Data Engineering | Term Project Proposal

Difficulty-Aware Active 3D Scanning

An Object Difficulty Database for Curriculum-Guided NBV Learning

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Team 14

POSTECH

Why 3D Scanning?



Real mounted dish



Digital documentation obtained through scanning

Preservation
Record shape before damage

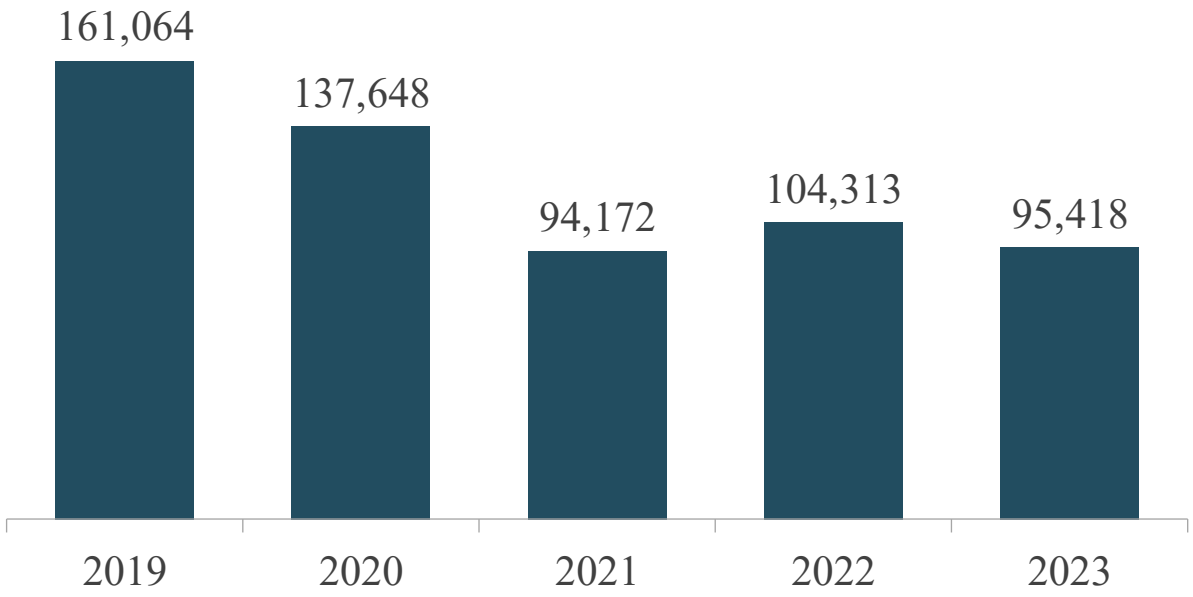
Restoration
Support reconstruction

Education & Research
Access without touching

3D scanning turns physical objects into reusable geometric data.

Why Automate 3D Scanning?

~100,000 artifacts excavated every year in Korea



Source: Korea Heritage Service, Heritage Statistics 2023

Expert-operated scanning



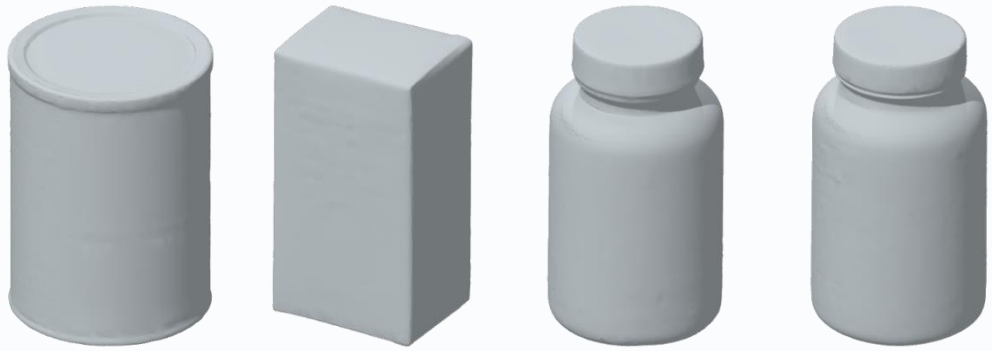
Manual scanning (×2.5 speed)

Our goal: automatically choose the next view to capture unseen areas.

