# Full-range hepatic fat fraction estimation by using magnitude MRI

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# Hepatic Steatosis (Fatty liver disease)

## What is it?

Deposits of fat in the liver, distinguished between alcoholic and non-alcoholic types.

May lead to liver fibrosis and cirrhosis.

## MRI Diagnostic

- Ultrasound
- Biopsy
- CT
- MRI

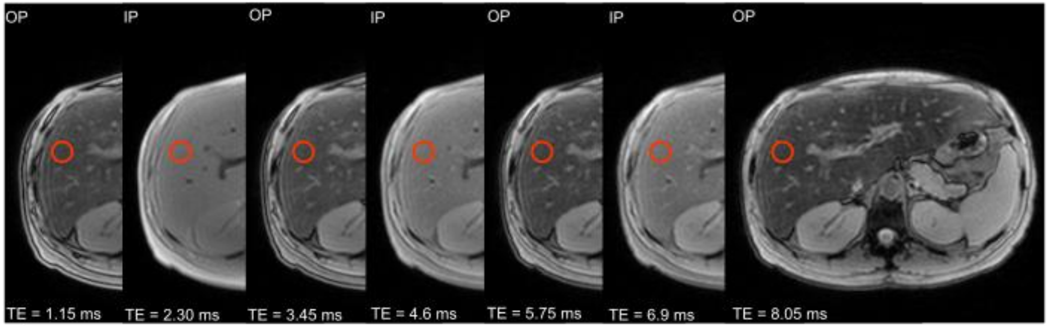
**Need for quantitative & non-invasive approach**

## Why magnitude-based?

- Clinically available
- Easy integration
- Off-site processing
- Vendor independent

**Estimation limited to 0-50% fat fraction**

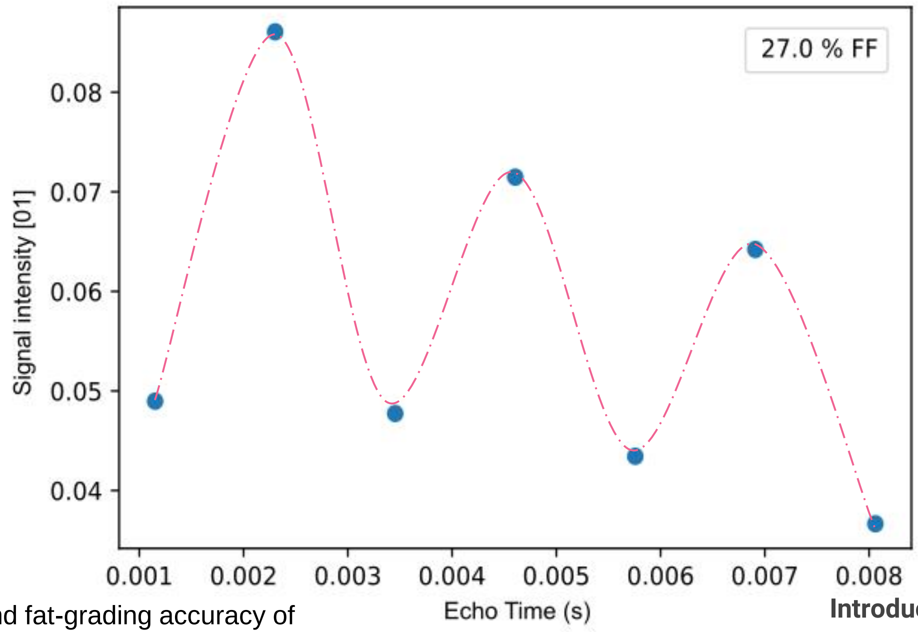
# Fat Fraction Estimation




$$FF = \frac{\rho_f}{\rho_w + \rho_f}$$

**Multi interference [1]**

- Nonlinear least squares fit
- Considers 3 lipid moieties
- Assumes single T2* decay
- Assumes water dominance
- Current state-of-the-art




[1] T. Yokoo et al. “Nonalchoholic fatty liver disease: diagnostic and fat-grading accuracy of low-flip-angle multiecho gradiente-recalled-echo MR imaging at 1.5 T”, Radiology, vol 251, no 1, pp 67-76, 5 2009

