARPO if they at least deploy the extension on their desktop while they are using YouTube without DE-HARPO on their mobile devices. For this to work, the user needs to be logged-in to the same Google account [58] on both their mobile app and desktop with DE-HARPO. We leave DE-HARPO's implementation as a standalone mobile browser app for future work.

Joint Training of Obfuscator and Denoiser. The *obfuscator* and *denoiser* in DE-HARPO are separately trained and their joint training might be much more effective. We experimented with jointly training the *obfuscator* and the *denoiser* using multi-objective reinforcement learning. Specifically, we started by training a *denoiser* model. Then, we trained the *obfuscator* to maximize the privacy against the surrogate model, while minimizing the loss of the *denoiser* with obfuscated user personas as inputs. After we trained the *obfuscator*, we retrained the *denoiser* and repeat the above process until both the *obfuscator* and the *denoiser* converge. We found that jointly training did not improve privacy or utility because of our use of the surrogate model, instead of YouTube in the wild, for practical reasons. When trained against the surrogate model, *denoiser* was able to trivially replicate the surrogate model. While in theory we could jointly train the *obfuscator* and the *denoiser* in the wild to avoid this issue, it would not be practical due to its time consuming nature. Future work can look into hybrid surrogate and in the wild joint training of *obfuscator* and *denoiser*.

8 Related Work

In this section, we discuss prior work on privacy-enhancing obfuscation in recommendation systems.

One line of prior research focuses on developing privacy-enhancing obfuscation approaches in online behavioral advertising. These efforts are relevant to our work because online behavioral advertising is essentially a recommendation system where the advertiser's goal is to "recommend" personalized ads to users based on their online activity. However, as we discuss next, most of these privacy-enhancing obfuscation approaches aimed towards online behavioral advertising are not designed to preserve the utility (i.e., relevance of personalized ads) [3, 5, 59–61]. These approaches generally randomly insert a curated set of obfuscation inputs to manipulate online behavioral advertising.

TrackThis [59] by Mozilla injects a curated list of 100 URLs to obfuscate a user's browsing profile. The approach is fairly simple because these obfuscation URLs are fixed, i.e., they do not vary across different users. AdNauseam [3] clicks a random set of ads to "confuse" advertisers. Note that AdNauseam's browser extension allows users to see the personalized ads that were targeted to them.

One subset of these efforts propose "pollution attacks" against online behavioral advertising that also serve a dual role as privacy-enhancing obfuscation [5, 60, 61]. Meng et al. [60] propose a pollution attack that can be launched by publishers to increase their advertising revenue by manipulating advertisers into targeting higher paying ads. The attack involves the addition of curated URLs into a user's browsing profile. The evaluation showed that the addition of even a small subset of these obfuscation URLs led to a significant increase in the categories of ads (e.g., Health) that generate higher revenue for publishers.

Degeling et al. [5] and Kim et al. [61] propose similar attacks but focus on two distinct stages of the online behavioral advertising pipeline: user profiling and ad targeting. Degeling et al. [5] propose an obfuscation approach that involves adding

URLs posted on Reddit into a user's browsing profile. Their evaluation shows that adding a small number of these obfuscation URLs is successful in triggering new interest segments in Oracle/BlueKai. Kim et al. [61] propose "AdbudgetKiller" that involves adding a sequence of URLs into a user's browsing profile to trigger retargeted ads, which are costly for advertisers and waste their advertising budget.

Moving beyond online behavioral advertising, Xing et al [9] propose pollution attacks against more general personalized recommendation systems such as YouTube, Amazon, and Google Search. The authors show that personalized recommendations could easily be manipulated by injecting random or curated obfuscation inputs. Since the attack's victim is the user, it does not take into account the utility of recommendations to the user. In contrast to this work, DE-HARPO is a privacy-enhancing obfuscation system that also takes into account the utility of the recommendations.

