Incremental Learning in Deep Convolutional Neural Networks Using Partial Network Sharing

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Abstract

Deep convolutional neural network (DCNN) based supervised learning is a widely practiced approach for large-scale image classification. However, retraining these large networks to accommodate new, previously unseen data demands high computational time and energy requirements. Also, previously seen training samples may not be available at the time of retraining. We propose an efficient training methodology and incrementally growing DCNN to allow new classes to be learned while sharing part of the base network. Our proposed methodology is inspired by transfer learning techniques, although it does not forget previously learned classes. An updated network for learning new set of classes is formed using previously learned convolutional layers (shared from initial part of base network) with addition of few newly added convolutional kernels included in the later layers of the network. We evaluated the proposed scheme on several recognition applications. The classification accuracy achieved by our approach is comparable to the regular incremental learning approach (where networks are updated with new training samples only, without any network sharing), while achieving energy efficiency, reduction in storage requirements, memory access and training time.

Keywords

Incremental learning · Catastrophic forgetting · Lifelong learning · Energy-efficient learning

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1 Introduction

Deep Convolutional Neural Networks (DCNNs) have achieved remarkable success in various cognitive applications, particularly in computer vision [24]. They have shown human-like performance on a variety of recognition, classification and inference tasks, albeit at a much higher energy consumption. One of the major challenges for convolutional networks is the computational complexity and the time needed to train large networks. Since training of DCNNs requires state-of-the-art accelerators like GPUs [2], large training overhead has restricted the usage of DCNNs to clouds and servers. It is common to pre-train a DCNN on a large dataset (e.g. ImageNet, which contains 1.2 million images with 1000 categories), and then use the trained network either as an initialization or a fixed feature extractor for the specific application [29]. A major downside of such DCNNs is the inability to learn new information since the learning process is static and only done once before it is exposed to practical applications. In real-world scenarios, classes and their associated labeled data are always collected in an incremental manner. To ensure applicability of DCNNs in such cases, the learning process needs to be continuous. However, retraining these large networks using both previously seen and unseen data to accommodate new data, is not feasible most of the time. The training samples for already learned classes may be proprietary, or simply too cumbersome to use in training a new task. Also, to ensure data privacy, training samples should be discarded after use. Incremental learning plays a critical role in alleviating these issues by ensuring continuity in the learning process through regular model update based only on the new available batch of data. Nevertheless, incremental learning can be computationally expensive and time consuming, if the network is large enough.

This paper focuses on incremental learning on deep convolutional neural network (DCNN) for image classification task. In doing so, we attempt to address the more fundamental issue: an efficient learning system must deal with new knowledge that it is exposed to, as humans do. To achieve this goal, there are two major challenges. First, as new data becomes available, we should not start learning from scratch. Rather, we leverage what we have already learned and combine them with new knowledge in a continuous manner. Second, to accommodate new data, if there is a need to increase the capacity of our network, we will have to do it in an efficient way. We would like to clarify that incremental learning is not a replacement of regular training. In the regular case, samples for all classes are available from the beginning of training. However, in incremental learning, sample data corresponding to new classes become available after the base network is already trained and sample data for already learned classes are no longer available for retraining the network to learn all classes (old and new) simultaneously. Our approach to incremental learning is similar to transfer learning [17] and domain adaptation methods [20]. Transfer learning utilizes knowledge acquired from one task assisting to learn another. Domain adaptation transfers the knowledge acquired for a task from a dataset to another (related) dataset. These paradigms are very popular in computer vision. Though incremental learning is similar in spirit to transfer, multi-task, and lifelong learning; so far, no work has provided a perfect solution to the problem of continuously adding
new classes based on adapting shared parameters without access to training data for previously learned classes.

There have been several prior works on incremental learning of neural networks. Many of them focus on learning new classes from fewer samples [4; 9] utilizing transfer learning techniques. To avoid learning new categories from scratch, Fei-Fei et al. [4] proposed a Bayesian transfer learning method using very few training samples. By introducing attribute-based classification the authors [9] achieved zero-shot learning (learning a new class from zero samples). These works rely on shallow models instead of DCNN, and the category size is small in comparison. The challenge of applying incremental learning (transfer learning as well) on DCNN lies in the fact that it consists of both feature extractor and classifier in one architecture. Polikar et al. [22] utilized ensemble of classifiers by generating multiple hypotheses using training data sampled according to carefully tailored distributions. The outputs of the resulting classifiers are combined using a weighted majority voting procedure. This method can handle an increasing number of classes, but needs training data for all classes to occur repeatedly. Inspired form Polikar et al. [22], Medera and Babinec [13] utilized ensemble of modified convolutional neural networks as classifiers by generating multiple hypotheses. The existing classifiers are improved in [22; 13] by combining new hypothesis generated from newly available examples without compromising classification performance on old data. The new data in [22; 13] may or may not contain new classes. Another method by Royer and Lampert [26] can adapt classifiers to a time-varying data stream. However, the method is unable to handle new classes. Pentina et al. [21] have shown that learning multiple tasks sequentially can improve classification accuracy. Unfortunately, for choosing the sequence, the data for all tasks must be available to begin with. Xiao et al. [32] proposed a training algorithm that grows a network not only incrementally but also hierarchically. In this tree-structured model, classes are grouped according to similarities, and self-organized into different levels of the hierarchy. All new networks are cloned from existing ones and therefore inherit learned features. These new networks are fully retrained and connected to base network. The problem with this method is the increase of hierarchical levels as new set of classes are added over time. Another hierarchical approach was proposed in Roy et al. [25] where the network grows in a tree-like manner to accommodate the new classes. However, in this approach, the root node of the tree structure is retrained with all training samples (old and new classes) during growing the network.

