Lifelong Learning with Searchable Extension Units

Wenjin Wang, Yunqing Hu, and Yin Zhang*

Abstract—Lifelong learning remains an open problem. One of its main difficulties is catastrophic forgetting. Many dynamic expansion approaches have been proposed to address this problem, but they all use homogeneous models of predefined structure for all tasks. The common original model and expansion structures ignore the requirement of different model structures on different tasks, which leads to a less compact model for multiple tasks and causes the model size to increase rapidly as the number of tasks increases. Moreover, they can not perform best on all tasks. To solve those problems, in this paper, we propose a new lifelong learning framework named Searchable Extension Units (SEU) by introducing Neural Architecture Search into lifelong learning, which breaks down the need for a predefined original model and searches for specific extension units for different tasks, without compromising the performance of the model on different tasks. Our approach can obtain a much more compact model without catastrophic forgetting. The experimental results on the PMNIST, the split CIFAR10 dataset, the split CIFAR100 dataset, and the Mixture dataset empirically prove that our method can achieve higher accuracy with much smaller model, whose size is about 25-33 percentage of that of the state-of-the-art methods.

Index Terms—lifelong learning, catastrophic forgetting, NAS, deep learning, machine learning.

I. INTRODUCTION

LIFELONG learning is an intrinsic ability of humans [1], [2]. It is natural for human beings to constantly learn new knowledge and accumulate it. Moreover, humans can also effectively use past knowledge to help them learn new knowledge. For an agent in a changing environment, the lifelong learning ability is very meaningful. But in the field of deep learning, despite recent advances [3], [4], lifelong learning remains an open question. A major problem with lifelong learning is catastrophic forgetting [5]. When learning a series of consecutive tasks, the knowledge learned from previous tasks is stored in weights of the deep neural network. Catastrophic forgetting means that the weights of the model are changed when learning a new task so that the knowledge of previous tasks will be forgotten [5]. To alleviate the catastrophic forgetting, many methods have been proposed. Depending on whether the model size changes, these methods fall into two broad categories: fix methods whose model structure is fixed, expansion methods whose model structure is variable.

Fix methods maintain the performance of model by retaining data information about previous tasks and the values of model parameters [6]–[10], [10]–[15]. In fact, due to limited capacity, methods with a fixed model structure are more likely to encounter a capacity bottleneck in continuous learning scenarios.

Expansion methods overcome the capacity bottleneck by introducing new model resources, i.e parameters, to better deal with new tasks [16]–[19]. The number of parameters allocated to different layers is different and different methods have different allocation strategies. In general, newly allocated parameters are learnable, while old parameters are fixed or regularized. After new parameters are allocated, there are two ways to learn the current task model. One is to use the entire model for the current task (see Fig 1(a)), and the other is to use only part of the entire model for the current task, namely the sub-model (see Fig 1(b)). The latter takes into account the impact of the structure of sub-model on the current task to some extent.

However, the number of model parameters in aforementioned methods tends to increase rapidly as the number of tasks increases. There are two main reasons. The first is that they all need a predefined original model to handle all tasks, which often leads to a bloated model. The second is that architectures of new resources assigned to new tasks are based on the same structure as the predefined model, which often leads to redundant unit parameters in the overall model. For example, if one layer of the original model is a $3 \times 3 \text{conv}$, then every time that the layer is added a $3 \times 3 \text{conv}$. The development of Neural Architecture Search (NAS) has shown that generic predefined original model and architecture of new resources cause: 1) too many redundant parameters. 2) limited performance on new tasks. To solve above problems and inspired by the Neural Architecture Search methods, in this paper, we propose a new concept called Extension Unit.

---

This work was supported by the NSFC (No. 61402403), Artificial Intelligence Research Foundation of Baidu Inc., Chinese Knowledge Center for Engineering Sciences and Technology, the Fundamental Research Funds for the Central Universities, and Engineering Research Center of Digital Library, Ministry of Education. (Corresponding author: Yin Zhang)

W. Wang, Y. Hu, and Y. Zhang are with the College of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China (e-mail: wangwenjin@zju.edu.cn; 11921141@zju.edu.cn; zhangyin98@zju.edu.cn).
(EU). Based on the EU, we propose a new lifelong learning framework named Searchable Extension Units (SEU), in order to break down the need for a predefined original model and search for specific Extension Units for different tasks. Without compromising the performance of the model on different tasks, our approach can achieve a more compact model without catastrophic forgetting (see Fig.1(c)).

Our primary contributions are as follows:

- To the best of our knowledge, we first propose to search different architectures of new neural networks for different tasks in Lifelong Learning problem by using the Neural Architectures Search methods.
- We present a new unit of new parameters in each layer of model called Extension Unit (EU) whose architecture is searchable. Based on the EU, we present a new lifelong learning framework named Searchable Extension Units, which can (1) search suitable architecture of EU for each layer of each task, (2) search suitable sub-model from the entire model for each task, (3) automatically construct the model from scratch.
- Our framework contains the following components: Extension Unit Searcher and Task Model Creator. Both component can adopt the appropriate methods. Therefore, our approach is flexible and expandable.
- We validate our framework on the MNIST, the split CIFAR10 dataset, the split CIFAR100 dataset and the Mixture dataset. Our method can achieve higher accuracy with the significantly smaller entire model.
- We propose a new metric named mixed score (MS) that takes account both the accuracy and the number of parameters of the lifelong learning model. Our method achieves the highest mixed scores on all four datasets.
- We release the source codes of experiments on github.

