Towards Robust Continual Learning Using an Enhanced Tree-CNN

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Abstract:
The ability to perform continual learning and the adaption to new tasks without losing the knowledge already acquired is still a problem that current machine learning models do not address well. This is a drawback, which needs to be tackled for different reasons. On the one hand, conserving knowledge without keeping all of the data over all tasks is a rising challenge with laws like the European General Data Protection Regulation. On the other hand, training models come along with CO_2 footprint. In the spirit of a Green AI the reuse of trained models will become more and more important. In this paper we discuss a simple but effective approach based on a Tree-CNN architecture. It allows knowledge transfer from past task when learning a new task, which maintains the model compact despite network expansion. Second, it avoids forgetting, i.e., learning new tasks without forgetting previous tasks. Third, it is cheap to train, to evaluate and requires less memory compared to a single monolithic model. Experimental results on a subset of the ImageNet dataset comparing different continual learning methods are presented.

1 INTRODUCTION

Continual learning (CL) is a key characteristic of human intelligence, which remains a daunting problem in machine intelligence. It refers to the ability of a neural network to learn consecutive tasks, crucially, without forgetting how to perform previously learned tasks.

Unfortunately, the term continual learning is sometimes used for a wide range of ideas of learning continually, incrementally and adaptively. In general, it means that the predictive model is able to smoothly update, take into account different tasks and data distributions, while still being able to keep useful knowledge and skills over time. This broad description can mean dealing with very different tasks like learning from a stream of different data distributions or just reusing neural networks in a context one might refer to as transfer learning. In this paper we concentrate on classification. We denote $\mathcal{F}$ as the feature space and $\mathcal{C}$ as the target space of classes. In this context, the goal of a CL method is to deal with a sequence of tasks, each containing a classification task $\mathcal{T}^t$

$$\mathcal{T}^t : \mathcal{F} \to \mathcal{C}^t \supset \mathcal{C}^{t-1}$$

In other words, the set of classes always grows from task to task and still contains the old classes as subsets. Training on task t is performed using a dataset $\mathcal{D}^t$. Therefore, without further modification in training, a naively trained neural network tends to overwrite its current weights, causing a replacement of knowledge about older tasks with the current tasks. This phenomenon is known to as the catastrophic forgetting problem (Goodfellow et al., 2013).

Beyond continual learning we discuss the aspect of robustness in the sense that not all misclassifications are equal. If classes belong to hierarchical structures, some of these classes are more related to each other than others. It is much more acceptable to misclassify a bee as wasp than as an elephant. A lot of tasks can be or even are inherently structured in trees, like the ones in Figure 1 – which will be used throughout the paper – derived as subset of ImageNet (Russakovsky et al., 2015). The role of *not here* (in Figure 1) is explained later on and these nodes can be ignored for now. As the figure shows, we have trees with different levels $\mathcal{L}^l$ with $l \in \{0, \cdots, 3\}$, where $\mathcal{L}^0$ is the root-node, while $\mathcal{L}^1 = \{animal, artifact, food\}$ is level 1. Nodes in the deeper levels are denoted as $\mathcal{L}^{2,m}$, e.g. $\mathcal{L}^{2,0\ldots2} = \{$*vertebrate, invertebrate, domestic animal*$\}$. $\mathcal{L}^{3,n} = \{$*bird, reptile, amphibian*$\}$ with $n = 0, \ldots, 2$, represents child of *vertebrate* in the deepest level $\mathcal{L}^3$. This scheme can be extended more and the extension can also be performed unbalanced. In this way, the next task could be just to go deep regarding birds.

There is a plethora of areas where the application of such a hierarchical sequential learning comes into play. Although a traditionally trained neural network performing joint learning – i.e., accessing all data at one during training – is in general more promising in terms of accuracy, this is not always possible or desired in some real-world scenarios, including but not limited to:

- Certification, e.g. w.r.t. occupational safety in a smart factory.
- Green AI, along with the accompanying need for model reuse.
- Data protection and privacy.

Employing machine learning in real life production with the risk of human harm or strict quality regulations - cf. e.g. the ISO 9000 family - comes up with huge demand regarding rigorous a priori testing of the model in different settings. Such settings include additional software solutions around the model to prevent statistical unlikely but not impossible behavior. Smoothly chaining the model such that it is composed of interlinked, but individually independent node partly alleviates this issue by reducing the size and number of components to be re-evaluated if a partial change to the database occurs.

The second challenge concerns the aspect of Green AI (see e.g. (Schwartz et al., 2020)), trying to prevent unnecessary usage of energy for training purpose. Moreover, in real-world applications like autonomous systems (e.g. autonomous units like robots or cars), access to computer resources is highly limited. Hence, restricting the training to necessary level of new applications is a strongly desired behavior.

