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HOHAI UNIVERSITY

Efficient Zero-Cost Neural Architecture Search for Personalized AI Systems in Cloud-Edge Networks

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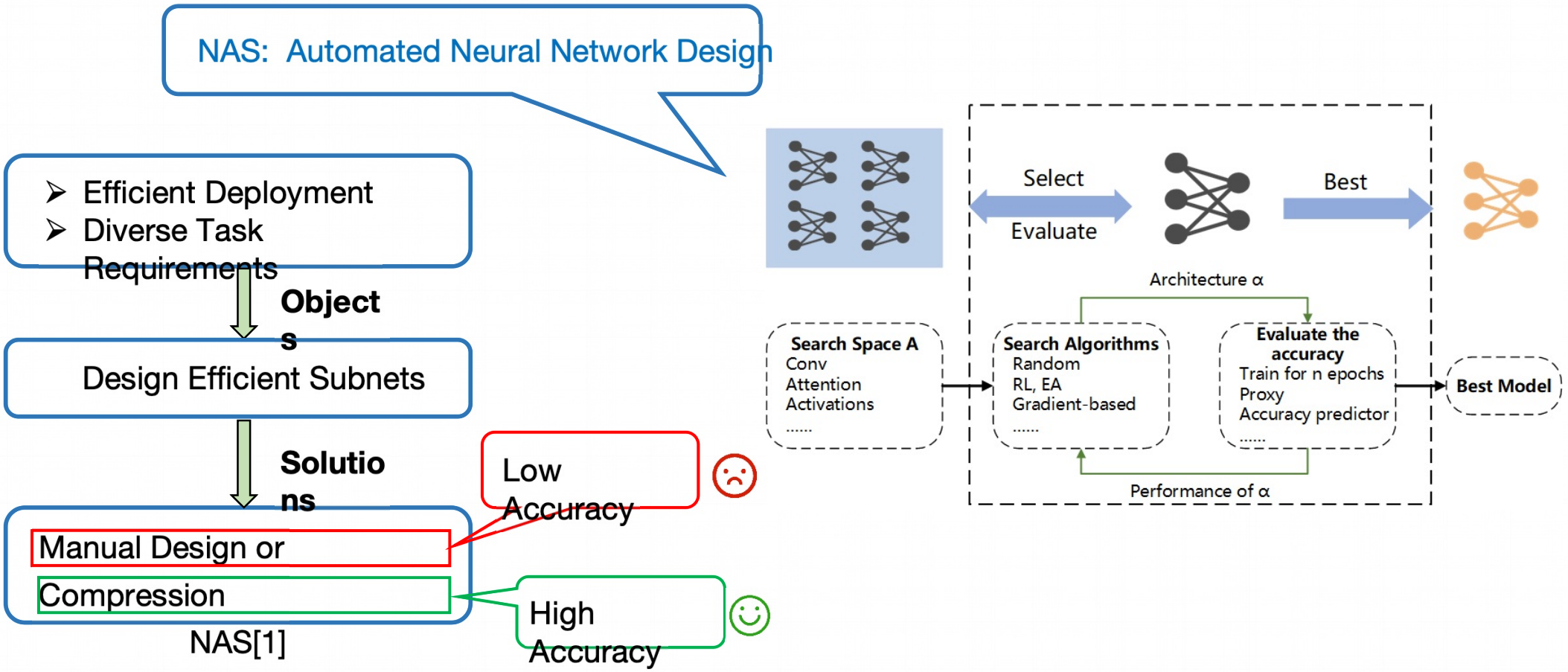
1.1 What is NAS (Neural Architecture Search)?



[1] B. Zoph and Q. V. Le, "Neural Architecture Search with Reinforcement Learning," in *Proc. Int. Conf. Learn. Represent (ICLR),* 2017, p. 2.

1.2 The Challenges of NAS

RL(Reinforcement Learning)
EA(Evolutionary Algorithm)

