PACE: marrying generalization in PArameter-efficient fine-tuning with Consistency rEgularization

Yao Ni[†] Shan Zhang[‡, †] Piotr Koniusz[§, †]

[†]The Australian National University [§]Data61♥CSIRO
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Yao Ni Seeking PostDoc Position. Scan his CV.

Background: Parameter-Efficient Fine-Tuning

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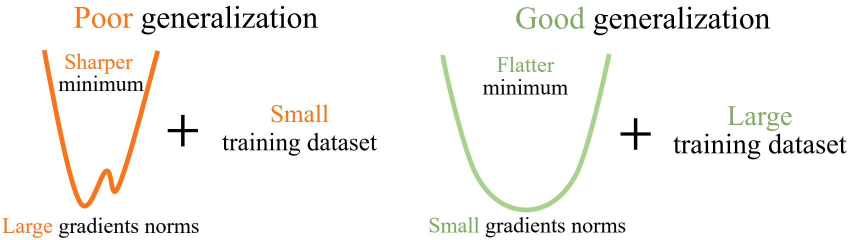
Goal: improve generalization & retain pre-trained knowledge.

Motivation: Theorem 1

Theorem 1: Smaller gradient norm and larger dataset lead to better generalization on unseen data.



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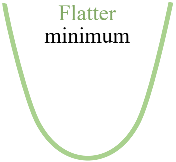
Poor generalization

Large gradients norms

+ Small training dataset

Good generalization



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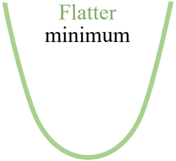

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Rich knowledge for unseen data

Solution for better generalization and retain knowledge

Smaller Gradients Norms
Larger dataset

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Pre-trained
$\boldsymbol{\theta}_0$

$\boldsymbol{x}$

Fine-tuned
$\boldsymbol{\theta}_0 + \Delta\theta$

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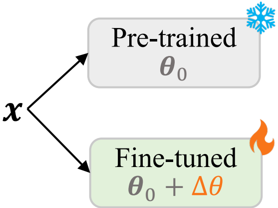

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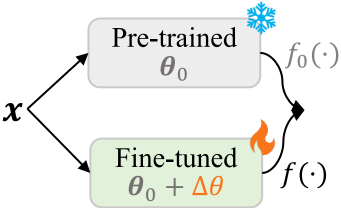

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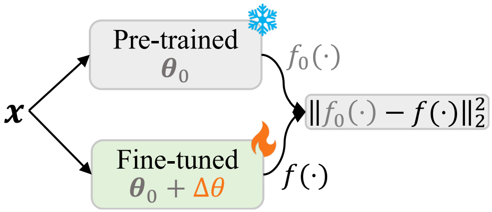

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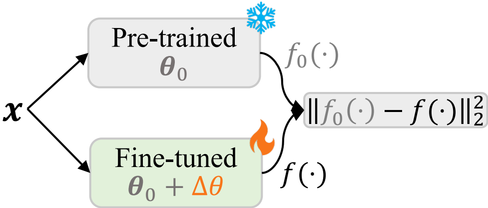

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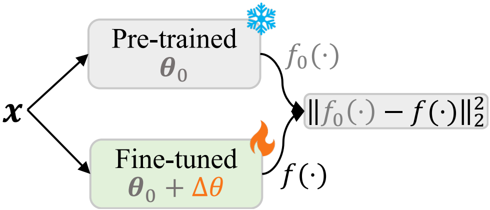

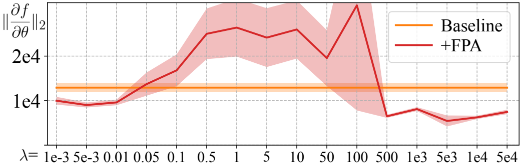

Gradient norms & reg. strength λ (CIFAR-100, ViT-B/16)

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Our method: PACE

To regularize gradients and align fine-tuned pre-trained models,
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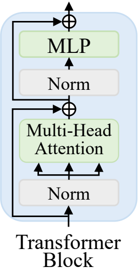