# Fat Fraction Estimation

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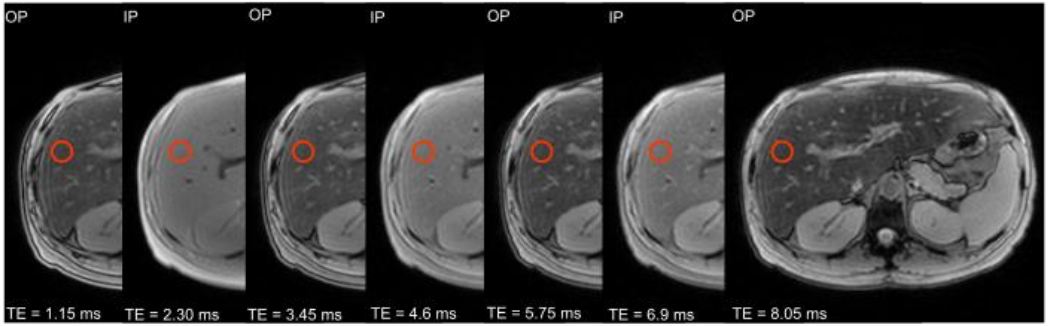
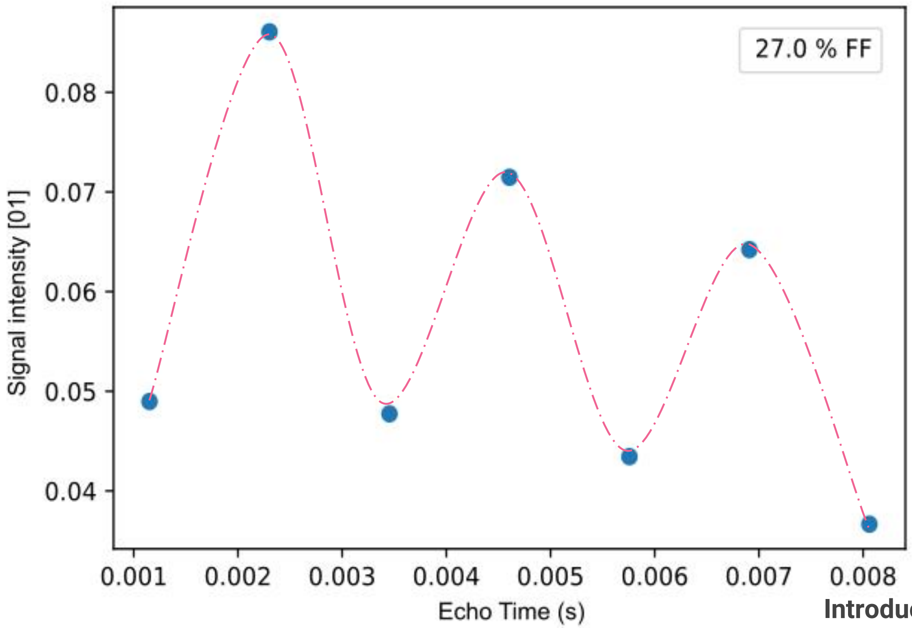
**What is to be improved?**

- Convergence depends on initialization parameters
- Tissue parameters may vary
- Looking for robustness to noise
- Explore fat fraction in full range

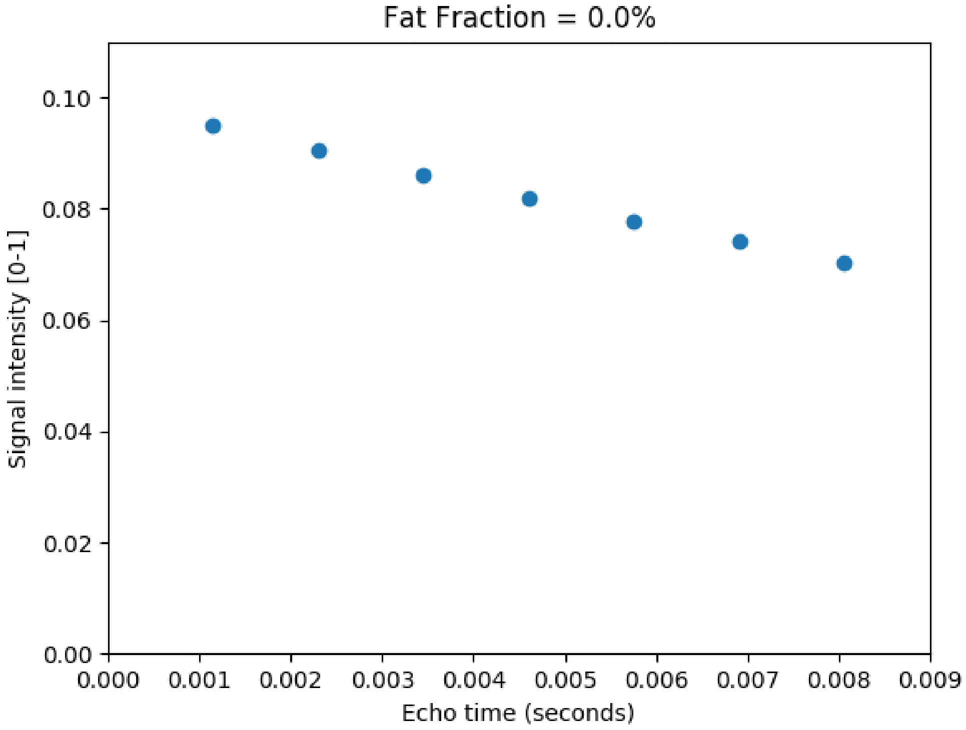


# Fat Fraction Estimation

$$S = |\, k\ \alpha \sum_n \rho_n\ \exp(-TE/T2^*{}_n)\ \exp(2\pi i f_n TE)\,|$$

$$FF = \frac{\rho_f}{\rho_w + \rho_f}$$

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- **Explore fat fraction in full range**

