

# Exercise 6 - DEEP LEARNING

## Code Implemented

- `SRDataset` class: in the `./code/dataset.py`
- `BasicSRModel` class: in the `./code/models.py`
- Training loop: in the `./code/train.py`
- Model evaluation:
  - in `./code/eval.py`
  - visualization is in `./code/eval.ipynb`
- The configurations are in `./configs`
- To run the code, make sure you use the following file structure

```
1 .
2   ├── configs
3   |   ├── 1e-2.yaml
4   |   ├── 1e-3.yaml
5   |   ├── 1e-5.yaml
6   |   ├── 1e-6.yaml
7   |   └── baseline.yaml
8   └── residual.yaml
9
10  └── runs
11      ├── baseline
12      ├── lr1e-2
13      ├── lr1e-3
14      ├── lr1e-5
15      ├── lr1e-6
16      └── residual
17
18  └── models
19      └── best_models
20          ├── model_best_lr_1E-02.pth
21          ├── model_best_lr_1E-03.pth
22          ├── model_best_lr_1E-04.pth
23          ├── model_best_lr_1E-05.pth
24          ├── model_best_lr_1E-06.pth
25          └── model_res_best_lr_1E-04.pth
26
27  └── train
28      └── eval
```

- Run
  - For the training (baseline model), you should use the command in `./code`:

```
1 | python train.py --config ../configs/baseline.yaml
```

- For the evaluation(baseline model), you should use the command in `./code` :

```
1 | python eval.py --config ../configs/baseline.yaml
```

- Or you can directly use the `eval.ipynb` file.

## 1.1. Task 1 - Datasets, Preprocessing and Data loading

- The result of dataset testing is

```
1 | * Dataset contains 301 image(s).
```

## 1.2. Task 2 - Derivations and deeper understanding

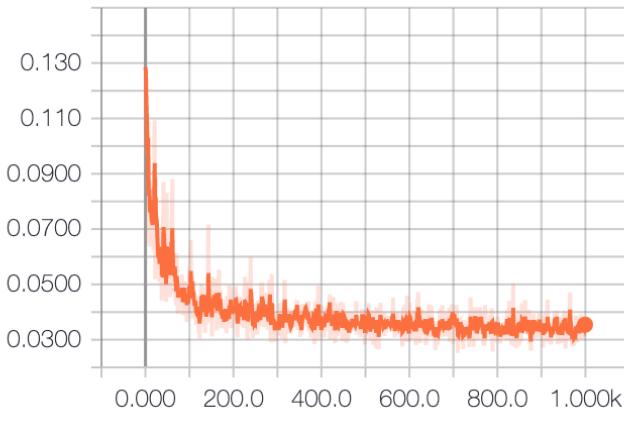
- The result of model testing is:

```
1 | 372803
```

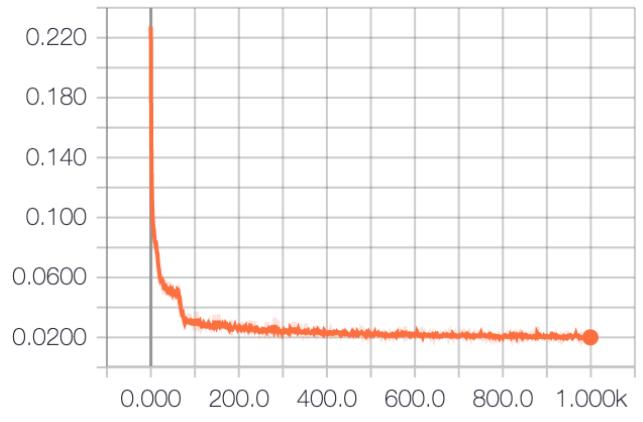
## 1.3. Task 3 - Implement the Training Loop