Li and Hoiem [10] proposed ‘Learning without Forgetting’ (LwF) to incrementally train a single network to learn multiple tasks. Using only examples for the new task, the authors optimize both for high accuracy for the new task and for preservation of responses on the existing tasks from the original network. Though only the new examples were used for training, the whole network must be retrained every time a new task needs to be learned. Recently, Rebuffi et al. [23] addressed some of the drawbacks in Li and Hoiem [10] with their decoupled classifier and representation learning approach. However, they rely on a subset of the original training data to preserve the performance on the old classes. Shmelkov et al. [30] proposed a solution by forming a loss function to balance the interplay between predictions on the new classes and a new distillation loss which minimizes the discrepancy between responses for old classes from the original and the updated networks. This method
can be performed multiple times, for a new set of classes in each step. However, every time it incurs a moderate drop in performance compared to the baseline network trained on the ensemble of data. Also, the whole process has substantial overhead in terms of compute energy and memory.

Another way to accommodate new classes is growing the capacity of the network with new layers [27], selectively applying strong per-parameter regularization [7]. The drawbacks to these methods are the rapid increase in the number of new parameters to be learned [27], and they are more suited to reinforcement learning [7]. Aljundi et al. [1] proposed a gating approach to select the model that can provide the best performance for the current task. It introduces a set of gating auto-encoders that learn a representation for the task at hand, and, at test time, automatically forward the test sample to the relevant expert. This method performs very well on image classification and video prediction problems. However, the training of autoencoders for each task requires significant effort. Incremental learning is also explored in Spiking Neural Networks (SNN) domain. An unsupervised learning mechanism is proposed by Panda et al. [18] for improved recognition with SNNs for on-line learning in a dynamic environment. This mechanism helps in gradual forgetting of insignificant data while retaining significant, yet old, information thus trying to addresses catastrophic forgetting.

In the context of incremental learning, most work has focused on how to exploit knowledge from previous tasks and transfer it to a new task. Little attention has gone to the related and equally important problem of hardware and energy requirements for model update. Our work differs in goal, as we want to grow a DCNN with reduced effort to accommodate new set of classes by network sharing, without forgetting the old classes. The novelty of this work lies in the fact that we developed an empirical mechanism to identify how much of the network can be shared as new classes are added. We also quantified the energy consumption, training time and memory storage savings associated with models trained with different amounts of sharing to emphasize the importance of network sharing from hardware point of view. Our proposed method is unique since it does not require any algorithmic changes and can be implemented in any existing hardware if additional memory is available for the supplementary parameters needed to learn new classes. There is no overhead of storing any data sample or statistical information of the learned classes. It also allows on-chip model update using a programmable instruction cache. Many of the state-of-the-art DNN accelerators support this feature. However, FPGAs are the kind of hardware architecture that is best suited for the proposed method. It offers highly flexible micro-architecture with reusable functional modules and additional memory blocks in order to account for dynamic changes.

In summary, the key contributions of our work are as follows:

- We propose sharing of convolutional layers to reduce computational complexity while training a network to accommodate new set of classes without forgetting old classes.
- We developed a methodology to identify optimal sharing of convolutional layers in order to get the best trade-off between accuracy and other parameters of interest, especially energy consumption, training time and memory access.
We developed a cost estimation model for quantifying energy consumption of the network during training, based on the Multiplication and Accumulation (MAC) operations and number of memory access in the training algorithm.

We substantiate the scalability and robustness of the proposed methodology by applying the proposed method to different network structures trained for different benchmark datasets.

We show that our proposed methodology leads to energy efficiency, reduction in storage requirements, memory access and training time, while maintaining classification accuracy without accessing training samples of old classes.

