# Exploiting Embodied Simulation to Detect Novel Object Classes Through Interaction

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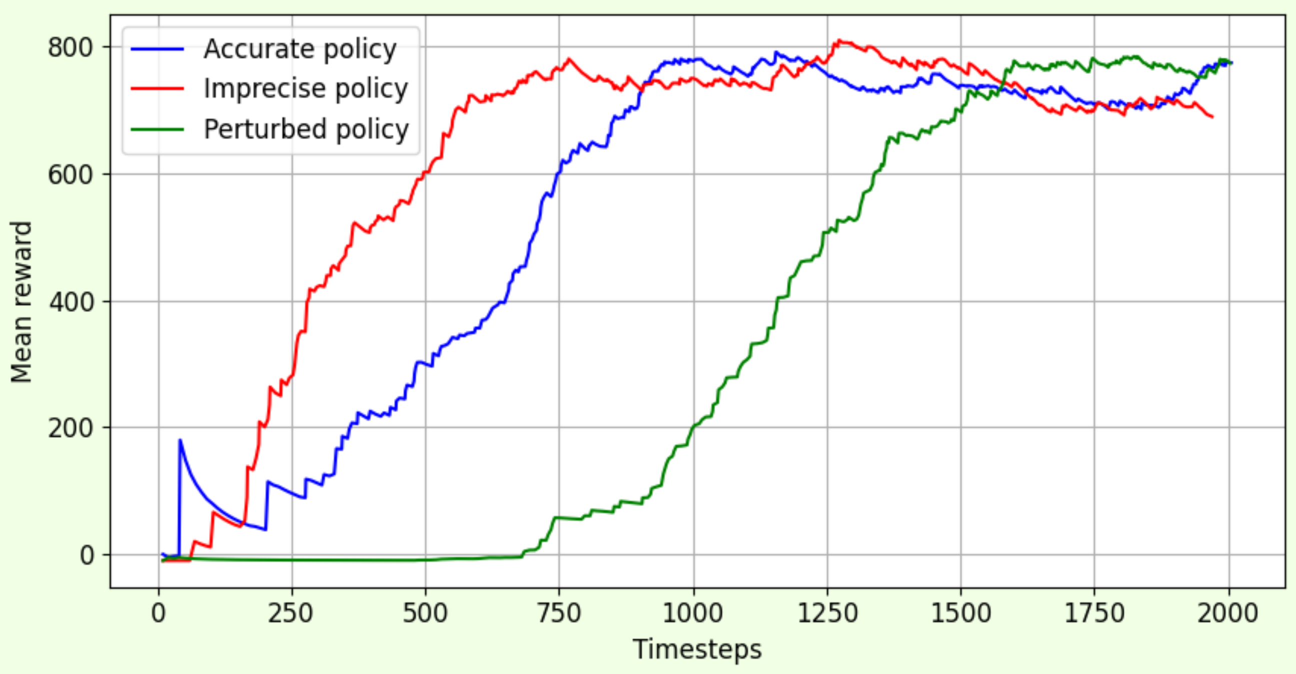
## Introduction

- Humans are efficient at seeking out maximally-informative experiences
- We rapidly expand concept vocabulary with few to no examples
- Artificial neural networks require large numbers of samples to train
- They do not easily expand to accommodate new concepts in real time
- We present a novel method to rapidly detect the introduction of a new class of object into an interactive environment
- We mix reinforcement learning, embodied simulation, and analysis of high-dimensional embedding spaces to determine when object behavior is inconsistent with the behavior of known objects
- Machine learning and simulation can be leveraged for their strengths to bootstrap new models
- Providing implicit information about *habitats* and *affordances* to the model is critical to performance

## Methodology

1. Train TD3 policy to perform stacking task with known object type (cube)
2. Attempt to use any object presented in the same task using trained policy
3. Use differences in the behaviors of various objects to identify if object instance is different enough from all known objects to constitute a new class

