Deep Learning for Image Super-Resolution

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1.1 Breif Introduction to Image Super Resolution

Low resolution image

Mapping(A+,SC,SRCNN,VDSR,etc)

High resolution image

Big&Sharp!

1.2 Challenges in Computer Vision

There are some key roadblocks in computer vision which may make it difficult for object detecting and recognizing:

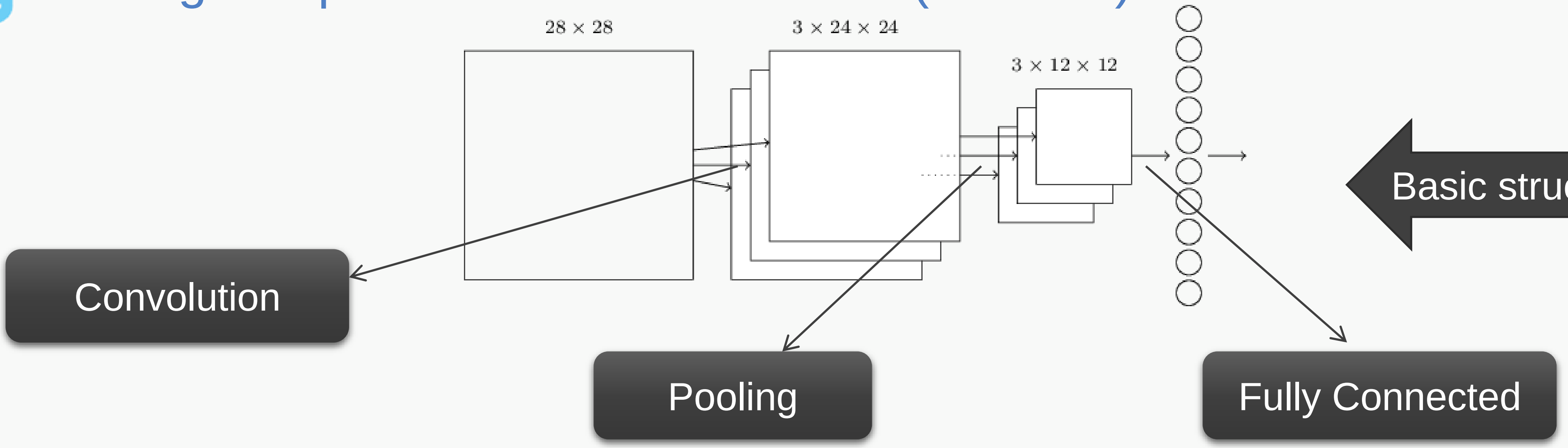
