RECSIM: A Configurable Simulation Platform for Recommender Systems*

Eugene Ie[†1], Chih-wei Hsu[1], Martin Mladenov[1], Vihan Jain[1],
Sanmit Narvekar[§,2], Jing Wang[1], Rui Wu[1], and Craig Boutilier[†,1]

[1]Google Research
[2]Department of Computer Science, University of Texas at Austin

September 27, 2019

Abstract

We propose RECSIM, a configurable platform for authoring simulation environments for recommender systems (RSs) that naturally supports *sequential interaction* with users. RECSIM allows the creation of new environments that reflect particular aspects of user behavior and item structure at a level of abstraction well-suited to pushing the limits of current reinforcement learning (RL) and RS techniques in sequential interactive recommendation problems. Environments can be easily configured that vary assumptions about: user preferences and item familiarity; user latent state and its dynamics; and choice models and other user response behavior. We outline how RECSIM offers value to RL and RS researchers and practitioners, and how it can serve as a vehicle for academic-industrial collaboration.

1 Introduction

Practical recommender systems (RSs) are rapidly evolving, as advances in artificial intelligence, machine learning, natural language understanding, automated speech recognition and voice user interfaces facilitate the development of *collaborative interactive recommenders (CIRs)*. While traditional recommenders, such as those based on collaborative filtering [Konstan et al., 1997, Breese et al., 1998, Salakhutdinov and Mnih, 2007], typically recommend items that *myopically* maximize predicted user engagement (e.g., through item rating, score or utility), CIRs explicitly use a *sequence of interactions* to maximize user engagement or satisfaction. CIRs often use conversational methods [Vinyals and Le, 2015, Ghazvininejad et al.,

*https://github.com/google-research/recsim

[1]Corresponding authors: {eugeneie,cboutilier}@google.com.
[2]Work done while at Google Research.

2018], example critiquing or preference elicitation [Chen and Pu, 2012, Christakopoulou et al., 2016], bandit-based exploration [Li et al., 2010, 2016, Christakopoulou and Banerjee, 2018], or reinforcement learning [Sun and Zhang, 2018] to *explore* the space of options in collaboration with the user to uncover good outcomes or maximize user engagement over extended horizons.

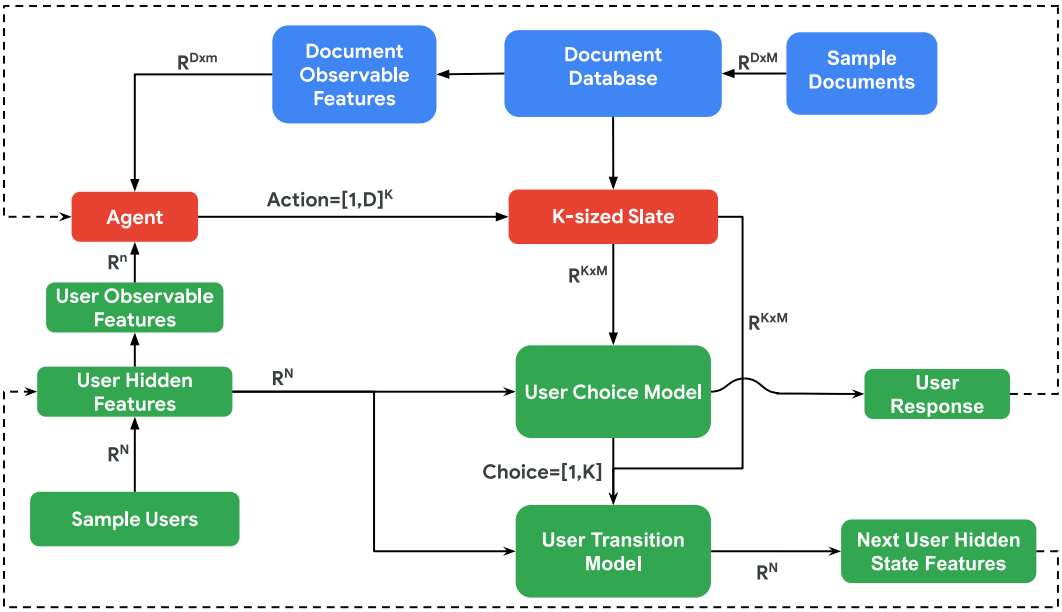
While a topic of increasing research activity in AI—especially in the subareas mentioned above—the deployment of CIRs in practice remains limited. This is due, in no small part, to several challenges that researchers in these areas face when developing modeling techniques and algorithms that adequately reflect qualitative characteristics of *user interaction dynamics*. The importance of modeling the dynamics of user interaction when devising good algorithmic and modeling techniques for CIRs is plainly obvious. The next generation of recommenders will increasingly focus on modeling sequential user interaction and optimizing users' long-term engagement and overall satisfaction. Setting aside questions of user interface design and natural language interaction,[1] this makes CIRs a natural setting for the use of *reinforcement learning (RL)*. Indeed, RSs have recently emerged as a useful application area for the RL community.

Unfortunately, the usual practice of developing recommender algorithms using static data sets—even those with temporal extent, e.g., the MovieLens 1M dataset [Harper and Konstan, 2016]—does not easily extend to the RL setting involving interaction sequences. In particular, the inability to easily extract predictions regarding the impact of *counterfactual actions* on user behavior makes applying RL to such datasets challenging. This is further exacerbated by the fact that data generated by RSs that optimize for myopic engagement are unlikely to follow action distributions similar to those of policies striving for long-term user engagement.[2]

To facilitate the study of RL algorithms in RSs, we developed RECSIM, a configurable platform for authoring simulation environments to allow both researchers and practitioners to challenge and extend existing RL methods in synthetic recommender settings. Our goal is not to create a "perfect" simulator; we do not expect policies learned in simulation to be deployed in live systems. Rather, we expect simulations that mirror *specific* aspects of user behavior found in real systems to serve as a controlled environment for developing, evaluating and comparing recommender models and algorithms (especially those designed for sequential user-system interaction). As an open-source platform, RECSIM will also aid reproducibility and sharing of models within the research community, which in turn, will support increased researcher engagement at the intersection of RL/RecSys. For the RS practitioner interested in applying RL, RECSIM can challenge assumptions made in standard RL algorithms in stylized recommender settings, identify pitfalls of those assumptions to allow practitioners to focus on additional abstractions needed in RL algorithms. This in turn reduces live experiment cycle time via rapid development and model refinement in simulation, and minimizes the potential fo negative impact on users in real-world systems.

[1] We return to these topics in the concluding section.

[2] This is itself will generally limit the effectiveness of off-policy techniques like inverse propensity scoring and other forms of importance weighting.



N - number of features that describe the user's hidden state
n - number of features that describe user's observed state
M - number of features describing document hidden state
m - number of features describing document observed state
D - total number of documents in the corpus
K - size of slate

Figure 1: Data Flow through components of RECSIM.

The remainder of the paper is organized as follows. We provide an overview of RECSIM along with its relations with RL and RecSys. We then conclude this introduction by elaborating specific goals (and non-goals) of the platform, and suggesting ways in which both the RecSys and RL research communities, as well as industrial practitioners, might best take advantage of RECSIM. We briefly discuss related efforts in Section 2. We outline the basic components of RECSIM in Section 3 and describe the software architecture in Section 4. We describe several case studies in Section 5 designed to illustrate some of the uses to which RECSIM can be put, and conclude with a discussion of potential future developments in Section 6.

