REMIND Your Neural Network to Prevent Catastrophic Forgetting

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Abstract—In lifelong machine learning, a robotic agent must be incrementally updated with new knowledge, instead of having distinct train and deployment phases. Conventional neural networks are often used for interpreting sensor data, however, if they are updated on non-stationary data streams, they suffer from catastrophic forgetting, with new learning overwriting past knowledge. A common remedy is replay, which involves mixing old examples with new ones. For incrementally training convolutional neural network models, prior work has enabled replay by storing raw images, but this is memory intensive and not ideal for embedded agents. Here, we propose REMIND, a tensor quantization approach that enables efficient replay with tensors. Unlike other methods, REMIND is trained in a streaming manner, meaning it learns one example at a time rather than in large batches containing multiple classes. Our approach achieves state-of-the-art results for incremental class learning on the ImageNet-1K dataset. We also probe REMIND’s robustness to different data ordering schemes using the CORE50 streaming dataset. We demonstrate REMIND’s generality by pioneering multi-modal incremental learning for visual question answering (VQA), which cannot be readily understood in an interactive way.

I. INTRODUCTION

Typically, a deep neural network is trained offline and then kept fixed during deployment. If more data arrives, updating the model involves re-initializing the network and re-training. During the learning process, examples are sampled in an independent and identically distributed (iid) manner, and the optimizer makes many passes through the training dataset. While highly successful, this approach is not optimal for on-device learning or for robotic systems that need to be updated frequently. This approach is ill-suited for lifelong or autonomous learning, and it shares little resemblance to how humans or animals learn. People incrementally learn from perceptual experience and they can immediately make use of what they learn.

There are multiple paradigms in which incremental machine learning has been studied [1]. In incremental batch learning, at each time step \( t \) an agent learns a data batch \( B_t \) containing \( N_t \) instances and their corresponding labels, where \( N_t \) is often 1000 or more. While there has been recent interest in incremental batch learning [2]–[8], streaming learning resembles robotic learning more closely and has many applications. In streaming learning, a model learns on a sample-by-sample basis in a single pass through the dataset, i.e., \( N_t = 1 \) for all \( t \). This means the agent cannot loop over any portion of the (possibly infinite) dataset, and it can be evaluated at any point rather than only between large batches.

Conventional deep neural networks suffer from catastrophic forgetting, the abrupt drop in performance on previously observed tasks, when the data samples are not iid. This happens for all forms of incremental learning [9]. Catastrophic forgetting occurs due to the stability-plasticity dilemma [10]: to learn, a network must be plastic by allowing its weights to change, but if weights critical to preserving past knowledge are overwritten, that knowledge is lost. Despite recent progress in mitigating catastrophic forgetting [2], [5], [11]–[13], incrementally trained models still perform worse than offline models, especially when instances are ordered by category [6].

For incremental class learning, replay (or rehearsal) methods work especially well at mitigating catastrophic forgetting [2], [6], [7], [14]. In full rehearsal, the learner stores all previously observed examples, and then to learn a new instance or batch of instances it mixes the new example with the stored examples and fine-tunes the model on this set. This approach overcomes catastrophic forgetting [14], but it is slow and requires unlimited memory resources, making it infeasible to train on resource constrained devices such as smart toys and robots. Instead, replay algorithms typically use a fixed auxiliary memory to cache some of the information gleaned from previously observed examples [2], [7], [12], [14], [15]. Replay resembles learning mechanisms in the mammalian brain, in which memories in the hippocampus, a fast learning network, are replayed during sleep to train the neocortex, which learns more slowly but is better at generalization [16].

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Fig. 1. In incremental batch learning, agents learn by looping through batches of data multiple times. In contrast, streaming learning requires learning on a per-sample basis, facilitating immediate use of new information, which is desirable for real-time robotic agents.

\begin{figure}[h!]
\centering
\includegraphics[width=0.8\textwidth]{figure1.png}
\caption{Fig. 1. In incremental batch learning, agents learn by looping through batches of data multiple times. In contrast, streaming learning requires learning on a per-sample basis, facilitating immediate use of new information, which is desirable for real-time robotic agents.}
\end{figure}
Replay methods store representations of the data, subject to a maximum memory budget. One way to implement this is by storing a subset of raw inputs. An alternative is to store cluster centers by using online vector clustering algorithms [14], which has been shown to work better than storing raw features with fully connected networks. However, it is not straightforward to use this approach to train convolutional layers because they operate on tensors rather than vectors, so incremental training of convolutional neural networks (CNNs) is typically done by storing a subset of the raw images for each batch. To make this strategy work, replay schemes typically use distillation with soft-targets to obtain more label information [2], [7], [17]–[19], which is sometimes combined with large amounts of data augmentation [2]. These approaches have only been explored for incremental batch learning, and it is not clear if they would be successful in the streaming learning setting.