1.Variations in Viewpoint

2. Difference in Illumination

3.Hidden parts of images

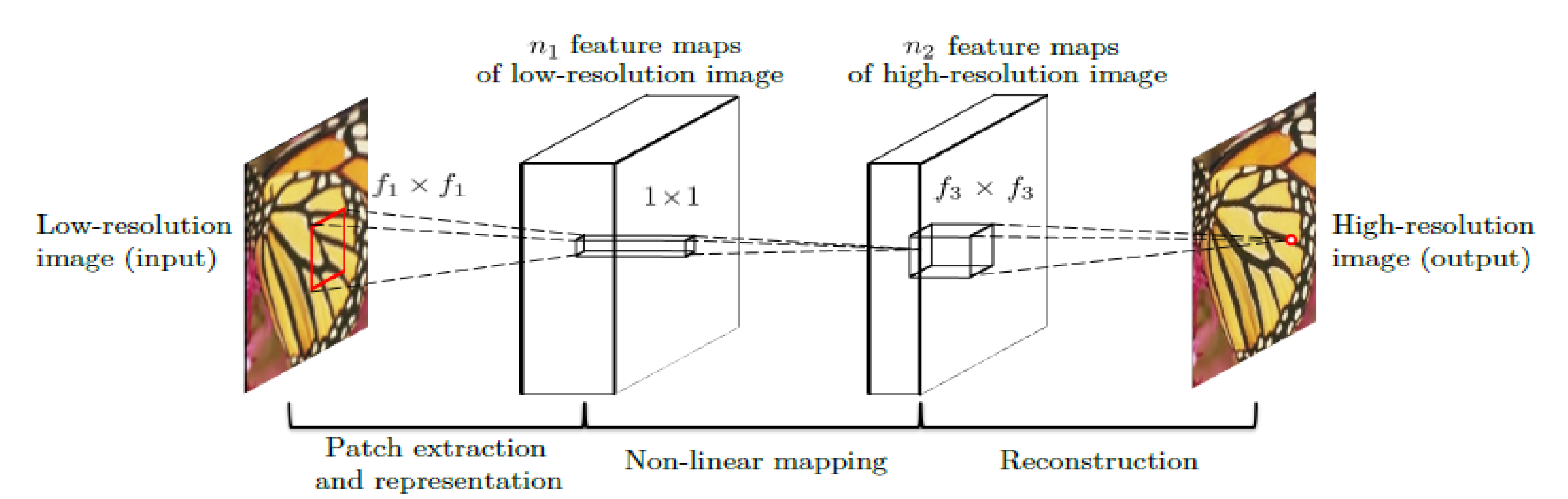
4. Background Clutter

1.3 Convolutional Nerual Networks (CNN) and Image Super-Resolution Using Deep Convolutional Networks(SRCNN)



Basic structure of CNN

A practical use of CNN：SRCNN



2.2 Sparse Coding vs SRCNN

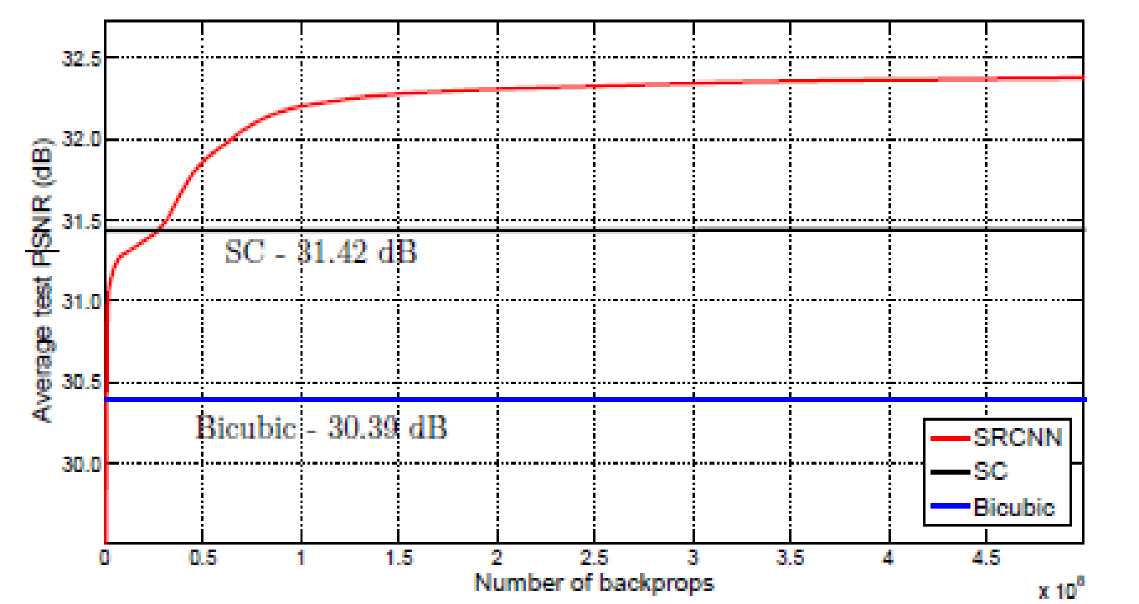


Fig.1[1]

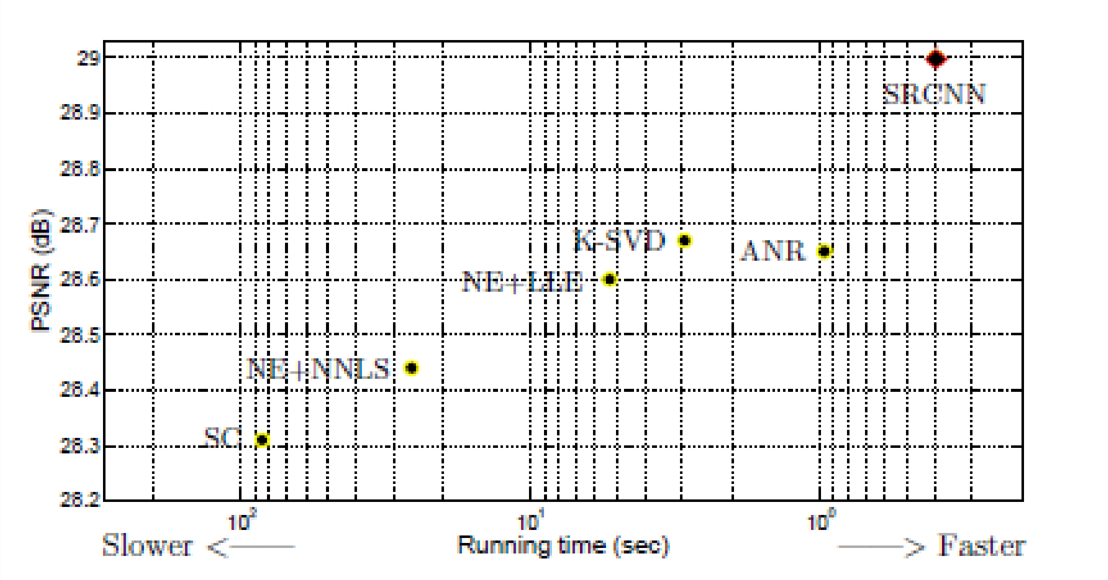


Fig.2[1]