The rest of this paper is organized as follows: Section II introduces our new framework Searchable Extension Units (SEU). Section III presents the evaluation protocol and results of our approach and examined ones. The related work of lifelong learning is introduced in Section IV. Finally, we summarize our work and present future research directions in section V.

II. LIFELONG LEARNING WITH SEARCHABLE EXTENSION UNITS (SEU)

A. Problem Formulation

A formal definition of lifelong learning is as follows: The model needs to learn a sequence of tasks \( T = \{T_1, T_2, ..., T_M\} \) one by one under two constraints. The first constraint is that the model can not forget the knowledge learned from previous tasks while learning a new task. And the second one is that only samples of the current task are available while learning the current task. Each task \( T_m \) goes with a training dataset \( D_m^{\text{train}} = \{(x_{m,i}, y_{m,i}): i = 1, 2, ..., n_m^{\text{train}}\} \), where \( x_{m,i} \) is the sample, \( y_{m,i} \) is the label and \( n_m^{\text{train}} \) is the number of samples. Similarly, task \( T_m \) goes with a validation dataset \( D_m^{\text{valid}} = \{(x_{m,i}, y_{m,i}): i = 1, 2, ..., n_m^{\text{valid}}\} \). Then, the entire datasets are \( D_m^{\text{train}} = \bigcup_{m=1}^{M} D_m^{\text{train}} \) and \( D_m^{\text{valid}} = \bigcup_{m=1}^{M} D_m^{\text{valid}} \). The second constraint means only \( D_m^{\text{train}} \) and \( D_m^{\text{valid}} \), not \( D_m^{\text{train}} \) and \( D_m^{\text{valid}} \), are available when learning task \( T_m \).

B. Basic Concepts and Framework

In this section, we present the terms used in this paper and briefly describe the basic components and workflow of SEU. The definitions of basic terms are as follows:

- Super Model is the entire multi-head model to handle all \( M \) tasks and it is empty at the beginning. It has \( N \) intermediate layers and 1 task-specific output layer.
- Task Model is part of Super Model and is responsible for a specific task \( T_m \). All task models have the same number of layers in this paper. Each intermediate layer of Task Model has only one EU that either is newly created for the current task or reuses the existing one.
- Task-specific Layer is the last output layer of the Super Model and contains \( M \) output heads (FC layers). Each Task Model has a corresponding output head.
- Intermediate Layer. All layers in the Super Model except the task-specific output layer are intermediate layers. Each intermediate layer is made up of multiple EUs. On each layer, each task has a specific EU and multiple tasks can share one EU.
- Extension Unit (EU) is the smallest model unit in this paper. The architecture of an Extension Unit is searched by Neural Architecture Search methods (see Fig.3). Each EU contains 2 input nodes, 4 intermediate nodes and 1 output nodes. The operation of the input edge of the intermediate node is searched out from a search space containing 8 operations.

Fig.2 shows the workflow of our approach, containing 2 main components: Extension Unit Searcher and Task Model Creator. The functions of these components are as follows:

- Extension Unit Searcher is used to search the most suitable architecture of EU for current task \( T_m \). Several
methods [20–22] that focus on searching a micro-architecture can be used here. We adopt the Multinomial Distribution Learning method in this paper due to its high-efficiency [22].

- **Task Model Creator** is used to create Task Model for current task $T_m$. It will select an EU out of candidate ones, i.e., the newly-created EU for new knowledge and existing EUs for past knowledge in each layer of Super Model.

For each task, the workflow of our approach consists of four phases (see Fig.2): (1) **Search EU**. At first, Extension Unit Searcher will search for a suitable architecture of EU for the current task from search space. (2) **Expand Super Model**. Based on the selected EU, the Super Model will expand a column, i.e., adding a new EU in each intermediate layer. (3) **Create Task Model**. Then, the Task Model Creator will select the best EU for current task in each intermediate layer of Super Model. With the corresponding output head, these EUs make up the Task Model. At the same time, new EUs introduced in second phase will be deleted except those that are selected. Note that different Task Models may share the same EU in some layers. (4) **Train Task Model**. Finally, the Task Model will be trained and reserved for later evaluation.

### C. Algorithm:SEU

Suppose current task is $T_t$, we denote the parameters of Task Model for task $(1, 2, ..., t)$ as $(θ_t, θ_{t+1}, ..., θ_T)$. So, our goal is to minimize cumulative loss of the model on tasks $(T_1, T_2, ..., T_t)$. The total loss $L_{total}$ is

$$L_{total} = \sum_{m=1}^{t} \sum_{i=1}^{n_{train}^m} \text{loss}_m(θ_m(x_{m,i}), y_{m,i})$$

where $loss_m$ is the loss function of task $T_m$ and $f_{θ_m}$ is the Task Model of task $T_m$. The problem is, limited by the constraint that only $D_{train}^t$ is available, the loss of data about previous tasks $L_{pre}$ is not directly calculable.

$$L_{total} = L_{pre} + L_t$$

$$L_{pre} = \sum_{m=1}^{t-1} \sum_{i=1}^{n_{train}^m} \text{loss}_m(θ_m(x_{m,i}), y_{m,i})$$

$$L_t = \sum_{i=1}^{n_{train}^t} \text{loss}_t(θ_t(x_{t,i}), y_{t,i})$$

Obviously, parameters $(θ_1, θ_2, ..., θ_{t-1})$ have been optimized before learning task $T_t$. We can denote $Θ_{t-1} = \bigcup_{m=1}^{t-1} Θ_m$. Then, by freezing $Θ_{t-1}$, we can keep $L_{pre}$ as a constant $C$ which is already a lower value. Then, we can get an approximate optimization target

$$\min_{θ_t} L_{total} = \min_{θ_t \in Θ_t} C + \sum_{i=1}^{n_{train}^t} \text{loss}_t(θ_t(x_{t,i}), y_{t,i})$$

where $Θ_t = \bigcup_{m=1}^{t} Θ_m$. It is important to note that $θ_i \cap θ_j$ where $i \neq j$ might not be an empty set. Model parameters can be shared between different tasks.