In both of the aforementioned scenarios (Certification and Green AI), there is always the – although undesirable – option to abandon the existing model and start the training from scratch since the old data are usually still available. This is however not the case, when the latter is subject to contemporary privacy and data protection legislation. One prominent example is the adoption of the General Data Protection Regulation (GDPR) by the European Union in 2018, which makes high demands on data protection and privacy including the requirement to delete data after a given amount of time. In a similar vein, the California Consumer Privacy Act enacted in 2020 promotes the need to continually delete consumer processed data over time.

In such scenarios, it is inherently necessary to incrementally build upon the existing model (as done in our method), since old data are either non-existent (has been deleted) or not accessible due to privacy concern, making retraining from scratch practically unfeasible. In this paper, we propose a novel method termed as enhanced Tree-CNN to address the continual learning problem aimed at overcoming the aforementioned problematic.

1.1 Related Work

Previous works addressing continual learning generally fall under three categories: regularization-based (Kirkpatrick et al., 2017; Jung et al., 2020), replay-based (Shin et al., 2017; Riemer et al., 2019) and architecture-based (Yoon et al., 2018; Li et al., 2019). Our work belongs to the architecture-based family and we only discuss this category. The reader is referred to (Parisi et al., 2019) for an extensive survey.

Methods in architecture-based family sidestep catastrophic forgetting by allocating non-overlapping subsets of model parameters to each task. This is often achieved by dynamically expending the network capacity (as in our approach) to handle a new task. For instance, (Rusu et al., 2016) proposed to expand the network by augmenting each layer by a fixed number of neurons for each new task, while keeping the old layers parameters fixed to avoid forgetting. However, this method results in a network with excessive size. (Yoon et al., 2018) proposed to overcome this limitation by expending each layer with only the necessary number of neurons, but they require several hyperparameters and involves cumbersome heuristics to decide how many neurons to add at each layer. More recently, (Li et al., 2019) developed a notion of network architecture search to decide, how much to reuse of the existing network neurons and how much to add. This method makes the network very compact but is not effective in term of training time due to the heavily search mechanism.

The publication originating from a different point of view by (Roy et al., 2020) employs tree-like, dynamically growing structures of neural networks. It contains the basic idea we improve and furthermore evaluate in our work, thus we discuss the basics and improvements later on in more details. Moreover, we will show that our approach is scalable and generic, making it applicable either as a standalone continual learning method or in combination with a regularization- or memory-based method.

1.2 Contribution

This paper improves and evaluates a tree-like modular approach for learning sustainable convolutional neural networks (CNNs) proposed in (Roy et al., 2020). The improved version can handle an unlimited number of tasks and avoid catastrophic forgetting. The main idea is to leverage neural network modularization via building a tree-CNN in a bottom-up fashion. This approach enhances continual learning and robustness. Beyond this, it can help to increase the transparency in the decision-making process, therefore it leads to the overall network being more trustworthy than a single monolithic model. Another significant benefit of this tree-like modularization scheme is the gained robustness of the network with only minor drawbacks in terms of accuracy. Nevertheless, tree-based approaches come along with some limitations not discussed in (Roy et al., 2020). The reason is that in (Roy et al., 2020) CIFAR-100 was used for benchmark problems. The issues mostly show up in cases with more complex and unbalanced tasks.

The main contributions of our work are summarized as follows:

- We extend the algorithm from (Roy et al., 2020) with the option of setbacks.
- We propose a lightweight full prediction approach for Tree-CNNs.
- We propose a metric to measure errors in tree structured datasets.
- We propose a subset of ImageNet as real life CL classification benchmark.
- We evaluate the algorithm from (Roy et al., 2020), our improved version, and EWC (Kirkpatrick et al., 2017) on this benchmark.
- The latter discussion includes success conditions for the different approaches.

The paper is organized as follows: Section 2 presents our improvements regarding (Roy et al., 2020), while in Section 3 we suggest an additional metric regarding robustness in structured datasets. Finally, Section 4 includes our suggestion for a benchmark problem taken from ImageNet as well as the results and discussion.

