Explicit MAP Optimization for Photo-Realistic Super Resolution

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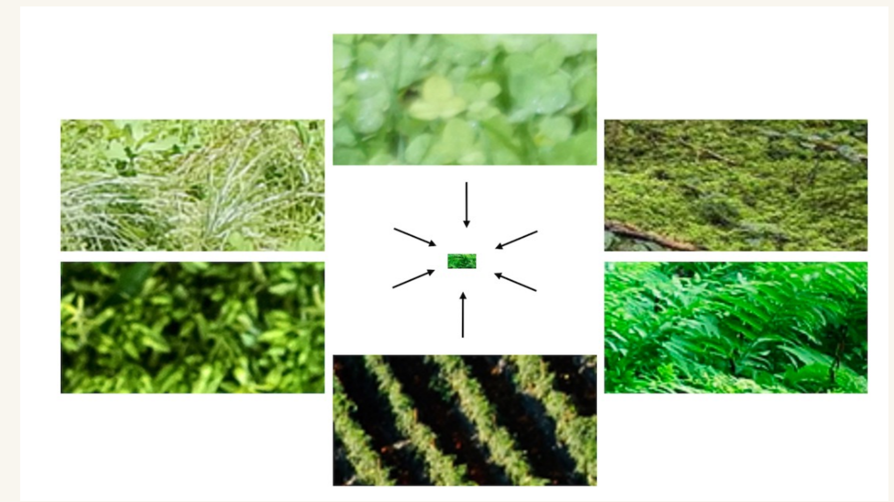
Motivation

Traditional super resolution techniques lead to **visually unpleasant** reconstructions, can we do better?

Problem Setting

We attribute the visually unpleasant reconstruction to the over-constrained optimization objective which admits only one of infinitely many possible solutions.



Contribution

1. We identify that the pixelwise loss used in traditional super resolution methods is directly at odds with allowing multiple feasible solutions.
2. We relax the aforementioned objective by explicitly modeling the MAP image restoration objective.
3. We model the regularization term in the MAP framework with the relativistic adversarial loss [1].
4. We adopt noise injection [2, 3] to explore the super resolution space [4].

Method

We optimize the super resolution network G using the following objective:

$$L_G = \alpha L_{\text{Fidelity}} + L^G_{\text{Adversarial}}$$

where in our experiment setting:

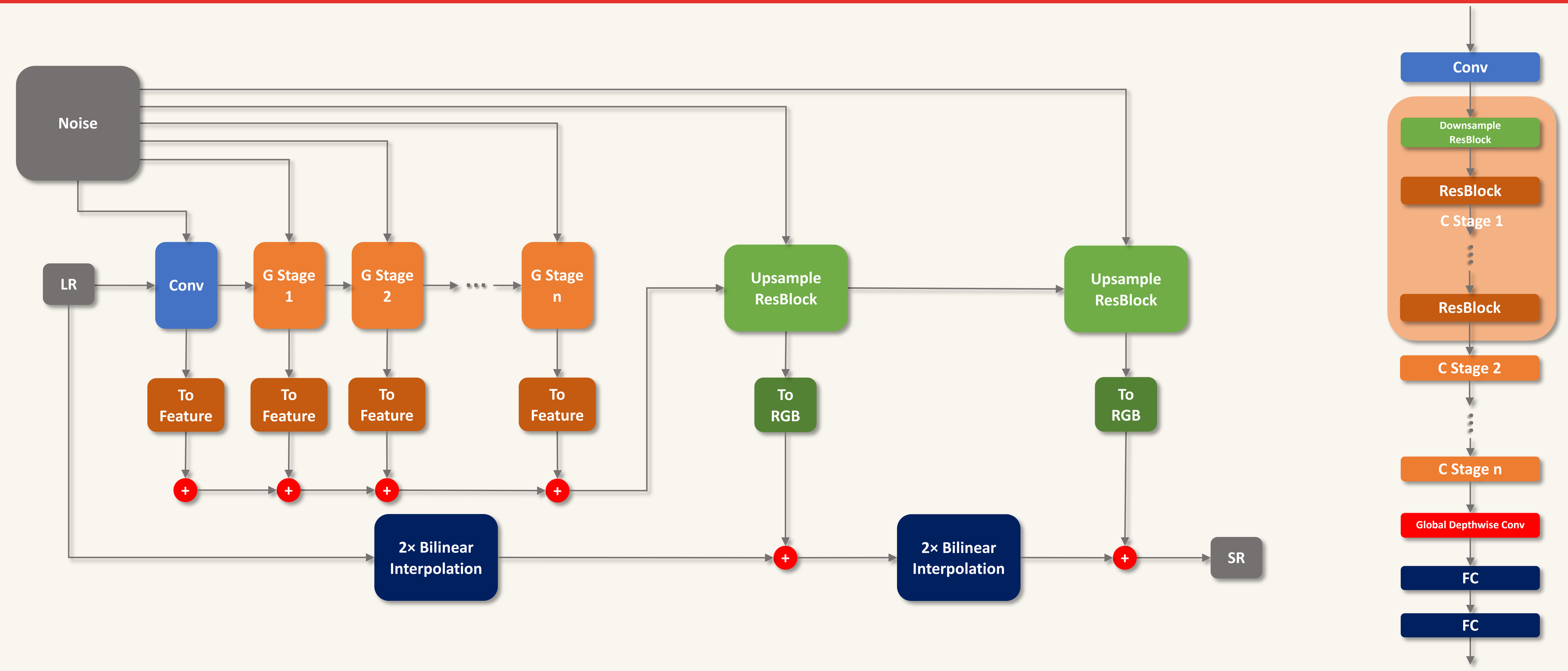
$$\alpha = 10 \quad L_{\text{Fidelity}} = \|y - G(y)_{\downarrow\text{bicubic}}\|_1 \quad L^G_{\text{Adversarial}} = \sup_{G:\mathcal{Y}\to\mathcal{X}} \mathbb{E}_{\substack{x\sim\text{HR}\\ y\sim\text{LR}}}[f(C(G(y)) - C(x))]$$

