Learning Task-specific Activation Functions using Genetic Programming

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Keywords: Deep Neural Networks, Activation Functions, Genetic Programming.

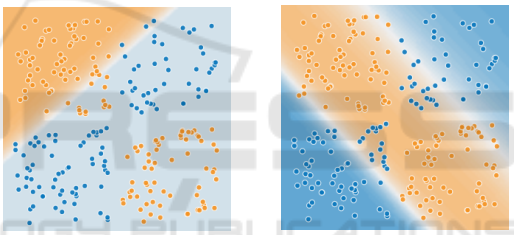
Abstract: Deep Neural Networks have been shown to be beneficial for a variety of tasks, in particular allowing for end-to-end learning and reducing the requirement for manual design decisions. However, still many parameters have to be chosen manually in advance, also raising the need to optimize them. One important, but often ignored parameter is the selection of a proper activation function. In this paper, we tackle this problem by learning task-specific activation functions by using ideas from genetic programming. We propose to construct piece-wise activation functions (for the negative and the positive part) and introduce new genetic operators to combine functions in a more efficient way. The experimental results for multi-class classification demonstrate that for different tasks specific activation functions are learned, also outperforming widely used generic baselines.

1 INTRODUCTION

Deep Neural Networks (DNNs) (Goodfellow et al., 2016; LeCun et al., 2015) have recently become popular and are now successfully applied for a wide range of applications. However, since increasingly more complex and deeper networks are of interest, strategies are required to make neural network training efficient and stable. While initialization (e.g., (Sutskever et al., 2013; Mishkin and Matas, 2017)) and normalization techniques (e.g., (Laurent et al., 2016)) are well studied, a relevant and important factor is often neglected: the role of activation functions (AF).

This is illustrated Figure 1, where we show the results of a simple experiment on a 2D dataset representing the XOR-problem. In particular, we trained a simple neural network with only one hidden layer consisting of only one neuron. It can be seen from Figure 1a that using a Rectified Linear Unit (`ReLU`) as Activation Function (AF), even this simple problem cannot be solved. In contrast, as shown in Figure 1b, using a more complex activation function such as obtained by our approach we get a significantly better result.

Even though recent work demonstrated that AFs are of high relevance (Klambauer et al., 2017; Ramachandran et al., 2018; Clevert et al., 2016; Elfwing et al., 2018; Glorot et al., 2011; Gulcehre et al., 2016)), due to its simplicity and reliability most deep learning approaches use Rectified Linear Units



(a) `ReLU`. (b) Our approach.

Figure 1: Importance of activation functions: Using `ReLU` even a simple problem like XOR-problem cannot be solved, whereas our approach yields a meaningful solution.

(`ReLU`) (Nair and Hinton, 2010).

Due to their universal approximation properties, the research in this field was concentrated on squashing functions such as `Sigmoid` and `Tanh` (Hornik, 1991). However, training DNNs using such functions suffers from the vanishing gradient problem (Hochreiter, 1998). To overcome this problem, various non-squashing functions were introduced, where the most notable one is (`ReLU`). In particular, as the derivative of positive inputs in `ReLU` is one, the gradient cannot vanish. In contrast, as all negative values are mapped to zero, there is no information flow in DNNs for negative values, which is known as dying `ReLU`.

To deal with this problem, various generalizations of `ReLU` such `Leaky ReLU` (Maas et al., 2013) have been proposed. Similarly, Exponential Linear Units (`ELU`) (Clevert et al., 2016) do not only elimi-

Basirat, M. and Roth, P.
Learning Task-specific Activation Functions using Genetic Programming.
DOI: 10.5220/0007408205330540
In *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2019)*, pages 533-540
ISBN: 978-989-758-354-4

nate the bias shift in the succeeding layers, but also push the mean activation value towards zero by returning a bounded exponential value for negative inputs. Although showing competitive results, ELU is not backed by a very strong theory. A theoretically proven extension, Scaled Exponentiation Linear Unites (SeLU) (Klambauer et al., 2017), makes DNN learning more robust. In fact, it is shown that the proposed self-normalizing network converges towards a normal distribution with zero mean and unit variance.

