

Exploratory Grasping: Performance Bounds and Asymptotically Optimal Algorithms for Learning to Robustly Grasp an Unknown Polyhedral Object

Michael Danielczuk^{*1}, Ashwin Balakrishna^{*1}, Daniel Brown², Ken Goldberg¹

* equal contribution

{mdanielczuk, ashwin_balakrishna}@berkeley.edu

Abstract: Learning robust robot grasping policies is an important step for robotics to be viable for commercial automation, such as household assistance, warehousing, and manufacturing. There has been significant prior work on data-driven algorithms for learning general-purpose grasping policies, but these policies can consistently fail to grasp certain objects which are significantly out of the distribution of objects seen during training or which have very few high quality grasps. For such objects, we study strategies for efficient grasp exploration to increase grasp reliability. Precisely, we formalize the problem of efficiently exploring grasps on an unknown polyhedral object through sequential interaction as a Markov Decision Process in a setting where a camera can be used to (1) distinguish stable poses and (2) determine grasp success/failure. We then present a bandit-style algorithm, Exploratory Grasping, which leverages the structure of the grasp exploration problem to rapidly find high performing grasps on new objects through online interaction. We provide vanishing regret guarantees for Exploratory Grasping under certain assumptions on the structure of the grasp exploration problem. Results suggest that Exploratory Grasping can significantly outperform both general-purpose grasping pipelines and two other online learning algorithms and achieves performance near that of the optimal policy on both the Dex-Net adversarial and EGAD! object datasets.

Keywords: Grasping, Online Learning

1 Introduction

Robot grasping systems have a broad array of applications such as warehousing, assistive robotics, and household automation [1, 2, 3, 4]. There has been significant prior work in geometric algorithms for defining grasping policies [5, 6, 7, 8], but these methods can often be difficult to apply when object geometry is unknown. These challenges have motivated a large array of recent work on utilizing large-scale datasets of previously attempted grasps both in simulation [4, 9, 1, 10] and in physical experiments [11, 3, 1, 12] to learn data-driven general-purpose grasping policies which can generalize to objects of varying geometries. To further enable generalization, there has also been work on applying reinforcement learning to learn grasping policies [2, 3, 13, 14]. However, while these techniques have shown significant success in practice, their generality comes at a cost: a single policy which aims to grasp every object may fail to generalize to certain objects [15, 16].

To address this challenge, we study the problem of online grasp exploration to systematically explore sampled grasps on an object to discover robust and stable grasps on a given object with unknown geometry. Specifically, we study a new setting in which a robot is tasked with interacting with an unknown polyhedral object so that it can reliably grasp the object in the future. To this end, we aim to design an algorithm which enables systematic and efficient grasp exploration on objects with sparse grasps and adversarial geometries, which can cause persistent failures in general-purpose grasping systems [16, 15]. The intuition is that while general-purpose grasping policies can be broadly applied to a large set of objects, there is still a large class of objects that cause these systems to struggle [15, 16]. This motivates developing algorithms for grasp exploration to learn

¹University of California, Berkeley. ²University of Texas at Austin.

40 per-object policies for such objects to explore a large set of possible grasps without the burden of
41 generalization to other objects. Then, when these difficult-to-grasp objects are encountered, the
42 resulting object-specific policies can be deployed instead of a general-purpose grasping policy.
43 We formulate the grasp exploration problem as a Markov Decision Process (MDP) and study how
44 parameters of this MDP affect the fundamental difficulty of grasp exploration. We then present
45 an efficient algorithm which leverages the structure of the grasping problem to efficiently explore
46 grasps across different object stable poses and can quickly learn robust grasping policies even for
47 objects that general-purpose grasping policies routinely fail to grasp. We formalize a new problem
48 setting in which an agent seeks to explore grasps across different stable poses of an object by
49 repeatedly attempting grasps on the object and dropping it when a grasp is successful to randomize
50 its stable pose and provide efficient algorithms for grasp exploration in this setting. This paper
51 contributes (1) a novel formulation of the grasp exploration problem as an MDP and intuitive
52 parameter-dependent performance bounds on a family of existing tabular reinforcement learning
53 algorithms for grasp exploration, (2) an efficient bandit-inspired algorithm, Exploratory Grasping, for
54 grasp exploration in this MDP with associated no-regret guarantees, and (3) experiments suggesting
55 that Exploratory Grasping is able to significantly outperform baseline algorithms which explore via
56 tabular reinforcement learning or select actions greedily with respect to general-purpose grasping
57 policies on both the Dex-Net adversarial and EGAD! object datasets.

58 2 Related Work

59 Work in analytic robot grasping assumes that object geometry and pose are known precisely and
60 leverages this knowledge to motivate geometric algorithms for grasp planning [5, 7, 8, 6]. Recently,
61 learning-based algorithms have been used to develop general-purpose algorithms for planning robust
62 grasps on a wide range of objects of varying geometries with data-driven strategies [14, 4, 11, 10, 1,
63 17, 18, 9] and online exploration through reinforcement learning [2, 3]. While the latter approaches
64 have been very effective in learning end-to-end policies for grasp planning from visual input, these
65 policies can consistently fail on certain objects [15, 16]. In this work, we study the problem of
66 systematic online grasp exploration across different stable poses of specific objects. Thus, in contrast
67 to prior work which attempts to learn a single policy to grasp a wide range of objects, we develop an
68 exploration strategy that can rapidly discover high-quality grasps on specific objects.

69 There have also been several papers that use a multi-armed bandit framework for online grasp
70 exploration [19, 20, 21, 22, 23, 24, 25]. In contrast to these works, we consider a formulation where
71 the robot must learn grasps across all poses of the object without human supervision. Laskey et al.
72 [20] consider the setting where some prior geometric knowledge is known, but present an algorithm
73 which is limited to 2D objects and cannot operate directly on visual inputs. Li et al. [22] and Oberlin
74 and Tellex [21] relax these assumptions by exploring grasps in one fixed stable pose of a 3D object
75 with RGB or depth observations. We extend these ideas by repeatedly dropping the object and
76 exploring grasps in all encountered stable poses. Thus, Exploratory Grasping naturally explores
77 grasps over the distribution of likely stable poses [26], yielding a robust policy which can reliably
78 grasp the object when randomly dropped or placed in front of the robot. Additionally, we provide
79 formal guarantees establishing asymptotic convergence of Exploratory Grasping to an oracle policy
80 which knows the best quality grasp in each object stable pose in advance.

