Abstract

Humans learn continually throughout their lifespan by accumulating diverse knowledge and fine-tuning it for future tasks. When presented with a similar goal, neural networks suffer from catastrophic forgetting if data distributions across sequential tasks are not stationary over the course of learning. An effective approach to address such continual learning (CL) problems is to use hypernetworks which generate task dependent weights for a target network. However, the continual learning performance of existing hypernetwork based approaches are affected by the assumption of independence of the weights across the layers in order to maintain parameter efficiency. To address this limitation, we propose a novel approach that uses a dependency preserving hypernetwork to generate weights for the target network while also maintaining the parameter efficiency. We propose to use recurrent neural network (RNN) based hypernetwork that can generate layer weights efficiently while allowing for dependencies across them. In addition, we propose novel regularisation and network growth techniques for the RNN based hypernetwork to further improve the continual learning performance. To demonstrate the effectiveness of the proposed methods, we conducted experiments on several image classification continual learning tasks and settings. We found that the proposed methods based on the RNN hypernetworks outperformed the baselines in all these CL settings and tasks.

1. Introduction

There are various applications where a computational system has to learn from a stream of data continually and adapt to the environment by using knowledge gained from past experiences. For example, Autonomous agents in the real world have to learn over continuous streams of data and need to remember the information from various non-stationary distributions without forgetting [20]. Deep neural networks have achieved high performance on many images classification benchmarks, comparable or even better than humans. However, while learning a new task, these networks forget the knowledge gained from previous ones. The process of forgetting knowledge or information gained from previous tasks due to drastic weight alteration while learning new tasks is known as catastrophic forgetting [18]. If data distributions across the sequential tasks is not stationary, the weights of the model alter drastically to classify the new task, leading to forgetting of knowledge gained from previous tasks. Ideally, performance of a newly learnt task should not have an impact on previous one (or vice versa). To overcome forgetting, computational systems or agents, on one hand, should be plastic to acquire new information and refine old information based on continuous input and, on the other hand, it should be stable to prevent the novel input from interfering with old information. This is referred to as plasticity-stability dilemma [7, 19]. Continual learning aims to develop machine learning and deep learning models which are stable enough to retain information learnt from old tasks but also has the required plasticity to learn new tasks [20].

Continual learning techniques for neural networks have gained significant attention recently [20]. Several continual learning methods have been proposed to avoid forgetting in neural networks. These can be broadly categorised into three approaches, Regularisation techniques [9, 12], dynamic architecture methods [2, 24] and replay based methods [5, 21]. Recently, Continual learning with hypernetworks has shown very promising results in dealing with forgetting at a meta level by generating task specific weights [4, 8, 28]. Hypernetwork is a meta neural network which generates parameters for the main network associated with the task (for instance, classification or regression network) by considering some task related information. During training, instead of directly trying to update parameters of the main network, hypernetwork parameters which generate them are updated. But generating the entire main network parameters will require a larger hypernetwork as it requires generating a very high dimensional output.
chunked hypernetworks [8, 28] generate them in smaller chunks (chunk referred to subset of main network weights) multiple times iteratively using smaller hypernetwork that is reusable and also helps in model compression significantly. A key limitation of chunked hypernetworks is that it assumes the weight matrices associated with the chunks to be independent, which affects the continual learning performance significantly. Chunked hypernetwork [28] uses a feed forward neural network to generate weights without considering dependencies across chunks. We propose to use recurrent neural networks (RNNs), in order to capture dependencies in weight matrix generation across the chunks. But standard RNNs suffer from vanishing gradient problems and may not be able to remember dependencies for a long time. So, a variant of RNN, LSTM [9] has been used to remember the weight matrix dependencies over a longer duration. Thus, we propose LSTM based hypernetwork that can efficiently generate weights of the main network while also maintaining the dependencies across the chunks.

While learning multiple tasks in sequential manner, the hypernetwork should remember the knowledge gained from previous tasks and should also be able to forward that knowledge to the upcoming tasks. To achieve this, we propose a novel hypernetwork regularisation technique, Importance Weighted Regularisation (IWR) that can further improve the performance of hypernetwork based continual learning by enabling forward transfer while also retaining previous information. IWR considers the importance of the main network parameters and allows more flexibility to the hypernetwork to adapt to the new task by considering this importance. We also propose a network growth technique for the LSTM based hypernetworks for continual learning. The approach is based on the idea that the dependence among the main network parameters across tasks remains the same while their exact values could be different. This is achieved by sharing the weights associated with the hidden states in the LSTM across the tasks. We still learn the input specific weights for each task separately. This approach improves the performance of continual learning with no extra regularisation and accelerates the model training. Our experimental results on real world data show that the proposed approaches along with LSTM based hypernetwork can effectively mitigate catastrophic forgetting and significantly improve the continual learning performance.