- Huge Search Space
- SubNets Training

Cause

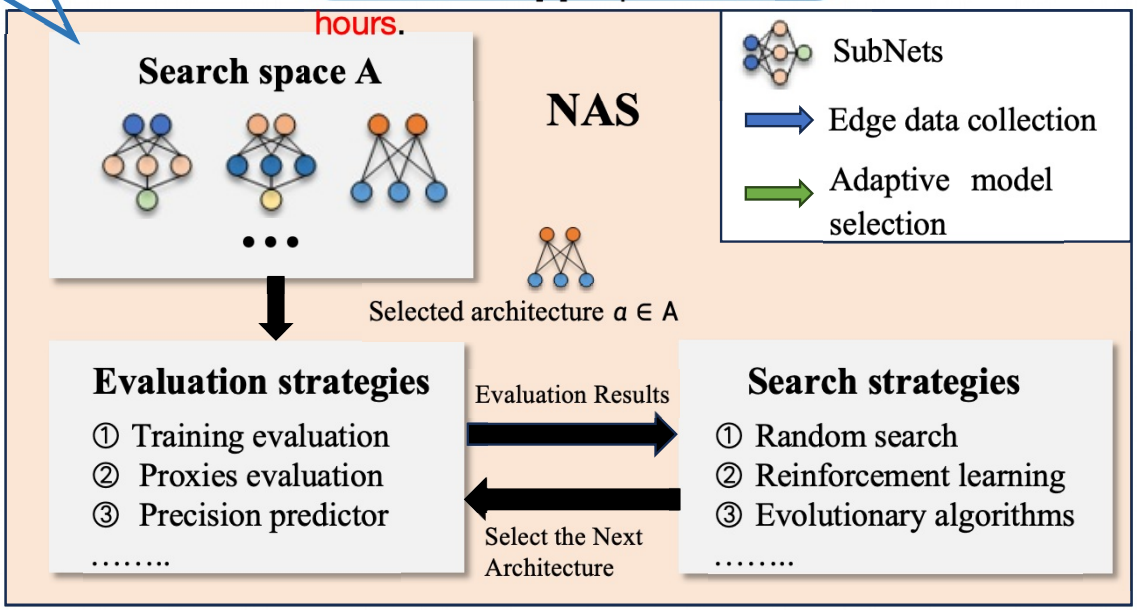
- High Computational Power
- Long Search Time

RL-based NAS[1] requires 2000 days.
EA-based NAS[2] requires 3000 hours.

