Hypothesis-driven Stream Learning with Augmented Memory

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Abstract

Stream learning refers to the ability to acquire and transfer knowledge across a continuous stream of data without forgetting and without repeated passes over the data. A common way to avoid catastrophic forgetting is to intersperse new examples with replays of old examples stored as image pixels or reproduced by generative models. Here, we considered stream learning in image classification tasks and proposed a novel hypotheses-driven Augmented Memory Network, which efficiently consolidates previous knowledge with a limited number of hypotheses in the augmented memory and replays relevant hypotheses to avoid catastrophic forgetting. The advantages of hypothesis-driven replay over image pixel replay and generative replay are two-fold. First, hypothesis-based knowledge consolidation avoids redundant information in the image pixel space and makes memory usage more efficient. Second, hypotheses in the augmented memory can be re-used for learning new tasks, improving generalization and transfer learning ability. We evaluated our method on three stream learning object recognition datasets. Our method performs comparably well or better than SOTA methods, while offering more efficient memory usage. All source code and data are publicly available [https://github.com/kreimanlab/AugMem](https://github.com/kreimanlab/AugMem).

1. Introduction

Stream learning enables continual acquisition and transfer of new knowledge from a temporally structured input sequence while retaining previously learnt experiences [10]. This ability is critical for artificial intelligence (AI) systems to interact with the world and process continuous streams of information [32]. Stream learning remains a long-standing challenge for neural networks that typically learn representations offline from stationary training batches [24, 27, 7]. When faced with streams where data are not independent and identically distributed (iid), and where data are provided continuously without access to old data, SOTA AI systems tend to fail to retain good performance across previously learnt tasks [11, 16, 23]. Numerous methods for alleviating catastrophic forgetting have been proposed, the simplest being to jointly...
train models on both old and new tasks, which demands a large amount of resources to store previous training data and hinders learning of novel data in real time.

Inspired by memory-augmented networks in few-shot image classification [30], memory retrieval tasks [8], and video prediction [9], we proposed an augmented memory architecture, Hypothesis-driven Augmented Memory Network (HAMN), for stream learning in image classification tasks. The network learns a set of hypotheses in the augmented memory, such that the latent representation of an image can be constructed by a linear combination of the hypotheses. Multi-head content-based attention allows the model to share the augmented memory over multiple image features, further compressing representations in memory and allowing features to be reconstructed from hypotheses in parallel.

To prevent catastrophic forgetting, we imposed three constraints on HAMN. First, to preserve encoded hypotheses in augmented memory, we regularized the network to write new hypotheses into rarely-used locations in memory. Second, we stored the memory indices activated by samples from previous tasks, reconstructed these samples from the corresponding hypotheses, and replayed the constructed samples during training. Finally, we applied logit matching [28] during replay to maintain the learnt class distributions from all previous tasks.

We evaluated our method under two typical stream learning protocols (Figure 1), incremental class iid and incremental class instance, across three benchmark datasets, CORe50 [21], Toybox [34] and iLab [3]. The performance of HAMN is comparable to or even better than state-of-the-art (SOTA) methods. HAMN demonstrates the capabilities of memory retention and adaptation to new tasks, even while going through a continuous stream of training examples only once.

2. Related Works

Stream learning approaches can be categorized into (1) weight regularization and (2) replay methods. Weight regularization stores the weights of the model trained on previous tasks and imposes constraints on weight updates for new tasks [12, 17, 37, 19, 22]. For example, Learning Without Forgetting (LwF) [20] stores all the model parameters on previously learnt tasks, estimates their importance on previous tasks, and penalizes future changes to these parameters on new tasks. However, selecting the “important” parameters for previous tasks via pre-defined thresholds complicates the implementation by necessitating exhaustive hyper-parameter tuning. In addition, state-of-the-art recognition models often involve millions of parameters, and therefore storing the “importance” values for each network parameter across all previous tasks can be costly [35].

In replay methods, a subset of images or features from a previous task are stored or generated and later shown to the model to prevent forgetting. Compared with weight regularization, replay methods lead to enhanced performance [28, 25]. Raw-pixel replay, where subsets of images from previous tasks are stored and later replayed, involves highly redundant information and is memory-inefficient. Moreover, relying on limited sets of replay images can lead to overfitting. In contrast, our method better generalizes by learning discriminative, information-rich hypotheses in latent space, which can then be re-used to construct multiple new samples in the latent space for replay and to transfer knowledge to new tasks.

