Combining Model Driven and Data Driven Approaches for Inverse Problems in Parameter Estimation and Image Reconstruction:

From Modelling to Validation

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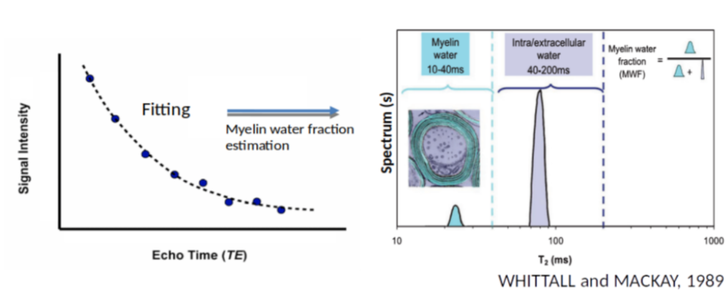

Can we integrate realistic models in a **supervised** machine learning approach to solve the highly ill-posed problem of recovering the T_2 distribution?

The following slides are based on the postprint version of the article: "Model-informed machine learning for multi-component T_2 relaxometry" published in Medical Image Analysis [Yu et al., 2021a]. DOI: 10.1016/j.media.2020.101940.

Within a single voxel, there are different tissues/materials each with different T_2's We can recover these properties through MR spin-echo/gradient echo acquisitions,

$$\mathbf{s}(TE_i) = \int EPG(TE_i, T_1, T_2, \alpha) p(T_2) \mathrm{d}T_2. \tag{1}$$

Traditional approaches include doing a non-parametric, non-negative least squares fitting using a dictionary of EPG signals:

$$\arg\min_{\mathbf{p} \geq 0} \|D_\alpha \mathbf{p} - \mathbf{s}\|_2^2 + \lambda \Phi(\mathbf{p}) \tag{2}$$

or modelling $p(T_2)$ as a mixture of distributions:

$$p(T_2) = \sum_{i=1}^{n} v_i F_i(\mathbf{m}_i, T_2) \tag{3}$$

and solving a nonlinear optimization problem.

1. State of the art non-parametric approaches tend to be highly sensitive to noise, with heuristic setting of regularization parameter. This leads to oversmoothing.
2. Gaussian mixture fitting requires long computation time and can be unstable without fixing parameters to set values. Furthermore, number of compartments need to be fixed.

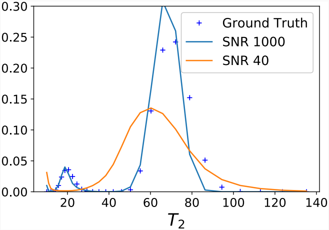

Figure 1: Reconstructions from two different SNRs (40,1000) using a non-parametric approach(NNLS with Laplacian regularization)

In brain tissue, several assumptions are traditionally made about the T_2 distributions:

1. In white matter, there are well-separated lobes corresponding to the myelin water and the intra/extra axonal space.
2. Overall, lobes of distinct tissue are well-separated.

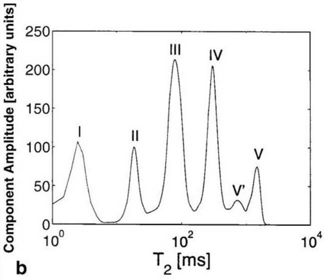

Figure 2: Multicomponent T_2 of frog nervous tissue (SNR 20,000) [Peled et al., 1999]

Proposed Solution

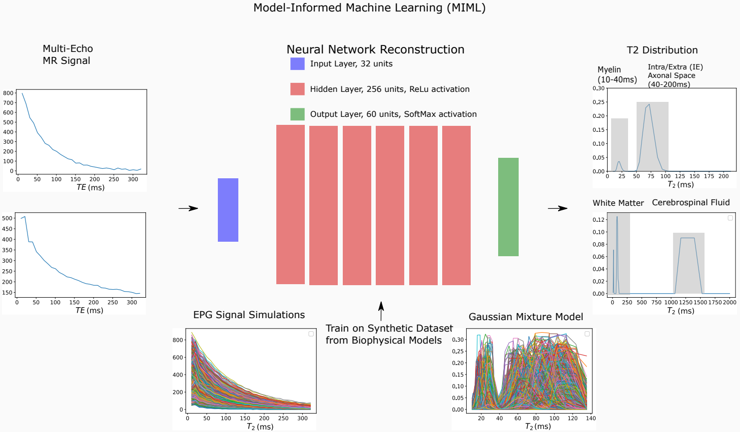

Figure 3: An overview of our proposed method for recovering T_2 distributions [Yu et al., 2021b].