Follow up privacy-enhancing obfuscation systems do attempt to take into account the utility-privacy trade-off. Beigi et al, [62] propose PBooster, a greedy search approach to obfuscate a user's browsing profile while also keeping utility in consideration. PBooster employs topic modeling to select a subset of target topics and corresponding obfuscation URLs to add in a user's browsing history. Zhang et al. [6] propose Harpo, a reinforcement learning approach to obfuscate a user's browsing profile such that a subset of interest segments are kept while others are modified. Huang et al. [63] propose a context-aware generative adversarial privacy (GAP) approach to train a "privatizer" for privacy-enhancing obfuscation against an adversary who attempts to infer sensitive information from input data. This approach is used to obfuscate mobile sensor data while navigating the privacy-utility tradeoff [64–66]. Beiga et al. [67] propose a crowd-based obfuscation approach that allows individual users to preserve privacy by scrambling their browsing profiles via mediator accounts, which are selected such that the personalized recommendations to these mediator accounts are still coherent and utility-preserving to the users behind each mediator account. However, this approach requires a collaboration across multiple users of a recommendation system, and cannot be used by standalone users.

While recent work on privacy-enhancing obfuscation has attempted to balance the privacy-utility tradeoff, they are limited to obfuscating the input to the recommendation system to achieve this balance. These approaches are fundamentally limited as to how much utility can be preserved without undermining privacy by obfuscating the input to the recommendation system (see Fig. 6). In contrast, DE-HARPO employs a two-step approach to this end. It first obfuscates the input to the recommendation system to preserve user privacy and then attempts to de-obfuscate the output recommendations to preserve utility. Thus, having our cake and eating it too!

9 Conclusion

In this paper, we proposed DE-HARPO, a privacy-enhancing and utility-preserving obfuscation approach for YouTube's recommendation system that does not rely on cooperation from YouTube. DE-HARPO used an *obfuscator* to inject obfuscation videos into a user's video watching history and a *denoiser* to remove the "noisy" recommended videos thus recovering the initial, unobfuscated recommendations. Our evaluation results demonstrated that DE-HARPO can reduce the utility loss by 2× for the same level of privacy compared to existing state-of-the-art obfuscation approaches. Our work provides a template for implementing such utility-preserving obfuscation approaches on other similar online platforms, such as TikTok [68] and Facebook [69]. We will publicly release our code in conjunction with this paper to facilitate follow-up research.

Acknowledgments

The authors would like to thank Sean Hackett for his help with the discussion of the denoiser idea, Muhammad Haroon for his help with the data collection and browser extension implementation, and Magdalena Wojcieszak for sharing the web browsing histories of real-world users.

References

[1] A. Rodriguez, "YouTube's recommendations drive 70% of what we watch. Quartz," https://qz.com/1178125/youtubes-recommendations-drive-70-of-what-we-watch, 2018.

[2] "YouTube Help: Manage your recommendations and search results." https://support.google.com/youtube/answer/6342839?hl=en, 2019.

[3] D. Howe and H. Nissenbaum, "Engineering privacy and protest: A case study of adnauseam," *CEUR Workshop Proceedings*, 2017.

[4] H. Nissenbaum and H. Daniel, "Trackmenot: Resisting surveillance in web search," 2009.

[5] M. Degeling and J. Nierhoff, "Tracking and tricking a profiler: Automated measuring and influencing of bluekai's interest profiling," in *Proceedings of the 2018 Workshop on Privacy in the Electronic Society*, 2018.

[6] J. Zhang, K. Psounis, M. Haroon, and Z. Shafiq, "Harpo: Learning to subvert online behavioral advertising," *NDSS*, 2022.

[7] "Google Ads Help: About audience targeting." https://support.google.com/google-ads/answer/2497941?hl=en#zippy=%2Cin-market-segments%2Caffinity-segments.

[8] A. Casas, E. Menchen-Trevino, and M. Wojcieszak, "Exposure to extremely partisan news from the other political side shows scarce boomerang effects," *Political Behavior*, pp. 1–40, 2022.