In order to better deal with task $T_t$, we need to introduce new parameters $θ_{t,n}$ for task $T_t$ into the super model, while employing the previous knowledge in the existing parameters $θ_{t,p}$. Then the parameters of task $T_t$ is $θ_t = θ_{t,n} \cup θ_{t,p}$ where $θ_{t,n} = θ_t \cap Θ_{t-1}$. If $θ_i ∈ Θ_{t-1}$, the optimization does not happen because of $θ_i \cap Θ_{t-1} = \emptyset$.

The acquisition of $θ_t$ is divided into two stages. At first, we search for a suitable architecture $θ^c$ of EU for task $T_t$ and add $θ_{t,p} = θ^c$ to each intermediate layer $l$ of Super Model. $θ_{new} = \bigcup_{l=1}^{N} θ_{t,l}$ where $N$ is the number of intermediate layers. Leave the details of producing $θ^c$ in section II-D, then we can select $θ_t$ from $Θ_t^* = Θ_{t-1} \cup θ_{new}$. The selected parameters for task $T_t = θ_t = θ_{t,n} \cup θ_{t,p}$, where $θ_{t,n} ∈ θ_{new}, θ_{t,p} ∈ Θ_{t-1}$ and will be trained. More details are presented in section II-E and we summarize the workflow as algorithm 1.

### Algorithm 1: SEU

**Input** $D_{train}^t = \{D_{train}^{t_1}, D_{train}^{t_2}, ..., D_{train}^{M_t}\}$

**Require** $Θ_0 = ∅$ # initialize Super Model

1: for $t = 1$ to $M$ do
2: $θ^c = ExtensionUnitSearcher(D_{train}^t)$
3: $Θ_t^* = ExtensionUnitSearcher(θ^c, Θ_{t-1})$
4: $θ_t = \text{ExpandSuperModel}(θ^c, Θ_{t-1})$
5: $θ_t = \text{TrainTaskModel}(D_{train}^t, θ_t)$
6: end for

### D. Search and Expansion

To introduce $θ_{new}$, SEU needs to allocate new EUs for task $T_t$. Before doing so, SEU first needs to determine the architecture of these new EUs. So, the Extension Unit Searcher should search for an $θ^c$ according to the training dataset of current task (see Fig.3). We directly adopt the Multinomial Distribution Learning [22] as the Extension Unit Searcher in this paper. The search space of an edge operation $o^{i,j}$ between node $i$ and $j$ contains $L (= 8)$ operations. So, we have

$$o^{i,j} = \begin{cases} o_1 & \text{with probability } p_1^{i,j} \\ o_2 & \text{with probability } p_2^{i,j} \\ \vdots & \vdots \\ o_L & \text{with probability } p_L^{i,j} \end{cases}$$

where $j \in (3, ..., 6)$ and $i \in (1, ..., j-1)$. The accuracy record and epoch record of operations between node $i$ and $j$ are denoted as $\{A_i^{i,j} : l = 1, 2, ..., L\}$ and $\{E_i^{i,j} : l = 1, 2, ..., L\}$. All of accuracy records and epoch records are initialized to zero and the probability of each operation in one edge is initialized with $\frac{1}{L}$.

$$A = \{A_i^{i,j} = 0\}; E = \{E_i^{i,j} = 0\}$$

$$P = \{p_i^{j} = \frac{1}{L}\}$$

where $j \in (3, ..., 6)$, $i \in (1, ..., j-1)$, and $l \in (1, ..., L)$. To update $P$, then, we will take $K$ samples. After each sample, the sampled network will be trained with one epoch where $s_{i,j}$ is the ID of selected operation in edge between node $i$ and $j$. Suppose the evaluation accuracy after training is $A^*$, the update rules of $A, E, P$ are as follows:

$$A_{s_{i,j}}^{i,j} = A^*; E_{s_{i,j}}^{i,j} = E_{s_{i,j}}^{i,j} + 1$$

$$\text{reward}_{s_{i,j}}^{i,j} = \sum_{l=1}^{L} I(A_{s_{i,j}}^{i,j} > A_{s_{i,j}}^{i,j}, E_{s_{i,j}}^{i,j} < E_{s_{i,j}}^{i,j})$$
have to do softmax on the updated probability. In order to make sure that the sum of probabilities is 1, we have to do softmax on the updated probability.

\[
penalty_{s_{i,j}}^{l} = \sum_{t=1}^{L}(A_{s_{i,j}}^{l,j} < A_{s_{i,j}}^{l,j}, E_{s_{i,j}}^{l,j} > E_{s_{i,j}}^{l,j})
\]

In order to make sure that the sum of probabilities is 1, we have to do softmax on the updated probability.

\[
\theta_{i,j}^{l} = \frac{p_{i,j}^{l}}{\sum_{l=1}^{L}p_{i,j}^{l}}
\]

After all samples have been taken, the operation of each side is selected as the one with the highest probability whose ID is \(i_{o}, j\) and the selected architecture of EU is

\[
\theta_{e} = \{o_{i,j}^{l}, o_{i,j}^{l}, \cdots, j^{l}, j^{l}, j^{l}, \cdots, 6\}
\]

The whole process is summarized in algorithm 2.

