# Value of Exploration: Measurements, Findings and Algorithms

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Effective exploration is believed to positively influence the long-term user experience on recommendation platforms. Determining its exact benefits, however, has been challenging. Regular A/B tests on exploration often measure neutral or even negative engagement metrics while failing to capture its long-term benefits. To address this, we present a systematic study to formally quantify the value of exploration by examining its effects on the content corpus, a key entity in the recommender system that directly affects user experiences. Specifically, we introduce new metrics and the associated experiment design to measure the benefit of exploration on the corpus change, and further connect the corpus change to the long-term user experience. Furthermore, we investigate the possibility of introducing the Neural Linear Bandit algorithm to build an exploration-based ranking system, and use it as the backbone algorithm for our case study. We conduct extensive live experiments on a large-scale commercial recommendation platform that serves billions of users to validate the new experiment designs, quantify the long-term values of exploration, and to verify the effectiveness of the adopted neural linear bandit algorithm for exploration.

CCS Concepts: • Information systems → Recommender systems.

Additional Key Words and Phrases: Recommendation systems, Experiment Design, Value of Exploration

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### 1 INTRODUCTION

Recommender systems are becoming ubiquitous in people's daily life, serving users with relevant content on recommendation platforms. Many of these systems are trained to predict and exploit users' immediate response to recommendations, such as click, dwell time, and purchase, achieving enormous success in personalization [15, 26, 42, 49]. However, these types of exploitation-based systems are known to suffer from the closed feedback loop effect [21, 23], for which the recommender system and the user are strongly connected and reinforce each other's choices. Users, presented with the recommended content, provide feedback only on the chosen content; the system, trained with the biased feedback data, further consolidates and reinforces users' profiles towards what they have interacted with before. As a result, users are increasingly confined to a narrower set of content, while a lot of the content on the platform remains undiscovered.

Exploration is the key to breaking such feedback loops. By exposing users to less certain contents [12, 21], it actively acquires future learning signals about the unknown user content pairs to fill in the knowledge gap in the system. Doing so, exploration can introduce users to novel content, which we refer to as user exploration [12, 44, 46]; it can also

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make more fresh and tail content (as well as content providers) discoverable on the platform, which we refer to as item exploration [4, 10]. We focus our discussion on item exploration. While efficient exploration techniques [2, 11, 33, 45] have been actively studied in the bandits and reinforcement learning literature, deploying them in real-world industrial systems has been proven difficult. The main challenge lies in *measuring* [10] the exact benefit of exploration, which then serves as concrete and measurable evidence to switch from a purely exploitation-based system to an exploration-based one. Although exploration techniques such as Upper-Confidence-Bound [5, 14] and Thompson Sampling [9, 41, 47] have been mathematically proven to attain better regret than greedy ones, it is unclear if this benefit translates to industrial recommendation settings with noisy and delayed feedback, as well as non-testable modeling assumptions.

There are three main challenges in measuring the benefit of exploration. The first one is the *metric* to be examined, as the benefit of exploration takes a long time to manifest and is hard to be captured in regular A/B testing. Meanwhile, recommending less certain content often leads to short-term user engagement metric loss. Therefore, it is critical to identify some intermediate entities that could serve as proxies connecting exploration to the long-term user experience. To address this, we study the value of exploration through its intermediate impact on the content corpus in the system <sup>1</sup>. Through an intervention study, we demonstrate the strong causal effect of the content corpus change on the user experience, and present a long-term study that shows how the advanced exploration-based systems could benefit the content corpus in a sustainable way. The second challenge is the *experiment design*, as we will explain later, the commonly used user-diverted A/B testing [25] cannot capture the benefit of exploration on the content corpus as the information leak between the control and experiment arms. We introduce a new experiment framework to measure the impact of exploration on the content corpus change. The last lies in the *design of the exploration-based systems* that could be served in real-world, large-scale setting. To this end, we adopt a scalable exploration algorithm, namely neural linear bandits, to fully unlock and examine the potential benefit of exploration.

In this paper, we present the first systematic study to quantify the value of exploration by examining its impact on the important entity of the system: content corpus. We define new metrics for measuring the content corpus change in the system; propose new user-corpus-codiverted experiment to evaluate any corpus change in an unbiased way; and examine the potential for using the Neural Linear Bandit algorithm (NLB) [41] to develop an exploration-based ranking system for our case study. NLB performs linear regression on top of the last-layer learned representation from deep neural networks as the contextual features to estimate uncertainty. It fits nicely into the modern deep learning-based recommender systems [15] while attaining simplicity in calculating accurate uncertainty estimates. We conduct live experiments on a large-scale commercial recommendation platform to measure the impact of exploration and present our findings from these real-world experiments. Together we make the following contributions:

- Methods for studying the benefit of exploration: We bring to light the measurement challenges of exploration and offer the first comprehensive study to systematically quantify the value of exploration in recommender systems. Our approach leverages content corpus as an important intermediate quantity to bridge the gap between exploration and the user experience.
- Metrics for evaluating the content corpus change: Short-term user engagement metrics fail to capture the
  benefit of exploration in the long run. To overcome this limitation, we propose novel metrics that capture the
  overall change in the content corpus of the recommender systems, which we prove to strongly impact user
  experience through an intervention study.

<sup>&</sup>lt;sup>1</sup>The value of exploration on model learning has been discussed in prior work [11, 19, 21].

- Experiment frameworks for measuring the value of exploration: To prevent corpus leakage between the control and treatment arm, we propose a new user-corpus-codiverted experiment to measure the effect of exploration on content corpus change in an unbiased manner.
- Designs of exploration-based system through Neural Linear Bandit: Though the NLB algorithm has been
  studied theoretically, we discuss the challenges of integrating it into real-world industrial recommender systems
  and detail our implementations used in the case study. We further validate its success through large-scale live
  experiments and point to exciting future directions for building exploration-based recommender systems.
- Validations and findings through real-world live experiments: We validate the overall design through
  extensive live experiments on a large-scale commercial recommender platform, which includes the verification
  of our experiment framework, and an intervention study to investigate how the content corpus acts as an
  intermediary between exploration and the user experience.

# 2 RELATED WORK

Our work falls into the general theme of exploration in recommender systems. Unlike prior works that mainly focus on algorithmic designs, we study the value of exploration from a measurement perspective. We then use the Neural Linear Bandit from the online learning literature as the backbone algorithm to build the effective exploration-based system. In this section, we discuss the literature along these two lines of research.

Exploration in Recommender Systems. The problem of exposure bias and its induced closed feedback loop [21] are well-known to the recommender system community. Exploration [10] is believed to be the key to breaking this closed feedback loop. Therefore, there has been considerable interest in developing new exploration-based systems. McInerney et al. [36] studied the benefit of  $\epsilon$ -greedy in balancing exploration with exploitation in production systems, focusing specifically on how exploration techniques could be coupled with recommendation explanations. Chen et al. [12] examined the direct role of exploration on users, i.e., helping them discover new interests and studied its effects on different aspects of the recommendation quality, such as diversity and serendipity. Similarly, Song et al. [46] studied effective user exploration techniques by introducing a hierarchical bandit framework that facilitates large-space user interest learning. In the domain of item exploration, a closely related research area is the cold-start item recommendation, which refers to the scenario where there is not enough historical information available for collaborative filtering to generate effective recommendations for new items. The main idea is to leverage the content features to handle the missing collaborative signal, with most work in this domain could be summarized into two categories: separate-training methods [7, 43] and joint-training methods [32, 48]. Contrary to these works, we examine the the value of exploration through the important but overlooked entity: content corpus. We argue that exploration can have a net positive long-term effect on users through the content corpus despite potential short-term user engagement loss. By designing new experiments and evaluating on a commercial recommendation platform serving billions of users, we connect the changes of content corpus with the long-term user experience. Our work provides a strong argument advocating for exploration-based systems.

