

OOPSIEVERSE: A Safety Benchmark with Damage-Aware Simulation for Robot Manipulation

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Abstract—While robotic manipulation capabilities have advanced rapidly, physical safety remains a major barrier to deploying household robots: task success is insufficient if the robot damages itself or its surroundings. Simulation offers a harm-free alternative to costly and dangerous real-world training and evaluation, yet existing simulators lack general mechanisms to detect, quantify, and represent damage. To address this gap, we introduce OOPSIEVERSE, a unified simulation framework and benchmark for damage-aware household manipulation. At a theoretical level, OOPSIEVERSE augments an existing Markov Decision Problem with additional damage-related observations, rewards and/or termination conditions based on user preferences. OOPSIEVERSE provides damage as an explicit, physically-grounded, and task-agnostic signal by converting sources such as contact forces, temperature changes, and liquid interactions into corresponding mechanical, thermal or fluid damage. OOPSIEVERSE comprises two core elements: (1) DAMAGESIM, a simulator-agnostic framework for detecting and quantifying damage during navigation and manipulation, and (2) a suite of household tasks designed to evaluate common damage modes and distinguish between task completion and safe execution. We demonstrate the generality of our framework by instantiating DAMAGESIM in two simulators with different physics backends, OmniGibson (Nvidia Omniverse) and RoboCasa (MuJoCo). We further showcase the utility of OOPSIEVERSE across multiple use cases, including (1) guiding safer demonstration collection via real-time damage feedback, (2) learning safer manipulation policies through damage-conditioned imitation learning and reinforcement learning, (3) benchmarking the safety of state-of-the-art Vision Language Action policies, and (4) improving real-world safety of sim-to-real transferred policies. Together, our results highlight the potential of OOPSIEVERSE as an open-source foundation for systematic, scalable research on safe robot manipulation. For code and additional information, please refer to <https://robin-lab.cs.utexas.edu/oopsieverse/>

I. INTRODUCTION

A central goal of robotics is to build capable assistants that can solve complex manipulation tasks in real-world environments. However, training and evaluating such systems directly in the physical world is difficult, expensive, and potentially unsafe, particularly when interactions involve damageable objects or the robot itself. Simulation is therefore widely used as a safe alternative, enabling learning and evaluation without real-world consequences. However, this safety is largely artificial: most simulators do not model or measure the damage that would result from unsafe interactions in the real world. As a result, manipulation benchmarks typically define success solely in terms of goal completion, making no distinction between behaviors that would be benign in the real world and those that would succeed only by causing damage. Policies

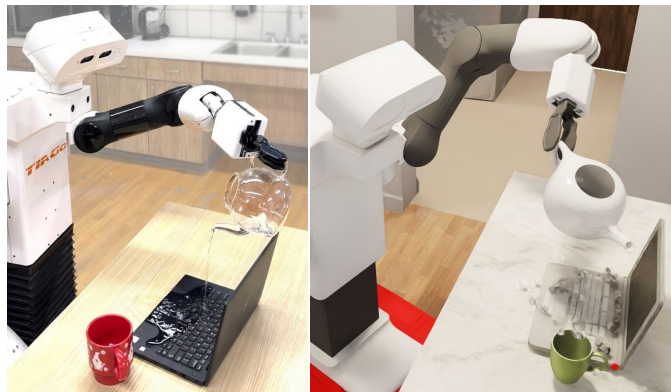


Fig. 1: *Oops, did I do that?* Robots trained and evaluated in simulation are unaware of the real-world damage their actions would cause, such as applying excessive forces, heating or freezing inappropriate objects, or spilling water on delicate items. OOPSIEVERSE addresses this gap by providing DamageSim, a general damage-aware simulation framework, including a plugin for multiple simulators (instantiated in Omniverse and MuJoCo) and OopsieBench, a benchmark of 32 household manipulation tasks for evaluating and developing safe robotic solutions.

trained or evaluated under this abstraction may therefore appear successful in simulation while relying on behaviors that would be unsafe or destructive when deployed (see Fig. 1); avoiding such behaviors requires task-specific reward shaping or hand-designed constraints that are brittle and difficult to scale across diverse environments and damage sources.

In this work, we introduce OOPSIEVERSE, a simulation framework for safety-aware robotics in household manipulation settings. Our framework enables training and systematic evaluation of safety by explicitly modeling damage incurred during task execution. OOPSIEVERSE consists of two core components: DAMAGESIM and OOPSIEBENCH.

First, DAMAGESIM is a damage detection plugin for object-centric detection, tracking and quantification of damage in manipulation and navigation tasks in household domains. DAMAGESIM models the three most common object and robot damage sources in this domain (see Fig. 2): 1) *mechanical damage*, produced by excessive forces due to impact and drops, or excessive compression or tension that deform or break objects, 2) *thermal damage*, arising from exposure to extreme temperatures, such as contact with hot surfaces, flames, or freezing temperatures, and 3) *fluid damage*, produced from

contact between liquids and objects that cause corrosion, or short-circuit electronics. For each damage source, DAmAGESIM continuously computes a unified damage value based on the simulator state (e.g., contact forces, temperatures, and liquid interactions) and object-dependent characteristics and tracks it in an object-centric *health* value. This provides a task-agnostic safety signal that can be applied uniformly across environments, tasks, objects and robots. Significantly, DAmAGESIM is not bounded to a specific simulator: we provide as part of OOPSIEVERSE implementations of DAmAGESIM in Behavior-1K/OmniGibson [1] (based on Nvidia’s Omniverse [2]) and RoboCasa/Robosuite [3, 4] (based on DeepMind’s MuJoCo [5]).

