

# Self-supervised deep learning to improve quantification of blood-brain barrier permeability from MRI data

Friday 22nd March 2024

Photo adapted from D koi on Unsplash[1]

- **Blood-brain barrier (BBB)**
  - Selectively permeable barrier <sup>1</sup> [2]
  - Maintains homeostasis in brain and CNS [3]

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  - Selectively permeable barrier <sup>1</sup> [2]
  - Maintains homeostasis in brain and CNS [3]
- **Dysfunction:** Pathogens and toxins leak from blood to brain [2]
  - Stroke
  - Multiple sclerosis
  - Tumours
  - Can occur early in disease
- **Biomarker**

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- **FEXI** (Filtered exchange imaging) - dMRI (Diffusion MRI) technique
  - Originally used to track water exchange across cell membranes
  - Can be used to track water exchange across the BBB

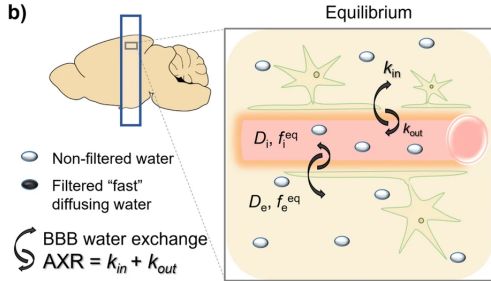
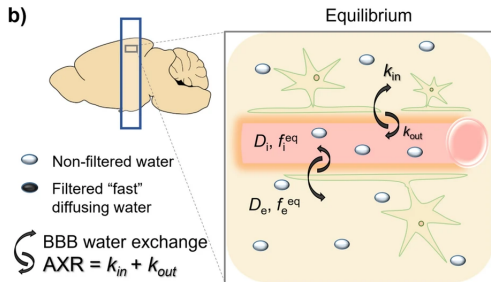


Figure: Adapted from [4]



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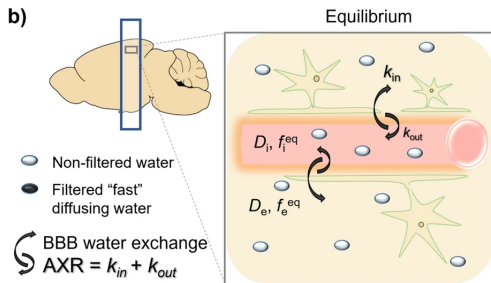


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- **Existing method:** Non-linear least squares fit (NLLS)
  - Suffers from bias and noise.
- **New method:** Neural networks (NN) show promise in other dMRI methods
  - ssVERDICT - A model of Prostate tumours
  - Reduced bias compared to existing NLLS method [5]
  - Side effect: Slow to train but quicker once implemented
    - 10s of minutes for NLLS
    - Fractions of a second

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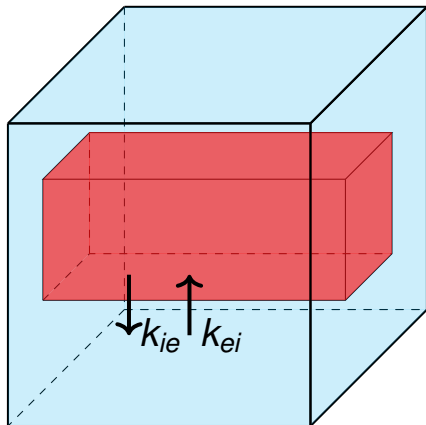
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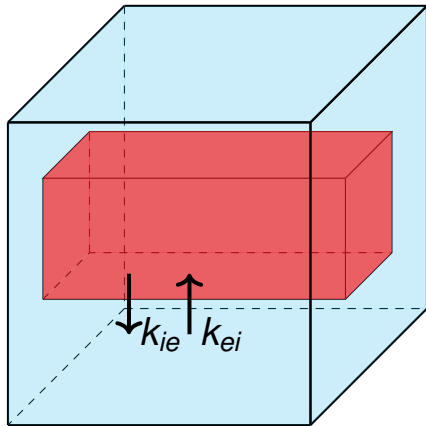
## **Objectives:**

- Simulate the MRI signal in Python using NumPy.
- Implement a baseline Non-linear least squares (NLLS) estimation to FEXI.
  - Previously made in MATLAB
- Create a self supervised deep learning model in PyTorch to estimate FEXI parameters.



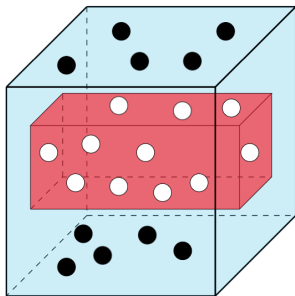
**Figure:** A FEXI voxel, extra-vascular compartment in blue and intra-vascular compartment in red.