To avoid having to store many images, generative replay systems complement each new task with “pseudo-data” that resembles historical data and is produced by a generative model [31, 29]. In particular, Deep Generative Replay (DGR) [31] is a Generative Adversarial Network that synthesizes training data over all previously learnt tasks. Generative approaches have succeeded with simple and artificial datasets but cannot tackle more complicated inputs [2]. Moreover, to synthesize historical data reasonably well, the size of the generative model tends to be large and expensive with respect to memory resources [35].

Finally, previous work [11] has suggested that instead of replay with raw pixels, replay of latent image features using memory indexing is more efficient and effective at preventing catastrophic forgetting. However, this method relies on Product Quantization [15], where a codebook for constructing the memory is pre-computed and fixed. This hinders the ability of the model to learn and adapt to new tasks. In this work, as opposed to fixed codebooks, our proposed method learns a set of discrete hypotheses on the fly and replays constructed samples from the set of learnt hypotheses based on a memory indexing mechanism learnt throughout new tasks.

3. Stream Learning Protocols and Datasets

3.1. Stream Learning Protocols

Both stream learning protocols are variations of the incremental class setting (Figure 1), defined below:

**Class-iid**: Within each task, all of the images from two classes are randomly shuffled. Each image in the task is seen by the model once.

**Class-instance**: Each task contains a series of temporally-ordered images from the object instances corresponding to the chosen classes. An object instance refers to a series of images of a particular object taken under specific conditions, such as a background or a spatial transformation. The model is trained for one epoch.
3.2. Datasets

The CORe50 dataset [21] contains sequences of video frames for a collection of 50 objects organized into 10 classes. Object instances are 15 second video clips of an object under particular conditions and poses, with 11 instances per object. We follow the work [11] to come up with the ordering, training and testing data splits.

The Toybox dataset [34] contains videos of toy objects from 12 classes. We used a subset of the full dataset containing 348 toy objects with 10 instances per object, each containing a spatial transformation of that object’s pose. We sampled each instance at 1 frame per second resulting in 15 images per transformation per object. We chose 3 of the 10 transformations for our test set, leaving the remaining instances for training.

The iLab dataset [3] contains images of toy vehicles. We used a subset of the full dataset containing 392 vehicle objects from 14 classes, with 8 distinct backgrounds (instances) per object and 15 images per instance. We chose 2 of the 8 instances per object for our test set, leaving the remaining instances for training.

4. Our proposed method (HAMN)

4.1. Overview

The HAMN model consists of a 2D convolutional neural network (2D-CNN) coupled with an augmented memory bank represented as a 2D matrix (Figure 2). The memory matrix stores a fixed number of hypotheses, with a single hypothesis per memory slot. In image classification, HAMN first takes an image as input and extracts its feature maps at an intermediate layer of the 2D-CNN. By computing the similarity between the extracted feature maps and the stored hypotheses, the reading attention mechanism guides the reading heads to select a linear combination of hypotheses, with higher attention weights assigned to memory slots with content more similar to the feature maps. To further compress the hypotheses in augmented memory while maintaining rich representations, we use a multi-head reading attention to interact with the memory bank. This is achieved by splitting the feature maps into segments, with each segment interacting with the same memory bank using its individual reading attention head. The number of plausible feature maps that can be constructed increases exponentially with the number of reading heads and hypotheses, enabling a diverse representation space.

The latter part of the 2D-CNN combines the constructed feature maps with the hypotheses in the memory bank for classification. To ensure the memory bank learns useful hypotheses for replay in later tasks, in addition to a classification loss, we imposed an additional logistic loss, commonly used in knowledge distillation [13], based on the soft class distribution predicted from the constructed and the extracted feature maps, respectively.