2 Incremental Learning

A crude definition of incremental learning is that it is a continuous learning process as batches of labeled data of new classes are gradually made available. In literature, the term “incremental learning” is also referred to incremental network growing and pruning or on-line learning. Moreover, various other terms, such as lifelong learning, constructive learning and evolutionary learning have also been used to denote learning new information. Development of a pure incremental learning model is important in mimicking real, biological brains. Owing to superiority of biological brain, humans and other animals can learn new events without forgetting old events. However, exact sequential learning does not work flawlessly in artificial neural networks. The reasons can be the use of a fixed architecture and/or a training algorithm based on minimizing an objective function which results in “catastrophic interference”. It is due to the fact that the minima of the objective function for one example set may be different from the minima for subsequent example sets. Hence each successive training set causes the network to partially or completely forget previous training sets. This problem is called the “stability-plasticity dilemma” [14]. To address these issues, we define an incremental learning algorithm that meets the following criteria:

i. It should be able to grow the network and accommodate new classes that are introduced with new examples.

ii. Training for new classes should have minimal overhead.

iii. It should not require access to the previously seen examples used to train the existing classifier.

iv. It should preserve previously acquired knowledge, i.e. it should not suffer from catastrophic forgetting.

In this work, we developed an efficient training methodology that can cover aforementioned criteria. Let us comprehend the concept with a simple example. Assume that a base network is trained with four classes, $C_1$ – $C_4$, and all training data of those four classes are discarded after training. Next, sample data for two more classes ($C_5$, $C_6$) arrive and the network needs to accommodate them while keeping knowledge of the initial four classes. Hence, the network capacity has to be increased and the network has to be retrained with only the new data (of $C_5$ and $C_6$) in an efficient way so that the updated network can classify all six classes, $C_1$ – $C_6$. Then again, if more data for new classes become available, the network again will have to grow in
a similar way to be able to learn new classes without forgetting old classes. Figure 1 shows the overview of the incremental learning model we use.

![Incremental Learning Model Diagram](image)

**Fig. 1** Incremental learning model: the network needs to grow its capacity with arrival of data of new classes.

2.1 Advantages

There are several major benefits of incremental learning.

2.1.1 Enable training in low power devices

Training a deep network from scratch requires enormous amount of time and energy which is not affordable for low power devices (embeded systems, mobile devices, IoTs etc.). Therefore, a deep network is trained off-chip and deployed in the edge devices. When data for new classes are available, it cannot be used for learning in the device because of two reasons; i) the device does not have access to sample data for already known classes, ii) the device does not possess the capability to retrain the whole network. However, the new classes can be learned incrementally by reusing knowledge from existing network without requiring data samples of old classes. This enables the low power devices to update the existing network by incrementally retraining it within their power budget and hardware limitations.

2.1.2 Speed up model update

If knowledge from existing network can be reused while learning new classes (with new data samples only) without forgetting old classes, then the updating process of an existing network will be very fast.
2.1.3 Ensure data privacy

Incremental learning do not require access to old training data. Therefore, all training samples can be discarded after each training session, which will disallow misuse of private data.

2.1.4 Reduce storage requirements

Deep networks require humongous amount of data to train. Since training data samples are not required to be stored for incremental learning, the storage requirement for updating a network is greatly reduced.

The following section will describe the design approach of the proposed scheme.

3 Design Approach

The superiority of DCNNs comes from the fact that it contains both feature extractor and classifier in the same network with many layers. ‘Sharing’ convolutional layers as fixed feature extractors is the base of our proposed training methodology. ‘Sharing’ means reusing already learned network parameters/layers to learn new set of classes. Note that in all cases, while learning new classes, only newly available data is used. Also, we assume that new classes will have similar features as the old classes. Therefore, we separate a single dataset into several sets so that they can be used as old and new data while updating the network. All accuracies reported in this work are test accuracies (training samples and test samples are mutually exclusive).

This section outlines the key ideas behind the proposed methodology.

3.1 Increasing Convolutional Kernels in the Last Layer

To accommodate more classes, the network must increase its capacity. The simplest way to do that is widening the final softmax layer to output the extra probabilities for the new classes. One obvious drawback of this approach is that the increment of learning capacity is small [32]. For example, let us consider a small CNN with two convolutional layers each containing 4 \((5 \times 5)\) convolutional kernels and a fully connected layer to connect the feature vector output with the output neurons. If the initial number of classes is 10, and 5 new classes are to be accommodated, then the increase in trainable parameters is only 17.8% compared to 50% increase in the number of classes. Since we do not want to forget the already learned classes, we can only train the small percentage of trainable parameters with the new examples. However, this does not result in a good inference accuracy for the new classes. For a large network with many convolutional layers, the increment of learning capacity reduces further and goes as low as less than 1%.

