Neural Architecture Search on ImageNet in Four GPU Hours: A Theoretically Inspired Perspective

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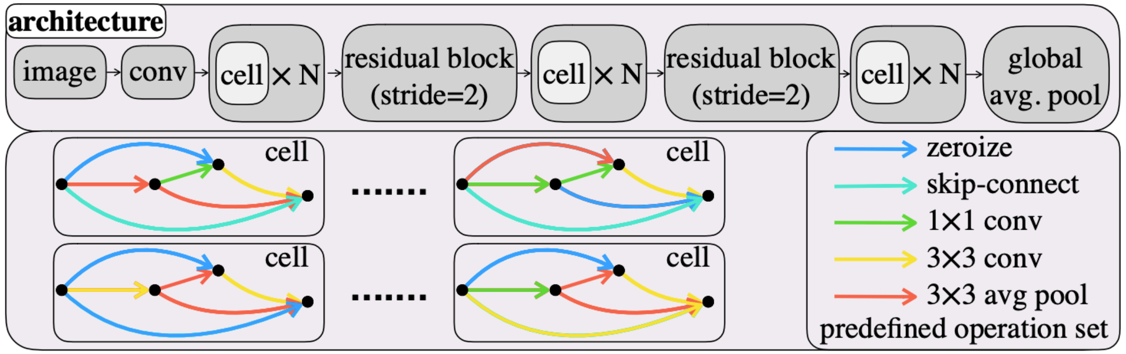
https://github.com/VITA-Group/TENAS

NAS Heavily Counts on Architecture Evaluation

- Training or Predictor based evaluation: high computation cost & slow!
- ***How to optimize*** NAS at network's initialization w.o. any training?

  ➔ Significantly reduce the NAS search cost.
- Can we define ***how to evaluate*** in NAS by analyzing the trainability & expressivity of architectures?



* Dong, Xuanyi, and Yi Yang. "Nas-bench-201: Extending the scope of reproducible neural architecture search." *ICLR 2020*.

Trainability: can NN be easily optimized by Gradient Descent?
Condition Number of NTK: Strong Correlation w.r.t. Accuracy

Jacobian: $$J_{i\alpha}(\boldsymbol{x}) = \partial_{\theta_\alpha} z_i^L(\boldsymbol{x})$$

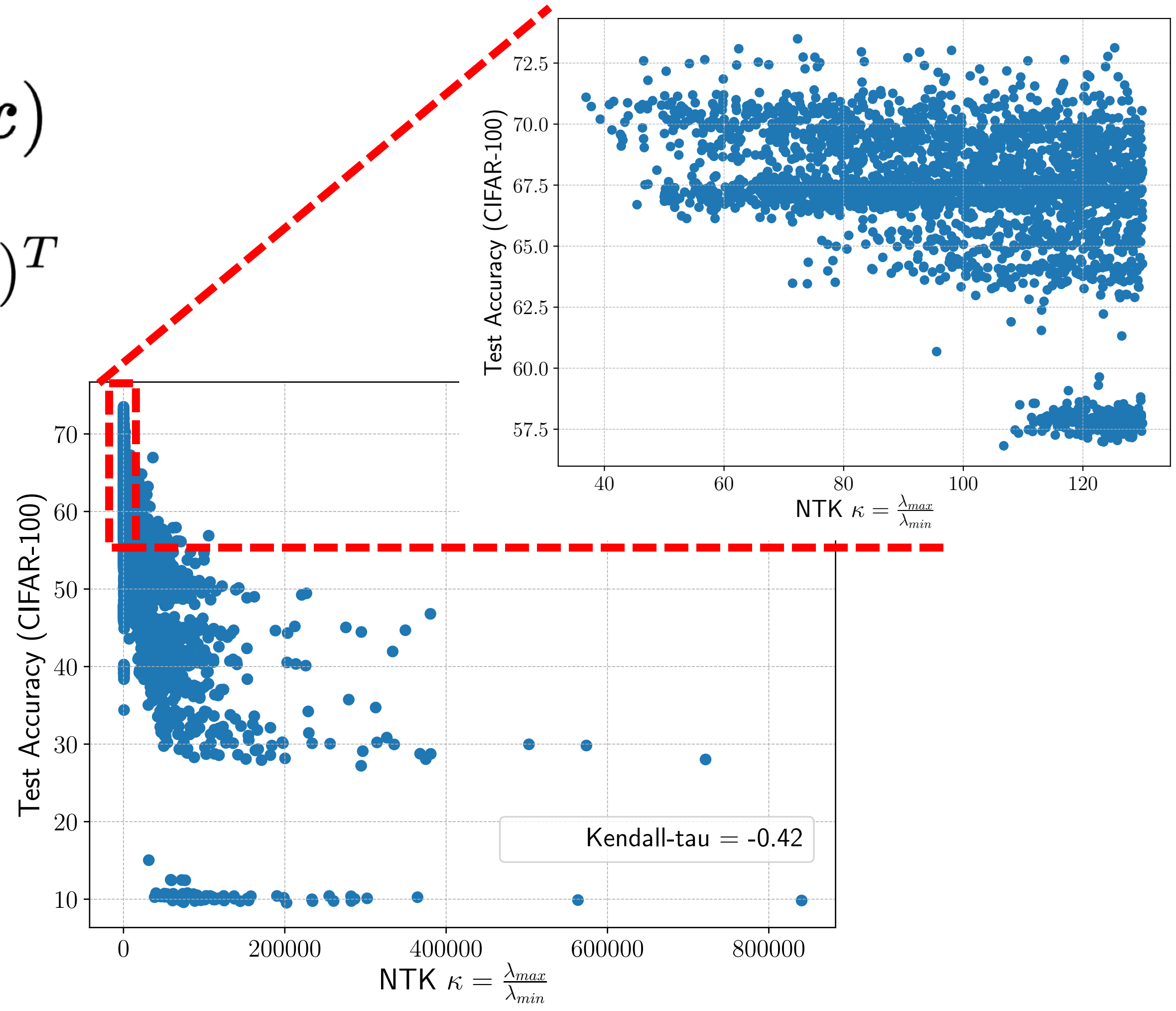
NTK: $$\hat{\Theta}(\boldsymbol{x}, \boldsymbol{x}') = J(\boldsymbol{x})J(\boldsymbol{x}')^T$$