- FEXI assumes a 2 compartment model in every voxel (Volume Element)
- FEXI tracks the water in each compartment. (Blood-water in the intra-vascular compartment)
- The main parameter of interest is the apparent exchange rate  $AXR = k_{ie} + k_{ei}$  between the compartments.



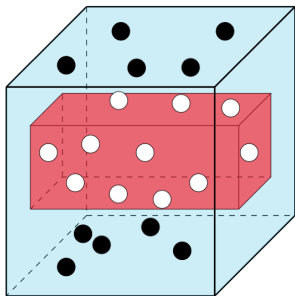
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- Other estimated parameters:
  - Apparent diffusion coefficient  $ADC$
  - Filter efficiency  $\sigma$



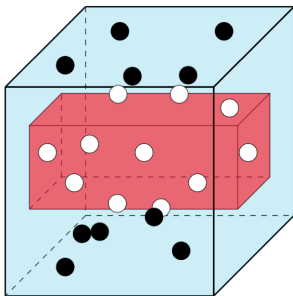
- The FEXI MRI sequence contains a mixing time
- There is water exchange between the 2 compartments during this time
- This is what  $AXR$  measures

**Figure:** Exchange of water between intra- and extra-vascular compartments during mixing time



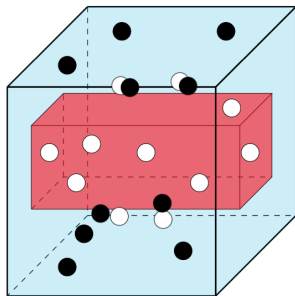
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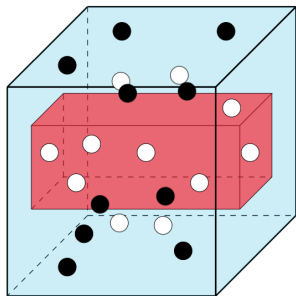
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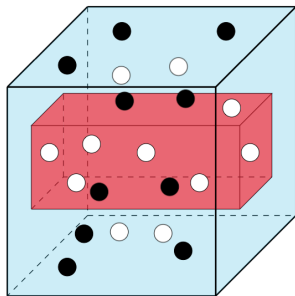
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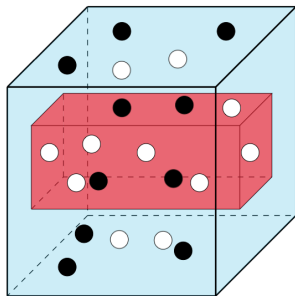
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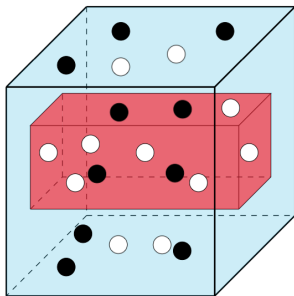
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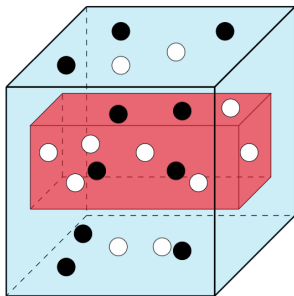
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- **Simulations**

- Simulate 10,000 voxels
  - Random distribution of underlying model parameters  $ADC$ ,  $\sigma$  and  $AXR$
- Calculate the signal produced by each voxel
- Add rician noise<sup>2</sup> (SNR=50) to the signals
  - The ground truth

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<sup>2</sup>"Rician is the thermal noise found in MRI due to the thermal agitation of electrons." [6]

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- **NLLS and Neural network**

- Input noisy MRI signal
- Estimate underlying model parameters  $ADC$ ,  $\sigma$  and  $AXR$
- Calculate the mean squared error between the estimated signal and the ground truth (with noise added).
- Iterate