Algorithms for Exploration. Multi-armed bandits and contextual bandits [2, 5, 30, 31] are natural frameworks to study exploration-exploitation trade-offs, which have been widely used in many domains, such as recommender systems [8, 22, 24, 33], healthcare [17, 37], dynamic pricing [38], and dialogue systems [35]. Among its variants, the most well-studied setting is bandits with linear payoffs [1, 5, 14], with LinUCB [14] and Thompson Sampling (TS) [3] being the two representative approaches. Compared with UCB, TS shows stronger performance empirically [9]. With the

success of deep learning models, there has been a surge of interest in exploring contextual bandits with neural networks in recent years. Riquelme et al. [41] proposed NeuralLinear algorithm, which performs Bayesian Linear Regression at the last layer of the network. Zhou et al. [51] studied it from a theoretical perspective by providing near-optimal regret bound for neural-network-based UCB. Zhang et al. [50] proposed Neural Thompson Sampling, which estimates the variance from the neural tangent features of the corresponding neural network and proves regret bounds matching other contextual bandits algorithms. In contrast to these studies, we address the challenges of deploying bandit algorithms in real-world, large-scale systems, discuss its benefit in exploration, and the lessons learned to bridge the gap between algorithms to applications.

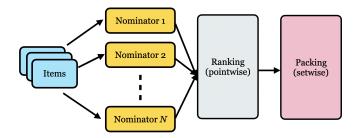


Fig. 1. The multi-stage recommender system, with candidate generation in the first stage followed by pointwise ranking and setwise packing.

#### 3 BACKGROUND ON THE OVERALL SYSTEM

We present our systematic study on one of the largest commercial recommendation platforms serving billions of users, over a period of three months. The production recommender system is a multi-stage system, as illustrate in Figure 1. The first stage consists of multiple retrieval systems to identify and nominate promising candidates from the overall content corpus. The second stage involves a ranking system to score and order the pool of candidates, followed by the final packing stage to achieve different business goals and diversify the whole slate. Unless otherwise specified, we use the production recommender system without the explicit exploration strategy as the control arm in all online A/B testing. We will describe the corresponding exploration treatment in Section 5.3.

# 4 THE CAUSAL EFFECT OF CONTENT CORPUS ON USER EXPERIENCE

Directly measuring the effects of exploration on user experience through the traditional user-diverted online A/B testing is challenging. To illustrate this, we present a two-week study to measure one exploration treatment using traditional user-diverted online A/B testing. The treatment involves a naive exploration strategy which forces the system to only recommend fresh and tail contents for several dedicated slots, while the control is the production system. Results are shown in Figure 2, with the y-axis represents the percentage change in the number of satisfied daily active users when comparing the exploration treatment with the purely exploitation-based production system, and the x-axis represents time over a period of two weeks. The negative result in the number of satisfied daily active users shows that exploring uncertain regions is typically accompanied with short-term user engagement costs. Meanwhile, its long-term benefit is hard to measure due to corpus leakage between experiment arms, which underscores the need for a new experiment framework to measure the value of exploration.

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To quickly assess the benefits of exploration within regular experiment cycles (typically lasting 2 to 3 weeks for most industrial systems), it is necessary to identify intermediate entities that can connect the exploration treatment to the change in long-term user experience. The two most desirable properties of these intermediate entities are:

- *Property 1:* The intermediate quantity should have a strong *causal relationship* between the exploration treatment and the user experience. In other words, the exploration treatment should impact the user experience by affecting the intermediate quantity.
- *Property 2*: The effect of exploration on the intermediate quantity should be *easily measurable* and *quickly observable* through a dedicated experiment design. This ensures the practicability and efficiency of the experimentation.

Chen [10] suggests that there are four possible intermediate entities in the recommender system that exploration might have a downstream effect on, i.e., 1) content corpus; 2) model, 3) user and 4) content provider ecosystem. We focus our discussion on the content corpus due to limited space <sup>2</sup>. In this section, we formally design a new intervention study to examine the causal effect of content corpus on user experience, providing evidence that the content corpus can serve as a valid intermediate entity that connects exploration to user experience (thereby satisfying *Property 1*). To complete the overall connection, we will examine how exploration treatment affects the content corpus change in Section 5. Furthermore, we introduce new metrics and corresponding experiment designs to ensure *Property 2* is also satisfied when the content corpus is used as the intermediate entity in the study (Section 5).



Fig. 2. The percentage change in terms of satisfied daily active users when compared the exploration system with the purely-exploitation system, using traditional A/B testing for a two-week period.

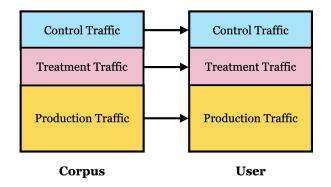


Fig. 3. User-Corpus-CoDiverted experiment diagram

# 4.1 Intervention Study

The objective of this study is to intervene the available corpus in the recommendation system, and measure how user experience changes with varying degrees of discoverable corpus<sup>3</sup> change. To quantify the user satisfaction, we will use a metric that counts the number of daily active users with satisfactory interactions on the platform, which we will refer to as *satisfied daily active users* throughout the paper.

<sup>&</sup>lt;sup>2</sup>The value of exploration on model learning has been discussed in prior work [11]. The direct impact of exploration on users, e.g., those favoring fresh, tail, and novel recommendation can be measured more or less in standard user-diverted A/B testing. The story on content provider is very similar to the one for content corpus, which we will briefly touch upon.

<sup>&</sup>lt;sup>3</sup>We refer to the part of the corpus that receive more than a certain number of positive user interactions (post exploration treatment) as discoverable corpus, the other undiscoverable part has no impressions (and interactions) with the user, hence bring no impact to the user.

# Algorithm 1: Corpus Ablation Procedure

**System:** We use the production multi-stage recommender system as depicted in Figure 1. Assume we have N nominators in the first stage, and each nominates  $n_i$  candidates initially.

**Ablating the corpus for** x%: upon a request from user u,

- Each nominator nominates  $n_i^{new} = \frac{n_i}{1-x\%}$  candidates  $\mathcal{A}_i$ .
- Set the user-specific random seed:  $s_u$ .
- Randomly filter x% of contents from the output of each nominator  $\mathcal{A}_i$  by randomly hashing the content ID using the seed  $s_u$  and denote the new set of candidates as  $\mathcal{A}_i^{new}$ .
- Pass  $\bigcup_{i=1}^{N} \mathcal{A}_{i}^{new}$  to the ranking and packing system, which ranks the candidates, packs them into a full page and presents to the user.

The crux of the study is to allow each user to access a reduced and fixed  $^4$  corpus  $C' \subset C$  by removing any nominations  $c \in C \setminus C'$  and observe the change in the number of satisfied daily active users  $^5$ . We conduct the ablation study for 4 weeks, with both the control and treatment arms running the same multi-stage recommender system as depicted in Figure 1. Each arm takes 5% of the overall traffic. The control arm receives all candidates outputted by the nominators, while the treatment randomly filters x% of the corpus from the platform  $^6$ , using the Corpus Ablation Procedure described in detail in Algorithm 1.

#### 4.2 Results

The results of the study are presented in Figure 4. From the left figure, we observe a significant decrease in terms of the satisfied daily active users across different ablation sizes. Moreover, the negative impact of the ablation grows over time, suggesting that it has a long-lasting negative effect on long-term user satisfaction. Interestingly, the right figure shows a monotone relationship between discoverable corpus size change and the number of satisfied daily active users (roughly linear), from which we hypothesize increasing discoverable corpus size will lead to positive user experience. However, it is worth mentioning that the linear relationship might only hold for a specific range of corpus size. Additionally, growing the corpus could have a saturating effect when the discoverable corpus reaches a certain size. Determining the exact nature of this relationship is an exciting direction for future research, but beyond the scope of this paper.

In summary, the content corpus change has a strong causal effect on the user experience change, which supports its use as an intermediate entity for investigating the benefit of exploration.