81 A key requirement for successful exploration of grasps on an object is discovering the object’s resting
82 stable poses, since the object will necessarily be in one of these poses when a grasp is planned. There
83 has been significant prior work on orienting parts into specific stable poses through a series of parallel
84 jaw gripper movements [27], toppling actions [28], and squeezing actions [29]. However, these
85 approaches require knowledge of an object’s geometry apriori to plan motions to achieve specific
86 stable poses. When an object’s geometry is not known, but assumed to be polyhedral, prior work [26]
87 has established that repeatedly dropping the object from a known initial distribution of poses onto a
88 flat workspace results in a stationary distribution over stable poses. Thus, this dropping procedure
89 provides a convenient method to explore grasps in new stable poses of an object. We leverage this
90 insight to (1) formulate the grasp exploration problem for an unknown object and (2) develop a grasp
91 exploration algorithm which can discover high-quality grasps across different object stable poses.

92 3 Grasp Exploration Problem Formulation

93 Given a single unknown polyhedral object on a planar workspace, the objective is to learn a grasping
94 policy that maximizes the likelihood of grasp success over stable poses of the object [26, 30]. We for-

95 simulate the grasp exploration problem as a Markov Decision Process (Section 3.1), define assumptions
 96 on the environment (Section 3.2) and formulate the policy learning objective (Section 3.3).

97 3.1 Grasp Exploration as an MDP

98 We consider exploring grasps on an unknown, rigid, polyhedral object \mathcal{O} which rests in one of a
 99 finite set of N distinguishable stable poses with associated drop probabilities $\{\lambda_s\}_{s=1}^N$. We study
 100 polyhedral objects since they admit a finite number of stable resting poses, but assume that the robot
 101 does not initially know any of these stable poses or the number of stable poses N . Note that any object
 102 for which a triangular mesh provides a high fidelity model can be well-modeled as polyhedral [31].
 103 The robot must discover new stable poses from experience by attempting grasps on the object in its
 104 current stable pose and re-dropping the object when grasps are successful. We assume an overhead
 105 digital camera that cannot reliably determine the 3D shape of the object, but can be used to recognize
 106 distinguishable 3D poses by performing planar translations and rotations of the image into a canonical
 107 orientation and translation. We also assume that the camera can be used after each grasp attempt to
 108 determine if the grasp is successful after the gripper is moved out of the camera’s field of the view.

109 We formulate this problem as a Markov decision process (MDP) [32] by defining a *grasp MDP*,
 110 $\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R)$, as follows:

- 111 1. **State:** We define a one-to-many mapping from the full set of object stable poses Σ to the set of
 112 overhead point clouds \mathcal{I} that are scale-invariant, translation-invariant, and rotationally-invariant
 113 about the vertical axis. Then, we define the state space as the set of *distinguishable* stable poses
 114 \mathcal{S} . We define \mathcal{S} as the set of equivalence classes within Σ , where two poses are equivalent if
 115 they map to the same set of overhead point clouds \mathcal{I} . We assume the point cloud \mathcal{I} is obtained
 116 from a depth image observation $o \in \mathbb{R}_{H \times W}^+$ from an overhead camera with known intrinsics.
- 117 2. **Grasp Actions:** We define a set \mathcal{A}_s of K grasp actions, such as parallel-jaw or suction grasps,
 118 in each stable pose $s \in \mathcal{S}$ of the object. The K grasps are sampled from the depth image
 119 observation for each stable pose as in Mahler et al. [33]. The full action space is the union of
 120 the actions available at each pose: $\mathcal{A} = \bigcup_{s \in \mathcal{S}} \mathcal{A}_s$.
- 121 3. **Transition Function:** An unknown transition probability distribution $P(s' | s, a)$ defining
 122 the probability of the object transitioning to stable pose s' if grasp action a is executed in stable
 123 pose s . If a is a successful grasp, then the object is dropped into the workspace to sample a
 124 new stable pose s' based on unknown drop probabilities $\{\lambda_s\}_{s=1}^N$, while if a is a failed grasp,
 125 the object topples into some new pose s' with unknown probability $\delta_{s,s'}$.
- 126 4. **Reward Function:** Rewards are drawn from a Bernoulli distribution with unknown parameter
 127 $\phi_{s,a}$: $R(s, a) \sim \text{Ber}(\phi_{s,a})$ for $a \in \mathcal{A}_s$. $R(s, a) = 1$ if executing a in stable pose s results in
 128 the object being successfully grasped and lifted, and 0 otherwise.

129 3.2 Assumptions

130 To study policy learning in a grasp MDP, we first establish assumptions on the system dynamics
 131 to ensure that all poses are reachable and which describe how the object pose can evolve when the
 132 object is (1) dropped or (2) when a grasp is attempted.

133 **Assumption 3.1. Grasp Dynamics:** If a grasp succeeds, we assume that the robot can randomize
 134 the pose of the object before dropping it to sample subsequent stable poses from the associated
 135 unknown stable pose drop probabilities $\{\lambda_s\}_{s=1}^N$ for \mathcal{O} . If a grasp fails, we assume that the object’s
 136 pose will either remain unchanged or topple into some other pose s' with unknown probability $\delta_{s,s'}$.

137 **Assumption 3.2. Drop Dynamics:** The categorical distribution over stable poses defined by drop
 138 probabilities $\{\lambda_s\}_{s=1}^N$ is a stationary distribution that is independent of prior actions and poses when
 139 \mathcal{O} is dropped from a fixed height with its orientation randomized as in Goldberg et al. [26].

140 **Assumption 3.3. Irreducibility:** We assume that there exists a policy π such that the Markov chain
 141 over stable poses induced by executing π in grasp MDP \mathcal{M} is irreducible, and thus can reach all
 142 stable poses with nonzero probability for any initialization.

