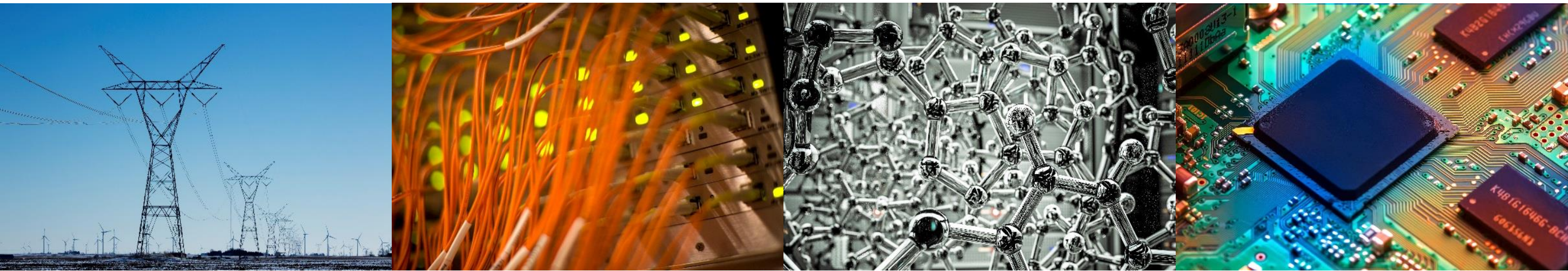


# Convolutional Neural Network for Inverse Problems in Imaging

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ECE 551 Course Project

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# Inverse Problems in Imaging

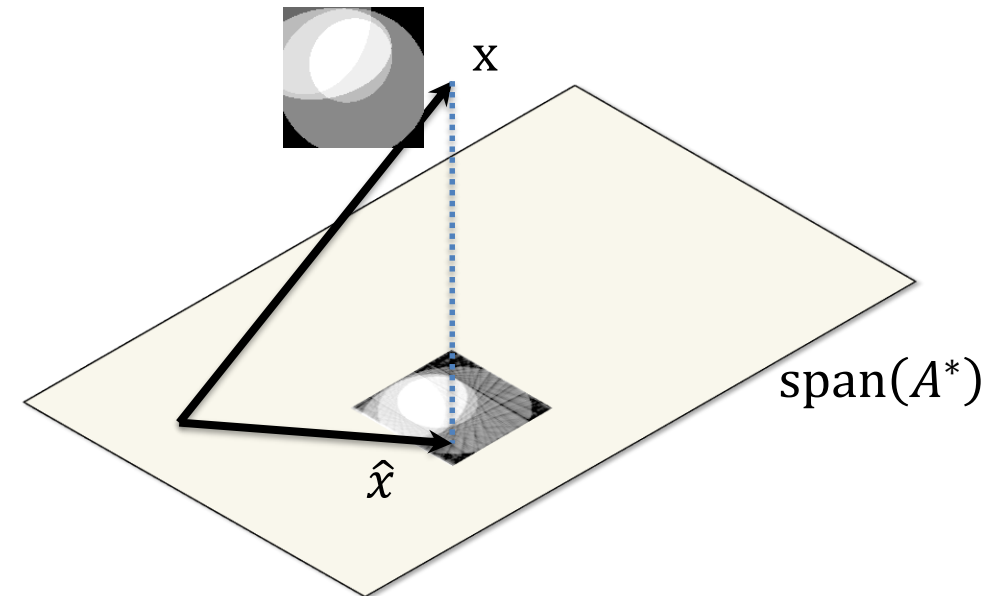
- “  $y = \text{blur}(x) + \text{noise}$ . This is all of applied science. ”

- Prof. Ivan Dokmanic

- Free space causes some blurring/low pass filtering that result in ill-posedness.

# Linear Inverse Problems

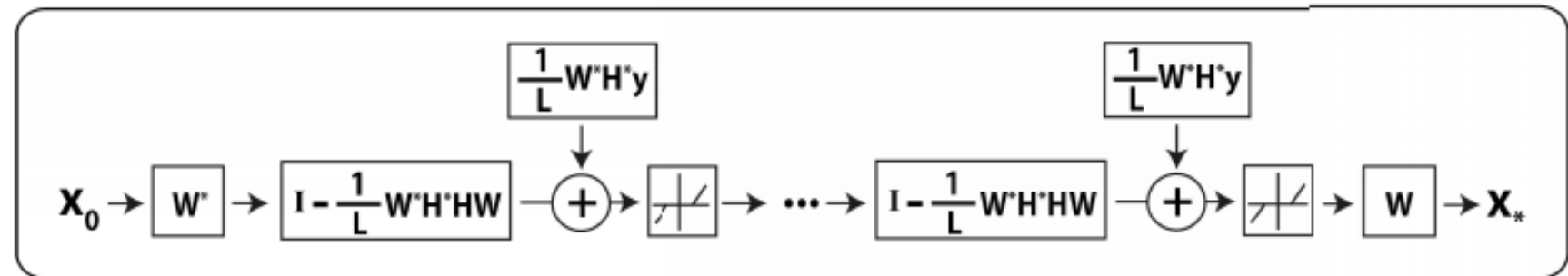
- $y = Ax + n$
- Direct inversion  $\hat{x}$  (with a pseudoinverse) resides in  $\text{span}(A^*)$
- Using sparsity in the object as prior information



