You Don't Bring Me Flowers: Mitigating Unwanted Recommendations Through Conformal Risk Control (Extended Abstract)*

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Abstract

Recommenders are significantly shaping online information consumption. While effective at personalizing content, these systems increasingly face criticism for propagating irrelevant, unwanted, and even harmful recommendations. Such content degrades user satisfaction and contributes to significant societal issues, including misinformation, radicalization, and erosion of user trust. Although platforms offer mechanisms to mitigate exposure to undesired content, these mechanisms are often insufficiently effective and slow to adapt to users' feedback. This paper introduces an intuitive, model-agnostic, and distribution-free method that uses conformal risk control to provably bound unwanted content in personalized recommendations by leveraging simple binary feedback on items. We also address a limitation of traditional conformal risk control approaches, *i.e.*, the fact that the recommender can provide a smaller set of recommended items, by leveraging implicit feedback on consumed items to expand the recommendation set while ensuring robust risk mitigation. Our experimental evaluation on data coming from a popular online video-sharing platform demonstrates that our approach ensures an effective and controllable reduction of unwanted recommendations with minimal effort.

1 Introduction

The widespread use of recommender systems on online platforms has significantly changed how users engage with content. These systems are integral to modern digital media, facilitating personalized navigation through extensive online content across domains such as e-commerce [Ghanem *et al.*, 2022; Loukili *et al.*, 2023], social media [Gao *et al.*, 2023; Sánchez-Fernández and Jiménez-Castillo, 2021], and content streaming [Deldjoo *et al.*, 2021; Elahi *et al.*, 2022], and tailoring experiences based on historical behaviors and expressed preferences [Fernández and Bellogín, 2020; Boratto *et al.*, 2021]. By leveraging user-generated data, recommenders aim to enhance user engagement [Xue *et al.*, 2023], satisfaction [Nguyen *et al.*, 2018], and platform profitability [Cai and Zhu, 2019]. However, despite their proven utility and benefits, the basic concepts that make recommendation algorithms effective, such as *similarity-based filtering* and *preference prediction*, can inadvertently contribute to the spread of unwanted content [Liu *et al.*, 2024]. Platforms have faced increasing criticism for creating *filter bubbles* and *rabbit holes* that reinforce existing beliefs, and for spreading potentially dangerous or harmful content [Tomlein *et al.*, 2021]. Such dynamics are often attributed to algorithms that prioritize *engagement*, sometimes at the expense of content quality and truthfulness [Tommasel *et al.*, 2021]. Features like the "*Not Interested*" button on YouTube [Liu *et al.*, 2024] suffer from issues like low user awareness, complexity of use, or limited effectiveness. The lack of transparency and explainability in such strategies further exacerbates these problems, making it difficult for users to understand why they are being shown certain content and how to avoid it. As a result, users develop "*folk theories*" to explain the recommendations they are getting and try to influence the recommender outcomes [Bernstein *et al.*, 2013; Eslami *et al.*, 2015; Eslami *et al.*, 2016; Liu *et al.*, 2024]. Recent works have studied how to mitigate unwanted content, biases, or ensure fairness in recommendations [Chee *et al.*, 2024; Ahn *et al.*, 2024], but it remains unclear how to grant users precise and transparent control over the systems' *risk*.

Our contributions. We propose a post-hoc method based on conformal prediction [Shafer and Vovk, 2008; Angelopoulos and Bates, 2023] to provably mitigate the exposure to unwanted recommendations *in expectation*. Conformal prediction is a framework for uncertainty quantification for machine learning models that constructs *prediction sets* containing the true output with a *user-specified confidence level*, assuming data exchangeability. It uses *non-conformity scores* from model outputs to provide *distribution-free*, *finite-sample* guarantees. Conformal methods have recently been applied to decision support in classification tasks [Straitouri *et*