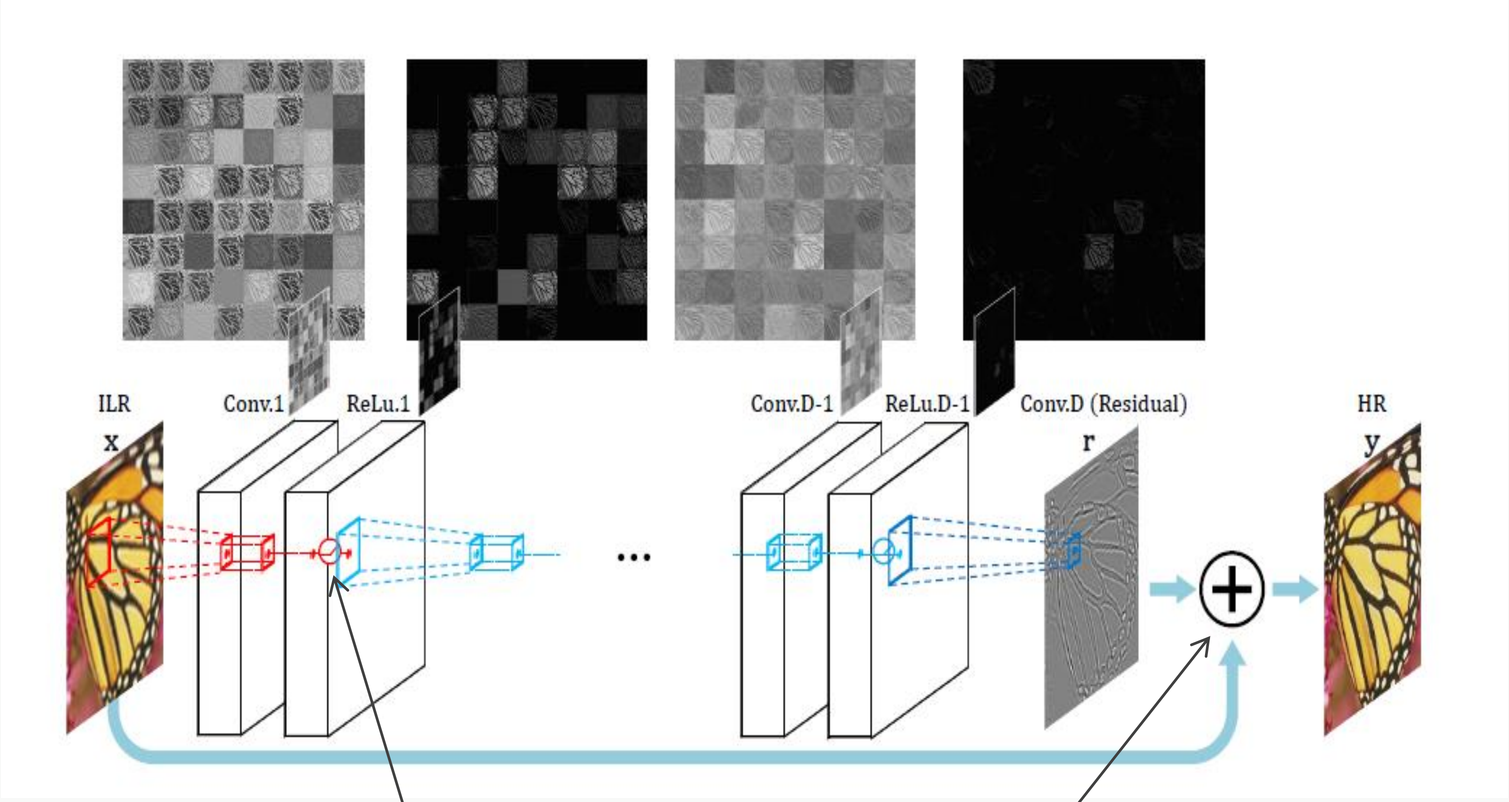
1. Provides superior accuracy comparing with state-of-the-art example-based methods.
2 Faster than a series of example-based methods
3. Restoration quality can be further imporved with larger model or more data

2.3 Accurate Image Super-Resolution Using Very Deep Convolutional Networks(VDSR)

1.Contextual information spread over very large image regions

2.Residual-learning and extremely high learning rates.