Second, OOPSIEBENCH is a suite of 32 ready-to-use household manipulation tasks designed to expose the distinction between goal achievement and safe execution measurable thanks to DAmAGESIM. The tasks span diverse scenes, objects, and interaction patterns, and include both short-horizon settings that isolate individual damage modalities and longer-horizon scenarios that require sustained safety-aware decision making. Each task admits multiple solution strategies, including unsafe goal-achieving shortcuts and alternative strategies that complete the objective without causing harm, enabling systematic evaluation of safety–performance trade-offs. We include a dataset of human-collected demonstrations as part of the benchmark. As DAmAGESIM, OOPSIEBENCH is cross-platform, including 17 tasks defined in OmniGibson and 15 tasks in RoboCasa. We believe this will broaden the accessibility to our work.

To demonstrate the wide range of uses of OOPSIEVERSE, we evaluate it across a range of learning and data-generation settings. First, we integrate live damage feedback in a teleoperation interface and show that it leads to significantly safer human demonstrations for several OOPSIEBENCH tasks. Second, we train safe imitation learning policies by using the damage feedback from DAmAGESIM to discourage using unsafer samples during the training process. Third, we use OOPSIEVERSE to develop a damage-aware reinforcement learning procedure that reduces damage, demonstrating the utility of our framework as universal safety reward. Finally, we evaluate some of the learned policies in the real world demonstrating the safer behaviors obtained thanks to OOPSIEVERSE. OOPSIEVERSE, with DAmAGESIM and OOPSIEBENCH, provides a general, practical, and scalable way to train and evaluate manipulation policies not only for task completion, but also for safety and we hope this tool facilitates research in this area.

II. RELATED WORK

Safety in Robotics. Safety has long been a central concern in robotics, with early approaches grounded in control theory and reachability analysis, including control barrier functions, Hamiltonian methods, and related formulations [6, 7, 8, 9]. These methods provide strong safety guarantees but require explicit definitions of safe and unsafe states and accurate system models, making them difficult to scale to complex, contact-rich manipulation scenarios [10].

More recent learning-based approaches aim to incorporate safety through learned reachability, value functions, recovery policies, or constraints that steer agents away from unsafe regions [11, 12, 13, 14, 15, 16, 17]. While effective in specific settings, these methods typically rely on hand-designed unsafe scenarios or task-specific cost functions, limiting their generality and making cross-task evaluation challenging [18]. OOPSIEVERSE is inspired by these approaches but targets a complementary goal: providing standardized environments and physically grounded damage models where such methods can be trained and evaluated consistently.

Safety Benchmarks. Several benchmarks have been proposed to study safe reinforcement learning. Safety Gym and its successor Safety-Gymnasium encode safety through constraint costs such as collisions or proximity to obstacles, focusing primarily on ‘navigation and low-dimensional control tasks’ [19, 20]. Similarly, safe-control-gym and GUARD standardize constrained RL problems across classic control domains [21, 22], while AI Safety Gridworlds study abstract safety failures such as reward hacking in discrete environments [23]. DSRL introduces a platform tailored for offline safe reinforcement learning [24] and ReDMan designs a benchmark for safe dexterous manipulation [25]. HASARD introduces a vision-based safe RL benchmark built on the game DOOM, with scalar safety costs for hazards such as lava [26]. While valuable for theoretical and algorithmic study, these benchmarks express safety through task-specific constraints or abstract costs rather than explicit models of physical damage.

In the context of household manipulation, large-scale simulation benchmarks such as BEHAVIOR-1K [1] and RoboCasa [3] provide diverse, realistic tasks built on simulators like OmniGibson and MuJoCo [5]. These benchmarks emphasize long-horizon manipulation and human-centric activities but define success purely in terms of goal completion; safety considerations must be encoded manually via rewards or termination conditions. In contrast, OOPSIEVERSE through the plugin DAmAGESIM augments such environments with a reusable, physics-grounded notion of damage that distinguishes safe from unsafe task execution independent of task success.

Overall, OOPSIEVERSE, with its simulation plugin DAmAGESIM and associated benchmark of safety household tasks OOPSIEBENCH, complements existing safe learning methods and simulation benchmarks by providing a unified framework that exposes the physical consequences of actions through measurable damage signals, enabling scalable evaluation and development of safety-aware manipulation policies.

III. DAmAGESIM

In this section we introduce DAmAGESIM, our simulation-based damage evaluation framework. After introducing our conceptual framing for a damage-aware POMDP formulation, we describe how we compute mechanical, thermal, and fluid damage signals from the simulator.

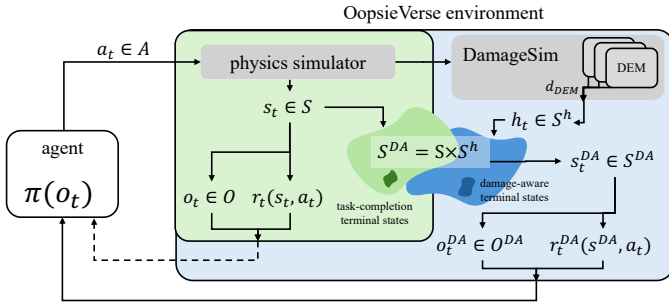


Fig. 2: **Damage-Augmented POMDP Implementation with DAMAGESIM in OOPSIEVERSE.** Conceptually, our DAMAGESIM plugin (blue) extends an existing POMDPs in simulation (green, dotted arrow to agent) by augmenting the state with *health*. The health state can in turn influence the observations and rewards, and/or provide access to new damage-aware terminal states. DAMAGESIM implements the health state to augment the original POMDP state into a *Damage Aware* state ($s^{DA} \in S^{DA} = S \times S^h$) as a per-object physical property, updated at every timestep by a set of *damage evaluator models* (DEM) that compute mechanical, thermal, and fluid damage (d_{DEM}) from simulator state and interactions, reducing per-entity health accordingly. The augmented POMDP provided by DAMAGESIM approximates better the conditions of the real-world task.

