How Does User Behavior Evolve During Exploratory Visual Analysis?

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Abstract

Exploratory visual analysis (EVA) is an essential stage of the data science pipeline, where users often lack clear analysis goals at the start and iteratively refine them as they learn more about their data. Accurate models of users' exploration behavior are becoming increasingly vital to developing responsive and personalized tools for exploratory visual analysis. Yet we observe a discrepancy between the static view of human exploration behavior adopted by many computational models versus the dynamic nature of EVA. In this paper, we explore potential parallels between the evolution of users' interactions with visualization tools during data exploration and assumptions made in popular online learning techniques. Through a series of empirical analyses, we seek to answer the question: how might users' exploration behavior evolve in response to what they have learned from the data during EVA? We present our findings and discuss their implications for the future of user modeling for system design.

1 Introduction

Data analysts often explore large datasets to find relevant information or discover interesting patterns in the data using **visual exploration systems (VES)**, like Tableau (Tableau 2004), Microsoft PowerBI (Microsoft 2015), etc. They interactively query the visualizations shown by the VES until they discover their desired information. This process, known as **exploratory visual analysis (EVA)**, is iterative and complex. EVA is particularly challenging as analysts often encounter new datasets with unknown structures and content. Complexity increases as they often commence EVA with only vague analysis goals in mind, e.g., to discover intriguing observations (Battle and Heer 2019; Liu and Heer 2014). The following example clarifies how users dynamically generate hypotheses and perform multiple interactions with a VES to achieve their goals.

Example 1.1. Suppose an analyst *explores snow cover from NASA satellite imagery to identify abnormally snowy regions in the USA, a potential consequence of global warming.* She has not analyzed this dataset before. So, initially, she does not know what snow levels are abnormal. She uses a VES (Figure 1) to explore different regions using pan and zoom operations. Through EVA, the analyst learns what areas have high snow levels, e.g., snowy mountain ranges. She eventually hypothesizes that outliers correspond to mountainous regions that deviate from expected high snow levels. With this intent, she alters her interaction strategy to test her hypothesis. This process of generating and testing hypotheses continues until she gains the desired insights.



Figure 1: Exploring satellite imagery using a VES.

During EVA, users generate a wide range of query workloads. For instance, in *Example 1.1*, the user may perform queries to compare multiple snowy regions at different levels of detail. Current systems offer optimization techniques to support demanding workloads under specific contexts, including re-using previously computed results and building specialized data structures such as stratified samples or data cubes (Battle and Scheidegger 2020). But users' ad-hoc queries during EVA can thwart standard optimization techniques (Battle et al. 2020). Studies have shown how these inefficiencies can lead to user frustration and even abandonment of exploration tasks (Liu, Jiang, and Heer 2013).

Understanding and modeling users' exploration behavior can help to customize VESs to match the user's interests, preferences, and exploration strategies (Zeng et al. 2021). Such systems can prefetch (Battle, Chang, and Stonebraker 2016), suggest relevant or interesting data regions (Wongsuphasawat et al. 2016), and recommend exploratory operations (Milo and Somech 2018). In *example 1.1*, a VES could infer that the user intends to compare mountainous snowy regions. Then, it can prefetch similar data areas to reduce system latency or recommend interesting regions to lessen users' exploration load. However, the VES must also detect shifts in users' exploration behavior after a hypothesis is formed, else, its predictions will become obsolete.

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We observe that user models in current VESs implicitly assume that users' intent and strategies are *fixed*, i.e., users' analysis goals and strategies for achieving it will not change much over time (Battle, Chang, and Stonebraker 2016). In contrast, users may enrich their understanding of the data during EVA, and may *change* their exploration strategies to better express their intents (Battle and Heer 2019).

As users may alter their exploration behavior in response to what they learn about the data during exploration, a natural question is whether known learning methods can model users' evolving information needs in real-time. Many online algorithms have shown promising results in modeling human behavior in game theory, cognitive psychology (Bush and Mosteller 1953; Niv 2009; Niv et al. 2012), etc. *This paper addresses the absence of an empirical investigation of these human behavior algorithms as models for the evolution of user reasoning during EVA*. Identifying and evaluating existing algorithms will help us decide if and when new algorithms are required, thereby guiding future efforts in building accurate models for VESs to further support EVA.

The goal of this paper is to investigate and model the evolution of users' exploration behavior in response to user learning using influential studies from the visualization community that apply distinct approaches to capturing exploration behavior. *This helps us to observe how current learning methods model behavioral changes across the gamut of exploration tasks rather than in just one tool or scenario.* In this work, we present our investigation on (Liu and Heer 2014) and (Battle, Chang, and Stonebraker 2016) for the sake of space and provide our investigation of (Battle and Heer 2019) in the appendix. Specifically, we seek answers to the following questions: (a) *How does learning manifest during exploratory visual analysis?* (b) *Does users' exploration behavior actually evolve?* and (c) *Can existing algorithms model users' exploration behavior in EVA?*

- In summary, we make the following contributions:
 We examine users' decision-making strategies in reallife EVA tasks with different characteristics, e.g., goals, complexity, and prior knowledge. Our preliminary findings demonstrate that user learning about the data affects users' exploration behavior.
- We use statistical tests to analyze *how users' exploration strategies evolve* and connect our findings with user learning. Test results indicate that user exploration behavior differs depending on the clarity and complexity of the exploration task. This variance is observable across *goal-directed, focused, and open-ended scenarios.*
- We utilize popular learning algorithms from reinforcement learning, economics, cognitive psychology, and neuroscience to model users' exploration behavior. They struggle more for *goal-directed tasks* (68%) and *openended tasks* (53%) (Subsections 4.5,5.5).
- We present common findings and challenges from our investigations and suggest future research directions for developing more accurate models of users' behavior during EVA and building learning-aware VES. (Section 6)

2 Related Works

Static View of Exploratory Visual Analysis (EVA): Researchers model user exploration behavior to improve how systems support EVA (Gotz and Wen 2009; Gotz and Zhou 2009; Battle, Chang, and Stonebraker 2016). For instance, ForeCache uses Markov chain models to infer users' exploration goals from their interactions, which it uses to prefetch corresponding data regions (Battle, Chang, and Stonebraker 2016). In contrast to our approach, these methods assume that users do not modify their strategies and follow a fixed exploration policy throughout the exploration process.

User Learning in Data Querying: Recent research using real-world keyword query workloads indicates that users learn to express specific and focused intents by modifying their keyword queries over time; furthermore, this learning behavior can be modeled using online learning algorithms (McCamish et al. 2018). In (Cen, Gan, and Bai 2013) researchers model users' evolving information-searching strategies from scholarly databases using Reinforcement Learning (RL). Unlike in data querying, users often lack a predefined and concrete intent during EVA. Therefore, EVA presents a significantly larger action space requiring users to make more complex decisions.