Another direction was pursued in (Ramachandran et al., 2018), finally introducing Swish. Different search spaces are created by varying the number of core units used to construct the AF. In addition, an RNN is trained to search the state space for a novel AF. The proposed approach shows competitive results for both shallow and deep neural networks, however, Swish was not found by the approach but was already included in the initial set of candidate solutions. Recently, a theoretic justification for the design has been given in (Hayou et al., 2018), showing that Swish propagates information better than ReLU. Moreover, (Pennington et al., 2018) showed that Swish along with orthogonal initialization provides a dynamical isometry, which allows for faster learning. Thus, existing approaches to estimate AFs are lacking theoretical foundation, are based on complex theory, which is hard to understand in the context of practical applications, or are based on inefficient search schemes, which still require to manually set several parameters.

To overcome these problems and to avoid the need for prior information (as in the case of Swish), we propose an approach based on ideas of Genetic Programming (GP) (Mitchell, 1996) to learn efficient activation functions better suited for a specific task. In particular, building on neuro-evolutionary algorithms (Schaffer et al., 1992), starting from simple initial AFs, more complex functions can be estimated. In particular, we define a set of piece-wise functions and combine them over several iterations based on their ability to solve a specific problem. For that purpose, we define new genetic operators, namely *Hybrid Crossover* and *Hybrid Mutation*, allowing us to explore the specific search space (i.e., functions and operators) in an efficient way.

To demonstrate the benefits of our approach, we apply it for image classification problems. We show that, compared to commonly used baselines, using the learned AFs we can obtain better classification results for the CIFAR-10 and CIFAR-100 benchmark datasets. In addition, we demonstrate that for different tasks different AFs are learned, better representing the characteristics of the problems.

The remainder of the paper is structured as follows: First, in Sec. 2, we discuss the related work in the context of GP for Neural Networks. Next, in Sec. 3, we introduce our new neuro-evolutionary algorithm for learning task-specific AFs. Then, in Sec. 4, we give an experimental evaluation of our approach and discuss the findings. Finally, in Sec. 5 we summarize and conclude our work.

2 RELATED WORK

Neuroevolution, i.e., applying evolutionary algorithms (EAs) in the optimization of DNNs (Whitley, 2001), is a vital field of research. In general, there are two main directions. First, optimizing training parameters such as hyper-parameters (Loshchilov and Hutter, 2016) or weights (Montana and Davis, 1989; Igel, 2003). In the latter case, in contrast to methods like gradient descent, also global optima can be estimated. Second, evolving an optimal DNN topology, which, however, is not straightforward. Therefore, existing approaches follow two strategies: constructive (Qiang et al., 2010) and destructive (Hancock, 1992). Constructive methods start from a simple topology and gradually increase the complexity until an optimality criterion is satisfied. In contrast, destructive approaches start from an initially complex topology and incrementally reduce the unnecessary structures.

Recently, co-evolution of topology and weights (TWEANNs) has shown to be more effective and efficient, where the most successful approach is NEAT (Stanley and Miikkulainen, 2002). NEAT follows the constructive strategy and gradually evolves a simple DNN topology towards unbounded complexity by adding nodes and connections between them while preserving the optimality of topology. Thus, there have been several extensions of NEAT. For instance, in (Miikkulainen et al., 2017) two extensions, DeepNEAT and CoDeepNEAT, have been proposed. In contrast to NEAT, in DeepNEAT a node represents a layer and consists of a table of hyper-parameters (i.e., number of neurons) related to it. In CoDeepNEAT, two populations (modules and blueprints) are initialized separately, where a module is a graph and represents a shallow DNN. A blueprint has also a graph structure and consists of nodes pointing out to specific module species. Both modules and blueprints evolve in parallel. Finally, the modules and blueprints are combined to build the topology of the DNN.

Similarly, (Suganuma et al., 2017) explored a CNN architecture via Cartesian GP (CGP) for image classification, where also high-level functions such as convolution or pooling operations are implemented.

Recently, (Liu et al., 2018) proposed a constructive hierarchical genetic representation approach for evolving DNN topologies. Initialized with small populations of primitives such as convolutional and pooling operations at the bottom of the hierarchy, the topology gets more and more complex by adding evolved primitives into a graph structure.