4.2. Feature Extraction and Classification

The 2D-CNN contains two nested functions: \( F(\cdot) \) for feature extraction, parameterized by \( \theta_F \), consisting of the first few convolution blocks; and \( P_t(\cdot) \) for classification, parameterized by \( \theta_P \), at task \( t \), consisting of the last few convolution blocks. Since the first few convolution layers in 2D-CNN are highly transferable [36], the feature extractor \( F(\cdot) \) keeps parameters \( \theta_F \) fixed over all tasks. \( \theta_T \) is trained for object recognition using ImageNet [6]. The parameters \( \theta_P \) in \( P_t(\cdot) \) depend on task \( t \). After pre-training on ImageNet, we fine-tune \( P_t(\cdot) \) such that HAMN learns new sets of hypotheses and decision boundaries incrementally to classify new object classes.

Up to task \( t \), HAMN has seen a total of \( C_t \) classes. Given an image \( I_t \) shown during task \( t \), we define the output tensor \( Z_t \) from the feature extraction step as \( Z_t = F(I_t) \). \( Z_t \) is of size \( S \times W \times H \) for channels, width, and height respectively. The output feature maps \( Z_t \) can then be used to produce a logits vector \( q_t = P_t(Z_t) \). The logits vector \( q_t \in \mathbb{R}^{C_t} \) contains the activation values over all \( C_t \) seen classes and is then passed as input to the \textit{softmax} function, which outputs the predicted probability vector \( p_t \in \mathbb{R}^{C_t} \) over all \( C_t \) classes.

We used \( p_t(c) \) and \( q_t(c) \) to denote the predicted probability and logit value for class \( c \) respectively. We define the loss as the cross-entropy loss between \( p_t \) and its corresponding ground truth class label \( y_c \): \[
L_{\text{class}}(p_t, y_c) = -\sum_{i=1}^{C_t} \delta(i = y_c) \log(p_t(i)) \tag{1}
\]
where \( \delta(x) = 1 \) if \( x = y_c \) and \( \delta(x) = 0 \) otherwise.

4.3. Augmented Memory

We define \( M_t \) as the contents of the memory bank of size \( N \times M \) at task \( t \). There are \( N \) memory slots, with each memory slot storing a hypothesis vector of dimension \( M \). We use index \( i \) to denote the \( i \)th memory slot \( (i \in \{1, 2, ..., N\}) \). Thus, we have \( M_t = [M_t(1), M_t(2), ..., M_t(i), ..., M_t(N)] \) where \( M_t(i) \) is a hypothesis vector indexed by \( i \).

\textbf{Multi-head content-based reading attention}

The feature extractor \( F(\cdot) \) serves as a controller and outputs the tensor \( Z_t \) as the reading key of image \( I_t \). Based on the content similarity between \( Z_t \) and each hypothesis in the memory bank \( M_t \), a content-based memory addressing mechanism is used to draw a hypothesis from \( M_t \). Ideally, one could store the individual \( Z_t \) of each image \( I_t \) as a hypothesis in the memory bank and replay each hypothesis to prevent catastrophic forgetting, but this requires extensive memory resources. To further compress
and remove redundancies in $Z_t$, we proposed a multi-head reading attention mechanism. For each image, the feature tensor $Z_t$ of size $S \times W \times H$ is split into groups, each of which interacts with the shared $M_t$. We partition $Z_t$ along $S$ channels into $D$ groups with each group $d$ of size $S/D \times W \times H$. We argue that a hypothesis should represent a local concept and be location-invariant. For example, the color red could be represented in a hypothesis regardless of which region of the image is red. Thus, $Z_t$ consists of multiple reading keys $z_{t,d,l}$ indexed by group $d$ and spatial location $l$ on $Z_t$ and $l \in \{1, 2, …, L = W \times H\}$:

$$Z_t = \{z_{t,1,1}, …, z_{t,d,1}, …, z_{t,D,L}\}, \quad z_{t,d,l} \in \mathbb{R}^{S/D} \tag{2}$$

For content-based addressing, each reading head compares its reading key $z_{t,d,l}$ with each hypothesis $M_t(i) \in \mathbb{R}^{S/D}$ by a similarity measure $K[\cdot, \cdot]$. To discourage attention blurring over all hypotheses, each reading head emits a positive constant value $\beta$ denoting the attention sharpening strength, which can amplify or attenuate the precision of hypothesis selection. The content-based addressing mechanism produces a reading attention vector $w_{t,d,l}$ over $N$ locations based on the content similarity.

$$w_{t,d,l}(i) = \frac{e^{\beta K[z_{t,d,l}, M_t(i)]}}{\sum_j e^{\beta K[z_{t,d,l}, M_t(j)]}} \tag{3}$$

where, the similarity measure is defined as the inner product $K[u, v] = \langle u, v \rangle$. The overall reading attention $w_t$ for all reading heads can then be written as $w_t = \{w_{t,1,1}, …, w_{t,d,1}, …, w_{t,D,L}\}$.