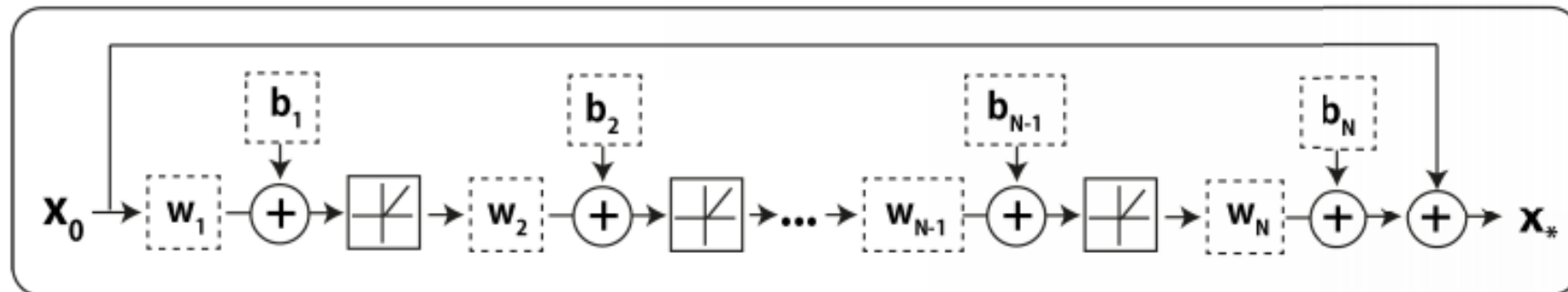
# Motivation for using CNNs

- CNN structure similar to unrolled iterations

Iterative algorithm



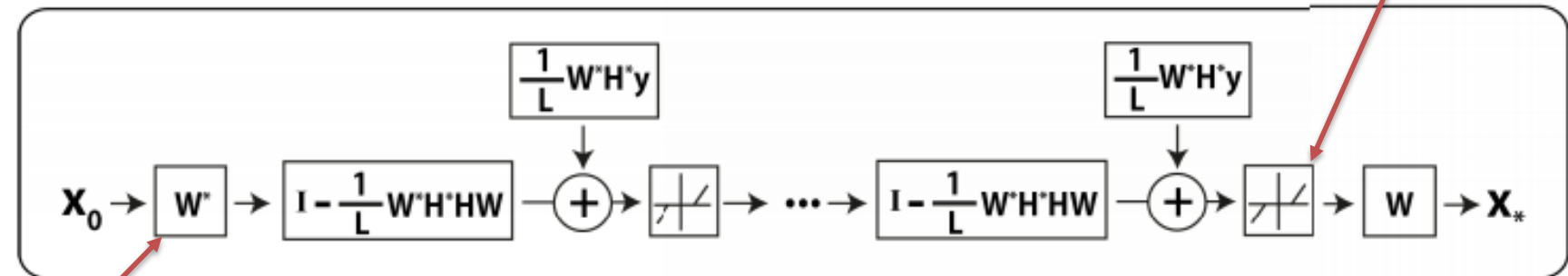
CNN



# Motivation for using CNNs

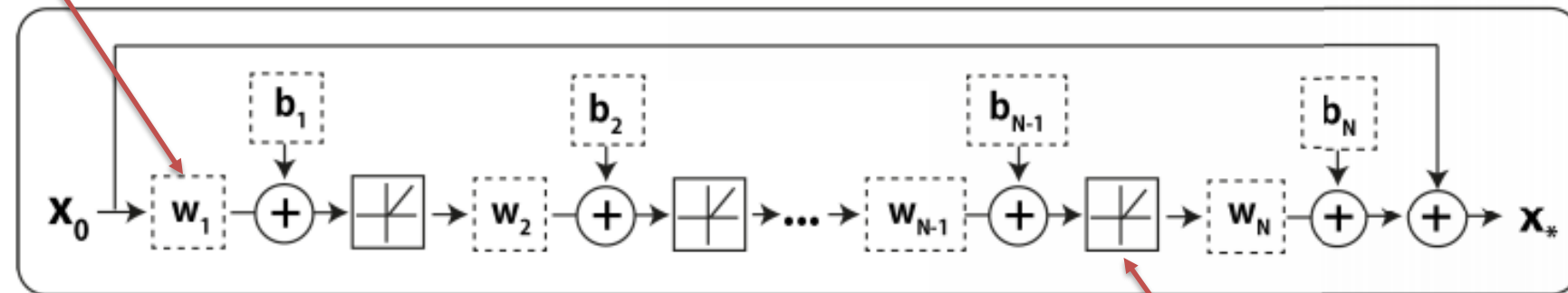
- CNN structure similar to unrolled iterations