Not All Objects Are Equally Easy to Scan

Simple Objects

Simple geometry



Irregular Objects

Concavities & protrusions



Easier to scan	Harder to scan
Fewer hidden areas	More hidden areas
Less dependent on viewing direction	More dependent on viewing direction
Fewer views may be enough	More carefully chosen views may be needed

Scanning difficulty varies with object geometry. → We train on a dataset of diverse 3D shapes.

EDA: Coverage vs. Number of Views

Easy · Bottle



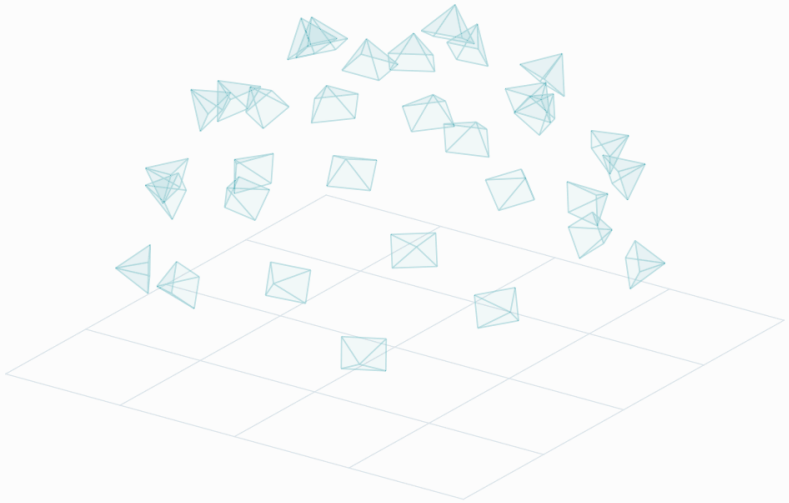
Hard · Dragon



Viewpoint sampling

Candidate viewpoint

Selected viewpoint





Harder-to-scan objects require more views to reach the same coverage level.

