

# GA-based Training-Free NAS Algorithm with Hybrid Score Function

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## ABSTRACT

Although the training-free NASs are typically faster than training-based NAS method, however, the correlation between score value and the result of an architecture is not well enough in most cases. To address this problem, we propose a genetic-based training-free NAS algorithm with hybrid training-free score function, which combines three highly heterogeneous training-free score functions to evaluate an architecture. In this method, the genetic algorithm plays a role to guide the searches of NAS algorithm while the hybrid training-free score function plays the role to evaluate a new candidate architecture during the convergence process of GA. More precisely, the first score function is noise immunity for neural architecture search without search (NINASWOT), as an evaluation of pattern recognition ability, second one is condition number of neural tangent kernel (NTK), as an evaluation of trainability.

To evaluate the performance of the proposed algorithm, this paper compared it with several NAS algorithms, including weight-sharing methods, non-weight-sharing methods, and several state-of-the-art training-free score functions. The final result shows that in big search space, like nats-bench sss, the proposed algorithm outperforms most of NAS methods.

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## 1 INTRODUCTION

Neural architecture search (NAS) has recently drawn a big amount of attention, since the ability to automatically design a "good" neural architecture. By leveraging machine learning algorithms [1], NAS algorithms can explore a search space, which is comprised of numerous potential architectures, to find out a good architectures that outperform those designed by human experts. "In recent years", the use of NAS is widespread, from object detection [2], image recognition [3] and speech recognition [4] [5] to natural language processing. [6] [7] [8]

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Despite the promising results of NAS, there are still many challenges to conquer. One major problem is the extremely high computational cost to search for an optimal architecture, which can make NAS impractical for real-world applications, particularly on resource-constrained platforms like embedded system. The reason why NAS is costly is that during the searching, a candidate architecture must be trained to evaluate how good of this architecture.

To overcome this challenge, recent works developed and proposed lots of method which is so called training-free NAS. For example, Mellor et al. [3] proposed the measurement of the correlation between the binary activation patterns, induced by the untrained network at two inputs, named as neural architecture search without training (NASWOT). On the other hand, Lee et al. [9] proposed pruning parameters based on a saliency matrix, which then extended further by Wang et al. [10] and Tanaka et al. [11]. In [11], Tanaka et al. proposed Iterative Synaptic Flow Pruning (SynFlow) algorithm which intends to deal with the layer collapse problem when pruning a network. The score function used in the algorithm is so-called *synaptic saliency* score. Later, Abdelfattah et al. [12] extended SynFlow to score a network architecture by summing synaptic saliency score over all parameters in the model. Cavagnero et al. [13] found that SynFlow is likely to suffer from gradient explosion, then proposed the LogSynFlow score function which prevents the problem. For another example, Chen et al. proposed to compute the condition number of neural tangent kernel (NTK) [14] [15] [16], which is used as the score to estimate the trainability of an architecture.

However, Table 1 shows most of score functions suffer from low correlation between score value and the final accuracy of an architecture, leading to a predicament that no matter how good the search method is used, we can hardly find an optimal architecture. The major problem causes the low correlation is that a single score function can only evaluate one perspective/characteristic of an architecture.

To address the problem, we propose cooperating three heterogeneous score functions with rank-based search method, which evaluate an architecture from different aspects. More specifically, the first score function is NI [18] as an indicator of the ability to distinguish two images. The second one is NASWOT as score to estimate the ability of expression of an architecture. The last one is logsynflow used as the measurement of trainability. By combining these three training-free score functions, this paper also compares the different search algorithms, e.g., random search, genetic algorithm (GA) [19], simulated annealing algorithm (SA) [20].

The major contribution of this paper can be summarized as follow:

- Cooperating three score functions to obtain better ability for searching top accuracy neural architectures.

**Table 1: THE KENDALL AND SPEARMAN CORRELATION BETWEEN TRAINING-FREE SCORE AND TEST ACCURACY, EVALUATED ON THE THREE DATASETS OF NATS-BENCH [17]. EACH METRIC HAS BEEN COMPUTED THREE TIMES WITH DIFFERENT INITIALISATIONS AND THE AVERAGE IS TAKEN AS FINAL SCORE. THE DATA IS FROM [13].**

Training-free score function	CIFAR-10		CIFAR-100		ImageNet-16-120	
	Kendall	Spearman	Kendall	Spearman	Kendall	Spearman
<b>NTK</b>	-0.33	-0.49	-0.30	-0.45	-0.39	-0.56
<b>Snip</b>	0.45	0.61	0.47	0.62	0.41	0.55
<b>Fisher</b>	0.39	0.54	0.40	0.55	0.36	0.48
<b>Grasp</b>	0.28	0.41	0.35	0.50	0.35	0.49
<b>NASWOT</b>	0.61	0.79	0.62	0.81	0.60	0.78
<b>SynFlow</b>	0.57	0.77	0.56	0.76	0.56	0.75
<b>LogSynFlow</b>	0.61	0.81	0.60	0.79	0.59	0.78

- Develop a rank-based neural architecture search with several search algorithms.

