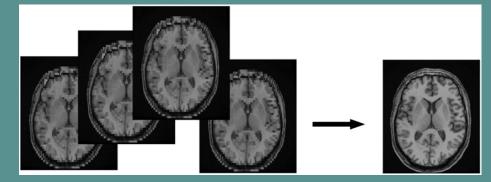
Reconstruction of High Resolution Images Using Deeping Learning

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Background

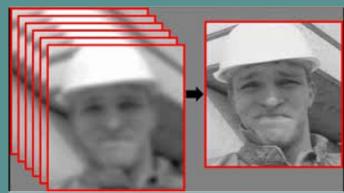
- In the field of digital image processing, High-resolution images or videos are commonly needed; but in many cases, people could only obtain low-resolution images.
- Image Super Resolution is a class of techniques that turn a lowresolution image into a high-resolution one for further analysis and processing.
- High-resolution images can provide more information for human interpretation, and improve the quality of automatic machine processing.

Applications



Medical diagnosis

surveillance



Applications



Regular video super-resolution

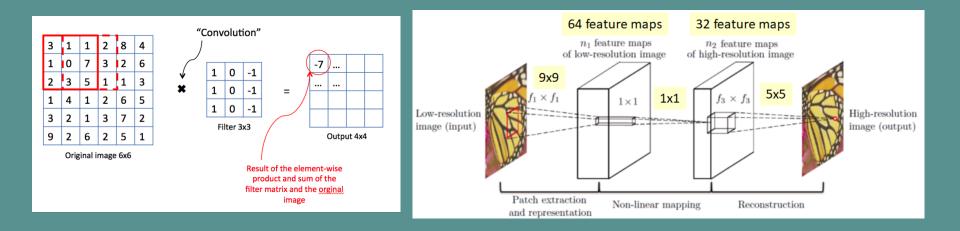
Astronomy photo super-resolution

Objective and Steps

- Test and compare current deep-learning based superresolution (SR) models, including single-image SR models and video SR models.
- Improve current SR models using the method of transfer learning.
- Implement our model on Magma DNN

Key Point -- Convolutional Neural Network

Convolutional Neural Network (CNN) is similar to ordinary neural networks. But the inputs of CNN are images, which enable us to encode certain properties into the architecture. In CNN, we add a particular type of layer, called convolutional layer, to extract features of images.



Key Point -- Transfer Learning

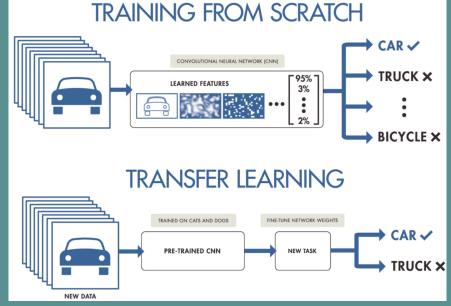
Drawbacks of training an entire neural network:

Sometimes difficult to obtain a dataset of sufficient size;

Training an entire network on a large data set is very time-consuming, sometimes takes even several weeks.

Important fact:

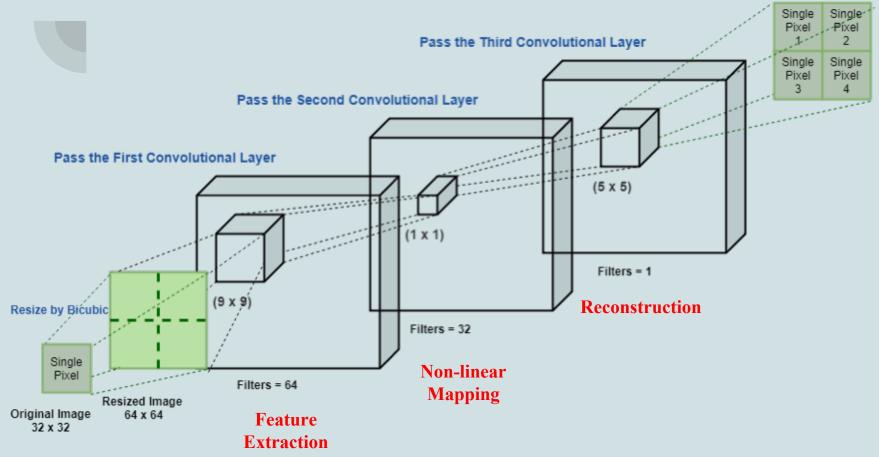
Pretrained neural network on a large dataset is usually a good feature extractor, thus can be reused in similar tasks.