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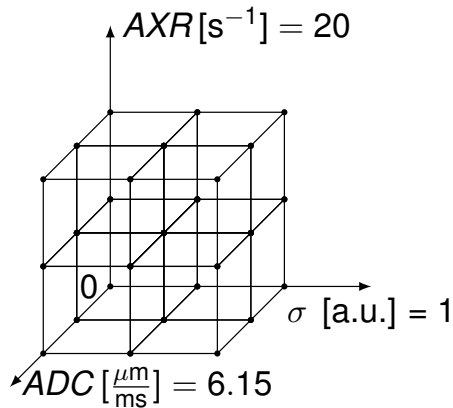
- The `scipy.optimize.minimize()` function [7] within Python was used to make the estimations.<sup>3</sup>
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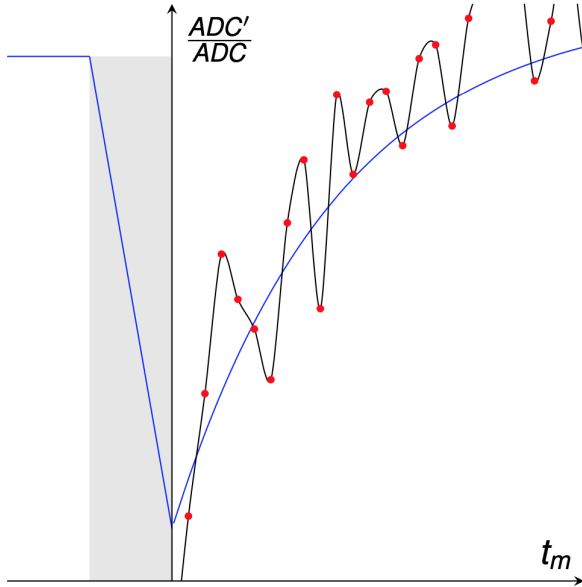
<sup>3</sup>Using the Limited-memory Broyden-Fletcher-Goldfarb-Shanno with Bounds algorithm 



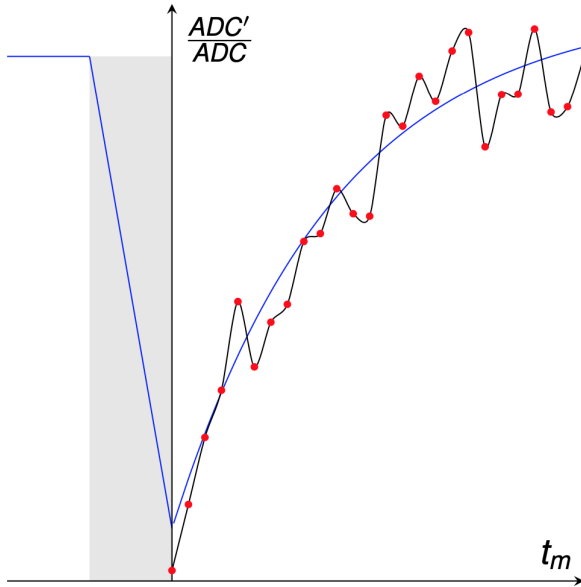
- The `scipy.optimize.minimize()` function [7] within Python was used to make the estimations.<sup>3</sup>
  - Minimising the sum of squares error between the estimated signal and the noisy ground truth signal.
- The function requires an initial value
  - 3 equally spaced initial values for each parameter ( $ADC$ ,  $\sigma$  and  $AXR$ ) were used, producing  $3^3 = 27$  initial starting points.
  - The best estimation from these 27 starting points was used
- Each parameter is bounded within the simulation range.



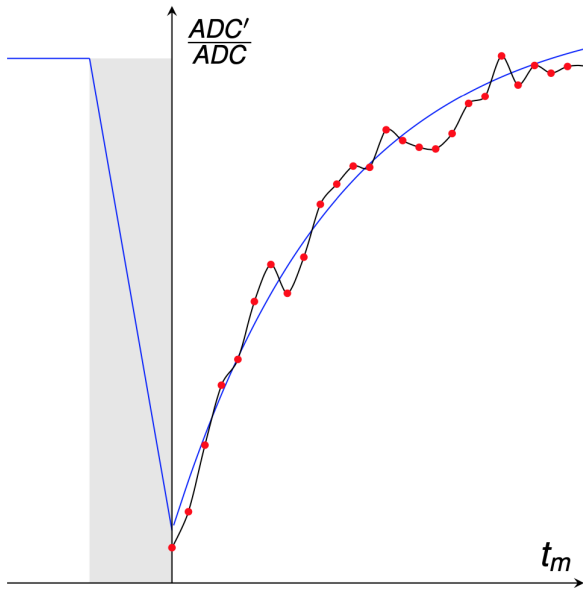
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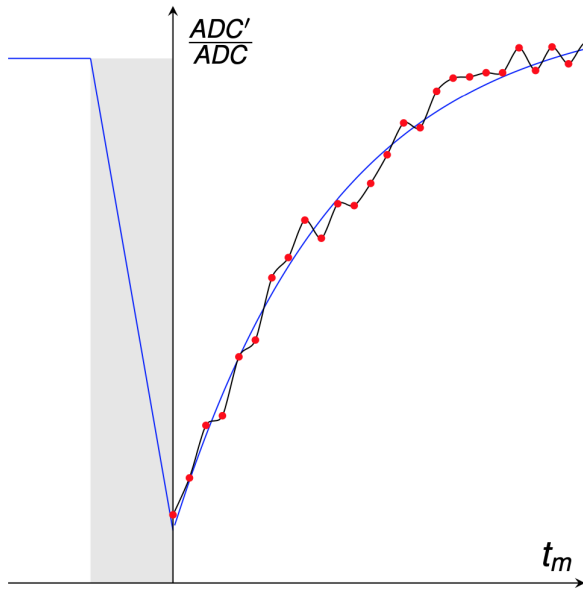
- Here is an example of fitting the curve using a NLLS fit