143 Note that Assumption 3.3 is satisfied if, for all poses $s \in \mathcal{S}$, $\lambda_s > 0$ and there exists a grasp with
 144 success probability $\epsilon > 0$. As a result, we assume that these conditions hold for analysis. However,

145 since object toppling is also possible, note that these conditions are sufficient but not necessary for
 146 ensuring irreducibility.

147 3.3 Learning Objective

148 The objective is to learn a policy $\pi : \mathcal{S} \rightarrow \mathcal{A}$ that maximizes the expected average reward over
 149 an infinite time horizon under the state distribution induced by π . Let $\tau = \{(s_t, \pi(s_t))\}_{t=1}^T$ be
 150 a trajectory of all states and actions when executing policy π over some time horizon T and let
 151 $r(\tau) = \sum_{t=1}^T r(s_t, \pi(s_t))$ be the sum of rewards for all states and actions in τ , and let $p(\tau|\pi)$ be the
 152 trajectory distribution induced by policy π . Then the expected average reward obtained from policy π
 153 in grasp MDP \mathcal{M} is given as:

$$J(\mathcal{M}, \pi, T) = \frac{1}{T} \mathbb{E}_{\tau \sim p(\tau|\pi)} [r(\tau)] \quad (1)$$

154 The objective is to find the policy which maximizes expected reward over an infinite time horizon:

$$\pi^* = \operatorname{argmax}_{\pi} \lim_{T \rightarrow \infty} J(\mathcal{M}, \pi, T) \quad (2)$$

155 4 Reinforcement Learning for Grasp MDPs

156 We first study the performance of reinforcement learning algorithms for grasp exploration and
 157 leverage the structure of the grasp MDP described in Section 3 to establish a bound on the cumulative
 158 regret for a variety of existing tabular reinforcement learning algorithms when applied to grasp MDPs.
 159 See Section A of the supplementary material for all proofs.

160 4.1 Analyzing Grasp MDPs

161 A common metric with which to measure policy performance in online-learning settings is *regret*,
 162 which has been analyzed in the reinforcement learning setting by a variety of prior work [34, 35, 36,
 163 37]. Intuitively, regret quantifies the difference in accumulated reward within T timesteps between a
 164 given policy π and optimal infinite horizon policy π^* for MDP \mathcal{M} . More precisely, we define average
 165 regret based on the definition in [34]:

$$\text{Regret}(\mathcal{M}, \pi, T) = \max_{\pi'} \left[\lim_{T \rightarrow \infty} J(\mathcal{M}, \pi', T) \right] - J(\mathcal{M}, \pi, T) \quad (3)$$

166 Recent theoretical work [34] on reinforcement learning for tabular MDPs yielded algorithms which
 167 can attain average regret proportional to the diameter of the MDP, a measure of the furthest distance
 168 between pairs of states under an appropriate policy. However, for general MDPs, this diameter can be
 169 arbitrarily large, making these regret bounds difficult to interpret in practical settings. We leverage
 170 the structure of grasp MDPs to derive an intuitive upper bound on the MDP diameter, which helps
 171 precisely quantify the difficulty of grasp exploration based on the parameters of the grasp MDP.

172 We begin by defining the Markov chain over \mathcal{S} induced by a stationary deterministic policy π .

173 **Definition 4.1. Pose Evolution under π :** Given stationary policy π , the transitions between pairs
 174 of states in \mathcal{M} is defined by a Markov chain. Precisely, the transition probabilities under π , denoted
 175 by P^π where $P^\pi[s, s'] = P(s' | s, a = \pi(s))$, are given as follows:

$$P^\pi[s, s'] = \phi_{s, \pi(s)} \lambda_{s'} + (1 - \phi_{s, \pi(s)}) \delta_{s, s'} \quad (4)$$

176 Given this Markov Chain over poses for a given policy π , we can now analyze the diameter of the
 177 grasp MDP, denoted $D(\mathcal{M})$, by considering the hitting time between stable poses in \mathcal{M} as defined
 178 in [38]. Note that by Assumption 3.3, the Markov chain corresponding to P^π is irreducible, and we
 179 can compute the hitting time between any pair of states in closed form [38].

180 **Definition 4.2.** Let $T_{s \rightarrow s'}^\pi$ denote the hitting time between states s and s' under policy π under the
 181 Markov chain defined in Definition 4.1. Then the diameter of \mathcal{M} is defined as follows [34]:

$$D(\mathcal{M}) = \max_{s \neq s'} \min_{\pi} \mathbb{E}[T_{s \rightarrow s'}^\pi] \quad (5)$$

182 Intuitively, $D(\mathcal{M})$ measures the temporal distance between the furthest apart states in an MDP
 183 under the policy which minimizes this distance. We now leverage the structure of the grasp MDP to
 184 establish an upper bound on $D(\mathcal{M})$.

185 **Lemma 4.1.** *The diameter of the grasp MDP \mathcal{M} can be bounded above as follows:*

$$D(\mathcal{M}) \leq \frac{1}{\epsilon \lambda_1}, \quad (6)$$

186 where ϵ is a lower bound on the success probability of the highest quality grasp over all stable poses
 187 and λ_1 is the drop probability for the least likely stable pose.

188 Lemma 4.1 captures the intuition that the diameter of the MDP should be large if the best grasp in
 189 each stable pose has a low success probability (ϵ is small), or if there exists a stable pose with very
 190 low drop probability (λ_1 is small).

191 Now we can establish regret bounds for a variety of tabular reinforcement learning algorithms when
 192 applied to \mathcal{M} by combining diameter dependent regret bounds from prior work and the bound on
 193 grasp MDP diameter established in Lemma 4.1.

194 **Theorem 4.1.** *UCRL2 [34], KL-UCRL [36] and PSRL [39] admit average regret bounded above as
 195 follows for any grasp MDP \mathcal{M} :*

$$\text{Regret}(\mathcal{M}, \pi, T) \sim \tilde{O} \left(\frac{N}{\epsilon \lambda_1} \sqrt{\frac{K}{T}} \right), \quad (7)$$

196 while UCRLV [35] admits the following average regret bound for grasp MDP \mathcal{M} .

$$\text{Regret}(\mathcal{M}, \pi, T) \sim \tilde{O} \left(\sqrt{\frac{NK}{\epsilon \lambda_1 T}} \right), \quad (8)$$

197 with N, K, T, ϵ and λ_1 defined as in Section 3.