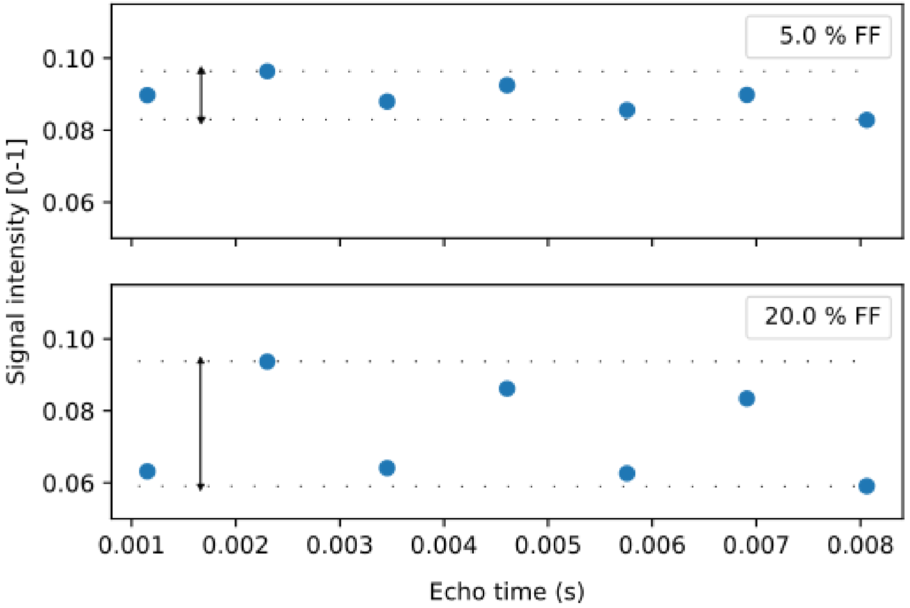
# Proposed Solution

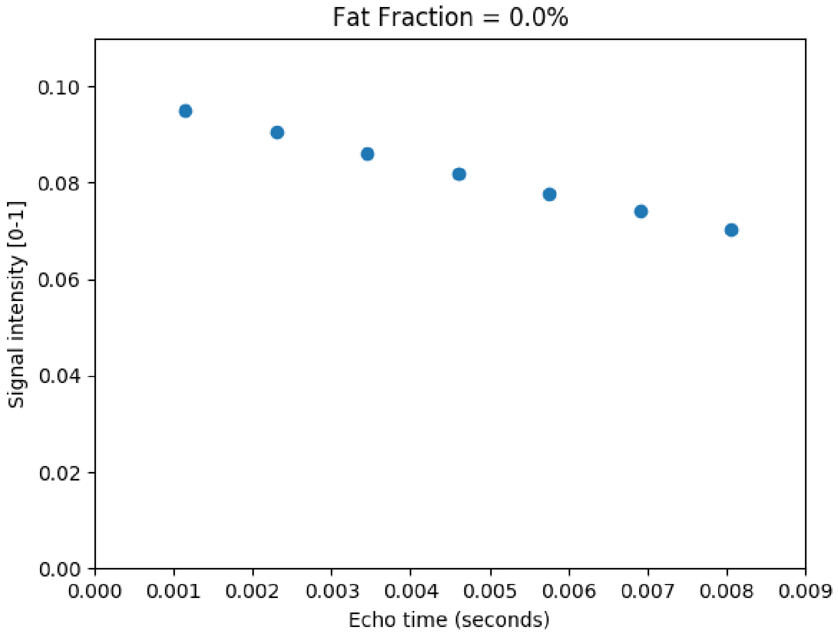
Signal shape as descriptor for fat fraction estimation

Goals:

- Understand how signal changes according to different parameters
- Train an artificial neural network (ANN) for fat fraction regression
- Evaluate results against a state-of-the-art method

# Signal shape at different Fat Fractions



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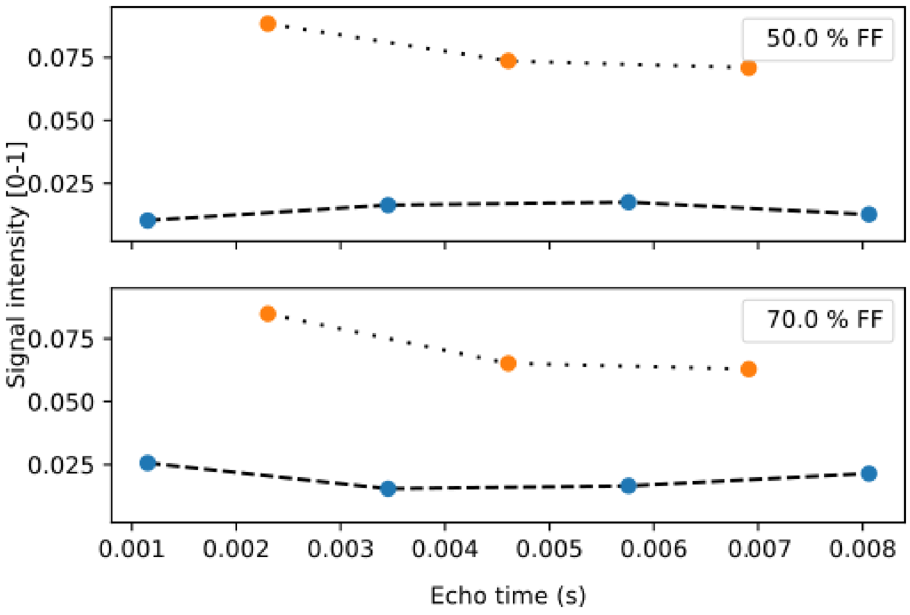