1.1 RECSIM: A Brief Sketch

RECSIM is a configurable platform that allows the natural, albeit abstract, specification of an environment in which a recommender interacts with a corpus of *documents* (or recommendable items) and a set of *users*, to support the development of recommendation algorithms. Fig. 1 illustrates its main components. We describe these in greater detail in Section 3, but provide a brief sketch here to allow deeper discussion of our motivations.

The *environment* consists of a *user model*, a *document model* and a *user-choice model*.

The *(recommender) agent* interacts with the environment by recommending slates of documents (fixed or dynamic length) to users. The agent has access to observable features of the users and (candidate) documents to make recommendations. The *user model* samples users from a prior distribution over (configurable) *user features*: these may include latent features such as personality, satisfaction, interests; observable features such as demographics; and behavioral features such as session length, visit frequency, or time budget. The *document model* samples items from a prior over *document features*, which again may incorporate latent features such as document quality, and observable features such as topic, document length and global statistics (e.g., ratings, popularity). The level of observability for both user and document features is customizable, so that developers have the flexibility to capture different RS operating regimes to investigate particular research questions.

When the agent recommends documents to a user, the *user response* is determined by a *user choice model*. The choice of document by the user depends on observable document features (e.g., topic, perceived appeal) and all user features (e.g., interests). Other aspects of a user's response (e.g., time spent with a document or post-consumption rating) can also depend on latent document features (e.g., document quality, length). Once a document is consumed, the user state undergoes a transition through a configurable *(user) transition model*. For example, user interest in a document's topic might increase/decrease; user remaining (time) budget may decrease at different rates depending on document quality; and user satisfaction may increase/decrease depending on document-interest match and document quality. Developers can evaluate overall user engagement in the simulated environment to compare policies derived using different RS or RL models and algorithms. We illustrate different configurations with three use cases in Section 5.

1.2 RECSIM and RL

One motivation for RECSIM is to provide environments that facilitate the development of new RL algorithms for recommender applications. While RL has shown considerable success in games, robotics, physical system control and computational modeling [Mnih et al., 2015, Silver et al., 2016, Haarnoja et al., 2018, Lazic et al., 2018], large-scale deployment of RL in real-world applications has proven challenging [Dulac-Arnold et al., 2019]. RSs, in particular, have recently emerged as a useful domain for the RL community that could serve to bridge this gap—the ubiquity of RSs in commercial products makes it ripe for demonstrating RL's real-world impact. Unfortunately, the application of RL to the real-world RSs poses many challenges not widely studied in the mainstream RL literature, among them:

- **Generalization across users**: Most RL research focuses on models and algorithms involving a single environment. A typical commercial RS interacts with millions of users—each user is a distinct (and possibly independent) partially observable Markov decision process (POMDP).[3] However, as in collaborative filtering, contextual bandits, and related models for recommendation, it is critical that the recommender agent

[3]For the purposes of RECSIM we treat an RS's interaction with one user as having no impact on the state of another user. We recognize that multi-agent interaction often occurs across users in practice, and that the RS's

generalizes across users, e.g., by modeling the different environments as a *contextual MDP* [Hallak et al., 2015]. Large-scale recommenders rarely have enough experience with any single user to make good recommendations without such generalization.

- **Combinatorial action spaces**: Many, if not most, recommenders propose slates of items to users. Slate recommendation has been explored in non-sequential settings, capturing point-wise user choice models using non-parametric means [Ai et al., 2018, Bello et al., 2018, Jiang et al., 2019]. However modeling such a combinatorial action space in the context of *sequential* recommendations poses challenges to existing RL algorithms [Sunehag et al., 2015, Metz et al., 2017], as the assumptions they make render them ineffective for exploration and generalization in large-scale recommenders.

- **Large, dynamic, stochastic action spaces**: The set of recommendable items is often generated dynamically and stochastically in many large-scale recommenders. For example, a video recommendation engine may operate over a pool of videos that are undergoing constant flux by the minute: injection of fresh content (e.g., latest news), change in content availability (e.g., copyright considerations or user-initiated deletions), surging/declining content popularity, to name a few. This poses an interesting challenge for standard RL techniques as the action space is not fixed [Boutilier et al., 2018, Chandak et al., 2019].

- **Severe partial observability and stochasticity**: Interaction with users means that an RS is operating in a latent-state MDP; hence it must capture various aspects of the user's state (e.g., interests, preferences, satisfaction, activity, mood, etc.) that generally emit very noisy signals via the user's observed behavior. Moreover, exogenous unobservable events further complicate the interpretation of a user's behavior (e.g., if a user turned off a music recommendation, was it because she did not like the recommendation, or did someone ring her doorbell?). Taken together, these factors mean that recommender agents must learn to act in environments that have extremely low signal-to-noise ratios [Mladenov et al., 2019].

- **Long-horizons**: There is evidence that some aspects of user latent state evolve very slowly over long horizons. For example, Hohnhold et al. [2015] show that ad quality and ad load induce slow but detectable changes in ads effectiveness over periods of months, while Wilhelm et al. [2018] show that video recommendation diversification on YouTube induces similarly slow, persistent changes in user engagement. Maximizing long-term user engagement often requires reasoning about MDPs with extremely long horizons, which can be challenging for many current RL methods [Mladenov et al., 2019]. In display advertising, user responses such as clicks and conversions can happen days after the recommendation [Chapelle and Li, 2011, Chapelle, 2014], which requires agents to model delayed feedback or abrupt changes in reward signals.

objectives (e.g., fairness) may induce further dependence in the policies applied to difference users. We ignore such considerations here (though see the concluding section).

- **Other practical challenges**: Other challenges include accurate off-policy estimation in inherently logs-based production environments and costly policy evaluation in live systems. In addition, there are often multiple evaluation criteria for RSs, among which the tradeoff [Rodriguez et al., 2012] and the corresponding reward function may not be obvious.

Because of these and other challenges, direct application of published RL approaches often fail to perform well or scale [Dulac-Arnold et al., 2019, Ie et al., 2019, Mladenov et al., 2019]. Broadly speaking RL research has often looked past many of these problems, in part because access to suitable data, real-world systems, or simulation environments has been lacking.

1.3 RECSIM and RecSys

Environments in which the user's state (both observed and latent) can evolve as the user interacts with a recommender pose new challenges not just for RL, but for RSs research as well. As noted above, traditional research in RSs deals with "static" users. However in recent years, RS research has increasingly started to explore sequential patterns in user interaction using HMMs, RNNs and related methods [He and McAuley, 2016, Hidasi et al., 2016, Wu et al., 2017]. Interest in the application of RL to optimizing these sequences has been rarer [Shani et al., 2005] though the recent successes of deep RL have spurred activity in the use of RL for recommendation [Gauci et al., 2018, Zheng et al., 2018, Chen et al., 2018, Zhao et al., 2018, Ie et al., 2019]. However, much of this work has been developed in proprietary RSs, has used specially crafted synthetic user models, or has adapted static data sets to the RL task.

The use of RECSIM will allow the more systematic exploration of RL methods in RS research. Moreover, the configurability of RECSIM can help support RS research on more static aspects of recommender algorithms. For instance, user transition models can be "vacuous" so that the user state never changes. However, RECSIM allows the developer to configure the user state (including it's relationship to documents) to be arbitrarily complex, and vary which parts of the state are observable to the recommender itself. In addition, the user choice model allows one to configure various methods by which users choose among recommended items and their induced responses or behaviors. This can be used to rapidly develop and refine novel collaborative filtering methods, contextual bandits algorithms and the like; or simply to test the robustness of existing recommendation schemes to various assumptions about user choice and response behavior.