Solution

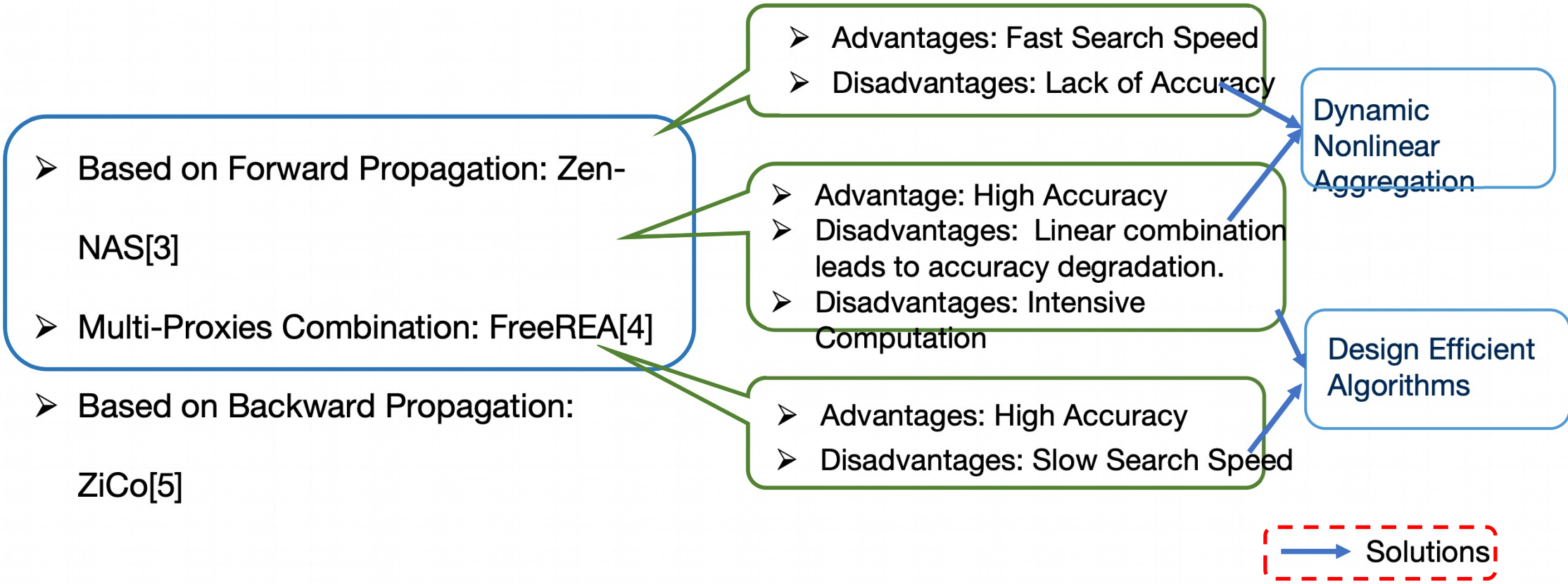
Zero-cost Proxy NAS

Design Train-Free Proxy Based on Features or Gradients



[1] B. Zoph and Q. V. Le, "Neural Architecture Search with Reinforcement Learning," in *Proc. Int. Conf. Learn. Represent (ICLR),* 2017, p. 2.
[2] E. Real et al., "Large-Scale Evolution of Image Classifiers," in *Proceedings of the 34th International Conference on Machine Learning, PMLR,* July 2017, pp. 2902–2911.

1.3 The Challenges of Current Zero-cost Proxy NAS



[3] Lin M, Wang P, Sun Z, et al. “Zen-Nas: A Zero-Shot Nas for High-Performance Image Recognition,”in *International Conference on Computer Vision(ICCV)*. 2021: 347-356.

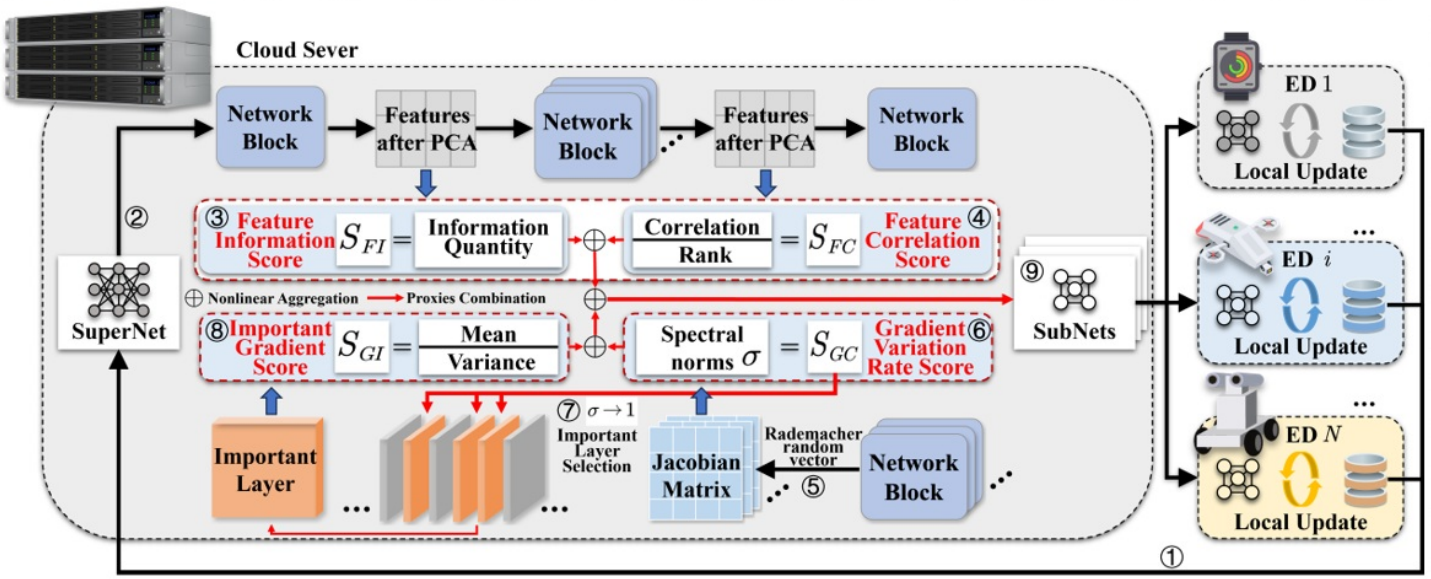
[4] N. Cavagnero, L. Robbiano, B. Caputo, and G. Averta, “FreeREA: Training-Free Evolution-based Architecture Search,” in *Winter Conference on Applications of Computer Vision (WACV)*, 2023 pp. 1493–1502.

[5] G. Li, Y. Yang, K. Bhardwaj, and R. Marculescu, "ZiCo: Zero-shot NAS via Inverse Coefficient of Variation on Gradients," in *Proc. Int. Conf. Learn. Representations (ICLR)*, 2023.

Outline

1. Introduction
2. Approach
3. Experimental Evaluation
4. Conclusion

2.1 Approach: FG-NAS(Featrue-Gradient Aggregated Zero-Cost Neural Architecture Search)



① Upload data characteristics.