2 ENHANCED TREE-BASED CNN

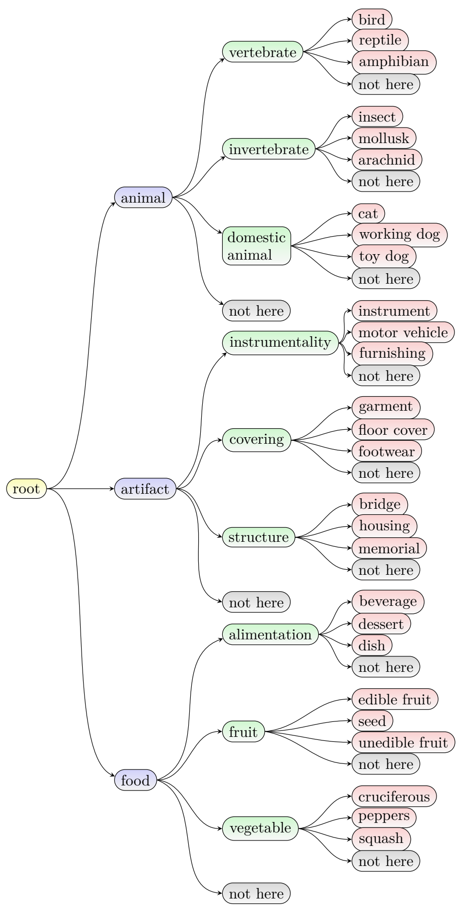


Figure 1: Our proposed subset of the ImageNet Dataset.

Problem Setting. As mentioned earlier, we consider the problem of sequential learning of deep convolutional neural network under the scenario, where an unknown number of tasks with new sets of classes and an unknown distribution of data are sequentially provided to the network. Specifically, our goal is to train a model for a sequence of tasks, where task t arrives with dataset

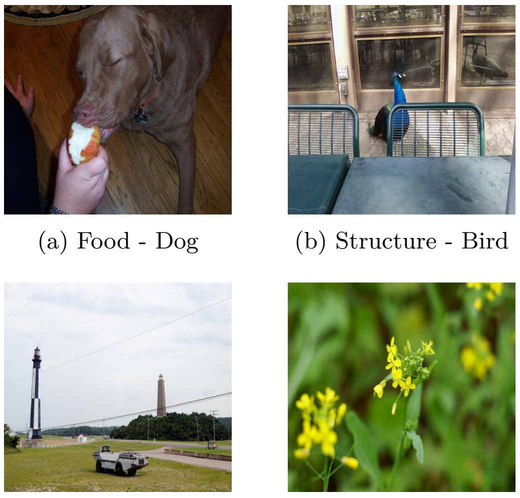
$D^t = \{x_i, y_i\}_{i=1}^{I^t}$, such that the final model performs well on the new task as well as on the previous tasks without considerable performance loss.

Notations. We denote $\mathcal{L}^l$ ($l \in \{0, \cdots, 3\}$) as a level of the tree, where $\mathcal{L}^0$ and $\mathcal{L}^3$ are the root and leaf levels, whereas $\mathcal{L}^1$ and $\mathcal{L}^2$ stand for the task-specific levels. Beyond this, let K, M be the number of tasks on level $\mathcal{L}^1, \mathcal{L}^2$ and N the number of leaf nodes or classes in $\mathcal{L}^3$. We further denote by $\mathcal{T} \in \left\{\{\mathcal{L}^{1,k}\}_{k=0}^{K}, \{\mathcal{L}^{2,m}\}_{m=0}^{M}\right\}$ the set of all tasks in the tree. Finally, M^k denotes the number of children of the k^{th} task in $\mathcal{L}^1$, whereas N^m stands for the number of children of the m^{th} task in $\mathcal{L}^2$.

Method Overview. Let's consider a model trained to tackle **task 1**, namely to classify images belonging to K different classes (e.g. *animal, artifact, food* as in Figure 1). This model can be viewed as the root node ($\mathcal{L}^0$) of the entire tree-based CNN and its children as the level 1 ($\mathcal{L}^1$) of the hierarchy. Each model in $\mathcal{L}^1$ is further trained to differentiate between its children, such that during a prediction, the tree can route samples to the corresponding next level nodes. The tree structure is illustrated in Figure 1.

Performing evaluations with this approach, we found that the root note is very important, because a misclassification performed on its level is inevitable. If – with a slightly higher probability – *artifact* has been chosen incorrectly instead of *animal*, the prediction will go wrong. This property is even worse, if one considers continual learning instead of incremental learning as in (Roy et al., 2020). In incremental learning, all the data are available to train e.g. the root node. In the use case of continual learning, it is possible that a tree-CNN is trained and below the class *bird* new sub-classes are introduced. It might be the case that the root model route the new bird images correctly into the animal branch. But maybe one of the new classes is penguin or ostrich. In this case, the trained convolution layer might end up less efficient. There are two strategies to make trees-approach – like (Roy et al., 2020) – capable for continual learning. One could retrain the root model with a technique, e.g. EWC (Kirkpatrick et al., 2017), which is capable to avoid the catastrophic forgetting, or one could introduce a setback mechanism deeper in the trees. Of course, it is possible to combine both techniques. We suggest to start with the introduction of a setback mechanism and just go for retraining if setbacks are not capable alone to handle the issue.

In Figure 1, for the setback, new classes *not here*, labeled as gray nodes are introduced. These *not here* classes are defined by using a given percentage of the images from one level below. This means e.g. *not here* at *domestic animals* consists of pictures from the database except *domestic animals*. Doing so, the model learns to recognize samples that do not belong to its position in the hierarchy. This leads to a kind of open world model, where *not here* is always the option that none of the given classes is the correct one, in the example of *domestic animals* it is neither a cat, working- or toy dog.