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- Input: 8 image volumes
- Passed through the weights of each layer
- 3 outputs:  $ADC$ ,  $\sigma$  and  $AXR$ . (Known as the forward model)
- Each parameter is bounded by the same bounds as the simulation.
- Mean squared error calculated between the ground truth noisy signals and estimated signals

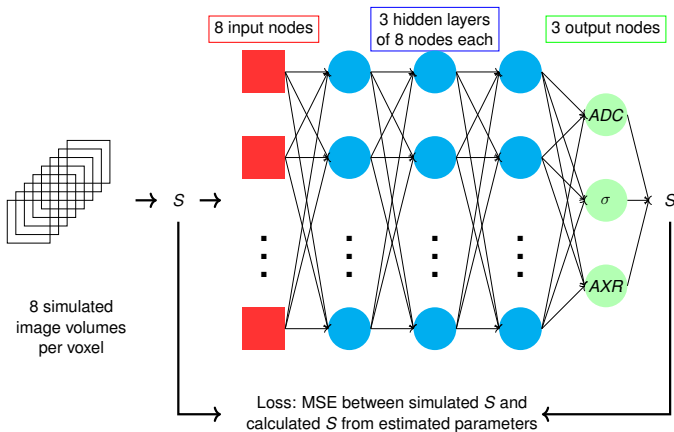


Figure: Neural network

- The gradients of the weights are calculated.
- If error improves, then the weights in the model are updated, with gradients giving the most efficient change (Known as backpropagation)
- This process (one epoch) is repeated, and stops after 100 epochs in a row where there is no improvement to the loss.

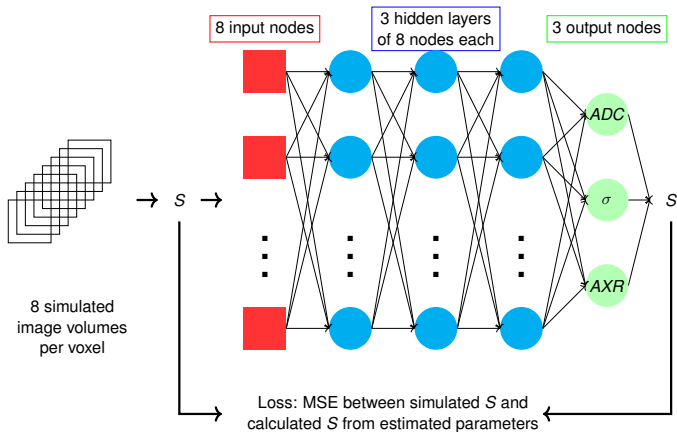


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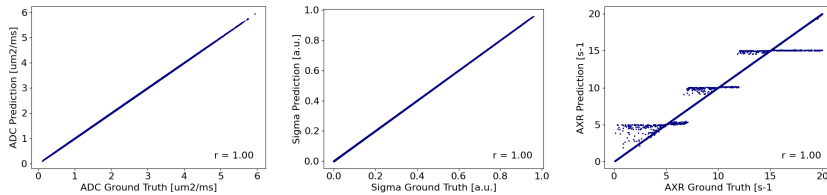