The remainder of this paper is organized as follows: Section 2 provides the detail about the three heterogeneous score functions. Section 3 gives a detailed description about the proposed method. Section 4 begins with parameters setting and provide the simulation results following is the experiment results in different search space. The conclusion and further prospect are given in Section 5.

## 2 RELATED WORKS

### 2.1 Training-free Score Function

In [3], Mellor et al. proposed a score function without the requirement for training which is named neural architecture search without training (NASWOT). Figure 1 gives a simple example to illustrate the procedure of NASWOT score function. Consider a mini-batch of data  $X = \{x_i\}_{i=1}^N$  passing through a neural network architecture as  $f(x_i)$ . The activated ReLU units in every layer of the architecture form a binary code  $c_i$  that define the linear region. The correlation between binary codes for the whole mini-batch can be examined by computing the kernel matrix

$$K_H = \begin{pmatrix} N_A - d_H(c_1, c_2) & \cdots & N_A - d_H(c_1, c_N) \\ \vdots & \ddots & \vdots \\ N_A - d_H(c_N, c_1) & \cdots & N_A - d_H(c_N, c_N) \end{pmatrix} \quad (1)$$

where  $N_A$  is the number of ReLU units and  $d_H(c_i, c_j)$  is the hamming distance between the binary code  $c_i$  and  $c_j$ . With the kernel matrix, the score of an architecture can be evaluate as follow:

$$s = \log|K_H| \quad (2)$$

The rationale behind is to see how dissimilar the linear region activated by the ReLU units between two inputs. An architecture shall learn better when inputs are well separated.

Wu et al. [18] found, in some case, an architecture with high NASWOT score may classify the same kind of input data into different classes. To fix this defect, Wu et al. proposed using noise immunity (NI) to evaluate an architecture. Figure 2 gives an example to illustrate how noise immunity score evaluate an architecture. The score function picks a mini-batch of data, denoted  $X$ , and then applies Gaussian noise on it. The process can be defined by  $X' = X + z$

where  $z$  is the Gaussian noise. By passing  $X$  and  $X'$  through the untrained architecture, then computing the difference of square of each feature maps captured at all pooling layers, denoted  $\eta$ . According to the fact that the input data are the same kind, the small  $\eta$  the better the noise immunity of the architecture is.

Besides from these two model-dependent aspects, Tanaka et al. [11] generalized synaptic saliency scores, and proposed SynFlow algorithm to avoids layer collapse when performing pruning. Inspired from [11], [10], [9], Abdelfattah et al. [12] proposed summing synaptic saliency scores over all parameters in the model as an accuracy estimator to a architecture.

Besides from these two model-dependent aspects, roots from The Lottery Ticket Hypothesis [21], saliency matrix is used on pruning network parameters in [9], which can be formula as

$$S_p(\theta) = \left| \frac{\partial \mathcal{L}}{\partial \theta} \odot \theta \right| \quad (3)$$

where  $\mathcal{L}$  is the loss function of a neural network with parameters  $\theta$  and  $\odot$  is the Hadamard product. The saliency matrix approximates the change in loss when pruning a specific parameters. Later, Wang et al. [10] approximates the change in gradient norm when pruning the network, which defined as

$$S_p(\theta) = -(H \frac{\partial \mathcal{L}}{\partial \theta}) \odot \theta \quad (4)$$

where  $\mathcal{L}$  is the change in gradient norm instead of loss function and  $H$  is the Hessian. In [11], Tanaka et al. generalized the synaptic saliency scores as

$$S_p(\theta) = \frac{\partial \mathcal{L}}{\partial \theta} \odot \theta \quad (5)$$

which is named SynFlow. Abdelfattah et al. [12] extended the work, conclude that summing synaptic saliency score over all parameters in the model can be used to score a network architecture, which is formula as

$$S_n = \sum_i^N S_p(\theta)_i \quad (6)$$

Finally, Cavagnero et al. [13] improved SynFlow, which is likely to fall into gradient explosion problem, and proposed LogSynFlow score function, simply scaling down the gradient. The formula is

