Emergent Instabilities in Algorithmic Feedback Loops

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Abstract
Algorithms that aid human tasks, such as recommendation systems, are ubiquitous. They appear in everything from social media to streaming videos to online shopping. However, the feedback loop between people and algorithms is poorly understood and can amplify cognitive and social biases (algorithmic confounding), leading to unexpected outcomes. In this work, we explore algorithmic confounding in collaborative filtering-based recommendation algorithms through teacher-student learning simulations. Namely, a student collaborative filtering-based model, trained on simulated choices, is used by the recommendation algorithm to recommend items to agents. Agents might choose some of these items, according to an underlying teacher model, with new choices then fed back into the student model as new training data (approximating online machine learning). These simulations demonstrate how algorithmic confounding produces erroneous recommendations which in turn lead to instability, i.e., wide variations in an item’s popularity between each simulation realization. We use the simulations to demonstrate a novel approach to training collaborative filtering models that can create more stable and accurate recommendations. Our methodology is general enough that it can be extended to other socio-technical systems in order to better quantify and improve the stability of algorithms. These results highlight the need to account for emergent behaviors from interactions between people and algorithms.

Introduction
We interact with computer algorithms throughout the day. Algorithms guide us to our destinations, finish our sentences in emails, automate business processes and decisions in healthcare, and recommend movies and music for us to enjoy. On social media platforms, algorithms select messages for our newsfeed and find new accounts for us to follow. Despite algorithms’ ubiquity and broad impact, the interaction between algorithms and people within socio-technical systems is still poorly understood, especially when algorithms learn from data based on past predictions (Sinha, Gleich, and Ramani [2016]). We have some evidence, however, that this interaction can have unexpectedly negative consequences, such as pushing people into filter bubbles (Ge et al. [2020]; Sirbu et al. [2019]) or reducing the diversity of recommended content in online platforms (Chaney, Stewart, and Engelhardt [2018]; Mansoury et al. [2020]). Something observed in crowdsourcing systems, but under-explored in other systems, is how the interplay between people and algorithms can stochastically make some options very popular or unpopular (known as instability), and the popularity of items has little relation to the items people prefer (Salganik, Dodds, and Watts [2006]; Burghardt et al. [2020]). Mitigating this problem in crowdsourcing systems is an ongoing struggle but, until now, it was unknown if this instability extends to other socio-technical systems, such as personalized recommendation. This feedback loop could make many items or videos more popular than better ones and generate more unpredictable trends. These emergent problems are bad for recommendation systems because they will recommend items or content users are less likely to want, reducing revenue. The unpredictability is a new challenge for businesses or content creators, who would be less certain about what items or content will be the next big thing. These problems lead us to explore two research questions in this paper:

**RQ1** How can we measure the stability of non-crowdsourced socio-technical systems?

**RQ2** Can we improve the stability and performance of a socio-technical system?

We address these gaps in knowledge by systematically studying the complex dynamics of an algorithmically-driven socio-technical system, and focus on recommender systems. There are many systems we could explore, such as predictive policing (Ensign et al. [2018]), or bank loans (D’Amour et al. [2020]), in which a feedback loop between people interacting with algorithms and the algorithms trained on these interactions could unfairly benefit some people over others. Recommender systems are chosen because they are a key component of social media platforms, e-commerce systems (Ge et al. [2020]), and are used by many music and video streaming services (Bell and Koren [2007]; Schaefer et al. [2007]). In order to better understand the feedback loop, known as algorithmic confounding, in recommendation systems, we create a teacher-student framework that approximates a continuously trained recommendation system (Lampinen and Ganguli [2018]), as shown in Fig. 1. The left panel of Fig. 1
Figure 1: Framework for simulating recommendation systems. Left panel: a ground truth (teacher) model that simulates how agents choose items. This model is composed of a probability matrix that agents choose an item recommended to them for reasons besides the intrinsic item features (Salganik, Dodds, and Watts 2006; Burghardt et al. 2020) plus a matrix that is the product of two low-rank matrices to approximate how user and item latent features affect what items are chosen (Funk 2006; Bell and Koren 2007; Koren, Bell, and Volinsky 2009; Portugal, Alencar, and Cowan 2018). Right panel: the recommendation algorithm. A collaborative filtering (student) model approximates the user-item matrix as the product of two low-rank matrices (Funk 2006; Bell and Koren 2007; Koren, Bell, and Volinsky 2009; Portugal, Alencar, and Cowan 2018), known as matrix factorization, while the learning framework consists of recommending new items, recording what user-item pairs have been chosen, and retraining the student model on all collected data at the end of the timestep.