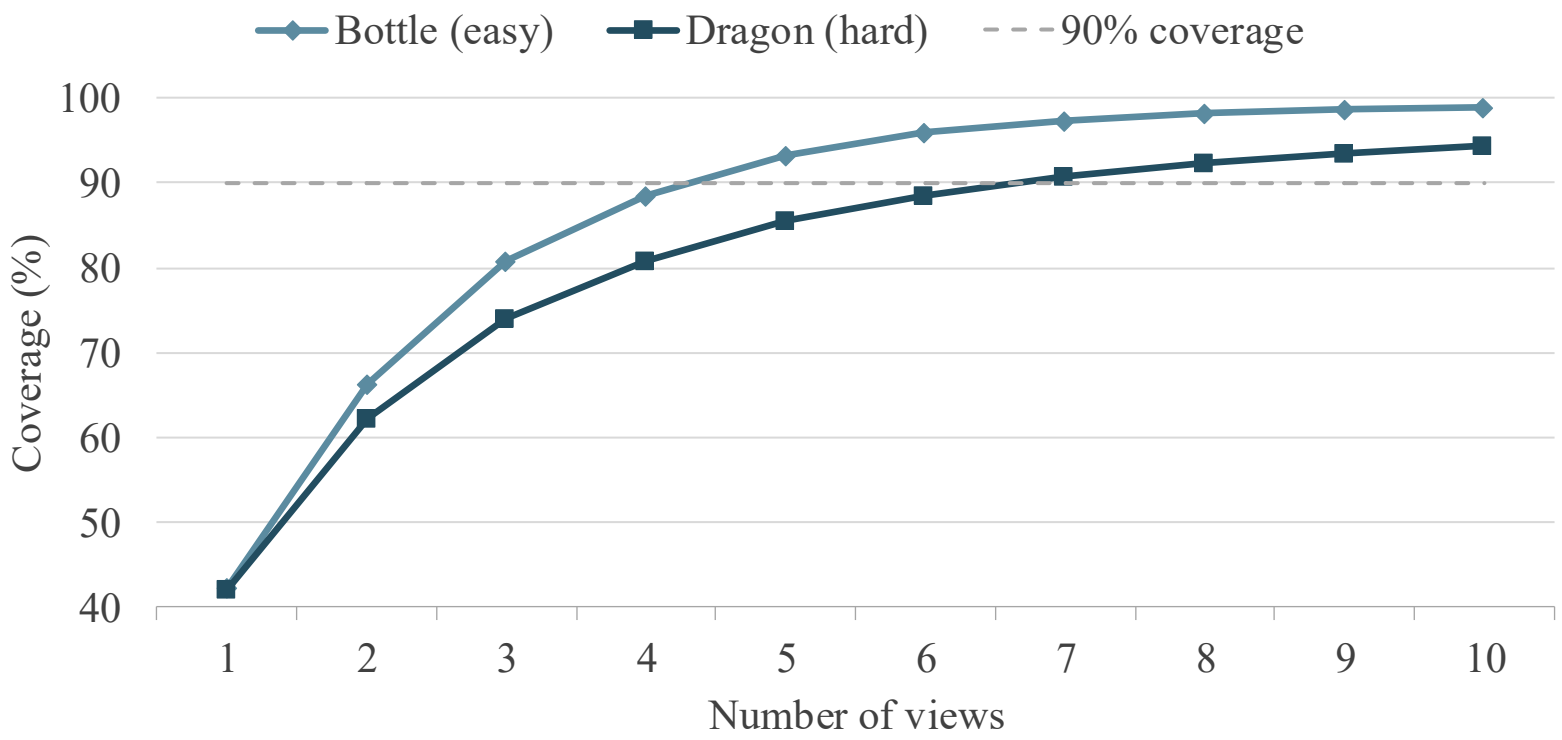
EDA: Coverage vs. Number of Views

Easy · Bottle



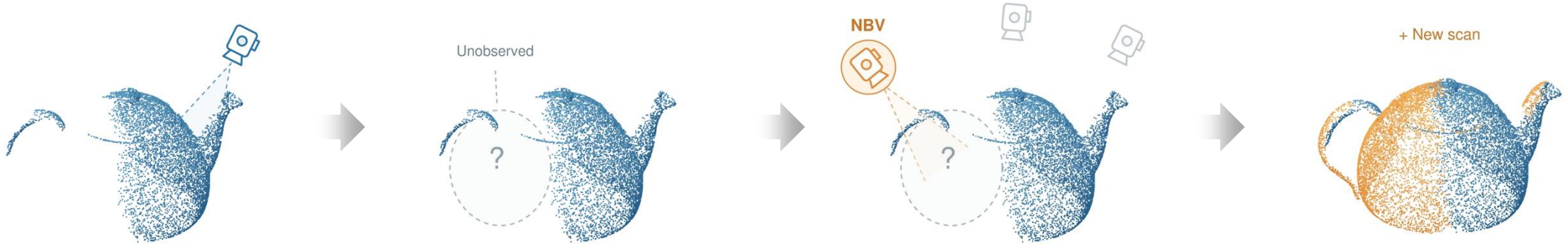
Hard · Dragon





Harder-to-scan objects require more views to reach the same coverage level.

What Is Next-Best-View (NBV)?



1 Observe
Get a partial 3D scan

2 Review scan
Use the observations collected so far

3 Select viewpoint
Choose a view expected to reveal new surface

4 Merge
Align and merge the new scan

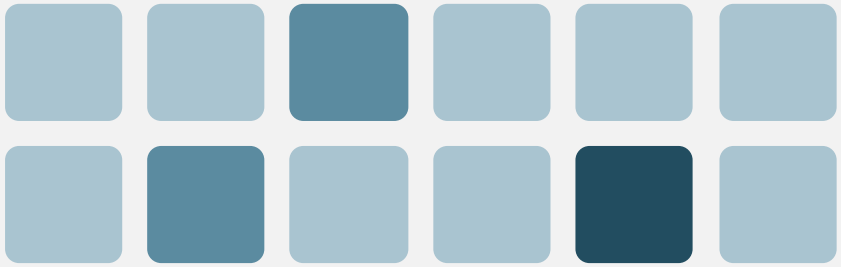
Repeat until the scan budget is used

In our project, an RL policy learns to choose the next view

Why Curriculum Learning for NBV?