(a) Food - Dog (b) Structure - Bird

(c) Structure - Vehicle (d) Invertebrate - Seed

Figure 2: Illustration of test samples, which benefited from the setback mechanisms to be correctly classified (right label in each image) after a first missclassification (left label in each image).

We observed that the proposed setback mechanism – as briefly described above and more details in Algorithm 1 – are useful, when it comes to continual learning. Figure 2 shows four scenarios, where this mechanism has proven to be effective. In the first scenario (Figure 2a), because of the apple, – the image is first classified incorrectly by the root node as *food*. This happened with a very small margin between the probabilities; *animal* (0.48), *artifact* (0.03), *food* (0.49). At the food level, the image further gets classified as *not here*. This happens because a portion of *domestic animal* images is contained in the *not here* category. It follows that the setback mechanism is activated and redirects the sample in the tree to $\mathcal{L}^1$ class with the next highest probability, i.e., *animal*, where the image is finally classified correctly

Algorithm 1 Prediction with Setbacks

```
1:  Input: $X$ image to predict
2:         $\mathcal{L}^0$ root trained model
3:         $\{\mathcal{L}^{1,k}\}_{k=0}^{K}$ level 1 trained tasks
4:         $\{\mathcal{L}^{2,m}\}_{m=0}^{M}$ level 2 trained tasks
5:  Output: $P(\{\mathcal{L}^{3,n}\}_{n=0}^{N})$ vector of leaf nodes
            class probabilities
6:  procedure:
7:  predict class $k$ using $\mathcal{L}^0(X)$, save probabilities
    and set $\tilde{k} = k$
8:  setback = False
9:  repeat
10:     predict class $m$ using $\mathcal{L}^{1,k}(X)$, save probabilities and set $\tilde{m} = m$
11:     mark $\mathcal{L}^{1,k}$ as visited
12:     while $m$ = not here do
13:         mark $\mathcal{L}^{2,m}$ as visited
14:         if all nodes visited in $\mathcal{L}^1$ then
15:             set $k = \tilde{k}$ and $m = \tilde{m}$
16:             break
17:         end if
18:         set $k$ to the value of the class with the
            next highest probability of $\mathcal{L}^0(X)$
19:         recalculate probabilities
20:         predict class $m$ using $\mathcal{L}^{1,k}(X)$ and save
            probabilities
21:         mark $\mathcal{L}^{1,k}$ as visited
22:     end while
23:     predict class $n$ using $\mathcal{L}^{2,m}(X)$ and save
        probabilities
24:     mark $\mathcal{L}^{2,m}$ as visited
25:     while $n$ = not here do
26:         set $m$ to the value of the class with the
            next highest probability of $\mathcal{L}^{1,k}(X)$
27:         recalculate probabilities
28:         mark $\mathcal{L}^{2,m}$ as visited
29:         if $m$ = not here or all children of $\mathcal{L}^{1,k}$
            were visited then
30:             Set $k$ to the value of the class with the
                next highest probability of $\mathcal{L}^0(X)$
31:             setback = True
32:         end if
33:         predict class $n$ using $\mathcal{L}^{2,m}(X)$ and save
            probabilities
34:     end while
35:     if all of $\mathcal{L}^{2,m}$ for $m = 0, \ldots, M$ were visited
        then
36:         evaluate the tree ignoring all setbacks
            and use the highest probabilities ignoring not here
37:     end if
38: until not setback
```

as a *dog*. The same happen in Figure 2b, 2c, 2d, where the *bird*, *vehicle* and *seed* firstly got misclassified as *Structure*, *Structure* and *Invertebrate* respectively, before being rescued by the setback mechanism.

Another new feature of our method belongs to the information provided by the algorithm during prediction. A tree-model built according to (Roy et al., 2020) – here CIFAR 100 was used – has the same structure as ours except the *not here* nodes. During prediction, the sample is rooted from the root node to a leaf node of the tree. The routing performed is based on the highest probability of a class. Algorithm 1 in section 3.2 of (Roy et al., 2020) returns the selected class. Following this scheme, any information about the distribution of the probability along the classes is lost. Theoretically, one can consider a second mode for the tree, in which all nodes are used for a prediction, and the probability is calculated along the branches of the tree. Unfortunately, this would come along with a huge increase of CPU usage during the prediction. To overcome both limitations (probability distribution lost and huge CPU usage), we propose a probability propagation and recalculation mechanism as described bellow.