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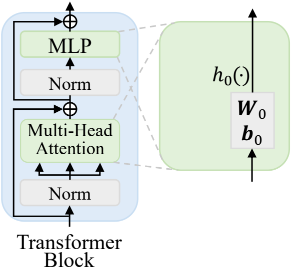

$\boldsymbol{W}_0 \& \boldsymbol{b}_0$, $\Delta\boldsymbol{W} \& \Delta\boldsymbol{b}$: pre-trained/adapter linear weights;

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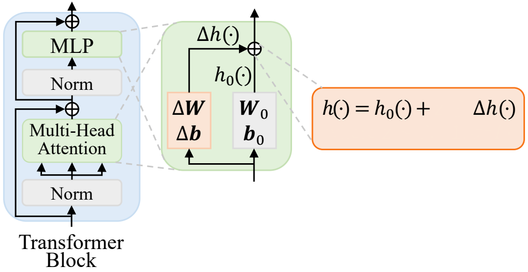

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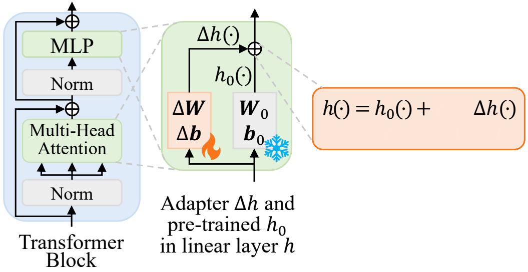

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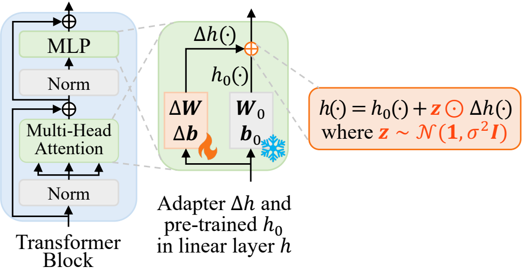
Transformer block with adapter perturbed by noise



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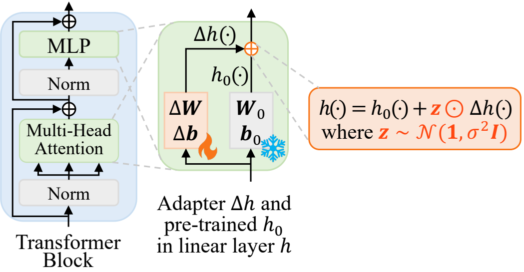

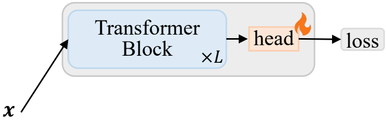

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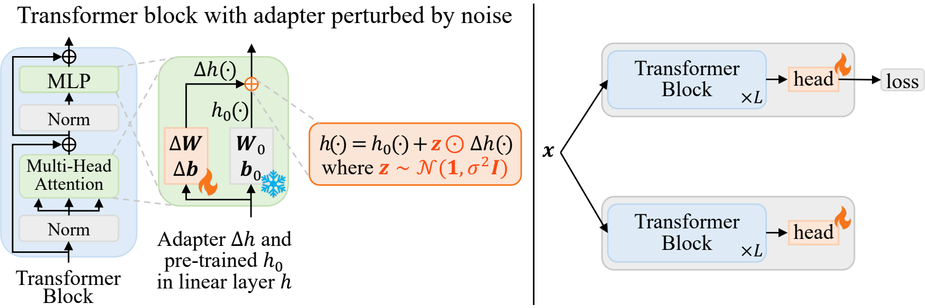

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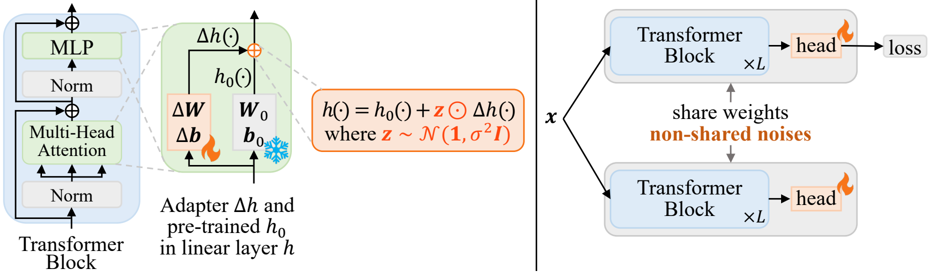