Here, we propose a novel method for incremental learning that operates in the streaming paradigm and rehearses on tensors from intermediate layers of a CNN instead of raw images. Rather than storing tensors directly for replay, we use quantized mid-network feature representations. With this approach, we incrementally store indices for incoming tensors in a replay buffer. This allows us to maintain the same memory footprint as state-of-the-art incremental batch learning methods, but with a larger replay buffer. We validate our novel method on four distinct datasets, including two multi-modal classification tasks.

Our main contributions are:

1) We introduce the REMIND (replay using memory indexing) model, a novel method for incremental batch and streaming learning for neural networks that uses vector quantization to enable replay with tensors rather than the original inputs or vectors. Unlike existing work for incrementally training CNNs, REMIND does not store raw images.

2) We quantify the benefit of ‘representation’ learning rather than using embeddings in incremental batch learning for CNNs, which has not been done previously.

3) Although REMIND uses streaming learning, it exceeds state-of-the-art incremental batch learning models at incremental class learning on the 1000 category ImageNet dataset and the temporally ordered CORe50 image classification dataset, which is designed to mimic the visual input to a robotic platform.

4) Using REMIND, we pioneer streaming learning for the multi-modal VQA task, in which an agent must answer questions about images. We achieve strong results on the TDIUC and CLEVR datasets and establish experimental paradigms, baselines, and metrics.

II. RELATED WORK

REMINd is the only method for streaming learning for CNNs, so we focus on comparing it against iCaRL [7] and End-to-End Incremental Learning [2], state-of-the-art incremental class batch learning methods for CNNs that use replay with distillation loss to prevent forgetting. Replay has been shown to be one of the most effective methods for mitigating catastrophic forgetting in neural networks [2], [5]–[7], [14], however, other methods for mitigating forgetting have also been developed. Regularization methods vary a weight’s plasticity based on how important it is to previous tasks. These methods include Elastic Weight Consolidation [11], Memory Aware Synapses [20], Synaptic Intelligence [8], Online Laplace Approximator [21], and Hard Attention to the Task [22]. Averaged Gradient Episodic Memory [15] extends Gradient Episodic Memory [12], which uses replay with regularization. Variational Continual Learning [13] combines Bayesian inference with replay, while the Meta-Experience Replay model [23] combines replay with meta-learning. All of these methods are typically used for incremental task learning where batches of data are labeled as different tasks and the model must be told which task (batch) a sample came from during inference. When task labels are not available at test time, which is often true for robotic agents operating in real-time, many methods cannot be used or they will fail [3], [6], [24]. Another approach to mitigating forgetting is to expand the network as new classes or tasks are observed, e.g., Progressive Neural Networks [25], Dynamically Expandable Networks [26], and Adaptation by Distillation [17]. However, these approaches also use task labels at test time, have growing memory requirements, and may not scale to datasets with thousands of categories, making them ill-suited for robotics applications. While there are incremental batch learning methods that do not use test-time task labels [5], [15], [27], these methods operate on vectors, rather than tensors and they cannot be easily used to train a CNN. An exception is RWalk [3], but it has only been tested on CIFAR-100 in a non-streaming setting.

III. REMIND: REPLAY USING MEMORY INDEXING

REMINd is a novel method for training the parameters of a CNN in the streaming setting using replay mini-batches. Learning involves two steps: 1) compressing the input and 2) reconstructing a subset of previously compressed representations, mixing them with the current input, and updating the plastic weights of the network with this mixture. While earlier work for incremental batch learning with CNNs stored raw images to use with partial rehearsal [2], [7], by storing compressed tensors, REMIND is able to store a much greater number of instances with a smaller memory budget. For example, iCaRL [7], a widely used method for incremental class learning, stores 20K examples for ImageNet-1K, whereas REMIND can store over 1M compressed instances using $2/3$ the memory by taking advantage of the learned representations in the network.

