World Modeling Without Resets

Taj Gillin[1*], Lucas Maes[1,2*], Randall Balestriero[1*]

[1]Brown University, [2]Mila *Equal Contribution

Motivation

Continual learning is typically framed as sequentially **acquiring new tasks** without forgetting previous knowledge. However, this task-centric view poorly suits world models, which learn **visual dynamics rather than task-specific policies**.

Potion Brewing Environment is designed specifically to test **continual learning capabilities in world models through compositional generalization** rather than task acquisition. World models should be evaluated on their ability to **understand and recombine visual primitives in novel ways**, not just on learning new isolated tasks.

Environment Design

A 2D top-down physics-based environment inspired by "Overcooked." An agent (square) must create potions by:

- Collecting colored essences (circles)
- Processing them through compositional tools
- Combining essences in a cauldron
- Delivering completed recipes

The tools consist of:

- **Enchanter**: Adds diagonal stripe patterns to any essence or combination. The pattern applies universally regardless of underlying essence color.
- **Refiner**: Adds dot patterns. Functions same as enchanter.
- **Cauldron**: Combines essences (including refined and enchanter) into a entity displayed as pie slices.

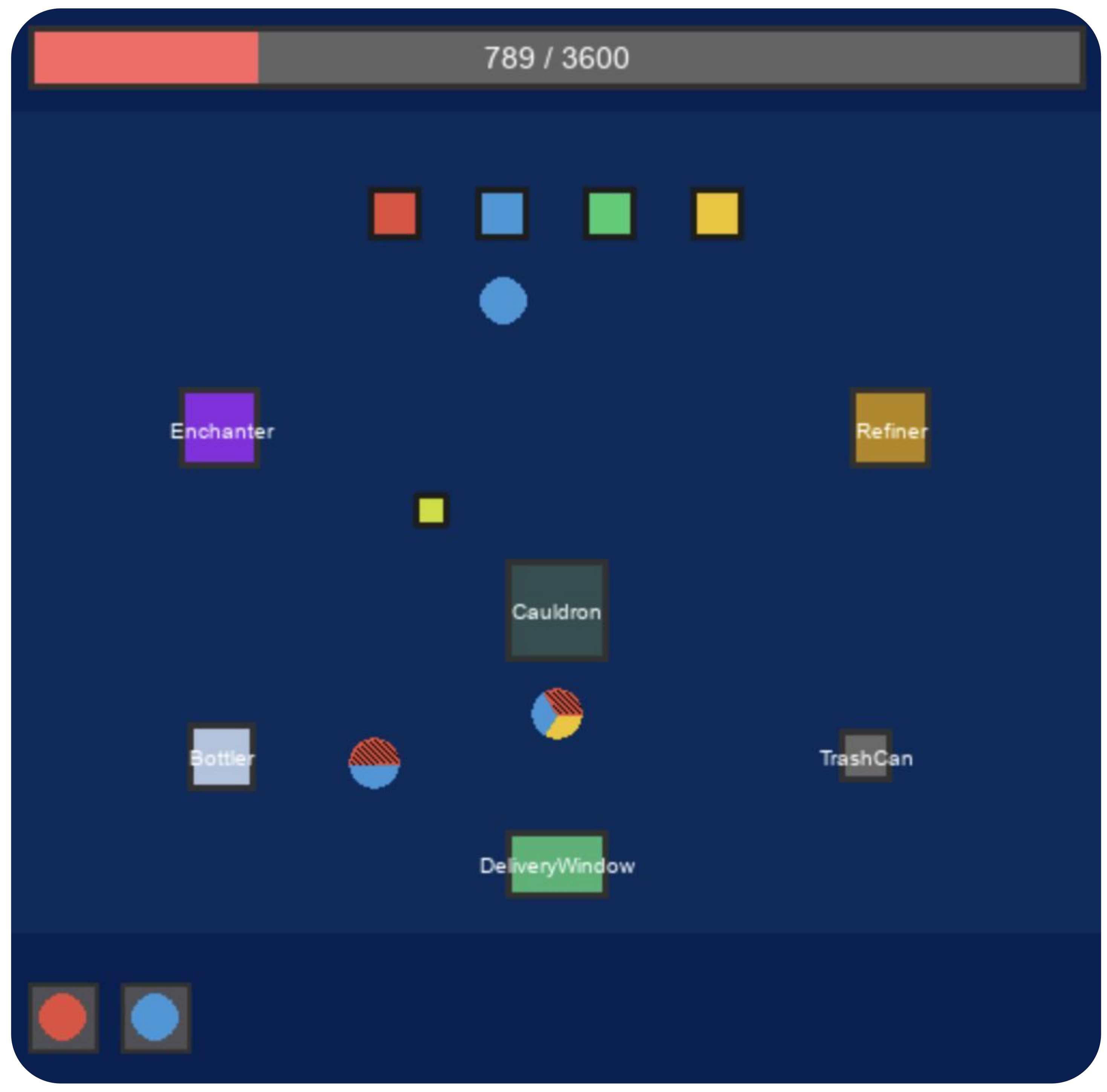
  Bottler: Adds a bottle pattern around any essence. Once bottled, no other tools can be applied.

