Resource-efficient Video Analytics on the Extreme Edge

Remembrall

Murali Ramanujam, Yinwei Dai, Kyle Jamieson, and Ravi Netravali

Video analytics

Classification, detection, segmentation

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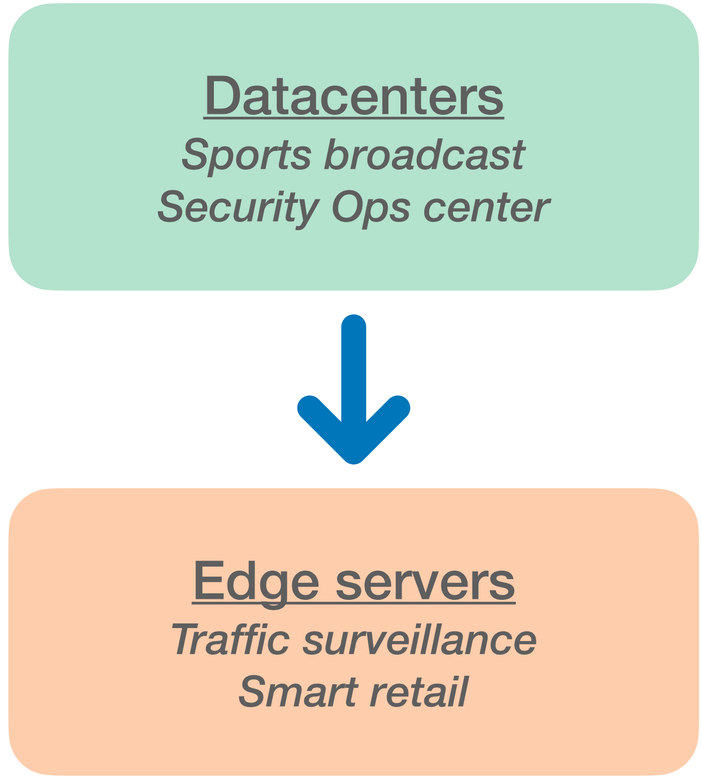
Datacenters
Sports broadcast
Security Ops center

Edge servers
Traffic surveillance
Smart retail

SoC-based mobile edge
Autonomous mobility
Search-and-rescue

Edge Challenges

Smaller models → repeated adaptation



Edge Challenges

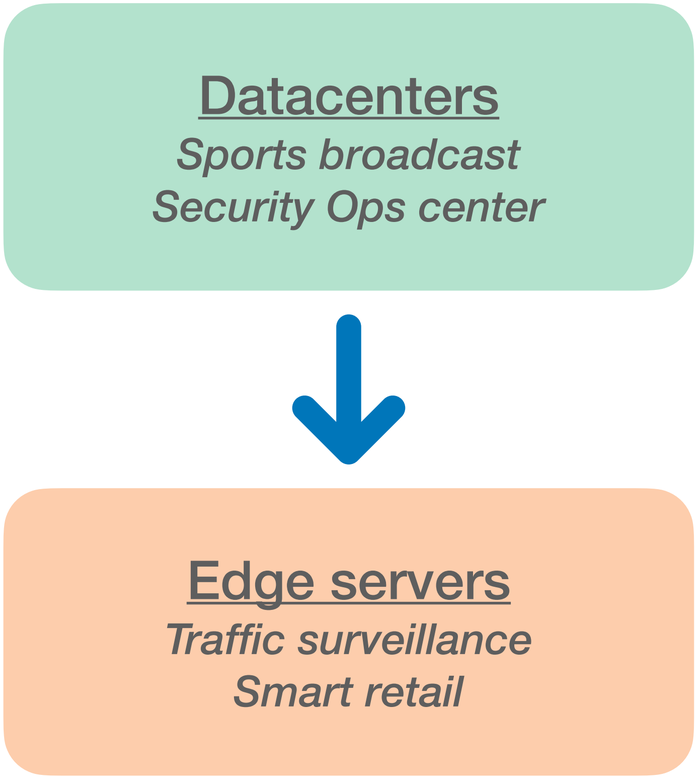
Smaller models → repeated adaptation

Restrictions when moving from Datacenters to Edge

Resource shrink mandates smaller models
e.g., ResNet50 instead of ResNet101

Vulnerable to scene drift
e.g., rush hour, weather changes → accuracy drops

Approach 1: Repeatedly train from most recent model
Approach 2: Store and reuse across many specialized models



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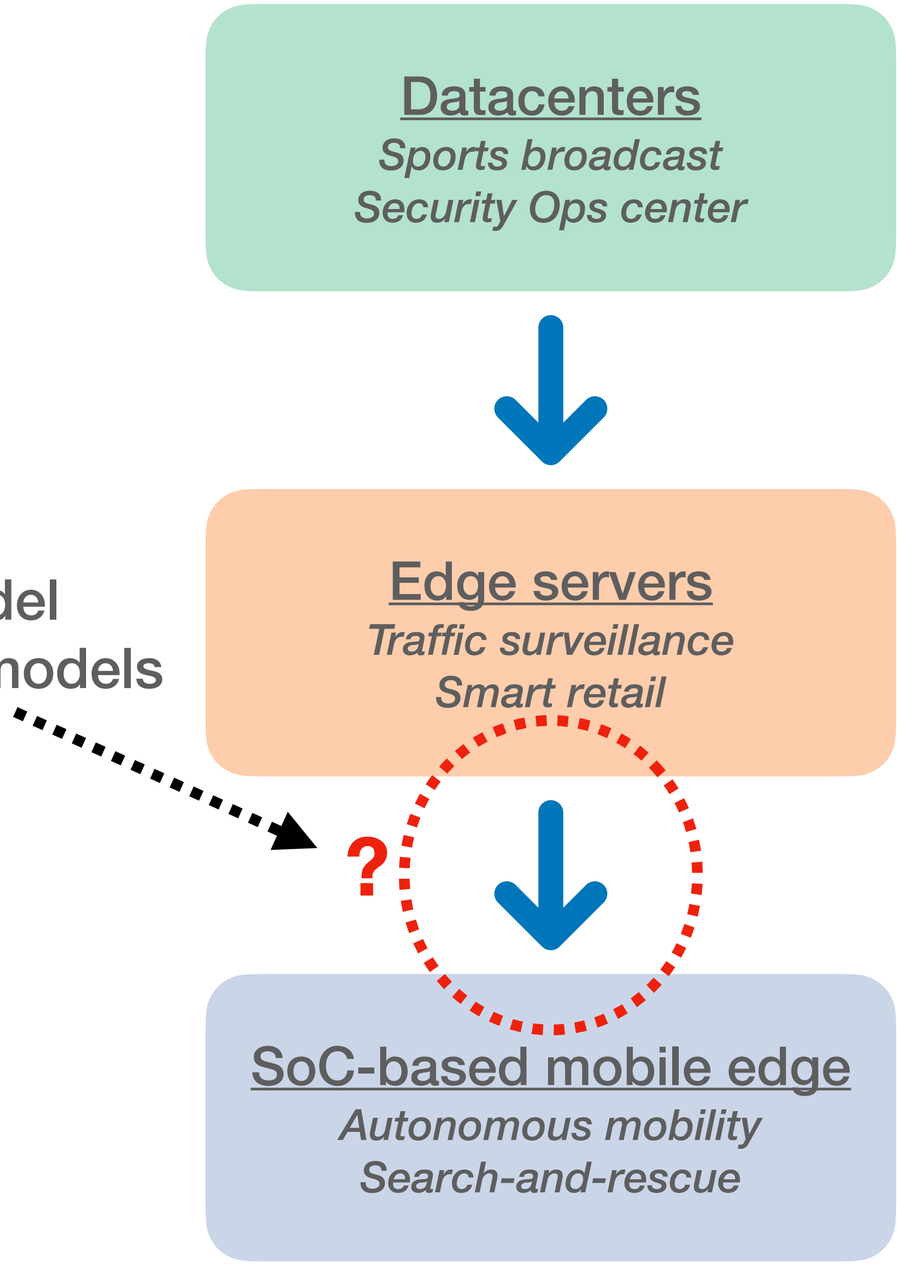
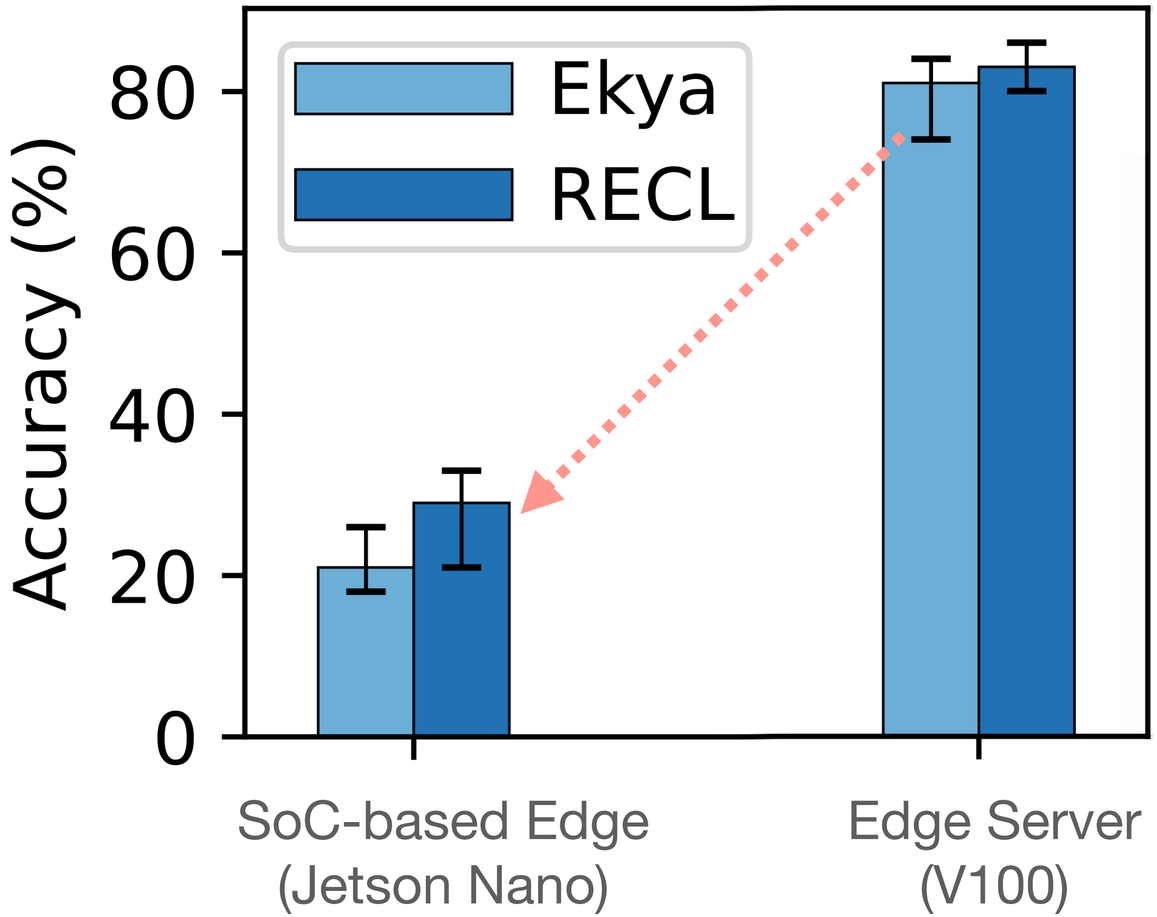


The Problem: Handling Drift

Existing approaches break down at the SoC-based edge

Approach 1: Periodically retrain the latest model used for inference with fresh data samples; e.g., Ekya (NSDI ’22).