② Input SuperNet.

③ Compute Feature Information Score.

④ Compute Feature Correlation Score.

⑤ Generate Jacobian Matrix.

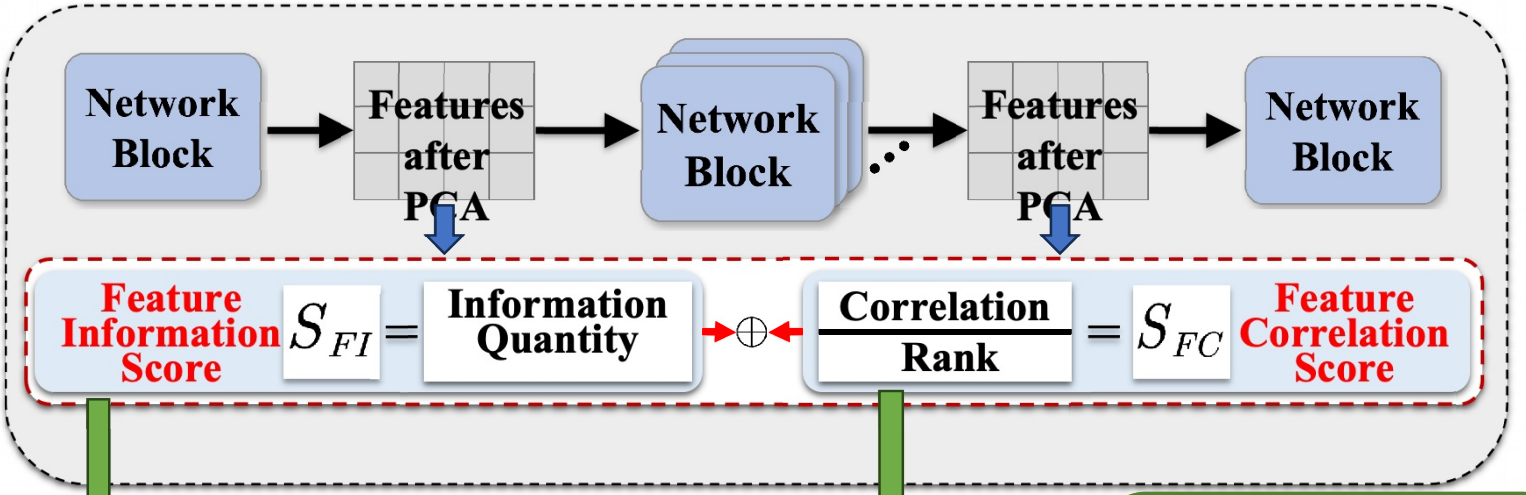
⑥ Compute Gradient Variation Rate Score.

⑦ Select Important Layer.

⑧ Compute Important Gradient Score.

⑨ Output the SubNet ranking and send the optimal SubNet to the ED.

