Adaptive Robot-Assisted Feeding: An Online Learning Framework for Acquiring Previously-Unseen Food Items

Ethan K. Gordon\textsuperscript{1}, Xiang Meng\textsuperscript{2}, Tapomayukh Bhattacharjee\textsuperscript{1}, Matt Barnes\textsuperscript{1} and Siddhartha S. Srinivasa\textsuperscript{1}

\textbf{Abstract}—Successful robot-assisted feeding requires bite acquisition of a wide variety of food items. Different food items may require different manipulation actions for successful bite acquisition. Therefore, a key challenge is to handle previously-unseen food items with very different action distributions. By leveraging contexts from previous bite acquisition attempts, a robot should be able to learn online how to acquire those previously-unseen food items. We construct an online learning framework for this problem setting and use the \(\epsilon\)-greedy and LinUCB contextual bandit algorithms to minimize cumulative regret within that setting. Finally, we demonstrate empirically on a robot-assisted feeding system that this solution can adapt quickly to a food item with an action success rate distribution that differs greatly from previously-seen food items.

I. INTRODUCTION

Eating is an activity of daily living. While many of us take eating for granted, according to a U.S. study in 2010, approximately 1.0 million people need assistance eating [1]. The ability to self feed would not only save time for caregivers, but also increase a person’s sense of self worth [2], [3]. While some commercial feeding systems exist [4], [5], these systems have minimal autonomy requiring pre-programmed movements, thus making it difficult to adapt to environmental changes. A robust autonomous robotic feeding system needs to be able to acquire a bite of food from an uncertain environment and transfer it safely to a potentially unpredictable user. We focus on bite acquisition, specifically the acquisition of food items that the robot may not have seen or manipulated before.

Different food items may require different manipulation actions for bite acquisition [6] and a robust system needs to be able to acquire these myriad types of food items that a user might want to eat. While we have achieved some recent successes in developing manipulation actions that can acquire a variety of food items [7], [8], a key challenge is to acquire previously-unseen food items that have very different action distributions. Even food items that look similar, such as ripe and un-ripe banana slices, can have very different consistencies. Our major contribution in this work is a contextual bandit framework for bite acquisition in an online learning setting. We propose the use of the \(\epsilon\)-greedy [9] and LinUCB [10] contextual bandit algorithms, and we furthermore show empirically that these algorithms are effective in picking up new food items. Our current action space of 3 fork roll angles \(\times\) 2 fork pitch angles limits us to discrete, solid food items, but future work can examine a richer action space to tackle bite acquisition on a more varied, realistic plate.

II. RELATED WORK

A. Robot-Assisted Feeding: Food Manipulation.

Food manipulation has been studied for various applications such as the packaging industry [11]–[16] with focus on the design of application-specific grippers for robust sorting and pick-and-place, as well as showing the need for visual sensing for quality control [17]–[19] and haptic sensing for grasping deformable food items without damaging them [11]–[16]. Research labs have also explored meal preparation [20], [21] as an exemplar multi-step manipulation problem, baking cookies [22], making pancakes [23], separating Oreos [24], and preparing meals [25] with robots. Most of these studies either interacted with a specific food item with a fixed manipulation strategy [22], [23] or used a set of food items for meal preparation which required a different set of manipulation strategies [25].

Existing autonomous robot-assisted feeding systems such as [7], [8], [26], and [27] can acquire a fixed set of food items and feed people, but it is not clear whether these
systems can adapt to very different food items that require completely different strategies. Feng et al. [7] developed a network SPANet and show generalization to previously-unseen food items, but only for those with similar bite acquisition strategies. The universe of food items is massive and thus, it is almost impossible to train these systems on every kind of food items that exist. Our paper aims to address this gap in food manipulation work by developing methods that can generalize to previously-unseen food items with very different action distributions. We propose to use an online learning framework in a contextual bandit setting for food manipulation.

B. Online Learning.

Bandit algorithms have seen widespread success in online advertising [28], [29], health interventions [30], [31], clinical trials [32], adaptive routing [33], education [34], music recommendations [35], financial portfolio design [36], or any application requiring a more optimized version of A/B testing. Adoption in robotics has been more limited, such as trajectory selection for object rearrangement planning [37], kicking strategies in robotic soccer [38], and perhaps most closely related, selecting among deformable object models for acquisition tasks [39]. Unlike previous work, we argue it is untennable to construct deformable object models for every food item, as conventional grocery stores typically stock in excess of 40,000 products [40]. Instead, we take a model-free approach which operates directly on the image context space.