Our results show that recommending items that agents are predicted to like most leads to item popularity instability, where the same item can be very popular or unpopular in different simulation realizations. We use the simulation to test an alternative recommendation strategy in which random items are sometimes recommended. This new strategy improves stability and model accuracy as well as mean item popularity (a proxy for purchases or view counts of videos) at a given time. Moreover, a side-benefit of this strategy is that it forces the algorithm to recommend diverse content, which could reduce recommendation filter bubbles.

To summarize, our contributions are the following:

1. We develop a novel framework to evaluate the stability of model training.
2. We quantify the stability of different recommendation algorithms to algorithmic confounding.
3. We provide a simple recommendation algorithm strategy that improves accuracy and stability.

These results demonstrate that personalized recommendation systems can produce exceedingly unstable recommendations. While the simulation is an idealized system, it gives new insight into why the systems work, why they sometimes fail, and algorithm strategies to mitigate their shortcomings.

**Related Work**

**Recommendation systems** There has been significant research into improving recommendation systems. Many methods exist to recommend everything from game characters (Conley and Perry 2013) to educative content (Tan, Guo, and Li 2008) to movies (Biancalana et al. 2011), and are often based on collaborative filtering (recommending based on the behavior of similar people), content filtering (recommending similar content), or a combination of both (Balabanović and Shoham 1997; Schafer et al. 2007; Portugal, Alencar, and Cowan 2018). Collaborative filtering, which the present paper simulates, can use a number of different models from more K-means and ensemble-based methods

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1The simulation code can be found here: https://github.com/KeithBurghardt/RecSim
to neural networks (He et al. 2017; Bell and Koren 2007; Kim et al. 2016).

A popular and accurate recommendation model is matrix factorization, in which the sparse matrix of users-items pairs, \( R^{data} \), is approximated as the product of two lower-rank matrices \( \approx P^T Q \) (Koren, Bell, and Volinsky 2009). Throughout the paper, matrices are bold while elements within a matrix are italicized. The intuition behind matrix factorization is that users and items may individually have latent features that make users more likely to pick one item (such as watching an action movie) over another (such as watching a romantic comedy). There has been significant interest in matrix factorization both due to its performance (Bell and Koren 2007; Kim et al. 2016), and relative ease to analyze theoretically (Lesieur, Krzakala, and Zdeborová 2017). This method is often used in conjunction with other models, but for simplicity we model matrix factorization alone in the present paper.

Algorithm biases Training on biased data, a common practice in recommendation systems, can enhance biases, leading to greater unfairness and more mistakes (Ensign et al. 2018; D’Amour et al. 2020; Jabbari et al. 2017; Joseph et al. 2016; Angwin et al. 2016). This is known as algorithmic bias or algorithmic confounding in recommendation systems (Mansoury et al. 2020; Chaney, Stewart, and Engelhardt 2018; Sinha, Gleich, and Ramani 2016). This bias might create filter bubbles that enhance polarization (Sirbu et al. 2019; Bessi et al. 2016).