198 While the diameter can be uninterpretable and difficult to directly compute or bound for general
 199 MDPs [34], Theorem 4.1 leverages the specific structure of grasp MDPs to relate the accumulated
 200 regret of common RL algorithms to intuitive parameters of the grasp MDP. This result also serves to
 201 shed light on the fundamental difficulty of grasp exploration in the context of reinforcement learning.

202 5 A Bandit-Style Algorithm for Efficient Learning in Grasp MDPs

203 One interesting feature of the grasp MDP \mathcal{M} is that most objects have a small, finite set of stable
 204 poses [26]. This motivates learning a set of N bandit policies, each of which explore their grasps in a
 205 particular object stable pose. However, the grasp exploration problem in each pose is not necessarily
 206 decoupled. For example, there may exist a pose s with no available high quality grasps but a high
 207 likelihood of a failed grasp causing the object to topple into another pose with high quality grasps.
 208 Then, the optimal policy may deliberately fail to grasp the object in pose s in order to obtain access
 209 to grasps in the more favorable stable pose, leading it to avoid grasp exploration in poses without
 210 high quality grasps. To avoid this behavior, we introduce Assumption 5.1.

211 **Assumption 5.1.** We assume that $\delta_{s,s'} \leq \epsilon \lambda_{s'}$ for all $s \neq s'$ where $\delta_{s,s'}$ is the probability of toppling
 212 into pose s' given a failed grasp in pose s , ϵ is a lower bound on the success probability of the highest
 213 quality grasp over all stable poses, and $\lambda_{s'}$ is the drop probability of pose s' .

214 Assumption 5.1 ensures that there exists a grasp in all stable poses s such that the probability of
 215 transitioning to new pose s' via a grasp attempt is higher than that of toppling from pose s to pose s' .
 216 Given this assumption, the optimal grasp exploration policy in \mathcal{M} reduces to selecting the grasp with
 217 highest success probability in each encountered pose, as this policy maximizes both reward at the
 218 current timestep and exploration of other stable poses when the object is re-dropped. In other words,
 219 the global optimal policy is the *greedy* policy. Given this structure, we can view the grasp exploration
 220 problem as N independent multi-armed bandit problems corresponding to grasp exploration in each
 221 pose. However, although grasp exploration can be performed independently in each pose, the success
 222 of a grasp exploration policy in one pose affects the time available to explore grasps in another pose.

223 We propose a simple and intuitive grasp exploration algorithm, Exploratory Grasping: maintain the
 224 parameters of N independent bandit policies $(\pi_s^B)_{s=1}^N$ for $\pi_s^B : s \rightarrow \mathcal{A}_s$ where π_s^B is only *active* in

225 stable pose s . We let $\pi^{\mathcal{B}}$ denote the meta policy induced by executing bandit policy $\pi_s^{\mathcal{B}}$ in pose s and
 226 assume that $\pi_s^{\mathcal{B}}$ is learned by running a no-regret online learning algorithm \mathcal{B} for grasp exploration in
 227 pose s . Some examples of no-regret algorithms for the stochastic multi-armed bandit problem include
 228 the UCB-1 algorithm [40] and Thompson Sampling [41]. We then formulate a new notion of regret
 229 capturing the gap between $\pi^{\mathcal{B}}$ and the optimal policy on their respective distributions, and show that
 230 Exploratory Grasping achieves vanishing average regret despite the interdependence between pose
 231 exploration times.

232 Let $p_T^{\mathcal{B}}$ denote the distribution of poses seen under the sequence of policies $\pi_{1:T}^{\mathcal{B}}$ at each round of
 233 learning up to time T and let p_T^* denote the distribution of poses seen when executing the optimal
 234 policy (π^*) in \mathcal{M} up to time T . We define the average regret accrued by Exploratory Grasping in
 235 grasp MDP \mathcal{M} after T rounds as the difference in accumulated reward of the optimal policy on pose
 236 distribution p_T^* and the accumulated reward of $\pi^{\mathcal{B}}$ on pose distribution $p_T^{\mathcal{B}}$.

237 **Definition 5.1.** The average regret accumulated by running \mathcal{B} in each stable pose is defined as the
 238 difference between the average regret for each pose visited by the optimal policy π^* weighted by the
 239 probability of it visiting each pose and the corresponding quantity for the executed policy $\pi^{\mathcal{B}}$:

$$\mathbb{E} [\mathcal{R}^{\mathcal{B}}(T)] = \sum_{s=1}^N p_T^*(s) \mathbb{E} \left[\frac{1}{T_s^*} \sum_{t=1}^{T_s^*} R(s, \pi^*(s)) \right] - \sum_{s=1}^N p_T^{\mathcal{B}}(s) \mathbb{E} \left[\frac{1}{T_s^{\mathcal{B}}} \sum_{t=1}^{T_s^{\mathcal{B}}} R(s, \pi_t^{\mathcal{B}}(s)) \right]$$

240 where T_s^* is the time spent by the optimal policy in pose s and $T_s^{\mathcal{B}}$ is the time spent by $\pi^{\mathcal{B}}$ in pose s .

241 In Section A of the supplementary material, we show that the average regret as defined in Definition 5.1
 242 vanishes to 0 in the limit as $T \rightarrow \infty$ as stated in Theorem 5.1.

243 **Theorem 5.1.** *The average regret accrued by Exploratory Grasping, when using any no-regret bandit
 244 algorithm \mathcal{B} for grasp exploration in each encountered stable pose, vanishes in the limit:*

$$\lim_{T \rightarrow \infty} \mathbb{E} [\mathcal{R}^{\mathcal{B}}(T)] = 0$$

245 This result leverages the precise structure of the grasp MDP, namely that the optimal policy is the
 246 greedy policy, to provide sublinear regret guarantees for Exploratory Grasping, which executes any
 247 standard no-regret online learning algorithm for grasp exploration in each stable pose.