1.4 Non-objectives

The main goal of RECSIM is to allow the straightforward specification and sharing of the main environment components involved in simulating the sequential interaction of an RS with a user. It does *not* (directly) provide learning algorithms (e.g., collaborative filtering or reinforcement learning agents) that generate recommendations. Its main aim is to support the

development, refinement, analysis and comparisons of such algorithms. That said, RECSIM is distributed with several baseline algorithms—both typical algorithms from the literature (e.g., a simple contextual bandit) and some recent RL-based recommender algorithms, as outlined below—to: (a) allow for straightforward "out-of-the-box" testing, and (b) serve as exemplars of the APIs for those implementing new recommender agents.

Instead of providing realistic recommender simulations in RECSIM that reflect user behavior with full fidelity, we anticipate that new environments will be created by researchers and practitioners that reasonably reflect particular aspects of user behavior at a level of abstraction well-suited to pushing the capabilities of existing modeling techniques and algorithms. RECSIM is released with a variety of different user state, transition and choice models, and several corresponding document models. Several of these correspond to those used in the case studies discussed in Sec. 5. These are included primarily as illustrations of the principles laid out above. Specifically, we do not advocate the use of these as benchmarks (with the exception of researchers interested in the very specific phenomena they study).

While RECSIM environments will not reflect the full extent of user behavior in most practical recommender settings, it can serve as a vehicle to facilitate collaboration and identify synergies between academic and industrial researchers. In particular, through the use of "stylized user models" that reflect certain aspects of user behavior, industrial researchers can share both qualitative and quantitative observations of user interaction in real-world systems that is detailed enough to meaningfully inform the development of models and algorithms in the research community while not revealing user data nor sensitive industrial practices. We provide an illustrative example of how this might work in one of the case studies outlined below.

2 Related Work

We briefly outline a selection of related work on the use of simulation, first in RL, and next in RS and dialogue systems.

2.1 RL Platforms

Simulation has played an outsized role in the evaluation of RL methods in recent years. The Arcade Learning Environment [Bellemare et al., 2013] (or ALE) introduced a now well-known platform for testing algorithms on a suite of Atari 2600 games. Since then numerous RL evaluation benchmarks and environments have been proposed. We only mention a few here to draw contrasts with our goals, and refer to Castro et al. [2018] for an overview of related work and the various goals such platforms can play.

The OpenAI Gym [Brockman et al., 2016] is one of the most widely used platforms, consisting of a collection of environments (including both discrete, e.g., Atari, and continuous, e.g., Mujoco-based, settings) against which RL algorithms can be benchmarked and compared. Our work shares OpenAI Gym's emphasis on offering environments rather than agents, but differs in that we focus on allowing the authoring of environments to push

development of algorithms that handle new domain characteristics rather than benchmarking. Once configured, however, the RECSIM environment is wrapped in an OpenAI Gym environment, which, given its popularity, can facilitate RL experimentation and evaluation. The Dopamine framework [Castro et al., 2018], by contrast, provides simple implementations of a variety of (value-based) RL methods that support the rapid development of new algorithms for research purposes. While easily plugged into new environments—RECSIM itself is integrated into Dopamine as discussed below—it does not provide support for authoring environments. Other frameworks also provide standard RL algorithms with libraries integrated with OpenAI Gym [Gauci et al., 2018, Guadarrama et al., 2018].

ELF [Tian et al., 2017] is a platform that allows configuration of real-time strategy games (RTSs) to support the development of new RL methods to overcome the challenges of doing research with commercial games (e.g., by allowing access to internal game state). It allows configuration of some aspects of the game (e.g., action space) and its parameters, sharing RECSIM's motivation of environment configurability. Like RECSIM, it also supports hierarchy and multi-timescale actions. Unlike RECSIM, ELF pays special attention to the support of different training regimes and is designed for fast performance.

Zhang et al. [2018] develop a set of "natural" RL benchmarks that augment traditional RL tasks with richer image- and video-based state input to "widen the state space of the MDP," seeking to overcome the simplicity of the state space in many simulated RL benchmarks. They share our motivation to press RL algorithms to address new phenomena, but RECSIM focuses on supporting configuring basic new structure in state space, action space, observability, system dynamics, agent objectives, etc., and emphasizes the use of stylized models to challenge the fundamental assumptions of many current RL models, algorithms and training paradigms.

2.2 RecSys and Dialogue Environments

Rohde et al. [2018] propose RecoGym, a stylized RS simulation environment integrated with the RL-based OpenAI Gym. It provides a configurable environment for studying sequential user interaction combining organic navigation with intermittent recommendation (or ads). While RecoGym supports sequential interaction, it does not allow user state transitions; instead the focus in on bandit-style feedback—RL/sequentiality is handled within the learning agent (especially exploration, CTR estimation, etc.). It does allow configuration of user response behavior, item/user dimensionality, etc.

The coupling offline of agent training with simulation of user behavior was studied by Schatzmann et al. [2007] using a rule-based approach. Similar rule-based environments have also been recently explored to aid evaluation of goal-oriented dialogue agents [Wei et al., 2018], while the use of learning to enhance rule-based environment dynamics has been explored in dialogue-based [Peng et al., 2018] and interactive search [Liu et al., 2019] systems. More recently, generative adversarial networks have been used to generate virtual users for high-fidelity recommender environments to support learning policies that can be transferred to real systems [Shi et al., 2019, Zhao et al., 2019]. As environments differ widely across systems and commercial products, we propose that *stylized models* of environments

that reflect specific aspects of user behavior will prove valuable in developing new RL/RS approaches of practical import. We thus emphasize ease of authoring environments using stylized models (and, in the future through plugging in learned models), rather than focusing on "sim-to-real" transfer using high-fidelity models.

3 Simulation Components

We discuss the main components of RECSIM in further detail (Sec. 3.1) and illustrate their role and interaction in a specific recommendation environment (Sec. 3.2).

3.1 Main Components

Fig. 1 illustrates the main components of RECSIM. The *environment* consists of a *user model*, a *document model* and a *user-choice model*. The *(recommender) agent* interacts with the environment by recommending slates of documents to a user. The agent uses *observable* user and (candidate) document features to make its recommendations. Since observable *history* is used in many RL/RS agents, we provide tools to allow the developer to add various summaries of user history to help with recommendation or exploration.

The *document model* also samples items from a prior over *document features*, including latent features such as document quality; and observable features such as topic, or global statistics (e.g., ratings, popularity). Agents and users can be configured to observe different document features, so developers have the flexibility to capture different RS operating regimes (e.g., model predictions or statistical summaries of other users' engagement with a document may be available to the agent but not observable to the user).

The *user model* samples users from a prior over (configurable) *user features*, including latent features such as personality, satisfaction, interests; observable features such as demographics; and behavioral features such as session length, visit frequency, and (time) budget. The user model also includes a transition model, described below.

When the agent recommends documents to a user, the *user response* is determined by a *user choice model* [Louviere et al., 2000]. The choice of document by the user depends on *observable* document features (e.g., topic, perceived appeal) and all user (latent or observable) features (e.g., interests). Other aspects of the response (e.g., time spent, rating) can themselves depend on *latent* (as well as obsevable) document features if desired (e.g., document quality, length). Specific choice models include the multinomial logit [Louviere et al., 2000] and exponentiated cascade [Joachims, 2002]. Once a document is consumed, the user state transitions through a configurable *(user) transition model*. For example, user interest in a document's topic might increase/decrease; user remaining (time) budget may decrease at different rates depending on document quality; and user satisfaction may increase/decrease depending on document-interest match and document quality. Developers can evaluate overall user engagement in the simulated environments to compare policies derived using different RL and recommendation approaches.

