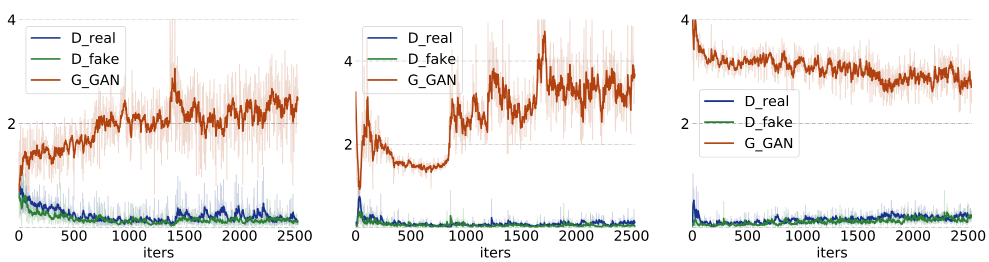
Revisiting Discriminator in GAN Compression: A Generator-discriminator Cooperative Compression Scheme (Appendix)

A Mode Collapse in SAGAN

We also observe that the phenomenon of mode collapse on SAGAN. As shown in Figure 1(b) that merely compressing the generator and retraining the original discriminator will cause obvious loss oscillation. Similarly, as shown in the middle part of Figure II, the generated results are not impressive. However, the loss curve is much stable and the quality of the generated images are greatly improved with the introduction of our proposed GCC.



(a) Original generator + original discriminator (b) 1/4 channels width generator + original discriminator (c) 1/4 channels width generator + GCC

Figure I: Loss curves under different training settings. The experiment is conducted on SAGAN based on the CelebA dataset. (a), (b) and (c) show loss curves of the original generator, the 1/4 channels width generator with the original discriminator, and the 1/4 channels width generator with our proposed GCC, respectively.

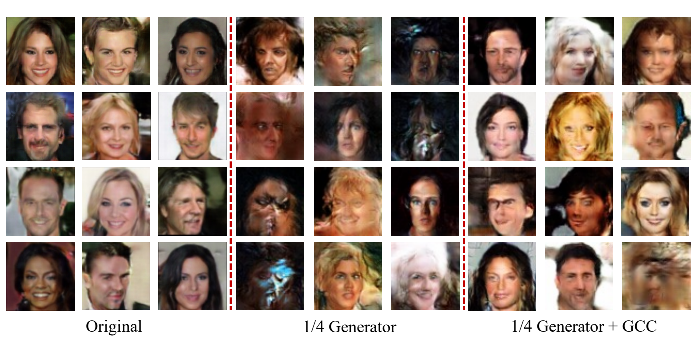


Figure II: Illustration of model collapse phenomenon.

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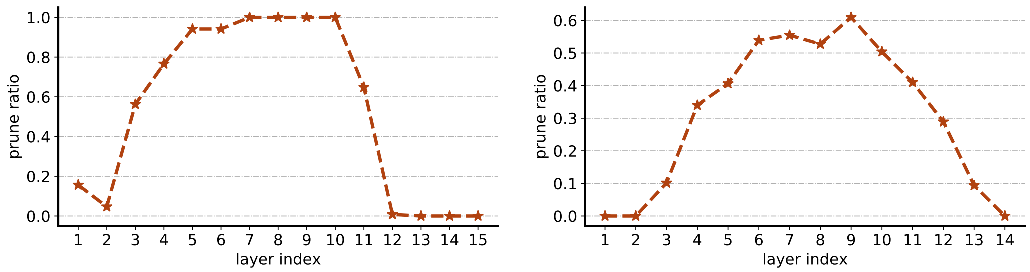

(a) L1-norm Pruning (b) Network Slimming

Figure III: The pruning rate of Pix2Pix model based on Cityscapes dataset after L1-norm pruning or slimming pruning.

B Pruning Details

Network slimming [3] adds L1 regularization to the scale parameter in the BN layer, and finally employs the absolute value of the scale parameter as the important metric of the corresponding convolution kernel. L1-norm pruning [2] also adds L1 regularization to the weights of all convolution kernels and then uses the L1-norm of the convolution kernel as its importance metric. To avoid the impact of adding additional L1 regularization on the performance of the generator and additional fine-tuning after pruning. We only use 1/10 of the original training epoch to add the L1 regularization to the generator, and then sort all the convolution kernels in ascending order according to their importance metric. Given computational constrain, the pruning method removes the convolution kernel with less importance until the requirements are met.