Even though there has been drawn a lot of attention to TWEANNs, evolving AFs was only of limited interest so far. The idea closest to ours is HA-NEAT (Hagg et al., 2017). HA-NEAT (Hagg et al., 2017) extends NEAT to evolve AFs of neurons, topology, and weights, resulting in a heterogeneous network. In contrast, we fix the topology and evolve piece-wise AFs on layer level. The proposed candidate solutions are more complicated (advanced) than those of HA-NEAT. More importantly, the complexity of evolved AFs is, in contrast to HA-NEAT, unbounded. Moreover, we can evolve our approach also along with topology.

3 EVOLVING PIECE-WISE ACTIVATION FUNCTIONS

The goal of this work is to estimate non-linear AFs better suited for specific tasks. To this end, we build on two ideas. First, as negative and positive inputs have a different influence on learning, we propose to use piece-wise AFs (i.e., separately defined positive and negative parts). Second, as the search space can be very large, we propose to build on the ideas of Genetic Programming to allow for a more efficient search.

3.1 Genetic Programming

Genetic Programming (GP) (e.g., (De Jong, 2006)), can be seen a population-based meta-heuristic to solve problems in the field of stochastic optimization. In particular, we are given a large set of candidate solutions, referred to as *population*, but we do not know how to estimate the optimal solution for the given task. The main idea to overcome this problem is to evolve a population towards a better solution.

The evolution typically starts from a population consisting of randomly selected candidate solutions, called *individuals*. These are described by a set of properties (*gens*), which can be altered by three bio-inspired operations: (a) *selection*, (b) *crossover*, and (c) *mutation*. Selection is the simple process of selecting individuals according to their fitness. In contrast, crossover is a stochastic operator, exchanging information between two individuals (often called *parents*: *mom* and *dad*) to form a new offspring. Similarly, mutation is also a stochastic operator, helping to increase the diversity of the population by randomly choosing one or more genes in an offspring and changing them.

Then, in an iterative process, where we refer an iteration to as *generation*, each individual is evaluated and based on their fitness, we select a set of parents solutions for breeding. Subsequently, we apply breeding operators on pairs of individuals to generate new pairs of offsprings. Eventually, we update the population with the set of parents and bred offsprings. This process is repeated until a pre-defined number of generations or a pre-defined optimality criterion is met.

3.2 Breeding Operators

Targeting to evolve piece-wise AFs, each individual in our population represents an AF, where a gene is either the left or the right part of an AF (see Figure 2).

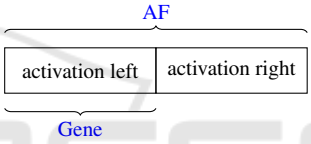


Figure 2: An individual in the population of our GP.

To evolve AFs as described above, we introduce new operators representing our specific problem.

3.2.1 Inheritance Crossover

The *Inheritance Crossover* operator inherits genes from both parents. The first (second) offspring inherits its left AF from the mom (dad), and its right AF from the dad (mom). This way, the operator resembles a one-point crossover operator. However, as we are dealing with piece-wise functions the cutoff point is pre-determined. This is illustrated in Figure 3.

(a) Offspring 1 (b) Offspring 2

Figure 3: Inheritance Crossover.

3.2.2 Mutation Operator

The *Mutation* operator randomly chooses a gene and then replaces it with a randomly selected pre-defined AF. In fact, this helps our approach to further explore the search space for new AFs. This is illustrated in Figure 4.

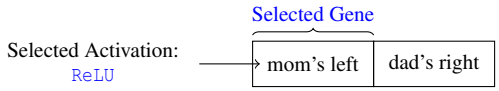


Figure 4: Mutation operator.

3.2.3 Hybrid Crossover

To combine multiple AFs, we additionally introduce the *Hybrid Crossover* operator. As for Inheritance Crossover, the cutoff point is fixed. Using a randomly selected mathematical operator, the first (second) offspring combines mom's and dad's (dad's and mom's) negative part of the AF to form its own negative part. Subsequently, the first (second) offspring's positive part of the AF is formed via a combination of mom's and dad's (dad's and mom's) positive part, as illustrated in Figure 5.

op_1 : mom's left : dad's left	op_2 : mom's right : dad's right

(a) Offspring 1

op_1 : dad's left : mom's left	op_2 : dad's right : mom's right

(b) Offspring 2

Figure 5: Hybrid Crossover operator, where op_1 and op_2 are chosen randomly.