Ranking instability in crowdsourcing A large body of literature has explored the behavior of crowdsourcing systems. In contrast to recommendation systems that personalize content, in crowdsourcing systems all users see the same content. These systems aggregate decisions of many people to find the best items, typically by ranking them. Examples include StackExchange, where users choose the best answers to questions, and Reddit, where users choose the most interesting stories for the front page. Past work has shown that ranking, especially by popularity, creates feedback loops that amplify human biases affecting item choices, such as choosing popular items or those they see first, rather than high-quality items (Lerman and Hogg 2014; Burghardt et al. 2017). Recent literature has also identified instabilities in crowdsourced ranking (Burghardt et al. 2020; Salganik, Dodds, and Watts 2006), in which the crowdsourced rank of items are strongly influenced by position and social influence biases. As a result, the emergent popularity of mid-range quality content is both unpredictable and highly uneven, although the best (worst) items usually end up becoming most (least) popular (Salganik, Dodds, and Watts 2006; Keith Burghardt and Lerman 2018). Along these lines, Burghardt et al. (2020) developed a model to explain how the better item in a two-item list was not guaranteed to become highest ranked, which implies good content is often harder to spot unless the ranking algorithm controls for these biases. Finally, content recommended by Reddit had a poor correlation with user preferences (Glenski et al. 2018), suggesting factors including algorithmic confounding have produced poor crowdsourced recommendations.
Reinforcement Learning  Reinforcement learning is the algorithmic technique of interacting with an environment with a set of actions and learning what actions maximize cumulative utility [Kaelbling, Littman, and Moore 1996]. A number of reinforcement learning methods exist, from genetic algorithms and dynamic programming [Kaelbling, Littman, and Moore 1996] to deep learning-based algorithms [Arulkumaran et al. 2017]. The typical goal is to initially explore the space of actions and then exploit actions learned that can optimize cumulative utility. Personalized recommendations are a natural fit for reinforcement learning because users choose items sequentially, and the metrics to optimize, e.g., money spent or videos viewed, can easily be interpreted as a cumulative utility to optimize. A growing body of literature has shown how reinforcement learning algorithms can learn a sequence of recommendations to increase the number of items bought or content viewed (Taghipour, Kardan, and Ghidary 2007; Lu and Yang 2016; Arulkumaran et al. 2017; Alsar, Crump, and Farì 2021). These algorithms are often trained on past users interacting with the system, which could lead to algorithmic confounding. The framework within the present paper can be extended in the future to measure algorithmic confounding within reinforcement learning-based recommendation systems and help companies develop new techniques to better train these models in online settings.

Our novelty  The present paper contrasts with previous work by developing a teacher-learner framework to model and better understand the interaction between recommendation algorithms and users. Furthermore, we use these findings to demonstrate how item instability can be a vexing feature of recommendation systems, in which popular or highly recommended items may not strongly correlate with items agents prefer. Finally, we provide a novel reinforcement learning-inspired approach to better train collaborative filtering models, which can improve stability and recommendation accuracy.

Methods  We introduce the teacher-student modeling framework, simulation assumptions, and the recommendation algorithm strategies for student model training. Terminology referenced this section is available in Table 1 and symbols can be referenced in Table 2.

Outline of our approach
We analyze recommendation systems using simulations that capture the essence of recommendation algorithms while being simple enough to make generalizable conclusions. Model simplifications include:

1. A recommendation algorithm recommends \( r = 1 \) items to each agent before retraining on past data.
2. We assume agents are roughly the same age within the system.
3. Agents make binary choices, alternatively interpreted as ratings (upvote or downvote) (Trnecka and Trneckova 2021).

Symbol | Definition
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\( R_{\text{data}} \) | User-item matrix
\( R_{\text{teacher}} \) | Teacher model
\( R_{\text{student}} \) | Student model
\( \beta \) | The teacher model probability to choose items independent of their features
\( \beta \) | Scalar value of all elements in \( \beta \) (free parameter between 0 and 1)
\( J \) | All-ones matrix
\( \circ \) | Hadamard product (element-by-element multiplication between matrices)
\( P, Q \) | The latent features of users \( (P) \) and items \( (Q) \) in the teacher model
\( P', Q' \) | The estimated latent features of users \( (P') \) and items \( (Q') \) in the student model
\( k \) | Number of latent features in the teacher model \((k = 4)\)
\( k' \) | Number of latent features in the student model \((k' = 5)\)
\( n \) | Number of agents \((n = 4000)\)
\( m \) | Number of items \((m = 200)\)
\( A_{ij} \) | \( i,j \)th element in a matrix \( A \)
\( T \) | Timestep (value from 1 to \( m \))

Table 2: Symbol definitions.

4. Agent decisions follow the teacher model seen in the left panel of Fig. 1.
5. Agent choices are the same regardless of the order items are offered.
6. Regardless of agent choice, the item is not recommended again to that agent. This captures how often items may have a lower utility to users than novel items [Chaney, Stewart, and Engelhardt 2018].

Additional realism can be built into the simulation in the future; the present work can be viewed as a proof-of-concept.