Understanding the User in Visual Data Analytics: Models based on high-level user reasoning have been developed to aid users in visual data analysis. The closest examples of modeling user learning in visualization involve measuring the acquisition of knowledge in the form of insights (Liu and Heer 2014; Battle and Heer 2019; Guo et al. 2016; He et al. 2021). However, insight-based analyses tend to focus on low-level metrics such as insight accuracy or insight generation rates (Battle and Heer 2019), rather than testing whether the user is learning. Several works conceptualize a user's reasoning process as they analyze a dataset (Liu and Stasko 2010; Patterson et al. 2014); however, these conceptualizations are unable to predict whether and how users learn from data analysis sessions. More recent work considers how users may update their prior beliefs in reaction to new data using Bayesian models (Karduni et al. 2021; Kim et al. 2019). We consider a more general idea of testing whether users are learning as they encounter new data.

3 Considerations for User Studies Selection

The objectives and properties of exploration tasks may significantly influence how users engage with a VES (Battle and Heer 2019). Our selection of existing user studies by Liu and Heer; Battle, Chang, and Stonebraker; Battle and Heer for analyzing user behavior is by no means complete. But we believe they consider sufficiently many characteristics of exploration tasks to answer "How Does User Behavior Evolve During Exploratory Visual Analysis?"

3.1 Characteristics of Exploration Tasks

Open-endedness: Researchers categorize exploration tasks into three groups based on how clear users' objectives are (Battle and Heer 2019).

Open-ended tasks are exploration tasks without a clear intent or hypothesis. For example, in the *imMens user study* (Table 1), participants search for *interesting* information from large data. In these cases, information need is opaque, causing uncertainty in what and where to search. To successfully carry out this task, users might need to learn about the

dataset during their exploration to be able to form relevant hypotheses and find interesting information.

In **goal-directed tasks**, analysts initiate exploration with a high-level goal or hypothesis. For example, in the *Fore-Cache user study* (Table 1), participants' goal is to capture screenshots of 3 different U.S. regions with the highest snow coverage in a map visualization. Users may have multiple approaches to meet the goal, e.g., *compare* snow coverage between various geographical regions, or *search* an area in detail. So, they need to learn about the data to find the set of queries (or paths) that deliver the desired result (goal).

In **focused tasks**, analysts have precisely defined goals and exploration paths. For instance, in the *Tableau user study focused task T2* (available in the appendix), users analyze how temperature changes over time. Users know what information to retrieve and which data area to explore as the question includes corresponding column names. Although, with the large data size, users may need additional interactions to find the provided locations.

Prior Experience: Users' prior knowledge about the dataset and familiarity with the exploration interface may influence the amount of information they should and will learn. In the imMens and ForeCache user studies, users have a limited time to get familiar with the dataset. On the other hand, in the Tableau user study, the analysis tasks require users to explore an unseen dataset (Perer and Shneiderman 2008).

Time Restriction: Users use the time between interactions to gather their thoughts, view data, draw comparisons, and plan their next steps (Battle, Chang, and Stonebraker 2016; Battle and Heer 2019). As a result, time can be a vital factor in users' choice of learning schemes. Our user study selection spans a diverse spectrum of time restrictions, ranging from *no restriction* on Forecache to a *30-minute limit* on im-Mens (Table 1).

Task Complexity: The number of interface operations (action space) of the VES and the amount of information displayed has been shown to contribute towards task complexity and thereby impact users' exploration behavior in EVA (Gwizdka 2010; Back and Oppenheim 2001; Lam 2008). Among the systems used in our selected studies, ForeCache has the smallest action space, with only two options for navigating a 2D map, resembling Google Maps. imMens has four actions to query the imMens visualizations. In contrast, Tableau (Tableau 2004) is a more complex system with the largest action space for selecting, and filtering data.

3.2 Methodology

We use the following methodology to analyze the evolution of users' exploration behavior across our selected studies.

Overview of Exploration Task: We describe the analysis tasks in each user study and connect them with the characteristics introduced in Table 1. Furthermore, we describe available user interface actions and associated interaction data utilized in our analysis.

Formalizing the User Learning Problem: To understand users' approach to solving the task, we examine *users' task activities* and identify the recurring strategies they exhibit. We define how users explore the dataset and make informed choices of exploration strategies, i.e., the **learning problem**.

Then, we draw parallels between the proposed formalization and objective functions from well-studied online learning frameworks (Auer et al. 2002; Ontanón 2013; Niv 2009). As neither visualization researchers nor database researchers have tested for the exact objective function humans use during EVA scenarios, we explore various online learning frameworks tailored to the formalized learning problem.

Statistically Analyzing Behavior Evolution: To better understand the evolution of user behavior, we perform statistical tests to check for changes in users' exploration strategies. Let us revisit Example 1.1. To test her hypothesis, the analyst randomly picks two different snowy mountain ranges and does lots of interactions to analyze them. She successfully identifies some outliers for one of the regions but finds her approach time-consuming. Additionally, she learns that areas with multiple mountain ranges have higher chances of containing an outlier. Armed with this learning, she changes her approach to enhance efficiency. Initially, she zooms out to find candidate areas of interest and then decides to explore candidates in descending order of snow coverage. This approach reduces the number of zoom operations and increases the chances of detecting outliers. By using statistical tests to analyze users' exploration patterns, we investigate changes in users' exploration behavior in different intervals.

Evaluated Learning Algorithms: In this paper, we address the absence of a comprehensive investigation of human learning during EVA. To fill this void, we employ human learning algorithms commonly utilized in economics (Bush and Mosteller 1953; Roth and Erev 1995), game theory (Tamura and Masuda 2015), artificial intelligence (McCamish et al. 2018; Cen, Gan, and Bai 2013; Zhang and Yu 2013), and cognitive psychology (Niv 2009; Niv et al. 2012; Glimcher 2011). We briefly describe the algorithms and justify their selection for modeling users' exploration behavior in our selected studies. We establish a consistent measure of *how well these learning algorithms can adapt to users' exploration strategy* by empirically evaluating their performance in predicting users' future actions.

4 ForeCache User Study

4.1 Overview of Exploration Task

Analysis Task: In the ForeCache user study task, participants explore a map visualization containing information on snow coverage in the US (Figure 1). The task goal is to look for areas with high snow coverage on the map. Users are expected to provide screenshots of three such areas as **results** (Battle, Chang, and Stonebraker 2016).

Characteristics: We show in Section 3.1 how analysts know the data features to search for but have unclear path ideas, making this EVA task goal-directed. Given the limited expected results (3 screenshots), there is no *time restriction*. Users complete a small training subtask before the task, so they had limited *prior experience* with the visualization tool. **Interface and Interaction Log:** ForeCache **interface** displays snow coverage (**snow level**) in shades of blue based on Normalized Snow Index (*NDSI*) calculations from NASA MODIS dataset (Rittger, Painter, and Dozier 2013). Snow

Characteristics	imMens user study (Liu and Heer 2014)	ForeCache user study (Battle, Chang, and Stonebraker 2016)	Tableau user study (Battle and Heer 2019)		
Characteristics	minitiens user study (End and fieer 2014)	Forecache user study (Battle, Chang, and Stonebraker 2010)	Task [T1, T2, T3]	Task [T4]	
Exploration need	Open-ended	Goal-Directed	Focused	Goal-Directed	
Prior experience	15 minutes with datasets	Training subtask with dataset	5 minutes with a different dataset		
Time restriction	30 minutes per dataset	No	7 minutes per dataset	5 minutes per dataset	
Task Complexity	Interactive querying using	Exploring 2D map	Analyzing visualizations generated by		
	imMens actions on summarized plots	using pan and zoom	Tableau based on users' query on datas		

Table 1: High-level dimensions in the exploration tasks of our selected user studies

levels are in the range [0: low snow level, 1: high snow level]. The interface supports pan to explore up, down, left, right, and zoom to observe snow coverage in different levels of detail (zoom levels). There are six different zoom levels, from 0 (coarse) to 6 (fine-grained). The interface's actions compel users to incrementally and sequentially retrieve only a fraction of the underlying dataset. For example, the user cannot directly jump from zoom level 0 to 4; she has to incrementally go through levels 1, 2, and 3. The interaction log from the user study, NDSI 2D Interaction Dataset (Battle 2017), comprises data exploration logs of 20 participants.