Our main contributions can be summarised as follows.

- We propose a novel dependency preserving LSTM hypernetwork for continual learning.
- We propose a novel regularisation technique for hypernetwork based continual learning and a network growth technique specifically for the LSTM based hypernetwork which does not require regularisation.
- We demonstrate the improvement in continual learning performance of the proposed approaches through experiments on several image classification data sets and for different CL settings.

2. Related Work

Several approaches were proposed recently for continual learning and to deal with catastrophic forgetting. Conceptually, these approaches are classified based on replaying the stored examples, methods that expand the model on seeing the new task and methods that regularise the parameter shift by retaining the network [20, 13]. Regularisation based approaches [11, 16, 30] avoid forgetting by imposing constraints on the update of parameters. With the advantage of no extra memory requirement, regularisation approaches are used for a broader variety of applications that have constraints on memory, computational resources, and data privacy. Elastic weight consolidation (EWC) [11] and Synaptic intelligence (SI) [30] are most well-known approaches, proposed to mitigate forgetting by constraining the update of important parameters of the task. It imposes a quadratic penalty on the difference between old and new parameters which helps to slow down the learning of new tasks by updating old parameters. But experiments in [10] showed that EWC is not effective in learning new classes incrementally.

Replay based methods [2, 17, 21] alleviate catastrophic forgetting by replaying old examples while learning new tasks. These methods either store examples from previous tasks or generate synthetic examples from trained generative models from learnt feature space. Variational autoencoders (VAEs) and Generative adversarial networks (GANs) are used to generate samples from feature space. iCaRL [21], stores a subset of samples per class in fixed memory and selected examples should best approximate the class means in feature space. But as the number of tasks grows, samples per class stored will become too few to ensure required performance. Various other approaches [6, 22, 3] have been proposed which generate samples for old tasks instead of storing them and these are replayed while learning a new task.

Dynamic architecture based methods provide a solution towards continual learning by growing or updating its model structure for each task [15, 29]. Progressive neural network (PNNs) [23] grow their architecture by expanding the network statically with new modules. Forgetting can be circumvented by adding lateral connections from previous modules. Instead of growing the network structure statically, Dynamically expandable network (DEN) grows network architecture for each task with only a limited number of units and identifies neurons that are important for the new task and train them selectively [29].

Recently, hypernetwork based approaches have been proposed [8, 10, 26, 28] which has the advantage of having a constrained search space compared to the main network. Hypernetwork based techniques use a secondary neural net-
work to generate the parameters of the main network and deal with forgetting at the hypernetwork level. To keep the size of the hypernetwork to be small compared to the main network, they generate the weights of the main network in small fixed sized chunks [8]. However, we notice that the process of independent generation of chunk weights ignores the dependence among main network parameters and thus affects the continual learning performance. To overcome this, we propose a LSTM based hypernetwork that can generate weights in smaller chunks while also maintaining dependency across them. Due to their ability to capture dependencies, LSTMs were used for learning from sequential data. Recently, continual learning methods for recurrent neural networks based on existing regularisation techniques and hypernetworks were proposed in [4]. In contrast to the work in [4], where the aim is to model continual learning for tasks involving sequence data using RNNs with existing CL techniques, the goal of this paper is to develop novel continual learning methodology based on RNNs (specifically LSTMs) by treating them as a hypernetwork. In addition, we also introduce novel continual learning techniques for such LSTM based hypernetworks such as importance weighted regularisation and network growth.

3. LSTM Hypernetwork and Regularization Techniques for Continual Learning

In many realistic real world learning scenarios, the tasks arrive in sequential manner. Continual learning aims to learn from a sequence of tasks where the data of all the tasks are not available at once and we have a fixed memory size. We assume that we are given a sequence of \( K \) tasks, where each task \( t \in T = \{1, \ldots, K\} \) contains input \( X^t = \{x^t_j\}_{j=1}^{n_t} \) and target label \( Y^t = \{y^t_j\}_{j=1}^{n_t} \) where \( n_t \) being the number of samples in task \( t \). The goal of main network \( m \) is to learn a function \( f^m_t(\cdot, \Theta^m_t) : X^t \rightarrow Y^t \) with parameters \( \Theta^m_t \) associated with task \( t \). While learning a task \( t \) we have access to only observations of current task \( t \) but no access to data of previous tasks.