Teacher-student framework
The recommendation system simulation has two components: a teacher model, \( R_{\text{teacher}} \), which models agent decisions, and a student model, \( R_{\text{student}} \), which models the recommendation engine. The student model is trained on a matrix of recommended items agents have or have not chosen, \( R_{\text{data}} \). The joint teacher-student framework has the following benefits: (1) the teacher model encodes agent preferences and can be made arbitrarily complex to improve realism, (2) the student model prediction can be directly compared to the teacher model ground truth, and (3) we can explore counterfactual conditions of how the recommendation system would behave if agents chose a different set of items.

The left panel of Fig. 1 shows the teacher model, which assumes that agents choose items stochastically according to a probability matrix that models both human biases and intrinsic preferences. The teacher model is

\[
R_{\text{teacher}} = \beta + (J - \beta) \circ PQ^T
\]  (1)
where $\beta$ is a matrix representing the probability a user will pick a given item regardless of its intrinsic qualities, $J$ is an all-ones matrix, $\circ$ is the Hadamard product, and $P$ and $Q$ are both low-rank matrices. This last term approximates how agents choose items due to their intrinsic preferences for items with particular latent features. The teacher model is similar to previous models of human decisions in crowdsourced systems (Burghardt et al. 2020), where agents stochastically choose items due to intrinsic qualities or at random due to human biases. The biases in real systems could vary in intensity for different scenarios, so we keep $\beta$ as a set of free parameters. For simplicity, we initially set the matrix $\beta = \beta J$, where $\beta$ is a scalar. For robustness, we compare our results to the case when the $\beta$ matrix are probabilities distributed uniformly at random between 0 and 1 (random $\beta$ condition).

To further simplify the simulation, we let $P$ and $Q$ be rank-$k$ whose elements are uniformly distributed between 0 and 1/k. This ensures that, after the rank-$k$ matrices are multiplied, the probabilities are always positive definite and less than 1 (on average 0.25, which avoids highly imbalanced datasets), while otherwise making minimal assumptions about the matrix element values. In this model, we arbitrarily choose $k = 4$ to ensure that $k < n$, $m$ as is typical in other recommendation systems (Bell and Koren 2007; Funk 2006). The student model approximates the user-item matrix, $R^{\text{data}}$, with matrix factorization

$$R^{\text{student}} = P^T Q^T$$

shown in the right panel of Fig. 7. Matrix factorization assumes that agent choices are best explained by a smaller number of latent factors (agent preferences) that can be learned from their observed choices, as we assume in the teacher model. The model’s output is the expected probability a user will choose a particular item. After agents decide which of the recommended items they will choose, their data are fed into the student model whose matrices have an arbitrary low rank $k'$ (not necessarily equal to $k = 4$). We chose $k' = 5$ in our simulations, although results are similar if we chose $k' = 2$, but the fit to data is worse. While some matrix factorization models train with a ridge regression loss term (Bell and Koren 2007; Funk 2006), we choose a slightly easier approach: stochastic gradient descent (SGD) with early stopping. We split the available data at random with 80% for training and 20% for validation and apply SGD until the 20% validation set’s brier score error is minimized (where the initial conditions are the matrix weights from the previous timestep). While this differs from some recommendation algorithms, previous work has shown that matrix factorization is a variant of dense neural networks that commonly implement this method (Lesieur, Krzakala, and Zdeborová 2017), and there is a close quantitative connection between ridge regression and early stopping (Gunasekar et al. 2018). Finally, this method allows us to stop training early, which makes simulations run faster. The recommendation algorithm uses this model to recommend $r = 1$ item to each agent following a strategy outlined below.

### Recommendation Algorithm Strategies

We propose a number of realistic strategies to recommend items, including a greedy strategy (recommending the content the student model predicts will most likely be chosen), an $\epsilon$-greedy strategy, in which random unchosen content is recommended with probability $\epsilon$, and a random strategy, in which random unchosen content is recommended with equal probability. We compare these against the best case scenario, the oracle strategy, in which we unrealistically set the student model equal to the teacher model. The $\epsilon$-greedy strategy is inspired by reinforcement learning systems (Kaelbling, Littman, and Moore 1996; Arulkumaran et al. 2017; Afsar, Crump, and Far 2021), where recommendations are usually built up from interactions between individuals and the system. In contrast to previous work (Afsar, Crump, and Far 2021), however, we incorporate reinforcement learning strategies into training a collaborative filtering model.

