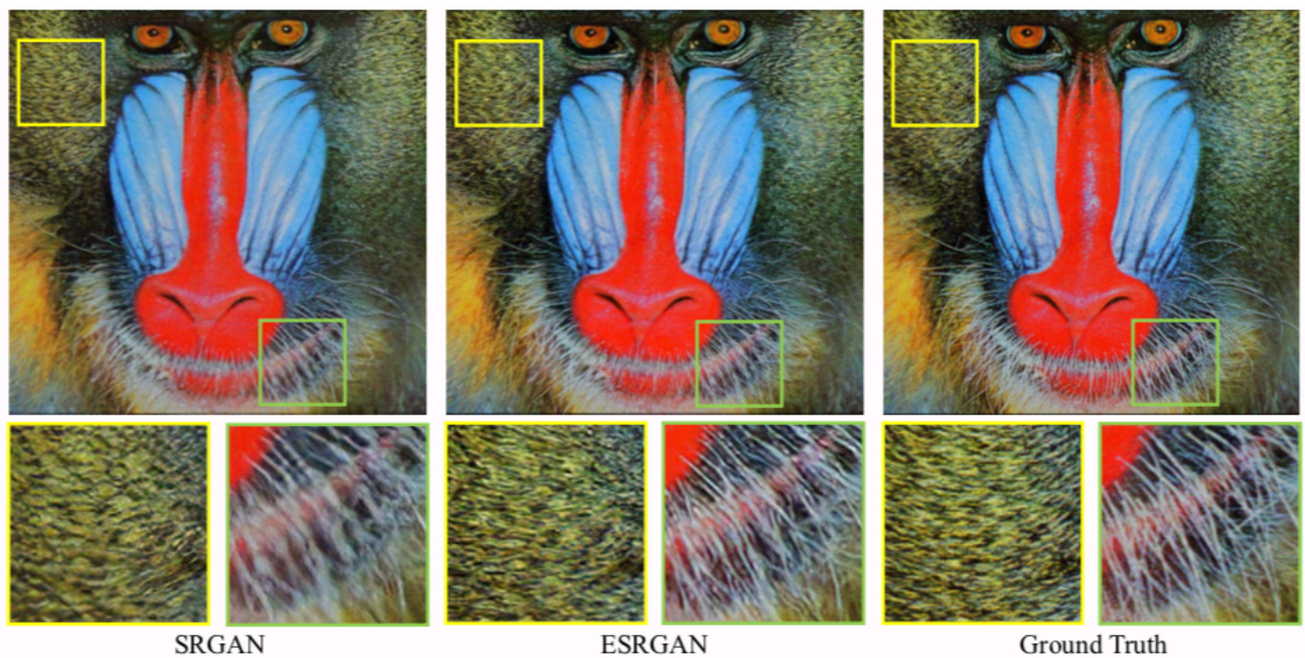
The Summary of ESRGAN

Paper link: https://arxiv.org/abs/1809.00219
Github link: https://github.com/xinntao/ESRGAN

Overview

This ESRGAN is enhanced version of pervious SRGAN, which figure out unpleasant artifacts in SRGAN.ESRGAN is capable
of generating more detailed structure while others fail to produce details.



Three key components

ESRGAN come up with three points from **network architecture, adversarial loss, perceptual loss**.

- Introduce the Residual-in-Residual Dense Block (RRDB) without batch normalization as the basic network building unit. RRDB is higher capacity and easier to train
- Borrow the idea from relativistic GAN to let the discriminator predict relative realness instead of the absolute value
- Improve the perceptual loss by using the features before activation, which could provide stronger supervision for brightness consistency and texture recovery.

Previous model

So many networks has impoved SR performance, especially **Peak Signal to Noise Ratio** value. The **drawback** is: since PSNR metric fundamentally disagree with the **subjective evaluation of human observers**, these PSNR-Oriented approcaches(SRCNN) tend to output **over-smoothed results** without sufficient **high-frequency details**.
In order to solve this problems which caused by PSNR-Oriented approcaches, **Perceptual-driven methods** have been proposed to improve the visual quality of SR results. The main contribution of those perceptual-driven methods is that **Perceptual loss**. **Perceptual loss** is proposed to optimize super-resolution model in a **feature space** instead of **pixel space**. SRGAN is milestones, which recovered texture details by further incorporated **semantic image prior**. The architecture of SRGAN is: residual blocks and optimized using perceptual loss in a GAN framework.