248 6 Simulation Experiments

249 In simulation experiments, we study three questions: (1) Does Exploratory Grasping facilitate grasp
 250 exploration on objects for which general-purpose grasping policies, such as Dex-Net 4.0 [4] and GG-
 251 CNN [1], perform poorly? (2) Does learning separate policies for each stable pose as in Exploratory
 252 Grasping accelerate grasp exploration? (3) Can Exploratory Grasping be applied in realistic settings
 253 in which objects may topple due to failed grasps? Unfortunately due to the pandemic, we were
 254 unable to run physical experiments for the paper. However, since Exploratory Grasping samples
 255 grasps on image based observations of the object and is evaluated in a similar simulation environment
 256 as used in Mahler et al. [42], which transferred learned grasping policies to physical bin picking
 257 environments, we expect that Exploratory Grasping can likely be extended to grasp exploration in the
 258 real world.

259 6.1 Experimental Setup

260 To evaluate each policy, we choose 7 objects from the set of Dex-Net 2.0 adversarial objects [33]
 261 as well as 39 evaluation objects from the EGAD! dataset [43]. We use these objects in experiments
 262 because general-purpose grasping policies for parallel-jaw grippers (Dex-Net 4.0 and GG-CNN)
 263 perform poorly on them, yet they contain high-quality grasps in multiple poses. We sample a set of
 264 K parallel-jaw grasps on the image observation of pose s of each object as in [33], and calculate the
 265 ground-truth quality of each grasp, $\phi_{s,a}$, using a wrench resistance metric that measures the ability
 266 of the grasp to resist gravity [42]. We remove poses that have no grasps with nonzero ground-truth
 267 quality and renormalize the stable pose distribution. Then, we randomize the initial pose of each
 268 object and execute Exploratory Grasping and baselines, sampling rewards from $\text{Ber}(\phi_{s,a})$. If the grasp
 269 succeeds, we randomize the pose, choosing a stable pose according to the stable pose distribution
 270 of the object. Otherwise, we leave the object in the same stable pose. We rollout each policy for 10

271 rollouts of 10 trials, where new grasps are sampled for each trial and each rollout evaluates the policy
272 over 10,000 timesteps of grasp exploration. Since there is stochasticity in both the grasp sampling
273 and the policies themselves, we average policy performance across the 10 rollouts and 10 trials. In
274 addition, we smooth policy performance across a sliding window of 20 timesteps and report average
275 reward for each timestep.

276 **6.2 Policies**

277 We compare 3 variants of Exploratory Grasping against 3 baselines to evaluate whether Exploratory
278 Grasping is able to (1) substantially outperform general-purpose grasping policies [4] on challenging
279 objects and (2) learn more efficiently than other online learning algorithms which update a grasp
280 quality convolutional network (GQCNN) online or explore grasps via reinforcement learning. We
281 also instantiate Exploratory Grasping with different algorithms for \mathcal{B} to study how this choice affects
282 grasp exploration efficiency and implement an oracle baseline to study whether Exploratory Grasping
283 is able to converge to the optimal policy. We compare the following baselines and Bandit Grasping
284 variants: **GQCNN**, which selects grasps greedily with respect to the Grasp Quality Convolutional
285 Network from Dex-Net 4.0 [4] with probability 0.95 and selects a grasp uniformly at random with
286 probability 0.05, **GQCNNFT**, which additionally fine tunes the GQCNN policy online from agent
287 experience, an implementation of **UCRL2** from [44], a tabular RL algorithm discussed in Section 4,
288 and instantiations of Exploratory Grasping with the UCB-1 algorithm [40] (**Exploratory Grasping**
289 (**UCB**)), Thompson sampling (**Exploratory Grasping (TS)**) with a uniform Beta distribution prior,
290 and Thompson sampling with a GQCNN prior of strength 5 (**Exploratory Grasping (TS-5)**) as
291 in [22]. Finally, we implement an oracle baseline that chooses grasps with the best ground-truth
292 metric at each timestep to establish an upper bound on performance.

293 **6.3 Policy Learning without Toppling**

294 We first evaluate the above baselines and Exploratory Grasping variants in a setting in which toppling
295 is not possible ($\delta_{s,s'} = 0, \forall s \neq s'$). This exacerbates the difficulty of grasp exploration since an
296 object must be successfully grasped in a given pose for policies to be able to explore grasps in other
297 poses. As shown in Figure 1, the GQCNN policy typically performs very poorly, achieving an average
298 reward of less than 0.1 per timestep. While the online learning policies also start poorly, they quickly
299 improve, and Exploratory Grasping (TS) eventually converges to the optimal policy. We also find
300 that Exploratory Grasping (TS-5), which leverages GQCNN as a prior using the method presented
301 in [22], further speeds convergence to the optimal policy. This result is promising, as it suggests
302 that the exploration strategy in Exploratory Grasping can be flexibly combined with general-purpose
303 grasping policies to significantly accelerate grasp exploration on unknown objects. We find that
304 the GQCNNFT policy performs very poorly even though it continues to update the weights of the
305 network online with the results of each grasp attempt and samples a random grasp with probability
306 0.05, which aids exploration. We hypothesize that this is due to the initial poor performance of
307 GQCNN—since the vast majority of fine-tuning grasps attain zero reward, the network is unable
308 to explore enough high-quality grasps on the object. Overall, these results suggest that Exploratory
309 Grasping can greatly increase grasp success rates on objects for which GQCNN performs poorly.

310 We also find that Exploratory Grasping policies greatly outperform the tabular RL policy UCRL2 by
311 leveraging the structure of the grasp MDP. Both the UCB and Thompson sampling implementations
312 maintain separate policies in each pose, thereby leveraging the fact that the optimal policy at each
313 timestep is the greedy policy. This allows the Exploratory Grasping policies to not waste timesteps
314 exploring the possible transitions to other states with low rewards. Thompson sampling additionally
315 leverages the fact that the rewards are distributed as Bernoulli random variables, which may explain
316 the significant performance gap between the Thompson sampling and UCB implementations. Thus,
317 the Exploratory Grasping policies quickly learn to choose high-quality grasps in each pose and
318 transition quickly to new, unexplored poses.

319 We also perform sensitivity analysis of Exploratory Grasping to the grasp MDP parameters ϵ and λ_1
320 and find that Exploratory Grasping quickly converges to the optimal policy unless ϵ or λ_1 is low. In
321 particular, we find that ϵ has an outsized effect on performance, which is intuitive given that ϵ affects
322 the ability of Exploratory Grasping to both achieve immediate grasp successes *and* explore new poses,
323 while λ_1 only influences the latter. See Section C of the supplementary material for details.