REMINd is inspired by the brain’s complementary learning systems [28], and it is heavily influenced by Hippocampal Indexing Theory [29]. In Hippocampal Indexing Theory, when regions of the hippocampus are activated, they project back to the neocortex to reactivate memories, enabling the hippocampus to act as an indexing mechanism for memory retrieval. This is analogous to REMIND’s reconstruction of examples from the indices alone. During waking hours, the
hippocampus learns quickly, which may be facilitated using neurogenesis [30]. During sleep, compressed representations in the hippocampus are re-activated to be replayed to the neocortex, resulting in generalizable knowledge [31], [32].

Formally, our CNN $y_i = F(G(X_i))$ is trained in a streaming paradigm, where $X_i$ is the input image and $y_i$ is the output category. The network is composed of two nested functions: $G(\cdot)$, parameterized by $\theta_G$, consists of the first $J$ layers of the CNN and $F(\cdot)$, parameterized by $\theta_F$, consists of the last $L$ layers. REMIND keeps $\theta_G$ fixed since early layers of CNNs have been shown to be highly transferable [33]. The later layers, $F(\cdot)$, are trained in the streaming paradigm using REMIND. We discuss how $G(\cdot)$ is initialized in Sec. [VI-B].

The output of $G(X_i)$ is a tensor $Z_i \in \mathbb{R}^{m \times m \times d}$, where $m$ is the dimension of the feature map and $d$ is the number of channels. After training $G(\cdot)$, we train a vector quantization model for the $Z_i$ tensors. As examples are observed during training, the quantization model is used to store the $Z_i$ features and their labels in a replay buffer as an $m \times m \times s$ array of integers using as few bits as necessary, where $s$ is the number of indices that will be stored. For replay, we uniformly select $r$ instances from the replay buffer, which was shown to work well in [3], and reconstruct them. Each of the reconstructed instances, $Z_i$, are mixed with the current input, and then $\theta_F$ is updated using backpropagation on this replay mini-batch of $r + 1$ instances. In our implementation, we uniformly sample $r$ instances from the replay buffer, where $r$ varied per dataset. Alternative selection strategies are discussed in Sec. [VI].

Our main version of REMIND uses product quantization (PQ) [34] to compress and store $Z_i$. For high-dimensional data, PQ tends to have much lower reconstruction error than models that use $k$-means alone. PQ partitions each $d$-dimensional tensor element into $s$ sub-vectors of size $\ell = d/s$. Using $k$-means, PQ learns a separate codebook of size $c$ for each partition. Quantization is done independently for each partition, resulting in $s$ integers for each $d$-dimensional tensor element. If $s$ is equal to one, then this approach is identical to using $k$-means for vector quantization, which we compare against in our experiments. For our CNN image classification models, we set $s = 32$ and $c = 256$, so that each integer can be stored with 1 byte. We explore alternative values of $s$ and $c$ in Sec. [VII]. In our experiments, we use the PQ implementation in the Faiss library [35].

A. Augmentation During Replay

To augment data during replay, REMIND uses random crops and a variant of manifold mixup [36] for image classification on the quantized tensors directly. The tensors are randomly cropped and bilinearly interpolated to match the original tensor dimensions. To produce more robust representations, REMIND also mixes features from multiple classes. That is, REMIND uses its replay buffer to reconstruct two randomly chosen sets of $r$ instances. The samples from the two sets are then linearly combined together to obtain $r$ mixed instances:

$$
(\tilde{Z}_{\text{mixed}}, \tilde{y}_{\text{mixed}}) = \left( \lambda \tilde{Z}_a + (1 - \lambda) \tilde{Z}_b, \lambda y_a + (1 - \lambda) y_b \right),
$$

where $a$ and $b$ denote the two sets and $\lambda \sim \beta(\alpha, \alpha)$ is the mixing coefficient drawn from a $\beta$-distribution parameterized by hyperparameter $\alpha$. We use $\alpha = 0.1$, which we found to work best in preliminary experiments. The current input is combined with the $r$ mixed samples, and $\theta_F$ is updated using this set of $r + 1$ instances.

