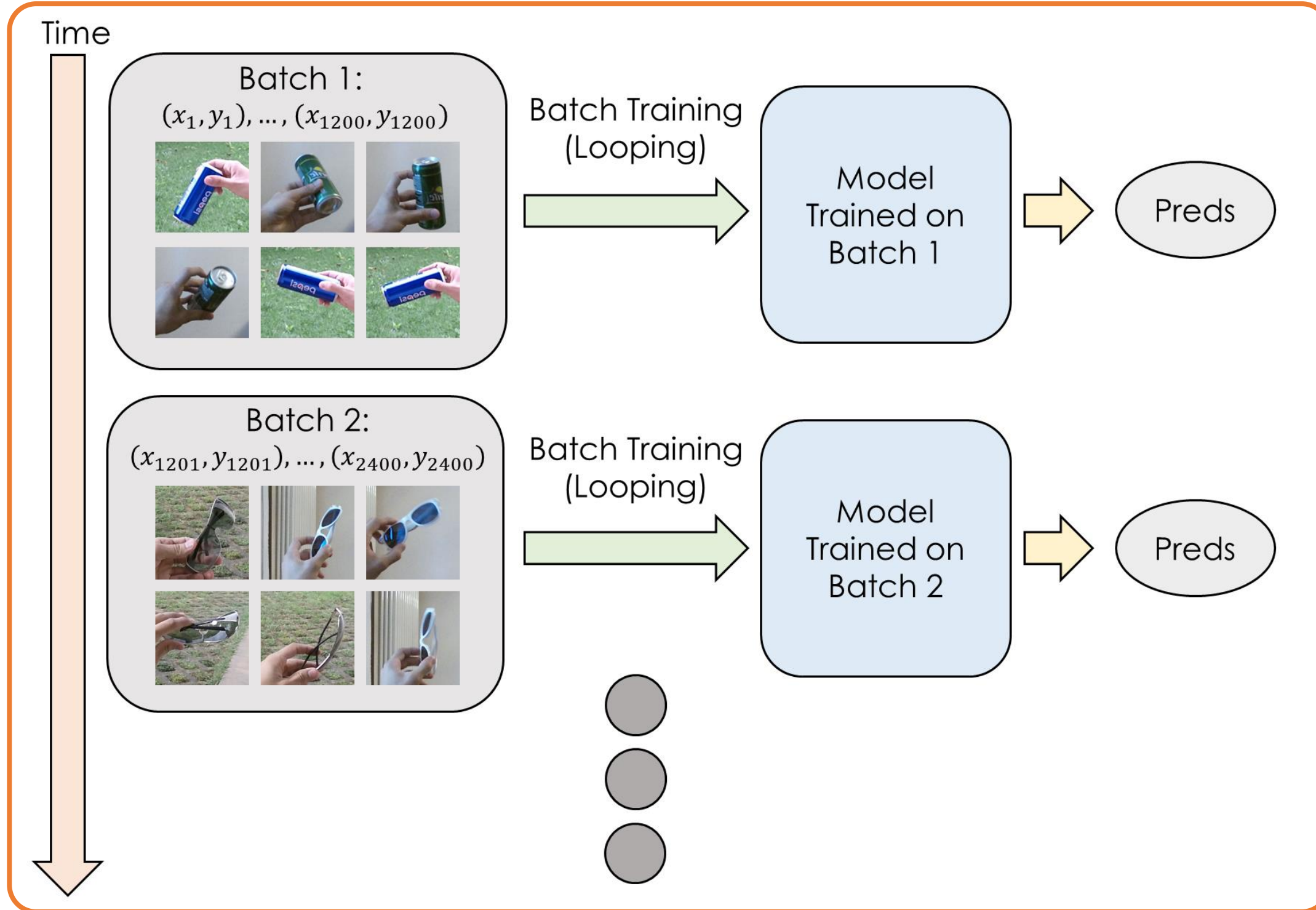


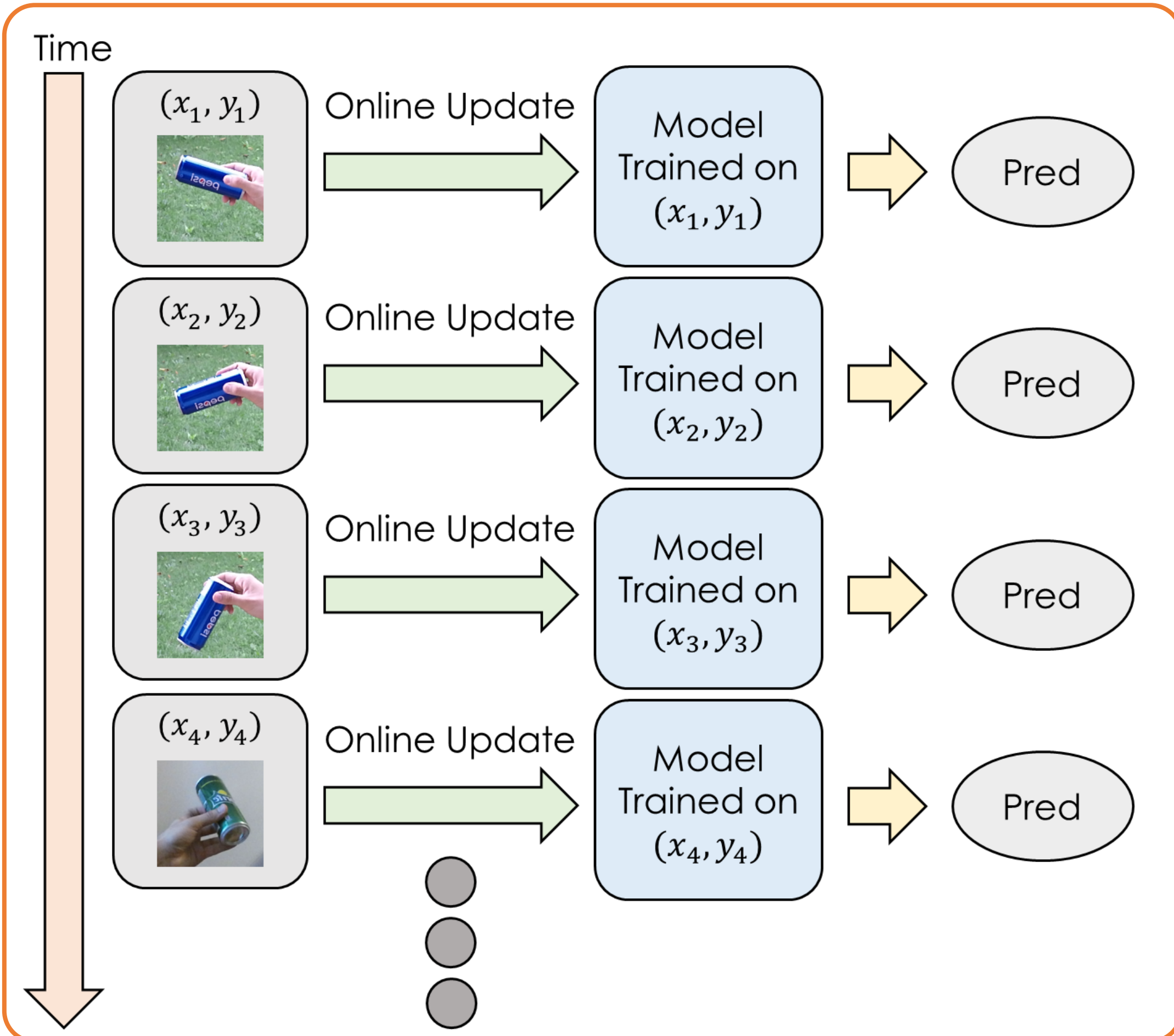
Overview

- ❖ Agents must be capable of learning and using information immediately.
- ❖ **Deep neural networks** (DNNs) are widely used for perception tasks, but if they are updated on changing data distributions, they **catastrophically forget** previous knowledge.
- ❖ **Streaming learning** requires agents to learn from non-independent and identically distributed (iid) data streams in real-time, i.e., one example at a time and a single pass through the dataset.
- ❖ **Deep Streaming Linear Discriminant Analysis (SLDA)** trains the output layer of a convolutional neural network (CNN) incrementally.
- ❖ SLDA outperforms recent incremental batch and streaming models with fewer memory and computational costs.