**Construction from multiple hypotheses**

The retrieved reading content vector $r_{t,d,l}$ for its reading key $z_{t,d,l}$ is of size $M$. It is computed as the expectation of sampled hypotheses modulated by the reading attention vector $w_{t,d,l}$:

$$r_{t,d,l} = \sum_i w_{t,d,l}(i) M_t(i) \tag{4}$$

Thus, we define the final feature tensor $\widetilde{Z}_t$ constructed with a set of hypotheses in the memory bank $M_t$ as a collection of reading content retrieved using each reading key $\widetilde{Z}_t = \{r_{t,1,1}, …, r_{t,d,1}, …, r_{t,D,L}\}$. To enforce that the hypothesis-driven tensor $\widetilde{Z}_t$ has discriminative
representations as $Z_i$, we perform classification on $\tilde{Z}_t$ using classifier $P_t(\cdot)$ attached with softmax and Eq. 1. In addition, we introduce the distillation loss $L_{\text{distill}}$ on the logits $q_t$ and $\tilde{q}_t$ of $Z_t$ and $\tilde{Z}_t$ respectively:

$$L_{\text{distill}}(q_t, \tilde{q}_t) = \sum_{i=1}^{C_t} q_t(i) \log(\tilde{q}_t(i)) + (1 - q_t(i)) \log(1 - \tilde{q}_t(i))$$  \hspace{1cm} (5)

Note that though HAMN makes class predictions based on both $\tilde{Z}_t$ and $Z_t$, we use the predictions from $Z_t$ as the final predicted result during testing.

### 4.4. Avoiding catastrophic forgetting

In the incremental class setting (Sec 3.1), HAMN is presented with images $I_t$ from new classes $c^{\text{new}}$ in task $t$ where $c^{\text{new}}$ belongs to the complement set of $\{1, ..., c^{\text{old}}, ..., C_t-1\}$ in $\{1, ..., c^{\text{old}}, ..., c^{\text{new}}, ..., C_t\}$. We take three measures below to avoid catastrophic forgetting.

#### Rarely-used memory locations

Every component in HAMN is differentiable, making it possible to learn hypotheses with gradient descent. For each new image $I_t$ in task $t$, HAMN learns a new set of hypotheses in $M_t$. The update of hypotheses could undesirably occur in recently-used memory locations from previous tasks. To emphasize accurate encoding of new hypotheses and preserve the old hypotheses in most-used memory locations learnt from the previous task $t - 1$, we keep track of the top $k$ most-used memory locations for each reading attention vector and aggregate those locations over all reading heads:

$$A_{t-1} = \bigcup_{I_{t-1}} \bigcup_{D} \bigcup_{L} m(w_{t-1,d,l}, k)$$  \hspace{1cm} (6)

where $m(\cdot)$ returns the top $k$ indices with largest attention values in $w_{t-1,d,l}$. Thus, we can define the memory usage loss $L_{\text{mem}} = \delta(A_{t-1})(M_t - M_{t-1})^2$. An indicator function $\delta(\cdot)$ returns a binary vector of size $N$ where the vector element at index $i$ is 1 if $i \in A_{t-1}$ and 0 otherwise.

#### Hypothesis replay

Instead of replaying raw pixels, replay using memory indexing has shown to be more efficient and effective in preventing catastrophic forgetting [11]. Ideally, we could store the reading attention $w_{t-1}$ from the previous task $t - 1$ and directly re-construct the feature tensor $\tilde{Z}_{t-1}$ from $M_t$, which would then be replayed in the current task $t$. However, in order to further compress the memory usage, we store the index with the largest attention value in $w_{t-1,d,l}$ for each reading head:

$$w_{t-1}^* = \{m(w_{t-1,1,1,1}), ..., m(w_{t-1,d,l,1}), ..., m(w_{t-1,D,L,1})\}$$  \hspace{1cm} (7)

Therefore, we can approximate $w_{t-1}$ with a one-hot vector generated using $\delta(w_{t-1}^*)$ and construct $\tilde{Z}_{t-1}^*$ using $M_t$ for replay. Storing only the top-1 index in each reading head greatly reduces its memory usage from $N \times D \times W \times H$ to $D \times W \times H$. We show that the replays are still effective in preventing catastrophic forgetting in Sec 6.