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al., 2023; Straitouri and Rodriguez, 2024; De Toni *et al.*, 2025a], natural language processing [Campos *et al.*, 2024], and recommendation systems [Angelopoulos *et al.*, 2023b; Xu *et al.*, 2024]. However, in recommender systems, current approaches often overlook key challenges, such as re-recommending unwanted items or balancing personalization with content filtering. To address this, we apply *conformal risk control* [Angelopoulos *et al.*, 2023a], which generalizes conformal prediction to control *general loss functions* (or "*risk*") rather than coverage. Our method builds recommendation sets by *filtering* potentially unsafe items and *replacing* them with previously consumed, *safe* content, while provably respecting a user-defined risk level. Specifically, our contributions include:

1. A comprehensive analysis of real data to understand *reporting patterns* and watch time behavior related to unwanted content, providing insights into how users interact with and respond to such content.
2. A method based on conformal risk control that provably limits unwanted content in recommendations, with theoretical guarantees, by leveraging *repeated content*.
3. A practical heuristic to choose *safe* alternative content, balancing the need for personalization and the goal of minimizing unwanted recommendations.
4. Experiments and ablations with a real-world dataset, highlighting our approach's effectiveness in significantly reducing unwanted content.

2 Case Study: A Video-Sharing Platform

We begin our study by examining data from a popular Chinese short-form video-sharing platform, *Kuaishou*, which has over 300 million daily users at the time of writing. We use the *KuaiRand* dataset [Gao *et al.*, 2022], which was collected by sampling 27000 Kuaishou users who collectively watched approximately 32 million videos over one month (from April 8 to May 8, 2022). This dataset contains various user interaction signals, such as watch time for each video and whether users liked or commented on a video. The dataset also includes *negative feedback* signals, such as when users click the *"Do not recommend"* or *"Report"* buttons while watching a video. We focus exclusively on short videos, removing advertisements and videos with zero duration (*e.g.*, dynamic photos). Notably, approximately 29% of users provided negative feedback on at least one video during the data collection period. Consequently, our analysis is restricted to this subset. After further filtering, our dataset consists of 7601 users, 56 million interactions, and 10 million unique videos. On average, a user watched $7,417$ videos during the collection period (median: $4,623$), with a large standard deviation of $9,223$.

Summary of the analysis. From our analysis[1], we report some key insights that will be useful in designing risk-controlling recommendation systems:

- The engagement and perceived harmfulness of videos are not fully correlated. Reported videos have the same watch time distribution as non-reported videos. Thus, *maximizing engagement does not imply providing less harmful videos to users.*
- In Kuaishou, the system suggests undesired content *despite explicit user feedback* (*cf.* ✗ → ✗/✓ Table 1). Since over 95% of users report less than 1% of videos they watch, recommender systems should maximize the usefulness of this little explicit negative feedback;
- With 21% of interactions resulting in no watch time and a strong peak near zero in view time distribution, very short engagement can serve as an *early indicator of harmful or undesired content*.

[1]The full in-depth analysis of *KuaiRand* is available in Section 3 of the main manuscript [De Toni *et al.*, 2025b].

Behaviour	I (%)	U (%)	Watch Time 1st (s)	Watch Time 2nd (s)
✓ → ✓	99.79	100.0	2.71 ± 12.15 (1.39)	10.48 ± 25.85 (7.95)
✓ → ✗	0.11	8.69	0.50 ± 7.41 (0.0)	10.73 ± 20.85 (10.13)
✗ → ✗	0.07	6.33	7.74 ± 15.83 (6.64)	7.85 ± 15.86 (6.72)
✗ → ✓	0.03	1.49	1.36 ± 6.91 (0.0)	6.46 ± 25.42 (2.5)

Table 1: User's behavior with repeated videos. Given a video I, the user can choose to report it (✗) or not (✓). We show the average watch time (1st time and 2nd time the user sees it), the standard deviation, and the third quartile in brackets.