4.2 Formalizing User Learning Problem

User Activities and Learning Problem: To comprehend how users are evolving in their exploration behavior, we need to capture users' strategies for solving the task. The raw ForeCache action space, e.g., zooming and panning, may not provide a meaningful categorization of users' exploration strategies (Battle, Chang, and Stonebraker 2016).

Visualization researchers address this challenge by characterizing users' strategies using high-level exploration stages (Gotz and Wen 2009; Saha, Termehchy, and Battle 2019). Therefore, we follow (Battle, Chang, and Stonebraker 2016) and use the three stages of exploration based on information foraging theory (Pirolli and Card 2005).

User Actions: To explore the dataset, the user starts foraging, i.e., looking for interesting patterns in the data at coarse zoom levels Figure (1). Her goal is to generate hypotheses for potential screenshot candidates in high snow-covered areas. Then, she gradually moves to fine-grained zoom levels, i.e., navigates to more detailed views of snow coverage. Having identified an area of interest at a fine-grained zoom level, she starts sensemaking, i.e., comparing snow coverage in detail. To test her hypothesis she verifies if this candidate area has high snow coverage. However, the user is not limited to analyzing a single area; she may also navigate back to a bird-eye view to forage for new snow areas or hypotheses. Exploration Stages: In Table 2, we present the three exploration stages derived from users' activities, i.e., low-level actions and goals: Foraging, Navigation, and Sensemaking. As shown in Figure 2, the sequential dependence between the stages of exploration (Foraging-then-Navigation-then-Sensemaking) makes users' exploration process suitable to be formalized as a Markov Decision Process (MDP).

Modeling Exploration Using MDP: We formalize users' exploration approach as MDP's state, action, and reward. Background for MDP is available in the Appendix A.1.

States We extend the stages in Table 2 as MDP states.

Actions: In Sensemaking and Foraging states, a user can perform two actions: switch or maintain (Figure 3). For instance, by picking action *switch*, the user changes her exploTable 2: Mapping actions and goals to exploration stages

Stage	Goal	Low-level action		
Foraging	Generate hypothe-	Pans at coarse Zoom		
	ses	Level		
Navigation	Navigate	Zoom in/out		
Sensemaking	Test hypotheses	Pans at fine-grained		
		Zoom Level		

ration strategy from Sensemaking to Navigation (and vice versa). In the Navigation state, the user's switch action can be further divided into switch-forage, taking them to the Foraging state and switch-sense for transitioning to Sensemaking. When the action is maintain, the user maintains the current exploration strategy and stays in the same state.

Reward: On instigating these transitions, user receives feedback from the interface environment. This feedback is a measure of how successful the user's actions are in achieving the task requirements of taking screenshots at high zoom levels and looking for high snow coverage. We extend this response from the interface as the reward in the MDP environment; *Reward* = *Snow level* × *Zoom level*

Learning Problem: At each interaction $(t \in [1, T])$, users should make a learned choice, given their current state, whether they should stay there or move to another one to maximize the chances of discovering high snow coverage. Similar to an MDP agent, a user's objective during exploration is to learn an optimal policy (π : State \rightarrow Action) that maximizes the expected sum of future reward,

 $\max_{\pi} \boldsymbol{E}\left[\sum_{\text{interaction}=t}^{T} \text{reward}(\pi, \text{interaction})\right].$

Learning in an MDP Setting: One approach to quantifying behavioral shifts is to analyze the improvement in accumulated rewards. For some users, we observe an increasing trend in rewards over interactions, indicative of users finding higher snow-covered regions as they progress through the task. Upon analyzing user behavior at different stages of the task, we observe a notable difference between early and later exploration interactions. Similar to most RL agents (Sutton and Barto 1998), users tend to explore more than exploit at the start. It involves staying in the Navigation state: switching between different zoom levels and exploring different snow areas. After learning more about the dataset, users can exploit each candidate area for detailed analysis.

4.3 Statistically Analyzing Behavior Evolution

We split each participant's exploration session into two partitions S_1 and S_2 . We chose to use a 50-50 split, as it represents the most fundamental level at which we would expect to observe changes in strategy. We extract the probability of a user preferring a specific state over other states. Given that



Figure 2: 6 random users' changing preference for three exploration stages: *Foraging*, *Navigation*, and *Sensemaking*.



Figure 3: All possible transitions between the 3 MDP states

Navigation accounts for over 50% of user interactions and state preferences are dependent, we calculate the probability of users preferring Navigation between S_1 and S_2 . Then we use the Wicoxon-Signed-Rank test (Woolson 2007) to test if all users' preference changes.

We find a significant difference in all users' state probabilities of preferring the Navigation state over other states (Statistic:28 p-value:0.002). This result provides quantitative evidence of users' changing preference for exploration stages, as visualized in Figure 2.

4.4 Evaluated Learning Algorithms

Our choice of algorithms includes human learning algorithms from neuroscience and cognitive psychology. We also include some heuristic algorithms, Win-Stay-Loose-Shift(WSLS), Greedy and Random (Section A.2). The **objective** of all chosen algorithms is to maximize reward. We avoid using overly sophisticated algorithms that require a lot of information and computation as research in (Vandekerckhove, Matzke, and Wagenmakers 2015) shows simple ones generally model human behavior more accurately.

We use value-based reinforcement learning (RL) algorithms, Q-learning (QLearn) and State-Action-Reward-State-Action (SARSA) as such algorithms have been used in explaining human learning (Glimcher 2011), and decisionmaking behavior (Niv 2009; Niv et al. 2012; Daw et al. 2011). Alternatively, some cognitive psychology researchers argue for using *value-free or policy-gradient* RL methods, or a combination of value-based and policy-gradients in explaining human behavior (Bennett, Davidson, and Niv 2022) and learning in brain (Joel, Niv, and Ruppin 2002). Reinforce and ActorCritic are used to represent such methods. Additional information about these algorithms and the justification of their selection is available in the appendix.

4.5 Performance Evaluation

Evaluation Procedure: User learning may vary at different stages of EVA. To capture this nuance, we train our algorithms using a varying range of training data, from a lower limit (users finish learning early on) of 5% to an upper limit

(users keep learning till the end) of 90% of all user interaction data. Using the training data within each threshold, we find the optimal hyperparameters and use them to train our models. Using remaining data, we evaluate each algorithm's performance in predicting **What** *action*(switch or maintain) a user will use in her next interaction.