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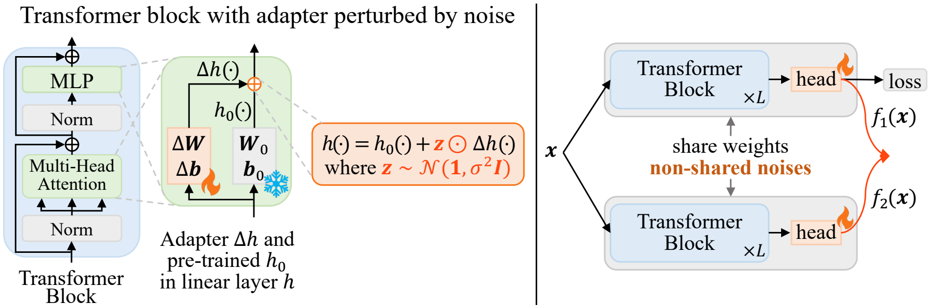

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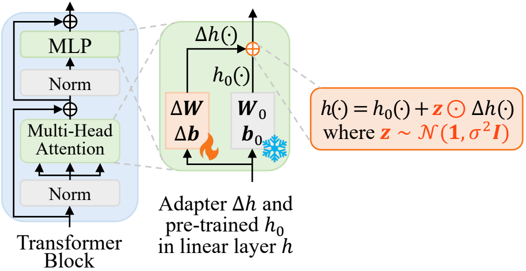
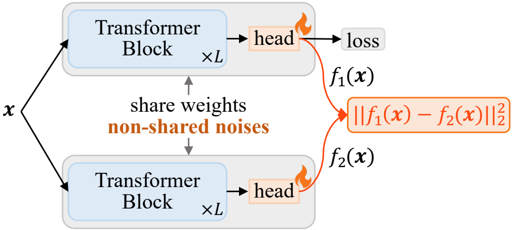


Consistency regularization between two outputs of $\boldsymbol{x}$



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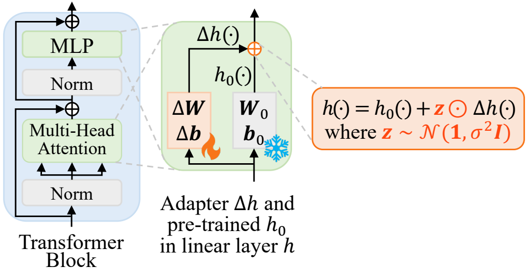

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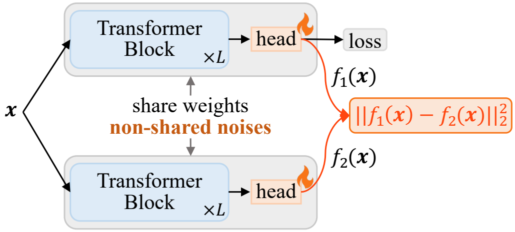

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PACE improves generalization and retains pre-trained knowledge

PACE: Theorem 2

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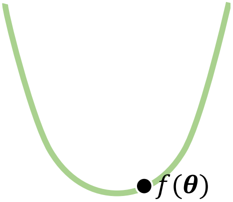
Large grad norm



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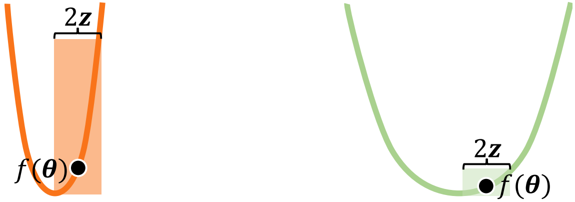

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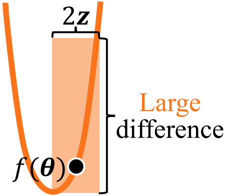