Let's consider predicting a test image X_i, then $\mathcal{O}(N,i) = P(\{\mathcal{L}^{3,n}\}_{n=0}^{N})$ is an output vector containing the probability of all leaf classes, which is obtained by propagating the probability of each node in $\mathcal{L}^1$ and $\mathcal{L}^2$ to its corresponding leaf node. Figures 3 and 4 illustrate this mechanism and show how $\mathcal{O}(N,i)$ is calculated. In Figure 3, the root node classifies the test sample as belonging to class B with a probability of 0.6. At node B, the sample is further classified as belonging to leaf node B_1 with a probability of 0.7. The dashed rectangle at the bottom shows the vector $\mathcal{O}(N,i)$, containing computed class probability of each leaf node. While the values for leaf nodes B_1 and B_2 are obvious, the computation of A_1 and A_2 probabilities demonstrates the *not here* propagation. In fact, $\sigma_B = 0.6 \times 0.1$ probability is associated to *not here* in B. This *not here* class in B was trained with images of A_1, A_2, C_1, C_2 nodes. Therefore, we propagate σ_B – probability of B *not here* – to these nodes and compute their final output probabilities as: $P(A_1) = P(A_2) = \frac{0.3}{2} + \sigma_B$ and $P(C_1) = P(C_2) = \frac{0.1}{2} + \sigma_B$ with $\sigma_B = \frac{0.6 \times 0.1}{4}$ being the propagated probability of B *not here* shared by A_1, A_2, C_1 and C_2.

In the case of Figure 4, there are two runs of the tree showed in red and blue respectively. During the first run, the root node classifies the

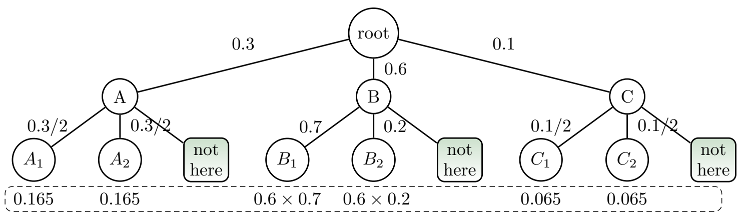


Figure 3: Tree demonstrating the computation of leaf node probability vector in one shot

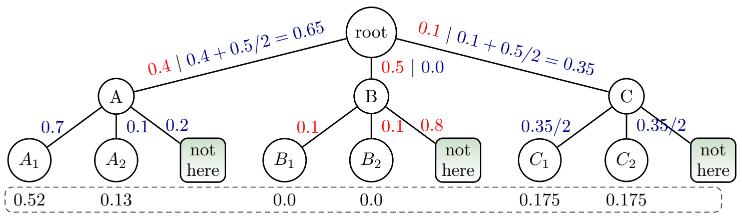


Figure 4: Tree demonstrating the computation of leaf node probability vector in two runs

image incorrectly as belonging to B. Fortunately, the setback mechanism gets activated at B and routes the image back to the root level. Now we choose to handle this decision as B *is impossible* statement. Thus, the probability of B is zeroed and equally distributed through A and C. Then the class with the next highest probability (during first run) gets selected, which is A. The probability flowing to A is then computed as the probability of A at the first run added to the distributed probability of B (at first run), i.e., $P(A) = 0.4 + \frac{0.5}{2}$. At A, the image is further classified as belonging to A_1 with a probability of 0.7. The *not here* class at A is predicted with a probability of 0.2, which is then distributed through $A1$ and $A2$. The final probability of A_1 and A_2 is then computed as $P(A_1) = \left(0.7 + \frac{0.2}{2}\right) \times 0.65$ and $P(A_2) = \left(0.1 + \frac{0.2}{2}\right) \times 0.65$ respectively. The probability $P(C_1)$ and $P(C_2)$ are computed via a similar strategy, which lead the three levels tree from the example of Figure 4 to the Output vector $\mathcal{O}(N,i) = [0.52,\ 0.13,\ 0,\ 0,\ 0.175,\ 0.175]$.

The behavior described above is denoted as *recalculate probabilities* in Algorithm 1. It goes along with the *not here* mechanisms, making them powerful tools for tree-CNNs as will be validated in the experiment section.

3 ADAPTING A NORM FOR ROBUST SEMANTIC PREDICTION

While it can be taken for granted, that through explicit structural definition and the availability of interim results, modularization in form of tree-CNNs simplifies interpretability and facilitates error traceability, the implications of the approach on model robustness or semantic accuracy necessitate further investigation. The standard accuracy is quite often misleading in class sets with a semantic distance. To elaborate this point, consider e. g. the obstacle detection system of an autonomous vehicle. In this case, it is of less importance for such a system to be able to accurately tell apart *men* and *woman* than it is to reliably distinguish between *humans* and e. g. *road signs.* We denote this as predictive conceptual proximity and discuss below, how to measure it by an appropriate norm.

