NEURAL INFORMATION PROCESSING SYSTEMS

NAR-Former V2: Rethinking Transformer for Universal Neural Network Representation Learning

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[1]This work was done while Yun Yi was an intern at Intellifusion.

Overview

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Modeling and learning the representation of neural networks

↓

predict networks' attributes
(without running the actual estimation procedures)

↓

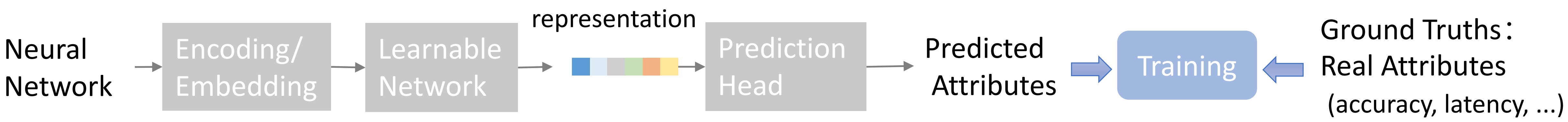
Improving the efficiency of network design and deployment

In this paper, we proposed NAR-Former V2,

- It can handle cell-structured networks as well as learn representations for the entire network
- We achieve this by incorporating graph-specific properties into the vanilla Transformer and introducing a graph-aided attention-based Transformer block.

Background

What is neural network representation learning



Motivation

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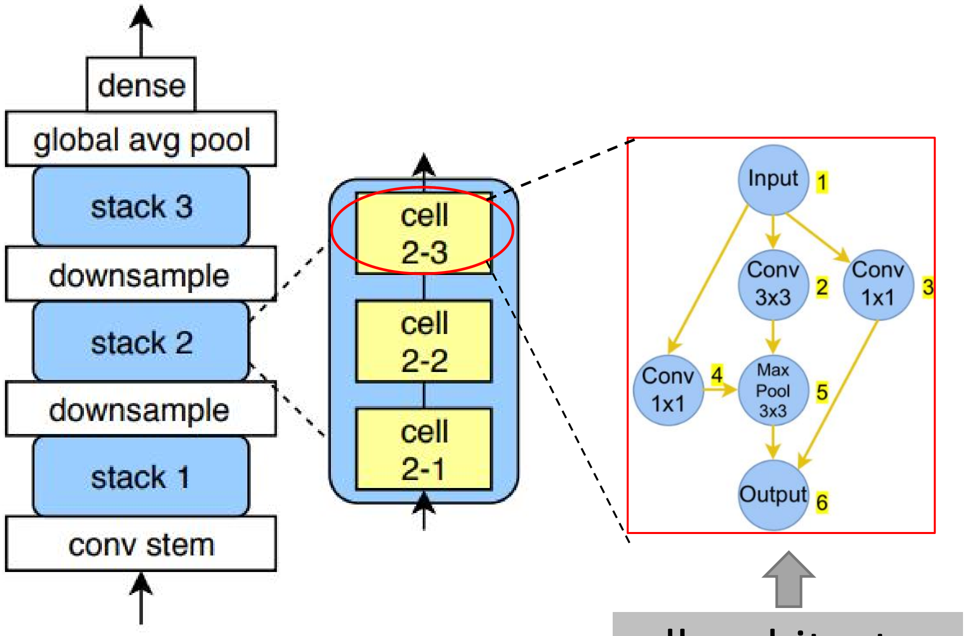
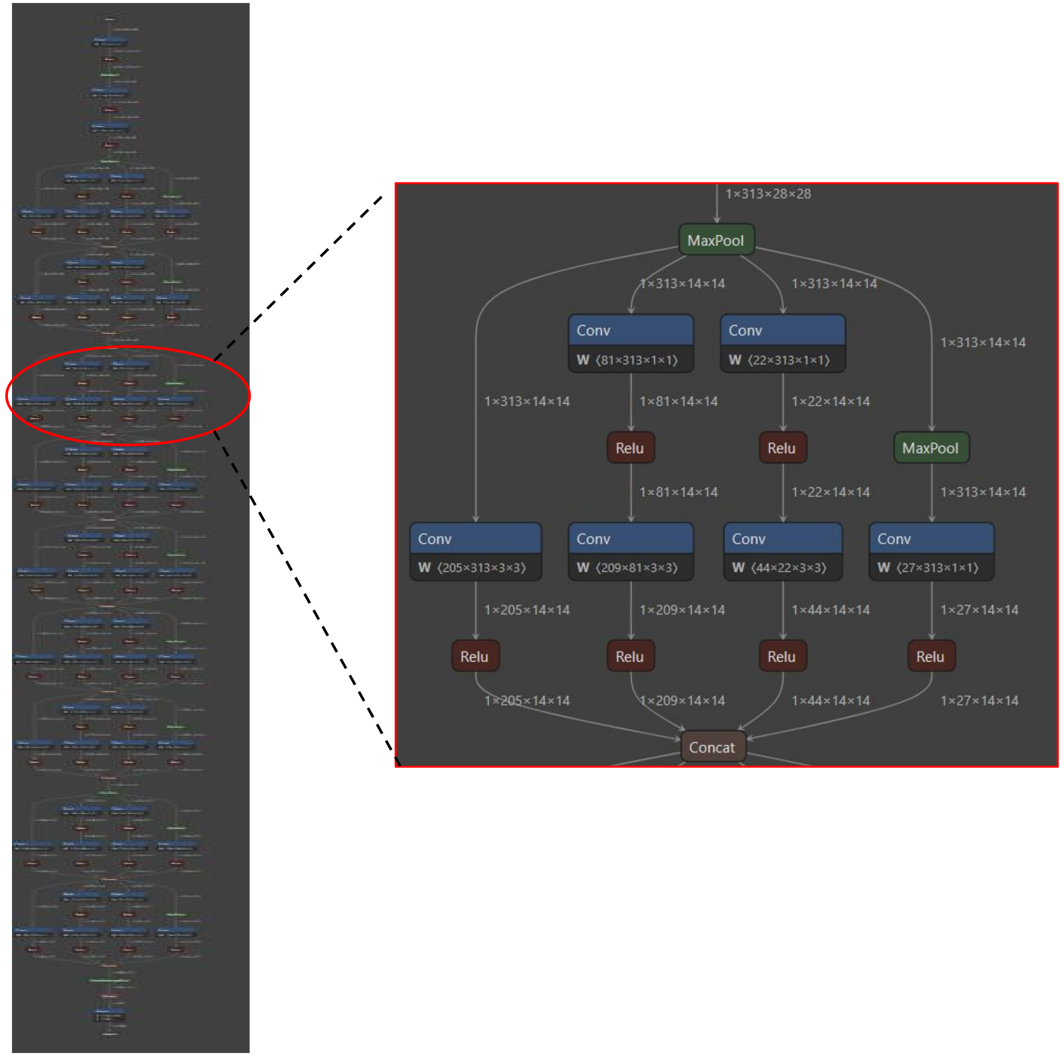
Neural network forms that may need to be encoded in reality:



Architecure in NAS-Bench-101

cell architecture



entire deep neural network

Motivation

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Existing methods reached the SOTA only in specific scenario

Transformer based methods

achieve leading performance on encoding the architectures of cells.

GNN-based methods

perform better when dealing with complete DNNs, or when the depth of the input data is unseen during training.

- We need to reconsider the two representation learning models
- propose an unified method

Motivation

Comparison

	Transformer	GNN
Information Aggregation	global	neighbouring
Feed-Forward Network	✔	-

Analyses

Why Transformer performs poor when encoding entire DNNs?

global modeling based on self-attention

↓

excessive sensitivity

↓

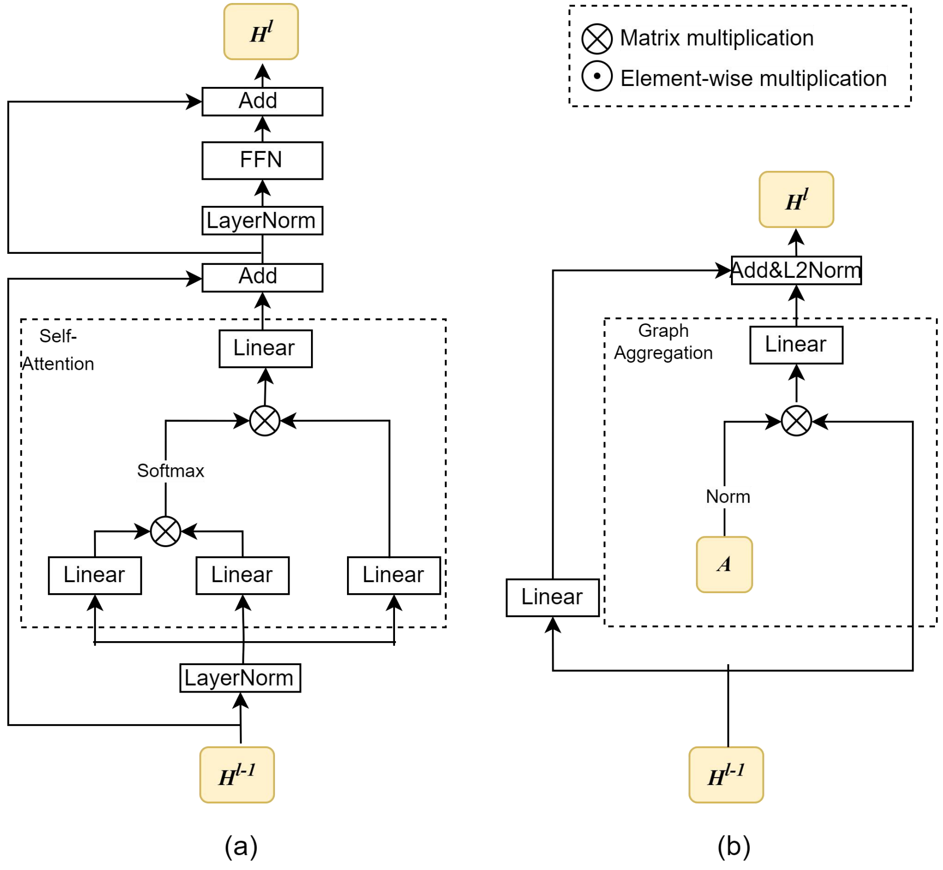
subtle variation can affect the whole representation