2.2 Feature Proxies



The Richness of Features Extracted by the Subnet

$$S_{FI} = \sum_{l=1}^{N} \frac{\ln(2\pi\sigma^2) + 1}{2}$$

Variance of the Feature Matrix ↑ σ → S_{FI} ↑

The Diversity of Features Extracted by the Subnet

$$S_{FC} = \sum_{l=1}^{N} \frac{\| f_l \|_{nuc}}{sum(P_{f_l})}$$

Nuclear Norm

Feature Extraction Capability

$$\| f_l \|_{nuc} = tr\left(\sqrt{f_l^T f_l}\right)$$

$\| f_l \|_{nuc}$ ↑ → S_{FC} ↑

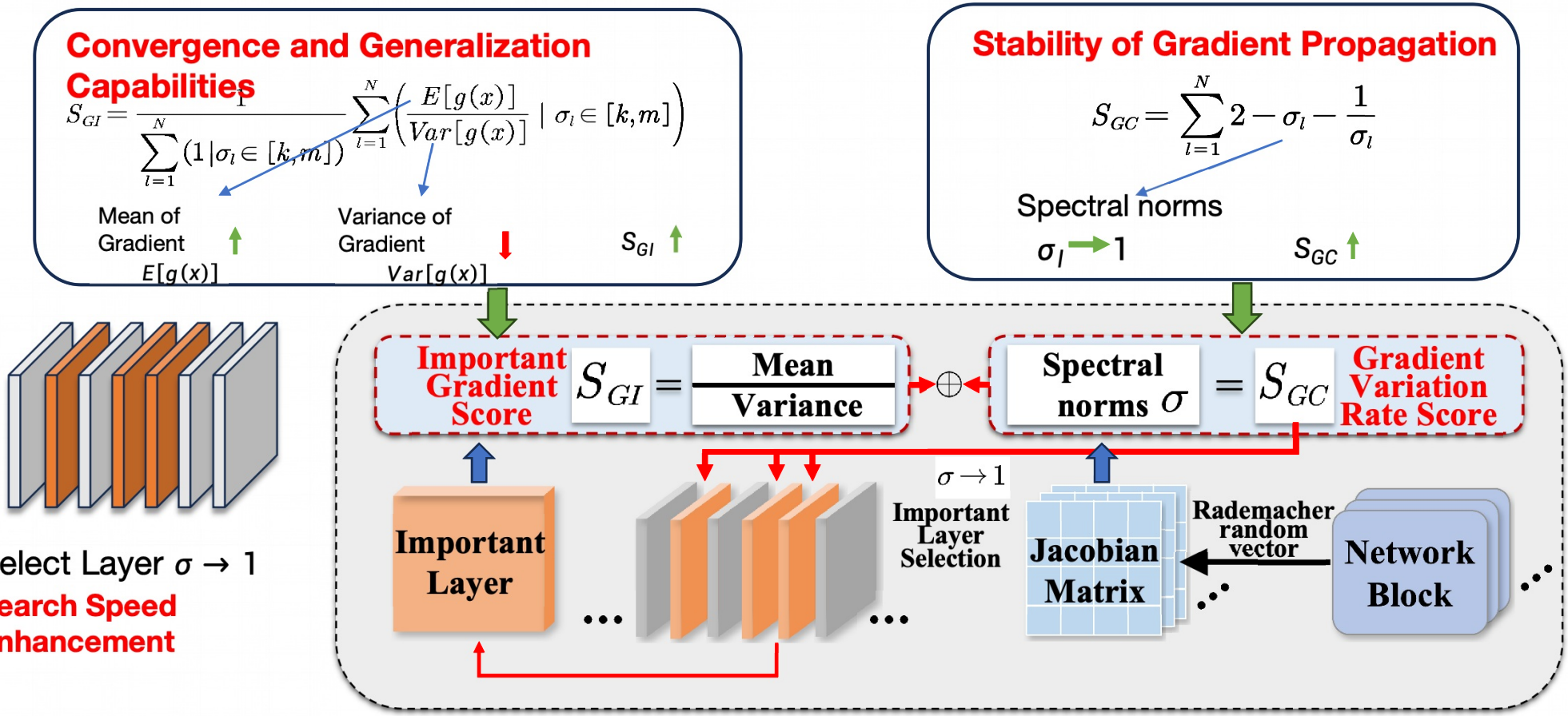
Pearson correlation coefficient