We first measure the semantic accuracy at each level by modifying the semantic distance – a metric – as defined by (Fergus et al., 2010).

$$S_{i,j} = \frac{\text{intersect}\left(\text{path}(i), \text{path}(j)\right)}{\max\left(\text{length}(\text{path}(i)), \text{length}(\text{path}(j))\right)}$$

In the definition taken from (Fergus et al., 2010) the semantic distance $S_{i,j}$ between classes i and j – which are leaves in the tree – is defined as the number of nodes shared by their two parent branches, divided by the length of the longest of the two branches. Therefore, path(i) is the path from the root node to the i-th node in a hierarchical label structure given by the nodes, whereas intersect gives the number of shared nodes. Thus, we have $0 < S_{i,j} \leq 1$, with 1 in case of an identical object and 0 as lower limit for two completely different objects.

Taking this as an initial concept, we now use this semantic distance as weight factor for errors performed by a model on a test set

$\mathcal{D} = \{(x_i, y_i) \,|\, i = 1, \dots, I\}$ to define the semantic accuracy$_p$ (sac$_p$):

$$\text{sac}_p = \frac{1}{n} \sum_{k=1}^{n} \left(\frac{S_{y_k, M(x_k)} - S_{\min}}{1 - S_{\min}} \right)^p \qquad (1)$$
$$\text{with } S_{\min} = \min_{i,j} S_{i,j}$$

If a model is 100% accurate, then the semantic accuracy$_p$ (sac$_p$) and the common accuracy are both 1. In any other case the semantic accuracy$_p$ will provide a more detailed description how robust the prediction is. In the example shown in Figure 1, $S_{\min}$ is $\frac{1}{4}$. Thus, the transformation leads again to the fact that a model, which would always predict the maximum distance class, will achieve a semantic accuracy$_p$ of zero. Like for the common p-norms, the value of p smooths or sharps the measurement. With this semantic accuracy$_p$ we now have a tool to compare different models regarding their robustness.

4 EXPERIMENTS AND ANALYSIS

In this section, we demonstrate the benefits of our method on hierarchical image classification datasets in a continual learning setup.

4.1 Dataset and Baselines

Some problems arise, when a dataset is unbalanced and comes along with a descent size. Consequently, many challenges can not be recognized in practice on datasets like CIFAR100 or MNIST. Hence, we conduct experiments on a split of the popular ImageNet, which is a more challenging and real world related datasets in comparison to common CL benchmarks like CIFAR or MNIST. Our split of ImageNet is generated as shown in Figure 1, representing 152 GB of images, which leads to a three level hierarchy consisting of twelve tasks presented to the CL models in the alphabetical order. Each class in level 3 (represented in red) – except the *not here* class – contain data of all its child classes in the ImageNet hierarchy. The resulting database is therefore unbalanced and contains for example more images regarding animals than food.

We compare our method against different baselines; first of all the elastic weight consolidation (EWC) (Kirkpatrick et al., 2017), which is a standard comparative baseline in CL research. The second baseline we compare with is the original tree-based incremental learning approach (Roy et al., 2020), which uses CIFAR as dataset. Beyond this, we provide an – in a way – upper-bound model, which learns on all the tasks jointly, that is by accessing training data at once in a traditional way. We refer to this model as the monolithic model.

4.2 Model and Training

The starting point for our models are NASNetMobile (Zoph et al., 2018) and NASNetLarge (Zoph et al., 2018). For both, we start with the weights trained on the whole ImageNet and adjust them on our sub-set of ImageNet. The EWC CL model in our setup is built by applying EWC to the NASNetLarge architecture with some modifications mentioned later on. The monolithic model as well is trained using the NASNetLarge network. For both tree-CNNs each of the 13 nodes contains a NASNetMobile version, which is trained for 15 epochs using a batch size of 256.

In summary, there are four big models, two based on NASNetLarge (EWC and monolithic) and two based on 13 NASNetMobile (original Tree-CNN and eTree-CNN). Table 2 indicates, that the full tree with 13 models of the size of NASNetMobile has still fewer degrees of freedom than the NASNetLarge network, which makes it cheaper to train and memory efficiently.

One aspect regrading the tree-CNN approaches, which is worth mentioning, is the fact that in higher levels the number of training examples shrink. Therefore, training these nodes relies more on reusing the weights from the next abstract level and carefully choosing optimisation parameters like the learning rate. Otherwise, one may face some kind of overfitting.

4.3 Evaluation

We use two metrics to evaluate continual learning algorithms in hierarchical datasets. The first one is the all-important average classification accuracy as defined in (Chaudhry et al., 2018). More specifically, after training on task t the reported accuracy is the average accuracy obtained from testing on task $1, \dots, t$. The second metric is the semantic accuracy as defined in Section 3.