Incremental Batch Learning



Streaming Learning



Deep Streaming Linear Discriminant Analysis

- ❖ SLDA stores a running mean per class (μ_k) and a tied covariance matrix (Σ).
- ❖ We compute the precision matrix $\Lambda = [(1 - \epsilon)\Sigma + \epsilon I]^{-1}$.
- ❖ Predictions are made by assigning to an input the label of the closest Gaussian in feature space using the stored means and covariance:

$$\hat{y} = \underset{k}{\operatorname{argmax}} \left[\Lambda \mu_k - \frac{1}{2} (\mu_k \cdot \Lambda \mu_k) \right].$$

Experimental Evaluation

- ❖ **ImageNet-1K**: Popular large-scale image classification dataset (1,000 classes).
- ❖ **CORE50**: Streaming dataset containing video sequences of 10 different object categories. Temporal dependences are natural for streaming.

$$\Omega_{all} = \frac{1}{T} \sum_{t=1}^T \frac{\alpha_t}{\alpha_{offline,t}} \quad \alpha_t = \text{accuracy of streaming learner at time } t$$

$$\alpha_{offline,t} = \text{accuracy of offline model at time } t$$

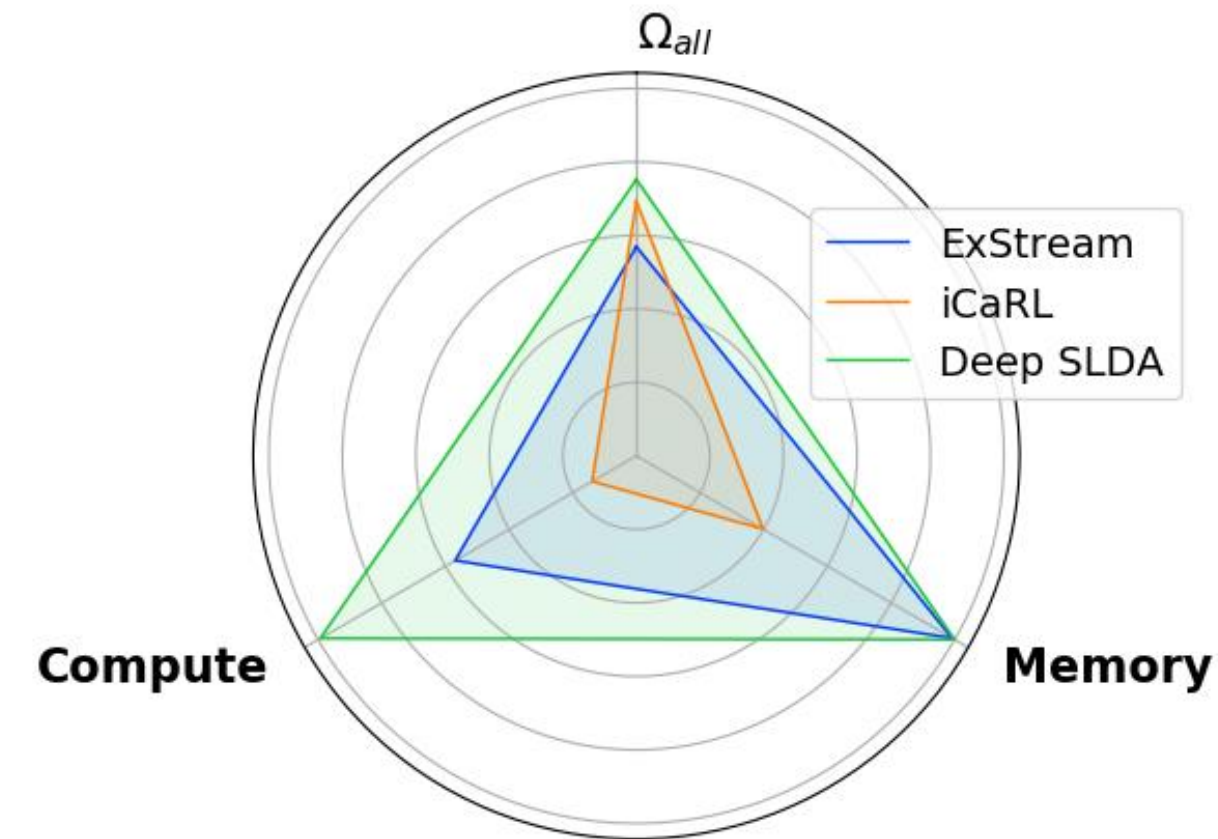
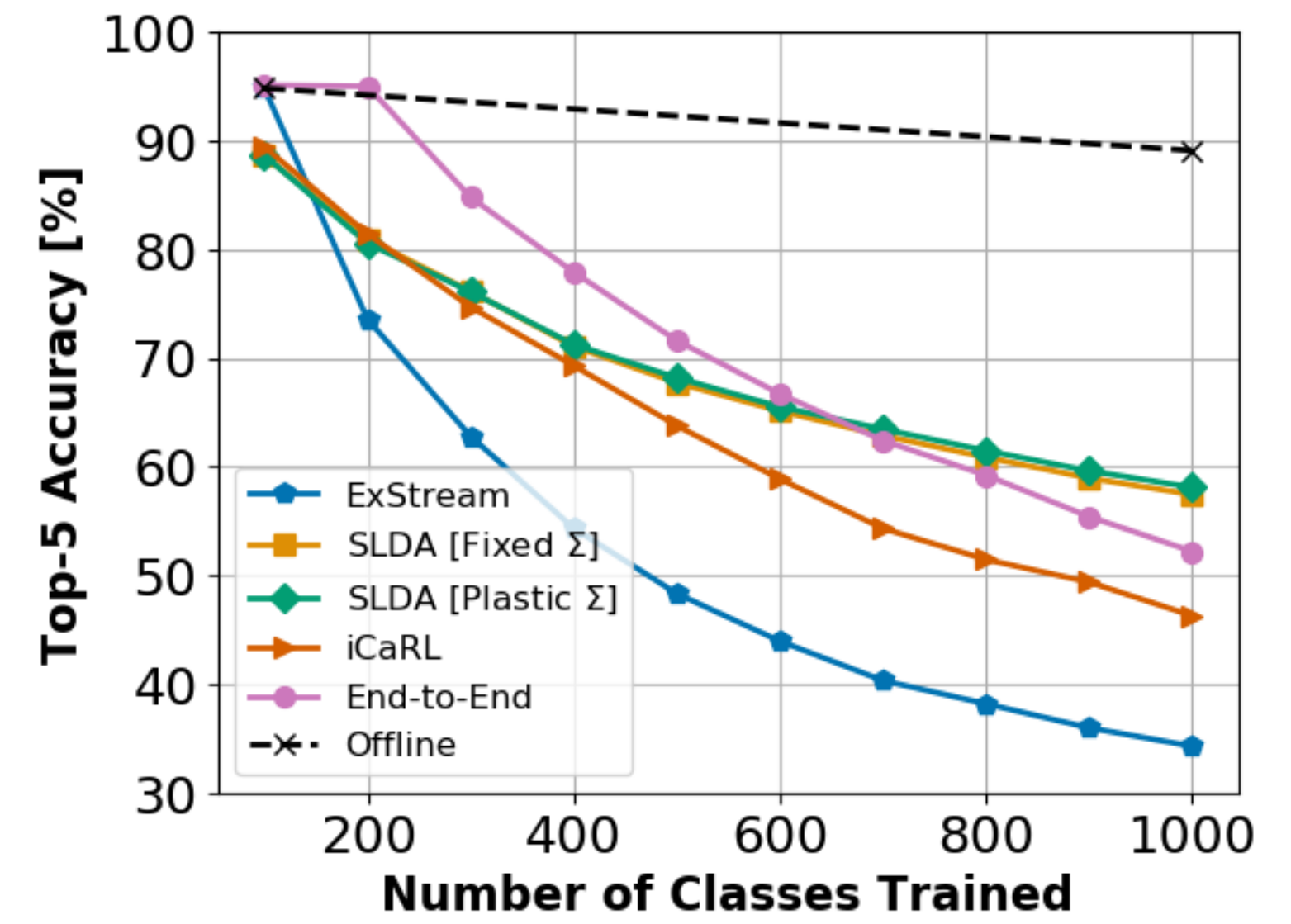
Streaming Learning Paradigms