To verify the adaptability of the pruning methods [2, 3] in the generator network, we visualize the pruning ratio of each layer in the Pix2Pix generator in Figure III. We find that the pruning ratio of each layer likes an inverted letter "U" as the number of network layers deepens. Pix2Pix generator takes U-Net as the backbone network, so the first/last few layers play a direct role in generating real-like fake images. The output feature map size is only 1×1 in the most intermediate network layer, which has little effect on the final 256×256 image. In conclusion, the pruning methods [2, 3] can better identify the important convolution kernel of the generator.

C Formulation of Texture loss function.

The purpose of Texture loss is to ensure that the two images have a similar style (*e.g.*, colors, textures, contrast). We directly use it to measure the similarity between two features. The feature similarity is regarded as the correlations between different feature channels and defined as the Gram matrix $G(O^l) \in \mathbb{R}^{c_l \times c_l}$, where c_l represents the number of channels in the l-th layer output feature map O^l. We denote $G_{ij}(O)$ as the inner product between the i-th channel feature map of O^l and j-th channel feature map of O. Then the texture loss function is calculated as follows:

$$\text{Texture}(\hat{O}, O) = \frac{1}{c_l^2} \sqrt{\sum_{i,j} \left(G_{ij}(\hat{O}) - G_{ij}(O) \right)^2} \tag{I}$$

where $\hat{O}$ and O respectively represent different output feature maps.

D Implementation Details

Table I: Hyperparameter settings in the experiment.

Model	Dataset	Training Epochs		Batch Size	γ_m	γ_t	GAN Loss	ngf		ndf
		Const	Decay					Teacher	Student	
SAGAN	CelebA	100	0	64	1	100	Hinge	64	48	64
CycleGAN	Horse2zebra	100	100	1	0.01	1e3	LSGAN	64	24	64
Pix2Pix	Cityscapes	100	150	1	50	1e4	Hinge	64	32	128
SRGAN	COCO	15	15	16	0.1	0.1	Vanilla	64	24	64

We use Pytorch to implement the proposed GCC on NVIDIA V100 GPU. We have conducted experiments on SAGAN[1], CycleGAN[2], Pix2Pix[3] and SRGAN[4] respectively, and hyperparameter settings are shown in Tab. I.

Selective Activation Discriminator. We optimize α via the ADAM optimizer with an initial learning rate of 0.0001, and decay by 0.1 every 100 epoch. The threshold τ of SAGAN, CycleGAN, Pix2Pix and SRGAN in Eq. 3 are set to 0.1, 0.1, 0.5, 0.1 respectively. In addition, we denote $|\mathcal{L}_G^T - \mathcal{L}_{D_{fake}}^T|$ of Eq.7 as $\mathcal{L}_{target}$. We use Exponential Moving Average (EMA) to stabilize $\mathcal{L}_{target}$ during the training process. The specific update strategy is as follows:

$$\mathcal{L}_{target} = \beta_t * \mathcal{L}_{target}^{t-1} + (1.0 - \beta_t) * \mathcal{L}_{target}^{t} \tag{II}$$

$$\beta_t = Epoch_{current}/Epoch_{total} \tag{III}$$

where t represents the current number of iterations. $Epoch_{current}$ / $Epoch_{total}$ represent the current / total epoch number of training.

Table II: Selection of distillation convolutional layer location. 'Total Number' represents the number of all convolution layers in the network, and 'Selected Number' represents the serial number of the selected convolutional layer.

Model	Dataset	Generator Position		Discriminator Position	
		Total Number	Selected Number	Total Number	Selected Number
SAGAN	CelebA	5	2, 4	5	2, 4
CycleGAN	Horse2zebra	24	3, 9, 15, 21	5	2, 4
Pix2Pix	Cityscapes	16	2, 4, 12, 14	5	2, 4
SRGAN	COCO	37	9, 17, 25, 33	4	2, 4

Distillation Layers. We show the position of the selected distillation layer in each network in Tab. II. We usually choose the nonlinear activation layer after the selected convolutional layer, otherwise we choose the normalization layer or the convolutional layer itself.