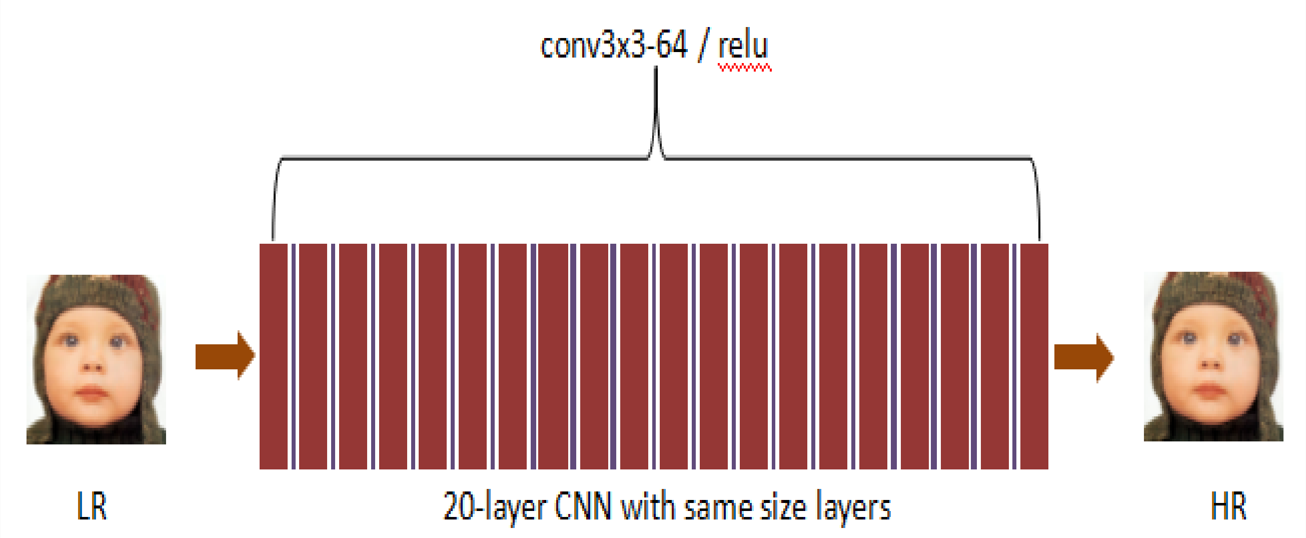
3.Multi-scale factor super-resolution

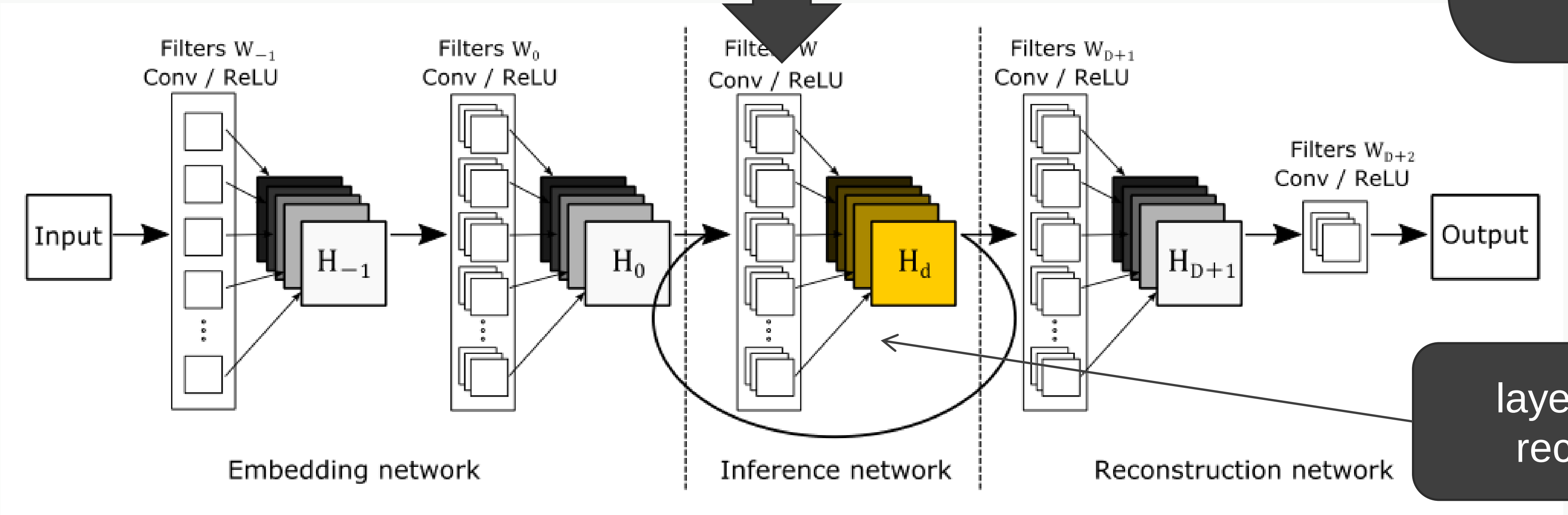


Larger image regions

Residual-learning

2.4 Deeply-Recursive Convolutional Network(DRCN)



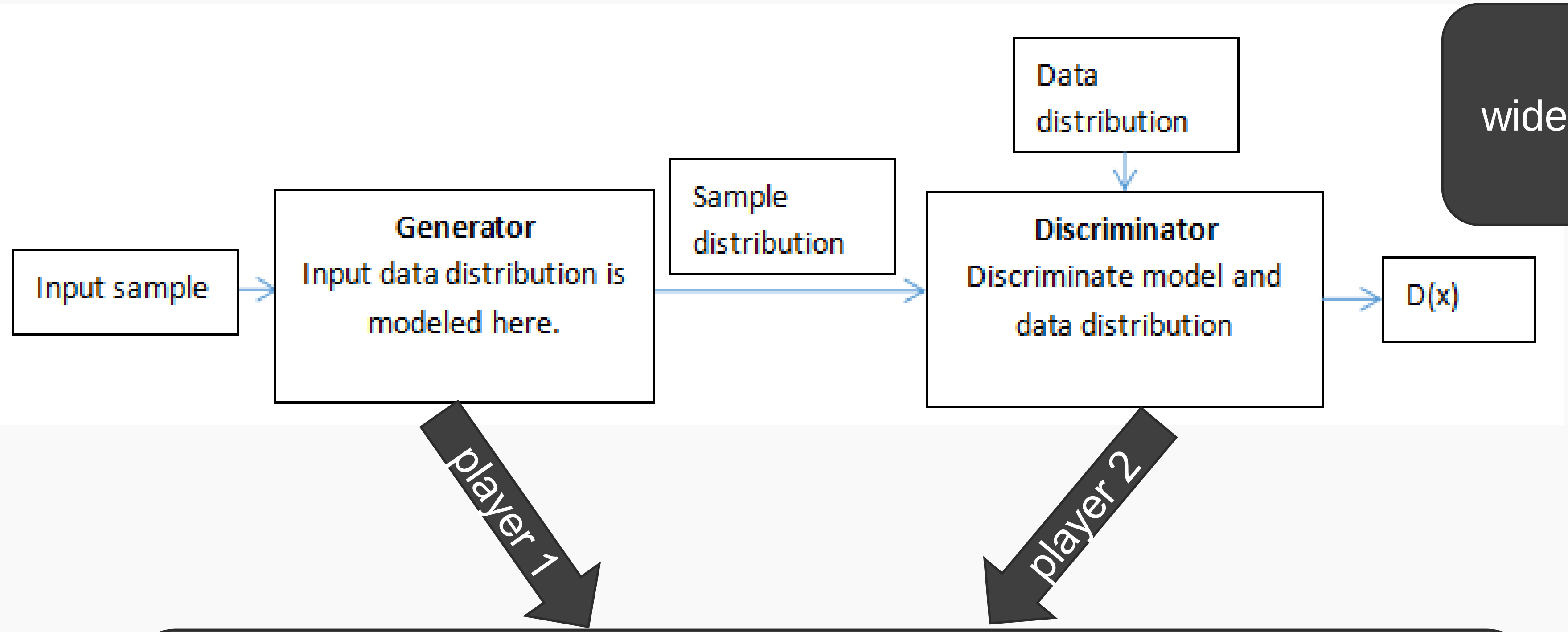


Same weight used for inference network so better performance with reduced parameters.

Hard to train!

layers added recursively

2.5 Deep Convolutional Generative Adversarial Networks(DCGAN)



widely used in SR

Player 1 and Player 2 compete with each other until an equilibrium is reached,both G and D optimized, with value function :