The critic network C is adversarially trained with R_1 gradient penalty [5]:

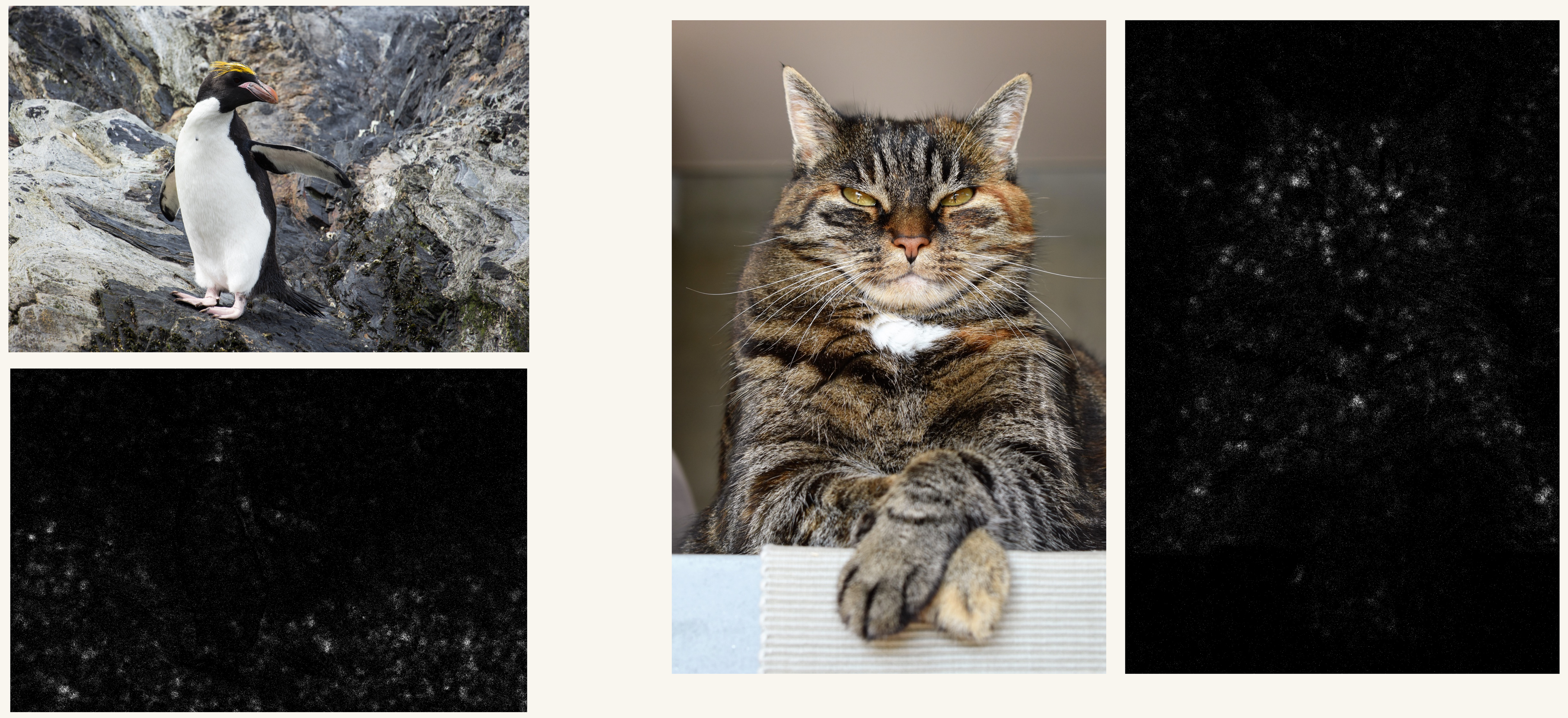
$$L_C = \sup_{C:\mathcal{X}\to\mathbb{R}} \mathbb{E}_{\substack{x\sim\text{HR}\\ y\sim\text{LR}}}[f(C(x) - C(G(y)))] + \frac{\gamma}{2}\mathbb{E}_{x\sim\text{HR}}\left[\|\nabla_x C(x)\|^2\right]$$