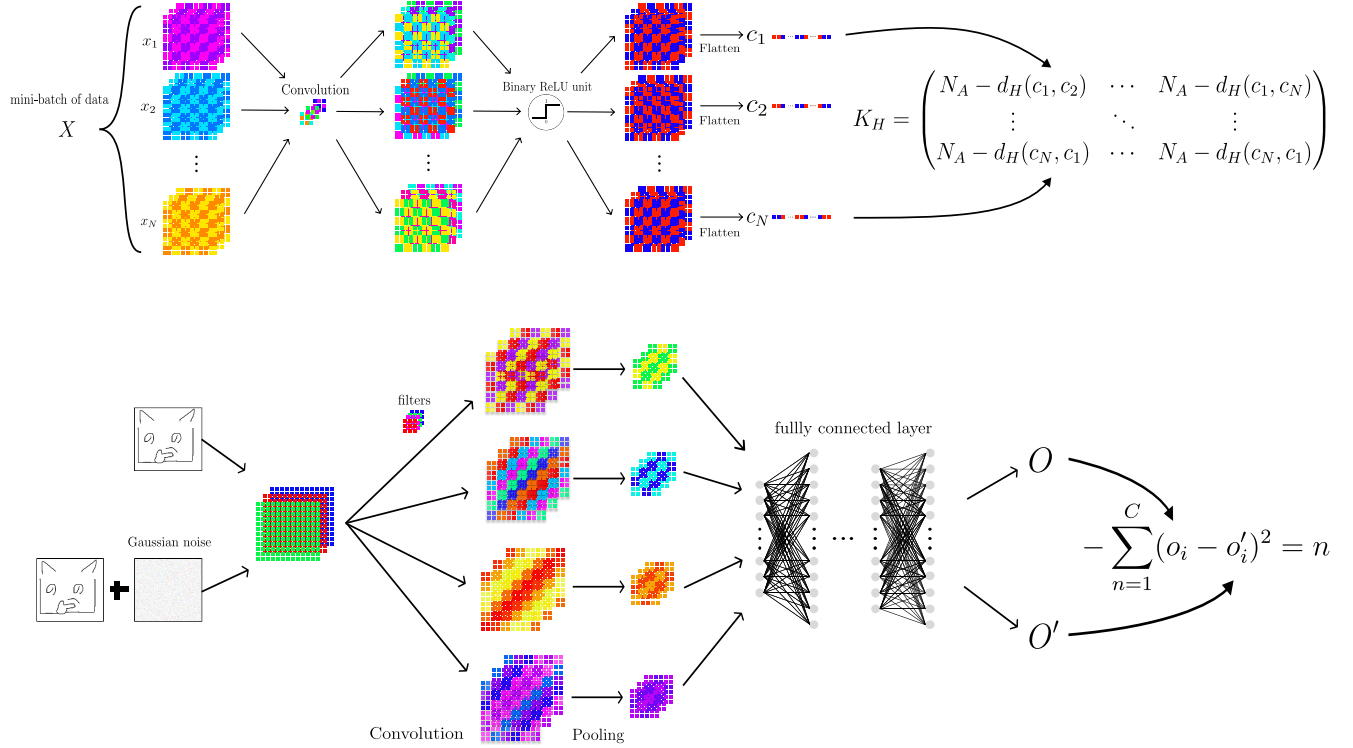


Figure 2: A simple example to illustrate the procedure of noise immunity.

defined by

$$S(\theta) = \theta \cdot \log\left(\frac{\partial \mathcal{L}}{\partial \theta} + 1\right) \quad (7)$$

## 2.2 Search Algorithm

## 3 THE PROPOSED ALGORITHM

In this work,

## 4 EXPERIMENT RESULT

natsbenchss

nasbench201

## 5 CONCLUSION

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**Table 2: COMPARISON OF RANK-BASED NAS AND ALL THE OTHER NAS ALGORITHMS.**