**Algorithm 2** ExtensionUnitSearcher

**Input** \(D_{t_{-1}}^{train}\) = \{(\(x_{t,i}, y_{t,i}\); \(i = 1, 2, \ldots, n_{t_{-1}}^{train}\)\)

**Require** \(K\) # the number of samples;

1. Initialize \(P, A, E\) according to Equation (7) and (8);
2. for \(k = 1\) to \(K\) do
3. \(\) Sample the network according to Equation (6);
4. \(\) Train the network with 1 epoch and evaluate it;
5. \(\) Update \(A, E\) according to Equation (9);
6. \(\) Update \(P\) according to Equation (10), (11), (12), (13);
7. \(\) end for
8. Generate \(\theta_{e}\) according to Equation (14);

**Return** \(\theta_{e}\)

Now, with \(\theta_{e}\), each layer of the Super Model will be expanded. We can denote the number of EUs that the Super Model already has in layer \(j\) as \(ne_{j}\) and parameters of EUs in layer \(j\) as \(\beta_{j,1}, \beta_{j,2}, \ldots, \beta_{j,ne_{j}}\). Then we have

\[
\Theta_{t_{-1}} = \bigcup_{j=1}^{N} \beta_{j,k}
\]

In each layer \(j\), a new EU is added whose parameters are contained in \(\beta_{j,ne_{j}+1}\). So, we have

\[
\theta_{new} = \{\beta_{j,ne_{j}+1} = \theta_{e}; j = 1, 2, \ldots, N\}
\]

\[
\Theta_{t_{-1}} = \Theta_{t_{-1}} \cup \theta_{new} = \Theta_{t_{-1}} \cup \bigcup_{j=1}^{N} \beta_{j,ne_{j}+1}
\]

And the expansion process is summarized in algorithm 3.

**Algorithm 3** ExpandSuperModel

**Input** \(\theta_{e}, \Theta_{t_{-1}}\)

1. Generate \(\theta_{new}\) according to Equation (15);
2. Expand \(\Theta_{t_{-1}}\) according to Equation (17);

**Return** \(\Theta_{t}^{*}\)

**E. Creation and Training**

After the model is expanded, SEU needs to create the Task Model for current task, i.e. select \(\theta_{i}\) from \(\Theta_{i}\) and only one EU will be used in each intermediate layer. There are two types of EUs in each layer, one that has been used and one that is new. If the selected EU has been used in the past, it will be frozen while learning task \(T_{i}\). The new EUs have no such restriction.

We adopt the same idea in the Multinomial Distribution Learning method to search for appropriate EUs [22]. We assign each EU in the Super Model a probability of being selected and all EUs in the same layer start with the same probability.
Each EU also has an accuracy record and a epoch record. The accuracy record represents the EU’s evaluation performance after it was last selected and the epoch record represents the total number it was sampled. The following loop is executed multiple times. (1) Sample an EU from each intermediate layer according to sampling probability of EUs in (c). Together with the task-specific layer, these EUs make up the Task Model. (2) Train the Task Model sampled on the current task data with an epoch. (3) Record the number of epochs each EU is selected and accuracy of the most recent training of each EU. (4) Update the Probability according to the Accuracy and Epoch in (c).

**Algorithm 4 TaskModelCreator**

**Input** $\Theta^*_t$,

**Input** $D_{train}^t = \{(x_i, y_i); i = 1, 2, ..., n\}$

**Require** $K$ # the number of training epochs;

1: Initialize $P, A, E$ according to Equation (18), (19);
2: for $k = 1$ to $K$ do
3:  sample $\theta^*_k$ according to Equation (21);
4:  Train $\theta^*_k$ according to Equation (24), (25);
5:  Compute $A^*$ and Update $A, E$ according to Equation (26), (27), (28), (29);
6:  Update $P$ according to Equation (30), (31), (32);
7: end for
8: Create $\theta_t$ according to Equation (33);
9: Update the Super Model according to Equation (34), (35);

**Return** $\Theta_t, \theta_t$.

Each EU also has an accuracy record and an epoch record. The accuracy record represents the EU’s evaluation performance after it was last selected and the epoch record represents the total number it was selected (see in Fig. 4). All of accuracy and epoch records are initialized to zero.

$$A = \{A_{j,k} = 0\}; E = \{E_{j,k} = 0\}$$ (18)

$$P = \{p_{j,k} = \frac{1}{n_{e_j} + 1}\}$$ (19)

where $j \in (1, 2, ..., N)$ and $k \in (1, 2, ..., n_{e_j} + 1)$. The probability of each EU will be updated according to accuracy and epoch record during sampling. Then, multiple samples are repeated (see Fig. 4). In each sample, the selected EUs form $t$-th Task Model which is trained one epoch. We can denote the selection operation in Super Model as $O(\Theta_t)$ and the selection result in layer $j$ as $o_j$. So we have

$$o_j = \left\{ \begin{array}{ll}
\beta_{j,1} & \text{with probability } p_{j,1} \\
\beta_{j,2} & \text{with probability } p_{j,2} \\
\vdots & \vdots \\
\beta_{j,n_{e_j}+1} & \text{with probability } p_{j,n_{e_j}+1}
\end{array} \right. \quad (20)$$