Objects differ in difficulty → what problem does this create for NBV policy learning?

Random sampling



Some difficulty levels can dominate

Difficulty-aware sampling



Control what the policy sees, and when

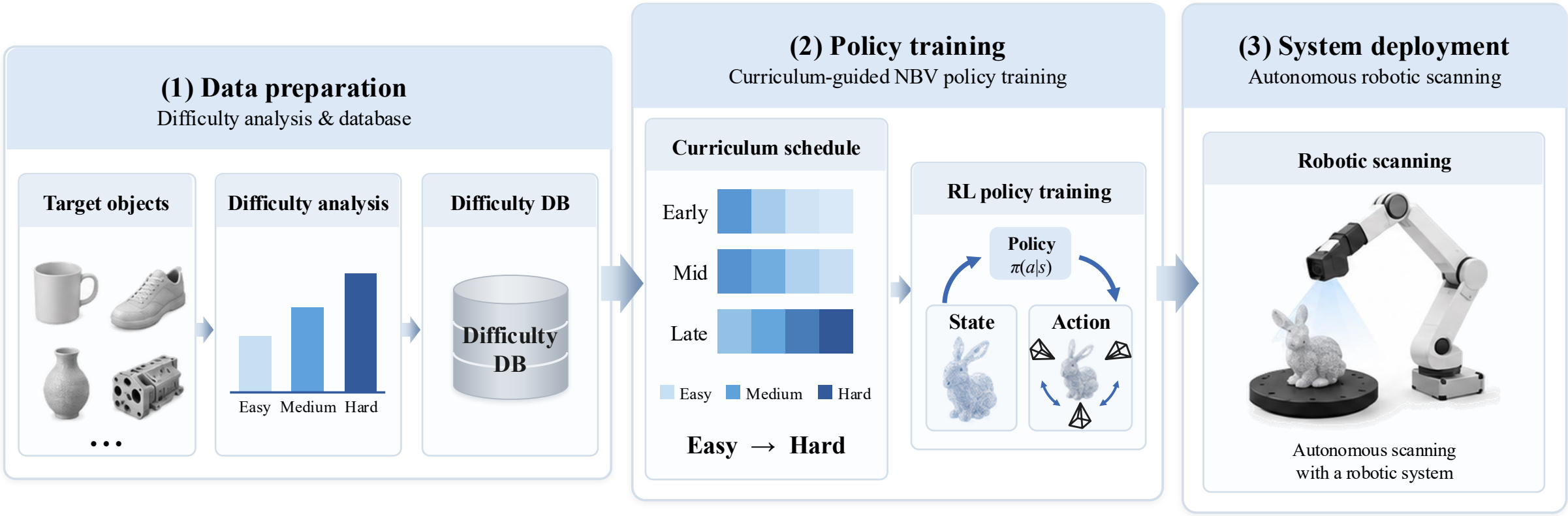
Easy Medium Hard

Research question

Can difficulty-aware data sampling improve NBV policy generalization and learning efficiency?

System Overview

Overview of our curriculum-guided RL for 3D scanning system

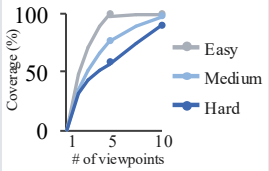


Scan Difficulty Analysis & Curriculum Design

Difficulty-aware curriculum design

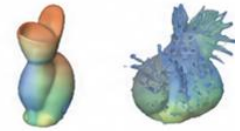
(1) Difficulty analysis

1. Observation completeness



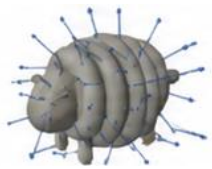
Greedy view selection

2. Surface complexity



Normal entropy

3. Viewpoint visibility



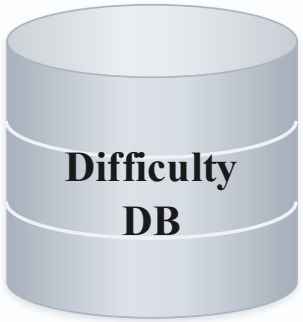
Visibility std.

