Continual Learning with Dependency Preserving Hypernetworks

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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. Instead, 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* [1, 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 network 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 $t \in \mathcal{T} = \{1, \dots, K\}$ contains input X^t=$\{x_j^t\}_{j=1}^{n_t}$ and target label Y^t=$\{y_j^t\}_{j=1}^{n_t}$ where n_t being the number of samples in task t. The goal of main network m is to learn a function $f_m^t(\cdot, \Theta_m^t) : X^t \to Y^t$ with parameters Θ_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 Θ_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 $f_h(\cdot, \Theta_h) : \mathbf{e^t} \to \Theta_m^t$ to generate the task specific parameter Θ_m^t given a task embedding $\mathbf{e^t}$ using trainable parameters Θ_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 Θ_h takes task embedding $\mathbf{e^t}$ and chunk embeddings $\mathbf{c} = \{\mathbf{c}_1, \dots, \mathbf{c}_{n_c}\}$ as input to generate set of main network weights, $\Theta_m^t = f_h(\mathbf{e^t}, \mathbf{c}, \Theta_h) = \{f_h(\mathbf{e^t}, \mathbf{c}_1, \Theta_h), f_h(\mathbf{e^t}, \mathbf{c}_2, \Theta_h), \dots, f_h(\mathbf{e^t}, \mathbf{c}_{n_c}, \Theta_h)\}$, 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 $P(\Theta_m^{t,1}, \Theta_m^{t,2}, \dots, \Theta_m^{t,n_c} | \mathbf{e^t}, \mathbf{c}) = P(\Theta_m^{t,1} | \mathbf{e^t}, \mathbf{c}_1) \times P(\Theta_m^{t,2} | \mathbf{e^t}, \mathbf{c}_2) \dots P(\Theta_m^{t,n_c} | \mathbf{e^t}, \mathbf{c}_{n_c})$. 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

$$\begin{aligned} &P(\Theta_m^{t,1}, \Theta_m^{t,2}, \dots, \Theta_m^{t,n_c} | \mathbf{e^t}, \mathbf{c}) = P(\Theta_m^{t,1} | \mathbf{e^t}, \mathbf{c}_1) \times \\ &P(\Theta_m^{t,2} | \Theta_m^{t,1}, \mathbf{e^t}, \mathbf{c}_2) \dots P(\Theta_m^{t,n_c} | \Theta_m^{t,1} \dots \Theta_m^{t,n_c-1}, \mathbf{e^t}, \mathbf{c}_{n_c}) \end{aligned} \tag{1}$$

The proposed *LSTM* hypernetwork uses hidden state $\mathbf{h_{j-1}^t}$ and cell state $\mathbf{s_{j-1}^t}$ of preceding chunk along with cur-

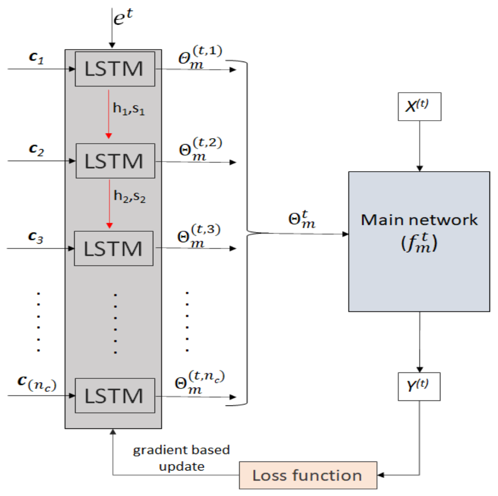


Figure 1: **LSTM based Hypernetwork** can generate main network weights Θ_m^t for task t in smaller chunks by using same hypernetwork iteratively but also by maintaining the dependencies across them using *LSTM*.

rent chunk embedding to generate the chunk weights. The following *LSTM* operations are used to generate the chunk weights assuming a single layer network where it takes task embedding $\mathbf{e^t}$ and chunk embedding $\mathbf{c_j}$ as input.