B. Initializing REMIND

During streaming learning, REMIND only updates $F(\cdot)$, i.e., the top of the CNN. It assumes that $G(\cdot)$, the lower level features of the CNN, are fixed. For this to be a valid assumption, the low-level visual representations must be highly transferable across image datasets, which is supported empirically [33]. There are multiple methods for training $G(\cdot)$, including supervised pre-training on a portion of the dataset, supervised pre-training on a different dataset, or unsupervised self-taught learning using a convolutional auto-encoder. Here, we follow the common incremental batch learning practice of doing a ‘base initialization’ of the CNN [2], [7]. This is done by training both $\theta_F$ and $\theta_G$ jointly on an initial subset of data offline, e.g., for class incremental learning on ImageNet we use the first 100 classes. After base initialization, $\theta_G$ is no longer plastic. All of the examples $X_i$ in the base initialization batch are pushed through the model to obtain $Z_i = G(X_i)$, and all of these $Z_i$ instances are used to learn the vector quantization model for $G(X_i)$. The vector quantization model is kept fixed once it is learned.

IV. Experiments: Image Classification

In this section, we describe our experiments on incrementally training CNN models for image classification. Following [2], [7], experiments are done using ResNet-18 [37].

A. Datasets, Data Orderings, & Metrics

We conduct incremental learning experiments in CNNs using two datasets: ImageNet-1K and CORE50. We divide both datasets into batches. The first batch is used for base initialization of each model. Subsequently, incremental batch
learning methods are sequentially fed each batch, which they loop over. **Streaming models use the same batches, but they are sequentially fed individual samples in the batches and they cannot revisit any instances in a batch.** For both datasets, the test set is kept constant and models are evaluated after each batch.

ImageNet-1K [38] has 1,000 categories, each with 732-1,300 training samples and 50 validation samples, which we use for testing. We study class incremental (class iid) learning with ImageNet. Following others [2], [7], each batch contains 100 randomly chosen classes, which are not contained in any other batch. Prior to base initialization, CNN weights are initialized randomly.

CORe50 [39] contains sequences of video frames, with an object in each frame, which closely matches the robotic perception of images. It has 10 classes, and each sequence is acquired with varied environmental conditions. CORe50 is ideal for evaluating streaming learners since it is naturally non-iid and requires agents to learn from temporally correlated video streams. For CORe50, we sample at 1 frame per second, obtaining 600 training images and 225 test images per class. We use the bounding box crops and splits from [39]. The test set has none of the object instances observed during training. Following [14], we use four training orderings:

- iid – Each batch has 1,200 random training images.
- class iid – Each batch has all of the images from two classes, which are randomly shuffled.
- instance – Each temporally ordered batch has images from 80 unique object instances.
- class instance – Each temporally ordered batch has all of the instances from two classes.

Across orderings, all batches have 1,200 images. Since CORe50 is small, prior to base initialization, CNN weights are initialized to pre-trained ImageNet-1K weights.

We use the $\Omega_{\text{all}}$ metric [6] for evaluation, which normalizes the performance of a lifelong learner with offline performance:

$$\Omega_{\text{all}} = \frac{1}{T} \sum_{t=1}^{T} \frac{\alpha_{t}}{\mathcal{O}_{\text{offline},t}},$$

where $T$ is the total number of testing events, $\alpha_{t}$ is the accuracy of the model for test $t$, and $\mathcal{O}_{\text{offline},t}$ is the accuracy of the optimized offline learner for test $t$. If $\Omega_{\text{all}} = 1$, then that means it matched the offline model. $\Omega_{\text{all}}$ is computed using top-1 accuracy for CORe50 and top-5 accuracy for ImageNet.

**B. Models Assessed for Incrementally Training CNNs**

While REMIND is a streaming learning method that learns per instance, most methods for incremental batch learning in CNNs do multiple loops through a batch. Despite this advantage, we compare REMIND against them. We evaluate the following streaming and incremental batch learning mechanisms:

- **REMIND** – Our main REMIND version uses PQ and replay augmentation. We also explore a version that omits data augmentation and a version that uses $k$-means rather than PQ.

- **Fine-Tuning (No Buffer)** – Fine-Tuning is a streaming baseline that fine-tunes a CNN one sample at a time with only one epoch through the dataset. This approach does not use a buffer and suffers from catastrophic forgetting [6]. We compare three versions: 1) update the output layer only, 2) update $\theta_{F}$ only, and 3) update $\theta_{F}$ and $\theta_{G}$.