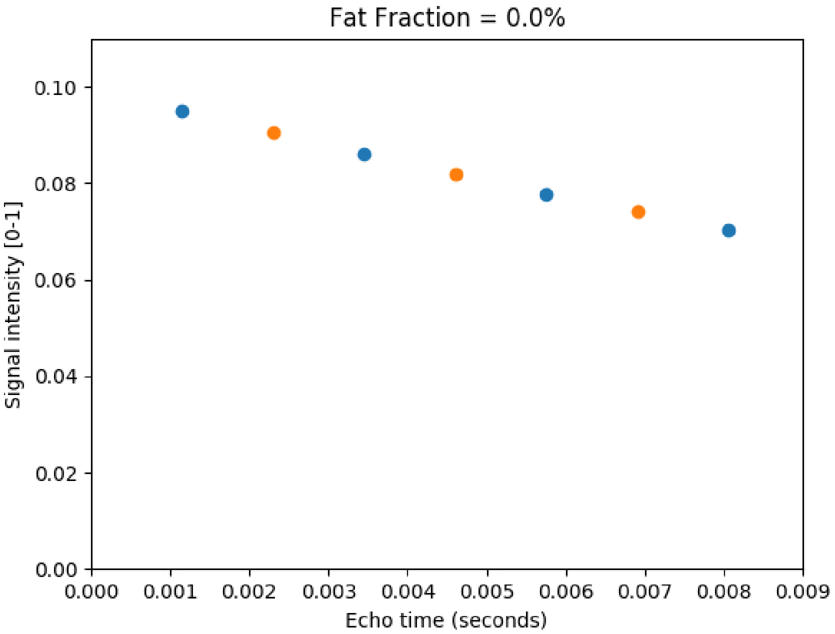

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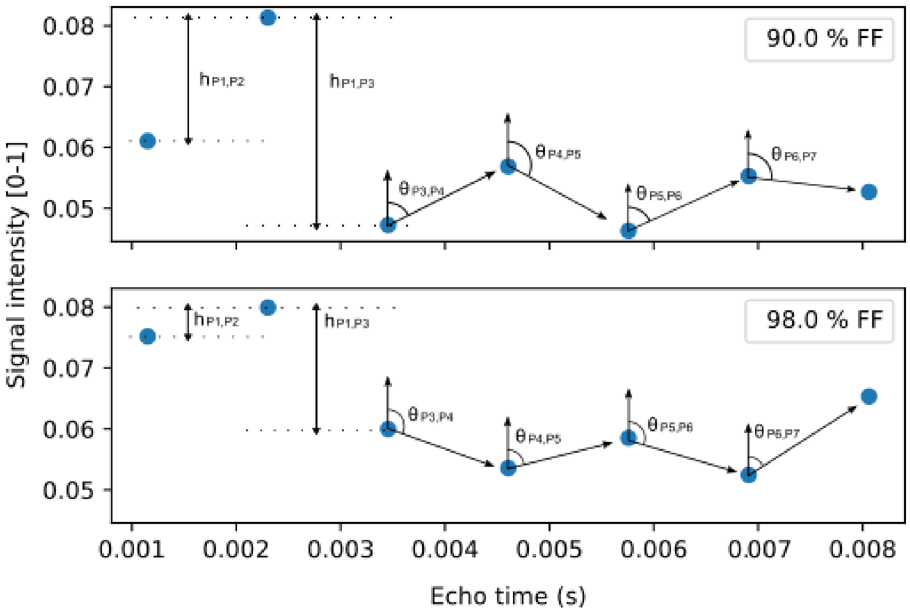