3.2.4 Hybrid Mutation Operator

The *Hybrid Mutation* operator helps our approach to discover any possible combination of AFs. Thus, it first picks two random pre-defined AFs and combines them with a random operator. Then it replaces a randomly chosen gene with newly the generated AF.

3.3 Evaluating of Activation Functions

The Hybrid crossover operator generates hybrid AFs, that we evaluate by parsing according to the following grammar:

$$\begin{aligned} \textit{expression} &:= f \mid (\textit{operation} : \textit{expression} : \textit{expression}) \\ \textit{operation} &:= + \mid - \mid \times \mid / \mid \min \mid \max \\ f &:= \texttt{HardSigmoid} \mid \texttt{Sigmoid} \mid \texttt{ELU} \mid \\ &\quad \texttt{Linear} \mid \texttt{ReLU} \mid \texttt{SeLU} \mid \texttt{Softplus} \mid \ldots \end{aligned} \tag{1}$$

where f represents the set of candidate solutions. The list is not fixed, and we can easily add additional *operations* and candidate solutions f.

Example: Given an AF generated by Hybrid crossover:

$$(\times : \texttt{Softplus} : \texttt{ELU})\,.$$

To compute the equivalent infix expression, we use (1) and parse above AF, as shown in Figure 6:

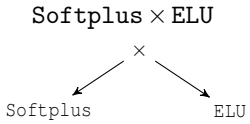


Figure 6: The parse tree of `Softplus` × `ELU`.

3.4 Learning Activation Functions

After defining the genetic operators and explaining the function evolution, we can describe our approach as summarized in Algorithm 1. Initially, we generate a population of random AFs (line 3). Next, by using the evaluate operator (line 4) the fitness of each AF is determined according to the classification performance on an independent test set. Then, our approach selects a set of parent AFs based on their fitness for breeding (line 7). To generate new AFs (line 11), we first apply the Crossover operators and then the Mutation operator as defined in Sec. 3.2. When applying the Crossover operator we stochastically choose between Inheritance and Hybrid as shown in Algorithm 2. Similarly, we update our population with the set of parents and bred offsprings. This procedure is iterated until a pre-defined optimality criterion is met.

Algorithm 1: GP.

```
1:  procedure GP(population-size)
2:      population ← ∅
3:      population ← INITIALIZE(population-size)
4:      EVALUATE(population)
5:      repeat
6:          children ← ∅
7:          parents ← SELECT(population, 30%)
8:          for i ≤ (population-size − |parents|)/2 do
9:              increment i by one
10:             ⟨mom, dad⟩ ∈ parents × parents
11:             offsprings ← CROSSOVER(mom, dad)
12:             for offspring ∈ offsprings do
13:                 offspring ← MUTATE(offspring)
14:             EVALUATE(offsprings)
15:             children ← children ∪ offsprings
16:         population ← parents ∪ children
17:     until termination condition
18:     return population
```

Algorithm 2.

```
1: procedure CROSSOVER(mom, dad)
2:     c ← toss a coin
3:     if c is heads then
4:         return INHERITANCE(mom, dad)
5:     return HYBRID(mom, dad)
```

4 EXPERIMENTAL RESULTS

To demonstrate the benefits of our approach, in Sec. 4.3, we apply the approach for two real-world benchmark datasets of different complexity, namely CIFAR-10[1] and CIFAR-100[1]. This way, we are also able to show that for different tasks different choices of AFs are meaningful. Moreover, to demonstrate the generality of the evolved AFs, we apply them to different architectures (i.e., ResNet (He et al., 2016) vs. VGG (Simonyan and Zisserman, 2015)). In addition, we give a baseline comparison to a random search for learning AFs in Sec. 4.2. For all experiments, we used the same experimental setup, which we describe in Sec. 4.1.

4.1 Experimental Setup and Implementation Details

Similar to (Ramachandran et al., 2018), we run our approach on shallow architectures (i.e., ResNet20). Then we use the learned AFs to train deeper networks (i.e., Resnet56). Moreover, to demonstrate that the learned functions are of general interest, we use them to train classifiers using the VGG-16 architecture. To this end, we used the default parameters for both architectures. To avoid random effects, all networks have been initialized using the same initialization (He et al., 2015). Our implementation of evolutionary learning builds on DeepEvolve[2], a neuroevolution framework developed to explore the optimal DNN topology for a given task. In our case, we fixed the DNN topology and defined the search-space based on the AFs. Throughout all experiments[3], we used a population size of 30 and evolved the population over 18 generations. The considered candidates for the initial population are shown in Table 1.