### Simulation Parameters

These recommendations are then stochastically chosen by agents following the teacher model probabilities, and the simulation repeats until all items have been recommended. The student model is first trained on a sparse initial set of data. More specifically, 0.1% of data was initially sampled uniformly a random with values $R_{ij}^{\text{data}} = 0$ or 1 depending on a Bernoulli distribution with probability $P_{ij}^{\text{teacher}}$. Many datasets, such as the Netflix Prize dataset, have a greater proportion of user-item pairs (roughly 1% of all possible pairs (Bell and Koren 2007). However, the user-item pairs were themselves recommended with Netflix’s in-house algorithm that was trained on an even smaller set of data, which we assume is 0.1% of all possible pairs.

We run this model for $n = 4000$ agents and $m = 200$ simulated items with ten realizations for each value of $\beta$ (or five realizations for the random $\beta$ teacher model). A realization is where we retrain the student model from scratch, starting with a random 0.1% of all pairs. We also generate a new teacher model, but keeping the same teacher model does not significantly affect results. The ratio of agents to items was chosen to approximately correspond to that of the Netflix prize data (Bell and Koren 2007), roughly 20 agents per item. Largely because of the number of times we fit the student model over the course of each simulation realization ($m = 200$ times), and because matrix factorization takes up $O(n \times m)$, the simulation takes $O(n \times m^2)$. This time complexity means that modeling our comparatively modest set of agents and items would take several computing days for one simulation realization if we were not run in parallel. We are able to finish all the simulations in this paper in roughly 1-2 weeks on three 48-logical-core servers using Python (see link to code in the Introduction).

### Results

We test whether the recommendation algorithm provides the agents with the items they want, whether items are ranked consistently, and finally how to improve recommendation algorithm stability.
Figure 2: Student model instability. (a) The correlation between item popularity at timestep 100 and the teacher model probability an item would be chosen as a function of the human bias parameter, $\beta$. An alternative random $\beta$ model, where the bias is uniformly distributed between 0 and 1 for each user-item pair, shows similar results. (b) The item popularity correlation between different realizations of the model after 100 timesteps.

We can gain intuition about how the greedy strategy affects the system in the limit that the student model’s low-rank matrices are rank-one matrices ($k' = 1$), which is even simpler than the simulation discussed in the rest of the paper ($k' = 5$). If we want to recommend the top items to each agent, $i$, then we want to find item $j$ with the largest value in the student model, $R_{\text{student}}^{ij} = P_i' \times Q_j'$. However, in this case, the system recommends the same item to each agent because the relative ranking of items only depends on $Q_j'$. This common ranking also implies that the recommendation system will only recommend popular content to agents rather than niche items agents may prefer. The homogeneity in recommendations and relationship between recommendations and popularity is seen in previous work on more realistic systems [Chaney, Stewart, and Engelhardt 2018; Mansoury et al. 2020], therefore even this simplified version of the simulation captures realism of more sophisticated systems. What is not captured in previous work, however, is that $Q_j'$ would vary dramatically depending on the initial conditions, which implies item popularity instability: the same item could be very popular or unpopular in different simulation realizations by chance. The $\epsilon$-greedy strategy, in contrast to the greedy strategy, promotes random items, which we will show reduces the inequality of the system and helps the recommendation algorithm quickly find the most preferred content.

**Instability of Recommendation Systems**

Figure 2 shows the stability and accuracy of the model. Figure 3 compares the popularity of items after 100 timesteps, when half of all recommendations are made, to the ground truth (popularity if all user-item pairs were fully sampled). We find that increasing the bias $\beta$ decreases the correlation between algorithm and ground truth popularity, therefore items that should be popular are not. Figure 2, in contrast, shows that larger $\beta$ decreases the item popularity correlation between simulation realizations, implying greater item popularity instability. This is alike to previous work on crowdsource systems [Burghardt et al. 2020; Salganik, Dodds, and Watts 2006], in which ranking items by a simple heuristic can drive some items to become popular by chance. Despite this finding, the $\epsilon$-greedy strategy creates much higher correlations between item popularity and the ground truth (Fig 2) and item popularities between each simulation realization (Fig 2). The new strategy, in other words, improves recommendation accuracy and reduces item popularity instability.
Figure 4: The evolution of item popularity. (a) Gini coefficient and (b) mean item popularity over time for $\beta = 0.0, 0.4$. Four different strategies are used for recommendation: oracle, greedy, $\epsilon$-greedy and random. Gini coefficient is generally lower for $\epsilon$-greedy and random strategies, and the $\epsilon$-greedy strategy makes more ideal recommendations, allowing mean item popularity to be higher than all but the oracle strategy.

