StackNet: Stacking feature maps for Continual learning

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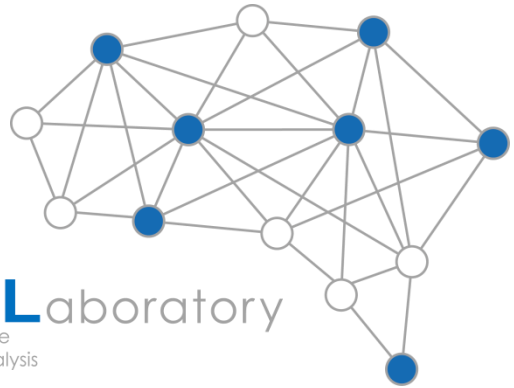
(*Equal Contribution)



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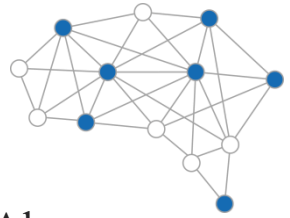
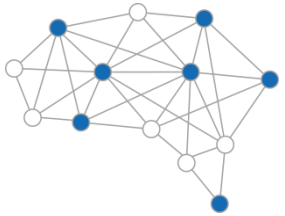
Introduction



- Usually, artificial neural network (ANN) models consist of a finite number of filters. Also, parameters and operations in the ANN do not possess the ability corresponding to the memory system of human brains.
- This structural limit leads to the problem called catastrophic forgetting, i.e., the newly coming information diverts the model from previously leaned knowledge
- In this paper, we propose a network which efficiently uses the capacity of the network for continual learning without degrading the performance of previous tasks
- We have built our method using two complementary components which are **StackNet** and **Index module**

Related works

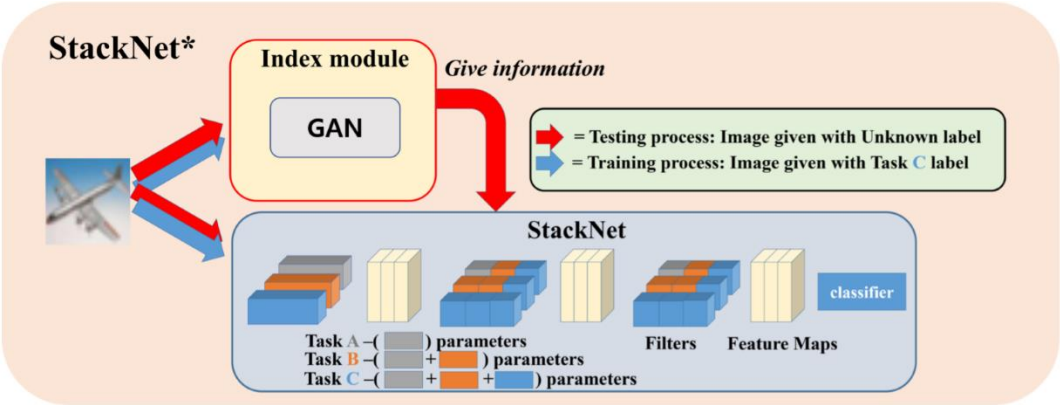


- Learning without forgetting (LwF) [1]
  - A method trying to retrain {the model by using the outcomes of the previously learned model as anchoring targets.
  - When training a new task, a considerably small learning rate is used to prevent the model from losing the learned knowledge.
- PackNet [2]
  - A method using the weight pruning method.
  - Leaving the remaining weights fixed after pruning, the model can solely focus on the task on interest.
  - Despite of its efficiency and performance, this method, referred as PackNet, requires the prior knowledge of a given input

[1] Li, Zhizhong, and Derek Hoiem. "Learning without forgetting." *IEEE transactions on pattern analysis and machine intelligence* 40.12 (2017): 2935-2947.
[2] Mallya, Arun, and Svetlana Lazebnik. "Packnet: Adding multiple tasks to a single network by iterative pruning." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.

Method

- After training the **StackNet** from the previous task with a certain amount of parameters, additional parameters in the convolutional modules are stacked and trained with the next task.
- In order to determine which combination of filters to use, we adopted a **index module** which can distinguish the origin of a given input sample.
- The combined **index module** and **StackNet** can prevent the catastrophic forgetting using different parameters for different tasks under the constraint network capacity.



StackNet* = StackNet + Index module

Index module (GAN)

- we introduce the index module inspired by [3] using several different methods, which is able to estimate the task of the given input data and inform this to the StackNet to specify which filters to use.
- We train a task-specific generative model using a GAN to generate pseudo-samples of each task.
- A task-wise binary classifier is trained to classify whether the given input is from the task or not.
- Index module can figure out the task of input data with maximum probability across the set of classifiers.

(a) Generated samples with the generator of index module (b) Real samples

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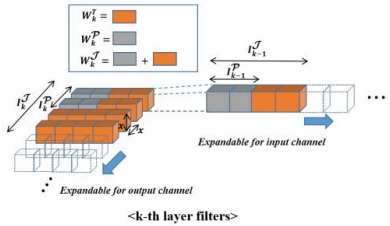
[3] Li, Zhizhong, and Derek Hoiem. "Learning without forgetting." *IEEE transactions on pattern analysis and machine intelligence* 40.12 (2017): 2935-2947.