A. Damage-Aware POMDP Formulation

Robotic tasks can be formulated as Partially Observable Markov Decision Processes (POMDP) [27] defined by the tuple $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \Omega, \mathcal{O}, \gamma)$, where $s \in \mathcal{S}$ is the state space, $a \in \mathcal{A}$ the action space, $\mathcal{T}(s' | s, a)$ the transition function, $\mathcal{R}(s, a)$ the reward function, $o \in \Omega$ the observation space, $\mathcal{O}(o | s)$ the observation function, and $\gamma \in [0, 1)$ the discount factor. In most existing simulators, this POMDP is specified purely in a task-completion-centric manner: the state, reward, and termination conditions only reflect whether the task has been completed. However, this neglects a common characteristic of the real world problems: to be correctly completed, the agent should avoid damaging the objects and itself when completing the task [28]. By omitting such damage considerations from the state, the resulting behaviors in simulation may seem successful, while leading to dangers that cannot be executed in the real world.

To address this divergence between sim and real, we propose a damage-aware POMDP $\mathcal{M}^{DA}$, an augmentation of the original simulation POMDP that explicitly includes a *health* state, $h \in S^h$, enabling the approximation of damage-inducing processes absent in existing simulators (see Fig. 2). In the damage-aware POMDP, $\mathcal{M}^{DA}$, the health-augmented state space, $s^{DA} \in S^{DA} = S \times S^h$, can serve as basis to generate new damage-aware elements for other components of the POMDP—the observations, the termination conditions, the reward—, better approximating the real-world task.

In the following, we describe how this damage-aware POMDP is instantiated in practice through our DAMAGESIM plugin, and how object health is computed by tracking and updating damage based on physically grounded interaction signals.

B. Damage-Aware POMDP Implementation: DAMAGESIM

While existing specialized simulators can compute complex damage such as fracture mechanics [29] or thermal effects, they rely on ad-hoc physical computation and detailed material properties, far from what existing robotics simulators provide. Our goal in DAMAGESIM is instead to expose a portable, physically grounded, task-agnostic signal that *approximates* real-world damage, can be computed based on common values provided by robotics simulators (forces, motion, ...), and can be used consistently for evaluation and learning. To achieve this goal, we represent damage through an explicit, unifying “health” state, an additional object-centric state variable that keeps the original task dynamics intact while still modeling the irreversible consequences of unsafe interactions. Health is tracked for each object and the robot by aggregating and accumulating damage in their composing links caused by different sources such as mechanical, thermal, and fluid elements.

Concretely, we assume the simulated scene contains multiple objects, $\mathcal{E} = \{e_1, \dots, e_N\}$, each one composed of one or multiple links, $(l_1 \dots, l_M)$, whose common physical state (pose, velocity, forces acting on it through contact, etc.) $s_{e_i}^{l_j}$, can be retrieved from an underlying physics simulator. To augment this state, we keep track of the health of each link of an object, $h_{e_i}^{l_j}$, and associate an object health to the minimum health of its links, $h_{e_i} = \min(h_{e_i}^{l_1}, \dots, h_{e_i}^{l_M})$. This provides a semantically meaningful health understanding: an object (or the robot) is fully damaged when one or more of its links are fully damaged. We rank health to range between a maximum value, h_{MAX} (completely undamaged), and 0 (completely damaged) for all objects and links, and use a unifying scale for all objects ($h_{MAX} = 100$) that enables easy comparisons of health state. The overall environment health state at time t is given by: $h_t = \{h_{e_1}, \dots, h_{e_N}\}$. The link health values are updated using a set of k *Damage Evaluation Models* (DEM). Each DEM models a specific source of physical damage (e.g., mechanical damage, thermal damage, etc.) using the current simulator state, s_t , to output a damage value d_{DEM_k} . The aggregated damage value across all DEMs represents the decrease in the object’s health: $h_{e_i}(t) = h_{e_i}(t-1) - \sum_k d_{DEM_k}(t)$.

Mechanical Damage Evaluation Model: Mechanical damage captures contact-induced harm that leads to undesired effects such as cracking, deformation, or breakage. In household manipulation, such damage typically arises from two classes of interactions: i) *impulsive* events that causes rapid changes in an object’s motion (e.g., collisions or drops), and ii) *sustained* or *constrained* contacts in which large forces are applied with little or no acceleration (e.g., compressing, stretching, or pushing against a fixed surface). While these regimes can be characterized using detailed physical quantities—such as momentum change or structure load analysis—computing them accurately is computationally expensive and unnecessary for distinguishing safe from unsafe behaviors. Instead, we approximate both regimes using a unified proxy derived from states available in standard robotics physics simulators, producing health-reducing