Network training dynamics:

$$\mu_t(\boldsymbol{X}_{\text{train}}) = (\mathbf{I} - e^{-\eta\hat{\Theta}_{\text{train}}t})\boldsymbol{Y}_{\text{train}}$$

$$\mu_t(\boldsymbol{X}_{\text{train}})_i = (\mathbf{I} - e^{-\eta\lambda_i t})\boldsymbol{Y}_{\text{train},i}$$

NTK condition number: $$\boxed{\kappa_{\mathcal{N}} = \frac{\lambda_0}{\lambda_m}}$$



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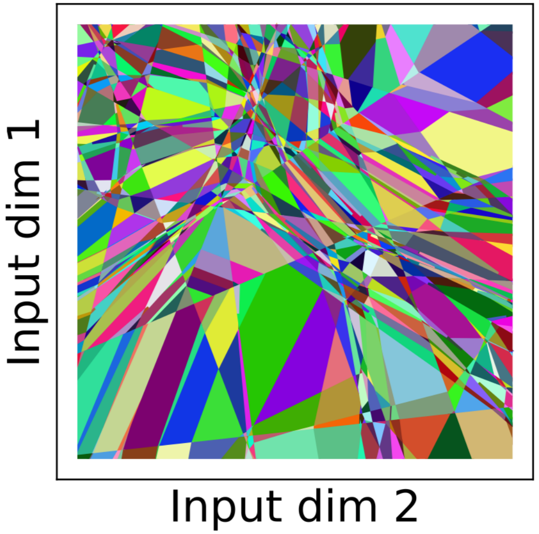
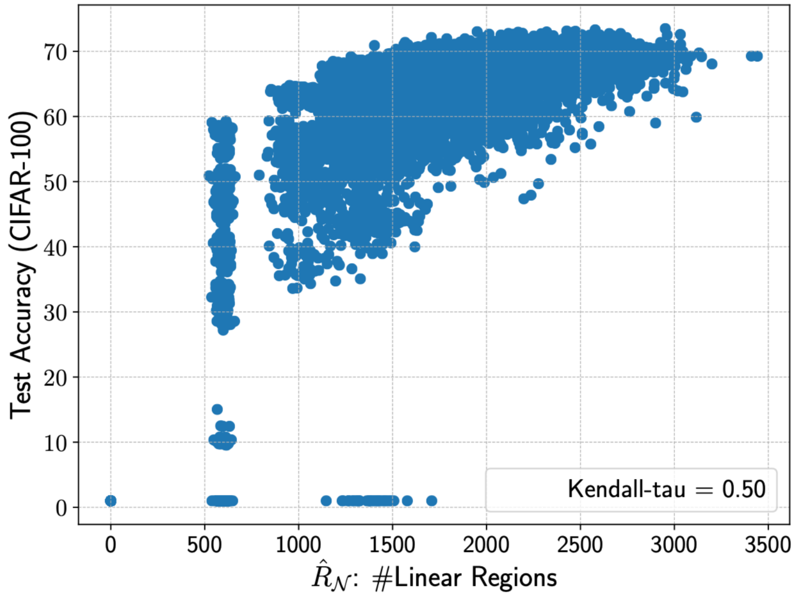
Expressivity: can NN represent complex functions
#Linear Regions: Strong Correlation w.r.t. Accuracy