Iterative algorithm



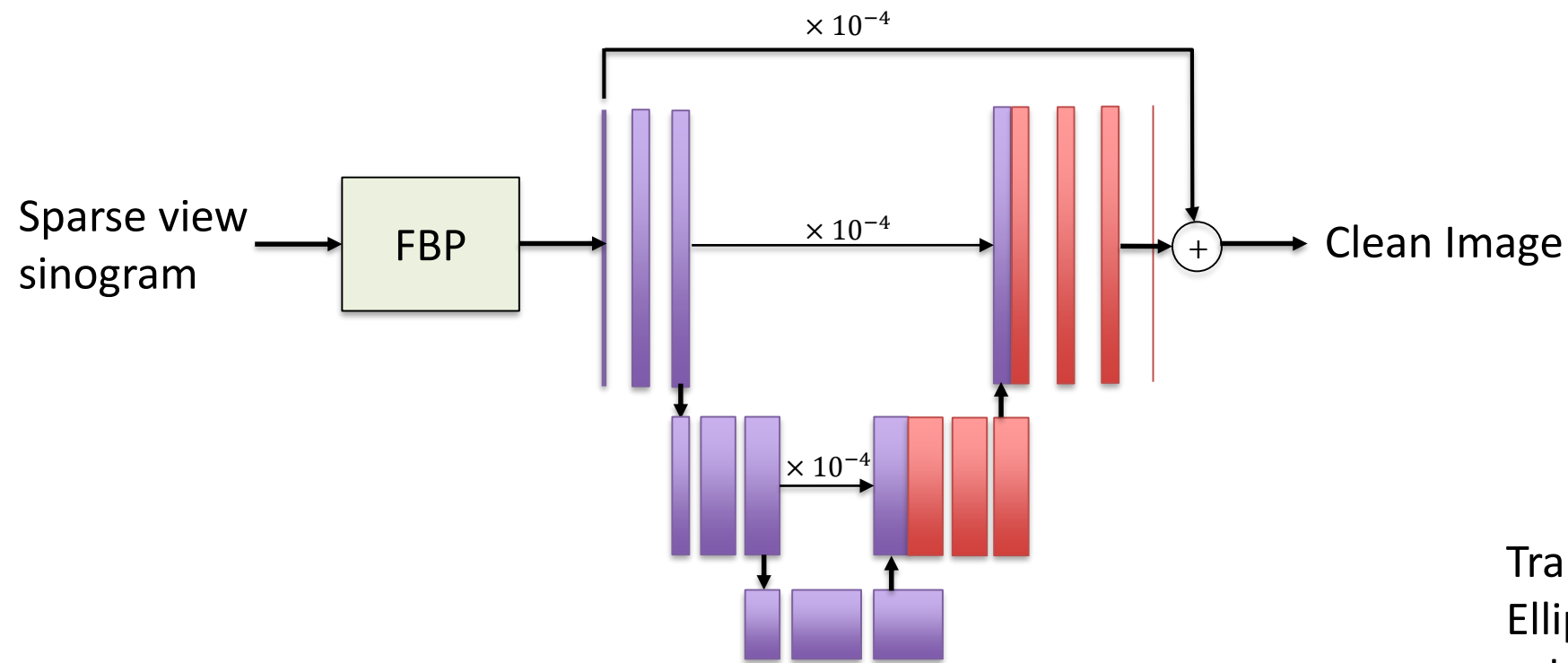
Filters

CNN



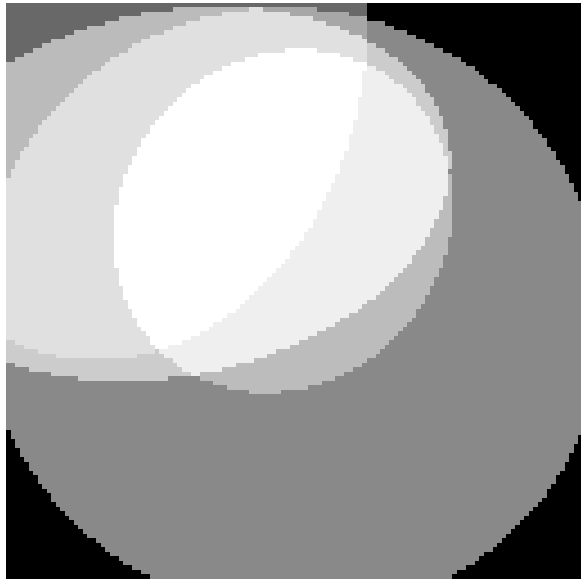
Nonlinear activation

# A specific implementation for CT - FBPConvnet

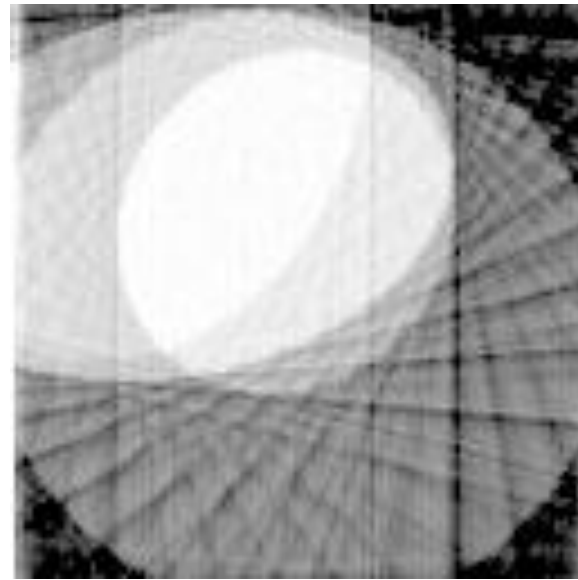


Trained on 700 ellipse images.  
Ellipse dataset generated by a random selection of number of ellipses, strength, major/minor axes and tilts in each image.

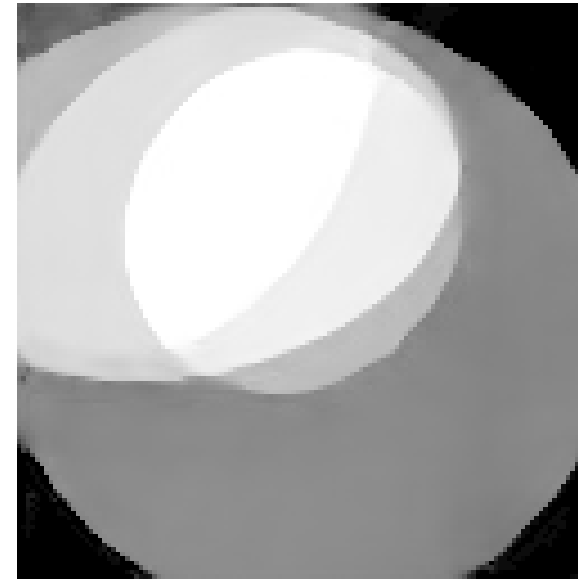
# Results



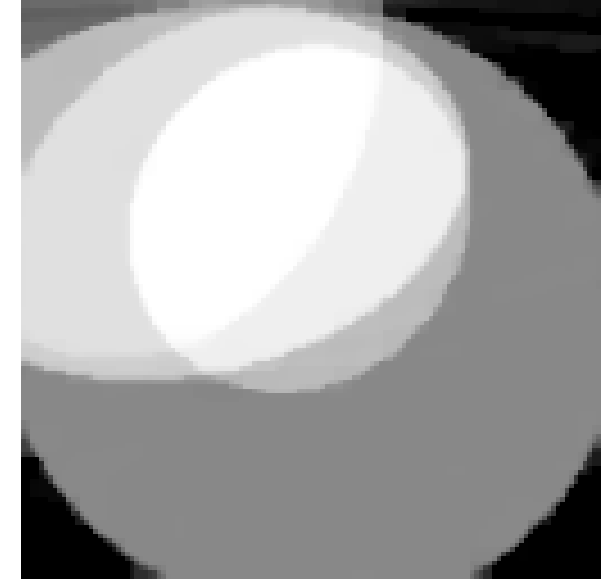
Ground truth



Filtered Backprojection  
 $\text{MSE } 8.7 \times 10^{-4}$



FBP-CNN  
 $\text{MSE } 2.2 \times 10^{-4}$



Iterative  
 $\text{MSE } 1.8 \times 10^{-4}$

# Conclusions

- Iterative algorithms still better for highly sparse (piecewise constant) images like ellipses.
- CNN could perform better in cases where the sparse basis is not obvious.



# References

- K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep convolutional neural network for inverse problems in imaging,” *IEEE Transactions on Image Processing*, vol. 26, no. 9, pp. 4509–4522, 2017.
- M. T. McCann, K. H. Jin, and M. Unser, “Convolutional neural networks for inverse problems in imaging: A review,” *IEEE Signal Processing Magazine*, vol. 34, no. 6, pp. 85–95, 2017.