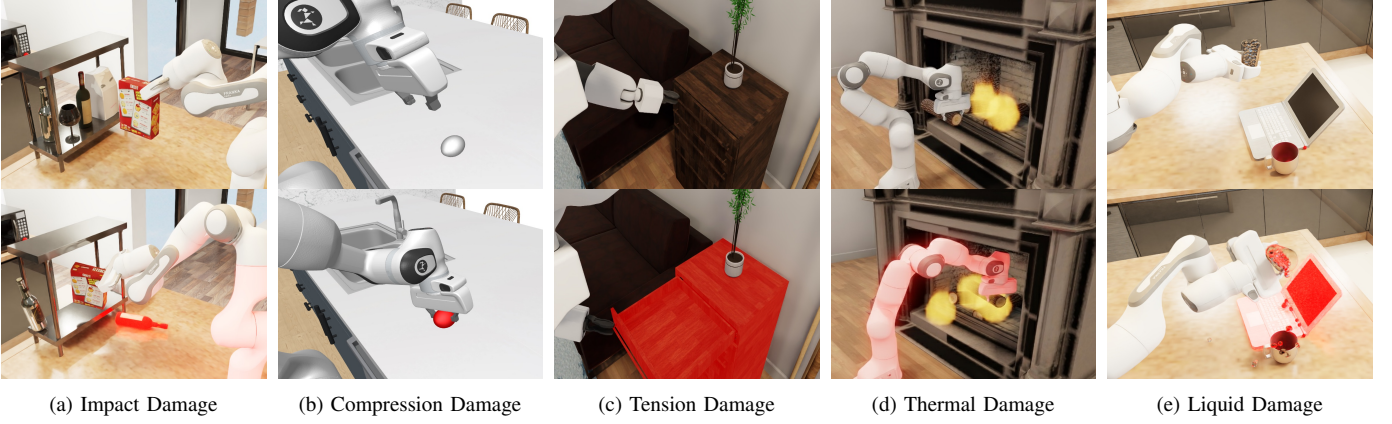


Fig. 3: **Types of physical damage detected by DAMAGESIM.** Object-level damage caused by excessive a) impact, b) compression forces, or c) tensile forces, by d) temperature changes, or by e) water spills are measured and tracked by our simulation plugin, DAMAGESIM, enabling learning and evaluating their effect in robot behaviors. In the pictures, the top row shows a state without damage while in the bottom row the pictures depict damaged objects (*most left: wine bottle, second left: egg, center: cabinet with drawer, second right: robot arm, right: laptop*), indicated by levels of red color.

effects that are qualitatively consistent with real-world object degradation.

Computing the effect of impulsive vs. constrained/sustained forces requires understanding the kinematic (motion) nature of the links. For each link, at each physics step t , we obtain from the physics simulator the set of contact forces acting on the link, $\{\mathbf{f}_1(t), \dots, \mathbf{f}_K(t)\}$, and the link’s kinematic information, which includes the link acceleration, $\mathbf{a}(t)$ (in the following, we drop the link suffixes for readability). We can then decompose each contact force, $\mathbf{f}_k(t)$, into components parallel and orthogonal to the direction of acceleration $\hat{\mathbf{a}}(t)$: $\mathbf{f}_{\parallel,k}(t) = (\mathbf{f}_k(t) \cdot \hat{\mathbf{a}}(t)) \hat{\mathbf{a}}(t)$ and $\mathbf{f}_{\perp,k}(t) = \mathbf{f}_k(t) - \mathbf{f}_{\parallel,k}(t)$, and aggregate them across contact points:

$$F_{\parallel}(t) = \sum_k \|\mathbf{f}_{\parallel,k}(t)\|, \quad F_{\perp}(t) = \sum_k \|\mathbf{f}_{\perp,k}(t)\|.$$

Intuitively, $F_{\parallel}(t)$ captures contact aligned with the change in motion (impulsive interactions), while $F_{\perp}(t)$ captures the remaining contact that is not aligned with it (i.e., sustained/constrained loading).

Inspired by the materials physics, we approximate the effective mechanical load acting on the link as $\varepsilon_{\text{mech}}(t) = \alpha F_{\parallel}(t) + \beta F_{\perp}(t)$, where α and β are user-specified coefficients that control sensitivity to sustained versus impulsive loading [30]. For example, a paper cup typically deforms more easily under sustained compressive loading (e.g., squeezing or crushing) than under brief impulsive contact (e.g., dropping it). Finally, DAMAGESIM models the incremental mechanical damage at time t as

$$d_{\text{mech}}(t) = \Lambda_{\text{mech}} \max(\varepsilon_{\text{mech}}(t) - \mathcal{E}_{\text{mech}}, 0),$$

where $\mathcal{E}_{\text{mech}}$ represents a minimal load threshold analogous to a material’s yield or fracture limit [29], and Λ_{mech} scales the rate at which damage accumulates beyond this threshold [31]. Both parameters can be specified per link to reflect material properties: brittle (fragile) objects are modeled with lower

thresholds and higher damage scaling, while ductile objects use larger threshold and lower scaling. Fig. 3 a), b) and c) depict common cases of mechanical damages due to impact, compression and tension obtained by our mechanical damage evaluation model.

Thermal Damage Evaluation Model: Thermal damage captures harm from exposure to temperatures outside an object’s safe operating range (e.g., melting, burning, or freeze damage). Modeling damage due to thermal harm is thus only possible in simulators that keep track of temperature and heat/cold sources. Therefore, while our model is object-centric and general, we provide an implementation of the thermal damage evaluation model of DAMAGESIM only in OmniGibson [11], which provides the necessary temperature readings.

Similar to our mechanical damage evaluation model, our thermal evaluation model evaluates if the temperature of an object goes over/under physically grounded thresholds and scales the damage according to material properties. At each timestep t , we retrieve the object temperature (OmniGibson provides only temperature per object, not link), $T(t)$, from the underlying physics simulator. Thermal damage is then modeled in DAMAGESIM as:

$$d_{\text{therm}}(t) = \begin{cases} \Lambda_{\text{hot}}(T(t) - \mathcal{T}_{\text{hot}}), & T(t) > \mathcal{T}_{\text{hot}}, \\ \Lambda_{\text{cold}}(\mathcal{T}_{\text{cold}} - T(t)), & T(t) < \mathcal{T}_{\text{cold}}, \\ 0, & \text{otherwise,} \end{cases}$$

where the thresholds ($\mathcal{T}_{\text{hot}}, \mathcal{T}_{\text{cold}}$) specify the range of tolerated temperatures, and $(\Lambda_{\text{hot}}, \Lambda_{\text{cold}})$ indicate how quickly damage accumulates beyond the range based on material properties, e.g., cookware exhibits high $\mathcal{T}_{\text{hot}}$ and/or small Λ_{hot} , while burnable plastic items like toys are defined with a lower $\mathcal{T}_{\text{hot}}$ and larger Λ_{hot} . Both thresholds can be made very large positive/negative values to indicate that an object cannot be damaged by fire or by freezing temperatures. Fig. 3d depicts an example of the results of our thermal damage evaluation model.