### 5 THE CAUSAL EFFECT OF EXPLORATION ON CORPUS CHANGE

In essence, exploration in uncertain regions increases the exposure and discoverability of fresh and tail contents and changes the overall corpus distribution, which in return improves the long-term user experience. Given the established causal effect of the corpus change on user experience, in this section, we present a comprehensive approach to study the effect of exploration on the content corpus. Specifically, we introduce a novel metric to measure the quality and discoverability of the content corpus by examining *post-exploration performance* (Section 5.1). To evaluate this metric in

 $<sup>^4</sup>$ To ensure that each user is only allowed access to a *fixed* reduced corpus, we use the same seed  $s_u$  for different requests from the same user (see Algorithm 1). However, to prevent any specific content from being dropped for all user traffic, we choose different seeds across users.

<sup>&</sup>lt;sup>5</sup>To eliminate any confounding factors, i.e., ensuring the same number of candidates are scored in the second stage (ranking) after filtering nomination candidates by the reduced corpus, we increased the number of nominations in the first stage accordingly.

<sup>&</sup>lt;sup>6</sup>There are various ways to perturb the content corpus and observe changes in user experience. One alternative is to directly removing various percentages of the "exploratory" content, however, this approach might be subject to the choice of the exploration system used in the filtering. Here, we present this more general approach in random filtering to decrease the discoverable corpus size, and we will establish a direct connection between the benefit of exploration and the discoverable corpus size change in Section 5.5, thus providing a complete argument.

#### **User Satisfaction Change** 10% -1 20% % Change in number of satisfied daily active users % Change in number of satisfied daily active users 30% -0.8 40% 50% -1.6 -2.4 -5 Percentage change of the exploration system compared with Control -3.2 15 20 30 45 50 Time Ablate Percentage

Fig. 4. Left: the percentage change of the number of satisfied daily active users across time, for different ablation size x%. Right: Linear interpolation of the change in terms of number of satisfied daily active users w.r.t. discoverable corpus size change.

an unbiased manner, we design a user-corpus-codiverted experiment to prevent any leakage between arms (Section 5.2). Additionally, we discuss the implementations of an exploration-based system through Neural Linear Bandit (Section 5.3) and evaluate its performance (Section 5.4), which serves as the treatment arm in our case study. With these tools in hand, we finally present our long-term study (Section 5.5) on how a dedicated exploration-based system can sustainably benefit the content corpus.

# 5.1 Discoverable Corpus: Post-Exploration Performance Metric

In this section, we discuss the metrics used to measure the change in the content corpus. Given that the size of the content corpus *users are exposed to* plays a crucial role in the user experience (Section 4), our aim with the corpus metric is to capture the discoverable corpus size change for corpus of varying qualities.

To avoid any confounding factors that might arise from a piece of content having better performance (i.e., receiving more interactions) simply because it receives more impressions from the exploration treatment, we use *post-exploration* corpus performance to measure the exploration effect. Specifically, we set a *graduation* threshold of X' positive user interactions for the contents. In other words, once a piece of content has received more than X' positive user interactions, it is no longer eligible for further exploration treatment. At this point, the content enters the *post-exploration* stage, and needs to survive on its own. That is to say, the exploration treatment is used to bootstrap cold-start content, but the content's success still mainly depends on its own quality and relevance to the audience once the entry barrier is removed. Given this, we formally define the *Discoverable Corpus* @X, Y for a system  $\pi$  as:

Discoverable Corpus @ $X, Y(\pi) :=$ # of contents receiving more than X positive user interactions within time period Y post-exploration.

This metric captures the change in quantity for a range of videos, from tail to head. For small X, it measures the performance of the tail content, while for large X, it measures the growth of the head and popular content. Ideally, the better the exploration-capability of the system is, the larger the Discoverable Corpus @X, Y days for various X buckets, while keeping a relatively neutral user experience as a guardrail<sup>7</sup>. Specifically, the value of the Discoverable Corpus

<sup>&</sup>lt;sup>7</sup>Our goal is not to solely focus on a pure exploration-based system that maximizes the corpus metrics. Instead, we aim to strike a balance between exploration and exploitation that maximizes the corpus metrics without compromising user engagement too much.

@X, Y depends on the time window used for evaluation, i.e., Y. In Section 5.5, we will provide a detailed discussion on how we assess the benefit of exploration on short-term and long-term Discoverable Corpus @X, Y.

### 5.2 User-Corpus-CoDiverted Experiment

Traditional user-diverted A/B testing [20, 25] provides a powerful tool to measure the effect of any recommendation changes on the *user* side. In the user-diverted A/B testing, we randomly assign users to the control and treatment group, exposing them to the corresponding treatments, and compare the user-side metrics, such as the number of clicks, satisfaction survey responses, as well as daily active users between the two arms. However, these experiments are unable to capture any corpus change, such as the number of contents receiving more impressions or user interactions due to the exploration treatment. As the two arms share the same corpus, any treatment effect on the corpus will leak between arms.

We thus propose *user-corpus-codiverted* A/B testing, which is an instance of the Multiple Randomization Designs (MRD) [6] by designing the specific assignment matrix. Particularly, it randomly assigns x% of the corpus<sup>8</sup> into the control and treatment arms respectively, in addition to randomly exposing x% users *in proportion* into control and experiment arms. As shown in Figure 3, the users in the control arm only receive recommendations from the control arm's corpus, while users in the treatment arm receive recommendations from the treatment arm's corpus. Compared to the original user-diverted experiment, this random splitting of the corpus prevents any information leakage and enables the measurement of the treatment effect on corpus-based metrics. We keep the user and corpus in proportion, e.g., 5% of users explore 5% corpus, so the effectiveness of the exploration treatment is consistent with full deployment when 100% of users are exploring the entire corpus. Otherwise, as one can imagine, using 5% of user traffic to explore the entire corpus (100%) will result in minimal changes to the corpus distribution.

# 5.3 Exploration-based System: Neural Linear Bandit

To fully demonstrate the benefit of exploration, it is critical to design an effective exploration system that will be used in our case study. As shown in figure 2, naive exploration strategies may lead to significant engagement loss, highlighting the need for more sophisticated exploration strategies that can enhance the discoverable corpus while maintaining (at least) neutral user satisfaction. Though various techniques have been studied theoretically in the literature, it remains unclear on how to build the efficient exploration-based systems for real-world, large-scale industrial systems. To address this challenge, we investigate the potential of Neural Linear Bandit (NLB) for ranking, which builds upon the NeuralLinear algorithm [41]. We choose NeuralLinear as the backbone algorithm as it leverages the representation power of DNNs, which is the foundation for many industrial systems, and computes the variance efficiently. Our focus is on the implementations and modifications we made to integrate the Neural Linear Bandit into the current existing industrial system pipeline. We also discuss the challenges we encountered and the exciting future directions for developing advanced exploration-based recommender systems.

## 5.3.1 Neural Linear Bandit.

Contextual Bandit Formulation. We frame recommendation as a contextual bandit problem: given the overall time horizon T, at each time-step  $t \in [T]$ , a user comes to the platform with contextual feature  $\mathbf{u}_t \in \mathbb{R}^{d_u}$  and  $\mathbf{u}_t \sim P_{\mathcal{U}}$ . The system  $\pi$  reacts to the user by selecting and presenting the action (i.e., content)  $a_t \in \mathcal{A}$  with feature  $\mathbf{a}_t \in \mathbb{R}^{d_a}$ . Then the

<sup>&</sup>lt;sup>8</sup>Note that we often further restrict the diversion by content providers. In other words, content belonging to the same provider are assigned to the same arm, to avoid treatment leakage between items from the same content provider.

system receives the feedback/reward (such as click, completion rate, likes, etc)  $\mathbf{r}_t \sim P(\cdot|\mathbf{u}_t, \mathbf{a}_t)$  with  $\mathbb{E}[\mathbf{r}_t] = f(\mathbf{u}_t, \mathbf{a}_t)$  and f being some unknown relevance function. The system then updates its model using the newly collected interaction data. The goal of the system  $\pi$  is to minimize the following regret:

$$R_T(\pi) := \mathbb{E}_{\mathbf{u}_t \sim P_{\mathcal{U}}, a_t \sim \pi(\cdot | \mathbf{u}_t), \mathbf{r}_t \sim P(\cdot | \mathbf{u}_t, \mathbf{a}_t)} \left[ \sum_{t=1}^T \mathbf{r}(\mathbf{u}_t, \mathbf{a}_t^*) - \mathbf{r}(\mathbf{u}_t, \mathbf{a}_t) \right]$$
(1)

with  $\mathbf{a}_t^* := \arg\max_{a \in \mathcal{A}} \mathbf{r}(\mathbf{u}_t, a)$  denotes the optimal action in hindsight, and  $\mathbf{a}_t$  is the action selected from system  $\pi$ . The randomness comes from the reward and the stochasticity in the system  $\pi$ .

