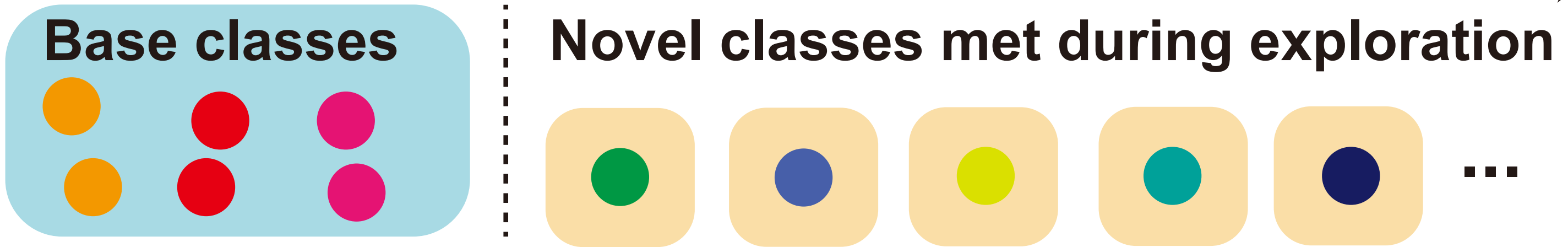
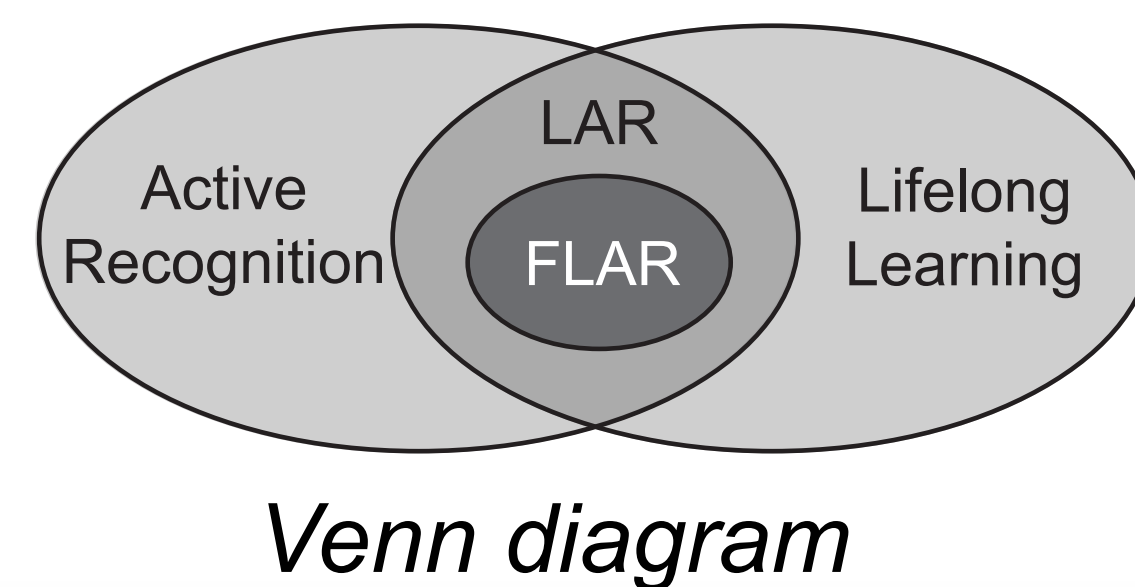