- **ExStream** – Like REMIND, ExStream is a streaming learning method, however, it can only train fully connected layers of the network. ExStream uses rehearsal by maintaining buffers of prototypes. It stores the input vector and combines the two nearest vectors in the buffer [14]. After the buffer gets updated, all samples from its buffer are used to train the fully connected layers of a network. We use ExStream to train the final layer of the network, which is the only fully connected layer in ResNet-18.

- **SLDA** – Streaming Linear Discriminant Analysis (SLDA) is a well-known streaming learning method from the data mining community and was recently shown to work well on deep CNN features [40]. It maintains running means for each class and a running tied covariance matrix, enabling it to be robust to catastrophic forgetting. It can be used to compute the output layer of the CNN.

- **iCaRL** – iCaRL [7] is an incremental batch learning algorithm for CNNs that requires looping over class batches of two or more categories. To mitigate catastrophic forgetting, iCaRL stores images from earlier classes for replay and it uses a distillation loss to preserve weights. For classification, it uses a nearest class mean classifier in feature space. We experiment with two versions: 1) update $\theta_{F}$ only, and 2) update $\theta_{F}$ and $\theta_{G}$.

- **End-to-End** – End-to-End [2], a state-of-the-art method for incremental batch learning, builds on iCaRL, but uses the CNN for classification. It uses a balanced fine-tuning stage, additional augmentation strategies (e.g., brightness enhancements, contrast normalization, random crops, and mirroring), and distillation with its replay data to improve performance. Like iCaRL, it is not capable of streaming learning.

- **Offline** – The offline model is trained in a traditional, non-streaming setting and serves as an upper-bound on performance. We use offline for normalization of $\Omega_{\text{all}}$. We compare two versions of the offline model 1) update only $\theta_{F}$, and 2) update both $\theta_{F}$ and $\theta_{G}$.

The same base CNN initialization procedure is used for all models. After initialization, all the parameters except the output layer are frozen for ExStream and SLDA, and we restart the streaming learning phase from the beginning of the data stream. CNNs for all models, except SLDA, are trained using cross-entropy loss with stochastic gradient descent and momentum. While there are a variety of other algorithms for incremental batch learning, iCaRL and End-to-End are state-
of-the-art for incremental learning in CNNs on ImageNet-1K.

For ResNet-18, we set \( G(\cdot) \), the non-plastic network, to be the first 15 convolutional and 3 downsampling layers, which have 6,455,872 parameters, and \( F(\cdot) \) to be the remaining 3 layers (2 convolutional and 1 fully connected), which have 5,233,640 parameters. The layers for \( G(\cdot) \) were chosen for memory efficiency in the vector quantization model with ResNet-18. Before incremental learning, for ImageNet-1K, ResNet-18 is initialized by training on a set of 100 randomly selected classes and for CORE50, it is initialized using pretrained weights from ImageNet-1K followed by fine-tuning on the base set of 1,200 images, as described in Sec. IV-A.

Streaming learning models are trained instance-by-instance, whereas the models that are only capable of incremental batch learning are trained using batches. For ImageNet, each batch consists of 100 classes and for CORE50, each batch consists of 1,200 points as described in Sec. IV-A. Except for the offline baseline, all models are trained with the same order, except incremental batch learning methods, which are allowed to loop through each batch. The iCaRL and End-to-End algorithms would require modification to handle the iid or instance ordered settings, so we do not provide results for these scenarios. The final offline model accuracy is 93.11% for CORE50 (top-1) and 89.08% for ImageNet-1K (top-5). For the \( k \)-means variant of REMIND, we use codebook sizes of 256 and 10,000 for CORE50 and ImageNet, respectively.

We employ per-class learning rate decay for ImageNet, using 0.1 as the starting learning rate and decaying it such that the learning rate becomes 0.001 after seeing all new samples for a class, at a step size of 100 new instances.