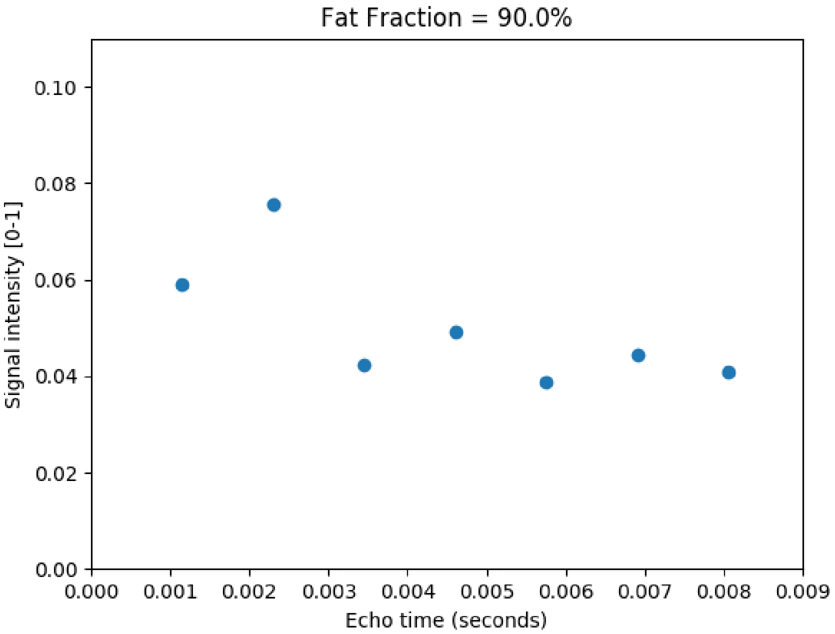

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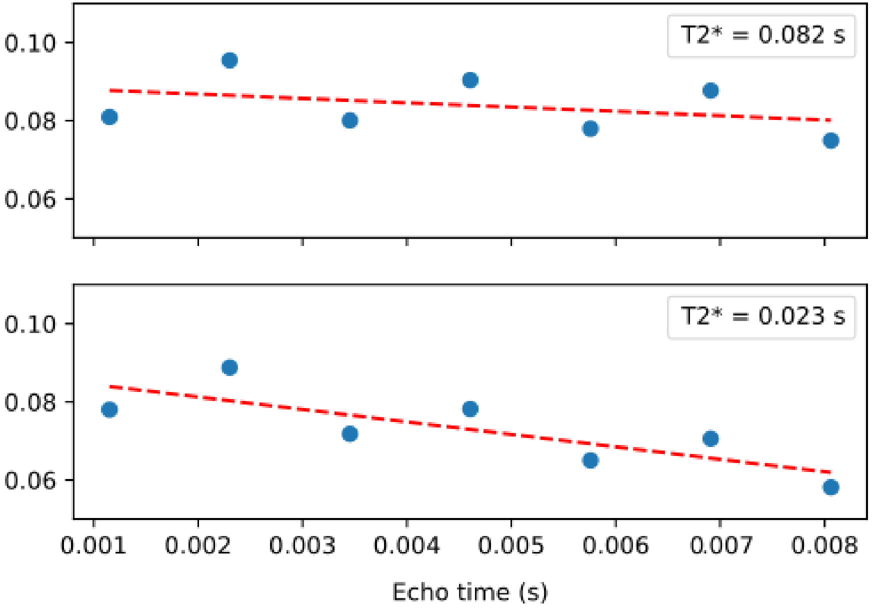
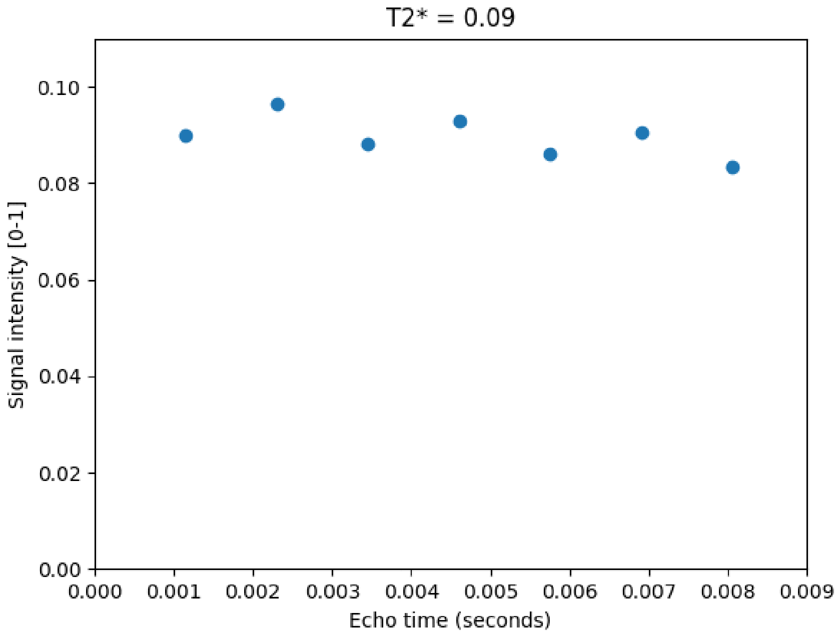
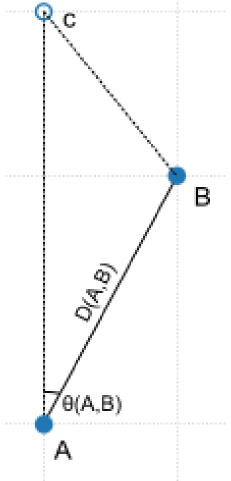
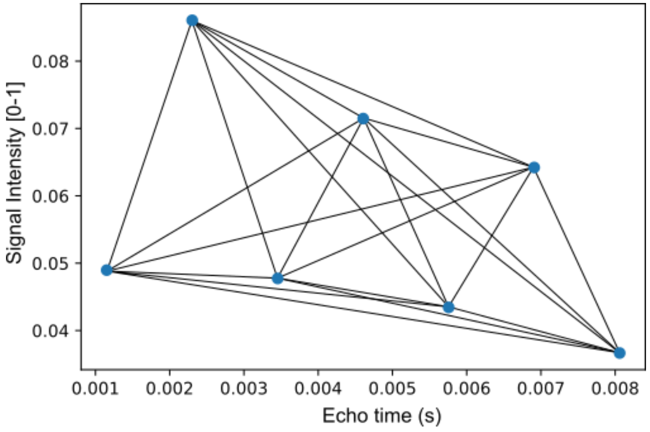
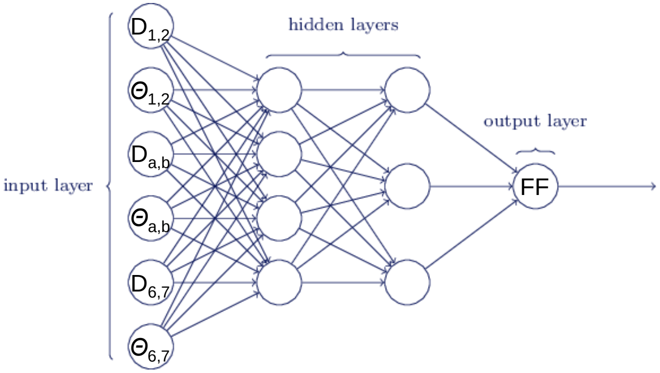


# Signal Descriptor and Network Training




21 Distances + 21 Angles = 42 features per instance

Input layer = $[D_{1,2}, \theta_{1,2}, ..., D_{6,7}, \theta_{6,7}]$
3 hidden layers (32, 16, 2)
Output layer = Fat fraction