Evaluation: In Figure 4, algorithms' accuracy increases with more training data. It is similar to how participants learn from new experiences during the task (Section 4.2).

Among the 7 algorithms, Reinforce has the highest prediction accuracy for 70% of the users, followed by Actor-Critic (20%) and Greedy (10%). It suggests that a single algorithm may capture most users' learning, despite users' having differences in exploration strategies (Figure 2).



Figure 4: Algorithm performance on different thresholds

Overall Results: When discussing algorithm performance, we report the aggregate results from Figure 4 with parenthesis alongside their name. Simple heuristics [Random (43%) and WSLS (42.1%)] were not enough to capture the nuances of user learning, failing to keep up with users' evolving exploration behavior. Policy gradient-based algorithms (Reinforce (68.6%), Actor-Critic (67.3%)) are better suited for capturing action choices because they provide a probability distribution over all actions without requiring fine-tuned exploration-exploitation parameter (ϵ). They can also approach deterministic policies asymptotically; as Sutton and Barto note, it is challenging to achieve with ϵ -greedy and action-value methods. The low task complexity with limited sequential actions and well-defined goals of the goal-directed task (Section 4.1) also supports policy gradient as

a more suitable learning scheme. Learning a policy with a value-based approach (QLearn (59.1%), SARSA (59.7%)) is a more complex two-step process where users first need to form value functions based on observed snow coverage and only then learn specific probabilities for taking actions (policy) (Bennett, Niv, and Langdon 2021). Lastly, we observe that the simpler Reinforce algorithm performs similarly, if not better, than the Actor-Critic, which justifies our inclination toward simpler algorithms to understand user learning.

5 imMens user study

5.1 Overview of Exploration Task

Analysis Task: In this user study by Liu and Heer 16 participants perform open-ended tasks on two datasets. They report any **interesting findings**, which the authors define as surprising events, data abnormalities, confirmations of common knowledge, or intuition; in other words, *new data or statistics* that the user did not know or was unsure of beforehand. The users explore following datasets: (a) travelers' check-in data on *Brightkite*, a location-based check-in service, and (b) US domestic flight performance data.

Characteristics: The task description and a few *'interesting findings'* examples give participants a vague idea of what they need to find. However, they lack precise knowledge of what to search for (i.e., data abnormalities, surprising events, etc.). Moreover, they are uncertain about the availability of new information and search locations. Therefore, without a clear goal of what to find and exactly which part of the data to explore, they proceed to complete this *open-ended* task.

The participants have a 30-minute *time restriction* per dataset but can quit analysis if they feel there is nothing more to discover. Additionally, 15 minutes of *prior experience* with the datasets and interface may impact their learning to a certain degree.



Figure 5: imMens user exploring flight performance data

imMens Interface: It displays four visualizations for the flight performance dataset (Figure 5). Participants can explore them using *brush & link, pan, zoom, and select*. The visualizations are (1) Scatter plot: 2D plot showing the relationship between arrival and departure delays. (2) Carriers: bar chart with flight information of various US airline carriers. (3) Year: bar chart, and (4) Month: histogram with flight information for the respective time units.

Similarly, upon uploading the travelers' check-in dataset, imMens presents five visualizations in its interface. They are (1) a multi-scale geographical heatmap depicting travelers' check-in locations worldwide. (2, 3, 4) Three histograms aggregating the number of check-ins by day, month, and hour, and (5) a bar chart showing the top 30 travelers with the highest check-ins in the current geographic bounding box. **imMens Interaction Log:** contains users' raw interactions (e.g., zoom, pan, brush, etc.) with imMens. Additionally, it has users' verbal feedback, where they explain their actions, findings, and reasonings, e.g., what type of information they want to find, if they have discovered anything new, etc.

5.2 Formalizing User Learning Problem

User Activities: In open-ended exploration, the user aims to learn new information without any specific exploration path or goal to complete a task. Users unravel new information by interacting with the imMens interface. After each interaction, the user analyzes the updated visualizations for new information. If the user discovers any findings, she reports them before continuing her exploration. In each step, *she makes a learned choice about which visualization to interact with to discover new information from that data area.*

In Figure 6, we show the chronological order of users' interactions with the linked visualizations while exploring the flight performance dataset. We can see that users perform multiple consecutive interactions with a visualization to find new information from a specific data area before switching. *Actions:* In each step t, the user selects one visualization v_t to interact with from K visualizations in the interface.

Reward: The information obtained from the interface serves as a reward for interacting with the visualization. The reward value depends on the effectiveness of users' decision to interact with the selected visualization towards new information. In our experiments, we utilize the feedback log to evaluate the effectiveness of each user's learned decision of visualization selection and assign a reward, $R \in [0, 1]$. When the user uncovers a piece of new information by interacting with a visualization, they receive the highest reward (R = 1). The feedback log allows us to identify meaningful information discoveries because users report their findings as part of the study protocol, such as answers to the question she was searching for, generalization to the observed patterns, and confirming a hypothesis.

Generating hypotheses or questions reveals a potential shift in user intent to uncover new information or patterns. We assign a reward (R = 1) for these cases. Besides these rewarding interactions, users learn about the data by observing the visualizations. Although users may not report any interesting findings during these interactions, they are still crucial for generating intent and progress toward the desired result. Therefore, we assign a small reward (R = 0.1) to such instances. Liu and Heer's categorization of user feedback helped us ensure a consistent reward assignment for the visualization selections. We assign R = 0 to instances where the users' visualization selection does not affect their goals, as they were configuring the interface.

Learning Problem: In each step t, a user makes a learned decision: (a) continue focusing on a specific visualization, or (b) pick a different one. Here $t \in [1, ..., T]$, where 1 is the starting point, and T represents the final time step. This decision may change based on their gained knowledge from the



Figure 6: Users focus on different visualizations in the imMens interface while exploring the flight performance dataset.

data and information need, which may influence the picked action v_t . The user learns the optimal policy by optimizing the objective function that maximizes the expected new information, $\sum_t^T \mathbb{E}[\mathbb{R}eward]$. A user following the optimal policy π^* may continue action v_t when generating a hypothesis or seeking answers. Or if she believes π^* will lead to more opportunities for intriguing discoveries. Conversely, after reporting an insight, the user may decide whether to switch to a different visualization. The user's perception of thoroughly exploring the current visualization, its potential for discovering new information, and the presence of a new hypothesis to test may influence such a switch.

5.3 Statistically Analyzing Behavior Evolution

We statistically evaluate users' preference changes in interacting with specific visualizations between two exploration stages. Each participant's exploration session is divided into equal halves and the probability of selecting particular visualizations in each partition is analyzed. Complete results of the tests are available in Appendix A.3. Let's focus on the travelers' check-in dataset, where users majorly interacted with geographical heatmap visualization (geo-plot). We use the Wilcoxon-Signed-Rank test and find no significant change in user preference for interacting with geo-plots between the partitioned exploration phases (statistic=6.0, pvalue=0.11). It aligns with users' reported insights being predominantly related to the geographical areas travelers are from, e.g., the continents, US states, and countries, and required users frequent interaction with the geo-plot. For none of the visualizations, we see any significant difference in users' behavior significantly evolving during this openended exploration.