The reason the greedy strategy performs poorly can be better understood when we plot student model error over time in Fig. 3. We show that model error generally decreases with time, as expected, but the greedy strategy has error decreasing slowly with time. The $\epsilon$-greedy strategy enhances the student model through a representative sample of the user-item matrix. Error for this strategy therefore drops to a small fraction of the greedy strategy and is nearly as small as the error for the random strategy.

Comparing Recommendation Quality

Next, we compare the quality of recommendations by observing the items chosen over time in Fig. 4. We show that the $\epsilon$-greedy strategy makes more diverse recommendations that are of higher quality on average than the random or greedy strategies. In Fig. 4a, we show the Gini coefficient of item popularity, a proxy for item popularity inequality. If items were fully sampled, their Gini coefficient would be less than 0.2 ($T = 200$ values on the right side of the figure). Under the idealized oracle strategy, the Gini coefficient is initially high (only a few of the best items are recommended) and steadily drops. The lower Gini coefficient for the $\epsilon$-greedy strategy is a product of more equal sampling. The greedy strategy Gini coefficient is, however, often higher than all alternative strategies, meaning some items are recommended far more frequently than they should be.

Next, we plot the mean popularity over time in Fig. 4b. If the mean popularity of items is high early on then agents are recommended items they really like. The mean popularity of items is highest in the oracle strategy because we know exactly what items users are most likely to choose and recommend those first. We find agents choose more items at any timepoint with the $\epsilon$-greedy strategy than alternatives implying it is the best non-oracle strategy. The random recommendations within the $\epsilon$-greedy strategy trains the student model better, and this in turn creates better recommendations on average.

Robustness of Results

The simulations shown in Figs. 3 & 4 make several simplifying assumptions, including a $\beta$ matrix whose elements are all the same. Instead $\beta$ elements could be very different, which we model as values that are independent and uniformly distributed between 0 and 1. We show in Fig. 2 that this does not change our finding that the greedy strategy is less stable than the $\epsilon$-greedy strategy. We similarly show that the model error and item popularity is qualitatively similar in Fig. 5. Namely, in Fig. 5a, we show that the greedy method has consistently higher model error than the $\epsilon$-greedy strategy. Similarly, the Gini coefficient (Fig. 5b) is higher and the mean popularity over time is very slightly, but statistically significantly, lower in Fig. 5c (shown more clearly in the inset, which shows the difference in item popularity over time). To test the statistical significance, we take the mean popularity difference across all timesteps between the greedy and $\epsilon$-greedy strategies and compare the z-score of this difference (which is greater than 15), making the p-value $< 10^{-6}$. This result is approximately the same when we compare the mean difference for individual realizations or the mean item popularity across five realizations; results stated above are for mean popularity across five realizations. Unlike in earlier results, however, the teacher model is now poorly approximated as a product of two lower-rank matrices, therefore error is typically higher. The oracle strategy in turn has a lower Gini coefficient and higher mean popularity than alternative strategies.

Discussion & Conclusions

In conclusion, we develop a teacher-student framework to understand the accuracy and stability of collaborative filtering models as they interact with agents. The simulations demonstrate that the greedy strategy produces unstable and inaccurate predictions over time. Namely, the recommendation algorithm recommends a small set of items (leading to a high popularity Gini coefficient) and this leads to higher error. In contrast, the $\epsilon$-greedy strategy follows a less intuitive
training regime in which random items are recommended to agents. This leads to better sampling (lower Gini coefficient), lower error, and more items picked at any given time because the items recommended are what agents prefer to choose. Finally, the $\epsilon$-greedy strategy might force users out of filter bubbles by exposing them to a more diverse set of items. This potential should be explored in future work. This paper adds to growing literature on the instability of ranking systems (Salganik, Dodds, and Watts 2006; Burghardt et al. 2020), but also gives greater insight into personalized ranking, and emergent properties, both desired and unintended, of these systems. For example, the sensitivity of the recommendation algorithm to initial conditions is reminiscent of chaotic systems, but future work is needed to test the relationship between these findings and non-linear dynamics or chaos theory.