- Number of Linear Regions = Number of **unique ReLU activation patterns** under given input samples.

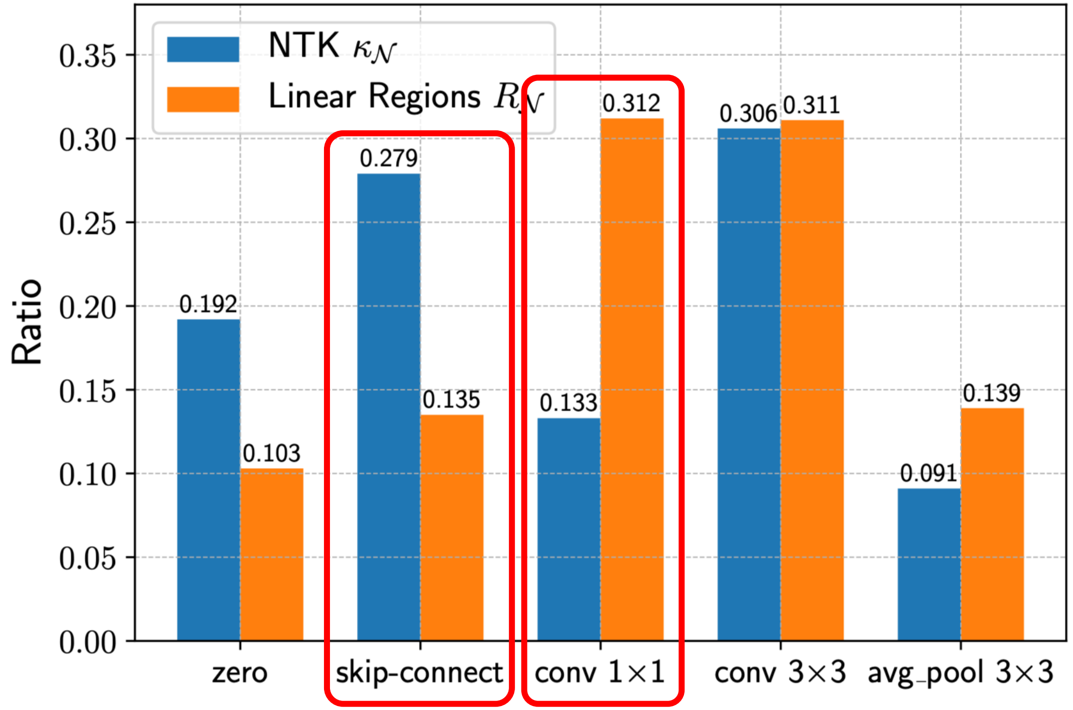
$$\boxed{\hat{R}_{\mathcal{N}} \simeq \mathbb{E}_{\theta} R_{\mathcal{N},\theta}}$$





κ_N v.s. R_N: Different Operator Preference

- κ_N: more skip-connect
  ➔ easier to train
- R_N: conv1x1
  ➔ stronger expressivity