Feature Extraction Capability

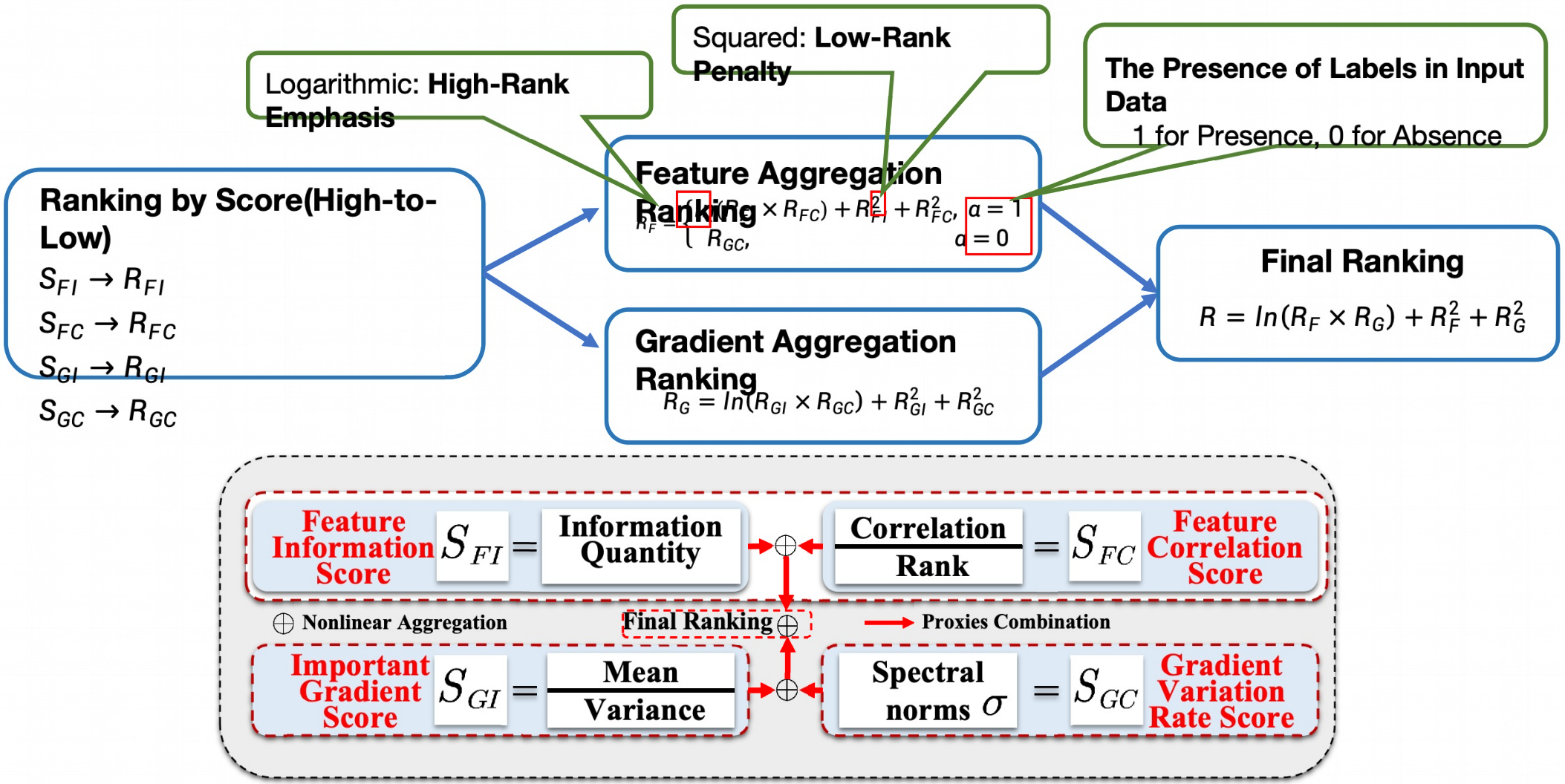
$$\rho(f_l^i, f_l^j) = \frac{\sum_{m=1}^{k}\left(f_l^{i,m} - \bar{f}_l^i\right)\left(f_l^{j,m} - \bar{f}_l^j\right)}{\sqrt{\sum_{m=1}^{k}\left(f_l^{i,m} - \bar{f}_l^i\right)^2 \sum_{m=1}^{k}\left(f_l^{j,m} - \bar{f}_l^j\right)^2}}$$

P_{f_l} ↓ → S_{FC} ↑

2.3 Gradient Proxies



2.4 Dynamic Nonlinear Aggregation



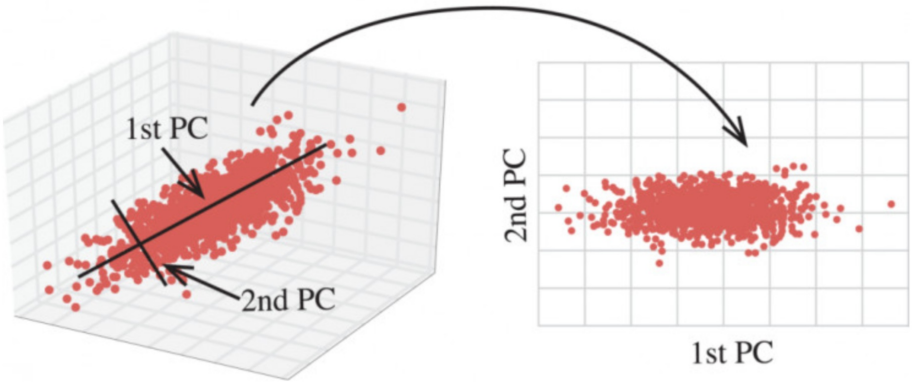
2.5 Dimensionality Reduction

Our Solution:

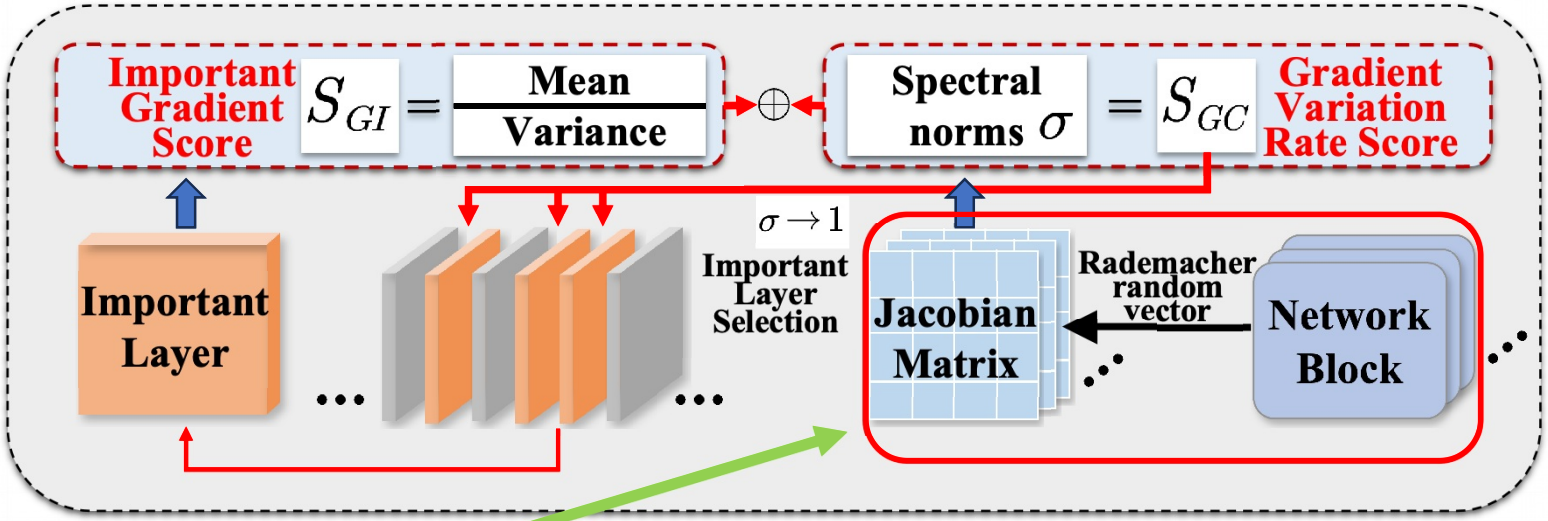
Principal Component Analysis (PCA) is a linear method for dimensionality reduction and feature extraction.

The purpose of dimensionality reduction

- Acceleration of the Subnet Evaluation Process
- Concentration on Important Features



2.6 Jacobian Matrix



Directly calculating Jacobain Martix needs high compute complexity.

$$J_l = \frac{\partial f_l}{\partial f_{l-1}}$$

Rademacher random vector

Reduce Compute Complexity with Rademacher Random Vector.

$$v_k' = Block(v_k^T), \quad J_l = \frac{1}{n}\sum_{k=1}^{n} v_k' v_k^T$$

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3.1 Experimental Environment and Search Space

Experimental Environment	
Cloud Servers	NVIDIA A100 GPUs with 80GB memory and 256GB RAM
End Devices(EDs)	Jetson Xavier NX equipped with 8GB memory and 6-core ARM CPUs
Datasets	CIFAR-10 CIFAR-100 ImageNet16-120

Jetson Xavier NX

Search Space

- **NAS-Bench-201**: Search Space with 15,625 Subnets
- **MobileNetV2**: Search Space with Inverted Residual Structures
- **AutoFormer**: Search Space for Evaluating Transformer Architectures

3.2 Baseline and Metrics

Baseline		
Zero-Cost Proxy Methods	/	#Params/FLOPS
	Based on Forward Propagation	NASWOT
	Based on Backward Propagation	SNIP ZiCo
	Multi-Proxies + Linear Aggregation	TE-NAS
Training-Based Methods	OFA	
	AutoFormer	

Metrics

- **Spearman ρ**: The Correlation Between Predicted Subnet Ranks and True Performance

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

- **Top-1 Accuracy**: Measure Accuracy of the Subnet

$$Top1\ acc. = \frac{\text{Number of Correctly Predicted Samples}}{\text{Total Number of Samples}}$$

- **Search Time**: Subnet Search Time

3.5 Spearman ρ

TABLE II
CORRELATION BETWEEN DIFFERENT ZERO-COST PROXIES AND MODEL ACCURACY IN THE NAS-BENCH-201 SUPERNET

Method	*Spearman* ρ			Time(ms)
	CIFAR-10	CIFAR-100	ImageNet16-120	
#Params/FLOPS	0.753	0.727	0.691	-
SNIP	0.615	0.619	0.539	304.8
NASWOT	0.743	0.769	0.760	**33.1**
TE-NAS	0.731	0.728	0.680	1209.1
ZiCo	0.809	0.785	0.778	342.6
FG-NAS	**0.853**	**0.849**	**0.843**	316.3

It demonstrates efficiency and accuracy of the FG-NAS.