No-regret algorithms for solving bandit problems include UCB [41] and EXP3 [41] for stochastic and adversarial reward distributions, respectively. This was also extended to the bandits-with-expert-advice setting (a generalization of the contextual bandit problem for small policy classes) in EXP4 [41]. Baseline methods for the contextual bandit problem include epoch-greedy [42] and greedy [43], both of which are simple to implement, perform well in practice, although do not achieve optimal regret guarantees. More recent advances include LinUCB [44], RegCB [45] and Online Cover [46], a computationally efficient approximation to an algorithm which achieves optimal regret. For a recent and thorough overview, see [47].

III. THE CASE FOR ONLINE LEARNING

We believe that exploring online learning methods for automated bite acquisition can lead to learning manipulation strategies that generalize to previously-unseen food items. This is due to (a) covariate shift from the training dataset, (b) the diversity of food categories and (c) the expensive process of collecting data on a physical robot. Factors which may contribute to covariate shift include changing lighting conditions, backgrounds, and not knowing the distribution of food items a priori.

Even when we control for covariate shift in a laboratory setting, SPANet is unable to generalize to some previously-unseen food categories (specifically kiwi and banana), as seen in [7] and Figure 3. We hypothesize this lack of generalization is due partly to the high diversity of actions for these food categories. For example, the most successful action for kiwi and banana was “tilted-angled”, which is very different from the rest of the food item dataset. To determine whether collecting additional training data would solve this problem, we controlled for both the number of training food classes and the total number of training examples. The results, shown in Figure 4, do not show a noticeable improvement in out-of-class performance. Finally, it is well known that collecting data on a physical robot is expensive and time-consuming. The dataset used to train SPANet took approximately 81 hours of supervision to collect.

An online learning scheme allows for the system to leverage data collected in real-world conditions and adapt to each user’s specific palate. Therefore, in this work, we propose an online learning framework for this problem setting and present multiple algorithms based on the contextual bandit literature that could provide potential solutions.

IV. ONLINE LEARNING FRAMEWORK

On a high level, we consider a plate consisting of multiple discrete food items. In the case of continuous items (e.g. mashed potatoes), we assume the existence of an algorithm that can logically segment the item into discrete, bite-sized pieces.

At each round \( t = 1, \ldots, T \), the interaction protocol consists of

1) Context observation The user selects a food item to acquire, perhaps in combination with a separate
object instance segmentation network. We observe the resulting RGBD image with size $h \times w$ containing the single desired food item. We pass the image through SPANet, as presented in II and use the penultimate layer as the context features $x_t \in \mathcal{X} = \mathbb{R}^d$.

2) **Action selection** The algorithm selects one manipulation strategy $a_t \in \mathcal{A} = \{1, 2, \ldots, K\}$. In our initial implementation, $K = 6$, with 3 pitch angles and 2 roll angles.

3) **Partial loss observation** The environment provides a binary loss $c_t \in \mathcal{C} = \{0, 1\}$, where $c_t = 0$ corresponds to the robot successfully acquiring the single desired food item.

The algorithm itself will consist of a stochastic policy $\pi(x_t) = \mathbb{P}(a_t = a|x_t)$, and the goal is to minimize the cumulative regret of this policy. In other words, we wish to minimize $R_T$, which is the difference in performance between our policy $\pi$ and the best possible policy $\pi^* \in \Pi$ for the lifetime of our program $T$. With $c_t \in \mathcal{C}$, $x_t \in \mathcal{X}$, $(n_t, a_t) \in \mathcal{A}$ at time $t$:

$$R_T := \sum_{t=1}^{T} c_t(\pi(\phi(x_t))) - \min_{\pi^* \in \Pi} \sum_{t=1}^{T} c_t(\pi^*(\phi(x_t)))$$

While we could potentially perform multiple actions on the same food item, each individual action only returns partial (or bandit) feedback. In other words, when our algorithm takes an action to pick up a food item, it can only see whether it has failed or succeeded with that action. It is not privy to the rewards of other actions. Therefore, a contextual bandit algorithm is a natural choice. The structure of this environment in relation to an arbitrary contextual bandit algorithm is presented formally in Algorithm 1.