Approach 2: Maintaining trained models in a zoo, and reusing the best candidate for each scene. The chosen model is then fine-tuned on recent data samples; e.g., RECL (NSDI ’23)



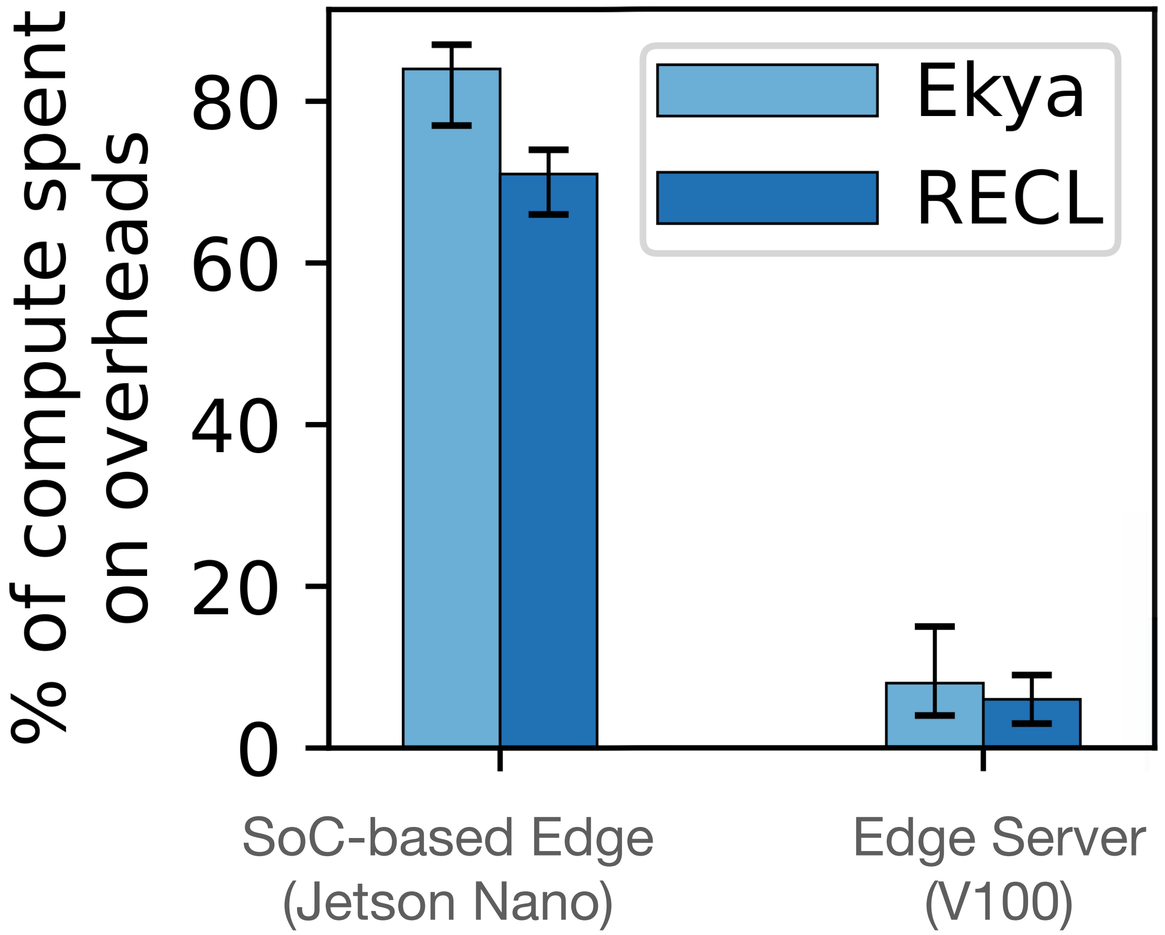
50 hours of drone/dashcam footage from YouTube.
Classification with ResNet18.
Bar shows median, errors span 25-75th percentile.

Why do existing approaches break down?

Compute overheads starve fruitful inference

Approach 1 Overheads: As resources shrink, Ekya's retraining consumes a growing share of GPU.

Approach 2 Overheads: Each time a new model is added to the zoo, RECL must retrain its gating network (used to select the best model from the zoo).



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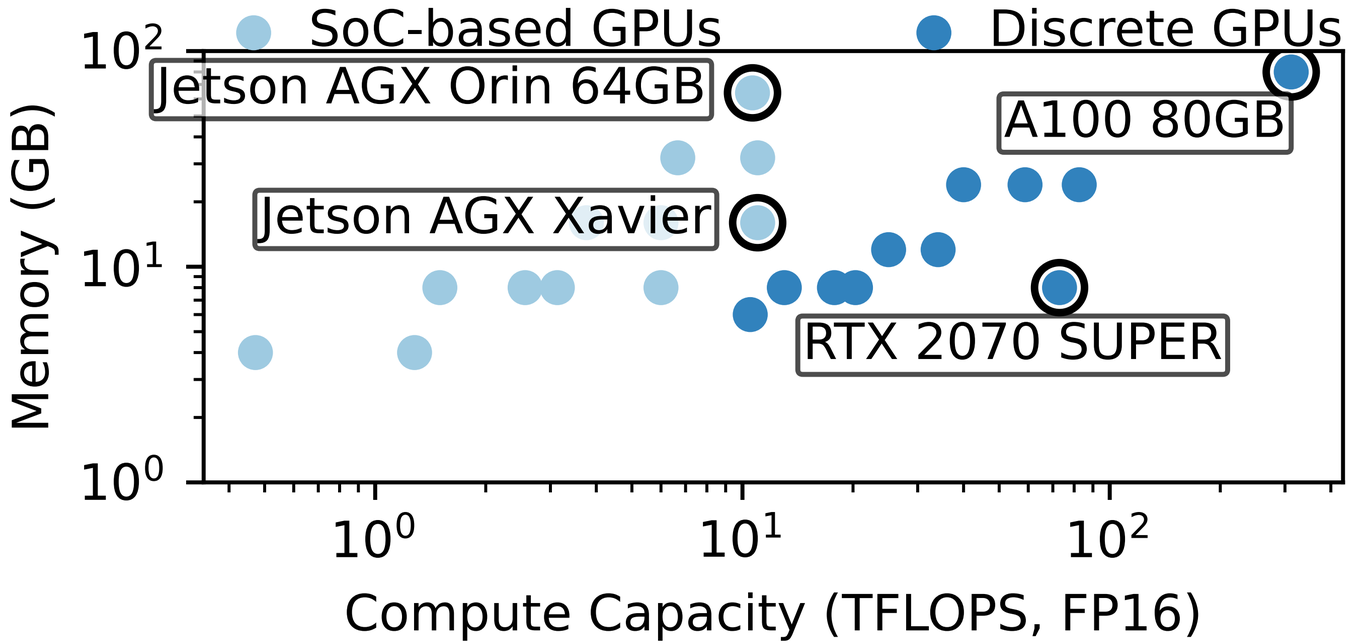
SoCs often have 10× less compute than discrete GPUs, but relatively large memory pools →



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The why

Current approaches naively use memory and stress compute to tame drift. A poor fit for SoCs.

Remembrall: principled use of (relatively abundant) memory.

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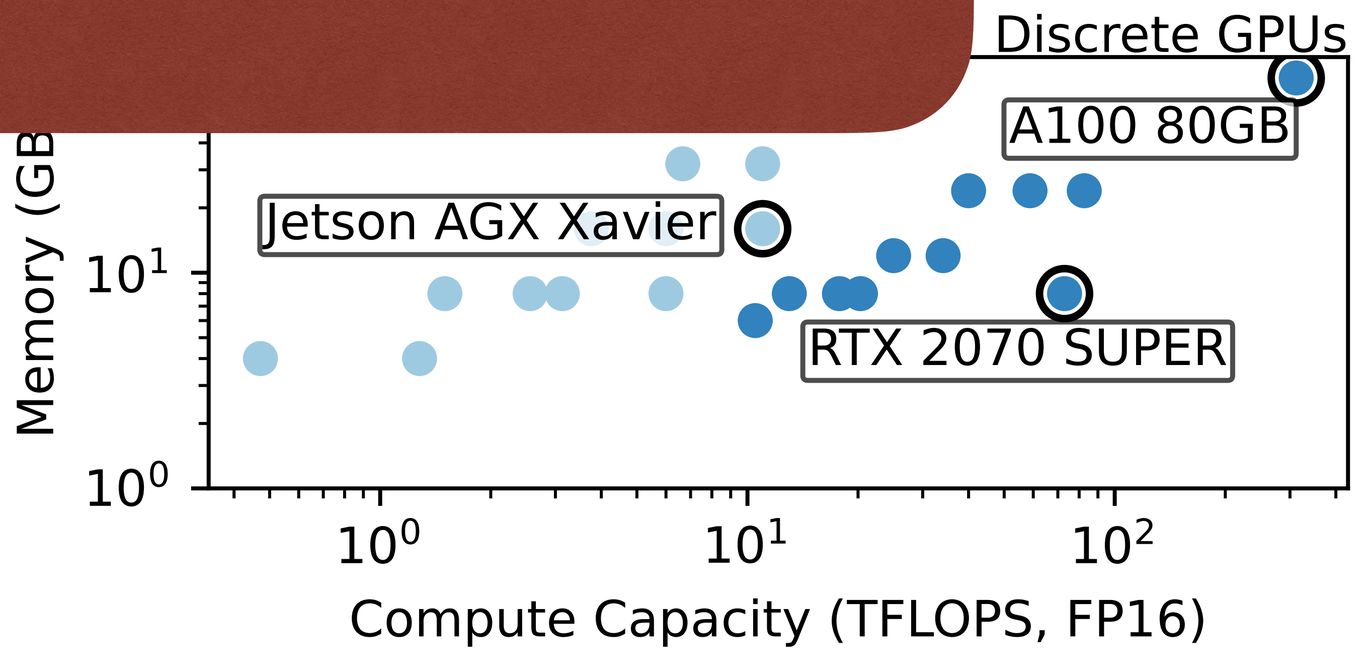