5.4 Evaluated Learning Algorithms

We repeat the same baseline, heuristics, and ϵ -Greedy based algorithms (Appendix B.3) to model users' evolving exploration behavior for this user study. In addition, we use mortal-arm bandit and contextual bandit algorithms, commonly utilized in modeling user behavior in online advertising, as detailed in Appendix A.4. Here, each visualization is considered an arm in the multi-arm bandit setting.

Evaluation Procedure: Similar to Section 4.5, we evaluate the algorithms using varying amounts of training data. and prediction accuracy on users' next choice of visualization.

5.5 Results

Figure 7 and 8 show that the greedy algorithm performs much better than ϵ -greedy based approaches with 49% accuracy. Greedy works well as user's visualization preferences do not significantly differ and they often continue interacting



Figure 7: Algorithm accuracy on different training threshold for flight performance dataset

with the same visualization to discover multiple new information and generate hypotheses related to a particular data area (Figure 6). Contextual-bandit (CB) performs the best with an average of 53% accuracy. In each step, CB observes a user's raw action to predict the user's next choice of visualization. However, doing it did not create any significant improvement over the greedy algorithms, as CB did not find a significant correlation between the raw action space and the picked visualization.

On the other hand, the ϵ -Greedy struggles to adapt quickly to changes in users' visualization choices as they navigate to different data areas. From Figure 6, we see users' interaction time with a particular visualization varies throughout the exploration session, which makes it hard to determine appropriate hyperparameters. As the user learns, their rate of exploration changes during EVA. ϵ -Greedy algorithm's hyperparameter (ϵ) trained on a specific EVA segment doesn't guarantee the user will have the same exploration rate for the remaining session. Moreover, fine-tuning the decay parameter in real-time is challenging, especially in non-stationary environments, without yielding substantial benefits. Adaptive ϵ -greedy and mortal bandit algorithms face the same limitation due to their reliance on hyper-parameters, step size, and lifetime, resulting in poor performance.

Simple heuristics and algorithms like WSLS, Greedy, and ϵ -Greedy exhibit limited adaptability to user behavior in intricate data exploration. Conversely, complex approaches such as adaptive ϵ -Greedy and mortal bandit lack the flexibility to adjust to users' future visualization preferences.

Certain users prefer to explore different visualizations within shorter timeframes during the later stages. Such behavior leads to performance declines in those periods, as the learned strategies from the initial stage's training data do not encompass such patterns. This trend is evident in Figure 7. However, greedily choosing recently rewarded visualization leads to relatively improved performance during those intervals. Meanwhile, similar to the ForeCache user study, some users start by exploring different data areas to evaluate the available information and subsequently leverage it for their benefit. As a result, the hyperparameters trained in the initial exploration phase cannot cope with the rate of changes in visualization selection.



Figure 8: Algorithm accuracy on different training threshold for travelers' check-in EVA

6 Discussion

To enrich the HCI and visualization communities' current understanding of the evolution of user exploration and its modeling process during EVA, we identify the common themes across popular studies, analyze users' behavior, and empirically evaluate algorithms from different domains.

6.1 Challenges in Modeling Behavioral Changes

We observe that for the three tools we studied, it is challenging for current models to predict users' future actions, particularly in open-ended tasks. These findings allude to a broader hypothesis that *current learning models may not be able to capture the evolution of users' exploration behavior in open-ended tasks*. Subsequent studies are needed to verify the precise scope at which current learning models can capture users' exploration behavior over time.

For instance, in the goal-directed task (Section 4.5), analysts use more interactions, and algorithms' performance improves with more training data. However, in the openended task (Section 5.5), while we still observe analysts learning from new experiences, the performance of algorithms does not show the same improvement with increasing training data. The issue mainly arises from the uncertainty of which action to choose next based on learned knowledge. While learning algorithms try to quantify this knowledge based on received rewards, their probabilistic approach fails when users decide to be exploratory. Because a user's prior knowledge, expertise in EVA, VES, and familiarity with the dataset may influence how to change her strategy, i.e., explore when the information need is not satisfied.

Unlike goal-directed and focused tasks, open-ended tasks lack clear, pre-defined objectives. Therefore, users have ex-

tremely dynamic strategies. Given these evolving strategies for data exploration, users' learning algorithms may change and require complex algorithms to capture such nuances. As a potential solution to this challenge, we aim to try an ensemble of models for user behavior for complex data exploration tasks in our future work. In this way, the system can pivot gracefully when the current model fails.

6.2 Characteristics of User Learning

Influence of Exploration Task Characteristics: If we want to observe how users learn, we must place them in environments that challenge them to learn. For example, if users have **prior experience** with a task with similar **complexity** as the current task, it may not require as much effort. This effect becomes apparent in the Tableau user study (Appendix B), where users complete three similar focused tasks before attempting the goal-directed task. Because of this prior experience, users often reuse attributes learned from focused tasks rather than exploring new ones. However, having limited prior experience still allows for the discovery of new data insights, as we observe in the Forecache user study.

These findings resonate with research by Csikszentmihalyi et al., suggesting that observing learning in exploration tasks may require participants to balance prior experience with what is being asked of them, otherwise learning may not occur within the controlled lab environment.

Learning Schemes: Our statistical analysis of user behavior reveals differences in exploration strategies across tasks. However, our tested algorithms can satisfactorily model the evolution of users' exploration behavior for the average user. In the ForeCache user study (Section 4.5), Reinforce, Actor-Critic, and Greedy sufficiently capture user learning, and even among these three, Reinforce is the top learning scheme for 70% of the participants. Interestingly, simpler algorithms outperform complex ones in modeling user exploration. For instance, Reinforce outperforms the more complex Actor-Critic in ForeCache's goal-directed task, while the Greedy approach closely matches the bestperforming methods in the imMens and Tableau studies. These findings endorse the preference of cognitive psychology and neuroscience researchers for simple algorithms as better candidates for modeling shifts in users' strategies (Bennett, Niv, and Langdon 2021).

6.3 Creating Versus Reusing Study Data

The diversity of our selected studies from the scholarly works of visualization and HCI provides an opportunity to observe, formalize, and model diverse users and their exploration behaviors. Further, these works cover a large gamut of data exploration, enabling thorough testing of our hypotheses across diverse scenarios. Additionally, designing a new user study poses significant challenges. First, recruiting a diverse user base is time-consuming. Second, devising tasks that span a wide range of open-endedness requires extensive research and domain expertise. Third, determining the appropriate visualization tools and level of detail to capture from user interactions adds to the layer of complexity (Gathani et al. 2022). Finally, as Zgraggen et al. observe, users lack the awareness or desire to explain everything they learn during EVA. Thus, conducting a new user study might not be more beneficial to analyze users' exploration behavior than pursuing established studies.

A Appendix

A.1 Markov Decision Process (MDP):

MDP is a framework for modeling decision-making in which an agent (user) learns to achieve its goals through repeated interactions with an environment (interface). In each interaction, the agent takes action based on its current state (exploration stage), and the environment (interface) responds with a reward (feedback). The agent uses these rewards to update its behavior and make better decisions in the future. The main objective of solving an MDP is to find an optimal **policy** (π), which is a function that maps each state to an action that maximizes the expected future reward.