3 Recommender Systems With Risk Control

Given the key insights obtained from the analysis of Kuaishou data, let us now define more formally a *risk-controlling recommender system*. Consider a finite set of items $\mathcal{I} \in \{i_1, \ldots, i_N\}$ and a finite set of users $\mathcal{U} \in \{u_1, \ldots, u_M\}$, each represented by d-dimensional feature vectors, respectively. Our recommender system outputs a set of items $S(U) \subseteq \mathcal{I}$ based on some relevance score estimated by a ranker $f(U, I) \in \mathbb{R}$ predicting how much an item I is relevant for a user U based on the information within U and I (*e.g.*, in terms of watch-time). In two-stage recommender systems, we might perform further *post-processing* activities to *filter* certain items, before presenting the final recommendation to the user. Similarly to [Angelopoulos *et al.*, 2023b], let us consider a post-processing step where we employ some threshold $\lambda \in \mathbb{R}$ to pick only certain items, based on a score $s : U \times I \to \mathbb{R}$. For example, consider $s(U, I = i) = f(U, I = i)$, we might want to keep only items with a predicted relevance above a certain base value:

$$T_\lambda(U) = \{i \in \mathcal{I} : s(U, I = i) \geq \lambda\} \tag{1}$$

After post-processing, our objective becomes providing the best set $S_\lambda(U) \subseteq T_\lambda(U)$ maximizing a target metric computed on the recommendations (*e.g.*, *serendipity* [Ge *et al.*, 2010]). Generally, we are interested in recommending the *most* relevant items to each user, under a budget $k \leq N$ *e.g.*, the number of slots in a YouTube main page. Let us define $\pi(\mathcal{I}) = \{i_1, \ldots, i_N\}$ as the order induced by sorting the items given the ranker scores $f(U, I = i_j)$. If our ranker is reasonably good, then the optimal solution would be simply picking up to the k-th item from $\pi(T_\lambda(U))$:

$$S_\lambda(U, k) = \{i_j \in \pi(T_\lambda(U)) : j \leq k\} \tag{2}$$

In classical learning-to-rank tasks, we try to learn the optimal ranker $f^* = \text{argmax}_{f \in \mathcal{F}} \mathbb{E}[\ell(S_\lambda(U,k))]$ where $\ell : \mathcal{I} \to \mathbb{R}$ is our target metric, such as the nDCG. Besides picking the most relevant items for the user, now we want to *control* the *risk* of the set $\mathcal{S}_\lambda(U,k)$ induced by the optimal ranker f^*. Let us assume we have a risk metric $R : \mathcal{I} \to (0,1)$ we would like to provably *bound* below a certain value $\alpha \in (0,1)$. For example, we might want the *fraction* of unwanted content in $S_\lambda(U,k)$ to be below a user-defined value. Since we want to avoid performing costly operations such as re-training the ranker f^*, an intuitive way to reach such an objective is by acting on the *post-processing* step, by finding the optimal λ threshold ensuring our *risk* is below a user-defined level $\alpha \in (0,1)$:

$$\lambda^* = \underset{\lambda \in \Lambda}{\text{argmax}}\, \mathbb{E}\left[\ell(S_\lambda(U,k))\right] \text{ s.t. } \mathbb{E}[R(S_\lambda(U,k))] \leq \alpha \quad (3)$$

In our setting, we consider an item *unwanted* for a user if she expresses distaste for it once seen within the recommendations. Given a set of recommendations $S_\lambda(U,k)$, we denote its overall *risk* as the fraction of items the user has flagged once presented with it:

$$R_H(S_\lambda(U,k)) = \frac{|\{i \in S_\lambda(U,k) : H(U, I=i) = 1\}|}{|S_\lambda(U,k)|} \quad (4)$$

3.1 Conformal Risk Control

By simply plugging the previous risk definition in Eq. (3), we have our optimization objective. However, how do we pick the threshold λ to control the risk defined by Eq. (4)? We can find the optimal threshold via *conformal risk control* [Angelopoulos *et al.*, 2023a] by employing a held-out calibration set $\{(u,i,h))_j\}_{i=1}^n$, where for each user-item pair we also record if it was flagged as *unwanted* ($h = 1$). We first state the main theorem from [Angelopoulos *et al.*, 2023a], and then we explain its practical implications.