We can learn \( \Theta^m_t \) separately for each task, but it results in a linear growth in the number of parameters and the fixed sized memory will not be sufficient to store them. If we maintain the main network parameter to be the same across all the tasks, the parameter values will get overwritten by the new task data which will result in catastrophic forgetting. To learn continuously over the tasks without requiring a linear growth in parameters, hypernetworks are proposed to generate the main network parameters for each task. The hypernetwork \( h \) learns a function \( f_h(\cdot, \Theta_h) : e^t \rightarrow \Theta^m_t \) to generate the task specific parameter \( \Theta^m_t \) given a task embedding \( e^t \) using trainable parameters \( \Theta_h \).

Generating the high dimensional main network parameters all at once requires a very large hypernetwork with a large number of outputs and is computationally costly to train them. With the motive of reducing the number of trainable parameters in hypernetworks, chunked hypernetworks [8, 28] are proposed to generate weights in smaller chunks (subsets of the weight matrix of main network) by reusing the same hypernetwork \( f_h \) multiple times with different chunk embeddings.

Thus, hypernetwork \( f_h \) with parameters \( \Theta_h \) takes task embedding \( e^t \) and chunk embeddings \( c = \{c_1, \ldots, c_{n_c}\} \) as input to generate set of main network weights, \( \Theta^m_t = f_h(e^t, c, \Theta_h) = \{f_h(e^t, c_1, \Theta_h), f_h(e^t, c_2, \Theta_h), \ldots, f_h(e^t, c_{n_c}, \Theta_h)\} \), where \( n_c \) being the number of chunks. Hypernetworks can still suffer from catastrophic forgetting when hypernetwork parameters are updated to generate main network parameters for the new task. In order to overcome this forgetting, an additional regularisation term is used while learning the parameters of the hypernetwork for a new task along with task specific loss [28].

Chunked hypernetworks generate weights of the main network in smaller chunks using a hypernetwork considering the task embedding and chunk embedding. We observe that they do not consider sequential nature and inter-dependence of weights between the chunks. We note that the chunked hypernetworks make conditional independence assumptions on the weights of the main network. Consequently, if we consider a probability distribution over weights, it gets decomposed over chunks as \( P(\Theta^{m,1}_t, \Theta^{m,2}_t, \ldots, \Theta^{m,n_c}_t | e^t, c) = P(\Theta^{m,1}_t | e^t, c_1) \times P(\Theta^{m,2}_t | e^t, c_2) \ldots P(\Theta^{m,n_c}_t | e^t, c_{n_c}) \). Assumption of independence across the chunks does not usually hold and can affect the main network parameter generation and the performance of the continual learning.

3.1. LSTM Hypernetworks

To capture the interdependence in the chunk weights and to be parameter efficient at the same time, we propose a recurrent neural network (RNN) and in particular long short term memory (LSTM) [9] based hypernetwork called LSTM_NET. LSTM_NET is capable of generating weights for the main network in smaller chunks while also maintaining the dependencies across the chunks. LSTMs are sequence models capable of capturing long range dependencies and will be able to generate a chunk weight depending on the weights associated with the preceding chunks. Consequently, it models the joint probability over the main network parameters as

\[ P(\Theta^{m,1}_t, \Theta^{m,2}_t, \ldots, \Theta^{m,n_c}_t | e^t, c) = P(\Theta^{m,1}_t | e^t, c_1) \times P(\Theta^{m,2}_t | e^t, c_2) \ldots P(\Theta^{m,n_c}_t | e^t, c_{n_c}) \] (1)

The proposed LSTM hypernetwork uses hidden state \( h_{t-1} \) and cell state \( s_{t-1} \) of preceding chunk along with cur-
is a regularisation

$F I$ are parameters of the hy-

perset, for task $t$, $\Theta_t^t$ are parameters of the hypernet-

ernetwork before learning task $T$. $\beta$ is a regularisation con-

stant which balances task specific loss and regulariza-

loss, and $\Delta \Theta_h$ is change in direction of the weights of

the hypernetwork evaluated on the task-specific loss. The

task-specific loss $L_{task}$ is the loss associated with the task

(for e.g., cross-entropy loss for classification). The regu-

larization loss constrains the hypernetwork learnt on the

new task to generate main network parameters similar to the

ones generated by previously learnt hypernetwork. Hyper-

network parameters $\Theta_h$ and chunk embeddings are learnt

by minimising the total loss $L_{total}$, and the task embeddings

are learnt using $L_{task}$ alone using backpropagation.