- The L1 loss during training is shown below

L1/evaluation



L1/train



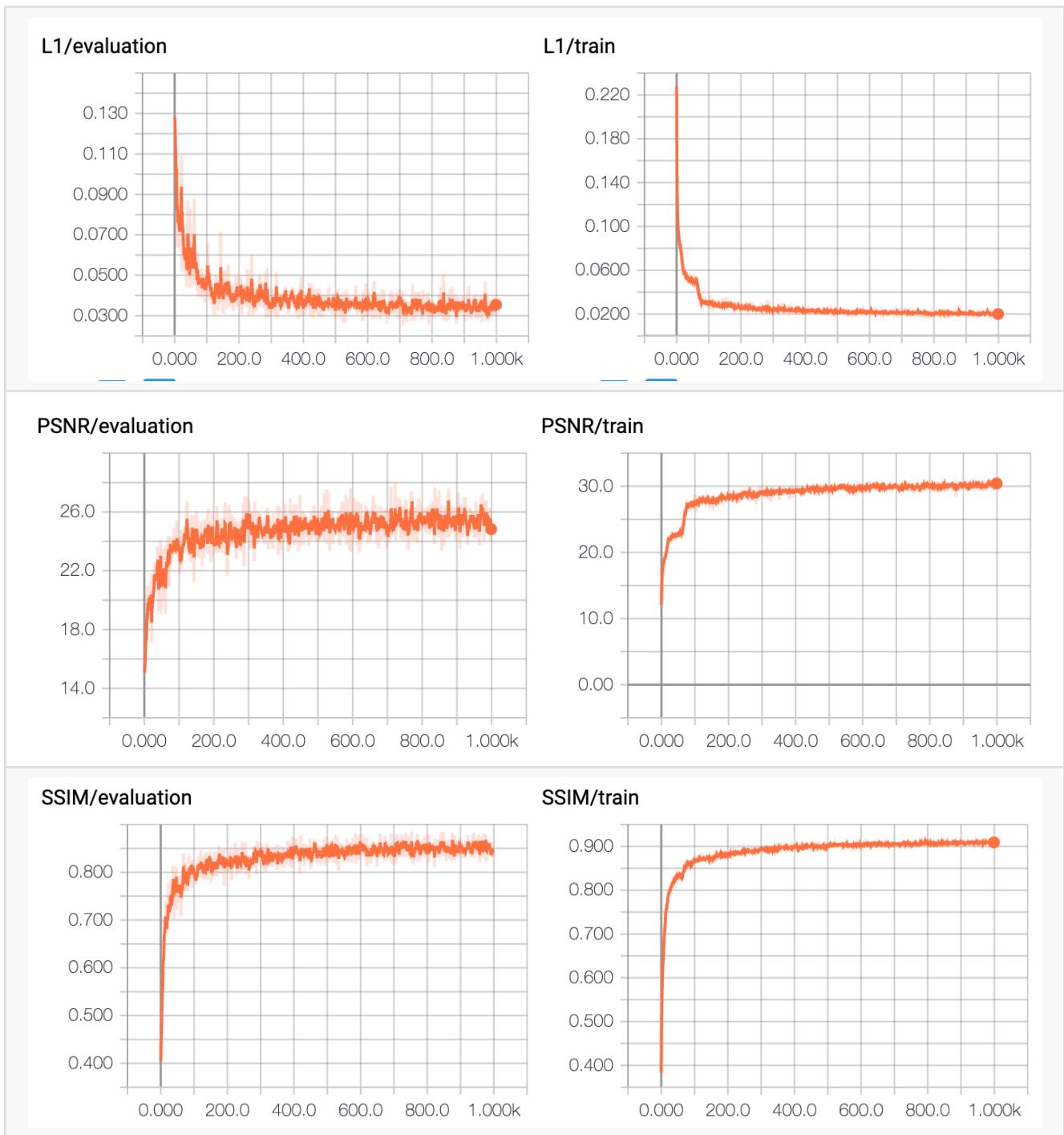
- The parameters are saved per 200 epochs, also, the model with minimum training loss is also saved .

## 1.4. Task 4 - Model Evaluation

- Table of evaluation result:

	PSNR	SSIM
Bilinear (baseline)	25.757679	0.867994
Bicubic (baseline)	24.444685	0.856417
Nearest (baseline)	21.104866	0.758209