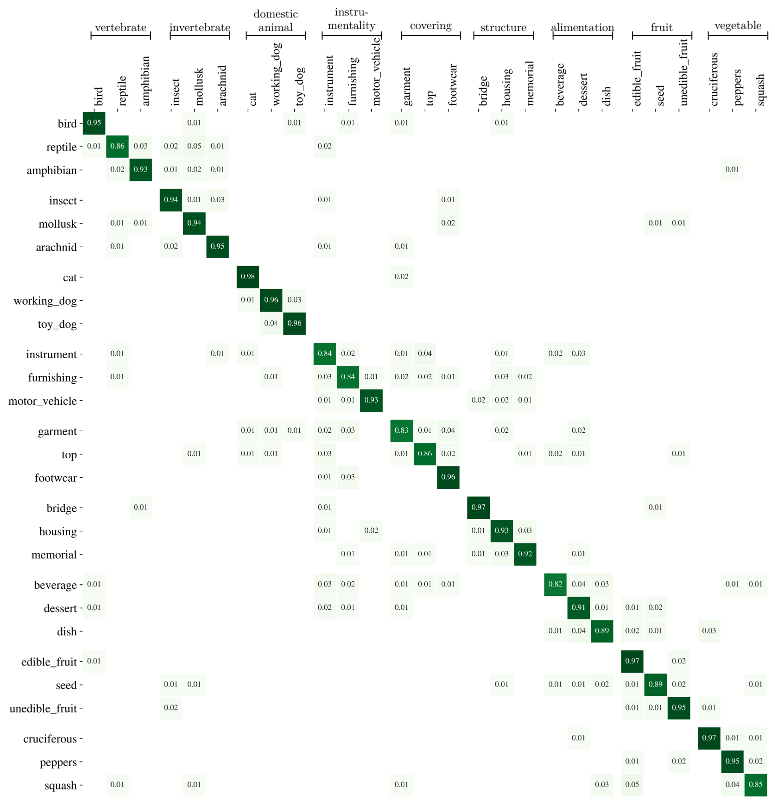


Figure 5: Results of eTree-CNN displayed in a confusion matrix with sub-sets of the different abstraction levels

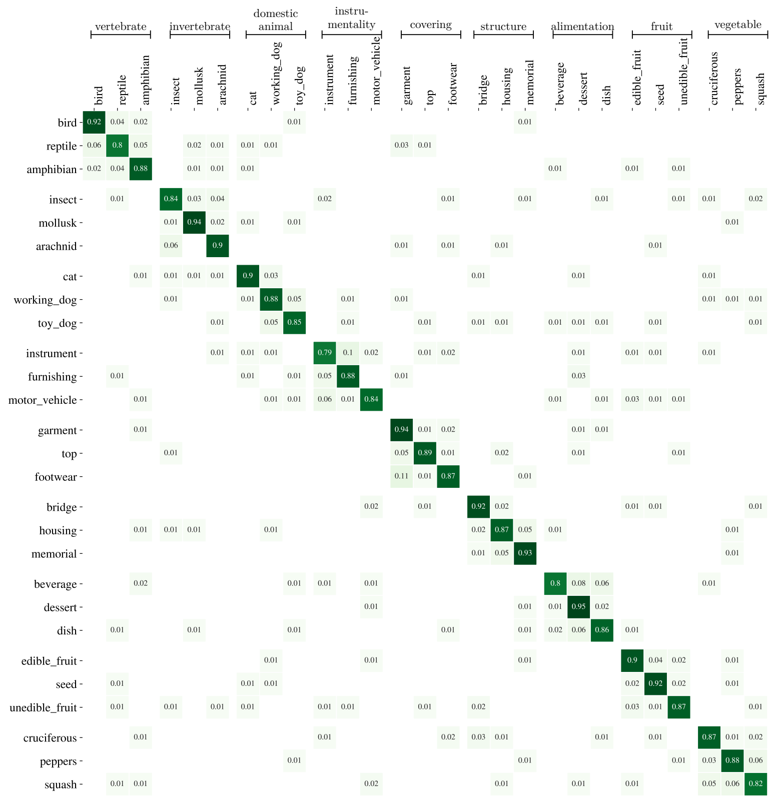


Figure 6: Results of EWC displayed in a confusion matrix with sub-sets of the different abstraction levels

Table 1: Achieved accuracy for different approaches with continual learning (CL) and a completely trained reference value (without CL).