Suppose the sampling result is $\theta^*_t = \bigcup_{j=1}^N \beta_{j,q_j}$. Then, we can train the $\theta^*_t$ one epoch and only update new parameters. The update rules of $A, E, P$ are as follows:

$$\Delta(\beta_{1,q_1}, \beta_{2,q_2}, ..., \beta_{N,q_N}) = \frac{\partial \Sigma_{i=1}^n \elloss_i(f_{\theta^*_t}(x_i), y_i)}{\partial \theta^*_t}$$ (22)

$$\beta_{j,q_j} = \left\{ \begin{array}{ll}
\beta_{j,q_j} - \mu \Delta \beta_{j,q_j}, & \text{if } q_j = n_{e_j} + 1 \\
\beta_{j,q_j}, & \text{otherwise}
\end{array} \right. \quad (23)$$

After training, the $t$-th Task Model will be evaluated and the performance is $A^*$.

$$A^* = \Sigma_{i=1}^n \mathbb{I}(f_{\theta^*_t}(x_i) == y_i)$$ (24)

The update rules of $A, E, P$ are as follows:

$$A_{j,q_j} = A^*; E_{j,q_j} = E_{j,q_j} + 1$$ (25)

$$\text{reward} = \Sigma_{x=1}^{n_{e_j}+1} \mathbb{I}(A_{j,q_j} > A_{j,z}, E_{j,q_j} < E_{j,z})$$ (26)

$$\text{penalty} = \Sigma_{x=1}^{n_{e_j}+1} \mathbb{I}(A_{j,q_j} < A_{j,z}, E_{j,q_j} > E_{j,z})$$ (27)

$$p_{j,q_j} = p_{j,q_j} + \alpha(\text{reward} - \text{penalty})$$ (28)
where \( j \in (1, 2, ..., N) \). In order to make sure that the sum of probabilities is 1, we need to do softmax on the updated probability.

\[
p_{j,k} = \frac{p_{j,k}}{\sum_{k=1}^{N} p_{j,k}}
\]

(29)

where \( j \in (1, 2, ..., N) \) and \( k \in (1, 2, ..., ne_j + 1) \). After all epochs, we select the EU with the highest probability in each layer.

\[
\theta_t = \bigcup_{j=1}^{N} \beta_{j,q}^t
\]

(30)

where \( p_{j,q}^t = \max(p_{j,1}, p_{j,2}, ..., p_{j,ne_j} + 1) \).

Then, the selected new EUs introduced in expansion stage will remain, and the others will be deleted. If \( p_{j,q}^t = p_{j,ne_j + 1} \), where \( j \in (1, N) \) which means the new EU is selected, then the EU will be preserved.

\[
ne_j = ne_j + 1 \text{ if } p_{j,q}^t = p_{j,ne_j + 1}
\]

(31)

Otherwise, it will be deleted.

\[
\Theta_t = \Theta_t^* \setminus \{\beta_{j,ne_j + 1} | p_{j,q}^t \neq p_{j,ne_j + 1}, j \in (1, N)\}
\]

(32)

The whole process is shown in Algorithm 4.

After the \( t \)-th Task Model is created, it will be trained on the training data of task \( t \). The Task Model contains two types of EUs: existing ones and new ones. The parameters of EUs of EU will be preserved.

\[
\beta = \begin{cases} 
\beta_j - \mu \Delta \beta_j, & \text{if } \beta_j \notin \Theta_{t-1}, \ j \in (1, N) \\
\beta_j, & \text{otherwise}
\end{cases}
\]

(34)

The training process is summarized in Algorithm 5.

**Algorithm 5 TrainTaskModel**

Input \( D^{train}_t = \{(x_{t,i}, y_{t,i}) | i = 1, 2, ..., n^{train}_t\} \)

Input \( \theta_t = \{\beta_j | j = 1, 2, ..., N\} \)

Require \( K \) # the number of training epochs;

1: for \( k = 1 \) to \( K \) do
2: Update parameters according to Equation (33), (34);
3: end for

Return \( \theta_t \)

### III. EXPERIMENTS

#### A. Baselines, Datasets, and Implementation Details

We compare our method (SEU) with SGD, EWC [11], Learn to Grow (LTG) [19], and Progressive Network (PN) [16]. The SGD trains the entire model when learning a new task. We conduct experiments on 4 different datasets: permuted MNIST (PMNIST), split CIFAR10, split CIFAR100, and Mixture dataset. The PMNIST comes from the MNIST [23] dataset. A unique fixed random permutation is used to shuffle the pixels of each sample to generate a task. The split CIFAR10 is split from CIFAR10 [24] and contains 5 2-class classification tasks. Similarly, the split CIFAR100 contains 5 20-class classification tasks. The Mixture contains 5 different task: EMNIST [25], MNIST [23], Fashion MNIST [26], SVHN [27], and KMNIST [28]. Each experiment is repeated 5 times in order to obtain stable results.

For SGD, EWC, PN, and LTG, we adopt the Alexnet as the initial model in all experiments. SGD, EWC, and PN only contain training stage. LTG is divided into training stage and search stage. SEU contains 3 stages: EU Searching, Task Model Creation, and training stage.

In the training stage of all methods, we adopt the Stochastic Gradient Descent as optimizer and it contains 5 hyper-parameters: an initial learning rate \( \alpha = 0.025 \) which is annealed to 0 following a cosine schedule, a momentum \( \beta = 0.9 \), a weight decay \( \lambda \), a number of training epochs \( e = 50 \), and a batch size \( b = 128 \). The value of \( \lambda \) is selected from \{0.0003, 0.001, 0.003\}, which yields the best experimental result. EWC contains one more hyper-parameter \( \lambda_e \) to adjust the proportion of penalty item in loss function. The value of \( \lambda_e \) is 05000 on the split CIFAR10 and 20000 on others.