#### Distillation across tasks

Similar to the work in [28] on image replay, we use a distillation loss to transfer knowledge from the same neural network between different tasks to ensure that the discriminative information learnt previously is not lost in the new task $t$. Thus, given constructed feature tensor $\tilde{Z}_{t-1}^*$ and its stored logits vector $q_{t-1}^*$, we compute its distillation loss $L_{\text{distill}}(q_{t-1}^*, P_t(\tilde{Z}_{t-1}^*))$ using Eq. 5.

#### Sampling strategy for replays

There have been some attempts to select representative image examples to store and replay based on different scoring functions [5, 18, 4]. However, random sampling uniformly across classes yields outstanding performance in continual learning tasks [35]. Hence, we adopt the same random sampling strategy and store $X$ logits and top-1 reading attention tensor pairs $(q_{t-1}^*, w_{t-1}^*)$ corresponding to images $I_{t-1}^{\text{old}}$ from old classes $c^{\text{old}}$ of previous tasks. Depending on the number of seen $C_t - 1$ classes, the storage for each old class contains $X/C_t - 1$ pairs. To prevent catastrophic forgetting, we define the total loss:

$$L_{\text{total}} = \gamma L_{\text{mem}} + \alpha \sum_{t=1}^{p_{\text{old}}} (L_{\text{classi}}(p_{t}^{\text{old}}, y_{c}^{\text{old}}) + L_{\text{distill}}(q_{t}^*, P_t(\tilde{Z}_{t-1}^*))) + \sum_{t=p_{\text{new}}} (L_{\text{classi}}(p_{t}^{\text{new}}, y_{c}^{\text{new}}) + L_{\text{distill}}(q_{t}^*, \tilde{q}_{t}))$$  \hspace{1cm} (8)

where $\alpha$ and $\gamma$ are regularization hyperparameters

### 4.5. Implementation and training details

We used the SqueezeNet [14] architecture for the 2D-CNN. Following PyTorch [26] layer conventions for SqueezeNet, the feature extractor $F(\cdot)$ includes convolution blocks up to layer 12 and the classification network $P_t(\cdot)$ includes the remaining layers. The tensor $Z_t$ after layer 12 is of size $S \times W \times H$ where $S = 512$ and $W = H = 13$. We split $Z_t$ into $D = 64$ groups, resulting in $13 \times 13 \times 64$ reading keys of dimension 8. We defined the memory bank capacity as $N = 100$ and $M = 8$ and initialized the memory bank randomly before training. Given that each reading head has 100 hypotheses to read from, HAMN could construct $100^{13 \times 13 \times 64}$ possible feature maps, which is sufficient for creating a rich latent space with ample diversity. We chose $k = 1$, taking the top-1 attention index in each reading head, to compute the aggregated attention vector $A_{t-1}$ for regularizing memory using $L_{\text{mem}}$. For each dataset,
Algorithm 1 Hypotheses-driven Augmented Memory Network at current task $t$

Input: stored $X = 200$ logit vectors $q^t_{s-1}$, corresponding top-1 attention index tensors $w^t_{s-1}$ and their class labels, a binary vector $\delta(A_{t-1})$ of dim $N = 100$ tracking the mostly used memory locations over previous tasks, new training images $I_t$ from new classes

Training:
for batch in training images do
    Train with $I_t$ based on $L_{\text{distill}}$ & $L_{\text{classi}}$ on $Z_t$ & $\tilde{Z}_t$
    if $t > 1$ then
        Randomly sample $x$ out of $X$ and replay:
        Re-construct hypothesis-driven $\tilde{Z}_{t-1}^s$ using $w_{t-1}^s$
        Train $P_t(\cdot)$ based on $L_{\text{distill}}$ using $q_{t-1}^t$ and $L_{\text{classi}}$
        Regularize $M_t$ using $L_{\text{mem}}$ on $\delta(A_{t-1})$
    end if
end for

Testing:
for batch in testing images do
    Compute $p_t$ using $P_t(F(\cdot))$ on test image
end for

HAMN stores $X = 200$ old samples. Empirically, we set the following hyperparameter values: $\beta = 5$, $\gamma = 1000$, $\alpha = 5$. Pseudocode is shown in Algorithm 1.