Norm	**EWC with CL**	**Tree-CNN with CL**	**Enhanced Tree-CNN with CL**	**Monolithic without CL**
(Level 3) accuracy	0.869 (90.5%)	0.890 (92.7%)	0.917 (95.4%)	0.960 (100%)
Level 2 accuracy	0.898 (92.3%)	0.927 (95.3%)	0.944 (97.0%)	0.973 (100%)
Level 1 accuracy	0.923 (93.5%)	0.952 (96.5%)	0.976 (98.9%)	0.987 (100%)
semantic accuracy$_1$	0.637 (79.4%)	0.681 (84.9%)	0.709 (88.4%)	0.802 (100%)
semantic accuracy$_2$	0.621 (87.5%)	0.653 (92.0%)	0.670 (94.4%)	0.71 (100%)

Table 2: Total degrees of freedom to be trained for different models

Methods	Model	Total DoF
eTree-CNN	NASNetMobile ×13	57.2 Mio
Tree-CNN	NASNetMobile ×13	57.2 Mio
EWC	NASNetLarge ×1	85.4 Mio
Monolithic	NASNetLarge ×1	85.4 Mio

4.4 Results and Analysis

Table 1 reports the accuracy of all four methods in different flavors. The first and second level accuracy presents the average classification accuracy – as defined in Section 4.3 – after training on $\mathcal{L}^1$ and $\mathcal{L}^2$ tasks respectively. The accuracy on $\mathcal{L}^3$ outlines a similar effect, however, since it is the last level in the hierarchy, it represents the same value as the overall model accuracy as such. In papers dealing with ImageNet, this is often denoted as Top-1-Accuracy. The last row of Table 1 provides results for the semantic accuracy defined in Section 3. Moreover, the last column shows results for the monolithic model, which is trained without the need of CL, therefore accessing all training data at once. We use this as an upper-bound reference model and provide percentage values for all other models compared to this one.

Figures 5 and 6 visualize the confusion matrices for enhanced Tree-CNN (eTree-CNN) and the EWC approach after training on all tasks. They provide further insides on how the misclassifications are finally distributed. Overall, the results indicate that all CL methods were capable to learn the multiple ImageNet tasks in sequence without forgetting. Consistently, we see that eTree-CNN is able to perform the results closest to the upper boundary given by the monolithic model by maintaining high performance on all previously learned tasks throughout learning later tasks. Furthermore, we observed that both tree-CNN approaches perform well regarding their robustness and semantic accuracy. In general, for all norms, the setback approach has proven to be helpful. Interestingly, as can be seen in Table 1, sac_2 reflects more or less the same relative behavior as the common accuracy. On one hand, it turned out, that higher p values are not more suitable to measure semantic accuracy than the common accuracy. On the other hand, lower p (here sac_1) are sensible to measure these changes. Using this norm, the differences between Tree-CNN, eTree-CNN and EWC regarding semantic accuracy are better emphasized. Over all of these different norms and derived metrics, one can see the advantage of the tree-models compared to EWC. While the difference on level 1 between the reference model and the eTree-CNN is about 1%, it is more than 6% for the EWC and over 3% for Tree-CNN. This is even worse for sac_1, which is more sensitive regarding errors performed outside the hierarchy structures. It delivers about 20%, 15%, 12% difference towards the reference model and EWC, Tree-CNN and eTree-CNN respectively.

A conclusion that can be taken from Table 1 is that our eTree-CNN outperforms all baselines significantly in terms of average accuracy and semantic distance, whereas Tree-CNN by (Roy et al., 2020) performs superior to EWC. However, it is worth noting that these superior results for both tree-CNN approaches come along with a limitation EWC does not contain. In fact, to use the Tree-CNNs, a dataset exhibiting a hierarchy structure is needed, while EWC can be applied on any dataset.

Moreover, we can observe in Figure 6 (EWC confusion matrix), that although the errors are mainly distributed within the level 2 hierarchy, the confusion matrix, however it is less sparse compared to eTree-CNN shown in Figure 5. This is due to the fact, that in ImageNet a lot of pictures contain patterns of more than one category, which makes the CL problem more challenging compared to standard CL benchmarks like MNIST or CIFAR. Some of such test samples containing more than one category can be seen in Figure 2, for example animal and food (2a) or animal and structure (2b). In such situations, our setback mechanism as described earlier allows eTree-CNN to still produce strong results at differentiating past tasks and current tasks (where structure of past task might appear).

An empirical conclusion, that can be made out of this is, that eTree-CNN consistently performs better than all other methods, partially thanks to the way it rescues some misclassification occurred mostly due to duplicate structure in the test sample. The idea of empowering the model with a setback mechanism along its recalculated probability tool seems to be working well with complex data-sets like ImageNet given directions for forthcoming work, where eTree-CNN can be extended to other real-world applications of CNNs.

5 CONCLUSION

We proposed eTree-CNN, a new tree-based continual learning method for overcoming catastrophic forgetting. A concept of stepbacks was introduced, which routes back to previous levels when evaluating the tree, to correct a possible misclassification. Using a suggested benchmark based on ImangeNet, the proposed approach provides higher accuracy and robustness compared to other continual learning methods. Moreover, it is cheaper to train and consumes much less memory than monolithic approaches.

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