To sum up, we summarize the proposed GCC framework in Algorithm 1.

E Additional Ablation Study

Selective Activation Discriminator. We report the ablative studies of selective activation discriminator in Table III. Motivated by discriminator-free method [1], we discard the student discriminator and train the lightweight generator only with $L_{distill}$, which obtains 35.50 mIOU. It may be due to

[1] SAGAN repository: https://github.com/heykeetae/Self-Attention-GAN
[2] CycleGAN repository: https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix
[3] Pix2Pix repository: https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix
[4] SRGAN repository: https://github.com/sgrvinod/a-PyTorch-Tutorial-to-Super-Resolution

Algorithm 1 The Proposed GCC Framework

Input: inputs $\boldsymbol{Z} = \{\boldsymbol{z}\}_i^N$, real images $\boldsymbol{X} = \{\boldsymbol{x}\}_i^N$, training epochs E, uncompressed generator G^T and discriminator D^T, selective activation discriminator D^S, and retention factor α.
Output: efficient lightweight generator.

 # First Step: Generator Compression
for epoch = 1 : E / 10 **do**
  Update G^T and D^T using Eq. 1 and Eq. 2 respectively, and L1 regularization is added to the BN scale parameter or weight of G^T.
end for
Prune G^T to obtain a lightweight generator G^S, and reinitialize G^T, D^T and G^S.
 # Second Step: Lightweight Generator Training
for epoch = 1 : E **do**
  Get a batch of $\boldsymbol{z}_1$ from $\boldsymbol{Z}$ and $\boldsymbol{x}_1$ from $\boldsymbol{X}$
  Update G^T and D^T using Eq. 1 and Eq. 2 respectively.
  Update G^S using the combination of Eq. 1 and Eq. 10.
  Freeze α and train D^S using Eq. 2.
  Get a batch of $\boldsymbol{z}_2$ from $\boldsymbol{Z}$ and $\boldsymbol{x}_2$ from $\boldsymbol{X}$
  Freeze D^S's weight parameter and update α using Eq. 8.
end for

Table III: Ablation study results in selective activation discriminator.

Name	Discriminator	Selective Activation	L_{global}	mIOU
Ours w/o discriminator	×	×	×	35.50
Ours w/o selective activation	✓	×	✓	37.24
Ours w/o L_{global}	✓	✓	×	40.21
GCC(Ours)	✓	✓	✓	**42.88**

the fact that although the discriminator-free method avoids the model collapse issue, it fails to take good advantage of GAN loss to provide more supervision information for the lightweight generator. In order to investigate whether selective activation discriminator and global coordination constraint L_{global} can work synergistically, we discard one of them and the experimental results indicate that the selective activation discriminator and L_{global} work mutually to achieve impressive results.

F Border Impact

Our proposed GCC needs a teacher model whose generator can conduct normal adversarial training with a discriminator. The teacher model guides the learning of selective activation discriminator and the lightweight generator. Therefore, GCC relies on a good teacher model to ensure the effectiveness of compression. In addition, due to the instability of adversarial training, GAN may generate results that distort objective facts. This may be potential negative social impacts of our work.

G More Qualitative Results

We show more qualitative results in Figure IV, V, VI, and VII, respectively.

References

[1] Yonggan Fu, Wuyang Chen, Haotao Wang, Haoran Li, Yingyan Lin, and Zhangyang Wang. Autogan-distiller: Searching to compress generative adversarial networks. *arXiv preprint arXiv:2006.08198*, 2020.

[2] Hao Li, Asim Kadav, Igor Durdanovic, Hanan Samet, and Hans Peter Graf. Pruning filters for efficient convnets. *arXiv preprint arXiv:1608.08710*, 2016.

[3] Zhuang Liu, Jianguo Li, Zhiqiang Shen, Gao Huang, Shoumeng Yan, and Changshui Zhang. Learning efficient convolutional networks through network slimming. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 2736–2744, 2017.

