



What Deep CNNs Benefit from Global Covariance Pooling:

An Optimization Perspective

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Paper



Code

Motivation and Contributions

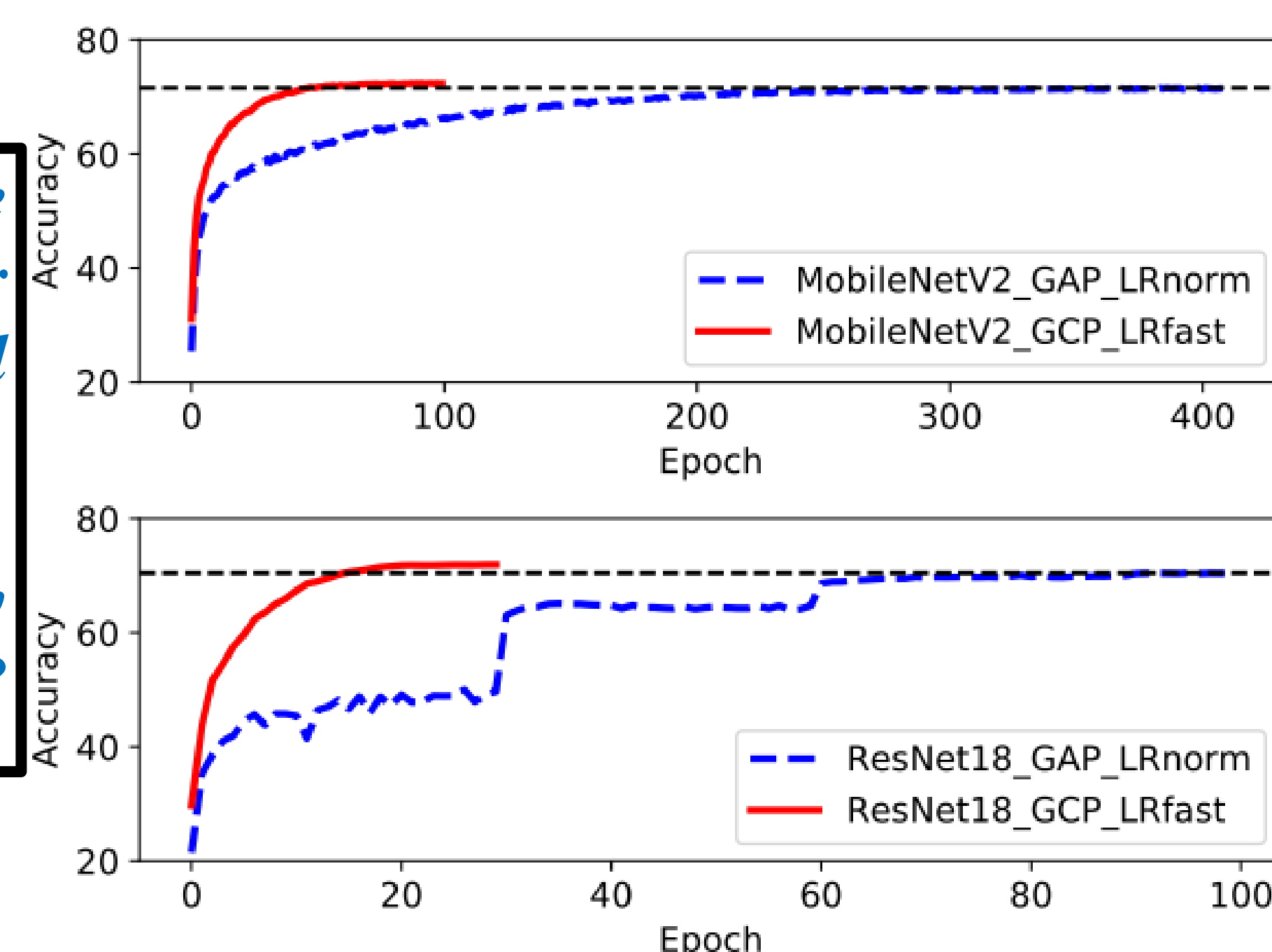
Motivation:

Recent works have demonstrated that global covariance pooling (GCP) has the ability to improve performance of deep CNNs.

- *Fine-grained Visual Recognition (4~10% gains)*
- *ImageNet Classification (2~6% gains)*
- *Texture Classification (~4% gains)*

Despite considerable advance, the reasons on effectiveness of GCP for deep CNNs have not been well studied.