↓

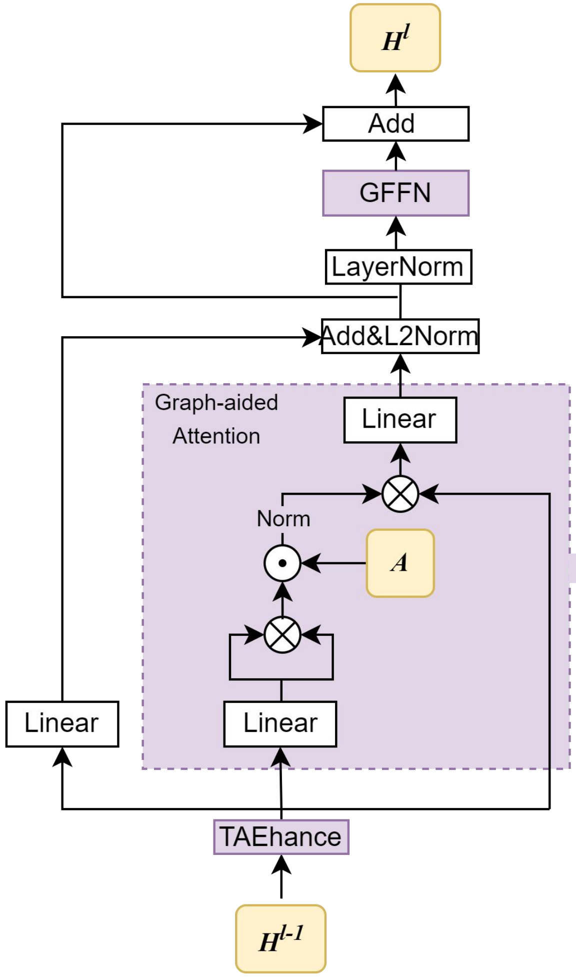
baised toward fitting the training data

↓

poor performance on unseen data



Transformer block vs. GNN block



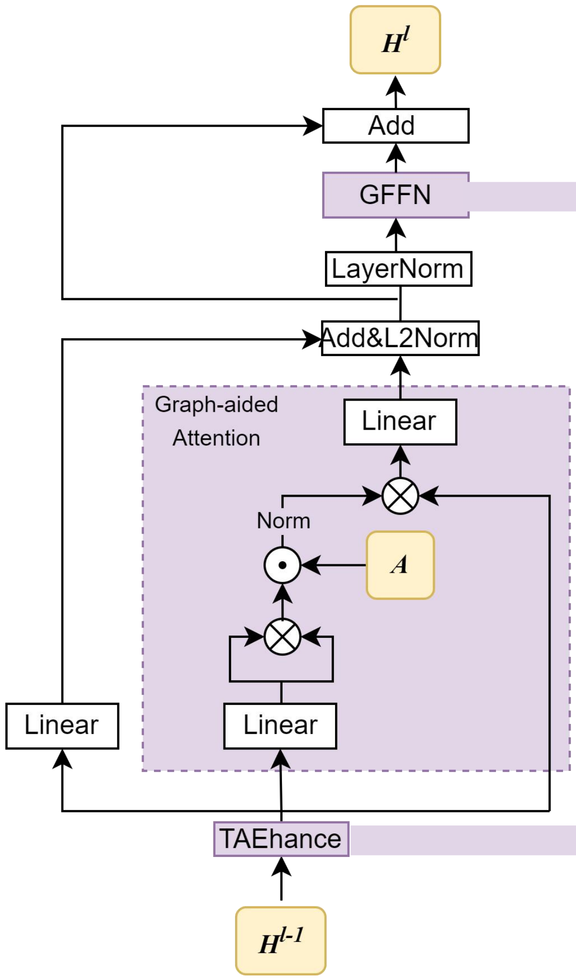
(c)

Graph-aided attention

Employ the adjacency matrix
to govern the attention calculation range

$$X^l = \mathrm{Sigmoid}(W_q^l \widetilde{H}^l + b_q^l),$$
$$S^l = (X^l X^{lT} / \sqrt{d}) \boxed{\odot A,}$$
$$Z^l = W_a^l(\mathrm{Norm}(S^l)\widetilde{H}^l) + b_a^l.$$

Proposed Method: NAR-Former-V2



(c)

Grouped Feed-Forward Network

Introduce group linear transformation into the original FFN to reduce the parameters and futher avoid overfitting problem.

Type-Aware enhancement module

Use the number of connected layers in each layer to assist the model in learning the type of layer.

$$\mathrm{TAEnhance}(H^{l-1}, D) = \mathrm{Sigmoid}(W_d^l \boxed{D} + b_d^l) \odot H^{l-1}.$$

Proposed Method: NAR-Former-V2

Be similar to that in NAR-Former

Be built upon the proposed improved transformer block

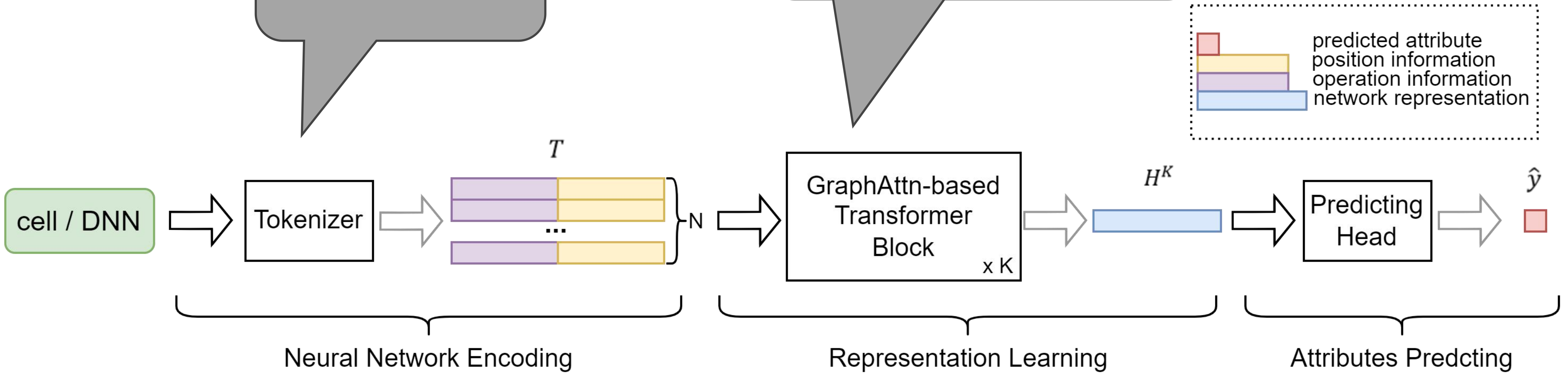


Table 1: Latency prediction on NNLQP [21]. Training and test sets have the same distribution.