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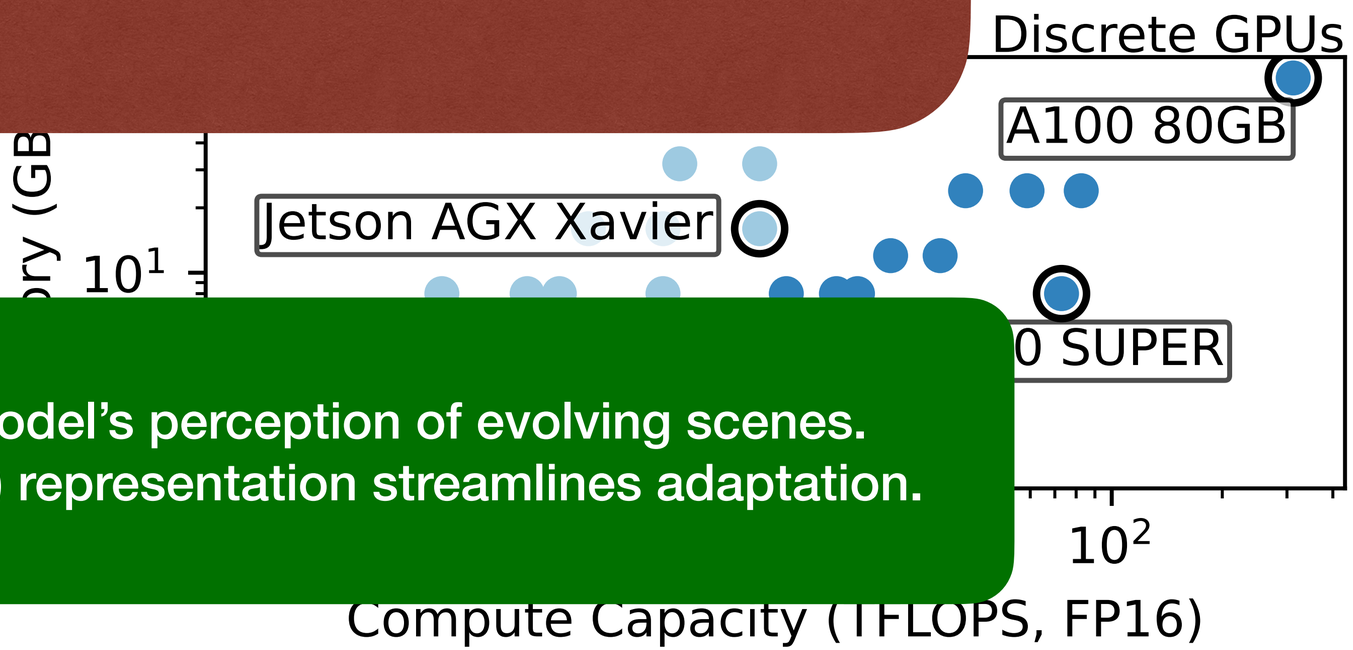
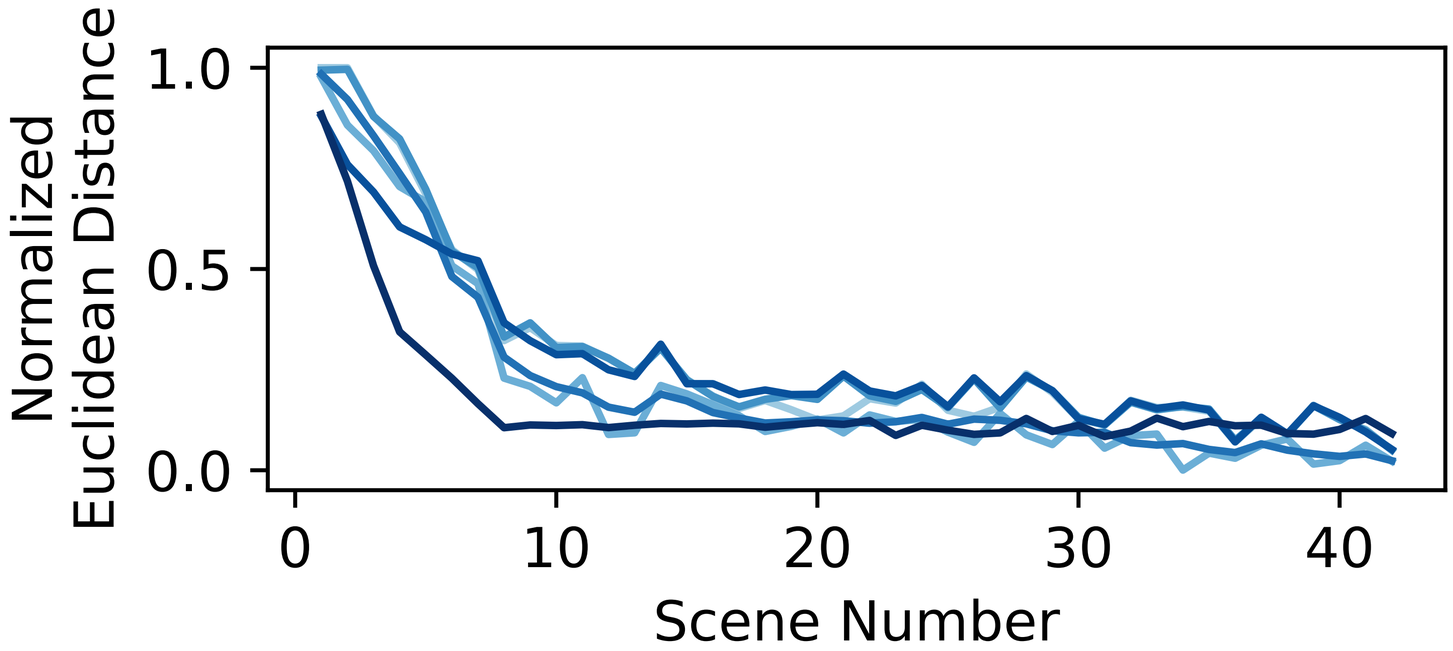


Key Idea: Strong stability in model's perception of evolving scenes. Starting from this stable (shared) representation streamlines adaptation.

Studying drift from the model's perspective

Evolving scenes exhibit stability in their embeddings



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Compute per-scene centroid from ResNet18 penultimate-layer object embeddings.

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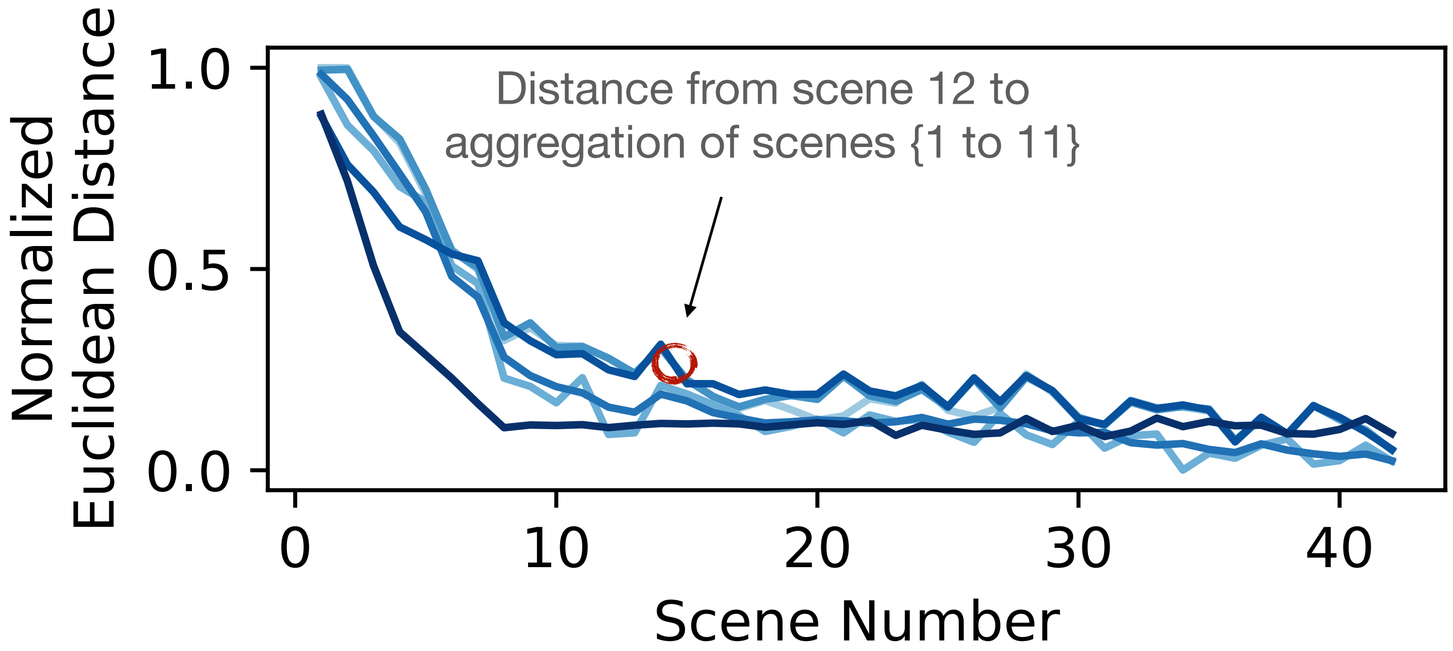

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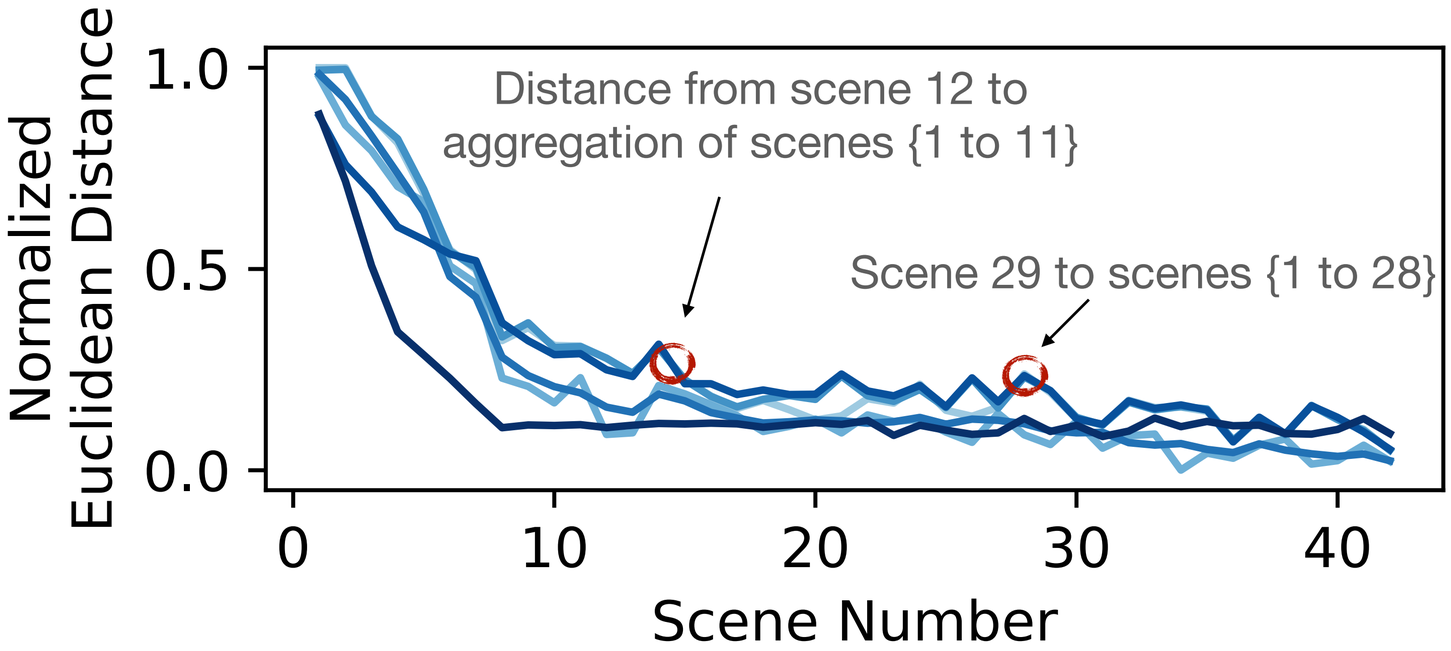

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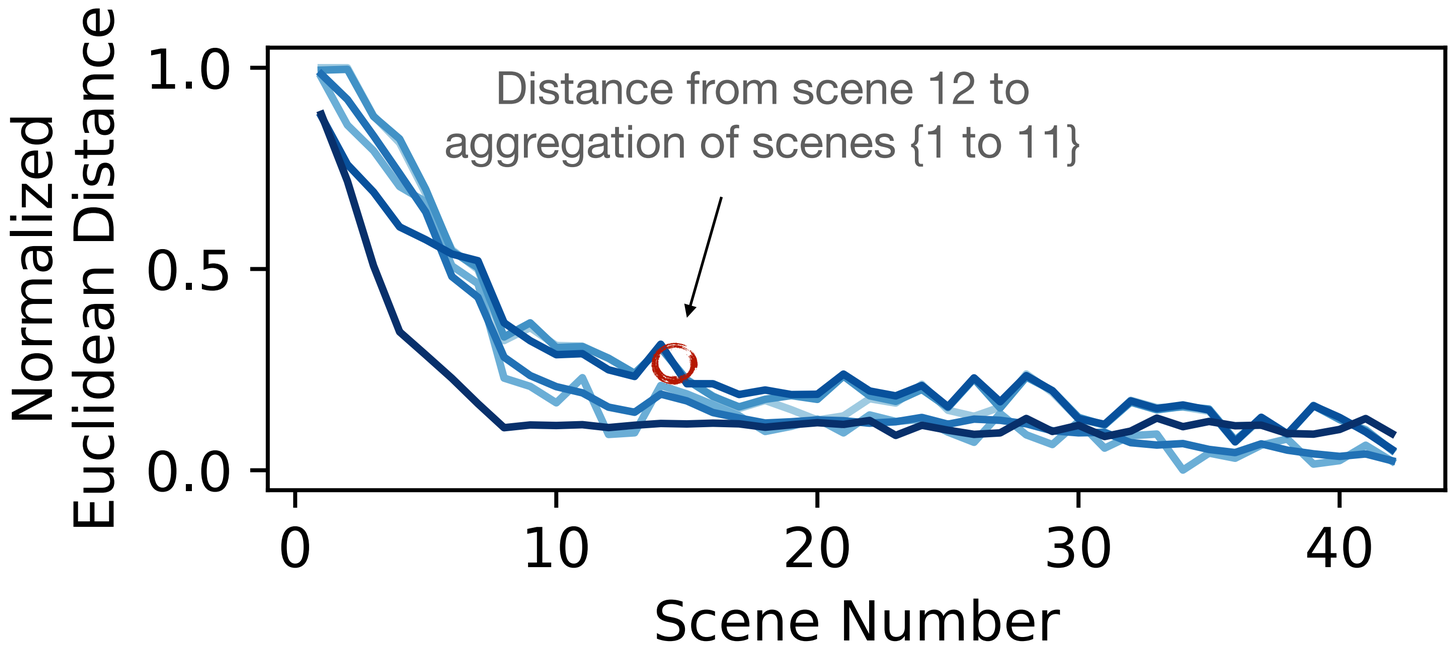
Distance from each scene's centroid to centroid of all prior scenes steadily decreases, then plateaus

Indicates representation saturation: the model's internal view converges despite ongoing content drift



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.. despite visual drift?