## Motivation

### Time (Robot Exploration)

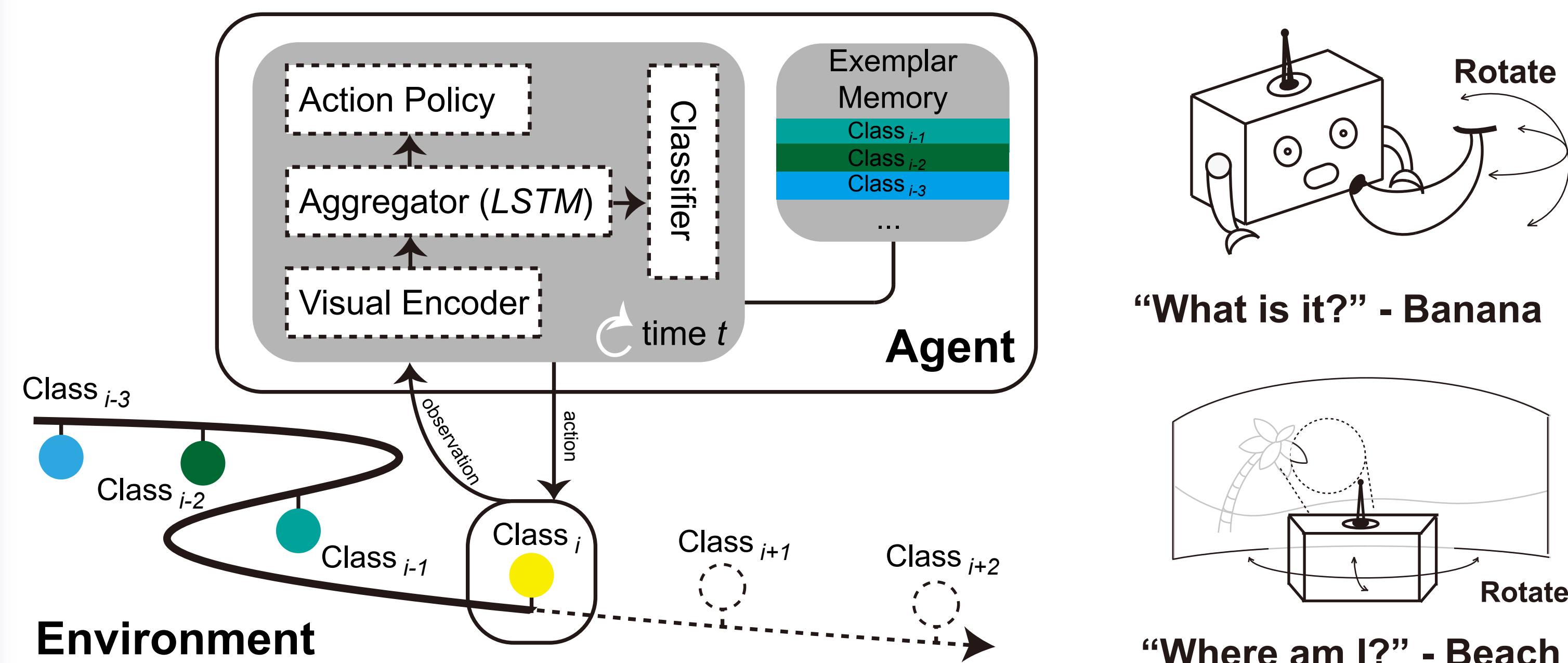


1. The **agent exploration** in a real-world environment is **inherently incremental**.
2. The ability to actively recognize novel classes that could not be known in advance is **demanded to be incorporated by the agent continuously**.



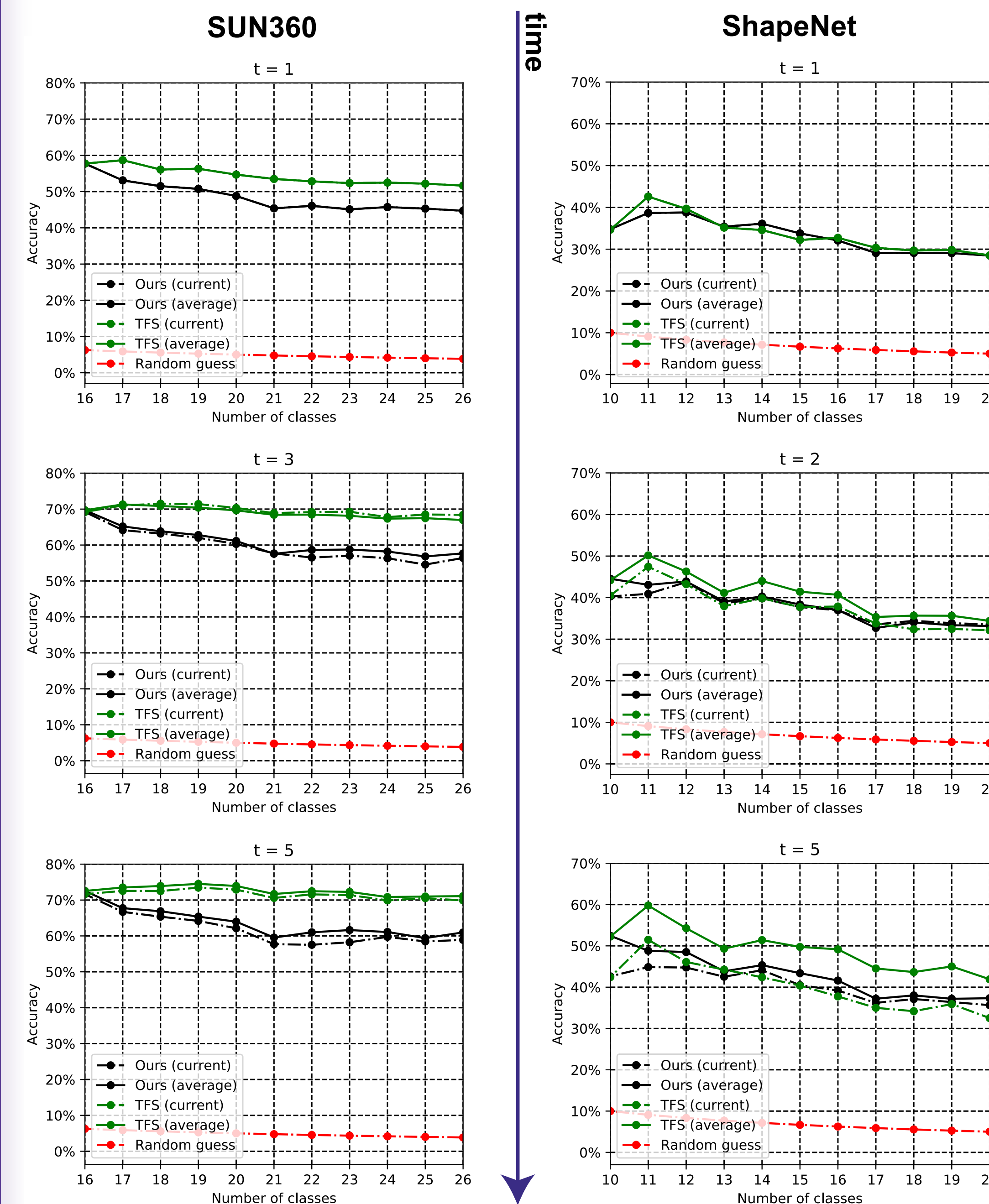
- AR - Active Recognition
- LAR - Lifelong Active Recognition
- FLAR - Few-sample Lifelong Active recognition