Test Model	MAPE↓			Acc(10%)↑		
	NAR-Former [47]	NNLP [21] avg / best	Ours avg / best	NAR-Former [47]	NNLP [21] avg / best	Ours avg / best
All	22.37%	3.47% / 3.44%	3.07% / 3.00%	35.00%	95.25% / 95.50%	96.41% / 96.30%
AlexNet	26.25%	6.37% / 6.21%	6.18% / 5.97%	27.00%	81.75% / 84.50%	81.90% / 84.00%
EfficientNet	13.91%	3.04% / 2.82%	2.34% / 2.22%	45.50%	98.00% / 97.00%	98.50% / 100.0%
GoogleNet	16.00%	4.18% / 4.12%	3.63% / 3.46%	39.00%	93.70% / 93.50%	95.95% / 95.50%
MnasNet	15.76%	2.60% / 2.46%	1.80% / 1.70%	33.00%	97.70% / 98.50%	99.70% / 100.0%
MobileNetV2	15.19%	2.47% / 2.37%	1.83% / 1.72%	39.00%	99.30% / 99.50%	99.90% / 100.0%
MobileNetV3	16.88%	3.50% / 3.43%	3.12% / 2.98%	36.00%	95.35% / 96.00%	96.75% / 98.00%
NasBench201	43.53%	1.46% / 1.31%	1.82% / 1.18%	55.50%	100.0% / 100.0%	100.0% / 100.0%
SqueezeNet	24.33%	4.03% / 3.97%	3.54% / 3.34%	23.00%	93.25% / 93.00%	95.95% / 96.50%
VGG	23.64%	3.73% / 3.63%	3.51% / 3.29%	26.50%	95.25% / 96.50%	95.85% / 96.00%
ResNet	28.18%	3.34% / 3.25%	3.11% / 2.89%	25.50%	98.40% / 98.50%	98.55% / 99.00%

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Table 2: Latency prediction on NNLQP [21]. "Test Model = AlexNet" means that only AlexNet models are used for testing, and the data from the other 9 model families are used for training. The best results refer to the lowest MAPE and corresponding ACC (10%) in 10 independent experiments. *: obtained based on the released code without using its fine-tuning step.

Metric	Test Model	FLOPs	FLOPs +MAC	nn-Meter [55]	TPU [17]	BRP-NAS [12]	NAR-Former [47]*	NNLP [21] (avg / best)	Ours (avg / best)
MAPE↓	AlexNet	44.65%	15.45%	7.20%	10.55%	31.68%	46.28%	10.64% / 9.71%	24.28% / 18.29%
	EfficientNet	58.36%	53.96%	18.93%	16.74%	51.97%	29.34%	21.46% / 18.72%	13.20% / 11.37%
	GoogleNet	30.76%	32.54%	11.71%	8.10%	25.48%	24.71%	13.28% / 10.90%	6.61% / 6.15%
	MnasNet	40.31%	35.96%	10.69%	11.61%	17.26%	26.70%	12.07% / 10.86%	7.16% / 5.93%
	MobileNetV2	37.42%	35.27%	6.43%	12.68%	20.42%	25.74%	8.87% / 7.34%	6.73% / 5.65%
	MobileNetV3	64.64%	57.13%	35.27%	9.97%	58.13%	33.99%	14.57% / 13.17%	9.06% / 8.72%
	NasBench201	80.41%	33.52%	9.57%	58.94%	13.28%	105.71%	9.60% / 8.19%	9.21% / 7.89%
	ResNet	21.18%	18.91%	15.58%	20.05%	15.84%	40.37%	7.54% / 7.12%	6.80% / 6.44%
	SqueezeNet	29.89%	23.19%	18.69%	24.60%	42.55%	74.59%	9.84% / 9.52%	7.08% / 6.56%
	VGG	69.34%	66.63%	19.47%	38.73%	30.95%	44.26%	7.60% / 7.17%	15.40% / 14.26%
	Average	47.70%	37.26%	15.35%	21.20%	30.76%	45.17%	11.55% / 10.27%	10.55% / 9.13%
Acc(10%)↑	AlexNet	6.55%	40.50%	75.45%	57.10%	15.20%	7.60%	59.07% / 64.40%	24.65% / 28.60%
	EfficientNet	0.05%	0.05%	23.40%	17.00%	0.10%	15.15%	25.37% / 28.80%	44.01% / 50.20%
	GoogleNet	12.75%	9.80%	47.40%	69.00%	12.55%	24.35%	36.30% / 48.75%	80.10% / 83.35%
	MnasNet	6.20%	9.80%	60.95%	44.65%	34.30%	20.90%	55.89% / 61.25%	73.46% / 81.60%
	MobileNetV2	6.90%	8.05%	80.75%	33.95%	29.05%	20.70%	63.03% / 72.50%	78.45% / 83.80%
	MobileNetV3	0.05%	0.05%	23.45%	64.25%	13.85%	16.05%	43.26% / 49.65%	68.43% / 70.50%
	NasBench201	0.00%	10.55%	60.65%	2.50%	43.45%	0.00%	60.70% / 70.60%	63.13% / 71.70%
	ResNet	26.50%	29.80%	39.45%	27.30%	39.80%	13.25%	72.88% / 76.40%	77.24% / 79.70%
	SqueezeNet	16.10%	21.35%	36.20%	25.65%	11.85%	11.40%	58.69% / 60.40%	75.01% / 79.25%
	VGG	4.80%	2.10%	26.50%	2.60%	13.20%	11.45%	71.04% / 73.75%	45.21% / 45.30%
	Average	7.99%	13.20%	47.42%	34.40%	21.34%	14.09%	54.62% / 60.65%	62.70% / 67.40%