4. Observability limits



Unobservable surface ratio

(2) Difficulty database



- Object ID
- Difficulty scores
- Overall difficulty level (Easy / Medium / Hard)
- Metadata

(3) Query & sampling

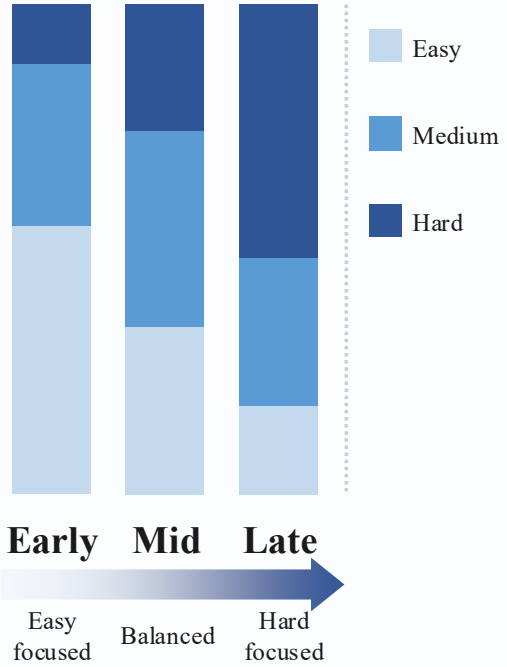
Query

```
SELECT *
FROM difficulty_db
WHERE difficulty_level = 'Easy'
  AND split = 'train'
ORDER BY RANDOM()
LIMIT 32;
```