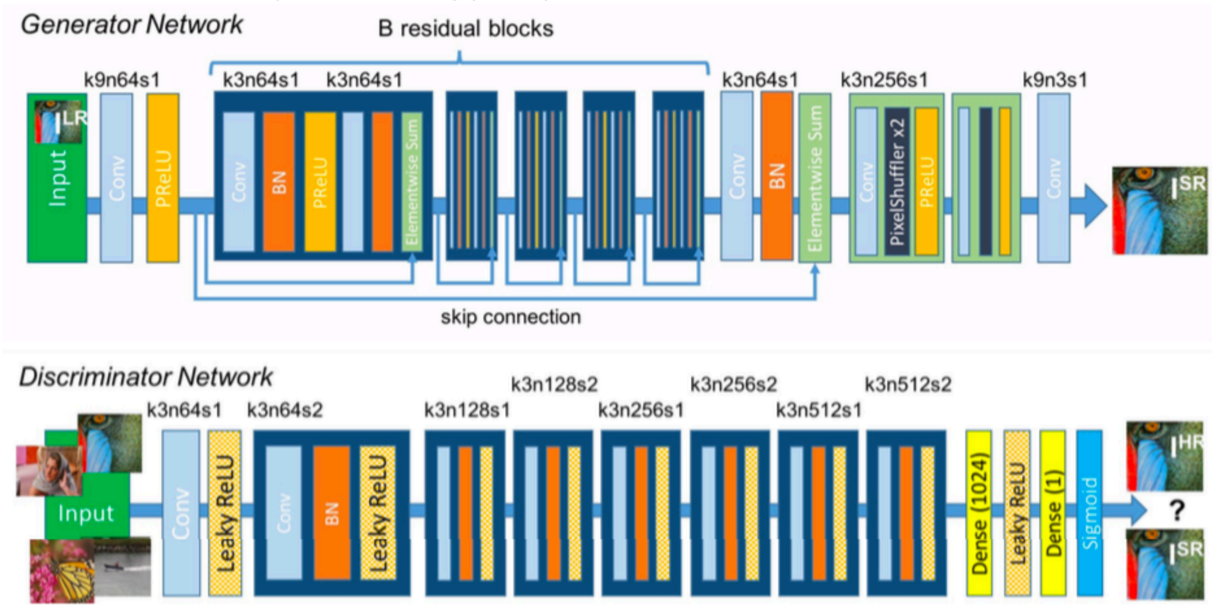


Figure 4: Architecture of Generator and Discriminator Network with corresponding kernel size (k), number of feature maps (n) and stride (s) indicated for each convolutional layer.

The drawbacks of SRGAN

Improve the SRGAN by three aspects

- First, improve the network structure by introducing the Residual-in-Residual Dense Block, which is easier to train. Also **remove BN layers**. From the paper we can know that removing BN can **save** the computational resources and memory usage. Futhermore, when a network is deeper and more complicated, the model with BN layer is more likely to introduce unpleasant artifacts.
- Second, Using **Relativistic average GAN** can let **generator** recover more realistic texture details. **Relativistic average GAN** is learning to judge **whether one image is more realistic than the other** rather than **whether one image is real or fake**. Befor we talk RD, we should know what is GAN's discriminator.The standard discriminator D in SRGAN, which estimates the probability that one input images **x** is real and natural.**But** for RD, it predict the probability that a real image x_r is relativistic **more realistic** than a fake one x_f
- Third, they propose an improved perceptual loss by **using the VGG features before activation**

instead of **after activation as in SRGAN**. They empirically find that this way can provide sharper edges and more visually pleasing results.