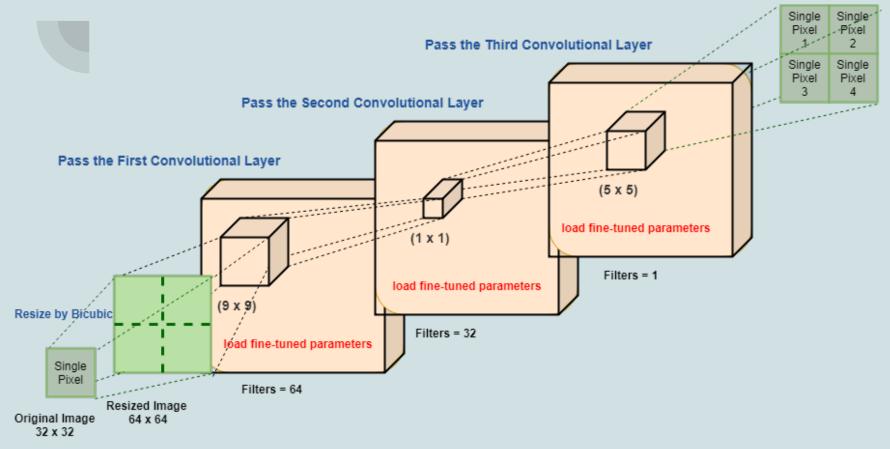
Models

SRCNN model -- for single-image Super-Resolution
Transfer Learning --fine-tuned parameter + self-trained layers
3D SRnet model -- for video Super-Resolution
Transfer Learning --fine-tuned parameter + 3D SRnet