Experiments

Table 3: Accuracy prediction on NAS-Bench-101 [48]. "SE" denotes the self-evolution strategy proposed by TNASP [26].

Backbone	Method	Training Samples 0.1% (424)	Training Samples 0.1% (424)	Training Samples 1% (4236)
		Test Samples 100	Test Samples all	Test Samples all
CNN	ReNAS [46]	0.634	0.657	0.816
LSTM	NAO [27]	0.704	0.666	0.775
	NAO+SE	0.732	0.680	0.787
GNN	NP [43]	0.710	0.679	0.769
	NP + SE	0.713	0.684	0.773
	CTNAS [3]	0.751	-	-
Transformer	TNASP [26]	0.752	0.705	0.820
	TNASP + SE	0.754	0.722	0.820
	NAR-Former [47]	0.801	0.765	**0.871**
	NAR-Former V2	**0.802**	**0.773**	0.861

Table 4: Accuracy prediction on NAS-Bench-201 [10]. "SE" denotes the self-evolution strategy proposed by TNASP [26].

Backbone	Model	Training Samples (781) 5%	Training Samples (1563) 10%
LSTM	NAO [27]	0.522	0.526
	NAO + SE	0.529	0.528
GNN	NP [43]	0.634	0.646
	NP + SE	0.652	0.649
Transformer	TNASP [26]	0.689	0.724
	TNASP + SE	0.690	0.726
	NAR-Former [47]	0.849	**0.901**
	NAR-Former V2	**0.874**	0.888

Experiments

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Table 5: Ablation studies on NNLQP [21]. "PE" denotes position encoding.

Row	Structure	Op Type	Op Attributes	Graph-Attn	GFFN	TA-Enhance	MAPE↓	Acc(10%)↑	Acc(5%)↑
1(Baseline)	GNN	One-hot	Real Num	-	-	-	3.48	95.26	77.80
2	GNN	PE	PE	-	-	-	3.43(-0.05)	95.11(-0.15)	79.58(+1.78)
3	GNN	One-hot	PE	-	-	-	3.33(-0.15)	95.57(+0.31)	80.19(+2.39)
4	Transformer	One-hot	PE	✓	-	-	3.20(-0.28)	96.00(+0.74)	81.86(+4.06)
5	Transformer	One-hot	PE	✓	✓	-	3.20(-0.28)	96.06(+0.80)	81.76(+3.96)
6	Transformer	One-hot	PE	✓	✓	✓	3.07(-0.41)	96.41(+1.15)	82.71(+4.91)

Conclusion

Overview:
we combine the strengths of Transformer and GNN to develop a universal neural network representation learning model, which is capable of effectively processing models of varying scales, ranging from several layers to hundreds of layers.

Experiments:
(1) Complete DNNs encoding & latency prediciton: our proposed method surpasses the GNN-based method NNLP by a significant margin on the NNLQP dataset.
(2) Cell encoding & accuracy prediciton: our method achieves highly comparable performance to other state-of-the-art methods on NASBench101 and NASBench201 datasets.

Future work:
We will focus on optimizing the design of the representation learning framework and applying it to a broader range of practical applications. Such as using the proposed model to search for the best mixed precision model inference strategies.

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Thanks for your listening!

IIP Lab: https://iip-xdu.github.io

Intellifusion: https://www.intellif.com/

Codes link: https://github.com/yuny220/NAR-Former-V2