A.2 ForeCache User Study Algorithm Details

Win-Stay-Lose-Shift (WSLS): is a popular heuristic to model human learning in games, offering an alternative to randomization in bandit problems (Tamura and Masuda 2015). This method repeats a successful strategy until it no longer yields rewards, then switches to other strategies with equal probabilities.

Greedy: requires the user to make decisions based on her previous experience. She decides upon an action that has yielded her the highest reward thus far (Sutton and Barto 1998).

 ϵ -Greedy: balances exploration-exploitation trade-off by choosing either a random action with a small probability (ϵ) or the action with the highest estimated reward with probability (1 - ϵ) (Zhang and Yu 2013).

Reinforcement learning (RL) algorithms selection criteria:

In RL, *value function (vf)* represents the expected future reward an agent can achieve by starting from a specific state and following a given policy(Sutton and Barto 1998). RL algorithms estimate and improve this *vf* through trial and error. Specifically, algorithms that learn the *vf* and take actions depending on this function are *value-based algorithms*. These algorithms have been used to explain workings of the human brain (Glimcher 2011), and choice behavior (Niv 2009; Niv et al. 2012; Daw et al. 2011). Qlearning(QLearn) and State-Action-Reward-State-Action (SARSA) are two popular value-based algorithms.

Alternatively, other cognitive psychology researchers (Bennett, Niv, and Langdon 2021) advocate for algorithms that directly learn a policy that can select actions without a vf. A vf may still be used to learn the parameters defining a policy but is not required for action selection (Sutton and Barto 1998). These algorithms are called value-free or policy-gradient . Researchers in (Bennett, Niv, and Langdon 2021) also suggest algorithms combining value-based and policy gradients that have shown promising results in modeling activities in neural structures (Joel, Niv, and Ruppin 2002) and explaining human behavior (Bennett, Davidson, and Niv 2022). Reinforce and ActorCritic are two popular policy-gradient based algorithms.

QLearning (Qlearn): iteratively updates a value function called the Q-value. Qlearn learns the optimal policy through trial and error, following a different policy (ϵ -greedy policy) during training. The goal of QLearn is to learn a policy that maximizes the expected reward in an environment (Watkins and Dayan 1992) based on the Q-value update rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Where $Q(s_t, a_t)$ is the value of taking action a in state s at time t. α is the learning rate and controls for the degree of Q-value (Q) update, r_t is the reward received at time t, γ is the discount factor to give more weight to r_t than future rewards, and s_{t+1} is the next state. The last hyper-parameter in this algorithm is ϵ for ϵ -greedy.

State Action Reward State Action (SARSA): is valuebased like QLearn (Rummery and Niranjan 1994). But unlike Qlearn, which updates its Q using the action that yields **maximum** Q-value in the next state, SARSA updates Q by following the action based on the ϵ -greedy policy (a_{t+1}):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma Q(s_{t+1}, \mathbf{a_{t+1}}) - Q(s_t, a_t)]$$

SARSA has the same hyperparameters as QLearn: γ, α, ϵ

Reinforce: is the simplest policy-gradient method (Sutton and Barto 1998). It directly improves the policy based on the observed rewards without any value function (Williams 1992). A set of parameters define the policy. These parameters are represented by a neural network and improved by following the gradient of the expected reward with respect to the parameters. Reinforce uses γ and α as hyperparameters.

Actor-Critic: extends Reinforce by improving the policy through learning a value function in parallel. It combines value-based (critic) methods with a policy-gradient side (actor) (Konda and Tsitsiklis 2003). A neural network acts as a function approximator to learn the policy and value parameters. This algorithm has the same hyperparameters as Reinforce.

A.3 imMens user study Statistical Test

Table 3 presents the outcomes of a statistical test conducted on two halves (initial and later) of participants' exploration sessions. All p-values exceed 0.05, indicating no significant differences observed between the initial and later exploration phases for any visualizations.

Explored Dataset	Visualization	P-value	Statistic	
Flight	Arrival Delay vs Departure Delay	0.055	4.0	
Performance	Carrier 0.11		6.0	
	Year	0.46	12.0	
	Month	1.0	14.0	
	Geographical Map	0.11	6.0	
Travelers'	Month	0.31	10.0	
Check-in	Day	0.13	5.0	
	Year	0.74	15.0	
	Travellers	0.84	16.0	

Table 3: Wilcoxon-Signed-Rank Test Results

A.4 imMens user study Algorithm details:

Mortal-arm bandit: Assume we have a K-arm bandit machine with unknown stochastic rewards. In each round, an agent pulls one arm and receives the reward. Mortal-arm bandit (Chakrabarti et al. 2008) (MoAB) introduces the concept of mortality, where each arm (i) has a finite lifetime (L_i) . Once an arm's lifetime ends, it is removed from the K-arm bandit and a new arm seamlessly replaces it, ensuring the bandit maintains a constant size of K arms.

The authors propose two mortality implementations: *budgeted death*, where each arm dies after L_i selections drawn from a geometric distribution with an expected budget of L, and *timed death*, where each arm dies with probability p and have a lifetime of L = 1/p. The algorithm's objective is to maximize the expected total reward by selecting an optimal sequence of arms to pull.

In the state-oblivious algorithm for MoAB (Chakrabarti et al. 2008), instead of pulling each arm once to estimate the payoff, each arm is pulled n times and abandoned if deemed unfavorable. The objective function of MoAB minimize regret, which is the difference between the expected payoff of the best alive arm and the payoff obtained by MoAB.

In short, MoAB considers that each visualization has a lifetime, after which the user will not use it again. Maybe the user has extracted all the information she wanted from that visualization. Additionally, we have the flexibility to introduce the killed visualization as users' future exploration choice.

Contextual multi-arm bandit: In our scenario, we have a set of K visualizations. At each time step (t), the user selects a specific visualization (action in this case) to interact with, resulting in a reward r_t . In the contextual bandit framework, an agent, guided by observed context (c_t) , chooses a visualization (v_t) as an action and receives rewards solely for the chosen action. Context, i.e., additional side information, assists the agent in maximizing the reward function. Our implementation uses the user's raw interactions (like pan, brush, range select, and zoom) as context, assuming potential latent correlations with visualization selection. For instance, users might frequently perform pan operations on geographical heat maps rather

than other raw interactions. Contextual multi-arm bandit frameworks are particularly beneficial in non-stationary environments—dynamically changing scenarios (Li et al. 2010)—with small action spaces.

B Tableau user study

In this user study by Battle et al. (Battle and Heer 2019), participants perform a series of focused and open-ended exploration tasks (*ordered by their open-endedness*) based on a particular dataset (table 4). These tasks encapsulate nearly the full spectrum of task complexity and open-endedness and provide the opportunity to investigate the nature of user learning in a wide range of exploration scenarios.

B.1 Overview of Exploration Task

Analysis Tasks: 27 Participants who use Tableau (Tableau 2004) regularly for academic or professional purposes are selected to complete a series of analysis tasks with varying requirements (e.g., table 4). Their expertise varied widely in Tableau and data analysis experience, from just learning Tableau to seasoned veteran analysts to Tableau power users.