Analyzed adjacent scene pairs using

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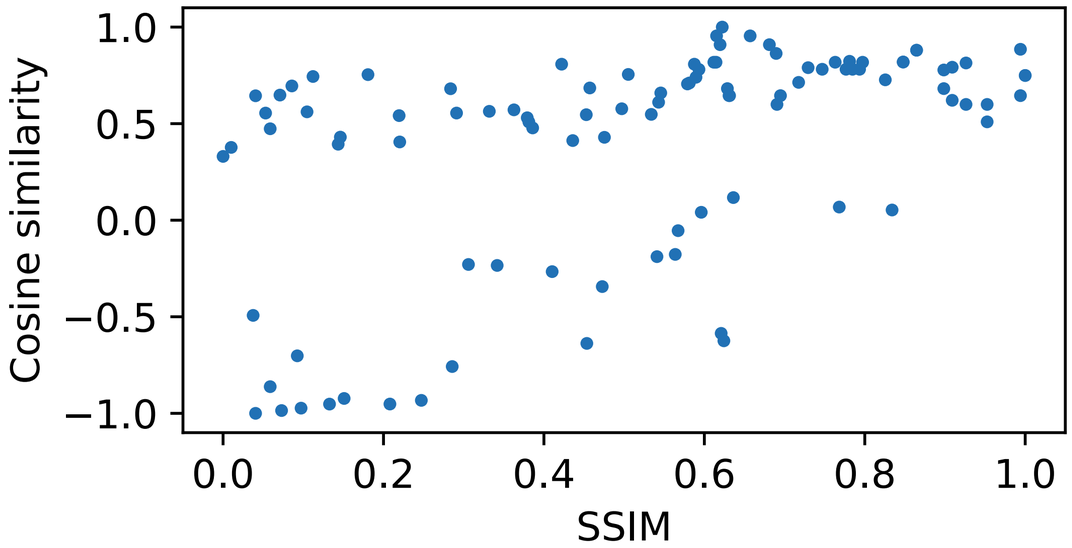

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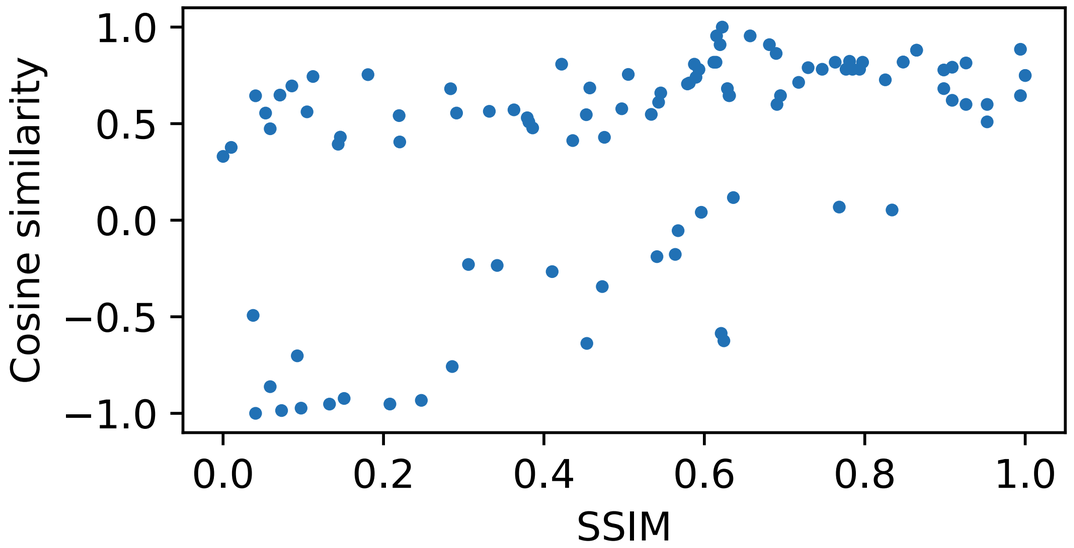

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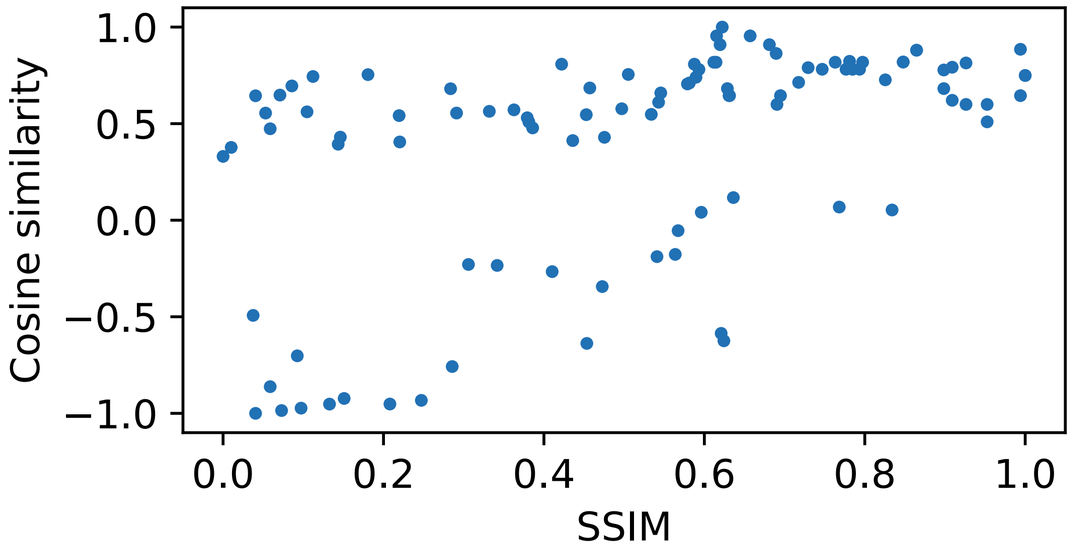

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Root cause: Models are trained to prioritize **structural cues** (e.g., geometry, layout) over surface-level features

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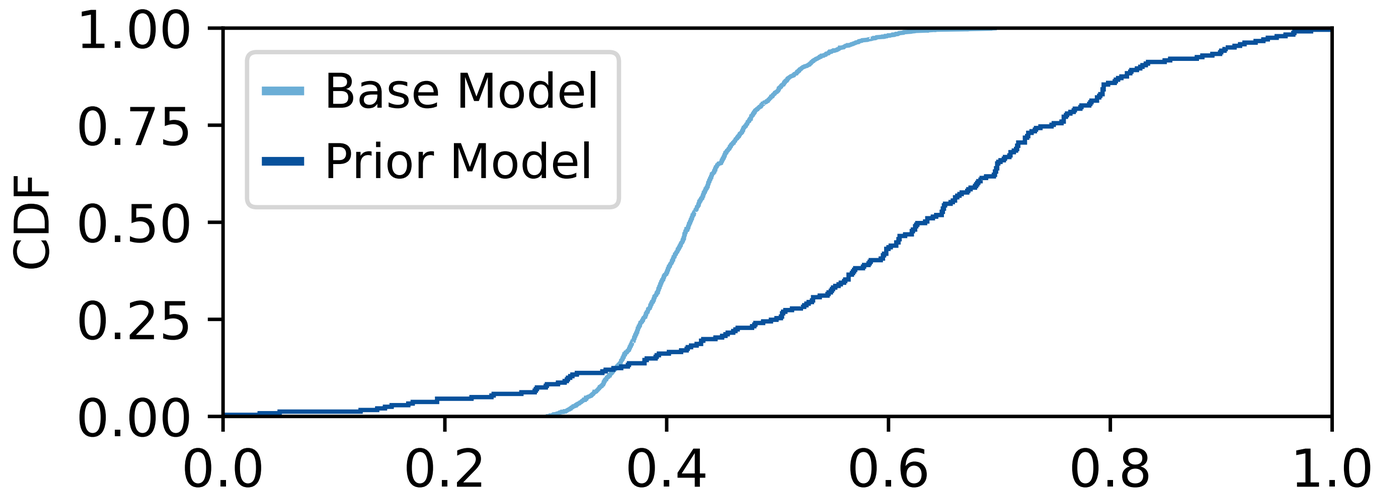

Normalized Euclidean Distance from each scene's specialized model to (i) prior scene's model (Ekya-style), and (ii) a base model (aggregated centroid) of prior scenes

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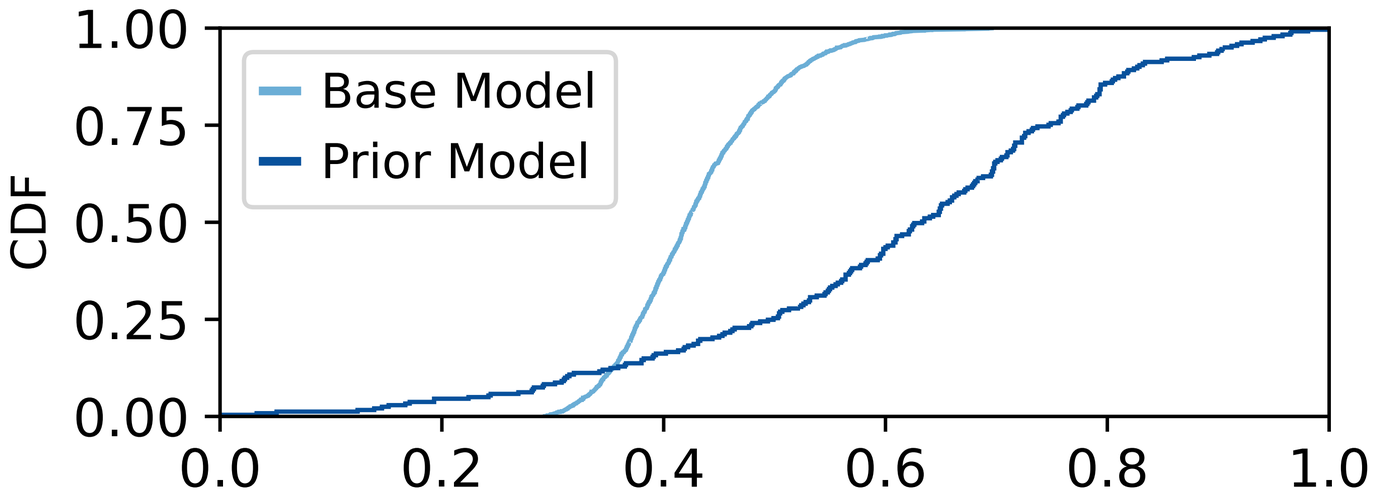
Lightweight retraining with few samples from a *base model* that incorporates this shared structure.

Base model consistently lies closer to the next specialized model than the previous one does.

Prior specialized models often overfit to scene-specific idiosyncrasies (e.g., transient lighting, rare classes), which must be unlearned first.

In contrast, starting from a base model that preserves general structure requires smaller weight updates, making retraining faster.



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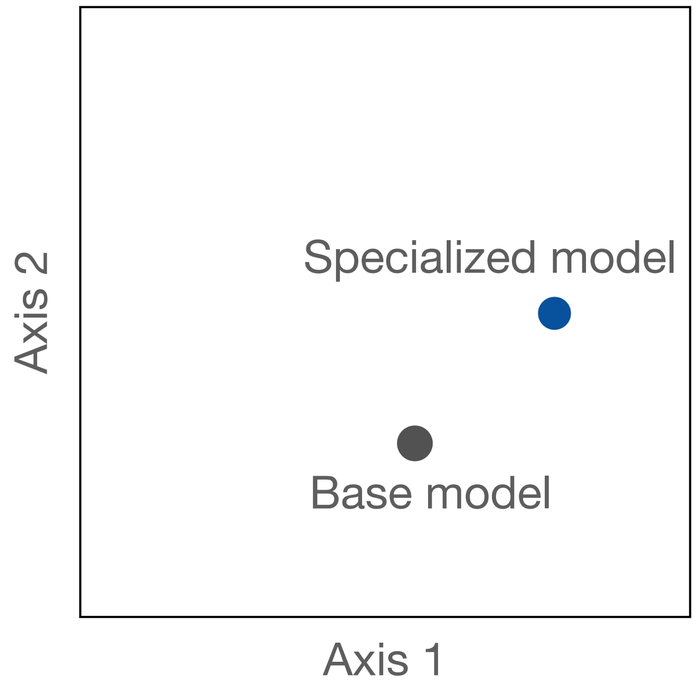
Tradeoff memory (two models) for lower compute costs when adapting to drift
Caters to SoC's unique resource profile

Studying Remembrall's models

This slide provides background using illustrative model coordinates.

