**Motivation**

- 3D Deconvolution is a typical problem faced by microscopists and astronomers which aims at reverse the effects of convolution on observed data.
- Computational complexity and not precisely known noise parameters (Gaussian, Poisson, Optical aberrations) make it challenging.
- Typically the three major categories of deconvolution algorithms are: Non-iterative (Wiener filtering), Iterative (RL, ADMM) and blind deconvolution.
- Changing certain microscopy parameters may change the point spread function (PSF) which requires recalibration. Sometimes, it is not trivial to model the image formation process because of complex optical setup.
- To circumvent these issues, we focus on using deep learning (Convolutional Neural Networks) for 3D deconvolution by efficiently learning the underlying ground truth from the blurred data.
- We also compare the results to standard methods like RL and ADMM.

**References**


**Methods**

Richardson Lucy (RL) Deconvolution[^11]

\[ b \sim P(Ax) \]

\[ x^{(q+1)} = \frac{A^T(b)}{A^T A + \lambda(\frac{D_x x}{|D_x x|} + \frac{D_y x}{|D_y x|} + \frac{D_z x}{|D_z x|})} x^{(q)} \]


\[ \text{minimize} \sum_k g(x_k) \]
\[ = g_1(x_1) + g_2(x_2) + g_3(x_3) \]

subject to

\[ \left[ A^T 1^T \right] x^* = \left[ x_1^* \ x_2^* \ x_3^* \right]^T \]

\[ \text{end} \]

Naïve Super-Resolution CNN[^22]

\[ g = p\left[ S_\alpha (h \otimes f) \right] + \eta \]
\[ p_{xy} = S_\alpha (\tilde{h} \otimes g_{xy}) \]
\[ C_{64,9,9} - C_{32,5,5} - C_{1,5,5} - C_{1,1,1} \]
\[ L = \sum_{n} \left[ 20 \log_{10} \max g_{xy,n} - 10 \log_{10} \left| f_{xy,n} - \tilde{g}_{xy,n} \right|^2 \right] \]

**Results and Discussion**

<table>
<thead>
<tr>
<th>Method</th>
<th>PSNR</th>
<th>Time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RL</td>
<td>20.842</td>
<td>326</td>
</tr>
<tr>
<td>ADMM</td>
<td>22.151</td>
<td>418</td>
</tr>
<tr>
<td>SRCNN</td>
<td>18.192</td>
<td>303</td>
</tr>
<tr>
<td>Isonet-1</td>
<td>23.151</td>
<td>780</td>
</tr>
</tbody>
</table>

RL – Performs reasonably well when there is Poisson Noise

ADMM – Faster convergence than RL but still we need to know the image formation process explicitly.

Naïve SRCNN – Ignores PSF and hence performs poorly

Isonet1 – Restores isotropic resolution by solving a super-resolution problem on subsampled data, and a deconvolution problem to correct for the PSF.

Detailed analysis of convergence and PSNR is available in the final report.