KuaiSAR: A Unified Search And Recommendation Dataset

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ABSTRACT

The confluence of Search and Recommendation (S&R) services is vital to online services, including e-commerce and video platforms. The integration of S&R modeling is a highly intuitive approach adopted by industry practitioners. However, there is a noticeable lack of research conducted in this area within academia, primarily due to the absence of publicly available datasets. Consequently, a substantial gap has emerged between academia and industry regarding research endeavors in joint optimization using user behavior data from both S&R services. To bridge this gap, we introduce the first large-scale, real-world dataset **KuaiSAR** of integrated *S*earch *A*nd *R*ecommendation behaviors collected from *Kuai*shou, a leading short-video app in China with over 350 million daily active users. Previous research in this field has predominantly employed publicly available semi-synthetic datasets and simulated [1, 13], with artificially fabricated search behaviors. Distinct from previous datasets, KuaiSAR contains genuine user behaviors, including the occurrence of each interaction within either search or recommendation service, and the users' transitions between the two services. This work aids in joint modeling of S&R, and utilizing search data for recommender systems (and recommendation data for search engines). Furthermore, due to the various feedback labels associated with user-video interactions, KuaiSAR also supports a broad range of tasks, including intent recommendation, multi-task learning, and modeling of long sequential multi-behavioral patterns. We believe this dataset will serve as a catalyst for innovative research and bridge the gap between academia and industry in understanding the S&R services in practical, real-world applications. The dataset is available at https://ethan00si.github.io/KuaiSAR/. The dataset is also shared at https://doi.org/10.5281/zenodo.8031220, following the submission guidelines.

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CCS CONCEPTS

• **Information systems** → **Information retrieval**.

KEYWORDS

Datasets; Recommendation; Search

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1 INTRODUCTION

Many online content platforms, *e.g.*, Kuaishou and TikTok, provide search and recommendation (**S&R**) services to satisfy users diverse information needs. The differentiation between S&R services may be absent to users on these platforms. The integration of S&R services is a highly intuitive approach adopted by industry practitioners. However, academic research is scarce in this domain, primarily due to the lack of publicly available datasets that support scholarly investigations. Consequently, a substantial gap has emerged between academia and industry regarding research endeavors in this particular domain.

The lack of large-scale, real-world datasets on user S&R behaviors has limited the research progress of joint modeling of S&R. Existing datasets in the field of recommendation systems (or personalized search) only contain user behavior sequences within the recommendation system (or search engine). Previous research in this field has usually depended on experiments conducted using proprietary industrial datasets [6, 23, 28] or simulated datasets [13, 25, 26], thereby hindering the participation of more researchers.

Existing public datasets suffer from the following two deficiencies: (1) There is no dataset that collects the behavioral history of users in both the recommender system and search engine. (2) The previous datasets are not based on a unified scenario that offers

Table 1: Statistics of user actions in KuaiSAR (top) and feature descriptions (bottom). 'S' and 'R' denote search and recommendation, respectively. All users have both S&R behaviors.

Dataset	#Users	#Items	#Queries	#Actions
S-data	25,877	2,012,476	267,608	3,171,231
R-data	25,877	2,281,034	-	7,493,101
Total	25,877	4,195,529	267,608	10,664,332

User&Item feature:	Users and items have abundant side information. 5 (18) features for users (items).
S-action feature:	S-actions have 9 features, *e.g.,* search session IDs, query keywords, and sources of entering the search service.
R-action feature:	R-actions has 12 features, including 9 types of user feedback, *e.g.,* likes, follows, and entering search.
Social network:	576 users have friends.

(a) (b) (c)

Figure 1: The integrated S&R scenarios in Kuaishou app. In the process of watching a video, users have two primary interaction modalities. They can either utilize the recommendation service, involving scrolling vertically to discover diverse videos (b) -> (a). Alternatively, they can tap the magnifying glass symbol to leverage the search service (b) -> (c).

interactive S&R services. In this scenario, the search service integrates elements of recommendation, while the recommendation service is closely intertwined with the search functionality. Numerous mobile applications have developed such integrated scenarios in recent years, exemplified by Kuaishou[1]. As depicted in Figure 1, users may transition to the search interface while utilizing the recommendation system, and they may also encounter recommended queries while using the search engine (details in Section 3.1).