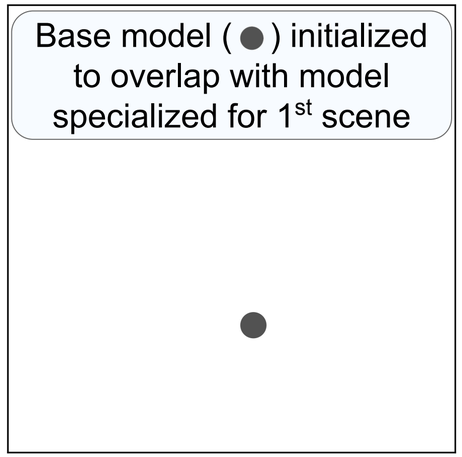


- We represent a model as a point in 2D plane, visualized by averaging ResNet18 penultimate-layer embeddings across detected objects.
- Embeddings are projected into 2D using Principal Component Analysis (PCA); axes correspond to the top two principal components.
- Absolute positions are not meaningful (axes are unlabeled), distances between points reflect changes in the model's internal representation.

Studying Remembrall's models

Evolution of models on an exemplar 90 min drone video stream.

t=0 sec



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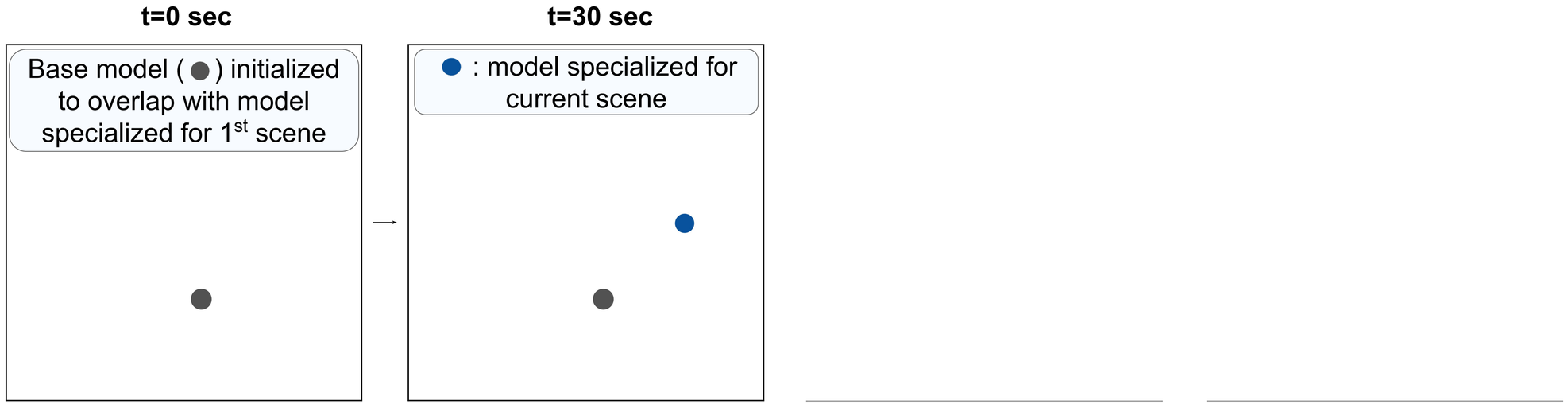

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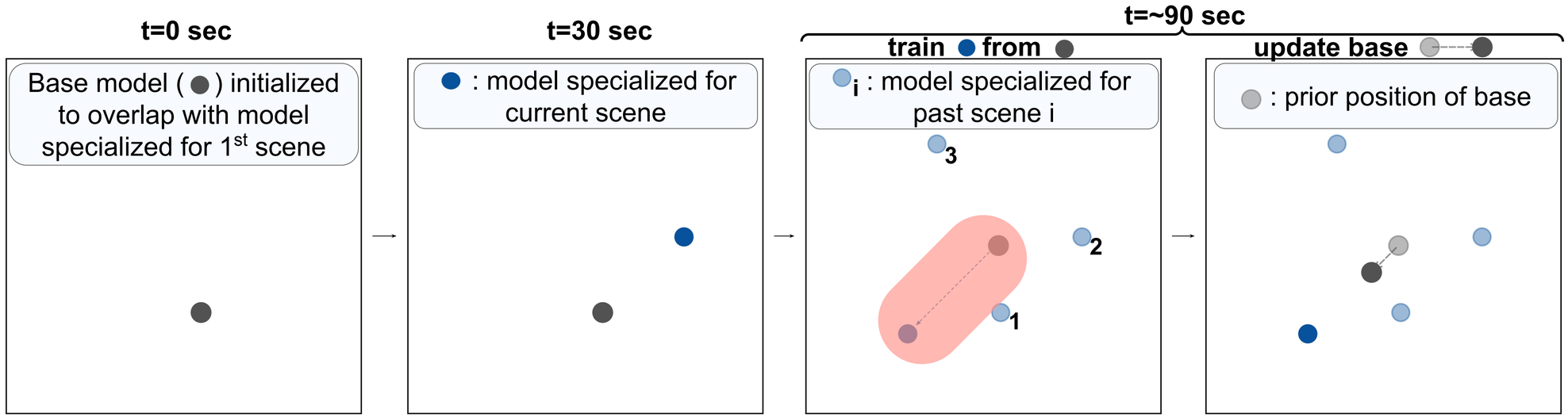

By **t=90 sec**, the ● is already in a "good position", as ● → ● (Remembrall-style) is shorter than 3 → ● (training with Ekya-style continual learning).

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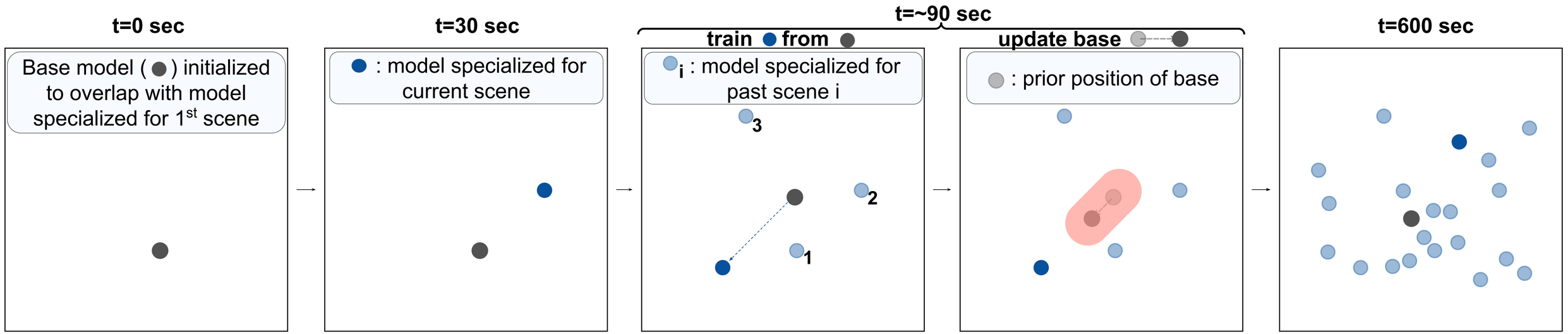

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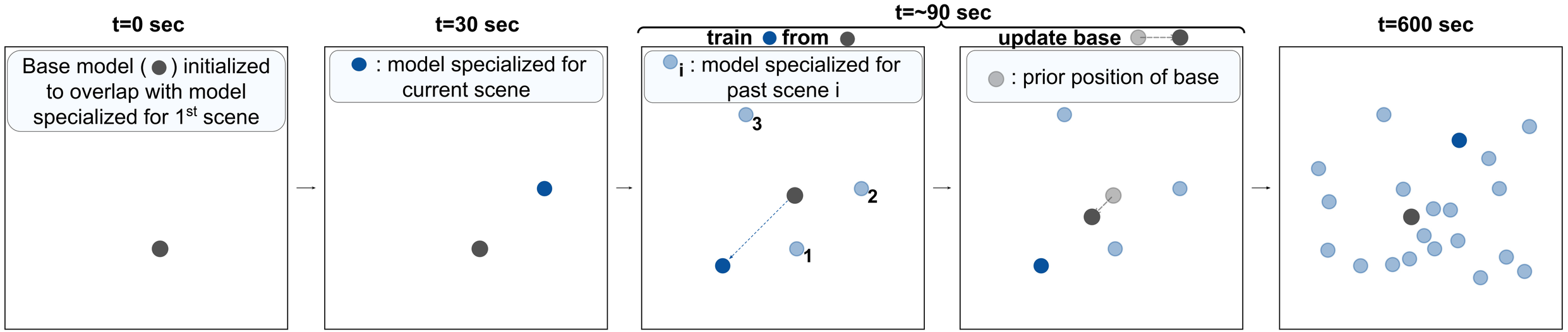

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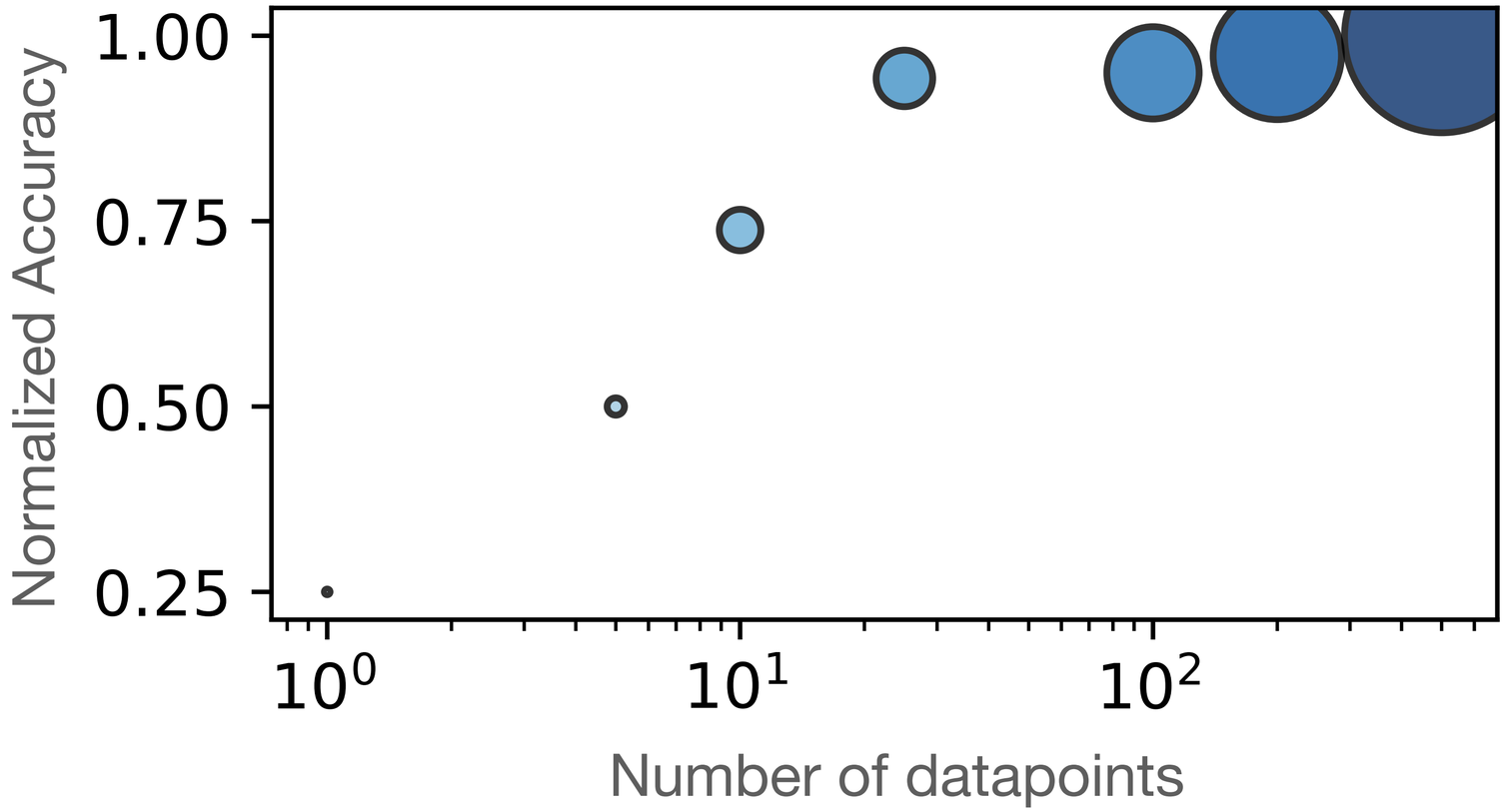
Remembrall is a natural instance of meta learning (learning-to-learn). Each scene is treated as a task and the base model serves as a learned initialization for fast per-task adaptation.