## Policy Training




## Data Gathering

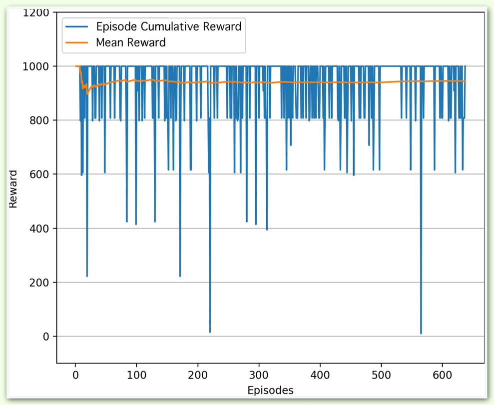
- Evaluate policy trained with cubes on different object types that have distinct stacking behavior

Sample test objects: sphere, cylinder, capsule (not shown: cube, small cube)

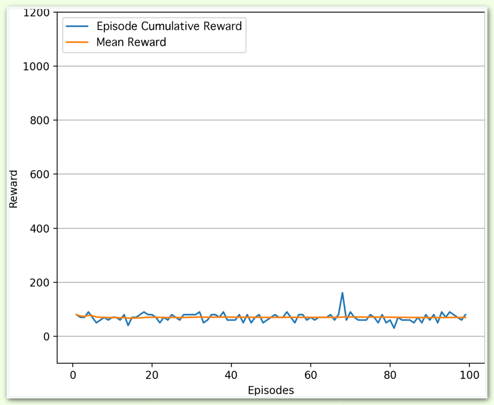
- 1,000 timesteps per object
- Small "jitter" to simulate object release
- Store: object type, rotation at episode start and at episode end, angle between object upright and world upright at start and at end, action executed, jitter vector, state observation, attempt reward, episode reward, episode mean reward

$$\left[\begin{array}{l}\textbf{cylinder}\\ \text{TYPE} = \left[\begin{array}{l}\text{HEAD} = \textbf{cylindroid}\\ \text{COMPONENTS} = \textbf{nil}\\ \text{ROTATSYM} = \{Y\}\\ \text{REFLSYM} = \{XY, YZ\}\end{array}\right]\end{array}\right]$$