Fig. 4: **Tasks in OOPSIEBENCH.** The image show 21 different tasks instantiated in Behavior-1k/OmniGibson (built on Nvidia Omniverse) and/or RoboCasa/Robosuite (built on DeepMind MuJoCo). The complete task suite includes 32 tasks combining both simulators spanning diverse household objects, scenes, and interaction patterns, and is designed to expose agents to potential hazards across multiple damage modalities, including mechanical (impact, compression, tension), thermal, and fluid interactions (main damage modality per task is indicated with icons at the top left corner of each image).

Fluid Damage Evaluation Model: Fluid damage models harm from liquid exposure (e.g., swelling, contamination, or short-circuiting). Similar to thermal damage, fluid damage can only be modeled for simulators that represent fluids; we provide an implementation of the fluid damage model in DAGESIM only in OmniGibson, which provides the necessary fluid computation.

Analogous to the previous evaluation models, in our fluid damage evaluation model we compute whether the fluid particles in contact with a link go over a given threshold and scale the effect into damage based on the resistance of the link to liquid harm. At each timestep t , we retrieve the amount of liquid particles in contact with each link, $c_\ell(t)$. DAGESIM then models fluid damage as:

$$d_{\text{fluid}}(t) = \Lambda_{\text{fluid}} \max(c_\ell(t) - C_{\text{fluid}}, 0),$$

where threshold C_{fluid} controls how much exposure is tolerated before damage begins, and Λ_{fluid} controls the rate at which damage accumulates thereafter. Waterproof objects can be modeled with large C_{fluid} and/or near-zero Λ_{fluid} , while electronics or liquid-delicate materials are defined with a low C_{fluid} and larger Λ_{fluid} . Fig. 3e depicts an example of the damage due to fluid obtained with our fluid damage evaluation model.

IV. OOPSIEBENCH

We introduce a suite of **32 task instances** across the **two simulators** (OmniGibson/OmniVerse for B1K tasks and MuJoCo for RoboCasa tasks), corresponding to **21 unique task designs** (see Fig. 4). The suite is built to (i) expose policies to *physically damaging failure modes* that arise naturally in household manipulation, and (ii) make the safety distinction *measurable*: for most tasks there exists an easy, tempting strategy that completes the goal but risks damage, alongside a safer strategy that typically requires more careful interaction (e.g., gentler contacts, safer approach directions, or avoiding hazardous regions/objects).

We include a shared core of short- and medium-horizon tasks instantiated in both simulators, spanning common kitchen

and household interactions such as opening doors/drawers, operating appliances, pick-and-place, grasping and shelving fragile objects, wiping a surface, and navigation followed by placement. We additionally include simulator-specific tasks that stress damage modes that are more naturally supported by a given backend or scene library. In RoboCasa, we include longer-horizon composite tasks (see Appendix) that chain multiple atomic skills in kitchen settings. In OmniGibson, we include tasks that explicitly stress *fluid* and *thermal* risks in contact-rich settings (e.g., pouring water near electronics, interacting with running water, and operating near fire/heat), as well as long-horizon activities adapted from BEHAVIOR-style household scenarios.

Across the suite, damaging shortcuts arise from realistic interaction pressures: slamming or forcing articulated objects (mechanical damage), operating near liquids and sensitive objects (fluid/electrical risk), and handling objects near heat sources (thermal damage). This structure lets us evaluate not only whether a policy reaches the goal, but whether it does so *without* incurring damage as quantified by OOPSIEVERSE. We provide the full task list, simulator instantiations, and per-task metadata in the Appendix.

Furthermore, as part of OOPSIEBENCH, we provide 90 demonstrations across five tasks (*Shelve Cereal Box*, *Lift Egg*, *Add Firewood*, *Pour Water*, *Wipe Countertop*), evenly split between demonstrations collected with and without the DAGESIM plugin (see Fig. 6 and Sec. V-A).

V. EXPERIMENTS

Our experiments are designed to demonstrate the utility and versatility of OOPSIEVERSE as a safety framework for robotic manipulation. We validate our framework by demonstrating the following use cases across two simulators (OmniGibson and Robocasa):

- A. Does OOPSIEVERSE provide a sufficiently accurate signal to collect safer data and/or to train safer policies with imitation learning (Sec. V-A)?

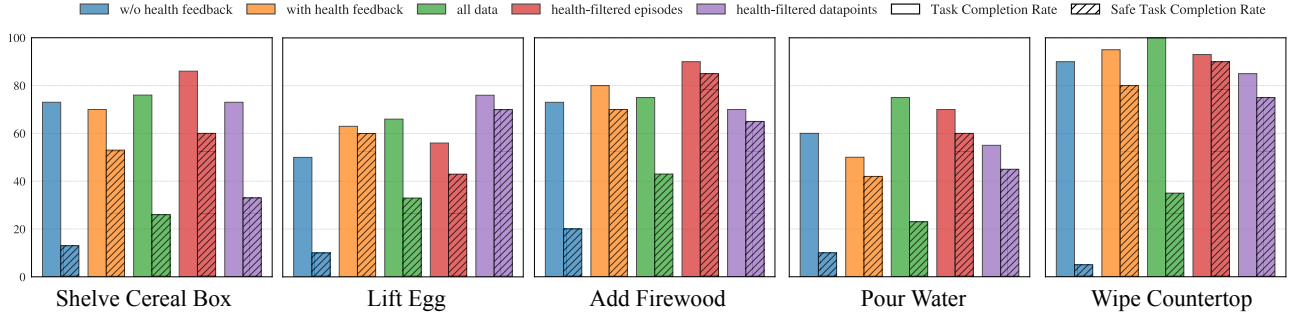


Fig. 5: **Imitation Learning with OOPSIEVERSE**. Task completion rate (solid bar) and safe task completion rate (striped bar) for policies trained with only demonstrations collected without health feedback (blue), only demonstrations collected with health feedback (orange), all the demonstrations (green), all demonstrations filtering entire episodes (red) and individual datapoints (purple) with health losses > 5 , for 5 tasks from OOPSIEBENCH. While using all demonstrations achieve higher task completion rates, they lead to significant unsafe execution (low safe task completion). Variants of IL using health information obtain higher safe task execution with minimal drop in task completion, indicating that OOPSIEVERSE’s information is a strong source for safe IL policy learning.