[9] X. Xing, W. Meng, D. Doozan, A. C. Snoeren, N. Feamster, and W. Lee, "Take this personally: Pollution attacks on personalized services," in *22nd {USENIX} Security Symposium ({USENIX} Security 13)*, 2013, pp. 671–686.

[10] C. Goodrow, "On YouTube's recommendation system," https://blog.youtube/inside-youtube/on-youtubes-recommendation-system/, 2021.

[11] P. Covington, J. Adams, and E. Sargin, "Deep neural networks for youtube recommendations," in *Proceedings of the 10th ACM conference on recommender systems*, 2016, pp. 191–198.

[12] P. Cuff and L. Yu, "Differential privacy as a mutual information constraint," in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, 2016, pp. 43–54.

[13] M. Clark and K. Psounis, "Optimizing primary user privacy in spectrum sharing systems," *IEEE/ACM Transactions on Networking*, vol. 28, no. 2, pp. 533–546, 2020.

[14] J. Zhang, L. Clark, M. Clark, K. Psounis, and P. Kairouz, "Privacy-utility trades in crowdsourced signal map obfuscation," *arXiv preprint arXiv:2201.04782*, 2022.

[15] A. R. Elkordy, J. Zhang, Y. H. Ezzeldin, K. Psounis, and S. Avestimehr, "How much privacy does federated learning with secure aggregation guarantee?" *arXiv preprint arXiv:2208.02304*, 2022.

[16] J. Parra-Arnau, D. Rebollo-Monedero, and J. Forné, "Measuring the privacy of user profiles in personalized information systems," *Future Generation Computer Systems*, vol. 33, pp. 53–63, 2014.

[17] J. Parra-Arnau, J. P. Achara, and C. Castelluccia, "Myadchoices: Bringing transparency and control to online advertising," *ACM Transactions on the Web (TWEB)*, vol. 11, no. 1, pp. 1–47, 2017.

[18] C. Dwork, A. Roth *et al.*, "The algorithmic foundations of differential privacy," *Foundations and Trends® in Theoretical Computer Science*, vol. 9, no. 3–4, pp. 211–407, 2014.

[19] D. J. MacKay, D. J. Mac Kay *et al.*, *Information theory, inference and learning algorithms*. Cambridge university press, 2003.

[20] "SentenceTransformers Documentation," https://www.sbert.net/.

[21] "OpenAI Baselines: ACKTR & A2C." https://openai.com/blog/baselines-acktr-a2c/.

[22] A. Mnih and R. R. Salakhutdinov, "Probabilistic matrix factorization," *Advances in neural information processing systems*, vol. 20, pp. 1257–1264, 2007.

[23] H. Shan and A. Banerjee, "Generalized probabilistic matrix factorizations for collaborative filtering," in *2010 IEEE International Conference on Data Mining*. IEEE, 2010, pp. 1025–1030.

[24] H. Ma, H. Yang, M. R. Lyu, and I. King, "Sorec: social recommendation using probabilistic matrix factorization," in *Proceedings of the 17th ACM conference on Information and knowledge management*, 2008, pp. 931–940.

[25] M. Jamali and M. Ester, "A matrix factorization technique with trust propagation for recommendation in social networks," in *Proceedings of the fourth ACM conference on Recommender systems*, 2010, pp. 135–142.

[26] H. Ma, D. Zhou, C. Liu, M. R. Lyu, and I. King, "Recommender systems with social regularization," in *Proceedings of the fourth ACM international conference on Web search and data mining*, 2011, pp. 287–296.

[27] J. Tang, X. Hu, H. Gao, and H. Liu, "Exploiting local and global social context for recommendation." in *IJCAI*, vol. 13. Citeseer, 2013, pp. 2712–2718.

[28] J. Tang, C. Aggarwal, and H. Liu, "Recommendations in signed social networks," in *Proceedings of the 25th International Conference on World Wide Web*, 2016, pp. 31–40.