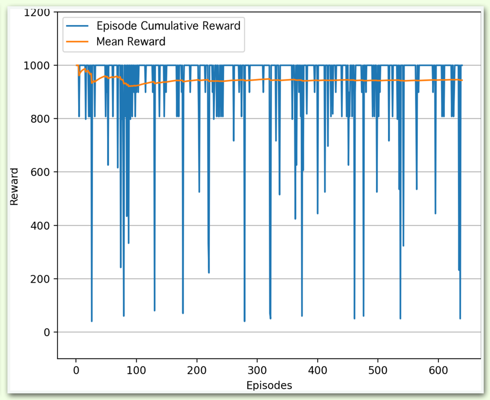
VoxML type semantics for cylinder



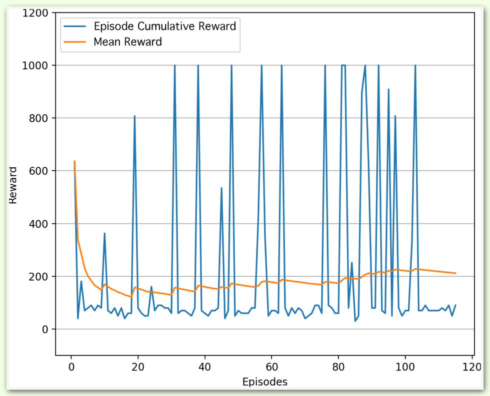
Cube reward plot



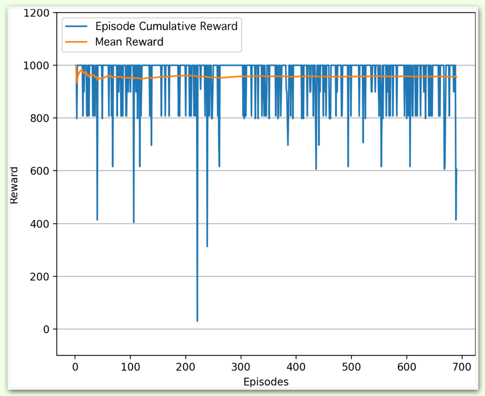
Sphere reward plot



Cylinder reward plot



Capsule reward plot



Small cube reward plot

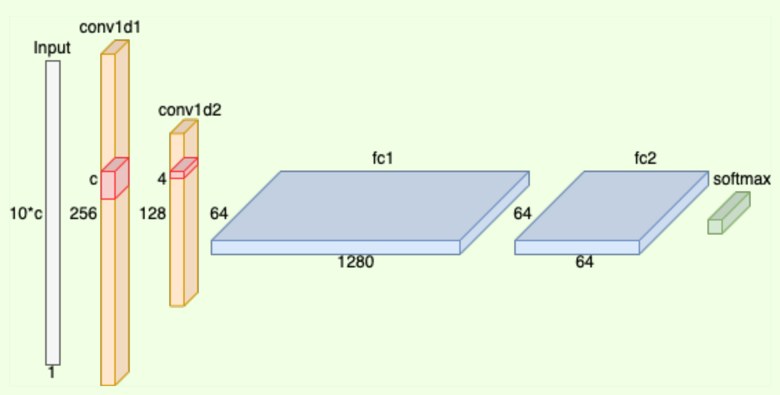
## Object Similarity Analysis

- Canonical correlation analysis (CCA) exposes correlations between objects with similar stacking behavior in a low-dimensional representation
- Cube and sphere least similar
- Prototypical "stackable" and "unstackable" objects

| | Cube | Sph. | Cyl. | Cap. | Sm. cube |
|---|---|---|---|---|---|
| Cube | 1 | 0.396 | **0.958** | 0.686 | **0.808** |
| Sphere | 0.399 | 1 | 0.366 | **0.832** | 0.376 |
| Cylinder | **0.974** | 0.366 | 1 | 0.692 | 0.528 |
| Capsule | 0.688 | **0.832** | 0.692 | 1 | 0.511 |
| Sm. cube | **0.808** | 0.376 | 0.527 | 0.511 | 1 |

## Object Classification

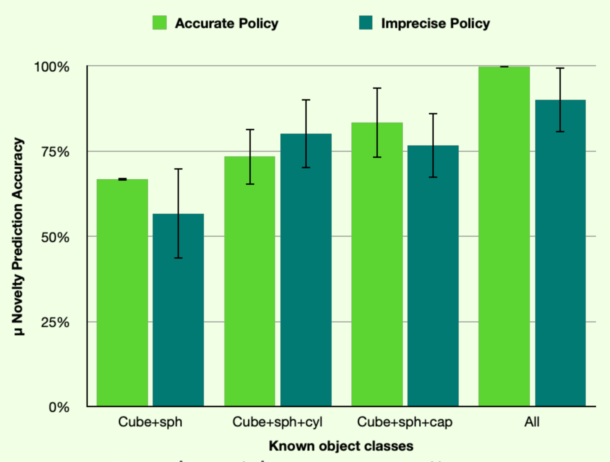
- Identify which known class an object sample is most similar to
- Known class identification by 1D CNN
- e.g., Given known classes cube and sphere, cylinders usually classified as cubes, capsules usually classified as spheres