### 3.2. Importance Weighted Regularisation

We propose a novel regularisation technique for continual

learning in hypernetworks which provides more flexi-

bility to the hypernetwork to adapt to the new task com-

pared to the regularisation in (2). The proposed importance

weighted regularisation (IWR) updates the hypernetwork

parameters based on the importance of the parameters as-

sociated with the main network for each task. IWR requires

the hypernetwork to generate only important main network

parameters associated with old tasks and not all the main

network parameters. We achieve this by considering the fis-

her information score of the main network parameters in

the regularisation term in (2). This will enforce hypernet-

work to give importance to significant main network param-

eters during generation of main network weights. Mean-

while, it provides flexibility to the hypernetwork to adapt

its parameters more freely to the new task as it is not con-

strained to generate all the main network parameters with

equal importance. The objective function considering the

$IWR$ regularisation is defined as

$$
\arg \min_{\hat{\theta}_h} L_{total} = L_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) + \frac{\beta}{T-1} \sum_{t=1}^{T-1} \left[ f_h(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) - f_h(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta \Theta_h) \right]^2
$$

(3)

where $f_h(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) = \Theta_m^t$ denotes all the parameters of

the main network for task $t$, $\Theta_m^t$ are parameters of the hy-

perset, for task $t$, $\Theta_t^t$ are parameters of the hypernet-

work before learning task $T$. $\beta$ is a regularisation con-

stant which balances task specific loss and regulariza-

loss, and $\Delta \Theta_h$ is change in direction of the weights of

the hypernetwork evaluated on the task-specific loss. The

task-specific loss $L_{task}$ is the loss associated with the task

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strained to generate all the main network parameters with

equal importance. The objective function considering the

$IWR$ regularisation is defined as

$$
\arg \min_{\hat{\theta}_h} L_{total} = L_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) + \frac{\beta}{T-1} \sum_{t=1}^{T-1} \sum_{i} \left[ f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) - f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta \Theta_h) \right]^2
$$

(3)

where the first term $L_{task}$ is task specific loss and the sec-

ond term is the IWR term that regularises the hypernetwork

parameters to avoid forgetting. The IWR term uses $F I^t$ which

is the fisher information matrix (defined below) over the

main network parameters associated with task $t$. $F I^t$ pro-

vides the importance of the main network parameters for

task $t$, and the index $i$ iterates over all the main network

parameters. $f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t)$ denotes the $i^{th}$ main

network parameter generated by the hypernetwork. We can

observe that if the Fisher information associated with the $i^{th}$ main

network parameter is high (implying that this parameter is

the Hadamard product. $w, u$ are the weights associated

with the input and hidden states respectively with subscript

denoting the corresponding gate. $\Theta_{m_{(i,j)}}$ is the $j^{th}$ chunk

of main network weights generated by LSTM hypernetwork.

Here, $W \in R^{d_i \times d_s}$ are the weights of the feed forward

layer producing the chunk weights.

We learn the LSTM parameters $\Theta_h$ when presented with

data from task $T$ by minimising the following loss consist-

ing of task specific loss and regularization loss [28].

$$
\arg \min_{\hat{\theta}_h} L_{total} = L_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) + \frac{\beta}{T-1} \sum_{t=1}^{T-1} \sum_{i} \left[ f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) - f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta \Theta_h) \right]^2
$$

(3)

where $f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) = \Theta_m^t$ denotes all the parameters of

the main network for task $t$, $\Theta_m^t$ are parameters of the hy-

perset, for task $t$, $\Theta_t^t$ are parameters of the hypernet-

work before learning task $T$. $\beta$ is a regularisation con-

stant which balances task specific loss and regulariza-

loss, and $\Delta \Theta_h$ is change in direction of the weights of

the hypernetwork evaluated on the task-specific loss. The

task-specific loss $L_{task}$ is the loss associated with the task

(for e.g., cross-entropy loss for classification). The regu-

larization loss constrains the hypernetwork learnt on the

new task to generate main network parameters similar to the

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sociated with the main network for each task. IWR requires

the hypernetwork to generate only important main network

parameters associated with old tasks and not all the main

network parameters. We achieve this by considering the fis-

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the regularisation term in (2). This will enforce hypernet-

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while, it provides flexibility to the hypernetwork to adapt

its parameters more freely to the new task as it is not con-

strained to generate all the main network parameters with

equal importance. The objective function considering the

$IWR$ regularisation is defined as

$$
\arg \min_{\hat{\theta}_h} L_{total} = L_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) + \frac{\beta}{T-1} \sum_{t=1}^{T-1} \sum_{i} \left[ f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t) - f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta \Theta_h) \right]^2
$$

(3)

where the first term $L_{task}$ is task specific loss and the sec-

ond term is the IWR term that regularises the hypernetwork

parameters to avoid forgetting. The IWR term uses $F I^t$ which

is the fisher information matrix (defined below) over the

main network parameters associated with task $t$. $F I^t$ pro-

vides the importance of the main network parameters for

task $t$, and the index $i$ iterates over all the main network

parameters. $f_i(\mathbf{e}^t, \mathbf{c}, \Theta_h^t)$ denotes the $i^{th}$ main

network parameter generated by the hypernetwork. We can

observe that if the Fisher information associated with the $i^{th}$ main

network parameter is high (implying that this parameter is
important), then hypernetwork is required to generate it exactly while it does not have to do the same for the unimportant parameters. Thus, IWR provides more flexibility to the hypernetwork to learn and adapt to the new tasks.