4.2 Random Search

First of all, we demonstrate the benefits of using a GP-based approach compared using a simple Random Search (RS). To this end, we run our approach as described in Section 4.1. For RS, we initially generate randomly selected AFs and consider them as "best solution". Then, randomly (by tossing a coin) we run either one of the following steps: (1) Combine two random AFs with a random operator for both parts of the AF and evaluate the whole AF based on the DNN performance on the independent test dataset. (2) Just two random AFs are selected for both parts. The evaluation is carried out as before. If the performance in any of the cases is better than that of the "best solution", we update the best one. Similarly, as in our approach, this process is repeated until a predefined number of iterations or a pre-defined optimality criterion is met. In both cases, we used a ResNet-20 as underlying network architecture.

Table 1: Candidate activation functions, where $y(x<0)$ and $y(x\geq 0)$ indicate the (left and right) part, respectively.

Function	Expression
`ReLU`	$y(x) = \max(x, 0)$
`ELU`	$y(x) = \begin{cases} e^x - 1 & x < 0 \\ x & x \geq 0 \end{cases}$
`SeLU`	$y(x) = \begin{cases} \lambda\alpha(e^x - 1) & x < 0 \\ \lambda x & x \geq 0 \end{cases}$
`Softplus`	$y(x) = \ln(1 + e^x)$
`HardSigmoid`	$y(x) = \max(0, \min(1, (x+1)/2))$
`Sigmoid`	$y(x) = 1/(1 + e^{-x})$
`Linear`	$y(x) = x$

The obtained results for our approach and for RS are given in Table 2 and Table 3, respectively. In addition, we give a comparison to three different widely used baselines, namely `ReLU`, `ELU`, and `SeLU`, and `Swish`, which has proven to work well on a variety of tasks. The results do not only demonstrate that our GP-based approach yields better solutions for the final classification problem, but also that the solutions are more stable! In fact, using RS also a few well-performing functions can be found by chance. However, since the search space is rather large, this is not very likely in practice; in particular, when the number of candidate solutions and possible mathematical operators is further increased.

4.3 CIFAR-10 and CIFAR-100

Next, we demonstrate our approach for the CIFAR-10 benchmark dataset. Again, we evolved a set of candidate AFs using our GP-based approach using ResNet-20 and used the evolved AFs to learn a classifier based on ResNet-56. The thus obtained results in terms of classification accuracy for the best performing solutions (also compared to the baselines) are shown in Table 4. It can be seen that the best results are obtained using the multiplication of `Softplus` and `ELU` in negative part and `HardSigmoid` and `Linear` in positive part (93.00%). For better understanding, we also illustrate the top 5 AFs plus `Swish` in Figure 7.

[1] https://www.cs.toronto.edu/ kriz/cifar.html

[2] https://github.com/jliphard/DeepEvolve

[3] The experiments were carried out on a standard PC (Core-i7, 64GB RAM) with two Titan-X GPUs attached.

Table 2: Performance of top 5 evolved AFs for CIFAR-10 obtained using ResNet-20.

	Accuracy	Activation Function
1.	79.24%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{ELU}$
2.	78.46%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \max(\texttt{ReLU}, \texttt{SeLU})$
3.	78.39%	$y(x<0) = \texttt{Sigmoid} \times \texttt{SeLU}$ and $y(x \geq 0) = \min(\texttt{Linear}, \texttt{ELU})$
4.	77.72%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{HardSigmoid} \times \texttt{Linear}$
5.	77.08%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{Sigmoid} \times \texttt{ReLU}$
6.	78.51%	$y(x) = \texttt{Swish}$
7.	73.00%	$y(x) = \texttt{ELU}$
8.	71.98%	$y(x) = \texttt{ReLU}$
9.	65.79%	$y(x) = \texttt{SeLU}$

Table 3: Perfromance of top 5 AFs found by Random Search on CIFAR-10 obtained using ResNet-20.