Sampling

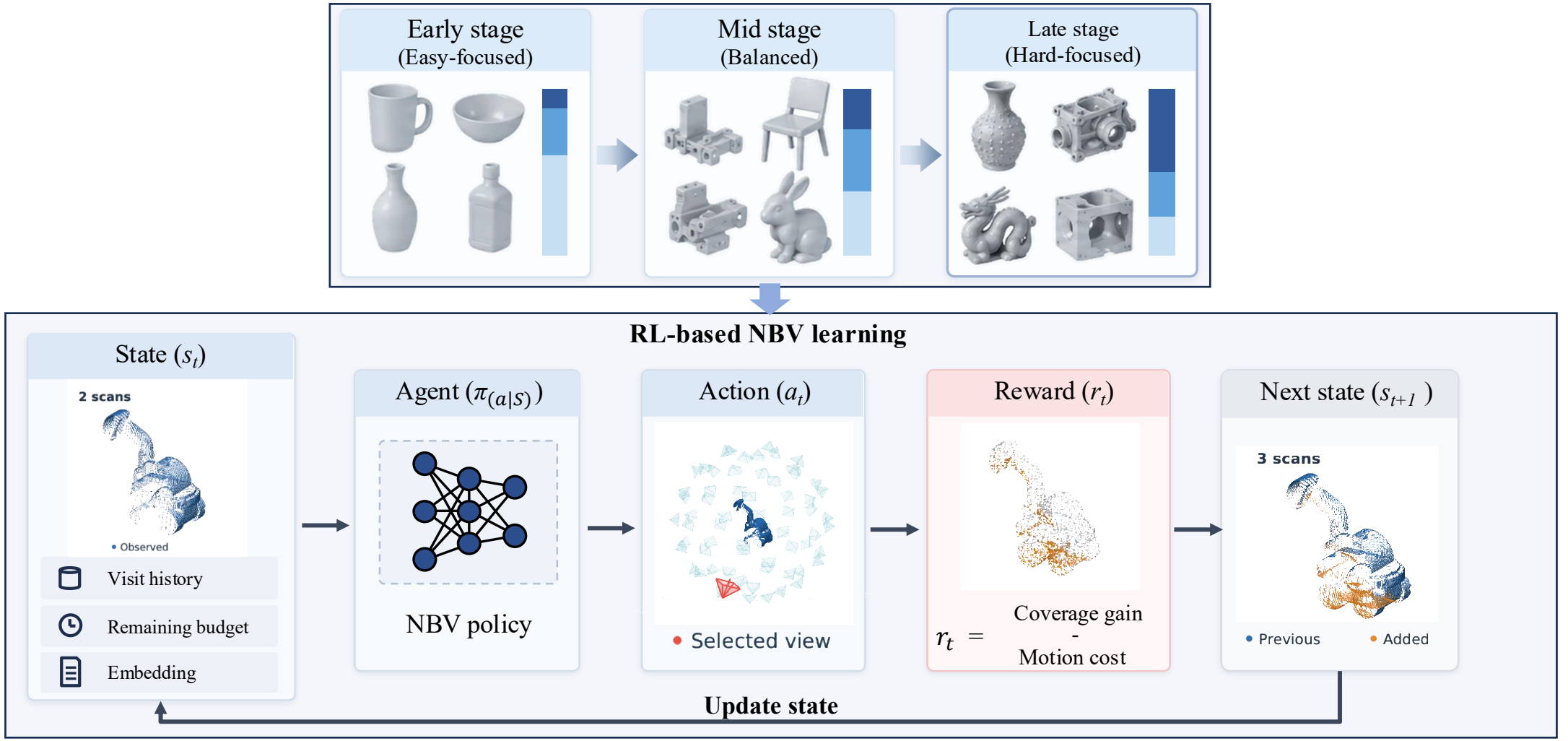


(4) Curriculum design

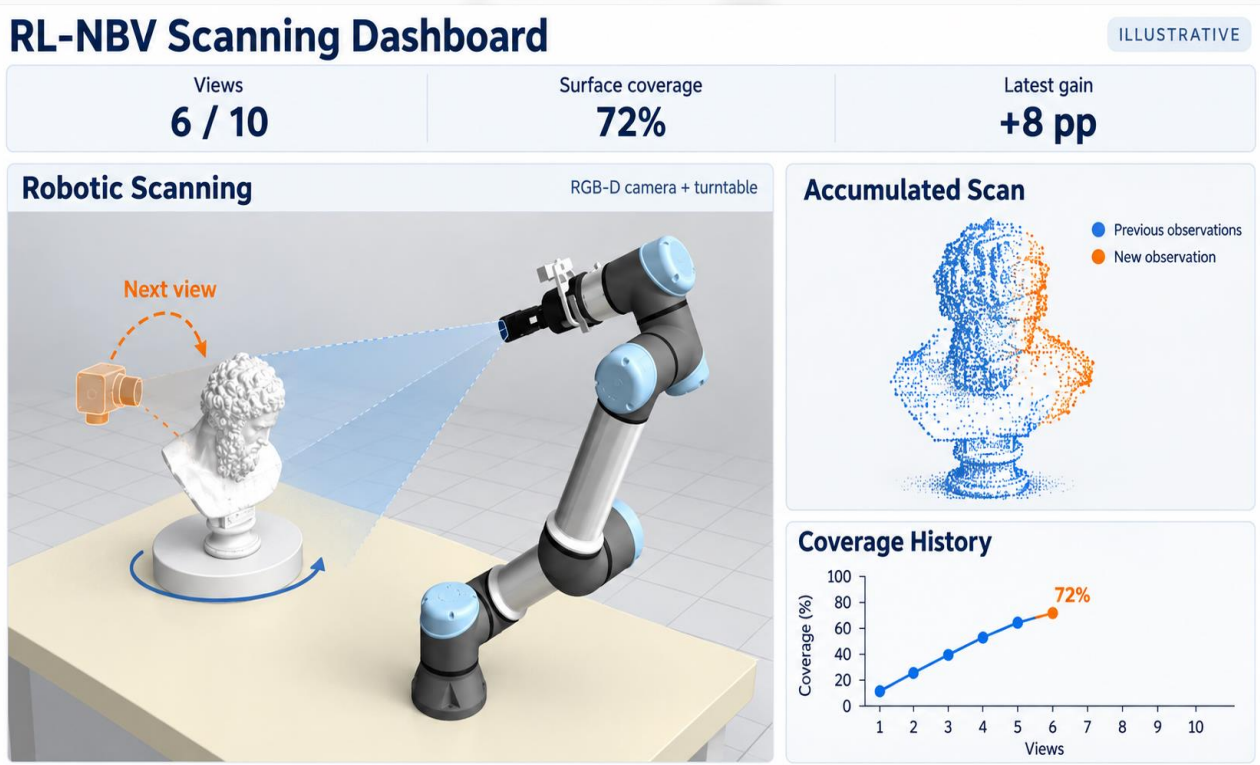


RL-based NBV System

Curriculum-guided NBV policy learning



Robotic Scanning Simulation



Isaac Sim environment from prior scanning work

1. **Observe**
   Camera captures a partial point cloud
2. **Select NBV**
   Curriculum RL policy picks the next view
3. **Execute**
   Robot arm and turntable work together to reach the selected viewpoint.
4. **Merge**
