# Supplemental : Blind Image Super-Resolution with Spatially Variant Degradations

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CCS Concepts: • **Computing methodologies → Image processing**; **Computational photography**.

Additional Key Words and Phrases: Super-resolution

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## 1 IMPLEMENTATION DETAILS

The architecture of the generator is based on the SR network proposed in [Wang et al. 2018]. We first extract 64 channel feature map with an initial $3 \times 3$ convolution layer. After that a cascade of dense compression units (DCUs) are used, followed by a sub-pixel convolution layer. The DCU consists of a modified densely connected block followed by 1ÃŮ1 convolution. We respectively used 4, 6 and 8 DCUs for 2×, 3× and 4× upscaling. In all cases the number of layers is 6 and the features extracted by each unit have 64 channels.

The blur kernels are centered with a size of $15 \times 15$. They are mapped to a latent representation with 2 fully connected NN layers, reducing each kernel to 15 values. We assume the blur kernels to be centered and with values summing up to 1.

## 2 ADDITIONAL RESULTS

Here we show a variety of additional upscaling results. First, we show that our blind approach is applicable to a variety of scaling factors in Figure 1. Here, we have used the factors 2×, 3×, and 4× which are commonly used in deep learned super resolution.

In Figure 2, we show 2× upscales of images taken with a DSLR camera. The images have not been downscaled before being upscaled. We compare to a state-of-the-art upscaling method and observe that our results are slightly sharper even though our generator network has one order of magnitude less parameters. Figure 3 shows the same experiment for images captured with a mobile phone camera.

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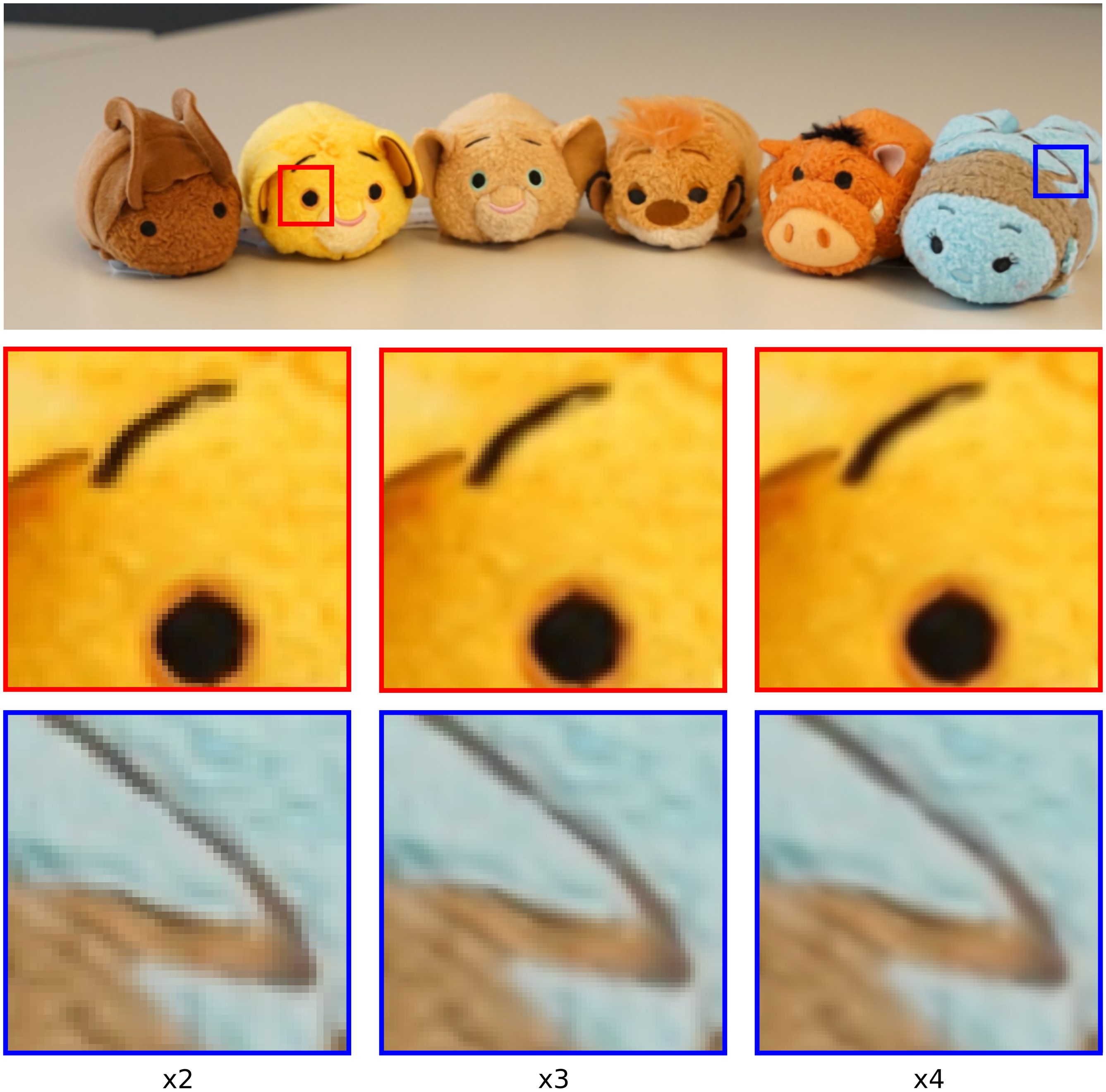