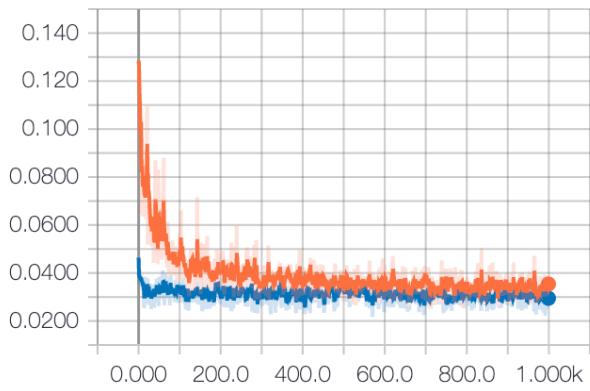
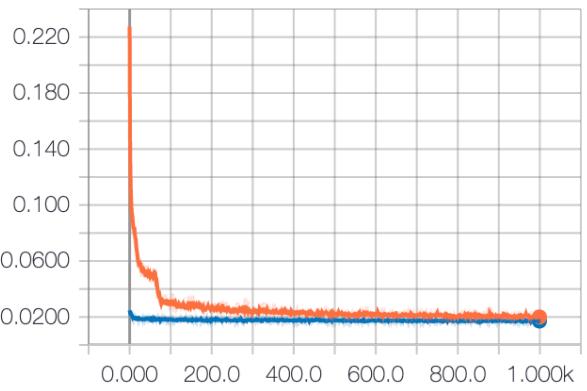
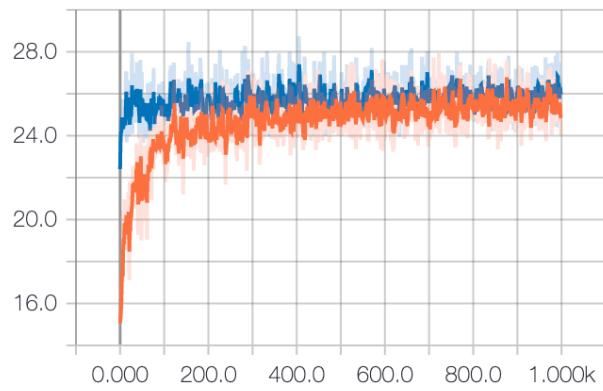
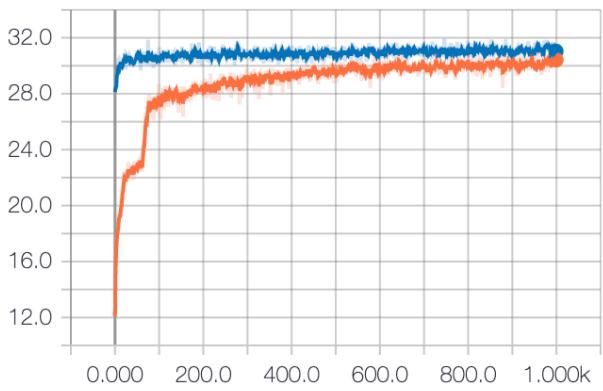
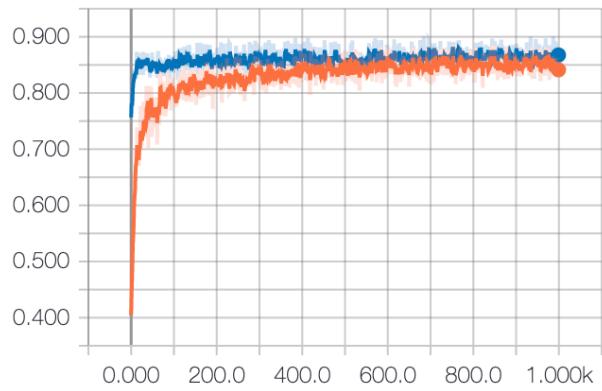
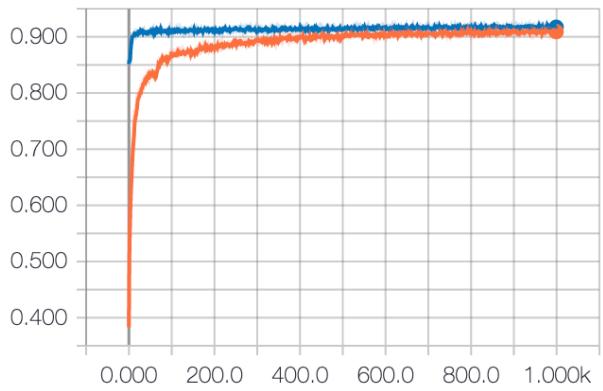
- The evolution of the validation loss and training loss (L1, PSNR and SSIM) is shown below:



## 1.5. Task 5 - Exploration

### A Different Model

- Training: The training loss plot is shown below (the blue one represents the residual, and the orange one represents the baseline model)
  - Comparison:** Since the residual connections directly add the result of bilinear interpolation to the output, the performance is always better than the baseline model (lower L1 loss and higher PSNR, SSIM).