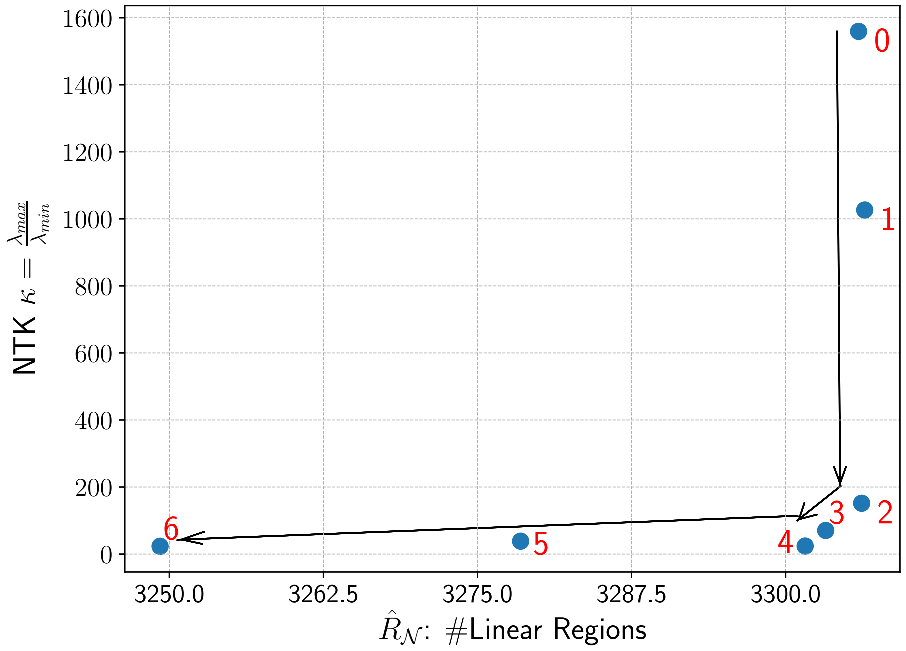


TE-NAS: Training-free & Label-free Efficient NAS

- Prune a supernet by ranking the importance of operators.
- First improve supernet's trainability ➔ then preserve expressivity.

Algorithm 1: TE-NAS: Training-free Pruning-based NAS via Ranking of $\kappa_{\mathcal{N}}$ and $\hat{R}_{\mathcal{N}}$.

Input: supernet $\mathcal{N}_0$ stacked by cells, each cell has E edges, each edge has $|\mathcal{O}|$ operators, step $t = 0$.
while *$\mathcal{N}_t$ is not a single-path network* **do**
    for *each operator o_j in $\mathcal{N}_t$* **do**
        $\Delta\kappa_{t,o_j} = \kappa_{\mathcal{N}_t} - \kappa_{\mathcal{N}_t \backslash o_j}$ ▷ the higher $\Delta\kappa_{t,o_j}$ the more likely we will prune o_j
        $\Delta R_{t,o_j} = R_{\mathcal{N}_t} - R_{\mathcal{N}_t \backslash o_j}$ ▷ the lower $\Delta R_{t,o_j}$ the more likely we will prune o_j
    Get importance by $\kappa_{\mathcal{N}}$: $s_\kappa(o_j) =$ index of o_j in descendingly sorted list $[\Delta\kappa_{t,o_1}, ..., \Delta\kappa_{t,o_{|\mathcal{N}_t|}}]$
    Get importance by $R_{\mathcal{N}}$: $s_R(o_j) =$ index of o_j in ascendingly sorted list $[\Delta R_{t,o_1}, ..., \Delta R_{t,o_{|\mathcal{N}_t|}}]$
    Get importance $s(o_j) = s_\kappa(o_j) + s_R(o_j)$
    $\mathcal{N}_{t+1} = \mathcal{N}_t$
    for *each edge e_i, $i = 1, ..., E$* **do**
        $j^* = \arg\min_j \{s(o_j) : o_j \in e_i\}$ ▷ find the operator with greatest importance on each edge.
        $\mathcal{N}_{t+1} = \mathcal{N}_{t+1} \backslash o_{j^*}$
    $t = t + 1$
return *Pruned single-path network $\mathcal{N}_t$.*



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Fast & Accurate: NAS-Bench-201 & DARTS Space

Table 1: Comparison with state-of-the-art NAS methods on NAS-Bench-201. Test accuracy with mean and deviation are reported. "optimal" indicates the best test accuracy achievable in NAS-Bench-201 search space.