Limitations

There are a number of potential limitations with the current method. First, our work must rely on synthetic data because we cannot know whether a user would choose an item they were not recommended in empirical data. Furthermore, assumptions built into the present simulation may not reflect the true human dynamics. For example, agents are the same age and equally active in the system. In reality, some agents may be much older and have much more data than others. In addition, the order items are recommended could affect agent decisions. For example, users might not buy a vinyl record unless they are first recommended a record player. Moreover, we use a simple student model to recommend items, but newer and more sophisticated collaborative filtering methods could be offered.

Ethical Considerations

The present simulations offer policy suggestions to improve recommendations by combining ideas from collaborative filtering with reinforcement learning. This current work does not, however, explore the potential adverse effects of recommendation systems, such as filter bubbles (Bessi et al. 2016). Items recommended by the $\epsilon$-greedy strategy could be of low-quality or promote harm, while we would expect such items are screened out when recommendation algorithms promote what agents should like. That said, this method actively fights filter bubbles by offering items outside of the user’s expected preferences, and a variation of this strategy, such as recommendations among a cleaned or popular set of items could provide users better and more diverse items.

Future Work

Additional realism, such as agents arriving or leaving the system, could easily be incorporated into the simulation. The present work is a baseline that researchers can modify for specific systems. Additional features should be explored, however, including polarization, in which people preferentially pick one type of content over another. While there has been a growing interest in algorithmic polarization (Sirbu et al. 2019), the dynamic interaction between agents and trained models should be explored in greater depth, especially if it can drive people away from echo chambers. Moreover, the teacher-student methodology in this paper can be extended to audit other socio-technical systems such as predictive policing (Ensign et al. 2018), bail (Kleinberg, Mullainathan, and Raghavan 2016), or banking loans, whose data is known to be intrinsically biased (D’Amour et al. 2020). The instability we could measure is, for example, who gets loans or goes to jail. If this varies due to the simulation realization and not the intrinsic features of the people, we could quantify, and find ways to address, the algorithm’s instability.

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Conflicts of Interest
The authors declare no conflicts of interest.

References
Afsar, M. M.; Crump, T.; and Far, B. 2021. Reinforcement learning based recommender systems: A survey. arXiv preprint arXiv:2101.06286.

Angwin, J.; Larson, J.; Mattu, S.; and Kirchner, L. 2016. Machine bias. ProPublica. See https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

Arulkumaran, K.; Deisenroth, M. P.; Brundage, M.; and Bharath, A. A. 2017. A Brief Survey of Deep Reinforcement Learning. arXiv preprint arXiv:1708.05866.

Balabanović, M.; and Shoham, Y. 1997. Fab: Content-Based, Collaborative Recommendation. Commun. ACM 40(3): 66–72. ISSN 0001-0782. doi:10.1145/245108.245124. URL https://doi.org/10.1145/245108.245124.

Bell, R. M.; and Koren, Y. 2007. Lessons from the Netflix Prize Challenge. SIGKDD Explor. Newsl. 9(2): 75–79. ISSN 1931-0145. doi:10.1145/1345448.1345465. URL https://doi.org/10.1145/1345448.1345465.

Bessi, A.; Zollo, F.; Del Vicario, M.; Puliga, M.; Scala, A.; Caldarelli, G.; Uzzi, B.; and Quattrociocchi, W. 2016. Users Polarization on Facebook and Youtube. PLOS ONE 11(8): 1–24. doi:10.1371/journal.pone.0159641. URL https://doi.org/10.1371/journal.pone.0159641.

Biancalana, C.; Gasparetti, F.; Micarelli, A.; Miola, A.; and Sansonetti, G. 2011. Context-aware movie recommendation based on signal processing and machine learning. In Proceedings of the 2nd Challenge on Context-Aware Movie Recommendation, 5–10. ACM.

Burghardt, K.; Alsina, E. F.; Girvan, M.; Rand, W.; and Lerman, K. 2017. The Myopia of Crowds: A Study of Collective Evaluation on Stack Exchange. PLOS ONE 12(3): e0173610.