# Signal Descriptor and Network Training

**Training:**
- 100 000 instances
- FF linearly distributed (1000 values each)
- Variable SNR (200 – 25)

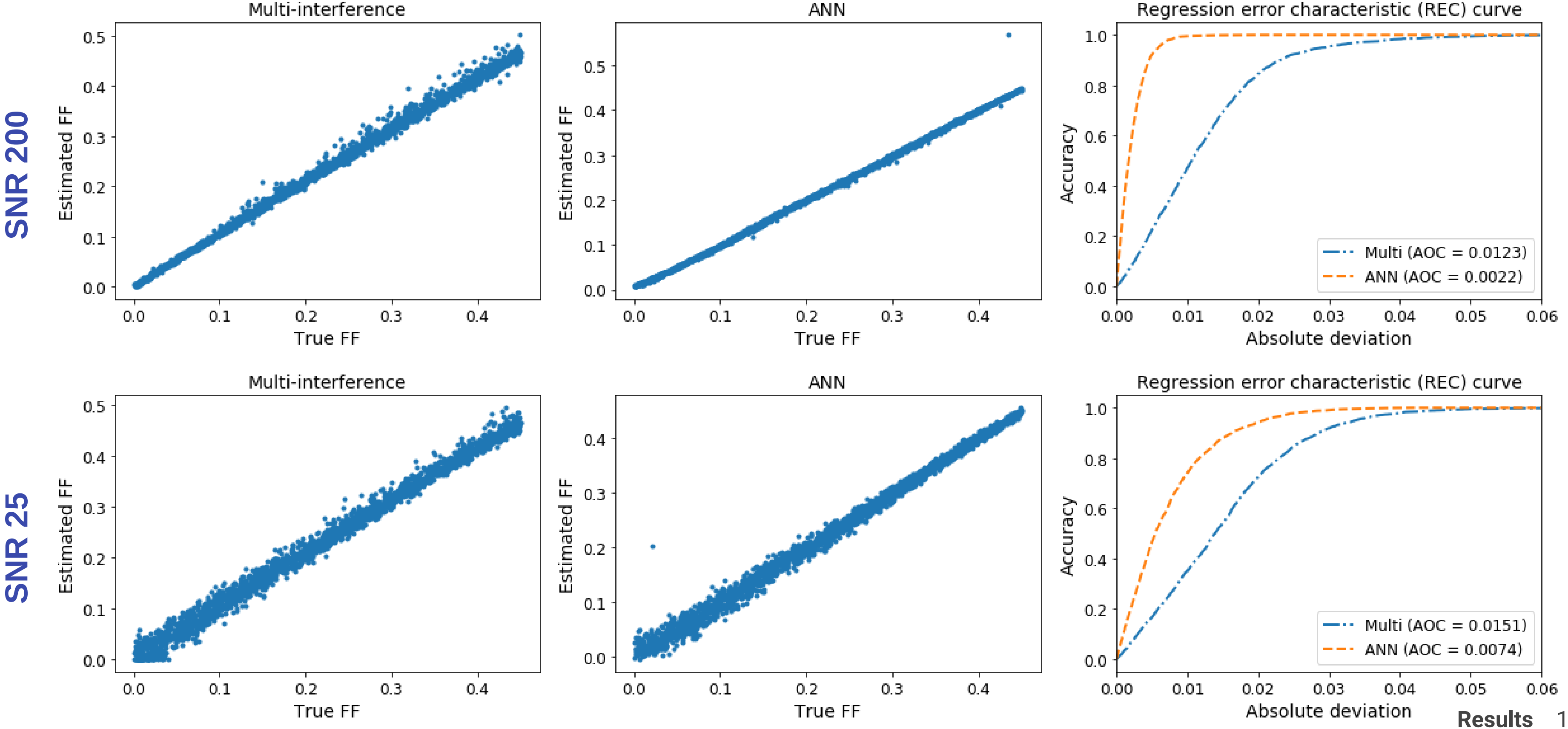
**Validating:**
- 20 000 instances
- FF uniformly distributed (unique)
- Variable SNR (200 – 25)

**Testing:**
- 10 000 instances
- FF uniformly distributed (unique)
- Fixed SNR (200, 100, 50, or 25)

All models described using 6 fat moieties + water [2]
each with variable T2* in Gaussian distributions according to literature

[2] G. Hamilton *et al.* "In vivo characterization of liver fat 1H MR spectrum", *NMR in Biomedicine*, vol 24, no. 7, pp 784-90, 8 2011