Therefore, it is prudent to widen the network by having more feature maps in the convolutional layers. To investigate this idea, we trained the above-mentioned network denoted by \([784 (5 \times 5)4c 2s (5 \times 5)4c 2s 10o]\) (CNN containing 784 input
neurons, 2 convolutional layers (4c) each followed by a sub-sampling layer (2s), and finally a fully connected layer with 10 output neurons (10o)), for 10 classes (digits 0-9 from TiCH dataset [12]). Then we added rest of the 26 classes (alphabets) to the existing network in five installments. Each time we retrain the network for new classes, we add two feature maps in the last convolutional layer. For example, when we add first 5 classes (A-E) with the existing 10 classes, we retrain the network [784 (5 × 5)4c 2s (5 × 5)6c 2s 5o]. We only increment the concluding convolutional layer since it has been shown by Yosinski et al. [33] that initial layers in a DCNN is more generic while last layers are more specific. Therefore, we only focus on incrementing and retraining the last few layers. Note that we added specifically 2 feature maps in the last convolutional layer (for each addition of 5-6 classes) in order to increase the model capacity while maintaining the existing class/filter ratio (~2.5 classes/filter) and prevent over-fitting. The new parameters are initialized using random numbers which have distribution similar to the learned weights. Cloning weights from learned filters provide similar results.

In the retraining process, only the 8 kernels corresponding to the 2 new feature maps and connections to the 5 new output neurons are trained with the new examples. Rest of the parameters are shared with the base network of 10 classes and as they are frozen, we will not forget the previously learned 10 classes. The new network becomes base network for the next 5 classes (F-J) to be added. That means, for any new set of classes, the network will be [784 (5 × 5)4c 2s (5 × 5)8c 2s 5o], where only the 8 kernels corresponding to the 2 new feature maps and connections to the 5 new output neurons will be trained with the new examples. The accuracy achieved by this approach is given in the Table 1.

### Table 1 Accuracy results for approach 1

| Classes | Network | Incremental Learning Accuracy (%) |
|---------|---------|-----------------------------------|
| 0-9 (base) | [784 (5 × 5)4c 2s (5 × 5)4c 2s 10o] | – | 96.68 |
| A-E | [784 (5 × 5)4c 2s (5 × 5)6c 2s 5o] | 98.50 | 98.82 |
| F-J | [784 (5 × 5)4c 2s (5 × 5)8c 2s 5o] | 98.95 | 99.90 |
| K-O | [784 (5 × 5)4c 2s (5 × 5)10c 2s 5o] | 98.03 | 98.14 |
| P-T | [784 (5 × 5)4c 2s (5 × 5)12c 2s 5o] | 98.17 | 98.41 |
| U-Z | [784 (5 × 5)4c 2s (5 × 5)14c 2s 5o] | 96.57 | 96.76 |

We can observe from the above table that the accuracy degradation due to ‘partial network sharing’ is negligible compared to the network ‘without partial sharing’. Note that ‘without partial network sharing’ is the case when new classes are learned using all trainable parameters, none of which are shared with the already learned network parameters. In the case of training ‘without partial network sharing’, the new layers are initialized using the model with data A (old), and then fine-tuned with data B (new) without freezing any parameters.
However, such an approach has scalability issues. If we keep on adding more classes and continue increasing feature maps in the last convolutional layer, the network will become inflated towards the end. And hence, there can be overfitting and convergence issues while retraining for the new set of classes. We take care of this problem by retraining the final convolutional layer completely, the details of which are described in the following section.

3.2 Adding Branch to Existing Network

The approach presented in section 3.1 is a straightforward one and shown in earlier related works. However, the limitations of such approach has motivated our search for a robust scalable method.

To learn new set of classes, we clone and retrain the final convolutional layer and subsequent layers. To clone a layer or layers, we create a new layer or layers with the exact same number of neurons as in the original layer/layers and initialize the new layer/layers with the same weight values so that both original and the cloned layer/layers have exactly same synaptic connections. A new network is formed every time we add new set of classes, which shares the initial convolutional layers with the base network, and has a separate final convolutional layer and layers following it to the output. The cloned and retrained layers of the new network thus become a branch of the existing network. The advantage of cloning the final layers is that we do not have to worry about the initialization of the new trainable parameters. Otherwise, new kernels initialized with too big or too small a random value will either ruin the existing model or make training tediously long. Another advantage of cloning is that it maximizes the transfer of learned features.

To investigate this approach, we implemented a deep CNN: [1024 × 3 (5 × 5)128c (1 × 1)100c (1 × 1)64c (3 × 3)mp (5 × 5)128c (1 × 1)128c (1 × 1)128c (3 × 3)mp (3 × 3)128c (1 × 1)100c (1 × 1)64c] (c: convolutional layer kernels, mp: max pooling layer kernel, o: output layer) for CIFAR10 [8] dataset using MatConvNet [31]. The network contained three MlpConv [11] blocks, each of which contained one convolutional layer consisting of 5 × 5 or 3 × 3 kernels, two convolutional layers consisting of 1 × 1 kernels and one max-pooling layer. The (1 × 1) convolutional layers can be considered as fully-connected layers. Hence, 'final convolutional layer' implies the convolutional layer in the last MlpConv block that contains 3 × 3 kernels.