Figure: NLLS estimations

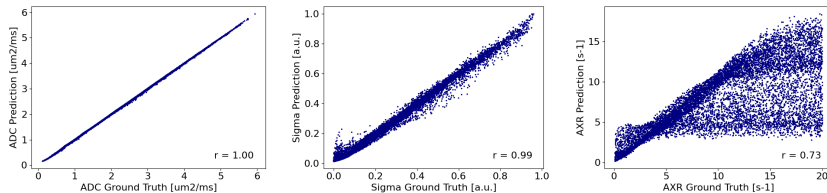


Figure: NN estimations



MSE			
Method	<i>ADC</i>	$\sigma$	<i>AXR</i>
NLLS	<b><math>1.75 \times 10^{-7}</math></b>	<b><math>1.03 \times 10^{-8}</math></b>	<b>0.331</b>
NN	2.53	0.104	56.3
Bias			
Method	<i>ADC</i>	$\sigma$	<i>AXR</i>
NLLS	<b><math>-3.02 \times 10^{-5}</math></b>	<b><math>-6.70 \times 10^{-6}</math></b>	<b><math>3.33 \times 10^{-3}</math></b>
NN	$3.57 \times 10^{-3}$	$-3.09 \times 10^{-3}$	-2.52
Variance			
Method	<i>ADC</i>	$\sigma$	<i>AXR</i>
NLLS	1.27	$5.27 \times 10^2$	32.2
NN	<b>1.26</b>	<b><math>5.07 \times 10^2</math></b>	<b>23.3</b>

Table: Comparing NLLS to NN (Best results are bolded)

$$\text{MSE} = \frac{1}{N} \sum_{i=0}^N (O_i - E_i)^2$$

$$\text{Bias} = \frac{1}{N} \sum_{i=0}^N (O_i - E_i)$$

$$\text{Variance} = \frac{1}{N} \sum_{i=0}^N (O_i - \bar{O})^2$$

Where  $O$  is ground truth parameter value,  $E$  is estimated value, and  $N$  is number of samples.

- NLLS fit outperforms NN in MSE and Bias for all parameters
- NN outperforms NLLS in variance for all parameters
- AXR is hardest parameter to estimate in both methods
  - *ADC* and  $\sigma$  have a linear relationship to the signal, but *AXR* has a exponential relationship.
- **Future work**
  - Use other variations hyper-parameters of NN.
  - Calculate the loss on a per parameter basis.
  - Physics informed network - Calculate AXR from other parameters rather than estimating in NN
  - Apply to in-vivo data

- [1] Unsplash. *Photo by D koi on Unsplash*. 2022-06-29. URL:  
[https://unsplash.com/photos/a-white-and-grey-striped-surface-GU\\_nNLVna\\_4](https://unsplash.com/photos/a-white-and-grey-striped-surface-GU_nNLVna_4) (visited on 2024-03-15).
- [2] Richard Daneman and Alexandre Prat. “The Blood–Brain Barrier”. In: *Cold Spring Harbor Perspectives in Biology* 7.1 (2015-01), a020412. ISSN: 1943-0264. DOI: 10.1101/cshperspect.a020412. URL:  
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4292164/> (visited on 2024-03-14).
- [3] Gerard J. Tortora and Bryan H. Derrickson. *Introduction to the Human Body*. 11th ed. Wiley, 2017-12-15. ISBN: 978-1-119-39273-6. URL:  
[https://bibliu.com/app/#/view/books/9781119392736/epub/OPS/c10.html#page\\_393](https://bibliu.com/app/#/view/books/9781119392736/epub/OPS/c10.html#page_393) (visited on 2024-03-07).

- [4] Yolanda Ohene et al. “Filter exchange imaging with crusher gradient modelling detects increased blood–brain barrier water permeability in response to mild lung infection”. In: *Fluids and Barriers of the CNS* 20.1 (2023-04-03), p. 25. ISSN: 2045-8118. DOI: 10.1186/s12987-023-00422-7. URL: <https://doi.org/10.1186/s12987-023-00422-7> (visited on 2024-03-21).
- [5] Snigdha Sen et al. *ssVERDICT: Self-Supervised VERDICT-MRI for Enhanced Prostate Tumour Characterisation*. 2023-09-27. DOI: 10.48550/arXiv.2309.06268. arXiv: 2309.06268[cs, eess]. URL: <http://arxiv.org/abs/2309.06268> (visited on 2024-03-21).

- [6] Divya Pankaj, Govind D., and Narayanankutty K.a. “A novel method for removing Rician noise from MRI based on variational mode decomposition”. In: *Biomedical Signal Processing and Control* 69 (2021-08-01), p. 102737. ISSN: 1746-8094. DOI: 10.1016/j.bspc.2021.102737. URL: <https://www.sciencedirect.com/science/article/pii/S1746809421003347> (visited on 2024-03-22).
- [7] *scipy.optimize.minimize* — *SciPy v1.12.0 Manual*. URL: <https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.minimize.html> (visited on 2024-03-14).

Thank you for listening!  
Any questions?

$$S(b_f, t_m, b) = S_0(b_f, t_m) e^{-b \cdot ADC'(t_m)} \quad (1)$$

where:

$$ADC'(t_m) = ADC(1 - \sigma e^{-t_m \cdot AXR})$$