Challenge 1: Selecting training datapoints

- Post-retraining accuracy and retraining time as a function of number of datapoints.
  - Circle area denotes relative retraining time.
  - ResNet18 classification, medians shown here from training on 1hr drone video.



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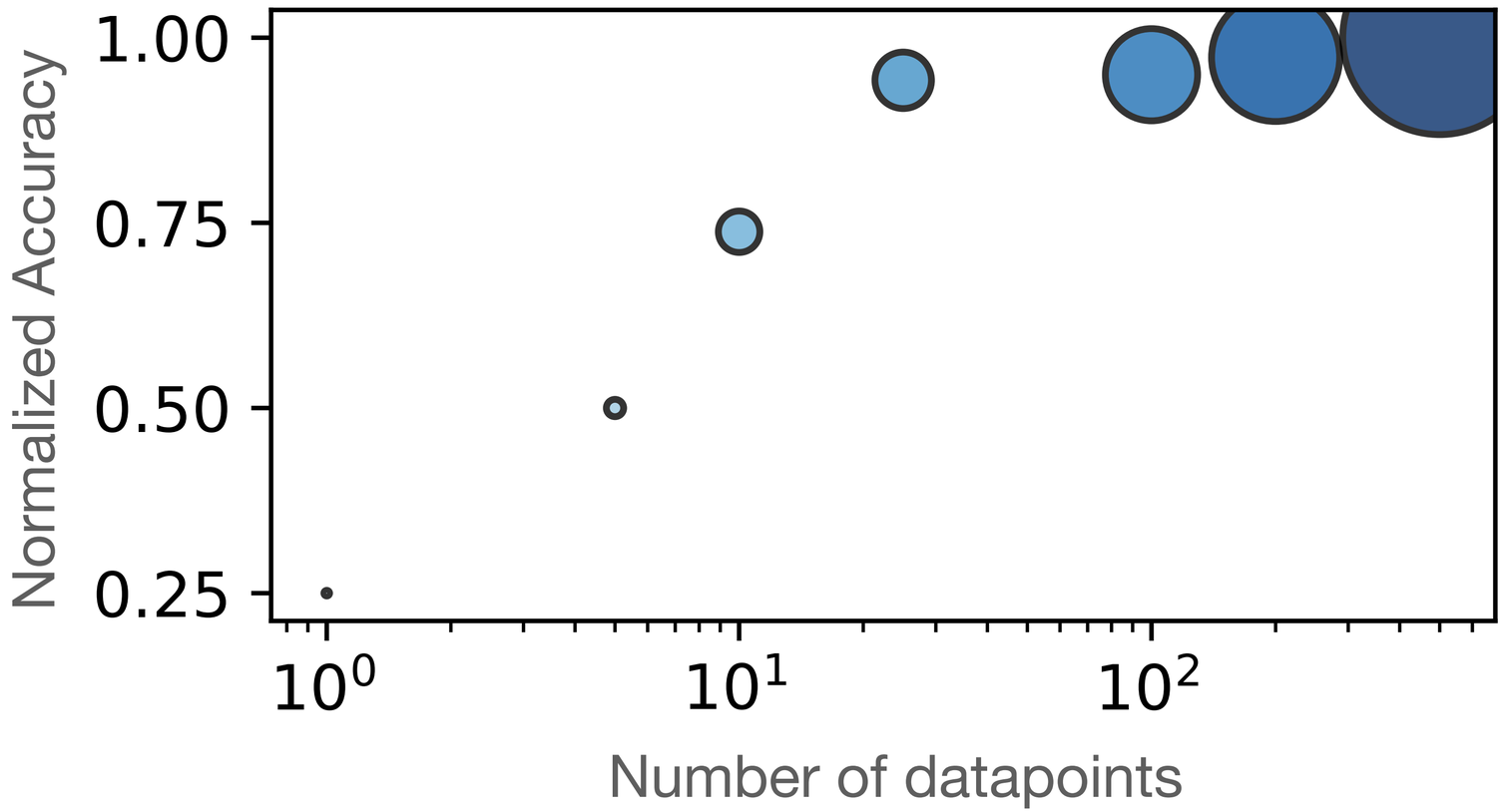
- Diminishing accuracy wins from larger training sets.
- Key challenge: right training datapoints.



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- Cache and reuse embeddings computed during inference by the specialized model.

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Deduplication via Embedding-Based Sampling

- Cache the embeddings from inference and apply a sampling algorithm (spatially correlated poisson sampling).
- Inclusion probability of a datapoint is inversely proportional to its distance to other datapoints
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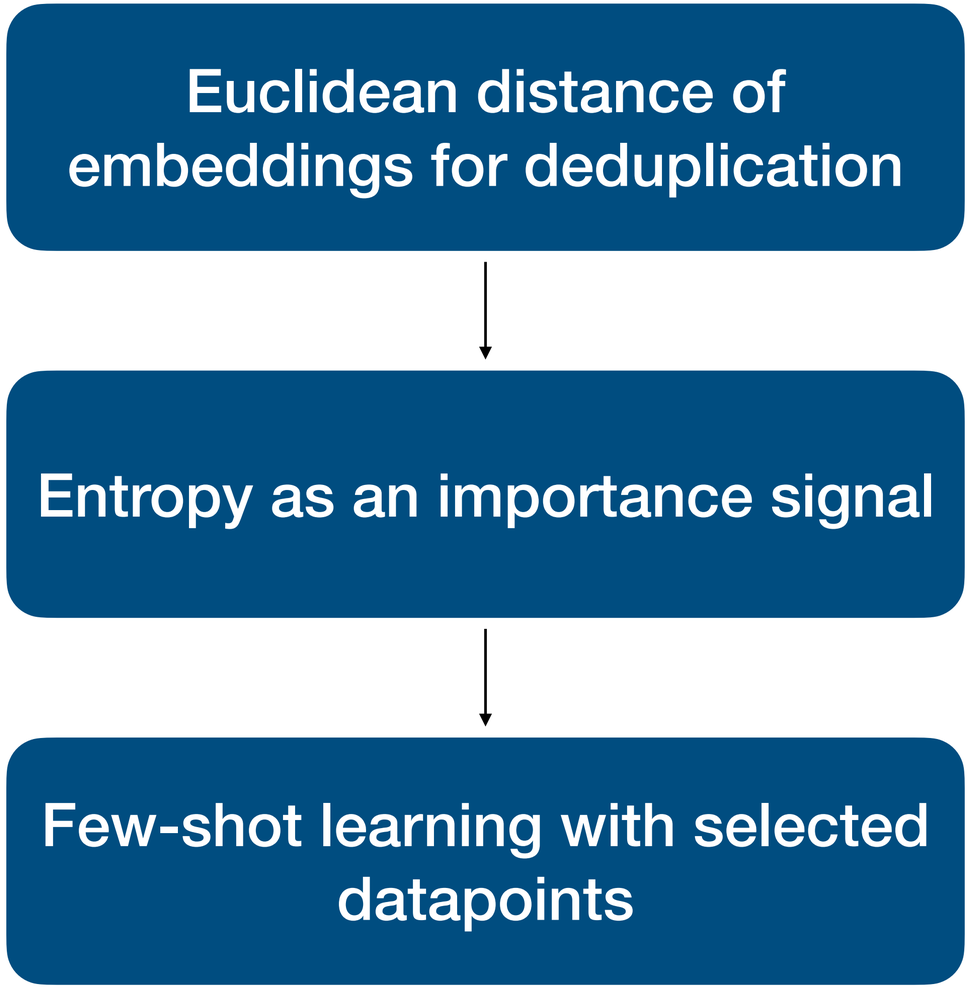

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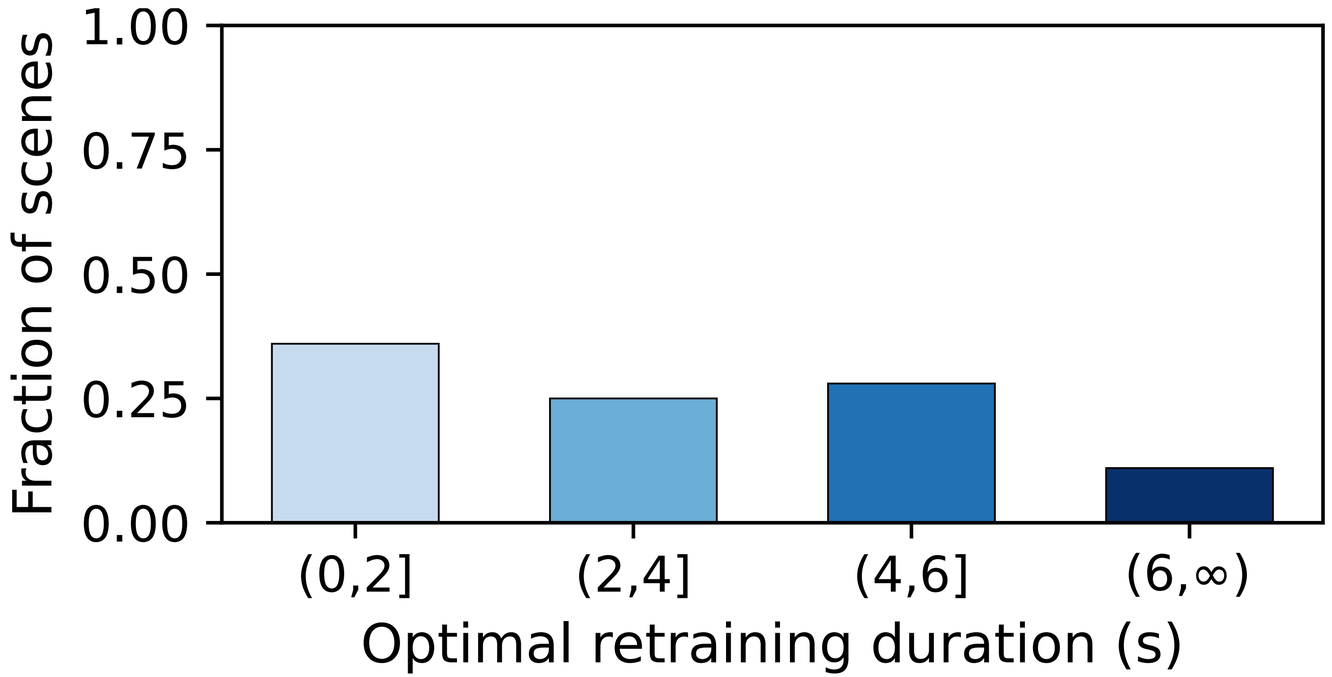