Neural Linear Bandit. Popular algorithms such as UCB [14, 33] and Thompson Sampling [3, 13, 28, 52] with linear payoff function [3, 14] have been studied extensively for its closed form update. Linear models however are restrictive in its representation power. We adopt NeuralLinear [41], a variant of Thompson Sampling algorithm that performs the linear Bayesian regression on the top of the last layer features of the neural network, which nicely combines the representation power of the deep neural network and the simplicity of the uncertainty estimate from linear models. The underlying assumption is given by:

Assumption 1. There exists a representation function  $\phi : \mathbb{R}^{d_u} \times \mathbb{R}^{d_a} \to \mathbb{R}^d$  and an unknown parameter  $\beta \in \mathbb{R}^d$ , such that for all  $(\mathbf{u}, \mathbf{a})$ , the mean reward  $\mathbf{r}(\mathbf{u}, \mathbf{a})$  is linear in the representation  $\phi(\mathbf{u}, \mathbf{a})$  with

$$\mathbb{E}[\mathbf{r}] = \phi(\mathbf{u}, \mathbf{a})^T \beta \tag{2}$$

Modern deep learning-powered recommendation models often take a (generalized) linear regression layer from the last layer embedding to the target. We thus use the learned last layer embedding as the representation function  $\phi$  and empirically verify that Assumption 1 roughly holds by examining various evaluation metrics.

It then assumes the reward  $\mathbf{r}_t$ , with embedding  $\phi(\mathbf{u}_t, \mathbf{a}_t)$  and parameter  $\beta$ , follows the Gaussian distribution  $\mathcal{N}(\phi(\mathbf{u}_t, \mathbf{a}_t)^T \beta, \sigma^2)$  with noise  $\sigma^2$ . At time step t, NLB samples an action  $\mathbf{a}_t$  under the new user context  $\mathbf{u}_t$  and observes reward  $\mathbf{r}_t$ . Assuming the prior distribution for the unknown parameter  $\beta$  is given by  $\mathcal{N}(\hat{\beta}_{t-1}, \sigma^2 \Sigma_{t-1}^{-1})$ , it then updates the posterior distribution for  $\beta$  as:

$$\mathbb{P}(\beta|\mathbf{r}_t) \propto \mathbb{P}(\beta)\mathbb{P}(\mathbf{r}_t|\beta) \propto \mathcal{N}(\hat{\beta}_t, \sigma^2 \Sigma_t^{-1})$$
(3)

The covariance matrix  $\Sigma_t$  and the parameter estimate  $\hat{\beta}_t$  are defined as

$$\Sigma_t := \epsilon I_d + \sum_{\tau=1}^t \phi(\mathbf{u}_{\tau}, \mathbf{a}_{\tau}) \phi(\mathbf{u}_{\tau}, \mathbf{a}_{\tau})^T, \quad \hat{\beta}_t := \Sigma_t^{-1} \left( \sum_{\tau=1}^t \phi(\mathbf{u}_{\tau}, \mathbf{a}_{\tau}) \mathbf{r}_{\tau} \right)$$
(4)

with  $\epsilon$  is the hyper-parameter that controls the regularization strength. The posterior distribution of the reward  $\mathbf{r}(\mathbf{u}, \mathbf{a})$  at round t+1 is therefore given by

$$\mathcal{N}(\phi(\mathbf{u}, \mathbf{a})^T \hat{\beta}_t, \sigma^2 \phi(\mathbf{u}, \mathbf{a})^T \Sigma_t^{-1} \phi(\mathbf{u}, \mathbf{a}))$$
 (5)

Neural Linear Bandit then samples the reward for each action from this posterior distribution, and pulls the action which attains the highest reward.

5.3.2 Implementation. Despite its simplicity, fitting NLB directly into the industrial training and serving pipeline however, faces challenges due to (1). the high frequency of model updates; (2). the stable and efficient implementation of the variance estimate (i.e.,  $\sigma^2 \phi(\mathbf{u}, \mathbf{a})^T \Sigma_t^{-1} \phi(\mathbf{u}, \mathbf{a})$ ) as well as (3). the extension of the model beyond regression tasks, as some labels/rewards are binary, such as clicks, likes, etc. In this section, we discuss practical implementations and

different design choices we made to enable the use of NLB in the industrial recommender system training pipeline. We provide the overall architecture in Figure 5 with detailed algorithm shown in Algorithm 2, and empirically evaluate it in Section 5.4.

Setup. We apply the Neural Linear Bandit to the ranking stage of the system (Figure 1), which ranks hundreds to thousands of candidates nominated from the first candidate generation stage. To use NLB, we replace the original prediction score of a candidate with a sample from the posterior distribution of the prediction, and then rank all the candidates greedily in decreasing order. We choose one particular classification task for simplicity, i.e., predicting whether or not a user completes<sup>9</sup> the recommended content as the binary reward r. The underlying model for this classification task is a deep neural network architecture shown in Figure 5. The user features u and content features a are concatenated as input features and pass through several dense layers to predict the final score of completion. We use the 128-dimensional last layer embedding of the neural network  $\phi(\mathbf{u}, \mathbf{a})^{10}$  as the contextual features used in the Neural Linear Bandit.

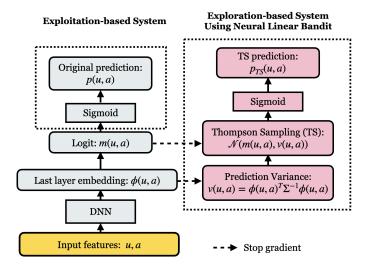


Fig. 5. The model architecture for the exploitation-based system (control) and the exploration-based system using Neural Linear Bandit (treatment), on a classification task.

Investigation 1: Model Update Frequency. The NLB algorithm updates the covariance matrix  $\Sigma_t$  per sample, which requires computationally intensive inversion calculation ( $\Sigma_t^{-1}$ ) at every sample that used for the variance estimate. On the other hand, most industrial recommendation models are trained in a batch setup [8, 22], where the model is continuously trained on a large set of logs, check-pointed, and exported daily or multiple times a day. To be more efficient, we decompose the updates of NLB into two stages:

• In the *training* stage, we keep updating the covariance matrix  $\Sigma_t$  using Equation 4 as we process each training data in the log, with the (changing) learned embedding function  $\phi$ ; When the training finishes, we update the

 $<sup>^9\</sup>mbox{We}$  mark the content as complete if the user consumes more than x% of the contents.

<sup>&</sup>lt;sup>10</sup>In experiment, we also concatenate the last layer embedding with several user and content features for better predictivity of the relevance and uncertainty.

precision matrix  $\Sigma_t^{-1}$  once, which ensures that the expensive inversion calculation is performed in a much less frequent manner, i.e., only once per training run.

• In the *serving* update, for each user **u** comes to the system, we calculate the prediction variance using the fixed precision matrix, and draws the predicted reward from the posterior distribution<sup>11</sup> defined in Equation 5. We present the top *K* results to the user and collect corresponding feedback.