The contributions of KuaiSAR are summarized as follows: To facilitate academic research in exploring the potential of integrating S&R services, we present a large-scale real-world dataset containing both S&R behaviors, called KuaiSAR. KuaiSAR is collected from the Kuaishou app, one of China's largest short-video apps with more than 350 million daily active users. Table 1 presents basic statistics of KuaiSAR. In contrast to the previous datasets, KuaiSAR contains rich information: First, it contains users *genuine* S&R behaviors, and explicitly records the *user-system interactions* in both the recommendation service and the search service. Moreover, it records whether users *transition* to the search service through the current video while using the recommendation service. Finally, it captures the sources of user entry into the search service, *e.g.,* actively typing a query and clicking on a recommended query.

It is noteworthy that KuaiSAR is the first dataset that records genuine user S&R behaviors within an interactive app that provides unified search and recommendation services. This dataset has the potential to advance the research of joint modeling for S&R [23, 25, 26, 28], facilitate better utilization of search data in recommendation systems [13–15, 17], utilization of recommendation data in search [1, 2], as well as the intent recommendation [3, 6]. Given the diverse labels for user-video interactions in the dataset, *e.g.,* whether search, like, and forward, KuaiSAR can also facilitate a wide range of tasks, including multi-task learning [12, 16] and multi-behavior sequential modeling [9, 24].

[1] https://www.kuaishou.com/en

2 RELATED WORK

2.1 Joint Search and Recommendation

An early study [5] pointed out that search (information retrieval) and recommendation (information filtering) are the two sides of the same coin. These two services share similar objectives [21], which are to provide users with information to fulfill their needs. The key distinction lies in whether the user's needs involve explicit queries.

Recently, many studies have recognized the potential for joint modeling of S&R. Several studies [23, 28] propose the design of a unified model that integrates S&R, effectively modeling user interests. Some works [25, 26] have devised joint loss functions to train S&R models simultaneously. Another research direction involves utilizing the behavioral data from one service to assist in modeling the other service. This direction entails leveraging search data to enhance recommendation models [13, 15, 17] or employing recommendation data to augment search models [1, 11]. Some industry practitioners have also realized the potential value of integrating S&R. Consequently, in practical scenarios, many search behaviors are initiated through the recommendation system. This particular type of recommendation service focused on recommending search queries, is commonly referred to as "Intent Recommendation" [3, 6, 29].

However, existing research in this field has primarily relied on private datasets [3, 17, 23, 28] or semi-synthetic public datasets [25, 26]. The lack of a large-scale, real-world dataset encompassing both S&R behaviors has constrained the advancement of this field.

2.2 Existing Dataset

The currently available search or recommendation datasets have predominantly been designed to cater to a single research field, focusing either on search or recommendation. For instance, MS MARCO [20] provides query and document information along with query-document interactions for research in the search domain. KuaiRec [4], on the other hand, offers user-item interactions in

Table 2: Comparison of currently available datasets for search and recommendation.

Property	MS MARCO	KuaiRec	Amazon	JDsearch	KuaiSAR
R-action	No	Yes	Yes	Yes[2]	Yes
S-action	Yes	No	Yes[1]	Yes	Yes
# Users	–	7,176	192,403	173,831	25,877
# Items	8,841,823	10,728	63,001	12,872,636	4,195,529
# Queries	509,919	–	3,221	171,728	267,608
# Actions	509,919	17,207,376	1,689,188	26,667,260	10,664,332

[1] Search actions in the Amazon dataset are artificially simulated.
[2] The JDsearch dataset lacks distinction between non-search data originating from recommendation scenarios or casual browsing.

the recommendation service, catering to research in the recommendation field. Only a few datasets attempt to provide user S&R behaviors concurrently. To the best of our knowledge, only two existing datasets provide both search and recommendation interactions.

We briefly introduce these two existing datasets. One is a widely used semi-synthetic dataset, while the other is a recently released real-world dataset.

• **Amazon** [1, 8]. This dataset was initially created for recommendation systems [8]. It consists of user review data and item metadata extracted from purchases made on Amazon. Some researchers [1] have utilized item metadata to construct pseudo queries, simulating user search behaviors and thereby enabling the dataset to encompass both user S&R behaviors. Due to the lack of publicly available data, this dataset has ultimately become the most commonly used dataset in the field of joint modeling of S&R [2, 11, 15, 25, 26]. The obvious drawback of this dataset is the lack of real user search behaviors.