Architecture	CIFAR-10	CIFAR-100	ImageNet-16-120	Search Cost (GPU sec.)	Search Method
ResNet (He et al., 2016)	93.97	70.86	43.63	-	-
RSPS (Li & Talwalkar, 2020)	87.66(1.69)	58.33(4.34)	31.14(3.88)	8007.13	random
ENAS (Pham et al., 2018)	54.30(0.00)	15.61(0.00)	16.32(0.00)	13314.51	RL
DARTS (1st) (Liu et al., 2018b)	54.30(0.00)	15.61(0.00)	16.32(0.00)	10889.87	gradient
DARTS (2nd) (Liu et al., 2018b)	54.30(0.00)	15.61(0.00)	16.32(0.00)	29901.67	gradient
GDAS (Dong & Yang, 2019)	93.61(0.09)	70.70(0.30)	41.84(0.90)	28925.91	gradient
NAS w.o. Training (Mellor et al., 2020)	91.78(1.45)	67.05(2.89)	37.07(6.39)	4.8	training-free
TE-NAS (ours)	**93.9(0.47)**	**71.24(0.56)**	**42.38(0.46)**	1558	training-free
Optimal	94.37	73.51	47.31	-	-

Table 2: Comparison with state-of-the-art NAS methods on CIFAR-10.

Architecture	Test Error (%)	Params (M)	Search Cost (GPU days)	Search Method
AmoebaNet-A (Real et al., 2019)	3.34(0.06)	3.2	3150	evolution
PNAS (Liu et al., 2018a)*	3.41(0.09)	3.2	225	SMBO
ENAS (Pham et al., 2018)	2.89	4.6	0.5	RL
NASNet-A (Zoph et al., 2018)	2.65	3.3	2000	RL
DARTS (1st) (Liu et al., 2018b)	3.00(0.14)	3.3	0.4	gradient
DARTS (2nd) (Liu et al., 2018b)	2.76(0.09)	3.3	1.0	gradient
SNAS (Xie et al., 2018)	2.85(0.02)	2.8	1.5	gradient
GDAS (Dong & Yang, 2019)	2.82	2.5	0.17	gradient
BayesNAS (Zhou et al., 2019)	2.81(0.04)	3.4	0.2	gradient
ProxylessNAS (Cai et al., 2018)†	2.08	5.7	4.0	gradient
P-DARTS (Chen et al., 2019)	2.50	3.4	0.3	gradient
PC-DARTS (Xu et al., 2019)	2.57(0.07)	3.6	0.1	gradient
SDARTS-ADV (Chen & Hsieh, 2020)	2.61(0.02)	3.3	1.3	gradient
TE-NAS (ours)	2.63(0.064)	3.8	0.05‡	training-free

* No cutout augmentation.
† Different space: PyramidNet (Han et al., 2017) as the backbone.
‡ Recorded on a single GTX 1080Ti GPU.

Table 3: Comparison with state-of-the-art NAS methods on ImageNet under the mobile setting.

Architecture	Test Error(%) top-1	Test Error(%) top-5	Params (M)	Search Cost (GPU days)	Search Method
NASNet-A (Zoph et al., 2018)	26.0	8.4	5.3	2000	RL
AmoebaNet-C (Real et al., 2019)	24.3	7.6	6.4	3150	evolution
PNAS (Liu et al., 2018a)	25.8	8.1	5.1	225	SMBO
MnasNet-92 (Tan et al., 2019)	25.2	8.0	4.4	-	RL
DARTS (2nd) (Liu et al., 2018b)	26.7	8.7	4.7	4.0	gradient
SNAS (mild) (Xie et al., 2018)	27.3	9.2	4.3	1.5	gradient
GDAS (Dong & Yang, 2019)	26.0	8.5	5.3	0.21	gradient
BayesNAS (Zhou et al., 2019)	26.5	8.9	3.9	0.2	gradient
P-DARTS (CIFAR-10) (Chen et al., 2019)	24.4	7.4	4.9	0.3	gradient
P-DARTS (CIFAR-100) (Chen et al., 2019)	24.7	7.5	5.1	0.3	gradient
PC-DARTS (CIFAR-10) (Xu et al., 2019)	25.1	7.8	5.3	0.1	gradient
TE-NAS (ours)	26.2	8.3	6.3	0.05	training-free
PC-DARTS (ImageNet) (Xu et al., 2019)†	24.2	7.3	5.3	3.8	gradient
ProxylessNAS (GPU) (Cai et al., 2018)†	24.9	7.5	7.1	8.3	gradient
TE-NAS (ours)†	24.5	7.5	5.4	0.17	training-free

† The architecture is searched on ImageNet, otherwise it is searched on CIFAR-10 or CIFAR-100.

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Thank you!

Code

Paper

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