$$
\begin{aligned}
\mathbf{i_j^t} &= \sigma(\mathbf{w_i} \times \langle \mathbf{e^t}, \mathbf{c_j} \rangle + \mathbf{u_i} \times \mathbf{h_{j-1}^t}) \\
\mathbf{f_j^t} &= \sigma(\mathbf{w_f} \times \langle \mathbf{e^t}, \mathbf{c_j} \rangle + \mathbf{u_f} \times \mathbf{h_{j-1}^t}) \\
\mathbf{o_j^t} &= \sigma(\mathbf{w_o} \times \langle \mathbf{e^t}, \mathbf{c_j} \rangle + \mathbf{u_o} \times \mathbf{h_{j-1}^t}) \\
\mathbf{g_j^t} &= Tanh(\mathbf{w_g} \times \langle \mathbf{e^t}, \mathbf{c_j} \rangle + \mathbf{u_g} \times \mathbf{h_{j-1}^t}) \\
\mathbf{s_j^t} &= \mathbf{f_j^t} \odot \mathbf{s_{j-1}^t} + \mathbf{i_j^t} \odot \mathbf{g_j^t} \\
\mathbf{h_j^t} &= \mathbf{o_j^t} \odot \tanh(\mathbf{s_j^t}) \\
\Theta_m^{(t,j)} &= \mathbf{h_j^t} W
\end{aligned}
$$

where $\mathbf{f}, \mathbf{i}, \mathbf{o}, \mathbf{g}$ are forget gate, input gate, output gate, and cell gate respectively. σ is the sigmoid function, and $\odot$ is the Hadamard product. $\mathbf{w}, \mathbf{u}$ are the weights associated with the input and hidden states respectively with subscript denoting the corresponding gate. $\Theta_m^{(t,j)}$ is the j^{th} chunk of main network weights generated by *LSTM* hypernetwork. Here, $W \in R^{d_1 \times d_2}$ are the weights of the feed forward layer producing the chunk weights.

We learn the *LSTM* parameters Θ_h when presented with data from task T by minimising the following loss consisting of task specific loss and regularization loss [28].

$$
\begin{aligned}
&\arg\min_{\Theta_h} \mathcal{L}_{total} = \mathcal{L}_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) \\
&+ \frac{\beta}{T-1} \sum_{t=1}^{T-1} ||f_h(\mathbf{e}^t, \mathbf{c}, \Theta_h^*) - f_h(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta\Theta_h)||^2
\end{aligned} \quad (2)
$$

where $f_h(\mathbf{e^t}, \mathbf{c}, \Theta_h) = \Theta_m^t$ denotes all the parameters of the main network for task t, Θ_h^* are parameters of the hypernetwork before learning task T, β is a regularisation constant which balances task specific loss and regularization 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 $\mathcal{L}_{task}$ is the loss associated with the task (for e.g., cross-entropy loss for classification). The regularization loss constraints the hypernetwork learnt on the new task to generate main network parameters similar to the ones generated by previously learnt hypernetwork. Hypernetwork parameters Θ_h and chunk embeddings are learnt by minimising the total loss $\mathcal{L}_{total}$, and the task embeddings are learnt using $\mathcal{L}_{task}$ alone using backpropagation.

3.2. Importance Weighted Regularisation

We propose a novel regularisation technique for continual learning in hypernetworks which provides more flexibility to the hypernetwork to adapt to the new task compared to the regularisation in (2). The proposed *importance weighted regularisation (IWR)* updates the hypernetwork parameters based on the importance of the parameters associated 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 fisher information score of the main network parameters in the regularisation term in (2). This will enforce hypernetwork to give importance to significant main network parameters during generation of main network weights. Meanwhile, it provides flexibility to the hypernetwork to adapt its parameters more freely to the new task as it is not constrained to generate all the main network parameters with equal importance. The objective function considering the *IWR* regularisation is defined as

$$
\begin{aligned}
&\arg\min_{\Theta_h} \mathcal{L}_{total} = \mathcal{L}_{task}(\Theta_h, \mathbf{e}^T, \mathbf{c}, X^T, Y^T) \\
&+ \frac{\beta}{T-1} \sum_{t=1}^{T-1} \sum_{i} FI_i^t (f_{h_i}(\mathbf{e}^t, \mathbf{c}, \Theta_h^*) - f_{h_i}(\mathbf{e}^t, \mathbf{c}, \Theta_h + \Delta\Theta_h))^2
\end{aligned} \quad (3)
$$

where the first term $\mathcal{L}_{task}$ is task specific loss and the second term is the *IWR* term that regularises the hypernetwork parameters to avoid forgetting. The *IWR* term uses FI^t which is the fisher information matrix (defined below) over the main network parameters associated with task t. FI^t provides the importance of the main network parameters for task t, and the index i iterates over all the main network parameters. $f_{h_i}(\mathbf{e}^t, \mathbf{c}, \Theta_h)$ 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

$$FI^t = \frac{1}{N_t}\sum_{j=1}^{N_t}\Big[\nabla_{\Theta_m^t} L_{task}(\Theta_h, \mathbf{e}^t, y_j^t, \mathbf{x}_j^t)\times \nabla_{\Theta_m^t} L_{task}(\Theta_h, \mathbf{e}^t, y_j^t, \mathbf{x}_j^t)^T\Big] \quad (4)$$