It is proved in [6] that $L^G_{\text{Adversarial}}$ and $L^C_{\text{Adversarial}}$ define a divergence, thus our objectives push G to produce results which lie on the natural image manifold.

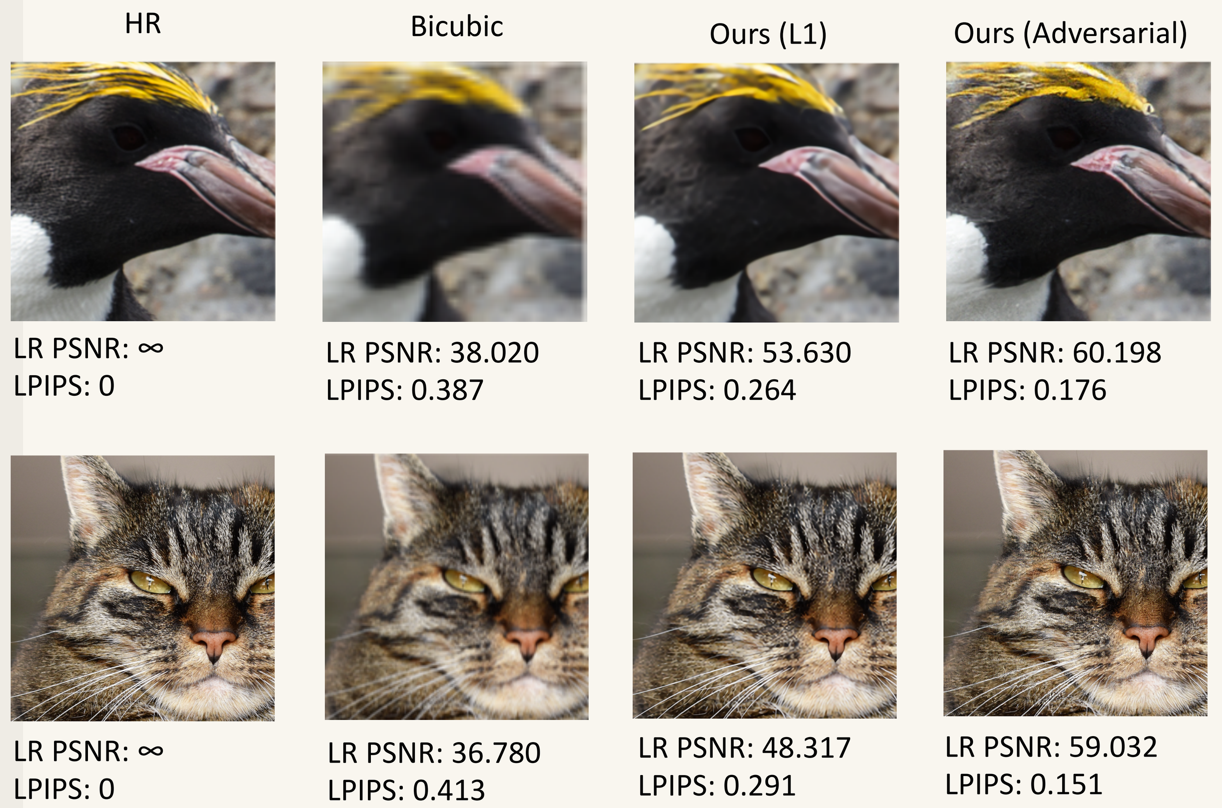