## Main Idea



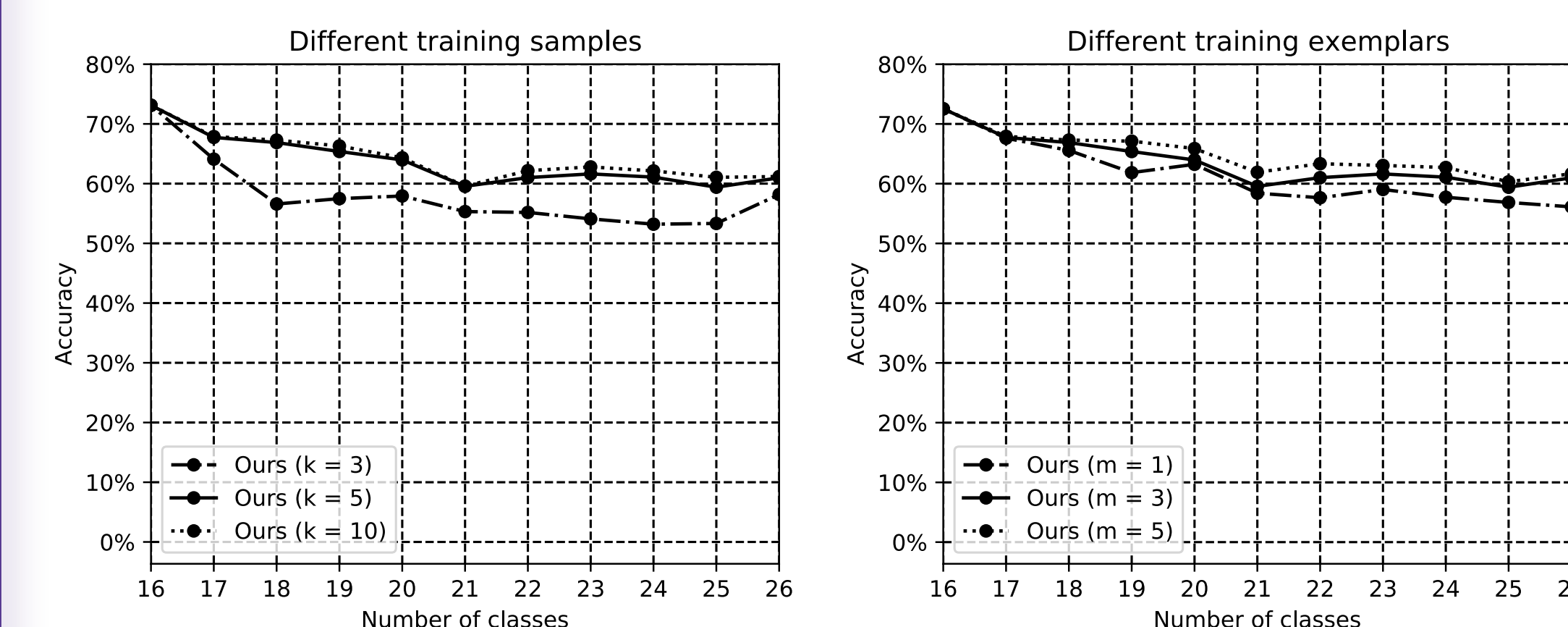
- The agent could **interact with the environment by obtaining observations and making movements**, which benefits recognition.
- As the agent exploring in the environment, the proposed method **expands its recognition ability to new classes**.