5. Experimental Details

5.1. Baselines

We compared our method with a variety of continual learning methods in several categories. To eliminate the effect of network architecture on performance, as in HAMN, we used SqueezeNet pre-trained [14] on ImageNet [6] for all methods across all experiments. Unlike the other methods, HAMN introduces an augmented memory bank between intermediate layers of SqueezeNet. Due to the additional, randomly-initialized parameters introduced by the augmented memory, we trained HAMN for 2 additional epochs on only the first task to allow HAMN to achieve similar performance to other methods on the first task, enabling a fair comparison on subsequent tasks.

Parameter Regularization Methods: We compared against Elastic Weight Consolidation (EWC) [17], Synaptic Intelligence (SI) [37], Memory Aware Synapses (MAS) [1], Gradient Episodic Memory (GEM) [22], and naive L2 regularization (L2) where the L2 distance indicating parameter changes between tasks is added to the loss [17].

Memory Distillation and Replay Methods: Incremental Classifier and Representation Learner (ICARL) [28] regularizes network behaviors with image replay and a distillation loss. Naive Rehearsal replays raw image pixels in subsequent tasks without any regularization constraints.

Lower bound is trained sequentially over all tasks without any measures to avoid catastrophic forgetting. Upper bound is trained on images from the current task and the sequential data from all previous tasks over multiple epochs. The sequence of training data presentation follows corresponding stream learning protocols.

Chance predicts class labels by randomly choosing 1 out of the total of $C_t$ classes up to current task $t$.

Top-1 classification accuracy on the current task for all seen $C_t$ classes is reported after 10 runs per protocol. We also provide the average top-1 classification accuracy over all tasks in the Supp. material.

5.2. Memory Footprint Comparison

SqueezeNet has $J \approx 1.2 \times 10^6$ parameters. Weight regularization methods have to store importance values for $J$ parameters in memory for each task, and so as the number of tasks increases, these methods require linearly growing memory. In more challenging classification tasks, the network size and corresponding memory usage tend to increase. In order to provide a fair comparison with the weight regularization methods, we allocated a comparable amount of memory to the replay methods for storing examples to replay in subsequent tasks. Since image replay methods require storing at least one image from each previous class, we store 15 images for all classes for all raw pixel replay methods over all three datasets.

To illustrate differences in memory usage, consider CORe50 in the class instance protocol. Weight regularization methods require memory of size $5J$, i.e., about 6 million parameters for the 5 tasks. The input RGB images are of size $3 \times 224 \times 224$. The dimension of the logit vector changes over tasks (i.e., 2, 4, etc.). For simplicity, we treated any logit vector $q_{t-1}^t$ of constant dimension 10 for all classes in the 5 tasks. The top-1 attention index tensor $w_{t-1}^s$ is of constant size $D \times W \times H = 10,816$ parameters. We store $X = 200$ old pairs of logit and attention indices, resulting in 2 million parameters - equivalent to storing $\approx 13$ images - which is 2 images fewer than raw pixel replay methods. Compared with parameter regularization methods, HAMN uses only one third as much memory.

6. Results and Discussion

6.1. Stream Learning Performance

A proficient stream learning method should not only show good memory retention and avoid catastrophic forgetting, but also be able to adapt to new tasks. A trivial algorithm that learns the first task perfectly and stops learning thereafter, could have perfect memory for Task 1 but fail to classify new objects in subsequent tasks. Thus, we report the top-1 classification accuracy over all learnt classes. Figure 3 reports the results of continual learning methods on the CORe50 dataset across two stream learning
Figure 3: Top-1 classification accuracies over all tasks in class iid and instance stream learning protocols on CORe50. See Sec 3 for experimental protocols and datasets. See Sec 5.1 for baselines. See Supp. material for results on Toybox and iLab. The error bars denote root mean squared error (RMSE) over total 10 runs.