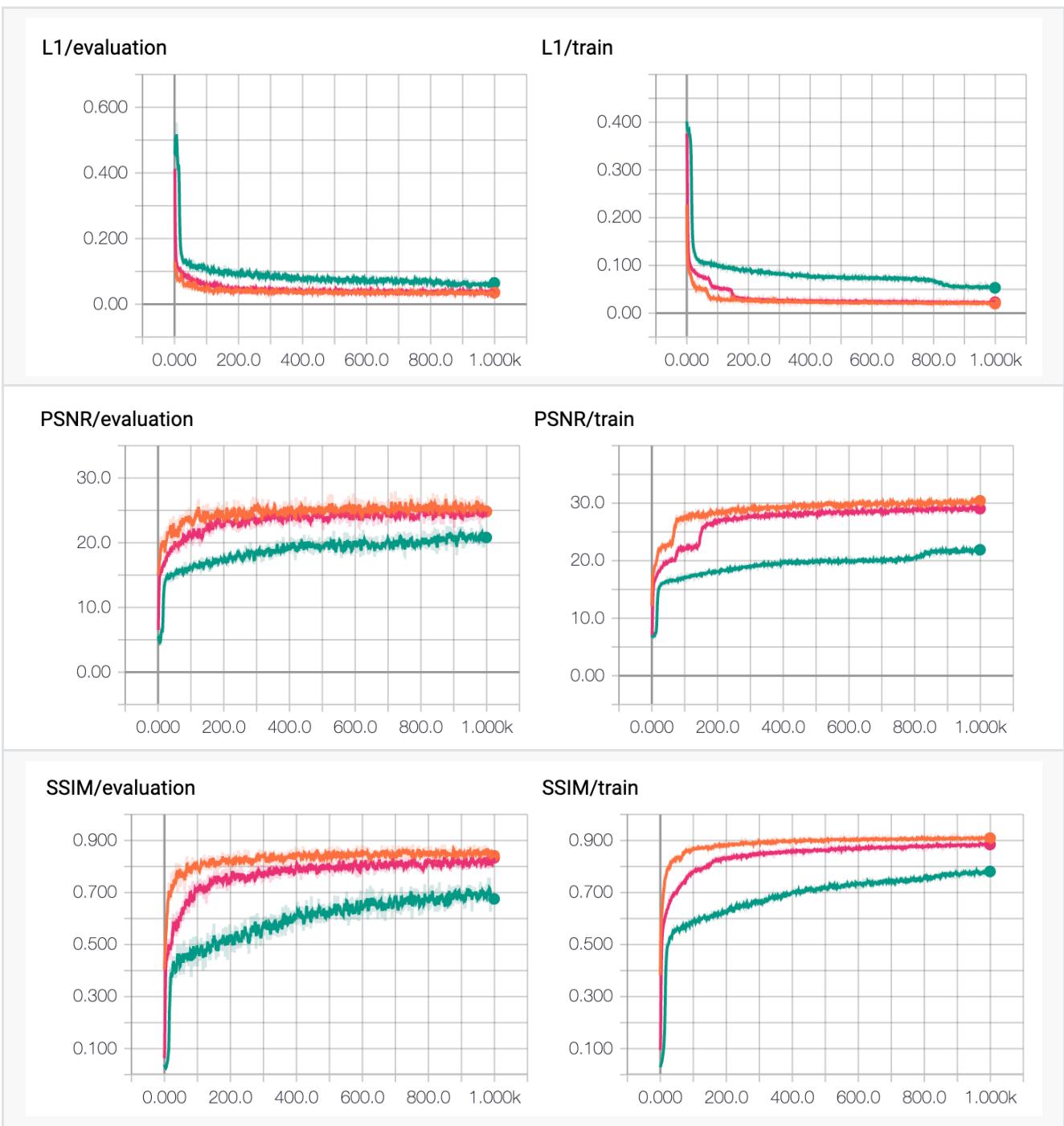
**L1/evaluation****L1/train****PSNR/evaluation****PSNR/train****SSIM/evaluation****SSIM/train**

- Evaluation: Table of evaluation result:

	<b>PSNR</b>	<b>SSIM</b>
Bilinear (baseline)	25.757679	0.867994
Bicubic (baseline)	24.444685	0.856417
Nearest (baseline)	21.104866	0.758209
Bilinear (Resnet)	27.583456	0.898651
Bicubic (Resnet)	26.075844	0.885841
Nearest (Resnet)	22.011930	0.780135