In the search stage of LTG, there are two optimizers. One for parameters of model (Stochastic Gradient Descent), and the other for parameters of architecture (Adam). The former contains an initial learning rate \( \alpha_m = 0.025 \), a momentum \( \beta_m = 0.9 \), and a weight decay \( \lambda_m = 0.0003 \). The latter contains an initial learning rate \( \alpha_m = 0.025 \), a momentum \( \beta_m = 0.5, \beta_2 = 0.999 \) and a weight decay \( \lambda_m = 0.001 \). The number of epochs \( e_a = 50 \) and the batch size \( b_a = 128 \). The coefficient of the penalty term for model size \( \lambda_{size} \) is selected from \{0, 0.001, 0.01, 0.1\}.

In SEU, EU Searching uses an optimizer (Stochastic Gradient Descent) that contains an initial learning rate \( \alpha_m = 0.025 \), a momentum \( \beta_m = 0.9 \), a weight decay \( \lambda_m \), the same as \( \lambda \). The coefficient of penalty update is \( \mu_{es} = 0.01 \) and the number of layers of model is \( l_{es} = 4 \). The number of epochs \( e_a = 100 \) and the batch size \( b_a = 512 \). The optimizer of Task Model Creation is the same as the one in EU Searching. The number of epochs \( e_{ts} = 100 \) and the batch size \( b_{ts} = 128 \). The number of layers of model \( l_{ts} \) is 5 on the PMNIST and 6 on others. The coefficient of probability update is \( \mu_{ts} = 0.01 \).

#### B. Ability to Resist Forgetting

To evaluate the ability of our method in overcoming catastrophic forgetting, we observe the model performance on all learned tasks after learning a new task each time.

We first look at performance on the split CIFAR10 (see Fig. 5a, 5b). After the first learning, SGD on task 1 is 92.02%. But after learning task 2, the accuracy on task 1 drops to 68.65% after learning task 3. This show that without any constraints, when learning a new task, the model quickly loses a lot of the knowledge learned from previous tasks. What’s more, as new tasks coming along, the loss of knowledge learned from previous tasks will
The experimental results are shown in Fig.6. NIST and Mixture datasets, and achieve similar performances. Relatively flat. We also perform the same experiment on PM-NET, also implement zero forgetting whose accuracy curves are flat. After learning a new task, the accuracy of the model on previous tasks do not change and all the forgetting problem. After learning task 2, the accuracy learned from previous task. After learning task 2, the accuracy 96.79% to 22.11%. EWC mitigates the rapid loss of knowledge accumulate. After completing all tasks, the accuracy on task 1 drops from 92.02% to 44.24% and on task 2 drops from 96.79% to 22.11%. EWC mitigates the rapid loss of knowledge learned from previous task. After learning task 2, the accuracy on task 1 drops from 91.84% to 90.30%. And it drops to 87.17% after learning task 3. After completing all tasks, the accuracy on task 1 drops from 91.84% to 83.73% and on task 2 drops from 70.11% to 68.96%. SEU, ltg, and Progressive Network all succeed in completely avoiding the catastrophic forgetting problem. After learning a new task, the accuracy of the model on previous tasks do not change and all the knowledge is retained.

The performance on the split CIAFR100 is similar (see Fig.6c-6d). The accuracy of SGD drops from 70.70% to 30.15% on task 1 and from 71.97% to 38.96% on task 2 after completing all tasks. SEU, ltg, and Progressive Network also implement zero forgetting whose accuracy curves are flat. EWC almost avoids forgetting and its accuracy curve is already relatively flat. We also perform the same experiment on PM-NIST and Mixture datasets, and achieve similar performances. The experimental results are shown in Fig.6.

C. Average Performance

The purpose of lifelong learning is to learn a series of tasks and get a great performance on each task. So, after learning each task, we compare the average accuracy of all tasks that have been learned. We first compare them on the PMNIST (see Fig.7a). The average accuracy curve of SGD drops rapidly with the arrival of the new task and the average accuracy drops from 98.12% to 22.09%. Although the rate of decline slowed, the average accuracy of EWC declines as the new task is learned and drops from 98.16% to 88.20%. The curves of all three methods with a growth model are relatively flat. All average accuracies are greater than 97% from start to finish. After learning all tasks, Progressive Network achieves the first performances (98.16%). Our method achieves second place (97.91%) with fewer parameters (see in Section III-D). The third place is taken by LTG (97.72%). On the split CIAFR100 (see Fig.7b), our method wins the first place (94.13%) and the second place is Progressive Network (93.32%). The third place is still taken by LTG (91.86%). On the split CIAFR100 (see Fig.7b), our method wins the first place (74.05%). The second is Progressive (66.76%) and the third is LTG (65.53%). On the Mixture (see Fig.7d), our method achieves third place (94.65%).

In order to further analyze the overall performance
different methods, we show the accuracy of each task that learned after learning current task in the form of a heat map (see in Fig.8). Note that only the upper triangle of the image makes sense. The image of SGD is only brighter on the diagonal which means it performs well only on the task it has just learned, and poorly on previous tasks. The color of the image of EWC is more even than SGD which means it performs better on previous tasks. But obviously, the diagonal of the image of EWC is darker than SGD. Therefore, in order to guarantee the performance on previous tasks, EWC limits the ability of the model to learn new tasks. Images of methods with a growth model look better and the color of the image of our method is more even and brighter especially on the split CIFAR100 (see Fig.8).