• **JDsearch** [10]. It is a recently released dataset designed specifically for personalized product search. It consists of user queries and diverse user-product interactions collected from JD.com, a popular Chinese e-commerce platform. The interactions may be from diverse channels, as stated in [10], including "search, recommendation, and casual browsing". The limitation of this dataset lies in its mere differentiation between non-search data, without capturing whether non-search data is in recommendation scenarios or the casual browsing scenario. Additionally, it does not document whether search interactions come from typing-in searches or clicking on recommended queries.

We compared KuaiSAR with the datasets above, and the comparison results are listed in Table 2. Compared with the existing datasets, KuaiSAR has the following key advantages: (1) it records and discriminates between users' authentic search and recommendation behaviors; (2) it documents the sources of users' search behaviors, *e.g.,* actively typing in searches and clicking on recommended queries; (3) it comprehensively captures users' transitions between S&R services, such as documenting whether users initiate a search while watching a video within the recommendation system; (4) it provides abundant side information for both users and items; and (5) it logs users' authentic interactions, including both positive and negative feedback.

3 DATASET DESCRIPTION

3.1 Characteristics of Kuaishou App

Kuaishou is one of the most popular short video-sharing platforms in China, with over 350 million daily active users. As shown in Figure 1, Kuaishou provides both S&R services. As users scroll down the screen, they can discover new recommended short videos they may be interested in. When users click on the magnifying glass, they can enter the main search page and use the search engine to find videos of interest.

In recent years, Kuaishou has focused on integrating S&R services to enhance user experiences. The recommender leverages query-based recommendations, such as suggesting queries in the comments section, to encourage users to explore new information and resources using the search service. Similarly, incorporating recommended queries on the main search page helps users discover content relevant to their interests, stimulating curiosity and prompting the exploration of more engaging material. For detailed examples, please visit our website. In summary, the collaborative efforts of these systems improve information delivery and enhance the user experience.

Considering the specific characteristics of the Kuaishou, we have introduced additional labels in the user behavior logs to foster potential research. These labels aim to capture the transitions occurring between S&R services accurately. For user recommendation behaviors, we record whether users tap on the magnifying glass to search while browsing videos within the recommendation system, as well as whether these queries are related to the current video. For user search behaviors, we record the sources of their entry into the search engine, such as clicking on recommended related queries, manually typing queries, and clicking on hot search topics. These labels can enhance our understanding of user behaviors within S&R services on a more comprehensive level.

3.2 Data Construction

To facilitate the research on integrating S&R services, KuaiSAR is constructed with the following steps:

First, we randomly sampled approximately 25,000 users who accessed both search and recommendation services in Kuaishou app between May 22, 2023 and May 31, 2023. The user interaction behaviors include *not only the positive feedback but also the negative feedback.* For instance, in the recommendation scenario, negative interactions include videos that were displayed but skipped by the users; In the search scenario, the negative interactions involve the search results that were exposed but not clicked by the users. In addition, *various user feedback* in the recommendation system is also recorded, including likes, shares, follows, and playing time. Considering that users may switch between search and recommendation services, we also capture whether users initiate a search while viewing a video (labeled as 'search') and whether the search query is related to the current video (labeled as 'search_photo_related'), as two additional labels. The diverse user feedback labels provide an opportunity to investigate the interest transition of users in the unified S&R scenario. The timestamps of these actions were also recorded in the dataset, providing temporal information for models. Moreover, the data is clearly documented, specifying their respective occurrence scenarios, *i.e.,* whether in the search or in the recommendation scenario. We also included users' social network information, which can be used to enrich research on social networks using comprehensive S&R data. Considering that users may actively initiate a search or enter the search service by clicking on triggered terms in recommendation, the sources of user search interactions are meticulously recorded, allowing for differentiation of different types of search behaviors.

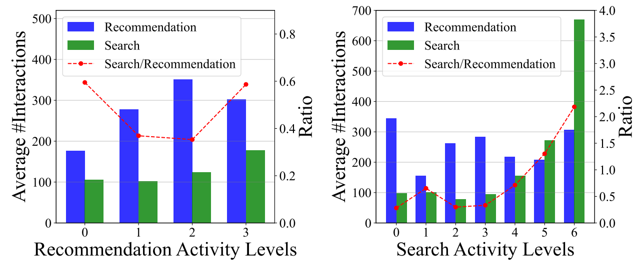
Second, we collected various side information for users and items. As for items, informative features include captions, author ID, photo types, uploading date, uploading type, music ID, topic tags, and category types of four levels. As for users, we recorded their activity levels in both search and recommendation services. We also included two encrypted features for each user.