Fig. 2 Network structure for investigating incremental learning by retraining the final convolutional layer.
Fist we separated the 10 classes of CIFAR10 dataset to three sets of 4, 3 and 3 classes. The classes were chosen randomly. We trained the base network using the set of 4 classes. Figure 2 shows the basic structure of the network. The last layer of the final MlpConv block is shown separately in the figure to specify it as the output layer. The max-pooling layers and final average pooling layer is not shown for simplicity. After training this base network, we added rest of the two set of classes to the existing network in two installments. Each time we retrain the network for new classes, we clone the last MlpConv [11] block (highlighted in table 2) and retrain it using new examples for the new set of classes. During this retraining, the initial two MlpConv blocks are shared from the base network which work as fixed feature extractors (learning parameters are frozen) and minimize learning overhead for new set of classes (figure 3). In figure 3a, the new MlpConv block is cloned from the base network and only that part is retrained with the new data samples for the new classes, while the last MlpConv block of the base network remains disconnected. Similarly, another branch is trained for the next set of new classes as shown in figure 3b. After retraining, the new MlpConv block is added to the existing network as a new branch. Figure 4a shows the updated network after adding the two sets of new classes.

We can observe from the Table 2 that the accuracy degradation due to partial network sharing (figure 3) is negligible when we train for additional class sets. On the other hand accuracy for updated network (figure 4a) of 10 classes suffers ~1.8% degradation compared to an incremental learning approach where we do not share the first two MlpConv blocks for learning the new classes. In this learning w/o sharing MlpConv blocks, each new branch is trained separately with 3 MlpConv blocks rather than 1 final block.

We would like to mention that ~89% (row 1, column 4 in table 2) classification accuracy can be achieved for CIFAR10 dataset using slightly modified NIN [11] architecture (figure 4b), if the training is done with all training samples applied together as in regular training. This performance can be considered as the upper-bound for incremental learning on this network, for this particular dataset. However, for
incremental learning, all training samples are not available together, hence it is not possible to get that high accuracy even without any network sharing.

Note that freezing a set of parameters in a pre-trained convolutional network is a standard practice for many applications involving knowledge transfer. But previous works [17] used this method to learn a different dataset using the frozen parameters as fixed feature extractors. In such case, the new network can only classify the new dataset, not previously learned dataset. On the other hand, in our proposed methodology, both old and new learned classes can be classified together. However, one question is still unanswered: in a large DCNN with many convolutional layers, is retraining the final convolutional layer enough? To answer this question, we move to our third and final approach which will be described in the next sub-section.

### Table 2 Accuracy results for approach 2

| Classes      | Network                          | Incremental Learning Accuracy (%) |
|--------------|----------------------------------|-----------------------------------|
| 10 (all classes) | [1024 × 3 (5 × 5)128c (1 × 1)]  | With partial network sharing   | Without partial network sharing |
| 4 (base)     | 100c (1 × 1)64c (3 × 3)mp        | –                                 | 88.90                             |
| 3            | (5 × 5)128c (1 × 1)128c (1 × 1)  | –                                 | 91.82                             |
| 10 (updated) | (1 × 1)128c 4/3/3/10o            | 89.60                             | 90.53                             |

### 3.3 Replacing Part of the Base Network with New Convolutional Layers

A large DCNN usually has many convolutional layers followed by a fully connected final classifier. To apply our approach in a large DCNN, we implemented ResNet [5; 6] for a real-world object recognition application. The network structure is depicted in figure 5. CIFAR100 [8] was used as the benchmark dataset. We trained a base network (ResNet101), that contained 100 convolutional layers, with 50 classes out of the 100 in CIFAR100. Then we added rest of the 50 classes to the existing network.
network in three installments of 10, 20 and 20. The classes for forming the sets were chosen randomly and each set is mutually exclusive. Each time we update the network for new classes, we clone the last convolutional layer, while sharing the initial convolutional layers from the base network, and retrain it using examples for the new set of classes only. That means we shared 99 convolutional layers and retrained only the last convolutional layer (figure 6a). After retraining the cloned layer, we add it to the existing network as a new branch as shown in figure 6b. We compared the accuracies achieved by this method with the accuracy of a network of same depth, trained without sharing any learning parameter, and observed that there is an 8-12% accuracy degradation for the former method. We also assessed the updated network accuracy for the all 100 classes by generating prediction probabilities from each of the separately trained networks and selecting the maximum probability. Even for the updated network, we observed about 10% accuracy degradation. To mitigate this accuracy loss, we reduced network sharing and allowed more freedom for retraining the networks. By gradually reducing sharing we observed improvement in the inference accuracy for both branch networks and the updated network.