Theorem 1. *Assume that $R_H(S_\lambda(U,k))$ is non-increasing in λ, right-continuous, $R_H(S_{\lambda_{max}}(U,k)) \leq \alpha$ and $\sup_\lambda R_H(S_\lambda(U,k)) \leq 1 < \infty$ almost surely. Consider $\hat{R}(\lambda) = \frac{1}{n}\sum_{j=1}^n R_H(S_\lambda(U=u_j,k))$, given a held-out calibration set. Given any desired risk upper bound $\alpha \in [0,1]$, if we choose a threshold as:*

$$\hat{\lambda} = \inf\left\{\lambda : \frac{n}{n+1}\hat{R}(\lambda) + \frac{1}{n+1} \leq \alpha\right\} \quad (5)$$

then, we have $\mathbb{E}[R(S_{\hat{\lambda}}(U,k))] \leq \alpha$.

In practice, as long as our risk function decreases as λ increases, by choosing $\hat{\lambda}$ as in Theorem 1, we are guaranteed the risk will be *provably* bound in expectation. If we consider the ranker output $s(U,I) = f(U,I)$ as a score, as we increase the threshold, fewer items will be contained within $T_\lambda(U)$. Thus, the likelihood of picking harmful items within $S_\lambda(U,k)$ decreases monotonically since by removing items, we cannot increase $R_H(S_\lambda(U,k))$.

4 Risk Control via Item Replacement

Recent applications of conformal prediction to recommender systems consider only the simple filtering approach as detailed in Eq. (1) [Angelopoulos *et al.*, 2023b; Xu *et al.*, 2024]. The approach ensures the monotonicity requirements of Theorem 1 but at the price of losing control of the size of the resulting set $S_\lambda(U,k)$ [De Toni *et al.*, 2025b, Prop. 5.1]. Rather than simply removing items, we take an alternative approach, which consists of *replacing* potentially unwanted items with safer ones. However, how do we choose these *safe items*? Our approach exploits a simple fact: *users consume previously seen items* [Anderson *et al.*, 2014; Dai *et al.*, 2024]. Inspired by the analysis in Section 2, if we consider items the user has seen before, *that were not reported as unwanted*, we might as well suggest them again in place of potentially unsafe items. As shown in Table 1, there exist *rare* items (*cf.* ✓ → ✗, 0.11%) that are reported only the second time a user watches them. Therefore, we need a sensible way to select previously seen videos for which we are reasonably sure the user will not report anew. We formalize this desideratum in a simple property that can be tested by employing historical interaction patterns:

Algorithm 1 Risk-controlling Recommender System

Require: U, user, $\mathcal{I}$, items, α, risk level, $f : U \times I \to \mathbb{R}$, ranker, $s : U \times I \to \mathbb{R}^+$, score function, k set size
1: $\hat{\lambda} \leftarrow \text{RiskControl}(\alpha)$ {Theorem 1}
2: $T_{\hat{\lambda}}(U) \leftarrow \{i \in \mathcal{I} : s(U,i) \geq \hat{\lambda}\}$
3: $T^{(\text{safe})} \leftarrow \{i' \in \mathcal{I}_U : H(U,i') = 0 \wedge W_\%(U,i') > \beta\}$
4: $T_{\hat{\lambda}}^{(\text{replace})}(U) \leftarrow T_{\hat{\lambda}}(U) \cup T^{(\text{safe})}(U)$
5: **return** $\{i_j \in \pi(T_{\hat{\lambda}}^{(\text{replace})}(U)) : j \leq k\}$