E.g., Why GCP can significantly speed up convergence of deep CNNs?



Contributions:

- The first attempt to understand the effectiveness of GCP in the context of deep CNNs from an optimization perspective.
- Showing and explaining several merits of GCP for training deep CNNs that have not been recognized previously or fully explored.

An Optimization Perspective for GCP

1. Smoothing Effect of GCP

Definitions[1]:

- *Stability of optimization loss (i.e., Lipschitzness):*

$$\Delta_l = \mathcal{L}(\mathbf{X} + \eta_l \nabla_{\mathbf{X}} \mathcal{L}(\mathbf{X})), \eta_l \in [a, b]$$

- *Stability of gradients (i.e., predictiveness):*

$$\Delta_g = \left\| \nabla \mathcal{L}(\mathbf{X}) - \nabla \mathcal{L}(\mathbf{X} + \eta_g \nabla \mathcal{L}(\mathbf{X})) \right\|_2, \eta_g \in [a, b]$$

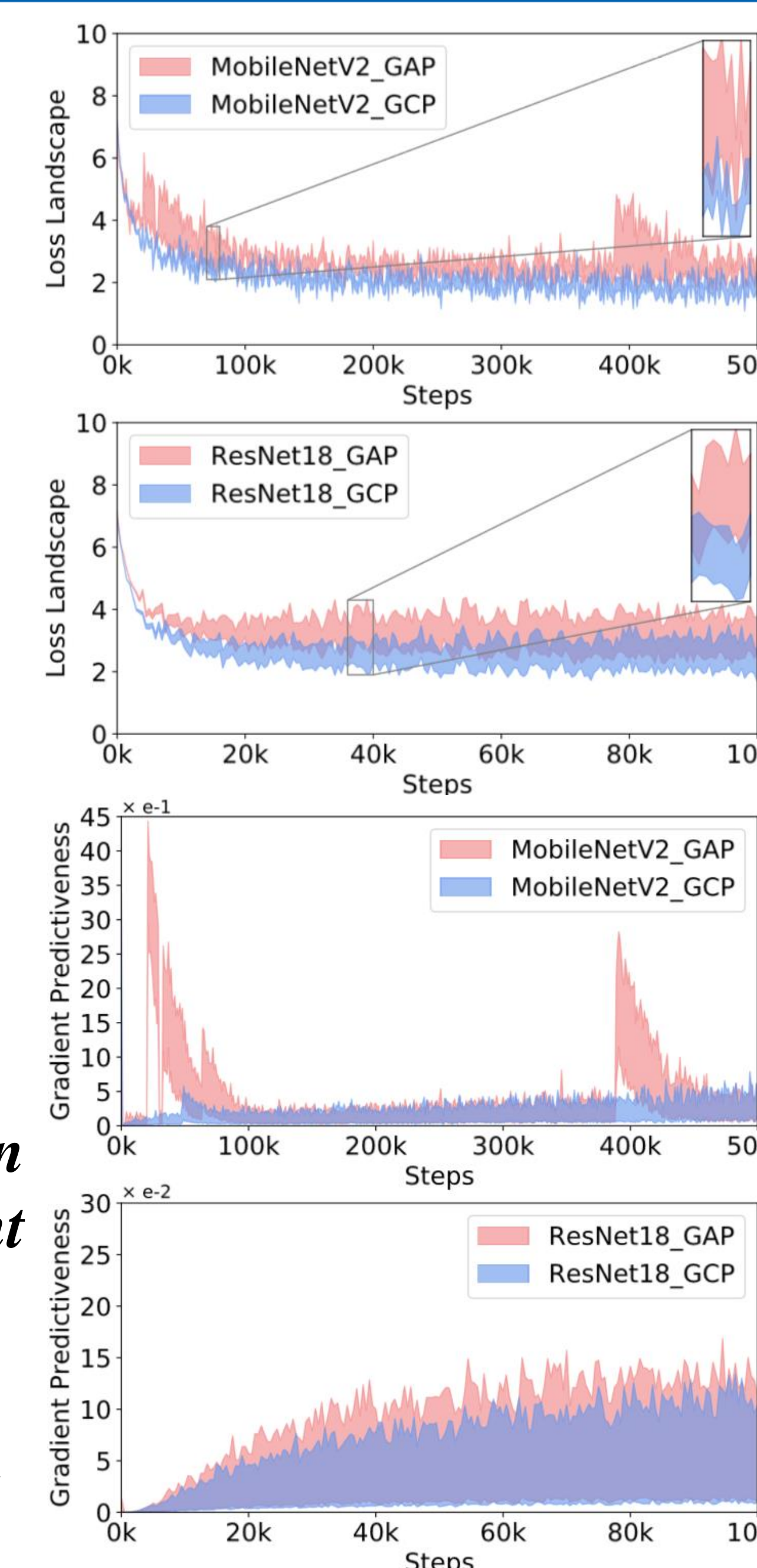
Results:

- Networks with GCP have **smaller variations** of the optimization loss than GAP-based ones.
- Gradients of networks with GCP are **more stable** than those of GAP-based ones.