# Results – 0-45% FF



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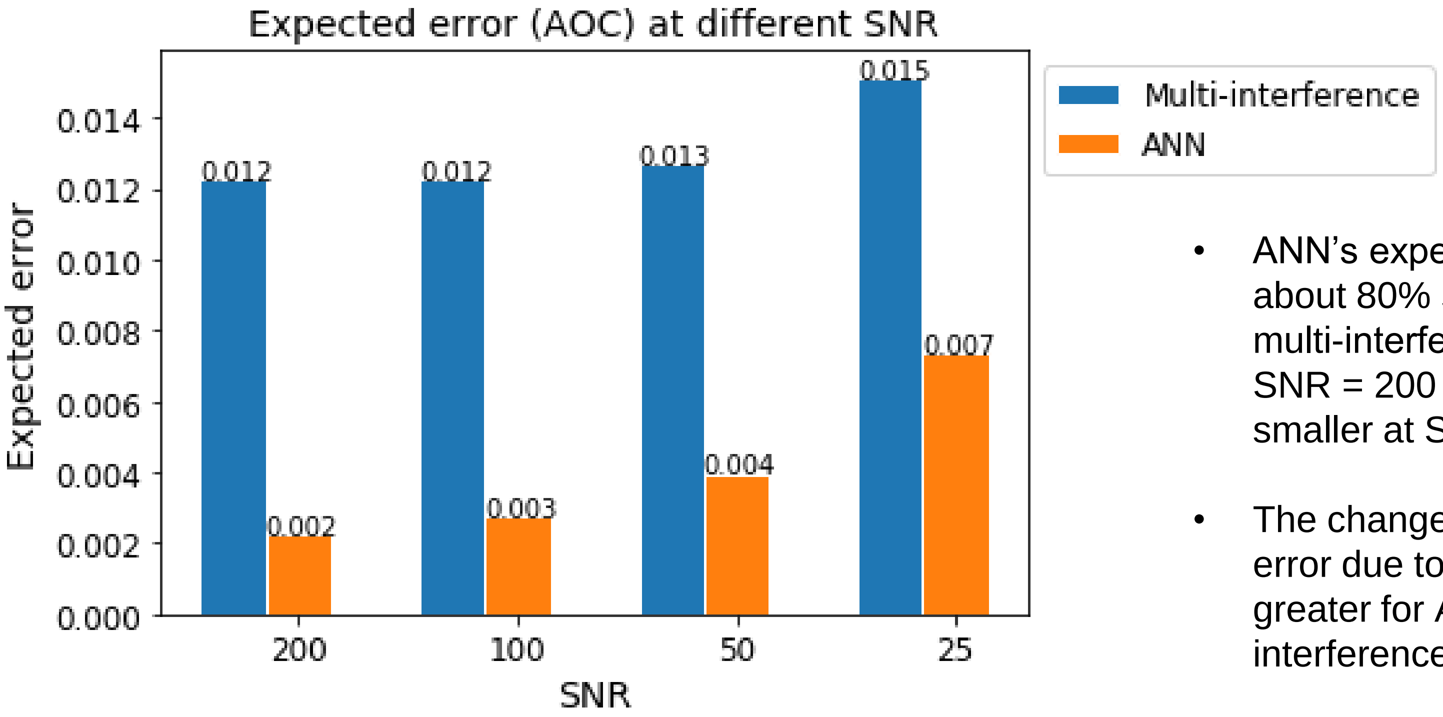
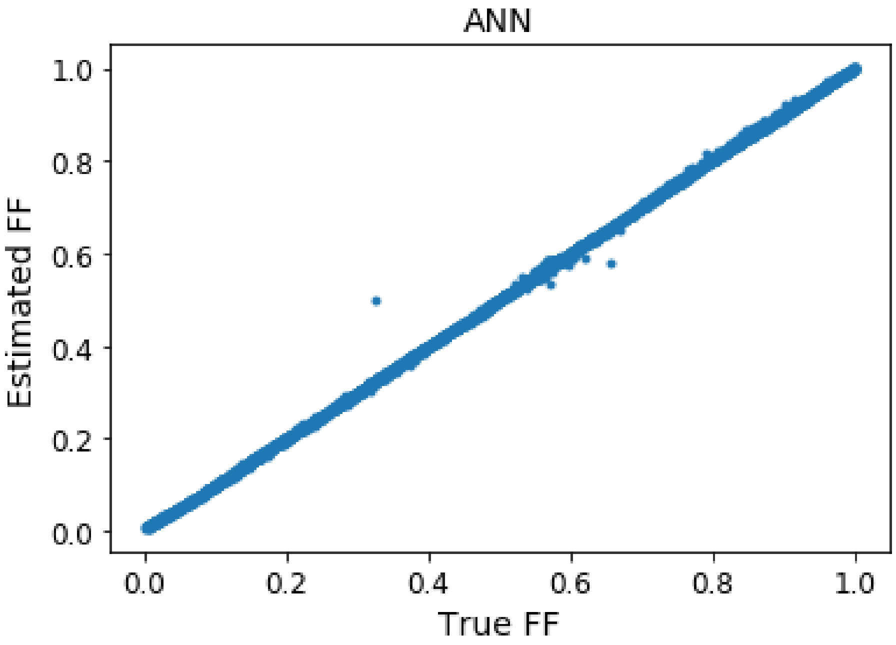