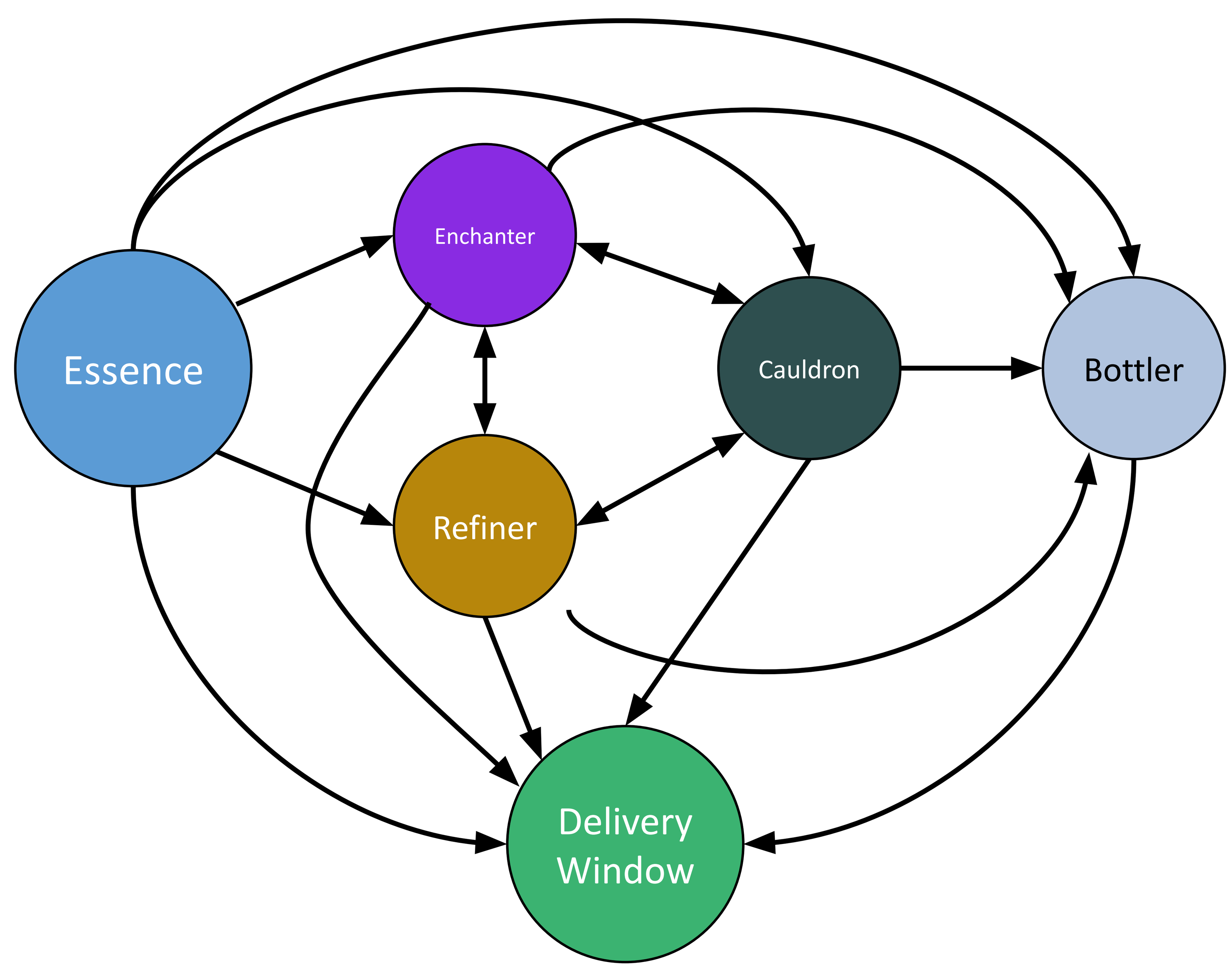
All interactions occur through **physics-based collisions**. This project is part of the larger stable-worldmodel project.

Progressive Difficulty

The environment consists of rounds with increasing complexity. The entire game is a single, continuous episode, emulating real-world continual learning scenarios. Each round has a time limit on which the episode terminates, with sparse rewards (only rewarded for completing a round) that test long-horizon planning.

The Potion Brewing Lab





Future Directions

This is a work in progress. We plan to release curated datasets including trajectories, ground truth states, and train/test splits.

Environment extensions include layouts with walls (spatial complexity), pixel art graphics (visual complexity), and partial observability. These maintain identical physics while testing robustness.

If you are interested in collaborating, please reach out to `taj_gillin@brown.edu`

References

Gaoyue Zhou et al. Dino-wm: World models on pre-trained visual features enable zero-shot planning, 2025.
Oriane Siméoni et al. Dinov3, 2025.