- ❖ **iid**: data stream is randomly shuffled.
- ❖ **Class iid**: data stream is organized by class.
- ❖ **Instance**: data stream is temporally ordered by object instances.
- ❖ **Class Instance**: data stream is temporally ordered by object instances by class.

Comparison Models

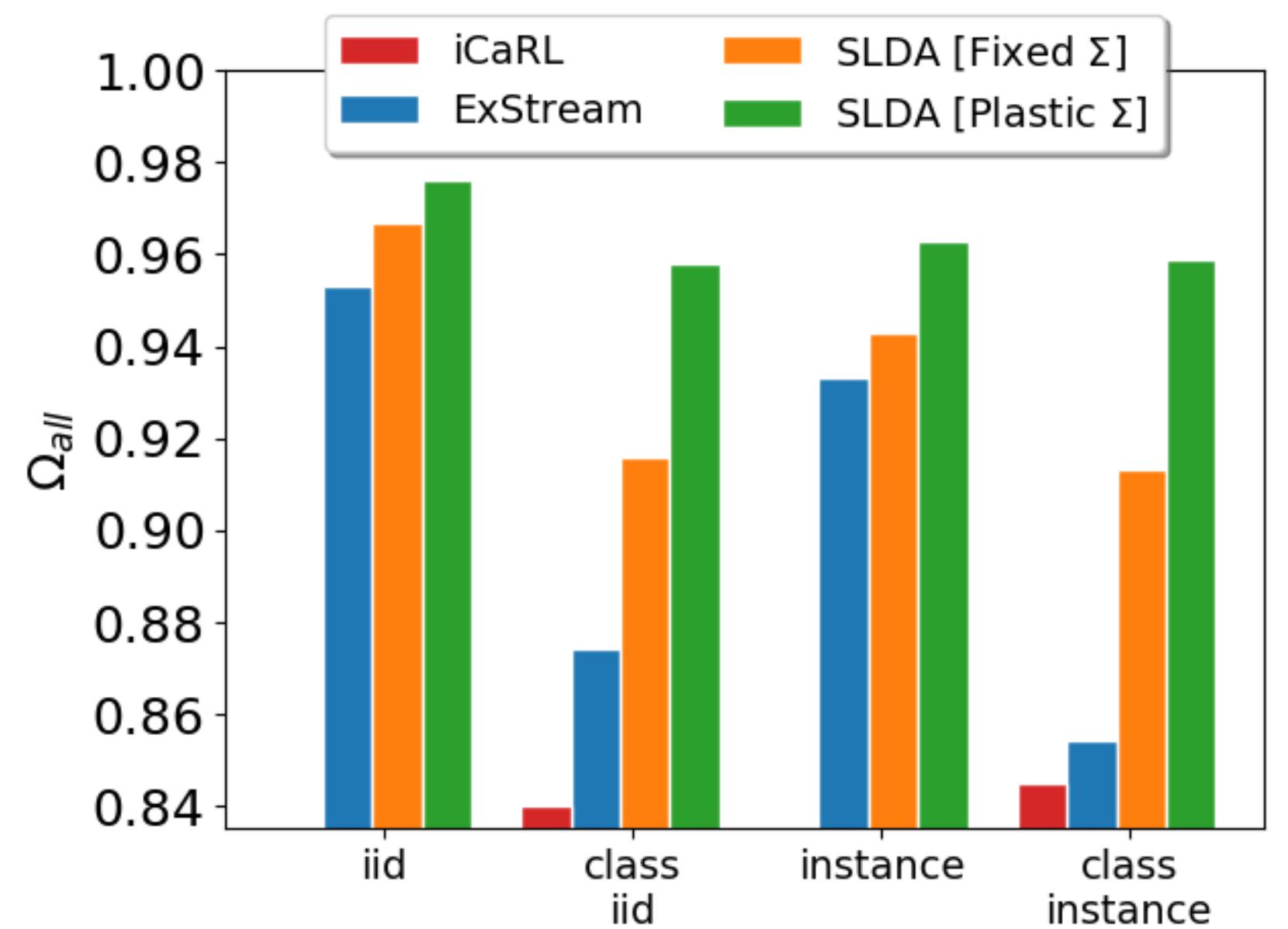
- ❖ We compare several models with the ResNet-18 CNN:
- ❖ **Deep SLDA**: Two variants: a fixed covariance and a plastic covariance.
- ❖ **ExStream**: Streaming learner that uses partial rehearsal and clustering.
- ❖ **iCaRL**: Popular incremental batch model that stores images for replay and uses distillation loss. Uses nearest class mean classifier.
- ❖ **End-to-End**: State-of-the-art incremental batch model on ImageNet-1K. Stores images for replay and uses distillation like iCaRL. Uses the CNN for classification and uses multiple augmentation techniques.
- ❖ **Offline**: Optimized offline learner. An upper bound on performance.

ImageNet-1K Results



SLDA runs 137x faster than iCaRL (in only 27 minutes) and saves over 1000x the memory!

CORE50 Results



Summary

- ❖ SLDA is popular in the data mining community but has not been used recently for **large classification datasets**.
- ❖ We **combine SLDA with a CNN** and exceed incremental batch learning models, while being much more **lightweight**.
- ❖ Our offline results suggest greater performance is achievable by training hidden layers, but we urge future developers to test only training the output layer to ensure gains are being realized.

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