Fig. 1. **Multiple Scaling Factor.** Our SR results with 2×, 3× and 4× scaling factor.

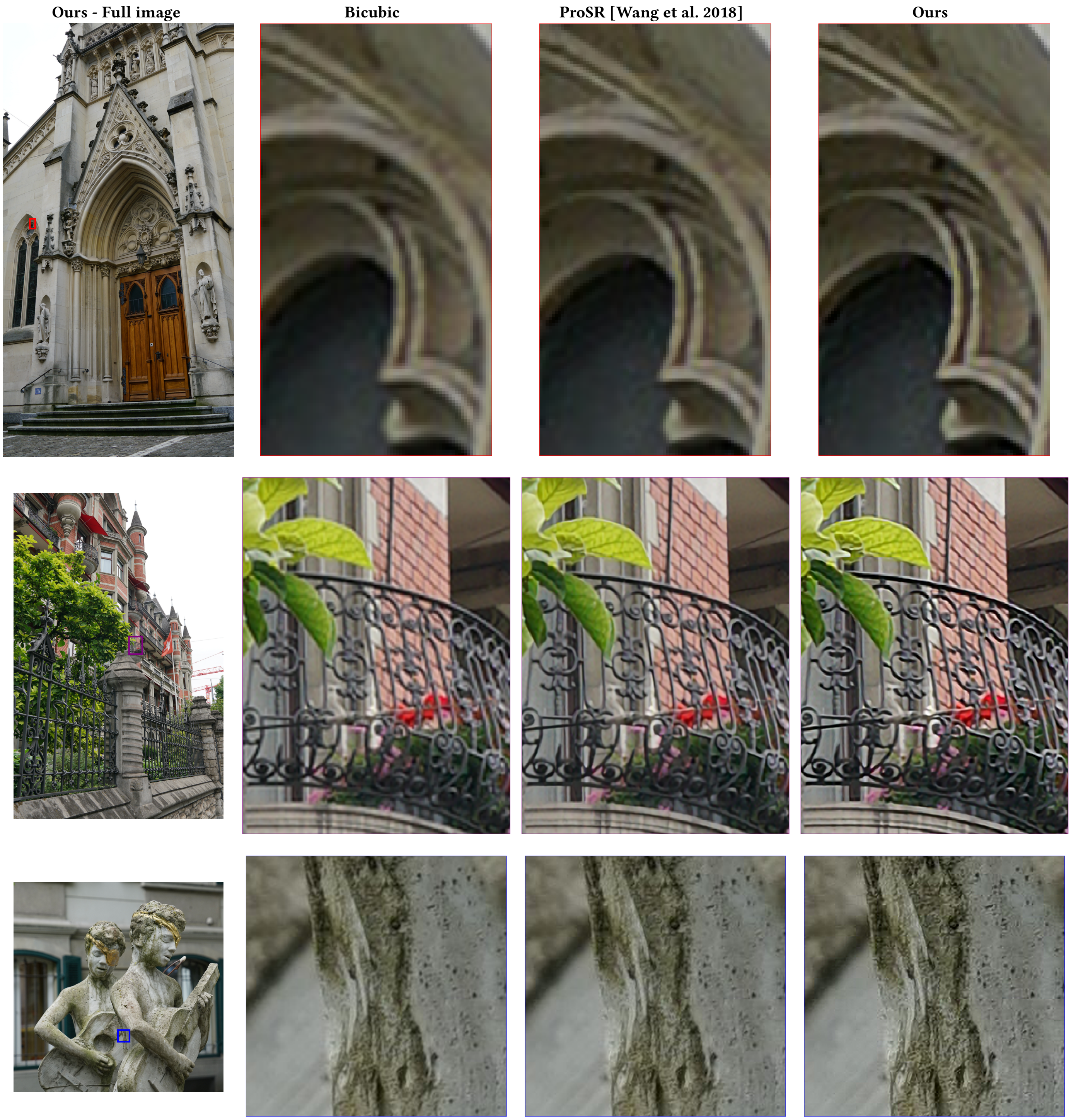


Fig. 2. **Images a from DSLR camera - upscaling results (x2).** In all cases our SR results are slightly sharper compared to ProSR trained for bicubic downsampling.