Property 1. *Denote with $H_{1st} \in \{0,1\}$ the event that the user has reported an item the first time they saw it. There exists a variable C and a value $\beta \in supp(C)$ such that the probability of an item being flagged a second time is zero $P(H = 1 \mid H_{1st} = 0, C > \beta) = 0$.*

In the case of Kuaishou, we can pick as C the watch time of videos. Then, we can simply choose videos on which the users have spent time $W_\%(U,I)$ above a certain threshold. If Property 1 holds, we can replace items with a score below the risk control threshold with items the user *has previously* seen and not flagged as harmful, for which we have $C > \beta$. Let us denote the pool of *safe* videos as:

$$T^{(\text{safe})} = \{i' \in \mathcal{I}_U : H(U,i') = 0 \wedge\ C(i') > \beta\} \quad (6)$$

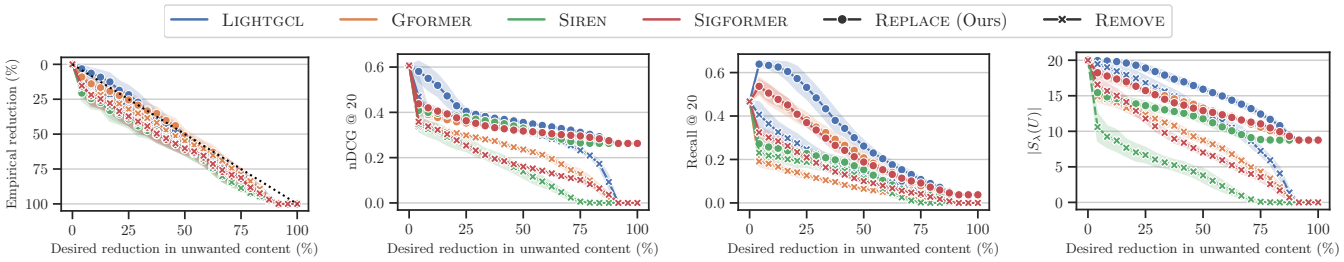
where $\mathcal{I}_U \subseteq \mathcal{I}$ indicates the items previously shown to the user U. Thus, the new pool of items will become:

$$T_\lambda^{(\text{replace})}(U) = T_\lambda(U) \cup T^{(\text{safe})}(U) \quad (7)$$

It is straightforward to show that the new set $T_\lambda^{(\text{replace})}(U)$ satisfies the monotonicity requirements of conformal risk control, and it ensures we can always pick k items to show to the user [De Toni *et al.*, 2025b, Proposition 2]. We consolidate the previous findings into Algorithm 1, a post-hoc algorithm applicable to *any* pre-trained recommender system.

5 Experiments With Real Data

We evaluate the effects of the risk control strategies (Eqs. (1) and (7)) on a simple two-stage recommender setup for a realistic video recommendation task, towards understanding what



(a) Reduction in $R_H(S_\lambda(U,k))$ (b) nDGC @ 20 (c) Recall @ 20 (d) Size of $S_\lambda(U)$

Figure 1: Results over *KuaiRand* ($k = 20$ and $\beta = 0$). The results and standard deviation (shaded areas) are over 10 runs.

the impact of the conformal risk control on standard evaluation metrics (*e.g.*, *Recall@k* and *nDCG@k*) is and what the effects of employing different strategies for risk control are (Eq. (1) and Eq. (7)). In the full paper, we further analyze other aspects, such as how many items we have to replace to achieve the desired risk level, or how approximately satisfying Property 1 impacts the desired unwanted content reduction [De Toni *et al.*, 2025b, Sec. 7].