The Fisher information matrix (FI) provides the information on the importance of each weight in the network. For the IWR in (3), the FI matrix is defined as

$$FI^t = \frac{1}{N_t} \sum_{j=1}^{N_t} \left[ \nabla_{\Theta_{m}} L_{t \_task}(\Theta_h, e^t_j, y^t_j, x^t_j) \times \nabla_{\Theta_{m}} L_{t \_task}(\Theta_h, e^t_j, y^t_j, x^t_j)^T \right]$$

We note that the derivatives are computed with respect to the main network parameters to assess the importance of those parameters and not with respect to the hypernetwork parameters that we are learning, unlike the standard regularization techniques. Thus, using Fisher information matrix we can find out the main network parameters which are important in learning the task. The existing regularisation for hypernetworks in (2) treats all the main network parameters equally. In practice, not all main network parameters contribute equally to solving a particular task. Hence, it is not required to exactly generate all the main network parameters by the hypernetwork but only important ones and can be achieved using the IWR regularisation. The IWR regularization is a generic technique that can be used with any hypernetwork and not only the LSTM hypernetwork to improve the continual learning performance.

3.3. Network Growth Technique

One potential problem with the regularisation approaches is that training time grows with the number of tasks as can be seen from Eq (2) and Eq (3). Moreover, the same hypernetwork parameters are used to generate all the task specific main parameters. This can become a bottleneck and affects continual learning performance in situations with a large number of tasks. We propose LSTM hypernetworks (LSTM_NET_GROW) based on network growth for continual learning. It provides more flexibility in adapting to the new task by maintaining task specific parameters and accelerates model training by requiring no regularisation. In order to transfer knowledge across the tasks, LSTM_NET_GROW also maintains a shared set of hypernetwork parameters.

We hypothesize that, though the actual main network parameters differ across the tasks, the dependencies existing among the main network parameters remain the same across the tasks. Based on this intuition, we define the shared and task specific parameters in the LSTM hypernetwork. In LSTM, the dependencies are captured by the weights associated with the hidden state. Hence, we assume them to be the same across the tasks in the proposed LSTM_NET_GROW model. The variability in parameter generation across the tasks is captured by having task specific weights associated with inputs. More specifically, the weights ($u_r, u_i, u_o, u_g$) of the LSTM are shared across the tasks and we maintain input weights ($w^t_r, w^t_i, w^t_o, w^t_g; W^t$) to be task specific. LSTM_NET_GROW uses the following LSTM operations to generate chunk weights of the main network parameters associated with task $t$.

$$i^t_j = \sigma(w^t_i \times (e^t_i, c_j) + u_i \times h^t_{j-1})$$
$$f^t_j = \sigma(w^t_f \times (e^t_i, c_j) + u_f \times h^t_{j-1})$$
$$o^t_j = \sigma(w^t_o \times (e^t_i, c_j) + u_o \times h^t_{j-1})$$
$$g^t_j = \tanh(w^t_g \times (e^t_i, c_j) + u_g \times h^t_{j-1})$$
$$s^t_j = f^t_j \odot s^t_{j-1} + i^t_j \odot g^t_j$$
$$h^t_j = o^t_j \odot \tanh(s^t_j)$$
$$\Theta_{m}^{(t,j)} = h^t_j W^t$$

The LSTM_NET_GROW model freezes the hidden weights ($u_r, u_i, u_o, u_g$) of the LSTM after learning first task and is shared across all the tasks. It keeps learning new task specific input weights ($w^t_r, w^t_i, w^t_o, w^t_g; W^t$) upon training on the new task and those are stored for inference at a later stage. This approach does not require the additional regularisation term and can be learned just based on task specific loss ($L_{task}$). In addition, the task specific weights provide extra flexibility to the LSTM hypernetwork in generating task specific main network weights.