Method	Search (s)	CIFAR-10		CIFAR-100		ImageNet-16-120	
		validation	test	validation	test	validation	test
Non-weight sharing							
AREA	12,000	84.62 ± 0.41	93.16 ± 0.16	59.24 ± 1.11	69.56 ± 0.96	37.58 ± 1.09	45.30 ± 0.91
REA	12,000	90.26 ± 0.22	93.17 ± 0.21	69.48 ± 0.76	69.49 ± 0.94	44.84 ± 0.72	45.47 ± 0.91
RS	12,000	90.08 ± 0.24	93.01 ± 0.29	69.14 ± 0.94	69.17 ± 1.00	44.66 ± 1.02	44.83 ± 1.05
RL	12,000	90.17 ± 0.23	93.08 ± 0.21	69.23 ± 0.87	69.29 ± 1.08	44.68 ± 0.91	45.05 ± 0.93
BOHB	12,000	90.05 ± 0.30	93.03 ± 0.20	69.04 ± 0.76	69.16 ± 0.90	44.71 ± 0.78	44.91 ± 1.05
Training-free							
NI (N=1,000)	X	89.56 ± 0.147	92.55 ± 0.187	X ± X	X ± X	X ± X	X ± X
NASWOT (N=1,000)	X	89.25 ± 0.412	92.21 ± 0.298	X ± X	X ± X	X ± X	X ± X
logsynflow (N=1,000)	X	89.61 ± 0.101	92.60 ± 0.188	X ± X	X ± X	X ± X	X ± X
rk (N=1000)	X	89.59 ± 0.136	92.51 ± 0.171	X ± X	X ± X	X ± X	X ± X
GA-rk	457.54	90.29 ± 0.149	93.27 ± 0.193	69.88 ± 0.497	70.06 ± 0.481	45.57 ± 0.425	46.19 ± 0.846
SA-rk	682.36	90.37 ± 0.204	93.29 ± 0.182	70.11 ± 0.457	70.32 ± 0.458	45.38 ± 0.499	46.45 ± 0.687

**Table 3: COMPARISON OF RANK-BASED NAS AND ALL THE OTHER NAS ALGORITHMS.**

Method	Search (s)	CIFAR-10		CIFAR-100		ImageNet-16-120	
		validation	test	validation	test	validation	test
Non-weight sharing							
AREA	12,000	91.18 ± 0.43	93.95 ± 0.39	71.84 ± 1.21	71.92 ± 1.29	45.04 ± 1.03	45.40 ± 1.14
REA	12,000	91.08 ± 0.54	93.89 ± 0.50	71.69 ± 1.34	71.83 ± 1.33	44.96 ± 1.41	45.30 ± 1.51
RS	12,000	90.91 ± 0.33	93.67 ± 0.33	70.91 ± 1.04	70.99 ± 0.99	44.52 ± 0.99	44.56 ± 1.25
RL	12,000	90.87 ± 0.41	93.63 ± 0.36	70.62 ± 1.08	70.77 ± 1.05	44.20 ± 1.22	44.23 ± 1.37
BOHB	12,000	88.47 ± 1.19	91.79 ± 1.11	67.18 ± 2.05	67.50 ± 2.05	38.94 ± 3.58	39.00 ± 3.73
Weight sharing							
RSWS	4,154	76.95 ± 16.74	82.60 ± 12.10	52.51 ± 18.33	52.93 ± 18.32	29.76 ± 9.50	29.16 ± 9.61
DARTS-V1	5,475	39.77 ± 0.00	54.30 ± 0.00	15.03 ± 0.00	15.61 ± 0.00	16.43 ± 0.00	16.32 ± 0.00
DARTS-V2	16,114	39.77 ± 0.00	54.30 ± 0.00	15.03 ± 0.00	15.61 ± 0.00	16.43 ± 0.00	16.32 ± 0.00
GDAS	11,183	90.05 ± 0.23	93.46 ± 0.13	71.02 ± 0.31	70.56 ± 0.24	41.77 ± 1.24	41.96 ± 0.90
SETN	16,787	84.25 ± 5.05	88.01 ± 4.52	59.72 ± 7.30	59.91 ± 7.51	33.93 ± 3.85	33.48 ± 4.22
ENAS	7,061	40.11 ± 3.28	56.33 ± 3.70	14.09 ± 1.60	14.77 ± 1.45	16.20 ± 0.48	15.93 ± 0.67
Training-free							
NI (N=1,000)	X	X ± X	X ± X	X ± X	X ± X	X ± X	X ± X
NASWOT (N=1,000)	X	X ± X	X ± X	X ± X	X ± X	X ± X	X ± X
logsynflow (N=1,000)	X	X ± X	X ± X	X ± X	X ± X	X ± X	X ± X
rk (N=1000)	X	X ± X	X ± X	X ± X	X ± X	X ± X	X ± X
GA-rk	747.25	89.93 ± 0.196	93.41 ± 0.083	70.70 ± 0.417	70.76 ± 0.378	42.70 ± 1.315	43.10 ± 1.428
SA-rk	X	89.95 ± 0.194	93.37 ± 0.114	70.69 ± 0.391	70.75 ± 0.532	X ± X	43.10 ± 1.506

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