D. Accuracy vs Number of Parameters

In lifelong learning, the accuracy of and the number of parameters of the model can better reflect whether the model is fully utilized. We show the relationship between the accuracy and the number of parameters of models obtained by different methods on the PMNIST, the split CIAFR10, and the CIAFR100 (see Fig[9]). For quantitative comparison purposes, a new metric \( f(a, n) \) considers both accuracy and number of parameters is needed, where \( a \) is the average accuracy(%) for all learned tasks and \( n \) is the number of parameters of the model. And it should obey the following properties:

Fig. 6: Accuracy curve and accuracy change on the PMNIST and Mixture.

Fig. 7: Average accuracy of all learned tasks after learning current task. (a) CIFAR10 (b) CIFAR100 (c) PMNIST (d) Mixture
We denote a mixture score of accuracy and number of parameters (MS) as follows and our method achieves the highest scores on all four datasets (see in Table [1]).

\[
\text{MS}(a, n) = \frac{\sqrt{a} \cos[\pi(1 - e^{-\log(n+1)/10})] + 1}{10} 
\]

We denote a mixture score of accuracy and number of parameters (MS) as follows and our method achieves the highest scores on all four datasets (see in Table [1]).

\[
\text{MS}(a, n) = \frac{\sqrt{a} \cos[\pi(1 - e^{-\log(n+1)/10})] + 1}{10} 
\]

In general, methods with a growth model have a larger number of parameters. However, since both EU and Task Model for each task are specifically searched, the model of our method is even more compact than methods with a fixed model. Although the Learn to Grow also tries to search for a better expansion operation, its expansion module always has a fixed architecture that is not compact enough. So, this experimental result proves empirically that searching for a suitable EU and Task Model for each new task is useful for a more compact model. Our method can achieve higher accuracy with fewer model parameters and achieve the highest mixed score.

IV. RELATED WORK

Lifelong learning is remaining a challenging task in the field of artificial intelligence [1], [2]. It focuses on the ability of intelligent agents to learn consecutive tasks without forgetting the knowledge learned in the past. A major problem with lifelong learning is catastrophic forgetting, which is still a big problem in deep learning [5]. Catastrophic forgetting occurs when a model that has been trained on some other tasks is trained on a new task. The weights which are important for previous tasks are changed to adapt to the new task. Up to now, many new methods have emerged to solve this problem.

One way to solve the problem directly is to use a memory system to alleviate forgetting, inspired by the complementary learning systems (CLS). The memory system stores previous data and replays these old samples when learning the new task [6], [7]. One obvious drawback to these methods is the need to store old information. So, [8] proposed a dual-model architecture consisting of a task solver and a generative model. In place of storing real samples of previous tasks, the memory system only needs to retrain the generative model after learning a new task.

In addition to retaining information about previous tasks by storing old examples, an agent can also try to store the
Another way to keep knowledge of previous tasks is by selecting different sub-network from a single fixed network for different tasks. Concretely speaking, when learning a new task, the sub-networks of previous tasks are protected and the network selects a sub-network for the new task from the parts that have never been used. The PathNet, proposed by [14], selects a path for the current new task by a tournament selection genetic algorithm. When learning the new task, the weights in paths of previous tasks are frozen so that the knowledge can be preserved. [15] brought up a concept named hard attention which implies the importance of weights for different tasks. Concretely speaking, when learning a new task, the weights whose hard attention to previous tasks is large will be protected to hold the knowledge. [10] considered splitting the parameters of the model into two parts. One of the two is shared by all tasks and the other is adapted to different samples.

As the number of tasks increases, a fixed network with a limited capacity will get into trouble. [10] proposed Progressive Network to assign additional fixed model resources to each task. When learning a new task, all of the weights of the model will be frozen and a list of new model modules will be trained. The new task can also reuse the previous knowledge by lateral connections between new and old modules. To avoid wasting resources, [17] proposed Dynamically Expandable Networks (DEN) and this method can remove unnecessary new modules by sparse regularization. Moreover, [18] assigned different new modules for different tasks by a controller trained by a reinforcement learning algorithm.

Except for the model weights, [19] attempted to take the model architecture into account and proposed the Learn to Grow algorithm. At each layer of a model, this approach allows the new task to reuse the weights of previous tasks or retrain the module. Furthermore, it allows the new task to get a new module by adapting the used module. However, this method should select an original model at first which is suitable for all possible tasks. But this is hard to guarantee in practice and such a model is always large. Moreover, such a predefined structure ignores the fact that different tasks might fit different model structures or even different micro-architectures.

Our method Searchable Extension Units (SEU), as one of the methods with dynamic expansion, breaks the limitation of a predefined model and can search for specific extension units for different tasks.

V. CONCLUSION

In this paper, we propose a new framework for lifelong learning named Searchable Extension Units. Our method can search for suitable EU and Task Model for different tasks and break the limitation of a predefined original model. So the model in our method is more compact than methods with a predefined original model and fixed architectures of new resources. We validate our method on 4 datasets and the experimental results empirically prove that our method can achieve higher accuracy with fewer model parameters than other methods. In the future, it will make sense to find more efficient tools for Extension Unit Searcher and Task Solver Creator in SEU.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their insightful comments on this paper.
REFERENCES

[1] G. I. Parisi, R. Kemker, J. L. Part, C. Kanu, and S. Wermter, “Continual lifelong learning with neural networks: A review,” Neural Networks, vol. 113, pp. 54–71, May 2019. Available: [link]

[2] S. Thrun, “A Lifelong Learning Perspective for Mobile Robot Control,” in IROS, 1994, p. 8.