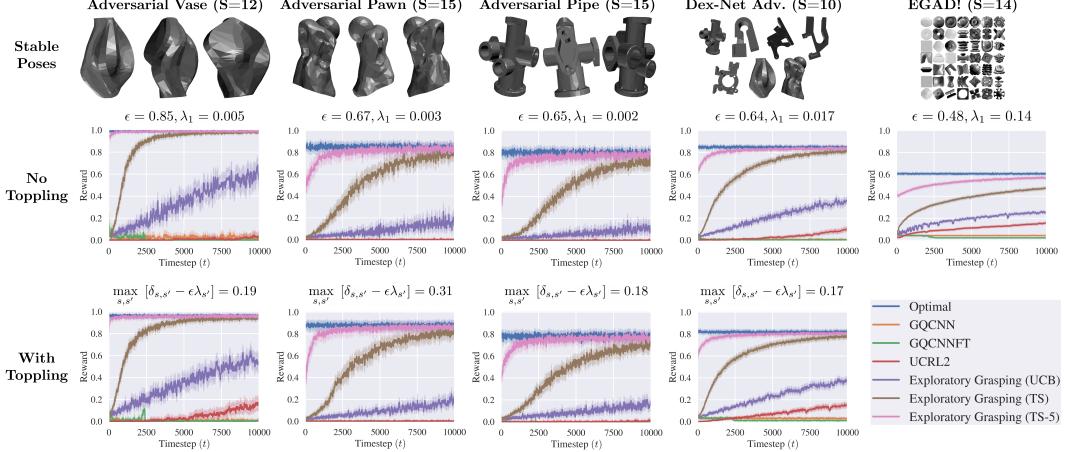


Figure 1: Simulation Experiments: Performance of each policy across the vase, pawn and pipe objects from the Dex-Net 2.0 adversarial object set [33] (first three columns), as well as aggregated performance over the 7 Dex-Net objects (fourth column) and the 39 EGAD! objects (fifth column). We report the number of distinguishable stable poses (S) for each object, as well as its ϵ (ground truth value for the lowest quality best grasp across poses) and λ_1 (least likely stable pose probability) values, and show a top-down view of its three most likely stable poses. We report mean values of each metric for the datasets. The first row of plots shows reward over time for each policy in the original setting, where the object stays in the same pose until successfully grasped. The second row shows policy performance in the more realistic setting where the object may topple into an alternate pose when a grasp is unsuccessful. The value above each plot with toppling indicates the maximum difference in transitioning via toppling and transitioning via grasping to a new pose. In both cases, Exploratory Grasping quickly converges to optimal performance, while the other algorithms fail to reach optimal performance even after 10,000 grasp attempts. This result holds even when Assumption 5.1 is violated.

324 6.4 Policy Learning with Toppling

325 We repeat the same experiments as in the previous section, with the additional condition that each
 326 object may now topple into another pose when a grasp is unsuccessful (Section 3.2). We use the
 327 toppling analysis from Correa et al. [28] to determine the toppling transition matrix for a given object.
 328 Specifically, we generate the distribution of next states from a given state by sampling non-colliding
 329 pushes across vertices on the object, finding their distribution of next states given perturbations
 330 around the nominal push point, and average the distribution from all of the pushes. Then, during
 331 policy rollouts, if a grasp fails, we choose the next state according to the corresponding topple
 332 transition probabilities. See the last row of Figure 1 for learning curves for Exploratory Grasping and
 333 baselines. Results suggest that even in cases where values of $\delta_{s,s'}$ are considerably larger than $\epsilon\lambda_{s'}$,
 334 Exploratory Grasping policies still achieve significantly better performance than baselines. These
 335 results suggest that although Assumption 5.1 is needed for analysis, in practice Exploratory Grasping
 336 can also efficiently explore grasps on objects where Assumption 5.1 is violated.

337 7 Conclusion

338 We study a new problem setting in which a robot is tasked with exploring grasps across stable
 339 poses of an object by repeatedly attempting grasps and dropping the object to explore grasps on
 340 new object poses. We formalize this problem as an MDP and study how the difficulty of grasp
 341 exploration depends on intuitive parameters of this MDP. We then present Exploratory Grasping,
 342 an efficient, bandit-inspired, algorithm for exploring grasps on an unknown polyhedral object.
 343 Exploratory Grasping can be flexibly used with any no-regret online learning algorithm such as UCB
 344 or Thompson sampling and results suggest that Exploratory Grasping is able to explore grasps on
 345 unknown polyhedral objects significantly more efficiently than online learning algorithms which
 346 do not effectively leverage the structure of the grasping problem. In future work, we will explore
 347 applying Exploratory Grasping to grasp exploration in a physical bin picking setup. One nice property
 348 of Exploratory Grasping is that in the process of exploring grasps, it also explores different stable
 349 poses of the object. Thus, we are excited to explore further applications of Exploratory Grasping
 350 beyond grasp exploration. For example, Exploratory Grasping could be used to explore different
 351 object poses to construct accurate 3D models of unknown objects or inspect parts for defects.

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1 **Exploratory Grasping: Performance Bounds and**
 2 **Asymptotically Optimal Algorithms for Learning to**
 3 **Robustly Grasp an Unknown Polyhedral Object**
 4 **Supplementary Material**

5 **A Proofs**

6 Here we provide the proofs for all results in Section 4 and Section 5 in the main text.

7 **A.1 Proof of Lemma 4.1**

8 Consider grasp MDP \mathcal{M}' for which the object stable pose does not change when a grasp fails. Thus,
 9 it must be the case that $\delta_{l,m} = 0$ when $l \neq m$ and $\delta_{l,l} = 1 \forall l$. Note that for any grasp MDP \mathcal{M} ,
 10 it must be the case that $D(\mathcal{M}) \leq D(\mathcal{M}')$ since the probability of transition between any pair of
 11 distinct states in \mathcal{M}' is at most the probability of transition in \mathcal{M} . Now we establish a bound on
 12 $D(\mathcal{M})$ by bounding $D(\mathcal{M}')$.