**A. Importance-Weighted Linear Regression**

In general, the learning portion of a contextual bandit algorithm operates by first using past observations to estimate the cost of all actions for a given context. This reduces the problem to off-policy supervised learning, with an oracle performing the underlying full-feedback classification or regression. All algorithms presented in the overview by Biette et al. [9] follow this general structure.

**V. CONTEXTUAL BANDIT ALGORITHMS**

**A. $\epsilon$-greedy**

This simplest approach to this problem is the $\epsilon$-greedy algorithm, as shown in Algorithm 3. This algorithm opts for the optimal action based on previous observations with probability $(1 - \epsilon)$ and explores all actions uniformly with probability $\epsilon$. We consider both purely greedy ($\epsilon = 0$) and exploratory ($\epsilon > 0$) variants.

With arbitrary contexts, the $\epsilon$-greedy algorithm (with optimized $\epsilon$) has a cumulative regret bound $R_T \sim O(T^{2/3})$, though it can perform well empirically [9]. The fixed variant may also provide a better regret bound, as it can provide
Algorithm 1: General Contextual Bandit with SPANet Features

**Input:** Trained SPANet $\phi$, Environment $E$

**Initialize** $N$ Contexts $x \in X \sim E$

for $t = 1, \ldots, T$ do

1. Find features $\phi(x)$
2. $p_t \leftarrow \text{explore}(\phi(x))$
3. Select action $a_t \sim p_t$
4. Receive $c_t \sim E|a_t$
5. $\text{learn}(\phi(x), a_t, c_t, p_t)$

if $c_t = 0$ then

1. Re-sample context $x \sim E$

else

1. continue

end

end

Algorithm 2: Importance-Weighted Regression Oracle

**Input:** Regularization parameter $\lambda$, $d$ (features)

**Initialize** $\forall a \in A$: $A_n \leftarrow \lambda I_{d \times d}$; $b_n \leftarrow 0$

**Function** $\text{oracle}(\pi, \phi(x), a_t, c_t, p_t(a_t))$:

1. $(A, b) \leftarrow \pi$
2. $A_n \leftarrow A_n + \frac{1}{p_t} \phi \phi^T$
3. $b_n \leftarrow b_n + \frac{\phi^T}{p_t}$
4. $\hat{\theta}_n \leftarrow A_n^{-1} b_n$
5. $\pi' \leftarrow (\theta, A, b)$

return

Algorithm 3: $\epsilon$-greedy

**Input:** Exploration parameter $\epsilon \in [0, 1)$

**Initialize** $\pi_0$

**Function** $\text{explore}(\phi(x))$:

1. $p_t(a) \leftarrow \frac{1}{K} + (1 - \epsilon)1\{\pi_t(\phi(x))\}$

return

**Function** $\text{learn}(\phi(x), a_t, c_t, p_t)$:

1. $\pi_{t+1} = \text{oracle}(\pi_t, \phi(x), a_t, c_t, p_t(a_t))$

return

Algorithm 4: LinUCB

**Input:** Width parameter $\alpha$

**Initialize** $\pi_0$

**Function** $\text{explore}(\phi(x))$:

1. for $a \in A$ do

2. $ucb_a \leftarrow \theta_a T \phi(x) + \alpha \sqrt{\phi(x)^T A_a \phi(x)}$ [10]

3. $p_t(a') \leftarrow 1\{a' = \arg \max_a ucb_a\}$

return

**Function** $\text{learn}(\phi(x), a_t, c_t, p_t)$:

1. $\pi_{t+1} = \text{oracle}(\pi_t, \phi(x), a_t, c_t, p_t(a_t))$

return

better-than-bandit feedback for a given context by taking multiple actions.