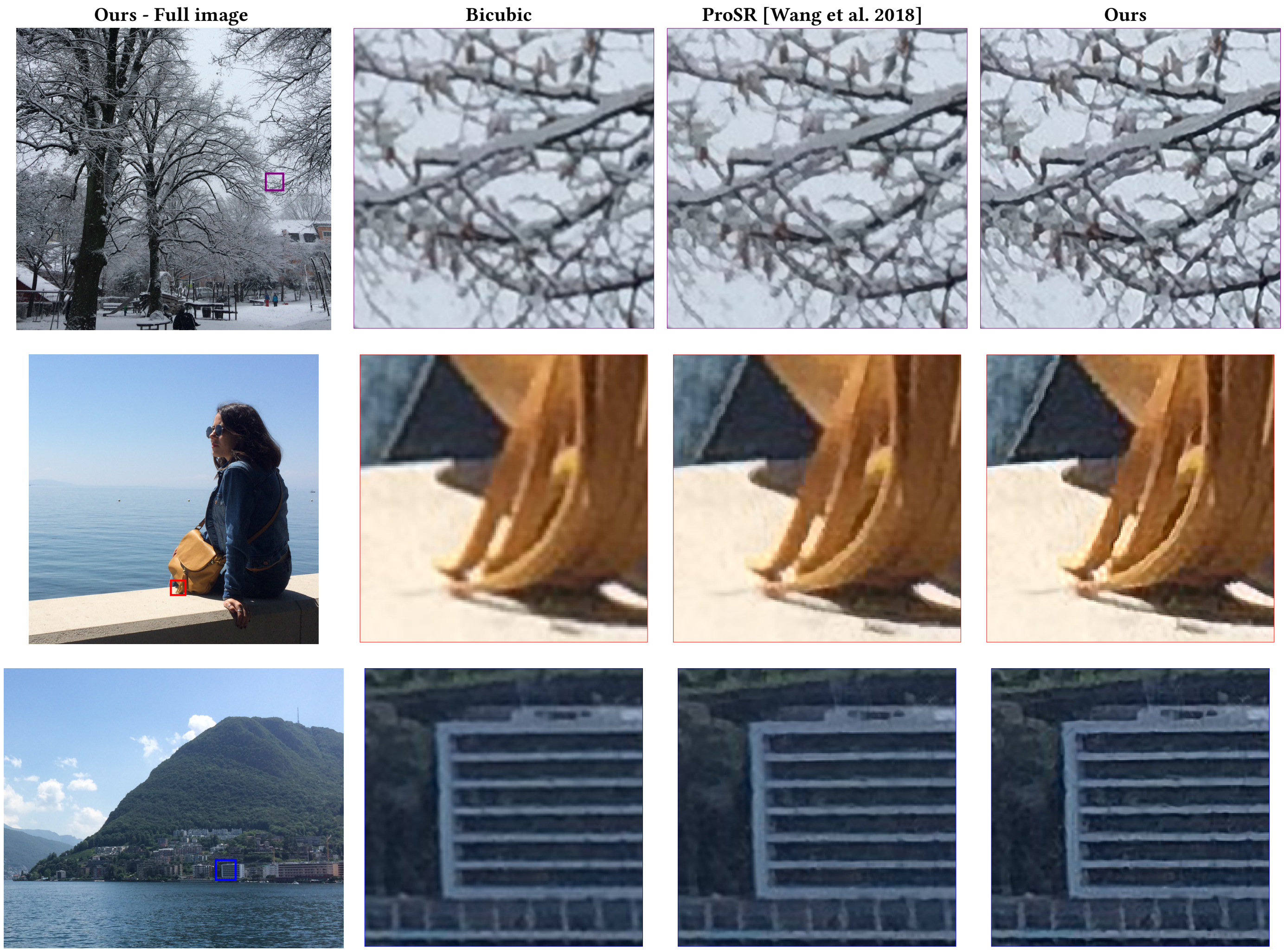


Fig. 3. **Images from a mobile phone camera - upscaling results (x2)**. In all cases our SR results are slightly sharper compared to ProSR trained for bicubic downsampling.