Investigation 2: Stability and Variants of Uncertainty Calculation. The uncertainty estimate requires the inversion of the covariance matrix  $\Sigma^{-1}$ , which brings the stability issue when the covariance matrix is close to singular. We investigate two stable and efficient ways for uncertainty calculation: Pseudo-inverse [39] and Cholesky decomposition [27, 40], by comparing their computational cost and estimation accuracy.

- *Pseudo-inverse* provides a natural way to solve the under-determined linear systems. To avoid singularity in the precision matrix update, we replace the inverse  $\Sigma^{-1}$  with its pseudo-inverse variant  $\Sigma^{\dagger}$ , which is equivalent to  $\Sigma^{-1}$  when the covariance matrix is of full rank. It provides the unique solution with the minimum  $L_2$  norm on the parameter  $\beta$  when the system is under-determined.
- Cholesky decomposition is another popular method to calculate the parameter and the quadratic uncertainty term, avoiding explicit matrix inversion. Specifically, it calculates the Cholesky decomposition of the positive definite covariance matrix  $\Sigma = LL^T$ , with L being the lower-triangular matrix. Following this, the variance term in Equation 5 could be rewritten as:

$$\sigma^{-1}\phi(\mathbf{u}, \mathbf{a})^T \Sigma^{-1}\phi(\mathbf{u}, \mathbf{a}) = \sigma^{-1}\phi(\mathbf{u}, \mathbf{a})^T (LL^T)^{-1}\phi(\mathbf{u}, \mathbf{a})$$
(6)

$$= \sigma^{-1} \phi(\mathbf{u}, \mathbf{a})^T L^{-T} L^{-1} \phi(\mathbf{u}, \mathbf{a})$$
 (7)

$$= \sigma^{-1} z(\mathbf{u}, \mathbf{a})^T z(\mathbf{u}, \mathbf{a}) \tag{8}$$

with  $z(\mathbf{u}, \mathbf{a}) := L^{-1}\phi(\mathbf{u}, \mathbf{a})$  and could be easily solved using the forward substitution  $Lz(\mathbf{u}, \mathbf{a}) = \phi(\mathbf{u}, \mathbf{a})$  with only  $O(d^2)$  complexity. Similarly, given the Cholesky decomposition, the parameter  $\beta$  could be solved by continuously solving two linear systems with the lower-triangular matrix L.

Here we investigate the pros and cons of these two approaches regarding estimation accuracy and training speed. Figure 6 (left) plots the mean absolute difference between the predicted reward (though we do not use it explicitly in our algorithm) and the neural network prediction  $\hat{r}(\mathbf{u}, \mathbf{a})$ , i.e.,  $|\phi(\mathbf{u}, \mathbf{a})^T\hat{\beta} - \hat{r}(\mathbf{u}, \mathbf{a})|$ , with  $\hat{r}(\mathbf{u}, \mathbf{a})$  served as a surrogate to the ground-truth  $\mathbb{E}[r(\mathbf{u}, \mathbf{a})]$ . We see that Cholesky decomposition does give a smaller error, which shows its advantage in the accuracy and stability of the solution. The training speed is shown in Figure 6 (right), and we do see the pseudo-inverse is much faster compared with Cholesky decomposition, as in our case, the size of the matrix is small with d=128. Hence we go forward with the Pseudo-inverse option.

Investigation 3: Extension to Classification Task. In cases such as predicting clicks and likes, the task is classification rather than regression. It is well known that generalized linear models (for example, logistic regression) show stronger performance than linear models when the reward is binary [18]. Prior work has studied efficient exploration techniques when the payoff is a generalized linear model of the contextual feature, i.e.,  $\mathbb{E}[\mathbf{r}] = \mu(\phi(\mathbf{u}, \mathbf{a})^T \beta)$  with known link function  $\mu$  and unknown parameter  $\beta$ , for example, GLM-UCB [34] and GLM-TSL [29]. In the generalized linear models (GLM) setting, the challenge lies in the fact that the maximum likelihood estimation (MLE) of  $\beta$  no longer admits a

 $<sup>\</sup>overline{}^{11}$ As discussed in the later, for the mean estimate  $\phi(\mathbf{u}, \mathbf{a})^T \beta$  used in the posterior distribution, we directly use the predictions derived from the original system.

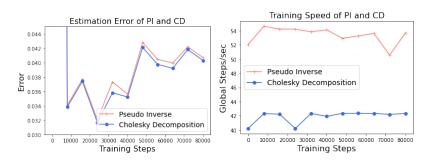


Fig. 6. Left: The estimation error (compared with neural network prediction) of Pseudo-inverse vs. Cholesky decomposition, the lower the better. Right: The training speed, the higher the better.

# Algorithm 2: Neural Linear Bandit (Classification Task)

**Input:** Total number of training runs T; Total number of batches per training run H; Initialize the model f with parameter  $\theta_0$  and last layer representation  $\phi_0$ ; Initialize the dataset  $\mathcal{D}_0 = \emptyset$ ; Initialize Neural Linear Bandit parameter  $\Sigma_0 := \epsilon \mathbf{I}, \beta_0 = \mathbf{0}$ ;

**for** each training run  $t = 1, 2, \cdots$  **do** 

# **Training Stage:**

Collect user log  $\mathcal{D}_{t-1}$ ;

**for** each batch  $h = 1, 2, \dots, H$  with batch data  $\mathcal{D}_{t-1,h}$  **do** 

Update the covariance matrix (with  $\Sigma_{1,0} := \Sigma_0$ ):

$$\Sigma_{t,h} \coloneqq \Sigma_{t,h-1} + \sum_{(\mathbf{u},\mathbf{a}) \in \mathcal{D}_{t-1,h}} \phi_{\theta_{t,h-1}}(\mathbf{u},\mathbf{a}) \phi_{\theta_{t,h-1}}(\mathbf{u},\mathbf{a})^T$$

Update the parameter of the ranking model  $\theta_{t,h-1} \to \theta_{t,h}$ , its associated last layer parameter  $\phi_{\theta_{t,h-1}} \to \phi_{\theta_{t,h}}$  and the parameter  $\beta_{t,h-1} \to \beta_{t,h}$  using stochastic gradient descent on batch data  $\mathcal{D}_{t-1,h}$ .

end

Update the precision matrix  $\Sigma_t^{\dagger}$  as pseudo-inverse of  $\Sigma_{t,H}$ ;

Take  $\Sigma_{t+1,0} := \Sigma_{t,H}$ ,  $\theta_t := \theta_{t,H}$  and  $\beta_t := \beta_{t,H}$ , and push the model  $\theta_t, \beta_t, \Sigma_t^{\dagger}$  for serving.

### **Serving Stage:**

**for** each user **u** comes to the system, for all nominations (actions)  $\mathbf{a} \in \mathcal{A}$  **do** 

Calculate the variance in the posterior distribution:

$$v_t(\mathbf{u}, \mathbf{a}) := \phi_{\theta_t}^T(\mathbf{u}, \mathbf{a}) \Sigma_t^{\dagger} \phi_{\theta_t}(\mathbf{u}, \mathbf{a})$$

Sample  $m_{TS}(\mathbf{u}, \mathbf{a})$  from posterior distribution, with  $m_{\theta_t}(\mathbf{u}, \mathbf{a}) := \phi_{\theta_t}(\mathbf{u}, \mathbf{a})^T \beta_t$ :

$$\mathcal{N}(m_{\theta_t}(\mathbf{u}, \mathbf{a}), v_t(\mathbf{u}, \mathbf{a}))$$

Modify the original ranking score with  $p_{TS}(\mathbf{u}, \mathbf{a}) := \mu(m_{TS}(\mathbf{u}, \mathbf{a}))$ , and  $\mu$  being the sigmoid function;

Present the top K ranked contents  $\mathcal{A}_k$  to the user;

Collect user feedback  $\mathbf{r}(\mathbf{u}, \mathbf{a})$  for  $\mathbf{a} \in \mathcal{A}_k$ ;