RECSIM can be viewed as a dynamic Bayesian network that defines a probability distribution over trajectories of slates, choices, and observations. In particular, the probability of a trajectory of user observations o_t and choices c_t, recommended slates A_t, and candidate documents D_t factorizes as:

$$
\begin{aligned}
&p(o_1, \ldots, o_N, c_1, \ldots, c_N, A_1, \ldots, A_N) \\
&= \sum_{(z_0, \ldots, z_N)} \Big[p(z_0) p(A_0) p(c_0 | A_0, z_0) \\
&\qquad \prod_{t=1}^{N} p(o_t | z_t) p(z_t | z_{t-1}, A_t, c_t) p(c_t | A_t, z_{t-1}) p(A_t | D_t, H_{t-1}) p(D_t) \Big],
\end{aligned}
$$

where z_i is the user state, $p(z_t|z_{t-1}, A_t, c_t)$ the transition model, $p(c_t|A_t, z_{t-1})$ the choice model, $p(o_t|z_t)$ the observation model, and $p(A_t|H_{t-1}, D_t)$ is the recommender policy, which may depend on the entire history of observables H_{t-1} up to that point.

RECSIM ships with several default environments and recommender agents, but developers are encouraged to develop their own environments to stress test recommendation algorithms and approaches to adequately engage users exhibiting a variety of behaviors.

3.2 SlateQ Simulation Environment

To illustrate how different RECSIM components can be configured, we describe a specific slate-based recommendation environment, used by Ie et al. [2019], that is constructed for testing RL algorithms with combinatorial actions in recommendation environments. We briefly review experiments using that environment in one of our use cases below.

To capture fundamental elements of user interest in the recommendation domain, the environment assumes a set of *topics* (or user interests) T. The documents are drawn from content distribution P_D over topic vectors. Each document d in the set of documents D has: an associated *topic vector* $\mathbf{d} \in [0, 1]^{|T|}$, where d_j is the degree to which d reflects topic j; a length $\ell(d)$ (e.g., length of a video, music track or news article); an *inherent quality* L_d, representing the topic-independent attractiveness to the average user. Quality varies randomly across documents, with document d's quality distributed according to $\mathcal{N}(\mu_{T(d)}, \sigma^2)$, where μ_t is a *topic-specific* mean quality for any $t \in T$. Other environment realizations may adopt assumptions to simplify the setup, such as, assuming each document d has only a single topic $T(d)$, so $\mathbf{d} = \mathbf{e}_i$ for some $i \leq |T|$ (i.e., a one-hot topic encoding); using the same constant length ℓ for all documents; or assuming fixed quality variance across all topics.

The *user model* assumes users $u \in U$ have various degrees of interests in topics (with some prior distribution P_U), ranging from -1 (completely uninterested) to 1 (fully interested), with each user u associated with an *interest vector* $\mathbf{u} \in [-1, 1]^{|T|}$. User u's interest in document d is given by the dot product $I(u, d) = \mathbf{ud}$. The user's interest in topics evolves over time as they consume different documents. A user's *satisfaction* $S(u, d)$ with a consumed document d is a function $f(I(u, d), L_d)$ of user u's interest and document d's quality. Alternative implementations could include: a convex combination to model user's satisfaction such as $S(u, d) = (1-\alpha)I(u, d)+\alpha L_d$ where α balances user-interest-driven and document-

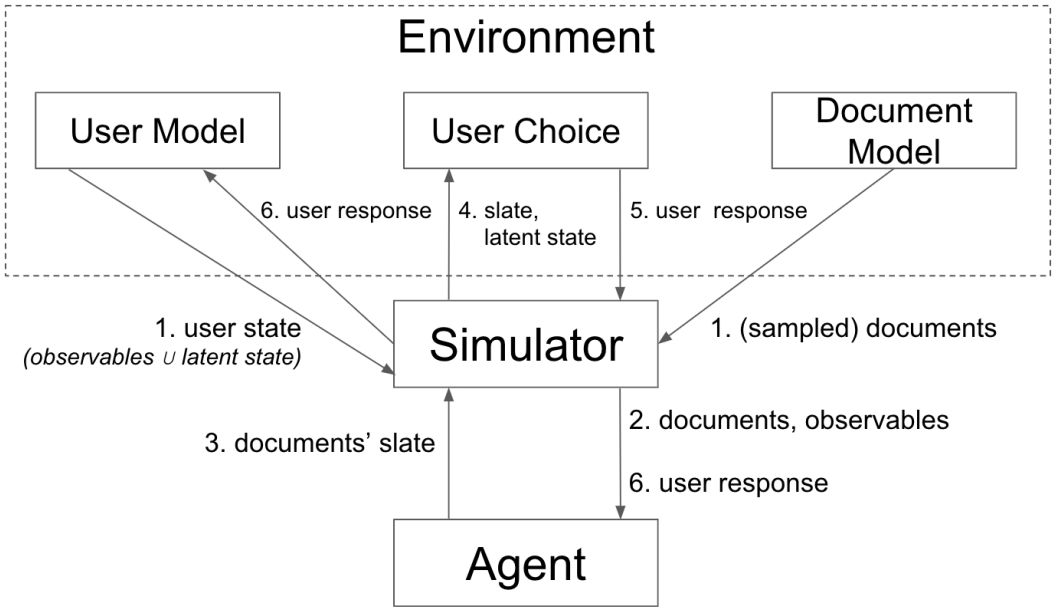


Figure 2: Control flow (single user) in the RecSim architecture.

quality-driven satisfaction; or a stylized model that stochastically nudges user interest I_t in topic $t = T(d)$ after consumption of document d using $\Delta_t(I_t) = (-y|I_t| + y) \cdot -I_t$, where $y \in [0, 1]$ denotes the fraction of the distance between the current interest level and the maximum level $(1, -1)$. Each user could also be assumed to have a fixed *budget* B_u of time to engage with content during a session. Each document d consumed reduces user u's budget by the document length $\ell(d)$ less a *bonus* $b < \ell(d)$ that increases with the document's appeal $S(u, d)$. Other session-termination mechanisms can also be configured in RECSIM.

To model realistic RSs, the user choice model assumes the recommended document's topic to be observable to the user before choice and consumption. However, the document's quality is not observable to the user prior to consumption, but is revealed afterward, and drives the user's state transition. Popular choice functions like the conditional choice model and exponential cascade model are provided in RECSIM to model user choice from a document slate.

4 Software Architecture

In this section, we provide a more detailed description of the simulator architecture and outline some common elements of the environment and recommender agents.

4.1 Simulator

Figure 2 presents the control flow for a single user in the RECSIM architecture. The environment consists of a user model, a document model, and a user-choice model. The simulator serves as the interface between the environment and the agent, and manages the interactions between the two using the following steps:

1. The simulator requests the user state from the user model, both the observable and latent user features. The simulator also queries the document model for a set of (candidate) documents that have been made available for recommendation. (These documents may be fixed, sampled, or determined in some other fashion.)