Table 1: Top-1 classification accuracies in the 5th task for the ablated HAMN models after 5 runs on CORe50 in the class iid and instance protocols. See Sec. 6.2 for each ablated method. ± value denotes root mean squared error (RMSE).

<table>
<thead>
<tr>
<th>Method</th>
<th>class_iid</th>
<th>instance</th>
</tr>
</thead>
<tbody>
<tr>
<td>HAMN (ours)</td>
<td>36.8 ± 2</td>
<td>29.6 ± 2</td>
</tr>
<tr>
<td>NumMemSlot</td>
<td>27.7 ± 1</td>
<td>27.6 ± 4</td>
</tr>
<tr>
<td>NumIndexReplays</td>
<td>33.3 ± 2</td>
<td>33.9 ± 6</td>
</tr>
<tr>
<td>MemSparseness</td>
<td>35.8 ± 3</td>
<td>33.0 ± 5</td>
</tr>
<tr>
<td>DistillationLoss</td>
<td>36.8 ± 4</td>
<td>25.1 ± 3</td>
</tr>
<tr>
<td>MemUsageLoss</td>
<td>33.2 ± 5</td>
<td>26.8 ± 5</td>
</tr>
<tr>
<td>NoReplay</td>
<td>16.0 ± 1</td>
<td>17.2 ± 1</td>
</tr>
</tbody>
</table>

Figure 4: Clusters of class embeddings learnt in task 1 remain separated in subsequent tasks after hypothesis replays. We provide t-sne [33] plots of logit vectors from each class after hypothesis replays within a class instance training run on the CORe50 dataset. Task 1 is a binary classification problem. Tasks 3 and 5 are 1-choose-6 and 1-choose-10 classification problems respectively. Colors correspond with the object classes in the legend. We use the shaded blobs to emphasize the clusters of cups and scissors from the 1st task and their corresponding locations in subsequent tasks.

For task 1, all the methods yield approximately the same performance, comparable to the upper bound. The upper bound yields slightly better performance because it is trained over multiple epochs whereas all the other algorithms are only trained for one epoch. As more tasks are added, performance for task 1 decreases due to forgetting (Supp. Fig S5). In task 5, several of the baseline methods are barely above chance level and are comparable to the lower bound. The best baseline methods are iCARL, L2, and NaiveRehearsal. Our method (HAMN, dark blue) achieves the overall highest classification accuracy among all compared methods (see also Supp. Fig S3a). Our method (blue) consistently outperforms the second best method (iCARL) across all tasks with an average improvement of 7%. This observation reveals that, given comparable memory usage with iCARL, our method can re-use learnt hypotheses and transfer knowledge from previous tasks more effectively. Similarly, the feature maps reconstructed from learnt hypotheses and used for replay seem to carry discriminative information between classes. Finally, compared with parameter regularization methods, our method is three fold more efficient in memory usage.

The class instance protocol is more challenging than class iid, as shown by the performance differences of each method between the two protocols (compare Figure 3a and Figure 3b). One reason the performance of HAMN is worse in the class instance setting is overfitting of the learnt hypotheses to particular tasks. One way to eliminate hypothesis overfitting is to decrease the hyperparameter controlling the attention strength $\beta$, encouraging the network to use many hypotheses drawn from different tasks simultaneously. In an ablation study described below, we show the importance of controlling the attention strength $\beta$ in the two protocols.

Figure 4 provides visualizations of the predicted logit vectors after hypotheses replays during the class instance protocol. We randomly choose 50 logit vectors from each class and project them onto 2D space via t-sne [33].
In this example, Task 1 involves separating two classes: cups and scissors. As expected, the representation of those two classes is quite distinct, which leads to a high classification accuracy. In Task 3 and 5, the plots show the representation of the added classes. Remarkably, the two initial classes remain distinctly separated despite the network never training on those classes after the first task. This shows HAMN accommodates new classes while maintaining the clustering of previous ones.

6.2. Ablation Study

We assessed the importance of design choices by training and testing ablated versions of the model on CORe50 (Table 1). First, we tested the importance of the number of memory slots \( N \) by reducing it from \( N = 100 \) to \( N = 50 \) (NumMemSlot). As expected, there is a drop in accuracy on the final task of almost 10% and 2% for the class iid and class instance protocols respectively. This observation implies that we need a sufficiently high number of hypotheses to discriminate between classes.