C. Main Results

Image classification results are given in Table I and a learning curve for ImageNet is shown in Fig. 3. Even without data augmentation, REMIND performed best across datasets and orderings compared to state-of-the-art incremental learning methods. This is especially remarkable because the streaming setting is harder than the incremental batch learning setting used by iCaRL and End-to-End. For ImageNet, compared to the next best incremental learning model (End-to-End), REMIND performed 7.6% better in terms of \( \Omega_{\text{all}} \) and for top-5 accuracy it was 13.9% higher at the final time step. On CORE50, REMIND nearly reaches the offline model’s performance; however, iCaRL only performed comparably to ExStream when \( \theta_F \) was updated and worse when \( \theta_G \) was trained. The \( k \)-means variant of REMIND performed poorly, and its performance only marginally improves when the codebook size is increased. Methods that only trained the output layer performed well on CORE50 and poorly on ImageNet. This is likely because the CORE50 CNNs are initialized with ImageNet-1K weights resulting in more robust representations, and this is supported by the offline results when only \( \theta_F \) is updated after base initialization.

D. Additional Experiments & Analysis

1) Computational & Memory Efficiency: Using the configuration in our main experiments, REMIND uses much less memory than iCaRL and End-to-End, making it more desirable for embedded applications. For ImageNet, iCaRL and End-to-End use 3010 MB to store 20K examples whereas REMIND uses only 2009 MB to store a representation of every sample in the training set. For CORE50, the relative benefit is greater, with REMIND storing 10 MB compared to 30 MB for the others. Moreover, both of these models use large amounts of additional memory to cache all of the information needed for distillation before learning a class batch in the incremental batch learning setting. Since REMIND learns in a streaming setting, it trains \( \sim 7 \) times faster than iCaRL on ImageNet on our workstation (only requiring 9 hours).

2) Changing \( F(\cdot) \) and \( G(\cdot) \): The offline CNN that only trains \( \theta_F \) is an upper bound on REMIND’s performance in our main experiments. Adding more trainable layers to \( \theta_F \) improves accuracy, but this results in a much greater memory burden (see Fig. 4).

3) Varying PQ Settings: In Fig. 4, we study how the hyperparameters of the PQ model affect performance. Using more than 32 codebooks does not help. Using larger codebooks does improve accuracy, but it greatly diminishes memory efficiency.
when using features from product quantization, showing that ordered triplets a streaming VQA model receives a sequence of temporally incremental learning for VQA (see Fig. 5). During training, answer to a natural language question about an image [41] – algorithms to analyze multi-modal data streams. One multi-performance was only 0.9% worse with quantization. 

Ω CORe50 when more than 20 samples were used for replay, size of replay batches. We found performance degradation on ImageNet and CORe50 respectively. In Fig. 4, we vary the size of replay batches. We found performance degradation on CORe50 when more than 20 samples were used for replay, however, for ImageNet we saw a 0.6% increase in $\Omega_{all}$ when using 50 replay samples, which is what we use for our main ImageNet experiments. 

5) Comparison with real features: REMIND achieved an $\Omega_{all}$ score of 0.984 on ImageNet when trained with real features (without any quantization) as compared to 0.975 when using features from product quantization, showing that performance was only 0.9% worse with quantization.

V. EXPERIMENTS: STREAMING VQA

Robots often contain multiple on-board sensors, requiring algorithms to analyze multi-modal data streams. One multi-modal problem is VQA, where a system must produce an answer to a natural language question about an image [41]–[43]. Here, we use REMIND to pioneer streaming and incremental learning for VQA (see Fig. 5). During training, a streaming VQA model receives a sequence of temporally ordered triplets $D = \{(x_t, q_t, a_t)\}_{t=1}^T$, where $x_t$ is an image, $q_t$ is the question (a string), and $a_t$ is the answer. If an answer is not provided at time $t$, then the agent must use knowledge from time 1 to $t - 1$ to predict $a_t$. We use REMIND for streaming VQA by having each quantized image representation stored along with a question string. The question string, reconstructed image features, and answer are used by REMIND to create replay mini-batches. REMIND can be used with almost any existing VQA system, including attention-based algorithms [44]–[46], compositional algorithms [47], [48], and bi-modal fusion mechanisms [49]–[51]. Additionally, REMIND can be easily applied to several other vision and language tasks including image captioning [52] and referring expression recognition [53]–[55].