13 Without loss of generality, let $\lambda_1 \leq \lambda_s \forall s \in \mathcal{S}$. Additionally, define π^* as the policy which selects
 14 the grasp with highest success probability on all poses, with associated probability transition matrix
 15 P^{π^*} and with hitting time $T_{s \rightarrow s'}^{\pi^*}$ defined as in Definition 4.1. Then, the diameter of \mathcal{M}' can be
 16 computed as follows.

17 For MDP \mathcal{M}' , it must be the case that

$$\min_{\pi} T_{s \rightarrow s'}^{\pi} = T_{s \rightarrow s'}^{\pi^*} \quad (9)$$

18 since π^* , the policy which always picks the highest quality grasp on each pose, minimizes the hitting
 19 time between any pair of poses s, s' . Furthermore, note that

$$\max_{s \neq s'} T_{s \rightarrow s'}^{\pi^*} = \max_s T_{s \rightarrow 1}^{\pi^*} \quad (10)$$

20 since for any starting pose s , the hitting time between s and s' will always be highest for $s' = 1$ (the
 21 pose with lowest drop probability) for any policy π . Thus, we see that

$$D(\mathcal{M}') = \max_s T_{s \rightarrow 1}^{\pi^*} \quad (11)$$

22 Finally, we leverage equation 11 to compute an upper bound on $D(\mathcal{M}')$ as follows.

23 Let π_ϵ be any policy which selects a grasp with success probability ϵ on each stable pose l . Note
 24 that by Assumption 3.3 we assume that there exists a grasp with success probability at least ϵ on
 25 each pose. Without loss of generality, we can consider the case that there exists a grasp with success
 26 probability exactly ϵ on each pose and the policy which selects these grasps since the hitting times
 27 under this policy will only be lower than those under a policy which selects grasps with success
 28 probability greater than ϵ . Then, it follows that

$$\min_{\pi} T_{s \rightarrow s'}^{\pi} \leq T_{s \rightarrow s'}^{\pi_\epsilon} \quad \forall s, s' \quad (12)$$

29 Now note that since we are considering pose evolution under π_ϵ , which selects a grasp of the same
 30 quality ϵ on any pose, the starting pose s does not affect the hitting time. Combining this with the
 31 fact that the hitting time to the least likely pose (pose 1) will always be the highest for any policy π
 32 and inequality (12) yields that

$$D(\mathcal{M}') \leq \max_{s \neq s'} T_{s \rightarrow s'}^{\pi_\epsilon} = T_{2 \rightarrow 1}^{\pi_\epsilon} \quad (13)$$

33 Since the choice of s does not matter under π_ϵ , we use $s = 2$ above without loss of generality.
 34 Now, note that the hitting time to pose 1 under π_ϵ is distributed as a geometric random variable with
 35 parameter $\epsilon \lambda_1$, which has mean $\frac{1}{\epsilon \lambda_1}$, yielding the desired result. \square

36 **A.2 Proof of Theorem 4.1**

37 The result immediately follows from combining the diameter bound from Lemma 4.1 and the regret
 38 bounds established for UCRL2 [1], KL-UCRL [2] and PSRL [3] (average regret $\tilde{O}(DS\sqrt{A/T})$) and
 39 for UCRLV [4] (average regret $\tilde{O}(\sqrt{DSA/T})$) where D is the MDP diameter and S and A are the
 40 cardinalities of the state space and action space respectively. \square

41 **A.3 Proof of Theorem 5.1**

42 We bound the expected regret of Exploratory Grasping by decomposing the regret into two terms,
 43 one which depends on the divergence between the distribution of poses seen by the optimal policy
 44 and $\pi^{\mathcal{B}}$, and the other of which depends on the difference in rewards attained by $\pi^{\mathcal{B}}$ and π^* when
 45 evaluated on the distribution of poses seen by $\pi^{\mathcal{B}}$. For simplicity, we refer to $\pi^{\mathcal{B}}$ as π for the proof.

$$\mathbb{E} [\mathcal{R}^{\mathcal{B}}(T)] = \sum_{s=1}^S p_T^*(s) \mathbb{E} \left[\frac{1}{T_s^*} \sum_{t=1}^{T_s^*} R(s, \pi^*(s)) \right] - \sum_{s=1}^S p_T^\pi(s) \mathbb{E} \left[\frac{1}{T_s^\pi} \sum_{t=1}^{T_s^\pi} R(s, \pi_t(s)) \right] \quad (14)$$

$$= \sum_{s=1}^S (p_T^*(s) - p_T^\pi(s)) g_s^*(T_s^*) + \sum_{s=1}^S p_T^\pi(s) (g_s^*(T_s^*) - g_s^\pi(T_s^\pi)) \quad (15)$$

$$= \mathbb{E} [\mathcal{R}_\pi^{\mathcal{B}}(T)] + \sum_{s=1}^S (p_T^*(s) - p_T^\pi(s)) g_s^*(T_s^\pi) \quad (16)$$

46 where (15) follows from letting $g_s^*(T_s^*) = \mathbb{E} \left[\frac{1}{T_s^*} \sum_{t=1}^{T_s^*} R(s, \pi^*(s)) \right]$ and $g_s^\pi(T_s^\pi) =$
 47 $\mathbb{E} \left[\frac{1}{T_s^\pi} \sum_{t=1}^{T_s^\pi} R(s, \pi_t(s)) \right]$ and (16) follows from letting $\mathbb{E} [\mathcal{R}_\pi^{\mathcal{B}}(T)]$ denote the expected regret on
 48 the distribution of poses visited by policy π and noting that the average reward for the optimal policy,
 49 g_s^* , is independent of the timesteps spent in the pose (i.e., $g_s^*(T_s^\pi) = g_s^*(T_s^*) \forall s$).