**B. LinUCB**

Given the linear regression function, we propose the use of LinUCB [48]. Each time step, we find the upper confidence bound (UCB) for each action. Treating the UCB as the cost for a given action implicitly encourages exploration, as in a choice between two actions with similar expected cost, the algorithm will opt for the one with higher variance. It is worth pointing out that we maintain different $\theta_i$’s for each action and observe one feature vector $\phi(x)$, while in [10], one $\theta$ is updated and $K$ feature vectors are observed. These settings can be shown to be equivalent for a proper choice of context, and the same regret bound will hold in both settings.

With arbitrary contexts, LinUCB has a cumulative regret bound $R_T \sim O(T^{1/2})$, which is an improvement over $\epsilon$-greedy in the worst case. Like $\epsilon$-greedy, the fixed set of contexts may improve this bound.

VI. EXPERIMENTS

A. Validation in Simulation

We first validate our algorithms by constructing a simulated environment using the data from [7]. Since this data, by necessity, was collected with bandit feedback, the original work imputed the full loss vector of each context by averaging the success rate of a given action across all food items of the same type. While simple, this can introduce a herding bias into the simulation relative to the real world. We eliminate bias in our dataset using a doubly-robust [49] estimator:

$$\hat{r}_{DR}(x_i, a) = \hat{r}_a + (\hat{r}_i - \hat{r}_a) \frac{1\{a_i = a\}}{p(a_i|x_i)}$$

where $\hat{r}_a$ is the imputed value from herding, $p(a_i|x_i)$ is the probability that we took action $a_i$ during data collection (in our case, since data was collected uniformly across all actions), and $\hat{r}_i$ the actual binary loss associated with that sample (only available for $a_i$). This estimator eliminates bias from our imputed values at the cost of added variance.

Using the original SPANet feature space of $\mathbb{R}^{2048}$, we found that we needed significant regularization (large $\lambda$) to see any results on our limited dataset. However, while reducing our feature-space dimensionality $d$ could in theory reduce our regret bounds (e.g., LinUCB’s $R_T \sim O(d)$), it empirically reduced our best possible ($\pi^*$) performance. This exposed us to a two-dimensional trade-off of bias vs. variance and performance vs. data-efficiency, necessitating a hyper-parameter grid search.

Figure 5 shows selected results from our hyper-parameter grid search across $(d, \lambda)$, and the exploration parameter $\epsilon$ for $\epsilon$-greedy. Rather than regret, the metric we used here was cross-validation: every 10 iterations, each algorithm was frozen and tested on $\frac{9}{10}$ of the data that was held back as a validation set. We found that LinUCB ($\alpha = 0.05$) was most robust to variation in hyper-parameters. While there were some hyper-parameter combinations (usually with larger $\lambda$) for which $\epsilon$-greedy ($\epsilon = 0.5$) performed better than LinUCB, the overperformance was never statistically significant, and
the overall result of all algorithms was generally poorer. The best result of the entire grid search was LinUCB with $d = 2048$, $\lambda = 100$. We therefore used this algorithm for our real robot experiment.

**B. Real Robot Experiment**

a) **System Description:** Our setup, the Autonomous Dexterous Arm (ADA) (Figure 6, left), consists of a 6 DoF JACO robotic arm [50]. The arm has 2 fingers that grab an instrumented fork (forque) using a custom-built, 3D-printed fork holder. The system uses visual and haptic modalities to perform the feeding task. For haptic input, we instrumented the forque with a 6-axis ATI Nano25 Force-Torque sensor [51]. We use haptic sensing to control the end effector forces during skewering. For visual input, we mounted a custom built wireless perception unit on the robot’s wrist; the unit includes the Intel RealSense D415 RGBD camera and the NVidia Jetson Nano for wireless transmission. Food is placed on a plate mounted on an anti-slip mat commonly found in assisted living facilities.

b) **Procedure:** For each trial, we place a single food item in the center of the plate. ADA positions itself vertically above the plate and performs object segmentation, featureization, and action selection using a checkpoint of SPANet that has been trained on 15 food items, excluding banana. After performing the requested action, the binary loss is recorded manually and used to update the online learning algorithm. For consistency, regardless of success, we removed and replaced the food item after every attempt. We first conducted 27 trials on deliberately under-ripe bananas. We hypothesized that, with the firmer texture, they would be relatively easy to pick up with most actions, leaving little incentive for the online learning algorithm to explore beyond the actions that generally performed well on the other 15 food items (VS and TV). The following 27 trials were conducted with ripe bananas. Previous data suggested that acquisition would be almost impossible for them with any action besides TA, making them the most unique item in our dataset and therefore the most resistant to generalization. Afterwards, we performed another 5 trials on a carrot (a previously-seen food item which requires VS to pick up consistently) followed by another 5 trials on ripe banana to test the online learning algorithm’s ability to retain its knowledge of the optimal action for each type of food without over-fitting. The identity of the food items was never made available to the online learning algorithm.