   Update the 3D model, then repeat

↻ *Repeat until the scan budget is used*

Goal: run our curriculum RL-NBV policy in a closed robotic scanning loop

3.1

Timeline

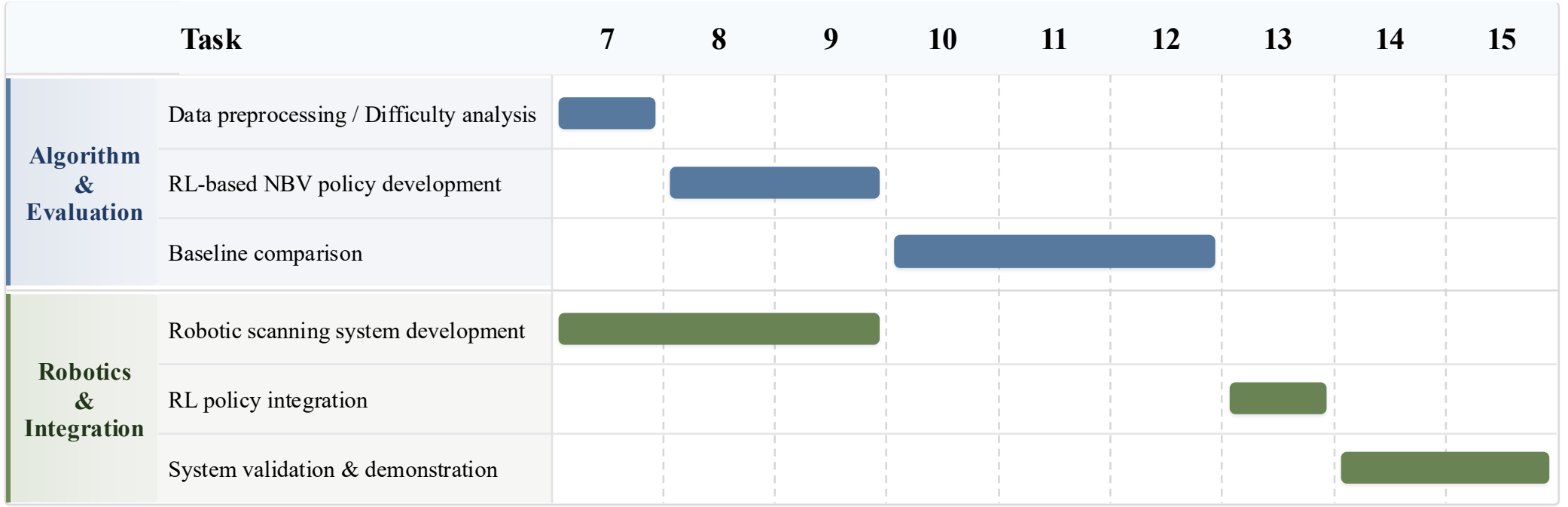
Development Goals & Timeline

- **Quantitative goal**

  Compare scanning coverage and path efficiency against baseline methods.

- **Qualitative goal**

  Integrate the learned NBV policy into an Isaac Sim-based robotic scanning system to validate its feasibility and effectiveness.



Thank You

Q & A