	Accuracy	Activation Function
1.	76.03%	$y(x<0) = \texttt{SeLU} \times \texttt{Sigmoid}$ and $y(x \geq 0) = \texttt{Sigmoid} \times \texttt{Linear}$
2.	74.35%	$y(x<0) = \texttt{HardSigmoid}$ and $y(x \geq 0) = \texttt{HardSigmoid}$
3.	72.40%	$y(x<0) = (\texttt{ELU} - \texttt{HardSigmoid})$ and $y(x \geq 0) = (\texttt{HardSigmoid} - \texttt{Linear})$
4.	62.58%	$y(x<0) = (\texttt{Linear} - \texttt{ReLU})$ and $y(x \geq 0) = (\texttt{Sigmoid} - \texttt{Sigmoid})$
5.	51.65%	$y(x<0) = \texttt{HardSigmoid}$ and $y(x \geq 0) = \texttt{Sigmoid}$

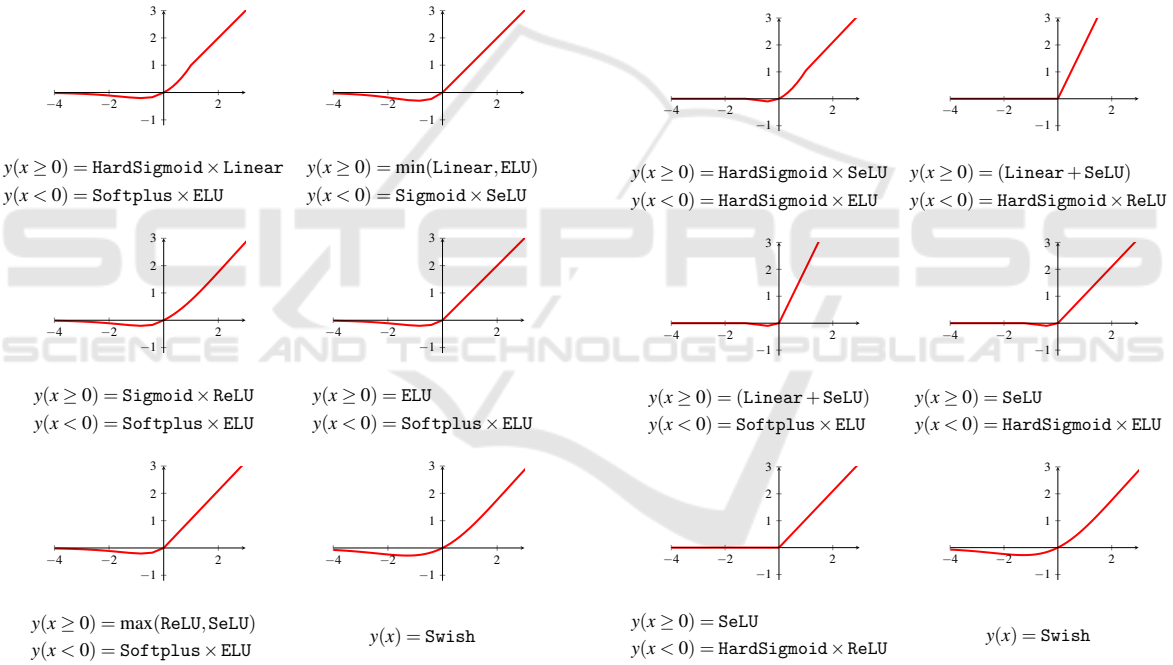


Figure 7: Top 5 evolved AFs plus `Swish` for CIFAR-10.

Figure 8: Top 5 evolded AFs plus `Swish` for CIFAR-100.

Next, we run the same experiment using the VGG-16 framework and show the results in Table 5. Even though the AFs have not been trained for this architecture, we get competitive results. Similarly, we get the best results again using the multiplication of `Softplus` and `ELU` in negative part and `HardSigmoid` and `Linear` in positive part (93.43%). These results clearly show, that not only similar functions are evolved, but that the results are competitive and outperforming the baseline in most cases.

Finally, we run experiments on CIFAR-100, where the results for ResNet-56 and VGG-16 are shown in Table 6 and Table 7, respectively. It can be seen that the multiplication of `ELU` and `HardSigmoid` in negative part and `SeLU` and `HardSigmoid` in positive part (73.84%) gives the best results for ResNet56. For VGG, the AF consisting of multiplication of `HardSigmoid` and `ReLU` in the negative part and `SeLU` in the positive part (71.36%) yields the best results. Again, the top 5 AFs compared to `Swish` are illustrated in Figure 8. It can also be seen that compared to CIFAR-10 the shapes of the evolved AFs are different!