4. Experiments

We perform extensive experiments on various continual learning setups and real world benchmarks datasets to show the effectiveness of our approach. We present our results on Split MNIST, permuted MNIST, CIFAR-10, and CIFAR-100 datasets. Through experiments we aim to demonstrate:

- impact of maintaining dependencies across the chunks using the LSTM based hypernetwork (LSTM_NET),
- impact of the proposed regularisation IWR on LSTM_NET (LSTM_NET_IWR) and on HNET (HNET_IWR) in mitigating catastrophic forgetting,
- improvement in performance using proposed dynamically growing LSTM based hypernetwork LSTM_NET_GROW,
- knowledge transfer and mitigating forgetting across the tasks using the challenging Cifar datasets.

4.1. Experimental Setup

Continual learning models are tested on three different continual learning scenarios [27].

**CL1 (Task incremental learning)**: It provides the task identity information to the model both at training and testing.

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1https://github.com/srikar1/LSTM_NET_CL
The effectiveness of the hypernetwork based CL techniques for parameter generation are also tested on two continual learning setups, replay based and non-replay based setups. In the non-replay-based setup, hypernetwork is trained to generate parameters of the classifier used for solving the image classification problems. In the non-replay based setup, we compare the proposed approach with regularisation baselines Elastic Weight Consolidation (EWC) [11], Synaptic Intelligence (SI) [30] and the baseline hypernetwork HNET [28]. In the replay based setup, we augment our system with a generative model, for e.g. variational auto-encoder (VAE) to generate synthetic examples from the previous tasks that can be replayed to aid the classifier to remember previous tasks. In this case, hypernetwork will generate weights for the replay network i.e. VAE but not the target classifier. In the replay based setup, we compare the proposed approach with baselines deep generative replay with distillation (DGR)[25], learning without forgetting (LWF)[14] and the baseline hypernetwork HNET[28].

We conduct experiments on the standard continual learning task of image classification on publicly available real world data sets such as split MNIST, permuted MNIST, CIFAR-10 and CIFAR-100. In these experiments, we use a single layer LSTM that takes a task and chunk embedding each of size 96. For MNIST, we consider an LSTM with hidden state size 64 and batch size 128. For CIFAR, hidden size and batch size are 128 and 32 respectively. For Split MNIST, the classifier is a fully connected network (FCN) with 2 layers each with size 400 [28]. For Permuted

Table 1: Comparison of average test accuracy (%) of Split MNIST and Permuted MNIST for all three scenarios of continual learning without generative replay

|                | CL1     | CL2     | CL3     |                | CL1     | CL2     | CL3     |
|----------------|---------|---------|---------|----------------|---------|---------|---------|
| EWC[11]        | 98.64±0.22 | 63.95±1.90 | 20.10±0.06 |                | 94.74±0.05 | 94.31±0.11 | 25.04±0.50 |
| Online EWC[11] | 99.12±0.11 | 64.32±1.90 | 19.96±0.07 |                | 95.96±0.06 | 94.42±0.13 | 33.88±0.49 |
| SI[30]         | 99.09±0.15 | 65.36±1.57 | 19.99±0.06 |                | 94.75±0.14 | 95.33±0.11 | 29.31±0.62 |
| HNET[28]       | 99.79±0.01 | 87.01±0.47 | 69.48±0.80 |                | 97.57±0.02 | 92.80±0.15 | 91.75±0.21 |
| HNET_IWR       | 99.79±0.01 | 88.51±0.18 | 71.90±0.11 |                | 97.60±0.04 | 93.90±0.11 | 92.15±0.19 |
| LSTM_NET       | 99.82±0.01 | 89.50±0.19 | 71.31±0.07 |                | 97.65±0.01 | 93.11±0.13 | 92.10±0.20 |
| LSTM_NET_IWR   | 99.85±0.02 | 90.17±0.25 | 71.54±0.04 |                | 97.74±0.03 | 94.26±0.10 | 92.21±0.23 |
| LSTM_NET_GROW  | 99.85±0.02 | 97.11±0.16 | 83.21±0.02 |                | 97.88±0.02 | 95.46±0.09 | 92.23±0.19 |

Table 2: Comparison of average test accuracy (%) of Split MNIST and Permuted MNIST for all three scenarios of continual learning with generative replay