Fig. 5 The ResNet [5; 6] network structure used for implementing large scale DCNN. For simplicity, the input bypass connections of ResNet is not shown here.

From figure 7a, we can observe that when we share ~80% of the learning parameters in the convolutional layers (and corresponding batch normalization and ReLU layers), we can achieve accuracy within ~1% of baseline. The baseline is an incrementally trained network, without network sharing (figure 7b). The accuracy results for this network configuration is listed in Table 3. Note that ~74% classification accuracy (row 1, column 4 in table 3) can be achieved for CIFAR100 using ResNet101, which is the upper-bound for incremental learning on this network, if the training is done with all training samples applied together. But for incremental learning, all training samples are not available together, hence it is not possible to get that high accuracy even without any network sharing. If we share more than 80% of the network parameters, classification accuracy degrades drastically. Based on this observation we developed the incremental training methodology for maximum benefits, which will be explained in the next sub-section.
Fig. 6 (a) Incremental training for accommodating new classes in the base network. The parameters of the shared layers are frozen. The semi-transparent rectangle implies that the part is disconnected from training. The new convolutional layer is cloned from the base network and only that part is retrained with the new data samples for the new classes, while the last convolutional layer of the base network remain disconnected. (b) After retraining the cloned layer, we add it to the existing network as a new branch, and form the updated network.

Fig. 7 (a) Updated network architecture for proposed training methodology. ‘%’ Sharing is the portion of trainable parameters which are frozen and shared between the base and the new network. This quantity is decided from the ‘Accuracy vs Sharing’ curve shown in the inset. (b) It is an incrementally trained network, without network sharing, used as baseline for comparison.

Table 3 Accuracy results for approach 3

| Classes          | Network                                                        | Incremental Learning Accuracy (%) |
|------------------|----------------------------------------------------------------|-----------------------------------|
|                  |                                                                | With partial network sharing | Without partial network sharing |
| 100 (all classes)| ResNet101 [5]: 100 Convolution, 100 Batch Normalization, 100 ReLU, 1 average pooling, 1 Output Prediction layer | –                             | 74.23                           |
| 50 (base)        |                                                                | –                             | 78.16                           |
| 10               | 100 Batch Normalization, 100 ReLU, 1 average pooling.         | 88.8                          | 87.2                            |
| 20               | 1 Output Prediction layer                                     | 78.3                          | 81.4                            |
| 20               |                                                                | 85.25                         | 86.9                            |
| 100 (updated)    |                                                                | 59.08                         | 60.65                           |

3.4 Training Methodology

The proposed training methodology is depicted in figure 8. A base network is trained with initially available set of classes. Then a clone of the base network is trained with new, previously unseen data for different sharing configurations. From the training results, an Accuracy vs Sharing curve is generated, from which the optimal sharing
configuration for this application and this network architecture is selected. This optimal configuration is then used for learning any new set of classes.

Note that in the top layers, there are branches for old and new set of classes. While retraining, and updating the network for new set of classes, only the branch of top layers corresponding to the new set of classes are retrained. Thus, the top layer filters keep information of their respective set of classes and the network do not suffer from catastrophic forgetting.

![Diagram](image)

**Fig. 8** Overview of the DCNN incremental training methodology with partial network sharing.

In this work, we do not try to grow a model with classes from datasets of different domains since the base network have learned features from data samples of a single dataset. For instance, if the base network is trained on object recognition dataset CIFAR10, then it will be able to accommodate new classes from CIFAR100 dataset as both of the datasets have similar type of basic features (image size, color, background etc.). However, the same base model should not be able to properly accommodate new classes from character recognition dataset (MNIST) because MNIST data has very different type of features compared to CIFAR10 data.

## 4 Simulation Framework

In this section, we discuss the circuit to system-level simulation framework used to analyze the effectiveness of the presented training scheme on DCNNs. We developed a computation energy model based on the number of MAC operations in the training algorithm. We implemented multiplier and adder units at the Register-Transfer Level (RTL) in Verilog and mapped them to IBM 45nm technology in 1 GHz clock frequency using Synopsys Design Compiler. The power and delay numbers from the Design Compiler were fed to the energy computation model to get energy consumption statistics. We also computed storage requirements and memory access energy for the overall network based on input size, number of convolutional layers, number of kernels in each layer, size of fully connected layer, number of neurons in the fully connected layer and number of output neurons. The memory structure (SRAM) in our proposed system was modelled using CACTI [15], in 45nm technology library, to estimate the corresponding component of the energy consumption.