Table 4: Performance of top 5 evolved activation functions for CIFAR-10 based on ResNet-56.

	Accuracy	Activation Function
1.	93.00%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{HardSigmoid} \times \texttt{Linear}$
2.	92.87%	$y(x<0) = \texttt{Sigmoid} \times \texttt{SeLU}$ and $y(x \geq 0) = \min(\texttt{Linear}, \texttt{ELU})$
3.	92.66%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{Sigmoid} \times \texttt{ReLU}$
4.	92.38%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{ELU}$
5.	92.27%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \max(\texttt{ReLU}, \texttt{SeLU})$
6.	92.43%	$y(x) = \texttt{ReLU}$
7.	91.45%	$y(x) = \texttt{ELU}$
8.	91.43%	$y(x) = \texttt{SeLU}$
6.	92.83%	$y(x) = \texttt{Swish}$

Table 5: Performance of top 5 evolved AFs for Cifar10-VGG16.

	Accuracy	Activation Function
1.	93.43%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{HardSigmoid} \times \texttt{Linear}$
2.	93.32%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{ELU}$
3.	93.18%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \max(\texttt{ReLU}, \texttt{SeLU})$
4.	93.14%	$y(x<0) = \texttt{Sigmoid} \times \texttt{SeLU}$ and $y(x \geq 0) = \min(\texttt{Linear}, \texttt{ELU})$
5.	92.89%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{Sigmoid} \times \texttt{ReLU}$
6.	93.00%	$y(x) = \texttt{ReLU}$
7.	92.60%	$y(x) = \texttt{ELU}$
8.	92.88%	$y(x) = \texttt{SeLU}$
9.	93.00%	$y(x) = \texttt{Swish}$

Table 6: Performance of top 5 evolved AFs for Cifar100-Resnet-56.

	Accuracy	Activation Function
1.	73.84%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{HardSigmoid} \times \texttt{SeLU}$
2.	73.81%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ReLU}$ and $y(x \geq 0) = \texttt{SeLU} + \texttt{Linear}$
3.	73.77%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{SeLU} + \texttt{Linear}$
4.	73.52%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{SeLU}$
5.	73.12%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ReLU}$ and $y(x \geq 0) = \texttt{SeLU}$
5.	73.31%	$y(x) = \texttt{ReLU}$
6.	72.58%	$y(x) = \texttt{ELU}$
7.	71.57%	$y(x) = \texttt{SeLU}$
8.	73.98%	$y(x) = \texttt{Swish}$

Table 7: Performance of top 5 evolved AFs for Cifar100-VGG16.

	Accuracy	Activation Function
1.	71.36%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ReLU}$ and $y(x \geq 0) = \texttt{SeLU}$
2.	71.28%	$y(x<0) = \texttt{Softplus} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{SeLU} + \texttt{Linear}$
3.	70.95%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ReLU}$ and $y(x \geq 0) = \texttt{SeLU} + \texttt{Linear}$
4.	70.22%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{HardSigmoid} \times \texttt{SeLU}$
5.	70.19%	$y(x<0) = \texttt{HardSigmoid} \times \texttt{ELU}$ and $y(x \geq 0) = \texttt{SeLU}$
5.	70.74%	$y(x) = \texttt{ReLU}$
6.	71.12%	$y(x) = \texttt{ELU}$
7.	70.59%	$y(x) = \texttt{SeLU}$
8.	71.23%	$y(x) = \texttt{Swish}$

5 CONCLUSION

Even though deep learning approaches allow end-to-end learning for a variety of applications, there are still many parameters which need to be manually set. An important parameter, which is often ignored, is the choice of AFs. Thus, we tackled this problem and studied the importance of AFs when learning DNNs for classification. In particular, we introduced a GP-based evolving procedure to learn the best AF for a given task. The presented results did not only show competitive results but also that for different tasks different AFs are learned. In contrast to random sampling, our approach guarantees that meaningful and

competitive AFs are found. This is remarkable as only very basic candidate solutions are provided (in contrast to, e.g., `Swish`). Moreover, our approach is adapting very well to different kinds of problems.

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