Motivation

- Solving inverse problems by directly applying CNN on the target image is a novel idea and avoids training on large datasets
- Original paper\(^1\) chooses Unet with skip connections but does not explain the reasons
- As the training proceeds network starts to overfit but we cannot predict when to stop

Related Work

- ResNet\(^2\) proves to be a performant CV architecture and identity mapping is desired in denoising\(^3\)
- Different residual blocks are investigated\(^4\)
- Combination of ResNet and Unet succeeds in problems like road extraction\(^5\)
- Variants on skip connections of Unet have been proposed\(^6\)
  - Unet++, Dense Unet, Adversarial Unet, …

References

\(^1\) Ulyanov et al. Deep image prior.
\(^2\) He et al. Deep residual learning for image recognition.
\(^3\) Zhang et al. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising.
\(^4\) He et al. Identity mappings in deep residual networks.
\(^5\) Zhang et al. Road extraction by deep residual u-net.
\(^6\) Siddique et al. U-net and its variants for medical image segmentation: A review of theory and applications

New Technique

- Try ResNet architecture - remove front-to-end skip connections
- Change hour-glass shape - remove downsampling and upsampling
- Fuse ResNet building block with Unet - Res-Unet
- Add dropout layer to solve overfitting

Experimental Results & Conclusions

- Problem setting: Denoising (may extend to other problems in the last two days)
- Evaluation Metrics: PSNR with original image
- Architectures
  - Unet outperforms ResNet mainly because of skip connections
  - Hour-glass shaped structure enhances training but does not improve PSNR
- Better model: residual block and dropout layer
  - Residual block can improve PSNR and learn faster
  - Dropout can significantly improve one-pass PSNR and slow down overfitting