Dataset & Metrics. We use the *KuaiRand* dataset [Gao *et al.*, 2022], which contains both positive and negative user feedback, along with information about interactions with previously seen videos. For our experiments, we focus on videos viewed at least twice by at least one user, resulting in a dataset that includes both repeated and single interactions. This leaves us with 5657 unique users, 117695 unique items, and more than 3 million interactions. Then, we partition the full interaction set into two datasets based on whether the interaction is repeated or not. We adopt a 10-core setting, randomly splitting the subset with only single interactions into training (70%), validation (15%), and test (15%) sets. The validation set also serves as a calibration set for determining the threshold λ as defined in Theorem 1. To ensure evaluation fidelity, we exclude all test set videos from the repeated interaction set. Thus, the repeated interaction set only considers videos previously seen by users — *i.e.*, those appearing in either training or validation. We compare the effect of the risk control and various strategies on two widely used metrics: *Recall@k* and *nDCG@k*. In our experiments, we set $k = 20$ as is usually done in the literature [Chen *et al.*, 2024]. We also measure the empirical *risk*, *i.e.*, the fraction of unwanted content in the recommendations, as defined in Eq. (4).

Models. Similar to previous studies [Wang and Joachims, 2023], we evaluate the effectiveness of risk control using a two-stage recommender architecture. We consider two risk-control strategies: REMOVE (Algorithm 1 without line 3 and $T^{(\text{safe})} = \{\}$) and REPLACE (Algorithm 1). REMOVE is the classical risk-control strategy for recommender systems [Angelopoulos *et al.*, 2023b]. For simplicity, under the REPLACE strategy, repeated items are not re-scored; instead, their original watch time is reused. We experiment with several state-of-the-art methods, including both sign-aware and unsigned graph-based models, depending on whether they incorporate negative user feedback (*e.g.*, reported videos): **LightGCL** [Cai *et al.*, 2023], **GFormer** [Li *et al.*, 2023], **SiReN** [Seo *et al.*, 2022], and **SIGFormer** [Chen *et al.*, 2024]. For the re-ranking stage, we adopt a simple Neural Collaborative Filtering (NCF) model [He *et al.*, 2017], as our focus is not on maximizing performance on the Kuaishou dataset, but rather on isolating the effects of risk control. Our full implementation is openly available[2] to support further research.

6 Results & Discussion

Fig. 1a shows how the level of harmfulness is tightly controlled across all strategies and ranking models. For any target reduction in unwanted content (α in Algorithm 1), the empirical reduction on the test set is equal to or better (*i.e.*, all points lie on or below the diagonal) than the desired target, confirming that *Algorithm 1 reliably enforces risk control*. In general, the REMOVE strategy tends to exceed the target reduction, removing more items than strictly necessary. This proves that Algorithm 1 provides a provable link between user actions (*e.g.*, flagging content) and the resulting changes in recommendations. Indeed, by specifying a desired reduction level, users can provably influence their experience with guarantees on the expected reduction in unwanted content. Figs. 1b and 1c show how risk control affects nDCG@20 and Recall@20. Removing items sharply degrades nDCG as the desired reduction level (α in Eq. (3)) increases, due to the shrinking pool of candidate items (Eq. (1)). In contrast, the REPLACE strategy retains a higher nDCG, though some degradation still occurs as previously seen items are reintroduced into the ranking. This performance drop is partly explained by our experimental setup: we do not re-score repeated items but instead reuse their original watch time, which may not reflect user interest upon second exposure. Recall decreases under both strategies, as removing or replacing items may discard potentially relevant, unseen content. Finally, Fig. 1d illustrates that, when full removal of unwanted content is required ($\alpha = 0$), the sole option is to *eliminate or replace all items in the recommendation set*. Moreover, for the REPLACE strategy, we might recommend fewer than k items at test time, since we have finite replacement options.

Ultimately, our experimental results demonstrate that our framework can controllably reduce exposure to unwanted recommendations by providing a trade-off between the recommendation set size and utility. These findings point toward developing safer and user-centric recommender systems.

[2]https://github.com/geektoni/mitigating-harm-recsys

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