StackNet

- We propose an efficient way to allocate the capacity of a network according to the given tasks.
- While training the StackNet with several tasks, each task uses a different part of the StackNet.
- we utilize a network divided into several parts and refer it as StackNet where each part takes charge of a particular task.
- we introduce a filter index I^J (J task). The filter index I^J defines the range of filters to use for the specific task J in every layers.
- To avoid Forgetting, when we train the new weight for new task, we freeze the previous weights and only update the new weights for new task.



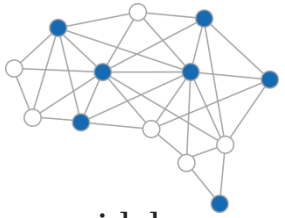
Algorithm 1 StackNet Training

Input: $W^{\mathcal{J}}, I^{\mathcal{P}}, I^{\mathcal{J}}$

Output: $W^{\mathcal{J}*}$

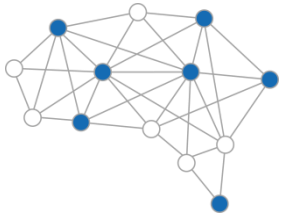
1: Freeze the $W^{\mathcal{P}} \subset W^{\mathcal{J}}$ using the information $I^{\mathcal{P}}$
2: Initialize the $W^{\mathcal{T}}$ with $W^{\mathcal{P}}$ and a random noise
3: $W^{\mathcal{J}*} \leftarrow \arg\min(\mathcal{L}_c)$
{Update W^T using backpropagation}

Results



- we verify the effectiveness of our method with MNIST, SVHN and CIFAR-10 which are widely used to evaluate image classification performance. Then, we evaluate our method on two subsets of ImageNet which is a real world image dataset
- We compare our method to various methods such as Learning without forgetting (LwF) and PackNet as well as networks trained for a single target task which shows the performance without conducting continual learning.
- To save the training time, two subsets of the ImageNet dataset each having 50 randomly chosen classes have been used for evaluation. They are referred to as ImageNet-A and ImageNet-B respectively in this paper.

Results



Datasets	Methods	Old(%)	New(%)	Avg. (%)
MNIST ↓ SVHN	single network (MNIST)	99.49	–	–
	single network (SVHN)	–	92.82	–
	LwF ($T = 1$)	98.27	86.40	92.34
	LwF ($T = 2$)	97.33	86.97	92.15
	PackNet	99.45	91.49	95.47
	StackNet*	99.43	92.20	95.82
	StackNet	99.43	92.37	95.90
SVHN ↓ CIFAR-10	single network (SVHN)	92.94	–	–
	single network (CIFAR)	–	79.69	–
	LwF ($T = 1$)	91.76	70.57	81.17
	LwF ($T = 2$)	90.19	71.94	81.07
	PackNet	92.84	76.78	84.81
	StackNet*	90.05	76.62	83.34
	StackNet	92.21	76.70	84.46

Datasets	Methods	MNIST(%)	SVHN(%)	CIFAR(%)	Avg(%)
MNIST ↓ SVHN ↓ CIFAR-10	single network (MNIST)	99.44	–	–	–
	single network (SVHN)	–	92.94	–	–
	single network (CIFAR)	–	–	79.69	–
	LwF ($T = 1$)	95.06	86.80	68.98	83.61
	LwF ($T = 2$)	86.09	85.07	69.63	80.26
	PackNet	99.38	91.93	66.34	85.88
	StackNet*	99.41	89.36	74.93	87.90
	StackNet	99.41	91.84	75.02	88.76

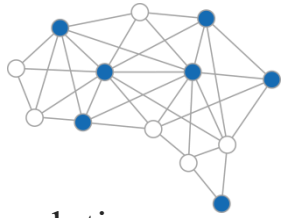
< Mean classification results on the basic datasets with LeNet like networks>

StackNet* = StackNet + Index module

datasets	Methods	Old(%)	New(%)	Avg. (%)
ImageNet-A ↓ ImageNet-B	single network (ImageNet-A)	83.28	–	–
	single network (ImageNet-B)	–	85.28	–
	LwF ($T = 1$)	82.2	86.72	84.46
	LwF ($T = 2$)	80.92	86.96	83.94
	PackNet	82.16	88.72	85.44
	StackNet	83.30	88.66	85.98

<ImageNet-A and ImageNet-B with ResNet-50>

StackNet – Only "Index module" Results

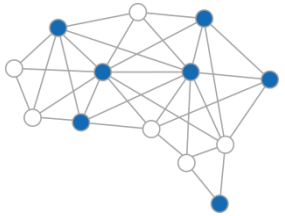


- Generative models usually have difficulties in generating realistic images with high resolution and there are few researches experimented on ImageNet data

Datasets	Methods	Old(%)	New(%)	Avg. (%)
MNIST→ SVHN	GAN	100	99.94	99.97
	Baseline	61.65	97.17	79.41
SVHN→ CIFAR-10	GAN	97.00	99.90	98.45
	Baseline	89.39	85.86	87.63

Datasets	Methods	MNIST(%)	SVHN(%)	CIFAR(%)	Avg(%)
MNIST→ SVHN CIFAR-10	GAN	100	96.65	99.83	98.83
	Baseline	52.88	90.89	75.7	73.16

<Experimental results of the index module on the basic datasets>



Thank you