- B. Can OOPSIEVERSE’s extended state be used to define safety-related reward to train/finetune policies with reinforcement learning (Sec. V-B)?
- C. Does OOPSIEVERSE reveal safety gaps in state-of-the-art VLA models that standard simulators miss (Sec. V-C)?
- D. Do the safety behaviors trained in OOPSIEVERSE transfer to real robot tasks (Sec. V-D)?

A. OOPSIEVERSE for Imitation Learning

We investigate whether OOPSIEVERSE’s damage-aware feedback can improve imitation learning in two distinct ways: by improving demonstration quality at collection time through real-time feedback, and by enabling automated curation of safe data from mixed-quality datasets without manual annotation. We consider five tasks spanning different damage failure modes from our task suite: shelving an item (mechanical damage), pouring water near sensitive objects (fluid damage), adding firewood to a fireplace (thermal damage), wiping dirt from a table (mechanical damage), and picking up a fragile egg (mechanical damage).

For each task, human operators collected demonstrations under two conditions. In the health-feedback condition, operators viewed real-time health bars provided by DAGESIM during teleoperation (see Fig. 6 for a visualization of the interface). In the no-health-feedback condition, operators can only observe the video frames without the health feedback, matching the standard simulator teleoperation setup. In the health-feedback condition, DAGESIM augments the interface with real-time safety visualizations in two ways. First, each damage-tracked object is associated with a live health bar that initializes at 100 and decreases as damage accumulates. This allows operators to immediately identify unsafe interactions, including failures that may occur outside the current camera view (e.g., the wine bottle falling behind furniture and being out of frame in Fig. 6). Secondly, DAGESIM can also optionally apply damage-based coloration, progressively tinting damaged objects red as health decreases. This provides an intuitive cue about which parts of the scene are experiencing unsafe interactions. Together,

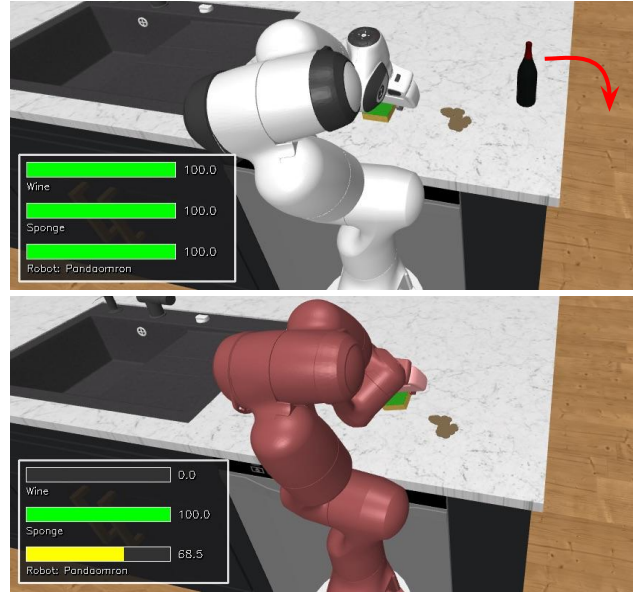


Fig. 6: **Real-time damage visualization provided by DAGESIM**. The interface tracks and displays to the teleoperator the per-object health as the interactions occur, enabling immediate identification and reaction to unsafe behaviors. It displays the health in two complementary ways: health bars, which allow for visualizing the health of objects out of frame, and as object coloration, which gives an intuitive cue of damage. These overlays are available in both simulators and can be enabled alongside standard teleoperation or policy execution.

health bars and damage coloration provide complementary feedback to the user without changing the existing physics of the simulator. Using these demonstrations, we train flow-based [32] imitation learning policies with action chunking under five data regimes:

All Data: keeps all demonstrations regardless of collection condition, establishing baseline performance without any data curation.

With Health Feedback: exclusively retains demonstrations collected with live health feedback, testing whether real-time feedback during collection provided by OOPSIEVERSE improves imitation learning policy safety.

Without Health Feedback: keeps demonstrations collected without feedback, providing a lower bound comparison on safety.

Health-Filtered Episodes: removes episodes from the full dataset where any object’s health falls below 95 at any timestep, testing whether episode-level curation can recover safety from mixed-quality data.

Health-Filtered Datapoints: removes individual timesteps from the full dataset whose subsequent N steps incur damage exceeding a certain threshold. This filtering strategy is a middle ground between *All Data* and *Health-Filtered Episodes*. It preserves more data, but is myopic if N is small. In this experiment, we set $N = 8$, which is the same as the action chunk length.