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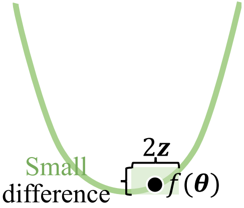

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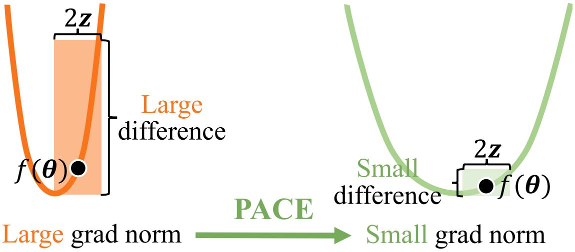

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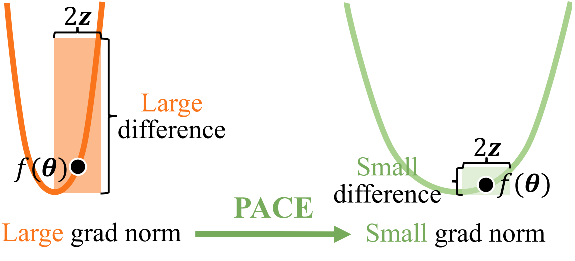

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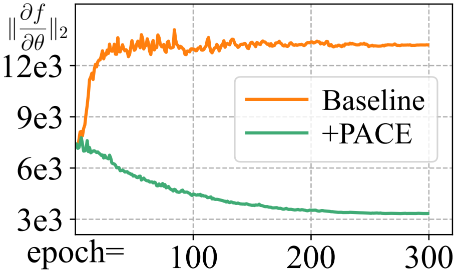

Gradient norms on CIFAR-100 w/ ViT-B/16

PACE:Theorem 3

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$f(\boldsymbol{\theta}_0)$

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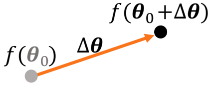

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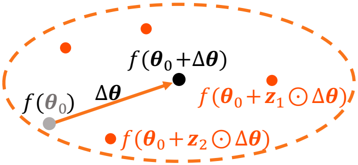

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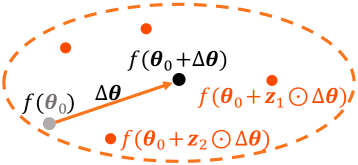

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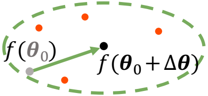

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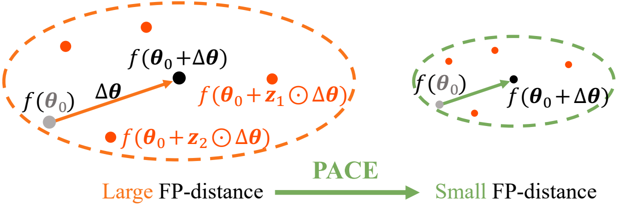

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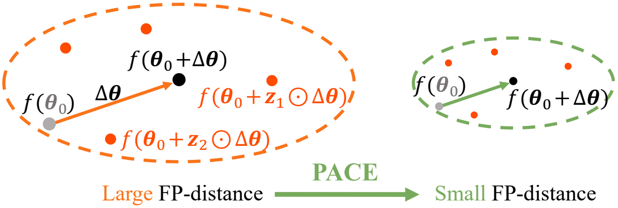

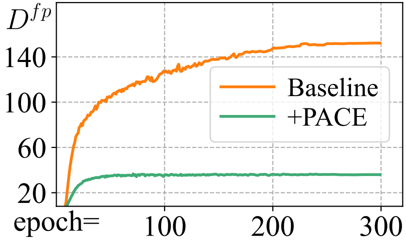

Distance between fine-tuned and pre-trained models (D^{fp}) on CIFAR-100 w/ ViT-B/16.

Experiments: Image Classification

Results on VTAB-1K with ViT-B/16.