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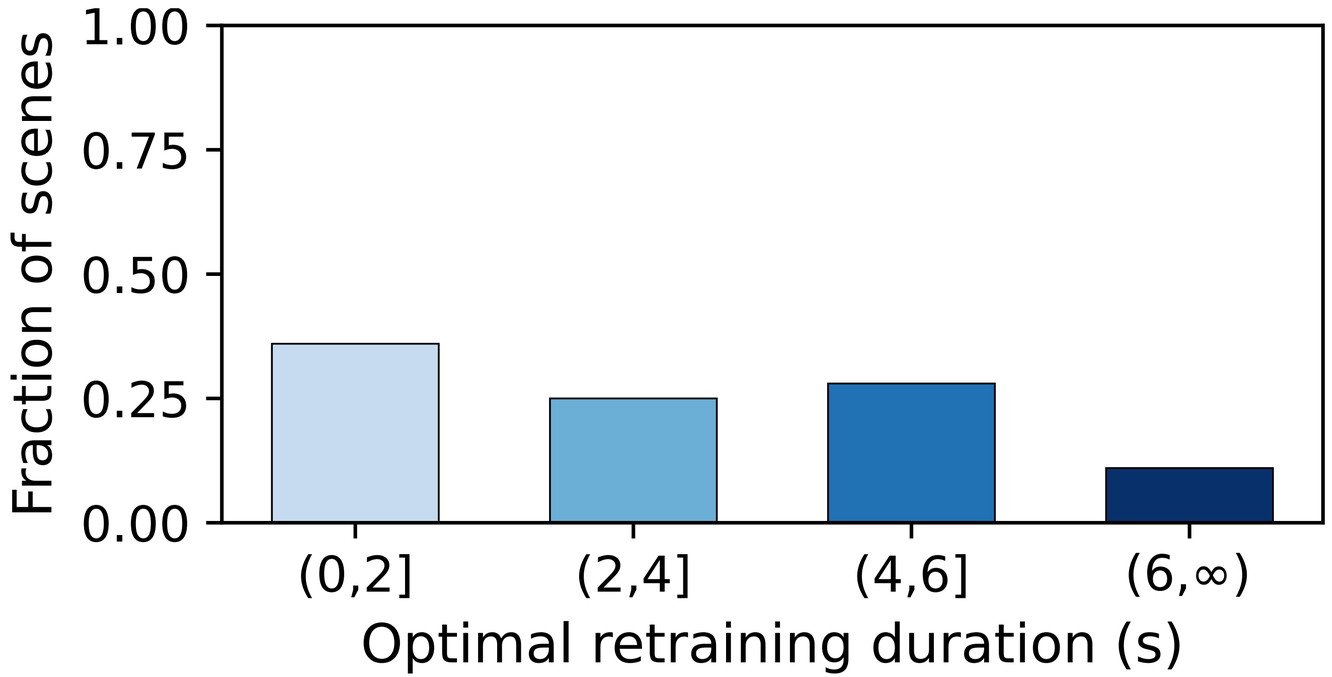
The optimal retraining duration is scene-dependent.

- Need an adaptive stopping policy.



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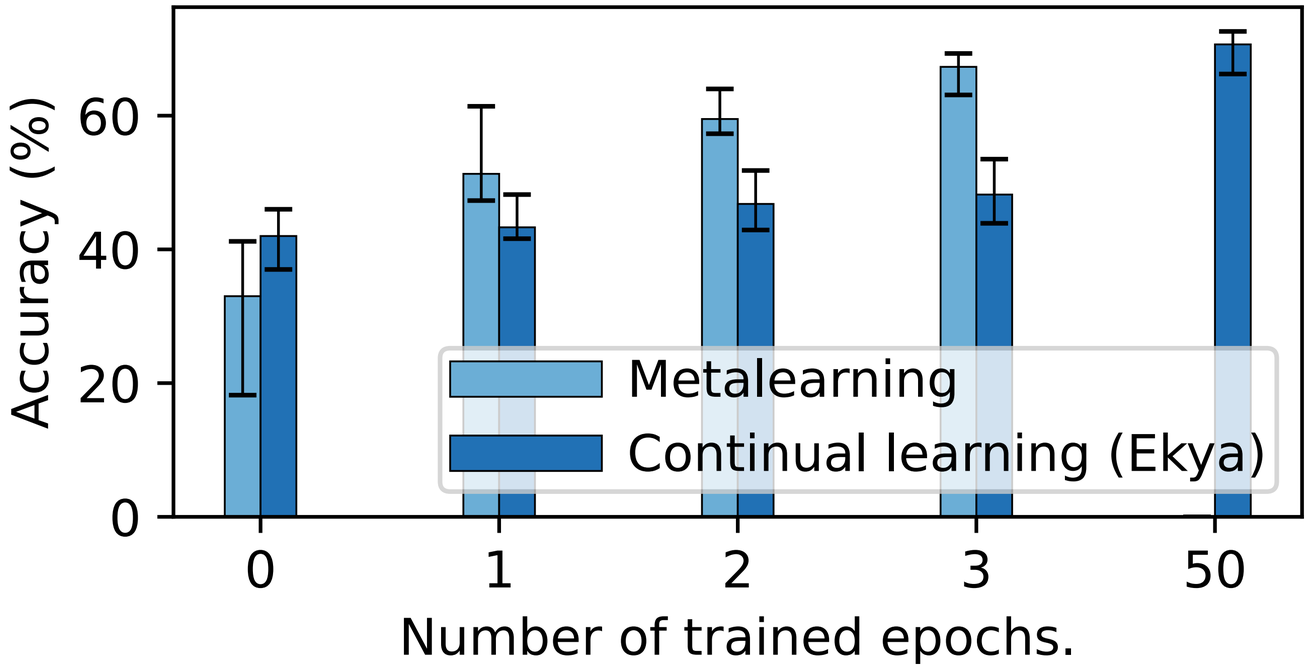

ResNet18 classification. Medians, errors span 25-75th percentiles.

Metalearning accuracy comparable to continual learning by epoch 5. Its bar at 50 is omitted to avoid overstating runtime.

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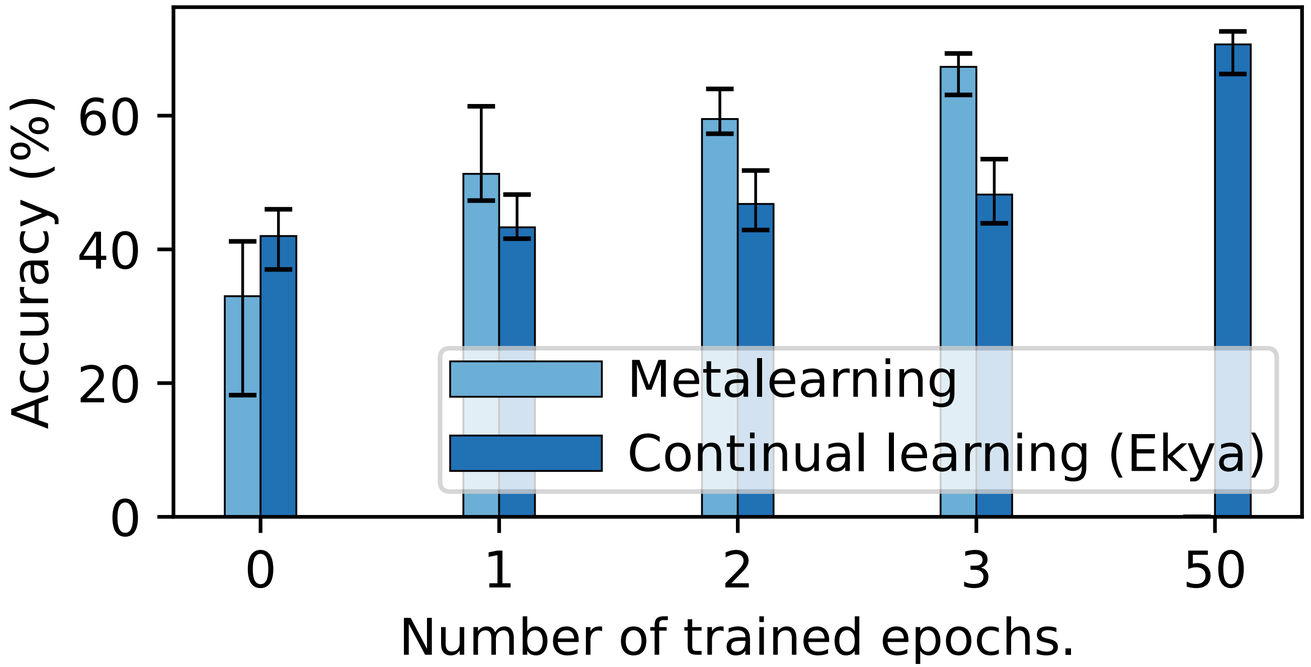

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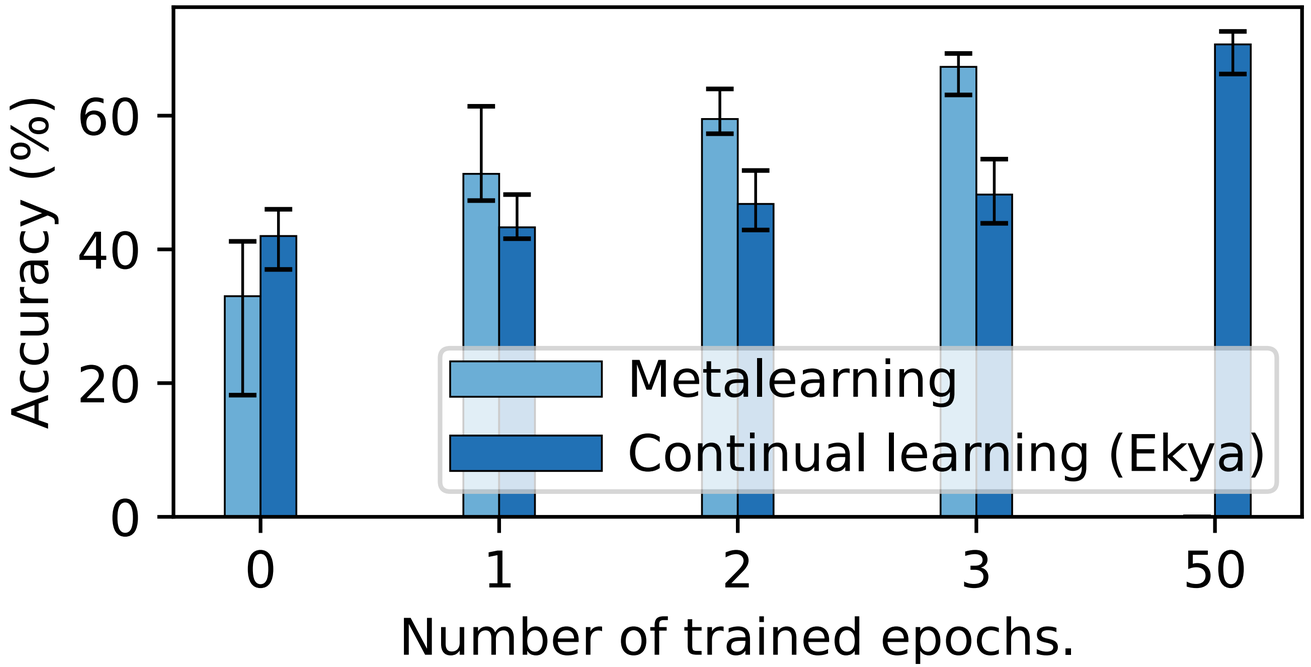