50 We first focus on the first term in (16). We know that $\mathbb{E} [\mathcal{R}_\pi^{\mathcal{B}}(T)]$ approaches zero if each pose is
 51 visited infinitely often in the limit as $T \rightarrow \infty$ provided that \mathcal{B} is a no-regret online learning algorithm:

$$\lim_{T \rightarrow \infty} p_T^\pi(s) > 0, \forall s \in \{1, 2, \dots, S\} \Rightarrow \lim_{T \rightarrow \infty} \mathbb{E} [\mathcal{R}_\pi^{\mathcal{B}}(T)] = 0 \quad (17)$$

52 Thus, it remains to be shown that under π , all poses are visited infinitely often in the limit as $T \rightarrow \infty$.
 53 Note that this statement is equivalent to showing that in the limit as $T \rightarrow \infty$, bandit algorithm \mathcal{B}
 54 selects grasps on each pose with non-zero success probability with non-zero probability. Suppose that
 55 this was not the case (i.e., that as $T \rightarrow \infty$, \mathcal{B} assigns zero grasp probability to all grasps with non-zero
 56 success probability). This would imply that \mathcal{B} only selects grasps with zero success probability, and
 57 thus incurs constant regret on its own distribution ($\lim_{T \rightarrow \infty} \mathbb{E} [\mathcal{R}_\pi^{\mathcal{B}}(T)] > 0$). This contradicts the
 58 initial assumption that \mathcal{B} is a no-regret online learning algorithm, showing that under π , all poses
 59 must be visited infinitely often in the limit as $T \rightarrow \infty$.

60 Now we shift our attention to the second term in (16). Given that \mathcal{B} is a no-regret online learning
 61 algorithm, it must be the case that $g_s^\pi(T_s^\pi) \xrightarrow[T_s^\pi \rightarrow \infty]{} g_s^*(T_s^\pi) \forall s$. This implies that in the limit as
 62 $T \rightarrow \infty$, π and π^* have the same success rate on all stable poses. Two policies with the same
 63 success rate on all stable poses induce the same Markov chain over \mathcal{S} , and thus admit the same stable
 64 pose distribution. Thus, $p_T^\pi(s) \xrightarrow[T \rightarrow \infty]{} p_T^*(s)$, implying that the second term also approaches 0 as
 65 $T \rightarrow \infty$. \square

66 **B Experimental Details**

67 **Object Selection:** We choose 7 objects from the set of adversarial objects in Dex-Net 2.0 [5] because
 68 these objects had empirically been shown to be difficult to grasp for the Dex-Net policy. Similarly, the
 69 recently-introduced EGAD! object dataset [6] was created to contain objects with few high-quality
 70 parallel-jaw grasps. For this dataset, we select all objects for which there exists at least one sampled
 71 grasp of quality $\epsilon = 0.1$ on at least one stable pose of the object. Of the 49 objects in the EGAD!
 72 evaluation dataset, 39 met this criterion.

73 **Pose Selection:** For each of the objects, we remove stable poses from the distribution in simulation
 74 if they occur with less than a 0.1% chance or if they do not contain a sampled grasp with quality at
 75 least $\epsilon = 0.1$. When a pose is removed, the remaining stable pose distribution is renormalized.

76 **Grasp Sampling:** We sample a set of $K = 100$ parallel-jaw grasps on the image observation of each
 77 pose of each object as in [5]. This sampling process is done using the depth image grasp sampler
 78 from the GQCNN repository and is repeated for up to 10 iterations. At each iteration, the sampled
 79 grasps' ground truth qualities are calculated using the robust wrench resistance metric that measures
 80 the ability of the grasp to resist gravity [7]. If no grasps are found with quality of at least $\epsilon = 0.1$, then
 81 the sampling process is repeated for another iteration where more grasps are sampled. If a grasp is
 82 found with quality at least ϵ , then that grasp is selected along with 99 other grasps chosen at random
 83 from the sampled grasps. If the maximum number of iterations are exceeded without finding a grasp
 84 with quality ϵ , the stable pose is discarded.

85 C Sensitivity Experiments

86 C.1 Sensitivity to Grasp MDP Parameters

87 We perform sensitivity analysis of Exploratory Grasping to the grasp MDP parameters ϵ and
 88 λ_1 . For these experiments, we evaluate the policy using a set of synthetic objects with $\lambda_1 =$
 89 $\{0.001, 0.01, 0.1, 0.2\}$ and $\epsilon = \{0.1, 0.25, 0.5, 0.75, 1.0\}$ and for simplicity consider the case in
 90 which toppling is not possible. In each case, we choose a single grasp on each pose to have reliability
 91 ϵ with all other grasps having a mean parameter of 0. The results are shown in Figure 1. These results
 92 suggest that unless ϵ or λ_1 are low, Exploratory Grasping quickly converges to the optimal policy. In
 93 particular, ϵ has an outsized effect on the accumulated reward; with $\epsilon \leq 0.10$, we observe that the
 94 policy fails to approach the optimal policy regardless of λ_1 through the first 10,000 timesteps.

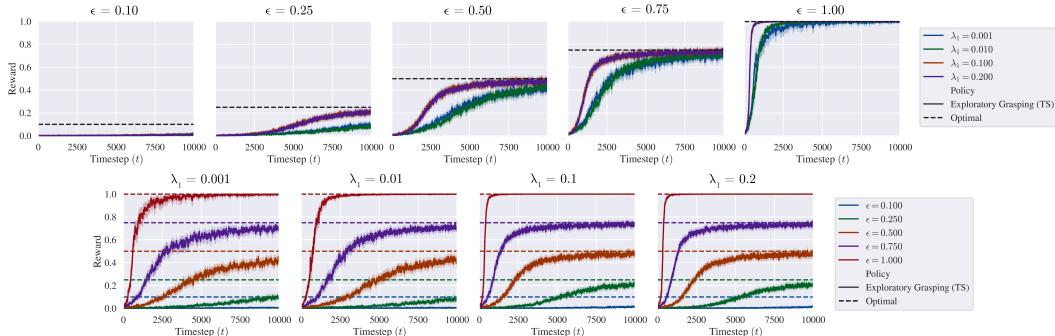


Figure 1: Sensitivity of Exploratory Grasping to the grasp MDP parameters ϵ and λ_1 , as shown across 20 synthetic objects. Unless ϵ or λ is low, Exploratory Grasping quickly converges to the optimal policy. However, when either is low, particularly ϵ , the policy converges much more slowly, taking even more than the 10,000 timesteps shown for some combinations.

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