$$\min_{G} \max_{D} V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

3.1 SRCNN and VDSR

Training data: 91 images   Testing data: Set5 Scale factor: 3

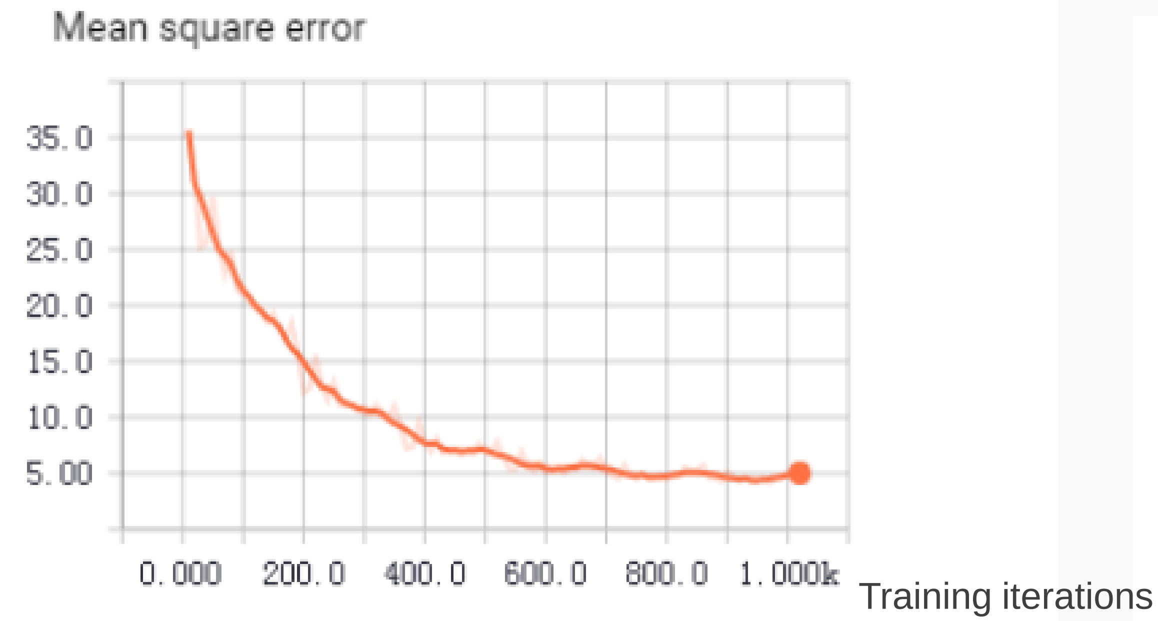


Fig.17 Mean square error for SRCNN for scale factor 3

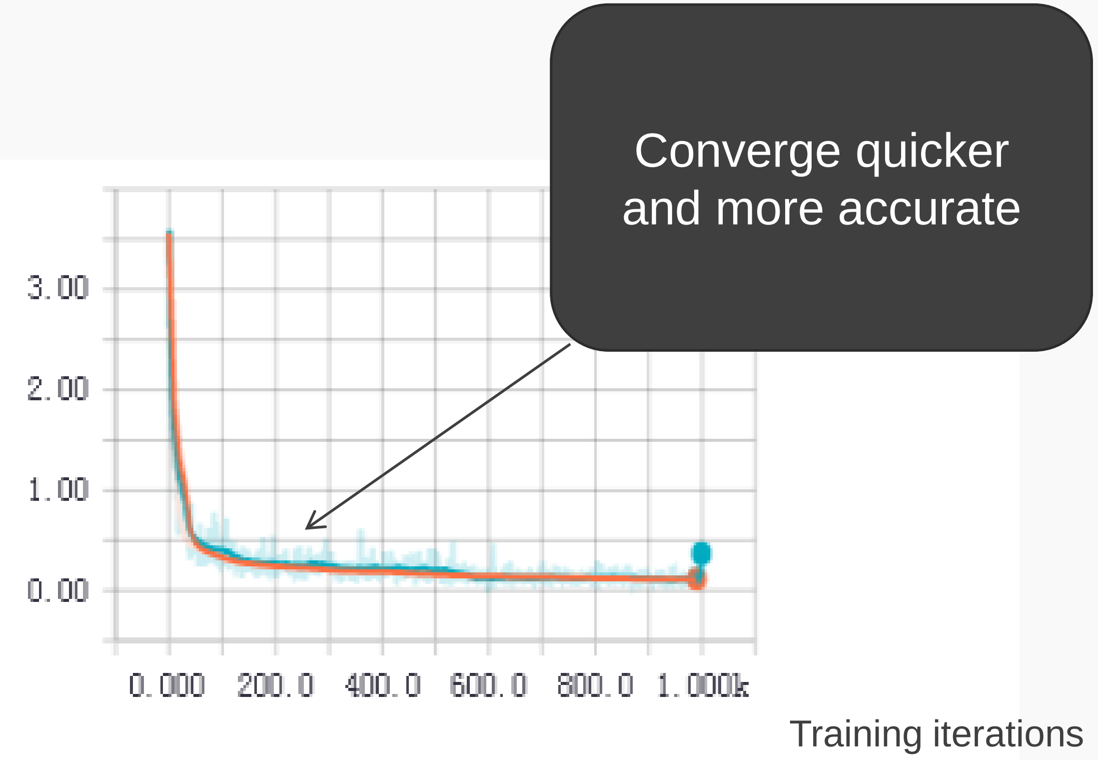
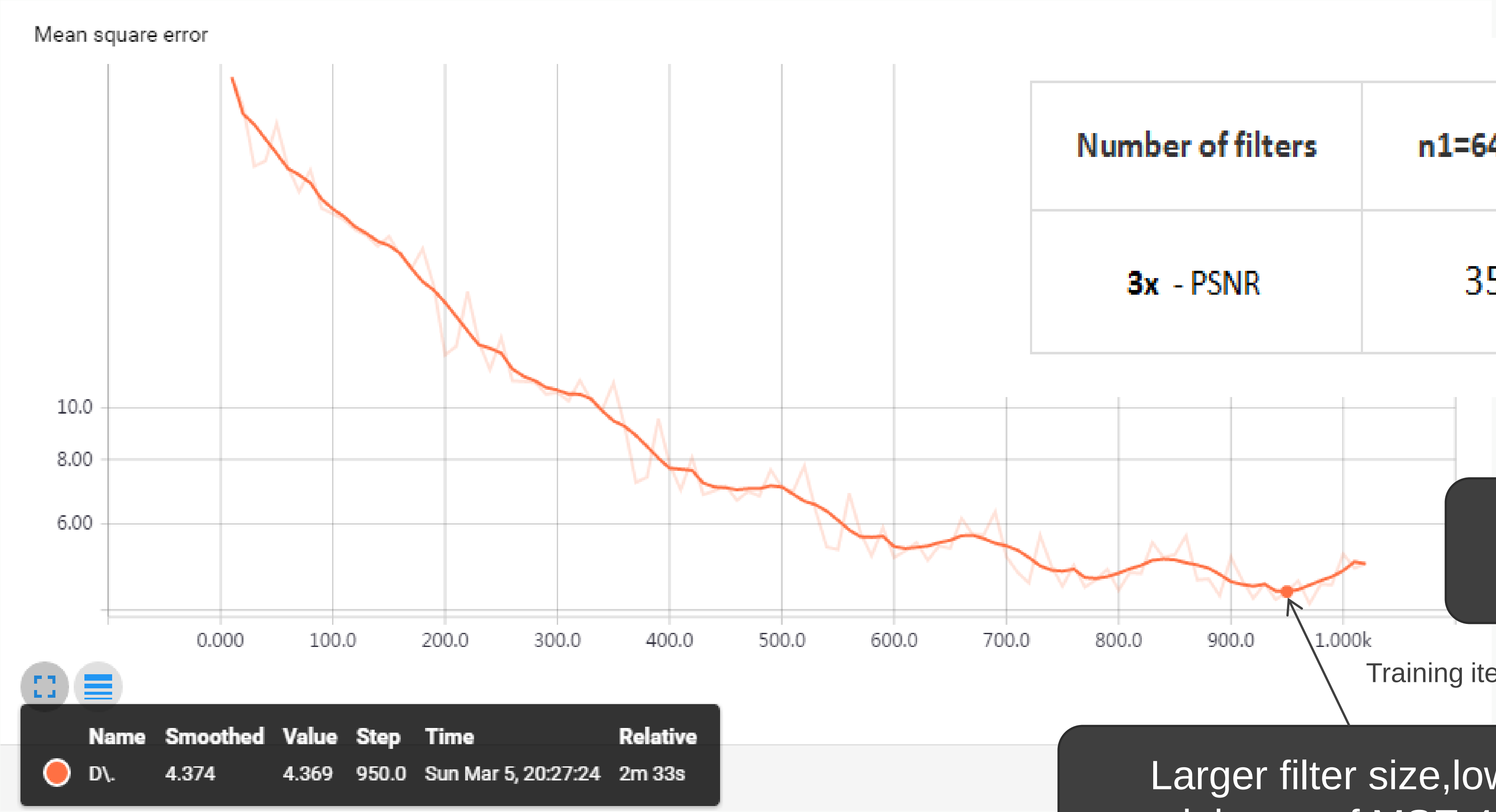