Details of ESRGAN

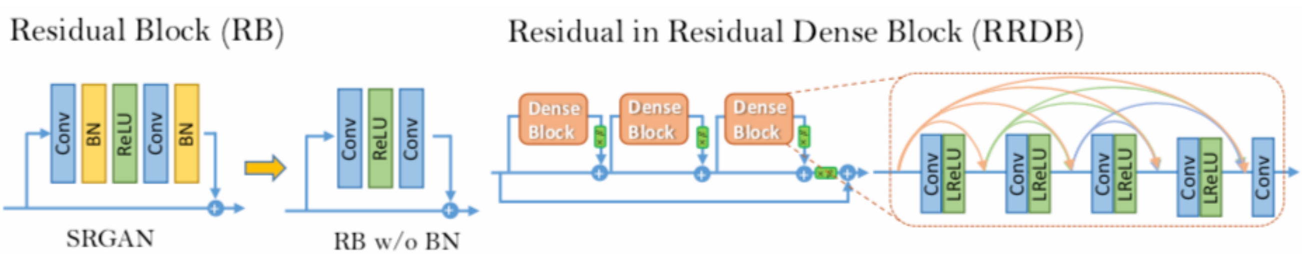
Network Architecture

Generator G

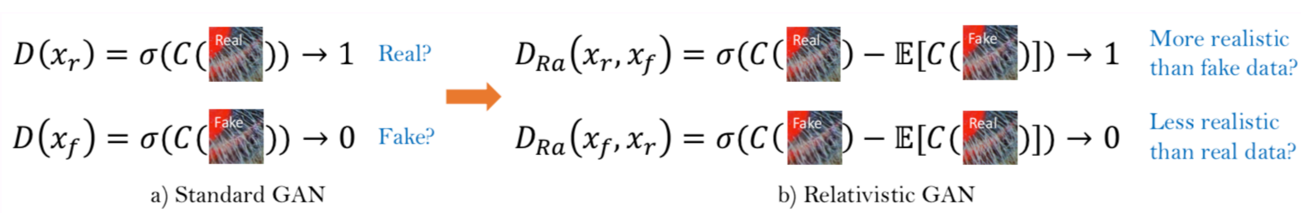
- remove all BN
- Replace the original basic block with RRDB, which combines **multi-level residual network and dense connections**

Residual in Residual Blocks

We keep the high-level architecture design of SRGAN and use a novel RRDB because based on observation that more **layers** and **connections** could always **boost performance**. RRDB employs a **deeper and more complex structure** than the original RB in SRGAN.RRDB use dense block in the main path, this way can make the network capacity becomes higher benefiting from the **dense connections**



Relativistic discriminator



From the diagram we can see that standard discriminator in SRGAN can be expressed as $D(x) = \sigma(C(x))$,where σ is the sigmoid function and $C(x)$ is the **non-transformed discriminator output**. Then the RaD formulated as $D_{Ra}(x_r, x_f) = \sigma(C_{x_r}) - E_{xf}[C(xf)]$ where $E_{xf}[*]$ represents the operation of taking average for all fake data in the mini-batch.

- The discriminator loss is then defind as : $L_D^{Ra} = -E_{xr}[log(D_{Ra(x_r,x_f)})] - E_{xf}[log(1 - D_{Ra}(x_f, x_r))]$
- The adversarial loss for generator is in a symmetical form $L_G^{Ra} = -E_{xr}[log(D_{Ra}(x_r, x_f) - E_{xf}[log(1 - D_{Ra}(x_f, x_r))]$
  From those equotion above we can observe $x_f = G_{x_i}$ and x_i is input LR image. It is observed that in adversarial loss for generator contains **both** x_r and x_f.**Therefore** , RA generator benefits

from the gradients from both **generated data and real data in adversarial training**, but in SRGAN we can see that only generated part takes effect
This RD is not only to **increase** the probability that generated data are real, but also to simultaneously **decrease** the probability that real data are real.(enhance SRGAN by using RAGAN)

Perceptual loss

Unlike SRGAN

constraining on features after activation, this way can cause many drawbacks

- the activated features are very sparse, especially after a very deep network, **the sparse activation** can provides weak supervision and thus leads to inferior performance.
- Using the activation also causes inconsistent reconstructed brightness compared with GT

ESRGAN develop an effective perceptual loss.