A. Experimental Setup

For our experiments, we use the TDIUC [56] and CLEVR [57] VQA datasets. TDIUC is composed of natural images and has over 1.7 million QA pairs organized into 12 question types, ranging from simple object recognition questions to complex counting, positional reasoning and attribute classification questions. TDIUC tests for generalization across different underlying tasks represented by VQA. CLEVR is made of over 700,000 QA pairs for 70,000 synthetically generated images and is organized into 5 question types. CLEVR specifically tests for multi-step compositional reasoning that is very rarely encountered in natural image VQA datasets. We combine REMIND with two popular VQA algorithms, using a modified version of the stacked attention network (SAN) [45], [58] for TDIUC, and a simplified version of the memory attention and control (MAC) [47], [59] network for CLEVR. ResNet-101 pre-trained on ImageNet-1K is used to extract features for both TDIUC and CLEVR. REMIND’s PQ model is trained using images from the first 10% of the respective training sets with 32 codebooks each of size 256.

For both datasets, we explore two orderings of the training data: iid and question type. For iid, the dataset is randomly

Fig. 5. REMIND enables streaming learning for multi-modal tasks such as visual question answering, which requires predicting an answer (A) to a question (Q) about an image.

Q: What color is the dog? A: White
Q: What color is the dog? A: Black
Q: What color is the dog? A: White

Table I: Comparative performance on ImageNet-1K and CORe50 using $\Omega_{all}$ classification results. The table shows the plastic/updated (PLAS.) parameters and streaming (STR.) methods. We explore performance across four different ordering schemes and report the average over 10 runs for CORe50. All experiments use ResNet-18.

| Model Class         | Model             | ImageNet              | COR50                |
|---------------------|-------------------|-----------------------|----------------------|
|                     |                   | PLAS. | STR. |                   |         | PLAS. | STR. |                   |         |
| Output Layer Only   |                   |       |     |                   |         |       |     |                   |         |
|                     | Fine-Tune (No Buffer) |    | Yes | 0.146          | 0.975  | 0.340 | 0.916 | 0.341          |         |
|                     | ExStream           | -    | Yes | 0.569          | 0.953  | 0.874 | 0.933 | 0.854          |         |
|                     | SLDA               | -    | Yes | 0.752          | 0.976  | 0.958 | 0.963 | 0.959          |         |
| Representation Learning |                 |       |     |                   |         |       |     |                   |         |
|                     | Fine-Tune (No Buffer) | $\theta_F$, $\theta_G$ | Yes | 0.121          | 0.923  | 0.335 | 0.287 | 0.334          |         |
|                     | Fine-Tune (No Buffer) | $\theta_F$ | Yes | 0.287          | 0.961  | 0.335 | 0.851 | 0.334          |         |
|                     | iCarL              | $\theta_F$, $\theta_G$ | No  | 0.692          | 0.840  | -    |     | 0.845          |         |
|                     | iCarL              | $\theta_F$ | No  | 0.586          | -      | 0.865 | -    | 0.865          |         |
|                     | End-to-End         | $\theta_F$, $\theta_G$ | No  | 0.780          | -      | -    | -    | -              |         |
|                     | REMIND (Full)      | $\theta_F$ | Yes | 0.856          | 0.978  | 0.978 | 0.967 | 0.975          |         |
| REMIND Variants     | REMIND (No Augmentation) | $\theta_F$ | Yes | 0.818          | 0.985  | 0.980 | 0.979 | 0.979          |         |
|                     | REMIND (k-Means)   | $\theta_F$ | Yes | 0.778          | 0.938  | 0.838 | 0.909 | 0.838          |         |
| Upper Bounds        | Offline (Top Only) | $\theta_F$ | No  | 0.929          | 0.989  | 0.985 | 0.985 | 0.985          |         |
|                     | Offline            | $\theta_F$, $\theta_G$ | No  | 1.000          | 1.000  | 1.000 | 1.000 | 1.000          |         |
We initialized REMIND’s vector quantization model during the base initialization phase. For deployed, on-device learning setting. Unlike iCaRL and End-to-End, REMIND outperformed iCaRL and End-to-End, which loop over groups of classes in batches. REMIND achieved this without using distillation, which is used by these methods to maximize the utility of replay with raw images. They pre-compute soft-targets for each stored image before beginning the next batch, which requires a large amount of auxiliary storage that is not desirable for embedded agents. While we could have employed distillation in REMIND, we expect it to provide less benefit, since REMIND can store far more quantized tensors than methods that store raw images.