Fig.19 Mean square error for VDSR for scale factor 3

3.2 More number of filters and larger filter size

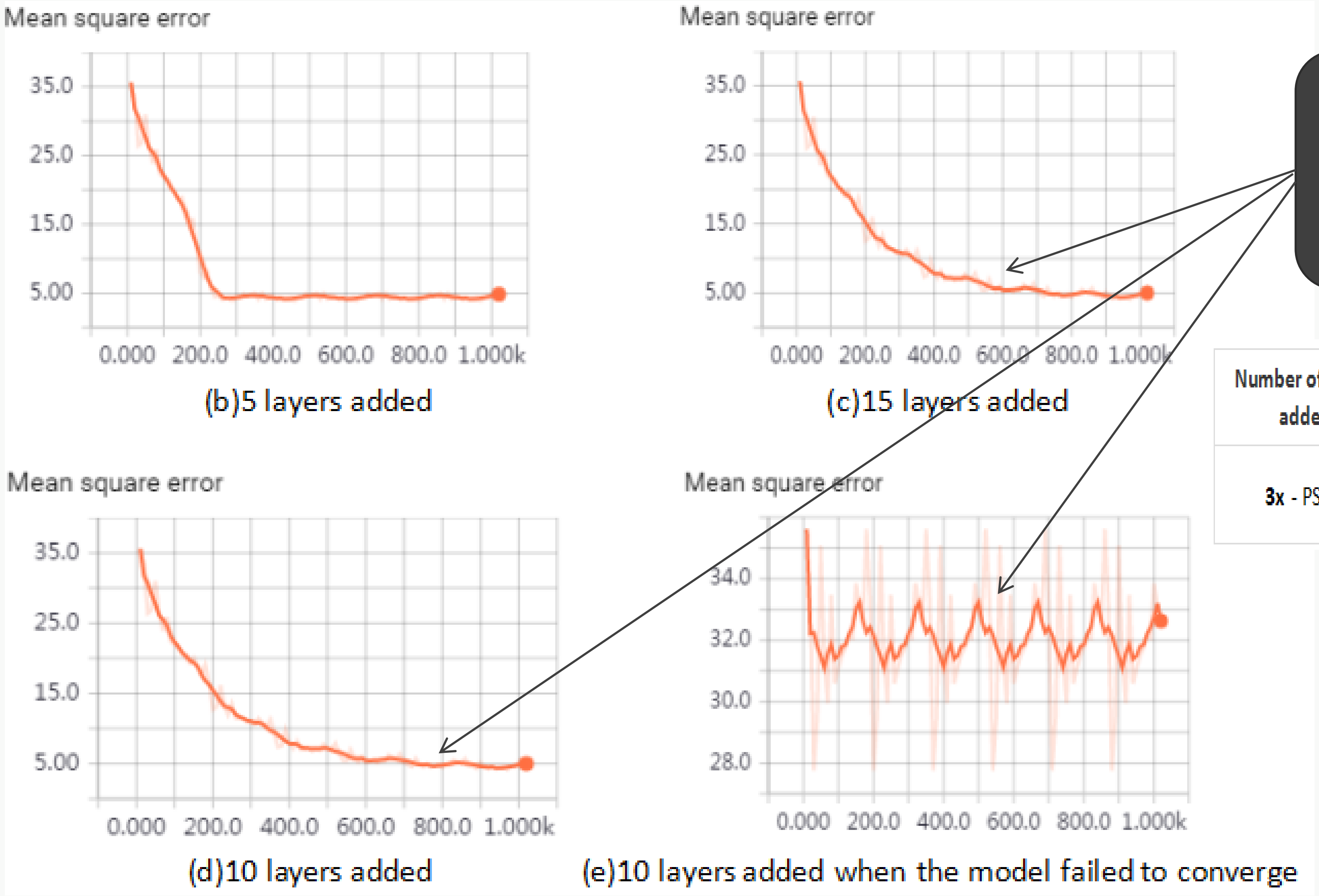


Number of filters	n1=64,n2=32	n1=128,n2=64
3x - PSNR	35.47	35.50

Double number of filters,higher PSNR

Larger filter size,lower minimum of MSE,4.37