At the system-level, the deep learning toolbox [16], MatConvNet [31], and PyTorch [19], which are open source neural network simulators in MATLAB, C++, and
Python, are used to apply the algorithm modifications and evaluate the classification accuracy of the DCNNs under consideration. The DCNNs were trained and tested using 4 NVIDIA Titan XP GPUs. In all experiments, previously seen data were not used in subsequent stages of learning, and in each case the algorithm was tested on an independent validation dataset that was not used during training. Details of the benchmarks used in our experiments are listed in Table 4:

| Application       | Dataset | DCNN Structure                                                                 |
|-------------------|---------|--------------------------------------------------------------------------------|
| Character Recog.  | TiCH    | [784 (5 × 5)c 2s (5 × 5)c 2s 10/5/6o]                                          |
| Object Recog.     | CIFAR10 | [1024 × 3 (5 × 5)128c 100fc 64fc (3 × 3)mp (5 × 5)128c 128fc 128c (3 × 3)mp (3 × 5)128c 128fc 4/3/3o] |
| Object Recog.     | CIFAR100| ResNet101                                                                       |
|                   |         | 100 Conv., 100 Batch Normalization, 100 ReLU, 1 average pooling, 1 Output Prediction layer |
| Object Recog.     | ImageNet| ResNet34                                                                        |
|                   |         | 33 Conv., 33 Batch Normalization, 33 ReLU, 1 average pooling, 1 Output Prediction layer |

### 5 Results

In this section, we present results that demonstrate the accuracy obtained, the energy efficiency and reduction in training time, storage requirements and memory access achieved by our proposed design.

**Fig. 9** Comparison of (a) energy/accuracy trade-off and (b) training time requirements, between incremental training with and without sharing convolutional layers, is shown for different sharing configurations.
5.1 Energy-Accuracy Trade-off

DCNNs are trained using the standard back-propagation rule with slight modification to account for the convolutional operators [16]. The main power hungry steps of DCNN training (back-propagation) are gradient computation and weight update of the convolutional and fully connected layers [28]. In our proposed training, we achieve energy efficiency by eliminating a large portion of the gradient computation and weight update operations, with minimal loss of accuracy or output quality. The normalized energy consumption per iteration for incremental training with and without sharing convolutional layers is shown in figure 9a. The accuracies reported in this work are obtained using test datasets, which are separate from the training datasets. Based on the accuracy requirement of a specific application the optimal sharing point can be chosen from the ‘Accuracy vs Sharing’ curve mentioned in section 3.4. The optimal sharing configuration for CIFAR100 is 80% in ResNet101. By sharing 80% of the base network parameters, we can achieve 1.89x computation energy saving while learning new set of classes. The energy numbers slightly depend on number of classes in the new set of classes to be learned. However, it does not affect much since only the output layer connections vary with the number of new classes, which is insignificant compared to total connections in the network. Note that the energy mentioned in this comparison is computation energy. Memory access energy is discussed in section 5.3.

5.2 Training Time Reduction

Since gradient computations and weight updates are not required for the shared convolutional layers, we achieve significant savings in computation time with our proposed approach. Figure 9b shows the normalized training time per iteration for learning a set of new classes. We observe 2.3-2.6× reduction in training time per iteration for CIFAR100 in ResNet101 [5] for different sharing configurations. As a byproduct of the proposed scheme, convergence becomes faster due to inheriting features from the base model. Note that the time savings cannot be used to improve accuracy of the networks by providing more epochs to the training. One way to improve accuracy is to retrain the networks with all the training samples (previously seen and unseen), which can be very time consuming and contradictory to the incremental learning principle.

5.3 Storage Requirement and Memory Access Reduction

Figure 10a shows the storage requirement reduction obtained using our proposed scheme for CIFAR100 in ResNet101 [5]. We achieve 66-99% reduction in storage requirement since we are sharing initial convolutional layers from the base network for the new branch networks. A large part of the training energy is spent on the memory read/write operations for the synapses. Proposed partial network sharing based training also provides 32-49% savings in memory access energy during training for
Fig. 10 Comparison of (a) storage and (b) memory access requirements, between incremental training with and without sharing convolutional layers, is shown for different sharing configurations.

CIFAR100 in ResNet101, since we do not need to write (update during backpropagation) the fixed kernel weights during training. Figure 10b shows the memory access requirement reduction obtained using proposed approach.