Proxy methods based on the forward propagation are significantly faster.

3.6 Top-1 Accuracy

TABLE III
EXPERIMENTAL RESULTS IN THE MOBILENETV2 SUPERNET

Constraint (Params, FLOPs)	Method	Type	*Top*-1	Search Cost (GPU Days)
(5M, 600M)	OFA	TB	78.7	50
	ZiCo	TF	79.1	0.4
	FG-NAS	TF	**79.5**	**0.35**
(3M, 450M)	OFA	TB	77.7	50
	ZiCo	TF	78.1	0.4
	FG-NAS	TF	**78.4**	**0.33**

TABLE IV
EXPERIMENTAL RESULTS IN THE AUTOFORMER SUPERNET

Constraint (Params, FLOPs)	Method	Type	*Top*-1	Search Cost (GPU Days)
(25M, 5G)	AutoFormer	TB	74.7	24
	TF-TAS	TF	75.3	0.5
	FG-NAS	TF	**75.9**	**0.25**
(5M, 1.5G)	AutoFormer	TB	81.7	24
	TF-TAS	TF	81.9	0.6
	FG-NAS	TF	**82.0**	**0.31**

TB(**T**raining-**b**ased methods)

TF(**T**raining-**f**ree methods)

Substantial Increase in Search Time Due to Training

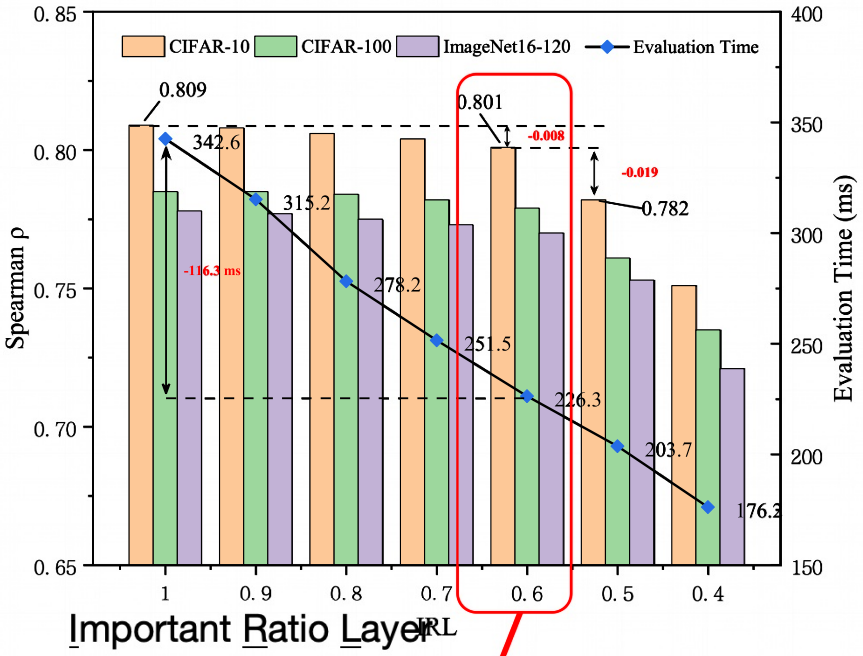
3.7 Search Time

TABLE V
EXPERIMENTAL RESULTS OF FG-NAS ABLATION

Method	*Spearman* ρ			Time(ms)
	CIFAR-10	CIFAR-100	ImageNet16-120	
-FP	0.803	0.782	0.779	282.6
-GP	0.787	0.771	0.762	**36.7**
-NL	0.839	0.815	0.798	311.4
FG-NAS	**0.853**	**0.849**	**0.843**	316.3

-FP(Remove Feature Proxy)
-GP(Remove Gradient Proxy)
-NL(Remove Dynamic Nonlinear Aggregation)

Proxy methods based on the forward propagation are significantly faster.



An important ratio layer of 0.6 achieves balance of the accuracy and search time.

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Conclusion

- The proposed FG-NAS framework introduces feature and gradient zero-cost proxies to achieve accurate and efficient subnet search.
- Dynamic nonlinear aggregation contributes to higher search accuracy.

Thank You!