## Quantitative Results



The comparison on recognition accuracy for both datasets.

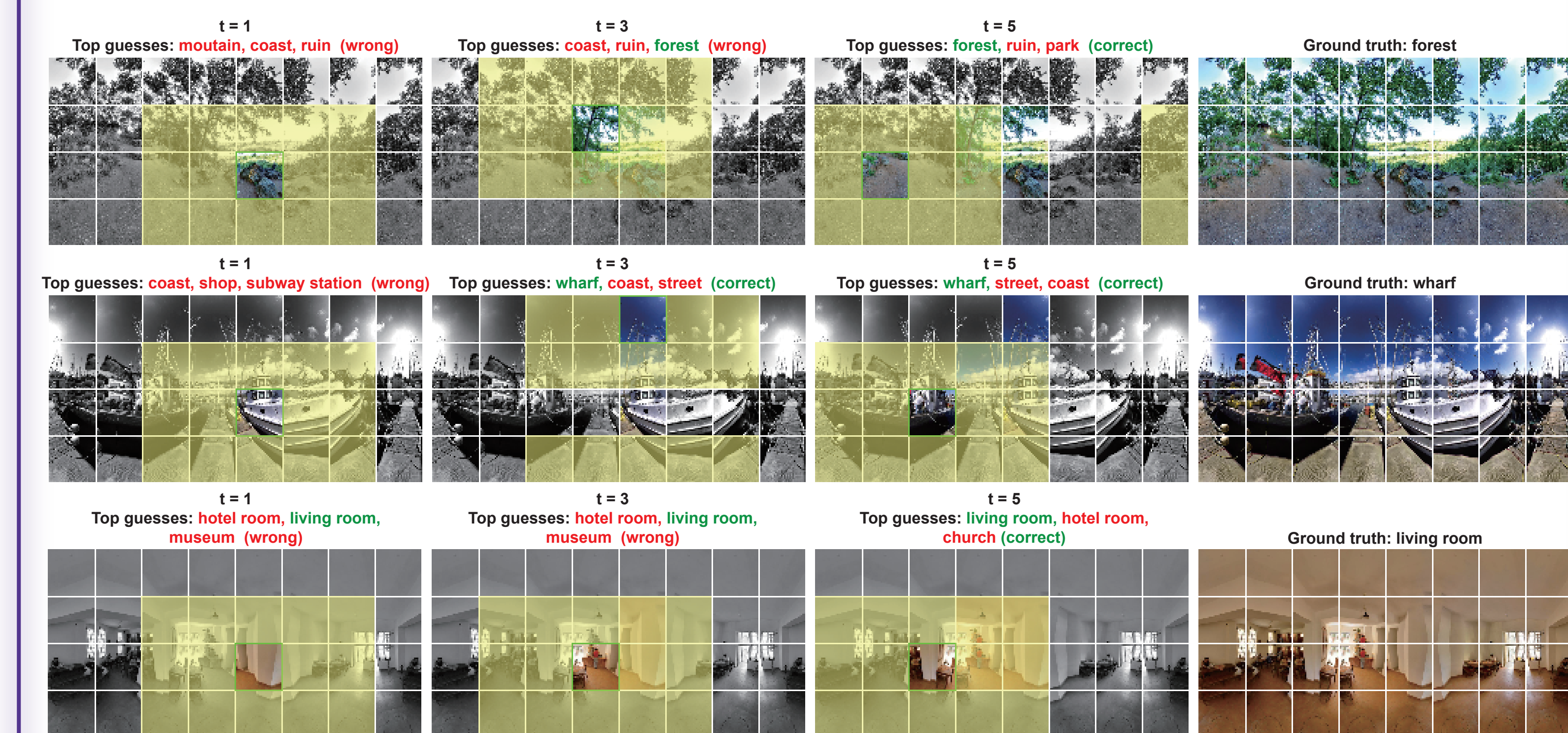
## Ablation studies



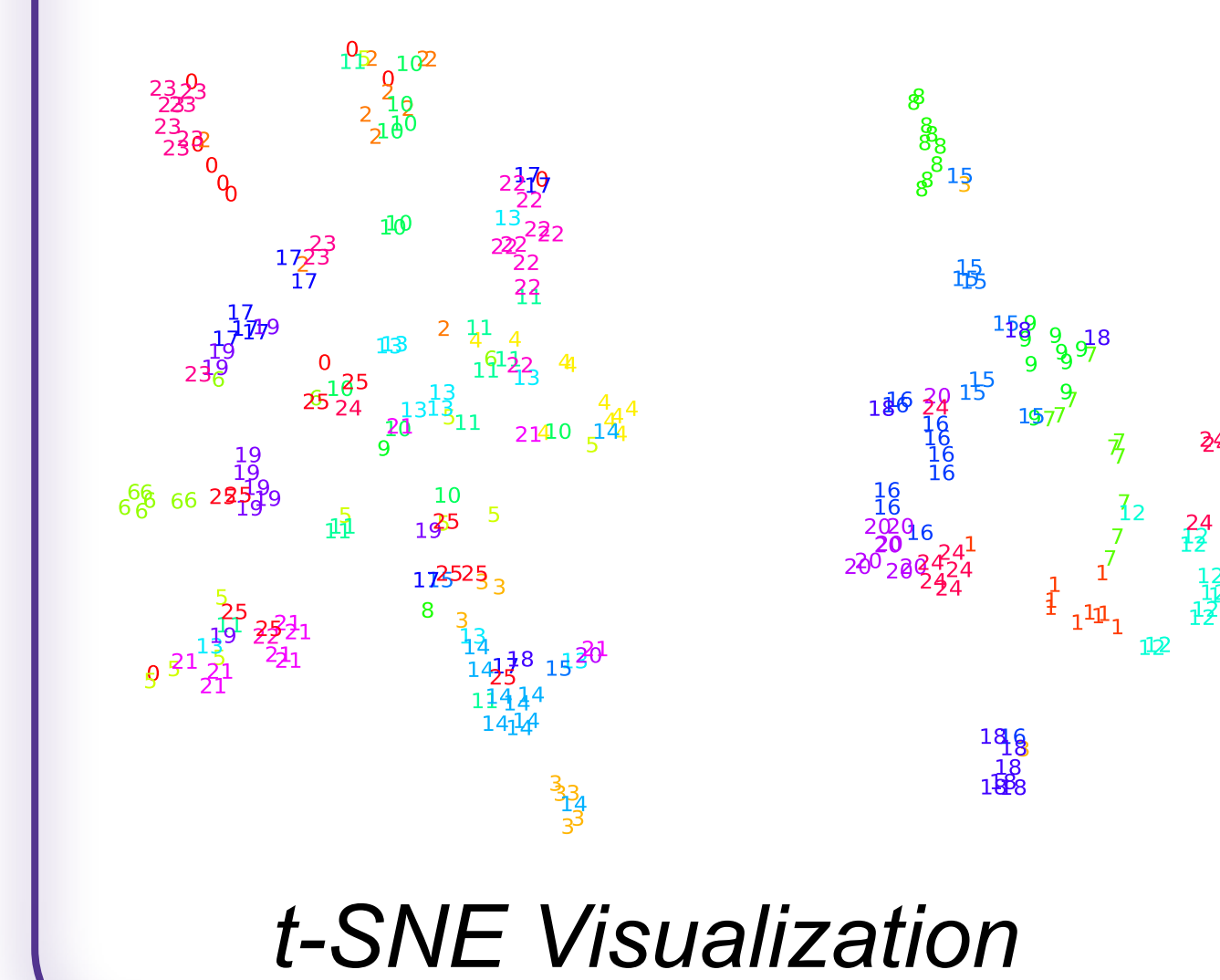
(a) Training sample sizes

(b) Exemplar sizes

## Qualitative Results



The active scene recognition process of the proposed approach.



- The t-SNE demonstration of learned features by our approach.
- The features from the **same category** are located close to each other.
- It demonstrates the **effectiveness of the proposed method in learning**

## Summary

- We derive the **prototype** as the representation for each category, which is **robust in handling limited training samples**.
- The novel designed reward **motivates the agent to achieve more discriminative features** by measuring distances in the embedding space.
- To alleviate catastrophic forgetting, the **knowledge distillation with exemplars** stored in the agent memory is applied during the policy training.