More layers



MSE is not improved

Number of layers added	0	5	10	15
3x - PSNR	35.47	35.51	35.46	35.44

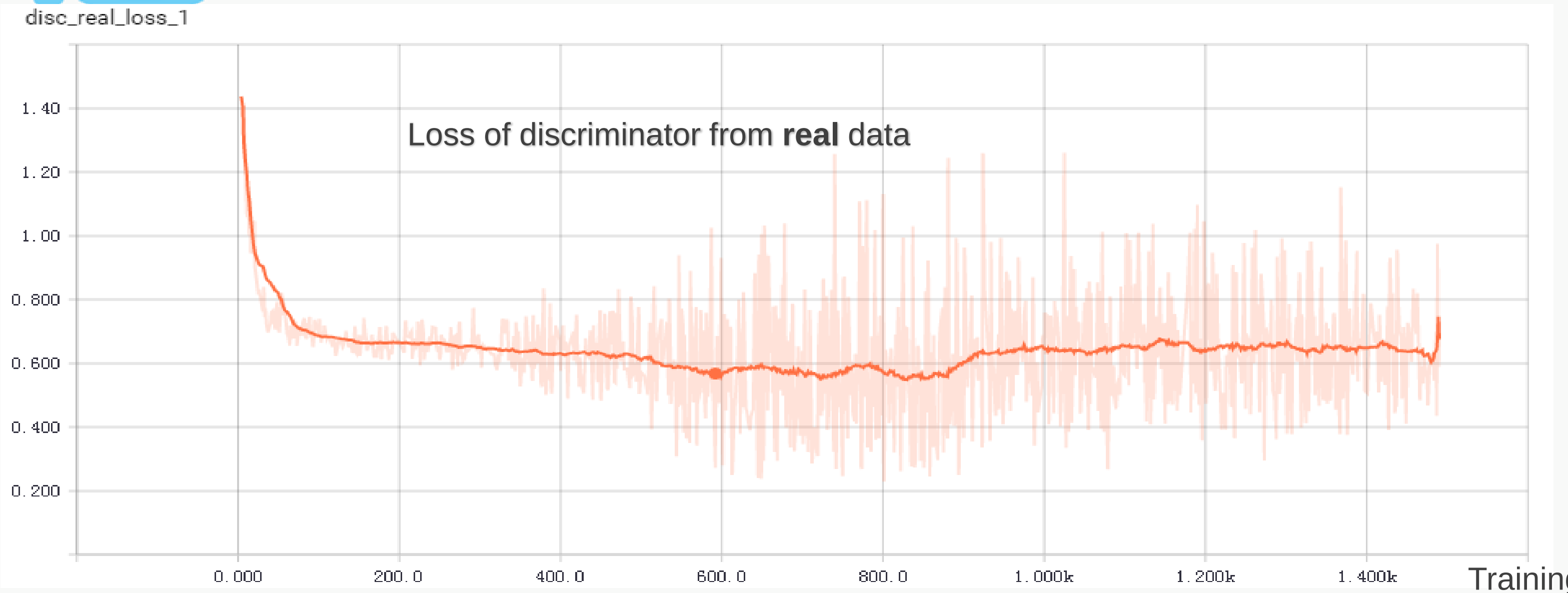
Even worse PSNR

Some result for SRCNN and VDSR

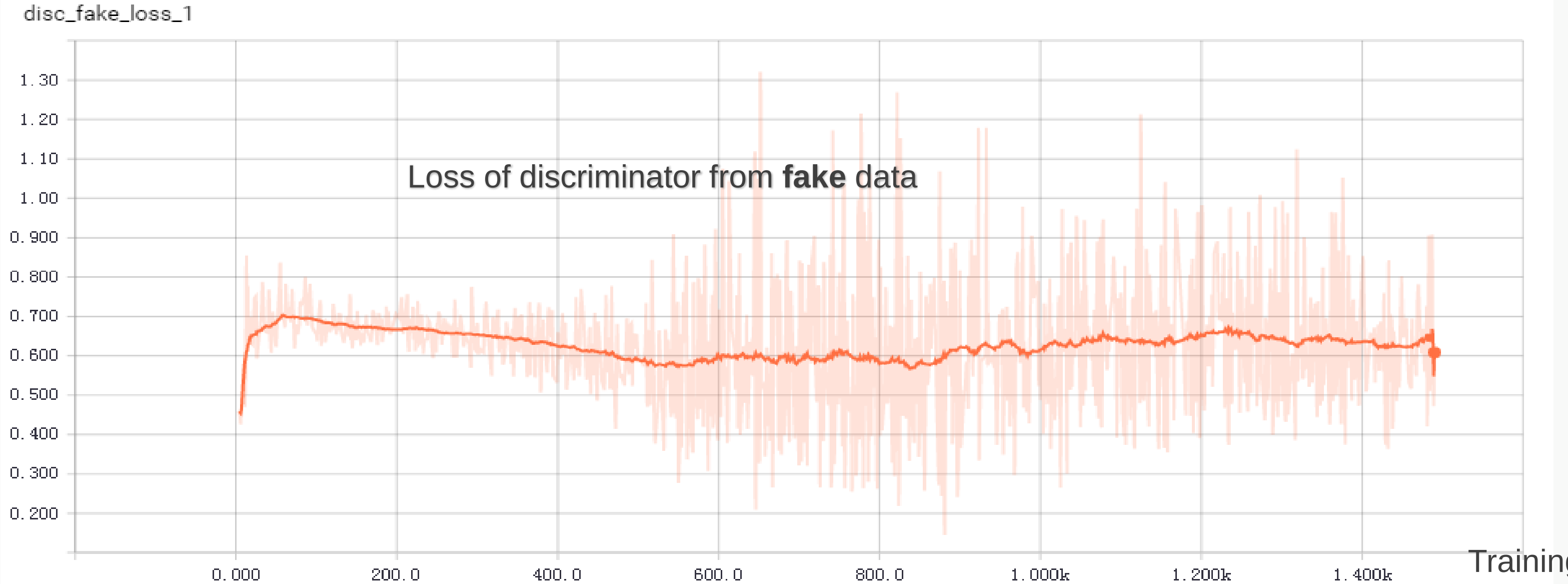
Scale	Bicubic	A+	SRCNN	VDSR
3x - PSNR	30.39	32.58	32.75	33.66