[3] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” in Advances in Neural Information Processing Systems 25. Curran Associates, Inc., 2012, pp. 1097–1105. [Online]. Available: [link]

[5] R. M. French, “Catastrophic forgetting in connectionist networks,” Trends in Cognitive Sciences, vol. 3, no. 4, p. 8, 1999.

[6] S.-A. Rebuffi, A. Kolesnikov, G. Sperl, and C. H. Lampert, “iCaRL: Incremental Classifier and Representation Learning,” in CVPR, 2017, pp. 2001–2010. [Online]. Available: [link]

[7] D. Lopez-Paz and M. A. Ranzato, “Gradient Episodic Memory for Continual Learning,” in Advances in Neural Information Processing Systems 30, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. Curran Associates, Inc., 2017, pp. 6467–6476. [Online]. Available: [link]

[8] H. Shin, J. K. Lee, J. Kim, and J. Kim, “Continual Learning with Deep Generative Replay,” in Advances in Neural Information Processing Systems 30, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. Curran Associates, Inc., 2017, pp. 2990–2999. [Online]. Available: [link]

[9] Y. Wu, Y. Chen, Y. Ye, Z. Liu, Y. Guo, Z. Zhang, and R. Fu, “Incremental Classifier Learning with Generative Adversarial Networks,” arXiv:1802.00853 [cs], Feb. 2018. arXiv: 1802.00853. [Online]. Available: [link]

[10] W. Hu, Z. Lin, B. Liu, C. Tao, Z. Tao, D. Zhiao, J. Ma, and R. Yan, “OVERCOMING CATASTROPHIC FORGETTING FOR CONTINUAL LEARNING VIA MODEL ADAPTATION,” in ICLR, 2019, p. 13.

[11] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska et al., “Overcoming catastrophic forgetting in neural networks,” Proceedings of the national academy of sciences, vol. 114, no. 13, pp. 3521–3526, 2017.

[12] F. Zenke, B. Poole, and S. Ganguli, “Continual learning through synaptic intelligence,” in Proceedings of the 34th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, D. Precup and Y. W. Teh, Eds., vol. 70. International Convention Centre, Sydney, Australia: PMLR, 06–11 Aug 2017, pp. 3987–3995. [Online]. Available: [link]

[13] R. Aljundi, F. Babili, M. Elfouhaily, M. Rohrbach, and T. Tuylfaaers, “Memory Aware Synapses: Learning what (not) to forget,” in ECCV, 2018, pp. 139–154. [Online]. Available: [link]

[14] C. Fernando, D. Banarse, C. Blundell, Y. Zwols, D. Ha, A. A. Rusu, A. Pritzel, and D. Wierstra, “PathNet: Evolution Channels Gradient Descent in Super Neural Networks,” arXiv:1701.08734 [cs], Jan. 2017. arXiv: 1701.08734. [Online]. Available: [link]

[15] J. Serr, D. Surs, M. Miron, and A. Karatzoglou, “Overcoming Catastrophic Forgetting with Hard Attention to the Task,” in PMLR, 2018, p. 10.

[16] A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirkpatrick, K. Kavukcuoglu, R. Pascanu, and R. Hadsell, “Progressive Neural Networks,” arXiv:1606.04671 [cs], Jun. 2016. arXiv: 1606.04671. [Online]. Available: [link]

[17] J. Yoon, E. Yang, J. Lee, and S. J. Hwang, “Lifelong Learning with Dynamically Expandable Networks,” in ICLR 2018, 2018, p. 11.

[18] J. Xu and Z. Zhu, “Reinforced Continual Learning,” in Advances in Neural Information Processing Systems 31, S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, Eds. Curran Associates, Inc., 2018, pp. 899–908. [Online]. Available: [link]

[19] X. Li, Y. Zhou, T. Wu, R. Socher, and C. Xiong, “Learn to Grow: A Continual Structure Learning Framework for Overcoming Catastrophic Forgetting,” in ICLR, 2019, p. 10.

[20] H. Liu, K. Simonyan, and Y. Yang, “DARTS: Differentiable architecture search,” in International Conference on Learning Representations, 2019. [Online]. Available: [link]

[21] Z. Zhong, J. Yan, W. Wu, J. Shao, and C.-L. Liu, “Practical block-wise neural network architecture generation,” in The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018.

[22] X. Zheng, R. Ji, T. Zeng, B. Zhu, J. Liu, and Q. Tian, “Multinomial distribution learning for effective neural architecture search,” in The IEEE International Conference on Computer Vision (ICCV), October 2019.

[23] Y. LeCun, “The mnist database of handwritten digits,” http://yann.lecun.com/exdb/mnist/.

[24] A. Krizhevsky et al., “Learning multiple layers of features from tiny images,” Citeseer, Tech. Rep., 2009.

[25] G. Cohen, S. Afshar, J. Tapson, and A. Van Schaik, “Emnist: Extending mnist to handwritten letters,” in 2017 International Joint Conference on Neural Networks (IJCNN). IEEE, 2017, pp. 2921–2926.

[26] H. Xiao, K. Rasul, and R. Vollgraf, “Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms,” ArXiv, vol. abs/1708.07747, 2017.

[27] Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu, and A. Y. Ng, “Reading digits in natural images with unsupervised feature learning,” 2011.

[28] T. Clanuwat, M. Bober-Irizar, A. Kitamoto, A. Lamb, K. Yamamoto, and D. Ha, “Deep learning for classical japanese literature,” ArXiv, vol. abs/1812.01718, 2018.