5.4 Results on ImageNet

The ImageNet [3] (ILSVRC2012) is one of the most challenging benchmarks for object recognition/classification. The data set has a total of ~1.2 million labeled images from 1000 different categories in the training set. The validation and test set contains 50,000 and 100,000 labeled images, respectively. We implemented ResNet18 and ResNet34 [5], and trained them on ImageNet2012 dataset. We achieved 69.73% (top 1%), 89.54% (top 5%) and 73.88% (top 1%), 91.70% (top 5%) classification accuracy for ResNet18 and ResNet34, respectively, in regular training (all 1000 classes trained together), which are the upper-bounds for the incremental learning on corresponding networks. Then we divided the dataset into 3 sets of 500, 300 and 200 classes for the purpose of incremental learning. The classes for forming the sets were chosen randomly and each set is mutually exclusive. The set of 500 classes were used to train the base network. The other 2 sets were used for incremental learning. Utilizing our proposed method, we obtained the optimal sharing configuration. For ResNet18, we were able to share only ~1.5% of the learning parameters from the base network and achieve classification accuracy within ~1% of the baseline (network w/o sharing) accuracy. On the other hand, using ResNet34, we were able to share up to 33% of the learning parameters from the base network. The classification accuracy results for ResNet34 with ~33% sharing configuration are listed in Table 5. By sharing ~33% of learning parameters, we achieved $\times 1.61$ improvement in computation energy. We also reduced training time per iteration by 50% and memory access up to ~17%.

Efficacy of incremental learning with partial network sharing largely depends on the quality of the base network. In table 5, we can observe that the updated network...
Table 5: Accuracy results for ResNet34 trained on ImageNet

| #Classes            | Accuracy(%) w/o sharing | Accuracy(%) w/ sharing |
|---------------------|-------------------------|------------------------|
|                     | Top 1% | Top 5%   | Top 1% | Top 5% |
| 1000 (all classes) | 73.88  | 91.70    | -      | -      |
| 500                 | 80.85  | 95.37    | -      | -      |
| 300                 | 74.3   | 90.67    | 71.25  | 89.2   |
| 200                 | 75.83  | 92.61    | 76.6   | 93.12  |
| 1000 (updated)     | 66.99  | 87.4     | 65.85  | 86.65  |

performance is close to the regular network compared to the performance on CI-
FAR10 and CIFAR100, on table 2 and 3, respectively. This is due to the fact that in
the case of ImageNet, the base network had learned sufficient features since it was
trained with large number of classes and examples. Another important fact to be noted
here is that the amount of network sharing is largely dependent on the network size.
Larger networks allow more learning parameters to be shared without performance
loss. We could share lot more of the learning parameters from the base network in
ResNet34 compared to ResNet18. Also for CIFAR100 trained using ResNet101, we
could share up to 80% of the learning parameters.

We will compare our approach of incremental learning with two standard ap-
proaches in figure 11. The standard approaches are:

1. **Cumulative**: In this approach the model is retrained with the samples of the
   new classes and all the previous learned classes (all previous data must be available).
   This is sort of an upper bound for ideal incremental learning. Since in incremental
   learning, the old data samples are not available, it will remain an open problem until
   an approach can match performance of the cumulative approach without using stored
   data for already learned classes.

2. **Naïve**: In this approach, the network is completely retrained with the data
   samples of new classes only. It suffers from catastrophic forgetting.

From figure 11, we can observe that the performance of our proposed method is not very far from the cumulative approach. We also observe that our proposed par-
tial network sharing approach performs almost same as the approach without partial
network sharing. While the Naïve approach always performs well for the new set of
classes only since the network forgets the old classes due to catastrophic forgetting.

6 Conclusion

The performance of DCNNs relies greatly on the availability of a representative set
of the training examples. Generally, in practical applications, data acquisition and
learning process is time consuming. Also, it is very likely that the data are avail-
able in small batches over a period of time. A competent classifier should be able to
support an incremental method of accommodating new data without losing ground
on old data inference capability. In this paper, we introduce an incremental learning
methodology for DCNNs, which employs partial network sharing. This method al-
ows us to accommodate new, previously unseen data without the need of retraining
the whole network with previously seen data. It can preserve existing knowledge, and
can accommodate new information. Importantly, all new networks start from an ex-
esting base network and share learning parameters. The new updated network inherits
features from the base network by sharing convolutional layers, leading to improved
computational effort and energy consumption during training and thus, speed up the
learning process.

Our proposed method is simple yet elegant. All the other incremental learning
approaches focus solely on getting higher accuracy without considering the increase
in the complexity of the incremental training process. Most of them retrain the whole
network with the new samples. Some of them reuse small percentage of the old train-
ing samples during updating the network. In comparison, our approach is an end-to-
end learning framework, where we focus on reducing the incremental training com-
plexity while achieving accuracy close to the upper-bound without using any of the
old training samples. Our method does not require any new components other than
the branches (regular convolutional and fully-connected layers) for the new classes.
The training, updating and inference procedure is the same as the regular supervised
learning. This is very useful for re-configurable hardware such as FPGAs where the
network capacity can be increased for accommodating new classes without requiring
significant effort. In the proposed incremental learning approach, other than show-
ing the learning performance, we directly quantified the effect on energy consump-
tion and memory. We applied the proposed method on different DCNNs trained on
real-world recognition applications. Results confirm the scalability of the proposed
approach with significant improvements.

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