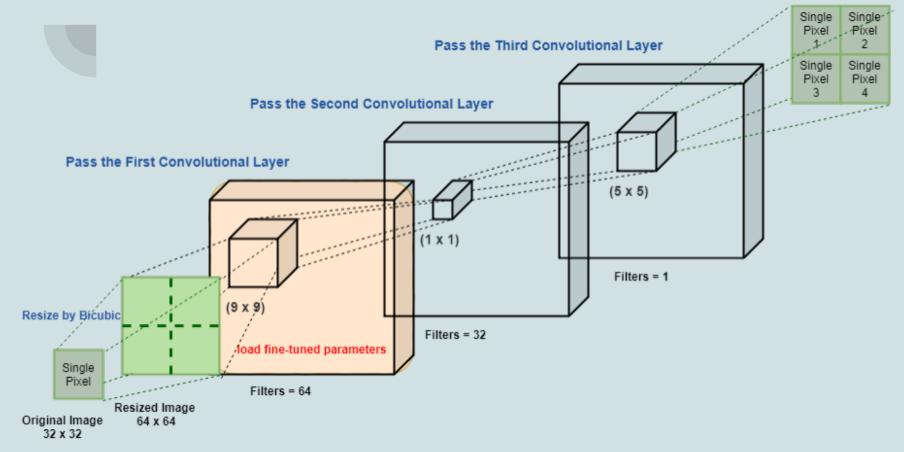
SRCNN model -- for single-image SR



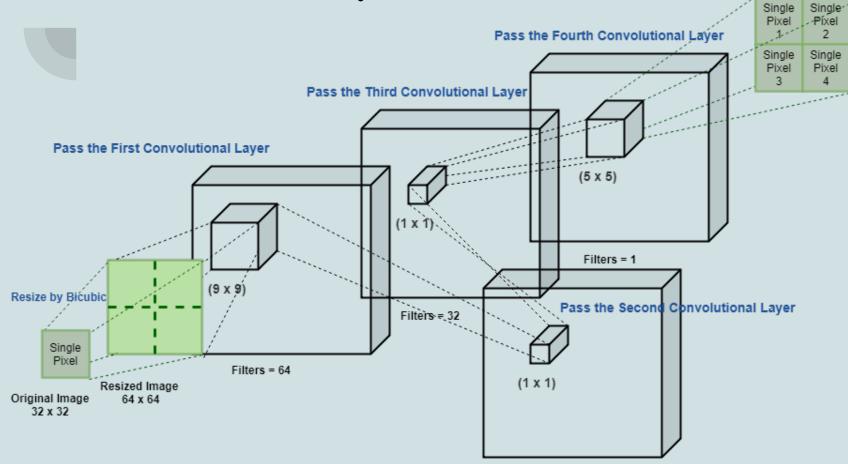
SRCNN model -- with fine-tuned parameters



Transfer Learning -- fine-tuned parameter + self-trained layers

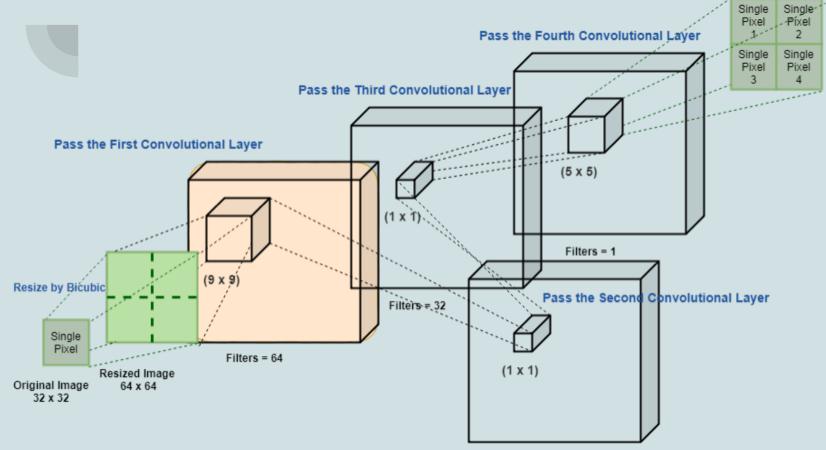


SRCNN -- add non-linearity





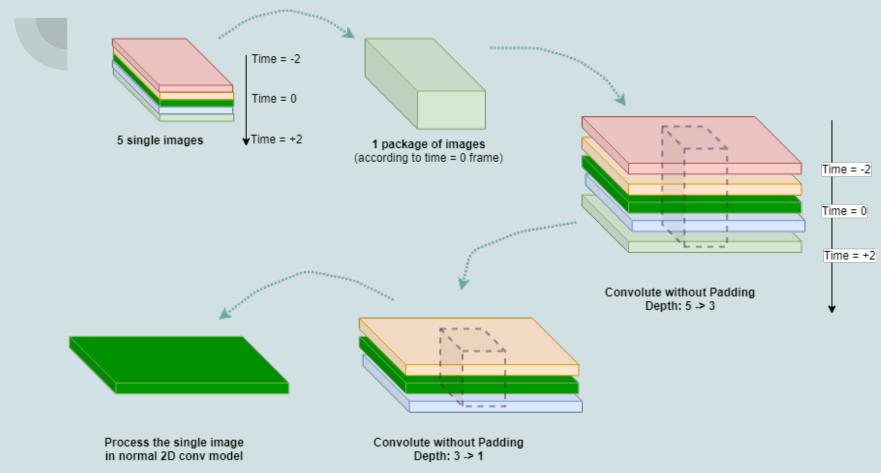
Transfer Learning -- fine-tuned parameter + non-linearity