Burghardt, K.; Hogg, T.; D’Souza, R.; Lerman, K.; and Posfai, M. 2020. Origins of Algorithmic Instabilities in Crowdsourced Ranking. Proc. ACM Hum.-Comput. Interact. 4(CSCW2). doi:10.1145/3415237. URL https://doi.org/10.1145/3415237.

Chaney, A. J. B.; Stewart, B. M.; and Engelhardt, B. E. 2018. How Algorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility. In Proceedings of the 12th ACM Conference on Recommender Systems, RecSys ’18, 224–232. New York, NY, USA: Association for Computing Machinery. ISBN 9781450359016. doi:10.1145/3240323.3240370. URL https://doi.org/10.1145/3240323.3240370.

Conley, K.; and Perry, D. 2013. How does he saw me? a recommendation engine for picking heroes in dota 2. Np, nd Web 7.

D’Amour, A.; Srinivasan, H.; Atwood, J.; Baljekar, P.; Sculley, D.; and Halpern, Y. 2020. Fairness is Not Static: Deeper Understanding of Long Term Fairness via Simulation Studies. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, FAT ’20, 525–534. New York, NY, USA: Association for Computing Machinery. ISBN 9781450369367. doi:10.1145/3351095.3372878. URL https://doi.org/10.1145/3351095.3372878.

Ensign, D.; Friedler, S. A.; Neville, S.; Scheidgen, C.; and Venkatasubramanian, S. 2018. Runaway Feedback Loops in Predictive Policing. In Friedler, S. A.; and Wilson, C., eds., Proceedings of the 1st Conference on Fairness, Accountability and Transparency, volume 81 of Proceedings of Machine Learning Research, 160–171. PMLR. URL https://proceedings.mlr.press/v81/ensign18a.html.

Funk, S. 2006. Netflix update: Try this at home.

Ge, Y.; Zhao, S.; Zhou, H.; Pei, C.; Sun, F.; Ou, W.; and Zhang, Y. 2020. Understanding Echo Chambers in E-Commerce Recommender Systems. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’20, 2261–2270. New York, NY, USA: Association for Computing Machinery. ISBN 9781450380164. doi:10.1145/3397271.3401431. URL https://doi.org/10.1145/3397271.3401431.

Glenski, M.; Stoddard, G.; Resnick, P.; and Wening, T. 2018. GuessTheKarma: A Game to Assess Social Rating Systems. Proc. ACM Hum.-Comput. Interact. 2(CSCW), doi:10.1145/3274328. URL https://doi.org/10.1145/3274328.

Gunasekar, S.; Woodworth, B.; Bhojanapalli, S.; Neyshabur, B.; and Srebro, N. 2018. Implicit Regularization in Matrix Factorization. In 2018 Information Theory and Applications Workshop (ITA), 1–10. doi:10.1109/ITA.2018.8503198.

He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; and Chua, T.-S. 2017. Neural Collaborative Filtering. In Proceedings of the 26th International Conference on World Wide Web, WWW ’17, 173–182. Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee. ISBN 9781450349130. doi:10.1145/3038912.3052569. URL https://doi.org/10.1145/3038912.3052569.

Jabbari, S.; Joseph, M.; Kearns, M.; Morgenstern, J.; and Roth, A. 2017. Fairness in Reinforcement Learning. In Precup, D.; and Teh, Y. W., eds., Proceedings of the 34th International Conference on Machine Learning, volume 70 of Proceedings of Machine Learning Research, 1617–1626. PMLR. URL https://proceedings.mlr.press/v70/jabbari17a.html.

Joseph, M.; Kearns, M.; Morgenstern, J. H.; and Roth, A. 2016. Fairness in Learning: Classic and Contextual Bandits. In Lee, D.; Sugiyama, M.; Luxburg, U.; Guyon, I.; and Garnett, R., eds., Advances in Neural Information Processing Systems, volume 29. Curran Associates, Inc. URL https://proceedings.neurips.cc/paper/2016/file/eb163729717cbba1ee208541a643c74-Paper.pdf.

Kaelbling, L. P.; Littman, M. L.; and Moore, A. W. 1996. Reinforcement Learning: A Survey. JAIR 4: 237–285.