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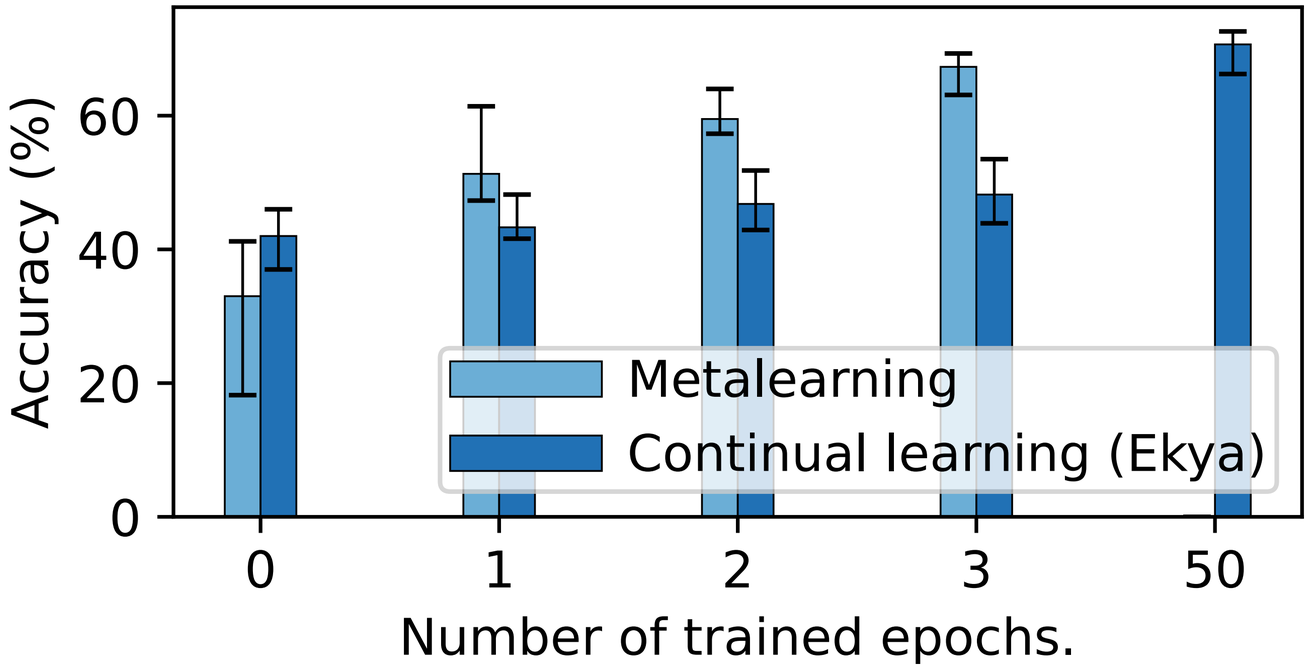
$$S_t = w_1 \cdot \frac{\Delta A_t}{\Delta A_{\max}} - w_2 \cdot \frac{D_t}{D_{\max}}$$

Evaluate after each epoch

Normalized accuracy gain

Normalized drift



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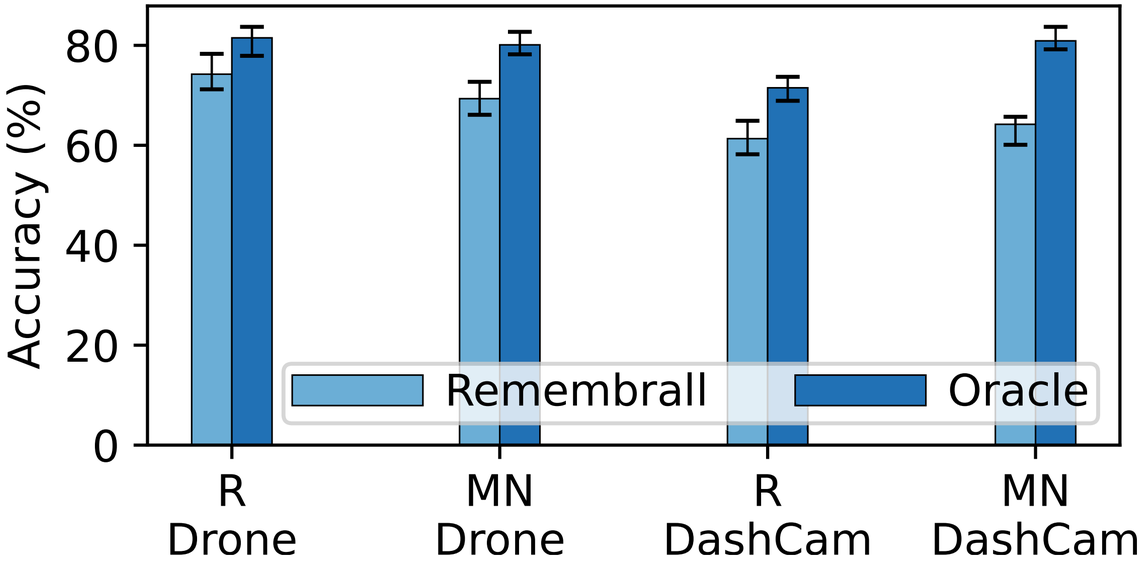
•Scene recurrence → benefits from gradual accumulation.

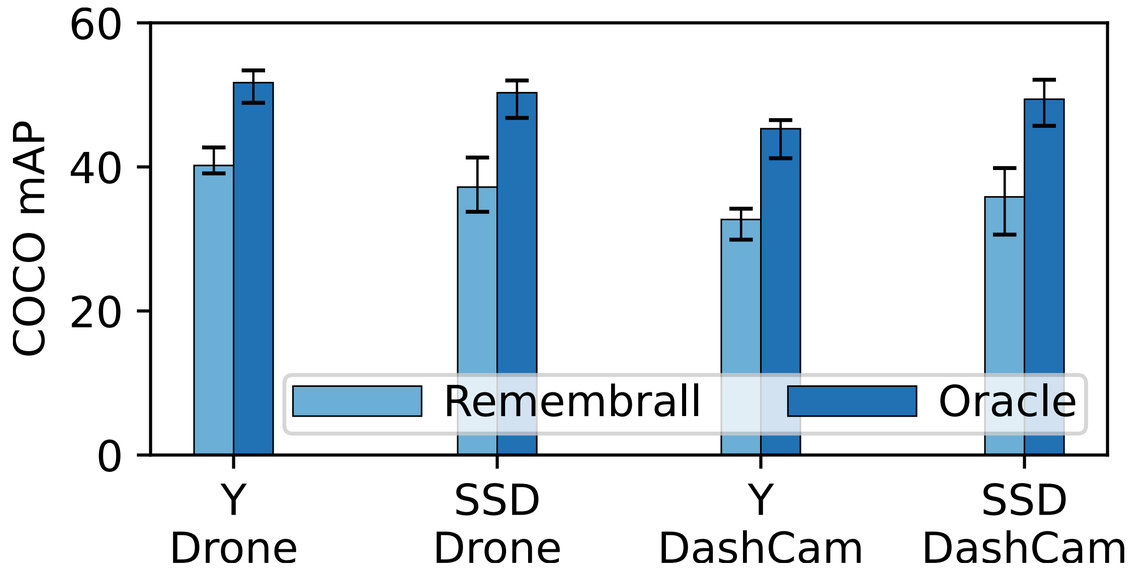
Evaluation

- How close does Remembrall's accuracy get to **oracle optimal**?
- How does Remembrall fare **against prior approaches**?
- How much does Remembrall reduce **overheads**?
- How do Remembrall's **contributions individually impact** the accuracy?
- How fast does Remembrall's base model **converge**?
- Can the converged **base model be reused** across videos?
- Robustness to transient vs. sustained drift.

Performance vs. Oracle

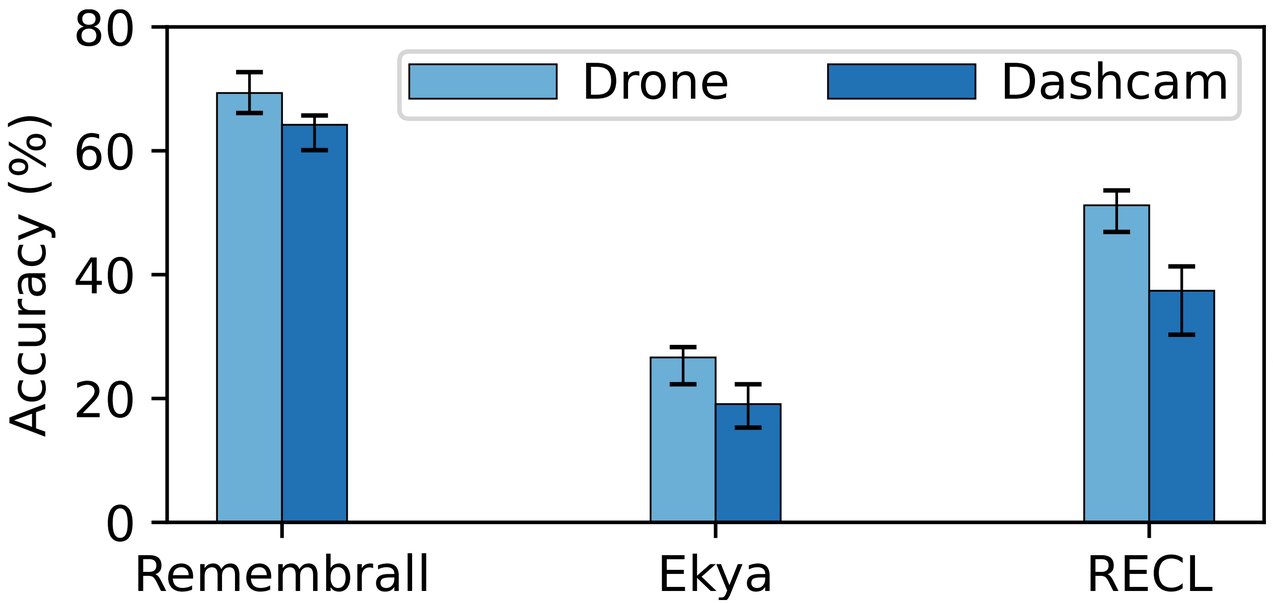


Classification. R=ResNet, MN=MobileNet.

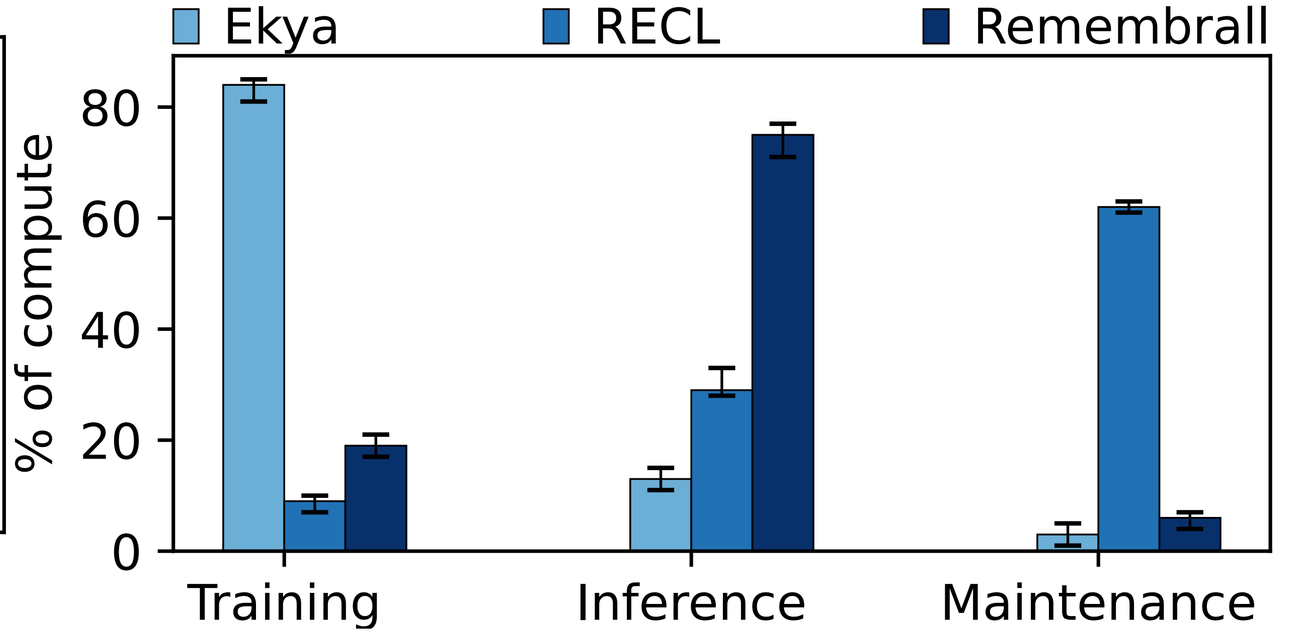


Detection. Y=YOLO, SSD=SSD-MobileNet.

Performance of Remembrall



Bars denote median overall classification accuracy (MobileNetV2) per video



Corresponding compute use on the Drone.

Error bars show 25th-75th percentile.

Summary

muralisr@princeton.edu

- ML-based video analytics is moving closer to the edge
- Prior approaches rely on compute-intensive retraining or large-scale model reuse
  - These approaches are fundamentally ill-suited to the SoC-based edge
- Remembrall instead **efficiently leverages memory to alleviate compute**
  - By incorporating cross-scene stability into a single extra base model
  - Embedding-guided sampling, inference-aware retraining, and lightweight meta-updates