Update  $\log \mathcal{D}_t \to \mathcal{D}_{t-1} \bigcup \{(\mathbf{u}, \mathbf{a}, \mathbf{r}(\mathbf{u}, \mathbf{a}))\}_{\mathbf{a} \in \mathcal{A}_k}$ 

end

end

one-off closed-form update as in linear models  $^{12}$ , i.e., in GLM, we need to get the MLE for  $\beta$  at every time step t by

 $<sup>\</sup>frac{1}{12}$  In linear models, one can derive  $\beta_t$  in a one-off close form update as in eq (4) by aggregating the reward weighted context features (the term in the parenthesis) per-sample.

solving [29, 34]:

$$\sum_{\tau=1}^{t-1} (\mathbf{r}_{\tau} - \mu(\phi(\mathbf{u}_{\tau}, \mathbf{a}_{\tau})^{T} \boldsymbol{\beta})) \phi(\mathbf{u}_{\tau}, \mathbf{a}_{\tau}) = 0$$
(9)

which uses all the previous observations at each round and brings expensive per-sample gradient updates. However, it is easy to see that the  $\hat{\beta}$  is only needed to predict the posterior distribution mean of the reward  $\mu(\phi(\mathbf{u}, \mathbf{a})^T\hat{\beta})$ . A cheap surrogate exists for it, i.e., the logit of the original binary label prediction  $\hat{\mathbf{r}}(\mathbf{u}, \mathbf{a})$ , which is a by-product of the current system and provides a consistent estimate of the mean. When choosing the optimal action to play, we select the action  $\mathbf{a}$  that maximizes  $\phi(\mathbf{u}, \mathbf{a})^T\beta$  as since it is equivalent to the argmax  $\mu(\phi(\mathbf{u}, \mathbf{a})^T\beta)$  when  $\mu$  is the stictly increasing function. This idea shares a similar flavor with the SGD-TS algorithm proposed by Ding et al. [16], which shows that under diversity assumption on the contextual features, online SGD with TS exploration could achieve  $\tilde{O}(\sqrt{T})$  regret for finite-arm GLM problems. Unlike SGD-TS, we calculate the exact matrix pseudo-inverse for a more accurate uncertainty estimate, instead of approximating it through a diagonal matrix. The uncertainty estimate is the same as the linear case, and we could calculate it by simply maintaining the covariance matrix. After the posterior sampling is done in the linear logit space, we could transform the sample into the original space through the link function  $\mu$ .

# 5.4 Empirical Evaluation of the Neural Linear Bandit.

In this section, we aim to perform an initial evaluation of the effectiveness of NLB. We conduct a series of online A/B testing to evaluate the performance of the Neural Linear Bandit based ranking system, on a large commercial recommendation platform. We also examine the properties and the reliability of the uncertainty measurement. In Section 5.5, we introduce a more comprehensive long-term analysis to demonstrate in detail how the dedicated exploration-based system can benefit the discoverable corpus in both short-term and long-term.

In this experiment, we ran the online A/B testing with 0.3% traffic on both the control and treatment arms for six weeks. The control arm is the original ranking model in production, and the treatment is the exploration-based ranking system that utilizes the Neural Linear Bandit. For NLB, as discussed in Section 5.3.2, we update the covariance matrix in streaming fashion while the precision matrix  $\Sigma^{\dagger}$  is updated offline per training run, to be consistent with the training pipeline. To ensure stability in the matrix inversion, we set the regularization hyper-parameter with  $\epsilon = 1e - 6$  (Equation 4). To pick the noise parameter  $\sigma^2$ , we calculate the uncertainty from the ensemble of 5 different training models (which serves as a costly ground-truth measure), and pick the constant hyper-parameter  $\sigma^2 = 10$  such that the uncertainty derived from ensembles and Neural Linear Bandit are roughly in the same order.

How does the Neural Linear Bandit affect corpus metric change? To examine the exploration capability of the Neural Linear Bandit, i.e., how it benefits the size of the content corpus, we perform the user-corpus-codiverted experiments. For the exploration-based ranking system built upon Neural Linear Bandit, we see a +5.33% increase for the Discoverable Corpus @100, 6-week period, and another +5.66% improvement for the Discoverable Corpus @1000, 6-week period. Compared with the exploitation-based system, Neural Linear Bandit distributes the contents more equitably. Specifically, the improvement in the post-exploration metrics suggests more discoverability of tail contents.

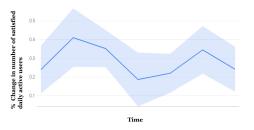
How does the Neural Linear Bandit perform, in terms of content freshness and user satisfaction? Intuitively, the uncertainty-based exploration system (e.g., NLB) gives more exposure to fresh and tail content, which changes the overall content corpus distribution and acquires valuable learning signals from these regions, and this further translates to user-engagement gain. Table 1 reports the increase in positive feedback on fresh contents published within different time periods. The time buckets (for example, 1h) in the header row group the contents based on different freshness

Table 1. The gain in various freshness related metric.

Positive feedback gain for different fresh contents	Mean	95% CI	
1h	1.49%	[1.20, 1.77]%	
3h	1.51%	[1.24, 1.77]%	
12h	1.45%	[1.19, 1.71]%	
1d	1.43%	[1.18, 1.69]%	
3 <b>d</b>	2.55%	[2.30, 2.81]%	
12d	1.16%	[0.92, 1.41]%	

levels. The significant increase of positive feedback on contents across different freshness levels verifies that exploration could help the system to explore fresh contents effectively and to acquire valuable learning signals. Interestingly, we also see a stable increase in the number of satisfied daily active users over time, as shown in Figure 7. We conjecture the gain might come from the following two aspects. First, the system helps users discover novel interests, as we also see a +1.25% gain in the number of unique topics that a user provides positive feedback on. Meanwhile, users prefer fresh contents on the specific surface specializing in short-form contents.

**User Satisfaction Change** 



Neural Linear Bandit		
$-0.35 \pm 0.003$		
$-0.26 \pm 0.003$		
$0.02 \pm 0.008$		

Fig. 7. The gain for the Neural Linear Bandit based ranking system in terms of the satisfied daily active users, compared with the the control production system, over a 6-week period.

Table 2. The Spearman's rank correlation (with standard errors over 20 runs) of different features and the uncertainty calculated by Neural Linear Bandit.

What are the properties of the uncertainty estimates and how reliable they are? One of the key components in the Neural Linear Bandit is the quadratic uncertainty term, which captures the strength of the exploration term for different (u, a) pairs. Though theoretically quantifiable, it remains an interesting question to visualize how the uncertainty differs for different users and content types. To examine this, we select three representative features, with two capturing content properties: (1). the number of days since the contents' publish time (i.e., content age); (2). the number of lifetime positive feedback (i.e., content popularity) and one capturing user property: (3). the total number of feedback a user provided on the platform (i.e., user activity). We measure the relationship between these features and the uncertainty term using Spearman's rank correlation coefficient, which assesses the monotone relationship between two variables. Table 2 reports the Spearman's rank correlation coefficient between the selected three features and the uncertainty calculated by Neural Linear Bandit. Interestingly, one can observe that the current system is more uncertain for fresh and less popular contents while being more or less indifferent to users of different activity levels. Furthermore, we compute the Spearman's rank correlations between the features and the uncertainties obtained from ensemble models, which shows -0.3 for both the content features and around 0 for user features. These results are similar to the ones calculated from the Neural Linear Bandit, suggesting the reliability of the uncertainty estimate.

In summary, the empirical evaluations in this section indicate the effectiveness of the Neural Linear Bandit as a dedicated exploration-based system. It successfully balances the trade-off between exploration and exploitation, allowing for increased coverage without sacrificing user experience.

# 5.5 Evaluation of the Exploration Effect on Corpus Change

In this section, we present a long-term study on the benefit of the exploration on the discoverable corpus change. We utilize the user-corpus-codiverted live experiment (Section 5.2) and use 5% of the overall traffic on both control and treatment arms. The control is a purely exploitation-based production system, while the treatment is a dedicated exploration-based system<sup>13</sup>. We begin by analyzing the *short-term benefits* of the exploration system by measuring the Discoverable Corpus  $@X_0$ , 7-day period.