Performance

	Raw Data	Self-Trained SRCNN model	SRCNN model with fine-tuned parameters	SRCNN with transfer- learning (1+2) model	Self-trained SRCNN with added non- linearity	SRCNN with transfer- learning (1+3) model
PSNR (Peak signal-to-noise ratio)	33.24609 81322429 9	33.9774122 589296	34.39533863 298893	34.568111435 612344	31.75340039 322545	34.420866851 485926
SSIM (structural similarity index)	0.912191 61971856 61	0.92989156 33331887	0.931424704 3105195	0.9339550069 793681	0.927639833 6420119	0.9340359732 007651
MAE (Mean Absolute Error)	0.016739 55861304 3767	0.01597587 670676589	0.015128582 491306834	0.0148824250 23144312	0.021569695 539644516	0.0152505775 26577434
MSE (Mean Squared Error)	0.000931 39330134 29778	0.00076756 489539201 49	0.000720391 6113815921	0.0006896958 805634528	0.000979942 1850334928	0.0007280809 308989662

3D SRnet model -- for video SR



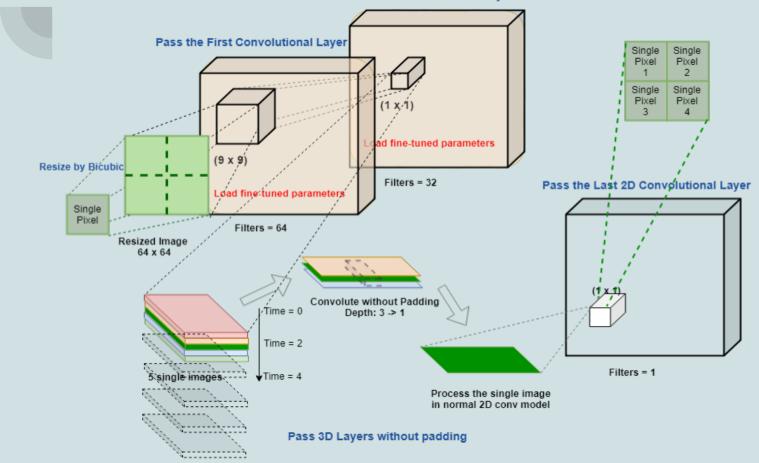
3D SRnet -- for sequential images

Output Shape Pa	ram #	
(None, 5, 64, 64, 32)	896	With Padding
(None, 5, 64, 64, 32)	27680	With Padding
(None, 5, 64, 64, 32)	27680	With Padding
(None, 3, 62, 62, 32)	27680	Without Padding
(None, 1, 60, 60, 32)	27680	Without Padding
(None, 60, 60, 32)	0	Reshape for 2d model
(None, 60, 60, 1)	1156	With Padding
	(None, 5, 64, 64, 32) (None, 5, 64, 64, 32) (None, 5, 64, 64, 32) (None, 5, 64, 64, 32) (None, 3, 62, 62, 32) (None, 1, 60, 60, 32) (None, 60, 60, 32)	Image: None, 5, 64, 64, 32) 896 (None, 5, 64, 64, 32) 27680 (None, 5, 64, 64, 32) 27680 (None, 5, 64, 64, 32) 27680 (None, 3, 62, 62, 32) 27680 (None, 1, 60, 60, 32) 27680 (None, 60, 60, 32) 0

Total params: 112,772

Transfer Learning -- fine-tuned parameter + 3D SRnet

Pass the Second Convolutional Layer



Conclusion

Pre-process dataset; Build and test typical models; Combine typical models by using transfer learning.

Implement transfer learning with 3D Model; Use different dataset; Fine tune hyper-parameters. Try MagmaDNN for implementation.

Reference

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