(a) Bicubic,PSNR=32.58dB (b) SRCNN,PSNR=35.47dB (c) VDSR,PSNR=36.23dB

3.4 Image super-resolution using DCGAN



Training iterations



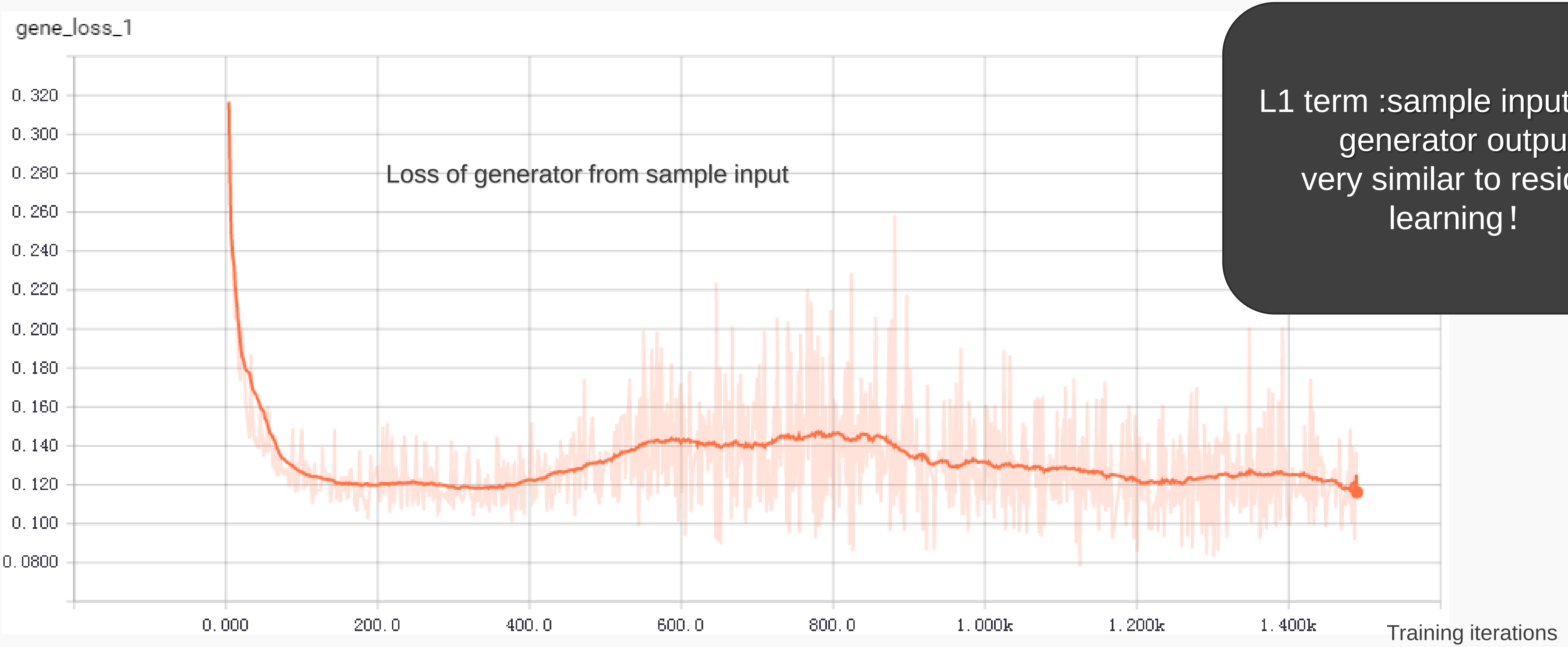
Training iterations

The loss for discriminator from real data decreases to around at 0.6 and remains at that level.

Equilibrium reached ！

The loss for discriminator from fake data increases to around at 0.6 and remains at that level.

Loss for generator



L1 term :sample input minus generator output,
very similar to residual learning !

Some Result for DCGAN

(a) (b)

Fig.18(a) Without L1 term,first 10 iterations(b) With L1 term ,first 10 iterations

Better result for model with L1 term added.

More details and shaper feature

(a)first 50 iterations (b)first 200 iterations (c)first 500 iterations

Fig.19 Training result for 50,200,500 iterations with L1 term

(a) (b)

Fig.20 Some result generated randomly from the dataset after 1500 iterations

4 Conclusion

1.Deep learning models can be well applied to image super resolution tasks and can generate some state-of-the-art result.

2. Can be applied to other image restoration problems easily.

3.The performance may yet to be further gained by trying different combinations of layer, filters or new structures.

THANK YOU

5 APPENDIX

[1]Learning a Deep Convolutional Network for Image Super-Resolution

[2]Accurate Image Super-Resolution Using Very Deep Convolutional Networks

[3]Generative Adversarial Nets