To demonstrate REMIND’s versatility, we pioneered streaming learning for the multi-modal VQA task and established strong baselines. If paired with a curious agent capable of asking useful questions about unknown concepts, REMIND enables new information to be immediately integrated with existing knowledge. In [62], a model was developed to improve VQA abilities by asking questions; however, the VQA model was trained offline, multiple times. Using REMIND would allow the VQA model to be immediately updated. REMIND could also be used to improve VQA models that exploit additional data during test time to answer new questions [63]. Currently, these approaches do not consolidate such additional information, and thus need to ask the same questions repeatedly. Here, REMIND could facilitate immediate consolidation of new information, making it available for future use.

### ACKNOWLEDGMENT

This work was supported in part by DARPA/MTO Lifelong Learning Machines program [W911NF-18-2-0263], AFOSR grant [FA9550-18-1-0121], and a gift from Adobe Research. We thank NVIDIA for the GPU donation. The views and conclusions contained herein are those of the authors and should not be interpreted as representing the official policies.
A1. PARAMETER SETTINGs

We provide parameter settings in Table A1. We use the ResNet-18 implementation from the PyTorch Torchvision package. For MAC, we use the publicly available PyTorch implementation (https://github.com/IBM/mi-prometheus). For SAN, we use our own PyTorch implementation. The code to replicate our experiments will be publicly released. For ExStream, we use 20 prototype vectors per class and the same parameters as the offline model. For SLDA, we use shrinkage regularization of $10^{-4}$. We were provided results by End-to-End’s creators for ImageNet-1K, and they stored 20 images per class. For iCaRL, we follow the original paper and store 20 images per class. For ImageNet, the parameters of iCaRL are kept the same as [7]. For CORe50 with iCaRL, we train each batch for 60 epochs with a batch size of 64, weight decay of 1e-4, and a learning rate of 0.01 that we lower at epochs 20 and 40 by a factor of 5.

A2. WHERE SHOULD RESNET-18 BE QUANTIZED?

Following others, we used ResNet-18 for our incremental learning image classification experiments. This constrained the layers we could choose for quantization. If we quantized earlier in the network, the spatial dimensions of the feature tensor would be too large, resulting in much greater auxiliary storage requirements (see Fig. A1). For example, in our ImageNet experiments, if we chose layer 3 of ResNet-18 for quantization, it would require 129 GB to store a representation of the entire training dataset; in contrast, the layer we used in our main experiments needs only 2 GB.

In our main experiments with REMIND, 45% of the CNN’s parameters are plastic during streaming learning. In our main paper, we explored the value of training more layers by evaluating REMIND’s performance on CORe50 as a function of the percentage of trainable parameters (see Fig. A1 from our main paper). We found that more trainable layers produces better results, but there are diminishing returns and it requires far more storage.

If the architecture of ResNet-18 was altered to decrease the spatial dimensions earlier in the network, with a corresponding increase in the feature dimensions, this would allow us to quantize earlier in the network. However, this would prevent us from comparing directly to prior work and may require a considerable amount of architectural search to find a good compromise.

A3. VQA LEARNING CURVES AND QUALITATIVE EXAMPLES

We provide learning curves for each of the VQA experiments in Fig. A2 and qualitative examples in Fig. A3.
TABLE A1
TRAINING PARAMETER SETTINGS FOR REMIND.

| PARAMETER  | IMAGE NET | CORE50 | TDIUC | CLEVR |
|------------|-----------|--------|-------|-------|
| Optimizer  | SGD       | SGD    | Adamax| Adam  |
| Learning Rate | 0.1    | 0.01   | 2e-3  | 1e-4  |
| Momentum   | 0.9       | 0.9    | -     | -     |
| Weight Decay | 1e-4   | 1e-4   | -     | -     |
| Streaming Batch Size | 51     | 21     | 51    | 51    |
| Offline Batch Size   | 128     | 256    | 512   | 64    |

Fig. A1. Auxiliary storage required to store quantized CNN features for the entire dataset as a function of the percentage of ResNet-18 layers used in the top of the CNN, $F(\cdot)$, which are updated during streaming learning in REMIND. Storage requirements are shown for CORE50 (left) and ImageNet-1K (right).

Fig. A2. Learning curves for each ordering of the TDIUC (top row) and CLEVR (bottom row) datasets.
Fig. A3. Qualitative VQA examples on the TDIUC (top row) and CLEVR (bottom row) datasets. We provide examples from the final REMIND model after being trained on the Q-Type ordering of each dataset.