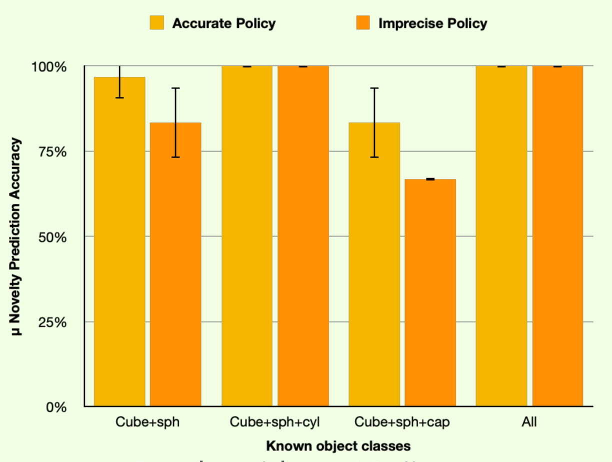

## Novel Class Detection

- Determine if object is different enough from most similar known class to be novel
- Compare 64D *embedding vectors* to embeddings of known class
- Let $\overrightarrow{\mu_S}$, $\overrightarrow{\sigma_S}$ be the mean, stdev of the known class, let $\overrightarrow{\mu_N}$ be the mean of the new batch, and let $\vec{v}$ be a single sample
- Let $\rho_{\vec{v}} = \frac{\cos(\overrightarrow{\mu_S}, \vec{v})}{\cos(\overrightarrow{\mu_S}, \overrightarrow{\mu_S} + \overrightarrow{\sigma_S})}$; if $\rho_{\vec{v}} > 1$, $\vec{v}$ is an outlier $\vec{o} \in O$
- For all new batch outliers $\overrightarrow{o_N} \in O_N$, and known class outliers $\overrightarrow{o_S} \in O_S$, let outlier ratio $OR = \frac{\sum_{\overrightarrow{o_N} \in O_N} \rho_{\overrightarrow{o_N}}}{\sum_{\overrightarrow{o_S} \in O_S} \rho_{\overrightarrow{o_S}}}$
- If $\frac{OR \times \cos(\overrightarrow{\mu_S}, \overrightarrow{\mu_N})}{\cos(\overrightarrow{\mu_S}, \overrightarrow{\mu_S} + \overrightarrow{\sigma_S}) \times \sum_{\overrightarrow{o_S} \in O_S} \rho_{\overrightarrow{o_S}}} > T$ (threshold), object is considered novel!

## Results




Results without VoxML jitter



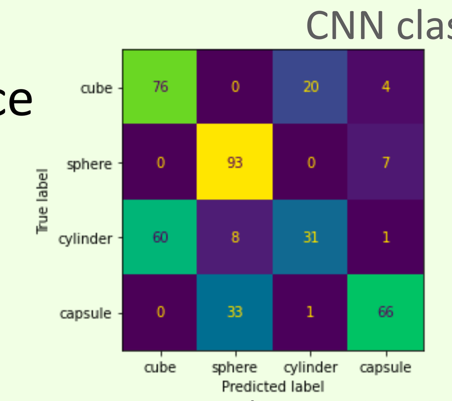

Results with VoxML jitter

- Can correctly identify the novelty of cylinders and capsules based on behavior alone
- Small cubes identified as same type as large cubes
- Imprecise policy data slightly more challenging

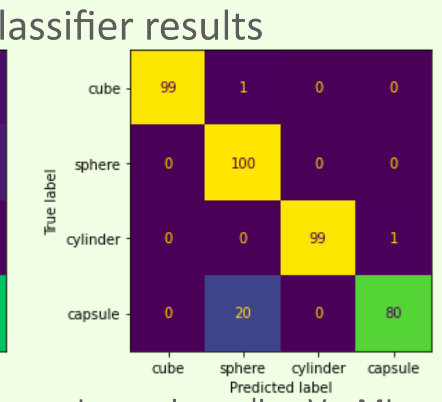
## Discussion and Conclusion

- Including implicit habitat/affordance information increases performance by ~25%
- Without habitat information, classifier confuses cylinders and cubes, capsules and spheres
- Order of concept acquisition matters
- Detecting capsule concept before cylinder impedes cylinder detection
- Method approximates certain metacognitive processes
- Provides potential step toward computational "fast mapping"

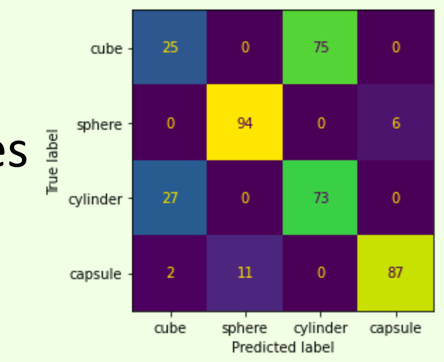
CNN classifier results



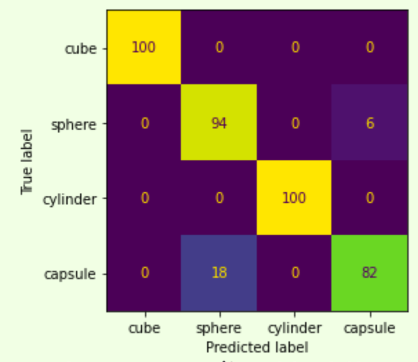
Imprecise policy, no VoxML



Imprecise policy, VoxML



Accurate policy, no VoxML



Accurate policy, VoxML