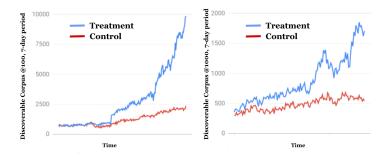


Fig. 8. Discoverable Corpus @100, 7-day period (left) and Discoverable Corpus @1000, 7-day period (right) for both control and treatment arms.

As shown in Figure 8, we observe a significantly increased number Discoverable Corpus @100, 7-day period (left) and Discoverable Corpus @1000, 7-day period (right) (i.e., the number of contents receiving more than  $X_0 = 100$  and  $X_0 = 1000$  post-exploration positive interactions). This validates that the exploration-based system is effective in boosting the number of contents that achieve early success in a short-term period. Furthermore, the gap between the control and treatment groups continues to widen over time, which we find is due to content providers in the treatment arm creating more discoverable contents than the ones in the control arm. Although we will not delve into the details of how exploration benefits content providers due to limited space, this topic is worth investigating in future research.

While achieving early success for content in the short term is important, it does not necessarily guarantee sustained long-term growth of the corpus. It is ideal for the exploration system to identify high-quality content that has the potential to go viral after the initial bootstrapping. To assess the *long-term post-exploration growth* of the contents, we analyze the Discoverable Corpus  $@X_l$ , 3-month period  $(X_l, X_l \gg X_0)$  for different  $X_l$  buckets. As shown in Table 3, the exploration treatment consistently increases the Discoverable Corpus  $@X_l$ , 3-month period across different  $X_l$  buckets. It is noteworthy that the percentage of increment remains remarkably consistent across the different  $X_l$  buckets, roughly around 50%.

To examine the full spectrum of the content quality distribution, we use the Discoverable Corpus @X, 3-month period at various threshold X as the quality indicator. Figure 9 shows the histograms of Discoverable Corpus @X, 3-month

<sup>&</sup>lt;sup>13</sup>It is worth pointing out that the exploration-based system is not purely based on Neural Linear Bandit. In fact, it includes a number of modifications to the system that facilitate the exploration effort, as this study spans over several months.

Table 3. Discoverable Corpus  $@X_I$ , 3-month period (i.e., the change in the number of contents receiving  $X_I$  number of post-exploration positive user interactions), between control and treatment arms.

$X_l$	100	1000	10K	1M	10M
	(in 7 days)	(in 7 days)			
Change of Discoverable Corpus $@X_l$ , 3-month period	+119.4%	+58.5%	+48.2%	+51.0%	+53.8%

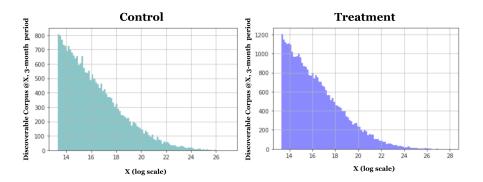


Fig. 9. The histogram of the Discoverable Corpus @X, 3-month period (number of contents receiving at least X positive feedback) for various X values, between control and treatment arms. The x-axis shows the value of X (in log scale), and the y-axis denotes the Discoverable Corpus @X, 3-month period.

period for both control (left) and treatment (right) arms. We focused on contents with at least 10k post-exploration positive feedback (i.e.,  $X \ge 10K$ ) to zoom in on the "high-quality" region of the corpus. The x-axis shows the number of post-exploration positive user interactions on a logarithmic scale (i.e., X), and the y-axis plots the number of contents in the specific bucket (i.e., Discoverable Corpus @X, 3-month period). While the numbers in the treatment arm (right) are higher, we observe a remarkably similar distribution between the two, implying that the quality distribution of contents discovered through the exploration system is comparable to that of the original contents. In other words, exploration not only helps contents achieve initial success, but also discovers the high-quality ones which will eventually reach viral. Given this, we have successfully demonstrated that the advanced exploration-based system could effectively grow the content corpus in a sustainable manner, which translates into a gain in the user satisfaction (verified in Section 4).

# 6 DISCUSSION AND FUTURE WORKS

In this paper, we conduct a systematic investigation into the long-term value of exploration on users through the crucial intermediaries in the system, namely the content corpus. We addressed the measurement challenges, designed new metrics and experimental frameworks to capture the benefits of exploration on the content corpus, and established a connection between the growth of the discoverable corpus and the gain in user satisfaction through an intervention study. We verify them via extensive real-world live experiments in a large-scale commercial recommendation platform and present our valuable findings. We further examine Neural Linear Bandit algorithm for building the uncertainty-based exploration system in production. However, it is important to note that the current setup is customized for single-task prediction and exploration. In contrast, most modern recommender systems aim to leverage multiple rich sources of feedback and often employ multi-task learning in practical applications. Therefore, exploring efficient ways to conduct exploration under these more complex multi-task settings presents an interesting avenue for future research.

Furthermore, as an initial attempt, this paper only examines the value of exploration through one entity of the system, i.e., the content corpus. This opens up opportunities for further research to investigate the value of exploration through other important entities such as content creators.