Conclusion:

- GCP has the ability to smoothen optimization landscape of deep CNNs and improve gradient predictiveness.

[1] Santurkar S, Tsipras D, Ilyas A, et al. How Does Batch Normalization Help Optimization? *NeurIPS*. 2018.



2. Connection to Second-order Optimization

Method	Gradient	Remark
GAP	$\eta \mathbf{C}^T \frac{\partial \mathcal{L}}{\partial \mathbf{Z}_{\text{GAP}}} \frac{\partial \mathbf{X}}{\partial \mathbf{W}_t}$	\mathbf{C} is a constant matrix
GCP	$\approx \mathbf{F}^{-1} \frac{\partial \mathcal{L}}{\partial \mathbf{Z}_{\text{GCP}}} \frac{\partial \mathbf{X}}{\partial \mathbf{W}_t}$	$\mathbf{F}^{-1} = \eta 2 \mathbf{J} \mathbf{X} \left(2 \mathbf{K}^T \circ \mathbf{\Lambda}^{\frac{1}{2}} + \frac{1}{2} \mathbf{\Lambda}^{-\frac{1}{2}} \right)$
K-FAC [35]	$\mathbf{H}^{-1} \mathbf{C}^T \frac{\partial \mathcal{L}}{\partial \mathbf{Z}_{\text{GAP}}} \frac{\partial \mathbf{X}}{\partial \mathbf{W}_t}$	$\mathbf{H}^{-1} = \eta \left(\frac{\partial \mathcal{L}}{\partial \mathbf{X}} \right)^{-1} \otimes \hat{\mathbf{X}}^{-1}$

Comparison of gradients involved in GAP, GCP and GAP with K-FAC

★ K-FAC is a second-order optimization method.

The relationship between GCP and K-FAC:

- *Inverse of Hessian matrix: (GCP-output \mathbf{X} and its eigenvalues) vs. (K-FAC-input and the gradient of output \mathbf{X}).*
- *The trimmed BP of GCP shares some similar philosophy with K-FAC.*

■ BP of GCP is a potential alternative of Hessian pre-conditioner.