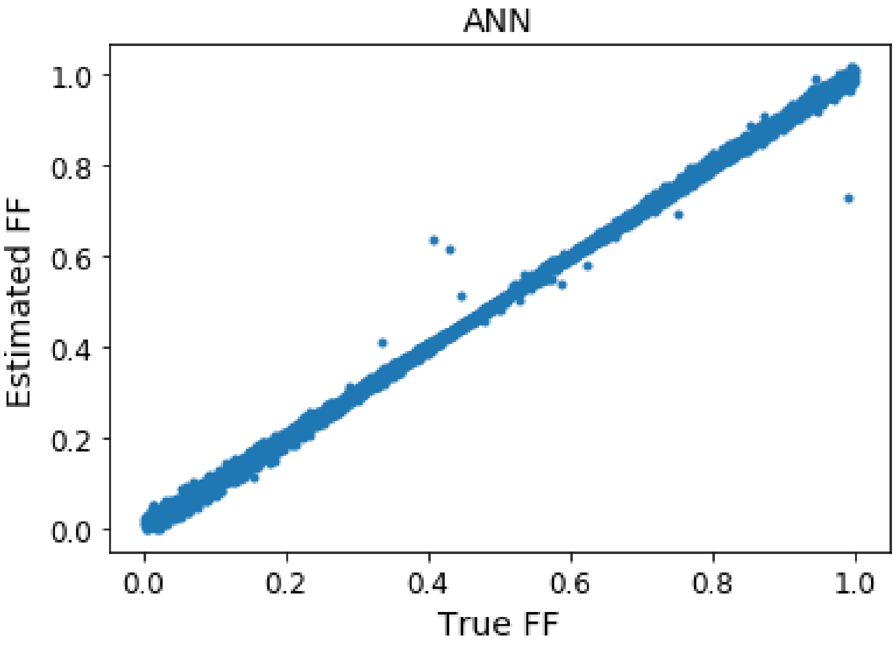

- ANN’s expected error is about 80% smaller than multi-interference’s at SNR = 200 and 50% smaller at SNR = 25.
- The change in expected error due to SNR is greater for ANN; multi-interference is steadier.

# Results – 0-100% FF

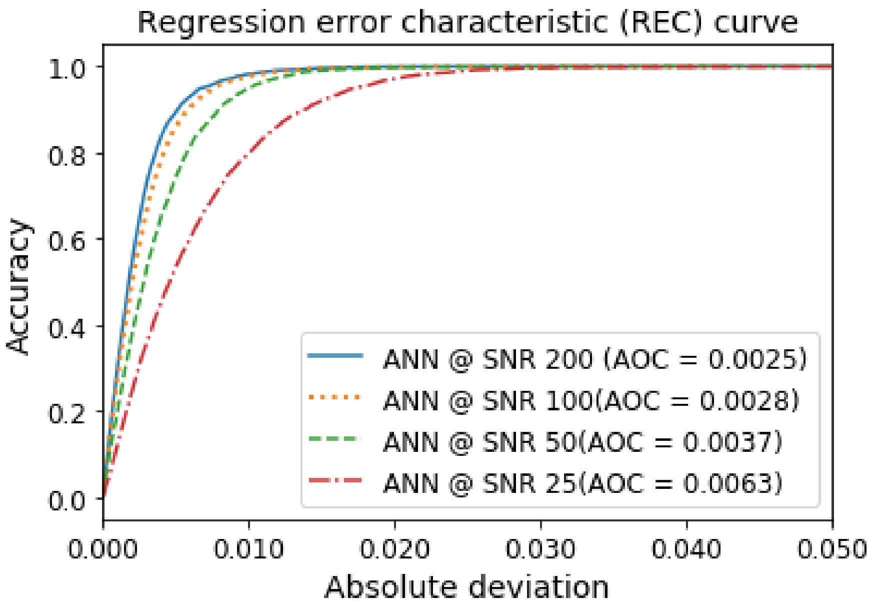
**SNR 200**

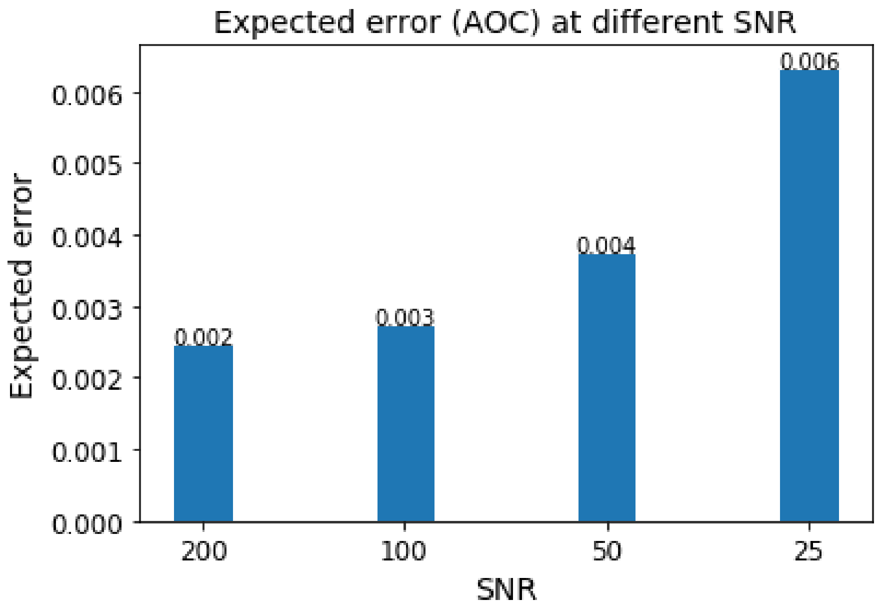



**SNR 25**



# Results – ANN 0-100% FF




- ANN's expected error is about the same for half-range or full-range estimation at each SNR.
- There are few outliers which relevance must be investigated with *in vivo* data

# Conclusion

- New path for liver fat estimation;
- Simulation results better than current literature;
- No need for changes in acquisition sequence;
- **Future perspective:**
    - *In vivo* validation
    - Applicability in other tissues
    - Better machine learning

# Thank you!

**Conflict of interest**
The authors have no conflict of interest to declare.

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