c) **Evaluation:** We define a bite acquisition attempt as a success ($l = 0$) if the target food item, either the whole piece or a cut portion remains on the fork for 5 seconds after removal from the plate. If the target food item is skewered with at least 2 out of 4 tines but the fork fails to pick it up or the food falls off soon after lift-off, the attempt is deemed a failure ($l = 1$). If less than 2 out of 4 tines touch a food item due to system-level errors (e.g., perception or planning), we discard the trial completely.

**VII. RESULTS**

The number of times the online learning algorithm selected an action, cumulative across each food item, is presented
in Figure 6. The empirical success rate of VS and TV on the under-ripe banana was 33% and 27%, respectively, not statistically significant from TA’s a priori success rate of \( \sim 30\% \) based on the previously-seen 15 food items. Therefore, as expected, we see the online learning algorithm primarily stick with VS and TV (with a slight bias towards VS), only beginning to explore TA late in trial 24.

The empirical success rate distribution abruptly flipped with the ripe bananas. VS and TV both had a success rate of 0 while TA exhibited an 83% success rate. LinUCB began experimenting with TA after 7 trials, and after trial 20, it was almost exclusively choosing that action.

For the final 10 trials, the online learning algorithm demonstrated that it did not forget the optimal action for previously-seen food items. It performed the optimal action on carrot (VS, 90° rotation) 5 times in a row, and when returning to the ripe banana, it performed the optimal action (TA, any rotation) 4 out of 5 times.

As an empirical baseline, we ran the exact same study on the Greedy algorithm as well. It attempted the TA action only 3 times during the first 55 banana trials, leading to a significantly worse overall success rate compared to LinUCB. The evolution of each algorithm’s estimated success rate for each action (or the upper confidence bound on that estimate in the case of UCB) is presented in Figure 7.

### VIII. DISCUSSION

One key takeaway from these results is that LinUCB prevails in this setting not because of its regret bounds, but because of its robust performance in an uncertain environment by rewarding both expectation and uncertainty. A fluke failure will not sink a high-expectation action, as increasing variance dampens the decreasing expectation. And a presumed-bad or unknown good action will rise quickly as each success increases the variance and expectation in tandem (at least at first).

That we found in our limited pool an algorithm with a smooth learning curve across our entire hyper-parameter grid suggest to us that the contextual bandit with discrete, dissimilar actions is a promising route to data-efficient adaptive bite acquisition. The real robot results even outperformed simulation, in the sense that the optimal action was discovered quickly, which suggests that there was a high variance in our doubly-robust estimator (and, by extension, a high bias in the original imputed values).

However, even 7-8 poke with a fork is enough to completely ruin a banana. We can still further tune hyper-parameters in this space (e.g., LinUCB’s exploration parameter). Additionally, we have not leveraged the fact that we have multiple contexts to choose from at once, and future work could either consider the entire plate of food items as a single compound state, or switch food items if the expected success rate of all actions is below some other hyper-parameter.

We also did not leverage all of the modalities our robot had access to, relying solely on RGBD features. Non-destructive probing can provide us a richer context with haptic feedback, especially if we need to differentiate between similar-looking food items with different material properties (say, because one is cooked or ripe). Other groups have found success using a vibration-detecting audio modality [52] as well.

Finally, we only investigated discrete, solid food items. In order to generalize to a realistic average plate with continuous and mixed foods, we will need to expand to a richer action space. Since adding more parameters to our action space will make it combinatorially large, we could leverage similarities between actions by modeling each one as a coupled slate of actions [53].
[53] M. Dimakopoulou, N. Vlassis, and T. Jebara, “Marginal posterior sampling for slate bandits,” in Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, 2019, pp. 2223–2229.