[29] B. Yang, Y. Lei, J. Liu, and W. Li, "Social collaborative filtering by trust," *IEEE transactions on pattern analysis and machine intelligence*, vol. 39, no. 8, pp. 1633–1647, 2016.

[30] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua, "Neural collaborative filtering," in *Proceedings of the 26th international conference on world wide web*, 2017, pp. 173–182.

[31] X. He, X. Du, X. Wang, F. Tian, J. Tang, and T.-S. Chua, "Outer product-based neural collaborative filtering," *arXiv preprint arXiv:1808.03912*, 2018.

[32] C. Chen, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Efficient neural matrix factorization without sampling for recommendation," *ACM Transactions on Information Systems (TOIS)*, vol. 38, no. 2, pp. 1–28, 2020.

[33] S. Deng, L. Huang, G. Xu, X. Wu, and Z. Wu, "On deep learning for trust-aware recommendations in social

networks," *IEEE transactions on neural networks and learning systems*, vol. 28, no. 5, pp. 1164–1177, 2016.

[34] X. Wang, X. He, L. Nie, and T.-S. Chua, "Item silk road: Recommending items from information domains to social users," in *Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval*, 2017, pp. 185–194.

[35] Z. Zhao, Q. Yang, H. Lu, T. Weninger, D. Cai, X. He, and Y. Zhuang, "Social-aware movie recommendation via multimodal network learning," *IEEE Transactions on Multimedia*, vol. 20, no. 2, pp. 430–440, 2017.

[36] W. Fan, Q. Li, and M. Cheng, "Deep modeling of social relations for recommendation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 32, no. 1, 2018.

[37] W. Fan, Y. Ma, D. Yin, J. Wang, J. Tang, and Q. Li, "Deep social collaborative filtering," in *Proceedings of the 13th ACM Conference on Recommender Systems*, 2019, pp. 305–313.

[38] M. Chen, A. Beutel, P. Covington, S. Jain, F. Belletti, and E. H. Chi, "Top-k off-policy correction for a reinforce recommender system," in *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, 2019, pp. 456–464.

[39] J. E. Solsman, "Youtube's ai is the puppet master over most of what you watch," 2021. [Online]. Available: https://www.cnet.com/news/youtube-ces-2018-neal-mohan/

[40] "Reddit Data Set Collection," https://files.pushshift.io/reddit/submissions/.

[41] "Web Historian: Visualize your web use to understand your habits." https://webhistorian.github.io/.

[42] "youtube-dl downloads," https://youtube-dl.org/.

[43] S. Axelsson, "The base-rate fallacy and the difficulty of intrusion detection," *ACM Transactions on Information and System Security (TISSEC)*, vol. 3, no. 3, pp. 186–205, 2000.

[44] "Terms of Service. YouTube," https://www.youtube.com/static?template=terms, 2021.

[45] "18 USC 1030: Fraud and related activity in connection with computers," https://uscode.house.gov/view.xhtml?req=(title:18%20section:1030%20edition:prelim).

[46] A. Mackey and K. Opsahl, "Van Buren is a Victory Against Overbroad Interpretations of the CFAA, and Protects Security Researchers. EFF." https://www.eff.org/deeplinks/2021/06/van-buren-victory-against-overbroad-interpretations-cfaa-protects-security, 2021.

[47] "Mozilla page visibility API," https://developer.mozilla.org/en-US/docs/Web/API/Page_Visibility_API.

[48] "Tab throttling and more performance improvements in Chrome M87." [Online]. Available: https://blog.chromium.org/2020/11/tab-throttling-and-more-performance.html

[49] "Wpears, Don't. "Blocks the Page Visibility API with some prototype hacking." Github," 2018.

[50] "Chromium-Blog," https://blog.chromium.org/2020/11/tab-throttling-and-more-performance.html.

[51] "Non-Active-Tabs," https://support.mozilla.org/si/questions/1228604.