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 $(\mathbf{u_f}, \mathbf{u_i}, \mathbf{u_o}, \mathbf{u_g})$ of the *LSTM* are shared across the tasks and we maintain input weights $(\mathbf{w_f^t}, \mathbf{w_i^t}, \mathbf{w_o^t}, \mathbf{w_g^t}, W^t)$ 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.

$$\begin{aligned}
\mathbf{i_j^t} &= \sigma(\mathbf{w_i^t} \times \langle \mathbf{e^t}, \mathbf{c_j}\rangle + \mathbf{u_i} \times \mathbf{h_{j-1}^t})\\
\mathbf{f_j^t} &= \sigma(\mathbf{w_f^t} \times \langle \mathbf{e^t}, \mathbf{c_j}\rangle + \mathbf{u_f} \times \mathbf{h_{j-1}^t})\\
\mathbf{o_j^t} &= \sigma(\mathbf{w_o^t} \times \langle \mathbf{e^t}, \mathbf{c_j}\rangle + \mathbf{u_o} \times \mathbf{h_{j-1}^t})\\
\mathbf{g_j^t} &= Tanh(\mathbf{w_g^t} \times \langle \mathbf{e^t}, \mathbf{c_j}\rangle + \mathbf{u_g} \times \mathbf{h_{j-1}^t})\\
\mathbf{s_j^t} &= \mathbf{f_j^t} \odot \mathbf{s_{j-1}^t} + \mathbf{i_j^t} \odot \mathbf{g_j^t}\\
\mathbf{h_j^t} &= \mathbf{o_j^t} \odot \tanh(\mathbf{s_j^t})\\
\mathbf{\Theta_m^{(t,j)}} &= \mathbf{h_j^t} W^t
\end{aligned}$$

The *LSTM_NET_GROW* model freezes the hidden weights $(\mathbf{u_f}, \mathbf{u_i}, \mathbf{u_o}, \mathbf{u_g})$ of the *LSTM* after learning first task and is shared across all the tasks. It keeps learning new task specific input weights $(\mathbf{w_f^t}, \mathbf{w_i^t}, \mathbf{w_o^t}, \mathbf{w_g^t}, W^t)$ 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 learnt 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 [1]. 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

[1]https://github.com/srikar1/LSTM_NET_CL

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

	Split MNIST			Permuted MNIST		
	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

	Split MNIST			Permuted MNIST		
	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**

time. Since task identity is available, dedicated components can be assigned to the tasks in the sequence. Multi-headed model is one such kind of model architecture used in continual learning.
CL2 (Domain incremental learning): It does not provide task identity information at test time, nor is it required to infer the task identity. Here, each task treats data to be from different domains but with the same classes. It considers the same number of classes across all the tasks in the sequence and utilises the same output heads for all the tasks.
CL3 (Class incremental learning): In this continual learning scenario, the model is not provided with the task identity. It not only requires learning the tasks incrementally but also requires to infer the task identity. Here, the task identity is inferred through the predictive distribution entropy. This scenario resembles most with the real time setting with new class objects appearing incrementally.

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 3: Test accuracy comparison of various methods on CIFAR-10 (C-10) and subsequent five splits ($S_{1...5}$) each with ten classes of CIFAR-100 (C-100).

	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

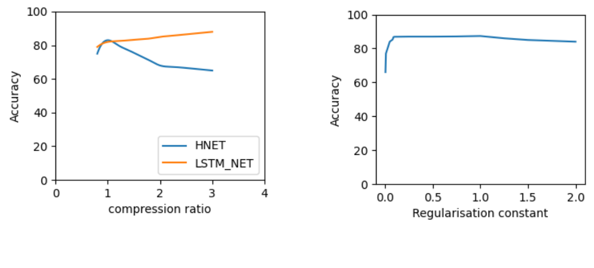
We further evaluate the effectiveness of the proposed approaches on a more challenging image classification data CIFAR-10 and CIFAR-100. The model is first trained on 10 classes of CIFAR-10, and subsequently on five sets of ten classes from cifar-100 following the experimental setup in [28]. Thus, the 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 using 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 (β) in the *IWR* regularization term in *LSTM_NET_IWR* on Cifar datasets. The performance is poor when the regularization term is neglected (low value of β) as expected and is high and stable for higher values of β.

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.



(a) Compression ratio effect (b) Regularization effect

Figure 2: In Figure 2a, plotted results of accuracies of *LSTM_NET* vs HNET with increase in compression ratio (ratio of trainable parameters in hypernetwork to main network) on Cifar datasets. In Figure 2b, plotted graph with accuracy values using *LSTM_NET_IWR* with varying regularisation constant (β) in the IWR on Cifar datasets.

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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