Finally, we anonymized the collected records to protect privacy according to the data-releasing policy. The ids of videos, users, and other entities were randomly hashed into integers. Textual information, such as queries and video titles, underwent word segmentation and sensitive word removal. Furthermore, terms in texts were randomly hashed into integers. The anonymization safeguards the dataset against any inclusion of personal and private information while maintaining its integrity.

3.3 Statistics

KuaiSAR contains genuine S&R behaviors of 25,877 users within a span of 9 days on the Kuaishou app. The basic statistics of KuaiSAR are summarized in Table 1. For more specific statistical data and usage, please refer to https://ethan00si.github.io/KuaiSAR/.

This dataset filters users based on a single condition: that users have used both S&R services within the specified time period. As a result, the final dataset encompasses users with diverse levels of activity in either the search or recommendation services, thereby offering a comprehensive representation of users with varying degrees of engagement. To illustrate the number of S&R behaviors among users with different activity levels, we counted the number of user-video interactions within two services respectively. We have grouped users based on their activity levels in the search or recommendation services. The activity level is determined by the number of active days within the past month using the respective service. A higher activity level indicates a larger number of active days. The results are illustrated in Figure 2. The average number of search or recommendation historical behaviors per user is over one hundred. The overall interaction frequency with the recommendation service surpasses that with the search service. Furthermore, we observed that within the groups with either the lowest or highest activity levels in recommendations, as well as within the group with high search activity, there is a higher proportion of search interactions.



(a) Users grouped by recommendation activity levels. **(b) Users grouped by search activity levels.**

Figure 2: Distribution of user interactions in S&R scenarios. A higher activity level indicates a higher level of user engagement. The red line represents the ratio of the number of search interactions to the number of recommendation interactions.

4 POTENTIAL RESEARCH DIRECTION

By open-sourcing KuaiSAR, we provide an opportunity to propel the development and innovation of joint modeling for S&R:

• **Unified Search and Recommendation.** In many mobile applications, the lines differentiating S&R services have become progressively blurred from the user's standpoint. Previous works have proposed the approach of joint training to simultaneously optimize S&R models [25, 26], or employing a unified model to provide both services concurrently [23, 28]. KuaiSAR is the pioneering one that provides authentic user behaviors in both services, encompassing the various users' genuine feedback, as well as rich side information of users and items.

• **Enhanced Recommendation by Search (or Enhanced Search by Recommendation).** It is reasonable and natural to employ one service to enhance the other. The recommendation model can leverage search data to comprehensively understand user interests or item representations [13, 15, 17]. The search model can alleviate cold-start issues [19] or enable more precise personalized search [2, 11] by incorporating recommendation data. KuaiSAR explicitly records whether each user-video interaction occurs in a search or recommendation scenario. Hence, it can support the research in enhancing one service through the other.

• **Intent Recommendation.** In real-world applications, the recommendation model can also stimulate users to engage in more search behaviors by suggesting queries (so-called intent recommendation) [3, 6, 22]. KuaiSAR captures how users initiate the search, such as by clicking recommended terms or clicking on related searches. Thus, KuaiSAR offers the opportunity to perform intent recommendations on the publicly available data for the first time.

Given the abundant labels covering various types of user actions, KuaiSAR can also unlock opportunities for several other promising research directions:

• **Multi-task Learning.** S&R, in essence, are different tasks designed to cater to different user needs: information retrieval and information filtering, respectively. KuaiSAR provides an opportunity for multi-task learning [12], tailored for these two closely related yet distinct tasks. Furthermore, S&R can also be seen as two scenarios, which can support research for multi-scenario models [29].

• **Sequential Multi-behavioral Modeling.** In these years, there has been a growing interest in exploring how user modeling can be performed based on multiple types of user behaviors in sequential recommendation [7, 18, 24] or streaming recommendation [27]. KuaiSAR captures various user feedback, *e.g.,* like and share, within the user's interaction with the recommendation system. Therefore, these characteristics present new research possibilities in sequential multi-behavioral modeling.

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