The datasets users explore are: (a) Weather station reports encompassing weather metrics and phenomena (35 columns, 56.2M rows), (b) US domestic flight performance data (31 columns, 34.5M rows), and (c) Aircraft striking wildlife reports, including contextual details (94 columns, 173K rows) (Battle and Heer 2019).

Task Characteristics: In this user study, the *focused tasks* contain *explicit hints* on which columns (inside square brackets in Table 4) to exploit for task completion. It allows us to investigate user learning, where the scope of exploration is limited, as users only need to locate the hinted data area. Also, we examine how learning affects tasks with different *open-ended characteristics* and varying task requirements (e.g., data quality assessment, evaluation of relation-ships between variables, causality, and prediction analysis). Furthermore, the lack of *prior knowledge* about the dataset, and the use of Tableau (with a *complex interface*), enriches our research of user learning in various exploration scenarios.

Interface and Interaction Log: Tableau presents *at-tributes* (columns of a dataset) for user exploration (shown in Figure 9). Users can choose which attribute to analyze and add to the Tableau Worksheet. Tableau then suggests visualizations, from which users can choose based on their interpretability. For our research, we analyze participants' interactions with the Tableau interface as recorded by Battle et al. (Battle and Heer 2019), who completed all tasks. The interaction log contains information on users' exploration activities, such as their choice of attributes, visualization, and time spent in each interaction. Participants provide feedback for the open-ended tasks, highlighting meaningful insights in their problem-solving approach.

Attributes Consolidation: In focused and goal-directed tasks, users start exploration with a clear understanding of the tasks' requirements. So, users may need fewer interactions than open-ended tasks to extract desired information. In this study, the given datasets are large and have many

	Task	Task Description
p	T1	Consider the following weather measurements: Heavy Fog[Heavy Fog], Mist [Mist], Drizzle [Drizzle], and Ground
Focused	11	Fog [Ground Fog]. Which measurements have more data?
Ŋ	T2	How have maximum temperatures [T Max] and minimum temperatures [T Min] changed over the
ГĽ.		duration of the dataset (i.e., over the [Date] column)?
	T3	How do wind measurements [High Winds] compare for the northeast and southwest regions of the US?
Goal Directed	T4	What weather predictions would you make for February 14th 2018 in Seattle, and why?

Table 4: Analysis tasks for Weather dataset



Figure 9: Analyzing attributes using Tableau interface

attributes but relatively few interactions. For example, the wildlife strikes dataset contains 94 attributes but has an average of 24 interactions across tasks. It poses a significant challenge in empirically analyzing and modeling user learning.

Thus, we reduce the search space for our learning algorithms by identifying attributes from similar domains and consolidating them into high-level attributes. For example, we observe the attributes t_max , t_min , t_minf and t_maxf (from T2 in table 4) all represent maximum and minimum temperature in C° and F° respectively. So, we consolidate them into high-level attributes: temp_max and temp_min. We are careful in this consolidation process so that it does not change users' intentions behind each interaction, which can affect our experiments on user learning.

B.2 Formalizing User Learning Problem

User Activities: One approach to analyzing how users' exploration behavior evolves is to examine the low-level Tableau interactions performed at each step. However, Tableau contains many interaction paths that ultimately lead to the same underlying data manipulations (Battle and Heer 2019). Thus, instead of focusing on how users navigate Tableau's massive action space, we instead analyze which attributes (i.e., data areas) users select to achieve their goals.

In each interaction, the users select a subset of attributes from the dataset to generate visualizations. They use information from these visualizations to make the following decisions, which *influences selection of future action*, i.e., *exploration strategy*: (a) spend more time understanding the current data area, or (b) switch focus to other data areas for additional information or new findings.

Actions: In each interaction, the user can use the actions, Keep, Add, Drop, and Reset, to modify the specific set of attributes she currently has on the Tableau worksheet for analysis. Keep reuses the same set of attributes from the previous time step. Add incorporates one or more attributes from the dataset into the current set. Drop removes one or more attributes from the current set. Reset removes all attributes from the worksheet and starts anew.

<u>Reward</u>: The user analyzes the Tableau visualization generated for her selected set of attributes. The *information in this visualization acts as a reward* through which she can measure the relevance of the current set of attributes to complete the analysis task. Based on the reward, the user decides her next set of actions.

In our experiment, we quantify the relevance of users' selected set of attributes. First, we identify the *attributes necessary (i.e., ground truth)* for task completion based on users' feedback and by analyzing the task requirements, dataset, and users' interactions. Then, for each interaction, we use the *size of the intersection between users' current selected attributes and the necessary ones for the tasks as a reward.* The utilization of necessary attributes is crucial for completing analysis tasks effectively. Increased usage of these attributes to create visualizations leads to more relevant information.

Learning Problem: A user's exploration strategy determines which action (a_t) to pick in interaction at time step t, spanning from the initial interaction at t = 1 to the last at t = T. At t, action choice a_t depends on the user's learned decision to keep, modify, or reset the current attribute set based on the received reward r_t . The exploration strategy outlines the decision-making process to optimize the objective function $f(a_t|(a_{\hat{t}}, r_{\hat{t}})) = \sum_t^T \mathbb{E}[Reward]$. Here, for time t, f quantifies the expected information gain of action a_t based on past actions $a_{\hat{t}}$ and corresponding rewards $r_{\hat{t}}$ (where $\hat{t} = 1, ..., t - 1$). f can be optimized by maximizing rewards. The learning problem involves optimizing f online to find the optimal strategy that will lead to the desired information. Using the optimal strategy, the user will pick an action that will influence the selection of ground truth attributes with the necessary information (yielding high rewards) for task completion.

B.3 Evaluated Learning Algorithms

Here we discuss the human learning algorithms used in this user study. We use these algorithms' objective functions to model users' exploration behavior during EVA tasks.

Random Strategy: In this approach, the agent always picks an action *uniformly at random* from the available choices. Action choice is made irrespective of the rewards received or consideration for potential outcomes. This strategy serves as the *baseline*.

Heuristics: Greedy and Win-Stay Lose-Shift may model user learning using prior experiences with relatively simple heuristics.

Greedy requires the user to pick an action for immediate success based on her previous experience. She chooses the action that has yielded her the highest reward thus far, hoping that it will increase her cumulative gains (Sutton and Barto 1998).

Win-Stay Lose-Shift is a popular heuristic to model human learning in games, offering an alternative to randomization in bandit problems (Tamura and Masuda 2015). It repeats a successful action until it no longer yields rewards, then switches to other actions with equal probabilities.

The simplicity of these approaches does not ensure globally optimal solutions. The primary objective of these approaches is to maximize the cumulative reward in the sequential decision-making process. But to achieve that, they rely solely on maximizing immediate rewards based on past actions, making them vulnerable to being stuck with suboptimal solutions.

Learning Algorithms from Game Theory: Bush & Mosteller (Bush and Mosteller 1953) and Roth & Erev (Erev and Roth 1995; Young 2004) have been popular in modeling human learning in games. Recent research shows their success in modeling human learning in information searching (McCamish et al. 2018; Cen, Gan, and Bai 2013).