2. The simulator sends the candidate documents and the *observable portion* of the user state to the agent. (Recall that the recommender agent does not have direct access to user latent features, though the agent is free to *estimate* them based on its interaction history with that user and/or all other users.)

3. The agent uses its current policy to returns a slate to the simulator to be "presented" to the user. (E.g., the agent might rank all candidate documents using some scoring function and return the top k.)

4. The simulator forwards the recommended slate of documents and the *full* user state (observable and latent) to the user choice model. (Recall that the user's choice, and other behavioral responses, can depend on all aspects of user state.)

5. Using the specified choice and response functions, the user choice model generates a (possibly stochastic) user choice/response to the recommended slate, which is returned to the simulator.

6. The simulator then sends the user choice and response to both: the user model so it can update the user state using the transition model; and the agent so it can update its policy given the user response to the recommended slate.

In the current design, the simulator sequentially simulates each user.[4] Each episode is a multi-turn history of the interactions between the agent and single user. At the beginning of each episode, the simulator asks the environment to sample a user model. An episode terminates when it is long enough or the user model transits to a terminal state. Similar to Dopamine [Castro et al., 2018], we also define an *iteration*, for bookkeeping purposes, to consist of a fixed number of turns spanning multiple episodes. At each iteration, the simulator aggregates and logs relevant metrics generated since last iteration. The simulator can also checkpoint the agent's model state, so that the agent can restart from that state after interruption.

[4]We recognize that this design is somewhat limiting. The next planned release of RECSIM will support interleaved user interaction.

An important consideration when applying RL to practical recommender applications is the importance of *batch RL* [Riedmiller, 2005]. A new RS will generally need to learn from data gathered by existing/legacy RSs, since on-policy training and exploration can have a negative impact on users. To facilitate batch RL investigations, RECSIM allows one to log the trace of all (simulated) user interactions for offline training using a suitable RL agent. Specifically, it logs each episode as a Tensorflow [Abadi et al., 2016] *SequenceExample*, against which developers can develop and test batch RL methods (and evaluate the resulting agent through additional environment interaction).

RECSIM relies on Tensorflow's Tensorboard to visualize aggregate metrics over time, whether during agent training or at evaluation time using freshly sampled users (and documents if desired). RECSIM includes a number of typical metrics (e.g., average cumulative reward and episode length) as well as some basic diversity metrics. It uses a separate simulation process to run evaluation (in parallel across multiple users), which logs metrics for a specified number of episodes. The evaluation phase can be configured in multiple ways to evaluate, say, the robustness of a trained recommendation agent to changes in the environment (e.g., changes to user state distribution, transition functions, or choice models). For example, as we discuss in one use case below, we can train the agent using trajectory data assuming a particular user-choice model, but evaluate the agent with simulated users instantiated with a different user-choice model. This separate evaluation process is analogous to the splitting of games into *train* and *test* sets in ALE (to assess over-fitting with hyperperameter tuning).

4.2 Environment

The environment provides APIs for the simulator to perform the steps described in Figure 2. Once all components in the environment are defined, the environment is wrapped in an OpenAI Gym [Brockman et al., 2016] environment. OpenAI Gym has proven to be popular for specifying novel environments to train/test numerous RL algorithms. Developers can readily incorporate state-of-the-art RL algorithms for application recommender domains. Because OpenAI Gym is intended for RL evaluation, developers are required to define a reward function for each environment—this is usually interpreted as the primary criterion (or at least one of the criteria) for evaluation of the recommender agent, and will generally be a function of a user's (history of) responses.

4.3 Recommender Agent Architecture

RECSIM provides several abstractions with APIs for the simulation steps in Figure 2 so developers can create agents in a configurable way with reusable modules. We do not focus on modules specific to RL algorithms (e.g., replay memory [Lin and Mitchell, 1992]). Instead, RECSIM offers stackable *hierarchical agent layers* intended to solve a more abstract recommendation problem. A hierarchical agent layer does not materialize a slate of documents (i.e., RS action), but relies on one or more base agents to do so. The hierarchical agent architecture in RECSIM can roughly be summarized as follows: a hierarchical agent

layer receives an observation and reward from the environment; it preprocesses the raw observation and passes it to one or more base agents. Each base agent outputs either a slate or an abstract action (depending on the use case), which is then post-processed by the agent to create/output the slate (concrete action). Hierarchical layers are recursively stackable in a fashion similar to Keras [Chollet et al., 2015] layers.

Hierarchical layers are defined by their pre- and post-processing functions and can play many roles depending how these are implemented. For example, a layer can be used as a pure feature injector—it can extract some feature from the (history of) observations and pass it to the base agent, while keeping the post-processing function vacuous. This allows decoupling of feature- and agent-engineering. Various regularizers can be implemented in a similar fashion by modifying the reward. Layers may also be stateful and dynamic, as the pre- or post-processing functions may implement parameter updates or learning mechanisms.

We demonstrate the use of the hierarchical agent layer using an environment with users having latent topic interests. In this environment, recommender agents are tasked with *exploration* to uncover user interests by showing documents with different topics. Exploration can be powered by, say, a contextual bandit algorithm. A hierarchical agent layer can be used to log bandit feedback (i.e., per-topic impression and click statistics). Its base agent exploits that bandit feedback to returns a slate of recommended documents with the "best" topic(s) using some bandit algorithm. These impression and click statistics should not be part of the user model—neither a user's choice nor transition depends on them—indeed, these are agent-specific. However, it is useful to have a common *ClusterClickStatsLayer* for modelling user history in RECSIM since many agents often use those statistics in their algorithms. Another set of sufficient statistics that is commonly used in POMDP reinforcement learning is that of finite histories of observables. We have implemented *FixedLengthHistoryLayer* which records observations about user, documents, and user responses during the last few turns. Agents can utilize that layer to, say, model temporal dynamic behavior without requiring direct access to the user model.

A slightly more subtle illustration can be found in the *TemporalAggregationLayer*. It was recently shown [Mladenov et al., 2019] how reducing the control frequency of an agent may improve performance in environments where observability is low and/or the available state representations are limited. The *TemporalAggregationLayer* reduces the control frequency of its base layer by calling its *step* function once every k steps, then remembering the features of the returned slate and trying to reproduce a similar slate for the remaining $k-1$ control periods. It also provides an optional switching cost regularizer that penalizes the agent for switching to a slate with different features. In this way, the concept of temporal aggregation/regularization can be applied to any base agent.

Finally, we provide a general hierarchical agent that can wrap an arbitrary list of agents as abstract actions, implementing arbitrary tree-structured hierarchical agent architectures.

RECSIM provides a set of baseline agents to facilitate the evaluation of new recommender agents. *TabularQAgent* implements the Q-learning algorithm [Watkins and Dayan, 1992] (by discretizing observations if necessary). The size of tabular representation of state-action space is exponential in the length of observations; and it enumerates all possible

recommendation slates (actions) in order to maximize over Q values during training and serving/evaluation—hence it is a suitable baseline only for the smallest environments. *FullSlateQAgent* implements a deep Q-Network (DQN) agent [Mnih et al., 2015] by treating each slate as a single action and querying the DQN for maximizing action. The inputs of this DQN are observations of the environment. Slate enumeration generally limits the number of candidate documents that can be evaluated at each interaction (but see the SlateQ use case below). *RandomAgent* recommends random slates with no duplicates. To be self-contained, RECSIM also provides an adapter for applying the DQN agent in Dopamine to the simulation environments packaged with RECSIM. In addition, several standard multi-armed bandit algorithms [Auer et al., 2002, Garivier and Cappe, 2011, Agrawal and Goyal, 2013] are provided to support experimentation with exploration (e.g., of latent topic interests).