Model Architecture

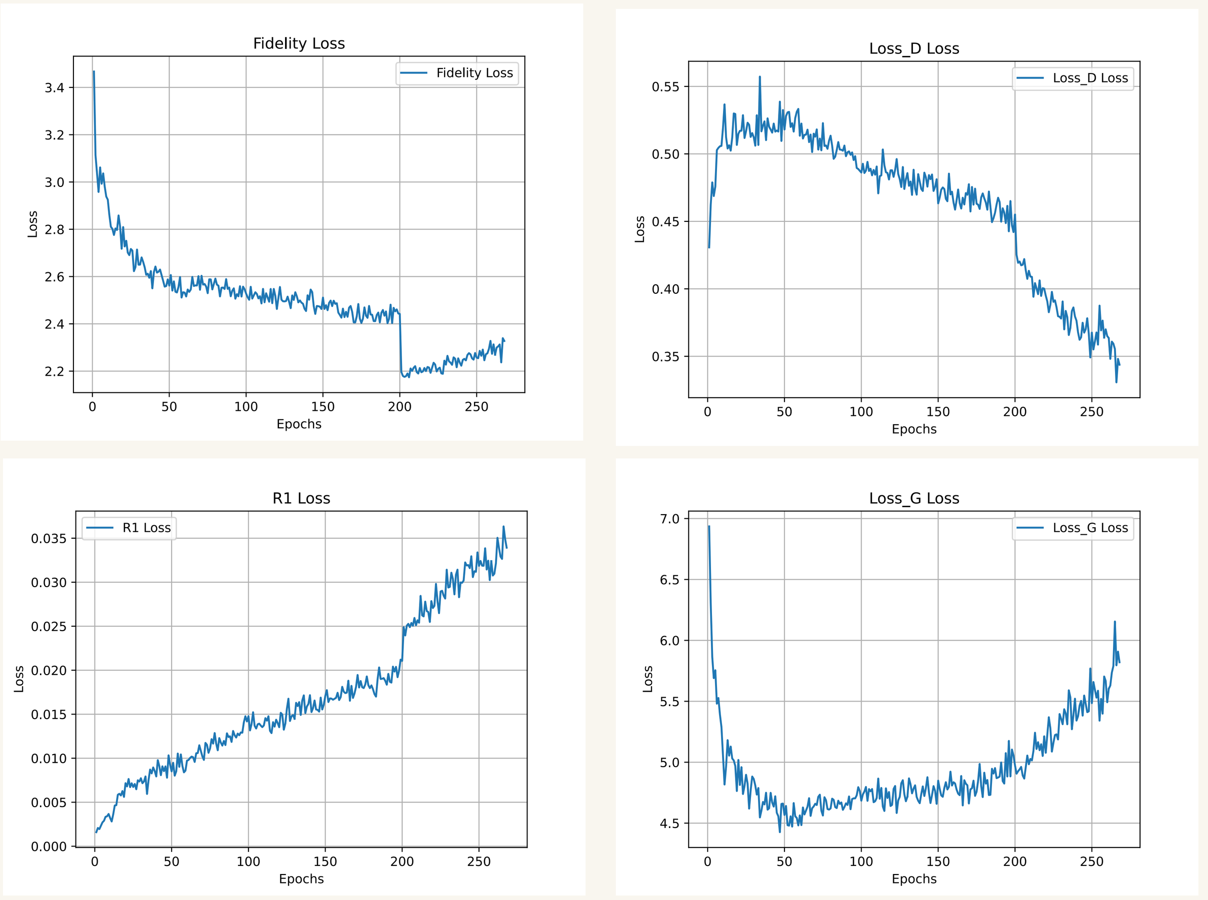


Reconstruction Stochasticity



Experiments





References

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Acknowledgements

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