[52] "HTML DOM API," https://developer.mozilla.org/en-US/docs/Web/API/HTML_DOM_API.

[53] S. Karami, P. Ilia, K. Solomos, and J. Polakis, "Carnus: Exploring the privacy threats of browser extension fingerprinting," in *Proceedings of the Symposium on Network and Distributed System Security (NDSS)*, 2020.

[54] O. Starov and N. Nikiforakis, "Xhound: Quantifying the fingerprintability of browser extensions," in *2017 IEEE Symposium on Security and Privacy (SP)*. IEEE, 2017, pp. 941–956.

[55] "Yandex," https://yandex.com.

[56] "KiwiBrowser," https://kiwibrowser.com.

[57] "Chrome Remote Desktop," https://remotedesktop.google.com/access.

[58] "Google Account," https://www.google.com/account/about.

[59] "Hey advertisers, track THIS," https://blog.mozilla.org/firefox/hey-advertisers-track-this, 2019.

[60] W. Meng, X. Xing, A. Sheth, U. Weinsberg, and W. Lee, "Your online interests: Pwned! a pollution attack against targeted advertising," in *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security*, ser. CCS '14. New York, NY, USA: Association for Computing Machinery, 2014, p. 129–140. [Online]. Available: https://doi.org/10.1145/2660267.2687258

[61] I. L. Kim, W. Wang, Y. Kwon, Y. Zheng, Y. Aafer, W. Meng, and X. Zhang, "Adbudgetkiller: Online advertising budget draining attack," in *Proceedings of the 2018 World Wide Web Conference*, ser. WWW '18. Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee, 2018, p. 297–307. [Online]. Available: https://doi.org/10.1145/3178876.3186096

[62] G. Beigi, R. Guo, A. Nou, Y. Zhang, and H. Liu, "Protecting user privacy: An approach for untraceable web browsing history and unambiguous user profiles," ser. WSDM '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 213–221. [Online]. Available: https://doi.org/10.1145/3289600.3291026

[63] C. Huang, P. Kairouz, X. Chen, L. Sankar, and R. Rajagopal, "Context-aware generative adversarial privacy," *Entropy*, vol. 19, 10 2017.

[64] N. Raval, A. Machanavajjhala, and J. Pan, "Olympus: Sensor privacy through utility aware obfuscation," *Proceedings on Privacy Enhancing Technologies*, vol. 2019, no. 1, pp. 5–25, 2019. [Online]. Available: https://doi.org/10.2478/popets-2019-0002

[65] M. Malekzadeh, R. G. Clegg, A. Cavallaro, and H. Haddadi, "Mobile sensor data anonymization," in *Proceedings of the International Conference on Internet of Things Design and Implementation*, ser. IoTDI '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 49–58. [Online]. Available: https://doi.org/10.1145/3302505.3310068

[66] S. Liu, J. Du, A. Shrivastava, and L. Zhong, "Privacy adversarial network: Representation learning for mobile data privacy," vol. 3, no. 4, dec 2019. [Online]. Available: https://doi.org/10.1145/3369816

[67] A. J. Biega, R. Saha Roy, and G. Weikum, "Privacy through solidarity: A user-utility-preserving framework to counter profiling," in *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, ser. SIGIR '17. New York, NY, USA: Association for Computing Machinery, 2017, p. 675–684. [Online]. Available: https://doi.org/10.1145/3077136.3080830

[68] "Inside Tiktok's Highly Secretive Algorithm," https://www.wsj.com/video/series/inside-tiktoks-highly-secretive-algorithm/investigation-how-tiktok-algorithm-figures-out-your-deepest-desires/6C0C2040-FF25-4827-8528-2BD6612E3796, 2021.

[69] O'Flaherty, "The 1 Facebook Setting You Should Change Now," https://www.forbes.com/sites/kateoflahertyuk/2021/11/20/facebook-has-hijacked-your-news-feed-heres-how-to-get-it-back/?sh=4c942aa62e79, 2021.