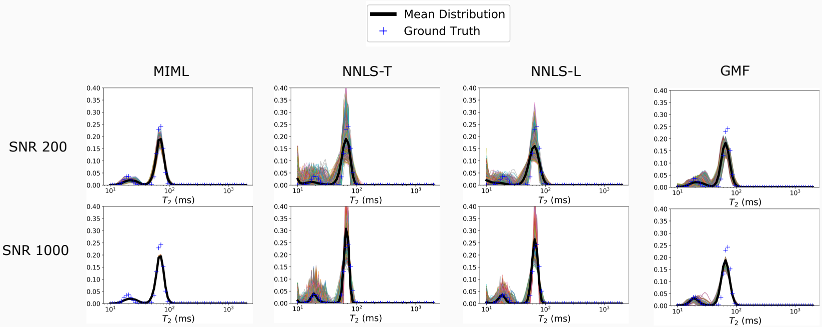

Figure 4: Results over a realistic, synthetic T_2 distribution

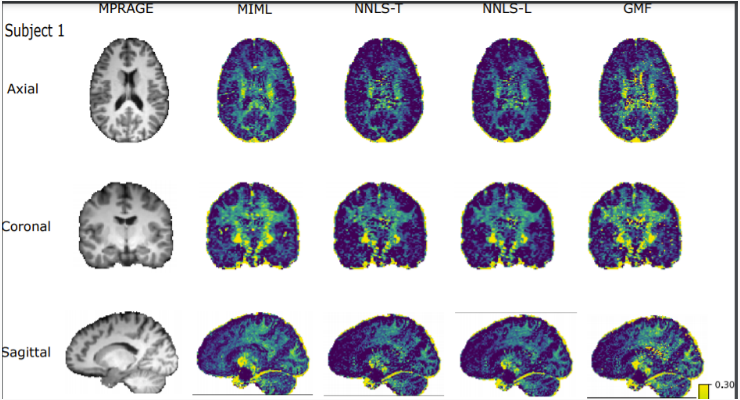

Figure 5: Myelin water fraction (MWF) maps from a healthy subject

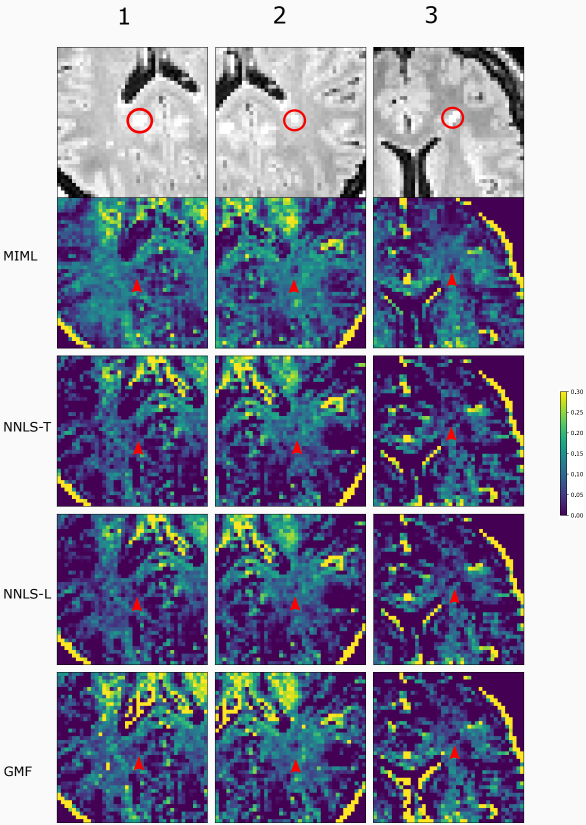

Figure 6: Closeup on MS lesions

Subject with MS

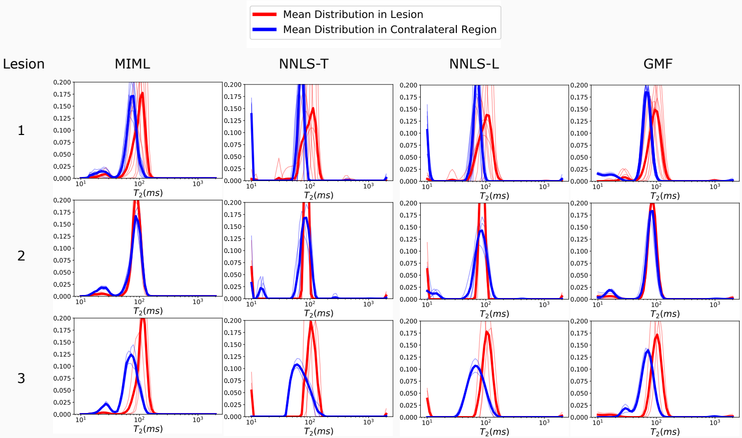

Figure 7: Mean T_2 distributions in MS lesions.

Conclusion

1. Supervised machine learning trained solely on synthetic data which encodes realistic modelling/common assumptions on the structure of solutions can robustly and accurately solve the ill-posed problem of multi-component T_2 estimation.
2. Furthermore, MIML is 22-4980 times faster than non-parametric or Gaussian mixture fitting.

Peled, S., Cory, D. G., Raymond, S. A., Kirschner, D. A., and Jolesz, F. A. (1999).
Water diffusion, t2, and compartmentation in frog sciatic nerve.
Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 42(5):911–918.

Yu, T., Canales-Rodriguez, E. J., Pizzolato, M., Piredda, G. F., Hilbert, T., Fischi-Gomez, E., Weigel, M., Barakovic, M., Bach Cuadra, M., Granziera, C., Kober, T., and Thiran, J.-P. (2021a).
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