Fig. 5 presents evaluation results averaged over 30 rollouts per task. We report two metrics to disentangle task performance from safety: *Task Completion Rate* measures success regardless of damage, while *Safe Task Completion Rate* requires both task success and all object health remaining above 95. The gap between these metrics quantifies how often policies succeed through unsafe behaviors. Results reveal a consistent pattern across all five tasks: policies trained on unfiltered data (green) or data collected without live feedback (blue) achieve high task completion rates but exhibit a substantial gap to safe task completion, indicating that these policies complete tasks through unsafe behaviors that standard evaluations would overlook. For instance, on *Wipe Countertop*, the unfiltered policy achieves perfect task completion but only 35% safe completion. In contrast, policies trained on data leveraging OOPSIEVERSE’s damage signal—whether through real-time feedback during collection (orange) or post-hoc filtering (red, purple)—substantially improves the safe task completion rates. Fig. 7 visualizes the trajectory distributions for the *Shelve Cereal Box* task, comparing policies trained without health feedback (red) versus with health-filtered episodes (green). The policy trained on filtered data exhibits a tighter distribution concentrated toward the right side of the shelf—a region free of fragile objects. In contrast, the unfiltered policy produces more trajectories that frequently place the cereal box near or against fragile items. These results confirm that OOPSIEVERSE provides sufficiently accurate feedback to guide both human operators in real time and automated curation after the fact toward safer imitation learning.

B. OOPSIEVERSE for Reinforcement Learning

We next investigate whether OOPSIEVERSE’s damage signal can serve as a reward for training safe policies via reinforcement learning. We evaluate three settings of RL training: steering a pre-trained flow-matching policy, fine-tuning a pre-trained Gaussian policy, and training from scratch.

Across all settings, we augment the task reward with a damage penalty derived from OOPSIEVERSE: whenever damage

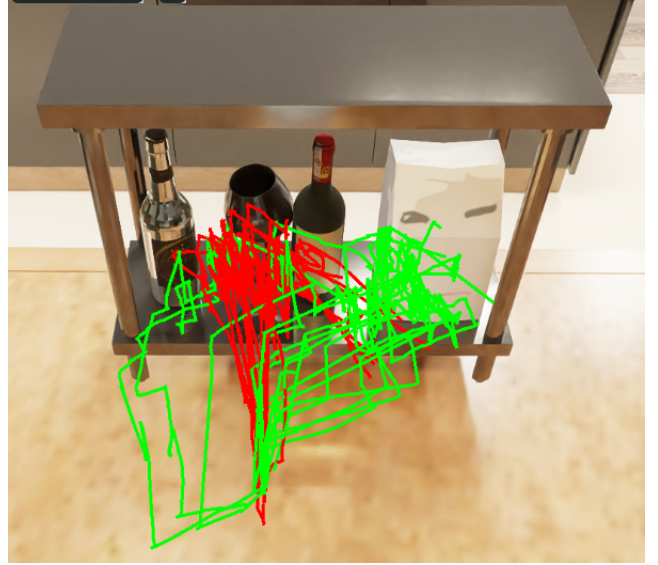


Fig. 7: **Trajectory differences based on damage feedback.** Trajectories generated by the policy trained on w/o health feedback dataset that is not aware of damage (red) constantly pushes towards fragile objects. In contrast, the policy trained with health-filtered episodes (green) more frequently directs its trajectories toward the paper bag—even though interaction is required—resulting in safer task completions.

is detected to any object, the agent receives a negative reward proportional to the damage caused. In our setup, we use a simple additive form of the two rewards

$$r(s_t) = \mathcal{R}_{\text{task}}(s_t) - w(d_{\text{mech}}(t) + d_{\text{therm}}(t) + d_{\text{fluid}}(t)),$$

where $\mathcal{R}_{\text{task}}$ denotes the task reward and w controls the weight of the damage penalty. This formulation encourages the policy to complete tasks while minimizing damage across all modalities.

We apply Diffusion Steering (DSRL) [33] to the IL policy trained on w/o health feedback from the previous section on the *Shelve Cereal Box* task. DSRL optimizes a learnable initial noise distribution for the flow-matching policy, steering sampled trajectories toward safe behavior without modifying the underlying policy weights. Second, we fine-tune a Gaussian policy pre-trained on mixed-quality demonstrations for the *Move Cup of Water* task, a modified version of *Pour Water*. Third, we train an RL policy from scratch on *Place Plate*, to verify that OOPSIEVERSE’s reward signal is sufficient for learning safe behaviors without any demonstration data. All settings use PPO [34] for optimization; hyperparameters are provided in Appendix.

Fig 8 summarizes evaluation results using the same metrics as Section V-A. DSRL improves safe task completion on *Shelve Cereal Box* from 13% to 33%. Fine-tuning the Gaussian policy yields a larger gain on *Move Cup of Water*, increasing safe success from 20% to 100%. These two fine-tuning results demonstrate that IL policies can be steered toward safety using the signals derived from DAMAGESIM. Finally, training from scratch with DAMAGESIM’s damage penalty achieves over 80% safe task completion compared to almost 0% when using

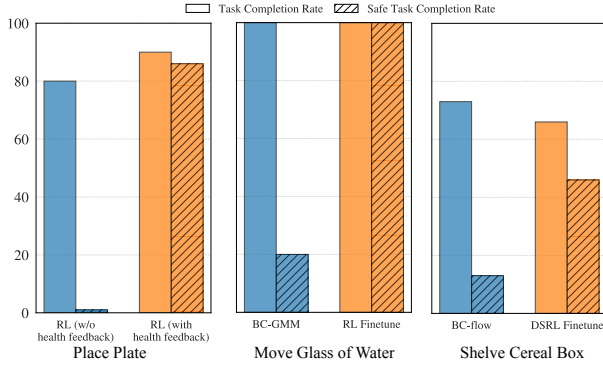


Fig. 8: **Reinforcement Learning with OOPSIEVERSE**. We evaluate three RL variants across 3 tasks: training from scratch, fine-tuning a BC-GMM policy, and DSRL fine-tuning. Comparing safe task completion rates between the baseline that does not use OOPSIEVERSE’s health information (blue) and methods that do (orange), shows that OOPSIEVERSE enables learning safer policies both from scratch and through the fine-tuning of existing policies.

task reward alone. These results confirm that OOPSIEVERSE provides a practical reward signal for training safe policies with RL—whether refining existing policies or training new ones—complementing its utility for imitation learning.