Second, we halved the number of stored samples (pairs of top-1 attention memory indices and their corresponding logits) for replay to \( X = 100 \) (NumIndexReplays). A moderate accuracy drop of about 5% is observed for class iid, indicating that the representations of each individual class are diverse and we need to store multiple samples per class to represent this diversity. Reducing \( X \) is not as harmful as reducing \( N \), suggesting that the hypotheses in the augmented memory are highly discriminative and representative and that there exist regularities among representations within the same class that reduce the need to store as many replay samples as in pixel-based replay methods. In contrast, we observed the opposite effect for the class instance protocol, where this ablation improved accuracy by 4%. This suggests that models more easily overfit in the class instance protocol.

Third, in MemSparseness, we decreased the reading attention strength \( \beta \) (Eq. 3) from 5 to 1. A higher \( \beta \) forces the model to attend to fewer memory slots. Setting \( \beta \) to 1 produces a more blurred distribution over all hypotheses, causing an accuracy drop of \( \approx 1\% \) in the class iid protocol. Surprisingly, the lower sparsity helps the model in the class instance protocol. One conjecture is that HAMN more easily overfits in the class instance protocol, so a blurred hypotheses distribution could help alleviate the strong preference for a single hypotheses during predictions.

Fourth, distillation loss is important for knowledge transfer between networks [13] and across sequential tasks [28]. We introduced two distillation losses in HAMN: (i) during replay with reconstructed feature maps to ensure the network retains discriminative representations for old classes; (ii) during training to ensure the network can construct feature maps as representative as maps directly extracted from the feature extractor \( F(\cdot) \). There was no significant effect of removing the distillation loss for the class iid protocol; however, there was a drop of 5% in classification performance for the class instance protocol.

Fifth, in MemUsageLoss, we removed the least used memory loss \( L_{\text{mem}} \), which was introduced to prevent useful old hypotheses from being over-written. Removing \( L_{\text{mem}} \) results in a 3% accuracy drop for both protocols, demonstrating that preventing interference between old and new hypotheses helps prevent catastrophic forgetting.

Lastly, we removed replay from the HAMN model (NoReplay). As expected, \( L_{\text{mem}} \) alone is not sufficient to avoid catastrophic forgetting. The large decrease in accuracy of 15-20% for both protocols emphasizes that replay is essential and demonstrates that replayed feature maps constructed from the learnt hypotheses capture representative information for old classes.

6.3. Memory Interpretation

To interpret what learnt hypothesis in the augmented memory represent, we provide a visualization of 2D probabilistic hypothesis activation maps for three hypotheses on an image from each class within a class instance training run on CORe50 (Figure 5). The brighter regions denote locations of higher probability where the selected hypotheses get activated.

Figure 5: Each hypothesis represents a concept and each learnt concept remains the same across tasks. To visualize what activates each hypothesis in the augmented memory, given any image \( I_t \), we used its top-1 attention index tensor \( w_t^i \) of size \( D \times W \times H \), selected the hypothesis index of interest, and computed its activation probability over all locations, resulting in a 2D probabilistic hypothesis activation map. We overlaid this map back to image pixels. The brighter regions denote locations of higher probability where the selected hypotheses get activated.
not observe a change of hypothesis patterns with new tasks, implying that the learnt hypotheses are not overwritten by new ones thanks to the least used memory loss $L_{\text{mem}}$. This is useful to avoid catastrophic forgetting and to assist transfer learning on new tasks. We also verified the importance of $L_{\text{mem}}$ in the ablation study in See 6.2.

7. Conclusion

We addressed the problem of stream learning for classification tasks by proposing a novel method of memory index replay using hypotheses stored in an augmented memory. In addition to significantly ameliorating catastrophic forgetting on benchmark datasets, our method features highly efficient memory usage compared to other methods, while also being generalizable to novel concepts even when trained only once on a continuous stream of data.

References

[23] Davide Maltoni and Vincenzo Lomonaco. Continuous learning in single-incremental-task scenarios. Neural Networks, 2019. 1