5 Case Studies

We outline three use cases developed within RECSIM, one a standard bandit approach, the other two driving recent research into novel RL techniques for recommendation. These illustrate the range of uses to which RECSIM can be put, even using environments with fairly simple, stylized models of user interaction.

5.1 Latent State Bandits

In this study, we examine how the tradeoff between immediate and long-term reward affects the value of exploration. The environment samples users whose latent topic interests are not directly observable by the agent. An agent can discover these interests using various exploration strategies.

This single-item recommendation environment assumes a set of *topics* (or user interests) T. The documents are drawn from content distribution P_D over topics. Each document d in the set of documents D has: an associated *topic vector* which is a one-hot topic encoding $\mathbf{d}$ of d's sole topic $T(d)$; an *inherent quality* L_d, representing the topic-independent attractiveness. L_d is distributed according to $\ln \mathcal{N}(\mu_{T(d)}, \sigma^2)$, where μ_t is a *topic-specific* mean quality for any $t \in T$. The *user model* assumes users $u \in U$ have various degrees of interests in topics (with some prior distribution P_U). Each user u has a static *interest vector* $\mathbf{u}$. User u's interest in document d is given by the dot product $I(u, d) = \mathbf{ud}$. The probability that u chooses d is proportional to a function depending on topic affinity $I(u, d)$ and document quality: $f(I(u, d) + L_d)$. We evaluate agents using total user clicks induced over a session.

We can configure P_U and the distribution over $\mathbf{d}$ conditioned on P_U so that topic affinity influences user choice more than document quality: $I(u, d) > L_d$. Intuitively, exploration or planning (RL) is critical in this case—it will be less so when $I(u, d) \sim L_d$ (low topic affinity). The following table presents the results of applying different exploration/planning strategies, using the agents described in Sec. 4: *RandomAgent*, *TabularQAgent*, *FullSlateQAgent*, and a bandit agent powered by UCB1 [Auer et al., 2002]. The latter three agents employ the *ClusterClickStatsLayer* for per-topic impression and click counts. We also implement an

"omniscient" greedy agent which knows the user choice model and user prior to myopically optimize expected reward $f(I(\hat{u}, d) + L_d)$, where $\hat{u}$ is an average user (interest). We see that UCB1 and Q-learning perform far better than the other agents in the high-affinity environment.

Strategy	Environment	Avg. CTR (%)	Environment	Avg. CTR (%)
Random	Low Topic Affinity	7.86	High Topic Affinity	14.97
Greedy	Low Topic Affinity	9.59 (22.01%)	High Topic Affinity	17.56 (17.30%)
TabularQ	Low Topic Affinity	8.24 (4.83%)	High Topic Affinity	20.16 (34.67%)
FullSlateQ	Low Topic Affinity	9.64 (22.60%)	High Topic Affinity	23.28 (55.51%)
UCB1	Low Topic Affinity	9.76 (24.17%)	High Topic Affinity	25.17 (68.14%)

5.2 Tractable Decomposition for Slate RL

Many RSs recommend *slates*, i.e., multiple items simultaneously, inducing an RL problem with a large combinatorial action space, that is challenging for exploration, generalization and action optimization. While recent RL methods for such combinatorial action spaces [Sunehag et al., 2015, Metz et al., 2017] take steps to address this problem, they are unable to scale to problems of the size encountered in large, real-world RSs.

Ie et al. [2019] used RECSIM to study decomposition techniques for estimating Q-values of whole recommendation slates. The algorithm exploits certain assumptions about *user choice behavior*—the process by which a user selects and/or engages with items on a slate—to construct a decomposition based on a linear combination of constituent item Q-values. While these assumptions are minimal and seem natural for recommender settings, the authors used RECSIM to study (a) the efficacy of the decomposed TD/Q-learning algorithm variants over myopic policies commonly found in commercial recommenders and (b) the robustness of the estimation algorithm under user choice model deviations.

In their simulations, user topic interests are observable and shift with exposure to documents with specific topics. The number of topics is finite, with some having high average quality and others having lower quality. Document quality impacts how quickly a user's (time) budget decays during a session. While users may have initial interest in low-quality topics, their interests shift to higher quality topics if the agent successfully determines which topics have greater long-term value. Their results demonstrate that using RL to plan long-term interactions can provide significant value in terms of overall engagement. While having full Q-learning that includes optimal slate search in both training and inference may result in the best overall long term user engagement, a significant portion of the gains can be captured using a less costly variant of on-policy TD-learning coupled with greedy slate construction at serving time. They also found that the decomposition technique is robust to user choice model shifts—gains over myopic approaches are still possible even if the assumed user choice model differs. We refer to Ie et al. [2019] for additional environment details and results.

5.3 Advantage Amplification over Long Horizons

Experiments in real world ads systems and RSs suggest that some aspects of user latent state evolve very slowly [Hohnhold et al., 2015, Wilhelm et al., 2018]. Such slow *user-learning* behavior in environments with a low *signal-to-noise ratio* (SNR) poses severe challenges for end-to-end *event-level RL*. Mladenov et al. [2019] used RECSIM to investigate this issue. The authors developed a simulation environment in which documents have an observable quality that ranges within $[0, 1]$. Documents on the 0-end of the scale are termed *chocolate*, and lead to large amounts of immediate engagement, while documents on the 1-end, termed *kale*, generate lower engagement, but tend to increase satisfaction. Users' satisfaction is modeled as variable in $[0, 1]$ that stochastically (and slowly) increases or decreases with the consumption of different types of content; pure chocolate documents generate engagement drawn from $\ln \mathcal{N}(\mu_{\text{choc}}, \sigma_{\text{choc}})$, pure kale documents resp. from $\ln \mathcal{N}(\mu_{\text{kale}}, \sigma_{\text{kale}})$, while mixed documents interpolate linearly between the parameters of the two distributions in proportion to their kaleness.

One possible response to the difficulties of learning in slowly evolving environments with low SNR is through the use of temporally-aggregated hierarchical policies. Mladenov et al. [2019] implement two approaches—temporal aggregation (repeating actions for some predetermined period k) and temporal regularization, i.e., subtracting a constant λ from the reward whenever $A_t \neq A_{t-1}$ (in terms of document features)—as hierarchical agent layers in RECSIM that can modify a base agent. These hierarchical agent nodes amplify the differences between Q-values of actions (the advantage function), making the learned policy less susceptible to low-SNR effects. In simulation, temporal aggregation was shown to improve the quality of learned policies to a point almost identical to the case where the user satisfaction is fully observed. We refer to Mladenov et al. [2019] for the environment details and results.

6 Next Steps

While RECSIM in its current form provides ample opportunity for researchers and practitioners to probe and question assumptions made by RL/RS algorithms in stylized environments, we recognize the broader interest in the community to develop models that address the "sim-to-real" gap. To that end, we are developing methodologies to fit stylized user models using production usage logs—as well as additional hooks in the framework to plug in such user models—to create environments that are more faithful to specific (e.g., commercial) RSs. We expect that such fitted stylized user models, especially when abstracted suitably to address concerns about data privacy and business practices, may facilitate industry/academic collaborations. That said, we view this less as directly tackling "sim-to-real" transfer, and more as a means of aligning research objectives around realistic problem characteristics that reflect the needs and behaviors of real users.