Method	Natural							Specialized				Structured								
	Cifar100	Caltech101	DTD	Flowers102	Pets	SVHN	Sun397	Camelyon	EuroSAT	Resisc45	Retinopathy	Clevr-Count	Clevr-Dist	DMLab	KITTI-Dist	dSpr-Loc	dSpr-Ori	sNORB-Azim	NsORB-Ele	Mean Acc.
Full	68.9	87.7	64.3	97.3	86.9	87.4	38.8	79.7	95.7	84.2	73.9	56.3	58.6	41.7	65.5	57.5	46.7	25.7	29.1	68.9
Linear	64.4	85.0	63.2	97.0	86.3	36.6	51.0	78.5	87.5	68.5	74.0	34.3	30.6	33.2	55.4	12.5	20.0	9.6	19.2	57.6
VPT-Deep	78.8	90.8	65.8	98.0	88.3	78.1	49.6	81.8	96.1	83.4	68.4	68.5	60.0	46.5	72.8	73.6	47.9	32.9	37.8	72.0
Adapter	69.2	90.1	68.0	98.8	89.9	82.8	54.3	84.0	94.9	81.9	75.5	80.9	65.3	48.6	78.3	74.8	48.5	29.9	41.6	73.9
AdaptFormer	70.8	91.2	70.5	99.1	90.9	86.6	54.8	83.0	95.8	84.4	76.3	81.9	64.3	49.3	80.3	76.3	45.7	31.7	41.1	74.7
LoRA	67.1	91.4	69.4	98.8	90.4	85.3	54.0	84.9	95.3	84.4	73.6	82.9	69.2	49.8	78.5	75.7	47.1	31.0	44.0	74.5
NOAH	69.6	92.7	70.2	99.1	90.4	86.1	53.7	84.4	95.4	83.9	75.8	82.8	68.9	49.9	81.7	81.8	48.3	32.8	44.2	74.2
RepAdapter	69.0	92.6	**75.1**	99.4	91.8	90.2	52.9	87.4	95.9	87.4	75.5	75.9	62.3	53.3	80.6	77.3	54.9	29.5	37.9	76.1
RLRR	75.6	92.4	72.9	99.3	91.5	89.8	57.0	86.8	95.2	85.3	75.9	79.7	64.2	53.9	82.1	83.9	53.7	33.4	43.6	76.7
GLoRA	76.4	92.9	74.6	**99.6**	**92.5**	91.5	57.8	87.3	**96.8**	88.0	76.0	83.1	67.3	54.5	**86.2**	83.8	52.9	37.0	41.4	78.0
Baseline	74.9	93.3	72.0	99.4	91.0	91.5	54.8	83.2	95.7	86.9	74.2	83.0	70.5	51.9	81.4	77.9	51.7	33.6	44.4	76.4
+PACE	**79.0**	**94.2**	73.6	99.4	92.4	**93.7**	**58.0**	**87.4**	96.4	**89.3**	**77.1**	**84.9**	**70.9**	**54.9**	84.3	**84.7**	**57.3**	**39.3**	**44.8**	**79.0**

Experiments: Text classification & generation

Results for GLUE w/ RoBERTa$_{\text{base}}$. Matthew's/Pearson correlation for COLA/STSB, and accuracy for others.

Method	COLA	STSB	MRPC	RTE	QNLI	SST2	Avg.
Full	63.6	91.2	90.2	78.7	92.8	94.8	85.2
BitFit	62.0	90.8	**92.7**	81.5	91.8	93.7	85.4
Adapt	62.6	90.3	88.4	75.9	93.0	94.7	84.2
VeRA	65.6	90.7	89.5	78.7	91.8	94.6	85.2
LoRA	63.4	91.5	89.7	86.6	93.3	95.1	86.6
+PACE	**66.2**	**92.0**	91.4	**86.9**	**93.6**	**95.6**	**87.6**

Results for GSM-8K w/ Phi-3-mini-4k-instruct.

Method	Accuracy
Pre-trained	62.01
Full	73.16
LoRA	75.66
+PACE	**78.77**

Conclusions

Conclusions:

- PACE perturbs adapter features and enforces consistency regularization across perturbations.
- PACE regularizes gradients for improved generalization and reduces fine-tuned pre-trained distance to retain knowledge.