Bush and Mosteller updates the probability of using an action at time step t, a(t) by an amount proportional to the received reward r(t) for using this action and its current probability (Bush and Mosteller 1953). If the user uses action $a_i \in 1, ..., n$ for a(t) then the model updates the probability distribution of the strategies P_i as follows:

$$P_{i}(t+1) = \begin{cases} P_{i}(t) + \alpha \times (1 - P_{i}(t)) \&\&a(t) = a_{i}, r(t) \ge 0\\ P_{i}(t) - \beta \times P_{i}(t) \&\&a(t) = a_{i}, r(t) < 0 \end{cases}$$
(1)

$$P_{i}(t+1) = \begin{cases} P_{i}(t) - \alpha \times P_{i}(t) \&\&a(t) \neq a_{i}, r(t) \ge 0\\ P_{i}(t) + \beta \times (1 - P_{i}(t)) \&\&a(t) \neq a_{i}, r(t) < 0 \end{cases}$$
(2)

 $\alpha \in [0,1]$ and $\beta \in [0,1]$ are the only hyper-parameters, where α determines the weighting for non-negative rewards, while β regulates negative rewards.

Roth and Erev reinforces action probabilities based on the rewards received after each action. Forgetting parameter, $\sigma \in [0, 1]$, controls the degree to which past outcomes influence future decisions (Erev and Roth 1995; Young 2004). A matrix, S(t), maintains the accumulated reward for using different actions over time, t. Its cell (i, t + 1) is updated after an action a_i is performed using, $S_i(t + 1) = S_i(t) \times (1 - \sigma) + r$. Given the users have n actions to pick

from, the probability of performing action a_j after time t is: $P_j(t+1) = S_j(t+1) \} / \sum_{j'}^n S_{j'}(t+1)$

It is important to note that these approaches do not have a fixed or standardized objective function. Intuitively, they try to find the action(s) that returns the most payoff in the future.

 ϵ -Greedy Based Algorithms: ϵ -Greedy and Adaptive ϵ greedy algorithms aim to maximize the overall cumulative reward by balancing the exploration-exploitation trade-off.

 ϵ -**Greedy** balances exploration-exploitation trade-off by choosing either a random action with a small probability (ϵ) or the action with the highest estimated reward with probability (1 - ϵ) (Zhang and Yu 2013).

Adaptive ϵ -Greedy extends ϵ -Greedy by changing the value of ϵ during learning using two hyper-parameters, l and f. l keeps track of how many times to run exploration before performing the adaptive action that changes the value of ϵ . f is for regularizing the change in average accumulated reward Δ , before and after the previous ϵ changes. The new value of ϵ is created using $sigmoid(\Delta)$, $\Delta = (reward_{current-\epsilon} - reward_{previous-\epsilon}) \times f$ (dos Santos Mignon and da Rocha 2017).

Combinatorial Multi-arm Bandit (CMAB): To aid in understanding, we will use the terminologies from our learning problem rather than the generic CMAB terms, e.g., *actions instead of arms*.

Let us consider a scenario where there are N actions, and at each step, a user chooses a subset of actions and receives rewards. We denote the set of all possible combinations or subsets of actions as A (size = n), represented by variable $A = \{A_1, ..., A_n\}$. The reward $R : \{\alpha_1 \times ... \times \alpha_{K_i}\} \to \mathbb{R}$ depends on the reward of the K_i actions in the picked subset (A_i) . The goal of the problem is to find a vector $V \subseteq \{0, 1\}^n$ representing the subset combination of actions that minimizes the regret, $\rho(\pi, t) = T\mu^* - \sum_{t=1}^T R(a_1^t, ..., a_n^t)$ (Ontanón 2013, 2017). The regret equation is for policy π , where $a_1^t, ..., a_n^t$ are the actions selected at time step T. Here, $\mu^* = \mathbb{E}(R(v_1^*, ..., v_n^*))$ is the maximum expected reward gained by following the optimal policy π^* .

Used approach: To solve the CMAB problem, we use the Vowpal Wabbit library (Wabbit; Swaminathan et al. 2017), whose CMAB implementation is heavily influenced by Bianchi and Lugosi (Cesa-Bianchi and Lugosi 2012). In this approach, the algorithm picks an action subset $K_t \in A$ for each time step, t = 1, 2, ... based on the distribution, $p_{t-1} = (1 - \gamma)q_{t-1} + \gamma\mu$. Where $q_t(k) = \overline{w}_t(k)/\overline{W}_t$ and \overline{W}_t corresponds to a weight vector that keeps track of the cumulative pseudo-loss. Upon predicting K_t , the algorithm observes cost $l_t(K_t)$. This cost updates a vector of pseudo-loss \tilde{l}_t , which consequently is used to update the $q_t(k)$. Prior distribution μ and mixing coefficient γ are the hyper-parameters.

B.4 Performance Evaluation

Evaluation Procedure: To evaluate the discussed algorithms' (B.3) performance in modeling user learning, we use them to predict **What** *action(s)* **a user will use in her next**

Datasets	Tasks	Random	Win-Stay	Greedy	Roth & Erev	Bush &	ϵ -greedy	Adaptive	Combinatorial
		Strategy	Lose-Shift	algorithm		Mosteller		ϵ -Greedy	Bandit
Wildlife	T3	0.17	0.19	0.78	0.68	0.71	0.73	0.73	0.43
Strikes	T4	0.17	0.16	0.65	0.59	0.56	0.65	0.65	0.38
Weather	T3	0.14	0.15	0.82	0.69	0.67	0.83	0.84	0.45
	T4	0.13	0.13	0.77	0.72	0.70	0.77	0.78	0.32
Flight	T3	0.12	0.13	0.64	0.50	0.56	0.65	0.62	0.40
Performance	T4	0.13	0.14	0.65	0.57	0.54	0.66	0.65	0.30

Table 5: Recall (K=3) value of discussed learning algorithms in the action prediction task.

interaction. How many attributes a user may add or drop in a future interaction is extremely difficult to predict and beyond the scope of this paper. To simplify our evaluation process, we employ algorithms to predict three actions for the next interaction, following a recall (k = 3) assessment. It is decided based on the average number of actions by the users in this user study.

Note that since users rarely need to and lack evidence of learning within T1 & T2, we exclude these tasks from evaluation.

Analyzing Performance of the Learning Models: We train the hyperparameters using 20% of the data to ensure that our models are properly tuned. Results in Table 5 show users mainly adopt the Greedy strategy. We also observe that users keep using the same set of attributes and exploit them for a long time when they yield high rewards. The ϵ -Greedy and adaptive ϵ - Greedy experiments support this observation, as we get the best results for $\epsilon = 0.001$. Such a low ϵ value indicates users rarely do any exploration and have a preference for exploitation based on past experiences.

Win-Stay Lose-Shift (WSLS) performs the worst as it has to pick future actions randomly at the start. However, even after categorizing the attributes, our action space is still large (e.g., 22 for weather) compared to the number of interactions. Under these circumstances, it is difficult for the models to choose 3 attributes randomly and get them correct in a limited number of interactions. Our Combinatorial bandit algorithm suffers from the same issue, although we fixed the subset size to 3 before generating all possible combinations.

Roth & Erev and the Bush & Mosteller model are slower than the Greedy approaches in adapting to users' current information needs, contributing to subpar performance.

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