C. Benchmarking VLAs on OOPSIEVERSE

We demonstrate OOPSIEVERSE’s ability to evaluate the safety of modern manipulation policies. We benchmark a state-of-the-art Vision Language Action (VLA) model, NVIDIA GR00T [35], which achieves strong task performance across a wide range of household manipulation scenarios. Our goal is to assess whether such high-performing policies also behave safely, or whether task success masks damaging interactions that would be unacceptable in real-world settings.

We evaluate GR00T (used off-the-shelf, without any task-specific fine-tuning) on tasks from both OmniGibson and RoboCasa. OmniGibson tasks are long-horizon household activities, and to focus evaluation on contact-rich interactions where damage is most likely to occur, we benchmark representative manipulation subtasks from each activity (reported in parentheses). RoboCasa provides a set of shorter-horizon kitchen manipulation tasks, enabling controlled evaluation in atomic interaction settings. We additionally report results for pi0 [36] in Appendix E.

We evaluate each task over 30 episodes. For every rollout, we record three metrics: **Task Completion**, indicating whether the task goal is achieved; **Safe Completion**, indicating successful task completion without incurring any damage events as measured by DAMAGESIM; and **Average Environment Health**, defined as the mean normalized health of the environment over the rollout. Together, these metrics distinguish policies that complete tasks from those that complete tasks safely.

Across both simulators, these results reveal a consistent gap between task performance and safety. Even when GR00T achieves high task success, it frequently incurs damage, leading to substantially lower safe success rates and degraded environment health. This highlights the limitation of evaluating VLAs solely based on task completion and motivates the need

TABLE I: VLA (Gr00t) evaluation on OOPSIEBENCH. C: Task Completion Rate, SC: Safe Task Completion Rate

Task	C [%]	SC [%]	Avg. Health
(B1K-OG) attach camera	8	4	71.25
(B1K-OG) open microwave door	92	4	33.55
(B1K-OG) pick up scrubber	28	8	85
(B1K-OG) ignite wood	60	0	8
(RC-MJC) Open Single Door	92	32	50.73
(RC-MJC) Turn On Microwave	92	12	41.48
(RC-MJC) PnP: Counter to Microwave	20	20	29.28
(RC-MJC) Turn On Stove	88	8	0.2192

for benchmarks and learning signals that explicitly account for damaging interactions.

D. Sim-to-real Transfer from OOPSIEVERSE

Finally, we test whether safety improvements enabled by DAMAGESIM transfer to the real world. We train policies in OmniGibson for two tasks—*shelve cereal box* and *pour water*—and evaluate two methods: *without_live_feedback* (damage-unaware) and *filtered_episodes* (damage-aware) on a Franka Panda robot. For both tasks, the input to the policy is proprioception and low-dim states (i.e. object poses). We directly transfer the corresponding low-dim policies from sim to real. The action space is 6 dof delta eef pose and gripper open/close. We use a OSC Pose controller to control the Emika Franka Panda robot.

Because simulator health is not directly observable on hardware, we instead report a qualitative safety outcome indicating whether the task is completed without observable object damage (e.g., breakage, spills onto sensitive objects, or unsafe contact). For the shelving task, success is defined as placing the cereal box on the shelf, while for the pouring task, success requires pouring at least 10ml into the cup. Unsafe behavior includes toppling fragile objects or spilling water onto a laptop. Aggregated across both tasks (10 trials per method per task) *filtered_episodes* achieves a 75% task completion rate, 65% safe completion rate and an unsafe behavior rate of 15%, compared to 70% and 5% and 75% respectively for *without_live_feedback*—a 60% reduction in unsafe behavior rate while maintaining comparable task performance. This shows that explicit damage signals obtained via OOPSIEVERSE can translate into improved safety on hardware.

VI. LIMITATIONS AND CONCLUSION

In this work we addressed the problem of evaluating and training safe robot policies in simulation. We presented OOPSIEVERSE, a novel framework composed of DAMAGESIM, a damage-aware simulation plugin implemented in two widely used simulators (OmniVerse and MuJoCo), OOPSIEBENCH, a benchmark with 32 tasks and 450 demonstrations collected with and without live damage feedback to the teleoperators. Through a comprehensive evaluation, we demonstrate the utility of OOPSIEVERSE to train imitation and reinforcement learning policies, evaluate VLAs for safety, and transfer safe behaviors to the real world. OOPSIEVERSE is not without limitations:



Fig. 9: **Sim-to-real transfer of policies trained in OOPSIEVERSE.** We evaluate baseline IL policy (without health feedback) with the IL policy with health-filtered episodes on Panda robot. The baseline IL policy often performs unsafe behaviors like spilling water on the laptop or pushing a fragile bottle over the shelf. Whereas the damage-aware filtered-episode IL policy learns safer behaviors. The damage-aware IL policy results in a 60 % safer execution as compared to the baseline IL policy. This shows that OOPSIEVERSE can enable transferring safer policies to the real world.

first, our damage evaluation models are approximations of the underlying physical processes (e.g., mechanical fracture, burning effects, liquid dynamics) and therefore, the computed damage may differ from the accurate one. However, through our evaluation we indicated that the approximations are sufficient to represent with enough fidelity the real world damage sources. Moreover, while many of the values can be inferred from the material properties of the objects, the computation of damage requires a manual annotation from the users to define per link/object parameters. We believe this process can be greatly automated making use of the common sense knowledge in LLMs and VLMs. Even with these limitations, we hope OOPSIEVERSE to facilitate research and development of safer robotic solutions.

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