SRGAN: Employ a generative adversarial network (GAN) [1] for 
image super-resolution (SR)

Perceptual Loss: Optimize a perceptual loss function based on a 
content loss calculated in VGG feature space [2,4] and a adversarial 
loss [1,3] that pushes the solutions to the natural image manifold.

MOS-Testing: Perform an extensive mean-opinion-score (MOS) 
test to confirm hugely significant gains in perceptual quality and 
limitations of mean-squared-error (MSE) based quality measures.

Super-resolve a low-resolution input image ILR that was 
obtained by 4x downscaling a high-resolution image IHR. We 
train a convolutional neural network (CNN) with optimal 
parameters such that:

\[
\theta_G = \arg\min_{\theta_D} \frac{1}{N} \sum_{n=1}^{N} I_{SR}(G_{\theta_G}(I_{LR}), I_{HR})
\]

The Limitation of MSE based optimization is that it encourages 
average-like solutions that are overly smooth and generally not 
reside on the manifold of natural images.

MOS averaged over scores from 26 human raters. Scores range 
from 1 (worst, nearest neighbor) to 5 (best, original HR image)

**Influence of Network Depth**
- Higher performance using skip-
  connections
- Depth is beneficial for PSNR
- SRGAN gets more difficult to 
  train for deeper networks

**Investigation of content loss**
- Loss on higher level VGG features yields better texture detail

**Comparison to state of the art (BSD100)**
- SRGAN closes the MOS gap between 
  the state of the art and original high 
  resolution images by more than 50%

**Evaluation Measures**
- PSNR
- MOS

**ExperimentsAndResults**

**Visuals**

**References**
  fficient statistics”, ICLR, 2016