L_{percep} use features before activation layers. This way can overcome two drawback as I mentioned above
Therefor the tota loss for the **generator** is
$L_G = L_{percep} + \lambda L_G^{Ra} + \eta L_1$
where $L_1 = E_{x_i} \|G(_{x_i}) - y\|_1$ is the **content loss** that evaluate the **1-norm** distance between **recovered image** G_{x_i} and the **ground-truth** y, and λ, η are the coefficients to balance different loss terms
Instead of using perceptual loss that adpots a VGG network trained for image classification. ESRGAN adopt **SR - MINC** loss,which based on fine-tuned VGG and focuses on **textures rather than object**

Network Interpolation

Two merits

- Interpolated model can produce meaningful results for any feasible α without introducing artifacts.
- Balance perceptual quality and fidelity without re-training the model

This strategy can solve unpleasant noise in GAN based methods.

- Train a PSNR-oriented network G_{PSNR}
- Then obtain a GAN-based network G_{GAN} by fine-tuning.
- Important last is **interpolate** all parameters of these two networks to **derive** an interpolated model G_{INTERP}
  $\theta_G^{INTEPR} = (1-\alpha)\theta_G^{PSNR} + \alpha\theta_G^{GAN}$
  where θ_G^{INTEPR}, θ_G^{PSNR}, θ_G^{GAN} are the parameters of $G_{INTEPER}$, G_{PSNR} and G_{GAN}, and $\alpha \in [0, 1]$ is the interpolation parameter.

Experiments

Training Details

- Obtain LR images by down-sampling HR imagesusing Bicubic kernel function.
- mini-batch size is set to 16 (larger patch size has larger receptive field which help to capture more semantic information)

Training process

Training stages

- First, train a PSNR-oriented model with L1 loss
- Then trained a PSNR-oriented model as an **initialization for the generator** , this generator is trained using the loss function is $L_G = L_{percep} + \lambda L_G^{Ra} + \eta L_1$ (with $\lambda = 5 * 10^{-3}$ and $\eta = 1 * 10^{-2}$) and the learning rate is set to $1 * 10^{-4}$ and halved at [50K,100K,200k,300K] iterations.
  Pre-training with pixel-wise loss helps GAN-based methods to obtain more pleasing results Beacuse :
  - It can avoid undesired local optima for the generator
  - after pre-training, the discriminator receives relatively good super-resolved images instead of extreme fake ones(black or noisy images) at the very begining, which helps it to focus more on texture discrimination

Optimization

Using Adam with $\beta_1 = 0.9$,$\beta_2 = 0.999$. They alternately update the generator and discriminator network until the model converages

Dataset

Training dataset

- DIV2K dataset (high-quality 2K resolution)
- Flickr2K dataset

Testing dataset

- Set5
- Set14
- BSD100
- Urban100
- PIRM self-validation dataset

Trick for training

- Residual Scaling: scaling down the residuals by multiplying a constant between 0 and 1 **before** adding them to the main path to **prevent instability**
- Smaller Initialization: If the **initial parametre variance** becomes smaller, the **residual architecture** is easier to train.

Remove BN layers

BN layers can introduce unpleasant **artifacts** and limit the **generalization ability** as well as increase **computational complexity**. The reason is that

- BN layers normalize the features using **mean** and **variance** in a batch during training and use **estimated mean** and variance of the whole training dataset during testing.
- They Empirically ovserve that BN layers are more likely to bring artifacts when the network is **deeper** and **trained under GAN**

These artifacts occasionally appear among **iterations** and **different settings** . So remove BN can help to training and consistent performance.

Aditional Knowledge

Perceptual loss

Perceptual loss is proposed to enhance the **visual quality** by minimizing the error in a **feature space instead of pixel space**

Contextual loss

Contextual loss is developed to generate images with natural image statistics by using an **objective** that focuses on the **feature distribution** rather than merely **comparing the appearance**

Spatial feature Transform

SFT effectively incorporate **semantic prior** in an image and improve the recovered textures.

The disadvantage of PSNR and SSIM

So many SR algorithms are evaluated by several **distortion measures** :PSNR and SSIM. But those metrics disagree with the **subjective evaluation of human ovservers**. So, which methods are suitable?---Ma's score and NIQE (Non-reference measures) are suitable for **perceptual quality evalution**

perceptual index
residual scaling
perception-distortion