## Effect of the Learning Rate

- Training: The training loss plot with different learning rate is shown below (the blue one represents the residual, and the orange one represents the baseline model)
  - Without large learning rate (without 1e-2, 1e-3): orange (1e-4), pink (1e-5), green (1e-6)
  - The performance is better as learning rate getting larger in this range



- However, for the large learning rate, the performance is not stable (1e-2 red, 1e-3 blue)



## Different Downscaling During Inference

- Table of evaluation result:

	PSNR	SSIM
Bilinear (baseline)	25.757679	0.867994
Bicubic (baseline)	24.444685	0.856417
Nearest (baseline)	21.104866	0.758209
Bilinear (Resnet)	27.583456	0.898651
Bicubic (Resnet)	26.075844	0.885841
Nearest (Resnet)	22.011930	0.780135

- Images of superresolution result with different downscaling methods

- As shown in the following two examples, the algorithm does have the effect to do superresolution task. However, the generated image is darker than the original one.
- Comparison:
  - Since we use bilinear interpolation to train the model, the result of bilinear interpolation is better than the other two (brighter and sharper result).
  - For the nearest neighbor, the detailed texture is different from the other two methods. The result is not smooth enough because there are some strange veins in the texture.
  - For the bicubic interpolation, the result is over smoothed compared with bilinear result.

**High resolution (ground truth)**



**Low resolution**



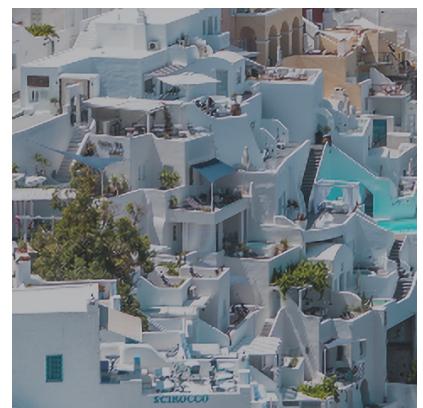
Bilinear



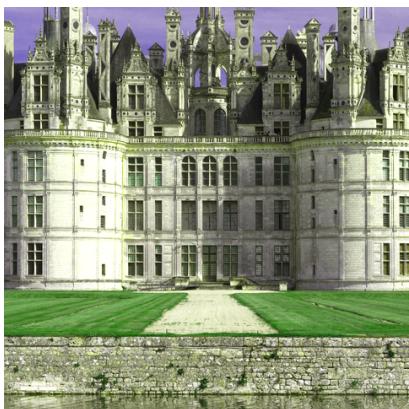
Bicubic



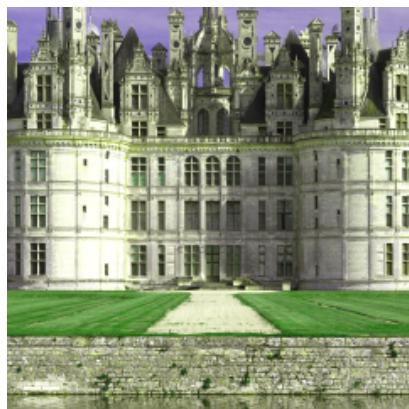
Nearest neighbor



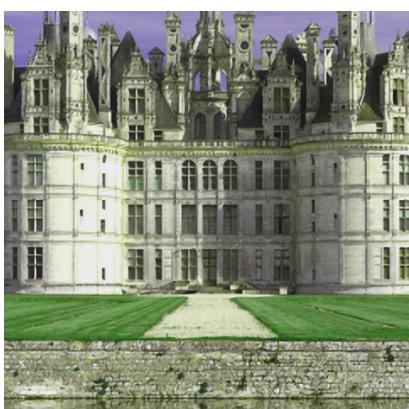
**High resolution (ground truth)**



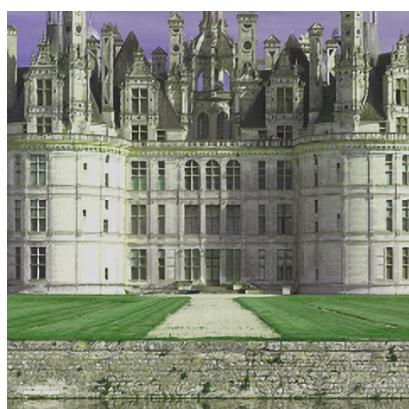
**Low resolution**



Bilinear



Bicubic



Nearest neighbor