|                | CL1     | CL2     | CL3     |                | CL1     | CL2     | CL3     |
|----------------|---------|---------|---------|----------------|---------|---------|---------|
| LWF[14]        | 99.57±0.02 | 71.50±1.63 | 23.85±0.44 |                | 69.84±0.46 | 72.64±0.52 | 22.64±0.23 |
| DGR[25]        | 99.50±0.03 | 95.72±0.25 | 90.79±0.41 |                | 92.52±0.08 | 95.09±0.04 | 92.19±0.09 |
| DGR+distill[25] | 99.61±0.02 | 96.83±0.20 | 91.79±0.32 |                | 97.51±0.01 | 97.35±0.02 | 96.38±0.03 |
| HNET+R[28]     | 99.83±0.01 | 98.00±0.03 | 95.30±0.13 |                | 97.87±0.01 | 97.60±0.01 | 97.76±0.01 |
| HNET_IWR+R     | 99.83±0.01 | 97.94±0.05 | 95.38±0.16 |                | 97.85±0.01 | 97.66±0.02 | 97.76±0.02 |
| LSTM_NET+R     | 99.83±0.01 | 98.17±0.02 | 95.46±0.11 |                | 97.87±0.01 | 97.60±0.01 | 97.77±0.01 |
| LSTM_NET_IWR+R | 99.83±0.01 | 98.39±0.05 | 96.50±0.19 |                | 97.87±0.01 | 97.66±0.01 | 97.80±0.02 |
| LSTM_NET_GROW+R| 99.83±0.01 | 98.43±0.05 | 97.01±0.13 |                | 97.90±0.01 | 97.70±0.02 | 97.80±0.01 |
Table 3: Test accuracy comparison of various methods on CIFAR-10 (C-10) and subsequent five splits ($S_1$...$S_5$) each with ten classes of CIFAR-100 (C-100).

| Method           | C-10 (%) | C-100 $S_1$ (%) | C-100 $S_2$ (%) | C-100 $S_3$ (%) | C-100 $S_4$ (%) | C-100 $S_5$ (%) | Average-accuracy (%) |
|------------------|----------|-----------------|-----------------|-----------------|-----------------|-----------------|-------------------|
| Finetuning       | 15.3     | 13.1            | 12.2            | 10.2            | 20.3            | 87.0            | 26.35             |
| Training-from-scratch | 88.6     | 79.3            | 77.0            | 83.0            | 74.4            | 81.1            | 80.60             |
| HNET[28]         | 88       | 83              | 79              | 82              | 81              | 82              | 82.50             |
| HNET_IWR         | 86.2     | 86.1            | 80.2            | 85.0            | 83.6            | 85.01           | 84.35             |
| LSTM_NET during  | 88.78    | 89.3            | 85.2            | 84.4            | 83.5            | 82.7            | 85.64             |
| LSTM_NET         | 88.74    | 89.1            | 84.9            | 84.3            | 83.4            | 82.7            | 85.52             |
| LSTM_NET_IWR     | 88.44    | 88.9            | 85.2            | 88.5            | 86.3            | 86.8            | 87.35             |
| LSTM_NET_GROW    | 88.98    | 87.7            | 86.3            | 88.2            | 89.2            | 89.1            | 88.25             |

MNIST, layer size is taken to be 1000 as done in [28]. For CIFAR datasets, Resnet-32 is used as the classifier. In replay based setup, we use VAE which uses an FCN with two layers each of size 400 both as the encoder and the decoder and uses a latent space of dimension 100.

4.2. Results

We demonstrate the results of our experiments on various image classification datasets used for the continual learning setup and several baselines. For fair comparison, we maintained the number of trainable parameters in the hypernetwork to be equal or lesser than the baseline methods.

4.2.1 Split MNIST:

Split MNIST is a popular continual learning benchmark for image classification. The dataset consists of images of ten digits (0-9) and form five binary classification tasks by pairing them sequentially i.e.\{(0,1), (2,3), (4,5), (6,7), (8,9)\}. The results are presented in Table 1 for non-replay based setup, and in Table 2 for the replay based setup. The results show the efficacy of our approach in achieving better continual learning performance in all the three CL scenarios and for each of the setups.

The proposed hypernetwork LSTM_NET outperforms the baselines EWC, SI and HNET in the non-replay based setup, and outperforms the baselines LWF, DGR and HNET in the replay based setup. The performance of HNET_IWR and LSTM_NET_IWR demonstrates that the proposed regularisation technique IWR further improves the performance of HNET and LSTM_NET in all the continual learning setups. While the methods provide comparable results for the easier CL1 setting, the improvement in performance using the proposed techniques are more evident in the more complex and realistic CL2 and CL3 settings. This is even more evident in the non-replay setup where the standard techniques struggle. We can observe that the proposed approach LSTM_NET_GROW has significantly improved the continual learning performance over the other models for these CL scenarios and setups. One of the major reasons for large improvement in accuracy of CL2 and CL3 with LSTM_NET_GROW is because of dynamically expanding network with new tasks, this helps each task to have task-specific parameters which won’t get updated while learning new tasks and contribute significantly for improvement in performance.