#### REFERENCES

- [1] Yasin Abbasi-Yadkori, Dávid Pál, and Csaba Szepesvári. 2011. Improved algorithms for linear stochastic bandits. Advances in neural information processing systems 24 (2011).
- [2] Alekh Agarwal, Daniel Hsu, Satyen Kale, John Langford, Lihong Li, and Robert Schapire. 2014. Taming the monster: A fast and simple algorithm for contextual bandits. In *International Conference on Machine Learning*. PMLR, 1638–1646.
- [3] Shipra Agrawal and Navin Goyal. 2013. Thompson sampling for contextual bandits with linear payoffs. In International conference on machine learning. PMLR. 127–135.
- [4] Michal Aharon, Oren Anava, Noa Avigdor-Elgrabli, Dana Drachsler-Cohen, Shahar Golan, and Oren Somekh. 2015. Excuseme: Asking users to help in item cold-start recommendations. In Proceedings of the 9th ACM Conference on Recommender Systems. 83–90.
- [5] Peter Auer, Nicolo Cesa-Bianchi, and Paul Fischer. 2002. Finite-time analysis of the multiarmed bandit problem. *Machine learning* 47, 2 (2002), 235–256.
- [6] Patrick Bajari, Brian Burdick, Guido W Imbens, Lorenzo Masoero, James McQueen, Thomas Richardson, and Ido M Rosen. 2021. Multiple randomization designs. arXiv preprint arXiv:2112.13495 (2021).
- [7] Iman Barjasteh, Rana Forsati, Farzan Masrour, Abdol-Hossein Esfahanian, and Hayder Radha. 2015. Cold-start item and user recommendation with decoupled completion and transduction. In Proceedings of the 9th ACM Conference on Recommender Systems. 91–98.
- [8] Walid Bendada, Guillaume Salha, and Théo Bontempelli. 2020. Carousel personalization in music streaming apps with contextual bandits. In Proceedings of the 14th ACM Conference on Recommender Systems. 420–425.
- [9] Olivier Chapelle and Lihong Li. 2011. An empirical evaluation of thompson sampling. Advances in neural information processing systems 24 (2011).
- [10] Minmin Chen. 2021. Exploration in recommender systems. In Fifteenth ACM Conference on Recommender Systems. 551-553.
- [11] Minmin Chen, Alex Beutel, Paul Covington, Sagar Jain, Francois Belletti, and Ed H Chi. 2019. Top-k off-policy correction for a REINFORCE recommender system. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. 456–464.
- [12] Minmin Chen, Yuyan Wang, Can Xu, Ya Le, Mohit Sharma, Lee Richardson, Su-Lin Wu, and Ed Chi. 2021. Values of User Exploration in Recommender Systems. In Fifteenth ACM Conference on Recommender Systems. 85–95.
- [13] Wang Chi Cheung, Vincent Tan, and Zixin Zhong. 2019. A Thompson sampling algorithm for cascading bandits. In The 22nd International Conference on Artificial Intelligence and Statistics. PMLR, 438–447.
- [14] Wei Chu, Lihong Li, Lev Reyzin, and Robert Schapire. 2011. Contextual bandits with linear payoff functions. In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics. JMLR Workshop and Conference Proceedings, 208–214.
- [15] Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep neural networks for youtube recommendations. In Proceedings of the 10th ACM conference on recommender systems. 191–198.
- [16] Qin Ding, Cho-Jui Hsieh, and James Sharpnack. 2021. An efficient algorithm for generalized linear bandit: Online stochastic gradient descent and thompson sampling. In International Conference on Artificial Intelligence and Statistics. PMLR, 1585–1593.
- [17] Audrey Durand, Charis Achilleos, Demetris Iacovides, Katerina Strati, Georgios D Mitsis, and Joelle Pineau. 2018. Contextual bandits for adapting treatment in a mouse model of de novo carcinogenesis. In Machine learning for healthcare conference. PMLR, 67–82.
- [18] Sarah Filippi, Olivier Cappe, Aurélien Garivier, and Csaba Szepesvári. 2010. Parametric bandits: The generalized linear case. Advances in Neural Information Processing Systems 23 (2010).
- [19] Rein Houthooft, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel. 2016. Vime: Variational information maximizing exploration. Advances in neural information processing systems 29 (2016).
- [20] Guido W Imbens and Donald B Rubin. 2015. Causal inference in statistics, social, and biomedical sciences. Cambridge University Press
- [21] Amir H Jadidinejad, Craig Macdonald, and Iadh Ounis. 2020. Using Exploration to Alleviate Closed Loop Effects in Recommender Systems. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 2025–2028.
- [22] Olivier Jeunen and Bart Goethals. 2021. Top-k contextual bandits with equity of exposure. In Proceedings of the 15th ACM Conference on Recommender Systems. 310–320
- [23] Ray Jiang, Silvia Chiappa, Tor Lattimore, Andr\u00e1s Gy\u00f6rgy, and Pushmeet Kohli. 2019. Degenerate feedback loops in recommender systems. In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society. 383–390.
- [24] Thorsten Joachims, Adith Swaminathan, and Maarten De Rijke. 2018. Deep learning with logged bandit feedback. In International Conference on Learning Representations.
- [25] Ron Kohavi, Diane Tang, and Ya Xu. 2020. Trustworthy online controlled experiments: A practical guide to a/b testing. Cambridge University Press.
- [26] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. Computer 42, 8 (2009), 30-37.
- [27] Aravindh Krishnamoorthy and Deepak Menon. 2013. Matrix inversion using Cholesky decomposition. In 2013 signal processing: Algorithms, architectures, arrangements, and applications (SPA). IEEE, 70–72.
- [28] Branislav Kveton, Ofer Meshi, Masrour Zoghi, and Zhen Qin. 2022. On the Value of Prior in Online Learning to Rank. In International Conference on Artificial Intelligence and Statistics. PMLR, 6880–6892.
- [29] Branislav Kveton, Manzil Zaheer, Csaba Szepesvari, Lihong Li, Mohammad Ghavamzadeh, and Craig Boutilier. 2020. Randomized exploration in generalized linear bandits. In International Conference on Artificial Intelligence and Statistics. PMLR, 2066–2076.
- [30] Tze Leung Lai, Herbert Robbins, et al. 1985. Asymptotically efficient adaptive allocation rules. Advances in applied mathematics 6, 1 (1985), 4-22.

- [31] John Langford and Tong Zhang. 2007. The epoch-greedy algorithm for multi-armed bandits with side information. Advances in neural information processing systems 20 (2007).
- [32] Jingjing Li, Mengmeng Jing, Ke Lu, Lei Zhu, Yang Yang, and Zi Huang. 2019. From zero-shot learning to cold-start recommendation. In Proceedings of the AAAI conference on artificial intelligence. Vol. 33, 4189–4196.
- [33] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. 2010. A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web. 661–670.
- [34] Lihong Li, Yu Lu, and Dengyong Zhou. 2017. Provably optimal algorithms for generalized linear contextual bandits. In *International Conference on Machine Learning*. PMLR, 2071–2080.
- [35] Bing Liu, Tong Yu, Ian Lane, and Ole J Mengshoel. 2018. Customized nonlinear bandits for online response selection in neural conversation models. In Thirty-Second AAAI Conference on Artificial Intelligence.
- [36] James McInerney, Benjamin Lacker, Samantha Hansen, Karl Higley, Hugues Bouchard, Alois Gruson, and Rishabh Mehrotra. 2018. Explore, exploit, and explain: personalizing explainable recommendations with bandits. In Proceedings of the 12th ACM conference on recommender systems. 31–39.
- [37] Yonatan Mintz, Anil Aswani, Philip Kaminsky, Elena Flowers, and Yoshimi Fukuoka. 2020. Nonstationary bandits with habituation and recovery dynamics. Operations Research 68, 5 (2020), 1493–1516.
- [38] Kanishka Misra, Eric M Schwartz, and Jacob Abernethy. 2019. Dynamic online pricing with incomplete information using multiarmed bandit experiments. Marketing Science 38, 2 (2019), 226–252.
- [39] Roger Penrose. 1955. A generalized inverse for matrices. In Mathematical proceedings of the Cambridge philosophical society, Vol. 51. Cambridge University Press, 406–413.
- [40] William H Press, Saul A Teukolsky, William T Vetterling, and Brian P Flannery. 2007. Numerical recipes 3rd edition: The art of scientific computing. Cambridge university press.
- [41] Carlos Riquelme, George Tucker, and Jasper Snoek. 2018. Deep bayesian bandits showdown: An empirical comparison of bayesian deep networks for thompson sampling. arXiv preprint arXiv:1802.09127 (2018).
- [42] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. 2001. Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th international conference on World Wide Web. 285–295.
- [43] Martin Saveski and Amin Mantrach. 2014. Item cold-start recommendations: learning local collective embeddings. In Proceedings of the 8th ACM Conference on Recommender systems. 89–96.
- [44] Tobias Schnabel, Paul N Bennett, Susan T Dumais, and Thorsten Joachims. 2018. Short-term satisfaction and long-term coverage: Understanding how users tolerate algorithmic exploration. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. 513–521.
- [45] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. 2016. Mastering the game of Go with deep neural networks and tree search. nature 529, 7587 (2016), 484–489.
- [46] Yu Song, Shuai Sun, Jianxun Lian, Hong Huang, Yu Li, Hai Jin, and Xing Xie. 2022. Show Me the Whole World: Towards Entire Item Space Exploration for Interactive Personalized Recommendations. In Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining. 947–956.
- [47] William R Thompson. 1933. On the likelihood that one unknown probability exceeds another in view of the evidence of two samples. Biometrika 25, 3-4 (1933), 285–294.
- [48] Maksims Volkovs, Guangwei Yu, and Tomi Poutanen. 2017. Dropoutnet: Addressing cold start in recommender systems. Advances in neural information processing systems 30 (2017).
- [49] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. 2019. Deep learning based recommender system: A survey and new perspectives. ACM Computing Surveys (CSUR) 52, 1 (2019), 1–38.
- [50] Weitong Zhang, Dongruo Zhou, Lihong Li, and Quanquan Gu. 2020. Neural thompson sampling. arXiv preprint arXiv:2010.00827 (2020).
- [51] Dongruo Zhou, Lihong Li, and Quanquan Gu. 2020. Neural contextual bandits with ucb-based exploration. In International Conference on Machine Learning. PMLR, 11492–11502.
- [52] Shi Zong, Hao Ni, Kenny Sung, Nan Rosemary Ke, Zheng Wen, and Branislav Kveton. 2016. Cascading bandits for large-scale recommendation problems. arXiv preprint arXiv:1603.05359 (2016).

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