Merits Benefited from GCP

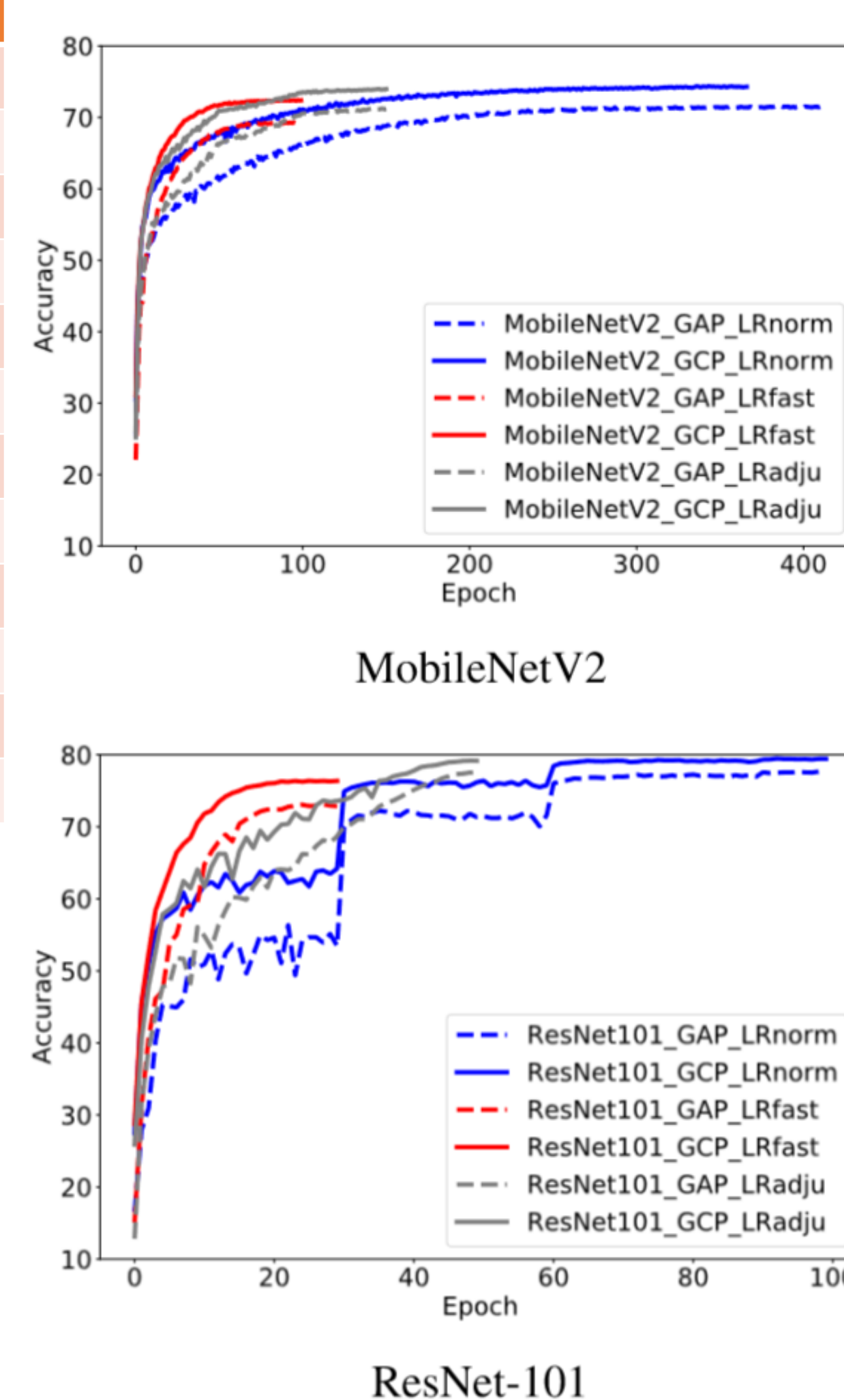
1. Acceleration of Network Convergence

Model	Method	lr	BS	Training Epochs	Matching Epoch	Top-1 Acc.	Top-5 Acc.
MobileNetV2	GAP	LR_{norm}	96	400	N/A	71.58	90.30
	GCP	LR_{adj}	192	150	68 ₍₁₃₃₂₎	73.97 _(12.39)	91.54 _(11.24)
ShuffleNetV2	GAP	LR_{norm}	1,024	240	N/A	67.96	87.84
	GCP	LR_{adj}	1,024	100	78 ₍₁₁₆₂₎	71.17 _(13.21)	89.74 _(11.90)
ResNet-18	GAP	LR_{norm}	256	100	N/A	70.47	89.62
	GCP	LR_{adj}	256	50	32 ₍₁₆₈₎	74.86 _(14.39)	91.81 _(12.19)
ResNet-34	GAP	LR_{norm}	256	100	N/A	74.19	91.61
	GCP	LR_{adj}	256	50	38 ₍₁₆₂₎	76.81 _(12.62)	93.09 _(11.48)
ResNet-50	GAP	LR_{norm}	256	100	N/A	76.17	92.93
	GCP	LR_{adj}	256	50	40 ₍₁₆₀₎	78.03 _(11.86)	93.95 _(11.02)
ResNet-101	GAP	LR_{norm}	256	100	N/A	77.67	93.89
	GCP	LR_{adj}	256	50	41 ₍₁₅₉₎	79.18 _(11.51)	94.51 _(10.62)

Comparison of model trained with GAP using LRnorm and with GCP using LRadj on ImageNet

■ GCP can significantly speed up convergence of deep CNNs with rapid decay of learning rates.

- GCP achieves matching accuracies to GAP using only about $\frac{1}{3}$ training epochs.
- GCP achieves **1.5%~4.4%** accuracy improvement over GAP using less than $\frac{1}{2}$ training epochs.