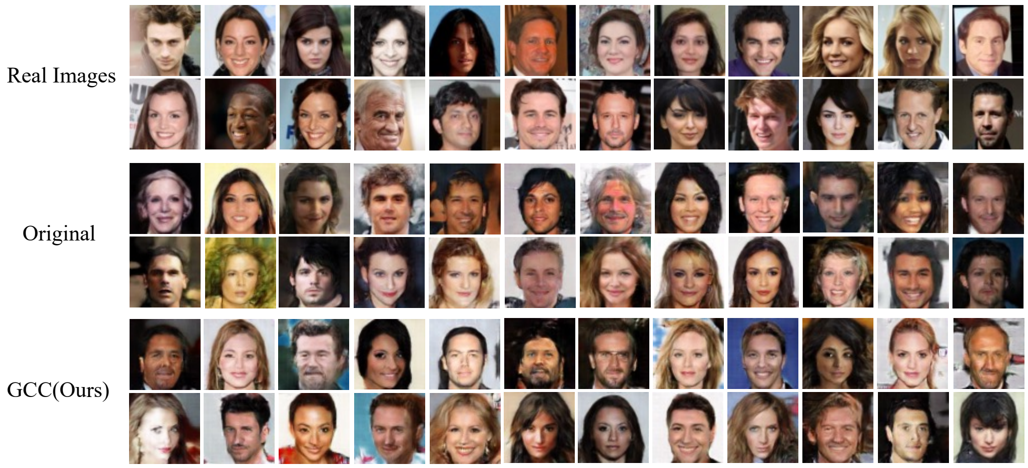

Figure IV: Qualitative results of SAGAN based on CelebA dataset.

Figure V: Qualitative results of CycleGAN based on Horse2zebra dataset.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Appendix F.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Appendix F.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No]

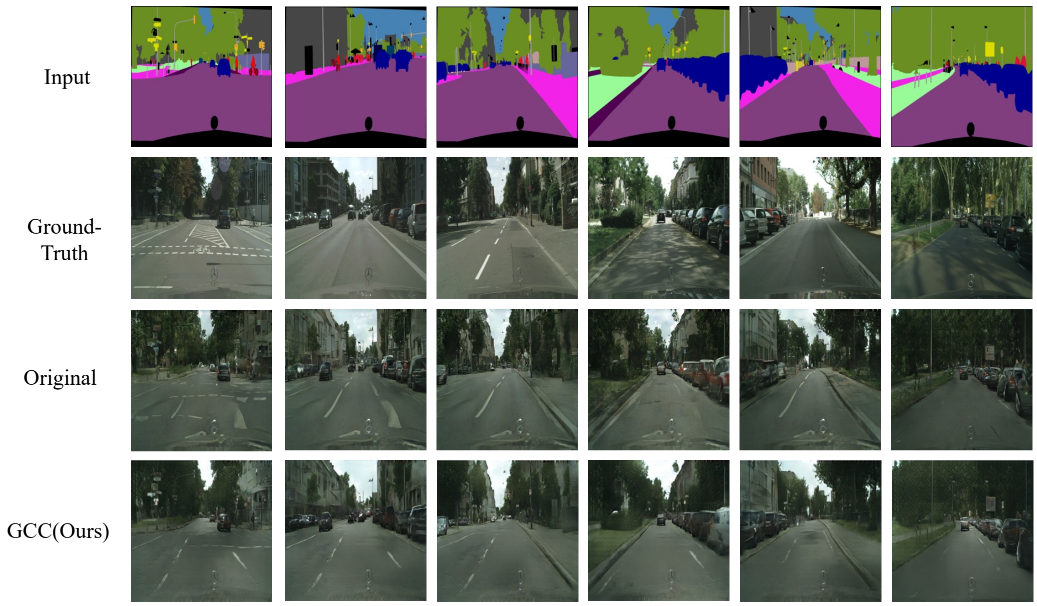

Figure VI: More qualitative results of Pix2Pix based on Cityscapes dataset.

Figure VII: More qualitative results of SRGAN based on Set5 / Set14 / BSD100 / Urban100 dataset.

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Appendix D.
(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix D.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [Yes]
(b) Did you mention the license of the assets? [No]
(c) Did you include any new assets either in the supplemental material or as a URL? [No]
(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [No]
(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [No]

5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]