Our initial emphasis in this release of RECSIM is facilitating the creation of new simulation environments that draw attention to modeling and algorithmic challenges pertinent to

RSs. Naturally, there are many directions for further development of RECSIM. For example, we are extending it to allow concurrent execution that deviates from the single-user control flow depicted in Fig. 2. Concurrent execution will not only improve simulation throughput, but also reflects how RS agents operate in real-world production settings. In particular, it will allow investigation of phenomena, such as "distributed exploration" across users, that are not feasible within the current serial user control flow.

Finally, modern CIRs will involve rich forms of mixed-mode interactions that cover a variety of system actions (e.g., preference elicitation, providing endorsements, navigation chips) and user responses (e.g., example critiquing, indirect/direct feedback, query refinements), not to mention unstructured natural language interaction. Furthermore, real-world users typically transition across the search-browsing spectrum over multiple RS sessions—our next major release will incorporate some of these interaction modalities.

References

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. TensorFlow: A system for large-scale machine learning. arXiv preprint arXiv:1605.08695, 2016.

Shipra Agrawal and Navin Goyal. Further optimal regret bounds for Thompson sampling. In *Proceedings of the 16th International Conference on Artificial Intelligence and Statistics*, pages 99–107, Scottsdale, AZ, 2013.

Qingyao Ai, Keping Bi, Jiafeng Guo, and W. Bruce Croft. Learning a deep listwise context model for ranking refinement. In *Proceedings of the 41st Annual International ACM Conference on Research and Development in Information Retrieval (SIGIR-18)*, pages 135–144, Ann Arbor, MI, 2018.

Peter Auer, Nicolò Cesa-Bianchi, and Paul Fischer. Finite-time analysis of the multiarmed bandit problem. *Machine Learning*, 47(2-3):235–256, 2002.

Marc G. Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The Arcade Learning Environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, 2013.

Irwan Bello, Sayali Kulkarni, Sagar Jain, Craig Boutilier, Ed Chi, Elad Eban, Xiyang Luo, Alan Mackey, and Ofer Meshi. Seq2Slate: Re-ranking and slate optimization with RNNs. `arXiv:1810.02019 [cs.IR]`, 2018.

Craig Boutilier, Alon Cohen, Avinatan Hassidim, Yishay Mansour, Ofer Meshi, Martin Mladenov, and Dale Schuurmans. Planning and learning with stochastic action sets. In *International Joint Conference on Artifical Intelligence (IJCAI)*, pages 4674–4682, Stockholm, 2018.

Jack S. Breese, David Heckerman, and Carl Kadie. Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence*, pages 43–52, Madison, WI, 1998.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. OpenAI gym. `arXiv:1606.01540 [cs.LG]`, 2016.

Pablo Samuel Castro, Subhodeep Moitra, Carles Gelada, Saurabh Kumar, and Marc G. Bellemare. Dopamine: A research framework for deep reinforcement learning. `arXiv:1812.06110 [cs.LG]`, 2018.

Yash Chandak, Georgios Theocharous, Blossom Metevier, and Philip S. Thomas. Reinforcement learning when all actions are not always available. `arXiv:1906.01772 [cs.LG]`, 2019.

Olivier Chapelle. Modeling delayed feedback in display advertising. In *The 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, (KDD-14)*, pages 1097–1105, 2014.

Olivier Chapelle and Lihong Li. An empirical evaluation of Thompson sampling. In *Advances in Neural Information Processing Systems 24 (NIPS-11)*, pages 2249–2257, 2011.

Li Chen and Pearl Pu. Critiquing-based recommenders: survey and emerging trends. *User Modeling and User-Adapted Interaction*, 22(1):125–150, Apr 2012. ISSN 1573-1391. doi: 10.1007/s11257-011-9108-6. URL https://doi.org/10.1007/s11257-011-9108-6.

Minmin Chen, Alex Beutel, Paul Covington, Sagar Jain, Francois Belletti, and Ed Chi. Top-k off-policy correction for a REINFORCE recommender system. In *12th ACM International Conference on Web Search and Data Mining (WSDM-19)*, pages 456–464, Melbourne, Australia, 2018.

François Chollet et al. Keras. https://github.com/fchollet/keras, 2015.

Konstantina Christakopoulou and Arindam Banerjee. Learning to interact with users: A collaborative-bandit approach. In *Proceedings of the 2018 SIAM International Conference on Data Mining, SDM 2018, May 3-5, 2018, San Diego Marriott Mission Valley, San Diego, CA, USA.*, pages 612–620, 2018.

Konstantina Christakopoulou, Filip Radlinski, and Katja Hofmann. Towards conversational recommender systems. In *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16, pages 815–824, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4232-2.

Gabriel Dulac-Arnold, Daniel Mankowitz, and Todd Hester. Challenges of real-world reinforcement learning. `arXiv:1904.12901 [cs.LG]`, 2019.

Aurelien Garivier and Olivier Cappe. The KL-UCB algorithm for bounded stochastic bandits and beyond. In *Proceeding of the 24th Annual Conference on Learning Theory*, pages 359–376, 2011.

Jason Gauci, Edoardo Conti, Yitao Liang, Kittipat Virochsiri, Yuchen He, Zachary Kaden, Vivek Narayanan, and Xiaohui Ye. Horizon: Facebook's open source applied reinforcement learning platform. `arXiv:1811.00260 [cs.LG]`, 2018.

Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wentau Yih, and Michel Galley. A knowledge-grounded neural conversation model. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)*, pages 5110–5117, New Orleans, 2018.

Sergio Guadarrama, Anoop Korattikara, Oscar Ramirez, Pablo Castro, Ethan Holly, Sam Fishman, Ke Wang, Ekaterina Gonina, Neal Wu, Chris Harris, Vincent Vanhoucke, and Eugene Brevdo. TF-Agents: A library for reinforcement learning in tensorflow. https://github.com/tensorflow/agents, 2018. Accessed 25-June-2019.

Tuomas Haarnoja, Aurick Zhou, Kristian Hartikainen, George Tucker, Sehoon Ha, Jie Tan, Vikash Kumar, Henry Zhu, Abhishek Gupta, Pieter Abbeel, and Sergey Levine. Soft actor-critic algorithms and applications. `arXiv:1812.05905 [cs.LG]`, 2018.

Assaf Hallak, Dotan Di Castro, and Shie Mannor. Contextual markov decision processes. `arXiv:1502.02259 [stat.ML]`, 2015.

F. Maxwell Harper and Joseph A. Konstan. The MovieLens datasets: History and context. *ACM Transactions on Interactive Intelligent Systems*, 5(4):19:1–19:19, 2016.

Ruining He and Julian McAuley. Fusing similarity models with Markov chains for sparse sequential recommendation. In *Proceedings of the IEEE International Conference on Data Mining (ICDM-16)*, Barcelona, 2016.

Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. Session-based recommendations with recurrent neural networks. In *4th International Conference on Learning Representations (ICLR-16)*, San Juan, Puerto Rico, 2016.

Henning Hohnhold, Deirdre O'Brien, and Diane Tang. Focusing on the long-term: It's good for users and business. In *Proceedings of the Twenty-first ACM International Conference on Knowledge Discovery and Data Mining (KDD-15)*, pages 1849–1858, Sydney, 2015.

Eugene Ie, Vihan Jain, Jing Wang, Sanmit Narvekar, Ritesh Agarwal, Rui Wu, Heng-Tze Cheng, Tushar Chandra, and Craig Boutilier. SlateQ: A tractable decomposition for reinforcement learning with recommendation sets. In *International Joint Conference on Artifical Intelligence (IJCAI)*, pages 2592–2599, Macau, 2019.