2. Robustness to Distorted Examples

Method	IMAGENET-C		IMAGENET-P	
	mCE	Relative mCE	mFP	mTSD
MobileNetV2+GAP	87.1	114.9	79.8	96.5
MobileNetV2+GCP	81.7 _(15.4)	110.6 _(4.3)	64.3 _(115.5)	87.6 _(18.9)
ShuffleNetV2+GAP	92.7	126.7	94.7	108.2
ShuffleNetV2+GCP	85.2 _(17.5)	112.6 _(14.1)	75.2 _(119.5)	95.5 _(112.7)
ResNet-18+GAP	84.7	103.9	72.8	87.0
ResNet-18+GCP	76.3 _(18.4)	101.3 _(12.6)	53.2 _(119.6)	77.1 _(19.9)
ResNet-34+GAP	77.9	98.7	61.7	79.5
ResNet-34+GCP	72.4 _(15.5)	96.9 _(11.8)	47.7 _(114.0)	72.4 _(17.1)
ResNet-50+GAP	76.7	105.0	58.0	78.3
ResNet-50+GCP	70.7 _(16.0)	97.9 _(17.1)	47.5 _(110.5)	74.6 _(13.7)
ResNet-101+GAP	70.3	93.7	52.6	73.9
ResNet-101+GCP	65.5 _(14.8)	89.1 _(14.6)	42.1 _(110.5)	68.3 _(15.6)

Comparison of GAP and GCP on IMAGENET-C and IMAGENET-P

■ GCP can greatly improve the robustness of deep CNNs to common image corruptions and perturbations.

- **5~8.5** and **2~14** improvement on ImageNet-C.
- **10~20** and **4~13** improvement on ImageNet-P.

3. Generalization Ability to Other Tasks

Backbone Model	Method	Detectors	AP	AP ₅₀	AP ₇₅	AP _s	AP _M	AP _L
ResNet-50	GAP	Faster R-CNN	36.4	58.2	39.2	21.8	40.0	46.2
	GCP _D		36.6 _(0.2)	58.4 _(0.2)	39.5 _(0.3)	21.3 _(0.5)	40.8 _(0.8)	47.0 _(0.8)
	GCP _M		37.1 _(0.7)	59.1 _(0.9)	39.9 _(0.7)	22.0 _(0.2)	40.9 _(0.9)	47.6 _(1.4)
ResNet-101	GAP	Faster R-CNN	38.7	60.6	41.9	22.7	43.2	50.4
	GCP _D		39.5 _(0.8)	60.7 _(0.1)	43.1 _(1.2)	22.9 _(0.2)	44.1 _(0.9)	51.4 _(1.0)
	GCP _M		39.6 _(0.9)	61.2 _(0.6)	43.1 _(1.2)	23.3 _(0.6)	43.9 _(0.7)	51.3 _(0.9)
ResNet-50	GAP	Mask R-CNN	37.2	58.9	40.3	22.2	40.7	48.0
	GCP _D		37.3 _(0.1)	58.8 _(0.1)	40.4 _(0.1)	22.0 _(0.2)	41.1 _(0.4)	48.2 _(0.2)
	GCP _M		37.9 _(0.7)	59.4 _(0.5)	41.3 _(1.0)	22.4 _(0.2)	41.5 _(0.8)	49.0 _(1.0)
ResNet-101	GAP	Mask R-CNN	39.4	60.9	43.3	23.0	43.7	51.4
	GCP _D		40.3 _(0.9)	61.5 _(0.6)	44.0 _(0.7)	24.1 _(1.1)	44.7 _(1.0)	52.5 _(1.1)
	GCP _M		40.7 _(1.3)	62.0 _(1.1)	44.6 _(1.3)	23.9 _(0.9)	45.2 _(1.5)	52.9 _(1.5)

Object detection of various deep CNN models using Faster R-CNN and Mask R-CNN on COCO val2017

Method	AP	AP ₅₀	AP ₇₅	AP _s	AP _M	AP _L
R-50+GAP	34.1	55.5	36.2	16.1	36.7	50.0
R-50+GCP _D	34.2	55.3	36.4	15.8	37.1	50.1
R-50+GCP _M	34.7	56.3	36.8	16.4	37.5	50.6
R-101+GAP	35.9	57.7	38.4	16.8	39.9	53.5
R-101+GCP _D	36.5	58.2	39.1	17.6	39.9	53.5
R-101+GCP _M	36.7	58.7	39.1	17.6	39.9	53.7

Instance segmentation of various deep CNN models using Mask R-CNN on COCO val2017

■ GCP has good generalization ability to other tasks.

- GCP improves **~0.9%** over GAP on object detection.
- GCP improves **~0.8%** over GAP on instance segmentation.