4.2.2 Permuted MNIST

This CL benchmark is a variant of MNIST, it consists of tasks which are created by performing random permutation over MNIST images. The sequence of $T=10$ tasks are obtained by repeating this procedure. We consider a dataset with a sufficiently long sequence of tasks ($T=10$) to investigate the remembering capacity of our continual learning model. The results presented in Table 1 and Table 2 for non-replay and replay based setups respectively demonstrates the effectiveness of the proposed approaches for continual learning on Permuted MNIST. The results follows a similar trend as in the split MNIST, with LSTM_NET_GROW giving the best results, followed by LSTM_NET_IWR and LSTM_NET, beating the baseline approaches.

4.2.3 CIFAR-10/100 dataset

We further evaluate the effectiveness of the proposed approaches on a more challenging image classification data CIFAR-10 and CIFAR-100. The model is first trained on 10 classes of CIFAR-10, and subsequently on five sets of ten classes from cifar-100 following the experimental setup in [28]. Thus, the model needs to learn $T=6$ tasks. We use ResNet-32 for classification of CIFAR-10/100 datasets and the hypernetworks are trained to generate parameters of ResNet-32 architecture. The experiments are conducted on the CL1 scenario and non-replay based setup following [28]. In addition to the baseline hypernetwork HNET, we
also consider baselines which allows us to demonstrate the knowledge transfer across the tasks. Training-from-scratch baseline independently and separately learns the main network parameters for each task and tests the performance on the corresponding task. The baseline Finetuning adapts the main network to the new tasks without taking into account catastrophic forgetting. The model adapted to the final task is then used for predicting performance on all the tasks. To demonstrate effectiveness of LSTM_NET in dealing with catastrophic forgetting, we also considered a baseline LSTM_NET_during, where we test LSTM_NET on each task immediately after training on that task instead of testing after training on all the tasks as in LSTM_NET.

We provide the results comparing all the approaches in Table 3. We can clearly observe from the results that our approach LSTM_NET outperforms HNET by a great margin on a challenging dataset like CIFAR-10/100. In Table 3, comparing results of LSTM_NET, LSTM_NET_IWR and LSTM_NET_GROW with Training-from-scratch, we can see that the knowledge transfer across the tasks helps the proposed approaches in getting a better performance. We can also observe that the LSTM_NET_during matches with LSTM_NET which indicates that LSTM based hypernetwork is very effective in dealing with catastrophic forgetting. We also perform experiments with different regularisation techniques. The proposed IWR regularisation achieves a better result than the baseline regularisation proposed in [28]. In fact, it improves the HNET performance as well, an improvement in the overall test accuracy by almost 2%. Hence, IWR is an effective regularisation technique for any hypernetwork based continual learning approaches. The performance improves further by using the LSTM_NET_GROW approach for continual learning in this data similar to MNIST.

### 4.2.4 Ablation Study

We conduct further ablation study on CIFAR-10/CIFAR-100 to understand the impact of compression ratio (Figure 2a) and regularisation constant (Figure 2b) on the proposed models. From Figure 2a, we can see that as the number of trainable parameters grows in hypernetwork compared to the main network, LSTM_NET performance further improves over the HNET. In Figure 2b, we study the effect of varying the regularisation constant ($\beta$) in the IWR regularisation term in LSTM_NET_IWR on Cifar datasets. The performance is poor when the regularisation term is neglected (low value of $\beta$) as expected and is high and stable for higher values of $\beta$.

From the experiments on CIFAR-10/CIFAR-100 tasks, we observe that training time using LSTM_NET with regularisations in Eq.2 and Eq.3 is approximately 28 hours but with LSTM_NET_GROW it is approximately 20 hours. The above results are calculated with a batch size of 32 and 200 epochs for each batch. As the number of tasks increases, training time of regularisation approaches grows linearly but that of LSTM_NET_GROW remains constant. On the other hand, the memory requirements of the regularisation approaches remains constant but LSTM_NET_GROW grows linearly with tasks due to some task specific parameters but is much lower than maintaining separate parameters for each task.

### 5. Conclusion

We propose a novel LSTM based hypernetwork for continual learning which could capture dependencies across the main network parameters while also maintaining the parameter efficiency. To improve continual learning performance using hypernetworks, we propose a novel regularisation Importance Weighted Regularisation (IWR) which is well-suited for hypernetwork based CL approaches. To further improve the continual learning performance of the proposed LSTM hypernetwork, we propose a network growth technique for LSTMs. Through experiments on several image classification tasks and datasets, we demonstrate the effectiveness of our proposed approaches, LSTM based hypernetwork, IWR regularisation for hypernetworks, and network growth on LSTMs. The proposed approaches improved the continual learning performance on all the CL tasks, settings, and datasets. As a future work, we would like to improve the parameter growth in LSTM_NET_GROW, and develop hybrid models combining the network growth and regularisation to further improve CL performance.
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