Ray Jiang, Sven Gowal, Timothy A. Mann, and Danilo J. Rezende. Beyond greedy ranking: Slate optimization via List-CVAE. In *Proceedings of the Seventh International Conference on Learning Representations (ICLR-19)*, New Orleans, 2019.

Thorsten Joachims. Optimizing search engines using clickthrough data. In *Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-02)*, pages 133–142, 2002.

Joseph A. Konstan, Bradley N. Miller, David Maltz, Jonathan L. Herlocker, Lee R. Gordon, and John Riedl. GroupLens: Applying collaborative filtering to Usenet news. *Communications of the ACM*, 40(3):77–87, 1997.

Nevena Lazic, Craig Boutilier, Tyler Lu, Eehern Wong, Binz Roy, MK Ryu, and Greg Imwalle. Data center cooling using model-predictive control. In *Advances in Neural Information Processing System 31*, pages 3818–3827, Montreal, 2018.

Lihong Li, Wei Chu, John Langford, and Robert E. Schapire. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th International Conference on World Wide Web (WWW-10)*, pages 661–670, 2010.

Shuai Li, Alexandros Karatzoglou, and Claudio Gentile. Collaborative filtering bandits. In *Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR-16)*, 2016.

Long-Ji Lin and Tom. M. Mitchell. Memory approaches to reinforcement learning in non-Markovian domains. Technical Report CS–92–138, Carnegie Mellon University, Department of Computer Science, May 1992.

Qianlong Liu, Baoliang Cui, Zhongyu Wei, Baolin Peng, Haikuan Huang, Hongbo Deng, Jianye Hao, Xuanjing Huang, and Kam-Fai Wong. Building personalized simulator for interactive search. In *Proceedings of the Twenty-eighth International Joint Conference on Artificial Intelligence (IJCAI-19)*, pages 5109–5115, Macau, 2019.

Jordan J. Louviere, David A. Hensher, and Joffre D. Swait. *Stated Choice Methods: Analysis and Application*. Cambridge University Press, Cambridge, 2000.

Luke Metz, Julian Ibarz, Navdeep Jaitly, and James Davidson. Discrete sequential prediction of continuous actions for deep RL. `arXiv:1705.05035 [cs.LG]`, 2017.

Martin Mladenov, Ofer Meshi, Jayden Ooi, Dale Schuurmans, and Craig Boutilier. Advantage amplification in slowly evolving latent-state environments. In *International Joint Conference on Artifical Intelligence (IJCAI)*, pages 3165–3172, Macau, 2019.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533, 2015.

Baolin Peng, Xiujun Li, Jianfeng Gao, Jingjing Liu, and Kam-Fai Wong. Deep Dyna-Q: Integrating planning for task-completion dialogue policy learning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (ACL-18)*, pages 2182–2192, Melbourne, 2018.

Martin Riedmiller. Neural fitted Q-iteration—first experiences with a data efficient neural reinforcement learning method. In *Proceedings of the 16th European Conference on Machine Learning*, pages 317–328, Porto, Portugal, 2005.

M. Rodriguez, C. Posse, and E. Zhang. Multiple objective optimization in recommender systems. In *Proceedings of the sixth ACM conference on Recommender systems*, pages 11–18. ACM, 2012.

David Rohde, Stephen Bonner, Travis Dunlop, Flavian Vasile, and Alexandros Karatzoglou. RecoGym: A reinforcement learning environment for the problem of product recommendation in online advertising. `arXiv:1808.00720 [cs.IR]`, 2018.

Ruslan Salakhutdinov and Andriy Mnih. Probabilistic matrix factorization. In *Advances in Neural Information Processing Systems 20 (NIPS-07)*, pages 1257–1264, Vancouver, 2007.

Jost Schatzmann, Blaise Thomson, Karl Weilhammer, Hui Ye, and Steve Young. Agenda-based user simulation for bootstrapping a POMDP dialogue system. In *Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers*, pages 149–152, Rochester, New York, April 2007. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/N07-2038.

Guy Shani, David Heckerman, and Ronen I. Brafman. An MDP-based recommender system. *Journal of Machine Learning Research*, 6:1265–1295, 2005.

Jing-Cheng Shi, Yang Yu, Qing Da, Shi-Yong Chen, and An-Xiang Zeng. Virtual-taobao: Virtualizing real-world online retail environment for reinforcement learning. In *Proceedings of the Thirty-third AAAI Conference on Artificial Intelligence (AAAI-19)*, pages 4902–4909, Honolulu, 2019.

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. Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587):484–489, 2016.

Yueming Sun and Yi Zhang. Conversational recommender system. `arXiv:1806.03277 [cs.IR]`, 2018.

Peter Sunehag, Richard Evans, Gabriel Dulac-Arnold, Yori Zwols, Daniel Visentin, and Ben Coppin. Deep reinforcement learning with attention for slate Markov decision processes with high-dimensional states and actions. `arXiv:1512.01124 [cs.AI]`, 2015.

Yuandong Tian, Qucheng Gong, Wenling Shang, Yuxin Wu, and C. Lawrence Zitnick. ELF: an extensive, lightweight and flexible research platform for real-time strategy games. In *Advances in Neural Information Processing Systems 30 (NIPS-17)*, pages 2659–2669, Long Beach, CA, 2017.

Oriol Vinyals and Quoc V. Le. A neural conversational model. `arXiv:1506.05869 [cs.CL]`, 2015.

Christopher J. C. H. Watkins and Peter Dayan. Q-learning. *Machine Learning*, 8:279–292, 1992.

Wei Wei, Quoc Le, Andrew Dai, and Jia Li. AirDialogue: An environment for goal-oriented dialogue research. In *Proceedings of 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP-18)*, pages 3844–3854, Brussels, 2018.

Mark Wilhelm, Ajith Ramanathan, Alexander Bonomo, Sagar Jain, Ed H. Chi, and Jennifer Gillenwater. Practical diversified recommendations on YouTube with determinantal point processes. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM18)*, pages 2165–2173, Torino, Italy, 2018.

Chao-Yuan Wu, Amr Ahmed, Alex Beutel, Alexander J. Smola, and How Jing. Recurrent recommender networks. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining (WSDM-17)*, pages 495–503, Cambridge, UK, 2017.

Amy Zhang, Yuxin Wu, and Joelle Pineau. Natural environment benchmarks for reinforcement learning. `arXiv:1811.06032 [cs.LG]`, 2018.

Xiangyu Zhao, Long Xia, Liang Zhang, Zhuoye Ding, Dawei Yin, and Jiliang Tang. Deep reinforcement learning for page-wise recommendations. In *Proceedings of the 12th ACM Conference on Recommender Systems (RecSys-18)*, pages 95–103, Vancouver, 2018.

Xiangyu Zhao, Long Xia, Zhuoye Ding, Dawei Yin, and Jiliang Tang. Toward simulating environments in reinforcement learning based recommendations. `arXiv:1906.11462 [cs.IR]`, 2019.

Guanjie Zheng, Fuzheng Zhang, Zihan Zheng, Yang Xiang, Nicholas Jing Yuan, Xing Xie, and Zhenhui Li. DRN: A deep reinforcement learning framework for news recommendation. In *Proceedings of the 2018 World Wide Web Conference (WWW-18)*, pages 167–176, 2018.